Applied Neural Network Model to Search for Target Credit Card Customers

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Abstract. Many credit card businesses are no longer profitable due to antiquated and increasingly obsolete methods of acquiring customers, and as importantly, they followed suit when identifying ideal customers. The objective of this study is to identify the high spending and revolving customers through the development of proper parameters. We combined the back propagation neural network, decision tree and logistic methods as a way to overcome each method's deficiency. Two sets of data were used to develop key eigenvalues that more accurately predict ideal customers. Eventually, after many rounds of testing, we settled on 14 eigenvalues with the lowest error rates when acquiring credit card customers with a significantly improved level of accuracy. It is our hope that data mining and big data can successfully utilize these advantages in data classification and prediction.

Keywords: Credit card · Target customer · Data mining · Neural network

1 Introduction

More than a century has elapsed since banks introduced credit cards. In Taiwan, credit card development has undergone four crucial stages of development. Stage 1 marked a time when 3 banks dominated the market. Most cardholders were required to pay an annual fee. Such a fee subsequently became one of the primary sources of income for issuing banks. Stage 2 began in the 1990s, in which the CTBC Bank became the primary credit card issuer; its success in credit card and consumer financing-related businesses became the learning model for China's China Merchants Bank, which ultimately became one of the early issuers of credit cards in China.

Following the huge hype created by the media, credit cards entered into their third stage of development. During Stage 3, Taiwanese and foreign banks viewed credit cards and cash cards as highly profitable businesses, prompting them to introduce numerous marketing schemes (e.g., gifts and bonuses to customers for their first credit card purchase, airport pickups/drop offs, cashbacks, department store anniversary deals, co-branded cards, and balance transfers) to boost credit card issuance. The competition resulted in the waiver of annual fees, decline in credit quality, surge in revolving balance, and yearly drop in credit card interest, leading to the Credit Card and Cash Card Crisis in Taiwan, the fourth stage of credit card development.

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Although the credit card business has grown rapidly, most of the new customers were not the ideal customers, which means they didn't spend or use the revolving credit line. Therefore per card revenue was much lower than per card cost resulting in a low breakeven percentage. This is a very crucial issue for banks because the incremental and incidental costs exceed the revenue resulting a non-profitable business. Traditionally, eigenvalues related to revolving lines of credit currently and commonly used included age, gender, education level, marital status (in which singles account for more than 50 %), and salary. However, banks that use only these variables and bank supervisors' judgments are inadequate to handle the influx of new customers in the Internet era. Banks possess adequate customer data, however they cannot accurately define and predict ideal customers [1]. This study aimed to quickly identify customers with revolving credit demands and issue them credit cards based on data mining techniques.

2 Literature Review

2.1 Credit Card Business in Taiwan

By approximately 2005, many credit card cardholders are in possession of multiple credit cards. Their credit card balance far exceeded their ability to repay. When these cardholders overspent, they simply applied for another credit card and used the new credit card to pay off old credit card balances. This ultimately engendered the Credit Card and Cash Card Crisis, in which credit card and cash card issuing banks experienced bad debts. A number of medium-sized banks were even forced to be sold to private funds, resulting in significant financial losses. This led to a change in credit card applications, in which a stringent credit checking process became the norm. Issuing banks avoided bad debts at all costs, even if it meant foregoing potential profits. As a result, most data mining-related literature after 2005 covered the topics of how to avoid bad debts as well as the early detection of bad debts [2, 3]. So very little literature concerning our topic of finding new customers using the 3 methods has been published after 2005.

However, according to statistics compiled by the Financial Supervisory Commission, in 2015, 36 banks still issued credit cards in Taiwan and the number of cards in circulation was 38 million. Questions thus arose concerning why banks continued to invest in the market as well as how many issuing banks actually made a profit in their credit card business. In reality, profits generated by credit card companies markedly declined since 2005. It is shown in Table 1 that, in 2005, the number of credit cards in circulation was 45 million and the revolving balance was NT$494.7 billion. In 2015, revolving balance diminished to $108.0 billion. This is a significant decline in the net interest income in the whole market and the possible negative trends for the credit card market. In addition, service charges from cash advances decreased by NT$6.7 billion during this period.

