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DATA MINING AND CRM IN TELECOMMUNICATIONS

D. Ćamilović*

BK Faculty of Management, Palmira Toljatija 3, Belgrade, Serbia

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Abstract

CRM cannot be practiced in business without tracking patterns within customer data. Since the goal of data mining is extracting meaningful patterns and relationships from large data sets, data mining can redefine and improve customer relationships. Fortunately, telecommunications companies know more about their customers than anyone else. They know who their customers are, they can easily keep track of their customers' activities. A huge amount of data generated by telecommunications companies cannot be analyzed in a traditional manner, by using manual data analysis. That is why different data mining techniques ought to be applied. Data mining helps a business understand its customers better. This paper will address the most valuable data mining applications for CRM in telecommunications.

Keywords: Data mining, customer relationship management, customer segmentation, churn management, telecommunications.

1. INTRODUCTION

The evolution of information technology has enabled collection and storage of huge amounts of data. The size of databases today can range to terabytes (Edelstein, 1999). It is almost impossible to analyze these volumes of data in a traditional manner. For this reason data mining has attracted a great deal of attention. We can find and explore data, generate hypotheses, and learn from data (Miller, 2005).

Data mining is the process of automatically discovering useful information in large data repositories (Tan, Steinbach and Kumar, 2006). It is supported by (Bain, Benkovich, Dewson, Ferguson, Graves, Joubert, Lee, Scott, Skoglund, Turley and Youness, 2001):

- Inexpensive data storage,
- Affordable processing power,
- Data availability,
- Many commercial data mining tools available.

* *Corresponding author: gagona@EUnet.yu*

Data mining can be useful for any business, but this paper will describe why it is valuable to the telecommunications industry. Since telecommunications companies are keen to implement the philosophy of a customer-centric enterprise, they are armed with various CRM tools. CRM applications that use Online Analytical Processing (OLAP) and data mining are called analytical CRM. This paper will describe the most valuable CRM data mining applications in telecommunications.

Data mining project for effective CRM consists of several phases:

1. Defining the problem to be solved. Each CRM application will have its own business objectives and requirements. Data mining model have to be defined according to these objectives. Talking to business people is the best way to define the problem to be solved. It is advisable to make a list of interesting questions.

2. Assembling and preparing the data. This step can sometimes be skipped, in case a data warehouse is used as the single source of data needed for analysis purposes. This is because the data has to be cleaned, integrated and transformed before entering into a data warehouse. Even if this is the case the analyst has to define the subset of data for processing. Of course, data can be accessed from a relational database, a flat file, a spreadsheet, or from some another sources as well. In this case preparation steps usually take a lot of time and effort, especially when the data needed resides in multiple data repositories. If the summary variables are going to be used, they have to be derived from the row data. Selecting the variables on which the model will be built is a critical step within the data mining process. Usually the variables have to be transformed in accordance with the requirements of the data mining algorithm chosen (Edelstein, 2000).

3. Modeling. In this phase the data is presented to a data mining software program. Sometimes the variables chosen are not the appropriate ones, and in this case the analyst has to go back and make some changes to the data he is using.

4. Interpreting the results. The results should be brought together into a coherent presentation and presented to the business people (Berry and Linoff, 2000). The model should be evaluated with respect to problem solving objectives.

5. Applying the results – changing an organization's behavior for competitive advantage. The ultimate goal is to apply what was discovered in order to solve the business problem defined (e.g. the customer churn). The lessons learned from customer information should be used to enhance business and customer relationship behaviors (Hall, 2004). It is important to determine how the model will be used for business advantage.

The five-phase sequence described is not strict, because data mining process itself is not linear. This means that one can move back and forth between different phases because the next phase in the sequence often depends on the outcomes associated with the preceding one.

The process model proposed is similar to CRISP-DM (Cross-Industry Standard Process for Data Mining) model described by Larose (2005) and Chapman, Clinton, Kerber, Rhabaza, Reinartz, Shearer and Wirth (2000), The Two Crows data mining process presented by Edelstein (2000), and the model introduced by Berry and Linoff (2000).

