Spring 2023: CS5710 – Machine Learning

In-Class Programming Assignment-5

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Link for Github:
https://github.com/Deepthi-gudibanda/MachineLearning.git

Imported all the required libraries such as pandas, numpy, sklearn and etc. And loaded the dataset “CC GENERAL.csv”

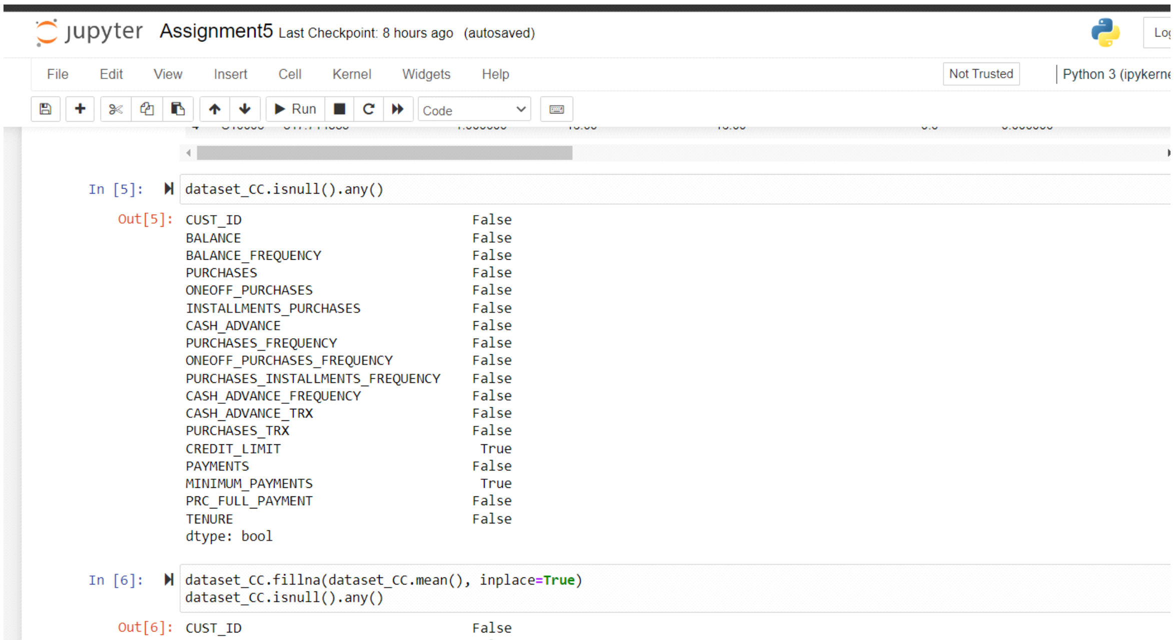
```
In [1]: # importing required libraries for assignment 5 here
        import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
        import seaborn as sns
        from sklearn import preprocessing, metrics
        from sklearn.preprocessing import StandardScaler, LabelEncoder
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
        from sklearn.decomposition import PCA
        from sklearn.cluster import KMeans
        sns.set(style="white", color_codes=True)
        import warnings
        warnings.filterwarnings("ignore")
```

```
In [2]: # Principal Component Analysis
        # a. Apply PCA on CC dataset.
        # b. Apply k-means algorithm on the PCA result and report your observation if the silhouette score
        # has improved or not?
        # c. Perform Scaling+PCA+K-Means and report performance.
```

```
In [5]: dataset_CC = pd.read_csv('datasets//CC GENERAL.csv')
        dataset_CC.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8950 entries, 0 to 8949
Data columns (total 18 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   CUST_ID                           8950 non-null   object
 1   BALANCE                           8950 non-null   float64
```

To apply PCA we need to remove all the null values that are present in the dataset. So, removed all the null values and applied PCA on the dataset.



In [5]:
```
dataset_CC.isnull().any()
```

Out[5]:
```
CUST_ID                             False
BALANCE                             False
BALANCE_FREQUENCY                   False
PURCHASES                           False
ONEOFF_PURCHASES                    False
INSTALLMENTS_PURCHASES              False
CASH_ADVANCE                        False
PURCHASES_FREQUENCY                 False
ONEOFF_PURCHASES_FREQUENCY          False
PURCHASES_INSTALLMENTS_FREQUENCY    False
CASH_ADVANCE_FREQUENCY              False
CASH_ADVANCE_TRX                    False
PURCHASES_TRX                       False
CREDIT_LIMIT                         True
PAYMENTS                            False
MINIMUM_PAYMENTS                     True
PRC_FULL_PAYMENT                    False
TENURE                              False
dtype: bool
```

In [6]:
```
dataset_CC.fillna(dataset_CC.mean(), inplace=True)
dataset_CC.isnull().any()
```

Out[6]:
```
CUST_ID                             False
```

First, Applied the elbow method to find the clusters required for performing the k-means implementation. Which is 3 from the obtained output.

