MACHINE LEARNING (CS-5710)

ASSIGNMENT - 5

Name: Neeraj Kumar Kajuluri

Student ID: 700742091

Git hub Link :- https://github.com/NeerajKumarKajuluri/ML-Assignment-5.git

Video Link: - https://drive.google.com/file/d/1rZgJMQwfSwbUIlO8kpWv6wnmN9RSXCTe/view?usp=sharing

1. Principal Component Analysis

a. Apply PCA on CC dataset.

b. Apply k-means algorithm on the PCA result and report your observation if the s ilhouette score has improved or not?

c. Perform Scaling+ PCA+K-Means and report performance.

In [249]:
```
#Loading the dataset

cc_dataset=pd.read_csv('datasets/CC.csv')
cc_dataset.head()
```

Out[249]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQ
0	C10001	40.900749	0.818182	95.40	0.00	95.4	0.000000	(
1	C10002	3202.467416	0.909091	0.00	0.00	0.0	6442.945483	(
2	C10003	2495.148862	1.000000	773.17	773.17	0.0	0.000000	'
3	C10004	1666.670542	0.636364	1499.00	1499.00	0.0	205.788017	(
4	C10005	817.714335	1.000000	16.00	16.00	0.0	0.000000	(

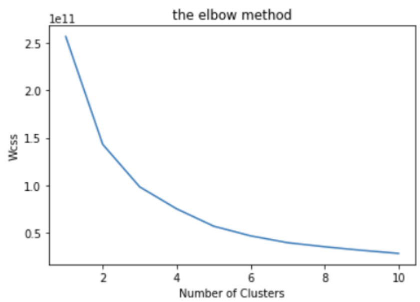
In [250]:
```
#Applying the imputer to the dataset to fill the null values that will prevent the PCA

X = cc_dataset.iloc[:,1:]
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
imputer = imputer.fit(X)
X = imputer.transform(X)
X=pd.DataFrame(X)
```

In [251]:
```
#a. Apply PCA on CC dataset

pca = PCA(2)
x_pca = pca.fit_transform(X)
df2 = pd.DataFrame(data=x_pca)
finaldf = pd.concat([df2, X.iloc[:,-1]], axis=1)
finaldf.head()
```

Out[251]:

	0	1	16
0	-4326.383956	921.566884	12.0
1	4118.916676	-2432.846347	12.0
2	1497.907660	-1997.578692	12.0
3	1394.548556	-1488.743450	12.0
4	-3743.351874	757.342659	12.0

In [252]:
```python
#Performing the elbow method to find the best number of suitable clusters for the given data to implement k-means
wcss = []
for i in range(1,11):
    kmeans = KMeans(n_clusters=i,init='k-means++',max_iter=300,n_init=10,random_state=0)
    kmeans.fit(finaldf)
    wcss.append(kmeans.inertia_)

plt.plot(range(1,11),wcss)
plt.title('the elbow method')
plt.xlabel('Number of Clusters')
plt.ylabel('Wcss')
plt.show()
```



In [253]:
```python
# Apply k-means algorithm on the PCA result and report your observation if the silhouette score has improved or not?

nclusters = 4
km = KMeans(n_clusters=nclusters)
km.fit(finaldf)
```

Out[253]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

In [254]:
```python
y_cluster_kmeans = km.predict(finaldf)
score = metrics.silhouette_score(finaldf, y_cluster_kmeans)
print('Silhoutte score for just PCA:',score)
```

```
Silhoutte score for just PCA: 0.504781047022562
```

In [255]:
```python
#Reload the dataset again
X = cc_dataset.iloc[:,1:]

imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
imputer = imputer.fit(X)

X = imputer.transform(X)

print(X)
X=pd.DataFrame(X)
```

```
[[4.09007490e+01 8.18182000e-01 9.54000000e+01 ... 1.39509787e+02
  0.00000000e+00 1.20000000e+01]
 [3.20246742e+03 9.09091000e-01 0.00000000e+00 ... 1.07234022e+03
  2.22222000e-01 1.20000000e+01]
 [2.49514886e+03 1.00000000e+00 7.73170000e+02 ... 6.27284787e+02
  0.00000000e+00 1.20000000e+01]
 ...
 [2.33986730e+01 8.33333000e-01 1.44400000e+02 ... 8.24183690e+01
  2.50000000e-01 6.00000000e+00]
 [1.34575640e+01 8.33333000e-01 0.00000000e+00 ... 5.57556280e+01
  2.50000000e-01 6.00000000e+00]
 [3.72708075e+02 6.66667000e-01 1.09325000e+03 ... 8.82889560e+01
  0.00000000e+00 6.00000000e+00]]
```

In [256]:

```
#Apply scaling on the dataset

scaler = StandardScaler()
scaler.fit(X)
x_scaler = scaler.transform(X)

#Apply PCA with k value as 2 again

pca = PCA(2)
x_pca = pca.fit_transform(x_scaler)
df2 = pd.DataFrame(data=x_pca)
finaldf = pd.concat([df2,cc_dataset[['TENURE']]],axis=1)
print(finaldf)
```

```
             0         1  TENURE
0    -1.682221 -1.076448      12
1    -1.138295  2.506477      12
2     0.969681 -0.383525      12
3    -0.873628  0.043166      12
4    -1.599434 -0.688578      12
...        ...       ...     ...
8945 -0.359630 -2.016142       6
8946 -0.564369 -1.639120       6
8947 -0.926204 -1.810782       6
8948 -2.336551 -0.657962       6
8949 -0.556421 -0.400473       6

[8950 rows x 3 columns]
```

In [257]:

```
#Apply k-means on the scaled PCA output

nclusters = 4
km = KMeans(n_clusters=nclusters)
km.fit(finaldf)
```

Out[257]:

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=4, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

In [258]:

```
y_cluster_kmeans = km.predict(finaldf)
score = metrics.silhouette_score(finaldf, y_cluster_kmeans)
print('Silhoutte score for scaled=pca=keans:',score)
```

```
Silhoutte score for scaled=pca=keans: 0.4378874170287716
```

#Observation:

The score is reduced after performing the PCa, so this data need not to be undergone with PCA.

