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The consumer loan default predicting model – An application of DEA–DA and neural network

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ABSTRACT

In this paper we construct the consumer loan default predicting model through conducting the empirical analysis on the customers of unsecured consumer loan from a certain financial institution in Taiwan, and adopt the borrower's demographic variables and money attitude as the real-timeaneous discriminant information. Furthermore, we construct respectively through four predicting methods, such as DA, LR, NN and DEA–DA, to compare the suitability of these four mentioned methods. The results show that DEA–DA and NN are possessed better predicting capability and they are the optimal predicting model that this study longing for. In addition, this study showed that the default loan predicting model will be possessed higher level of predicting capability after added money attitude.

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1. Introduction

Along with the impact of the financial crisis in Southeast Asia on the financial and industrial sectors, the assets structure of financial institutions in Asian counties has been reconstructed due to the enormous bad debt of enterprises. Therefore, the personal consumer finance loan with relative high yield rate has become a popular financial product. Since 1999, financial institutions of Hong Kong and South Korea are cooperated to their governments' incentive policy to substantially promote the consumer finance to stimulate the private consumption for advancing the economic recovery. Influenced by such trend, financial institutions in Taiwan are numerously expanded their consumer finance business. Based on the statistics that made by the Directorate General of Budget, Accounting and Statistics (DGBAS) of Executive Yuan during 2002–2005, it showed that the ratio of consumer loan to GDP has swiftly rose from 43% to about 67%, and this outcome thus indicated the positive meaning for that the consumer loan business drove the private consumption to stimulate the economic growth. However, the negative effect has gradually emerged due to the excessive competition in the market. For example, in 2001, because of the excessively high amount of bad debt that resulted from the excessive expansion of personal consumer finance, which caused a serous financial crisis in South Korea. Later, in 2006, the "McKinsey Research Report on Taiwan's Card Debt" showed the bad debt amount of both dual cards (cash card and credit card) and personal credit loan for all banks in Taiwan has reached a record high with more than NT$380 billion. The occurring frequency of bad debt customer seemed to be higher; therefore, that has triggered many social problems and influenced the socioeconomic development. To solve the problem like bad debt, Malhotra and Malhotra (2002) and Brill (1998) are mentioned that an effective consumer credit risk management system may not only reduce the borrower default rate and loan loss, but also decrease the credit analysis cost. Therefore, it definitely has the necessity and urgency to construct a set of effective consumer loan default predicting model to make the banking industry and financial institutions able to effectively promote their loan business and avoid the customer default to reduce the overdue loan.

The loan default predicting model is an analytic technique which is adopted the current and historic information of the credit customer to make prediction about that whether the credit customer will repay the debt on time. Among the previous researches on the review models of credit loan, they were mainly studied by dividing into two topics. Topic 1 is explored the influencing factors in the loan default behavior: through demographic variables, historic loan status or economic variables to understand the influence on the default behavior (Avery, Calem, & Canner, 2004; Desai, Crook, & Overstreet, 1996; Rock, 1984; Steenackers & Goovaerts, 1989; Thomas, 2000; Updegrave, 1987; Zandi, 1998). Topic 2 is focused on developing the predicting method to construct an optimal model; however, under the difference between the loan system and consumption culture in different countries, the accuracies of different predicting methods also existed difference (Baesens, Gestel, Stepanova, Poel, & Vanthienen, 2005; Chen & Huang, 2003; Desai et al., 1996; Lee & Chen, 2005; Lee, Chiu, Chou, & Lu,

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2006; Lee, Chiu, Lu, & Chen, 2002; Li, Shiue, & Huangc, 2006; Malhotra & Malhotra, 2002; Noh, Rohb, & Hana, 2005; Ong, Huang, & Tzeng, 2005; West, 2000). Therefore, there is no specific predicting method which can be regarded as the most optimal model. Currently, the predicting methods that frequently used are the statistics-oriented discriminant analysis (DA) and logistic regression (LR), and the neural networks (NN) or gene algorithm (GA) and non-parametric model which are based on the technique of artificial intelligence (Thomas, 2000). In addition, Sueyoshi (1999) used the mathematic programming viewpoint to integrate the integer programming concept within the data envelopment analysis structure to develop the innovative method of advanced Data Envelopment Analysis–Discriminant Analysis (DEA–DA), which is not only able to explore the predicting model for enterprise bankruptcy, but it is also able to display a good predicting capability (Sueyoshi, 2004, 2005, 2006; Sueyoshi & Hwang, 2004); however, it is rarely applied to the studies on the prediction of loan default. In terms of the predicting variables, many researches have mentioned about that the personal money attitude is one of key factors in influencing the loan or excessive consumption behavior (Hayhoe, Leach, & Turner, 1999; Lim & Teo, 1997; Lim, Teo, & Loo, 2003; Lin & Lin, submitted for publication; Roberts & Jones, 2001; Roberts & Sepulveda, 1999). However, as for the current consumer loan, it is rare to take the Individual Intrinsic Traits Variables as the main to conduct the exploration of whether these variables are the influencing factors of consumer loan default behavior or not. Therefore, on the basis of this factor and the response to the current consumption financial market, the primary purpose of this study is to construct the consumer loan default predicting model through conducting the empirical analysis on the customers of unsecured consumer loan from a certain Taiwanese financial institution, and adopting the borrower's demographic variables and money attitude as the real-timeaneous discriminant information. In this study, the consumer loan default predicting model will be constructed respectively through four predicting methods, such as DA, LR, NN and DEA–DA, and such empirical data will be adopted to compare the suitability of these four mentioned methods to construct the consumer loan predicting model, which is able to provide the banking industry with more effective risk control model to reduce the probability of customer default and the loss of banking business.

