LINEAR ALGEBRA ASSIGNMENT

Unit 4

1.

Data Set: MNIST (Mixed National Institute of Standards and Technology) computer vision digit Dataset or any other similar data sets.

Implementation of Dimensionality Reduction Techniques:

1. Principal Component Analysis
2. Independent Component Analysis
3. Methods Based on Projections

Code

Data Set:

- MNIST computer vision digit Dataset

Technique used:

- Implemented using principal component Analysis

Output screen-shots

Implementing PCA(Principal Component Analysis) on MNIST Dataset

Importing our mandatory python libraries which are required for the implementation of PCA.

In [145]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

loading our MNIST dataset from our computer which is stored in .csv format.

In [146]:
```
df = pd.read_csv('mnist_train.csv')
print("the shape of data is :", df.shape)
```

```
the shape of data is : (42000, 785)
```

In [147]:
```
#Displaying first few data's
df.head()
```

Out[147]:

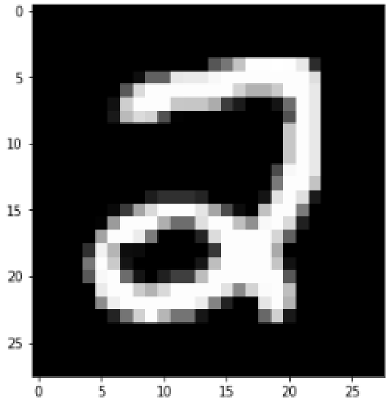
	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	pixel780	pixel781	pi
0	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
3	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	

5 rows × 785 columns

Extracting label column from the dataset

Plotting a random sample data point from The dataset using matplotlib imshow() method

In [148]:
```
label = df['label']
df.drop('label', axis = 1, inplace = True)
ind = np.random.randint(0, 20000)
plt.figure(figsize = (20, 5))
grid_data = np.array(df.iloc[ind]).reshape(28,28)
plt.imshow(grid_data, interpolation = None, cmap = 'gray')
plt.show()
print('The above values is',label[ind])
```



```
The above values is 2
```

2D Visualization using PCA

Picking first 20K data-points out of 42k data-points to work on for time-effeciency.

In [149]:
```
labels = label.head(20000)
data = df.head(20000)
print("the shape of sample data = ", data.shape)
```

```
the shape of sample data =  (20000, 784)
```

Data-preprocessing : standardizing tha dataset

In [150]:
```
#Column standardization of our dataset using StandardScalar class of sklearn.preprocessing module.
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
std_df = scaler.fit_transform(df)
std_df.shape
```

Out[150]:
```
(42000, 784)
```

Finding the Co-Variance matrix which is AT * A using NumPy matmul method

In [151]:
```
covar_mat = np.matmul(std_df.T, std_df)
covar_mat.shape
```

Out[151]:
```
(784, 784)
```

After multiplication, the dimensions of our Co-Variance matrix is 784 * 784 ,because AT(784 * 20000) * A(20000 * 784).

Finding the top two Eigen-values and corresponding eigenvectors for projecting onto a 2D surface.

In [152]:
```
#converting the eigenvectors into (2,d) form for easiness of further computations
from scipy.linalg import eigh
values, vectors = eigh(covar_mat, eigvals = (782, 783))
print("Dimensions of Eigen vector:", vectors.shape)
vectors = vectors.T
print("Dimensions of Eigen vector:", vectors.shape)
```

```
Dimensions of Eigen vector: (784, 2)
Dimensions of Eigen vector: (2, 784)
```

here the vectors[1] represent the eigenvector corresponding 1st principal eigenvector

here the vectors[0] represent the eigenvector corresponding 2nd principal eigenvector

If we multiply the two top vectors to the Co-Variance matrix, we found our two principal components PC1 and PC2.

In [153]:
```
final_df = np.matmul(vectors, std_df.T)
print(" vectros:", vectors.shape,"\n", "std_df:", std_df.T.shape,"\n", "final_df:", final_df.shape)
```

```
 vectros: (2, 784)
 std_df: (784, 42000)
 final_df: (2, 42000)
```

Now we vertically stack our final_df and label and then Transpose them,then we found the NumPy data table so with the help of pd.DataFraame we create the data frame of our two components with class labels.