2. Use pd_speech_features.csv

a. Perform Scaling

b. Apply PCA (k=3)

c. Use SVM to report performance.

In [269]:

```
#Load the dataset

speech_df=pd.read_csv('datasets/pd_speech_features.csv')
speech_df.head()
```

Out[269]:

	id	gender	PPE	DFA	RPDE	numPulses	numPeriodsPulses	meanPeriodPulses	stdDevPeriodPulses	locPctJitter	...	tqwt_kurtosisValue_dec_2
0	0	1	0.85247	0.71826	0.57227	240	239	0.008064	0.000087	0.00218	...	1.562
1	0	1	0.76686	0.69481	0.53966	234	233	0.008258	0.000073	0.00195	...	1.558
2	0	1	0.85083	0.67604	0.58982	232	231	0.008340	0.000060	0.00176	...	1.564
3	1	0	0.41121	0.79672	0.59257	178	177	0.010858	0.000183	0.00419	...	3.780
4	1	0	0.32790	0.79782	0.53028	236	235	0.008162	0.002669	0.00535	...	6.172

5 rows × 755 columns

In [272]:

```
#Apply scaling on the dataset

x =speech_df.iloc[:,1:]
scaler = StandardScaler()
scaler.fit(x)
speech_x_scaler = scaler.transform(x)

#Apply PCA with value 3

pca = PCA(3)
speech_x_pca = pca.fit_transform(speech_x_scaler)
speech_df2 = pd.DataFrame(data=speech_x_pca)
speech_finaldf = pd.concat([speech_df2,speech_df[['class']]],axis=1)
print(speech_finaldf)
```

```
             0         1          2  class
0   -10.052430  1.476819  -6.828359      1
1   -10.641066  1.590408  -6.811675      1
2   -13.520081 -1.243924  -6.794537      1
3    -9.142525  8.848870  15.300289      1
4    -6.758090  4.624220  15.645673      1
..         ...       ...        ...    ...
751  22.377449  6.470194   1.439479      0
752  13.503270  1.450496   9.344896      0
753   8.328507  2.392509  -0.911248      0
754   4.074595  5.417625  -0.847067      0
755   4.052810  6.076461  -2.022293      0

[756 rows x 4 columns]
```

In [273]:

```
#Apply SVM classifier

clf = SVC(kernel='linear')
x =speech_finaldf.iloc[:,:-1]
y =speech_finaldf.iloc[:,-1]
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=42)
clf.fit(X_train, y_train)
y_pred=clf.predict(X_test)
accuracy_score(y_test, y_pred)
print("SVM accuracy =", accuracy_score(y_test, y_pred))
```

```
SVM accuracy = 0.768
```

In [274]:

```
#Classification report for the above classifier

print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.82      0.20      0.33        69
           1       0.76      0.98      0.86       181

    accuracy                           0.77       250
   macro avg       0.79      0.59      0.59       250
weighted avg       0.78      0.77      0.71       250
```

Question 3

Apply Linear Discriminant Analysis (LDA) on Iris.csv dataset to reduce dimensionality of data to k=2

-

In [276]:

```
#Load the IRIS dataset

iris_df = pd.read_csv("datasets/iris.csv")
iris_df.head()
```

Out[276]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [281]:

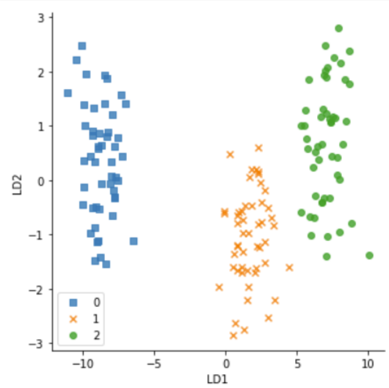
```python
#apply the standard scaling

stdsc = StandardScaler()
X_train_std = stdsc.fit_transform(iris_df.iloc[:,:-1].values)

#Label encoding the species column
class_le = LabelEncoder()
y = class_le.fit_transform(iris_df['Species'].values)

#Applying LDA on the Datset

lda = LinearDiscriminantAnalysis(n_components=2)
X_train_lda = lda.fit_transform(X_train_std,y)

data=pd.DataFrame(X_train_lda)
data['class']=y
data.columns=["LD1","LD2","class"]
data.head()
```

Out[281]:

	LD1	LD2	class
0	-10.036763	-0.451330	0
1	-9.172930	-1.477234	0
2	-9.480989	-0.979693	0
3	-8.818119	-1.408602	0
4	-9.960200	-0.112546	0

In [284]:

```python
markers = ['s', 'x', 'o']
colors = ['y', 'b', 'g']
sns.lmplot(x="LD1", y="LD2", data=data, hue='class', markers=markers, fit_reg=False, legend=False)
plt.legend()
plt.show()
```



Question 4

Briefly identify the difference between PCA and LDA.

Answer: PCA performs better in case where number of samples per class is less. Whereas LDA works better with large dataset having multiple classes; class separability is an important factor while reducing dimensionality. PCA finds directions of maximum variance regardless of class labels while LDA finds directions of maximum class separability.