2. Literature review

Along with the opening financial market in Taiwan, the credit business of the banking industry is rapidly expanded within the excessive competition in current market; at the same time, the arising consumption intention for common people and the change in consumption method have turned the consumer loan into the major competitive market. As for the term of ''Consumer Loan'', according to the banking laws stipulated by the Ministry of Finance, Taiwan, it has been defined as the personal credit quota that provided by the financial institutions in the method of installment payment for the purpose of personal or family consumption, or for paying the emergent expenses, such as medical treatment, education, travel and entertainment, or even for paying off the accumulated debt with the purpose of consumption. However, this study is mainly tried to explore the consumer loan default prediction model therefore, it will be focused on the predicator variables and predicting methods of the default prediction model and they will be respectively explained as follows.

2.1. Predictor variables

Among the analysis on the variables that may have influenced the consumer credit loan default, Rock (1984) thought that the considering factors should include seven types of variable, such as the relationship with creditors, annual income, debt-income ratio, occupation, resident/work duration, housing ownership, and whether possessed the checking or saving account; Updegrave (1987)discovered the key factors of the credit risk that influenced the credit card or short-term loan were eight variables: the number of creditors, the historic repayment record, whether declared bankruptcy or not, work/resident duration, income, occupation, age and whether possessed the checking or saving account; Steenackers and Goovaerts (1989) obtained the borrower's age, resident/work duration, district, occupation, whether owned a phone and worked in public sector or not, monthly income, housing ownership, loan duration and numbers have a significant relationship with exercising repayment; overall speaking, there are many factors that can influence the default behavior, and different influencing variables will be based on the difference between the loan targets; in addition, the basic demographic variables (such as gender, age, education, monthly income and occupation) cannot only be found as the variables that all related loan issues will be included to consider, but they are also able to be proved to possess a certain influencing level according to various research outcomes. Therefore, this study will be primarily included the basic demographic variables as the influencing factors in exploring the consumer loan default behavior.

In addition to the demographic variables, Crook and Banasik (2004) thought that the model assessment should not be solely understood the historic loan record as the only information for the approved borrower, and Chiang, Chow, and Liu (2002) pointed out that the individual characteristics, such as characteristic and attitude of the borrower, can be applied to observe the default risk for the borrower. Furthermore, Roberts and Sepulveda (1999) also thought that the money attitude may influence all aspects of individual life, and included the spending behavior which related to the loan behavior. Hayhoe et al. (1999) has further adopted the money and debt attitudes to understand the using behavior of credit cards for university students to approve that the loan behavior is certainly influenced by individual money and loan attitudes. To sum up, the consumer loan default behavior will be possibly influenced by individual attitude toward money; in addition, Lin and Lin (submitted for publication) once used the actual borrower's information to understand the influence of money attitude on the default behavior, and approved that the default behavior is able to be influenced by the money attitude; however, after included the money attitude, such predicting model is able to relatively increase the predicting accuracy rate of the model with only regarding the basic characteristics as the variables. As a result, except for considering the borrower's demographic variables, in terms of selecting the predicting variables, this study is also added borrower's money attitude to expectably make more accurate prediction about the possibility of default.

2.2. Predicting methods

In terms of the predicting methods, previous scholars have applied discriminant analysis, logistic regression, linear programming and neural networks to solve the problem in borrower credit risk management.

Desai et al. (1996) used the personal loan information of three certain credit unions in US to study the accuracy rate of credit scoring models under different constructing methods, which included LR, DA, and the two types of the NN: multilayer perceptron, modular neural network. And the empirical results showed that different methods have different outcomes when predicting different groups.

Malhotra and Malhotra (2002) also adopted the loan information of credit unions in US as the sample, and has successively applied the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Back Propagation Network (BPN) to construct the consumer loan assessment model, and then conducted the comparison with multiple discriminant analysis (MDA). The research outcomes of ANFIS and BPN showed better result than MDA.

Chen and Huang (2003) used the actual borrower's data of UCI Database as the sample to mutually compare the analysis on credit risk of DA, classification and regression tree (CART) and BPN, and discovered that each of them has its own specialty.

Noh et al. (2005) applied the information of credit card center in South Korea to develop the predicting model of personal credit risk with considering the time-dependent factors and reviewed information as the predicting variables, and adopted survival analysis (SA) to compare the predicting capability with LR and NN. Generally speaking, the overall hit rate of these three models are similar, but LR and NN have better accuracy rate for good borrowers, and SA has better sensitivity of predicting the default borrower.

Lee et al. (2002) adopted the Hybrid Neural Discriminant Model (HNDM) to conduct the credit risk assessment on the credit card customers of certain bank in Taiwan, and compared the assessing capability among DA, LR and BNP. In addition, used nine variables, such as the basic demographic variables, the loan quota, etc., to construct the predicting model. The outcomes showed that HNDM is better than other methods.

Lee and Chen (2005) integrated the multivariate adaptive regression splines (MARS) and BPN to develop a two-phase credit scoring model, and conducted the empirical research through the mortgage customer information in Taiwan. The research result showed that the accuracy rates of average classification for the two-phase mixing method, BPN and MARS are reached 80%, among which, the two-phase mixing method has the best accuracy rate.

Lee et al. (2006) took the information of credit card customer in Taiwan as the sample, and applied CART, MARS, DA, LR and NN to conduct the comparison with the predicting capability of credit scoring models, and the research result showed that MARS and CART have better average classifying accuracy rate than three other models.

