# CS 5710 Machine Learning

Assignment-5

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***GitHub Link:*** https://github.com/gakrish5/MachineLearning/tree/main/Assignment%205

***Video Link:***

https://drive.google.com/file/d/10PwKAqwnHisiq66aCDYBLcBcqJv4Lvvs/view?usp=share_link

**Importing the required libraries.**

```
# importing required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import seaborn as sns
sns.set(style="white", color_codes=True)

import warnings
warnings.filterwarnings("ignore")

from sklearn.decomposition import PCA
from sklearn import preprocessing, metrics
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
from sklearn.svm import SVC
```

## 1. Principal Component Analysis:

## Question 1. a:

Apply PCA on CC dataset.

***Part-1:***

***Source code:***

```
# Loading the CC General csv file
df_CC = pd.read_csv('CC GENERAL.csv')

# displaying the info
print(df_CC.info())

#displaying the first 5 rows of dataframe
df_CC.head()
```

***Output:***

```
<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
 2   BALANCE_FREQUENCY                 8950 non-null   float64
 3   PURCHASES                         8950 non-null   float64
 4   ONEOFF_PURCHASES                  8950 non-null   float64
 5   INSTALLMENTS_PURCHASES            8950 non-null   float64
 6   CASH_ADVANCE                      8950 non-null   float64
 7   PURCHASES_FREQUENCY               8950 non-null   float64
 8   ONEOFF_PURCHASES_FREQUENCY        8950 non-null   float64
 9   PURCHASES_INSTALLMENTS_FREQUENCY  8950 non-null   float64
 10  CASH_ADVANCE_FREQUENCY            8950 non-null   float64
 11  CASH_ADVANCE_TRX                  8950 non-null   int64  
 12  PURCHASES_TRX                     8950 non-null   int64  
 13  CREDIT_LIMIT                      8949 non-null   float64
 14  PAYMENTS                          8950 non-null   float64
 15  MINIMUM_PAYMENTS                  8637 non-null   float64
 16  PRC_FULL_PAYMENT                  8950 non-null   float64
 17  TENURE                            8950 non-null   int64  
dtypes: float64(14), int64(3), object(1)
memory usage: 1.2+ MB
None
```

| | CUST_ID | BALANCE | BALANCE_FREQUENCY | PURCHASES | ONEOFF_PURCHASES | INSTALLMENTS_PURCHASES | CASH_ADVANCE | PURCHASES_FREQUEN |
|---|---|---|---|---|---|---|---|---|
| **0** | C10001 | 40.900749 | 0.818182 | 95.40 | 0.00 | 95.4 | 0.000000 | 0.166 |
| **1** | C10002 | 3202.467416 | 0.909091 | 0.00 | 0.00 | 0.0 | 6442.945483 | 0.000 |
| **2** | C10003 | 2495.148862 | 1.000000 | 773.17 | 773.17 | 0.0 | 0.000000 | 1.000 |
| **3** | C10004 | 1666.670542 | 0.636364 | 1499.00 | 1499.00 | 0.0 | 205.788017 | 0.083 |
| **4** | C10005 | 817.714335 | 1.000000 | 16.00 | 16.00 | 0.0 | 0.000000 | 0.083 |

## ***Part-2:***

***Source code & Output:***

```
In [3]: # checking for null data in the dataset using isnull() function
        df_CC.isnull().any()

Out[3]: 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
```

## *Part-3:*

### *Source code & Output:*

```
In [4]: # replacing the null data with the mean by using fillena() function
        df_CC.fillna(df_CC.mean(), inplace=True)

        # checking for null data in the dataset using isnull() function, after replacing
        df_CC.isnull().any()

Out[4]: 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                         False
        PAYMENTS                             False
        MINIMUM_PAYMENTS                     False
        PRC_FULL_PAYMENT                     False
        TENURE                               False
        dtype: bool
```

## *Part-4:*

### *Source code & Output:*

```
'''x is selecting all rows and all columns from the second column to the second-to-last column.
This is equivalent to selecting all columns except for the first and last columns'''
x = df_CC.iloc[:,1:-1]

# y is selecting all rows and only the last column that is TENURE
y = df_CC.iloc[:,-1]

# printing the shape of x and y, which is the number of rows and columns in each subset of data
print(x.shape,y.shape)

(8950, 16) (8950,)
```

