q1

April 3, 2020

1 Question 1, PCA ANALYSIS

[40]:
```
url="/home/abhishek/dev/Semester_2/SMAI/Assignments/Assignment_3/dataset"
```

[41]:
```
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
from skimage import transform,io
import warnings
warnings.filterwarnings('ignore')
from mpl_toolkits.mplot3d import Axes3D
```

[42]:
```
class PCA:

    def read_image(self,url):
        print("Reading Image from directory...")
        dir_list = os.listdir(url)
        faces = []
        image_labels = []
        for image in dir_list:
            labels = image.split("_")
            image_labels.append(labels[0])

        for image in dir_list:
            img = io.imread(url+"/"+image)
            img = img.astype(np.uint8)
            # converting to grayscale
            rgb_weights = [0.2989, 0.5870, 0.1141]
            grayscale_image = np.dot(img[...,:3], rgb_weights)
            #normalizing image
            small_grey = transform.resize(grayscale_image, (64,64),␣
↪mode='symmetric', preserve_range=True)
            reshape_img = small_grey.reshape(1, 4096)
            faces.append(reshape_img[0])
        X_train = np.asarray(faces)
```

```
        # print(self.X_train[0])
        print(X_train.shape)
        print("Reading Image from directory Done...")
        return image_labels,X_train

    def apply_pca(self,X):
        print("Applying PCA.......")
        eig_val, eig_mat = np.linalg.eig(np.cov(X))
        idx = eig_val.argsort()[::-1]
        eig_val = eig_val[idx]
        eig_mat = eig_mat[:,idx]
        print("Eigen Matrix calculation done..")
        # taking principal components
        M = []
        print(eig_mat.shape)
        full_pc = eig_mat.shape[0]
        for numpc in range(0,full_pc,10):
            eigen_coeff = eig_mat[:,range(numpc)]
            score_mat = np.dot(eigen_coeff.T,X)
            final_score = np.dot(eigen_coeff,score_mat).T
            # print(final_score.shape)
            val = np.linalg.norm(X.T-final_score,'fro')
            M.append(val)
            # print(val)

        mse = np.asarray(M)
        print("Applying PCA done..............")
        return mse,eig_mat,eig_val

    def plot_mse_vs_principal_component(self,mse,eig_mat):
        full_pc = eig_mat.shape[1]
        plt.figure()
        plt.plot(range(0,full_pc,10),mse,'r')
        plt.show()

    def no_of_component_such_that_mse_less_than_20(self,eig_mat,X):
#         N = 20 #from observation no of principal compenent = 50
        eigen_coeff = eig_mat[:,range(24)]
        score_mat = np.dot(eigen_coeff.T,X)
        final = np.dot(eigen_coeff,score_mat).T
        final = final*255
        final_score = final.astype(int)
        fig,axes = plt.subplots(4,5,figsize=(9,9),subplot_kw={'xticks':[],␣
↪'yticks':[]},gridspec_kw=dict(hspace=0.01, wspace=0.01))
        for i, ax in enumerate(axes.flat):
            ax.imshow(final_score[i].reshape(64,64),cmap='gray')
```

```
        plt.show()
        return final_score


    def scatter_plot_pca(self,X_new,X):
        #1-D plot
        val=0
        plt.plot(X[:,0],np.zeros_like(X[:,0])+val,'o')
        plt.plot(X_new[:,0],np.zeros_like(X_new[:,0])+val,"x")
        plt.show()

        # 2-D plot
        plt.scatter(X[:,0],X[:,1], alpha=0.2)
        plt.scatter(X_new[:,0],X_new[:,1], alpha=0.8)#=self.image_labels)
        plt.show()

        #3-D plot
        fig = plt.figure()
        ax = fig.add_subplot(111, projection='3d')
        ax.scatter(X[:,0], X[:,1], X[:,2], marker='o')
        ax.scatter(X_new[:,0], X_new[:,1], X_new[:,2], marker='^')
        ax.set_xlabel('X Label')
        ax.set_ylabel('Y Label')
        ax.set_zlabel('Z Label')
        plt.show()
```

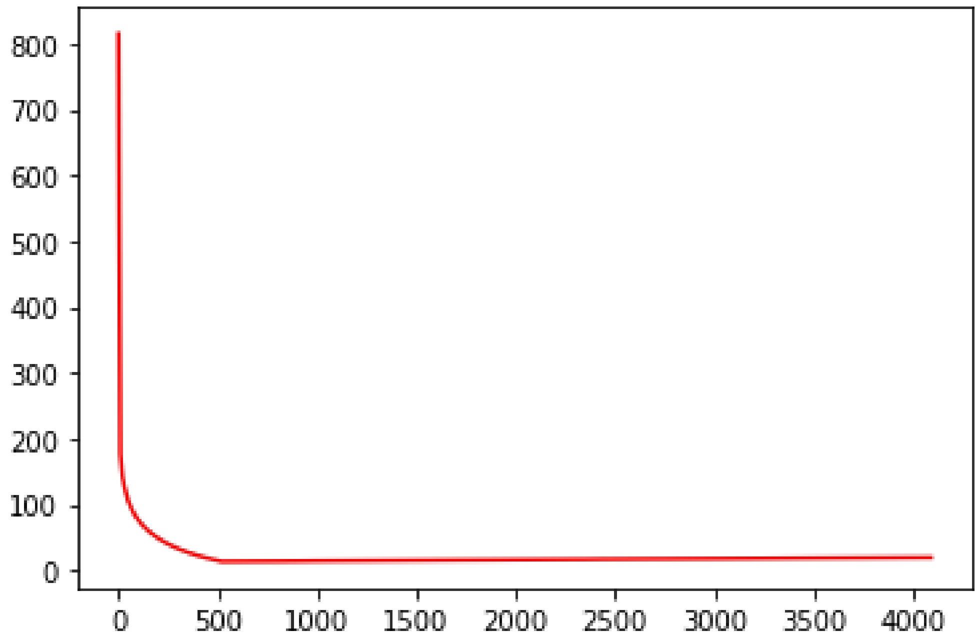
[43]:

```
pca = PCA()
image_label,X_train = pca.read_image(url)
#normalization
X = X_train
X_train = X_train/255
#applying PCA
mse,eig_mat,eig_val = pca.apply_pca(X_train.T)
```

```
Reading Image from directory…
(520, 4096)
Reading Image from directory Done…
Applying PCA…
Eigen Matrix calculation done..
(4096, 4096)
Applying PCA done…
```

[44]:

```
pca.plot_mse_vs_principal_component(mse,eig_mat)
```



[45]:
```
final_score = pca.no_of_component_such_that_mse_less_than_20(eig_mat,X_train.T)
```

[46]:
```
## Check N has Mean Squared error has less than 20%
```

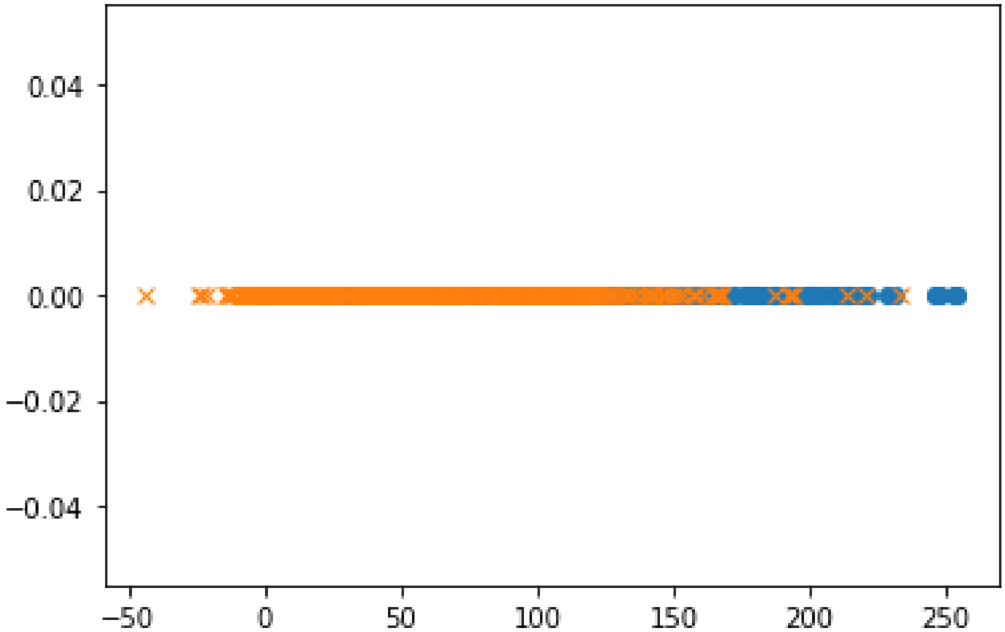
[47]:
```
eigen_val_n = eig_val[0:24]
x = np.sum(eigen_val_n)
y = np.sum(eig_val)
print(x/y)
```

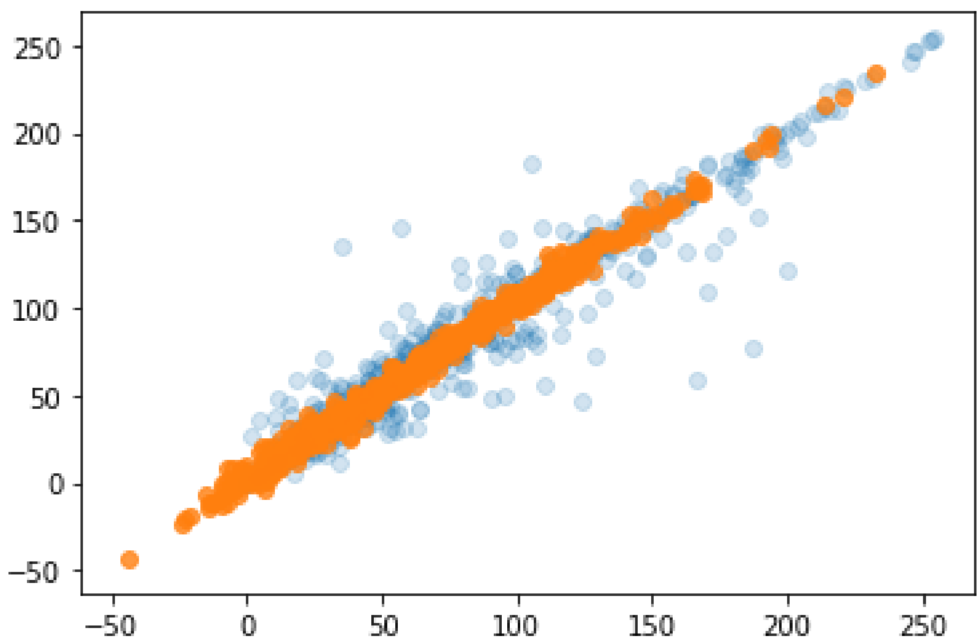
```
(0.804354886673874-5.750783086893538e-33j)
```

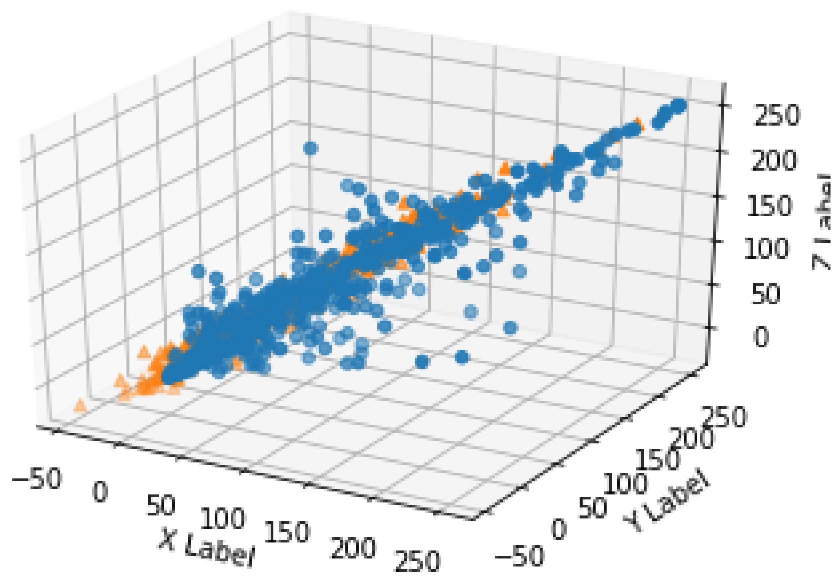
[48]:
```
## for N = 24, mean square error is less than 20%
```

1.1 pca.scatter_plot_pca(final_score,X)

