

**Exp No: 5**

## **Clustering with K-Means and Dimensionality Reduction with PCA**

**Date : 28/8/25**

### **Aim:**

To demonstrate the application of Unsupervised Learning models, specifically K-Means clustering for grouping data points and Principal Component Analysis (PCA) for dimensionality reduction and visualization, using a suitable dataset.

### **Algorithm:**

#### **1. K-Means Clustering**

K-Means is an iterative clustering algorithm that aims to partition  $n$  observations into  $k$  clusters, where each observation belongs to the cluster with the nearest mean (centroid).

#### **Steps:**

1. **Initialization:** Choose  $k$  initial centroids randomly from the dataset.
2. **Assignment:** Assign each data point to the cluster whose centroid is closest (e.g., using Euclidean distance).
3. **Update:** Recalculate the centroids as the mean of all data points assigned to that cluster.
4. **Iteration:** Repeat steps 2 and 3 until the centroids no longer move significantly or a maximum number of iterations is reached.

#### **2. Principal Component Analysis (PCA)**

PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.

#### **Steps:**

1. **Standardization:** Standardize the dataset (mean = 0, variance = 1).
2. **Covariance Matrix Calculation:** Compute the covariance matrix of the standardized data.
3. **Eigenvalue Decomposition:** Calculate the eigenvalues and eigenvectors of the covariance matrix.
4. **Feature Vector Creation:** Sort the eigenvectors by decreasing eigenvalues and select the top  $k$  eigenvectors to form a feature vector (projection matrix).
5. **Projection:** Project the original data onto the new feature space using the feature vector.

### **CODE:**

```
# =====  
# EXPERIMENT — K-Means & PCA
```

```

# =====

# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.datasets import make_blobs
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score

# --- Part 1: K-Means Clustering ---

print("--- Part 1: K-Means Clustering ---")

# 1. Generate dataset
X, y = make_blobs(n_samples=300, centers=3, cluster_std=0.60, random_state=42)
df_kmeans = pd.DataFrame(X, columns=['Feature_1', 'Feature_2'])
print("\nOriginal K-Means Dataset Head:")
print(df_kmeans.head())

# 2. Elbow Method
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10,
random_state=42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.figure(figsize=(10, 6))
plt.plot(range(1, 11), wcss, marker='o', linestyle='--')
plt.title('Elbow Method for Optimal K (K-Means)')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('WCSS')
plt.grid(True)
plt.show()

# 3. Apply K-Means with chosen K
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, init='k-means++', max_iter=300, n_init=10,
random_state=42)
clusters = kmeans.fit_predict(X)
df_kmeans['Cluster'] = clusters

# 4. Visualize K-Means clusters
plt.figure(figsize=(10, 8))
sns.scatterplot(x='Feature_1', y='Feature_2', hue='Cluster', data=df_kmeans, palette='viridis',

```

```

s=100, alpha=0.8)
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=300, c='red',
marker='X', label='Centroids')
plt.title(f'K-Means Clustering with K={optimal_k}')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.legend()
plt.grid(True)
plt.show()

```

#### # 5. Silhouette Score

```

silhouette_avg = silhouette_score(X, clusters)
print(f"\nSilhouette Score for K-Means (K={optimal_k}): {silhouette_avg:.3f}")

```

#### # --- Part 2: Dimensionality Reduction with PCA ---

```

print("\n--- Part 2: Dimensionality Reduction with PCA ---")

```

#### # 1. Generate 4D dataset

```

X_pca, y_pca = make_blobs(n_samples=500, n_features=4, centers=4, cluster_std=1.0,
random_state=25)
df_pca_original = pd.DataFrame(X_pca, columns=[f'Feature_{i+1}' for i in
range(X_pca.shape[1])])
df_pca_original['True_Cluster'] = y_pca
print("\nOriginal PCA Dataset Head:")
print(df_pca_original.head())
print(f'Original PCA Dataset Shape: {df_pca_original.shape}')

