Preventing Churn in Telecommunications: The Forgotten Network

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ABSTRACT. This paper outlines an approach developed as a part of a company-wide churn management initiative of a major European telecom operator. We are focusing on explanatory churn model for the postpaid segment, assuming that the mobile telecom network, the key resource of operators, is also a churn driver in case it under delivers to customers' expectations. Typically, insights generated by churn models are deployed in marketing campaigns; our model's insights are used in network optimization in order to remove the key network related churn drivers and therefore prevent churn, rather than cure it. The insights generated by the model have caused a paradigm shift in managing the network with the operator where the research was conducted.

Keywords: Mobile Network, Churn Prevention, Postpaid, Explanatory Model, Customer Centricity

1 Introduction

The phenomenon of churn, which denotes loss of a client to competitors, is a key problem across industries. New customers are difficult to find, especially in saturated markets, such as the European mobile communications market. Furthermore, it is far less expensive to retain existing customers than to acquire new ones. Retention is usually a process that identifies customers that are likely to churn, using various predictive modeling techniques, followed by approaching these customers with suitable offers that would persuade the customer into extending the contract. But, can the customer be prevented from even wanting to churn? Can the main churn drivers be mitigated beforehand?

This paper is focused on a company-wide churn reduction initiative conducted in one of the largest European telecom operators. As explained above, churn/customer retention is typically a marketing based process. But, despite of the involvement of predictive analytics, this process is in its nature reactive, because the customer has already decided to churn and an action is being taken to stop this.

In this research we are taking a completely different approach: the model generated here is not to be used for campaigning. Our method attempts to tackle churn by identifying the key reasons why customers decide to churn in order to alleviate them, rather than identify prospective churners. This approach is even more justified taking into

adfa, p. 1, 2011.

account the current and future stringent European Data Privacy regulations, which limit operators use of customers' data for campaigning purposes. This is especially the case with Internet usage data.

The mobile telecommunications network is a key resource for telecom operators. It is the means of service delivery as well as the most frequent touch-point with the customers. Problems with ability to use the network (services) have been identified by surveys internal to the company, as well as in literature (section 2), as one of the key reasons to churn. But, most of the time, customers are not experts and cannot pinpoint what exactly is going wrong. Most of the time, this is generalized as "coverage problems". This research is taking a deep dive into various network problems and their relation to customer churn. The main objective here is to identify the problems that customers that have churned were experiencing, so that they can be corrected for the current customer base and reduce their likelihood of churn. In other words, rather than treating symptoms, we are treating the cause of the disease. This research and its outcome have caused a paradigm shift in managing the network with the operator where the research was conducted.

In this research we are focusing on the post-paid customer segment. Even though these customers are bound by contract, which makes the task of churn prediction slightly less challenging, the revenues that are typically generated here are much higher than in the prepaid segment. Furthermore, postpaid customers' service usage is much higher, compared to the prepaid segment; therefore they would be more prone to experiencing network related issues which can potentially lead to churn. The combination of higher usage and revenues makes it easier to justify the network investments needed to remedy their problems.

The rest of the paper is structured as follows. Section 2 describes the related work on telecom churn. Section 3 discusses the dataset and methodology we used. Section 4 contains the results, their application. Limitations and future work are discussed in section 5. Finally, we present our conclusions in section 6.

2 Telecom Churn in Literature

Churn in various industries has been a growing topic of research for the last 15 years [1]. According to [2], churn management consists of predicting which customers are going to churn and evaluating which action is most effective in retaining these customers. Retention strategies are in the focus of [3]. However, most often churn prediction and improving model performance is analyzed following one of these two strategies: adding/improving the data to mine and inventing new algorithms or improving the existing ones [2].

The remark above is certainly valid in the case of telecom churn literature. Many papers are trying to find the best algorithm that would outperform all others: Logistic Regression, Decision Trees, Neural Networks, evolutionary learning, discriminant analysis, Bayesian approaches are examined in [4,5,6,7]; Support Vector Machines, Random Forest, Rotation Forest, Bagging and Boosting are analyzed in [1,8,9,10]. In our view, the value of this research is somewhat limited, at least for real world data mining, given the No Free Lunch theorem [11]. In recent years the overwhelming theme in (telecom) churn research is Social Networks Analysis (SNA), claiming to largely improve on existing churn models [12,13,14,15,16,17,18,19]. However, some of our recent work has demonstrated that this claim is not generally applicable, at least not in prepaid churn prediction on a European market [20]. Most of the SNA research focuses on the Asian or US Markets.

