A CASE BASED REASONING SYSTEM FOR CUSTOMER CREDIT SCORING: COMPARATIVE STUDY OF SIMILARITY MEASURES

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ABSTRACT

To deal with the customers' credit assessment problem in a small company, we have developed a case-based reasoning system. The system assesses the credit score of a target customer only based on the features data which can be easily retrieved from daily transaction data stored in the database of the management information system. Since the credit score of a target customer is to be reasoned on the basis of similarity to past cases, it is very important how to evaluate properly the degree of similarity between a target customer and past cases. In our previous study, the Euclidean distance was used as a similarity metric between a target customer and cases. This paper aims at investigating the effect of similarity metrics on the performance of the proposed system. We consider six distances which are used as similarity metrics for case retrieval and case adaptation. These distances are based on weighted Manhattan distance and Euclidean distance, and the weights are calculated by using linear regression and multivariate discriminant analysis. We evaluate the distances by applying the system to solve the real credit assessment problems of the company and examining how the performance of the system depends on the choice of distances.
Keywords: case based reasoning, customer evaluation, credit scoring, similarity measure

INTRODUCTION

In today's increasingly competitive business environmental, successful risk management is very important. Credit risk is one of management risks being faced frequently and most simply defined as the potential that counterparty will fail to meet its obligations in accordance with agreed terms. Because there are many types of counterparties -- from individuals to sovereign governments -- and many different types of obligations -- from auto loans to derivatives transactions -- credit risk takes many forms.

There have been significant prior researches on credit analysis or credit evaluation. The models and methodologies published so far for credit risk assessment generally fall into two categories: default models and credit scoring models. Default models assess the likelihood of default by an obligor. Credit scoring models are used to assess the credit quality of counterparty. These models differ from each other in two ways:

- Credit scoring is usually applied to individuals or small businesses. Default models are applied more to larger credits such as corporation or sovereigns.

- Credit scoring models are largely statistical, regressing instances of default against various risk indicators, such as an obligor's income, home renter/owner status, etc. Default models directly model the default process, and are typically calibrated to market variables, such as the obligor's stock price or the credit spread on its bonds.

Application of statistical techniques to credit analysis started in the 1960's with the development of computers. The first technique introduced was discriminant analysis (DA). Beaver (1966), one of the first researchers to study bankruptcy prediction, investigated the predictability of the 14 financial ratios using 158 samples consisted of failed and non-failed firms. Altman (1968, 1983) also used multivariate discriminant analysis (MDA) to identify the companies into known categories. The classification of

Altman's model based on the value obtained for the Z score has a predictive power of 96% for prediction 1 year prior to bankruptcy.

From the 1980's, the DA method was replaced by other statistical techniques. Ohlson (1980) applied the logit analysis to bankruptcy prediction. Ederington (1985) used multinomial logit, Gentry et al. (1988) and Jackson and Boyd (1988) used probit analysis, and Mar et al. (1996) used multidimensional scaling for solving problems of credit rating or bond ratings predicting. Reiter and Emery (1991) and Iskandar-Datta and Emery (1994) use both ordinary least squares (OLS) and probit analysis for bond rating problems and they found similar results for both models. All these studies used a variety of samples and statistical techniques with the results typically falling between 55% and 65% in classification accuracy.

Artificial Intelligence (AI) techniques, particularly rule-based expert systems, case-based reasoning systems and machine learning techniques such as neural networks have been used to credit rating or bankruptcy analysis. A number of studies have demonstrated that artificial intelligence methods achieved better performance than traditional statistical methods. Desai et al. (1996) investigated neural networks, linear discriminant analysis and logistic regression for scoring credit decision. They concluded that neural networks outperform linear discriminant analysis in classifying loan applicants into good and bad credits, and logistic regression is comparable to neural networks. West (2000) investigated the credit scoring accuracy of several neural networks. The results were benchmarked against traditional statistical methods such as linear discriminant analysis, logistic regression, k-nearest neighbour and decision trees. Malhotra et al. (2002) applied neuro-fuzzy models to analyze consumer loan applications and compared the advantages of neuro-fuzzy systems over traditional statistical techniques in credit-risk evaluation. Hoffmann et al. (2002) applied a genetic fuzzy and a neuro-fuzzy classifier for credit scoring. Baesens et al. (2003) benchmarked state-of-the-art classification algorithms for credit scoring.

