MACHINE LEARNING

ASSSIGNMENT –5

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LINK:
https://github.com/Manisha3196/ML/blob/7978f6382fd83c525712a2a9e98c025fde39b3f3/README.md

VIDEO LINK: Screen Recording 2023-04-15 at 7.50.31 PM.mov

1. Principal Component Analysis

a. Apply PCA on CC dataset.

```
from google.colab import drive
drive.mount('/content/gdrive')
path_to_csv = '/content/gdrive/My Drive/datasets/CC GENERAL.csv'
import warnings
warnings.filterwarnings("ignore")
```

```
from sklearn.model_selection import train_test_split
import pandas as pd
from sklearn.decomposition import PCA
#Reading the csv file using pandas
cc = pd.read_csv(path_to_csv)
# Fill null values with mean
cc.fillna(cc.mean(),inplace=True)
cc = cc.drop(['CUST_ID'], axis=1)

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
# Fit on data
scaler.fit(cc)
# Apply transform on the data
cc_scaler = scaler.transform(cc)
pca = PCA(2)
cc_pca = pca.fit_transform(cc_scaler)
cc_pca_df = pd.DataFrame(data=cc_pca, columns=['PC1','PC2'])
print(cc_pca_df)
```

```
            PC1       PC2
0    -1.682220 -1.076449
1    -1.138293  2.506498
2     0.969680 -0.383515
3    -0.873626  0.043171
4    -1.599434 -0.688581
...        ...       ...
8945 -0.359630 -2.016150
8946 -0.564366 -1.639141
8947 -0.926203 -1.810792
8948 -2.336550 -0.657981
8949 -0.556423 -0.400476

[8950 rows x 2 columns]
```

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

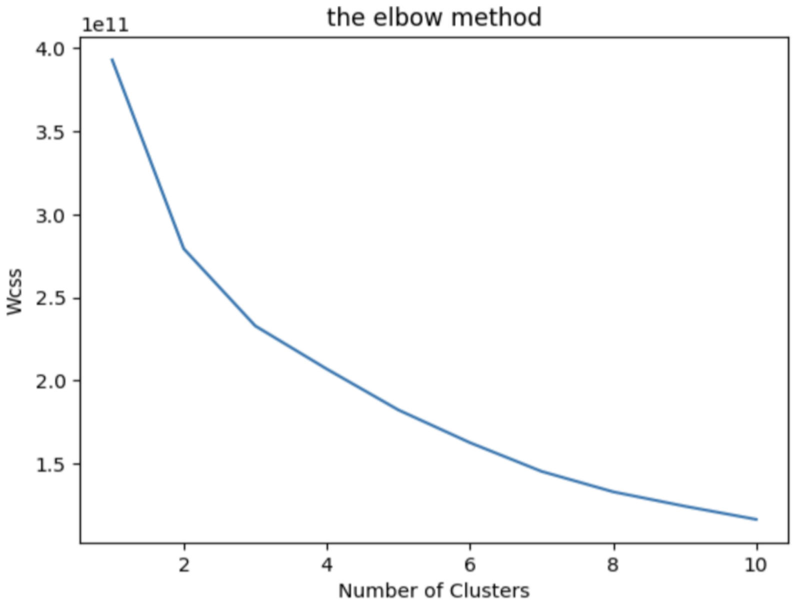
```
[ ] from sklearn.cluster import KMeans
    nclusters = 3
    km = KMeans(n_clusters=nclusters)
    km.fit(cc_scaler)

    # predicting the cluster for each data point
    cc_cluster_kmeans = km.predict(cc_scaler)
    from sklearn import metrics
    score = metrics.silhouette_score(cc_scaler, cc_cluster_kmeans)
    print('Silhoutte score on the original data:', score)

    Silhoutte score on the original data: 0.25059934300557285
```

```
[ ] km_pca = KMeans(n_clusters=nclusters)
    km_pca.fit(cc_pca)

    # predict the cluster for each data point
    cc_pca_kmeans = km_pca.predict(cc_pca)

    score_pca = metrics.silhouette_score(cc_pca, cc_pca_kmeans)
    print('Silhoutte score on the PCA result:', score_pca)

    Silhoutte score on the PCA result: 0.45232482021149406
```

As, We can see the silhoute score is improved.

