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Modeling Data Mining Applications for Prediction of Prepaid Churn in Telecommunication Services

This paper defines an advanced methodology for modeling applications based on Data Mining methods that represents a logical framework for development of Data Mining applications. Methodology suggested here for Data Mining modeling process has been applied and tested through Data Mining applications for predicting Prepaid users churn in the telecom industry. The main emphasis of this paper is defining of a successful model for prediction of potential Prepaid churners, in which the most important part is to identify the very set of input variables that are high enough to make the prediction model precise and reliable. Several models have been created and compared on the basis of different Data Mining methods and algorithms (neural networks, decision trees, logistic regression). For the modeling examples we used WEKA analysis tool.

Key words: Data Mining applications, Prepaid churn model, Neural networks, Decision trees, Logistic regression

Modeliranje Data Mining aplikacija za detekciju churna Prepaid korisnika telekomunikacijskih usluga.
U radu je definirana unaprijeđena metodologija za proces modeliranja aplikacija zasnovanih na metodama dubinske analiza podataka (*Data Mining*), koja predstavlja logički okvir (*framework*) za razvoj različitih *Data Mining* aplikacija. Predložena metodologija je primjenjena na primjeru *Data Mining* aplikacije za detekciju churna Prepaid korisnika telekomunikacijskih usluga. Glavno težište ovog rada je na definiranju uspješnog modela za predviđanje potencijalnih Prepaid churn-era. Najvažniji dio izgradnje modela je definiranje onog skupa ulaznih varijabli koje su u toj mjeri snažne da model predviđanja bude točan i pouzdan. Kroz navedeni primjer je kreirano i uspoređeno više modela zasnovanih na različitim *Data Mining* metodama i algoritmima (neuronske mreže, stabla odlučivanja, logistička regresija). Za primjere modeliranja korišten je analitički alat WEKA.

Ključne riječi: aplikacije dubinske analize podataka, prepaid churn model, neuronske mreže, stabla odlučivanja, logistička regresija

1 INTRODUCTION

In the late 20th century, scientists were focused on theoretical bases for Data Mining, and improvements and upgrading of the Data Mining algorithms and methods [2].

In the 21st century, the focus is moved toward scientific research on Data Mining applications, in other words application of Data Mining methods in real environment, which resulted in real necessity for these applications on the market [1],[3],[16],[17].

Modeling and planning of development process of Data Mining applications has been recognized as a new challenging field for research [5],[6],[7],[8],[9].

Currently, only a small number of users (less than 20%) apply one of the defined methodologies (CRISP-DM, SEMMA etc.) for development of predictive Data Mining applications [4],[11].

There is obviously available space and need for further research that would result in new methodologies that could

meet all requirements today's business sets for applicative solutions based on Data Mining methods and algorithms.

This paper will define an advanced methodology for modeling of applications based on Data Mining analysis that represents a logical framework for development of Data Mining applications. A focus is on a more precise definition of initial stages (defining Business and Data Mining goals), as well as final stages of modeling processes of Data Mining applications. These stages are recognized as especially important and critical due to the transition between a Business and Data Mining domain (initial stage) and vice versa (final stage), that happen in these steps.

Suggested methodology for modeling process of Data Mining applications has been applied and tested on a Data Mining application for prediction of Prepaid users churn in telecommunications.

In contrast to Postpaid segment, Prepaid segment

doesn't imply any contractual obligation between users and a telecom operator, so the very definition of Prepaid churn is not simple [13],[14],[15]. In addition, the data available on Prepaid users are much more inadequate as compared to Postpaid users, especially when it comes to customer data domain. This fact adds to complexity of modeling process of predictive Data Mining applications related to Prepaid churn.

2   METHODOLOGIES AND MODELS FOR DEVELOPMENT OF DATA MINING APPLICATIONS

It is often heard in business world that there is a will to use Data Mining applications since they result in visible benefits, but process of knowledge discovering based on Data Mining still seems to be not so easy to understand.

Precisely defined steps within a methodological framework and actions to be undertaken at each stage contribute to demystification of the process of Data Mining application development. Also, big project teams cannot function properly without such a clearly defined process of application development and modeling, since it considerably facilitates project design, time scheduling and project supervision.

