Pytorch Lightning Introduction

Welcome to the introduction to `PyTorchLightning` (https://www.pytorchlightning.ai/). PyTorch Lightning is a wrapper for PyTorch that is focused towards building neural networks model quickly by removing the boilerplate code. It also extends the functionality of PyTorch, for example, with model Callbacks and automatic porting to GPU to accelerate computations.

Let's get started by installing PyTorch Lightning.

Installing Pytorch Lightning

In [1]:
```
# remove the "> /dev/null" if you want to see the output of installation status
!pip install pytorch-lightning==1.0.8 > /dev/null
```

In [2]:
```
import pytorch_lightning as pl
print(f"Lightning version: {pl.__version__}")
if not pl.__version__.startswith("1.0"):
    print("You are using another version of pytorch lightning. We expect pytorch lightning 1.0.8. You can continue with your version but it"
          " might cause dependency and compatibility issues.")
```

```
Lightning version: 1.0.8
```


1. Idea behind PyTorch Lightning

Codes in a Deep learning project consists of three main categories:

1. **Research code**
   This is the exciting part of the experiment where you configure the model architecture and try out different optimizers and target task. This is managed by the `LightningModule` of PyTorch Lightning.
2. **Engineering code**
   This is the same set of code that remain the same for all deep learning projects.Recall the training block of previous notebooks where we loop through the epochs and mini-batches. The `Trainer` class of PyTorch Lightning takes care of this part of code.
3. **Non-essential code** It is very important that we log our training metrics and organize different training runs to have purposeful experimentation of models. The `Callbacks` class PyTorch Lightning helps us with this section.

Let's look at each of these modules in detail.

1. **LightningModules** contain all model related code. This is the part where we are working on when creating a new project. The idea is to have all important code in one module, e.g., the model's architecture and the evaluation of training and validation metrics. This provides a better overview as repeated elements, such as the training procedure, are not stored in the code that we work on. The lightning module also handles the calls `.to(device)` or `.train()` and `.eval()` . Hence, there is no need anymore to switch between the cpu and gpu and to take care of the model's mode as this is automated by the LightningModule. The framework also enables easy parallel computation on multiple gpus.
2. **Trainer** contains all code needed for training our neural networks that doesn't change for each project ("one size fits all"). Usually, we don't touch the code automated by this class. The arguments that are specific for one training such as learning rate and batch size are provided as initialization arguments for the LightningModule.
3. **Callbacks** automate all parts needed for logging hyperparameters or training results such as the tensorboard logger. Logging becomes very important for research later since the results of experiments need to be reproducible.

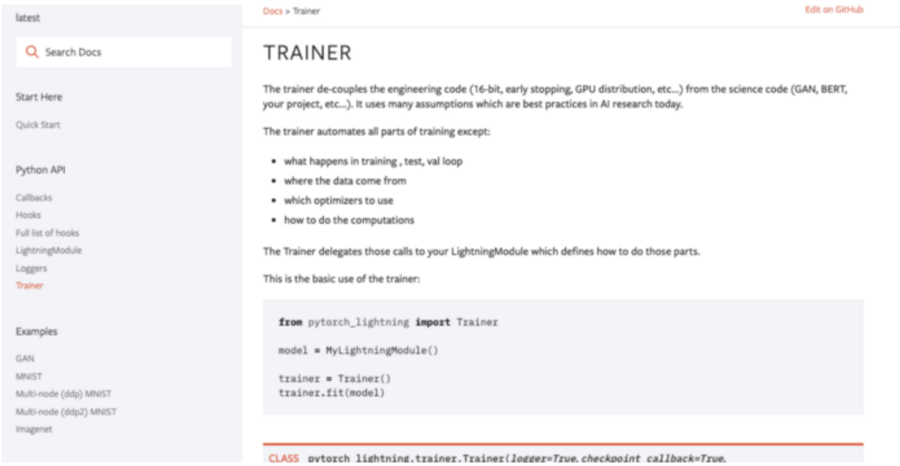
All in all, PyTorch is a framework that handles all (annoying) "engineering" stuff for you such that you have more time for exciting research and scientific coding. This also results in the advantage that automated parts are guaranteed to be bug-free. Hence, you can't include a bug in a part of your code that is often used but not often checked.

