Mobile Gift Recommendation Algorithm

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Abstract: The mobile application market and e-commerce sales have grown steadily, along with the growth of studies and product recommendation solutions implemented in e-commerce systems. In this context, this paper proposes a recommendation algorithm for mobile devices based on the COREL framework. The proposed recommendation algorithm is a customization of the COREL framework, based on the complexity of the implementation associated with iOS mobile applications. Therefore, this work aims to customize a gift recommendation algorithm in the context of mobile devices using as main input the user preferences for the gifts recommendation in the Giftr application.

1 INTRODUCTION

The e-commerce in recent years has seen an intense growth in sales in Brazil, festive dates of the year like Mother's Day, Valentine's Day, Children's Day, Christmas Day, etc. are the time of year in which the demand for this type of trade intensifies e-commerce(Mendes, 2016). This scenario provides a business opportunity for software applications that offer the consumer the opportunity to gift someone on those festive dates by cross-referencing user profile data to offer the best related gifts.

To improve the user experience and increase their sales, online companies use product recommendation algorithms according to the characteristics of their consumers. There are several types of algorithms, and despite the success of some of them, most of them have problems. Therefore, it is important that companies have a consistent and relevant algorithm to recommend products to their (Gama et al., 2011).

One of the problems encountered in creating recommendation algorithms is that, initially, the system has not much user information. That hinders the learning and performance of the algorithms. Thus, it is necessary to use mechanisms that reduce the learning time of the algorithms and predict based on the little available information(Gama et al., 2011).

The e-commerce began in the 90s, when the first sales websites were created. Initially, the volume of transactions was very low. But the change in the world market made it become the largest and most voluminous way to market products (do Nascimento et al., 2009). According to a survey released by Buscapé in 2015, billions of brazilian reais are collected on commemorative dates for e-commerce sales. The revenue for Christmas in 2015 was 7.40 billion brazilian reais through purchases made on the internet(de Souza, 2013).

Several studies are being done in the area of e-commerce, especially about algorithms of recommendations, widely used in web systems. The article Predicting Customer Purchase Behavior in the E-Commerce Context is an example of a study that proposes an improvement of recommendation systems using techniques that aim to predict the behavior of the user, later to use it as input for the recommendation of Products itself (Qiu et al., 2015).

The Giftr application is an example of an initiative in this context. This application was designed and developed by Ruyther Costa, Caíque Pereira, Caio Sanchez and Victor Bruno, during the BEPiD project in the period of February 2 and December 11, 2015.

This research seeks to recommend gifts that best suit the user, based on information of his profile and personal preferences that he has registered in the application Giftr.

One of the problems found in e-commerce stores and sales applications is the creation of good products by means of recommendation algorithms for their users. These algorithms help both the user experience and the increased sales of the companies.

Due to this difficulty, this work proposes the following question:

Q1. How to create a gift recommendation algo-

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rithm that fits the demand of a mobile app?

Answering this question, this work may contribute to the improvement of other recommendation algorithms. The data collected here can be used for future work related to the algorithms of recommendations focused on the e-commerce for gifts. The general objective of this work is to develop a gift suggestion algorithm that recommends the best products to the user, based on their profile.

The secondary objectives of this work are: Investigate possible gift recommendation solutions that take into account the user profile;Substantiate the adopted solution with other algorithms solutions.

2 THEORETICAL BASIS

The recommendation systems are intended to assist in the suggestion of items, products, services and contents, partially or fully automatically, according to the user's interests and needs (Burke, 2002). These systems can provide information that helps the user in the decision making of which items to choose, which can be, for example, books, music, movies, products, as well as recommendation systems can, based on a user's profile, suggest Items to the user directly without the intermediation of the same, such as gifts that the user may have interest based on his profile.

According to Resnick, a recommendation system has as input data that the user giver, the system then uses them to make the recommendations and then directs them to the relevant recipients (Resnick and Varian, 1997). The term "recommendation systems" came to replace the term "collaborative filtering", after which collaborative filtering refers to a specific recommendation algorithm. In general, recommendation systems are referred to systems that recommend a list of user products or systems that help users evaluate products.

The systems of recommendations are classified based on how the recommendations are made. Among the main systems of recommendations cited are Brke (Burke, 2002), Balabanovic and Shoham (Balabanovi and Shoham, 1997) and finally Adomavicius and Tuzhilin (Adomavicius and Tuzhilin, 2005). These systems will be presented in the following subsections.

