PyTorch-Lightning Documentation

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William Falcon et al.

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START HERE

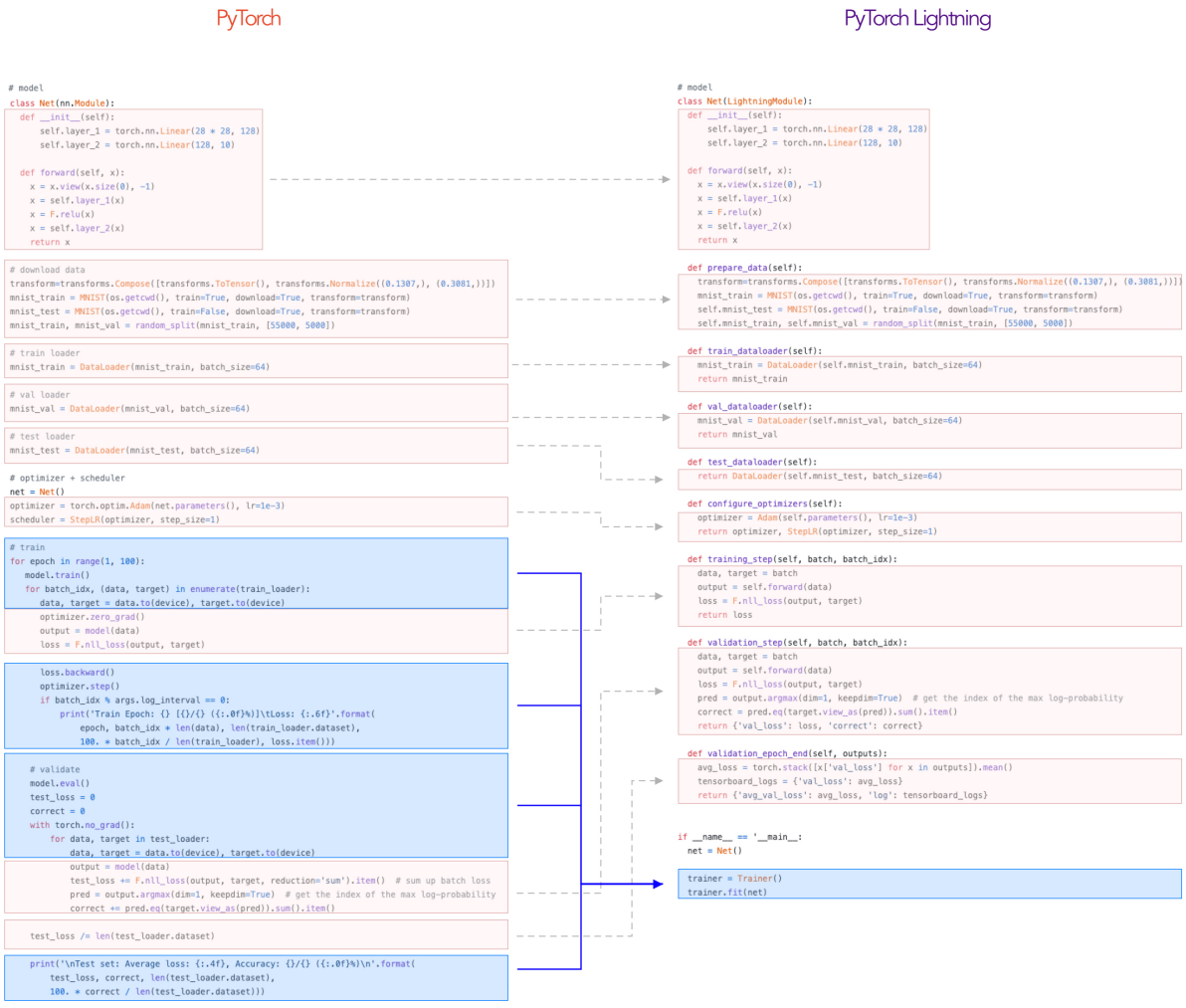
CHAPTER

ONE

QUICK START

PyTorch Lightning is nothing more than organized PyTorch code. Once you've organized it into a LightningModule, it automates most of the training for you.

To illustrate, here's the typical PyTorch project structure organized in a LightningModule.



1.1 Step 1: Define a LightningModule

```
import os

import torch
from torch.nn import functional as F
from torch.utils.data import DataLoader
from torchvision.datasets import MNIST
from torchvision import transforms
from pytorch_lightning.core.lightning import LightningModule

class LitModel(LightningModule):

    def __init__(self):
        super().__init__()
        self.l1 = torch.nn.Linear(28 * 28, 10)

    def forward(self, x):
        return torch.relu(self.l1(x.view(x.size(0), -1)))

    def training_step(self, batch, batch_idx):
        x, y = batch
        y_hat = self(x)
        loss = F.cross_entropy(y_hat, y)
        tensorboard_logs = {'train_loss': loss}
        return {'loss': loss, 'log': tensorboard_logs}

    def configure_optimizers(self):
        return torch.optim.Adam(self.parameters(), lr=0.001)

    def train_dataloader(self):
        dataset = MNIST(os.getcwd(), train=True, download=True, transform=transforms.
↪ToTensor())
        loader = DataLoader(dataset, batch_size=32, num_workers=4, shuffle=True)
        return loader
```

1.2 Step 2: Fit with a Trainer

```
from pytorch_lightning import Trainer

model = LitModel()

# most basic trainer, uses good defaults
trainer = Trainer(gpus=8, num_nodes=1)
trainer.fit(model)
```

Under the hood, lightning does (in high-level pseudocode):

```
model = LitModel()
train_dataloader = model.train_dataloader()
optimizer = model.configure_optimizers()

for epoch in epochs:
    train_outs = []
```

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```
    for batch in train_dataloader:
        loss = model.training_step(batch)
        loss.backward()
        train_outs.append(loss.detach())

        optimizer.step()
        optimizer.zero_grad()

    # optional for logging, etc...
    model.training_epoch_end(train_outs)
```

1.3 Validation loop

To also add a validation loop add the following functions

```
class LitModel(LightningModule):

    def validation_step(self, batch, batch_idx):
        x, y = batch
        y_hat = self(x)
        return {'val_loss': F.cross_entropy(y_hat, y)}

    def validation_epoch_end(self, outputs):
        avg_loss = torch.stack([x['val_loss'] for x in outputs]).mean()
        tensorboard_logs = {'val_loss': avg_loss}
        return {'val_loss': avg_loss, 'log': tensorboard_logs}

    def val_dataloader(self):
        # TODO: do a real train/val split
        dataset = MNIST(os.getcwd(), train=False, download=True, transform=transforms.
↪ToTensor())
        loader = DataLoader(dataset, batch_size=32, num_workers=4)
        return loader
```

And now the trainer will call the validation loop automatically

```
# most basic trainer, uses good defaults
trainer = Trainer(gpus=8, num_nodes=1)
trainer.fit(model)
```

Under the hood in pseudocode, lightning does the following:

```
# ...
for batch in train_dataloader:
    loss = model.training_step()
    loss.backward()
    # ...

    if validate_at_some_point:
        model.eval()
        val_outs = []
        for val_batch in model.val_dataloader:
            val_out = model.validation_step(val_batch)
            val_outs.append(val_out)
```

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```
        model.validation_epoch_end(val_outs)
        model.train()
```

The beauty of Lightning is that it handles the details of when to validate, when to call .eval(), turning off gradients, detaching graphs, making sure you don't enable shuffle for val, etc...

Note: Lightning removes all the million details you need to remember during research

1.4 Test loop

You might also need a test loop

```
class LitModel(LightningModule):

    def test_step(self, batch, batch_idx):
        x, y = batch
        y_hat = self(x)
        return {'test_loss': F.cross_entropy(y_hat, y)}

    def test_epoch_end(self, outputs):
        avg_loss = torch.stack([x['test_loss'] for x in outputs]).mean()
        tensorboard_logs = {'test_loss': avg_loss}
        return {'avg_test_loss': avg_loss, 'log': tensorboard_logs}

    def test_dataloader(self):
        # TODO: do a real train/val split
        dataset = MNIST(os.getcwd(), train=False, download=True, transform=transforms.
↪ToTensor())
        loader = DataLoader(dataset, batch_size=32, num_workers=4)
        return loader
```

However, this time you need to specifically call test (this is done so you don't use the test set by mistake)

```
# OPTION 1:
# test after fit
trainer.fit(model)
trainer.test()

# OPTION 2:
# test after loading weights
model = LitModel.load_from_checkpoint(PATH)
trainer = Trainer(num_tpu_cores=1)
trainer.test()
```

Again, under the hood, lightning does the following in (pseudocode):

```
model.eval()
test_outs = []
for test_batch in model.test_dataloader:
    test_out = model.test_step(val_batch)
    test_outs.append(test_out)
```

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```
model.test_epoch_end(test_outs)
```

1.5 Datasets

If you don't want to define the datasets as part of the LightningModule, just pass them into fit instead.

```
# pass in datasets if you want.
train_dataloader = DataLoader(dataset, batch_size=32, num_workers=4)
val_dataloader, test_dataloader = ...

trainer = Trainer(gpus=8, num_nodes=1)
trainer.fit(model, train_dataloader, val_dataloader)

trainer.test(test_dataloader=test_dataloader)
```

The advantage of this method is the ability to reuse models for different datasets. The disadvantage is that for research it makes readability and reproducibility more difficult. This is why we recommend to define the datasets in the LightningModule if you're doing research, but use the method above for production models or for prediction tasks.

1.6 Why do you need Lightning?

Notice the code above has nothing about .cuda() or 16-bit or early stopping or logging, etc... This is where Lightning adds a ton of value.

Without changing a SINGLE line of your code, you can now do the following with the above code

```
# train on TPUs using 16 bit precision with early stopping
# using only half the training data and checking validation every quarter of a␣
↪training epoch
trainer = Trainer(
    nb_tpu_cores=8,
    precision=16,
    early_stop_checkpoint=True,
    train_percent_check=0.5,
    val_check_interval=0.25
)

# train on 256 GPUs
trainer = Trainer(
    gpus=8,
    num_nodes=32
)

# train on 1024 CPUs across 128 machines
trainer = Trainer(
    num_processes=8,
    num_nodes=128
)
```

And the best part is that your code is STILL just PyTorch... meaning you can do anything you would normally do.

```
model = LitModel()
model.eval()

y_hat = model(x)

model.anything_you_can_do_with_pytorch()
```

1.7 Summary

In short, by refactoring your PyTorch code:

1. You STILL keep pure PyTorch.
2. You DON't lose any flexibility.
3. You can get rid of all of your boilerplate.
4. You make your code generalizable to any hardware.
5. Your code is now readable and easier to reproduce (ie: you help with the reproducibility crisis).
6. Your LightningModule is still just a pure PyTorch module.

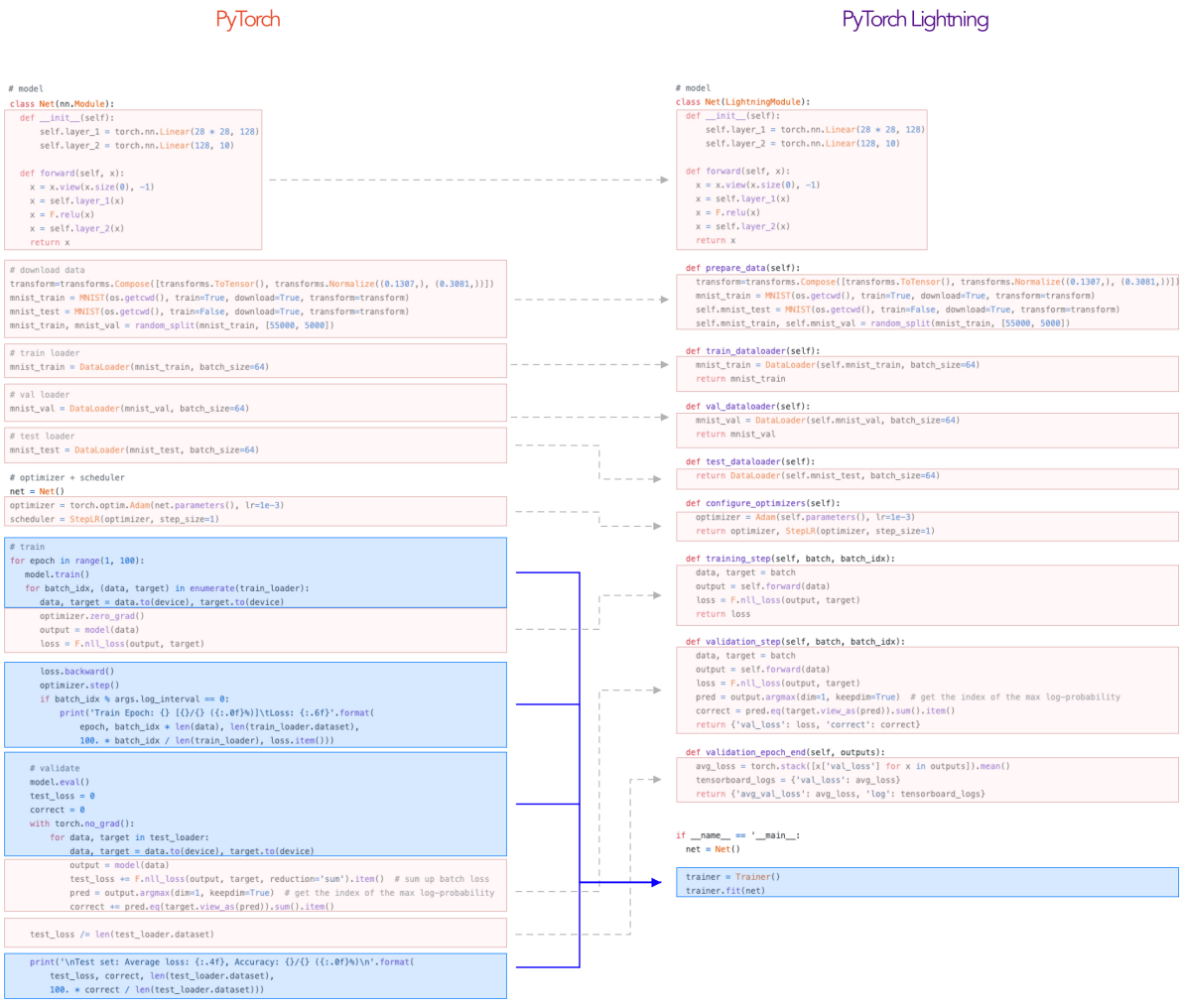
CHAPTER

TWO

INTRODUCTION GUIDE

PyTorch Lightning provides a very simple template for organizing your PyTorch code. Once you've organized it into a LightningModule, it automates most of the training for you.

To illustrate, here's the typical PyTorch project structure organized in a LightningModule.



As your project grows in complexity with things like 16-bit precision, distributed training, etc… the part in blue quickly becomes onerous and starts distracting from the core research code.

2.1 Goal of this guide

This guide walks through the major parts of the library to help you understand what each parts does. But at the end of the day, you write the same PyTorch code... just organize it into the LightningModule template which means you keep ALL the flexibility without having to deal with any of the boilerplate code

To show how Lightning works, we'll start with an MNIST classifier. We'll end showing how to use inheritance to very quickly create an AutoEncoder.

Note: Any DL/ML PyTorch project fits into the Lightning structure. Here we just focus on 3 types of research to illustrate.

2.2 Installing Lightning

Lightning is trivial to install.

```
conda activate my_env
pip install pytorch-lightning
```

Or without conda environments, anywhere you can use pip.

```
pip install pytorch-lightning
```

2.3 Lightning Philosophy

Lightning factors DL/ML code into three types:

- Research code
- Engineering code
- Non-essential code

2.3.1 Research code

In the MNIST generation example, the research code would be the particular system and how it's trained (ie: A GAN or VAE). In Lightning, this code is abstracted out by the *LightningModule*.

```
l1 = nn.Linear(...)
l2 = nn.Linear(...)
decoder = Decoder()

x1 = l1(x)
x2 = l2(x2)
out = decoder(features, x)

loss = perceptual_loss(x1, x2, x) + CE(out, x)
```

2.3.2 Engineering code

The Engineering code is all the code related to training this system. Things such as early stopping, distribution over GPUs, 16-bit precision, etc. This is normally code that is THE SAME across most projects.

In Lightning, this code is abstracted out by the *Trainer*.

```
model.cuda(0)
x = x.cuda(0)

distributed = DistributedParallel(model)

with gpu_zero:
    download_data()

dist.barrier()
```

2.3.3 Non-essential code

This is code that helps the research but isn't relevant to the research code. Some examples might be: 1. Inspect gradients 2. Log to tensorboard.

In Lightning this code is abstracted out by *Callbacks*.

```
# log samples
z = Q.rsample()
generated = decoder(z)
self.experiment.log('images', generated)
```

2.4 Elements of a research project

Every research project requires the same core ingredients:

1. A model
2. Train/val/test data
3. Optimizer(s)
4. Training step computations
5. Validation step computations
6. Test step computations

2.4.1 The Model

The LightningModule provides the structure on how to organize these 5 ingredients.

Let's first start with the model. In this case we'll design a 3-layer neural network.

```
import torch
from torch.nn import functional as F
from torch import nn
from pytorch_lightning.core.lightning import LightningModule

class LitMNIST(LightningModule):

  def __init__(self):
    super().__init__()

    # mnist images are (1, 28, 28) (channels, width, height)
    self.layer_1 = torch.nn.Linear(28 * 28, 128)
    self.layer_2 = torch.nn.Linear(128, 256)
    self.layer_3 = torch.nn.Linear(256, 10)

  def forward(self, x):
    batch_size, channels, width, height = x.size()

    # (b, 1, 28, 28) -> (b, 1*28*28)
    x = x.view(batch_size, -1)

    # layer 1
    x = self.layer_1(x)
    x = torch.relu(x)

    # layer 2
    x = self.layer_2(x)
    x = torch.relu(x)

    # layer 3
    x = self.layer_3(x)

    # probability distribution over labels
    x = torch.log_softmax(x, dim=1)

    return x
```

Notice this is a *LightningModule* instead of a *torch.nn.Module*. A LightningModule is equivalent to a PyTorch Module except it has added functionality. However, you can use it EXACTLY the same as you would a PyTorch Module.

```
net = LitMNIST()
x = torch.Tensor(1, 1, 28, 28)
out = net(x)
```

Out:

```
torch.Size([1, 10])
```

2.4.2 Data

The Lightning Module organizes your dataloaders and data processing as well. Here's the PyTorch code for loading MNIST

```
from torch.utils.data import DataLoader, random_split
from torchvision.datasets import MNIST
import os
from torchvision import datasets, transforms

# transforms
# prepare transforms standard to MNIST
transform=transforms.Compose([transforms.ToTensor(),
                              transforms.Normalize((0.1307,), (0.3081,))])

# data
mnist_train = MNIST(os.getcwd(), train=True, download=True)
mnist_train = DataLoader(mnist_train, batch_size=64)
```

When using PyTorch Lightning, we use the exact same code except we organize it into the LightningModule

```
from torch.utils.data import DataLoader, random_split
from torchvision.datasets import MNIST
import os
from torchvision import datasets, transforms

class LitMNIST(LightningModule):

    def train_dataloader(self):
        transform=transforms.Compose([transforms.ToTensor(),
                                      transforms.Normalize((0.1307,), (0.3081,))])
        mnist_train = MNIST(os.getcwd(), train=True, download=False,
                            transform=transform)
        return DataLoader(mnist_train, batch_size=64)
```

Notice the code is exactly the same, except now the training dataloading has been organized by the LightningModule under the *train_dataloader* method. This is great because if you run into a project that uses Lightning and want to figure out how they prepare their training data you can just look in the *train_dataloader* method.

Usually though, we want to separate the things that write to disk in data-processing from things like transforms which happen in memory.

```
class LitMNIST(LightningModule):

    def prepare_data(self):
        # download only
        MNIST(os.getcwd(), train=True, download=True)

    def train_dataloader(self):
        # no download, just transform
        transform=transforms.Compose([transforms.ToTensor(),
                                      transforms.Normalize((0.1307,), (0.3081,))])
        mnist_train = MNIST(os.getcwd(), train=True, download=False,
                            transform=transform)
        return DataLoader(mnist_train, batch_size=64)
```

Doing it in the *prepare_data* method ensures that when you have multiple GPUs you won't overwrite the data. This is a contrived example but it gets more complicated with things like NLP or Imagenet.

In general fill these methods with the following:

```
class LitMNIST(LightningModule):

    def prepare_data(self):
        # stuff here is done once at the very beginning of training
        # before any distributed training starts

        # download stuff
        # save to disk
        # etc...
        ...

    def train_dataloader(self):
        # data transforms
        # dataset creation
        # return a DataLoader
        ...
```

2.4.3 Optimizer

Next we choose what optimizer to use for training our system. In PyTorch we do it as follows:

```
from torch.optim import Adam
optimizer = Adam(LitMNIST().parameters(), lr=1e-3)
```

In Lightning we do the same but organize it under the configure_optimizers method.

```
class LitMNIST(LightningModule):

    def configure_optimizers(self):
        return Adam(self.parameters(), lr=1e-3)
```

Note: The LightningModule itself has the parameters, so pass in self.parameters()

However, if you have multiple optimizers use the matching parameters

```
class LitMNIST(LightningModule):

    def configure_optimizers(self):
        return Adam(self.generator(), lr=1e-3), Adam(self.discriminator(), lr=1e-3)
```

2.4.4 Training step

The training step is what happens inside the training loop.

```
for epoch in epochs:
    for batch in data:
        # TRAINING STEP
        # ....
        # TRAINING STEP
        loss.backward()
```

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```
        optimizer.step()
        optimizer.zero_grad()
```

In the case of MNIST we do the following

```
for epoch in epochs:
    for batch in data:
        # TRAINING STEP START
        x, y = batch
        logits = model(x)
        loss = F.nll_loss(logits, y)
        # TRAINING STEP END

        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
```

In Lightning, everything that is in the training step gets organized under the *training_step* function in the LightningModule

```
class LitMNIST(LightningModule):

    def training_step(self, batch, batch_idx):
        x, y = batch
        logits = self(x)
        loss = F.nll_loss(logits, y)
        return {'loss': loss}
        # return loss (also works)
```

Again, this is the same PyTorch code except that it has been organized by the LightningModule. This code is not restricted which means it can be as complicated as a full seq-2-seq, RL loop, GAN, etc...

2.5 Training

So far we defined 4 key ingredients in pure PyTorch but organized the code inside the LightningModule.

1. Model.
2. Training data.
3. Optimizer.
4. What happens in the training loop.

For clarity, we'll recall that the full LightningModule now looks like this.

```
class LitMNIST(LightningModule):
    def __init__(self):
        super().__init__()
        self.layer_1 = torch.nn.Linear(28 * 28, 128)
        self.layer_2 = torch.nn.Linear(128, 256)
        self.layer_3 = torch.nn.Linear(256, 10)

    def forward(self, x):
```

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```
        batch_size, channels, width, height = x.size()
        x = x.view(batch_size, -1)
        x = self.layer_1(x)
        x = torch.relu(x)
        x = self.layer_2(x)
        x = torch.relu(x)
        x = self.layer_3(x)
        x = torch.log_softmax(x, dim=1)
        return x

    def train_dataloader(self):
        transform=transforms.Compose([transforms.ToTensor(),
                                      transforms.Normalize((0.1307,), (0.3081,))])
        mnist_train = MNIST(os.getcwd(), train=True, download=False,␣
↪transform=transform)
        return DataLoader(mnist_train, batch_size=64)

    def configure_optimizers(self):
        return Adam(self.parameters(), lr=1e-3)

    def training_step(self, batch, batch_idx):
        x, y = batch
        logits = self(x)
        loss = F.nll_loss(logits, y)

        # add logging
        logs = {'loss': loss}
        return {'loss': loss, 'log': logs}
```

Again, this is the same PyTorch code, except that it's organized by the LightningModule. This organization now lets us train this model

2.5.1 Train on CPU

```
from pytorch_lightning import Trainer

model = LitMNIST()
trainer = Trainer()
trainer.fit(model)
```

You should see the following weights summary and progress bar

```
  | Name    | Type   | Params
------------------------------
0 | layer_1 | Linear | 100 K
1 | layer_2 | Linear | 33 K
2 | layer_3 | Linear | 2 K
Epoch 1: 27% 250/938 [00:08<00:22, 30.10it/s, loss=0.353, v_num=2]
```

2.5.2 Logging

When we added the *log* key in the return dictionary it went into the built in tensorboard logger. But you could have also logged by calling:

```
def training_step(self, batch, batch_idx):
    # ...
    loss = ...
    self.logger.summary.scalar('loss', loss)
```

Which will generate automatic tensorboard logs.

```
[31] # Start tensorboard.
     %load_ext tensorboard
     %tensorboard --logdir lightning_logs/
```

```
The tensorboard extension is already loaded. To reload it, use:
  %reload_ext tensorboard
```

But you can also use any of the *number of other loggers* we support.

2.5.3 GPU training

But the beauty is all the magic you can do with the trainer flags. For instance, to run this model on a GPU:

```
model = LitMNIST()
trainer = Trainer(gpus=1)
trainer.fit(model)
```

```
INFO:root:GPU available: True, used: True
INFO:root:VISIBLE GPUS: 0
INFO:root:
  | Name    | Type   | Params
------------------------------
0 | layer_1 | Linear | 100 K
1 | layer_2 | Linear | 33 K
2 | layer_3 | Linear | 2 K
Epoch 1: 53% 500/938 [00:07<00:07, 61.53it/s, loss=0.206, v_num=3]
```

2.5.4 Multi-GPU training

Or you can also train on multiple GPUs.

```
model = LitMNIST()
trainer = Trainer(gpus=8)
trainer.fit(model)
```

Or multiple nodes

```
# (32 GPUs)
model = LitMNIST()
trainer = Trainer(gpus=8, num_nodes=4, distributed_backend='ddp')
trainer.fit(model)
```

Refer to the *distributed computing guide for more details*.

2.5.5 TPUs

Did you know you can use PyTorch on TPUs? It's very hard to do, but we've worked with the xla team to use their awesome library to get this to work out of the box!

Let's train on Colab (full demo available here)

First, change the runtime to TPU (and reinstall lightning).

Next, install the required xla library (adds support for PyTorch on TPUs)

```
import collections
from datetime import datetime, timedelta
import os
import requests
import threading

_VersionConfig = collections.namedtuple('_VersionConfig', 'wheels,server')
VERSION = "torch_xla==nightly"  #@param ["xrt==1.15.0", "torch_xla==nightly"]
CONFIG = {
    'xrt==1.15.0': _VersionConfig('1.15', '1.15.0'),
    'torch_xla==nightly': _VersionConfig('nightly', 'XRT-dev{}'.format(
```

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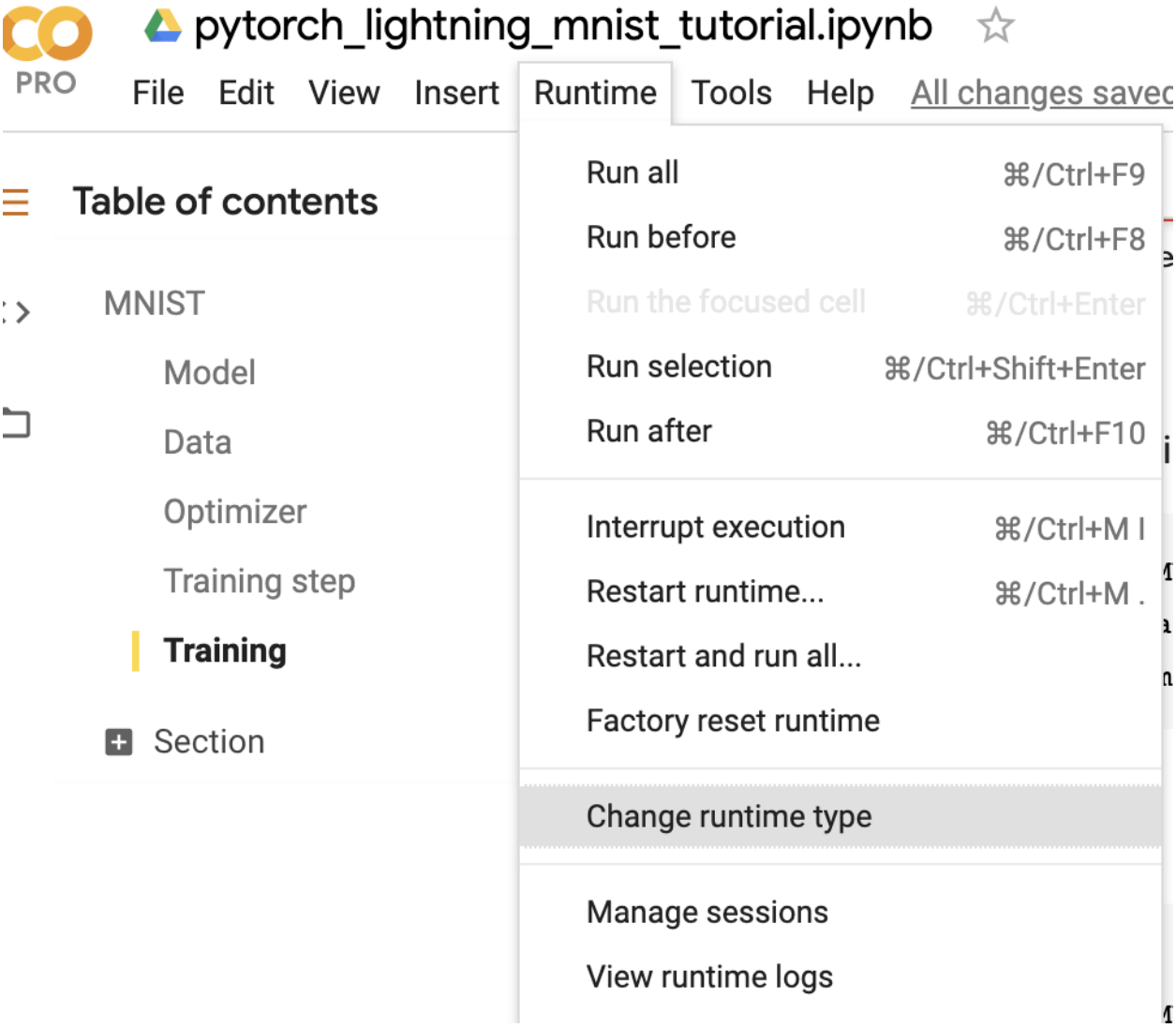
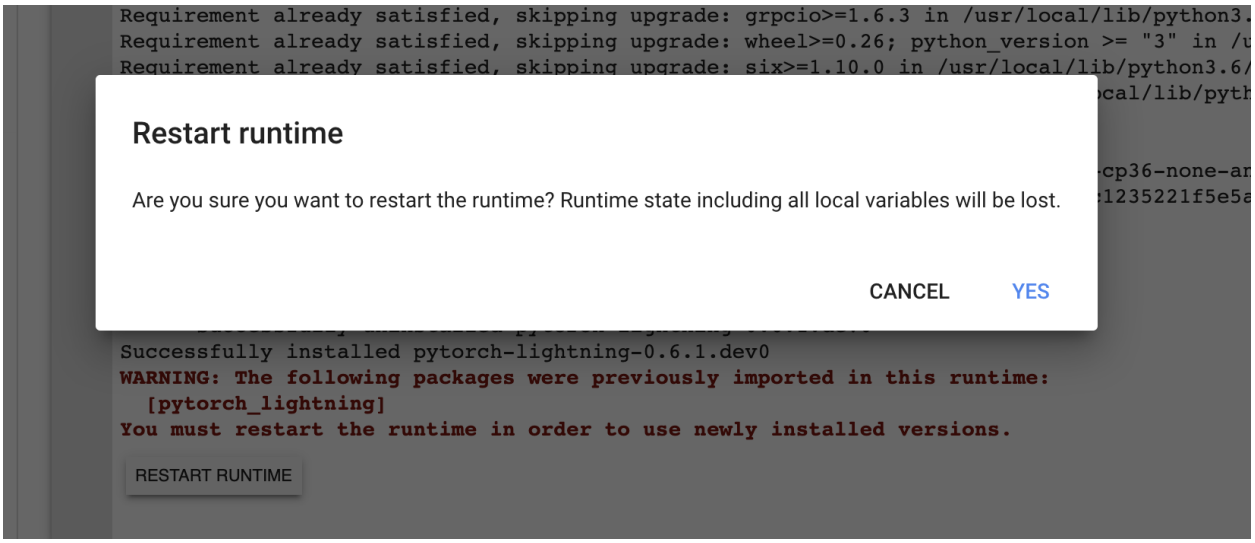

pytorch_lightning_mnist_tutorial.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Table of contents
MNIST
Model
Data
Optimizer
Training step
Training
Section
Run all ⌘/Ctrl+F9
Run before ⌘/Ctrl+F8
Run the focused cell ⌘/Ctrl+Enter
Run selection ⌘/Ctrl+Shift+Enter
Run after ⌘/Ctrl+F10
Interrupt execution ⌘/Ctrl+M I
Restart runtime... ⌘/Ctrl+M .
Restart and run all...
Factory reset runtime
Change runtime type
Manage sessions
View runtime logs


Restart runtime
Are you sure you want to restart the runtime? Runtime state including all local variables will be lost.
CANCEL
YES
Successfully installed pytorch-lightning-0.6.1.dev0
WARNING: The following packages were previously imported in this runtime:
[pytorch_lightning]
You must restart the runtime in order to use newly installed versions.
RESTART RUNTIME

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```
        (datetime.today() - timedelta(1)).strftime('%Y%m%d'))),
}[VERSION]
DIST_BUCKET = 'gs://tpu-pytorch/wheels'
TORCH_WHEEL = 'torch-{}-cp36-cp36m-linux_x86_64.whl'.format(CONFIG.wheels)
TORCH_XLA_WHEEL = 'torch_xla-{}-cp36-cp36m-linux_x86_64.whl'.format(CONFIG.wheels)
TORCHVISION_WHEEL = 'torchvision-{}-cp36-cp36m-linux_x86_64.whl'.format(CONFIG.wheels)

# Update TPU XRT version
def update_server_xrt():
  print('Updating server-side XRT to {} ...'.format(CONFIG.server))
  url = 'http://{TPU_ADDRESS}:8475/requestversion/{XRT_VERSION}'.format(
      TPU_ADDRESS=os.environ['COLAB_TPU_ADDR'].split(':')[0],
      XRT_VERSION=CONFIG.server,
  )
  print('Done updating server-side XRT: {}'.format(requests.post(url)))

update = threading.Thread(target=update_server_xrt)
update.start()
```

```
# Install Colab TPU compat PyTorch/TPU wheels and dependencies
!pip uninstall -y torch torchvision
!gsutil cp "$DIST_BUCKET/$TORCH_WHEEL" .
!gsutil cp "$DIST_BUCKET/$TORCH_XLA_WHEEL" .
!gsutil cp "$DIST_BUCKET/$TORCHVISION_WHEEL" .
!pip install "$TORCH_WHEEL"
!pip install "$TORCH_XLA_WHEEL"
!pip install "$TORCHVISION_WHEEL"
!sudo apt-get install libomp5
update.join()
```

In distributed training (multiple GPUs and multiple TPU cores) each GPU or TPU core will run a copy of this program. This means that without taking any care you will download the dataset N times which will cause all sorts of issues.

To solve this problem, move the download code to the *prepare_data* method in the LightningModule. In this method we do all the preparation we need to do once (instead of on every gpu).

```
class LitMNIST(LightningModule):
    def prepare_data(self):
        # transform
        transform=transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
↪1307,), (0.3081,))])

        # download
        mnist_train = MNIST(os.getcwd(), train=True, download=True,␣
↪transform=transform)
        mnist_test = MNIST(os.getcwd(), train=False, download=True,␣
↪transform=transform)

        # train/val split
        mnist_train, mnist_val = random_split(mnist_train, [55000, 5000])

        # assign to use in dataloaders
        self.train_dataset = mnist_train
        self.val_dataset = mnist_val
        self.test_dataset = mnist_test
```

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```
    def train_dataloader(self):
        return DataLoader(self.train_dataset, batch_size=64)

    def val_dataloader(self):
        return DataLoader(self.val_dataset, batch_size=64)

    def test_dataloader(self):
        return DataLoader(self.test_dataset, batch_size=64)
```

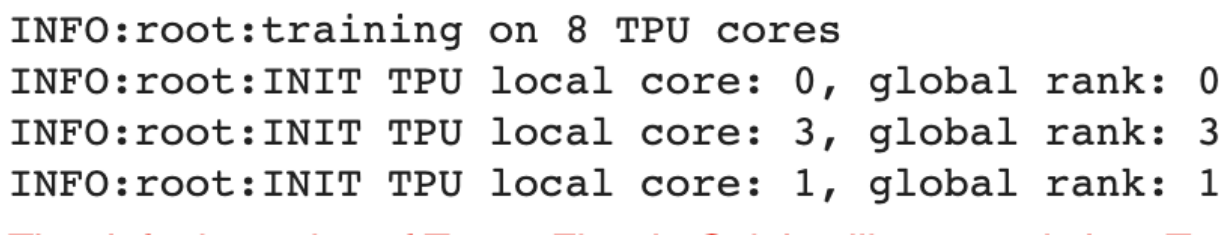
The *prepare_data* method is also a good place to do any data processing that needs to be done only once (ie: download or tokenize, etc...).

Note: Lightning inserts the correct DistributedSampler for distributed training. No need to add yourself!

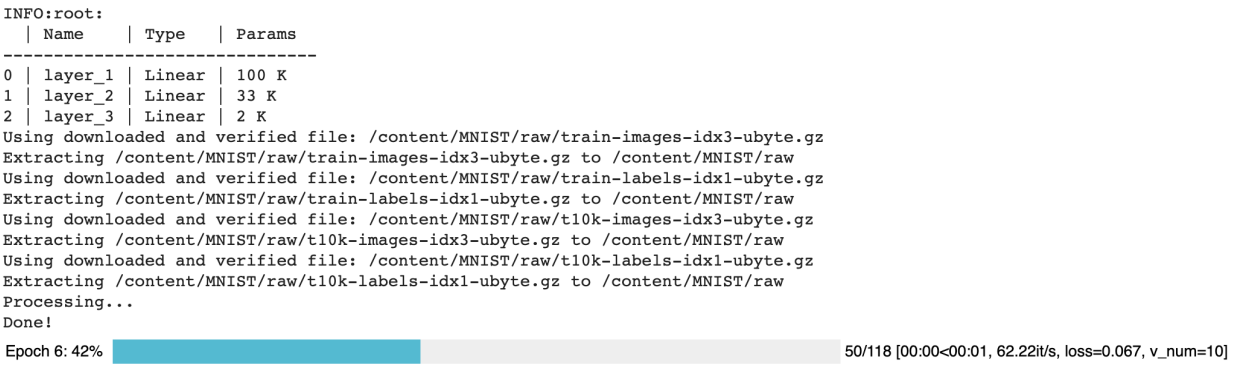
Now we can train the LightningModule on a TPU without doing anything else!

```
model = LitMNIST()
trainer = Trainer(num_tpu_cores=8)
trainer.fit(model)
```

You'll now see the TPU cores booting up.



Notice the epoch is MUCH faster!



2.6 Hyperparameters

Lightning has utilities to interact seamlessly with the command line ArgumentParser and plays well with the hyperparameter optimization framework of your choice.

2.6.1 ArgumentParser

Lightning is designed to augment a lot of the functionality of the built-in Python ArgumentParser

```
from argparse import ArgumentParser
parser = ArgumentParser()
parser.add_argument('--layer_1_dim', type=int, default=128)
args = parser.parse_args()
```

This allows you to call your program like so:

```
python trainer.py --layer_1_dim 64
```

2.6.2 Argparser Best Practices

It is best practice to layer your arguments in three sections.

1. Trainer args (gpus, num_nodes, etc...)
2. Model specific arguments (layer_dim, num_layers, learning_rate, etc...)
3. Program arguments (data_path, cluster_email, etc...)

We can do this as follows. First, in your LightningModule, define the arguments specific to that module. Remember that data splits or data paths may also be specific to a module (ie: if your project has a model that trains on Imagenet and another on CIFAR-10).

```
class LitModel(LightningModule):

    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = ArgumentParser(parents=[parent_parser], add_help=False)
        parser.add_argument('--encoder_layers', type=int, default=12)
        parser.add_argument('--data_path', type=str, default='/some/path')
        return parser
```

Now in your main trainer file, add the Trainer args, the program args, and add the model args

```
# ----------------
# trainer_main.py
# ----------------
from argparse import ArgumentParser
parser = ArgumentParser()

# add PROGRAM level args
parser.add_argument('--conda_env', type=str, default='some_name')
parser.add_argument('--notification_email', type=str, default='will@email.com')

# add model specific args
parser = LitModel.add_model_specific_args(parser)
```

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```
# add all the available trainer options to argparse
# ie: now --gpus --num_nodes ... --fast_dev_run all work in the cli
parser = Trainer.add_argparse_args(parser)

hparams = parser.parse_args()
```

Now you can call run your program like so

```
python trainer_main.py --gpus 2 --num_nodes 2 --conda_env 'my_env' --encoder_layers 12
```

Finally, make sure to start the training like so:

```
# YES
model = LitModel(hparams)
trainer = Trainer.from_argparse_args(hparams, early_stopping_callback=...)

# NO
# model = LitModel(learning_rate=hparams.learning_rate, ...)
# trainer = Trainer(gpus=hparams.gpus, ...)
```

2.6.3 LightningModule hparams

Normally, we don't hard-code the values to a model. We usually use the command line to modify the network and read those values in the LightningModule

```
class LitMNIST(LightningModule):

    def __init__(self, hparams):
        super().__init__()

        # do this to save all arguments in any logger (tensorboard)
        self.hparams = hparams

        self.layer_1 = torch.nn.Linear(28 * 28, hparams.layer_1_dim)
        self.layer_2 = torch.nn.Linear(hparams.layer_1_dim, hparams.layer_2_dim)
        self.layer_3 = torch.nn.Linear(hparams.layer_2_dim, 10)

    def train_dataloader(self):
        return DataLoader(mnist_train, batch_size=self.hparams.batch_size)

    def configure_optimizers(self):
        return Adam(self.parameters(), lr=self.hparams.learning_rate)

    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = ArgumentParser(parents=[parent_parser], add_help=False)
        parser.add_argument('--layer_1_dim', type=int, default=128)
        parser.add_argument('--layer_2_dim', type=int, default=256)
        parser.add_argument('--batch_size', type=int, default=64)
        parser.add_argument('--learning_rate', type=float, default=0.002)
        return parser
```

Now pass in the params when you init your model

```
parser = ArgumentParser()
parser = LitMNIST.add_model_specific_args(parser)
hparams = parser.parse_args()
model = LitMNIST(hparams)
```

The line *self.hparams = hparams* is very special. This line assigns your hparams to the LightningModule. This does two things:

1. It adds them automatically to TensorBoard logs under the hparams tab.
2. Lightning will save those hparams to the checkpoint and use them to restore the module correctly.

2.6.4 Trainer args

To recap, add ALL possible trainer flags to the argparser and init the Trainer this way

```
parser = ArgumentParser()
parser = Trainer.add_argparse_args(parser)
hparams = parser.parse_args()

trainer = Trainer.from_argparse_args(hparams)

# or if you need to pass in callbacks
trainer = Trainer.from_argparse_args(hparams, checkpoint_callback=..., callbacks=[...
↪])
```

2.6.5 Multiple Lightning Modules

We often have multiple Lightning Modules where each one has different arguments. Instead of polluting the main.py file, the LightningModule lets you define arguments for each one.

```
class LitMNIST(LightningModule):

    def __init__(self, hparams):
        super().__init__()
        self.layer_1 = torch.nn.Linear(28 * 28, hparams.layer_1_dim)

    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = ArgumentParser(parents=[parent_parser])
        parser.add_argument('--layer_1_dim', type=int, default=128)
        return parser
```

```
class GoodGAN(LightningModule):

    def __init__(self, hparams):
        super().__init__()
        self.encoder = Encoder(layers=hparams.encoder_layers)

    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = ArgumentParser(parents=[parent_parser])
        parser.add_argument('--encoder_layers', type=int, default=12)
        return parser
```

Now we can allow each model to inject the arguments it needs in the `main.py`

```
def main(args):

    # pick model
    if args.model_name == 'gan':
        model = GoodGAN(hparams=args)
    elif args.model_name == 'mnist':
        model = LitMNIST(hparams=args)

    model = LitMNIST(hparams=args)
    trainer = Trainer.from_argparse_args(args)
    trainer.fit(model)

if __name__ == '__main__':
    parser = ArgumentParser()
    parser = Trainer.add_argparse_args(parser)

    # figure out which model to use
    parser.add_argument('--model_name', type=str, default='gan', help='gan or mnist')

    # THIS LINE IS KEY TO PULL THE MODEL NAME
    temp_args, _ = parser.parse_known_args()

    # let the model add what it wants
    if temp_args.model_name == 'gan':
        parser = GoodGAN.add_model_specific_args(parser)
    elif temp_args.model_name == 'mnist':
        parser = LitMNIST.add_model_specific_args(parser)

    args = parser.parse_args()

    # train
    main(args)
```

and now we can train MNIST or the GAN using the command line interface!

```
$ python main.py --model_name gan --encoder_layers 24
$ python main.py --model_name mnist --layer_1_dim 128
```

2.6.6 Hyperparameter Optimization

Lightning is fully compatible with the hyperparameter optimization libraries! Here are some useful ones:

- Hydra
- Optuna

2.7 Validating

For most cases, we stop training the model when the performance on a validation split of the data reaches a minimum.

Just like the *training_step*, we can define a *validation_step* to check whatever metrics we care about, generate samples or add more to our logs.

```
for epoch in epochs:
    for batch in data:
        # ...
        # train

    # validate
    outputs = []
    for batch in val_data:
        x, y = batch                          # validation_step
        y_hat = model(x)                      # validation_step
        loss = loss(y_hat, x)                 # validation_step
        outputs.append({'val_loss': loss})    # validation_step

    full_loss = outputs.mean()                # validation_epoch_end
```

Since the *validation_step* processes a single batch, in Lightning we also have a *validation_epoch_end* method which allows you to compute statistics on the full dataset after an epoch of validation data and not just the batch.

In addition, we define a *val_dataloader* method which tells the trainer what data to use for validation. Notice we split the train split of MNIST into train, validation. We also have to make sure to do the sample split in the *train_dataloader* method.

```
class LitMNIST(LightningModule):
    def validation_step(self, batch, batch_idx):
        x, y = batch
        logits = self(x)
        loss = F.nll_loss(logits, y)
        return {'val_loss': loss}

    def validation_epoch_end(self, outputs):
        avg_loss = torch.stack([x['val_loss'] for x in outputs]).mean()
        tensorboard_logs = {'val_loss': avg_loss}
        return {'val_loss': avg_loss, 'log': tensorboard_logs}

    def val_dataloader(self):
        transform=transforms.Compose([transforms.ToTensor(),
                                      transforms.Normalize((0.1307,), (0.3081,))])
        mnist_train = MNIST(os.getcwd(), train=True, download=False,
                            transform=transform)
        _, mnist_val = random_split(mnist_train, [55000, 5000])
        mnist_val = DataLoader(mnist_val, batch_size=64)
        return mnist_val
```

Again, we've just organized the regular PyTorch code into two steps, the *validation_step* method which operates on a single batch and the *validation_epoch_end* method to compute statistics on all batches.

If you have these methods defined, Lightning will call them automatically. Now we can train while checking the validation set.

```
from pytorch_lightning import Trainer
```

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```
model = LitMNIST()
trainer = Trainer(num_tpu_cores=8)
trainer.fit(model)
```

You may have noticed the words *Validation sanity check* logged. This is because Lightning runs 5 batches of validation before starting to train. This is a kind of unit test to make sure that if you have a bug in the validation loop, you won't need to potentially wait a full epoch to find out.

Note: Lightning disables gradients, puts model in eval mode and does everything needed for validation.

2.8 Testing

Once our research is done and we're about to publish or deploy a model, we normally want to figure out how it will generalize in the "real world." For this, we use a held-out split of the data for testing.

Just like the validation loop, we define exactly the same steps for testing:

- test_step
- test_epoch_end
- test_dataloader

```
class LitMNIST(LightningModule):
    def test_step(self, batch, batch_idx):
        x, y = batch
        logits = self(x)
        loss = F.nll_loss(logits, y)
        return {'val_loss': loss}

    def test_epoch_end(self, outputs):
        avg_loss = torch.stack([x['val_loss'] for x in outputs]).mean()
        tensorboard_logs = {'val_loss': avg_loss}
        return {'val_loss': avg_loss, 'log': tensorboard_logs}

    def test_dataloader(self):
        transform=transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
↪1307,), (0.3081,))])
        mnist_train = MNIST(os.getcwd(), train=False, download=False,␣
↪transform=transform)
        _, mnist_val = random_split(mnist_train, [55000, 5000])
        mnist_val = DataLoader(mnist_val, batch_size=64)
        return mnist_val
```

However, to make sure the test set isn't used inadvertently, Lightning has a separate API to run tests. Once you train your model simply call *.test()*.

```
from pytorch_lightning import Trainer

model = LitMNIST()
trainer = Trainer(num_tpu_cores=8)
trainer.fit(model)
```

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```
# run test set
trainer.test()
```

Out:

```
--------------------------------------------------------------
TEST RESULTS
{'test_loss': tensor(1.1703, device='cuda:0')}
--------------------------------------------------------------
```

You can also run the test from a saved lightning model

```
model = LitMNIST.load_from_checkpoint(PATH)
trainer = Trainer(num_tpu_cores=8)
trainer.test(model)
```

Note: Lightning disables gradients, puts model in eval mode and does everything needed for testing.

Warning: .test() is not stable yet on TPUs. We're working on getting around the multiprocessing challenges.

2.9 Predicting

Again, a LightningModule is exactly the same as a PyTorch module. This means you can load it and use it for prediction.

```
model = LitMNIST.load_from_checkpoint(PATH)
x = torch.Tensor(1, 1, 28, 28)
out = model(x)
```

On the surface, it looks like *forward* and *training_step* are similar. Generally, we want to make sure that what we want the model to do is what happens in the *forward*. whereas the *training_step* likely calls forward from within it.

```
class MNISTClassifier(LightningModule):

    def forward(self, x):
        batch_size, channels, width, height = x.size()
        x = x.view(batch_size, -1)
        x = self.layer_1(x)
        x = torch.relu(x)
        x = self.layer_2(x)
        x = torch.relu(x)
        x = self.layer_3(x)
        x = torch.log_softmax(x, dim=1)
        return x

    def training_step(self, batch, batch_idx):
        x, y = batch
```

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```
        logits = self(x)
        loss = F.nll_loss(logits, y)
        return loss
```

```
model = MNISTClassifier()
x = mnist_image()
logits = model(x)
```

In this case, we've set this LightningModel to predict logits. But we could also have it predict feature maps:

```
class MNISTRepresentator(LightningModule):

    def forward(self, x):
        batch_size, channels, width, height = x.size()
        x = x.view(batch_size, -1)
        x = self.layer_1(x)
        x1 = torch.relu(x)
        x = self.layer_2(x1)
        x2 = torch.relu(x)
        x3 = self.layer_3(x2)
        return [x, x1, x2, x3]

    def training_step(self, batch, batch_idx):
        x, y = batch
        out, l1_feats, l2_feats, l3_feats = self(x)
        logits = torch.log_softmax(out, dim=1)
        ce_loss = F.nll_loss(logits, y)
        loss = perceptual_loss(l1_feats, l2_feats, l3_feats) + ce_loss
        return loss
```

```
model = MNISTRepresentator.load_from_checkpoint(PATH)
x = mnist_image()
feature_maps = model(x)
```

Or maybe we have a model that we use to do generation

```
class LitMNISTDreamer(LightningModule):

    def forward(self, z):
        imgs = self.decoder(z)
        return imgs

    def training_step(self, batch, batch_idx):
        x, y = batch
        representation = self.encoder(x)
        imgs = self(representation)

        loss = perceptual_loss(imgs, x)
        return loss
```

```
model = LitMNISTDreamer.load_from_checkpoint(PATH)
z = sample_noise()
generated_imgs = model(z)
```

How you split up what goes in *forward* vs *training_step* depends on how you want to use this model for prediction.

2.10 Extensibility

Although lightning makes everything super simple, it doesn't sacrifice any flexibility or control. Lightning offers multiple ways of managing the training state.

2.10.1 Training overrides

Any part of the training, validation and testing loop can be modified. For instance, if you wanted to do your own backward pass, you would override the default implementation

```
def backward(self, use_amp, loss, optimizer):
    if use_amp:
        with amp.scale_loss(loss, optimizer) as scaled_loss:
            scaled_loss.backward()
    else:
        loss.backward()
```

With your own

```
class LitMNIST(LightningModule):

    def backward(self, use_amp, loss, optimizer):
        # do a custom way of backward
        loss.backward(retain_graph=True)
```

Or if you wanted to initialize ddp in a different way than the default one

```
def configure_ddp(self, model, device_ids):
    # Lightning DDP simply routes to test_step, val_step, etc...
    model = LightningDistributedDataParallel(
        model,
        device_ids=device_ids,
        find_unused_parameters=True
    )
    return model
```

you could do your own:

```
class LitMNIST(LightningModule):

    def configure_ddp(self, model, device_ids):

        model = Horovod(model)
        # model = Ray(model)
        return model
```

Every single part of training is configurable this way. For a full list look at *LightningModule*.

2.11 Callbacks

Another way to add arbitrary functionality is to add a custom callback for hooks that you might care about

```
from pytorch_lightning.callbacks import Callback

class MyPrintingCallback(Callback):

    def on_init_start(self, trainer):
        print('Starting to init trainer!')

    def on_init_end(self, trainer):
        print('Trainer is init now')

    def on_train_end(self, trainer, pl_module):
        print('do something when training ends')
```

And pass the callbacks into the trainer

```
trainer = Trainer(callbacks=[MyPrintingCallback()])
```

Note: See full list of 12+ hooks in the *Callbacks*.

2.12 Child Modules

Research projects tend to test different approaches to the same dataset. This is very easy to do in Lightning with inheritance.

For example, imagine we now want to train an Autoencoder to use as a feature extractor for MNIST images. Recall that *LitMNIST* already defines all the dataloading etc... The only things that change in the *Autoencoder* model are the init, forward, training, validation and test step.

```
class Encoder(torch.nn.Module):
    pass

class Decoder(torch.nn.Module):
    pass

class AutoEncoder(LitMNIST):

    def __init__(self):
        super().__init__()
        self.encoder = Encoder()
        self.decoder = Decoder()

    def forward(self, x):
        generated = self.decoder(x)

    def training_step(self, batch, batch_idx):
        x, _ = batch
```

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```
        representation = self.encoder(x)
        x_hat = self(representation)

        loss = MSE(x, x_hat)
        return loss

    def validation_step(self, batch, batch_idx):
        return self._shared_eval(batch, batch_idx, 'val')

    def test_step(self, batch, batch_idx):
        return self._shared_eval(batch, batch_idx, 'test')

    def _shared_eval(self, batch, batch_idx, prefix):
        x, y = batch
        representation = self.encoder(x)
        x_hat = self(representation)

        loss = F.nll_loss(logits, y)
        return {f'{prefix}_loss': loss}
```

and we can train this using the same trainer

```
autoencoder = AutoEncoder()
trainer = Trainer()
trainer.fit(autoencoder)
```

And remember that the forward method is to define the practical use of a LightningModule. In this case, we want to use the *AutoEncoder* to extract image representations

```
some_images = torch.Tensor(32, 1, 28, 28)
representations = autoencoder(some_images)
```

2.13 Transfer Learning

2.13.1 Using Pretrained Models

Sometimes we want to use a LightningModule as a pretrained model. This is fine because a LightningModule is just a *torch.nn.Module*!

Note: Remember that a LightningModule is EXACTLY a torch.nn.Module but with more capabilities.

Let's use the *AutoEncoder* as a feature extractor in a separate model.

```
class Encoder(torch.nn.Module):
    ...

class AutoEncoder(LightningModule):
    def __init__(self):
        self.encoder = Encoder()
        self.decoder = Decoder()
```

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```
class CIFAR10Classifier(LightningModule):
    def __init__(self):
        # init the pretrained LightningModule
        self.feature_extractor = AutoEncoder.load_from_checkpoint(PATH)
        self.feature_extractor.freeze()

        # the autoencoder outputs a 100-dim representation and CIFAR-10 has 10 classes
        self.classifier = nn.Linear(100, 10)

    def forward(self, x):
        representations = self.feature_extractor(x)
        x = self.classifier(representations)
        ...
```

We used our pretrained Autoencoder (a LightningModule) for transfer learning!

2.13.2 Example: Imagenet (computer Vision)

```
import torchvision.models as models

class ImagenetTransferLearning(LightningModule):
    def __init__(self):
        # init a pretrained resnet
        num_target_classes = 10
        self.feature_extractor = models.resnet50(
                                    pretrained=True,
                                    num_classes=num_target_classes)
        self.feature_extractor.eval()

        # use the pretrained model to classify cifar-10 (10 image classes)
        self.classifier = nn.Linear(2048, num_target_classes)

    def forward(self, x):
        representations = self.feature_extractor(x)
        x = self.classifier(representations)
        ...
```

Finetune

```
model = ImagenetTransferLearning()
trainer = Trainer()
trainer.fit(model)
```

And use it to predict your data of interest

```
model = ImagenetTransferLearning.load_from_checkpoint(PATH)
model.freeze()

x = some_images_from_cifar10()
predictions = model(x)
```

We used a pretrained model on imagenet, finetuned on CIFAR-10 to predict on CIFAR-10. In the non-academic world we would finetune on a tiny dataset you have and predict on your dataset.

2.13.3 Example: BERT (NLP)

Lightning is completely agnostic to what's used for transfer learning so long as it is a *torch.nn.Module* subclass.

Here's a model that uses Huggingface transformers.

```
class BertMNLIFinetuner(LightningModule):

    def __init__(self):
        super().__init__()

        self.bert = BertModel.from_pretrained('bert-base-cased', output_
↪attentions=True)
        self.W = nn.Linear(bert.config.hidden_size, 3)
        self.num_classes = 3


    def forward(self, input_ids, attention_mask, token_type_ids):

        h, _, attn = self.bert(input_ids=input_ids,
                               attention_mask=attention_mask,
                               token_type_ids=token_type_ids)

        h_cls = h[:, 0]
        logits = self.W(h_cls)
        return logits, attn
```

CHAPTER

THREE

CALLBACKS

Lightning has a callback system to execute arbitrary code. Callbacks should capture NON-ESSENTIAL logic that is NOT required for your *LightningModule* to run.

An overall Lightning system should have:

1. Trainer for all engineering
2. LightningModule for all research code.
3. Callbacks for non-essential code.

Example:

```
class MyPrintingCallback(Callback):

    def on_init_start(self, trainer):
        print('Starting to init trainer!')

    def on_init_end(self, trainer):
        print('trainer is init now')

    def on_train_end(self, trainer, pl_module):
        print('do something when training ends')

trainer = Trainer(callbacks=[MyPrintingCallback()])
```

```
Starting to init trainer!
trainer is init now
```

We successfully extended functionality without polluting our super clean *LightningModule* research code.

3.1 Callback Base

Abstract base class used to build new callbacks.

class pytorch_lightning.callbacks.base.**Callback**
Bases: abc.ABC

Abstract base class used to build new callbacks.

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends.

on_batch_start(*trainer*, *pl_module*)
Called when the training batch begins.

on_epoch_end(*trainer*, *pl_module*)
Called when the epoch ends.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_init_end(*trainer*)
Called when the trainer initialization ends, model has not yet been set.

on_init_start(*trainer*)
Called when the trainer initialization begins, model has not yet been set.

on_sanity_check_end(*trainer*, *pl_module*)
Called when the validation sanity check ends.

on_sanity_check_start(*trainer*, *pl_module*)
Called when the validation sanity check starts.

on_test_batch_end(*trainer*, *pl_module*)
Called when the test batch ends.

on_test_batch_start(*trainer*, *pl_module*)
Called when the test batch begins.

on_test_end(*trainer*, *pl_module*)
Called when the test ends.

on_test_start(*trainer*, *pl_module*)
Called when the test begins.

on_train_end(*trainer*, *pl_module*)
Called when the train ends.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)
Called when the validation batch ends.

on_validation_batch_start(*trainer*, *pl_module*)
Called when the validation batch begins.

on_validation_end(*trainer*, *pl_module*)
Called when the validation loop ends.

on_validation_start(*trainer*, *pl_module*)
Called when the validation loop begins.

3.2 Early Stopping

Stop training when a monitored quantity has stopped improving.

class pytorch_lightning.callbacks.early_stopping.**EarlyStopping**(*monitor='val_loss'*, *min_delta=0.0*, *patience=3*, *verbose=False*, *mode='auto'*, *strict=True*)

Bases: *pytorch_lightning.callbacks.base.Callback*

Parameters

- **monitor** (str) – quantity to be monitored. Default: 'val_loss'.
- **min_delta** (float) – minimum change in the monitored quantity to qualify as an improvement, i.e. an absolute change of less than *min_delta*, will count as no improvement. Default: 0.
- **patience** (int) – number of epochs with no improvement after which training will be stopped. Default: 0.
- **verbose** (bool) – verbosity mode. Default: False.
- **mode** (str) – one of {auto, min, max}. In *min* mode, training will stop when the quantity monitored has stopped decreasing; in *max* mode it will stop when the quantity monitored has stopped increasing; in *auto* mode, the direction is automatically inferred from the name of the monitored quantity. Default: 'auto'.
- **strict** (bool) – whether to crash the training if *monitor* is not found in the metrics. Default: True.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import EarlyStopping
>>> early_stopping = EarlyStopping('val_loss')
>>> trainer = Trainer(early_stop_callback=early_stopping)
```

_validate_condition_metric(*logs*)

Checks that the condition metric for early stopping is good :param _sphinx_paramlinks_pytorch_lightning.callbacks.early_stopping.EarlyStopping._validate_condition_metric.logs: :return:

on_epoch_end(*trainer*, *pl_module*)

Called when the epoch ends.

on_train_end(*trainer*, *pl_module*)

Called when the train ends.

on_train_start(*trainer*, *pl_module*)

Called when the train begins.

3.3 Model Checkpointing

Automatically save model checkpoints during training.

class pytorch_lightning.callbacks.model_checkpoint.**ModelCheckpoint**(*filepath=None*, *monitor='val_loss'*, *verbose=False*, *save_top_k=1*, *save_weights_only=False*, *mode='auto'*, *period=1*, *prefix=''*)

Bases: *pytorch_lightning.callbacks.base.Callback*

Save the model after every epoch.

Parameters

- **filepath** (Optional[str]) – path to save the model file. Can contain named formatting options to be auto-filled.

  Example:

```
# custom path
# saves a file like: my/path/epoch_0.ckpt
>>> checkpoint_callback = ModelCheckpoint('my/path/')

# save any arbitrary metrics like `val_loss`, etc. in name
# saves a file like: my/path/epoch=2-val_loss=0.2_other_metric=0.3.
↪ckpt
>>> checkpoint_callback = ModelCheckpoint(
...     filepath='my/path/{epoch}-{val_loss:.2f}-{other_metric:.2f}
↪'
... )
```

  Can also be set to *None*, then it will be set to default location during trainer construction.

- **monitor** (str) – quantity to monitor.
- **verbose** (bool) – verbosity mode. Default: False.
- **save_top_k** (int) – if *save_top_k == k*, the best k models according to the quantity monitored will be saved. if save_top_k == 0, no models are saved. if save_top_k == -1, all models are saved. Please note that the monitors are checked every *period* epochs. if save_top_k >= 2 and the callback is called multiple times inside an epoch, the name of the saved file will be appended with a version count starting with *v0*.
- **mode** (str) – one of {auto, min, max}. If save_top_k != 0, the decision to overwrite the current save file is made based on either the maximization or the minimization of the monitored quantity. For *val_acc*, this should be *max*, for *val_loss* this should be *min*, etc. In *auto* mode, the direction is automatically inferred from the name of the monitored quantity.
- **save_weights_only** (bool) – if True, then only the model's weights will be saved (model.save_weights(filepath)), else the full model is saved (model.save(filepath)).
- **period** (int) – Interval (number of epochs) between checkpoints.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import ModelCheckpoint

# saves checkpoints to 'my/path/' whenever 'val_loss' has a new min
>>> checkpoint_callback = ModelCheckpoint(filepath='my/path/')
>>> trainer = Trainer(checkpoint_callback=checkpoint_callback)

# save epoch and val_loss in name
# saves a file like: my/path/sample-mnist_epoch=02_val_loss=0.32.ckpt
>>> checkpoint_callback = ModelCheckpoint(
...     filepath='my/path/sample-mnist_{epoch:02d}-{val_loss:.2f}'
... )
```

format_checkpoint_name(*epoch*, *metrics*, *ver=None*)
Generate a filename according to the defined template.

Example:

```
>>> tmpdir = os.path.dirname(__file__)
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch}'))
>>> os.path.basename(ckpt.format_checkpoint_name(0, {}))
'epoch=0.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch:03d}'))
>>> os.path.basename(ckpt.format_checkpoint_name(5, {}))
'epoch=005.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch}-{val_loss:.2f}'))
>>> os.path.basename(ckpt.format_checkpoint_name(2, dict(val_loss=0.123456)))
'epoch=2-val_loss=0.12.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{missing:d}'))
>>> os.path.basename(ckpt.format_checkpoint_name(0, {}))
'missing=0.ckpt'
```

on_validation_end(*trainer*, *pl_module*)
Called when the validation loop ends.

3.4 Gradient Accumulator

Change gradient accumulation factor according to scheduling.

class pytorch_lightning.callbacks.gradient_accumulation_scheduler.**GradientAccumulationSched**
Bases: *pytorch_lightning.callbacks.base.Callback*

Change gradient accumulation factor according to scheduling.

Parameters **scheduling** (dict) – scheduling in format {epoch: accumulation_factor}

> **Warning:** Epochs indexing starts from "1" until v0.6.x, but will start from "0" in v0.8.0.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import GradientAccumulationScheduler
```

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```
# at epoch 5 start accumulating every 2 batches
>>> accumulator = GradientAccumulationScheduler(scheduling={5: 2})
>>> trainer = Trainer(callbacks=[accumulator])

# alternatively, pass the scheduling dict directly to the Trainer
>>> trainer = Trainer(accumulate_grad_batches={5: 2})
```

on_epoch_start (*trainer*, *pl_module*)
Called when the epoch begins.

3.5 Progress Bars

Use or override one of the progress bar callbacks.

class pytorch_lightning.callbacks.progress.**ProgressBar**(*refresh_rate=1*, *process_position=0*)
Bases: *pytorch_lightning.callbacks.progress.ProgressBarBase*

This is the default progress bar used by Lightning. It prints to *stdout* using the `tqdm` package and shows up to four different bars:

- **sanity check progress:** the progress during the sanity check run
- **main progress:** shows training + validation progress combined. It also accounts for multiple validation runs during training when *val_check_interval* is used.
- **validation progress:** only visible during validation; shows total progress over all validation datasets.
- **test progress:** only active when testing; shows total progress over all test datasets.

For infinite datasets, the progress bar never ends.

If you want to customize the default `tqdm` progress bars used by Lightning, you can override specific methods of the callback class and pass your custom implementation to the *Trainer*:

Example:

```
class LitProgressBar(ProgressBar):

    def init_validation_tqdm(self):
        bar = super().init_validation_tqdm()
        bar.set_description('running validation ...')
        return bar

bar = LitProgressBar()
trainer = Trainer(callbacks=[bar])
```

Parameters

- **refresh_rate** (`int`) – Determines at which rate (in number of batches) the progress bars get updated. Set it to `0` to disable the display. By default, the *Trainer* uses this implementation of the progress bar and sets the refresh rate to the value provided to the *progress_bar_refresh_rate* argument in the *Trainer*.

- **process_position** (int) – Set this to a value greater than 0 to offset the progress bars by this many lines. This is useful when you have progress bars defined elsewhere and want to show all of them together. This corresponds to *process_position* in the *Trainer*.

disable()
You should provide a way to disable the progress bar. The *Trainer* will call this to disable the output on processes that have a rank different from 0, e.g., in multi-node training.

Return type None

enable()
You should provide a way to enable the progress bar. The *Trainer* will call this in e.g. pre-training routines like the *learning rate finder* to temporarily enable and disable the main progress bar.

Return type None

init_sanity_tqdm()
Override this to customize the tqdm bar for the validation sanity run.

Return type tqdm

init_test_tqdm()
Override this to customize the tqdm bar for testing.

Return type tqdm

init_train_tqdm()
Override this to customize the tqdm bar for training.

Return type tqdm

init_validation_tqdm()
Override this to customize the tqdm bar for validation.

Return type tqdm

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_sanity_check_end(*trainer*, *pl_module*)
Called when the validation sanity check ends.

on_sanity_check_start(*trainer*, *pl_module*)
Called when the validation sanity check starts.

on_test_batch_end(*trainer*, *pl_module*)
Called when the test batch ends.

on_test_end(*trainer*, *pl_module*)
Called when the test ends.

on_test_start(*trainer*, *pl_module*)
Called when the test begins.

on_train_end(*trainer*, *pl_module*)
Called when the train ends.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)
Called when the validation batch ends.

on_validation_end(*trainer*, *pl_module*)
Called when the validation loop ends.

on_validation_start(*trainer*, *pl_module*)
Called when the validation loop begins.

class pytorch_lightning.callbacks.progress.**ProgressBarBase**
Bases: *pytorch_lightning.callbacks.base.Callback*

The base class for progress bars in Lightning. It is a *Callback* that keeps track of the batch progress in the *Trainer*. You should implement your highly custom progress bars with this as the base class.

Example:

```
class LitProgressBar(ProgressBarBase):

    def __init__(self):
        super().__init__()  # don't forget this :)
        self.enable = True

    def disable(self):
        self.enable = False

    def on_batch_end(self, trainer, pl_module):
        super().on_batch_end(trainer, pl_module)  # don't forget this :)
        percent = (self.train_batch_idx / self.total_train_batches) * 100
        sys.stdout.flush()
        sys.stdout.write(f'{percent:.01f} percent complete \r')

bar = LitProgressBar()
trainer = Trainer(callbacks=[bar])
```

disable()
You should provide a way to disable the progress bar. The *Trainer* will call this to disable the output on processes that have a rank different from 0, e.g., in multi-node training.

enable()
You should provide a way to enable the progress bar. The *Trainer* will call this in e.g. pre-training routines like the *learning rate finder* to temporarily enable and disable the main progress bar.

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_init_end(*trainer*)
Called when the trainer initialization ends, model has not yet been set.

on_test_batch_end(*trainer*, *pl_module*)
Called when the test batch ends.

on_test_start(*trainer*, *pl_module*)
Called when the test begins.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)
Called when the validation batch ends.

on_validation_start(*trainer*, *pl_module*)
Called when the validation loop begins.

property test_batch_idx
The current batch index being processed during testing. Use this to update your progress bar.

Return type int

property total_test_batches
The total number of training batches during testing, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the test dataloader is of infinite size.

Return type int

property total_train_batches
The total number of training batches during training, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the training dataloader is of infinite size.

Return type int

property total_val_batches
The total number of training batches during validation, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the validation dataloader is of infinite size.

Return type int

property train_batch_idx
The current batch index being processed during training. Use this to update your progress bar.

Return type int

property val_batch_idx
The current batch index being processed during validation. Use this to update your progress bar.

Return type int

pytorch_lightning.callbacks.progress.**convert_inf**(*x*)
The tqdm doesn't support inf values. We have to convert it to None.

3.6 Logging of learning rates

Log learning rate for lr schedulers during training

class pytorch_lightning.callbacks.lr_logger.**LearningRateLogger**
Bases: *pytorch_lightning.callbacks.base.Callback*

Automatically logs learning rate for learning rate schedulers during training.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import LearningRateLogger
>>> lr_logger = LearningRateLogger()
>>> trainer = Trainer(callbacks=[lr_logger])
```

Logging names are automatically determined based on optimizer class name. In case of multiple optimizers of same type, they will be named *Adam*, *Adam-1* etc. If a optimizer has multiple parameter groups they will be named *Adam/pg1*, *Adam/pg2* etc. To control naming, pass in a *name* keyword in the construction of the learning rate schdulers

Example:

```
def configure_optimizer(self):
    optimizer = torch.optim.Adam(...)
    lr_scheduler = {'scheduler': torch.optim.lr_schedulers.LambdaLR(optimizer, ...
↪)
                    'name': 'my_logging_name'}
    return [optimizer], [lr_scheduler]
```

_extract_lr(*trainer*, *interval*)
Extracts learning rates for lr schedulers and saves information into dict structure.

on_batch_start(*trainer*, *pl_module*)
Called when the training batch begins.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_train_start(*trainer*, *pl_module*)
Called before training, determines unique names for all lr schedulers in the case of multiple of the same type or in the case of multiple parameter groups

CHAPTER

FOUR

MODEL HOOKS

There are cases when you might want to do something different at different parts of the training/validation loop. To enable a hook, simply override the method in your LightningModule and the trainer will call it at the correct time.

