Identify Churn

A study in how transaction data can be used to identify churn for merchants

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En studie i hur transaktionsdata kan användas för att identifiera churn för företag

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# Abstract

In this thesis we propose a model for churn detection by the use of transaction data. The model aims to support Wrapp to identify customer churn for merchants, which in turn can target marketing towards these customers through Wrapp’s application. Transaction data holds many different parameters that can indicate churn. In this study, we have tried to break this handful of indicators down into one single model that is easy to understand and use for both merchants as well as employees at Wrapp. To the best of our knowledge, the result is a model that combines what literature and interviews regard as the two most important parameters, spend and frequency. A customer is considered defected if spend and frequency at the merchant decreases while it is constant or decreases less at the competitors. To add to this, we have extended the definition of churn to also include something we refer to as opportunity churn. Opportunity churn is churn due to an increase in purchases at competitors rather than a decrease at the merchant. Furthermore, the model was tested together with a large fashion retailer in Sweden, where customers identified by the model received an offer through the application. The result indicated that retaining defected customers requires lower incentives than acquiring new customers. Moreover, in order to verify the robustness of the model, we validated whether customers identified as defected by the model one period, also were identified as defected at the next. The results showed that a vast majority were defected in both periods, which indicate that the model is rather robust. Lastly, even though this study primarily has taken Wrapp’s and its merchants’ need into consideration, our belief is
that the model is applicable to any company that receives transaction data from customers.

Key Words: Customer Churn, Transaction Data, Customer Retention, Loyalty Programme
Sammanfattning

kunder.

**Nyckelord:** Kundchurn, Transaktionsdata, Kundretention, Lojalitetsprogram
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**All employees at Wrapp**

**All our interviewees**
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1 Introduction

This section describes the background and problematization of our topic. Further, we define the purpose of the thesis and our research questions. We also present what we believe will be the thesis main contributions to research, the limitations of the thesis, our definition of churn as well as the authors' contribution.

1.1 Background

The digitalization has over the last two decades made significant changes in many areas whereas marketing is no exception. The digital implications have led to a shift in marketing strategies which are typically no longer focusing on quantity but rather on quality. In more detail, the digitalization has made it possible to gather data on consumer behaviour and with this information tailor marketing campaigns (Ryan, 2014). In this so-called data driven marketing, retargeting is dominant. Retargeting is data driven marketing where the data is collected from people’s Internet browsing behaviour. Even though retargeting is an advancement from before, experts are stressing a few issues with this method. One being the lack of correlation between one's browsing history and actual purchase behaviour (Lambrecht and Tucker, 2013).

With regard to the above-mentioned in combination with the advancements in the banking service and the constant increase in cashless payments, another opportunity has arisen. This opportunity is marketing based on bank transactions, in other words, based on actual purchases (Cameron and Nichols, 2008). This is today somewhat limited since the transaction data is owned by the banks. This results in a bothersome need for collaboration with banks for companies to acquire this information. However, in 2018 a new EU directive, called PSD2, will be implemented into Swedish legislation. This directive will result in a change of ownership in bank transaction information, making individuals owners of their own data (European Commission, 2016). With this change of ownership, the barrier to acquire this information partly disappears. The usage of transaction data and with this transaction based marketing will thus become
Even today, there are companies that collect transaction data in order to target marketing campaigns. Wrapp Operations, which this thesis is in close collaboration with, is an application where the users connect their bank card which and allow the merchants to target offers based on the consumers’ purchase behaviour. The merchants offer customers, or potential customers, so-called cashbacks, which is a subsequent payback on purchases. Merchants connected to Wrapp can target these cashback offers to either existing customers as a loyalty bonus, or to potential new customers in order to acquire them. These two segments are identified with transaction data which Wrapp receives through bank collaborations, which allows Wrapp to collect transaction data of customers connected to the application.

1.2 Problematization

Today merchants typically have transaction information about purchases made at their own stores. However, they have no information about their customers’ purchases at other merchants, thus, limited information about potential new customers.

As mentioned above, there are two segments which Wrapp can identify as targets; existing customers and potential new customers. However, there is another segment that Wrapp currently cannot target, which is defected customers. These are customers who, through transaction data, have been defined as customers but show a transaction trend that indicates a lost interest in a specific merchant. Since these customers have shown previous loyalty to the merchant, the segment is believed to be highly valuable to retain (Reichheld and Sasser, 1990), and in turn, also identification of these customers.

Additionally, Wrapp aims to position itself as a loyalty application, however, the company has challenges with merchants in general only using them in order to acquire new customers. Therefore, the model to retain defected customers will also support Wrapp to be regarded as a loyalty application.
1.3 Purpose

The purpose of this thesis is to investigate how customer churn can be identified through customer transaction data. In practice, to develop a model that Wrapp can use to identify customers that are likely to churn from merchants and with this make merchants able to target offers to those customers.

1.4 Research question

With the purpose in mind, the main research question is formulated as following:

- How can transaction data be used by merchants for churn identification?

To answer this question and to concretize the purpose, five additional questions have been formulated:

- How do merchants currently work to prevent churn and what is the demand for identifying defected customers?
- What are the different types of churn and which of these can be prevented?
- Which parameters in transaction data can indicate churn?
- What should define customer churn and how can churn identification be modeled?
- How does the purchase behaviour differ between defected customers and new customers when given an offer through Wrapp?

1.5 Hypothesis

The study is based on the following hypothesis:

H1: It requires lower incentives to retain previous loyal customers than acquiring new customers.
1.6 Definitions

The definition of churn is largely depending on business sector and area of use. In general terms, churn can be explained as customers who, for any reason, leaves a company or brand. The most used form of measuring churn is in terms of churn rate, more specifically the percentage of an entire customer base that leaves a company or brand. This form of measuring churn is depending on knowing the number of existing customers as well as being able to measure the number of leaving customers. This is commonly used in subscription services where this information is available. However, this thesis will primarily concern merchants where this information is either non-existent or unreliable.

Previous literature uses several terminologies for the concept of churn. Among those are customer defection, customer attrition and customer turnover. This thesis will however use the terms churn and defection throughout the entire thesis.

In this study the term merchants refer to companies that offers products or services to consumers and merchant segments refers to groups of merchants that offer similar products to its’ customers. Merchants in the same merchant segment are typically each other’s competitors.

1.7 Expected contribution to research

The attempt to investigate how transaction data can be used in order to prevent customer churn is as far as we know an untouched area by academics and researchers. Although existing researches covers the areas of customer churn, retention strategies and transaction data targeting, there are no research found combining all three. This research aims to be the first to prove how merchants can use transaction data in order to try to identify customer churn and we hope that this will spur further researches and investigations within the area.
1.8 Delimitations

Due to lack of time and resources, some limitations will be inevitable. Following limitations have been made:

- This thesis will only focus on identifying customer churn and for that reason does not concern the actual strategy of retaining the customers. Wrapp’s business model of target offers to customers in order to retain them, will therefore not be questioned.

- Merchants will be categorized depending on what merchandise they offer and as a consequence, generalizations will therefore be made. However, the data provided from the transactions does not consist of information about the merchandise. Therefore, there are also some limitations in categorizing merchants who offer a wide range of products in their assortment.

- Only transaction data from Sweden will be used, which makes any generalization about the consumer behaviour limited to the population of Sweden.

- Previous experiences at Wrapp have shown that features including complicating models have been unsuccessful. In practice, the feature and the underlying model need to be understood by representatives from the merchants. In short sales meeting this is hard to achieve and for this reason the complexity and number of parameters will be limited in our model.

- We believe that the churn model is more adaptable for merchants within industries where the purchase frequency and spend are more or less constant. We have therefore chosen to customize the model for those kind of merchants and limitations are therefore made regarding the applicability of the model. We have chosen to mainly study merchants within groceries, large fast fashion retailers, coffee shops and department stores. However, there are most certainly similar industries that the model could be applicable for.

- Since the purchase frequency for subscription services are constant until a customer unsubscribes, there are challenges in predicting churn based
on transaction data for those merchants. Therefore, we will not consider merchants within subscription services when developing the churn model.

1.9 Authors contribution

The authors have made equal contribution to the thesis. The authors have both participated during the acquisition of the qualitative data, more specifically the interviews, in order to avoid misinterpretation. Additionally, the authors have both participated in writing of every part of the thesis and have revised the content critically. Both authors have given approval of the final version.
2 Literature Review

This section describes previous research within customer retention, data driven marketing and customer churn. It aims to provide an understanding of different types of churn as well as current methods to prevent it.

