**Target:**

```
-- In the last step, we saw that the training accuracy is increasing but the test accuracy is going up and down a little (which means
```

**Results:**

```
-- Parameters: 9,907
-- Best Training Accuracy: 97.89
-- Best Test Accuracy: 99.36
```

**Analysis:**

```
-- The accuracy has increased a little (from 99.31 to 99.36) after introducing learning rate scheduler.
-- The training accuracy is same as previous step.
-- In the lest few epochs, the test accuracy is not introducing with increase in train accuracy. this means the model starts overfitt
```

# 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.RandomRotation((-7.0, 7.0), fill=(1,)),
                                      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
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to ./data/MNIST/raw/train-images-idx3-ubyte.g
```

## Dataloader Arguments & Test/Train Dataloaders (without normalization)

```
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
```

```
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(
```

## Data Transformations (with normalization)

```
# Train Phase transformations
train_transforms = transforms.Compose([
                                      transforms.RandomRotation((-7.0, 7.0), fill=(1,)),
                                      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()
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if cuda:
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# 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
```

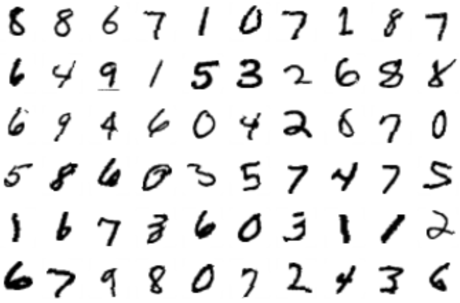
## plot some images to see which image augmentation to use (with normalization)

We will plot some images to see which image augmentation technique we can use

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

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

figure = plt.figure()
num_of_images = 60
for index in range(1, num_of_images + 1):
    plt.subplot(6, 10, index)
    plt.axis('off')
    plt.imshow(images[index].numpy().squeeze(), cmap='gray_r')
```



**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 = 16, kernel_size = 3, padding = 1),
                                    nn.BatchNorm2d(16),
                                    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 = 16, 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 = 16, kernel_size = 3, padding = 1),
                                    nn.BatchNorm2d(16),
                                    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 = 16, out_channels = 12, kernel_size = 3, padding = 1),
                                    nn.BatchNorm2d(12),
                                    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 = 12, out_channels = 15, kernel_size = 3, padding = 1),
                                    nn.BatchNorm2d(15),
                                    nn.ReLU(),
                                    nn.Dropout(dropout_value)) #R_in = 9, 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 = 15, out_channels = 12, kernel_size = 3, padding = 1),
                                    nn.BatchNorm2d(12),
                                    nn.ReLU(),
                                    nn.Dropout(dropout_value)) #R_in = 13, 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 = 17, C_in = 14, K = 4, P = 1, S = 1, J_in = 2, J_out = 2, R_out = R_in + (