Taking into account the data perspective, most of the literature, especially the one focusing on SNA, is using features extracted from Call Detail Records (CDRs). Contractual, demographic, billing, handset, customer service, market (competitor's offers), and customer survey data is used by [3,4,5,6,7,8] in addition to CDRs. Just a few of these papers take into account any network usage related problems as possible factors affecting churn. For instance, dropped calls are considered in [4,21] as potential churn influencers. Service quality in general and innovativeness is marked as churn detractor by [22].

Predictive models trying to explain churn have not received as much attention in literature [2,23]. Nevertheless, there are studies in industries other than telecom illustrating the need to gain insight into causes of churn [24,25]. Furthermore, research based on customer surveys claims that network coverage, mobile signal strength and voice call drops are reasons for customers to churn [21,22,26,27,28]. However, all these papers are based on survey data, thus perception of quality and not actual network counters.

It is apparent that in most recent telecom churn research the physical telecom network- the means of delivering telecom services, has been largely neglected. At best quality (or the lack of) of voice call usage is considered. To the best of our knowledge, there is little or no research on how Internet usage on a mobile network and its quality parameters might affect churn. This is one of the key reasons why the topic of our research is an explanatory churn model for telecommunications with actual network quality usage parameters as its focus, not just the customers' perception of network quality. In addition, this model, unlike the related work, is not focusing on retention; instead, it is concentrating on eliminating what we see as one of the crucial causes of telecom churn- poor experience using the services on the network.

3 Dataset and Methodology

In this section we will describe the process and the data set used in this research. As mentioned previously, this research was not started with retention campaigns in mind. It was a part of a cross departmental company-wide churn tackling initiative, executed in parallel with regular churn campaigns. Therefore, the objective of this research was not to compete with churn models created for campaigning, but to detect whether there are telecom network quality related factors influencing churn and identify potential remedies.

Table 1. List of contractual, demographic and CDR based features

Contractual and demographic features	Features Extracted from CDRs
Contract expiry List of services/ products used Subscription fee Monthly Bill for each of services Age, gender, zip code Handset	Amount of Voice Calls, SMS and Internet Volume (MB) used, both local and roaming Breakdowns of Voice Calls and SMS onto national-international, internal-external(competitors network)

Table 2. List of network quality features per category

General Network Quality	Voice and SMS quality	Internet quality
2G and 3G Coverage at home Provisioning Errors	Voice Call and SMS Dropped Voice Call Setup Failures Voice Call and SMS drop rate Voice Call Setup Duration (Maximum and Average)	3G and 2G Data Attempts 3G and 2G Data Errors 3G and 2G Success Rate Ratio of 3G usage vs. 2G usage

3.1 Dataset

The results presented here are based on a random sample of 150,000 consumer postpaid subscribers of the operator from September 2012. This is just a fraction of the overall base, the exact percentage is confidential. There was a limitation enforced on the dataset related to contract expiry date: the sample was limited to subscribers whose contracts were expiring in three months or have already expired; thus only customers at risk of churn were taken into account. Churn was measured for the following two months, October and November 2012, combined.

The final dataset consisted of 750 features, gathered by merging tables from CRM and Network databases. In addition to the attributes similar to what was described in section 2 (see Table 1) we added so called Network quality or usability features [29] (see Table 2). The features extracted from CDRs and the network quality features represent monthly aggregates. We also examined their respective three-month aggregates, as well as if there is a rising or declining trend in the past three months for any of these features and use these as potential predictors of churn.

3.2 Methodology

Our research setup is similar to what we have described in [29]. The data originally residing in various CRM and Network quality databases was collected into a single Oracle database, which allowed easier manipulation and data cleansing [30]. For Data analysis, Predictor Selection and Model Development and Assessment we used the commercial tool Pegasystems Predictive Analytics Director [31].

We divided the sample into training, validation and testing set using the ratio 50:25:25. The validation set is used during the data analysis stage as a “pre-test” set, in order to verify the univariate performance of each predicting variable with relation to churn, established on the training set.

The performance measure used to evaluate the performance of each individual predictor, as well as the models, was Coefficient of Concordance (CoC), a rank correlation measure related to Kendall’s tau, suitable for evaluating scoring models [31,32]. The CoC (Figure 1) is a measure equivalent to the Area under the ROC (AUC). One interpretation of the CoC measure is that in a scoring model it gives the probability that a randomly chosen positive case will get a higher score than a randomly chosen negative case. The CoC measures the grey area in the graph depicted on Figure 1 and can thus be translated to the Gini coefficient. The CoC value ranges from 50 to 100. The random choice has a CoC value of 50.