2.1 Customer retention

Customer retention has gained much popularity in previous literature and researches have pointed out that merchants with loyal customers, with high retention, have a higher share of their segment’s spending as well as are more likely to recommend others to become customers (Keiningham et al., 2007). Customer retention has therefore been identified as a key driver of a company’s profitability and according to Reichheld and Sasser (2016), a company can increase profits by almost 100 percent by retaining just five percent more of their customers. To understand customer retention and how to create it is therefore an important topic for management in any company. A common way of increasing retention is by increasing customer satisfaction. Previous researches have been focusing around the relationship between retention and customer satisfaction and it has shown that information on customer satisfaction often tends to rely on a feedback system, commonly consisting of surveys aiming to measure satisfaction (Keiningham et al., 2007). However, it has been pointed out that there often is a non-linear relationship between customer satisfaction and customer retention. The non-linear relationship tends to be a result of a discrepancy in what customer answer in the surveys and their actual consumer behaviour. Subsequently, to avoid these prediction errors a more extensive data driven approach is required (Langhe et al., 2017).

2.2 Data driven marketing

In a dynamic and fast changing business environment, decision making become increasingly complex. Questions such as what customer to target and what to offer these customers become important but are yet difficult for companies to answer. In order to create successful marketing strategies and answer these questions, companies have to know the needs and preferences of their customers.
By understanding the marketplace, the customers and what they need, competitive advantages in marketing strategies can be achieved (Mulvenna, Norwood and Büchner, 1998). Customer segmentation is a fundamental part in marketing strategies and Dolnicar (2002) explains the two main approaches to this, the conceptual approach and the data driven approach. The conceptual approach is a segmentation approach where customer criteria is known in advance, such as age and gender. This typological attitude on customer segmentation has in last decades been put aside for data driven, or in some literature referred to as post hoc customer segmentation. This approach differs from the typological approach in being empirical and it usually uses some sort of data set as a starting point. The data set, which could be surveys, purchase history or basically anything else, are later analyzed to derive some sort of grouping. Dolnicar explains that the conceptual approach has small chances of creating any competitive advantage compared to data driven strategy. Since data driven marketing let organizations identify segments of customers where each group has the actual needs alike it can make target marketing much more efficient. Data driven marketing can be used in several aspects of target marketing, and in the case of churn prediction, it is more or less pre-forced to use some sort of data analysis to identify this group.

2.3 Customer churn

Predicting future purchases is a large part in churn prevention and something previous researchers have tried to investigate (Hung, Yen and Wang, 2006). The following chapter describes different types of churn followed by current ways to identify and prevent it.

2.3.1 Different types of churn

There are many reasons why merchants experience churn and they can generally be divided into two categories; voluntary and involuntary churn (Klepac, Mrsic and Kopal, 2015). Involuntary churn refers to churn due to merchants suspending the consumers and the reason for which often relates to lack of payments, fraud or similar. These defected consumers are therefore easy to identify and not really in focus in churn management. The other category, voluntary churn,
can be divided into two subcategories; incidental churn and deliberate churn. Incidental churn refers to churn due to changes in circumstances which prevent the customer from continuing as a customer. The reasons for these changes can be many, often related to changes in personal finance or place of residence. Deliberate churn is explained as customers actively choosing a competitor and are therefore the type of churn that companies generally tries to prevent (see Figure 1) (Shaaban et al., 2012).

![Figure 1: Deliberate churn is the type of churn merchants try to prevent.](image)

### 2.3.2 Customer lifetime and expected churn

The concept of churn is closely related to customer lifetime. In most industries, the customer lifetime is finite, more specifically, customers are not expected to be customers for a lifetime, which can be referred to as expected churn. Expected churn can have several reasons but one of the most common reasons is due to changes in circumstances. Such reasons can be when children grow up and their parents consequently stop buying toys. The expected churn is also connected to customer lifetime value, a concept which is relevant in retention strategies. According to researches, preventing customer churn is not appropriate for all kind of companies (Cokins, 2014; Reinartz and Kumar, 2002).
Generally, this is the case for companies where the cost of retention exceeds the customer lifetime value. Customer lifetime value is often calculated based on the expected profit generated from a customer. This key performance indicator is used to support companies in decision-making when setting the budget for their retention strategies. Factors that influence the customer lifetime value are average number of purchases per customer, average gross margin per product, direct marketing cost per customer, average spend per purchase etcetera (Gallo, 2015).

2.3.3 Conversion and recovery

Previous loyalty is an important factor to take into account in churn prevention. More specifically, there is a different between customers that have not converted after a few purchases and customers that decreases in purchase frequency after being loyal for a long period (Traynor, 2017). Consequently, the value to retain these customer segments probably differ and they should therefore be targeted with different incentives in order to be retained. See Figure 2 for a visualization of this segmentation.

![Figure 2: Segmentation on previous loyalty.](image)

2.4 How to identify churn

According to Neslin et al. (2006), in order to prevent churn, companies have to find patterns in their customers’ behaviour and detect factors that could indi-
cate churn. One way of identifying customers that should be targeted for churn prevention is to use the customer lifetime value (Liu and Shih, 2005). According to Coussen et al. (2014) variables for predicting churn can be many, such as recency, frequency and monetary value (Reinartz and Kumar, 2002). Recency refers to the elapsed time since the last purchases, thus, as time pass the risk for churn increases. More specifically, the likeliness for a customer to make a purchase today is higher for a customer that made a purchase last week than for a customer that made a purchase last year. Frequency refers to the time between each purchase, or equivalently the number of purchases in a specific time period. Customers with higher frequency has typically higher probability to stay loyal to the company. Monetary value is the customers’ spend, calculated during a specific period, the larger the spend, the higher probability for loyalty. Additionally, the length of customer relationship has also shown to have an impact on loyalty, in other words, the customer lifetime (Ballings and Van den Poel, 2012).

In previous research, the concept of churn is often described as cancellation within subscription services. However, cancellations are often the last activity the customers make when ending their commercial relationships. Therefore, giving incentives to those customers with the purpose to retain them, is at that time probably too late. Instead, activity churn is probably a better indicator to forecast that type of churn (Traynor, 2017). Activity churn is described as less utilization of a product or service but can also be explained as less frequented purchases of a product or service. Usually customers do not end their commercial relations over one night. Instead, customers typically decrease the use of a product gradually while increasing the use of another.

2.4.1 Existing models for predicting churn

Literature suggest that one way of predicting customers’ future purchases is through analyses of past purchases. Using predictions about future purchases to target marketing campaigns provides companies with a capability to be proactive, instead of reactive. Therefore, instead of acting after customers have churn, companies can instead act on signs indicating that customers will churn (H. Davenport, 2006).
Previous researches have tried to find models for churn prevention and in general terms it can be said that models for churn prediction are similar to methods that can be used in other types of predictions (Vafeiadis et al., 2015). One common technique used for predictive analysis is machine learning, which also is popular for churn prediction in particular. Machine learning enables a computer to learn to predict future events without human interference. Artificial Neural Network, Support Vector Machines, Decision trees learning and Naïve Bayes are machine learning methods commonly used for churn prediction (Vafeiadis et al., 2015).

Another common method in predictive analysis is regression analysis, which describes how a dependent variable relate to independent variables, also called covariates, and the correlation between these (Lang, 2014). This method can be used together with hypothesis testing in order to investigate which covariates that have an impact on the dependent variable, and hence, which parameters that should be included in the model (Verbeek, 2015). Additionally, it measures how big this impact is, which corresponds to how the included parameters should be weighted. In hypothesis testing, a so-called “zero hypotheses” is set. The zero hypothesis refers to that the coefficient of the current covariate is zero, which is equivalent to the exclusion of the covariate from the model. The researcher then tries to reject this zero hypothesis. This is done by calculating a test statistic based on an observed sample. The calculation is moreover based on a given distribution during the assumption that the zero hypothesis is true. Then, to test if the zero hypothesis is to be rejected, a so-called p-value is calculated to determine if the value from the observed sample is unlikely to come from the given distribution, which would indicate that the zero hypothesis is not true, and that the covariate have impact on the dependent variable (Hill, 2016). However, regression analysis is only useful for predictions of continuous values which limits the range of use of this method in terms of churn prediction (Vafeiadis et al., 2015).

