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PUTTING THE BRAIN TO WORK: CREDIT INDEX EVALUATION FOR P2P LENDING BASED ON ARTIFICIAL NEURAL NETWORK MODELING

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Abstract

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Effective assessment of a borrower's various credit indexes is key for unravelling the problem of information asymmetry in the context of Peer-to-Peer Lending (P2P). Mitigating adverse selection of high default potential borrowers continues to plague P2P lending platforms. In order to understand which factors determine borrower credit status (ie. loan approval, loan repayment potential, risk of default), this study renders an Artificial Neural Network Model on one of the most popular P2P lending platforms. Our results show that the interest rate, the ratio of loan to income and the loan term are the most important indicators in reflecting the borrower's credit status, while the frequency of inquiries, the borrowing category have a relatively low degree of importance. This study finds that the borrower's credit index status is better explained at the lower quantiles and becomes more difficult to discern at higher quantiles. This work also finds that for longer loan terms, the borrower repayment pressure and the default rates rise with higher loan-to-income ratios and higher interest rates. Additionally, we find that higher credit rankings and higher expected returns lead to higher probabilities of defaulting. To reduce the probability of borrower default, this study recommends building lending groups or lending pools, selecting higher income credit candidates and increasing credit limits. To validate our results, we perform robustness tests that modify the learning coefficient and the training-to-validation data ratio in order to show that the empirical results of this paper are robust and effective.

Keywords: *Peer-to-peer lending, Artificial Neural Network, Credit index evaluation.*

JEL: *G10, G20.*

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PONIENDO EL CEREBRO A TRABAJAR: EVALUACIÓN DEL ÍNDICE DE CRÉDITO PARA PRÉSTAMOS P2P BASADOS EN EL MODELO DE REDES NEURONALES ARTIFICIALES

Resumen

La evaluación efectiva de los diversos índices de crédito de un prestatario es clave para desentrañar el problema de la asimetría de la información en el contexto del préstamo entre pares (P2P). La mitigación de la selección adversa de prestatarios con alto potencial de incumplimiento continúa plagando las plataformas de préstamos P2P. Para comprender cuales son los factores que determinan el estado crediticio del prestatario (es decir, la aprobación del préstamo, el potencial de pago del préstamo, y el riesgo de incumplimiento), este estudio presenta un Modelo de Redes Neurales en una de las plataformas de préstamos P2P más populares. Nuestros resultados muestran que la tasa de interés, la relación entre el préstamo y el ingreso, y el plazo del préstamo son los indicadores más importantes para reflejar el estado crediticio del prestatario, mientras que la frecuencia de las consultas, la categoría de endeudamiento tiene un grado relativamente bajo de importancia. Este estudio encuentra que el estado del índice de crédito del prestatario se explica mejor en los cuantiles más bajos y se vuelve más difícil de discernir en cuantiles superiores. Este trabajo también concluye que para plazos de préstamo más largos, la presión de la amortización del prestatario y las tasas de incumplimiento aumentan con mayores ratios de préstamo en relación al ingreso y mayores tasas de interés. Además, encontramos que las clasificaciones de crédito más altas y los rendimientos esperados más altos conducen a mayores probabilidades de incumplimiento. Para reducir la probabilidad de impago del prestatario, este estudio recomienda construir grupos de préstamos, seleccionar candidatos de mayor ingreso y aumentar los límites de crédito. Para validar nuestros resultados, realizamos pruebas de robustez que modifican el coeficiente de aprendizaje y la relación de datos de entrenamiento a validación para mostrar que los resultados empíricos de este documento son sólidos y efectivos.

Palabras clave: *Préstamo de igual a igual, Red Neuronal Artificial, Evaluación de índices de crédito.*

JEL: *G10, G20.*

1. Introduction

P2P lending is an unsecured loan conducted through an Internet lending platform, without the intermediation of financial institutions, and conducted directly between lenders and borrowers. In this marketplace, borrowers submit applications for loan listings, specifying details like loan amount, rates, and terms. The platform then proceeds to partially fund these listings with other respective lenders. Due to the elimination of a traditional financial intermediary, and more dynamic environment, P2P lending has the potential to reduce financing costs, increase efficiency of the financial market, improve the quality of financial services, accelerates the marketization of interest rates, and facilitates the development of inclusive finance (see: Greiner, & Aronson, 2009; Peng, Zhao, & Wang, 2014; Guo et al., 2016; Knaack & Gruin, 2017.)

However, information asymmetry consisting of adverse selection and moral hazard, as well as the borrower's information superiority gives rise to the likelihood of loan defaults in P2P lending platforms. Likewise, irrational decisions made by lenders based on the borrower's self-disclosed information also account for default risks. Lender's herding effect also amplifies irrationality rapidly (Lee & Lee, 2012) and adds to the uncertainty and risk of P2P lending. The effective assessment of borrowers' credit is therefore of paramount importance in developing effective P2P lending.

Existing research mainly concentrates on how information asymmetry and information disclosure affect P2P lending behavior. Conversely, researchers have rarely studied how borrower credit indexes discern and affect credit status. Therefore, this paper attempts to examine the importance of the borrower credit index in reflecting credit status and its various responses to credit index obtained through artificial neural networks methods. Data used in this paper comes from Prosper, the largest P2P lending platform in the world.

2. Literature Review

Previous research has shown that information asymmetry and information disclosure have a significant impact of on P2P lending behavior. Based on transferability concepts, Stein (2002) classified information into "soft" and "hard" information. The "hard" information can be verified objectively, whereas the "soft" information cannot. Research has shown that the "hard" information does influence P2P lending behavior. For instance, using transaction data from Prosper, Herzenstein et al. (2008) revealed that indicators like credit and borrower's personal information have significant influence on interest rates and loan success rate approval. Lin et al. (2009) found a negative correlation between loan success rate and borrower credit rating. Iyer et al. (2009) indicated that lenders can significantly increase the predictive accuracy of default by utilizing non-standard information, such as interest rate, listing durations, listing categories, location of borrowers, among other factors. Michels (2012) points out that the more information the borrowers with bad credit ratings disclose, the more they are likely to obtain loans.