## ***Part-5:***

### *Source code & Output:*

```
In [6]: # Applying PCA on CC Dataset
        # Datasets can be analyzed with PCA so that redundant features can be removed without losing too much information.
        '''PCA(3)- performs principal component analysis (PCA) on dataset x, reducing the dimensionality
        of the data from the original number of features to 3 principal components.'''
        pca = PCA(3)  #Instantiate PCA

        '''fit_transform()- method of the PCA object is called on the data x to obtain a transformed version of the data,
        where each observation is represented by its three principal components.'''
        x_pca = pca.fit_transform(x)

        # creates a new DataFrame 'principalDf' with the transformed data, where each column corresponds to a principal component
        principalDf = pd.DataFrame(data = x_pca,
                                   columns = ['principal component 1',
                                              'principal component 2',
                                              'principal component 3'])

        '''creating a new DataFrame 'finalDf' using concat() function with the transformed data and
        the original target variable (the 'TENURE' column) for each observation.'''
        finalDf = pd.concat([principalDf,
                             df_CC.iloc[:,-1]],
                            axis = 1)
        finalDf.head()
```

Out[6]:

| | principal component 1 | principal component 2 | principal component 3 | TENURE |
|---|---|---|---|---|
| **0** | -4326.383979 | 921.566882 | 183.708383 | 12 |
| **1** | 4118.916665 | -2432.846346 | 2369.969289 | 12 |
| **2** | 1497.907641 | -1997.578694 | -2125.631328 | 12 |
| **3** | 1394.548536 | -1488.743453 | -2431.799649 | 12 |
| **4** | -3743.351896 | 757.342657 | 512.476492 | 12 |

### *Explanation:*

Here in the code, I have used ***read_csv*( ), *info*( )** and ***head*( )**functions to read CSV file (CC GENERAL.csv), display the info and to display the first 5 rows of the *DataFrame* respectively.

Checked for null values and as the null values are found, replaced them with mean using *fillna*( ) function.

Making two Data Frame’s namely x and y from the original DataFrame after replacing null values. x contains all columns except the TENURE column which is a target variable. y contains the DataFrame with target variable.

PCA with 3 principal components is applied on x. Finally, made data frame containing principal components and target variable column with the help of *concat*( ) function.

## Question 1. b:

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

### *Part-1:*

### *Source code & Output:*

```
''' X- predictor variable- contains all rows of finalDf except for the last column,
representing the principal components generated by PCA'''
X = finalDf.iloc[:, 0:-1]

# y- target variable- contains only the last column of finalDf, representing the target variable.
y = finalDf.iloc[:, -1]

print(X.shape, y.shape)
```

```
(8950, 3) (8950,)
```

### *Part-2:*

### *Source code:*

```
# Number of clusters
nclusters = 3

#Kmeans()- is used to perform Kmeans clustering on transformed data X with the specified number of clusters
km = KMeans(n_clusters=nclusters)

#fit()- method is called on the KMeans object to cluster the data.
km.fit(X)

''' predict() method is used to assign each data point to a cluster based on the clustering
performed by K-means and cluster alignment is stored in y_cluster_kmeans'''
y_cluster_kmeans = km.predict(X)

# generates a confusion matrix that summarizes the number of TP, FP, TN, FN for each class
print('Confusion Matrix:\n', confusion_matrix(y, y_cluster_kmeans))

''' classification_report()- summary of predictions made by the classifier,
Zero_division = parameter is set to 1 to avoid errors when a cluster is not assigned any data points.'''
print('\nclassification Report:\n', classification_report(y, y_cluster_kmeans, zero_division=1))

# computing the accuracy of the clustering results obtained using K-means algorithm
train_accuracy = accuracy_score(y, y_cluster_kmeans)
print("\nAccuracy for our Training dataset with PCA:", train_accuracy)

'''The silhouette score ranges from -1 to 1 and is a measure of how similar an object is to its own cluster
compared to other clusters, where a higher score indicates better clustering'''
score = metrics.silhouette_score(X, y_cluster_kmeans)
print("Silhouette Score: ", score)
```

***Output:***

```
Confusion Matrix:
 [[   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]
 [5390  126 2068    0    0    0    0    0    0    0]]

classification Report:
               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


Accuracy for our Training dataset with PCA: 0.0
Silhouette Score:  0.5109769750121257
```

***Explanation:***

Here in the code, I have split the finalDf of made previously into 2 Data frames one as X (Predictor variable) and y (target variable). The $KMeans(\ )$ function is used to create a KMeans object with the number of clusters specified. The $fit(\ )$ method is then called on the KMeans object to cluster the data. The $predict(\ )$ method is used to assign each data point to a cluster based on the clustering performed by K-means, and the resulting cluster assignments are stored in y_cluster_kmeans.