2.5 Critical arguments

Since purchase behaviours differ across countries (Mooij, 1998), and this study solely concerns Sweden, it will be questionable whether general conclusion can
be made based on literature from countries other than Sweden. Another critical argument is the fact that card payments in other countries are yet to be developed as in Sweden (Henley, 2016). This limits the number of previous researches in the field of marketing based on transaction data, thus, limiting the width and strength of our literature study.
3 Method

This section introduces the scientific methods which our study was conducted with, together with critical arguments about the methodology and how it might affect the outcome of the thesis.

3.1 Research approach

To reach an answer to the research questions, the first step was the collection of empirical data. The two main sources of empirical data were interviews and transaction data. Interviews were held with merchants in order to receive a contextual understanding of the demand for identifying churn as well as how merchants currently work with churn and customer loyalty. The transaction data were received from Wrapp users, gathered when users make purchases with their bank card connected to Wrapp. The literature review was made in order to get further insights in previous researches in the area and also worked as a complement to our interviews for the decisions regarding the churn model. After establishing the churn model, it was tested together with merchants to answer the hypothesis that retaining defected customers requires lower incentives than acquiring new customer.

3.2 Pre-study

According to Bryman and Bell (2011) a pre-study can be made in order to validate hypotheses that the main study is based on. Therefore, to validate if retaining churning customers require lower incentives than acquiring new customers, a pre-study was conducted. Additionally, our intent was to test the model throughout the process, realizing mistakes early rather than in the end of the work. Therefore, the pre-study also worked as a prototype attempt of our model. Since this was early in the process, the pre-study model was simplified, taking only one parameter into account. According to previous research, recency, that is the time passed since the last purchase, correlates with churn and we therefore chose this parameter for the pre-study model (Reinartz and Kumar, 2002). In the pre-study we therefore intended to test the result of an offer given to defected customers, so-called churn offer, compared to an acquisi-
tion offer, in order to compare their redemption rates. If the redemption rate for the churn offer would be higher than the redemption rate from the acquisition offer, it would support our hypothesis. The redemption rate was calculated by the number of redemptions of the offer divided by number of activations of the offer. To activate the offer, the customer had to see it in the application and further to redeem the offer the customer had to make a purchase at the merchant. New customers were simply users that had not made any purchases since they connected their bank card to Wrapp. Defected customers were defined as customers who had made previous purchases at the merchant, but not in recent time. The time since the last purchase for the customer were compared to the average frequency in the customer segment that the customer belonged to. If the customer had not made any purchase within the average frequency at the merchant, plus 50 percent, the customer was considered as churned and received a churn offer.

The pre-study also aimed to initiate a first contact with the merchant regarding churn, so that our completed model could be tested as soon as possible when is was developed. Additionally, to be able to have accurate calculations for the suggested budgets of the later on performed tests, we wanted to estimate the activation rate and the redemption rate of the offers. Hence, the cost for the offers is much depending on the number of redemptions and since the number of redemptions are correlated with the number of activations, the cost of the offer is also depending on the activations. We also intended to try different types of offers in order to see which offers that had highest return on investment, in other words, which offer made the customers spent the most in comparison the given cashback. These offers would be the offers to use during the tests with the completed churn model. The offers during the pre-study were different depending on different customer segment, where customers that spent more in the merchant segment received more favorable offers.

3.3 Interviews

The interviews conducted were semi-structured and primarily aimed to establish the demand for identifying churn, but also to get insights in what merchant
believe is the most important indicators of churn. The interviewees were made with a broad range of merchants, both partner merchants and potential partner merchants to Wrapp. Among the companies were online retail and e-commerce startups as well as some of the largest offline retail companies in Sweden (see Appendix A). The interviewees were mainly CRM-managers, responsible for the loyalty programs, and all interviews were conducted with the same interview guide (See Appendix B). Apart from interviews with merchants, an additional interview was made with a management consultancy firm, specialized in marketing and communication processes, which have been working with loyalty programs at various merchants. All interviews were recorded and transcribed into written form.

The reason for choosing qualitative interviews instead of quantitative surveys were mostly because we believed that surveys require vast knowledge in the field in order to ask relevant questions, something we did not have at an early stage. Additionally, our intent was to build relations with the interviewees to be able to test the model with them once it was established.

### 3.4 Churn modeling

Based on the pre-study, literature review and interviews the churn model was developed. The included parameters were the parameters which we believed had the highest correlation with churn according to the literature and interviews. To implement the model, we had to involve different competences within the company in order to understand technical limitations as well as receive input from the sales department about the demand from merchants. We also had to be in close communication with these departments in order to find the balance between having a comprehensive model yet easy to understand making the sales team able to sell it to merchants. Due to limitations in time as well as resources from the technology department, we were not able to implement the model into Wrapp’s internal system where the offers are usually set up. Instead, we used Periscope to apply our model, which is a visualization tool for SQL queries in order to analyze data. We built the model such that the user ID for the merchants’ defected customers are received when choosing which merchant that
is of interest. The user IDs could then be targeted with offers through Wrapp. The purpose for choosing Periscope as a tool was to have an easy handover once our project is over, since Wrapp already uses Periscope for their internal dashboards.

3.5 Model validation

To validate the model, we performed two different types of tests, a robustness test to validate the accuracy of the model and an offer test, were offers in the Wrapp application were targeted to defected customers.

3.5.1 Robustness test

To validate the accuracy of the model, i.e if the customers identified by the model actually are defected, we performed a robustness test. The test was performed on historic data were we studied if the customers that were defected one period, also were identified as defected the next period. Otherwise, we believed that the model would either be sensitive to small changes in purchase behaviour or that the reason for such fluctuations is due to churn being difficult to predict. The test was made for different merchants, thresholds and number of previous transaction at the merchant and in the merchant segment. More specifically, we ran the model on data for merchants within the grocery segment and studied if the customers that were identified as defected 30 days ago also would have been identified as defected today.

3.5.2 Offer test

To prove our point with the highest credibility reached, we intended to test our churn model with merchants. The test also aimed to provide Wrapp with more information of how the model performed before choosing if the model should be fully implemented. After identifying the parameters, which we believed correlates with churn, we contacted merchants which we believed were suitable for the tests. The test was similar to what we did in the pre-study but this time with the more comprehensive churn model. Our pre-study showed us that the redemption rate for offers to defected customers was higher than the redemption rate for offer to new customers and we intended to test if this still is true for the
new model. The purpose with these tests was therefore to receive an answer to our hypothesis that retaining defected customer requires lower incentives than acquiring new customers but also that previous loyal customer have, on average, higher potential of becoming loyal again than new customers becoming loyal. The purpose the test was also to be able to evaluate how these offers affected retention of defected customers in the long term. These tests also aimed to be able to improve our churn model, both in terms of which parameters to include and the relationship between them but also regarding decisions of time periods, thresholds and number of purchases required to enter the model.

The tests consisted of two offers, one offer targeted to defected customers identified by our model, and the same offer targeted to the same number of new customer. New customers were customers that have made at least 50 purchases with their card connected to Wrapp, however, have not made any purchases at the merchant. To be able to compare the long term effect of the offer, the churn offer was only targeted to half of the merchants’ identified defected customers. By comparing the long term purchase behaviour between defected customers that received the offer compared with defected customers that did not receive the offer, we believed that we could measure if the offer actually had a long term effect on retention. Furthermore, by targeting the same offer to defected customers as to the same number of new customers, we could compare the redemption rates in order to answer the hypotheses that retaining defected customers requires lower incentives than acquiring new customers. Additionally, by comparing the long term purchase behaviour between the defected customers that received the offer and the new customers that received an offer, we could measure if the offer had an effect on loyalty and in return understand whether previous loyal customer have higher potential of becoming loyal again than new customers becoming loyal. Due to time limitations in the study it is likely that conclusions on the long term effects will not be considered highly reliable and therefore this was left to future studies. Since our time was limited we chose to perform the test with a rather high frequency merchant, which enabled us to receive enough data in a fairly short period of time. More specifically, the model was tested together with a large fashion retailer and the offer was valid.
for redemption for 14 days. Additionally, a push notification was sent out to increase the likeliness of customers to open the application and activate the offer. The offer was a 50 SEK cashback for a minimum purchase of 50 SEK and was given to 2176 new customers and to 2176 defected customer, which was half of the customers identified as defected. Since the merchant in the test wishes to be anonymous it is not the actual test offer that is visualized in Figure 3. Furthermore, the algorithm for the test offer is described in Appendix C.

![Image showing an offer in the Wrapp application](image)

Figure 3: Example of an offer in the Wrapp application.

