A Review And Analysis Of Churn Prediction Methods For Customer Retention In Telecom Industries

AMMAR A AHMED
Department of CSE
Rathnavel Subramaniam College of Arts & Science
Coimbatore, India
ammar.aqahmed@gmail.com

Dr. D. Maheswari linen
Department of CSE
Rathnavel Subramaniam College of Arts & Science
Coimbatore, India
mahelenin@gmail.com

***Abstract*—Customer churn prediction has gathered greater interest in business especially in telecommunications industries. Many authors have presented different versions of the churn prediction models greatly based on the data mining concepts employing the machine learning and meta-heuristic algorithms. This aim of this paper is to study some of the most important churn prediction techniques developed over the recent years. The primary objective is on the churn in telecom industries to accurately estimate the customer survival and customer hazard functions to gain the complete knowledge of churn over the customer tenure. Another objective is the identification of the customers who are at the blink of churn and approximating the time they will churn. This paper focuses on analyzing the churn prediction techniques to identify the churn behavior and validate the reasons for customer churn. This paper summarizes the churn prediction techniques in order to have a deeper understanding of the customer churn and it shows that most accurate churn prediction is given by the hybrid models rather than single algorithms so that telecom industries become aware of the needs of high risk customers and enhance their services to overturn the churn decision.**

Keywords—churn prediction, data mining, telecom industry, hybrid models

I. INTRODUCTION

Churn is one of the most important service aspects in the telecommunications industry [1]. The broad definition of churn can be said as the actions of a customer's service is terminated either by the customer themselves or the service provider for violation of service agreements [2], [3]. However, the major and most often cause of churn is the customer due to non-satisfaction in the service by a provider or due to more enhanced affordable service by other service-provider [4], [5]. However these are not the only reasons. Often the customer initiated churn is complicated and the factors for churn vary for each customer. Hence in this study the problem of customer churn is elaborated and the most recently proposed techniques are analyzed.

In telecom industries, both voice and data service customers are able to select a service-provider from a vast range of companies and have the freedom to switch their rights from one service provider to another whom they feel to be better. As the competition is fiercely increasing, the customers demand tailored products and almost best services at considerably lesser prices [6]. Many telecom companies deploy the retention strategies [7] to synchronize the services to keep customers for a longer tenure. As is the case, the churn reduction has become the number one business goal. In order to support telecommunications companies perform churn reduction, it is necessary to predict high risk customers and also to estimate their time of churn in order to incorporate their needs for preventing churning [8]. In general many data mining techniques [9], [10] are employed in predicting churn as there are closely related to sentiment analysis. The machine learning and meta-heuristic techniques [11] are greatly introduced as churn prediction methods.

Abbas Keramati et al, [12], [13] in which the authors presented a case study of customer churn prediction using meta-heuristic, machine learning, neural networks and data mining techniques. However each technique is adaptable for different datasets and also the hybrid techniques can further improve the accuracy. In order to take forward our research of churn prediction, this proposed review and analysis forms the foundation.

II. ANALYSIS OF CUSTOMER CHURN PREDICTION METHODOLOGIES

Most existing churn prediction methods utilized machine learning and meta-heuristic algorithms for highly accurate prediction. Some authors used algorithms like SVM, ANN, etc. while others focused on enhancing the data samples through efficient pre-processing and including social features [14], feature extraction and selection algorithms. This type of surveys plays important role in moving forward with novel concepts for the traditional churn problem [15].

Pre-processing, Imbalance problem and Sampling based churn prediction

J. Burez et al, [16] insisted on the importance of the balanced data for prediction of the customer churn.

Sampling (random and advanced under-sampling), boosting (gradient boosting machine) and a cost-sensitive learner (weighted random forests) are used for balancing inorder to increase churn prediction accuracy. But of these techniques namely random selection of variables reduces the efficiency. Veronikha Effendy et al, [17] proposed an efficient technique for imbalanced data handling problem inorder to enhance the customer churn prediction. The proposed technique employs a combination of sampling and Weighted Random Forest (WRF) for dataset balancing so that the churn prediction accuracy is enhanced. The sampling process is itself a combination of under-sampling and SMOTE. The core process involves sampling for imbalance data problem while WRF classifies the data for accurate churn prediction. Combined sampling process increases the F-measure and accuracy values proving the reduction of data records for accurate prediction. Though the performance is pretty good, the use of general under-sampling scheme is not significant.

