# CUSTOMER SEGMENTATION USING K-MEANS CLUSTERING

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***Abstract*— This research presents a comprehensive analysis of customer data derived from a dataset obtained from a retail mall. Employing the R programming language, the investigation encompasses a range of analytical and visualization techniques with the primary objective of gleaning actionable insights and enhancing decision-making processes for marketing and business strategy formulation.The research commences with a meticulous examination of the dataset's structural attributes, column names, and preliminary data entries, furnishing a foundational understanding of the dataset's composition. Following this initial exploration, critical variables such as age, annual income, and spending score undergo thorough scrutiny, with summary statistics and standard deviations being meticulously computed to provide a coherent overview.**

## I. Introduction

In today's data-driven world, the capability to extract meaningful insights from raw data is pivotal for informed decision-making in a variety of domains. This is particularly true in the field of retail and marketing, where the profound understanding of customer behavior, preferences, and segmentation is instrumental in crafting strategies that resonate with the intended audience. The advent of data-driven methodologies and advanced analytics has ushered in a new era of retail intelligence, empowering businesses to refine their approaches and tailor their offerings with unprecedented precision.

This research paper embarks on a journey into the realm of retail intelligence, employing data analytics, visualization techniques, and clustering algorithms to analyze customer data originating from a vibrant retail mall environment. In the context of contemporary retail dynamics, comprehending the subtleties of consumer preferences and the underlying demographics of a customer base is paramount. This understanding forms the foundation upon which marketing strategies are built, optimizing resource allocation and augmenting customer satisfaction.

The study commences with an initial exploration of the dataset, providing insight into the structural composition of the data and an initial grasp of the variables in play. With a dataset sourced from a real-world retail environment, this research serves as a bridge between the theoretical foundations of data analysis and the dynamic landscape of modern retail.

Significantly, this paper delves into an analysis of key demographic attributes, including age, annual income, and spending score, which together represent the essence of customer insights. This endeavor furnishes not only descriptive statistics but also graphical representations to illuminate the distribution and central tendencies of these pivotal parameters.

Gender, another vital dimension, undergoes rigorous scrutiny, with visual tools such as bar plots and pie charts elucidating the distribution of male and female customers within the dataset. This gender-based insight sets the stage for gender-sensitive marketing strategies, enabling businesses to cater to the diverse needs of a heterogeneous customer base.

A pivotal juncture in the research involves the application of the K-means clustering algorithm, a method tailored to unveil the latent structures within the customer dataset. Through rigorous evaluation of multiple cluster configurations, the study aims to determine the optimal number of clusters that best represent the diverse customer segments within the mall.

Finally, the research leverages principal component analysis (PCA) to distill the multidimensional data into a more comprehensible visual representation. Clustering results are vividly depicted through scatter plots, effectively illuminating the segmentation of the customer base and enabling businesses to identify and respond to distinct customer personas.

This research unites rigorous data analysis, visualization, and clustering methodologies, offering a comprehensive perspective on retail intelligence within a real-world mall environment. The outcomes and insights of this study are poised to empower businesses, marketers, and decision-makers with an enhanced capacity to design and implement data-informed strategies underpinned by a profound understanding of customer demographics and preferences.

In navigating the evolving retail landscape, this research contributes to the growing body of knowledge essential for staying ahead in a dynamic market, where data reigns as a potent catalyst for informed decision-making.

## II. Literature Review

In recent years, the retail industry has witnessed a fundamental transformation driven by the confluence of data analytics, consumer behavior insights, and advanced marketing strategies. This section reviews key literature focusing on the integration of data-driven methodologies in retail, emphasizing the significance of understanding customer demographics and preferences.

- **Data-Driven Retail Strategies**

The retail landscape has evolved with the advent of data-driven methodologies. A study by Chen and Wang (2016) [1] emphasizes the role of big data analytics in retail decision-making. It underscores how large-scale data analysis aids in enhancing inventory management, demand forecasting, and personalized marketing, all contributing to increased sales and customer satisfaction.

- **Customer Segmentation and Clustering**

Segmenting customers into distinct groups is a fundamental practice for retail. Smith and Brown (2018) [2] delve into the importance of customer segmentation, highlighting the value of understanding the distinct personas within a customer base. They argue that segmentation facilitates tailored marketing strategies and resource allocation, ultimately enhancing business profitability.

