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PREDICTIVE ANALYSIS OF CUSTOMER CHURN IN BANK BY FUZZY PETRI NETS

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Abstract

Analysis and estimation of customer churns play a significant role in maintaining consumer relationships and improve benefit of enterprise. Fuzzy Petri networks are important specifications as they cover every real-time application domain's competition and inaccuracy regulation. Data mining technology may detect essential information behind large volumes of data by creating a predictive model for customers churn and then operate more effectively. This paper presented a Fuzzy Petri net model which used data mining classifiers to predict customer churn. This study aims to determine whether or not the customer will be leaving the bank.

1. Introduction

Customer retention has a prodigious effect on the bottom line of the bank's earnings, and this form of effect has surpassed that caused by size, market share, unit cost and other similar competitive advantage factors [1, 2]. Customer churn would not only carry the sales-related opportunity cost, but would also reduce the new customers [3, 4]. A modest change in the retention rate for consumers would result in a large increase in earnings. And various marketing campaigns may be applied for different customer base by

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2. Materials and Methods

2.1. Fuzzy Petri Nets

One of the most known and applicable class of Petri nets in the domain of Artificial Intelligence are fuzzy Petri nets [6, 7]. They are a modification of classical Petri nets relying on interpretation of net places as logical variables with values belonging to the closed interval [0,1] of all real numbers from 0 to 1 (0 and 1 are included). The concrete values of such variables represent a truth degree of statements assigned to the variables. Net transitions are interpreted as logical implications in which input places of a transition represent premises of a given implication corresponding to the transition whereas output places of the transition represent its conclusions.

2.2. Data Set:

Kaggle is the website providing datasets for free for the research purposes of all kind of domains. For our experiment, we took the data which is Bank Customer Churn Prediction dataset. The amount of instances is 2000 and the amount of attributes is 13 including the class attribute. The details of the attributes are described below.

- Row Number-corresponds to the record (row) number and has no effect on the output.

- Customer Id-contains random values and has no effect on customer leaving the bank.

- Surname-the surname of a customer has no impact on their decision to leave the bank.

- Credit Score-can have an effect on customer churn, since a customer with a higher credit score is less likely to leave the bank.

• Geography-a customer's location can affect their decision to leave the bank.

• Gender-it's interesting to explore whether gender plays a role in a customer leaving the bank.

• Age-this is certainly relevant, since older customers are less likely to leave their bank than younger ones.

• Tenure-refers to the number of years that the customer has been a client of the bank. Normally, older clients are more loyal and less likely to leave a bank.

• Balance-also a very good indicator of customer churn, as people with a higher balance in their accounts are less likely to leave the bank compared to those with lower balances.

• Num of Products-refers to the number of products that a customer has purchased through the bank.

• Has Cr Card-denotes whether or not a customer has a credit card.

• Is Active Member-active customers are less likely to leave the bank.

• Estimated Salary-as with balance, people with lower salaries are more likely to leave the bank compared to those with higher salaries.

• Exited-whether or not the customer left the bank. (binary variable 0 if the customer stays and 1 if the client exit).

2.3. Methodology

We use different search methods; attribute evaluators, and classifier techniques in this paper.

Attribute evaluators [8]: The Attribute Evaluator is the method by which subsets of attributes are assessed. Various attribute evaluators are available in WEKA. We used (Weka, 3.8.4) a learning machine tool in this work which includes Cfs Subset Evaluator, Info Gain Attribute Evaluator, Correlation Attribute Evaluator, Gain ratio Attribute Evaluator, Relief *F* Attribute Evaluator, Symmetrical Uncert Attribute Evaluator and One *R* Attribute Evaluator.

Search Method [8]: The Search Method is the structured way in which the search space of possible attribute subsets is navigated based on the subset evaluation. We used a Best First, Greedy Stepwise and Ranker methods in this work.

Classifier: [8] All schemes for numeric or nominal prediction in Weka implement this interface. In this work, we used a JRip, PART, One R and Zero R claasifier.

3. Experimental Result

Table I. Evaluation of different feature selection methods based on J Rip Classifier.

