UCS2612 Machine Learning Laboratory

A6 – K-Means Clustering Algorithm

Name: C B Ananya
Reg No: 3122215001010

Question:

Download the Human Activity Recognition Using Smartphones dataset from the link given below:
https://www.kaggle.com/datasets/uciml/human-activity-recognition-with-smartphones?resource=download

Human Activity Recognition database built from the recordings of 30 subjects performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors.

Develop a python program to cluster the human activity using K-means clustering algorithm. Visualize the features from the dataset and interpret the results obtained by the model using Matplotlib library. [CO1, K3]

Use the following steps to do implementation:

1. Loading the dataset.
2. Pre-Processing the data (Handling missing values, Encoding, Normalization, Standardization).
3. Exploratory Data Analysis.
4. Feature Engineering techniques.
5. Split the data into training, testing and validation sets.
6. Cluster the data using Euclidean distance metric.
7. Measure the performance of the model.
8. Represent the clustered data using graphs.

GitHub Main Branch Link:
https://github.com/CB-Ananya/ML-Lab

Import necessary Modules

In [ ]:
```
import pandas as pd
import numpy as np

from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif

from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
from sklearn.decomposition import PCA

from sklearn.linear_model import Ridge
from sklearn.feature_selection import SelectFromModel

import matplotlib.pyplot as plt

from sklearn.preprocessing import LabelEncoder

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, davies_bouldin_score
```

Loading and Reading the Training and Testing Dataset

In [ ]:
```
train_df=pd.read_csv("train.csv")
test_df=pd.read_csv("test.csv")
```

Display the Details about Training and Testing Dataset details

In [ ]:
```
print("\n\nThe Size of The Training Dataset : ",train_df.shape)
print("\nThe Size of The Training Dataset : ",test_df.shape)
```

```
The Size of The Training Dataset :  (7352, 563)

The Size of The Training Dataset :  (2947, 563)
```

Printing The Training and Testing Dataset Examples

In [ ]:
```
train_df
```

Out[ ]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185	-0.923527	-0.934724
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914	-0.957686	-0.943068
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668	-0.977469	-0.938692
3	0.279174	-0.026201	-0.123283	-0.996091	-0.983403	-0.990675	-0.997099	-0.982750	-0.989302	-0.938692
4	0.276629	-0.016570	-0.115362	-0.998139	-0.980817	-0.990482	-0.998321	-0.979672	-0.990441	-0.942469
...	...	...	...	...	...	...	...	...	...	...
7347	0.299665	-0.057193	-0.181233	-0.195387	0.039905	0.077078	-0.282301	0.043616	0.060410	0.210795
7348	0.273853	-0.007749	-0.147468	-0.235309	0.004816	0.059280	-0.322552	-0.029456	0.080585	0.117440
7349	0.273387	-0.017011	-0.045022	-0.218218	-0.103822	0.274533	-0.304515	-0.098913	0.332584	0.043999
7350	0.289654	-0.018843	-0.158281	-0.219139	-0.111412	0.268893	-0.310487	-0.068200	0.319473	0.101702
7351	0.351503	-0.012423	-0.203867	-0.269270	-0.087212	0.177404	-0.377404	-0.038678	0.229430	0.269013

7352 rows × 563 columns

In [ ]:
```
test_df
```

Out[ ]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X
0	0.257178	-0.023285	-0.014654	-0.938404	-0.920091	-0.667683	-0.952501	-0.925249	-0.674302	-0.894088
1	0.286027	-0.013163	-0.119083	-0.975415	-0.967458	-0.944958	-0.986799	-0.968401	-0.945823	-0.894088
2	0.275485	-0.026050	-0.118152	-0.993819	-0.969926	-0.962748	-0.994403	-0.970735	-0.963483	-0.939260
3	0.270298	-0.032614	-0.117520	-0.994743	-0.973268	-0.967091	-0.995274	-0.974471	-0.968897	-0.938610
4	0.274833	-0.027848	-0.129527	-0.993852	-0.967445	-0.978295	-0.994111	-0.965953	-0.977346	-0.938610
...	...	...	...	...	...	...	...	...	...	...
2942	0.310155	-0.053391	-0.099109	-0.287866	-0.140589	-0.215088	-0.356083	-0.148775	-0.232057	0.185361
2943	0.363385	-0.039214	-0.105915	-0.305388	0.028148	-0.196373	-0.373540	-0.030036	-0.270237	0.185361
2944	0.349966	0.030077	-0.115788	-0.329638	-0.042143	-0.250181	-0.388017	-0.133257	-0.347029	0.007471
2945	0.237594	0.018467	-0.096499	-0.323114	-0.229775	-0.207574	-0.392380	-0.279610	-0.289477	0.007471
2946	0.153627	-0.018437	-0.137018	-0.330046	-0.195253	-0.164339	-0.430974	-0.218295	-0.229933	-0.111527