Contributing If there's a hook you'd like to add, simply:

1. Fork PyTorchLightning.
2. Add the hook to *pytorch_lightning.core.hooks.ModelHooks*.
3. Add it in the correct place in *pytorch_lightning.trainer* where it should be called.

4.1 Hooks lifecycle

4.1.1 Training set-up

- *init_ddp_connection()*
- *init_optimizers()*
- *configure_apex()*
- *configure_ddp()*
- *train_dataloader()*
- *test_dataloader()*
- *val_dataloader()*
- *summarize()*
- *restore_weights()*

4.1.2 Training loop

- *on_epoch_start()*
- *on_batch_start()*
- *tbptt_split_batch()*
- *training_step()*
- *training_step_end()* (optional)
- *on_before_zero_grad()*

- *backward()*
- *on_after_backward()*
- optimizer.step()
- *on_batch_end()*
- *training_epoch_end()*
- *on_epoch_end()*

4.1.3 Validation loop

- model.zero_grad()
- model.eval()
- torch.set_grad_enabled(False)
- *validation_step()*
- *validation_step_end()*
- *validation_epoch_end()*
- model.train()
- torch.set_grad_enabled(True)
- *on_post_performance_check()*

4.1.4 Test loop

- model.zero_grad()
- model.eval()
- torch.set_grad_enabled(False)
- *test_step()*
- *test_step_end()*
- *test_epoch_end()*
- model.train()
- torch.set_grad_enabled(True)
- *on_post_performance_check()*

class pytorch_lightning.core.hooks.**ModelHooks**(**args*, ***kwargs*)
Bases: torch.nn.Module

backward(*trainer*, *loss*, *optimizer*, *optimizer_idx*)
Override backward with your own implementation if you need to.

Parameters

- **trainer** – Pointer to the trainer
- **loss** (Tensor) – Loss is already scaled by accumulated grads
- **optimizer** (Optimizer) – Current optimizer being used

- **optimizer_idx** (int) – Index of the current optimizer being used

Called to perform backward step. Feel free to override as needed.

The loss passed in has already been scaled for accumulated gradients if requested.

Example:

```
def backward(self, use_amp, loss, optimizer):
    if use_amp:
        with amp.scale_loss(loss, optimizer) as scaled_loss:
            scaled_loss.backward()
    else:
        loss.backward()
```

Return type None

on_after_backward()

Called in the training loop after loss.backward() and before optimizers do anything. This is the ideal place to inspect or log gradient information.

Example:

```
def on_after_backward(self):
    # example to inspect gradient information in tensorboard
    if self.trainer.global_step % 25 == 0:  # don't make the tf file huge
        params = self.state_dict()
        for k, v in params.items():
            grads = v
            name = k
            self.logger.experiment.add_histogram(tag=name, values=grads,
                                                 global_step=self.trainer.
↪global_step)
```

Return type None

on_batch_end()

Called in the training loop after the batch.

Return type None

on_batch_start(*batch*)

Called in the training loop before anything happens for that batch.

If you return -1 here, you will skip training for the rest of the current epoch.

Parameters **batch** (Any) – The batched data as it is returned by the training DataLoader.

Return type None

on_before_zero_grad(*optimizer*)

Called after optimizer.step() and before optimizer.zero_grad().

Called in the training loop after taking an optimizer step and before zeroing grads. Good place to inspect weight information with weights updated.

This is where it is called:

```
for optimizer in optimizers:
    optimizer.step()
    model.on_before_zero_grad(optimizer) # < ---- called here
    optimizer.zero_grad
```

Parameters **optimizer** (Optimizer) – The optimizer for which grads should be zeroed.

Return type None

on_epoch_end()
Called in the training loop at the very end of the epoch.

Return type None

on_epoch_start()
Called in the training loop at the very beginning of the epoch.

Return type None

on_post_performance_check()
Called at the very end of the validation loop.

Return type None

on_pre_performance_check()
Called at the very beginning of the validation loop.

Return type None

on_sanity_check_start()
Called before starting evaluation.

> **Warning:** Deprecated. Will be removed in v0.9.0.

on_train_end()
Called at the end of training before logger experiment is closed.

Return type None

on_train_start()
Called at the beginning of training before sanity check.

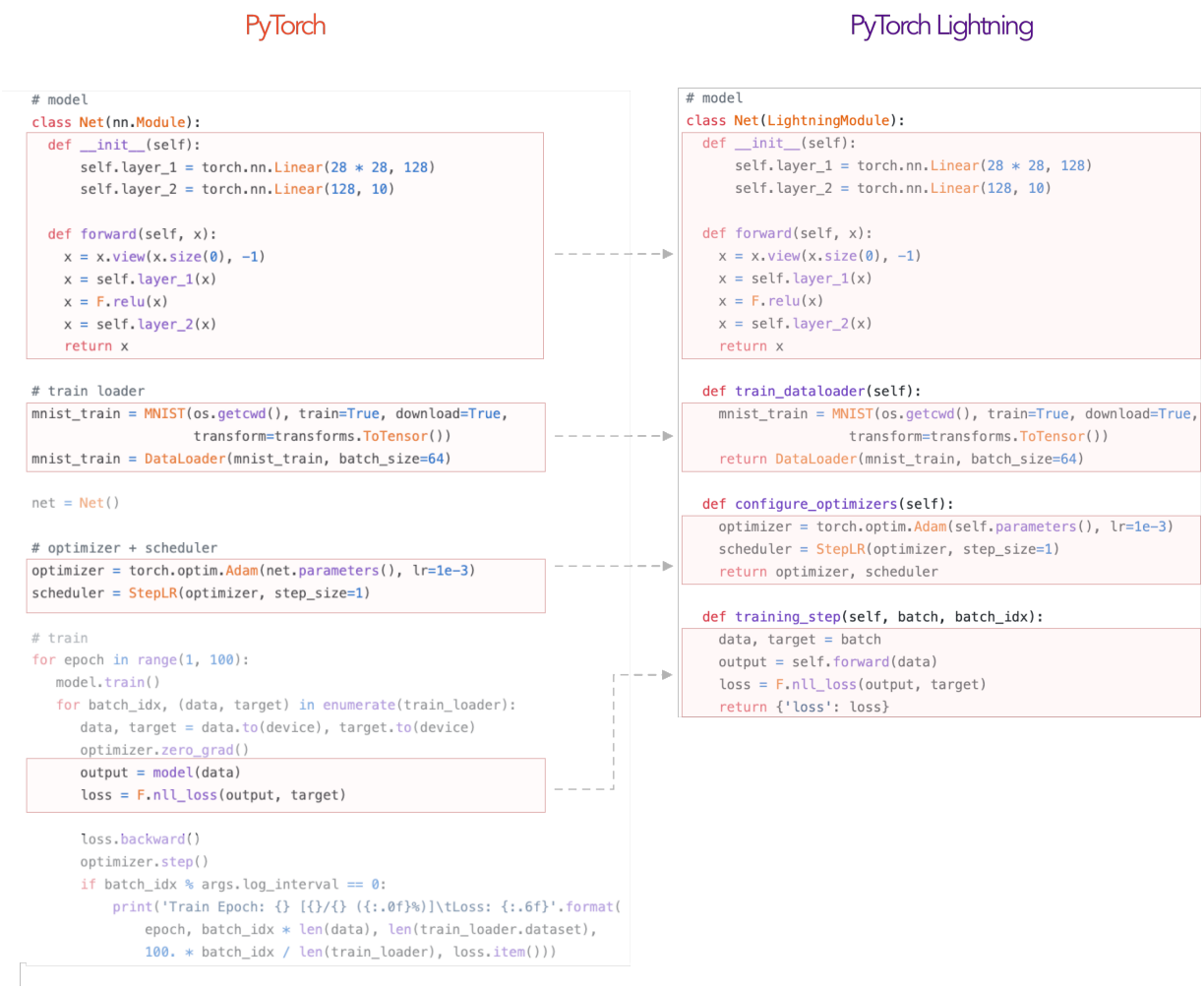
Return type None

CHAPTER

FIVE

LIGHTNINGMODULE

A *LightningModule* organizes your PyTorch code into the following sections:



Notice a few things.

1. It's the SAME code.
2. The PyTorch code IS NOT abstracted - just organized.
3. All the other code that's not in the *LightningModule* has been automated for you by the trainer.

```
net = Net()
trainer = Trainer()
trainer.fit(net)
```

4. There are no .cuda() or .to() calls... Lightning does these for you.

```
# don't do in lightning
x = torch.Tensor(2, 3)
x = x.cuda()
x = x.to(device)

# do this instead
x = x  # leave it alone!

# or to init a new tensor
new_x = torch.Tensor(2, 3)
new_x = new_x.type_as(x.type())
```

5. There are no samplers for distributed, Lightning also does this for you.

```
# Don't do in Lightning...
data = MNIST(...)
sampler = DistributedSampler(data)
DataLoader(data, sampler=sampler)

# do this instead
data = MNIST(...)
DataLoader(data)
```

6. A *LightningModule* is a `torch.nn.Module` but with added functionality. Use it as such!

```
net = Net.load_from_checkpoint(PATH)
net.freeze()
out = net(x)
```

Thus, to use Lightning, you just need to organize your code which takes about 30 minutes, (and let's be real, you probably should do anyhow).

5.1 Minimal Example

Here are the only required methods.

```
>>> import pytorch_lightning as pl
>>> class LitModel(pl.LightningModule):
...
...     def __init__(self):
...         super().__init__()
...         self.l1 = torch.nn.Linear(28 * 28, 10)
...
...     def forward(self, x):
...         return torch.relu(self.l1(x.view(x.size(0), -1)))
...
...     def training_step(self, batch, batch_idx):
```

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```
...         x, y = batch
...         y_hat = self(x)
...         return {'loss': F.cross_entropy(y_hat, y)}
...
...     def train_dataloader(self):
...         return DataLoader(MNIST(os.getcwd(), train=True, download=True,
...                                 transform=transforms.ToTensor()), batch_size=32)
...
...     def configure_optimizers(self):
...         return torch.optim.Adam(self.parameters(), lr=0.02)
```

Which you can train by doing:

```
trainer = pl.Trainer()
model = LitModel()

trainer.fit(model)
```

5.2 Training loop structure

The general pattern is that each loop (training, validation, test loop) has 3 methods:

- `___step`
- `___step_end`
- `___epoch_end`

To show how Lightning calls these, let's use the validation loop as an example:

```
val_outs = []
for val_batch in val_data:
    # do something with each batch
    out = validation_step(val_batch)
    val_outs.append(out)

# do something with the outputs for all batches
# like calculate validation set accuracy or loss
validation_epoch_end(val_outs)
```

If we use dp or ddp2 mode, we can also define the `XXX_step_end` method to operate on all parts of the batch:

```
val_outs = []
for val_batch in val_data:
    batches = split_batch(val_batch)
    dp_outs = []
    for sub_batch in batches:
        dp_out = validation_step(sub_batch)
        dp_outs.append(dp_out)

    out = validation_step_end(dp_outs)
    val_outs.append(out)

# do something with the outputs for all batches
```

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```
# like calculate validation set accuracy or loss
validation_epoch_end(val_outs)
```

5.2.1 Add validation loop

Thus, if we wanted to add a validation loop you would add this to your *LightningModule*:

```
>>> class LitModel(pl.LightningModule):
...     def validation_step(self, batch, batch_idx):
...         x, y = batch
...         y_hat = self(x)
...         return {'val_loss': F.cross_entropy(y_hat, y)}
...
...     def validation_epoch_end(self, outputs):
...         val_loss_mean = torch.stack([x['val_loss'] for x in outputs]).mean()
...         return {'val_loss': val_loss_mean}
...
...     def val_dataloader(self):
...         # can also return a list of val dataloaders
...         return DataLoader(...)
```

5.2.2 Add test loop

```
>>> class LitModel(pl.LightningModule):
...     def test_step(self, batch, batch_idx):
...         x, y = batch
...         y_hat = self(x)
...         return {'test_loss': F.cross_entropy(y_hat, y)}
...
...     def test_epoch_end(self, outputs):
...         test_loss_mean = torch.stack([x['test_loss'] for x in outputs]).mean()
...         return {'test_loss': test_loss_mean}
...
...     def test_dataloader(self):
...         # can also return a list of test dataloaders
...         return DataLoader(...)
```

However, the test loop won't ever be called automatically to make sure you don't run your test data by accident. Instead you have to explicitly call:

```
# call after training
trainer = Trainer()
trainer.fit(model)
trainer.test()

# or call with pretrained model
model = MyLightningModule.load_from_checkpoint(PATH)
trainer = Trainer()
trainer.test(model)
```

5.3 Training_step_end method

When using *LightningDataParallel* or *LightningDistributedDataParallel*, the *training_step()* will be operating on a portion of the batch. This is normally ok but in special cases like calculating NCE loss using negative samples, we might want to perform a softmax across all samples in the batch.

For these types of situations, each loop has an additional __step_end method which allows you to operate on the pieces of the batch:

```
training_outs = []
for train_batch in train_data:
    # dp, ddp2 splits the batch
    sub_batches = split_batches_for_dp(batch)

    # run training_step on each piece of the batch
    batch_parts_outputs = [training_step(sub_batch) for sub_batch in sub_batches]

    # do softmax with all pieces
    out = training_step_end(batch_parts_outputs)
    training_outs.append(out)

# do something with the outputs for all batches
# like calculate validation set accuracy or loss
training_epoch_end(val_outs)
```

5.4 Remove cuda calls

In a *LightningModule*, all calls to .cuda() and .to(device) should be removed. Lightning will do these automatically. This will allow your code to work on CPUs, TPUs and GPUs.

When you init a new tensor in your code, just use type_as():

```
def training_step(self, batch, batch_idx):
    x, y = batch

    # put the z on the appropriate gpu or tpu core
    z = sample_noise()
    z = z.type_as(x)
```

5.5 Data preparation

Data preparation in PyTorch follows 5 steps:

1. Download
2. Clean and (maybe) save to disk
3. Load inside Dataset
4. Apply transforms (rotate, tokenize, etc...)
5. Wrap inside a DataLoader

When working in distributed settings, steps 1 and 2 have to be done from a single GPU, otherwise you will overwrite these files from every GPU. The *LightningModule* has the *prepare_data* method to allow for this:

```
>>> class LitModel(pl.LightningModule):
...     def prepare_data(self):
...         # download
...         mnist_train = MNIST(os.getcwd(), train=True, download=True,
...                             transform=transforms.ToTensor())
...         mnist_test = MNIST(os.getcwd(), train=False, download=True,
...                            transform=transforms.ToTensor())
...
...         # train/val split
...         mnist_train, mnist_val = random_split(mnist_train, [55000, 5000])
...
...         # assign to use in dataloaders
...         self.train_dataset = mnist_train
...         self.val_dataset = mnist_val
...         self.test_dataset = mnist_test
...
...     def train_dataloader(self):
...         return DataLoader(self.train_dataset, batch_size=64)
...
...     def val_dataloader(self):
...         return DataLoader(self.mnist_val, batch_size=64)
...
...     def test_dataloader(self):
...         return DataLoader(self.mnist_test, batch_size=64)
```

Note: *prepare_data()* is called once.

Note: Do anything with data that needs to happen ONLY once here, like download, tokenize, etc...

5.6 Lifecycle

The methods in the *LightningModule* are called in this order:

1. `__init__()`
2. *prepare_data()*
3. *configure_optimizers()*
4. *train_dataloader()*

If you define a validation loop then

5. *val_dataloader()*

And if you define a test loop:

6. *test_dataloader()*

Note: *test_dataloader()* is only called with `.test()`

In every epoch, the loop methods are called in this frequency:

1. *validation_step()* called every batch
2. *validation_epoch_end()* called every epoch

5.7 Live demo

Check out this COLAB for a live demo.

5.8 LightningModule Class

class pytorch_lightning.core.**LightningModule**(**args*, ***kwargs*)

Bases: abc.ABC, *pytorch_lightning.core.properties.DeviceDtypeModuleMixin*, *pytorch_lightning.core.grads.GradInformation*, *pytorch_lightning.core.saving.ModelIO*, *pytorch_lightning.core.hooks.ModelHooks*

_init_slurm_connection()

Sets up environment variables necessary for pytorch distributed communications based on slurm environment.

Return type None

configure_apex(*amp*, *model*, *optimizers*, *amp_level*)

Override to init AMP your own way. Must return a model and list of optimizers.

Parameters

- **amp** (object) – pointer to amp library object.
- **model** (*LightningModule*) – pointer to current *LightningModule*.
- **optimizers** (List[Optimizer]) – list of optimizers passed in *configure_optimizers()*.
- **amp_level** (str) – AMP mode chosen ('O1', 'O2', etc...)

Return type Tuple[*LightningModule*, List[Optimizer]]

Returns Apex wrapped model and optimizers

Examples

```
# Default implementation used by Trainer.
def configure_apex(self, amp, model, optimizers, amp_level):
    model, optimizers = amp.initialize(
        model, optimizers, opt_level=amp_level,
    )

    return model, optimizers
```

configure_ddp(*model*, *device_ids*)

Override to init DDP in your own way or with your own wrapper. The only requirements are that:

1. On a validation batch the call goes to model.validation_step.
2. On a training batch the call goes to model.training_step.

3. On a testing batch, the call goes to `model.test_step`.+

Parameters

- **model** (*LightningModule*) – the *LightningModule* currently being optimized.
- **device_ids** (List[int]) – the list of GPU ids.

Return type DistributedDataParallel

Returns DDP wrapped model

Examples

```
# default implementation used in Trainer
def configure_ddp(self, model, device_ids):
    # Lightning DDP simply routes to test_step, val_step, etc...
    model = LightningDistributedDataParallel(
        model,
        device_ids=device_ids,
        find_unused_parameters=True
    )
    return model
```

configure_optimizers()

Choose what optimizers and learning-rate schedulers to use in your optimization. Normally you'd need one. But in the case of GANs or similar you might have multiple.

Return type Union[Optimizer, Sequence[Optimizer], Dict, Sequence[Dict], Tuple[List, List], None]

Returns

Any of these 6 options.

- Single optimizer.
- List or Tuple - List of optimizers.
- Two lists - The first list has multiple optimizers, the second a list of LR schedulers.
- Dictionary, with an 'optimizer' key and (optionally) a 'lr_scheduler' key.
- Tuple of dictionaries as described, with an optional 'frequency' key.
- None - Fit will run without any optimizer.

Note: The 'frequency' value is an int corresponding to the number of sequential batches optimized with the specific optimizer. It should be given to none or to all of the optimizers. There is a difference between passing multiple optimizers in a list, and passing multiple optimizers in dictionaries with a frequency of 1: In the former case, all optimizers will operate on the given batch in each optimization step. In the latter, only one optimizer will operate on the given batch at every step.

Examples

```
# most cases
def configure_optimizers(self):
    opt = Adam(self.parameters(), lr=1e-3)
    return opt

# multiple optimizer case (e.g.: GAN)
def configure_optimizers(self):
    generator_opt = Adam(self.model_gen.parameters(), lr=0.01)
    disriminator_opt = Adam(self.model_disc.parameters(), lr=0.02)
    return generator_opt, disriminator_opt

# example with learning rate schedulers
def configure_optimizers(self):
    generator_opt = Adam(self.model_gen.parameters(), lr=0.01)
    disriminator_opt = Adam(self.model_disc.parameters(), lr=0.02)
    discriminator_sched = CosineAnnealing(discriminator_opt, T_max=10)
    return [generator_opt, disriminator_opt], [discriminator_sched]

# example with step-based learning rate schedulers
def configure_optimizers(self):
    gen_opt = Adam(self.model_gen.parameters(), lr=0.01)
    dis_opt = Adam(self.model_disc.parameters(), lr=0.02)
    gen_sched = {'scheduler': ExponentialLR(gen_opt, 0.99),
                 'interval': 'step'}  # called after each training step
    dis_sched = CosineAnnealing(discriminator_opt, T_max=10) # called every␣
↪epoch
    return [gen_opt, dis_opt], [gen_sched, dis_sched]

# example with optimizer frequencies
# see training procedure in `Improved Training of Wasserstein GANs`,␣
↪Algorithm 1
# https://arxiv.org/abs/1704.00028
def configure_optimizers(self):
    gen_opt = Adam(self.model_gen.parameters(), lr=0.01)
    dis_opt = Adam(self.model_disc.parameters(), lr=0.02)
    n_critic = 5
    return (
        {'optimizer': dis_opt, 'frequency': n_critic},
        {'optimizer': gen_opt, 'frequency': 1}
    )
```

Note: Some things to know:

- Lightning calls `.backward()` and `.step()` on each optimizer and learning rate scheduler as needed.
- If you use 16-bit precision (`precision=16`), Lightning will automatically handle the optimizers for you.
- If you use multiple optimizers, *`training_step()`* will have an additional `optimizer_idx` parameter.
- If you use LBFGS Lightning handles the closure function automatically for you.
- If you use multiple optimizers, gradients will be calculated only for the parameters of current optimizer at each training step.

- If you need to control how often those optimizers step or override the default `.step()` schedule, override the *optimizer_step()* hook.
- If you only want to call a learning rate scheduler every `x` step or epoch, or want to monitor a custom metric, you can specify these in a dictionary:

```
{
    'scheduler': lr_scheduler,
    'interval': 'step'  # or 'epoch'
    'monitor': 'val_f1',
    'frequency': x
}
```

---

abstract forward(**args*, ***kwargs*)

Same as `torch.nn.Module.forward()`, however in Lightning you want this to define the operations you want to use for prediction (i.e.: on a server or as a feature extractor).

Normally you'd call `self()` from your *training_step()* method. This makes it easy to write a complex system for training with the outputs you'd want in a prediction setting.

Parameters

- ***args** – Whatever you decide to pass into the forward method.
- ****kwargs** – Keyword arguments are also possible.

Returns Predicted output

Examples

```
# example if we were using this model as a feature extractor
def forward(self, x):
    feature_maps = self.convnet(x)
    return feature_maps

def training_step(self, batch, batch_idx):
    x, y = batch
    feature_maps = self(x)
    logits = self.classifier(feature_maps)

    # ...
    return loss

# splitting it this way allows model to be used a feature extractor
model = MyModelAbove()

inputs = server.get_request()
results = model(inputs)
server.write_results(results)

# -------------
# This is in stark contrast to torch.nn.Module where normally you would have␣
↪this:
def forward(self, batch):
    x, y = batch
    feature_maps = self.convnet(x)
    logits = self.classifier(feature_maps)
    return logits
```

freeze()
Freeze all params for inference.

Example

```
model = MyLightningModule(...)
model.freeze()
```

Return type None

get_progress_bar_dict()
Additional items to be displayed in the progress bar.

Return type Dict[str, Union[int, str]]

Returns Dictionary with the items to be displayed in the progress bar.

get_tqdm_dict()
Additional items to be displayed in the progress bar.

Return type Dict[str, Union[int, str]]

Returns Dictionary with the items to be displayed in the progress bar.

> **Warning:** Deprecated since v0.7.3. Use *get_progress_bar_dict()* instead.

init_ddp_connection(*proc_rank*, *world_size*, *is_slurm_managing_tasks=True*)
Override to define your custom way of setting up a distributed environment.

Lightning's implementation uses env:// init by default and sets the first node as root for SLURM managed cluster.

Parameters

- **proc_rank** (int) – The current process rank within the node.
- **world_size** (int) – Number of GPUs being use across all nodes. (num_nodes * num_gpus).
- **is_slurm_managing_tasks** (bool) – is cluster managed by SLURM.

Return type None

classmethod load_from_checkpoint(*checkpoint_path*, **args*, *map_location=None*, *hparams_file=None*, *tags_csv=None*, *hparam_overrides=None*, ***kwargs*)
Primary way of loading a model from a checkpoint. When Lightning saves a checkpoint it stores the hyperparameters in the checkpoint if you initialized your *LightningModule* with an argument called hparams which is an object of dict or Namespace (output of parse_args() when parsing command line arguments). If you want *hparams* to have a hierarchical structure, you have to define it as dict. Any other arguments specified through *args and **kwargs will be passed to the model.

Example

```
# define hparams as Namespace
from argparse import Namespace
hparams = Namespace(**{'learning_rate': 0.1})

model = MyModel(hparams)

class MyModel(LightningModule):
    def __init__(self, hparams: Namespace):
        self.learning_rate = hparams.learning_rate

# ----------

# define hparams as dict
hparams = {
    drop_prob: 0.2,
    dataloader: {
        batch_size: 32
    }
}

model = MyModel(hparams)

class MyModel(LightningModule):
    def __init__(self, hparams: dict):
        self.learning_rate = hparams['learning_rate']
```

Parameters

- **checkpoint_path** (str) – Path to checkpoint.
- **args** – Any positional args needed to init the model.
- **map_location** (Union[Dict[str, str], str, device, int, Callable, None]) – If your checkpoint saved a GPU model and you now load on CPUs or a different number of GPUs, use this to map to the new setup. The behaviour is the same as in torch.load().
- **hparams_file** (Optional[str]) – Optional path to a .yaml file with hierarchical structure as in this example:

  ```
  drop_prob: 0.2
  dataloader:
      batch_size: 32
  ```

  You most likely won't need this since Lightning will always save the hyperparameters to the checkpoint. However, if your checkpoint weights don't have the hyperparameters saved, use this method to pass in a .yaml file with the hparams you'd like to use. These will be converted into a dict and passed into your *LightningModule* for use.

  If your model's *hparams* argument is Namespace and .yaml file has hierarchical structure, you need to refactor your model to treat *hparams* as dict.

  .csv files are acceptable here till v0.9.0, see tags_csv argument for detailed usage.

- **tags_csv** (Optional[str]) –

> **Warning:** Deprecated since version 0.7.6.
>
> *tags_csv* argument is deprecated in v0.7.6. Will be removed v0.9.0.

Optional path to a .csv file with two columns (key, value) as in this example:

```
key,value
drop_prob,0.2
batch_size,32
```

Use this method to pass in a .csv file with the hparams you'd like to use.

- **hparam_overrides** (Optional[Dict]) – A dictionary with keys to override in the hparams
- **kwargs** – Any keyword args needed to init the model.

Return type *LightningModule*

Returns *LightningModule* with loaded weights and hyperparameters (if available).

Example

```
# load weights without mapping ...
MyLightningModule.load_from_checkpoint('path/to/checkpoint.ckpt')

# or load weights mapping all weights from GPU 1 to GPU 0 ...
map_location = {'cuda:1':'cuda:0'}
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    map_location=map_location
)

# or load weights and hyperparameters from separate files.
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    hparams_file='/path/to/hparams_file.yaml'
)

# override some of the params with new values
MyLightningModule.load_from_checkpoint(
    PATH,
    hparam_overrides={'num_layers': 128, 'pretrained_ckpt_path': NEW_PATH}
)

# or load passing whatever args the model takes to load
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    learning_rate=0.1, # These arguments will be passed to the model using␣
↪**kwargs
    layers=2,
    pretrained_model=some_model
)

# predict
pretrained_model.eval()
```

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```
pretrained_model.freeze()
y_hat = pretrained_model(x)
```

classmethod load_from_metrics(*weights_path*, *tags_csv*, *map_location=None*)

> **Warning:** Deprecated in version 0.7.0. You should use *load_from_checkpoint()* instead. Will be removed in v0.9.0.

on_load_checkpoint(*checkpoint*)

Called by Lightning to restore your model. If you saved something with *on_save_checkpoint()* this is your chance to restore this.

Parameters **checkpoint** (Dict[str, Any]) – Loaded checkpoint

Example

```
def on_load_checkpoint(self, checkpoint):
    # 99% of the time you don't need to implement this method
    self.something_cool_i_want_to_save = checkpoint['something_cool_i_want_to_
↪save']
```

> **Note:** Lightning auto-restores global step, epoch, and train state including amp scaling. There is no need for you to restore anything regarding training.

Return type None

on_save_checkpoint(*checkpoint*)

Called by Lightning when saving a checkpoint to give you a chance to store anything else you might want to save.

Parameters **checkpoint** (Dict[str, Any]) – Checkpoint to be saved

Example

```
def on_save_checkpoint(self, checkpoint):
    # 99% of use cases you don't need to implement this method
    checkpoint['something_cool_i_want_to_save'] = my_cool_pickable_object
```

> **Note:** Lightning saves all aspects of training (epoch, global step, etc...) including amp scaling. There is no need for you to store anything about training.

Return type None

optimizer_step(*epoch*, *batch_idx*, *optimizer*, *optimizer_idx*, *second_order_closure=None*)

Override this method to adjust the default way the *Trainer* calls each optimizer. By default, Lightning calls `step()` and `zero_grad()` as shown in the example once per optimizer.

Parameters

- **epoch** (int) – Current epoch
- **batch_idx** (int) – Index of current batch
- **optimizer** (Optimizer) – A PyTorch optimizer
- **optimizer_idx** (int) – If you used multiple optimizers this indexes into that list.
- **second_order_closure** (Optional[Callable]) – closure for second order methods

Examples

```
# DEFAULT
def optimizer_step(self, current_epoch, batch_idx, optimizer, optimizer_idx,
                   second_order_closure=None):
    optimizer.step()
    optimizer.zero_grad()

# Alternating schedule for optimizer steps (i.e.: GANs)
def optimizer_step(self, current_epoch, batch_idx, optimizer, optimizer_idx,
                   second_order_closure=None):
    # update generator opt every 2 steps
    if optimizer_idx == 0:
        if batch_idx % 2 == 0 :
            optimizer.step()
            optimizer.zero_grad()

    # update discriminator opt every 4 steps
    if optimizer_idx == 1:
        if batch_idx % 4 == 0 :
            optimizer.step()
            optimizer.zero_grad()

    # ...
    # add as many optimizers as you want
```

Here's another example showing how to use this for more advanced things such as learning rate warm-up:

```
# learning rate warm-up
def optimizer_step(self, current_epoch, batch_idx, optimizer,
                   optimizer_idx, second_order_closure=None):
    # warm up lr
    if self.trainer.global_step < 500:
        lr_scale = min(1., float(self.trainer.global_step + 1) / 500.)
        for pg in optimizer.param_groups:
            pg['lr'] = lr_scale * self.hparams.learning_rate

    # update params
    optimizer.step()
    optimizer.zero_grad()
```

Note: If you also override the *on_before_zero_grad()* model hook don't forget to add the call to it before `optimizer.zero_grad()` yourself.

Return type None

prepare_data()
Use this to download and prepare data. In distributed (GPU, TPU), this will only be called once. This is called before requesting the dataloaders:

```
model.prepare_data()
model.train_dataloader()
model.val_dataloader()
model.test_dataloader()
```

Examples

```
def prepare_data(self):
    download_imagenet()
    clean_imagenet()
    cache_imagenet()
```

Return type None

print(**args*, ***kwargs*)
Prints only from process 0. Use this in any distributed mode to log only once.

Parameters

- ***args** – The thing to print. Will be passed to Python's built-in print function.
- ****kwargs** – Will be passed to Python's built-in print function.

Example

```
def forward(self, x):
    self.print(x, 'in forward')
```

Return type None

tbptt_split_batch(*batch*, *split_size*)
When using truncated backpropagation through time, each batch must be split along the time dimension. Lightning handles this by default, but for custom behavior override this function.

Parameters

- **batch** (Tensor) – Current batch
- **split_size** (int) – The size of the split

Return type list

Returns List of batch splits. Each split will be passed to *training_step()* to enable truncated back propagation through time. The default implementation splits root level Tensors and Sequences at dim=1 (i.e. time dim). It assumes that each time dim is the same length.

Examples

```
def tbptt_split_batch(self, batch, split_size):
  splits = []
  for t in range(0, time_dims[0], split_size):
      batch_split = []
      for i, x in enumerate(batch):
          if isinstance(x, torch.Tensor):
              split_x = x[:, t:t + split_size]
          elif isinstance(x, collections.Sequence):
              split_x = [None] * len(x)
              for batch_idx in range(len(x)):
                  split_x[batch_idx] = x[batch_idx][t:t + split_size]

          batch_split.append(split_x)

      splits.append(batch_split)

  return splits
```

Note: Called in the training loop after *on_batch_start()* if *truncated_bptt_steps* > 0. Each returned batch split is passed separately to *training_step()*.

---

test_dataloader()

Implement one or multiple PyTorch DataLoaders for testing.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to `True`.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*
- ...
- *prepare_data()*
- *train_dataloader()*
- *val_dataloader()*
- *test_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

Return type Union[DataLoader, List[DataLoader]]

Returns Single or multiple PyTorch DataLoaders.

Example

```
def test_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=False, transform=transform,
                    download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=False
    )

    return loader
```

Note: If you don't need a test dataset and a *test_step()*, you don't need to implement this method.

test_end(*outputs*)

Warning: Deprecated in v0.7.0. Use *test_epoch_end()* instead. Will be removed in 1.0.0.

test_epoch_end(*outputs*)

Called at the end of a test epoch with the output of all test steps.

```
# the pseudocode for these calls
test_outs = []
for test_batch in test_data:
    out = test_step(test_batch)
    test_outs.append(out)
test_epoch_end(test_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *test_step_end()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader

Returns

Dict has the following optional keys:

- progress_bar -> Dict for progress bar display. Must have only tensors.
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc).

Return type Dict or OrderedDict

Note: If you didn't define a *test_step()*, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, specify it with the 'step' key in the 'log' Dict

Examples

With a single dataloader:

```
def test_epoch_end(self, outputs):
    test_acc_mean = 0
    for output in outputs:
        test_acc_mean += output['test_acc']

    test_acc_mean /= len(outputs)
    tqdm_dict = {'test_acc': test_acc_mean.item()}

    # show test_loss and test_acc in progress bar but only log test_loss
    results = {
        'progress_bar': tqdm_dict,
        'log': {'test_acc': test_acc_mean.item()}
    }
    return results
```

With multiple dataloaders, *outputs* will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each test step for that dataloader.

```
def test_epoch_end(self, outputs):
    test_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
        for output in dataloader_outputs:
            test_acc_mean += output['test_acc']
            i += 1

    test_acc_mean /= i
    tqdm_dict = {'test_acc': test_acc_mean.item()}

    # show test_loss and test_acc in progress bar but only log test_loss
    results = {
        'progress_bar': tqdm_dict,
        'log': {'test_acc': test_acc_mean.item(), 'step': self.current_epoch}
    }
    return results
```

test_step(**args*, ***kwargs*)

Operates on a single batch of data from the test set. In this step you'd normally generate examples or calculate anything of interest such as accuracy.

```
# the pseudocode for these calls
test_outs = []
for test_batch in test_data:
    out = test_step(test_batch)
    test_outs.append(out)
test_epoch_end(test_outs)
```

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – The index of this batch.

- **dataloader_idx** (*int*) – The index of the dataloader that produced this batch (only if multiple test datasets used).

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *test_epoch_end()* method. If you defined *test_step_end()* it will go to that first.

```
# if you have one test dataloader:
def test_step(self, batch, batch_idx)

# if you have multiple test dataloaders:
def test_step(self, batch, batch_idx, dataloader_idx)
```

Examples

```
# CASE 1: A single test dataset
def test_step(self, batch, batch_idx):
    x, y = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, y)

    # log 6 example images
    # or generated text... or whatever
    sample_imgs = x[:6]
    grid = torchvision.utils.make_grid(sample_imgs)
    self.logger.experiment.add_image('example_images', grid, 0)

    # calculate acc
    labels_hat = torch.argmax(out, dim=1)
    val_acc = torch.sum(y == labels_hat).item() / (len(y) * 1.0)

    # all optional...
    # return whatever you need for the collation function test_epoch_end
    output = OrderedDict({
        'val_loss': loss_val,
        'val_acc': torch.tensor(val_acc), # everything must be a tensor
    })

    # return an optional dict
    return output
```

If you pass in multiple validation datasets, *test_step()* will have an additional argument.

```
# CASE 2: multiple test datasets
def test_step(self, batch, batch_idx, dataset_idx):
    # dataset_idx tells you which dataset this is.
```

Note: If you don't need to validate you don't need to implement this method.

Note: When the *test_step()* is called, the model has been put in eval mode and PyTorch gradients have been disabled. At the end of the test epoch, the model goes back to training mode and gradients are

enabled.

---

test_step_end(**args*, ***kwargs*)

Use this when testing with dp or ddp2 because *test_step()* will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to change your code.

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
batch_parts_outputs = [test_step(sub_batch) for sub_batch in sub_batches]
test_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *test_step()* for each batch part.

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *test_epoch_end()*.

Examples

```
# WITHOUT test_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def test_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with test_step_end to do softmax over the full batch
def test_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def test_step_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

tng_dataloader()

> **Warning:** Deprecated in v0.5.0. Use *train_dataloader()* instead. Will be removed in 1.0.0.

train_dataloader()
Implement a PyTorch DataLoader for training.

Return type DataLoader

Returns Single PyTorch DataLoader.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to True.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*
- ...
- *prepare_data()*
- *train_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

Example

```
def train_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=True, transform=transform,
                    download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=True
    )
    return loader
```

training_end(**args*, ***kwargs*)

> **Warning:** Deprecated in v0.7.0. Use *training_step_end()* instead.

training_epoch_end(*outputs*)
Called at the end of the training epoch with the outputs of all training steps.

```
# the pseudocode for these calls
train_outs = []
for train_batch in train_data:
    out = training_step(train_batch)
```

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```
    train_outs.append(out)
training_epoch_end(train_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *training_step()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader.

Return type Dict[str, Dict[str, Tensor]]

Returns

Dict or OrderedDict. May contain the following optional keys:

- log (metrics to be added to the logger; only tensors)
- progress_bar (dict for progress bar display)
- any metric used in a callback (e.g. early stopping).

Note: If this method is not overridden, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, you can specify the 'step' key in the 'log' dict.

Examples

With a single dataloader:

```
def training_epoch_end(self, outputs):
    train_acc_mean = 0
    for output in outputs:
        train_acc_mean += output['train_acc']

    train_acc_mean /= len(outputs)

    # log training accuracy at the end of an epoch
    results = {
        'log': {'train_acc': train_acc_mean.item()},
        'progress_bar': {'train_acc': train_acc_mean},
    }
    return results
```

With multiple dataloaders, `outputs` will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each training step for that dataloader.

```
def training_epoch_end(self, outputs):
    train_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
        for output in dataloader_outputs:
            train_acc_mean += output['train_acc']
            i += 1
```

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```
    train_acc_mean /= i

    # log training accuracy at the end of an epoch
    results = {
        'log': {'train_acc': train_acc_mean.item(), 'step': self.current_
↪epoch}
        'progress_bar': {'train_acc': train_acc_mean},
    }
    return results
```

training_step(**args*, ***kwargs*)

Here you compute and return the training loss and some additional metrics for e.g. the progress bar or logger.

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – Integer displaying index of this batch
- **optimizer_idx** (*int*) – When using multiple optimizers, this argument will also be present.
- **hiddens** (Tensor) – Passed in if *truncated_bptt_steps* > 0.

Return type Union[int, Dict[str, Union[Tensor, Dict[str, Tensor]]]]

Returns

Dict with loss key and optional log or progress bar keys. When implementing *training_step()*, return whatever you need in that step:

- loss -> tensor scalar **REQUIRED**
- progress_bar -> Dict for progress bar display. Must have only tensors
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc)

In this step you'd normally do the forward pass and calculate the loss for a batch. You can also do fancier things like multiple forward passes or something model specific.

Examples

```
def training_step(self, batch, batch_idx):
    x, y, z = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, x)

    logger_logs = {'training_loss': loss} # optional (MUST ALL BE TENSORS)

    # if using TestTubeLogger or TensorBoardLogger you can nest scalars
    logger_logs = {'losses': logger_logs} # optional (MUST ALL BE TENSORS)

    output = {
        'loss': loss, # required
```

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```
        'progress_bar': {'training_loss': loss}, # optional (MUST ALL BE␣
↪TENSORS)
        'log': logger_logs
    }

    # return a dict
    return output
```

If you define multiple optimizers, this step will be called with an additional `optimizer_idx` parameter.

```
# Multiple optimizers (e.g.: GANs)
def training_step(self, batch, batch_idx, optimizer_idx):
    if optimizer_idx == 0:
        # do training_step with encoder
    if optimizer_idx == 1:
        # do training_step with decoder
```

If you add truncated back propagation through time you will also get an additional argument with the hidden states of the previous step.

```
# Truncated back-propagation through time
def training_step(self, batch, batch_idx, hiddens):
    # hiddens are the hidden states from the previous truncated backprop step
    ...
    out, hiddens = self.lstm(data, hiddens)
    ...

    return {
        "loss": ...,
        "hiddens": hiddens  # remember to detach() this
    }
```

Notes

The loss value shown in the progress bar is smoothed (averaged) over the last values, so it differs from the actual loss returned in train/validation step.

training_step_end(**args*, ***kwargs*)

Use this when training with dp or ddp2 because *training_step()* will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to change your code

---

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
batch_parts_outputs = [training_step(sub_batch) for sub_batch in sub_batches]
training_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *training_step* for each batch part.

Return type Dict[str, Union[Tensor, Dict[str, Tensor]]]

Returns

Dict with loss key and optional log or progress bar keys.

- loss -> tensor scalar **REQUIRED**
- progress_bar -> Dict for progress bar display. Must have only tensors
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc)

Examples

```
# WITHOUT training_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def training_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with training_step_end to do softmax over the full batch
def training_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def training_step_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

unfreeze()

Unfreeze all parameters for training.

```
model = MyLightningModule(...)
model.unfreeze()
```

Return type None

val_dataloader()

Implement one or multiple PyTorch DataLoaders for validation.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to True.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*

- ...
- *prepare_data()*
- *train_dataloader()*
- *val_dataloader()*
- *test_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware There is no need to set it yourself.

Return type Union[DataLoader, List[DataLoader]]

Returns Single or multiple PyTorch DataLoaders.

Examples

```
def val_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=False,
                    transform=transform, download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=False
    )

    return loader

# can also return multiple dataloaders
def val_dataloader(self):
    return [loader_a, loader_b, ..., loader_n]
```

Note: If you don't need a validation dataset and a *validation_step()*, you don't need to implement this method.

Note: In the case where you return multiple validation dataloaders, the *validation_step()* will have an argument `dataset_idx` which matches the order here.

validation_end(*outputs*)

Warning: Deprecated in v0.7.0. Use *validation_epoch_end()* instead. Will be removed in 1.0.0.

validation_epoch_end(*outputs*)
Called at the end of the validation epoch with the outputs of all validation steps.

```
# the pseudocode for these calls
val_outs = []
for val_batch in val_data:
    out = validation_step(val_batch)
    val_outs.append(out)
validation_epoch_end(val_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *validation_step()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader.

Return type Dict[str, Dict[str, Tensor]]

Returns

Dict or OrderedDict. May have the following optional keys:

- progress_bar (dict for progress bar display; only tensors)
- log (dict of metrics to add to logger; only tensors).

Note: If you didn't define a *validation_step()*, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, you can specify the 'step' key in the 'log' dict.

Examples

With a single dataloader:

```
def validation_epoch_end(self, outputs):
    val_acc_mean = 0
    for output in outputs:
        val_acc_mean += output['val_acc']

    val_acc_mean /= len(outputs)
    tqdm_dict = {'val_acc': val_acc_mean.item()}

    # show val_acc in progress bar but only log val_loss
    results = {
        'progress_bar': tqdm_dict,
        'log': {'val_acc': val_acc_mean.item()}
    }
    return results
```

With multiple dataloaders, *outputs* will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each validation step for that dataloader.

```
def validation_epoch_end(self, outputs):
    val_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
```

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```
        for output in dataloader_outputs:
            val_acc_mean += output['val_acc']
            i += 1

    val_acc_mean /= i
    tqdm_dict = {'val_acc': val_acc_mean.item()}

    # show val_loss and val_acc in progress bar but only log val_loss
    results = {
        'progress_bar': tqdm_dict,
        'log': {'val_acc': val_acc_mean.item(), 'step': self.current_epoch}
    }
    return results
```

validation_step(**args*, ***kwargs*)

Operates on a single batch of data from the validation set. In this step you'd might generate examples or calculate anything of interest like accuracy.

```
# the pseudocode for these calls
val_outs = []
for val_batch in val_data:
    out = validation_step(train_batch)
    val_outs.append(out)
    validation_epoch_end(val_outs)
```

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – The index of this batch
- **dataloader_idx** (*int*) – The index of the dataloader that produced this batch (only if multiple val datasets used)

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to *validation_epoch_end()*. If you defined *validation_step_end()* it will go to that first.

```
# pseudocode of order
out = validation_step()
if defined('validation_step_end'):
    out = validation_step_end(out)
out = validation_epoch_end(out)
```

```
# if you have one val dataloader:
def validation_step(self, batch, batch_idx)

# if you have multiple val dataloaders:
def validation_step(self, batch, batch_idx, dataloader_idx)
```

Examples

```
# CASE 1: A single validation dataset
def validation_step(self, batch, batch_idx):
    x, y = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, y)

    # log 6 example images
    # or generated text... or whatever
    sample_imgs = x[:6]
    grid = torchvision.utils.make_grid(sample_imgs)
    self.logger.experiment.add_image('example_images', grid, 0)

    # calculate acc
    labels_hat = torch.argmax(out, dim=1)
    val_acc = torch.sum(y == labels_hat).item() / (len(y) * 1.0)

    # all optional...
    # return whatever you need for the collation function validation_epoch_end
    output = OrderedDict({
        'val_loss': loss_val,
        'val_acc': torch.tensor(val_acc), # everything must be a tensor
    })

    # return an optional dict
    return output
```

If you pass in multiple val datasets, validation_step will have an additional argument.

```
# CASE 2: multiple validation datasets
def validation_step(self, batch, batch_idx, dataset_idx):
    # dataset_idx tells you which dataset this is.
```

Note: If you don't need to validate you don't need to implement this method.

Note: When the *validation_step()* is called, the model has been put in eval mode and PyTorch gradients have been disabled. At the end of validation, the model goes back to training mode and gradients are enabled.

validation_step_end(**args*, ***kwargs*)

Use this when validating with dp or ddp2 because *validation_step()* will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to change your code.

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
```

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```
batch_parts_outputs = [validation_step(sub_batch) for sub_batch in sub_
↪batches]
validation_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *validation_step()* for each batch part.

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *validation_epoch_end()* method.

Examples

```
# WITHOUT validation_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def validation_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with validation_step_end to do softmax over the full batch
def validation_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def validation_epoch_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

_device = None
device reference

_dtype = None
Current dtype

current_epoch = None
The current epoch

global_step = None
Total training batches seen across all epochs

logger = None
Pointer to the logger object

on_gpu = None
True if your model is currently running on GPUs. Useful to set flags around the LightningModule for different CPU vs GPU behavior.

trainer = None
Pointer to the trainer object

use_amp = None
True if using amp

use_ddp = None
True if using ddp

use_ddp2 = None
True if using ddp2

use_dp = None
True if using dp

pytorch_lightning.core.**data_loader**(*fn*)
Decorator to make any fx with this use the lazy property.

> **Warning:** This decorator deprecated in v0.7.0 and it will be removed v0.9.0.

CHAPTER

SIX

LOGGERS

Lightning supports the most popular logging frameworks (TensorBoard, Comet, Weights and Biases, etc. . .). To use a logger, simply pass it into the *Trainer*. Lightning uses TensorBoard by default.

```
from pytorch_lightning import Trainer
from pytorch_lightning import loggers
tb_logger = loggers.TensorBoardLogger('logs/')
trainer = Trainer(logger=tb_logger)
```

Choose from any of the others such as MLflow, Comet, Neptune, WandB, . . .

```
comet_logger = loggers.CometLogger(save_dir='logs/')
trainer = Trainer(logger=comet_logger)
```

To use multiple loggers, simply pass in a `list` or `tuple` of loggers . . .

```
tb_logger = loggers.TensorBoardLogger('logs/')
comet_logger = loggers.CometLogger(save_dir='logs/')
trainer = Trainer(logger=[tb_logger, comet_logger])
```

Note: All loggers log by default to `os.getcwd()`. To change the path without creating a logger set `Trainer(default_root_dir='/your/path/to/save/checkpoints')`

6.1 Custom Logger

You can implement your own logger by writing a class that inherits from *LightningLoggerBase*. Use the `rank_zero_only()` decorator to make sure that only the first process in DDP training logs data.

```
from pytorch_lightning.utilities import rank_zero_only
from pytorch_lightning.loggers import LightningLoggerBase
class MyLogger(LightningLoggerBase):

    @rank_zero_only
    def log_hyperparams(self, params):
        # params is an argparse.Namespace
        # your code to record hyperparameters goes here
        pass

    @rank_zero_only
    def log_metrics(self, metrics, step):
```

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```
        # metrics is a dictionary of metric names and values
        # your code to record metrics goes here
        pass

    def save(self):
        # Optional. Any code necessary to save logger data goes here
        pass

    @rank_zero_only
    def finalize(self, status):
        # Optional. Any code that needs to be run after training
        # finishes goes here
        pass
```

If you write a logger that may be useful to others, please send a pull request to add it to Lighting!

6.2 Using loggers

Call the logger anywhere except `__init__` in your *LightningModule* by doing:

```
from pytorch_lightning import LightningModule
class LitModel(LightningModule):
    def training_step(self, batch, batch_idx):
        # example
        self.logger.experiment.whatever_method_summary_writer_supports(...)

        # example if logger is a tensorboard logger
        self.logger.experiment.add_image('images', grid, 0)
        self.logger.experiment.add_graph(model, images)

    def any_lightning_module_function_or_hook(self):
        self.logger.experiment.add_histogram(...)
```

Read more in the Experiment Logging use case.

6.3 Supported Loggers

class pytorch_lightning.loggers.**LightningLoggerBase**(*agg_key_funcs=None*, *agg_default_func=numpy.mean*)

Bases: abc.ABC

Base class for experiment loggers.

Parameters

- **agg_key_funcs** (Optional[Mapping[str, Callable[[Sequence[float]], float]]]) – Dictionary which maps a metric name to a function, which will aggregate the metric values for the same steps.
- **agg_default_func** (Callable[[Sequence[float]], float]) – Default function to aggregate metric values. If some metric name is not presented in the *agg_key_funcs* dictionary, then the *agg_default_func* will be used for aggregation.

Note: The *agg_key_funcs* and *agg_default_func* arguments are used only when one logs metrics with the *agg_and_log_metrics()* method.

_aggregate_metrics(*metrics*, *step=None*)
Aggregates metrics.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type Tuple[int, Optional[Dict[str, float]]]

Returns Step and aggregated metrics. The return value could be None. In such case, metrics are added to the aggregation list, but not aggregated yet.

_finalize_agg_metrics()
This shall be called before save/close.

static _flatten_dict(*params*, *delimiter='/'*)
Flatten hierarchical dict, e.g. {'a': {'b': 'c'}} -> {'a/b': 'c'}.

Parameters

- **params** (Dict[str, Any]) – Dictionary containing the hyperparameters
- **delimiter** (str) – Delimiter to express the hierarchy. Defaults to '/'.

Return type Dict[str, Any]

Returns Flattened dict.

Examples

```
>>> LightningLoggerBase._flatten_dict({'a': {'b': 'c'}})
{'a/b': 'c'}
>>> LightningLoggerBase._flatten_dict({'a': {'b': 123}})
{'a/b': 123}
```

_reduce_agg_metrics()
Aggregate accumulated metrics.

static _sanitize_params(*params*)
Returns params with non-primitvies converted to strings for logging.

```
>>> params = {"float": 0.3,
...           "int": 1,
...           "string": "abc",
...           "bool": True,
...           "list": [1, 2, 3],
...           "namespace": Namespace(foo=3),
...           "layer": torch.nn.BatchNorm1d}
>>> import pprint
>>> pprint.pprint(LightningLoggerBase._sanitize_params(params))
{'bool': True,
 'float': 0.3,
 'int': 1,
```

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```
'layer': "<class 'torch.nn.modules.batchnorm.BatchNorm1d'>",
'list': '[1, 2, 3]',
'namespace': 'Namespace(foo=3)',
'string': 'abc'}
```

Return type Dict[str, Any]

agg_and_log_metrics(*metrics*, *step=None*)
Aggregates and records metrics. This method doesn't log the passed metrics instantaneously, but instead it aggregates them and logs only if metrics are ready to be logged.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

abstract log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Namespace) – Namespace containing the hyperparameters

abstract log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

save()
Save log data.

Return type None

update_agg_funcs(*agg_key_funcs=None*, *agg_default_func=numpy.mean*)
Update aggregation methods.

Parameters

- **agg_key_funcs** (Optional[Mapping[str, Callable[[Sequence[float]], float]]]) – Dictionary which maps a metric name to a function, which will aggregate the metric values for the same steps.

- **agg_default_func** (Callable[[Sequence[float]], float]) – Default function to aggregate metric values. If some metric name is not presented in the *agg_key_funcs* dictionary, then the *agg_default_func* will be used for aggregation.

abstract property experiment
Return the experiment object associated with this logger.

Return type Any

abstract property name
Return the experiment name.

Return type str

abstract property version
Return the experiment version.

Return type Union[int, str]

class pytorch_lightning.loggers.**LoggerCollection**(*logger_iterable*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

The *LoggerCollection* class is used to iterate all logging actions over the given *logger_iterable*.

Parameters **logger_iterable** (Iterable[*LightningLoggerBase*]) – An iterable collection of loggers

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()
Save log data.

Return type None

property experiment
Return the experiment object associated with this logger.

Return type List[Any]

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

class pytorch_lightning.loggers.**TensorBoardLogger**(*save_dir*, *name='default'*, *version=None*, ***kwargs*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log to local file system in TensorBoard format. Implemented using `SummaryWriter`. Logs are saved to `os.path.join(save_dir, name, version)`. This is the default logger in Lightning, it comes preinstalled.

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TensorBoardLogger
>>> logger = TensorBoardLogger("tb_logs", name="my_model")
>>> trainer = Trainer(logger=logger)
```

Parameters

- **save_dir** (str) – Save directory
- **name** (Optional[str]) – Experiment name. Defaults to `'default'`. If it is the empty string then no per-experiment subdirectory is used.
- **version** (Union[int, str, None]) – Experiment version. If version is not specified the logger inspects the save directory for existing versions, then automatically assigns the next available version. If it is a string then it is used as the run-specific subdirectory name, otherwise `'version_${version}'` is used.
- ****kwargs** – Other arguments are passed directly to the `SummaryWriter` constructor.

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*, *metrics=None*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()
Save log data.

Return type None

property experiment
Actual tensorboard object. To use TensorBoard features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_tensorboard_function()
```

Return type SummaryWriter

property log_dir
The directory for this run's tensorboard checkpoint. By default, it is named 'version_${self.version}' but it can be overridden by passing a string value for the constructor's version parameter instead of None or an int.

Return type str

property name
Return the experiment name.

Return type str

property root_dir
Parent directory for all tensorboard checkpoint subdirectories. If the experiment name parameter is None or the empty string, no experiment subdirectory is used and the checkpoint will be saved in "save_dir/version_dir"

Return type str

property version
Return the experiment version.

Return type int

class pytorch_lightning.loggers.**CometLogger**(*api_key=None*, *save_dir=None*, *workspace=None*, *project_name=None*, *rest_api_key=None*, *experiment_name=None*, *experiment_key=None*, ***kwargs*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Comet.ml. Install it with pip:

```
pip install comet-ml
```

Comet requires either an API Key (online mode) or a local directory path (offline mode).

ONLINE MODE

Example

```
>>> import os
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import CometLogger
>>> # arguments made to CometLogger are passed on to the comet_ml.Experiment class
>>> comet_logger = CometLogger(
...     api_key=os.environ.get('COMET_API_KEY'),
...     workspace=os.environ.get('COMET_WORKSPACE'),  # Optional
...     save_dir='.',  # Optional
...     project_name='default_project',  # Optional
...     rest_api_key=os.environ.get('COMET_REST_API_KEY'),  # Optional
...     experiment_name='default'  # Optional
... )
>>> trainer = Trainer(logger=comet_logger)
```

OFFLINE MODE

Example

```
>>> from pytorch_lightning.loggers import CometLogger
>>> # arguments made to CometLogger are passed on to the comet_ml.Experiment class
>>> comet_logger = CometLogger(
...     save_dir='.',
...     workspace=os.environ.get('COMET_WORKSPACE'),  # Optional
...     project_name='default_project',  # Optional
...     rest_api_key=os.environ.get('COMET_REST_API_KEY'),  # Optional
...     experiment_name='default'  # Optional
... )
>>> trainer = Trainer(logger=comet_logger)
```

Parameters

- **api_key** (Optional[str]) – Required in online mode. API key, found on Comet.ml
- **save_dir** (Optional[str]) – Required in offline mode. The path for the directory to save local comet logs
- **workspace** (Optional[str]) – Optional. Name of workspace for this user
- **project_name** (Optional[str]) – Optional. Send your experiment to a specific project. Otherwise will be sent to Uncategorized Experiments. If the project name does not already exist, Comet.ml will create a new project.
- **rest_api_key** (Optional[str]) – Optional. Rest API key found in Comet.ml settings. This is used to determine version number
- **experiment_name** (Optional[str]) – Optional. String representing the name for this particular experiment on Comet.ml.
- **experiment_key** (Optional[str]) – Optional. If set, restores from existing experiment.

finalize(*status*)
When calling `self.experiment.end()`, that experiment won't log any more data to Comet. That's why, if you need to log any more data, you need to create an ExistingCometExperiment. For example, to log data when testing your model after training, because when training is finalized *CometLogger.finalize()* is called.

This happens automatically in the *experiment()* property, when `self._experiment` is set to `None`, i.e. `self.reset_experiment()`.

Return type `None`

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (`Union[Dict[str, Any], Namespace]`) – `Namespace` containing the hyperparameters

Return type `None`

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (`Dict[str, Union[Tensor, float]]`) – Dictionary with metric names as keys and measured quantities as values
- **step** (`Optional[int]`) – Step number at which the metrics should be recorded

Return type `None`

property experiment
Actual Comet object. To use Comet features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_comet_function()
```

Return type `BaseExperiment`

property name
Return the experiment name.

Return type `str`

property version
Return the experiment version.

Return type `str`

class pytorch_lightning.loggers.**MLFlowLogger**(*experiment_name='default'*, *tracking_uri=None*, *tags=None*, *save_dir=None*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using MLflow. Install it with pip:

```
pip install mlflow
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import MLFlowLogger
>>> mlf_logger = MLFlowLogger(
...     experiment_name="default",
...     tracking_uri="file:./ml-runs"
... )
>>> trainer = Trainer(logger=mlf_logger)
```

Use the logger anywhere in you *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_ml_flow_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.whatever_ml_flow_supports(...)
```

Parameters

- **experiment_name** (str) – The name of the experiment
- **tracking_uri** (Optional[str]) – Address of local or remote tracking server. If not provided, defaults to the service set by `mlflow.tracking.set_tracking_uri`.
- **tags** (Optional[Dict[str, Any]]) – A dictionary tags for the experiment.

finalize (*status='FINISHED'*)

Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams (*params*)

Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics (*metrics*, *step=None*)

Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

property experiment

Actual MLflow object. To use mlflow features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_mlflow_function()
```

Return type MlflowClient

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

class pytorch_lightning.loggers.**NeptuneLogger**(*api_key=None*, *project_name=None*, *close_after_fit=True*, *offline_mode=False*, *experiment_name=None*, *upload_source_files=None*, *params=None*, *properties=None*, *tags=None*, ***kwargs*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Neptune. Install it with pip:

```
pip install neptune-client
```

The Neptune logger can be used in the online mode or offline (silent) mode. To log experiment data in online mode, *NeptuneLogger* requires an API key. In offline mode, the logger does not connect to Neptune.

ONLINE MODE

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import NeptuneLogger
>>> # arguments made to NeptuneLogger are passed on to the neptune.experiments.
↪Experiment class
>>> # We are using an api_key for the anonymous user "neptuner" but you can use␣
↪your own.
>>> neptune_logger = NeptuneLogger(
...     api_key='ANONYMOUS',
...     project_name='shared/pytorch-lightning-integration',
...     experiment_name='default',  # Optional,
...     params={'max_epochs': 10},  # Optional,
...     tags=['pytorch-lightning', 'mlp']  # Optional,
... )
>>> trainer = Trainer(max_epochs=10, logger=neptune_logger)
```

OFFLINE MODE

Example

```
>>> from pytorch_lightning.loggers import NeptuneLogger
>>> # arguments made to NeptuneLogger are passed on to the neptune.experiments.
↪Experiment class
>>> neptune_logger = NeptuneLogger(
...     offline_mode=True,
...     project_name='USER_NAME/PROJECT_NAME',
...     experiment_name='default',  # Optional,
...     params={'max_epochs': 10},  # Optional,
...     tags=['pytorch-lightning', 'mlp']  # Optional,
... )
>>> trainer = Trainer(max_epochs=10, logger=neptune_logger)
```

Use the logger anywhere in you *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # log metrics
...         self.logger.experiment.log_metric('acc_train', ...)
...         # log images
...         self.logger.experiment.log_image('worse_predictions', ...)
...         # log model checkpoint
...         self.logger.experiment.log_artifact('model_checkpoint.pt', ...)
...         self.logger.experiment.whatever_neptune_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.log_metric('acc_train', ...)
...         self.logger.experiment.log_image('worse_predictions', ...)
...         self.logger.experiment.log_artifact('model_checkpoint.pt', ...)
...         self.logger.experiment.whatever_neptune_supports(...)
```

If you want to log objects after the training is finished use `close_after_fit=False`:

```
neptune_logger = NeptuneLogger(
    ...
    close_after_fit=False,
    ...
)
trainer = Trainer(logger=neptune_logger)
trainer.fit()

# Log test metrics
trainer.test(model)

# Log additional metrics
from sklearn.metrics import accuracy_score

accuracy = accuracy_score(y_true, y_pred)
neptune_logger.experiment.log_metric('test_accuracy', accuracy)

# Log charts
from scikitplot.metrics import plot_confusion_matrix
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(16, 12))
```

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```
plot_confusion_matrix(y_true, y_pred, ax=ax)
neptune_logger.experiment.log_image('confusion_matrix', fig)

# Save checkpoints folder
neptune_logger.experiment.log_artifact('my/checkpoints')

# When you are done, stop the experiment
neptune_logger.experiment.stop()
```

See also:

- An Example experiment showing the UI of Neptune.
- Tutorial on how to use Pytorch Lightning with Neptune.

Parameters

- **api_key** (Optional[str]) – Required in online mode. Neptune API token, found on https://neptune.ai. Read how to get your API key. It is recommended to keep it in the *NEPTUNE_API_TOKEN* environment variable and then you can leave `api_key=None`.
- **project_name** (Optional[str]) – Required in online mode. Qualified name of a project in a form of "namespace/project_name" for example "tom/minst-classification". If `None`, the value of *NEPTUNE_PROJECT* environment variable will be taken. You need to create the project in https://neptune.ai first.
- **offline_mode** (bool) – Optional default `False`. If `True` no logs will be sent to Neptune. Usually used for debug purposes.
- **close_after_fit** (Optional[bool]) – Optional default `True`. If `False` the experiment will not be closed after training and additional metrics, images or artifacts can be logged. Also, remember to close the experiment explicitly by running `neptune_logger.experiment.stop()`.
- **experiment_name** (Optional[str]) – Optional. Editable name of the experiment. Name is displayed in the experiment's Details (Metadata section) and in experiments view as a column.
- **upload_source_files** (Optional[List[str]]) – Optional. List of source files to be uploaded. Must be list of str or single str. Uploaded sources are displayed in the experiment's Source code tab. If `None` is passed, the Python file from which the experiment was created will be uploaded. Pass an empty list (`[]`) to upload no files. Unix style pathname pattern expansion is supported. For example, you can pass `'\*.py'` to upload all python source files from the current directory. For recursion lookup use `'\**/\*.py'` (for Python 3.5 and later). For more information see `glob` library.
- **params** (Optional[Dict[str, Any]]) – Optional. Parameters of the experiment. After experiment creation params are read-only. Parameters are displayed in the experiment's Parameters section and each key-value pair can be viewed in the experiments view as a column.
- **properties** (Optional[Dict[str, Any]]) – Optional. Default is `{}`. Properties of the experiment. They are editable after the experiment is created. Properties are displayed in the experiment's Details section and each key-value pair can be viewed in the experiments view as a column.
- **tags** (Optional[List[str]]) – Optional. Default is `[]`. Must be list of str. Tags of the experiment. They are editable after the experiment is created (see: `append_tag()`

and `remove_tag()`). Tags are displayed in the experiment's Details section and can be viewed in the experiments view as a column.

append_tags(*tags*)
Appends tags to the neptune experiment.

Parameters **tags** (Union[str, Iterable[str]]) – Tags to add to the current experiment. If str is passed, a single tag is added. If multiple - comma separated - str are passed, all of them are added as tags. If list of str is passed, all elements of the list are added as tags.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_artifact(*artifact*, *destination=None*)
Save an artifact (file) in Neptune experiment storage.

Parameters

- **artifact** (str) – A path to the file in local filesystem.
- **destination** (Optional[str]) – Optional. Default is None. A destination path. If None is passed, an artifact file name will be used.

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_image(*log_name*, *image*, *step=None*)
Log image data in Neptune experiment

Parameters

- **log_name** (str) – The name of log, i.e. bboxes, visualisations, sample_images.
- **image** (Union[str, Image, Any]) – The value of the log (data-point). Can be one of the following types: PIL image, *matplotlib.figure.Figure*, path to image file (str)
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_metric(*metric_name*, *metric_value*, *step=None*)
Log metrics (numeric values) in Neptune experiments.

Parameters

- **metric_name** (str) – The name of log, i.e. mse, loss, accuracy.
- **metric_value** (Union[Tensor, float, str]) – The value of the log (data-point).
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_metrics(*metrics*, *step=None*)
Log metrics (numeric values) in Neptune experiments.

Parameters

- **metrics** (Dict[str, Union[Tensor, float]]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_text(*log_name*, *text*, *step=None*)
Log text data in Neptune experiments.

Parameters

- **log_name** (str) – The name of log, i.e. mse, my_text_data, timing_info.
- **text** (str) – The value of the log (data-point).
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

set_property(*key*, *value*)
Set key-value pair as Neptune experiment property.

Parameters

- **key** (str) – Property key.
- **value** (Any) – New value of a property.

Return type None

property experiment
Actual Neptune object. To use neptune features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_neptune_function()
```

Return type Experiment

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

class pytorch_lightning.loggers.**TestTubeLogger**(*save_dir*, *name='default'*, *description=None*, *debug=False*, *version=None*, *create_git_tag=False*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log to local file system in TensorBoard format but using a nicer folder structure (see full docs). Install it with pip:

```
pip install test_tube
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TestTubeLogger
>>> logger = TestTubeLogger("tt_logs", name="my_exp_name")
>>> trainer = Trainer(logger=logger)
```

Use the logger anywhere in your *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_method_summary_writer_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.add_histogram(...)
```

Parameters

- **save_dir** (str) – Save directory
- **name** (str) – Experiment name. Defaults to 'default'.
- **description** (Optional[str]) – A short snippet about this experiment
- **debug** (bool) – If True, it doesn't log anything.
- **version** (Optional[int]) – Experiment version. If version is not specified the logger inspects the save directory for existing versions, then automatically assigns the next available version.
- **create_git_tag** (bool) – If True creates a git tag to save the code used in this experiment.

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()
Save log data.