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

```
[ ] # elbow method to know the number of clusters
    import matplotlib.pyplot as plt
    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(cc)
        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()
```



By considering the above graph, we can conisder k=2 and k=3.

Below is the report performance for k=2

```
[ ] # For k = 2
    #Reading the csv file using pandas
    cc = pd.read_csv(path_to_csv)
    cc = cc.drop(['CUST_ID'], axis=1)
    cc.fillna(cc.mean(), inplace=True)
    scaler = StandardScaler()
    # Fit and transform on the data
    cc_scaler = scaler.fit_transform(cc)
    pca = PCA(2)
    cc_pca = pca.fit_transform(cc_scaler)
    km = KMeans(n_clusters=2)
    km.fit(cc_pca)
    cc_pca_kmeans = km.predict(cc_pca)

    score = metrics.silhouette_score(cc_pca, cc_pca_kmeans)
    # Find accuracy, classification repport and silhoutte score
    print('Accuracy:',metrics.accuracy_score(cc_cluster_kmeans,cc_pca_kmeans))
    print('Report:',metrics.classification_report(cc_cluster_kmeans,cc_pca_kmeans))
    print('Silhoutte score for k=2:', score)
```

```
Accuracy: 0.6751955307262569
Report:               precision    recall  f1-score   support

           0       0.80      0.97      0.88      6119
           1       0.08      0.08      0.08      1599
           2       0.00      0.00      0.00      1232

    accuracy                           0.68      8950
   macro avg       0.29      0.35      0.32      8950
weighted avg       0.56      0.68      0.61      8950

Silhoutte score for k=2: 0.4647557458980701
```

Below is the report performance for k=3

```
[ ] # For k = 3
    #Reading the csv file using pandas
    cc = pd.read_csv(path_to_csv)
    cc = cc.drop(['CUST_ID'], axis=1)
    cc.fillna(cc.mean(), inplace=True)
    scaler = StandardScaler()
    cc_scaler = scaler.fit_transform(cc)
    pca = PCA(2)
    cc_pca = pca.fit_transform(cc_scaler)
    km = KMeans(n_clusters=3)
    km.fit(cc_pca)
    cc_pca_kmeans = km.predict(cc_pca)

    score = metrics.silhouette_score(cc_pca, cc_pca_kmeans)
    # Find accuracy, classification repport and silhoutte score
    print('Accuracy:',metrics.accuracy_score(cc_cluster_kmeans,cc_pca_kmeans))
    print('Report:',metrics.classification_report(cc_cluster_kmeans,cc_pca_kmeans))
    print('Silhoutte score for k=3:', score)
```

```
Accuracy: 0.6748603351955307
Report:               precision    recall  f1-score   support

           0       0.99      0.99      0.99      6119
           1       0.01      0.01      0.01      1599
           2       0.00      0.00      0.00      1232

    accuracy                           0.67      8950
   macro avg       0.33      0.33      0.33      8950
weighted avg       0.68      0.67      0.68      8950

Silhoutte score for k=3: 0.452324328180543
```

