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

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| **Article Info** |  | **ABSTRACT** |
| ***Keywords:***  *Clustering*  *K-Means*  *K-Means Elbow Method*  *Principal Component Analysis*  *Silhouette Score*  *Davies-Bouldin Score* |  | This study applies K-Means clustering to segment credit card customers based on demographic, behavioral, and transactional data. By analyzing a dataset that includes spending habits, payment frequencies, and credit usage, the research identified that four clusters represent the optimal segmentation. This conclusion was supported by the Elbow Method, which showed diminishing Within-Cluster Sum of Squares (WCSS) beyond four clusters, and validated through a Silhouette Score of 0.405 and a Davies-Bouldin Index of 0.803. The clustering analysis revealed distinct customer segments: Inactive Users with low activity, Moderate Spenders with consistent spending with minimal cash advances, Balanced Spenders with steady spending with occasional cash advances, and Heavy Spenders with high-frequency users relying on cash advances. These insights demonstrate the value of clustering in crafting targeted marketing strategies, enhancing customer engagement, and optimizing resource allocation. The study highlights K-Means as a scalable and practical approach for transforming raw customer data into actionable insights for data-driven decision-making. |
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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 research aims to address these gaps by applying the K-Means clustering algorithm to segment credit card customers based on their demographic, behavioral, and transactional attributes. The primary goal is to determine the optimal number of clusters that represent the distinct behavioral patterns within the dataset. By leveraging clustering validation techniques such as the Elbow Method, Silhouette Score, and Davies-Bouldin Index, the study identifies the most cohesive and distinct segmentation structure, which in this case is four clusters. Each cluster provides actionable insights into customer behavior, including their spending patterns, credit utilization, and payment habits.

The findings of this study are designed to help businesses implement effective, data-driven marketing strategies that cater to the unique characteristics of each segment. For instance, identifying cost-conscious customers or heavy spenders allows for targeted campaigns, personalized offers, and improved customer satisfaction. Furthermore, the research underscores the value of clustering as a scalable approach for transforming raw data into actionable insights, offering a foundation for ongoing customer analytics and engagement strategies.

1. **LITERATURE REVIEW**

**2.1. Clustering**

Clustering is an essential unsupervised machine learning technique used to group data points based on their similarities. The primary objective is to maximize intra-cluster cohesion while ensuring inter-cluster separation. Popular clustering algorithms include K-Means, DBSCAN, and Hierarchical Clustering, each suited for different data structures and objectives [10]. The versatility of clustering has been demonstrated across diverse domains. For example, DBSCAN is often utilized in anomaly detection due to its ability to handle noise and outliers effectively [12]. K-Means is widely recognized for its efficiency and simplicity, particularly in customer segmentation tasks where actionable insights into purchasing behaviors and payment patterns are derived [13]. Hierarchical Clustering, frequently employed in bioinformatics, enables the exploration of hierarchical relationships among data points, offering a different perspective on clustering structures [14].

**2.2. Customer Segmentation**

Customer segmentation involves dividing a user base into distinct groups with shared characteristics, such as spending habits, demographics, or engagement levels [15]. This process enables businesses to design targeted marketing strategies, optimize resource allocation, and enhance customer satisfaction [16].

In financial services, customer segmentation is invaluable. For instance, a study on telecom customers applied K-Means clustering to group users based on call durations and data usage, leading to enhanced service delivery and reduced churn [17]. Similarly, e-commerce businesses have used clustering to identify high-value and low-value customer groups, which guide promotional strategies and resource allocation [18]. These examples underscore the significance of segmentation in enabling data-informed decision-making and operational efficiency [19].

**2.3 K-Means Clustering**

K-Means is a widely adopted clustering algorithm due to its computational efficiency and straightforward implementation. 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. For instance, Mini-Batch K-Means enhances scalability for large datasets by processing smaller data chunks, while Weighted K-Means assigns varying importance to features, making it ideal for customer segmentation [21][22].

Recent studies highlight the utility of K-Means in analyzing financial datasets. For instance, researchers applied Weighted K-Means to segment credit card users based on spending frequency and payment consistency, facilitating personalized marketing strategies and optimized resource allocation [23]. Another study demonstrated the capability of Mini-Batch K-Means to efficiently process large-scale e-commerce datasets while maintaining clustering precision [24]. These advancements emphasize the pivotal role of K-Means in clustering tasks across industries [25].

**2.4 Evaluation Metrics for Clustering**

The quality of clustering solutions is often assessed using validation metrics, including the Elbow Method, Silhouette Score, and Davies-Bouldin Index. The Elbow Method identifies the optimal number of clusters by analyzing the Within-Cluster Sum of Squares (WCSS). The point where the decrease in WCSS diminishes significantly forms an "elbow," indicating the optimal cluster count [32]. The Silhouette Score evaluates cluster cohesion and separation, with scores ranging from -1 to 1. Higher values indicate well-separated clusters, while lower values suggest overlapping clusters or poor separation [33]. The Davies-Bouldin Index measures the average similarity between clusters and their most similar neighbors, where lower scores suggest better-defined clusters [34]. These metrics are essential for ensuring that clustering results are interpretable and actionable.

**2.5 Principal Component Analysis (PCA) in Clustering**

High-dimensional datasets often require dimensionality reduction techniques like Principal Component Analysis (PCA) to improve clustering performance. PCA transforms original features into uncorrelated principal components, retaining the most significant variance in the data [30][31].

