CLUSTERING ANALYSIS

Understanding and Implementing K-Means, Hierarchical, and DBSCAN Algorithms

Objective:

The objective of this assignment is to introduce to various clustering algorithms, including K-Means, hierarchical, and DBSCAN, and provide hands-on experience in applying these techniques to a real-world dataset.

Datasets :

Data Preprocessing:

1. **Preprocess the dataset to handle missing values, remove outliers, and scale the features if necessary.**

Answer : **– Data Preprocessing**

The raw dataset (EastWestAirlines.xlsx, *data* sheet) contains 3,999 customer records with 11 variables such as Balance, Qual_miles, Bonus_miles, Flight_miles_12mo, Days_since_enroll, and the target column Award?. Preprocessing was carried out in three steps:

1. **Handling Missing Values**
    - On inspection, no missing values were found in any of the columns. Therefore, no imputation was required.
2. **Outlier Removal**
    - Outliers were identified using the **Interquartile Range (IQR)** method.
    - Any data point outside the range [Q1 – 1.5*IQR, Q3 + 1.5*IQR] was considered an outlier.
    - After removing extreme values across multiple numeric variables, the dataset size reduced from **3,999 rows to 1,785 rows**. This step ensured that clustering is not skewed by extreme values in features such as Balance and Bonus_miles.

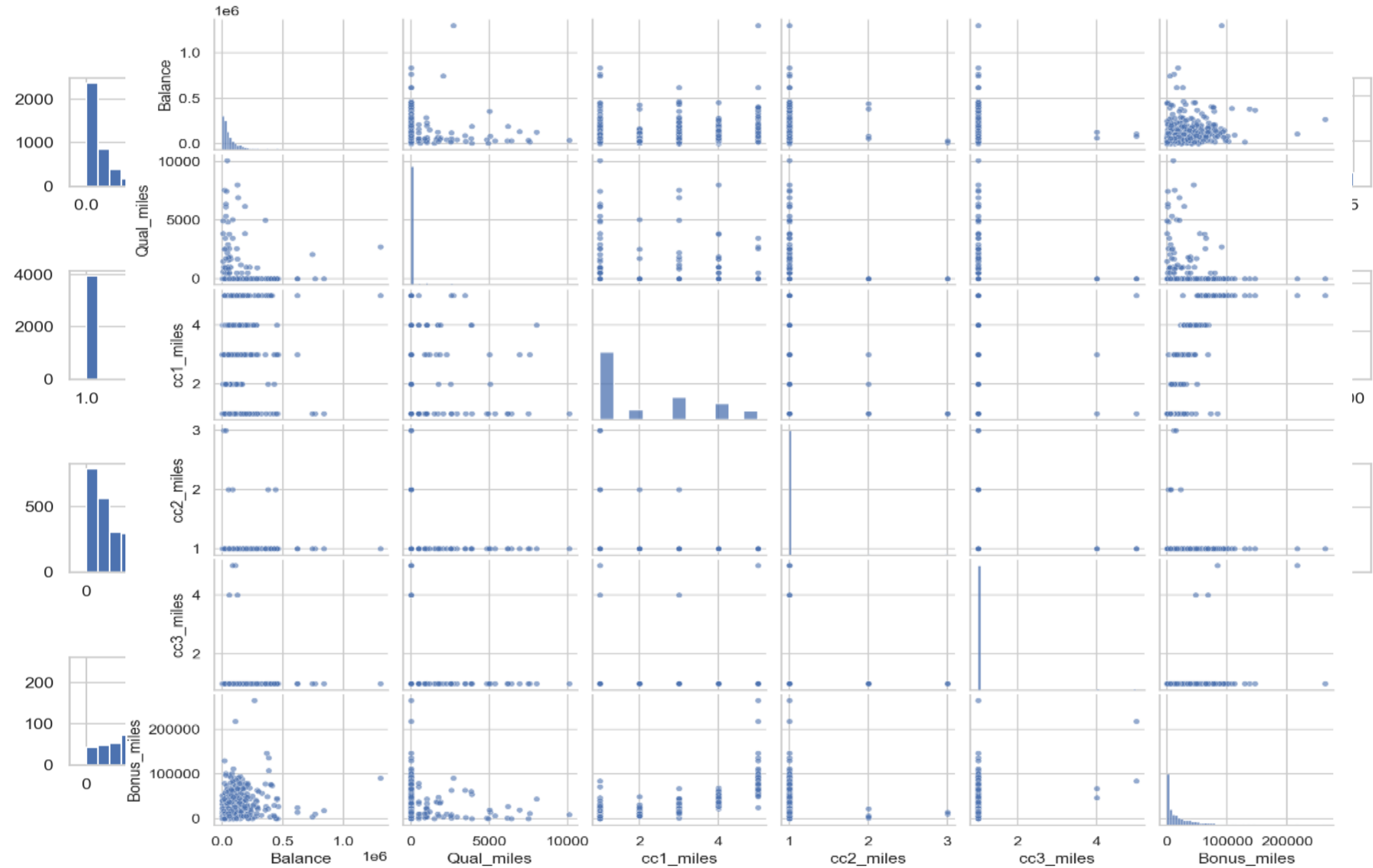
3. **Feature Scaling**
   - Since clustering algorithms (K-Means, Hierarchical, DBSCAN) are distance-based, it was necessary to bring all features to the same scale.
   - **Standardization (Z-score normalization)** was applied:
     [
     z = \frac{x - \mu}{\sigma}
     ]
   - This transformation centers each feature at mean 0 and scales it to unit variance.