To sum up, within the analysis of these predicting methods, it can be found that each method has its own specialty and uniqueness; for example, DA and LR are able to analyze the predicting variables that may significantly influence the default loan and to predict the occurring probability of events which possessed good predicting effect (Desai et al., 1996; West, 2000); NN is able to construct the non-linear model and adopt the variables from various types of information as the input variables, and it has better adaptation, thus many researches showed that NN has a better predicting capability (Baesens et al., 2005; Chen & Huang, 2003; Salchenberger, Cinar, & Lash, 1992); in addition, Hardy and Adrian (1985) once pointed out that the complicate hypothesis can be avoided from the statistic method if using linear programming model to construct the credit scoring model, and it can be even achieved the more optimal predicting capability through the capability of weight adjustment; along with the viewpoint of mathematic goal programming that applied by Sueyoshi (1999) to develop the DEA–DA method. Then, in 2004, it has integrated those aforementioned concepts and methods with the Fixed Integer programming concept to develop the completed DEA–DA method, which has been empirically practiced on predicting the bankruptcy risk for banks or companies, and has shown better capability of predicting classification (Sueyoshi, 2004, 2005, 2006; Sueyoshi & Hwang, 2004). In the view of that, this study will apply these four methods: DA, LR, NN and DEA–DA to conduct the comparison with the consumer loan default predicting model.

3. Methodology

In order to achieve the purpose of this study, the research subject and tool, and the research methodology will be described in this following section.

3.1. Data sample and tools

This study is adopted the consumer loan customers of certain financial institution in Taiwan as the primary research subject, and the survey duration is from November 15 to 30, 2005. With focusing on the customers who applied certain financial businesses at the counters of the specific financial institution within the aforementioned duration, we handed out the questionnaire to those customers and asked them to fill in the personal information and Money Attitude Scale (MAS) (Yamauchi & Templer's, 1982). Then, we integrated the MAS and the survey of demographic variables to construct the main questionnaire of this study.

In addition, the financial institution will provide the repayment records of its loan customers for assessing whether those customers have any default or not. Among which, the term of Overdue and Default Borrower that defined in this study is in accordance with the regulations and laws of Bank Overdue Loan, it is indicated the person who has the default, delayed payment, collecting records, and the unpaid-off loan and other types of credit loan for more than three months in any financial institution or Joint Credit Information Center.

3.2. Research methods

The research methods that adopted in this study are these four aforementioned methods of constructing the default behavior predicting model: DA, LR, NN and DEA–DA. The concept of each method that applied to this study is as follows:

(1) *Discriminant analysis* (*DA*): It is a technique of dividing groups, which is aimed at the known population classification, in accordance with the discriminant criteria of that significant different groups have minimum variation inside the groups, to seek the optimal weight value (w_i) for the linear combination ($Z = w_0 + w_1X_1 + w_2X_2 + \cdots + w_iX_i$) of the discriminant variables ($X_1, \ldots, X_i$). This study will used the demographic variables and MAS as the discriminant variables, and then applied the sample information to find out the fitted discriminant score for being the discriminant criteria of discriminating the non-default or default borrowers.

(2) *Logistic regression* (*LR*): Its concept is similar to the traditional linear-regression, the difference between them is only consisted in that the dependent variable of the logistic function of occurrence probability for the classified variable. This study is through the demographic variables and MAS to be the independent variables to construct the logistic function of default probability, transform the information into the data type that between 0 and 1, and then the model will yield the output variables.

(3) *Neural networks* (*NN*): NN is an information processing and computing system that used an enormous amount of simple linking artificial nerves to simulate the capability of biological neural network (Freeman & Skapura, 1992); among which, BPN is the most representative and popular for issues of classification and prediction (Vellido, Lisboa, & Vaughan, 1999). Therefore, this study will apply the BPN structure to construct the loan predicting model, and its input layer, hidden layer and output layer are as follows:

Input layer: it included 14 input values which are nine factors of money attitude and five demographic variables.
Hidden layer: one hidden layer, four neuron integers.
Output layer: one output value which classified the non-default or default behavior.

(4) *DEA–discriminant* analysis (*DEA–DA*): This method has applied the two-phase concept to make the discrimination by Sueyoshi (2004): First Phase is the Classification and Overlap Identification which will firstly validate whether it possessed the overlap sample or not; Second Phase is the process of Handling Overlap, which will make even more detailed classification with aiming at the observing samples within the overlapped area in order to reduce the misclassification and effectively enhance the capability of classification. This study is used the Integer Programming, took the minimum overlapped area in First Phase as the target function, and adopted demographic variables, the money attitude of borrowers and the threshold value of groups, to construct the constraint equation to discriminate whether the overlapped area is existed or not; if so, took the minimum integers of misclassification as the target function and adopted the demographic variables and borrowers' money attitude to construct the constraint equation, and then through these aforementioned two-phase procedures to construct the DEA–DA predicting model.

3.3. Measure of goodness of fit for predicting model

West (2000) mentioned that the cross-validation has been frequently applied to construct the credit scoring model to reduce the mutual influencing effect among samples and upgrade the reliability of the assessing results. Therefore, this study will be randomly sampled 2/3 samples to construct the training model and 1/3 samples to be the testing samples for conducting the cross-validation. After constructing the model, it then conducted the comparison between models through the following benchmarks, as well as comparing with the consumer loan default predicting model.

