the LISBON MBA
católica | nova
international
a collaboration with MIT

MIT Sloan Management
In collaboration with

Title: **Churn Management in Telecom Operators**
The Portuguese Case

Purpose: Dissertation for obtaining Master of Science in Business Administration

Author: Alberto Eduardo Prazeres Lino da Silva

Date: March 2011

Contents

Executive summary

Considering the actual maturity of the Portuguese Telecommunication market, it has become more lucrative for Telecom companies to significantly invest in a customer relationship model based on retention than to invest efforts in consistently achieve growth through the acquisition of new customers.

In order to successfully retain customers, it is crucial to identify what are the main drivers related to the risk to potentially churn (i.e. proportion of subscribers who leave an operator during a given time period) and what actions can be undertaken in order to avoid customers to leave/switch to competitors.

To achieve it while being cost effective, retention efforts must be adjusted to the risk and value of each client. To do so, it is necessary to segment the active customer base in terms of context and consumption patterns that can predict an intention to churn, may it be voluntary or involuntary and. By doing so, Telecom operators assure that resources are invested in strategies that will result in significant return on investment, while strengthening their competitive positioning.

In this context, churn management has become a fundamental management tool for telecom operators. The definition of a conceptual framework to understand the causes and predicting customers intention to churn is crucial to reduce the overall churn rate. This report intends to describe the methodological approach used in designing a specific churn management model for one of the biggest Portuguese Telecom player. The approach used translated into the identification of behavior patterns by analyzing both contextual and historical data, going one step further than the traditional approaches focused only on data mining techniques (i.e. analysis of historical data generated from billing and contract transactions) . From that, segmented strategies where designed, aimed to tackle the specific causes of churn while strengthening the operator’s relationship with its customers.

Management problem

Currently, churn costs to European and U.S. telecom operators more than €4 billion per year, representing churners a huge burden to the commercial operation of any operator. (Kentritas, S. (ND). Customer Relationship Management: The SAS Perspective). Moreover, operators with high churn rates (30% or plus per year) do not manage to have a return for new customer since it takes in average three years to recuperate the acquisition cost.

Modisette identified three different types of churn according to the cause that lead clients to switch/cancel their subscription with a telecom operator: unavoidable churn, involuntary churn and voluntary churn (Modisette, L. (1999). Milking wireless churn for profit. *Telecommunications*, *Debham, Feb*). Unavoidable churn happens whenever customers dye or move away from the company's operating area. This is the "natural" churn that every telecom operator faces and that cannot or is hardly predictable and upon no management practices can be undertaken in order to mitigate it. Involuntary churn happens when a subscriber is disconnected by the operator due to lack of payment. Service disconnection due to theft or fraud is also considered to be involuntary churn. Finally, voluntary churn is a service disconnection decision taken by the customer who wishes to switch from one operator to the other.

Schmitt also proposed the categorization of churn according to two variables: financial/non financial and voluntary/involuntary churn (Schmitt, J. (1999). Churn: Can carriers cope? *Telecommunications, Debham, Feb*). Financial churn is originated from bad-debt customers while non-financial churn is originated by paying customers. On the other hand, voluntary churn is the churn originated by the own will of the customer while involuntary churn is originated in a service disconnection carried out by the operator. (Figure 1)

Schmitt (1999) – Types of churn

	Involuntary	Voluntary
Financial	• Bad-debt customers whose subscription is canceled due to lack of payment	• Bad-debt customers who intentionally decide to defect
Non-financial	• Paying customers who died or moved away from the company's operating area	• Paying customers who intentionally decide to defect due to insatisfaction with the operator (e.g. Service;Price) or the competitive actions of other operators (e.g. Promotions)

Figure 1 (Schmitt, J. (1999). Churn: Can carriers cope? *Telecommunications, Debham, Feb)*

The churn rate in the analyzed Portuguese telecom operator means an annual revenue loss of around 30M€. The main responsible for that loss comes from the involuntary churn rate (from now on designated as non-payment churn - NP Churn), being an issue of major concern to the company.

Thus, it became crucial to the company to understand the profile of the clients deactivated for non-payment in order to predict default risk and assess possible improvement opportunities that could reduce the overall churn rate. The profile assessment focused on identifying which context, consumption pattern, payment profile and satisfaction index could influence the probability or not to default the company. Additionally, there was also the need to design a segmented management model, where customers would be classified in terms of risk and value, to proceed with more accurate and effective retention and collection procedures.

Relevance of the management problem for business organizations

The increased maturity and market liberalization in the Telecom industry in general, where it is now usual to see all carriers competing across a multitude of services – from mobile to fixed voice, from broadband to TV – has changed the industry making it more fierce than ever. Switching from carrier to carrier has become more and more attractive, as promotions have been an incentive for customers.

In this context churn has become a major concern for Telecom operators. There are now critical issues that must be addressed in order for operators to maintain their market competitiveness. How can we predict which clients are more leaned to switch? How can we detect those clients? How can we predict when that change will happen?

In Europe, the monthly churn rate for mobile operators varies between 25 to 30 percent a year. Considering that in average each lost customer represents around 500€ in lost revenues, there is a high interest in investing in retention. Empirical studies show that acquiring new subscribers is five times more expensive than retaining existing clients (Berson et al. 2000; Wei and Chiu 2002; Hung, Yen and Wang 2006; Ahn, Han and Lee 2006).

