Practical 7 : PCA on MNIST dataset

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In [1]:
```
## PCA using MNIST Dataset

import re
import math
from sklearn.decomposition import PCA
import numpy as np
import scipy.linalg as la
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:
```
df = pd.read_csv("mnist_train.csv")
df.head()
```

Out[2]:

	label	1x1	1x2	1x3	1x4	1x5	1x6	1x7	1x8	1x9	...	28x19	28x20	28x21	28x22	28x23
0	5	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
2	4	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
4	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0

5 rows × 785 columns

In [3]:
```
col_names = df.columns.tolist()
# col_names
len(col_names)
```

Out[3]: 785

In [4]:
```
len(col_names[1:])
```

Out[4]: 784

In [5]:
```
#Indexing by labels  names
indexes = df.iloc[1:,0]
df = df.iloc[1:,1:len(df)]
df.set_index(indexes)
df
```

Out[5]:

	1x1	1x2	1x3	1x4	1x5	1x6	1x7	1x8	1x9	1x10	...	28x19	28x20	28x21	28x22	2!
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
3	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	
5	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
59995	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
59996	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
59997	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
59998	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	
59999	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	

59999 rows × 784 columns

In [6]:
```
df_zscore = df.iloc[:]
for col in df_zscore.columns:
    df_zscore[col] = df_zscore[col].astype(int)
    df_zscore[col] = df_zscore[col] - df_zscore[col].mean()
```

In [7]:
```
df_zscore.head(10)
```

Out[7]:

	1x1	1x2	1x3	1x4	1x5	1x6	1x7	1x8	1x9	1x10	...	28x19	28x20	28x21	
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	-0.200437	-0.088868	-0.045634	-0

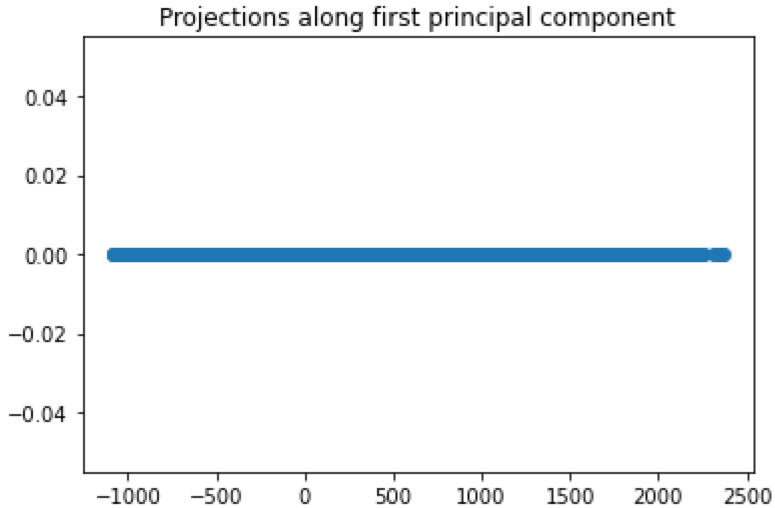
10 rows × 784 columns

In [8]:
```
#Convert into numpy array first
X_zscore = np.array(df_zscore.values[:,:], dtype='float64')
```

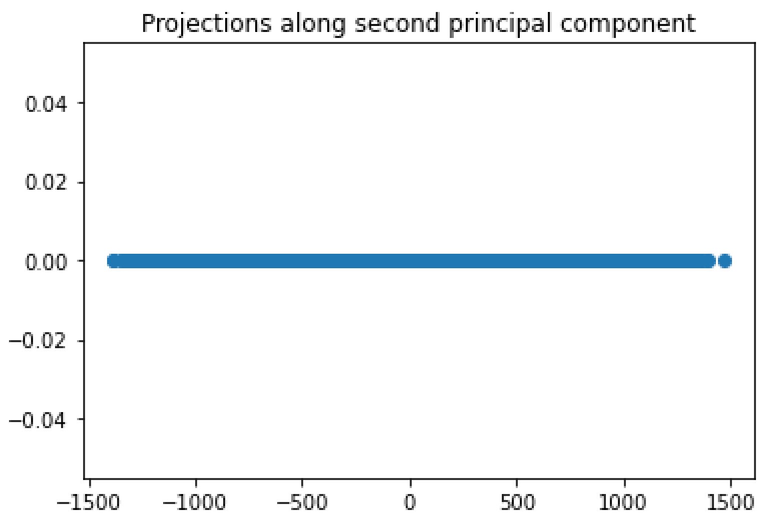
In [9]:
```
def pcaCompute(X,name):

    pca = PCA(n_components=3)
    pca.fit(X)
    projected = pca.components_.T

    a_1 = projected[:,0].T
    a_2 = projected[:,1].T
    a_3 = projected[:,2].T

    #print(a_1)
    #print(a_2)
    #print(np.argmax(a_1,axis=-1))

    feature_names = list(df_zscore.columns)