(1) By using the cross-validation to compare the predicting capability of models, where the capability that can be accurately predicted the non-default borrower is called "accuracy rate", while accurately predicted the default borrower is called "sensitive rate" and the model predicting accuracy rate is called "hit rate".
(2) With the Press's *Q* value of Proportional Chance Criterion to examine the goodness of fit for the predicting model, when the Press's *Q* value is greater than the chi-square value which indicated the predicting result of such model has better fit.
(3) By applying the misclassification costs to compare the risk influencing degree of each model to the financial institutions. In terms of this analysis, Roszbach (2004) pointed out that the purpose of effective predicting model for banks to make the loan decision to the consumption loan customers is not only minimized the probability of customer default, but also reduced the misclassification. Among which, the financial institutions generally thought the error cost (C_{21}) that misclassified the default borrowers from the non-default borrowers will be higher than the error cost (C_{12}) that classified the non-default borrowers to the default borrowers.
(4) This study is adopted such correlation and applied Eq. (1) to solve the misclassification cost and through the concept of the minimized misclassification cost to select the more fit predicting model. The expected misclassification costs should be shown as follows (Frydman, Altman, & Kao, 1985):

$$\begin{aligned}\mu &= C_{12}P(\text{errors} \cap \text{non} - \text{default}) + C_{21}P(\text{errors} \cap \text{default}) \\ &= C_{12}P(\text{non} - \text{default})P(\text{errors}|\text{non} - \text{default}) \\ &\quad + C_{21}P(\text{default})P(\text{errors}|\text{default})\end{aligned} \tag{1}$$

In addition, we consider the related misclassification costs should be $C_{21} = 5 \cdot C_{12}$ (West, 2000).

4. Empirical research

This study used the questionnaire survey to collect the consumer loan information of a certain bank in Taiwan, 350 were sent out and 281 valid returned, and the response rate is 80.2%. Hereunder will be respectively explained the sample structure and how to apply these four methods: DA, LR, NN and DEA–DA, to construct the consumer loan predicting model, and conduct the comparison with the predicting capability between models.

4.1. Sample structure

The borrowers' information is sampled from the loan customers of a certain financial institution in Taiwan, from January 2002 to November 2005. The number of consumer loan that undertook by this financial institution is 1877; among which, 1504 cases are classified to the non-default borrowers, 373 cases are classified to the default. Within the sampling result, there're 207 non-default borrowers and 74 default borrowers. In order to understand whether this sampling result can be represented the characteristic of the population information or not, thus through the chi-square test, the chi-square value is 6.21 which is statistically significant at $p < 0.05$. Hence, the sampling result is conformed to the characteristic of the population.

Table 1 presented the descriptive statistical analysis, including borrower's gender, age, education, monthly income, occupation and loan behavior, it showed the male is the majority of borrowers, age is mainly from 30 to 39, monthly income is between 30,000 and 39,999, university level is the educational background for most of them and semiprofessional and general administrative personnel is also the majority of their occupations; in addition, the ratio of the non-default borrower is 73.7% which is greater than the default borrower, 26.3%.

4.2. The predicting model of consumer loan default behavior

This study will discriminate the performance of models through the DA, LR, NN and DEA–DA predicting models, and conduct the selection of the fitted cutoff value with using LR and NN, which aimed at the probability as the classified criteria to provide the predicting model for another classified criteria. At last, compare the accuracy rate, sensitive rate and hit rate of prediction with focusing on these six aforementioned predicting models, and further supplemented with each benchmark to seek the default predicting model that suitable for this study. Table 2 is the symbol table of predicting variables for this predicting model.

4.2.1. DA

As for the predicting model that constructed by the DA, the Wilks' Lambda value is 0.652 which is statistically significant at $p < 0.05$, it implied that the predicting model is good-fit. And, the centroids of discriminant-function for loan default and non-default behavior are 1.219 and −0.433, respectively. Thus, the threshold value is 0.393. This linear-discriminant-function is as listed in Eq. (2):

Table 1
Sample structure analysis.

Property	Content	Percentage (%)	Property	Content	Percentage (%)
Gender	Men	62.3	Education	Below the junior high school	0.0
	Female	37.7		Junior high school	5.7
Age	20–29	28.5		Senior high school	27.8
	30–39	49.1		University	56.2
	40–49	13.9		Graduate school	1.4
	Above 50	8.5	Occupation	Non-technician	24.9
Monthly income ($NT)	Less than 9999	9.3		Technician	14.6
	10,000–19,999	15.7		General administrator	38.4
	20,000–29,999	27.8		Middle-level executives	22.1
	30,000–39,999	35.2		High-level manager	0.0
	40,000–49,999	6.4	Behavior	Non-default	73.7
	50,000-plus	5.7		Default	26.3

Table 2
List for predictor variables.

X_i^G	Gender	$X_i^{V\cdot D}$	Distrust of value
X_i^A	Age	$X_i^{S\cdot PP}$	Power—prestige of success
X_i^I	Monthly income	$X_i^{B\cdot RT}$	Retention—time of budget
X_i^E	Education	$X_i^{S\cdot A}$	Anxiety of lack
X_i^C	Occupation	X_i^{Other}	Other attitude
$X_i^{R\cdot PP}$	Power—prestige of respect	$X_i^{O\cdot A}$	Anxiety of opportunity
$X_i^{C\cdot RT}$	Retention—time of conservation	$X_i^{C\cdot A}$	Anxiety of cheap

$$\begin{aligned} Z_j = {} & 1.899 + 0.284X_i^G + 0.15X_i^A + 0.092X_i^I + 0.044X_i^E \\ & + 0.379X_i^C - 0.157X_i^{R\cdot PP} - 0.902X_i^{C\cdot RT^{***}} + 0.001X_i^{V\cdot D} \\ & - 0.17X_i^{S\cdot PP} - 0.413X_i^{B\cdot RT^{***}} + 0.464X_i^{S\cdot A} + 0.4X_i^{Other} \\ & + 0.117X_i^{O\cdot A} - 0.145X_i^{C\cdot A^{***}} \end{aligned} \tag{2}$$

Note: $^{***}p$-value < 0.001.