Return type None

property experiment
Actual TestTube object. To use TestTube features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_test_tube_function()
```

Return type Experiment

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type int

class pytorch_lightning.loggers.**WandbLogger**(*name=None*, *save_dir=None*, *offline=False*, *id=None*, *anonymous=False*, *version=None*, *project=None*, *tags=None*, *log_model=False*, *experiment=None*, *entity=None*, *group=None*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Weights and Biases. Install it with pip:

```
pip install wandb
```

Parameters

- **name** (Optional[str]) – Display name for the run.
- **save_dir** (Optional[str]) – Path where data is saved.
- **offline** (bool) – Run offline (data can be streamed later to wandb servers).
- **id** (Optional[str]) – Sets the version, mainly used to resume a previous run.
- **anonymous** (bool) – Enables or explicitly disables anonymous logging.
- **version** (Optional[str]) – Sets the version, mainly used to resume a previous run.
- **project** (Optional[str]) – The name of the project to which this run will belong.
- **tags** (Optional[List[str]]) – Tags associated with this run.

- **log_model** (bool) – Save checkpoints in wandb dir to upload on W&B servers.
- **experiment** – WandB experiment object
- **entity** – The team posting this run (default: your username or your default team)
- **group** (Optional[str]) – A unique string shared by all runs in a given group

Example

```
>>> from pytorch_lightning.loggers import WandbLogger
>>> from pytorch_lightning import Trainer
>>> wandb_logger = WandbLogger()
>>> trainer = Trainer(logger=wandb_logger)
```

See also:

- Tutorial on how to use W&B with Pytorch Lightning.

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

property experiment
Actual wandb object. To use wandb features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_wandb_function()
```

Return type Run

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

class pytorch_lightning.loggers.**TrainsLogger**(*project_name=None*, *task_name=None*, *task_type='training'*, *reuse_last_task_id=True*, *output_uri=None*, *auto_connect_arg_parser=True*, *auto_connect_frameworks=True*, *auto_resource_monitoring=True*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using allegro.ai TRAINS. Install it with pip:

```
pip install trains
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TrainsLogger
>>> trains_logger = TrainsLogger(
...     project_name='pytorch lightning',
...     task_name='default',
...     output_uri='.',
... )
TRAINS Task: ...
TRAINS results page: ...
>>> trainer = Trainer(logger=trains_logger)
```

Use the logger anywhere in your *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_trains_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.whatever_trains_supports(...)
```

Parameters

- **project_name** (Optional[str]) – The name of the experiment's project. Defaults to None.
- **task_name** (Optional[str]) – The name of the experiment. Defaults to None.
- **task_type** (str) – The name of the experiment. Defaults to 'training'.
- **reuse_last_task_id** (bool) – Start with the previously used task id. Defaults to True.
- **output_uri** (Optional[str]) – Default location for output models. Defaults to None.
- **auto_connect_arg_parser** (bool) – Automatically grab the ArgumentParser and connect it with the task. Defaults to True.
- **auto_connect_frameworks** (bool) – If True, automatically patch to trains backend. Defaults to True.
- **auto_resource_monitoring** (bool) – If True, machine vitals will be sent along side the task scalars. Defaults to True.

Examples

```
>>> logger = TrainsLogger("pytorch lightning", "default", output_uri=".")
TRAINS Task: ...
TRAINS results page: ...
>>> logger.log_metrics({"val_loss": 1.23}, step=0)
>>> logger.log_text("sample test")
sample test
>>> import numpy as np
>>> logger.log_artifact("confusion matrix", np.ones((2, 3)))
>>> logger.log_image("passed", "Image 1", np.random.randint(0, 255, (200, 150, 3),
↪ dtype=np.uint8))
```

classmethod bypass_mode()
Returns the bypass mode state.

Note: *GITHUB_ACTIONS* env will automatically set bypass_mode to `True` unless overridden specifically with `TrainsLogger.set_bypass_mode(False)`.

Return type bool

Returns If True, all outside communication is skipped.

finalize(*status=None*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (Optional[str]) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_artifact(*name*, *artifact*, *metadata=None*, *delete_after_upload=False*)
Save an artifact (file/object) in TRAINS experiment storage.

Parameters

- **name** (str) – Artifact name. Notice! it will override the previous artifact if the name already exists.
- **artifact** (Union[str, Path, Dict[str, Any], ndarray, Image]) – Artifact object to upload. Currently supports:
  - string / pathlib.Path are treated as path to artifact file to upload If a wildcard or a folder is passed, a zip file containing the local files will be created and uploaded.
  - dict will be stored as .json file and uploaded
  - pandas.DataFrame will be stored as .csv.gz (compressed CSV file) and uploaded
  - numpy.ndarray will be stored as .npz and uploaded
  - PIL.Image.Image will be stored to .png file and uploaded
- **metadata** (Optional[Dict[str, Any]]) – Simple key/value dictionary to store on the artifact. Defaults to None.
- **delete_after_upload** (bool) – If True, the local artifact will be deleted (only applies if artifact is a local file). Defaults to False.

Return type None

log_hyperparams(*params*)
Log hyperparameters (numeric values) in TRAINS experiments.

Parameters **params** (Union[Dict[str, Any], Namespace]) – The hyperparameters that passed through the model.

Return type None

log_image(*title*, *series*, *image*, *step=None*)
Log Debug image in TRAINS experiment

Parameters

- **title** (str) – The title of the debug image, i.e. "failed", "passed".
- **series** (str) – The series name of the debug image, i.e. "Image 0", "Image 1".
- **image** (Union[str, ndarray, Image, Tensor]) – Debug image to log. If numpy.ndarray or torch.Tensor, the image is assumed to be the following:
  - shape: CHW
  - color space: RGB
  - value range: [0., 1.] (float) or [0, 255] (uint8)
- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_metric(*title*, *series*, *value*, *step=None*)
Log metrics (numeric values) in TRAINS experiments. This method will be called by the users.

Parameters

- **title** (str) – The title of the graph to log, e.g. loss, accuracy.
- **series** (str) – The series name in the graph, e.g. classification, localization.
- **value** (float) – The value to log.
- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_metrics(*metrics*, *step=None*)
Log metrics (numeric values) in TRAINS experiments. This method will be called by Trainer.

Parameters

- **metrics** (Dict[str, float]) – The dictionary of the metrics. If the key contains "/", it will be split by the delimiter, then the elements will be logged as "title" and "series" respectively.
- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_text(*text*)
Log console text data in TRAINS experiment.

Parameters **text** (str) – The value of the log (data-point).

Return type None

classmethod set_bypass_mode(*bypass*)
Will bypass all outside communication, and will drop all logs. Should only be used in "standalone mode", when there is no access to the *trains-server*.

Parameters **bypass** (bool) – If True, all outside communication is skipped.

Return type None

classmethod set_credentials(*api_host=None*, *web_host=None*, *files_host=None*, *key=None*, *secret=None*)
Set new default TRAINS-server host and credentials. These configurations could be overridden by either OS environment variables or trains.conf configuration file.

Note: Credentials need to be set *prior* to Logger initialization.

Parameters

- **api_host** (Optional[str]) – Trains API server url, example: host='http://localhost:8008'
- **web_host** (Optional[str]) – Trains WEB server url, example: host='http://localhost:8080'
- **files_host** (Optional[str]) – Trains Files server url, example: host='http://localhost:8081'
- **key** (Optional[str]) – user key/secret pair, example: key='thisisakey123'
- **secret** (Optional[str]) – user key/secret pair, example: secret='thisisseceret123'

Return type None

property experiment
Actual TRAINS object. To use TRAINS features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_trains_function()
```

Return type Task

property id
ID is a uuid (string) representing this specific experiment in the entire system.

Return type Optional[str]

property name
Name is a human readable non-unique name (str) of the experiment.

Return type Optional[str]

property version
Return the experiment version.

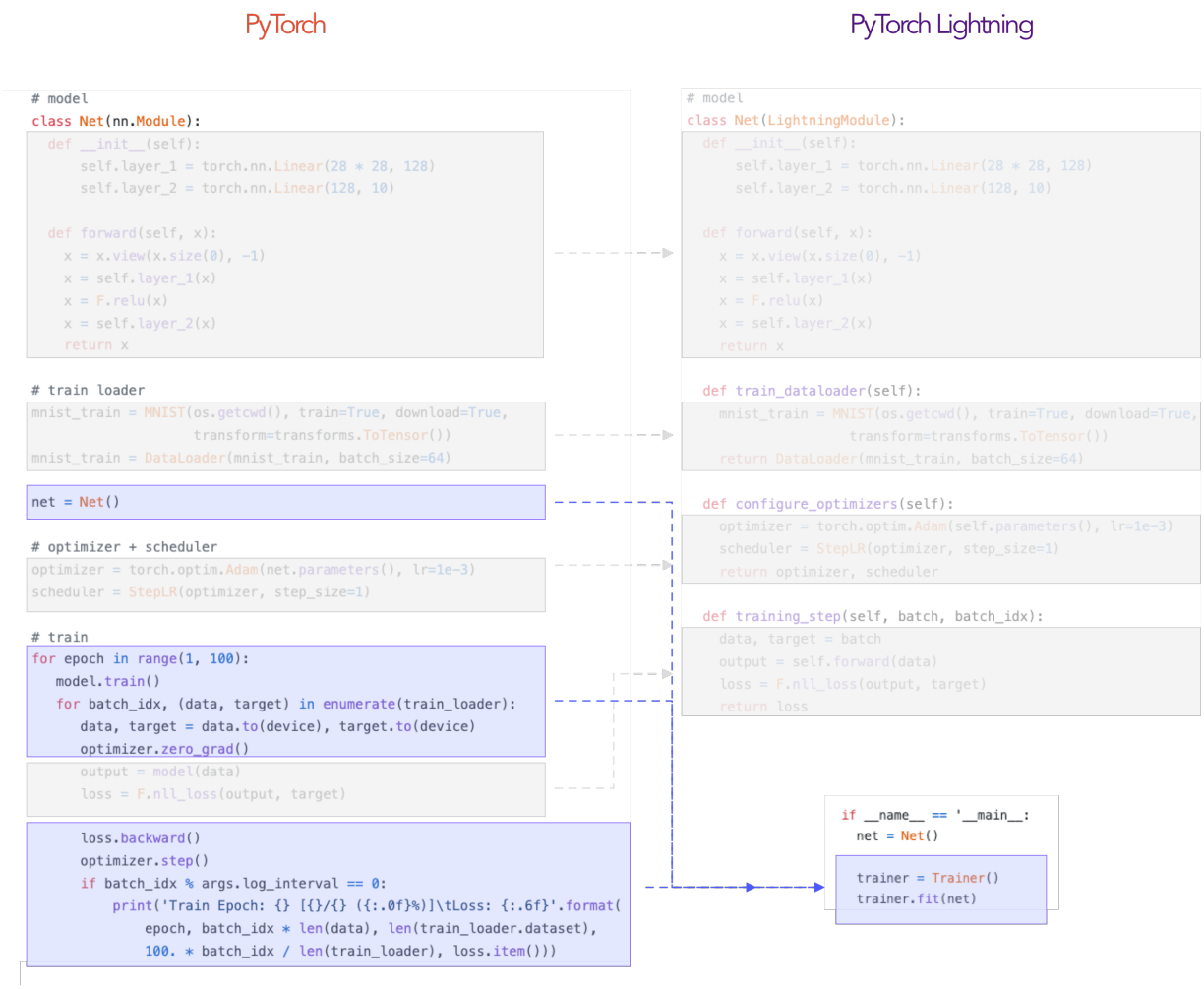
Return type Optional[str]

CHAPTER

SEVEN

TRAINER

Once you've organized your PyTorch code into a LightningModule, the Trainer automates everything else.



This abstraction achieves the following:

1. You maintain control over all aspects via PyTorch code without an added abstraction.
2. The trainer uses best practices embedded by contributors and users from top AI labs such as Facebook AI Research, NYU, MIT, Stanford, etc...
3. The trainer allows overriding any key part that you don't want automated.

7.1 Basic use

This is the basic use of the trainer:

```
from pytorch_lightning import Trainer

model = MyLightningModule()

trainer = Trainer()
trainer.fit(model)
```

7.2 Best Practices

For cluster computing, it's recommended you structure your main.py file this way

```
from argparse import ArgumentParser

def main(hparams):
    model = LightningModule()
    trainer = Trainer(gpus=hparams.gpus)
    trainer.fit(model)

if __name__ == '__main__':
    parser = ArgumentParser()
    parser.add_argument('--gpus', default=None)
    args = parser.parse_args()

    main(args)
```

So you can run it like so:distributed_backend

```
python main.py --gpus 2
```

Note: If you want to stop a training run early, you can press "Ctrl + C" on your keyboard. The trainer will catch the *KeyboardInterrupt* and attempt a graceful shutdown, including running callbacks such as *on_train_end*. The trainer object will also set an attribute *interrupted* to *True* in such cases. If you have a callback which shuts down compute resources, for example, you can conditionally run the shutdown logic for only uninterrupted runs.

7.3 Testing

Once you're done training, feel free to run the test set! (Only right before publishing your paper or pushing to production)

```
trainer.test()
```

7.4 Deployment / prediction

You just trained a LightningModule which is also just a torch.nn.Module. Use it to do whatever!

```
# load model
pretrained_model = LightningModule.load_from_checkpoint(PATH)
pretrained_model.freeze()

# use it for finetuning
def forward(self, x):
    features = pretrained_model(x)
    classes = classifier(features)

# or for prediction
out = pretrained_model(x)
api_write({'response': out}
```

7.5 Reproducibility

To ensure full reproducibility from run to run you need to set seeds for pseudo-random generators, and set `deterministic` flag in `Trainer`.

```
from pytorch-lightning import Trainer, seed_everything

seed_everything(42)
# sets seeds for numpy, torch, python.random and PYTHONHASHSEED.
model = Model()
trainer = Trainer(deterministic=True)
```

7.6 Trainer flags

7.6.1 accumulate_grad_batches

Accumulates grads every k batches or as set up in the dict.

```
# default used by the Trainer (no accumulation)
trainer = Trainer(accumulate_grad_batches=1)
```

Example:

```
# accumulate every 4 batches (effective batch size is batch*4)
trainer = Trainer(accumulate_grad_batches=4)

# no accumulation for epochs 1-4. accumulate 3 for epochs 5-10. accumulate 20 after␣
↪that
trainer = Trainer(accumulate_grad_batches={5: 3, 10: 20})
```

7.6.2 amp_level

The optimization level to use (O1, O2, etc...) for 16-bit GPU precision (using NVIDIA apex under the hood).

Check NVIDIA apex docs for level

Example:

```
# default used by the Trainer
trainer = Trainer(amp_level='O1')
```

7.6.3 auto_scale_batch_size

Automatically tries to find the largest batch size that fits into memory, before any training.

```
# default used by the Trainer (no scaling of batch size)
trainer = Trainer(auto_scale_batch_size=None)

# run batch size scaling, result overrides hparams.batch_size
trainer = Trainer(auto_scale_batch_size='binsearch')
```

7.6.4 auto_lr_find

Runs a learning rate finder algorithm (see this paper) before any training, to find optimal initial learning rate.

```
# default used by the Trainer (no learning rate finder)
trainer = Trainer(auto_lr_find=False)
```

Example:

```
# run learning rate finder, results override hparams.learning_rate
trainer = Trainer(auto_lr_find=True)

# run learning rate finder, results override hparams.my_lr_arg
trainer = Trainer(auto_lr_find='my_lr_arg')
```

Note: See the *learning rate finder guide*

7.6.5 benchmark

If true enables cudnn.benchmark. This flag is likely to increase the speed of your system if your input sizes don't change. However, if it does, then it will likely make your system slower.

The speedup comes from allowing the cudnn auto-tuner to find the best algorithm for the hardware [see discussion here].

Example:

```
# default used by the Trainer
trainer = Trainer(benchmark=False)
```

7.6.6 deterministic

If true enables cudnn.deterministic. Might make your system slower, but ensures reproducibility. Also sets `$HOROVOD_FUSION_THRESHOLD=0`.

For more info check [pytorch docs].

Example:

```
# default used by the Trainer
trainer = Trainer(deterministic=False)
```

7.6.7 callbacks

Add a list of user defined callbacks. These callbacks DO NOT replace the explicit callbacks (loggers, EarlyStopping or ModelCheckpoint).

Note: Only user defined callbacks (ie: Not EarlyStopping or ModelCheckpoint)

```
# a list of callbacks
callbacks = [PrintCallback()]
trainer = Trainer(callbacks=callbacks)
```

Example:

```
from pytorch_lightning.callbacks import Callback

class PrintCallback(Callback):
    def on_train_start(self):
        print("Training is started!")
    def on_train_end(self):
        print(f"Training is done. The logs are: {self.trainer.logs}")
```

7.6.8 check_val_every_n_epoch

Check val every n train epochs.

Example:

```
# default used by the Trainer
trainer = Trainer(check_val_every_n_epoch=1)

# run val loop every 10 training epochs
trainer = Trainer(check_val_every_n_epoch=10)
```

7.6.9 checkpoint_callback

Callback for checkpointing.

```
trainer = Trainer(checkpoint_callback=checkpoint_callback)
```

Example:

```
from pytorch_lightning.callbacks import ModelCheckpoint

# default used by the Trainer
checkpoint_callback = ModelCheckpoint(
    filepath=os.getcwd(),
    save_top_k=True,
    verbose=True,
    monitor='val_loss',
    mode='min',
    prefix=''
)
```

7.6.10 default_root_dir

Default path for logs and weights when no logger or *pytorch_lightning.callbacks.ModelCheckpoint* callback passed. On certain clusters you might want to separate where logs and checkpoints are stored. If you don't then use this method for convenience.

Example:

```
# default used by the Trainer
trainer = Trainer(default_root_path=os.getcwd())
```

7.6.11 distributed_backend

The distributed backend to use.

- (`dp`) is DataParallel (split batch among GPUs of same machine)
- (`ddp`) is DistributedDataParallel (each gpu on each node trains, and syncs grads)
- (`ddp_cpu`) is DistributedDataParallel on CPU (same as *ddp*, but does not use GPUs. Useful for multi-node CPU training or single-node debugging. Note that this will **not** give a speedup on a single node, since Torch already makes effient use of multiple CPUs on a single machine.)

- **(`ddp2`) dp on node, ddp across nodes. Useful for things like increasing** the number of negative samples

```
# default used by the Trainer
trainer = Trainer(distributed_backend=None)
```

Example:

```
# dp = DataParallel
trainer = Trainer(gpus=2, distributed_backend='dp')

# ddp = DistributedDataParallel
trainer = Trainer(gpus=2, num_nodes=2, distributed_backend='ddp')

# ddp2 = DistributedDataParallel + dp
trainer = Trainer(gpus=2, num_nodes=2, distributed_backend='ddp2')
```

Note: this option does not apply to TPU. TPUs use `ddp` by default (over each core)

7.6.12 early_stop_callback

Callback for early stopping. early_stop_callback (*pytorch_lightning.callbacks.EarlyStopping*)

- **`True`: A default callback monitoring `'val_loss'` is created.** Will raise an error if `'val_loss'` is not found.
- `False`: Early stopping will be disabled.
- `None`: The default callback monitoring `'val_loss'` is created.
- Default: `None`.

```
trainer = Trainer(early_stop_callback=early_stop_callback)
```

Example:

```
from pytorch_lightning.callbacks import EarlyStopping

# default used by the Trainer
early_stop_callback = EarlyStopping(
    monitor='val_loss',
    patience=3,
    strict=False,
    verbose=False,
    mode='min'
)
```

Note: If `'val_loss'` is not found will work as if early stopping is disabled.

7.6.13 fast_dev_run

Runs 1 batch of train, test and val to find any bugs (ie: a sort of unit test).

Under the hood the pseudocode looks like this:

```
# loading
__init__()
prepare_data

# test training step
training_batch = next(train_dataloader)
training_step(training_batch)

# test val step
val_batch = next(val_dataloader)
out = validation_step(val_batch)
validation_epoch_end([out])
```

Example:

```
# default used by the Trainer
trainer = Trainer(fast_dev_run=False)

# runs 1 train, val, test  batch and program ends
trainer = Trainer(fast_dev_run=True)
```

7.6.14 gpus

- Number of GPUs to train on
- or Which GPUs to train on
- can handle strings

Example:

```
# default used by the Trainer (ie: train on CPU)
trainer = Trainer(gpus=None)

# int: train on 2 gpus
trainer = Trainer(gpus=2)

# list: train on GPUs 1, 4 (by bus ordering)
trainer = Trainer(gpus=[1, 4])
trainer = Trainer(gpus='1, 4') # equivalent

# -1: train on all gpus
trainer = Trainer(gpus=-1)
trainer = Trainer(gpus='-1') # equivalent

# combine with num_nodes to train on multiple GPUs across nodes
# uses 8 gpus in total
trainer = Trainer(gpus=2, num_nodes=4)
```

Note: See the *multi-gpu computing guide*

7.6.15 gradient_clip_val

Gradient clipping value

- 0 means don't clip.

Example:

```
# default used by the Trainer
trainer = Trainer(gradient_clip_val=0.0)
```

gradient_clip:

> **Warning:** Deprecated since version 0.5.0.
>
> Use *gradient_clip_val* instead. Will remove 0.8.0.

7.6.16 log_gpu_memory

Options:

- None
- 'min_max'
- 'all'

Example:

```
# default used by the Trainer
trainer = Trainer(log_gpu_memory=None)

# log all the GPUs (on master node only)
trainer = Trainer(log_gpu_memory='all')

# log only the min and max memory on the master node
trainer = Trainer(log_gpu_memory='min_max')
```

Note: Might slow performance because it uses the output of nvidia-smi.

7.6.17 log_save_interval

Writes logs to disk this often.

Example:

```
# default used by the Trainer
trainer = Trainer(log_save_interval=100)
```

7.6.18 logger

Logger (or iterable collection of loggers) for experiment tracking.

```
Trainer(logger=logger)
```

Example:

```
from pytorch_lightning.loggers import TensorBoardLogger

# default logger used by trainer
logger = TensorBoardLogger(
    save_dir=os.getcwd(),
    version=self.slurm_job_id,
    name='lightning_logs'
)
```

7.6.19 max_epochs

Stop training once this number of epochs is reached

Example:

```
# default used by the Trainer
trainer = Trainer(max_epochs=1000)
```

max_nb_epochs:

Warning: Deprecated since version 0.5.0.

Use *max_epochs* instead. Will remove 0.8.0.

7.6.20 min_epochs

Force training for at least these many epochs

Example:

```
# default used by the Trainer
trainer = Trainer(min_epochs=1)
```

min_nb_epochs:

Warning: deprecated:: 0.5.0 Use *min_epochs* instead. Will remove 0.8.0.

7.6.21 max_steps

Stop training after this number of steps Training will stop if max_steps or max_epochs have reached (earliest).

```
# Default (disabled)
trainer = Trainer(max_steps=None)
```

Example:

```
# Stop after 100 steps
trainer = Trainer(max_steps=100)
```

7.6.22 min_steps

Force training for at least these number of steps. Trainer will train model for at least min_steps or min_epochs (latest).

```
# Default (disabled)
trainer = Trainer(min_steps=None)
```

Example:

```
# Run at least for 100 steps (disable min_epochs)
trainer = Trainer(min_steps=100, min_epochs=0)
```

7.6.23 num_nodes

Number of GPU nodes for distributed training.

Example:

```
# default used by the Trainer
trainer = Trainer(num_nodes=1)

# to train on 8 nodes
trainer = Trainer(num_nodes=8)
```

nb_gpu_nodes:

Warning: Deprecated since version 0.5.0.

Use *num_nodes* instead. Will remove 0.8.0.

7.6.24 num_processes

Number of processes to train with. Automatically set to the number of GPUs when using `distrbuted_backend="ddp"`. Set to a number greater than 1 when using `distributed_backend="ddp_cpu"` to mimic distributed training on a machine without GPUs. This is useful for debugging, but **will not** provide any speedup, since single-process Torch already makes effient use of multiple CPUs.

Example:

```
# Simulate DDP for debugging on your GPU-less laptop
trainer = Trainer(distributed_backend="ddp_cpu", num_processes=2)
```

7.6.25 num_sanity_val_steps

Sanity check runs n batches of val before starting the training routine. This catches any bugs in your validation without having to wait for the first validation check. The Trainer uses 5 steps by default. Turn it off or modify it here.

Example:

```
# default used by the Trainer
trainer = Trainer(num_sanity_val_steps=5)

# turn it off
trainer = Trainer(num_sanity_val_steps=0)
```

nb_sanity_val_steps:

Warning: Deprecated since version 0.5.0.

Use *num_sanity_val_steps* instead. Will remove 0.8.0.

7.6.26 num_tpu_cores

How many TPU cores to train on (1 or 8).

A single TPU v2 or v3 has 8 cores. A TPU pod has up to 2048 cores. A slice of a POD means you get as many cores as you request.

Your effective batch size is batch_size * total tpu cores.

Note: No need to add a DistributedDataSampler, Lightning automatically does it for you.

This parameter can be either 1 or 8.

Example:

```
# your_trainer_file.py

# default used by the Trainer (ie: train on CPU)
trainer = Trainer(num_tpu_cores=None)

# int: train on a single core
trainer = Trainer(num_tpu_cores=1)

# int: train on all cores few cores
trainer = Trainer(num_tpu_cores=8)

# for 8+ cores must submit via xla script with
# a max of 8 cores specified. The XLA script
# will duplicate script onto each TPU in the POD
trainer = Trainer(num_tpu_cores=8)

# -1: train on all available TPUs
trainer = Trainer(num_tpu_cores=-1)
```

To train on more than 8 cores (ie: a POD), submit this script using the xla_dist script.

Example:

```
python -m torch_xla.distributed.xla_dist
--tpu=$TPU_POD_NAME
--conda-env=torch-xla-nightly
--env=XLA_USE_BF16=1
-- python your_trainer_file.py
```

7.6.27 overfit_pct

Uses this much data of all datasets (training, validation, test). Useful for quickly debugging or trying to overfit on purpose.

Example:

```
# default used by the Trainer
trainer = Trainer(overfit_pct=0.0)

# use only 1% of the train, test, val datasets
trainer = Trainer(overfit_pct=0.01)

# equivalent:
trainer = Trainer(
    train_percent_check=0.01,
    val_percent_check=0.01,
    test_percent_check=0.01
)
```

See also:

- *train_percent_check*
- *val_percent_check*
- *test_percent_check*

7.6.28 precision

Full precision (32), half precision (16). Can be used on CPU, GPU or TPUs.

If used on TPU will use torch.bfloat16 but tensor printing will still show torch.float32.

Example:

```
# default used by the Trainer
trainer = Trainer(precision=32)

# 16-bit precision
trainer = Trainer(precision=16)

# one day
trainer = Trainer(precision=8|4|2)
```

7.6.29 print_nan_grads

Warning: Deprecated since version 0.7.2..

Has no effect. When detected, NaN grads will be printed automatically. Will remove 0.9.0.

7.6.30 process_position

Orders the progress bar. Useful when running multiple trainers on the same node.

Example:

```
# default used by the Trainer
trainer = Trainer(process_position=0)
```

Note: This argument is ignored if a custom callback is passed to *callbacks*.

7.6.31 profiler

To profile individual steps during training and assist in identifying bottlenecks.

See the *profiler documentation*. for more details.

Example:

```
from pytorch_lightning.profiler import Profiler, AdvancedProfiler

# default used by the Trainer
trainer = Trainer(profiler=None)

# to profile standard training events
trainer = Trainer(profiler=True)

# equivalent to profiler=True
profiler = Profiler()
trainer = Trainer(profiler=profiler)

# advanced profiler for function-level stats
profiler = AdvancedProfiler()
trainer = Trainer(profiler=profiler)
```

7.6.32 progress_bar_refresh_rate

How often to refresh progress bar (in steps). In notebooks, faster refresh rates (lower number) is known to crash them because of their screen refresh rates, so raise it to 50 or more.

Example:

```
# default used by the Trainer
trainer = Trainer(progress_bar_refresh_rate=1)
```

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(continued from previous page)

```
# disable progress bar
trainer = Trainer(progress_bar_refresh_rate=0)
```

Note: This argument is ignored if a custom callback is passed to *callbacks*.

7.6.33 reload_dataloaders_every_epoch

Set to True to reload dataloaders every epoch.

```
# if False (default)
train_loader = model.train_dataloader()
for epoch in epochs:
    for batch in train_loader:
        ...

# if True
for epoch in epochs:
    train_loader = model.train_dataloader()
    for batch in train_loader:
```

7.6.34 replace_sampler_ddp

Enables auto adding of distributed sampler.

Example:

```
# default used by the Trainer
trainer = Trainer(replace_sampler_ddp=True)
```

By setting to False, you have to add your own distributed sampler:

Example:

```
# default used by the Trainer
sampler = torch.utils.data.distributed.DistributedSampler(dataset, shuffle=True)
dataloader = DataLoader(dataset, batch_size=32, sampler=sampler)
```

7.6.35 resume_from_checkpoint

To resume training from a specific checkpoint pass in the path here.

Example:

```
# default used by the Trainer
trainer = Trainer(resume_from_checkpoint=None)

# resume from a specific checkpoint
trainer = Trainer(resume_from_checkpoint='some/path/to/my_checkpoint.ckpt')
```

7.6.36 row_log_interval

How often to add logging rows (does not write to disk)

Example:

```
# default used by the Trainer
trainer = Trainer(row_log_interval=10)
```

add_row_log_interval:

> **Warning:** Deprecated since version 0.5.0.
>
> Use *row_log_interval* instead. Will remove 0.8.0.

use_amp:

> **Warning:** Deprecated since version 0.7.0.
>
> Use *precision* instead. Will remove 0.9.0.

7.6.37 show_progress_bar

> **Warning:** Deprecated since version 0.7.2.
>
> Set *progress_bar_refresh_rate* to 0 instead. Will remove 0.9.0.

7.6.38 test_percent_check

How much of test dataset to check.

Example:

```
# default used by the Trainer
trainer = Trainer(test_percent_check=1.0)

# run through only 25% of the test set each epoch
trainer = Trainer(test_percent_check=0.25)
```

7.6.39 val_check_interval

How often within one training epoch to check the validation set. Can specify as float or int.

- use (float) to check within a training epoch
- use (int) to check every n steps (batches)

```
# default used by the Trainer
trainer = Trainer(val_check_interval=1.0)
```

Example:

```
# check validation set 4 times during a training epoch
trainer = Trainer(val_check_interval=0.25)

# check validation set every 1000 training batches
# use this when using iterableDataset and your dataset has no length
# (ie: production cases with streaming data)
trainer = Trainer(val_check_interval=1000)
```

7.6.40 track_grad_norm

- no tracking (-1)
- Otherwise tracks that norm (2 for 2-norm)

```
# default used by the Trainer
trainer = Trainer(track_grad_norm=-1)
```

Example:

```
# track the 2-norm
trainer = Trainer(track_grad_norm=2)
```

7.6.41 train_percent_check

How much of training dataset to check. Useful when debugging or testing something that happens at the end of an epoch.

Example:

```
# default used by the Trainer
trainer = Trainer(train_percent_check=1.0)

# run through only 25% of the training set each epoch
trainer = Trainer(train_percent_check=0.25)
```

7.6.42 truncated_bptt_steps

Truncated back prop breaks performs backprop every k steps of a much longer sequence.

If this is enabled, your batches will automatically get truncated and the trainer will apply Truncated Backprop to it.

(Williams et al. "An efficient gradient-based algorithm for on-line training of recurrent network trajectories.")

Example:

```
# default used by the Trainer (ie: disabled)
trainer = Trainer(truncated_bptt_steps=None)

# backprop every 5 steps in a batch
trainer = Trainer(truncated_bptt_steps=5)
```

Note: Make sure your batches have a sequence dimension.

Lightning takes care to split your batch along the time-dimension.

```
# we use the second as the time dimension
# (batch, time, ...)
sub_batch = batch[0, 0:t, ...]
```

Using this feature requires updating your LightningModule's *pytorch_lightning.core.LightningModule.training_step()* to include a *hiddens* arg with the hidden

```
# Truncated back-propagation through time
def training_step(self, batch, batch_idx, hiddens):
    # hiddens are the hiddens from the previous truncated backprop step
    out, hiddens = self.lstm(data, hiddens)

    return {
        "loss": ...,
        "hiddens": hiddens  # remember to detach() this
    }
```

To modify how the batch is split, override *pytorch_lightning.core.LightningModule.tbptt_split_batch()*:

```
class LitMNIST(pl.LightningModule):
    def tbptt_split_batch(self, batch, split_size):
        # do your own splitting on the batch
        return splits
```

7.6.43 val_percent_check

How much of validation dataset to check. Useful when debugging or testing something that happens at the end of an epoch.

Example:

```
# default used by the Trainer
trainer = Trainer(val_percent_check=1.0)

# run through only 25% of the validation set each epoch
trainer = Trainer(val_percent_check=0.25)
```

7.6.44 weights_save_path

Directory of where to save weights if specified.

```
# default used by the Trainer
trainer = Trainer(weights_save_path=os.getcwd())
```

Example:

```
# save to your custom path
trainer = Trainer(weights_save_path='my/path')

# if checkpoint callback used, then overrides the weights path
# **NOTE: this saves weights to some/path NOT my/path
```

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```
checkpoint_callback = ModelCheckpoint(filepath='some/path')
trainer = Trainer(
    checkpoint_callback=checkpoint_callback,
    weights_save_path='my/path'
)
```

7.6.45 weights_summary

Prints a summary of the weights when training begins. Options: 'full', 'top', None.

Example:

```
# default used by the Trainer (ie: print all weights)
trainer = Trainer(weights_summary='full')

# print only the top level modules
trainer = Trainer(weights_summary='top')

# don't print a summary
trainer = Trainer(weights_summary=None)
```

7.7 Trainer class

class pytorch_lightning.trainer.**Trainer**(*logger=True*, *checkpoint_callback=True*, *early_stop_callback=False*, *callbacks=None*, *default_root_dir=None*, *gradient_clip_val=0*, *process_position=0*, *num_nodes=1*, *num_processes=1*, *gpus=None*, *auto_select_gpus=False*, *num_tpu_cores=None*, *log_gpu_memory=None*, *progress_bar_refresh_rate=1*, *overfit_pct=0.0*, *track_grad_norm=-1*, *check_val_every_n_epoch=1*, *fast_dev_run=False*, *accumulate_grad_batches=1*, *max_epochs=1000*, *min_epochs=1*, *max_steps=None*, *min_steps=None*, *train_percent_check=1.0*, *val_percent_check=1.0*, *test_percent_check=1.0*, *val_check_interval=1.0*, *log_save_interval=100*, *row_log_interval=10*, *add_row_log_interval=None*, *distributed_backend=None*, *precision=32*, *print_nan_grads=False*, *weights_summary='full'*, *weights_save_path=None*, *num_sanity_val_steps=2*, *truncated_bptt_steps=None*, *resume_from_checkpoint=None*, *profiler=None*, *benchmark=False*, *deterministic=False*, *reload_dataloaders_every_epoch=False*, *auto_lr_find=False*, *replace_sampler_ddp=True*, *progress_bar_callback=True*, *terminate_on_nan=False*, *auto_scale_batch_size=False*, *amp_level='O1'*, *default_save_path=None*, *gradient_clip=None*, *nb_gpu_nodes=None*, *max_nb_epochs=None*, *min_nb_epochs=None*, *use_amp=None*, *show_progress_bar=None*, *nb_sanity_val_steps=None*, ***kwargs*)

Bases: *pytorch_lightning.trainer.training_io.TrainerIOMixin*, *pytorch_lightning.trainer.optimizers.TrainerOptimizersMixin*, *pytorch_lightning.trainer.auto_mix_precision.TrainerAMPMixin*, *pytorch_lightning.trainer.distrib_parts.TrainerDPMixin*, *pytorch_lightning.trainer.distrib_data_parallel.TrainerDDPMixin*, *pytorch_lightning.trainer.logging.TrainerLoggingMixin*, *pytorch_lightning.trainer.model_hooks.TrainerModelHooksMixin*, *pytorch_lightning.trainer.training_tricks.TrainerTrainingTricksMixin*, *pytorch_lightning.trainer.data_loading.TrainerDataLoadingMixin*, *pytorch_lightning.trainer.evaluation_loop.TrainerEvaluationLoopMixin*, *pytorch_lightning.trainer.training_loop.TrainerTrainLoopMixin*, *pytorch_lightning.trainer.callback_config.TrainerCallbackConfigMixin*, *pytorch_lightning.trainer.callback_hook.TrainerCallbackHookMixin*, *pytorch_lightning.trainer.lr_finder.TrainerLRFinderMixin*, *pytorch_lightning.trainer.deprecated_api.TrainerDeprecatedAPITillVer0_8*, *pytorch_lightning.trainer.deprecated_api.TrainerDeprecatedAPITillVer0_9*

Customize every aspect of training via flags

Parameters

- **logger** (Union[*LightningLoggerBase*, Iterable[*LightningLoggerBase*], bool]) – Logger (or iterable collection of loggers) for experiment tracking.
- **checkpoint_callback** (Union[*ModelCheckpoint*, bool]) – Callback for checkpointing.
- **early_stop_callback** (*pytorch_lightning.callbacks.EarlyStopping*) –
- **callbacks** (Optional[List[*Callback*]]) – Add a list of callbacks.
- **default_root_dir** (Optional[str]) – Default path for logs and weights when no logger/ckpt_callback passed
- **default_save_path** –

  Warning: Deprecated since version 0.7.3.

  Use *default_root_dir* instead. Will remove 0.9.0.

- **gradient_clip_val** (float) – 0 means don't clip.
- **gradient_clip** –

  Warning: Deprecated since version 0.7.0.

  Use *gradient_clip_val* instead. Will remove 0.9.0.

- **process_position** (int) – orders the progress bar when running multiple models on same machine.
- **num_nodes** (int) – number of GPU nodes for distributed training.
- **nb_gpu_nodes** –

  Warning: Deprecated since version 0.7.0.

  Use *num_nodes* instead. Will remove 0.9.0.

- **gpus** (Union[List[int], str, int, None]) – Which GPUs to train on.
- **auto_select_gpus** (bool) – If enabled and *gpus* is an integer, pick available gpus automatically. This is especially useful when GPUs are configured to be in "exclusive mode", such that only one process at a time can access them.
- **num_tpu_cores** (Optional[int]) – How many TPU cores to train on (1 or 8).
- **log_gpu_memory** (Optional[str]) – None, 'min_max', 'all'. Might slow performance
- **show_progress_bar** –

  Warning: Deprecated since version 0.7.2.

  Set *progress_bar_refresh_rate* to positive integer to enable. Will remove 0.9.0.

- **progress_bar_refresh_rate** (int) – How often to refresh progress bar (in steps). Value 0 disables progress bar. Ignored when a custom callback is passed to *callbacks*.
- **overfit_pct** (float) – How much of training-, validation-, and test dataset to check.
- **track_grad_norm** (int) – -1 no tracking. Otherwise tracks that norm
- **check_val_every_n_epoch** (int) – Check val every n train epochs.
- **fast_dev_run** (bool) – runs 1 batch of train, test and val to find any bugs (ie: a sort of unit test).
- **accumulate_grad_batches** (Union[int, Dict[int, int], List[list]]) – Accumulates grads every k batches or as set up in the dict.
- **max_epochs** (int) – Stop training once this number of epochs is reached.
- **max_nb_epochs** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *max_epochs* instead. Will remove 0.9.0.

- **min_epochs** (int) – Force training for at least these many epochs
- **min_nb_epochs** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *min_epochs* instead. Will remove 0.9.0.

- **max_steps** (Optional[int]) – Stop training after this number of steps. Disabled by default (None).
- **min_steps** (Optional[int]) – Force training for at least these number of steps. Disabled by default (None).
- **train_percent_check** (float) – How much of training dataset to check.
- **val_percent_check** (float) – How much of validation dataset to check.
- **test_percent_check** (float) – How much of test dataset to check.
- **val_check_interval** (float) – How often within one training epoch to check the validation set
- **log_save_interval** (int) – Writes logs to disk this often
- **row_log_interval** (int) – How often to add logging rows (does not write to disk)
- **add_row_log_interval** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *row_log_interval* instead. Will remove 0.9.0.

- **distributed_backend** (Optional[str]) – The distributed backend to use.
- **use_amp** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *precision* instead. Will remove 0.9.0.

- **precision** (int) – Full precision (32), half precision (16).
- **print_nan_grads** (bool) –

> **Warning:** Deprecated since version 0.7.2.
>
> Has no effect. When detected, NaN grads will be printed automatically. Will remove 0.9.0.

- **weights_summary** (Optional[str]) – Prints a summary of the weights when training begins.
- **weights_save_path** (Optional[str]) – Where to save weights if specified. Will override default_root_dir for checkpoints only. Use this if for whatever reason you need the checkpoints stored in a different place than the logs written in *default_root_dir*.
- **amp_level** (str) – The optimization level to use (O1, O2, etc...).
- **num_sanity_val_steps** (int) – Sanity check runs n batches of val before starting the training routine.
- **nb_sanity_val_steps** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *num_sanity_val_steps* instead. Will remove 0.8.0.

- **truncated_bptt_steps** (Optional[int]) – Truncated back prop breaks performs backprop every k steps of
- **resume_from_checkpoint** (Optional[str]) – To resume training from a specific checkpoint pass in the path here.
- **profiler** (Union[*BaseProfiler*, bool, None]) – To profile individual steps during training and assist in
- **reload_dataloaders_every_epoch** (bool) – Set to True to reload dataloaders every epoch
- **auto_lr_find** (Union[bool, str]) – If set to True, will *initially* run a learning rate finder, trying to optimize initial learning for faster convergence. Sets learning rate in self.hparams.lr | self.hparams.learning_rate in the lightning module. To use a different key, set a string instead of True with the key name.
- **replace_sampler_ddp** (bool) – Explicitly enables or disables sampler replacement. If not specified this will toggled automatically ddp is used
- **benchmark** (bool) – If true enables cudnn.benchmark.
- **deterministic** (bool) – If true enables cudnn.deterministic
- **terminate_on_nan** (bool) – If set to True, will terminate training (by raising a *ValueError*) at the end of each training batch, if any of the parameters or the loss are NaN or +/-inf.

- **auto_scale_batch_size** (Union[str, bool]) – If set to True, will *initially* run a batch size finder trying to find the largest batch size that fits into memory. The result will be stored in self.hparams.batch_size in the LightningModule. Additionally, can be set to either *power* that estimates the batch size through a power search or *binsearch* that estimates the batch size through a binary search.

_Trainer__set_random_port()
When running DDP NOT managed by SLURM, the ports might collide :return:

classmethod add_argparse_args(*parent_parser*)
Extends existing argparse by default *Trainer* attributes.

Parameters **parent_parser** (ArgumentParser) – The custom cli arguments parser, which will be extended by the Trainer default arguments.

Only arguments of the allowed types (str, float, int, bool) will extend the *parent_parser*.

Examples

```
>>> import argparse
>>> import pprint
>>> parser = argparse.ArgumentParser()
>>> parser = Trainer.add_argparse_args(parser)
>>> args = parser.parse_args([])
>>> pprint.pprint(vars(args))
{...
 'check_val_every_n_epoch': 1,
 'checkpoint_callback': True,
 'default_root_dir': None,
 'deterministic': False,
 'distributed_backend': None,
 'early_stop_callback': False,
 ...
 'logger': True,
 'max_epochs': 1000,
 'max_steps': None,
 'min_epochs': 1,
 'min_steps': None,
 ...
 'profiler': None,
 'progress_bar_callback': True,
 'progress_bar_refresh_rate': 1,
 ...}
```

Return type ArgumentParser

check_model_configuration(*model*)
Checks that the model is configured correctly before training is started.

Parameters **model** (*LightningModule*) – The model to test.

fit(*model*, *train_dataloader=None*, *val_dataloaders=None*)
Runs the full optimization routine.

Parameters

- **model** (*LightningModule*) – Model to fit.

- **train_dataloader** (Optional[DataLoader]) – A Pytorch DataLoader with training samples. If the model has a predefined train_dataloader method this will be skipped.
- **val_dataloaders** (Union[DataLoader, List[DataLoader], None]) – Either a single Pytorch Dataloader or a list of them, specifying validation samples. If the model has a predefined val_dataloaders method this will be skipped

Example:

```
# Option 1,
# Define the train_dataloader() and val_dataloader() fxs
# in the lightningModule
# RECOMMENDED FOR MOST RESEARCH AND APPLICATIONS TO MAINTAIN READABILITY
trainer = Trainer()
model = LightningModule()
trainer.fit(model)

# Option 2
# in production cases we might want to pass different datasets to the same␣
↪model
# Recommended for PRODUCTION SYSTEMS
train, val = DataLoader(...), DataLoader(...)
trainer = Trainer()
model = LightningModule()
trainer.fit(model, train_dataloader=train, val_dataloader=val)

# Option 1 & 2 can be mixed, for example the training set can be
# defined as part of the model, and validation can then be feed to .fit()
```

classmethod from_argparse_args(*args*, ***kwargs*)

create an instance from CLI arguments

Example

```
>>> parser = ArgumentParser(add_help=False)
>>> parser = Trainer.add_argparse_args(parser)
>>> args = Trainer.parse_argparser(parser.parse_args(""))
>>> trainer = Trainer.from_argparse_args(args)
```

Return type *Trainer*

classmethod get_deprecated_arg_names()

Returns a list with deprecated Trainer arguments.

Return type List

classmethod get_init_arguments_and_types()

Scans the Trainer signature and returns argument names, types and default values.

Returns (argument name, set with argument types, argument default value).

Return type List with tuples of 3 values

Examples

```
>>> args = Trainer.get_init_arguments_and_types()
>>> import pprint
>>> pprint.pprint(sorted(args))
[('accumulate_grad_batches',
  (<class 'int'>, typing.Dict[int, int], typing.List[list]),
  1),
 ...
 ('callbacks',
  (typing.List[pytorch_lightning.callbacks.base.Callback],
   <class 'NoneType'>),
   None),
 ('check_val_every_n_epoch', (<class 'int'>,), 1),
 ...
 ('max_epochs', (<class 'int'>,), 1000),
 ...
 ('precision', (<class 'int'>,), 32),
 ('print_nan_grads', (<class 'bool'>,), False),
 ('process_position', (<class 'int'>,), 0),
 ('profiler',
  (<class 'pytorch_lightning.profiler.profilers.BaseProfiler'>,
   <class 'bool'>,
   <class 'NoneType'>),
  None),
 ...
```

static parse_argparser(*arg_parser*)

Parse CLI arguments, required for custom bool types.

Return type Namespace

run_pretrain_routine(*model*)

Sanity check a few things before starting actual training.

Parameters **model** (*LightningModule*) – The model to run sanity test on.

test(*model=None*, *test_dataloaders=None*)

Separates from fit to make sure you never run on your test set until you want to.

Parameters

- **model** (Optional[*LightningModule*]) – The model to test.
- **test_dataloaders** (Union[DataLoader, List[DataLoader], None]) – Either a single Pytorch Dataloader or a list of them, specifying validation samples.

Example:

```
# Option 1
# run test after fitting
test = DataLoader(...)
trainer = Trainer()
model = LightningModule()

trainer.fit(model)
trainer.test(test_dataloaders=test)

# Option 2
# run test from a loaded model
```

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```
test = DataLoader(...)
model = LightningModule.load_from_checkpoint('path/to/checkpoint.ckpt')
trainer = Trainer()
trainer.test(model, test_dataloaders=test)
```

property num_gpus
this is just empty shell for code implemented in other class.

Type Warning

Return type int

property progress_bar_dict
Read-only for progress bar metrics.

Return type dict

property slurm_job_id
this is just empty shell for code implemented in other class.

Type Warning

Return type int

pytorch_lightning.trainer.**seed_everything**(*seed=None*)
Function that sets seed for pseudo-random number generators in: pytorch, numpy, python.random and sets PYTHONHASHSEED environment variable.

Return type int

CHAPTER

EIGHT

16-BIT TRAINING

Lightning offers 16-bit training for CPUs, GPUs and TPUs.

8.1 GPU 16-bit

Lightning uses NVIDIA apex to handle 16-bit precision training.

To use 16-bit precision, do two things:

1. Install Apex
2. Set the "precision" trainer flag.

8.1.1 Install apex

```
$ git clone https://github.com/NVIDIA/apex
$ cd apex

# ------------------------
# OPTIONAL: on your cluster you might need to load cuda 10 or 9
# depending on how you installed PyTorch

# see available modules
module avail

# load correct cuda before install
module load cuda-10.0
# ------------------------

# make sure you've loaded a cuda version > 4.0 and < 7.0
module load gcc-6.1.0

$ pip install -v --no-cache-dir --global-option="--cpp_ext" --global-option="--cuda_
↪ext" ./
```

8.1.2 Enable 16-bit

```
# turn on 16-bit
trainer = Trainer(amp_level='O1', precision=16)
```

If you need to configure the apex init for your particular use case or want to use a different way of doing 16-bit training, override *pytorch_lightning.core.LightningModule.configure_apex()*.

8.2 TPU 16-bit

16-bit on TPus is much simpler. To use 16-bit with TPUs set precision to 16 when using the tpu flag

```
# DEFAULT
trainer = Trainer(num_tpu_cores=8, precision=32)

# turn on 16-bit
trainer = Trainer(num_tpu_cores=8, precision=16)
```

CHAPTER

NINE

COMPUTING CLUSTER (SLURM)

Lightning automates job the details behind training on a SLURM powered cluster.

9.1 Multi-node training

To train a model using multiple-nodes do the following:

1. Design your LightningModule.
2. Enable ddp in the trainer

```
# train on 32 GPUs across 4 nodes
trainer = Trainer(gpus=8, num_nodes=4, distributed_backend='ddp')
```

3. It's a good idea to structure your train.py file like this:

```
# train.py
def main(hparams):
    model = LightningTemplateModel(hparams)

    trainer = pl.Trainer(
        gpus=8,
        num_nodes=4,
        distributed_backend='ddp'
    )

    trainer.fit(model)


if __name__ == '__main__':
    root_dir = os.path.dirname(os.path.realpath(__file__))
    parent_parser = ArgumentParser(add_help=False)
    hyperparams = parser.parse_args()

    # TRAIN
    main(hyperparams)
```

4. Create the appropriate SLURM job

```
# (submit.sh)
#!/bin/bash -l

# SLURM SUBMIT SCRIPT
```

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```
#SBATCH --nodes=4
#SBATCH --gres=gpu:8
#SBATCH --ntasks-per-node=8
#SBATCH --mem=0
#SBATCH --time=0-02:00:00

# activate conda env
source activate $1

# ------------------------
# debugging flags (optional)
 export NCCL_DEBUG=INFO
 export PYTHONFAULTHANDLER=1

# on your cluster you might need these:
# set the network interface
# export NCCL_SOCKET_IFNAME=^docker0,lo

# might need the latest cuda
# module load NCCL/2.4.7-1-cuda.10.0
# ------------------------

# run script from above
srun python3 train.py
```

5. If you want auto-resubmit (read below), add this line to the submit.sh script

```
#SBATCH --signal=SIGUSR1@90
```

6. Submit the SLURM job

```
sbatch submit.sh
```

Note: using `DistributedSampler` is already handled by Lightning.

9.2 Walltime auto-resubmit

When you use Lightning in a SLURM cluster, lightning automatically detects when it is about to run into the walltime, and it does the following:

1. Saves a temporary checkpoint.
2. Requeues the job.
3. When the job starts, it loads the temporary checkpoint.

To get this behavior make sure to add the correct signal to your SLURM script

```
# 90 seconds before training ends
#SBATCH --signal=SIGUSR1@90
```

CHAPTER

TEN

CHILD MODULES

Research projects tend to test different approaches to the same dataset. This is very easy to do in Lightning with inheritance.

For example, imagine we now want to train an Autoencoder to use as a feature extractor for MNIST images. Recall that *LitMNIST* already defines all the dataloading etc... The only things that change in the *Autoencoder* model are the init, forward, training, validation and test step.

```
class Encoder(torch.nn.Module):
    pass

class Decoder(torch.nn.Module):
    pass

class AutoEncoder(LitMNIST):

    def __init__(self):
        super().__init__()
        self.encoder = Encoder()
        self.decoder = Decoder()

    def forward(self, x):
        generated = self.decoder(x)

    def training_step(self, batch, batch_idx):
        x, _ = batch

        representation = self.encoder(x)
        x_hat = self(representation)

        loss = MSE(x, x_hat)
        return loss

    def validation_step(self, batch, batch_idx):
        return self._shared_eval(batch, batch_idx, 'val')

    def test_step(self, batch, batch_idx):
        return self._shared_eval(batch, batch_idx, 'test')

    def _shared_eval(self, batch, batch_idx, prefix):
        x, y = batch
        representation = self.encoder(x)
        x_hat = self(representation)

        loss = F.nll_loss(logits, y)
```

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```
        return {f'{prefix}_loss': loss}
```

and we can train this using the same trainer

```
autoencoder = AutoEncoder()
trainer = Trainer()
trainer.fit(autoencoder)
```

And remember that the forward method is to define the practical use of a LightningModule. In this case, we want to use the *AutoEncoder* to extract image representations

```
some_images = torch.Tensor(32, 1, 28, 28)
representations = autoencoder(some_images)
```

CHAPTER

ELEVEN

DEBUGGING

The following are flags that make debugging much easier.

11.1 Fast dev run

This flag runs a "unit test" by running 1 training batch and 1 validation batch. The point is to detect any bugs in the training/validation loop without having to wait for a full epoch to crash.

(See: *fast_dev_run* argument of *Trainer*)

```
trainer = Trainer(fast_dev_run=True)
```

11.2 Inspect gradient norms

Logs (to a logger), the norm of each weight matrix.

(See: *track_grad_norm* argument of *Trainer*)

```
# the 2-norm
trainer = Trainer(track_grad_norm=2)
```

11.3 Log GPU usage

Logs (to a logger) the GPU usage for each GPU on the master machine.

(See: *log_gpu_memory* argument of *Trainer*)

```
trainer = Trainer(log_gpu_memory=True)
```

11.4 Make model overfit on subset of data

A good debugging technique is to take a tiny portion of your data (say 2 samples per class), and try to get your model to overfit. If it can't, it's a sign it won't work with large datasets.

(See: *overfit_pct* argument of *Trainer*)

```
trainer = Trainer(overfit_pct=0.01)
```

11.5 Print the parameter count by layer

Whenever the .fit() function gets called, the Trainer will print the weights summary for the lightningModule. To disable this behavior, turn off this flag:

(See: *weights_summary* argument of *Trainer*)

```
trainer = Trainer(weights_summary=None)
```

11.6 Set the number of validation sanity steps

Lightning runs a few steps of validation in the beginning of training. This avoids crashing in the validation loop sometime deep into a lengthy training loop.

(See: *num_sanity_val_steps* argument of *Trainer*)

```
# DEFAULT
trainer = Trainer(num_sanity_val_steps=5)
```

CHAPTER

TWELVE

EXPERIMENT LOGGING

12.1 Comet.ml

Comet.ml is a third-party logger. To use *CometLogger* as your logger do the following. First, install the package:

```
pip install comet-ml
```

Then configure the logger and pass it to the *Trainer*:

```
import os
from pytorch_lightning.loggers import CometLogger
comet_logger = CometLogger(
    api_key=os.environ.get('COMET_API_KEY'),
    workspace=os.environ.get('COMET_WORKSPACE'),  # Optional
    save_dir='.',  # Optional
    project_name='default_project',  # Optional
    rest_api_key=os.environ.get('COMET_REST_API_KEY'),  # Optional
    experiment_name='default'  # Optional
)
trainer = Trainer(logger=comet_logger)
```

The *CometLogger* is available anywhere except `__init__` in your *LightningModule*.

```
class MyModule(LightningModule):
    def any_lightning_module_function_or_hook(self):
        some_img = fake_image()
        self.logger.experiment.add_image('generated_images', some_img, 0)
```

See also:

CometLogger docs.

12.2 MLflow

MLflow is a third-party logger. To use *MLFlowLogger* as your logger do the following. First, install the package:

```
pip install mlflow
```

Then configure the logger and pass it to the *Trainer*:

```
from pytorch_lightning.loggers import MLFlowLogger
mlf_logger = MLFlowLogger(
    experiment_name="default",
    tracking_uri="file:./ml-runs"
)
trainer = Trainer(logger=mlf_logger)
```

See also:

MLFlowLogger docs.

12.3 Neptune.ai

Neptune.ai is a third-party logger. To use *NeptuneLogger* as your logger do the following. First, install the package:

```
pip install neptune-client
```

Then configure the logger and pass it to the *Trainer*:

```
from pytorch_lightning.loggers import NeptuneLogger
neptune_logger = NeptuneLogger(
    api_key='ANONYMOUS',  # replace with your own
    project_name='shared/pytorch-lightning-integration',
    experiment_name='default',  # Optional,
    params={'max_epochs': 10},  # Optional,
    tags=['pytorch-lightning', 'mlp'],  # Optional,
)
trainer = Trainer(logger=neptune_logger)
```

The *NeptuneLogger* is available anywhere except `__init__` in your *LightningModule*.

```
class MyModule(LightningModule):
    def any_lightning_module_function_or_hook(self):
        some_img = fake_image()
        self.logger.experiment.add_image('generated_images', some_img, 0)
```

See also:

NeptuneLogger docs.

12.4 allegro.ai TRAINS

allegro.ai is a third-party logger. To use *TrainsLogger* as your logger do the following. First, install the package:

```
pip install trains
```

Then configure the logger and pass it to the *Trainer*:

```
from pytorch_lightning.loggers import TrainsLogger
trains_logger = TrainsLogger(
    project_name='examples',
    task_name='pytorch lightning test',
```

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```
)
trainer = Trainer(logger=trains_logger)
```

The *TrainsLogger* is available anywhere in your *LightningModule*.

```
class MyModule(LightningModule):
    def __init__(self):
        some_img = fake_image()
        self.logger.experiment.log_image('debug', 'generated_image_0', some_img, 0)
```

See also:

TrainsLogger docs.

12.5 Tensorboard

To use TensorBoard as your logger do the following.

```
from pytorch_lightning.loggers import TensorBoardLogger
logger = TensorBoardLogger('tb_logs', name='my_model')
trainer = Trainer(logger=logger)
```

The *TensorBoardLogger* is available anywhere except __init__ in your *LightningModule*.

```
class MyModule(LightningModule):
    def any_lightning_module_function_or_hook(self):
        some_img = fake_image()
        self.logger.experiment.add_image('generated_images', some_img, 0)
```

See also:

TensorBoardLogger docs.

12.6 Test Tube

Test Tube is a TensorBoard logger but with nicer file structure. To use *TestTubeLogger* as your logger do the following. First, install the package:

```
pip install test_tube
```

Then configure the logger and pass it to the *Trainer*:

```
from pytorch_lightning.loggers import TestTubeLogger
logger = TestTubeLogger('tb_logs', name='my_model')
trainer = Trainer(logger=logger)
```

The *TestTubeLogger* is available anywhere except __init__ in your *LightningModule*.

```
class MyModule(LightningModule):
    def any_lightning_module_function_or_hook(self):
        some_img = fake_image()
        self.logger.experiment.add_image('generated_images', some_img, 0)
```

See also:

TestTubeLogger docs.

12.7 Weights and Biases

Weights and Biases is a third-party logger. To use *WandbLogger* as your logger do the following. First, install the package:

```
pip install wandb
```

Then configure the logger and pass it to the *Trainer*:

```
from pytorch_lightning.loggers import WandbLogger
wandb_logger = WandbLogger()
trainer = Trainer(logger=wandb_logger)
```

The *WandbLogger* is available anywhere except __init__ in your *LightningModule*.

```
class MyModule(LightningModule):
    def any_lightning_module_function_or_hook(self):
        some_img = fake_image()
        self.logger.experiment.log({
             "generated_images": [wandb.Image(some_img, caption="...")]
        })
```

See also:

WandbLogger docs.

12.8 Multiple Loggers

Lightning supports the use of multiple loggers, just pass a list to the *Trainer*.

```
from pytorch_lightning.loggers import TensorBoardLogger, TestTubeLogger
logger1 = TensorBoardLogger('tb_logs', name='my_model')
logger2 = TestTubeLogger('tb_logs', name='my_model')
trainer = Trainer(logger=[logger1, logger2])
```

The loggers are available as a list anywhere except __init__ in your *LightningModule*.

```
class MyModule(LightningModule):
    def any_lightning_module_function_or_hook(self):
        some_img = fake_image()
        # Option 1
        self.logger.experiment[0].add_image('generated_images', some_img, 0)
        # Option 2
        self.logger[0].experiment.add_image('generated_images', some_img, 0)
```

CHAPTER

THIRTEEN

EXPERIMENT REPORTING

Lightning supports many different experiment loggers. These loggers allow you to monitor losses, images, text, etc... as training progresses. They usually provide a GUI to visualize and can sometimes even snapshot hyperparameters used in each experiment.

13.1 Control logging frequency

It may slow training down to log every single batch. Trainer has an option to log every k batches instead.

```
k = 10
trainer = Trainer(row_log_interval=k)
```

13.2 Control log writing frequency

Writing to a logger can be expensive. In Lightning you can set the interval at which you want to log using this trainer flag.

See also:

Trainer

```
k = 100
trainer = Trainer(log_save_interval=k)
```

13.3 Log metrics

To plot metrics into whatever logger you passed in (tensorboard, comet, neptune, TRAINS, etc...)

1. training_epoch_end, validation_epoch_end, test_epoch_end will all log anything in the "log" key of the return dict.

```
def training_epoch_end(self, outputs):
    loss = some_loss()
    ...

    logs = {'train_loss': loss}
    results = {'log': logs}
    return results
```

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```
def validation_epoch_end(self, outputs):
    loss = some_loss()
    ...

    logs = {'val_loss': loss}
    results = {'log': logs}
    return results

def test_epoch_end(self, outputs):
    loss = some_loss()
    ...

    logs = {'test_loss': loss}
    results = {'log': logs}
    return results
```

2. In addition, you can also use any arbitrary functionality from a particular logger from within your LightningModule. For instance, here we log images using tensorboard.

```
def training_step(self, batch, batch_idx):
    self.generated_imgs = self.decoder.generate()

    sample_imgs = self.generated_imgs[:6]
    grid = torchvision.utils.make_grid(sample_imgs)
    self.logger.experiment.add_image('generated_images', grid, 0)

    ...
    return results
```

13.4 Modify progress bar

Each return dict from the training_end, validation_end, testing_end and training_step also has a key called "progress_bar".

Here we show the validation loss in the progress bar

```
def validation_epoch_end(self, outputs):
    loss = some_loss()
    ...

    logs = {'val_loss': loss}
    results = {'progress_bar': logs}
    return results
```

13.5 Snapshot hyperparameters

When training a model, it's useful to know what hyperparams went into that model. When Lightning creates a checkpoint, it stores a key "hparams" with the hyperparams.

```
lightning_checkpoint = torch.load(filepath, map_location=lambda storage, loc: storage)
hyperparams = lightning_checkpoint['hparams']
```

Some loggers also allow logging the hyperparams used in the experiment. For instance, when using the TestTubeLogger or the TensorBoardLogger, all hyperparams will show in the hparams tab.

13.6 Snapshot code

Loggers also allow you to snapshot a copy of the code used in this experiment. For example, TestTubeLogger does this with a flag:

```
from pytorch_lightning.loggers import TestTubeLogger
logger = TestTubeLogger('.', create_git_tag=True)
```

CHAPTER

FOURTEEN

EARLY STOPPING

14.1 Stopping an epoch early

You can stop an epoch early by overriding `on_batch_start()` to return *-1* when some condition is met.

If you do this repeatedly, for every epoch you had originally requested, then this will stop your entire run.

14.2 Default Epoch End Callback Behavior

By default early stopping will be enabled if *'val_loss'* is found in *validation_epoch_end()*'s return dict. Otherwise training will proceed with early stopping disabled.

14.3 Enable Early Stopping using Callbacks on epoch end

There are two ways to enable early stopping using callbacks on epoch end.

- Set early_stop_callback to True. Will look for 'val_loss' in validation_epoch_end() return dict. If it is not found an error is raised.

```
trainer = Trainer(early_stop_callback=True)
```

- Or configure your own callback

```
early_stop_callback = EarlyStopping(
    monitor='val_loss',
    min_delta=0.00,
    patience=3,
    verbose=False,
    mode='min'
)
trainer = Trainer(early_stop_callback=early_stop_callback)
```

In any case, the callback will fall back to the training metrics (returned in *training_step()*, *training_step_end()*) looking for a key to monitor if validation is disabled or *validation_epoch_end()* is not defined.

See also:

- *Trainer*
- *EarlyStopping*

14.4 Disable Early Stopping with callbacks on epoch end

To disable early stopping pass `False` to the *early_stop_callback*. Note that `None` will not disable early stopping but will lead to the default behaviour.

See also:

- *Trainer*
- *EarlyStopping*

CHAPTER

FIFTEEN

FAST TRAINING

There are multiple options to speed up different parts of the training by choosing to train on a subset of data. This could be done for speed or debugging purposes.

15.1 Check validation every n epochs

If you have a small dataset you might want to check validation every n epochs

```
# DEFAULT
trainer = Trainer(check_val_every_n_epoch=1)
```

15.2 Force training for min or max epochs

It can be useful to force training for a minimum number of epochs or limit to a max number.

See also:

Trainer

```
# DEFAULT
trainer = Trainer(min_epochs=1, max_epochs=1000)
```

15.3 Set validation check frequency within 1 training epoch

For large datasets it's often desirable to check validation multiple times within a training loop. Pass in a float to check that often within 1 training epoch. Pass in an int k to check every k training batches. Must use an int if using an IterableDataset.

```
# DEFAULT
trainer = Trainer(val_check_interval=0.95)

# check every .25 of an epoch
trainer = Trainer(val_check_interval=0.25)

# check every 100 train batches (ie: for IterableDatasets or fixed frequency)
trainer = Trainer(val_check_interval=100)
```

15.4 Use data subset for training, validation and test

If you don't want to check 100% of the training/validation/test set (for debugging or if it's huge), set these flags.

```
# DEFAULT
trainer = Trainer(
    train_percent_check=1.0,
    val_percent_check=1.0,
    test_percent_check=1.0
)

# check 10%, 20%, 30% only, respectively for training, validation and test set
trainer = Trainer(
    train_percent_check=0.1,
    val_percent_check=0.2,
    test_percent_check=0.3
)
```

Note: `train_percent_check`, `val_percent_check` and `test_percent_check` will be overwritten by `overfit_pct` if `overfit_pct` > 0. `val_percent_check` will be ignored if `fast_dev_run=True`.

Note: If you set `val_percent_check=0`, validation will be disabled.

CHAPTER

SIXTEEN

HYPERPARAMETERS

Lightning has utilities to interact seamlessly with the command line ArgumentParser and plays well with the hyperparameter optimization framework of your choice.

16.1 ArgumentParser

Lightning is designed to augment a lot of the functionality of the built-in Python ArgumentParser

```
from argparse import ArgumentParser
parser = ArgumentParser()
parser.add_argument('--layer_1_dim', type=int, default=128)
args = parser.parse_args()
```

This allows you to call your program like so:

```
python trainer.py --layer_1_dim 64
```

16.2 Argparser Best Practices

It is best practice to layer your arguments in three sections.

1. Trainer args (gpus, num_nodes, etc...)
2. Model specific arguments (layer_dim, num_layers, learning_rate, etc...)
3. Program arguments (data_path, cluster_email, etc...)

We can do this as follows. First, in your LightningModule, define the arguments specific to that module. Remember that data splits or data paths may also be specific to a module (ie: if your project has a model that trains on Imagenet and another on CIFAR-10).

```
class LitModel(LightningModule):

    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = ArgumentParser(parents=[parent_parser], add_help=False)
        parser.add_argument('--encoder_layers', type=int, default=12)
        parser.add_argument('--data_path', type=str, default='/some/path')
        return parser
```

Now in your main trainer file, add the Trainer args, the program args, and add the model args

```
# ----------------
# trainer_main.py
# ----------------
from argparse import ArgumentParser
parser = ArgumentParser()

# add PROGRAM level args
parser.add_argument('--conda_env', type=str, default='some_name')
parser.add_argument('--notification_email', type=str, default='will@email.com')

# add model specific args
parser = LitModel.add_model_specific_args(parser)

# add all the available trainer options to argparse
# ie: now --gpus --num_nodes ... --fast_dev_run all work in the cli
parser = Trainer.add_argparse_args(parser)

hparams = parser.parse_args()
```

Now you can call run your program like so

```
python trainer_main.py --gpus 2 --num_nodes 2 --conda_env 'my_env' --encoder_layers 12
```

Finally, make sure to start the training like so:

```
# YES
model = LitModel(hparams)
trainer = Trainer.from_argparse_args(hparams, early_stopping_callback=...)

# NO
# model = LitModel(learning_rate=hparams.learning_rate, ...)
# trainer = Trainer(gpus=hparams.gpus, ...)
```

16.3 LightningModule hparams

Normally, we don't hard-code the values to a model. We usually use the command line to modify the network and read those values in the LightningModule

```
class LitMNIST(LightningModule):

    def __init__(self, hparams):
        super().__init__()

        # do this to save all arguments in any logger (tensorboard)
        self.hparams = hparams

        self.layer_1 = torch.nn.Linear(28 * 28, hparams.layer_1_dim)
        self.layer_2 = torch.nn.Linear(hparams.layer_1_dim, hparams.layer_2_dim)
        self.layer_3 = torch.nn.Linear(hparams.layer_2_dim, 10)

    def train_dataloader(self):
        return DataLoader(mnist_train, batch_size=self.hparams.batch_size)

    def configure_optimizers(self):
        return Adam(self.parameters(), lr=self.hparams.learning_rate)
```

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```
    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = ArgumentParser(parents=[parent_parser], add_help=False)
        parser.add_argument('--layer_1_dim', type=int, default=128)
        parser.add_argument('--layer_2_dim', type=int, default=256)
        parser.add_argument('--batch_size', type=int, default=64)
        parser.add_argument('--learning_rate', type=float, default=0.002)
        return parser
```

Now pass in the params when you init your model

```
parser = ArgumentParser()
parser = LitMNIST.add_model_specific_args(parser)
hparams = parser.parse_args()
model = LitMNIST(hparams)
```

The line *self.hparams = hparams* is very special. This line assigns your hparams to the LightningModule. This does two things:

1. It adds them automatically to TensorBoard logs under the hparams tab.
2. Lightning will save those hparams to the checkpoint and use them to restore the module correctly.

16.4 Trainer args

To recap, add ALL possible trainer flags to the argparser and init the Trainer this way

```
parser = ArgumentParser()
parser = Trainer.add_argparse_args(parser)
hparams = parser.parse_args()

trainer = Trainer.from_argparse_args(hparams)

# or if you need to pass in callbacks
trainer = Trainer.from_argparse_args(hparams, checkpoint_callback=..., callbacks=[...
↪])
```

16.5 Multiple Lightning Modules

We often have multiple Lightning Modules where each one has different arguments. Instead of polluting the main.py file, the LightningModule lets you define arguments for each one.

```
class LitMNIST(LightningModule):

    def __init__(self, hparams):
        super().__init__()
        self.layer_1 = torch.nn.Linear(28 * 28, hparams.layer_1_dim)

    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = ArgumentParser(parents=[parent_parser])
```

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```
        parser.add_argument('--layer_1_dim', type=int, default=128)
        return parser
```

```
class GoodGAN(LightningModule):

    def __init__(self, hparams):
        super().__init__()
        self.encoder = Encoder(layers=hparams.encoder_layers)

    @staticmethod
    def add_model_specific_args(parent_parser):
        parser = ArgumentParser(parents=[parent_parser])
        parser.add_argument('--encoder_layers', type=int, default=12)
        return parser
```

Now we can allow each model to inject the arguments it needs in the `main.py`

```
def main(args):

    # pick model
    if args.model_name == 'gan':
        model = GoodGAN(hparams=args)
    elif args.model_name == 'mnist':
        model = LitMNIST(hparams=args)

    model = LitMNIST(hparams=args)
    trainer = Trainer.from_argparse_args(args)
    trainer.fit(model)

if __name__ == '__main__':
    parser = ArgumentParser()
    parser = Trainer.add_argparse_args(parser)

    # figure out which model to use
    parser.add_argument('--model_name', type=str, default='gan', help='gan or mnist')

    # THIS LINE IS KEY TO PULL THE MODEL NAME
    temp_args, _ = parser.parse_known_args()

    # let the model add what it wants
    if temp_args.model_name == 'gan':
        parser = GoodGAN.add_model_specific_args(parser)
    elif temp_args.model_name == 'mnist':
        parser = LitMNIST.add_model_specific_args(parser)

    args = parser.parse_args()

    # train
    main(args)
```

and now we can train MNIST or the GAN using the command line interface!

```
$ python main.py --model_name gan --encoder_layers 24
$ python main.py --model_name mnist --layer_1_dim 128
```

16.6 Hyperparameter Optimization

Lightning is fully compatible with the hyperparameter optimization libraries! Here are some useful ones:

- Hydra
- Optuna

CHAPTER

SEVENTEEN

LEARNING RATE FINDER

For training deep neural networks, selecting a good learning rate is essential for both better performance and faster convergence. Even optimizers such as *Adam* that are self-adjusting the learning rate can benefit from more optimal choices.

To reduce the amount of guesswork concerning choosing a good initial learning rate, a *learning rate finder* can be used. As described in this paper a learning rate finder does a small run where the learning rate is increased after each processed batch and the corresponding loss is logged. The result of this is a *lr* vs. *loss* plot that can be used as guidance for choosing a optimal initial lr.

Warnings: - For the moment, this feature only works with models having a single optimizer. - LR support for DDP is not implemented yet, it is comming soon.

17.1 Using Lightnings build-in LR finder

In the most basic use case, this feature can be enabled during trainer construction with `Trainer(auto_lr_find=True)`. When `.fit(model)` is called, the lr finder will automatically be run before any training is done. The `lr` that is found and used will be written to the console and logged together with all other hyperparameters of the model.

```
# default, no automatic learning rate finder
trainer = Trainer(auto_lr_find=True)
```

When the `lr` or `learning_rate` key in hparams exists, this flag sets your learning_rate. In both cases, if the respective fields are not found, an error will be thrown.

```
class LitModel(LightningModule):

    def __init__(self, hparams):
        self.hparams = hparams

    def configure_optimizers(self):
        return Adam(self.parameters(), lr=self.hparams.lr|self.hparams.learning_rate)

# finds learning rate automatically
# sets hparams.lr or hparams.learning_rate to that learning rate
trainer = Trainer(auto_lr_find=True)
```

To use an arbitrary value set it in the parameter.

```
# to set to your own hparams.my_value
trainer = Trainer(auto_lr_find='my_value')
```

Under the hood, when you call fit, this is what happens.