All models developed are scoring models, i.e. we calculate probabilities that someone will churn, without setting a cutoff point. As mentioned above, these models are not to be used for campaigning, but for network improvements, therefore setting a cutoff point to strictly classify whether an instance is a churner or not is not necessary. For this reason, using measures such as recall and precision are not applicable in our case.

During the data analysis stage, the continuous variables are discretized into bins. Bins without significant performance difference are then grouped together. Basically, this is a supervised, bottom-up approach to discretization of continuous variables. One of the advantages of this approach is that it can address non-linear effects of variables onto churn: namely, each separate bin gets a score which is concordant to churn and this score is used for modeling. This process is similar for symbolic variables. Variables can be inspected via histograms and the discretization settings can be manually changed if deemed necessary. The next step in the process is predictor grouping which assists feature selection. Namely, variables that are correlated to each other are grouped together. A given predictor may have a high univariate performance, but also be correlated with other candidate predictors that are even stronger, hence not adding value to a model.

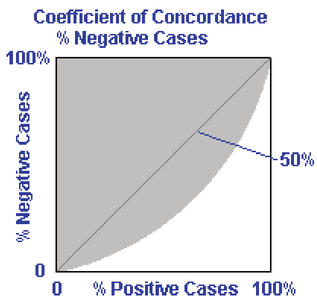

Fig. 1. Coefficient of Concordance

We first used the best predictor of each group and then selected/deselected variables manually to develop the models with a good performance, but also good explanatory value.

As explained previously, the topic of this research is not finding the next best algorithm. That is why we used standard algorithms, such as Logistic Regression and Decision Trees based on the CHAID splitting method [33]. These methods also perfectly fit the explanatory nature of our research, because they are easy to interpret. This is an advantage in commercial settings, where people that need to make investment decisions based on the model and implement its results are not data miners.

The modeling process results in scoring models: each instance is allocated a rank score concordant with the probability of being a churner. The CoC (AUC) measure is used to measure model quality. In addition, we use gain charts as visual representation of model performance. On the y-axis, these charts show the captured proportion of the desired class (i.e. churners in selection divided by total number of churners) with increasing selection sizes (x-axis, from highest scoring to lowest scoring) (see Figure 2).

4 Results, Application and Discussion

Even though optimizing model performance is not the topic of our paper, we deem it necessary to benchmark our network against the campaigning model. The performance (CoC) of the models we created is presented on Table 3.

It is worthwhile mentioning that all models presented here were built using Decision Trees with CHAID splitting criterion, which have an inherent characteristic of dealing with non-linear data. We also tested models using Logistic Regression, but they had somewhat worse performance (0.5 CoC points). Please note that due to the discretization process described in the methodology section, this implementation of logistic regression is able to handle non-linear dependencies too. It is worthwhile mentioning that in order to test for non-linear interaction effects between a combination of two variables and churn we created close to 280,000 new predictors using two way combinations of all of the 750 variables. However, no strong non-linear effects were noted.

Table 3. Model Performance

Model Description	Number of Predictors	Performance on Training set (CoC)	Performance on Test set (CoC)
Campaign	3	76.0	75.9
Campaign_PlusNetwork	6	76.8	76.7
ContractEnd_PlusNetwork	5	75.1	74.7
Campaign_MinusContractEnd	5	68.7	68.1
PurelyNetworkBased	5	66.6	66.5

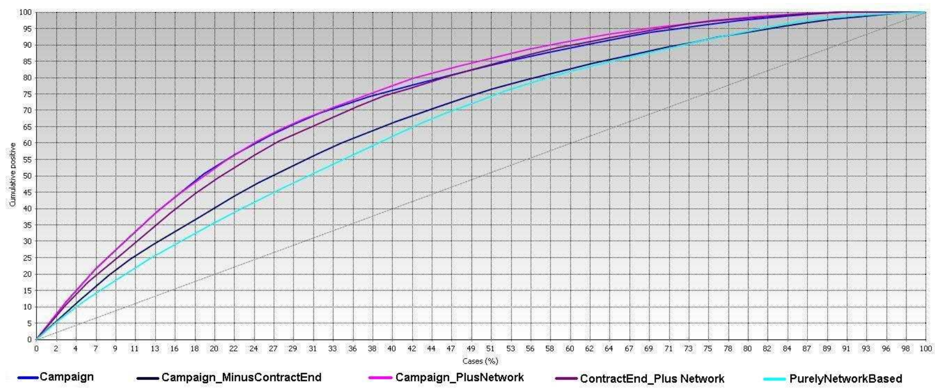

Fig. 2. Gain Charts of Models used

As can be seen on Table 3, adding network related features to a campaigning model (Model Campaign_PlusNetwork) only marginally increases performance (1 CoC point), visible on Figure 2 only after the 40th percentile of cases ranked by churn, which confirms our result from [29]. However, campaigning wise, this has no meaning because rarely do campaigns address more than 40% of the base that is at churn risk.

