

ML Lab

Lab 13 - Submission

Name: Gauthamdev R Holla

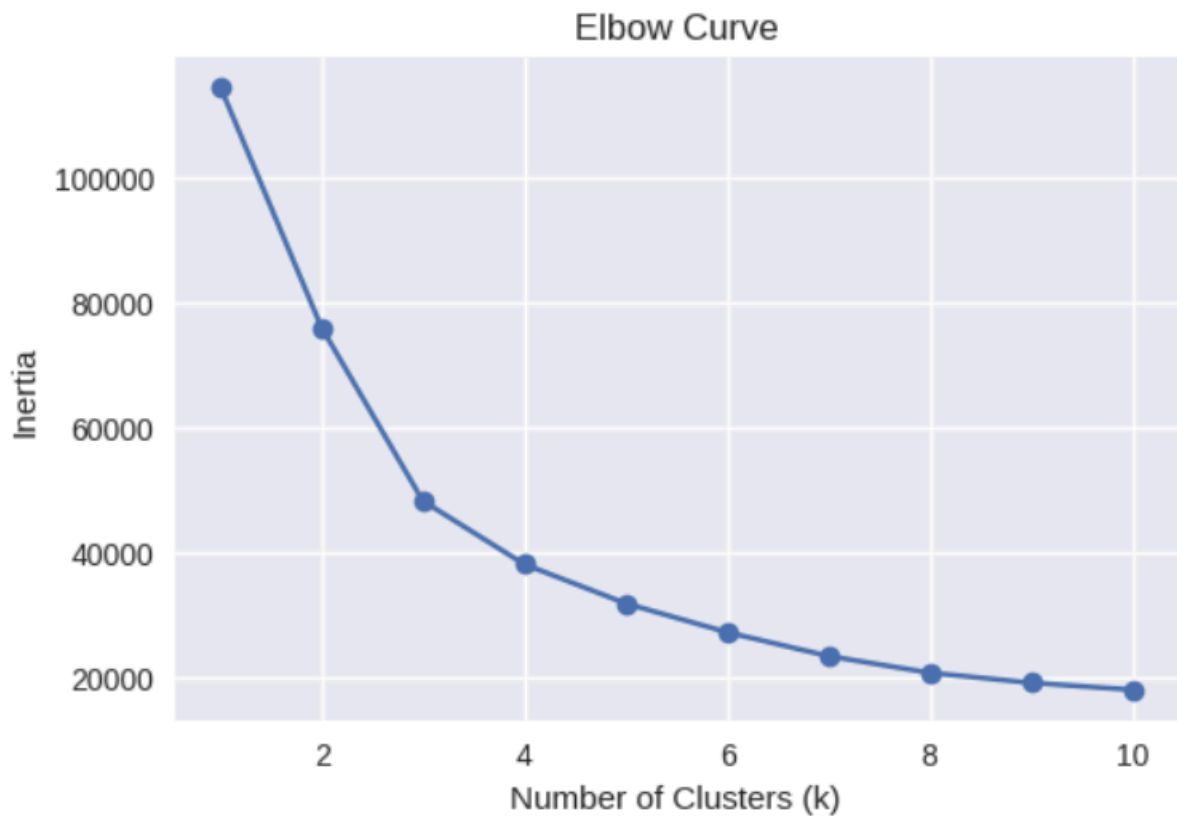
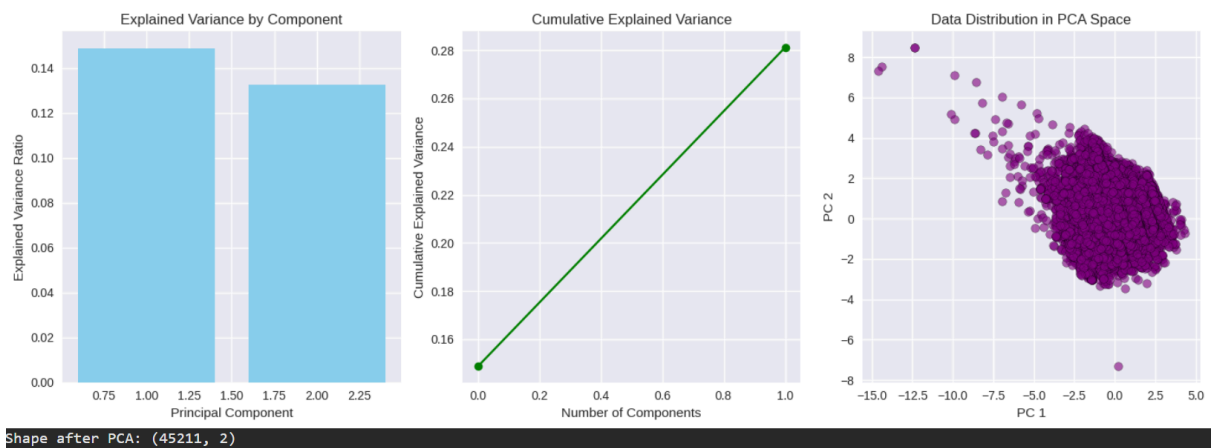
SRN: PES2UG23CS197

