Customer segmentation combining to Customer targeting : Overview

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Abstract*—Optimizing marketing campaigns is a very important process for companies to maximize their return on investment. However, this process goes through several stages in order to guarantee an optimal result. In this paper, we discuss two key phases of the marketing campaign optimization process, namely, customer segmentation and customer targeting. Customer segmentation involves segmenting customers into different similar groups in order to be able to make a prediction of the acceptability, by a given customer, of a given product offering. Customer targeting is mentioned just after this segmentation in order to determine which product to offer and to which customer in order to maximize the company's return on investment (ROI) while respecting some business constraints and based on the exit from the preceding phase which is the segmentation. This paper presents an overview on segmentation and the use of a machine learning algorithm for predicting customer behavior towards product offerings, and customer targeting using metaheuristics hybridization.

Keywords*—Customer segmentation, Customer targeting Optimization, Machine Learning, Metaheuristic Hybridization, K-Means, Bat Algorithm

I. Introduction

Machine Learning has demonstrated its segmentation efficiency in several areas; fraud detection, medical diagnostics, character recognition and others [1]. It is also efficient in customer segmentation which is an important concept in preparing and executing a marketing campaign plan and targeting the best customers in order to maximize the profit and ensure effective customer retention. Good customer segmentation is always seen as the key to a successful business strategy. This way of working allows business units to analyze and profile customers and produce an effective business plan. Customer segmentation can be defined as a model on which a company is based to offer new profitable offers capable of retaining customers and building loyalty; And in general, customers have similarity in their need as long as they have similar characteristics [1]. Various experimental researches have appeared annually in this field. However, it is always difficult to make comparisons between the different methods adopted to segment customers [2]. Previously, the concept of dividing customers by classifying it into similar groups was generally not based on the dependent / target variable. Marketing experts deduce that segmentation is a tool to achieve an objective, not an end in itself. As the majority of companies aim to maximize their ROI, Marketers concluded that the best customers will need to be separated from the rest of the customers through effective segmentation; hence the perceived popularity of clustering techniques while being based on a dependent variable [3]

II. Motivation & Methodology

This paper is an overview of two previous works dealing separately with customer segmentation on the one hand, and customer targeting maximization in a marketing campaign on the other hand. The objective is to give an overview on a third work which will combine the two concepts mentioned above; the result of this possible study is to create a Framework which combine these two phases in a single process in order to produce a successful and optimal Marketing plan by maximizing the return on investment while taking into account the business constraints of a company. The first phase will be based on the RFM (Recency Frequency Monetary) segmentation model to predict customer behavior concerning the products that will be offered to them. A probability between 0 and 1 will be assigned to each segment. This prediction will make possible to calculate the value r_{ij} which is the expected revenue of the company from the offer of a product “j” to customer “i”, where $r_{ij} = p_{ij}\, DFV_{ij}$.. DFV_{ij} is the return to the firm when customer i responds positively to the offer of product j, and p_{ij} is the probability that customer “i” respond positively to product “j” offer [4].

A. RFM segmentation

RFM segmentation is a widely used technique in identifying customer groups in Retail Marketing. It is a technique that aims to target specific groups with relevant characteristics of customer behavior and thus ensure a very high retention rate. By adopting an RFM segmentation technique, marketers will gain a very effective and in-depth understanding of their customers by analyzing three quantifiable factors:

- Recency: This parameter gives an idea of the time spent since the last purchase of a given customer. Sometimes, other variations may be considered other than a purchase, such as a customer's last visit to an online store. And generally, it is more likely that a customer, who has recently interacted with products, will respond positively to an offer.
- Frequency: This parameter gives an idea of the frequency of a customer's purchase (or reaction to an offer) during a specific period. The more frequent a customer is, the higher the probability of reacting to an offer.
- Monetary: this parameter gives an idea of the degree to which a customer is spending on products during a given period. Generally, Customers who spend the most should be treated in a special way compared to those who spend less.

