UCS2612 Machine Learning Lab

Assignment on K Means Clustering with User Defined Functions

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Write the python code from scratch to implement K Means Clustering Algorithm without using Scikit-learn library or built in functions.

Code and Output

```
Importing Necessary Libraries
```

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix
import numpy as np
from scipy.optimize import linear_sum_assignment
```

```
Load The data Sets
```

```
train_set = pd.read_csv('train.csv')
test_set = pd.read_csv('test.csv')
train_set['index'] = train_set.index
test_set['index'] = test_set.index
```

```
y_train = train_set["Activity"]
X_train = train_set.drop(["Activity","subject"], axis=1)
y_test = test_set["Activity"]
X_test = test_set.drop(["Activity","subject"], axis=1)
```

```python
print("Column Names:", X_train.columns)
print("First few rows of X_train:")
print(X_train.head())
```

```
Column Names: Index(['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',
       ...
       'fBodyBodyGyroJerkMag-skewness()', 'fBodyBodyGyroJerkMag-kurtosis()',
       'angle(tBodyAccMean,gravity)', 'angle(tBodyAccJerkMean),gravityMean)',
       'angle(tBodyGyroMean,gravityMean)',
       'angle(tBodyGyroJerkMean,gravityMean)', 'angle(X,gravityMean)',
       'angle(Y,gravityMean)', 'angle(Z,gravityMean)', 'index'],
      dtype='object', length=562)
First few rows of X_train:
   tBodyAcc-mean()-X  tBodyAcc-mean()-Y  tBodyAcc-mean()-Z  tBodyAcc-std()-X  \
0           0.288585          -0.020294          -0.132905         -0.995279
1           0.278419          -0.016411          -0.123520         -0.998245
2           0.279653          -0.019467          -0.113462         -0.995380
3           0.279174          -0.026201          -0.123283         -0.996091
4           0.276629          -0.016570          -0.115362         -0.998139

   tBodyAcc-std()-Y  tBodyAcc-std()-Z  tBodyAcc-mad()-X  tBodyAcc-mad()-Y  \
0         -0.983111         -0.913526         -0.995112         -0.983185
1         -0.975300         -0.960322         -0.998807         -0.974914
2         -0.967187         -0.978944         -0.996520         -0.963668
3         -0.983403         -0.990675         -0.997099         -0.982750
4         -0.980817         -0.990482         -0.998321         -0.979672
...
3              0.181935             -0.047663      3
4              0.185151             -0.043892      4
```

```
Standarize the Columns
```

```python
scaler = StandardScaler()
for col in X_train.columns:
    X_train[col]  = scaler.fit_transform(X_train[[col]])
for col in X_test.columns:
    X_test[col]  = scaler.fit_transform(X_test[[col]])
```

```python
class KMeans:
    def _init_(self, n_clusters, max_iters=300):
        self.n_clusters = n_clusters
        self.max_iters = max_iters

    def fit(self, X):
        self.centroids = X[np.random.choice(X.shape[0], self.n_clusters,
replace=False)]

        for _ in range(self.max_iters):
            labels = self._assign_clusters(X)
            new_centroids = self._update_centroids(X, labels)
            if np.allclose(self.centroids, new_centroids):
                break

            self.centroids = new_centroids

        self.labels_ = self._assign_clusters(X)

    def _assign_clusters(self, X):
        distances = np.sqrt(((X - self.centroids[:,
np.newaxis])**2).sum(axis=2))
        return np.argmin(distances, axis=0)

    def _update_centroids(self, X, labels):
        new_centroids = np.zeros_like(self.centroids)
        for i in range(self.n_clusters):
            cluster_points = X[labels == i]
            if len(cluster_points) > 0:
                new_centroids[i] = cluster_points.mean(axis=0)
            else:
                new_centroids[i] = self.centroids[i]
        return new_centroids
```

```python
kmeans = KMeans(n_clusters=2)
kmeans.fit(X_train[['angle(X,gravityMean)',
'angle(tBodyAccMean,gravity)']].values)
y_pred_2 = kmeans.labels_
```