[49]:
```
pca.scatter_plot_pca(final_score,X)
```



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150
200
250
X Label
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0
50
100
150
200
250
Y Label
0
50
100
150
200
250
Z Label

```
[ ]:
```

q2

April 3, 2020

1 Q2 - Logistic Regression After applying PCA

[15]:
```python
import os
import sys
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from skimage import transform,io
from sklearn.metrics import accuracy_score

url_train_csv = "/home/abhishek/dev/Semester_2/SMAI/Assignments/Assignment_3/q2/
↪sample_train_2.txt"
url_test_csv = "/home/abhishek/dev/Semester_2/SMAI/Assignments/Assignment_3/q2/
↪sample_test_2.txt"
sample_output_csv = "/home/abhishek/dev/Semester_2/SMAI/Assignments/
↪Assignment_3/q2/output_of_sample_test_2.txt"

class LogisticRegression:
    def read_csv_file(self,marker):
        image_files = []
        f = None
        if(marker == "train"):
            f = open(url_train_csv,'r')
        elif(marker == "test"):
            f = open(url_test_csv,'r')
        else:
            f = open(sample_output_csv,'r')

        lines = f.readlines()
        for line in lines:
            image_files.append(line.strip())
        return image_files

    def split_image_dir_and_label(self,images_directory,marker):
        if(marker == "train"):
            # print("splitting directory and labels")
            label = []
```

```
            directory = []
            for l in images_directory:
                x = l.split(" ")
                label.append(x[1])
                directory.append(x[0])
            # print("splitting directory and labels done ....")
            return label, directory
        elif(marker == "test"):
            # print("read lines...")
            lines = []
            for l in images_directory:
                lines.append(l)
            # print("reading lines done...")
            return lines

    def read_image_from_directory_to_grayscale(self,directory):
        # print("reading images from directory and downscaling images")
        faces = []
        for i in directory:
            img = io.imread(i)
            img = img.astype(np.uint8)
            # converting to grayscale
            rgb_weights = [0.2989, 0.5870, 0.1141]
            grayscale_image = np.dot(img[...,:3], rgb_weights)
            small_grey = transform.resize(grayscale_image, (64,64),␣
↪mode='symmetric', preserve_range=True)
            reshape_img = small_grey.reshape(1, 4096)
            faces.append(reshape_img[0])
        X = np.asarray(faces)
        # print("reading images from directory and downscaling images done...")
        return X

    def apply_pca(self,X):
        # print("Applying PCA on the image set")
        eig_val, eig_mat = np.linalg.eig(np.cov(X))
        idx = eig_val.argsort()[::-1]
        eig_val = eig_val[idx]
        eig_mat = eig_mat[:,idx]
        eigen_coeff = eig_mat[:,range(50)]
        X_PCA = np.dot(eigen_coeff.T,X)
        # print("Applying PCA on the image set done .......")
        return X_PCA.T

    def sigmoid(self,z):
        return 1/(1+np.exp(-z))

    def cost(self,w,b,X,y,lmd=10):
```

```
        # print("Calculating Cost")
        m = X.shape[0]
        z = np.matmul(X,w) + b
        hx = self.sigmoid(z)
        J = (-1/m)*( np.sum( y * np.log(hx) + (1. - y) * np.log(1.- hx) ) )
        J += (lmd/(2*m))* np.matmul(w,w)
        # print("Calculating Cost done ..")
        return J

    def gradient_descent(self,w,b,X,y,learning_rate=0.
↪01,lmd=10,no_of_iteration=10000):
        # print("Applying Gradient Descent")
        m = X.shape[0]
        # print("Initial cost: {}".format( self.cost(w,b,X,y) ))
        for i in range(no_of_iteration):
            z = np.matmul(X,w) + b
            hx = self.sigmoid(z)
            dw = (1/m)*np.matmul(X.T,hx-y)
            db = (1/m)*np.sum(hx-y)
            factor = 1-( (learning_rate * lmd)/m)
            w = w*factor - learning_rate*dw
            b = b - learning_rate*db
            # if i % 500 == 0:
                # print("Iteration {} cost :{}".format(i,self.cost(w,b,X,y)))
        # print("Final cost: {}".format( self.cost(w,b,X,y) ))
        # print("Applying Gradient Descent done ....")
        return w,b

    def accuracy(self,w,b,X,y):
        # print("Calculating Accuracy")
        m = X.shape[0]
        z = np.matmul(X,w) + b
        hx = self.sigmoid(z)
        pred = np.round(hx)
        correct_pred = (pred==y)
        total = np.sum(correct_pred)
        # print("Calculating Accurcy done .....")
        return (total*100)/m

    def test(self,w,b,X):
        # m = X.shape[0]
        z = np.matmul(X,w)+b
        hx = self.sigmoid(z)
        pred = np.round(hx)
        return pred

lr = LogisticRegression()
```

[ ]:
```
## Applying PCA on the above dataset
```

[2]:
```
lines = lr.read_csv_file("train")
# print(images_directory)
label, directory = lr.split_image_dir_and_label(lines,"train")
# label = np.asarray(label)
# print(label)
unique_labels = np.unique(np.asarray(label))
# print(unique_labels)
X_train = lr.read_image_from_directory_to_grayscale(directory)
# normalizing
X_train = X_train/255
#applying PCA
X_PCA = lr.apply_pca(X_train.T)
# print(X_PCA.shape)
# print(X_PCA[0])
m = X_train.shape[0]
```

[3]:
```
print(X_PCA.shape)
```

```
(520, 50)
```

[7]:
```
## Training Multi-Class Classifier for each unique class in Tranining set
```

[4]:
```
weight_label_map = {}
i = 0
THETA = []
BIAS = []

for unique in unique_labels:
    y_train = []
    for l in label:
        if(unique == l):
            y_train.append(1)
        else:
            y_train.append(0)

    weight_label_map[i] = unique
    i = i+1
    y_train = np.asarray(y_train)
    # print(y_train)
    w = np.zeros(X_PCA.shape[1],dtype=np.float64)
    b = 0.0
    w,b = lr.gradient_descent(w,b,X_PCA,y_train)
    THETA.append(w)
    BIAS.append(b)
```

[5]:
```python
## ALL Unique Labels in Training set
```

[6]:
```python
print(weight_label_map)
```

```
{0: '000', 1: '001', 2: '002', 3: '003', 4: '004', 5: '005', 6: '006', 7: '007'}
```

[12]:
```python
## Applying PCA on Test Data set
```

[7]:
```python
THETA = np.asarray(THETA)
BIAS = np.asarray(BIAS)

lr1 = LogisticRegression()
lines = lr1.read_csv_file("test")
directory = lr1.split_image_dir_and_label(lines,"test")
X_test = lr1.read_image_from_directory_to_grayscale(directory)
X_test = X_test/255
X_Test_PCA = lr1.apply_pca(X_test.T)
# print(X_Test_PCA.shape)
```

[8]:
```python
## Predicting The labels of Test Data by taking maximum sigmoid value of label␣
↪along all classifier
```

[9]:
```python
y_pred = []
for X in X_Test_PCA:
    i = 0
    max_hx = 0.0
    index = 0
    for w,b in zip(THETA,BIAS):
        pred = lr1.test(w,b,X)
        if(pred > max_hx):
            max_hx = pred
            index = i
        i = i+1
    y_pred.append(weight_label_map[index])

y_pred = np.asarray(y_pred)
for prediction in y_pred:
    print(prediction)
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[16]:
```python
labels = lr.read_csv_file("label")
```

[18]:
```python
print(len(labels))
```

```
520
```

[20]:
```python
labels = np.asarray(labels)
```

[21]:
```python
print(labels.shape)
```

```
(520,)
```

[ ]:
```python
## Accuracy Score for predicting the labels
```

[22]:
```python
accuracy_score(labels,y_pred)
```

[22]: 0.5846153846153846

```
[ ]:
```

q3

April 3, 2020

0.1 Question 3 - MNIST Classsification using PyTorch

[0]:
```python
import torch
import numpy as np
```

Load Data Sets

[2]:
```python
from torchvision import datasets
import torchvision.transforms as transforms

# number of subprocesses to use for data loading
num_workers = 0
# how many samples per batch to load
batch_size = 20

# convert data to torch.FloatTensor
transform = transforms.ToTensor()

# choose the training and test datasets
train_data = datasets.MNIST(root='data', train=True,
                                   download=True, transform=transform)
test_data = datasets.MNIST(root='data', train=False,
                                  download=True, transform=transform)

# prepare data loaders
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,
    num_workers=num_workers)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size,
    num_workers=num_workers)
```

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

```
HBox(children=(IntProgress(value=1, bar_style='info', max=1), HTML(value='')))
```

```
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 to
data/MNIST/raw/train-labels-idx1-ubyte.gz
```

```
HBox(children=(IntProgress(value=1, bar_style='info', max=1), HTML(value='')))
```

```
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 to
data/MNIST/raw/t10k-images-idx3-ubyte.gz
```

```
HBox(children=(IntProgress(value=1, bar_style='info', max=1), HTML(value='')))
```

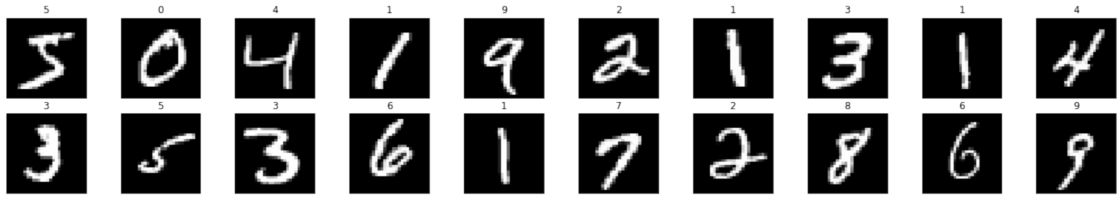
```
Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to
data/MNIST/raw/t10k-labels-idx1-ubyte.gz
```

```
HBox(children=(IntProgress(value=1, bar_style='info', max=1), HTML(value='')))
```

```
Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw
Processing…
Done!
```

Visualize a batch of Training Set

[3]:
```
import matplotlib.pyplot as plt
%matplotlib inline

# obtain one batch of training images
dataiter = iter(train_loader)
images, labels = dataiter.next()
images = images.numpy()

# plot the images in the batch, along with the corresponding labels
fig = plt.figure(figsize=(25, 4))
for idx in np.arange(20):
    ax = fig.add_subplot(2, 20/2, idx+1, xticks=[], yticks=[])
    ax.imshow(np.squeeze(images[idx]), cmap='gray')
    # print out the correct label for each image
    # .item() gets the value contained in a Tensor
    ax.set_title(str(labels[idx].item()))
```



Define the Network Architecture

[0]:
```
import torch.nn as nn
import torch.nn.functional as F

## Define the NN architecture
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(28 * 28, 512)
        # linear layer (n_hidden -> hidden_2)
        self.fc2 = nn.Linear(512, 512)
        # linear layer (n_hidden -> 10)
        self.fc3 = nn.Linear(512, 10)
        # dropout layer (p=0.2)
        # dropout prevents overfitting of data
        self.dropout = nn.Dropout(0.2)

    def forward(self, x):
        # flatten image input
        x = x.view(-1, 28 * 28)
        # add hidden layer, with relu activation function
        x = F.relu(self.fc1(x))
        return x
```

[5]:
```
# initialize the NN
model = Net()
print(model)
```

```
Net(
  (fc1): Linear(in_features=784, out_features=512, bias=True)
  (fc2): Linear(in_features=512, out_features=512, bias=True)
  (fc3): Linear(in_features=512, out_features=10, bias=True)
  (dropout): Dropout(p=0.2, inplace=False)
)
```

Specify Loss Function and Optimizer

[0]:
```
criterion = nn.CrossEntropyLoss()

# specify optimizer
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
```

Train the Network

[7]:

```python
n_epochs = 30  # suggest training between 20-50 epochs

model.train() # prep model for training

for epoch in range(n_epochs):
    # monitor training loss
    train_loss = 0.0

    ###################
    # train the model #
    ###################
    for data, target in train_loader:
        # clear the gradients of all optimized variables
        optimizer.zero_grad()
        # forward pass: compute predicted outputs by passing inputs to the model
        output = model(data)
        # calculate the loss
        loss = criterion(output, target)
        # backward pass: compute gradient of the loss with respect to model␣
 ↪parameters
        loss.backward()
        # perform a single optimization step (parameter update)
        optimizer.step()
        # update running training loss
        train_loss += loss.item()*data.size(0)

    # print training statistics
    # calculate average loss over an epoch
    train_loss = train_loss/len(train_loader.dataset)

    print('Epoch: {} \tTraining Loss: {:.6f}'.format(
        epoch+1,
        train_loss
        ))
```