The $confusion\_matrix(\ )$ function is used to generate a confusion matrix that summarizes the number of TP, FP, TN, and FN for each class.

The $classification\_report(\ )$ function is used to produce a summary of the predictions made by the classifier, with zero_division parameter set to 1 to avoid errors when a cluster is not assigned any data points.

The *accuracy_score*( ) function is used to compute the accuracy of the clustering results obtained using the K-means algorithm.

Finally, the *silhouette_score*( ) function from *metrics* library is used to compute the silhouette score, which is a measure of how similar an object is to its own cluster compared to other clusters, with a higher score indicating better clustering.

Confusion matrix, classification report, accuracy score and silhouette score are printed.

## Question 1. c:

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

### *Part-1:*

### *Source code & Output:*

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

```
(8950, 16) (8950,)
```

### *Part-2:*

### *Source code & Output:*

```
In [10]: # Scale the dataset; This is very important before you apply PCA
scaler = StandardScaler()
scaler.fit(x)
X_scaled_array = scaler.transform(x)

'''PCA(3)- performs principal component analysis (PCA) on dataset x, reducing the dimensionality
of the data from the original number of features to 3 principal components.'''
pca = PCA(3)

'''fit_transform()- method of the PCA object is called on the data x to obtain a transformed version of the data,
where each observation is represented by its three principal components.'''
x_pca = pca.fit_transform(X_scaled_array)

# creates a new DataFrame 'principalDf' with the transformed data, where each column corresponds to a principal component
principalDf = pd.DataFrame(data = x_pca,
                           columns = ['principal component 1',
                                      'principal component 2',
                                      'principal component 3'])

'''creating a new DataFrame 'finalDf' using concat() function with the transformed data and
the original target variable (the 'TENURE' column) for each observation.'''
finalDf = pd.concat([principalDf,
                    df_CC.iloc[:,-1]],
                   axis = 1)
finalDf.head()
```

Out[10]:

| | principal component 1 | principal component 2 | principal component 3 | TENURE |
|---|---|---|---|---|
| **0** | -1.718893 | -1.072940 | 0.535662 | 12 |
| **1** | -1.169306 | 2.509322 | 0.628084 | 12 |
| **2** | 0.938414 | -0.382601 | 0.161150 | 12 |
| **3** | -0.907502 | 0.045859 | 1.521708 | 12 |
| **4** | -1.637830 | -0.684976 | 0.425637 | 12 |

## Part-3:

### Source code & Output:

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

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

```
(8950, 3) (8950,)
```

## Part-4:

### Source code:

```
# Number of clusters
nclusters = 3

#Kmeans()- is used to perform Kmeans clustering on transformed data X with the specified number of clusters
km = KMeans(n_clusters=nclusters)

#fit()- method is called on the KMeans object to cluster the data.
km.fit(X_train,y_train)

''' predict() method is used to assign each data point to a cluster based on the clustering
performed by K-means and cluster alignment is stored in y_cluster_kmeans'''
y_clus_train = km.predict(X_train)

# generates a confusion matrix that summarizes the number of TP, FP, TN, FN for each class
print('Confusion Matrix:\n',confusion_matrix(y_train, y_clus_train))

''' classification_report()- summary of predictions made by the classifier,
Zero_division = parameter is set to 1 to avoid errors when a cluster is not assigned any data points.'''
print('\nclassification Report:\n', classification_report(y_train, y_clus_train, zero_division=1))

# computing the accuracy of the clustering results obtained using K-means algorithm
train_accuracy = accuracy_score(y_train, y_clus_train)
print("Accuracy for our Training dataset with PCA:", train_accuracy)

'''The silhouette score ranges from -1 to 1 and is a measure of how similar an object is to its own cluster
compared to other clusters, where a higher score indicates better clustering'''
score = metrics.silhouette_score(X_train, y_clus_train)
print("Silhouette Score: ",score)
```

