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Measuring Customer Value and Credit Risk Management Decision using Artificial Neural Network

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Abstract

Customer value (CV) and delinquency behavior are two of the most important firm key performance indicators at the banking industry, and at any other business scenario in which customers are granted credits or loans. Coordination in decisions regarding these two important variables is essential to achieve overall firm performance. We develop a dynamic method that allows simultaneous coordination between CV and credit risk management decisions while taking into account their time varying behavior, the observed and unobserved customer heterogeneity, and the panel data structure inherent to the CV-credit risk context. The method, which is a combination of the neural network algorithm for exponential family of distributions and a fixed effects model has not been illustrated and/or implemented before. Therefore, we show its validity form a theoretical and computational point of view, and how its results can be interpreted to make the desired decision coordination task using synthetic data.

Keywords: customer life time value, credit risk management, neural network.

1. Introduction

In recent years, many companies at several types of industries have made the shift from product orientation to customer orientation, i.e. firms now focus on acquiring and retaining profitable customers rather than increasing profits from each product. This change of perspective has led to a new paradigm for making and evaluating marketing decisions [2] based on customer value (CV). This new perspective requires the understanding of the total profit a firm can expect to earn from a customer during the time it continues to maintain a relationship with that customer. Such understanding allows evaluating the profitability of customers, the consequent customization of marketing programs for individual clients, and the optimization of marketing investments [3]. The CV perspective has been widely implemented within the financial and retailing industries given their ability to use sophisticated information systems to track and manage detailed customer behavior over time. Such detailed tracking offers great opportunities for companies to have an overall customer profitability evaluation that takes into account every angle of the customer relationship with the firm. Among firms such as banks or retailers offering the opportunity for its customers to buy on credit, the customer payment behavior is an interesting and important angle of the customer relationship. The profitability that each client generates for the firm directly depends on his/her ability to fully refund the granted loan or credit within an agreed deadline. Therefore, such ability it is an important element that should be considered when making profitability assessment, and subsequent marketing decisions, both at the customer and the firm level. In other words, the credit risk management process (credit granting decisions) should be a customer relationship angle considered when evaluating customer lifetime value. Moreover, coordination between CV maximization and optimal credit risk decision making (and vice versa) can highly contribute to a firm's overall profit. According to Finlay [4] making lending decisions based on the forecast of financial measures such as customer contribution to profit, is the true objective of commercial lenders. Such an objective allows companies to efficiently target profitable customers with special offers to improve retention, or to restrict credit limits on unprofitable customers to reduce losses. Interestingly and to the best of our knowledge, the customer's credit risk angle is not considered when evaluating customers' value on both the academic and the business scenario. Moreover, credit risk and customer lifetime value decisions are typically made disjoint, and are not coordinated in terms of statistical approaches and available databases. According to [5] coordination between customer profitability and credit risk management procedures has not been very popular among the credit scenario. According to Finlay [4] this is due to three main reasons:

- The difficulty to have an overall customer profitability view from different angles of the customer relationship at different points in time, which requires efficient data warehouses and systems.

- The lack of an accurate and robust definition of the profitable customer.
- The sensitivity of profit measures to the actions taken on accounts that occur over the course of the outcome period, i.e. the relationship between the customer profile at the start of the outcome period and the profit generated by the end of the outcome period is in general weak. This sensitivity has made it difficult for researchers to adequately model the time-variant nature of profitability.

This dynamic behavior can be explained at the customer level by the different marketing actions used by the firm to retain the customer, and to ensure his/her good payment behavior, besides other customer specific aspects such as socio-demographic characteristics (income, education, etc.). In addition to these reasons for the lack of synchronization on the decision making process, we also believe that the time-varying behavior of the credit risk management related variables, such as payment behavior, also adds complexity to the task. In the same line of reasoning, a customer can be a good or a bad payer according to the firm actions, the customer socio demographic characteristics, the credit limits, and many other factors that also change over time. The time-varying behavior of the CV and credit risk indicators and their related variables, which are measured at the customer level, suggest the need of evaluating the CV-credit risk decision making process within a panel data structure. Such structure allows taking into account the individual dynamic behavior to consequently incorporate it in an overall evaluation at the customer base level.