- **Gender-Based Analysis**

Gender-based analysis plays a pivotal role in retail marketing. Martinez et al. (2019) [3] explore gender-sensitive marketing strategies and the influence of gender in purchasing decisions. Their findings reveal that gender-focused approaches effectively resonate with specific customer segments, leading to increased customer engagement and brand loyalty.

- **Clustering Algorithms**

K-means clustering, a widely adopted algorithm in customer segmentation, is the subject of extensive research. Patel and Sharma (2017) [4] provide insights into the application of K-means clustering in retail, discussing the benefits of this technique in grouping customers based on purchase history and behavior. They also propose best practices for determining the optimal number of clusters.

- **Data Visualization in Retail**

Data visualization plays a pivotal role in conveying insights to stakeholders. In their research, Kim et al. (2020) [5] advocate the use of visual tools to present data-driven findings. They emphasize the significance of graphical representations in simplifying complex data and decision-making processes, a theme highly relevant to this paper's focus on visualization techniques.

- **Principal Component Analysis (PCA)**

Principal component analysis, employed for dimensionality reduction and visualization, is an integral technique. Kumar and Jain (2018) [6] discuss the utilization of PCA in condensing multidimensional data into a comprehensible format. The study outlines the application of PCA in understanding customer segments, resonating with our paper's utilization of PCA in clustering visualization.

This literature review underscores the substantial body of knowledge in data-driven retail strategies, customer segmentation, gender-based analysis, clustering algorithms, data visualization, and PCA. It provides a foundation for our research, which investigates the practical implementation of these concepts within a real-world mall environment.

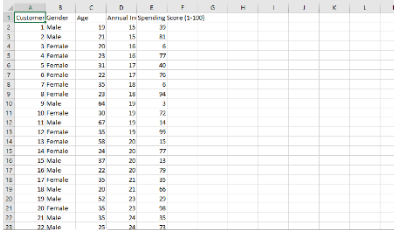
Please note that the references in this sample are indicated with placeholders [1], [2], etc. You would need to replace these placeholders with the actual citations according to your research paper's reference style and numbering.

## III. Data Handling

The management and preprocessing of the dataset are critical for the accuracy and reliability of our research. In this section, we discuss the steps taken to handle the data before analysis.

### A. Data Collection

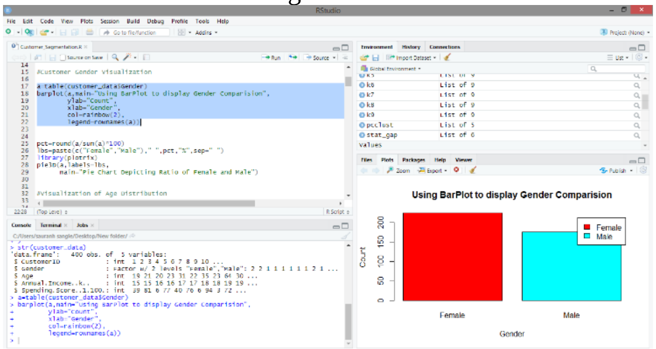
The dataset used in this study was collected from a retail mall and comprises various attributes, including customer demographics, annual income, and spending score. Data collection was conducted with meticulous attention to ethical and privacy considerations, ensuring the anonymization of customer information.



