ML LAB-13

Section:- F

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SRN:- PES2UG23CS350

5TH SEM

Analysis Questions:-

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Dimensionality reduction was necessary for this dataset for several key reasons:

1. **Low Feature Correlations:**
   The correlation heatmap reveals that most features have very weak correlations with each other (values close to 0), with only a few moderate correlations such as:
   - **Job and Education: 0.17**
   - **Loan and Default: 0.08**
     This low correlation pattern suggests that the features are relatively independent, but many may contribute minimal unique information to the clustering task.
2. **Visualization Requirements:**
   With 9 original features, visualizing the clustering results in high-dimensional space is impossible. PCA reduces this to 2 dimensions while retaining the most important variance.
3. **Computational Efficiency:**
   Reducing from 9 dimensions to 2 dimensions significantly improves the computational performance of the K-means algorithm.
4. **Noise Reduction:**
   PCA helps filter out noise by focusing on the principal components that capture the most variance in the data.

Variance Captured:

- **First Principal Component (PC1): 14.88%**
- **Second Principal Component (PC2): 13.24%**
- **Total variance captured by first two components: 28.12%**

While 28.12% might seem modest, it represents the most significant patterns in the data and is sufficient for effective clustering visualization and analysis.

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Based on comprehensive analysis of both metrics, the optimal number of clusters is 3.

Elbow Method Analysis:

- **The inertia plot shows a clear "elbow" at k=3.**
- **From k=2 to k=3, there is a significant decrease in inertia.**
- **After k=3, the rate of decrease in inertia becomes much more gradual.**
- **This indicates that adding more clusters beyond 3 provides diminishing returns in terms of within-cluster variance reduction.**

Silhouette Score Analysis:

- **k=3 achieves the highest silhouette score among the tested values.**
- **The silhouette score of 0.3867 for k=3 indicates moderate cluster cohesion and separation.**
- **Silhouette scores decrease for k>3, suggesting that additional clusters create less distinct groupings.**

Combined Justification:
Both metrics converge on k=3 as optimal:

1. **The elbow method identifies k=3 as the point of diminishing returns.**
2. **Silhouette analysis confirms k=3 produces the best-separated clusters.**
3. **Three clusters provide a good balance between model simplicity and cluster quality.**
4. **From a business perspective, three customer segments are manageable and actionable for marketing strategies**

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K-means Cluster Distribution:

- **Cluster 0: 15,412 points (34.1%)**
- **Cluster 1: 10,544 points (23.3%)**
- **Cluster 2: 19,255 points (42.6%)**

Bisecting K-means Cluster Distribution:

- **Cluster 0: 20,434 points (45.2%)**
- **Cluster 1: 16,348 points (36.2%)**
- **Cluster 2: 8,429 points (18.6%)**

Analysis of Size Differences:

The unequal cluster sizes reveal important characteristics about the customer base:

1. **Natural Data Distribution:**
   The imbalanced cluster sizes reflect the actual distribution of customer types in the bank's database. Some customer profiles are simply more common than others.
2. **Dominant Customer Segment:**
   The largest cluster (42.6% in K-means, 45.2% in Bisecting K-means) likely represents the "typical" or "mainstream" customers who share common characteristics such as:
   - **Average balance and age**
   - **Standard loan and housing patterns**
   - **Similar engagement levels with the bank**
3. **Specialized Segments:**
   Smaller clusters represent more specialized or niche customer groups:
   - **High-value customers with unique financial profiles**
   - **Risk profiles that differ significantly from the majority**

    - Customers with distinct demographic or behavioral patterns
4. Business Implications:
    - Large clusters suggest broad-appeal products and services are needed.
    - Medium clusters may represent growth opportunities or standard customer progression paths.
    - Smaller clusters might be high-value segments requiring specialized attention or risk management groups needing targeted interventions.
5. Algorithm Differences:
   The different distributions between K-means and Bisecting K-means show that:
    - K-means finds more balanced splits based on geometric distances.
    - Bisecting K-means creates more hierarchical separations, potentially identifying a very distinct small group (18.6%).