It is evident that for mobile operators to succeed nowadays in mature markets such as the Portuguese one, emphasis must be put on retaining more than acquiring. As such, effective churn management models have become an important competitive tool, and crucial to the customer relationship management. Those are able to predict with some certainty what is the typical profile of clients that present a high probability of churning and those who present more loyalty/stability, while identifying the main causes related to churn.

Therefore, churn management models are the base to define retention strategies. First because it allows to understand what customers do a operator really want to retain? Is it worth to invest effort in managing the life cycle of a customer unprofitable or that present a very low margin? What win-back strategies must be employed for each type of client? Second because it also allows for an operator to understand what type of clients are being acquired. Knowing the profile of churners, it is easier to know which customers to attract and to which extent can we improve the value proposition. How can we be cost-effective in acquiring new clients?

Nonetheless, predicting customer churn isn't a fairly easy task even more when considering the involuntary churn, were customers don't even signal their intention to leave the carrier. Customers simply stop paying their invoices until they are completely disconnected.

Traditional management techniques are focused on identifying which groups of customers are more prone to defect than others (Marco Richeldi and Alessandro Perrucci (2002). Churn Analysis Case Study. *Telecom Italia Lab*). To do so, data mining techniques are the most common used tool, since such techniques allow to identify churn patterns according to historical transactional data (e.g. billing). But the growing complexity of the Telecom market and the competitive urge as put a bigger emphasis in looking at the reasons that lead customers to churn more than identifying when and who will churn.

As such, modern churn management models are focused not only in the data mining techniques but also in the analysis of contextual data as the path to improve customer satisfaction and therefore loyalty. Predicting who and when customers will churn is a crucial tool for telecommunications companies to implement successful retention strategies. Reviewing processes or customer incentive scheme can lead to higher retention capabilities. Also, identifying causes of churn, may it be the lack of financial resources, insatisfaction with the service or better offers from the competition is also important to assess what organizational/business changes are needed to mitigate those factors.

Literature review

Data mining is described as a way to extract customer sensitive information from large databases in a way that predictive informations are identified and isolated. The SAS Institute describes data mining as "the process of selecting, exploring, and modeling large amounts of data to uncover previously unknown patterns for a business advantage" (LU, Junxiang (2001). Predicting Customer Churn in the Telecommunications – An application of Survival Analysis Modeling Using SAS. *Kansas – USA, Sprint Communication Company*).

Many fields of study have used data mining techniques in order to solve managerial issues. The technique has been used in several different industries in order to identify certain specific patterns, and has been increasingly been used by telecommunication companies. Research literature on data mining tools for predicting churn patterns are mainly focused on using specific techniques like clusterization or decisions trees to identify links among several sets of data. Understanding those links allow to identify specific behavioral patterns that translate into a given probability to churn (Tsau Young Lin,Ying Xie,Anita Wasilewska (ND). Data Mining: Foundations and Practice.).

Wei and Chang used data mining techniques in order to identify a specific customer group who would be more responsive into subscribing to additional fixed landlines (Wei and Chang (2000). Telecommunication Data Mining for Target Marketing. *Journal of computer*). To do so, they have analyzed individual call patterns in order to indentify patterns that would match the defined criteria's for the target group. The results of the data mining have showed great success since the target identified by the research was three times more responsive than the rest of the customers into subscribing to additional fixed landlines.

Anand, S. S., Patricj, A. R., Hughes, J. G., and Bell D. A. have defined a data mining methodology for cross-sales in the financial sector (Anand, S. S., Patricj, A. R., Hughes, J. G.,and Bell D. A. (1998). A data mining methodology for cross-sales. *Knowledge-based systems, 10, 449-461*). The conceptual frameworks relied on identifying customers common characteristics and define rules that would cater a unique set of different outcomes in terms of cross-sales potential. Moreover, the researchers identified, during the data mining analysis, additional relevant informations and patterns that were considered to have great

potential to be applied in other service sectors, something also referred by Anand et Al when assessing the data mining application in a specific context.
On the other hand, and focusing in a more broad concept of customer relationship management, Hung, Yen and Wang (2006) describe churn management as a practice based on two main analytical processes: a first step based on identifying which type of customers are prone to churn and a second step focused on designing a reactive strategy to retain clients when they decide to desert.

Nonetheless, academic research has shown that the traditional approach based on data mining techniques is a limited tool to face the challenge of retaining customers in the current context. Data mining techniques are seen as a way to act on the consequences rather than to act on the cause itself. As such, more than who and when, the challenge is to understand why.

From a management perspective, the process to understand the causes that lead the customers to churn are restricted in terms of the resources employed in this sort of complex analysis (Berson 2000; Wei and Chiu 2002; Hung, Yen and Wang 2006; Ahn, Han and Lee 2006; Sohn and Kim 2008;Owczarczuk 2010; Bose and Chen 2009). Nowadays, identifying the causes that lead customer to churn is a crucial component for the customer relationship management and is seen as a very demanding task since churn related causes depend on a wide variety of reasons related to each customer context (Koustuv Dasgupta, Rahul Singh, Balaji Viswanathan, Dipanjan Chakraborty, Sougata Mukherjea, Amit A. Nanavati. Social Ties and their Relevance to Churn in Mobile Telecom Networks. *IBM India Research Lab.*). To deeply understand what motivates certain customers to churn and others not, it is important to analyze more than just the data related to consumption patterns, focusing also on contextual data such as region of origin or activation channel.

