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A Survey On Data Mining Techniques In Customer Churn Analysis For Telecom Industry

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ABSTRACT
Customer churn prediction in Telecom Industry is a core research topic in recent years. A huge amount of data is generated in Telecom Industry every minute. On the other hand, there is lots of development in data mining techniques. Customer churn has emerged as one of the major issues in Telecom Industry. Telecom research indicates that it is more expensive to gain a new customer than to retain an existing one. In order to retain existing customers, Telecom providers need to know the reasons of churn, which can be realized through the knowledge extracted from Telecom data. This paper surveys the commonly used data mining techniques to identify customer churn patterns. The recent literature in the area of predictive data mining techniques in customer churn behavior is reviewed and a discussion on the future research directions is offered.
***Keywords* -** Customer churn, Customer retention, Customer relationship management (CRM), Data mining techniques, Telecom industry.

I. INTRODUCTION

Data volume has been growing at a tremendous pace over the last two decades due to advancements in information technology. At the same time there has been enormous development in data mining. Many new methods and techniques have been added to process data and gather information. The data gathered from any source is raw data in which the valuable information is hidden. Data mining can be defined as the process of extracting valuable information from data. Data mining techniques have been successfully applied in many different domains.

The most difficult problem faced by telecom industry is customer churn. Customer churn models aim to detect customers with a high probability to jump or leave the service provider. A database of customers who might churn allows the company to target those customers and start retention strategies that reduce the percentage of customer churning.

Retention of old customers is always the preferable option to the company. Attracting new customers costs almost five to six times more than retaining the old customers. Attracting a new customer includes new recruits of manpower, cost of publicity and discounts. A loyal customer, who has been with a business for quite a long time, tends to generate higher revenues and is less sensitive to competitor prices. Such customers also cost less to keep and in addition, provide valuable word-of-mouth marketing to the business by referring their relatives, friends, and other acquaintances. In telecom Industry, the system is built to provide service to some average number of customers, when the customer number falls below the calculated number. It is considered as loss to the company [1].

A small step towards retaining an existing customer can lead to a significant increase in revenues and profits. The requirement of retaining customers craves for accurate customer churn prediction models that are both accurate and comprehensible. The Models have to identify customers who are about to churn and their reason for churn to avoid the losses to the telecom industry, a model should be developed to identify the reasons to churn and the improvements required to retain customers.

This paper is organized as follows: Section 2 describes the concept of customer relationship management (CRM) and customer churn in telecommunication sector followed by the main economical value of customer retention in the telecommunication market. In Section 3 we review the most commonly used data mining techniques in churn prediction. Finally, Section 4 concludes the paper with some future research directions.

II. CUSTOMER CHURN AND RETENTION IN TELECOM INDUSTRY

Customer churn is a popular measure of lost customers. Telecommunication companies often lose valuable customers and, thus, revenues to the competition. The telecommunication industry has gone through tremendous changes over the last few decades such as addition of new services, technological advancements and increased competition due to deregulation [2]. Customer churn prediction in telecommunication has, thus, become important to industry players in order to protect their loyal customer base, organization growth, and improve its customer relationship management (CRM) [3] [4]. Retaining customers with high churn risk is one of the toughest challenges in telecommunication industry today [5]. Due to greater number of service providers as well as more intense competition, customers today have a variety of options to churn. Thus, the telecommunication industry players are waking up to the importance of retaining existing customers as opposed to acquiring new ones [3].

There are many factors that influence customer to churn. Unlike post-paid customers, prepaid customers are not bound by service contracts and they often churn for simplest reasons. Thus, it is quite difficult to predict their churn rate. Another factor is customer loyalty that may be determined by customer service and product quality offered by the service providers. Issues like network coverage issues and reception quality may influence customers to move to the competitor with broader reach and better reception quality. Other factors that increase probability of customers defecting to the competition include slow or inadequate response to complaints and billing errors. Factors such as packaging prices, inadequate features, and older technology may also cause customers to defect to the competition. Customers often compare their providers with others and churn to whoever they feel provides better overall value [6].