S.No	Search Method	Attribute Evaluator	Classifier	Accuracy	No of Rules generated	Mean absolute Error	ROC Area	Time (seconds)
1.	Best First	Cfs Subset	J Rip	66.6%	2	0.2315	0.655	10.66
			PART	51.05%	1	0.2646	0.497	0.56
			One R	51.05%	-	0.2447	0.500	0.03
			Zero R	51.05%	-	0.2649	0.497	0
2.	Greedy Stepwise	Cfs Subset	J Rip	66.6%	2	0.2315	0.655	10.66
			PART	51.05%	1	0.2646	0.497	0.56
			One R	51.05%	-	0.2447	0.500	0.03
			Zero R	51.05%	-	0.2649	0.497	0
3.	Ranker	Info Gain	J Rip	79.9	3	0.2954	0.620	0.56
			PART	77.1	461	0.2942	0.619	2.66
			One R	79.2	-	0.208	0.500	0
			Zero R	79.2		0.3297	0.496	0.02
4.	Ranker	Correlation	J Rip	80	4	0.2989	0.597	0.64
			PART	77.1	461	0.2942	0.619	2.62
			One R	79.2	-	0.208	0.500	0
			Zero R	79.2	-	0.3297	0.496	0
5.	Ranker	Gain Ratio	J Rip	80.3	4	0.2941	0.629	0.43
			PART	77.1	461	0.2942	0.619	3.79
			One R	79.2	-	0.208	0.500	0
			Zero R	79.2	-	0.3297	0.496	0
6.	Ranker	Relief F	J Rip	80.3	3	0.298	0.619	0.41
			PART	77.1	461	0.2942	0.619	2.63
			One R	79.2	-	0.208	0.500	0
			Zero R	79.2	-	0.3297	0.496	0
7.	Ranker	Symmetrical	J Rip	80.15	3	0.3044	0.589	0.32
			PART	77.1	461	0.2942	0.619	2.31
			One R	79.2	-	0.208	0.500	0
			Zero R	79.2	-	0.3297	0.496	0
8.	Ranker	One R	J Rip	80.2	4	0.3037	0.590	0.41
			PART	77.1	461	0.2942	0.619	2.64
			One R	79.2	-	0.208	0.500	0.02
			Zero R	79.2	-	0.3297	0.496	0

The above tables show that we need to identify suitable combination of classifier attribute selection with accuracy level, mean absolute error, AUC of ROC as maximum, minimum, high respectively. Based on this optimal solution we choose combination of classifier attribute selection. Here, the high accuracy 80.3%, low error 0.2941 and high ROC 0.629. The above combinations generate the JRip rules. Using CPN tool to show the below combinations rules.

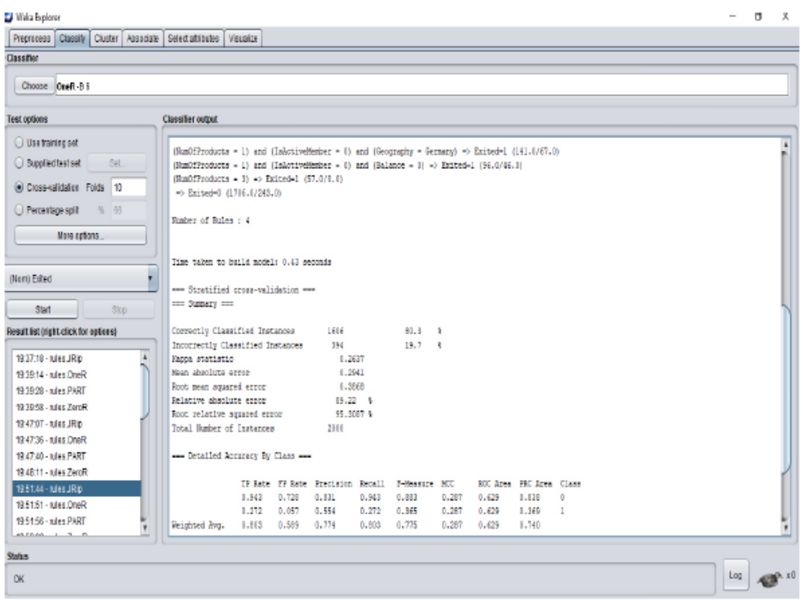
R1: (Number of Products = 1) and (Is Active Member = 0) and (Geography = Germany) =>
Exited=1 (141.0/67.0)

R2: (Number of Products = 1) and (Is Active Member = 0) and (Balance = 0) => Exited=1 (96.0/46.0)

R3: (Number of Products = 3) => Exited=1 (57.0/8.0)

R4: => Exited=0 (1706.0/243.0)

Table 2. Classifier output of the JRip model.



The corresponding Petri net model is illustrated in Figure 1. In the Petri net model [9, 10], according to the proportions dedicated to each place, transitions 1 to 3 respectively represent rules 1 to 4 in the introduced rule base above and firing each transition means the corresponding rule is fulfilled.

