Data Warehousing & Data Mining LAB - G2
EXPERIMENT 7

- ASHISH KUMAR
- 2K18/SE/041

Aim:- Write a program to implement K-Means Clustering Algorithm in any Language.

Theory: - **K-Means Clustering** is an Unsupervised Learning algorithm, which groups the unlabeled dataset into different clusters. Here K defines the number of pre-defined clusters that need to be created in the process, as if K=2, there will be two clusters, and for K=3, there will be three clusters, and so on.
It is an iterative algorithm that divides the unlabeled dataset into k different clusters in such a way that each dataset belongs only one group that has similar properties.

It allows us to cluster the data into different groups and a convenient way to discover the categories of groups in the unlabeled dataset on its own without the need for any training.

It is a centroid-based algorithm, where each cluster is associated with a centroid. The main aim of this algorithm is to minimize the sum of distances between the data point and their corresponding clusters.

Note: I have used **"old_faithful.csv"** data for this experiment.

Source Code (in python):

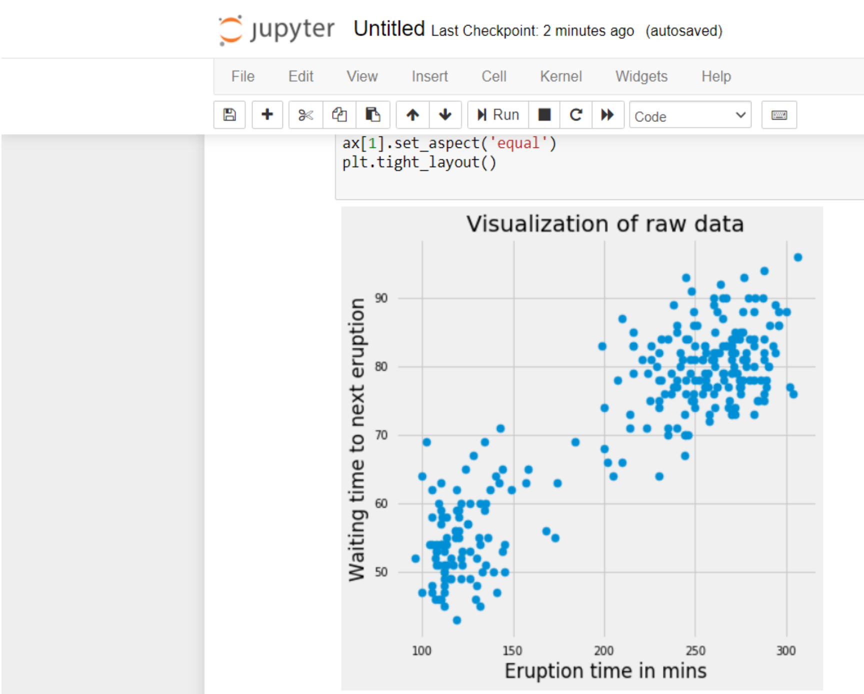
```
import numpy as np
from numpy.linalg import norm
import matplotlib.pyplot as plt
from matplotlib.image import imread
import pandas as pd
import seaborn as sns
from sklearn.datasets.samples_generator import (make_blobs, make_circles, make_moons)
from sklearn.cluster import KMeans, SpectralClustering
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_samples, silhouette_score

class Kmeans:
    '''Implementing Kmeans algorithm.'''

    def __init__(self, n_clusters, max_iter=100, random_state=123):
        self.n_clusters = n_clusters
        self.max_iter = max_iter
```