As such, the project undertaken at one of the leading Portuguese Telecom company has used not only an approach based on data mining techniques, but also on identifying and acting upon the main causes of churn. Considering the relevant literature review, a methodology based on several steps was employed to assess (1) churners profile by segmenting the customer base and define probability of default and (2) main causes of churn (Figure 2)

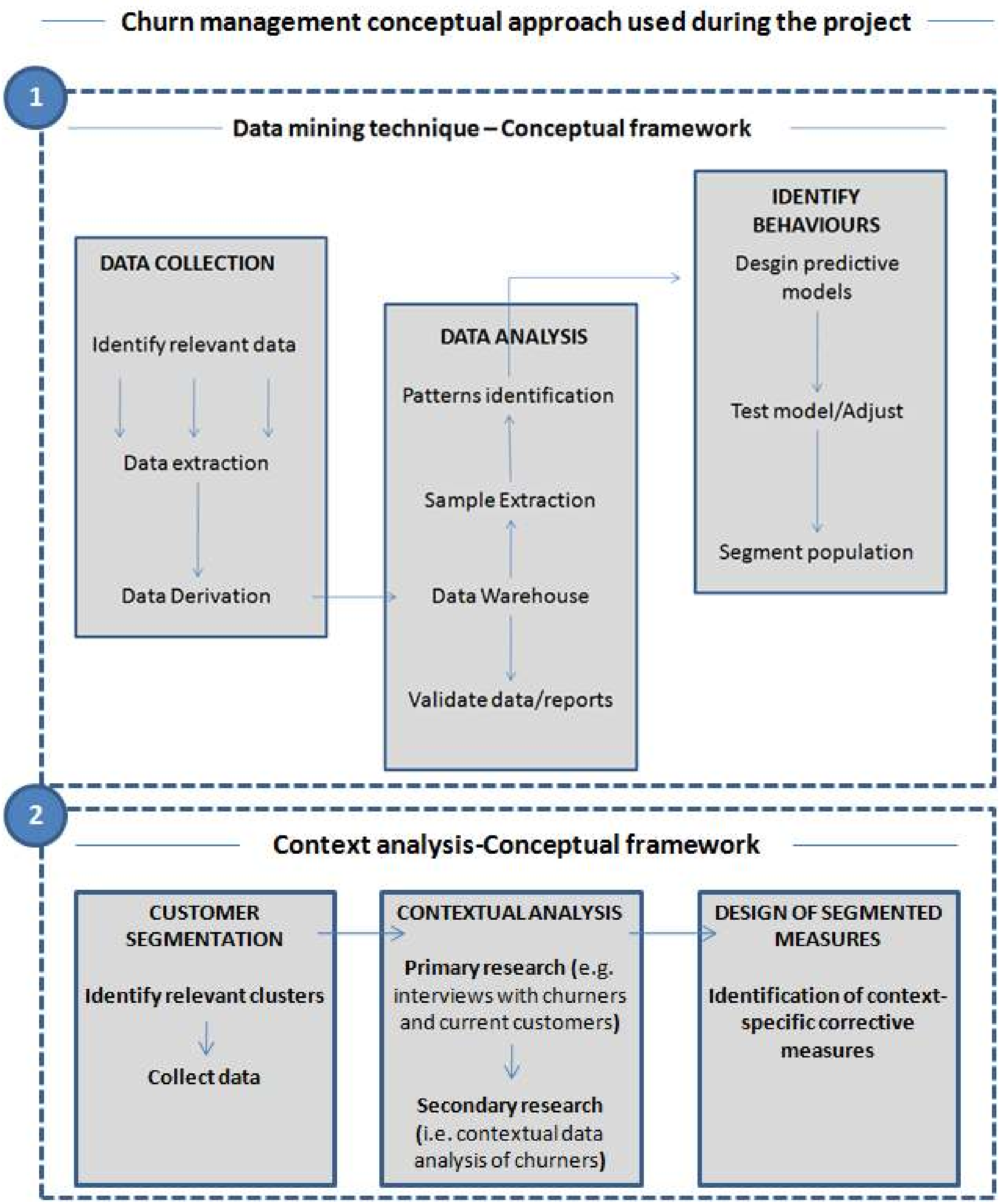


Figure 2

Data sources and methods used to collect data

In order to analyze churn indicators using data mining techniques and identify the main causes of churn, both quantitative and qualitative data was collected.

The quantitative analysis was critical to sustain the project early hypotheses and was one of the main activities of the project. A set of different indicators were analyzed in order to (1) typify the profile of clients deactivated by non-payment and (2) typify the profile of the current active base of postpaid customers. To do so, two main types of data were collected:

1. **Billing and collection indicators**
   - Evolution of postpaid billing
   - Evolution of provisions for uncollectable debts
   - Evolution of bad dept and its distribution in terms of number of days (60,90 and more than 90 days)
2. **Client data (both for deactivated clients and active clients in June 2010)**
   - Client identification data (e.g. NIF; Account number; Service number)
   - Client "natural attributes" (e.g. Type of client; Contract duration; Sale channel)
   - Client consumption data (e.g. Average revenue per user (ARPU); Minutes of usage (MOU))
   - Satisfaction index (e.g. Number and type of complaints)
   - Collection data (e.g. Payment record data)

All the collected data was desegregated by client segment and the considered time horizon was minimum one year (July 2009 to June 2010) in order to isolate possible seasonability effects.