The good news is that credit card transaction volume increased from NT$1.4 trillion in 2005 to NT$2.2 trillion in 2015 according to the Financial Supervisory Commission, resulting in higher fee income also shown in Table 1.

The increase of fee income cannot off-set the decrease in the interest income. Further, banks invest considerable amounts of money in hardware, marketing, credit card

Table 1. Credit card interest, credit card transaction services charges, and cash advances in Taiwan. Source: FSC Banking Bureau.

	Revolving balance	Credit card transactions	Cash advance balance
2005	NT$494.7 billion	NT$1.4 trillion	NT$215 billion
2015	NT$108.0 billion	NT$2.2 trillion	NT$27.0 billion
Increase/Decrease	−NT$398.7 billion	+NT$800 billion	−NT$188.0 billion

promotion, bonuses, while customer rewards continue to rise, which significantly cut into the banks' pre-tax income.

Therefore we need a way to identify high spending and revolving customers as a way to maximize the profits of credit card business.

To answer increasingly fierce competition, substantial adjustments were made to the previous customer development model, which involved setting up booths in crowded locations and asking passers-by to apply for a credit card. In addition to challenges from banking industry competitors, credit card issuing banks face competition from online and microfinancing companies. The emergence of online banking is rapidly eroding profits that can made from the credit card and personal credit/loan markets. Because online companies enjoy an enormous customer base (e.g., Tencent has more than 600 million WeChat customers), revenue that can be generated from the introduction of payment and loan services by online companies is unmatched by traditional banks, which possess a limited customer base and relatively small business models. When faced with such tests, the banking industry must find effective contingency plans to elevate the profitability of credit cards. Banks should avoid issuing credit cards to customers who might never use them and only increase the banks' costs.

2.2 A Brief Introduction of the Neural Network

In 1943, Warren McCulloch and Walter Pitts proposed a mathematical model that imitated neurons which facilitated the birth of artificial intelligence-related studies. However, the model itself possessed no computational capability. In 1949, neurologists argued that the human brain learning process begins with neural synapses. In 1957, Rosenblatt combined the two aforementioned theories to create the first-generation perceptron, which could be used to identify text. However, in 1969, artificial intelligence scientist Marvin Minsky reported that perceptron was unable to solve the exclusive or gate (XOR) problem, driving the neural network to its "dark age" that lasted more than a decade. In 1982, John Hopfield invented the back propagation method. This method trains a neutral network to automatically correct its weights when processing data; the neural network then reprocesses the data until an optimal weight is found. Such a breakthrough re-popularized neural network research and resulted in the usage of neural networks in various domains (e.g., image recognition, stock market forecasts, and industrial engineering) over the last decade [4].

The steps of back propagation network are as follows:

(a) Set up the back propagation architecture by setting the parameters, such as number of layers, number of nodes, learning rates, and maximum number of learning;
(b) Use a computer to randomly select the first weight, while the user selects the activation function (e.g., hard limit, sign, linear S-type, and hyperbolic tangent) that best represents the revolver sign function;
(c) Calculate the forward propagation output transmitted to the hidden layer; enter the eigenvalue (i.e., X) of various data [5]. The eigenvalues are used to determine whether a customer will become a revolver. X is multiplied with the weight automatically and randomly selected by a computer before being added to form the hidden layer output (i.e., Z). Next, calculate the hidden and output layers. Here, the Z value becomes the input value of the next layer and is multiplied with the weight randomly selected by the computer before being added. Using the sign function, calculate the Y value. Compare the Y value with the target value d (where a d value of 1 signifies a revolver). However, if the differences are extensive, the back propagation process is initiated;
(d) Identify ways for the error function E [3] to diminish error(s) between target and output values (i.e., a process that minimizes the error function), which is referred to as the gradient descent learning method (1);

$$E = \frac{1}{2} \sum_{k=1}^{q} \left(d_k - y_k\right)^2 \tag{1}$$

(e) Calculate intervals; compute the partial derivative of the weight W using E to produce the interval δ. Subsequently, readjust the weight;
(f) Calculate the correction; back propagation returns to the area between the original hidden layer and output layer. Modify the weight before entering it back to the hidden layer. Revise the weight until the optimal weight combination is found. Changes in weight Δw = learning rate η * error value δ * input value.
(g) Update weights: Return to Steps c) to g) until convergence or preset maximum learning number/time is reached.

