Predicting Credit Risk Levels in Online Peer to Peer Lending Using Neural Network

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ABSTRACT

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Peer to peer lending is growing rapidly, providing an alternative to traditional banking. The purpose of the thesis is to study the credit risk in peer to peer lending. The thesis attempts to predict the credit risk of borrowers to support lenders in selecting profitable borrowers. The data for the research is collected from a European peer to peer lending company, Bondora.

Data mining techniques are used for the research process. Artificial neural network is applied in the study to study the borrowers' behaviour from the historical loan data for predicting default probability of borrowers. A feed forward back propagation neural network is employed for constructing a credit score model. The model classifies the borrowers into predefined groups of default or non default, providing lenders helpful information on selecting loan applications. Furthermore, the model identifies the variables that have higher influence on determining the default probability of borrowers.

Neural network was more effective in constructing the credit score model compared to logistic regression. The results of the study were successful in providing practical guidance to lenders in selecting a new investment.

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1 INTRODUCTION

Credit loans have always been an imperative part of financial industry and investors are constantly probing for better measures of minimizing the credit risk. Credit risk has been a widely studied topic in banking for years and has been the most important and difficult risk to manage and evaluate (Pacelli & Azzollini, 2011). With the advancement in information technology, an increasing amount of research is being conducted with the intention of developing sophisticated techniques for credit risk management. The continuous growth in scale and complexity of financial institutions along with the large volume of their transactions has generated the need for employing sophisticated risk management techniques (Angelini, et al., 2008). Ghatge and Halkarnikar (2013) view credit risk evaluation decisions as vital to avoid huge amounts of losses by taking inappropriate credit decisions.

The advent of web 2.0 has made it easy to create online markets and online peer- to-peer lending (henceforth P2P) is one of the growing web 2.0 applications. P2P lending is a platform or a marketplace where lenders and borrowers can meet virtually to conduct a loan transaction (Emekter et al., 2015). P2P lending has added new dynamics to the microfinance industry but is equally exposed to credit risk as other microfinance markets. P2P lending markets are gaining popularity among small scale borrowers, such as individuals and small firms. Small scale borrowers are particularly attracted to P2P lending due to the uncollateralized nature of lending (Iyer et al., 2009). Everett (2010) points out that the growth of P2P lending within the broader business and finance communities has been boosted by the benefits offered to borrowers and lenders due to lack of financial intermediaries.

Since the start of P2P lending in year 2005, consumers, entrepreneurs and small businesses worldwide have borrowed billions of dollars from individual investors through P2P platforms, challenging the traditional banks and financial institutions. The financial crisis in 2008 has moderately helped P2P lending to take a "quasi- explosive" growth (Gonzalez & Loureiro, 2014). P2P lending has been growing at a rapid pace of 84% in average annually since the second quarter of 2007. The number of investors in the P2P market has been increasing and the lenders have extended from individuals to

institutional investors, such as community banks (Samaad, 2014). In the UK, the P2P lending market in 2014 has grown to more than $2.1 billion, which is double the amount in 2013 (Reuters, 2015).

Luo et al. (2011) consider P2P as a novel economic lending model which has also introduced new challenges in making effective investment decisions. Wang and Greiner (2011) identify the fundamental problem of lending money over P2P lending as receiving the investment back, since the loans offered are unsecured. Furthermore, lenders are exposed to higher risk and, therefore, their involvement in processing loan description and borrower's information is extensive with high motivation (Larrimore et al., 2011). According to Renaud Laplanche, cofounder and CEO of Lending Club, only 10% of borrowers with the best credit history are accepted, while the remaining 90% are rejected (Forbes, 2012). Hence, the data revealed by Laplanche proves the necessity of selecting creditworthy borrowers due to the high risk of a loan being default in P2P lending.

According to Klafft (2008), most lenders in P2P are not skilled in evaluating investment risks and thus face difficulty in judging the quality of a loan application. Similarly, Lee and Lee (2012) mention that lenders in the P2P market are not professional investors and they are prone to higher risk due to the uncollateralized nature of lending. Mild et al. (2014) stress on the necessity of assessing borrowers' creditworthiness due to P2P loans not being secured by collateral.

It is clear that P2P lending is successfully imposing its popularity among small enterprises and individuals as an alternative to traditional banking credit systems. However, the presence of high risks in P2P, especially to investors as mentioned by many studies, cannot be neglected. Therefore, analyzing the risks and screening profitable customers is essential to safeguard investors' investment in P2P lending. In addition, Bekhet and Eletter (2014) point out that accepting bad applications and providing loans to customers with high default probability increases the likelihood of financial suffering and business failure.