A telecommunication company can do just fine if it can take care of existing customers even if it means acquiring no new customers. Globally, the average churn rate among mobile users in telecom industry has been estimated at about 2 percent, which translates to total annual loss of about $100 billion [7]. Kotler [8] estimated that the cost for convincing a regular customer not to churn to the competitor is 16 times less than the cost of searching and establishing contact with a new customer and the cost of attracting new customers is 5 to 6 times more than that for retaining existing ones. Reichheld and Sasser [9] estimated that a service provider can increase profits by between 25 and 85 percent by reducing customer churn rate by 5 percent. This shows the huge impact customer churn rate can have on the business achievement. An analysis of churn rate in different industries shows that it is particularly a major problem in telecommunication industry where it ranges between 20 to 40 percent annually [7].

Technological advancements have helped companies understand that their competitive strategies should ensure high customer retention rates in order to survive in the industry [10]. This especially applies to the telecommunication industry. Thus, significant research activity is now focused on identifying customers with high probability of fleeing to the competition [11]. The deregulation of the telecom industry has increased competition and the situation is only made worse by the fact that customers have more choices than ever. Thus, telecommunication companies should better understand their customers' needs and meet them in order to prevent their flee to the competition [12]. The significance of managing customer churn is also signified by large number of researches that consider it a crucial component of CRM [13]. CRM requires the organization to know and understand its markets and its customers. CRM involves knowing the customer's performance so that it can retain the most profitable customers and identify those whose churn no longer makes any difference. CRM also plans the development of the offer and discounts: which product to sell to which customers and through which medium and which product needs advertisements [14].

Just an improvement of 1 percent in customer retention rate could boost company's share price by 5 percent [13]. Poel and Lariviere [15] stated some economical value of customer retention; Successful customer retention means businesses don't have to seek potentially high-risk customers, thus, it can better focus on the needs of existing customers. Having stored data about long term customers helps companies to understand them well and they become less costly to serve and satisfy. Another economical benefit is that long-term customers are less responsive to competitors' messages. Usually people tend to share negative experience more than positive ones with friends and relatives. This will create negative perceptions of the company among prospective customers [15].

III. DATA MINING TECHNIQUES AND THEIR APPLICATIONS IN CUSTOMER CHURN ANALYSIS

The first paragraph under each heading or subheading should be flush left, and subsequent paragraphs should have a five-space indentation. A colon is inserted before an equation is presented, but there is no punctuation following the equation. All equations are numbered and referred to in the text solely by a number enclosed in a round bracket (i.e., (3) reads as "equation 3"). Ensure that any miscellaneous numbering system you use in your paper cannot be confused with a reference [4] or an equation (3) designation.

In the last few decades there have been significant improvement and changes in the data volumes stored in files, databases, and other repositories. To aid in the decision-making process, it is necessarily vital to come up with powerful techniques of data analysis and interpretation as well as develop tools that can be important in the extraction of interesting hidden patterns and knowledge [16]. Data mining algorithm has the capability of unveiling these patterns and their hidden relationships, and it is an integral component of a complex process that is commonly known as the Knowledge Discovery in Databases (KDD) which explains the steps that must be taken to ensure comprehensive data analysis [17]. According to Shearer [18], CRISP-DM model stands for Cross-Industry Standard Process for data mining model. It is mainly for conducting a data mining process, whose life cycle consists of six phases as shown in Fig 1.

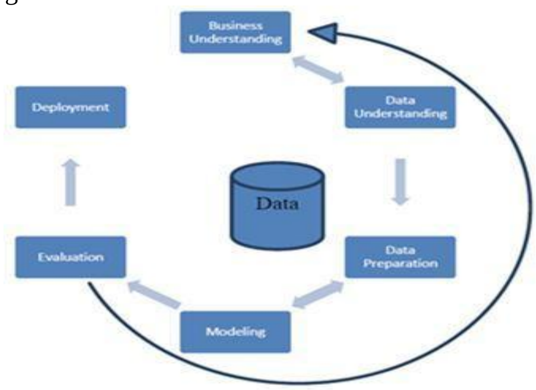

Fig 1: The phases of the CRISP data mining model

The first step is to understand the data that serves commercial values. Data preparation entails preprocessing of the raw data containing limited information. This may sometimes involve removal of missing values, quantizing, conversion of categorical variables into numerical. The modeling process involves building a suitable model used to extract the information and also evaluate the information to serve business purposes and accepting the same model after checking for important attributes like performances and accuracy. The final stage involves generation of a report or implementing a repeatable data mining process across the entire firm involved as a deployment and last phase [18].

Application of data analysis to churn is targeted towards prediction of whether an individual customer will churn, the time that churn is expected to happen and reasons for which the churn takes place. Through prediction of the customers that are most likely to churn, telecommunication companies are able to cut down the rate of churn through offering customers alternative and better incentives or packages to find reasons to stay [19]. To successfully manage the churn prediction challenge, different researchers have put into use different machine-learning algorithms in addition to data mining tools. This section presents the major data mining methods (neural networks, statistical based techniques, decision trees, and covering algorithms) and their usage in the context of customer churn Analysis.

3.1. NEURAL NETWORKS

Neural Networks is a data mining technique that has the capability of learning from errors [11]. Neural Networks are motivated by the brain. This happens in the sense that the brain learns a few new things which then will be transmitted via neurons. Equally, the neural network neuron with learning algorithms is able to learn from training data; this makes them be referred to as Artificial Neural Networks (ANN) [20]. The results of Lazarov and Capota [21] work showed that ANNs gave the best results as compared to other known algorithms. Moreover they argued that an appropriate prediction model requires constant updating, and should put into application a variety of data mining algorithms. Au et al. [22] believe that the largest limitation of neural networks is that they hardly uncover patterns in an easily understandable manner. Their study also had shown that neural networks outdo decision trees for prediction of churn through identification of more churners compared to C4.5 decision trees. This is in line with the research provided by Mozer et al. in [23] which shows that the nonlinear neural network outdoes the decision tree and logistic regression. In their paper, Sharma and Panigrahi [24] propose a neural network-based approach in the prediction of customer churn in line with cellular wireless services. The outcomes of experiments on a churn dataset of UCI repository indicate that neural network based approach can predict customer churn with accuracy more than 92%. Accuracy that is achieved by neural networks fully outweighs the limitation that they need large volumes of data sets and a lot of time to calculate a considerable load for the predictor attributes [21].

3.2. STATISTICAL BASED TECHNIQUES

Statistical techniques are a collection of methods applied in data mining used to process large volumes of data. They are used in learning links between both the dependent and independent attributes. This section presents the major statistical based data mining techniques (Linear regression, Logistic regression, Naive Bayes Classifier and K-nearest neighbors algorithm) and their usage in the context of customer churn Analysis.

Techniques based on regression have been associated with good results in prediction and estimation of churn. In Customer churn problem, there is often a two decisions' categorical outcome. The result is Yes or No or true or false or churns or no churns. The remaining variables are mostly continuous in nature because of that logistic regression appeared to be the best choice [20]. Lazarov & Capota [21] discussed commonly used data mining algorithm in customer churn analysis and prediction. Regression tree techniques were discussed along with other popular data mining methods like

Decision Trees, Rule based learning and Neural Networks. The conclusion was that good prediction models have to be constantly developed and a combination of the proposed techniques has to be used. Qureshi et al. [20] also applied logistic regression techniques on telecom industry data to identify churners. It failed to perform well because only 45% of the total number of churners were correctly identified which is a very low percentage. On the contrary, the logistic regression did a good job by identifying 78% of the total number of active users correctly. Another application is done by Nie et al. [25] who used two data mining algorithms; decision trees and logistic regression to construct a churn prediction model. They used credit card data from a real Chinese bank. The test result graded regression ahead of decision trees.

Naive Bayes is a supervised learning module which makes predictions about unseen data based on Bayesian theorem [21]. Nath & Behara [26] came up with a prediction model of customer churn. This was based on Naive Bayes algorithm in wireless customer data. It obtained 68 % accuracy in the first pass that was based on the Bayesian model.

