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A New Marketing Recommendation System Using a Hybrid Approach to Generate Smart Offers

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***Abstract* – In order to increase sales, companies try their best to develop relevant offers that anticipate customer needs. One way to achieve this is by leveraging artificial intelligence algorithms that process data collected based on customer transactions, extract insights and patterns from them, and then present them in a user-friendly way to human or artificial intelligence decision makers. This study is based on a hybrid approach, it starts with an online marketplace dataset that contains many customers' purchases and ends up with global personalized offers based on three different datasets. The first one, generated by a recommendation system, identifies for each customer a list of products they are most likely to buy. The second is generated with an Apriori algorithm. Apriori is used as an associate rule mining technique to identify and map frequent patterns based on support, confidence, and lift factors, and also to pull important rules between products. The third and last one describes, for each customer, their purchase probability in the next few weeks, based on the BG/NBD model and the average of transactions using the Gamma-Gamma model, as well as the satisfaction based on the CLV and RFMTS models. By combining all three datasets, specific and targeted promotion strategies can be developed. Thus, the company is able to anticipate customer needs and generate the most appropriate offers for them while respecting their budget, with minimum operational costs and a high probability of purchase transformation.**

***Keywords* – Apriori algorithm, BG/NBD Gamma-Gamma CLV & RFMTS models, marketing recommendation system, smart offer generation.**

I. Introduction

Nowadays, consumers are particularly concerned about the quality of the services and products offered. They are more loyal to brands that make them feel pampered and privileged. However, the loyalty of customers is critical to the prosperity and success of a business [1]. Thus, companies are increasingly trying to anticipate customer needs and generate personalized product or service offers, which makes it possible to initiate, convert and build a relationship with customers. In order to keep customers and increase their satisfaction, a marketing strategy must extend far beyond conventional usage patterns, such as customer segmentation, addressing customers by first name in a promotional email, or showing relevant advertisements on a website. To provide a truly personalized customer experience, companies use more innovative and intelligent ways to customize the online experience; generating personalized global offers is one of the most efficient ways used. A global offer in marketing is defined as the combination of the main offer with a secondary offer. The main offer corresponds to a product or service that meets a basic customer need. Whereas the secondary offering, also called an associated offer, is the equivalent of the service or product offered along with the main one. Who is the customer? What will they buy? When will they buy it? And how much will they spend? These are classic questions that companies should answer to face the competition. Thus, the objective of the hybrid approach proposed in this study, which is an extension of a previous work [2], is to generate global offers by identifying, for each customer, a list of the most likely to purchase products, the probability of purchase in the next few weeks, and the average transaction value. Furthermore, to make the most complete offers on the market, the associated products that are generally bought with the initial ones are determined as illustrated in Fig. 1.

II. Context

The success of any business mainly depends on an attractive marketing offer and an appropriate call to action. To facilitate the task of the customers, to attract more prospects and increase company's sales, it is very important to have a good business strategy. In this section, the context and the utility of this work, which generate relevant and impactful marketing offers to attract the attention of target customers, are presented. Selling cannot be improvised; a client cannot be forced to buy. To sell, customers' needs should be first identified in order to offer a product or service that meets their needs. To differentiate from competitors, a global marketing offer is the key to success. A global offer combines the main offer that solves customer needs with a secondary offer that contains associated items.

In this modern world, massive data can lead to information overload problems for digital customers [3]. The consumer feels unable to find the suitable product among the multitude of items offered on the online marketplace. To overcome this problem and help the consumer in decision-making, recommendation systems (RSs), proven to be a useful technology [4], have been developed. These systems reduce the number of options that the customer has to choose from by analysing the needs or behaviours. In general, recommendation