1. Run learning rate finder.
2. Run actual fit.

```
# when you call .fit() this happens
# 1. find learning rate
# 2. actually run fit
trainer.fit(model)
```

If you want to inspect the results of the learning rate finder before doing any actual training or just play around with the parameters of the algorithm, this can be done by invoking the `lr_find` method of the trainer. A typical example of this would look like

```
model = MyModelClass(hparams)
trainer = Trainer()

# Run learning rate finder
lr_finder = trainer.lr_find(model)

# Results can be found in
lr_finder.results

# Plot with
fig = lr_finder.plot(suggest=True)
fig.show()

# Pick point based on plot, or get suggestion
new_lr = lr_finder.suggestion()

# update hparams of the model
model.hparams.lr = new_lr

# Fit model
trainer.fit(model)
```

The figure produced by `lr_finder.plot()` should look something like the figure below. It is recommended to not pick the learning rate that achives the lowest loss, but instead something in the middle of the sharpest downward slope (red point). This is the point returned py `lr_finder.suggestion()`.

The parameters of the algorithm can be seen below.

class pytorch_lightning.trainer.lr_finder.**TrainerLRFinderMixin**

Bases: abc.ABC

_run_lr_finder_internally(*model*)

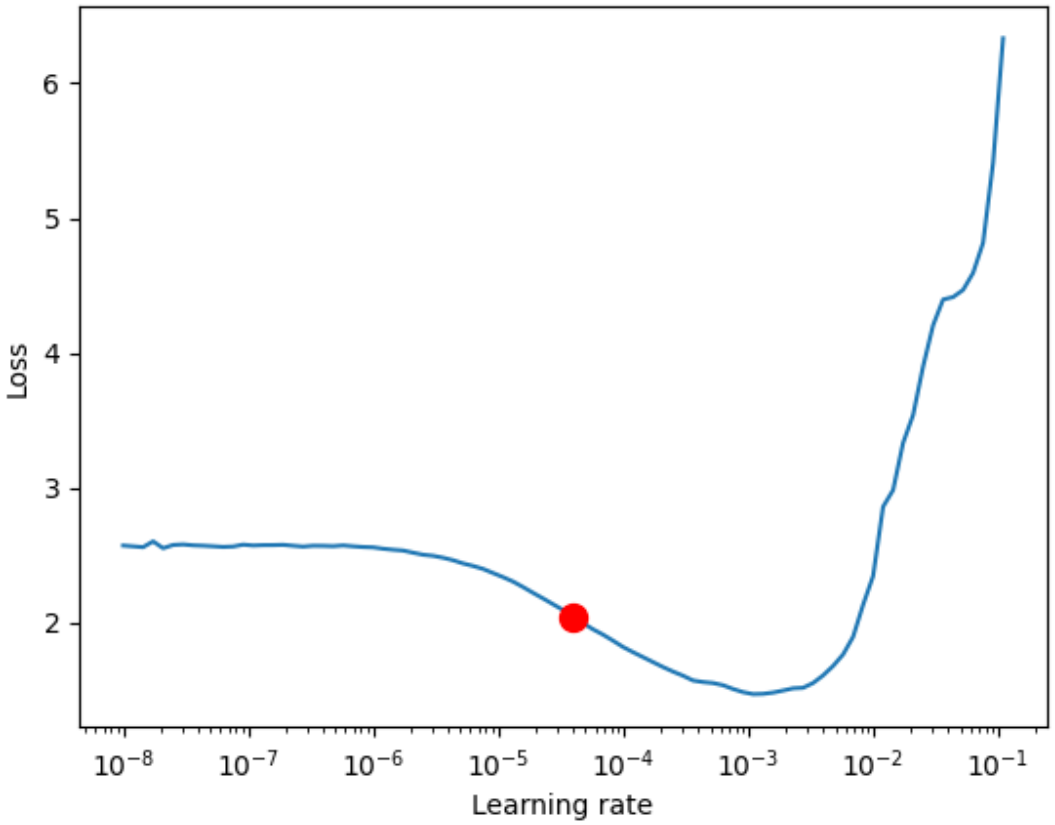
Call lr finder internally during Trainer.fit()

lr_find(*model*, *train_dataloader=None*, *val_dataloaders=None*, *min_lr=1e-08*, *max_lr=1*, *num_training=100*, *mode='exponential'*, *early_stop_threshold=4.0*, *num_accumulation_steps=None*)

lr_find enables the user to do a range test of good initial learning rates, to reduce the amount of guesswork in picking a good starting learning rate.

Parameters

- **model** (*LightningModule*) – Model to do range testing for
- **train_dataloader** (Optional[DataLoader]) – A PyTorch DataLoader with training samples. If the model has a predefined train_dataloader method this will be


Loss
6
5
4
3
2
10^{-8}
10^{-7}
10^{-6}
10^{-5}
10^{-4}
10^{-3}
10^{-2}
10^{-1}
Learning rate

skipped.

- **min_lr** (float) – minimum learning rate to investigate
- **max_lr** (float) – maximum learning rate to investigate
- **num_training** (int) – number of learning rates to test
- **mode** (str) – search strategy, either 'linear' or 'exponential'. If set to 'linear' the learning rate will be searched by linearly increasing after each batch. If set to 'exponential', will increase learning rate exponentially.
- **early_stop_threshold** (float) – threshold for stopping the search. If the loss at any point is larger than early_stop_threshold*best_loss then the search is stopped. To disable, set to None.
- **num_accumulation_steps** – deprepecated, number of batches to calculate loss over. Set trainer argument `accumulate_grad_batches` instead.

Example:

```
# Setup model and trainer
model = MyModelClass(hparams)
trainer = pl.Trainer()

# Run lr finder
lr_finder = trainer.lr_find(model, ...)

# Inspect results
fig = lr_finder.plot(); fig.show()
suggested_lr = lr_finder.suggestion()

# Overwrite lr and create new model
hparams.lr = suggested_lr
model = MyModelClass(hparams)

# Ready to train with new learning rate
trainer.fit(model)
```

abstract restore(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract save_checkpoint(**args*)
Warning: this is just empty shell for code implemented in other class.

CHAPTER

EIGHTEEN

MULTI-GPU TRAINING

Lightning supports multiple ways of doing distributed training.

18.1 Preparing your code

To train on CPU/GPU/TPU without changing your code, we need to build a few good habits :)

18.1.1 Delete .cuda() or .to() calls

Delete any calls to .cuda() or .to(device).

```
# before lightning
def forward(self, x):
    x = x.cuda(0)
    layer_1.cuda(0)
    x_hat = layer_1(x)

# after lightning
def forward(self, x):
    x_hat = layer_1(x)
```

18.1.2 Init using type_as

When you need to create a new tensor, use *type_as*. This will make your code scale to any arbitrary number of GPUs or TPUs with Lightning

```
# before lightning
def forward(self, x):
    z = torch.Tensor(2, 3)
    z = z.cuda(0)

# with lightning
def forward(self, x):
    z = torch.Tensor(2, 3)
    z = z.type_as(x, device=self.device)
```

Every LightningModule knows what device it is on. You can access that reference via *self.device*.

18.1.3 Remove samplers

For multi-node or TPU training, in PyTorch we must use *torch.nn.DistributedSampler*. The sampler makes sure each GPU sees the appropriate part of your data.

```
# without lightning
def train_dataloader(self):
    dataset = MNIST(...)
    sampler = None

    if self.on_tpu:
        sampler = DistributedSampler(dataset)

    return DataLoader(dataset, sampler=sampler)
```

With Lightning, you don't need to do this because it takes care of adding the correct samplers when needed.

```
# with lightning
def train_dataloader(self):
    dataset = MNIST(...)
    return DataLoader(dataset)
```

Note: If you don't want this behavior, disable it with *Trainer(replace_sampler_ddp=False)*

Note: For iterable datasets, we don't do this automatically.

18.1.4 Make Model Picklable

It's very likely your code is already picklable, so you don't have to do anything to make this change. However, if you run distributed and see an error like this:

```
self._launch(process_obj)
File "/net/software/local/python/3.6.5/lib/python3.6/multiprocessing/popen_spawn_
↪posix.py", line 47,
in _launch reduction.dump(process_obj, fp)
File "/net/software/local/python/3.6.5/lib/python3.6/multiprocessing/reduction.py",␣
↪line 60, in dump
ForkingPickler(file, protocol).dump(obj)
_pickle.PicklingError: Can't pickle <function <lambda> at 0x2b599e088ae8>:
attribute lookup <lambda> on __main__ failed
```

This means you have something in your model definition, transforms, optimizer, dataloader or callbacks that is cannot be pickled. By pickled we mean the following would fail.

```
import pickle
pickle.dump(some_object)
```

This is a limitation of using multiple processes for distributed training within PyTorch. To fix this issue, find your piece of code that cannot be pickled. The end of the stacktrace is usually helpful.

```
self._launch(process_obj)
File "/net/software/local/python/3.6.5/lib/python3.6/multiprocessing/popen_spawn_
↪posix.py", line 47,
```

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```
in _launch reduction.dump(process_obj, fp)
File "/net/software/local/python/3.6.5/lib/python3.6/multiprocessing/reduction.py",␣
↪line 60, in dump
ForkingPickler(file, protocol).dump(obj)
_pickle.PicklingError: Can't pickle [THIS IS THE THING TO FIND AND DELETE]:
attribute lookup <lambda> on __main__ failed
```

ie: in the stacktrace example here, there seems to be a lambda function somewhere in the user code which cannot be pickled.

18.2 Distributed modes

Lightning allows multiple ways of training

- Data Parallel (*distributed_backend='dp'*) (multiple-gpus, 1 machine)
- DistributedDataParallel (*distributed_backend='ddp'*) (multiple-gpus across many machines).
- DistributedDataParallel2 (*distributed_backend='ddp2'*) (dp in a machine, ddp across machines).
- Horovod (*distributed_backend='horovod'*) (multi-machine, multi-gpu, configured at runtime)
- TPUs (*num_tpu_cores=8|x*) (tpu or TPU pod)

Note: If you request multiple GPUs without setting a mode, ddp will be automatically used.

18.2.1 Data Parallel (dp)

DataParallel splits a batch across k GPUs. That is, if you have a batch of 32 and use dp with 2 gpus, each GPU will process 16 samples, after which the root node will aggregate the results.

Warning: DP use is discouraged by PyTorch and Lightning. Use ddp which is more stable and at least 3x faster

```
# train on 2 GPUs (using dp mode)
trainer = Trainer(gpus=2, distributed_backend='dp')
```

18.2.2 Distributed Data Parallel

DistributedDataParallel works as follows.

1. Each GPU across every node gets its own process.
2. Each GPU gets visibility into a subset of the overall dataset. It will only ever see that subset.
3. Each process inits the model.

Note: Make sure to set the random seed so that each model inits with the same weights

---

4. Each process performs a full forward and backward pass in parallel.

5. The gradients are synced and averaged across all processes.
6. Each process updates its optimizer.

```
# train on 8 GPUs (same machine (ie: node))
trainer = Trainer(gpus=8, distributed_backend='ddp')

# train on 32 GPUs (4 nodes)
trainer = Trainer(gpus=8, distributed_backend='ddp', num_nodes=4)
```

18.2.3 Distributed Data Parallel 2

In certain cases, it's advantageous to use all batches on the same machine instead of a subset. For instance you might want to compute a NCE loss where it pays to have more negative samples.

In this case, we can use ddp2 which behaves like dp in a machine and ddp across nodes. DDP2 does the following:

1. Copies a subset of the data to each node.
2. Inits a model on each node.
3. Runs a forward and backward pass using DP.
4. Syncs gradients across nodes.
5. Applies the optimizer updates.

```
# train on 32 GPUs (4 nodes)
trainer = Trainer(gpus=8, distributed_backend='ddp2', num_nodes=4)
```

18.2.4 Horovod

Horovod allows the same training script to be used for single-GPU, multi-GPU, and multi-node training.

Like Distributed Data Parallel, every process in Horovod operates on a single GPU with a fixed subset of the data. Gradients are averaged across all GPUs in parallel during the backward pass, then synchronously applied before beginning the next step.

The number of worker processes is configured by a driver application (*horovodrun* or *mpirun*). In the training script, Horovod will detect the number of workers from the environment, and automatically scale the learning rate to compensate for the increased total batch size.

Horovod can be configured in the training script to run with any number of GPUs / processes as follows:

```
# train Horovod on GPU (number of GPUs / machines provided on command-line)
trainer = Trainer(distributed_backend='horovod', gpus=1)

# train Horovod on CPU (number of processes / machines provided on command-line)
trainer = Trainer(distributed_backend='horovod')
```

When starting the training job, the driver application will then be used to specify the total number of worker processes:

```
# run training with 4 GPUs on a single machine
horovodrun -np 4 python train.py

# run training with 8 GPUs on two machines (4 GPUs each)
horovodrun -np 8 -H hostname1:4,hostname2:4 python train.py
```

See the official Horovod documentation for details on installation and performance tuning.

18.2.5 DP/DDP2 caveats

In DP and DDP2 each GPU within a machine sees a portion of a batch. DP and ddp2 roughly do the following:

```
def distributed_forward(batch, model):
    batch = torch.Tensor(32, 8)
    gpu_0_batch = batch[:8]
    gpu_1_batch = batch[8:16]
    gpu_2_batch = batch[16:24]
    gpu_3_batch = batch[24:]

    y_0 = model_copy_gpu_0(gpu_0_batch)
    y_1 = model_copy_gpu_1(gpu_1_batch)
    y_2 = model_copy_gpu_2(gpu_2_batch)
    y_3 = model_copy_gpu_3(gpu_3_batch)

    return [y_0, y_1, y_2, y_3]
```

So, when Lightning calls any of the *training_step*, *validation_step*, *test_step* you will only be operating on one of those pieces.

```
# the batch here is a portion of the FULL batch
def training_step(self, batch, batch_idx):
    y_0 = batch
```

For most metrics, this doesn't really matter. However, if you want to add something to your computational graph (like softmax) using all batch parts you can use the *training_step_end* step.

```
def training_step_end(self, outputs):
    # only use when  on dp
    outputs = torch.cat(outputs, dim=1)
    softmax = softmax(outputs, dim=1)
    out = softmax.mean()
    return out
```

In pseudocode, the full sequence is:

```
# get data
batch = next(dataloader)

# copy model and data to each gpu
batch_splits = split_batch(batch, num_gpus)
models = copy_model_to_gpus(model)

# in parallel, operate on each batch chunk
all_results = []
for gpu_num in gpus:
    batch_split = batch_splits[gpu_num]
    gpu_model = models[gpu_num]
    out = gpu_model(batch_split)
    all_results.append(out)

# use the full batch for something like softmax
full out = model.training_step_end(all_results)
```

to illustrate why this is needed, let's look at dataparallel

```
def training_step(self, batch, batch_idx):
    x, y = batch
    y_hat = self(batch)

    # on dp or ddp2 if we did softmax now it would be wrong
    # because batch is actually a piece of the full batch
    return y_hat

def training_step_end(self, batch_parts_outputs):
    # batch_parts_outputs has outputs of each part of the batch

    # do softmax here
    outputs = torch.cat(outputs, dim=1)
    softmax = softmax(outputs, dim=1)
    out = softmax.mean()

    return out
```

If *training_step_end* is defined it will be called regardless of tpu, dp, ddp, etc... which means it will behave the same no matter the backend.

Validation and test step also have the same option when using dp

```
def validation_step_end(self, batch_parts_outputs):
    ...

def test_step_end(self, batch_parts_outputs):
    ...
```

18.2.6 Implement Your Own Distributed (DDP) training

If you need your own way to init PyTorch DDP you can override `pytorch_lightning.core.LightningModule.()`.

If you also need to use your own DDP implementation, override: *pytorch_lightning.core.LightningModule.configure_ddp()*.

18.3 Batch size

When using distributed training make sure to modify your learning rate according to your effective batch size.

Let's say you have a batch size of 7 in your dataloader.

```
class LitModel(LightningModule):

    def train_dataloader(self):
        return Dataset(..., batch_size=7)
```

In (DDP, Horovod) your effective batch size will be 7 * gpus * num_nodes.

```
# effective batch size = 7 * 8
Trainer(gpus=8, distributed_backend='ddp|horovod')

# effective batch size = 7 * 8 * 10
Trainer(gpus=8, num_nodes=10, distributed_backend='ddp|horovod')
```

In DDP2, your effective batch size will be 7 * num_nodes. The reason is that the full batch is visible to all GPUs on the node when using DDP2.

```
# effective batch size = 7
Trainer(gpus=8, distributed_backend='ddp2')

# effective batch size = 7 * 10
Trainer(gpus=8, num_nodes=10, distributed_backend='ddp2')
```

Note: Huge batch sizes are actually really bad for convergence. Check out: Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour

18.4 PytorchElastic

Lightning supports the use of PytorchElastic to enable fault-tolerent and elastic distributed job scheduling. To use it, specify the 'ddp' or 'ddp2' backend and the number of gpus you want to use in the trainer.

```
Trainer(gpus=8, distributed_backend='ddp')
```

Following the PytorchElastic Quickstart documentation, you then need to start a single-node etcd server on one of the hosts:

```
etcd --enable-v2
     --listen-client-urls http://0.0.0.0:2379,http://127.0.0.1:4001
     --advertise-client-urls PUBLIC_HOSTNAME:2379
```

And then launch the elastic job with:

```
python -m torchelastic.distributed.launch
        --nnodes=MIN_SIZE:MAX_SIZE
        --nproc_per_node=TRAINERS_PER_NODE
        --rdzv_id=JOB_ID
        --rdzv_backend=etcd
        --rdzv_endpoint=ETCD_HOST:ETCD_PORT
        YOUR_LIGHTNING_TRAINING_SCRIPT.py (--arg1 ... train script args...)
```

See the official PytorchElastic documentation for details on installation and more use cases.

CHAPTER

NINETEEN

MULTIPLE DATASETS

Lightning supports multiple dataloaders in a few ways.

1. Create a dataloader that iterates both datasets under the hood.
2. In the validation and test loop you also have the option to return multiple dataloaders which lightning will call sequentially.

19.1 Multiple training dataloaders

For training, the best way to use multiple-dataloaders is to create a Dataloader class which wraps both your dataloaders. (This of course also works for testing and validation dataloaders).

(reference)

```
class ConcatDataset(torch.utils.data.Dataset):
    def __init__(self, *datasets):
        self.datasets = datasets

    def __getitem__(self, i):
        return tuple(d[i] for d in self.datasets)

    def __len__(self):
        return min(len(d) for d in self.datasets)

class LitModel(LightningModule):

    def train_dataloader(self):
        concat_dataset = ConcatDataset(
            datasets.ImageFolder(traindir_A),
            datasets.ImageFolder(traindir_B)
        )

        loader = torch.utils.data.DataLoader(
            concat_dataset,
            batch_size=args.batch_size,
            shuffle=True,
            num_workers=args.workers,
            pin_memory=True
        )
        return loader

    def val_dataloader(self):
        # SAME
```

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```
        ...

    def test_dataloader(self):
        # SAME
        ...
```

19.2 Test/Val dataloaders

For validation, test dataloaders lightning also gives you the additional option of passing in multiple dataloaders back from each call.

See the following for more details:

- *val_dataloader()*
- *test_dataloader()*

```
def val_dataloader(self):
    loader_1 = Dataloader()
    loader_2 = Dataloader()
    return [loader_1, loader_2]
```

CHAPTER

TWENTY

SAVING AND LOADING WEIGHTS

Lightning can automate saving and loading checkpoints.

20.1 Checkpoint saving

A Lightning checkpoint has everything needed to restore a training session including:

- 16-bit scaling factor (apex)
- Current epoch
- Global step
- Model state_dict
- State of all optimizers
- State of all learningRate schedulers
- State of all callbacks
- The hyperparameters used for that model if passed in as hparams (Argparse.Namespace)

20.1.1 Automatic saving

Checkpointing is enabled by default to the current working directory. To change the checkpoint path pass in:

```
trainer = Trainer(default_save_path='/your/path/to/save/checkpoints')
```

To modify the behavior of checkpointing pass in your own callback.

```
from pytorch_lightning.callbacks import ModelCheckpoint

# DEFAULTS used by the Trainer
checkpoint_callback = ModelCheckpoint(
    filepath=os.getcwd(),
    save_top_k=True,
    verbose=True,
    monitor='val_loss',
    mode='min',
    prefix=''
)

trainer = Trainer(checkpoint_callback=checkpoint_callback)
```

Or disable it by passing

```
trainer = Trainer(checkpoint_callback=False)
```

The Lightning checkpoint also saves the hparams (hyperparams) passed into the LightningModule init.

Note: hparams is a Namespace.

```
from argparse import Namespace

# usually these come from command line args
args = Namespace(learning_rate=0.001)

# define you module to have hparams as the first arg
# this means your checkpoint will have everything that went into making
# this model (in this case, learning rate)
class MyLightningModule(LightningModule):

    def __init__(self, hparams, *args, **kwargs):
        self.hparams = hparams
```

20.1.2 Manual saving

You can manually save checkpoints and restore your model from the checkpointed state.

```
model = MyLightningModule(hparams)
trainer.fit(model)
trainer.save_checkpoint("example.ckpt")
new_model = MyModel.load_from_checkpoint(checkpoint_path="example.ckpt")
```

20.2 Checkpoint Loading

To load a model along with its weights, biases and hyperparameters use following method.

```
model = MyLightingModule.load_from_checkpoint(PATH)
model.eval()
y_hat = model(x)
```

The above only works if you used *hparams* in your model definition

```
class LitModel(LightningModule):

    def __init__(self, hparams):
        self.hparams = hparams
        self.l1 = nn.Linear(hparams.in_dim, hparams.out_dim)
```

But if you don't and instead pass individual parameters

```
class LitModel(LightningModule):

    def __init__(self, in_dim, out_dim):
        self.l1 = nn.Linear(in_dim, out_dim)
```

you can restore the model like this

```
model = LitModel.load_from_checkpoint(PATH, in_dim=128, out_dim=10)
```

20.3 Restoring Training State

If you don't just want to load weights, but instead restore the full training, do the following:

```
model = LitModel()
trainer = Trainer(resume_from_checkpoint='some/path/to/my_checkpoint.ckpt')

# automatically restores model, epoch, step, LR schedulers, apex, etc...
trainer.fit(model)
```

CHAPTER

TWENTYONE

OPTIMIZATION

21.1 Learning rate scheduling

Every optimizer you use can be paired with any LearningRateScheduler.

```
# no LR scheduler
def configure_optimizers(self):
   return Adam(...)

# Adam + LR scheduler
def configure_optimizers(self):
   optimizer = Adam(...)
   scheduler = ReduceLROnPlateau(optimizer, ...)
   return [optimizer], [scheduler]

# Two optimziers each with a scheduler
def configure_optimizers(self):
   optimizer1 = Adam(...)
   optimizer2 = SGD(...)
   scheduler1 = ReduceLROnPlateau(optimizer1, ...)
   scheduler2 = LambdaLR(optimizer2, ...)
   return [optimizer1, optimizer2], [scheduler1, scheduler2]

# Same as above with additional params passed to the first scheduler
def configure_optimizers(self):
   optimizers = [Adam(...), SGD(...)]
   schedulers = [
      {
         'scheduler': ReduceLROnPlateau(optimizers[0], ...),
         'monitor': 'val_recall', # Default: val_loss
         'interval': 'epoch',
         'frequency': 1
      },
      LambdaLR(optimizers[1], ...)
   ]
   return optimizers, schedulers
```

21.2 Use multiple optimizers (like GANs)

To use multiple optimizers return > 1 optimizers from *pytorch_lightning.core.LightningModule.configure_optimizers()*

```
# one optimizer
def configure_optimizers(self):
   return Adam(...)

# two optimizers, no schedulers
def configure_optimizers(self):
   return Adam(...), SGD(...)

# Two optimizers, one scheduler for adam only
def configure_optimizers(self):
   return [Adam(...), SGD(...)], [ReduceLROnPlateau()]
```

Lightning will call each optimizer sequentially:

```
for epoch in epochs:
   for batch in data:
      for opt in optimizers:
         train_step(opt)
         opt.step()

   for scheduler in scheduler:
      scheduler.step()
```

21.3 Step optimizers at arbitrary intervals

To do more interesting things with your optimizers such as learning rate warm-up or odd scheduling, override the `optimizer_step()` function.

For example, here step optimizer A every 2 batches and optimizer B every 4 batches

```
def optimizer_step(self, current_epoch, batch_nb, optimizer, optimizer_i, second_
↪order_closure=None):
    optimizer.step()
    optimizer.zero_grad()

# Alternating schedule for optimizer steps (ie: GANs)
def optimizer_step(self, current_epoch, batch_nb, optimizer, optimizer_i, second_
↪order_closure=None):
    # update generator opt every 2 steps
    if optimizer_i == 0:
        if batch_nb % 2 == 0 :
            optimizer.step()
            optimizer.zero_grad()

    # update discriminator opt every 4 steps
    if optimizer_i == 1:
        if batch_nb % 4 == 0 :
            optimizer.step()
            optimizer.zero_grad()
```

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```
    # ...
    # add as many optimizers as you want
```

Here we add a learning-rate warm up

```
# learning rate warm-up
def optimizer_step(self, current_epoch, batch_nb, optimizer, optimizer_i, second_
↪order_closure=None):
    # warm up lr
    if self.trainer.global_step < 500:
        lr_scale = min(1., float(self.trainer.global_step + 1) / 500.)
        for pg in optimizer.param_groups:
            pg['lr'] = lr_scale * self.hparams.learning_rate

    # update params
    optimizer.step()
    optimizer.zero_grad()
```

CHAPTER

TWENTYTWO

PERFORMANCE AND BOTTLENECK PROFILER

Profiling your training run can help you understand if there are any bottlenecks in your code.

22.1 Built-in checks

PyTorch Lightning supports profiling standard actions in the training loop out of the box, including:

- on_epoch_start
- on_epoch_end
- on_batch_start
- tbptt_split_batch
- model_forward
- model_backward
- on_after_backward
- optimizer_step
- on_batch_end
- training_step_end
- on_training_end

22.2 Enable simple profiling

If you only wish to profile the standard actions, you can set *profiler=True* when constructing your *Trainer* object.

```
trainer = Trainer(..., profiler=True)
```

The profiler's results will be printed at the completion of a training *fit()*.

```
Profiler Report

Action                  |  Mean duration (s)    |  Total time (s)
-----------------------------------------------------------------
on_epoch_start          |  5.993e-06            |  5.993e-06
get_train_batch         |  0.0087412            |  16.398
on_batch_start          |  5.0865e-06           |  0.0095372
```

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```
model_forward           |  0.0017818           |  3.3408
model_backward          |  0.0018283           |  3.4282
on_after_backward       |  4.2862e-06          |  0.0080366
optimizer_step          |  0.0011072           |  2.0759
on_batch_end            |  4.5202e-06          |  0.0084753
on_epoch_end            |  3.919e-06           |  3.919e-06
on_train_end            |  5.449e-06           |  5.449e-06
```

22.3 Advanced Profiling

If you want more information on the functions called during each event, you can use the *AdvancedProfiler*. This option uses Python's cProfiler to provide a report of time spent on *each* function called within your code.

```
profiler = AdvancedProfiler()
trainer = Trainer(..., profiler=profiler)
```

The profiler's results will be printed at the completion of a training *fit()*. This profiler report can be quite long, so you can also specify an *output_filename* to save the report instead of logging it to the output in your terminal. The output below shows the profiling for the action *get_train_batch*.

```
Profiler Report

Profile stats for: get_train_batch
        4869394 function calls (4863767 primitive calls) in 18.893 seconds
Ordered by: cumulative time
List reduced from 76 to 10 due to restriction <10>
ncalls  tottime  percall  cumtime  percall filename:lineno(function)
3752/1876    0.011    0.000   18.887    0.010 {built-in method builtins.next}
    1876     0.008    0.000   18.877    0.010 dataloader.py:344(__next__)
    1876     0.074    0.000   18.869    0.010 dataloader.py:383(_next_data)
    1875     0.012    0.000   18.721    0.010 fetch.py:42(fetch)
    1875     0.084    0.000   18.290    0.010 fetch.py:44(<listcomp>)
    60000    1.759    0.000   18.206    0.000 mnist.py:80(__getitem__)
    60000    0.267    0.000   13.022    0.000 transforms.py:68(__call__)
    60000    0.182    0.000    7.020    0.000 transforms.py:93(__call__)
    60000    1.651    0.000    6.839    0.000 functional.py:42(to_tensor)
    60000    0.260    0.000    5.734    0.000 transforms.py:167(__call__)
```

You can also reference this profiler in your LightningModule to profile specific actions of interest. If you don't want to always have the profiler turned on, you can optionally pass a *PassThroughProfiler* which will allow you to skip profiling without having to make any code changes. Each profiler has a method *profile()* which returns a context handler. Simply pass in the name of your action that you want to track and the profiler will record performance for code executed within this context.

```
from pytorch_lightning.profiler import Profiler, PassThroughProfiler

class MyModel(LightningModule):
    def __init__(self, hparams, profiler=None):
        self.hparams = hparams
        self.profiler = profiler or PassThroughProfiler()

    def custom_processing_step(self, data):
        with profiler.profile('my_custom_action'):
```

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```
            # custom processing step
        return data

profiler = Profiler()
model = MyModel(hparams, profiler)
trainer = Trainer(profiler=profiler, max_epochs=1)
```

class pytorch_lightning.profiler.**BaseProfiler**(*output_streams=None*)
Bases: abc.ABC

If you wish to write a custom profiler, you should inhereit from this class.

Params: stream_out: callable

describe()
Logs a profile report after the conclusion of the training run.

Return type None

profile(*action_name*)
Yields a context manager to encapsulate the scope of a profiled action.

Example:

```
with self.profile('load training data'):
    # load training data code
```

The profiler will start once you've entered the context and will automatically stop once you exit the code block.

Return type None

abstract start(*action_name*)
Defines how to start recording an action.

Return type None

abstract stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

abstract summary()
Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.**SimpleProfiler**(*output_filename=None*)
Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This profiler simply records the duration of actions (in seconds) and reports the mean duration of each action and the total time spent over the entire training run.

Params:

output_filename (str): optionally save profile results to file instead of printing to std out when training is finished.

describe()
Logs a profile report after the conclusion of the training run.

start(*action_name*)
Defines how to start recording an action.

Return type None

stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

summary()
Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.**AdvancedProfiler**(*output_filename=None*, *line_count_restriction=1.0*)
Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This profiler uses Python's cProfiler to record more detailed information about time spent in each function call recorded during a given action. The output is quite verbose and you should only use this if you want very detailed reports.

Parameters

- **output_filename** (Optional[str]) – optionally save profile results to file instead of printing to std out when training is finished.
- **line_count_restriction** (float) – this can be used to limit the number of functions reported for each action. either an integer (to select a count of lines), or a decimal fraction between 0.0 and 1.0 inclusive (to select a percentage of lines)

describe()
Logs a profile report after the conclusion of the training run.

start(*action_name*)
Defines how to start recording an action.

Return type None

stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

summary()
Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.**PassThroughProfiler**
Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This class should be used when you don't want the (small) overhead of profiling. The Trainer uses this class by default.

Params: stream_out: callable

start(*action_name*)
Defines how to start recording an action.

Return type None

stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

summary()
Create profiler summary in text format.

Return type str

CHAPTER

TWENTYTHREE

SINGLE GPU TRAINING

Make sure you are running on a machine that has at least one GPU. Lightning handles all the NVIDIA flags for you, there's no need to set them yourself.

```
# train on 1 GPU (using dp mode)
trainer = Trainer(gpus=1)
```

CHAPTER

TWENTYFOUR

SEQUENTIAL DATA

Lightning has built in support for dealing with sequential data.

24.1 Packed sequences as inputs

When using PackedSequence, do 2 things:

1. return either a padded tensor in dataset or a list of variable length tensors in the dataloader collate_fn (example above shows the list implementation).
2. Pack the sequence in forward or training and validation steps depending on use case.

```
# For use in dataloader
def collate_fn(batch):
    x = [item[0] for item in batch]
    y = [item[1] for item in batch]
    return x, y

# In module
def training_step(self, batch, batch_nb):
    x = rnn.pack_sequence(batch[0], enforce_sorted=False)
    y = rnn.pack_sequence(batch[1], enforce_sorted=False)
```

24.2 Truncated Backpropagation Through Time

There are times when multiple backwards passes are needed for each batch. For example, it may save memory to use Truncated Backpropagation Through Time when training RNNs.

Lightning can handle TBTT automatically via this flag.

```
# DEFAULT (single backwards pass per batch)
trainer = Trainer(truncated_bptt_steps=None)

# (split batch into sequences of size 2)
trainer = Trainer(truncated_bptt_steps=2)
```

Note: If you need to modify how the batch is split, override *pytorch_lightning.core.LightningModule.tbptt_split_batch()*.

Note: Using this feature requires updating your LightningModule's *pytorch_lightning.core.LightningModule.training_step()* to include a *hiddens* arg.

24.3 Iterable Datasets

Lightning supports using IterableDatasets as well as map-style Datasets. IterableDatasets provide a more natural option when using sequential data.

Note: When using an IterableDataset you must set the val_check_interval to 1.0 (the default) or to an int (specifying the number of training batches to run before validation) when initializing the Trainer. This is due to the fact that the IterableDataset does not have a __len__ and Lightning requires this to calculate the validation interval when val_check_interval is less than one.

```
# IterableDataset
class CustomDataset(IterableDataset):

    def __init__(self, data):
        self.data_source

    def __iter__(self):
        return iter(self.data_source)

# Setup DataLoader
def train_dataloader(self):
    seq_data = ['A', 'long', 'time', 'ago', 'in', 'a', 'galaxy', 'far', 'far', 'away']
    iterable_dataset = CustomDataset(seq_data)

    dataloader = DataLoader(dataset=iterable_dataset, batch_size=5)
    return dataloader
```

```
# Set val_check_interval
trainer = Trainer(val_check_interval=100)
```

CHAPTER

TWENTYFIVE

TRAINING TRICKS

Lightning implements various tricks to help during training

25.1 Accumulate gradients

Accumulated gradients runs K small batches of size N before doing a backwards pass. The effect is a large effective batch size of size KxN.

See also:

Trainer

```
# DEFAULT (ie: no accumulated grads)
trainer = Trainer(accumulate_grad_batches=1)
```

25.2 Gradient Clipping

Gradient clipping may be enabled to avoid exploding gradients. Specifically, this will clip the gradient norm computed over all model parameters together.

See also:

Trainer

```
# DEFAULT (ie: don't clip)
trainer = Trainer(gradient_clip_val=0)

# clip gradients with norm above 0.5
trainer = Trainer(gradient_clip_val=0.5)
```

25.3 Auto scaling of batch size

Auto scaling of batch size may be enabled to find the largest batch size that fits into memory. Larger batch size often yields better estimates of gradients, but may also result in longer training time.

See also:

Trainer

```
# DEFAULT (ie: don't scale batch size automatically)
trainer = Trainer(auto_scale_batch_size=None)

# Autoscale batch size
trainer = Trainer(auto_scale_batch_size=None|'power'|'binsearch')
```

Currently, this feature supports two modes *'power'* scaling and *'binsearch'* scaling. In *'power'* scaling, starting from a batch size of 1 keeps doubling the batch size until an out-of-memory (OOM) error is encountered. Setting the argument to *'binsearch'* continues to finetune the batch size by performing a binary search.

Note: This feature expects that a *batch_size* field in the *hparams* of your model, i.e., *model.hparams.batch_size* should exist and will be overridden by the results of this algorithm. Additionally, your *train_dataloader()* method should depend on this field for this feature to work i.e.

```
def train_dataloader(self):
    return DataLoader(train_dataset, batch_size=self.hparams.batch_size)
```

Warning: Due to these constraints, this features does *NOT* work when passing dataloaders directly to *.fit()*.

The scaling algorithm has a number of parameters that the user can control by invoking the trainer method *.scale_batch_size* themself (see description below).

```
# Use default in trainer construction
trainer = Trainer()

# Invoke method
new_batch_size = trainer.scale_batch_size(model, ...)

# Override old batch size
model.hparams.batch_size = new_batch_size

# Fit as normal
trainer.fit(model)
```

The algorithm in short works by:

1. Dumping the current state of the model and trainer
2. **Iteratively until convergence or maximum number of tries *max_trials* (default 25) has been reached:**
    - Call *fit()* method of trainer. This evaluates *steps_per_trial* (default 3) number of training steps. Each training step can trigger an OOM error if the tensors (training batch, weights, gradients ect.) allocated during the steps have a too large memory footprint.
    - If an OOM error is encountered, decrease batch size else increase it. How much the batch size is increased/decreased is determined by the choosen stratrgy.
3. The found batch size is saved to *model.hparams.batch_size*
4. Restore the initial state of model and trainer

class pytorch_lightning.trainer.training_tricks.**TrainerTrainingTricksMixin**

Bases: abc.ABC

abstract fit(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract get_model()
Warning: this is just empty shell for code implemented in other class.

abstract restore(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract save_checkpoint(**args*)
Warning: this is just empty shell for code implemented in other class.

scale_batch_size(*model*, *mode='power'*, *steps_per_trial=3*, *init_val=2*, *max_trials=25*, *batch_arg_name='batch_size'*)
Will iteratively try to find the largest batch size for a given model that does not give an out of memory (OOM) error.

Parameters

- **model** (*LightningModule*) – Model to fit.
- **mode** (str) – string setting the search mode. Either *power* or *binsearch*. If mode is *power* we keep multiplying the batch size by 2, until we get an OOM error. If mode is 'binsearch', we will initially also keep multiplying by 2 and after encountering an OOM error do a binary search between the last successful batch size and the batch size that failed.
- **steps_per_trial** (int) – number of steps to run with a given batch size. Idealy 1 should be enough to test if a OOM error occurs, however in practise a few are needed
- **init_val** (int) – initial batch size to start the search with
- **max_trials** (int) – max number of increase in batch size done before algorithm is terminated

Warning: Batch size finder is not supported for DDP yet, it is coming soon.

CHAPTER

TWENTYSIX

TRANSFER LEARNING

26.1 Using Pretrained Models

Sometimes we want to use a LightningModule as a pretrained model. This is fine because a LightningModule is just a *torch.nn.Module*!

Note: Remember that a LightningModule is EXACTLY a torch.nn.Module but with more capabilities.

Let's use the *AutoEncoder* as a feature extractor in a separate model.

```
class Encoder(torch.nn.Module):
    ...

class AutoEncoder(LightningModule):
    def __init__(self):
        self.encoder = Encoder()
        self.decoder = Decoder()

class CIFAR10Classifier(LightningModule):
    def __init__(self):
        # init the pretrained LightningModule
        self.feature_extractor = AutoEncoder.load_from_checkpoint(PATH)
        self.feature_extractor.freeze()

        # the autoencoder outputs a 100-dim representation and CIFAR-10 has 10 classes
        self.classifier = nn.Linear(100, 10)

    def forward(self, x):
        representations = self.feature_extractor(x)
        x = self.classifier(representations)
        ...
```

We used our pretrained Autoencoder (a LightningModule) for transfer learning!

26.2 Example: Imagenet (computer Vision)

```
import torchvision.models as models

class ImagenetTransferLearning(LightningModule):
    def __init__(self):
        # init a pretrained resnet
        num_target_classes = 10
        self.feature_extractor = models.resnet50(
                                    pretrained=True,
                                    num_classes=num_target_classes)
        self.feature_extractor.eval()

        # use the pretrained model to classify cifar-10 (10 image classes)
        self.classifier = nn.Linear(2048, num_target_classes)

    def forward(self, x):
        representations = self.feature_extractor(x)
        x = self.classifier(representations)
        ...
```

Finetune

```
model = ImagenetTransferLearning()
trainer = Trainer()
trainer.fit(model)
```

And use it to predict your data of interest

```
model = ImagenetTransferLearning.load_from_checkpoint(PATH)
model.freeze()

x = some_images_from_cifar10()
predictions = model(x)
```

We used a pretrained model on imagenet, finetuned on CIFAR-10 to predict on CIFAR-10. In the non-academic world we would finetune on a tiny dataset you have and predict on your dataset.

26.3 Example: BERT (NLP)

Lightning is completely agnostic to what's used for transfer learning so long as it is a *torch.nn.Module* subclass.

Here's a model that uses Huggingface transformers.

```
class BertMNLIFinetuner(LightningModule):

    def __init__(self):
        super().__init__()

        self.bert = BertModel.from_pretrained('bert-base-cased', output_
↪attentions=True)
        self.W = nn.Linear(bert.config.hidden_size, 3)
        self.num_classes = 3
```

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```
    def forward(self, input_ids, attention_mask, token_type_ids):

        h, _, attn = self.bert(input_ids=input_ids,
                               attention_mask=attention_mask,
                               token_type_ids=token_type_ids)

        h_cls = h[:, 0]
        logits = self.W(h_cls)
        return logits, attn
```

CHAPTER

TWENTYSEVEN

TPU SUPPORT

Lightning supports running on TPUs. At this moment, TPUs are only available on Google Cloud (GCP). For more information on TPUs watch this video.

27.1 Live demo

Check out this Google Colab to see how to train MNIST on TPUs.

27.2 TPU Terminology

A TPU is a Tensor processing unit. Each TPU has 8 cores where each core is optimized for 128x128 matrix multiplies. In general, a single TPU is about as fast as 5 V100 GPUs!

A TPU pod hosts many TPUs on it. Currently, TPU pod v2 has 2048 cores! You can request a full pod from Google cloud or a "slice" which gives you some subset of those 2048 cores.

27.3 How to access TPUs

To access TPUs there are two main ways.

1. Using google colab.
2. Using Google Cloud (GCP).

27.4 Colab TPUs

Colab is like a jupyter notebook with a free GPU or TPU hosted on GCP.

To get a TPU on colab, follow these steps:

1. Go to https://colab.research.google.com/.
2. Click "new notebook" (bottom right of pop-up).
3. Click runtime > change runtime settings. Select Python 3, and hardware accelerator "TPU". This will give you a TPU with 8 cores.
4. Next, insert this code into the first cell and execute. This will install the xla library that interfaces between PyTorch and the TPU.

```
import collections
from datetime import datetime, timedelta
import os
import requests
import threading

_VersionConfig = collections.namedtuple('_VersionConfig', 'wheels,server')
VERSION = "xrt==1.15.0"  #@param ["xrt==1.15.0", "torch_xla==nightly"]
CONFIG = {
    'xrt==1.15.0': _VersionConfig('1.15', '1.15.0'),
    'torch_xla==nightly': _VersionConfig('nightly', 'XRT-dev{}'.format(
        (datetime.today() - timedelta(1)).strftime('%Y%m%d'))),
}[VERSION]
DIST_BUCKET = 'gs://tpu-pytorch/wheels'
TORCH_WHEEL = 'torch-{}-cp36-cp36m-linux_x86_64.whl'.format(CONFIG.wheels)
TORCH_XLA_WHEEL = 'torch_xla-{}-cp36-cp36m-linux_x86_64.whl'.format(CONFIG.wheels)
TORCHVISION_WHEEL = 'torchvision-{}-cp36-cp36m-linux_x86_64.whl'.format(CONFIG.
↪wheels)

# Update TPU XRT version
def update_server_xrt():
  print('Updating server-side XRT to {} ...'.format(CONFIG.server))
  url = 'http://{TPU_ADDRESS}:8475/requestversion/{XRT_VERSION}'.format(
      TPU_ADDRESS=os.environ['COLAB_TPU_ADDR'].split(':')[0],
      XRT_VERSION=CONFIG.server,
  )
  print('Done updating server-side XRT: {}'.format(requests.post(url)))

update = threading.Thread(target=update_server_xrt)
update.start()
```

```
# Install Colab TPU compat PyTorch/TPU wheels and dependencies
!pip uninstall -y torch torchvision
!gsutil cp "$DIST_BUCKET/$TORCH_WHEEL" .
!gsutil cp "$DIST_BUCKET/$TORCH_XLA_WHEEL" .
!gsutil cp "$DIST_BUCKET/$TORCHVISION_WHEEL" .
!pip install "$TORCH_WHEEL"
!pip install "$TORCH_XLA_WHEEL"
!pip install "$TORCHVISION_WHEEL"
!sudo apt-get install libomp5
update.join()
```

5. Once the above is done, install PyTorch Lightning (v 0.7.0+).

```
!pip install pytorch-lightning
```

6. Then set up your LightningModule as normal.

27.5 DistributedSamplers

Lightning automatically inserts the correct samplers - no need to do this yourself!

Usually, with TPUs (and DDP), you would need to define a DistributedSampler to move the right chunk of data to the appropriate TPU. As mentioned, this is not needed in Lightning

Note: Don't add distributedSamplers. Lightning does this automatically

If for some reason you still need to, this is how to construct the sampler for TPU use

```
import torch_xla.core.xla_model as xm

def train_dataloader(self):
    dataset = MNIST(
        os.getcwd(),
        train=True,
        download=True,
        transform=transforms.ToTensor()
    )

    # required for TPU support
    sampler = None
    if use_tpu:
        sampler = torch.utils.data.distributed.DistributedSampler(
            dataset,
            num_replicas=xm.xrt_world_size(),
            rank=xm.get_ordinal(),
            shuffle=True
        )

    loader = DataLoader(
        dataset,
        sampler=sampler,
        batch_size=32
    )

    return loader
```

Configure the number of TPU cores in the trainer. You can only choose 1 or 8. To use a full TPU pod skip to the TPU pod section.

```
import pytorch_lightning as pl

my_model = MyLightningModule()
trainer = pl.Trainer(num_tpu_cores=8)
trainer.fit(my_model)
```

That's it! Your model will train on all 8 TPU cores.

27.6 Distributed Backend with TPU

The `distributed_backend` option used for GPUs does not apply to TPUs. TPUs work in DDP mode by default (distributing over each core)

27.7 TPU Pod

To train on more than 8 cores, your code actually doesn't change! All you need to do is submit the following command:

```
$ python -m torch_xla.distributed.xla_dist
--tpu=$TPU_POD_NAME
--conda-env=torch-xla-nightly
-- python /usr/share/torch-xla-0.5/pytorch/xla/test/test_train_imagenet.py --fake_data
```

27.8 16 bit precision

Lightning also supports training in 16-bit precision with TPUs. By default, TPU training will use 32-bit precision. To enable 16-bit, also set the 16-bit flag.

```
import pytorch_lightning as pl

my_model = MyLightningModule()
trainer = pl.Trainer(num_tpu_cores=8, precision=16)
trainer.fit(my_model)
```

Under the hood the xla library will use the bfloat16 type.

27.9 About XLA

XLA is the library that interfaces PyTorch with the TPUs. For more information check out XLA.

Guide for troubleshooting XLA

CHAPTER

TWENTYEIGHT

TEST SET

Lightning forces the user to run the test set separately to make sure it isn't evaluated by mistake

28.1 Test after fit

To run the test set after training completes, use this method

```
# run full training
trainer.fit(model)

# run test set
trainer.test()
```

28.2 Test pre-trained model

To run the test set on a pre-trained model, use this method.

```
model = MyLightningModule.load_from_checkpoint(
    checkpoint_path='/path/to/pytorch_checkpoint.ckpt',
    hparams_file='/path/to/test_tube/experiment/version/hparams.yaml',
    map_location=None
)

# init trainer with whatever options
trainer = Trainer(...)

# test (pass in the model)
trainer.test(model)
```

In this case, the options you pass to trainer will be used when running the test set (ie: 16-bit, dp, ddp, etc...)

CHAPTER

TWENTYNINE

CONTRIBUTOR COVENANT CODE OF CONDUCT

29.1 Our Pledge

In the interest of fostering an open and welcoming environment, we as contributors and maintainers pledge to making participation in our project and our community a harassment-free experience for everyone, regardless of age, body size, disability, ethnicity, sex characteristics, gender identity and expression, level of experience, education, socio-economic status, nationality, personal appearance, race, religion, or sexual identity and orientation.

29.2 Our Standards

Examples of behavior that contributes to creating a positive environment include:

- Using welcoming and inclusive language
- Being respectful of differing viewpoints and experiences
- Gracefully accepting constructive criticism
- Focusing on what is best for the community
- Showing empathy towards other community members

Examples of unacceptable behavior by participants include:

- The use of sexualized language or imagery and unwelcome sexual attention or advances
- Trolling, insulting/derogatory comments, and personal or political attacks
- Public or private harassment
- Publishing others' private information, such as a physical or electronic address, without explicit permission
- Other conduct which could reasonably be considered inappropriate in a professional setting

29.3 Our Responsibilities

Project maintainers are responsible for clarifying the standards of acceptable behavior and are expected to take appropriate and fair corrective action in response to any instances of unacceptable behavior.

Project maintainers have the right and responsibility to remove, edit, or reject comments, commits, code, wiki edits, issues, and other contributions that are not aligned to this Code of Conduct, or to ban temporarily or permanently any contributor for other behaviors that they deem inappropriate, threatening, offensive, or harmful.

29.4 Scope

This Code of Conduct applies both within project spaces and in public spaces when an individual is representing the project or its community. Examples of representing a project or community include using an official project e-mail address, posting via an official social media account, or acting as an appointed representative at an online or offline event. Representation of a project may be further defined and clarified by project maintainers.

29.5 Enforcement

Instances of abusive, harassing, or otherwise unacceptable behavior may be reported by contacting the project team at waf2107@columbia.edu. All complaints will be reviewed and investigated and will result in a response that is deemed necessary and appropriate to the circumstances. The project team is obligated to maintain confidentiality with regard to the reporter of an incident. Further details of specific enforcement policies may be posted separately.

Project maintainers who do not follow or enforce the Code of Conduct in good faith may face temporary or permanent repercussions as determined by other members of the project's leadership.

29.6 Attribution

This Code of Conduct is adapted from the Contributor Covenant, version 1.4, available at https://www.contributor-covenant.org/version/1/4/code-of-conduct.html

For answers to common questions about this code of conduct, see https://www.contributor-covenant.org/faq

CHAPTER

THIRTY

CONTRIBUTING

Welcome to the PyTorch Lightning community! We're building the most advanced research platform on the planet to implement the latest, best practices that the amazing PyTorch team rolls out!

30.1 Main Core Value: One less thing to remember

Simplify the API as much as possible from the user perspective. Any additions or improvements should minimize things the user needs to remember.

For example: One benefit of the validation_step is that the user doesn't have to remember to set the model to .eval(). This avoids all sorts of subtle errors the user could make.

30.2 Lightning Design Principles

We encourage all sorts of contributions you're interested in adding! When coding for lightning, please follow these principles.

30.2.1 No PyTorch Interference

We don't want to add any abstractions on top of pure PyTorch. This gives researchers all the control they need without having to learn yet another framework.

30.2.2 Simple Internal Code

It's useful for users to look at the code and understand very quickly what's happening. Many users won't be engineers. Thus we need to value clear, simple code over condensed ninja moves. While that's super cool, this isn't the project for that :)

30.2.3 Force User Decisions To Best Practices

There are 1,000 ways to do something. However, something eventually becomes standard practice that everyone does. Thus we pick one way of doing it and force everyone to do it this way. A good example is accumulated gradients. There are many ways to implement, we just pick one and force users to use that one. A bad forced decision would be to make users use a specific library to do something.

When something becomes a best practice, we add it to the framework. This likely looks like code in utils or in the model file that everyone keeps adding over and over again across projects. When this happens, bring that code inside the trainer and add a flag for it.

30.2.4 Simple External API

What makes sense to you may not make sense to others. Create an issue with an API change suggestion and validate that it makes sense for others. Treat code changes how you treat a startup: validate that it's a needed feature, then add if it makes sense for many people.

30.2.5 Backward-compatible API

We all hate updating our deep learning packages because we don't want to refactor a bunch of stuff. In Lightning, we make sure every change we make which could break an API is backwards compatible with good deprecation warnings.

You shouldn't be afraid to upgrade Lightning :)

30.2.6 Gain User Trust

As a researcher you can't have any part of your code going wrong. So, make thorough tests that ensure an implementation of a new trick or subbtle change is correct.

30.2.7 Interoperability

Have a favorite feature from other libraries like fast.ai or transformers? Those should just work with lightning as well. Grab your favorite model or learning rate scheduler from your favorite library and run it in Lightning.

30.3 Contribution Types

Currently looking for help implementing new features or adding bug fixes.

A lot of good work has already been done in project mechanics (requirements.txt, setup.py, pep8, badges, ci, etc. . .) we're in a good state there thanks to all the early contributors (even pre-beta release)!

30.3.1 Bug Fixes:

1. Submit a github issue - try to decried what happen so other can reproduce it too.
2. Try to ix it or recommend a solution. . .
3. Submit a PR!

30.3.2 New Features:

1. Submit a github issue - describe what is motivation of such feature (plus an use-case).
2. Let's discuss to agree on the feature scope.
3. Submit a PR! (with updated docs and tests).

30.4 Guidelines

30.4.1 Coding Style

1. Use f-strings for output formation (except logging when we stay with lazy `logging.info("Hello %s!`, name).
2. Test the code with flake8, run locally PEP8 fixes:

```
autopep8 -v -r --max-line-length 120 --in-place .
```

30.4.2 Documentation

We are using Sphinx with Napoleon extension. Moreover we set Google style to follow with type convention.

- Napoleon formatting with Google style
- ReStructured Text (reST)
- Paragraph-level markup

See following short example of a sample function taking one position string and optional

```
from typing import Optional

def my_func(param_a: int, param_b: Optional[float] = None) -> str:
    """Sample function.

    Args:
        param_a: first parameter
        param_b: second parameter

    Return:
        sum of both numbers

    Example:
        Sample doctest example...
```

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```
        >>> my_func(1, 2)
        3

    .. note:: If you want to add something.
    """
    p = param_b if param_b else 0
    return str(param_a + p)
```

When updating the docs make sure to build them first locally and visually inspect the html files (in the browser) for formatting errors. In certain cases, a missing blank line or a wrong indent can lead to a broken layout. Run these commands

```
cd docs
pip install -r requirements.txt
make html
```

and open `docs/build/html/index.html` in your browser.

When you send a PR the continuous integration will run tests and build the docs. You can access a preview of the html pages in the *Artifacts* tab in CircleCI when you click on the task named *ci/circleci: Build-Docs* at the bottom of the PR page.

30.4.3 Testing

Test your work locally to speed up your work since so you can focus only in particular (failing) test-cases. To setup a local development environment, install both local and test dependencies:

```
pip install -r requirements.txt
pip install -r tests/requirements-devel.txt
```

You can run the full test-case in your terminal via this bash script:

```
bash .run_local_tests.sh
```

Note: if your computer does not have multi-GPU nor TPU these tests are skipped.

For convenience, you can use also your own CircleCI building which will be triggered with each commit. This is useful if you do not test against all required dependencies version. To do so, login to CircleCI and enable your forked project in the dashboard. It will just work after that.

30.4.4 Pull Request

We welcome any useful contribution! For convinece here's a recommended workflow:

1. Think about what you want to do - fix a bug, repair docs, etc.
2. Start your work locally (usually until you need our CI testing)
    - create a branch and prepare your changes
    - hint: do not work with your master directly, it may become complicated when you need to rebase
    - hint: give your PR a good name! it will be useful later when you may work on multiple tasks/PRs
3. Create a "Draft PR" which is clearly marked which lets us know you don't need feedback yet.
4. When you feel like you are ready for integrating your work, turn your PR to "Ready for review".

5. Use tags in PR name for following cases:
    - **[blocked by #]** if you work is depending on others changes
    - **[wip]** when you start to re-edit your work, mark it so no one will accidentally merge it in meantime

30.4.5 Question & Answer

1. **How can I help/contribute?**

   All help is very welcome - reporting bug, solving issues and preparing bug fixes. To solve some issues you can start with label good first issue or chose something close to your domain with label help wanted. Before you start to implement anything check that the issue description that it is clear and self-assign the task to you (if it is not possible, just comment that you take it and we assign it to you. . .).

2. **Is there a recommendation for branch names?**

   We do not rely on the name convention so far you are working with your own fork. Anyway it would be nice to follow this convention `<type>/<issue-id>_<short-name>` where the types are: `bugfix`, `feaure`, `docs`, `tests`, ...

3. **How to rebase my PR?**

   We recommend to create a PR in separate branch different from `master`, especially if you plan to submit several changes and do not want to wait until the fist one is resolved (we can work on them in parallel). Update your master with upstream (assuming you have already set upstream)

   ```
   git fetch --all --prune
   git checkout master
   git merge upstream/master
   ```

   checkout your feature branch

   ```
   git checkout my-PR-branch
   git rebase master
   # follow git instructions to resolve conflists
   git push -f
   ```

CHAPTER

THIRTYONE

HOW TO BECOME A CORE CONTRIBUTOR

Thanks for your interest in joining the Lightning team! We're a rapidly growing project which is poised to become the go-to framework for DL researchers! We're currently recruiting for a team of 5 core maintainers.

As a core maintainer you will have a strong say in the direction of the project. Big changes will require a majority of maintainers to agree.

31.1 Code of conduct

First and foremost, you'll be evaluated against these core values. Any code we commit or feature we add needs to align with those core values.

31.2 The bar for joining the team

Lightning is being used to solve really hard problems at the top AI labs in the world. As such, the bar for adding team members is extremely high. Candidates must have solid engineering skills, have a good eye for user experience, and must be a power user of Lightning and PyTorch.

With that said, the Lightning team will be diverse and a reflection of an inclusive AI community. You don't have to be an engineer to conntribute! Scientists with great usability intuition and PyTorch ninja skills are welcomed!

31.3 Responsibilities:

The responsibilities mainly revolve around 3 things.

31.3.1 Github issues

- Here we want to help users have an amazing experience. These range from questions from new people getting into DL to questions from researchers about doing something esoteric with Lightning Often, these issues require some sort of bug fix, document clarification or new functionality to be scoped out.
- To become a core member you must resolve at least 10 Github issues which align with the API design goals for Lightning. By the end of these 10 issues I should feel comfortable in the way you answer user questions Pleasant/helpful tone.
- Can abstract from that issue or bug into functionality that might solve other related issues or makes the platform more flexible.

- Don't make users feel like they don't know what they're doing. We're here to help and to make everyone's experience delightful.

31.3.2 Pull requests

- Here we need to ensure the code that enters Lightning is high quality. For each PR we need to:
- Make sure code coverage does not decrease
- Documents are updated
- Code is elegant and simple
- Code is NOT overly engineered or hard to read
- Ask yourself, could a non-engineer understand what's happening here?
- Make sure new tests are written
- Is this NECESSARY for Lightning? There are some PRs which are just purely about adding engineering complexity which have no place in Lightning. Guidance
- Some other PRs are for people who are wanting to get involved and add something unnecessary. We do want their help though! So don't approve the PR, but direct them to a Github issue that they might be interested in helping with instead!
- To be considered for core contributor, please review 10 PRs and help the authors land it on master. Once you've finished the review, ping me for a sanity check. At the end of 10 PRs if your PR reviews are inline with expectations described above, then you can merge PRs on your own going forward, otherwise we'll do a few more until we're both comfortable :)

31.3.3 Project directions

There are some big decisions which the project must make. For these I expect core contributors to have something meaningful to add if it's their area of expertise.

31.3.4 Diversity

Lightning should reflect the broader community it serves. As such we should have scientists/researchers from different fields contributing!

The first 5 core contributors will fit this profile. Thus if you overlap strongly with experiences and expertise as someone else on the team, you might have to wait until the next set of contributors are added.

31.3.5 Summary: Requirements to apply

- Solve 10 Github issues. The goal is to be inline with expectations for solving issues by the last one so you can do them on your own. If not, I might ask you to solve a few more specific ones.
- Do 10 PR reviews. The goal is to be inline with expectations for solving issues by the last one so you can do them on your own. If not, I might ask you to solve a few more specific ones.

If you want to be considered, ping me on gitter and start tracking your progress here.

CHAPTER

THIRTYTWO

BEFORE SUBMITTING

- [ ] Was this discussed/approved via a Github issue? (no need for typos and docs improvements)
- [ ] Did you read the contributor guideline, Pull Request section?
- [ ] Did you make sure to update the docs?
- [ ] Did you write any new necessary tests?
- [ ] If you made a notable change (that affects users), did you update the CHANGELOG?

32.1 What does this PR do?

Fixes # (issue).

32.2 PR review

Anyone in the community is free to review the PR once the tests have passed.If we didn't discuss your PR in Github issues there's a high chance it will not be merged.

32.3 Did you have fun?

Make sure you had fun coding

CHAPTER

THIRTYTHREE

PYTORCH LIGHTNING GOVERNANCE | PERSONS OF INTEREST

33.1 Leads

- William Falcon (williamFalcon) (Lightning founder)
- Jirka Borovec (Borda)
- Ethan Harris (ethanwharris) (Torchbearer founder)
- Matthew Painter (MattPainter01) (Torchbearer founder)
- Justus Schock (justusschock) (Former Core Member PyTorch Ignite)

33.2 Core Maintainers

- Nic Eggert (neggert)
- Jeff Ling (jeffling)
- Jeremy Jordan (jeremyjordan)
- Tullie Murrell (tullie)
- Adrian Wälchli (awaelchli)

CHAPTER

THIRTYFOUR

INDICES AND TABLES

- genindex
- modindex
- search

34.1 pytorch_lightning.core package

A *LightningModule* organizes your PyTorch code into the following sections:

Notice a few things.

1. It's the SAME code.
2. The PyTorch code IS NOT abstracted - just organized.
3. All the other code that's not in the *LightningModule* has been automated for you by the trainer.

```
net = Net()
trainer = Trainer()
trainer.fit(net)
```

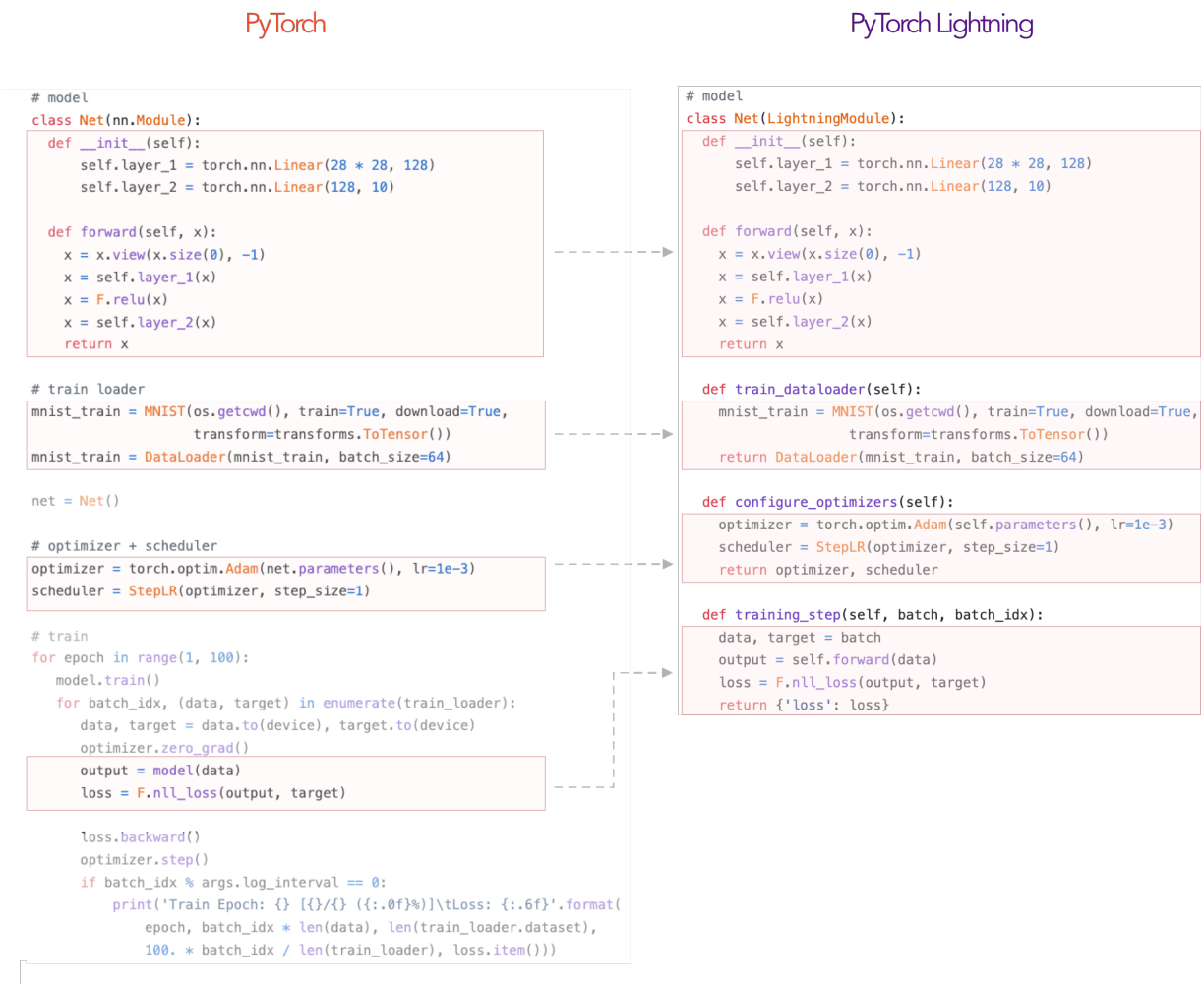
4. There are no .cuda() or .to() calls... Lightning does these for you.

```
# don't do in lightning
x = torch.Tensor(2, 3)
x = x.cuda()
x = x.to(device)

# do this instead
x = x  # leave it alone!

# or to init a new tensor
new_x = torch.Tensor(2, 3)
new_x = new_x.type_as(x.type())
```

5. There are no samplers for distributed, Lightning also does this for you.

```
# Don't do in Lightning...
data = MNIST(...)
sampler = DistributedSampler(data)
DataLoader(data, sampler=sampler)

# do this instead
```

(continues on next page)


PyTorch
PyTorch Lightning
# model
class Net(nn.Module):
def __init__(self):
self.layer_1 = torch.nn.Linear(28 * 28, 128)
self.layer_2 = torch.nn.Linear(128, 10)
def forward(self, x):
x = x.view(x.size(0), -1)
x = self.layer_1(x)
x = F.relu(x)
x = self.layer_2(x)
return x
# train loader
mnist_train = MNIST(os.getcwd(), train=True, download=True,
transform=transforms.ToTensor())
mnist_train = DataLoader(mnist_train, batch_size=64)
net = Net()
# optimizer + scheduler
optimizer = torch.optim.Adam(net.parameters(), lr=1e-3)
scheduler = StepLR(optimizer, step_size=1)
# train
for epoch in range(1, 100):
model.train()
for batch_idx, (data, target) in enumerate(train_loader):
data, target = data.to(device), target.to(device)
optimizer.zero_grad()
output = model(data)
loss = F.nll_loss(output, target)
loss.backward()
optimizer.step()
if batch_idx % args.log_interval == 0:
print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
epoch, batch_idx * len(data), len(train_loader.dataset),
100. * batch_idx / len(train_loader), loss.item()))
# model
class Net(LightningModule):
def __init__(self):
self.layer_1 = torch.nn.Linear(28 * 28, 128)
self.layer_2 = torch.nn.Linear(128, 10)
def forward(self, x):
x = x.view(x.size(0), -1)
x = self.layer_1(x)
x = F.relu(x)
x = self.layer_2(x)
return x
def train_dataloader(self):
mnist_train = MNIST(os.getcwd(), train=True, download=True,
transform=transforms.ToTensor())
return DataLoader(mnist_train, batch_size=64)
def configure_optimizers(self):
optimizer = torch.optim.Adam(self.parameters(), lr=1e-3)
scheduler = StepLR(optimizer, step_size=1)
return optimizer, scheduler
def training_step(self, batch, batch_idx):
data, target = batch
output = self.forward(data)
loss = F.nll_loss(output, target)
return {'loss': loss}

(continued from previous page)

```
data = MNIST(...)
DataLoader(data)
```

6. A *LightningModule* is a `torch.nn.Module` but with added functionality. Use it as such!

```
net = Net.load_from_checkpoint(PATH)
net.freeze()
out = net(x)
```

Thus, to use Lightning, you just need to organize your code which takes about 30 minutes, (and let's be real, you probably should do anyhow).

34.1.1 Minimal Example

Here are the only required methods.