The data was directly extracted from the internal Data Warehouse and then analyzed using data treatment software (mainly Access) and other statistical software, since no internal reports considered this specific information as part of the monitored KPIs. Due to the extent of the data to be analyzed and the need to cross several indicators, this was a time consuming activity and a very sensitive activity to realize, since the resulting data would be from then on considered as the valid internal benchmark.

In terms of the qualitative analysis carried on, it was critical to assess the main causes that lead clients to be deactivated by non-payment. Additionally, it was also important to understand what additional procedures could be implemented in order to facilitate the payment management.

In order to do so, two set of different types of clients were interviewed via phone: 1256 clients whose invoice was due and 1.415 clients who had been deactivated by non-payment (after all collection procedures failed). To them two additional questions (close format) were asked along with the other collection/deactivation procedures:

1. **What were the main reasons for the delay in the payment?**
    - Didn’t receive the invoice
    - Invoice was wrong
    - Client pretended a invoice duplicate
    - Service was defective/had problems
    - Does not have financial resources to pay
    - Forgot
    - Has a non-resolved complaint
    - Other (open answer)
2. **What procedures could make your (the client) payment management easier?**
    - Phone contact from the operator
    - More warnings (via SMS or email)
    - Payment agreements
    - Extension of the payment term
    - Other (open answer)

In addition to both the quantitative and qualitative analysis, an extensive benchmark with other operations from the group was also carried on.

The benchmark considered 5 other European operations that demonstrated consistent indicators in at least one or more indicators relevant to the analysis carried on in the Portuguese operation (e.g. Bad debt; Direct Debit payment penetration; Involuntary churn).

In order to gather the data, video conferences with each one of the operations was held with the local credit managers/churn managers and data regarding the above issues was collected:

- Rationale for the good indicators (e.g. Low bad debt rate despite high level of acceptance and low level direct debit payments)
- Organizational structure
- Collection procedures
- Past, present and future initiatives regarding churn and credit control

Data treatment and analysis

In terms of data treatment, the project was very demanding due to the extent of data to be analyzed and sources from which the data was extracted.

One major issue regarding the treatment of data was the constant need to cross-check the extracted data with other sources of information in order to validate each source. The fact that different information was extracted from different sources (e.g for the same client, account informations and service informations were extracted from different sources) meant that a huge work of cleaning the information base was needed previous to the data analysis. As such, one of the main challenges was to stabilize the analyzed indicators (i.e. monthly active customer base greatly differed from source to source). Deviations had to be identified and isolate in order to get the same base across sources and therefore manage to achieve comparable and congruent analysis.

According to several work hypotheses that were defined early on during the project, a different set of analysis were carried on in order to identify the profile of churners and the context related attributes that had a high correlation with the involuntary churn rate (Appendix 1):

1. **Analysis of the churn and revenue contribution per segment (i.e. Consumer, SOHO, SME and Government), identifying which segments were crucial to address in order to effectively reduce involuntary churn rate and revenue loss.**
   - Analysis of the individual contribution of each postpaid segment to the overall involuntary churn rate, identifying the segment that most contributed to the non-payment churn rate.
   - Analysis of the individual contribution of each postpaid segment to the overall postpaid billing, identifying the most important segment in terms of revenue generator.
   - The matrix considering those two analysis allowed to identify priority targets to address
2. **Analysis of the customers "natural attributes"**

- Analysis of the impact of the origin of the client in terms of the probability of defaulting, considering the percentage of total deactivations, involuntary churn rate and standard deviation per district.
- Analysis of the impact of the activation channel (i.e. direct vs indirect channel) and sub-channel in terms of the probability of defaulting, considering the percentage of total deactivations, involuntary churn rate and standard deviation per channel.
- Analysis of the impact of the type of payment method chosen by the customer (i.e. Direct Debit or other methods) in terms of the probability of defaulting, considering the percentage of total deactivations, involuntary churn rate and standard deviation per payment method.
- Analysis of the impact of the type of handset (i.e. 2/2,5G vs 3/3,5G) in terms of the probability of defaulting, considering the percentage of total deactivations, involuntary churn rate and standard deviation per type of handset.
- Analysis of the probability of defaulting according to the life cycle of the client (e.g. early defaulting; defaulting when near contract end), analyzing unusual deactivation patterns during the key moments of the client lifecycle.

3. **Analysis of the customers consumption data**
   - Analysis of the involuntary churn rate per type of product (i.e. Voice, Mobile broadband or ADSL) and within each type of pricing plan.
   - Analysis of unusual consumption patterns in terms of MOU and ARPU (i.e. high increases/decreases of consumption near deactivation) that can denote a high probability of defaulting.
   - Analysis of the probability of defaulting according to the client score and indirectly client value (i.e. higher scores mean higher client value for the company). The analysis meant to identify if the client management matched its value for the company in terms of effort to retention.
4. **Analysis of the customers satisfaction index**
   - Analysis of the impact of the satisfaction index in the probability of defaulting. Clients with pending complaints have different collection procedures, being therefore clearly identifiable. As for, assessing the involuntary churn rate of this group is indicative of how well customers are satisfied with the company’s customer service and how well can complaints predict future defaulting patterns.

- Identification of the main problems (e.g. technical assistance; billing) related to customer insatisfaction, measured by percentage of total complaints by motive.