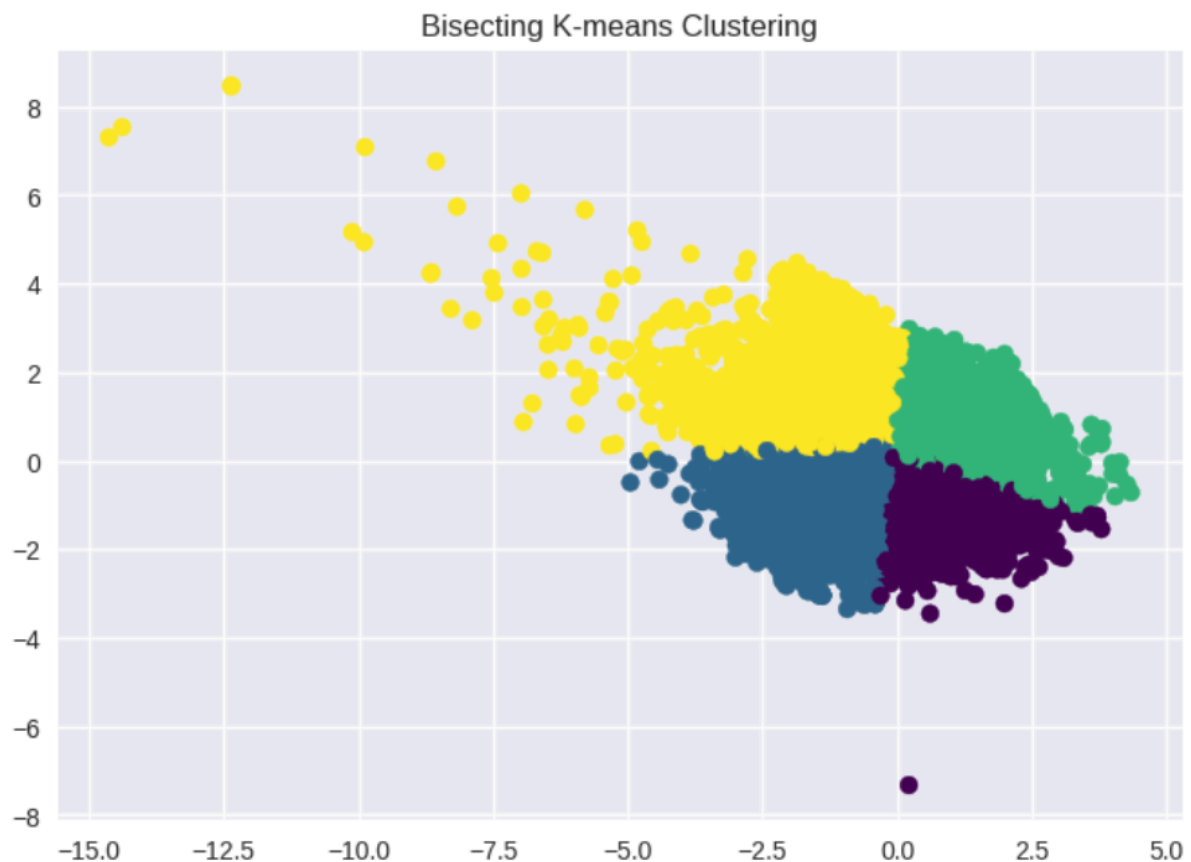
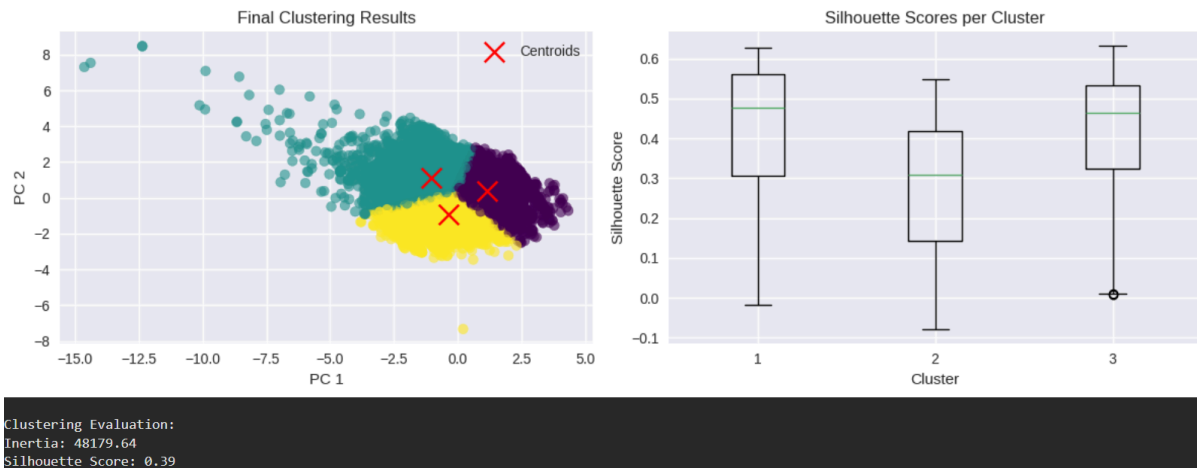
Branch: CSE