The PurelyNetworkBased model, which is the topic of our research, has the weakest performance. Nevertheless, just for comparison reasons, we built Campaign models without the strongest predictor - Contract End (Campaign_MinusContractEnd) and a model based on a combination of just the Contract End and Network Factors (ContractEnd_PlusNetwork). The Campaign_MinusContractEnd performs only somewhat better than the Pure Network Model (1.5 CoC on the test set in Table 3, or 5% more churners in the Top 20% of the scores on Figure 2), and the Model ContractEnd_PlusNetwork performs only marginally worse than the campaigning model (1.3 CoC on the test set in Table 3, or 4% less churners in the Top 20% of the scores on Figure 2). The conclusion here is that, less the Contract End variable, the network quality parameters from our Purely Network Based Model perform nearly as well as the other predictors.

However, performance was not the main topic of our research. The main aim was explanatory value of our model. On Figure 2 it is shown that Purely Network Based Model can address the 35% of churners in the top 20% of scores, while the Campaign model addresses nearly 55% of all churners in the top 20% of scores. This may be interpreted as the Network factors being “responsible” for the 35% out of 55% of churners in the Top 20% of all scores and that correcting these parameters would mitigate at least a part of them[1]. The rest of the churn (the other 20%) is due to other reasons, e.g. a better competitor offer. Having this in mind, it was worthwhile analyzing the parameters that constitute this Purely Network Based model.

1 In retention campaigns too, one cannot expect 100% acceptance rate

Table 4. Univariate performance of predictors (CoC)

Variable	Performance (CoC)
Contract End Date	73.1
Total Duration of Provisioning Errors in the past six months	62.5
Average Ratio of 2G and 3G Data Events in the past three Months	59.2
Count of 2G Data Events in the past three Months	57.5
Sum of Call Drops and Call Setup Failures in the past three months	56.8
Average Voice Call Setup Duration for the past three months	52.4

Due to confidentiality reasons we cannot disclose the exact numbers and weights of the parameters constituting our model. Nevertheless, we can disclose parameters of which our network model is consisted, ranked by their individual performance (CoC): The Total Duration of Provisioning Errors in the past six months; The Average Ratio of 2G and 3G Data Events in the Past three months; The Count of 2G Data Events in the past three Months; The Sum of Call Drops and Call Setup Failures in the past three months and The Average Voice Call Setup Duration for the past three months. The individual influence (CoC) of each of these parameters onto churn is presented on Table 4. Just for comparison, we also show the performance of the best predictor, the contract end date, which has a superior prediction power. However, the purpose of these models is to models is to investigate why customers churn from a network perspective and offer means of alleviating these reasons. In this case, the relationship with contract end date is secondary. When customers get closer to the end of their contract, there is a higher risk of churn. Moreover, customers out of contract for a longer period of time have proven to be loyal, as the other customers have left.

The influence of each of these parameters onto customer experience and therefore churn can be explained and is agreed upon by the company experts. First of all, it is interesting to note that the Sum of Call Drops and Call Setup Failures in the past three months is not a rate, but an absolute count. Namely, it is irrelevant if a customer dropped two calls out of 30 or out of a 100, the two dropped calls drive churn. The parameter Average Voice Call Setup Duration for the past three months implies that customers do not appreciate having to wait a long time to establish a voice call. Provisioning errors are errors where customers have not been enabled to use certain services on the network even though they have subscribed for them (e.g. not being provisioned to use Internet), or do not have the appropriate quality of service (e.g. being provisioned to used Internet at 1 Mbps when subscribed to 3 Mbps). These errors do not occur frequently but are deemed by experts to have a severely negative influence onto satisfaction even if they occur once during the contract duration; therefore we summed up six months of these errors' history. It is interesting to see the growing influence of mobile Internet services onto churn, especially the strong preference of customers to use the 3G network, which is by design much faster than the 2G network[2]. The low 2G speed is not deemed satisfactory, it can be in fact perceived by the customers as not being connected at all. The influence of quality of Internet services

2 3G networks reach speed of 21Mbps, while for 2G the maximum speed is only 64 Kbps

onto churn is represented via the Number of 2G Data Events and the Ratio of 3G vs. 2G Data Events.