2.3 Related Works

This section will detail two critical data processing procedures, which are data organization and data classification. Concerning data organization, it is asserted that because bank data are multidimensional, data preprocessing must be made [6]. The data preprocessing quality has a significant effect on study results. For example, ATM data provides information regarding customers' cash usage habits, whereas online bill payment (OBP) offers insight into customers' payment behavior. However, if all the data were used as variables, the operation would become markedly tedious; the transaction data comprised 13 data source-related categories, which are automated clearing house (ACH), adjustments to account (ADJ), automated teller machine (ATM), bill payment (BPY), credit card (CC), check (CHK), debit card (DC), account fees (FEE), interest on account (INT), wire transfer (WIR), internal transfer (XFR), miscellaneous deposit or withdrawal

(MSC), and unidentifiable channel (BAD) [6]. These 13 categories can be further divided into 138 subcategories. Therefore, identifying variables that are useful to a study during the preprocessing stage becomes critical.

Regarding data classification, it is indicated that most neural network and credit card-related studies focus on credit analysis scoring and seldom discuss existing clients' consumer behavior [7, 8]. Therefore, the clients were classified into three categories, namely, convenience users, transactors, and revolvers. In addition, a neural-based behavioral scoring model was devised to improve the management strategies of customer types [7]. It is recommended that customer data be divided into account information and transaction information in this study [7]. The clients were divided into three categories (i.e., inactive clients, interest-paying clients, and noninterest-paying clients) and employed the linear discriminant analysis and logistic regression model to identify whether clients were revolvers [9]. However, because variables in this analysis and model were demographic data-type variables, identifying customers thus became exceedingly difficult.

Numerous studies published around the golden age of credit card development of 2005 investigated the use of data mining techniques in the credit card market [10, 11]. However, the credit card market underwent considerable changes between the years 2005–2015: (a) the Credit Card and Cash Card Crisis: many banks that issued credit card and cash card suffered considerable losses. Credit information centers began to build databases for personal credit information, marking the end of an era in which people regularly owned dozens of bank cards and used new credit cards to pay off old credit card balances. Balance transfers were also highly regulated, in which a person's total credit card limit could not exceed 22 times their salary; (b) the subprime mortgage crisis in 2008: following the global economic crisis, banks stopped adopting lenient credit policies for individual customers. This resulted in revolvers' inability to borrow funds from banks, which forced them to borrow money from underground institutions; and (c) the Internet era: online companies employed advanced scoring systems and customer analyses, such as the know your customer (KYC) technique to acquire information needed by the companies to offer their core products and/or services to customers, whereas banks still use traditional and time consuming methods to gather customers' information. Customers subsequently compared the two service providers and ultimately chose online companies because of the level of convenience they provided. Instead of generating new business and acquiring customers, Taiwan data mining literature in the past 10 years primarily focused on bad debt avoidance.

3 Methodology

3.1 Defining Target Customers

In general, credit card customers can be divided into the following categories: (1) customers who normally do not use credit cards and only use them when banks are offering promotions and/or when customers can receive superior discounts or bonuses; (2) customers who use credit cards and who pay the balance at the end of the month so they do not use revolving credit; (3) credit card users who use revolving credit. These users can afford to pay the credit card debt, but need time to pay it back; and (4) credit card users who become bad debt customers. These customers cannot afford to pay back the credit card debts and credit card interest. The third and fourth types of customers look very similar on the surface. However, the revolvers do have the ability to pay the money back. It is important to differentiate the revolvers from the bad debt customers.