According to the Gartner base, two most commercially complete Data Mining tools, in terms of their visions and potentials, are SPSS and SAS. SPSS uses CRISP-DM methodology, while SAS uses its own SEMMA methodology (although it might be wrong to call SEMMA a methodology), and for this reason the two methodologies (CRISP-DM and SEMMA) are best known and most commonly used for development of Data Mining applications [4].
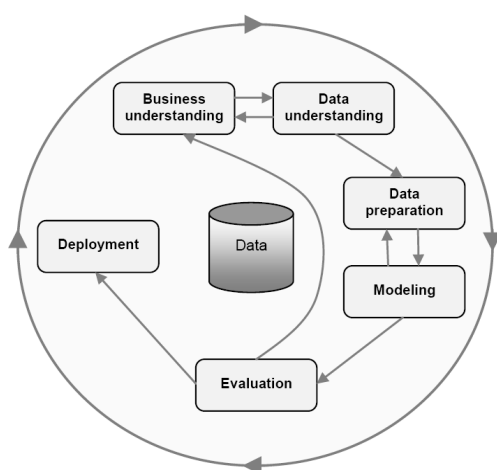

Fig. 1. CRISP-DM process

CRISP-DM (*CRoss-Industry Standard Process for Data Mining*) consists of six phases (Business understanding,

Data understanding, Data preparation, Modeling, Evaluation, Deployment) intended as a cyclical process (see Fig. 1.) [12].

The CRISP-DM Special Interest Group was created with the goal of supporting the model. At the moment this groups has more than a hundred members participating actively in work on the version 2.0 [19].

SAS has defined SEMMA (Sample, Explore, Modify, Model, Assess) model that was incorporated into the commercial Data Mining platform – SAS Enterprise Miner (Fig. 2) [4].
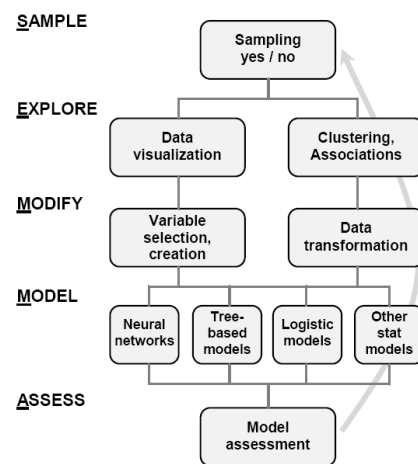

Fig. 2. Steps in SEMMA process

Latest research prove that less than 20% of consumers use one of the defined methodologies for development of predictive Data Mining applications, among which large majority relates to the most represented CRISP-DM methodology. Half of the users apply "their own" methodology, and others either doesn't use any specific one or rely on consulting knowledge of the outside company and their methodological frameworks (Fig. 3). [11].
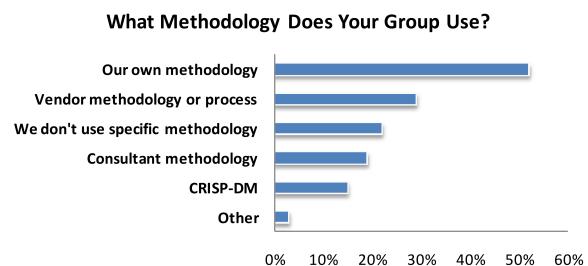

Fig. 3. Based on 167 respondents who have implemented predictive analytics.

Cios and Kurgan adjusted CRISP-DM model to serve the needs of research in an academic community, and they

did it by adding several feedback mechanisms that did not exist in the previous models, and putting emphasis on the fact that the knowledge revealed within one domain can be applied in other domains (areas) as well [5],[6].

Reinartz's model combines the tasks of data selection, cleaning and transformation as a single data preparation task [8].

Berry and Linoff have defined a methodology in 11 steps, emphasizing a need for defining a methodology that would help avoid situations in which things learned are not true, or they are true but useless at the same time [1].

Recently there have been attempts to improve existing analytics methodologies and allow them to become more effective and reliable in providing useful insights in business contexts [9],[10].

However, it is important to stress that the potential value of analytics has not been fully realised or utilised in business settings as yet.

2.1 Defining a Framework for the Process of Data Mining Applications Development

There is obviously space and need for further research that would result in newly defined methodologies that would meet all requirements today's business sets for applicative solutions based on Data Mining methods and algorithms.

