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Predicting Credit Risk in Peer-to-Peer Lending: A Neural Network Approach

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***Abstract*— Emergence of peer-to-peer lending has opened an appealing option for micro-financing and is growing rapidly as an option in the financial industry. However, peer-to-peer lending possesses a high risk of investment failure due to the lack of expertise on the borrowers' creditworthiness. In addition, information asymmetry, the unsecured nature of loans as well as lack of rigid rules and regulations increase the credit risk in peer-to-peer lending. This paper proposes a credit scoring model using artificial neural networks in classifying peer-to-peer loan applications into default and non-default groups. The results indicate that the neural network-based credit scoring model performs effectively in screening default applications.**

I. Introduction

In peer-to-peer (P2P) lending, scoring of borrowers' creditworthiness is one of the most important problems to be addressed in order for P2P lending to gain market share in financial industry. Assessing borrowers' creditworthiness is a common problem in micro-financing [1]. In P2P lending, loans are typically uncollateralized and lenders seek higher returns as a compensation for the financial risk they take. In addition, they need to make decisions under information asymmetry that works in favor of the borrowers [2]. In order to make rational decisions, lenders want to minimize the risk of default of each lending decision, and realize the return that compensates for the risk.

In general, rational investors maximize the expected value of their investment portfolio by optimizing the return with respect to risk and diversifying their risk by choosing assets with uncorrelated returns. Namvar [3] suggests that investors can utilize P2P loans as low-correlation, low-volatility assets to diversify portfolios. The lack of current and historical asset return data can make the task of finding correlations within a portfolio of P2P loans problematic. However, lenders can assess default risks of individual loan applications and define appropriate interest rates for each application. As the basis of this assessment, first lenders need to evaluate if there is enough information about both individual loan applications and potential borrowers as a basis for a credit decision. After the evaluation, lenders either make the decision to issue credit (interest revenue expected, subtracted with the search cost) or turn down the application (search cost is accrued). As borrowers have the advantage of choosing what information to disclose, the P2P loan marketplace is highly asymmetric and results in adverse selection and higher rates of return [4].

Credit loans have always been an imperative part of the financial industries and investors are constantly probing for better measures to minimize the credit risk. Credit risk is a crucial challenge and a complex task to manage and evaluate [5]. Risk evaluation is a vital part of credit decisions and its precision has a significant consequence on credit management [6]. Khashman [7] emphasizes credit risk evaluation as a significant issue in financial risk management that is a major concern for the financial and banking industry. The need for and the measures of credit risk evaluation have been a widely studied topic. The incapability of correctly identifying risk can adversely affect credit decisions, which can lead to investment failure. Therefore, correctly identifying credit risk is essential to secure investments.

Lenders in P2P lending abide the risk of investment failure due to the unsecured nature of the loans, even though the lending platform takes strict measures in evaluating borrowers' creditworthiness. In addition, most of the lenders, being non-professionals, have difficulties in screening borrowers. Assessing credit risk manually requires a high level of expertise, with the probability of making errors still not negligible. Data mining tools can access and utilize the hidden knowledge in collected data that can be used in credit risk assessment with significantly reduced manual errors in credit decisions [6].

In P2P lending platforms, potential lenders and borrowers meet and exchange information for a loan agreement. To enable loan agreements, routines to facilitate loan negotiations are aimed at decreasing information asymmetry by providing the lenders with information about the loan history of potential borrowers. Finding critical pieces of information in a database can be difficult. As lenders' expertise to utilize this information is often limited, new tools to make better informed decisions, such as various data mining methods, are potentially attractive to lenders. We argue and demonstrate that lenders can use Artificial Neural Networks (ANN) as a tool for identifying the features of borrowers that indicate belonging to either default or non-default classes.