"Soft" information also has an impact on P2P lending behavior. Freedman and Jin (2008) report that informal social networks (i.e. endorsement from friends) contribute to alleviating information asymmetry. By studying the geographic effect of crowdfunding, Argawal et al. (2011) found that social networks play an important role in P2P lending behavior, and that the elimination of geographic distance brought by online transactions does not eliminate off-line social-related frictions. Past experiences with P2P lending transactions are also associated with the success rate and default rate of loans. For instance, mentioning previous successful experiences in P2P lending raises the success rate of obtaining loans, while redundant descriptions in loan listings are accompanied by high default risks (Herzenstein et a., 2011; Larrimore et al., 2011). Lin et al. (2013) analyze the transaction data of P2P lending from Prosper and report that verifiable social network information of borrowers not only mitigated adverse selection, but also decreased the interest rate and default rate, and increased the success rate of loans. Freedman and Jin (2014) consider information a double-edge sword as it might help mitigate information asymmetry, but also send wrong investment signals to lenders.

The aforementioned research focuses mainly on explaining the impact of information asymmetry and information disclosure on theoretical lending behavior. Most of these studies utilize linear regression methods. The way credit indexes themselves affect the credit status of borrowers, and the non-linear relationship between credit indexes and credit status open numerous research opportunities. This is where artificial neural network (ANN) models become useful for this study. ANNs have been widely applied to various research fields due to its capabilities for self-adaption, self-organization, real-time learning and being able to cope with non-linear relationships. Specifically, Pacelli and Azzollini (2011) highlighted that neural networks have emerged as an effective tool for credit scoring because of their ability to model complex relations between dependent and independent variables. In order to overcome the current limitations of P2P credit index assessment, we employ artificial neural networks based on Khashman (2009, 2011) and Tsai & Huang's (2014) contributions to examine the importance of borrower's credit indexes and the non-linear relationship between credit indexes and borrower credit status.

3. Research Design

3.1. Data and Description

We select the historical transaction data of overdue loans released on Prosper.com as our sample, starting from July 13th, 2009 to November 13th, 2014. The timeframe represents the moment the corresponding underlying assets became public. Prosper is currently the world's largest P2P lending platform. Dating from November 9th, 2005, Prosper has accumulated a vast amount of transactional data with over 200,000 transactions, and has been regarded as an important data source by many researchers[5]. Prosper requires rigorous authentication and evaluation of borrowers' personal credit documents, e.g., personal credit score from Experian (one of the three main US credit bureaus). Therefore, the authenticity and completeness of data from Prosper minimizes research bias due to fake information. Moreover, the quality of data is constantly improving as Prosper adopts new methods to conduct credit scoring. For instance on July 13th, 2009, Prosper added new variables like effective yield rate, estimated loss, and estimated return. To avoid the potential influence of adopting new credit scoring methods, we chose to use the data after July 13th, 2009 since the evaluation of credit indexes relies heavily

[5] With over 80-million-dollar investment from venture capitals and loans the value, of which is over 354 million dollars, provided to its 1.37 million users, Prosper is currently the world's largest P2P lending platform. Prosper allows lenders and borrowers to directly transact with each other without traditional financial institutions. Lenders can obtain comparatively higher returns than most other financial products, while borrowers are able to obtain loans at lower interest rates. Both lenders and borrowers benefit from P2P lending.

on the borrowers' actual repayment. Therefore, choosing data on overdue loans is primordial for our intentions and purposes.

Lending Club and Prosper are the most popular platforms to apply for a peer-to-peer loan. However, our choice for choosing Prosper's data relies on data availability. Prosper's loan data is instantly available to potential investors through their web interface, while Lending Club publishes its internal CSV for download only. In addition, nearly 30% of Lending Club's loan data is not available to the public, while Proper's data is available to everyone. Prosper's data is also richer in information since it considers borrowers with lower credit ratings, thus increasing its loan product diversity. For instance, Lending club starts considering borrowers' applications if they have a credit score of no less than 660, while Prosper borrowers need a credit score of at least 640 in order to be considered for a loan.

The sample data contains documents like listing information (amount, minimum interest rate, loan term, etc.), credit information (total amount of default cases, credit records in banks, credit scoring, etc.), income of borrowers (income level, being a homeowner or not, etc.), rating of borrowers, membership of Prosper groups, etc. Generally, personal credit indexes are divided into three categories, namely personal, economic, and credit indexes. Personal indexes involve family and employment background as well as moral characteristics. By analyzing personal indexes, we can indirectly assess the willingness and the ability of credit candidates in repaying loans. Economic indexes consist of borrowers' balance sheet, income level, collaterals, etc., and are the direct reflections of the borrower's capacity to repay loans on time. Credit indexes refer to the credit records of borrowers, including credit records from banks (or similar credit institutions) and tax records showing the credibility of borrowers.

The exact manner that P2P platforms perform their own credit assessment is often considered a trade secret. Since the purpose of our study is not to recreate Prosper's "secret sauce", but to determine the factors that determine a borrower's loan status through the application of an Artificial Neural Network Model (reasons explained in the modelling section). At this point, it is also important to clarify that this paper does not compare its results to other models. To validate the results, we perform robustness tests that are standard in the literature of ANNs.

One of our first steps is to create our own appropriate profile credit index. We chose 14 credit indexes as independent variables taking measurability, predictability, and feasibility into consideration. We selected loan status as the dependent variable. Table 1 gives the brief description of all selected variables.