5. **Analysis of the customers collection data**
   - Analysis of the recurrence level of customers who enter in collection procedures (i.e. is there always the same customers?)
   - Breakdown of the number of customers per collection procedures:
     - Analysis of the volume in each step – letters, SMS and calls - (from warning the customer to total deactivation)
     - Identification of the collection procedures that most impact the customers in terms of intention to pay.
6. **Analysis of the main causes of non-payment**
   - Qualitative analysis of the main causes for non-payment from the customer perspective, contrasting it with the preliminary work hypotheses.
   - Identification of potential improvement opportunities for the payment management model and collection procedures that could be translated into more payment volumes in a shortest amount of time.

Conclusions

The completion of the quantitative and qualitative analysis allowed to identify which were the main causes to churn and attributes of the clients who were deactivated for non-payment. In summary, the analysis concluded that:

- There are significant differences of non-payment churn rates in terms of the district of origin of the client. Those can be explained mainly to economic differences of each region, especially relevant in the SOHO and SME segments. As such, the place of origin as been considered as an important aspect to predict possible default patterns.
- There are significant differences of non-payment churn rates in terms of acquisition channel. The indirect channel presents a much higher non-payment churn rate than the one of the direct channel. This difference is once more very relevant for the SOHO and SME segment. This difference can be explained by the difference of sales skills and type of clients approached. The fact that the direct channel is a channel that is much more trained and prepared to sell, and that only approaches the high-end SME (that naturally have a lesser default probability) allows it to a have better performance in terms of non-payment churn rate. Therefore, the channel of acquisition has been considered as an important criterion for the non-payment churn for its high correlation and standard deviation.
- In terms of correlation of the client score (attributed according to the client value to the company) with the non-payment churn rate, the quantitative analysis showed that there is an asymmetry of the client value and its retention rate. The churn rate increases from the low to the middle score and then decreases from the middle score to the high score. As such, there might be an improvement opportunity to adequate the service/monitoring of each client to its value.
- Although there are no big churn rate differences in the Voice and ADSL products, the Mobile Broadband clearly stands out with almost the double churn rate than the other products. This is clearly related to specificity of the product itself. Unlike he voice product, where the phone number is an important aspect of the customer loyalty to a certain operator, in the case of the mobile broadband there are no

specific attributes of the product that don't make it easily replaceable. As such, the probability of default increases dramatically, even more when considering that those customers are hard to reach in order to implement the collection procedures (most of the clients don't have an alternative phone number – the only registered phone number is the one associated with the mobile broadband service). The type of product has been considered highly correlated to the probability of churning for non-payment.

- The type of payment is highly correlated with the non-payment churn. The Direct debit method can present as much as 10 times less probability of default than other means of payment. Although it is not clear is this a cause or a consequence (i.e. are clients who adhere to direct debit naturally better payers, or is it the payment method who dictates if the customer will or not be a good payer?), the direct debit presents many vantages compared to other ways of payment. Not only it reduces the churn probability but also increases the company available cash flow since payment are almost always due on time and never enter in the collection process (saving operational costs to the operator).
- Depending on the life cycle of the client, there are specific periods where the probability of non-payment churn increases dramatically. The two main critical moments where default occurs is (1) during the first 3 months of life (i.e. after activation) of a customer. During this period many situations can happen, from activating a client with clear fraud intentions to unsatisfied customers who refuse to pay (e.g. the services are not correctly activated/not working properly), that lead to increase churn rates and (2) near contract ending since from the ending of the contract onwards no more penalties are applied to customers who decide to leave (i.e. they simply have to pay the overdue last invoice and change operator). In this case it is crucial to successfully lead a customer life cycle management program that guarantees and effective monitoring o each client during the critical moments of its life cycle. In this case also the client antiquity is seen as a crucial information in order to assess the customer probability of defaulting.
- In terms of consumption pattern, more than 50% of customers that were deactivated for non-payment presented a very unusual consumption pattern the month before being deactivated. If the majority of those cases were customers who

registered a drastic reduction of the consumption (i.e a reduction of more than 50% of the usual average monthly consumption) there was also a significant number of cases were the consumption increased dramatically (i.e. an increase of more than 100% of the usual average monthly consumption). In this last case, and although in some cases that difference can be explained by real communication needs variance, in most of the cases are related to clients who are fraud since they already know that they are being disconnected for non-payment. This is one of the clearest indicators of probability of default that was encountered during the analysis, and is a trigger that must be constantly monitorized in order to pre-identify churner and take counter-measures.

- There is a high correlation of clients who have pending complaints and the probability of being disconnected for non-payment. Additionally the analysis showed that from the clients disconnected for non-payment, more than 50% had had at least one complaint in the 6 months previous to the deactivation. This high correlation can be attributable mainly to two main causes: (1) the operator fails to satisfy the client in terms of their complaints. The insatisfaction may arise from the fact that the problem ends up not being solved or simply because the solution takes too long. (2) some clients already are aware of the special collection policies for customers with pending complaints (that are less strict) and therefore use that strategy in their favor to continue to use the service without paying/having a broader payment time. Once more, the complaint factor is seen as very relevant factor when assessing the probability of a customer to eventually churn.
- In terms of the collection procedures, there is a high number of repeats, meaning that the customers whose invoice pass the due date are mostly all same. This can be explained by the fact that most of the customers already are aware of the collection procedures and timings, using it in their favor in order to delay as much as possible the due payment. This happens mainly because the segmentation level of collection procedures is not broad enough and mainly because it is static, allowing customer to be aware of each collection step. Nonetheless, the quantitative analysis as allowed to identify that early collection procedures have a much bigger impact in clients, allowing to recover most of the debt, and that phone calls are much more effective into convincing the customers to pay than SMS reminders.