### Output:

```
Confusion Matrix:
 [[   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]
 [ 105    4   30    0    0    0    0    0    0    0]
 [ 108    1   26    0    0    0    0    0    0    0]
 [  96    4   28    0    0    0    0    0    0    0]
 [  89    2   27    0    0    0    0    0    0    0]
 [ 107    6   38    0    0    0    0    0    0    0]
 [ 185   11   66    0    0    0    0    0    0    0]
 [3393  739  842    0    0    0    0    0    0    0]]

classification Report:
               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     139.0
           7       1.00      0.00      0.00     135.0
           8       1.00      0.00      0.00     128.0
           9       1.00      0.00      0.00     118.0
          10       1.00      0.00      0.00     151.0
          11       1.00      0.00      0.00     262.0
          12       1.00      0.00      0.00    4974.0

    accuracy                           0.00    5907.0
   macro avg       0.70      0.30      0.00    5907.0
weighted avg       1.00      0.00      0.00    5907.0

Accuracy for our Training dataset with PCA: 0.0
Silhouette Score:  0.381207702204633
```

## ***Part-5:***

### *Source code:*

```
''' predict() method is used to assign each data point to a cluster based on the clustering
performed by K-means and cluster alignment is stored in y_cluster_kmeans'''
y_clus_test = km.predict(X_test)

# generates a confusion matrix that summarizes the number of TP, FP, TN, FN for each class
print('Confusion Matrix:\n', confusion_matrix(y_test, y_clus_test))

''' classification_report()- summary of predictions made by the classifier,
Zero_division = parameter is set to 1 to avoid errors when a cluster is not assigned any data points.'''
print('\n classification Report:\n', classification_report(y_test, y_clus_test, zero_division=1))

# computing the accuracy of the clustering results obtained using K-means algorithms
train_accuracy = accuracy_score(y_test, y_clus_test)
print("\nAccuracy for our Training dataset with PCA:", train_accuracy)

'''The silhouette score ranges from -1 to 1 and is a measure of how similar an object is to its own cluster
compared to other clusters, where a higher score indicates better clustering'''
score = metrics.silhouette_score(X_test, y_clus_test)
print("Silhouette Score: ",score)
```

### *Output:*

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

 classification Report:
               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


Accuracy for our Training dataset with PCA: 0.0
Silhouette Score:  0.38332239118154726
```

***Explanation:***

Here in the code, made two Data Frame's namely x and y from the original DataFrame after replacing null values. x contains all columns except the TENURE column which is a target variable. y contains the DataFrame with target variable. The features in x are standardized by subtracting the mean and dividing by the standard deviation of each feature using the $StandardScaler$ object.

PCA with 3 principal components is applied on scaled x. Finally, made a data frame containing principal components and target variable column with the help of $concat(\,)$ function. I have split the finalDf made previously into 2 Data frames one as X (Predictor variable) and y (target variable). With X and y we have made train and test data using $train\_test\_split(\,)$ function.

The following are performed for the test data as well as train data.

- The $KMeans(\,)$ function is used to create a KMeans object with the number of clusters specified. The $fit(\,)$ method is then called on the KMeans object to cluster the data. The $predict(\,)$ method is used to assign each data point to a cluster based on the clustering performed by K-means, and the resulting cluster assignments are stored in y_cluster_kmeans.
- The $confusion\_matrix(\,)$ function is used to generate a confusion matrix that summarizes the number of TP, FP, TN, and FN for each class.
- The $classification\_report(\,)$ function is used to produce a summary of the predictions made by the classifier, with zero_division parameter set to 1 to avoid errors when a cluster is not assigned any data points.
- The $accuracy\_score(\,)$ function is used to compute the accuracy of the clustering results obtained using the K-means algorithm.
- Finally, the $silhouette\_score(\,)$ function from $metrics$ library is used to compute the silhouette score, which is a measure of how similar an object is to its own cluster compared to other clusters, with a higher score indicating better clustering.
- Confusion matrix, classification report, accuracy score and silhouette score are printed.

## **Observation:**

The Silhouette score is reduced after performing the scaling, so this data need not be undergone with scaling.

## 2. Use pd_speech_features.csv:

## Question 2. a:

Perform Scaling.

### *Part-1:*

### *Source code & Output:*

