Predicting Credit Card Customer Loyalty Using Artificial Neural Networks

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Abstract

Customer loyalty is one of the key factors in customer retention and segmentation. However, quantitative research in this area based on non-subjective data has been rare in the literature. This paper shows how back propagation neural networks can be used to predict the loyalty level of credit card customers based on transaction records. In the meantime, a set of decision rules are also extracted from the trained neural networks in order to improve the clarity and explicability of the loyalty model.

Keywords: credit card, customer loyalty, neural networks, rule extraction

1. Introduction

With the unprecedented advancement of information technology in recent years, customer relationship management (CRM) is playing an essential role in the transformation of business strategy from product-centric to customer-centric. The core concept of CRM is to maximize customer value by creating a deeper understanding of customers [10].

In nowadays, due to the highly competitive markets and the availability of numerous brands for similar products and services, customers have never been given more choices and preferences. As a result, customer retention has become a central subject within the CRM domain and it is not surprising either that customer loyalty has become a major theme in marketing research and a fundamental concern for managers in the past three decades [5].

Since loyalty is often regarded as being subjective, research in this area has mostly been relied on data acquired from specifically designed questionnaires. However, due to various limitations in practice, such kind of research may not always be conducted easily and the quality of the returned questionnaires may also be subject to question. As the complement to this traditional research method, in this paper, an analytic customer loyalty model is built on the transaction records of credit card customers. It would be interesting to see if the loyalty of a customer (at least some aspects) can be discovered from his/her transaction behaviors.

The rest part of this paper is structured as follows. Section 2 gives an overview of customer loyalty and existing research in the literature. Section 3 gives an introduction of the major techniques employed. Experimental results are presented in Section 4. This paper is concluded in Section 5 with a list of future work directions.

2. An Overview of Customer Loyalty

In general, it is widely accepted that loyalty should be viewed from two aspects including behavioral dimension and attitudinal dimension [3][15][14]. Oliver [11] gives a commonly accepted definition of loyalty: "*a deeply held commitment to re-buy or re-patronize a preferred product/service consistently in the future, thereby causing repetitive same-brand or same brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behavior*". This definition emphasizes both aspects, neither of which could be neglected when investigating a customer's loyalty [7].

Researchers are often interested in finding determinants or antecedents of customer loyalty through structural equation modeling technique using data acquired by questionnaire.

Luarn and Lin [12] use a theoretical model to explain how trust, customer satisfaction, perceived value and commitment influence attitudinal and behavioral loyalty for e-service context, and validate it empirically. Beerli, Martín and Quintana [2] propose a structural equation model of customer loyalty in the retail banking market. Eshghi, Haughton and Topi [1] develop and test a model that aids further understanding of the determinants of customer loyalty in the wireless telecommunication industry. Buckinx [17] illustrates that a retail store's customer behavioral loyalty can be predicted to a reasonable degree using the transactional database. They use three different predictive techniques and design an effective variable-selection procedure to demonstrate that Multiple Linear Regression significantly outperforms the other models including random forests and automatic relevance determination neutral networks. They find that the most important indicator of behavioral loyalty consists of the variety of products previously purchased.

Recently, there is a more and more clear trend of increasing credit card consumption in China and the acceptance and penetration rates of credit cards in the mainland are likely to grow comparably to Taiwan and Hong Kong [13].

However, the problem of customer loyalty prediction has not drawn enough attention in the credit card market in China yet. As a result, the focus of this paper is to develop a model for predicting customer loyalty using customers' static attributes and credit card transactions.

3. Methodology

In this paper, the well known back propagation neural network model is used to predict the loyalty of customers. Apart from its advantage at solving high dimensional nonlinear classification and regression problems, one of its inherent practical limitations is the lack of comprehensibility of the model.

In order to solve this issue, extensive research has been conducted on how to extract well defined decision rules from trained neural networks. Algorithms for rule extraction can be largely divided into two categories: decompositional and pedagogical algorithms [6]. The first class of algorithms focuses on heuristically searching and extracting rules in neurons of neural networks individually. The second class of algorithms aims to extract rules that map inputs directly into outputs [9].

In this paper, Binarized Input-Output Rule Extraction (BIO-RE), which is a technique belonging to the pedagogical algorithm category, was employed in order to extract binary rules from neural networks trained with "binary" inputs, based on its input-output mapping [8]. If the original inputs are not binary, they need to be binarized:

$$y_i = \begin{cases} 1, & if \quad x_i > \lambda_i \\ 0, & otherwise \end{cases} \qquad (1)$$

In (1), x_i is the value of i^{th} original input and λ_i is the mean value of x_i. The resulting binary value is denoted by y_i.

Suppose the number of input neurons is *N*. All 2^N possible inputs are fed into the trained neural network and are split into two disjoint sets according to the outputs. Next, a simplification of the two sets is performed using *Espresso* [8] to get the rules of the neural network, which are linguistically comprehensible and can help people better understand the model.