The obvious first phase in creating an RFM model is assigning recency, frequency, and currency values to customers. Historically, raw data came from surveys and questionnaires sent to customers. Currently, a company's CRM or transactional databases make the task of data collection easier. The second step divides the set of customers into several groups of different levels for each Recency, Frequency, and Monetary dimension, so that each customer is assigned a level in each dimension. During the third step, groups of similar customers will be defined and will be sent specific types of communications according to the required RFM clusters. here are some examples to illustrate:

- Best Customers - This segment includes all customers who have transacted recently, do so multiple times, and spend larger amounts than the rest of the customers.
- New High Spend Customers - this second type of group concerns customers who have completed a single transaction, but with high value and very recently.
- Loyal active customers who spend the least - This is a type of customer who spends less but has been shopping recently and buys often.
- Churned Best Customers - This segment includes customers who buy frequently and with high amounts but their last transactions are long ago.

The fourth step actually goes beyond the RFM segmentation itself: crafting specific messaging that is tailored for each customer group. Based on the pattern of behavior of particular groups, RFM segmentation enables very effective communication with all customers and plays an important role in customer retention.

B. K-Means algorithm

One of the simplest unsupervised machine learning algorithms is K-Means clustering, which is widely used in solving clustering problems. The principle of this algorithm is to classify a set of data into a number of similar segments grouped into clusters. The letter k denotes a predefined number of clusters. Values belonging to the same cluster are very similar to each other on the one hand, and values between different clusters are very different on the other hand; This is precisely the role of K-Means in subdividing data into non-overlapping subsets. [5, 6].

The difficulty with K-Means lies in the fact that it takes precision to determine the cluster k, because the initialization of the cluster center can change in such a way as to cause unstable segmentation of the data [5, 6].

The K-Means clustering will be used to create customer segments based on the value of the probability that a customer will accept the offer of a given product while basing itself on quantitative FRM values for each customer.

C. Customer Targeting

Customer targeting is the act of reaching out to a portion of your customer list to re-engage them and drive sales. Popular tactics for these campaigns include direct mail and email. Social media and digital ads provide newer avenues to connect with your customer base with more speed and precision. In direct marketing campaigns, the optimization of targeted offers problem is a big business concern. The main goal is to maximize the company's profit by reaching the right customers. The main challenge faced by companies when advertising, is to configure properly a campaign by choosing the appropriate target, so it is guaranteed a high acceptance of users to advertisements [7].Direct Marketing is a tool that allows firms to promote their products directly to customers, and measure results quickly. One of the most important benefits of Direct Marketing is "Upgrading firm's loyalty strategies" in order to maximize the companies' Return on Investment. Nobibon et al. [4], and Cohen [8] before, presented the formulation of the product targeting problem as a mixed-integer programming (MIP) problem including more business constraints, and it can be rewritten as follows:

Given a set of m customers $C = [c_1, c_2 ... c_m]$, and a set of n products' offers $P = [p_1, p_2 … p_n]$, the objective is to maximize the Return on Investment under these business constraints:

- The corporate hurdle rate: each company defines its hurdle rate (HR) to make sure that the Return on Investment is equal, at least, to a value of HR.
- During the campaign, the budget of each product is limited.
- A limitation is imposed on the total number of products offered to each customer.
- And there is also a Minimum Quantity Commitment (MQC), which is the number of units of a product to be offered in order for that product to be part of the campaign. It means that no customer will receive an offer of a product which is not part of the campaign. If the product belongs to the proposed ones then at least Pj > 0 customers will receive an offer.

A solution is represented by a binary array $R_{|C|\times|P|}$, where C indicates the set of available costumers, and P represents the possible products to be used in the campaign. If a given cell $s_{i,j}$ $|i \in C, j \in P$ is equal to "1" (true), the product j will be offered to the customer i; otherwise, the value would be "0" (false). There are two basic parameters of the customer lifetime value's computation; p_{ij} is the probability that customer i responds positively to an offer of product j, and DFV_{ij} is the return to the firm when customer i responds positively to the offer of product j [4, 10]. A basic formulation for the product targeting problem can be expressed, as modeled in [8], as:

$$\sum_{i=1}^{m}\sum_{j=1}^{n}(r_{ij}-c_{ij})x_{ij} - \sum_{j=1}^{m} fc_j y_j \qquad (1)$$