### 3.6 Data quality

To ensure that the results of this study stand up to rigorous questioning, the concepts of reliability and validity was considered when designing the study.
3.6.1 Reliability

Reliability refers to the repeatability of findings, more specifically, that the study is repeatable but still generate similar results. In our study, reliability demands robustness of the model and consistency during the interviews. In order to guarantee robustness, we tested the model for validations as mentioned earlier. The reliability in the thesis can be partly questioned since the demand for identifying churn relies on qualitative interviews (Golafshani, 2003; Blomkvist and Hallin, 2015). However, to be able to make judgment on the reliability we have attach the interview guide to the thesis (See Appendix B). Additionally, the fact that same questions provided to different applicant can be interpreted differently can also question the reliability (Holm-Hansen, 2007).

Regarding the offer test, since we only made one test, with one type of offer, it is questionable which conclusions that could be drawn from it. However, we believe that the range of offers in the Wrapp application are similar enough to the offer in the test for it to generate the same result. More specifically, the type of offer used in the test does not affect the result in any larger extent and consequently conclusions about differences between the groups in the test can be made. However, we do not claim that the result of our test will be generalized to any type of offer.

3.6.2 Validity

Validity is the concept of which a study measures what it actually claims to measures. In detail, to be able to ensure validity, the results obtained have to align with research questions and fulfill the purpose of the research (Blomkvist and Hallin, 2015).

Internal validity is the extent to which conclusions about causality can be made (Bryman and Bell, 2011). Whether causality exists between the parameters in our model and churn is questionable, however, our study aims to find correlation rather than causality. Moreover, external validity is the extent to which the results of the study can be generalized beyond the context of the research (Bryman and Bell, 2011). Essentially, to ensure external validity the observed
sample have to be able to represent the population it intended to examine. When defining a defected customer, the transaction data from Wrapp’s users was used. Since the data comprises around 200 000 unique users, not evenly distributed across demographics, geographies etcetera, we had to make generalizations, which can question the external validity of our result. Validity also demands the study to have randomized sample groups. Therefore, when choosing the groups for the test of the model, we used a function to split the group randomly and also ensured that the groups had similar purchase behaviour.

The choice of interviewees can also affect the result of this thesis and it is therefore questionable whether it was the right merchant to interview as well the right employee at that merchant. To avoid this, we have as mentioned interviewed a wide range of merchants as well asked the same question to every merchant. However, the interviewees accepting to participate in the interviews may have been suffering from selection bias, and hence, misjudgments may have occurred in the study concerning the demand for our model. For instance, merchants that accepted the interviews may have a higher level of defected customers than those who declined. This could therefore result in us overestimating the interest of the model. Additionally, we are also aware that there can be disadvantages of interviewing too early in the process, since it may influence unconsciously biases and cause misaligned questions from not being sufficiently well-read.
4 Result

This section describes the result of our work, including a compilation of the qualitative interviews with merchants and analyses of the customer transaction data. The interviews together with the data analyses have formed the basis for the churn model, which also is presented in this chapter.

4.1 Pre-Study

The conducted pre-study supported the hypothesis that retaining defected customers requires lower incentives than acquiring new customers. This conclusion was drawn from the offers made in the pre-study, where the average redemption rate for the churn offers were higher than the average redemption rate for the acquisition offers.

4.2 Interviews

This chapter presents the findings from our interviews with merchants. It primarily aims to answer the question to how merchants work to prevent churn and what the demand for identifying defected customers is. Furthermore, it aims to get an insight in which parameters merchants value as churn indicators as well as to make an initial contact to follow up on when the model is ready to test with merchants. The chapter begins with a description of merchants’ loyalty programs as a step in understanding merchant’s current work with loyalty and customer retention. Additionally, to understand merchants’ definition of a customer and which customers that are most valuable to retain we present a section of how merchants usually segment their customers. This is followed by an overarching picture of merchants’ view of churn in general, how they work against it today and what they see are missing from their current work.

4.2.1 Loyalty and bonus programs

Loyalty and bonus programs serve several reasons for merchants, however, from the interviews it was understood that the underlying purpose with most of these programs is to receive and gather data on customers. The data gives merchants customer insights which is used for different reasons, such as target marketing
or planning the assortment. In return for the customer to share information about their behaviour, and to increase the customer satisfaction, customers receives offers based on their purchases. Usually offers are based on the customers spend during a specific period. (Holmberg, 2017; Interviewee A, 2017; Holmstrand, 2017). The offers, which usually comes in monetary value or as a percentage discount, often aim to reward the customer by giving an offer within the same merchant segment/on the same product that the customer bought before. However, it can also aim to increase cross selling by giving offers in a merchant segment where the customer has not made any purchases (Holmberg, 2017; Holmstrand, 2017).

Digital start-ups as well as e-commerce businesses generally do not have loyalty programs (Fierro, 2017; Stålnacke, 2017). Since they are gathering data about their customers through their apps/websites they are not in the same need for these type of programs. Neither the telecom company Tre have a loyalty program, however, Tre distinguishes themselves from the other merchants since they are a subscription service that use lock-up periods. Their main focus is therefore to acquiring customers but also to extend subscriptions for the customers with new lock-up periods when their previous lock-up period begins to end. However, Tre have seen that customers are more reluctant to commit to the same extent anymore resulting in a greater challenge to gain customer loyalty in the future (Asperen, 2017).

ICA, which have one of Sweden’s biggest membership clubs, have its loyalty program divided into two parts, one common part for ICA as a whole and one local part that is different for each store. The common part includes product discounts, monetary rewards, discounts on travel or entertainment and self-scanning etcetera. The local part on the other hand is difficult to say something about since differs between every store. David Holmstrand (2017), strategist for ICA Sweden’s loyalty program, believes that it might be misleading to call their membership club a loyalty program. Holmstrand are doubtful that customers are choosing ICA because of the membership club, however, customers who do come to ICA uses their card which gives ICA valuable data. The offers in their
membership club is solely based on spend. A specific example is customers who spend at least 1200 SEK per month, which gives discounts on the most purchased products.

Another loyalty program, which differs from the others, is Espresso House’s. Even though they do not want to refer to it as an official loyalty program, they have a card and an app which can be loaded with money that the customer use for purchases. The purpose is to work as a lock-in effect in order to increase retention (Wallgren 2017).

4.2.2 Customer segmentation

In general terms, merchants use few and broad segmentations, whilst more specific segmentations rather are made ad-hoc to fit every specific marketing campaign. For instance, ICA with over 4 million members in their membership club only segment based on loyal and non-loyal customers where a loyal customer is defined by spending 1200 SEK or more during one month (Holmstrand, 2017). Holmstrand also states that segmentation is primarily used to decide which kind of offers to provide to which customers, where the higher spending segment receives more favorable offers. Interviewee C (2017), who has been working with ICAs loyalty program explains that the reason for ICA to have such few segments is that the cost of producing offers to each segment is rising heavily with the number of segments. He explains that in many cases the effect of making specific offers to small segments is lower than the extra cost for it.

Caroline Holmberg (2017) at Åhléns explains that Åhléns, with millions of members in their membership club, like ICA, also make few segmentations. Currently, members are mainly segmented based on spend and can be placed in three different segments; less than 1500 SEK, more than 1500 SEK and more than 10000 SEK in yearly spend. The segments are used to provide both bonus refunds to the customer in form of bonus checks and also, to some extent, personalized offers. However, Holmberg explains that they to some extent also uses further segmentation depending on RFM (recency, frequency and monetary value), demography, highest category spend etcetera.
4.2.3 Churn

The extent of merchants work against churn are seemingly largely influenced by the size of the merchant. Merchants such as Åhléns and ICA with large customer bases generally have their CRM focusing on already existing customers, on how to increase retention but also how to increase loyalty and prevent customers from churning. On the other side of the spectrum, companies such as Urb-it and NA-KD, with smaller customer bases and often fairly new on the market, focus more towards acquisition of new customers rather than preventing existing customers from churning (Fierro, 2017; Stålnacke, 2017).

One of the main conclusion from the interviews is that merchants put small resources into preventing churn and that the merchants existing work often is characterized by very simplified models based on data received from their membership clubs. Caroline Holmberg (2017) says that Åhléns current work against churn consists of an automatic email with 20 percent discount on an optional item after a certain months of absence, further discount after additional months of absence and after some additional months the customer is seen as defected. ICA, which are similar to Åhléns in terms of having one of Sweden’s largest membership clubs, also uses recency and frequency in their work with churn as they send out special offers to customers that have not been at ICA for some time (Holmstrand, 2017). However, not all of the larger merchants work with churn. Interviewee A (2017), head of merchandising for one large fashion retailer, says that they currently do not work with churn apart from the churn campaigns in our pre-study. Another merchant that has been interviewed is J.Lindeberg, which put relatively small efforts into existing customers. Their only communication with existing customers is through a general newsletter and can hardly be considered as work against churn (Sveningson, 2017).