We will define an advanced methodology for modeling process of Data Mining applications which represents a logical framework for development of Data Mining applications.
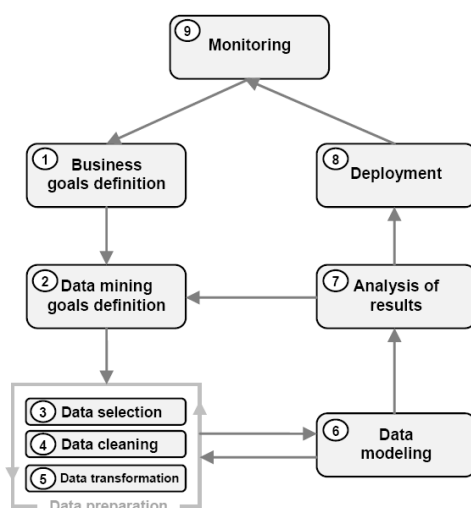

Fig. 4. Framework for development of DM applications

This methodology defines the following stages of development (Fig. 4):

1) Business goals definition
2) Data mining goals definition
3) Data preparation
   a) Data selection
   b) Data cleaning
   c) Data transformation
4) Data modeling
5) Analysis of results
6) Deployment
7) Monitoring

Data selection, Data cleaning and Data transformation can be named together as Data preparation.

We will present advantages of this methodology as compared to the existing one (described previously).

The first systems for knowledge discovering were intended primarily for experienced users familiar with Data Mining methods and algorithms. Commercial success of these systems was minimal.

With new tools with graphically intuitive interface, Data Mining has become available to a large number of users, but at the same time grew the number of meaningless data analysis by "experts" without sufficient knowledge on the data they analyzed, or on the Data Mining methods and algorithms available (neural networks, decision trees, logistic regression, fuzzy expert systems, clustering, Bayesian networks, etc.).

Terms such as „data fishing" or „data dredging" were empty terms for (sometimes desperate) attempts to find statistically indicative data, and they are definitely not part of Data Mining analysis [5].

To avoid such "analyses" with no purpose, a change was introduced relating to the initial development stages.

Firstly, each project has to have from the very beginning, clearly defined business goals. The second key step is proper mapping of business goals into Data Mining goals. Failure to properly translate the business problem into a Data Mining problem leads to one of the dangers we are trying to avoid - learning things that are true, but not useful.

Business goals and Data Mining goals have to be measurable, reachable, realistic and well-timed. It is important to avoid words such as improve, optimize, clarify, help etc. These words are vague and a person using them is obviously not capable of measuring their results.

Also, a disadvantage of the existing methodologies is visible in the domain of integration of ready-made Data Mining models into business and analytic information systems of companies (BI, CRM etc.). Even the very defining of Data Mining should include thinking about presentation of the analysis results to the target users, to ensure that the model results become an integral part of a business process

of a company, comprehensible to the users even without Data Mining knowledge.

A crucial step that is often forgotten is control and maintenance of the model after implementation.

It has been emphasized already that goals set at the beginning are to be measurable. Only clearly defined and measurable things can be unambiguously controlled and their efficiency tested (plan/goal vs. implementation).

Control can be on a daily, weekly, monthly or other basis, depending on the type of the analysis performed.

By observing duration of each step within development methodology and its role within a whole development process, it is visible that most of the time (60-70%) is spent on preparing data for analysis.

About 10% of time is consumed on setting business and Data Mining goals, around 15% on creation of a Data Mining model and 10% on implementation, monitoring and maintenance of the model (Fig. 5).
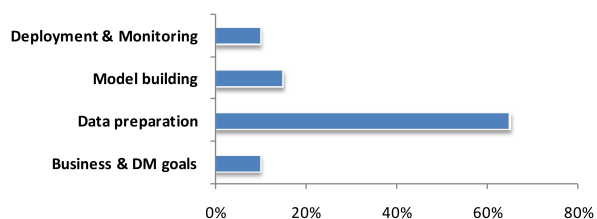

Fig. 5. Estimate of time (without DW)

If a company owns a Data Warehouse (DW) and time for data preparation, that will reduce time consumption considerably (30-40%).
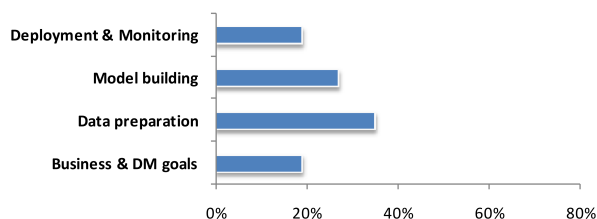

Fig. 6. Estimate of time (with DW)

By applying described methodologies for the process of modeling of applications based on Data Mining analysis, we'll perform an analysis for prediction of Prepaid users churn in telecommunication industry (Section 4.).