```python
import matplotlib.pyplot as plt

X = X_train[['angle(X,gravityMean)', 'angle(tBodyAccMean,gravity)']].values
```

```python
kmeans = KMeans(n_clusters=2)
kmeans.fit(X)
```

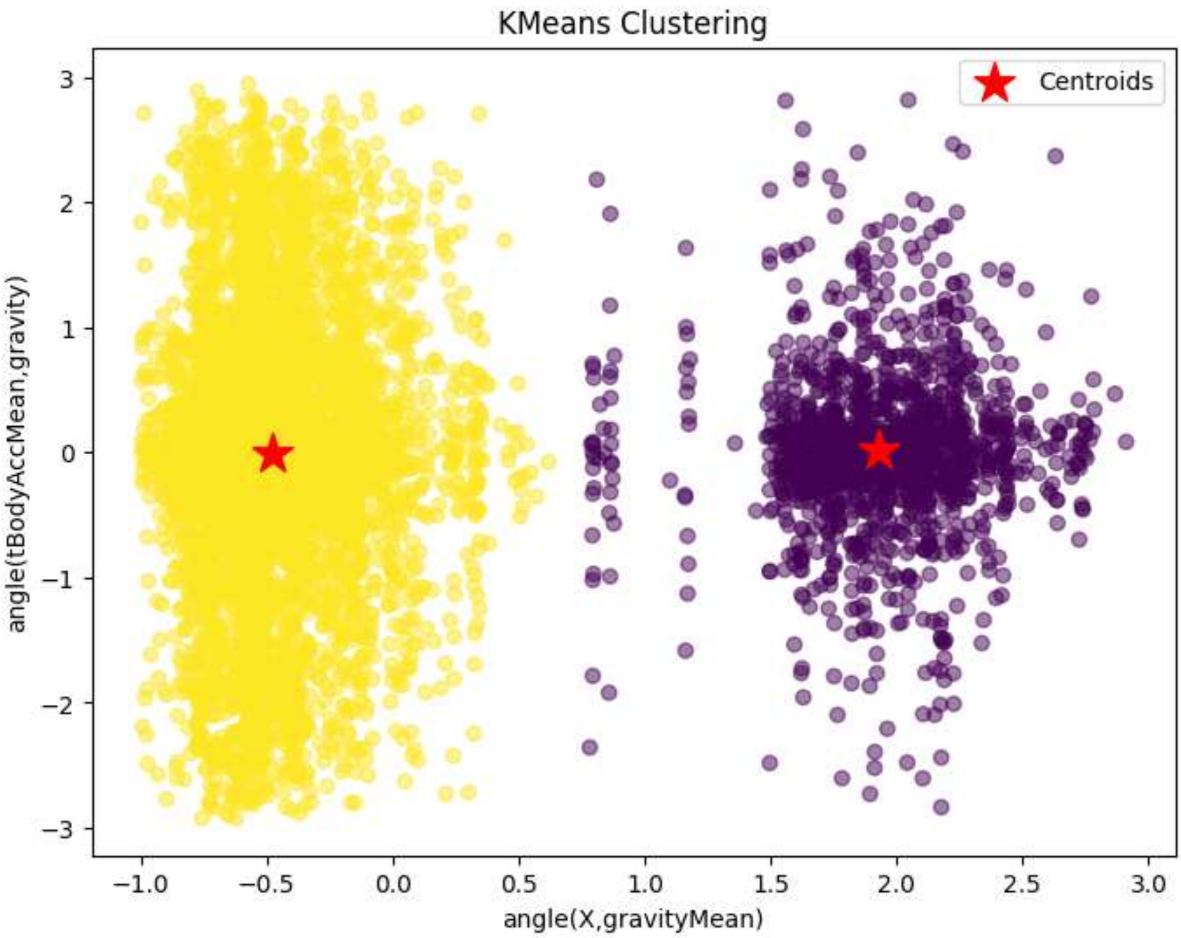
```
KMeans
KMeans(n_clusters=2)
```

```python
kmeans.fit(X_train[['angle(X,gravityMean)',
'angle(tBodyAccMean,gravity)']].values)
```

