ALLLIFE BANK CUSTOMER SEGMENTATION REVIEW

Service Delivery Clustering Analysis

AIML : University of Texas Austin McCombs School of Business

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Presented By Greg Wenzel

CONTENTS

EXECUTIVE SUMMARY

Problem Statement:

AllLife Bank aims to enhance its credit card customer base by improving market penetration. The Marketing team intends to implement personalized campaigns for both acquiring new customers and upselling to existing ones. Concurrently, the Operations team seeks to enhance customer support services to expedite query resolution. In response, the Data Science team is tasked with identifying customer segments based on spending patterns and past interactions to provide recommendations for targeted marketing and service improvement. This analysis employs clustering algorithms to uncover these segments and offer actionable recommendations to improve marketing and customer service.

Data Overview:

The dataset comprises customer data, including features like average credit limit, total credit cards, and various customer interaction channels. There are 660 rows and 7 columns in the dataset.

EXECUTIVE SUMMARY - CONTINUED

Data Preprocessing:

Duplicate values in the 'Customer_Key' column were identified and removed.

Irrelevant columns ('Sl_No' and 'Customer_Key') were dropped.

Univariate analysis revealed that the data is numeric, with no missing values.

The distribution of numerical variables, such as credit limit and the number of credit cards, varies significantly.

Bivariate analysis and correlation heatmaps highlighted potential relationships between variables.

EXECUTIVE SUMMARY - CONTINUED

Clustering

Clustering algorithms, such as hierarchical and k-means clustering, will be used to segment customers.

The 'Avg_Credit_Limit,' 'Total_Credit_Cards,' 'Total_visits_bank,' 'Total_visits_online,' and 'Total_calls_made' features will be used for clustering.

Hierarchical clustering was performed to create segments ('HC_segments'), and **k-means** clustering produced additional labels ('HC_Clusters').

Next Steps:

Further analysis, such as comparing hierarchical and k-means clusters and deriving insights from these segments, will help formulate recommendations.

Targeted marketing campaigns can be designed based on spending patterns, and customer service can be improved by addressing specific issues identified within each segment.

This analysis provides a foundation for AllLife Bank to enhance customer engagement, tailor marketing efforts, and optimize customer support services, ultimately boosting customer satisfaction and business growth.

EXECUTIVE SUMMARY - CONTINUED

Additional Insights :

Linkage and Distance Metrics: The analysis explored various linkage methods (ward, complete, average, single) with different distance metrics (Euclidean, Manhattan, Cosine, Chebyshev, Mahalanobis) to find the combination with the highest cophenetic correlation. This is important because higher cophenetic correlation suggests better preservation of pairwise distances in the dendrogram. It was found that the highest cophenetic correlation (0.9278) was achieved with Cosine distance and average linkage.

Dendrogram Visualization: Dendrograms were created for each linkage method, allowing for a visual understanding of the hierarchical cluster structures. The dendrogram with average linkage showed distinct and separate cluster trees, reinforcing the choice of linkage method.

Dendrogram Analysis: Dendrograms provide valuable visualizations of hierarchical clustering structures. Decision-makers should explore dendrograms to gain a deeper understanding of how clusters are formed and assess their suitability for the business problem.

Cluster Profiling: Cluster profiles should be thoroughly examined to understand the characteristics of each segment. These profiles can guide marketing and service improvement strategies.

EXECUTIVE SUMMARY - CONTINUED

Clustering Technique Selection: The choice between K-means and Hierarchical Clustering can depend on factors like execution time and the specific problem context. Both techniques produced consistent results in this analysis, but the decision should consider computational resources and the desired level of interpretability.

Boxplots for Cluster Analysis: Boxplots of numerical variables for each cluster provide a clear visual representation of how clusters differ in terms of these variables. These plots can help in tailoring marketing and service strategies to the unique needs of each cluster.

Further analysis, such as comparing hierarchical and k-means clusters and deriving insights from these segments, will help formulate recommendations.

Targeted marketing campaigns can be designed based on spending patterns, and customer service can be improved by addressing specific issues identified within each segment.

This analysis provides a foundation for AllLife Bank to enhance customer engagement, **tailor marketing efforts**, and optimize customer support services, ultimately boosting customer satisfaction and business growth.

BUSINESS PROBLEM OVERVIEW AND SOLUTION APPROACH

•AllLife Bank aims to enhance its credit card customer base and address customer support issues. To achieve these goals, the bank seeks to identify distinct customer segments based on spending patterns and interactions with the bank.

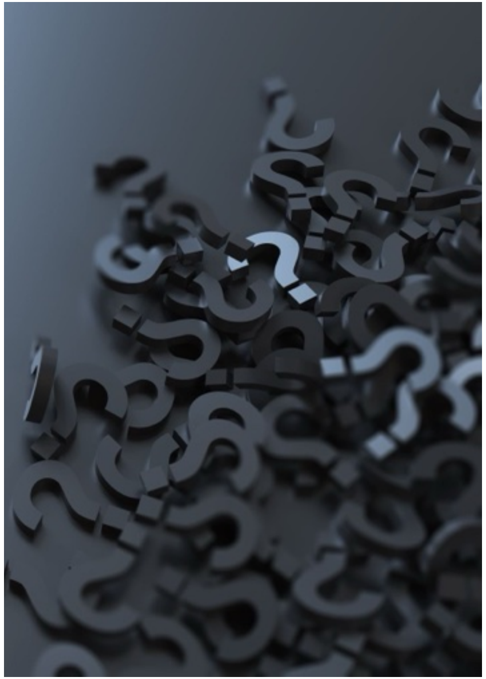
•**Solution Approach / Methodology:**

•To address AllLife Bank's business problem, we propose the following solution approach:

•**Data Preprocessing:**

•**Outlier Detection:** Identify and handle outliers in the dataset to ensure that they do not unduly influence clustering results. This involves using statistical methods like z-scores or interquartile ranges.

•**Scaling:** Standardize the data to ensure that all features have the same scale. Standardization is important for clustering algorithms like K-means, where differences in scales can lead to biased results.



BUSINESS PROBLEM OVERVIEW AND SOLUTION APPROACH - CONTINUED

Exploratory Data Analysis (EDA):

Perform univariate and bivariate analysis to gain insights into the data distribution, identify potential relationships between variables, and understand data characteristics.

Clustering:

Utilize clustering algorithms to segment customers into distinct groups based on their spending patterns and interactions. The selected features for clustering include 'Avg_Credit_Limit,' 'Total_Credit_Cards,' 'Total_visits_bank,' 'Total_visits_online,' and 'Total_calls_made.'

Two clustering algorithms, K-means and Hierarchical Clustering, are applied to the dataset to evaluate their effectiveness in creating meaningful customer segments.

Determining the Optimal Number of Clusters:

For K-means, the optimal number of clusters is determined using the Elbow Method and Silhouette Scores. These methods help in selecting the most appropriate number of clusters that best represent the underlying structure in the data.

BUSINESS PROBLEM OVERVIEW AND SOLUTION APPROACH - CONTINUED

Cluster Profiling:

After clustering, profile each segment to understand the characteristics of customers within each cluster. Key attributes like 'Avg_Credit_Limit,' 'Total_Credit_Cards,' and 'Total_visits_bank' can provide insights into the unique features of each cluster.

Comparison of Clustering Algorithms:

Compare the results of K-means and Hierarchical Clustering, considering factors such as execution time, cluster separation, observation consistency, and the number of clusters obtained.

Recommendations:

Based on the insights gained from cluster profiling, formulate actionable recommendations for AllLife Bank. These recommendations may include targeted marketing campaigns tailored to each customer segment and improvements in customer service based on specific issues identified within each cluster.

BUSINESS PROBLEM OVERVIEW AND SOLUTION APPROACH - CONTINUED

Future Analysis:

Continuously monitor customer behavior within the clusters to adapt marketing and service strategies as needed. Consider additional data sources or features for a more comprehensive analysis.

By following this methodology, AllLife Bank can enhance customer engagement, optimize marketing efforts, and improve customer support services, ultimately leading to increased customer satisfaction and business growth. It's important to note that the choice of clustering algorithm and the number of clusters may require fine-tuning based on domain expertise and specific business objectives.

PROPOSED SOLUTION AND RECOMMENDATIONS FOR CUSTOMER SEGMENTATION

The optimal solution involves segmenting customers into three distinct clusters to tailor marketing efforts and enhance customer support.

Utilize Hierarchical Clustering

- Engage hierarchical clustering with cosine distance and average linkage.
  - Provides high cophenetic correlation indicating good cluster separation.
  - Dendrograms show distinct and separate cluster trees.

Employ Cluster Profiling

- Analyze cluster profiles to understand characteristics of each segment.
- Focus on 'Average Credit Limit', 'Total Credit Cards', & 'Total Bank Visits'

Recommendations

- Targeted Marketing Campaigns
  - Focus on 3 specific segments supported by the data observations
- Customer Support Enhancement
  - Target 3 segments to aid customers, develop support resources & premium customer support

Full Summary of Solutions & Recommendations

EDA RESULTS

[UNIVARIATE]

[BIVARIATE]

Overall, the exploratory data analysis has provided insights into the distribution and relationships between various features in the dataset. These insights will be valuable in the subsequent steps of clustering analysis and segmentation of customers based on their spending patterns and interactions with the bank.

UNIVARIATE ANALYSIS

Avg_Credit_Limit Distribution: The distribution of average credit limits among customers varies, with some having significantly higher credit limits than others. This suggests a diverse customer base in terms of creditworthiness.

Total_Credit_Cards Distribution: The number of total credit cards held by customers also shows variation, ranging from fewer cards to more cards. This indicates differences in the financial behavior of customers.

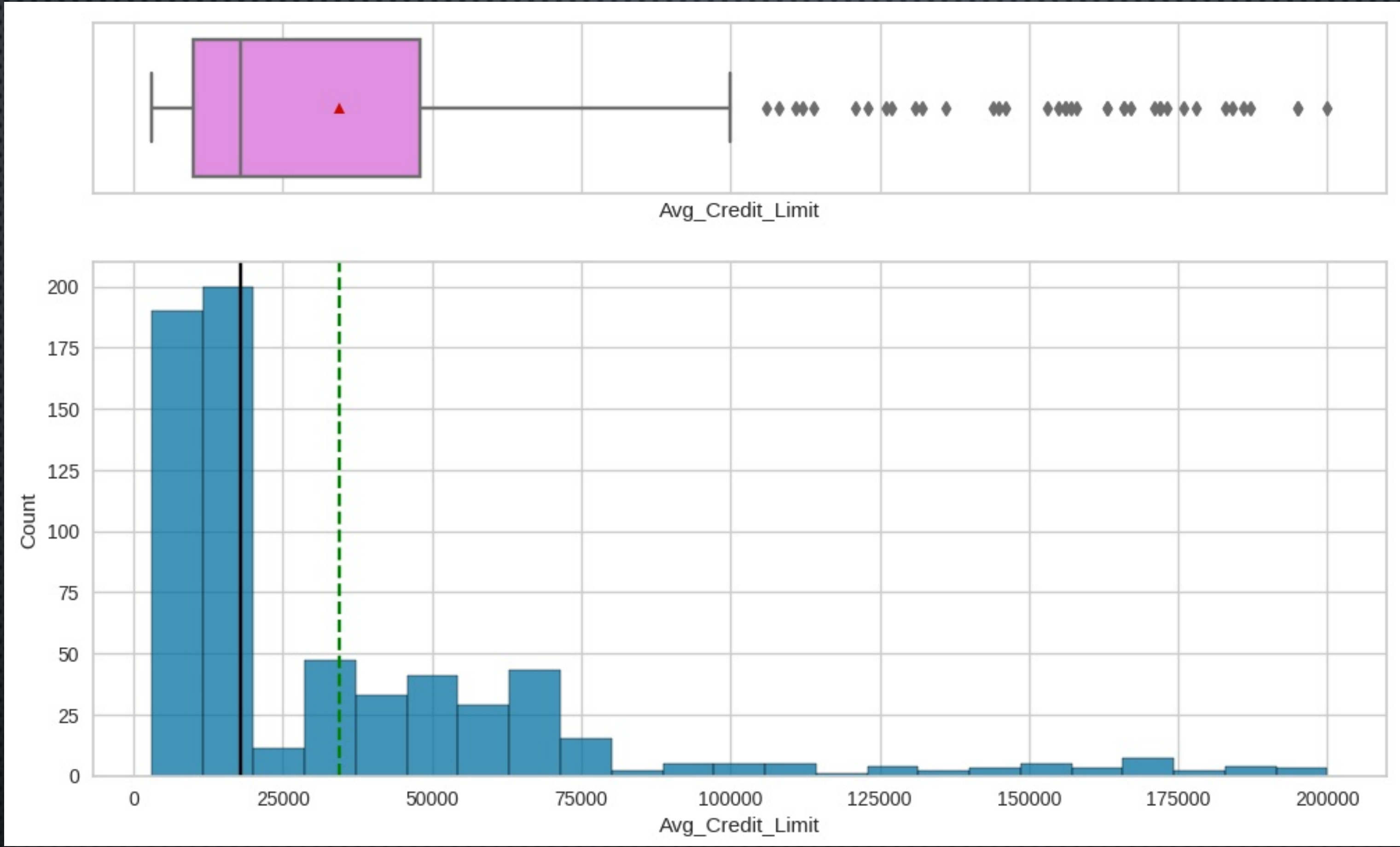
Total_visits_bank Distribution: The distribution of total visits to the bank appears to be somewhat bimodal, with peaks at two different values. This suggests the presence of two distinct customer segments in terms of in-person interactions with the bank.