```
Epoch: 1        Training Loss: 0.804222
Epoch: 2        Training Loss: 0.411707
Epoch: 3        Training Loss: 0.370065
Epoch: 4        Training Loss: 0.348959
Epoch: 5        Training Loss: 0.335502
Epoch: 6        Training Loss: 0.325918
Epoch: 7        Training Loss: 0.318626
Epoch: 8        Training Loss: 0.312826
Epoch: 9        Training Loss: 0.308064
Epoch: 10       Training Loss: 0.304058
Epoch: 11       Training Loss: 0.300624
Epoch: 12       Training Loss: 0.297635
```

```
Epoch: 13       Training Loss: 0.294999
Epoch: 14       Training Loss: 0.292651
Epoch: 15       Training Loss: 0.290539
Epoch: 16       Training Loss: 0.288626
Epoch: 17       Training Loss: 0.286881
Epoch: 18       Training Loss: 0.285279
Epoch: 19       Training Loss: 0.283802
Epoch: 20       Training Loss: 0.282434
Epoch: 21       Training Loss: 0.281160
Epoch: 22       Training Loss: 0.279970
Epoch: 23       Training Loss: 0.278856
Epoch: 24       Training Loss: 0.277808
Epoch: 25       Training Loss: 0.276820
Epoch: 26       Training Loss: 0.275887
Epoch: 27       Training Loss: 0.275002
Epoch: 28       Training Loss: 0.274163
Epoch: 29       Training Loss: 0.273365
Epoch: 30       Training Loss: 0.272604
```

Test the Trained Network¶

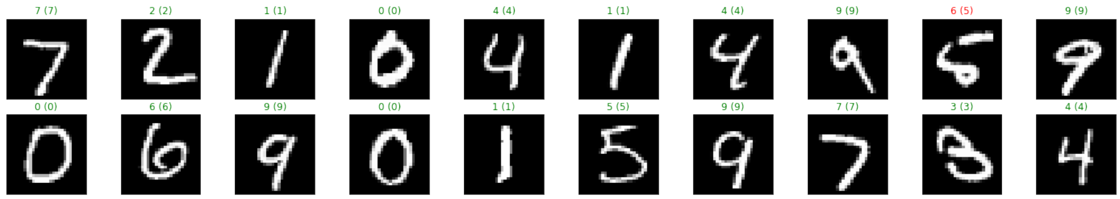
[8]:
```python
test_loss = 0.0
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))

model.eval() # prep model for *evaluation*

for data, target in test_loader:
    # forward pass: compute predicted outputs by passing inputs to the model
    output = model(data)
    # calculate the loss
    loss = criterion(output, target)
    # update test loss
    test_loss += loss.item()*data.size(0)
    # convert output probabilities to predicted class
    _, pred = torch.max(output, 1)
    # compare predictions to true label
    correct = np.squeeze(pred.eq(target.data.view_as(pred)))
    # calculate test accuracy for each object class
    for i in range(batch_size):
        label = target.data[i]
        class_correct[label] += correct[i].item()
        class_total[label] += 1

# calculate and print avg test loss
test_loss = test_loss/len(test_loader.dataset)
print('Test Loss: {:.6f}\n'.format(test_loss))
```

```
for i in range(10):
    if class_total[i] > 0:
        print('Test Accuracy of %5s: %2d%% (%2d/%2d)' % (
            str(i), 100 * class_correct[i] / class_total[i],
            np.sum(class_correct[i]), np.sum(class_total[i])))
    else:
        print('Test Accuracy of %5s: N/A (no training examples)' % (classes[i]))

print('\nTest Accuracy (Overall): %2d%% (%2d/%2d)' % (
    100. * np.sum(class_correct) / np.sum(class_total),
    np.sum(class_correct), np.sum(class_total)))
```

```
Test Loss: 0.274007

Test Accuracy of     0: 98% (962/980)
Test Accuracy of     1: 97% (1109/1135)
Test Accuracy of     2: 88% (918/1032)
Test Accuracy of     3: 90% (914/1010)
Test Accuracy of     4: 92% (909/982)
Test Accuracy of     5: 87% (781/892)
Test Accuracy of     6: 94% (910/958)
Test Accuracy of     7: 92% (946/1028)
Test Accuracy of     8: 88% (864/974)
Test Accuracy of     9: 90% (916/1009)

Test Accuracy (Overall): 92% (9229/10000)
```

Visualize Sample Test Results

[9]:
```
dataiter = iter(test_loader)
images, labels = dataiter.next()

# get sample outputs
output = model(images)
# convert output probabilities to predicted class
_, preds = torch.max(output, 1)
# prep images for display
images = images.numpy()

# plot the images in the batch, along with predicted and true labels
fig = plt.figure(figsize=(25, 4))
for idx in np.arange(20):
    ax = fig.add_subplot(2, 20/2, idx+1, xticks=[], yticks=[])
    ax.imshow(np.squeeze(images[idx]), cmap='gray')
    ax.set_title("{} ({})".format(str(preds[idx].item()), str(labels[idx].
 ↪item())),
                 color=("green" if preds[idx]==labels[idx] else "red"))
```



0.2 MNIST Classification using CNN

[0]:
```python
import numpy as np # to handle matrix and data operation
import pandas as pd # to read csv and handle dataframe

import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.utils.data
from torch.autograd import Variable

from sklearn.model_selection import train_test_split
```

[0]:
```python
from keras.datasets import mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

[0]:
```python
x_train = x_train.reshape(60000,784)
x_test = x_test.reshape(10000,784)
```

[0]:
```python
BATCH_SIZE = 32
```

[0]:
```python
torch_X_train = torch.from_numpy(x_train).type(torch.LongTensor)
torch_y_train = torch.from_numpy(y_train).type(torch.LongTensor)
```

[0]:
```python
torch_X_test = torch.from_numpy(x_test).type(torch.LongTensor)
torch_y_test = torch.from_numpy(y_test).type(torch.LongTensor)
```

[0]:
```python
train = torch.utils.data.TensorDataset(torch_X_train,torch_y_train)
test = torch.utils.data.TensorDataset(torch_X_test,torch_y_test)
```

[0]:
```python
train_loader = torch.utils.data.DataLoader(train, batch_size = BATCH_SIZE, shuffle = False)
test_loader = torch.utils.data.DataLoader(test, batch_size = BATCH_SIZE, shuffle = False)
```

[59]:
```python
class MLP(nn.Module):
    def __init__(self):
        super(MLP, self).__init__()
        self.linear1 = nn.Linear(784,250)
        self.linear2 = nn.Linear(250,100)
        self.linear3 = nn.Linear(100,10)

    def forward(self,X):
        X = F.relu(self.linear1(X))
        X = F.relu(self.linear2(X))
        X = self.linear3(X)
        return F.log_softmax(X, dim=1)

mlp = MLP()
print(mlp)
```

```
MLP(
  (linear1): Linear(in_features=784, out_features=250, bias=True)
  (linear2): Linear(in_features=250, out_features=100, bias=True)
  (linear3): Linear(in_features=100, out_features=10, bias=True)
)
```

[0]:
```python
def fit(model, train_loader):
    optimizer = torch.optim.Adam(model.parameters())#,lr=0.001, betas=(0.9,0.
↪999))
    error = nn.CrossEntropyLoss()
    EPOCHS = 5
    model.train()
    for epoch in range(EPOCHS):
        correct = 0
        for batch_idx, (X_batch, y_batch) in enumerate(train_loader):
            var_X_batch = Variable(X_batch).float()
            var_y_batch = Variable(y_batch)
            optimizer.zero_grad()
            output = model(var_X_batch)
            loss = error(output, var_y_batch)
            loss.backward()
            optimizer.step()

            # Total correct predictions
            predicted = torch.max(output.data, 1)[1]
            correct += (predicted == var_y_batch).sum()
            #print(correct)
            if batch_idx % 50 == 0:
                print('Epoch : {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}\t Accuracy:{:.
↪3f}%'.format(
```

```
                    epoch, batch_idx*len(X_batch), len(train_loader.dataset),␣
↪100.*batch_idx / len(train_loader), (loss.data), float(correct*100) /␣
↪float(BATCH_SIZE*(batch_idx+1))))
```