2. REASONS FOR APPLYING DATA MINING TECHNIQUES FOR CRM IN TELECOMMUNICATIONS

There are several reasons for applying data mining techniques for CRM in telecommunications:

- *Competitive market*. After years of being a monopoly market, the telecommunications market is now highly competitive. A monopoly does not change much, but competitive markets change constantly. Customers are able to switch providers easily, because there are many of them available. For this reason telecommunications companies explore data mining solutions to achieve competitive advantage. By understanding the demographic characteristics and customers' behavior, telecommunications companies can successfully tailor their marketing strategies to reach those most likely to use their services, to increase customer loyalty and improve customer profitability.
- *High churn rates*. Churn refers to the monthly or the annual turnover of the customer base (Strouse, 1999). Competitive climate naturally results in high churn rates. Initially, growth in the telecommunications market was exponential, and since many new customers arrived, the churn was not a problem (Berry and Linoff, 2000). Eventually, the market matured and the churn rates became high. Maturing of the market and increasing competition were leading telecommunications companies to focus on their existing customers and to find a way not to let them go (Berry and Linoff, 2000). Data mining may be used in churn analysis to predict whether a particular customer will churn and why.
- *Massive data collection*. Telecommunications companies collect massive amounts of data. Since the main product of the company is the call, its customers create hundreds of thousands transactions per day. Call detail records are stored in the database and they are a very large data source. Telecommunications firms also collect customer data, which describes their customers, and network data, which describes the state of the components in the network (Weiss, 2005). All of these can be presented to some data mining tool.

3. THE DATA TO BE MINED

A huge amount of data generated by telecommunications companies cannot be analyzed in a traditional manner, by using manual data analysis. That is why different data mining techniques ought to be applied.

As mentioned before, information about each and every call customers make is stored in the database. These are known as call detail records. Call detail records usually include information about originating and terminating phone numbers, the date and time of the call and its duration (Weiss, 2005). But those records are often not suitable for data mining itself, so they have to be transformed. This is because the goal of data mining is to discover patterns that concern customers, not calls. So, raw data should be collected and aggregated to the customer level. Many different summary variables can be used. Weiss (2005) suggests the average call duration, the percentage of no-answer calls, the percentage of calls to/from a different area code, the percentage of weekday calls (Monday – Friday), the percentage of daytime calls (9:00 A.M. – 5:00 P.M.), the average number of calls received per day, the average number of calls originated per day. Some other features, like minutes of call in regular time frame, minutes of call in discount time frame, minutes of call in night time frame, minutes of domestic call, minutes of international call, or minutes of total call (Baragoin, Andersen, Bayerl, Bent, Lee and Schommer, 2001), can be used as well. These variables are derived from call detail data collected over some time period (e.g. one, three, or six months).

All features above can be used for customer profiling, which is one of the most valuable data mining applications in telecommunications. Generating useful features is a critical step within the data mining process (Weiss, 2005).

Besides call detail records, telecommunications companies store many other data in their databases. For example, they collect information about their customers (at least name, address, age and gender information). Customer data can be used in conjunction with call detail data in order to get better data mining results, as it is displayed in Figure 1.

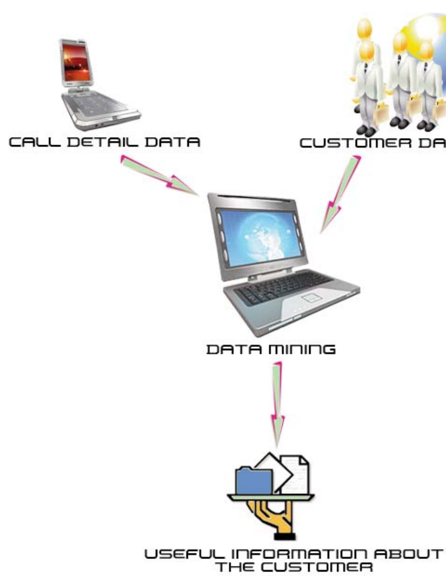

Figure 1. Combining call detail and customer data for better data mining results

Telecommunications firms know more about their customers than anyone else. They know who their customers are, they can easily keep track of their customers' behavior. This is particularly important for CRM, the topic that will be discussed in the following section.

4. CRM IN TELECOMMUNICATIONS

According to the International Engineering Consortium (2005) telecommunications companies can accept one of the two basic strategies:

- Product strategy
- Customer strategy.