Total_visits_online Distribution: The distribution of total online visits shows variability, with some customers using online services more frequently than others. This indicates differences in customer preferences for online interactions with the bank.

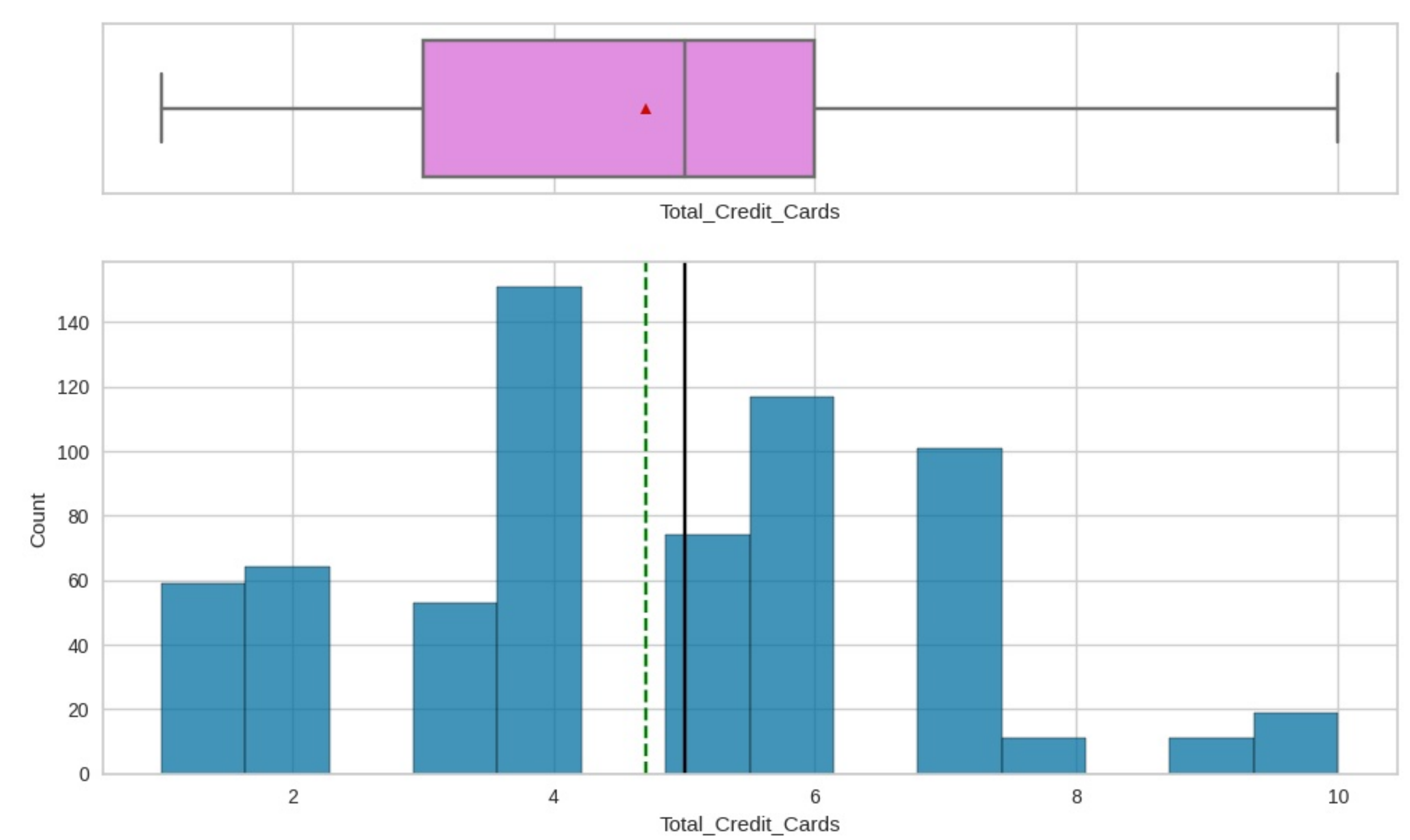
Total_calls_made Distribution: The distribution of total calls made to customer support shows variation, with some customers making more calls than others. This suggests differences in the level of customer support needed.

Bar Plots: Bar plots provide a visual representation of the distribution of categorical variables. These plots reveal the frequency of different levels within each categorical feature, such as the number of credit cards. This information can be valuable for understanding the categorical data distribution.

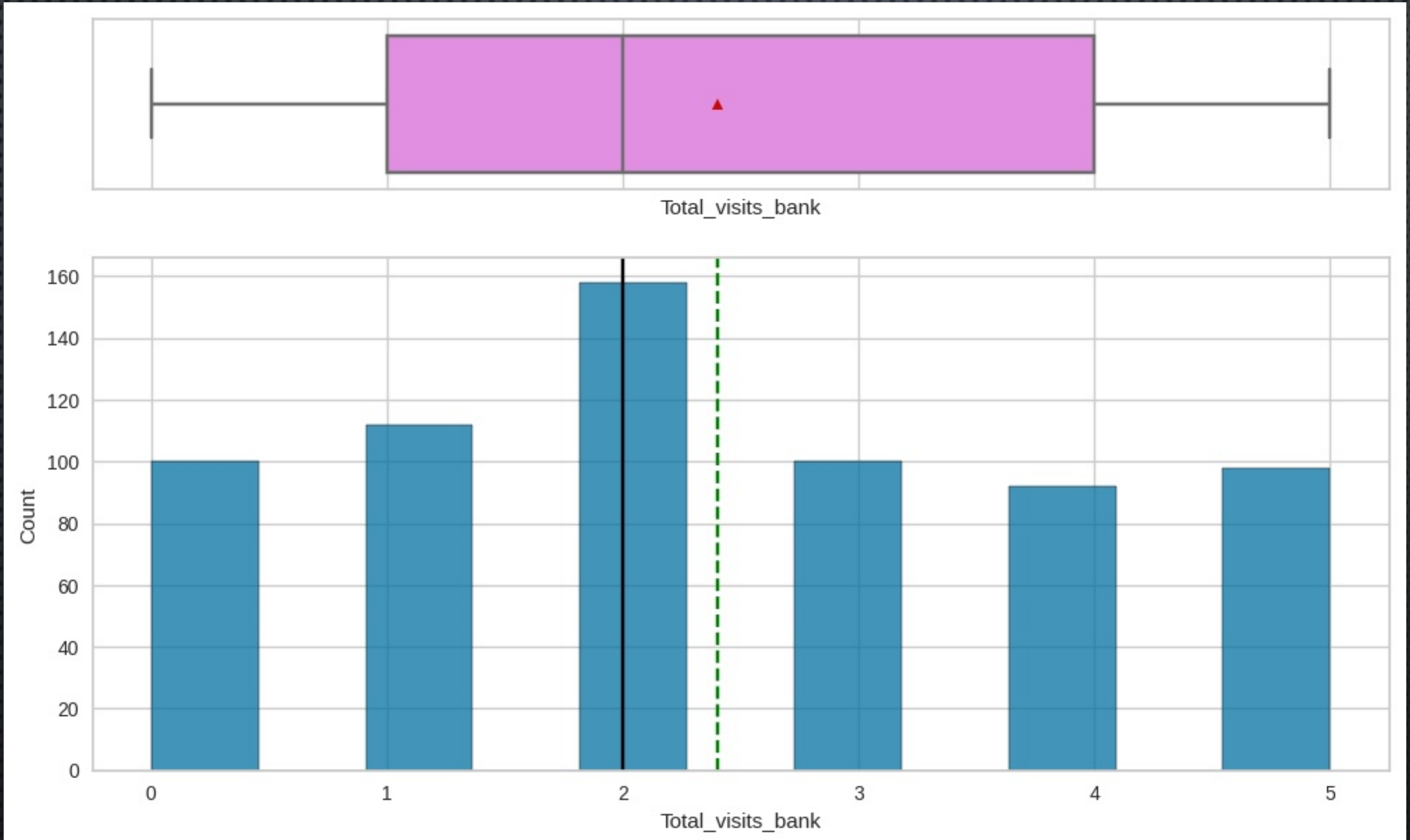
UNIVARIATE – AVERAGE CREDIT LIMIT DISTRIBUTION



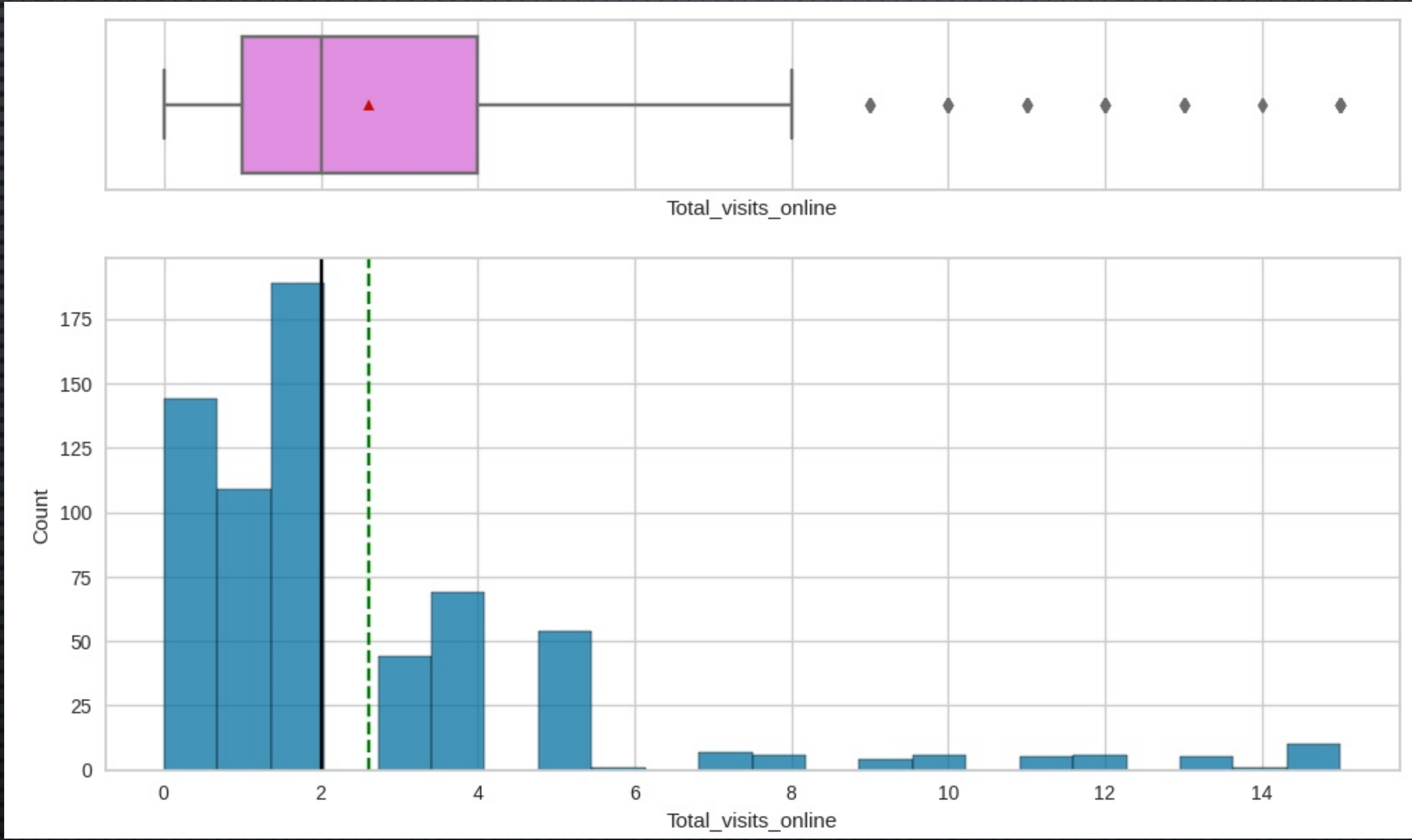
UNIVARIATE – TOTAL CREDIT CARD DISTRIBUTION



