ILLINOIS INSTITUTE OF TECHNOLOGY

Bank of America Marketing Strategy

Course: Marketing Research & Engg (MAX-503-01)

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OVERVIEW

The goal of this study is to help Bank of America create a customer segmentation for credit card customers, build a marketing plan, and offer a suggestion based on the behavioral analysis findings. Customers' interactions and transactions with their bank, as well as which channels, they use and how frequently, and which products they accept, are all part of behavioral analysis. We'll look at credit card usage from beginning to end in this article.

The purpose of this report is to develop a customer segmentation for credit card users for Bank of America, define a marketing strategy, and make a recommendation using the behavioral analysis results. Behavioral analysis is the interaction and transactions between customers and their bank, which channels they use and how often, and which products they adopt. In this, we will be looking at the full end-to-end credit card usage patterns of the customers.

According to the results of several recent evaluations of trends in commercial banking, accurate classification of borrowers is critical to the development of a successful organization. The use of modern market tactics and tailored customer approaches is necessitated by increasing competition in both the banking and non-banking sectors. Improving customer segmentation and incorporating it into the design and distribution of new products is one of the main concerns of the banking sector. A popular method of improving competitiveness is to develop a special product and service offering for loyal customers or to offer special discounts on existing products. A database of 8950 observations and 18 variables from a Bank of America branch that provides secured consumer loans is analyzed. Customers are defined as loyal based on their purchase history. Three variables are used for segmentation. First, the initial segmentation variables are used as input data for the analysis, and further research is conducted on standardized segmentation variables. The potential segmentation strategies are formulated depending on the leading segmentation variable. A comparative analysis of the results of the two methods studied (using hierarchical clustering hclust(), clustering data based on similarity or similar groups kmeans(), and model-based clustering Mclust() methods) is performed by default within each of the strategies. It is indicated which type of cluster analysis best fits each of the strategies.

ANALYSIS

Market segmentation is a marketing technique that divides clients into groups (also known as segments) based on their characteristics (demographics, shopping behavior, preference, etc.) Customers in the same market category have comparable reactions to marketing strategies. Therefore, the segmentation process can help companies understand their customer groups, target the right groups, and tailor effective marketing strategies for different target groups.

Market segmentation provides bank management with the opportunity to develop appropriate strategies for more efficient investments based on an in-depth knowledge of customer groups. One of the objectives of segmentation is to determine the attitude of individual customer groups toward a particular product or service. It enables financial institutions to tailor their service offerings to current and potential market participants and to develop long-term market strategies. Today, segmentation of the banking market is a key factor in the development of a successful business.

Our major goal is to use clustering to identify customer segments that are best suited to the data. The two types of clustering employed in the analysis are as follows:

1. Distance-based clustering: Hierarchical clustering (h-Clust)
2. K-means clustering
3. M-Clust (model-based clustering)

Data collection is always a problem in terms of determining the optimum set of attributes that will provide meaningful insights. The most difficult task for marketers is determining who they are marketing to. Knowing your buyer profiles allows you to customize your targeting and offerings to maximize their happiness and, as a result, your revenue. When you already have a group of clients and enough data about them, segmenting them can be incredibly valuable. The dataset used in the investigation is largely made up of unlabeled behavioral and transactional data from credit cards.

DATA

This case requires to develop a customer segmentation to define marketing strategy. The sample Dataset summarizes the usage behavior of about 9000 active credit card holders from Bank of America. The file is at a customer level with 19 behavioral variables.

The dimensions of this data set: 8950 obs. of 19 variables

The sample dataset summarizes the following:

1. CUST_ID: Identification of Credit Card holder (Categorical)
2. BALANCE: Balance amount left in their account to make purchases
3. BALANCE_FREQUENCY: How frequently the Balance is updated, score between 0. and 1 (1 = frequently updated, 0 = not frequently updated)
4. PURCHASES: Number of purchases made from account
5. ONEOFF_PURCHASES: Maximum purchase amount done in one-go.
6. INSTALLMENTS_PURCHASES: Amount of purchase done in installment.
7. CASH_ADVANCE: Cash in advance given by the user.
8. PURCHASES_FREQUENCY: How frequently the Purchases are being made, score between 0 and 1 (1 = frequently purchased, 0 = not frequently purchased)
9. ONEOFFPURCHASESFREQUENCY: How frequently Purchases are happening in one-go (1= frequently purchased, 0 = not frequently purchased)
10. PURCHASESINSTALLMENTSFREQUENCY: How frequently purchases in installments are being done (1 = frequently done, 0 = not frequently done)
11. CASHADVANCEFREQUENCY: How frequently the cash in advance being paid
12. CASHADVANCETRX: Number of Transactions made with "Cash in Advanced"
13. PURCHASES_TRX: Number of purchase transactions made
14. CREDIT_LIMIT: Limit of Credit Card for user
15. PAYMENTS: Amount of Payment done by user
16. MINIMUM_PAYMENTS: Minimum number of payments made by user
17. PRCFULLPAYMENT: Percent of full payment paid by user
18. TENURE: Tenure of credit card service for user

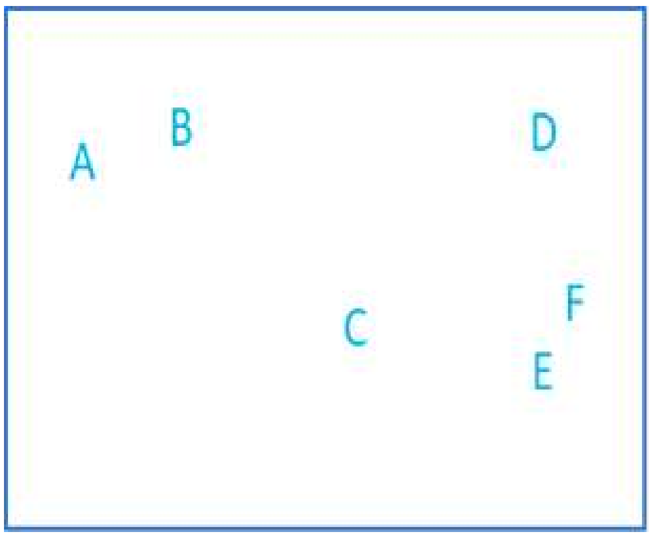
Structure of the data:

```
'data.frame':   8950 obs. of  19 variables:
 $ X                               : int  1 2 3 4 5 6 7 8 9 10 ...
 $ CUST_ID                         : Factor w/ 8950 levels "C10001","C10002",..: 1 2 3 4 5 6 7 8
9 10 ...
 $ BALANCE                         : num  40.9 3202.5 2495.1 1666.7 817.7 ...
 $ BALANCE_FREQUENCY               : num  0.818 0.909 1 0.636 1 ...
 $ PURCHASES                       : num  95.4 0 773.2 1499 16 ...
 $ ONEOFF_PURCHASES                : num  0 0 773 1499 16 ...
 $ INSTALLMENTS_PURCHASES          : num  95.4 0 0 0 0 ...
 $ CASH_ADVANCE                    : num  0 6443 0 206 0 ...
 $ PURCHASES_FREQUENCY             : num  0.1667 0 1 0.0833 0.0833 ...
 $ ONEOFF_PURCHASES_FREQUENCY      : num  0 0 1 0.0833 0.0833 ...
 $ PURCHASES_INSTALLMENTS_FREQUENCY: num  0.0833 0 0 0 0 ...
 $ CASH_ADVANCE_FREQUENCY          : num  0 0.25 0 0.0833 0 ...
 $ CASH_ADVANCE_TRX                : int  0 4 0 1 0 0 0 0 0 0 ...
 $ PURCHASES_TRX                   : int  2 0 12 1 1 8 64 12 5 3 ...
 $ CREDIT_LIMIT                    : num  1000 7000 7500 7500 1200 1800 13500 2300 7000 11000 ...
 $ PAYMENTS                        : num  202 4103 622 0 678 ...
 $ MINIMUM_PAYMENTS                : num  140 1072 627 0 245 ...
 $ PRC_FULL_PAYMENT                : num  0 0.222 0 0 0 ...
 $ TENURE                          : int  12 12 12 12 12 12 12 12 12 12 ...
```

