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Estimating the utility value of individual credit card delinquents

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ABSTRACT

Excessive issue of credit cards has contributed to increased credit card delinquencies, which have become a burden for credit card companies. In such a negative situation, companies should build and use models to estimate maximum profits from credit card delinquents. However, traditional classification models used to classify customers into good or bad groups are not useful in estimating profits from credit card delinquents. Therefore, this paper suggests two models to estimate the utility value of individual credit card delinquents. After showing that the best classification model does not necessarily result in the best utility model, we explain a model that could be used to estimate utility value of individual credit card delinquents. Such models are expected to give much more value to the credit card companies than the traditional classification models.

1. Introduction

In the past decade, several Asian nations, including South Korea, China, Hong Kong and Taiwan, have experienced not only credit card booms but also financial risks (Kang, 2007), and both governments and credit card companies have endeavored to overcome these financial risks. For example, in Korea, the Ministry of Finance and Economy published "The Integrated Measure for Credit Card Risk" in 2002 to reduce overuse and indiscrete use of credit cards (The Ministry of Finance, 2002). In addition, the Korea Federation on Banks revised The Act of Utilization and Caring of Personal Credit Information in late 2004 in order to provide a measure of relief for those with bad credit and to help reduce moral hazard of delinquency (Korea Federation of Banks, 2004). Credit card companies have tried to reduce indiscrete issuance of credit cards and to put tighter controls on credit limits. While these efforts reduced financial risk in Korea appreciably, there are new signs of new credit risk, particularly too many credit card delinquents (Lee, 2007). This new risk was caused by excessive competition of credit card companies for new customers. Since credit risk can occur at any time, credit card companies must find a way try to create as much value as possible, even in a bad situation.

Traditionally, credit card companies have made use of classification models to develop competition strategy, to monitor credit risks, or for other purposes. While those models may help credit card companies filter out high-risk customers, they are not useful for finding economic value in credit card delinquents. Thus, the objective of this paper is twofold: to suggest a method by which to calculate the utility value of classification models and to show how to build a model to estimate the utility value of individual credit card delinquents. We believe such models will give much more value to the credit card companies than will the traditional classification models.

The remainder of this paper is organized as follows: Section 2 examines the literature about classification models and utility-based data mining; Section 3 describes data preparation, problems and our approach to solving them; Section 4 shows the experimental results and their interpretations, and Section 5 presents our conclusion, including shortcomings, contributions, and suggestions for future studies.

2. Literature review

2.1. Classification models

Classification is the process of developing a set of models which can be used to predict the class of objects whose class label is unknown (Han & Kamber, 2001). Techniques that have been used to build classification models have included artificial intelligence techniques (e.g., neural networks, decision tree, etc.) and statistical techniques (e.g., discriminant analysis and logistic regression). Recently, the support vector machine, rough sets and hybrid techniques have frequently been used (Ahn, Cho, & Kim, 2000; Huang, Liao, & Chen, 2008; Polat, Güneş, & Arslan, 2008; Wang, 2005).

Most research on the classification task has addressed the development of classification models and comparison of their performance with those of other models developed using other techniques by hit ratio. For example, West compared the performances

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of five different neural network models[1] (West, 2000), Stark and Pfeiffer compared the performance of various decision-tree models[2] with that of the linear regression model (Stark & Pfeiffer, 1999), and Colombet et al. compared the performance of CART, neural networks and logistic models in the medical domain (Colombet et al., 2000).

Credit classification models have also been developed to estimate and classify the financial credit of organizations or individuals as good or bad. While traditional statistical methods were once used frequently (Hand & Henley, 1997), machine learning, artificial intelligence and various other techniques are more frequently used now. Performances of credit classification models were also compared by hit ratio between statistical techniques (e.g., discriminant analysis and logit regression) and neural network models (Desai, Crook, & Overstreet, 1996), among which were SVM technique, neural networks, genetic algorithm and decision-tree models (Huang, Chen, & Wang, 2007). In addition, various hybrid credit classification models were developed. For example, Lee et al. combined a neural network model with discriminant analysis to overcome the limitations of pure the neural network model, which include the difficulty of deciding the networks' topology, the difficulty of selecting potential input variables, and the long training process (Lee, Chiu, Lu, & Chen, 2002). Lee and Chen developed another hybrid when they used the significant variables in multivariate adaptive regression splines model as the input nodes for the neural networks model (Lee & Chen, 2005), and Hsieh used clustering techniques before developing a neural network model with the objective of classifying unrepresentative samples into isolated and inconsistent clusters (Hsieh, 2005). Fuzzy classification rules were derived as a credit classification model, which showed high flexibility and explanation power (Hoffmann, Baesens, Mues, Gestel, & Vanthienen, 2007) by integrating if–then rules and discriminant functions to increase understandability (Huang, Tzeng, & Ong, 2006).

