NOVA IMS Information Management School

MDSAA

Master's Degree Program in
Data Science and Advanced Analytics

Business Cases with Data Science

Case 3: - Recommendation System for Recheio

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1. EXECUTIVE SUMMARY

Recheio is the biggest retail company in Portugal, ranking number 1 in the Cash and Carry Portuguese market. However, its competitors are always looking to close the discrepancy gap. Consequently, the company is looking into new strategies to keep the upper hand in the market. Although the company has had great success and currently has been able to bring its sales back to normal, COVID-19 impacted the profitability of the HoReCa segment, one of the most profitable activity channels of the company. Therefore, this project will guide Recheio through in how to keep and extend its customer relationships by developing a recommender system that can enable sustainable growth in its sector of activity.

The approach taken to reach these results followed CRISP-DM which means that the company and the data were analysed, and then the data was pre-processed. Afterwards, models were created, evaluated and deployed. The models developed were Content-Based Filtering, Collaborative filtering, Popularity-Based Recommendation, Smart Basket Recommendation, and Page Rank Recommendation.

In the projects disclosure deployment and maintenance plans were made available for each sales channel (salesperson, website, on-store, call centre). Moreover, on a final note Recheio can also find some recommendations.

2. BUSINESS NEEDS AND REQUIRED OUTCOME

For this project, the implemented methodology to be followed refers to the CRISP-DM (Cross-Industry Standard Process for Data Mining) detailed approach. This methodology guided the work developed throughout the project and was used to describe and analyse the different key areas of the project, namely the Business Understanding, Data Understanding, Modelling, Evaluation and Deployment and Maintenance Plans steps of the project.

2.1. BUSINESS INTRODUCTION

Established over 50 years ago, Recheio is a Portuguese company of excellence that has been able to position itself in the Portuguese retail wholesale market, as well as leaving its mark at an international level. Responsible for providing its clients with the very best products, it is currently the Portuguese leader in the Cash & Carry segment. The company is therefore concentrating its efforts and resources on the wholesale retail market segment, with a special focus on “HoReCa” line of business. The “HoReCa” segment specialises in supplying ingredients and products to a wide range of businesses, such as restaurants, hotels and coffee shops, and includes two different types of target clients: traditional and social restaurants, which seek to buy the cheapest products and ingredients on the market, and modern restaurants, which seek a higher level of service and therefore higher quality products and ingredients. An example of a specific project for these haute cuisine restaurants consists in “Recheio MasterChef” line of products, concentrated in Lisbon, Oporto and the Algarve.

2.2. BUSINESS OBJECTIVES

The main objective of this project is to develop an effective recommendation system for Recheio, capable of significantly increasing sales volumes and revenues, as well as contributing significantly to the development of new and specialised product lines according to customer preferences and transaction history. In this sense, the definition of tangible business objectives must be aligned with Recheio's business strategy, as well as with the expectations of the company's stakeholders for the project.

First and foremost, it is expected that by implementing the new model, the company will gain data transparency - by creating and implementing a recommendation model, it is necessary to understand the company’s available data, as well as how it was collected. Increasing sales volume is another defined business objective, as the implementation of a recommender system will allow the company to gain a deeper understanding of customer behaviour and experience, which are essential tools for developing tailored marketing strategies and product recommendations for the company's clients. An example of this is the promotion of cross-selling and up-selling, which consists of increasing sales by promoting premium upgrades and complementary products. In addition, another business objective for this project is to achieve an increase in sales revenue, as the implementation of a strong and accurate recommender system will enable to develop a more personalised shopping experience for clients by analysing and creating special approaches based on their purchase history, which can encourage both new and repeated more frequent purchases, without losing such clients to competitors.

In addition, this project will allow shareholders to make data-driven decisions, which will automatically improve the decision-making process, as decisions will be made on the basis of data profiled to the market in which the company operates. In addition, the implementation of such a system will allow for an effective approach to resource allocation, as the company will know where to focus and what tools to use to achieve its goals, and in this sense it will allow for the improvement of pricing strategies, which are essential to gain competitive advantage in its market segment.

2.3. BUSINESS SUCCESS CRITERIA

In order to evaluate the quality of the implemented recommendation system, business success criteria refer to metrics that assess whether the business objectives are being met or whether the solution needs to be improved. Subsequently, the identified business success criteria are mostly related to the previously defined business objectives.

In this sense, one of the most important business success criteria defined is the improvement of customer satisfaction. One of the most important objectives regarding the use of recommendation system algorithms is to improve customer satisfaction by providing personalised product recommendations, especially in a wholesale retail context such as the one in which Recheio is deployed. Such an improvement can lead to gains in competitive advantage, allowing the company to provide a better service to its customers. In order to measure this improvement, customer feedback surveys will be distributed to track the results of the model implementation, as well as to evaluate the increase in customer retention rates in line with the set targets. Accordingly, Recheio should aim for an average satisfaction score of at least 8 out of 10 in customer feedback surveys following the implementation of the recommendation system.

In addition, another important business success criterion relates to the increase in Recheio's sales volume and revenue. The implementation of a recommendation system has the power to increase the company's sales volume and revenue, which can be measured by comparing the average sales per customer before and after implementation. In this sense, concrete targets should be set, such as a 5% increase in total sales, both in terms of volume and revenue, in the six-month period after model readjustments, compared to the same period before system implementation.

Increasing the variety of products in the shopping basket is also one of the business success criteria for such project. The aim of the recommendation system implemented is to encourage customers to purchase a greater variety of products. In order to evaluate such increase, an assessment of the average number of unique products per transaction before and after the implementation of the recommendation system should be carried out, as well as the definition of a target of a 10% increase in the average number of unique products purchased per customer in relation to a six-month period before and after system readjustments, in comparison to the same period before implementation.

Improving the efficiency of marketing campaigns also constitutes one of the defined business success criteria for implementing a recommendation system, in the context of Recheio's business. In this sense, the knowledge gained from its implementation can be put at the service of the company's business, in the form of effective marketing campaigns that are able to fulfil Recheio's business strategy and objectives, with the ability to target new types of customers and improve sales of specific product categories. In this sense, the evaluation of this improvement is proposed to be based on a target of a 10% increase in the ROI (Return on Investment) of the marketing campaigns in the six months after model readjustments, compared to the same period before implementation.

In addition, reduced customer churn is also included in the set of defined business success criteria, as the implemented recommender system can help Recheio to provide a more personalised and interactive shopping experience to its clients, thus improving customer retention and consequently reducing customer churn. In this sense, a proper evaluation of these two aspects should be carried out, in particular by comparing both the customer churn rate and the average time spent on Recheio's website between the six-month period before the implementation of the system, and the same period after the model readjustments. Targets would then be set to reduce the customer churn rate by 5% and increase the average time spent on the website by 10%, between these two periods.

2.4. SITUATION ASSESSMENT

The situation assessment phase of the project encloses a detailed analysis of resources, risk assessment and cost-benefit analysis of implementing a recommender system for Recheio, which should be included in the preparation of the project plan and related business objectives and success criteria. This step also includes consideration of the data provided for analysis, as well as the intrinsic business context in which such a project is inserted.

Currently, Recheio recognises that clients only buy certain products and product categories, which translates into a wide variety of business opportunities that Recheio can potentially explore and that are not being best exponentiated to serve the company's interests, as well as the needs of current and future customers. Considering this perspective, as well as the impact that Covid-19 has had on Recheio's business market, exploring such opportunities encapsulates a crucial approach that can serve as the basis for the company's view on business strategy and objectives, allowing to increase sales volumes and revenues.

The dataset used for the development of this project consisted of the file 'Case3_Recheio_v2.xlsx', which consisted of 4 different sheets: 'CLIENTS', 'PRODUCTS', 'TRANSACTIONS' and 'CLIENT TYPES'. The 'CLIENTS' sheet initially consisted of 930 rows, representing information on different clients, and 3 related columns: 'Client ID', referring to a unique identifier for each client; 'ZIP Code', consisting of the first 4 digits referring to the origin of each client; and 'ID Client Type', a unique ID identifier for each different type/category of client. Furthermore, the 'PRODUCTS' sheet was composed of 2498 rows representing information on the different products from Recheio's product catalogue, and 3 related columns: 'Product ID', a unique identifier for each product; 'Product Description', representing the full descriptive name of each product; and 'Product Category ID', referring to the category of products to which a product belongs. The 'Transactions' sheet consisted of 234224 rows, representing the unique transactions of a product and the corresponding date that occurred during the 3-month period from 03/01/2019 to 31/05/2019, as well as the corresponding product and customer identifier, and 3 corresponding columns: 'DATE', consisting of the date of each transaction; 'CLIENT ID', the unique identifier for each client; and 'ID PRODUCT', a unique identifier for each product. Finally, the 'CLIENT TYPES' sheet provided information on the category of activity to which each client belonged, with 28 rows and 2 columns: 'ID Client Type', the unique identifier for each client type; and 'Client Type Description', the associated descriptive category that each client type represents.

This data was, then, explored and prepared for the next phase of the project, using some well-known Python libraries, such as *pandas* and *numpy* for data preparation, and *matplotlib* and *seaborn* for data visualisation. The libraries chosen for the modelling step were the following: *sklearn, networkx* and *mlextend.*

Developing such a project also means identifying potential obstacles or events that may affect the timeframe, cost, or results of the project, as well as identifying resources and actions that can be taken to minimise such impacts. A thorough assessment of risks and contingency plans must therefore be carried out to improve capacity and preparedness to deal with these situations.

Similarly, poor data quality poses a potential risk to the development of the project, such as data inconsistencies or lack of relevant data for analysis. To address this potential risk, appropriate data cleansing techniques were carefully implemented to achieve a clean, accurate and business-relevant pre-processed dataset that could be used in the subsequent modelling phase, thus avoiding the risk of major problems during model implementation. In addition, ensuring data quality, accuracy and consistency avoids biased and unreliable results and contributes significantly to extracting improved recommendations for Recheio's clients, which can translate into significant growth in business volume and revenue for the company.

In addition, lack of domain knowledge can also lead to inaccurate recommendation outputs from the implemented system, as well as out-of-context or missing assumptions and relevant product and customer information that can reduce the quality of the recommender system outputs. Intensive research was therefore carried out on the company, its competitors, and the market sector, which helped to build up domain knowledge that could be further applied in the work developed for the subsequent phases of the project.

Data diversity and representativeness issues also emerge as a risk for the project, as the provided dataset only includes transaction data for 3 full months, from March to May 2019. This period is not fully representative of Recheio's full transaction history, which may limit the quality and accuracy of the recommendations that the systems will provide. In addition, the lack of relevant information to be provided to the recommender systems, such as the quantity and price of the products traded, may also affect the quality of the insights extracted by the system. Therefore, ensuring data richness and diversity by possibly requesting access to more complete data in the future may help to overcome this risk.

The choice between different types of recommendation algorithms, as well as suboptimal parameterisation, may also have an impact on the results and insights of the project, as suboptimal algorithm selection or parameter tuning may result in poor recommendation accuracy and quality for the customer's purchases, as well as underperformance in terms of the expectations of Recheio's stakeholders for the project. The selection and respective parameter tuning of different types of recommendation systems to be applied, such as content-based filtering, collaborative filtering, and hybrid recommendations, ensured the diversity of approaches in order to gain insights into the most effective and accurate product recommendations for Recheio's clients, that can be turned into significant value for the company.

Furthermore, inaccurate communication of key findings and recommendations to Recheio's stakeholders can become a barrier to implementation. For this reason, ensuring an effective and business-oriented project presentation is critical to the success of the project, where actionable findings and resulting recommendations from the system are addressed in a clear and concise manner.

In terms of the cost-benefit analysis of the project, the potential direct and indirect costs include computing resources, data processing and modelling, system maintenance, training on how to interpret and use the results of the recommender system, as well as changes in the strategic paradigm for Recheio. On the other hand, the benefits of the project relate to an increase in transaction volume and revenue through personalised product recommendations provided by the system, generating higher conversion rates; improved customer satisfaction and retention rates through an enhanced shopping experience for customers, as well as the provision of relevant and timely product recommendations; optimisation of business processes and strategy, promoted through appropriate target marketing and resource allocation; and the competitive advantage gained through the implementation of innovative recommender systems, capable of positioning Recheio as a market leader in the wholesale retail sector.

2.5. DETERMINE DATA MINING GOALS

The definition of data mining objectives is a fundamental step in the development of this project, as it includes the technical terms that will allow the pursuit of the previously defined business objectives. Accordingly, the data mining goals should establish the technical guidelines and expected results for the work developed, contributing to a robust recommendation system for Recheio that can suggest relevant products to customers in an accurate and timely manner, based on their purchase history and preferences.

Firstly, refining product descriptions is one of the data mining goals of this project, since it will allow the recommender systems to generate item recommendations based on relevant and appropriate product descriptions, thus ensuring the quality, accuracy, and relevance of the generated product recommendations. In this sense, the reorganisation of products based on their descriptions allow to improve the accuracy and relevance of the recommender system outputs.