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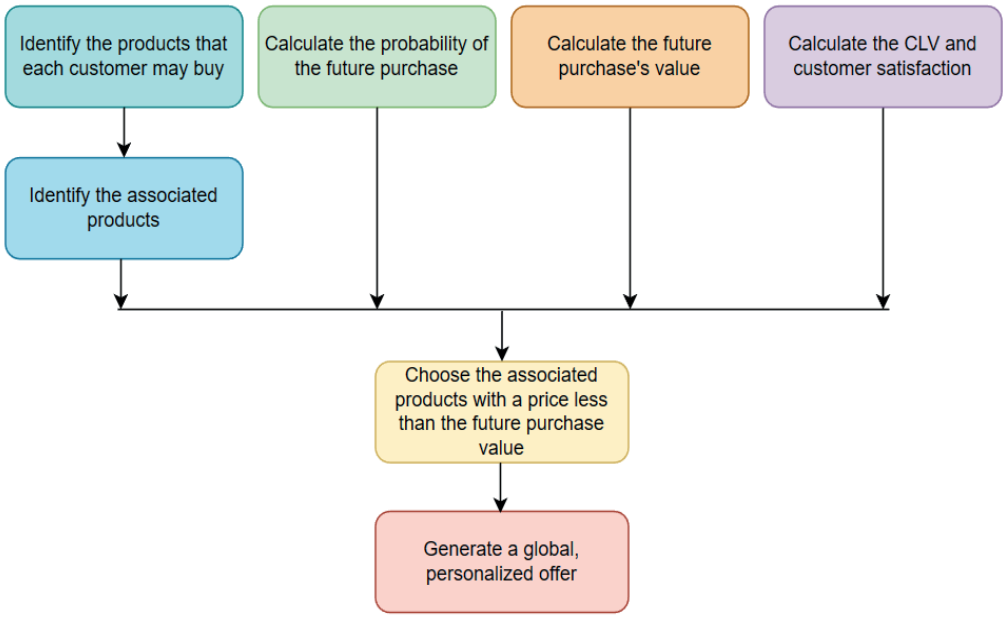


Fig. 1. Process of the offer generation approach.

systems aim at helping customers make the right purchase decisions [5]–[7] by analysing and aggregating suggestions from other customers [8]–[10]. Many websites, such as AliExpress, Netflix, YouTube, and Spotify, use recommendation-based algorithms [11]. The wide application of those recommender systems, based on either the deep learning approach or the machine learning approach, in the e-commerce marketplace is of increasing interest to researchers [12]–[21]. While some studies have focused on targeted offers, i.e., the selection of customers who will receive an offer consisting of one or more products during the campaign [22], [23], this study generates personalized offers that best match the preferences of each customer.

Consumers are constantly bombarded, mainly by email [24], with proposals for offers that often do not correspond to their profile or their needs. On the supplier's side, this translates into additional costs since it is necessary to send several thousand emails to be able to achieve poor results and into a questioning of its image because a large number of people perceive its proposals as an annoyance and a saturation of their email [25]. It is to remedy such problems that the approach proposed in the context of this article is inscribed and which generates an irresistible and personalized offer that best matches the customer's preferences, thus, on the one hand, providing value and enticing customers to purchase and, on the other hand, efficiently reducing the problem of information overload. The delivered offers have a high transformation factor due to the combination of several methods such as recommendation systems, the Apriori algorithm, association rules, the BG/NBD model, and the Gamma-Gamma model, as explained in the following sections.

This article is organised as follows: Section II provides an overview of the context related to marketing offer generation. Section III presents the construction and evaluation of the various models used. A discussion of the obtained results is presented in Section IV. Finally, Section V discusses the conclusions and future research areas.

III. Implementation

Instead of identifying targeted customers for a specific offer, this study takes the opposite route and generates offers by anticipating customer needs. As an effective tool to help companies develop targeted marketing strategies, the approach presented in this paper, as shown in Fig. 1, exploits artificial intelligence techniques deployed in parallel sections to create personalized offers by:

- Building a recommendation system by anticipating customer needs based on historical data, then generating association rules to identify frequent patterns between items and to identify associated ones;
- Identifying the probability of purchase in the next 4, 8, and 12 weeks;
- Predicting the value of next purchase;
- Calculating customer's profitability and satisfaction;
- Generating a global, personalized offer.

A. About the Used Dataset

The dataset used in this article is called "Brazilian E-Commerce Public Dataset", provided by Olist Store and accessible on the Kaggle website (https://www.kaggle.com). This dataset contains multiple purchases from 2016 to 2018 at various stores using the Olist service. In this study, only the Customers (99 441 rows), Orders (99 478 rows), Reviews (98 410 rows) and Payments (99 478 rows) sub-datasets are used since they contain the useful variables for this study approach. The three sub-datasets are filtered and prepared, then merged by their respective primary keys into a single initial dataset as shown in Table I.

In order to identify the probability of future purchases in the next few weeks, the value of the next one, as well as customer

satisfaction, five variables, which are recency (*R*), frequency (*F*), monetary value (*M*), interpurchase time (*T*), and satisfaction (*S*), should be first calculated. To do so, the RFMTS model [2] is used, Table II presents the dataset after generating the *R*, *F*, *M*, *T*, and *S* variables for each customer.