3 CHURN TYPES IN TELECOMMUNICATION INDUSTRY

In the most of the European countries, penetration of mobile network users has gone beyond 100% (e.g. in Croatia 130%). Acquisition of new users is made more difficult,

since there are no new users. There are only users of rival companies that are exposed to numerous, carefully designed marketing campaigns in attempts to win them over. At the same time, a continuous work on customer retention and churn prevention becomes a necessity, because the competition has similar acquisition issues. Retention of the existing users is important since it is 5 up to 7 times cheaper to retain a consumer than to acquire a new one [16],[17].

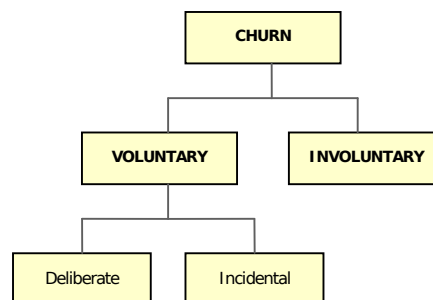Two basic categories of churners are voluntary and involuntary churners (Fig. 7.) [13].

Fig. 7. Churn taxonomy

Involuntary churners are the customers that telecommunication company decides to remove from the subscribers list. This category includes people that are churned for fraud (customers who cheat), non-payment (customers with credit problem), and under-utilization (customers who don't use the phone).

Voluntary churn occurs when the customer initiates termination of the service contract. When people think about Telco churn it is usually the voluntary kind that comes to mind. Under the category of voluntary churn we recognize two major types of voluntary churn: incidental churn and deliberate churn.

Incidental churn occurs, not because the customers planned on it but because something happened in their lives. For example: change in financial condition churn, change in location churn, etc.

Deliberate churn happens for reasons of technology (customers wanting newer or better technology), economics (price sensitivity), service quality factors, social or psychological factors, and convenience reasons.

Deliberate churn is the problem that most churn management solutions try to solve.

3.1 Postpaid and Prepaid Churn

When considering Postpaid churn, the deactivation date, i.e. the date that a customer is disconnected from the network, is equal to the churn date [14]. After all, this is the actual date a customer stops using the operator's services.

In contrast to Postpaid segment, Prepaid segment does not imply contractual obligations between users and a telecom operator, so the very definition of Prepaid churn is not that simple.

In the case of Prepaid churn however, the deactivation date does not necessarily have to match the churn date.

In general, it takes a long period before a Prepaid customer is actually disconnected from the network. In many cases customers are churned long before they are disconnected from the network. This is exactly the reason why the deactivation date is not a suitable indicator for churn. Thus, we are interested in a churn definition which indicates when a customer has permanently stopped using his Prepaid SIM-card [18].

4 PREDICTING OF PREPAID CHURN IN TELECOMMUNICATION INDUSTRY

Successful detection of potential churners enables companies to define activities for their retention. Data Mining enables us to predict behavior of mobile networks users [13],[14],[15].

This example will show a Data Mining application for prediction of Prepaid churn in the telecommunication company HT Mostar (Bosnia & Herzegovina) by using previously defined methodology (see section 2.1).

Data that are going to be analyzed relate to a six-month period (from 1st July 2009 to 1st January 2010).

4.1 Business Goals Definition

As we mentioned earlier, a business goal is to be measurable, reachable, realistic and well-timed.

Business goal: To decrease churn rate of Prepaid users by 20% in a three-month time.

What is missing in the definition above to be comprehensible to everybody without ambiguity is a clear definition of what churn is in a Prepaid segment.

A Prepaid churn user in this example is defined as a user who has neither had any calls or incoming calls during the last three months, nor used any other services (SMS, MMS, mobile internet. . .), nor any additional payment within these three months.

4.2 Data Mining Goals Definition

One of the greatest risks in the project was definitely mapping of business goals into Data Mining goals. Experts from business and Data Mining domain have to cooperate in defining business and Data Mining project goals.