In particular, we propose to use a generalized machine learning algorithm model using the neural network algorithm which captures the time varying behavior of the context by updating the parameter estimates on time. Then, we account for customer heterogeneity and the panel data structure by combing the state space and filter with a fixed effects model. This method allows understanding how different marketing and credit risk management decisions (firm-specific characteristics) influence the time-variant behavior of both customer profitability (CV) and customer payment behavior, through different customer-specific characteristics. It is noteworthy that to the best of our knowledge there are no studies using the neural network for the case of two dependent variables, the CV and the credit risk management variables that have different probability distributions: the normal and the binary distribution, respectively. Therefore it is also the aim of this article to show that the mentioned algorithm works well form a theoretical and computational point of view.

2. Customer Value

The Customer Value (CV) is a very useful metric to measure the long-term profitability of customers that allows identifying the value each client represents for the firm. It is generally defined as the present value of all future profits obtained from a customer over his or her life of relationship with a firm [5]. CV is similar to the discounted cash flow approach used in finance, except from the fact that CV is generally estimated at the individual level and incorporates the possibility of customers defecting to competitors in the future. CV can be used to guide the firm's acquisition and retention activities to make a more efficient use of marketing resources, and can be aggregated over customers as a measure of firm or segment value [6]. The CV for a customer (omitting customer subscript) is as follows [7]:

$$CV = \sum_{t=1}^{\infty} \frac{r_t (p_t - c_t)}{(1+\delta)^t} - AC$$

Where:

P_t = Revenues generated by the customer at time t,

C_t = direct cost of servicing the customer at time t,

δ = Discount rate or cost of capital for the firm,

R_t =Retention probability: probability of customer repeat buying or being "alive" at time t,

AC= acquisition cost,

T =time horizon for estimating CV.

Based on equation it is possible to conclude that the Customer Value has four main components:

- The retention probability
- The generated revenues
- The incurred costs and
- The discount rate.

Each component can be computed or forecasted through different methodologies which will be explained on posterior sections. Once the components are predicted or computed, they are included in equation in order to compute the Customer Value.

3. Credit Risk Management and Scoring

Credit scoring is the set of predictive models and their underlying techniques that are useful for the assessment of the risk associated with granting credits. This risk is the possibility that counterparty in a financial contract or credit will not fulfill a contractual commitment to meet her/his obligation stated in the contract [7]. In other words, credit risk is the uncertainty about the client's ability to fully refund the loan within the agreed maturity deadline. If the client does not fulfill the contractual agreement, we say that the client defaults or is delinquent, or that the default event occurs. Given its essential role on the credit granting decision making process, credit scoring models have become of primary importance in the financial environment [8]. Accordingly, the main objective of a credit scoring model is to decide whether or not to grant a credit to an applicant. It uses the observable characteristic variables of the credit applicant and calculates a score to represent the credit risk and classify applicants into different risk levels. Therefore, credit scoring models basically belong to the field of classification problems [9]. The relationship between historical information and future credit performance can be described by the following formula [10]:

$$y_i = f(x_1, x_2, x_3, \ldots, x_m)$$

Where y_i denotes if customer i is good or bad (non-delinquent or delinquent); the good/bad definition is based on three major components [11]:

- The client's number of days after the due date (days past due, DPD).
- The amount past due.
- The time horizon in which these two components will be traced.

Each component is set to a specific value according to the type of financial product (mortgages have longer maturities than consumer loans), the company's internal calculation, its marketing strategy and credit policy. Then, customers who have accounts fulfilling each of the three set values will be considered as a bad client. For example, a bad client can be defined as having more than 60 DPD in 12 months from the first due date with an amount past due higher than 3 euros.

The explanatory variables x_1, x_2, x_3,….,x_m are customer and product-related features such age, income, past credit behavior or interest rates, and f is the function or the credit scoring model. According to [12] credit scoring models can be classified into parametric statistical methods such as Linear Discriminant Analysis [13,14], non-parametric statistical methods such as k nearest neighbor [15] and decision trees[16], and other computing approaches such as Artificial Neural Networks [17].