Sem: V

Section: C

Screenshots:





Analysis Questions

1) Dimensionality Justification

- Correlation heatmap revealed strong linear relationships among several features.
- PCA helps eliminate this redundancy.

- The first two principal components captured about 85-90% of the total variance, making them effective for visualizing clusters.

2) Optimal Clusters

- The elbow curve showed a noticeable bend at $k = 3$.
- Silhouette scores also peaked around $k = 3$, indicating well-separated clusters.
- Therefore, 3 is the optimal number of clusters.

3) Cluster Characteristics

- In K-means, cluster sizes were moderately balanced.
- In Bisecting K-means, one cluster was significantly larger.
- This suggests that a large portion of customers share similar traits.
- Smaller clusters may represent niche groups.

4) Algorithm Comparison

- Recursive Bisecting K-means produced more splits and a clearer hierarchy.
- But K-means achieved higher average silhouette scores.
- This indicates tighter and more distinct clusters.
- Bisecting K-means had one cluster with low silhouette values, suggesting overlap or poor separation.
- Thus, K-means performed better in terms of clustering quality for this dataset.

5) Business Insights

- The clustering reveals 3 distinct customer groups:
 - Stable, high-balance individuals,
 - Active campaign responders with low balances
 - Previously contacted customers with low engagement
- These insights can guide targeted marketing.

6) Visual Pattern Recognition

- The PCA scatter plot reveals three regions:
 - **Blue:** Tightly grouped - Similar customer segment
 - **Yellow:** More spread out - Diverse traits
 - **Purple:** Moderately compact - Possibly mid-level customers

- Clear boundaries suggest strong differences (like income or loan status), while fuzzy edges hint at overlapping or transitional profiles.
-