Where:

- r_{ij} is the expected revenue of the company from the offer of product "j" to customer "i", and $r_{ij} = p_{ij}\, DFV_{ij}$
- c_{ij} is the cost associated with the offer of product "j" to customer "i"
- M_i is the upper bound of products to offer to a customer "i"
- P_j is the minimum quantity commitment bound associated with product "j"
- B_j is the budget, in the campaign, allocated to the product "j"
- fc_j is the cost needed if a product j is used in the campaign
- O_j is the minimum quantity commitment bound associated with product j,
- HR is the hurdle rate specific to each company

The goal is to maximize the evaluation function given by Eq. (1), by finding the optimal combination of the two matrices X and Y:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \text{ and } Y = \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}$$

Where:

$$x_{ij} = \begin{cases} 1 \text{ If product } j \text{ is offered to customer } i, \\ 0 \text{ Otherwise} \end{cases}$$

and,

$$y_j = \begin{cases} 1 \text{ If product } j \text{ is used in the campaign}, \\ 0 \text{ Otherwise} \end{cases}$$

The business constraints can be modeled as follows:

1. $$\sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij}x_{ij} \geq (1+HR)\left[\sum_{i=1}^{m}\sum_{j=1}^{n} c_{ij}x_{ij} + \sum_{j=1}^{n} fc_j y_j\right] \qquad (2)$$
2. $$\sum_{i=1}^{m} c_{ij}x_{ij} \leq B_j \quad \text{for each } j = 1\ldots, m \qquad (3)$$
3. $$\sum_{j=1}^{n} x_{ij} \leq M_i \quad \text{for each } i = 1\ldots, m \qquad (4)$$
4. $$\sum_{i=1}^{m} x_{ij} \leq m y_j \quad \text{for each } j = 1\ldots, n \qquad (5)$$
5. $$\sum_{i=1}^{m} x_{ij} \geq P_j y_j \quad \text{for each } j = 1\ldots, n \qquad (6)$$
6. $$x_{ij}, y_{ij} \in \{0,1\} \quad \text{for each } i = 1\ldots m \text{ and } j = 1\ \ldots, n \qquad (7)$$

D. Metaheuristic Hybridization :

In general, we use a hybridization of metaheuristics to solve very complex optimization problems in a very optimal response time. The first technique of relay hybridization means applying a set of metaheuristics in a sequential way (one after the other); each metaheuristic uses the output of the previous one as input. The second technique uses several metaheuristics but in a parallel way; it is a cooperative optimization model; each agent (method) launches a search in a search space while acting with the other agents [10]. This type of hybridization is more efficient in terms of response time and can give better results depending on the problem treated. Four classes are derived from this hierarchical taxonomy:

- Low-level Relay Hybrid (LRH): It is a class of algorithm characterized by the integration of a metaheuristic into a Single Solution-based metaheuristic (Talbi 2009).
- Low-level teamwork hybrid (LTH): It is a very popular type of hybridization and has proven to be effective in many types of optimization problems. In this type of hybridization, a metaheuristic is combined with a P-metaheuristic (a type of memetic algorithm). [10]
- High-level Relay Hybrid (HRH): In this type of hybridization, two or more metaheuristics are executed in an independent and sequential manner. A metaheuristic can be initialized with another metaheuristic to guarantee the generation of a feasible and good quality initial solution; this positively impacts the performance of the optimization process [10].
- High-level Teamwork Hybrid (HTH) : Several algorithms perform searches autonomously and in parallel with other metaheuristics while cooperating to optimize the result. In any case, the performance of the HTH is guaranteed to be at least the same level as any metaheuristics involved

E. Dataset :

To measure the effectiveness of using metaheuristics, Nobibon et al [4] created a randomly generated dataset as follows:

- Cost c_{ij} is randomly generated from the set {1,2,3}.
- The return of the firm r_{ij} is an integer generated randomly between 0 and 16.
- The corporate hurdle rate HR can take 5%, 10%, and 15% values.
- In this paper, there are three different values of the number of customers: 100 customers for small category S, 1000 customers for medium category M, and 10,000 customers for large category L.
- For each category of customers, we have two different numbers of product n: 5 and 10 products.
- For each combination (category of customer and number of products), a minimum-quantity

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commitment bound P_j is randomly generated between $\left[\frac{\sum_i M_i}{n}\right]$ and $\left[2\frac{\sum_i M_i}{n}\right]$.