```
In [14]: dataset_pd = pd.read_csv('pd_speech_features.csv')
         print(dataset_pd.info())
         dataset_pd.head()

<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
None
```

Out[14]:

| | id | gender | PPE | DFA | RPDE | numPulses | numPeriodsPulses | meanPeriodPulses | stdDevPeriodPulses | locPctJitter | ... | tqwt_kurtosisValue_dec_28 | tq |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 1 | 0.85247 | 0.71826 | 0.57227 | 240 | 239 | 0.008064 | 0.000087 | 0.00218 | ... | 1.5620 | |
| **1** | 0 | 1 | 0.76686 | 0.69481 | 0.53966 | 234 | 233 | 0.008258 | 0.000073 | 0.00195 | ... | 1.5589 | |
| **2** | 0 | 1 | 0.85083 | 0.67604 | 0.58982 | 232 | 231 | 0.008340 | 0.000060 | 0.00176 | ... | 1.5643 | |
| **3** | 1 | 0 | 0.41121 | 0.79672 | 0.59257 | 178 | 177 | 0.010858 | 0.000183 | 0.00419 | ... | 3.7805 | |
| **4** | 1 | 0 | 0.32790 | 0.79782 | 0.53028 | 236 | 235 | 0.008162 | 0.002669 | 0.00535 | ... | 6.1727 | |

5 rows × 755 columns

### *Part-2:*

### *Source code & Output:*

```
In [15]: dataset_pd.isnull().any()

Out[15]: id                           False
         gender                       False
         PPE                          False
         DFA                          False
         RPDE                         False
                                      ...
         tqwt_kurtosisValue_dec_33    False
         tqwt_kurtosisValue_dec_34    False
         tqwt_kurtosisValue_dec_35    False
         tqwt_kurtosisValue_dec_36    False
         class                        False
         Length: 755, dtype: bool
```

### *Part-3:*

### *Source code:*

```
# dropping the target variable class from main data frame and creates a new data from X
X = dataset_pd.drop('class',axis=1).values

# Y returns the class column which is a target variable from the main data frame
y = dataset_pd['class'].values

#Scaling Data
'''StandardScaler to scale the input X, this is important as it ensures that all the features are on the same scale
and prevents features with larger magnitude from dominating the distance calculations'''
sc = StandardScaler()

# Applies the fit_transform() method of the StandardScaler instance to the feature matrix X to perform feature scaling
X_Scale = sc.fit_transform(X)
```

***Explanation:***

Here in the code, I have used $\boldsymbol{read\_csv}(\,)$, $\boldsymbol{info}(\,)$ and $\boldsymbol{head}(\,)$functions to read CSV file (pd_speech_features.csv), display the info and to display the first 5 rows of the $DataFrame$ respectively. Checked for any null values and there are no null values.

Made two Data Frame's namely X and y from the original DataFrame. X contains all columns except the **class** column which is a target variable. y contains the DataFrame with target variable. The features in $\boldsymbol{X}$ are standardized by subtracting the mean and dividing by the standard deviation of each feature using the $StandardScaler$ object.

## Question 2. b:

Apply PCA ($k = 3$).

***Part-1:***

***Source code & Output:***

```
# 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 Component 3'])

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

| | principal component 1 | principal component 2 | Principal Component 3 | class |
|---|---|---|---|---|
| **0** | -10.047372 | 1.471077 | -6.846407 | 1 |
| **1** | -10.637725 | 1.583750 | -6.830977 | 1 |
| **2** | -13.516185 | -1.253542 | -6.818699 | 1 |
| **3** | -9.155084 | 8.833599 | 15.290915 | 1 |
| **4** | -6.764470 | 4.611465 | 15.637133 | 1 |

***Explanation:***

Here in the code, PCA with 3 principal components is applied on scaled x.

Finally, made a data frame containing principal components and target variable column with the help of $concat(\,)$ function.

## Question 2. c:

Use SVM to report performance.