2. Overview of the PyTorch Lightning code

Research relevant code goes into the `LightningModule` . The advantage is that we have all the model building, training & validation steps within a single class. These are the components that usually change based on the projects and tasks.

![tensorBoard Interface]

The remaining code is automated by the `Trainer` class which takes care of the tasks of our mechanical training loops components such as iterating through the minibatches and gradient updating steps.



We could already see how much more readable and concise our code is, after being transformed by PyTorch Lightning.

Let us now train a neural network model with PyTorch Lightning.

4. Training with PyTorch Lightning

We will build a two-layer neural network to train on the the [`Fashion-MNIST` (https://research.zalando.com/welcome/mission/research-projects/fashion-mnist/)](https://research.zalando.com/welcome/mission/research-projects/fashion-mnist/) dataset for this notebook.

4.1 Define A LightningModule

We define our network as an instance of `pl.LightningModule` which replaces our `PyTorch` network based on the class `nn.Module` . Additionally, it contains all the relevant parts that are used for training and evaluating different models on various tasks.

Let's have a look at the implementation of `TwoLayerNet` in `exercise_code.lightning_models` .

The `__init__()` and `forward()` function defining the forward pass remain the same. Hence, we can just copy the code from the `nn.Module` .

```
class TwoLayerNet(pl.LightningModule):
    def __init__(self, hparams, input_size=1 * 28 * 28, hidden_size=512, num
_classes=10):
        super().__init__()
        self.hparams = hparams

        self.model = nn.Sequential(
            nn.Linear(input_size, hidden_size),
            nn.Sigmoid(),
            nn.Linear(hidden_size, num_classes),
        )

    def forward(self, x):
        # flatten the image  before sending as input to the model
        N, _, _, _ = x.shape
        x = x.view(N, -1)

        x = self.model(x)

        return x
```

We will now define the training and validation steps since they also vary with different tasks and projects. Consequently, it is useful to integrate these parts into our instance of `LightningModule` . Validation loss is returned for each validation mini-batch and averaged at the end of the epoch.

```
    def training_step(self, batch, batch_idx):
        images, targets = batch

        # Perform a forward pass on the network with inputs
        out = self.forward(images)

        # calculate the loss with the network predictions and ground truth t
argets
        loss = F.cross_entropy(out, targets)

        # Find the predicted class from probabilities of the image belonging
to each of the classes
        # from the network output
        _, preds = torch.max(out, 1)

        # Calculate the accuracy of predictions
        acc = preds.eq(targets).sum().float() / targets.size(0)

        # Log the accuracy and loss values to the tensorboard
        self.log('loss', loss)
        self.log('acc', acc)

        return {'loss': loss}

    def validation_step(self, batch, batch_idx):
        images, targets = batch

        # Perform a forward pass on the network with inputs
        out = self.forward(images)

        # calculate the loss with the network predictions and ground truth t
argets
        loss = F.cross_entropy(out, targets)

        # Find the predicted class from probabilities of the image belonging
to each of the classes
        # from the network output
        _, preds = torch.max(out, 1)

        # Calculate the accuracy of predictions
        acc = preds.eq(targets).sum().float() / targets.size(0)

        # Visualise the predictions  of the model
        if batch_idx == 0:
            self.visualize_predictions(images, out.detach(), targets)

        return {'val_loss': loss, 'val_acc': acc}
```



```
    def validation_epoch_end(self, outputs):

        # Average the loss over the entire validation data from it's mini-ba
tches
        avg_loss = torch.stack([x['val_loss'] for x in outputs]).mean()
        avg_acc = torch.stack([x['val_acc'] for x in outputs]).mean()

        # Log the validation accuracy and loss values to the tensorboard
        self.log('val_loss', avg_loss)
        self.log('val_acc', avg_acc)
```