Prosper divides loan status into "Completed", "Charged Off", and "Past Due". In this paper, we consider both "Charged Off" and "Past Due" as loan default. Dummy variable *Loan Status* equals to 1 if the loan is completed and 0 if the loan defaults (being charged off or past due). Prosper provides three types of loan term (12, 36, and 60 months), and we assign the corresponding number of loan terms (in months) to Term. Borrowers are classified into 7 categories in terms of *Credit Grade*[6] . The purpose of a loan also has 7 categories: debt consolidation, home improvement, business loan, personal loan, student loan, vehicle loan, and other. We assign different numbers ranging from 1 to 7 to *Listing Category* according to different purposes. *Home Owner, Group Key*[7], and *Recommendations* are all dummy variables;

[6] There are two factors determining credit rating: first, credit scoring provided by official credit bureaus. Second, credit scoring provided by Prosper itself, based on the historical records of borrowers. The seven levels of *Rating* are: AA, A, B, C, D, E, and HR (High Risk).

[7] A borrower on Prosper can be a member of groups led by group leaders, the compensations of which are determined by the repayment of group members. So is the level of the group. Therefore, group leaders have the

the value of each variable is 0 if the borrower is not a homeowner/ not in a group/ has no recommendations, whereas the value 1 represents the opposite condition. In addition to 0 and 1, we assign 2 to *Inquiries* and *Delinquencies*[8] if the values of them are greater than 1 for the sample sufficiency, considering that most of their values equal to 0 or 1. I*ncome Range* contains 5 levels, which are $0-24999, $25000-49999, $50000-74999, $75000-99999, and $100000+. The remaining 7 variables are all continuous variables. Particularly, *Credit Score* is the mean value of the upper and lower bound of credit score range obtained from original credit score. After omitting missing values, we have 41,438 observations, of which 32,356 are completed loans and 9,082 are default.

Table 1: Credit Indexes of Borrowers on Prosper

Code	Variable	Definition	Type/Value
O	$LoanStatus$	The status of loan, completed or default	Discrete/0、1
I1	$Term$	The term of loans	Discrete / 12、36、60
I2	$Rating$	The rating of a borrower from Prosper	Discrete /1、2、3、4、5、6、7
I3	$ListingCategory$	The purpose of a loan	Discrete /1、2、3、4、5、6、7
I4	$IsBorrowerHomeowner$	Is a borrower a homeowner or not	Discrete /0、1
I5	$GroupKey$	Is a borrower in a Prosper group or not	Discrete /0、1
I6	$CreditScore$	The score of a borrower from Prosper	Continuous
I7	$CreditLine$	The credit lines of a borrower provided by Prosper	Continuous
I8	$Inquiries$	Number of inquiries from Prosper in last 6 months	Discrete /0、1、2
I9	$Delinquencies$	Number of delinquencies	Discrete /0、1、2
I10	$Income$	The income range of a borrower	Discrete /1、2、3、4、5
I11	$Recommendations$	Is a borrower with recommendations or not	Discrete /0、1
I12	$InterestRate$	The interest rate of a loan	Continuous
I13	$EstimatedReturn$	The estimated return of a loan	Continuous
I14	$DebtToIncomeRatio$	The share of debt in the income of a borrower	Continuous

Conclusions based on data attributes such as data dimension and inappropriate forms of data can degrade the performance of our models. In order to resolve these distortions, we normalized the data so that the influence of attributes with large values on model performance diminishes and the speed of classification learning can be accelerated. The normalization of data refers to mapping the value of attributes to a small interval following certain rules, hence the influence of different independent variables on the dependent variable can be comparable. According to Khashman (2009, 2011), we normalize credit indexes by dividing all the values of each attribute by the maximum value within a corresponding attribute. Consequently, the numerical values of attributes are all normalized to values between 0 and 1. Table 2 shows the borrowers' credit indexes of the first 10 cases before and after normalization together with the maximum value of each attribute.

motivation and pressure to assure that group members repay on time. Meanwhile, group leaders also release public information to vouch for their group members, or lend money to group members directly. Besides, group members in same groups may become friends, so that they can back or invest in each other directly.

[8] $Inquiries$ refers to the total number of inquiries from Prosper to borrowers after borrowers submit credit documents.

Table 2: Normalized input data-attribute numerical values for the first 5 cases

Pre-normalization	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	O
Case 1	36	1	7	1	1	829.5	7	0	0	2	0	0.09	0.06	0.05	1
Case 2	36	4	1	1	0	649.5	19	0	0	2	0	0.18	0.08	0.26	1
Case 3	36	5	1	0	0	649.5	6	0	0	2	0	0.26	0.12	0.26	0
Case 4	36	1	7	1	0	829.5	21	0	0	1	0	0.1	0.05	0.81	1
Case 5	36	1	7	0	1	789.5	12	1	0	3	0	0.06	0.03	0.03	1
Maximum value	3	7	7	1	1	889.5	4	2	2	5	1	0.42	0.28	10.01	
Normalization	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	O
Case 1	0.67	0.14	1.00	1.00	1.00	0.93	0.12	0.00	0.00	0.40	0.00	0.21	0.21	0.00	1
Case 2	0.67	0.57	0.14	1.00	0.00	0.73	0.32	0.00	0.00	0.40	0.00	0.43	0.29	0.03	1
Case 3	0.67	0.71	0.14	0.00	0.00	0.73	0.10	0.00	0.00	0.40	0.00	0.62	0.43	0.03	0
Case 4	0.67	0.14	1.00	1.00	0.00	0.93	0.36	0.00	0.00	0.20	0.00	0.24	0.18	0.08	1
Case 5	0.67	0.14	1.00	0.00	1.00	0.89	0.20	0.50	0.00	0.60	0.00	0.14	0.11	0.00	1

3.2. Artificial Neural Networks

Artificial neural networks (ANNs) are a type of mathematical model that apply structures inspired by the synaptic connections of the brain nervous system to information processing. As an algorithm model, ANNs consist of various nodes (neurons) connected to each other. Each neuron represents a specific output function, named activation function. The connection of every two neurons is the weight of the signal passing through the connection, appearing as the equivalent of memory to ANNs. The larger the weight, the bigger is the contribution of the corresponding neuron to the output neuron. The ANNs output varies upon weight, the way it is connected changes on the ANNs activation function. Hornik et al. (1989) prove that well-trained three-layer ANNs are capable of approximating all non-linear functions at any given accuracy, provided that the hidden layer has enough neurons. Accordingly, we constructed a three-layer ANN with a hidden layer, the structure of which is shown in Figure 1.