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P2P lending as a financial model has been studied extensively in recent years. However, there have been only few studies utilizing data mining techniques for improving lending decision in P2P lending. Therefore, the objective of this paper is to apply artificial neural networks to develop a credit scoring model for P2P lending. Furthermore, the aim of this study is to classify loan applications into default and non-default groups to assist the lenders in selecting loan applications for the investment. The results from the study would potentially improve the ability of lenders in making credit decisions.

The rest of the paper is structured as follows. Section 2 introduces the basic concepts related to P2P lending, followed by a literature review on credit scoring, neural network and some relevant previous studies, in Section 3. In Section 4, the methodology and data used in the analysis are discussed. The results are provided in Section 5 followed by the discussion in Section 6. Finally some conclusions, limitation and future direction of this study are presented in Section 7.

II. PEER-TO-PEER LENDING

Peer-to-peer (P2P) lending is a form of online micro-financing that has been growing as an alternative to traditional credit financing. P2P lending allows individuals to lend or borrow directly from each other without financial intermediaries, through an internet based platform [8]. P2P lending came into existence in 2005 and within a short period it has experienced a "quasi-explosive" growth, challenging traditional banks and financial institutions [9]. According to Klafft [10], P2P lending is similar to an auction process, where borrowers place a request for loan and lenders bid to fund the loan through an online platform. The lack of financial intermediaries together with the possibility of quick access to a credit has enabled P2P lending to achieve a rapid growth.

The P2P lending process begins with the loan applications from the borrowers. When placing a loan request, borrowers provide information on the purpose of the loan, the amount requested, interest willing to be paid, and their personal and financial information. The information provided by the borrowers are processed through underwritings from the lending platform. The loan requests, after being approved by the lending platform, are assigned to a credit group and then listed in the market for investors to bid on. Based on the information provided by the borrowers, investors select a loan offer from the listing and make decisions on the amount to invest in the loan offer. A borrower is then provided the loan when the loan amount is fully funded or has attracted enough bids to be funded.

Lenders in P2P lending mostly make investment decisions based on information provided by borrowers, such as demographic characteristics, financial strength, effort indicators, loan amount, interest rate and duration of loan request [11]. In addition, trust between lenders and borrowers is an important decision making factor. The exchange of messages between borrowers and lenders and even the borrowers' picture plays a decisive role in building trust [9]. Furthermore, the lenders display herding behavior while selecting a loan offer, as they tend to invest on loans with more bids.

Due to the lack of financial intermediaries and collateral, borrowers who have difficulties in securing loans from traditional banks are more attracted to P2P lending. The loan request generally ranges from small amounts to medium, with a payback period of usually less than or equal to three years. P2P lending offers various benefits to both borrowers and lenders. Borrowers can receive a loan quickly without a collateral, while lenders are offered with a higher return on their investments.

Klafft [10] states that most lenders in P2P lending are not skilled in evaluating investment risks and thus face difficulty in judging the quality of a loan application. According to Herzenstein et al. [11], there are no explicit rules that guide lenders to make a decision on how to lend their money. Wang and Greiner [12] identify receiving the investment back as the fundamental problem of lending money over P2P lending, since the loans offered are not secured with a collateral. Yum et al. [13] state that P2P lenders may misinterpret the creditworthiness of borrowers due to the information asymmetry between lenders and borrowers, as it is sharper compared to the other financial markets. Lenders are at a high risk of becoming a victim to fraud by dishonest borrowers' fraudulent behavior. In addition, the lenders may encounter the risk by considering inappropriate factors in selecting borrowers [14]. Hence, the presence of information asymmetry and the fact that P2P loans are not secured by a collateral constitute the necessity of assessing the borrowers' credit risk.

III. LITERATURE REVIEW

A. *Credit Scoring*

Credit scoring is one of the most prominent analytical techniques used by financial institutions in credit risk evaluation of credit applications. Ghatge and Halkarnikar [15] define credit scoring as a statistical method used to predict the creditworthiness of a customer, i.e. to estimate whether a loan will default or succeed. Bahrammirzaee [16] views credit scoring as a typical classification problem, where objects are classified into predefined groups or classes based on the observed attributes of the object. According to Malhotra and Malhotra [17], credit scoring systems are developed using historical loan data in analytical models to determine creditworthiness of a borrower, and use the probability of default as a basis of classification. The objective of credit scoring models is to identify certain characteristics that distinguish between good and bad credits, i.e. predicting the likelihood of customers to default with their repayments [18].

