```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
# Data visualizaiton packages
import matplotlib.pyplot as plt
%matplotlib inline
# Deep learning packages
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
import torch.utils.data as data_utils
import torchvision.transforms as transforms
from torchvision import datasets
df = pd.read_csv('/content/train.csv', dtype=np.float32)
labels = df['label'].values
img = df.drop(labels='label', axis=1).values / 255 # Normalization
# Show the shape of the dataset
print("Image shape: {}".format(img.shape))
print("Labels shape: {}".format(labels.shape))
     Image shape: (42000, 784)
     Labels shape: (42000,)
df.head()
        label pixel0 pixel1 pixel2 pixel3 pixel4 pixel5 pixel6 pixel7 pixel8 ... pixel774 pixel775 pixel776 pixel777 p
                   0.0
                                           0.0
                                                   0.0
                                                           0.0
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                                                                                                                      0.0
           1.0
      1
           0.0
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      3
           4.0
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      4
           0.0
                   0.0
                           0.0
                                                                   0.0
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                                                                                   0.0
                                                                                                  0.0
                                                                                                                      0.0
     5 rows × 785 columns
      1
df["label"].value counts(ascending=True)
            3795
     5.0
     8.0
            4063
     4.0
            4072
     0.0
            4132
     6.0
            4137
     2.0
            4177
     9.0
            4188
            4351
     3.0
     7.0
            4401
            4684
     1.0
     Name: label, dtype: int64
df["label"].value_counts(normalize=True)*100
            11.152381
            10.478571
     7.0
```

10.359524 3.0 9.0 9.971429 9.945238 2.0 9.850000 6.0 9.838095 0.0 4.0 9.695238 8.0 9.673810 5.0 9.035714

Name: label, dtype: float64

img = img.reshape(-1, 1, 28, 28)

```
# Define batch_size, epoch and iteration
batch_size = 100
n_{iters} = 2000
num_epochs = n_iters / (len(img_train) / batch_size)
num epochs = int(num epochs)
# Convert train set to tensors
img train = torch.from numpy(img train)
labels_train = torch.from_numpy(labels_train).type(torch.LongTensor)
# Convert validation set to tensors
img_val = torch.from_numpy(img_val)
labels_val = torch.from_numpy(labels_val).type(torch.LongTensor)
# Convert test set to tensors
img test = torch.from numpv(img test)
labels_test = torch.from_numpy(labels_test).type(torch.LongTensor)
# Define Pytorch train and validation set
train = data_utils.TensorDataset(img_train, labels_train)
val = data_utils.TensorDataset(img_val, labels_val)
test = data_utils.TensorDataset(img_test, labels_test)
# Define data loader
train_loader = data_utils.DataLoader(train,
                                     batch_size=batch_size,
                                     shuffle=True, num_workers=16)
valid_loader = data_utils.DataLoader(val,
                                     batch_size=batch_size,
                                     shuffle=True, num workers=16)
test_loader = data_utils.DataLoader(test,
                                    batch_size=batch_size,
                                    shuffle=True, num_workers=16)
loaders = {'train': train_loader,
           'valid': valid_loader,
           'test': test_loader}
```

/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:561: UserWarning: This DataLoader will create 16 worker proc warnings.warn(_create_warning_msg(