Previous studies have shown that neural networks are usually useful to perform classification, pattern recognition, optimization, clustering and prediction tasks efficiently and effectively. Pacelli and Azzollini highlighted that neural networks have emerged as an effective tool for credit scoring because of their ability to model complex relations between dependent and independent variables. Bahrammirazee (2010) performed a comparative research review of three artificial intelligent techniques: artificial neural networks, expert systems and hybrid intelligence systems. The results showed that ANNs models are superior to the traditional methods in dealing with financial problems. Baesens et al. (2003) analyzed three real life credit risk data sets using neural network rule extraction techniques to build intelligent and explanatory credit-risk evaluation systems. They concluded that neural networks are powerful tools for building advanced and user-friendly decision support systems to evaluate credit risk.

Ince and Aktan (2009) applied four different techniques to explore credit scoring in bank's credit card policy. They designed credit score models with logistic regression, discriminant analysis, neural network and decision trees. The results revealed that neural network model had the lowest Type II error compared to the other three methods. Therefore, they concluded that ANNs reduce the risk due to misclassification associated with Type II errors.

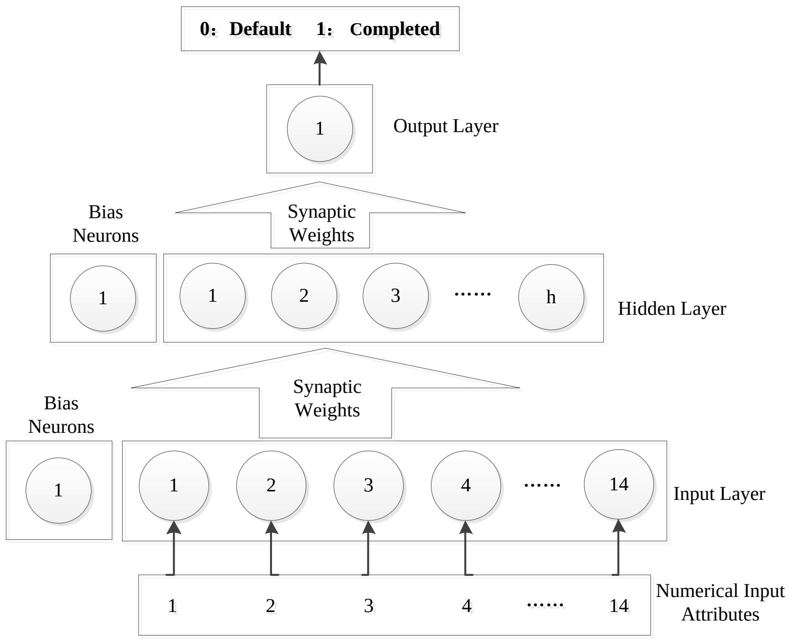
West (2000) revised the credit scoring accuracy of five neural network architectures and compared them with the traditional linear methods: linear discriminant, logistic regression, decision trees, kernel density estimation and nearest neighbor. The results confirmed that neural network credit scoring models can outperform linear models in obtaining credit scoring accuracy by fractional improvement, from 0.5 to 3%.

Blanco et al. (2013) used a database of 5,500 borrowers from a Peruvian microfinance bank to construct a credit scoring model based on multilayer perceptron approach. In addition, the study also benchmarked the performance of the neural network credit scoring model against other statistical techniques: linear discriminant analysis, quadratic discriminant analysis and logistic regression. The results indicated the superiority of neural networks over statistical techniques with a higher accuracy and a lower misclassification cost.

Our main reasons for choosing ANN to accomplish the task we have set forth in this study has to do with the relationship between the borrower's credit index and the credit status nonlinearity. The structure of artificial neural network is made up of non-linear changing units, and has strong non-linear mapping ability. Artificial neural networks can also perform self-learning variations based on the data, which is superior to the linear model since ANNs can adaptively adjust coefficients to approximate any linear or nonlinear function.

Artificial neural networks are configured based on the input layer to the hidden layer, and the hidden layer to the output layer, which is also connected to the weight coefficient, thus it can determine the relative importance of the input variables. In addition to this feature, ANN can also estimate the sensitivity of loan status to credit indexes based on a profile function that we can we design or tune to our specifications. This latter is of utter importance and the focus of our research since determining the factors or variables that influence on whether a borrower can default would confirm our expectations.

Figure 1: General topology of Neural Network model for P2P borrower' credit index evaluation



As depicted in Figure 1, our three-layer ANN comprises of an input layer, a hidden layer, and an output layer. Every neuron in each layer is connected to all the neurons in neighboring layers, and every connection is assigned a synaptic weight to adjust the connection value. In addition, we also set two bias layers, B_1 and B_2, which point to a node with neurons of the hidden layer and output layer respectively. The bias layer contains the non-input related activation tendency of the sensors, and can be interpreted as the offset for the activation function or the given basic neural activity level. The learning of ANNs is in fact the process of modifying synaptic weights and bias.[9] With I_1, I_2, ..., I_{14} denoting input neurons, H_1, H_2, ..., H_h denoting the hidden layer neurons, and W_{ij} denoting the weight of the connection between I_i and H_j, the value of hidden layer neuron is calculated as:

$$H_j = TF(\sum_{i=1}^{h} W_{ij} \times I_i) \tag{1}$$

Similarly, the output neuron value is:

$$O_k = TF(\sum_{i=1}^{14} W_{jk} \times H_i) \tag{2}$$

where TF is the non-linear transformation function, attempting to capture the non-linear relationship between input neurons and output neuron. It is noteworthy that the input layer neurons represent the credit indexes of borrowers (I1-I14) in Table 1. We choose the Sigmoid function:

$$f(x) = \frac{1}{1+e^{-u}} \tag{3}$$

which is commonly applied for classification tasks and capable of transforming linear ANNs to non-linear ANNs. If the value of output neuron O_1 is greater than 0.5, it indicates that the borrowers are likely to repay in full on time, whereas the value smaller than 0.5 suggests high default likelihood.

