NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Faculty of Computer Science
Bachelor's Programme "HSE and University of London Double Degree Programme
in Data Science and Business Analytics"

BACHELOR'S THESIS

Testing the effect of promotions in retail using machine learning methods

Research project

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Аннотация

В данной работе изучается влияние промо-акций на количество продаж в розничной торговле. В работе исследовано, как метод CasualImpact от Google может быть использован для определения влияния рекламных кампаний на продажи как всей сети магазинов, так и конкретных единиц товара. Это также позволяет понять, как промоакция на один товар может повлиять на продажи всей категории, и, следовательно, на основе такой методологии можно сделать вывод о том, как следует управлять промоакциями, чтобы поддерживать продажи наиболее важных (наиболее маржинальных товаров) на должном уровне.

Abstract

This paper studies the effect of promotions on unit sales in retail. In this work explored how the CasualImpact method by Google can be used to determine the effect of promotional campaigns on sales of the whole store chain as well as on concrete units. It also provides understanding how promotion on one good can affect sales of the whole category and therefore from such methodology can be drawn an insight on how promotions should be managed in order to maintain sales on the most important(most marginal goods)on an appropriate level.

Contents

1 Introduction

In today's realities, in the conditions of a modern market economy, when there is an unlimited number of different companies that create conditions for serious competition for each other, enterprises need to come up with different ways to stay afloat, and maximise profits and remain competitive. The most common method of promoting products and services for greater profits is marketing, which helps companies to understand the market deeper. However, when implementing marketing, companies may have problems, and doubts about the effectiveness of a marketing campaign. And before taking on the risk of extra costs that may not pay off in the end, which will lead to loss of money, it would be great for enterprises to be able to understand where the decision to implement the action will lead. If the results, let's say, of an advertising campaign do not make themselves felt or are not practically noticeable, it would be possible to replay it in advance, cancel it, and understand what the problem is. Previously, any marketing research took a lot of time and cost a lot. Now it is possible to apply machine learning methods to predict the result of a particular marketing decision. One of the existing methods for predicting changes in sales over time is 'CausalImpact' by Google. This is a method that allows you to determine the impact of some intrusion in the time series. The purpose of this work is to determine the usefulness of the 'CausalImpact' machine learning method for predicting the impact of a marketing campaign on retail sales.

1.1 Relevance and Novelty

This work is undoubtedly very relevant since marketing is an extremely important area of the economy in the modern world, and research on its benefits for strengthening the company's position in the market is very important. Moreover, there are very few such studies now, which shows its novelty. The relevance of this work is that the basis is created, there is a development of this method for application in the field of retail trade.

1.2 Research goals

The main task of the study is to apply the 'CausalImpact' method to data from the retail industry, building visualisations to demonstrate its work.

2 Literature Review

As part of the work, I studied several scientific papers. The first article, "Causal Quantification of Cannibalization During Promotional Sales in Grocery Retail" by Carlos Aguilar-Palacios, Sergio Munoz-Romero and And Jose Luis Rojo-Alvarez, which touches on the topic of retail marketing campaigns, examines the quantification of the effect of cannibalization (the promoted product has a domino effect on sales of the unadvertised). This topic is important for retailers as it can lead to product spoilage and lost profits. The article also notes that there are no identical reactions to marketing campaigns, as there are many factors that influence: the characteristics of stores, their geographical location, etc. Since the article considers precisely the effect of cannibalization, it is noted here that the same situation of character is also for cannibalization, everything is individual. The essence of the work is to understand cannibalization as a causal effect: with an increase in sales due to the promotion of a certain product, it affects the decrease in sales of what is not on the marketing campaign. Thus, this paper raises the issue of measuring the impact of cannibalization, that is, roughly speaking, the effect of "eating" sales of one product by sales of another due to promotion using a causal inference. The method considers each advertised product and determines the "cannibals" and those products that lost their sales due to these "cannibals". Next, each such pair is analysed using the time series method to draw a conclusion about the causal effect of the promotion intervention. The paper discusses the practical application of the detection of "cannibalism" in sales. The study is performed on big data about promotions in several stores with different types of products. In addition, the Appendix discusses the application of explainable prediction to cannibalization on a surrogate model.

In “Inferring causal impact using bayesian structural time-series models” by Kay H. Brodersen, Fabian Gallusser, Jim Koehler, Nicolas Remy and Steven L. Scott proposes to infer a causal effect based on a diffusion-regression state-space model that predicts a counterfactual market reaction under artificial control. Such a response would occur if there were no intervention. Here the Monte Carlo algorithm is used with a Markov chain for a posteriori inference. The statistical properties of this approach are shown on simulated data. The paper also proves the practical utility of the approach in estimating the causal effect of an advertising campaign on the Internet. The implementation of the approach is carried out with the help of the CausalImpact package in R.

In summary, these articles helped me to understand how the method I researched works. I saw how it is applied in practice and got ideas for its application for business development in the retail sector.

3 Data

3.1 Data description

This paper uses data on the sales of thousands of products in retail stores. These are the stores of the retail chain "Corporación Favorita SA" located in Ecuador. The dataset includes information about the daily sales of each product (specifying the id of the product and the exact date of its sale in a year-month-day format). Also, the dataset has a Boolean variable that determines whether the product is covered by a promotion (1 - yes; 0 - no), this information is very important to work with because it is what determines the tipping point for the analysis. It doesn't contain any information about the promotion itself, but it's not needed, since the key is the presence of a marketing campaign. For a more in-depth analysis, there are additional data sets about public holidays and local events. The data set lacks information about prices, availability of SKU in stores, and descriptions. The data set highlights several types of items: beverages, bakery products, dairy products, deli meats, eggs, frozen foods, grocery I, grocery II, poultry, cleaning, meat, liquor/wine/beer, underwear, personal care products, prepared foods, automotive, hardware products. There are also several types of stores called 'A', 'B', 'C', 'D', 'E'. Moreover, the dataset contains information about whether products are perishable as a boolean variable (1 - yes; 0 - no). All data from all stores, on all days, will be used for our work. So, from the variables that we use in our further computations «onpromotion», «type», «family», and «perishable» are categorical and «unit_sales» is numeric.

	id	date	store_nbr	item_nbr	unit_sales	onpromotion	month	type	family	perishable
0	21668508	2014-04-01	9	554145	11.0	ЛОЖЬ	4	B	GROCERY I	0
1	21770711	2014-04-03	9	554145	15.0	ЛОЖЬ	4	B	GROCERY I	0
2	22221275	2014-04-12	9	554145	3.0	ЛОЖЬ	4	B	GROCERY I	0
3	22273569	2014-04-13	9	554145	2.0	ЛОЖЬ	4	B	GROCERY I	0
4	22716417	2014-04-22	9	554145	6.0	ЛОЖЬ	4	B	GROCERY I	0

Table 1: Data

3.2 Exploratory data analysis

The data set has an additional set with information about the location of stores. It is used to build a map, which shows the distribution of stores on the territory of Ecuador. The areas highlighted in darker green are the most densely populated with stores.

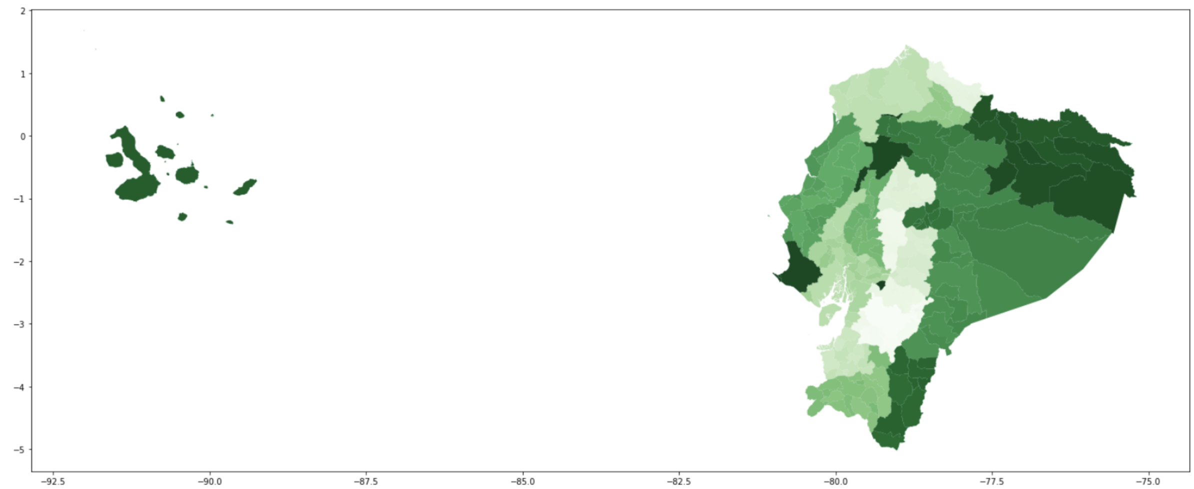

Figure 1: Map

For a better understanding of the data used for further work, an analysis was carried out with the help of visualisation. In the beginning, it is considered which categories of goods are bought more than others. Below is a graph showing that the most popular category of goods is 'grocery I', there are also categories like 'automotive', 'hardware', 'lingerie', which are practically not bought.

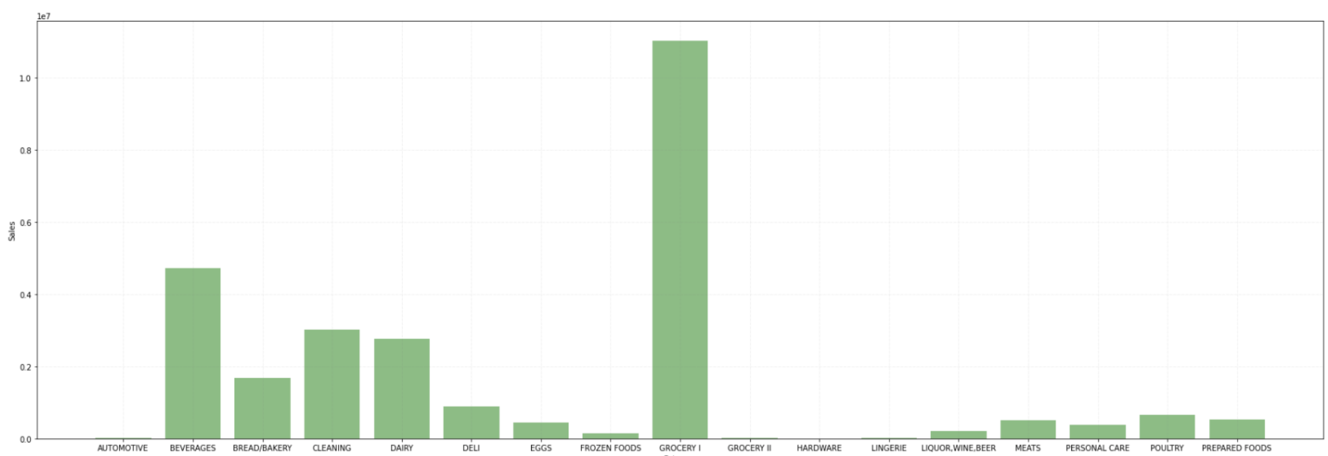

Figure 2: Categories

It was also obtained during the analysis that more products that are not on the promotion are bought. The number of sales of such products exceeds the promotional products by almost 10 times. It also turned out that most of the products to which promotional campaigns are applied are perishable. Moreover, analysis shows that perishable foods are bought much more often than those that can stay fresh longer.

Below we consider which types of stores sell the most frequently purchased goods. The graph below shows that sales are almost evenly distributed across all types of stores, except for store type 'A', its sales figures are the lowest and differ from the others by a significant number (more than two times less than the others).

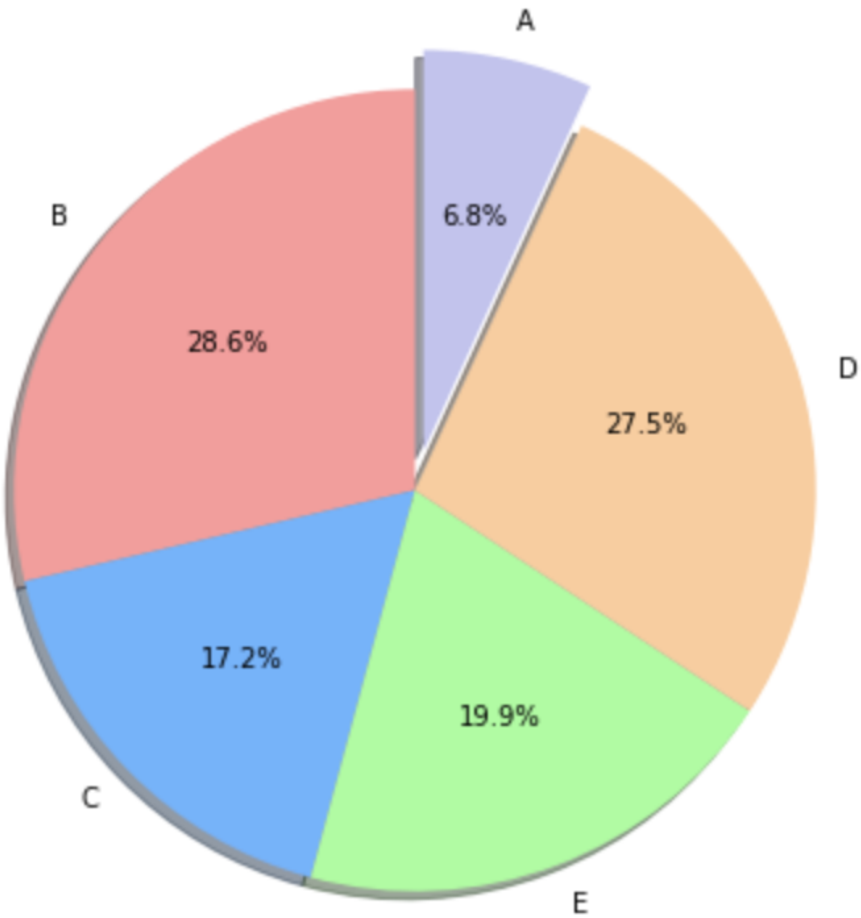

Figure 3: Sales

The last type of sales comparison would be to compare the number of sales depending on the category and whether or not the product has a marketing campaign in place. The colours here indicate whether the product belongs to a promotion, and the product types are located on the abscissa axis. Looking at the height of the columns corresponding to the categories, you can determine that, for example, products without promotions sold more regardless of category.

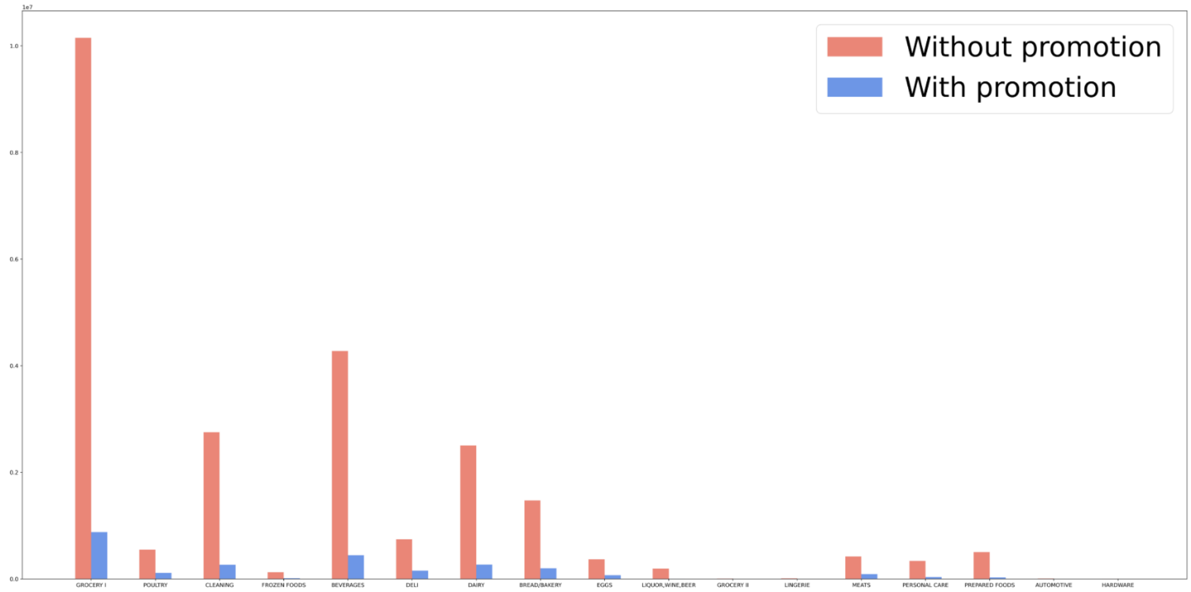

Figure 4: Sales vs Category vs Promotion

Now let's build a similar graph to the previous one, only the distribution is not by product type but by store type. Once again, we see that products without promotions were purchased more regardless of store type.

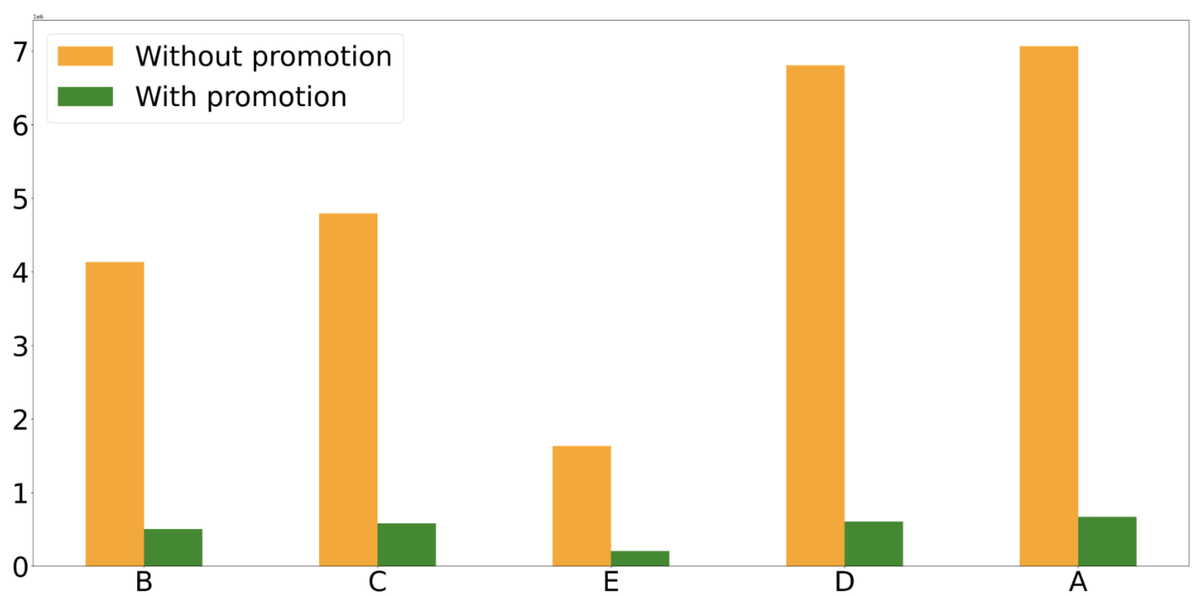

Figure 5: Sales vs Stores vs Promotions

3.3 Segmentation

3.3.1 Clusterisation Metods' Review

Clustering is the task of grouping a set of objects into subsets (clusters) so that objects from one cluster are more similar to each other than to objects from other clusters by some criterion. clustering is used for such tasks as: searching for patterns within data, finding anomalies, data compression. In this paper, the closest purpose is the purpose of clustering for marketing: to segment customers, competitors, market research.

There are several methods of clustering. For example, k-means, DBSCAN, EM-algorithm. In this study, I chose k-means to partition the data into clusters. The main idea of the method is that at each iteration the center of mass is recalculated for each cluster obtained at the previous step, then the vectors are divided into clusters again according to which of the new centers was closer according to the chosen metric. The reason for the choice of the method was the numerous advantages of the method. The main advantages of this algorithm are: accuracy, ease of interpretation, and time savings when working with large data sets such as ours.

The first step taken for data analysis is to apply the elbow method to determine the optimal number of clusters by selecting a model with a range of values for k. The inflection point on the line plotted for the elbow method (the inflection point, the "elbow" itself) shows the point at which the underlying clustering model will work best. In the graphs below, the above "elbow" is indicated by a dotted line.

3.3.2 Distortion Score Elbow Method

The first graph (presented below) shows how KElbowVisualizer (an elbow method found in the Yellowbrick library) fits the KMeans model for a range of values from 2 to 8 on a sample two-dimensional dataset with 7 random point clusters. Here distortion is chosen as the metric. This metric counts the sum of the squares of the distances from each point to its assigned centre. The elbow (black vertical dotted line) coincides with the value of k=4, this number is the optimal number of clusters. Moreover, this library, namely the KElbowVisualizer method, allows displaying the amount of time to train the clustering model. This time is shown in the graph as a green dashed line.

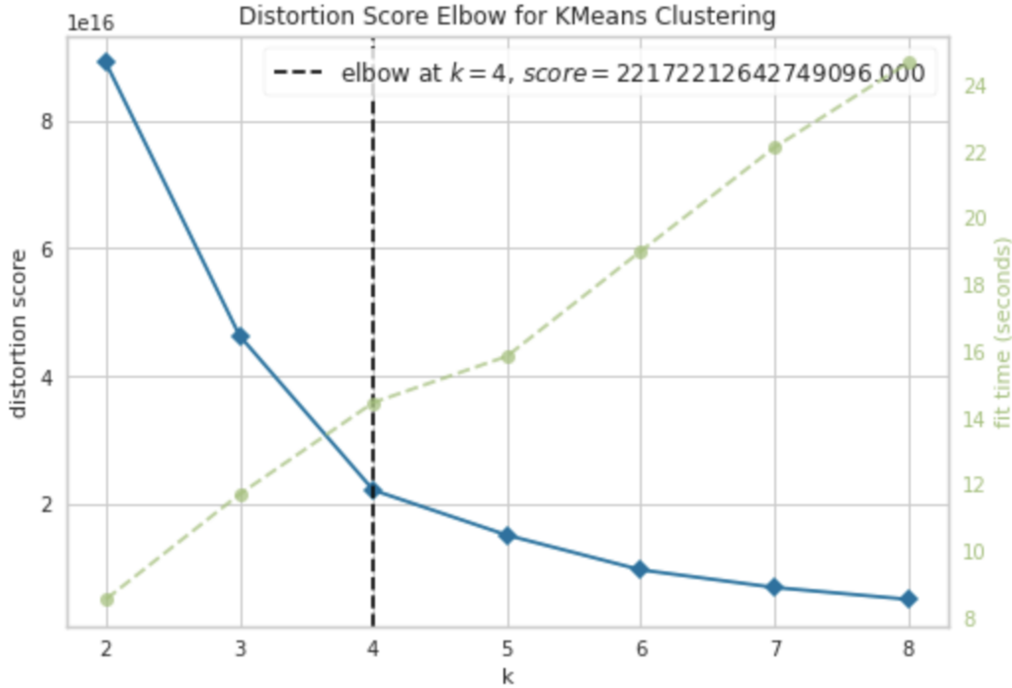

Figure 6: Distortion Score Elbow for KMeans Clustering

3.3.3 Calinski Harabasz Elbow Method

In the second graph, the KMeans model is fitted for a range of values from 3 to 8 on a sample two-dimensional dataset with 6 random point clusters. Here calinski_harabasz is chosen as the metric. This metric calculates the ratio of the variance between clusters and within clusters. The elbow in this case (black vertical dotted line) coincides with the value of k=4, this number is the optimal number of clusters. In this graph, the green dashed line again shows the time required to train the clustering model.

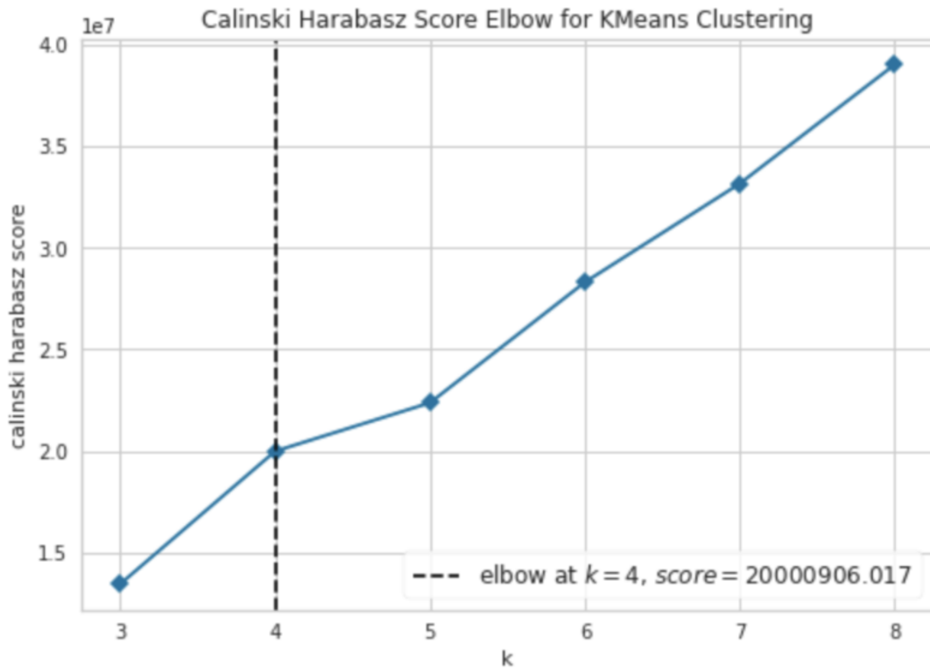

Figure 7: Calinski Harabasz Score Elbow for KMeans Clustering

3.3.4 K-Means Clustering

Next, the main part of segmentation is applying the KMeans clustering method to the data. The KMeans method is available in the 'sklearn' library. As it was obtained by the methods above the most optimal number of clusters is 4, therefore a partitioning into 4 clusters is assigned. The model is fitted on all data and then predicts the distribution of data into clusters. As a result, four clusters are obtained: 'Cluster 0', 'Cluster 1', 'Cluster 2', 'Cluster 3'; where all data is distributed with a percentage of 22.9%, 24.2%, 22.85%, 30.05% respectively.

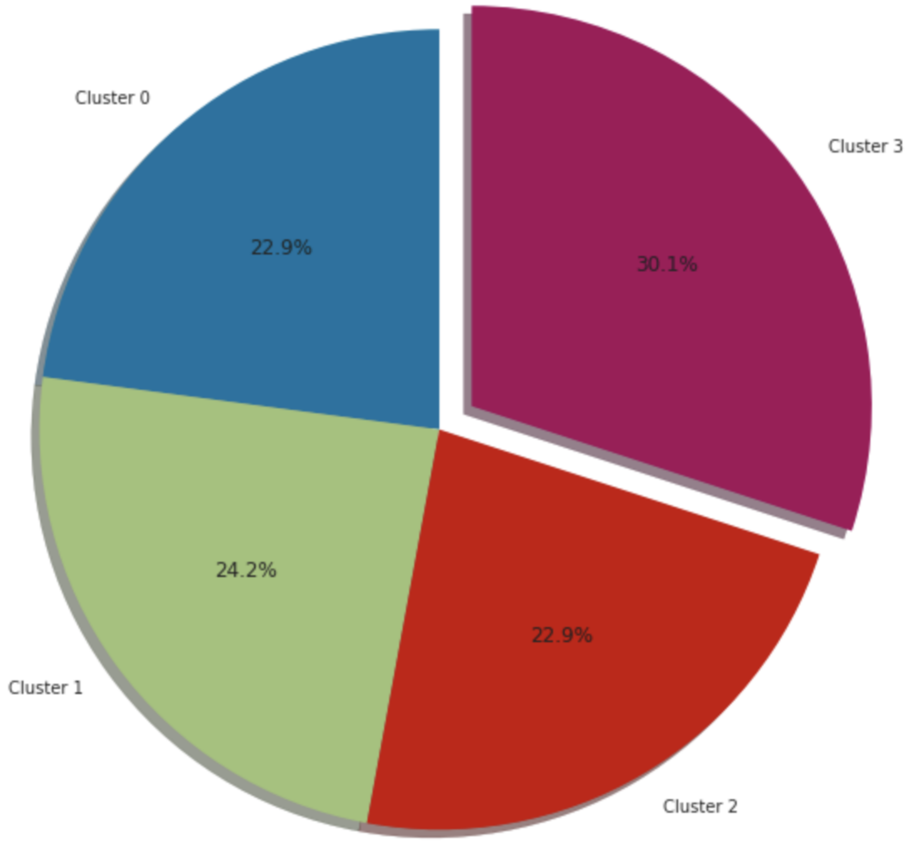

Figure 8: Clusters

3.3.5 Description of clusters

Finally, some descriptive statistics about how the data are distributed across clusters. The first graph below shows the distribution of items on a marketing campaign by cluster in percentage. One can see that the most items in the campaign were in the 'Cluster 1', and the least in the 'Cluster 2'. However, the difference in the number of such goods in the clusters is not significant and it can be said that the distribution is fairly even.

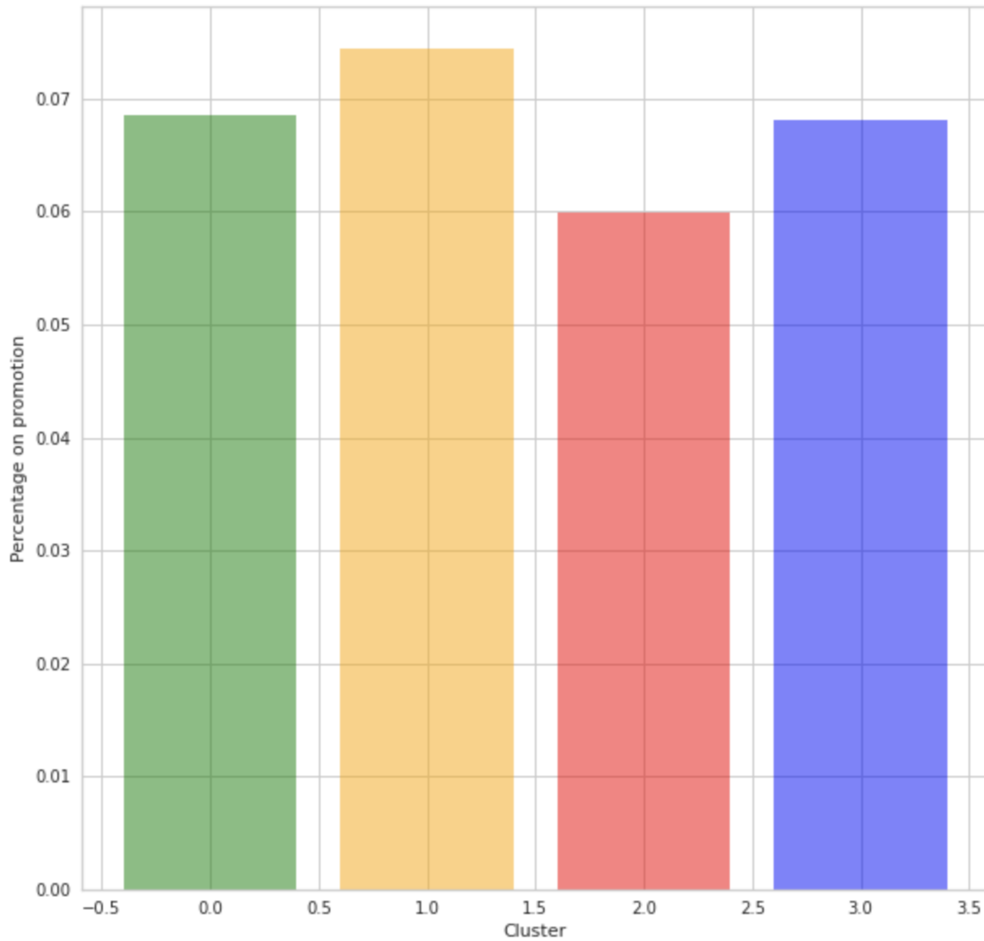

Figure 9: Category vs Cluster

The second graph shows how each store type is allocated to clusters: clusters are marked with different colours as indicated in the legend, the abscissa axis shows store types as they were named in the original table and the ordinate axis shows how many stores of a particular type belong to a particular cluster. It can be noticed that in general types A and D stores are in the clusters in higher numbers than the others, and each of the store types belongs to cluster number 3 with a higher probability.

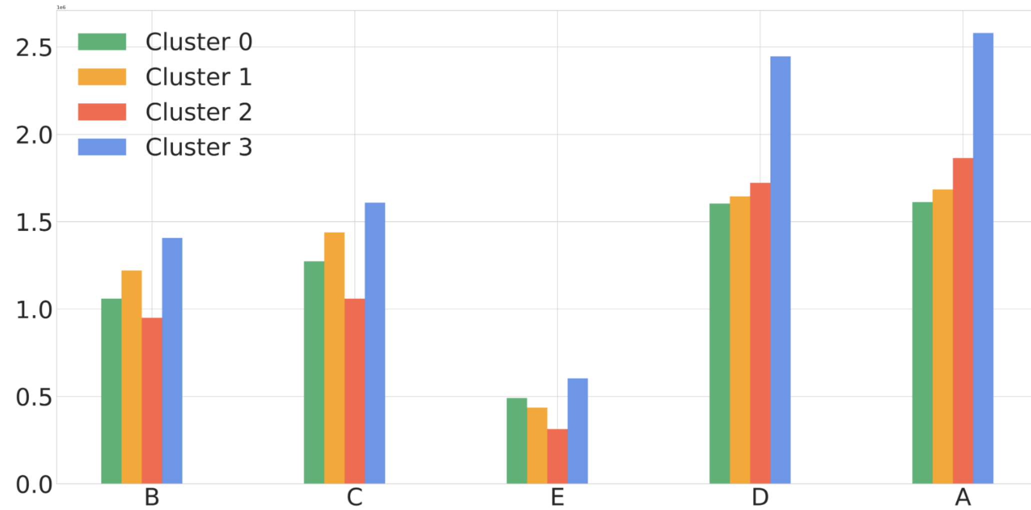

Figure 10: Clusters vs Stores

The third graph below demonstrates the distribution of goods that are perishable by cluster in percentage. One can see that the bigger part of perishable products is in the 'Cluster 3', and the least in the 'Cluster 2'.

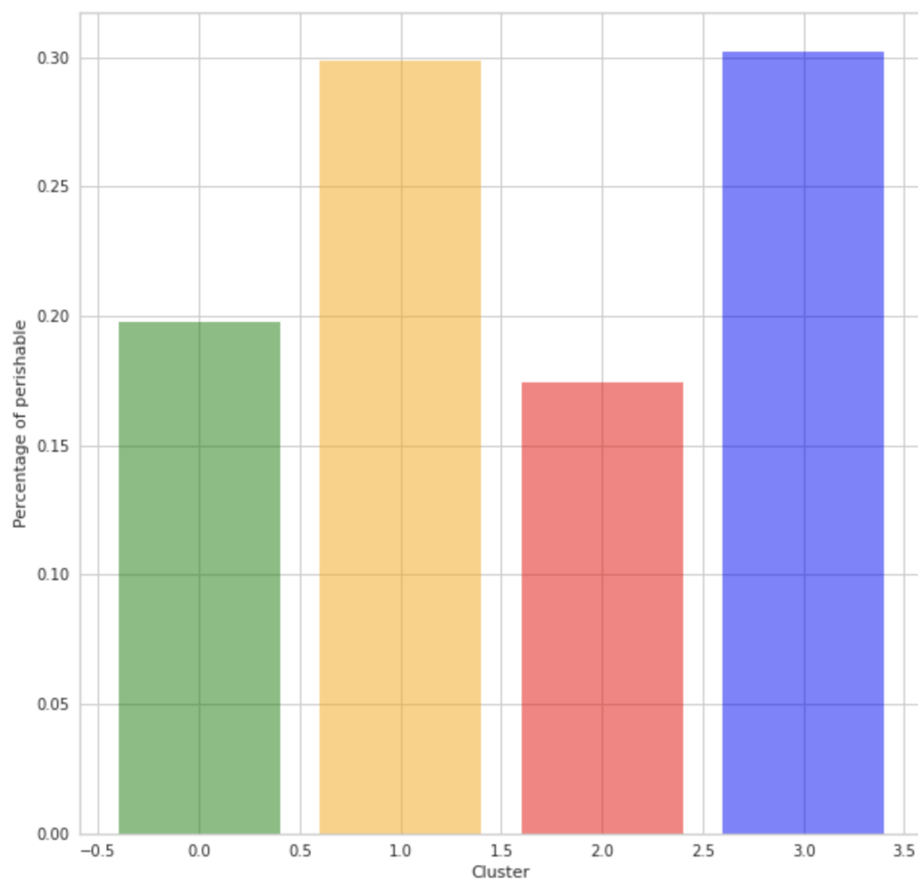

Figure 11: Cluster vs Perishable

4 Method Description

4.1 Mathematical formulation

This package, presented in both R and Python, implements an approach to estimate the causal effect of the developed intervention on the time series. For example, how did the advertising campaign affect website conversion rates, the number of daily clicks on certain products, customer returns, retail sales, etc? Such studies are quite difficult to conduct in the absence of the possibility of a randomised experiment, for example, in cases where it is impossible to identify a sample of people (a control group). However, there is a set of methods designed to address just such a problem, also known as Causal Impact inference.

The basic model used in this paper is called "CausalImpact". "CausalImpact" is a method developed by Google specifically for causal analysis of time series. The work of this model is based on fitting a Bayesian structural model of the time series to the observed (past) data. The past data to which this method is applied reflects everything that happened before the intervention at a particular time period. That is, for example, a marketing campaign that began on a strictly defined date, which is reflected in the change of the variable. A Bayesian structural time series model is used to predict the outcomes that would have occurred if there had been no intervention. And the model compares the predicted series with the actual series (the data that was actually observed) to draw statistical conclusions about the intervention.

In order to run the model, you necessarily only need the observed data - y; the covariates - X, which help the model via linear regression. We also need a well-defined period that shows everything as it was before the intervention and a period with data after the mentioned intervention.

Bayesian structural time series models can be stated by the equations:

$$y_t = Z_t^T \alpha_t + \beta X_t + G_t \epsilon_t a_{t+1} = T_t \alpha_t + R_t \eta_t \epsilon_t \sim N(0, \sigma_t^2) \eta_t \sim N(0, Q_t)$$

,where:

α - a "state" of the series

y_t - a linear combination of the states plus a linear regression with the covariates X

ϵ- measurement noise, that follows a zero-mean normal distribution

Z, T, G, R - matrices, by varying which several different models of time series behaviour can be simulated. For example, even the very famous ARMA and ARIMA.

In this package, any time series model that fits your data can be selected. If no model is used as input data, the local level is constructed by default. Then y_t is:

$$y_t = \mu_t + \gamma_t + \beta X_t + \epsilon_t \mu_{t+1} = \mu_t + \eta_{\mu,t}$$

- μ_t - random walk component (the "local level" component is used to model the moment in time; the component increases as other arguments do not add much signal to the explanation of the data, since just randomness is modeled and no needed information is added)

- γ_t - variable that models the seasonal components

βX_t - linear regression of covariates (better this component is lower than μ_t)

- ϵ_t - parameter modelling the noise associated with the y_t measurement (follows a normal distribution with zero mean and standard deviation - σ_ϵ)

Assumptions (reliable inferences require serious assumptions):

1. There is a set of control time series.

   There are time series that were not affected by the intervention. If not, there would be a risk of mistakenly underestimating or overestimating the true effect (or misidentifying the very presence of the effect).

2. The relationship established in the pre period between the covariates and the treated time series remains stable throughout the post period

4.2 Comparison with other methods

This test has several advantages over other statistical tests. First of all, this is the possibility of testing the effect on a certain long time period, where the effect is estimated over time. Classical methods, such as the t-test for equality of means before and after an intervention, test only for the change in the mean before and after the effect, without any temporal context.

The method used in this work is also somewhat similar to A/B testing, but there are several significant differences. First of all, it's about time. In A/B testing, the best result can be achieved by doing the test at the same time, making the test and control groups as homogeneous as possible. In our method, with the help of Bayesian time series, a synthetic control group is generated, with which a comparison is then made. Thus, since the time series is trained on the data before the intervention, then its predictions have the same properties and parameters. Therefore, we get that this method can be used offline, without the risk of creating heterogeneous control and test groups.

5 Results

5.1 Preparation

At the beginning of the work, we connect the library 'causalimpact' for python and load the data, which we sort in ascending order by date. For each date, the number of sales is counted (by the 'unit_sales' column) and a dataframe with columns is created:

x - indices (dates)

y - values (sales)

x1 - numbered dates (each date is assigned a number from 1 to n = number of dates)

x2 - promotions (number of promotions on a certain date)

By looking at the chart below we can see that the percentage of goods sold with promotion sharply increased at one moment in time. So, we can conclude that the store decided to start a big promotional campaign at that time so the percentage of goods sold on promotion increased from less than 10% on average to around 15%. It was found that the first day of the sharp increase in promotions is the 876th day from the first day in our dataset. So we decided that this is the date of the start of a new great promotional campaign.

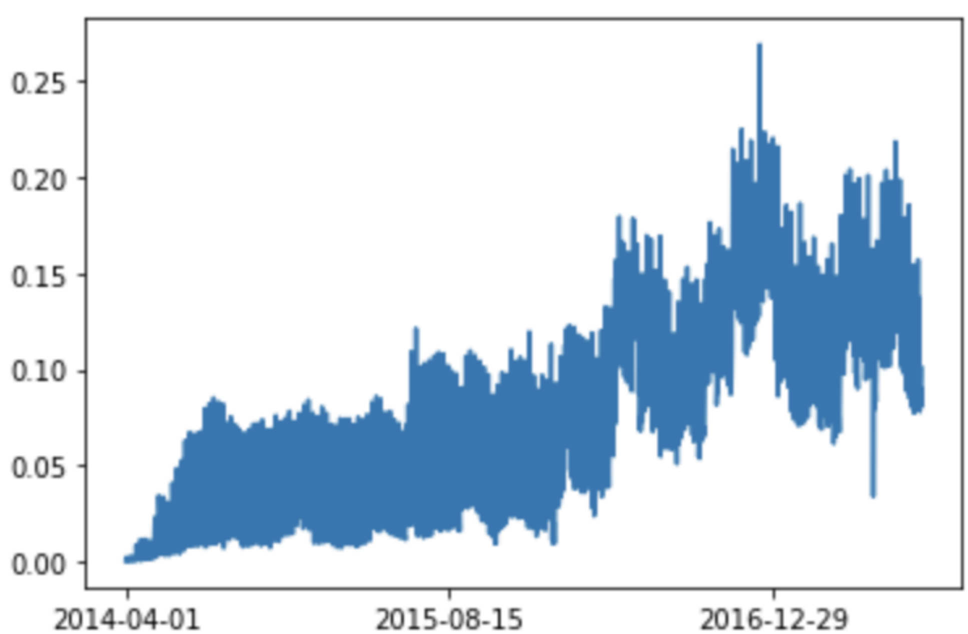

Figure 12: Goods Sold vs Time

5.2 Model for the whole data

Now we build the CausalImpact model by columns y, x1 and x2, that produces a graph that consists of three subgraphs. On each of the graphs, the grey dashed line corresponds to day 876 (the turning point). In the first graph, the red dotted line represents predicted sales, and the black line represents actual sales (this is indicated in the legend). The second graph shows the difference between the real data and the predicted sales at each point. This difference is shown by the red dotted line. Finally, the 3rd graph shows the cumulative effect. This graph is the most useful, it shows that after the tipping point the cumulative effect goes up. Accordingly, the overall effect is positive and sales did increase due to the intervention. Also, deriving the statistical summary, you can see that the causal effect has a positive response with a probability of about 90%, which is good enough.

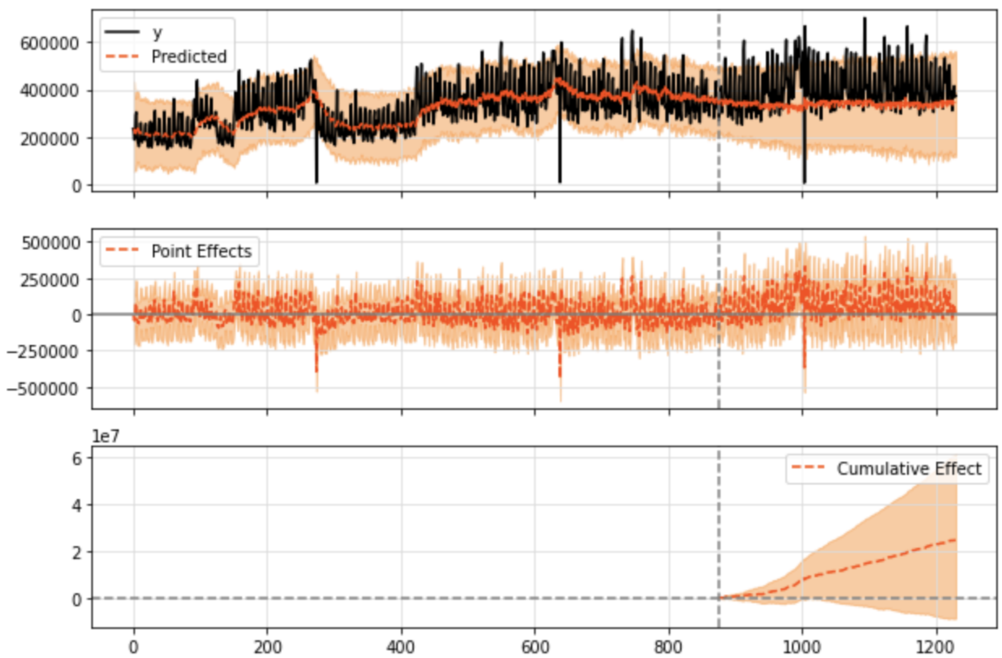

Figure 13: CausalImpact

5.3 Model for the stores

Next we build the same CausalImpact model, but in more detail - for each type of store. From the other graphs it can be obtained that for all types of stores the effect is about the same: the overall effect grows after the fracture. However, we can see that for stores of type B and C this growth occurs less sharply.

5.4 Determining individual promotions

It is worth noting that the processes described above can be called a general increase in the number of promotions. However, consider the case where there are products that have been sold for a very long time only with a marketing campaign applied to them in the form of a promotion. The study of such a case begins with the fact that a certain product (unique number) is considered and it is determined that if for 15 days or more it has been sold only with a promotion, then it is determined that some long promotion has been applied to it. The item was sold for more than two weeks with a discount only. We collect a file that reflects the id of the product, the number of days it was on promotion (the maximum number that is available is 138 days), and how many of its units were sold during those days with promotion.

Further, it was considered, if there is such a unique product and very long and carefully promoted it, whether it will be worse for some other products (its substitues) in the category to which the selected item belongs.

5.5 Testing the effect of individual promotions

So, let us study such an impact on the example of the already mentioned longest promotion of a single item. Promotion of this item lasts for 138 days and during this time it was sold 708 times. This item belongs to the "Home care" category, so we will study the effect of this promotion on the sales of this category (excluding this item sales from it). We will pick the sales of the promoted item as a covariate for CausalImpact as well as the number of promotions as we did previously on the whole data (again excluding the number of promotions of an item that we are studying). Besides the fact that not necessarily all the items in the "Home care" category should be the substitutes for our particular item, and some of them may be even complements, we can see on the figure below that increase in sales associated with a promotion in this item results in a decrease of sales for the whole category.

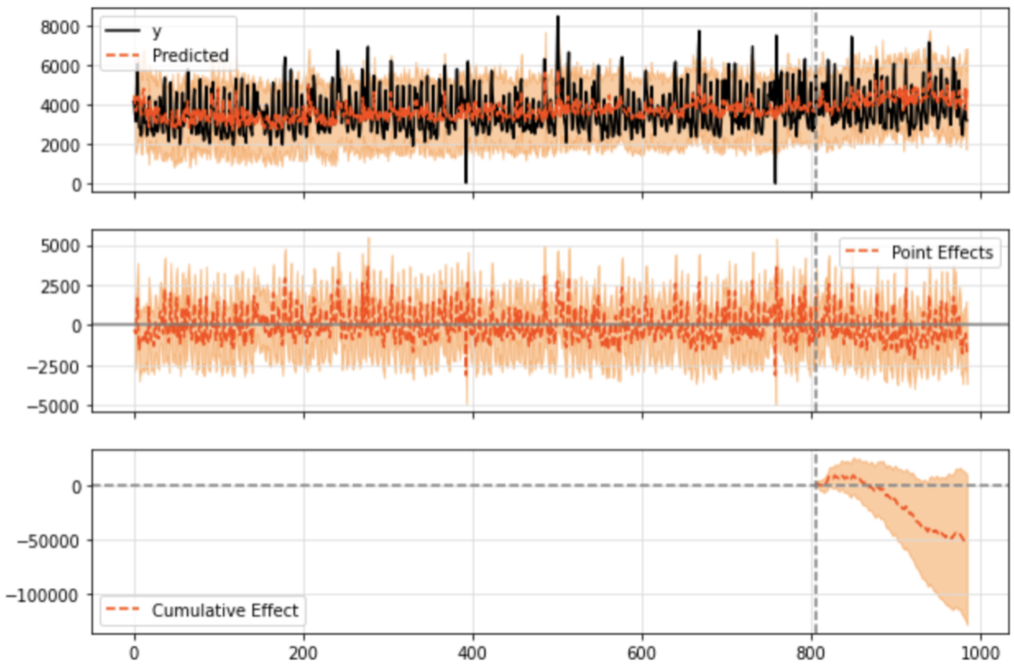

Figure 14: CausalImpact

Summarizing results on the effects of individual promotions

So, having this effect (eating up the purchase of goods in the category due to the promotion on one of them) on the longest promotion, the idea came up to test the presence of this effect on all such promotions, to track whether this effect happens massively. That is, consider all the cases where 100% of one good was sold with promotion for more than 15 days in a row, and statistically check how much the promotions taken affect the sale of other goods in the same category. In this way, it will be possible to identify how widespread the described phenomenon is, which is very important for research and the correct implementation of marketing campaigns, because in order to increase company profits, it is important to correctly distribute promotions and prices so that people spend more money on more profitable and important for the company products.

5.5.1 Key statistics

Then, let us calculate the key statistics: detailed data and exact figures are shown in the figure below. The average effect, which is a measure of the percentage change in sales in the presence of intervention, calculated at this point is negative and is about 5 percent. Which means that our concerns are confirmed - we should actually care of what items are promoted as the effect on the other items in the same category is on average negative. However, it is worth noting that the percentage of cases with a significant effect is about 47 percent, which equals almost half of the observations.

Considering only the significant part, we get the average significant negative effect, which is equal to 9 percent, which is greater (in absolute values) than the overall average effect. So, we can conclude that such effect does not always occur, but in cases where we can be statistically sure this effect is quite serious. Another statistic worth mentioning is the percentage of cases with a negative effect. The percentage of cases with a negative effect is approximately 70 percent, which implies that the negative average effect seen previously is not biased by some outliers, but actually shows us that negative effect is quite often a thing in our analysis. The confidence interval corresponding to this effect: [-0.437; 0.241]. This means that we can say with 90 percent confidence effect on the sales of the goods in the same category as promoted one, ranges from -43.7% to 024.1%.

```
Average effect: -0.05022148849202494
Percentage of cases with negative effect: 0.7065693430656934
Percentage cases with significant effect: 0.47883211678832116
Average significant effect: -0.09796420764178038
Confidence interval of effect: [-0.43706351132242455, 0.2411350960388638]
```

Figure 15: Statistics

Below is a two-part graph to make it clearer. This graph shows that all categories except school and stationery have a negative average effect. This phenomenon means that marketing campaigns and promotions should be applied with great caution to products in all of these categories, because increased attention to some products will lead to a decrease in the popularity of others. This is extremely dangerous for stores, as there is a chance of hurting the more marginal items and getting the opposite of the desired effect for the entire chain. The absence of such a strong effect in the above-mentioned exclusion category (school and office supplies) can be explained by the fact that stationery products are complementary goods and very many products are bought only in sets. For example, pens are bought with notebooks, and coloring books with colored pencils.

Figure 16: Categories

5.5.2 Logit analysis

After that, a logit analysis was also done. In it, the target was assigned 1 in the case of a negative effect on sales of goods in the same category as promoted one and 0 in the opposite case. As predictors we took the length of promotion in days and number of sold units of promoted goods. This analysis was carried out in order to show how these factors affect this effect. A table with statistics is attached further down.

	coefficient	**Standard error**	**z**	**p-value**	**[0.025**	**0.975]**
Items Sold	0.0022	0.001	2.854	0.004	0.001	0.004
Promo Length	0.0149	0.006	2.458	0.014	0.003	0.027

Figure 17: statistics

5.5.3 Coefficients' interpretation

The coefficients for both of the above indicators are statistically significant at the 95% confidence level, this can be seen by the p-value corresponding to the indicator

(<0.05). Thus, we can say that the number of goods sold and the length of the action have an impact on the presence of the effect under study. And having the coefficients positive, we can say that, for example, a greater length of promotion increases the probability of the presence of the effect (length of promotion to a greater extent than items sold). Or, in other words, have a positive relationship with the target. As we use logistic regression, relationship with the target can be described as follows:

$$probability\_of\_negative\_effect = e^{\beta_1 \cdot promo\_length + \beta_1 \cdot items\_sold}$$

Which in our case is:

$$probability\_of\_negative\_effect = e^{0.0149 \cdot promo\_length + 0.0022 \cdot items\_sold}$$

So, we can interpret the result in terms of both our variables as follows: Any additional day of promotion will multiply probability of negative effect in the whole category by $e^{0.0149} = 1.015$ i.e increase by 1.5% (do not mess up with percentage points increase!). It comes from the logit equation as

$$probability\_of\_negative\_effect = e^{0.0149 \cdot (promo\_length + 1) 0.0022 \cdot items\_sold}$$

$$probability\_of\_negative\_effect = e^{0.0149 \cdot promo\_length + 0.0149 + 0.0022 \cdot items\_sold}$$

$$probability\_of\_negative\_effect = e^{0.0149 \cdot promo\_length + 0.0022 \cdot items\_sold} \cdot e^{0.0149}$$

By the same logic, additional item sold in promotion will increase probability of negative effect in the whole category by $e^{0.0022} = 1.002$

So, making an intermediate conclusion, we can say that this study did reveal the impact of promotions on sales. In this case, we are talking about a campaign for a particular product, which absorbs the purchase of other products. In general, promotions have a positive impact because they increase the number of goods sold, but these purchased goods may be of the same type, as the action is not carried out on all goods and it is the goods on promotion that are bought in a greater volume, and this has a bad effect on the sales of separate groups of goods and can lead to a loss of significant profit if the goods on promotion are not marginal.

6 Conclusion

In this study, we looked at a very important question for retailers: how to properly apply marketing campaigns in order to get an increase in profits and not make things worse for the company. Currently, there are already methods that evaluate the impact of promotions on sales volume and other important indicators of campaign effectiveness. However, they all require a fair amount of time, effort and manual work to interpret the results correctly. This paper shows the most convenient way to solve the above problem. Google has developed a library that allows to estimate the causal effect on the process occurring over a period of time. We applied this library to track the effect in sales of a marketing campaign taken as an intervention. By constructing a time line and tracking when the intervention occurred and correctly selecting the products to which the action was applied, we used the CausalImpact model to show how the action affected the sales of products that were in the promotion and how it affected the sales of those products that remained at the same price and conditions. The study described that in general sales on the marketing campaign sold much better than before it, as well as much better than all the other products in the same category. This increase overall unit sales, but can be damagable for the profit of the promotion. It can be not optimal or even negative. This can happen due to the fact that promotions happened on less marginal goods "eat up" sales of more marginal goods. Such an outcome is, of course, deplorable for the store chain, which is why it is necessary to properly apply promotions to all merchandise. So, presented in this work mechanism of assesing promotion is a great tool for any retailer. By using proposed methodology retailer can easily indentify promotion of which goods is the optimal to increase its sales but not at cost of decreasing sales of more important items. Moreover, presence of Bayesian time series also implies that effect of the promotion on all the items can be predicted in all time points as the percentage change, and on base of this prediction retailer can more precisely asses and control future sales. Thereby, retailer can not only decrease number of unsuccessful promotions but also find optimal ones. For this, it is of course necessary to check all pairwise relations of goods in one category, such an analysis can be considered as the future work for this study.

Moreover, we need to know the price and margin of each product for a more accurate regulation of the promotionsand the skillful application of the method described to the data. The methos thus will be more concrete and retailers will be able to use it without any further development

References

[1] Carlos Aguilar, Sergio Munoz-Romero, and José Luis Rojo-Álvarez. Causal quantification of cannibalization during promotional sales in grocery retail. *IEEE Access*, PP:1–1, 02 2021.

[2] Kay H. Brodersen, Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. Inferring causal impact using bayesian structural time-series models. *The Annals of Applied Statistics*, 9(1), mar 2015.

[3] Sunil Gupta. Impact of sales promotions on when, what, and how much to buy. *Journal of Marketing Research*, 25(4):342–355, 1988.

[4] Carlos Aguilar Palacios, Sergio Muñoz Romero, and José Luis Rojo Álvarez. Forecasting promotional sales within the neighbourhood. 2019.

GitHub Repository

GitHub