[67]:
```
fit(mlp, train_loader)
```

```
Epoch : 0 [0/60000 (0%)]        Loss: 0.028779   Accuracy:100.000%
Epoch : 0 [1600/60000 (3%)]     Loss: 0.135546   Accuracy:96.875%
Epoch : 0 [3200/60000 (5%)]     Loss: 0.161492   Accuracy:97.061%
Epoch : 0 [4800/60000 (8%)]     Loss: 0.029837   Accuracy:97.144%
Epoch : 0 [6400/60000 (11%)]    Loss: 0.251311   Accuracy:97.233%
Epoch : 0 [8000/60000 (13%)]    Loss: 0.288707   Accuracy:96.987%
Epoch : 0 [9600/60000 (16%)]    Loss: 0.001341   Accuracy:96.564%
Epoch : 0 [11200/60000 (19%)]   Loss: 0.147621   Accuracy:96.270%
Epoch : 0 [12800/60000 (21%)]   Loss: 0.162637   Accuracy:96.213%
Epoch : 0 [14400/60000 (24%)]   Loss: 0.040754   Accuracy:96.182%
Epoch : 0 [16000/60000 (27%)]   Loss: 0.053642   Accuracy:96.214%
Epoch : 0 [17600/60000 (29%)]   Loss: 0.021809   Accuracy:96.257%
Epoch : 0 [19200/60000 (32%)]   Loss: 0.007951   Accuracy:96.339%
Epoch : 0 [20800/60000 (35%)]   Loss: 0.117186   Accuracy:96.376%
Epoch : 0 [22400/60000 (37%)]   Loss: 0.001032   Accuracy:96.438%
Epoch : 0 [24000/60000 (40%)]   Loss: 0.240103   Accuracy:96.451%
Epoch : 0 [25600/60000 (43%)]   Loss: 0.097887   Accuracy:96.497%
Epoch : 0 [27200/60000 (45%)]   Loss: 0.023727   Accuracy:96.500%
Epoch : 0 [28800/60000 (48%)]   Loss: 0.015119   Accuracy:96.528%
Epoch : 0 [30400/60000 (51%)]   Loss: 0.070183   Accuracy:96.537%
Epoch : 0 [32000/60000 (53%)]   Loss: 0.012500   Accuracy:96.544%
Epoch : 0 [33600/60000 (56%)]   Loss: 0.110607   Accuracy:96.530%
Epoch : 0 [35200/60000 (59%)]   Loss: 0.357193   Accuracy:96.540%
Epoch : 0 [36800/60000 (61%)]   Loss: 0.010914   Accuracy:96.549%
Epoch : 0 [38400/60000 (64%)]   Loss: 0.176304   Accuracy:96.555%
Epoch : 0 [40000/60000 (67%)]   Loss: 0.098055   Accuracy:96.530%
Epoch : 0 [41600/60000 (69%)]   Loss: 0.044533   Accuracy:96.539%
Epoch : 0 [43200/60000 (72%)]   Loss: 0.099969   Accuracy:96.551%
Epoch : 0 [44800/60000 (75%)]   Loss: 0.024746   Accuracy:96.576%
Epoch : 0 [46400/60000 (77%)]   Loss: 0.333618   Accuracy:96.550%
Epoch : 0 [48000/60000 (80%)]   Loss: 0.118122   Accuracy:96.565%
Epoch : 0 [49600/60000 (83%)]   Loss: 0.100130   Accuracy:96.555%
Epoch : 0 [51200/60000 (85%)]   Loss: 0.101556   Accuracy:96.549%
Epoch : 0 [52800/60000 (88%)]   Loss: 0.163493   Accuracy:96.555%
Epoch : 0 [54400/60000 (91%)]   Loss: 0.001940   Accuracy:96.550%
Epoch : 0 [56000/60000 (93%)]   Loss: 0.151699   Accuracy:96.552%
Epoch : 0 [57600/60000 (96%)]   Loss: 0.085508   Accuracy:96.577%
Epoch : 0 [59200/60000 (99%)]   Loss: 0.006413   Accuracy:96.607%
Epoch : 1 [0/60000 (0%)]        Loss: 0.066838   Accuracy:96.875%
Epoch : 1 [1600/60000 (3%)]     Loss: 0.038393   Accuracy:95.895%
Epoch : 1 [3200/60000 (5%)]     Loss: 0.088629   Accuracy:96.566%
```

```
Epoch : 1 [4800/60000 (8%)]     Loss: 0.073845   Accuracy:96.978%
Epoch : 1 [6400/60000 (11%)]    Loss: 0.323887   Accuracy:97.015%
Epoch : 1 [8000/60000 (13%)]    Loss: 0.080831   Accuracy:97.049%
Epoch : 1 [9600/60000 (16%)]    Loss: 0.028484   Accuracy:97.103%
Epoch : 1 [11200/60000 (19%)]   Loss: 0.217653   Accuracy:97.044%
Epoch : 1 [12800/60000 (21%)]   Loss: 0.015726   Accuracy:97.015%
Epoch : 1 [14400/60000 (24%)]   Loss: 0.031854   Accuracy:96.993%
Epoch : 1 [16000/60000 (27%)]   Loss: 0.102694   Accuracy:97.050%
Epoch : 1 [17600/60000 (29%)]   Loss: 0.314560   Accuracy:97.164%
Epoch : 1 [19200/60000 (32%)]   Loss: 0.043562   Accuracy:97.192%
Epoch : 1 [20800/60000 (35%)]   Loss: 0.078116   Accuracy:97.211%
Epoch : 1 [22400/60000 (37%)]   Loss: 0.010395   Accuracy:97.214%
Epoch : 1 [24000/60000 (40%)]   Loss: 0.008545   Accuracy:97.241%
Epoch : 1 [25600/60000 (43%)]   Loss: 0.087680   Accuracy:97.285%
Epoch : 1 [27200/60000 (45%)]   Loss: 0.016307   Accuracy:97.264%
Epoch : 1 [28800/60000 (48%)]   Loss: 0.070700   Accuracy:97.295%
Epoch : 1 [30400/60000 (51%)]   Loss: 0.283281   Accuracy:97.315%
Epoch : 1 [32000/60000 (53%)]   Loss: 0.124514   Accuracy:97.331%
Epoch : 1 [33600/60000 (56%)]   Loss: 0.077984   Accuracy:97.265%
Epoch : 1 [35200/60000 (59%)]   Loss: 0.018130   Accuracy:97.272%
Epoch : 1 [36800/60000 (61%)]   Loss: 0.063739   Accuracy:97.277%
Epoch : 1 [38400/60000 (64%)]   Loss: 0.262766   Accuracy:97.250%
Epoch : 1 [40000/60000 (67%)]   Loss: 0.040512   Accuracy:97.252%
Epoch : 1 [41600/60000 (69%)]   Loss: 0.088825   Accuracy:97.235%
Epoch : 1 [43200/60000 (72%)]   Loss: 0.161225   Accuracy:97.213%
Epoch : 1 [44800/60000 (75%)]   Loss: 0.050391   Accuracy:97.232%
Epoch : 1 [46400/60000 (77%)]   Loss: 0.577136   Accuracy:97.194%
Epoch : 1 [48000/60000 (80%)]   Loss: 0.154128   Accuracy:97.183%
Epoch : 1 [49600/60000 (83%)]   Loss: 0.199059   Accuracy:97.155%
Epoch : 1 [51200/60000 (85%)]   Loss: 0.163394   Accuracy:97.146%
Epoch : 1 [52800/60000 (88%)]   Loss: 0.163188   Accuracy:97.161%
Epoch : 1 [54400/60000 (91%)]   Loss: 0.007887   Accuracy:97.163%
Epoch : 1 [56000/60000 (93%)]   Loss: 0.123494   Accuracy:97.150%
Epoch : 1 [57600/60000 (96%)]   Loss: 0.084630   Accuracy:97.167%
Epoch : 1 [59200/60000 (99%)]   Loss: 0.041318   Accuracy:97.197%
Epoch : 2 [0/60000 (0%)]        Loss: 0.101924   Accuracy:93.750%
Epoch : 2 [1600/60000 (3%)]     Loss: 0.192111   Accuracy:96.078%
Epoch : 2 [3200/60000 (5%)]     Loss: 0.070167   Accuracy:97.123%
Epoch : 2 [4800/60000 (8%)]     Loss: 0.023145   Accuracy:97.413%
Epoch : 2 [6400/60000 (11%)]    Loss: 0.164375   Accuracy:97.217%
Epoch : 2 [8000/60000 (13%)]    Loss: 0.206731   Accuracy:97.261%
Epoch : 2 [9600/60000 (16%)]    Loss: 0.013814   Accuracy:97.228%
Epoch : 2 [11200/60000 (19%)]   Loss: 0.189980   Accuracy:97.302%
Epoch : 2 [12800/60000 (21%)]   Loss: 0.094958   Accuracy:97.319%
Epoch : 2 [14400/60000 (24%)]   Loss: 0.015213   Accuracy:97.367%
Epoch : 2 [16000/60000 (27%)]   Loss: 0.093988   Accuracy:97.287%
Epoch : 2 [17600/60000 (29%)]   Loss: 0.621408   Accuracy:97.221%
Epoch : 2 [19200/60000 (32%)]   Loss: 0.108640   Accuracy:97.223%
```

```
Epoch : 2 [20800/60000 (35%)]   Loss: 0.021036   Accuracy:97.216%
Epoch : 2 [22400/60000 (37%)]   Loss: 0.001247   Accuracy:97.209%
Epoch : 2 [24000/60000 (40%)]   Loss: 0.015268   Accuracy:97.233%
Epoch : 2 [25600/60000 (43%)]   Loss: 0.101386   Accuracy:97.261%
Epoch : 2 [27200/60000 (45%)]   Loss: 0.131324   Accuracy:97.239%
Epoch : 2 [28800/60000 (48%)]   Loss: 0.069168   Accuracy:97.243%
Epoch : 2 [30400/60000 (51%)]   Loss: 0.025075   Accuracy:97.282%
Epoch : 2 [32000/60000 (53%)]   Loss: 0.016453   Accuracy:97.300%
Epoch : 2 [33600/60000 (56%)]   Loss: 0.020328   Accuracy:97.273%
Epoch : 2 [35200/60000 (59%)]   Loss: 0.872610   Accuracy:97.298%
Epoch : 2 [36800/60000 (61%)]   Loss: 0.101088   Accuracy:97.296%
Epoch : 2 [38400/60000 (64%)]   Loss: 0.088246   Accuracy:97.294%
Epoch : 2 [40000/60000 (67%)]   Loss: 0.119826   Accuracy:97.302%
Epoch : 2 [41600/60000 (69%)]   Loss: 0.052212   Accuracy:97.324%
Epoch : 2 [43200/60000 (72%)]   Loss: 0.325394   Accuracy:97.305%
Epoch : 2 [44800/60000 (75%)]   Loss: 0.062563   Accuracy:97.310%
Epoch : 2 [46400/60000 (77%)]   Loss: 0.133759   Accuracy:97.273%
Epoch : 2 [48000/60000 (80%)]   Loss: 0.219807   Accuracy:97.271%
Epoch : 2 [49600/60000 (83%)]   Loss: 0.019319   Accuracy:97.288%
Epoch : 2 [51200/60000 (85%)]   Loss: 0.045573   Accuracy:97.273%
Epoch : 2 [52800/60000 (88%)]   Loss: 0.129453   Accuracy:97.265%
Epoch : 2 [54400/60000 (91%)]   Loss: 0.037412   Accuracy:97.270%
Epoch : 2 [56000/60000 (93%)]   Loss: 0.061451   Accuracy:97.275%
Epoch : 2 [57600/60000 (96%)]   Loss: 0.268131   Accuracy:97.278%
Epoch : 2 [59200/60000 (99%)]   Loss: 0.029599   Accuracy:97.316%
Epoch : 3 [0/60000 (0%)]        Loss: 0.151179   Accuracy:93.750%
Epoch : 3 [1600/60000 (3%)]     Loss: 0.128003   Accuracy:96.446%
Epoch : 3 [3200/60000 (5%)]     Loss: 0.006657   Accuracy:97.308%
Epoch : 3 [4800/60000 (8%)]     Loss: 0.015271   Accuracy:97.392%
Epoch : 3 [6400/60000 (11%)]    Loss: 0.127014   Accuracy:97.404%
Epoch : 3 [8000/60000 (13%)]    Loss: 0.137492   Accuracy:97.323%
Epoch : 3 [9600/60000 (16%)]    Loss: 0.011746   Accuracy:97.290%
Epoch : 3 [11200/60000 (19%)]   Loss: 0.193034   Accuracy:97.391%
Epoch : 3 [12800/60000 (21%)]   Loss: 0.151988   Accuracy:97.506%
Epoch : 3 [14400/60000 (24%)]   Loss: 0.001826   Accuracy:97.561%
Epoch : 3 [16000/60000 (27%)]   Loss: 0.038850   Accuracy:97.493%
Epoch : 3 [17600/60000 (29%)]   Loss: 0.005036   Accuracy:97.533%
Epoch : 3 [19200/60000 (32%)]   Loss: 0.041748   Accuracy:97.577%
Epoch : 3 [20800/60000 (35%)]   Loss: 0.061989   Accuracy:97.552%
Epoch : 3 [22400/60000 (37%)]   Loss: 0.000083   Accuracy:97.562%
Epoch : 3 [24000/60000 (40%)]   Loss: 0.010684   Accuracy:97.562%
Epoch : 3 [25600/60000 (43%)]   Loss: 0.035633   Accuracy:97.554%
Epoch : 3 [27200/60000 (45%)]   Loss: 0.003687   Accuracy:97.536%
Epoch : 3 [28800/60000 (48%)]   Loss: 0.059841   Accuracy:97.562%
Epoch : 3 [30400/60000 (51%)]   Loss: 0.055981   Accuracy:97.581%
Epoch : 3 [32000/60000 (53%)]   Loss: 0.057697   Accuracy:97.596%
Epoch : 3 [33600/60000 (56%)]   Loss: 0.099345   Accuracy:97.589%
Epoch : 3 [35200/60000 (59%)]   Loss: 0.004503   Accuracy:97.593%
```

```
Epoch : 3 [36800/60000 (61%)]    Loss: 0.132729   Accuracy:97.597%
Epoch : 3 [38400/60000 (64%)]    Loss: 0.078958   Accuracy:97.580%
Epoch : 3 [40000/60000 (67%)]    Loss: 0.049452   Accuracy:97.577%
Epoch : 3 [41600/60000 (69%)]    Loss: 0.001719   Accuracy:97.574%
Epoch : 3 [43200/60000 (72%)]    Loss: 0.175857   Accuracy:97.580%
Epoch : 3 [44800/60000 (75%)]    Loss: 0.034069   Accuracy:97.589%
Epoch : 3 [46400/60000 (77%)]    Loss: 0.021272   Accuracy:97.599%
Epoch : 3 [48000/60000 (80%)]    Loss: 0.064088   Accuracy:97.620%
Epoch : 3 [49600/60000 (83%)]    Loss: 0.003137   Accuracy:97.625%
Epoch : 3 [51200/60000 (85%)]    Loss: 0.014169   Accuracy:97.628%
Epoch : 3 [52800/60000 (88%)]    Loss: 0.221221   Accuracy:97.625%
Epoch : 3 [54400/60000 (91%)]    Loss: 0.001268   Accuracy:97.612%
Epoch : 3 [56000/60000 (93%)]    Loss: 0.063965   Accuracy:97.596%
Epoch : 3 [57600/60000 (96%)]    Loss: 0.254212   Accuracy:97.604%
Epoch : 3 [59200/60000 (99%)]    Loss: 0.000153   Accuracy:97.633%
Epoch : 4 [0/60000 (0%)]         Loss: 0.077204   Accuracy:96.875%
Epoch : 4 [1600/60000 (3%)]      Loss: 0.160978   Accuracy:97.059%
Epoch : 4 [3200/60000 (5%)]      Loss: 0.022128   Accuracy:97.463%
Epoch : 4 [4800/60000 (8%)]      Loss: 0.087849   Accuracy:97.641%
Epoch : 4 [6400/60000 (11%)]     Loss: 0.282174   Accuracy:97.512%
Epoch : 4 [8000/60000 (13%)]     Loss: 0.022924   Accuracy:97.572%
Epoch : 4 [9600/60000 (16%)]     Loss: 0.057789   Accuracy:97.456%
Epoch : 4 [11200/60000 (19%)]    Loss: 0.173873   Accuracy:97.480%
Epoch : 4 [12800/60000 (21%)]    Loss: 0.177891   Accuracy:97.498%
Epoch : 4 [14400/60000 (24%)]    Loss: 0.058999   Accuracy:97.568%
Epoch : 4 [16000/60000 (27%)]    Loss: 0.087360   Accuracy:97.493%
Epoch : 4 [17600/60000 (29%)]    Loss: 0.002993   Accuracy:97.544%
Epoch : 4 [19200/60000 (32%)]    Loss: 0.007460   Accuracy:97.577%
Epoch : 4 [20800/60000 (35%)]    Loss: 0.172938   Accuracy:97.576%
Epoch : 4 [22400/60000 (37%)]    Loss: 0.003647   Accuracy:97.597%
Epoch : 4 [24000/60000 (40%)]    Loss: 0.003558   Accuracy:97.616%
Epoch : 4 [25600/60000 (43%)]    Loss: 0.123521   Accuracy:97.651%
Epoch : 4 [27200/60000 (45%)]    Loss: 0.062108   Accuracy:97.650%
Epoch : 4 [28800/60000 (48%)]    Loss: 0.079932   Accuracy:97.683%
Epoch : 4 [30400/60000 (51%)]    Loss: 0.002716   Accuracy:97.703%
Epoch : 4 [32000/60000 (53%)]    Loss: 0.218044   Accuracy:97.687%
Epoch : 4 [33600/60000 (56%)]    Loss: 0.009926   Accuracy:97.693%
Epoch : 4 [35200/60000 (59%)]    Loss: 0.001960   Accuracy:97.707%
Epoch : 4 [36800/60000 (61%)]    Loss: 0.003491   Accuracy:97.706%
Epoch : 4 [38400/60000 (64%)]    Loss: 0.193213   Accuracy:97.684%
Epoch : 4 [40000/60000 (67%)]    Loss: 0.121122   Accuracy:97.677%
Epoch : 4 [41600/60000 (69%)]    Loss: 0.058635   Accuracy:97.672%
Epoch : 4 [43200/60000 (72%)]    Loss: 0.121910   Accuracy:97.668%
Epoch : 4 [44800/60000 (75%)]    Loss: 0.020887   Accuracy:97.711%
Epoch : 4 [46400/60000 (77%)]    Loss: 0.099990   Accuracy:97.676%
Epoch : 4 [48000/60000 (80%)]    Loss: 0.167490   Accuracy:97.677%
Epoch : 4 [49600/60000 (83%)]    Loss: 0.096079   Accuracy:97.671%
Epoch : 4 [51200/60000 (85%)]    Loss: 0.009618   Accuracy:97.687%
```

```
Epoch : 4 [52800/60000 (88%)]   Loss: 0.322359   Accuracy:97.714%
Epoch : 4 [54400/60000 (91%)]   Loss: 0.001315   Accuracy:97.702%
Epoch : 4 [56000/60000 (93%)]   Loss: 0.065532   Accuracy:97.717%
Epoch : 4 [57600/60000 (96%)]   Loss: 0.120293   Accuracy:97.729%
Epoch : 4 [59200/60000 (99%)]   Loss: 0.000217   Accuracy:97.758%
```