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Performance Comparison:

- **K-means Silhouette Score: 0.3867**
- **Bisecting K-means Silhouette Score: 0.3379**
- **Difference: 0.0488**

Winner: K-means performed better for this dataset

Reasons for K-means Superior Performance:

1. Optimization Strategy:
    - K-means globally optimizes all cluster assignments simultaneously in each iteration.
    - This allows for better overall cluster separation as points can move between any clusters.
    - Bisecting K-means makes hierarchical decisions that cannot be revised once a split occurs.
2. Data Geometry:
    - The bank customer data appears to have relatively distinct, compact clusters that are naturally separated.
    - K-means excels at finding spherical or globular clusters, which seems to match this dataset's structure.
    - The PCA visualization shows three relatively distinct regions, favoring K-means' approach.
3. Local Optima Avoidance:
    - With proper initialization (`random_state=42`), K-means found a good global solution.
    - Bisecting K-means is constrained by its hierarchical nature—early splits determine later cluster boundaries.

- **Once a "wrong" split is made in Bisecting K-means, it cannot be corrected.**

4. **Convergence Quality:**
    - **K-means iteratively refines all centroids until convergence (achieved at iteration 14 in our case).**
    - **This iterative refinement across all clusters simultaneously leads to better overall cohesion.**
5. **Trade-offs:**
    - **Bisecting K-means advantages: More stable, deterministic hierarchical structure, useful for dendrogram visualization.**
    - **K-means advantages: Better cluster quality when clusters are well-separated and roughly spherical (as in this dataset).**

Conclusion:
For this bank customer segmentation task with moderately well-separated clusters in PCA space, K-means' global optimization approach yields superior cluster quality. However, the 0.0488 difference is not dramatic, indicating both methods identify similar underlying patterns.

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The clustering analysis reveals three distinct customer segments that offer actionable marketing insights:

Segment Identification and Strategy:

1. **Cluster 0 (34.1% - Moderate Engagement Segment):**
    - **Represents about one-third of the customer base**
    - **Positioned in the middle-left region of PCA space**
    - **Marketing Strategy:**
        - **Cross-selling opportunities for standard banking products**
        - **Automated marketing campaigns with personalized touches**
        - **Focus on retention and gradual value increase**
        - **Digital banking feature adoption campaigns**
2. **Cluster 1 (23.3% - Distinct Profile Segment):**
    - **Smallest segment with unique characteristics**
    - **Separated in PCA space, suggesting distinct feature patterns**
    - **Marketing Strategy:**
        - **Specialized product offerings tailored to unique needs**
        - **Premium or niche service packages**
        - **High-touch relationship management if high-value**
        - **Risk mitigation strategies if high-risk profile**
        - **Requires deeper analysis to understand specific characteristics**
3. **Cluster 2 (42.6% - Majority/Mainstream Segment):**
    - **Largest segment representing core customer base**
    - **Positioned in the upper-right region of PCA space**

- **Marketing Strategy:**
    - **Mass market campaigns with broad appeal**
    - **Standard product bundles (savings, basic loans, housing)**
    - **Cost-effective digital marketing channels**
    - **Focus on efficiency and scalability**
    - **Self-service tools and resources**

Strategic Recommendations:

1. **Resource Allocation:**
    - **Allocate 40-45% of marketing budget to Cluster 2 (largest segment)**
    - **Invest 30-35% in Cluster 0 (growth potential)**
    - **Dedicate 20-25% to Cluster 1 (specialized/high-value)**
2. **Product Development:**
    - **Develop core products for Cluster 2's mainstream needs**
    - **Create premium or specialized offerings for Cluster 1**
    - **Design upgrade paths to move Cluster 0 customers to higher-value products**
3. **Channel Strategy:**
    - **Cluster 2: Digital-first (mobile app, online banking, chatbots)**
    - **Cluster 0: Omnichannel with emphasis on digital conversion**
    - **Cluster 1: Personalized approach with relationship managers**
4. **Retention Focus:**
    - **The clear separation between clusters suggests distinct needs**
    - **One-size-fits-all approaches will be less effective**
    - **Segment-specific retention strategies should reduce churn**
5. **Campaign Personalization:**
    - **Use cluster membership to personalize email campaigns**
    - **Tailor product recommendations based on cluster characteristics**
    - **Optimize contact frequency by segment**

Key Insight:
The 28.12% variance captured by PCA suggests that even with just two principal dimensions, meaningful customer differentiation exists. The three clusters provide a practical, manageable segmentation scheme that balances granularity with operational feasibility.