In [154]:
```
final_dfT = np.vstack((final_df, label)).T
dataFrame = pd.DataFrame(final_dfT, columns = ['1st_principle component analysis', '2nd_principle component analysis', 'label'])
dataFrame
```

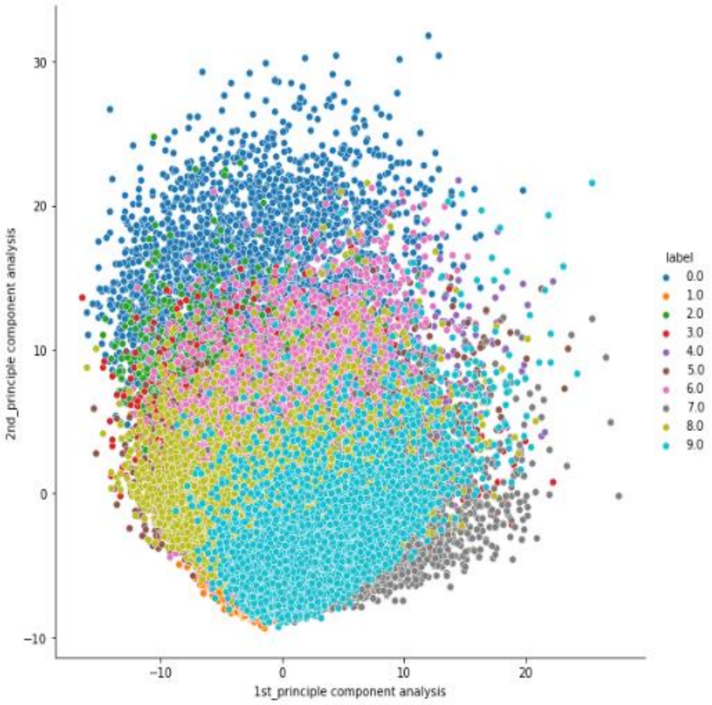
Out[154]:

	1st_principle component analysis	2nd_principle component analysis	label
0	-5.226445	-5.140478	1.0
1	6.032996	19.292332	0.0
2	-1.705813	-7.644503	1.0
3	5.836139	-0.474207	4.0
4	6.024818	26.559574	0.0
...	...	...	...
41995	-1.350366	13.678849	0.0
41996	-1.187360	-8.869582	1.0
41997	7.076277	0.495391	7.0
41998	-4.344513	2.307240	6.0
41999	1.559121	-4.807670	9.0

42000 rows × 3 columns

visualizing the final data with help of the seaborn FacetGrid method.

In [155]:
```
sns.FacetGrid(dataFrame, hue = 'label', height = 8).map(sns.scatterplot, '1st_principle component analysis', '2nd_principle compo
plt.show()
```

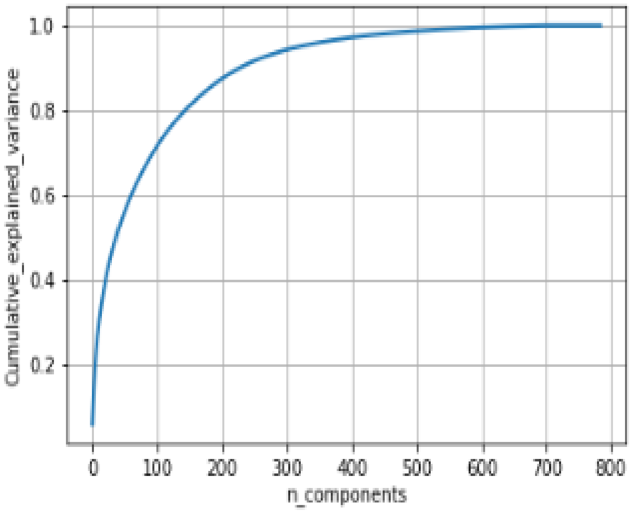


Visualized data of PCA on MNIST dataset

PCA for dimensionality redcution

In [156]:
```
# using SKlearn importing PCA
from sklearn import decomposition
pca = decomposition.PCA()
```

In [157]:
```
# PCA for dimensionality redcution (non-visualization)

pca.n_components = 784
pca_data = pca.fit_transform(std_df)

percentage_var_explained = pca.explained_variance_ / np.sum(pca.explained_variance_);

cum_var_explained = np.cumsum(percentage_var_explained)

# Plot the PCA spectrum
plt.figure(1, figsize=(6, 4))

plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()


# If we take 200-dimensions, approx. 90% of variance is expalined.
```



In [158]:
```
# directly entering parameters
pca.n_components = 2
pca_data = pca.fit_transform(std_df)

print('shape of pca_reduced data = ',pca_data.shape)
```

```
shape of pca_reduced data =  (42000, 2)
```

In [161]:
```
# Data massaging - adding label colomn to the reduced matrix
pca_data = np.vstack((pca_data.T,label)).T
```

In [162]:
```
# dataframing and plotting the pca data
pca_df = pd.DataFrame(data=pca_data,columns=('1st_principal','2nd_principal','labels'))
sns.FacetGrid(pca_df,hue='labels',height=6).map(plt.scatter,'1st_principal','2nd_principal').add_legend()
plt.show()
```