The training and predicting results of DA are as shown in Table 3. The training accuracy rate of discriminating the non-default borrowers is 85.51%; the training sensitive rate of discriminating the default borrowers is 75.51%, and the hit rate of overall model is reached 82.89%; after conducting the cross-validation, the predicting effect of this model can be understood and the predication accuracy rate of discriminating the non-default borrowers is 76.81%; the predication sensitive rate of discriminating the default borrowers is 68%, and the predicting model hit rate is 74.47%. The difference between the training and predication accuracy rate is not much, and the discriminant capability for the non-default borrowers is better than the capability for the default borrowers, thus it showing that DA's predicting models have possessed a certain level of predicting performance.

4.2.2. LR

As for the predicting model that constructed by applying the LR, the chi-square of its model fitness is 89.675 and has reached the significant level; in addition, it showed that LR possessed a better interpreting capability and fitness. Such LR-model is as shown in Eq. (3):

$$\begin{aligned} Logit(P_i) = {} & -0.476 - 0.214X_i^G - 0.434X_i^A - 0.498X_i^{I^{**}} - 0.07X_i^E \\ & - 0.785X_i^{C^{***}} + 0.396X_i^{R\cdot PP} + 2.012X_i^{C\cdot RT^{***}} + 0.32X_i^{V\cdot D} \\ & + 0.304X_i^{S\cdot PP} + 1.324X_i^{B\cdot RT^{***}} - 1.26X_i^{S\cdot A^{***}} - 1.492X_i^{Other^{***}} \\ & - 0.56X_i^{O\cdot A^{**}} + 0.186X_i^{C\cdot A} \end{aligned} \tag{3}$$

Note: $^{***}p$-value < 0.001.

The training and predicting results of LR are as shown in Table 4. The training accuracy rate of discriminating the non-default borrowers is 94.2%; the training sensitive rate of discriminating the default borrowers is 71.43%, and the hit rate of overall model is reached 88.24%. After conducting the cross-validation, the predication accuracy rate of discriminating the non-default borrowers is 92.75%; the predication sensitive rate of discriminating the default borrowers is 60%, and the predicting model hit rate is 84.04%. It showed that, under the LR predicting model, the discriminant capability for the non-default borrowers is better than the capability for the default borrowers; especially the results of the predication accuracy rate are very significant and the difference between these two accuracy rates is large.

From the aforementioned results that we can find that when using the general probability 0.5 to classify the borrower, the discriminant capability for the default borrower will be enormously lower than the discriminant capability for the non-default borrower. Such condition will result in the unequilibrium discrimination for both two types of borrowers and increase the intangible cost; thus, through the selection of the fitted cutoff values to upgrade the discriminant capability for the default borrower. Fig. 1 is showed the discriminant accuracy rates with different cutoff values, and it can be known that the intersection point of the corrected rate for discriminating the non-default and default is 0.71, thus it is another fitted cutoff value which is able to equilibrate the predicting capability for these tow types of borrowers.

Table 3
The predicted results of discriminate analysis model.

		Predicted result		Corrected rate (%)
		Non-default	Default	
Training sample				
Real	Non-default	118	20	85.51
	Default	12	37	75.51
Hit rate				82.89
Testing sample				
Real	Non-default	53	16	76.81
	Default	8	17	68
Hit rate				74.47

Table 4
The predicted results of logistic regression model-cutoff value is 0.5.

		Predicted result		Corrected rate (%)
		Non-default	Default	
Training sample				
Real	Non-default	130	8	94.2
	Default	14	35	71.43
Hit rate				88.24
Testing sample				
Real	Non-default	64	5	92.75
	Default	10	15	60
Hit rate				84.04

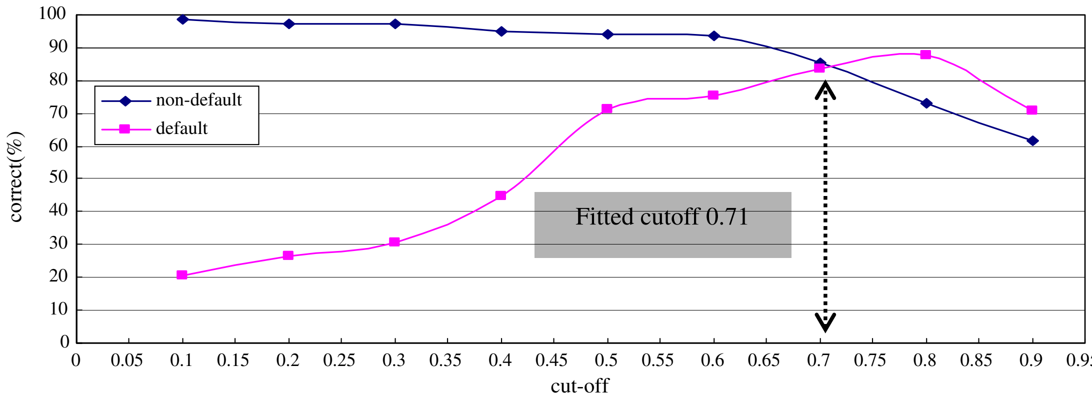

Fig. 1. Fitted values for the logistic regression model.

To redo the examination of cross-validation to the predicting model by using the fitted cutoff value, as showed in Table 5, it found that three training corrected rates in this model are about 80%, which have significantly improved the difference while the cutoff value is 0.5; in terms of the predicting result, even the model's accuracy has decreased from 92.75% to 76.81%; however, its sensitivity has enhanced from 60% to 68%. Although the changing range of these two values are different, such model already showed the purpose to equally discriminate these two types of borrowers; in addition, its hit rate is also reached 74.47% which showed the model of the fitted cutoff value can be reached a higher predicting default corrected rate.