Ning Lu et al, [18] have previously proposed a boosting based churn prediction model for telecom industry. In this approach, logistic regression is used as a basis learner whose performance is enhanced using a boosting technique such as Gentle AdaBoost. But both the techniques have their own set of limitations namely non-consideration of class rarity and inability to finalize the reasons for churn respectively. Xiaojun Wu et al, [19] proposed a prediction method based on improved SMOTE (Synthetic Minority Oversampling Technique) and AdaBoost for predicting e-commerce customer churn. In this approach, initially improved SMOTE is applied inorder to process the unbalanced datasets using the combination of over-sampling and under-sampling. Then the balanced dataset is trained in the AdaBoost learning algorithm for weak classifier to categorize the customers and predict the churn.

G. Ganesh Sundarkumar et al, [20] proposed one-class SVM based under-sampling for improving the churn and insurance fraud detection. Initially the data are under-sampled using one-class SVM and then classification is performed using machine learning algorithms. Based on the results it is concluded that the Decision tree performs better than other classification algorithms and along with one-class SVM it reduces system complexity and improves the prediction accuracy.

Qiu Yihui et al, [21] suggested that the existing customer churn prediction methods do not have a set of scientific, system theory and method so that unable to completely satisfy the application needs. The authors proposed a feature selection method based on orientation ordering pruning Method (OOPM) is proposed. This approach instead of attribute selection performs the pruning question of classifier combination. In the second step, a feature extraction method using Random Forest and Transduction (FE_RF&T) is proposed to extract multiple features from higher order customer data. From the evaluation results it can be found that the FE_RF&T with OOPM improve the churn prediction

Feature based Churn prediction improvement

Qiuhua Shen et al, [22] proposed a framework of complementary fusion of the multilayer features in order to improve the churn prediction rate. The proposed framework employed feature factorization and feature construction for fusion of features. This approach increases the churn prediction accuracy by resolving high dimensionality and unbalanced data problem. However, the feature selection process is sufficient and hence the unbalanced data problem re-emerges.

Sebastián Maldonado et al, [23] proposed an efficient feature selection method using SVM based on the profit model. This approach focuses on selecting best features for the classifier phase. The SVM classifier is constructed on a profit basis while the feature variables are also selected with consideration on profit. The approach flexibly allows the kernel functions for enhanced prediction accuracy. However the regulatory reasons are not satisfied in SVM as base classifier.

Ensemble Methods

Aimee Backiel et al, [24] suggested the use of a combination of local and social features for churn prediction as the two feature models detect different set of churners. An ensemble approach is employed for combining the two features. The customer data and social data from a mobile telephone service provider are used for evaluation. The proposed model contains a spreading activation algorithm which spreads the local and social variables among the relational and local model and an ensemble model to combine these features together. The outcome of the evaluation concludes that the churn prediction is improved when using a combined model of features instead of using individual models or spread feature models. However, the main limitation of this approach is that the omission of non-customer nodes in the creation of call graph due to larger volume of data reduces the effectiveness of churn prediction. Another drawback in this approach is the non-inclusion of negative energies from the social network. Social network analysis can enhance the customer churn prediction was said by Aimée Backiel et al, [25]. The authors illustrated the incorporation of social network data into ensemble churn prediction model using local attributes and real-time attributes. The evaluation results prove that the churn prediction is improved in terms of accuracy, AUC and lift percentage. However the network's high degree of homophily will be under scrutiny when additional datasets are evaluated.

Pretam Jayaswal et al, [26] proposed an ensemble approach for the prediction of churn. The proposed approach employed customer usage and related information1for the analysis of telecom customer churn. The decision trees and its ensembles, Random forest and Gradient Boosted trees are utilized for the building of binary churn classifier. The evaluation shows that these ensemble based approaches especially the residual feedback-improvement based Gradient boosted tree ensemble has better accuracy and sensitivity for customer churn prediction. However, the approach is not tested on the real time data and this limits the reliability on this model.