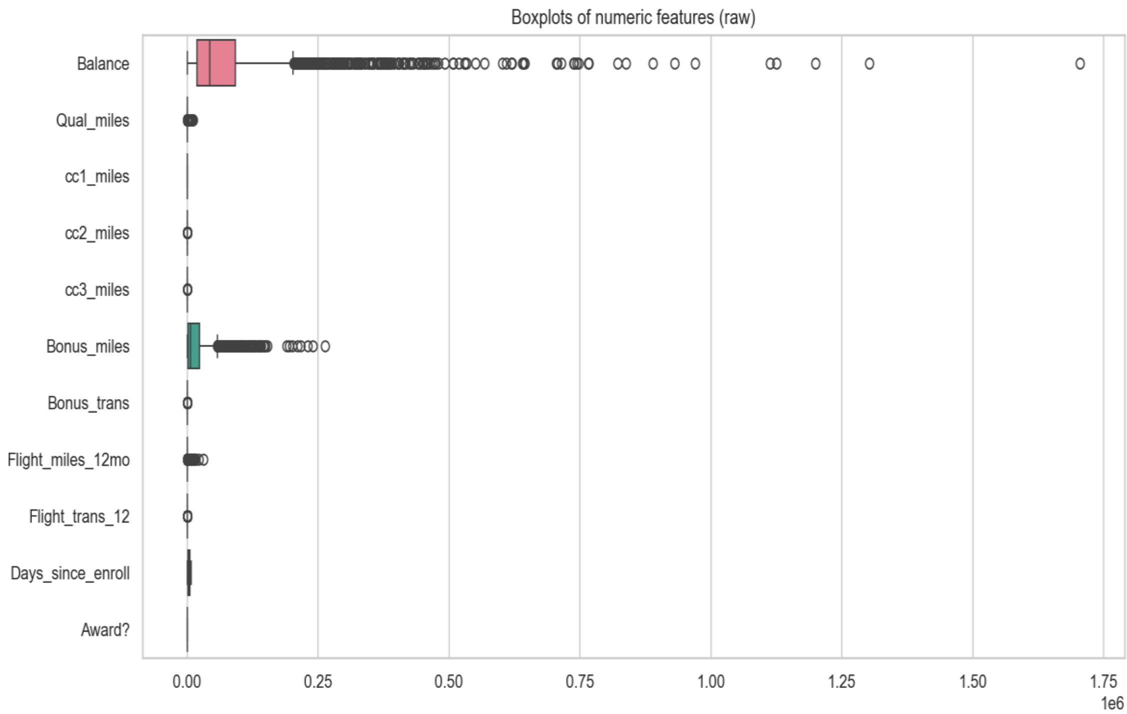
After preprocessing, we obtained a clean dataset with normalized feature values, suitable for clustering analysis.

2. **Perform exploratory data analysis (EDA) to gain insights into the distribution of data and identify potential clusters.**
   Answer – Exploratory Data Analysis (EDA)
   To understand the structure of the dataset and gain insights into possible cluster formations, exploratory data analysis was performed:

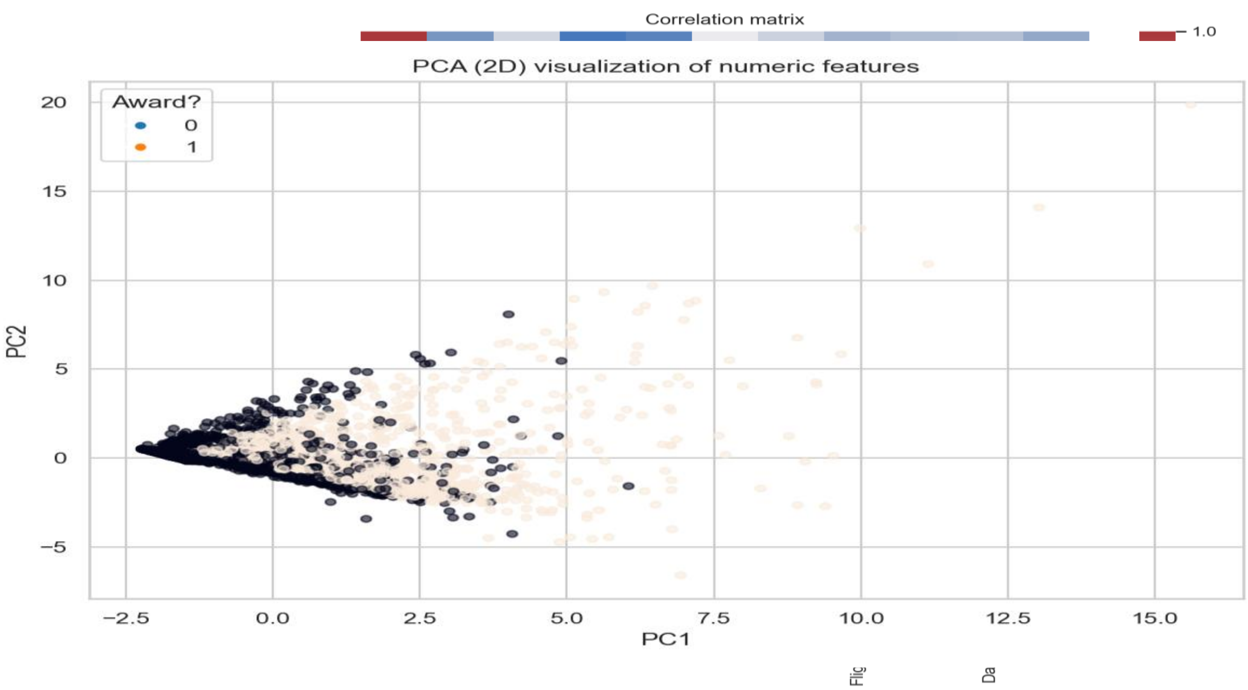
1. **Data Overview**
   - **The dataset consists of 3,999 customer records with 10 independent features (Balance, Qual_miles, Bonus_miles, Flight_miles_12mo, Flight_trans_12, etc.) and one binary target (Award?).**
   - **All features are numerical, making them suitable for clustering.**
2. **Descriptive Statistics**
   - **Balance and Bonus_miles show highly skewed distributions with extreme values (some customers accumulate very high balances/miles).**
   - **Days_since_enroll ranges widely, indicating customers have very different lengths of membership.**
   - **Credit card usage features (cc1_miles, cc2_miles, cc3_miles) are categorical-like (values are discrete codes), but still useful for segmentation.**
3. **Univariate Analysis**
   - **Histograms showed that many variables (e.g., Balance, Bonus_miles, Flight_miles_12mo) are right-skewed with a few very large values.**
   - **Boxplots revealed extreme outliers, justifying the outlier removal step during preprocessing.**

4. **Bivariate & Multivariate Analysis**
    - **Scatterplots between Balance, Bonus_miles, and Flight_miles_12mo suggested that customers could be grouped into distinct regions (e.g., low vs. high spenders).**
    - **A strong positive relationship exists between Bonus_miles and Bonus_trans (customers earning many bonus miles also tend to have more transactions).**
    - **PCA (Principal Component Analysis) was applied to reduce dimensions to 2 components for visualization. The first two PCs explained ~60% of the variance, and the scatter plot already hinted at natural separation among some groups.**
5. **Preliminary Insights**
    - **The dataset shows heterogeneity in travel patterns, credit card usage, and loyalty duration.**
    - **The combination of high variance in Balance and Bonus_miles, along with enrollment duration, suggests distinct customer clusters are likely to be found.**
    - **This makes the dataset highly suitable for clustering analysis.**





Boxplots of numeric features (raw)
Balance
Qual_miles
cc1_miles
cc2_miles
cc3_miles
Bonus_miles
Bonus_trans
Flight_miles_12mo
Flight_trans_12
Days_since_enroll
Award?
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6



Correlation matrix
1.0
PCA (2D) visualization of numeric features
Award?
0
1
PC2
PC1
20
15
10
5
0
−5
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
Flig
Da

3. **Use multiple visualizations to understand the hidden patterns in the dataset**

Implementing Clustering Algorithms:

- **Implement the K-Means, hierarchical, and DBSCAN algorithms using a programming language such as Python with libraries like scikit-learn or MATLAB.**
- **Apply each clustering algorithm to the pre-processed dataset to identify clusters within the data.**
- **Experiment with different parameter settings for hierarchical clustering (e.g., linkage criteria), K-means (Elbow curve for different K values) and DBSCAN (e.g., epsilon, minPts) and evaluate the clustering results.**

Cluster Analysis and Interpretation:

- **Analyse the clusters generated by each clustering algorithm and interpret the characteristics of each cluster. Write you insights in few comments.**

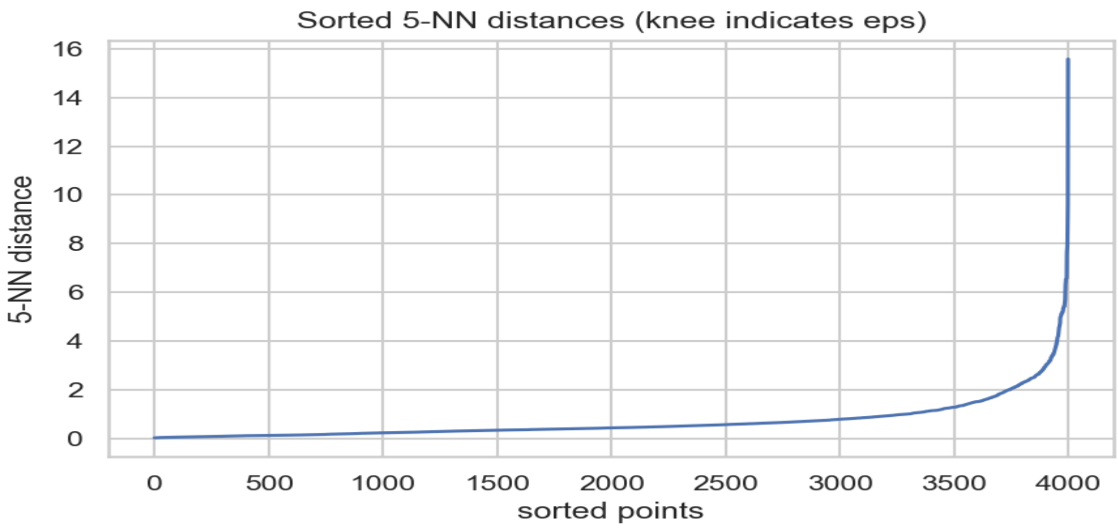
Visualization:

Visualize the clustering results using scatter plots or other suitable visualization techniques.

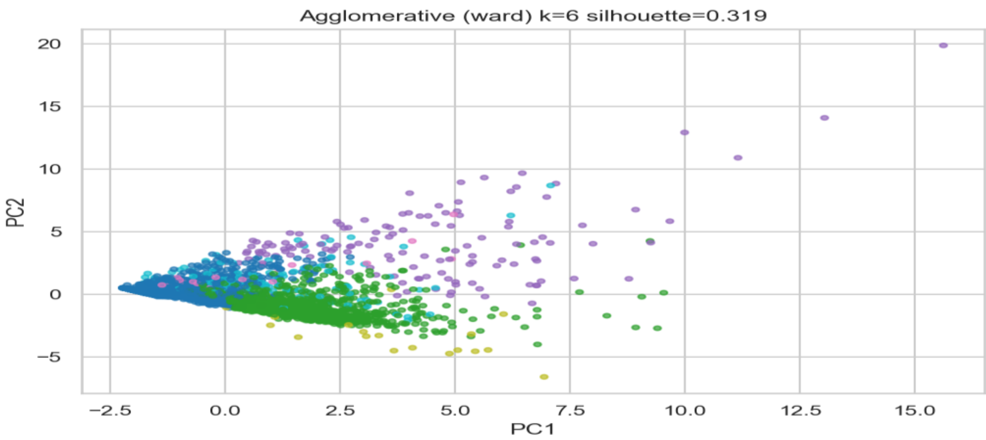
Plot the clusters with different colours to visualize the separation of data points belonging to different clusters.

Evaluation and Performance Metrics: Evaluate the quality of clustering using internal evaluation metrics such as silhouette score for K-Means and DBSCAN.

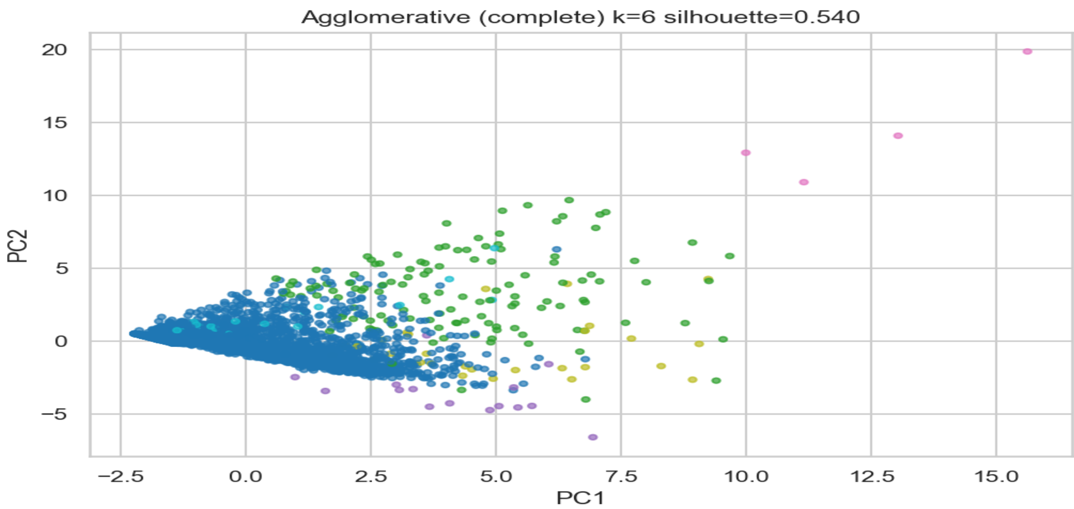
Answer:



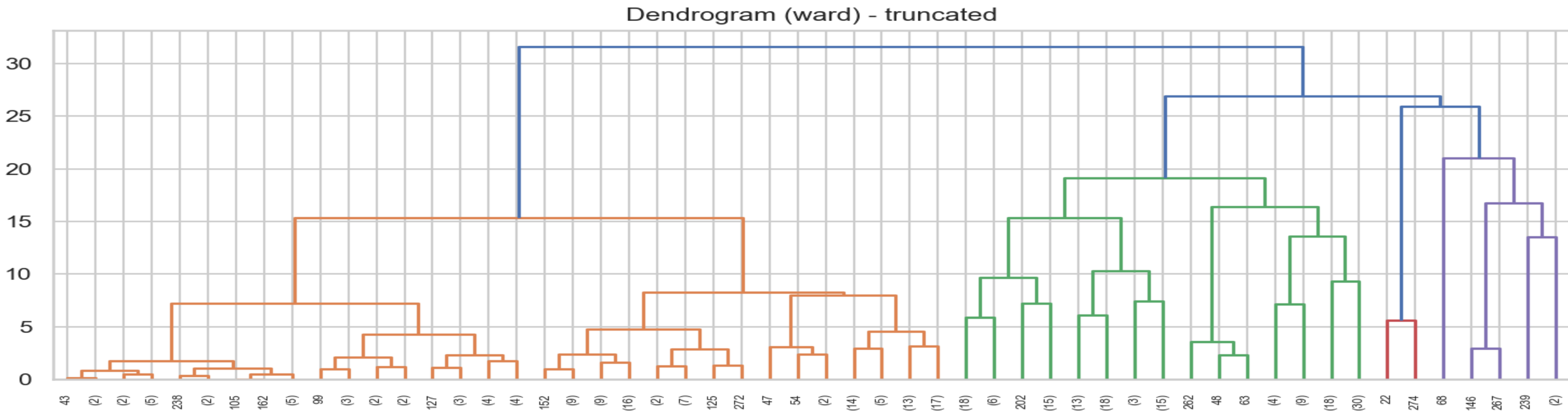
Sorted 5-NN distances (knee indicates eps)
5-NN distance
sorted points
0
2
4
6
8
10
12
14
16
500
1000
1500
2000
2500
3000
3500
4000