K-nearest Neighbors algorithm is one of the basic traditional statistical classification approaches. The class label assignment of the unseen instance is based on the dominant class label of the k neighbor instances. This classifier consider only the k closest entries in the training set [4]. Zhang et al. [27] who presented in their research a hybrid approach of the k-nearest neighbor algorithm and also the logistic regression method for constructing a binary classifier named KNN-LR. They carried out a comparison between KNN-LR with logistic regression, C4.5 and radial basis function (RBF) network. The result was that KNN-LR outperformed RBF on all the four benchmark datasets. In addition, it also outperformed logistic regression on these benchmark data sets, only that they have very close performance on the Wisconsin breast cancer data set. The outcome also indicated its superiority over RBF and C4.5 but C4.5 just exceeded KNN-LR on telecom dataset. The novel model presented by Huang & Kechadi [28] indicates a hybrid model that joins a modified k-means clustering algorithm with a classic rule inductive technique (FOIL) for predicting customer churn behavior. A comparison was done to the model based on six techniques. These were original k-means, decision tree, logistic regression, PART, SVM, KNN, and OneR and other Hybrid techniques like k-NN-LR, SePI. Out of all these six classifiers, hybrid models and benchmark datasets, the proposed system was 12 times better. There was then the computation of the average AUC values (measurement of prediction accuracy) for each classification technique, and the hybrid model still has the maximum average value.

3.3. DECISION TREES

Decision trees are the most common methods used in predicting and evaluating the classification of customer churn problems. Decision trees are developed using the concept of divide-and-conquer. To evaluate a customer's dataset by developing a decision tree the classification is done by altering the tree until a leaf node is attained. When evaluating a customer record a value of churner or non churner is assigned to its leaf node. Fig 2 presents a simplified decision tree for customer churn prediction in telecom industry [21].

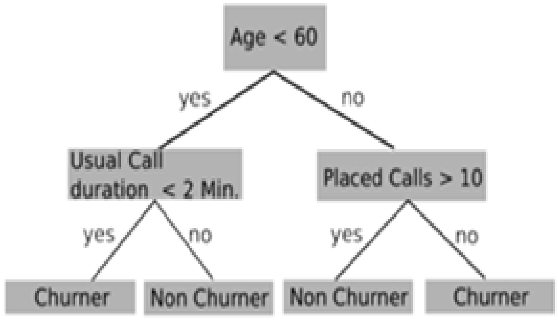

Fig 2 : A simplified churn prediction decision tree

Decision trees have the limitation that they are not suitable for complex and non-linear relationships between the attributes. However research points out that pruning the decision tree helps to improve the classification accuracy of decision tree [21]. The research by Umayaparvathi and Iyakutti [29] used ANNs and decision trees to perform customer churn prediction and they found out that decision trees outdo the neural networks in terms of accuracy. This is supported by Jahormi et al. [30] in their research which aimed to find a solution to the problem of customer churn in pre-paid mobile telephony organizations. This was done by constructing a predictive model that was a dual step multi-algorithm approach of Neural Networks and decision tree algorithms C5.0, CART and CHAID. Arguing on the Gain Measure as their evaluation criteria, the researchers found that decision tree algorithms outdo neural networks. In addition, they stated that to maximize the model performance it was recommended to adopt a combination of Decision Tree algorithms.

Oseman et al. [19] introduced how to put into application classification decision tree techniques for churn analysis in telecommunication industry. A sample set is used to carry out an experiment of customer churn factor using ID3 decision tree. In their results they found that the area of the subscriber was the main classification feature that contributed to customer churn, other than two minor causes for customer to churn.

In Taiwan, Wei & Chiu [31] put into use C4.5 based methodologies on one of the largest local mobile telecommunication companies and it identified 28.32% of the subscribers that contained some of the true churners with a lift factor of 2.30 and the retention time of 14 days. This can be compared to the research by Jahormi et al. [30] that aimed at developing a predictive model for customer churn in pre-paid mobile telephony organizations. They applied decision trees' techniques such as C5.0 with neural network and it was discovered that based on gain measure decision trees performed better than neural networks. A related study was carried out by Yeshwanth [32] in which he combined J48 decision tree along Genetic algorithm and constructed a hybrid evolutionary approach for churn prediction in mobile networks. He obtained 72% accurate results for largest telecom company in developing countries. Kaur et al. [4] applied Naive Bayes, J48 and the support vector machines classifiers to process the data so as to identify the significant features of customers that help in predicting churn of bank customers. In their findings, they concluded that success prediction of loyal class is less than the prediction success rate percentage of churn class. In addition, they also found that J48 decision tree had better performance compared to other techniques

Soein & Rodpysh [33] preformed some experiments in Iran involving applying several well-known data mining approaches:, C5.0, QUEST, CART, CHAID, Bayesian networks and Neural networks to find out the optimal method of customers' churn prediction in an Iranian Insurance Company. The results showed that CART decision tree had better performance than other techniques. The other researchers, Hadden et al. [34] had the aim of specifying the most relevant model for churn prediction analysis. They conducted an evaluation on different algorithms like neural networks, CART trees and regression and tested their accuracy in predicting customer churn. They found that decision trees outperform the rest of the other techniques with an overall accuracy percentage of 82%.