Churn Prediction from big data

Telco big data for churn prediction is a challenging task which is performed by Yiqing Huang et al, [27]. Telco big data utilizes the concepts of business support systems and operations support systems. It employs efficient feature engineering techniques based on which the classifiers such as RF, LIBFM, LIBLINEAR (L2-regularized logistic regression) and GBDT are used as classifiers for churn prediction. However the approach is totally a hardware based technique which is affordable only for larger business organizations while also the failures in hardware require specialized handling.

Yong Liu et al, [28] analysed the churn prediction process on big data by utilizing customer segmentation and misclassification cost. Initially the customer segmentation performed by k-means method followed by the classification of the data. The classification is done using C5.0 with misclassification cost. This approach improved the prediction accuracy and enhanced the coverage of data for analysis. The major advantages of this approach are much simpler and efficient but it has its own limitations in the form of non-availability of feature selection process in clustering.

Machine Learning Methods

Xia Guo-en et al, [29] suggested the use of SVM for the structural risk minimization in order to improve the churn prediction accuracy. The proposed approach focuses on predicting the risks associated with the infrastructure and finds the relationship between them and the customer churn. The main advantages are high accuracy even in cases of abundant attribute, big churn rate, less missing record, and nonlinearity data. However the selection of kernel function and weighting customer samples is not proper. Also the high dimensionality and non-linear time series are not processed accurately.

Yaya Xie et al, [30] proposed improved balanced random forests (IBRF) based churn prediction. This approach integrates sampling techniques and cost-sensitive learning with random forests to predict churn. However, the time varying variables are not employed in prediction causing limitations in performance.

Anuj Sharma et al, [31] proposed a neural network based approach for the prediction of customer churn in cellular wireless service subscriptions. The neural network models the input data into nodes and are implemented using Clementine 12.0. The over-training problems are overcome in neural networks by randomly selecting training data for network training. The results indicate a prediction accuracy of 92% which is significantly higher. However, only data reduction is performed without applying dimensionality reduction, thus increasing complexity.

Pınar Kisioglu et al, [32] proposed a churn prediction model based on the Bayesian Belief networks (BBN). In this approach CHAID (Chi-squared Automatic Interaction Detector) algorithm is employed for discretizing the continuous data variables. This is followed by the casual map as base of BBN to analyze the call and other customer services. However the approach does not consider the relationship between the variables.

The implementation of machine learning algorithms namely neural networks, support vector machines (SVM) and Bayesian networks (BN) for churn prediction has been applied by Ionut Brândusoiu et al, [33]. The authors employed Multi-layer perceptron (MLP), SVM and BN on the telecom industry data. Initially the dataset is pre-processed using Principle Component Analysis (PCA) which is followed by the machine learning classification. From evaluation results it can be found that SVM provides higher accuracy than MLP and BN. However the major area of concern is the churn prediction is carried out using efficient but individual algorithms instead of hybrid machine learning or ensemble methods.

Preeti K. Dalvi et al, [34] proposed a churn prediction technique using decision trees and logistic regression. The proposed technique is based on employing a combination and comparative analysis of data mining technique with a machine learning approach. Logistic Regression is used to determine the degree to which each feature affects the decision of churn while the decision tree provides a graphical overview of the available data based on the rules and strategies. The prediction accuracy is enhanced by employing this approach which is evident from the evaluation results. The approach also reduces the time for churn prediction but the limitation is that the classification is only limited to few classes.

Meta-heuristic Methods

Wouter Verbeke et al, [35] proposed the use of advanced rule induction techniques for churn prediction. The AntMiner+ and Active Learning Based Approach (ALBA) are used for detecting the churn from available data. However this technique requires more time for rule-set generation. T.Sumathi [36] proposed a churn prediction model using meta-heuristic especially for the huge sparse telecom data. The proposed model employs the Particle Swarm Optimization (PSO) for predicting the customer churn. It provides enhanced prediction with the problems of hugeness, sparsity and imbalanced nature of the dataset resolved effectively. This approach increases the accuracy of prediction. However, the number of false positives is increased by this approach.