    #output block
    self.convblock7 = nn.Sequential(nn.Conv2d(in_channels = 12, 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.gap(x)
    x = self.convblock7(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, 16, 28, 28]             160
       BatchNorm2d-2           [-1, 16, 28, 28]              32
              ReLU-3           [-1, 16, 28, 28]               0
           Dropout-4           [-1, 16, 28, 28]               0
            Conv2d-5           [-1, 12, 28, 28]           1,740
       BatchNorm2d-6           [-1, 12, 28, 28]              24
              ReLU-7           [-1, 12, 28, 28]               0
           Dropout-8           [-1, 12, 28, 28]               0
            Conv2d-9           [-1, 16, 28, 28]           1,744
      BatchNorm2d-10           [-1, 16, 28, 28]              32
             ReLU-11           [-1, 16, 28, 28]               0
          Dropout-12           [-1, 16, 28, 28]               0
           Conv2d-13           [-1, 12, 28, 28]           1,740
      BatchNorm2d-14           [-1, 12, 28, 28]              24
             ReLU-15           [-1, 12, 28, 28]               0
          Dropout-16           [-1, 12, 28, 28]               0
        MaxPool2d-17           [-1, 12, 14, 14]               0
           Conv2d-18           [-1, 15, 14, 14]           1,635
      BatchNorm2d-19           [-1, 15, 14, 14]              30
             ReLU-20           [-1, 15, 14, 14]               0
          Dropout-21           [-1, 15, 14, 14]               0
           Conv2d-22           [-1, 12, 14, 14]           1,632
      BatchNorm2d-23           [-1, 12, 14, 14]              24
             ReLU-24           [-1, 12, 14, 14]               0
          Dropout-25           [-1, 12, 14, 14]               0
        AvgPool2d-26             [-1, 12, 3, 3]               0
           Conv2d-27             [-1, 10, 1, 1]           1,090
          Dropout-28             [-1, 10, 1, 1]               0
================================================================
Total params: 9,907
Trainable params: 9,907
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 1.52
Params size (MB): 0.04
Estimated Total Size (MB): 1.56
----------------------------------------------------------------
```

### 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=0.1466168761253357 Batch_id=468 Accuracy=88.36: 100%|██████████| 469/469 [00:18<00:00, 25.57it/s]

Test set: Average loss: 0.0775, Accuracy: 9770/10000 (97.70%)

EPOCH: 1
Loss=0.08993557095527649 Batch_id=468 Accuracy=96.20: 100%|██████████| 469/469 [00:18<00:00, 25.42it/s]

Test set: Average loss: 0.0516, Accuracy: 9845/10000 (98.45%)

EPOCH: 2
Loss=0.04991336166858673 Batch_id=468 Accuracy=96.79: 100%|██████████| 469/469 [00:19<00:00, 24.00it/s]

Test set: Average loss: 0.0374, Accuracy: 9873/10000 (98.73%)

EPOCH: 3
Loss=0.061887603253126144 Batch_id=468 Accuracy=97.03: 100%|██████████| 469/469 [00:18<00:00, 25.55it/s]

Test set: Average loss: 0.0670, Accuracy: 9775/10000 (97.75%)

EPOCH: 4
Loss=0.07905120402574539 Batch_id=468 Accuracy=97.36: 100%|██████████| 469/469 [00:18<00:00, 25.63it/s]

Test set: Average loss: 0.0314, Accuracy: 9893/10000 (98.93%)

EPOCH: 5
Loss=0.04209110513329506 Batch_id=468 Accuracy=97.39: 100%|██████████| 469/469 [00:18<00:00, 25.21it/s]

Test set: Average loss: 0.0333, Accuracy: 9891/10000 (98.91%)

EPOCH: 6
Loss=0.018541911616921425 Batch_id=468 Accuracy=97.73: 100%|██████████| 469/469 [00:18<00:00, 25.14it/s]

Test set: Average loss: 0.0220, Accuracy: 9931/10000 (99.31%)

EPOCH: 7
Loss=0.019929351285099983 Batch_id=468 Accuracy=97.72: 100%|██████████| 469/469 [00:19<00:00, 24.11it/s]

Test set: Average loss: 0.0228, Accuracy: 9924/10000 (99.24%)

EPOCH: 8
Loss=0.06206450238823891 Batch_id=468 Accuracy=97.79: 100%|██████████| 469/469 [00:18<00:00, 25.69it/s]

Test set: Average loss: 0.0213, Accuracy: 9940/10000 (99.40%)

EPOCH: 9
Loss=0.0771336480975151 Batch_id=468 Accuracy=97.81: 100%|██████████| 469/469 [00:18<00:00, 25.18it/s]

Test set: Average loss: 0.0212, Accuracy: 9931/10000 (99.31%)

EPOCH: 10
Loss=0.056498948484659195 Batch_id=468 Accuracy=97.77: 100%|██████████| 469/469 [00:18<00:00, 25.47it/s]

Test set: Average loss: 0.0204, Accuracy: 9937/10000 (99.37%)

EPOCH: 11
Loss=0.041885796934366226 Batch_id=468 Accuracy=97.77: 100%|██████████| 469/469 [00:18<00:00, 25.03it/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')
```