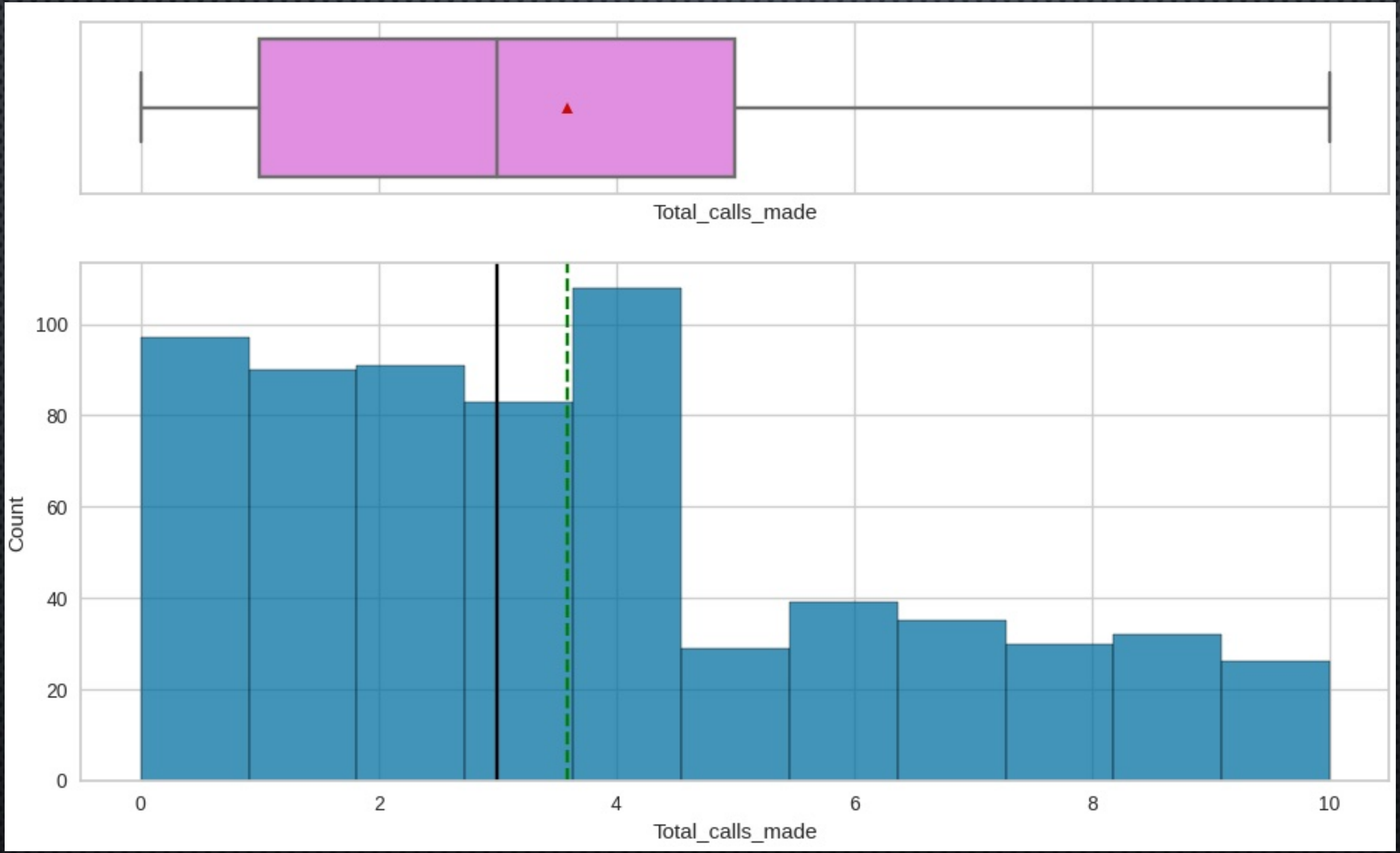
UNIVARIATE – TOTAL BANK VISITS BY CUSTOMER



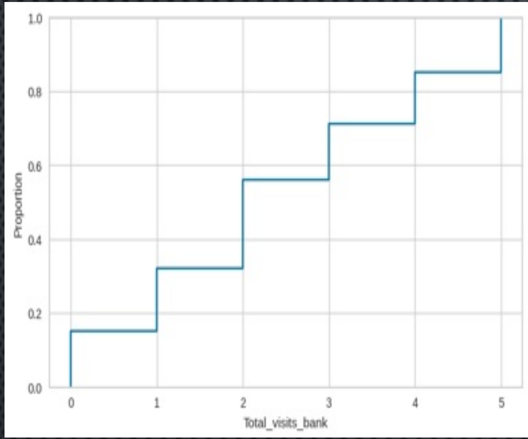
UNIVARIATE – TOTAL ONLINE CUSTOMER VISITS

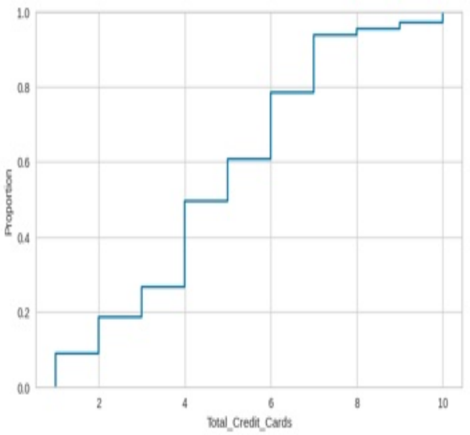


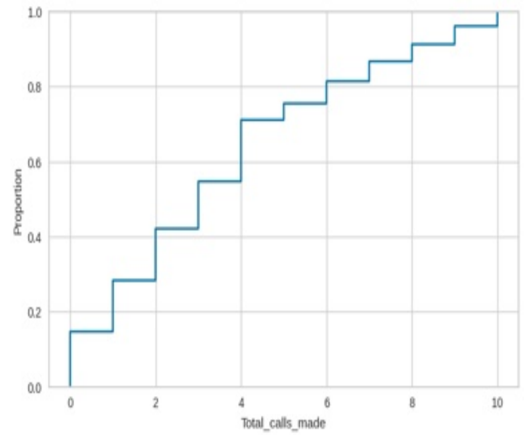
UNIVARIATE – TOTAL PHONE CALLS MADE BY CUSTOMER

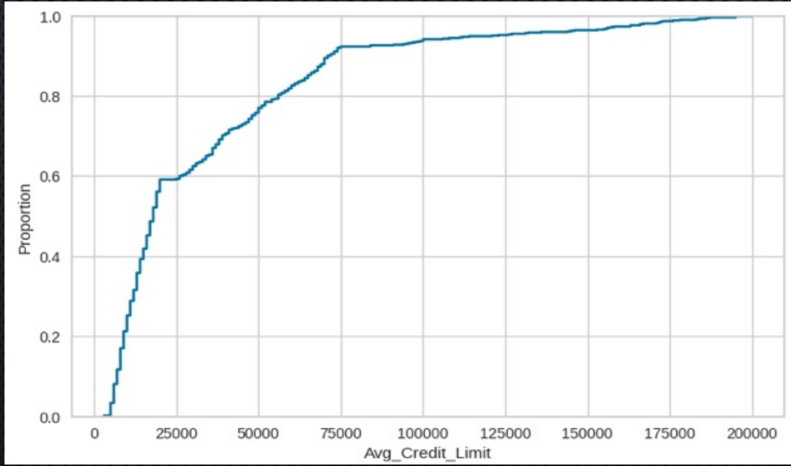


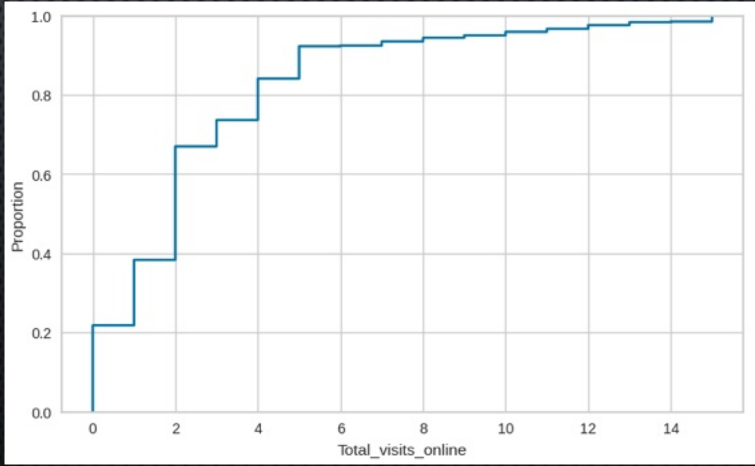
UNIVARIATE – CDF PLOT OF NUMERICAL VALUES



