Target:

```
-- In the previous step we had 9,970 parameters. In this step we want to
improve this accuracy by using dropouts. We will use a dropout rate of 0.05
```

Results:

```
-- Parameters: 9,970
-- Best Training Accuracy: 98.07
-- Best Test Accuracy: 99.33
```

Analysis:

```
-- There is a slight drop in test accuracy after introducing dropouts.
-- In last few epochs, we can see that the training accuracy is increasing but the test accuracy is going up and down. This might be
```

Import libraries

```
from __future__ import print_function
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms
```

Data Transformations (without normalization)

```
# Train Phase transformations
train_transforms = transforms.Compose([
                                      transforms.ToTensor()
                                       ])

# Test Phase transformations
test_transforms = transforms.Compose([
                                      transforms.ToTensor()
                                       ])
```

Dataset and Creating Train/Test Split (without normalization)

```
train = datasets.MNIST('./data', train=True, download=True, transform=train_transforms)
test = datasets.MNIST('./data', train=False, download=True, transform=test_transforms)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
```

Dataloader Arguments & Test/Train Dataloaders (without normalization)

```
SEED = 1

# CUDA?
cuda = torch.cuda.is_available()
print("CUDA Available?", cuda)

# For reproducibility
torch.manual_seed(SEED)

if cuda:
    torch.cuda.manual_seed(SEED)

# dataloader arguments - something you'll fetch these from cmdprmt
dataloader_args = dict(shuffle=True, batch_size=128, num_workers=4, pin_memory=True) if cuda else dict(shuffle=True, batch

# train dataloader
train_loader = torch.utils.data.DataLoader(train, **dataloader_args)

# test dataloader
test_loader = torch.utils.data.DataLoader(test, **dataloader_args)
```

```
CUDA Available? True
/usr/local/lib/python3.8/dist-packages/torch/utils/data/dataloader.py:554: UserWarning: This DataLoader will create 4
  warnings.warn(_create_warning_msg(
```

Getting data statistics (without normalization)

We will use the mean and standard deviation that we get from code below to normalize the data

```
import numpy as np

train_data = train.train_data
train_data = train.transform(train_data.numpy())

print('[Train]')
print(' - Numpy Shape:', train.train_data.cpu().numpy().shape)
print(' - Tensor Shape:', train.train_data.size())
print(' - min:', torch.min(train_data))
print(' - max:', torch.max(train_data))
print(' - mean:', torch.mean(train_data))
print(' - std:', torch.std(train_data))
print(' - var:', torch.var(train_data))

dataiter = iter(train_loader)
images, labels = next(dataiter)

print(images.shape)
print(labels.shape)

# Let's visualize some of the images
%matplotlib inline
import matplotlib.pyplot as plt

plt.imshow(images[0].numpy().squeeze(), cmap='gray_r')
```

```
/usr/local/lib/python3.8/dist-packages/torchvision/datasets/mnist.py:75: Us
  warnings.warn("train_data has been renamed data")
[Train]
 - Numpy Shape: (60000, 28, 28)
 - Tensor Shape: torch.Size([60000, 28, 28])
 - min: tensor(0.)
 - max: tensor(1.)
 - mean: tensor(0.1307)
 - std: tensor(0.3081)
 - var: tensor(0.0949)
```

Data Transformations (with normalization)

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

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

Dataset and Creating Train/Test Split (with normalization)

```
train = datasets.MNIST('./data', train=True, download=True, transform=train_transforms)
test = datasets.MNIST('./data', train=False, download=True, transform=test_transforms)
```

Dataloader Arguments & Test/Train Dataloaders (with normalization)

```
SEED = 1

# CUDA?
cuda = torch.cuda.is_available()
print("CUDA Available?", cuda)

# For reproducibility
torch.manual_seed(SEED)

if cuda:
    torch.cuda.manual_seed(SEED)

# dataloader arguments - something you'll fetch these from cmdprmt
dataloader_args = dict(shuffle=True, batch_size=128, num_workers=4, pin_memory=True) if cuda else dict(shuffle=True, batch

# train dataloader
train_loader = torch.utils.data.DataLoader(train, **dataloader_args)

# test dataloader
test_loader = torch.utils.data.DataLoader(test, **dataloader_args)
```

```
CUDA Available? True
```

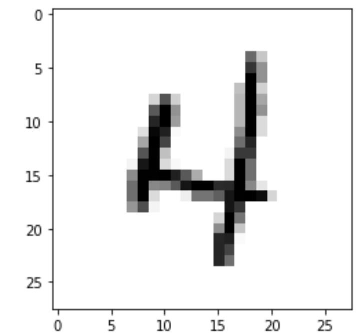
Getting data statistics (with normalization)

