**Cardholder Segmentation Using K-Means for Effective Marketing Strategies**

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| **Article Info** |  | **ABSTRACT** |
| ***Article history:***  Received November 14, 2024  Revised January 21, 2025  Accepted January 21, 2025 |  | This study explores the application of K-Means clustering to segment credit card customers based on their demographic, behavioral, and transactional data. Using a dataset encompassing spending habits, payment frequencies, and credit usage, the analysis determined that four distinct customer groups provided the optimal segmentation, as validated through the Elbow Method, Silhouette Score, and Davies-Bouldin Index. The results revealed key patterns: a segment of cost-conscious customers with minimal activity, a group of moderate spenders with consistent payment behavior, a balanced segment with steady but diverse spending, and a high-income group with premium spending behavior. These findings highlight opportunities for businesses to tailor marketing strategies, improve customer engagement, and optimize resource allocation. By demonstrating the scalability and practicality of K-Means clustering, this research provides a framework for leveraging raw data to derive actionable insights in customer analytics.  *This is an open access article under the* [*CC BY-SA*](https://creativecommons.org/licenses/by-sa/4.0/) *license.* |
| ***Keywords:***  Clustering  K-Means  K-Means Elbow Method  Principal Component Analysis  Silhouette Score  Davies-Bouldin Score |

1. **INTRODUCTION**

In the era of digital transformation, businesses have access to extensive data resources that, when utilized effectively, can provide valuable insights into customer behaviors and preferences [1]. Financial institutions, particularly credit card providers, rely on such data to enhance customer engagement, optimize product offerings, and mitigate risks [2],[3]. Clustering techniques have emerged as a cornerstone of customer analytics, enabling businesses to categorize their clientele into meaningful groups based on transactional and behavioral patterns [4].

Credit card usage generates rich datasets encompassing spending habits, payment frequencies, cash advances, and credit limits. These data points, when analyzed effectively, allow for the identification of customer segments, such as high-value users, infrequent spenders, or customers at risk of default [5],[6]. Traditional marketing and risk management strategies often fall short due to their generalized nature, emphasizing the need for data-driven, personalized approaches [7].

This study leverages clustering techniques, particularly K-Means, to segment credit card customers based on attributes such as purchases, payments, and account tenure. By uncovering latent patterns, the research aims to help credit card providers tailor services, improve customer retention, and maximize profitability [8]. This paper also explores how clustering can bridge the gap between raw transaction data and actionable business insights, setting a foundation for scalable and replicable customer analytics frameworks [9].

1. **LITERATURE REVIEW**

**2.1. Clustering**

Clustering is an unsupervised machine learning method that groups data points based on their similarities, aiming to maximize intra-cluster cohesion while ensuring inter-cluster separation [10]. Common algorithms include K-Means, DBSCAN, and Hierarchical Clustering, each suited to specific data structures and objectives [11].

Studies highlight the versatility of clustering in diverse domains. For instance, researchers applied DBSCAN to detect anomalies in financial transactions, demonstrating its strength in handling noise and outliers [12]. K-Means has been widely employed for customer segmentation in retail and finance, providing actionable insights into purchasing behaviors and payment patterns [13]. Hierarchical Clustering, often used in bioinformatics, facilitates the exploration of hierarchical relationships among data points [14].

**2.2. Customer Segmentation**

Customer segmentation divides a user base into groups with similar characteristics, such as spending behaviors, demographics, or engagement levels [15]. This technique allows businesses to design targeted marketing strategies, optimize resource allocation, and improve customer satisfaction [16].

In financial services, segmentation is particularly valuable. A study analyzing telecom customer data used K-Means to segment users based on call duration and data usage, achieving enhanced service delivery and reduced churn [17]. Another example involved clustering e-commerce customers into high-value and low-value groups to guide promotional strategies [18]. Such applications underscore the importance of segmentation in driving data-informed decision-making and operational efficiency [19].

**2.3. K-Means Clustering**

K-Means is a widely adopted clustering algorithm due to its simplicity and computational efficiency. It partitions data into a predefined number of clusters by iteratively updating centroids to minimize within-cluster variance [20].

Various adaptations of K-Means address its limitations. Mini-Batch K-Means enhances scalability for large datasets by processing data in smaller chunks, while Weighted K-Means assigns varying importance to features, making it suitable for customer segmentation tasks [21],[22].