Recently, researchers have proposed the hybrid data mining approach in the design of an effective credit scoring model. Hsieh (2005) proposed a hybrid system based on clustering and neural network techniques. Lee and Chen (2005) proposed a two-stage hybrid modelling procedure with artificial neural networks and multivariate adaptive regression splines. Lee et al. (2002) integrated the backpropagation neural networks with traditional discriminant analysis approach. Chen and Huang (2003) presents a work involving two interesting credit analysis problems and resolves them by applying neural networks and genetic algorithms techniques. Huang et al. (2004) obtained prediction accuracy around 80% for both backpropagation neural networks and support vector machines (SVM) methods to predict credit ratings in the United States and Taiwan markets.

Case-based reasoning (CBR) is an analogical reasoning method, which solves problems by relating some previously solved problem or experience to a current unsolved problem to form analogical inferences for problem solving (Kolodner, 1993). CBR has been described in the literature as a machine-learning technique that overcomes some of the deficiencies in statistical models and neural networks in classification problems, and preliminary research indicates that the predictive accuracy of CBR is high. Quite a few researchers have investigated the application of CBR to credit scoring problems. Bryant (1997) has applied CBR to predict corporate bankruptcy, and however it was argued that Ohlson's (1980) logit models have superior predictive accuracy than the CBR models. Shin and Han (2001) proposed a case-based reasoning approach to predict bond rating of firms. They used inductive learning for case indexing, and used nearest-neighbour matching algorithms to retrieve similar past cases. They demonstrated that their system had higher prediction accuracy (75.5%) than the MDA (60%) and ID3 (59%) methods. They used Korean bond-rating data and the prediction was for five categories. Park and

Han (2002) also presented a CBR model using feature weights derived by the AHP model and showed that the CBR model performs very well in predicting bankruptcy.

Since credit scoring models vary regarding the type and quantity of the data needed for decision making, most of prior studies are limited to be applied mainly in financial community companies such as commercial banks where the customers are usually required to submit their financial data and/or others. However, many of companies of non-financial community cannot require financial data and/or others from their customers. It is difficult in particular to obtain the customers' data in the situation where the customers are small businesses without disclosing financial information. Due to the available data and difference in business environments, most of models and methods for credit assessment which are suitable and effective to commercial banks or large business can not always be applied to small business.

To deal with the customers' credit assessment problem in a small company, we have developed a case-based reasoning system (DONG, 2006a and 2006b). This system can assess customers' credit scores only based on daily transaction data and can be easily incorporated into the existing information system. Since the credit score of a target customer is to be reasoned on the basis of similarity to past cases, it is very important how to evaluate properly the degree of similarity between a target customer and past cases. In this paper we consider six distances as similarity measures, which are based on Manhattan distance and Euclidean distance. We evaluate the considered distances by applying the system to solve the real credit assessment problems and examining the influence of similarity metrics on the system's performance.

This paper is organized as follows. At first, we introduce the credit assessment problem in a small company. Then we give a brief description of the proposed case-based reasoning system for solving the problem and give a detailed description of cases representation and the credit scoring procedure. Furthermore, we consider six distances as similarity metrics and show some experiment results by applying the system to some real problems. Finally, we give several discussions of the experiment results.

CREDIT ASSESSMENT PROBLEM IN A SMALL COMPANY

This paper considers the credit assessment problem in a small company that the main business is selling school uniforms and accessories at wholesale. There are 20 employees in the company, and the annual sale is about 600 million Japanese yen. Orders come from about 800 customers that are classified into three types as shown in

Table1. Type of customers

Type	Customers
retailer	Co-ops or retailers to them products are usually sold on credit.
school	Nominal customers that are used to treat the sales directly to the students of each school at the beginning of a school year.
other	Nominal customers that are used to treat the over-the-counter sales or orders coming from the sales team. Students' circles or clubs, and any other association.

Table 1.

The customers' credit has been assessed through a four-grade credit score: score of 1 meaning a solvent customer for which all orders are accepted, score of 2 meaning a customer for which orders are accepted and limited to a given amount, score of 3 meaning a customer for which orders are accepted only in cash sale, and score of 4 meaning an insolvent customer for which all of orders are rejected.

Because most of the customers are minor small businesses without disclosure of financial information, it is almost impossible to obtain their financial data. It is also difficult to frequently ask an agency for evaluating customers' credit due to limited budget. For these reasons, it is obviously preferable to develop a system being able to assess the customers' credit only based on daily transaction data such as sales, payments by customers, amount of overdue payment, etc.