We will use the mean and standard deviation that we get from code below to normalize the data

```
import numpy as np

train_data = train.train_data
train_data = train.transform(train_data.numpy())

print('[Train]')
print(' - Numpy Shape:', train.train_data.cpu().numpy().shape)
print(' - Tensor Shape:', train.train_data.size())
print(' - min:', torch.min(train_data))
```

```
print(' - max:', torch.max(train_data))
print(' - mean:', torch.mean(train_data))
print(' - std:', torch.std(train_data))
print(' - var:', torch.var(train_data))

dataiter = iter(train_loader)
images, labels = next(dataiter)

print(images.shape)
print(labels.shape)

# Let's visualize some of the images
%matplotlib inline
import matplotlib.pyplot as plt

plt.imshow(images[0].numpy().squeeze(), cmap='gray_r')
```

```
[Train]
 - Numpy Shape: (60000, 28, 28)
 - Tensor Shape: torch.Size([60000, 28, 28])
 - min: tensor(-0.4242)
 - max: tensor(2.8215)
 - mean: tensor(-0.0001)
 - std: tensor(1.0000)
 - var: tensor(1.0001)
torch.Size([128, 1, 28, 28])
torch.Size([128])
<matplotlib.image.AxesImage at 0x7fc45d805220>
```



Model

```
dropout_value·=·0.05
class·Net(nn.Module):
··def·__init__(self):
····super(Net,·self).__init__()

····#input·block
····self.convblock1·=·nn.Sequential(nn.Conv2d(in_channels·=·1,·out_channels·=·10,·kernel_size·=·3,·padding·=·1),
····································nn.BatchNorm2d(10),
····································nn.ReLU(),
····································nn.Dropout(dropout_value))·#R_in·=·1,·C_in·=·28,·K·=·3,·P·=·1,·S·=·1,·J_in·=·1,·J_out·
····
····#conv·block·1
····self.convblock2·=·nn.Sequential(nn.Conv2d(in_channels·=·10,·out_channels·=·12,·kernel_size·=·3,·padding·=·1),
····································nn.BatchNorm2d(12),
····································nn.ReLU(),
····································nn.Dropout(dropout_value))·#R_in·=·3,·C_in·=·28,·K·=·3,·P·=·1,·S·=·1,·J_in·=·1,·J_out·
····
····#conv·block·2
····self.convblock3·=·nn.Sequential(nn.Conv2d(in_channels·=·12,·out_channels·=·14,·kernel_size·=·3,·padding·=·1),
····································nn.BatchNorm2d(14),
····································nn.ReLU(),
····································nn.Dropout(dropout_value))·#R_in·=·5,·C_in·=·28,·K·=·3,·P·=·1,·S·=·1,·J_in·=·1,·J_out·
····
····#transition·block1
····self.convblock4·=·nn.Sequential(nn.Conv2d(in_channels·=·14,·out_channels·=·16,·kernel_size·=·3,·padding·=·1),
····································nn.BatchNorm2d(16),
····································nn.ReLU(),
····································nn.Dropout(dropout_value))·#R_in·=·7,·C_in·=·28,·K·=·3,·P·=·1,·S·=·1,·J_in·=·1,·J_out·

····self.pool1·=·nn.MaxPool2d(2,·2)·#R_in·=·9,·C_in·=·28,·K·=·2,·P·=·0,·S·=·2,·J_in·=·1,·J_out·=·2,·R_out·=·R_in·+·(K-1)*J

····#conv·block·3
····self.convblock5·=·nn.Sequential(nn.Conv2d(in_channels·=·16,·out_channels·=·12,·kernel_size·=·3,·padding·=·1),
····································nn.BatchNorm2d(12),
····································nn.ReLU(),
····································nn.Dropout(dropout_value))·#R_in·=·10,·C_in·=·14,·K·=·3,·P·=·1,·S·=·1,·J_in·=·2,·J_out
```

```
····
····#conv·block·4
····self.convblock6·=·nn.Sequential(nn.Conv2d(in_channels·=·12,·out_channels·=·12,·kernel_size·=·3,·padding·=·1),
····································nn.BatchNorm2d(12),
····································nn.ReLU(),
····································nn.Dropout(dropout_value))·#R_in·=·14,·C_in·=·14,·K·=·3,·P·=·1,·S·=·1,·J_in·=·2,·J_out

····#conv·block·4
····self.convblock7·=·nn.Sequential(nn.Conv2d(in_channels·=·12,·out_channels·=·10,·kernel_size·=·3,·padding·=·1),
····································nn.BatchNorm2d(10),
····································nn.ReLU(),
····································nn.Dropout(dropout_value))·#R_in·=·18,·C_in·=·14,·K·=·3,·P·=·1,·S·=·1,·J_in·=·2,·J_out
····#gap·layer·
····self.gap·=·nn.Sequential(
············nn.AvgPool2d(kernel_size=4))··#R_in·=·22,·C_in·=·14,·K·=·4,·P·=·1,·S·=·1,·J_in·=·2,·J_out·=·2,·R_out·=·R_in·+·

····#output·block
····self.convblock8·=·nn.Sequential(nn.Conv2d(in_channels·=·10,·out_channels·=·10,·kernel_size·=·3,·padding·=·0),·nn.Dropc

··def·forward(self,·x):
····x·=·self.convblock1(x)
····x·=·self.convblock2(x)
····x·=·self.convblock3(x)
····x·=·self.convblock4(x)
····x·=·self.pool1(x)
····x·=·self.convblock5(x)
····x·=·self.convblock6(x)
····x·=·self.convblock7(x)
····x·=·self.gap(x)
····x·=·self.convblock8(x)
····x·=·x.view(-1,·10)
····return·F.log_softmax(x,·dim=-1)
```

