Customer Analytics

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Introduction

This report outlines the findings from analyzing customer habit patterns for the year 2017.

Purpose of the Analysis

Understanding customer behaviour and loyalty, leverage customer information to profitably optimize engagement and predict future demand across all customer touch points using high-level KPIs and statistical modelling methods.

Methodology

Before starting the analysis it is important to segment the customers, with RFMscore that is based on 3 main factors: *Recency* of last purchase, *Frequency* of purchase and *Monetary* value of customers.

RFMscore = w1 * Recency + w2 * Frequency + w3 * Monetary value

w = weight

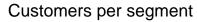
Using the above formula the following six classes are formed.

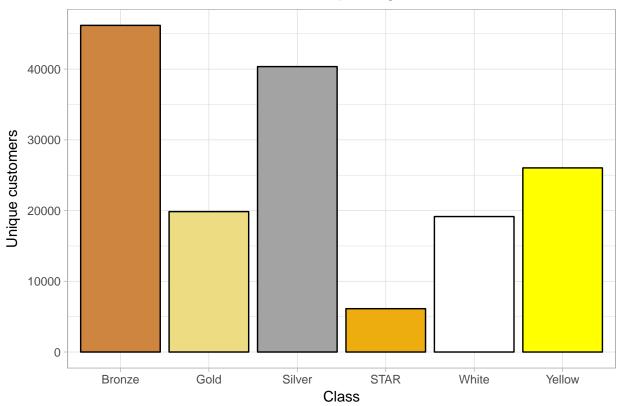
##		${\tt Classes}$	${\tt Count}$	<pre>Sum(Grandtotal)</pre>	${\tt Sum}({\tt Transactions}$	Avg_basket
##	1	Bronze	46186	1428048	74153	19.3
##	2	Gold	19853	3188052	133618	23.9
##	3	Silver	40357	2792465	117897	23.7
##	4	STAR	6128	1601385	68999	23.2
##	5	White	19154	147340	20699	7.1
##	6	Yellow	26033	367181	31365	11.7

Analysis

Evaluation of Key Performance Indicators

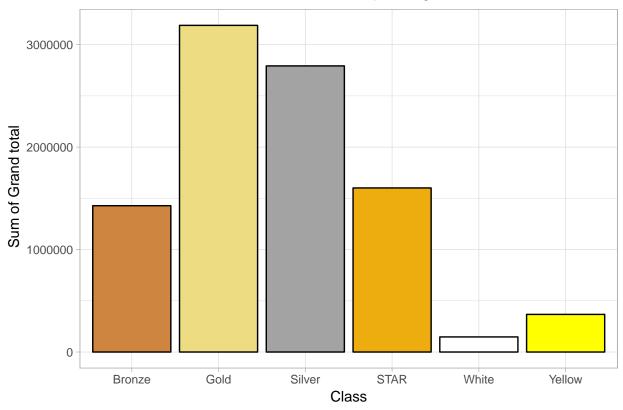
In the next graph appear the number of customers per segment. The most populated classes are the *Bronze* and the *Silver*. The Star is the least crowded and the Gold, Yellow and White, fall somewhere in the middle with small differences between them





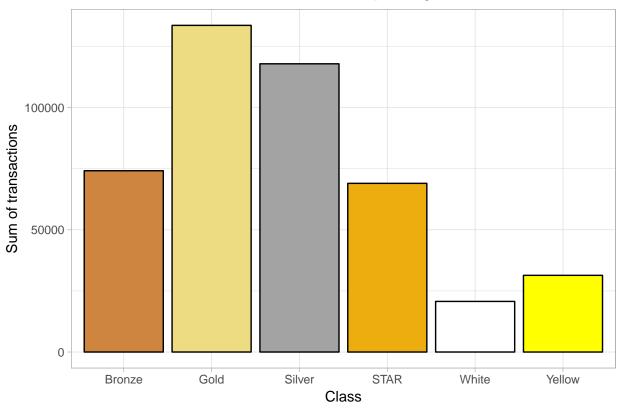
Here, the class with the highest grand total is the Gold followed by the Silver. The White and the Yellow are unsurprisingly in the lower scale.

Sum of Grandtotal per segment

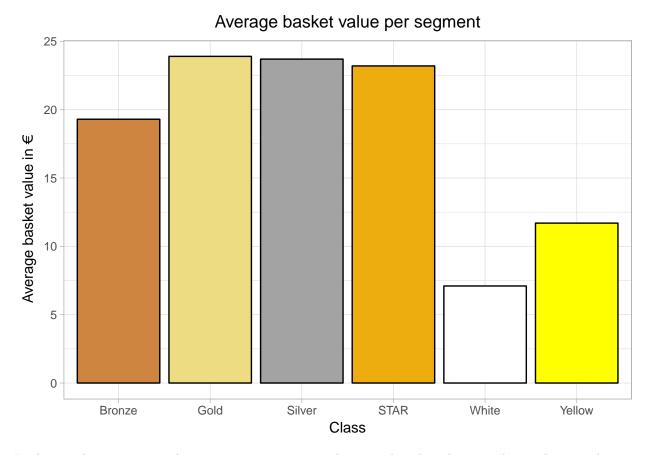


Similar patterns appear in the $Sum\ of\ transactions$ graph.

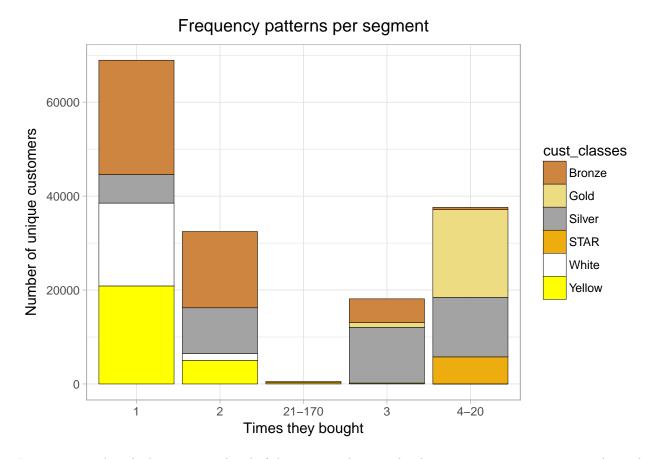
Sum of transactions per segment



The Average basket value is about the same for the Gold, Silver and Star classes with the Bronze following.

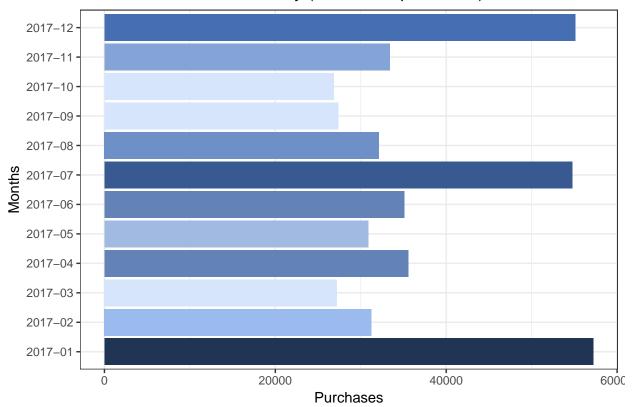


In this graph we can notice how many times customers have purchased in the year. The numbers can be seen through the class each individual customer is part of.



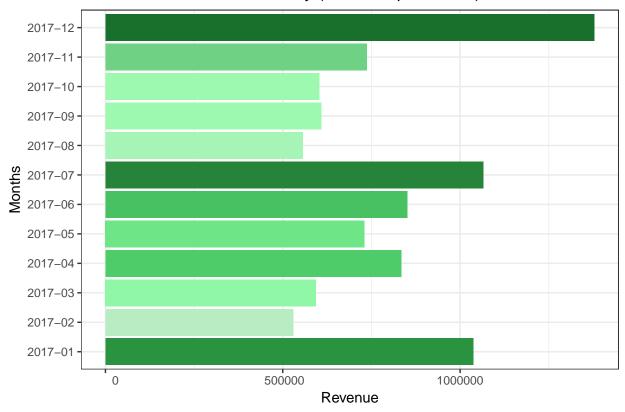
It is apparent that the beginning and end of the year are the periods where customers are most active. Around the Summer the increased purchases are present as well.

Seasonality (Purchases per month)



Very similar norm can be observed with the highest revenue graph.

Seasonality (Revenue per month)

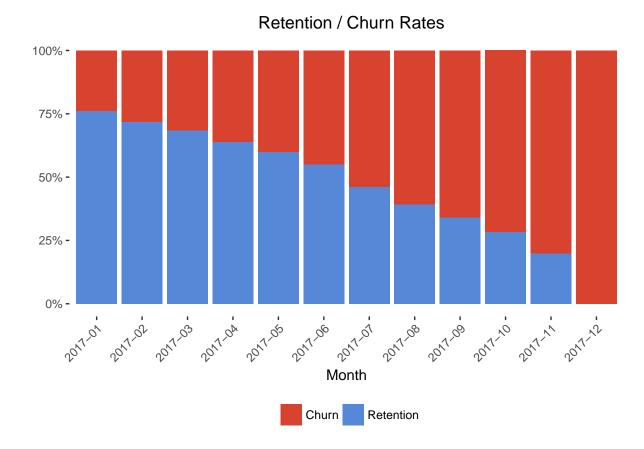


Here, the $State\ of\ Customers$ is based on how recent their purchases were. Furthermore, campaign recommendation to increase revenue tailored to their behavioural patterns are also suggested.

State of customers * Campaign recommendations Reactivation Campaign Churned state Active At_Risk * Retention Campaign At_Risk Churned * Up-sell/Cross-sell Campaign Active 0 20000 40000 60000 Number of customers

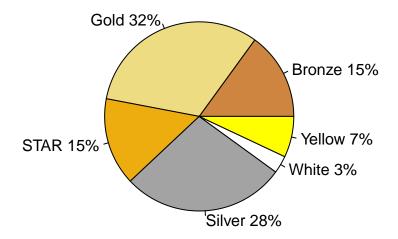
Below are shown the Retention/Churn rates of the customers where even though previous graphs supported the idea that some months are busiest than others we can speculate that most customers are new that rarely purchase more than a few times within the same year.

Joining, by = "month"



Finally in this pie chart we can notice the revenue accumulated from each customer class. The highest percentage is derived from the Gold class and lowest from the White.

Revenue by customer class



Modelling

Prediction of customer class given one parameter

Logistic Regression

For this case a model was created to predict the customer class given only one parameter from the RFM information.

ANOVA

Calculating for Analysis of Variance produced that the variances of classes from their corresponding means in purchases per customer are statistically different. That is because of the rejection of the null hypothesis since the p-value was way less than alpha (0.05) with confidence level of 95%.

Results / Discussion

The main object of this analysis was to define and examine KPIs in order to extract valuable insights about the current state of the market and perform predictions for the customer behaviour. This can influence the decision making in a very productive manner.

Analyzing customer segments can help customize products, services, and marketing strategies to better increase profitability and customer satisfaction for each segment. In this case the results showed that seasonality has an effect on peoples' behaviour and amount of revenue. Specifically during the Winter holidays

and the mid-Summer period is were the most spending took place. On the other hand people tend to not be long term customers. Another conclusion is that the most active customers spend low amounts of money compared to the ones that spend less regularly. To conclude, the *Star* class has members that have high recency, frequency and monetary value rates yet it is not much populated in comparison to classes like *Bronze* and *Silver*.

Therefore in order to increase the Star population it is important to focus on retention and reactivation approaches. For this to happen it is crucial to:

- Improve marketing focus (vastly disparate segments may not respond to the same marketing messages or campaigns).
- Predict future purchase patterns (knowing that certain customers are more likely to purchase other products based on past purchases helps with planning and marketing).
- Build loyal relationships (fully meeting the customers' expectations through customized service and uniquely designed products at a price they can afford helps build customer loyalty).