Failure to properly translate the business problem into a Data Mining problem leads to one of the dangers we are trying to avoid - learning things that are true, but not useful.

Data mining goal: To create a model that will predict potential Prepaid churners with 90% accuracy.

4.3 Data Preparation (Data Selection, Cleaning and Transformation)

The data set used throughout this work is from a telecommunication company in Bosnia and Herzegovina (HT Mostar).

HT Mostar company has a DW/BI system implemented in its infrastructure since 2007. Data Warehouse (DW) is organized as a "star-schema" data model (or snowflake-schema" data model when it was necessary), and it contains all available data of Postpaid/Prepaid users and services they used.

ETL procedure enabled data extraction from source systems, their cleaning, transformation and aggregation, as well as data import into DW, so data preparation is considerably made shorter and simplified for the Data Mining analysis.

Also, the data warehouse contained aggregated data (on a monthly basis) on services by Prepaid users, which additionally facilitates necessary data preparation.

From DW we extracted data in the period between 1st July 2009 and 1st January 2010.

There are three groups of variables plus target variable that have been combined to create the dataset:
–   customer data
–   traffic (usage) data (outgoing/incoming)
–   recharge data

Customer data:
–   RATE_PLAN (TARIFF MODEL)
–   CUSTOMER_MONTH_DURATION

Outgoing traffic (usage) data:
–   OUTGOING_SMS_NUMBER
–   Δ OUTGOING_SMS_NUMBER
–   OUTGOING_CALLS_NUMBER
–   Δ OUTGOING_CALLS_NUMBER
–   OUTGOING_CALLS_MINUTES
–   Δ OUTGOING_CALLS_MINUTES
–   SERVICE_CALLS_NUMBER
–   Δ SERVICE_CALLS_NUMBER
–   COMPETITION_SERVICE_CALLS_NUMBER
–   Δ COMPETITION_SERVICE_CALLS_NUMBER

Incoming traffic (usage) data:
–   INCOMING_SMS_NUMBER
–   Δ INCOMING_SMS_NUMBER
–   INCOMING_CALLS_NUMBER
–   Δ INCOMING_CALLS_NUMBER
–   INCOMING_CALLS_MINUTES
–   Δ INCOMING_CALLS_MINUTES

Recharge data:

- NUMBER_OF_RECHARGES
- Δ NUMBER_OF_RECHARGES
- TOTAL_RECHARGED_AMOUNT
- Δ TOTAL_RECHARGED_AMOUNT

Delta (Δ) variables (VAR) relate to the change of a variable between the two periods (p1 and p2) according to the following formula:

$$\Delta \text{VAR.} = \frac{\text{VAR.(p2)} - \text{VAR.(p1)}}{\text{VAR.(p1)}} \qquad (1)$$

where:

p2 = period 2 (October, November and December 2009.)

p1 = period 1 (July, August and September 2009.). E.g. for the variable Δ OUTGOING_CALLS_MINUTES (OCM):

$$\Delta \text{OCM} = \frac{\text{OCM(p2)} - \text{OCM(p1)}}{\text{OCM(p1)}} \qquad (2)$$

where:

OCM = Outgoing_Calls_Minutes

p2 = period 2 (October, November and December 2009.)

p1 = period 1 (July, August and September 2009.)

Naturally, the variables indicating changes between the two periods (p1 i p2) are valid only if a condition is met.

CUSTOMER_MONTH_DURATION >= 6

Other variables relate to the period 2 (10th, 11th and 12th month in 2009). That means that analysis took into consideration last three months, i.e. variables relating to the change (Δ), and the change within last three months as compared to the previous three month period.

In the data preparing process, most of the time was spent on calculation of variables relating to the change (Δ), since these variables are not present in DW.

Target data

The target data for customer is represented by a 0 (FALSE) for non-churner or a 1 (TRUE) for churner.

4.4   Data Modeling

Churn predictive modeling refers to the task of building a model for the target variable (churner or non-churner) as a function of the explanatory variables [2].

