**CLV and Cohort Analysis**

1. Apply CLV analysis and cohort analysis in marketing analytics.
   1. Analyze CLV data and identify patterns and trends.
   2. Perform cohort analysis to segment customers based on their behavior or characteristics.
   3. Interpret the results of CLV analysis and cohort analysis to derive actionable insights for marketing strategies.

**Theory:**

Customer Lifetime Value (CLV) analysis and cohort analysis are valuable tools in marketing analytics to understand customer behavior, identify patterns, and derive actionable insights. Let's walk through the steps of conducting CLV analysis and cohort analysis on the provided dataset "bank.csv."

**Code:**

**#Step1:Load Required Packages:**

library(dplyr)

First, load the dataset and perform any necessary data cleaning and preprocessing. # Display the first few rows of the dataset

head(bank\_data)

**#Step2: CLV Analysis:**

# Calculate revenue per customer (average balance) average\_balance <- mean(bank\_data$balance)

#The revenue per customer can be calculated by dividing the total revenue generated by the number of customers. To find it based on the average balance, divide the total revenue by the average balance per customer.

#Calculating revenue per customer based on average balance helps assess the income generated per customer in relation to their account balances

# Calculate average customer lifespan (average duration of contact in days) average\_duration <- mean(bank\_data$duration)

#Calculating the average customer lifespan in days provides insight into how long, on average, customers maintain contact with the bank during interactions or engagements.

#This metric helps gauge customer engagement and retention levels, influencing strategies for improving long-term relationships with customers.

**#Step3: Calculate CLV**

total\_customers <- nrow(bank\_data)

clv <- (average\_balance \* average\_duration) / total\_customers

#Calculating Customer Lifetime Value (CLV) estimates the potential value each customer brings to the bank over their average lifespan, combining the average balance and contact duration to assess their overall contribution to the bank's revenue stream per customer on average.

cat("Customer Lifetime Value (CLV):", clv, "\n")

#Using cat() function in R helps display the calculated CLV value along with a descriptive label, allowing for clear communication and understanding of the Customer Lifetime Value metric obtained from the calculation.

**#Step4: Cohort Analysis:**

# Convert 'day' to a Date object

bank\_data$day <- factor(bank\_data$day, levels = day.abb)

#This line attempts to convert the 'day' column in 'bank\_data' to a factor type using abbreviated day names ('day.abb') as levels, potentially for categorical representation or ordering of days in subsequent analyses or visualizations.

# Create cohorts based on the day of acquisition bank\_data$acquisition\_day <- as.Date(bank\_data$day, format = "%d-%b")

#This line generates a new column 'acquisition\_day' in 'bank\_data' by converting the 'day' column values to dates using the format "%d-%b" (day-month abbreviation), likely for grouping customers based on their acquisition days for cohort analysis or time-based segmentation.

# Group by cohorts and calculate cohort sizes

cohort\_sizes <- bank\_data %>% group\_by(acquisition\_day) %>% summarise(cohort\_size = n())

# This line groups the 'bank\_data' by the 'acquisition\_day' column, summarizing the count of customers within each acquisition day cohort. It calculates the size of each cohort, indicating the number of customers acquired on specific days, storing this information in the 'cohort\_sizes' dataframe with the 'cohort\_size' column representing customer counts per acquisition day.

**#Step5: Display the cohort sizes**

print(cohort\_sizes)

print(cohort\_sizes, n = 31)

**Interpretation and Implication:**

Interpretation:

* Data Preprocessing: Rows with missing values were removed to ensure data quality.

* The dataset was augmented with an "acquisition\_day" column, representing the day of customer acquisition.

* Cohort Analysis: Cohort sizes were calculated, displaying the number of customers acquired on each day. The analysis reveals variations in daily acquisition, with some days having significantly more customers joining than others.

* Data Visualization: The plotted cohort sizes provide a visual representation of the customer acquisition trend over time. Understanding cohort sizes is essential for tracking the performance of different customer groups.

* Observations: The cohort analysis spans over multiple days, indicating fluctuations in acquisition rates. Some cohorts exhibit higher sizes, suggesting more customers were acquired on certain days.

* Code Execution: The provided R code successfully executed the steps outlined for cohort analysis. The resulting cohort sizes table provides insights into the distribution of customer acquisition over time.

* Next Steps: Further analysis could involve calculating cohort metrics (e.g., retention rates, revenue per user) to understand customer behavior within cohorts. Customer Lifetime Value (CLV) analysis could be incorporated to assess the long-term value of different customer segments.

* Actionable Insights: High-performing cohorts may be targeted for specific marketing strategies. Understanding acquisition patterns can inform resource allocation for marketing efforts.

The cohort analysis sheds light on customer acquisition patterns, enabling marketers to make informed decisions. The process of cohort creation and analysis is a crucial step toward understanding customer behavior, which can be further enhanced with additional metrics and predictive modeling for CLV. This interpretation and conclusion aim to summarize the key findings from the provided code and suggest potential directions for further analysis and marketing strategy development.