2.1 Content-based Recommendation

Also known as content-based filtering, this technique consists of recommending similar items to the user to those that the user chose in the past, that is, according to the history of items that he has rated as favorite or acquired in the past.

According to (Burke, 2002), each item in a set I is defined by characteristics associated with it, a product, for example, may have characteristics such as: name, price, category, etc. Based on these characteristics that the items can be compared and the similarity between them, this characterization serves as input to this recommendation system, since the items recommended to the user that may be of his interest are those similar to what he used on the past and are recorded on his history.

Content-based recommendation systems originate from information retrieval techniques and the research done by (Burke, 2002), (Balabanovi and Shoham, 1997) and (Adomavicius and Tuzhilin, 2005) on information filtering searches.

2.2 Collaborative Recommendation

The Collaborative Recommendation is the one which the user will be recommended items that people with similar tastes and preferences liked in the past. In other words, it tries to predict the relevance of items for a particular user based on the items previously rated by other users.(Adomavicius and Tuzhilin, 2005)

2.3 Hybrid Approach

This method proposes to combine two or more types of data recommendation techniques. The main objective of the use of this method is what concerns some limitation that may exist in the individual use of other types of techniques.

As an example, the main approach that can occur with the combination of content-based recommendation systems and the collaborative recommendation, based on the analysis made by (Adomavicius and Tuzhilin, 2005), are:

1. **Implement the Collaborative and Content-based Methods Separately and Combine Their Predictions.** This way you can combine the finalized recommendations of the two techniques and offer the user a final recommendation. Another possibility is the system check which of the two techniques offered the user the best recommendations and then, select and present one of the two;
2. **Integrating Some Content-based Features into a Collaborative Approach.** The system maintains content-based user profiles, and can compare users to determine which ones are the most similar, and finally use collaborative filtering. Thus, in addition to having the recommendations based on

items that were well evaluated by the user, items that were also well evaluated by other users with similar profile would be another input for the final recommendation;

3. **Incorporating Some Collaborative Features into a Content-based Approach.** The most common approach in this approach is the use of a dimensionality reduction technique for the collaborative creation of a group of content-based profiles;

4. **Construct a Unified Model That Incorporates Features of Content-based and Collaborative Approaches.** This approach is extensively studied and aims to make recommendations more accurate.

2.4 e-Commerce Recommendation Systems

This algorithm suggests future consumer products aggregating transactions of similar consumers. The algorithm computes similarity using a vector-line function. A greater similarity indicates that consumers may have similar preferences, since they have purchased similar products.

The item-based algorithm is similar to the User-based algorithm, it only changes that the similarities of the products are computed rather than the similarities of the consumers. This algorithm has been shown to be highly efficient and of better quality than the user-based algorithm. This algorithm computes the similarities by means of a matrix that calculates the potential products to be purchased for each consumer.

The algorithm based on dimensionality reduction condenses the original interaction of the matrix and generates recommendations based on the condensed and less dispersed matrix to alleviate the dispersivity problem. Recommendations are generated in a similar way to the user-based algorithm.

2.5 Related Work

Several studies in the field of e-commerce recommendation algorithms have been developed, and this in particular proposes a framework that aims to predict user behavior in the context of e-commerce (Qiu et al., 2015). The great differential presented in this article is that it aims to predict consumer behavior, in other words, the consumer's preferences to buy some product in an ecommerce system. The article points out that through traditional algorithms there is no satisfactory execution of predictive tasks, so the article proposes a framework, COREL, a solution capable of solving this very common challenge in the traditional business context.

The framework proposed in this study, called COREL, is divided into two stages. The first stage is to make an association between products by raising what is common among them and from these data to predict the motivations that lead the consumer to buy a particular product, and then build a list of products candidates for purchase by this consumer. The second stage is to predict the main characteristics that the consumer will be interested in a particular type of product and through these data define the products in which the consumer will be interested, based on the list of candidate products generated at the end of the first stage.