CASE－BASED REASONING SYSTEM FOR CREDIT SCORING

Case-based reasoning (CBR) is an effective method that integrates reasoning methodology and representation of domain knowledge. Figure 1 shows the architecture of the credit scoring system. It solves the customers' credit assessing problem by using case-based reasoning approach and decides the credit score of a target customer through the following process (Kolodner, 1993):

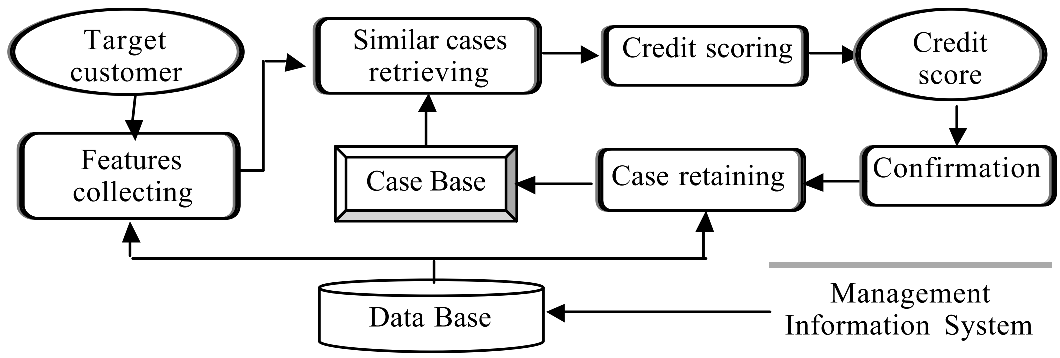

Figure 1. Case-Based Credit Scoring System

(1) Features collecting: when a target customer to be evaluated is given, the features data is collected from the database of the management information system.

(2) Similar cases retrieving: evaluating the degree of similarity of features data between the target customer and cases stored in the case base, the similar cases are retrieved.

(3) Credit scoring: the credit score of the target customer is decided as the same credit score as that of the similar cases.

(4) Confirmation: the credit score of the target customer decided at the previous step is confirmed and revised if necessary by the financial managers.

(5) Case retaining: after the credit score has been confirmed by the financial manager, the credit score and the features data of the target customer are stored into the case base as a new case.

Case Representation

Let n be the number of cases stored in the case base and C_i be the i-th case (i=1,2,…,n). Then C_i is represented as the following data structure:

$$C_i: (\ s_i, x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}, x_{i6}, x_{i7}, x_{i8}, cs_i\ ) \tag{1}$$

where s_i is the index number of the customer, cs_i is the credit score and $x_{i1} \sim x_{i8}$ are the features of customer s_i defined as following:

x_{i1}, x_{i2}: 0-1 variables representing the type of customer s_i as shown in Table 2.

x_{i3}: average amount of overdue payment in the year considered.

x_{i4}: maximum overdue days for all of overdue payment in the year considered.

x_{i5}: number of times that overdue payment occurs in the year considered.

Table 2. 0-1 Variables x_{i1} and x_{i2}

Type of customers	x_{i1}	x_{i2}
retailer	0	0
school	0	1
other	1	0

x_{i6}: total sales in the year considered.

x_{i7}: rate of the average amount of overdue payment to the total sales, i.e. $x_{i7} = x_{i3} / x_{i6}$.

x_{i8}: number of transaction months that any order from the customer is fulfilled in the year considered.

Furthermore, features $x_{i3} \sim x_{i8}$ are dimensionless quantities derived by the following standardization equation (2).

$$x_{ij} = \frac{\text{raw value of } x_{ij} - \text{the mean of raw value of } x_{ij}}{\text{the standard deviation of raw value of } x_{ij}},\ i=1,2,\ldots,n;\ j=3,4,\ldots,8 \tag{2}$$

Similar Cases Retrieving

(1) The target customer

Given a target customer NC, its credit score is to be decided, then its features data can be collected and NC can be denoted as:

$$NC: (\ y_1, y_2, y_3, y_4, y_5, y_6, y_7, y_8, fcs, ncs\ ) \tag{3}$$

where $y_1, y_2, \ldots, y_8$ have the same definitions as $x_{i1}, x_{i2}, \ldots, x_{i8}$. ncs is the new credit score to be decided and fcs is the former credit score which was given to target customer NC up to the present. It is referred to as fcs=0 when the former credit score was undecided.