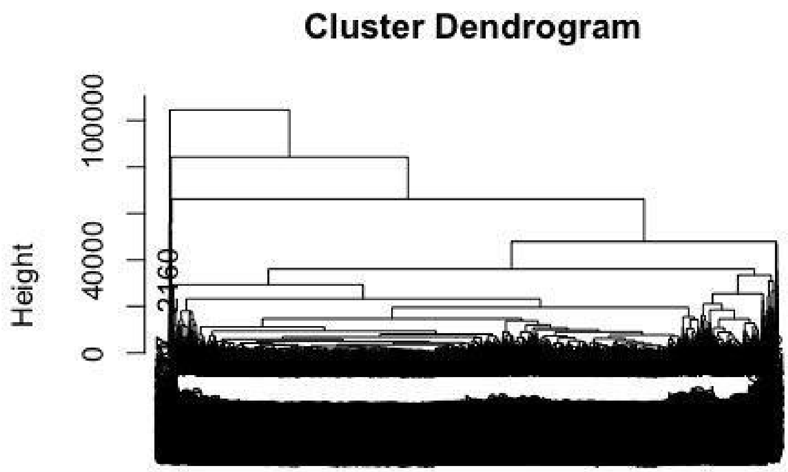
HIERARCHICAL CLUSTERING

Hierarchical Clustering is an unsupervised machine learning technique for grouping elements that are similar. This method creates a group of clusters with data points that are comparable to one another.

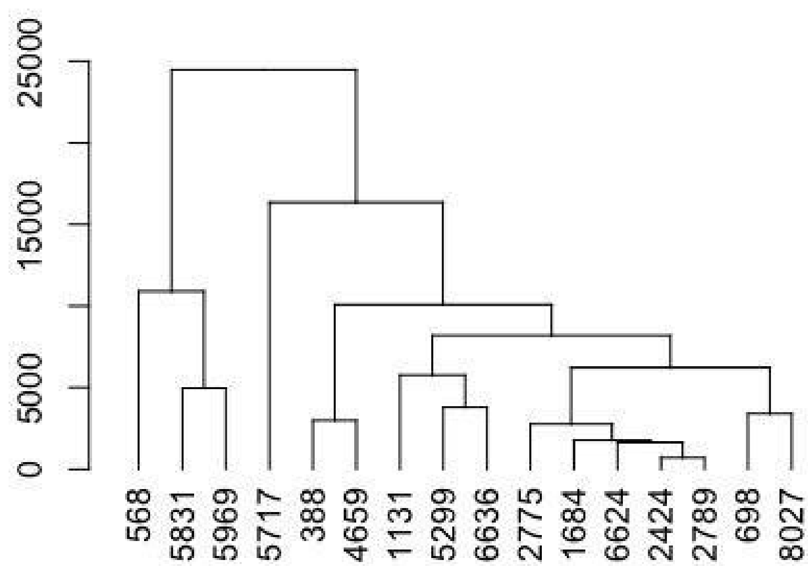
The algorithm divides objects into clusters based on their similarity. The endpoint is a collection of clusters or groups, each of which is distinct from the others and whose contents are similar.



In a hierarchical clustering, closest neighbors (defined in many ways) are put together in progressively larger groupings. hclust () is a distance-based technique that uses an N-by-N dissimilarity matrix to return a distance metric for each pair of data. In the hierarchical clustering approach, each observation is assigned to its own cluster. It then links neighboring observations or clusters one by one, based on their distances, until all observations are linked. We use the complete linkage method to merge observations and groups, which determines the distance between each member. The agglomerative technique is the process of combining observations and groupings on a regular basis.