```
>>> import pytorch_lightning as pl
>>> class LitModel(pl.LightningModule):
...
...     def __init__(self):
...         super().__init__()
...         self.l1 = torch.nn.Linear(28 * 28, 10)
...
...     def forward(self, x):
...         return torch.relu(self.l1(x.view(x.size(0), -1)))
...
...     def training_step(self, batch, batch_idx):
...         x, y = batch
...         y_hat = self(x)
...         return {'loss': F.cross_entropy(y_hat, y)}
...
...     def train_dataloader(self):
...         return DataLoader(MNIST(os.getcwd(), train=True, download=True,
...                                 transform=transforms.ToTensor()), batch_size=32)
...
...     def configure_optimizers(self):
...         return torch.optim.Adam(self.parameters(), lr=0.02)
```

Which you can train by doing:

```
trainer = pl.Trainer()
model = LitModel()

trainer.fit(model)
```

34.1.2 Training loop structure

The general pattern is that each loop (training, validation, test loop) has 3 methods:

- `___step`
- `___step_end`
- `___epoch_end`

To show how Lightning calls these, let's use the validation loop as an example:

```
val_outs = []
for val_batch in val_data:
    # do something with each batch
    out = validation_step(val_batch)
    val_outs.append(out)

# do something with the outputs for all batches
# like calculate validation set accuracy or loss
validation_epoch_end(val_outs)
```

If we use dp or ddp2 mode, we can also define the `XXX_step_end` method to operate on all parts of the batch:

```
val_outs = []
for val_batch in val_data:
    batches = split_batch(val_batch)
    dp_outs = []
    for sub_batch in batches:
        dp_out = validation_step(sub_batch)
        dp_outs.append(dp_out)

    out = validation_step_end(dp_outs)
    val_outs.append(out)

# do something with the outputs for all batches
# like calculate validation set accuracy or loss
validation_epoch_end(val_outs)
```

Add validation loop

Thus, if we wanted to add a validation loop you would add this to your *LightningModule*:

```
>>> class LitModel(pl.LightningModule):
...     def validation_step(self, batch, batch_idx):
...         x, y = batch
...         y_hat = self(x)
...         return {'val_loss': F.cross_entropy(y_hat, y)}
...
...     def validation_epoch_end(self, outputs):
...         val_loss_mean = torch.stack([x['val_loss'] for x in outputs]).mean()
...         return {'val_loss': val_loss_mean}
...
...     def val_dataloader(self):
...         # can also return a list of val dataloaders
...         return DataLoader(...)
```

Add test loop

```
>>> class LitModel(pl.LightningModule):
...     def test_step(self, batch, batch_idx):
...         x, y = batch
...         y_hat = self(x)
...         return {'test_loss': F.cross_entropy(y_hat, y)}
...
...     def test_epoch_end(self, outputs):
...         test_loss_mean = torch.stack([x['test_loss'] for x in outputs]).mean()
...         return {'test_loss': test_loss_mean}
...
...     def test_dataloader(self):
...         # can also return a list of test dataloaders
...         return DataLoader(...)
```

However, the test loop won't ever be called automatically to make sure you don't run your test data by accident. Instead you have to explicitly call:

```
# call after training
trainer = Trainer()
trainer.fit(model)
trainer.test()

# or call with pretrained model
model = MyLightningModule.load_from_checkpoint(PATH)
trainer = Trainer()
trainer.test(model)
```

34.1.3 Training_step_end method

When using *LightningDataParallel* or *LightningDistributedDataParallel*, the *training_step()* will be operating on a portion of the batch. This is normally ok but in special cases like calculating NCE loss using negative samples, we might want to perform a softmax across all samples in the batch.

For these types of situations, each loop has an additional __step_end method which allows you to operate on the pieces of the batch:

```
training_outs = []
for train_batch in train_data:
    # dp, ddp2 splits the batch
    sub_batches = split_batches_for_dp(batch)

    # run training_step on each piece of the batch
    batch_parts_outputs = [training_step(sub_batch) for sub_batch in sub_batches]

    # do softmax with all pieces
    out = training_step_end(batch_parts_outputs)
    training_outs.append(out)

# do something with the outputs for all batches
# like calculate validation set accuracy or loss
training_epoch_end(val_outs)
```

34.1.4 Remove cuda calls

In a *LightningModule*, all calls to `.cuda()` and `.to(device)` should be removed. Lightning will do these automatically. This will allow your code to work on CPUs, TPUs and GPUs.

When you init a new tensor in your code, just use `type_as()`:

```
def training_step(self, batch, batch_idx):
    x, y = batch

    # put the z on the appropriate gpu or tpu core
    z = sample_noise()
    z = z.type_as(x)
```

34.1.5 Data preparation

Data preparation in PyTorch follows 5 steps:

1. Download
2. Clean and (maybe) save to disk
3. Load inside `Dataset`
4. Apply transforms (rotate, tokenize, etc…)
5. Wrap inside a `DataLoader`

When working in distributed settings, steps 1 and 2 have to be done from a single GPU, otherwise you will overwrite these files from every GPU. The *LightningModule* has the *prepare_data* method to allow for this:

```
>>> class LitModel(pl.LightningModule):
...     def prepare_data(self):
...         # download
...         mnist_train = MNIST(os.getcwd(), train=True, download=True,
...                             transform=transforms.ToTensor())
...         mnist_test = MNIST(os.getcwd(), train=False, download=True,
...                            transform=transforms.ToTensor())
...
...         # train/val split
...         mnist_train, mnist_val = random_split(mnist_train, [55000, 5000])
...
...         # assign to use in dataloaders
...         self.train_dataset = mnist_train
...         self.val_dataset = mnist_val
...         self.test_dataset = mnist_test
...
...     def train_dataloader(self):
...         return DataLoader(self.train_dataset, batch_size=64)
...
...     def val_dataloader(self):
...         return DataLoader(self.mnist_val, batch_size=64)
...
...     def test_dataloader(self):
...         return DataLoader(self.mnist_test, batch_size=64)
```

Note: *prepare_data()* is called once.

Note: Do anything with data that needs to happen ONLY once here, like download, tokenize, etc...

34.1.6 Lifecycle

The methods in the *LightningModule* are called in this order:

1. `__init__()`
2. *prepare_data()*
3. *configure_optimizers()*
4. *train_dataloader()*

If you define a validation loop then

5. *val_dataloader()*

And if you define a test loop:

6. *test_dataloader()*

Note: *test_dataloader()* is only called with `.test()`

In every epoch, the loop methods are called in this frequency:

1. *validation_step()* called every batch
2. *validation_epoch_end()* called every epoch

34.1.7 Live demo

Check out this COLAB for a live demo.

34.1.8 LightningModule Class

class pytorch_lightning.core.**LightningModule**(**args*, ***kwargs*)

Bases: abc.ABC, *pytorch_lightning.core.properties.DeviceDtypeModuleMixin*, *pytorch_lightning.core.grads.GradInformation*, *pytorch_lightning.core.saving.ModelIO*, *pytorch_lightning.core.hooks.ModelHooks*

_init_slurm_connection()

Sets up environment variables necessary for pytorch distributed communications based on slurm environment.

Return type None

classmethod _load_model_state(*checkpoint*, **args*, ***kwargs*)

Return type *LightningModule*

configure_apex(*amp*, *model*, *optimizers*, *amp_level*)
Override to init AMP your own way. Must return a model and list of optimizers.

Parameters

- **amp** (object) – pointer to amp library object.
- **model** (*LightningModule*) – pointer to current *LightningModule*.
- **optimizers** (List[Optimizer]) – list of optimizers passed in *configure_optimizers()*.
- **amp_level** (str) – AMP mode chosen ('O1', 'O2', etc...)

Return type Tuple[*LightningModule*, List[Optimizer]]

Returns Apex wrapped model and optimizers

Examples

```
# Default implementation used by Trainer.
def configure_apex(self, amp, model, optimizers, amp_level):
    model, optimizers = amp.initialize(
        model, optimizers, opt_level=amp_level,
    )

    return model, optimizers
```

configure_ddp(*model*, *device_ids*)
Override to init DDP in your own way or with your own wrapper. The only requirements are that:

1. On a validation batch the call goes to model.validation_step.
2. On a training batch the call goes to model.training_step.
3. On a testing batch, the call goes to model.test_step.+

Parameters

- **model** (*LightningModule*) – the *LightningModule* currently being optimized.
- **device_ids** (List[int]) – the list of GPU ids.

Return type DistributedDataParallel

Returns DDP wrapped model

Examples

```
# default implementation used in Trainer
def configure_ddp(self, model, device_ids):
    # Lightning DDP simply routes to test_step, val_step, etc...
    model = LightningDistributedDataParallel(
        model,
        device_ids=device_ids,
        find_unused_parameters=True
    )
    return model
```

configure_optimizers()

Choose what optimizers and learning-rate schedulers to use in your optimization. Normally you'd need one. But in the case of GANs or similar you might have multiple.

Return type Union[Optimizer, Sequence[Optimizer], Dict, Sequence[Dict], Tuple[List, List], None]

Returns

Any of these 6 options.

- Single optimizer.
- List or Tuple - List of optimizers.
- Two lists - The first list has multiple optimizers, the second a list of LR schedulers.
- Dictionary, with an 'optimizer' key and (optionally) a 'lr_scheduler' key.
- Tuple of dictionaries as described, with an optional 'frequency' key.
- None - Fit will run without any optimizer.

Note: The 'frequency' value is an int corresponding to the number of sequential batches optimized with the specific optimizer. It should be given to none or to all of the optimizers. There is a difference between passing multiple optimizers in a list, and passing multiple optimizers in dictionaries with a frequency of 1: In the former case, all optimizers will operate on the given batch in each optimization step. In the latter, only one optimizer will operate on the given batch at every step.

Examples

```
# most cases
def configure_optimizers(self):
    opt = Adam(self.parameters(), lr=1e-3)
    return opt

# multiple optimizer case (e.g.: GAN)
def configure_optimizers(self):
    generator_opt = Adam(self.model_gen.parameters(), lr=0.01)
    disriminator_opt = Adam(self.model_disc.parameters(), lr=0.02)
    return generator_opt, disriminator_opt

# example with learning rate schedulers
def configure_optimizers(self):
    generator_opt = Adam(self.model_gen.parameters(), lr=0.01)
    disriminator_opt = Adam(self.model_disc.parameters(), lr=0.02)
    discriminator_sched = CosineAnnealing(discriminator_opt, T_max=10)
    return [generator_opt, disriminator_opt], [discriminator_sched]

# example with step-based learning rate schedulers
def configure_optimizers(self):
    gen_opt = Adam(self.model_gen.parameters(), lr=0.01)
    dis_opt = Adam(self.model_disc.parameters(), lr=0.02)
    gen_sched = {'scheduler': ExponentialLR(gen_opt, 0.99),
                 'interval': 'step'}  # called after each training step
    dis_sched = CosineAnnealing(discriminator_opt, T_max=10) # called every␣
↪epoch
```

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```
    return [gen_opt, dis_opt], [gen_sched, dis_sched]

# example with optimizer frequencies
# see training procedure in `Improved Training of Wasserstein GANs`,␣
↪Algorithm 1
# https://arxiv.org/abs/1704.00028
def configure_optimizers(self):
    gen_opt = Adam(self.model_gen.parameters(), lr=0.01)
    dis_opt = Adam(self.model_disc.parameters(), lr=0.02)
    n_critic = 5
    return (
        {'optimizer': dis_opt, 'frequency': n_critic},
        {'optimizer': gen_opt, 'frequency': 1}
    )
```

Note: Some things to know:

- Lightning calls `.backward()` and `.step()` on each optimizer and learning rate scheduler as needed.
- If you use 16-bit precision (`precision=16`), Lightning will automatically handle the optimizers for you.
- If you use multiple optimizers, *`training_step()`* will have an additional `optimizer_idx` parameter.
- If you use LBFGS Lightning handles the closure function automatically for you.
- If you use multiple optimizers, gradients will be calculated only for the parameters of current optimizer at each training step.
- If you need to control how often those optimizers step or override the default `.step()` schedule, override the *`optimizer_step()`* hook.
- If you only want to call a learning rate scheduler every `x` step or epoch, or want to monitor a custom metric, you can specify these in a dictionary:

```
{
    'scheduler': lr_scheduler,
    'interval': 'step'  # or 'epoch'
    'monitor': 'val_f1',
    'frequency': x
}
```

---

abstract forward(**args*, ***kwargs*)

Same as `torch.nn.Module.forward()`, however in Lightning you want this to define the operations you want to use for prediction (i.e.: on a server or as a feature extractor).

Normally you'd call `self()` from your *`training_step()`* method. This makes it easy to write a complex system for training with the outputs you'd want in a prediction setting.

Parameters

- ***args** – Whatever you decide to pass into the forward method.
- ****kwargs** – Keyword arguments are also possible.

Returns Predicted output

Examples

```
# example if we were using this model as a feature extractor
def forward(self, x):
    feature_maps = self.convnet(x)
    return feature_maps

def training_step(self, batch, batch_idx):
    x, y = batch
    feature_maps = self(x)
    logits = self.classifier(feature_maps)

    # ...
    return loss

# splitting it this way allows model to be used a feature extractor
model = MyModelAbove()

inputs = server.get_request()
results = model(inputs)
server.write_results(results)

# -------------
# This is in stark contrast to torch.nn.Module where normally you would have␣
↪this:
def forward(self, batch):
    x, y = batch
    feature_maps = self.convnet(x)
    logits = self.classifier(feature_maps)
    return logits
```

freeze()
Freeze all params for inference.

Example

```
model = MyLightningModule(...)
model.freeze()
```

Return type None

get_progress_bar_dict()
Additional items to be displayed in the progress bar.

Return type Dict[str, Union[int, str]]

Returns Dictionary with the items to be displayed in the progress bar.

get_tqdm_dict()
Additional items to be displayed in the progress bar.

Return type Dict[str, Union[int, str]]

Returns Dictionary with the items to be displayed in the progress bar.

> **Warning:** Deprecated since v0.7.3. Use `get_progress_bar_dict()` instead.

init_ddp_connection(*proc_rank*, *world_size*, *is_slurm_managing_tasks=True*)
Override to define your custom way of setting up a distributed environment.

Lightning's implementation uses env:// init by default and sets the first node as root for SLURM managed cluster.

Parameters

- **proc_rank** (int) – The current process rank within the node.
- **world_size** (int) – Number of GPUs being use across all nodes. (num_nodes * num_gpus).
- **is_slurm_managing_tasks** (bool) – is cluster managed by SLURM.

Return type None

classmethod load_from_checkpoint(*checkpoint_path*, **args*, *map_location=None*, *hparams_file=None*, *tags_csv=None*, *hparam_overrides=None*, ***kwargs*)
Primary way of loading a model from a checkpoint. When Lightning saves a checkpoint it stores the hyperparameters in the checkpoint if you initialized your `LightningModule` with an argument called `hparams` which is an object of `dict` or `Namespace` (output of `parse_args()` when parsing command line arguments). If you want *hparams* to have a hierarchical structure, you have to define it as `dict`. Any other arguments specified through *args and **kwargs will be passed to the model.

Example

```
# define hparams as Namespace
from argparse import Namespace
hparams = Namespace(**{'learning_rate': 0.1})

model = MyModel(hparams)

class MyModel(LightningModule):
    def __init__(self, hparams: Namespace):
        self.learning_rate = hparams.learning_rate

# ----------

# define hparams as dict
hparams = {
    drop_prob: 0.2,
    dataloader: {
        batch_size: 32
    }
}

model = MyModel(hparams)

class MyModel(LightningModule):
    def __init__(self, hparams: dict):
        self.learning_rate = hparams['learning_rate']
```

Parameters

- **checkpoint_path** (str) – Path to checkpoint.
- **args** – Any positional args needed to init the model.
- **map_location** (Union[Dict[str, str], str, device, int, Callable, None]) – If your checkpoint saved a GPU model and you now load on CPUs or a different number of GPUs, use this to map to the new setup. The behaviour is the same as in torch.load().
- **hparams_file** (Optional[str]) – Optional path to a .yaml file with hierarchical structure as in this example:

```
drop_prob: 0.2
dataloader:
    batch_size: 32
```

  You most likely won't need this since Lightning will always save the hyperparameters to the checkpoint. However, if your checkpoint weights don't have the hyperparameters saved, use this method to pass in a .yaml file with the hparams you'd like to use. These will be converted into a dict and passed into your *LightningModule* for use.

  If your model's *hparams* argument is Namespace and .yaml file has hierarchical structure, you need to refactor your model to treat *hparams* as dict.

  .csv files are acceptable here till v0.9.0, see tags_csv argument for detailed usage.

- **tags_csv** (Optional[str]) –

  Warning: Deprecated since version 0.7.6.

  tags_csv argument is deprecated in v0.7.6. Will be removed v0.9.0.

  Optional path to a .csv file with two columns (key, value) as in this example:

```
key,value
drop_prob,0.2
batch_size,32
```

  Use this method to pass in a .csv file with the hparams you'd like to use.

- **hparam_overrides** (Optional[Dict]) – A dictionary with keys to override in the hparams
- **kwargs** – Any keyword args needed to init the model.

Return type *LightningModule*

Returns *LightningModule* with loaded weights and hyperparameters (if available).

Example

```
# load weights without mapping ...
MyLightningModule.load_from_checkpoint('path/to/checkpoint.ckpt')

# or load weights mapping all weights from GPU 1 to GPU 0 ...
map_location = {'cuda:1':'cuda:0'}
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    map_location=map_location
)

# or load weights and hyperparameters from separate files.
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    hparams_file='/path/to/hparams_file.yaml'
)

# override some of the params with new values
MyLightningModule.load_from_checkpoint(
    PATH,
    hparam_overrides={'num_layers': 128, 'pretrained_ckpt_path': NEW_PATH}
)

# or load passing whatever args the model takes to load
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    learning_rate=0.1, # These arguments will be passed to the model using␣
↪**kwargs
    layers=2,
    pretrained_model=some_model
)

# predict
pretrained_model.eval()
pretrained_model.freeze()
y_hat = pretrained_model(x)
```

classmethod load_from_metrics(*weights_path*, *tags_csv*, *map_location=None*)

> **Warning:** Deprecated in version 0.7.0. You should use *load_from_checkpoint()* instead. Will be removed in v0.9.0.

on_load_checkpoint(*checkpoint*)

Called by Lightning to restore your model. If you saved something with *on_save_checkpoint()* this is your chance to restore this.

Parameters **checkpoint** (Dict[str, Any]) – Loaded checkpoint

Example

```
def on_load_checkpoint(self, checkpoint):
    # 99% of the time you don't need to implement this method
    self.something_cool_i_want_to_save = checkpoint['something_cool_i_want_to_
↪save']
```

Note: Lightning auto-restores global step, epoch, and train state including amp scaling. There is no need for you to restore anything regarding training.

Return type None

on_save_checkpoint(*checkpoint*)

Called by Lightning when saving a checkpoint to give you a chance to store anything else you might want to save.

Parameters **checkpoint** (Dict[str, Any]) – Checkpoint to be saved

Example

```
def on_save_checkpoint(self, checkpoint):
    # 99% of use cases you don't need to implement this method
    checkpoint['something_cool_i_want_to_save'] = my_cool_pickable_object
```

Note: Lightning saves all aspects of training (epoch, global step, etc...) including amp scaling. There is no need for you to store anything about training.

Return type None

optimizer_step(*epoch*, *batch_idx*, *optimizer*, *optimizer_idx*, *second_order_closure=None*)

Override this method to adjust the default way the *Trainer* calls each optimizer. By default, Lightning calls step() and zero_grad() as shown in the example once per optimizer.

Parameters

- **epoch** (int) – Current epoch
- **batch_idx** (int) – Index of current batch
- **optimizer** (Optimizer) – A PyTorch optimizer
- **optimizer_idx** (int) – If you used multiple optimizers this indexes into that list.
- **second_order_closure** (Optional[Callable]) – closure for second order methods

Examples

```
# DEFAULT
def optimizer_step(self, current_epoch, batch_idx, optimizer, optimizer_idx,
                   second_order_closure=None):
    optimizer.step()
    optimizer.zero_grad()

# Alternating schedule for optimizer steps (i.e.: GANs)
def optimizer_step(self, current_epoch, batch_idx, optimizer, optimizer_idx,
                   second_order_closure=None):
    # update generator opt every 2 steps
    if optimizer_idx == 0:
        if batch_idx % 2 == 0 :
            optimizer.step()
            optimizer.zero_grad()

    # update discriminator opt every 4 steps
    if optimizer_idx == 1:
        if batch_idx % 4 == 0 :
            optimizer.step()
            optimizer.zero_grad()

    # ...
    # add as many optimizers as you want
```

Here's another example showing how to use this for more advanced things such as learning rate warm-up:

```
# learning rate warm-up
def optimizer_step(self, current_epoch, batch_idx, optimizer,
                   optimizer_idx, second_order_closure=None):
    # warm up lr
    if self.trainer.global_step < 500:
        lr_scale = min(1., float(self.trainer.global_step + 1) / 500.)
        for pg in optimizer.param_groups:
            pg['lr'] = lr_scale * self.hparams.learning_rate

    # update params
    optimizer.step()
    optimizer.zero_grad()
```

Note: If you also override the *on_before_zero_grad()* model hook don't forget to add the call to it before `optimizer.zero_grad()` yourself.

Return type `None`

prepare_data()

Use this to download and prepare data. In distributed (GPU, TPU), this will only be called once. This is called before requesting the dataloaders:

```
model.prepare_data()
model.train_dataloader()
model.val_dataloader()
model.test_dataloader()
```

Examples

```
def prepare_data(self):
    download_imagenet()
    clean_imagenet()
    cache_imagenet()
```

Return type None

print(**args*, ***kwargs*)

Prints only from process 0. Use this in any distributed mode to log only once.

Parameters

- ***args** – The thing to print. Will be passed to Python's built-in print function.
- ****kwargs** – Will be passed to Python's built-in print function.

Example

```
def forward(self, x):
    self.print(x, 'in forward')
```

Return type None

summarize(*mode*)

Return type None

tbptt_split_batch(*batch*, *split_size*)

When using truncated backpropagation through time, each batch must be split along the time dimension. Lightning handles this by default, but for custom behavior override this function.

Parameters

- **batch** (Tensor) – Current batch
- **split_size** (int) – The size of the split

Return type list

Returns List of batch splits. Each split will be passed to *training_step()* to enable truncated back propagation through time. The default implementation splits root level Tensors and Sequences at dim=1 (i.e. time dim). It assumes that each time dim is the same length.

Examples

```
def tbptt_split_batch(self, batch, split_size):
  splits = []
  for t in range(0, time_dims[0], split_size):
      batch_split = []
      for i, x in enumerate(batch):
          if isinstance(x, torch.Tensor):
              split_x = x[:, t:t + split_size]
          elif isinstance(x, collections.Sequence):
              split_x = [None] * len(x)
```

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```
                for batch_idx in range(len(x)):
                    split_x[batch_idx] = x[batch_idx][t:t + split_size]

            batch_split.append(split_x)

        splits.append(batch_split)

    return splits
```

Note: Called in the training loop after *on_batch_start()* if *truncated_bptt_steps* > 0. Each returned batch split is passed separately to *training_step()*.

---

test_dataloader()

Implement one or multiple PyTorch DataLoaders for testing.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to True.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*
- ...
- *prepare_data()*
- *train_dataloader()*
- *val_dataloader()*
- *test_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

Return type Union[DataLoader, List[DataLoader]]

Returns Single or multiple PyTorch DataLoaders.

Example

```
def test_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=False, transform=transform,
                    download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=False
    )

    return loader
```

Note: If you don't need a test dataset and a *test_step()*, you don't need to implement this method.

test_end(*outputs*)

Warning: Deprecated in v0.7.0. Use *test_epoch_end()* instead. Will be removed in 1.0.0.

test_epoch_end(*outputs*)

Called at the end of a test epoch with the output of all test steps.

```
# the pseudocode for these calls
test_outs = []
for test_batch in test_data:
    out = test_step(test_batch)
    test_outs.append(out)
test_epoch_end(test_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *test_step_end()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader

Returns

Dict has the following optional keys:

- progress_bar -> Dict for progress bar display. Must have only tensors.
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc).

Return type Dict or OrderedDict

Note: If you didn't define a *test_step()*, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, specify it with the 'step' key in the 'log' Dict

Examples

With a single dataloader:

```
def test_epoch_end(self, outputs):
    test_acc_mean = 0
    for output in outputs:
        test_acc_mean += output['test_acc']

    test_acc_mean /= len(outputs)
    tqdm_dict = {'test_acc': test_acc_mean.item()}

    # show test_loss and test_acc in progress bar but only log test_loss
```

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```
    results = {
        'progress_bar': tqdm_dict,
        'log': {'test_acc': test_acc_mean.item()}
    }
    return results
```

With multiple dataloaders, *outputs* will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each test step for that dataloader.

```
def test_epoch_end(self, outputs):
    test_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
        for output in dataloader_outputs:
            test_acc_mean += output['test_acc']
            i += 1

    test_acc_mean /= i
    tqdm_dict = {'test_acc': test_acc_mean.item()}

    # show test_loss and test_acc in progress bar but only log test_loss
    results = {
        'progress_bar': tqdm_dict,
        'log': {'test_acc': test_acc_mean.item(), 'step': self.current_epoch}
    }
    return results
```

test_step(**args*, ***kwargs*)

Operates on a single batch of data from the test set. In this step you'd normally generate examples or calculate anything of interest such as accuracy.

```
# the pseudocode for these calls
test_outs = []
for test_batch in test_data:
    out = test_step(test_batch)
    test_outs.append(out)
test_epoch_end(test_outs)
```

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – The index of this batch.
- **dataloader_idx** (*int*) – The index of the dataloader that produced this batch (only if multiple test datasets used).

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *test_epoch_end()* method. If you defined *test_step_end()* it will go to that first.

```
# if you have one test dataloader:
def test_step(self, batch, batch_idx)
```

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```
# if you have multiple test dataloaders:
def test_step(self, batch, batch_idx, dataloader_idx)
```

Examples

```
# CASE 1: A single test dataset
def test_step(self, batch, batch_idx):
    x, y = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, y)

    # log 6 example images
    # or generated text... or whatever
    sample_imgs = x[:6]
    grid = torchvision.utils.make_grid(sample_imgs)
    self.logger.experiment.add_image('example_images', grid, 0)

    # calculate acc
    labels_hat = torch.argmax(out, dim=1)
    val_acc = torch.sum(y == labels_hat).item() / (len(y) * 1.0)

    # all optional...
    # return whatever you need for the collation function test_epoch_end
    output = OrderedDict({
        'val_loss': loss_val,
        'val_acc': torch.tensor(val_acc), # everything must be a tensor
    })

    # return an optional dict
    return output
```

If you pass in multiple validation datasets, `test_step()` will have an additional argument.

```
# CASE 2: multiple test datasets
def test_step(self, batch, batch_idx, dataset_idx):
    # dataset_idx tells you which dataset this is.
```

Note: If you don't need to validate you don't need to implement this method.

Note: When the `test_step()` is called, the model has been put in eval mode and PyTorch gradients have been disabled. At the end of the test epoch, the model goes back to training mode and gradients are enabled.

test_step_end(**args*, ***kwargs*)

Use this when testing with dp or ddp2 because `test_step()` will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to

change your code.

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
batch_parts_outputs = [test_step(sub_batch) for sub_batch in sub_batches]
test_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *test_step()* for each batch part.

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *test_epoch_end()*.

Examples

```
# WITHOUT test_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def test_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with test_step_end to do softmax over the full batch
def test_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def test_step_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

tng_dataloader()

> **Warning:** Deprecated in v0.5.0. Use *train_dataloader()* instead. Will be removed in 1.0.0.

train_dataloader()

Implement a PyTorch DataLoader for training.

Return type DataLoader

Returns Single PyTorch DataLoader.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to True.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*
- ...
- *prepare_data()*
- *train_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

Example

```
def train_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=True, transform=transform,
                    download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=True
    )
    return loader
```

training_end(**args*, ***kwargs*)

Warning: Deprecated in v0.7.0. Use *training_step_end()* instead.

training_epoch_end(*outputs*)

Called at the end of the training epoch with the outputs of all training steps.

```
# the pseudocode for these calls
train_outs = []
for train_batch in train_data:
    out = training_step(train_batch)
    train_outs.append(out)
training_epoch_end(train_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *training_step()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader.

Return type Dict[str, Dict[str, Tensor]]

Returns

Dict or OrderedDict. May contain the following optional keys:

- log (metrics to be added to the logger; only tensors)
- progress_bar (dict for progress bar display)
- any metric used in a callback (e.g. early stopping).

Note: If this method is not overridden, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, you can specify the 'step' key in the 'log' dict.

Examples

With a single dataloader:

```
def training_epoch_end(self, outputs):
    train_acc_mean = 0
    for output in outputs:
        train_acc_mean += output['train_acc']

    train_acc_mean /= len(outputs)

    # log training accuracy at the end of an epoch
    results = {
        'log': {'train_acc': train_acc_mean.item()},
        'progress_bar': {'train_acc': train_acc_mean},
    }
    return results
```

With multiple dataloaders, `outputs` will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each training step for that dataloader.

```
def training_epoch_end(self, outputs):
    train_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
        for output in dataloader_outputs:
            train_acc_mean += output['train_acc']
            i += 1

    train_acc_mean /= i

    # log training accuracy at the end of an epoch
    results = {
        'log': {'train_acc': train_acc_mean.item(), 'step': self.current_
↪epoch}
        'progress_bar': {'train_acc': train_acc_mean},
    }
    return results
```

training_step(**args*, ***kwargs*)

Here you compute and return the training loss and some additional metrics for e.g. the progress bar or logger.

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – Integer displaying index of this batch
- **optimizer_idx** (*int*) – When using multiple optimizers, this argument will also be present.
- **hiddens** (Tensor) – Passed in if *truncated_bptt_steps* > 0.

Return type Union[int, Dict[str, Union[Tensor, Dict[str, Tensor]]]]

Returns

Dict with loss key and optional log or progress bar keys. When implementing *training_step()*, return whatever you need in that step:

- loss -> tensor scalar **REQUIRED**
- progress_bar -> Dict for progress bar display. Must have only tensors
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc)

In this step you'd normally do the forward pass and calculate the loss for a batch. You can also do fancier things like multiple forward passes or something model specific.

Examples

```
def training_step(self, batch, batch_idx):
    x, y, z = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, x)

    logger_logs = {'training_loss': loss} # optional (MUST ALL BE TENSORS)

    # if using TestTubeLogger or TensorBoardLogger you can nest scalars
    logger_logs = {'losses': logger_logs} # optional (MUST ALL BE TENSORS)

    output = {
        'loss': loss, # required
        'progress_bar': {'training_loss': loss}, # optional (MUST ALL BE␣
↪TENSORS)
        'log': logger_logs
    }

    # return a dict
    return output
```

If you define multiple optimizers, this step will be called with an additional `optimizer_idx` parameter.

```
# Multiple optimizers (e.g.: GANs)
def training_step(self, batch, batch_idx, optimizer_idx):
```

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```
    if optimizer_idx == 0:
        # do training_step with encoder
    if optimizer_idx == 1:
        # do training_step with decoder
```

If you add truncated back propagation through time you will also get an additional argument with the hidden states of the previous step.

```
# Truncated back-propagation through time
def training_step(self, batch, batch_idx, hiddens):
    # hiddens are the hidden states from the previous truncated backprop step
    ...
    out, hiddens = self.lstm(data, hiddens)
    ...

    return {
        "loss": ...,
        "hiddens": hiddens  # remember to detach() this
    }
```

Notes

The loss value shown in the progress bar is smoothed (averaged) over the last values, so it differs from the actual loss returned in train/validation step.

training_step_end(**args*, ***kwargs*)

Use this when training with dp or ddp2 because *training_step()* will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to change your code

---

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
batch_parts_outputs = [training_step(sub_batch) for sub_batch in sub_batches]
training_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *training_step* for each batch part.

Return type Dict[str, Union[Tensor, Dict[str, Tensor]]]

Returns

Dict with loss key and optional log or progress bar keys.

- loss -> tensor scalar **REQUIRED**
- progress_bar -> Dict for progress bar display. Must have only tensors
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc)

Examples

```
# WITHOUT training_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def training_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with training_step_end to do softmax over the full batch
def training_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def training_step_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

unfreeze()

Unfreeze all parameters for training.

```
model = MyLightningModule(...)
model.unfreeze()
```

Return type None

val_dataloader()

Implement one or multiple PyTorch DataLoaders for validation.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to True.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*
- ...
- *prepare_data()*
- *train_dataloader()*
- *val_dataloader()*
- *test_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware There is no need to set it yourself.

Return type Union[DataLoader, List[DataLoader]]

Returns Single or multiple PyTorch DataLoaders.

Examples

```
def val_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=False,
                    transform=transform, download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=False
    )

    return loader

# can also return multiple dataloaders
def val_dataloader(self):
    return [loader_a, loader_b, ..., loader_n]
```

Note: If you don't need a validation dataset and a *validation_step()*, you don't need to implement this method.

Note: In the case where you return multiple validation dataloaders, the *validation_step()* will have an argument `dataset_idx` which matches the order here.

validation_end(*outputs*)

Warning: Deprecated in v0.7.0. Use *validation_epoch_end()* instead. Will be removed in 1.0.0.

validation_epoch_end(*outputs*)

Called at the end of the validation epoch with the outputs of all validation steps.

```
# the pseudocode for these calls
val_outs = []
for val_batch in val_data:
    out = validation_step(val_batch)
    val_outs.append(out)
validation_epoch_end(val_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *validation_step()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader.

Return type Dict[str, Dict[str, Tensor]]

Returns

Dict or OrderedDict. May have the following optional keys:

- progress_bar (dict for progress bar display; only tensors)
- log (dict of metrics to add to logger; only tensors).

Note: If you didn't define a *validation_step()*, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, you can specify the 'step' key in the 'log' dict.

Examples

With a single dataloader:

```
def validation_epoch_end(self, outputs):
    val_acc_mean = 0
    for output in outputs:
        val_acc_mean += output['val_acc']

    val_acc_mean /= len(outputs)
    tqdm_dict = {'val_acc': val_acc_mean.item()}

    # show val_acc in progress bar but only log val_loss
    results = {
        'progress_bar': tqdm_dict,
        'log': {'val_acc': val_acc_mean.item()}
    }
    return results
```

With multiple dataloaders, *outputs* will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each validation step for that dataloader.

```
def validation_epoch_end(self, outputs):
    val_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
        for output in dataloader_outputs:
            val_acc_mean += output['val_acc']
            i += 1

    val_acc_mean /= i
    tqdm_dict = {'val_acc': val_acc_mean.item()}

    # show val_loss and val_acc in progress bar but only log val_loss
    results = {
```

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```
        'progress_bar': tqdm_dict,
        'log': {'val_acc': val_acc_mean.item(), 'step': self.current_epoch}
    }
    return results
```

validation_step(**args*, ***kwargs*)

Operates on a single batch of data from the validation set. In this step you'd might generate examples or calculate anything of interest like accuracy.

```
# the pseudocode for these calls
val_outs = []
for val_batch in val_data:
    out = validation_step(train_batch)
    val_outs.append(out)
    validation_epoch_end(val_outs)
```

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – The index of this batch
- **dataloader_idx** (*int*) – The index of the dataloader that produced this batch (only if multiple val datasets used)

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to *validation_epoch_end()*. If you defined *validation_step_end()* it will go to that first.

```
# pseudocode of order
out = validation_step()
if defined('validation_step_end'):
    out = validation_step_end(out)
out = validation_epoch_end(out)
```

```
# if you have one val dataloader:
def validation_step(self, batch, batch_idx)

# if you have multiple val dataloaders:
def validation_step(self, batch, batch_idx, dataloader_idx)
```

Examples

```
# CASE 1: A single validation dataset
def validation_step(self, batch, batch_idx):
    x, y = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, y)

    # log 6 example images
```

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```
    # or generated text... or whatever
    sample_imgs = x[:6]
    grid = torchvision.utils.make_grid(sample_imgs)
    self.logger.experiment.add_image('example_images', grid, 0)

    # calculate acc
    labels_hat = torch.argmax(out, dim=1)
    val_acc = torch.sum(y == labels_hat).item() / (len(y) * 1.0)

    # all optional...
    # return whatever you need for the collation function validation_epoch_end
    output = OrderedDict({
        'val_loss': loss_val,
        'val_acc': torch.tensor(val_acc), # everything must be a tensor
    })

    # return an optional dict
    return output
```

If you pass in multiple val datasets, validation_step will have an additional argument.

```
# CASE 2: multiple validation datasets
def validation_step(self, batch, batch_idx, dataset_idx):
    # dataset_idx tells you which dataset this is.
```

Note: If you don't need to validate you don't need to implement this method.

Note: When the *validation_step()* is called, the model has been put in eval mode and PyTorch gradients have been disabled. At the end of validation, the model goes back to training mode and gradients are enabled.

validation_step_end(**args*, ***kwargs*)

Use this when validating with dp or ddp2 because *validation_step()* will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to change your code.

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
batch_parts_outputs = [validation_step(sub_batch) for sub_batch in sub_
↪batches]
validation_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *validation_step()* for each batch part.

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *validation_epoch_end()* method.

Examples

```
# WITHOUT validation_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def validation_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with validation_step_end to do softmax over the full batch
def validation_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def validation_epoch_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

_device = None
device reference

_dtype = None
Current dtype

current_epoch = None
The current epoch

global_step = None
Total training batches seen across all epochs

logger = None
Pointer to the logger object

on_gpu = None
True if your model is currently running on GPUs. Useful to set flags around the LightningModule for different CPU vs GPU behavior.

trainer = None
Pointer to the trainer object

use_amp = None
True if using amp

use_ddp = None
True if using ddp

use_ddp2 = None
True if using ddp2

use_dp = None
True if using dp

pytorch_lightning.core.**data_loader**(*fn*)
Decorator to make any fx with this use the lazy property.

> **Warning:** This decorator deprecated in v0.7.0 and it will be removed v0.9.0.

34.1.9 Submodules

pytorch_lightning.core.decorators module

pytorch_lightning.core.decorators.**data_loader**(*fn*)
Decorator to make any fx with this use the lazy property.

> **Warning:** This decorator deprecated in v0.7.0 and it will be removed v0.9.0.

pytorch_lightning.core.grads module

Module to describe gradients

class pytorch_lightning.core.grads.**GradInformation**(**args*, ***kwargs*)
Bases: torch.nn.Module

grad_norm(*norm_type*)

Return type Dict[str, int]

pytorch_lightning.core.hooks module

class pytorch_lightning.core.hooks.**ModelHooks**(**args*, ***kwargs*)
Bases: torch.nn.Module

backward(*trainer*, *loss*, *optimizer*, *optimizer_idx*)
Override backward with your own implementation if you need to.

Parameters

- **trainer** – Pointer to the trainer
- **loss** (Tensor) – Loss is already scaled by accumulated grads
- **optimizer** (Optimizer) – Current optimizer being used
- **optimizer_idx** (int) – Index of the current optimizer being used

Called to perform backward step. Feel free to override as needed.

The loss passed in has already been scaled for accumulated gradients if requested.

Example:

```
def backward(self, use_amp, loss, optimizer):
    if use_amp:
        with amp.scale_loss(loss, optimizer) as scaled_loss:
            scaled_loss.backward()
    else:
        loss.backward()
```

Return type None

on_after_backward()
Called in the training loop after loss.backward() and before optimizers do anything. This is the ideal place to inspect or log gradient information.

Example:

```
def on_after_backward(self):
    # example to inspect gradient information in tensorboard
    if self.trainer.global_step % 25 == 0:  # don't make the tf file huge
        params = self.state_dict()
        for k, v in params.items():
            grads = v
            name = k
            self.logger.experiment.add_histogram(tag=name, values=grads,
                                                 global_step=self.trainer.
↪global_step)
```

Return type None

on_batch_end()
Called in the training loop after the batch.

Return type None

on_batch_start(*batch*)
Called in the training loop before anything happens for that batch.

If you return -1 here, you will skip training for the rest of the current epoch.

Parameters **batch** (Any) – The batched data as it is returned by the training DataLoader.

Return type None

on_before_zero_grad(*optimizer*)
Called after optimizer.step() and before optimizer.zero_grad().

Called in the training loop after taking an optimizer step and before zeroing grads. Good place to inspect weight information with weights updated.

This is where it is called:

```
for optimizer in optimizers:
    optimizer.step()
    model.on_before_zero_grad(optimizer) # < ---- called here
    optimizer.zero_grad
```

Parameters **optimizer** (Optimizer) – The optimizer for which grads should be zeroed.

Return type None

on_epoch_end()
Called in the training loop at the very end of the epoch.

Return type None

on_epoch_start()
Called in the training loop at the very beginning of the epoch.

Return type None

on_post_performance_check()
Called at the very end of the validation loop.

Return type None

on_pre_performance_check()
Called at the very beginning of the validation loop.

Return type None

on_sanity_check_start()
Called before starting evaluation.

> **Warning:** Deprecated. Will be removed in v0.9.0.

on_train_end()
Called at the end of training before logger experiment is closed.

Return type None

on_train_start()
Called at the beginning of training before sanity check.

Return type None

pytorch_lightning.core.lightning module

class pytorch_lightning.core.lightning.**LightningModule**(**args*, ***kwargs*)
Bases: abc.ABC, *pytorch_lightning.core.properties.DeviceDtypeModuleMixin*, *pytorch_lightning.core.grads.GradInformation*, *pytorch_lightning.core.saving.ModelIO*, *pytorch_lightning.core.hooks.ModelHooks*

_init_slurm_connection()
Sets up environment variables necessary for pytorch distributed communications based on slurm environment.

Return type None

classmethod _load_model_state(*checkpoint*, **args*, ***kwargs*)

Return type *LightningModule*

configure_apex(*amp*, *model*, *optimizers*, *amp_level*)
Override to init AMP your own way. Must return a model and list of optimizers.

Parameters

- **amp** (object) – pointer to amp library object.
- **model** (*LightningModule*) – pointer to current *LightningModule*.

- **optimizers** (List[Optimizer]) – list of optimizers passed in *configure_optimizers()*.
- **amp_level** (str) – AMP mode chosen ('O1', 'O2', etc...)

Return type Tuple[*LightningModule*, List[Optimizer]]

Returns Apex wrapped model and optimizers

Examples

```
# Default implementation used by Trainer.
def configure_apex(self, amp, model, optimizers, amp_level):
    model, optimizers = amp.initialize(
        model, optimizers, opt_level=amp_level,
    )

    return model, optimizers
```

configure_ddp(*model*, *device_ids*)

Override to init DDP in your own way or with your own wrapper. The only requirements are that:

1. On a validation batch the call goes to `model.validation_step`.
2. On a training batch the call goes to `model.training_step`.
3. On a testing batch, the call goes to `model.test_step`.+

Parameters

- **model** (*LightningModule*) – the *LightningModule* currently being optimized.
- **device_ids** (List[int]) – the list of GPU ids.

Return type DistributedDataParallel

Returns DDP wrapped model

Examples

```
# default implementation used in Trainer
def configure_ddp(self, model, device_ids):
    # Lightning DDP simply routes to test_step, val_step, etc...
    model = LightningDistributedDataParallel(
        model,
        device_ids=device_ids,
        find_unused_parameters=True
    )
    return model
```

configure_optimizers()

Choose what optimizers and learning-rate schedulers to use in your optimization. Normally you'd need one. But in the case of GANs or similar you might have multiple.

Return type Union[Optimizer, Sequence[Optimizer], Dict, Sequence[Dict], Tuple[List, List], None]

Returns

Any of these 6 options.

- Single optimizer.
- List or Tuple - List of optimizers.
- Two lists - The first list has multiple optimizers, the second a list of LR schedulers.
- Dictionary, with an 'optimizer' key and (optionally) a 'lr_scheduler' key.
- Tuple of dictionaries as described, with an optional 'frequency' key.
- None - Fit will run without any optimizer.

Note: The 'frequency' value is an int corresponding to the number of sequential batches optimized with the specific optimizer. It should be given to none or to all of the optimizers. There is a difference between passing multiple optimizers in a list, and passing multiple optimizers in dictionaries with a frequency of 1: In the former case, all optimizers will operate on the given batch in each optimization step. In the latter, only one optimizer will operate on the given batch at every step.

Examples

```
# most cases
def configure_optimizers(self):
    opt = Adam(self.parameters(), lr=1e-3)
    return opt

# multiple optimizer case (e.g.: GAN)
def configure_optimizers(self):
    generator_opt = Adam(self.model_gen.parameters(), lr=0.01)
    disriminator_opt = Adam(self.model_disc.parameters(), lr=0.02)
    return generator_opt, disriminator_opt

# example with learning rate schedulers
def configure_optimizers(self):
    generator_opt = Adam(self.model_gen.parameters(), lr=0.01)
    disriminator_opt = Adam(self.model_disc.parameters(), lr=0.02)
    discriminator_sched = CosineAnnealing(discriminator_opt, T_max=10)
    return [generator_opt, disriminator_opt], [discriminator_sched]

# example with step-based learning rate schedulers
def configure_optimizers(self):
    gen_opt = Adam(self.model_gen.parameters(), lr=0.01)
    dis_opt = Adam(self.model_disc.parameters(), lr=0.02)
    gen_sched = {'scheduler': ExponentialLR(gen_opt, 0.99),
                 'interval': 'step'}  # called after each training step
    dis_sched = CosineAnnealing(discriminator_opt, T_max=10) # called every␣
↪epoch
    return [gen_opt, dis_opt], [gen_sched, dis_sched]

# example with optimizer frequencies
# see training procedure in `Improved Training of Wasserstein GANs`,␣
↪Algorithm 1
# https://arxiv.org/abs/1704.00028
def configure_optimizers(self):
    gen_opt = Adam(self.model_gen.parameters(), lr=0.01)
    dis_opt = Adam(self.model_disc.parameters(), lr=0.02)
    n_critic = 5
```

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```
    return (
        {'optimizer': dis_opt, 'frequency': n_critic},
        {'optimizer': gen_opt, 'frequency': 1}
    )
```

Note: Some things to know:

- Lightning calls `.backward()` and `.step()` on each optimizer and learning rate scheduler as needed.
- If you use 16-bit precision (`precision=16`), Lightning will automatically handle the optimizers for you.
- If you use multiple optimizers, *training_step()* will have an additional `optimizer_idx` parameter.
- If you use LBFGS Lightning handles the closure function automatically for you.
- If you use multiple optimizers, gradients will be calculated only for the parameters of current optimizer at each training step.
- If you need to control how often those optimizers step or override the default `.step()` schedule, override the *optimizer_step()* hook.
- If you only want to call a learning rate scheduler every `x` step or epoch, or want to monitor a custom metric, you can specify these in a dictionary:

```
{
    'scheduler': lr_scheduler,
    'interval': 'step'  # or 'epoch'
    'monitor': 'val_f1',
    'frequency': x
}
```

abstract forward(**args*, ***kwargs*)

Same as `torch.nn.Module.forward()`, however in Lightning you want this to define the operations you want to use for prediction (i.e.: on a server or as a feature extractor).

Normally you'd call `self()` from your *training_step()* method. This makes it easy to write a complex system for training with the outputs you'd want in a prediction setting.

Parameters

- ***args** – Whatever you decide to pass into the forward method.
- ****kwargs** – Keyword arguments are also possible.

Returns Predicted output

Examples

```
# example if we were using this model as a feature extractor
def forward(self, x):
    feature_maps = self.convnet(x)
    return feature_maps

def training_step(self, batch, batch_idx):
    x, y = batch
    feature_maps = self(x)
    logits = self.classifier(feature_maps)

    # ...
    return loss

# splitting it this way allows model to be used a feature extractor
model = MyModelAbove()

inputs = server.get_request()
results = model(inputs)
server.write_results(results)

# -------------
# This is in stark contrast to torch.nn.Module where normally you would have␣
↪this:
def forward(self, batch):
    x, y = batch
    feature_maps = self.convnet(x)
    logits = self.classifier(feature_maps)
    return logits
```

freeze()
Freeze all params for inference.

Example

```
model = MyLightningModule(...)
model.freeze()
```

Return type None

get_progress_bar_dict()
Additional items to be displayed in the progress bar.

Return type Dict[str, Union[int, str]]

Returns Dictionary with the items to be displayed in the progress bar.

get_tqdm_dict()
Additional items to be displayed in the progress bar.

Return type Dict[str, Union[int, str]]

Returns Dictionary with the items to be displayed in the progress bar.

> **Warning:** Deprecated since v0.7.3. Use `get_progress_bar_dict()` instead.

init_ddp_connection(*proc_rank*, *world_size*, *is_slurm_managing_tasks=True*)
Override to define your custom way of setting up a distributed environment.

Lightning's implementation uses env:// init by default and sets the first node as root for SLURM managed cluster.

Parameters

- **proc_rank** (int) – The current process rank within the node.
- **world_size** (int) – Number of GPUs being use across all nodes. (num_nodes * num_gpus).
- **is_slurm_managing_tasks** (bool) – is cluster managed by SLURM.

Return type None

classmethod load_from_checkpoint(*checkpoint_path*, **args*, *map_location=None*, *hparams_file=None*, *tags_csv=None*, *hparam_overrides=None*, ***kwargs*)
Primary way of loading a model from a checkpoint. When Lightning saves a checkpoint it stores the hyperparameters in the checkpoint if you initialized your `LightningModule` with an argument called `hparams` which is an object of `dict` or `Namespace` (output of `parse_args()` when parsing command line arguments). If you want *hparams* to have a hierarchical structure, you have to define it as `dict`. Any other arguments specified through *args and **kwargs will be passed to the model.

Example

```
# define hparams as Namespace
from argparse import Namespace
hparams = Namespace(**{'learning_rate': 0.1})

model = MyModel(hparams)

class MyModel(LightningModule):
    def __init__(self, hparams: Namespace):
        self.learning_rate = hparams.learning_rate

# ----------

# define hparams as dict
hparams = {
    drop_prob: 0.2,
    dataloader: {
        batch_size: 32
    }
}

model = MyModel(hparams)

class MyModel(LightningModule):
    def __init__(self, hparams: dict):
        self.learning_rate = hparams['learning_rate']
```

Parameters

- **checkpoint_path** (str) – Path to checkpoint.
- **args** – Any positional args needed to init the model.
- **map_location** (Union[Dict[str, str], str, device, int, Callable, None]) – If your checkpoint saved a GPU model and you now load on CPUs or a different number of GPUs, use this to map to the new setup. The behaviour is the same as in torch.load().
- **hparams_file** (Optional[str]) – Optional path to a .yaml file with hierarchical structure as in this example:

```
drop_prob: 0.2
dataloader:
    batch_size: 32
```

  You most likely won't need this since Lightning will always save the hyperparameters to the checkpoint. However, if your checkpoint weights don't have the hyperparameters saved, use this method to pass in a .yaml file with the hparams you'd like to use. These will be converted into a dict and passed into your *LightningModule* for use.

  If your model's *hparams* argument is Namespace and .yaml file has hierarchical structure, you need to refactor your model to treat *hparams* as dict.

  .csv files are acceptable here till v0.9.0, see tags_csv argument for detailed usage.

- **tags_csv** (Optional[str]) –

  Warning: Deprecated since version 0.7.6.

  tags_csv argument is deprecated in v0.7.6. Will be removed v0.9.0.

  Optional path to a .csv file with two columns (key, value) as in this example:

```
key,value
drop_prob,0.2
batch_size,32
```

  Use this method to pass in a .csv file with the hparams you'd like to use.

- **hparam_overrides** (Optional[Dict]) – A dictionary with keys to override in the hparams
- **kwargs** – Any keyword args needed to init the model.

Return type *LightningModule*

Returns *LightningModule* with loaded weights and hyperparameters (if available).

Example

```
# load weights without mapping ...
MyLightningModule.load_from_checkpoint('path/to/checkpoint.ckpt')

# or load weights mapping all weights from GPU 1 to GPU 0 ...
map_location = {'cuda:1':'cuda:0'}
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    map_location=map_location
)

# or load weights and hyperparameters from separate files.
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    hparams_file='/path/to/hparams_file.yaml'
)

# override some of the params with new values
MyLightningModule.load_from_checkpoint(
    PATH,
    hparam_overrides={'num_layers': 128, 'pretrained_ckpt_path': NEW_PATH}
)

# or load passing whatever args the model takes to load
MyLightningModule.load_from_checkpoint(
    'path/to/checkpoint.ckpt',
    learning_rate=0.1, # These arguments will be passed to the model using␣
↪**kwargs
    layers=2,
    pretrained_model=some_model
)

# predict
pretrained_model.eval()
pretrained_model.freeze()
y_hat = pretrained_model(x)
```

classmethod load_from_metrics(*weights_path*, *tags_csv*, *map_location=None*)

> **Warning:** Deprecated in version 0.7.0. You should use *load_from_checkpoint()* instead. Will be removed in v0.9.0.

on_load_checkpoint(*checkpoint*)

Called by Lightning to restore your model. If you saved something with *on_save_checkpoint()* this is your chance to restore this.

Parameters **checkpoint** (Dict[str, Any]) – Loaded checkpoint

Example

```
def on_load_checkpoint(self, checkpoint):
    # 99% of the time you don't need to implement this method
    self.something_cool_i_want_to_save = checkpoint['something_cool_i_want_to_
↪save']
```

Note: Lightning auto-restores global step, epoch, and train state including amp scaling. There is no need for you to restore anything regarding training.

Return type None

on_save_checkpoint(*checkpoint*)

Called by Lightning when saving a checkpoint to give you a chance to store anything else you might want to save.

Parameters **checkpoint** (Dict[str, Any]) – Checkpoint to be saved

Example

```
def on_save_checkpoint(self, checkpoint):
    # 99% of use cases you don't need to implement this method
    checkpoint['something_cool_i_want_to_save'] = my_cool_pickable_object
```

Note: Lightning saves all aspects of training (epoch, global step, etc...) including amp scaling. There is no need for you to store anything about training.

Return type None

optimizer_step(*epoch*, *batch_idx*, *optimizer*, *optimizer_idx*, *second_order_closure=None*)

Override this method to adjust the default way the *Trainer* calls each optimizer. By default, Lightning calls step() and zero_grad() as shown in the example once per optimizer.

Parameters

- **epoch** (int) – Current epoch
- **batch_idx** (int) – Index of current batch
- **optimizer** (Optimizer) – A PyTorch optimizer
- **optimizer_idx** (int) – If you used multiple optimizers this indexes into that list.
- **second_order_closure** (Optional[Callable]) – closure for second order methods

Examples

```
# DEFAULT
def optimizer_step(self, current_epoch, batch_idx, optimizer, optimizer_idx,
                   second_order_closure=None):
    optimizer.step()
    optimizer.zero_grad()

# Alternating schedule for optimizer steps (i.e.: GANs)
def optimizer_step(self, current_epoch, batch_idx, optimizer, optimizer_idx,
                   second_order_closure=None):
    # update generator opt every 2 steps
    if optimizer_idx == 0:
        if batch_idx % 2 == 0 :
            optimizer.step()
            optimizer.zero_grad()

    # update discriminator opt every 4 steps
    if optimizer_idx == 1:
        if batch_idx % 4 == 0 :
            optimizer.step()
            optimizer.zero_grad()

    # ...
    # add as many optimizers as you want
```

Here's another example showing how to use this for more advanced things such as learning rate warm-up:

```
# learning rate warm-up
def optimizer_step(self, current_epoch, batch_idx, optimizer,
                   optimizer_idx, second_order_closure=None):
    # warm up lr
    if self.trainer.global_step < 500:
        lr_scale = min(1., float(self.trainer.global_step + 1) / 500.)
        for pg in optimizer.param_groups:
            pg['lr'] = lr_scale * self.hparams.learning_rate

    # update params
    optimizer.step()
    optimizer.zero_grad()
```

Note: If you also override the *on_before_zero_grad()* model hook don't forget to add the call to it before `optimizer.zero_grad()` yourself.

Return type `None`

prepare_data()

Use this to download and prepare data. In distributed (GPU, TPU), this will only be called once. This is called before requesting the dataloaders:

```
model.prepare_data()
model.train_dataloader()
model.val_dataloader()
model.test_dataloader()
```

Examples

```
def prepare_data(self):
    download_imagenet()
    clean_imagenet()
    cache_imagenet()
```

Return type None

print(**args*, ***kwargs*)

Prints only from process 0. Use this in any distributed mode to log only once.

Parameters

- ***args** – The thing to print. Will be passed to Python's built-in print function.
- ****kwargs** – Will be passed to Python's built-in print function.

Example

```
def forward(self, x):
    self.print(x, 'in forward')
```

Return type None

summarize(*mode*)

Return type None

tbptt_split_batch(*batch*, *split_size*)

When using truncated backpropagation through time, each batch must be split along the time dimension. Lightning handles this by default, but for custom behavior override this function.

Parameters

- **batch** (Tensor) – Current batch
- **split_size** (int) – The size of the split

Return type list

Returns List of batch splits. Each split will be passed to *training_step()* to enable truncated back propagation through time. The default implementation splits root level Tensors and Sequences at dim=1 (i.e. time dim). It assumes that each time dim is the same length.

Examples

```
def tbptt_split_batch(self, batch, split_size):
  splits = []
  for t in range(0, time_dims[0], split_size):
      batch_split = []
      for i, x in enumerate(batch):
          if isinstance(x, torch.Tensor):
              split_x = x[:, t:t + split_size]
          elif isinstance(x, collections.Sequence):
              split_x = [None] * len(x)
```

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```
                for batch_idx in range(len(x)):
                    split_x[batch_idx] = x[batch_idx][t:t + split_size]

            batch_split.append(split_x)

        splits.append(batch_split)

    return splits
```

Note: Called in the training loop after *on_batch_start()* if *truncated_bptt_steps* > 0. Each returned batch split is passed separately to *training_step()*.

---

test_dataloader()

Implement one or multiple PyTorch DataLoaders for testing.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to `True`.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*
- ...
- *prepare_data()*
- *train_dataloader()*
- *val_dataloader()*
- *test_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

Return type Union[DataLoader, List[DataLoader]]

Returns Single or multiple PyTorch DataLoaders.

Example

```
def test_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=False, transform=transform,
                    download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=False
    )

    return loader
```

Note: If you don't need a test dataset and a *test_step()*, you don't need to implement this method.

test_end(*outputs*)

Warning: Deprecated in v0.7.0. Use *test_epoch_end()* instead. Will be removed in 1.0.0.

test_epoch_end(*outputs*)

Called at the end of a test epoch with the output of all test steps.

```
# the pseudocode for these calls
test_outs = []
for test_batch in test_data:
    out = test_step(test_batch)
    test_outs.append(out)
test_epoch_end(test_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *test_step_end()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader

Returns

Dict has the following optional keys:

- progress_bar -> Dict for progress bar display. Must have only tensors.
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc).

Return type Dict or OrderedDict

Note: If you didn't define a *test_step()*, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, specify it with the 'step' key in the 'log' Dict

Examples

With a single dataloader:

```
def test_epoch_end(self, outputs):
    test_acc_mean = 0
    for output in outputs:
        test_acc_mean += output['test_acc']

    test_acc_mean /= len(outputs)
    tqdm_dict = {'test_acc': test_acc_mean.item()}

    # show test_loss and test_acc in progress bar but only log test_loss
```

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```
    results = {
        'progress_bar': tqdm_dict,
        'log': {'test_acc': test_acc_mean.item()}
    }
    return results
```

With multiple dataloaders, *outputs* will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each test step for that dataloader.

```
def test_epoch_end(self, outputs):
    test_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
        for output in dataloader_outputs:
            test_acc_mean += output['test_acc']
            i += 1

    test_acc_mean /= i
    tqdm_dict = {'test_acc': test_acc_mean.item()}

    # show test_loss and test_acc in progress bar but only log test_loss
    results = {
        'progress_bar': tqdm_dict,
        'log': {'test_acc': test_acc_mean.item(), 'step': self.current_epoch}
    }
    return results
```

test_step(**args*, ***kwargs*)

Operates on a single batch of data from the test set. In this step you'd normally generate examples or calculate anything of interest such as accuracy.

```
# the pseudocode for these calls
test_outs = []
for test_batch in test_data:
    out = test_step(test_batch)
    test_outs.append(out)
test_epoch_end(test_outs)
```

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – The index of this batch.
- **dataloader_idx** (*int*) – The index of the dataloader that produced this batch (only if multiple test datasets used).

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *test_epoch_end()* method. If you defined *test_step_end()* it will go to that first.

```
# if you have one test dataloader:
def test_step(self, batch, batch_idx)
```

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```
# if you have multiple test dataloaders:
def test_step(self, batch, batch_idx, dataloader_idx)
```

Examples

```
# CASE 1: A single test dataset
def test_step(self, batch, batch_idx):
    x, y = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, y)

    # log 6 example images
    # or generated text... or whatever
    sample_imgs = x[:6]
    grid = torchvision.utils.make_grid(sample_imgs)
    self.logger.experiment.add_image('example_images', grid, 0)

    # calculate acc
    labels_hat = torch.argmax(out, dim=1)
    val_acc = torch.sum(y == labels_hat).item() / (len(y) * 1.0)

    # all optional...
    # return whatever you need for the collation function test_epoch_end
    output = OrderedDict({
        'val_loss': loss_val,
        'val_acc': torch.tensor(val_acc), # everything must be a tensor
    })

    # return an optional dict
    return output
```

If you pass in multiple validation datasets, `test_step()` will have an additional argument.

```
# CASE 2: multiple test datasets
def test_step(self, batch, batch_idx, dataset_idx):
    # dataset_idx tells you which dataset this is.
```

Note: If you don't need to validate you don't need to implement this method.

Note: When the `test_step()` is called, the model has been put in eval mode and PyTorch gradients have been disabled. At the end of the test epoch, the model goes back to training mode and gradients are enabled.

test_step_end(**args*, ***kwargs*)

Use this when testing with dp or ddp2 because `test_step()` will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to

change your code.

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
batch_parts_outputs = [test_step(sub_batch) for sub_batch in sub_batches]
test_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *test_step()* for each batch part.

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *test_epoch_end()*.

Examples

```
# WITHOUT test_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def test_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with test_step_end to do softmax over the full batch
def test_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def test_step_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

tng_dataloader()

> **Warning:** Deprecated in v0.5.0. Use *train_dataloader()* instead. Will be removed in 1.0.0.

train_dataloader()

Implement a PyTorch DataLoader for training.

Return type DataLoader

Returns Single PyTorch DataLoader.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to True.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*
- ...
- *prepare_data()*
- *train_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

Example

```
def train_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=True, transform=transform,
                    download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=True
    )
    return loader
```

training_end(**args*, ***kwargs*)

Warning: Deprecated in v0.7.0. Use *training_step_end()* instead.

training_epoch_end(*outputs*)

Called at the end of the training epoch with the outputs of all training steps.

```
# the pseudocode for these calls
train_outs = []
for train_batch in train_data:
    out = training_step(train_batch)
    train_outs.append(out)
training_epoch_end(train_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *training_step()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader.

Return type Dict[str, Dict[str, Tensor]]

Returns

Dict or OrderedDict. May contain the following optional keys:

- log (metrics to be added to the logger; only tensors)
- progress_bar (dict for progress bar display)
- any metric used in a callback (e.g. early stopping).

Note: If this method is not overridden, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, you can specify the 'step' key in the 'log' dict.

Examples

With a single dataloader:

```
def training_epoch_end(self, outputs):
    train_acc_mean = 0
    for output in outputs:
        train_acc_mean += output['train_acc']

    train_acc_mean /= len(outputs)

    # log training accuracy at the end of an epoch
    results = {
        'log': {'train_acc': train_acc_mean.item()},
        'progress_bar': {'train_acc': train_acc_mean},
    }
    return results
```

With multiple dataloaders, `outputs` will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each training step for that dataloader.

```
def training_epoch_end(self, outputs):
    train_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
        for output in dataloader_outputs:
            train_acc_mean += output['train_acc']
            i += 1

    train_acc_mean /= i

    # log training accuracy at the end of an epoch
    results = {
        'log': {'train_acc': train_acc_mean.item(), 'step': self.current_
↪epoch}
        'progress_bar': {'train_acc': train_acc_mean},
    }
    return results
```

training_step(**args*, ***kwargs*)

Here you compute and return the training loss and some additional metrics for e.g. the progress bar or logger.

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – Integer displaying index of this batch
- **optimizer_idx** (*int*) – When using multiple optimizers, this argument will also be present.
- **hiddens** (Tensor) – Passed in if *truncated_bptt_steps* > 0.

Return type Union[int, Dict[str, Union[Tensor, Dict[str, Tensor]]]]

Returns

Dict with loss key and optional log or progress bar keys. When implementing *training_step()*, return whatever you need in that step:

- loss -> tensor scalar **REQUIRED**
- progress_bar -> Dict for progress bar display. Must have only tensors
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc)

In this step you'd normally do the forward pass and calculate the loss for a batch. You can also do fancier things like multiple forward passes or something model specific.

Examples

```
def training_step(self, batch, batch_idx):
    x, y, z = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, x)

    logger_logs = {'training_loss': loss} # optional (MUST ALL BE TENSORS)

    # if using TestTubeLogger or TensorBoardLogger you can nest scalars
    logger_logs = {'losses': logger_logs} # optional (MUST ALL BE TENSORS)

    output = {
        'loss': loss, # required
        'progress_bar': {'training_loss': loss}, # optional (MUST ALL BE␣
↪TENSORS)
        'log': logger_logs
    }

    # return a dict
    return output
```

If you define multiple optimizers, this step will be called with an additional `optimizer_idx` parameter.

```
# Multiple optimizers (e.g.: GANs)
def training_step(self, batch, batch_idx, optimizer_idx):
```

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```
    if optimizer_idx == 0:
        # do training_step with encoder
    if optimizer_idx == 1:
        # do training_step with decoder
```

If you add truncated back propagation through time you will also get an additional argument with the hidden states of the previous step.

```
# Truncated back-propagation through time
def training_step(self, batch, batch_idx, hiddens):
    # hiddens are the hidden states from the previous truncated backprop step
    ...
    out, hiddens = self.lstm(data, hiddens)
    ...

    return {
        "loss": ...,
        "hiddens": hiddens  # remember to detach() this
    }
```

Notes

The loss value shown in the progress bar is smoothed (averaged) over the last values, so it differs from the actual loss returned in train/validation step.

training_step_end(**args*, ***kwargs*)

Use this when training with dp or ddp2 because *training_step()* will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to change your code

---

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
batch_parts_outputs = [training_step(sub_batch) for sub_batch in sub_batches]
training_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *training_step* for each batch part.

Return type Dict[str, Union[Tensor, Dict[str, Tensor]]]

Returns

Dict with loss key and optional log or progress bar keys.

- loss -> tensor scalar **REQUIRED**
- progress_bar -> Dict for progress bar display. Must have only tensors
- log -> Dict of metrics to add to logger. Must have only tensors (no images, etc)

Examples

```
# WITHOUT training_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def training_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with training_step_end to do softmax over the full batch
def training_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def training_step_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

unfreeze()

Unfreeze all parameters for training.

```
model = MyLightningModule(...)
model.unfreeze()
```

Return type None

val_dataloader()

Implement one or multiple PyTorch DataLoaders for validation.

The dataloader you return will not be called every epoch unless you set *reload_dataloaders_every_epoch* to True.

It's recommended that all data downloads and preparation happen in *prepare_data()*.

- *fit()*
- ...
- *prepare_data()*
- *train_dataloader()*
- *val_dataloader()*
- *test_dataloader()*

Note: Lightning adds the correct sampler for distributed and arbitrary hardware There is no need to set it yourself.

Return type Union[DataLoader, List[DataLoader]]

Returns Single or multiple PyTorch DataLoaders.

Examples

```
def val_dataloader(self):
    transform = transforms.Compose([transforms.ToTensor(),
                                    transforms.Normalize((0.5,), (1.0,))])
    dataset = MNIST(root='/path/to/mnist/', train=False,
                    transform=transform, download=True)
    loader = torch.utils.data.DataLoader(
        dataset=dataset,
        batch_size=self.hparams.batch_size,
        shuffle=False
    )

    return loader

# can also return multiple dataloaders
def val_dataloader(self):
    return [loader_a, loader_b, ..., loader_n]
```

Note: If you don't need a validation dataset and a *validation_step()*, you don't need to implement this method.

Note: In the case where you return multiple validation dataloaders, the *validation_step()* will have an argument `dataset_idx` which matches the order here.

validation_end(*outputs*)

Warning: Deprecated in v0.7.0. Use *validation_epoch_end()* instead. Will be removed in 1.0.0.

validation_epoch_end(*outputs*)

Called at the end of the validation epoch with the outputs of all validation steps.

```
# the pseudocode for these calls
val_outs = []
for val_batch in val_data:
    out = validation_step(val_batch)
    val_outs.append(out)
validation_epoch_end(val_outs)
```

Parameters **outputs** (Union[List[Dict[str, Tensor]], List[List[Dict[str, Tensor]]]]) – List of outputs you defined in *validation_step()*, or if there are multiple dataloaders, a list containing a list of outputs for each dataloader.

Return type Dict[str, Dict[str, Tensor]]

Returns

Dict or OrderedDict. May have the following optional keys:

- progress_bar (dict for progress bar display; only tensors)
- log (dict of metrics to add to logger; only tensors).

Note: If you didn't define a *validation_step()*, this won't be called.

- The outputs here are strictly for logging or progress bar.
- If you don't need to display anything, don't return anything.
- If you want to manually set current step, you can specify the 'step' key in the 'log' dict.

Examples

With a single dataloader:

```
def validation_epoch_end(self, outputs):
    val_acc_mean = 0
    for output in outputs:
        val_acc_mean += output['val_acc']

    val_acc_mean /= len(outputs)
    tqdm_dict = {'val_acc': val_acc_mean.item()}

    # show val_acc in progress bar but only log val_loss
    results = {
        'progress_bar': tqdm_dict,
        'log': {'val_acc': val_acc_mean.item()}
    }
    return results
```

With multiple dataloaders, *outputs* will be a list of lists. The outer list contains one entry per dataloader, while the inner list contains the individual outputs of each validation step for that dataloader.

```
def validation_epoch_end(self, outputs):
    val_acc_mean = 0
    i = 0
    for dataloader_outputs in outputs:
        for output in dataloader_outputs:
            val_acc_mean += output['val_acc']
            i += 1

    val_acc_mean /= i
    tqdm_dict = {'val_acc': val_acc_mean.item()}

    # show val_loss and val_acc in progress bar but only log val_loss
    results = {
```

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```
        'progress_bar': tqdm_dict,
        'log': {'val_acc': val_acc_mean.item(), 'step': self.current_epoch}
    }
    return results
```

validation_step(**args*, ***kwargs*)

Operates on a single batch of data from the validation set. In this step you'd might generate examples or calculate anything of interest like accuracy.

```
# the pseudocode for these calls
val_outs = []
for val_batch in val_data:
    out = validation_step(train_batch)
    val_outs.append(out)
    validation_epoch_end(val_outs)
```

Parameters

- **batch** (Tensor | (Tensor, ...) | [Tensor, ...]) – The output of your DataLoader. A tensor, tuple or list.
- **batch_idx** (*int*) – The index of this batch
- **dataloader_idx** (*int*) – The index of the dataloader that produced this batch (only if multiple val datasets used)

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to *validation_epoch_end()*. If you defined *validation_step_end()* it will go to that first.

```
# pseudocode of order
out = validation_step()
if defined('validation_step_end'):
    out = validation_step_end(out)
out = validation_epoch_end(out)
```

```
# if you have one val dataloader:
def validation_step(self, batch, batch_idx)

# if you have multiple val dataloaders:
def validation_step(self, batch, batch_idx, dataloader_idx)
```

Examples

```
# CASE 1: A single validation dataset
def validation_step(self, batch, batch_idx):
    x, y = batch

    # implement your own
    out = self(x)
    loss = self.loss(out, y)

    # log 6 example images
```

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```
    # or generated text... or whatever
    sample_imgs = x[:6]
    grid = torchvision.utils.make_grid(sample_imgs)
    self.logger.experiment.add_image('example_images', grid, 0)

    # calculate acc
    labels_hat = torch.argmax(out, dim=1)
    val_acc = torch.sum(y == labels_hat).item() / (len(y) * 1.0)

    # all optional...
    # return whatever you need for the collation function validation_epoch_end
    output = OrderedDict({
        'val_loss': loss_val,
        'val_acc': torch.tensor(val_acc), # everything must be a tensor
    })

    # return an optional dict
    return output
```

If you pass in multiple val datasets, validation_step will have an additional argument.

```
# CASE 2: multiple validation datasets
def validation_step(self, batch, batch_idx, dataset_idx):
    # dataset_idx tells you which dataset this is.
```

Note: If you don't need to validate you don't need to implement this method.

Note: When the *validation_step()* is called, the model has been put in eval mode and PyTorch gradients have been disabled. At the end of validation, the model goes back to training mode and gradients are enabled.

validation_step_end(**args*, ***kwargs*)

Use this when validating with dp or ddp2 because *validation_step()* will operate on only part of the batch. However, this is still optional and only needed for things like softmax or NCE loss.

Note: If you later switch to ddp or some other mode, this will still be called so that you don't have to change your code.