4. Methodology

- Data and Variables

Data has been collected through stratified random sampling method over the period 2006-2011, based on documents and records of applicants for an Iranian commercial bank. Sample estimation has been done by a pretest sample size of 90 cases and according to the sample size formula, 497 are selected as the number of samples, which are derived from individual customers' profiles. The variables are as follows:

i. Dependent variable: good and bad customers; in this study we are aim to estimate the likelihood of good or bad customer being and also realize that how important are those factors. In this regard, good customer is a person who repays its loan plus the profit at the due date and in contrast, bad customer is a person who don't repay at the due date. To differentiate between good and bad customers in our neural network model calculations, we assign 0 to indicate good customers and 1 to indicate bad customers.

ii. Independent variables: In this study based on the previous researches and interview with bank experts, 18 variables are defined as independent variables:

- Gender: data samples are divided to female and male according to their gender.
- Age: data samples are divided to four groups; 18-25, 26-40, 41-60 and more than 60 years.
- Education: data samples are divided to four groups; uneducated, primary education, high school and university degree holder.
- Job: data samples are divided to following groups; self-employed, farmers and farm related jobs, Doctors, teachers, military personnel and office staff.
- Work experience: data samples are divided into four groups; less than 5 years of job experience, 6-10 years, 11-20 years and 21-30 years.
- Type of loan: data samples are divided into four groups according to their Islamic banking contracts.
- Amount of loan: amount of money that is given to the customer.
- Individual loan frequency: number of times that customer has received loans from bank.
- Individual account turnover average: average of monthly account balance and turnover.
- Time period of loan: that is divided to six groups; less than 7 months, 7-12 months, 13-24 months, 25-36 months, 37-60 months, more than 60 months.
- Type of collateral: data samples are divided in two categories: physical assets like home and property; and financial assets like equity and long term deposit.
- Interest rates: it expressed as percentage and it determine amount of bank's profit.
- Penalty rates: The amount of money that customer has to pay for any delay in repayment of the loan (this is apart from the bank profit).
- History of customer relationship with the bank: The time period that customer is in relation with the bank.

- Received services: The service quantity that a customer receives from bank (bank's services that provided to customers).
- Status of customer's bank account: it indicates whether a customer had any returned check or not.
- Bank's branch ranking: it determines the rank of a certain bank's branch.
- Value of collateral: it should be determined accordance with amount of loan.

We apply data into neural network model to estimate the probability that the customers are good or bad. Table 1 shows network information.

Table 1. Network information

Input Layer	Factors	1	gender
		2	Age
		3	Education
		4	Job
		5	Work experience
		6	Type of loan
		7	Amount of loan
		8	Individual loan frequency
		9	Individual account turnover average
		10	Time period of loan
		11	Type of collateral
		12	Interest rates
		13	Penalty rates
		14	History of customer relationship with bank
		15	Received services
		16	Status of customer's bank account
		17	Bank's branch ranking
		18	Value of collateral
	Number of Units		600
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units (Excluding the bias unit) in Hidden Layer 1		12
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Bad Customer
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy

The data description is shown in Table 1. The dependent variable (Y) is an ordinal variable. Some of the independent variables are also ordinal and some of them are scale. SPSS (version 19) software is used for modeling. 70 percent of data is considered for training of neural network model, 20 percent of data is considered for testing model during training and also 10 percent of data is considered for testing model after completion. For building the provided model, only one hidden layer with hyper tangent activation function is used. The numbers of nodes in the inner layer will be selected automatically. The output of software analysis is shown in Table 2.