The last step missing in our `LightningModule` is the optimizer. This method needs to be defined in every `ightningModule`.

```
def configure_optimizers(self):
        optim = torch.optim.SGD(self.model.parameters(), self.hparams["learn
ing_rate"], momentum=0.9)

        return optim
```

Now that we have set up the model and the training steps, we will now establish the data pipeline. PyTorch Lightning provides the `LightningDataModule` for setting up the dataloaders.

Let's have a look at the implementation of `FashionMNISTDataModule` in `exercise_code.data_class`.

The `prepare_data()` function intends to set up the dataset and the related transforms for it. As previously, we download the `FashionMNIST` dataset using `torchvision` and split the total training data into a training and validation set for tuning hyperparameters.

```
class FashionMNISTDataModule(pl.LightningDataModule):

    def __init__(self, batch_size=4):
        super().__init__()
        self.batch_size = batch_size

    def prepare_data(self):

        # Define the transform
        transform = transforms.Compose([transforms.ToTensor(),
                                        transforms.Normalize((0.5,), (0.5
,))])

        # Download the Fashion-MNIST dataset
        fashion_mnist_train_val = torchvision.datasets.FashionMNIST(root=
'../datasets', train=True,
                                                                    download=
True, transform=transform)

        self.fashion_mnist_test = torchvision.datasets.FashionMNIST(root=
'../datasets', train=False,
                                                                   download=Tr
ue, transform=transform)

        # Apply the Transforms
        transform = transforms.Compose([transforms.ToTensor(),
                                        transforms.Normalize((0.5,), (0.5
,))])

        # Perform the training and validation split
        self.train_dataset, self.val_dataset = random_split(
            fashion_mnist_train_val, [50000, 10000])
```

We shall now define `Dataloaders` for each of the data-splits. These data loaders can be directly called during model training!


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

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

    def test_dataloader(self):
        return DataLoader(self.fashion_mnist_test, batch_size=self.batch_siz
e)
```

You can notice now that most of the code of these steps can be directly copied from a Vanilla PyTorch code. Lightning just rearranges them. This marks the end of the research part of the code.

Let's see now how the `Trainer` class works:

4.2 Fitting the model with a Trainer

We will initialize the model and the data with a set of hyperparameters given in the dictionary `hparams` .

In [3]:
```
from IPython.display import clear_output

from exercise_code.lightning_models import TwoLayerNet
from exercise_code.data_class import FashionMNISTDataModule

hparams = {
    "batch_size": 16,
    "learning_rate": 1e-3,
}


model = TwoLayerNet(hparams)

data=FashionMNISTDataModule(hparams["batch_size"])
data.prepare_data()
```

PyTorch Lightning provides ample flexibility for training using [`Trainer` (https://pytorch-lightning.readthedocs.io/en/latest/trainer.html)](https://pytorch-lightning.readthedocs.io/en/latest/trainer.html) class. Have a look at the documentation to know more about them!

Let's initialize it now!

In [4]:
```
trainer = pl.Trainer(
    weights_summary=None,
    max_epochs=1,
    progress_bar_refresh_rate=25, # to prevent notebook crashes in Googl
e Colab environments
    # Uncomment to use GPU if available
    # gpus=1
)
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
```

The argument `max_epochs` sets the maximum number of epochs for training. The argument `weights_summary` prints a summary of the number of weights per layer at the beginning of the training. Set it to None if the summary is not required.

Here comes the actual training cell. The `fit` (https://pytorch-lightning.readthedocs.io/en/latest/_modules/pytorch_lightning/trainer/trainer.html#Trainer.fit) function takes in the model and data to train the model with a lot more optional arguments for customization.

In [5]:
```
trainer.fit(model,train_dataloader=data.train_dataloader(),val_dataloade
rs=data.val_dataloader())
```