```
# pseudocode
sub_batches = split_batches_for_dp(batch)
batch_parts_outputs = [validation_step(sub_batch) for sub_batch in sub_
↪batches]
validation_step_end(batch_parts_outputs)
```

Parameters **batch_parts_outputs** – What you return in *validation_step()* for each batch part.

Return type Dict[str, Tensor]

Returns Dict or OrderedDict - passed to the *validation_epoch_end()* method.

Examples

```
# WITHOUT validation_step_end
# if used in DP or DDP2, this batch is 1/num_gpus large
def validation_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    loss = self.softmax(out)
    loss = nce_loss(loss)
    return {'loss': loss}

# --------------
# with validation_step_end to do softmax over the full batch
def validation_step(self, batch, batch_idx):
    # batch is 1/num_gpus big
    x, y = batch

    out = self(x)
    return {'out': out}

def validation_epoch_end(self, outputs):
    # this out is now the full size of the batch
    out = outputs['out']

    # this softmax now uses the full batch size
    loss = nce_loss(loss)
    return {'loss': loss}
```

See also:

See the *Multi-GPU training* guide for more details.

_device = None
device reference

_dtype = None
Current dtype

current_epoch = None
The current epoch

global_step = None
Total training batches seen across all epochs

logger = None
Pointer to the logger object

on_gpu = None
True if your model is currently running on GPUs. Useful to set flags around the LightningModule for different CPU vs GPU behavior.

trainer = None
Pointer to the trainer object

use_amp = None
True if using amp

use_ddp = None
True if using ddp

use_ddp2 = None
True if using ddp2

use_dp = None
True if using dp

pytorch_lightning.core.memory module

Generates a summary of a model's layers and dimensionality

class pytorch_lightning.core.memory.**ModelSummary**(*model*, *mode='full'*)
Bases: object

Generates summaries of model layers and dimensions.

get_layer_names()
Collect Layer Names

Return type None

get_parameter_nums()
Get number of parameters in each layer.

Return type None

get_parameter_sizes()
Get sizes of all parameters in *model*.

Return type None

get_variable_sizes()
Run sample input through each layer to get output sizes.

Return type None

make_summary()
Makes a summary listing with:

Layer Name, Layer Type, Input Size, Output Size, Number of Parameters

Return type None

named_modules()

Return type List[Tuple[str, Module]]

summarize()

Return type None

pytorch_lightning.core.memory.**_format_summary_table**(**cols*)
Takes in a number of arrays, each specifying a column in the summary table, and combines them all into one big string defining the summary table that are nicely formatted.

Return type str

pytorch_lightning.core.memory.**count_mem_items**()

Return type Tuple[int, int]

pytorch_lightning.core.memory.**get_gpu_memory_map**()
Get the current gpu usage.

Return type Dict[str, int]

Returns A dictionary in which the keys are device ids as integers and values are memory usage as integers in MB.

pytorch_lightning.core.memory.**get_human_readable_count**(*number*)
Abbreviates an integer number with K, M, B, T for thousands, millions, billions and trillions, respectively.

Examples

```
>>> get_human_readable_count(123)
'123  '
>>> get_human_readable_count(1234)  # (one thousand)
'1 K'
>>> get_human_readable_count(2e6)   # (two million)
'2 M'
>>> get_human_readable_count(3e9)   # (three billion)
'3 B'
>>> get_human_readable_count(4e12)  # (four trillion)
'4 T'
>>> get_human_readable_count(5e15)  # (more than trillion)
'5,000 T'
```

Parameters **number** (int) – a positive integer number

Return type str

Returns A string formatted according to the pattern described above.

pytorch_lightning.core.memory.**get_memory_profile**(*mode*)
Get a profile of the current memory usage.

Parameters **mode** (str) – There are two modes:

- 'all' means return memory for all gpus
- 'min_max' means return memory for max and min

Return type Union[Dict[str, int], Dict[int, int]]

Returns

A dictionary in which the keys are device ids as integers and values are memory usage as integers in MB. If mode is 'min_max', the dictionary will also contain two additional keys:

- 'min_gpu_mem': the minimum memory usage in MB
- 'max_gpu_mem': the maximum memory usage in MB

pytorch_lightning.core.memory.**print_mem_stack**()

Return type None

pytorch_lightning.core.model_saving module

Warning: *model_saving* module has been renamed to *saving* since v0.6.0. The deprecated module name will be removed in v0.8.0.

pytorch_lightning.core.properties module

class pytorch_lightning.core.properties.**DeviceDtypeModuleMixin**(**args*, ***kwargs*)

Bases: torch.nn.Module

cpu()
Moves all model parameters and buffers to the CPU. :returns: self :rtype: Module

cuda(*device=None*)
Moves all model parameters and buffers to the GPU. This also makes associated parameters and buffers different objects. So it should be called before constructing optimizer if the module will live on GPU while being optimized.

Parameters **device** (Optional[int]) – if specified, all parameters will be copied to that device

Returns self

Return type Module

double()
Casts all floating point parameters and buffers to double datatype.

Returns self

Return type Module

float()
Casts all floating point parameters and buffers to float datatype.

Returns self

Return type Module

half()
Casts all floating point parameters and buffers to half datatype.

Returns self

Return type Module

to(**args*, ***kwargs*)
Moves and/or casts the parameters and buffers.

This can be called as .. function:: to(device=None, dtype=None, non_blocking=False) .. function:: to(dtype, non_blocking=False) .. function:: to(tensor, non_blocking=False) Its signature is similar to torch.Tensor.to(), but only accepts floating point desired *dtype* s. In addition, this method will only cast the floating point parameters and buffers to *dtype* (if given). The integral parameters and buffers will be moved *device*, if that is given, but with dtypes unchanged. When non_blocking is set, it tries to convert/move asynchronously with respect to the host if possible, e.g., moving CPU Tensors with pinned memory to CUDA devices. See below for examples.

Note: This method modifies the module in-place.

Parameters

- **device** – the desired device of the parameters and buffers in this module
- **dtype** – the desired floating point type of the floating point parameters and buffers in this module
- **tensor** – Tensor whose dtype and device are the desired dtype and device for all parameters and buffers in this module

Returns self

Return type Module

Example::

```
>>> class ExampleModule(DeviceDtypeModuleMixin):
...     def __init__(self, weight: torch.Tensor):
...         super().__init__()
...         self.register_buffer('weight', weight)
>>> _ = torch.manual_seed(0)
>>> module = ExampleModule(torch.rand(3, 4))
>>> module.weight
tensor([[...]])
>>> module.to(torch.double)
ExampleModule()
>>> module.weight
tensor([[...]], dtype=torch.float64)
>>> cpu = torch.device('cpu')
>>> module.to(cpu, dtype=torch.half, non_blocking=True)
ExampleModule()
>>> module.weight
tensor([[...]], dtype=torch.float16)
>>> module.to(cpu)
ExampleModule()
>>> module.weight
tensor([[...]], dtype=torch.float16)
```

type(*dst_type*)

Casts all parameters and buffers to `dst_type`.

Parameters **dst_type** (*type or string*) – the desired type

Returns self

Return type Module

_device: ... = None

_dtype: Union[str, torch.dtype] = None

property device

Return type Union[str, device]

property dtype

Return type Union[str, dtype]

pytorch_lightning.core.root_module module

Warning: *root_module* module has been renamed to *lightning* since v0.6.0. The deprecated module name will be removed in v0.8.0.

pytorch_lightning.core.saving module

class pytorch_lightning.core.saving.**ModelIO**
Bases: object

on_hpc_load(*checkpoint*)
Hook to do whatever you need right before Slurm manager loads the model.

Parameters **checkpoint** (Dict[str, Any]) – A dictionary with variables from the checkpoint.

Return type None

on_hpc_save(*checkpoint*)
Hook to do whatever you need right before Slurm manager saves the model.

Parameters **checkpoint** (Dict[str, Any]) – A dictionary in which you can save variables to save in a checkpoint. Contents need to be pickleable.

Return type None

on_load_checkpoint(*checkpoint*)
Do something with the checkpoint. Gives model a chance to load something before state_dict is restored.

Parameters **checkpoint** (Dict[str, Any]) – A dictionary with variables from the checkpoint.

Return type None

on_save_checkpoint(*checkpoint*)
Give the model a chance to add something to the checkpoint. state_dict is already there.

Parameters **checkpoint** (Dict[str, Any]) – A dictionary in which you can save variables to save in a checkpoint. Contents need to be pickleable.

Return type None

pytorch_lightning.core.saving.**convert**(*val*)

Return type Union[int, float, bool, str]

pytorch_lightning.core.saving.**load_hparams_from_tags_csv**(*tags_csv*)
Load hparams from a file.

```
>>> hparams = Namespace(batch_size=32, learning_rate=0.001, data_root='./any/path/
↪here')
>>> path_csv = './testing-hparams.csv'
>>> save_hparams_to_tags_csv(path_csv, hparams)
>>> hparams_new = load_hparams_from_tags_csv(path_csv)
>>> vars(hparams) == hparams_new
True
>>> os.remove(path_csv)
```

Return type Dict[str, Any]

pytorch_lightning.core.saving.**load_hparams_from_yaml**(*config_yaml*)
Load hparams from a file.

```
>>> hparams = Namespace(batch_size=32, learning_rate=0.001, data_root='./any/path/
↪here')
>>> path_yaml = './testing-hparams.yaml'
>>> save_hparams_to_yaml(path_yaml, hparams)
>>> hparams_new = load_hparams_from_yaml(path_yaml)
>>> vars(hparams) == hparams_new
True
>>> os.remove(path_yaml)
```

Return type Dict[str, Any]

pytorch_lightning.core.saving.**save_hparams_to_tags_csv**(*tags_csv*, *hparams*)

Return type None

pytorch_lightning.core.saving.**save_hparams_to_yaml**(*config_yaml*, *hparams*)

Return type None

pytorch_lightning.core.saving.**update_hparams**(*hparams*, *updates*)
Overrides hparams with new values

```
>>> hparams = {'c': 4}
>>> update_hparams(hparams, {'a': {'b': 2}, 'c': 1})
>>> hparams['a']['b'], hparams['c']
(2, 1)
>>> update_hparams(hparams, {'a': {'b': 4}, 'c': 7})
>>> hparams['a']['b'], hparams['c']
(4, 7)
```

Parameters

- **hparams** (dict) – the original params and also target object
- **updates** (dict) – new params to be used as update

Return type None

34.2 pytorch_lightning.callbacks package

class pytorch_lightning.callbacks.**Callback**
Bases: abc.ABC

Abstract base class used to build new callbacks.

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends.

on_batch_start(*trainer*, *pl_module*)
Called when the training batch begins.

on_epoch_end(*trainer*, *pl_module*)
Called when the epoch ends.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_init_end(*trainer*)
Called when the trainer initialization ends, model has not yet been set.

on_init_start(*trainer*)
Called when the trainer initialization begins, model has not yet been set.

on_sanity_check_end(*trainer*, *pl_module*)
Called when the validation sanity check ends.

on_sanity_check_start(*trainer*, *pl_module*)
Called when the validation sanity check starts.

on_test_batch_end(*trainer*, *pl_module*)
Called when the test batch ends.

on_test_batch_start(*trainer*, *pl_module*)
Called when the test batch begins.

on_test_end(*trainer*, *pl_module*)
Called when the test ends.

on_test_start(*trainer*, *pl_module*)
Called when the test begins.

on_train_end(*trainer*, *pl_module*)
Called when the train ends.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)
Called when the validation batch ends.

on_validation_batch_start(*trainer*, *pl_module*)
Called when the validation batch begins.

on_validation_end(*trainer*, *pl_module*)
Called when the validation loop ends.

on_validation_start(*trainer*, *pl_module*)
Called when the validation loop begins.

class pytorch_lightning.callbacks.**EarlyStopping**(*monitor='val_loss'*, *min_delta=0.0*, *patience=3*, *verbose=False*, *mode='auto'*, *strict=True*)

Bases: *pytorch_lightning.callbacks.base.Callback*

Parameters

- **monitor** (str) – quantity to be monitored. Default: `'val_loss'`.
- **min_delta** (float) – minimum change in the monitored quantity to qualify as an improvement, i.e. an absolute change of less than *min_delta*, will count as no improvement. Default: `0`.
- **patience** (int) – number of epochs with no improvement after which training will be stopped. Default: `0`.
- **verbose** (bool) – verbosity mode. Default: `False`.
- **mode** (str) – one of {auto, min, max}. In *min* mode, training will stop when the quantity monitored has stopped decreasing; in *max* mode it will stop when the quantity monitored has stopped increasing; in *auto* mode, the direction is automatically inferred from the name of the monitored quantity. Default: `'auto'`.

- **strict** (bool) – whether to crash the training if *monitor* is not found in the metrics. Default: True.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import EarlyStopping
>>> early_stopping = EarlyStopping('val_loss')
>>> trainer = Trainer(early_stop_callback=early_stopping)
```

_validate_condition_metric(*logs*)
Checks that the condition metric for early stopping is good :param _sphinx_paramlinks_pytorch_lightning.callbacks.EarlyStopping._validate_condition_metric.logs: :return:

on_epoch_end(*trainer*, *pl_module*)
Called when the epoch ends.

on_train_end(*trainer*, *pl_module*)
Called when the train ends.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

mode_dict = {'max': torch.gt, 'min': torch.lt}

property monitor_op

class pytorch_lightning.callbacks.**ModelCheckpoint**(*filepath=None*, *monitor='val_loss'*, *verbose=False*, *save_top_k=1*, *save_weights_only=False*, *mode='auto'*, *period=1*, *prefix=''*)

Bases: *pytorch_lightning.callbacks.base.Callback*

Save the model after every epoch.

Parameters

- **filepath** (Optional[str]) – path to save the model file. Can contain named formatting options to be auto-filled.

  Example:

```
# custom path
# saves a file like: my/path/epoch_0.ckpt
>>> checkpoint_callback = ModelCheckpoint('my/path/')

# save any arbitrary metrics like `val_loss`, etc. in name
# saves a file like: my/path/epoch=2-val_loss=0.2_other_metric=0.3.
↪ckpt
>>> checkpoint_callback = ModelCheckpoint(
...     filepath='my/path/{epoch}-{val_loss:.2f}-{other_metric:.2f}
↪'
... )
```

  Can also be set to *None*, then it will be set to default location during trainer construction.

- **monitor** (str) – quantity to monitor.
- **verbose** (bool) – verbosity mode. Default: False.
- **save_top_k** (int) – if *save_top_k == k*, the best k models according to the quantity monitored will be saved. if save_top_k == 0, no models are saved. if save_top_k

`== -1`, all models are saved. Please note that the monitors are checked every *period* epochs. if `save_top_k >= 2` and the callback is called multiple times inside an epoch, the name of the saved file will be appended with a version count starting with *v0*.

- **mode** (`str`) – one of {auto, min, max}. If `save_top_k != 0`, the decision to overwrite the current save file is made based on either the maximization or the minimization of the monitored quantity. For *val_acc*, this should be *max*, for *val_loss* this should be *min*, etc. In *auto* mode, the direction is automatically inferred from the name of the monitored quantity.
- **save_weights_only** (`bool`) – if `True`, then only the model's weights will be saved (`model.save_weights(filepath)`), else the full model is saved (`model.save(filepath)`).
- **period** (`int`) – Interval (number of epochs) between checkpoints.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import ModelCheckpoint

# saves checkpoints to 'my/path/' whenever 'val_loss' has a new min
>>> checkpoint_callback = ModelCheckpoint(filepath='my/path/')
>>> trainer = Trainer(checkpoint_callback=checkpoint_callback)

# save epoch and val_loss in name
# saves a file like: my/path/sample-mnist_epoch=02_val_loss=0.32.ckpt
>>> checkpoint_callback = ModelCheckpoint(
...     filepath='my/path/sample-mnist_{epoch:02d}-{val_loss:.2f}'
... )
```

_del_model(*filepath*)

_do_check_save(*filepath*, *current*, *epoch*)

_save_model(*filepath*)

check_monitor_top_k(*current*)

format_checkpoint_name(*epoch*, *metrics*, *ver=None*)

Generate a filename according to the defined template.

Example:

```
>>> tmpdir = os.path.dirname(__file__)
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch}'))
>>> os.path.basename(ckpt.format_checkpoint_name(0, {}))
'epoch=0.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch:03d}'))
>>> os.path.basename(ckpt.format_checkpoint_name(5, {}))
'epoch=005.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch}-{val_loss:.2f}'))
>>> os.path.basename(ckpt.format_checkpoint_name(2, dict(val_loss=0.123456)))
'epoch=2-val_loss=0.12.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{missing:d}'))
>>> os.path.basename(ckpt.format_checkpoint_name(0, {}))
'missing=0.ckpt'
```

on_validation_end(*trainer*, *pl_module*)

Called when the validation loop ends.

class pytorch_lightning.callbacks.**GradientAccumulationScheduler**(*scheduling*)
Bases: *pytorch_lightning.callbacks.base.Callback*

Change gradient accumulation factor according to scheduling.

Parameters **scheduling** (dict) – scheduling in format {epoch: accumulation_factor}

> **Warning:** Epochs indexing starts from "1" until v0.6.x, but will start from "0" in v0.8.0.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import GradientAccumulationScheduler

# at epoch 5 start accumulating every 2 batches
>>> accumulator = GradientAccumulationScheduler(scheduling={5: 2})
>>> trainer = Trainer(callbacks=[accumulator])

# alternatively, pass the scheduling dict directly to the Trainer
>>> trainer = Trainer(accumulate_grad_batches={5: 2})
```

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

class pytorch_lightning.callbacks.**LearningRateLogger**
Bases: *pytorch_lightning.callbacks.base.Callback*

Automatically logs learning rate for learning rate schedulers during training.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import LearningRateLogger
>>> lr_logger = LearningRateLogger()
>>> trainer = Trainer(callbacks=[lr_logger])
```

Logging names are automatically determined based on optimizer class name. In case of multiple optimizers of same type, they will be named *Adam*, *Adam-1* etc. If a optimizer has multiple parameter groups they will be named *Adam/pg1*, *Adam/pg2* etc. To control naming, pass in a *name* keyword in the construction of the learning rate schdulers

Example:

```
def configure_optimizer(self):
    optimizer = torch.optim.Adam(...)
    lr_scheduler = {'scheduler': torch.optim.lr_schedulers.LambdaLR(optimizer, ...
↪)
                    'name': 'my_logging_name'}
    return [optimizer], [lr_scheduler]
```

_extract_lr(*trainer*, *interval*)
Extracts learning rates for lr schedulers and saves information into dict structure.

_find_names(*lr_schedulers*)

on_batch_start(*trainer*, *pl_module*)
Called when the training batch begins.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_train_start(*trainer*, *pl_module*)
Called before training, determines unique names for all lr schedulers in the case of multiple of the same type or in the case of multiple parameter groups

class pytorch_lightning.callbacks.**ProgressBarBase**
Bases: *pytorch_lightning.callbacks.base.Callback*

The base class for progress bars in Lightning. It is a *Callback* that keeps track of the batch progress in the *Trainer*. You should implement your highly custom progress bars with this as the base class.

Example:

```
class LitProgressBar(ProgressBarBase):

    def __init__(self):
        super().__init__()  # don't forget this :)
        self.enable = True

    def disable(self):
        self.enable = False

    def on_batch_end(self, trainer, pl_module):
        super().on_batch_end(trainer, pl_module)  # don't forget this :)
        percent = (self.train_batch_idx / self.total_train_batches) * 100
        sys.stdout.flush()
        sys.stdout.write(f'{percent:.01f} percent complete \r')

bar = LitProgressBar()
trainer = Trainer(callbacks=[bar])
```

disable()
You should provide a way to disable the progress bar. The *Trainer* will call this to disable the output on processes that have a rank different from 0, e.g., in multi-node training.

enable()
You should provide a way to enable the progress bar. The *Trainer* will call this in e.g. pre-training routines like the learning rate finder to temporarily enable and disable the main progress bar.

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_init_end(*trainer*)
Called when the trainer initialization ends, model has not yet been set.

on_test_batch_end(*trainer*, *pl_module*)
Called when the test batch ends.

on_test_start(*trainer*, *pl_module*)
Called when the test begins.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)
Called when the validation batch ends.

on_validation_start(*trainer*, *pl_module*)
Called when the validation loop begins.

property test_batch_idx
The current batch index being processed during testing. Use this to update your progress bar.

Return type int

property total_test_batches
The total number of training batches during testing, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the test dataloader is of infinite size.

Return type int

property total_train_batches
The total number of training batches during training, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the training dataloader is of infinite size.

Return type int

property total_val_batches
The total number of training batches during validation, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the validation dataloader is of infinite size.

Return type int

property train_batch_idx
The current batch index being processed during training. Use this to update your progress bar.

Return type int

property trainer

property val_batch_idx
The current batch index being processed during validation. Use this to update your progress bar.

Return type int

class pytorch_lightning.callbacks.**ProgressBar**(*refresh_rate=1*, *process_position=0*)
Bases: *pytorch_lightning.callbacks.progress.ProgressBarBase*

This is the default progress bar used by Lightning. It prints to *stdout* using the `tqdm` package and shows up to four different bars:

- **sanity check progress:** the progress during the sanity check run
- **main progress:** shows training + validation progress combined. It also accounts for multiple validation runs during training when *val_check_interval* is used.
- **validation progress:** only visible during validation; shows total progress over all validation datasets.
- **test progress:** only active when testing; shows total progress over all test datasets.

For infinite datasets, the progress bar never ends.

If you want to customize the default `tqdm` progress bars used by Lightning, you can override specific methods of the callback class and pass your custom implementation to the *Trainer*:

Example:

```
class LitProgressBar(ProgressBar):

    def init_validation_tqdm(self):
        bar = super().init_validation_tqdm()
        bar.set_description('running validation ...')
        return bar

bar = LitProgressBar()
trainer = Trainer(callbacks=[bar])
```

Parameters

- **refresh_rate** (int) – Determines at which rate (in number of batches) the progress bars get updated. Set it to 0 to disable the display. By default, the *Trainer* uses this implementation of the progress bar and sets the refresh rate to the value provided to the *progress_bar_refresh_rate* argument in the *Trainer*.
- **process_position** (int) – Set this to a value greater than 0 to offset the progress bars by this many lines. This is useful when you have progress bars defined elsewhere and want to show all of them together. This corresponds to *process_position* in the *Trainer*.

disable()
You should provide a way to disable the progress bar. The *Trainer* will call this to disable the output on processes that have a rank different from 0, e.g., in multi-node training.

Return type None

enable()
You should provide a way to enable the progress bar. The *Trainer* will call this in e.g. pre-training routines like the learning rate finder to temporarily enable and disable the main progress bar.

Return type None

init_sanity_tqdm()
Override this to customize the tqdm bar for the validation sanity run.

Return type tqdm

init_test_tqdm()
Override this to customize the tqdm bar for testing.

Return type tqdm

init_train_tqdm()
Override this to customize the tqdm bar for training.

Return type tqdm

init_validation_tqdm()
Override this to customize the tqdm bar for validation.

Return type tqdm

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_sanity_check_end(*trainer*, *pl_module*)
Called when the validation sanity check ends.

on_sanity_check_start(*trainer*, *pl_module*)
Called when the validation sanity check starts.

on_test_batch_end(*trainer*, *pl_module*)
Called when the test batch ends.

on_test_end(*trainer*, *pl_module*)
Called when the test ends.

on_test_start(*trainer*, *pl_module*)
Called when the test begins.

on_train_end(*trainer*, *pl_module*)
Called when the train ends.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)
Called when the validation batch ends.

on_validation_end(*trainer*, *pl_module*)
Called when the validation loop ends.

on_validation_start(*trainer*, *pl_module*)
Called when the validation loop begins.

property is_disabled

Return type bool

property is_enabled

Return type bool

property process_position

Return type int

property refresh_rate

Return type int

34.2.1 Submodules

pytorch_lightning.callbacks.base module

Callback Base

Abstract base class used to build new callbacks.

class pytorch_lightning.callbacks.base.**Callback**
Bases: abc.ABC

Abstract base class used to build new callbacks.

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends.

on_batch_start(*trainer*, *pl_module*)
Called when the training batch begins.

on_epoch_end(*trainer*, *pl_module*)
Called when the epoch ends.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_init_end(*trainer*)
Called when the trainer initialization ends, model has not yet been set.

on_init_start(*trainer*)
Called when the trainer initialization begins, model has not yet been set.

on_sanity_check_end(*trainer*, *pl_module*)
Called when the validation sanity check ends.

on_sanity_check_start(*trainer*, *pl_module*)
Called when the validation sanity check starts.

on_test_batch_end(*trainer*, *pl_module*)
Called when the test batch ends.

on_test_batch_start(*trainer*, *pl_module*)
Called when the test batch begins.

on_test_end(*trainer*, *pl_module*)
Called when the test ends.

on_test_start(*trainer*, *pl_module*)
Called when the test begins.

on_train_end(*trainer*, *pl_module*)
Called when the train ends.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)
Called when the validation batch ends.

on_validation_batch_start(*trainer*, *pl_module*)
Called when the validation batch begins.

on_validation_end(*trainer*, *pl_module*)
Called when the validation loop ends.

on_validation_start(*trainer*, *pl_module*)
Called when the validation loop begins.

pytorch_lightning.callbacks.early_stopping module

Early Stopping

Stop training when a monitored quantity has stopped improving.

class pytorch_lightning.callbacks.early_stopping.**EarlyStopping**(*monitor='val_loss'*, *min_delta=0.0*, *patience=3*, *verbose=False*, *mode='auto'*, *strict=True*)

Bases: *pytorch_lightning.callbacks.base.Callback*

Parameters

- **monitor** (str) – quantity to be monitored. Default: 'val_loss'.
- **min_delta** (float) – minimum change in the monitored quantity to qualify as an improvement, i.e. an absolute change of less than *min_delta*, will count as no improvement. Default: 0.
- **patience** (int) – number of epochs with no improvement after which training will be stopped. Default: 0.
- **verbose** (bool) – verbosity mode. Default: False.
- **mode** (str) – one of {auto, min, max}. In *min* mode, training will stop when the quantity monitored has stopped decreasing; in *max* mode it will stop when the quantity monitored has stopped increasing; in *auto* mode, the direction is automatically inferred from the name of the monitored quantity. Default: 'auto'.
- **strict** (bool) – whether to crash the training if *monitor* is not found in the metrics. Default: True.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import EarlyStopping
>>> early_stopping = EarlyStopping('val_loss')
>>> trainer = Trainer(early_stop_callback=early_stopping)
```

_validate_condition_metric(*logs*)
Checks that the condition metric for early stopping is good :param _sphinx_paramlinks_pytorch_lightning.callbacks.early_stopping.EarlyStopping._validate_condition_metric.logs: :return:

on_epoch_end(*trainer*, *pl_module*)
Called when the epoch ends.

on_train_end(*trainer*, *pl_module*)
Called when the train ends.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

mode_dict = {'max': torch.gt, 'min': torch.lt}

property monitor_op

pytorch_lightning.callbacks.gradient_accumulation_scheduler module

Gradient Accumulator

Change gradient accumulation factor according to scheduling.

class pytorch_lightning.callbacks.gradient_accumulation_scheduler.**GradientAccumulationSche**
Bases: *pytorch_lightning.callbacks.base.Callback*

Change gradient accumulation factor according to scheduling.

Parameters **scheduling** (dict) – scheduling in format {epoch: accumulation_factor}

> **Warning:** Epochs indexing starts from "1" until v0.6.x, but will start from "0" in v0.8.0.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import GradientAccumulationScheduler

# at epoch 5 start accumulating every 2 batches
>>> accumulator = GradientAccumulationScheduler(scheduling={5: 2})
>>> trainer = Trainer(callbacks=[accumulator])

# alternatively, pass the scheduling dict directly to the Trainer
>>> trainer = Trainer(accumulate_grad_batches={5: 2})
```

on_epoch_start (*trainer*, *pl_module*)
Called when the epoch begins.

pytorch_lightning.callbacks.lr_logger module

Logging of learning rates

Log learning rate for lr schedulers during training

class pytorch_lightning.callbacks.lr_logger.**LearningRateLogger**
Bases: *pytorch_lightning.callbacks.base.Callback*

Automatically logs learning rate for learning rate schedulers during training.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import LearningRateLogger
>>> lr_logger = LearningRateLogger()
>>> trainer = Trainer(callbacks=[lr_logger])
```

Logging names are automatically determined based on optimizer class name. In case of multiple optimizers of same type, they will be named *Adam*, *Adam-1* etc. If a optimizer has multiple parameter groups they will be named *Adam/pg1*, *Adam/pg2* etc. To control naming, pass in a *name* keyword in the construction of the learning rate schdulers

Example:

```
def configure_optimizer(self):
    optimizer = torch.optim.Adam(...)
    lr_scheduler = {'scheduler': torch.optim.lr_schedulers.LambdaLR(optimizer, ...
↪)
                    'name': 'my_logging_name'}
    return [optimizer], [lr_scheduler]
```

_extract_lr (*trainer*, *interval*)
Extracts learning rates for lr schedulers and saves information into dict structure.

_find_names (*lr_schedulers*)

on_batch_start (*trainer*, *pl_module*)
Called when the training batch begins.

on_epoch_start (*trainer*, *pl_module*)
Called when the epoch begins.

on_train_start (*trainer*, *pl_module*)
Called before training, determines unique names for all lr schedulers in the case of multiple of the same type or in the case of multiple parameter groups

pytorch_lightning.callbacks.model_checkpoint module

Model Checkpointing

Automatically save model checkpoints during training.

class pytorch_lightning.callbacks.model_checkpoint.**ModelCheckpoint**(*filepath=None*, *monitor='val_loss'*, *verbose=False*, *save_top_k=1*, *save_weights_only=False*, *mode='auto'*, *period=1*, *prefix=''*)

Bases: *pytorch_lightning.callbacks.base.Callback*

Save the model after every epoch.

Parameters

- **filepath** (Optional[str]) – path to save the model file. Can contain named formatting options to be auto-filled.

  Example:

```
# custom path
# saves a file like: my/path/epoch_0.ckpt
>>> checkpoint_callback = ModelCheckpoint('my/path/')

# save any arbitrary metrics like `val_loss`, etc. in name
# saves a file like: my/path/epoch=2-val_loss=0.2_other_metric=0.3.
↪ckpt
>>> checkpoint_callback = ModelCheckpoint(
...     filepath='my/path/{epoch}-{val_loss:.2f}-{other_metric:.2f}
↪'
... )
```

  Can also be set to *None*, then it will be set to default location during trainer construction.

- **monitor** (str) – quantity to monitor.
- **verbose** (bool) – verbosity mode. Default: False.
- **save_top_k** (int) – if *save_top_k == k*, the best k models according to the quantity monitored will be saved. if save_top_k == 0, no models are saved. if save_top_k == -1, all models are saved. Please note that the monitors are checked every *period* epochs. if save_top_k >= 2 and the callback is called multiple times inside an epoch, the name of the saved file will be appended with a version count starting with *v0*.

- **mode** (str) – one of {auto, min, max}. If `save_top_k != 0`, the decision to overwrite the current save file is made based on either the maximization or the minimization of the monitored quantity. For *val_acc*, this should be *max*, for *val_loss* this should be *min*, etc. In *auto* mode, the direction is automatically inferred from the name of the monitored quantity.
- **save_weights_only** (bool) – if `True`, then only the model's weights will be saved (`model.save_weights(filepath)`), else the full model is saved (`model.save(filepath)`).
- **period** (int) – Interval (number of epochs) between checkpoints.

Example:

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.callbacks import ModelCheckpoint

# saves checkpoints to 'my/path/' whenever 'val_loss' has a new min
>>> checkpoint_callback = ModelCheckpoint(filepath='my/path/')
>>> trainer = Trainer(checkpoint_callback=checkpoint_callback)

# save epoch and val_loss in name
# saves a file like: my/path/sample-mnist_epoch=02_val_loss=0.32.ckpt
>>> checkpoint_callback = ModelCheckpoint(
...     filepath='my/path/sample-mnist_{epoch:02d}-{val_loss:.2f}'
... )
```

_del_model(*filepath*)

_do_check_save(*filepath*, *current*, *epoch*)

_save_model(*filepath*)

check_monitor_top_k(*current*)

format_checkpoint_name(*epoch*, *metrics*, *ver=None*)

Generate a filename according to the defined template.

Example:

```
>>> tmpdir = os.path.dirname(__file__)
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch}'))
>>> os.path.basename(ckpt.format_checkpoint_name(0, {}))
'epoch=0.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch:03d}'))
>>> os.path.basename(ckpt.format_checkpoint_name(5, {}))
'epoch=005.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{epoch}-{val_loss:.2f}'))
>>> os.path.basename(ckpt.format_checkpoint_name(2, dict(val_loss=0.123456)))
'epoch=2-val_loss=0.12.ckpt'
>>> ckpt = ModelCheckpoint(os.path.join(tmpdir, '{missing:d}'))
>>> os.path.basename(ckpt.format_checkpoint_name(0, {}))
'missing=0.ckpt'
```

on_validation_end(*trainer*, *pl_module*)

Called when the validation loop ends.

pytorch_lightning.callbacks.progress module

Progress Bars

Use or override one of the progress bar callbacks.

class pytorch_lightning.callbacks.progress.**ProgressBar**(*refresh_rate=1*, *process_position=0*)

Bases: *pytorch_lightning.callbacks.progress.ProgressBarBase*

This is the default progress bar used by Lightning. It prints to *stdout* using the `tqdm` package and shows up to four different bars:

- **sanity check progress:** the progress during the sanity check run
- **main progress:** shows training + validation progress combined. It also accounts for multiple validation runs during training when *val_check_interval* is used.
- **validation progress:** only visible during validation; shows total progress over all validation datasets.
- **test progress:** only active when testing; shows total progress over all test datasets.

For infinite datasets, the progress bar never ends.

If you want to customize the default `tqdm` progress bars used by Lightning, you can override specific methods of the callback class and pass your custom implementation to the *Trainer*:

Example:

```
class LitProgressBar(ProgressBar):

    def init_validation_tqdm(self):
        bar = super().init_validation_tqdm()
        bar.set_description('running validation ...')
        return bar

bar = LitProgressBar()
trainer = Trainer(callbacks=[bar])
```

Parameters

- **refresh_rate** (`int`) – Determines at which rate (in number of batches) the progress bars get updated. Set it to `0` to disable the display. By default, the *Trainer* uses this implementation of the progress bar and sets the refresh rate to the value provided to the *progress_bar_refresh_rate* argument in the *Trainer*.
- **process_position** (`int`) – Set this to a value greater than `0` to offset the progress bars by this many lines. This is useful when you have progress bars defined elsewhere and want to show all of them together. This corresponds to *process_position* in the *Trainer*.

disable()

You should provide a way to disable the progress bar. The *Trainer* will call this to disable the output on processes that have a rank different from 0, e.g., in multi-node training.

Return type `None`

enable()

You should provide a way to enable the progress bar. The *Trainer* will call this in e.g. pre-training routines like the learning rate finder to temporarily enable and disable the main progress bar.

Return type `None`

init_sanity_tqdm()
Override this to customize the tqdm bar for the validation sanity run.

Return type tqdm

init_test_tqdm()
Override this to customize the tqdm bar for testing.

Return type tqdm

init_train_tqdm()
Override this to customize the tqdm bar for training.

Return type tqdm

init_validation_tqdm()
Override this to customize the tqdm bar for validation.

Return type tqdm

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends.

on_epoch_start(*trainer*, *pl_module*)
Called when the epoch begins.

on_sanity_check_end(*trainer*, *pl_module*)
Called when the validation sanity check ends.

on_sanity_check_start(*trainer*, *pl_module*)
Called when the validation sanity check starts.

on_test_batch_end(*trainer*, *pl_module*)
Called when the test batch ends.

on_test_end(*trainer*, *pl_module*)
Called when the test ends.

on_test_start(*trainer*, *pl_module*)
Called when the test begins.

on_train_end(*trainer*, *pl_module*)
Called when the train ends.

on_train_start(*trainer*, *pl_module*)
Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)
Called when the validation batch ends.

on_validation_end(*trainer*, *pl_module*)
Called when the validation loop ends.

on_validation_start(*trainer*, *pl_module*)
Called when the validation loop begins.

property is_disabled

Return type bool

property is_enabled

Return type bool

property process_position

Return type int

property refresh_rate

Return type int

class pytorch_lightning.callbacks.progress.**ProgressBarBase**

Bases: *pytorch_lightning.callbacks.base.Callback*

The base class for progress bars in Lightning. It is a *Callback* that keeps track of the batch progress in the *Trainer*. You should implement your highly custom progress bars with this as the base class.

Example:

```
class LitProgressBar(ProgressBarBase):

    def __init__(self):
        super().__init__()  # don't forget this :)
        self.enable = True

    def disable(self):
        self.enable = False

    def on_batch_end(self, trainer, pl_module):
        super().on_batch_end(trainer, pl_module)  # don't forget this :)
        percent = (self.train_batch_idx / self.total_train_batches) * 100
        sys.stdout.flush()
        sys.stdout.write(f'{percent:.01f} percent complete \r')

bar = LitProgressBar()
trainer = Trainer(callbacks=[bar])
```

disable()

You should provide a way to disable the progress bar. The *Trainer* will call this to disable the output on processes that have a rank different from 0, e.g., in multi-node training.

enable()

You should provide a way to enable the progress bar. The *Trainer* will call this in e.g. pre-training routines like the learning rate finder to temporarily enable and disable the main progress bar.

on_batch_end(*trainer*, *pl_module*)

Called when the training batch ends.

on_epoch_start(*trainer*, *pl_module*)

Called when the epoch begins.

on_init_end(*trainer*)

Called when the trainer initialization ends, model has not yet been set.

on_test_batch_end(*trainer*, *pl_module*)

Called when the test batch ends.

on_test_start(*trainer*, *pl_module*)

Called when the test begins.

on_train_start(*trainer*, *pl_module*)

Called when the train begins.

on_validation_batch_end(*trainer*, *pl_module*)

Called when the validation batch ends.

on_validation_start(*trainer*, *pl_module*)

Called when the validation loop begins.

property test_batch_idx
The current batch index being processed during testing. Use this to update your progress bar.

Return type int

property total_test_batches
The total number of training batches during testing, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the test dataloader is of infinite size.

Return type int

property total_train_batches
The total number of training batches during training, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the training dataloader is of infinite size.

Return type int

property total_val_batches
The total number of training batches during validation, which may change from epoch to epoch. Use this to set the total number of iterations in the progress bar. Can return `inf` if the validation dataloader is of infinite size.

Return type int

property train_batch_idx
The current batch index being processed during training. Use this to update your progress bar.

Return type int

property trainer

property val_batch_idx
The current batch index being processed during validation. Use this to update your progress bar.

Return type int

pytorch_lightning.callbacks.progress.**convert_inf**(*x*)
The tqdm doesn't support inf values. We have to convert it to None.

34.3 pytorch_lightning.loggers package

Lightning supports the most popular logging frameworks (TensorBoard, Comet, Weights and Biases, etc. . .). To use a logger, simply pass it into the *Trainer*. Lightning uses TensorBoard by default.

```
from pytorch_lightning import Trainer
from pytorch_lightning import loggers
tb_logger = loggers.TensorBoardLogger('logs/')
trainer = Trainer(logger=tb_logger)
```

Choose from any of the others such as MLflow, Comet, Neptune, WandB, . . .

```
comet_logger = loggers.CometLogger(save_dir='logs/')
trainer = Trainer(logger=comet_logger)
```

To use multiple loggers, simply pass in a `list` or `tuple` of loggers . . .

```
tb_logger = loggers.TensorBoardLogger('logs/')
comet_logger = loggers.CometLogger(save_dir='logs/')
trainer = Trainer(logger=[tb_logger, comet_logger])
```

Note: All loggers log by default to `os.getcwd()`. To change the path without creating a logger set `Trainer(default_root_dir='/your/path/to/save/checkpoints')`

34.3.1 Custom Logger

You can implement your own logger by writing a class that inherits from *LightningLoggerBase*. Use the `rank_zero_only()` decorator to make sure that only the first process in DDP training logs data.

```
from pytorch_lightning.utilities import rank_zero_only
from pytorch_lightning.loggers import LightningLoggerBase
class MyLogger(LightningLoggerBase):

    @rank_zero_only
    def log_hyperparams(self, params):
        # params is an argparse.Namespace
        # your code to record hyperparameters goes here
        pass

    @rank_zero_only
    def log_metrics(self, metrics, step):
        # metrics is a dictionary of metric names and values
        # your code to record metrics goes here
        pass

    def save(self):
        # Optional. Any code necessary to save logger data goes here
        pass

    @rank_zero_only
    def finalize(self, status):
        # Optional. Any code that needs to be run after training
        # finishes goes here
        pass
```

If you write a logger that may be useful to others, please send a pull request to add it to Lighting!

34.3.2 Using loggers

Call the logger anywhere except `__init__` in your *LightningModule* by doing:

```
from pytorch_lightning import LightningModule
class LitModel(LightningModule):
    def training_step(self, batch, batch_idx):
        # example
        self.logger.experiment.whatever_method_summary_writer_supports(...)

        # example if logger is a tensorboard logger
        self.logger.experiment.add_image('images', grid, 0)
```

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```
        self.logger.experiment.add_graph(model, images)

    def any_lightning_module_function_or_hook(self):
        self.logger.experiment.add_histogram(...)
```

Read more in the Experiment Logging use case.

34.3.3 Supported Loggers

class pytorch_lightning.loggers.**LightningLoggerBase**(*agg_key_funcs=None*, *agg_default_func=numpy.mean*)

Bases: abc.ABC

Base class for experiment loggers.

Parameters

- **agg_key_funcs** (Optional[Mapping[str, Callable[[Sequence[float]], float]]]) – Dictionary which maps a metric name to a function, which will aggregate the metric values for the same steps.
- **agg_default_func** (Callable[[Sequence[float]], float]) – Default function to aggregate metric values. If some metric name is not presented in the *agg_key_funcs* dictionary, then the *agg_default_func* will be used for aggregation.

Note: The *agg_key_funcs* and *agg_default_func* arguments are used only when one logs metrics with the *agg_and_log_metrics()* method.

_aggregate_metrics(*metrics*, *step=None*)

Aggregates metrics.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type Tuple[int, Optional[Dict[str, float]]]

Returns Step and aggregated metrics. The return value could be None. In such case, metrics are added to the aggregation list, but not aggregated yet.

static _convert_params(*params*)

Return type Dict[str, Any]

_finalize_agg_metrics()

This shall be called before save/close.

static _flatten_dict(*params*, *delimiter='/'*)

Flatten hierarchical dict, e.g. {'a': {'b': 'c'}} -> {'a/b': 'c'}.

Parameters

- **params** (Dict[str, Any]) – Dictionary containing the hyperparameters
- **delimiter** (str) – Delimiter to express the hierarchy. Defaults to '/'.

Return type Dict[str, Any]

Returns Flattened dict.

Examples

```
>>> LightningLoggerBase._flatten_dict({'a': {'b': 'c'}})
{'a/b': 'c'}
>>> LightningLoggerBase._flatten_dict({'a': {'b': 123}})
{'a/b': 123}
```

_reduce_agg_metrics()
Aggregate accumulated metrics.

static _sanitize_params(*params*)
Returns params with non-primitvies converted to strings for logging.

```
>>> params = {"float": 0.3,
...           "int": 1,
...           "string": "abc",
...           "bool": True,
...           "list": [1, 2, 3],
...           "namespace": Namespace(foo=3),
...           "layer": torch.nn.BatchNorm1d}
>>> import pprint
>>> pprint.pprint(LightningLoggerBase._sanitize_params(params))
{'bool': True,
 'float': 0.3,
 'int': 1,
 'layer': "<class 'torch.nn.modules.batchnorm.BatchNorm1d'>",
 'list': '[1, 2, 3]',
 'namespace': 'Namespace(foo=3)',
 'string': 'abc'}
```

Return type Dict[str, Any]

agg_and_log_metrics(*metrics*, *step=None*)
Aggregates and records metrics. This method doesn't log the passed metrics instantaneously, but instead it aggregates them and logs only if metrics are ready to be logged.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

abstract log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Namespace) – Namespace containing the hyperparameters

abstract log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

save()
Save log data.

Return type None

update_agg_funcs(*agg_key_funcs=None*, *agg_default_func=numpy.mean*)
Update aggregation methods.

Parameters

- **agg_key_funcs** (Optional[Mapping[str, Callable[[Sequence[float]], float]]]) – Dictionary which maps a metric name to a function, which will aggregate the metric values for the same steps.
- **agg_default_func** (Callable[[Sequence[float]], float]) – Default function to aggregate metric values. If some metric name is not presented in the *agg_key_funcs* dictionary, then the *agg_default_func* will be used for aggregation.

abstract property experiment
Return the experiment object associated with this logger.

Return type Any

abstract property name
Return the experiment name.

Return type str

abstract property version
Return the experiment version.

Return type Union[int, str]

class pytorch_lightning.loggers.**LoggerCollection**(*logger_iterable*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

The *LoggerCollection* class is used to iterate all logging actions over the given *logger_iterable*.

Parameters **logger_iterable** (Iterable[*LightningLoggerBase*]) – An iterable collection of loggers

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()
Save log data.

Return type None

property experiment
Return the experiment object associated with this logger.

Return type List[Any]

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

class pytorch_lightning.loggers.**TensorBoardLogger**(*save_dir*, *name='default'*, *version=None*, ***kwargs*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log to local file system in TensorBoard format. Implemented using SummaryWriter. Logs are saved to os.path.join(save_dir, name, version). This is the default logger in Lightning, it comes preinstalled.

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TensorBoardLogger
>>> logger = TensorBoardLogger("tb_logs", name="my_model")
>>> trainer = Trainer(logger=logger)
```

Parameters

- **save_dir** (str) – Save directory
- **name** (Optional[str]) – Experiment name. Defaults to 'default'. If it is the empty string then no per-experiment subdirectory is used.
- **version** (Union[int, str, None]) – Experiment version. If version is not specified the logger inspects the save directory for existing versions, then automatically assigns the next available version. If it is a string then it is used as the run-specific subdirectory name, otherwise 'version_${version}' is used.
- ****kwargs** – Other arguments are passed directly to the SummaryWriter constructor.

_get_next_version()

finalize(*status*)

Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*, *metrics=None*)

Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)

Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()

Save log data.

Return type None

NAME_HPARAMS_FILE = 'hparams.yaml'

property experiment

Actual tensorboard object. To use TensorBoard features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_tensorboard_function()
```

Return type SummaryWriter

property log_dir
The directory for this run's tensorboard checkpoint. By default, it is named 'version_${self.version}' but it can be overridden by passing a string value for the constructor's version parameter instead of None or an int.

Return type str

property name
Return the experiment name.

Return type str

property root_dir
Parent directory for all tensorboard checkpoint subdirectories. If the experiment name parameter is None or the empty string, no experiment subdirectory is used and the checkpoint will be saved in "save_dir/version_dir"

Return type str

property version
Return the experiment version.

Return type int

class pytorch_lightning.loggers.**CometLogger**(*api_key=None*, *save_dir=None*, *workspace=None*, *project_name=None*, *rest_api_key=None*, *experiment_name=None*, *experiment_key=None*, ***kwargs*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Comet.ml. Install it with pip:

```
pip install comet-ml
```

Comet requires either an API Key (online mode) or a local directory path (offline mode).

ONLINE MODE

Example

```
>>> import os
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import CometLogger
>>> # arguments made to CometLogger are passed on to the comet_ml.Experiment class
>>> comet_logger = CometLogger(
...     api_key=os.environ.get('COMET_API_KEY'),
...     workspace=os.environ.get('COMET_WORKSPACE'),  # Optional
...     save_dir='.',  # Optional
...     project_name='default_project',  # Optional
...     rest_api_key=os.environ.get('COMET_REST_API_KEY'),  # Optional
...     experiment_name='default'  # Optional
... )
>>> trainer = Trainer(logger=comet_logger)
```

OFFLINE MODE

Example

```
>>> from pytorch_lightning.loggers import CometLogger
>>> # arguments made to CometLogger are passed on to the comet_ml.Experiment class
>>> comet_logger = CometLogger(
...     save_dir='.',
...     workspace=os.environ.get('COMET_WORKSPACE'),  # Optional
...     project_name='default_project',  # Optional
...     rest_api_key=os.environ.get('COMET_REST_API_KEY'),  # Optional
...     experiment_name='default'  # Optional
... )
>>> trainer = Trainer(logger=comet_logger)
```

Parameters

- **api_key** (Optional[str]) – Required in online mode. API key, found on Comet.ml
- **save_dir** (Optional[str]) – Required in offline mode. The path for the directory to save local comet logs
- **workspace** (Optional[str]) – Optional. Name of workspace for this user
- **project_name** (Optional[str]) – Optional. Send your experiment to a specific project. Otherwise will be sent to Uncategorized Experiments. If the project name does not already exist, Comet.ml will create a new project.
- **rest_api_key** (Optional[str]) – Optional. Rest API key found in Comet.ml settings. This is used to determine version number
- **experiment_name** (Optional[str]) – Optional. String representing the name for this particular experiment on Comet.ml.
- **experiment_key** (Optional[str]) – Optional. If set, restores from existing experiment.

finalize(*status*)

When calling `self.experiment.end()`, that experiment won't log any more data to Comet. That's why, if you need to log any more data, you need to create an ExistingCometExperiment. For example, to log data when testing your model after training, because when training is finalized *CometLogger.finalize()* is called.

This happens automatically in the *experiment()* property, when `self._experiment` is set to `None`, i.e. `self.reset_experiment()`.

Return type None

log_hyperparams(*params*)

Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)

Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, Union[Tensor, float]]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

reset_experiment()

property experiment

Actual Comet object. To use Comet features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_comet_function()
```

Return type BaseExperiment

property name

Return the experiment name.

Return type str

property version

Return the experiment version.

Return type str

class pytorch_lightning.loggers.**MLFlowLogger**(*experiment_name='default'*, *tracking_uri=None*, *tags=None*, *save_dir=None*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using MLflow. Install it with pip:

```
pip install mlflow
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import MLFlowLogger
>>> mlf_logger = MLFlowLogger(
...     experiment_name="default",
...     tracking_uri="file:./ml-runs"
... )
>>> trainer = Trainer(logger=mlf_logger)
```

Use the logger anywhere in you *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_ml_flow_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.whatever_ml_flow_supports(...)
```

Parameters

- **experiment_name** (str) – The name of the experiment
- **tracking_uri** (Optional[str]) – Address of local or remote tracking server. If not provided, defaults to the service set by mlflow.tracking.set_tracking_uri.
- **tags** (Optional[Dict[str, Any]]) – A dictionary tags for the experiment.

finalize(*status='FINISHED'*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

property experiment
Actual MLflow object. To use mlflow features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_mlflow_function()
```

Return type MlflowClient

property name
Return the experiment name.

Return type str

property run_id

property version
Return the experiment version.

Return type str

class pytorch_lightning.loggers.**NeptuneLogger**(*api_key=None*, *project_name=None*, *close_after_fit=True*, *offline_mode=False*, *experiment_name=None*, *upload_source_files=None*, *params=None*, *properties=None*, *tags=None*, ***kwargs*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Neptune. Install it with pip:

```
pip install neptune-client
```

The Neptune logger can be used in the online mode or offline (silent) mode. To log experiment data in online mode, *NeptuneLogger* requires an API key. In offline mode, the logger does not connect to Neptune.

ONLINE MODE

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import NeptuneLogger
>>> # arguments made to NeptuneLogger are passed on to the neptune.experiments.
↪Experiment class
>>> # We are using an api_key for the anonymous user "neptuner" but you can use␣
↪your own.
>>> neptune_logger = NeptuneLogger(
...     api_key='ANONYMOUS',
...     project_name='shared/pytorch-lightning-integration',
...     experiment_name='default',  # Optional,
...     params={'max_epochs': 10},  # Optional,
...     tags=['pytorch-lightning', 'mlp']  # Optional,
... )
>>> trainer = Trainer(max_epochs=10, logger=neptune_logger)
```

OFFLINE MODE

Example

```
>>> from pytorch_lightning.loggers import NeptuneLogger
>>> # arguments made to NeptuneLogger are passed on to the neptune.experiments.
↪Experiment class
>>> neptune_logger = NeptuneLogger(
...     offline_mode=True,
...     project_name='USER_NAME/PROJECT_NAME',
...     experiment_name='default',  # Optional,
...     params={'max_epochs': 10},  # Optional,
...     tags=['pytorch-lightning', 'mlp']  # Optional,
... )
>>> trainer = Trainer(max_epochs=10, logger=neptune_logger)
```

Use the logger anywhere in you *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
```

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```
...         # log metrics
...         self.logger.experiment.log_metric('acc_train', ...)
...         # log images
...         self.logger.experiment.log_image('worse_predictions', ...)
...         # log model checkpoint
...         self.logger.experiment.log_artifact('model_checkpoint.pt', ...)
...         self.logger.experiment.whatever_neptune_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.log_metric('acc_train', ...)
...         self.logger.experiment.log_image('worse_predictions', ...)
...         self.logger.experiment.log_artifact('model_checkpoint.pt', ...)
...         self.logger.experiment.whatever_neptune_supports(...)
```

If you want to log objects after the training is finished use `close_after_fit=False`:

```
neptune_logger = NeptuneLogger(
    ...
    close_after_fit=False,
    ...
)
trainer = Trainer(logger=neptune_logger)
trainer.fit()

# Log test metrics
trainer.test(model)

# Log additional metrics
from sklearn.metrics import accuracy_score

accuracy = accuracy_score(y_true, y_pred)
neptune_logger.experiment.log_metric('test_accuracy', accuracy)

# Log charts
from scikitplot.metrics import plot_confusion_matrix
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(16, 12))
plot_confusion_matrix(y_true, y_pred, ax=ax)
neptune_logger.experiment.log_image('confusion_matrix', fig)

# Save checkpoints folder
neptune_logger.experiment.log_artifact('my/checkpoints')

# When you are done, stop the experiment
neptune_logger.experiment.stop()
```

See also:

- An Example experiment showing the UI of Neptune.
- Tutorial on how to use Pytorch Lightning with Neptune.

Parameters

- **api_key** (Optional[str]) – Required in online mode. Neptune API token, found on https://neptune.ai. Read how to get your API key. It is recommended to keep it in the

NEPTUNE_API_TOKEN environment variable and then you can leave `api_key=None`.

- **project_name** (Optional[str]) – Required in online mode. Qualified name of a project in a form of "namespace/project_name" for example "tom/minst-classification". If `None`, the value of *NEPTUNE_PROJECT* environment variable will be taken. You need to create the project in https://neptune.ai first.
- **offline_mode** (bool) – Optional default `False`. If `True` no logs will be sent to Neptune. Usually used for debug purposes.
- **close_after_fit** (Optional[bool]) – Optional default `True`. If `False` the experiment will not be closed after training and additional metrics, images or artifacts can be logged. Also, remember to close the experiment explicitly by running `neptune_logger.experiment.stop()`.
- **experiment_name** (Optional[str]) – Optional. Editable name of the experiment. Name is displayed in the experiment's Details (Metadata section) and in experiments view as a column.
- **upload_source_files** (Optional[List[str]]) – Optional. List of source files to be uploaded. Must be list of str or single str. Uploaded sources are displayed in the experiment's Source code tab. If `None` is passed, the Python file from which the experiment was created will be uploaded. Pass an empty list (`[]`) to upload no files. Unix style pathname pattern expansion is supported. For example, you can pass `'\*.py'` to upload all python source files from the current directory. For recursion lookup use `'\**/\*.py'` (for Python 3.5 and later). For more information see `glob` library.
- **params** (Optional[Dict[str, Any]]) – Optional. Parameters of the experiment. After experiment creation params are read-only. Parameters are displayed in the experiment's Parameters section and each key-value pair can be viewed in the experiments view as a column.
- **properties** (Optional[Dict[str, Any]]) – Optional. Default is `{}`. Properties of the experiment. They are editable after the experiment is created. Properties are displayed in the experiment's Details section and each key-value pair can be viewed in the experiments view as a column.
- **tags** (Optional[List[str]]) – Optional. Default is `[]`. Must be list of str. Tags of the experiment. They are editable after the experiment is created (see: `append_tag()` and `remove_tag()`). Tags are displayed in the experiment's Details section and can be viewed in the experiments view as a column.

_create_or_get_experiment()

append_tags(*tags*)

Appends tags to the neptune experiment.

Parameters **tags** (Union[str, Iterable[str]]) – Tags to add to the current experiment. If str is passed, a single tag is added. If multiple - comma separated - str are passed, all of them are added as tags. If list of str is passed, all elements of the list are added as tags.

Return type None

finalize(*status*)

Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_artifact(*artifact*, *destination=None*)
Save an artifact (file) in Neptune experiment storage.

Parameters

- **artifact** (str) – A path to the file in local filesystem.
- **destination** (Optional[str]) – Optional. Default is None. A destination path. If None is passed, an artifact file name will be used.

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_image(*log_name*, *image*, *step=None*)
Log image data in Neptune experiment

Parameters

- **log_name** (str) – The name of log, i.e. bboxes, visualisations, sample_images.
- **image** (Union[str, Image, Any]) – The value of the log (data-point). Can be one of the following types: PIL image, *matplotlib.figure.Figure*, path to image file (str)
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_metric(*metric_name*, *metric_value*, *step=None*)
Log metrics (numeric values) in Neptune experiments.

Parameters

- **metric_name** (str) – The name of log, i.e. mse, loss, accuracy.
- **metric_value** (Union[Tensor, float, str]) – The value of the log (data-point).
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_metrics(*metrics*, *step=None*)
Log metrics (numeric values) in Neptune experiments.

Parameters

- **metrics** (Dict[str, Union[Tensor, float]]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_text(*log_name*, *text*, *step=None*)
Log text data in Neptune experiments.

Parameters

- **log_name** (str) – The name of log, i.e. mse, my_text_data, timing_info.
- **text** (str) – The value of the log (data-point).
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

set_property(*key*, *value*)
Set key-value pair as Neptune experiment property.

Parameters

- **key** (str) – Property key.
- **value** (Any) – New value of a property.

Return type None

property experiment
Actual Neptune object. To use neptune features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_neptune_function()
```

Return type Experiment

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

class pytorch_lightning.loggers.**TestTubeLogger**(*save_dir*, *name='default'*, *description=None*, *debug=False*, *version=None*, *create_git_tag=False*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log to local file system in TensorBoard format but using a nicer folder structure (see full docs). Install it with pip:

```
pip install test_tube
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TestTubeLogger
>>> logger = TestTubeLogger("tt_logs", name="my_exp_name")
>>> trainer = Trainer(logger=logger)
```

Use the logger anywhere in your *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_method_summary_writer_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.add_histogram(...)
```

Parameters

- **save_dir** (str) – Save directory
- **name** (str) – Experiment name. Defaults to 'default'.
- **description** (Optional[str]) – A short snippet about this experiment
- **debug** (bool) – If True, it doesn't log anything.
- **version** (Optional[int]) – Experiment version. If version is not specified the logger inspects the save directory for existing versions, then automatically assigns the next available version.
- **create_git_tag** (bool) – If True creates a git tag to save the code used in this experiment.

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()
Save log data.

Return type None

property experiment
Actual TestTube object. To use TestTube features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_test_tube_function()
```

Return type Experiment

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type int

class pytorch_lightning.loggers.**WandbLogger**(*name=None*, *save_dir=None*, *offline=False*, *id=None*, *anonymous=False*, *version=None*, *project=None*, *tags=None*, *log_model=False*, *experiment=None*, *entity=None*, *group=None*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Weights and Biases. Install it with pip:

```
pip install wandb
```

Parameters

- **name** (Optional[str]) – Display name for the run.
- **save_dir** (Optional[str]) – Path where data is saved.
- **offline** (bool) – Run offline (data can be streamed later to wandb servers).
- **id** (Optional[str]) – Sets the version, mainly used to resume a previous run.
- **anonymous** (bool) – Enables or explicitly disables anonymous logging.
- **version** (Optional[str]) – Sets the version, mainly used to resume a previous run.
- **project** (Optional[str]) – The name of the project to which this run will belong.
- **tags** (Optional[List[str]]) – Tags associated with this run.
- **log_model** (bool) – Save checkpoints in wandb dir to upload on W&B servers.
- **experiment** – WandB experiment object
- **entity** – The team posting this run (default: your username or your default team)
- **group** (Optional[str]) – A unique string shared by all runs in a given group

Example

```
>>> from pytorch_lightning.loggers import WandbLogger
>>> from pytorch_lightning import Trainer
>>> wandb_logger = WandbLogger()
>>> trainer = Trainer(logger=wandb_logger)
```

See also:

- Tutorial on how to use W&B with Pytorch Lightning.

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

watch(*model*, *log='gradients'*, *log_freq=100*)

property experiment
Actual wandb object. To use wandb features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_wandb_function()
```

Return type Run

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

class pytorch_lightning.loggers.**TrainsLogger**(*project_name=None*, *task_name=None*, *task_type='training'*, *reuse_last_task_id=True*, *output_uri=None*, *auto_connect_arg_parser=True*, *auto_connect_frameworks=True*, *auto_resource_monitoring=True*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using allegro.ai TRAINS. Install it with pip:

```
pip install trains
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TrainsLogger
>>> trains_logger = TrainsLogger(
...     project_name='pytorch lightning',
...     task_name='default',
...     output_uri='.',
... )
TRAINS Task: ...
TRAINS results page: ...
>>> trainer = Trainer(logger=trains_logger)
```

Use the logger anywhere in your *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_trains_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.whatever_trains_supports(...)
```

Parameters

- **project_name** (Optional[str]) – The name of the experiment's project. Defaults to None.
- **task_name** (Optional[str]) – The name of the experiment. Defaults to None.
- **task_type** (str) – The name of the experiment. Defaults to 'training'.
- **reuse_last_task_id** (bool) – Start with the previously used task id. Defaults to True.
- **output_uri** (Optional[str]) – Default location for output models. Defaults to None.
- **auto_connect_arg_parser** (bool) – Automatically grab the ArgumentParser and connect it with the task. Defaults to True.
- **auto_connect_frameworks** (bool) – If True, automatically patch to trains backend. Defaults to True.
- **auto_resource_monitoring** (bool) – If True, machine vitals will be sent along side the task scalars. Defaults to True.

Examples

```
>>> logger = TrainsLogger("pytorch lightning", "default", output_uri=".")
TRAINS Task: ...
TRAINS results page: ...
>>> logger.log_metrics({"val_loss": 1.23}, step=0)
>>> logger.log_text("sample test")
sample test
>>> import numpy as np
>>> logger.log_artifact("confusion matrix", np.ones((2, 3)))
>>> logger.log_image("passed", "Image 1", np.random.randint(0, 255, (200, 150, 3),
↪ dtype=np.uint8))
```

classmethod bypass_mode()
Returns the bypass mode state.

Note: *GITHUB_ACTIONS* env will automatically set bypass_mode to `True` unless overridden specifically with `TrainsLogger.set_bypass_mode(False)`.

Return type bool

Returns If True, all outside communication is skipped.

finalize(*status=None*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (Optional[str]) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_artifact(*name*, *artifact*, *metadata=None*, *delete_after_upload=False*)
Save an artifact (file/object) in TRAINS experiment storage.

Parameters

- **name** (str) – Artifact name. Notice! it will override the previous artifact if the name already exists.
- **artifact** (Union[str, Path, Dict[str, Any], ndarray, Image]) – Artifact object to upload. Currently supports:
  - string / pathlib.Path are treated as path to artifact file to upload If a wildcard or a folder is passed, a zip file containing the local files will be created and uploaded.
  - dict will be stored as .json file and uploaded
  - pandas.DataFrame will be stored as .csv.gz (compressed CSV file) and uploaded
  - numpy.ndarray will be stored as .npz and uploaded
  - PIL.Image.Image will be stored to .png file and uploaded
- **metadata** (Optional[Dict[str, Any]]) – Simple key/value dictionary to store on the artifact. Defaults to None.
- **delete_after_upload** (bool) – If True, the local artifact will be deleted (only applies if artifact is a local file). Defaults to False.

Return type None

log_hyperparams(*params*)
Log hyperparameters (numeric values) in TRAINS experiments.

Parameters **params** (Union[Dict[str, Any], Namespace]) – The hyperparameters that passed through the model.

Return type None

log_image(*title*, *series*, *image*, *step=None*)
Log Debug image in TRAINS experiment

Parameters

- **title** (str) – The title of the debug image, i.e. "failed", "passed".
- **series** (str) – The series name of the debug image, i.e. "Image 0", "Image 1".
- **image** (Union[str, ndarray, Image, Tensor]) – Debug image to log. If numpy.ndarray or torch.Tensor, the image is assumed to be the following:
  - shape: CHW
  - color space: RGB
  - value range: [0., 1.] (float) or [0, 255] (uint8)
- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_metric(*title*, *series*, *value*, *step=None*)
Log metrics (numeric values) in TRAINS experiments. This method will be called by the users.

Parameters

- **title** (str) – The title of the graph to log, e.g. loss, accuracy.
- **series** (str) – The series name in the graph, e.g. classification, localization.
- **value** (float) – The value to log.
- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_metrics(*metrics*, *step=None*)
Log metrics (numeric values) in TRAINS experiments. This method will be called by Trainer.

Parameters

- **metrics** (Dict[str, float]) – The dictionary of the metrics. If the key contains "/", it will be split by the delimiter, then the elements will be logged as "title" and "series" respectively.
- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_text(*text*)
Log console text data in TRAINS experiment.

Parameters **text** (str) – The value of the log (data-point).

Return type None

classmethod set_bypass_mode(*bypass*)
Will bypass all outside communication, and will drop all logs. Should only be used in "standalone mode", when there is no access to the *trains-server*.

Parameters **bypass** (bool) – If True, all outside communication is skipped.

Return type None

classmethod set_credentials(*api_host=None*, *web_host=None*, *files_host=None*, *key=None*, *secret=None*)
Set new default TRAINS-server host and credentials. These configurations could be overridden by either OS environment variables or trains.conf configuration file.

Note: Credentials need to be set *prior* to Logger initialization.

Parameters

- **api_host** (Optional[str]) – Trains API server url, example: host='http://localhost:8008'
- **web_host** (Optional[str]) – Trains WEB server url, example: host='http://localhost:8080'
- **files_host** (Optional[str]) – Trains Files server url, example: host='http://localhost:8081'
- **key** (Optional[str]) – user key/secret pair, example: key='thisisakey123'
- **secret** (Optional[str]) – user key/secret pair, example: secret='thisisseceret123'

Return type None

_bypass = None

property experiment
Actual TRAINS object. To use TRAINS features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_trains_function()
```

Return type Task

property id
ID is a uuid (string) representing this specific experiment in the entire system.

Return type Optional[str]

property name
Name is a human readable non-unique name (str) of the experiment.

Return type Optional[str]

property version
Return the experiment version.

Return type Optional[str]

34.3.4 Submodules

pytorch_lightning.loggers.base module

class pytorch_lightning.loggers.base.**DummyExperiment**
Bases: object

Dummy experiment

nop(***kw*)

class pytorch_lightning.loggers.base.**DummyLogger**
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Dummy logger for internal use. Is usefull if we want to disable users logger for a feature, but still secure that users code can run

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** – Namespace containing the hyperparameters

log_metrics(*metrics*, *step*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** – Dictionary with metric names as keys and measured quantities as values
- **step** – Step number at which the metrics should be recorded

property experiment
Return the experiment object associated with this logger.

property name
Return the experiment name.

property version
Return the experiment version.

class pytorch_lightning.loggers.base.**LightningLoggerBase**(*agg_key_funcs=None*, *agg_default_func=numpy.mean*)
Bases: abc.ABC

Base class for experiment loggers.

Parameters

- **agg_key_funcs** (Optional[Mapping[str, Callable[[Sequence[float]], float]]]) – Dictionary which maps a metric name to a function, which will aggregate the metric values for the same steps.
- **agg_default_func** (Callable[[Sequence[float]], float]) – Default function to aggregate metric values. If some metric name is not presented in the *agg_key_funcs* dictionary, then the *agg_default_func* will be used for aggregation.

Note: The *agg_key_funcs* and *agg_default_func* arguments are used only when one logs metrics with the *agg_and_log_metrics()* method.

_aggregate_metrics(*metrics*, *step=None*)
Aggregates metrics.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type Tuple[int, Optional[Dict[str, float]]]

Returns Step and aggregated metrics. The return value could be None. In such case, metrics are added to the aggregation list, but not aggregated yet.

static _convert_params(*params*)

Return type Dict[str, Any]

_finalize_agg_metrics()
This shall be called before save/close.

static _flatten_dict(*params*, *delimiter='/'*)
Flatten hierarchical dict, e.g. {'a': {'b': 'c'}} -> {'a/b': 'c'}.

Parameters

- **params** (Dict[str, Any]) – Dictionary containing the hyperparameters
- **delimiter** (str) – Delimiter to express the hierarchy. Defaults to '/'.

Return type Dict[str, Any]

Returns Flattened dict.

Examples

```
>>> LightningLoggerBase._flatten_dict({'a': {'b': 'c'}})
{'a/b': 'c'}
>>> LightningLoggerBase._flatten_dict({'a': {'b': 123}})
{'a/b': 123}
```

_reduce_agg_metrics()
Aggregate accumulated metrics.

static _sanitize_params(*params*)
Returns params with non-primitvies converted to strings for logging.

```
>>> params = {"float": 0.3,
...           "int": 1,
...           "string": "abc",
...           "bool": True,
...           "list": [1, 2, 3],
...           "namespace": Namespace(foo=3),
...           "layer": torch.nn.BatchNorm1d}
>>> import pprint
>>> pprint.pprint(LightningLoggerBase._sanitize_params(params))
{'bool': True,
 'float': 0.3,
 'int': 1,
 'layer': "<class 'torch.nn.modules.batchnorm.BatchNorm1d'>",
 'list': '[1, 2, 3]',
 'namespace': 'Namespace(foo=3)',
 'string': 'abc'}
```

Return type Dict[str, Any]

agg_and_log_metrics(*metrics*, *step=None*)
Aggregates and records metrics. This method doesn't log the passed metrics instantaneously, but instead it aggregates them and logs only if metrics are ready to be logged.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

abstract log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Namespace) – Namespace containing the hyperparameters

abstract log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

save()
Save log data.

Return type None

update_agg_funcs(*agg_key_funcs=None*, *agg_default_func=numpy.mean*)
Update aggregation methods.

Parameters

- **agg_key_funcs** (Optional[Mapping[str, Callable[[Sequence[float]], float]]]) – Dictionary which maps a metric name to a function, which will aggregate the metric values for the same steps.
- **agg_default_func** (Callable[[Sequence[float]], float]) – Default function to aggregate metric values. If some metric name is not presented in the *agg_key_funcs* dictionary, then the *agg_default_func* will be used for aggregation.

abstract property experiment
Return the experiment object associated with this logger.

Return type Any

abstract property name
Return the experiment name.

Return type str

abstract property version
Return the experiment version.

Return type Union[int, str]

class pytorch_lightning.loggers.base.**LoggerCollection**(*logger_iterable*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

The *LoggerCollection* class is used to iterate all logging actions over the given *logger_iterable*.

Parameters **logger_iterable** (Iterable[*LightningLoggerBase*]) – An iterable collection of loggers

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()
Save log data.

Return type None

property experiment
Return the experiment object associated with this logger.

Return type List[Any]

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

pytorch_lightning.loggers.base.**merge_dicts**(*dicts*, *agg_key_funcs=None*, *default_func=numpy.mean*)
Merge a sequence with dictionaries into one dictionary by aggregating the same keys with some given function.

Parameters

- **dicts** (Sequence[Mapping]) – Sequence of dictionaries to be merged.
- **agg_key_funcs** (Optional[Mapping[str, Callable[[Sequence[float]], float]]]) – Mapping from key name to function. This function will aggregate a list of values, obtained from the same key of all dictionaries. If some key has no specified aggregation function, the default one will be used. Default is: None (all keys will be aggregated by the default function).
- **default_func** (Callable[[Sequence[float]], float]) – Default function to aggregate keys, which are not presented in the *agg_key_funcs* map.

Return type Dict

Returns Dictionary with merged values.

Examples

```
>>> import pprint
>>> d1 = {'a': 1.7, 'b': 2.0, 'c': 1, 'd': {'d1': 1, 'd3': 3}}
>>> d2 = {'a': 1.1, 'b': 2.2, 'v': 1, 'd': {'d1': 2, 'd2': 3}}
>>> d3 = {'a': 1.1, 'v': 2.3, 'd': {'d3': 3, 'd4': {'d5': 1}}}
>>> dflt_func = min
>>> agg_funcs = {'a': np.mean, 'v': max, 'd': {'d1': sum}}
>>> pprint.pprint(merge_dicts([d1, d2, d3], agg_funcs, dflt_func))
{'a': 1.3,
 'b': 2.0,
 'c': 1,
 'd': {'d1': 3, 'd2': 3, 'd3': 3, 'd4': {'d5': 1}},
 'v': 2.3}
```

pytorch_lightning.loggers.comet module

Comet

class pytorch_lightning.loggers.comet.**CometLogger**(*api_key=None*, *save_dir=None*, *workspace=None*, *project_name=None*, *rest_api_key=None*, *experiment_name=None*, *experiment_key=None*, ***kwargs*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Comet.ml. Install it with pip:

```
pip install comet-ml
```

Comet requires either an API Key (online mode) or a local directory path (offline mode).