Hybrid Churn Prediction Methods

Dong BackSeo et al, [37] proposed a two-level model of churn prediction based on a binary logistic regression model and a two-level hierarchical linear model (HLM). The regression model reveals the relationship between the demographic factors and customer churn behaviors. After detecting a weak relationship, the HLM explores the relationship between the independent variables namely length of association, service plan complexity, handset sophistication and the quality of connectivity and the dependent variable (customer retention behavior). In the next level, the same techniques are used to analyze how the demographic factors affect the churn, in order efficiently predict the customer churn. However, the study does not consider the switching costs and all of the customer satisfaction factors. Similarly only age and gender are considered as demographic factors while omitted income, education, occupation and location factors.

Table 1 : Comparison of Churn Prediction Methods

AUTHOR	METHOD	DATASET	ADVANTAGES	DISADVANTAGES
J. Burez et al, [16]	Random and advanced under-sampling, Gradient boosting machine and WRF	Six real-life proprietary European churn modeling datasets	Increases churn prediction accuracy.	Individual issues reduces the overall performance
Veronikha Effendy et al, [17]	Combined sampling with WRF	Categorical type churn data	High values of prediction accuracy and F-measure. Resolves imbalance data problem.	Most general under-sampling process is employed
Ning Lu et al, [18]	Logistic regression with Gentle AdaBoost	Telecom data (2010)	Accurate definition of high risk customer group	Unable to finalize the reasons for customers churn
Xiaojun Wu et al, [19]	Improved SMOTE &AdaBoost	Data from B2C e-commerce site	Higher accuracy with low cost processing. Flexible to utilize in different fields.	Does not consider class rarity
G. Ganesh Sundarkumar et al, [20]	One-class SVM under-sampling with Decision tree	Insurance dataset	High accuracy and reduced system complexity	More applicable for fraud detection than churn prediction
Qiu Yihui et al, [21]	OOPM Feature selection and FE_RF&T feature extraction	Business analysis system of Chie Mobile communication	Highly accurate churn prediction Removes irrelevant information.	Application needs are fulfilled only based on distribution information of test samples
Qiuhua Shen et al, [22]	Churn prediction based on complementary fusion of multi-layer features	European telecommunications company data	High prediction with better dimensionality reduction	Unbalanced data problem re-occurs when feature selection is not withstanding
Sebastián Maldonado et al, [23]	Profit based SVM	UCI-Telecom, Operator 1, Cell2Cell	Increased accuracy with profit priority	Regulatory reasons are not satisfied in SVM
Aimee Backiel et al, [24]	Spreading activation algorithm and Ensemble method	Prepaid Mobile telephone provider data & Call Data Records	Combined features increases the accuracy of churn prediction	Omits non-customer nodes due to larger volume of data
Aimée Backiel et al, [25]	Ensemble method	Belgian Telecom data along with Call Data records	Better prediction with high accuracy and AUC values	Does not handle many datasets at the same time
Pretam Jayaswal et al, [26]	Decision tree ensemble, RF and Gradient boosted trees	Data from Wireless telecom company publically available by SGI	High accuracy and sensitivity. Reliable performance in telecom industry data.	Not applied on real-time data
Yiqing Huang et al, [27]	RF, LIBFM, LIBLINEAR (L2-regularized logistic regression)	KDD CUP data	Churn prediction has cost-cutting and revenue increasing benefits	Hardware failures can totally abort the prediction process