```
/opt/anaconda3/lib/python3.7/site-packages/pytorch_lightning/utilities/
distributed.py:45: UserWarning: The dataloader, val dataloader 0, does
not have many workers which may be a bottleneck. Consider increasing th
e value of the `num_workers` argument` (try 4 which is the number of cp
us on this machine) in the `DataLoader` init to improve performance.
  warnings.warn(*args, **kwargs)


/opt/anaconda3/lib/python3.7/site-packages/pytorch_lightning/utilities/
distributed.py:45: UserWarning: The dataloader, train dataloader, does
not have many workers which may be a bottleneck. Consider increasing th
e value of the `num_workers` argument` (try 4 which is the number of cp
us on this machine) in the `DataLoader` init to improve performance.
  warnings.warn(*args, **kwargs)
```

Out[5]: 1

Checkout the directory `lightning_logs` . For each run there is a new directory `version_xx` created. The rightmost argument in the progress bar, the `v_num` variable above shows the version of the current run. Each directory automatically contains a folder with checkpoints, logs and the hyperparameters for this run.

As seen in the last notebook, you can have a look at the logs of the runs in the TensorBoard
Use the command as in the previous notebook in your terminal

```
tensorboard --logdir lightning_logs
```

Make sure to use the above command as the same directory as `exercise_07` .

If you are using Google Colab, run the following cell to load the TensorBoard extension within the notebook. You may have to scroll to this block whenever you need to look at the TensorBoard interface.

In [6]:
```
# %load_ext tensorboard
# %tensorboard --logdir lightning_logs
```

4.3 Add images to tensorboard

The tensorboard logger is a submodule of the `LightningModule` and can be accessed via `self.logger`. We can add images to the logging module by calling

```
self.logger.experiment.add_image('tag', image)
```

to add an image.

We will log the first batch of validation images in a grid together with the predicted class labels and the ground truth labels.

```
if batch_idx == 0:
            self.visualize_predictions(images, out.detach(), targets)
```

Let's have a look at the implementation of `visualize_predictions()` function in `exercise_code.lightning_models`.

```
def visualize_predictions(self, images, preds, targets):
        class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
                       'dog', 'frog', 'horse', 'ship', 'truck']

        # determine size of the grid based on given batch size
        num_rows = torch.tensor(len(images)).float().sqrt().floor()

        fig = plt.figure(figsize=(10, 10))
        for i in range(len(images)):
            plt.subplot(num_rows ,len(images) // num_rows + 1, i+1)
            plt.imshow(images[i].permute(1, 2, 0))
            plt.title(class_names[torch.argmax(preds, axis=-1)[i]] + f'\n[{c
lass_names[targets[i]]}]')
            plt.axis('off')

        self.logger.experiment.add_figure('predictions', fig, global_step=se
lf.global_step)
```

You can view the logged images in your `IMAGES` tab of TensorBoard.

We have now looked at how to train a model using PyTorch Lightning. PyTorch Lightning is very active in developement and the features set are continously expanded and updated.

4. Other Features of PyTorch Lightning

Checking training timings

The argument `profiler=True` of the `Trainer` class measures the time taken in different steps such as dataloading, forward and backward pass.

Run the cell below to see for yourself.

In [7]:
```
trainer = pl.Trainer(
    weights_summary=None,
    profiler=True,
    max_epochs=1,
    progress_bar_refresh_rate=25, # to prevent notebook crashes in Googl
e Colab environments,
    # gpus=1 # Use GPU if available

)

trainer.fit(model,train_dataloader=data.train_dataloader(),val_dataloade
rs=data.val_dataloader())
```

```
GPU available: False, used: False
TPU available: False, using: 0 TPU cores
```