ONLINE MODE

Example

```
>>> import os
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import CometLogger
>>> # arguments made to CometLogger are passed on to the comet_ml.Experiment class
>>> comet_logger = CometLogger(
...     api_key=os.environ.get('COMET_API_KEY'),
...     workspace=os.environ.get('COMET_WORKSPACE'),  # Optional
...     save_dir='.',  # Optional
...     project_name='default_project',  # Optional
...     rest_api_key=os.environ.get('COMET_REST_API_KEY'),  # Optional
...     experiment_name='default'  # Optional
... )
>>> trainer = Trainer(logger=comet_logger)
```

OFFLINE MODE

Example

```
>>> from pytorch_lightning.loggers import CometLogger
>>> # arguments made to CometLogger are passed on to the comet_ml.Experiment class
>>> comet_logger = CometLogger(
...     save_dir='.',
...     workspace=os.environ.get('COMET_WORKSPACE'),  # Optional
...     project_name='default_project',  # Optional
...     rest_api_key=os.environ.get('COMET_REST_API_KEY'),  # Optional
...     experiment_name='default'  # Optional
... )
>>> trainer = Trainer(logger=comet_logger)
```

Parameters

- **api_key** (Optional[str]) – Required in online mode. API key, found on Comet.ml
- **save_dir** (Optional[str]) – Required in offline mode. The path for the directory to save local comet logs
- **workspace** (Optional[str]) – Optional. Name of workspace for this user
- **project_name** (Optional[str]) – Optional. Send your experiment to a specific project. Otherwise will be sent to Uncategorized Experiments. If the project name does not already exist, Comet.ml will create a new project.
- **rest_api_key** (Optional[str]) – Optional. Rest API key found in Comet.ml settings. This is used to determine version number
- **experiment_name** (Optional[str]) – Optional. String representing the name for this particular experiment on Comet.ml.
- **experiment_key** (Optional[str]) – Optional. If set, restores from existing experiment.

finalize(*status*)
When calling `self.experiment.end()`, that experiment won't log any more data to Comet. That's why, if you need to log any more data, you need to create an ExistingCometExperiment. For example, to log data when testing your model after training, because when training is finalized *CometLogger.finalize()* is called.

This happens automatically in the *experiment()* property, when `self._experiment` is set to `None`, i.e. `self.reset_experiment()`.

Return type `None`

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (`Union[Dict[str, Any], Namespace]`) – `Namespace` containing the hyperparameters

Return type `None`

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (`Dict[str, Union[Tensor, float]]`) – Dictionary with metric names as keys and measured quantities as values
- **step** (`Optional[int]`) – Step number at which the metrics should be recorded

Return type `None`

reset_experiment()

property experiment
Actual Comet object. To use Comet features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_comet_function()
```

Return type `BaseExperiment`

property name
Return the experiment name.

Return type `str`

property version
Return the experiment version.

Return type `str`

pytorch_lightning.loggers.mlflow module

MLflow

class pytorch_lightning.loggers.mlflow.**MLFlowLogger**(*experiment_name='default'*, *tracking_uri=None*, *tags=None*, *save_dir=None*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using MLflow. Install it with pip:

```
pip install mlflow
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import MLFlowLogger
>>> mlf_logger = MLFlowLogger(
...     experiment_name="default",
...     tracking_uri="file:./ml-runs"
... )
>>> trainer = Trainer(logger=mlf_logger)
```

Use the logger anywhere in you *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_ml_flow_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.whatever_ml_flow_supports(...)
```

Parameters

- **experiment_name** (str) – The name of the experiment
- **tracking_uri** (Optional[str]) – Address of local or remote tracking server. If not provided, defaults to the service set by mlflow.tracking.set_tracking_uri.
- **tags** (Optional[Dict[str, Any]]) – A dictionary tags for the experiment.

finalize(*status='FINISHED'*)

Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*)

Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

property experiment
Actual MLflow object. To use mlflow features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_mlflow_function()
```

Return type MlflowClient

property name
Return the experiment name.

Return type str

property run_id

property version
Return the experiment version.

Return type str

pytorch_lightning.loggers.neptune module

Neptune

class pytorch_lightning.loggers.neptune.**NeptuneLogger**(*api_key=None*, *project_name=None*, *close_after_fit=True*, *offline_mode=False*, *experiment_name=None*, *upload_source_files=None*, *params=None*, *properties=None*, *tags=None*, ***kwargs*)
Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Neptune. Install it with pip:

```
pip install neptune-client
```

The Neptune logger can be used in the online mode or offline (silent) mode. To log experiment data in online mode, *NeptuneLogger* requires an API key. In offline mode, the logger does not connect to Neptune.

ONLINE MODE

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import NeptuneLogger
>>> # arguments made to NeptuneLogger are passed on to the neptune.experiments.
↪Experiment class
>>> # We are using an api_key for the anonymous user "neptuner" but you can use␣
↪your own.
>>> neptune_logger = NeptuneLogger(
...     api_key='ANONYMOUS',
...     project_name='shared/pytorch-lightning-integration',
...     experiment_name='default',  # Optional,
...     params={'max_epochs': 10},  # Optional,
...     tags=['pytorch-lightning', 'mlp']  # Optional,
... )
>>> trainer = Trainer(max_epochs=10, logger=neptune_logger)
```

OFFLINE MODE

Example

```
>>> from pytorch_lightning.loggers import NeptuneLogger
>>> # arguments made to NeptuneLogger are passed on to the neptune.experiments.
↪Experiment class
>>> neptune_logger = NeptuneLogger(
...     offline_mode=True,
...     project_name='USER_NAME/PROJECT_NAME',
...     experiment_name='default',  # Optional,
...     params={'max_epochs': 10},  # Optional,
...     tags=['pytorch-lightning', 'mlp']  # Optional,
... )
>>> trainer = Trainer(max_epochs=10, logger=neptune_logger)
```

Use the logger anywhere in you *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # log metrics
...         self.logger.experiment.log_metric('acc_train', ...)
...         # log images
...         self.logger.experiment.log_image('worse_predictions', ...)
...         # log model checkpoint
...         self.logger.experiment.log_artifact('model_checkpoint.pt', ...)
...         self.logger.experiment.whatever_neptune_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.log_metric('acc_train', ...)
...         self.logger.experiment.log_image('worse_predictions', ...)
...         self.logger.experiment.log_artifact('model_checkpoint.pt', ...)
...         self.logger.experiment.whatever_neptune_supports(...)
```

If you want to log objects after the training is finished use `close_after_fit=False`:

```
neptune_logger = NeptuneLogger(
    ...
```

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```
    close_after_fit=False,
    ...
)
trainer = Trainer(logger=neptune_logger)
trainer.fit()

# Log test metrics
trainer.test(model)

# Log additional metrics
from sklearn.metrics import accuracy_score

accuracy = accuracy_score(y_true, y_pred)
neptune_logger.experiment.log_metric('test_accuracy', accuracy)

# Log charts
from scikitplot.metrics import plot_confusion_matrix
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(16, 12))
plot_confusion_matrix(y_true, y_pred, ax=ax)
neptune_logger.experiment.log_image('confusion_matrix', fig)

# Save checkpoints folder
neptune_logger.experiment.log_artifact('my/checkpoints')

# When you are done, stop the experiment
neptune_logger.experiment.stop()
```

See also:

- An Example experiment showing the UI of Neptune.
- Tutorial on how to use Pytorch Lightning with Neptune.

Parameters

- **api_key** (Optional[str]) – Required in online mode. Neptune API token, found on https://neptune.ai. Read how to get your API key. It is recommended to keep it in the *NEPTUNE_API_TOKEN* environment variable and then you can leave `api_key=None`.
- **project_name** (Optional[str]) – Required in online mode. Qualified name of a project in a form of "namespace/project_name" for example "tom/minst-classification". If `None`, the value of *NEPTUNE_PROJECT* environment variable will be taken. You need to create the project in https://neptune.ai first.
- **offline_mode** (bool) – Optional default `False`. If `True` no logs will be sent to Neptune. Usually used for debug purposes.
- **close_after_fit** (Optional[bool]) – Optional default `True`. If `False` the experiment will not be closed after training and additional metrics, images or artifacts can be logged. Also, remember to close the experiment explicitly by running `neptune_logger.experiment.stop()`.
- **experiment_name** (Optional[str]) – Optional. Editable name of the experiment. Name is displayed in the experiment's Details (Metadata section) and in experiments view as a column.

- **upload_source_files** (Optional[List[str]]) – Optional. List of source files to be uploaded. Must be list of str or single str. Uploaded sources are displayed in the experiment's Source code tab. If None is passed, the Python file from which the experiment was created will be uploaded. Pass an empty list ([]) to upload no files. Unix style pathname pattern expansion is supported. For example, you can pass '*.py' to upload all python source files from the current directory. For recursion lookup use '**/*.py' (for Python 3.5 and later). For more information see glob library.
- **params** (Optional[Dict[str, Any]]) – Optional. Parameters of the experiment. After experiment creation params are read-only. Parameters are displayed in the experiment's Parameters section and each key-value pair can be viewed in the experiments view as a column.
- **properties** (Optional[Dict[str, Any]]) – Optional. Default is {}. Properties of the experiment. They are editable after the experiment is created. Properties are displayed in the experiment's Details section and each key-value pair can be viewed in the experiments view as a column.
- **tags** (Optional[List[str]]) – Optional. Default is []. Must be list of str. Tags of the experiment. They are editable after the experiment is created (see: append_tag() and remove_tag()). Tags are displayed in the experiment's Details section and can be viewed in the experiments view as a column.

_create_or_get_experiment()

append_tags(*tags*)
Appends tags to the neptune experiment.

Parameters **tags** (Union[str, Iterable[str]]) – Tags to add to the current experiment. If str is passed, a single tag is added. If multiple - comma separated - str are passed, all of them are added as tags. If list of str is passed, all elements of the list are added as tags.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_artifact(*artifact*, *destination=None*)
Save an artifact (file) in Neptune experiment storage.

Parameters

- **artifact** (str) – A path to the file in local filesystem.
- **destination** (Optional[str]) – Optional. Default is None. A destination path. If None is passed, an artifact file name will be used.

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_image(*log_name*, *image*, *step=None*)
Log image data in Neptune experiment

Parameters

- **log_name** (str) – The name of log, i.e. bboxes, visualisations, sample_images.
- **image** (Union[str, Image, Any]) – The value of the log (data-point). Can be one of the following types: PIL image, *matplotlib.figure.Figure*, path to image file (str)
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_metric(*metric_name*, *metric_value*, *step=None*)
Log metrics (numeric values) in Neptune experiments.

Parameters

- **metric_name** (str) – The name of log, i.e. mse, loss, accuracy.
- **metric_value** (Union[Tensor, float, str]) – The value of the log (data-point).
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_metrics(*metrics*, *step=None*)
Log metrics (numeric values) in Neptune experiments.

Parameters

- **metrics** (Dict[str, Union[Tensor, float]]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

log_text(*log_name*, *text*, *step=None*)
Log text data in Neptune experiments.

Parameters

- **log_name** (str) – The name of log, i.e. mse, my_text_data, timing_info.
- **text** (str) – The value of the log (data-point).
- **step** (Optional[int]) – Step number at which the metrics should be recorded, must be strictly increasing

Return type None

set_property(*key*, *value*)
Set key-value pair as Neptune experiment property.

Parameters

- **key** (str) – Property key.
- **value** (Any) – New value of a property.

Return type None

property experiment
Actual Neptune object. To use neptune features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_neptune_function()
```

Return type Experiment

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

pytorch_lightning.loggers.tensorboard module

TensorBoard

class pytorch_lightning.loggers.tensorboard.**TensorBoardLogger**(*save_dir*, *name='default'*, *version=None*, ***kwargs*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log to local file system in TensorBoard format. Implemented using `SummaryWriter`. Logs are saved to `os.path.join(save_dir, name, version)`. This is the default logger in Lightning, it comes preinstalled.

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TensorBoardLogger
>>> logger = TensorBoardLogger("tb_logs", name="my_model")
>>> trainer = Trainer(logger=logger)
```

Parameters

- **save_dir** (str) – Save directory
- **name** (Optional[str]) – Experiment name. Defaults to `'default'`. If it is the empty string then no per-experiment subdirectory is used.
- **version** (Union[int, str, None]) – Experiment version. If version is not specified the logger inspects the save directory for existing versions, then automatically assigns the next available version. If it is a string then it is used as the run-specific subdirectory name, otherwise `'version_${version}'` is used.
- ****kwargs** – Other arguments are passed directly to the `SummaryWriter` constructor.

_get_next_version()

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*, *metrics=None*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()
Save log data.

Return type None

NAME_HPARAMS_FILE = 'hparams.yaml'

property experiment
Actual tensorboard object. To use TensorBoard features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_tensorboard_function()
```

Return type SummaryWriter

property log_dir
The directory for this run's tensorboard checkpoint. By default, it is named 'version_${self.version}' but it can be overridden by passing a string value for the constructor's version parameter instead of None or an int.

Return type str

property name
Return the experiment name.

Return type str

property root_dir
Parent directory for all tensorboard checkpoint subdirectories. If the experiment name parameter is None or the empty string, no experiment subdirectory is used and the checkpoint will be saved in "save_dir/version_dir"

Return type str

property version
Return the experiment version.

Return type int

pytorch_lightning.loggers.test_tube module

Test Tube

class pytorch_lightning.loggers.test_tube.**TestTubeLogger**(*save_dir*, *name='default'*, *description=None*, *debug=False*, *version=None*, *create_git_tag=False*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log to local file system in TensorBoard format but using a nicer folder structure (see full docs). Install it with pip:

```
pip install test_tube
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TestTubeLogger
>>> logger = TestTubeLogger("tt_logs", name="my_exp_name")
>>> trainer = Trainer(logger=logger)
```

Use the logger anywhere in your *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_method_summary_writer_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.add_histogram(...)
```

Parameters

- **save_dir** (str) – Save directory
- **name** (str) – Experiment name. Defaults to 'default'.
- **description** (Optional[str]) – A short snippet about this experiment
- **debug** (bool) – If True, it doesn't log anything.
- **version** (Optional[int]) – Experiment version. If version is not specified the logger inspects the save directory for existing versions, then automatically assigns the next available version.
- **create_git_tag** (bool) – If True creates a git tag to save the code used in this experiment.

close()
Do any cleanup that is necessary to close an experiment.

Return type None

finalize(*status*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (str) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

save()
Save log data.

Return type None

property experiment
Actual TestTube object. To use TestTube features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_test_tube_function()
```

Return type Experiment

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type int

pytorch_lightning.loggers.trains module

TRAINS

class pytorch_lightning.loggers.trains.**TrainsLogger**(*project_name=None*, *task_name=None*, *task_type='training'*, *reuse_last_task_id=True*, *output_uri=None*, *auto_connect_arg_parser=True*, *auto_connect_frameworks=True*, *auto_resource_monitoring=True*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using allegro.ai TRAINS. Install it with pip:

```
pip install trains
```

Example

```
>>> from pytorch_lightning import Trainer
>>> from pytorch_lightning.loggers import TrainsLogger
>>> trains_logger = TrainsLogger(
...     project_name='pytorch lightning',
...     task_name='default',
...     output_uri='.',
... )
TRAINS Task: ...
TRAINS results page: ...
>>> trainer = Trainer(logger=trains_logger)
```

Use the logger anywhere in your *LightningModule* as follows:

```
>>> from pytorch_lightning import LightningModule
>>> class LitModel(LightningModule):
...     def training_step(self, batch, batch_idx):
...         # example
...         self.logger.experiment.whatever_trains_supports(...)
...
...     def any_lightning_module_function_or_hook(self):
...         self.logger.experiment.whatever_trains_supports(...)
```

Parameters

- **project_name** (Optional[str]) – The name of the experiment's project. Defaults to None.
- **task_name** (Optional[str]) – The name of the experiment. Defaults to None.
- **task_type** (str) – The name of the experiment. Defaults to 'training'.
- **reuse_last_task_id** (bool) – Start with the previously used task id. Defaults to True.
- **output_uri** (Optional[str]) – Default location for output models. Defaults to None.

- **auto_connect_arg_parser** (bool) – Automatically grab the ArgumentParser and connect it with the task. Defaults to True.
- **auto_connect_frameworks** (bool) – If True, automatically patch to trains backend. Defaults to True.
- **auto_resource_monitoring** (bool) – If True, machine vitals will be sent along side the task scalars. Defaults to True.

Examples

```
>>> logger = TrainsLogger("pytorch lightning", "default", output_uri=".")
TRAINS Task: ...
TRAINS results page: ...
>>> logger.log_metrics({"val_loss": 1.23}, step=0)
>>> logger.log_text("sample test")
sample test
>>> import numpy as np
>>> logger.log_artifact("confusion matrix", np.ones((2, 3)))
>>> logger.log_image("passed", "Image 1", np.random.randint(0, 255, (200, 150, 3),
↪ dtype=np.uint8))
```

classmethod bypass_mode()
Returns the bypass mode state.

Note: *GITHUB_ACTIONS* env will automatically set bypass_mode to True unless overridden specifically with TrainsLogger.set_bypass_mode(False).

Return type bool

Returns If True, all outside communication is skipped.

finalize(*status=None*)
Do any processing that is necessary to finalize an experiment.

Parameters **status** (Optional[str]) – Status that the experiment finished with (e.g. success, failed, aborted)

Return type None

log_artifact(*name*, *artifact*, *metadata=None*, *delete_after_upload=False*)
Save an artifact (file/object) in TRAINS experiment storage.

Parameters

- **name** (str) – Artifact name. Notice! it will override the previous artifact if the name already exists.
- **artifact** (Union[str, Path, Dict[str, Any], ndarray, Image]) – Artifact object to upload. Currently supports:
  - string / pathlib.Path are treated as path to artifact file to upload If a wildcard or a folder is passed, a zip file containing the local files will be created and uploaded.
  - dict will be stored as .json file and uploaded
  - pandas.DataFrame will be stored as .csv.gz (compressed CSV file) and uploaded
  - numpy.ndarray will be stored as .npz and uploaded

– PIL.Image.Image will be stored to .png file and uploaded

- **metadata** (Optional[Dict[str, Any]]) – Simple key/value dictionary to store on the artifact. Defaults to None.
- **delete_after_upload** (bool) – If True, the local artifact will be deleted (only applies if artifact is a local file). Defaults to False.

Return type None

log_hyperparams(*params*)
Log hyperparameters (numeric values) in TRAINS experiments.

Parameters **params** (Union[Dict[str, Any], Namespace]) – The hyperparameters that passed through the model.

Return type None

log_image(*title*, *series*, *image*, *step=None*)
Log Debug image in TRAINS experiment

Parameters

- **title** (str) – The title of the debug image, i.e. “failed”, “passed”.
- **series** (str) – The series name of the debug image, i.e. “Image 0”, “Image 1”.
- **image** (Union[str, ndarray, Image, Tensor]) – Debug image to log. If numpy.ndarray or torch.Tensor, the image is assumed to be the following:
  - shape: CHW
  - color space: RGB
  - value range: [0., 1.] (float) or [0, 255] (uint8)
- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_metric(*title*, *series*, *value*, *step=None*)
Log metrics (numeric values) in TRAINS experiments. This method will be called by the users.

Parameters

- **title** (str) – The title of the graph to log, e.g. loss, accuracy.
- **series** (str) – The series name in the graph, e.g. classification, localization.
- **value** (float) – The value to log.
- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_metrics(*metrics*, *step=None*)
Log metrics (numeric values) in TRAINS experiments. This method will be called by Trainer.

Parameters

- **metrics** (Dict[str, float]) – The dictionary of the metrics. If the key contains “/”, it will be split by the delimiter, then the elements will be logged as “title” and “series” respectively.

- **step** (Optional[int]) – Step number at which the metrics should be recorded. Defaults to None.

Return type None

log_text(*text*)
Log console text data in TRAINS experiment.

Parameters **text** (str) – The value of the log (data-point).

Return type None

classmethod set_bypass_mode(*bypass*)
Will bypass all outside communication, and will drop all logs. Should only be used in "standalone mode", when there is no access to the *trains-server*.

Parameters **bypass** (bool) – If True, all outside communication is skipped.

Return type None

classmethod set_credentials(*api_host=None*, *web_host=None*, *files_host=None*, *key=None*, *secret=None*)
Set new default TRAINS-server host and credentials. These configurations could be overridden by either OS environment variables or trains.conf configuration file.

Note: Credentials need to be set *prior* to Logger initialization.

Parameters

- **api_host** (Optional[str]) – Trains API server url, example: host='http://localhost:8008'
- **web_host** (Optional[str]) – Trains WEB server url, example: host='http://localhost:8080'
- **files_host** (Optional[str]) – Trains Files server url, example: host='http://localhost:8081'
- **key** (Optional[str]) – user key/secret pair, example: key='thisisakey123'
- **secret** (Optional[str]) – user key/secret pair, example: secret='thisisseceret123'

Return type None

_bypass = None

property experiment
Actual TRAINS object. To use TRAINS features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_trains_function()
```

Return type Task

property id
ID is a uuid (string) representing this specific experiment in the entire system.

Return type Optional[str]

property name
Name is a human readable non-unique name (str) of the experiment.

Return type Optional[str]

property version
Return the experiment version.

Return type Optional[str]

pytorch_lightning.loggers.wandb module

Weights and Biases

class pytorch_lightning.loggers.wandb.**WandbLogger**(*name=None*, *save_dir=None*, *offline=False*, *id=None*, *anonymous=False*, *version=None*, *project=None*, *tags=None*, *log_model=False*, *experiment=None*, *entity=None*, *group=None*)

Bases: *pytorch_lightning.loggers.base.LightningLoggerBase*

Log using Weights and Biases. Install it with pip:

```
pip install wandb
```

Parameters

- **name** (Optional[str]) – Display name for the run.
- **save_dir** (Optional[str]) – Path where data is saved.
- **offline** (bool) – Run offline (data can be streamed later to wandb servers).
- **id** (Optional[str]) – Sets the version, mainly used to resume a previous run.
- **anonymous** (bool) – Enables or explicitly disables anonymous logging.
- **version** (Optional[str]) – Sets the version, mainly used to resume a previous run.
- **project** (Optional[str]) – The name of the project to which this run will belong.
- **tags** (Optional[List[str]]) – Tags associated with this run.
- **log_model** (bool) – Save checkpoints in wandb dir to upload on W&B servers.
- **experiment** – WandB experiment object
- **entity** – The team posting this run (default: your username or your default team)
- **group** (Optional[str]) – A unique string shared by all runs in a given group

Example

```
>>> from pytorch_lightning.loggers import WandbLogger
>>> from pytorch_lightning import Trainer
>>> wandb_logger = WandbLogger()
>>> trainer = Trainer(logger=wandb_logger)
```

See also:

- Tutorial on how to use W&B with Pytorch Lightning.

log_hyperparams(*params*)
Record hyperparameters.

Parameters **params** (Union[Dict[str, Any], Namespace]) – Namespace containing the hyperparameters

Return type None

log_metrics(*metrics*, *step=None*)
Records metrics. This method logs metrics as as soon as it received them. If you want to aggregate metrics for one specific *step*, use the *agg_and_log_metrics()* method.

Parameters

- **metrics** (Dict[str, float]) – Dictionary with metric names as keys and measured quantities as values
- **step** (Optional[int]) – Step number at which the metrics should be recorded

Return type None

watch(*model*, *log='gradients'*, *log_freq=100*)

property experiment
Actual wandb object. To use wandb features in your *LightningModule* do the following.

Example:

```
self.logger.experiment.some_wandb_function()
```

Return type Run

property name
Return the experiment name.

Return type str

property version
Return the experiment version.

Return type str

34.4 pytorch_lightning.overrides package

34.4.1 Submodules

pytorch_lightning.overrides.data_parallel module

class pytorch_lightning.overrides.data_parallel.**LightningDataParallel**(**args*, ***kwargs*)

Bases: torch.nn.DataParallel

Override the forward call in lightning so it goes to training and validation step respectively

forward(**inputs*, ***kwargs*)

parallel_apply(*replicas*, *inputs*, *kwargs*)

class pytorch_lightning.overrides.data_parallel.**LightningDistributedDataParallel**(**args*, ***kwargs*)

Bases: torch.nn.parallel.DistributedDataParallel

Override the forward call in lightning so it goes to training and validation step respectively

forward(**inputs*, ***kwargs*)

parallel_apply(*replicas*, *inputs*, *kwargs*)

pytorch_lightning.overrides.data_parallel.**_find_tensors**(*obj*)
Recursively find all tensors contained in the specified object.

pytorch_lightning.overrides.data_parallel.**auto_squeeze_dim_zeros**(*output*)
In DP or DDP2 we need to unsqueeze dim 0 :param _sphinx_paramlinks_pytorch_lightning.overrides.data_parallel.auto_squeeze_
:return:

pytorch_lightning.overrides.data_parallel.**get_a_var**(*obj*)

pytorch_lightning.overrides.data_parallel.**parallel_apply**(*modules*, *inputs*, *kwargs_tup=None*, *devices=None*)

Applies each *module* in `modules` in parallel on arguments contained in `inputs` (positional) and `kwargs_tup` (keyword) on each of `devices`.

Parameters

- **modules** (*Module*) – modules to be parallelized
- **inputs** (*tensor*) – inputs to the modules
- **devices** (*list of int or torch.device*) – CUDA devices

`modules`, `inputs`, `kwargs_tup` (if given), and `devices` (if given) should all have same length. Moreover, each element of `inputs` can either be a single object as the only argument to a module, or a collection of positional arguments.

pytorch_lightning.overrides.override_data_parallel module

Warning: *override_data_parallel* module has been renamed to *data_parallel* since v0.6.0. The deprecated module name will be removed in v0.8.0.

34.5 pytorch_lightning.profiler package

Profiling your training run can help you understand if there are any bottlenecks in your code.

34.5.1 Built-in checks

PyTorch Lightning supports profiling standard actions in the training loop out of the box, including:

- on_epoch_start
- on_epoch_end
- on_batch_start
- tbptt_split_batch
- model_forward
- model_backward
- on_after_backward
- optimizer_step
- on_batch_end
- training_step_end
- on_training_end

34.5.2 Enable simple profiling

If you only wish to profile the standard actions, you can set *profiler=True* when constructing your *Trainer* object.

```
trainer = Trainer(..., profiler=True)
```

The profiler's results will be printed at the completion of a training *fit()*.

```
Profiler Report

Action                  |  Mean duration (s)    |  Total time (s)
-----------------------------------------------------------------
on_epoch_start          |  5.993e-06            |  5.993e-06
get_train_batch         |  0.0087412            |  16.398
on_batch_start          |  5.0865e-06           |  0.0095372
model_forward           |  0.0017818            |  3.3408
model_backward          |  0.0018283            |  3.4282
on_after_backward       |  4.2862e-06           |  0.0080366
optimizer_step          |  0.0011072            |  2.0759
on_batch_end            |  4.5202e-06           |  0.0084753
```

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```
on_epoch_end            |  3.919e-06            |  3.919e-06
on_train_end            |  5.449e-06            |  5.449e-06
```

34.5.3 Advanced Profiling

If you want more information on the functions called during each event, you can use the *AdvancedProfiler*. This option uses Python's cProfiler to provide a report of time spent on *each* function called within your code.

```
profiler = AdvancedProfiler()
trainer = Trainer(..., profiler=profiler)
```

The profiler's results will be printed at the completion of a training *fit()*. This profiler report can be quite long, so you can also specify an *output_filename* to save the report instead of logging it to the output in your terminal. The output below shows the profiling for the action *get_train_batch*.

```
Profiler Report

Profile stats for: get_train_batch
        4869394 function calls (4863767 primitive calls) in 18.893 seconds
Ordered by: cumulative time
List reduced from 76 to 10 due to restriction <10>
ncalls  tottime  percall  cumtime  percall filename:lineno(function)
3752/1876    0.011    0.000   18.887    0.010 {built-in method builtins.next}
    1876     0.008    0.000   18.877    0.010 dataloader.py:344(__next__)
    1876     0.074    0.000   18.869    0.010 dataloader.py:383(_next_data)
    1875     0.012    0.000   18.721    0.010 fetch.py:42(fetch)
    1875     0.084    0.000   18.290    0.010 fetch.py:44(<listcomp>)
    60000    1.759    0.000   18.206    0.000 mnist.py:80(__getitem__)
    60000    0.267    0.000   13.022    0.000 transforms.py:68(__call__)
    60000    0.182    0.000    7.020    0.000 transforms.py:93(__call__)
    60000    1.651    0.000    6.839    0.000 functional.py:42(to_tensor)
    60000    0.260    0.000    5.734    0.000 transforms.py:167(__call__)
```

You can also reference this profiler in your LightningModule to profile specific actions of interest. If you don't want to always have the profiler turned on, you can optionally pass a *PassThroughProfiler* which will allow you to skip profiling without having to make any code changes. Each profiler has a method *profile()* which returns a context handler. Simply pass in the name of your action that you want to track and the profiler will record performance for code executed within this context.

```
from pytorch_lightning.profiler import Profiler, PassThroughProfiler

class MyModel(LightningModule):
    def __init__(self, hparams, profiler=None):
        self.hparams = hparams
        self.profiler = profiler or PassThroughProfiler()

    def custom_processing_step(self, data):
        with profiler.profile('my_custom_action'):
            # custom processing step
        return data

profiler = Profiler()
model = MyModel(hparams, profiler)
trainer = Trainer(profiler=profiler, max_epochs=1)
```

class pytorch_lightning.profiler.**BaseProfiler**(*output_streams=None*)
Bases: abc.ABC

If you wish to write a custom profiler, you should inhereit from this class.

Params: stream_out: callable

describe()
Logs a profile report after the conclusion of the training run.

Return type None

profile(*action_name*)
Yields a context manager to encapsulate the scope of a profiled action.

Example:

```
with self.profile('load training data'):
    # load training data code
```

The profiler will start once you've entered the context and will automatically stop once you exit the code block.

Return type None

profile_iterable(*iterable*, *action_name*)

Return type None

abstract start(*action_name*)
Defines how to start recording an action.

Return type None

abstract stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

abstract summary()
Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.**SimpleProfiler**(*output_filename=None*)
Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This profiler simply records the duration of actions (in seconds) and reports the mean duration of each action and the total time spent over the entire training run.

Params:

output_filename (str): optionally save profile results to file instead of printing to std out when training is finished.

describe()
Logs a profile report after the conclusion of the training run.

start(*action_name*)
Defines how to start recording an action.

Return type None

stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

summary()
Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.**AdvancedProfiler**(*output_filename=None*, *line_count_restriction=1.0*)
Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This profiler uses Python's cProfiler to record more detailed information about time spent in each function call recorded during a given action. The output is quite verbose and you should only use this if you want very detailed reports.

Parameters

- **output_filename** (Optional[str]) – optionally save profile results to file instead of printing to std out when training is finished.
- **line_count_restriction** (float) – this can be used to limit the number of functions reported for each action. either an integer (to select a count of lines), or a decimal fraction between 0.0 and 1.0 inclusive (to select a percentage of lines)

describe()
Logs a profile report after the conclusion of the training run.

start(*action_name*)
Defines how to start recording an action.

Return type None

stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

summary()
Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.**PassThroughProfiler**
Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This class should be used when you don't want the (small) overhead of profiling. The Trainer uses this class by default.

Params: stream_out: callable

start(*action_name*)
Defines how to start recording an action.

Return type None

stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

summary()
Create profiler summary in text format.

Return type str

34.5.4 Submodules

pytorch_lightning.profiler.profilers module

class pytorch_lightning.profiler.profilers.**AdvancedProfiler**(*output_filename=None*, *line_count_restriction=1.0*)

Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This profiler uses Python's cProfiler to record more detailed information about time spent in each function call recorded during a given action. The output is quite verbose and you should only use this if you want very detailed reports.

Parameters

- **output_filename** (Optional[str]) – optionally save profile results to file instead of printing to std out when training is finished.
- **line_count_restriction** (float) – this can be used to limit the number of functions reported for each action. either an integer (to select a count of lines), or a decimal fraction between 0.0 and 1.0 inclusive (to select a percentage of lines)

describe()

Logs a profile report after the conclusion of the training run.

start(*action_name*)

Defines how to start recording an action.

Return type None

stop(*action_name*)

Defines how to record the duration once an action is complete.

Return type None

summary()

Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.profilers.**BaseProfiler**(*output_streams=None*)

Bases: abc.ABC

If you wish to write a custom profiler, you should inhereit from this class.

Params: stream_out: callable

describe()

Logs a profile report after the conclusion of the training run.

Return type None

profile(*action_name*)

Yields a context manager to encapsulate the scope of a profiled action.

Example:

```
with self.profile('load training data'):
    # load training data code
```

The profiler will start once you've entered the context and will automatically stop once you exit the code block.

Return type None

profile_iterable(*iterable*, *action_name*)

Return type None

abstract start(*action_name*)
Defines how to start recording an action.

Return type None

abstract stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

abstract summary()
Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.profilers.**PassThroughProfiler**
Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This class should be used when you don't want the (small) overhead of profiling. The Trainer uses this class by default.

Params: stream_out: callable

start(*action_name*)
Defines how to start recording an action.

Return type None

stop(*action_name*)
Defines how to record the duration once an action is complete.

Return type None

summary()
Create profiler summary in text format.

Return type str

class pytorch_lightning.profiler.profilers.**SimpleProfiler**(*output_filename=None*)
Bases: *pytorch_lightning.profiler.profilers.BaseProfiler*

This profiler simply records the duration of actions (in seconds) and reports the mean duration of each action and the total time spent over the entire training run.

Params:

output_filename (str): optionally save profile results to file instead of printing to std out when training is finished.

describe()
Logs a profile report after the conclusion of the training run.

start(*action_name*)
Defines how to start recording an action.

Return type None

stop(*action_name*)
Defines how to record the duration once an action is complete.

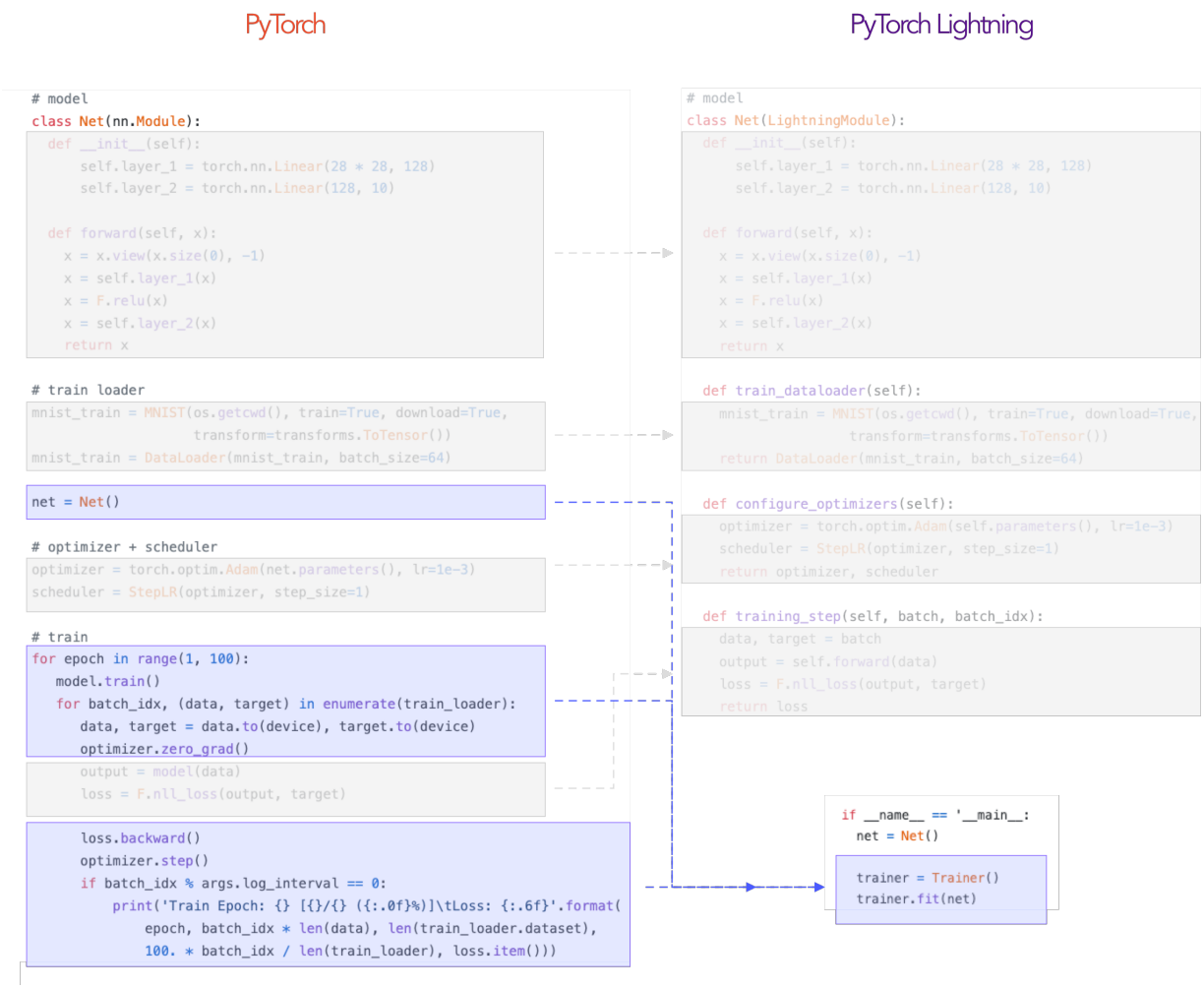
Return type None

summary()
Create profiler summary in text format.

Return type str

34.6 pytorch_lightning.trainer package

Once you've organized your PyTorch code into a LightningModule, the Trainer automates everything else.



This abstraction achieves the following:

1. You maintain control over all aspects via PyTorch code without an added abstraction.
2. The trainer uses best practices embedded by contributors and users from top AI labs such as Facebook AI Research, NYU, MIT, Stanford, etc...
3. The trainer allows overriding any key part that you don't want automated.

34.6.1 Basic use

This is the basic use of the trainer:

```
from pytorch_lightning import Trainer

model = MyLightningModule()

trainer = Trainer()
trainer.fit(model)
```

34.6.2 Best Practices

For cluster computing, it's recommended you structure your main.py file this way

```
from argparse import ArgumentParser

def main(hparams):
    model = LightningModule()
    trainer = Trainer(gpus=hparams.gpus)
    trainer.fit(model)

if __name__ == '__main__':
    parser = ArgumentParser()
    parser.add_argument('--gpus', default=None)
    args = parser.parse_args()

    main(args)
```

So you can run it like so:distributed_backend

```
python main.py --gpus 2
```

Note: If you want to stop a training run early, you can press "Ctrl + C" on your keyboard. The trainer will catch the *KeyboardInterrupt* and attempt a graceful shutdown, including running callbacks such as *on_train_end*. The trainer object will also set an attribute *interrupted* to *True* in such cases. If you have a callback which shuts down compute resources, for example, you can conditionally run the shutdown logic for only uninterrupted runs.

34.6.3 Testing

Once you're done training, feel free to run the test set! (Only right before publishing your paper or pushing to production)

```
trainer.test()
```

34.6.4 Deployment / prediction

You just trained a LightningModule which is also just a torch.nn.Module. Use it to do whatever!

```
# load model
pretrained_model = LightningModule.load_from_checkpoint(PATH)
pretrained_model.freeze()

# use it for finetuning
def forward(self, x):
    features = pretrained_model(x)
    classes = classifier(features)

# or for prediction
out = pretrained_model(x)
api_write({'response': out}
```

34.6.5 Reproducibility

To ensure full reproducibility from run to run you need to set seeds for pseudo-random generators, and set `deterministic` flag in `Trainer`.

```
from pytorch-lightning import Trainer, seed_everything

seed_everything(42)
# sets seeds for numpy, torch, python.random and PYTHONHASHSEED.
model = Model()
trainer = Trainer(deterministic=True)
```

34.6.6 Trainer flags

accumulate_grad_batches

Accumulates grads every k batches or as set up in the dict.

```
# default used by the Trainer (no accumulation)
trainer = Trainer(accumulate_grad_batches=1)
```

Example:

```
# accumulate every 4 batches (effective batch size is batch*4)
trainer = Trainer(accumulate_grad_batches=4)

# no accumulation for epochs 1-4. accumulate 3 for epochs 5-10. accumulate 20 after␣
↪that
trainer = Trainer(accumulate_grad_batches={5: 3, 10: 20})
```

amp_level

The optimization level to use (O1, O2, etc...) for 16-bit GPU precision (using NVIDIA apex under the hood).

Check NVIDIA apex docs for level

Example:

```
# default used by the Trainer
trainer = Trainer(amp_level='O1')
```

auto_scale_batch_size

Automatically tries to find the largest batch size that fits into memory, before any training.

```
# default used by the Trainer (no scaling of batch size)
trainer = Trainer(auto_scale_batch_size=None)

# run batch size scaling, result overrides hparams.batch_size
trainer = Trainer(auto_scale_batch_size='binsearch')
```

auto_lr_find

Runs a learning rate finder algorithm (see this paper) before any training, to find optimal initial learning rate.

```
# default used by the Trainer (no learning rate finder)
trainer = Trainer(auto_lr_find=False)
```

Example:

```
# run learning rate finder, results override hparams.learning_rate
trainer = Trainer(auto_lr_find=True)

# run learning rate finder, results override hparams.my_lr_arg
trainer = Trainer(auto_lr_find='my_lr_arg')
```

Note: See the learning rate finder guide

benchmark

If true enables cudnn.benchmark. This flag is likely to increase the speed of your system if your input sizes don't change. However, if it does, then it will likely make your system slower.

The speedup comes from allowing the cudnn auto-tuner to find the best algorithm for the hardware [see discussion here].

Example:

```
# default used by the Trainer
trainer = Trainer(benchmark=False)
```

deterministic

If true enables cudnn.deterministic. Might make your system slower, but ensures reproducibility. Also sets `$HOROVOD_FUSION_THRESHOLD=0`.

For more info check [pytorch docs].

Example:

```
# default used by the Trainer
trainer = Trainer(deterministic=False)
```

callbacks

Add a list of user defined callbacks. These callbacks DO NOT replace the explicit callbacks (loggers, EarlyStopping or ModelCheckpoint).

Note: Only user defined callbacks (ie: Not EarlyStopping or ModelCheckpoint)

```
# a list of callbacks
callbacks = [PrintCallback()]
trainer = Trainer(callbacks=callbacks)
```

Example:

```
from pytorch_lightning.callbacks import Callback

class PrintCallback(Callback):
    def on_train_start(self):
        print("Training is started!")
    def on_train_end(self):
        print(f"Training is done. The logs are: {self.trainer.logs}")
```

check_val_every_n_epoch

Check val every n train epochs.

Example:

```
# default used by the Trainer
trainer = Trainer(check_val_every_n_epoch=1)

# run val loop every 10 training epochs
trainer = Trainer(check_val_every_n_epoch=10)
```

checkpoint_callback

Callback for checkpointing.

```
trainer = Trainer(checkpoint_callback=checkpoint_callback)
```

Example:

```
from pytorch_lightning.callbacks import ModelCheckpoint

# default used by the Trainer
checkpoint_callback = ModelCheckpoint(
    filepath=os.getcwd(),
    save_top_k=True,
    verbose=True,
    monitor='val_loss',
    mode='min',
    prefix=''
)
```

default_root_dir

Default path for logs and weights when no logger or *pytorch_lightning.callbacks.ModelCheckpoint* callback passed. On certain clusters you might want to separate where logs and checkpoints are stored. If you don't then use this method for convenience.

Example:

```
# default used by the Trainer
trainer = Trainer(default_root_path=os.getcwd())
```

distributed_backend

The distributed backend to use.

- (`dp`) is DataParallel (split batch among GPUs of same machine)
- (`ddp`) is DistributedDataParallel (each gpu on each node trains, and syncs grads)
- (`ddp_cpu`) is DistributedDataParallel on CPU (same as *ddp*, but does not use GPUs. Useful for multi-node CPU training or single-node debugging. Note that this will **not** give a speedup on a single node, since Torch already makes effient use of multiple CPUs on a single machine.)
- **(`ddp2`) dp on node, ddp across nodes. Useful for things like increasing** the number of negative samples

```
# default used by the Trainer
trainer = Trainer(distributed_backend=None)
```

Example:

```
# dp = DataParallel
trainer = Trainer(gpus=2, distributed_backend='dp')

# ddp = DistributedDataParallel
trainer = Trainer(gpus=2, num_nodes=2, distributed_backend='ddp')
```

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```
# ddp2 = DistributedDataParallel + dp
trainer = Trainer(gpus=2, num_nodes=2, distributed_backend='ddp2')
```

Note: this option does not apply to TPU. TPUs use `ddp` by default (over each core)

early_stop_callback

Callback for early stopping. early_stop_callback (*pytorch_lightning.callbacks.EarlyStopping*)

- **`True`: A default callback monitoring `'val_loss'` is created.** Will raise an error if `'val_loss'` is not found.
- `False`: Early stopping will be disabled.
- `None`: The default callback monitoring `'val_loss'` is created.
- Default: `None`.

```
trainer = Trainer(early_stop_callback=early_stop_callback)
```

Example:

```
from pytorch_lightning.callbacks import EarlyStopping

# default used by the Trainer
early_stop_callback = EarlyStopping(
    monitor='val_loss',
    patience=3,
    strict=False,
    verbose=False,
    mode='min'
)
```

Note: If `'val_loss'` is not found will work as if early stopping is disabled.

fast_dev_run

Runs 1 batch of train, test and val to find any bugs (ie: a sort of unit test).

Under the hood the pseudocode looks like this:

```
# loading
__init__()
prepare_data

# test training step
training_batch = next(train_dataloader)
training_step(training_batch)

# test val step
val_batch = next(val_dataloader)
```

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```
out = validation_step(val_batch)
validation_epoch_end([out])
```

Example:

```
# default used by the Trainer
trainer = Trainer(fast_dev_run=False)

# runs 1 train, val, test  batch and program ends
trainer = Trainer(fast_dev_run=True)
```

gpus

- Number of GPUs to train on
- or Which GPUs to train on
- can handle strings

Example:

```
# default used by the Trainer (ie: train on CPU)
trainer = Trainer(gpus=None)

# int: train on 2 gpus
trainer = Trainer(gpus=2)

# list: train on GPUs 1, 4 (by bus ordering)
trainer = Trainer(gpus=[1, 4])
trainer = Trainer(gpus='1, 4') # equivalent

# -1: train on all gpus
trainer = Trainer(gpus=-1)
trainer = Trainer(gpus='-1') # equivalent

# combine with num_nodes to train on multiple GPUs across nodes
# uses 8 gpus in total
trainer = Trainer(gpus=2, num_nodes=4)
```

Note: See the multi-gpu computing guide

gradient_clip_val

Gradient clipping value

- 0 means don't clip.

Example:

```
# default used by the Trainer
trainer = Trainer(gradient_clip_val=0.0)
```

gradient_clip:

Warning: Deprecated since version 0.5.0.

Use *gradient_clip_val* instead. Will remove 0.8.0.

log_gpu_memory

Options:

- None
- 'min_max'
- 'all'

Example:

```
# default used by the Trainer
trainer = Trainer(log_gpu_memory=None)

# log all the GPUs (on master node only)
trainer = Trainer(log_gpu_memory='all')

# log only the min and max memory on the master node
trainer = Trainer(log_gpu_memory='min_max')
```

Note: Might slow performance because it uses the output of nvidia-smi.

log_save_interval

Writes logs to disk this often.

Example:

```
# default used by the Trainer
trainer = Trainer(log_save_interval=100)
```

logger

Logger (or iterable collection of loggers) for experiment tracking.

```
Trainer(logger=logger)
```

Example:

```
from pytorch_lightning.loggers import TensorBoardLogger

# default logger used by trainer
logger = TensorBoardLogger(
    save_dir=os.getcwd(),
    version=self.slurm_job_id,
    name='lightning_logs'
)
```

max_epochs

Stop training once this number of epochs is reached

Example:

```
# default used by the Trainer
trainer = Trainer(max_epochs=1000)
```

max_nb_epochs:

Warning: Deprecated since version 0.5.0.

Use *max_epochs* instead. Will remove 0.8.0.

min_epochs

Force training for at least these many epochs

Example:

```
# default used by the Trainer
trainer = Trainer(min_epochs=1)
```

min_nb_epochs:

Warning: deprecated:: 0.5.0 Use *min_epochs* instead. Will remove 0.8.0.

max_steps

Stop training after this number of steps Training will stop if max_steps or max_epochs have reached (earliest).

```
# Default (disabled)
trainer = Trainer(max_steps=None)
```

Example:

```
# Stop after 100 steps
trainer = Trainer(max_steps=100)
```

min_steps

Force training for at least these number of steps. Trainer will train model for at least min_steps or min_epochs (latest).

```
# Default (disabled)
trainer = Trainer(min_steps=None)
```

Example:

```
# Run at least for 100 steps (disable min_epochs)
trainer = Trainer(min_steps=100, min_epochs=0)
```

num_nodes

Number of GPU nodes for distributed training.

Example:

```
# default used by the Trainer
trainer = Trainer(num_nodes=1)

# to train on 8 nodes
trainer = Trainer(num_nodes=8)
```

nb_gpu_nodes:

> **Warning:** Deprecated since version 0.5.0.
>
> Use *num_nodes* instead. Will remove 0.8.0.

num_processes

Number of processes to train with. Automatically set to the number of GPUs when using `distrbuted_backend="ddp"`. Set to a number greater than 1 when using `distributed_backend="ddp_cpu"` to mimic distributed training on a machine without GPUs. This is useful for debugging, but **will not** provide any speedup, since single-process Torch already makes effient use of multiple CPUs.

Example:

```
# Simulate DDP for debugging on your GPU-less laptop
trainer = Trainer(distributed_backend="ddp_cpu", num_processes=2)
```

num_sanity_val_steps

Sanity check runs n batches of val before starting the training routine. This catches any bugs in your validation without having to wait for the first validation check. The Trainer uses 5 steps by default. Turn it off or modify it here.

Example:

```
# default used by the Trainer
trainer = Trainer(num_sanity_val_steps=5)

# turn it off
trainer = Trainer(num_sanity_val_steps=0)
```

nb_sanity_val_steps:

> **Warning:** Deprecated since version 0.5.0.
>
> Use *num_sanity_val_steps* instead. Will remove 0.8.0.

num_tpu_cores

How many TPU cores to train on (1 or 8).

A single TPU v2 or v3 has 8 cores. A TPU pod has up to 2048 cores. A slice of a POD means you get as many cores as you request.

Your effective batch size is batch_size * total tpu cores.

Note: No need to add a DistributedDataSampler, Lightning automatically does it for you.

This parameter can be either 1 or 8.

Example:

```
# your_trainer_file.py

# default used by the Trainer (ie: train on CPU)
trainer = Trainer(num_tpu_cores=None)

# int: train on a single core
trainer = Trainer(num_tpu_cores=1)

# int: train on all cores few cores
trainer = Trainer(num_tpu_cores=8)

# for 8+ cores must submit via xla script with
# a max of 8 cores specified. The XLA script
# will duplicate script onto each TPU in the POD
trainer = Trainer(num_tpu_cores=8)

# -1: train on all available TPUs
trainer = Trainer(num_tpu_cores=-1)
```

To train on more than 8 cores (ie: a POD), submit this script using the xla_dist script.

Example:

```
python -m torch_xla.distributed.xla_dist
--tpu=$TPU_POD_NAME
--conda-env=torch-xla-nightly
--env=XLA_USE_BF16=1
-- python your_trainer_file.py
```

overfit_pct

Uses this much data of all datasets (training, validation, test). Useful for quickly debugging or trying to overfit on purpose.

Example:

```
# default used by the Trainer
trainer = Trainer(overfit_pct=0.0)

# use only 1% of the train, test, val datasets
trainer = Trainer(overfit_pct=0.01)
```

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```
# equivalent:
trainer = Trainer(
    train_percent_check=0.01,
    val_percent_check=0.01,
    test_percent_check=0.01
)
```

See also:

- *train_percent_check*
- *val_percent_check*
- *test_percent_check*

precision

Full precision (32), half precision (16). Can be used on CPU, GPU or TPUs.

If used on TPU will use torch.bfloat16 but tensor printing will still show torch.float32.

Example:

```
# default used by the Trainer
trainer = Trainer(precision=32)

# 16-bit precision
trainer = Trainer(precision=16)

# one day
trainer = Trainer(precision=8|4|2)
```

print_nan_grads

Warning: Deprecated since version 0.7.2..

Has no effect. When detected, NaN grads will be printed automatically. Will remove 0.9.0.

process_position

Orders the progress bar. Useful when running multiple trainers on the same node.

Example:

```
# default used by the Trainer
trainer = Trainer(process_position=0)
```

Note: This argument is ignored if a custom callback is passed to *callbacks*.

profiler

To profile individual steps during training and assist in identifying bottlenecks.

See the profiler documentation. for more details.

Example:

```
from pytorch_lightning.profiler import Profiler, AdvancedProfiler

# default used by the Trainer
trainer = Trainer(profiler=None)

# to profile standard training events
trainer = Trainer(profiler=True)

# equivalent to profiler=True
profiler = Profiler()
trainer = Trainer(profiler=profiler)

# advanced profiler for function-level stats
profiler = AdvancedProfiler()
trainer = Trainer(profiler=profiler)
```

progress_bar_refresh_rate

How often to refresh progress bar (in steps). In notebooks, faster refresh rates (lower number) is known to crash them because of their screen refresh rates, so raise it to 50 or more.

Example:

```
# default used by the Trainer
trainer = Trainer(progress_bar_refresh_rate=1)

# disable progress bar
trainer = Trainer(progress_bar_refresh_rate=0)
```

Note: This argument is ignored if a custom callback is passed to *callbacks*.

reload_dataloaders_every_epoch

Set to True to reload dataloaders every epoch.

```
# if False (default)
train_loader = model.train_dataloader()
for epoch in epochs:
    for batch in train_loader:
        ...

# if True
for epoch in epochs:
    train_loader = model.train_dataloader()
    for batch in train_loader:
```

replace_sampler_ddp

Enables auto adding of distributed sampler.

Example:

```
# default used by the Trainer
trainer = Trainer(replace_sampler_ddp=True)
```

By setting to False, you have to add your own distributed sampler:

Example:

```
# default used by the Trainer
sampler = torch.utils.data.distributed.DistributedSampler(dataset, shuffle=True)
dataloader = DataLoader(dataset, batch_size=32, sampler=sampler)
```

resume_from_checkpoint

To resume training from a specific checkpoint pass in the path here.

Example:

```
# default used by the Trainer
trainer = Trainer(resume_from_checkpoint=None)

# resume from a specific checkpoint
trainer = Trainer(resume_from_checkpoint='some/path/to/my_checkpoint.ckpt')
```

row_log_interval

How often to add logging rows (does not write to disk)

Example:

```
# default used by the Trainer
trainer = Trainer(row_log_interval=10)
```

add_row_log_interval:

> **Warning:** Deprecated since version 0.5.0.
>
> Use *row_log_interval* instead. Will remove 0.8.0.

use_amp:

> **Warning:** Deprecated since version 0.7.0.
>
> Use *precision* instead. Will remove 0.9.0.

show_progress_bar

> **Warning:** Deprecated since version 0.7.2.
>
> Set *progress_bar_refresh_rate* to 0 instead. Will remove 0.9.0.

test_percent_check

How much of test dataset to check.

Example:

```
# default used by the Trainer
trainer = Trainer(test_percent_check=1.0)

# run through only 25% of the test set each epoch
trainer = Trainer(test_percent_check=0.25)
```

val_check_interval

How often within one training epoch to check the validation set. Can specify as float or int.

- use (float) to check within a training epoch
- use (int) to check every n steps (batches)

```
# default used by the Trainer
trainer = Trainer(val_check_interval=1.0)
```

Example:

```
# check validation set 4 times during a training epoch
trainer = Trainer(val_check_interval=0.25)

# check validation set every 1000 training batches
# use this when using iterableDataset and your dataset has no length
# (ie: production cases with streaming data)
trainer = Trainer(val_check_interval=1000)
```

track_grad_norm

- no tracking (-1)
- Otherwise tracks that norm (2 for 2-norm)

```
# default used by the Trainer
trainer = Trainer(track_grad_norm=-1)
```

Example:

```
# track the 2-norm
trainer = Trainer(track_grad_norm=2)
```

train_percent_check

How much of training dataset to check. Useful when debugging or testing something that happens at the end of an epoch.

Example:

```
# default used by the Trainer
trainer = Trainer(train_percent_check=1.0)

# run through only 25% of the training set each epoch
trainer = Trainer(train_percent_check=0.25)
```

truncated_bptt_steps

Truncated back prop breaks performs backprop every k steps of a much longer sequence.

If this is enabled, your batches will automatically get truncated and the trainer will apply Truncated Backprop to it.

(Williams et al. "An efficient gradient-based algorithm for on-line training of recurrent network trajectories.")

Example:

```
# default used by the Trainer (ie: disabled)
trainer = Trainer(truncated_bptt_steps=None)

# backprop every 5 steps in a batch
trainer = Trainer(truncated_bptt_steps=5)
```

Note: Make sure your batches have a sequence dimension.

Lightning takes care to split your batch along the time-dimension.

```
# we use the second as the time dimension
# (batch, time, ...)
sub_batch = batch[0, 0:t, ...]
```

Using this feature requires updating your LightningModule's *pytorch_lightning.core.LightningModule.training_step()* to include a *hiddens* arg with the hidden

```
# Truncated back-propagation through time
def training_step(self, batch, batch_idx, hiddens):
    # hiddens are the hiddens from the previous truncated backprop step
    out, hiddens = self.lstm(data, hiddens)

    return {
        "loss": ...,
        "hiddens": hiddens  # remember to detach() this
    }
```

To modify how the batch is split, override *pytorch_lightning.core.LightningModule.tbptt_split_batch()*:

```
class LitMNIST(pl.LightningModule):
    def tbptt_split_batch(self, batch, split_size):
```

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```
        # do your own splitting on the batch
        return splits
```

val_percent_check

How much of validation dataset to check. Useful when debugging or testing something that happens at the end of an epoch.

Example:

```
# default used by the Trainer
trainer = Trainer(val_percent_check=1.0)

# run through only 25% of the validation set each epoch
trainer = Trainer(val_percent_check=0.25)
```

weights_save_path

Directory of where to save weights if specified.

```
# default used by the Trainer
trainer = Trainer(weights_save_path=os.getcwd())
```

Example:

```
# save to your custom path
trainer = Trainer(weights_save_path='my/path')

# if checkpoint callback used, then overrides the weights path
# **NOTE: this saves weights to some/path NOT my/path
checkpoint_callback = ModelCheckpoint(filepath='some/path')
trainer = Trainer(
    checkpoint_callback=checkpoint_callback,
    weights_save_path='my/path'
)
```

weights_summary

Prints a summary of the weights when training begins. Options: 'full', 'top', None.

Example:

```
# default used by the Trainer (ie: print all weights)
trainer = Trainer(weights_summary='full')

# print only the top level modules
trainer = Trainer(weights_summary='top')

# don't print a summary
trainer = Trainer(weights_summary=None)
```

34.6.7 Trainer class

class pytorch_lightning.trainer.**Trainer**(*logger=True*, *checkpoint_callback=True*, *early_stop_callback=False*, *callbacks=None*, *default_root_dir=None*, *gradient_clip_val=0*, *process_position=0*, *num_nodes=1*, *num_processes=1*, *gpus=None*, *auto_select_gpus=False*, *num_tpu_cores=None*, *log_gpu_memory=None*, *progress_bar_refresh_rate=1*, *overfit_pct=0.0*, *track_grad_norm=-1*, *check_val_every_n_epoch=1*, *fast_dev_run=False*, *accumulate_grad_batches=1*, *max_epochs=1000*, *min_epochs=1*, *max_steps=None*, *min_steps=None*, *train_percent_check=1.0*, *val_percent_check=1.0*, *test_percent_check=1.0*, *val_check_interval=1.0*, *log_save_interval=100*, *row_log_interval=10*, *add_row_log_interval=None*, *distributed_backend=None*, *precision=32*, *print_nan_grads=False*, *weights_summary='full'*, *weights_save_path=None*, *num_sanity_val_steps=2*, *truncated_bptt_steps=None*, *resume_from_checkpoint=None*, *profiler=None*, *benchmark=False*, *deterministic=False*, *reload_dataloaders_every_epoch=False*, *auto_lr_find=False*, *replace_sampler_ddp=True*, *progress_bar_callback=True*, *terminate_on_nan=False*, *auto_scale_batch_size=False*, *amp_level='O1'*, *default_save_path=None*, *gradient_clip=None*, *nb_gpu_nodes=None*, *max_nb_epochs=None*, *min_nb_epochs=None*, *use_amp=None*, *show_progress_bar=None*, *nb_sanity_val_steps=None*, ***kwargs*)

Bases: *pytorch_lightning.trainer.training_io.TrainerIOMixin*, *pytorch_lightning.trainer.optimizers.TrainerOptimizersMixin*, *pytorch_lightning.trainer.auto_mix_precision.TrainerAMPMixin*, *pytorch_lightning.trainer.distrib_parts.TrainerDPMixin*, *pytorch_lightning.trainer.distrib_data_parallel.TrainerDDPMixin*, *pytorch_lightning.trainer.logging.TrainerLoggingMixin*, *pytorch_lightning.trainer.model_hooks.TrainerModelHooksMixin*, *pytorch_lightning.trainer.training_tricks.TrainerTrainingTricksMixin*, *pytorch_lightning.trainer.data_loading.TrainerDataLoadingMixin*, *pytorch_lightning.trainer.evaluation_loop.TrainerEvaluationLoopMixin*, *pytorch_lightning.trainer.training_loop.TrainerTrainLoopMixin*, *pytorch_lightning.trainer.callback_config.TrainerCallbackConfigMixin*, *pytorch_lightning.trainer.callback_hook.TrainerCallbackHookMixin*, *pytorch_lightning.trainer.lr_finder.TrainerLRFinderMixin*, *pytorch_lightning.trainer.deprecated_api.TrainerDeprecatedAPITillVer0_8*, *pytorch_lightning.trainer.deprecated_api.TrainerDeprecatedAPITillVer0_9*

Customize every aspect of training via flags

Parameters

- **logger** (Union[*LightningLoggerBase*, Iterable[*LightningLoggerBase*], bool]) – Logger (or iterable collection of loggers) for experiment tracking.
- **checkpoint_callback** (Union[*ModelCheckpoint*, bool]) – Callback for checkpointing.
- **early_stop_callback** (*pytorch_lightning.callbacks.EarlyStopping*) –
- **callbacks** (Optional[List[*Callback*]]) – Add a list of callbacks.
- **default_root_dir** (Optional[str]) – Default path for logs and weights when no logger/ckpt_callback passed
- **default_save_path** –

  Warning: Deprecated since version 0.7.3.

  Use *default_root_dir* instead. Will remove 0.9.0.

- **gradient_clip_val** (float) – 0 means don't clip.
- **gradient_clip** –

  Warning: Deprecated since version 0.7.0.

  Use *gradient_clip_val* instead. Will remove 0.9.0.

- **process_position** (int) – orders the progress bar when running multiple models on same machine.
- **num_nodes** (int) – number of GPU nodes for distributed training.
- **nb_gpu_nodes** –

  Warning: Deprecated since version 0.7.0.

  Use *num_nodes* instead. Will remove 0.9.0.

- **gpus** (Union[List[int], str, int, None]) – Which GPUs to train on.
- **auto_select_gpus** (bool) – If enabled and *gpus* is an integer, pick available gpus automatically. This is especially useful when GPUs are configured to be in "exclusive mode", such that only one process at a time can access them.
- **num_tpu_cores** (Optional[int]) – How many TPU cores to train on (1 or 8).
- **log_gpu_memory** (Optional[str]) – None, 'min_max', 'all'. Might slow performance
- **show_progress_bar** –

  Warning: Deprecated since version 0.7.2.

  Set *progress_bar_refresh_rate* to positive integer to enable. Will remove 0.9.0.

- **progress_bar_refresh_rate** (int) – How often to refresh progress bar (in steps). Value 0 disables progress bar. Ignored when a custom callback is passed to *callbacks*.
- **overfit_pct** (float) – How much of training-, validation-, and test dataset to check.
- **track_grad_norm** (int) – -1 no tracking. Otherwise tracks that norm
- **check_val_every_n_epoch** (int) – Check val every n train epochs.
- **fast_dev_run** (bool) – runs 1 batch of train, test and val to find any bugs (ie: a sort of unit test).
- **accumulate_grad_batches** (Union[int, Dict[int, int], List[list]]) – Accumulates grads every k batches or as set up in the dict.
- **max_epochs** (int) – Stop training once this number of epochs is reached.
- **max_nb_epochs** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *max_epochs* instead. Will remove 0.9.0.

- **min_epochs** (int) – Force training for at least these many epochs
- **min_nb_epochs** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *min_epochs* instead. Will remove 0.9.0.

- **max_steps** (Optional[int]) – Stop training after this number of steps. Disabled by default (None).
- **min_steps** (Optional[int]) – Force training for at least these number of steps. Disabled by default (None).
- **train_percent_check** (float) – How much of training dataset to check.
- **val_percent_check** (float) – How much of validation dataset to check.
- **test_percent_check** (float) – How much of test dataset to check.
- **val_check_interval** (float) – How often within one training epoch to check the validation set
- **log_save_interval** (int) – Writes logs to disk this often
- **row_log_interval** (int) – How often to add logging rows (does not write to disk)
- **add_row_log_interval** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *row_log_interval* instead. Will remove 0.9.0.

- **distributed_backend** (Optional[str]) – The distributed backend to use.
- **use_amp** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *precision* instead. Will remove 0.9.0.

- **precision** (int) – Full precision (32), half precision (16).
- **print_nan_grads** (bool) –

> **Warning:** Deprecated since version 0.7.2.
>
> Has no effect. When detected, NaN grads will be printed automatically. Will remove 0.9.0.

- **weights_summary** (Optional[str]) – Prints a summary of the weights when training begins.
- **weights_save_path** (Optional[str]) – Where to save weights if specified. Will override default_root_dir for checkpoints only. Use this if for whatever reason you need the checkpoints stored in a different place than the logs written in *default_root_dir*.
- **amp_level** (str) – The optimization level to use (O1, O2, etc...).
- **num_sanity_val_steps** (int) – Sanity check runs n batches of val before starting the training routine.
- **nb_sanity_val_steps** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *num_sanity_val_steps* instead. Will remove 0.8.0.

- **truncated_bptt_steps** (Optional[int]) – Truncated back prop breaks performs backprop every k steps of
- **resume_from_checkpoint** (Optional[str]) – To resume training from a specific checkpoint pass in the path here.
- **profiler** (Union[*BaseProfiler*, bool, None]) – To profile individual steps during training and assist in
- **reload_dataloaders_every_epoch** (bool) – Set to True to reload dataloaders every epoch
- **auto_lr_find** (Union[bool, str]) – If set to True, will *initially* run a learning rate finder, trying to optimize initial learning for faster convergence. Sets learning rate in self.hparams.lr | self.hparams.learning_rate in the lightning module. To use a different key, set a string instead of True with the key name.
- **replace_sampler_ddp** (bool) – Explicitly enables or disables sampler replacement. If not specified this will toggled automatically ddp is used
- **benchmark** (bool) – If true enables cudnn.benchmark.
- **deterministic** (bool) – If true enables cudnn.deterministic
- **terminate_on_nan** (bool) – If set to True, will terminate training (by raising a *ValueError*) at the end of each training batch, if any of the parameters or the loss are NaN or +/-inf.

- **auto_scale_batch_size** (Union[str, bool]) – If set to True, will *initially* run a batch size finder trying to find the largest batch size that fits into memory. The result will be stored in self.hparams.batch_size in the LightningModule. Additionally, can be set to either *power* that estimates the batch size through a power search or *binsearch* that estimates the batch size through a binary search.

_Trainer__attach_dataloaders(*model*, *train_dataloader=None*, *val_dataloaders=None*, *test_dataloaders=None*)

_Trainer__set_random_port()
When running DDP NOT managed by SLURM, the ports might collide :return:

_allowed_type()

Return type Union[int, str]

_arg_default()

Return type Union[int, str]

classmethod add_argparse_args(*parent_parser*)
Extends existing argparse by default *Trainer* attributes.

Parameters **parent_parser** (ArgumentParser) – The custom cli arguments parser, which will be extended by the Trainer default arguments.

Only arguments of the allowed types (str, float, int, bool) will extend the *parent_parser*.

Examples

```
>>> import argparse
>>> import pprint
>>> parser = argparse.ArgumentParser()
>>> parser = Trainer.add_argparse_args(parser)
>>> args = parser.parse_args([])
>>> pprint.pprint(vars(args))
{...
 'check_val_every_n_epoch': 1,
 'checkpoint_callback': True,
 'default_root_dir': None,
 'deterministic': False,
 'distributed_backend': None,
 'early_stop_callback': False,
 ...
 'logger': True,
 'max_epochs': 1000,
 'max_steps': None,
 'min_epochs': 1,
 'min_steps': None,
 ...
 'profiler': None,
 'progress_bar_callback': True,
 'progress_bar_refresh_rate': 1,
 ...}
```

Return type ArgumentParser

check_model_configuration(*model*)
Checks that the model is configured correctly before training is started.

Parameters **model** (*LightningModule*) – The model to test.

check_testing_model_configuration(*model*)

classmethod default_attributes()

fit(*model*, *train_dataloader=None*, *val_dataloaders=None*)
Runs the full optimization routine.

Parameters

- **model** (*LightningModule*) – Model to fit.
- **train_dataloader** (Optional[DataLoader]) – A Pytorch DataLoader with training samples. If the model has a predefined train_dataloader method this will be skipped.
- **val_dataloaders** (Union[DataLoader, List[DataLoader], None]) – Either a single Pytorch Dataloader or a list of them, specifying validation samples. If the model has a predefined val_dataloaders method this will be skipped

Example:

```
# Option 1,
# Define the train_dataloader() and val_dataloader() fxs
# in the lightningModule
# RECOMMENDED FOR MOST RESEARCH AND APPLICATIONS TO MAINTAIN READABILITY
trainer = Trainer()
model = LightningModule()
trainer.fit(model)

# Option 2
# in production cases we might want to pass different datasets to the same␣
↪model
# Recommended for PRODUCTION SYSTEMS
train, val = DataLoader(...), DataLoader(...)
trainer = Trainer()
model = LightningModule()
trainer.fit(model, train_dataloader=train, val_dataloader=val)

# Option 1 & 2 can be mixed, for example the training set can be
# defined as part of the model, and validation can then be feed to .fit()
```

classmethod from_argparse_args(*args*, ***kwargs*)
create an instance from CLI arguments

Example

```
>>> parser = ArgumentParser(add_help=False)
>>> parser = Trainer.add_argparse_args(parser)
>>> args = Trainer.parse_argparser(parser.parse_args(""))
>>> trainer = Trainer.from_argparse_args(args)
```

Return type *Trainer*

classmethod get_deprecated_arg_names()
Returns a list with deprecated Trainer arguments.

Return type List

classmethod get_init_arguments_and_types()
Scans the Trainer signature and returns argument names, types and default values.

Returns (argument name, set with argument types, argument default value).

Return type List with tuples of 3 values

Examples

```
>>> args = Trainer.get_init_arguments_and_types()
>>> import pprint
>>> pprint.pprint(sorted(args))
[('accumulate_grad_batches',
  (<class 'int'>, typing.Dict[int, int], typing.List[list]),
  1),
 ...
 ('callbacks',
  (typing.List[pytorch_lightning.callbacks.base.Callback],
   <class 'NoneType'>),
   None),
 ('check_val_every_n_epoch', (<class 'int'>,), 1),
 ...
 ('max_epochs', (<class 'int'>,), 1000),
 ...
 ('precision', (<class 'int'>,), 32),
 ('print_nan_grads', (<class 'bool'>,), False),
 ('process_position', (<class 'int'>,), 0),
 ('profiler',
  (<class 'pytorch_lightning.profiler.profilers.BaseProfiler'>,
   <class 'bool'>,
   <class 'NoneType'>),
  None),
 ...
```

static parse_argparser(*arg_parser*)
Parse CLI arguments, required for custom bool types.

Return type Namespace

run_pretrain_routine(*model*)
Sanity check a few things before starting actual training.

Parameters **model** (*LightningModule*) – The model to run sanity test on.

test(*model=None*, *test_dataloaders=None*)
Separates from fit to make sure you never run on your test set until you want to.

Parameters

- **model** (Optional[*LightningModule*]) – The model to test.
- **test_dataloaders** (Union[DataLoader, List[DataLoader], None]) – Either a single Pytorch Dataloader or a list of them, specifying validation samples.

Example:

```
# Option 1
# run test after fitting
test = DataLoader(...)
trainer = Trainer()
```

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```
model = LightningModule()

trainer.fit(model)
trainer.test(test_dataloaders=test)

# Option 2
# run test from a loaded model
test = DataLoader(...)
model = LightningModule.load_from_checkpoint('path/to/checkpoint.ckpt')
trainer = Trainer()
trainer.test(model, test_dataloaders=test)
```

DEPRECATED_IN_0_8 = ('gradient_clip', 'nb_gpu_nodes', 'max_nb_epochs', 'min_nb_epochs'

DEPRECATED_IN_0_9 = ('use_amp', 'show_progress_bar', 'training_tqdm_dict')

accumulate_grad_batches = None

checkpoint_callback = None

property data_parallel

Return type bool

early_stop_callback = None

logger = None

lr_schedulers = None

model = None

property num_gpus

this is just empty shell for code implemented in other class.