    print(f'Component 1 correlates most with ',feature_names[np.argmax(a_1,axi
s=-1)])
    print(f'Component 2 correlates most with ',feature_names[np.argmax(a_2,axi
s=-1)])
    print(f'Component 3 correlates most with ',feature_names[np.argmax(a_3,axi
s=-1)])


    scores_a_1 = np.matmul(X,a_1)
    scores_a_2 = np.matmul(X,a_2)
    scores_a_3 = np.matmul(X,a_3)

    plt.scatter(scores_a_1, np.zeros_like(scores_a_1))
    plt.title('Projections along first principal component')
    plt.show()

    print('Variance along first principal component: ', scores_a_1.var())

    plt.scatter(scores_a_2, np.zeros_like(scores_a_2))
    plt.title('Projections along second principal component')
    plt.show()

    print('Variance along second principal component: ', scores_a_2.var())

    plt.scatter(scores_a_3, np.zeros_like(scores_a_3))
    plt.title('Projections along Third principal component')
    plt.show()

    print('Variance along second principal component: ', scores_a_3.var())

    plt.scatter(scores_a_1,scores_a_2)
    plt.xlabel('PC1')
    plt.ylabel('PC2')

    plt.scatter(scores_a_2,scores_a_3)
    plt.xlabel('PC2')
    plt.ylabel('PC3')


    plt.scatter(scores_a_1,scores_a_3)
```

```
    plt.xlabel('PC1')
    plt.ylabel('PC3')


    plt.show()

    #PCA also helps in finding outliers
    #We can see in the graph PC1 and PC2 the one of extreme right is an outlie
r
    #find which city is belongs too

    for idx,score in enumerate(scores_a_1):
        if(score > 40000):
            print('Found Outlier city for zscore is ',indexes[idx+1])
            break

pcaCompute(X_zscore,'zscore')
```

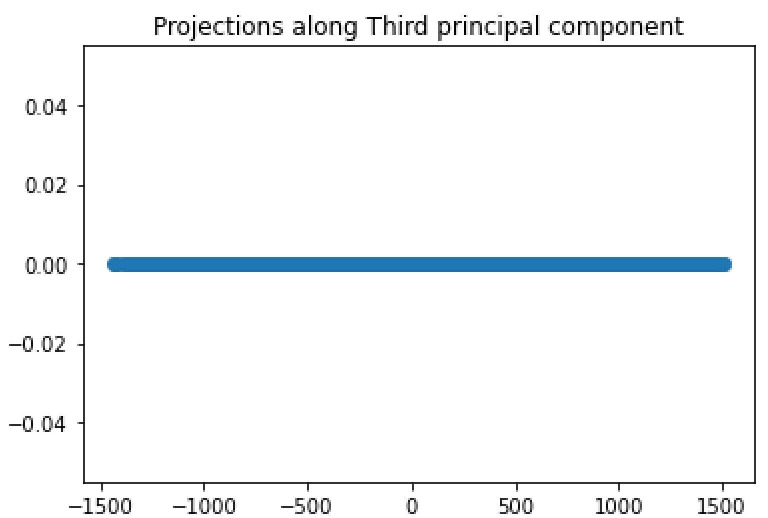
```
Component 1 correlates most with  20x19
Component 2 correlates most with  17x17
Component 3 correlates most with  20x14
```



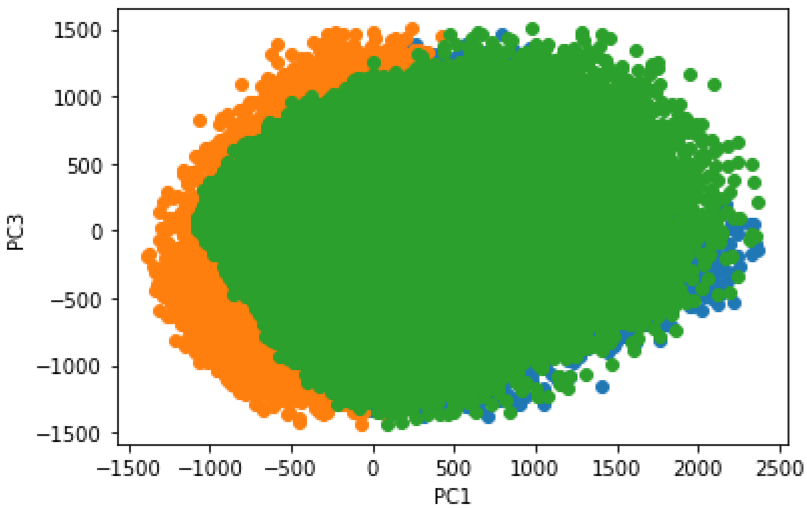

```
Variance along first principal component:  332724.4115046809
```




```
Variance along second principal component:  243282.30996937043
```



```
Variance along second principal component:  211507.35531880741
```



In [10]:
```
## thus we after PCA on MNIST dataset got the top 3 Principal component across all the 785 dimensions
```