The values assigned to input neurons by ANNs hinge on the importance of the information carried by neurons. The values of hidden layer neurons represent their contributions to outcome. Therefore, we can evaluate the influence of some neurons by calculating the contributions of input neurons. We use the algorithm from Garson (1991) to compute the contribution of neurons. The contribution of input neuron i to output neuron *o* through hidden neuron j is calculated by multiplying synaptic weights. The relative contribution of i to j is:

$$r_{ijo} = |w_{ij} \times w_{jo}| \div (\sum_{i=1}^{14} |w_{ij} \times w_{jo}|) \tag{4}$$

where w_{ij} denotes the weight of connection between i and j. Furthermore, The total contribution of i is:

$$T_i = \sum_{i=1}^{14} r_{ijo} \tag{5}$$

[9] Similarly to living organisms, neurons will activate and send out nerve impulses when the nerve excitability exceeds its limits. Artificial neural networks are derived) meaning, neural networks have threshold values (also called bias) that activate the neurons depending on the threshold value. Neurons will not activate until the weighted sum of input exceeds the threshold value.

Based on Eq.4 and Eq.5, we finally obtain the relative importance of input neuron i:

$$RI_i = \frac{T_i}{\sum_{i=1}^{14} T_i} \tag{6}$$

Thus, the most widely used backpropagation Neural Network learning algorithm is selected, the calculation process of the three-layer ANN follows some rules: first, we compute the connection weight matrixes from the input layer to the hidden layer and from the hidden layer to output layer randomly, and set a total convergence error. Second, we implement a supervised learning scheme on ANNs based on the learning matrix sample, and calculate the errors between actual output and estimated output of the ANNs. Based on the errors obtained from the backward propagation learning algorithm, we adjust the connection weight coefficients from the input layer to the hidden layer and from the hidden layer to the output layer. Third, if the output error of the model is greater than the total convergence error given in the first step, we go back to the second step, otherwise, the learning process ends and we calculate the predicted value according to the connection weight coefficients and the threshold value (bias) using Eq.2. It is important to mention that the supervised learning process sets an error function as the reference of convergence error, and is calculated thusly:

$$\mathrm{E} = \frac{1}{2}\sum_{l=1}^{L}\sum_{h=1}^{H}(o_{lh} - y_{lh})^2 \tag{7}$$

where $l = 1,2,3,\cdots,L$ denotes the value of input and output, $h = 1,2,3,\cdots,H$ denotes the output neuron, o_{lh} is the predicted output, and y_{lh} is the actual output. In fact, the learning process of feedforward neural networks consist of minimizing the convergence error E.

4. Empirical Results

4.1. Moodeling of the Artificial Neural Network

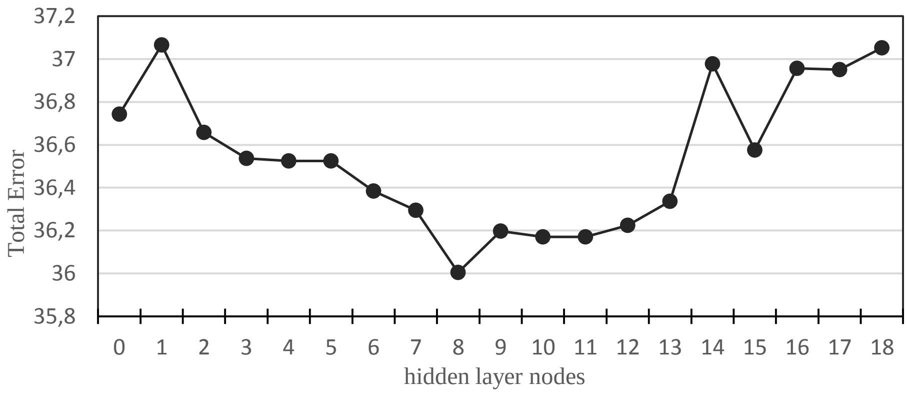
In modeling ANNs, it is of vital importance to select the number of hidden neural layers. Neural networks with insufficient hidden neural layers have a poor capacity of fault-tolerance and are not capable to deal with complex questions, whereas redundant hidden layer neurons may cause the learning process of neural networks to consume too much time in overtraining, and may even lead neural networks to be non-convergent (Moody, 1996). To construct the optimal neural network model with objectivity and accuracy, we determine the number of hidden layer neurons by adopting the strategy that gradually increases the number of hidden layer neurons by one each time. The total errors, containing training errors and prediction errors are the standard we rely on to judge the optimal model. Considering that the output of neural networks varies in different models with different learning coefficients[10] and training-to-validation ratios, we choose the learning coefficient to be 0.0081, and the training-to-validation ratio of 1:1 after repeated trials and comparisons, and reference to Khashman (2009, 2011)[11].

[10] The value of learning coefficient determines the variation range of weights. Small learning coefficients lead to time-consuming learning process whereas large learning coefficients may cause significant changes to weights and thusly miss the optimum result.

[11] Based on Khashman (2009, 2011), to determine the learning coefficient and training-to-validation data ratio, we select learning coefficient of 0.0081, 0.0095, and 0.0075, and training-to-validation data ratio of (1:1), (2:3), and (3:2) respectively. Additionally, we have also tried to use large learning coefficient of 0.01, 0.05, and 0.1.