Credit scoring systems have the ability to process a large volume of credit applications in less time, with minimal labor and reduced cost [15,19,20] . The growing rate of credit defaults in the financial industry leading to investment failures has enlarged the significance of credit scoring for lenders. In addition, credit scoring has been studied extensively in accounting and financial literature as a critical topic for improved lending decisions and profitability [21].

Credit scoring models are usually built using linear methods, such as linear discriminant analysis and logistic regression. Furthermore, artificial intelligence and machine learning techniques, such as artificial neural networks, decision trees and support vector machines are applied in building credit scoring models [6,21]. However, artificial neural networks have proven to be superior to linear methods in credit scoring problems. The accuracy of neural networks in credit scoring has been successfully displayed in recent studies performed in different business applications [7,17,19,20,21].

B. *Neural Networks*

Artificial neural networks (ANN) emulate biological nervous systems and brain structure and can generally be viewed as information processing systems that use learning and generalization capabilities [16]. Malhotra and Malhotra [17] state that neural networks are non-linear models that use pattern recognition capabilities for classification. ANN can be used in modeling complex relationships between inputs and outputs for discovering patterns from data.

ANN is a system comprised of highly interconnected processing elements called as neurons or nodes [17,18,]. Most neural networks are commonly comprised of three types of layers: the input layer, the hidden layer(s), and the output layer, also known as multi-layer perceptron [21]. A simplified three layer artificial neural network is shown in Fig 1. The input layer receives raw external information, which corresponds to independent variables in the data. The neurons in the input layer send signal to hidden layer. The signal from the input layer is processed in the hidden layer and sent to the output layer. The output layer transmits the information outside the network as the target output ,which corresponds to a dependent variable in the data [18,21].

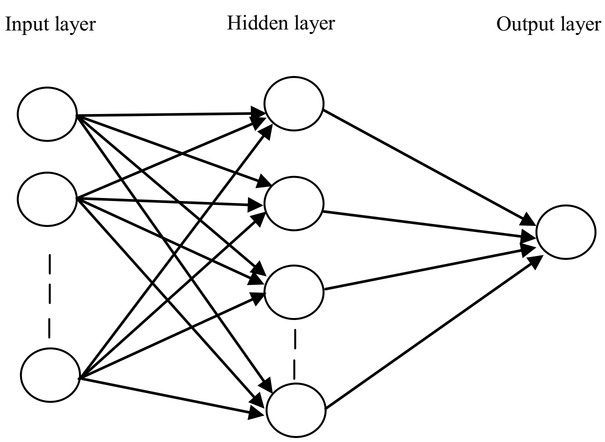

Fig 1. A simplified three layer neural network

A neural network learning process is comprised of two stages, training and testing. In the training phase, the model is trained with training data and then is later tested with testing data. The training stage can either be supervised or unsupervised. In supervised training, the network is trained with both inputs and outputs, while in unsupervised training, the network is only provided with the inputs, as there is no explicit target output.

C. *Previous Studies*

Data mining techniques, such as various machine learning techniques and neural networks, have been extensively used in different business applications. In this section, the latest studies on the application of neural networks for building credit scoring models will be presented to highlight the importance of neural networks in credit risk evaluation. Furthermore, the studies presented emphasizes on the effectiveness of neural network applications to support credit decisions in P2P lending.

Neural networks are typically applied to efficiently and effectively perform tasks, such as classification, pattern recognition, optimization, clustering and prediction [6,22,23]. Pacelli and Azzollini [5] pointed out 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. Furthermore, problems in accounting and finance have been the major focus of researches with neural networks, where common problems are bankruptcy prediction, credit evaluation, fraud detection, insolvency prediction and property evaluation [16,23].