```
KMeans
KMeans(n_clusters=2)
```

```python
centroids = kmeans.cluster_centers_
labels = kmeans.labels_
```

```python
plt.figure(figsize=(8, 6))
plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis', alpha=0.5)
plt.scatter(centroids[:, 0], centroids[:, 1], marker='*', c='red', s=300,
label='Centroids')
plt.title('KMeans Clustering')
plt.xlabel('angle(X,gravityMean)')
plt.ylabel('angle(tBodyAccMean,gravity)')
plt.legend()
plt.show()
```




```
def two_labels(dataset):
    dataset_copied = dataset.copy()
    for label in range(len(dataset)):
        if dataset[label] == "SITTING":
            dataset[label] = 0
        elif dataset[label] == "LAYING":
            dataset[label] = 0
        elif dataset[label] == "STANDING":
            dataset[label] = 0
        elif dataset[label] == "WALKING_UPSTAIRS":
            dataset[label] = 1
        elif dataset[label] == "WALKING_DOWNSTAIRS":
            dataset[label] = 1
        elif dataset[label] == "WALKING":
            dataset[label] = 1
    return dataset_copied, dataset
```

```
y_train, y_train_2 = two_labels(y_train)
y_test, y_test_2 = two_labels(y_test)
```

```
conf_matrix = np.zeros((2,2))
for train_label, pred_label in zip(y_train_2.values, y_pred_2):
    conf_matrix[train_label][pred_label] +=1

row_ind, col_ind = linear_sum_assignment(1/conf_matrix)

interpret = dict(zip(col_ind, row_ind))
predicted_labels = np.array([interpret[label]
                            for label in y_pred_2])
print("Accuracy",np.mean(predicted_labels == y_train_2))
```

```
Accuracy 0.6451305767138193
```

```
class KMeans:
    def __init__(self, n_clusters, max_iters=300):
        self.n_clusters = n_clusters
        self.max_iters = max_iters

    def fit(self, X):
        self.centroids = X[np.random.choice(X.shape[0], self.n_clusters,
replace=False)]

        for _ in range(self.max_iters):
            labels = self._assign_clusters(X)
            new_centroids = self._update_centroids(X, labels)
            if np.allclose(self.centroids, new_centroids):
                break
            self.centroids = new_centroids
        self.labels_ = self._assign_clusters(X)
    def _assign_clusters(self, X):
        distances = np.sqrt(((X - self.centroids[:,
np.newaxis])**2).sum(axis=2))
        return np.argmin(distances, axis=0)
    def _update_centroids(self, X, labels):
        new_centroids = np.zeros_like(self.centroids)
        for i in range(self.n_clusters):
            cluster_points = X[labels == i]
            if len(cluster_points) > 0:
                new_centroids[i] = cluster_points.mean(axis=0)
```

```
            else:
                new_centroids[i] = self.centroids[i]

        return new_centroids
kmeans = KMeans(n_clusters=2)
kmeans.fit(X_train[['angle(X,gravityMean)',
'angle(tBodyAccMean,gravity)']].values)
y_pred_2 = kmeans.labels_
```

```
epsilon = 1e-9

conf_matrix += epsilon * np.eye(conf_matrix.shape[0])
cost_matrix = 1 / conf_matrix
row_ind, col_ind = linear_sum_assignment(cost_matrix)
interpret = dict(zip(col_ind, row_ind))
predicted_labels = np.array([interpret[label] for label in y_pred_2])
```

```
accuracy = np.mean(predicted_labels == y_train_2)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.6451305767138193
```

Learning outcomes

- Implement K-means clustering using user-defined functions to understand its core algorithmic concepts.
- Preprocess data effectively for K-means clustering, including techniques such as normalization and feature scaling.
- Utilize distance metrics like Euclidean distance to calculate cluster centroids and assign data points.
- Experiment with different values of 'k' to optimize cluster formation in K-means clustering.
- Evaluate clustering results using metrics such as silhouette score and within-cluster sum of squares (WCSS).
- Recognize challenges like selecting the appropriate number of clusters and handling outliers in K-means clustering.