- *R*: represents the period between the current moment and the customer's last purchase. A low recency rate indicates that customers buy frequently.
- *F*: represents the number of transactions made by a customer. A high frequency rate indicates a high level of loyalty.
- *M*: represents the average amount of a specific customer's purchases. A high monetary value implies that the customer brings high profits to the company.
- *T*: represents the time between a customer's two successive purchases.
- *S*: represents the total of a customer's ratings divided by the number of reviews.

TABLE I

INITIAL DATASET

Customer ID	Order ID	Order purchase time	Payment value	Review score
000…1e2	e4…f7	10/2/2017 10:56	10.11	4
000…be3	9c…3c	10/2/2017 10:56	18.12	4
000…064	11…62	10/2/2017 10:56	25.59	3
…	…	…	…	…
fff…684	53…51	7/24/2018 20:41	142.14	4
fff…30a	47…5d	8/8/2018 8:38	20.46	1

TABLE II

DATASET AFTER CALCULATING *R*, *F*, *M*, *T* AND *S* VALUES

Customer ID	*R*	*F*	*M*	*T*	*S*
000…1e2	1428.77	2.10	120.66	432.67	1.20
000…be3	230.48	2.24	180.04	345.89	3.15
000…064	428.96	1.63	80.23	115.66	4.22
…	…	…	…	…	…
fff…684	149.52	1.96	71.99	109.71	4.64
fff…30a	230.41	2.15	44.84	84.32	3.27

B. Recommendation Systems

In recommender systems, two algorithms are mainly used: content-based filtering (CBF) and collaborative filtering (CF). The CBF technique is primarily based on customer and product information. It recommends a product to a customer based on the profile, feedback, and item information, etc. Its main restriction is the limited analysis of content as well as the specialization [26]. CF recommends products to consumers based on their previous ratings to alleviate the above problems. This technique is based on the preferences of the top k similar neighbours to recommend an article to a target customer [3], [27].

Collaborative Filtering Model (CF)

Recommendation systems often use collaborative filtering. It builds on the idea that the best recommendations come from other customers with similar taste. This means using similar customer review history to predict how a customer will rate a product. CF models can recommend a product to any user X based on the preferences of a like-minded user Y [28]. Collaborative filtering has two subcategories: model-based and memory-based. This study covers collective memory-based filtering given that user-based (user-user) and item-based (item-to-item) filtering belong to this category. The difference between the two mainly lies in the considerations when calculating the recommendation.

- User-based collaborative filtering: it focuses on the "nearest neighbour" approach [29] to recommend items by looking at user ratings to find the "nearest neighbours" with ratings similar to the targeted customer. In other words, user-based filtering finds users with similar spending habits and provides recommendations based on their interests.
- Item-based collaborative filtering: first introduced by Amazon in 1998 [30]. Contrary to user-based collaborative filters, item-based filtering finds patterns of similarity between different elements by considering the number of users who have purchased items A and B simultaneously. If the correlation between item A and B is high enough, it can be assumed that the two items are similar to each other. As a result, customers who purchase item B will receive a recommendation of item A and vice versa.

Fig. 2 shows the various collaborative filtering approaches based on the user and the item. The dotted arrows on the left represent recommendations based on user similarity and preference, and the dotted arrows on the right represent recommendations based on similar items.

Evaluation

In machine learning, the accuracy of a model is evaluated by mathematically taking the root mean square of the error that has occurred between the test and the predicted values [31]. This error value is used as a defensive score to decrease the individual effects of individual measurement errors so that there are no significant assumptions that substantially distort the results [11]. The RMSE (Root Mean Square Error) is a method for determining the accuracy of a predictive target value model [32]. It is the estimate of the average difference between the actual value and the estimated value, which is calculated as shown in (1). Where n is the number of estimates, y_j represents the current estimate, and $\hat{y}_j$ represents the average value of the estimates. The comparison of the user-based model and item-based model results based on the RMSE value is represented Table III. This shows that the user-based model gave a better result, with a minimum RMSE error value.