Modeling is simply the act of building a model in one situation where you know the answer and then applying it to another situation that you don't (Fig. 8).
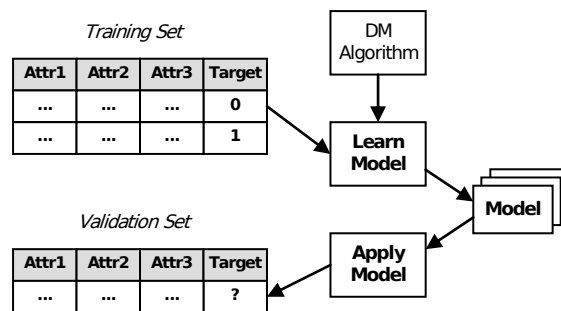

Fig. 8. Data modeling
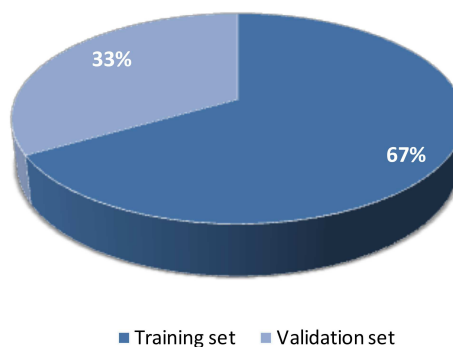

■ Training set ■ Validation set

Fig. 9. Training and validation set for modeling

The most important thing to remember about model building is that it is an iterative process. No single method works best in all cases.

For training and model validation, we used a sample of 3,000 users, out of which 2/3 is training set (2,000 users) and 1/3 the validation set (1,000 users) (Fig. 9).

Users who cannot be churners for any reason were excluded from the sample (test users, employees of HT Mostar).

The training set had 259 churners, and 1,741 non-churners (Fig. 10). The validation set had 123 churners and 877 non-churners (Fig. 11).

Fig. 10. Training set for modeling

The predictive power of different Data Mining models (Neural Network, Decision Tree and Logistic Regression) were analyzed and compared.
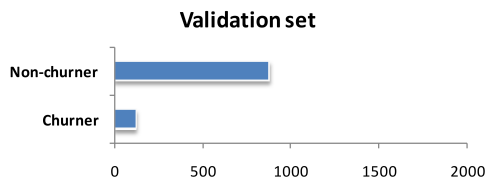
Validation set

Fig. 11. Validation set for modeling

We decided to use Open source Data Mining software for analyzing and our choice was Weka. Weka was developed at the University of Waikato in New Zealand, and the name stands for Waikato Environment for Knowledge Analysis. The system is written in Java and distributed under the terms of the GNU General Public Licence [2],[20].

It runs on almost any platform and has been tested under Linux, Windows, and Macintosh operating systems.

Evolution of the performance of a prediction model is based on the counts of test records correctly and incorrectly predicted by the model. These counts are tabulated in a table known as a confusion matrix (Table 1).

Table 1. Confusion matrix for a 2-class problem

Actual class	Predicted class	
	NON-CHURNER	*CHURNER*
NON-CHURNER	f00	f01
CHURNER	f10	f11

Confusion matrix is shown for each model. Based on the entries in the confusion matrix we can calculate the total number of correct and incorrect predictions.

Table 2. Confusion matrix (neural network model)

Actual class	Predicted class	
	NON-CHURNER	*CHURNER*
NON-CHURNER	**85,6%** *(751 / 877)*	**14,4%** *(126 / 877)*
CHURNER	**13,8%** *(17 / 123)*	**86,2%** *(106 / 123)*

Table 3. Confusion matrix (logistic regression model)

Actual class	Predicted class	
	NON-CHURNER	*CHURNER*
NON-CHURNER	**83,8%** *(735 / 877)*	**16,2%** *(142 / 877)*
CHURNER	**17,9%** *(22 / 123)*	**82,1%** *(101 / 123)*

Table 4. Confusion matrix (decision tree model)

Actual class	Predicted class	
	NON-CHURNER	*CHURNER*
NON-CHURNER	**91,1%** *(799 / 877)*	**8,9%** *(78 / 877)*
CHURNER	**10,6%** *(13 / 123)*	**89,4%** *(110 / 123)*

4.5 Analysis of Results

Although a confusion matrix provides the information needed to determine how well a prediction model performs, summarizing this information with a single number would make it more convenient to compare the performance of different models. This can be done using a performance metric such as accuracy and error rate [2].