The first one was very popular in the past when companies were marketing their services to the masses. This resulted in very high marketing costs, and on the other hand customer loyalty was very low. For this reason companies today tailor their products according to their customers' needs. In order to deliver relevant services to their customers most telecommunications firms accepted the second of these two strategies. They realize that it is necessary to understand their customers' behavior and quickly respond to their needs, because if one does not do it, the competitor will. Today's companies are customer-centric. They have to make an environment that allows a business to take a 360-degree view of their customers.

To create a better environment for managing customer relationships, companies need to look to a new approach called CRM. This is a strategy for achieving competitive advantage.

CRM is defined as a set of activities a business performs to identify, qualify, acquire, develop and retain loyal and profitable customers by delivering the right product or service, to the right customer, through the right channel, at the right time and the right cost (Galbreath and Rogers, 1999). The right product or service means that only a product or a service that meets customers' needs should be considered. The right customer means that not all the customers are the same, so the company's interactions with customers need to move toward segmented marketing campaigns that target individual preferences (Sumathi and Sivanandam, 2006). There are a number of mediums available, and a company must choose the right one (that is what the right channel means). The right time is a result of the fact that there are continuous interactions with customers (Sumathi and Sivanandam, 2006). The goal of each and every company is to reduce costs. Since many customers are price sensitive, the right costs component should be carefully considered.

CRM usually acquires the transformation of the entire enterprise and how it conducts business with its customers. Every organization, particularly a telecommunications company, should have a clearly defined CRM strategy, because satisfying customers is the foundation of any organization's success.

Meta Group classifies CRM into three different types:

- Operational CRM, which is concerned with automation of business processes involving front-office customer contact points (Payne, 2005). According to Beck and Summer (2001) these applications include sales force automation, customer service and marketing.
- Analytical CRM, which includes the use of customer data for analysis, modeling and evaluation (Beck and Summer, 2001). It applies methodologies such as data mining and OLAP to CRM applications.
- Collaborative CRM includes the use of collaborative services and infrastructure in order to enable interaction between a company and its channels (Payne, 2005).

This paper will be concerned with the analytical CRM for the telecommunications industry.

The past several years have witnessed an explosion in CRM software applications. Everything from campaign management software to call center software is now marked as CRM tool (Berry and Linoff, 2004). In order to discover patterns in data, and to make predictions about the future, data mining techniques are used. These techniques support a customer-centric enterprise and help a telecommunications company to exploit the vast amounts of data generated by its customers. As mentioned before, those are call detail and customer data.

Data mining can build models that can explain customers' behavior and predict it, but it is only a step in a much larger process. The successfulness of data mining is determined by the business process, especially by marketing activities, because marketers are the primary users of CRM tools. Marketers have to understand the results of data mining before they put them into action (Berson, Smith and Thearling, 1999). Since data mining extracts hidden patterns of customers' behavior, understanding the results can be a bit complicated. But it is necessary in order to improve campaign management. Data mining software should be used together with campaign management software in order to apply a customer-centric business approach. Data mining can be used for marketing campaign design, response modeling and marketing optimization (Lo, 2006).

Data mining technology supports customer relationship strategy, but technology does not equal strategy (Anderson and Kerr, 2002). Confusing technology with strategy is the main reason why many CRM investments have not delivered its promised potential. As presented in Figure 2, an organization has to start with a CRM strategy and the strategy should drive its business process. Data mining can only help business activities to execute the strategy, but it cannot make sure that the enterprise is going to be customer-centric. The key to CRM success is developing and implementing strategy.

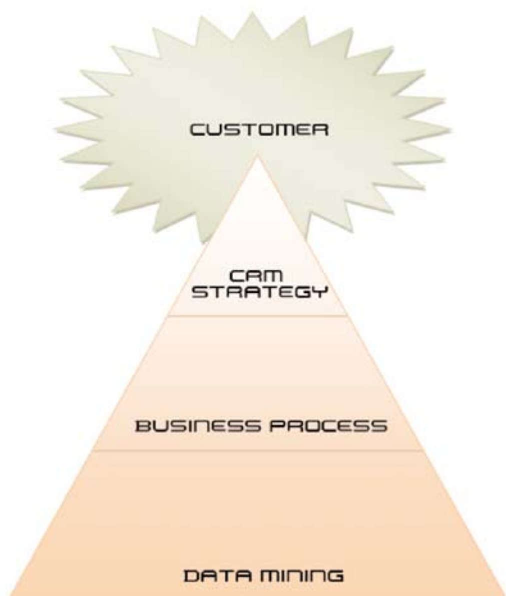

Figure 2. CRM strategy drives business and data mining processes

There are several data mining applications that support CRM and they will be fully described in the next section.

5. BUILDING DATA MINING APPLICATIONS FOR CRM

The two most valuable data mining applications for CRM in telecommunications are concerning customer segmentation and churn prediction. These data mining models utilize the necessary data that exists in a database to build patterns that are relevant to CRM.

5.1. Customer segmentation

Customer segmentation is one of the most important data mining methodologies used in marketing and CRM (Saarenvirta, 1998). It helps telecommunications companies to discover the characteristics of their customers and make them derive appropriate marketing activities according to the information discovered.

Customer segmentation is grouping similar customers together, based on many different criteria. In this way it is possible to target each and every group depending on their characteristics. Customer segmentation helps companies develop appropriate marketing campaigns and pricing strategies. For example, it is possible to offer a special price or free minutes to a certain group (Baragoin, Andersen, Bayerl, Bent and Schommer, 2001).

In data mining terminology the term segmentation is rarely used. A more appropriate term to use is clustering. The clustering algorithm looks for clusters in the data. It finds sets of cases that are more similar to one another than they are to cases in other sets.

Clustering is a good way to analyze large and complex set of data. By applying clustering technique, the analyst can break down a large problem into a number of groups with common characteristics (Bain, Benkovich, Dewson, Ferguson, Graves, Joubert, Lee, Scott, Skoglund, Turley and Youness, 2001). Since each cluster provides a description, the analyst can understand the nature of the problem better. But the analyst has to experiment with the model's variables.

Clustering is an undirected data mining technique. This means that there are no dependent variables used to find a specific outcome (Seidman, 2001). When preparing data mining model, the analyst does not know its outcome. But this is one of the strengths of clustering, because it analyzes the complete set of data, looking for patterns that can be missed by a directed technique (Bain, Benkovich, Dewson, Ferguson, Graves, Joubert, Lee, Scott, Skoglund, Turley and Youness, 2001). It can handle large data sets and work on any type of data (Bain, Benkovich, Dewson, Ferguson, Graves, Joubert, Lee, Scott, Skoglund, Turley and Youness, 2001). But sometimes results are difficult to understand and interpret.

Identifying groups of customers with similar characteristics helps telecommunications firms to understand their customers' behavior. It can be a powerful means to identify and meet customers' demands.

The main challenge of applying data mining techniques for customer segmentation purposes is that proper variables are chosen for the segmentation process (Baragoin, Andersen, Bayerl, Bent, Lee and Schommer, 2001). The data to be mined usually includes:

- Behavioral data (call detail data)
- Demographic data (customer data).

Behavioral data helps one to identify groups of customers who have similar calling behaviors. In this way it is possible to focus on what customers do rather than what they are (Strouse, 2004). Identifying customers' needs only from their demographic data does not produce much value in the market. This is why it is highly recommended to combine behavioral with demographic data, as shown in Figure 3.