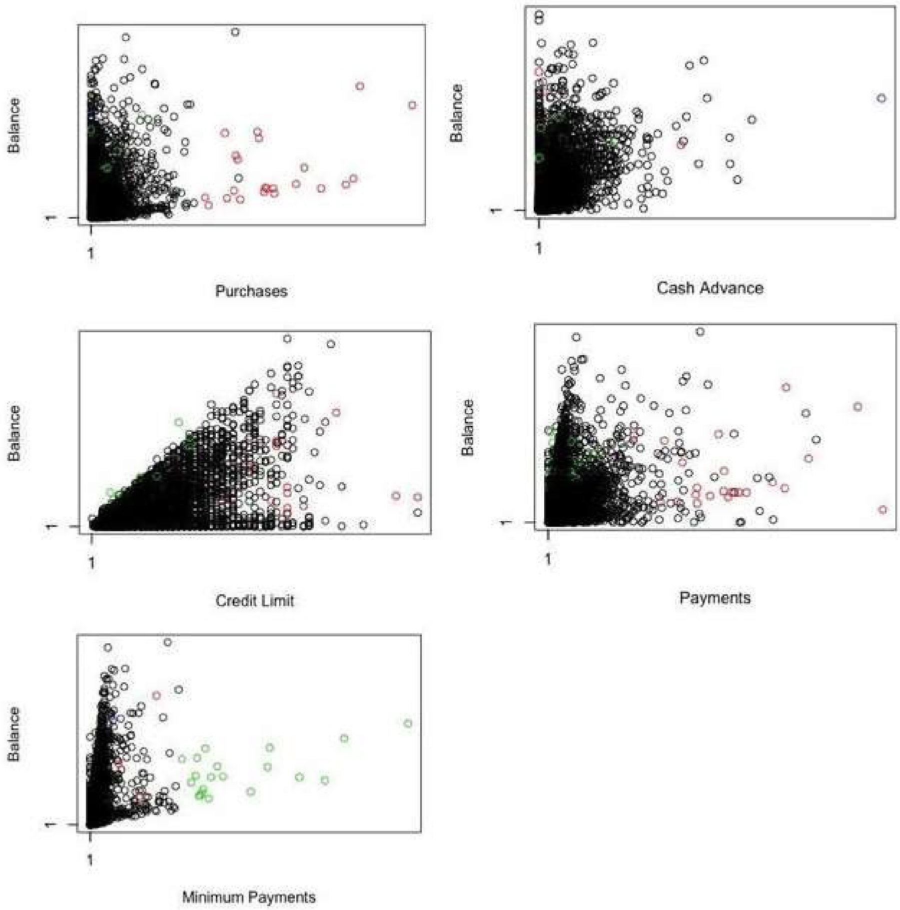


After plotting the h-Clust, the above diagram depicts a cluster dendrogram (). The dissimilarity between the pieces that are linked is represented by the height of the branch. For a clear picture of the cluster tree, we can cut the cluster dendrogram at a specific point through the y-axis and plot only one branch.



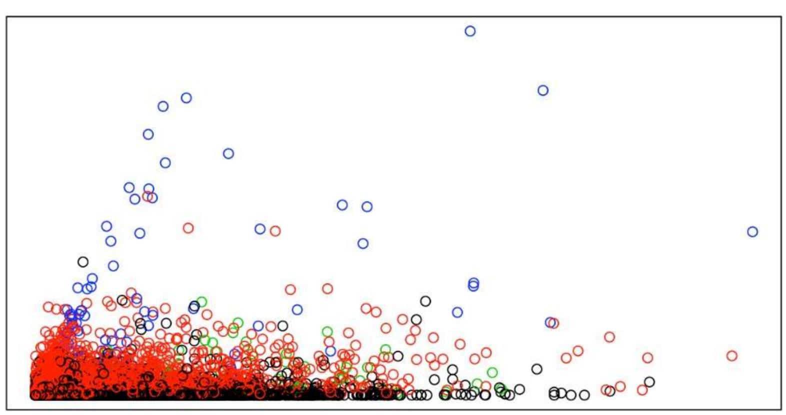
For performing our analysis on customer segments, we will be considering the below six plots.

- Balance vs Purchase
- Balance vs Cash Advance
- Balance vs Credit Limit
- Balance vs Payment
- Balance vs Minimum Payments



Comparing the dendrogram to the distance matrix in this case, **CPCC > 0.5** indicates a relatively strong fit.