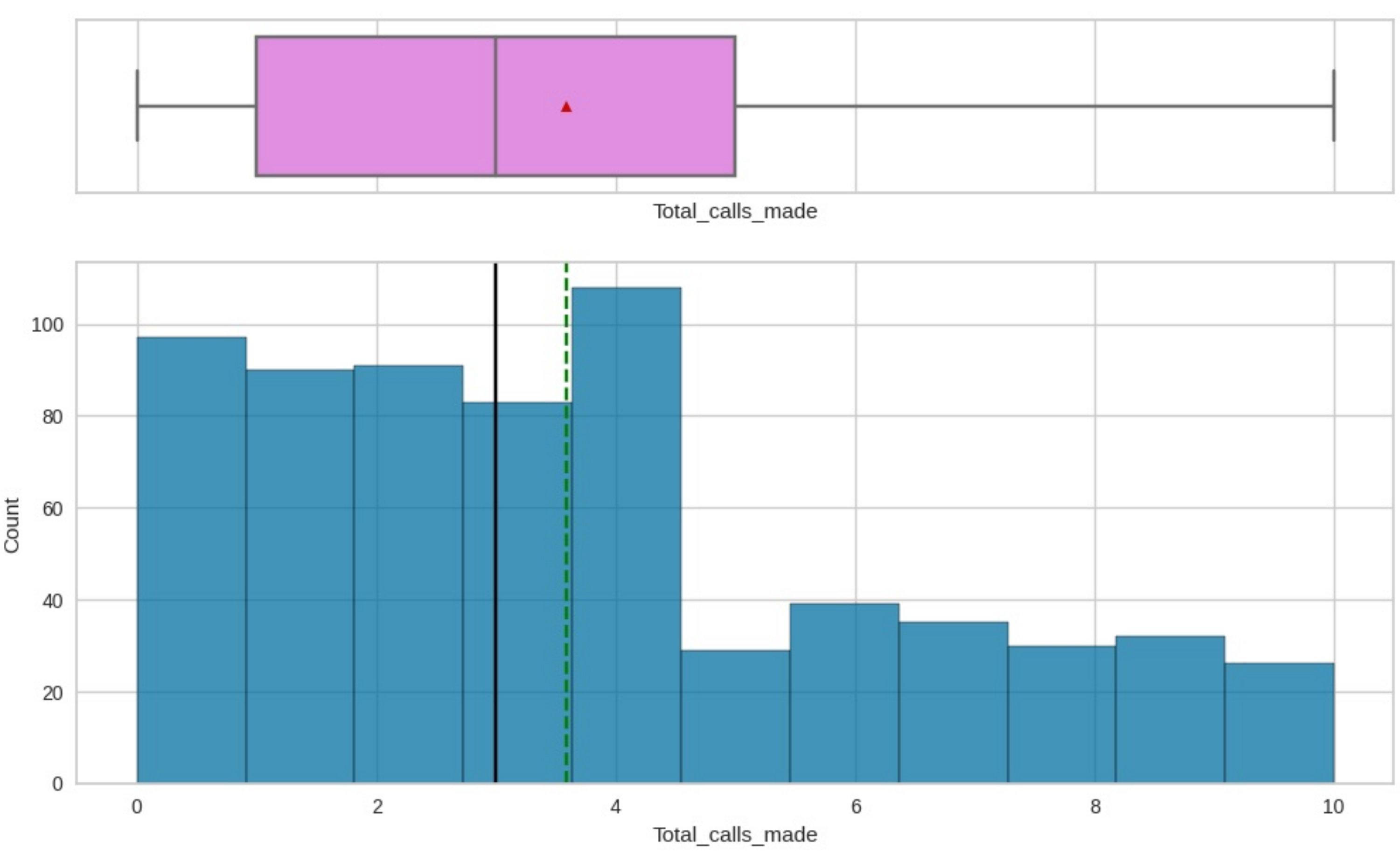








UNIVARIATE – TOTAL PHONE CALLS MADE BY CUSTOMER



BIVARIATE ANALYSIS

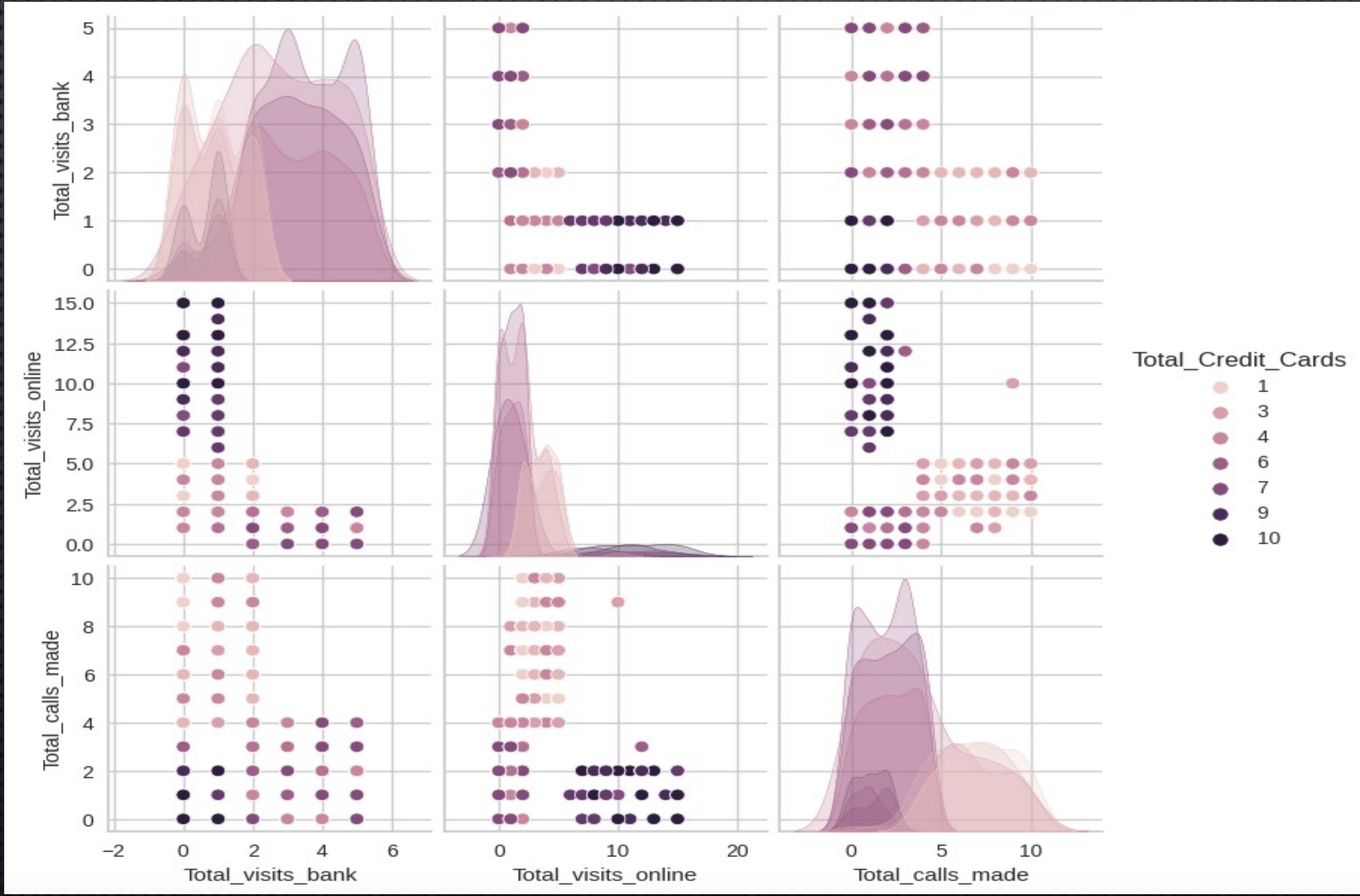
Correlation Heatmap: The correlation heatmap shows correlations between numerical features. Notably, 'Total_visits_bank' and 'Total_Calls_Made' have a negative correlation, indicating that customers who visit the bank more often tend to make fewer customer support calls. And as expected, there is a positive correlation between 'Total Credit Cards' and 'Average Credit Limit'.

Pair Plots: Pair plots display pairwise relationships between numerical features. These plots help visualize potential clusters or patterns in the data. For example, there seems to be a negative relationship between 'Total_Credit_Cards' and 'Total_Calls_Made,' suggesting that customers with more credit cards make fewer customer support calls.

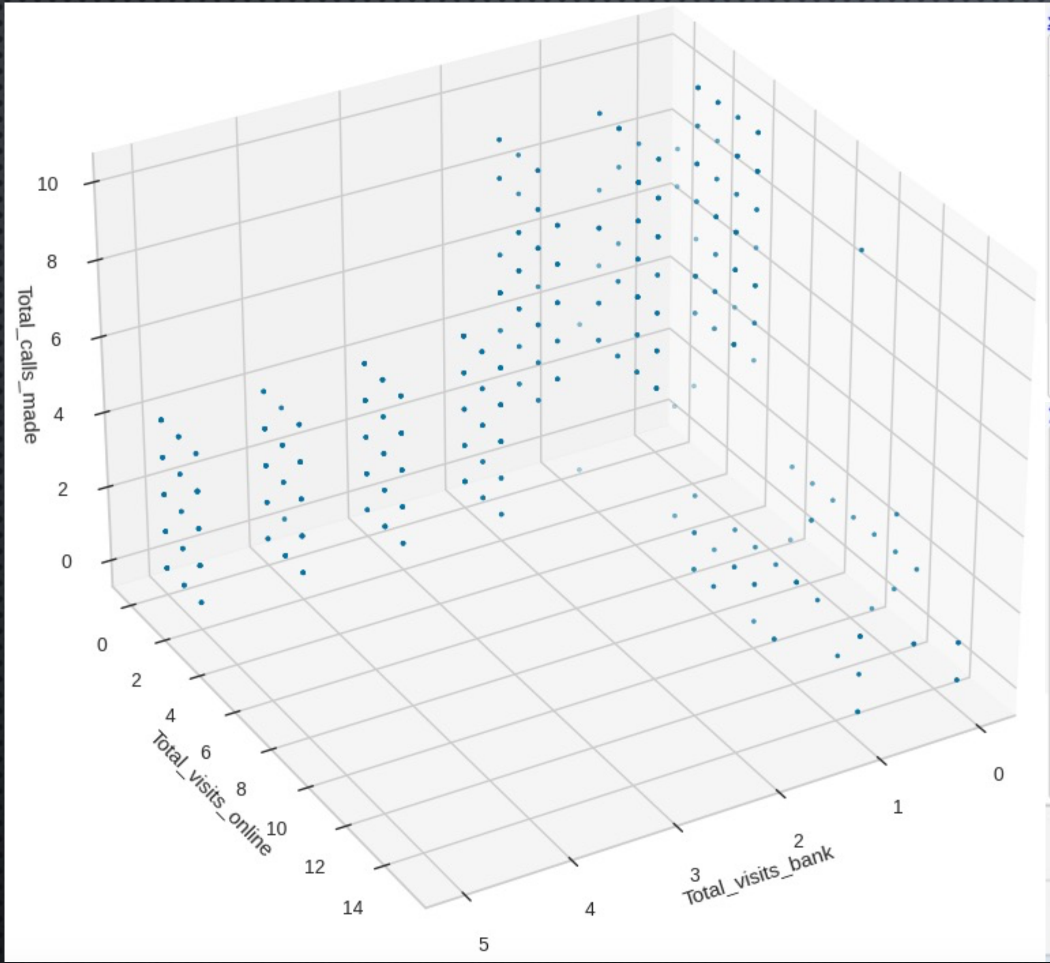
3D Scatter Plot: The 3D scatter plot visualizes the relationships between 'Total_visits_bank,' 'Total_visits_online,' and 'Total_calls_made.' It provides a 3D perspective on customer interactions with the bank, showing different clusters of points based on these variables.

BIVARIATE – HEATMAP

BIVARIATE – PAIRPLOT



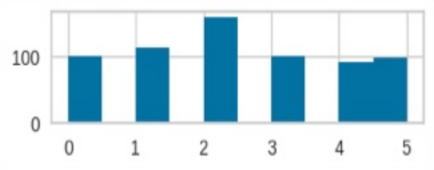
BIVARIATE – 3D SCATTERPLOT




```
x = df["Total_visits_bank"]
```

Series: x

Total_visits_bank *int64*

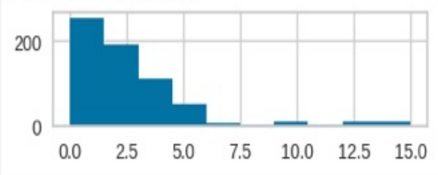


count	660.0
min	0.0
25%	1.0

```
y = df["Total_visits_online"]
```

Series: y

Total_visits_online *int64*



count	660.0
min	0.0
25%	1.0

```
float64: z
-0.5530048835518464
```

DATA PREPROCESSING

- Duplicate value check
- Missing value treatment
- Outlier check (treatment if needed)
- Data preparation for modeling

DATA PREPROCESSING

Data preprocessing is a crucial step in preparing the dataset for clustering and modeling. This involves several key processes, as outlined in the executive summary:

Duplicate Value Check: Duplicate values in the 'Customer_Key' column were identified and removed. Duplicate records can introduce bias and affect the accuracy of clustering algorithms. By removing duplicates, the dataset is made more consistent and reliable.

Missing Value Treatment: The exploratory data analysis (EDA) revealed that there were no missing values in the dataset. This is a positive finding as missing data can complicate clustering and modeling processes. The absence of missing values ensures that the dataset is complete and ready for analysis.

Outlier Check: Outlier detection was carried out using z-scores with different threshold values (2, 2.5, 3, and 3.5). Outliers were primarily identified in the 'Avg_Credit_Limit' and 'Total_Calls_Made' columns. Addressing outliers is an important consideration, as extreme values can skew clustering results.