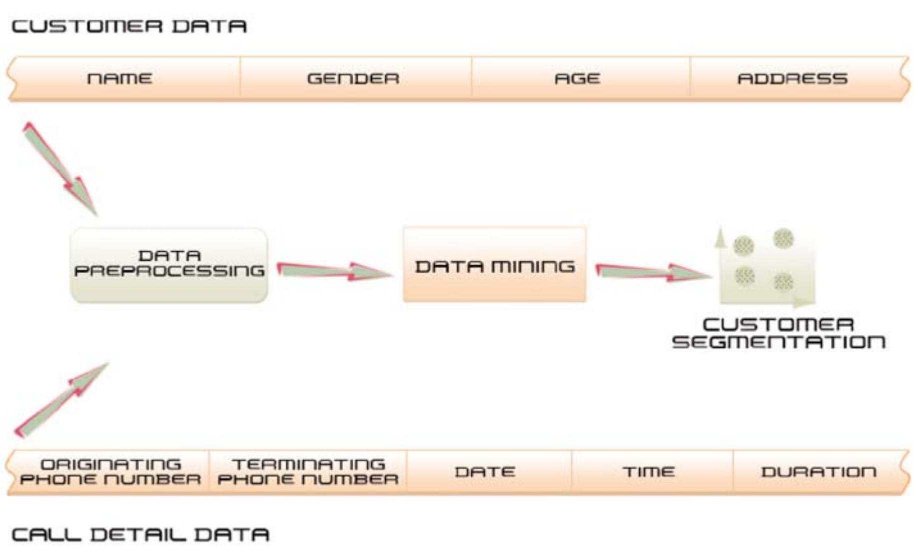

Figure 3. The data available for customer segmentation

Different clustering techniques can be used. According to Strouse (2004) there are two forms of cluster analysis: hierarchical and nonhierarchical partitioning. Hierarchical partitioning begins with individuals and merges them into clusters, while nonhierarchical partitioning begins with possible segmentation variables and assigns individuals into groups, but later reassigns them if it improves the clusters (Strouse, 2004). No matter which clustering technique is chosen, as a result several groups of customers i.e. clusters should be formed. The goal of clustering is to identify groups of customers with similar needs and behavior patterns. Therefore the segmentation model should be used in the marketing campaign process. What is needed today is not blanket marketing campaigns, but targeted campaigns directed at those customers who might be interested in services on offer (Todman, 2000).

It is clear that customer segmentation gives a new value to telecommunications companies business and helps them to gain competitive advantage by offering services that better fit the customers' needs than competitors' do. In order to gain a business insight, data mining models should be deployed within the business operations of the call center and marketing department. This requires the ability to integrate data mining models both within the existing CRM systems and into the business processes.

Telecommunications companies have to make efforts to recruit new customers, but they also have to concentrate on not letting the existing ones go. Customer retention is the topic that will be discussed in the next section.

5.2. Churn prediction

Customer loyalty is something that telecommunications companies have to take into account. It can cost ten times as much to recruit a new customer as it does to retain an existing one (Todman, 2000). On the other hand, the cost of keeping customers around is significantly lower than the cost of bringing them back after they leave (Berson, Smith and Thearling, 1999). This is why data mining is used for the purposes of churn prediction.

Churn can be defined as the gross rate of customer loss during a given period and shown as follows (Geppert, 2003):

Monthly Churn = (Cstart + Cnew - Cend) / Cstart

Where:

Cstart = Number of customers at the start of the month

Cend = Number of customers at the end of the month

Cnew = Gross new customers during the month.

So, the key question is: How to predict the customers who are likely to leave? Data mining techniques can be used to answer this question.

By using data mining it is possible to generate the customer list with high probability to leave the company (Baragoin, Andersen, Bayerl, Bent, Lee and Schommer, 2001). Data mining techniques can help telecommunications companies to identify churn behavior patterns before the customers are being lured away by better offers from competitors. In this way they can plan their actions to prevent the churn in advance.

Churn can be broken down into voluntary and involuntary churn. If a customer first initiates the action, we can call it voluntary churn (Baragoin, Andersen, Bayerl, Bent, Lee and Schommer, 2001). Involuntary is the one where the carrier cuts off the service, usually due to a repeated non-payment of invoices (Geppert, 2003). It is important to define different types of churn based on the churn reasons (Baragoin, Andersen, Bayerl, Bent, Lee and Schommer, 2001). Some of the reasons for voluntary churn are presented in Figure 4.