Figure 2 shows the total errors of neural networks with different hidden neural layers, the given learning coefficient and the set training-to-validation data ratio. It is noticeable that the model with 8 hidden neural layers gives the best fit with the least total error. It is worth mentioning that the neural network is the same as the linear logistic model when the number of hidden neural layers is 0.

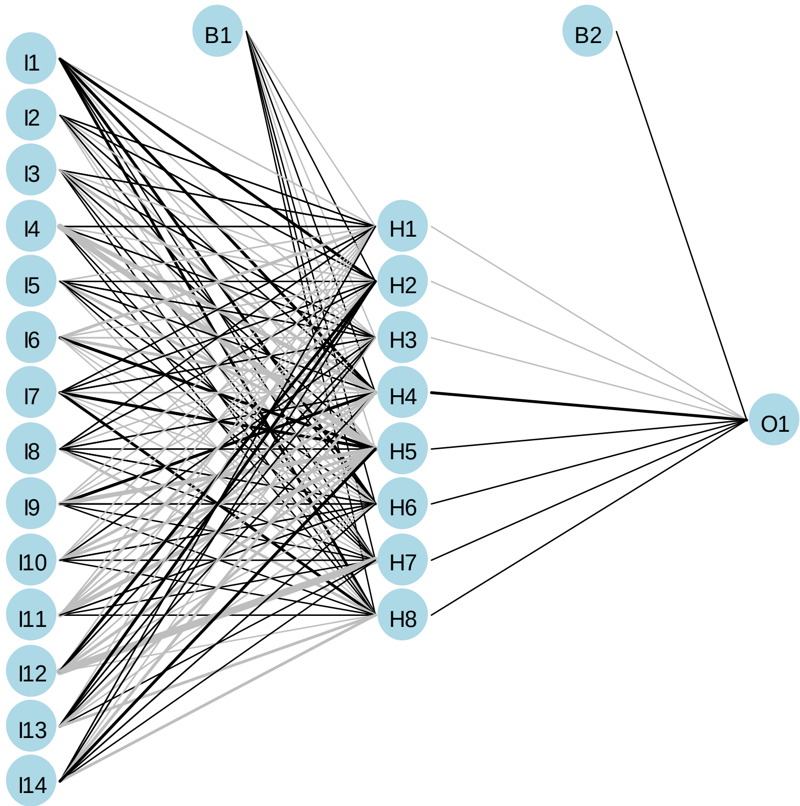
Figure 2: The optimal Neural Network for different hidden layer nodes



All the parameters of the final neural network model are set as follow: 14 input neurons, 1 output neuron, the interval of random initial weights is [-0.3:0.3], the largest accepted error is 0.02, and the maximum number of iterations is 2000. Finally, we obtained the optimal neural network model for borrowers' credit indexes evaluation depicted in Figure 3. I1-I14 are the neurons representing the information of borrowers (credit indexes), and each of them is connected to all 8 neurons: H1-H8 in the hidden layer. Similarly, every hidden layer neuron is connected to an output neuron. Every connection represents a weight. B1 and B2 are both bias layers, which are adjustable and will be activated when the weighted sum of input neurons is greater than 0. The output layer O1 shows loan status. The final training parameters of the optimum neural network model are: error is 0.018, the accuracy rate of training data is 94% (19476/20719), the accuracy rate of validation data is 76% (15746/20719), and the total efficiency is 85%.

According to our results, the learning coefficient of 0.0081 and training-to-validation data ratio of (1:1) give the best fit.

Figure 3: Optimal Neural Network Structure for P2P borrower' credit index evaluation



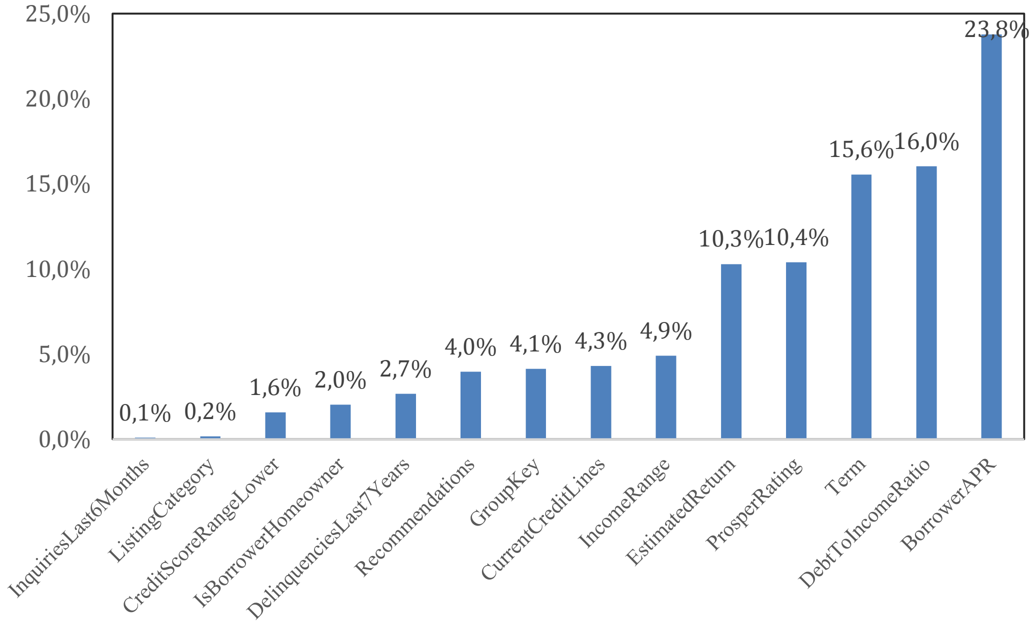
To describe more explicitly the learning process of neural networks, we present part of the connection weights of the optimum neural networks. The connection weights of two input layer neurons I1 ($Term$) and I2 ($ProsperRating$), two hidden layer neurons H1 and H2, two bias layers B1 and B2, and the response of loan status O1 are given in Figure 3. We began by randomly assigning all the connection weights in neural networks with values selected from the interval [-0.3:0.3]. Then, after inputting a group of borrower credit indexes, the neural networks will calculate the weighted sum of the credit indexes and give the final output based on the non-linear calculations utilizing Eq.1 and Eq.2. Under that circumstance, the output of "1" (Completed) and "0" (Default) share the same probability of 50%. If the value of output is correct, the neural networks will increase the connection weight of the corresponding response allowing the neural networks to make correct decisions under similar borrower credit indexes. Additionally, neural networks would also lower the connection weights of corresponding responses if the output of neural networks is wrong, in order to decrease the likelihood of making wrong decisions when confronted with similar borrower credit indexes. In regard to the learning process, by repeatedly inputting the borrower credit indexes to neural networks, the loan status ("Completed" or "Default") and its corresponding borrower credit indexes are recorded in the form of connection weights. As a result, neural networks are capable of identifying and judging any specific status rapidly and accurately. Finally, owing to the learning process of adjusting weight and bias, we can obtain the optimal neural networks.