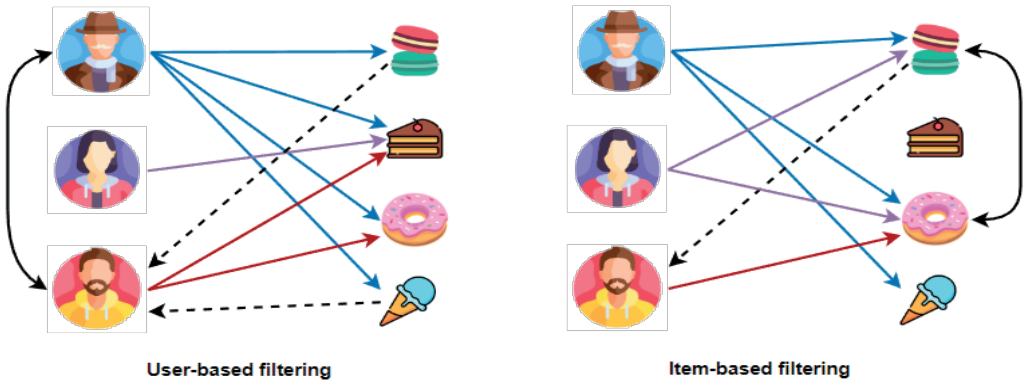


Fig. 2. User-based and item-based collaborative filtering approaches.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(Y_j - \overline{Y}_j\right)^2}\,. \quad (1)$$

The implementation of the user-based model on the dataset identifies the top 5 recommended items for each customer, based on customer's preferences (as shown in Table IV).

C. Generating Association Rules by Applying Apriori Algorithm

Market basket analysis (MBA) is a data mining technique commonly used to identify which products tend to be purchased together [33], [34] and predict customer purchasing behaviour. It discovers the association between the activities performed by the customers [35]. Although the primary focus of MBA is on shopping carts and customers [36]–[38], it also includes fields such as highway-railroad safety [39], fraud detection [40], mobile showroom [41], and others. MBA tries to identify purchase patterns in a large number of customer transactions. This is where association rules play an essential role by finding relations between different items and discovering frequent ones [34], [42]. Association rules do not capture individual preferences but instead look for relationships between different sets of elements in each transaction. This is what makes them different from collaborative filtering, which is used in recommendation systems [43]. To obtain the networks of products, the Apriori algorithm, the most frequent and efficient algorithm for association rule generation [44], [45], is applied in this research to generate these rules.

The Apriori algorithm was the first to determine Boolean association rules by extracting patterns from datasets [46]. It is used in different fields, in medicine to discover frequent image patterns in mammogram images [47], in education to predict system of learning [48], in traffic accidents to identify the main causes and trends related with it [49]. The Apriori algorithm is a method to find recurring items in a transactional dataset and to generate associated rules. It first determines frequent, unique items through transactions, then generates association rules [45]. The set of frequently occurring items corresponds to the set of frequently occurring functions measured by the parameter support. Confidence and lift parameters are used to measure the association rules corresponding to implication rules (A→B) [45]. Rules, whose lift is greater than 1, are the practicable association rules, which implies that item A has a positive effect on the appearance of item B. The support for a set of items is the percentage of the dataset that contains this set of items [50], [51]. Let I = $\{i_a, i_b,...,i_z\}$ be a set of items and A – a set of some items in I. Equation (2) defines the support of A, where Count (A) is the number of times item-set A appears in all transactions and *N* is the number of transactions.

TABLE III
USER-BASED AND THE ITEM-BASED MODELS RESULTS BASED ON THE RMSE VALUE

Model	RMSE
user-based model	1.063122817661801
item-based model	1.343641161111319

$$\text{Support (A)} = \frac{\text{Count (A)}}{N}\,. \quad (2)$$

For rule A⇒B (antecedent →consequent), the Support, Confidence and Lift equations are the same presented in [52]:

- The support of the A→B association rule is the percentage of transactions that include both elements A and B. It is defined as shown in (3).

$$\text{Support (A} \rightarrow \text{B)} = \frac{\{\text{A,B}\}}{N}\,. \quad (3)$$

- Confidence measures the number of times items in B appear in transactions involving A [53]. The Confidence is calculated as shown in (4).

$$\text{Confidence } (A \rightarrow \text{B}) = \frac{\{\text{A,B}\}}{\text{Support (A)}}. \quad (4)$$

- Lift is a probability that event B occurs independently as a consequence of another event A [35]. Equation (5) defines the lift of the association rule A→B.

$$\text{Lift (A} \rightarrow \text{B)} = \frac{\{\text{A,B}\}}{\text{Support (B)}}. \quad (5)$$

The traditional approach to association rules is to mine records for common item-sets with a minimum threshold of "support" and then use another minimum threshold of "confidence" to generate rules for the collected common item-sets [54] (Fig. 3). Applying the priori association algorithm to each customer transaction set produced meaningful association rules with high confidence (greater than 0.7) as shown in Table V. These results, which determine which products are frequently bought together, allow companies to develop customer loyalty strategies by generating global offers.

