Customer Churn Prediction in Mobile Operator Using Combined Model

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Abstract: Data Mining technologies are developing very rapidly nowadays. One of the biggest fields of application of data mining is prediction of churn in service provider companies. Customers who switch to another service provider are called churned customers. In this study are described main techniques and processes of Data Mining. Customer churn is defined, different types and causes of churn are discussed. Social aspects of churn are brought to attention and specifically related to realities of Azerbaijan.

1 INTRODUCTION

Mobile market is very competitive and changing all the time. Due to those changes companies have to spend more resources to prevent customers from switching service provider because it is getting much more expensive to attract new customer rather than to retain existing one.

Relevance of this work is defined by high competition on mobile operator market after third company entered with lower prices. It is also planned to implement MNP (Mobile Number Portability) service this year what will enable subscribers to switch service provider and keep their old number. Churn is a worldwide problem because it is very difficult to win customers' loyalty in modern virtualized world. There are almost none personal bonds between mass service providers and their subscribers.

This work, like all other researches, also has its limitations. One of the major limitations of this research was data classification and data confidentially in mobile operator that prevented from having access to a part of customer‘s data such as billing and credit data as well as call details records. This helped to build social graph of people interaction and apply social analysis techniques for determining strong ties and how people's decision to churn is affected by their social group. For companies, the cost of acquiring new customers is increasing day by day. Therefore, a new era has begun in marketing industry. Instead of organizing campaigns to win new customers, companies are searching different variety of programs to emphasis on customer satisfaction, to increase customer-based earnings and to have higher customer loyalty. The only method to achieve those goals is preventing customer churn before it happens. At this point, customer churn modeling has created an important competitive advantage and a new workspace. A good modeling reveals which customer is close to churn and which is loyal. With the development in database systems and the variability of customer behavior, an extraordinary increase in the size of the data has occurred. This causes to extract previously unknown information and relationships in huge amount of data. This information requires applying different techniques according to the structure of the data sets to be analyzed. The results of the analysis are used to plan a comprehensive promotional campaigns and new strategies (Huang, 2012).

1.2 Churn and Its Prediction

Customer churn is term to denote the customers which are willing to leave for competing companies. It is estimated that to attract new customer is five times more expensive than to keep existing one. Customer churn is accepted as inevitable part of the market (Geppert, 2003).

There are several concepts and methods to detect customers who are about to switch to another operator. A good churn prediction system should not only detect at potential churners, but also provide a sufficiently long term forecast. When potential

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churners are identified, the marketing department usually contacts them and, if the customers are established as high churn risk, takes appropriate actions to prevent loss of customers.

Modern churn-analysis tools are divided into two categories: tools based on patterns of usage and ones based on billing data. Usage-based tools watch for customer usage patterns and try to predict when a customer will leave. Diagnostic models based on usage can be as simple as tracking price-plan changes or as complicated as watching certain customers' day-to-day usage. A usage-based model, for example, might record that a customer on a $75 monthly service plan switched to a $49 plan. The next month, he switched to a $29 plan. That pattern signifies the customer is significantly altering his usage and likely will churn soon (Geppert, 2003).

The next generation of churn-analysis tools is more complex and uses more variables. It takes into account thousands of factors, such as where a customer called, when he called and his cell-site movement patterns, to predict when he is likely to churn. These churn-analysis models have not been fully implemented by any mobile operator yet. Parts of this model were implemented by some companies, but the models they use are proprietary. Churn analysis of next generation requires a heavy commitment and careful planning, which many operators do not want to do.

2 CUSTOMER CHURN

2.1 Churn Definition

If a customer stops the contract with one company and becomes a customer of a competitor, this customer is considered lost customer or churn customer. Customer loss is very closely related with customer loyalty. Today's economic trend dictates that price cuts are not the only way to build customer loyalty. Accordingly, adding new value added services to the products has become an industry norm to have loyal customer. The main goal of customer lost study is to figure out a customer who will likely be lost and is to calculate cost of obtaining those customers back again. During the analysis, the most important point is the definition of the churner customer. In some cases, to make a definition is very difficult. A credit card customer, for instance, can easily start using another bank's credit card without cancelling credit card of current bank. In this specific case, a decrease in spending can be taken into consideration to understand the customer's loss. Customer's loss is a major problem for companies which are likely to lose their customers easily. Banks, insurance and telecommunication companies can be given as examples (Lazarov, 2007).

2.2 Types of Churn

- Active/Deliberate – customer decides to quit his contract and to switch to another provider. Reasons for this may include: dissatisfaction with the quality of service, too high prices, no rewards for customer loyalty, bad support, no information about reasons and predicted resolution time for service problems, privacy concerns.
- Rotational/Incidental – the customer quits contract without the aim of switching to a competitor. It usually happens because of changes in the circumstances that make it impossible to use the service, e.g. financial problems, when customer can't pay; or change of the geographical location which is not covered by company.
- Passive/Non-voluntary – the company discontinues the contract itself. Reason can be fraud, debt or long period of inactivity (Tuğba, 2010).

There are two categories of rotational churn: when subscriber stops paying after contract ends or while it is still active. Jonathan Burez calls them commercial and financial churn respectively (Burez, 2008).

Voluntary churn (active, rotational) is hard to predict. And while incidental churn only explains a small fraction of overall churn it is very useful to predict and react taking appropriate action to prevent deliberate churn. To prevent voluntary churn operator has to identify churner with high probability and to find reasons why he wanted to switch mobile operator.

Furthermore, churning can be divided also into three other groups:

- Total – the agreement is officially cancelled;
- Hidden – the contract is not cancelled, but the customer is not actively using the service since a long period of time;
- Partial – the agreement is not cancelled, but the customer is not using the services to a full extent and is using only parts of it, and is instead using constantly a service of a competitor.

Depending on the company, the contract type and the business model that is being applied hidden or partial churning can lead to considerable money loss and also needs to be identified and action should be taken in order not to lose completely the customer (Khalatyan, 2010).

2.3 Problems and Threats

Preventing customer churn is critical for the survival of mobile service providers because it is estimated that the cost of acquiring a new customer is about $300 or more if the advertising, marketing, and technical support are all taken into consideration. On the other hand, the cost of retaining a current customer is usually as low as the cost of a single customer retention call or a single mail solicitation (Berson *et al.*, 2002). High acquisition cost makes it imperative for mobile service providers to devise ways to predict the churn behavior and execute appropriate proactive actions before customers leave the company (Berson *et al.*, 2002).

In addition to lost revenue, customer churn means increased activation and deactivation costs. In the global wireless industry, these amount to $10 billion per year, according to an August 2001 study by International Data Corporation (Geppert, 2003).

Geppert (2003) indicated that a high churn rate also puts pressure on companies to win new customers. The cost of acquiring each new customer ranges from $350 to $475 and providers need to retain these new customers for more than four years to break even (Geppert, 2003).

Replacing old customers with new ones carries other burdens. In addition to marketing and advertising, companies incur costs associated with provisioning new customers, as well as increased risks associated with billing issues and other revenue assurance matters. Customer churn also generates soft costs: loss of brand value when dissatisfied customers tell others about their experiences, lost opportunities for cross-selling of complementary products and services, and a potential domino effect with respect to the carrier‘s remaining customer base. Further, the deactivation and disconnection of customers brings inherent risk of revenue and margin deterioration, particularly when multiple service providers are involved. Finally, the potential impacts on profitability that come from inactive, underutilized, and otherwise unprofitable network facilities must be considered

2.4 Techniques for Churn Prediction

Marcin Owczarczuk (2010) in his article “Churn Models for Prepaid Customers in the Cellular Telecommunication Industry Using Large Data Marts” described methods to predict churn for prepaid customers where big data marts are available for analyses. He used datasets with 1381 variables for each of about 80000 customers.

“In this article, we evaluated usefulness of regression and decision trees approach to the problem of modeling churn in the prepaid sector of the cellular telecommunication company. Linear models are more stable than decision trees that get old quickly and their performance weakens in time, especially in top deciles of the score. Nevertheless, we showed that prepaid churn can be effectively predicted using large data mart” (Owczarczuk, 2010).

Situation described in Marcin Owczarczuk’s work is somehow similar to the one in this work. In this work is also used big datamart of prepaid customers containing 637 fields. But an attempt to reduce amount of variables is made to make understanding of model easier and to reduce time needed to build a model. It was also experimentally proven that small number of variables is enough to churn with high accuracy (Verbeke *et al.*, 2012).

“Customer Churn Analysis in Telecommunication Sector” by Umman Tuğba Şimşek Gürsoy. used similar techniques like Decision Tree and Logistic Regression Analysis but focuses mostly on determining the reasons why customers decide to churn. He compared and analyzed different parameters and variables for churning and non-churning customers and got interesting results. He discovered that incoming calls have big influence on customers’ decision as well as discount offers which they get (Tuğba *et al.*, 2010).

In their article “Turning Telecommunications Call Details to Churn Prediction: a Data Mining Approach” Chih-Ping Weia and I-Tang Chiub were using call detail data to determine customer behavior: “.. we propose, design, and experimentally evaluate a churn-prediction technique that predicts churning from subscriber contractual information and call pattern changes extracted from call details. This proposed technique is capable of identifying potential churners at the contract level for a specific prediction time-period. In addition, the proposed technique incorporates the multi-classifier class-combiner approach to address the challenge of a highly skewed class distribution between churners and non-churners“ (Weia *et al.*, 2002).

V. Yeshwanth *et al.* and Ying Huang, Tahar Kechadi paper presents predictive modeling of customer behavior based on the application of hybrid learning approaches for churn prediction in the mobile network: “Our proposed framework deals with a better and more accurate churner prediction technique compared to the existing ones as it incorporates hybrid learning method which is a combination of tree induction system and genetic programming to derive the rules for classification based on the customer behavior" (Yeshwanth *et al.*, 2011).

Next work has similar objectives: "To obtain more accurate predictive results, we present a novel hybrid model-based learning system, which integrates the supervised and unsupervised techniques for predicting customer behavior" (Huang *et al.*, 2013).

These articles helped to make decision to use neural network, cox regression and decision tree techniques in conjunction to build model that predicts churn customers with high probability like neural networks and which decisions could be explained like decision tree model.

2.5 Social Ties and Their Influence

Churn is not only statistical phenomenon; it also should be discussed from sociological point of view. Customers make decision to churn based not only on their personal preferences or some objective reasons such as price and quality of the service but also based on their social surrounding, influence from family members and friends.

First in the list, the oldest and most cited article is "Social Ties and their Relevance to Churn in Mobile Telecom Networks" by Koustuv Dasgupta *et al.* (2008). In this article authors used detailed call record data of mobile operator for one month. Data contains detailed information about voice calls, SMS, value-added calls of users. They built graph for all connections between subscribers based on calls made between them. To reduce graph's size and eliminate biased data they excluded one-direction only connections and short numbers. They possessed only this CDR files and no additional information about customers like demographics, when he started using service, how much spent during last months. Such practical limitations made the problem very challenging, but authors succeed to demonstrate how reasonable prediction accuracy can still be achieved using only link information.

In another work "An Efficient Method of Building the Telecom Social Network for Churn Prediction" by Pushpa and G Shobha, authors made accent on finding groups of customers within social graph. Contrary to the previous article they paid a lot of attention on the types of relationships between nodes. They wroite about two types of social networks: Homogeneous and Heterogeous. Homogeneous social networks are those where is only one kind of relationship between the customer for example the relationship may be friendship between the two customers are linked heterogeneous social networks represent several kinds of relationship between customers, and can be called as Multi-relational social networks. Example of different relationship types may be: friendship, acquaintance, professional, family. Based on the duration of voice calls, call frequency etc. for each of these relationship types it is possible to define unique behavioral pattern. Authors concluded that the accuracy of the churning model can be increased by considering the multiple relationship between the customers while construction of the telecom social network to extract the hidden communities of the churners and non-churners (Pushpa *et al.*, 2012).