(2) Distance between the target customer and cases

It is essential how to evaluate the degree of similarity between target customer NC and past cases. One of the most obvious measures of similarity is the distance. Here, we denote the distance between case C_i and target customer NC as d_i, which is to be defined in the next section.

(3) Average distance and similar cases

Let G be the set consisting of all cases, G={C_i; i=1,2,…,n}. According the credit score of every case, G can be divided into four subsets G_k (k=1,2,3,4) as the following equation (4).

$$G_k = \{C_i \mid cs_i = k;\ C_i \in G\},\ k=1,2,3,4 \tag{4}$$

Denote the number of cases belonging to subset G_k as n_k (k=1,2,3,4), we have $n=n_1+n_2+n_3+n_4$.

For subset G_k, the distance between target customer *NC* and the cases belonging to subset G_k can be arranged in ascending order as following:

$$d_{k_1} \le d_{k_2} \le d_{k_3} \le \ldots \le d_{k_{n_k}} \;;\quad k=1,2,3,4 \tag{5}$$

Then $K(K \le n)$ cases with shorter distance to target customer *NC*, that is $C_{k_1}, C_{k_2}, \ldots, C_{k_K}$, are chosen as the similar cases, here *K* is a given integer.

The average distance between target customer *NC* and subset G_k, denoted as gd_k, can be calculated as the following equation (6).

$$gd_k = \sum_{j=1}^{N_k} d_{k_j} / N_k \,,\; k=1,2,3,4 \tag{6}$$

where N_k =min (K, n_k) ; k=1,2,3,4.

Credit Scoring

If a customer was evaluated as an insolvent one (credit score >1), the payment is limited to cash and the financial managers usually give more attention to the payment from the customer. As the result, the overdue payment from insolvent customers decreases rapidly, and therefore it is difficult to distinguish solvent customers from others only according to their features data. For this reason, it is reasonable to take the former credit score into account and so we introduce a revised distance between target customer *NC* and subset G_k, which is denoted as rd_k, and calculated as the following equation (7).

$$rd_k = \begin{cases} gd_k & ; \quad fcs \le k \\ p_{fcs,k}\, gd_k & ; \quad fcs > k \end{cases} ,\; k=1,2,3,4 \tag{7}$$

Where *fcs* is the former credit score that was given to target customer *NC* up to the present. $p_{fcs,k}$ are penalties and satisfy $p_{fcs,k} > 1$ ($fcs>k$).

Finally, the credit score of target customer *NC* is decided as the same score as the similar cases belonging to subset G_k which has the shortest revised distance to target customer *NC*. Denote the new credit score of target customer *NC* as *ncs*, we have

$$ncs = \text{Argmin}\,\{\, rd_k,\, k=1,2,3,4 \,\} \tag{8}$$

DISTANCE AND SIMILARITY MEASURES

Since CBR systems solve new problems based on solutions of similar past problems, the key issues in CBR systems are retrieving similar cases in the case base, and measuring case similarity to match the best case, Many CBR systems are derivatives of the nearest- neighbor method. It is a simple approach that computes the similarity between stored cases and new input case based on weight features. A typical evaluation function is used to compute nearest-neighbor matching (Kolodner, 1993) as shown in equation (9).

$$Similarity(Case_I, Case_R) = \frac{\sum_{j=1}^{m} w_j \times sim(f_j^I - f_j^R)}{\sum_{j=1}^{m} w_j} \tag{9}$$

Where m is the number of attributes in each case, w_j is the importance weight of feature j, *sim* is the similarity function of features, and f_j^I and f_j^R are the values for feature j in the input and retrieved cases respectively.

Several studies have shown that nearest-neighbor methods provide an effective measure of how similar a previous case is to a given problem, and however the nearest-neighbor performance is highly sensitive to the definition of its similarity function and the choice of the feature weights. Many nearest-neighbor methods have applied a similarity function using weighted Euclidean distance and quite a few researchers have investigated empirical work on the weight setting of nearest-neighbor algorithms. Many researchers suggest that the weight of all features be acquired by domain knowledge from experts (Kolodner, 1993), by machine learning techniques such as genetic algorithms (Shin & Han, 1999), by the AHP model (Park and Han, 2002) and induction, or by statistical methods such as multiple discriminant analysis and regression.

In our previous study (DONG, 2006a and 2006b), we chose the standard Euclidean distance as the similarity metric between case C_i and target customer *NC*. The Euclidean distance is reasonable implicitly on the assumption that each of the features has a uniform effect or equal importance to evaluate the degree of similarity. Since this assumption is not necessarily true, here we consider the following six distances as similarity measures, which are based on Manhattan distance and Euclidean distance.