2. Use pd_speech_features.csv

a. Perform Scaling. b. Apply PCA (k=3) c. Use SVM to report performance

```
] path = '/content/gdrive/My Drive/datasets/pd_speech_features.csv'
  #Reading the csv file using pandas
  sf = pd.read_csv(path)
  X = sf.iloc[:, 1:-1].values
  y = sf.iloc[:, -1].values
  scaler = StandardScaler()
  sf_scaler = scaler.fit_transform(X)
  pca = PCA(3)
  sf_pca = pca.fit_transform(sf_scaler)
  X_train, X_test, y_train, y_test = train_test_split(sf_pca, y, test_size = 0.2, random_state = 0)
  # SVM model
  from sklearn.svm import SVC

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

  y_pred = classifier.predict(X_test)

  # Summary of the predictions made by the classifier
  print(metrics.classification_report(y_test, y_pred))
  print(metrics.confusion_matrix(y_test, y_pred))
  # Accuracy score
  from sklearn.metrics import accuracy_score
  print('accuracy is',accuracy_score(y_pred,y_test))
```

```
              precision    recall  f1-score   support

           0       0.67      0.42      0.52        38
           1       0.83      0.93      0.88       114

    accuracy                           0.80       152
   macro avg       0.75      0.68      0.70       152
weighted avg       0.79      0.80      0.79       152

[[ 16  22]
 [  8 106]]
accuracy is 0.8026315789473685
```

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

```python
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
path_to_iris = '/content/gdrive/My Drive/datasets/Iris.csv'
#Reading the csv file using pandas
iris = pd.read_csv(path_to_iris)
x = iris.iloc[:,[1,2,3,4]]
y = iris.iloc[:,-1]
lda = LinearDiscriminantAnalysis(n_components=2)
pca = PCA(n_components=2)
iris_lda = lda.fit_transform(x, y)
iris_pca = pca.fit_transform(x)
iris_lda_df = pd.DataFrame(data=iris_lda, columns=['PC1','PC2'])
iris_lda_df
```

	PC1	PC2
0	8.084953	0.328454
1	7.147163	-0.755473
2	7.511378	-0.238078
3	6.837676	-0.642885
4	8.157814	0.540639
...	...	...
145	-5.674013	1.661346
146	-5.197129	-0.365506
147	-4.981712	0.812973
148	-5.901486	2.320751
149	-4.684009	0.325081

150 rows × 2 columns

```python
iris_pca_df = pd.DataFrame(data=iris_pca, columns=['PC1','PC2'])
iris_pca_df
```

	PC1	PC2
0	-2.684207	0.326607
1	-2.715391	-0.169557
2	-2.889820	-0.137346
3	-2.746437	-0.311124
4	-2.728593	0.333925
...	...	...
145	1.944017	0.187415
146	1.525664	-0.375021
147	1.764046	0.078519
148	1.901629	0.115877
149	1.389666	-0.282887

150 rows × 2 columns

```
[ ]  iris.var()
```

```
Id                  1887.500000
SepalLengthCm          0.685694
SepalWidthCm           0.188004
PetalLengthCm          3.113179
PetalWidthCm           0.582414
dtype: float64
```

```
[ ]  iris.mean()
```

```
Id                  75.500000
SepalLengthCm        5.843333
SepalWidthCm         3.054000
PetalLengthCm        3.758667
PetalWidthCm         1.198667
dtype: float64
```

As we can see, the absolute values of result of lda are around mean values whereas the absolute values of the results of pca are around the variance.

4. Briefly identify the difference between PCA and LDA

Both PCA and LDA are linear transformation techniques. However, PCA is an unsupervised while LDA is a supervised dimensionality reduction technique.

Principal Component Analysis

PCA summarizes the feature set without relying on the output. PCA tries to find the directions of the maximum variance in the dataset. In a large feature set, there are many features that are merely duplicate of the other features or have a high correlation with the other features. Such features are basically redundant and can be ignored. The role of PCA is to find such highly correlated or duplicate features and to come up with a new feature set where there is minimum correlation between the features or in other words feature set with maximum variance between the features. Since the variance between the features doesn't depend upon the output, therefore PCA doesn't take the output labels into account.

Linear Discriminant Analysis

LDA tries to reduce dimensions of the feature set while retaining the information that discriminates output classes. LDA tries to find a decision boundary around each cluster of a class. It then projects the data points to new dimensions in a way that the clusters are as separate from each other as possible and the individual elements within a cluster are as close to the centroid of the cluster as possible. The new dimensions are ranked on the basis of their ability to maximize the distance between the clusters and minimize the distance between the data points within a cluster and their centroids. These new dimensions form the linear discriminants of the feature set.