```
Profiler Report

Action                  |  Mean duration (s)    |  Total time (s)
-----------------------------------------------------------------
on_fit_start            |  1.7694e-05           |  1.7694e-05
on_validation_start     |  0.01104              |  0.02208
on_validation_epoch_start       |  1.9471e-05           |  3.8942e-05
on_validation_batch_start       |  1.8555e-05           |  0.011634
validation_step_end     |  1.533e-05            |  0.0096116
on_validation_batch_end |  9.274e-05            |  0.058148
on_validation_epoch_end |  2.089e-05            |  4.178e-05
on_validation_end       |  0.0050911            |  0.010182
on_train_start          |  0.032192             |  0.032192
on_epoch_start          |  0.0025501            |  0.0025501
on_train_epoch_start    |  2.0567e-05           |  2.0567e-05
get_train_batch         |  0.0028552            |  8.9225
on_batch_start          |  2.6541e-05           |  0.082941
on_train_batch_start    |  1.4643e-05           |  0.04576
training_step_end       |  1.4319e-05           |  0.044748
model_forward           |  0.00077123           |  2.4101
model_backward          |  0.00062037           |  1.9387
on_after_backward       |  1.5048e-05           |  0.047024
optimizer_step          |  0.0021905            |  6.8454
on_batch_end            |  2.409e-05            |  0.075282
on_train_batch_end      |  0.00014676           |  0.45862
on_epoch_end            |  1.5578e-05           |  1.5578e-05
on_train_epoch_end      |  1.2707e-05           |  1.2707e-05
on_train_end            |  0.0014644            |  0.0014644
```

Out[7]: 1

We can see an overview of the time taken for different steps. This enables us to detect bottlenecks in the model more easily. A bottleneck can be, for example, long times in dataloading. It becomes very important later, especially, when you start to implement custom layers or loss functions.

Some more debugging Options

- `fast_dev_run` (https://pytorch-lightning.readthedocs.io/en/latest/trainer.html#fast-dev-run): Runs of batch of each train, validation and test pass (if validation and test datalaoders are passed as arguments).This is a fast way to check if everything works (dataloading, validation metric, model saving/loading) without having to wait for a full epoch.
- `track_grad_norm` (https://pytorch-lightning.readthedocs.io/en/latest/trainer.html#track-grad-norm): Logs the norm of the gradients (set to `1` for the $L1$ norm or `2` for the $L2$ norm) for each layer. You can check whether the network is actually doing something. If the gradients are too small or too high, you won't have a good training (due to vanishing/ exploding gradients).

Other Features

Finally, we want to mention some other useful options in the Trainer class:

- `resume_from_checkpoint` (https://pytorch-lightning.readthedocs.io/en/latest/trainer.html#resume-from-checkpoint): Start the training from a checkpoint saved earlier. Argument is the path to the saved model file.
- `Callbacks` (https://pytorch-lightning.readthedocs.io/en/latest/callbacks.html#callback): Callbacks are extremely useful system during training that automate non essential code such as storing model checkpoints , saving weights values among others.

Let's have the look at the `EarlyStopping` (https://pytorch-lightning.readthedocs.io/en/latest/early_stopping.html#early-stopping-based-on-metric-using-the-earlystopping-callback) callback.

It interrupts the training if the `monitor` metric variable does not improve for `patience` number of epochs.

Below is a code example on how to apply it!

```
from pytorch_lightning.callbacks.early_stopping import EarlyStopping

early_stop_callback = EarlyStopping(
   monitor='val_accuracy',
   patience=3,
   verbose=False,
   mode='max'
)

trainer = Trainer(max_epochs=10,callbacks=[early_stop_callback])
```

References

1. PyTorch Lightining `Source Code` (https://github.com/PyTorchLightning/pytorch-lightning) with a nice introduction
2. PyTorch Lightining `Documentation` (https://pytorch-lightning.readthedocs.io/en/latest/#) Explore it! The features are very well explained.