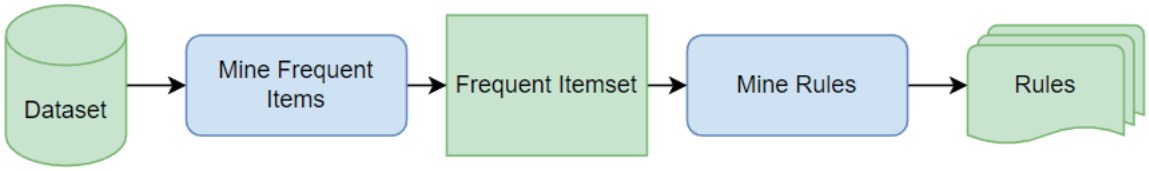


Fig. 3. Association rule mining.

TABLE IV
TOP 5 RECOMMENDATIONS FOR EACH CUSTOMER

Customer ID	Top 5 recommended items
000…1e2	B00CGW74YU (Laptop), B000Q8UAWY (Phone), B003TXZCYE (Perfume), B008DW95NA (T-shirt), B005N3TPJQ (Gaming mouse)
000…be3	B000P6G7YW (Perfume), B00000JX3C (Baby toy), B000GC2DDE (Baby clothes), B001PB17YY (Backpack), B0022TQXWG (Diaper)
000…064	B0002KR13M (Dress), B000VAIMF4 (Sunscreen), B002ZYQE0Y (Perfume), B0058SYDTI (Swimsuit), B004TLL730 (Makeup)
…	…

TABLE V
ASSOCIATION RULES

Rule	Antecedents	Consequents	Support	Conf	Lift
0	e0c…a26	368…2db	0.37	0.79	1.68
…	…	…	…	…	…
125	389…0f4	0bc…cdd	0.40	0.84	1.68
126	0bc…894	537…48c	0.39	0.80	1.70
127	537…f73	0bc…48c	0.41	0.86	1.70
…	…	…	…	…	…

D. Calculation of the Probability of a Future Purchase by Application of the BG / NBD Model

The BG/NBD model [55] is used in this study to estimate, for each customer, the probability of carrying out transactions in a future period. The BG/NBD is a simplified substitutional model to the well-known Pareto/NBD model [56], which is based on Bayesian probability in a hierarchical way to make its estimates. These two models are particularly used in marketing research, especially in the analysis of the customer database. They are rooted in the theory of customer lifetime value [57]–[59] that forecasts future customer behaviour based on stochastic aspects of interaction behaviour, such as departure [56].

The application of the BG/NBD model to this article dataset, including the RFT data generated previously, makes it possible to create the Frequency-Recency Matrix shown in Fig. 4. The visualization of this matrix, over four weeks (Fig. 4), shows the probability of future customer purchases at a given time. This probability increases if the number of purchases and the duration since its last purchase are important. It should be noted that the probabilities of future purchases are quite low over the next four weeks and are limited to a few customers; this is explained by the pattern of sporadic purchases seen in the studied dataset.

Based on the previous model, predictions could be made for any chosen period. In the case of this study, predictions are created for the first 4, 8, and 12 weeks, as these are a strong short-term indicator for focusing a vendor's efforts on their customers with the highest likelihood of future purchases. Table VI shows the probability of purchase in the next 4, 8, and 12 weeks for each customer.

BG/NBD Validation

Model predictions cannot be used blindly, they must be validated with reality. For this purpose, the last three months of results, when the numbers of transactions of each customer are already known, are compared with the BG/NBD model results.

As can be seen in Fig. 5, the lines are quite close to each other, which means that the model makes predictions quite close to the margin of error. In all cases, the model is close on certain points to reality. Similarly, extending the duration of the test could improve the validation of the model.