COREL uses probability calculations to investigate the decision-making process the consumer is conducting on an e-commerce website. At first, the probability of the product d_i to be acquired, $P(d_i)$ is calculated, as is $P(d_j|d_i)$ indicating the conditional probability of the consumer buying the product d_j given the purchase of d_i. Another computation used is $P(d_i|c_k)$, which indicates the probability of the consumer c_k to buy product d_i. In addition, the formula 1 indicates the probability, after a time t of c_k buying d_i, and also buy d_j later:

$$P(d_j|c_k,\, d_i) = \frac{P(d_i|c_k, d_j)P(d_j,\, c_k)}{P(d_i, c_k)} \tag{1}$$

If the event of purchase of the product by the consumer is arbitrary, with no relation to the purchase of d_i, the calculation of the probability of the equation 1 changes:

$$P(d_j|c_k,\, d_i) = \frac{P(d_j|d_i)P(d_j|c_k)}{P(d_j)} \tag{2}$$

The calculation of $P(d_j|c_k, d_i)$ occurs for each product $d_j \varepsilon w$, since w is the collection of candidate products $[w = (d_1, ..., d_{i-1}, d_{i+1}, ..., d_m)]$. Therefore, the calculation of a predictive framework can be specified as:

$$P(d_j|c_k,\, d_i)\ \alpha\ P(d_j|d_i)P(d_j|c_k) \tag{3}$$

The parameter $P(d_j|c_k)$ may also indicate the preference that c_k has for d_j. Each product contains several features, such as color and price, and the user may have a preference for some of these features. Thus, the author of the paper proposes a way to predict which feature c_k prefers in certain d_j, taking into account the assumption that each user has his or her own preferences for the characteristics of a product, regardless of another user of the system. Thus, $P(d_j|c_k)$ is obtained as follows:

$$P(d_j|c_k) = P(f_{j1},...,f_{jn}|c_k) = \prod_{l=1}^{n} P(f_{jl}|c_k) \quad (4)$$

Then according to the article, the preferences of c_k for certain characteristics of some product are determinant for the calculation of the probability of the consumer to buy product d_j. In this way, the proposed framework, COREL, takes the following formula:

$$P(d_j|c_k) = \frac{1}{Z} P(d_j|d_i) \prod_{l=1}^{n} P(f_{jl}|c_k) \quad (5)$$

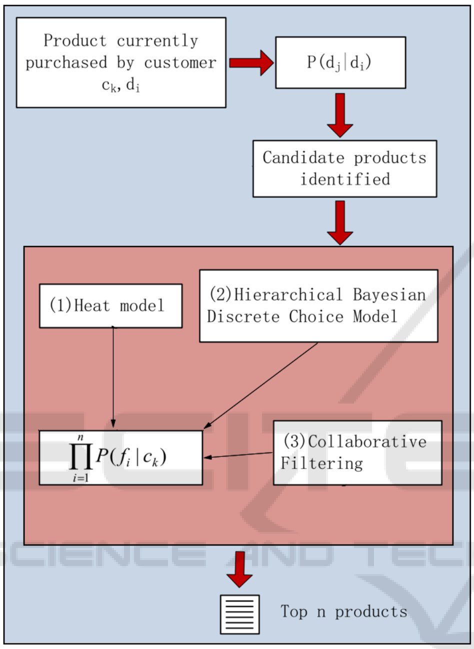

Figure 1: Process workflow of COREL (Qiu et al., 2015).

The Figure 1 shows the flow of the COREL framework methodology, which is divided into the following steps: identifying the product d_i purchased by the consumer c_k, calculate the probability $(P(d_j,d_i))$ of the consumer to purchase d_i after the purchase of d_j and list candidate products for consumer purchase. The subsequent steps are iterative $(\prod_{i=1}^{n} P(f_i,c_k))$ and aims to list products (w) that consumer c_k may be of interested, based on the f_i characteristics of a particular product that it prefers, they are: (1) calculate the popularity of a product based on its characteristics(Heat Model), (2) calculating the probability $DC(c_k,d_j)$ of the consumer c_k buying d_j based on his preferences and finally (3) estimating the grade which would be given by the consumer to a product based on the rating given to a product by a consumer with product preferences similar to his. After the initial steps and iterations of the framework, the products recommended to the consumer are listed.

In a more detailed way, the first step is to identify the products purchased by the consumer in the e-commerce system, after all this data will be an important input for the subsequent steps that will try to predict, for example, what the characteristics are (Examples: price , color, brand, and others) of the product that the consumer believes is decisive when purchasing a product.

$$P(d_j,d_i) = \frac{|d_i \cap d_j|}{d_i} \quad (6)$$

$$P(d_j,d_i) = \frac{|Thr(d_i) \cap Thr(d_j|)}{Thr(d_i)} \quad (7)$$

The second step is defined by calculating the equation 7, based on the likelihood model (Ponte and Croft, 1998), equation 6, which represents an association in which the products d_i and d_j, that is, given the purchase of the product d_i would be calculated the probability of the consumer to get product d_j, d_i in the equation 6 is the number of products d_i acquired and $|d_i \cap d_j|$ the frequency that the products d_i e d_j occur based on the same e-commerce system. However, the author's proposal to construct an association between categories with the objective of obtaining a relation with the selected candidate products coming from several categories with a particular product, for that reason, the author introduces the equation 6, being $Thr(d_i)$ representing the third-level product categories d_i. In the third step, the identification of the candidate products is carried out, based on the execution of the previous steps.

The steps that integrate COREL's second stage, consumer preferences, already identified, are used to identify which candidate products are most likely to be purchased. For further refinement of the selected candidate products, the author investigates three product categories, they are:

1. Heat Model: It is intended to predict the characteristics that the consumer may be interested in by calculating the popularity of these characteristics, based on the SVR model, using some characteristics as basis for the model, they are: Qr, Qs, Qa and Qu;
2. A hierarchical Bayesian discrete choice model: The author proposes to develop a discrete choice Bayesian hierarchical model to calculate the probability of c_k choosing product d_j based on its brand preference and price sensitivity;
3. Collaborative filtering: The model aims to predict the evaluation that the consumer would give to some product, based on the other consumers of the system that has similar tastes to his.

3 RESEARCH PROTOCOL

The objective of this systematic mapping is to identify articles related to recommendation algorithms based on the user profile that can be found in the literature and answer the research questions raised in the application of this technique.

3.1 Research Questions

The systematic review will seek to answer the following research questions:

- **(Q.1)** What is Recommendation Algorithm?
- **(Q.2)** What are the recommendation algorithms in the literature?
- **(Q.3)** What are the recommendation algorithms most used in the literature to select a desired item?
- **(Q.4)** Can existing algorithms be used or should customize and create a selection algorithm?

3.2 Search String

To answer the research questions, the definition of the string is a necessary step to carry out the research in some digital scientific bases. The string construction is based on the guidelines defined by (Keele, 2007), which consists of identifying keywords from search queries and uses AND connectors to combine keywords and ORs to match synonyms.

The search string created for the research was:

(algorithm OR algoritmo) AND (recommendation based on profile OR recomendação baseado no perfil OR recommendation OR recomendação) AND (e-commerce)

3.3 Results

According to the Systematic Review process, the research questions were answered.

Q.1 What is Recommendation Algorithm?
Recommendation systems are widely used in many applications to suggest services and information to potential consumers. Services like Amazon.com, Netflix.com, Half.com have used referral systems and increased the loyalty of their consumers. Good recommendation algorithms are needed for the operation of these recommendation systems (Zan Huang, 2004).

Q.2 What are the recommendation algorithms in the literature?
The recommendation algorithms that were found are content-based, collaborative recommendation, hybrid approach, user-based algorithm, item-based algorithm, and dimensionality reduction algorithm.

Q.3 What are the recommendation algorithms most used in the literature to select a desired item?
Algorithms based on user behavior.

Q.4 Can existing algorithms be used or should customize and create a selection algorithm?
The existing algorithms are not enough to fit the context of this work. However, some can be availed. Therefore, it is necessary to customize the recommendation algorithm for the desired context.

4 DEVELOPMENT

The Giftr application was created in the BEPiD (de Braslia, 2016) project with the idea of helping people give gifts to each other. The solution found by the team was to develop a social network where each user registers their favorite products, tastes and sizes (shoes, t-shirts, etc), and with this data the user has the possibility to give another through the application.

The functionality of the search application, both user and product has a fundamental role in the application, because through them users can find other users and thus invite them to be your friends. Already the search for products allows the user to find products in general, based on the products available from the API of the Lomadee (Lomadee, 2016b), enabling the user to make the purchase of products and evaluate the products, with a variation of zero to five points, to show in the system how much the user wants to be presented with that product.

The data control functionality of the profile allows the user to change and add personal information of the user, this being the means that the same has to register their tastes, fundamental for the operation of the algorithm of recommendation, and the measures, the size of footwear used by him. The registration of the tastes occurs through the entry by the user of a string that represents a taste of yours, for example, ”iPhone”, and later inform which category of the Buscapé is associated with preference, for example ”cellular and smartphone”.