On checking if the result is interesting, we can derive that it is not. This can be proven by checking the scatterplot below:

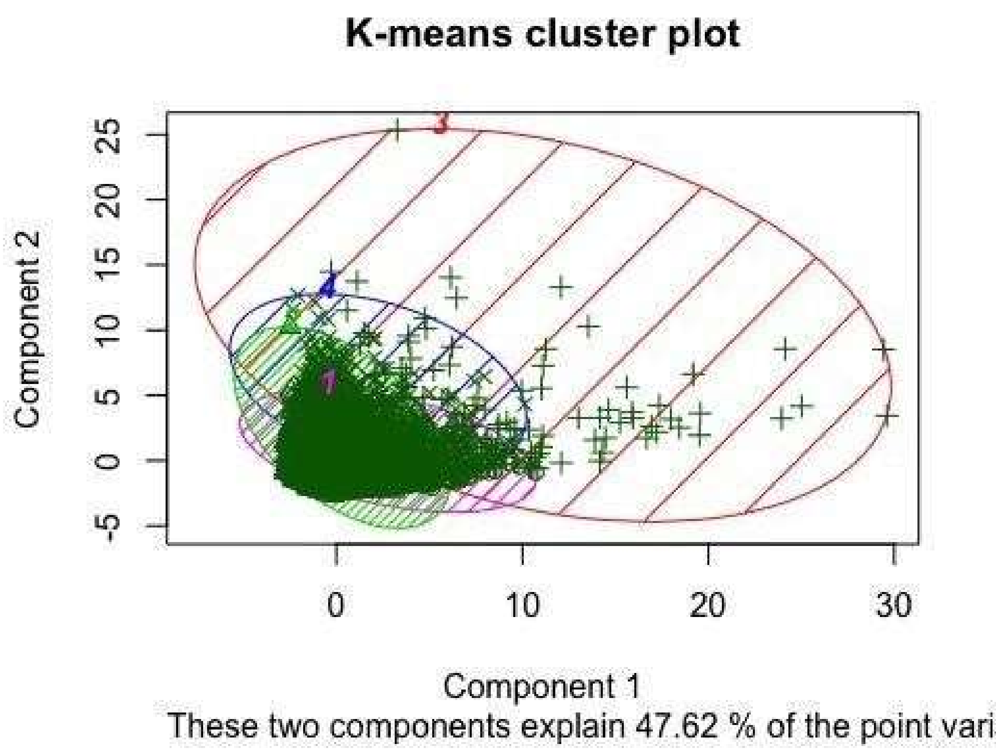


K-MEANS CLUSTERING

Unsupervised machine learning technique K-Means clustering divides data into the number of groups specified. In this scenario, the "K" stands for the number of preset clusters that must be built. It's a centroid-based method, which means each cluster is given a unique centroid. The primary objective is to reduce the distance between data points and the cluster centroid.

K-Means is simple to implement. It is very scalable and can be used on small and big datasets. However, there is an issue with determining the number of clusters, or K. In addition, as dimensions rise, so does stability. However, K Means is a simple and robust approach that simplifies clustering.

The individual elements' distribution is examined first to see the substantial differences. The k-means cluster plot is then plotted to show the observations on a multidimensional scaling plot with group membership identified by the ellipses.