E. Predictive Calculation of the Future Purchase Value by Application of the Gamma-Gamma Model

The probability of having each customer's purchases forecast for the following months can be known, but not their number. A customer who buys 20 times on average 5 USD is not the same as another who buys 2 times 400 USD. It is at this stage that the Gamma-Gamma model initially proposed by Colombo and Jiang [60] is used to give an estimate of the profitability of each customer, using the monetary value (*M*) column previously generated.

One of the requirements of the Gamma-Gamma model is to only work with observations with a purchase frequency different from 0 (retain only customers with more than one purchase) [61]. Similarly, it must be ensured that there is no

correlation between the frequency (*F*) and the monetary value (*M*) of each consumer [62]. In practice, the Gamma-Gamma model must check whether the Pearson correlation [63] between the two vectors is close to 0 (Fig. 6).

One of the faculties of this model is to calculate the conditional expectation of the average profit per transaction for each customer as shown in Table VII.

F. Customer Profitability and Satisfaction

Customer Lifetime Value (CLV or CLTV) is a marketing metric [64] that, in a nutshell, reflects the profit that a certain customer will provide to a business over a given period of time. This makes it possible to get out of the subjectivism of the value of a customer, in order to quantify it in a more exploitable field linked to the profitability it brings to the company. The concept of customer lifetime value is well accepted by researchers and marketers [58] who agree that long-term customers are more profitable. The reason commonly given for increasing the profitability of long-term customers is the increase in profit from loyal customers, which is determined by the price premium they pay, the additional profit from sales through referrals, and the benefits in relation to cost savings due to the increased sales in their regard [65].

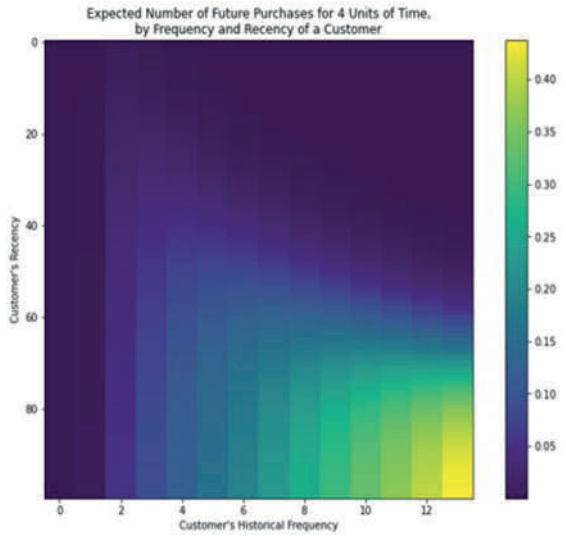


Fig. 4. Frequency recency matrix.

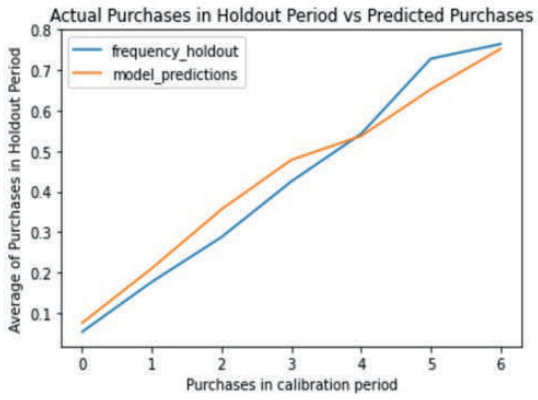


Fig. 5. Actual purchases in holdout period vs. predicted purchase.

TABLE VI

PURCHASE PREDICTIONS OF NEXT 4, 8, AND 12 WEEKS

Customer ID	Expected 4 weeks	Expected 8 weeks	Expected 12 weeks
000…1e2	0.02	0.04	0.05
000…be3	0.03	0.07	0.01
000…064	0.02	0.04	0.07
…	…	…	…
fff…84	0.02	0.04	0.07
ffff371b4d645b6ecea244b27531430a	0.02	0.01	0.01

TABLE VII

CUSTOMER'S NEXT AVERAGE TRANSACTION VALUE

Customer ID	Avg transaction
0000366f3b9a7992bf8c76cfdf3221e2	12 398.64
0000b849f77a49e4a4ce2b2a4ca5be3	4542.78
0000f46a3911fa3c0805444483337064	6608.59
…	…
fffcf5a5ff07b0908bd4e2dbc735a684	344.3
ffff371b4d645b6ecea244b27531430a	69.25