```

#### # 2. Standardize

```

scaler = StandardScaler()
X_pca_scaled = scaler.fit_transform(X_pca)

```

#### # 3. PCA (4D → 2D)

```

pca = PCA(n_components=2)
principal_components = pca.fit_transform(X_pca_scaled)
df_principal_components = pd.DataFrame(principal_components,
columns=['Principal_Component_1', 'Principal_Component_2'])
df_principal_components['True_Cluster'] = y_pca
explained_variance = pca.explained_variance_ratio_
print("\nPrincipal Components Head:")
print(df_principal_components.head())
print(f"\nExplained Variance Ratio: {explained_variance}")
print(f"Total Explained Variance by 2 PCs: {explained_variance.sum():.3f}")

```

#### # 4. Visualize PCA result

```

plt.figure(figsize=(10, 8))
sns.scatterplot(x='Principal_Component_1', y='Principal_Component_2', hue='True_Cluster',
data=df_principal_components, palette='Paired', s=100, alpha=0.8)
plt.title('PCA - Dimensionality Reduction to 2 Components')
plt.xlabel(f'PC1 ({explained_variance[0]*100:.2f}%)')

```

```

plt.ylabel(f'PC2 ({explained_variance[1]*100:.2f}%)')
plt.grid(True)
plt.show()

# 5. K-Means on PCA-reduced data
kmeans_pca = KMeans(n_clusters=4, init='k-means++', max_iter=300, n_init=10,
random_state=42)
clusters_pca = kmeans_pca.fit_predict(principal_components)
df_principal_components['KMeans_Cluster_on_PCA'] = clusters_pca

plt.figure(figsize=(10, 8))
sns.scatterplot(x='Principal_Component_1', y='Principal_Component_2',
hue='KMeans_Cluster_on_PCA',
data=df_principal_components, palette='viridis', s=100, alpha=0.8)
plt.scatter(kmeans_pca.cluster_centers[:, 0], kmeans_pca.cluster_centers[:, 1], s=300,
c='red', marker='X', label='Centroids')
plt.title('K-Means Clustering on PCA-Reduced Data')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.grid(True)
plt.show()

# 6. Silhouette Score for PCA-reduced KMeans
silhouette_avg_pca = silhouette_score(principal_components, clusters_pca)
print(f"\nSilhouette Score for K-Means on PCA-Reduced Data (K=4):
{silhouette_avg_pca:.3f}")

```

## OUTPUT:

```

--- Part 1: K-Means Clustering ---

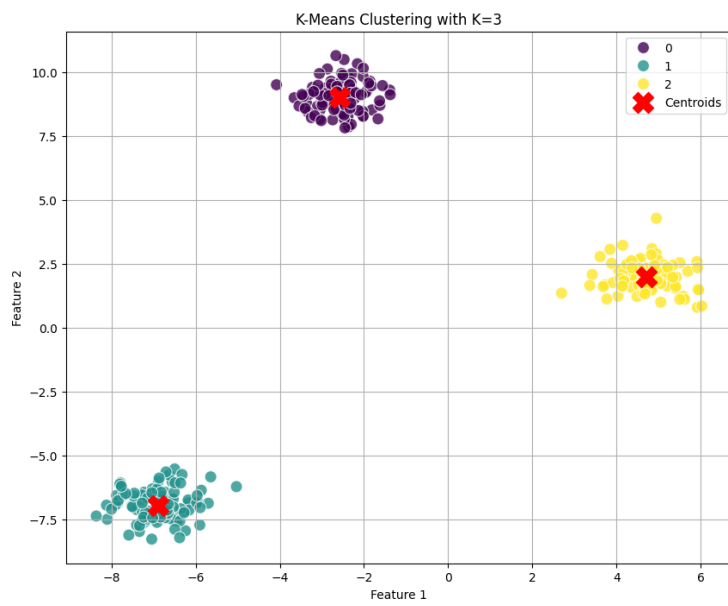
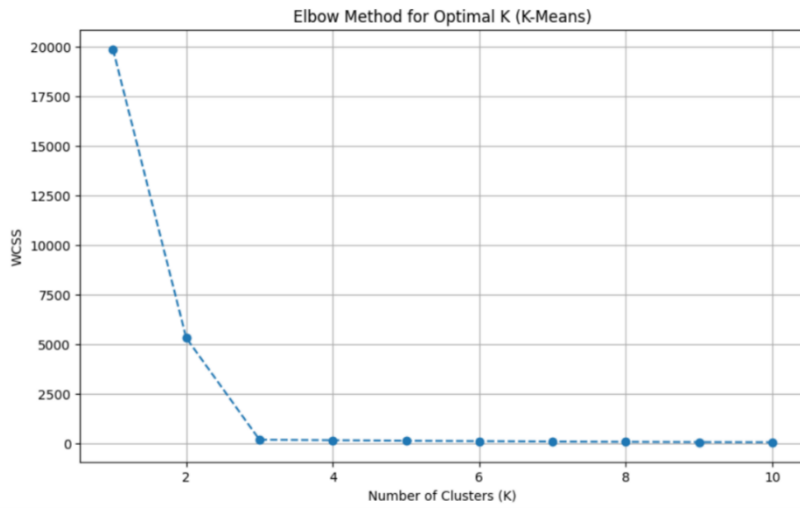
```

```

Original K-Means Dataset Head:

```

	Feature_1	Feature_2
0	-7.155244	-7.390016
1	-7.395875	-7.110843
2	-2.015671	8.281780
3	4.509270	2.632436
4	-8.102502	-7.484961



Silhouette Score for K-Means (K=3): 0.908

--- Part 2: Dimensionality Reduction with PCA ---

Original PCA Dataset Head:

	Feature_1	Feature_2	Feature_3	Feature_4	True_Cluster
0	-0.638667	1.110057	-6.400722	-0.204990	3
1	-2.951556	-7.657445	3.844794	0.903589	1
2	-0.253177	2.125103	-7.869801	0.559678	3
3	-2.151209	3.401400	-5.734930	0.965230	3
4	-2.347519	-7.230467	3.478891	-0.443440	1

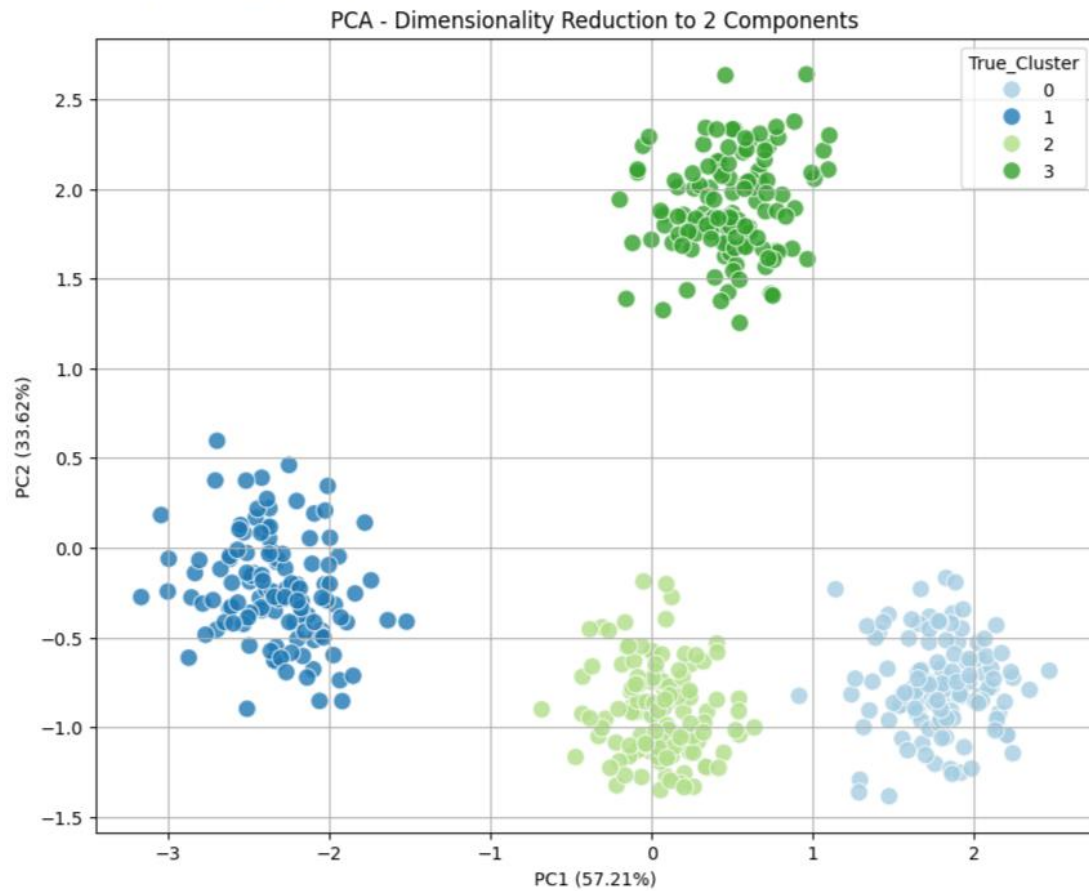
Original PCA Dataset Shape: (500, 5)