4. Experiments

4.1. Data Description

The credit card data set used in the experiments was provided by a leading domestic commercial bank, which contained 4,563 customer records in March 2008. For each customer, ten attributes were used as the inputs to the neural networks: Credit Limit, Available Credit Limit, Special Consumption Points, Debt, Total Consumption Amount, Consumption Frequency, Consumption Type, Age, Gender and Gold Card Flag.

For instance, Credit Limit and Available Credit Limit are credit card's indispensably basic characters. Special Consumption Points is the total consumption points of particular use such as dining or golf.

4.2. Customer Loyalty Determination

Unlike the research on other aspects of credit card customers, the major difficulty in loyalty research is that the data usually come unlabelled. So the key issue is how to determine a customer's loyalty level (Low or High in this paper)? Also, it is very difficult for us to directly contact card holders in the dataset to conduct an investigation using questionnaires in order to get their individual loyalty levels.

Due to the lack of an existing practically well defined loyalty measure, we consulted with a few customer managers from different commercial banks in order to have a deep understanding on what kind of credit card records can be reasonably used as the indicators of customer loyalty.

According to the interviews with the customer managers, usage period, financial asset and consumption point are most relevant to customer loyalty. More specifically, usage period is closely related to customer satisfaction, an overall evaluation based on the purchase experience [4]. Financial asset represents a customer's contribution to the bank and shows how the customer relies on the bank at the same time. As a result, it represents the technical, financial and psychological factors that make it difficult or expensive for a customer to change brand (switching cost) [16]. Consumption point indicates a customer's perceived value, which is his/her overall assessment of what is received relative to what is given [18].

We further acquired the above three attribute values for each of the 4,563 customers. Since these attributes are all time-varying, for the unique predicting purpose of this paper, the data were collected as of the end of March 2008.

In order to come up with a single numerical value as the loyalty measure, the three attribute values were normalized to [0, 1] and the average value was used as the threshold above which a customer's loyalty was regarded as being in the high level. The number of each class of customers is shown in Table 1.

Table 1: The distribution of customers

Loyalty Class	Number	Proportion
Low Level	3377	74.01%
High Level	1186	25.99%

4.3. Neural Networks Training

According to Sections 4.1&4.2, the unique objective of training a neural network in this paper was to *predict* a customer's loyalty level one month later using his/her current 10 attributes, which can be regarded as a two-class classification problem.

The original dataset was divided equally into a training set and a test set. The test set consisted of 1689 low loyalty customers randomly selected from the original low loyalty set and 593 high loyalty customers randomly selected from the original high loyalty set. As shown in Table 1, the low loyalty customers were almost three times as many as the high loyalty customers, which could cause some problems in the training process.

In order to handle this unbalanced training set, the random resampling method was adopted, which at each time randomly selected one sample from the 593 high loyalty customers and added it to the training set until there were equal number of high loyalty customers and low loyalty customers. By doing so, the final training set consisted of 1688 low loyalty customers and high loyalty customers respectively.

The neural network had 10, 20 and 2 neurons on the input, hidden and output layers respectively. The two output neurons represented high level and low level respectively and the loyalty level was determined by the neuron with the higher value. The training process (back propagation) ended up with MSE 0.14 after 6152 epochs (Fig. 1).

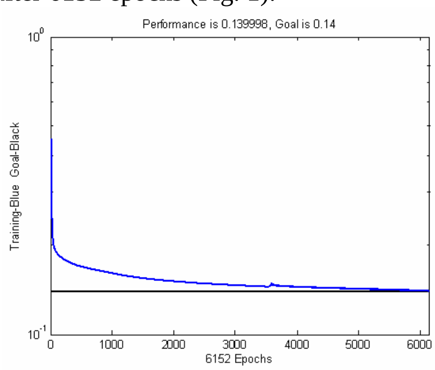

Fig. 1: The training error curve of the back propagation neural network

4.4. Prediction Results

The effectiveness of the trained neural network on predicting the loyalty level of unknown customers was validated on the test set. Table 2 shows the confusion matrix of the test results where 458 out of 593 actual high loyalty customers were predicted correctly, resulting in a prediction accuracy of 77.23%.

Note that the successful recognition of high loyalty customers is of major interest to the bank and the goal is to identify as many as possible high royalty customers with as few as possible falsely identified samples.

Table 2: The predictive performance of the neural network using confusion matrix

	Low	**High**
Low (Predicted)	67.91%	22.77%
High (Predicted)	32.09%	77.23%

4.5. Rule Extraction

Some typical decision rules extracted from the trained neural network using techniques described in Section 3 are shown in Table 3 (Appendix). The performance of the set of rules is shown in Table 4, which was somewhat inferior to the performance of the neural network in recognizing high loyalty customers.

Table 4: The predictive performance of the set of rules extracted from the neural network

	Low	**High**
Low (Predicted)	80.46%	44.52%
High (Predicted)	19.54%	55.48%

Although a predication accuracy of 55.48% does not look significant by itself, only 659 out of 2,282 test samples were classified as high loyalty customers. In other words, this set of rules successfully recognized 55.48% of real high loyalty customers by testing just 28.88% of the whole customers, which is still a reasonable result in terms of the *lift* value.