TABLE VIII

NORMALIZED CLV AND *S*

Customer unique id	CLV	*S*
0000366f3b9a7992bf8c76cfdf3221e2	0.928328	0.05
0000b849f77a49e4a4ce2b2a4ca5be3	0.870307	0.5375
0000f46a3911fa3c0805444483337064	0.662116	0.805
…	…	
fffcf5a5ff07b0908bd4e2dbc735a684	0.098976	0.91
ffff371b4d645b6ecea244b27531430a	0.095563	0.5675

Customer satisfaction and trust are respectively the first and second important antecedents of customer loyalty [66]. After calculating the CLV for each customer, based on the RFMTS model [2], the CLV and satisfaction (S) values are normalized to a range between 0 and 1, using the well-known statistic normalization formula (6), as indicated in Table VIII.

$$X\ \text{norm} = \frac{Xi - \min(X)}{\max(X) - \min(X)}. \tag{6}$$

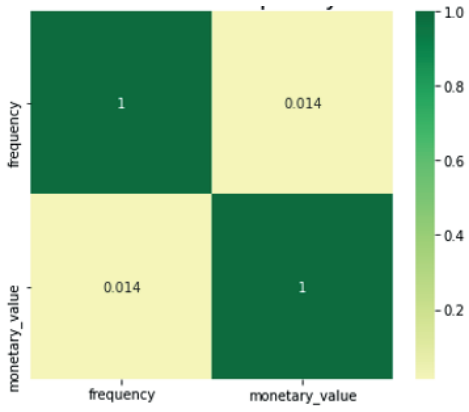


Fig. 6. Frequency & Monterey correlation matrix.

IV. Results and Discussion: How to Create a Global Offer Based on Different Information Generated Previously

Predicting future customer behaviour and generating a dedicated global offer for each of them allows the company to consolidate its customer relationships, differentiate itself from its competitors, and increase its earnings. It is in this context that the study presented here takes place, with the aim of anticipating customer needs in order to generate a global offer by following the steps illustrated in Fig. 1. The global offer is made up of the main offer and associated offer for customers who are probably likely to accept the offer positively based on their needs. The main offer corresponds to a product or service that satisfies consumer's basic needs. While associated offer is added to the main one with additional products or services that are generally purchased with the bought one. The global offer creation is divided into two steps. The first step is the main offer creation; in this step a recommendation system is used to identify, for each customer, the top 5 products that meet the customer needs (Table IV). The second step is the associated offer creation; in this step Apriori algorithm is used to determine associated products as shown in Table V. After determining the products of interest to a specific customer, as well as the associated products, the third step takes place, which aims to calculate the probability for a customer to transact in a future period using the BG/NBD model. The probabilities of customer's future purchases in the next 4, 8 and 12 weeks give an idea of the ideal time to communicate to the customer a personalized offer. With the above, the probability of each customer purchase in the next few months is known but not its amount. This is where the role of the next step comes in, which consists in calculating the future purchase value by application of the Gamma-Gamma model. Knowing the value of the next purchase helps choose the associated products, identified in Step 2, while respecting the customer's budget, in other words, the top products, the total price of which does not exceed the client's next purchase value, are chosen. Combining all the information generated in the above steps makes it possible to generate a global personalized offer with a high transform value. All customers are not the same, and so they should not be treated the same way. A loyal customer deserves eventually more promotions and services added to the offer. Thus, to identify the value of a customer, it is necessary to calculate the CLV value (calculated based on customer recency, frequency and monetary value) and satisfaction value (calculated based on customer review rating). By following the approach proposed in this study, a global offer that contains associated products and personalized services is generated for each customer. In addition to the probability of purchase, the global offer respects the customer's budget as well. Fig. 7 represents an example of a personalized offer generated based on the approach described above for a specific customer, where "Laptop" is the main customer's need, and the remaining items are additional ones with the additional option of checking and unchecking the items proposed while adapting the price to make it attractive. All methods used in this study are integrated into a global algorithm, so generation is automatic which takes as input information about customers and their purchases and outputs generated offers. The global algorithm developed in this study makes it possible to implement parallel sections of the process simultaneously to reduce processing time, and then the results of each section are combined to provide a personalized offer.

V. Validation

In addition to the different evaluation factors concerning each technique used at different stages of this study, the offer transformation rate is used in the end to validate and evaluate the proposed offer generation algorithm. The conversion rate is a key factor in the financial success of a platform [67]. It is a percentage metric that helps companies analyse the performance of their marketing strategies and can be calculated by dividing the number of sales by the total number of communicated offers and multiplying by 100 %, as shown in (7).

$$\text{Conversion rate} = \frac{\text{Number of sales}}{\text{Number of communicated offers}} \cdot 100. \quad (7)$$

To validate our approach, the data are split into two parts, with the last 20 % used for the validation and 80 % used for testing. The analysis of the 80 % of data has made it possible to determine for each customer the products of interest, the associated products, purchase time and purchase amount, and the value of CLV and satisfaction. Let us take as an example a set of 65 customers identified by our model as being interested in the product "laptop" and that their CLV and satisfaction scores are close. Fig. 1 represents the personalized offer generated for those 65 customers. The conversion rate value of this offer, calculated by (7), is 70 %, which is a high value that means an average of 45 customers out of 65 positively interacted with the generated offer.

VI. Conclusion

Recent advances in technology are impacting not just consumers, but merchants as well. On the one hand, today's consumers are constantly changing, and digitization is the major reason for this change in behaviour. On the other hand, AI algorithms have given marketers the ability to process and extract insights from collected customer transaction data and thereby increase profitability with minimum operational cost, which is the goal of any type of business. Hence, this article has represented a process of generating personalized offers as part of an overall marketing strategy aimed at anticipating customer needs and developing targeted and specific promotional strategies. First, a recommendation system is built based on customer historical data, and then association rules are generated to identify frequent patterns between items. After determining what each customer may buy, the next step is to determine the best time and the value of the next purchase. Finally, the profitability and satisfaction of each customer are identified.

Due to the approach presented in this study, customer overload problems are minimised since the customers receive

personalized offers about products that meet their needs. Competition is getting tougher, and to differentiate themselves from competitors and increase the conversion rate of offers, companies must forget about old marketing strategies and opt for personalization. In addition to the customization of the offers, which is the objective of this study, choosing the right moment and the right sending channel to send the offer increases customer satisfaction. Thus, in future research, the approach presented in this paper can be reinforced by taking into consideration other parameters, in particular the probability of purchase, the profile of the customer, as well as the budget, to plan the sending of the offer while respecting the customer's schedule and personalizing the associated message according to the profile (age, gender, residence, etc.).

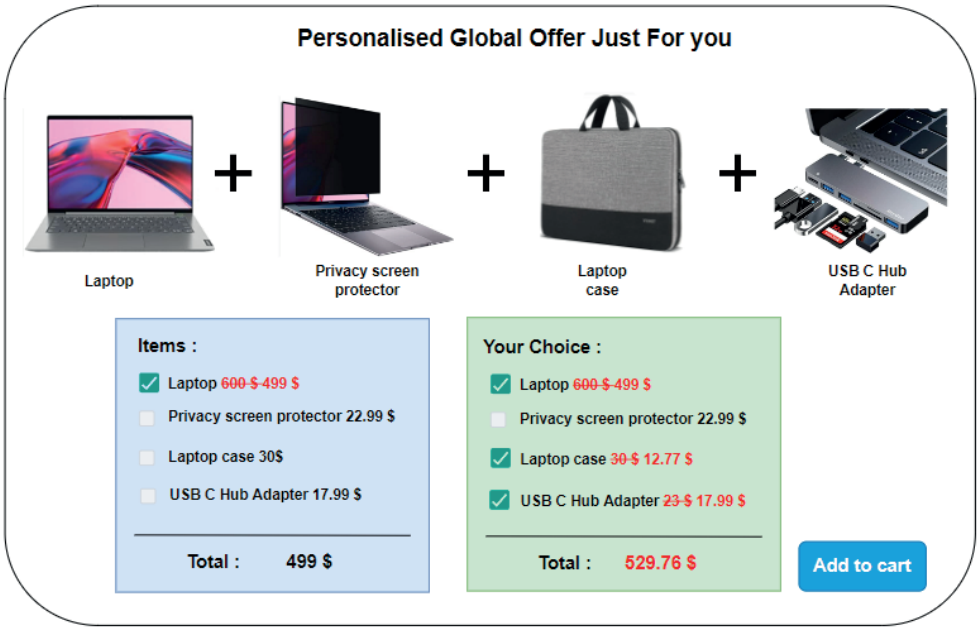


Fig. 7. Global offer example.

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