Bahrammirazee [16] performed a comparative research review of three artificial intelligent techniques: artificial neural networks, expert systems and hybrid intelligence systems. The results from the study showed that artificial intelligence methods are superior to the traditional methods in dealing with financial problems. Baesens et al. [24] 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 management tools for building advanced and user-friendly decision support systems to evaluate credit risk.

Ince and Aktan [19] applied four different techniques to explore credit scoring in bank's credit card policy. They designed credit score models with dicriminant analysis, logistic regression, neural network and decision trees. The results revealed that neural network model had the lowest Type II error compared to the other three approaches. Therefore, they consider neural network to successfully reduce the risk of extra cost due to misclassification costs associated with Type II errors.

West [20] reviewed 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%.

Malhotra and Malhotra [17] compared the effectiveness of neural networks and multiple discriminant analysis in identifying potential loans. They collected data from 12 different credit unions and combined them into a single data set. The results clearly indicate the robustness and effectiveness of neural networks over multiple discriminant analysis, in identifying potential loan defaulters. Similarly, Angelini et al. [22] demonstrated the successful application of neural networks in credit risk evaluation. They developed two neural network credit scoring models, one based on classical feed forward architecture and another with a special purpose architecture. Real data from Italian small businesses was used in developing the credit scoring models. The results from both the models proved the effectiveness of neural networks in credit risk assessment with a low error rate.

Khashman [7] studied credit risk evaluation using a neural network model based on back propagation learning algorithm using real world cases from an Australian credit approval database. The experimental outcome from the study suggested that neural networks demonstrate effective results in automatic processing of credit applications. Recently, Bekhet and Eletter [6] employed radial basis function (RBF) neural network and logistic regression for developing a credit score model to support the credit decisions of Jordan commercial banks. The results indicated that neural networks perform better than logistic regression in screening rejected applicants.

In another study, Blanco et al. [25] used a database of 5500 borrowers from a Peruvian microfinance institution to build 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 three statistical techniques: linear discriminant analysis, quadratic discriminant analysis and logistic regression. The results of the study indicated that neural network credit scoring is suitable for micro financing institutions. The results also confirmed the superiority of neural networks over statistical techniques with a higher accuracy and a lower misclassification cost.

IV. RESEARCH METHODOLOGY AND DATA

A. *Data and Variable definition*

Data for the study has been retrieved from a publicly available data set of a leading European P2P lending platform Bondora[1]. The retrieved data is a pool of both defaulted and non-defaulted loans from the time period between 1st March 2009 and 15th February 2015. The data comprises of demographic and financial information of borrowers, and loan transactions. After removing the non-funded loans from the data set, the data comprises of 16,037 observations. The data sample included 15.77% defaulted loans and 84.23% non-defaulted loans. Furthermore, based on the relevant literature and a preliminary analysis, the data collection resulted in 15 variables. The definition of the variables and their types is shown in Table I. It would be possible to consider also the time of the loan and look at the changes as the effect of important real-life events (such as the financial crisis). We decided not to pursue this direction as the popularity of Bondora started to increase significantly in the second half of 2013, so we would have only a small portion of cases before that time, which would not allow for a proper comparison between the two time periods.

The dependent or the output variable is the actual default (AD), which is a binary variable with two values 1 and 0. The value 1 represents the defaulted loans and 0 represents the non-defaulted loans.

B. *Research Methodology*

The neural network credit scoring model was built with the programming language R as it has been extensively used for academic purpose in the field of data mining. The packages of R applied in developing the model are nnet, NeuralNetTools, caTools, and ROCR. Back propagation algorithm was applied to build the neural network credit scoring model. The data was partitioned into two subsets: 70% of the observations were used for training and 30% was used for model testing. In addition, the partition was performed randomly in a way that both the training and testing sets contain default cases of approximately to the same percentage. Table II shows the summary of the data used in the model development process.