Data Preparation for Modeling: Before clustering, the data underwent preparation to ensure all features have the same scale. This is crucial for algorithms like K-means clustering. StandardScaler was applied to selected columns, including 'Avg_Credit_Limit,' 'Total_Credit_Cards,' 'Total_Visits_Bank,' 'Total_Visits_Online,' and 'Total_Calls_Made.' Standardization transforms the data into a format where each feature has a mean of 0 and a standard deviation of 1, allowing for meaningful distance calculations during clustering.

In summary, data preprocessing for this project included duplicate value removal, missing value treatment (no missing values were found), and data standardization. Additionally, the presence of outliers was detected but not addressed in the provided information. Proper outlier treatment may be necessary depending on the specific goals of the clustering analysis. With these preprocessing steps completed, the dataset is in a suitable form for clustering algorithms and further analysis.

K-MEANS CLUSTERING SUMMARY

Optimal Number of Clusters:

The optimal number of clusters determined using K-Means clustering was 3 based on the Elbow Method and Silhouette Scores.

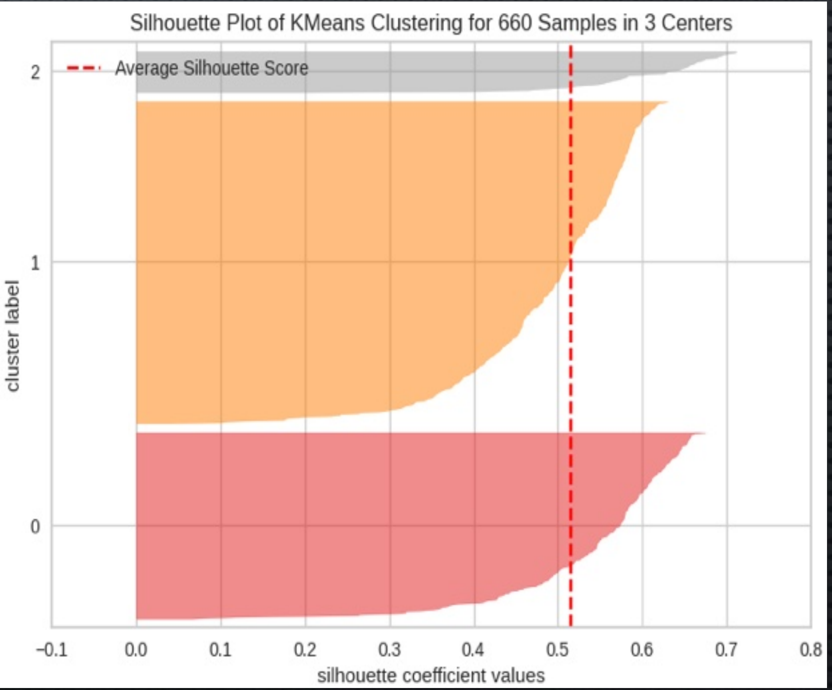
Cluster Profiling: Cluster profiles for the K-Means clustering results are as follows:

Cluster 0:

Customers in this cluster prefer visiting the bank in person with a relatively high number of Total_visits_bank.
They have a relatively low Avg_Credit_Limit.
They possess a moderate number of Total_Credit_Cards.
Their online interaction, as indicated by Total_visits_online, is low.
They make a moderate number of Total_calls_made.
This cluster is labeled as K-Means Segment 0 and contains 385 customers.

Cluster 1:

Customers in this cluster exhibit a very low Avg_Credit_Limit.
They have a low number of Total_Credit_Cards.
They rarely visit the bank in person with a very low Total_visits_bank.
Online interaction, measured by Total_visits_online, is moderate.
They make a relatively high number of Total_calls_made.
This cluster is labeled as K-Means Segment 1 and contains 224 customers.



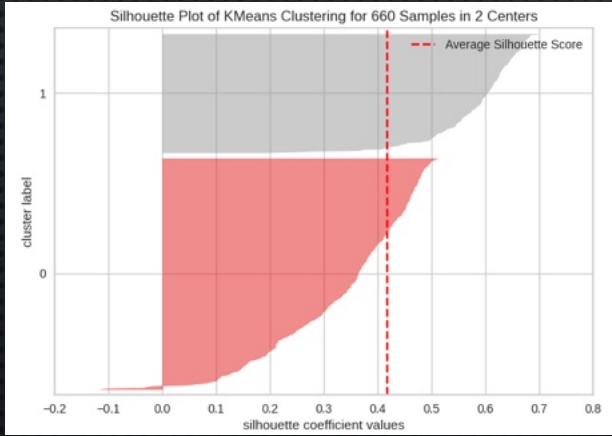
K-MEANS CLUSTERING SUMMARY - CONTINUED

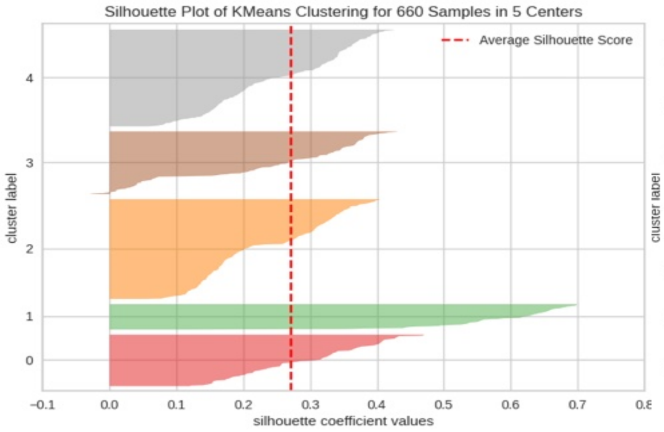
Cluster 2:

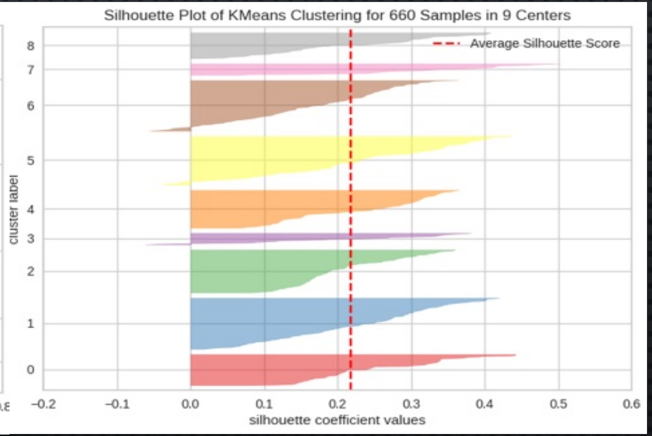
Customers in this cluster have a high Avg_Credit_Limit.
They possess a high number of Total_Credit_Cards.
They rarely visit the bank in person, indicated by a very low Total_visits_bank.
Online interaction is very high, with a substantial Total_visits_online.
They make a low number of Total_calls_made.
This cluster is labeled as K-Means Segment 2 and contains 51 customers.

Additionally, the count of customers in each segment is provided, indicating the number of customers belonging to each cluster.

These cluster profiles offer insights into distinct customer segments based on their financial behavior and interactions with the bank, providing valuable information for targeted marketing and service improvement strategies.







HIERARCHICAL CLUSTERING SUMMARY

Cophenetic Correlation:

The cophenetic correlation measures the quality of hierarchical clustering by assessing how faithfully the hierarchy preserves pairwise distances between data points.

The highest cophenetic correlation obtained was 0.9278 using Cosine distance and average linkage, indicating a strong hierarchical structure.

Linkage Methods Evaluation:

Different linkage methods were applied, including ward, complete, average, and single.

Cophenetic correlation values for each combination of linkage methods and distance metrics were calculated to determine the best-performing combination.

Dendrogram Analysis:

Dendrograms were plotted for each linkage method with Euclidean distance.

The dendrogram with average linkage showed distinct and separate cluster trees, indicating the presence of meaningful clusters.

HIERARCHICAL CLUSTERING SUMMARY - CONTINUED

Final Hierarchical Clustering Model:

The hierarchical clustering model with the following parameters was created:
Number of clusters: 3 | Affinity metric: Cosine distance | Linkage method: Average linkage
Hierarchical clustering labels were assigned to the original and scaled dataframes.

Cluster Profiling Results:

Following are cluster profiles for the hierarchical clustering using the Cosine distance and average linkage:

Cluster 0:

Customers in this cluster have relatively high Avg_Credit_Limit.
They possess a moderate number of Total_Credit_Cards.
They rarely visit the bank or access services online.
They have the highest number of Total_calls_made, indicating a preference for phone interactions with the bank.

Cluster 1:

Customers in this cluster exhibit moderate Avg_Credit_Limit.
They have a moderate number of Total_Credit_Cards.
They prefer online interactions, with a high number of Total_visits_online.
The number of Total_calls_made is relatively low

Cluster 2:

Customers in this cluster have relatively low Avg_Credit_Limit.
They possess a high number of Total_Credit_Cards.
They frequently visit the bank in person.
They have a moderate number of Total_visits_online.
The number of Total_calls_made is relatively low.

These cluster profiles provide valuable insights into customer segments based on their financial behavior and interactions with the bank.

HIERARCHICAL CLUSTERING SUMMARY -COPHENETIC CORRELATION

Cophenetic correlation for Euclidean distance and ward linkage is 0.7977695571808646
Cophenetic correlation for Euclidean distance and complete linkage is 0.8963207432763411
Cophenetic correlation for Euclidean distance and average linkage is 0.9249418571700024
Cophenetic correlation for Euclidean distance and single linkage is 0.7575532453100348

Cophenetic correlation for Manhattan distance and complete linkage is 0.9025715155105
Cophenetic correlation for Manhattan distance and average linkage is 0.9223664020134967
Cophenetic correlation for Manhattan distance and single linkage is 0.7485023246420628

Cophenetic correlation for Cosine distance and complete linkage is 0.9076297437816067
Cophenetic correlation for Cosine distance and average linkage is 0.9278387131739531
Cophenetic correlation for Cosine distance and single linkage is 0.8733961713756968

Cophenetic correlation for Chebyshev distance and complete linkage is 0.8953825192381583
Cophenetic correlation for Chebyshev distance and average linkage is 0.9043295696204086
Cophenetic correlation for Chebyshev distance and single linkage is 0.7744067914816417

Cophenetic correlation for Mahalanobis distance and complete linkage is 0.7929147514581971
Cophenetic correlation for Mahalanobis distance and average linkage is 0.796857323801983
Cophenetic correlation for Mahalanobis distance and single linkage is 0.7493818555459922

APPENDIX

DATA BACKGROUND AND CONTENTS

The dataset used in this analysis is from AllLife Bank and contains customer data, including features like average credit limit, total credit cards, and various customer interaction channels. There are 660 rows and 7 columns in the dataset. Data preprocessing steps involved removing duplicate values, checking for missing data (none found), and standardizing relevant columns. Outliers were also detected but not explicitly treated in the provided information. Duplicate values in the ‘Customer_Key’ column were ignored as the feature was dropped from the DataFrame.

