CS306: DATA ANALYSIS AND VISUALIZATION

LAB 7: MNIST dataset for Dimensionality Reduction using PCA

STUDENT ID: 201801407

NAME: PRATVI SHAH

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
%matplotlib inline
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler,RobustScaler
from numpy import linalg as LA
import seaborn as sns
import matplotlib.colors as mcolors
from sklearn.metrics import mean_squared_error as mse
import warnings
warnings.filterwarnings('ignore')
```

Import data

In [2]:

```
data_train=pd.read_csv('mnist_train.csv',header=None)
data_test=pd.read_csv('mnist_test.csv',header=None)
data_train.head()
```

Out[2]:

	0	1	2	3	4	5	6	7	8	9	...	775	776	777	778	779	780	781	782	783	784
0	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 785 columns

Standardizing & Destandardizing functions

In [3]:

```
def standardize(df1):
    scaler=StandardScaler()
    df1=scaler.fit_transform(df1)
    return pd.DataFrame(df1)

def destandardize(df2,mean,std):
    df=df2
    for i in range(df2.shape[1]):
        df[i]=(df[i]*std[i] + mean[i])
    return pd.DataFrame(df)
```

Remove the null and inf values if any and standardize the data

In [4]:

```
#Training data
data_train=data_train.replace([-np.inf,np.inf],np.nan)
data_train=data_train.dropna()
data_train=standardize(data_train)
```

In [5]:

```
cols=data_train.columns
#Removing the class label
df_train=data_train[cols[1:]]
```

Perform PCA on training data (Q2)

In [6]:

```
def pca_func(max_limit,df_train,df_test):
    pca = PCA(n_components=max_limit,svd_solver='full')
    pca=pca.fit(df_train)
    ans=[]
    #Encoded training data
    df_pca=pca.transform(df_train)

    #Decoded training data
    df_new=pd.DataFrame(pca.inverse_transform(df_pca))
    comp=pca.components_
    ans.append('Percentage limit: '+str(max_limit*100)+'\nNumber of components: '+str(len(co
mp)))

    #Encoded testing data based on the PCs obtained by training data with max_limit% varianc
e
    df_test_pca=pca.transform(df_test)

    #Decoded testing data for reconstruction of image
    df_test_decoded=pd.DataFrame(pca.inverse_transform(df_test_pca))

    return df_test_decoded,ans
```

Sort the testing data and get values for each label

In [7]:

```
data_test2=data_test.sort_values(by=[0]).reset_index(drop=True)

count=[0 for i in range(10)]
df_test=[]
for idx in range(len(data_test2[0])):
    i=data_test2[0][idx]
    if count[i]<10:
        count[i]+=1
        df_test.append(data_test2.iloc[idx])
df_test2=pd.DataFrame(df_test)
df_test=pd.DataFrame(df_test)
```

Keeping copy of unstandardized data

In [8]:

```
df_test=df_test.reset_index(drop=True)
df_test2=df_test2.reset_index(drop=True)
```

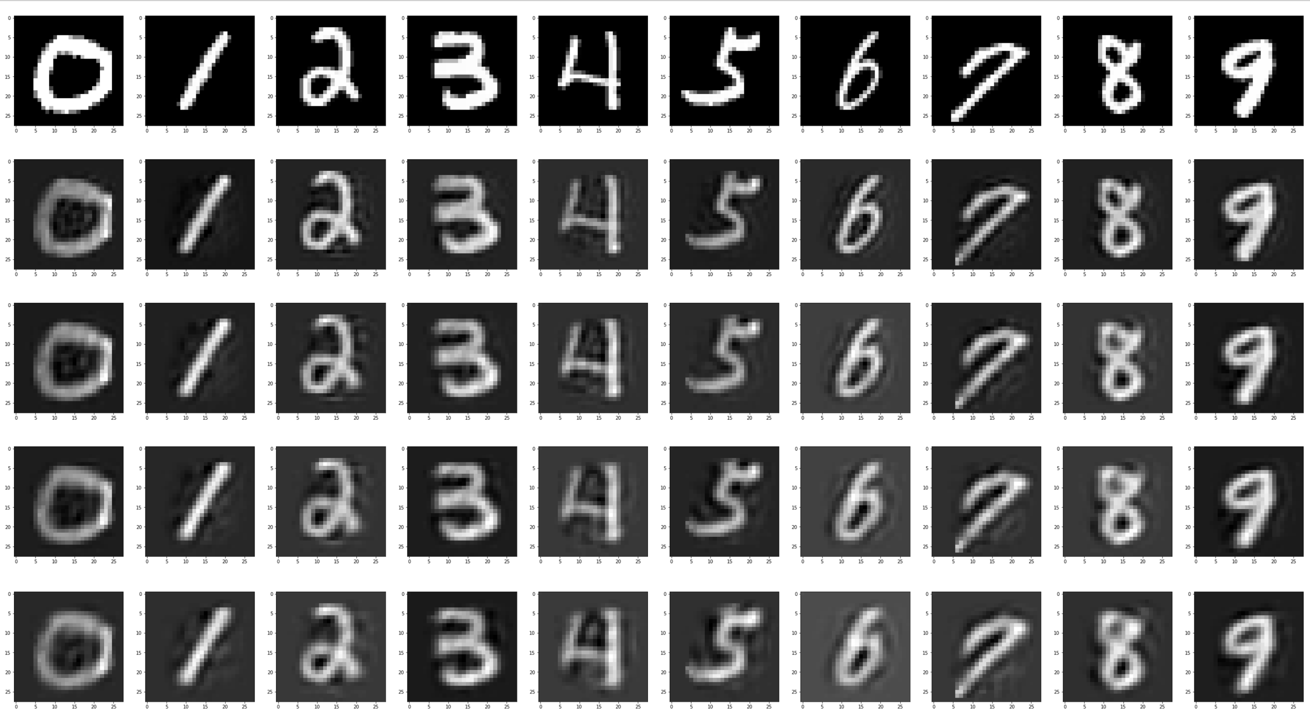
In [9]:

```
#Testing data standardization
df_test=df_test.replace([-np.inf,np.inf],np.nan)
df_test=df_test.dropna()
df_test=standardize(df_test)
cols_test=df_test.columns
```

Calling pca_func() and displaying decoded images (Q3 & 4)

In [17]:

```
limits=[0.95,0.90,0.85,0.75]

#Original plot
fig,axes=plt.subplots(1,10,figsize=[50,5])
mean_test=df_test2.mean(axis=0)
std_test=df_test2.std(axis=0)
for idx in range(10):
    grid_data=df_test2[cols_test[1:]].iloc[idx*10].as_matrix().reshape(28,28)
    axes[idx].imshow(grid_data,interpolation=None,cmap='gray')
plt.show()



df=[]
#Stores the number of components required
no_of_comp=[]
j=0
for max_limit in limits:
    decoded_test,ans=pca_func(max_limit,df_train,df_test[cols_test[1:]])
    no_of_comp.append(ans)

    #Calculating rmse
    rmse=[0 for i in range(10)]
    for i in range(10):
        for j in range(10):
            rmse[j]+=np.sqrt(mse(decoded_test.iloc[j+i*10],df_test[cols_test[1:]].iloc[j+i*1
0]))/10
    df.append(rmse)

    #Decoded testing data with max_limit as the variance taken into consideration
    decoded_test=destandardize(decoded_test,mean_test,std_test)
    fig,axes=plt.subplots(1,10,figsize=[50,5])
    for idx in range(10):
        grid_data=decoded_test.iloc[idx*10].as_matrix().reshape(28,28)
        axes[idx].imshow(grid_data,interpolation=None,cmap='gray')
    plt.show()
```



Number of Components required for given variance limit (Part of Q2)

In [18]:

```
for i in range(len(no_of_comp)):
    print(no_of_comp[i][0])
    print()
```

```
Percentage limit: 95.0
Number of components: 331

Percentage limit: 90.0
Number of components: 236

Percentage limit: 85.0
Number of components: 185

Percentage limit: 75.0
Number of components: 120
```

RMSE for all 10 digits in the 4 categories (Q5)

In [19]:

```
lim=[str(limits[i]*100)+'% variance'  for i in range(len(limits))]
table=pd.DataFrame(np.array(df).transpose(),columns=lim)
table
```

Out[19]:

	95.0% variance	90.0% variance	85.0% variance	75.0% variance
0	0.208142	0.274055	0.317282	0.369694
1	0.194507	0.257033	0.301514	0.363702
2	0.183368	0.247136	0.290320	0.341339
3	0.175464	0.230589	0.271414	0.314559
4	0.210962	0.271594	0.309839	0.364881
5	0.193258	0.251710	0.292489	0.350413
6	0.195859	0.263296	0.309925	0.374809
7	0.192489	0.250972	0.299187	0.362663
8	0.158922	0.211013	0.251338	0.299961
9	0.199755	0.262194	0.309208	0.374692

We can observe from the above two results that the number of components required for accommodating greater variance is high and the corresponding RMSE thereby reduces.

In [ ]: