CLUSTERING RESULTS REPORT

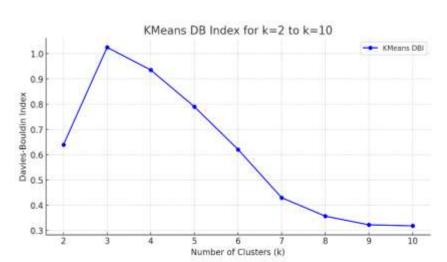
This report presents the clustering performance of KMeans, Hierarchical and DBSCAN Clustering algorithms on the customer data, using two important evaluation metrics: **Davies-Bouldin Index** and **Silhouette Score**. The results cover the clustering performance for different values of k (number of clusters), from 2 to 10.

KMeans Clustering Results

Davies-Bouldin Index for KMeans (k=2 to k=10):

The **Davies-Bouldin Index (DBI)** is a metric used to evaluate the clustering quality, where a lower score indicates better clustering. Below are the DBI values for different values of k:

| k (Number of Clusters) | DB Index |
|------------------------|----------|
| 2 | 0.6396 |
| 3 | 1.0255 |
| 4 | 0.9357 |
| 5 | 0.7903 |
| 6 | 0.6210 |
| 7 | 0.4298 |
| 8 | 0.3566 |
| 9 | 0.3223 |
| 10 | 0.3183 |

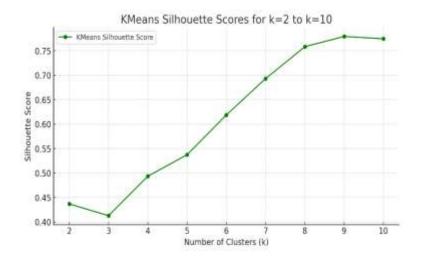


• Interpretation: As the number of clusters increases from k=2 to k=10, the Davies-Bouldin Index steadily decreases, with the lowest value observed at k=10 (0.3183). This indicates that clustering quality improves as the number of clusters increases. The DBI reaches its minimum at k=10, suggesting that this is the most well-separated set of clusters.

Silhouette Scores for KMeans (k=2 to k=10):

The **Silhouette Score** measures how similar each point is to its own cluster (cohesion) compared to other clusters (separation). The values range from -1 to +1, with higher values indicating better clustering.

| k (Number of Clusters) | Silhouette Score |
|------------------------|------------------|
| 2 | 0.4369 |
| 3 | 0.4128 |
| 4 | 0.4935 |
| 5 | 0.5373 |
| 6 | 0.6188 |
| 7 | 0.6932 |
| 8 | 0.7585 |
| 9 | 0.7794 |
| 10 | 0.7747 |



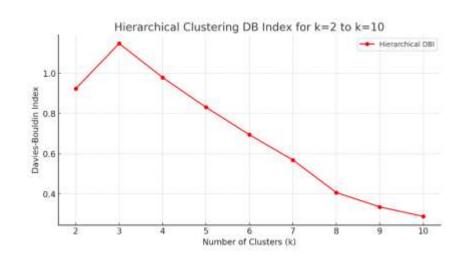
• Interpretation: The Silhouette Score increases as the number of clusters grows, peaking at k=9 with a value of 0.7794. This suggests that the clustering becomes more cohesive and well-separated as the number of clusters increases, with the highest score at k=9. However, the Silhouette Score slightly decreases at k=10, indicating that adding more clusters beyond this point does not significantly improve clustering quality.

Hierarchical Clustering Results

Davies-Bouldin Index for Hierarchical Clustering (k=2 to k=10):

The **Davies-Bouldin Index (DBI)** for hierarchical clustering shows the following trend for different values of k:

| k (Number of Clusters) | DB Index |
|------------------------|----------|
| 2 | 0.9229 |
| 3 | 1.1478 |
| 4 | 0.9791 |
| 5 | 0.8310 |
| 6 | 0.6946 |
| 7 | 0.5691 |
| 8 | 0.4072 |
| 9 | 0.3361 |
| 10 | 0.2887 |

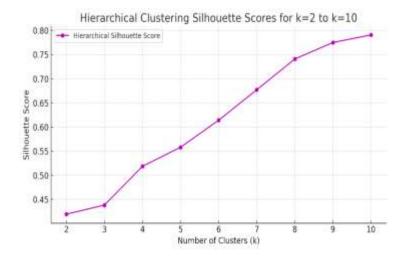


Interpretation: Similar to KMeans, the Davies-Bouldin Index for hierarchical clustering decreases as the number of clusters increases, reaching its minimum value at k=10 (0.2887). This indicates that as more clusters are formed, the clusters become increasingly well-separated.

Silhouette Scores for Hierarchical Clustering (k=2 to k=10):

The **Silhouette Score** for hierarchical clustering is presented below:

| k (Number of Clusters) | Silhouette Score |
|------------------------|------------------|
| 2 | 0.4194 |
| 3 | 0.4382 |
| 4 | 0.5186 |
| 5 | 0.5581 |
| 6 | 0.6141 |
| 7 | 0.6772 |
| 8 | 0.7409 |
| 9 | 0.7750 |
| 10 | 0.7907 |

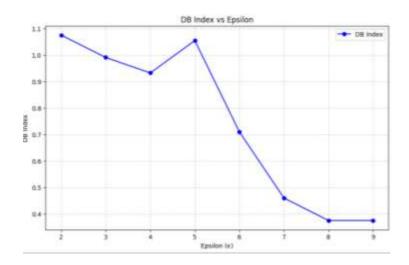


• Interpretation: The Silhouette Score increases with the number of clusters, peaking at k=10 with a score of **0.7907**. This suggests that hierarchical clustering improves as the number of clusters increases, achieving the highest cohesion and separation at k=10. The Silhouette Score for hierarchical clustering suggests that this model performs well when more clusters are created, with the best performance at k=10.

DBSCAN Clustering Results

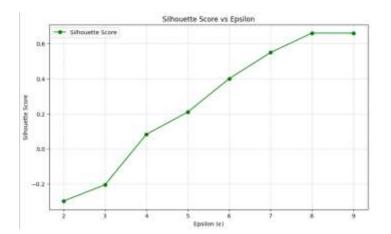
Davies-Bouldin Index (DBI) for varying ϵ values:

| E | DB Index |
|---|----------|
| 2 | 1.0758 |
| 3 | 0.9911 |
| 4 | 0.9326 |
| 5 | 1.0550 |
| 6 | 0.7101 |
| 7 | 0.4596 |
| 8 | 0.3746 |
| 9 | 0.3746 |



- Interpretation: Similar to KMeans, the Davies-Bouldin Index for DBSCAN decreases as the value of ε increases, reaching its minimum value at ε=8 (0.3746). This indicates that as more clusters are formed, the clusters become increasingly well-separated.
- Silhouette Scores for varying ε:

| €\epsilon | Silhouette Score | |
|-----------|------------------|--|
| 2 | -0.2978 | |
| 3 | -0.2053 | |
| 4 | 0.0827 | |
| 5 | 0.2102 | |
| 6 | 0.4005 | |
| 7 | 0.5499 | |
| 8 | 0.6607 | |
| 9 | 0.6607 | |



Interpretation: Similar to KMeans, the Silhouette Score for DBSCAN increases as the value of
 ϵ increases, reaching its minimum value at ϵ=8 (0.6607). This indicates that as more clusters
 are formed, the clusters become increasingly cohesive and well-separated.

Comparison of All three Clustering methods

| Metric | KMeans (Best k) | Hierarchical (Best k) | DBSCAN (∈) |
|----------------------|-----------------|-----------------------|------------------|
| Davies-Bouldin Index | 0.3183 (k=10) | 0.2887 (k=10) | 0.3746(∈=8 or 9) |
| Silhouette Score | 0.7794 (k=9) | 0.7907 (k=10) | 0.6607(∈=8 or 9) |

- Davies-Bouldin Index: Both algorithms show a similar trend, with hierarchical clustering achieving a slightly lower DBI value at k=10, indicating that it may offer slightly better separation of clusters than KMeans at this point.
- Silhouette Score: Hierarchical clustering achieves a higher silhouette score than KMeans, peaking at 0.7907 at k=10 compared to KMeans' peak of 0.7794 at k=9. This suggests that hierarchical clustering produces better-defined clusters than KMeans at its optimal number of clusters.

Conclusion

- Optimal Number of Clusters: Based on the evaluation metrics of best performing algorithms, the optimal number of clusters for both KMeans and Hierarchical clustering is 10 clusters.
 While both clustering algorithms show improvement with more clusters, hierarchical clustering produces the most well-defined clusters at k=10 according to both the Davies-Bouldin Index and the Silhouette Score.
- Best Algorithm: While both methods show good clustering quality, Hierarchical Clustering has a slight edge over KMeans in terms of Silhouette Score, indicating that it generates more cohesive and well-separated clusters at the optimal value of k=10.