[68]:

```
def evaluate(model):
#model = mlp
    correct = 0
    for test_imgs, test_labels in test_loader:
        #print(test_imgs.shape)
        test_imgs = Variable(test_imgs).float()
        output = model(test_imgs)
        predicted = torch.max(output,1)[1]
        correct += (predicted == test_labels).sum()
    print("Test accuracy:{:.3f}% ".format( float(correct) /
 ↪(len(test_loader)*BATCH_SIZE)))
evaluate(mlp)
```

```
Test accuracy:0.971%
```

##Since a CNN needs a image shape as input let's reshape our flatten images to real image

[69]:

```
torch_X_train = torch_X_train.view(-1, 1,28,28).float()
torch_X_test = torch_X_test.view(-1,1,28,28).float()
print(torch_X_train.shape)
print(torch_X_test.shape)

# Pytorch train and test sets
train = torch.utils.data.TensorDataset(torch_X_train,torch_y_train)
test = torch.utils.data.TensorDataset(torch_X_test,torch_y_test)

# data loader
train_loader = torch.utils.data.DataLoader(train, batch_size = BATCH_SIZE,
 ↪shuffle = False)
test_loader = torch.utils.data.DataLoader(test, batch_size = BATCH_SIZE,
 ↪shuffle = False)MB
```

```
torch.Size([60000, 1, 28, 28])
torch.Size([10000, 1, 28, 28])
```

[70]:

```
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, kernel_size=5)
        self.conv2 = nn.Conv2d(32, 32, kernel_size=5)
        self.conv3 = nn.Conv2d(32,64, kernel_size=5)
        self.fc1 = nn.Linear(3*3*64, 256)
```

```
        self.fc2 = nn.Linear(256, 10)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        #x = F.dropout(x, p=0.5, training=self.training)
        x = F.relu(F.max_pool2d(self.conv2(x), 2))
        x = F.dropout(x, p=0.5, training=self.training)
        x = F.relu(F.max_pool2d(self.conv3(x),2))
        x = F.dropout(x, p=0.5, training=self.training)
        x = x.view(-1,3*3*64 )
        x = F.relu(self.fc1(x))
        x = F.dropout(x, training=self.training)
        x = self.fc2(x)
        return F.log_softmax(x, dim=1)

cnn = CNN()
print(cnn)

it = iter(train_loader)
X_batch, y_batch = next(it)
print(cnn.forward(X_batch).shape)
```

```
CNN(
  (conv1): Conv2d(1, 32, kernel_size=(5, 5), stride=(1, 1))
  (conv2): Conv2d(32, 32, kernel_size=(5, 5), stride=(1, 1))
  (conv3): Conv2d(32, 64, kernel_size=(5, 5), stride=(1, 1))
  (fc1): Linear(in_features=576, out_features=256, bias=True)
  (fc2): Linear(in_features=256, out_features=10, bias=True)
)
torch.Size([32, 10])
```