4.1.1. Analysis of Relative Importance

Figure 4 shows the relative importance of each credit index utilizing the Garson algorithm in Eq.3. Noticeably, $BorrowerAPR$ outperforms all the other credit indexes with a relative importance of 23.8%, showing its ability to help evaluate the willingness and capacity of borrowers to repay their loans through P2P lending. Generally, higher interest rates motivate lenders to lend more while exerting a heavier burden of repayment on borrowers. Following $BorrowerAPR$, $DebtToIncomeRatio$ and $Term$ share a similar relative importance, which is around 16%. $DebtToIncomeRatio$ shows that the higher the ratio, the more likely is the borrower to default as his/her income cannot cover the loan. As for $Term$, considering that P2P lending is unsecured, lenders have to weigh in between return and risks, making the loan term an important index. Longer term comes with higher risk premiums and thus borrowers have to undertake a heavier repayment burden. Iyer et al. (2009) support that the loan term has an impact on the willingness and capacity of borrowers to repay. The relative importance of $ProsperRating$ and $EstimatedReturn$ are both approximately 10%. Prosper evaluates the rating of a borrower based on his historical credit records comprehensively. Borrowers with low ratings are offered higher interest rate than those with high-rating, while lenders have to undertake higher default risks if they lend to low-rating borrowers. $EstimatedReturn$ indicates the repayment pressure for borrowers, and also plays a role in inferring loan status.

Comparatively, the remaining indexes with small relative importance are indistinguishable for inferring the loan status of borrowers. In fact, P2P lending mainly involves short-term and small loan amounts. As a result, $IncomeRange$, $GroupKey$, $EstimatedReturn$,$CurrentCreditLines$ and $IsBorrowerHomeowner$ which are important in long-term and large-amount loans, are not sensitive to loan status in P2P lending. $Recommendations$ reflects a borrower's social networks, which might mitigate information asymmetry (Lin et al., 2013) although it might also send wrong investment signals to lenders (Freedman & Jin, 2014). Therefore, the influence of $Recommendations$ is unclear, and does not fully reveal its importance to loan status. It is notable that the relative importance of $CreditScoreRangeLower$ contradicts the assumption that credit scoring is a great determinant of credit indexes in the credit market. Some possible reasons behind the contradiction may be that credit scoring is a comprehensive evaluation performed by banks mostly, and that the target customers of P2P lending do not fully correspond with those of traditional banks as these P2P borrowers do not have enough transaction records in banking institutions. Therefore, the lack of accuracy in credit scoring for P2P lending is relatively unimportant. $InquiriesLast6Months$ and $ListingCategory$ are the two least important indexes with near to zero relative importance. Both indexes have greater early-phase influence in deciding whether a borrower gets a loan or not, but are not reflective of the loan status.

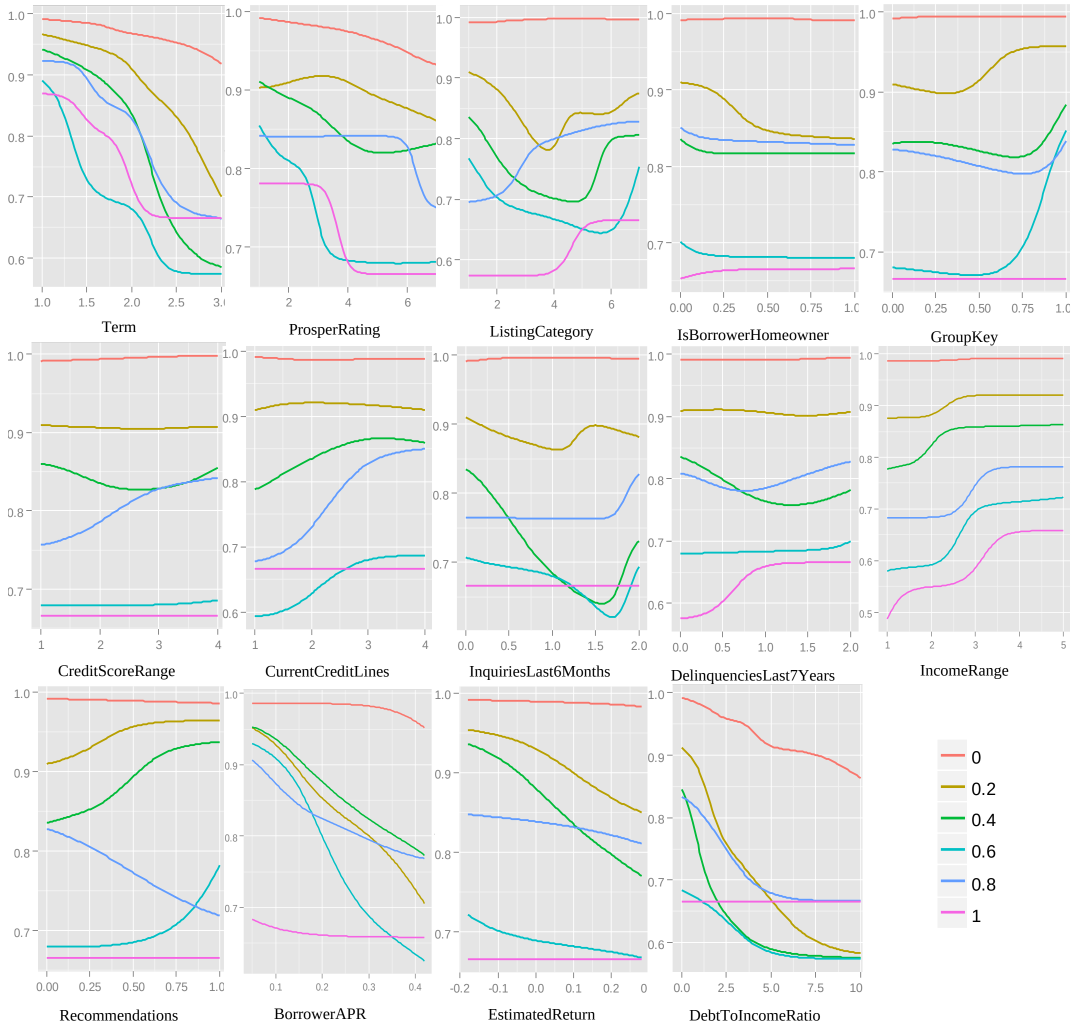
Figure 4: The relative importance of P2P borrower's credit index