For instance, in a dataset with numerous features, PCA can reduce the dimensionality while preserving critical patterns, allowing clustering algorithms like K-Means to perform more effectively. By reducing noise and redundancy, PCA facilitates better cluster formation and interpretability.

**2.6 Applications of Clustering in Financial Services**

Clustering has emerged as a cornerstone of customer analytics in financial services. Credit card providers, for example, leverage clustering to categorize users based on spending patterns, payment consistency, and credit utilization.

In one study, clustering techniques identified customer segments such as high-value users and cost-conscious consumers, enabling tailored marketing strategies and risk mitigation [5][6]. Another application involved grouping customers based on repayment behaviors to develop targeted financial products and interventions [7].

These applications highlight clustering's potential to enhance decision-making, improve customer engagement, and optimize resource allocation in financial services.

1. **METHODOLOGY**

**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.

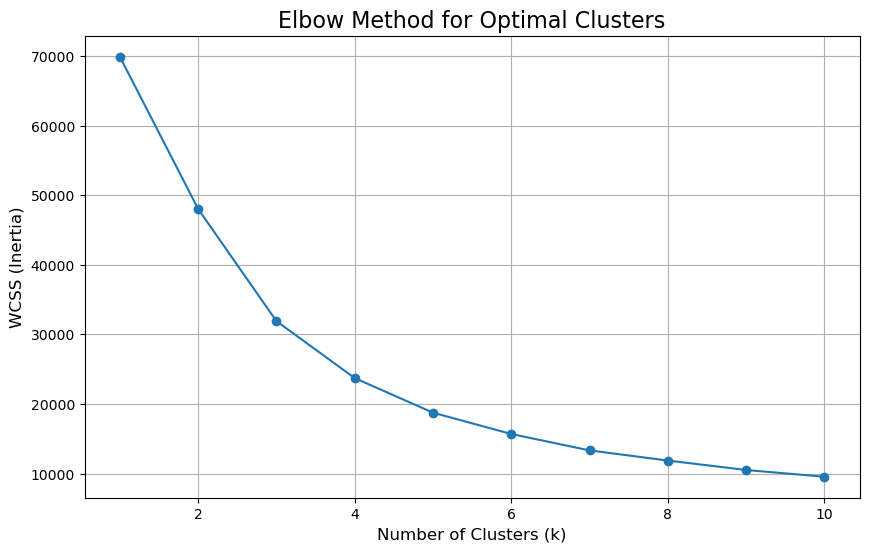
**3.7. Davies-Bouldin Score**

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)

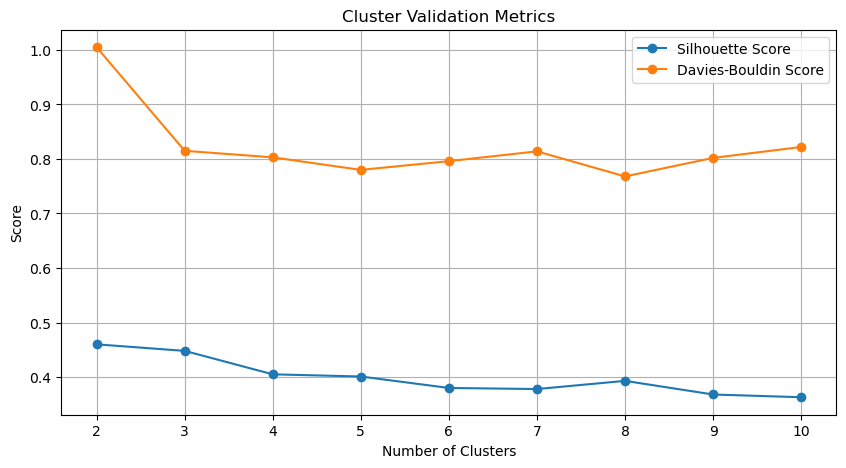
Where represents the number of clusters, the average distance of all points in cluster to the centroid of cluster , and is the distance between the centroids of clusters and .

1. **RESULTS AND DISCUSSION**

**4.1. Elbow Method for Optimal Clusters**

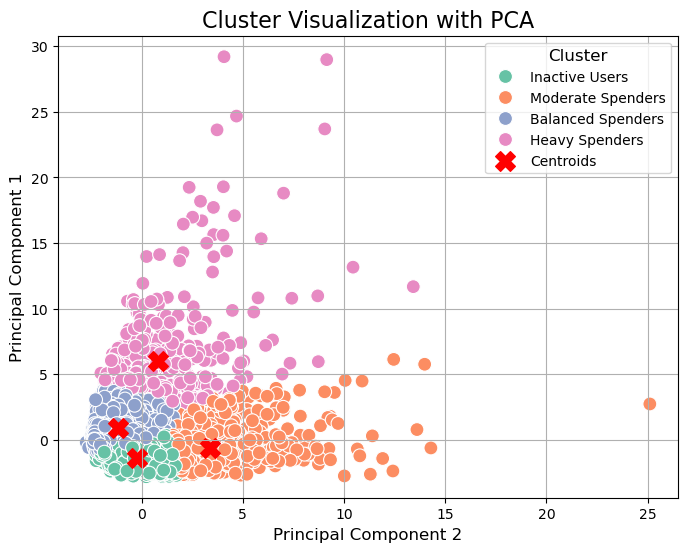
**Figure 1.** Elbow Method

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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