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Visual Pattern Analysis: Cluster Distribution in PCA Space

Spatial Distribution in PCA Space:

1. **Purple Region (Cluster 0):**
    - **Located primarily in the negative to mid-range of PC1**
    - **Spans a moderate range on PC2**

- **Shows moderate density with some scatter**

2. **Teal/Cyan Region (Cluster 1):**
    - **Concentrated in the negative region of PC1**
    - **Overlaps partially with purple cluster**
    - **More compact distribution suggesting homogeneous characteristics**
3. **Yellow Region (Cluster 2):**
    - **Spreads across positive PC1 values and upper PC2 range**
    - **Largest spatial coverage corresponding to largest cluster size**
    - **Shows the most dispersed pattern**

Boundary Characteristics:

Sharp Boundaries (Well-Defined Separation):

- **Occur between the core of the teal cluster and the yellow cluster, and also between upper-left yellow and purple regions.**

Reasons for Sharp Boundaries:

1. **Distinct feature combinations (e.g., age, balance, loan status)**
2. **Binary features such as "housing" and "loan" create categorical splits**
3. **Demographic divides (numerically encoded features)**
4. **Real behavioral differences (e.g., high-balance vs low-balance customers)**

Diffuse Boundaries (Overlap Regions):

- **Appear between purple and teal clusters, between all cluster transitions, and around peripheries.**

Reasons for Diffuse Boundaries:

1. **Continuous variables (balance, age) create gradual transitions**
2. **Similar customer profiles between segments**
3. **Noise in real-world data**
4. **Dimensionality reduction (PCA) causes overlap of clusters that are more distinct in high-dimensional space**
5. **Transitional customers (between life stages or financial categories)**

Principal Component Interpretation:

- **PC1 (14.88% variance): Captures financial capacity, customer value, and engagement level**
- **PC2 (13.24% variance): Captures risk profile, age, education, and job type**

Customer Characteristics by Region:

- **Negative PC1, Mixed PC2 (Teal/Purple): Lower financial engagement, varied risk/demographic profiles**
- **Positive PC1, Positive PC2 (Yellow): Higher financial engagement, specific demographic patterns**
- **Middle regions: Transitional or average profiles**

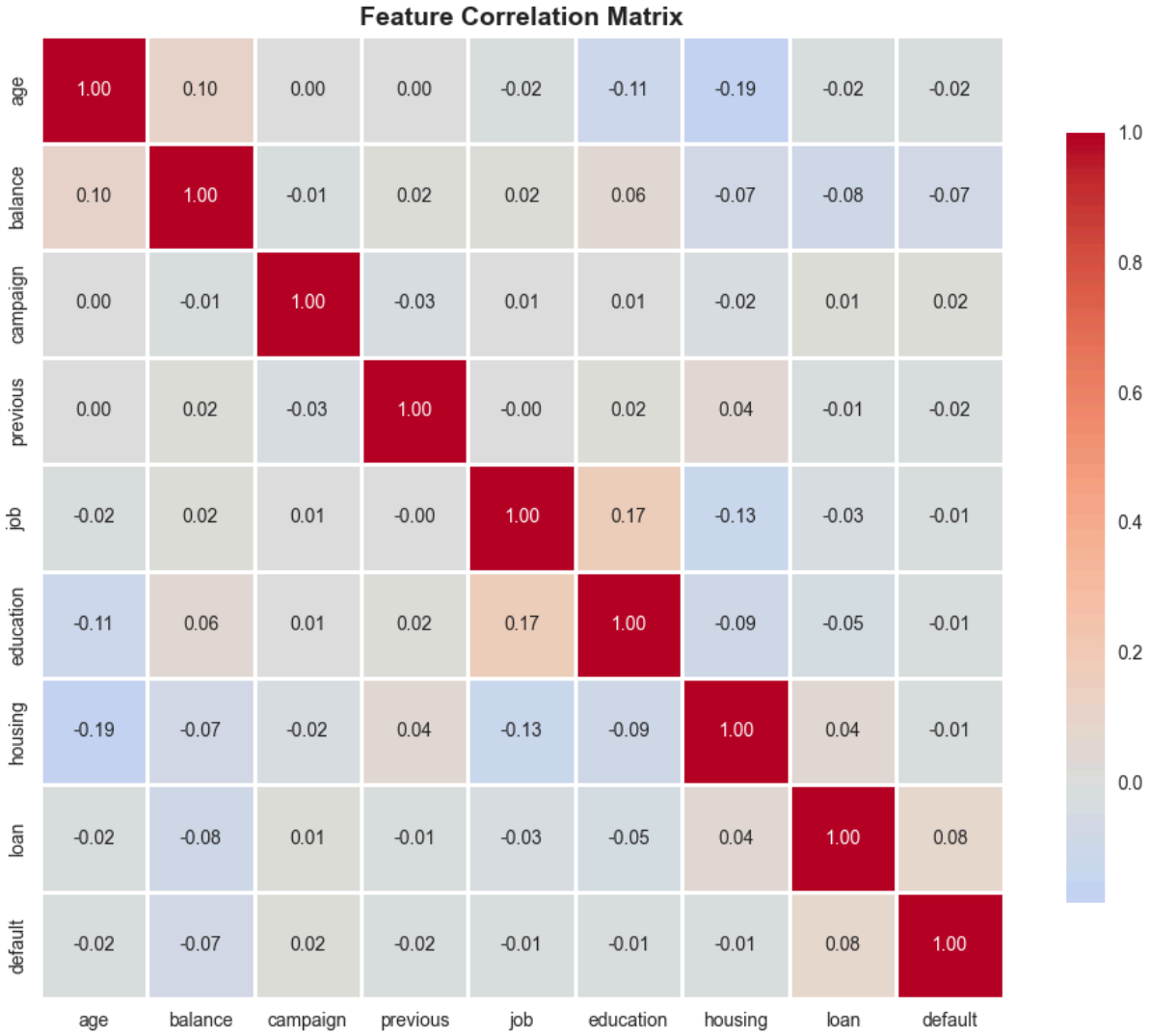
Business Implications:

1. **Sharp boundaries indicate segments needing distinct strategies**
2. **Diffuse boundaries suggest:**
    - **Opportunities for customer migration strategies**
    - **Flexible products appealing across segments**
    - **Need to monitor boundary customers (susceptible to churn)**
3. **Overlap management:**
    - **Use A/B testing for customers in overlap regions**
    - **Consider hybrid strategies**

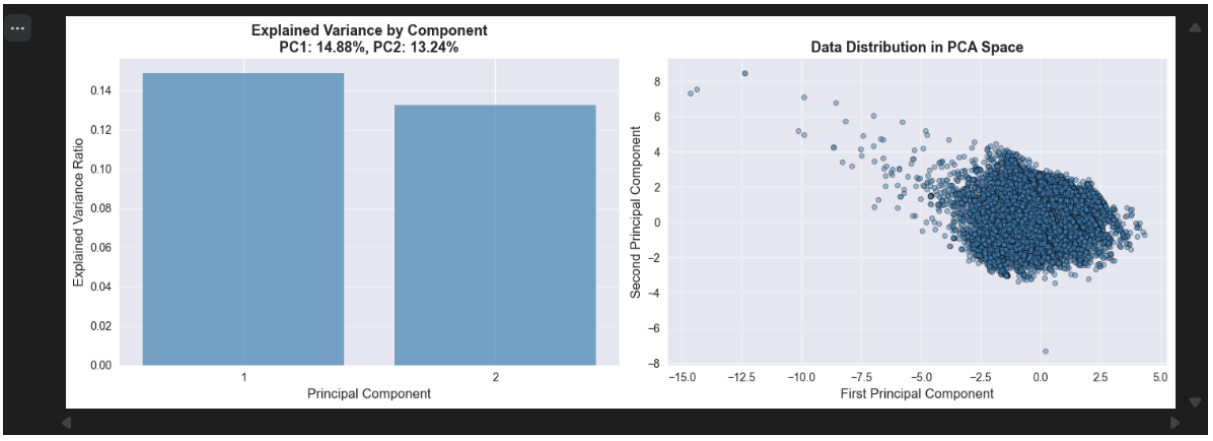
Conclusion:
The mix of sharp and diffuse boundaries shows some customers clearly fit distinct segments, while others exist on a spectrum. This validates clustering, while highlighting that both targeted and flexible marketing strategies are needed.