4.1.2. Sensitivity Analysis

The way borrower credit indexes affect the loan status is also of paramount importance in P2P lending. Following Lek et al. (1996), we employ a profile function to estimate the sensitivity of loan status to credit indexes. Figure 5 shows the results. After entering the credit indexes into the neural network model, we obtain the prediction values of the corresponding loan status. Also, we illustrate the response curves for loan status to credit indexes at different quantiles (0%, 20%, 40%, 60%, 80%, and 100%), ceteris paribus. In every sub-figure, different curves represent the varying binary relationships between loan status and the corresponding credit indexes at different quantiles, other variables remaining constant

Figure 5: The response curve of borrower's loan status indicator



We can see that the loan status is very sensitive to credit indexes and the reaction decreases with increasing quantiles. In other words, the borrower's credit indexes best reflect loan status at a small likelihood of happening. It is reasonable in reality that the more irregular the information is, the more likely the credit indexes would reflect the loan status, especially when the borrower defaults. It is noteworthy that the response curves of loan status to credit indexes carry non-linear features that cannot be captured by linear models.

Keeping other variables constant, we can see that loan status manifests a downward trend when loan term increases. That is to say, the extension of a loan term increases its likelihood to default. The response curves of loan status to $ListingCategory$ demonstrate that personal loan, student loan, and vehicle loan tend to more likely default than the loans for debt consolidation and other purposes. $BorrowerAPR$ and $DebtToIncomeRatio$ take on a similar trend. Higher interest rates and debt-to-income ratio contribute to borrower higher repayment pressure, leading borrowers to default at a higher likelihood. In contrast, the response curves of loan status to $Recommendations$ and $GroupKey$ indicate that recommendations and being a member of a group to some extent decrease the likelihood of default. Still, borrowers with high income and available credit lines are less likely to default. The response curves of loan status to $IsBorrowerHomeowner$ and $DelinquenciesLast7Years$ are comparatively flat, which means that the two credit indexes have little impact on loan status, and is consistent with foregoing analysis in terms of relative importance. It is worth mentioning that borrowers default more if their credit grading and estimated loan return are high. It is probably because the grading of borrowers and estimated return are the two main credit indexes lenders refer to in making lending decisions. Lenders pay less attention to other hidden default-risks related to credit indexes, making it easier for borrowers to obtain loans and default, despite the high credit scores and high returns.[12]

4.1.3. Robustness Test

The output of the neural network models varies depending on the different configuration of connections, weights, and activation functions. We test the robustness of the empirical results by changing learning coefficients and training-to-validation data ratios, thusly constructing different neural network models. Based on Khashman (2009, 2011), leaving other parameters constant, we set learning coefficient as 0.0075 and 0.0095; also, we set training-to-validation data ratio as (2:3) and (3:2), while other parameters remain constant. We find that even though the numerical values of relative importance have changed, the top three important indexes still remain $BorrowerAPR$, $DebtToIncomeRatio$, and $Term$. The other 11 credit indexes differ in different models in terms of relative importance, but still remain comparatively important in minor scales. In particular, the values of relative importance of $EstimatedReturn$, $ProsperRating$, and $IncomeRange$ are all greater than the mean value. Based on general trends and developments, the response curves are robust with slight differences. Therefore, our empirical results are robust.

5. Conclusions

The importance of credit indexes and how they affect the credit of borrowers are of paramount importance in mitigating information asymmetry in P2P lending. In recent years, some countries, particularly China, have begun to pay attention to Internet finance. As an important part of Internet finance, P2P lending is in urgent need of constructing its own evaluation system of credit indexes to improve service quality, decrease risks, and appeal to more investors. To accomplish that, screening the importance of different credit indexes is necessary. In this paper, we employ artificial neural networks and bear results that contribute to underscore the importance of credit indexes, and eventually facilitate the development of P2P lending.

[12] There exist differentiation in the changing trend of responsive curves. For instance, the trend of the response curves of $ListingCategory$ at the quantile of 80% and 100% differ from the remaining quantiles. It is because $ListingCategor$ is a category variable, the number of which cannot be explained with the trend. Besides, the distribution of purposes of loans is not even. As a result, the response curve of loan status to $ListingCategory$ does not have substantial meaning from the sense of economics. In addition, credit indexes including Inquiries, Delinquencies and Recommendations also present similar situations, though having little influence on our conclusions because of small relative importance.

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