4.2.3. NN

Used NN to construct the predicting model of consumer loan default, after inputting 14 variables that included demographic variables and money attitude, etc., the minimum square root of mean squared error (RMSE) is 0.026 after the training model has been converged, and the process of convergence is as shown in Fig. 2. From Table 6, it can be known that in terms of the training results, the training accuracy rate of non-default borrower is 97.83%, the training sensitive rate of the discriminant default borrower is 93.88%, and the hit rate is up to 96.79%; as for the predicting results after the process of cross-validation, the predication accuracy rate is up to 98.5%. Among 25 default borrowers, 5 of them are misclassified as the non-default borrowers. The predication sensitive rate is also reached the mark of 80% and the overall hit rate can be as high as 93.62%, which there seems to be almost no difference between it and the training result, thus it showed that NN has excellent predicting capability and its misclassified probability is relatively low.

NN and LR have same probability, and the general model is usually set the same occurrence probability for these two types of borrowers, which adopted 0.5 as the threshold value. However,

Table 5
The predicted results of logistic regression model-fitted cutoff value is 0.71.

		Predicted result		Corrected rate (%)
		Non-default	Default	
Training sample				
Real	Non-default	117	21	84.78
	Default	8	41	83.67
Hit rate				84.49
Testing sample				
Real	Non-default	53	16	76.81
	Default	8	17	68
Hit rate				74.47

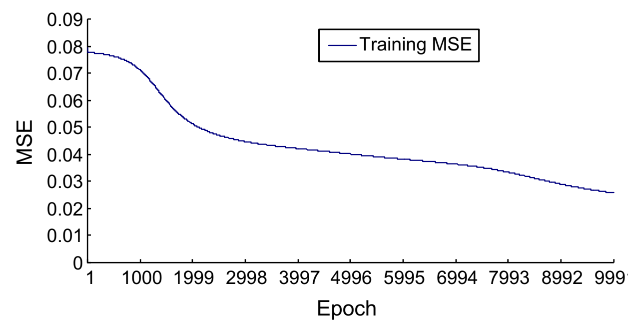

Fig. 2. The convergence plot of training mean squared error for neural networks.

Table 6
The predicted results of neural networks model-cutoff value is 0.5.

		Predicted result		Corrected rate (%)
		Non-default	Default	
Training sample				
Real	Non-default	135	3	97.83
	Default	3	46	93.88
Hit rate				96.79
Testing sample				
Real	Non-default	68	1	98.5
	Default	5	20	80
Hit rate				93.62

through the predicting results of aforementioned LR it can be found that if selecting the fitted cutoff value as the new threshold value, which is able to equilibrate the discriminant performance for two types of borrowers. On the basis of same concept, the discriminant correct rate of NN within different cutoff values is as shown in Fig. 3, and the fitted discriminant cutoff value is 0.68.

As shown Table 7, when the fitted cutoff value is 0.68, then the model training accuracy rate will be 94.93%, default borrowers have slight changes and still maintained the accuracy rate as high as 95.92% which has no significant difference when the general cutoff value is 0.5; as for the testing results, the accuracy rate has decreased to 86.96%, and the hit rate has also enormously decreased to 85.11% which indicated the adjusted cutoff value did not significantly upgrade the predication accuracy rate.

4.2.4. DEA–DA

Applied the two-phase DEA–DA method that proposed by Sueyoshi (2004) to construct the predicting model, inputted the variables of training sample to the model and, underwent the

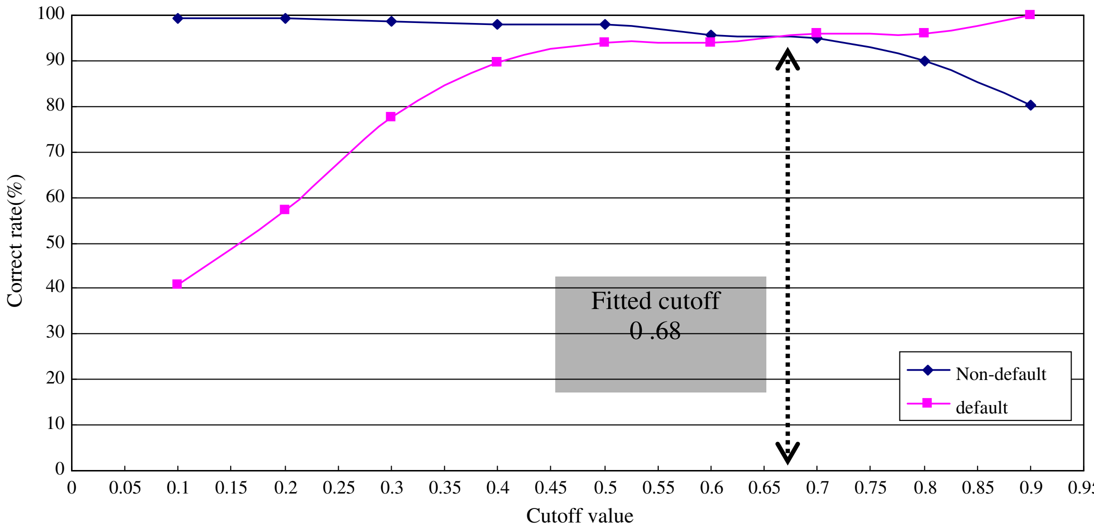

Fig. 3. Fitted values for neural networks model.

Table 7
The predicted results of neural networks model-fitted cutoff value is 0.68.