2947 rows × 563 columns

Data Preprocessing (Handling Missing values)

In [ ]:
```
print("The Missing Values in The Training Dataset\n\n",train_df.isnull().sum())
```

```
The Missing Values in The Training Dataset

 tBodyAcc-mean()-X       0
tBodyAcc-mean()-Y       0
tBodyAcc-mean()-Z       0
tBodyAcc-std()-X        0
tBodyAcc-std()-Y        0
                       ..
angle(X,gravityMean)    0
angle(Y,gravityMean)    0
angle(Z,gravityMean)    0
subject                 0
Activity                0
Length: 563, dtype: int64
```

In [ ]:
```
print("The Missing Values in The Testing Dataset\n\n",test_df.isnull().sum())
```

```
The Missing Values in The Testing Dataset

 tBodyAcc-mean()-X       0
tBodyAcc-mean()-Y       0
tBodyAcc-mean()-Z       0
tBodyAcc-std()-X        0
tBodyAcc-std()-Y        0
                       ..
angle(X,gravityMean)    0
angle(Y,gravityMean)    0
angle(Z,gravityMean)    0
subject                 0
Activity                0
Length: 563, dtype: int64
```

Display The Features in Dataset

In [ ]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7352 entries, 0 to 7351
Columns: 563 entries, tBodyAcc-mean()-X to Activity
dtypes: float64(561), int64(1), object(1)
memory usage: 31.6+ MB
```

In [ ]:
```
x=train_df.drop(columns={"Activity"})
y=train_df["Activity"]
```

Feature Engineering Techniques

1. Select Best K (Filter method)

2. Ridge Regression (Embedded Method)

3. PCA

1) Select Best K (Filter method)

In [ ]:
```
test = SelectKBest(score_func=f_classif, k=5)
fit = test.fit(x, y)
np.set_printoptions(precision=10)

features = fit.transform(x)

selected_indices = fit.get_support(indices=True)

selected_feature_names = x.columns[selected_indices]

print("Selected feature names : \n")
print(selected_feature_names)
```

```
Selected feature names :

Index(['tGravityAcc-mean()-X', 'tGravityAcc-max()-X', 'tGravityAcc-min()-X',
       'fBodyAccJerk-entropy()-X', 'fBodyAccJerk-entropy()-Y'],
      dtype='object')
```

In [ ]:
```
train_df1 = train_df[selected_feature_names].copy()
test_df1 = test_df[selected_feature_names].copy()
```

In [ ]:
```
print("\nAfter Feature Selection The Shape of The Training Dataset : ",train_df1.shape)
print("After Feature Selection The Shape of The Testing Dataset  : ",test_df1.shape)
```

```
After Feature Selection The Shape of The Training Dataset :  (7352, 5)
After Feature Selection The Shape of The Testing Dataset  :  (2947, 5)
```

In [ ]:
```
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, n_init=10, random_state=42)
kmeans.fit(train_df1)
train_clusters = kmeans.predict(train_df1)
test_clusters = kmeans.predict(test_df1)
cluster_centroids = kmeans.cluster_centers_
```

In [ ]:
```
silhouette_avg11 = silhouette_score(train_df1, train_clusters)
silhouette_avg12 = silhouette_score(test_df1, test_clusters)
print(f"Silhouette Score ( Training dataset )   : {silhouette_avg11}")
print(f"Silhouette Score ( Testing dataset  )   : {silhouette_avg12}")
```

```
Silhouette Score ( Training dataset )   : 0.8270090285139965
Silhouette Score ( Testing dataset  )   : 0.830854104944898
```

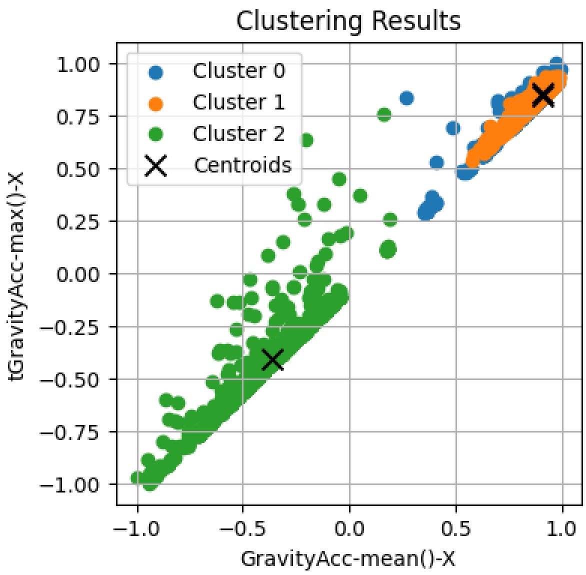
In [ ]:
```
plt.figure(figsize=(4, 4))