4.1 Lomadee Platform

Buscapé (Company, 2016) offers some very robust platforms, among which is Lomadee (Lomadee, 2016c), which provides several APIs for data access available in the Buscapé system. Lomadee offers several APIs (Lomadee, 2016a), they are:

- Offers API: it allows to retrieve data of categories, products, offers and evaluations of users and stores of Buscapé;

- Coupon API: enables you to query for active coupons on the Lomadee platform;
- Reporting API: Enables the retrieval of transaction or commission data in detail.

The API used in the Giftr application is that of the Offers on the Lomadee platform, because through it there is the possibility to retrieve data from categories, products, offers and evaluations of Buscapé users and stores, which are fundamental to the Giftr application and to the recommendation algorithm of gifts. This API provides several types of query for data recovery and among them the ones that are used are:

- Find Category List: returns detailed information of existing product categories in Buscapé and Lomadee;
- Top Products: returns the best products from Buscapé and Lomadee, processed and filtered by a exclusive technology of the platform;
- Find Products List: lists with detailed product information on Buscapé and Lomadee;
- View User Ratings: returns general user rating data about a specific product;
- Top Offers: returns the most searched products in Buscapé/Lomadee;
- Find Offer List: returns a list of the sites that are offering the product.

In addition to the outputs that each type of query returns, it is necessary to have a well-structured input so that the results are correct, the complete description of the inputs and outputs of each query available on the website of the Lomadee platform (Lomadee, 2016b).

4.2 Gift Recommendation Algorithm on Mobile Devices

The algorithm proposed in this article will be based in another article, the Predicting Customer Purchase Behavior in the e-Commerce Context (Qiu et al., 2015), which will be customized to be accordance with mobile applications.

The framework COREL was proposed for a e-commerce context, which aims predict the costumer behavior and recommend products based on that prediction. The context proposed for this algorithm is a mobile application that it helps people give a present to the other, recommending products based on the user profile.

The figure 2 shows the flow from the proposed algorithm with a hybrid approach (Section 2.3), little similar to the one that COREL uses, and the subsections below detail each step.

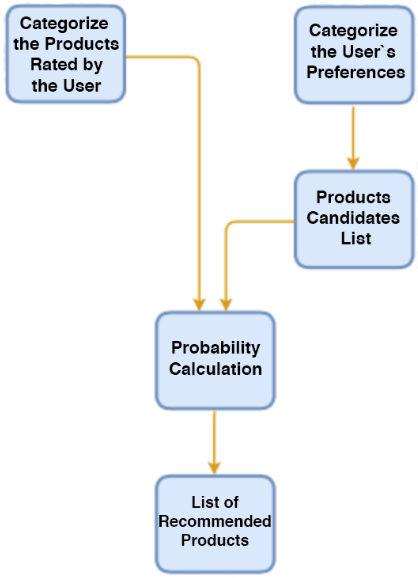

Figure 2: Proposed Algorithm with a hybrid approach.

4.2.1 Categorize the Products Rated by the User

In the first step from COREL, the "product currently purchase by costumer c_k, d_i", which consists of verifying the product d_i bought by the purchased by the consumer c_k, given to the framework a base product that will allow the probability calculations to be performed later. This context, however, differs a lot of the one that the proposed algorithm is, because the main goal is to recommend gifts based on the user profile through a mobile application, the Giftr.

Having this in mind, the proposed algorithm, instead verify the product (d_i) that the consumer (c_k) purchased, identify the product (p_i) that the user rated in the mobile application, with a range from zero to five. The product rated (p_i) is wrote in a user‘s purchased products list (l_p) for further use in the algorithm.

The Lomadee API returns many product‘s attributes, usual from all products listed in the platform. Choose the right attributes to store is important and determinant as an input to the proposed algorithm, so the ones selected are: product name (p_n), product category (p_c), minimum price ($Qpmn$), maximum price ($Qpmx$), user average rating (Qs) and number of comments (Qr).

4.2.2 Categorize the User‘s Preferences

In COREL, the user‘s preferences are predict identified, in other words, through the interactive steps (1) Heat Model, (2) A hierarchical Bayesian Discrete Choice Model and (3) Collaborative Filtering, shown in the figure 1. The model seeks to predict the tastes that the consumer will have for a given product from data of products that the same has already acquired, of product preferences data (number of comments, user average rating, etc.) reported by the consumer that is believed to be of greater relevance and consumers who have similar tastes, to predict the preferences that certain user of the system will have at the moment of purchase of products.