		Predicted result		Corrected rate (%)
		Non-default	Default	
Training sample				
Real	Non-default	131	7	94.93
	Default	2	47	95.92
Hit rate				95.19
Testing sample				
Real	Non-default	60	9	86.96
	Default	5	20	80
Hit rate				85.11

computing process of the optimal solution, then the target value is obtained as $s^* = 0.0978 > 0$, and threshold value $d^* = -0.0074$; in addition, it showed that overlapped area existed in the First Phase to primarily make classification and define the discriminant equation for overlapped area as shown in Eq. (4). When $T_j > 0.0904$, it will be immediately classified to the non-default group; when $T_j < -0.1052$, then it will be classified to the default group. Borrowers who have been correctly classified during this phase are included the number of non-default borrowers $C_1 = 72$ and the number of default borrowers $C_2 = 16$, and 88 borrowers in total. Therefore, the samples that need to be conducted the Second Phase Classification are included the number of default borrowers $D_1 = 66$ and the number of default borrowers $D_2 = 33$, and 99 borrowers in total:

$$\begin{aligned} T_j = {} & -0.1562X_i^G - 0.0918X_i^A - 0.031X_i^I + 0.039X_i^E - 0.0762X_i^C \\ & - 0.0305X_i^{R\cdot PP} + 0.1612X_i^{C\cdot RT} + 0.0299X_i^{V\cdot D} + 0.0397X_i^{S\cdot PP} \\ & + 0.0858X_i^{B\cdot RT} - 0.1081X_i^{S\cdot A} - 0.0992X_i^{Other} - 0.0242X_i^{O\cdot A} \\ & - 0.0274X_i^{C\cdot A} \\ C_1 = {} & \{j \in G_1 | T_j > 0.0904 (= d^* + s^*)\} \\ C_2 = {} & \{j \in G_2 | T_j < -0.1052 (= d^* - s^*)\} \end{aligned} \tag{4}$$

After the trial computation of the Second Phase, it obtained the most optimal target value $Y_j = 3$ and threshold value $z^* = -0.1726$, which the equation of discriminant sample is as shown in Eq. (5), when $T_j \geqslant -0.1726$, it is classified to the non-default group, and when $T_j \leqslant -0.1756$, it is then classified to the default group. The final classification result of the predicting model is as shown in Table 8, where the non-default borrowers are completely and correctly classified, and three of the default borrowers are misclassified, the classification accuracy rate is 93.88%, and the hit rate of the training model is as high as 98.4%:

$$\begin{aligned} T_j = {} & -0.3243X_i^G - 0.003X_i^A + 0.0299X_i^I - 0.058X_i^E \\ & + 0.1401X_i^C + 0.0703X_i^{R\cdot PP} - 0.0765X_i^{C\cdot RT} - 0.0213X_i^{V\cdot D} \\ & - 0.0601X_i^{S\cdot PP} - 0.0423X_i^{B\cdot RT} + 0.0494X_i^{S\cdot A} \\ & + 0.0434X_i^{Other} - 0.003X_i^{O\cdot A} + 0.0778X_i^{C\cdot A} \\ Y_j = {} & \begin{cases} 0, & \begin{cases} R_1 = \{j \in G_1 | T_j \geqslant -0.1726 (= z^*)\} \\ R_2 = \{j \in G_2 | T_j \leqslant -0.1756 (= z^* - \varepsilon)\} \end{cases} \\ 1, & -0.1756 < T_j < -0.1726 \end{cases} \end{aligned} \tag{5}$$

By using the aforementioned constructed discriminant equations, and after conducting the cross-validation through 94 testing samples, the results showed that the samples correctly classified in the First Phase are $C_1 = 36$ and $C_2 = 6$, the samples that fell on the overlapped area are $D_1 = 33$ and $D_2 = 19$, total 52 cases that need to redo the classification. Then the predicting result that obtained from the discriminant equations in the Second Phase can be found in Table 8, the results showed that the predicting capability of non-default borrowers is as high as 100%, and the predicting capability of default borrowers is also able to reach the mark of 80%. There are five borrowers who have been misclassified, and the predicted hit rate of both two types of borrowers is 94.68%.

Table 8
The predicted results of DEA–DA model.

		Predicted result		Corrected rate (%)
		Non-default	Default	
Training sample				
Real	Non-default	138	0	100
	Default	3	46	93.88
Hit rate				98.4
Testing sample				
Real	Non-default	69	0	100
	Default	5	20	80
Hit rate				94.68

4.3. Comparison between predicting models

As for the predicting models that constructed by applying these four methods: DA, LR, NN and DEA–DA, except for understanding the classification capability for each model, it also needs to validate each model's predicting performance through the testing sample. In order to achieve the purpose of seeking the optimal default predicting model, hereunder this study will conduct the comparison among these benchmarks: accuracy rate, sensitive rate, hit rate, Press's *Q* and misclassification cost, etc., with aiming at the predicting capability after validated these six types of models. From the results of comparison in Table 9, they can be concluded into three points as follows:

(1) In the accuracy rate aspect, DEA–DA has the highest rate of 100%, next is 98.55% for NN–0.5, and then 92.75% for the LR–0.5; as for the rest of three models, their accuracy rates are all reached 75%, and the result is indicated that all of these models have possessed sufficient capability to predict the non-default borrower.
(2) In the sensitive rate aspect, DEA–DA, NN–0.5 and NN–0.68 have the highest value of 80%, which the result is indicated that all of these three models have possessed sufficient capability to predict the default borrower, and the sensitive rate for the rest of three models is 60%.
(3) In the hit rate aspect, DEA–DA still has the highest value of 94.68%, next is 93.62% for NN–0.5 which indicated these two models have the optimal predicting effect. Closely, LR–0.5 and NN–0.68 also have the predicting capability as high as 85% and the rest two models have relative lower predicting capability by comparing with other models; however, their predicting capability is also reached the mark of 75%. Overall speaking, these six models have possessed good predicting capability to discriminate between good and bad borrowers, among which, DEA–DA and NN–0.5 are the optimal predicting models.