5. Conclusions

The major contribution of our work is a credit card customer loyalty model based on objective measures (mostly transaction data), which is capable of predicting each customer's loyalty level in the future. Experimental results showed that the neural network model as well as the rule set can predict with a reasonably good accuracy a customer's royalty level, especially high loyalty customers.

Certainly, there is still a lot of improvement that can be done in order to make the current model more effective in practice. For example, the loyalty determination rule itself used in this paper is by no means a very accurate indicator of real customer loyalty, which could be made more plausible should loyalty measures from traditional methods such as questionnaire investigation be incorporated. In the meantime, the predication accuracy may be also be further increased by using other classification models and having a better understanding of the distribution of the two classes of customers.

Acknowledgement

This research was supported by National Natural Science Foundation of China (NSFC, Project no.: 70671059).

References

[1] A. Eshghi, D. Haughton and H. Topi, "Determinants of customer loyalty in the wireless telecommunications industry", *Telecommunications Policy*, Vol. 31, 2007, pp.93-106.

[2] A. Beerli, J. D. Martín and A. Quintana, "A model of customer loyalty in the retail banking market", *European Journal of Marketing*, Vol. 38, No. 1/2, 2004, pp.253-275.

[3] A.S. Dick and K. Basu, "Customer loyalty: toward and integrated conceptual framework", *Journal of the Academy of Marketing Science*, Vol. 22 No. 2, 1994, pp. 99-103.

[4] C. Fornell, "National satisfaction barometer: the Swedish experience", *Journal of Marketing*, Vol. 56, 1992, pp.6-21.

[5] G. Bodet, "Customer satisfaction and loyalty in service: Two concepts, four constructs, several relationships", *Journal of Retailing and Consumer Services*, Vol. 15, 2008, pp.156-162.

[6] H. Tsukimoto, "Extracting Rules from Trained Neural Networks", *IEEE Transactions on Neural Networks*, Vol. 11, No. 2, 2000, pp.377-389.

[7] H. Lin and Y. Wang, "An examination of the determinants of customer loyalty in mobile commerce contexts", *Information & Management*, Vol. 43, 2006, pp.271-282.

[8] I. A. Taha and J. Ghosh, "Symbolic Interpretation of Artificial Neural Networks", *IEEE Transactions on Knowledge and Data Engineering*, Vol. 11, No. 3, 1999, pp.448-463.

[9] J.S. Heh, J.C. Chen and M. Chang, "Designing a decompositional rule extraction algorithm for neural networks with bound decomposition tree", *Neural Computing & Applications*, Vol. 17, 2008, pp.297-309.

[10] E.W.T. Ngai, X. Li and D.C.K. Chau, "Application of data mining techniques in customer relationship management: A literature review and classification", *Expert Systems with Applications* (2008),

[11] R.L. Oliver, "Whence consumer loyalty?", *Journal of Marketing*, Vol. 63, 1999, Special Issue: pp.33-44.

[12] P. Luarn and H. Lin, "A Customer Loyalty Model for E-Service

Context", *Journal of Electronic Commerce Research*, Vol. 4, No. 4, 2003, pp.156-167.

[13] W. Qi, Y.J. Li and Y.Y. Hao, "The Determinants of Credit Card Customer Loyalty: An Empirical Study in a Chinese Context", *2007 International Conference on Management Science & Engineering*, 2007, pp.1080-1085.

[14] R. Hallowell, "The relationship of customer satisfaction, customer loyalty, and profitability: an empirical study", *International Journal of Service Industry Management*, Vol. 7, No. 4, 1996, pp.27-42.

[15] F. Reichheld, "The Loyalty Effect: The Hidden Force Behind Growth, Profits, and Lasting Value." *Harvard Business School Press*, 1996, Boston.

[16] F. Selnes, "An examination of the effect of product performance on brand reputation, satisfaction and loyalty", *Journal of Marketing*, Vol. 27, No. 9, 1993, pp.19-35.

[17] W. Buckinx, G. Verstraeten and D.V. Poel, "Predicting customer loyalty using the internal transactional database", *Expert Systems with Applications*, Vol. 32, 2007, pp.125-134.

[18] VA. Zeithaml, "Consumer perceptions of price, quality and value: a means-end model and synthesis of evidence", *Journal of Marketing*, Vol. 52, 1988, pp.2-22.

Appendix

Table 3. Some typical rules extracted from the neural network

	High Loyalty		Low Loyalty	
	Rule 1	Rule 2	Rule 1	Rule 2
Credit Limit	<2314637	-	<2314637	<2314637
Available Credit Limit	>=2227083	<2227083	>=2227083	>=2227083
Special Consumption Points	<91859	>=91859	-	>=91859
Debt	No	Yes	-	No
Total Consuming Amount	<344693	-	-	<344693
Consumption Frequency	>=5.7352	>=5.7352	>=5.7352	-
Consumption Mode	<1	>=1	-	-
Age	<41	<41	-	<41
Gender	Female	Female	Male	-
Gold Card Flag	Ordinary	Gold	Ordinary	Ordinary