3.2 Collecting and Classifying Eigenvalues of Data

Once the target customer was determined, the second step was to collect the eigenvalues of the data. The most important step before analysis was to organize the data [12]. Banks currently have many different types of data that are similar to those described in a previous study [6]. First, we selected revolvers and non-revolvers. We then made the personal data untraceable and organized data and put into two tables. Table 2 shows the users' personal data, which are organized together with their credit status. Table 3 shows customers' purchasing behavior and credit card usage conditions. Data eigenvalues were then examined individually. For example, spending NT$10,000 using the credit card at one instance and slowly accumulating revolving credit is different from spending NT $100,000 once a year. These two items have different eigenvalues. However, accumulating more than NT$5,000 in credit card debt is not much different than accumulating more than NT$10,000 in credit debt, so these two do not require differentiated eigenvalues. Credit cards used in supermarkets to buy daily supplies is different from credit cards used in department stores to buy clothes and cosmetics. Data after initial classification are shown below: personal data had 11 eigenvalues and transaction data had 48 eigenvalues.

Table 2. Demographic data-based eigenvalues.

Data type	Data eigenvalues
Age	
Sex	Male Female
Marital status	Married/not married/divorced/other/ Number of dependents
Education level	
Annual income	
Real estate	House with no mortgage/house with mortgage/individual rental/rental with other/house guest
Profession	Agriculture/manufacturing/transportation and logistics/retail/service industry/financial industry/medical industry/accounting industry/lawyer/military, public servant, or teacher/student/retired/housekeeper/freelancer/other
Title	Chairman of the board/general manager/vice president/manager/other
Total asset	
Savings	Checking account/savings account/fixed rate deposit
Loans	Personal credit and loan/mortgage/credit cards/private loans

Table 3. Eigenvalue of transaction information.

Did the customer use cash advance? (3 items)
Did the customer pay in installments? (3 items)
Did the customer use preauthorized payment?
Credit card limit
Number of credit card transactions
Credit card transactions (in NT$) (7 items)
Number of times that customer applied for credit limit increase
Number of defaults
Number of credit cards that the customer has in his/her possession
Location where credit card is used (17 items)
Number of credit cards held by the customer that were issued by other banks (3 items)
Customer's spending habits using credit card(s) issued by other banks (4 items)
Customer's payment habits with other banks (5 items)

Note: After combing and filtering, we arrived at 13 categories with 48 items.

3.3 Data Preprocessing

The third step involved an essential data preprocessing process. This was performed because the data had different scales and some could not be calculated, which would make the research results biased. For the preprocessing process, we first converted the nominal scales and proportion scales to neural network codes (e.g., the northern area was {1,0,0,0,0} and the central area was {0,1,0,0,0}). Next, we integrated the variables to create new variables (e.g., variables "transaction amount (in NT$)" and "income from transactions" were merged to produce a variable with higher discriminability than the two variables by themselves).

3.4 Selecting Neural Model and Parameters

The fourth step was to select the neural model and set the parameters in SAS sytem. This study used the back propagation model because this study covered the topic of supervised learning, and the model is relatively more suitable for processing nonlinear problems. This study set its target values as Y1 and Y2, which represented the revolving credit usage frequency and revolving balance (in NT$), respectively. The two target values were set to enable us to gain insight into the effect that changes to the definition of revolvers have on revolving credit-related results. Because no standard parameters are available for the selection of neural network parameters, this study chose the following parameters and performed the first round of experiments.

Hidden layer: begins from the first layer; the number of layers is gradually increased
Number of units in the hidden layers: 5
Learning rate: 0.2
Maximum learning number/time: 1,000 or 1 h
Initial variables were randomly selected by the neural network
Data distribution: 60 % training, 30 % verification, and 10 % test

Standardization: 0.2–0.8 interval (self - minimum value)/(maximum value - minimum value)

The reason for disregarding the mean divided by standardization is due to possible distortion because of large variable differences

Function selected: logistic function

Momentum: 0.5

3.5 Choosing Data Eigenvalues with High Discriminability

Our sample size included 10,000 revolvers, which were credit card users who used revolving more than 6 times in the past 12 months, and 10,000 non-revolvers, which were credit card users who never used revolving in the past 1 year. We chose these combined 20,000 samples from an existing credit card user portfolio.