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 660 entries, 0 to 659
Data columns (total 7 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Sl_No                660 non-null    int64
 1   Customer_Key         660 non-null    int64
 2   Avg_Credit_Limit     660 non-null    int64
 3   Total_Credit_Cards   660 non-null    int64
 4   Total_visits_bank    660 non-null    int64
 5   Total_visits_online  660 non-null    int64
 6   Total_calls_made     660 non-null    int64
dtypes: int64(7)
memory usage: 36.2 KB
```

```
df.isnull().sum()

Sl_No                  0
Customer_Key           0
Avg_Credit_Limit       0
Total_Credit_Cards     0
Total_visits_bank      0
Total_visits_online    0
Total_calls_made       0
dtype: int64
```

K-MEANS CLUSTERING TECHNIQUE

Application of K-Means Clustering:

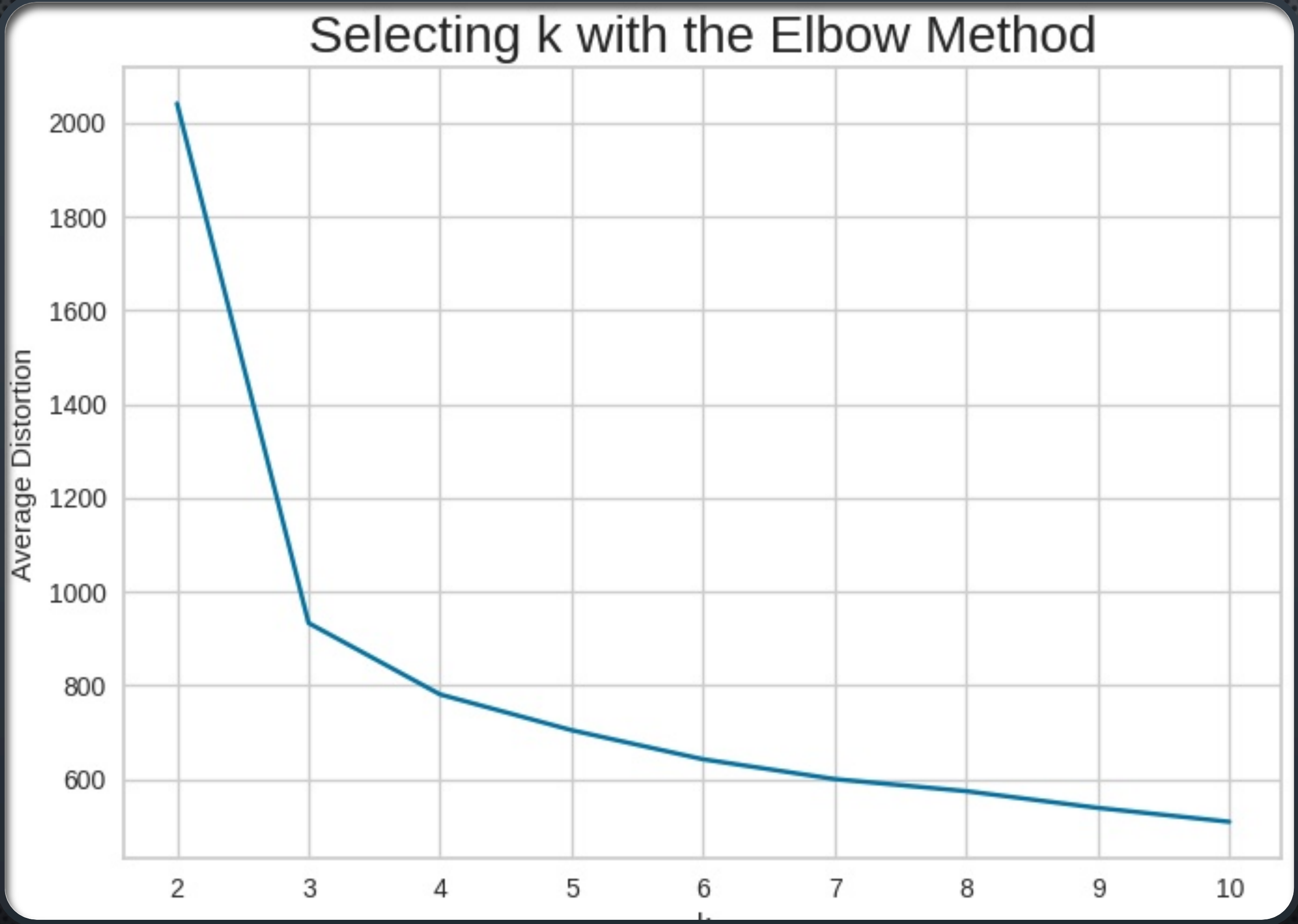
K-Means clustering was applied to the dataset to segment customers based on their financial behavior and interactions with the bank. The goal was to identify distinct customer groups to tailor marketing strategies and improve customer service.

Observations using Elbow Curve:

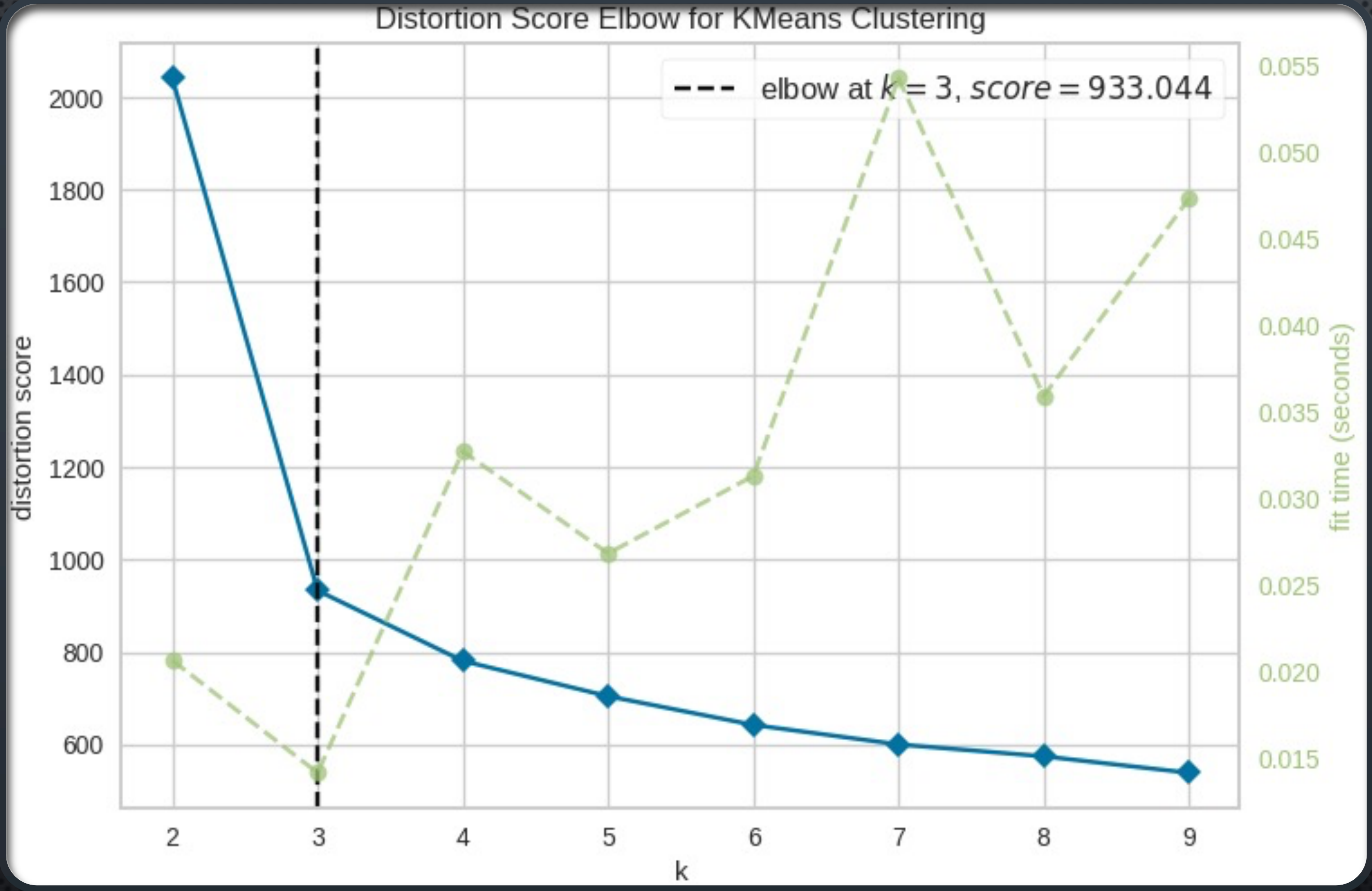
The Elbow Method was employed to determine the optimal number of clusters. It involved plotting the average distortion (inertia) for different numbers of clusters. While there was no clear "elbow" point, indicating an optimal cluster count, the distortion continued to decrease as the number of clusters increased. This suggested that the dataset could be effectively clustered into 3 segments.

Observations from Silhouette Scores:

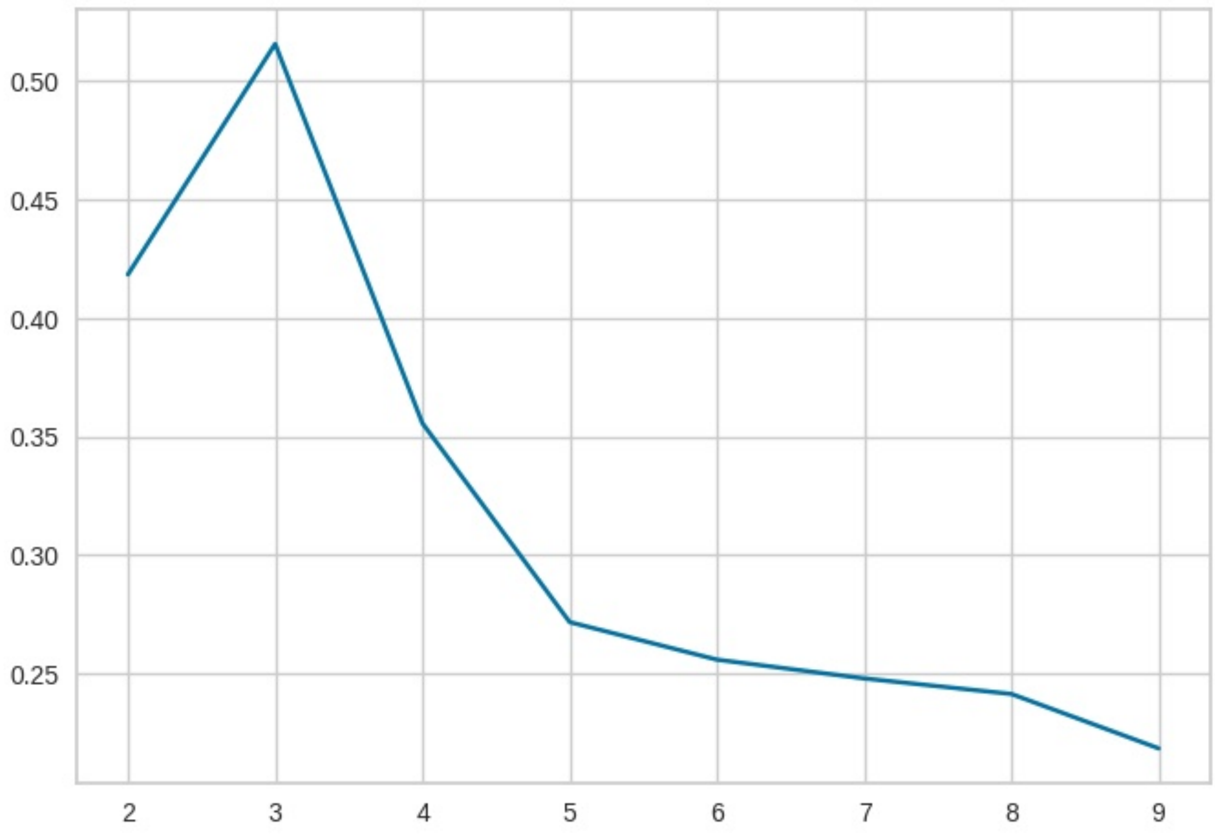
Silhouette scores were calculated for cluster numbers ranging from 2 to 9. Silhouette scores measure how similar data points are to their own cluster compared to other clusters. The scores indicated that 3 clusters had the highest silhouette score of 0.5157, reinforcing the choice made using the Elbow Method.



K-MEANS ELBOW METHOD PLOT

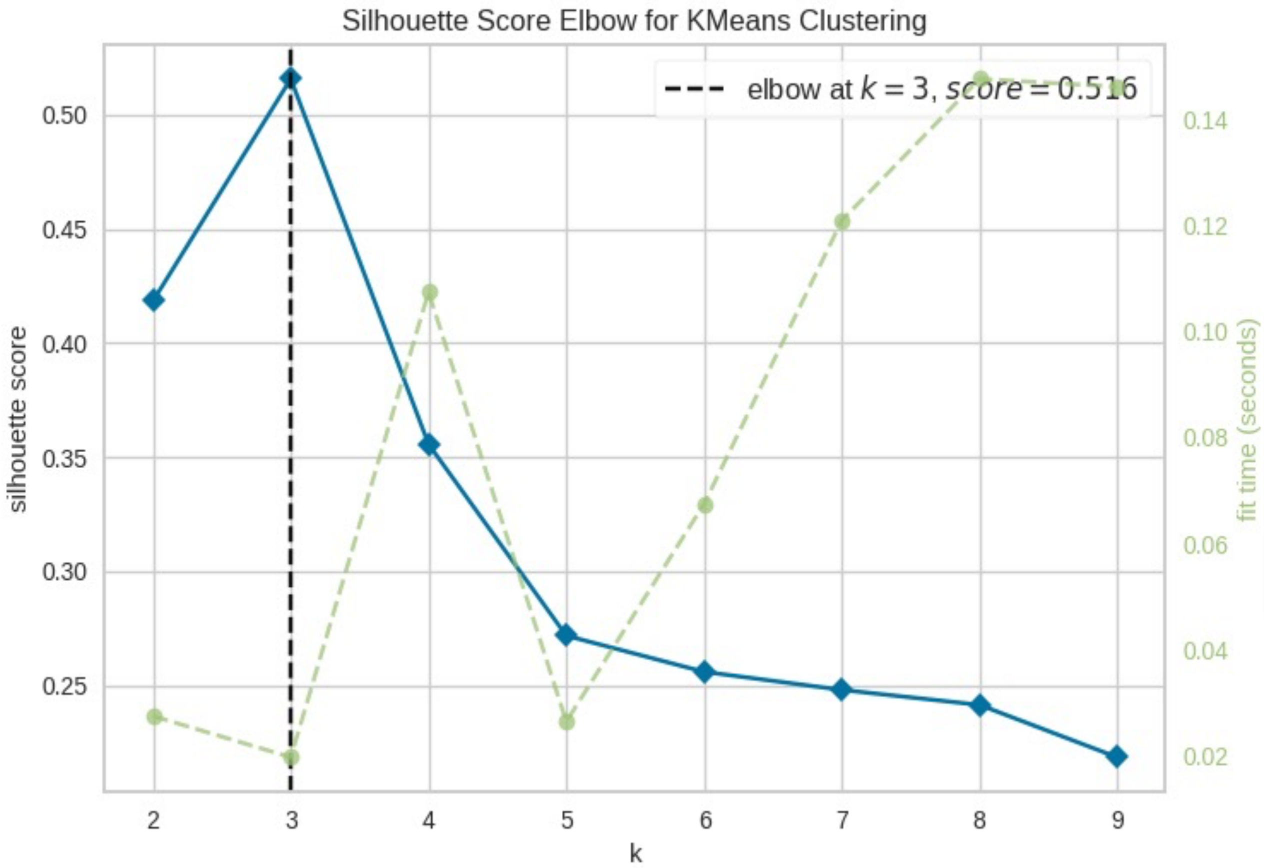


K-MEANS DISTORTION SCORE



K-Means Silhouette Score

Range (2 , 10)



K-Means

Elbow Silhouette Score

HIERARCHICAL CLUSTERING TECHNIQUE

Application of Hierarchical Clustering:

Hierarchical clustering was applied to the dataset to identify customer segments based on their financial behavior and interactions. Different linkage methods (ward, complete, average, and single) were used in combination with various distance metrics (Euclidean, Manhattan, Cosine, Chebyshev, and Mahalanobis) to evaluate the optimal clustering structure.