AUTHOR	METHOD	DATASET	ADVANTAGES	DISADVANTAGES
	and GBDT			
Yong Liu et al, [28]	K-means & C5.0 with misclassification cost	Chinese Telecommunication data	Simple method with high accuracy. High coverage of big data.	Lack of feature selection Misclassification cost is not optimized
Xia Guo-en et al, [29]	SVM	UCI data & Home telecommunication carry dataset	Better accuracy even in the presence of abundant attribute, big churn rate, etc	Selection of kernel function & weights not proper. High dimensionality problem occurs
Yaya Xie et al, [30]	IBRF	Chinese Bank Dataset	High accuracy, scalability and faster training and testing speeds in churn prediction	Only internal time in-varying variables are used
Anuj Sharma et al, [31]	Neural Networks	Churn data from UCI	92% accuracy of churn prediction with early warning model	Feature dimensionality reduction is not performed
Pınar Kisioglu et al, [32]	BBN	Turkish Telecommunication data	Predicts the number customers leaving and the factors very efficiently	Do not consider the relationship between the variables
Ionut Brândusoiu et al, [33]	MLP, SVM & BN	Churn data from UCI	SVM provides high prediction accuracy of almost 100%	Only individual algorithms are utilized for prediction
Preeti K. Dalvi et al, [34]	Decision tree & Logistic regression	Telecom churn data	High accuracy with less time for churn prediction	Only suitable for few classes
Wouter Verbeke et al, [35]	Advanced Rule induction techniques	KDD library data	Accurate & comprehensive rule-sets for churn prediction	High Time complexity for rule-set generation
T.Sumathi [36]	PSO	Orange Dataset	High values of accuracy and precision	Increased number of false positives
DongBack Seo et al, [37]	Binary Logistic regression model and Two-level hierarchical linear model	US Top 10 national wireless provider's data	Better accuracy due to inclusion of demographic factors	Does not consider switching costs, customer satisfaction factors and professional level demographic factors
Chih-Fong Tsaib et al, [38]	Hybrid Neural networks	CRM dataset from American telecom industries	ANN-ANN hybrid model provides high accuracy in churn prediction with high stability	Dimensionality reduction or feature selection process is not performed
Amjad Hudaib et al, [39]	Hybrid model using clustering & MLP-ANN	Jordanian Telecommunication Company Data	Higher accuracy than single models	Processing time does not vary with the data size, thus consuming more time for small datasets
Hsiu-Yu Liao et al, [40]	Hybrid classification with combined features	Roomi dataset	High prediction accuracy within less time	Multi-objective problem occurs

Chih-Fong Tsaib et al, [38] developed a hybrid neural network model by combining back-propagation artificial neural networks (ANN) and self-organizing maps (SOM) for accurate churn prediction. This approach provides stable prediction with high accuracy; however the non-performance of dimensionality reduction questions the final output.

Amjad Hudaib et al, [39] proposed three hybrid data mining models for the churn prediction application. The hybrid models are developed based on two phases namely the clustering phase for customer data filtering and the prediction phase for predicting customer behaviour. The first model utilizes k-means algorithm for data filtering while Multilayer Perceptron Artificial Neural Networks (MLP-ANN) is employed for churn prediction. The second hybrid model employs hierarchical clustering along with MLP-ANN for prediction. The third model employs self-organizing maps (SOM) with MLP-ANN. On evaluation it is found that the hybrid models outperform the single models while the first hybrid model provides higher prediction accuracy than the other two models. The limitation with this approach is that the MLP-ANN consumes almost equal processing time for large as well as smaller datasets.

Hsiu-Yu Liao et al, [40] proposed a concept for predicting churn prediction in virtual worlds. In this work, the authors employed hybrid classification model based on meta-heuristic and machine learning algorithms. It considers and combines the monetary cost, user behaviour and social neighbour features in the determination of customer behaviour. Thus the proposed model detects the churn with high accuracy within less prediction time. Though the hybrid model with combined features enhances churn prediction, the multi-objective problem occurs when considering many features.

III. COMPARISON OF CHURN PREDICTION METHODOLOGIES

In this section, the analysed methods are summarized and compared based on their advantages and disadvantages. The comparisons are shown in Table 1. Using this table it can be much easier in understanding the various techniques and enables the readers to come to terms with the research objective. From the table, it can be found that the hybrid methods either hybrid machine learning, hybrid meta-heuristics or sometimes both, provide high accuracy of churn prediction. Hybrid models using SVM, ANN, SOM, etc provides high accuracy with reduced computation complexity.

IV. CONCLUSION

In this paper, initially the problem of customer churn and the benefits of predicting churn in telecom industries are provided to enhance the objective of this paper. We have reviewed and analyzed some of the most important existing churn prediction methods in detail and summarized them in the table above with the evaluated dataset details. The most important aspect of our review is that it focuses not only on predicting the churn accurately but also on the reasons for churn and the drawbacks of existing methods. The customer churn prediction is the aim of all these methodologies of which some used direct methods based on machine learning and meta-heuristic algorithms while others through indirect methods of improving data pre-processing and feature selection methods. From this analysis, it can be concluded that the most accurate churn prediction is obtained when utilizing hybrid methods instead of single algorithms. The research on churn prediction has greater scope which influences us to come up with our own version of hybrid model of churn prediction in future.

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