Type Warning

Return type int

num_training_batches = None

on_gpu = None

on_tpu = None

optimizers = None

proc_rank = None

property progress_bar_dict

Read-only for progress bar metrics.

Return type dict

resume_from_checkpoint = None

root_gpu = None

property slurm_job_id

this is just empty shell for code implemented in other class.

Type Warning

Return type int

use_ddp = None

use_ddp2 = None

use_horovod = None

weights_save_path = None

pytorch_lightning.trainer.**seed_everything**(*seed=None*)
Function that sets seed for pseudo-random number generators in: pytorch, numpy, python.random and sets PYTHONHASHSEED environment variable.

Return type int

34.6.8 Submodules

pytorch_lightning.trainer.auto_mix_precision module

class pytorch_lightning.trainer.auto_mix_precision.**TrainerAMPMixin**
Bases: abc.ABC

init_amp(*use_amp*)

precision: int = None

property use_amp

Return type bool

use_native_amp: bool = None

pytorch_lightning.trainer.callback_config module

class pytorch_lightning.trainer.callback_config.**TrainerCallbackConfigMixin**
Bases: abc.ABC

configure_checkpoint_callback()
Weight path set in this priority: Checkpoint_callback's path (if passed in). User provided weights_saved_path Otherwise use os.getcwd()

configure_early_stopping(*early_stop_callback*)

configure_progress_bar()

abstract save_checkpoint(**args*)
Warning: this is just empty shell for code implemented in other class.

callbacks: List[Callback] = None

checkpoint_callback: ModelCheckpoint = None

ckpt_path: str = None

default_root_dir: str = None

logger: Union[LightningLoggerBase, bool] = None

process_position: int = None

progress_bar_refresh_rate: int = None

abstract property slurm_job_id
this is just empty shell for code implemented in other class.

Type Warning

Return type int

weights_save_path: str = None

pytorch_lightning.trainer.callback_hook module

class pytorch_lightning.trainer.callback_hook.**TrainerCallbackHookMixin**

Bases: abc.ABC

on_batch_end()
Called when the training batch ends.

on_batch_start()
Called when the training batch begins.

on_epoch_end()
Called when the epoch ends.

on_epoch_start()
Called when the epoch begins.

on_init_end()
Called when the trainer initialization ends, model has not yet been set.

on_init_start()
Called when the trainer initialization begins, model has not yet been set.

on_sanity_check_end()
Called when the validation sanity check ends.

on_sanity_check_start()
Called when the validation sanity check starts.

on_test_batch_end()
Called when the test batch ends.

on_test_batch_start()
Called when the test batch begins.

on_test_end()
Called when the test ends.

on_test_start()
Called when the test begins.

on_train_end()
Called when the train ends.

on_train_start()
Called when the train begins.

on_validation_batch_end()
Called when the validation batch ends.

on_validation_batch_start()
Called when the validation batch begins.

on_validation_end()
Called when the validation loop ends.

on_validation_start()
Called when the validation loop begins.

pytorch_lightning.trainer.data_loading module

class pytorch_lightning.trainer.data_loading.**TrainerDataLoadingMixin**
Bases: abc.ABC

_percent_range_check(*name*)

Return type None

_reset_eval_dataloader(*model*, *mode*)
Generic method to reset a dataloader for evaluation.

Parameters

- **model** (*LightningModule*) – The current *LightningModule*
- **mode** (str) – Either *'val'* or *'test'*

Return type Tuple[int, List[DataLoader]]

Returns Tuple (num_batches, dataloaders)

_worker_check(*dataloader*, *name*)

Return type None

auto_add_sampler(*dataloader*, *train*)

Return type DataLoader

determine_data_use_amount(*train_percent_check*, *val_percent_check*, *test_percent_check*, *overfit_pct*)
Use less data for debugging purposes

Return type None

abstract is_overridden(**args*)
Warning: this is just empty shell for code implemented in other class.

request_dataloader(*dataloader_fx*)
Handles downloading data in the GPU or TPU case.

Parameters **dataloader_fx** (Callable) – The bound dataloader getter

Return type DataLoader

Returns The dataloader

reset_test_dataloader(*model*)
Resets the validation dataloader and determines the number of batches.

Parameters **model** – The current *LightningModule*

Return type None

reset_train_dataloader(*model*)
Resets the train dataloader and initialises required variables (number of batches, when to validate, etc.).

Parameters **model** (*LightningModule*) – The current *LightningModule*

Return type None

reset_val_dataloader(*model*)
Resets the validation dataloader and determines the number of batches.

Parameters **model** (*LightningModule*) – The current *LightningModule*

Return type None

num_test_batches: Union[int, float] = None

num_training_batches: Union[int, float] = None

num_val_batches: Union[int, float] = None

proc_rank: int = None

replace_sampler_ddp: bool = None

shown_warnings: ... = None

test_dataloaders: List[DataLoader] = None

test_percent_check: float = None

tpu_local_core_rank: int = None

train_dataloader: DataLoader = None

train_percent_check: float = None

use_ddp: bool = None

use_ddp2: bool = None

use_horovod: bool = None

use_tpu: bool = None

val_check_batch: ... = None

val_check_interval: float = None

val_dataloaders: List[DataLoader] = None

val_percent_check: float = None

pytorch_lightning.trainer.data_loading.**_has_len**(*dataloader*)

Checks if a given Dataloader has __len__ method implemented i.e. if it is a finite dataloader or infinite dataloader

Return type bool

pytorch_lightning.trainer.deprecated_api module

Mirroring deprecated API

class pytorch_lightning.trainer.deprecated_api.**TrainerDeprecatedAPITillVer0_8**

Bases: abc.ABC

property default_save_path

Back compatibility, will be removed in v0.8.0

property gradient_clip

Back compatibility, will be removed in v0.8.0

property max_nb_epochs

Back compatibility, will be removed in v0.8.0

property min_nb_epochs

Back compatibility, will be removed in v0.8.0

property nb_gpu_nodes

Back compatibility, will be removed in v0.8.0

property nb_sanity_val_steps

Back compatibility, will be removed in v0.8.0

property num_gpu_nodes
Back compatibility, will be removed in v0.8.0

property tng_tqdm_dic
Back compatibility, will be removed in v0.8.0

class pytorch_lightning.trainer.deprecated_api.**TrainerDeprecatedAPITillVer0_9**
Bases: abc.ABC

property show_progress_bar
Back compatibility, will be removed in v0.9.0

property training_tqdm_dict
Back compatibility, will be removed in v0.9.0

pytorch_lightning.trainer.distrib_data_parallel module

Lightning supports model training on a cluster managed by SLURM in the following cases:

1. Training on a single cpu or single GPU.
2. Train on multiple GPUs on the same node using DataParallel or DistributedDataParallel
3. Training across multiple GPUs on multiple different nodes via DistributedDataParallel.

Note: A node means a machine with multiple GPUs

Running grid search on a cluster

To use lightning to run a hyperparameter search (grid-search or random-search) on a cluster do 4 things:

(1). Define the parameters for the grid search

```
from test_tube import HyperOptArgumentParser

# subclass of argparse
parser = HyperOptArgumentParser(strategy='random_search')
parser.add_argument('--learning_rate', default=0.002, type=float, help='the learning␣
↪rate')

# let's enable optimizing over the number of layers in the network
parser.opt_list('--nb_layers', default=2, type=int, tunable=True, options=[2, 4, 8])

hparams = parser.parse_args()
```

Note: You must set *Tunable=True* for that argument to be considered in the permutation set. Otherwise test-tube will use the default value. This flag is useful when you don't want to search over an argument and want to use the default instead.

---

(2). Define the cluster options in the SlurmCluster object (over 5 nodes and 8 gpus)

```
from test_tube.hpc import SlurmCluster

# hyperparameters is a test-tube hyper params object
```

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```
# see https://williamfalcon.github.io/test-tube/hyperparameter_optimization/
↪HyperOptArgumentParser/
hyperparams = args.parse()

# init cluster
cluster = SlurmCluster(
    hyperparam_optimizer=hyperparams,
    log_path='/path/to/log/results/to',
    python_cmd='python3'
)

# let the cluster know where to email for a change in job status (ie: complete, fail,␣
↪etc...)
cluster.notify_job_status(email='some@email.com', on_done=True, on_fail=True)

# set the job options. In this instance, we'll run 20 different models
# each with its own set of hyperparameters giving each one 1 GPU (ie: taking up 20␣
↪GPUs)
cluster.per_experiment_nb_gpus = 8
cluster.per_experiment_nb_nodes = 5

# we'll request 10GB of memory per node
cluster.memory_mb_per_node = 10000

# set a walltime of 10 minues
cluster.job_time = '10:00'
```

(3). Make a main function with your model and trainer. Each job will call this function with a particular hparams configuration.:

```
from pytorch_lightning import Trainer

def train_fx(trial_hparams, cluster_manager, _):
    # hparams has a specific set of hyperparams

    my_model = MyLightningModel()

    # give the trainer the cluster object
    trainer = Trainer()
    trainer.fit(my_model)

`
```

(4). Start the grid/random search:

```
# run the models on the cluster
cluster.optimize_parallel_cluster_gpu(
    train_fx,
    nb_trials=20,
    job_name='my_grid_search_exp_name',
    job_display_name='my_exp')
```

Note: *nb_trials* specifies how many of the possible permutations to use. If using *grid_search* it will use the depth first ordering. If using *random_search* it will use the first k shuffled options. FYI, random search has been shown to be just as good as any Bayesian optimization method when using a reasonable number of samples (60), see this paper

for more information.

Walltime auto-resubmit

Lightning automatically resubmits jobs when they reach the walltime. Make sure to set the SIGUSR1 signal in your SLURM script.:

```
# 90 seconds before training ends
#SBATCH --signal=SIGUSR1@90
```

When lightning receives the SIGUSR1 signal it will: 1. save a checkpoint with 'hpc_ckpt' in the name. 2. resubmit the job using the SLURM_JOB_ID

When the script starts again, Lightning will: 1. search for a 'hpc_ckpt' checkpoint. 2. restore the model, optimizers, schedulers, epoch, etc...

class pytorch_lightning.trainer.distrib_data_parallel.**TrainerDDPMixin**

Bases: abc.ABC

_set_horovod_backend()

check_horovod()

Raises a *MisconfigurationException* if the Trainer is not configured correctly for Horovod.

configure_slurm_ddp(*num_gpu_nodes*)

abstract copy_trainer_model_properties(**args*)

Warning: this is just empty shell for code implemented in other class.

ddp_train(*process_idx*, *model*)

Entry point into a DP thread :param _sphinx_paramlinks_pytorch_lightning.trainer.distrib_data_parallel.TrainerDDPMixin.d
:param _sphinx_paramlinks_pytorch_lightning.trainer.distrib_data_parallel.TrainerDDPMixin.ddp_train.model:
:param _sphinx_paramlinks_pytorch_lightning.trainer.distrib_data_parallel.TrainerDDPMixin.ddp_train.cluster_obj:
:return:

determine_ddp_node_rank()

static has_horovodrun()

Returns True if running with *horovodrun* using Gloo or OpenMPI.

abstract init_optimizers(**args*)

Warning: this is just empty shell for code implemented in other class.

init_tpu()

load_spawn_weights(*original_model*)

Load the temp weights saved in the process To recover the trained model from the ddp process we load the saved weights :param _sphinx_paramlinks_pytorch_lightning.trainer.distrib_data_parallel.TrainerDDPMixin.load_spawn_weights.model:
:return:

resolve_root_node_address(*root_node*)

abstract run_pretrain_routine(**args*)

Warning: this is just empty shell for code implemented in other class.

save_spawn_weights(*model*)

Dump a temporary checkpoint after ddp ends to get weights out of the process :param _sphinx_paramlinks_pytorch_lightning.trainer.distrib_data_parallel.TrainerDDPMixin.save_spawn_weights.model:
:return:

set_distributed_mode(*distributed_backend*)

set_nvidia_flags(*is_slurm_managing_tasks*, *data_parallel_device_ids*)

amp_level: str = None

checkpoint_callback: Union[ModelCheckpoint, bool] = None

data_parallel_device_ids: ... = None

default_root_dir: str = None

distributed_backend: str = None

logger: Union[LightningLoggerBase, bool] = None

num_gpu_nodes: int = None

abstract property num_gpus
this is just empty shell for code implemented in other class.

Type Warning

Return type int

num_processes: int = None

on_gpu: bool = None

progress_bar_callback: ... = None

abstract property use_amp
this is just empty shell for code implemented in other class.

Type Warning

Return type bool

use_native_amp: bool = None

use_tpu: bool = None

pytorch_lightning.trainer.distrib_parts module

Lightning makes multi-gpu training and 16 bit training trivial.

Note: None of the flags below require changing anything about your lightningModel definition.

Choosing a backend

Lightning supports two backends. DataParallel and DistributedDataParallel. Both can be used for single-node multi-GPU training. For multi-node training you must use DistributedDataParallel.

DataParallel (dp)

Splits a batch across multiple GPUs on the same node. Cannot be used for multi-node training.

DistributedDataParallel (ddp)

Trains a copy of the model on each GPU and only syncs gradients. If used with DistributedSampler, each GPU trains on a subset of the full dataset.

DistributedDataParallel-2 (ddp2)

Works like DDP, except each node trains a single copy of the model using ALL GPUs on that node. Very useful when dealing with negative samples, etc...

You can toggle between each mode by setting this flag.

```
# DEFAULT (when using single GPU or no GPUs)
trainer = Trainer(distributed_backend=None)

# Change to DataParallel (gpus > 1)
trainer = Trainer(distributed_backend='dp')

# change to distributed data parallel (gpus > 1)
trainer = Trainer(distributed_backend='ddp')

# change to distributed data parallel (gpus > 1)
trainer = Trainer(distributed_backend='ddp2')
```

If you request multiple nodes, the back-end will auto-switch to ddp. We recommend you use DistributedDataparallel even for single-node multi-GPU training. It is MUCH faster than DP but *may* have configuration issues depending on your cluster.

For a deeper understanding of what lightning is doing, feel free to read this guide.

Distributed and 16-bit precision

Due to an issue with apex and DistributedDataParallel (PyTorch and NVIDIA issue), Lightning does not allow 16-bit and DP training. We tried to get this to work, but it's an issue on their end.

Below are the possible configurations we support.

1 GPU	1+ GPUs	DP	DDP	16-bit	command
Y					*Trainer(gpus=1)*
Y				Y	*Trainer(gpus=1, use_amp=True)*
	Y	Y			*Trainer(gpus=k, distributed_backend='dp')*
	Y		Y		*Trainer(gpus=k, distributed_backend='ddp')*
	Y		Y	Y	*Trainer(gpus=k, distributed_backend='ddp', use_amp=True)*

You also have the option of specifying which GPUs to use by passing a list:

```
# DEFAULT (int) specifies how many GPUs to use.
Trainer(gpus=k)

# Above is equivalent to
Trainer(gpus=list(range(k)))

# You specify which GPUs (don't use if running on cluster)
Trainer(gpus=[0, 1])

# can also be a string
Trainer(gpus='0, 1')

# can also be -1 or '-1', this uses all available GPUs
# this is equivalent to list(range(torch.cuda.available_devices()))
Trainer(gpus=-1)
```

CUDA flags

CUDA flags make certain GPUs visible to your script. Lightning sets these for you automatically, there's NO NEED to do this yourself.

```
# lightning will set according to what you give the trainer
os.environ["CUDA_DEVICE_ORDER"] = "PCI_BUS_ID"
os.environ["CUDA_VISIBLE_DEVICES"] = "0"
```

However, when using a cluster, Lightning will NOT set these flags (and you should not either). SLURM will set these for you.

16-bit mixed precision

16 bit precision can cut your memory footprint by half. If using volta architecture GPUs it can give a dramatic training speed-up as well. First, install apex (if install fails, look here):

```
$ git clone https://github.com/NVIDIA/apex
$ cd apex

# -------------------------
# OPTIONAL: on your cluster you might need to load cuda 10 or 9
# depending on how you installed PyTorch

# see available modules
module avail

# load correct cuda before install
module load cuda-10.0
# -------------------------

# make sure you've loaded a cuda version > 4.0 and < 7.0
module load gcc-6.1.0

$ pip install -v --no-cache-dir --global-option="--cpp_ext" --global-option="--
↪cuda_ext" ./
```

then set this use_amp to True.:

```
# DEFAULT
trainer = Trainer(amp_level='O2', use_amp=False)
```

Single-gpu

Make sure you're on a GPU machine.:

```
# DEFAULT
trainer = Trainer(gpus=1)
```

Multi-gpu

Make sure you're on a GPU machine. You can set as many GPUs as you want. In this setting, the model will run on all 8 GPUs at once using DataParallel under the hood.

```
# to use DataParallel
trainer = Trainer(gpus=8, distributed_backend='dp')

# RECOMMENDED use DistributedDataParallel
trainer = Trainer(gpus=8, distributed_backend='ddp')
```

Custom device selection

The number of GPUs can also be selected with a list of indices or a string containing a comma separated list of GPU ids. The table below lists examples of possible input formats and how they are interpreted by Lightning. Note in particular the difference between *gpus=0*, *gpus=[0]* and *gpus="0"*.

gpus	Type	Parsed	Meaning
None	NoneType	None	CPU
0	int	None	CPU
3	int	[0, 1, 2]	first 3 GPUs
-1	int	[0, 1, 2, ...]	all available GPUs
[0]	list	[0]	GPU 0
[1, 3]	list	[1, 3]	GPUs 1 and 3
"0"	str	[0]	GPU 0
"3"	str	[3]	GPU 3
"1, 3"	str	[1, 3]	GPUs 1 and 3
"-1"	str	[0, 1, 2, ...]	all available GPUs

Multi-node

Multi-node training is easily done by specifying these flags.

```
# train on 12*8 GPUs
trainer = Trainer(gpus=8, num_nodes=12, distributed_backend='ddp')
```

You must configure your job submission script correctly for the trainer to work. Here is an example script for the above trainer configuration.

```
#!/bin/bash -l

# SLURM SUBMIT SCRIPT
#SBATCH --nodes=12
#SBATCH --gres=gpu:8
#SBATCH --ntasks-per-node=8
#SBATCH --mem=0
#SBATCH --time=0-02:00:00

# activate conda env
conda activate my_env

# ------------------------
# OPTIONAL
# ------------------------
# debugging flags (optional)
# export NCCL_DEBUG=INFO
# export PYTHONFAULTHANDLER=1

# PyTorch comes with prebuilt NCCL support... but if you have issues with it
# you might need to load the latest version from your  modules
# module load NCCL/2.4.7-1-cuda.10.0

# on your cluster you might need these:
# set the network interface
# export NCCL_SOCKET_IFNAME=^docker0,lo
# ------------------------

# random port between 12k and 20k
export MASTER_PORT=$((12000 + RANDOM % 20000))

# run script from above
python my_main_file.py
```

Note: When running in DDP mode, any errors in your code will show up as an NCCL issue. Set the *NCCL_DEBUG=INFO* flag to see the ACTUAL error.

Normally now you would need to add a distributed sampler to your dataset, however Lightning automates this for you. But if you still need to set a sampler Lightning will not interfere nor automate it.

Here's an example of how to add your own sampler (again no need with Lightning).

```
# ie: this:
dataset = myDataset()
dataloader = Dataloader(dataset)

# becomes:
dataset = myDataset()
dist_sampler = torch.utils.data.distributed.DistributedSampler(dataset)
dataloader = Dataloader(dataset, sampler=dist_sampler)
```

Auto-slurm-job-submission

Instead of manually building SLURM scripts, you can use the SlurmCluster object to do this for you. The SlurmCluster can also run a grid search if you pass in a HyperOptArgumentParser.

Here is an example where you run a grid search of 9 combinations of hyperparams. The full examples are here.

```
# grid search 3 values of learning rate and 3 values of number of layers for your net
# this generates 9 experiments (lr=1e-3, layers=16), (lr=1e-3, layers=32),
#  (lr=1e-3, layers=64), ... (lr=1e-1, layers=64)
parser = HyperOptArgumentParser(strategy='grid_search', add_help=False)
parser.opt_list('--learning_rate', default=0.001, type=float,
                options=[1e-3, 1e-2, 1e-1], tunable=True)
parser.opt_list('--layers', default=1, type=float, options=[16, 32, 64], tunable=True)
hyperparams = parser.parse_args()

# Slurm cluster submits 9 jobs, each with a set of hyperparams
cluster = SlurmCluster(
    hyperparam_optimizer=hyperparams,
    log_path='/some/path/to/save',
)

# OPTIONAL FLAGS WHICH MAY BE CLUSTER DEPENDENT
# which interface your nodes use for communication
cluster.add_command('export NCCL_SOCKET_IFNAME=^docker0,lo')

# see output of the NCCL connection process
# NCCL is how the nodes talk to each other
cluster.add_command('export NCCL_DEBUG=INFO')

# setting a master port here is a good idea.
cluster.add_command('export MASTER_PORT=%r' % PORT)

# ************** DON'T FORGET THIS ***************
# MUST load the latest NCCL version
cluster.load_modules(['NCCL/2.4.7-1-cuda.10.0'])

# configure cluster
cluster.per_experiment_nb_nodes = 12
cluster.per_experiment_nb_gpus = 8

cluster.add_slurm_cmd(cmd='ntasks-per-node', value=8, comment='1 task per gpu')

# submit a script with 9 combinations of hyper params
# (lr=1e-3, layers=16), (lr=1e-3, layers=32), (lr=1e-3, layers=64), ... (lr=1e-1,␣
↪layers=64)
cluster.optimize_parallel_cluster_gpu(
    main,
    nb_trials=9, # how many permutations of the grid search to run
    job_name='name_for_squeue'
)
```

The other option is that you generate scripts on your own via a bash command or use another library...

Self-balancing architecture

Here lightning distributes parts of your module across available GPUs to optimize for speed and memory.

class pytorch_lightning.trainer.distrib_parts.**TrainerDPMixin**
Bases: abc.ABC

_TrainerDPMixin__transfer_data_to_device(*batch*, *device*, *gpu_id=None*)

copy_trainer_model_properties(*model*)

dp_train(*model*)

horovod_train(*model*)

abstract init_optimizers(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract run_pretrain_routine(**args*)
Warning: this is just empty shell for code implemented in other class.

single_gpu_train(*model*)

tpu_train(*tpu_core_idx*, *model*)

transfer_batch_to_gpu(*batch*, *gpu_id*)

transfer_batch_to_tpu(*batch*)

amp_level: str = None

current_tpu_idx: ... = None

data_parallel_device_ids: ... = None

logger: Union[LightningLoggerBase, bool] = None

on_gpu: bool = None

precision: ... = None

proc_rank: int = None

progress_bar_callback: ... = None

root_gpu: ... = None

single_gpu: bool = None

testing: bool = None

tpu_global_core_rank: int = None

tpu_local_core_rank: int = None

abstract property use_amp
this is just empty shell for code implemented in other class.

Type Warning

Return type bool

use_ddp: bool = None

use_ddp2: bool = None

use_dp: bool = None

use_native_amp: bool = None

use_tpu: bool = None

pytorch_lightning.trainer.distrib_parts.**check_gpus_data_type**(*gpus*)

Parameters **gpus** – gpus parameter as passed to the Trainer Function checks that it is one of: None, Int, String or List Throws otherwise

Returns return unmodified gpus variable

pytorch_lightning.trainer.distrib_parts.**determine_root_gpu_device**(*gpus*)

Parameters **gpus** – non empty list of ints representing which gpus to use

Returns designated root GPU device

pytorch_lightning.trainer.distrib_parts.**get_all_available_gpus**()

Returns a list of all available gpus

pytorch_lightning.trainer.distrib_parts.**normalize_parse_gpu_input_to_list**(*gpus*)

pytorch_lightning.trainer.distrib_parts.**normalize_parse_gpu_string_input**(*s*)

pytorch_lightning.trainer.distrib_parts.**parse_gpu_ids**(*gpus*)

Parameters **gpus** – Int, string or list An int -1 or string '-1' indicate that all available GPUs should be used. A list of ints or a string containing list of comma separated integers indicates specific GPUs to use An int 0 means that no GPUs should be used Any int N > 0 indicates that GPUs [0..N) should be used.

Returns

List of gpus to be used

If no GPUs are available but the value of gpus variable indicates request for GPUs then a misconfiguration exception is raised.

pytorch_lightning.trainer.distrib_parts.**pick_multiple_gpus**(*n*)

pytorch_lightning.trainer.distrib_parts.**pick_single_gpu**(*exclude_gpus=[]*)

pytorch_lightning.trainer.distrib_parts.**retry_jittered_backoff**(*f*, *num_retries=5*)

pytorch_lightning.trainer.distrib_parts.**sanitize_gpu_ids**(*gpus*)

Parameters **gpus** – list of ints corresponding to GPU indices Checks that each of the GPUs in the list is actually available. Throws if any of the GPUs is not available.

Returns unmodified gpus variable

pytorch_lightning.trainer.evaluation_loop module

Validation loop

The lightning validation loop handles everything except the actual computations of your model. To decide what will happen in your validation loop, define the *validation_step* function. Below are all the things lightning automates for you in the validation loop.

Note: Lightning will run 5 steps of validation in the beginning of training as a sanity check so you don't have to wait until a full epoch to catch possible validation issues.

Check validation every n epochs

If you have a small dataset you might want to check validation every n epochs

```
# DEFAULT
trainer = Trainer(check_val_every_n_epoch=1)
```

Set how much of the validation set to check

If you don't want to check 100% of the validation set (for debugging or if it's huge), set this flag

val_percent_check will be overwritten by overfit_pct if *overfit_pct > 0*

```
# DEFAULT
trainer = Trainer(val_percent_check=1.0)

# check 10% only
trainer = Trainer(val_percent_check=0.1)
```

Set how much of the test set to check

If you don't want to check 100% of the test set (for debugging or if it's huge), set this flag

test_percent_check will be overwritten by overfit_pct if *overfit_pct > 0*

```
# DEFAULT
trainer = Trainer(test_percent_check=1.0)

# check 10% only
trainer = Trainer(test_percent_check=0.1)
```

Set validation check frequency within 1 training epoch

For large datasets it's often desirable to check validation multiple times within a training loop. Pass in a float to check that often within 1 training epoch. Pass in an int k to check every k training batches. Must use an int if using an IterableDataset.

```
# DEFAULT
trainer = Trainer(val_check_interval=0.95)

# check every .25 of an epoch
trainer = Trainer(val_check_interval=0.25)

# check every 100 train batches (ie: for IterableDatasets or fixed frequency)
trainer = Trainer(val_check_interval=100)
```

Set the number of validation sanity steps

Lightning runs a few steps of validation in the beginning of training. This avoids crashing in the validation loop sometime deep into a lengthy training loop.

```
# DEFAULT
trainer = Trainer(num_sanity_val_steps=5)
```

You can use *Trainer(num_sanity_val_steps=0)* to skip the sanity check.

Testing loop

To ensure you don't accidentally use test data to guide training decisions Lightning makes running the test set deliberate.

test

You have two options to run the test set. First case is where you test right after a full training routine.

```
# run full training
trainer.fit(model)

# run test set
trainer.test()
```

Second case is where you load a model and run the test set

```
model = MyLightningModule.load_from_checkpoint(
    checkpoint_path='/path/to/pytorch_checkpoint.ckpt',
    hparams_file='/path/to/test_tube/experiment/version/hparams.yaml',
    map_location=None
)

# init trainer with whatever options
trainer = Trainer(...)

# test (pass in the model)
trainer.test(model)
```

In this second case, the options you pass to trainer will be used when running the test set (ie: 16-bit, dp, ddp, etc...)

class pytorch_lightning.trainer.evaluation_loop.**TrainerEvaluationLoopMixin**

Bases: abc.ABC

_evaluate(*model*, *dataloaders*, *max_batches*, *test_mode=False*)

Run evaluation code.

Parameters

- **model** (*LightningModule*) – PT model
- **dataloaders** – list of PT dataloaders
- **max_batches** (int) – Scalar
- **test_mode** (bool) –

abstract add_progress_bar_metrics(**args*)

Warning: this is just empty shell for code implemented in other class.

abstract copy_trainer_model_properties(**args*)
Warning: this is just empty shell for code implemented in other class.

evaluation_forward(*model*, *batch*, *batch_idx*, *dataloader_idx*, *test_mode=False*)

abstract get_model()
Warning: this is just empty shell for code implemented in other class.

abstract is_overridden(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract log_metrics(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract reset_test_dataloader(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract reset_val_dataloader(**args*)
Warning: this is just empty shell for code implemented in other class.

run_evaluation(*test_mode=False*)

abstract transfer_batch_to_gpu(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract transfer_batch_to_tpu(**args*)
Warning: this is just empty shell for code implemented in other class.

callback_metrics: ... = None

current_epoch: int = None

data_parallel_device_ids: ... = None

fast_dev_run: ... = None

model: LightningModule = None

num_test_batches: int = None

num_val_batches: int = None

on_gpu: bool = None

on_test_batch_end: Callable = None

on_test_batch_start: Callable = None

on_test_end: Callable = None

on_test_start: Callable = None

on_validation_batch_end: Callable = None

on_validation_batch_start: Callable = None

on_validation_end: Callable = None

on_validation_start: Callable = None

proc_rank: int = None

process_output: ... = None

progress_bar_dict: ... = None

reload_dataloaders_every_epoch: ... = None

single_gpu: bool = None

test_dataloaders: DataLoader = None

use_ddp: bool = None

use_ddp2: bool = None

use_dp: bool = None

use_horovod: bool = None

use_tpu: bool = None

val_dataloaders: DataLoader = None

pytorch_lightning.trainer.ignored_warnings module

pytorch_lightning.trainer.ignored_warnings.**ignore_scalar_return_in_dp**()

pytorch_lightning.trainer.logging module

class pytorch_lightning.trainer.logging.**TrainerLoggingMixin**

Bases: abc.ABC

add_progress_bar_metrics(*metrics*)

configure_logger(*logger*)

log_metrics(*metrics*, *grad_norm_dic*, *step=None*)

Logs the metric dict passed in. If *step* parameter is None and *step* key is presented is metrics, uses metrics["step"] as a step

Parameters

- **metrics** (*dict*) – Metric values
- **grad_norm_dic** (*dict*) – Gradient norms
- **step** (*int*) – Step for which metrics should be logged. Default value corresponds to *self.global_step*

metrics_to_scalars(*metrics*)

process_output(*output*, *train=False*)

Reduces output according to the training mode.

Separates loss from logging and progress bar metrics

reduce_distributed_output(*output*, *num_gpus*)

current_epoch: int = None

default_root_dir: str = None

global_step: int = None

log_gpu_memory: ... = None

logger: Union[LightningLoggerBase, bool] = None

num_gpus: int = None

on_gpu: bool = None

proc_rank: int = None

progress_bar_metrics: ... = None

slurm_job_id: int = None

use_ddp2: bool = None

use_dp: bool = None

pytorch_lightning.trainer.lr_finder module

Trainer Learning Rate Finder

class pytorch_lightning.trainer.lr_finder.**TrainerLRFinderMixin**
Bases: abc.ABC

_TrainerLRFinderMixin__lr_finder_dump_params(*model*)

_TrainerLRFinderMixin__lr_finder_restore_params(*model*)

_run_lr_finder_internally(*model*)
Call lr finder internally during Trainer.fit()

lr_find(*model*, *train_dataloader=None*, *val_dataloaders=None*, *min_lr=1e-08*, *max_lr=1*, *num_training=100*, *mode='exponential'*, *early_stop_threshold=4.0*, *num_accumulation_steps=None*)
lr_find enables the user to do a range test of good initial learning rates, to reduce the amount of guesswork in picking a good starting learning rate.

Parameters

- **model** (*LightningModule*) – Model to do range testing for
- **train_dataloader** (Optional[DataLoader]) – A PyTorch DataLoader with training samples. If the model has a predefined train_dataloader method this will be skipped.
- **min_lr** (float) – minimum learning rate to investigate
- **max_lr** (float) – maximum learning rate to investigate
- **num_training** (int) – number of learning rates to test
- **mode** (str) – search strategy, either 'linear' or 'exponential'. If set to 'linear' the learning rate will be searched by linearly increasing after each batch. If set to 'exponential', will increase learning rate exponentially.
- **early_stop_threshold** (float) – threshold for stopping the search. If the loss at any point is larger than early_stop_threshold*best_loss then the search is stopped. To disable, set to None.
- **num_accumulation_steps** – deprepecated, number of batches to calculate loss over. Set trainer argument accumulate_grad_batches instead.

Example:

```
# Setup model and trainer
model = MyModelClass(hparams)
trainer = pl.Trainer()

# Run lr finder
lr_finder = trainer.lr_find(model, ...)
```

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```
# Inspect results
fig = lr_finder.plot(); fig.show()
suggested_lr = lr_finder.suggestion()

# Overwrite lr and create new model
hparams.lr = suggested_lr
model = MyModelClass(hparams)

# Ready to train with new learning rate
trainer.fit(model)
```

abstract restore(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract save_checkpoint(**args*)
Warning: this is just empty shell for code implemented in other class.

class pytorch_lightning.trainer.lr_finder.**_ExponentialLR**(*optimizer*, *end_lr*, *num_iter*, *last_epoch=-1*)
Bases: torch.optim.lr_scheduler._LRScheduler

Exponentially increases the learning rate between two boundaries over a number of iterations.

Parameters

- **optimizer** (Optimizer) – wrapped optimizer.
- **end_lr** (float) – the final learning rate.
- **num_iter** (int) – the number of iterations over which the test occurs.
- **last_epoch** (int) – the index of last epoch. Default: -1.

get_lr()

property lr

class pytorch_lightning.trainer.lr_finder.**_LRCallback**(*num_training*, *early_stop_threshold=4.0*, *progress_bar_refresh_rate=False*, *beta=0.98*)
Bases: *pytorch_lightning.callbacks.base.Callback*

Special callback used by the learning rate finder. This callbacks log the learning rate before each batch and log the corresponding loss after each batch.

Parameters

- **num_training** (int) – number of iterations done by the learning rate finder
- **early_stop_threshold** (float) – threshold for stopping the search. If the loss at any point is larger than early_stop_threshold*best_loss then the search is stopped. To disable, set to None.
- **progress_bar_refresh_rate** (bool) – rate to refresh the progress bar for the learning rate finder
- **beta** (float) – smoothing value, the loss being logged is a running average of loss values logged until now. beta controls the forget rate i.e. if beta=0 all past information is ignored.

on_batch_end(*trainer*, *pl_module*)
Called when the training batch ends, logs the calculated loss

on_batch_start(*trainer*, *pl_module*)
Called before each training batch, logs the lr that will be used

class pytorch_lightning.trainer.lr_finder.**_LRFinder**(*mode*, *lr_min*, *lr_max*, *num_training*)

Bases: object

LR finder object. This object stores the results of Trainer.lr_find().

Parameters

- **mode** (str) – either *linear* or *exponential*, how to increase lr after each step
- **lr_min** (float) – lr to start search from
- **lr_max** (float) – lr to stop search
- **num_training** (int) – number of steps to take between lr_min and lr_max

Example:: # Run lr finder lr_finder = trainer.lr_find(model)

Results stored in lr_finder.results

Plot using lr_finder.plot()

Get suggestion lr = lr_finder.suggestion()

_get_new_optimizer(*optimizer*)

Construct a new *configure_optimizers()* method, that has a optimizer with initial lr set to lr_min and a scheduler that will either linearly or exponentially increase the lr to lr_max in num_training steps.

Parameters **optimizer** (Optimizer) – instance of *torch.optim.Optimizer*

plot(*suggest=False*, *show=False*)
Plot results from lr_find run :type _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LRFinder.plot.suggest: bool :param _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LRFinder.plot.suggest: if True, will mark suggested lr to use with a red point :type _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LRFinder.plot.show: bool :param _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LRFinder.plot.show: if True, will show figure

suggestion(*skip_begin=10*, *skip_end=1*)
This will propose a suggestion for choice of initial learning rate as the point with the steepest negative gradient.

Returns suggested initial learning rate to use skip_begin: how many samples to skip in the beginning. Prevent too naive estimates skip_end: how many samples to skip in the end. Prevent too optimistic estimates

Return type lr

class pytorch_lightning.trainer.lr_finder.**_LinearLR**(*optimizer*, *end_lr*, *num_iter*, *last_epoch=-1*)

Bases: torch.optim.lr_scheduler._LRScheduler

Linearly increases the learning rate between two boundaries over a number of iterations. :type _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LinearLR.optimizer: Optimizer :param _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LinearLR.optimizer: wrapped optimizer. :type _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LinearLR.end_lr: float :param

_sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LinearLR.end_lr: the final learning rate. :type _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LinearLR.num_iter: int :param _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LinearLR.num_iter: the number of iterations over which the test occurs. :type _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LinearLR.last_epoch: int :param _sphinx_paramlinks_pytorch_lightning.trainer.lr_finder._LinearLR.last_epoch: the index of last epoch. Default: -1.

get_lr()

property lr

pytorch_lightning.trainer.lr_finder.**_nested_hasattr**(*obj*, *path*)

pytorch_lightning.trainer.lr_finder.**_nested_setattr**(*obj*, *path*, *val*)

pytorch_lightning.trainer.model_hooks module

class pytorch_lightning.trainer.model_hooks.**TrainerModelHooksMixin**
Bases: abc.ABC

abstract get_model()
Warning: this is just empty shell for code implemented in other class.

has_arg(*f_name*, *arg_name*)

is_function_implemented(*f_name*)

is_overridden(*method_name*, *model=None*)

Return type bool

pytorch_lightning.trainer.optimizers module

class pytorch_lightning.trainer.optimizers.**TrainerOptimizersMixin**
Bases: abc.ABC

configure_schedulers(*schedulers*)

init_optimizers(*model*)

Return type Tuple[List, List, List]

class pytorch_lightning.trainer.optimizers.**_MockOptimizer**
Bases: torch.optim.optimizer.Optimizer

The *_MockOptimizer* will be used inplace of an optimizer in the event that *None* is returned from *configure_optimizers*.

add_param_group(*param_group*)

load_state_dict(*state_dict*)

state_dict()

step(*closure=None*)

zero_grad()

pytorch_lightning.trainer.seed module

Helper functions to help with reproducibility of models.

pytorch_lightning.trainer.seed.**_select_seed_randomly**(*min_seed_value=0*, *max_seed_value=255*)

Return type int

pytorch_lightning.trainer.seed.**seed_everything**(*seed=None*)

Function that sets seed for pseudo-random number generators in: pytorch, numpy, python.random and sets PYTHONHASHSEED environment variable.

Return type int

pytorch_lightning.trainer.supporters module

class pytorch_lightning.trainer.supporters.**TensorRunningAccum**(*window_length*)

Bases: object

Tracks a running accumulation values (min, max, mean) without graph references.

Examples

```
>>> accum = TensorRunningAccum(5)
>>> accum.last(), accum.mean()
(None, None)
>>> accum.append(torch.tensor(1.5))
>>> accum.last(), accum.mean()
(tensor(1.5000), tensor(1.5000))
>>> accum.append(torch.tensor(2.5))
>>> accum.last(), accum.mean()
(tensor(2.5000), tensor(2.))
>>> accum.reset()
>>> _= [accum.append(torch.tensor(i)) for i in range(13)]
>>> accum.last(), accum.mean(), accum.min(), accum.max()
(tensor(12.), tensor(10.), tensor(8.), tensor(12.))
```

_agg_memory(*how*)

append(*x*)

Add an element to the accumulator.

last()

Get the last added element.

max()

Get maximal value from stored elements.

mean()

Get mean value from stored elements.

min()

Get minimal value from stored elements.

reset()

Empty the accumulator.

Return type None

pytorch_lightning.trainer.trainer module

class pytorch_lightning.trainer.trainer.**Trainer**(*logger=True*, *checkpoint_callback=True*, *early_stop_callback=False*, *callbacks=None*, *default_root_dir=None*, *gradient_clip_val=0*, *process_position=0*, *num_nodes=1*, *num_processes=1*, *gpus=None*, *auto_select_gpus=False*, *num_tpu_cores=None*, *log_gpu_memory=None*, *progress_bar_refresh_rate=1*, *overfit_pct=0.0*, *track_grad_norm=-1*, *check_val_every_n_epoch=1*, *fast_dev_run=False*, *accumulate_grad_batches=1*, *max_epochs=1000*, *min_epochs=1*, *max_steps=None*, *min_steps=None*, *train_percent_check=1.0*, *val_percent_check=1.0*, *test_percent_check=1.0*, *val_check_interval=1.0*, *log_save_interval=100*, *row_log_interval=10*, *add_row_log_interval=None*, *distributed_backend=None*, *precision=32*, *print_nan_grads=False*, *weights_summary='full'*, *weights_save_path=None*, *num_sanity_val_steps=2*, *truncated_bptt_steps=None*, *resume_from_checkpoint=None*, *profiler=None*, *benchmark=False*, *deterministic=False*, *reload_dataloaders_every_epoch=False*, *auto_lr_find=False*, *replace_sampler_ddp=True*, *progress_bar_callback=True*, *terminate_on_nan=False*, *auto_scale_batch_size=False*, *amp_level='O1'*, *default_save_path=None*, *gradient_clip=None*, *nb_gpu_nodes=None*, *max_nb_epochs=None*, *min_nb_epochs=None*, *use_amp=None*, *show_progress_bar=None*, *nb_sanity_val_steps=None*, ***kwargs*)

Bases: *pytorch_lightning.trainer.training_io.TrainerIOMixin*, *pytorch_lightning.trainer.optimizers.TrainerOptimizersMixin*, *pytorch_lightning.trainer.auto_mix_precision.TrainerAMPMixin*, *pytorch_lightning.trainer.distrib_parts.TrainerDPMixin*, *pytorch_lightning.*

trainer.distrib_data_parallel.TrainerDDPMixin, *pytorch_lightning.trainer.logging.TrainerLoggingMixin*, *pytorch_lightning.trainer.model_hooks.TrainerModelHooksMixin*, *pytorch_lightning.trainer.training_tricks.TrainerTrainingTricksMixin*, *pytorch_lightning.trainer.data_loading.TrainerDataLoadingMixin*, *pytorch_lightning.trainer.evaluation_loop.TrainerEvaluationLoopMixin*, *pytorch_lightning.trainer.training_loop.TrainerTrainLoopMixin*, *pytorch_lightning.trainer.callback_config.TrainerCallbackConfigMixin*, *pytorch_lightning.trainer.callback_hook.TrainerCallbackHookMixin*, *pytorch_lightning.trainer.lr_finder.TrainerLRFinderMixin*, *pytorch_lightning.trainer.deprecated_api.TrainerDeprecatedAPITillVer0_8*, *pytorch_lightning.trainer.deprecated_api.TrainerDeprecatedAPITillVer0_9*

Customize every aspect of training via flags

Parameters

- **logger** (Union[*LightningLoggerBase*, Iterable[*LightningLoggerBase*], bool]) – Logger (or iterable collection of loggers) for experiment tracking.
- **checkpoint_callback** (Union[*ModelCheckpoint*, bool]) – Callback for checkpointing.
- **early_stop_callback** (*pytorch_lightning.callbacks.EarlyStopping*) –
- **callbacks** (Optional[List[*Callback*]]) – Add a list of callbacks.
- **default_root_dir** (Optional[str]) – Default path for logs and weights when no logger/ckpt_callback passed
- **default_save_path** –

  Warning: Deprecated since version 0.7.3.

  Use *default_root_dir* instead. Will remove 0.9.0.

- **gradient_clip_val** (float) – 0 means don't clip.
- **gradient_clip** –

  Warning: Deprecated since version 0.7.0.

  Use *gradient_clip_val* instead. Will remove 0.9.0.

- **process_position** (int) – orders the progress bar when running multiple models on same machine.
- **num_nodes** (int) – number of GPU nodes for distributed training.
- **nb_gpu_nodes** –

  Warning: Deprecated since version 0.7.0.

  Use *num_nodes* instead. Will remove 0.9.0.

- **gpus** (Union[List[int], str, int, None]) – Which GPUs to train on.

- **auto_select_gpus** (bool) – If enabled and *gpus* is an integer, pick available gpus automatically. This is especially useful when GPUs are configured to be in "exclusive mode", such that only one process at a time can access them.
- **num_tpu_cores** (Optional[int]) – How many TPU cores to train on (1 or 8).
- **log_gpu_memory** (Optional[str]) – None, 'min_max', 'all'. Might slow performance
- **show_progress_bar** –

> **Warning:** Deprecated since version 0.7.2.
>
> Set *progress_bar_refresh_rate* to positive integer to enable. Will remove 0.9.0.

- **progress_bar_refresh_rate** (int) – How often to refresh progress bar (in steps). Value 0 disables progress bar. Ignored when a custom callback is passed to *callbacks*.
- **overfit_pct** (float) – How much of training-, validation-, and test dataset to check.
- **track_grad_norm** (int) – -1 no tracking. Otherwise tracks that norm
- **check_val_every_n_epoch** (int) – Check val every n train epochs.
- **fast_dev_run** (bool) – runs 1 batch of train, test and val to find any bugs (ie: a sort of unit test).
- **accumulate_grad_batches** (Union[int, Dict[int, int], List[list]]) – Accumulates grads every k batches or as set up in the dict.
- **max_epochs** (int) – Stop training once this number of epochs is reached.
- **max_nb_epochs** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *max_epochs* instead. Will remove 0.9.0.

- **min_epochs** (int) – Force training for at least these many epochs
- **min_nb_epochs** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *min_epochs* instead. Will remove 0.9.0.

- **max_steps** (Optional[int]) – Stop training after this number of steps. Disabled by default (None).
- **min_steps** (Optional[int]) – Force training for at least these number of steps. Disabled by default (None).
- **train_percent_check** (float) – How much of training dataset to check.
- **val_percent_check** (float) – How much of validation dataset to check.
- **test_percent_check** (float) – How much of test dataset to check.

- **val_check_interval** (float) – How often within one training epoch to check the validation set
- **log_save_interval** (int) – Writes logs to disk this often
- **row_log_interval** (int) – How often to add logging rows (does not write to disk)
- **add_row_log_interval** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *row_log_interval* instead. Will remove 0.9.0.

- **distributed_backend** (Optional[str]) – The distributed backend to use.
- **use_amp** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *precision* instead. Will remove 0.9.0.

- **precision** (int) – Full precision (32), half precision (16).
- **print_nan_grads** (bool) –

> **Warning:** Deprecated since version 0.7.2.
>
> Has no effect. When detected, NaN grads will be printed automatically. Will remove 0.9.0.

- **weights_summary** (Optional[str]) – Prints a summary of the weights when training begins.
- **weights_save_path** (Optional[str]) – Where to save weights if specified. Will override default_root_dir for checkpoints only. Use this if for whatever reason you need the checkpoints stored in a different place than the logs written in *default_root_dir*.
- **amp_level** (str) – The optimization level to use (O1, O2, etc...).
- **num_sanity_val_steps** (int) – Sanity check runs n batches of val before starting the training routine.
- **nb_sanity_val_steps** –

> **Warning:** Deprecated since version 0.7.0.
>
> Use *num_sanity_val_steps* instead. Will remove 0.8.0.

- **truncated_bptt_steps** (Optional[int]) – Truncated back prop breaks performs backprop every k steps of
- **resume_from_checkpoint** (Optional[str]) – To resume training from a specific checkpoint pass in the path here.
- **profiler** (Union[*BaseProfiler*, bool, None]) – To profile individual steps during training and assist in

- **reload_dataloaders_every_epoch** (bool) – Set to True to reload dataloaders every epoch
- **auto_lr_find** (Union[bool, str]) – If set to True, will *initially* run a learning rate finder, trying to optimize initial learning for faster convergence. Sets learning rate in self.hparams.lr | self.hparams.learning_rate in the lightning module. To use a different key, set a string instead of True with the key name.
- **replace_sampler_ddp** (bool) – Explicitly enables or disables sampler replacement. If not specified this will toggled automatically ddp is used
- **benchmark** (bool) – If true enables cudnn.benchmark.
- **deterministic** (bool) – If true enables cudnn.deterministic
- **terminate_on_nan** (bool) – If set to True, will terminate training (by raising a *ValueError*) at the end of each training batch, if any of the parameters or the loss are NaN or +/-inf.
- **auto_scale_batch_size** (Union[str, bool]) – If set to True, will *initially* run a batch size finder trying to find the largest batch size that fits into memory. The result will be stored in self.hparams.batch_size in the LightningModule. Additionally, can be set to either *power* that estimates the batch size through a power search or *binsearch* that estimates the batch size through a binary search.

_Trainer__attach_dataloaders(*model*, *train_dataloader=None*, *val_dataloaders=None*, *test_dataloaders=None*)

_Trainer__set_random_port()
When running DDP NOT managed by SLURM, the ports might collide :return:

_allowed_type()

Return type Union[int, str]

_arg_default()

Return type Union[int, str]

classmethod add_argparse_args(*parent_parser*)
Extends existing argparse by default *Trainer* attributes.

Parameters **parent_parser** (ArgumentParser) – The custom cli arguments parser, which will be extended by the Trainer default arguments.

Only arguments of the allowed types (str, float, int, bool) will extend the *parent_parser*.

Examples

```
>>> import argparse
>>> import pprint
>>> parser = argparse.ArgumentParser()
>>> parser = Trainer.add_argparse_args(parser)
>>> args = parser.parse_args([])
>>> pprint.pprint(vars(args))
{...
 'check_val_every_n_epoch': 1,
 'checkpoint_callback': True,
 'default_root_dir': None,
 'deterministic': False,
 'distributed_backend': None,
```

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```
'early_stop_callback': False,
...
'logger': True,
'max_epochs': 1000,
'max_steps': None,
'min_epochs': 1,
'min_steps': None,
...
'profiler': None,
'progress_bar_callback': True,
'progress_bar_refresh_rate': 1,
...}
```

Return type ArgumentParser

check_model_configuration(*model*)
Checks that the model is configured correctly before training is started.

Parameters **model** (*LightningModule*) – The model to test.

check_testing_model_configuration(*model*)

classmethod default_attributes()

fit(*model*, *train_dataloader=None*, *val_dataloaders=None*)
Runs the full optimization routine.

Parameters

- **model** (*LightningModule*) – Model to fit.
- **train_dataloader** (Optional[DataLoader]) – A Pytorch DataLoader with training samples. If the model has a predefined train_dataloader method this will be skipped.
- **val_dataloaders** (Union[DataLoader, List[DataLoader], None]) – Either a single Pytorch Dataloader or a list of them, specifying validation samples. If the model has a predefined val_dataloaders method this will be skipped

Example:

```
# Option 1,
# Define the train_dataloader() and val_dataloader() fxs
# in the lightningModule
# RECOMMENDED FOR MOST RESEARCH AND APPLICATIONS TO MAINTAIN READABILITY
trainer = Trainer()
model = LightningModule()
trainer.fit(model)

# Option 2
# in production cases we might want to pass different datasets to the same␣
↪model
# Recommended for PRODUCTION SYSTEMS
train, val = DataLoader(...), DataLoader(...)
trainer = Trainer()
model = LightningModule()
trainer.fit(model, train_dataloader=train, val_dataloader=val)
```

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```
# Option 1 & 2 can be mixed, for example the training set can be
# defined as part of the model, and validation can then be feed to .fit()
```

classmethod from_argparse_args(*args*, ***kwargs*)
create an instance from CLI arguments

Example

```
>>> parser = ArgumentParser(add_help=False)
>>> parser = Trainer.add_argparse_args(parser)
>>> args = Trainer.parse_argparser(parser.parse_args(""))
>>> trainer = Trainer.from_argparse_args(args)
```

Return type *Trainer*

classmethod get_deprecated_arg_names()
Returns a list with deprecated Trainer arguments.

Return type List

classmethod get_init_arguments_and_types()
Scans the Trainer signature and returns argument names, types and default values.

Returns (argument name, set with argument types, argument default value).

Return type List with tuples of 3 values

Examples

```
>>> args = Trainer.get_init_arguments_and_types()
>>> import pprint
>>> pprint.pprint(sorted(args))
[('accumulate_grad_batches',
  (<class 'int'>, typing.Dict[int, int], typing.List[list]),
  1),
 ...
 ('callbacks',
  (typing.List[pytorch_lightning.callbacks.base.Callback],
   <class 'NoneType'>),
   None),
 ('check_val_every_n_epoch', (<class 'int'>,), 1),
 ...
 ('max_epochs', (<class 'int'>,), 1000),
 ...
 ('precision', (<class 'int'>,), 32),
 ('print_nan_grads', (<class 'bool'>,), False),
 ('process_position', (<class 'int'>,), 0),
 ('profiler',
  (<class 'pytorch_lightning.profiler.profilers.BaseProfiler'>,
   <class 'bool'>,
   <class 'NoneType'>),
  None),
 ...
```

static parse_argparser(*arg_parser*)
Parse CLI arguments, required for custom bool types.

Return type Namespace

run_pretrain_routine(*model*)
Sanity check a few things before starting actual training.

Parameters **model** (*LightningModule*) – The model to run sanity test on.

test(*model=None*, *test_dataloaders=None*)
Separates from fit to make sure you never run on your test set until you want to.

Parameters

- **model** (Optional[*LightningModule*]) – The model to test.
- **test_dataloaders** (Union[DataLoader, List[DataLoader], None]) – Either a single Pytorch Dataloader or a list of them, specifying validation samples.

Example:

```
# Option 1
# run test after fitting
test = DataLoader(...)
trainer = Trainer()
model = LightningModule()

trainer.fit(model)
trainer.test(test_dataloaders=test)

# Option 2
# run test from a loaded model
test = DataLoader(...)
model = LightningModule.load_from_checkpoint('path/to/checkpoint.ckpt')
trainer = Trainer()
trainer.test(model, test_dataloaders=test)
```

DEPRECATED_IN_0_8 = ('gradient_clip', 'nb_gpu_nodes', 'max_nb_epochs', 'min_nb_epochs'

DEPRECATED_IN_0_9 = ('use_amp', 'show_progress_bar', 'training_tqdm_dict')

accumulate_grad_batches = None

checkpoint_callback = None

property data_parallel

Return type bool

early_stop_callback = None

logger = None

lr_schedulers = None

model = None

property num_gpus
this is just empty shell for code implemented in other class.

Type Warning

Return type int

num_training_batches = None

on_gpu = None

on_tpu = None

optimizers = None

proc_rank = None

property progress_bar_dict
Read-only for progress bar metrics.

Return type dict

resume_from_checkpoint = None

root_gpu = None

property slurm_job_id
this is just empty shell for code implemented in other class.

Type Warning

Return type int

use_ddp = None

use_ddp2 = None

use_horovod = None

weights_save_path = None

class pytorch_lightning.trainer.trainer.**_PatchDataLoader**(*dataloader*)
Bases: object

Callable object for patching dataloaders passed into trainer.fit(). Use this class to override model.*_dataloader() and be pickle-compatible.

Parameters **dataloader** (Union[List[DataLoader], DataLoader]) – Dataloader object to return when called.

__call__()
Call self as a function.

Return type Union[List[DataLoader], DataLoader]

pytorch_lightning.trainer.training_io module

Lightning can automate saving and loading checkpoints

Checkpointing is enabled by default to the current working directory. To change the checkpoint path pass in:

```
Trainer(default_root_dir='/your/path/to/save/checkpoints')
```

To modify the behavior of checkpointing pass in your own callback.

```
from pytorch_lightning.callbacks import ModelCheckpoint

# DEFAULTS used by the Trainer
checkpoint_callback = ModelCheckpoint(
    filepath=os.getcwd(),
    save_top_k=1,
    verbose=True,
```

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```
    monitor='val_loss',
    mode='min',
    prefix=''
)

trainer = Trainer(checkpoint_callback=checkpoint_callback)
```

Restoring training session

You might want to not only load a model but also continue training it. Use this method to restore the trainer state as well. This will continue from the epoch and global step you last left off. However, the dataloaders will start from the first batch again (if you shuffled it shouldn't matter).

Lightning will restore the session if you pass a logger with the same version and there's a saved checkpoint.

```
from pytorch_lightning import Trainer

trainer = Trainer(
    resume_from_checkpoint=PATH
)

# this fit call loads model weights and trainer state
# the trainer continues seamlessly from where you left off
# without having to do anything else.
trainer.fit(model)
```

The trainer restores:

- global_step
- current_epoch
- All optimizers
- All lr_schedulers
- Model weights

You can even change the logic of your model as long as the weights and "architecture" of the system isn't different. If you add a layer, for instance, it might not work.

At a rough level, here's what happens inside Trainer `pytorch_lightning.base_module.model_saving.py`:

```
self.global_step = checkpoint['global_step']
self.current_epoch = checkpoint['epoch']

# restore the optimizers
optimizer_states = checkpoint['optimizer_states']
for optimizer, opt_state in zip(self.optimizers, optimizer_states):
    optimizer.load_state_dict(opt_state)

# restore the lr schedulers
lr_schedulers = checkpoint['lr_schedulers']
for scheduler, lrs_state in zip(self.lr_schedulers, lr_schedulers):
    scheduler['scheduler'].load_state_dict(lrs_state)
```

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```
# uses the model you passed into trainer
model.load_state_dict(checkpoint['state_dict'])
```

class pytorch_lightning.trainer.training_io.**TrainerIOMixin**

Bases: abc.ABC

_atomic_save(*checkpoint*, *filepath*)

Saves a checkpoint atomically, avoiding the creation of incomplete checkpoints.

This will create a temporary checkpoint with a suffix of `.part`, then copy it to the final location once saving is finished.

Parameters

- **checkpoint** – The object to save. Built to be used with the `dump_checkpoint` method, but can deal with anything which `torch.save` accepts.
- **filepath** (`str`) – The path to which the checkpoint will be saved. This points to the file that the checkpoint will be stored in.

dump_checkpoint()

get_model()

hpc_load(*folderpath*, *on_gpu*)

hpc_save(*folderpath*, *logger*)

max_ckpt_in_folder(*path*, *name_key='ckpt_'*)

register_slurm_signal_handlers()

restore(*checkpoint_path*, *on_gpu*)

Restore training state from checkpoint. Also restores all training state like: - epoch - callbacks - schedulers - optimizer

restore_hpc_weights_if_needed(*model*)

If there is a set of hpc weights, use as signal to restore model.

restore_training_state(*checkpoint*)

Restore trainer state. Model will get its change to update :param _sphinx_paramlinks_pytorch_lightning.trainer.training_io.TrainerIOMixin.restore_training_state.checkpoint: :return:

restore_weights(*model*)

We attempt to restore weights in this order: 1. HPC weights. 2. if no HPC weights restore checkpoint_path weights 3. otherwise don't restore weights

save_checkpoint(*filepath*)

sig_handler(*signum*, *frame*)

term_handler(*signum*, *frame*)

accumulate_grad_batches: int = None

checkpoint_callback: ... = None

early_stop_callback: ... = None

logger: Union[LightningLoggerBase, bool] = None

lr_schedulers: ... = None

model: LightningModule = None

```
num_training_batches: int = None
on_gpu: bool = None
on_tpu: bool = None
optimizers: ... = None
proc_rank: int = None
resume_from_checkpoint: ... = None
root_gpu: ... = None
use_ddp: bool = None
use_ddp2: bool = None
use_horovod: bool = None
weights_save_path: str = None
```

pytorch_lightning.trainer.training_loop module

The lightning training loop handles everything except the actual computations of your model. To decide what will happen in your training loop, define the *training_step* function.

Below are all the things lightning automates for you in the training loop.

Accumulated gradients

Accumulated gradients runs K small batches of size N before doing a backwards pass. The effect is a large effective batch size of size KxN.

```
# DEFAULT (ie: no accumulated grads)
trainer = Trainer(accumulate_grad_batches=1)
```

Force training for min or max epochs

It can be useful to force training for a minimum number of epochs or limit to a max number

```
# DEFAULT
trainer = Trainer(min_epochs=1, max_epochs=1000)
```

Force disable early stop

To disable early stopping pass None to the early_stop_callback

```
# DEFAULT
trainer = Trainer(early_stop_callback=None)
```

Gradient Clipping

Gradient clipping may be enabled to avoid exploding gradients. Specifically, this will clip the gradient norm computed over all model parameters `together.

```
# DEFAULT (ie: don't clip)
trainer = Trainer(gradient_clip_val=0)

# clip gradients with norm above 0.5
trainer = Trainer(gradient_clip_val=0.5)
```

Inspect gradient norms

Looking at grad norms can help you figure out where training might be going wrong.

```
# DEFAULT (-1 doesn't track norms)
trainer = Trainer(track_grad_norm=-1)

# track the LP norm (P=2 here)
trainer = Trainer(track_grad_norm=2)
```

Set how much of the training set to check

If you don't want to check 100% of the training set (for debugging or if it's huge), set this flag.

train_percent_check will be overwritten by overfit_pct if *overfit_pct > 0*

```
# DEFAULT
trainer = Trainer(train_percent_check=1.0)

# check 10% only
trainer = Trainer(train_percent_check=0.1)
```

Packed sequences as inputs

When using PackedSequence, do 2 things: 1. return either a padded tensor in dataset or a list of variable length tensors in the dataloader collate_fn (example above shows the list implementation). 2. Pack the sequence in forward or training and validation steps depending on use case.

```
# For use in dataloader
def collate_fn(batch):
    x = [item[0] for item in batch]
    y = [item[1] for item in batch]
    return x, y

# In module
def training_step(self, batch, batch_idx):
    x = rnn.pack_sequence(batch[0], enforce_sorted=False)
    y = rnn.pack_sequence(batch[1], enforce_sorted=False)
```

Truncated Backpropagation Through Time

There are times when multiple backwards passes are needed for each batch. For example, it may save memory to use Truncated Backpropagation Through Time when training RNNs.

When this flag is enabled each batch is split into sequences of size truncated_bptt_steps and passed to training_step(...) separately. A default splitting function is provided, however, you can override it for more flexibility. See *tbptt_split_batch*.

```
# DEFAULT (single backwards pass per batch)
trainer = Trainer(truncated_bptt_steps=None)

# (split batch into sequences of size 2)
trainer = Trainer(truncated_bptt_steps=2)
```

NaN detection and intervention

When the *terminate_on_nan* flag is enabled, after every forward pass during training, Lightning will check that

1. the loss you return in *training_step* is finite (not NaN and not +/-inf)
2. the model parameters have finite values.

Lightning will terminate the training loop with an error message if NaN or infinite values are detected. If this happens, you should investigate numerically unstable operations in your model.

```
# DEFAULT (won't perform the NaN check)
trainer = Trainer(terminate_on_nan=False)

# (NaN check each batch and terminate on NaN or infinite values)
trainer = Trainer(terminate_on_nan=True)
```

class pytorch_lightning.trainer.training_loop.**TrainerTrainLoopMixin**
Bases: abc.ABC

_get_optimizers_iterable()

abstract add_progress_bar_metrics(**args*)
Warning: this is just empty shell for code implemented in other class.

call_checkpoint_callback()

call_early_stop_callback()

abstract clip_gradients()
Warning: this is just empty shell for code implemented in other class.

abstract detect_nan_tensors(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract get_model()
Warning: this is just empty shell for code implemented in other class.

abstract has_arg(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract is_function_implemented(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract is_overridden(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract log_metrics(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract process_output(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract reset_train_dataloader(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract reset_val_dataloader(*model*)
Warning: this is just empty shell for code implemented in other class.

abstract run_evaluation(**args*)
Warning: this is just empty shell for code implemented in other class.

run_training_batch(*batch*, *batch_idx*)

run_training_epoch()

run_training_teardown()

train()

training_forward(*batch*, *batch_idx*, *opt_idx*, *hiddens*)
Handle forward for each training case (distributed, single gpu, etc...) :param _sphinx_paramlinks_pytorch_lightning.trainer.training_loop.TrainerTrainLoopMixin.training_forward.batch: :param _sphinx_paramlinks_pytorch_lightning.trainer.training_loop.TrainerTrainLoopMixin.training_forward.batch_idx: :return:

abstract transfer_batch_to_gpu(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract transfer_batch_to_tpu(**args*)
Warning: this is just empty shell for code implemented in other class.

update_learning_rates(*interval*)
Update learning rates.

Parameters **interval** (str) – either 'epoch' or 'step'.

accumulate_grad_batches: int = None

accumulation_scheduler: ... = None

batch_idx: int = None

callback_metrics: ... = None

callbacks: List[Callback] = None

check_val_every_n_epoch: ... = None

checkpoint_callback: ... = None

data_parallel_device_ids: ... = None

disable_validation: bool = None

early_stop_callback: ... = None

enable_early_stop: ... = None

fast_dev_run: ... = None

```
global_step: int = None
interrupted: bool = None
log_save_interval: float = None
logger: Union[LightningLoggerBase, bool] = None
lr_schedulers: ... = None
max_epochs: int = None
max_steps: int = None
min_epochs: int = None
min_steps: int = None
model: LightningModule = None
num_training_batches: int = None
num_val_batches: int = None
on_batch_end: Callable = None
on_batch_start: Callable = None
on_epoch_end: Callable = None
on_epoch_start: Callable = None
on_gpu: bool = None
on_train_end: Callable = None
on_train_start: Callable = None
on_validation_end: Callable = None
optimizer_frequencies: ... = None
optimizers: ... = None
precision: ... = None
proc_rank: int = None
profiler: ... = None
progress_bar_dict: ... = None
reduce_lr_on_plateau_scheduler: ... = None
reload_dataloaders_every_epoch: bool = None
row_log_interval: float = None
running_loss: ... = None
single_gpu: bool = None
terminate_on_nan: bool = None
testing: bool = None
total_batch_idx: int = None
track_grad_norm: ... = None
train_dataloader: DataLoader = None
```

truncated_bptt_steps: ... = None

use_ddp: bool = None

use_ddp2: bool = None

use_dp: bool = None

use_horovod: bool = None

use_tpu: bool = None

val_check_batch: ... = None

pytorch_lightning.trainer.training_loop.**_with_is_last**(*iterable*)
Pass through values from the given iterable with an added boolean indicating if this is the last item. See https://stackoverflow.com/a/1630350

pytorch_lightning.trainer.training_tricks module

class pytorch_lightning.trainer.training_tricks.**TrainerTrainingTricksMixin**
Bases: abc.ABC

_TrainerTrainingTricksMixin__scale_batch_dump_params()

_TrainerTrainingTricksMixin__scale_batch_reset_params(*model*, *steps_per_trial*)

_TrainerTrainingTricksMixin__scale_batch_restore_params()

clip_gradients()

configure_accumulated_gradients(*accumulate_grad_batches*)

detect_nan_tensors(*loss*)

Return type None

abstract fit(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract get_model()
Warning: this is just empty shell for code implemented in other class.

print_nan_gradients()

Return type None

abstract restore(**args*)
Warning: this is just empty shell for code implemented in other class.

abstract save_checkpoint(**args*)
Warning: this is just empty shell for code implemented in other class.

scale_batch_size(*model*, *mode='power'*, *steps_per_trial=3*, *init_val=2*, *max_trials=25*, *batch_arg_name='batch_size'*)
Will iteratively try to find the largest batch size for a given model that does not give an out of memory (OOM) error.

Parameters

- **model** (*LightningModule*) – Model to fit.
- **mode** (str) – string setting the search mode. Either *power* or *binsearch*. If mode is *power* we keep multiplying the batch size by 2, until we get an OOM error. If mode is 'binsearch', we will initially also keep multiplying by 2 and after encountering an OOM

error do a binary search between the last successful batch size and the batch size that failed.

- **steps_per_trial** (int) – number of steps to run with a given batch size. Idealy 1 should be enough to test if a OOM error occurs, however in practise a few are needed
- **init_val** (int) – initial batch size to start the search with
- **max_trials** (int) – max number of increase in batch size done before algorithm is terminated

gradient_clip_val: ... = None

on_gpu: bool = None

precision: ... = None

pytorch_lightning.trainer.training_tricks.**_adjust_batch_size**(*trainer*, *batch_arg_name='batch_size'*, *factor=1.0*, *value=None*, *desc=None*)

Function for adjusting the batch size. It is expected that the user has provided a model that has a hparam field called *batch_size* i.e. *model.hparams.batch_size* should exist.

Parameters

- **trainer** – instance of pytorch_lightning.Trainer
- **batch_arg_name** (str) – field where batch_size is stored in *model.hparams*
- **factor** (float) – value which the old batch size is multiplied by to get the new batch size
- **value** (Optional[int]) – if a value is given, will override the batch size with this value. Note that the value of *factor* will not have an effect in this case
- **desc** (Optional[str]) – either *succeeded* or *failed*. Used purely for logging

pytorch_lightning.trainer.training_tricks.**_run_binsearch_scaling**(*trainer*, *model*, *new_size*, *batch_arg_name*, *max_trials*)

Batch scaling mode where the size is initially is doubled at each iteration until an OOM error is encountered. Hereafter, the batch size is further refined using a binary search

pytorch_lightning.trainer.training_tricks.**_run_power_scaling**(*trainer*, *model*, *new_size*, *batch_arg_name*, *max_trials*)

Batch scaling mode where the size is doubled at each iteration until an OOM error is encountered.

34.7 pytorch_lightning.utilities package

General utilities

34.7.1 Submodules

pytorch_lightning.utilities.distributed module

pytorch_lightning.utilities.distributed.**_warn**(**args*, ***kwargs*)

pytorch_lightning.utilities.distributed.**rank_zero_only**(*fn*)

pytorch_lightning.utilities.distributed.**rank_zero_warn**(**args*, ***kwargs*)

pytorch_lightning.utilities.exceptions module

exception pytorch_lightning.utilities.exceptions.**MisconfigurationException**
Bases: Exception

pytorch_lightning.utilities.memory module

pytorch_lightning.utilities.memory.**garbage_collection_cuda**()
Garbage collection Torch (CUDA) memory.

pytorch_lightning.utilities.memory.**is_cuda_out_of_memory**(*exception*)

pytorch_lightning.utilities.memory.**is_cudnn_snafu**(*exception*)

pytorch_lightning.utilities.memory.**is_oom_error**(*exception*)

pytorch_lightning.utilities.memory.**is_out_of_cpu_memory**(*exception*)

pytorch_lightning.utilities.memory.**recursive_detach**(*in_dict*)
Detach all tensors in *in_dict*.

May operate recursively if some of the values in *in_dict* are dictionaries which contain instances of *torch.Tensor*. Other types in *in_dict* are not affected by this utility function.

Parameters **in_dict** (dict) –

Returns

Return type out_dict

pytorch_lightning.utilities.parsing module

pytorch_lightning.utilities.parsing.**clean_namespace**(*hparams*)
Removes all functions from hparams so we can pickle :param _sphinx_paramlinks_pytorch_lightning.utilities.parsing.clean_names
:return:

pytorch_lightning.utilities.parsing.**strtobool**(*val*)
Convert a string representation of truth to true (1) or false (0). Copied from the python implementation distutils.utils.strtobool

True values are ‘y’, ‘yes’, ‘t’, ‘true’, ‘on’, and ‘1’; false values are ‘n’, ‘no’, ‘f’, ‘false’, ‘off’, and ‘0’. Raises ValueError if ‘val’ is anything else.

```
>>> strtobool('YES')
1
>>> strtobool('FALSE')
0
```

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