Pytorch with the MNIST Dataset - MINST

```
## import libraries
from __future__ import print_function
import argparse
import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision

import torch.optim as optim
from torchvision import datasets, transforms
from torch.autograd import Variable
```

```
print(torch.__version__)
```

```
2.5.0+cu121
```

```
args={}
kwargs={}
args['batch_size']=32
args['test_batch_size']=32
args['epochs']=1  #The number of Epochs is the number of times you go through the full dataset.
args['lr']=0.01 #Learning rate is how fast it will decend.
args['momentum']=0.5 #SGD momentum (default: 0.5) Momentum is a moving average of our gradients (helps to keep direction).

args['seed']=1 #random seed
args['log_interval']=10
args['cuda']=True #if the computer has a GPU, type True, otherwise, False
```

This code is adopted from the pytorch examples repository. It is licensed under BSD 3-Clause "New" or "Revised" License. Source: https://github.com/pytorch/examples/ LICENSE: https://github.com/pytorch/examples/blob/master/LICENSE

Load Dataset

The first step before training the model is to import the data. We will use the MNIST dataset which is like the Hello World dataset of machine learning.

Besides importing the data, we will also do a few more things:

- We will tranform the data into tensors using the `transforms` module
- We will use `DataLoader` to build convenient data loaders or what are referred to as iterators, which makes it easy to efficiently feed data in batches to deep learning models.
- As hinted above, we will also create batches of the data by setting the `batch` parameter inside the data loader. Notice we use batches of `32` in this tutorial but you can change it to `64` if you like. I encourage you to experiment with different batches.

```
## transformations
transform = transforms.Compose([
                       transforms.ToTensor(),
                       transforms.Normalize((0.1307,), (0.3081,))
                   ])

## download and load training dataset
trainset = datasets.MNIST(root='../data', train=True, download=True, transform=transform)
train_loader = torch.utils.data.DataLoader(trainset, batch_size=args['batch_size'], shuffle=True, **kwargs)

## download and load testing dataset
testset = torchvision.datasets.MNIST(root='./data', train=False, download=True, transform=transform)
test_loader = torch.utils.data.DataLoader(testset, batch_size=args['test_batch_size'], shuffle=True, **kwargs)
```

```
<urlopen error [SSL: CERTIFICATE_VERIFY_FAILED] certificate verify failed: certificate has expired (_ssl.c:1007)>

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz to ../data/MNIST/raw/t10k-labels-idx1-ubyte.
100%|██████████| 4.54k/4.54k [00:00<00:00, 2.83MB/s]
Extracting ../data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ../data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Failed to download (trying next):
<urlopen error [SSL: CERTIFICATE_VERIFY_FAILED] certificate verify failed: certificate has expired (_ssl.c:1007)>

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ubyte.gz to ./data/MNIST/raw/train-images-idx3-ubyte
100%|██████████| 9.91M/9.91M [00:00<00:00, 16.3MB/s]
Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Failed to download (trying next):
<urlopen error [SSL: CERTIFICATE_VERIFY_FAILED] certificate verify failed: certificate has expired (_ssl.c:1007)>

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ubyte.gz to ./data/MNIST/raw/train-labels-idx1-ubyte
100%|██████████| 28.9k/28.9k [00:00<00:00, 501kB/s]
Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Failed to download (trying next):
<urlopen error [SSL: CERTIFICATE_VERIFY_FAILED] certificate verify failed: certificate has expired (_ssl.c:1007)>

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw/t10k-images-idx3-ubyte.g
100%|██████████| 1.65M/1.65M [00:00<00:00, 4.54MB/s]
Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Failed to download (trying next):
<urlopen error [SSL: CERTIFICATE_VERIFY_FAILED] certificate verify failed: certificate has expired (_ssl.c:1007)>

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw/t10k-labels-idx1-ubyte.g
100%|██████████| 4.54k/4.54k [00:00<00:00, 6.83MB/s]Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
```

Exploring the Data

As a practioner and researcher, I am always spending a bit of time and effort exploring and understanding the dataset. It's fun and this is a good practise to ensure that everything is in order.

Let's check what the train and test dataset contains. I will use `matplotlib` to print out some of the images from our dataset.