Next work is called "Predicting customer churn in mobile networks through analysis of social groups" by Yossi Richter *et al.* (2010). In this work author implemented opposite approach to on in previous article by concentrating on social groups first and eliminating weak ties between groups. By doing so he got several completely separated groups. Richter calls it the group-first social networks approach because first he calculates churn prediction for the group rather than individual customer as is done in most researches. He used decision tree algorithm for scoring each group's churn based on defined KPI's of the group. After that author calculated churn prediction for individual subscribers by first computing their relative churn score (Tuğba *et al.*, 2010).

Xiaohang Zhang (2012) "Predicting Customer Churn through Interpersonal Influence" used methods for social network analysis described in aforementioned article by Koustuv Dasgupta (2008) but also combined it with personal characteristic of the customer. He built three models based only on network attributes, only traditional attributes and combination of both. He applied three popular data classification techniques including logistic regression (LR), decision tree (DT) and neural network (NN) methods. Then author compared the prediction results of traditional attributes-based models, network attributes-based models and combined attributes models and found that incorporating network attributes into predicting models can greatly improve prediction accuracy. In addition he proposed a novel prediction model based on the propagation process that accounts for interpersonal influence and customers' personalized characters. The empirical results show that the proposed propagation model outperforms traditional classification models (Zhang, 2012).

And the last article in this review of social aspect of churn is called "Estimating the effect of word of mouth on churn and cross-buying in the mobile phone market with Markov logic networks" by Torsten Dierkes *et al*. (2011). His main goal was to optimize network analysis process by introducing Markov logic networks (MLNs) as this method have recently been suggested as a significant step forward in this field. The method draws on Markov Random Fields and ILP (inductive logic programming) and is able to handle larger data sets compared to earlier ILP implementations such as FOIL. They collected customers' call data and built social graph just like researchers from previous articles that was described. But this time authors inserted this data in a relational database creating multiple relations between nodes. They used Alchemy – open source software for learning Markov logic networks from data. Markov logic networks (MLNs) are a collection of formulas from first-order logic, to each of which a weight is assigned. In other words, it describes a probabilistic logic. Ideas from estimating Markov networks are then applied to learn the weights of the formulas. The vertices of the MLN graph are atomic formulas, and the edges are the logical connectives used to construct the logical formula. A Markov network is a model for the joint distribution of the properties of underlying objects and relations among them. It was established that MLNs have higher predictive accuracy (+8%) and sensitivity (+19.7%) than the benchmark logistic regression (Dierkes *et al.*, 2011).

2.6 Concept of Customer Retention

In order to reduce amount of people who stop using service of the company different customer retention techniques are being used. Marketing department should use information provided by data analysis team and offer to customers who are predicted to churn new services to keep them. Because companies have limited human resources to call or somehow interact with customers who are suspected to churn some bonuses or discounts could be offered to larger group of customers without significant effort. But even for these campaigns there should be reasonable amount of subscribers to whom campaign is offered. Usually top 10% of predicted customers who have highest probabilities of churn and most value for the company are contacted personally and offered some discounts. Next 2-3 deciles are offered some free minutes or time-limited discounts.

Usually each customer is considered individually during churn prediction. The goal is to predict each customer's likelihood of churning in the near future, where usually a forecast horizon of a month to three months is considered. To this end, dozens to hundreds of complex Key Performance Indicators (KPIs) are generated per customer; these KPIs span the customer's personal characteristics as well as trends in their call activities over a long period. The information then serves as input to a statistical regression model (usually a logistic regression variant) that outputs a churn score. In other words, this approach focuses on identifying patterns that are uncommon to a given customer, and are correlated with churn (Kim *et al.*, 2012).

Other system try to solve churn prediction problem by monitoring customers' calls to the mobile carrier's call center, such systems apply speech and emotion analysis to the calls, and together with additional information (number and length of calls by the customer, number of transfers, hold period, etc.) try to quantify the customer's dissatisfaction level and hence the associated churn risk. The system can then react by prioritizing pending 'churners', even suggesting retention packages. This approach has a major disadvantage: although it may accurately pinpoint the potential churners, the forecast horizon it provides is very short as the system identifies customers that have already expressed dissatisfaction with the service. At this stage, retention prospects are lower while cost is significantly higher. Even when combining the long term and ad-hoc churn prediction systems, one drawback is fairly obvious: we clearly rely on the assumption that a churning customer either changes calling patterns or contacts the carrier's call center to express dissatisfaction prior to switching carriers. While this may be true in some cases, there are certainly many scenarios in which these assumptions are violated. For example, this may occur when customers come to believe that they have found a better deal with a competitor and churn immediately. Another, less obvious, drawback of traditional solutions is that they focus exclusively on the individual customer without taking into account any social influence. Clearly, there are many social aspects to churn, as witnessed in other consumer areas, where a dominant example is when a churning customer influences other customers to churn as well. Thus, developing churn prediction systems that take social aspects into account poses an emerging theoretical challenge with potentially great practical implications.

The nature of the churn prediction problem dictates a specific non-standard performance measure. Recall that once the prediction system produces its churn scores, the retention department makes contact with the subscribers that are most likely to churn, in an attempt to preserve each customer that is established to be a churn risk. Naturally, only a small fraction of the subscriber pool can be contacted at any given time, and the subscribers with the highest churn scores are assigned top priority. Therefore, a churn prediction system should be measured by its ability to identify churners within its top predictions. Formally, performance is measured using the lift metric. For any given fraction 0 < T < 1, lift is defined as the ratio between the number of churners among the fraction of T subscribers that are ranked highest by the proposed system, and the expected number of churners in a random sample from the general subscribers pool of equal size. For example, a lift of 3 at a fraction T = 0:01 means that if we contact the 1% of subscribers ranked highest by the proposed system, we expect to see three times more people who planned to churn in this population than in a 0:01-fraction random sample of the population (Kim *et al.*, 2012).

3 BUILDING CHURN MODELS

In this part models based on the data that were prepared are being built. For modeling it was planned to use several available modeling nodes.

For modeling and evaluating of models data set was divided into training and testing partitions. Separating data into training and testing sets is an important part of evaluating data mining models. By using similar data for training and testing it is possible to minimize the effects of data discrepancies and better understand the characteristics of the model.

After running C5.0 model it produced output in a form of decision tree. Predictor importance chart is also shown in the model output window. As can be observed from the picture below the most important predictor is chosen total credit amount on the subscriber's account during week 1. Among other most important fields are Count of outgoing destination calls on week 1, duration of incoming weekend calls for week 1 and sum of consecutive two-day periods without outgoing calls.

Strange thing here is that all subscribers with total credit of less than 112.532 were classified as non-churners. Even though prediction is remarkably precise and results hold for other data sets model should be revised often to eliminate over fitting problem.

Precision of prediction is shown on Figure 1.

Cox regression model was used as a specific implementation of survival analysis.

Normally one model is used to predict a target. It is possible to try several types of models, but in the end there will be one model left. Most of data-mining projects also develop one model, but data mining implies usage of several approaches to analysis. Neural Network and Cox regression models' outcomes are combined since they had lower accuracy than C5.0 model.

At the picture below on the left side are results of full data set analysis and on the right – for reduced fields. It can be seen that results for reduced fields are slightly worse than for full set but not significantly.

4 TESTS AND RESULTS

4.1 Evaluation of Models

There is 91.44% accuracy against 87.13% for

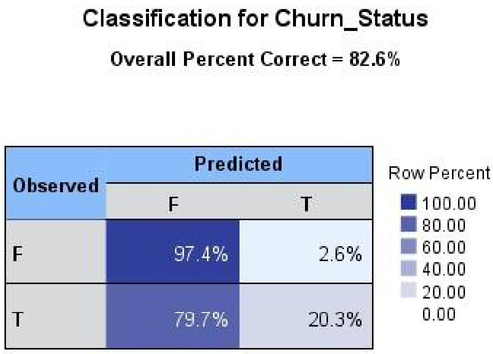

Figure 1: Neural network model results.

