Research Trends In Customer Churn Prediction: A Data Mining Approach

ABSTRACT

This study aims to present a very recent literature review on customer churn prediction based on 40 relevant articles published between 2010 and June 2020. For searching the literature, the 40 most relevant articles according to Google Scholar ranking were selected and collected. Then, each of the articles were scrutinized according to six main dimensions: Reference; Areas of Research; Main Goal; Dataset; Techniques; outcomes. The research has proven that the most widely used data mining techniques are decision tree(DT) , support vector machines(SVM) and Logistic Regression(LR). The process combined with the massive data accumulation in the telecom industry and the increasingly mature data mining technology motivates the development and application of customer churn model to predict the customer behavior. Therefore, the telecom company can effectively predict the churn of customers, and then avoid customer churn by taking measures such as reducing monthly fixed fees.

The present literature review offers recent insights on customer churn prediction scientific literature, revealing research gaps, providing evidences on current trends and helping to understand how to develop accurate and efficient Marketing strategies. The most important finding is that artificial intelligence techniques are are obviously becoming more used in recent years for telecom customer churn prediction. Especially, artificial NN are outstandingly recognized as a competent prediction method. This is a relevant topic for journals related to other social sciences, such as Banking, and also telecom data make up an outstanding source for developing novel prediction modeling techniques. Thus, this study can lead to recommendations for future customer churn prediction improvement, in addition to providing an overview of current research trends.

Keywords - Telecom, Data Mining, Customer Churn Prediction

1. Introduction

With the rapid development of computer and Internet technologies, people's lives have undergone earth-shaking changes. Changes in the form of communication have prompted the telecommunications industry to flourish (Sun, 2018). In the "Big Data era" of information explosion, as one of the leading industries in the information age, the development of the telecom industry depends not only on communication technology, but also on the resource optimization and configuration capabilities of enterprises, and the management of huge information and data resources becomes an enterprise. Massive data accumulation in the telecommunication (telecom) industry and the widespread application of data warehouse technology make it possible to gain insight into customer behavior characteristics and potential needs through systematic customer historical data records. It also provides prerequisites for targeted Marketing in the telecom industry (Wang, Kung & Byrd, 2018).

Telecom operators have accumulated a large amount of customer information and consumption data during their development. These data truly and objectively reflect the behavior of consumers.

Combining data mining technology with the rich data resources of the telecom industry can effectively help telecommunications companies predict customer churn and develop more accurate, efficient and effective Marketing strategies.

2. Overview

This research investigates 40 relevant articles published between 2010 and June 2020 and characterizes the customer churn prediction using data mining studies on their areas of research, main goals, dataset volume, techniques adopted and the outcomes according to each study. Most research areas of these articles are telecom. These studies are selected to represent different and recent literature analysis methodologies on research areas closely related to customer churn prediction, which is the focus of the proposed research. It is also taken into account that each of those studies mention the goal and method of research, expressed in the columns of Table 1, to enable comparing different approaches with the proposed method.

Customer churn prediction modelling is significantly affected by diverse factors, such as data mining techniques and their specificities, available data, data quality and data granularity. Other features such as modelling decisions conduct different operation of success and how it is evaluated. In terms of datasets, there is a big difference regarding source, volume, nature and quality. The data source used for customer churn studies is mostly originated from the big telecommunication companies or operators. There is a lot of explanatory features which could be found in literature, some researches use only a few features, but other researches make use of hundreds of features. The further investigation has been carried out through gathering the most popular features and divide them into distinct clustering groups, such as: demographic features, business features, industry features and SMS message features. Table 1 answers the following questions: Which are the most used techniques in the customer churn forecast? Thus, it is possible to verify that decision tree(DT) , support vector machines(SVM) and Logistic Regression(LR) are the three most popular and useful method. By analyzing each method, it can be observed that these three methods are efficient techniques for extracting implicit information from the database and with high accuracy.

3. Literature review

Nowadays, customer churn is one of the growing issues of today's competitive and rapidly growing telecom industry. The focus of the telecom industry has shifted from acquiring new customers to retaining existing customers owing to the associated high cost (Hadden et al., 2007). The telecom industry can save Marketing cost and increase sales through retaining the existing customers. Therefore, it is essential to evaluate and analyze the customers’ satisfaction as well as to conduct customer churn prediction activity for telecom industry to make strategic decision and relevant plan.

