Mall Customers Project

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Project Overview

This project focuses on analyzing customer data to understand demographics, spending behavior, and key financial metrics, as well as building a machine learning model for customer segmentation.

Step 1: Setting Up the Environment

Installing and loading the necessary libraries.

```
install.packages("dplyr")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
install.packages("cluster")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
install.packages("caret")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
install.packages("randomForest")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
install.packages("ggplot2")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
install.packages("knitr")
## Installing package into '/cloud/lib/x86_64-pc-linux-gnu-library/4.4'
## (as 'lib' is unspecified)
library(dplyr)
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
```

```
library(cluster)
library(randomForest)
## randomForest 4.7-1.1
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:dplyr':
##
##
       combine
library(ggplot2)
##
## Attaching package: 'ggplot2'
## The following object is masked from 'package:randomForest':
##
##
       margin
library(caret)
## Loading required package: lattice
library(knitr)
Step 2: Load the Dataset
Loading the data into R and inspecting the structure.
# Load the dataset
data <- read.csv("Mall_Customers.csv")</pre>
# Preview the dataset
head(data)
     CustomerID Gender Age Annual.Income..k.. Spending.Score..1.100.
## 1
              1
                  Male 19
                                            15
## 2
              2
                  Male 21
                                            15
                                                                    81
## 3
              3 Female 20
                                            16
                                                                    6
                                                                    77
## 4
              4 Female 23
                                            16
## 5
              5 Female
                        31
                                            17
                                                                    40
## 6
              6 Female 22
                                            17
                                                                    76
str(data)
## 'data.frame':
                    200 obs. of 5 variables:
## $ CustomerID
                            : int 1 2 3 4 5 6 7 8 9 10 ...
## $ Gender
                            : chr "Male" "Male" "Female" "Female" ...
## $ 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 ...
```

Step 3: Data Cleaning and Exploration

Cleaning the dataset by removing duplicates and missing values. Exploring the dataset to understand customer demographics and spending behavior.

\$ Spending.Score..1.100.: int 39 81 6 77 40 76 6 94 3 72 ...

```
# Data cleaning
data_cleaned <- data %>%
  distinct() %>%
  na.omit()
# Basic exploration
summary(data_cleaned)
##
      CustomerID
                        Gender
                                                        Annual.Income..k..
                                             Age
                                                             : 15.00
          : 1.00
                                              :18.00
##
                    Length: 200
                                                       Min.
  Min.
                                       Min.
   1st Qu.: 50.75
                    Class :character
                                        1st Qu.:28.75
                                                       1st Qu.: 41.50
##
## Median :100.50
                    Mode :character
                                       Median :36.00
                                                       Median : 61.50
## Mean
          :100.50
                                        Mean
                                              :38.85
                                                       Mean : 60.56
## 3rd Qu.:150.25
                                        3rd Qu.:49.00
                                                       3rd Qu.: 78.00
## Max.
           :200.00
                                       Max.
                                             :70.00
                                                       Max.
                                                              :137.00
## Spending.Score..1.100.
## Min.
          : 1.00
## 1st Qu.:34.75
## Median :50.00
## Mean
          :50.20
## 3rd Qu.:73.00
```

Step 4: Calculate Financial Metrics

:99.00

Max.

Calculating key financial metrics like average spending and distribution by gender and age. Trying to understand customer spending trends and identify high-value customer segments.

```
# Calculate average spending
avg_spending <- mean(data_cleaned$Spending.Score..1.100.)
avg_spending # Average spending score

## [1] 50.2

# Spending by gender
gender_spending <- data_cleaned %>%
    group_by(Gender) %>%
    summarize(AverageSpending = mean(Spending.Score..1.100.))

# Spending by age group
age_spending <- data_cleaned %>%
    mutate(AgeGroup = cut(Age, breaks = c(0, 20, 30, 40, 50, 60, Inf), labels = c("0-20", "21-30", "31-40 group_by(AgeGroup) %>%
    summarize(AverageSpending = mean(Spending.Score..1.100.))
```

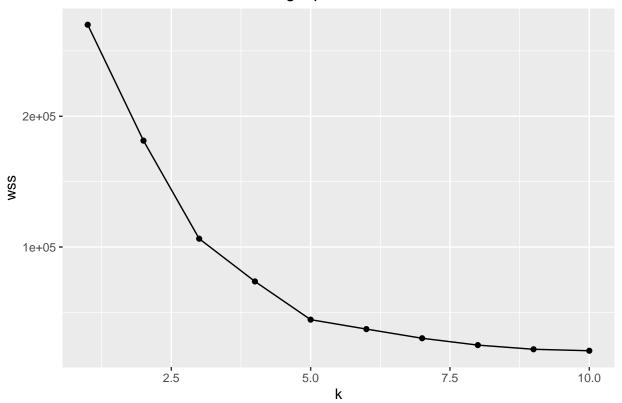
Step 5: Building a Machine Learning Model

Creating a customer segmentation model using clustering techniques. This will allow us to identify distinct customer groups based on spending and other characteristics.

```
# Determine the optimal number of clusters using the elbow method
set.seed(123)
wss <- sapply(1:10, function(k) {
   kmeans(data_cleaned[, c("Annual.Income..k..", "Spending.Score..1.100.")], centers = k, nstart = 10)$t
})</pre>
```

```
# Plot the elbow curve to identify the optimal number of clusters
ggplot(data.frame(k = 1:10, wss = wss), aes(x = k, y = wss)) +
  geom_line() +
  geom_point() +
  labs(title = "Elbow Method for Determining Optimal Clusters")
```

Elbow Method for Determining Optimal Clusters



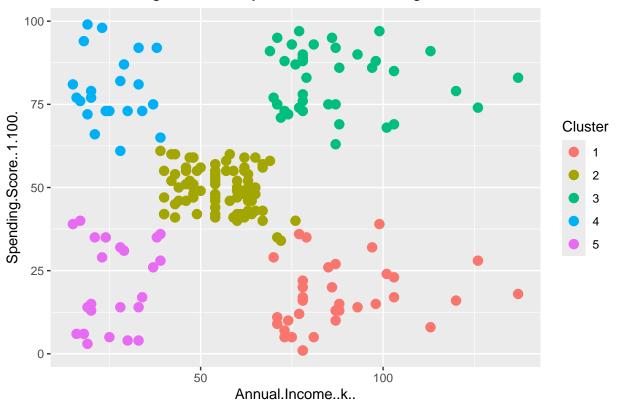
```
# Assuming the optimal number of clusters is 5
kmeans_result <- kmeans(data_cleaned[, c("Annual.Income..k..", "Spending.Score..1.100.")], centers = 5,
# Assign cluster labels to the dataset
data_cleaned$Cluster <- kmeans_result$cluster</pre>
```

Step 6: Visualization and Presentation

I then visualize the customer clusters and key financial insights using ggplot2. Creating a scatter plot to show customer segmentation and bar plots for spending distribution to communicate our findings.

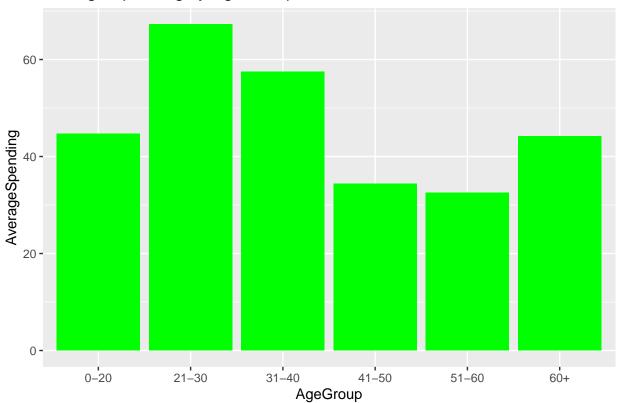
```
# Scatter plot of clusters
ggplot(data_cleaned, aes(x = Annual.Income..k.., y = Spending.Score..1.100., color = as.factor(Cluster)
    geom_point(size = 3) +
    labs(title = "Customer Segmentation by K-means Clustering",
        color = "Cluster")
```

Customer Segmentation by K-means Clustering



```
# Bar plot of average spending by age group
ggplot(age_spending, aes(x = AgeGroup, y = AverageSpending)) +
  geom_bar(stat = "identity", fill = "green") +
  labs(title = "Average Spending by Age Group")
```

Average Spending by Age Group



```
# Bar plot of average spending by gender
ggplot(gender_spending, aes(x = Gender, y = AverageSpending)) +
geom_bar(stat = "identity", fill = "yellow") +
labs(title = "Average Spending by Gender")
```