Qureshi et al. [20] in their research predict active churners in a Telecom industry by applying several data mining techniques such as CHAID, Exhaustive CHAID, Neural Network, Linear and Logistic Regression, CART, QUEST, and K-Means Clustering. They found that Exhaustive CHAID performed better compared to all other techniques. 60% was the percentage of correctly identified churners which was the highest percentage among all other techniques. However, other decision trees variants did not show as high performance as well as Exhaustive CHAID. Jahromi et al. [30] conducted research with the aim of developing a predictive model for customer churn in pre-paid mobile telephony companies. They carried out tests on performance of various model-building algorithms like Neural Networks, C5.0, CART, and CHAID. Through evaluation and comparison of the performance of the algorithms, they concluded that on cluster number 4 and based on gain measure for top 10% and 20% clients of each cluster CHAID algorithm score 40% and 80% respectively which represent the high percentage of accuracy among the other techniques.

3.4. COVERING ALGORITHMS

There are many covering algorithms families like AQ, CN2, RIPPER, and RULES family where rules are directly induced from a given set of training examples. This can be illustrated using Verbeke et al. [1] application of two novel data mining methods to customer churn prediction. They also benchmarked to ancient rule induction techniques for example C4.5, RIPPER, SVM, and logistic regression. They used both ALBA and AntMiner+ to stimulate accurate and understandable rules for classification. The experiments results proved that in order to get the highest accuracy a combination of ALBA with C4.5 or RIPPER is needed. If C4.5 and RIPPER are applied on an oversampled dataset the sensitivity will be on the highest level.

RULE Extraction System (RULES) was distinguished from the other covering algorithms families because of its simplicity. The first member of RULES family of algorithms RULES-1 [35], has been published in 1995. After that several versions of the algorithm have been developed and applied in several domains [36]. From the literature review, we found out that there has been little research work on inductive learning covering algorithms and their applications in customer Churn in telecom industry. RULES family algorithms are very suitable tools for data mining applications. For example, Aksoy et al. [37] have stated that RULES-3 Inductive Learning Algorithm is a very good choice for data mining. In a study [37] they used RULES-3 on eleven real life data sets for data mining by comparing it with three statistical, two lazy, and six rule-based data mining algorithms in terms of learning rate, accuracy and robustness to noisy and incomplete data. The good performance of RULES-3 is because of its following features: RULES-3 can handle a large sets of examples without having to break them up into smaller subsets; it can produce only rules that contain only relevant conditions; it allows a degree of control over the number of rules to be extracted; it could be applied to problems involving numerical attributes as well as nominal attributes and it gives a high flexibility for the user to control the precision of the rules to be generated, which can help in building better models.

IV. CONCLUSION

A conclusion section must be included and should indicate clearly the advantages, limitations, and possible applications of the paper. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions. Customer churn has been identified as a major problem in Telecom industry and aggressive research has been conducted in this by applying various data mining techniques. Decision tree based techniques, Neural Network based techniques and regression techniques are generally applied in customer churn. From the review of literature we found that decision tree based techniques specially C5.0 and CART have outperformed some of the existing data mining techniques such as regression in terms of accuracy. On other cases neural networks outdo the former method due to the size of datasets used and different feature selection methods applied.

There are likely to be tremendous rates of research in data mining and their applications in customer churn, but still it is an active research field and researchers are searching for more accurate solutions. In this paper we provide a summary of the different data mining methods, and their applications in customer churn prediction. However from the literature survey it is evident that there has been little research work on covering algorithms and their applications in customer churn, especially when it comes to applying Rules family algorithms in customer churn analysis. Our future work will be applying RULES family techniques on telecom datasets and compare the results with some of the most commonly used techniques in churn prediction as they are very suitable tools for data mining applications.

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