Among the 20,000 samples, the customer dimensions were classified by demographic, transactional behavior and life-style. For example, in our samples, we used marital status, age, mortgage status, education, profession and other demographic variables. Likewise, transactional behavior included total spending, cash advances, purchases and installment amount type of data for our samples. Life-style examples included poor money management skills, impulse buying, just married, first mortgage and first job. Please refer to Tables 2 and 3 for demographic and transactional dimensions. Currently, we do have life-style data such as first mortgage and first job, however, we do not have data concerning impulse buying and money management skills. Further study for developing a meaningful life-style database is needed.

The organization stage of data eigenvalues entailed the longest operation time. This stage involved determining the data to be retained, the data to be omitted, and the fields to be merged. For the first phase, all available variables were narrowed down to selective variables, which were subsequently divided into "demographic information" and "transaction information" groups. We hypothesized that demographic information features low discriminability and can be immediately obtained when customers apply for a credit card, and that transaction information features high discriminability but can only be obtained over time after applicants become formal customers. However, the most useful life-style information includes personality traits and behavioral data (e.g., impulse buyers, uninsured individuals with illnesses, and people with poor financial management skills) is difficult to acquire. Due to limited data sources, this study will only focus on finding valuable transactional eigenvalues.

The first round of computation used the SAS neural network function only. We used two sets of data, the first set was comprised of 10,000 revolvers. The second set was made up of 10,000 non-revolvers. The first round result using the neural network and two sets of data yielded eigenvalues with low discriminability and an error rate of 0.49, which proved the limitations of the neural network. The first round computation result from neural network showed that the ranking of eigenvalues by weight was not significant. Therefore, to supplement and overcome the neural network limitations, we also used the decision tree and logistic regression models to obtain and test data eigenvalues with higher discriminability.

Using the SAS decision tree function with the same two sets of data, we came up with four classification layers and five critical eigenvalues with high discriminability. Applying the SAS logistic function to the same two sets of data, we developed 4 eigenvalues with high discriminability.

Finally, as the way to retain the super calculability characteristic of the neural network, we picked the top 5 eigenvalues from the first round computation results, plus 5 from the decision tree and 4 from the logistic regression model results. For the second computation round, the 14 eigenvalues were again put back into the neural network system yielding a new classification error rate of 0.128. This suggested that the 14 eigenvalues possess very high discriminability features.

4 Result

The chart information was sourced from SAS system. The Blue line represents the decision tree method. The Red line represents the logistic regression method and the Dark Brown represents the neural network method (Fig. 1).

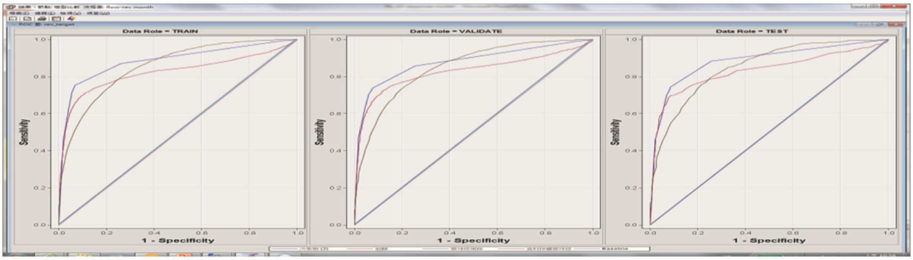

Fig. 1. Training and testing data result (Color figure online)

The first round computation in the chart on the left-hand side, shows that 8,000 training data were used to test 3 models. The result was that the decision tree was the most effective predictive data mining method with 16 % misclassification rate, followed by the logistic method with 20 % and neural network as the least effective.

The chart in the middle used 2,000 testing data with the same probability distribution to validate the training result stability shown in the left-hand chart. The similarity of the two charts proves the training result stability of the models.

The chart on the right-hand side used 10,000 data with different probability distribution. The result was consistent with the first two charts.

In the second round computation, we used 14 eigenvalues with high discriminability and put them back into the SAS neural network model to verify the model accuracy shown in Fig. 2. The misclassification rate was further reduced from 16 % to 11 %.