2.2. Utility-based data mining

Utility-based data mining has been introduced to the machine learning discipline as cost-sensitive learning, cost of data acquisition, active/query learning, and so on (Abe, 2005). Thus, utility-based data mining is concerned with cost or profit, while the hit ratio simply represents the rate of correct classification rate. Fig. 1 shows a confusion matrix in the case of binary target problems. As in Eq. (1), hit ratio (HR) is defined as the number of correct predictions to the total number of predictions

$$\mathrm{HR} = (\mathrm{TP}+\mathrm{TN})/(\mathrm{TP}+\mathrm{FP}+\mathrm{FN}+\mathrm{TN}) \tag{1}$$

Actually, we can use the hit ratio measure under the implicit assumption that the values incurred from classifying each cell (TP, FP, FM and TN) are exactly same. However, this is not the case in the real world, and using the hit ratio to estimate the performance of classification models could result in bad decisions in terms of financial profits because interpreting the models in detail can be difficult (Holte & Drummond, 2005). Therefore, hit ratio is not a proper measure for estimating classification models in a practical sense.

Hit ratio takes into account only the number of cases that are correctly classified. However, in order for the classification model to be useful in the business environment, it must take into consideration what value the model can bring to business, as the positive value of correctly classifying class A may be different from that of correctly classifying class B, and the negative value of incorrectly classifying class A to class B will differ from that of incorrectly classifying class B to class A. Further, the value of correct classification will certainly be different from that of incorrect classification, so a new perspective of data mining, *utility*-based data mining, drew the attention of data mining researchers at recent workshops.[3]

real / prediction	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Fig. 1. Confusion matrix.

Several studies used the *utility* concept to estimate the financial value of classification models. Arnt and Zilberstein considered three kinds of cost—error cost, feature measurement cost and response time cost—to develop a classification model (Arnt & Zilberstein, 2005). Ciraco et al. examined whether the utility of a classification model can be improved by altering the misclassification cost ratio[4] (Ciraco, Rogalewski, & Weiss, 2005) by assuming the variation of misclassification cost ratio as 1:10, 2:10, 3:10, ∼, 10:10, 10:9, 10:8, ∼, 10:1. Zadrozny proposed a cost-sensitive learning whose goal is to find a classification model that maximizes its expected benefit (Zadrozny, 2005). Chawla and Li made a classification model framework that considers the profit of each customer based on his or her probability of default (Chawla & Li, 2006).

Melville et al. predicted null values of attributes in the data preprocessing step, considering utility concept (Melville, Saar-Tsechansky, Provost, & Mooney, 2005a, 2005b). Their first study proposed a method that can show the cost-down effects on prediction values of null attributes, while their second study proposed a selective null-value prediction method that predicts only relatively low-cost attributes. McCarthy et al. proposed a sampling method that can be used in a data set with a heavily skewed target value distribution and compared a cost-sensitive learning method with a random sampling technique that can balance the distribution of target values (McCarthy, Zabar, & Weiss, 2006).

Tseng et al. proposed a method that can choose high utility item sets instead of frequent item sets (Tseng, Chu, & Liang, 2006). Weiss and Tian introduced a technique that can decide proper data quantity in a high learning cost situation and compared the performances of various random sampling techniques (Weiss & Tian, 2006). Yan and Baldasare proposed an ROI maximization method that would have been impossible in the existing cost-sensitive learning method (Yan & Baldasare, 2006). Yao et al. made an integrated framework for utility-based measures of a model's performance (Yao, Hamilton, & Geng, 2006).

These utility-based data mining studies are summarized by subject in Table 1.

3. Building a classification model to estimate profits from credit card delinquency data

3.1. Data preparation

The raw data set was collected from February 2002 to August 2003 from customers who had been in arrears on credit card payments at least once. We collected the original data sets from three data sources. The first is an integrated information of arrearages from five credit card companies which agreed to share information about customers who were in arrearages over five days or

[1] Multilayer perception, mixture-of-experts, radial basis function, learning vector quantization and fuzzy adaptive resonance.

[2] ID3, C4.5, CHAID and CART.

[3] Knowledge discovery and data mining workshop on utility-based data mining, 2005 and 2006.

[4] The ratio of false positive misclassification costs to false negative misclassification costs.