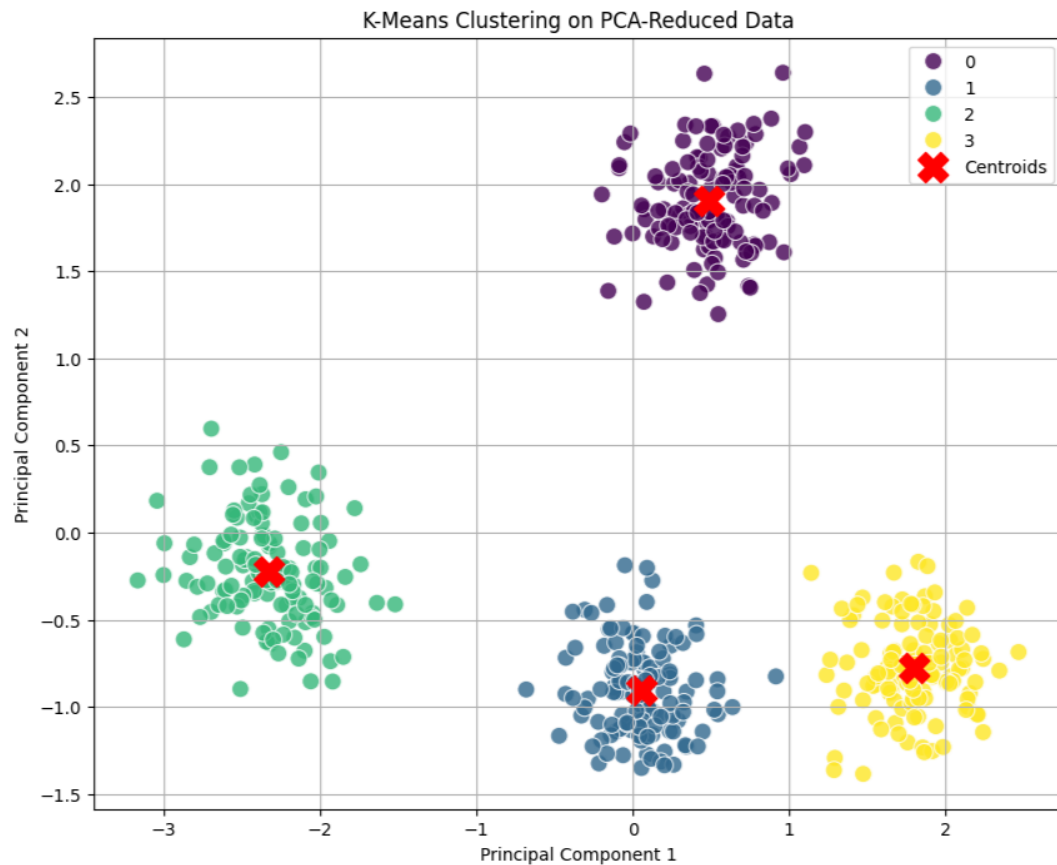
Principal Components Head:

	Principal_Component_1	Principal_Component_2	True_Cluster
0	0.455305	1.623917	3
1	-2.705622	0.375012	1
2	0.810234	1.966926	3
3	0.427139	2.149626	3
4	-2.407508	0.099250	1

Explained Variance Ratio: [0.57208431 0.33622342]

Total Explained Variance by 2 PCs: 0.908





Silhouette Score for K-Means on PCA-Reduced Data (K=4): 0.776

### Result:

The experiment showed how **K-Means** can group similar data points into clusters and how **PCA** can reduce high-dimensional data into simpler 2D form for visualization. Both methods worked well — K-Means formed clear clusters, and PCA kept the main data patterns while reducing complexity.