- Finally, the qualitative analysis allowed to identify that most customers who are deactivated for non-payment claim that the major problem was related to the fact that they forgot to pay, despite the time lag between the invoice and all the reminders. As ways to improve their payment management capacity of was referred that more contacts via phone would be an effective mean to increase. But more interesting than the affirmative questions was to assess that a very few percentage of clients actually referred financial problems as one of the main problems of their non-payment.

After having identified the attributes that most correlate to the involuntary churn rate and the main causes of associated to non-payment, it was possible to segment the customer base according to the risk/value of each customer (Figure 3) and define segmented actions (Appendix 2).

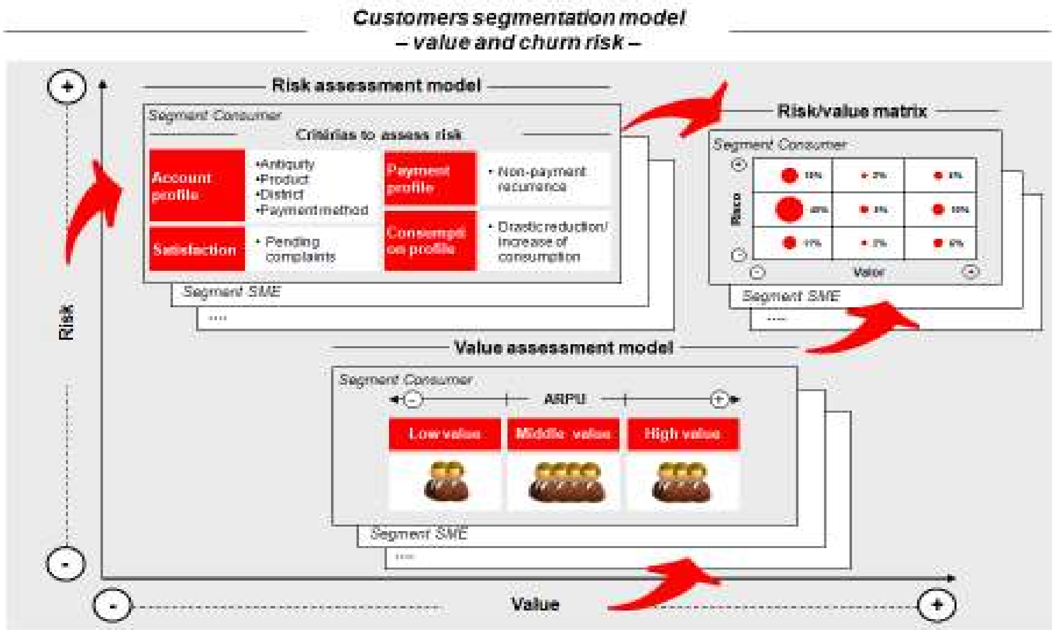


Figure 3: Customer segmentation model

Main learning's

I considered this project has a very instructive one from different point of views.

First it allowed me to define a clear framework, adaptable to other similar type of projects, to identify causes, understand consequences and define actions through data mining techniques and context analysis. It was critical for the success of the project to trace early hypotheses of what could eventually be related to the involuntary churn rate. From that point develop a quantitative and qualitative approach to validate/dismiss criteria's and identify the typical profile of a "non-payment churner". Finally to identify operational/commercial/financial improvement opportunities that can lead to better retention and financial performance.

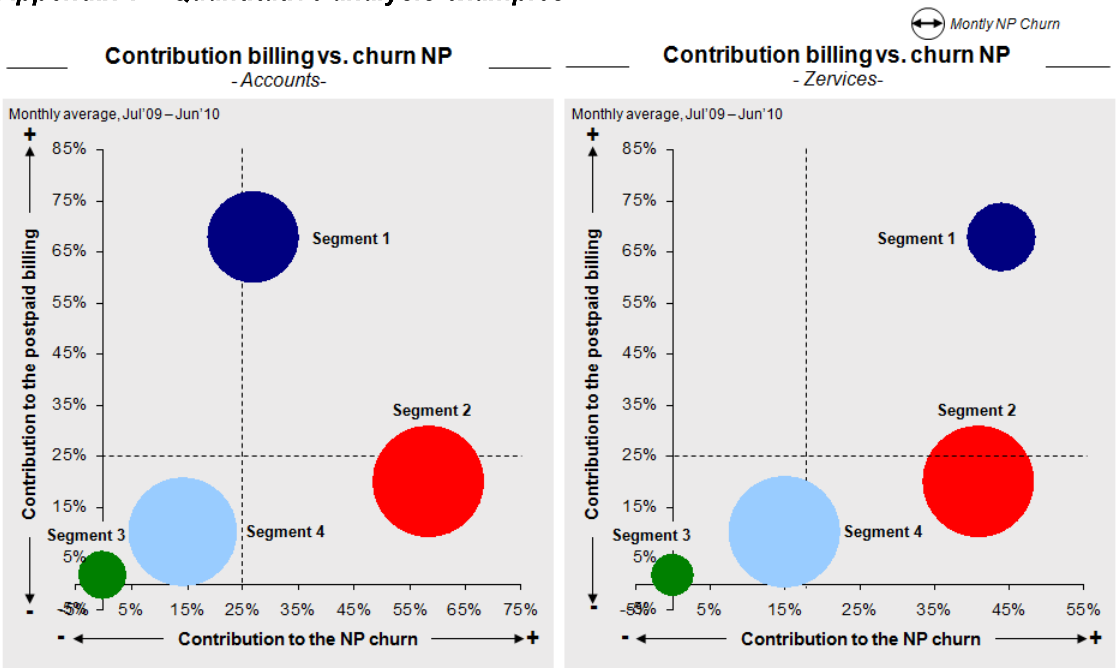
Second, it allowed to get in touch with the Telecom industry in Portugal and have a broader understanding of certain limitations imposed both externally and internally. Although Portugal has a very competitive Telecom market, recognized has one of the most innovative in the world, it is also true that there are some cultural and procedural limitations vis-à-vis other markets that limit the competitiveness of the national telecom industry.