On applying the K-means algorithm for the PCA result we get the Silhoutte score as 0.5109

```
score = metrics.silhouette_score(X, y_cluster_kmeans)
print("Sihouette Score: ",score)

"""
Sihouette Score- ranges from -1 to +1 , a high value indicates that the object is well matched to its own cluster and poorly
"""
```

```
              precision    recall  f1-score   support

           0       0.00      1.00      0.00       0.0
           1       0.00      1.00      0.00       0.0
           2       0.00      1.00      0.00       0.0
           6       1.00      0.00      0.00     204.0
           7       1.00      0.00      0.00     190.0
           8       1.00      0.00      0.00     196.0
           9       1.00      0.00      0.00     175.0
          10       1.00      0.00      0.00     236.0
          11       1.00      0.00      0.00     365.0
          12       1.00      0.00      0.00    7584.0

    accuracy                           0.00    8950.0
   macro avg       0.70      0.30      0.00    8950.0
weighted avg       1.00      0.00      0.00    8950.0

[[   0    0    0    0    0    0    0    0    0    0]
 [   0    0    0    0    0    0    0    0    0    0]
 [   0    0    0    0    0    0    0    0    0    0]
 [ 175    1   28    0    0    0    0    0    0    0]
 [ 173    2   15    0    0    0    0    0    0    0]
 [ 169    0   27    0    0    0    0    0    0    0]
 [ 149    0   26    0    0    0    0    0    0    0]
 [ 188    1   47    0    0    0    0    0    0    0]
 [ 284    3   78    0    0    0    0    0    0    0]
 [5389  126 2069    0    0    0    0    0    0    0]]

Accuracy for our Training dataset with PCA: 0.0
Sihouette Score:  0.5109307274319468
```

Reload the dataset to perform the scaling

In [11]:

```
nclusters = 3 # this is the k in kmeans
km = KMeans(n_clusters=nclusters)
km.fit(X)

# predict the cluster for each data point
y_cluster_kmeans = km.predict(X)


# Summary of the predictions made by the classifier
print(classification_report(y, y_cluster_kmeans, zero_division=1))
print(confusion_matrix(y, y_cluster_kmeans))


train_accuracy = accuracy_score(y, y_cluster_kmeans)
print("\nAccuracy for our Training dataset with PCA:", train_accuracy)


#Calculate sihouette Score
score = metrics.silhouette_score(X, y_cluster_kmeans)
print("Sihouette Score: ",score)

"""
Sihouette Score- ranges from -1 to +1 , a high value indicates that the object is well matched to its own cluster and poorly
"""
```

```
              precision    recall  f1-score   support
```

Apply the Scaling and perform PCA on the dataset

```
In [13]: #Scaling
         scaler = StandardScaler()
         scaler.fit(x)
         X_scaled_array = scaler.transform(x)
         #PCA
         pca = PCA(3)
         x_pca = pca.fit_transform(X_scaled_array)
         principalDf = pd.DataFrame(data = x_pca, columns = ['principal component 1', 'principal component 2','principal component 3']
         finalDf = pd.concat([principalDf, dataset_CC.iloc[:,-1]], axis = 1)
         finalDf.head()
```

Out[13]:

	principal component 1	principal component 2	principal component 3	TENURE
0	-1.718893	-1.072939	0.535670	12
1	-1.169306	2.509320	0.628027	12
2	0.938414	-0.382600	0.161198	12
3	-0.907503	0.045859	1.521689	12
4	-1.637830	-0.684975	0.425658	12

```
In [14]: X = finalDf.iloc[:,0:-1]
         y = finalDf["TENURE"]
         print(X.shape,y.shape)

         (8950, 3) (8950,)

In [15]: X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.34,random_state=0)
```

Now performing the k-means on the scaled PCA data, which gives the result of 0.383. Which has reduced from the previous k-means value.

```
"""
Sihouette Score- ranges from −1 to +1 , a high value indicates that the object is well matched to its own cluster and poorly
"""
```

```
              precision    recall  f1-score   support

           0       0.00      1.00      0.00       0.0
           1       0.00      1.00      0.00       0.0
           2       0.00      1.00      0.00       0.0
           6       1.00      0.00      0.00      65.0
           7       1.00      0.00      0.00      55.0
           8       1.00      0.00      0.00      68.0
           9       1.00      0.00      0.00      57.0
          10       1.00      0.00      0.00      85.0
          11       1.00      0.00      0.00     103.0
          12       1.00      0.00      0.00    2610.0

    accuracy                           0.00    3043.0
   macro avg       0.70      0.30      0.00    3043.0
weighted avg       1.00      0.00      0.00    3043.0

[[   0    0    0    0    0    0    0    0    0    0]
 [   0    0    0    0    0    0    0    0    0    0]
 [   0    0    0    0    0    0    0    0    0    0]
 [  41   21    3    0    0    0    0    0    0    0]
 [  42   12    1    0    0    0    0    0    0    0]
 [  57   10    1    0    0    0    0    0    0    0]
 [  35   22    0    0    0    0    0    0    0    0]
 [  63   17    5    0    0    0    0    0    0    0]
 [  69   30    4    0    0    0    0    0    0    0]
 [1763  450  397    0    0    0    0    0    0    0]]

Accuracy for our Training dataset with PCA: 0.0
Sihouette Score:  0.383322340968964
```