The context of the previous paragraph is not the same that Giftr has, after all the user will inform his tastes based in products of different categories, as smartphone, computer, among others. This preferences will be use to make this step of the recommendation algorithm, which does not have any method to predict the tastes of the user as COREL.

As presented in section 4.2.1, the user must insert a string (p_s) which represents the preferences of the user and the category (p_c) associated, based on the categories from Buscapé (Buscapé, 2016). In this way, this data will serve as input to the next step of the recommendation algorithm, and for this motive it will be saved.

4.2.3 Products Candidates List

In this step will be fulfilled the products listening (p_j) that it will be used for the calculations in the next step. To list the candidates products is need to inform two important data for the use of the Offers API of Lomadee, using the consult API called "Find Product List", the keyword (p_s) and the category (p_c) of the preference informed by the user in the mobile application to the API returns the existent products in Buscapé associated with p_s and p_c.

In the Lomadee API, the data input is made through a url and the products that are returned using the API does not have a defined quantity, therefore it is necessary define in a empirical way the quantity of products that will be in the candidates products list, given that the algorithm will run in a mobile application with a limited hardware.

The Giftr user has the possibility to inform many of his preferences and categories associated it, for this reason, the scope to the products listing is limited a one single category ($p_c = 1$), nevertheless, having the possibility of have one or more keywords associated to this category ($s \in Z | s > 1$), for example, "iPhone" and "Samsung Galaxy" as keywords and the category being "cellphone and smartphone".

In the final of this step, there are "n" candidates products listed w.

4.2.4 Probability Calculation

This step consists, briefly, in the calculation of the user (c_k) to be interested by the product (p_j), comparing the characteristics $Qpmn$ and $Qpmx$ of this product with the one rated product (p_i), both in the same category.

The probability calculation proposed in this article differs a lot of the base article (Qiu et al., 2015), because in it the calculation is accomplished using a methodology shown in the figure 1 through the probability calculation of $P(d_j|c_k)$ (equation 5). In the calculations of the proposed algorithm in this article, it will not be a specific equation for the probability calculation, in this case it will be a sequence of steps that will define the products with the highest probability that the user will be interested.

To do so, this step will be subdivided into three substeps so that the products with the highest probability are listed, they are:

1. Make a price comparison between the favored product and the candidate;
2. Filter the candidate products that deviate from the minimum and maximum price of the favored product;
3. Elaborate the rank of the candidate products based on the minimum and maximum prices.

4.2.5 Make a Price Comparison between the Favored Product and the Candidate Product

The first step in this substep is the search of the stored data of the product favored by the user, output from the step described in the section 4.2.2, because they will be the basis for comparisons with the candidate products, as well as to retrieve the data of all products from the candidate product list (w), output of the substep described in the section 4.2.3.

The parameters that will be used are from the product evaluated by the user: p_n, $Qpmn$ and $Qpmx$. The first parameter will be necessary for the identification of the product, the second and third are the parameters that best show the characteristic of this product, among other parameters that the API returns in the query and the parameters that will be used for pc will be the same as pn.

Given the parameters to be used, the calculations to be performed for the comparison of p_j and p_i are:

$$PQmn = \frac{Qpmn(p_j)}{Qpmn(p_i)} \tag{8}$$

where,

$Qpmn(p_j)$ is the minimum price of p_j, $Qpmn(p_i)$ is the minimum price of p_i, $PQmn$ the proportion of $Qpmn(p_j)$ in relation to $Qpmn(p_i)$, and

$$PQmx = \frac{Qpmx(p_j)}{Qpmx(p_i)} \tag{9}$$

where,

$Qpmx(p_j)$ is the maximum price of p_j, $Qpmx(p_i)$ is the maximum price of p_i, $PQmx$ the proportion of $Qpmx(p_j)$ in relation to $Qpmx(p_i)$.

A separate calculation for the minimum (*PQmn*) and maximum (*PQmx*) prices shall be performed, where the calculations are intended to show how proportionally the maximum and minimum price of p_j in relation to p_i, and thereby identify the p_j which most closely resemble the prices of p_i. This substep is then terminated and the generated data is saved for use in the next substeps of the algorithm, in this way the list of candidate products (w) is updated with the values of the proportions calculated from equations 8 and 9.