- The fixed cost fc_j is generated randomly between $\frac{O_j}{2m(1+HR)}\sum_i\left[p_{ij}-(1+HR)c_{ij}\right]$ and $\frac{O_j}{m(1+HR)}\sum_i\left[p_{ij}-(1+HR)c_{ij}\right]$
- For budget B_j, three values are adopted: the two values of $\left[O_j\frac{\sum_i c_{ij}}{m}\right]$ $\left[2\frac{\sum_i M_i}{n}\frac{\sum_i c_{ij}}{m}\right]$ and a random integer between $\left[O_j\frac{\sum_i c_{ij}}{m}\right]$ and $\left[2\frac{\sum_i c_{ij}}{n}\right]$.
- The upper bound M_i is selected between 1 and n/5.

However, the objective of the Framework that will are proposing in a future work, is to combine the customer segmentation with the optimization of the customer targeting in a single Framework to ensure an optimal and successful marketing campaign. In this case, the value of r_{ij} will not be random but rather calculated from the value p_{ij} which is the probability that a customer i responds positively to a product offer j. This value is a prediction calculated with an unsupervised Machine learning algorithm such as K-Means.
Once the r_{ij} values are computed, we proceed to an optimization of the fitness function in equation (1) while using an HRH hybridization. In [7], we combined the Genetic Algorithm (GA) to generate an initial solution that is feasible and of good quality, followed by the Binary Bat Algorithm (BBA) which is characterized by its speed of convergence. In order to optimize the BBA, we modified the BA in such a way as to escape stagnation in a local optimal as proposed by [11]. Figure Fig.1 shows the efficiency of the hybridization adopted as well as the modification made to the BBA.

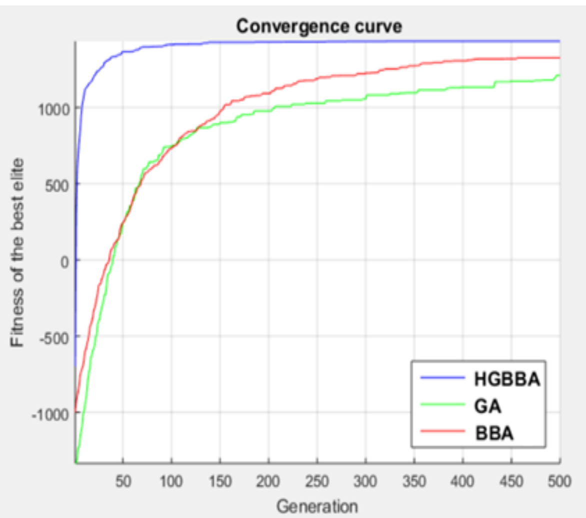

Fig. 1: Example of execution of three different algorithm for customer targeting optimization

III. Conclusion

This paper presents an overview of two works done with the same objective of optimizing a marketing campaign and maximizing the return on investment of a company. The two works are complementary and it is very wise to combine them in order to approach the problem of optimizing a company's marketing plan; the first phase, which is segmentation, is essential to make a prediction about a customer's behavior and the probability that he will respond positively to a given product offer. The second phase is there to complete the process and to launch an optimization of the fitness function with the objective of determining which product to offer and to which customer in order to reach a maximum profit. The segmentation phase is handled by building an RFM model and predicting the probabilities of customer response to offers through a Machine Learning algorithm which is the K-Means algorithm. The customer targeting optimization phase is just a classical non-linear optimization problem that is treated by a metaheuristic hybridization to guarantee a better result and with the best performances.

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