Load the pd_speech_features dataset

In [18]:
```
dataset_pd = pd.read_csv('datasets//pd_speech_features.csv')
dataset_pd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 756 entries, 0 to 755
Columns: 755 entries, id to class
dtypes: float64(749), int64(6)
memory usage: 4.4 MB
```

In [19]:
```
dataset_pd.head()
```

Out[19]:

	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 [20]:
```
dataset_pd.isnull().any()
```

We are doing the scaling on the pd_speech_features dataset and then apply PCA with k=3 value

```
X_Scale = scaler.fit_transform(X)
```

In [23]:
```
# Apply PCA with k =3
pca3 = PCA(n_components=3)
principalComponents = pca3.fit_transform(X_Scale)

principalDf = pd.DataFrame(data = principalComponents, columns = ['principal component 1', 'principal component 2','Principal

finalDf = pd.concat([principalDf, dataset_pd[['class']]], axis = 1)
finalDf.head()
```

Out[23]:

	principal component 1	principal component 2	Principal Component 3	class
0	-10.047372	1.471076	-6.846402	1
1	-10.637725	1.583749	-6.830976	1
2	-13.516185	-1.253542	-6.818696	1
3	-9.155084	8.833601	15.290906	1
4	-6.764470	4.611468	15.637121	1

In [24]:
```
X = finalDf.drop('class',axis=1).values
y = finalDf['class'].values
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.34,random_state=0)
```

We have used the SVM classifier to report the performance which is 0.810 and got the classification report

```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.34,random_state=0)
```

In [25]:
```
#2.c Support Vector Machine's

from sklearn.svm import SVC

svmClassifier = SVC()
svmClassifier.fit(X_train, y_train)

y_pred = svmClassifier.predict(X_test)

# Summary of the predictions made by the classifier
print(classification_report(y_test, y_pred, zero_division=1))
print(confusion_matrix(y_test, y_pred))
# Accuracy score
glass_acc_svc = accuracy_score(y_pred,y_test)
print('accuracy is',glass_acc_svc )

#Calculate sihouette Score
score = metrics.silhouette_score(X_test, y_pred)
print("Sihouette Score: ",score)
```

```
              precision    recall  f1-score   support

           0       0.67      0.42      0.51        62
           1       0.84      0.93      0.88       196

    accuracy                           0.81       258
   macro avg       0.75      0.68      0.70       258
weighted avg       0.80      0.81      0.79       258

[[ 26  36]
 [ 13 183]]
accuracy is 0.810077519379845
Sihouette Score:  0.2504463929631217
```

Load the Iris dataset to perform LDA.

Apply Standard Scaling on the data

```
Silhouette Score:  0.2504465929651217
```

In [26]:
```python
#3.Apply Linear Discriminant Analysis (LDA) on Iris.csv dataset to reduce dimensionality of data to k=2.
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
dataset_iris = pd.read_csv('datasets//Iris.csv')
dataset_iris.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             150 non-null    int64  
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object 
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [27]:
```python
dataset_iris.isnull().any()
```

Out[27]:
```
Id               False
SepalLengthCm    False
SepalWidthCm     False
PetalLengthCm    False
PetalWidthCm     False
Species          False
```

Reducing the dataset dimensionality to k=2 jupyter Assignment5 Last Checkpoint: 9 hours ago (autosaved)

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Not Trusted | Python 3 (ipykernel)

Run Code

```
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

```
In [27]: dataset_iris.isnull().any()
```

```
Out[27]: Id               False
         SepalLengthCm    False
         SepalWidthCm     False
         PetalLengthCm    False
         PetalWidthCm     False
         Species          False
         dtype: bool
```

```
In [28]: x = dataset_iris.iloc[:,1:-1]
         y = dataset_iris.iloc[:,-1]
         print(x.shape,y.shape)

         (150, 4) (150,)
```

```
In [29]: X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=0)
```

```
In [30]: sc = StandardScaler()
         X_train = sc.fit_transform(X_train)
         X_test = sc.transform(X_test)
         le = LabelEncoder()
         y = le.fit_transform(y)
```

```
In [31]: from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
         lda = LDA(n_components=2)
         X_train = lda.fit_transform(X_train, y_train)
         X_test = lda.transform(X_test)
         print(X_train.shape,X_test.shape)

         (105, 2) (45, 2)
```

4. Briefly identify the difference between PCA and LDA?

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.