Observations using Different Linkage Methods:

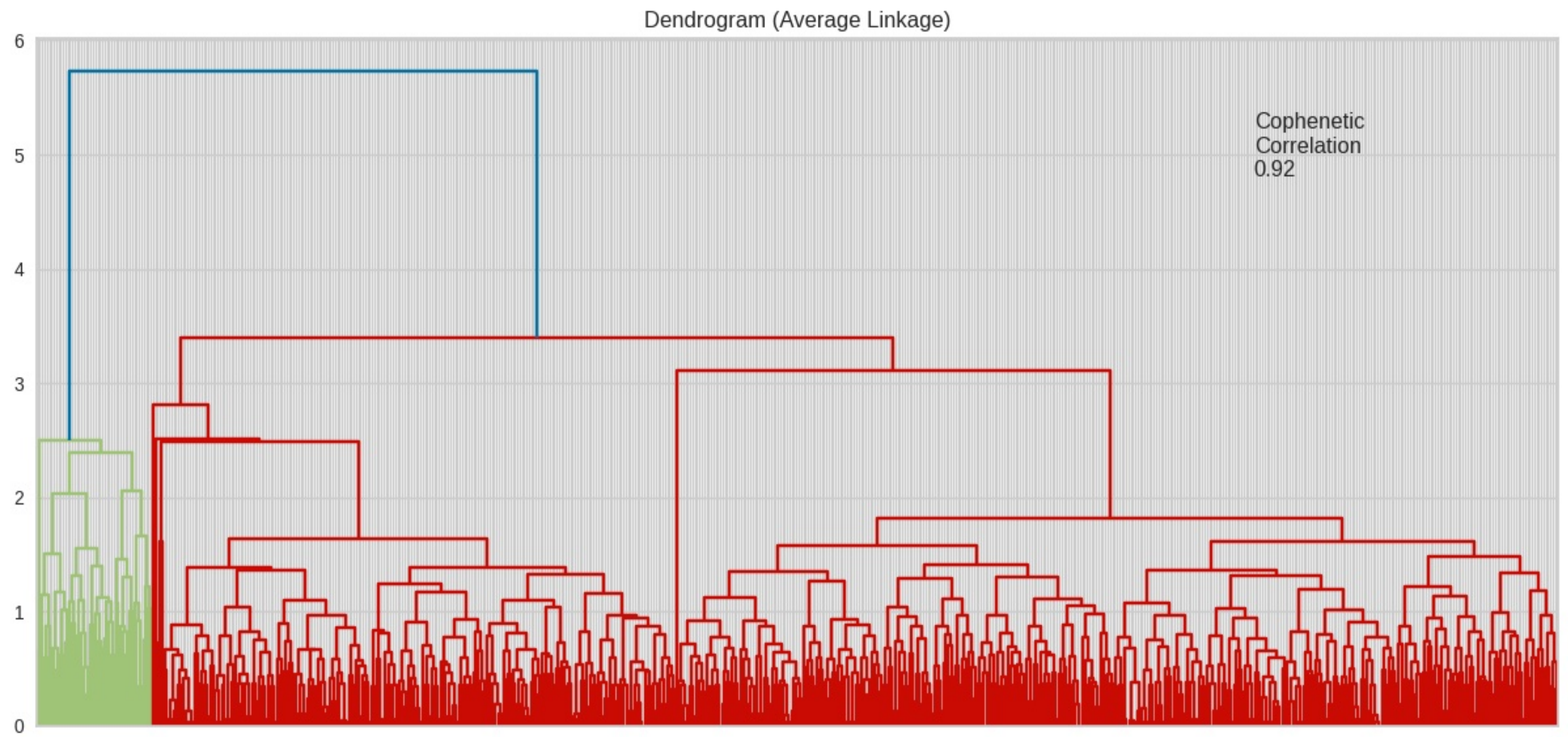
Among the linkage methods, average linkage with Cosine distance yielded the highest cophenetic correlation of 0.9278, indicating good cluster quality.

The dendrogram produced using average linkage showed distinct and separate cluster trees, reinforcing the choice of this linkage method.

Observations from Cophenetic Correlation:

Cophenetic correlation coefficients were calculated for different combinations of distance metrics and linkage methods. The combination of Cosine distance and average linkage achieved the highest cophenetic correlation of 0.9278, signifying strong cluster coherence.

HIERARCHICAL CLUSTERING – DENDOGRAM AVERAGE LINKING



The Dendogram with Average Linking has the highest cophenetic correlation and indicates distinct cluster patterns.

K-MEANS VS HIERARCHICAL CLUSTERING

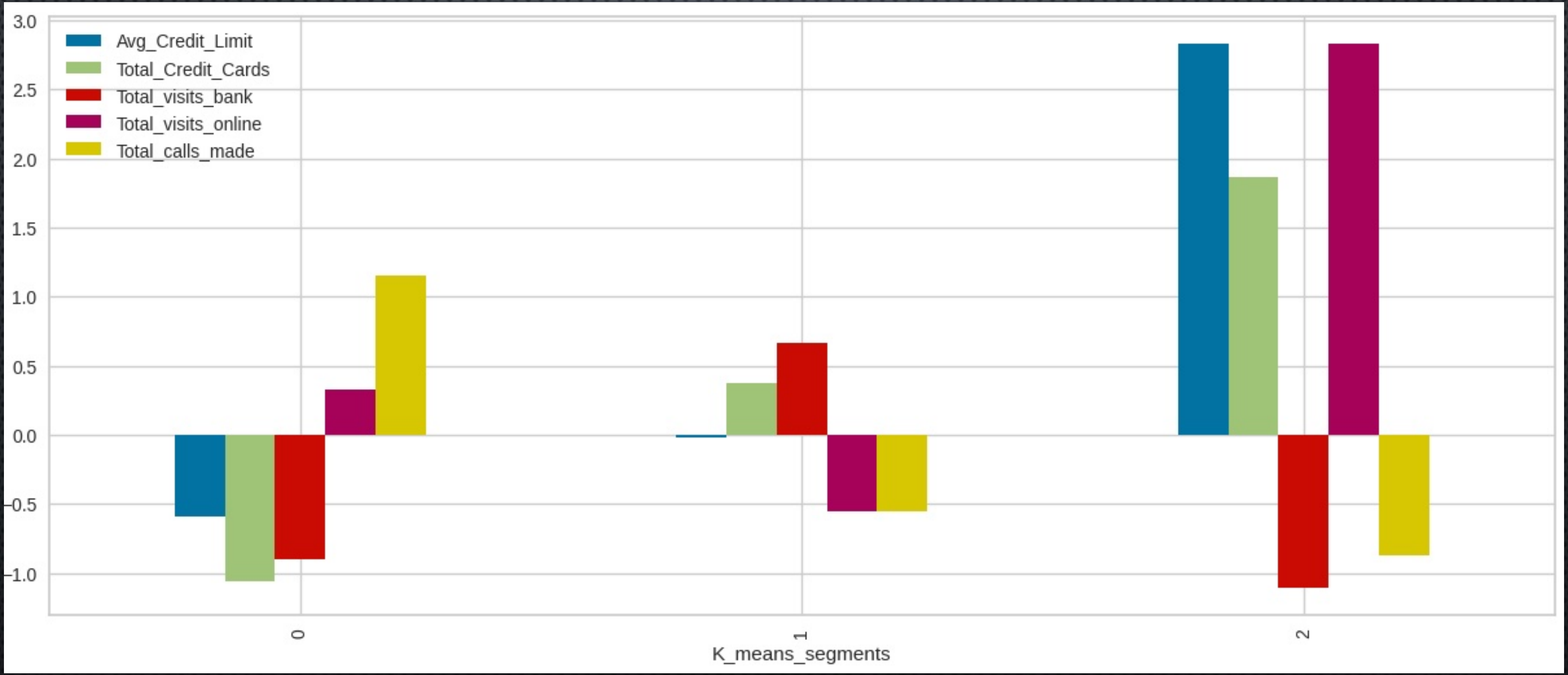
Comparison of Clusters:

Both K-Means and Hierarchical Clustering resulted in 3 distinct clusters as suitable for this dataset, providing consistent cluster assignments. Further details about the comparison, such as cluster profiles and attributes' mean values, were mentioned to be largely consistent between the two methods. The choice between the two techniques may depend on factors like execution time, cluster structure, and the specific problem context.

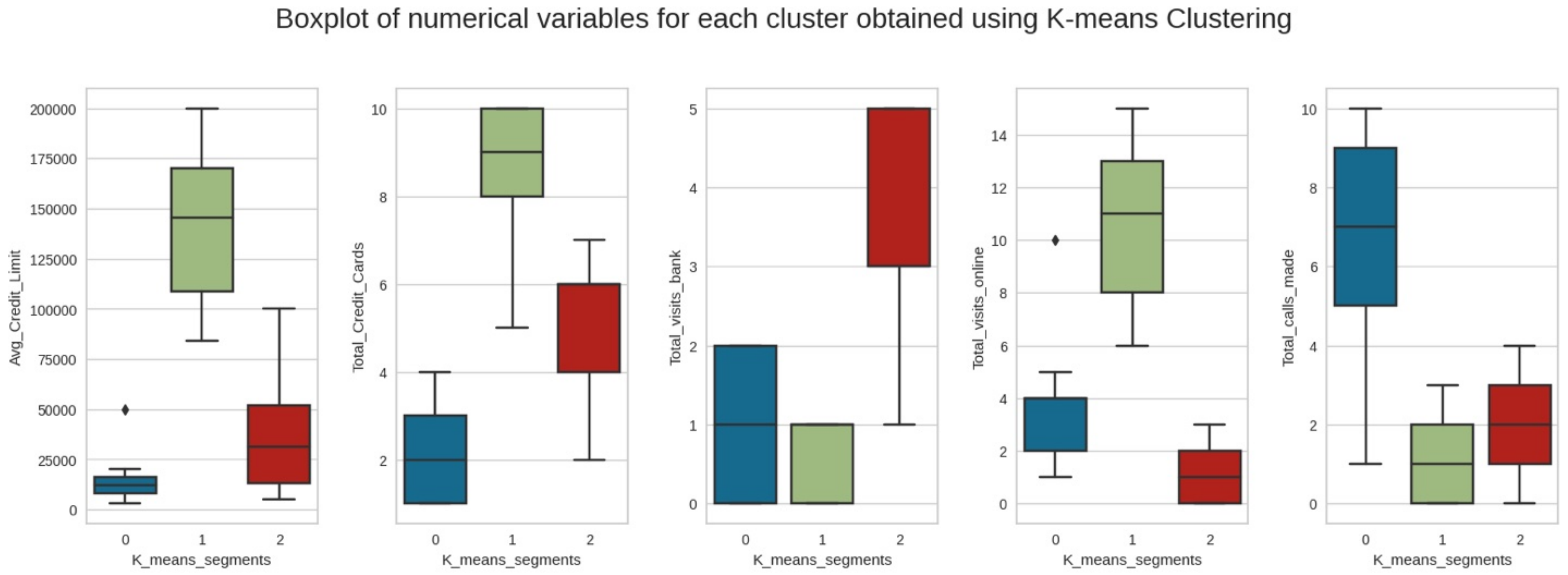
K-Means Segment 0 was similar to Hierarchical Cluster 1, K-Means Segment 1 was similar to Hierarchical Cluster 0, and K-Means Segment 2 was similar to Hierarchical Cluster 2.

Both clustering techniques provided valuable insights into customer segmentation, which can guide targeted marketing efforts and service improvements. The choice between the two methods may depend on factors like execution time and specific problem context.

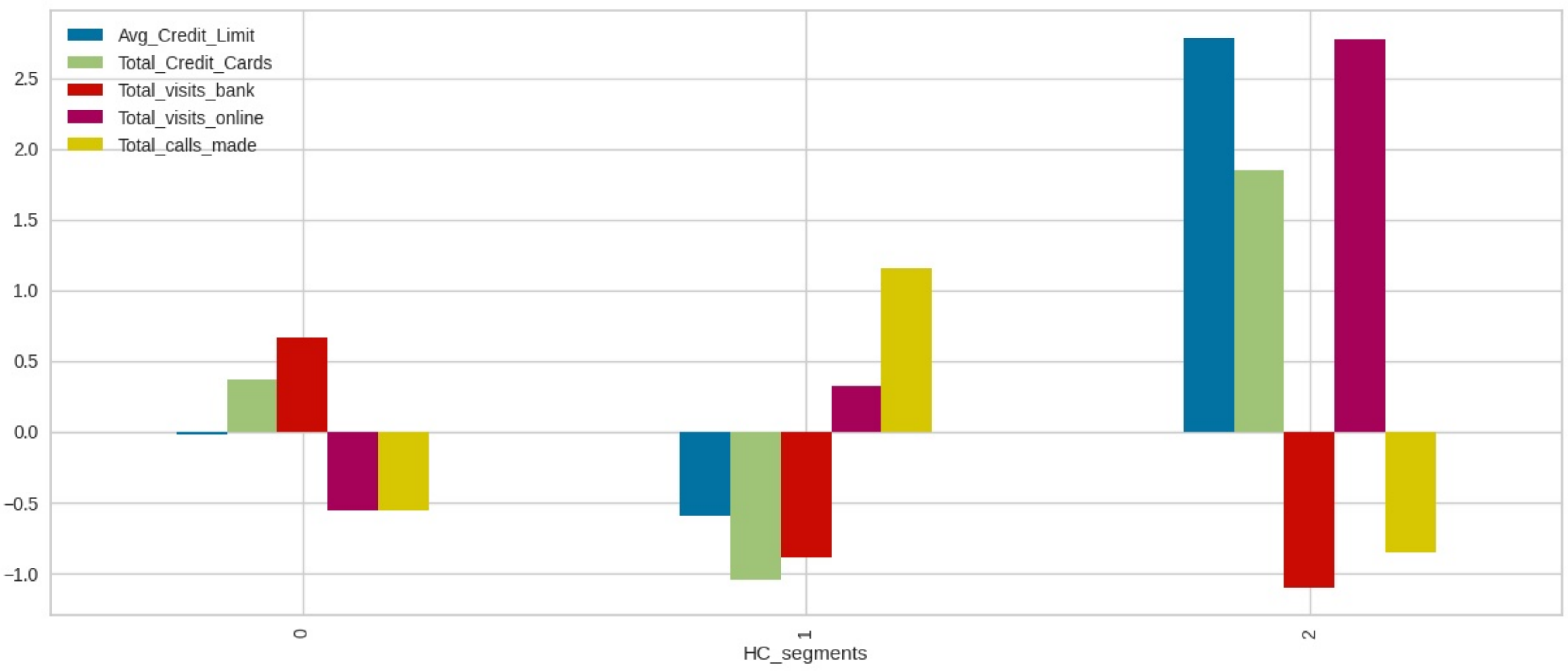
AVERAGE K-MEANS CLUSTERING SEGMENTS PLOT



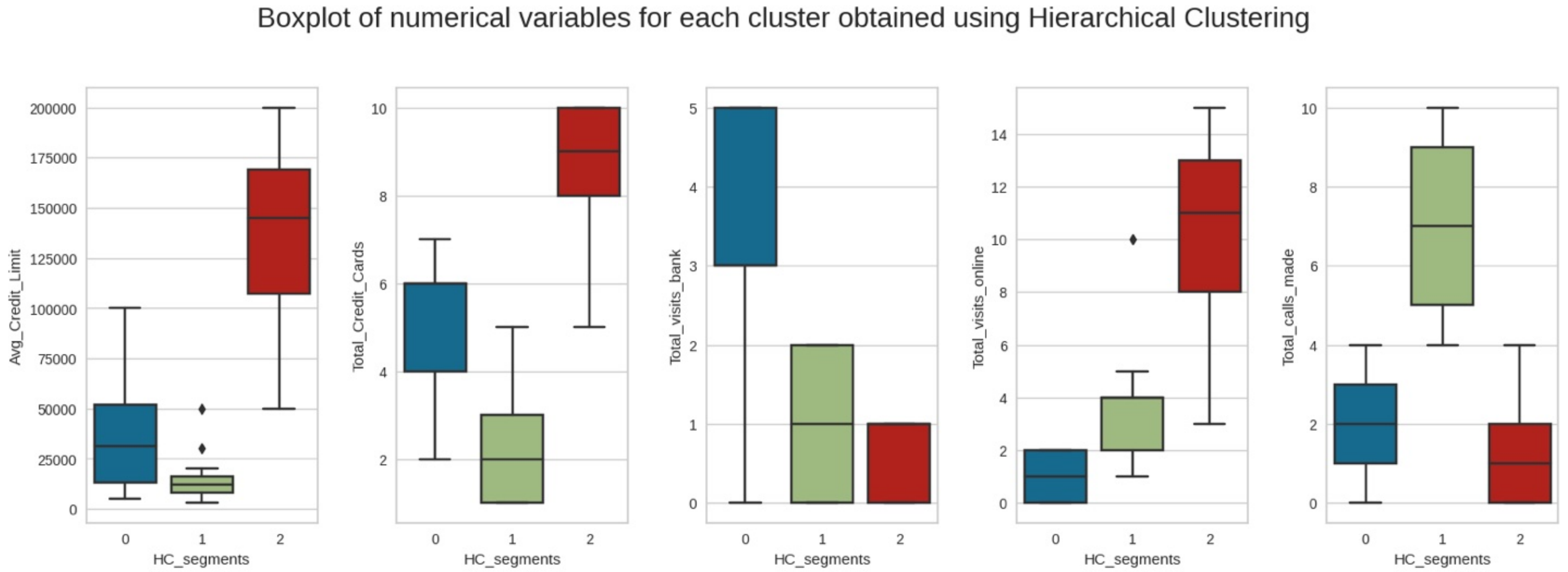
K-MEANS BOXPLOT FEATURE CLUSTERING



MEAN HIERARCHICAL CLUSTERING SEGMENTS PLOT



HIERARCHICAL BOXPLOT FEATURE CLUSTERING



OPTIMAL SOLUTION AND RECOMMENDATIONS

Objective: AllLife Bank aims to enhance its credit card customer base by improving market penetration and customer support services. The optimal solution involves segmenting customers into three distinct clusters to tailor marketing efforts and enhance customer support.

