Automate Engineering Code with Pytorch Lightning

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Disclaimer

Even though this presentation will sound like a sales pitch for pytorch lightning, I am not associated with the pytorch lightning project and I have not contributed to it.

It is a tool that I find useful and think you will also find useful.

Engineering Code vs. Research Code

What is engineering code?

Engineering code:

- Training/validation/test loops.
- Debug functionality.
- Early stopping.
- GPU and distributed computing.
- And other boilerplate, boring stuff.

Research code:

- Model.
- Training/validation/test step.
- And other interesting stuff.

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An example of boilerplate code

LIVE CODING EXAMPLE

An example of boilerplate code

With boring stuff:

```
class MyClass():
    def __init__(self, a, b):
        self._a = a
        self._b = b
```

Without boring stuff:

```
@dataclass
class MyDataClass():
    a: int
    b: float
```

Flexibility vs. Readability

Higher flexibility

Messier code

More error prone:

```python
class MyClass():
    def __init__(self, a, b):
        self._a = a
        self._b = b
```

Lower flexibility

Cleaner code

Less error prone:

```python
@dataclass
class MyDataClass():
    a: int
    b: float
```

Opinions on PyTorch vs TensorFlow

PyTorch:

Flexible models (“normal” code)*
Easy debugging (`print()` works)*

Deployment is manual and requires a lot of boilerplate code

TensorFlow:

Models are difficult to change*
Difficult debugging*

Deployment is streamlined

*Common thoughts about PyTorch vs. TensorFlow online

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Introduction to `pytorch-lightning`

What is `pytorch-lightning`

Pytorch-lightning is a tool to organize pytorch code.
Pytorch-lightning organizes code into 3 categories:

1. Research code
2. Engineering code (Boilerplate)
3. Non-essential research code (logging)

Comparing pure torch to `pytorch-lightning`

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Research code

PyTorch

```
# 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()))
```

PyTorch Lightning

```
# 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}
```

Engineering code

PyTorch

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  def training_step(self, batch, batch_idx):
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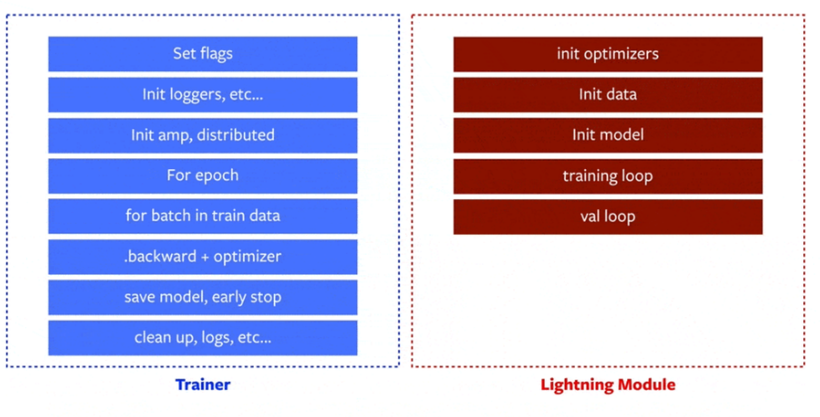
    return loss
```

```python
if __name__ == '__main__':
  net = Net()

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

Summary thus far



Question break

Validation, Testing, Progress Bar, and Logging

Validation

To do validation, you add two methods and a dataloader:

```python
def validation_step(self, batch, batch_idx):
    """ Calculate validation for batch """

def validation_epoch_end(self, outputs):
    """ Average results over all batches """

def val_dataloader(self):
    """ Returns a validation dataloader """
```

Testing

Testing is similar to validation:

```
def test_step(self, batch, batch_idx):
    """ Calculate test for batch """

def test_epoch_end(self, outputs):
    """ Average results over all batches """
```

Progress Bar and Logging

All `_step` and `_epoch_end` methods *must* return a dictionary where you choose what is logged and shown in the progress bar.

```
def training_step(self, batch, batch_idx):
    return {'loss', {None}}

def validation_epoch_end(self, batch, batch_idx):
    return {'progress_bar': {null},
        'log': {None}}
```

Customizable loggers

Tensorboard is used as the default logger, and can be swapped to any other logger compatible with Pytorch Lightning, see `https://pytorch-lightning.readthedocs.io/en/latest/loggers.html`. For example TestTube:

```
def main():
    from pytorch_lightning.loggers import TestTubeLogger
    ttlogger = TestTubeLogger('tb_logs', name='my_model')
    trainer = pl.Trainer(logger=ttlogger)
```

Full code example

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Summary of section

To add *validation* or *testing* functionality, you add `step` and `epoch_end` (collation) methods, as well as a dataloader for each functionality.

Logging is easily added, and logger behaviour can be changed.

Debugging

Validation sanity checks

Pytorch Lightning runs a few validation steps (5 by default) before training to find errors before costly training begins. Can be customized:

```
trainer = Trainer(num_sanity_val_steps=5)
```

Fast dev run

To quickly check that the model runs through all steps correctly, you can set the `fast_dev_run` flag:

```
trainer = Trainer(fast_dev_run=True)
```

Overfitting checks

You can tell the trainer to overfit on a small subset of your data to check that the loss goes to 0.

```
trainer = pl.Trainer(
        overfit_pct=0.01, # Overfits on 1% of the data
        training_percent_check=0.01, # Overfits on 1% of the training data
```

Customizing the training loop

Callbacks

Non-essential functionality is put in callbacks, some important ones are already defined such as early stopping and model checkpointing

```
from pytorch_lightning.callbacks import EarlyStopping, \

 ModelCheckpoint

early_stopping = EarlyStopping('val_loss')
checkpoint_callback = ModelCheckpoint(filepath='my/path/')

trainer = Trainer(early_stop_callback=early_stopping,
                                    checkpoint_callback=checkpoint_callback)
```

Callbacks

Each callback can be further customized to suit specific tasks, and new callbacks can be written if needed, see `https://pytorch-lightning.readthedocs.io/en/latest/callbacks.html`.

Model Hooks

The *model hooks* are the methods that comprise the model interface.
`training_step` is a model hook.

Each hook represent a behaviour of the model, and all hooks can be changed to change the behaviour.

Hooks example: `on_epoch_start`

Used if you have something you need to do at the start of each epoch:

```
class Net(pl.LightningModule):
        def on_epoch_start():
                print('new epoch started')
                self.a *= 1.1
```

More Hooks

Consult the documentation for more hooks, some are very specific and they are open to suggestions for new hooks.

`https://pytorch-lightning.readthedocs.io/en/latest/api/pytorch_lightning.core.hooks.html`

What else?

Some other interesting things in no particular order:

- Use multiple optimizers and learning rate schedulers (GANs for instance)
- Profiling performance (Nice to find bottlenecks)
- GPU training is easier to do (Set one flag)
- Distributed training (Haven't tried this myself)
- Other things I have no use for but you might!

Summary

Summary

Pytorch Lightning is a framework for Pytorch that strives to reduce the amount of engineering code in your projects, letting you focus on research.

Logging is automatic.

Debugging functionality is built-in.

Little flexibility is lost due to flexible callbacks and model hooks.

“Standardizes” training code in Pytorch (to those who use it).

Questions and Discussion