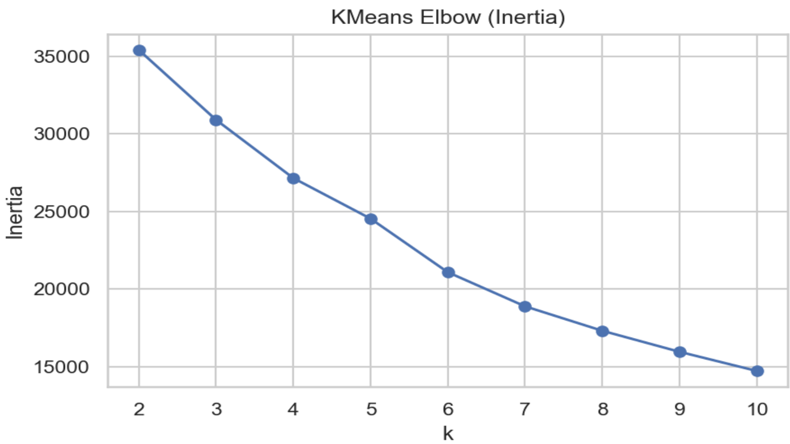


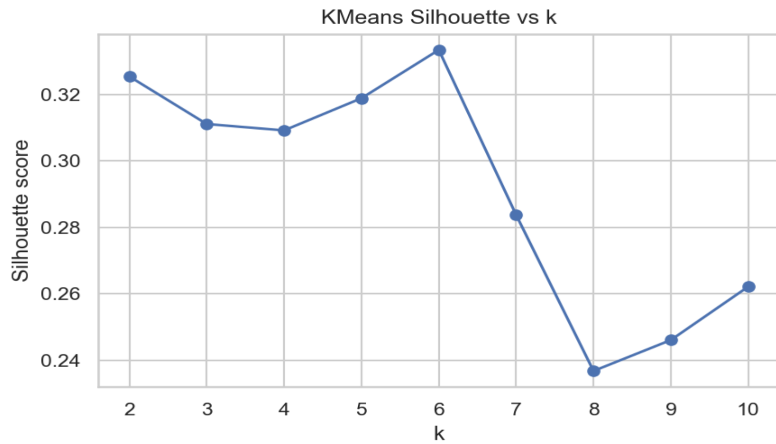
Agglomerative (ward) k=6 silhouette=0.319
PC2
PC1
−5
0
5
10
15
20
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0