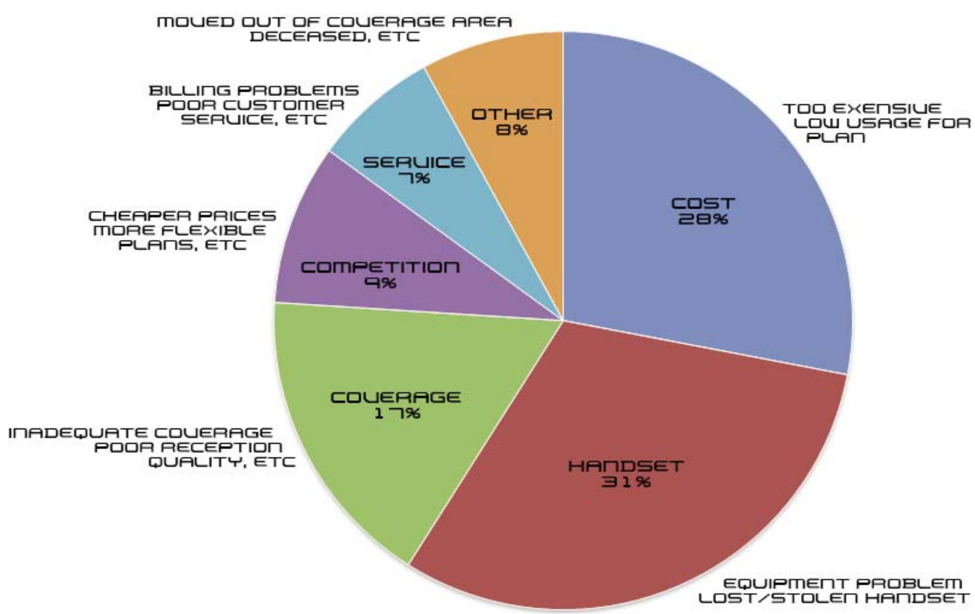

Figure 4. Voluntary deactivations by reason (Booz•Allen & Hamilton, 2001)

Geppert (2003) suggest another list of causes of churn:

- Price,
- Service quality,
- Fraud,
- Lack of carrier responsiveness,
- Brand disloyalty,
- Privacy concerns,
- Lack of features,
- New technology introduced by competitor,
- New competitor enter the market,
- Billing or service disputes.

The Walker Loyalty Report (2004) showed that while price is important to customers, it is not the main driver of their loyalty. Winning customers on price, rather than on services, results in high churn rates.

The company has to decide which type of churn it wants to predict, and use data mining techniques in order to do it. Telecommunications companies usually focus on those customers who leave for a better offer. But it is very important that the data mining model for voluntary churn does not predict by chance involuntary churn as well (Berry and Linoff, 2000)

Customer churn is predicted by mining the historical data. Data mining techniques used for this purposes typically utilize billing data, call detail data, subscription information and customer information (Weiss, 2005). It is necessary to have a target variable on which the prediction model is built and, in this case, it is a churn indicator (Baragoin, Andersen, Bayerl, Bent, Lee and Schommer, 2001). Time-series data such as monthly usage can be looked at, but it is recommended to calculate e.g. the change in three-month average usage and use it as a predictor (Edelstein, 2000). Some other factors, like the average number of calls and the change in the average number of calls are also good predictors (Edelstein, 2000).

Several different techniques can be used for the purpose of churn prediction, but the most popular ones are:

- Decision trees
- Neural networks
- Regression.

The churn prediction model can be developed on the entire customer base or specifically for a few segments (Baragoin, Andersen, Bayerl, Bent, Lee and Schommer, 2001). It is recommended to build several models and combine it for better data mining results.

The data mining model should be deployed in the retention campaign process (according to Strouse (2004) retention is the inverse of churn). Without having to make major new investments in support systems, this approach enables a fundamental improvement in customer retention. But, although technology tools are necessary for identifying likely churners, they are not sufficient (Strouse, 2004). It is necessary to develop adequate retention strategies focused on those customers who are likely to leave.

6. CONCLUSION

Capabilities for collecting data have been increasing rapidly in all industries over the last decades, especially in the telecommunications industry. The volume of data is expected to continue to grow in the future and many companies have not been able to capitalize on its value. That is why they need automated tools that can transform these vast amounts of data into useful information and knowledge. An increasing number of telecommunications companies use data mining models to improve their business. .

Why is it wise to use data mining in telecommunications? Because the telecommunications industry is highly competitive, and telecommunications companies realize that customers are their major assets. In order to gain competitive advantage they have to:

- Understand customers' behavior
- Interact with customers and deliver them advanced and flexible services according to their needs.

Data mining models can help them achieve these goals by enabling customer segmentation and churn prediction. These data mining applications were described in the paper.

Data mining can be a very effective means of implementing a customer relationship management strategy and helping telecommunications companies to keep their customers happy. In today's competitive business landscape the customer is a king, and the sooner one realizes it, the better.

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