

AIM:

To perform customer segmentation using kMeans clustering on the Mall customers dataset, and to implement and evaluate ensemble clustering (cSPA) on the Wine dataset for improved clustering accuracy and visualization.

PROGRAM CODE:

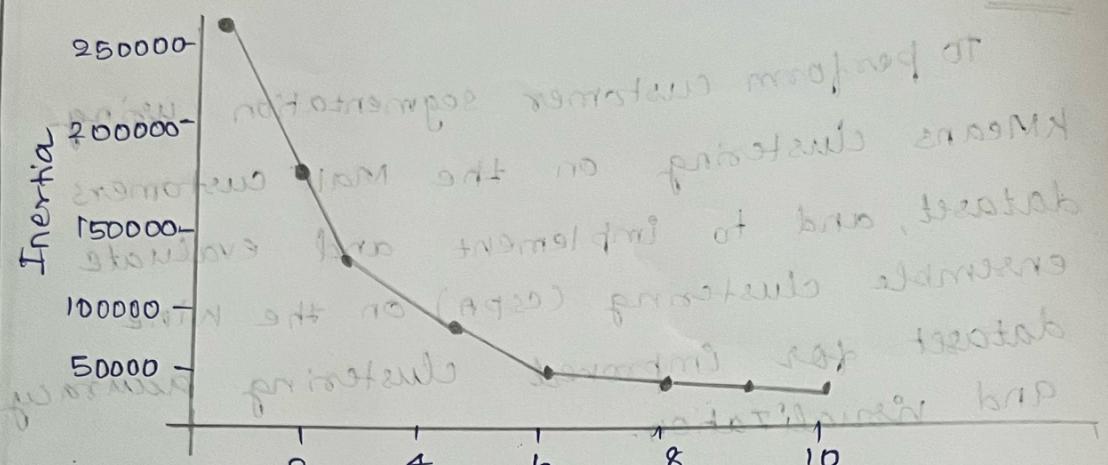
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
import seaborn as sns.

df = pd.read_csv(r"C:\Users\DELL\Downloads\Mall customers.csv")
kmeans = KMeans(n_clusters=5, random_state=42)
df['cluster'] = kmeans.fit_predict(df[['Annual Income (K$)', 'Spending Score (1-100)']])

distortions = []
for i in range(1, 11):
    km = KMeans(n_clusters=i, random_state=42)
    km.fit(df[['Annual Income (K$)', 'Spending Score (1-100)']])
    distortions.append(km.inertia_)