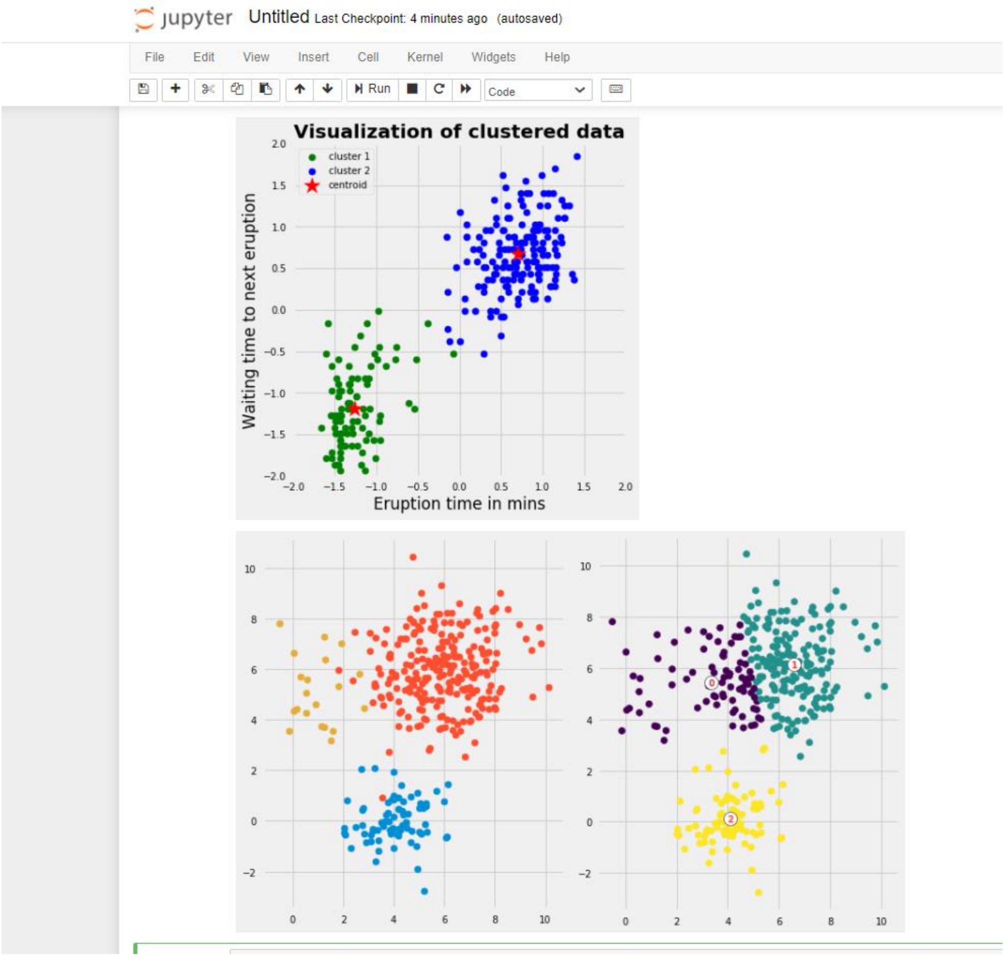
```
        self.random_state = random_state

    def initializ_centroids(self, X):
        np.random.RandomState(self.random_state)
        random_idx = np.random.permutation(X.shape[0])
        centroids = X[random_idx[:self.n_clusters]]
        return centroids

    def compute_centroids(self, X, labels):
        centroids = np.zeros((self.n_clusters, X.shape[1]))
        for k in range(self.n_clusters):
            centroids[k, :] = np.mean(X[labels == k, :], axis=0)
        return centroids

    def compute_distance(self, X, centroids):
        distance = np.zeros((X.shape[0], self.n_clusters))
        for k in range(self.n_clusters):
            row_norm = norm(X - centroids[k, :], axis=1)
            distance[:, k] = np.square(row_norm)
        return distance

    def find_closest_cluster(self, distance):
        return np.argmin(distance, axis=1)

    def compute_sse(self, X, labels, centroids):
        distance = np.zeros(X.shape[0])
        for k in range(self.n_clusters):
            distance[labels == k] = norm(X[labels == k] - centroids[k], axis=1)
        return np.sum(np.square(distance))

    def fit(self, X):
        self.centroids = self.initializ_centroids(X)
        for i in range(self.max_iter):
            old_centroids = self.centroids
            distance = self.compute_distance(X, old_centroids)
            self.labels = self.find_closest_cluster(distance)
            self.centroids = self.compute_centroids(X, self.labels)
            if np.all(old_centroids == self.centroids):
                break
        self.error = self.compute_sse(X, self.labels, self.centroids)

    def predict(self, X):
        distance = self.compute_distance(X, old_centroids)
        return self.find_closest_cluster(distance)
```

```
%matplotlib inline
sns.set_context('notebook')
plt.style.use('fivethirtyeight')
from warnings import filterwarnings
filterwarnings('ignore')

# Import the data
df = pd.read_csv('old_faithful.csv')

# Plot the data
plt.figure(figsize=(6, 6))
plt.scatter(df.iloc[:, 0], df.iloc[:, 1])
plt.xlabel('Eruption time in mins')
plt.ylabel('Waiting time to next eruption')
plt.title('Visualization of raw data');

# Standardize the data
X_std = StandardScaler().fit_transform(df)

# Run local implementation of kmeans
km = Kmeans(n_clusters=2, max_iter=100)
km.fit(X_std)
centroids = km.centroids

# Plot the clustered data
fig, ax = plt.subplots(figsize=(6, 6))
plt.scatter(X_std[km.labels == 0, 0], X_std[km.labels == 0, 1], c='green', label='cluster 1')
plt.scatter(X_std[km.labels == 1, 0], X_std[km.labels == 1, 1], c='blue', label='cluster 2')
plt.scatter(centroids[:, 0], centroids[:, 1], marker='*', s=300, c='r', label='centroid')
plt.legend()
plt.xlim([-2, 2])
plt.ylim([-2, 2])
plt.xlabel('Eruption time in mins')
plt.ylabel('Waiting time to next eruption')
plt.title('Visualization of clustered data', fontweight='bold')
ax.set_aspect('equal');

# Create data from three different multivariate distributions
X_1 = np.random.multivariate_normal(mean=[4, 0], cov=[[1, 0], [0, 1]], size=75)
X_2 = np.random.multivariate_normal(mean=[6, 6], cov=[[2, 0], [0, 2]], size=250)
X_3 = np.random.multivariate_normal(mean=[1, 5], cov=[[1, 0], [0, 2]], size=20)
df = np.concatenate([X_1, X_2, X_3])
```

```
# Run kmeans
km = KMeans(n_clusters=3)
km.fit(df)
labels = km.predict(df)
centroids = km.cluster_centers_

# Plot the data
fig, ax = plt.subplots(1, 2, figsize=(10, 10))
ax[0].scatter(X_1[:, 0], X_1[:, 1])
ax[0].scatter(X_2[:, 0], X_2[:, 1])
ax[0].scatter(X_3[:, 0], X_3[:, 1])
ax[0].set_aspect('equal')
ax[1].scatter(df[:, 0], df[:, 1], c=labels)
ax[1].scatter(centroids[:, 0], centroids[:, 1], marker='o',
              c="white", alpha=1, s=200, edgecolor='k')
for i, c in enumerate(centroids):
   ax[1].scatter(c[0], c[1], marker='$%d$' % i, s=50, alpha=1, edgecolor='r')
ax[1].set_aspect('equal')
plt.tight_layout()
```

<u>OUTPUT-</u>





Findings and Learning:

- We have successfully implemented k-means clustering in Python.
- K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem.