Data Consultancy in Action

Impact of a Loyalty Program on the Buying Behavior of Customers

– TEAM 9 –
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Executive summary

This report presents the results of the project that was conducted together with L-Founders. L-Founders offers to design loyalty campaigns to retailers that aim to change the behavior of their customers, such that become more loyal. The goal of this project was to gain insights into the the effectiveness of a loyalty program that L-Founders provided for a large retailer. To achieve this, more detailed objective questions were formulated. Namely, did the loyalty campaign: Increase the total customer base, increase customer retention, increase total revenue, and reward the most loyal customers? During the analysis it was crucial to isolate the effect of the campaign such that external factors would not influence the result. One way to accomplish this, was to use a difference-in-difference analysis to account for changes over time.

The analysis produced the following results. Customers that redeemed their reward in the loyalty campaign became significantly more loyal compared to non-redeeming customers. Moreover, it was found that the number of redeeming customers increases when loyalty increases. Hence, it could be concluded that the loyalty campaign rewarded loyal customers more than non-loyal customers. The results also showed that the campaign had effects on revenue and the number of store visits. There was a significant increase in the revenue in the post-treatment period while controlling for external effects by 1.47 million per day (the currency is unknown is this case). In addition, the number of total visits was also significantly increased by 273 extra visits per day in the post-treatment period, again controlling for external effects. Finally, it was found that the campaign had the strongest effect on Friday.

Introduction and Background

This report presents the findings of a consultancy project conducted in collaboration with L-Founders, a leading group specializing in tactical loyalty solutions for food retailers. L-Founders aims to modify customer behavior by offering high-quality rewards at substantial discounts through their loyalty programs. By incentivizing customers to collect stamps, which can be redeemed for rewards, the retailer seeks to increase customer loyalty, frequency of store visits, and overall basket size.

L-Founders has engaged in a collaboration with a master course at the Jheronimus Academy of Data Science (JADS) in the form of a consultancy project with a twofold purpose: to assess the methodologies employed by students and to leverage the findings to enhance their own processes for future consultancy projects. This collaboration allows L-Founders to gain fresh insights while providing an valuable learning experience for the students, enabling them to apply their theoretical knowledge to real-world scenarios. Under guidance of Ruud Jansen, Global Director Data & Analytics, and PhD. Alec Minnema, Director Loyalty at PRIME, the project was shaped and the objectives were identified.

A large supermarket chain, for this report assumed to be stationed in the Netherlands, has implemented a loyalty campaign, and they now are interested in detailed insights into its effectiveness. Selecting a robust measurement methodology that can isolate the effect of the loyalty program is essential for providing the client with relevant insights on their campaign success. Given the dynamic nature of the retail market, which is influenced by various internal and external factors such as inflation, competition, and seasonality, it is essential to develop a methodology that effectively isolates the impact of the loyalty program from other factors. Moreover, the chosen methodology should be easily understandable by non-technical audiences and applicable to tactical loyalty programs worldwide.

The primary objective of this consultancy project is to analyze the impact of the supermarket chain its loyalty campaign. The project its terms of reference boil down to the following key aspects:

1. Measurement Methodology - Develop a measurement methodology that can isolate the effect of the loyalty program while considering the influence of other internal and external factors affecting the food retail market. The methodology should be easily explainable to non-technical audiences and applicable to similar loyalty programs globally.

2. Insights and Recommendations - Provide detailed insights into the effectiveness of the loyalty campaign, identifying customer segments that have exhibited changes in behavior. Additionally, offer recommendations for enhancing future campaigns based on the drivers of the current campaign.

Using these general key aspects and the input of L-founders, the following more detailed objectives were identified:

- Increase Customer Base - By analyzing the number of unique customers, the growth rate can be tracked and factors can be identified that contribute to customer acquisition. Additionally, the customer acquisition trends over time will also be examined to uncover patterns and accordingly target strategies to attract new customers.

- Increase Customer Retention - Retaining existing customers is equally important as acquiring new ones. Understanding customer churn and identifying the factors that contribute to it can help implement targeted retention strategies and enhance customer loyalty.

- Increase Total Revenue - Driving revenue growth is a fundamental objective for any business. By analyzing revenue trends over time, we can identify periods of growth or decline and uncover the underlying factors driving these trends.

- Reward Existing customers - Recognizing and rewarding existing customers is crucial for fostering long-term relationships and increasing customer satisfaction. By analyzing customer segments, insights can be gained into the different types of customers that shop at the supermarket. This information can be used for targeting marketing campaigns to incentivize existing customers and enhance their loyalty. Besides, it should be evaluated whether the right customer groups were rewarded.

By undertaking this consultancy project, we aim to support the supermarket chain in their pursuit of understanding the impact of their tactical loyalty campaign and empowering them to make informed decisions for future endeavors.

Data description

The data is stored in Parquet files and was made accessible through an AWS (Amazon Web Services) S3 bucket by L-Founders. The provided data consists of a diverse set of information that is of relevance for analyzing the impact of the loyalty program on customer buying behavior. Each row is a transaction done by a customer, the dataset contains over three million transactions whereas there are over forty thousand unique customers. The data did not contain any duplicates nor missing values in the columns that were used in this analysis.

The dataset provides a rich source of transactional data spanning approximately 1.5 years, offering an extensive foundation for analyzing customer behavior. Key columns include customer IDs, transaction dates, revenue per transaction, and quantity per transaction. However, for the purpose of this analysis, the quantity per transaction information has been disregarded due to inconsistencies in measurement units.

The store data within the dataset comprises numeric IDs, serving as unique identifiers for the stores participating in the loyalty program. There is also a column indicating the type of store. Additionally, the dataset includes data pertaining to customer segments, providing insights into different customer groups. However, since the data has been fully anonymized, this particular variable did not contribute to the analysis either.

Furthermore, the dataset includes binary information indicating whether specific customers were redeemers or not, highlighting their participation in the loyalty program. For this dataset, 32 % of the customers were redeemers. This binary variable serves as an important aspect in understanding the impact of the loyalty program on customer behavior.

The dataset includes period data that specifically captures information regarding the promotional periods associated with the loyalty program. Notably, the data is structured into four distinct periods: Pre-Program This Year, Program Period This Year, Pre-Program Last Year, and Program Period Last Year. Each period is 140 days and the start of period 1 is at 2020-06-29, the end of period 4 is at 2022-04-03. This means that COVID-19 has been part of the measurement data which should be noted during isolation of the campaign effect.
This division facilitates comparative analysis across different time frames, enabling a comprehensive understanding of the loyalty program its effectiveness over time. By leveraging the period data, additional features can be identified to enhance the analysis. These features encompass details such as the duration, timing, and specific characteristics of the promotional periods.

Methodology

For the first objective, the loyalty score needed to be defined. This was done through an extensive literature review. Common practise in the relevant literature suggested to include several metrics to calculate the loyalty score. These metrics depend on the available data, statistical methods and preferences of the writer, but included the following factors: Purchase frequency [1], Purchase amount [2], Customer retention rate [3], Net Promoter Score [4], Repeat purchase rate [5] and Engagement [6].
As discussed, the data this research received was rather slim, and therefore the usage of some of the factors was not possible. The loyalty definition of this research consisted of the amount of visits, purchase amount, and purchase fluctuation. All these factors were given a weight of $\frac{1}{3}$, to give an equal importance to each of the contributing factors. The normalized visits score was defined by counting the number of visits per customer and calculating the average amount of visits. Then, the visits score is calculated by dividing the amount of visits by the average. This score is then normalized using the following formula: $\frac{Visits\_score - mean\_visits\_score}{std\_visits\_score}$ The second component of the loyalty definition is calculated similarly, but by replacing number of visits with the amount of money spent. The third component required a more elaborate approach. Firstly the average purchase amount fluctuation per customer and in total are calculated by using the standard deviation. After this, this value is normalized by subtracting the mean and dividing by the standard deviation. Then, the values are mirrored to ensure the direction of fluctation_score is the same as the other two components.
After the definition, the customers are distributed in 5 loyalty groups, based on their value of the loyalty score. The groups were constructed as follows:

$$max\_value = loyalty\_score.quantile(0.75) \tag{1}$$

$$min\_value = loyalty\_score.quantile(0.25) \tag{2}$$

$$step = \frac{abs(min\_value) + abs(max\_value)}{5} \tag{3}$$

This was done twice, once for period 1-3 and once for period 4, in order to calculate how many customers moved to different loyalty groups during the campaign. This is an important metric for retailers to assess the success of a loyalty campaign. In addition to this, it allows calculating how many people redeemed the loyalty campaign in the last period, which is used to assess the success of the first objective. The findings of these calculations will be elaborated upon in the Findings section.

Group	**Subset (on loyalty_score)**
Very Loyal	*> max_value*
Really Loyal	*> min_value + (step*3) & < max_value*
Average	*> min_value + (step*2) & < min_value + (step*3)*
Not really Loyal	*> min_value + (step*1) & < min_value + (step*3)*
Not Loyal	*< min_value + (step*1)*

Figure 1: Loyalty group definitions

In order to effectively evaluate whether the loyalty program has achieved its objectives of increasing the customer base and total revenue, it is crucial to develop a methodology that can account for external factors that may influence the outcomes, such as inflation, weather changes, seasonality, etc. The chosen evaluation method needs to be resistant to these external factors to ensure that any observed changes in the customer base and total revenue can be attributed specifically to the loyalty program, rather than being influenced by other factors beyond its control.

Among the common techniques available for evaluating the impact of the loyalty program, two main approaches were considered: Difference-in-Differences (DID) [7] and Regression Discontinuity (RD) [8] analysis.

The DID approach was selected as the preferred method due to its ability to address external factors and effectively isolate the causal effect of the loyalty campaign. By examining the differences between-yearly and within-yearly effects of the year before the loyalty program (periods 1 & 2) and the during program year (periods 3 & 4), DID allows for the consideration of external factors while evaluating the program's impact. In contrast, employing Regression Discontinuity (RD) would involve comparing the loyalty program period (period 4) with all other periods (periods 1, 2 & 3), which would not enable the explicit control of yearly factors. Additionally, RD analysis was not feasible in this case due to the presence of a gap between periods 2 and 3. Therefore, the DID approach was deemed more suitable for our evaluation.

DID approach involves comparing two distinct groups: the control group and the treated group. In our case, the treated group corresponds to the period during the loyalty program year, while the control group represents the year prior to it. The outcome variable of interest is the number of customers.

To estimate the treatment effect of the loyalty program, the changes in the number of customers between the treatment and control groups are compared. Specifically, the difference in the change in the number of customers between the treatment and control groups during the loyalty program period (period 2 and 4) and before the loyalty program periods (period 1 and 3) is examined. This approach allows for the assessment of the differential impact of the loyalty program.

To assess the statistical significance of this difference, either a t-test or a regression model can be employed. These statistical tests allow us to evaluate whether the observed difference in the treatment effect is statistically significant, indicating that it is unlikely to have occurred by chance alone.

Figure 5 visually demonstrates the concept of comparing the changes in the outcome variable (number of customers) between the treated and control groups over time and highlights the computation of the treatment effect using the DID methodology.

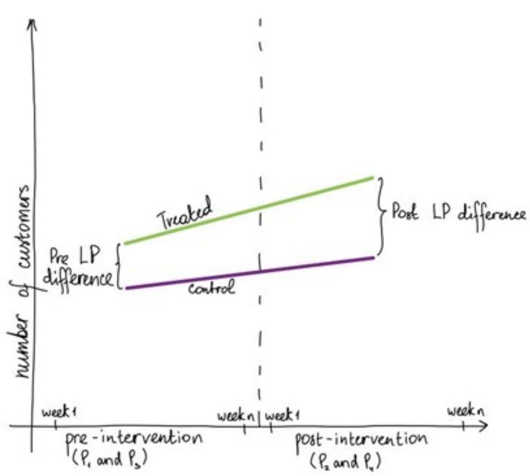


Figure 2: Difference in differences

By defining the outcome variable as total revenue instead of the number of customers, this methodology can be adjusted to evaluate the effects of the loyalty program on revenue.

Findings

To see whether the loyalty campaign succeeded in rewarding the most loyal customers, the first step is to see whether the campaign influenced the loyalty of the customer. This is achieved by calculating the loyalty score in periods 1-3 and calculating the loyalty score in period 4. After this, a check is constructed to see whether a customer moved to a different group. This is done for redeemers and non-redeemers. The results of this can be seen in the two figures below.

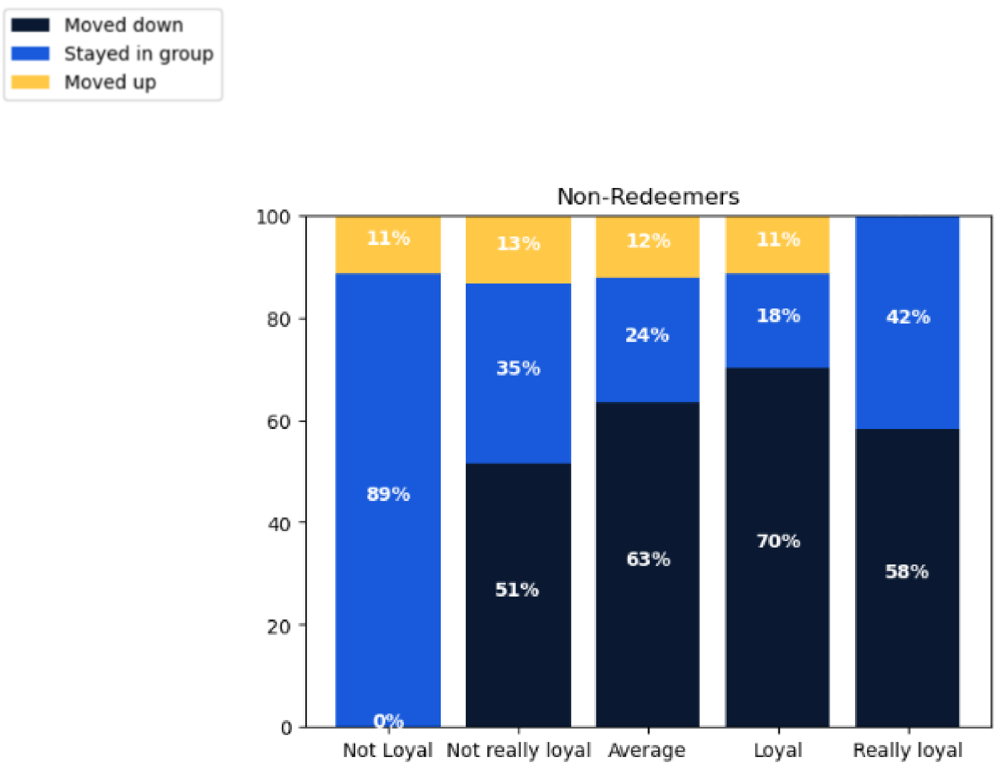


Figure 3: Loyalty group movement of Non-Redeemers

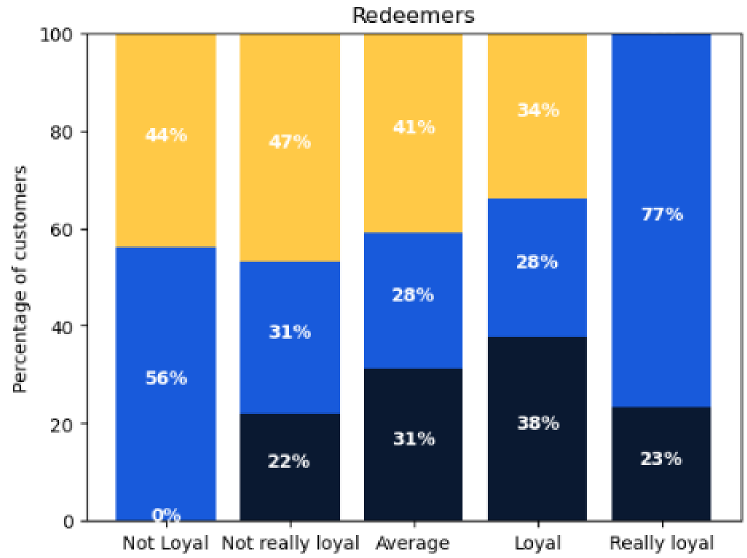


Figure 4: Loyalty group movement of Redeemers

Redeeming customers demonstrated a shift towards more loyal groups, highlighting a positive influence on loyalty scores. In essence, customers who did not redeem the loyalty campaign showed limited potential for increased loyalty. Conversely, customers who did redeem the campaign exhibited enhanced loyalty throughout the campaign. Additionally, customers who redeemed the loyalty campaign were less prone to decreased loyalty compared to those who did not redeem it.
Using the loyalty groups from period 1-3 from the Methodology section, the average amount of redeemers per group has been calculated. The results can be found in Figure 4.

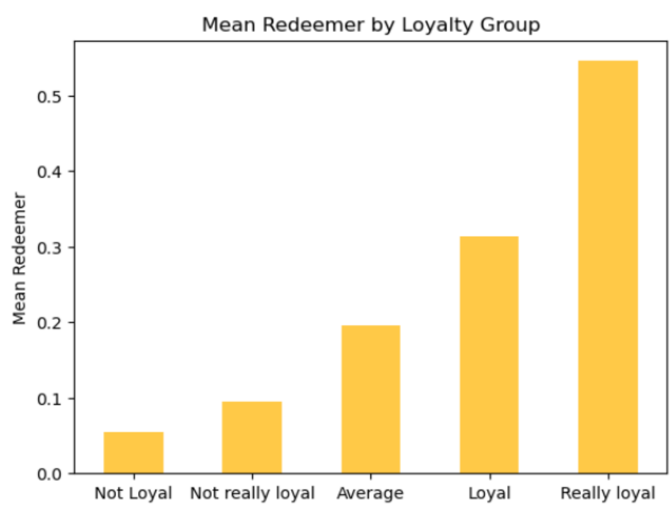


Figure 5: Average amount of redeemers per loyalty group

As can be seen, the more loyal the customer is, the higher the Mean Redeemer value. This means that the number of redeeming customers increases when loyalty increases. Therefore, it can be

concluded that the loyalty campaign rewarded loyal customers more than non-loyal customers. This conclusion is also backed up by the results of all the statistical tests. All the tests indicated that there was a significant difference between the mean Redeemer of one group, compared to the other group. This is done for all possible combinations of groups. The result of this can be found in Appendix B. This indicates that the loyalty campaign was successful in the first Objective of rewarding the most loyal customers.
In conclusion, the loyalty campaign effectively incentivized and rewarded the most loyal customers. By analyzing customer loyalty scores, loyalty group transitions, and the proportion of redeemers in each loyalty group, a clear picture emerges, indicating that the campaign positively influenced customer loyalty and successfully achieved the objective of rewarding the most loyal customers.
To evaluate the impact of the loyalty campaign on customer behavior, the effect was isolated using the previously discussed method known as difference in differences. The impact of the loyalty campaign on the total revenue and the total number of visits for all stores was examined. This was accomplished by aggregating the data per day and subsequently creating boolean variables "treatment" and "post," which indicated whether the day belonged to the first year (pre-treatment year) or the second year (the treatment year), and whether the period was the first part (pre-treatment) or the second part (post-treatment) of the year, respectivly. By generating interaction variables between "treatment" and "post," the effect of the loyalty campaign could be isolated while controlling for seasonal effects (e.g., holidays, weather seasons) and yearly effects (e.g., inflation rates, governmental policies). The OLS - linear regression model was employed to evaluate the effects. The interpretation of the results focused on the coefficient of the interaction term "treatment-post." It was determined that there was a significant increase in revenue during the post-treatment period, amounting to 1.47 million per day, while controlling for the aforementioned time-related effects. Moreover, the total number of visits also experienced a significant increase of 273 visits per day during the "treatment-post" period, with all time-related effects held constant. It is important to note that for the model to estimate the underlying effects of the loyalty campaign, the assumption that the time-related trends observed in the previous periods persist in the "treatment-post" periods must hold true.
In order to enhance our comprehension of the most effective timeframe for the loyalty campaign, additional variables, including indicators for days of the week, were incorporated into the linear regression model. This decision was made based on our observations during the data exploration phase, where we identified varying seasonal effects within the two years of the provided data. Please refer to Figure 6 for further details on the revenue per day.

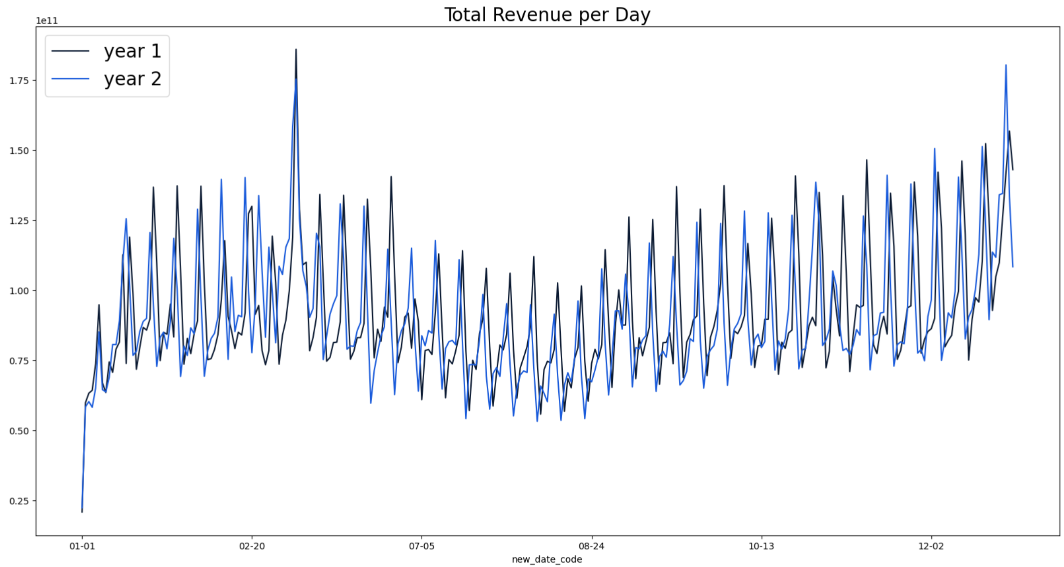
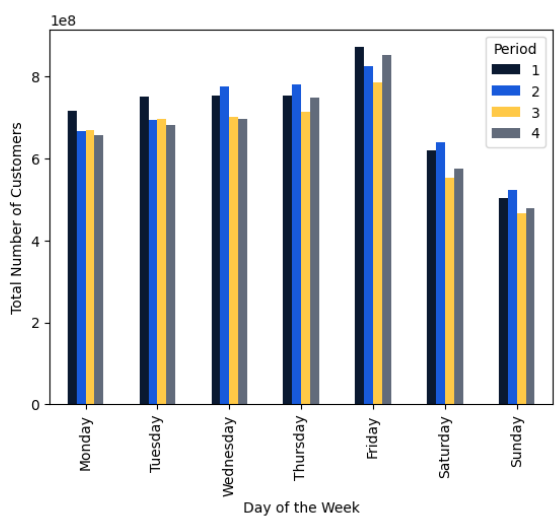
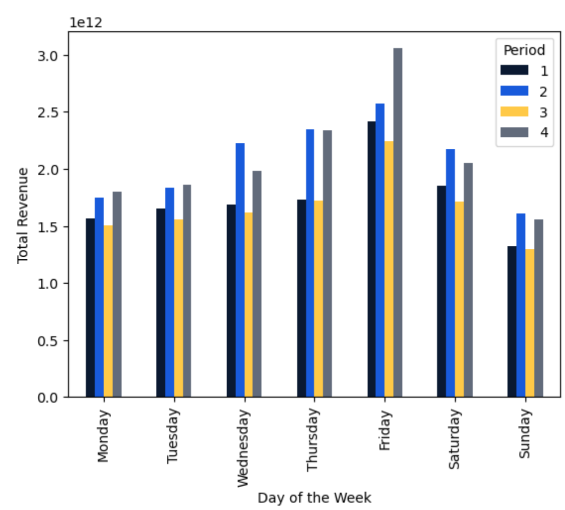


Figure 6: Total Revenue per Day

The findings indicate that Fridays exhibited the most pronounced impact from the loyalty campaign. In comparison to other days, Fridays experienced a stronger effect, resulting in an additional expenditure of 2.45 million and an increase of 208 customers per day, while holding all other factors constant. To provide a visual representation of the revenue and the number of customer visits across weekdays and time periods, please refer to Figure **??**.



(a) Number of Customers per Day per Period



(b) Revenue per Day per Period

Moreover, in order to examine whether the effect of the campaign varied throughout the weeks, the variable indicating the week number was included, along with its interaction with the treatment-post period. The results have revealed that, on average, the effect diminished as time progressed from the beginning of the campaign. Specifically, there was a decrease of 20 visits per week and a reduction in revenue of 104 thousand for each consecutive week. This effect could potentially be attributed to a decline in people's confidence in being able to redeem the campaign's reward as the weeks elapsed or due to a change in the marketing strategy towards weekends. To estimate the effect of the loyalty campaign on both the average customer and customers belonging to different loyalty groups, the data was aggregated in a manner where each row represented aggregated information about a customer's purchase history within a specific time period. Consequently, for customers present in all four periods, four rows of data were available. The primary focus was on investigating the impact of the loyalty campaign on customers who actively participated as redeemers. A comparison was made between these customers' behavior before and after the campaign commenced, while accounting for time-related effects, as previously explained.

The previously established model was adapted with the newly aggregated data, incorporating indicators to identify whether a customer was a redeemer or not. The analysis revealed that, on average, customers who redeemed increased their store visits by 8 and revenue by 54 thousand during the loyalty campaign period. Both of these increases were statistically significant.

Additionally, a custom classification of customers into different loyalty groups was performed, considering only data prior to the loyalty campaign. The objective was to assess how the effects of the loyalty campaign varied across these groups. By introducing interaction terms between loyalty groups, treatment-post periods, and the redeemer indicator, the campaign's effects for each variable were estimated.

Regarding the number of visits, the strongest effect was observed among the "not loyal" and "not so loyal" customers. In other words, the customers who were least loyal but participated in the loyalty campaign significantly increased their store visits compared to before. Concerning the increase in revenue, the most substantial effect was found among the "not loyal" and "really loyal" customers. This indicates that both the least and most loyal customers demonstrated the highest increase in spending at the store due to the loyalty campaign.

Recommendations

In this section, a number of actions that the client is advised to take will be discussed. These recommendations are all focused on the data gathering process, because during the project it was found that the data was somewhat unsuitable or even incomplete to come up with a solution to answer some objective questions. Hence, the inconveniences of the dataset will be discussed and solutions are provided such that in future projects these problems can be avoided.

Lack of data before period 1

During a conversation with L-Founders, an important objective question was identified: Did the loyalty campaign attract new customers? This question is of great interest to retailers as they aim to acquire new customers through loyalty campaigns to increase revenue and gain an advantage over competitors. However, the current dataset does not allow us to answer this question effectively.

The dataset covers four periods: period 4 represents the loyalty campaign period, period 3 represents the weeks before the campaign, period 2 corresponds to the same period as period 4 but from a year earlier, and period 1 represents the weeks before period 2. To answer the objective question, we need to compare the difference in the number of new customers between period 3 and 4 with the difference between period 1 and 2. This requires information on the number of new customers in all periods.
To determine the number of new customers in a given period, we subtract the count of "old" customers (those who have previously shopped with the retailer) from the total count of distinct customers in that period. However, the issue arises in period 1 where we lack information about the number of "old" customers since the dataset doesn't include data before the start of period 1. To address this, the client should include data from the weeks preceding period 1. This additional data will enable us to calculate the count of "old" customers for period 1 and accurately assess the impact of the loyalty campaign on new customer acquisition.

Lack of usable variables

The dataset provided has limitations in terms of variables, which hinders the production of reliable predictive models. Additionally, some of the variables are ambiguous or not usable for analysis.

For example, the customer segmentation variables are undefined, making it challenging to assess if loyal customers are being rewarded more in the loyalty program. To address this, the team had to create new customer segments based on loyalty, resulting in extra time and effort. In future projects, it would be beneficial to have explanations for all variables, including customer segmentation, to streamline the analysis process.
Another problematic variable is "quantity," which captures the number of items purchased per visit. However, it is inconsistently defined for certain items like minced meat, where the quantity is measured in grams instead of the number of packages. This inconsistency makes it impossible to compare cases accurately. A potential solution is to redefine the quantity variable, ensuring similar cases have a comparable quantity value in the dataset. For example, applying a rule that 100 grams equals 1 portion would standardize the measurement. Adjusting the quantity variable's definition

would enhance its accuracy and enable its use in the analysis. In objective 1, the quantity variable could even be employed to define loyal customers since they are likely to make purchases with higher quantities.
Furthermore, the dataset lacks certain variables that could be valuable for analysis. For instance, including a variable indicating whether a customer is new (their first appearance in the dataset) would address the issue of identifying new customers in period 1.
To summarize, the limitations of the dataset include the lack of data before period 1, which prevents assessing the impact of the loyalty campaign on new customers. Ambiguous or faulty variables, such as customer segmentation variables, further hinder the analysis. The dataset's lack of continuity also restricts the applicability of certain statistical tests, like regression discontinuity tests. //
To address these limitations in future projects, the following steps should be taken:

- Include information about customers' first appearance in the database to identify new customers or include data before period 1 to track their behavior accurately.

- Define ambiguous variables clearly, ensuring a consistent understanding of their meaning and computation.

- Redefine the "quantity" variable to make it more reliable and comparable across different items, considering standardization or a consistent measurement approach.

- Fill the gap between period 2 and 3 in the dataset to make it continuous, enabling the use of additional statistical tests like regression discontinuity tests.

By implementing these improvements, future projects can overcome the limitations, enhance the accuracy of analysis, and save time and effort in data processing and interpretation.

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Appendices

A. Data Ethics Canvas

Figure 8: Data Ethics Canvas

B. Results of loyalty group tests

Comparison	Ranksums Statistic	Ranksums p-value	Median Test Chi2-Statistic	Median Test p-value	Mann-Whitney U Statistic	Mann-Whitney U p-value	Kruskal-Wallis Statistic	Kruskal -Wallis p-value
Very Loyal vs Loyal	49.4642	0.0	2143.5237	0.0	2815344.0	0.0	2446.7068	0.0
Very Loyal vs Average	54.0689	0.0	1793.8069	0.0	4897746.0	0.0	2923.4457	0.0
Very Loyal vs Not really Loyal	57.8877	0.0	1564.4447	0.0	9497817.0	0.0	3350.9880	0.0
Very Loyal vs Not Loyal	60.1529	0.0	1448.9144	0.0	18076149.0	0.0	3618.3657	0.0
Loyal vs Very Loyal	-49.4642	0.0	2143.5237	0.0	0.0	0.0	2446.7068	0.0
Loyal vs Average	63.6639	0.0	3348.0775	0.0	7877856.0	0.0	4053.0900	0.0
Loyal vs Not really Loyal	70.1698	0.0	2756.7824	0.0	15276912.0	0.0	4923.8006	0.0
Loyal vs Not Loyal	74.3192	0.0	2457.4345	0.0	29074864.0	0.0	5523.3404	0.0
Average vs Very Loyal	-54.0689	0.0	1793.8069	0.0	0.0	0.0	2923.4457	0.0
Average vs Loyal	-63.6639	0.0	3348.0775	0.0	0.0	0.0	4053.0900	0.0

Figure 9: Loyalty Group statistical tests results 1

Comparison	Ranksums Statistic	Ranksums p-value	Median Test Chi2-Statistic	Median Test p-value	Mann-Whitney U Statistic	Mann-Whitney U p-value	Kruskal-Wallis Statistic	Kruskal -Wallis p-value
Average vs Not really Loyal	85.5966	0.0	5609.0132	0.0	0.0	0.0	6074.5931	0.0
Average vs Not Loyal	94.1874	0.0	4914.1395	0.0	0.0	0.0	7124.6029	0.0
Not really Loyal vs Very Loyal	-57.8877	0.0	1564.4447	0.0	0.0	0.0	3350.9880	0.0
Not really Loyal vs Loyal	-70.1698	0.0	2756.7824	0.0	0.0	0.0	4923.8006	0.0
Not really Loyal vs Average	-85.5966	0.0	5609.0132	0.0	0.0	0.0	6074.5931	0.0
Not really Loyal vs Not Loyal	10.4040	0.0	4933.0130	0.0	98047608.0	0.0	8773.0214	0.0
Not Loyal vs Very Loyal	-60.1529	0.0	1448.9144	0.0	0.0	0.0	3618.3657	0.0
Not Loyal vs Loyal	-74.3192	0.0	2457.4345	0.0	0.0	0.0	5523.3404	0.0
Not Loyal vs Average	-94.1874	0.0	4914.1395	0.0	0.0	0.0	7124.6029	0.0
Not Loyal vs Not really Loyal	-10.4040	0.0	4933.0130	0.0	0.0	0.0	8773.0214	0.0

Figure 10: Loyalty Group statistical tests results 2

Comparison	Ranksums Statistic	Ranksums p-value	Median Test Chi2-Statistic	Median Test p-value	Mann-Whitney U Statistic	Mann-Whitney U p-value	Kruskal-Wallis Statistic	Kruskal -Wallis p-value
Not really Loyal vs Loyal	70.1698	0.0	2756.7824	0.0	15276912.0	0.0	4923.8006	0.0
Not really Loyal vs Average	85.5966	0.0	5609.0132	0.0	0.0	0.0	6074.5931	0.0
Not really Loyal vs Not Loyal	10.4040	0.0	4933.0130	0.0	98047608.0	0.0	8773.0214	0.0
Not Loyal vs Very Loyal	-60.1529	0.0	1448.9144	0.0	0.0	0.0	3618.3657	0.0
Not Loyal vs Loyal	-74.3192	0.0	2457.4345	0.0	0.0	0.0	5523.3404	0.0
Not Loyal vs Average	-94.1874	0.0	4914.1395	0.0	0.0	0.0	7124.6029	0.0
Not Loyal vs Not really Loyal	-10.4040	0.0	4933.0130	0.0	0.0	0.0	8773.0214	0.0

Figure 11: Loyalty Group statistical tests results 3