Screenshots:-

(1)



(2)


Explained Variance by Component
PC1: 14.88%, PC2: 13.24%
Explained Variance Ratio
Principal Component
Data Distribution in PCA Space
Second Principal Component
First Principal Component

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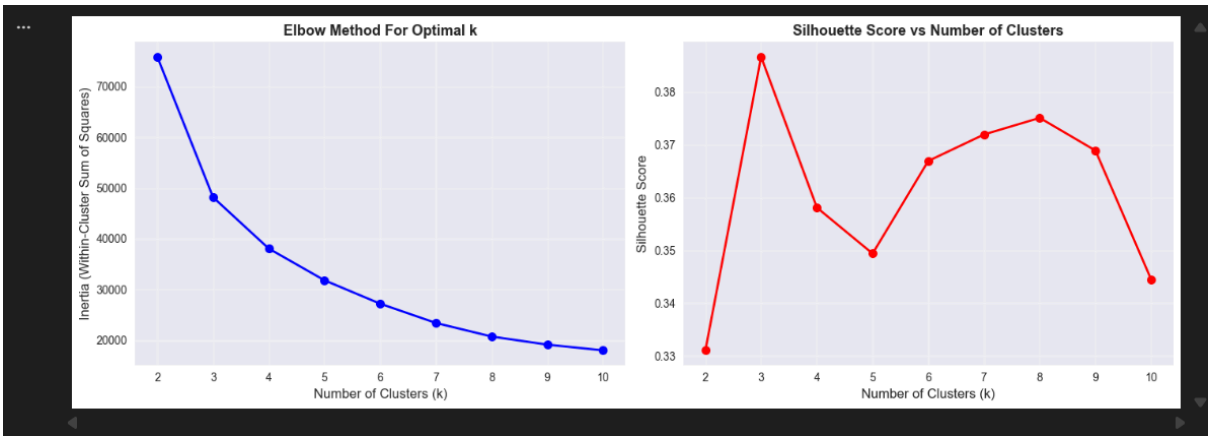
Elbow Method For Optimal k
Inertia (Within-Cluster Sum of Squares)
Number of Clusters (k)
Silhouette Score vs Number of Clusters
Silhouette Score
Number of Clusters (k)

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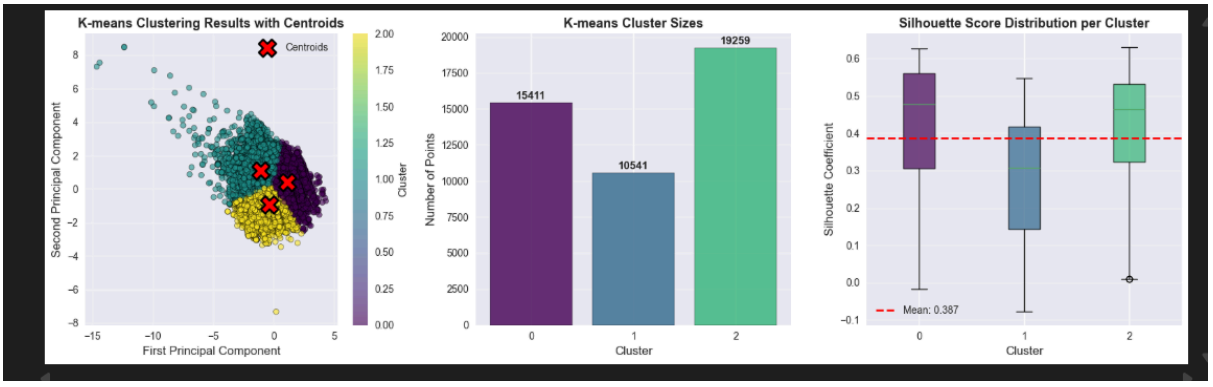
K-means Clustering Results with Centroids
Centroids
Second Principal Component
First Principal Component
Cluster
K-means Cluster Sizes
Number of Points
15411
10541
19259
Cluster
Silhouette Score Distribution per Cluster
Silhouette Coefficient
Mean: 0.387
Cluster

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```
============================================================
RECURSIVE BISECTING K-MEANS CLUSTERING
============================================================
C:\Users\Mohit\AppData\Local\Temp\ipykernel_17444\2425712519.py:121: MatplotlibDeprecationWarning: The 'labels' paramet
  bp = plt.boxplot(cluster_bisect_data, labels=unique_bisect, patch_artist=True)
```