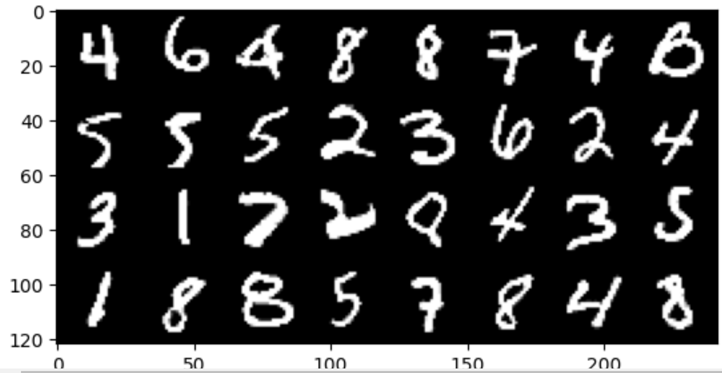
```
import matplotlib.pyplot as plt
import numpy as np

## functions to show an image
def imshow(img):
    #img = img / 2 + 0.5     # unnormalize
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))

## get some random training images
dataiter = iter(train_loader)
images, labels = next(dataiter)

## show images
imshow(torchvision.utils.make_grid(images))
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers
```



Let's check the dimensions of a batch.

```
for images, labels in train_loader:
    print("Image batch dimensions:", images.shape)
    print("Image label dimensions:", labels.shape)
    break
```

```
Image batch dimensions: torch.Size([32, 1, 28, 28])
Image label dimensions: torch.Size([32])
```

The Model

We provide two fully-connected neural net as the initial architecture.

Here are a few notes for those who are beginning with PyTorch:

- The model below consists of an `__init__()` portion which is where you include the layers and components of the neural network. In our model, we have two fully-connected netork network. We are dealing with an image dataset that is in a grayscale so we only need one channel going in, hence `in_channels=1`.
- After the first layer, we also apply an activation function such as `ReLU`. For prediction purposes, we then apply a `softmax` layer to the last transformation and return the output of that.

```
class Net(nn.Module):
    #This defines the structure of the NN.
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 25, 3) #1x28x28 --> 25x26x26
        self.pool = nn.MaxPool2d(2, 2) #25x26x26 --> 25x13x13
        self.fc1 = nn.Linear(25 * 13 * 13, 256)
        self.fc2 = nn.Linear(256, 10)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = self.pool(x)
        x=x.view(-1,25 * 13 * 13)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        #Softmax gets probabilities.
        return F.log_softmax(x, dim=1)
```

Now, add one CNN layer with a pooling to the above neural network and rerun the code to see whether you get higher prediction accuracy on the test set.

For example, you may try `out_channels=32`. Kernel size is 5, and for the rest of parameters we use the default values which you can find here.

- In short, the convolutional layer transforms the input data into a specific dimension that has to be considered in the linear layer.

Make sure your flatten the output of CNN layer excluding # of batch so that the input of each example/batch has the same size of the first neural net.

Tips: You can use x.view(-1, # of input size of the first fully-connected layer) or you can use torch.flatten(x, 1).

I always encourage to test the model with 1 batch to ensure that the output dimensions are what we expect.

```
Start coding or generate with AI.
```

```
## test the model with 1 batch
model = Net()
#print(model)
for images, labels in train_loader:
    print("batch size:", args['batch_size'])
    out = model(images)
    print(out.shape)
    break
```

```
batch size: 32
torch.Size([32, 10])
```