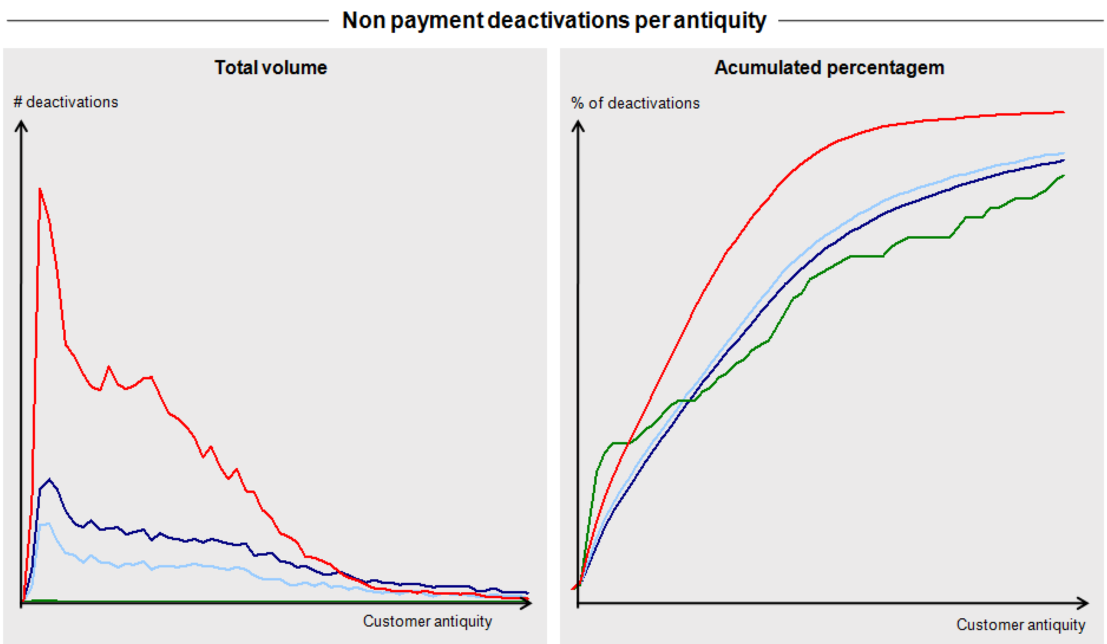
References

- LU, Junxiang (2001). **Predicting Customer Churn in the Telecommunications – An application of Survival Analysis Modeling Using SAS**. Kansas – USA, Sprint Communication Company.
- Koustuv Dasgupta, Rahul Singh, Balaji Viswanathan, Dipanjan Chakraborty, Sougata Mukherjea, Amit A. Nanavati. **Social Ties and their Relevance to Churn in Mobile Telecom Networks**. IBM India Research Lab.
- Marco Richeldi and Alessandro Perrucci (2002). **Churn Analysis Case Study**. Telecom Italia Lab
- Tsau Young Lin,Ying Xie,Anita Wasilewska (**ND**). **Data Mining: Foundations and Practice.**
- Anand, S. S., Patricj, A. R., Hughes, J. G.,and Bell D. A. (1998). **A data mining methodology for cross-sales**. Knowledge-based systems, 10, 449-461.
- Kentritas, S. (ND). **Customer Relationship Management: The SAS Perspective**.
- Wei and Chang (2000). **Telecommunication Data Mining for Target Marketing**. Journal of computer.
- Modisette, L. (1999). **Milking wireless churn for profit.** Telecommunications, Debham, Feb
- Schmitt, J. (1999). **Churn: Can carriers cope?.** Telecommunications, Debham, Feb