4.2.6 Filter the Candidate Products that Diverge of the Minimum and Maximum Price of the Favored Product

This substep has as input the updated list w, with the values of the proportions of the minimum and maximum prices of the products p_j. Thus, the objective of this sub-step is to filter products that diverge from "x" percent of the base (minimum and maximum) prices of p_i and exclude those that exceed a threshold percentage value.

To calculate the proportional percentage that the parameters $Qpmx$ and $Qpmn$ of p_j have relative to the same parameters of p_i, it is necessary to perform the following calculations:

$$PcQmx = PQmx \times 100 \tag{10}$$

$$PcQmn = PQmn \times 100 \tag{11}$$

The equations 10 and 11 indicate the proportional percentage of the minimum and maximum price of p_j in relation to p_i. In order for filtering of products p_j to occur, a threshold percentage value (p_l) is required both downward and upward of the base value, such as, for example, ten percent up and down of the one hundred percent of the minimum and maximum price of p_i, and the definition of the value of p_l is made empirically.

Then with the percentage values *PcQmx* and *PcQmn* for each product, the classification of those that comply with the percent limit p_l is carried out. If any product has *PcQmx* and *PcQmn* outside the percent limit p_l, it is excluded from the list of candidate products, if only one of the percentage values is not in the limit p_l the product Is not excluded from the w list, as is the case that *PcQmx* and *PcQmn* are within the limit, as shown in Table 1.

Table 1: Truth Table.

$Qpmn$	$Qpmx$	$Qpmn \bigvee Qpmx$	**Result**
1	1	1	It is not excluded
1	0	1	It is not excluded
0	1	1	It is not excluded
0	0	0	It is excluded

If there are many candidate products at the end of this filtering, it may be necessary to define a limit number so that there are no performance problems in the algorithm, this number must be defined empirically.

4.2.7 Elaborate the Rank of the Candidate Products based on the Minimum and Maximum Prices

Based on the calculations of the previous substep of the price ratio $Qpmn$ and $Qpmx$ of p_j with respect to p_i, the list w contains the p_j all disordered. The purpose of this substep is to sort the list based on the *PcQpmn* and *PcQpmx* data.

$$Pcm = \frac{PcQmx + PcQmn}{2} \tag{12}$$

Since there are two distinct data, *PcQmn* and *PcQmx*, in order to sort the list in a way that is more optimized, the arithmetic mean of these two values (*Pcm*) will be given so that only one value For the comparison at the time of the descending ordering of the products, as shown in the equation 12.

4.3 List of Recommended Products

The purpose of this step is to reorder the list w based on the comparison of two more parameters of p_j and p_i, Qs and Qr. The motivation of this reordering is to give more credibility to the ordering of products in the list, based on the data that Lomadee makes available in its API.

The parameter Qr informs the amount of comments that a product obtained in Buscapé, and can be used as a way to give credence to the value given by Qs, that is, if a product has Qs equal to 9.0 and another one has 9.0, what has a higher value of comments (Qr) will have a greater relevance in relation to the other.

$$Pd = \frac{Qs}{Qr} \tag{13}$$

The parameter Pd then indicates the credibility to the value of Qs, in case the closer to zero Pd is, the greater the credibility of Qs, because Qr tends to be a larger value. Then for the reordering will be used Pd, plus the list w already found, so that the reordering is re-done without taking into account the one performed by the step of the previous algorithm, the value of pd will be added to Pcm:

$$Pw = pd + Pcm. \tag{14}$$

Pw is the base value for descending reordering of the w list, which takes into account Pcm of the first ordering of the third substep described in Section 4.2.7. At the end of this step, the w list has the products p_j in the order of importance to be recommended to the user.

5 CONCLUSIONS

Through the execution of this work, it was possible to perceive the relevance of a product recommendation algorithm in the context of e-commerce applications. Therefore, the solution of this problem by means of an algorithm has been intensely discussed in academic papers that seek to create better algorithms as presented in the Systematic Review.

Through the Systematic Review, we investigated possible gift recommendation solutions that take into account the user profile. Among the solutions found, the one that best matches the context of this work is the COREL framework.

The Giftr application is an iOS platform application that uses the Lomadee API, provided by Buscapé, where you can search for products and subscribe to user preferences. However, this application does not use the data received to process suggestions of the best products to the user.

5.1 Future Works

So the next step is to implement this algorithm in the mobile application Giftr and define the value of some variables in the algorithm which needed to be defined empirically. Then, run tests and optimize this proposed algorithm for mobile devices.

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