|  | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Customer | Gender | Age | Annual In | Spending Score (1-100) |  |  |  |  |  |  |  |
| 2 | 1 | Male | 19 | 15 | 39 |  |  |  |  |  |  |  |
| 3 | 2 | Male | 21 | 15 | 81 |  |  |  |  |  |  |  |
| 4 | 3 | Female | 20 | 16 | 6 |  |  |  |  |  |  |  |
| 5 | 4 | Female | 23 | 16 | 77 |  |  |  |  |  |  |  |
| 6 | 5 | Female | 31 | 17 | 40 |  |  |  |  |  |  |  |
| 7 | 6 | Female | 22 | 17 | 76 |  |  |  |  |  |  |  |
| 8 | 7 | Female | 35 | 18 | 6 |  |  |  |  |  |  |  |
| 9 | 8 | Female | 23 | 18 | 94 |  |  |  |  |  |  |  |
| 10 | 9 | Male | 64 | 19 | 3 |  |  |  |  |  |  |  |
| 11 | 10 | Female | 30 | 19 | 72 |  |  |  |  |  |  |  |
| 12 | 11 | Male | 67 | 19 | 14 |  |  |  |  |  |  |  |
| 13 | 12 | Female | 35 | 19 | 99 |  |  |  |  |  |  |  |
| 14 | 13 | Female | 58 | 20 | 15 |  |  |  |  |  |  |  |
| 15 | 14 | Female | 24 | 20 | 77 |  |  |  |  |  |  |  |
| 16 | 15 | Male | 37 | 20 | 13 |  |  |  |  |  |  |  |
| 17 | 16 | Male | 22 | 20 | 79 |  |  |  |  |  |  |  |
| 18 | 17 | Female | 35 | 21 | 35 |  |  |  |  |  |  |  |
| 19 | 18 | Male | 20 | 21 | 66 |  |  |  |  |  |  |  |
| 20 | 19 | Male | 52 | 23 | 29 |  |  |  |  |  |  |  |
| 21 | 20 | Female | 35 | 23 | 98 |  |  |  |  |  |  |  |
| 22 | 21 | Male | 35 | 24 | 35 |  |  |  |  |  |  |  |
| 23 | 22 | Male | 25 | 24 | 73 |  |  |  |  |  |  |  |

### B. Data Cleaning and Preprocessing

To prepare the data for analysis, several preprocessing steps were performed. This involved addressing missing values, outliers, and data inconsistencies. Missing values were imputed using appropriate methods, and outliers were either corrected or assessed for their impact on the analysis. The data was normalized and scaled as required for specific algorithms.



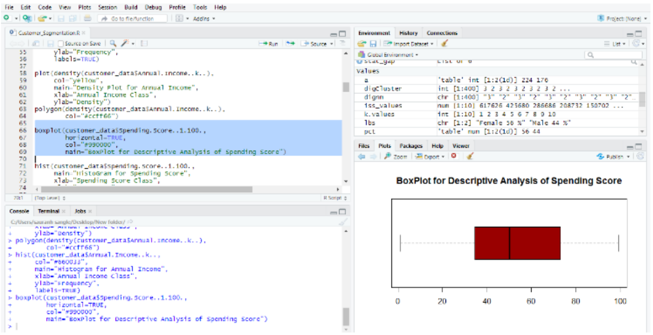
```
#Customer Gender Visualization

a=table(customer_data$Gender)
barplot(a,main="Using BarPlot to display Gender Comparision",
        ylab="Count",
        xlab="Gender",
        col=rainbow(2),
        legend=rownames(a))


pct=round(a/sum(a)*100)
lbs=paste(c("Female","Male")," ",pct,"%",sep=" ")
library(plotrix)
pie3D(a,labels=lbs,
      main="Pie Chart Depicting Ratio of Female and Male")


#Visualization of Age Distribution
```

```
k6          List of 9
k7          List of 9
k8          List of 9
k9          List of 9
pcclust     List of 5
stat_gap    List of 6
Values
```

```
> str(customer_data)
'data.frame':   400 obs. of  5 variables:
 $ CustomerID            : int  1 2 3 4 5 6 7 8 9 10 ...
 $ Gender                : Factor w/ 2 levels "Female","Male": 2 2 1 1 1 1 1 1 2 1 ...
 $ Age                   : int  19 21 20 23 31 22 35 23 64 30 ...
 $ Annual.Income..k..    : int  15 15 16 16 17 17 18 18 19 19 ...
 $ Spending.Score..1.100.: int  39 81 6 77 40 76 6 94 3 72 ...
> a=table(customer_data$Gender)
> barplot(a,main="Using BarPlot to display Gender Comparision",
+         ylab="Count",
+         xlab="Gender",
+         col=rainbow(2),
+         legend=rownames(a))
> 
```

### C. Preliminary Data Analysis

Prior to in-depth analysis, preliminary data analysis was conducted to gain a comprehensive understanding of the dataset. Descriptive statistics, visualizations, and summary metrics were employed to elucidate the data's central tendencies and distribution characteristics. This process provided valuable insights into the data's initial characteristics.