[71]:
```
fit(cnn,train_loader)
```

```
Epoch : 0 [0/60000 (0%)]        Loss: 24.703955   Accuracy:6.250%
Epoch : 0 [1600/60000 (3%)]     Loss: 1.980315    Accuracy:17.279%
Epoch : 0 [3200/60000 (5%)]     Loss: 1.460487    Accuracy:29.115%
Epoch : 0 [4800/60000 (8%)]     Loss: 0.748759    Accuracy:38.949%
Epoch : 0 [6400/60000 (11%)]    Loss: 1.238455    Accuracy:45.553%
Epoch : 0 [8000/60000 (13%)]    Loss: 0.865389    Accuracy:50.461%
Epoch : 0 [9600/60000 (16%)]    Loss: 0.764462    Accuracy:54.485%
Epoch : 0 [11200/60000 (19%)]   Loss: 0.602340    Accuracy:58.191%
Epoch : 0 [12800/60000 (21%)]   Loss: 0.548422    Accuracy:60.793%
Epoch : 0 [14400/60000 (24%)]   Loss: 0.491586    Accuracy:63.089%
Epoch : 0 [16000/60000 (27%)]   Loss: 0.702923    Accuracy:64.814%
Epoch : 0 [17600/60000 (29%)]   Loss: 0.591373    Accuracy:66.640%
Epoch : 0 [19200/60000 (32%)]   Loss: 0.427941    Accuracy:68.225%
Epoch : 0 [20800/60000 (35%)]   Loss: 0.508253    Accuracy:69.772%
Epoch : 0 [22400/60000 (37%)]   Loss: 0.220711    Accuracy:71.122%
```

```
Epoch : 0 [24000/60000 (40%)]   Loss: 0.182511   Accuracy:72.121%
Epoch : 0 [25600/60000 (43%)]   Loss: 0.578731   Accuracy:73.174%
Epoch : 0 [27200/60000 (45%)]   Loss: 0.405716   Accuracy:74.104%
Epoch : 0 [28800/60000 (48%)]   Loss: 0.335528   Accuracy:75.035%
Epoch : 0 [30400/60000 (51%)]   Loss: 0.524058   Accuracy:75.710%
Epoch : 0 [32000/60000 (53%)]   Loss: 0.522807   Accuracy:76.346%
Epoch : 0 [33600/60000 (56%)]   Loss: 0.353773   Accuracy:77.019%
Epoch : 0 [35200/60000 (59%)]   Loss: 0.348661   Accuracy:77.677%
Epoch : 0 [36800/60000 (61%)]   Loss: 0.335008   Accuracy:78.307%
Epoch : 0 [38400/60000 (64%)]   Loss: 0.295484   Accuracy:78.841%
Epoch : 0 [40000/60000 (67%)]   Loss: 0.330925   Accuracy:79.359%
Epoch : 0 [41600/60000 (69%)]   Loss: 0.761555   Accuracy:79.790%
Epoch : 0 [43200/60000 (72%)]   Loss: 0.308168   Accuracy:80.204%
Epoch : 0 [44800/60000 (75%)]   Loss: 0.039641   Accuracy:80.661%
Epoch : 0 [46400/60000 (77%)]   Loss: 0.347005   Accuracy:81.032%
Epoch : 0 [48000/60000 (80%)]   Loss: 0.695292   Accuracy:81.404%
Epoch : 0 [49600/60000 (83%)]   Loss: 0.664559   Accuracy:81.742%
Epoch : 0 [51200/60000 (85%)]   Loss: 0.267460   Accuracy:82.083%
Epoch : 0 [52800/60000 (88%)]   Loss: 0.457143   Accuracy:82.418%
Epoch : 0 [54400/60000 (91%)]   Loss: 0.123103   Accuracy:82.742%
Epoch : 0 [56000/60000 (93%)]   Loss: 0.171987   Accuracy:83.040%
Epoch : 0 [57600/60000 (96%)]   Loss: 0.293099   Accuracy:83.320%
Epoch : 0 [59200/60000 (99%)]   Loss: 0.139004   Accuracy:83.656%
Epoch : 1 [0/60000 (0%)]        Loss: 0.197437   Accuracy:93.750%
Epoch : 1 [1600/60000 (3%)]     Loss: 0.182057   Accuracy:93.137%
Epoch : 1 [3200/60000 (5%)]     Loss: 0.449420   Accuracy:94.028%
Epoch : 1 [4800/60000 (8%)]     Loss: 0.116307   Accuracy:93.729%
Epoch : 1 [6400/60000 (11%)]    Loss: 0.029951   Accuracy:93.797%
Epoch : 1 [8000/60000 (13%)]    Loss: 0.101050   Accuracy:93.875%
Epoch : 1 [9600/60000 (16%)]    Loss: 0.333615   Accuracy:93.625%
Epoch : 1 [11200/60000 (19%)]   Loss: 0.426801   Accuracy:93.643%
Epoch : 1 [12800/60000 (21%)]   Loss: 0.298322   Accuracy:93.462%
Epoch : 1 [14400/60000 (24%)]   Loss: 0.108020   Accuracy:93.528%
Epoch : 1 [16000/60000 (27%)]   Loss: 0.474114   Accuracy:93.469%
Epoch : 1 [17600/60000 (29%)]   Loss: 0.277469   Accuracy:93.455%
Epoch : 1 [19200/60000 (32%)]   Loss: 0.163615   Accuracy:93.506%
Epoch : 1 [20800/60000 (35%)]   Loss: 0.227395   Accuracy:93.568%
Epoch : 1 [22400/60000 (37%)]   Loss: 0.010190   Accuracy:93.630%
Epoch : 1 [24000/60000 (40%)]   Loss: 0.085058   Accuracy:93.633%
Epoch : 1 [25600/60000 (43%)]   Loss: 0.092341   Accuracy:93.606%
Epoch : 1 [27200/60000 (45%)]   Loss: 0.161767   Accuracy:93.548%
Epoch : 1 [28800/60000 (48%)]   Loss: 0.029576   Accuracy:93.573%
Epoch : 1 [30400/60000 (51%)]   Loss: 0.205116   Accuracy:93.589%
Epoch : 1 [32000/60000 (53%)]   Loss: 0.252389   Accuracy:93.581%
Epoch : 1 [33600/60000 (56%)]   Loss: 0.318719   Accuracy:93.583%
Epoch : 1 [35200/60000 (59%)]   Loss: 0.124187   Accuracy:93.583%
Epoch : 1 [36800/60000 (61%)]   Loss: 0.110199   Accuracy:93.636%
Epoch : 1 [38400/60000 (64%)]   Loss: 0.135114   Accuracy:93.633%
```

```
Epoch : 1 [40000/60000 (67%)]   Loss: 0.337480   Accuracy:93.608%
Epoch : 1 [41600/60000 (69%)]   Loss: 0.151904   Accuracy:93.637%
Epoch : 1 [43200/60000 (72%)]   Loss: 0.201784   Accuracy:93.651%
Epoch : 1 [44800/60000 (75%)]   Loss: 0.120788   Accuracy:93.670%
Epoch : 1 [46400/60000 (77%)]   Loss: 0.631979   Accuracy:93.638%
Epoch : 1 [48000/60000 (80%)]   Loss: 0.330198   Accuracy:93.644%
Epoch : 1 [49600/60000 (83%)]   Loss: 0.092436   Accuracy:93.667%
Epoch : 1 [51200/60000 (85%)]   Loss: 0.046334   Accuracy:93.693%
Epoch : 1 [52800/60000 (88%)]   Loss: 0.316572   Accuracy:93.701%
Epoch : 1 [54400/60000 (91%)]   Loss: 0.114109   Accuracy:93.695%
Epoch : 1 [56000/60000 (93%)]   Loss: 0.394695   Accuracy:93.727%
Epoch : 1 [57600/60000 (96%)]   Loss: 0.083526   Accuracy:93.792%
Epoch : 1 [59200/60000 (99%)]   Loss: 0.015199   Accuracy:93.860%
Epoch : 2 [0/60000 (0%)]        Loss: 0.217455   Accuracy:90.625%
Epoch : 2 [1600/60000 (3%)]     Loss: 0.406698   Accuracy:94.056%
Epoch : 2 [3200/60000 (5%)]     Loss: 0.423212   Accuracy:94.864%
Epoch : 2 [4800/60000 (8%)]     Loss: 0.065729   Accuracy:94.454%
Epoch : 2 [6400/60000 (11%)]    Loss: 0.006236   Accuracy:94.325%
Epoch : 2 [8000/60000 (13%)]    Loss: 0.204239   Accuracy:94.410%
Epoch : 2 [9600/60000 (16%)]    Loss: 0.303900   Accuracy:94.248%
Epoch : 2 [11200/60000 (19%)]   Loss: 0.255757   Accuracy:94.436%
Epoch : 2 [12800/60000 (21%)]   Loss: 0.152741   Accuracy:94.459%
Epoch : 2 [14400/60000 (24%)]   Loss: 0.082564   Accuracy:94.471%
Epoch : 2 [16000/60000 (27%)]   Loss: 0.283941   Accuracy:94.374%
Epoch : 2 [17600/60000 (29%)]   Loss: 0.014378   Accuracy:94.380%
Epoch : 2 [19200/60000 (32%)]   Loss: 0.083600   Accuracy:94.452%
Epoch : 2 [20800/60000 (35%)]   Loss: 0.360928   Accuracy:94.556%
Epoch : 2 [22400/60000 (37%)]   Loss: 0.102351   Accuracy:94.593%
Epoch : 2 [24000/60000 (40%)]   Loss: 0.109202   Accuracy:94.653%
Epoch : 2 [25600/60000 (43%)]   Loss: 0.092279   Accuracy:94.714%
Epoch : 2 [27200/60000 (45%)]   Loss: 0.241476   Accuracy:94.679%
Epoch : 2 [28800/60000 (48%)]   Loss: 0.107590   Accuracy:94.704%
Epoch : 2 [30400/60000 (51%)]   Loss: 0.188392   Accuracy:94.759%
Epoch : 2 [32000/60000 (53%)]   Loss: 0.298663   Accuracy:94.699%
Epoch : 2 [33600/60000 (56%)]   Loss: 0.165397   Accuracy:94.690%
Epoch : 2 [35200/60000 (59%)]   Loss: 0.109414   Accuracy:94.738%
Epoch : 2 [36800/60000 (61%)]   Loss: 0.111880   Accuracy:94.790%
Epoch : 2 [38400/60000 (64%)]   Loss: 0.247883   Accuracy:94.786%
Epoch : 2 [40000/60000 (67%)]   Loss: 0.241609   Accuracy:94.799%
Epoch : 2 [41600/60000 (69%)]   Loss: 0.274725   Accuracy:94.809%
Epoch : 2 [43200/60000 (72%)]   Loss: 0.335197   Accuracy:94.828%
Epoch : 2 [44800/60000 (75%)]   Loss: 0.005174   Accuracy:94.872%
Epoch : 2 [46400/60000 (77%)]   Loss: 1.024677   Accuracy:94.889%
Epoch : 2 [48000/60000 (80%)]   Loss: 0.283337   Accuracy:94.860%
Epoch : 2 [49600/60000 (83%)]   Loss: 0.264172   Accuracy:94.854%
Epoch : 2 [51200/60000 (85%)]   Loss: 0.145659   Accuracy:94.857%
Epoch : 2 [52800/60000 (88%)]   Loss: 0.662844   Accuracy:94.893%
Epoch : 2 [54400/60000 (91%)]   Loss: 0.017660   Accuracy:94.922%
```

```
Epoch : 2 [56000/60000 (93%)]   Loss: 0.118975   Accuracy:94.960%
Epoch : 2 [57600/60000 (96%)]   Loss: 0.390172   Accuracy:94.961%
Epoch : 2 [59200/60000 (99%)]   Loss: 0.000941   Accuracy:95.016%
Epoch : 3 [0/60000 (0%)]        Loss: 0.039304   Accuracy:96.875%
Epoch : 3 [1600/60000 (3%)]     Loss: 0.274808   Accuracy:94.424%
Epoch : 3 [3200/60000 (5%)]     Loss: 0.082404   Accuracy:95.142%
Epoch : 3 [4800/60000 (8%)]     Loss: 0.180459   Accuracy:95.281%
Epoch : 3 [6400/60000 (11%)]    Loss: 0.055648   Accuracy:95.134%
Epoch : 3 [8000/60000 (13%)]    Loss: 0.032606   Accuracy:95.219%
Epoch : 3 [9600/60000 (16%)]    Loss: 0.057986   Accuracy:94.975%
Epoch : 3 [11200/60000 (19%)]   Loss: 0.275520   Accuracy:95.103%
Epoch : 3 [12800/60000 (21%)]   Loss: 0.070716   Accuracy:94.950%
Epoch : 3 [14400/60000 (24%)]   Loss: 0.027030   Accuracy:94.928%
Epoch : 3 [16000/60000 (27%)]   Loss: 0.066866   Accuracy:94.941%
Epoch : 3 [17600/60000 (29%)]   Loss: 0.028506   Accuracy:94.941%
Epoch : 3 [19200/60000 (32%)]   Loss: 0.219603   Accuracy:94.998%
Epoch : 3 [20800/60000 (35%)]   Loss: 0.051435   Accuracy:94.993%
Epoch : 3 [22400/60000 (37%)]   Loss: 0.011864   Accuracy:95.047%
Epoch : 3 [24000/60000 (40%)]   Loss: 0.177396   Accuracy:95.073%
Epoch : 3 [25600/60000 (43%)]   Loss: 0.050125   Accuracy:95.154%
Epoch : 3 [27200/60000 (45%)]   Loss: 0.215653   Accuracy:95.131%
Epoch : 3 [28800/60000 (48%)]   Loss: 0.357761   Accuracy:95.106%
Epoch : 3 [30400/60000 (51%)]   Loss: 0.303260   Accuracy:95.127%
Epoch : 3 [32000/60000 (53%)]   Loss: 0.435719   Accuracy:95.042%
Epoch : 3 [33600/60000 (56%)]   Loss: 0.038899   Accuracy:95.008%
Epoch : 3 [35200/60000 (59%)]   Loss: 0.157955   Accuracy:95.084%
Epoch : 3 [36800/60000 (61%)]   Loss: 0.065332   Accuracy:95.127%
Epoch : 3 [38400/60000 (64%)]   Loss: 0.087521   Accuracy:95.145%
Epoch : 3 [40000/60000 (67%)]   Loss: 0.119639   Accuracy:95.131%
Epoch : 3 [41600/60000 (69%)]   Loss: 0.089203   Accuracy:95.143%
Epoch : 3 [43200/60000 (72%)]   Loss: 0.412446   Accuracy:95.152%
Epoch : 3 [44800/60000 (75%)]   Loss: 0.103714   Accuracy:95.211%
Epoch : 3 [46400/60000 (77%)]   Loss: 0.355738   Accuracy:95.202%
Epoch : 3 [48000/60000 (80%)]   Loss: 0.139295   Accuracy:95.191%
Epoch : 3 [49600/60000 (83%)]   Loss: 0.194295   Accuracy:95.189%
Epoch : 3 [51200/60000 (85%)]   Loss: 0.083338   Accuracy:95.181%
Epoch : 3 [52800/60000 (88%)]   Loss: 0.779976   Accuracy:95.192%
Epoch : 3 [54400/60000 (91%)]   Loss: 0.033422   Accuracy:95.196%
Epoch : 3 [56000/60000 (93%)]   Loss: 0.117889   Accuracy:95.208%
Epoch : 3 [57600/60000 (96%)]   Loss: 0.146757   Accuracy:95.232%
Epoch : 3 [59200/60000 (99%)]   Loss: 0.007108   Accuracy:95.286%
Epoch : 4 [0/60000 (0%)]        Loss: 0.037586   Accuracy:96.875%
Epoch : 4 [1600/60000 (3%)]     Loss: 0.532983   Accuracy:95.282%
Epoch : 4 [3200/60000 (5%)]     Loss: 0.141879   Accuracy:95.575%
Epoch : 4 [4800/60000 (8%)]     Loss: 0.068667   Accuracy:95.882%
Epoch : 4 [6400/60000 (11%)]    Loss: 0.088112   Accuracy:95.740%
Epoch : 4 [8000/60000 (13%)]    Loss: 0.112370   Accuracy:95.754%
Epoch : 4 [9600/60000 (16%)]    Loss: 0.098440   Accuracy:95.650%
```

```
Epoch : 4 [11200/60000 (19%)]    Loss: 0.284854   Accuracy:95.593%
Epoch : 4 [12800/60000 (21%)]    Loss: 0.082128   Accuracy:95.605%
Epoch : 4 [14400/60000 (24%)]    Loss: 0.066085   Accuracy:95.468%
Epoch : 4 [16000/60000 (27%)]    Loss: 0.137398   Accuracy:95.422%
Epoch : 4 [17600/60000 (29%)]    Loss: 0.083179   Accuracy:95.389%
Epoch : 4 [19200/60000 (32%)]    Loss: 0.296649   Accuracy:95.372%
Epoch : 4 [20800/60000 (35%)]    Loss: 0.079538   Accuracy:95.387%
Epoch : 4 [22400/60000 (37%)]    Loss: 0.021219   Accuracy:95.399%
Epoch : 4 [24000/60000 (40%)]    Loss: 0.045635   Accuracy:95.460%
Epoch : 4 [25600/60000 (43%)]    Loss: 0.025185   Accuracy:95.431%
Epoch : 4 [27200/60000 (45%)]    Loss: 0.313549   Accuracy:95.384%
Epoch : 4 [28800/60000 (48%)]    Loss: 0.358900   Accuracy:95.384%
Epoch : 4 [30400/60000 (51%)]    Loss: 0.290802   Accuracy:95.354%
Epoch : 4 [32000/60000 (53%)]    Loss: 0.031017   Accuracy:95.367%
Epoch : 4 [33600/60000 (56%)]    Loss: 0.085758   Accuracy:95.362%
Epoch : 4 [35200/60000 (59%)]    Loss: 0.152539   Accuracy:95.416%
Epoch : 4 [36800/60000 (61%)]    Loss: 0.162986   Accuracy:95.441%
Epoch : 4 [38400/60000 (64%)]    Loss: 0.174990   Accuracy:95.444%
Epoch : 4 [40000/60000 (67%)]    Loss: 0.521610   Accuracy:95.456%
Epoch : 4 [41600/60000 (69%)]    Loss: 0.122210   Accuracy:95.484%
Epoch : 4 [43200/60000 (72%)]    Loss: 0.318961   Accuracy:95.503%
Epoch : 4 [44800/60000 (75%)]    Loss: 0.035795   Accuracy:95.550%
Epoch : 4 [46400/60000 (77%)]    Loss: 0.384703   Accuracy:95.535%
Epoch : 4 [48000/60000 (80%)]    Loss: 0.491851   Accuracy:95.561%
Epoch : 4 [49600/60000 (83%)]    Loss: 0.055732   Accuracy:95.561%
Epoch : 4 [51200/60000 (85%)]    Loss: 0.087599   Accuracy:95.583%
Epoch : 4 [52800/60000 (88%)]    Loss: 0.285666   Accuracy:95.597%
Epoch : 4 [54400/60000 (91%)]    Loss: 0.043655   Accuracy:95.602%
Epoch : 4 [56000/60000 (93%)]    Loss: 0.363469   Accuracy:95.604%
Epoch : 4 [57600/60000 (96%)]    Loss: 0.103343   Accuracy:95.624%
Epoch : 4 [59200/60000 (99%)]    Loss: 0.018067   Accuracy:95.676%
```

0.3 SVM Classifer for MNIST DATA SET

[0]:
```python
from keras.datasets import mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

[0]:
```python
x_train = x_train.reshape(60000,784)
x_test = x_test.reshape(10000,784)
```

[0]:
```python
## Applying HOG feature extraction
```

[0]:
```python
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from skimage.feature import hog
from sklearn import preprocessing
```