Furthermore, maximising the accuracy of the recommendations by aiming at the highest possible F1 score, for some of the applied recommender systems, is also considered as a data mining goal for this project. This is calculated as the harmonic mean of precision and recall, where precision is the proportion of recommended items that are relevant, and recall is the proportion of relevant items that are recommended. Maximising the F1 score improves the accuracy of predicting different customer preferences and the ability of the recommendation algorithm to provide accurate and relevant product recommendations for different customers. By implementing recommendation algorithms that aim to maximise prediction accuracy; by using different evaluation metrics to assess the performance of recommendation models, such as F1 score, precision, recall and hit rate; and by fine-tuning the model parameters and algorithms to optimise recommendation accuracy based on cross-validation results, it is possible to achieve significantly higher F1 scores that can lead to more appropriate and relevant product recommendations for Recheio's clients.

The next defined data mining goal relates to minimising false positives and false negatives, for some of the recommendation algorithms used. False positives occur when the recommendation algorithms suggest irrelevant items, while false negatives refer to situations where the system fails to recommend relevant items. In this way, minimising the number of false positives and false negatives ensures that the recommendation algorithms produce relevant recommendations that can be applied to the customer's shopping process.

Moreover, maximising similarity measures, where applied, is also considered as one of the defined data mining goals, since increasing the similarity between recommended products and client’s product preferences based on transaction history allows to enhance the relevance of the product recommendations generated by the system. In this sense, calculating similarity measures, such as Cosine similarity or Jaccard similarity, allows to capture nuanced relationships between clients and products, and ultimately contribute to accurate and relevant product recommendations.

In addition, another data mining goal for the project relates to incorporate purchase frequency and recency based on transactional data into the recommender systems’ consideration, since it provides valuable insights into customer preferences and behaviour over time, which can be used by some recommender systems to generate more accurate and personalised product recommendations.

Another important data mining goal is to scale the recommendation algorithms not only to a partial dataset containing only 3 months of transactional data, but also to larger datasets that can contain hundreds of thousands of transactions and customers, and that refer to a longer period of time. This will allow the algorithm to be used in much more other general contexts within Recheio's business operations, with larger amounts of data.

Optimising the ranking of recommended products is also one of the defined data mining objectives, including recommender systems that prioritise products with the highest likelihood of purchase. To this end, the implementation of ranking algorithms such as collaborative ranking and matrix factorisation, allows recommended products to be ordered based on predicted preferences for different types of customers, while ensuring effective and relevant prioritisation.

In addition, one of the defined data mining objectives is to increase the diversity and personalisation of product recommendations, effectively exposing different clients to a wider and more personalised range of product options, and encouraging customer discovery of new products that are aligned with both their preferences and Recheio's business strategy. In some cases, the inclusion of diversity constraints in recommendation algorithms to promote diversity in recommended items, as well as the exploration of product recommendations that bring a unique sense of personalisation for each client and client type, allows the diversity and personalization factors to be taken into account by the algorithms when generating product recommendations, ensuring a balanced mix of familiar and novel recommendations.

Finally, ensuring the privacy and security of customer and transactional data is another of the defined data mining objectives for this project, including ensuring that the data available for this project is anonymous and does not reveal sensitive information, both for Recheio and its clients.

3. METHODOLOGY

3.1. DATA UNDERSTANDING

For this project, we received a single dataset with information concerning Recheio's products, clients, client types (which was merged into the clients table) and transactions, with no table presenting any duplicates or missing values.

Regarding clients, we had information about their zip code, client type, with our group adding extra information about their location and region. Here, we concluded that there were 930 distinct clients and 28 client types, with the vast majority coming from the Lisboa e Vale do Tejo region, where the 5 locations with the most clients are Lisboa, Amadora, Vila France de Xira, Almada and Setúbal. The client type that is most catered to is "Cozinha Portuguesa", representing over 200 of Recheio's clients.

When it comes to products, we were given information on their description and category. This table has 2498 distinct products, with the caveat that two products share the same description, and 33 different product categories. Our analysis showed there were 15 products manufactured by Recheio themselves, all soups, and the 3 most prominent product categories were "Alimentação Corrente", "Frutas e Vegetais" and "Congelados"(fig. 1).

As for transactions, we were given information the client who participated in the purchase, the purchased products and the data of the transaction. Despite there being 234224 transactions, only 17607 of these involved the purchase of a product, with every client and product appearing at least once. These transactions range from 1 to 138 products, with the average of products bought being 13, and 50% of the clients buying 10 or less products. Analysing the data revealed to us that "Cozinha Portuguesa" is the most frequent client type, with clients of ID 4426, 8049 and 7911 being the most popular clients, with all 3 hovering at around 2000 transactions. Product wise, "Alimentação Corrente" and "Frutas e Vegetais" are the most bought product categories by a large margin, with "Açúcar MChef Branco Papel KG" being the most purchased item (fig. 2). Finally, we analyzed how the transactions behaved over time, where we discovered the sales numbers have been growing each month, while the purchases per week stay relatively constant with a low sales number in the first week (due to the dataset beginning on a Friday) and a spike in popularity in May. However, analyzing through weekday shows a bigger fluctuation in buying tendencies: Tuesdays and Fridays are by far the busiest days, while Monday is the day with the least purchases.

3.2. Data Preparation

Given there were no duplicates or missing values, we move on straight to feature engineering, which was only applied to the Clients table. Here, by matching the zip code provided in the dataset with its corresponding location on the map, we added the Region and Location columns to aid in understanding the geographical distribution of Recheio's customers. Remaining on the client table, we removed all clients of type "Fornecedor" and "Colaborador", as well as any client not in the "Lisboa" or "Vale do Tejo" regions, both per the company's request. In the product table, we assumed the products with identical descriptions were a case of a Slowly Changing Dimension where a change to the product's packaging or price demanded the creation of a new code, despite being the same product. Therefore, we assumed one of the codes to be the old one and replaced it with the new one. Afterwards, we remove any product with the description "Annual Rappel" and alter the products' names by replacing some of the keywords we deemed necessary and removing any word related to the product's weight, volume, length. Finally, all columns of type 'object' were altered to be of type 'category' for performance reasons and the columns "Client Type", "ID Product Category" and "Product Description" were given a capitalization to their first letter. With the data treated, we created a new table with "Date", "Client_ID", "ID Client Type", "Client Type Description", ID Product" and "Product Description", which was then used to create a pivot table of the clients and of how many times they purchased each product for modelling.

3.3. Modelling

For the modelling part, we chose to try a myriad of algorithms. The first one consisted of a content-based algorithm, a model that recommends new products based on how similar they are to the items previously bought and how frequently items are bought together, with similarity being evaluated on a product-product matrix using a cosine similarity metric. The 10 products with the highest similarity metric are then recommended to the customer.

Our second solution was a collaborative filtering algorithm, a type of model that recommends products according to what items similar customers purchase. For this model, both the cosine and Jaccard similarity metrics were tested, but cosine was chosen since both gave similar results in similar times. This metric evaluates a customer-product matrix and returns the 10 most related products.

The third model is a popularity system, which only suggests the most bought products in a chosen timeframe, which was kept intact due to its small size. Besides a default popularity system that recommends the overall top products, we also implemented a popularity model based on client type and for each client. To complement this section, the popularity model per client was used to create the "Did you forget?" approach, using the top 10 clients' products, and removing any that already featured in the basket, following the line of popularity.

The fourth system is a smart basket algorithm based on the idea that customers who buy a certain group of products are more likely to buy another set of items, so it depends solely on the type of products already in the basket. This model calculates how purchasing one item or group of items influences the purchase of other items relative if it hadn't been purchased in the first place, and delivers the 10 most likely products as recommendations. However, this model only takes into consideration products that appear in at least 1.1% of transactions, as a way to guarantee its' significance and efficiency when running the code.

The final recommender system we built was the Page Rank Recommendation, an algorithm that determines the importance of a product according to the number of products that connect to it, as well as the importance of those products, so it suggests the same items to all customers. From this model, we then chose 10 products to be recommended.

3.4. Evaluation

For most of the models, it was hard to perform evaluations due to the fact they offered new options to the ones the client buys, so any solution would be different to the actual reality, so it was used the whole dataset. For the popularity and Page Rank models, however, we were able to calculate the precision, f1 score (a metric that combines precision and recall) and hit rate (at least one of the products recommended is correct) by split the dataset into a training dataset, representing the transaction history, and a test dataset, representing new customers. The general popularity model had the worst metrics on all fronts, resulting in precision of 0.0948, F1 score of 0.0843 and a hit rate of 0.5903. The client type-based popularity model had improved results, with precision of 0.1472, F1 score of 0.1424 and a hit rate of 0.6948. The client-based popularity algorithm had the best results of all, with precision being 0.4159, F1 score of 0.4103 and hit rate of 0.9182. For the page Rank system, we observed a precision of 0.2411, an F1 score of 0.2073 and a hit rate of 0.7979.

4. RESULTS EVALUATION

4.1. General Idea

As well as the previously analysed offline evaluation methods, online evaluation should also be applied, enabling the evaluation of the chosen recommender system in the context of a real-world scenario, in which users interact with the system and provide feedback on the product recommendations generated by the system. In that sense, the recommendation model's performance should also be assessed not only in terms of the accuracy, timeliness and quality of the recommendations based on products that are part of each client's transaction history data, but also for products that were never bought by the clients and that can be part of new or rising lines of products, seen by Recheio as potentially lucrative and dully incorporated in the company's business strategy and objectives. By following this evaluation approach, Recheio will be able to extract valuable insights from the implementation of the system on-live, as well as to feel its clients' reaction to its implementation, that can translate into important adjustments to the models and its implementation and, ultimately, in increased system performance and fulfilment of both business objectives and success criteria.

There are several aspects that must be encompassed in the online evaluation of the outputted recommendations from the system. The first aspect starts with the implementation and deployment of the recommender system across the diverse customer channels that are part of Recheio's business strategy, ensuring its accessibility to the users and integration with the user's interface. Moving on, user interactions are also an important part of online evaluation, in the sense that client should interact with the system through the diverse customer channels and provide the due feedback on the generated product recommendations, by the means of clicks, views and purchases of recommended items.

Moreover, to assess users' interaction and feedback, online evaluation englobes metrics such as click-through rate (CTR – the percentage of users that click on the recommended items in Recheio's website, to evaluate the effectiveness of the recommender system in capturing user interest), dwell time (the amount of time a user spends interacting with a recommended item or page of Recheio's website), conversion rate (the percentage of users who purchase recommended items across the different customer channels, evaluating the impact of the recommender system on Recheio' sales volume and revenue), average rating (the average rating given by the users to recommended items, to evaluate the quality of recommendations), user satisfaction (the percentage of users who are satisfied with the generated recommendations, through surveys or feedback forms) and sales lift (the increase in sales volume or revenue coming from the implementation of the recommender system).

In another perspective, different online evaluation methods can be applied, depending on the customer channel involved. As so, for example, for the contact centre customer channel, results can be evaluated by measuring the average handling time of calls and email chains when the customer sales representatives or contact centre operators use the recommender system during the purchase process. Additionally, surveys and user studies can be conducted to gather feedback on the usefulness and relevance of the generated item recommendations by the system, both from customer sales representatives and clients. For in-store customer channels, results can be evaluated through the increase in sales or average order value when the customers received personalized recommendations. As for salesperson customer channel, results can be evaluated by the conversion rate when the salesperson uses the recommender system. For all of these approaches, feedback through different methods should be collected to assess the quality and relevance of the generated item recommendations.

Besides specific metrics, it is recommended performing A/B testing of different recommendation systems in analysis. This is a fundamental part of the online evaluation process, consisting in the deployment of two versions of the recommender system, in which one of the versions is randomly assigned to part of Recheio's customer channels, while the other version is assigned to another subset of customer channels. The performance of the two versions should be compared, having per base the different client's interactions and feedback through the different customer channels.

At the end, results analysis should be performed, by interpreting the different established metrics and user interactions to finally evaluate each recommender system's performance and guaranteeing the significance of the results and insights obtained in respect to the recommender system's performance.

4.2. ROADMAP

The baseline of this evaluation process consists of having people developing the above evaluation system while the model makes its entrance into the market so that after the six months of its usage, the company can have an idea of how it has been performing. Subsequently, some metrics depend on customer opinion so for a period of a month these tools will be available for them to express themselves. Afterwards, data scientists shall analyse the results and check if these are accurate with their expectations. During this process, all offline evaluations will be calculated so that the workload is balanced through time.

After all the results are evaluated and analysed, it is necessary to look where the major flaws are found and re-strategize and put the model out there once again, always keeping a close eye on it.

Moreover, this is a heavy evaluation approach so it is recommended to only be done annually. However, a simpler and more straightforward tactic can be designed to make evaluations on a quarter bases, for example.

5. DEPLOYMENT AND MAINTENANCE PLANS

Regardless of the previous Recommender Systems the company finds the fittest for the purpose they want, the system provides the company with a list of products to recommend to its customers. However this implies resource usage, costs[1], and time which changes according to the channel used to close deals.

The budgets that shall be presented, all take into consideration that the extra workload to the financial, and management departments does not require the employment of another person or any extra hours to be paid. However, for each budget is being added the cost of hiring a data scientist which annually costs around 25 000 € and specifically for this project, this person accounts for 12 500€ which includes the development, testing and quality assurance time as well as maintenance (6-month worth of work – although the timeframe only exposes 5 months of workload there is always setbacks and other factors that are not being accounted in this scenario that can expand this period so an extra month is being considered as a contingency), considering that the remaining data scientists, even with the extra work, do not need to do any extra hour.

The models' implementation cost are the following:

Content-Based Filtering – 3 000€

Development tools and Software	**Infrastructure**
Software Licenses: 2 000 €	Any type of equipment: 1 000 €

Collaborative Filtering – 5 000€

Development tools and Software	**Infrastructure**
Software Licenses: 3 000 €	Any type of equipment: 2 000 €

Popularity-Based Recommendation -> General Popularity – 2 500€

Development tools and Software	**Infrastructure**
Software Licenses: 1 500 €	Any type of equipment: 1 000 €

Popularity-Based Recommendation -> Popularity Per Client Type – 3 500€

Development tools and Software	**Infrastructure**
Software Licenses: 2 000 €	Any type of equipment: 1 500 €

Popularity-Based Recommendation -> Popularity Per Client – 4 300€

Development tools and Software	**Infrastructure**
Software Licenses: 2 500 €	Any type of equipment: 1 800 €

Popularity-Based Recommendation -> Did You Forget? Approach – 5 000€

Development tools and Software	**Infrastructure**
Software Licenses: 3 000 €	Any type of equipment: 2 000 €

Smart Basket Recommendation – 6 000€

Development tools and Software	**Infrastructure**
Software Licenses: 3 500 €	Any type of equipment: 2 500 €

Page Rank Recommendation – 7 000€

Development tools and Software	**Infrastructure**
Software Licenses: 4 000 €	Any type of equipment: 3 000 €

It is crucial to outline that if all strategies are applied not just one some costs will be inter shared. For example, if the company applies all 4 plans, there is no necessity to hire 4 extra employees and the same for the cost of designing a flyer/catalogue, it only needs to be designed once.

[1] All model costs were established based on the argument that can be found in the **APPENDIX - Model Costs Justification.**

5.1. Sales by Salesperson

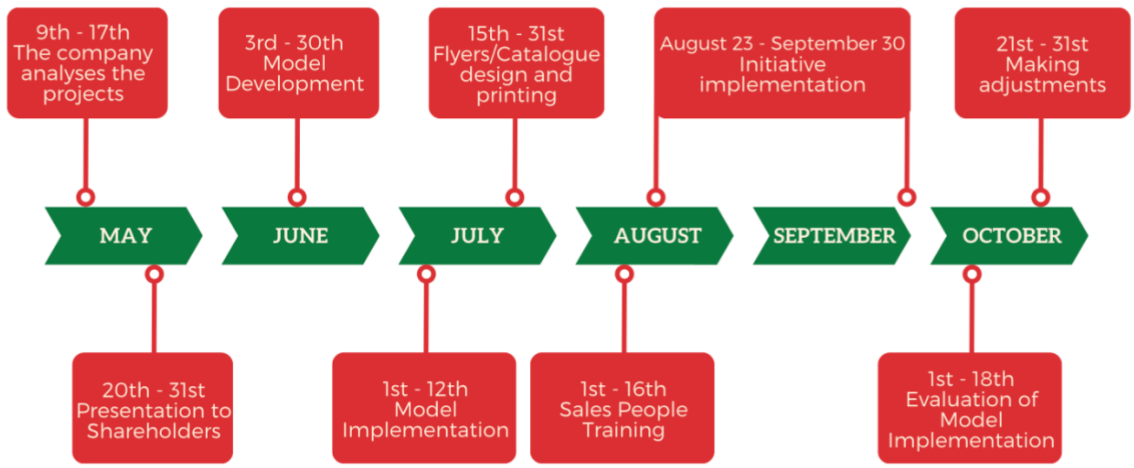
5.1.1. General Idea

The rough idea of this plan is that each salesperson before meeting its customers consults the client's information along with the list of products that the system believes to be good recommendations for the customer to purchase and therefore increase the number of orders with Recheio. Therefore, this person takes a flyer/catalogue to present to the consumer and when talking with the client gives them this information. However, if the customer feels that needs a more tailor-made solution (because the fliers are made by customer type), the employee can always use the tablet to once again consult the clients purposed list.

5.1.2. Roadmap

Considering that the idea was accepted by the responsible stakeholders, the plan starts by exposing the idea to the data science team, check the concept's feasibility and the required resources. Then, it is crucial to expose the case to the financial department to get the approval in terms of budget. With the approval, it is time for the data scientists to develop the model. Later, employees (salesman) should be informed of the new business process and be trained accordingly. Simultaneously, an order to design and print the flyers/catalogues.
Afterwards, comes the process of maintenance where data scientists together with the financial department analyse the results of the initiative, if it reached the business objectives and if there are arrangements that should be performed to improve it.

5.1.3. Timeframe



5.1.4. Costs

Considering the general costs already mentioned this initiative also includes the printing value of 1800€, this value accounts for any extra hours required by the marketing department (500€) and for printing costs (1300€).

TOTAL COST PER MODEL INCLUDING A 10% CONTINGENCY

CONTENT-BASED FILTERING		19 030€
COLLABORATIVE FILTERING		21 230€
POPULARITY-BASED RECOMMENDATION	**General Popularity**	18 480€
	Popularity Per Client Type	19 580€
	Popularity Per Client	20 460€
	Did You Forget? Approach	21 230€
SMART BASKET RECOMMENDATION		22 330€
PAGE RANK RECOMMENDATION		23 430€

5.2. Sales on the website

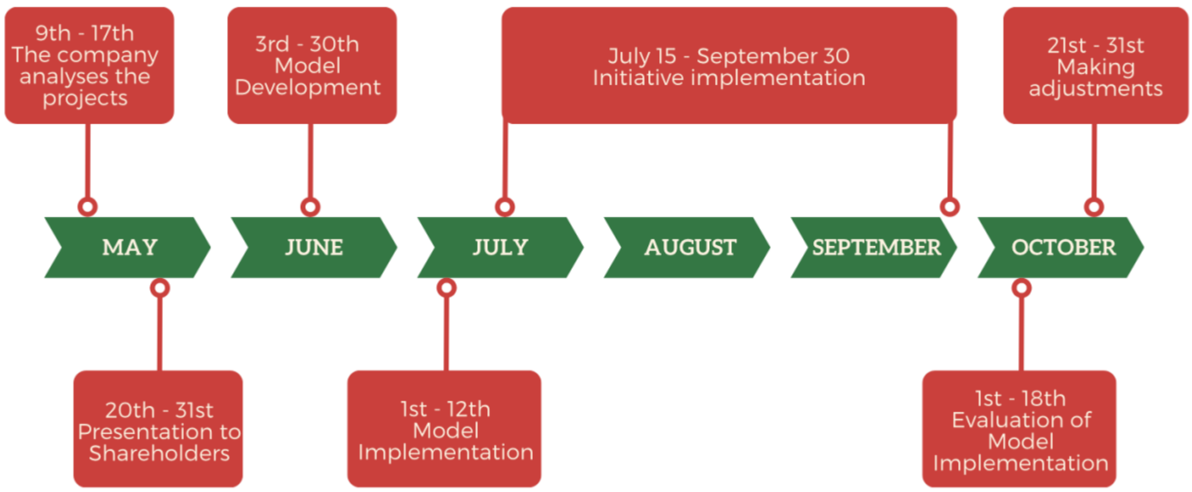
5.2.1. General Idea

To increase sales on the website the idea is, after customers enter in their account, the system shows a popup of 10 products that fit the company's profile.

5.2.2. Roadmap

Subsequently, to choosing this approach the idea should be exposed to the shareholders. When accepted should be exposed to the departments that will work on the project (data science, finance and marketing) to check for the feasibility, to develop, and to implement. A while after implementation it is crucial to evaluate if the solution actually brought in more revenue and adjust it according with the challenges that were found.

5.2.3. Timeframe



5.2.4. Costs

These concept mostly only requires the general costs mentioned, does not need any other type of resources. Making the final costs per model the following:

TOTAL COST PER MODEL INCLUDING A 10% CONTINGENCY

CONTENT-BASED FILTERING		17 050€
COLLABORATIVE FILTERING		19 250€
POPULARITY-BASED RECOMMENDATION	**General Popularity**	16 500€
	Popularity Per Client Type	17 600€
	Popularity Per Client	18 480€
	Did You Forget? Approach	19 250€
SMART BASKET RECOMMENDATION		20 350€
PAGE RANK RECOMMENDATION		21 450€

5.3. Sales in Store

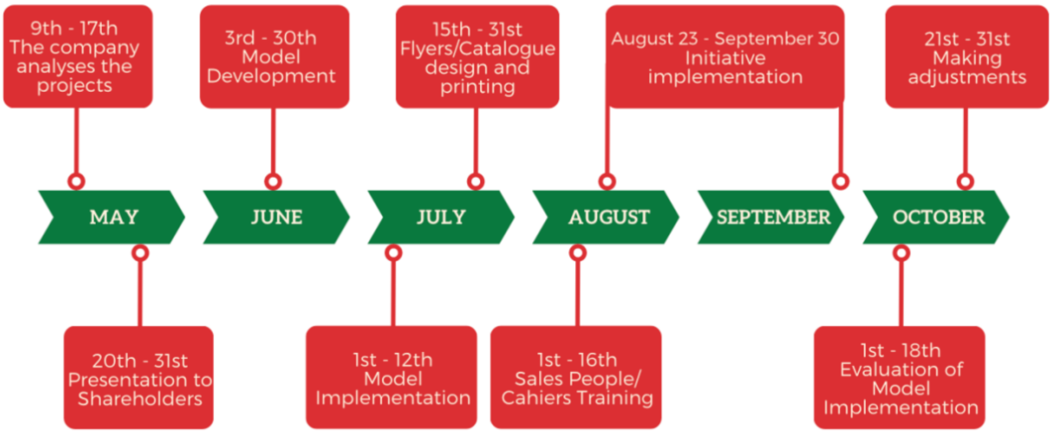
5.3.1. General Idea

In store there are salespeople that with them carry a tablet with the company's system so whenever a client asks for their help to acquire a product, they can go to the system and see which product should be recommended that goes with what they asked. Moreover, also in store whenever someone checks out, it is expected that it pops up the type of client they are so that the cashier can give them an appropriate flyer/catalogue with recommendation of products that they might need.

5.3.2. Roadmap

Considering that Recheio finds this idea suitable to what the company is looking for, the next phase starts by letting all the needed departments know about the new initiative so that they can start developing and analysing all resources that shall be needed. In the sequence of developing the model that the company desires, it should be deployed. Salesman and cashiers must then be trained to put this tool in practise. After being in use for a while the team should recheck if the initiative was as fruitful as it should be.

5.3.3. Timeframe



5.3.4. Costs

Besides including the general costs of employing an extra person there is the printing costs 1800€ (1300€ printing costs + 500€ design).

Regarding models, in this specific case not all of them seem to be fitted to all the steps of the operation. For salespeople the best model would then be Popularity based recommendation -> General Popularity or page rank recommendation since they are not looking into the client's profile but rather the product association. As for cashiers, it depends on how the company intends to do advertisement.

Additionally, it is believed that if employees input more time with their customers that may be necessary to add an extra worker which would have the annual cost of about 18 000€ (specifically for the project would cost around 9 000€ if it extends to 6 months).

TOTAL COST PER MODEL INCLUDING A 10% CONTINGENCY		
CONTENT-BASED FILTERING		28 930€
COLLABORATIVE FILTERING		31 130€
POPULARITY-BASED RECOMMENDATION	**General Popularity**	28 380€
	Popularity Per Client Type	29 480€
	Popularity Per Client	30 360€
	Did You Forget? Approach	31 130€
SMART BASKET RECOMMENDATION		32 230€
PAGE RANK RECOMMENDATION		33 330€

5.4. Contact Centre

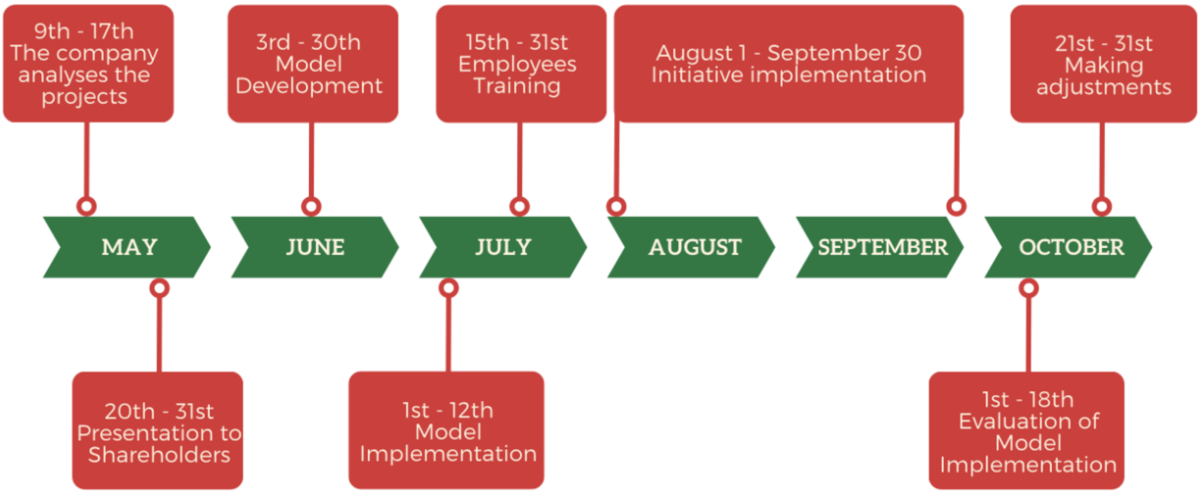
5.4.1. General Idea

Nowadays, there are still a few consumers that make their orders online but through email. Therefore, to increase sales through this channel, it is expected for Recheio's employees whenever they receive an order to put the information into the system and check which products it recommends for that customer. Subsequently, send an email response saying some product suggestions if they would like to add to their order.