There are two popular algorithms with good predictive performance and comprehensibility in the customer churn prediction area: decision trees (DT) and logistic regression (LR) (Verbeke et al., 2012). But these two algorithms also have their shortcomings: decision trees are inclined to have problems to deal with linear relations between variables and logistic regression has problem with interaction effects between variables. Therefore, the logit leaf model (LLM) is proposed, which is a new algorithm that could better classify data. LLM tends to construct different models on segments of the data (not on the entire dataset), which could have better predictive performance while keeping the comprehensibility from the models. The LLM be composed of two stages: a segmentation stage and a prediction stage. Customer segments are recognized in the first stage and a model is formulated for each leaf of the tree in the second stage. After test and case study, we found some key advantage of the LLM compared to decision trees or logistic regression. (Caignya, Coussement & Bock, 2018)

Customer churn problems could be solved from two different angles. One is to improve customer churn prediction models and boost the predictive performance (Verbeke et al., 2012). Another is trying to understand the most important factors that drive customer churn such as customer satisfaction. Customer churn prediction is considered as a managerial problem which is driven by the individual choice. Therefore, many researchers mention the managerial value for customer segmentation (Hansen, Samuelson, & Sallis, 2013). By considering the two research angles, customer churn prediction models need to create actionable insights and have good predictive performance.

Customer churn predication is part of customer relationship management since retaining and satisfying the existing customers is more profitable than attracting new customers for the following reasons: (1) Profitable companies normally keep long term and good relationships with their existing customers so that they can focus on their customer needs rather than searching new and not very profitable customers with a higher churn rate (Reinartz & Kumar, 2003); (2) the lost customers can influence other customers to do the same thing using their social media (Nitzan & Libai, 2011); (3) long-term customers have both profit and cost advantages. On the profit dimension, long term customers have tendency to buy more and they can recommend people to the company using positive words. On the cost dimension, they have less service cost since a company already masters information about them and understands their customer needs (Ganesh et al., 2000). (4) Competitive marketing actions have less effect on long term customers (Colgate et al., 1996); (5) Customer churn increases the demand and the cost to draw new customers and decreases the potential profits by the lost sales and opportunities. These effects lead to that retaining an existing customer has much smaller cost than drawing a new customer (Torkzadeh, Chang, & Hansen, 2006). Therefore, customer churn prediction is very necessary in a customer retention strategy.

Currently, Customer Relationship Management (CRM) is valued by many companies, since customer retention, which concentrate on developing and keeping long-term, loyal and profitable customer relationship, is an important factor for the company to win investment. Developing effective retention methods is critical for businesses, especially for telecom operators since they lose 20% to 40% of customers per year (Orozco. Tarhini, Masa’deh, & Tarhini, 2015). Retaining existing customers doesn’t have the cost of advertising, educating or creating new accounts as attracting new customers. Consequently, compared with attracting new customers, retaining an existing customer is five times cheaper (McIlroy & Barnett, 2000). Decreasing customer churn rate from 20% to 10% can lead to annually saving about £25 million to the mobile operator Orange (Aydin & Özer, 2005).

Predicting customer churn has been a subject for data mining. Compared with traditional surveys, using data mining is better at investigating customer churn (Huang, Kechadi, & Buckley, 2012). Traditional surveys suffer from high cost and limited access to the customer. However, data mining overcomes this kind of problem, which provides conclusion based on the analysis of historical data. Therefore, data mining becomes the most common method in customer retention to predict if customer will churn or not and identify patterns using customers’ historical data (Liu & Fan, 2014).

Many methods were used to predict customer churn in telecom companies. Most of these methods have applied data mining and machine learning. Most of the related work used only one method of data mining to obtain knowledge, and the other works tried to compare several different methods to predict churn (Ahmad & Aljoumaa, 2019). (Brandusoiu et al., 2016) proposed an up-to-date data mining method to predict the prepaid customers' churn using 3333 customers' dataset with 21 features, and a dependent churn variable with two values: Yes/No. Some features consist of data about the number of customers' messages and voicemail. The author used "PCA"(the principal component analysis algorithm) to decrease data sizes. Tree machine learning algorithms including Bayes Networks and Neural Networks are used to predict churn factor. AUC is applied to measure the performance of the algorithms. The AUC values for Bayes Networks is 99.10%, for Neural networks is 99.55%. The dataset is small and there is no missing values in this study.

Makhtar et al. (2017) presented a telecom customer churn prediction model using rough set theory. The authors mentioned that, compared with other algorithms such as Decision Tree (DT), Linear Regression (LR), rough set classification algorithm achieves better predictive performance. Nevertheless, most approaches only focus on predicting customer churn with higher accuracy, very few approaches investigated the intuitiveness and understandability of a churn prediction system to recognize the customer churn reason (Bock, & Poel, 2012). However, (Idris, Iftikhar, & Rehman, 2017) presented an advanced churn prediction method based on genetic programming (GP)'s strong searching ability supported by AdaBoost, which can recognize the factors leading to telecom customer's churn behavior. This study aims to apply the searching and learning ability of GP-AdaBoost method to design an intuitive and effective telecom customer churn prediction system.