The work against churn is also influenced by the type of business the merchant operates in. Anders Asperen at Tre explains that the telecom business, is one example which differ from other businesses. As customers usually have a period of commitment the marketing activities is primarily focusing in the beginning or the end of the customer relationship. The work against churn
naturally occurs in the end of each period and aims to prolong the period of commitment and consists of different marketing campaigns through their different sales channels. However, Asperen believes that the reasons for churn can be derived from many things during the whole subscription period and states that the work against churn should be made during the whole period rather than only when subscription comes to the end. Another problem for merchants in the work against churn is to find the reason why customers churn. This is something merchants with large assortments struggle with. Holmberg (2017) stresses that it is very difficult to find the reason for churn where customers can make such a wide variety of purchases.

A relevant part in the work against churn is firstly to decide how to define a customer and secondly when to consider a customer as lost. All merchant interviewed answered unanimously that a customer is someone that has made one purchase at any time. When it comes to defining a lost customer the answers differ a lot between each merchant. Åhléns, for instance, have a clear definition and states that a customer is lost after a certain number of months without any purchase. J.Lindeberg does not have an articulated definition but claims that a reasonable approach would be to measure activity in the two fall/spring seasons, where a customer would be considered defected if one does not make a purchase during one of these seasons (Sveningson and Ericsson, 2017).

Regarding which parameters that are interesting when identifying churn, merchants seem to have a fairly mutual understanding. Merchants that do work with churn only use simplified models, where the most common parameter referred to is recency. In terms of transaction data, frequency and spend are emphasized as important factors that should be included in a churn model (Holmberg, 2017; Holmstrand, 2017). Some businesses have access to more data, which also can be valuable for identifying churn. Anders Asperen (2017) claims that the most important parameter for Tre is the time left on the subscription. Choice Hotels pointed out that a change of membership level, which is determined by the number of nights stayed at their hotels, would be a good indicator of churn and J.Lindeberg emphasizes the soft numbers such as customer satisfaction (Dzafic
and Lunden, 2017; Sveningson and Ericsson, 2017).

4.3 Churn model

This chapter aims to describe how our model for identifying churn is modeled. It will firstly give an overarching picture of churn indicators as that have been found in literature and in interviews. Furthermore, we will present our extended definition of churn before describing how our model works. Lastly, we present the result of the two different tests of the model.

4.3.1 Churn indicators

A large part of interviewing merchants was to understand how they work with churn, both in general terms but also based on transaction data. Below are churn indicators that either were discussed during interviews or common in previous research and literature.

*Frequency* is in this study referred to as the number of purchases during a specific period. According to both literature and interviews, customers with higher frequency typically have a higher probability to stay loyal to the company, which is the main reason for including this parameter in the model. Additionally, by including frequency, special cases when customers make expensive rarities are excluded.

*Spend* is the most common parameter merchants use in current customer segmentations. Even though frequency and recency can indicate churn, spend is what generates revenue, hence, probably the most important parameter for churn.

*Recency* refers to the time since the last purchase and is, as spend and frequency, easily obtained through transaction data. However, instead of only studying the time since the last purchase, as done in the pre-study, we intended to implement a so-called decay function into the model. The decay function weights purchases made a long time ago less than purchases made closer in time, something that could show a more realistic picture of the customer’s current preferences. This
will be further elaborated on under future improvements below.

*Share of wallet* refers to the merchant’s share of the customer’s spend compared to its competitors. In this study we use an extended version of share of wallet to also include the frequency. More specifically, the share of the merchant’s customer’s number of purchases compared to its competitors.

*Usage* was mentioned in some interviews as an indicator of churn. This is relevant for services where a decrease in usage could be a churn indicator. However, since transaction data do not hold information on usage of merchandise we were not able to include this in the model.

*Customer satisfaction*, or more specifically a decrease in customer satisfaction, is another possible churn indicator. However, much like the usage, transaction data do not hold this information. Additionally, research has shown that there is a nonlinear relationship between customer satisfaction and customer retention, which strengthen the argument about excluding this variable.

### 4.3.2 Extended definition of churn

As a result of interviewing merchants and studying previous research, another and more extended definition of churn was developed. The result was to extend the concept of churn to not only include defected customers as defined before, but also customers with purchase potential, which from now on is referred to as opportunity churn. The reason for this was because it appears natural for merchants to not only targeting customers that show a decreasing purchase trend at their stores, but also those who show an increasing purchase trend at the competitors.

### 4.3.3 The churn model

In essence, the churn model we have come to create is a model comparing the two, what we believe is the, most important parameters, spend and frequency. Spend refers to the total spend during a specific period and frequency is as mentioned the number of purchases in the same time period. It also includes
data on both the merchant and its competitors in a way that it measures the customer’s change in spend and frequency at the merchant compared with the change at the competitors. The change is measured between two equally long time periods. If the change has decreased during these periods, and more specifically, if the customer has a negative so-called churn score, then the customer is classified as defected. An example of churn is visualized in Figure 4. To make the model less sensitive to small changes in spend and frequency we have decided to introduce a threshold for how low the churn score have to be in order to be considered as churn. The limit for the threshold is further elaborated on below.

\[
Churn\ space = W_1 \times \Delta S + W_2 \times \Delta F
\]  
\[
W_1 + W_2 = 1
\]  
\[
\Delta S = \Delta S_{Merchant} - \Delta S_{Segment}
\]  
\[
\Delta F = \Delta F_{Merchant} - \Delta F_{Segment}
\]

\[
\Delta S_{Merchant} = \frac{S_{Merchant_2} - S_{Merchant_1}}{S_{Merchant_1}}
\]

\[
\Delta S_{Segment} = \frac{S_{Segment_2} - S_{Segment_1}}{S_{Segment_1}}
\]

\[
\Delta F_{Merchant} = \frac{F_{Merchant_2} - F_{Merchant_1}}{F_{Merchant_1}}
\]

\[
\Delta F_{Segment} = \frac{F_{Segment_2} - F_{Segment_1}}{F_{Segment_1}}
\]

, where index 1 refers to period 1 and index 2 to period 2

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4.3.4 Model scenarios

We here present three of the most general scenarios in our model. For a decision tree showing every specific case, we refer to appendix D.

- Churn: The consumer’s spend and frequency at the merchant has decreased, but is constant or has increased at its competitors
- Opportunity churn: The consumer’s spend and frequency at the merchant is constant or has increased, but has increased more at its competitors
- Not churn: The consumer’s spend and frequency is constant or has increased compared to competitors

4.3.5 Time periods

The spend and frequency are calculated for two equally long time periods. The length of the periods depends on the average frequency at the merchant which the model are applied to. In high frequent industries such as groceries the period could be relatively short whereas in industries such as electronics, the period
has to be longer. In our tests, the time periods were set to a fix number of days, however, it is our hope that the time periods could be set automatically depending on the merchant’s purchase frequency or that the time periods are decided in advance for every merchant segment. This will be elaborated on in future improvements below.

4.3.6 Thresholds

The churn score is compared to a threshold which defines if the customer will be classified as churn or not. The customer will be considered as defected if the churn score is below the threshold, and if above, not defected. When testing the model this was set ad hoc to fit merchants’ budget preferences. However, we have during this study found two methods of deciding the threshold. One method is by performing robustness test find the optimal level of the threshold such that the model identifies all customers who are churning yet not miss any churning customer by being too narrow. We have found that the higher threshold and higher number of purchases before entering the model, the higher likelihood that the customers are churning. However, it is a balance between having a robust model and identifying customers before it is too late. The second method is to compare the customer lifetime as a reference point when deciding the threshold, which is further elaborated on later on.

4.3.7 Weights

The weights in the model decide how large impact each parameter will have on the churn score. The perception from the interviews was that spend and frequency were equally important and they are therefore weighted equally in the model. However, we suggest using regression analysis to analyze the impact of these two parameters under future improvements.