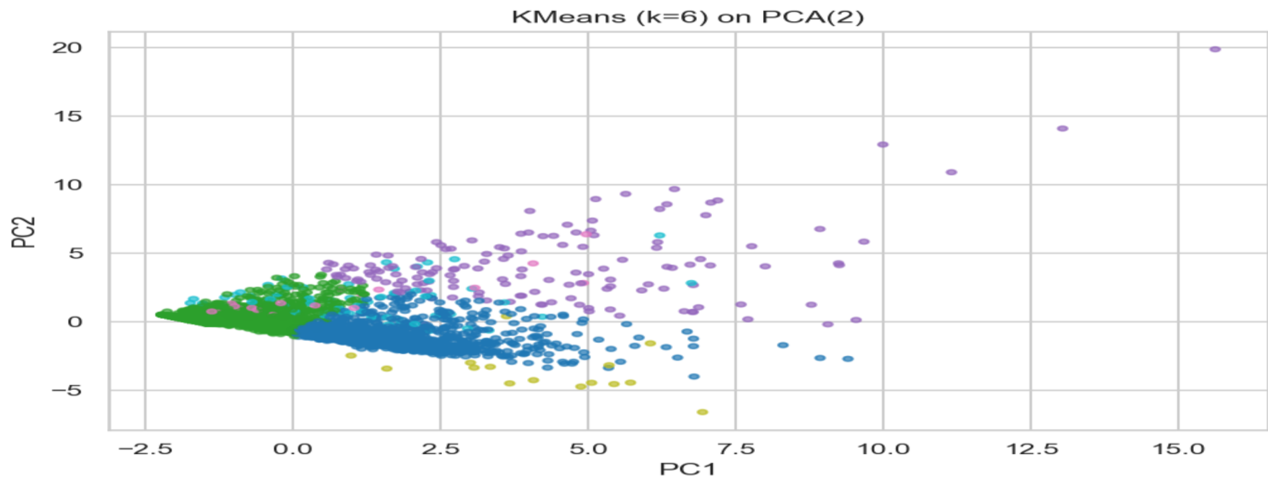


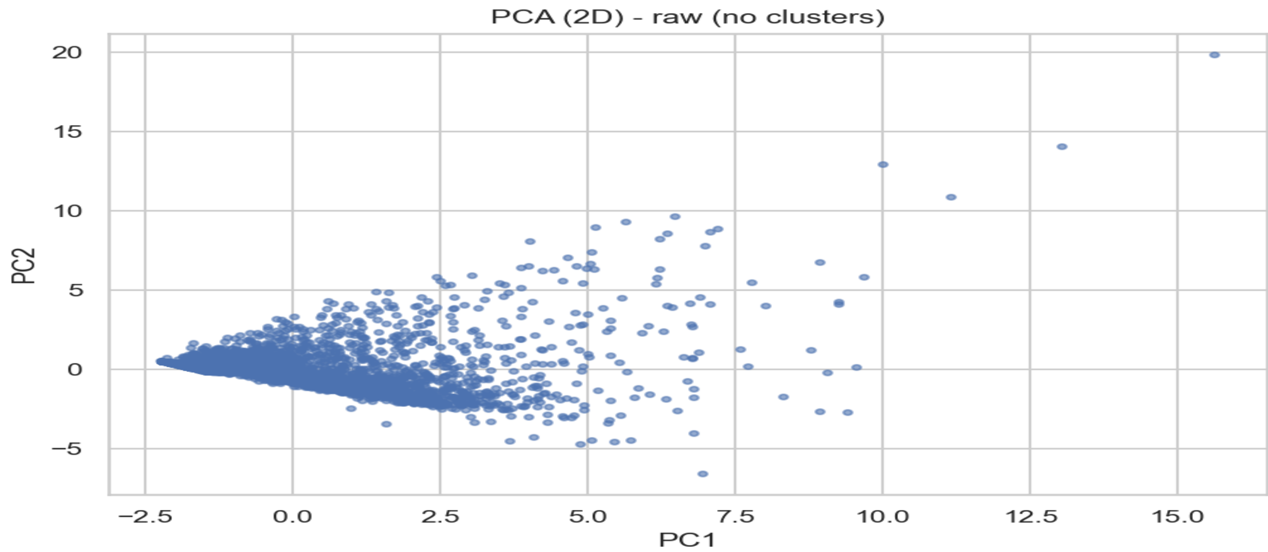
Agglomerative (complete) k=6 silhouette=0.540
PC2
PC1
−5
0
5
10
15
20
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0


Dendrogram (ward) - truncated
30
25
20
15
10
5
0


KMeans Elbow (Inertia)
Inertia
35000
30000
25000
20000
15000
2
3
4
5
6
7
8
9
10
k


KMeans Silhouette vs k
Silhouette score
0.32
0.30
0.28
0.26
0.24
2
3
4
5
6
7
8
9
10
k


KMeans (k=6) on PCA(2)
PC2
PC1
20
15
10
5
0
−5
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0