Training the Model

Now we are ready to train the model.

```
def train(epoch):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        if args['cuda']:
            data, target = data.cuda(), target.cuda()
        #Variables in Pytorch are differenciable.
        data, target = Variable(data), Variable(target)
        #This will zero out the gradients for this batch.
        optimizer.zero_grad()
        output = model(data)
        # Calculate the loss The negative log likelihood loss. It is useful to train a classification problem with C classes.
        loss = F.nll_loss(output, target)
        #dloss/dx for every Variable
        loss.backward()
        #to do a one-step update on our parameter.
        optimizer.step()
        #Print out the loss periodically.
        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.data.item()))


def test():
    model.eval()
    test_loss = 0
    correct = 0

    with torch.no_grad():
      for data, target in test_loader:
          if args['cuda']:
              data, target = data.cuda(), target.cuda()
          data, target = Variable(data), Variable(target)
          output = model(data)
          test_loss += F.nll_loss(output, target, size_average=False).data.item() # sum up batch loss
          pred = output.data.max(1, keepdim=True)[1] # get the index of the max log-probability
          correct += pred.eq(target.data.view_as(pred)).long().cpu().sum()

    test_loss /= len(test_loader.dataset)
    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        100. * correct / len(test_loader.dataset)))


model = Net()
if args['cuda']:
    model.cuda()

optimizer = optim.SGD(model.parameters(), lr=args['lr'], momentum=args['momentum'])

for epoch in range(1, args['epochs'] + 1):
    train(epoch)
    test()
```

```
Train Epoch: 1 [0/60000 (0%)]   Loss: 2.372720
Train Epoch: 1 [320/60000 (1%)] Loss: 1.802728
Train Epoch: 1 [640/60000 (1%)] Loss: 1.231960
Train Epoch: 1 [960/60000 (2%)] Loss: 0.903316
Train Epoch: 1 [1280/60000 (2%)]        Loss: 0.557140
Train Epoch: 1 [1600/60000 (3%)]        Loss: 0.635397
Train Epoch: 1 [1920/60000 (3%)]        Loss: 0.507572
Train Epoch: 1 [2240/60000 (4%)]        Loss: 0.887186
Train Epoch: 1 [2560/60000 (4%)]        Loss: 0.572372
Train Epoch: 1 [2880/60000 (5%)]        Loss: 0.420833
Train Epoch: 1 [3200/60000 (5%)]        Loss: 0.218439
```

```
Train Epoch: 1 [3520/60000 (6%)]	Loss: 0.237025
Train Epoch: 1 [3840/60000 (6%)]	Loss: 0.367036
Train Epoch: 1 [4160/60000 (7%)]	Loss: 0.186796
Train Epoch: 1 [4480/60000 (7%)]	Loss: 0.315542
Train Epoch: 1 [4800/60000 (8%)]	Loss: 0.234172
Train Epoch: 1 [5120/60000 (9%)]	Loss: 0.526702
Train Epoch: 1 [5440/60000 (9%)]	Loss: 0.429692
Train Epoch: 1 [5760/60000 (10%)]	Loss: 0.461097
Train Epoch: 1 [6080/60000 (10%)]	Loss: 0.884914
Train Epoch: 1 [6400/60000 (11%)]	Loss: 0.434885
Train Epoch: 1 [6720/60000 (11%)]	Loss: 0.315350
Train Epoch: 1 [7040/60000 (12%)]	Loss: 0.360749
Train Epoch: 1 [7360/60000 (12%)]	Loss: 0.348866
Train Epoch: 1 [7680/60000 (13%)]	Loss: 0.361742
Train Epoch: 1 [8000/60000 (13%)]	Loss: 0.388472
Train Epoch: 1 [8320/60000 (14%)]	Loss: 0.422414
Train Epoch: 1 [8640/60000 (14%)]	Loss: 0.493869
Train Epoch: 1 [8960/60000 (15%)]	Loss: 0.304426
Train Epoch: 1 [9280/60000 (15%)]	Loss: 0.163742
Train Epoch: 1 [9600/60000 (16%)]	Loss: 0.192996
Train Epoch: 1 [9920/60000 (17%)]	Loss: 0.327874
Train Epoch: 1 [10240/60000 (17%)]	Loss: 0.125876
Train Epoch: 1 [10560/60000 (18%)]	Loss: 0.406872
Train Epoch: 1 [10880/60000 (18%)]	Loss: 0.193155
Train Epoch: 1 [11200/60000 (19%)]	Loss: 0.404689
Train Epoch: 1 [11520/60000 (19%)]	Loss: 0.561336
Train Epoch: 1 [11840/60000 (20%)]	Loss: 0.099842
Train Epoch: 1 [12160/60000 (20%)]	Loss: 0.095993
Train Epoch: 1 [12480/60000 (21%)]	Loss: 0.374357
Train Epoch: 1 [12800/60000 (21%)]	Loss: 0.368063
Train Epoch: 1 [13120/60000 (22%)]	Loss: 0.233614
Train Epoch: 1 [13440/60000 (22%)]	Loss: 0.490324
Train Epoch: 1 [13760/60000 (23%)]	Loss: 0.376398
Train Epoch: 1 [14080/60000 (23%)]	Loss: 0.282401
Train Epoch: 1 [14400/60000 (24%)]	Loss: 0.211902
Train Epoch: 1 [14720/60000 (25%)]	Loss: 0.257408
Train Epoch: 1 [15040/60000 (25%)]	Loss: 0.365946
Train Epoch: 1 [15360/60000 (26%)]	Loss: 0.186456
Train Epoch: 1 [15680/60000 (26%)]	Loss: 0.370927
Train Epoch: 1 [16000/60000 (27%)]	Loss: 0.215926
Train Epoch: 1 [16320/60000 (27%)]	Loss: 0.097077
Train Epoch: 1 [16640/60000 (28%)]	Loss: 0.232138
Train Epoch: 1 [16960/60000 (28%)]	Loss: 0.696414
Train Epoch: 1 [17280/60000 (29%)]	Loss: 0.135584
Train Epoch: 1 [17600/60000 (29%)]	Loss: 0.324681
Train Epoch: 1 [17920/60000 (30%)]	Loss: 0.101354
```

Start coding or generate with AI.