Results from the two computation rounds supported our hypothesis (i.e., demographic information with low discriminability): none of the 14 eigenvalues were from the demographic category. The results also revealed that demographic information filled out by new customers on banks' credit card applications can be used to determine

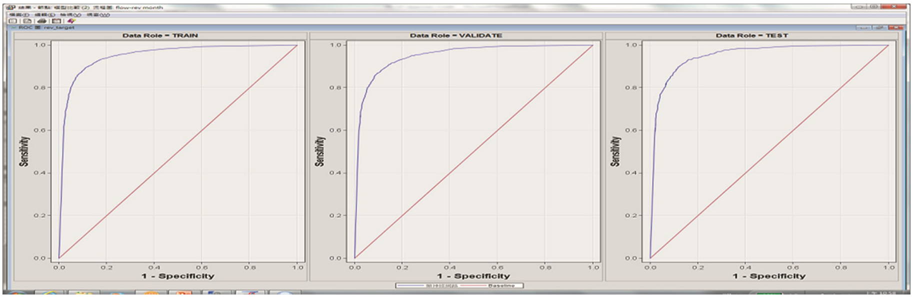

Fig. 2. 14 eigenvalues with the highest discriminability (Color figure online)

whether the applicants have good credit, but not whether they will become major credit card users or revolvers.

To verify whether demographic information truly features low discriminability, we entered 11 demographic eigenvalues into the back propagation model for further tests. The test produced a classification error rate that was approximately 0.5, confirming that eigenvalues of demographic information are ineffective in discriminating between customers.

This study featured a study framework that differed considerably from other studies in four ways: First, this study separated data eigenvalues into different categories right from the beginning. Although neural networks possesses powerful computational capabilities and can process all eigenvalues, separating data into different categories (according to their attributes) beforehand enables future users to use the study results more easily in practice. To make this study more complete, we not only separated customer data into demographic and transaction information, but also divided all original eigenvalues into three groups of eigenvalues to be entered into the system, which facilitated result comparisons. Second, this study identified data eigenvalues with high discriminability by employing back propagation, decision trees, and logistic functions, which enabled subsequent comparisons. The results were highly similar: all three methods produced similar eigenvalues with high discriminability. However, all three methods also had their own limitations: for example, neural networks have the worst explanatory power, whereas decision trees (despite featuring rapid data classification speed) are unable to guarantee that all omitted eigenvalues are irrelevant. Third, this study constantly changed eigenvalues, in which eigenvalues that were easily obtained but featured low discriminability were replaced with those that were not easily obtained but featured high discriminability. Fourth, this study enabled general rules derived from eigenvalue combination searches to be applied to finance-related operations (e.g., identifying ways to find active financial management clients and safe investment-type insurance clients) and even non finance-related operations (e.g., tourism industry and department stores looking for ways to locate their target customer base, and prosecutors finding the physical features of criminals), illustrating the high practical values of such general rules in information management.

5 Conclusions

When searching for new customers, the method introduced in this study enables users to easily identify valuable customers, eliminates instances in which credit cards are issued to customers with no credit card needs, and allows more meaningful questions to be provided on credit card applications to obtain eigenvalues with high discriminability that allows you to better identify ideal customers. Another method for improving credit card-related business performance is to combine several transaction-based eigenvalues into life-style eigenvalues that feature higher discriminability.

Nevertheless, the present study is merely a beginning. Traditional banking has used traditional labels to identify customers, i.e. age, occupation and income. These labels are no longer adequate. With the arrival of the online economy, everyone has been given numerous personality traits and behavioral labels with various eigenvalues. Therefore, businesses that have a full understanding of consumers' personality traits and behavioral labels will be able to create new value for themselves and their customers.

The neural network model has its own advantages and disadvantages. Therefore, combining the decision tree and the logistic models work to overcome the neural network model disadvantages and help to better improve the search for target credit card customers. This will increase the effectiveness of each model used in data classification and prediction as well as enhance their practical values in regards to financial industries.

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