```
from collections import Counter
```

[38]:
```
list_hog_train = []
for feature in x_train:
    fd = hog(feature.reshape((28,28)), orientations=10,␣
↪pixels_per_cell=(7,7),cells_per_block=(1,1),visualize=False )
    list_hog_train.append(fd)
hog_features = np.array(list_hog_train, 'float64')
preProcess = preprocessing.MaxAbsScaler().fit(hog_features)
hog_features_transformed_train = preProcess.transform(hog_features)
print(hog_features_transformed_train.shape)
```

```
(60000, 160)
```

[0]:
```
## Extracting hog feature for test data
```

[41]:
```
list_hog_test = []
for feature in x_test:
    fd = hog(feature.reshape((28,28)), orientations=10,␣
↪pixels_per_cell=(7,7),cells_per_block=(1,1),visualize=False )
    list_hog_test.append(fd)
hog_features_test = np.array(list_hog_test, 'float64')
preProcess = preprocessing.MaxAbsScaler().fit(hog_features_test)
hog_features_transformed_test = preProcess.transform(hog_features_test)
print(hog_features_transformed_test.shape)
```

```
(10000, 160)
```

[0]:
```
model = SVC()
model.fit(hog_features_transformed_train,y_train)
y_pred = model.predict(hog_features_transformed_test)
```

Fitting the model with best parameters

[43]:
```
print(accuracy_score(y_test, y_pred))
```

```
0.9713
```

q4

April 3, 2020

1 Question-4 House Electricity Consumption Prediction

[0]:
```
from zipfile import ZipFile
file_name="household_power_consumption.zip"

with ZipFile(file_name,'r') as zip:
  zip.extractall()
  print('Done')

# !unzip /content/household_power_consumption.zip
```

```
Done
```

2 Reading the data file

[0]:
```
%tensorflow_version 1.x
import pandas as pd

headers = ['Date', 'Time', 'Global_active_power', 'Global_reactive_power',
           'Voltage', 'Global_intensity', 'Sub_metering_1', 'Sub_metering_2',
           'Sub_metering_3']

dtypes = {'Date':'str', 'Time':'str', 'Global_active_power':'float',
          'Global_reactive_power': 'float', 'Voltage':'float',
          'Global_intensity':'float', 'Sub_metering_1':'float',
          'Sub_metering_2':'float', 'Sub_metering_3':'float'}

df = pd.read_csv('household_power_consumption.txt', sep=';',
                 dtype=dtypes, na_values=['?'])
df.head()
```

[0]:
```
         Date      Time  …  Sub_metering_2  Sub_metering_3
0  16/12/2006  17:24:00  …             1.0            17.0
1  16/12/2006  17:25:00  …             1.0            16.0
2  16/12/2006  17:26:00  …             2.0            17.0
```

```
3  16/12/2006  17:27:00  …            1.0            17.0
4  16/12/2006  17:28:00  …            1.0            17.0

[5 rows x 9 columns]
```

[0]:
```
import numpy as np
from multiprocessing import cpu_count, Pool

def parallel_map(data, func):
    n_cores = cpu_count()
    data_split = np.array_split(data, n_cores)
    pool = Pool(n_cores)
    data = pd.concat(pool.map(func, data_split))
    pool.close()
    pool.join()
    return data

def parse(row):
    row['DateTime'] = pd.to_datetime(row['DateTime'],
                                     format='%d/%m/%Y %H:%M:%S')
    return row
```

[0]:
```
df['DateTime'] = df['Date'] + ' ' + df['Time']
df = parallel_map(df, parse)
df.dtypes
```

[0]:
```
Date                             object
Time                             object
Global_active_power             float64
Global_reactive_power           float64
Voltage                         float64
Global_intensity                float64
Sub_metering_1                  float64
Sub_metering_2                  float64
Sub_metering_3                  float64
DateTime                 datetime64[ns]
dtype: object
```

[0]:
```
df.drop(['Date', 'Time'], axis=1, inplace=True)
df = df[[df.columns[-1]] + list(df.columns[:-1])]
df.set_index('DateTime', inplace=True)
df.head()
```

[0]:
```
                     Global_active_power  …  Sub_metering_3
DateTime                                  …
2006-12-16 17:24:00                4.216  …            17.0
2006-12-16 17:25:00                5.360  …            16.0
```

```
2006-12-16 17:26:00                5.374  …             17.0
2006-12-16 17:27:00                5.388  …             17.0
2006-12-16 17:28:00                3.666  …             17.0

[5 rows x 7 columns]
```

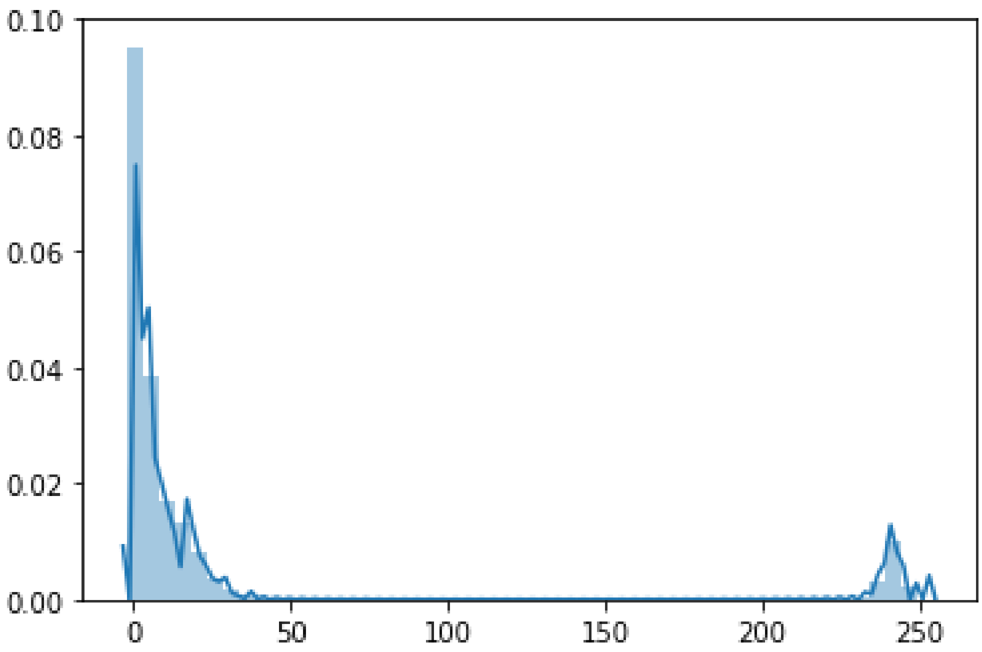
[0]:
```
df['hour'] = df.index.hour
df['day'] = df.index.day
df['month'] = df.index.month
df['day_of_week'] = df.index.dayofweek
```

[0]:
```
df['Rest_active_power'] = df['Global_active_power'] * 1000 / 60 - \
                          df['Sub_metering_1'] - df['Sub_metering_2'] - \
                          df['Sub_metering_3']
```

3 Identifying and handling Missing Data

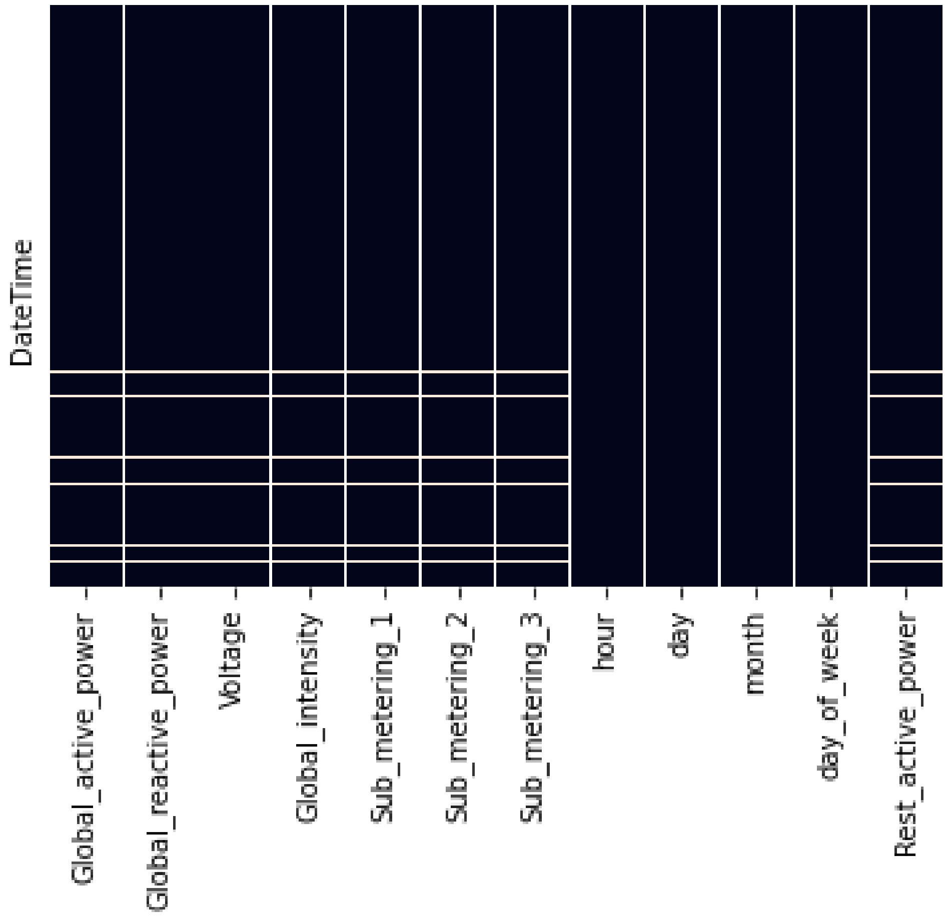
[0]:
```
import seaborn as sns
sns.distplot(df)
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbcef5a8358>



[0]:
```
sns.heatmap(df.isnull(),yticklabels=False,cbar=False)
```

[0]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbd67132198>



[0]:
```
number = len(df) - len(df.dropna())
percentage = number * 100 / len(df)
print(f'Number of points with missing values is: {number}')
print(f'Percentage of points with missing values is: {percentage}\n')
print(f'Missing value counts:\n{df.isnull().sum(axis=0)}\n')
```

```
Number of points with missing values is: 25979
Percentage of points with missing values is: 1.2518437457686005

Missing value counts:
Global_active_power      25979
Global_reactive_power    25979
Voltage                  25979
Global_intensity         25979
Sub_metering_1           25979
Sub_metering_2           25979
```

```
Sub_metering_3          25979
hour                        0
day                         0
month                       0
day_of_week                 0
Rest_active_power       25979
dtype: int64
```

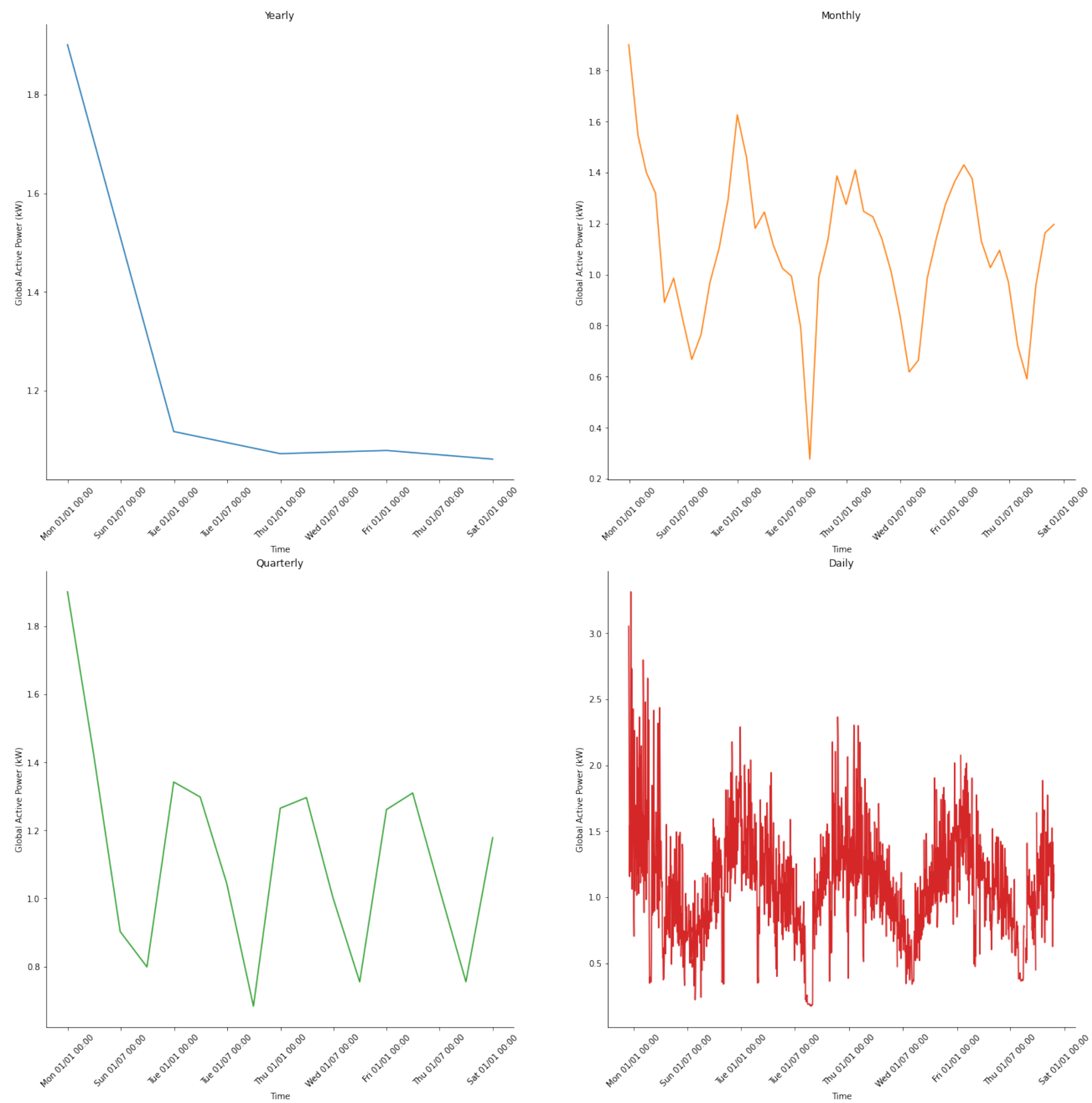
#Power consumption over the whole timespan

Average global active power over resampled data yearly, quarterly, monthly, and daily.