TABLE I. Proposed variables for building the credit score model

Variables	Type	Description	References
CreditDecision	Binary	Credit decision taken by Bondora	[6]
NewCreditCustomer	Binary	Did the customer have prior credit history in Bondora	[20]
Age	Scale	Age of the borrower (years)	[6,25]
Country	Nominal	Residency of the borrower	[6]
CreditGroup	Ordinal	Credit Group of the borrower	
AppliedAmount	Scale	Amount applied	[20]
Interest	Scale	Maximum interest rate accepted in the loan application	[25]
LoanDuration	Scale	The loan term	[25]
UseOfLoan	Nominal	Purpose of the loan applied	[6,20]
ApplicationType	Nominal	Type of application made	
NewOfferMade	Binary	Underwriters restructured the initial application and either offered longer term, higher/lower loan amount or higher interest rate	
Marital status	Nominal	Current marital status	[25]
Employment status	Nominal	Current employment status	[20]
Income total	Scale	Total income	[6]
AD (Actual Default)	Binary	Credit status of a loan	

TABLE II. Data partition summary

Samples	No. of observations	Percentage (%)
Training	11,226	70%
Testing	4,811	30%
Total	16,037	100%

The neural network comprises of 14 neurons in the input layer, corresponding to the number of independent variables

[1] https://www.bondora.fi/en/invest/statistics/data_export

in the data. Similarly, the hidden layer was assigned 5 neurons and the output layer with 1 neuron. The selection of the neurons in the hidden layer was finalized following an evaluation process using AUC (area under curve) approach. AUC is calculated as the area under the ROC (receiver operating characteristic) curve. ROC curve depicts the relationship between true positive and false positive rates in a classification problem for different threshold values. In our application, the threshold value for the classification of the loans was chosen to be 0.16, with the emphasis on classifying more default loans correctly. The maximum number of iteration was used as the stopping criteria, where the training process of the model stopped automatically after 100 iterations. Fig 2 represents the neural network credit scoring model for the classifications of loans.

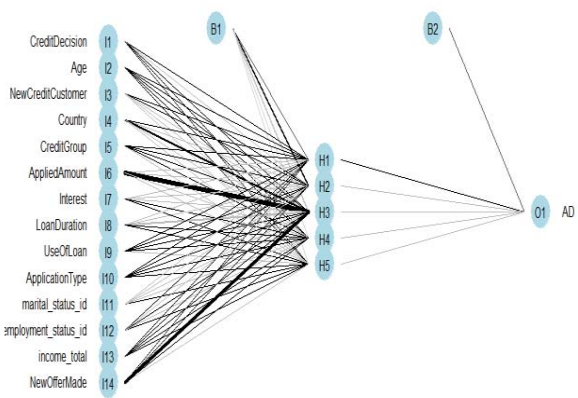

Fig 2. Neural network credit scoring model

V. RESULTS

The neural network credit scoring model was successful in classifying default and non-default loans. Hence, the P2P lenders can reduce the risk of investment failure by selecting profitable borrowers after processing the loan applications through the model. The model correctly classified 64.47% of the non-default loans and 74.75% of the default loans of the training data set. Similarly, it correctly classified 62.70% of non-default loans and 74.38% of default loans of the testing data set. Table III presents the classification results of the model. When looking at the financial value of these results, we can calculate that by using these estimations the amount of defaulted loans that would have been identified correctly is 1085077.4 €, which corresponds to 10% of the total amount of loans for the given data points (test set).

TABLE III. Classification results

	Actual	**Predicted**		
		Non Default	***Default***	***% Correct***
Training	***Non Default***	6022	3322	64.47
	Default	431	1276	74.75
Testing	***Non Default***	2517	1497	62.70
	Default	188	546	74.38

Fig. 3 shows the relative importance of all the variables in the model. In the model the importance is calculated according to the process described in [26], relying on the decomposition of the model weights. The importance of the variables signifies the extent to which the model's outcome can vary for different values of the independent variables.