PCA (2D) - raw (no clusters)
PC2
PC1
20
15
10
5
0
−5
−2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0

```
(.venv) PS D:\python apps> & "D:/python apps/my-streamlit-app/.venv/Scripts/python.exe"
"d:/python apps/clustering/cluster3.py"
PCA explained variance (first 2): [0.29867646 0.15709627]
KMeans: best k by silhouette in range 2-10: 6 silhouette: 0.3334326918980287
KMeans cluster counts:
 1    2484
0    1253
2     143
5      61
3      43
4      15
Name: count, dtype: int64
KMeans silhouette: 0.3334326918980287
Agglomerative (ward) silhouette: 0.3193 counts:
 0    2446
1    1232
5     130
2     130
3      43
4      18
Name: count, dtype: int64
Agglomerative (complete) silhouette: 0.5404 counts:
 0    3782
1     127
5      43
4      28
2      15
3       4
Name: count, dtype: int64
Agglomerative (average) silhouette: 0.6618 counts:
 0    3974
1      15
2       5
3       3
5       1
4       1
Name: count, dtype: int64
DBSCAN eps=0.3, min_samples=4 -> clusters=34, silhouette=-0.1860, noise=2233
DBSCAN eps=0.3, min_samples=6 -> clusters=20, silhouette=-0.0584, noise=2478
DBSCAN eps=0.3, min_samples=8 -> clusters=14, silhouette=0.1864, noise=2653
DBSCAN eps=0.5, min_samples=4 -> clusters=28, silhouette=0.1084, noise=1317
DBSCAN eps=0.5, min_samples=6 -> clusters=13, silhouette=0.1494, noise=1486
DBSCAN eps=0.5, min_samples=8 -> clusters=11, silhouette=0.1507, noise=1628
DBSCAN eps=0.7, min_samples=4 -> clusters=24, silhouette=0.1446, noise=843
DBSCAN eps=0.7, min_samples=6 -> clusters=15, silhouette=0.1584, noise=954
DBSCAN eps=0.7, min_samples=8 -> clusters=13, silhouette=0.1640, noise=1048
DBSCAN eps=0.9, min_samples=4 -> clusters=9, silhouette=0.0159, noise=626
DBSCAN eps=0.9, min_samples=6 -> clusters=5, silhouette=0.2751, noise=692
```

```
DBSCAN eps=0.9, min_samples=8 -> clusters=3, silhouette=0.3232, noise=753
DBSCAN eps=1.1, min_samples=4 -> clusters=7, silhouette=0.2654, noise=477
DBSCAN eps=1.1, min_samples=6 -> clusters=5, silhouette=0.2974, noise=524
DBSCAN eps=1.1, min_samples=8 -> clusters=4, silhouette=0.2977, noise=556
Best DBSCAN: 0.9 8 silhouette: 0.32321824454732395
Saved cluster means for kmeans_k6 to D:\DATA SCIENCE\ASSIGNMENTS\8 clustering\Clustering\kmeans_k6_cluster_feature_means.csv

KMeans cluster means (truncated):
cluster           0         1  ...          4         5
Balance     0.433744 -0.298517  ...   0.639719  0.457104
Qual_miles -0.108033 -0.131435  ...  -0.084433  6.731092
cc1_miles   1.195566 -0.604366  ...   1.022084 -0.043229
cc2_miles  -0.098242 -0.098242  ...  -0.098242 -0.098242
cc3_miles  -0.054590 -0.060704  ...  15.646299 -0.062767

[5 rows x 6 columns]
Saved cluster means for agg_ward to D:\DATA SCIENCE\ASSIGNMENTS\8 clustering\Clustering\agg_ward_cluster_feature_means.csv

Agglomerative(ward) cluster means (truncated):
cluster           0         1  ...          4         5
Balance    -0.270655  0.428302  ...   0.559233  0.363407
Qual_miles -0.174627 -0.138437  ...  -0.101411  4.341199
cc1_miles  -0.592297  1.171874  ...   0.965591 -0.143800
cc2_miles  -0.098242 -0.098242  ...  -0.098242 -0.098242
cc3_miles  -0.062767 -0.062767  ...  13.881875 -0.062767

[5 rows x 6 columns]
Saved cluster means for dbscan_eps0.9_ms8 to D:\DATA SCIENCE\ASSIGNMENTS\8 clustering\Clustering\dbscan_eps0.9_ms8_cluster_feature_means.csv

DBSCAN cluster means (truncated):
cluster          -1         0         1         2
Balance     0.901219 -0.222978 -0.175165 -0.458785
Qual_miles  0.791748 -0.184783 -0.181127 -0.186299
cc1_miles   0.425571 -0.307267  0.378405 -0.769578
cc2_miles   0.333542 -0.098242 -0.098242  6.675367
cc3_miles   0.270571 -0.062767 -0.062767 -0.062767

--- FINAL SUMMARY ---
KMeans k=6 silhouette=0.3334
Agglomerative (ward) silhouette=0.3193
Agglomerative (complete) silhouette=0.5404
Agglomerative (average) silhouette=0.6618
Best DBSCAN eps=0.9, min_samples=8 silhouette=0.3232
All plots and CSV outputs saved to: D:\DATA SCIENCE\ASSIGNMENTS\8 clustering\Clustering
(.venv) PS D:\python apps>
```