reduced fields for testing data partition (Figure 2). Analysis revealed that the best results are achieved using C5.0 decision tree model. Principal components analysis reduction technique was used to reduce number of fields and compared how the same model performed on full set of fields against reduced data set. Results for neural network and Cox regression models are significantly less even though they were built over all available fields except those that were removed during data preparation phase. On the Figure 3 results for both models are reflected. On the left side is shown result for neural network which is 79.04% accurate on testing partition. And on the right side Cox regression output is presented with 77% accuracy. One way to increase accuracy of the model is already described method of combining models. Pay attention to the ‘Comparing agreement with Churn Status’ table and if to be more precisely, to the correct percentage in the testing column. Their combined accuracy increased to 83.84% compared to 79.04% and 77% they had respectively.It is also possible to evaluate model with Evaluation node which shows how model performed on graph.

5 CONCLUSIONS AND RECOMMENDATIONS

Churn is directly related to customer loyalty and defines a process of switching service provider. Churn can be of several categories which are defined based on the reasons why it happened. These types are active or deliberate churn, rotational or incidental churn and passive or non-voluntary. Active churn is initiated by subscriber which wants to change service provider, rotational happens without intention to switch but for different reasons. It is not easy to distinguish those two. And passive churn covers cases when provider disconnects customer for inactivity. It is the most dangerous type because is difficult to discover. Various reasons which lead to customer churn are also discussed. Establishing reasons of churn usually happen based on questionnaires and surveys.

Social network and interpersonal relationship specific to Azerbaijan were discussed. As a result few points related to Azerbaijani society were brought to attention.

Achieved results showed that C5.0 is still the most precise model while neural network and cox regression perform worse. After combining last two models result was improved but was still worse compared to C5.0 model. Main downside of C5.0 model is that it can be over fitted to the expected result. That’s why this model should be reviewed and calibrated for new data sets.

During preparation of this work several recommendations to mobile operator came up which are worth mentioning. From social network analysis

Results for output field Churn_Status

Comparing $C-Churn_Status with Churn_Status

'Partition'	1_Training		2_Testing	
Correct	11,773	93.7%	4,883	91.44%
Wrong	792	6.3%	457	8.56%
Total	12,565		5,340	

Coincidence Matrix for $C-Churn_Status (rows show actuals)

'Partition' = 1_Training	F	T
F	9,841	324
T	468	1,932
'Partition' = 2_Testing	**F**	**T**
F	4,122	191
T	266	761

Results for output field Churn_Status

Comparing $C-Churn_Status with Churn_Status

'Partition'	1_Training		2_Testing	
Correct	10,849	86.34%	4,653	87.13%
Wrong	1,716	13.66%	687	12.87%
Total	12,565		5,340	

Coincidence Matrix for $C-Churn_Status (rows show actuals)

'Partition' = 1_Training	F	T
F	9,785	380
T	1,336	1,064
'Partition' = 2_Testing	**F**	**T**
F	4,150	163
T	524	503

Figure 2: C5.0 for all fields vs reduced factors results.

Results for output field Churn_Status

Comparing $N-Churn_Status with Churn_Status

'Partition'	1_Training		2_Testing	
Correct	9,912	78.89%	4,221	79.04%
Wrong	2,653	21.11%	1,119	20.96%
Total	12,565		5,340	

Coincidence Matrix for $N-Churn_Status (rows show actuals)

'Partition' = 1_Training	F	T	$null$
F	9,441	251	473
T	1,844	471	85
'Partition' = 2_Testing	**F**	**T**	**$null$**
F	4,005	101	207
T	772	216	39

Results for output field Churn_Status

Comparing $C-Churn_Status-1 with Churn_Status

'Partition'	1_Training		2_Testing	
Correct	9,692	77.13%	4,112	77%
Wrong	2,873	22.87%	1,228	23%
Total	12,565		5,340	

Coincidence Matrix for $C-Churn_Status-1 (rows show actuals)

'Partition' = 1_Training	F	$null$
F	9,692	473
T	2,316	84
'Partition' = 2_Testing	**F**	**$null$**
F	4,112	201
T	988	39

Figure 3: Neural network (left), Cox regression (right) results.

part where mentality of Azerbaijani society was discussed recommendations were to consider giving higher value to married, working men because they have more influence on the family and can be cause of his family members' churn if he decides to change mobile operator himself; other important factor is prestige and willingness to show it which can be used to create positive impression around the brand and particular product; parents can have strong influence on their children even if they are not underage anymore because most of young people live with parents till marriage and respect their opinion very much. Other approach of using social information could be creation of social network graph of the customers using call data records.