The results show that the variable "new offer made" scored the highest importance, followed by "applied amount", "income total" and "country". "New offer made", having the highest importance, strongly influences the outcome of the model (credit decision). However, "marital status" has the lowest importance, which suggests that it has no influence on the model's predicted value of credit decision. Hence, from the results it can be concluded that financial attributes are more influencing than demographic attributes in determining credit risk.

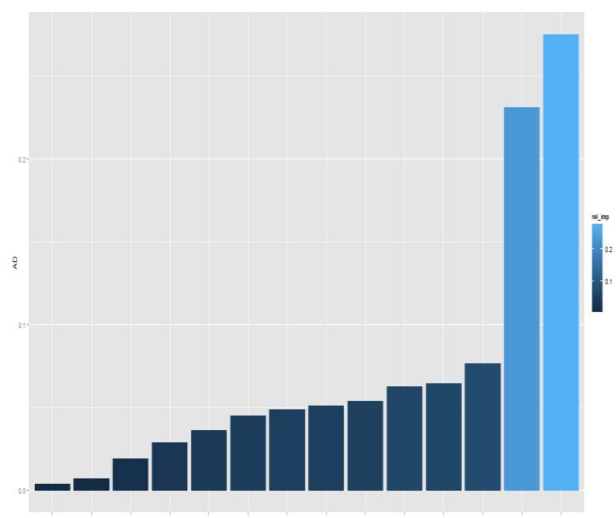

Fig 3. Relative importance of the variables calculated based on the method described in [26] and implemented in the NeuralNet Tools package in R

VI. DISCUSSION

The applied neural network credit scoring model successfully demonstrates the applicability of neural networks in credit scoring for classification and prediction of credit risk. Studies in credit risk evaluation using data mining techniques have shown neural networks to outperform statistical techniques in terms of accuracy [6,17,19,20,25]. The data used to build the neural network credit scoring model was used for building a logistic regression model in order to verify the effectiveness of neural networks. The comparison of the classification results from neural networks and logistic regression is shown in Table IV.

From Table IV, it is evident that logistic regression is more accurate in predicting non default loans than neural network (65.34% vs. 62.70%). However, neural network performed much better than logistic regression in classifying default loans (74.38% vs. 61.03%).The results indicate that neural network is more powerful and accurate than logistic regression in screening default loans.

The credit scoring model presented in this study can be effectively used by P2P lenders to screen the loan applications. Lenders can supply the selected features of borrowers to the model for predicting the default probability of borrowers. Hence, based on the output provided by the model, lenders can select the potential loan applications to invest in. Lenders can avoid investing in loan applications that have default as the model output, as they have a higher probability of defaulting. However, if lenders are risk takers and would like to invest in loans classified as default, they can charge a high interest rate from borrowers, considering the risk associated with it being default.

TABLE IV. Comparison between neural network and logistic regression with test data

	Actual	**Predicted**		
		Non Default	***Default***	***% Correct***
Neural Network	***Non Default***	2517	1497	62.70
	Default	188	546	74.38
Logistic Regression	***Non default***	2623	1391	65.34
	Default	286	448	61.03

VII. CONCLUSION

The neural network credit scoring model has shown a promising result in classifying credit applications in P2P lending, allowing the lenders to make a smart decision in selecting a loan application. Furthermore, the comparison of the model with logistic regression model shows that neural network performs more accurately in screening default loans. Hence, identifying default loans in advance allows the lenders to reduce their financial loss by avoiding investing in bad applicants.

The current paper provides an insight in applying neural networks to screen loan applications in P2P lending. The results suggest that neural network is effective in screening the bad applications. However, the study considers only one P2P lending case. Thus, in future research the similarities and differences in the results from other P2P lending cases, operating in different financial environment will be analyzed.

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