Model parameters

```
!pip install torchsummary
from torchsummary import summary

use_cuda = torch.cuda.is_available()
device = torch.device("cuda" if use_cuda else "cpu")

model = Net().to(device)
summary(model, input_size = (1, 28, 28))
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: torchsummary in /usr/local/lib/python3.8/dist-packages (1.5.1)
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 10, 28, 28]             100
       BatchNorm2d-2           [-1, 10, 28, 28]              20
              ReLU-3           [-1, 10, 28, 28]               0
           Dropout-4           [-1, 10, 28, 28]               0
            Conv2d-5           [-1, 12, 28, 28]           1,092
       BatchNorm2d-6           [-1, 12, 28, 28]              24
              ReLU-7           [-1, 12, 28, 28]               0
           Dropout-8           [-1, 12, 28, 28]               0
            Conv2d-9           [-1, 14, 28, 28]           1,526
      BatchNorm2d-10           [-1, 14, 28, 28]              28
             ReLU-11           [-1, 14, 28, 28]               0
          Dropout-12           [-1, 14, 28, 28]               0
           Conv2d-13           [-1, 16, 28, 28]           2,032
      BatchNorm2d-14           [-1, 16, 28, 28]              32
             ReLU-15           [-1, 16, 28, 28]               0
          Dropout-16           [-1, 16, 28, 28]               0
        MaxPool2d-17           [-1, 16, 14, 14]               0
           Conv2d-18           [-1, 12, 14, 14]           1,740
      BatchNorm2d-19           [-1, 12, 14, 14]              24
             ReLU-20           [-1, 12, 14, 14]               0
          Dropout-21           [-1, 12, 14, 14]               0
           Conv2d-22           [-1, 12, 14, 14]           1,308
      BatchNorm2d-23           [-1, 12, 14, 14]              24
             ReLU-24           [-1, 12, 14, 14]               0
          Dropout-25           [-1, 12, 14, 14]               0
           Conv2d-26           [-1, 10, 14, 14]           1,090
      BatchNorm2d-27           [-1, 10, 14, 14]              20
             ReLU-28           [-1, 10, 14, 14]               0
          Dropout-29           [-1, 10, 14, 14]               0
        AvgPool2d-30             [-1, 10, 3, 3]               0
           Conv2d-31             [-1, 10, 1, 1]             910
          Dropout-32             [-1, 10, 1, 1]               0
```

```
================================================================
Total params: 9,970
Trainable params: 9,970
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 1.47
Params size (MB): 0.04
Estimated Total Size (MB): 1.51
----------------------------------------------------------------
```