4.3.8 Churn eligible customer

Customers entering the model have to make a certain number of purchases at the merchant and in the merchant segment during the considered period. This requirement is to ensure that the customer have been a previous loyal customer at the merchant as well as are using the card connected to Wrapp. The required
number of purchases to enter the model is depending on the length of the time period as well as the average frequency at the merchant. These limits are in our model set manually, but a future improvement could be to have this connected with the frequency at the merchant. However, we also see the value in having this parameter flexible for the merchants’ preferences, for example to be able to segment churning customers depending on level of previous loyalty.

4.3.9 Churn segmentation

We are here presenting two preferred ways of segmenting defected customers identified by our model. The reason is to, in a simple way, show flexibility and give merchants options to target different types of defected customers.

Level of churn
Defected customers can be segmented depending of level of churn, and in other words, depending on their churn score. The purpose of this is for merchant to be able to choose to give different offer to customers with different level of churn. This also gives them a possibility to focus on the most critical customers if their budget is limited.

Level of previous loyalty
Defected customers can also be segmented depending on their previous loyalty. The purpose with this segmentation is that merchants are more prone to give higher discounts to customer with a higher customer loyalty than customer with a lower customer loyalty. This give merchants options to have different offers to different customers, as well as focus higher resources on their more valuable customers.

4.4 Model validation

Below are the results of our validation tests presented. Firstly, a robustness test to verify that customers identified as defected actually are defected over a longer period of time are presented, and secondly a test where offers were targeted to defected as well as new customers in order to compare the purchase behaviour of these customer segments.
4.4.1 Robustness test

In order to verify the robustness, i.e. the correctness, of the model, we validated whether customers identified by the model one period, also were identified the next period. The robustness test was a result from a meeting we had with Coop, one of Sweden’s largest grocery stores. In order to pursue the churn offer with Wrapp, a requirement from Coop was that we could guarantee that customers identified as defective, actually are defected. More specifically, that we could ensure that the model was not sensitive for small fluctuations in purchase behaviour. As a result, we tested the model on historic data for several of merchants and different thresholds. The tests were mainly done for the grocery segment and the result showed that 66 percent of the customers identified as defected by our model also were identified as defected the next period. Additionally, 78 percent of the customers had still decreased in spend the next period, however though, not as much for all of them to be considered as defected. However, if lowering the threshold, they would be identified as defected. Of all the identified defected customers, 22 percent return to their previous level or higher.

4.4.2 Offer test

The offer test was done in collaboration with a large fashion retailer in Sweden that wishes to be anonymous in this report. As mentioned, the churn offer was given to half of the merchant’s defected customers and the acquisition offer were given to the same number of new customers, that is customer that have not made any previous purchase at the merchant. The result from the test showed that 350 customers redeemed the churn offer and that 67 customers redeemed the acquisition offer. The activation rates were similar for both offers with a resulting redemption rate of 48 percent for the churn offer and 9 percent for the acquisition offer. Moreover, the test showed that the churn offer reactivated 16 percent of the defected customer that received the churn offer and that the acquisition offer acquired 3 percent of the customers that received the acquisition offer. This additionally support our hypothesis that retaining defected customers requires lower incentives than acquiring new customers. In other words, the new customers probably require a more favorable offer in order to reach the same redemption rate as the defected customers, for specific numbers
Moreover, we studied the average receipt for both groups of customers and it showed that the average receipt were 46 percent higher for the churn offer than for the acquisition offer. The average receipt can be used to calculate the so-called cashback rate, which is the cashback divided by the average receipt. In other words, the cashback rate describes the actual discount on the offer. The lower the cashback rate, the lower the discount, which result in a higher return on investment for the merchant. Since our test showed that the churn offer had a higher average receipt, hence, a lower discount, it can be regarded as a more favorable investment for the merchant. The higher average receipt for the churn offer is therefore an additional argument to target offers to defected customers rather than to new customers.

We also studied the control group, which is the group of defected customers that did not receive a churn offer. This group was compared to the group that received an offer in order to understand the offer’s impact on purchase behaviour. The result showed that 34 percent more customers in the group that got an offer made a purchase, and that the number of purchases was 27 percent higher for this group. However, by comparing the retention in the two groups we found that 49 percent of the churn offer group should probably have visited the merchant anyway. This conclusion was drawn based on the assumption that the both groups of defected customers would have made the same number of purchases if not given any offers to any of the groups. Since our robustness test with higher threshold showed other results we believe that the reason for high retention in the control group is probably due to setting a low threshold that resulted in a model sensitive to changes in purchase behaviour. Our recommendation is therefore to higher the threshold in future tests with merchants. However, the model does not solely aim to identify customers that stopped shopping at the merchant, but also customers that decreased their purchases at the merchant. Therefore, there is as mention a balance between having a robust model and identify all customers likely to churn.
<table>
<thead>
<tr>
<th></th>
<th>Churn offer</th>
<th>Acquisition offer</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of offers</td>
<td>2176</td>
<td>2176</td>
</tr>
<tr>
<td>No. of activations</td>
<td>736</td>
<td>704</td>
</tr>
<tr>
<td>Activation rate</td>
<td>34%</td>
<td>32%</td>
</tr>
<tr>
<td>No. of redemptions</td>
<td>350</td>
<td>67</td>
</tr>
<tr>
<td>Redemption rate</td>
<td>48%</td>
<td>10%</td>
</tr>
<tr>
<td>Cashback</td>
<td>50 SEK</td>
<td>50 SEK</td>
</tr>
<tr>
<td>Average receipt</td>
<td>264 SEK</td>
<td>179 SEK</td>
</tr>
<tr>
<td>Cashback rate</td>
<td>19%</td>
<td>28%</td>
</tr>
</tbody>
</table>

Table 1: The results of the churn and acquisition offer tested with a large fashion retailer.
5 Discussion

In this section we will present a discussion regarding different topics and thoughts that have occurred during our work. We will point out a few different concerns and questions that have been raised during interviews and in discussion with employees at Wrapp. We will also present how we would like to see the model be further developed as well as highlight a few areas where we believe further research could contribute.

5.1 Applicability of the model

Rather than creating a model that is accurate for a special type of merchant, the wish from Wrapp was to have a model applicable for, if not all, at least the majority of its partner merchants. During our test though, we have focused towards merchants with high frequency. As we have mention, the reason for this is due to time limitations and our intent was therefore to have the test offer live for a shorter period, which would not have been as suitable for merchants with low frequently visiting customers. Even though the test were limited to high frequency merchants, our belief is that the model’s applicability is not. If the time periods are lengthened, we believe that the model could be used for merchants independent of their frequency. However, our recommendation is that the model is primarily applicable for large high frequency merchants, i.e within the grocery and coffee shop segments. This is due to that companies that have rather low number of customers, in return, have even lower defected customers, which mean that it probably would be more time-consuming to set up the offer than it would impact revenue.

Another concern regarding the applicability, is that the model requires merchants to have competitors and for some merchants, competitors can be complex to define. Such merchants are for example department stores, as Åhléns, which has a broad assortment and offers many different products to their customers. The data Wrapp receive do not show information about the merchandise, and in return, which products or product segment customers are defected from. Therefore, it can be hard to understand whether the customer is defected from
a product segment in particular or from Åhléns in general. The same concern applies for new merchants on the market with unusual value propositions. Since it is complex to define competitors for these merchants, our churn model will be hard to apply. However, these companies usually focus more on customer acquisition, hence, are not the primary target for our model.

We believe that the core of our model, which is to measure parameters at the merchant compare to its competitors, can be useful in other areas. One of which could be for resellers to use our model internally. For instance, Åhléns could measure how the distribution of spend and purchase frequency changes between brands in their store and in return provide the brands with customers that are defected to its competitors. Another example, a bit outside the box, would be to suggest that this could be used for mobile producers in terms of application usage. If the producer could measure the usage and perhaps other parameters between applications in their devices, they can possibly identify churn between these applications.

5.2 Excluded churn

There are several different reasons for churn and, as we have mentioned, this report does not aim to describe nor identify these reasons. However, since the purpose of the model is to identify defected customers who can be retained by an offer, the reason for churn is still relevant to have in mind. Our belief is that churn due to changes in life circumstances that result in churning from the whole merchant segment is a reason for churn that is complicated for Wrapp to do something about. Such reason could be when children grow up and parents stop buying toys, loss of employment, etcetera. Our intent from the beginning have been to try to exclude this type of churn from the model and solely focus on churn that could be prevented by an offer from Wrapp. The result was to have a model which only consider the change between the merchant and competitors, and hence, not consider a customer that churn from the whole merchant segment. We believe this is relevant to point out since it differs from the general definition of churn.
5.3 Variation concerns

One common question and concern that have been expressed during our work is how the model handle seasonal variation and other type of occurrences such as such as holidays and salary payment. Our belief is that these events does not affect the model since the model includes the share of the customers purchases that goes to the merchant. For example, the customers will probably shop less at the merchant in January compared to December, but at the same time also less in the merchant segment. These seasonal variations and other types of occurrences will affect the merchant and the merchants segment proportionally and therefore not have an impact on the churn score.

Another issue is whether or not the model can handle larger external factors, such as for instance recession. We believe that this differs between the merchant segments. For instance, during a recession the consumers are more likely to go from buying high end clothes and eating at restaurant to buying low end clothes and cooking their own food than during a boom. In this scenario the fashion segment would probably be affected by the recession since high end and low end brands are in the same merchant segment. More specifically, customers would be defected from the high end clothing stores, according to the model. On the contrary, merchants such as restaurants and grocery stores would probably not be affected in any larger extent, even though they are each other’s substitutes, since they are in the different merchant segments. Overarching all of this though, is the question to whether or not this will affect the model at all. Since recessions takes place gradually and over larger periods and the model measures changes rather on a monthly basis, our belief is that this will not affect the model.

5.4 Critical reflections

One critical reflection concern is the so-called new customer segment. At Wrapp, a new customer as mentioned defined as customers that have not made any purchases at the merchant. However, this is only measured since the time the customers’ bank card was connected to Wrapp. More specifically, the segment will probably include customers that made purchases at the merchant before
connected their bank card, which means that they actually are not new customers. This probably result in a higher redemption rate for this segment. To avoid this, we have required a minimum number of purchases with the Wrapp connected card.

Another critical reflection is the question to whether or not it is worth for merchants to identify and spend resources into retaining defected customers. Today’s technology with smartphones has resulted in easily available information of products and high price transparency on the market, and in return, higher price awareness for the consumers. This rise concern for how effective the long term effect of offers to defected customer actual is. The risk is, as we see it, that customers only will return for the offer and then continue choosing the cheapest option for the next purchase. Therefore, our suggestion is that the strategy of retaining this customer segment can not only include one offer. Instead, the strategy has to include a more comprehensive churn program during a longer period in order for the customer to become loyal again.

The model does not include customers who have defected outside the periods measured in the model. In detail, if a customer has not made any purchase in period 1, then the customer will not enter the model, and hence, cannot be considered as defected. Therefore, customer that are already defected when running the model will not be identified as defected. However, this will not be a problem in the longer perspective since the model will include these customers over time. It will only be the case the first time the model is being used for a merchant.

5.5 Implication and contribution

We are aware that there are challenges in predicting customers’ future behaviour, however, we do not aim to deliver a churn model that is one hundred percent correct. Instead, our aim is to improve the existing methods of identifying churn that merchants use. We believe that the core value of our model lies in two aspects. Firstly, the model does not only include purchase data from the merchant but also from the competitors. Those merchants that currently tries
to target defected customers, are only able to identify customers that decrease purchasing at their stores, and not customers that increase purchasing at their competitors. Therefore, we have chosen to include competitors in the churn model, since we believe this is one of Wrapp’s unique selling point. Secondly, the model treats every customer individually. In other words, there is no general rule or limit to decide whether a customer is defected or not. For example, a customer who decrease from ten to two purchases are more valuable to retain than a customer that decreases from two to one purchase. If not including the customers’ potential, the mistake of targeting incentives to the customer that dropped from two to one purchases could be made to increase the customers to the same level, rather than focusing on the other customer with a significant higher potential. These are, according to us, the two major contributions of this model.

5.6 Future improvements

As mentioned above, due to time limitations, some parts in our work have been left for future improvements at Wrapp. Firstly, one improvement is to include a decay function in the model, which weights purchases made a long time ago less than purchases made closer in time. The reason for including the decay function is because it is more likely that recent purchases are better indications of the users’ current preferences. This is especially true for merchant where customers make many purchases. Therefore, the decay function should also include purchase frequency at the merchant such that purchases made at high frequency merchants are weighted lower than purchases made at low frequency merchants.

As of right now, the limit of the number of purchases a customer must have made to even be eligible for churn, is done manually. A future improvement is to have this limit calculated automatically, more specifically, correlated to the average frequency at a merchant. For instance, the limit could be such that to enter the model the customer must have made a number of purchases that represent at least 50 percent of the average number of purchases at the merchant. However, in order to be able to segment churning customers based on previous level of loyalty, there is a value having this parameter flexible, and hence,
manually set. Moreover, similar argumentation can be made for the length of the time periods. As of right now we only state that high frequency merchants should have shorter periods, however, we believe that the average frequency at the merchant could be used to decide this automatically or that the time periods are decided in advance for every merchant segment. The threshold deciding how much a customer must decrease in order to be treated as churn can also benefit from further analysis. More specifically, to find a threshold that ensure that the customers that are identified as defected one period actually are defected the next and yet not miss any defected customers. However, by having this flexible, there is a possibility of segmenting churning customers on level of churn.

Another improvement, or even an alternative method, is to estimating the relationships between the parameters spend and frequency on churn by using regression analysis. In detail, regression analysis could be used to investigate how the parameters separately impact the churn score and could therefore be used when choosing the weights of the model. Regression analysis could also have been used in an earlier stage in the choice of which parameters to include in the model.

5.7 Future research

In this study we have focused on identifying churn based on interviews with merchants. We have however not been interviewing the actual customers in order to understand the reason for churn. We therefore encourage any attempt to explain the underlying reason for churn from the customers’ point of view. We also encourage using other methods for understanding how different parameters impact on churn, using for instance regression analysis on transaction data to decide both which parameters to include in the model as well as their relationship. We also encourage to include additional parameters for explaining churn. For instance, by including the location of the purchases could be an indicator of churn which the merchant cannot do anything about, i.e. incidental churn. For instance, if a customer is buying groceries in a new geographic area it can be due to changes in place of residence. This is examples of changes in the circumstances that the merchants probably cannot do anything about, and in
return, customers that probably should be excluded from receiving a churn offer.

Another future research that could build on our work is to investigate how the customer lifetime value matter in terms of churn. The result from our interviews suggest that customer lifetime is something not all merchant use. However, when trying to identify churn it could be of value to know the expected lifetime in a merchant segment in order to use as a reference point when deciding the thresholds. Hence, the customer lifetime value work as a sanity check in order to make sure that the model has identified a reasonable number of defected customers.

Another interesting topic to investigate with regard to this study, is the question to what is considered as successful in preventing churn, and more specifically, when targeting incentives in order to retain them. Since there is an expected lifetime for every customer for a merchant, churn is impossible to fully avoid. However, slowing the churn rate, or in other words, increasing the customer lifetime value, rather than retain the customer to their previous level, could also be seen as successful.

Due to time limitations we were not able to study the testing groups in a longer term as we had hope for, and could therefore not answer whether previous loyal customer have higher potential of becoming loyal again than new customers have of becoming loyal. This is therefore left to future research and we encourage Wrapp to continue executing a/b tests with merchants in order to fully understand the long term implications of retaining defected customers for merchant. We believe that this would be an additional sales argument for purchasing the churn offers and would in turn strengthen Wrapp's reputation as a loyalty application.
6 Conclusion

The main purpose of this study was to investigate how customer churn can be identified through customer transaction data in order to improve marketing strategies for merchants. To answer this questions, five research questions were formulated and this section aims to summarize our answers to these research questions.

How do merchants currently work with churn and what is the demand for identifying defected customers?

Rather unanimously merchants answered that they put little or even no resources into churn prevention. Additionally, merchants that do work with churn uses simplified models, often only including the time passed since the last purchase. As expected, smaller companies answered that they rather focus on customer acquisition than churn. Larger merchants expressed that churn is a concern, however, not a concern they have a current strategy for. Regarding the demand of identifying churn, we have seen a high demand, especially due to the fact that our model includes how customers perform at their competitors. Therefore, all interviewed merchants communicated an interest of being updated on our work and possibly being involved in testing the model.

What are the different types of churn and which of these can be prevented?