(1) Manhattan distance (MD):

$$d_i = \sum_{j=1}^{8} \left| x_{ij} - y_j \right| \tag{10}$$

(2) Manhattan distance weighted with standardized beta coefficients of linear regression (MD-LR):

$$d_i = \sum_{j=1}^{8} \left| a_j (x_{ij} - y_j) \right| \tag{11}$$

(3) Manhattan distance weighted with standardized beta coefficients of discriminant analysis (MD-DA):

$$d_i = \sum_{j=1}^{8} \left| b_j (x_{ij} - y_j) \right| \tag{12}$$

(4) Euclidean distance (ED):

$$d_i = \sqrt{\sum_{j=1}^{8} (x_{ij} - y_j)^2} \quad (13)$$

(5) Euclidean distance weighted with standardized coefficients of linear regression (ED-LR):

$$d_i = \sqrt{\sum_{j=1}^{8} |a_j| (x_{ij} - y_j)^2} \quad (14)$$

(6) Euclidean distance weighted with standardized coefficients of discriminant analysis (ED-DA):

$$d_i = \sqrt{\sum_{j=1}^{8} |b_j| (x_{ij} - y_j)^2} \quad (15)$$

The coefficients a_j and b_j (j=1,2,…,8) in the above equations are calculated by using the following two procedures respectively.

[Procedure 1: calculating coefficients a_j**]**

[Step 1] Let the credit scores of the customers in a given financial year and their features data be observed data, the credit score cs_i be the response variable and the features data x_{ij} (i=1,2,…,n; j=1,2,…,8) be the explanatory variables.

[Step 2] Apply regression method to obtain a linear regression equation.

[Step 3] Calculate standardized beta coefficient a_j for feature j (j=1,2,…,8).

[Procedure 2: calculating coefficients b_j**]**

[Step 1] Let the credit scores of the customers in a given financial year and their features data be observed data. Divide the observed data into two groups: the one consists of the customers with credit score of 1 and the other consists of the customers with credit scores of 2, 3 and 4.

[Step 2] Use the features data x_{ij} (i=1,2,…,n; j=1,2,…,8) as predictors and do discriminant function analysis to find a discriminant function which provides the most overall discrimination between the two groups.

[Step 3] Calculate standardized beta coefficient b_j for feature j (j=1,2,…,8) in the discriminant (canonical) function.

EXPERIMENT RESULTS AND DISCUSSION

To investigate the effect of the choice of distances on effectiveness and performance of the proposed system, we apply it to solve the real credit assessing problems of the company and examine how reasoning results change when the six distances are used respectively. As shown in the Table 3, credit scores of the customers in 2001 financial year and their features data are collected and stored as cases.

The coefficients a_j and b_j (j=1,2,…,8) are calculated by using features data of 2001's customers. The parameter K in equation (6) is chosen as K =5 and the penalties p_{st} in equation (7) are chosen uniformly as p_{st} =300 if s>t and otherwise p_{st} =1 (s,t=1,2,3,4).

Table 3.Å Features Data of 2001's Customers Stored as Cases

Features	Mean	Standard deviation	Distributions of Credit Scores	
x_{i3}	196,171	762,532	Credit score	Number of customers
x_{i4}	56.37	73.30	1	474
x_{i5}	2.92	3.06	2	2
x_{i6}	1,201,390	3,706,057	3	2
x_{i7}	0.22	0.37	4	20

Ability for Classification

To investigate the ability of the system for classification, we choose every customer in 2001 financial year as the target customer and decide its new credit score by applying the proposed system. When a customer is chosen as the target customer, its features data is left off the case base temporally. These new credit scores provided by the system are compared with that given by the financial managers of the company. The comparison results are shown in Table 4.