Table 2. Classification

Sample	Observed	Predicted		
		.00	1.00	Percent Correct
Training	.00	209	31	87.1%
	1.00	14	119	89.5%
	Overall Percent	59.8%	40.2%	87.9%
Testing	.00	3	1	75.0%
	1.00	0	5	100.0%
	Overall Percent	33.3%	66.7%	88.9%
Holdout	.00	4	1	80.0%
	1.00	1	3	75.0%
	Overall Percent	55.6%	44.4%	77.8%

Table 2 is divided to three parts: Training, Testing and Holdout. In the first part of table (Training), 87.1 percent of customers who classified to good customers and 89.5 percent of customers who classified to bad customers were estimated correctly. In second part of table (Testing), the correct predicted percent's are 75% and 100%. In third part of table (Holdout), the correct predicted percent's are 80% and 75%. Also according to Table 3, overall percent error for holdout data is 22.2%. It is clear that in provided model, all the variables don't have the same effect on estimation and some are more effective in this model. In Table 2 and Table 3, dependent variable is bad customer. In Figure 2, importance of variables in the model is presented as normalized. Based on this figure, individual loan frequency (X8) and amount of loan (X7) have greatest effect on customer's good or bad estimation.

Table 3. Model summary

Training	Cross Entropy Error	111.195
	Percent Incorrect Predictions	12.1%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error
	Training Time	00:00:10.047
Testing	Cross Entropy Error	1.950
	Percent Incorrect Predictions	11.1%
Holdout	Percent Incorrect Predictions	22.2%

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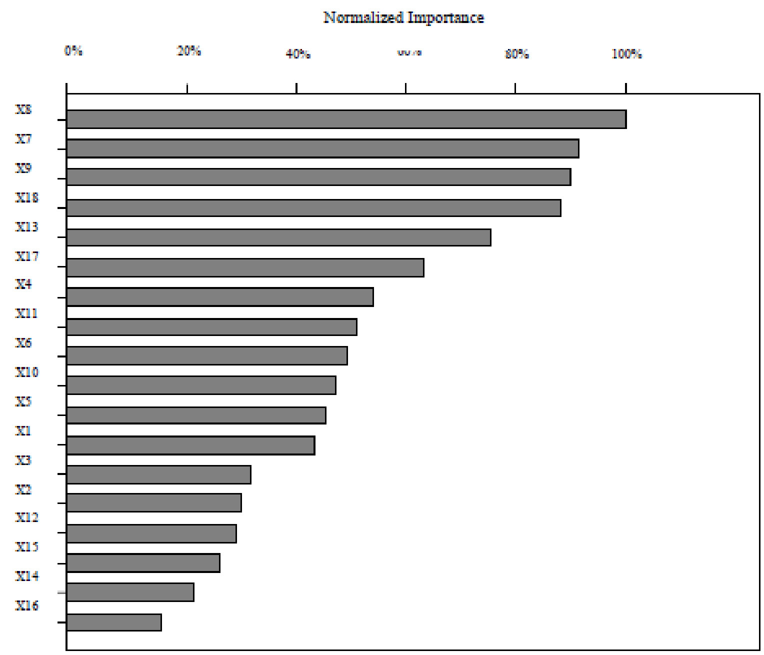

Figure 1. Importance of variables [15].

5. Conclusion

In this paper we investigated the theoretical and computational validity of the neural network when having two dependent variables with different distributions among the exponential family of distributions, in specific the normal and binary distributions. This was done with the aim of having a dynamic method that could capture the time-varying behavior of two of the most important key performance indicators within a firm: CV and delinquency. Given that we also wanted to account for customer heterogeneity (observed and unobserved), customer-specific neural network were used in combination with a fixed effects model that could capture the mentioned customer differences and the longitudinal nature of the business scenario. Given the lack of real data, we test our method using simulated longitudinal data that follows the neural network specification. Also we have presented an application of artificial neural network to measure bank customers' credit risk. We discussed the importance and necessity of customers' credit risk measurement and explained the architecture of ANN models. After determining of required variables, the collected data were entered into the model. Results of this study show that individual loan frequency and amount of loan have most important effect in identifying classification criteria of good customers and bad customers and also status of customer's bank account, history of customer relationship with bank and received services have least important effect. It means that bank managers and policy makers should focus on number of times that customers have received loans from bank and each time, how much was the amount of loan. This strategy reduces risk of non-repayments and increases the bank's profit.

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