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Customer Churn Analysis for Brokerage Data using Deep Learning

Kalyani B. Zope, S. S. Kumbhar

M. Tech. Student, Dept. of Computer Engineering, College of Engineering, Pune, India

Assistant Professor, Dept. of Computer Engineering & I.T., College of Engineering, Pune, India

ABSTRACT: Customer churn analysis is a classification problem. In this paper, broker churn is analysed and described by recurrent neural networks(RNNs) model and an ensemble of the results of RNN with Random forest Classifier (RFC) are shown. Principal Attribute Analysis (PAA) eliminates redundant information from data, makes the data compact and reasonable. Out-of-Sample validation is used to evaluate the accuracy and stability of the model. In this paper, performance metrics results are obtained for all attributes using RNN model in univariate mode and important attributes are selected using PAA. using RNN and RFC together outperforms the results of RNN and RFC only. Finally, ensemble results of using both RNN and RFC combined are compared with other well-known model : Support Vector Machine (SVM).

KEYWORDS: Customer churn, recurrent neural networks, Random forest classifier, support vector machine (SVM), principal attribute analysis.

I. INTRODUCTION

Churning is a process when customer stops using your service and starttheir business with competitor.Companies in the consumer market have to deal with churn. Customer churn rate affects the business growth. Gaining new customer costs more than continuing the business with existing ones [1]. Decreasing churn of existing customers can have a large impact on overall revenue growth rate. Currently statistical and Neural Network techniques such as RFC, SVM, Artificial Intelligence models are used tominimize the customer loss.[2] However, brokerage data has some multidimensional and nonlinear attributes which causes decrease in accuracy of model. Customer churn analysis on brokerage data based on RNN and RFC ensemble model and PAA is set up in this paper. With this RNN, RFC ensemble model proved that it gives better results for large input data with good accuracy. Companies could use this ensemble model and provides insight to retain and increase customer base and avoid losing customers who will starts acting like churners.

II. THEORETICAL BACKGROUND

A. *Random Forest Classifier:*

Random Forest Classifiers (RFC) algorithm is fast and effective machine learning classification algorithm. It starts with the root node and builds the tree from top to bottom recursively and compare the attribute values with internal node. Each non-leaf node in the decision tree acts like decision node and leaf nodes are the class labels. It divides the training samples in to subsets until we get the similar classes in leaf node. This method gives high classification accuracy rate by training different subsets of training data in order to reduce variance. [9]

B. *Recurrent Neural Network:*

Recurrent neural network (RNN) is a class of neural networks. These are the mathematical expressions motivated from functioning of human brain. Traditional feed forward neural network performs well for independent inputs (and outputs). RNN performs well on sequential data. If we have to predict next element in series then we must know the previous elements of series. RNN is composed of number of neurons with loops and memory to store the previous

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elements information. They perform the same operation for every element in sequence. The neurons are arranged in layers. A system assign weights to connection of neurons and calculates the flow of through the network. According to [5], recurrent networks can be very sensitive, and can adept to past inputs. This makes RNN a robust learning algorithm. One of RNN advantage as machine learning is that their potential for dealing with two sorts of temporal behaviors. RNN is capable of solving complex set of problems and used extensively in many domains to solve compound real-world problems.

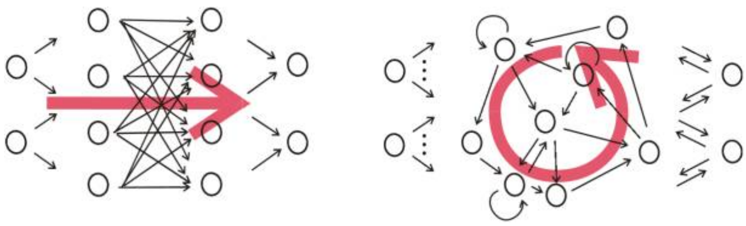


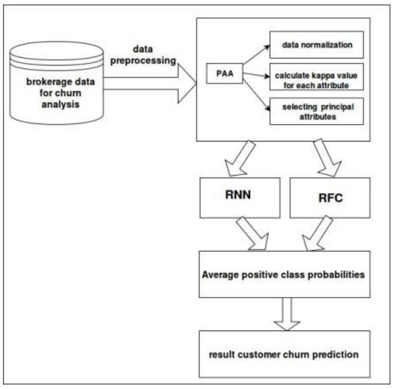
Fig 1: Structure of a feed forward network (left) and a recurrent network (right)

C. *Attributes of Brokerage Data:*

The data set is provided by AlgoAnalytics Financial Consultancy Pvt. Ltd. The indices of brokerage data included total 34 features i.e. input variables and target variables. Target is categorical variable. It gives the state of customers either active or dormant. State of customers is derived from trades done by customer in last three months.

III.PROPOSED ALGORITHM

A. *RNN, RFC Ensemble Model based on PAA:*



The main objective of the ensemble models in this study is to be able to predict active and dormant customers with as much high accuracy as possible. An ensemble classfier consists of two or more base classifiers trained individually. Predictions from base classifiers can be combined in many ways, like weighted un-weighted voting, while classifying new record (Kuncheva, 2004) [10]. It is observed that most of the times ensemble classifiers gives more accuracy than base classifiers (Dietterich, 1997). The Principal Attribute Analysis is univariate analysis approach which reduces number of attributes and gives principal attributes. Brokerage data which we have taken has 34 attributes. For each attribute kappa value is calculated using RNN model. kappa coefficient is a measure of agreement between categorical items. It is one of the most commonly used statistics for testing interrater reliability. The kappa can range from -1 to +1 and to improve accuracy of the prediction model, attributes with kappa value greater than 0.45 are selected.RNN and RFC models are trained for train data and class probabilities for both models are stored. Then the probabilities for positive class from both models are averaged and performance metrics results (Accuracy, kappa, sensitivity, specificity, PPV, NPV, AUC) are calculated for test data.