Table 4. Classification Results for 2001's Customers

Distance	Hit rate (number of customers)				
	Score=1 (474)	Score=2 (2)	Score=3 (2)	Score=4 (20)	Total (498)
MD	98.5% (467)	50.0% (1)	0.0% (0)	95.0% (19)	97.8% (487)
MD-LR	98.7% (468)	50.0% (1)	50.0% (1)	85.0% (17)	97.8% (487)
MD-DA	98.7% (468)	50.0% (1)	0.0% (0)	85.0% (17)	97.6% (486)
ED	98.9% (469)	0.0% (0)	50.0% (1)	95.0% (19)	98.2% (489)
ED-LR	98.9% (469)	50.0% (1)	50.0% (1)	85.0% (17)	98.0% (488)
ED-DA	98.9% (469)	50.0% (1)	50.0% (1)	85.0% (17)	98.0% (488)

The results in Table 4 show that:

- Credit scores for the customers with score of 1 provided by the system are more than 98% in agreement with the judgments of the financial managers of the company, and the performance of the system for classifying the customers with score of 1 are consistently good and it is almost not sensitive to the choice of distances.

- As there are only every two cases with score of 2 and 3, and they are too less than the number of the cases with score of 1, the system's ability to recognize the customers with score of 2 or 3 is poor at hit rate of a maximum of 50%.

- The hit rates for classifying the customers with score of 4 are more than 85% in agreement with the judgments of the financial managers of the company, and the classification performance of the standard Manhattan distance and Euclidean distance is better than the weighted distances.

- The system using the standard Euclidean distance gave the best overall classification performance at hit rate of 98.2% and on the whole, the overall classification performance of the Euclidean distances are better than the Manhattan distances. But the difference in hit rates is very little and therefore the performance of the system is not remarkably sensitive to the choice of distances.

Ability for Prediction

As target customers, the features data of 493 companies in 2002 financial year was collected. For every customer of 2002 financial year, a new credit score is predicted by the system based on the cases of 2001 financial year. Furthermore, these prediction results are also compared with the credit scores given by the financial managers of the company and the hit rates of prediction are summarized in Table 5.

Table 5. Prediction Results for 2002's Customers Based on the 2001's Cases

Distance	Hit rate (number of customers)				
	Score=1 (469)	Score=2 (2)	Score=3 (2)	Score=4 (20)	Total (493)
MD	98.7% (463)	50.0% (1)	100.0% (2)	95.0% (19)	98.4% (485)
MD-LR	98.7% (463)	100.0% (2)	100.0% (2)	90.0% (18)	98.4% (485)
MD-DA	98.7% (463)	100.0% (2)	100.0% (2)	90.0% (18)	98.4% (485)
ED	98.9% (464)	50.0% (1)	100.0% (2)	95.0% (19)	98.6% (486)
ED-LR	98.7% (463)	50.0% (1)	100.0% (2)	90.0% (18)	98.2% (484)
ED-DA	98.7% (463)	50.0% (1)	100.0% (2)	90.0% (18)	98.2% (485)

The prediction results of Table 5 showed that credit scores for the customers with score of 1 provided by the system are more than 98% in agreement with the judgments of the financial managers of the company. The system showed very high overall prediction performance at hit rate of more than 98% and the performance is almost not sensitive to the choice of distances.

Table 6 shows a detailed prediction result of the system for the customers of 2002 financial year, while the standard Manhattan distance is chosen as the similarity metric. Since the system did not make any wrong judgment to predict customers with scores larger than 1(insolvent customer) to be solvent ones with score of 1, it is acceptable from the view of point that the loss caused by non-payment of insolvent customers should be avoided as much as possible.

CONCLUDING REMARKS

This paper described a case-based reasoning system for solving customers' credit scoring problems in a small company. It assesses the credit score of a target customer on the basis of similarity to past cases stored in the case base. A case is represented by its features data including the type of customers, sales, amount of overdue payment, maximum overdue days, etc. Because the features data can be easily retrieved from daily transaction data and can be extracted almost automatically from the database of the management information system, the system is suitable to be applied to many of organizations where customers do not disclose their financial data. In other words, the system assesses credit scores of customers based only on internal data and has an advantage of a low cost for collecting data over other systems.

Table 6. Detailed Reasoning Result for 2002's Customers

Number of customers		Credit score provided by the system				Hit rate (%)
		1	2	3	4	
Credit score given by the financial managers	1	463	0	0	5	98.7%
	2	0	1	1	0	100.0%
	3	0	0	2	0	100.0%
	4	0	0	1	19	95.0%

In order to investigate the effect of similarity metrics on the performance of the proposed system, we considered six distances as similarity metrics and evaluated them by applying the system to solve the real credit assessment problems of the company. The experiment results showed that the system has very high overall ability for both classification and prediction, and the system's performance is almost not sensitive to the choice of distances. It is different from our expectation that the system's performance could not be improved obviously even if the relative importance of each feature is to be considered and the weighted distances are used as similarity metrics.

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