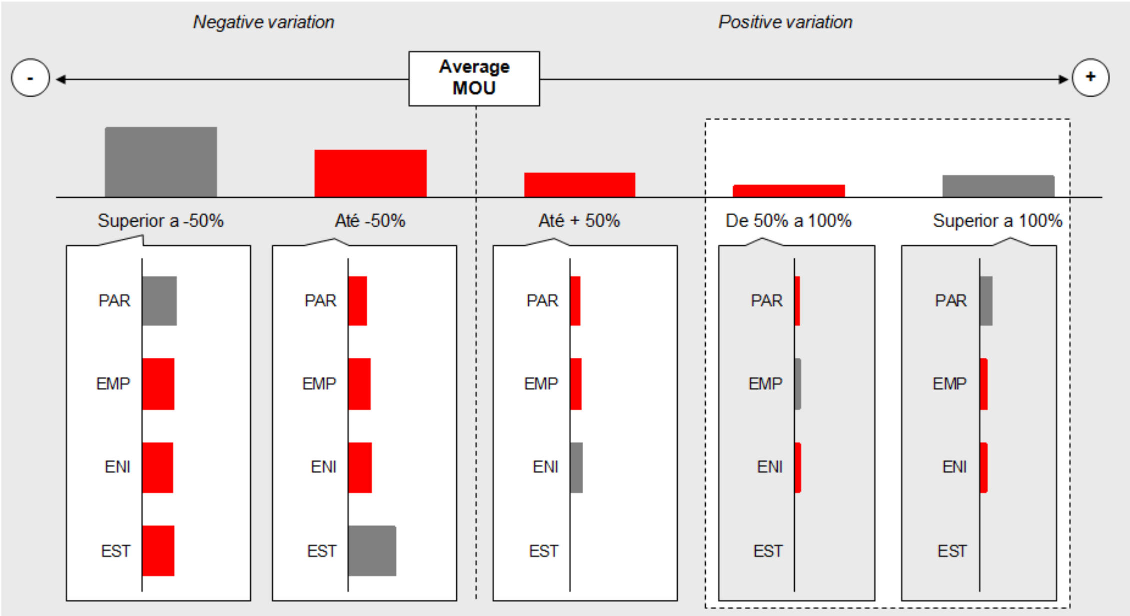
Appendices

Appendix 1 – Quantitative analysis examples

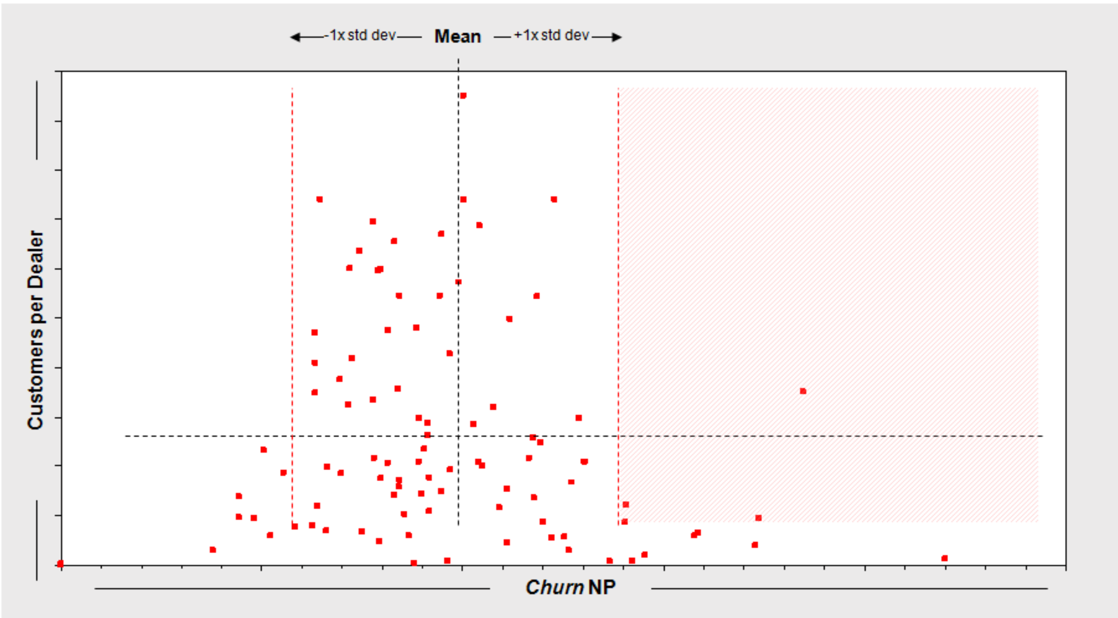




Consumption variation one month before deactivation



Churn *NP*[(1)] vs Customers per Dealer



Appendix 2 – Example of segmented collection procedures

CR 1

	0	A	B	C	D	1	E	2	F	G	H	I	3
Modelo actual		1	4	8	12	15	16	19	22	24	-	29	29
Seg. Vermelho		1	3	6	10	13	OC 14	17	18	20	22	25	25
Seg. Laranja		1	4	8	12	15	OC 16	19	21	23	25	27	27
Seg. Amarelo		1	3	6	10	13	14	17	18	20	22	25	25
Seg. Azul		1	4	8	12	15	16	19	21	23	25	27	27
Seg. Verde		1	4	8	12	15	16	19	22	SMS 24	27	29	29

CR 2

	0	A	B	C	D	1	E	2	F	G	H	I	3
Modelo actual		1	3	6	11	13	14	17	19	22	-	29	29
Seg. Vermelho		1	3	6	11	13	OC 14	16	18	20	22	25	25
Seg. Laranja		1	3	6	11	13	OC 14	17	19	22	24	27	27
Seg. Amarelo		1	3	6	11	13	14	16	18	20	22	25	25
Seg. Azul		1	3	6	11	13	14	17	19	22	24	27	27
Seg. Verde		1	3	6	11	13	14	17	19	SMS 22	25	29	29