5.4.2. Roadmap

Once again if this idea goes ahead all the required departments should be informed and start developing the project which when deployed it is time to train employees to make use of the system. Afterward, it is necessary to see if the initiative is going according to plan or if it needs to be modified.

5.4.3. Timeframe



5.4.4. Costs

On top of the general costs, it is believed that adding an extra call centre employee would have great benefits into increasing the quality of the results so it adds the annual value of 20 000€ which 10 000€ are specific for this project. Therefore, the following table expresses the total cost of the imitative for each model since it is a company's decision to see which one fits the best with their technology and ideas.

TOTAL COST PER MODEL INCLUDING A 10% CONTINGENCY

CONTENT-BASED FILTERING		28 050€
COLLABORATIVE FILTERING		30 250€
POPULARITY-BASED RECOMMENDATION	**General Popularity**	27 500€
	Popularity Per Client Type	28 600€
	Popularity Per Client	29 480€
	Did You Forget? Approach	30 250€
SMART BASKET RECOMMENDATION		31 350€
PAGE RANK RECOMMENDATION		32 450€

6. CONCLUSIONS

6.1. Complementary Plan To Help Increase The success Of The Recommender System

This specific recommendation looks into complementing the implementation of the recommender system, to incentivise customers to take the company's suggestions more seriously. The concept essentially is rewarding clients with a 1% reward of the total expenses of the company with Recheio as long as it reaches above the threshold defined (it is suggested to establish it at least 20% above the average total expenses per company). The costs associated to this initiative are the total cash rewarded. For example, let's imagine that the annual revenue of Recheio is 4 million; let's assume that the average expenses value per client annually is around 2 million. So it is recommended to define the threshold for a customer to receive the cash reward if they reach a value 20% above the average so in this case 2.4 million. Moreover, if the company has 5 companies that pass this threshold, then the total cash reward = (2.4M x 1%) x 5 = 24 000 x 5 = 120 000 €. Therefore, it is estimated that this idea will cost the company 132 000 € annually. Although this initiative shows high costs to Recheio, it is believed to produce long term advantages such as an increase of around 10% in its sales.

Nevertheless, it requires a large number of funds to which many shareholders have to accept so in order to make it a success, both managers and the financial department must be persuaded. However, these people sometimes need numbers to make a well based decision so if there is a partial approval for simply studying the terms to which this program would work, it is of the utmost importance to develop a tracking system to check how sales are going and understand where customers come from. Consequently, these values will be the ground bases to establish a reasonable baseline of rules to which a customer has the write profile and behaviour to be considered for the price.

This timeframe is a possible implementation scenario but it depends on many factors that only Recheio is aware, such as policies, business processes, human capital, etc. The timeframe is the following: Project evaluation: 9th May to 23rd May -> Idea evaluation: 24th May to 7th June -> Communication of the program: 10th June to 24th June -> Tracking System: 25th June to 26th August -> Parameter Calculation: 27th August to 10th September -> Tracking if the calculations fit the trends happening: 11th September to 25th September -> Program evaluation: 16th September to 30th September -> Program explosion to employees: 1st October to 22nd October -> Program advertisement: 25th October to 31st December -> Implementation date: 1st January of 2025.

6.2. Considerations for model improvement

Although the company has a great deal of data available, it is thought to be poorly organised since the names given to the products do not allow to have a complete view of the product groups as the names have many nomenclatures which in the system represent different products that in reality are the same. Consequently, a suggestion would be each group being inserted in the system in a different structure. Let's take products "Arroz Carolino Masterchef 1kg" and "Atum Lombo Descongelado RCH CX 1 UN" (this is the name used in the column Product Description) as an example. In the new organization system, the product would be inserted as follow:

Category	General Product	Subcategory	Brand	Type of package
Bens Essenciais	Arroz	Carolino	Masterchef	1 kg
Peixe	Atum	Lombo congelado	RCH	1 cx

In conclusion, it is believed that if Recheio takes into consideration the previous suggestions and recommendations that its revenue will increase because the benefits definitely outweigh the costs. However, these many ideas were just paper ideas and so the group would be more than delighted to participate in the next stage of this project.

7. REFERENCES

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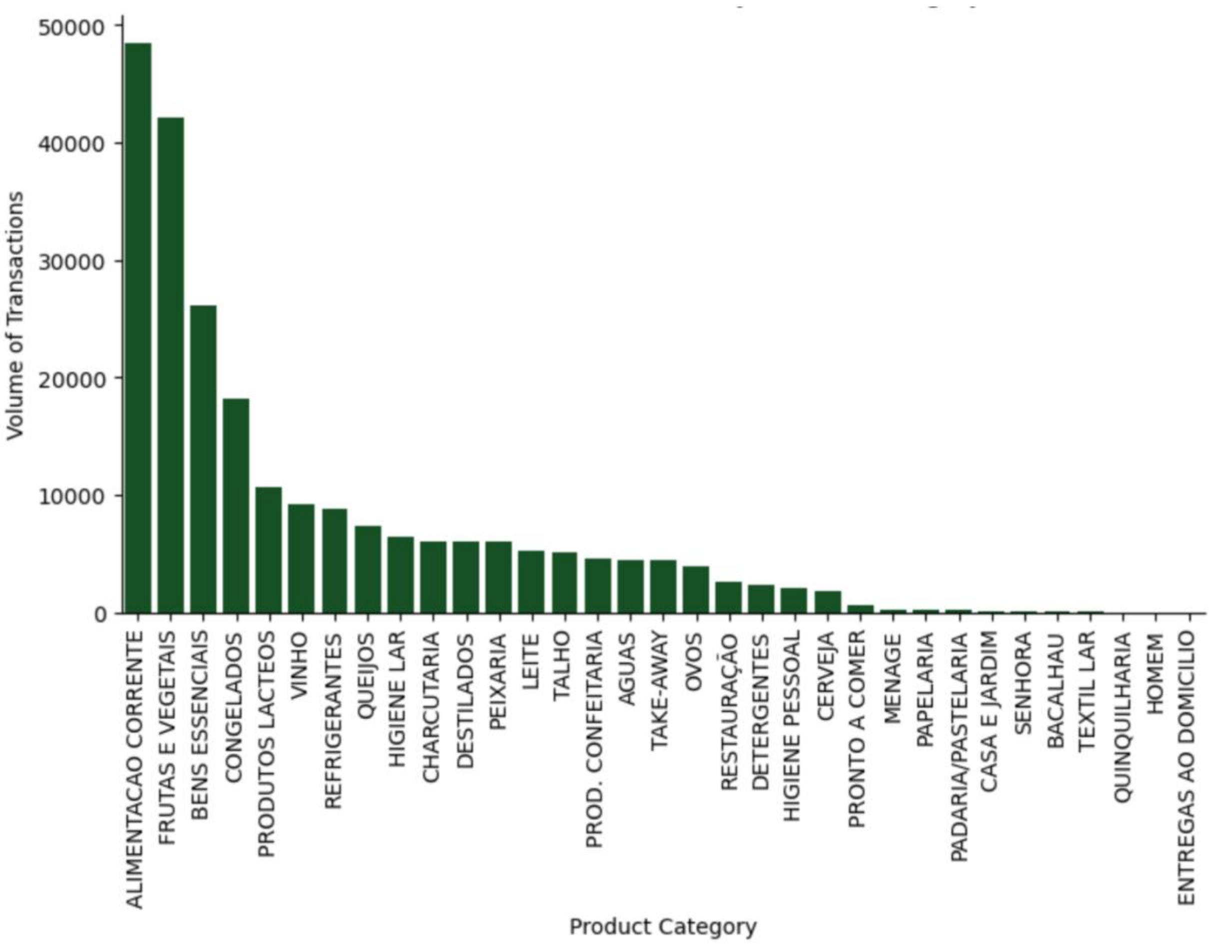
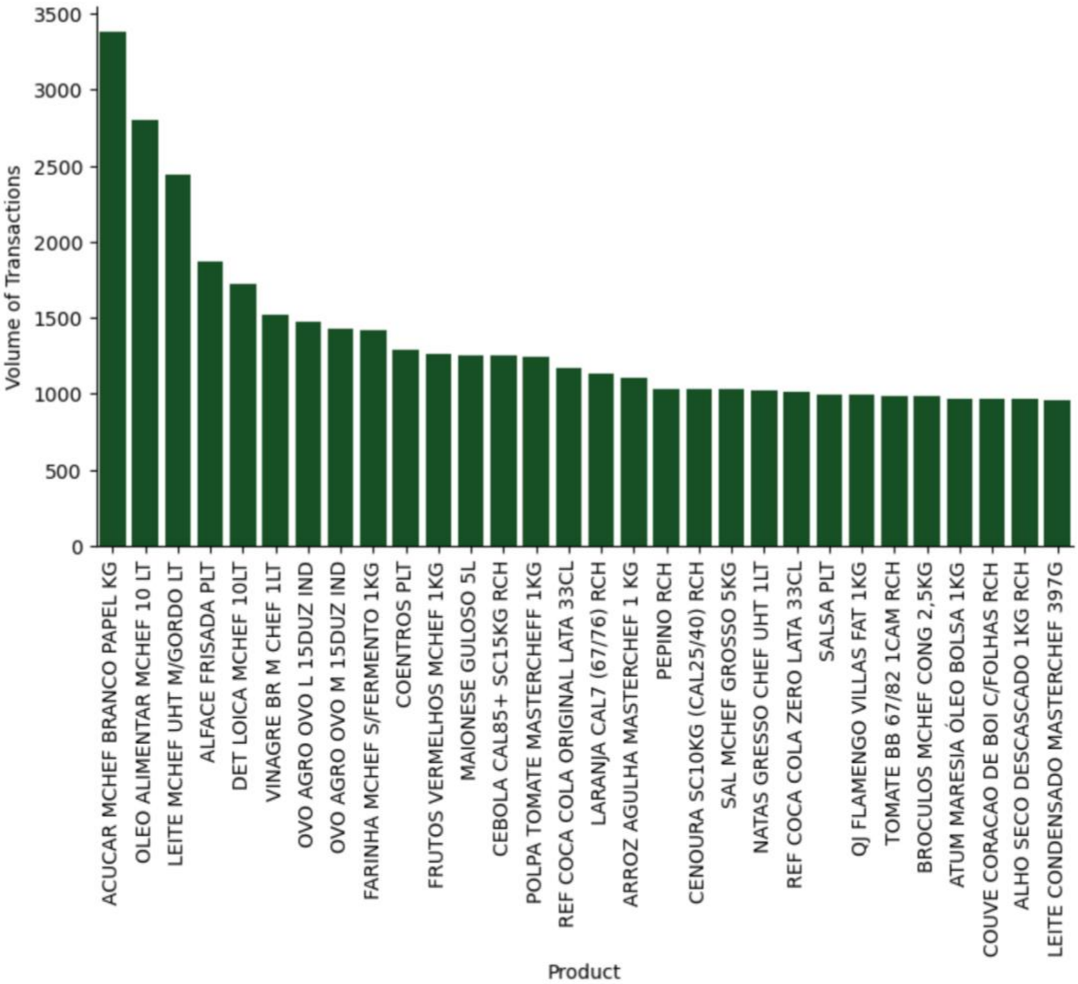
8. APPENDIX

8.1. FIGURES

8.1.1. fig.1 - Total Volume of Transactions by Product Category



8.1.2. fig.2 - Top 30 Total Volume of Transactions by Product



8.2. Model Costs Justification

Popularity-Based Recommendation -> General Popularity depend on aggregating data according to item popularity, which is easily available and requires less computational resources compared to content-based filtering and Popularity-Based Recommendation -> Popularity Per Client Type. Moreover, Content-based filtering and Popularity-Based Recommendation -> Popularity Per Client Type involves analysing thoroughly each items attributes as well as customer preferences, which may require more complex algorithms and data processing. Consequently, Popularity-Based Recommendation -> Popularity Per Client is more expensive because it makes this analysis for each client not by group, requiring more computational power.

Nevertheless, Popularity-Based Recommendation -> Did You Forget? Approach is more expensive because it analyses patterns in clients' behaviour to recognise related items to tailor make recommendations (looks at the previous purchases and sees which products are always bought together). Similarly, Collaborative Filtering is more expensive than Popularity-Based Recommendation -> Popularity Per Client because it has the extra characteristic of also finding resemblances between customer preferences.

Smart Basket Recommendation uses characteristics of predictive models as it relies mostly on real-time data making it more complex and expensive. However, when compared with Page Rank Recommendation, it is cheaper since Page Rank looks into networks of user-items interactions and uses ranking algorithm.