4. Research methodology

This study conducts a literature review on customer churn prediction. Therefore, the first task is to collect relevant literature on the domain being analyzed for building a comprehensive body of knowledge (Moro et al., 2015). The reason for this is to identify the research gap and see where this research may contribute to existing body of knowledge. Google Scholar is one of the most popular search engines to search academic articles and publications (Harzing, 2013). The following search query: "Telecom" OR "Customer churn forecast" OR "Data mining" OR "machine learning" was chosen for querying its database for articles. The filters used included setting the timeframe period for publications/articles from 2010 up to the present and keeping out patents. The number of hits is 17,800, and the 40 most relevant articles published in journals were gathered for a deeper analysis with roots on the famous Google's search engine. Only articles/publications from experiments using data-driven approaches for customer churn forecasting, for example, empirical analyzes based on real data were considered. Each of the articles was checked carefully for investigating what method was used for data analysis , what was the timeframe and from which country were the data come. These three dimensions made up the three key element for the critical analysis and comparative analysis of the literature gathered. The study aspires to better understand the inherent laws of the telecom market business and obtain a control method for telecom customer management risk.

5. Results

The 40 articles gathered were published in a total of 30 different journals (Table I shows those from which more than one article was selected), corresponding to 11 different publishers (Table II for those publishers with more than one article selected). Such numbers prove that telecom forecasting is not totally limited to specific telecom literature, even though telecom gets the largest share, with 68 per cent of articles; on the contrary, the investigations found a bigger range of sciences, with a special emphasis on bank, energy and online social network literature (Table III). The fact that big data in telecom industry are currently helpful for discovering using cutting edge information technologies makes it an interesting subject for empirical investigations to evaluate novel data modeling approaches and applications (Mikalef et al., 2019). Even so, it is a leading telecom journal such as Expert Systems with Applications that accommodates the highest number of publications focusing on telecom forecasting. From the perspective of the publisher, Elsevier and ieeexplore.ieee.org are currently the two publishers clearly ahead in telecom forecasting journal article publications. Based on the 40 articles analyzed, three main aspects were analyzed:

(1) the main goal and outcome of each study;

(2) the dataset(from where the data were extracted and data volume); and

(3) the techniques adopted.

Since all the articles present empirical data-driven experiments, it is interesting to understand from which years are the data gathered for the experiments to evaluate if the periods are recent enough. It shows that most of the articles perform experiments based on data from the yearly 2011's, with few articles before 2010. One of the key dimensions of data-driven knowledge discovery is the recency of data, especially considering that telecom customers' behavior changes over the years. Therefore, using recent data decreases the risk of negatively influencing models built on these data for forecasting telecom business demand.

In additional, artificial intelligence techniques such as SVM (adopted 10 times) and NN (applied for 4 times) appear now as the dominant method, It would be attractive to observe what future reserves for artificial intelligence applications to telecom customer churn forecasting.

Table I. Journals from which more than one article was selected

Journal	No. of articles
Expert systems with Applications	10
IEEE Transactions on Industrial	4
European Journal of operational research	3
Decision support systems	2
Neurocomputing	2

Table II. Publishers from which more than one article was selected

Publisher	No. of articles
Elsevier	26
ieeexplore.ieee.org	6
Springer	3
researchgate.net	2
Citeseer	1
arxiv.org	1

Table III. Research domain from journals from which articles were selected

Research domain	No. of articles
Telecom	28
Banking	1
Energy	1
Financial Service	1
Online Social Network	1
Newspaper	1

6. Conclusions

Forecasting telecom customer churn is a quite old problem where many researchers have focused on. However, since the telecom industry is under pressure for predicting future demand and if customer will churn of not, so it is one of the most important problems.

The present investigation is designed to provide a very recent literature review on data-based empirical researches for forecasting customer churn. Through providing a summary of the literature covering 40 relevant publications mostly after 2010 up to June 2019, thus a very recent timeframe. The present article offers a review on the most recent trends in this domain, focusing on what the future holds regarding customer churn prediction and trying to find the research gap.

The findings show that decision tree(DT) , support vector machines(SVM) and Logistic Regression(LR) are the three most popular and useful method. Besides, artificial intelligence techniques are already demonstrating a significant use in what concerns to predicting customers' behavior. Especially, artificial NN are outstandingly recognized as a competent prediction method. In additional, the literature found is not limited to telecom journals, verifying that telecom themes are also of interest for a larger range of social sciences (e.g. Banking) and that telecom data comprises an important asset for evaluating novel for prediction modeling technologies. Based on the result of this study above described, a customer churn model to predict whether the telecom customer will be lost or retained will be establish. The model will combine data mining technology with the rich data resources of the telecom industry and the latest Marketing theories, which will not only maximize customer acceptance of telecom package within a manageable risk range, but also help increase the company's business volume and revenue. It would also be attractive to study that which trends will emerge on customer churn prediction in the future.

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