### *Part-1:*

### *Source code:*

```
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)
```

### *Part-2:*

### *Source code:*

```
# Creating an instance of the SVM classifier with default hyperparameters.
svmClassifier = SVC()

# Fitting the training data X_train and y_train to the SVM classifier.
svmClassifier.fit(X_train, y_train)

# Predicting the target variable using the test set X_test.
y_pred = svmClassifier.predict(X_test)

# Summary of the predictions made by the classifier
print('Confusion Matrix:\n', confusion_matrix(y_test, y_pred))
print('\nclassification Report:\n', classification_report(y_test, y_pred, zero_division=1))

# Accuracy score
glass_acc_svc = accuracy_score(y_pred,y_test)
print('accuracy is', glass_acc_svc )

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

### *Output:*

```
Confusion Matrix:
 [[ 26  36]
 [ 13 183]]

classification Report:
              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

accuracy is 0.810077519379845
Silhouette Score:  0.2504463899791047
```

***Explanation:***

Here in the code, I have split the finalDf made previously into 2 Data frames one as X (Predictor variable) and y (target variable). With X and y we have made train and test data using $train\_test\_split(\ )$ function.

Created an instance of an SVM classifier with default hyperparameters and fits it to the training data (X_train and y_train). The classifier is then used to predict the target variable using the test set (X_test). The confusion matrix, classification report, accuracy score and silhouette score are computed and are printed.

## Question 3:

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

***Part-1***

***Source code:***

```
# Loading the dataset
df_iris = pd.read_csv('Iris.csv')
print(df_iris.info())
df_iris.head()
```

***Output:***

```
<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
None
```

| | 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 |

## *Part-2*

### *Source code & Output:*

```
df_iris.isnull().any()
```

```
Id               False
SepalLengthCm    False
SepalWidthCm     False
PetalLengthCm    False
PetalWidthCm     False
Species          False
dtype: bool
```

## *Part-3*

### *Source code & Output:*

```
x = df_iris.iloc[:,1:-1].values
y = df_iris.iloc[:,-1].values
print(x.shape,y.shape)

X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.3, random_state=0)
```

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

## *Part-4*

### *Source code & Output:*

```
sc = StandardScaler()

# fit and transform the scaler object on our training data and only transform our test data.
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

# LabelEncoder to encode our target variable y into numerical values.
le = LabelEncoder()
y_test = le.fit_transform(y_test)
y_train = le.fit_transform(y_train)

# (LDA) is used to perform dimensionality reduction on our input features x.
# Here, we are reducing the number of input features to 2 using n_components=2
lda = LDA(n_components=2)