REFERENCES

Ballings, M., Poel, D., V., 2012. Customer Event History for Churn Prediction: How Long Is Long Enough?, *Expert Systems with Applications: An International Journal archyve*, Vol. 39 Issue: 13517-13522.

Berson, A., Smith S and Thearling K, New York, 2002, Building Data Mining Applications for CRM, ISBN 978-0071344449.

Burez, J., Poel, D., 2008. Separating financial from commercial customer churn: A modeling step towards resolving the conflict between the sales and credit department, *Expert Systems With Applications*, 35(1-2): 497-514

Dasgupta, K., Singh, R., Viswanathan, B., *et al*, 2008. Social Ties and their Relevance to Churn in Mobile Telecom Networks, EDBT: 668-677

Dierkes, T., Bichler, M., Krishnan, M., 2011. Estimating the effect of word of mouth on churn and cross-buying in the mobile phone market with Markov logic networks, *Decision Support Systems archyve*, Vol. 51 Issue 3: 361-371.

Geppert, KPMG & Associates, 2003. Customer Churn Management: Retaining High-Margin Customers with Customer Relationship Management Techniques, *Journal of International Business Disciplines*, Volume 4, Number 2: 18-19.

Huang, B., Kechadi, M., T., Buckley, B., 2012. Customer Churn Prediction in Telecommunications, *Expert Systems with Applications: An International Journal archyve*, Vol. 39 Issue 1: 1414-1425.

Huang, Y., Kechadi, T., 2013. An Effective Hybrid Learning System for Telecommunication Churn Prediction, *Expert Systems with Applications*.

Yeshwanth, V., Raj, V., Saravanan, M., 2011. Evolutionary Churn Prediction in Mobile Networks Using Hybrid Learning, *FLAIRS Conference*, AAAI Press.

Khalatyan, A., 2010. Churn Management in Telecommunications, iSCHANNEL 05: 21-26.

Kim, Y.,S., Moon, S., 2012. Measuring the Success of Retention Management Models Built on Churn Probability, Retention Probability, And Expected Yearly Revenues, *Expert Systems with Applications*, Vol. 39, Issue 14: 11718–11727.

Lazarov, V., Capota, M., 2007. Churn Prediction, *TUM computer science*.

Owczarczuk, M., 2010. Churn Models for Prepaid Customers in the Cellular Telecommunication Industry Using Large Data Marts, *Expert Systems with Applications*: *An International Journal archyve*, Vol. 37 Issue 6: 4710-4712.

Pushpa, Shobha, G., 2012. An Efficient Method of Building the Telecom Social Network for Churn Prediction, *International Journal of Data Mining & Knowledge Management Process*, Vol. 2, Number 3.

Richter, Y., Yom-Tovy, E., Slonim, N., 2010. Predicting customer Churn in Mobile Networks through Analysis of Social Groups, SDM: 732-741.

Tuğba, U., Gürsoy, Ş, 2010. Customer Churn Analysis in Telecommunication Sector, *Journal of The School of Business Administration*, Vol.39, Number 1: 35-49.

Verbeke, W., Dejaeger, K., Martens, D., Hur, J., Baesens, B., 2012. New Insights into Churn Prediction in The Telecommunication Sector: A Profit Driven Data Mining Approach*, European Journal of Operational Research*, Vol. 218, issue 1: 211-229.

Weia, C.-P., Chiub, I.-T., 2002. Turning Telecommunications Call Details To Churn Prediction: A Data Mining Approach, *Expert Syst. Appl*. 23(2): 103-112.

Zhang, X., Zhu, J., Xu, S., Wan, Y., 2012. Predicting Customer Churn Through Interpersonal Influence, *Knowl.-Based Syst*. 28: 97-104.