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}$$

$$Error\ rate = \frac{Number\ of\ wrong\ predictions}{Total\ number\ of\ predictions}$$

Table 5. Comparison of different DM models

Model	*ACCURACY*	*ERROR RATE*
Neural network	**85,7%** *(857 / 1000)*	**14,3%** *(143 / 1000)*
Log.regression	**83,6%** *(836 / 1000)*	**16,4%** *(164 / 1000)*
Decision tree	**90,9%** *(909 / 1000)*	**9,1%** *(91 / 1000)*

Decision tree method proved to be the most successful for concrete application in modeling Prepaid users churn prediction (Table 5).

Decision trees are a Data Mining method aimed at classification of attributes with regard to the set target variable (in this case CHURN).

A record enters the tree at the root node. The root node applies a test to determine which child node the record will encounter next. There are different algorithms for choosing the initial test, but the goal is always the same: *To choose the test that best discriminates among the target classes.* This process is repeated until the record arrives at a leaf node. All the records that end up at a given leaf of the tree are classified the same way. There is a unique path from the root to each leaf. That path is an expression of the rule used to classify the records (churn = TRUE or churn = FALSE) [1].

The main advantage of this method is that it presents its results in the form of easily readable rules that can be of great value, with a possibility of churn prediction for an individual user. Besides, this method can indicate dominant variable.

It is important, though, to stress that variable dominance can be observed in both directions:
- Domination toward churn (user churn)
- Domination against churn (user retention)

4.6 Deployment

When defining goals we had a very important and sensitive issue of merging business and Data Mining environments (mapping business goals into Data Mining goals). Now we have a similar goal to merge these two environments, only in an opposite direction. It is necessary to transform results from Data Mining environment into business environment and present them in a more comprehensible way.

In this example we created an OLAP cube (by using Microsoft SQL Server Analysis Services 2007) with all results gained from the analysis. Users had direct approach to the cube through Excel 2007 environment.

Based on the data available and identified potential churners, Marketing and Sales decided to undertake retention activities. E.g. an offer to switch to a more convenient tariff model, an account bonus, more favorable price for mobile phone purchase, etc...

Especially important is to undertake activities on retention of profitable Prepaid users (e.g. those with consumption of more than 15 EUR).

4.7 Monitoring

Data mining model building is an iterative process that can not be fully automated due to the constant change in business processes and environment.

Model control and maintenance in this example is going to be performed on a monthly basis, when its accuracy will be checked with the new set of data. From the DW data is always extracted for a last six-month period.

According to the needs, this model can be adjusted by e.g. adding new available variables that influence accuracy of the model prediction. It is possible to apply a selected algorithm (a decision tree), since with a new variable and new set of data some better predictive characteristics might be revealed (neural networks, logistic regression).

Of course that after the first results it is possible to make decisions on adjusting set business and Data Mining goals.

5   FUTURE RESEARCH

Future research will deal with building of the whole system for prevention of Prepaid churn.

Data Mining model defined and described here for detection of potential Prepaid churners is just one part of that system.

Detection model results are to be matched with defined segments of users, and for each segment it is necessary to define appropriate action. This work is with Prepaid users much more complex than in the case of Postpaid users who are mostly bound by their contractual obligations (e.g. for 1 or 2 years), so the most critical points are expire dates of the contracts. Prepaid doesn't imply contractual obligations which means that users are able to stop using services at any point, without previous notification.

In the Prepaid world it is common for users to have more than one card from different telecom companies. It is then great challenge to detect such users and keep them by additional cross-sell / up-sell offers within one network and prevent churn in that way.

6   CONCLUSION

This paper emphasizes a necessity for development of Data Mining applications in line with a clearly defined methodological framework.

An understandable development methodology is one of the key parameters for successful modeling of applications for Prepaid users churn prediction in telecommunications, which was proved in the section 4. of this paper.

The main emphasis of this paper was defining of a successful model for prediction of potential Prepaid churners, in which the most important part was to identify the very set of input variables that were high enough to make the prediction model precise and reliable.

Definition of Prepaid churn and the very modeling of an application is more complex than the same task for Postpaid users. More complexity is brought into modeling by a lower data amount available for Prepaid users, so the variables are often set by using traffic data (calls, SMS, MMS, mobile internet...) and data on additional payments.

A successful model for prediction and prevention of Prepaid churn in telecommunication companies can influence very positively an overall profit of companies, due to the fact that far less money needs to be invested into development of a predictive Data Mining model and marketing preventive action to retain users, as compared to the possible loss cause by these users churn.

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