# we transform our training and test data using the fit_transform and transform methods of the LDA object respectively
X_train = lda.fit_transform(X_train, y_train)
X_test = lda.transform(X_test)
print(X_train.shape, X_test.shape)
```

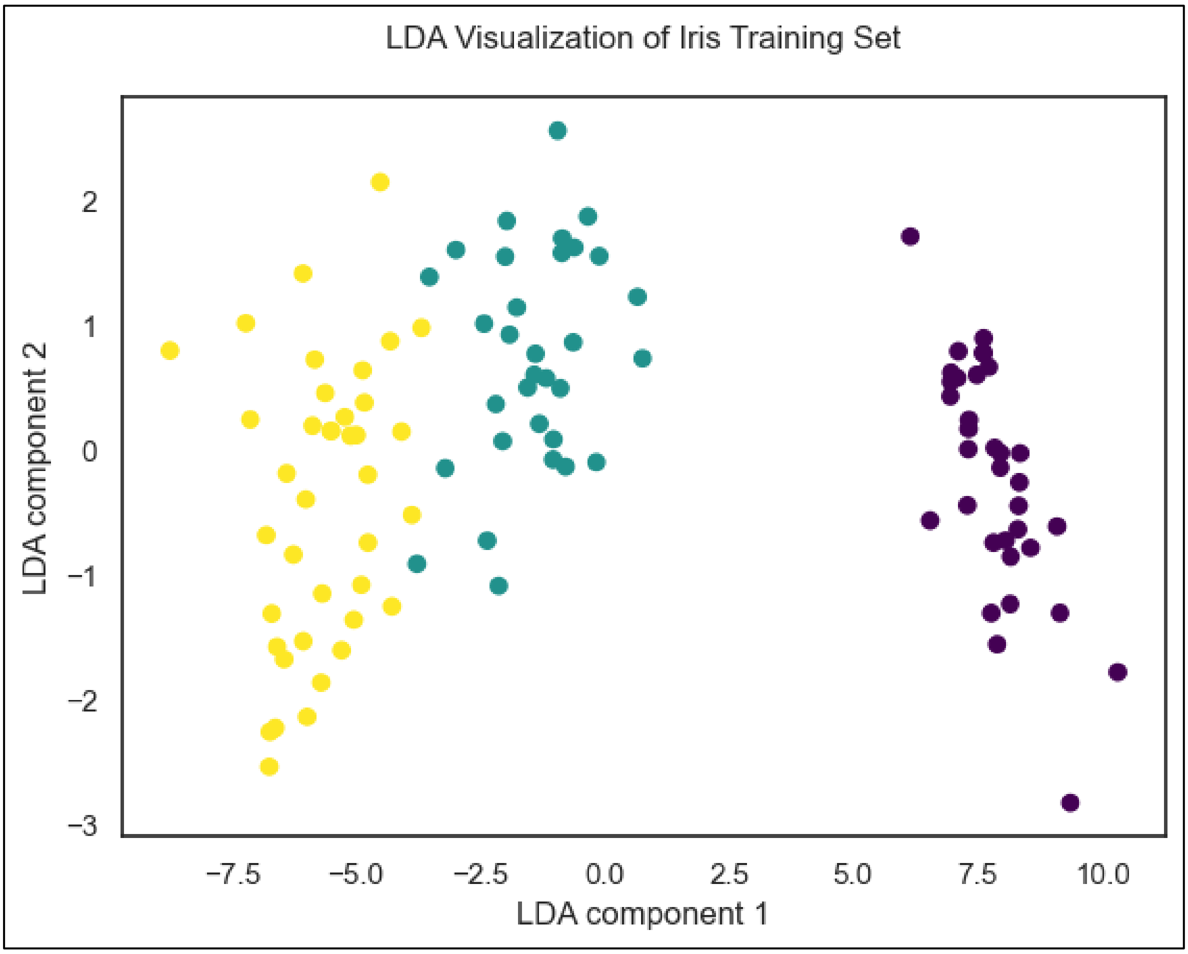
```
(105, 2) (45, 2)
```

## *Part-5*

### *Source code:*

```
# Plot the training set
plt.figure(figsize=(7, 5))
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap='viridis')
plt.xlabel('LDA component 1')
plt.ylabel('LDA component 2')
plt.title('LDA Visualization of Iris Training Set\n')
plt.show()
```

***Output:***

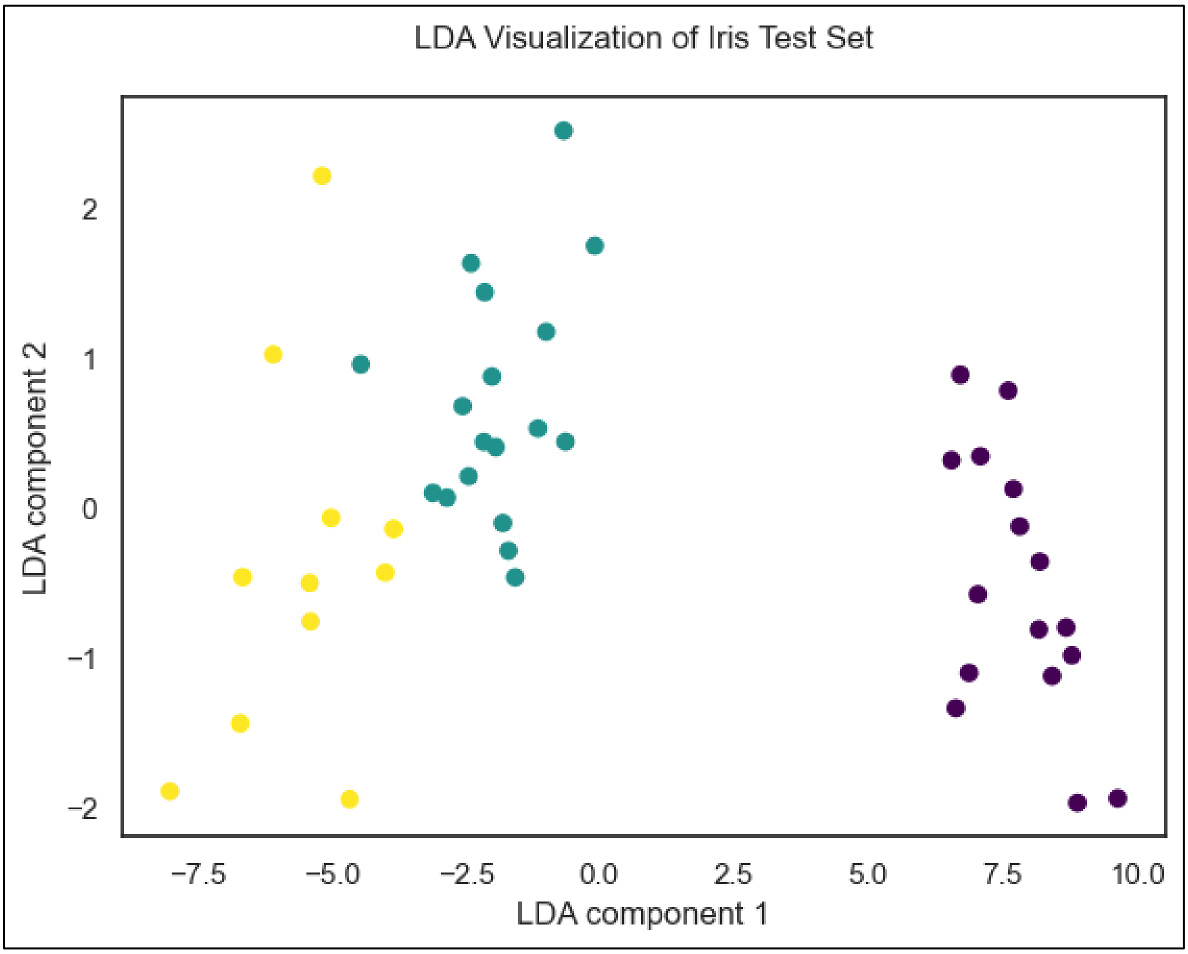



***Part-6***

***Source code:***

