MKT 680: Pricing Strategy

Proposed Plan to Boost Pernalonga's Revenue through Strategic Price Changes

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Executive Summary

Portuguese grocery stores are required to make careful pricing decisions to ensure their customers continue shopping with them and do not lose them due to higher shelf prices or low discounts. Additionally, understanding price elasticity is crucial to recognize which products to discount or mark-up and also to personalize pricing and promotions towards customers based on their price sensitivity.

We will be exploring all of Pernalonga's stores to identify variance in product pricing for the week of April 12th to 18th in 2016 and 2017 and use that as our basis to suggest price changes for 100 products ranging across two categories in 2021. We calculated the price elasticity for all these store-product pairs and picked “fine wines” and “coffee and roasted mixtures” as our top two categories. We incorporated complement and substitute goods for all these products using association rules to acquire a coefficient to control for in our price response function. Lastly, we also accounted for seasonality and the effect of holidays across the years by using a weekly index to study the week over week difference in transaction revenue and unit changes. Using all these controls, we were able to build a logit price function model that predicted demand for our top store-product pairs and suggest price changes, thereby improving Pernalonga's revenue by over €2000 across 10 stores.

Introduction

Background

The Portuguese food industry sector has seen dramatic changes in the past few years driven by a rise in the introduction of e-commerce channels and demographic changes. Broadly, the food industry can be divided into the retail food sector, comprising sales of food items consumed at home, and the food service sector, comprising sales of prepared food that is consumed away from home. In such a climate, where food retailers are facing increasing competition not only from other retailers but also from the food service sector, the fight for the modest increase in consumer dollars spent on retail food is intense. Pricing is tantamount to survival. If prices are too low, you're leaving money on the table. If they're too high, buyers walk away empty-handed. Adopting a successful price optimization strategy has become more important than ever to profitability — and even viability.

Pernalonga, the large supermarket chain in Lunitunia, Portugal, is looking for ways to improve revenue through adjusting shelf prices of certain products. Having over 400 stores and selling over 10,000 unique products, competition is fierce and characterised by thin margins. Small adjustments to price charges can have significant implications on retailer performance. Dolan and Simon's (1996) study suggested a 10% improvement in pricing resulted in a 33% improvement in profit; far higher than any other business lever. As a result, pricing decisions are regarded as being among the most crucial and difficult aspects in retail marketing. Despite the importance of price to profits, it is suggested that retailers are not particularly strategic in price management – most business owners do not use price as a basis for achieving a sustainable competitive advantage and prefer to use cost-plus pricing or market-based pricing versus customer focused value pricing. As Portuguese consumers show a greater appetite for promotional campaigns and cheaper prices, this analysis aims to help Pernalonga better price a select number of products that will improve their revenue while maintaining overall profitability.

Proposed Approach

Our goal is to recommend price changes for 100 products between April 12th - 18th, 2021 with the purpose of improving revenue. We assumed that the promotion schedule for the week of April 12th - 18th, 2021 would be the same as the one for the same week in 2017 and 2016. Since April 12th - 18th is the 15th week of 2021, we mapped and analyzed the 15th week of 2016/2017.

In order to achieve this goal we will first identify what categories of products and what specific products we want to target. We will do this by looking at price variance on a weekly basis to see which products have no price variance (and no change in demand and a result) and will not consider them. We will then identify target stores based on which store is selling most of our target products and then identifying stores similar to this target store. Lastly, we will consider weekly price, weekly discount, seasonality, occurrence of holidays, and complement and substitute goods in order to provide recommended price changes for the targeted products.

Method

Data Cleaning and Preparation

We started our data cleaning and preparation process by creating a new transaction id for each transaction as the transaction ID did not uniquely identify every purchase made due to data import constraints. The new transaction ID combined the unique store ID and customer ID with the date of transaction. The assumption made here is 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.

We then removed all transactions 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.

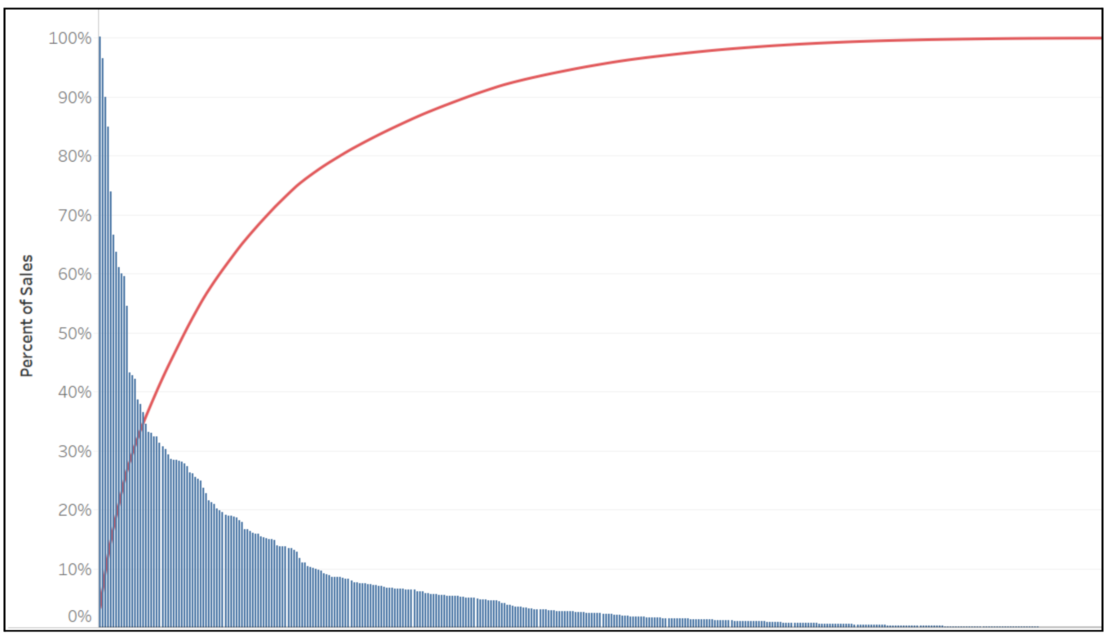
Next, there were eight transactions in the dataset that consisted of discount amounts that were larger than the paid amount. We assumed that these discounts were logged into the dataset to offset the original paid amount because the particular customer was returning their products. We decided to remove 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.

Pernalonga specified excluding all products that are considered “fresh”. Our assumption here is that anything not a consumer packaged good is considered fresh, so items like poultry, fish, and produce are fresh. In order to account for this we created a binary variable where fresh products received the value of 0 and all other products received a value of 1. We did this in order to be able to count these products as either complements or substitutes later in the analysis.

Lastly, we created an index to account for changes in price on a weekly basis. We chose to look at price changes on a weekly basis as we do not have daily transaction information, and so a weekly aggregate gives us a holistic understanding of the changes in both price and demand. Additionally, the price changes did not occur at Pernalonga on a daily basis, rather they happen over a period of time, so this approach accounts for that slow change as well.

Data Exploration

We began our data exploration phase by looking at the top categories of products sold and how many products were in each of those categories. Per Pernalonga's request, we have to make price changes on the same 100 products in only 2 categories in 10 stores. Understanding the top 5 categories and looking at the long tail graph will help us understand the distribution of sales across all products. We found that 25% of the categories of products sold at Pernalonga are responsible for 65% of Pernalonga's overall sales so we used this as our basis for narrowing down our category search to look at the top 5 categories (so that we can later target 2).



Product Category	Sales	Number of Products
Fine Wines	€1,871,559.75	393
Dry Salt Cod	€1,802,909.11	26
Beer With Alcohol	€1,679,127.67	83
Washing Machine Detergents	€1,584,916.20	242

Coffee and Roasted Mixtures	€1,380,611,94	134

We then analyzed the 15th week of 2016 and 2017 respectively to get a better understanding of what kinds of promotions and sales were the stores having during this time period. The first thing we noticed was that there were no discounts being offered during the 15th week of 2017 and moreso, there were no significant changes in shelf price either. Because of this, there was also no significant change in demand as compared to the same week in 2016. There are approximately 310,000 transactions that take place during this time period in 2017 and approximately 250,000 transactions in 2016. This leads us to believe that Pernalonga could benefit from price optimization during this time period so as to improve long-term revenue.

Before we proceeded with selecting stores and products, we removed transactions with no price variance on a weekly basis, i.e. these products have a fixed price. We did this because we want to observe changes in demand caused by a change in price (looking at calculating elasticity). When there is no price variance we cannot observe this change, and these products cannot serve as complement or substitute goods either, so these products have been removed from the dataset.

Choosing Stores & Product Pairs

Pernalonga specified that we are to make these price changes in 10 stores due to constrained resources. In order to get the best improvement in revenue we decided to look at store product combinations as a way to maximize the possibilities to boost revenue. With this focus in mind, we first identified the store with the highest number of target categories currently being sold (store 342). After some further investigation, we found that this store has changed prices of our target categories in the past and so we can assume they will be more accepting of price changes in the future.

We then looked at what other stores have the most number of target categories in common to store 342 and selected the top 15 stores from there. We decided to select more than 10 stores to allow some buffer in selecting the final 10 stores we want to target. Our top 15 stores are; **342, 349, 347, 346, 345, 343, 588, 344, 335, 341, 395, 320, 525, 157,** and **398**. By doing this, we were able to narrow down our store-product combinations to 62,206 combinations with 720 unique products in our target categories at 15 stores.

We proceeded with narrowing down the store-product pairs by looking at elasticity for each combination on a weekly basis. In order to find the elasticities for all our products, we used the following formula:

$$\boxed{\text{The } \textbf{point elasticity} \text{ is defined as } \epsilon(p) = \frac{pd'(p)}{d(p)}}$$

We first looked at the shelf-price for each of the products in our dataset. We observed when the price price change occurred and calculated the average price and average demand for each of the products. We then calculated the slope of the demand curve to use to calculate the final elasticity for each product. We ended up with 8,139 elasticities for the unique store-product combinations in the dataset. We wanted to consider both highly elastic and highly inelastic products as there are no restrictions on whether we need to increase or decrease price.

Category Description	Number of Products
Fine Wines	166
Dry Salt Cod	13
Beer With Alcohol	62
Washing Machine Detergents	71
Coffee and Roasted Mixtures	81

From the chart we can see that Fine Wines and Coffee and Roasted Mixtures are our top two categories. Between the two categories we have 247 products that we can choose from to maximize revenue improvement and we will continue to explore all store-product combinations as there might be an opportunity for more revenue maximization with another store-product combination.

Complementary & Substitute Goods

In order to better understand the demand for our target categories, we must look at complement and substitute goods. For the purpose of this analysis we define a complement good as a good that is frequently purchased with our target categories. This complement good can be in any category and so is not limited to the target categories we are looking at. Substitute goods on the other hand, are goods that are similar or comparable to items in our target categories. Our assumption in looking at substitutes is that the items will lie within the same subcategory and these items will not (or rarely) be purchased together. Looking at an example, for complement goods the fall in price of GoodX will lead to an expansion in quantity demanded for GoodX and might lead to a higher demand for complement GoodY. On the other hand, if goods are substitutes; a rise in the price of GoodX will lead to a contraction in demand for GoodX and might cause consumers to switch to a rival product GoodY.

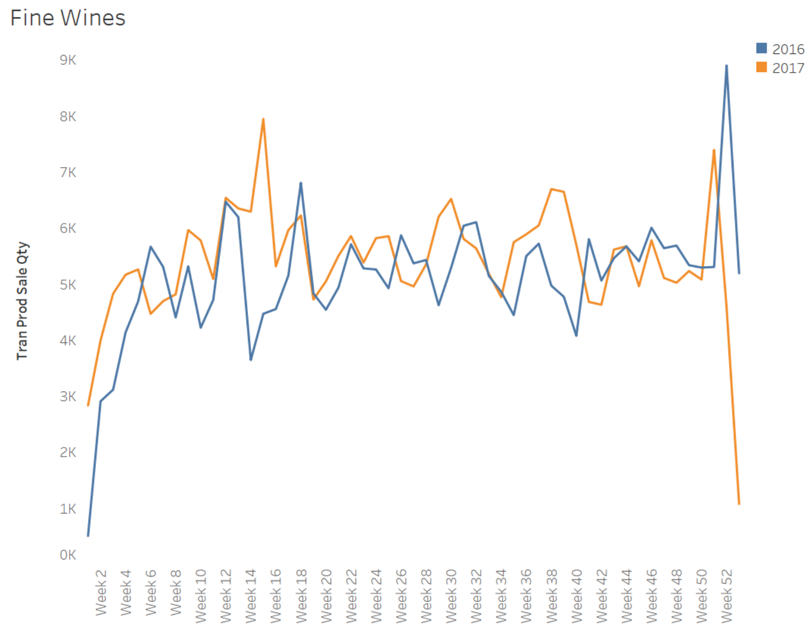
Similar to the Recommender System Project we worked on for Pernalonga, we used Association Rules to observe any complement/substitute goods. For complement goods, we looked at the rules generated by the algorithm by observing co-purchasing behaviors. We looked at what items were frequently purchased together. However, because we want to look at the data on a more granular level like at the subcategory and product level, the propensity of finding complement goods decreases severely. To put this into perspective, I can buy burgers and as a result must buy burger buns. However, the next time I shop I purchase the same burger brand but different buns. So, burgers and burger buns in general are complementary goods, however, we can't say for sure what is the exact complement to that specific burger brand. Using a confidence level of 0.20 we found complement goods for each product in our list, however not every product yielded a complement.

In order to find the substitute goods of a product we looked at the subcategory level to see within a subcategory what other products could people be purchasing. We got a list of all products co-purchased and then looked at lift values to understand which products could be substitutes. Lift (A -> B) refers to the increase in the ratio of sale of B when A is sold. A Lift of 1 means there is no association between products A and B. Lift of greater than 1 means products A and B are more likely to be bought together. A Lift less than 1 means the items have an inverse relationship, i.e. the purchasing of one negatively affects another. We used this last criteria to understand which products are substitutes for our target categories.

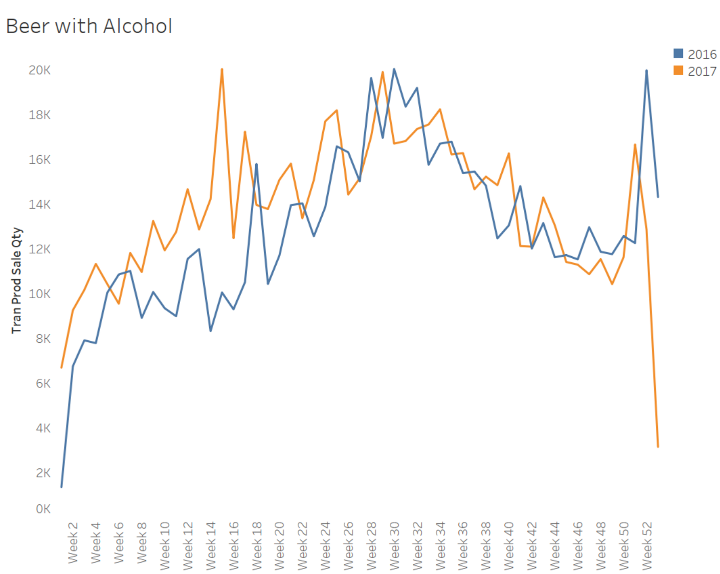
Seasonality

To calculate the seasonality for transactions between the two years, we started off by exploring the total transaction sale amount for all the products at the fifteen chosen stores. Additionally, we also explored the changes in prices for the target categories - fine wine and beer. To account for seasonality in our pricing model, we used the weekly index and weekly change in price variables that we created earlier during the data preparation process. Our goal was to use this week-over-week difference for the years 2016 and 2017 and then calculate the correlation coefficient between them. A higher correlation coefficient value would indicate that the transaction amounts for both the years were similar.

We started off by exploring the variance in purchase quantities for our target categories separately.



For fine wines, we noticed a much larger peak in 2017 compared to 2016 around the week 13 to 15 period. We also saw a similar peak for purchases around the holidays time at the end of the year but lower quantities for 2017 compared to 2016. As for our second category - beer, we see some similar peaks in purchase quantities around the mid year mark and then again during the end of the year in the holiday period. For week 15, we can see the purchases in 2017 were more compared to 2016 and do not entirely line together. To check for seasonality, we compiled the week-over-week differences we had for 52 weeks and received a correlation coefficient value of -0.05 between the two years. Since this value is extremely low, we will go ahead and assume there is no significant correlation between the two years.



Holidays can have a significant impact on demand and so must be accounted for in the model. Carnival, similar to Mardi Gras, is a popular holiday celebrated in Lunitunia, Portugal. Carnival is the biggest festival of the year and draws in people from all around the world. It usually happens in February, right before lent starts and signals the end of winter and ushers in the religious period of giving up meat. From this understanding alone we know that demand for meat might fall in following weeks so accounting for this holiday helps explain patterns of behavior in the data. Additionally, in preparation for Carnival demand for certain goods like eggs and sugar (for Pastel del

Nata) go up and so accounting for this effect in the response function will help isolate the effect of price changes.

Optimal Pricing Model

We built a logit response function to see the optimal price because of its ability to better predict at extreme price changes and because the elasticity of the logit response function is non-constant and increases in magnitude as price increases. To find the optimal prices we used price levels, level of discount offered, price of the substitutes, price of the complements, and seasonality and holidays for each store-product combination in the following function:

weekly_volume ~ weekly_price + weekly_discount + week_index + holiday_index + complement_price + substitute_price

We did not want to fluctuate price too much because upon researching; retail price changes typically don't fall below costs because it does not yield profitability, and if a retailer increases prices too high, they may lose customer following for that product. We chose to vary the price between -25% and 25% with a 1% periodic increase/decrease. With all this information we were able to predict the demand for all store-product combinations. We can further parse this to see which combination of stores and products will give us the maximum revenue.

From the results of this model, we calculated the projected profits after the price change and from that were able to narrow down our categories to "Fine Wine" and "Beer with Alcohol". From there we found 10 stores where the revenue was maximum. We then selected our target 100 products which are attached in an excel file.

Results

As a result of the price changes, we can see that Pernalonga has improved revenue and there is more possibility for growth expanding past these 10 stores.

Store ID	Change in Sales Quantity	Change in Sales Amount	Profitability
342	86.50	864.60	456.34
344	64.30	386.23	264.33
345	14	223.42	152.40
398	76.20	342.96	195.52
588	32.38	216.36	108.63
349	89.98	453.71	222.46
346	96.32	294.87	155.34
341	50.12	342.23	198.64
343	73.82	246.50	129.29
335	45.16	352.80	152.48
Total	**628.78 units**	**€3,723.68**	**€2,135.43**

Conclusion

Looking at the four P's of marketing: product, promotion, place, and pricing, each one is integral to a good marketing strategy but pricing is an extremely effective measurement of continuous communication of value to customers. With this analysis we can see that demand response functions to optimize prices can lead to significant improvements in revenue and profitability at the store level. We targeted categories that already contribute a lot to sales to further boost the revenue and Pernalonga can implement this strategy on a larger scale, across more stores, and combine it with the personalized promotion campaign to further boost the revenue.

Next steps for Pernalonga will be to create a communication plan for how they plan on introducing the new pricing scheme to their customers. It is important for them to stay committed to the new value proposition and communicate the plan thoroughly to the customers. If there are pain points about the change, it is important to listen to that and incorporate that feedback. This could be in terms of purchasing patterns but also verbal feedback. The new pricing scheme is a great chance to reconnect with customers on the value of the products and just how much better it is today than a year ago.