From literature we have seen that churn often are divided into voluntary and involuntary churn, where involuntary can be due to the company suspending the customers and therefore not really in focus in churn management. Voluntary churn can be divided into incidental and deliberate churn where incidental refers to churn due to change in life circumstances. An example is when children are growing up and parents stop being toys. Voluntary churn is churn due to the customers actively choosing a competitor and is the churn we have tried to identify. Our view is therefore that deliberate churn is the type of churn that can be prevented by targeting incentives and this was also confirmed during both interviews and in discussion with management at Wrapp.
Which parameters in transaction data can indicate customer churn?
During the study we found several useful parameters that could be provided by transaction data, where spend and frequency was emphasized as the most important parameters. However, both recency and share of wallet are other churn indicators that could be useful.

What should define customer churn and how can churn identification be modeled?
In order to identify deliberate churn we have come to the conclusion that churn in our model is when a customer decrease in purchase frequency and spend from the merchant compared to the merchant segment. However, we have also included when a customer is increasing at the merchant compared to the merchant. More specifically, churn is calculated as the difference between the change in purchase frequency and spend at the merchant compared to the merchant segment. If this number is negative, then the customers is considered as defected. However, in order to not propose a model sensitive to small fluctuations in purchase behaviour, we have included a threshold, which is the limit for when the customer is considered as defected.

How does the purchase behaviour differ between defected customers and new customers when given an offer through Wrapp?
To answer this question as well as test our hypothesis we performed a test where an offer was given to both new customer and defected customer identified by our model. The test was done with a large fashion retailer and showed that 48 percent of the defected customers redeemed the offer while only 9 percent of new customers did. To add to this, the average receipt for defected customers was 46 percent higher than for new customers. This test supported our hypothesis and showed that defected customers not only is easier to retain but also spend more in average than new customers. To give a more comprehensive answer to this question the test should be followed and analyzed in longer terms, something we have to leave for future improvements at Wrapp.
7 References


A Overview of Interviewees

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<tr>
<th>Date</th>
<th>Respondent</th>
<th>Profession</th>
<th>Company</th>
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<tr>
<td>2017-02-01</td>
<td>Celine Fierro</td>
<td>Head of Marketing</td>
<td>Urb-It</td>
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<td>2017-02-06</td>
<td>Mikael Stålnecke</td>
<td>Head of Sales</td>
<td>NA-KD</td>
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<td>2017-02-16</td>
<td>Per Wallgren</td>
<td>Business Controller</td>
<td>Espresso House</td>
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<td>2017-02-20</td>
<td>Caroline Holmberg Aurelius</td>
<td>CRM Manager</td>
<td>Ähléns</td>
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<td>2017-02-23</td>
<td>Christian Lundén &amp; Dzafic Maja</td>
<td>Dir. of Future Business &amp; CRM</td>
<td>Nordic Choice Hotel</td>
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<td>2017-02-27</td>
<td>Interviewee A</td>
<td>Head of Merchandising</td>
<td>Large fashion retailer</td>
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<td>2017-02-28</td>
<td>David Holmstrand</td>
<td>Strategist</td>
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<td>2017-03-08</td>
<td>Anders Asperén</td>
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<td>2017-03-13</td>
<td>Emil Sveningson &amp; Jessica Ericsson</td>
<td>Digital Business &amp; Operations Manager</td>
<td>J.Lindeberg</td>
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Table 2: Summary of interviewees and their positions
B Interview Guide

B.1 Merchants

1. Introduction
   - What is your role and your responsibilities?
   - We describe our thesis and Wrapp in general
   - We describe our definition of churn

2. Loyalty
   - Can you describe your loyalty program?
   - What is the purpose with the loyalty program?
   - How is the loyalty program structured?
   - What determine what offers the customer receives?
   - How loyal is a customer in your industry?
   - Would you say that customers are more or less loyal in your industry compared to other industries?
   - In general, does your customers make purchases from several merchants?
   - How easy would you say that it is for the customer to change merchant?

3. Customers
   - How do you define “a customer”? After a certain number of purchases, or if the customers hold a certain purchase frequency?
   - What is the general purchasing behaviour in your industry?
   - What is the average purchase frequency?
   - How much do the customer spend on average per purchase?
   - How do your customers differ from other merchants’ customers?
   - How are you different from other merchants?
• How do you analyze customers’ purchasing behaviour?
• What is the lifetime of a customer in your industry?

4. Customer Segmentation
• How do you segment your customers? If so, how?
• What is general customer behaviour in the different segments?
• Do you segment your customers based on purchasing behaviour?
• Do you have any idea of how much you think a customer is worth? (more specifically, customer lifetime value)
• Do you segment your customers based on value? If so, how?
• Do you segment your customers based on potential? If so, how?
• Do you focusing your marketing activities towards a specific segment? (new, existing or lost customers)
• Do you take “share of wallet” into account when segmenting customers? If so, how?

5. Churn
• How do you work today in order to prevent churn?
• How would you define a defected customer?
• Are you trying to identify customers who are lost/soon to be defected?
• What parameters are important in order to understand that a customer is lost/soon to be defected?
• If you had access to all transaction data of your customers, including their transaction to your competitors but also in other segments, how would you want to use it to identify churn?
• What do you think is the biggest reason for customers to choose you as a merchant?
• What do you think is the biggest reason why a customer choose a different merchant?

• What have you identified as reasons for churn that is possible to do something about?

• What reasons have you identified that you can not do anything about?

• Do you segment your customers based on conversion/recovery? (Customers who have not yet become frequent customers but are churning/customers who have been frequent customers but reduces their frequency)

6. Other

• How does the data driven marketing work that you use?

• Do you use any more information about your customers than the information given by your membership club?

7. Conclusion

• Is there anything you want to add? Something that you think is relevant to consider regarding this topic that we have not asked you about?

• Is there any person/company you recommend that we contact?

• If we could make offers to customers who are churning, do you want us to contact you?

• When we come up with a churn model, would you like to participate and test it?

• Do you have any questions for us?

• If we publish something you say, would you like read it and approve it before?
B.2 Experts

1. Introduction
   - What is your role and your responsibilities?
   - We describe our thesis and Wrapp in general
   - We describe our definition of churn

2. Loyalty
   - In what way have you been in contact with merchants’ loyalty programs?
   - Can you describe your experiences regarding how merchants’ work with loyalty programs, how they are structured?
   - What would you say is the purpose of loyalty programs?

3. Data driven Marketing
   - What kind of data do merchant generally gather about their customers?
   - Do merchant use more than the data gather from their membership clubs?
   - Can you describe common marketing strategies that merchants use?
   - Can you describe common data driven marketing strategies that merchants use?
   - What would you say are the advantages/disadvantages with different marketing strategies?
   - What would you say are the advantages/disadvantages with different data driven marketing strategies?
   - What do you think of the use of transaction data to target marketing? Advantages/disadvantages?
   - What segment do merchants generally target? New, existing och churned customers?
   - What is your experience regarding that merchants take the customer lifetime value in consideration when doing marketing campaigns?
4. Churn

- Can you describe your experiences regarding how merchants’ work against churn?
- What kind of merchants work against churn?
- Those merchants that does not work with churn, what do you think are the reasons for that?
- What are merchants’ strategies against churn in general?
- Do you have any customer case stories about this topic, that you can tell us about?
- Which industry/industries would you say has the most loyal customers, and vice versa?
- What parameters do you think is important when identifying churn?
- What do you think are the main reasons for churn?
- What purpose do you think our work fulfills? Does this sound like something your customers would be interested in?
- What are the biggest challenges you see with our work?

5. Conclusion

- Is there anything you want to add? Something that you think is relevant to consider regarding this topic that we have not asked you about?
- Is there any person/company you recommend that we contact?
- Do you have any suggestions on literature in our field?
- Do you have any questions for us?
- If we publish something you say, would you like read it and approve it before?
C The algorithm for the test offer

1. Choose merchant
2. Select User-id, Amount Spent and Transaction Date from raw data
3. Divide the transactions into Period 1 and Period 2 based on the transaction date
4. Count the user’s number of transactions and sum the amount spent for the two periods
5. Identify the user ids that made at least a certain number of purchases at the merchant and merchant segment in Period 1
6. Calculate the change in frequency between Period 1 and Period 2 at the merchant
7. Calculate the change in spend between Period 1 and Period 2 at the merchant
8. Calculate the change in frequency between Period 1 and Period 2 at the merchant segment
8. Calculate the change in spend between Period 1 and Period 2 at the merchant segment
9. Calculate the change between the merchant and merchant segment for the both parameters Decide the weights for each parameters and add the parameters together with the decided weights
10. Decide the threshold
11. Use the model to identify defected customers for the merchant with the decided threshold
12. Randomly divide this group into two groups
13. Target one of the groups with the chosen offer
Figure 5: Churn decision tree.