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B. *Data pre-processing*

Step 1: Unreal values are eliminated. Lack of values are compensated firstly in order to clean the data. Then, some unimportant attribute such as city is removed.

Step 2: The time window for train data begins from November 2014 to October 2015. The targeted variables are from November 2015 to January 2016. Time window of test data begins from February 2015 to January 2016. The targeted variables of test data are from February 2016 to April 2016.

Step 3: training data set has 151829 samples and testing data set has 150304 samples.After analyzing training data set, it is observed that 64832 customers are active and others are active within three months. Train and test data set has large number of samples satisfying the conditions of RNN learning. The RNN model is build and trained on training data set and accuracy is predicted using test data.

Step 4: Train data samples values are normalized by:

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

The values *x_new* Є [0,1] after normalization. Target = 0 are called as dormant customers and target = 1 are called as active customers.

C. *Selection of Principal Attribute:*

Principal attributes are selected by calculating the kappa value for each attribute using RNN model. Some attributes kappa value is shown in Table1

TABLE 1. THE KAPPA VALUE AND ATTRIBUTES

Attribute	**Kappa Value**
x1	0.5662
x2	0.5301
x3	x10.5262
x4	0.51
x5	0.4637
x6	0.4312
x7	0.4244

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TABLE 2. BROKERAGE DATA SAMPLES FOR CUSTOMER CHURN ANALYSIS

ID	**Attributes**					**Active/ Dormant**
	X1	X2	X3	X4	x5	Target
2	0.6284	664.375	960.295	72.421	35	1
13	1.823	911.853	11.233	1.994	4	1
17	0.556	0	381.703	0	0	1
32	0	126.111	0	0.556	1	0
38	2.567	791.285	0	69.901	19	1
56	1.259	0	66.826	2.238	7	1
83	0	954.905	0	5.910	0	0
181	0	891.148	56.004	0	14	0
224	5.692	0	721.47	52.280	17	1

IV. ENSEMBLE RESULTS

The whole experimental analysis in performed in python programming language using TensorFlow library. The training data set is normalized and RNN, RFC models are trained using training data. The test samples active or dormant are predicted using these models. Other classification algorithms such as SVM are used to predict test data labels in order to compare to the RNN, RFC (with PAA). The result is shown in Table3.

TABLE 3. PREDICATION MODELS AND RESULTS

Prediction model	SVM	RFC	RNN	RNN,RFC Ensemble
Accuracy(%)	67.94	79.88	81.06	85.65
Kappa value	0.3938	0.5807	0.6028	0.6938
TP	53555	44956	44704	45252
TN	48573	75107	77145	83489
FP	42293	15759	13721	7377
FN	5883	14482	14734	14186
True positive rate(%)	90.10	75.63	75.21	76.13
False positive rate(%)	46.54	17.34	15.10	8.11

Since there are two categories namely active and dormant customers, four possibilities can be defined to measure the effectiveness of the models.
TP (True Positive): Number of dormant customers correctly identified as dormant.
TN (True Negatives): Number of correctly rejected, active customers correctly identified as active.
FP (False Positives): Number of which the active customers are incorrectly identified as dormant.
FN (False Negatives): Number of incorrectly rejected, dormant customers incorrectly identified as active.

High percentage of FP imply large number of active misclassified as dormant resulting in more careful follow-up which will lead to unnecessary expenditure to the company [7]. On the other hand, high percentage of FN will result in paying less attention to the

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dormant and consequently lead to a higher churn rate. In the same token, it is important to maximize the TP and TN. Maximizing TP and TN will automatically minimize FP and FN.

Accuracy: (TN+TP)/ (TN+FP+ FN+ TP)
True positive rate: TP/ (FN+TP)
False positive rate : FP/ (TN+ FP)

It is tested and proved that RNN, RFC ensemble model outperforms SVM, decision tree and RNN. Although difference in performance metrics values may be relatively low, note that even a small gain in prediction performance can yield considerable cost savings for financial firms.

V. CONCLUSION AND FUTURE WORK

In this work, we have surveyed different classification models for churn analysis. RNN, RFC ensemble model of customer churn for brokerage data is suggested because both models runs efficiently on large data sets. In general, ensemble has produced the better results using PAA, which leads to better cost savings in churn applications.On the other hand, comparing to SVM, higher dimension of data samples has lower accuracy and requires more computing time than RNN, RFC.

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BIOGRAPHY

Kalyani Bharat Zopeis a Master of Technology student in Department of Computer Science and Information Technology, College of Engineering Pune (COEP), Savitribai Phule Pune University. She has completed her Bachelor of Computer Engineering from Savitribai Phule Pune University and worked for 2 years as Research Associate at Indian Institute of Technology (IIT) Bombay. Her research interests are Machine Learning, Data Analytics and Compilers.