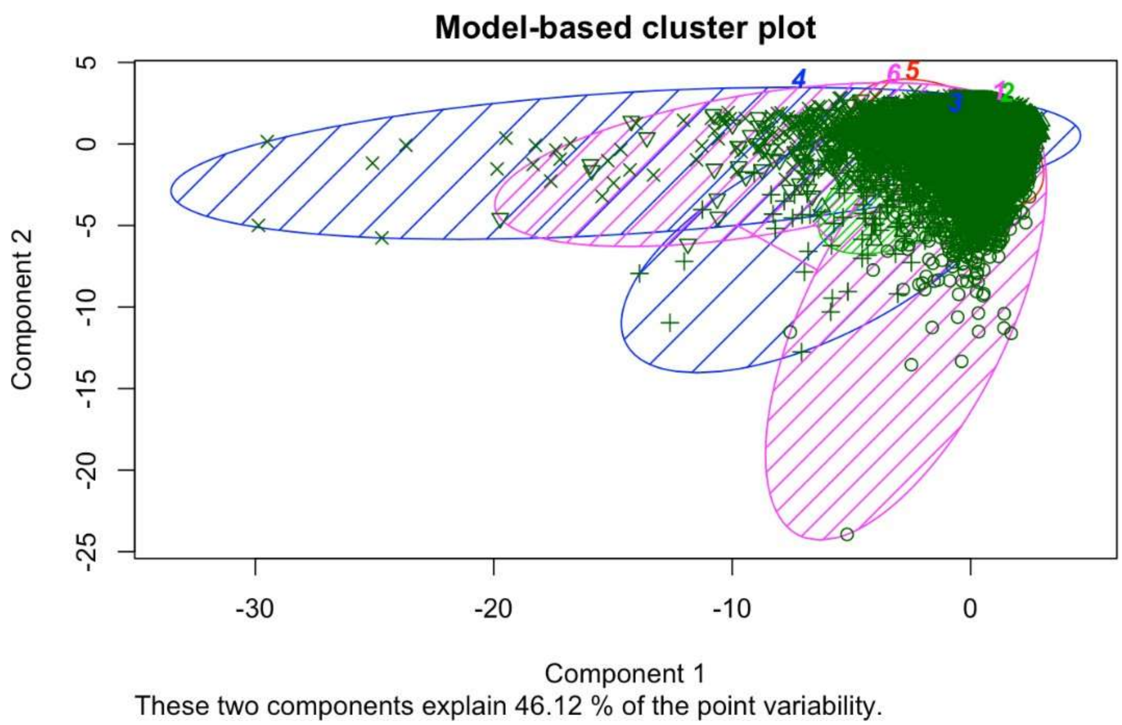


From the above figure we can see that Groups 1, 2 and 4 are largely overlapping while Group 3 is differentiated. About 47.62% of the variability is explained by this model.

M-CLUST

M-Clust is a R package that does model-based clustering, classification, and density estimation using finite normal mixture modeling. It offers utilities for simulation using these models as well as algorithms for parameter estimation using the EM technique for normal mixture models with varied covariance structures. There are other functions for comprehensive clustering, density estimation, and discriminant analysis that integrate model-based hierarchical clustering, EM for mixture estimation, and the Bayesian Information Criterion (BIC). Additional capabilities include the ability to display and visualize fitted models, as well as clustering, classification, and density estimation results.

Mixture modeling (model-based clustering) presupposes that observations come from populations with various statistical distributions (such as different means and variances). The algorithms look for the optimal set of underlying distributions that can explain the given data. We investigate model-based clustering to see how this works. The underlying population parameters and the mixing proportion are being estimated. Mclust assumes that clusters are formed by a combination of normal (also known as Gaussian) distributions. Mclust is one tool for locating such models (flexmix is another). The information must be numerical. Unlike hclust and kmeans, Mclust uses fit statistics to recommend the number of groups.



Most of the data points are nested and close to being concentric. About 46.12% of the variability is explained by this model too.

OBSERVATIONS

The following observations were made from the graphs.

- High Balance, High Purchase - These people made expensive purchases, but they also had higher balances to support these purchases. They also made large payments and can be the target for market research.
- High Balance, Low Purchase (Higher purchase values)- These are the people who had higher balances but made lower purchases and had medium or high credit limits and took out large cash advances.
- Medium Balance, Medium Purchase - These customers did not have low or high balances and they also did not make big or small purchases, but they did everything in a medium level. They are the second smallest group of customers currently.
- Frugal Customers (low balance, low purchase) - These are the customers that made the smallest purchases and since their credit limit was also low, this means that the customers did not make these purchases frequently. Therefore, it can be assumed that these customers churned out, and marketing strategies can be devised to target these customers. They are the smallest group.

A marketing strategy that focuses on the above four customer segments would prove to be highly effective for the next quarter of 2020.

RECOMMENDATION

I was able to create a clustering model that divided our credit card customers into various categories. The prime sector, revolvers, and transactors were among them, but was also able to identify inactive users. Understanding client behavior at this level of granularity is critical for personalizing offers that increase customer retention and revenue. The following are some suggestions.

- We can entice frugal clients to boost their engagement by providing cash back, discounts, and free Uber trips.
- We can tempt top consumers (high balance, high buy) to expand their purchasing habits by increasing their credit limits even further.

The above recommendations are proposed keeping in mind the very short timeline to the next quarter. With the implementation in the next phase, there is an anticipated increase in revenue for the company and better reach.