for cluster in range(n_clusters):
    cluster_data = train_df1[train_clusters == cluster]

    plt.scatter(cluster_data['tGravityAcc-mean()-X'], cluster_data['tGravityAcc-max()-X'], label=f'Cluster {clus

plt.scatter(cluster_centroids[:, 0], cluster_centroids[:, 1], marker='x', color='black', s=100, label='Centroids

plt.title('Clustering Results')
plt.xlabel('GravityAcc-mean()-X')
plt.ylabel('tGravityAcc-max()-X')
plt.legend()
plt.grid(True)
plt.show()
```



2) Ridge Regression (Embedded Method)

In [ ]:
```
label_encoder = LabelEncoder()
y_encoded = label_encoder.fit_transform(y)

ridge = Ridge(alpha=1.0)
select_from_model = SelectFromModel(ridge, max_features=8)
select_from_model.fit(x, y_encoded)
features_selected = select_from_model.transform(x)
selected_indices = select_from_model.get_support(indices=True)
selected_feature_names = x.columns[selected_indices]
print("Selected feature names : \n")
print(selected_feature_names)
```

```
Selected feature names :

Index(['tBodyAcc-std()-X', 'tBodyAcc-sma()', 'tGravityAcc-std()-X',
       'tBodyGyroJerk-std()-Z', 'tBodyGyroJerk-energy()-Z', 'fBodyAcc-std()-X',
       'fBodyGyro-bandsEnergy()-9,16.2', 'fBodyGyro-bandsEnergy()-17,32.2'],
      dtype='object')
```

In [ ]:
```
train_df2 = train_df[selected_feature_names].copy()
test_df2 = test_df[selected_feature_names].copy()
```

In [ ]:
```
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, n_init=10, random_state=42)
kmeans.fit(train_df2)
train_clusters = kmeans.predict(train_df2)
test_clusters = kmeans.predict(test_df2)
cluster_centroids = kmeans.cluster_centers_
```

In [ ]:
```
silhouette_avg21 = silhouette_score(train_df2, train_clusters)
silhouette_avg22 = silhouette_score(test_df2, test_clusters)
print(f"Silhouette Score ( Training dataset )   : {silhouette_avg21}")
print(f"Silhouette Score ( Testing dataset  )   : {silhouette_avg22}")
```

```
Silhouette Score ( Training dataset )   : 0.7140380577893611
Silhouette Score ( Testing dataset  )   : 0.7355803254687658
```

In [ ]:
```
plt.figure(figsize=(4, 4))

for cluster in range(n_clusters):
    cluster_data = train_df2[train_clusters == cluster]

    plt.scatter(cluster_data['tBodyAcc-std()-X'], cluster_data['tBodyAcc-sma()'], label=f'Cluster {cluster}')

plt.scatter(cluster_centroids[:, 0], cluster_centroids[:, 1], marker='x', color='black', s=100, label='Centroids

plt.title('Clustering Results')
plt.xlabel('GravityAcc-mean()-X')
plt.ylabel('tGravityAcc-max()-X')
plt.legend()
plt.grid(True)
plt.show()
```

3) PCA

In [ ]:
```
pca = PCA(n_components=11)

pca.fit(x)

selected_feature_indices = pca.components_

selected_feature_names = [x.columns[i] for i in range(len(selected_feature_indices))]

print("Selected feature names:")
print(selected_feature_names)
```

```
Selected feature names:
['tBodyAcc-mean()-X', 'tBodyAcc-mean()-Y', 'tBodyAcc-mean()-Z', 'tBodyAcc-std()-X', 'tBodyAcc-std()-Y', 'tBodyAcc
-std()-Z', 'tBodyAcc-mad()-X', 'tBodyAcc-mad()-Y', 'tBodyAcc-mad()-Z', 'tBodyAcc-max()-X', 'tBodyAcc-max()-Y']
```

In [ ]:
```
train_df3 = train_df[selected_feature_names].copy()
test_df3 = test_df[selected_feature_names].copy()
```

In [ ]:
```
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, n_init=10, random_state=42)
kmeans.fit(train_df3)
train_clusters = kmeans.predict(train_df3)
test_clusters = kmeans.predict(test_df3)
cluster_centroids = kmeans.cluster_centers_
```

In [ ]:
```
silhouette_avg31 = silhouette_score(train_df3, train_clusters)
silhouette_avg32 = silhouette_score(test_df3, test_clusters)
print(f"Silhouette Score ( Training dataset )   : {silhouette_avg31}")
print(f"Silhouette Score ( Testing dataset  )   : {silhouette_avg32}")
```