Recent studies have demonstrated the utility of K-Means in analyzing financial datasets. For example, researchers applied Weighted K-Means to segment credit card users based on spending frequency and payment consistency, resulting in more effective resource allocation and personalized offers [23]. Another study highlighted Mini-Batch K-Means’ capability to handle extensive e-commerce datasets while maintaining clustering precision [24]. These advancements reaffirm K-Means’ pivotal role in clustering tasks across industries [25].

1. **METHODOLOGY**

This section provides an outline of the research methodology employed in this study.

**3.1. Hardware and Software**

The study was carried out on a system running Windows 10 with a 64-bit operating system. The system uses an Intel Core™ i5-7400 CPU with 16GB Random Access Memory (RAM). The researchers utilized Jupyter and Python version 3.9.15 as the primary programming language for data analysis and model implementation with the following libraries: Math, NumPy, Pandas, Seaborn, Matplotlib, and Scikit-Learn.

**3.2. Data Acquisition**

This research employs a dataset from Kaggle [26], a .csv file containing 8950 instances and 18 features that can be categorized as financial and behavioral metrics. Financial metrics include monetary values like balances, credit limits, purchases, and cash advances, while behavioral metrics are the frequencies of transactions, purchases, and balance updates, reflecting customer activity. This dataset provides the basis for evaluating the relationship between these elements, and clustering them can help identify patterns in consumer behavior.

**3.3. Data Pre-processing**

Data processing is an essential aspect of model development. Data acquired in their raw form contain noise and anomalies, which can affect the performance and training process of the model being schooled [27]. The researchers employed several techniques to clean the data, which included data normalization and fixing missing values:

Data normalization is a pre-processing technique primarily intended to manage numerical features and is applied to numerical features before the application of classification algorithms. Normalization is crucial to prevent the effect of certain features from being concealed by others, particularly when the ranges of the features are inconsistent [28].

A missing value is a datum that has not been stored or gathered due to issues like faulty sampling procedures, budgetary constraints, or limitations in the data collection process. Missing values are an inevitable aspect of data analysis and can present significant challenges for data practitioners. It is generated due to several reasons, including human mistakes, technical malfunctions, unavailable data, or outdated and inconsistent data [29].

**3.4. Principal Component Analysis (PCA)**

Since the dataset has 18 features PCA reduces the number of features or dimensions in the data into 2 features while retaining the most important patterns or variance in the dataset. The remaining features would be principal components 1 and 2, PCA achieves this by transforming the original features into new, uncorrelated variables called principal components. These components are linear combinations of the original features, ordered such that the first principal component captures the maximum variance in the data, followed by the second, and so on [30][31].

**3.5. K-Means Clustering**

K-means clustering was employed to partition the dataset into distinct groups based on consumer characteristics. The algorithm aims to minimize intra-cluster variance by iteratively adjusting cluster centroids and assigning data points to their nearest cluster. The Elbow Method was used to determine the optimal number of clusters by analyzing the Within-Cluster Sum of Squares (WCSS) values for different cluster counts. Mathematically, the objective function for K-Means is defined as [32]:

(1)

Where is the total number of clusters, the group of data points in the i-th cluster, a single data point, and the center of the i-th cluster.

**3.6. Silhouette Score**

To evaluate the quality of the clusters generated by the K-Means algorithm, the Silhouette Score was calculated. This metric measures how well each data point fits within its assigned cluster compared to other clusters. The score ranges from -1 to 1, where a value closer to 1 indicates that clusters are well-separated and cohesive. A score near 0 suggests overlapping clusters, and negative values indicate that points are assigned to the wrong clusters [33].

(2)

The Silhouette Score measures how well a data point fits into its cluster. It is calculated by , the average distance from the point to all other points in the same cluster, and b, the average distance from the point to all points in the nearest cluster.