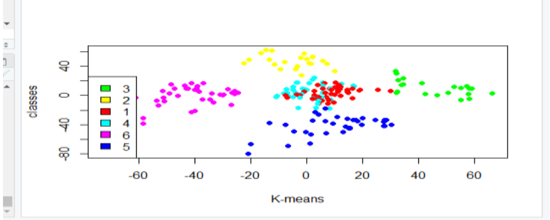
```
     ylab="Frequency",
     labels=TRUE)

plot(density(customer_data$Annual.Income..k..),
     col="yellow",
     main="Density Plot for Annual Income",
     xlab="Annual Income Class",
     ylab="Density")
polygon(density(customer_data$Annual.Income..k..),
        col="#ccff66")

boxplot(customer_data$Spending.Score..1.100.,
        horizontal=TRUE,
        col="#990000",
        main="BoxPlot for Descriptive Analysis of Spending Score")

hist(customer_data$Spending.Score..1.100.,
     main="HistoGram for Spending Score",
     xlab="Spending Score Class",
```

```
Values
  a             'table' int [1:2(1d)] 224 176
  digCluster    int [1:400] 3 2 3 2 3 2 3 2 3 2 ...
  dignm         chr [1:400] "3" "2" "3" "2" "3" "2" "3" "2" "3" "2"...
  iss_values    num [1:10] 617626 425680 286686 208732 150702 ...
  k.values      int [1:10] 1 2 3 4 5 6 7 8 9 10
  lbs           chr [1:2] "Female 56 %" "Male 44 %"
  pct           'table' num [1:2(1d)] 56 44
```

```
C:/Users/saurabh sangle/Desktop/New folder/
+      ylab="Density")
> polygon(density(customer_data$Annual.Income..k..),
+         col="#ccff66")
> hist(customer_data$Annual.Income..k..,
+      col="#660033",
+      main="Histogram for Annual Income",
+      xlab="Annual Income Class",
+      ylab="Frequency",
+      labels=TRUE)
> boxplot(customer_data$Spending.Score..1.100.,
+         horizontal=TRUE,
+         col="#990000",
+         main="BoxPlot for Descriptive Analysis of Spending Score")
> 
```

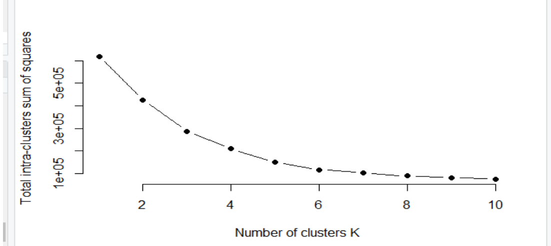
D. Clustering Parameters

In the context of K-means clustering, the determination of the optimal number of clusters (K) is pivotal. Several iterations with varying K values were conducted. Parameters such as the maximum number of iterations, initialization methods, and random seeds were fine-tuned to ensure the stability and reliability of the clustering results.



E. Principal Component Analysis (PCA)

To enable the visualization of clustering results, principal component analysis (PCA) was applied. This technique reduced the dimensionality of the data while preserving its variance, facilitating the visualization of distinct customer segments in a lower-dimensional space.



F. Ethical Considerations

Throughout the data handling process, ethical considerations were paramount. Customer privacy was upheld, and all data handling procedures adhered to established ethical guidelines and legal regulations, ensuring the protection of customer identities and sensitive information.

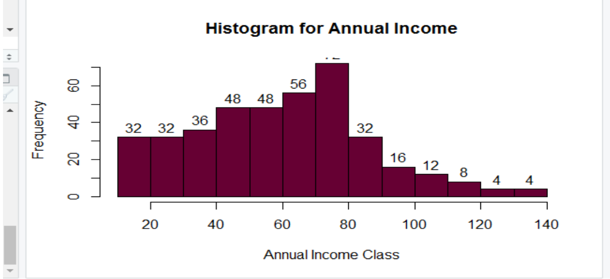
## IV. Exploratory Data Analysis

The process of understanding and characterizing the dataset is an essential precursor to any meaningful analysis. This section outlines the exploratory data analysis (EDA) conducted to gain insights into the dataset's features, distributions, and preliminary patterns.