CNN Architecture

```
num_classes = 10
# check if CUDA is available
use_cuda = torch.cuda.is_available()
# Define the CNN architecture
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        ## Define layers of a CNN
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=32, kernel_size=5, padding=1)
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=32, kernel_size=5, padding=1)
        self.conv3 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.conv4 = nn.Conv2d(in_channels=64, out_channels=64, kernel_size=3, padding=1)
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=1)
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        self.fc1 = nn.Linear(64 * 11 * 11, 2048)
        self.fc2 = nn.Linear(2048, num_classes)
        self.dropout = nn.Dropout(0.5)
```

```
def forward(self, x):
       ## Define forward behavior
       x = self.conv1(x)
       x = self.pool1(F.relu(self.conv2(x)))
       x = self.dropout(x)
       x = self.conv3(x)
       x = self.pool2(F.relu(self.conv4(x)))
       x = self.dropout(x)
       #print(x.shape)
       x = x.view(-1, 64 * 11 * 11)
       x = self.dropout(x)
       x = F.relu(self.fc1(x))
       x = self.dropout(x)
       x = self.fc2(x)
       return x
# instantiate the CNN
model = Net()
# move tensors to GPU if CUDA is available
if use_cuda:
    model.cuda()
print(model)
     Net(
       (conv1): Conv2d(1, 32, kernel_size=(5, 5), stride=(1, 1), padding=(1, 1))
       (conv2): Conv2d(32, 32, kernel_size=(5, 5), stride=(1, 1), padding=(1, 1))
       (conv3): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
       (conv4): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
       (pool1): MaxPool2d(kernel_size=2, stride=1, padding=0, dilation=1, ceil_mode=False)
       (pool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
       (fc1): Linear(in_features=7744, out_features=2048, bias=True)
       (fc2): Linear(in_features=2048, out_features=10, bias=True)
       (dropout): Dropout(p=0.5, inplace=False)
### Define loss function
criterion = nn.CrossEntropyLoss()
### Define optimizer
optimizer = optim.RMSprop(model.parameters(),
                                 lr=0.001,
                                 alpha=0.9,
                                 eps=1e-08,
                                 weight_decay=0.0001)
# The following import is required for training to be robust to truncated images
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True
def train(n_epochs, loaders, model, optimizer, criterion, use_cuda, save_path):
    """returns trained model"""
    # initialize tracker for minimum validation loss
    valid_loss_min = np.Inf
   loss_list = []
   epoch_list = []
    for epoch in range(1, n_epochs+1):
       # initialize variables to monitor training and validation loss
        train_loss = 0.0
       valid_loss = 0.0
       #####################
       # train the model #
       model.train()
        for batch_idx, (data, target) in enumerate(loaders['train']):
           # move to GPU
           if use_cuda:
               data, target = data.cuda(), target.cuda()
           ## find the loss and update the model parameters accordingly
           optimizer.zero_grad()
           output = model(data)
           loss = criterion(output, target)
           loss.backward()
           optimizer.step()
           train_loss = train_loss + ((1 / (batch_idx + 1)) * (loss.data - train_loss))
        # validate the model #
```

```
model.eval()
        for batch_idx, (data, target) in enumerate(loaders['valid']):
            # move to GPU
            if use cuda:
               data, target = data.cuda(), target.cuda()
            ## update the average validation loss
            output = model(data)
            loss = criterion(output, target)
            valid_loss = valid_loss + ((1 / (batch_idx + 1)) * (loss.data - valid_loss))
        # print training/validation statistics
        print('Epoch: {} \tTraining Loss: {:.6f} \tValidation Loss: {:.6f}'.format(
            epoch,
            train_loss,
            valid loss
            ))
        ## Save the model if validation loss has decreased
        if valid_loss < valid_loss_min:</pre>
            print('Validation loss decreased ({:.6f} --> {:.6f}). Saving model ...'.format(valid_loss_min, valid_loss))
            torch.save(model.state_dict(), save_path)
            valid_loss_min = valid_loss
    # return trained model
    return model
# Train the model
model = train(10, loaders, model, optimizer,
             criterion, use_cuda, 'cnn_digit_recognizer.pt')
                    Training Loss: 0.381951
     Epoch: 1
                                                      Validation Loss: 0.110209
     Validation loss decreased (inf --> 0.110209). Saving model \dots
     Epoch: 2
                    Training Loss: 0.133255
                                                      Validation Loss: 0.079129
     Validation loss decreased (0.110209 --> 0.079129). Saving model .
                    Training Loss: 0.120103
                                                     Validation Loss: 0.066536
     Epoch: 3
     Validation loss decreased (0.079129 --> 0.066536). Saving model .
                    Training Loss: 0.108853
                                                      Validation Loss: 0.054784
     Validation loss decreased (0.066536 --> 0.054784). Saving model ..
               Training Loss: 0.108210 Validation Loss: 0.070331
     Epoch: 5
                     Training Loss: 0.105188
                                                      Validation Loss: 0.055226
     Epoch: 6
                Training Loss: 0.105188 Validation Loss: 0.055226
Training Loss: 0.102114 Validation Loss: 0.059520
Training Loss: 0.102387 Validation Loss: 0.085768
Training Loss: 0.102462 Validation Loss: 0.049350
     Epoch: 7
     Enoch: 8
     Epoch: 9
     Validation loss decreased (0.054784 --> 0.049350). Saving model ..
     Epoch: 10
                    Training Loss: 0.101559
                                                     Validation Loss: 0.080661
def test(loaders, model, criterion, use_cuda):
    # monitor test loss and accuracy
    test_loss = 0.
    correct = 0.
    total = 0.
    model.eval()
    for batch_idx, (data, target) in enumerate(loaders['test']):
        # move to GPU
        if use_cuda:
           data, target = data.cuda(), target.cuda()
        # forward pass: compute predicted outputs by passing inputs to the model
        output = model(data)
        # calculate the loss
       loss = criterion(output, target)
        # update average test loss
        test_loss = test_loss + ((1 / (batch_idx + 1)) * (loss.data - test_loss))
        # convert output probabilities to predicted class
        pred = output.data.max(1, keepdim=True)[1]
        # compare predictions to true label
        correct += np.sum(np.squeeze(pred.eq(target.data.view_as(pred))).cpu().numpy())
        total += data.size(0)
    print('Test Loss: {:.6f}\n'.format(test_loss))
    print('\nTest Accuracy: %2d%% (%2d/%2d)' % (
        100. * correct / total, correct, total))
# call test function
test(loaders, model, criterion, use_cuda)
```

```
# helper function to un-normalize and display an image
def imshow(img):
    img = img.numpy() * 255 # unnormalize and convert from Tensor image
    plt.imshow(img[0]) # show image
classes = ['0', '1', '2', '3', '4',
           '5', '6', '7', '8', '9']
# obtain one batch of test images
dataiter = iter(test_loader)
images, labels = next(dataiter)
images.numpy()
\ensuremath{\text{\#}} move model inputs to cuda, if GPU available
if use_cuda:
    images = images.cuda()
# get sample outputs
output = model(images)
\# convert output probabilities to predicted class
_, preds_tensor = torch.max(output, 1)
preds = np.squeeze(preds_tensor.numpy()) if not use_cuda else np.squeeze(preds_tensor.cpu().numpy())
# plot the images in the batch, along with predicted and true labels
fig = plt.figure(figsize=(20, 5))
for idx in np.arange(10):
    ax = fig.add_subplot(2, 5, idx+1, xticks=[], yticks=[])
    imshow(images.cpu()[idx])
    ax.set_title("Predicted: {} - Actual: {}".format(classes[preds[idx]], classes[labels[idx]]),
                 color=("green" if preds[idx]==labels[idx].item() else "red"))
                                                                                               Predicted: 9 - Actual: 9
 Predicted: 0 - Actual: 0
                                    Predicted: 3 - Actual: 3
                                                                 Predicted: 4 - Actual: 4
                                                                                                                            Predicted: 8 - Actual: 8
```



Predicted: 2 - Actual: 2



Predicted: 3 - Actual:

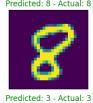
Predicted: 7 - Actual: 7











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