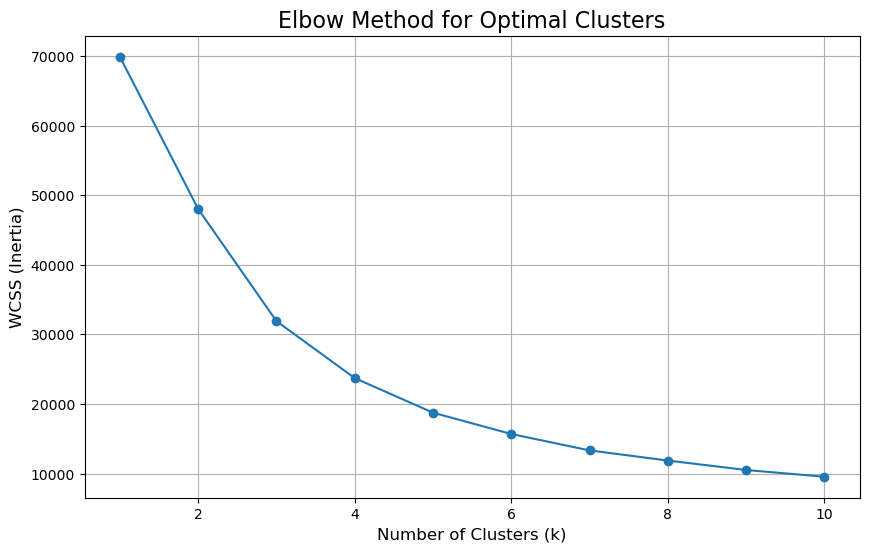
**3.7. Davies-Bouldin Score**

To evaluate the quality of the clusters generated by the K-Means algorithm, the Davies-Bouldin Score was calculated. This metric measures the average similarity ratio between each cluster and its most similar neighboring cluster. Lower Davies-Bouldin Scores indicate better-defined clusters, where each cluster is compact and distinct from others [34].

(3)

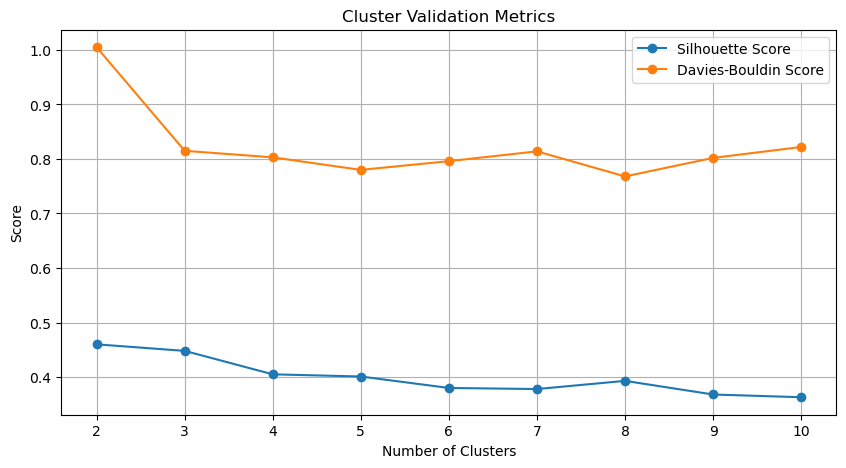
Where represents the number of clusters, the average distance of all points in cluster to the centroid of cluster , and is the distance between the centroids of clusters and .

1. **RESULTS AND DISCUSSION**

**4.1. Elbow Method for Optimal Clusters**

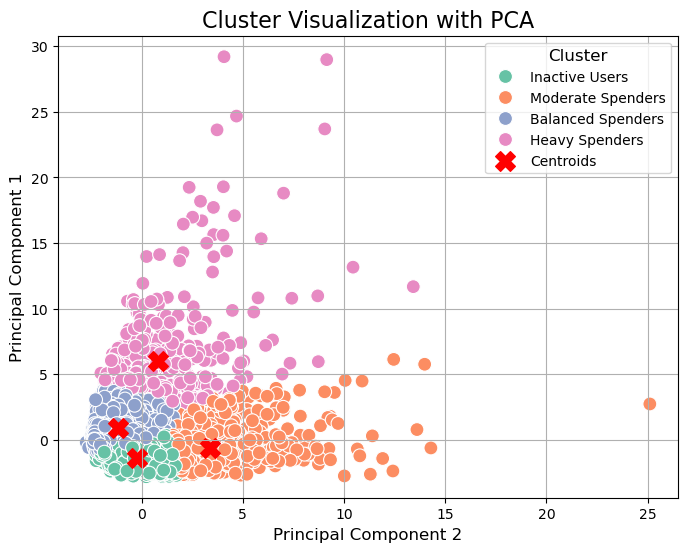
**Figure 1.** Elbow Method

The curve initially shows a steep decline in WCSS as the number of clusters increases, particularly between 1 and 3 clusters. After this point, the reduction becomes more gradual, forming a visible "elbow" at k = 4. This point is where the decrease in WCSS becomes less steep, indicating diminishing returns for adding more clusters, and indicates that four clusters are the optimal solution.