Through the concept of Press's *Q* value and misclassification cost to seek for better predicting model, from the information stated in Table 9, the Press's *Q* values of these six models all reached the significant level statistically, and possessed good fitness. Among which, DEA–DA and NN–0.5 have the optimal values, which implied that their fitness is better than other predicting models. In the misclassification cost aspect, if set the occurrence probability of these two types of borrowers to be identical, and then the misclassification cost of DEA–DA, NN–0.5 and NN–0.68 models is about 0.5 which their cost is relative lower among these six aforementioned models. If set the probability to be 0.74 for the non-default behavior and 0.26 for the default behavior in accordance with the samples that collected in this study, and then the misclassification cost of all six models will be enormously lower than the cost with same probability. These three models: DEA–DA, NN–0.5 and NN–0.68 still have the lowest cost about 0.3.

After integrating and comparing with each benchmark, it showed that each aspect is the predicting variable through the demographic variable and borrower's money attitude, and the most optimal predicting model of the consumer loan default behavior is constructed by using DEA–DA and NN–0.5 methods; among which, the DEA–DA predicting model that not yet applied by previous researches has the best performance, which is not only able to discriminate between good or bad borrowers, but also can have the lower misclassification cost.

5. Discussion and conclusion

The main purpose of this study is to integrate borrower's personal information and money attitude, and through four different predicting methods: DA, LR, NN and DEA–DA to develop a predicting model which is even more fit for the consumer loan default behavior. In this study, by taking the consumer loan customer of financial institutions in Taiwan to conduct the empirical analysis, and then the results showed the real-time information, such as borrower's personal information and money attitude, etc., is the predicting variable. In addition, the predicting efficiency of the default model that constructed by respectively applying these four methods is all more than 75%, and this result is also better than the model that constructed by some scholars with adopting the historic information of borrowers (Desai et al., 1996; Li et al., 2006; Malhotra & Malhotra, 2002; West, 2000). Among which, DA's accuracy and sensitivity is about 70%, and its hit rate is reached about 75%, which indicated that such model has possessed a certain level of predicting efficiency; within the regular dividing value LR is only reached 60% of sensitive rate which is enormously lower than the accuracy rate of 90%, and the predicted hit rate is 84.04%; therefore, through the application of the fitted cutoff value 0.71 to enhance the model sensitive rate up to 68%. Although the hit rate has decreased to be identical to the discriminant analyzing model, it still achieved the goal of equilibrating the predicting capability for two types of borrowers. Besides, the misclassification cost of two aforementioned models is between 0.5 and 1 that is higher than other models as well. In addition, as for NN, its accuracy rate within the regular cutoff values has already reached the mark of 98%; the sensitive rate has also up to 80% and possessed the high hit rate of 94%. However, the selection of fitted cutoff values has no significant upgrading effect on model's sensitive rate, but it still possessed 85% predicting capability integrally, which indicated if it has better predicting capability within original cutoff values, then the influencing effect of fitted cutoff value will not obvious. Furthermore, the DEA–DA model possessed the ultra high accuracy rate of the capability for conducting the completed and corrected classification, but its sensitive rate is as same as NN, and it has a high hit rate of 94.68%; in addition, the misclassification cost range of these three rates is about 0.3–0.5 which is significantly lower. To sum up, DEA–DA and NN are possessed better predicting capability and they are the optimal predicting model that this study longing for.

Table 9
The comparison between predicting models.

Models methods	Accuracy rate (%)	Sensitive rate (%)	Hit rate (%)	Press's *Q*	Misclassification cost	
					$\pi_1 = 0.5,\ \pi_2 = 0.5$	$\pi_1 = 0.74,\ \pi_2 = 0.26$
Discriminant analysis	76.81	68	74.47	22.5106***	0.9159	0.5853
Logistic regression–0.5	92.75	60	84.4	43.5745***	1.0362	0.5729
Logistic regression–0.71	76.81	68	74.47	22.5106***	0.9159	0.5853
Neural networks–0.5	98.55	80	93.62	71.5319***	0.5072	0.2706
Neural networks–0.68	86.96	80	85.11	46.34***	0.5652	0.3552
DEA–DA	100	80	94.68	75.0638***	0.5	0.26

*** $p < 0.01$.

In addition, this study showed that the default loan predicting model will be possessed higher level of predicting capability after added money attitude; therefore, as for the risk control of the consumer loan business and customer validation and sieving, if banking industry and financial institutions want to achieve the purpose of eliminating the potential default borrowers, sorting the non-default customers, making profit from stable business, and reducing the loss for banks, except for referring to the historic loan information of borrowers, this study also suggested them to apply the real-time information of borrowers, such as the tendency of their money attitude and basic personal attribute, etc., to effectively understand the probability of borrowers who will make the payment on time. It is able to increase the efficiency of the review and credit operations for the consumer loan to achieve the goal of locking the risk and rapid issuing. However, the money attitude that this study proposed needs to be measured by using the questionnaire, but the banking industry may still need to consider with the influences on other aspects when practically conducting such questionnaire survey. Therefore, this study suggested the follow-up scholars and researchers who shall conduct the research analysis on aiming at the feasibility of practically implementing such questionnaire survey to provide related industries with smoothly promoting the solution of their questionnaire towards money attitude. On the other hand, Chen and Volpe (1998), Mandell (2005) and Jacobs-Lawson and Hershey (2005) once pointed out that the knowledge level of personal financial management will also influence the concept and decision-making behavior of personal financial management; thus this study suggested the follow-up scholars and researchers to adopt such influencing concept and cooperating with methods from different fields to explore the even precise default predicting model.

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