1. Utilize Hierarchical Clustering:

   •Method Choice: Employ hierarchical clustering with cosine distance and average linkage.

   - The cophenetic correlation for this method is the highest (0.9278), indicating good cluster separation.
   - Dendrograms show distinct and separate cluster trees.

2. Cluster Profiling:

   •Analyze the cluster profiles to understand the characteristics of each segment.

   •Focus on attributes such as "Average Credit Limit", "Total Credit Cards" and "Total Bank Visits."

OPTIMAL SOLUTION AND RECOMMENDATIONS

3. Recommendations:

a. Targeted Marketing Campaigns:

- Segment 1 (Low Credit Limit, Few Credit Cards, Few Bank Visits):
    - Target with credit card offerings suitable for lower-income individuals.
- Segment 2 (Medium Credit Limit, Moderate Credit Cards, Moderate Bank Visits):
    - Offer a mix of credit card products and promote online banking services.
- Segment 3 (High Credit Limit, Many Credit Cards, Few Bank Visits):
    - Focus on premium credit card products and personalized service.

b. Customer Support Enhancement:

- Segment 1:
    - Invest in online support channels to aid customers with fewer bank visits.
- Segment 2:
    - Develop resources for online and phone support.
- Segment 3:
    - Provide personalized, high-touch customer service for premium customers.

c. Monitoring and Adaptation:

- Continuously monitor customer behavior within each cluster.
- Adapt marketing strategies and service offerings based on evolving needs.

OPTIMAL SOLUTION AND RECOMMENDATIONS

4. Benefits of the Proposed Solution:

•Improve Customer Satisfaction: Tailored services & offerings for customer satisfaction.
•Targeted Marketing: Precision marketing increases conversion rates.
•Operational Efficiency: Optimized support resources reduce costs.
•Business Growth: Satisfied customers lead to business growth.

5. Actions:

•Implement hierarchical clustering with cosine distance and average linkage.
•Analyze cluster profiles and identify specific strategies for each segment.
•Develop targeted marketing campaigns and customer support enhancements.
•Continuously monitor customer behavior and adapt strategies as needed.

This optimal solution leverages hierarchical clustering for precise customer segmentation and provides actionable recommendations to boost AllLife Bank's customer satisfaction and business growth.