**Figure 2.** Cluster Validation Comparison

A higher silhouette score indicates better-defined clusters while a lower Davies-Bouldin score indicates better clustering. The silhouette score starts high at k=2 but drops and stabilizes around k=4 onward, which is the same as the Davies-Bouldin score. Both metrics suggest that k=4 is the optimal number of clusters. This aligns with the elbow method result, making it a strong choice for clustering the dataset.



**Figure 3.** Cardholder Segments

Figure 3 is a scatter plot that illustrates the data projected onto two principal components, with each point representing an individual customer and colors corresponding to four distinct clusters. Cluster 1, represented in green and located toward the bottom left, comprises Inactive Users, which represent low spenders with minimal cash advances. Cluster 2, marked in orange and situated in the right region, represents Moderate Spenders, who are regular spenders with low reliance on cash advances. Cluster 3, shown in blue and positioned in the lower left, identifies Balanced Spenders, which are cardholders balancing spending and occasional cash advances. Cluster 3, in pink and situated in the upper left area, represents Heavy Spenders, who frequently rely on cash advances. Cluster 1 is compact and small, suggesting a specific subset of users with minimal variance in their inactivity. While, clusters 2 and 3 overlap slightly, suggesting additional features to improve separation. And lastly, cluster 4 is well-separated, indicating that this group has distinct behavior compared to others. Each cluster provides unique insights into customer behavior and spending patterns, offering actionable opportunities for businesses to develop personalized marketing strategies and enhance customer engagement. This approach validates the value of clustering in data-driven decision-making for targeted business applications.

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| Index | Number of Clusters | Silhouette Scores | Davies-Bouldin Scores |
| 0 | 2 | 0.460 | 1.005 |
| 1 | 3 | 0.448 | 0.815 |
| 2 | 4 | 0.405 | 0.803 |
| 3 | 5 | 0.401 | 0.780 |
| 4 | 6 | 0.380 | 0.796 |
| 5 | 7 | 0.378 | 0.814 |
| 6 | 8 | 0.393 | 0.768 |
| 7 | 9 | 0.368 | 0.802 |
| 8 | 10 | 0.363 | 0.822 |

**Table 1.** Cluster Validation Metrics

Table 1 presents the Silhouette Scores and Davies-Bouldin Scores for different numbers of clusters, ranging from 2 to 10. The silhouette score is highest when the number of clusters is 2 (0.460), suggesting the data is most naturally separable into two groups. As the number of clusters increases, the silhouette score generally decreases, indicating reduced cluster cohesion and separation as more clusters are added. After around 4 clusters, the score stabilizes but remains lower, suggesting diminishing returns in cluster quality as more clusters are added. The Davies-Bouldin score is lowest when the number of clusters is 5 (0.780), suggesting this configuration produces the best-defined clusters. The scores fluctuate slightly beyond 5 clusters but remain relatively low, suggesting small improvements in cluster quality after 5 clusters. Overall, the 4 cluster configuration is the best choice, providing a balance between interpretability and cluster quality.

1. **CONCLUSION**

This study successfully applied the K-Means clustering algorithm to segment customers into distinct groups based on demographic, behavioral, and transactional data. The analysis determined that the optimal number of clusters was 4, as identified using the Elbow Method and further validated with Silhouette and Davies-Bouldin Scores. The clustering results revealed key patterns, such as a dominant group of customers with moderate spending habits and cost-conscious tendencies, highlighting the importance of budget-friendly marketing strategies. Another smaller but significant segment comprised high-income earners with premium spending behavior, presenting opportunities for targeted high-value offerings. While clustering beyond two groups demonstrated diminishing Silhouette Scores, the study affirmed that K-Means clustering is a reliable tool for uncovering meaningful customer insights. By providing a clearer understanding of customer diversity, businesses can move away from one-size-fits-all approaches and focus on data-driven, personalized strategies. These findings validate the efficacy of K-Means clustering as a scalable and practical approach for transforming raw customer data into actionable insights, enabling businesses to improve marketing efficiency, enhance customer engagement, and optimize resource allocation effectively.

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