```
# Plot the test set
plt.figure(figsize=(7, 5))
plt.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap='viridis')
plt.xlabel('LDA component 1')
plt.ylabel('LDA component 2')
plt.title('LDA Visualization of Iris Test Set\n')
plt.show()
```

***Output:***




***Explanation:***

Here in the code, I have used $\boldsymbol{read\_csv}(\,)$, $\boldsymbol{info}(\,)$ and $\boldsymbol{head}(\,)$functions to read CSV file (Iris.csv), display the info and to display the first 5 rows of the $DataFrame$ respectively. Checked for any null values and there are no null values.

Made two Data Frame's namely X and y from the original DataFrame. X contains all columns except the **class** column which is a target variable. y contains the DataFrame with target variable. With X and y we have made train and test data using $train\_test\_split(\,)$ function.

The features in $\boldsymbol{X\_train}$ are standardized by subtracting the mean and dividing by the standard deviation of each feature using the $StandardScaler$ object. $LabelEncoder$ to encode our target variable y into numerical values.

Linear Discriminant Analysis (LDA) is used to perform dimensionality reduction on the input features x. The $n\_components$ parameter is set to 2 to reduce the number of input features to 2. The $fit\_transform(\,)$ method of LDA is used to transform the training data and the

$transform()$ method is used to transform the test data. Finally, the shape of the transformed training and test data is printed.

Based on the reduced dimension components, scatter plots were drawn separately for the Training set and the test set.

## Question 4:

Briefly identify the difference between PCA and LDA.

***Answer:***

Machine learning and data analysis commonly use dimensionality reduction techniques, which include Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

By discovering new features that are linear combinations of the original features, PCA is an unsupervised technique that lowers the dimensionality of the data. According to how much variance in the data they account for, these additional attributes are ranked. PCA seeks to maximize data variance while using the fewest possible characteristics.

LDA, on the other hand, is a supervised approach that maximizes the separation between several classes while projecting the data into a lower-dimensional space. Finding a new feature space with well-separated classes in the data is the aim of LDA. The goal of LDA is to maximize the difference between-class variance and within-class variance ratio.

In conclusion, LDA is a supervised method that seeks to identify features that maximize class separability, in contrast to PCA, which is an unsupervised method that strives to retain the general structure of the data by maximizing variance.

**- - - - *End* - - - -**