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Title:	Implementation of any one clustering algorithm using
	languages like JAVA/ python.
Date of	
Performance:	
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Vidyavardhini's College of Engineering and Technology

Department of Artificial Intelligence & Data Science

Aim: To Study and Implement K-Means algorithm

Objective:- Understand the working of K-Means algorithm and its implementation using python.

Theory:

In statistics and machine learning, k-means clustering is a method of cluster analysis which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean.

Input

K:-number of clusters

D:- data set containing n objects

Output

A set of k clusters

Given k, the k-means algorithm is implemented in 5 steps:

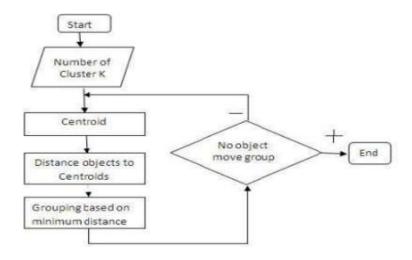
Step 1: Arbitrarily choose k objects from D as the initial cluster centers.

Step 2: Find the distance from each object in the dataset with respect to cluster centers

Step 3: Assign each object to the cluster with the nearest seed point based on the mean value of the objects in the cluster.

Step 4: Update the cluster means i.e calculate the mean value of the objects for each cluster.

Step 5: Repeat the procedure, until there is no change in meaning.



Example: $d = \{2,4,10,12,3,20,30,11,25\} k = 2$

1. Randomly assign mean m1=3 and m2=4

Therefore, $k1 = \{2,3\}$ Therefore, $k1 = \{4,10,12,20,30,11,25\}$

2. Randomly assign mean m1=2.5 and m2=16

Therefore, $k1 = \{2,3,4\}$ Therefore, k1 =

{4,10,12,20,30,11,25}

3. Randomly assign mean m1=3 and m2=18



Therefore, $k1 = \{2,3,4,10\}$ Therefore, $k1 = \{12,20,30,11,25\}$

4. Randomly assign mean m1=7 and m2=25

Therefore, $k1 = \{2,3,4,10,11,12\}$ Therefore, $k1 = \{20,30,25\}$

5. Randomly assign mean m1=7 and m2=25

Therefore, we stop as we are getting same mean values.

6. Therefore, Final clusters are: $k1 = \{2,3,4,10,11,12\}$ Therefore, $k1 = \{20,30,25\}$

CODE:

import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.cluster import KMeans

from sklearn.metrics import silhouette score, classification report

from sklearn.datasets import load iris

from sklearn.impute import SimpleImputer

Load the Iris dataset (or replace it with your dataset)

iris = load iris()

X = iris.data # Features

y = iris.target # Target labels (optional, if you're doing comparison)

Split the data into training and test sets

X train, X test, y train, y test = train test split(X, y, test size=0.3, random state=42)

Initialize and train the K-Means model

kmeans model = KMeans(n clusters=len(set(y)), random state=42)

kmeans model.fit(X train)



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# Predict the cluster labels on the test set
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y_pred = kmeans_model.predict(X_test)

Evaluate the model using Silhouette Score (common for clustering)

sil score = silhouette score(X test, y pred)

print(fSilhouette Score: {sil score}')

Optionally, compare predicted clusters with true labels using a classification report print(fClassification Report (with original labels):\n{classification report(y test, y pred)}')

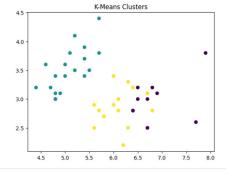
Plotting the clusters (optional, useful for visualizing 2D data)

plt.scatter(X test[:, 0], X test[:, 1], c=y pred, cmap='viridis')

plt.title('K-Means Clusters')

plt.show()

OUTPUT:





CONCLUSION:

What types of data preprocessing are necessary before applying the K-Means algorithm?

Before applying the K-Means algorithm, the following data preprocessing steps are necessary:

- 1. Data Cleaning: Remove duplicates and handle missing values (imputation or removal).
- 2. **Feature Scaling**: Normalize or standardize features to ensure they are on the same scale, as K-Means is sensitive to the magnitude of data.
- 3. **Encoding Categorical Variables**: Convert categorical variables to numerical format using techniques like one-hot encoding or label encoding.
- 4. **Outlier Detection**: Identify and address outliers, as they can skew the results of the clustering.
- 5. **Dimensionality Reduction**: If necessary, apply techniques like PCA to reduce the number of features and improve clustering performance.
- 6. **Data Transformation**: Consider transforming features (e.g., log transformation) to achieve a more normal distribution if needed.
- 7. **Selection of Relevant Features**: Use feature selection techniques to keep only the most relevant features for clustering.
- 8. Choosing the Number of Clusters (k): Use methods like the Elbow method or Silhouette score to determine an appropriate number of clusters.