[0]:
```
# Tableau colors
tableau20 = [(31, 119, 180), (174, 199, 232), (255, 127, 14), (255, 187, 120),
             (44, 160, 44), (152, 223, 138), (214, 39, 40), (255, 152, 150),
             (148, 103, 189), (197, 176, 213), (140, 86, 75), (196, 156, 148),
             (227, 119, 194), (247, 182, 210), (127, 127, 127), (199, 199, 199),
             (188, 189, 34), (219, 219, 141), (23, 190, 207), (158, 218, 229)]

# Scale the RGB values to the [0, 1] range, which is the format matplotlib␣
↪accepts.
for i in range(len(tableau20)):
    r, g, b = tableau20[i]
    tableau20[i] = (r / 255., g / 255., b / 255.)
```

[0]:
```
import matplotlib.pylab as plt
import matplotlib.dates as mdates
from pandas.plotting import register_matplotlib_converters
register_matplotlib_converters()
my_fmt = mdates.DateFormatter('%a %d/%m %H:%M')

fig, ax = plt.subplots(nrows=2, ncols=2, figsize=(22, 22))

frequencies = ['1Y', '1M', '1Q', '1D']

dic = {'1Y':'Yearly', '1M':'Monthly', '1Q':'Quarterly', '1D':'Daily'}

i = 0
for row in ax:
    for col in row:
        for tick in col.get_xticklabels():
            tick.set_rotation(45)
        col.plot(df[['Global_active_power']].resample(frequencies[i]).mean(),
                 color=tableau20[i * 2])
        col.set_xlabel('Time')
        col.set_ylabel('Global Active Power (kW)')
        col.set_title(dic[frequencies[i]])
```

```python
        col.xaxis.set_major_formatter(my_fmt)

        # Aesthetics
        col.spines["top"].set_visible(False)
        col.spines["right"].set_visible(False)
        i += 1
```



4 supervised learning

Predict global active power at time $t+h$ given all the variables at times $t, t-1, ..., t-w$, where h is the prediction horizon and w is the window size. Here's a function that takes as input a time series dataframe, a window size, a horizon, a set of variables to be lagged and a set of variables to be forecasted and outputs the dataframe transformed and ready for supervised learing.

[0]:
```
from pandas import DataFrame
from pandas import concat

def series_to_supervised(data, window_size=1, horizon=1, inputs='all',␣
↪targets='all'):
    """
    Frame a time series as a supervised learning dataset.

    Arguments:
        data: A pandas DataFrame containing the time series
        (the index must be a DateTimeIndex).
        window_size: Number of lagged observations as input.
        horizon: Number of steps to forecast ahead.
        inputs: A list of the columns of the dataframe to be lagged.
        targets: A list of the columns of the dataframe to be forecasted.

    Returns:
        Pandas DataFrame of series framed for supervised learning.
    """

    if targets == 'all':
        targets = data.columns

    if inputs == 'all':
        inputs = data.columns


    result = DataFrame(index=df.index)
    names = []

    # input sequence (t-w, ..., t-1)
    for i in range(window_size, 0, -1):
        result = pd.concat([result, data[inputs].shift(i)], axis=1)
        names += [(f'{data[inputs].columns[j]}(t-{i})') for j in␣
↪range(len(inputs))]

    # the input not shifted (t)
    result = pd.concat([result, data.copy()], axis=1)
    names += [(f'{column}(t)') for column in data.columns]

    # forecast (t+h)
    for i in [horizon]:
        result = pd.concat([result, data[targets].shift(-i)], axis=1)
```

```
        names += [(f'{data[targets].columns[j]}(t+{i})') for j in␣
↪range(len(targets))]

    # put it all together
    result.columns = names

    # drop rows with NaN values
    result.dropna(inplace=True)
    return result
```

[0]:
```
inputs = ['Global_active_power', 'Global_reactive_power', 'Voltage',
          'Global_intensity', 'Sub_metering_1', 'Sub_metering_2',
          'Sub_metering_3', 'Rest_active_power']

targets = ['Global_active_power']

df_supervised = series_to_supervised(df, window_size=5, horizon=1,␣
↪inputs=inputs, targets=targets)
df_supervised.head()
```

[0]:
```
                     Global_active_power(t-5)  …  Global_active_power(t+1)
DateTime                                       …
2006-12-16 17:29:00                     4.216  …                     3.702
2006-12-16 17:30:00                     5.360  …                     3.700
2006-12-16 17:31:00                     5.374  …                     3.668
2006-12-16 17:32:00                     5.388  …                     3.662
2006-12-16 17:33:00                     3.666  …                     4.448

[5 rows x 53 columns]
```

[0]:
```
#storing into some file to visualize at different window size
#df_supervised.to_csv('supervised_w10_h1.csv', index=True)
```

5 Supervised Machine Learning

[0]:
```
# import pandas as pd

# df_supervised = pd.read_csv('supervised_w10_h1.csv', parse_dates=['DateTime'])
# df_supervised.set_index('DateTime', inplace=True)
```

6 Splitting data

splitting data into train,validate and test

[0]:
```
def train_validate_test_split(df, train_percent=.6, validate_percent=.2,␣
↪seed=None):
    np.random.seed(seed)
    m = len(df)
    train_end = int(train_percent * m)
    validate_end = int(validate_percent * m) + train_end
    train = df.iloc[:train_end]
    validate = df.iloc[train_end:validate_end]
    test = df.iloc[validate_end:]
    return train, validate, test
```

[0]:
```
train,validate, test = train_validate_test_split(df_supervised)
```

[0]:
```
print(type(train))
train.shape
```

```
<class 'pandas.core.frame.DataFrame'>
```

[0]:
```
(1229311, 53)
```

[0]:
```
X_train = train.values[:, :-1]
y_train = train.values[:, -1]

X_validate = validate.values[:, :-1]
y_validate = validate.values[:, -1]

X_test = test.values[:, :-1]
y_test = test.values[:, -1]
```

[0]:
```
X_test.shape
```

[0]:
```
(409772, 52)
```

[0]:
```
X_train.shape
```

[0]:
```
(1229311, 52)
```

[0]:
```
X_validate.shape
```

[0]:
```
(409770, 52)
```

7 Mean absolute percentage Error

[0]:
```
# #from sklearn.utils import check_arrays
# def mean_absolute_percentage_error(y_true, y_pred):
#     #y_true, y_pred = check_arrays(y_true, y_pred)
#     return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

[0]:
```
from sklearn.metrics import mean_squared_error
from math import sqrt
from sklearn.metrics import accuracy_score
```

[0]:
```
import numpy as np

def mean_absolute_percentage_error(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100
```

8 Linear Regression

[0]:
```
from sklearn.linear_model import LinearRegression

model = LinearRegression()
model.fit(X_train, y_train)
predictions = model.predict(X_validate)
```

[0]:
```
from sklearn.metrics import mean_squared_error

mean_squared_error(predictions, y_validate)
```

[0]: 0.055878991130430315

[0]:
```
mean_absolute_percentage_error(y_validate, predictions)
```

[0]: 10.996608631396205

[0]:
```
rms = sqrt(mean_squared_error(y_validate, predictions))
print(rms)
```

0.23638737515026118

[0]:
```
#accuracy_score(y_validate, predictions, normalize=False)
```

9 Multilayer Perceptron

[0]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_validate = scaler.transform(X_validate)
X_test = scaler.transform(X_test)
```

[0]:
```
from keras.layers import Input, Dense, Dropout, LSTM, Reshape, Flatten
from keras import Sequential

#from tensorflow.keras.optimizers import SGD
from keras.callbacks import EarlyStopping

model = Sequential()
model.add(Dense(100, activation='relu', input_shape=(X_train.shape[1], )))
model.add(Dropout(0.2))
model.add(Dense(1))
```

```
Using TensorFlow backend.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:66: The name tf.get_default_graph
is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:541: The name tf.placeholder is
deprecated. Please use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:4432: The name tf.random_uniform is
deprecated. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:148: The name
tf.placeholder_with_default is deprecated. Please use
tf.compat.v1.placeholder_with_default instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3733: calling dropout (from
tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed
in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 -
keep_prob`.
```

[0]:
```python
from keras.optimizers import Adam
model.compile(loss='mean_squared_error',
              optimizer=Adam(lr=0.001))

history = model.fit(X_train, y_train,batch_size=1024,epochs=100,
                    verbose=1,
                    validation_data=(X_validate, y_validate),
                    callbacks=[EarlyStopping(patience=1)])
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/optimizers.py:793: The name tf.train.Optimizer is deprecated.
Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is
deprecated. Please use tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is
deprecated. Please use tf.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3005: The name tf.Session is
deprecated. Please use tf.compat.v1.Session instead.

Train on 1229311 samples, validate on 409770 samples
Epoch 1/100
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:190: The name
tf.get_default_session is deprecated. Please use
tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:197: The name tf.ConfigProto is
deprecated. Please use tf.compat.v1.ConfigProto instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:207: The name tf.global_variables
is deprecated. Please use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:216: The name
tf.is_variable_initialized is deprecated. Please use
tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:223: The name
```

```
tf.variables_initializer is deprecated. Please use
tf.compat.v1.variables_initializer instead.

1229311/1229311 [==============================] - 7s 6us/step - loss: 0.1475 -
val_loss: 0.0584
Epoch 2/100
1229311/1229311 [==============================] - 7s 5us/step - loss: 0.0833 -
val_loss: 0.0542
Epoch 3/100
1229311/1229311 [==============================] - 6s 5us/step - loss: 0.0781 -
val_loss: 0.0521
Epoch 4/100
1229311/1229311 [==============================] - 7s 5us/step - loss: 0.0756 -
val_loss: 0.0515
Epoch 5/100
1229311/1229311 [==============================] - 7s 5us/step - loss: 0.0743 -
val_loss: 0.0506
Epoch 6/100
1229311/1229311 [==============================] - 7s 5us/step - loss: 0.0737 -
val_loss: 0.0506
Epoch 7/100
1229311/1229311 [==============================] - 7s 5us/step - loss: 0.0731 -
val_loss: 0.0508
```

[0]:
```
predictions = model.predict(X_validate)
```

[0]:
```
mean_squared_error(predictions, y_validate)
```

[0]:
```
0.05082758861318869
```

[0]:
```
#mean_absolute_percentage_error(y_validate, predictions)
```

[0]:
```
rms = sqrt(mean_squared_error(y_validate, predictions))
print(rms)
```

```
0.2254497474232089
```

10 Visualizing the data

Predicting for the test data

[0]:
```
predictions = model.predict(X_test)
```

[0]:
```
df_to_plot = test[['Global_active_power(t+1)']].copy()
df_to_plot['Global_active_power(t+1)_predicted'] = predictions
```

[0]:
```
import matplotlib.pylab as plt

df_to_plot[:1000].plot()
plt.show()
```