The added value of these parameters is that they denote clear actions for the technology department on which actions to take in order to prevent churn. In order to develop these actions, we went back to analyzing the predictors mentioned above. Namely, we were looking for thresholds in these parameters that, once crossed, point to higher churn probabilities (e.g. Customers having more than 5 dropped calls in 3 months are 2 times more likely to churn). Projects have been developed to maintain and correct these parameters and their respective critical values (increased churn risk thresholds). This also had a profound effect onto the mindset of the department maintaining the network: the focus has shifted from a network centric approach to a customer centric approach in managing the network. We will explain what this means using the example of Voice Call Drops. The network centric approach in managing this key performance indicator would be to just measure a network wide call drop rate and attempt to maintain it above a certain threshold by giving priority to fixing network cells with a large number of dropped calls. The customer centric approach in managing this parameter is to monitor the number of customers experiencing dropped calls and giving highest priority to network cells where *most customers* experience dropped calls. The customer centric approach allows addressing the problem of a higher number of customers, rather than focusing on network cells where only few customers experience a large number of dropped calls. It has already been implemented and has helped reduce the number of customers experiencing dropped calls in general, which resulted in improved satisfaction in customer surveys (internal to the operator), implicating that churn reduction should follow. Similar approaches are developed to address the other parameters from our model. Also, it is possible that the solution applied to a given network cell to reduce the number of customers experiencing dropped voice calls may also influence some of the other quality parameters, especially in a case of a 3G network cell (e.g. increasing the coverage area or adding extra capacity to a 3G cell might reduce both the number of customers experiencing dropped calls and prevent them from falling back to a neighboring 2G cell when using Internet). As an extension of this approach, it can be envisioned that cells where a high number of customers that are already at churn risk experience dropped calls are given priority, but this is subject to legal limitations with regard to data privacy[3].

To summarize, even though our churn model based entirely on network quality parameters has lesser performance compared to a normal campaigning models, it does have many other advantages: it addressed churn in a preventive manner, as it is not necessary to run retention campaigns with it; it provided guidance on what are the critical network parameters that need to be corrected in order to address churn from a network perspective; and it created a mind-shift in the department managing the network into a customer centric perspective, which already resulted in increased customer satisfaction.

[3] It involves storing the cells/locations of particular customers

5 Limitations And Future Work

The first limitation we would like to address is the lack of coverage data per customer. We were only able to calculate (not measure) the coverage at home for each customer. Loss of coverage for each customer is impossible to measure from the network side. Having adequate coverage information could have improved our model. However, the Ratio between 2G and 3G data events does imply the influence of loss of 3G coverage or insufficient 3G capacity in certain areas onto churn.

Other limitations of this research are of legal nature. Namely, in most European countries stringent Data Privacy Acts or Net Neutrality Laws (will soon) exist. This makes it impossible to look into individual consumption of different types of Internet use (e.g. browsing, streaming, messaging, VoIP etc), which could provide even better insights into what type of service degradation leads to churn.

Next, as usage patterns change, so do the expectations from the service quality that the network provides. Therefore, in time we expect a change in the influence on churn of the various factors that we discussed which makes the model outdated. This will especially be the case after the introduction of 4G (LTE) networks, which allow much faster Internet speed (throughput). However, these issues can be addressed by remodeling.

As future work, we would like to go one step further, and investigate the benefits network experience measured directly on the phone, via a preinstalled app, of course with customers' permission. We believe that this would provide a 360 degrees view of customers' network experience and close the gap created by the data that is difficult to obtain due to technical or legal limitations. Measurements taken directly on the phone are the ultimate determinant of customer's network experience.

6 Conclusions

In this paper we presented an atypical approach to churn management in commercial settings. We succeeded in explaining at least a part of churn via actual measurements of network quality. The main benefits of our approach are the following: First, we managed to build an explanatory churn model by sacrificing only a part of the performance. Second, our churn model is based on features that are extracted from actual network parameters rather than surveys (real network experience vs. perception). Third, this model generates insights on which network parameters are necessary to be corrected in order to reduce churn, which is a new way of churn reduction. The insights generated caused a shift from network centricity towards customer centricity in managing the telecom network. Using this process, the churn mitigation process is no longer just a retention campaign: the churn efforts are no longer the responsibility of just the CRM teams, Marketing and Customer service, but also the Technology department, managing the network is involved. Finally, our research is deployed and in use in one of the largest European telecom operators and has already contributed to increased customer satisfaction, implicating that churn reduction should follow.

Last but not least, we would like to point out the possibility of applying our research onto domains other than mobile telecom. Obviously, this approach can be mirrored onto fixed telecommunications and potentially into churn in other industries, but also in many other cases where prevention is more important than the cure, like certain medical research.

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