```
Silhouette Score ( Training dataset )   : 0.6488163273987868
Silhouette Score ( Testing dataset  )   : 0.6478744052260157
```

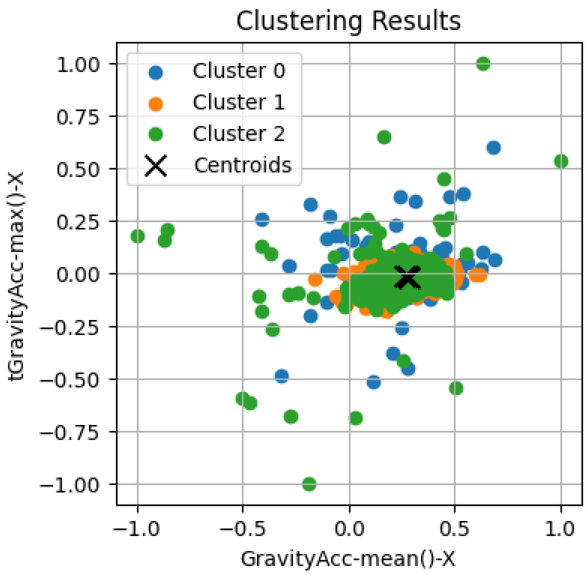
In [ ]:
```
plt.figure(figsize=(4, 4))

for cluster in range(n_clusters):
    cluster_data = train_df3[train_clusters == cluster]

    plt.scatter(cluster_data['tBodyAcc-mean()-X'], cluster_data['tBodyAcc-mean()-Y'], label=f'Cluster {cluster}'

plt.scatter(cluster_centroids[:, 0], cluster_centroids[:, 1], marker='x', color='black', s=100, label='Centroids

plt.title('Clustering Results')
plt.xlabel('GravityAcc-mean()-X')
plt.ylabel('tGravityAcc-max()-X')
plt.legend()
plt.grid(True)
plt.show()
```



-1 <= Silhouette score <= 1

A Silhouette score of 1 indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters.

A Silhouette score of 0 indicates that the object is on or very close to the decision boundary between two neighboring clusters.

A Silhouette score of -1 indicates that the object is poorly matched to its own cluster and well matched to neighboring clusters.

1. Select Best K (Filter method)

print(f"Silhouette Score (Training dataset) : {silhouette_avg11}") print(f"Silhouette Score (Testing dataset) : {silhouette_avg12}")

2. Ridge Regression

print(f"Silhouette Score (Training dataset) : {silhouette_avg21}") print(f"Silhouette Score (Testing dataset) : {silhouette_avg22}")

3. PCA

print(f"Silhouette Score (Training dataset) : {silhouette_avg31}") print(f"Silhouette Score (Testing dataset) : {silhouette_avg32}")

In [ ]:
```
print("\n\n1) Select Best K  (  Filter method )")

print(f"Silhouette Score ( Training dataset )   : {silhouette_avg11}")
print(f"Silhouette Score ( Testing dataset  )   : {silhouette_avg12}")


print("\n\n2) Ridge Regression")

print(f"Silhouette Score ( Training dataset )   : {silhouette_avg21}")
print(f"Silhouette Score ( Testing dataset  )   : {silhouette_avg22}")

print("\n\n3) PCA")

print(f"Silhouette Score ( Training dataset )   : {silhouette_avg31}")
print(f"Silhouette Score ( Testing dataset  )   : {silhouette_avg32}")
```

```
1) Select Best K  (  Filter method )
Silhouette Score ( Training dataset )   : 0.8270090285139965
Silhouette Score ( Testing dataset  )   : 0.830854104944898


2) Ridge Regression
Silhouette Score ( Training dataset )   : 0.7140380577893611
Silhouette Score ( Testing dataset  )   : 0.7355803254687658


3) PCA
Silhouette Score ( Training dataset )   : 0.6488163273987868
Silhouette Score ( Testing dataset  )   : 0.6478744052260157
```

The Model which was build using the Select best K feature Engineering techniques gives the best Silhouette Score. So This is the Best Model