Training and Testing

```
from tqdm import tqdm

train_losses = []
test_losses = []
train_acc = []
test_acc = []

def train(model, device, train_loader, optimizer, epoch):
  model.train()
  pbar = tqdm(train_loader)
  correct = 0
  processed = 0
  for batch_idx, (data, target) in enumerate(pbar):
    # get samples
    data, target = data.to(device), target.to(device)

    # Init
    optimizer.zero_grad()
    # In PyTorch, we need to set the gradients to zero before starting to do backpropragation because PyTorch accumulates
    # Because of this, when you start your training loop, ideally you should zero out the gradients so that you do the par

    # Predict
    y_pred = model(data)

    # Calculate loss
    loss = F.nll_loss(y_pred, target)
    train_losses.append(loss)

    # Backpropagation
    loss.backward()
    optimizer.step()

    # Update pbar-tqdm

    pred = y_pred.argmax(dim=1, keepdim=True)  # get the index of the max log-probability
    correct += pred.eq(target.view_as(pred)).sum().item()
    processed += len(data)

    pbar.set_description(desc= f'Loss={loss.item()} Batch_id={batch_idx} Accuracy={100*correct/processed:0.2f}')
    train_acc.append(100*correct/processed)

def test(model, device, test_loader):
    model.eval()
    test_loss = 0
    correct = 0
    with torch.no_grad():
        for data, target in test_loader:
            data, target = data.to(device), target.to(device)
            output = model(data)
            test_loss += F.nll_loss(output, target, reduction='sum').item()  # sum up batch loss
            pred = output.argmax(dim=1, keepdim=True)  # get the index of the max log-probability
            correct += pred.eq(target.view_as(pred)).sum().item()

    test_loss /= len(test_loader.dataset)
    test_losses.append(test_loss)

    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.2f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        100. * correct / len(test_loader.dataset)))

    test_acc.append(100. * correct / len(test_loader.dataset))
```

```
from torch.optim.lr_scheduler import StepLR

model =  Net().to(device)
```

```
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)
# scheduler = StepLR(optimizer, step_size=6, gamma=0.1)


EPOCHS = 15
for epoch in range(EPOCHS):
    print("EPOCH:", epoch)
    train(model, device, train_loader, optimizer, epoch)
    # scheduler.step()
    test(model, device, test_loader)
```

```
EPOCH: 0
Loss=0.09847403317689896 Batch_id=468 Accuracy=88.59: 100%|██████████| 469/469 [00:19<00:00, 24.44it/s]

Test set: Average loss: 0.0915, Accuracy: 9720/10000 (97.20%)

EPOCH: 1
Loss=0.05309741571545601 Batch_id=468 Accuracy=96.39: 100%|██████████| 469/469 [00:20<00:00, 23.25it/s]

Test set: Average loss: 0.0486, Accuracy: 9851/10000 (98.51%)

EPOCH: 2
Loss=0.018912313506007195 Batch_id=468 Accuracy=97.04: 100%|██████████| 469/469 [00:15<00:00, 30.16it/s]

Test set: Average loss: 0.0480, Accuracy: 9848/10000 (98.48%)

EPOCH: 3
Loss=0.022453108802437782 Batch_id=468 Accuracy=97.13: 100%|██████████| 469/469 [00:16<00:00, 27.77it/s]

Test set: Average loss: 0.0407, Accuracy: 9872/10000 (98.72%)

EPOCH: 4
Loss=0.039117444306612015 Batch_id=468 Accuracy=97.51: 100%|██████████| 469/469 [00:15<00:00, 29.87it/s]

Test set: Average loss: 0.0399, Accuracy: 9872/10000 (98.72%)

EPOCH: 5
Loss=0.020529208704829216 Batch_id=468 Accuracy=97.68: 100%|██████████| 469/469 [00:15<00:00, 29.99it/s]

Test set: Average loss: 0.0324, Accuracy: 9900/10000 (99.00%)

EPOCH: 6
Loss=0.08593115955591202 Batch_id=468 Accuracy=97.67: 100%|██████████| 469/469 [00:16<00:00, 28.35it/s]

Test set: Average loss: 0.0297, Accuracy: 9912/10000 (99.12%)

EPOCH: 7
Loss=0.035492051392793655 Batch_id=468 Accuracy=97.70: 100%|██████████| 469/469 [00:15<00:00, 30.35it/s]

Test set: Average loss: 0.0370, Accuracy: 9878/10000 (98.78%)

EPOCH: 8
Loss=0.0680157020688057 Batch_id=468 Accuracy=97.77: 100%|██████████| 469/469 [00:15<00:00, 30.58it/s]

Test set: Average loss: 0.0235, Accuracy: 9927/10000 (99.27%)

EPOCH: 9
Loss=0.02738688886165619 Batch_id=468 Accuracy=97.84: 100%|██████████| 469/469 [00:15<00:00, 30.25it/s]

Test set: Average loss: 0.0246, Accuracy: 9925/10000 (99.25%)

EPOCH: 10
Loss=0.03704260662198067 Batch_id=468 Accuracy=97.94: 100%|██████████| 469/469 [00:15<00:00, 29.90it/s]

Test set: Average loss: 0.0246, Accuracy: 9918/10000 (99.18%)

EPOCH: 11
Loss=0.035303425043821335 Batch_id=468 Accuracy=97.97: 100%|██████████| 469/469 [00:16<00:00, 27.68it/s]
```

```
train_losses = [i.item() for i in train_losses]
%matplotlib inline
import matplotlib.pyplot as plt
fig, axs = plt.subplots(2,2,figsize=(15,10))
axs[0, 0].plot(train_losses)
axs[0, 0].set_title("Training Loss")
axs[1, 0].plot(train_acc[4000:])
axs[1, 0].set_title("Training Accuracy")
axs[0, 1].plot(test_losses)
axs[0, 1].set_title("Test Loss")
axs[1, 1].plot(test_acc)
axs[1, 1].set_title("Test Accuracy")
```

```
Text(0.5, 1.0, 'Test Accuracy')
```