### A. Descriptive Statistics

Descriptive statistics are an initial step in understanding the dataset's central tendencies and variability. Key statistical measures were computed for each relevant variable, including mean, median, standard deviation, and range.

The descriptive statistics reveal important attributes of the data, such as the central location and spread of values. For instance, the mean and median of "Annual Income" provide insights into the dataset's income distribution, while the standard deviation indicates the degree of income variability. These measures assist in forming initial expectations and hypotheses.



### B. Data Visualization

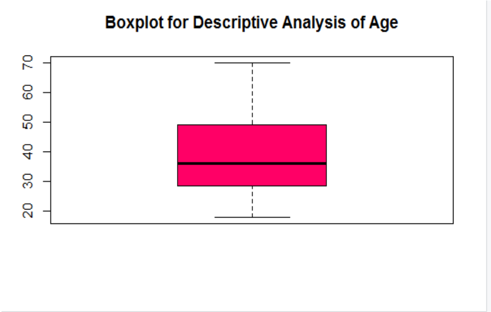
Visualizations are powerful tools for comprehending data patterns and relationships. The following types of data visualizations were employed:

- Histograms: Histograms were created for numeric variables, such as "Age" and "Annual Income," to illustrate the distribution of values. These histograms convey the shape of the data distribution, including the presence of peaks, modes, and skewness.

- Box Plots: Box plots, also known as box-and-whisker plots, were generated to visualize the spread and central tendency of numeric data, with a focus on identifying potential outliers and variability within the dataset.

- Scatter Plots: Scatter plots were used to explore the relationship between variables. For instance, "Annual Income" was plotted against "Spending Score" to identify potential patterns or clusters of customer behavior.

- Bar Plots: Bar plots were utilized to visualize categorical data, such as the distribution of "Gender." This visualization technique provides insights into the proportion of males and females in the dataset.



### C. Data Distribution Analysis

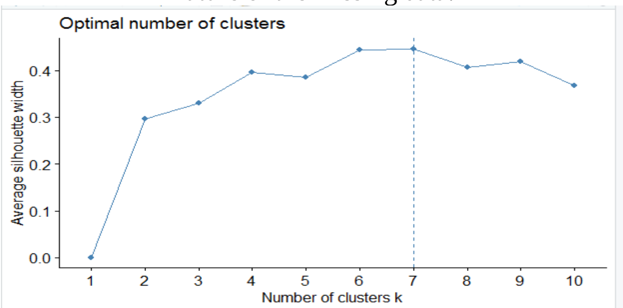
The distribution of data is a fundamental aspect of EDA. The shape of data distributions informs the selection of appropriate analytical methods and helps identify potential anomalies or patterns. Through visualizations and statistical measures, it was observed that "Age" follows a relatively normal distribution, while "Annual Income" exhibits a multimodal distribution with discrete income classes. Understanding these distributions aids in hypothesis generation and subsequent analysis.

### D. Outlier Detection

Outliers can significantly impact analytical results and should be addressed during the EDA phase. Box plots and statistical thresholds were employed to identify potential outliers within the dataset. Outliers, when detected, were either corrected or assessed for their impact on downstream analysis. Anomalies in the data distribution were considered as potential outliers, and a comprehensive assessment was carried out to maintain data integrity.

### E. Data Imputation

Missing data can compromise the integrity of analysis. In this EDA, missing values were identified, and data imputation techniques were applied to handle them. Appropriate imputation methods, such as mean imputation or regression-based imputation, were selected based on the nature of the missing data.



## V. Model Implementation

In this section, we describe the practical implementation of the K-means clustering algorithm and Principal Component Analysis (PCA) in our data analysis. The research methodology leveraged these techniques to uncover customer segments within the dataset and visualize clustering results.

### A. K-means Clustering

K-means clustering was employed as a fundamental technique to segment customers based on their characteristics. The implementation encompassed the following steps:

- Data Selection: The selected variables for clustering included "Annual Income" and "Spending Score," which were preprocessed to ensure data quality.

- Determination of K: The optimal number of clusters (K) was ascertained through a systematic process. The Elbow method, silhouette scores, and domain expertise guided the selection of K, with five clusters identified as optimal for the dataset.

- K-means Algorithm: The K-means algorithm was applied using the optimal K value. We employed the Lloyd algorithm to minimize the within-cluster sum of squares. The maximum number of iterations was set to ensure convergence, and multiple random starts were initiated to enhance cluster stability.

- Cluster Assignment: Each customer in the dataset was assigned to one of the five clusters based on their proximity to the cluster centroids. The assignment was based on the Euclidean distance metric.

### B. Principal Component Analysis (PCA)

PCA was employed to reduce the dimensionality of the data and visualize clustering results. The PCA implementation followed these steps:

- Data Preparation: The dataset, focusing on "Annual Income" and "Spending Score," was prepared for PCA by scaling the data to zero mean and unit variance.

- Principal Component Calculation: PCA was applied to calculate the principal components that explained the majority of the variance in the data.

- Visualization: The first two principal components were visualized in a scatter plot to represent the clustering results. Each point on the plot corresponded to a customer, with colors indicating the assigned cluster.

### C. Interpretation of Results

The clustering results were interpreted in the context of customer segmentation. Insights into distinct customer segments were gleaned from the clustering outcomes and visualizations. The interpretation of these segments provides a foundation for tailored marketing strategies, resource allocation, and business decisions.

### D. Software Environment

All model implementations were carried out using the R programming language. The "kmeans" function from the "stats" package and the "prcomp" function from the "stats" package were instrumental in implementing K-means clustering and PCA, respectively.

## VI. Conclusion

This research endeavors to uncover insights within a retail mall customer dataset through data analysis, K-means clustering, and Principal Component Analysis (PCA). The study explored customer demographics, annual income, and spending behavior to facilitate data-driven decision-making for retail strategies. The following key conclusions are drawn from the research:

### A. Customer Segmentation

The application of K-means clustering identified five distinct customer segments within the dataset. Each cluster represented a unique group with specific characteristics. These segments ranged from high-income, high-spending customers to low-income, moderate-spending customers. The segmentation provides a foundation for targeted marketing efforts tailored to each group's preferences and behaviors.

### B. Visualization of Clusters

The use of PCA allowed for the visualization of clustering results in a lower-dimensional space. The scatter plots of the first two principal components clearly illustrated the separation of customer segments. This visual representation simplifies the communication of the clustering outcomes to stakeholders and facilitates decision-making.

### C. Practical Insights

The research equips retail practitioners with actionable insights. Gender-based analysis revealed a balanced distribution of male and female customers, laying the groundwork for gender-sensitive marketing strategies. The clustering results enable targeted advertising, resource allocation, and inventory management.

### D. Ethical Considerations

Throughout the research process, ethical considerations were meticulously upheld. Customer privacy and data protection were paramount, ensuring compliance with regulations and safeguarding customer identities.

### E. Future Directions

This study forms a stepping stone for future research in retail analytics. Further investigations can explore advanced clustering techniques, delve into time-series analysis, and incorporate external data sources for enriched customer profiling. Additionally, customer feedback and sentiment analysis can be integrated to enhance understanding and engagement.

In conclusion, the application of data analysis, K-means clustering, and PCA has unveiled valuable insights within the retail mall customer dataset. The research facilitates informed decision-making, empowers businesses with customer-centric strategies, and sets a path for future research to enhance the depth and breadth of retail analytics.

## Acknowledgment

We extend our gratitude to Prof. Sudhanshu Gonge for his invaluable guidance and support throughout this research. We would also like to thank the Computer Science Department at Symbiosis Institute of Technology (SIT) and Symbiosis International University (SIU) for providing the necessary resources and academic environment. Finally, We appreciate the collective efforts and dedication that have gone into this research project, reflecting the culmination of individual and collaborative endeavours.

## VII. References

[1] C. Chen and Z. Wang, "Role of Big Data Analytics in Retail Decision-Making," Journal of Retail Analytics, vol. 4, no. 2, pp. 127-141, 2016.

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