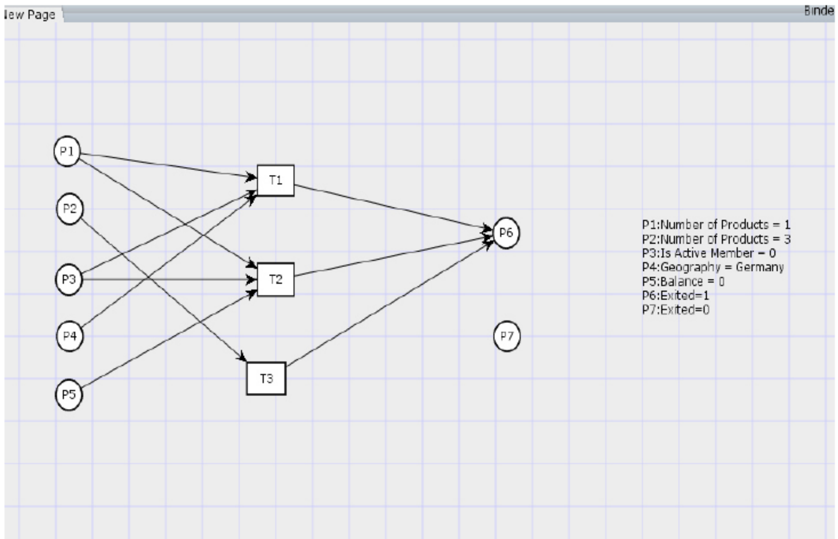


Figure 1. CPN Tool Snapshot for Customer churn in Bank.

Conclusion

We create the connection of Petri net's behavior for implementing the decision rules. Churn customer prediction is an operation conducted to determine whether or not the customer is leaving the bank. This work is carried out using a data mining technique to predict the effectiveness of all classifiers based on rules. Classification Accuracy is used as a measure of the performance of different algorithms. Comparisons between classifiers are also considered based on the accuracy, mean absolute error, and receiver operating characteristic curve values. Tuning parameters as well as the selection of attributes achieve maximum accuracy of around 80%. For the future one may go with more attributes of significance for different data sizes.

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References

[1] T. O. Jones and W. E. Sasser, Why satisfied customers defect, Harvard Business Review 73 (1999), 88-99.

[2] Y. Z. Xu, G. Robert and V. D. H. Beatrice, Customer Perception, Customer Satisfaction, and Customer Loyalty Within Chinese Securities Business: Towards a Mediation Model for Predicting Customer Behavior, Journal of Relationship Marketing 5 (2007), 79-104.

[3] M. C. Mozer, R. Wolniewicz, D. B. Grimes, E. Johnson and H. Kaushansky, Predicting subscriber dissatisfaction and improving retention in the wireless telecommunications industry, IEEE Transactions on Neural Networks 11 (2000), 690-696.

[4] Y. Shih and K. Fang, Customer defections analysis: an examination of online bookstores, TQM Magazine 17 (2005), 425-439.

[5] J. T. Choi and Y. H. Choi, Fuzzy neural network based predictive control of chaotic nonlinear systems, IEICE Trans, Fundamentals E87-A, no. 5 (2004), 1270-1279.

[6] C. G. Looney, Fuzzy Petri Nets for Rule-Based Decision-making, IEEE Trans, Syst., Man, Cybernetics 18-1 (1988), 178-183.

[7] T. Murata, Petri Nets: Properties, Analysis and Applications, Proc. of the IEEE 77(1989), 541-580.

[8] http://weka.sourceforge.net/doc.dev/weka/attribute Selection.

[9] M. Kouzehgar, M. A. Badamchizadeh and S. Khanmohammadi, Fuzzy Petri nets for human behavior verification and validation, Int. J. Adv. Comput. Sci. Appl. 2(12) (2011), 106-114.

[10] S. Meher Taj and A. Dr. Kumaravel, Measuring employee performance key indicators by Fuzzy Petri Nets, 2015.

[11] G. Jenitha and A. Kumaravel, An instance of reinforcement learning based on fuzzy cognitive maps, International Journal of Computational and Applied Mathematics 12(1) (2017), 200-207.

[12] I. Paulraj Jayasimman, T. Dhivya and J. Joseline Manora, Inverse Majority Neighborhood Number of a Graph, IOP Journal of Physics Conference Series (2018) 1-6.