



MKT 680: Recommender System

Proposed Plan to Increase Nestlé Market Share

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Executive Summary

The European chocolate confectionery market has grown tremendously over the years. The market can be divided into 4 main players providing 60% of the chocolate products; Mondelez International, Mars, Inc., Ferrero Group, and Nestlé. Narrowing in on Lunitunia, Portugal, the chocolate industry is a little behind compared to the rest of Europe. Annual per capita consumption is 2kg; compared to the 4kg for Spain and 9kg for Switzerland. This could be because of high taxation on chocolate (23% tax) or the changing consumer behavior where factors like health and wellness and looking for a good bargain drive consumer behavior. For this analysis our focus is on Nestlé and improving their market share within the Pernalonga stores. In order to do this we looked at customers who were similar to our average Nestlé chocolate purchaser. Based on this, we looked at which category customers fell in using cosine similarity; purchasing other chocolate brands, purchasing other Nestlé items and other chocolate brands, purchasing other Nestlé items but not chocolate. We also used association rules to see which items were bought frequently to better suggest promotion strategies.

With this information we were able to make educated recommendations to target populations and therefore increase Nestlé market share.

Introduction

Background

The European chocolate confectionery market is in the maturity phase of its lifecycle. In 2014, it reached the value of 35.575€ million, and shows promise of steady growth rates. Being well established, this industry has four main players (and their subsidiaries) that represent 60% of its distribution: Mondelez International Inc. (Milka, Toblerone, Cadbury), Mars, Inc. (M&M's, Mars, Twix, Maltesers, Dove), Ferrero Group (Kinder Chocolate, Ferrero Rocher, Mon Cheri) and Nestlé (KitKat, Smarties, Crunch, After Eight, Baci, Caja Roja, Lion). The product offering is diverse and adapted to different segments. The four companies operate in over 90 countries combined, with a large number of distribution centres. Mondelez, for example, controls about 130 distribution centres as of 2016, which implies high entrance barriers. In regards to the European market distribution, the main channels are supermarkets and hypermarkets, which account for 35.5%, followed by independent retailers (23.1%), convenience stores (20.9%), specialist retailers (5.1%) and others (15.6%).

Focusing specifically on Lunitunia, Portugal, the chocolate market reached sales of 200€ million in 2017, with an annual per capita consumption of 2kg. This number is low in comparison to other European countries. For instance, per capita consumption in Spain is 4kg/year and per capita consumption is the highest in the world in Switzerland, at about 9kg/year. This is partially attributed to the high taxes on chocolate in Portugal: it is the highest in Europe at 23% (Spain – 10%), which leads to higher prices. To illustrate, a 100g Milka Oreo chocolate bar costs €1.59 in Portugal and €0.83 in Spain. Nevertheless, Portugal shows promise of a sustained growth trend, both in demand and expenditure.

Nielsen has studied the Portuguese consumer trends in several reports. The first notable finding is concerned with purchasing trends where the Portuguese are becoming increasingly concerned with health, directly impacting food choices they are making. 53% of consumers are choosing sugar-free products (higher than the European average), shifting market needs. Lastly, as discussed previously, price and promotions are some of the main drivers of choice in the country. Taking both these factors into account while framing our recommendations is important.

Proposed Approach

Our goal is to increase Nestlé's market share within the chocolate industry. We have identified 4 key ways to increase market share;

1. Increasing the number of customers
2. Increasing the number of units purchased
3. Increasing the frequency of transaction
4. Raising prices

Since the shoppers at Pernalonga love a good deal and are leading down the more health conscious path, we are focusing our marketing efforts on how to increase the number of customers who purchase Nestlé and increase the number of units of Nestlé chocolate items one purchases. In order to achieve this goal we will first identify target customers and products through business understanding. For example; finding the customers who only buy Nestlé chocolates versus other brands, which customers are the most profitable, and which customers frequently buy Nestlé chocolates. We will then compare them to key populations to see which specific customers to target. For products, we will see which Nestlé chocolate products contribute most to their current revenue, which products are most

promoted, and seasonality of any products. Combining this information we can generate a meaningful marketing campaign for Pernalonga.

Method

Data Cleaning

We started our data cleaning process by grouping the transactions and products to study the different variables presented. We noticed that the largest sales volume consisted of private label bags. Our assumption was that these bags were being bought during the checkout process and their cost was attributed to the plastic bag tax levied in Portugal in 2015. Since this tax did not directly contribute to the revenue of the stores, we decided to exclude the plastic bags from our analysis.

Next, there were eight transactions in the dataset that consisted of discount amounts that were larger than the paid amount. We assumed that these discounts were logged into the dataset to offset the original paid amount because the particular customer was returning their products. We decided to remove these negative transactions along with the original to avoid any discrepancies in the data. Additionally, there are 3 products in the transaction table that do not map to the product table. As we have no information about the products, we removed those transactions from the data.

Lastly, upon grouping all the transactions, we noticed that the transaction ID did not uniquely identify every purchase made due to data import constraints. To combat this, we created a new transaction ID that combined the unique store ID and customer ID with the date of transaction. We did so under the assumption that each customer only visits a specific store not more than once on a particular date. Each transaction in the dataset now corresponds to a single product purchase and could be grouped together to find all the products in a single transaction.

Data Exploration

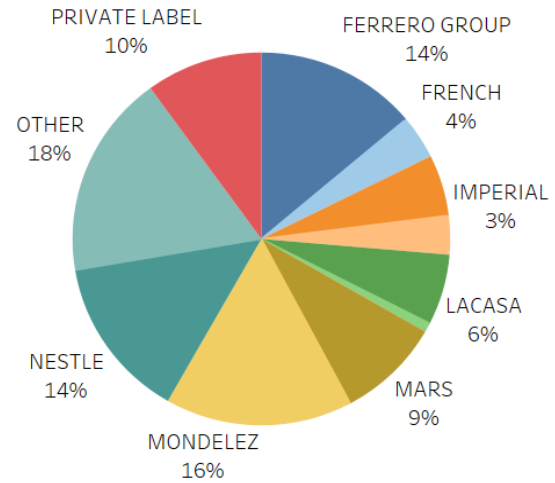
We started our exploration process by extracting all the chocolate products offered in the dataset. There are 315 products that fall in the chocolate/candy category sold at Pernalonga consisting of chocolate bars, bonbons, seasonal Christmas chocolates, and all other types of chocolates. Since our analysis only focuses on chocolate products, we chose to remove chocolate drinks as their product features differ from other conventional chocolate products to allow for direct comparison. Out of the 303 remaining products, Nestlé is selling 46 products. Our background research asserted that the 4 main

brands (Nestlé, Mondelez International, Mars, and Ferrero Group) had an umbrella of brands and subsidiaries under it and thus, we created a new variable named “big brand” that combined the multiple chocolate brands under the parent company.

Out of the total 30 million transactions, about 300,000 transactions were for chocolate products ranging across all brands. This forms 1% of total transactions, which is a very small percentage of transactions. Out of these transactions, about 50,000 were for Nestlé chocolates that were bought across 417 stores.

Thus, Nestlé has a market share of 14% for chocolate products and making Mondelez its biggest competitor with 16% market share. It is

important to note that the “big brand” “Other” contains one off brands that did not individually have a large market share. 9,143 people purchased Nestlé branded items (yogurt, cereal, animal food) but not chocolates (any brand) and 1020 people purchased Nestlé branded items and non-Nestlé brands of chocolates.



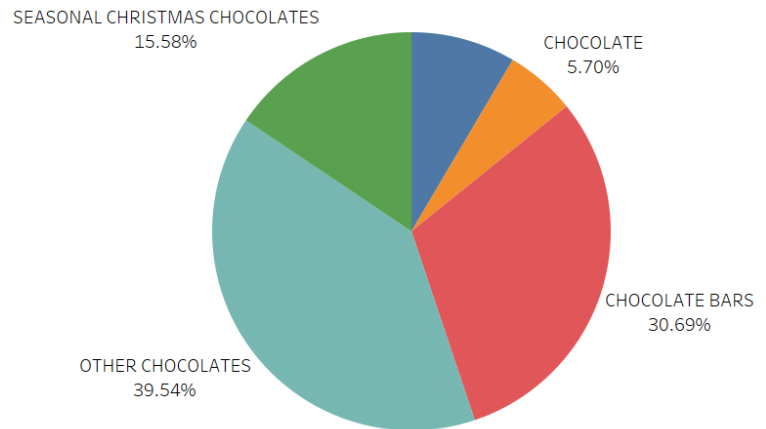
Nestlé Product Categories and Sales

In order to better understand Nestlé as a whole, we combined all Nestlé subsidiaries, like Kitkat, After Eight, Lion etc., into the main arch of “Nestlé”. Our understanding from this is that many subsidiaries are probably also included under Nestlé below as Kit Kat only contributed to 10.9% of sales at Pernalonga.

Sub-Category	Total Revenue	Sales Contribution
Nestlé	€300,047	79.9%
Kit Kat	€41,069	10.9%
Lion	€18,641	5.0%

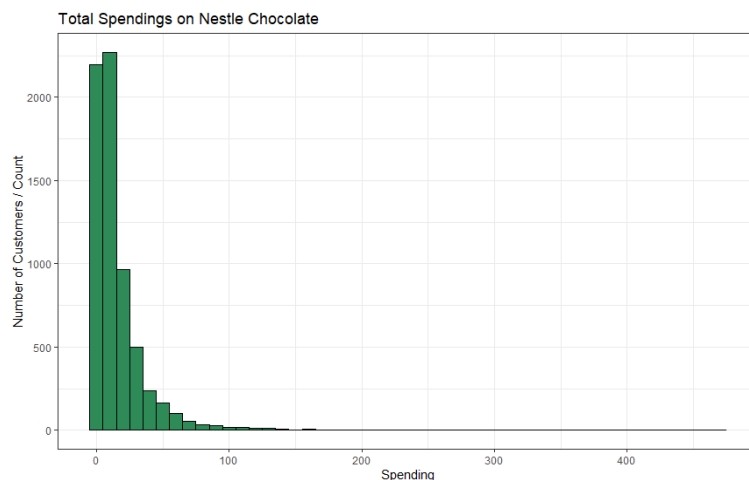
After Eight	€14,804	3.94%
Smarties	€777	0.99%

We also inspected the highest-ranking product categories in terms of contribution to sales. “Other Chocolates” contribute €63,686 (39.54%) making it the most lucrative product. Nestlé doesn’t specialize in making any type of chocolate and it doesn’t rely heavily on revenue streams from certain categories of chocolate either. We can use this data to better inform our analysis of which products should be more heavily promoted versus others.



Nestlé Chocolate Customers

Pernalonga stores have a total of 6642 unique customers that account for 53,000 transactions. The highest spending customer accounts for about €468 on Nestlé chocolates. However, the distribution of total transaction amounts has a long right tail with most transactions accounting for a median of €26 spent and about 1 to 2 units of Nestlé chocolates bought per transaction. By studying the various variables available in the transaction data, we can identify Nestlé’s chocolate customer segments based on the four segments identified in Pernalonga’s stores - bargain hunters, volume discounters, average



need-based customer, and all-at-one-go buyers.

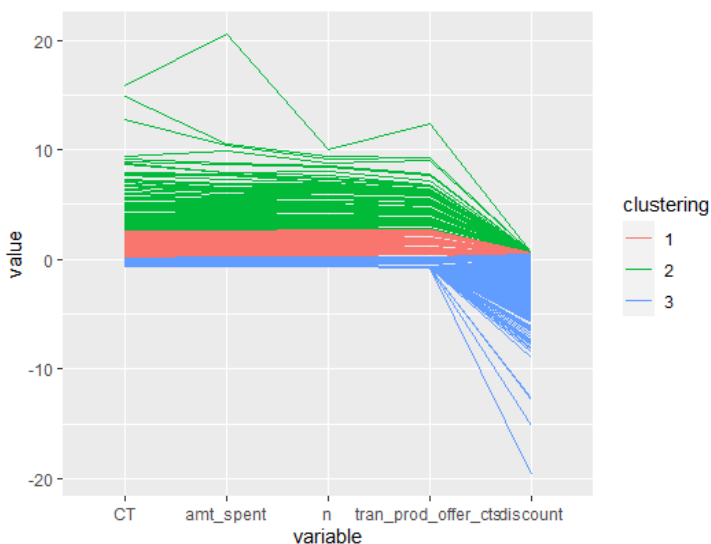
While exploring the purchasing behavior of Nestlé chocolate customers, we noticed that there were certain customers who frequently bought chocolates in bulk amounts, such as 38 to 40 units per transaction. Additionally, they made

these purchases rather frequently throughout the period of two years. We assumed that these customers preferred to purchase all their chocolates in bulk either to sell or to cater for large events. However, they did not exactly resemble our volume discounters segment since they did not use coupons or offers excessively. On inspecting their past purchases, it was clear that they preferred to buy all their products (such as bananas, carrots, water, etc.) in large quantities as well. Next, we aimed to identify the bargain hunters, i.e. those customers who preferred to buy Nestlé chocolates at large discount rates. The average lifetime discount amount for Nestlé chocolates is about €17, however, the same for our bargain hunters went up to €230 and accounted for more than 60% discount rate on their transaction amount. Since these Nestlé chocolate customers closely resembled our original bargain hunters segment, we were interested in studying them in depth to compare potential target customers.

In order to formalize these customer segments, we decided to run a k-means cluster analysis on all the customers who purchased Nestlé chocolates in order to group them based on their shopping behavior. The variables used for grouping these customers matched the ones we previously used for segmenting Pernalonga's customers - quantity of chocolates bought, total transaction amount spent, number of chocolates bought in each transaction, number of offers used in each transaction, and total discount amount per transaction. We scaled the data and used an iterative process to identify the optimal number of clusters through the Elbow and Average Silhouette analysis method. The results grouped our Nestlé chocolate customers into 3 clusters and using the input variables, we were able to confirm that these customer clusters were extremely similar to our initial exploratory insights. The first cluster consisted of customers who bought Nestlé chocolates in large amounts per transaction and frequently but did not accrue very large discounts. The second cluster consisted of the average customer

who purchased about the median amount of chocolates on a frequent basis with median discount amounts. And lastly, the third cluster consisted of customers who bought median amounts of chocolates but at very large discount amounts.

To identify our target population, we started by identifying Pernalonga's customers based on three conditions:



1. Those who bought chocolates (regardless of brand)
2. Those who bought Nestlé items but did not buy chocolates
3. Those who bought Nestlé items and bought chocolates from other brands

There were some customers who overlapped across these three categories and we adjusted them into their respective groups based on purchase frequency in order to avoid any double counting. We proceeded to build an item-based collaborative filtering system that would utilize the three customer segments identified in Nestlé's chocolate customers and provide us with a cosine similarity for all the three groups of target customers listed above. Based on this cosine similarity, we will be able to find specific customers to target in each of the three populations to improve Nestlé's market share in chocolate products at Pernalonga.

Model Building and Strategy

Collaborative Filtering

Our goal with collaborative filtering was to look at all the three customer segments and use them as a baseline to find potential customers from the three target populations identified. In order to do this, we needed to compare the similarity between both these customer groups. We used cosine which measures the similarity between two users based on the cosine of the angle between them and can range from 0 to 1 with 1 being the most similar. We ensured that all our variables had the same range for comparison to avoid any discrepancies. We also focused on three variables that we studied on our Nestlé chocolate customer segments - the total quantity of products bought in each transaction, the total transaction amount, and the discount percent for every transaction and scaled them so that we had one value for each variable for all 3 customer segments. Then, using each customer segment, we calculated the cosine similarity for customers in every target population, thus, giving us 9 columns of cosine similarity. Since the range extended from 0 to 1, it was important to set a threshold that would allow us to focus on a set of customers to target who would have the highest similarity, and thus, the highest likelihood of purchasing Nestlé's chocolates. This threshold can be varied over time based on the needs and the marketing budget of Pernalonga. We used our threshold of 0.94 across all the 9 categories to identify the ideal target customers. With a 0.94 cosine similarity score, we received over 300 potential customers to target across the three target populations. With a higher threshold, the likelihood of the

customers buying Nestlé's chocolate increased but also the overall number of customers to target decreased.

Thus, using our collaborative filtering model, we were able to recognize which customers to target for bulk buying, average transactions, and largest discounts. This can be especially helpful to Pernalonga and Nestlé to design offers or products to attract customers with such interests, thereby, moving them over from other chocolate brands or turning them from non-buyers to buyers.

Association Rules

As our end goal is to increase Nestlé's market share, we can turn to association rules to gain a better understanding of relationships between products; which products are bought together with high confidence and which products show up in the dataset together frequently. We can then use this information to identify target products, bundle them into a promotion, and target them to specific customers.

Looking at confidence as our metric, we found a heavy load of customers who purchased yogurt, specifically subtypes 145519008, 145519011, 145519012, also bought Nestlé chocolate products with high confidence. Most of the yogurts purchased were from the brand *Activia*. Upon further research we found that *Activia* (a *Danone* brand) dominated the yogurt market in 2017 due to the emphasis on lactose-free, dairy-free, and sugar-free yogurts. They also make a large majority of the yogurt brands at Pernalonga and so it helps explain the high purchasing pattern for this brand.

A powerful way to use this would be to build bundle promotions for these product pairs. Even though *Activia* is not a Nestlé brand, Pernalonga can pair the two items together to make them more attractive than competitors, thereby increasing sales of both items. On the other hand, only 2123 (out of 7,436) Nestlé yogurt (certain sub-categories) purchasers also bought Nestlé chocolate, giving us a lot more scope and flexibility for promotion. Getting more information on product classification will be helpful to understand how to effectively promote them. For example, if the product is a traffic driver, we can heavily promote that instead of heavily promoting the chocolate, increasing the sales of the additional products. Our current action item is to recommend Nestlé chocolates to the customers who currently purchase *Activia* brand yogurts or Nestlé brand yogurts.

Recommendations

Based on the three identified clusters of Nestlé chocolate buyers (bulk buyers, average buyers, and discount buyers) and the three target populations - chocolate buyers (regardless of brand), customers who buy non-Nestlé chocolates, and Nestlé customers who buy other brands of chocolates, we were able to collect insights through an IBCF model (based on cosine similarity) and association rules to identify our target customers during a 2 week promotional campaign.

Our IBCF results show that target customers recommended from the first cluster (bulk-buyers) buy mostly private-label chocolates. This could be due to price differences of private-label chocolates compared to name brand chocolates from Nestlé. Additionally, they also purchase a large amount of yogurt, which we will be exploring in the next section. Our second cluster recommendations (average customers) mostly buy chocolates across the range of different brands, but do not have any customers that have ever bought Nestlé chocolates. However, they do buy Nestlé yogurt and chocolate drinks. Thus, targeting them with introductory offers for Nestlé chocolates could be helpful in bringing awareness to Nestlé's chocolate products. Our last cluster of recommended customers (discount customers) purchase some chocolates but mostly spend their money on produce. This is a difficult group to target as we know the taxes on chocolates are pretty high and thus, discounts do not help much. However, introducing bundle offers during seasonal times can be attractive for such customers.

Upon closer inspection of the Nestlé chocolates, we found that "Seasonal Chocolates" provide a high revenue during the holiday season. As the stock of these chocolates need to be purchased before the holiday season is over, it's

imperative to run promotional strategies on them early on. Bearing this in mind, we can run a promotional campaign at the product level. For example; customers can receive small discounts on other products if they purchase "Seasonal Chocolates", increasing revenue and quantity sold. Another way to approach this

is to give better promotional discounts during Easter, which does not have as high a spike as Christmas,



to develop the brand loyalty early on so customers come back and purchase Christmas chocolate or vice versa. This will come at a very small cost as a small discount amount will go a long way.

In order to make personalized offers to current and future Nestlé customers, we looked at past transaction behavior around price paid and discount percentage. Using this information we created a promotion bucket for each customer group. This promotion bucket looked at the average discount percent all the people in that customer group used and then grouped into 2% increments. The Nestlé Fans already purchase Nestlé chocolates and don't need a further incentive to purchase them, rather, they need incentive to purchase more or purchase more frequently. Offering coupons on volume-drivers can help bring them (and other customer segments) in-store and therefore purchase more chocolate.

Customer Group	Promotion Bucket
Nestlé Fans	Bucket 1 (lowest promotion)
Competitors	Bucket 3 (medium promotion)
Other Nestlé Products + No Chocolate	Bucket 2 (low promotion)
Other Nestlé Products + Competitor Chocolate	Bucket 4 (highest promotion)

Business Impact

Understanding the business impact of this promotional campaign will aid in seeing how successful this campaign really is. In order to do so, we first quantify the expected volume and discount amount based on the offers given from this promotion.



We looked at our target customers and products from the analysis above and used the cosine similarity as the probability that they will accept an offer. Our assumption is that these potentially new customers will have similar spending behaviors as their baseline counterparts and so we can calculate incremental volume using baseline quantities and that all customers respond to the promotion. In order to calculate Incremental Volume we used:

$$\Sigma (\text{Probability a person will buy Nestlé} * \text{Average Quantity sold})$$

For our analysis, we use our threshold cosine similarity as a proxy for the probability a person will buy Nestlé; 0.94. With this we get an incremental volume of 1.26 units per customer, leading to a total incremental volume of 380 units (for the 300 customers). This will lead to an expected incremental revenue of €810 within the proposed 2 week period.

$$\Sigma (\text{Incremental Volume} * \text{Unit price of Nestlé Chocolates})^{**}$$

***Unit Price calculated by $\Sigma(\text{proportion of each Nestlé chocolate} * \text{price of each product})$*

When looking at the expected total redemption cost for the promotion we can see that with a baseline discount percentage of 26%, the total discounts redeemed per person would be close to 32%. With a unit price of 2.13, the total discounts redeemed would be close to €200.

$$\Sigma (\text{Incremental Volume} * \text{Average Discount Percentage})$$

We can see from this that Pernalonga would have a 710% return on investment and effectively increase their market share from 14% to 14.2% with the proposed promotional ideas during a two week period. Therefore based on our analysis, we believe it is a good idea for Nestlé to target its own customers and its competitors customers in order to drive business growth.

Conclusion and Next Steps

Based on our findings throughout this paper, we propose Pernalonga use our promotional campaign for a 2 week trial in June, as it allows them to test the waters before their heavier foot-traffic months (July). In order to fully measure the success of this effort, the next steps we recommend are determining incremental impact through difference-in-difference testing. Ideally, we can randomly assign the target customers into test and control groups at the store-level. This will help solidify the promotional amounts for the product(s). After this, the test group would receive personalized promotions related to Nestle chocolates and we can then measure sales on these promoted items for both groups, before and after the promotion. If the difference-in-difference value is positive (i.e. the promotion increased revenue) then Pernalonga can scale this promotional strategy across all stores bringing in new customer segments, and can expand this to other products for the best return on investment.