plt.plot(range(1, 11), distortions, marker='o')
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()
```

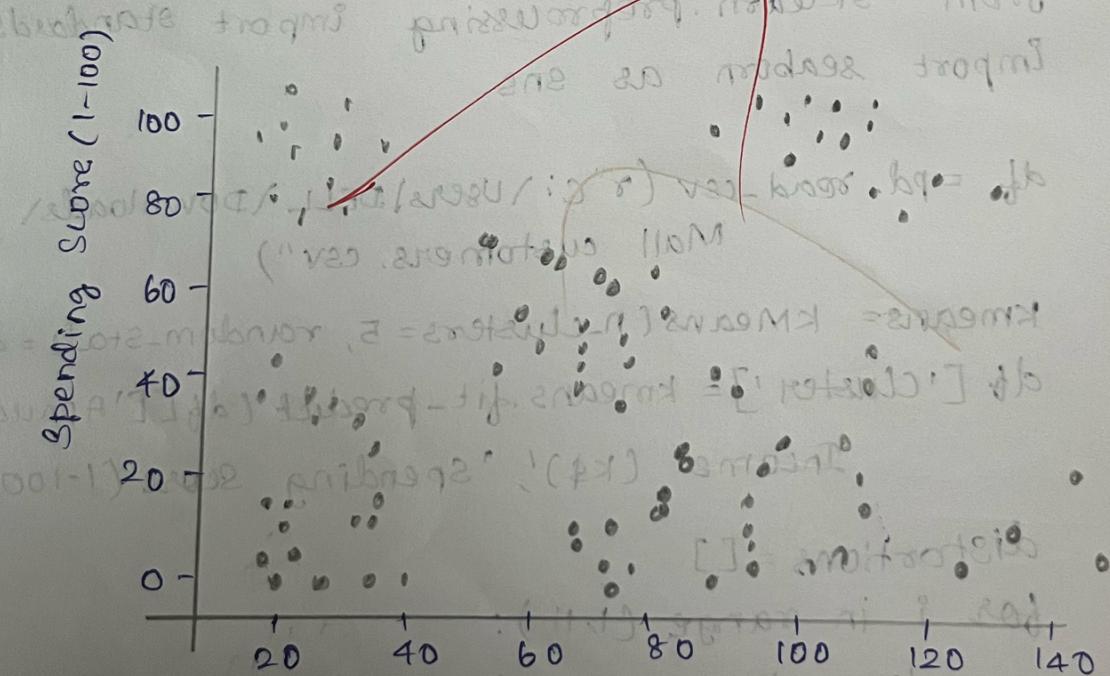
ELBOW METHOD



INERTIA
NO. OF CLUSTERS

Scree plot showing Inertia vs. Number of Clusters. The curve shows a sharp drop in inertia from 250,000 at 1 cluster to about 100,000 at 2 clusters, then gradually leveling off as the number of clusters increases. A horizontal line is drawn at approximately 10,000 inertia, and a vertical line connects this point to the curve, indicating the optimal number of clusters is 2.

CUSTOMER SEGMENTS



ANNUAL INCOME (K\$)

```
sns.scatterplot(data=df, x='Annual Income (k$)',  
y='Spending Score (1-100)',  
hue='Cluster',  
palette='Set2')
```

```
plt.title('Customer Segments')  
plt.show()
```

```
from sklearn.datasets import load_wine  
from sklearn.decomposition import PCA  
from sklearn.metrics import silhouette_score  
from sklearn.cluster import SpectralClustering  
import numpy as np
```

```
wine = load_wine()
```

```
X = pd.DataFrame(wine.data, columns=wine.feature_names)
```

```
X_scaled = StandardScaler().fit_transform(X)
```

```
base_clusterings = []
```

```
for k in [3, 4, 5]:
```

```
km = KMeans(n_clusters=k, random_state=42)
```

```
base_clusterings.append(km.fit_predict(X_scaled))
```

```
def cspa_ensemble(clusterings):
```

```
n_samples = len(clusterings[0])
```

```
similarity_matrix = np.zeros((n_samples, n_samples))
```

```
for clustering in clusterings:
```

```
    for i in range(n_samples):
```

```
        for j in range(n_samples):
```

```
            if clustering[i] == clustering[j]:
```

```
                similarity_matrix[i][j] += 1
```

```
similarity_matrix = similarity_matrix / len(clusterings)
```

```

ensemble_labels = SpectralClustering(
    n_clusters=3,
    affinity='precomputed',
    random_state=42).fit_predict(similarity_matrix)

return ensemble_labels

ensemble_labels = cspa_ensemble(base_clusterings)
print("Silhouette Score:", silhouette_score(x_scaled,
                                              ensemble_labels))

pca = PCA(n_components=2)
x_pca = pca.fit_transform(x_scaled)

plt.figure(figsize=(10, 6))

plt.scatter(x_pca[:, 0], x_pca[:, 1],
            c=ensemble_labels, cmap='viridis',
            s=50, edgecolor='k')

plt.title("CSPA Ensemble Clustering on Wine Dataset (PCA-reduced)")

plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.colorbar(label='cluster_label')
plt.grid(True)
plt.show()

```

RESULT:

The kMeans algorithm successfully segmented mall customers into distinct groups based on income & spending scores, revealing clear customer clusters.