The exponential growth of the P2P market has made P2P lending an attractive investment choice for investors. However, lack of clear and rigid rules and regulations in the industry leads to uncertainty regarding the return on investments. In addition, the uncollateralized loans and unfamiliar borrowers add risks for investors. Hence,

accurately assessing loan applications is a key to securing the investments. Most of the literature on P2P lending focuses on studying borrowers' characteristics and behavior. However, there are only a few studies with the focus on investors and guiding them for safe investments. In addition, Puro et al. (2011) mention that online auctions offer an excellent source of data for empirical research to study many interesting research questions that can benefit the academic community.

1.1 Peer-to-Peer platforms and markets

Zopa was the first P2P platform which launched the peer-to-peer lending concept during pre-financial crisis period in 2005. The concept in the beginning was intended for niche market, but the financial crisis resulted in a dramatic growth of P2P lending (Prosser, 2014). Peer-to-peer lending has been expanding in many countries with an exponential growth rate. P2P loan volumes in Britain are doubling every six months. The two largest P2P lenders in America, Prosper and Lending Club, occupy 98% of the market (*The Economist*, 2014). The Peer-to-Peer Finance Association reported that the size of the P2P market has doubled since the end of 2013 and there has been an exceeding growth in the number of lenders and borrowers in the market (Out-law.com, 2015).

The rapid growth of the P2P market has been successful in attracting venture capitalists and institutional investors to invest huge amounts in the industry. The loan volume in the P2P markets is increasing rapidly. There are over 200 companies globally which provide an online marketplace for consumer credit. The growth is at an extreme level in the leading P2P lending markets: the US, the UK and China. The growth rate of the two leading P2P lenders in the US, Lending Club and Prosper is close to 200% a year. With the current growth of the market, the P2P lending industry is estimated to reach a value of $1 trillion globally by 2025 (Ward, 2014).

The market size of P2P lending in the UK has crossed the mark of 2.1 billion pounds, where the lenders in 2014 invested 1.24 billion pounds in the industry (Scuffham & Winterbottom, 2015). It is estimated that the market size of P2P lending will be worth 5 billion pounds in the UK, 20 billion pounds in the US and 40 billion pounds globally.

Although the industry is booming quickly, there are P2P platforms that have failed (PR Newswire, 2015).

According to Renton (2014), the P2P lending market is flourishing all over Europe while the UK is dominating the market. The success of the P2P lending market in the UK has made it a popular alternative source of financing in Europe leading to a dynamic P2P lending industry in Europe. Several P2P platforms exist across the European countries. Some of the big and important platforms in Europe, as listed by Lendit, are shown in Table 1.

Company	**Founded**	**Country**	**Total Loans Funded(in £)**	**Types of Loan**
Assetz Capital	2012	UK	50 million	Small business and property
Auxmoney	2007	Germany	125million	Consumer
Bondora	2009	Estonia	27,5 million	Consumer
Funding Circle	2010	UK	419 million	Small business and property
Lendico	2013	Germany		Consumer
LendInvest	2013	UK	166 million	Property
MarketInvoice	2011	UK	284 million	Invoicing financing
Pret d union	2009	France	116 million	Consumer
Ratesetter	2010	UK	394 million	Consumer
Trustbuddy	2009	Sweden		Consumer
Wellesly & Co	2013	UK	109 million	Small business and property
Zopa	2005	UK	665 million	Consumer

Table 1: The 12 Most Important European P2P companies (Lendit, 2014)

In Table 1, it can clearly be seen that the UK is the biggest market for P2P lending in Europe. Table 1 also shows that P2P loans are not only limited to individual customers, but are diversified to other areas, such as small businesses and property and invoicing. Most of the P2P companies have a very short history of less than five years but have shown a big growth in terms of the amount of loans funded.

Besides Europe, USA has been growing as a leading market in P2P lending. Similarly, the growth is seen in other countries, as well, and it is expected to increase more. Table 2 illustrates the growth of some of the popular P2P platforms globally.

Company	Country	New loans (millions Euro)	vs previous month	vs last years month
Albrate	The UK	0,0	-100%	not available
Assetz Capital	The UK	0,0	0%	-100%
Auxmoney	Germany	10,7	13%	269%
Bondora	Estonia	2,0	5 %	52%
Communitae	Spain	1,1	11 %	352%
Estateguru	Estonia	0,1	Not available	Not available
Finansowo	Poland	0,1	0 %	Not available
Fixura	Finland	0,9	10%	-49%
Folk2Folk	The UK	3,1	50%	14%
FundingCircle	The UK	42,5	-6 %	124%
FundinKnight	The UK	1,5	311%	37%
FundingSecure	The UK	Not available	Not avilable	Not available
Geldvoorelkaar	Netherlands	3,2	-1%	58%
Kokos	Poland	0,3	-7 %	Not available
Lending Club	USA	Not available	Not available	Not available
Lending Works	The Uk	1,0	-21%	Not avialble
Loanbook Capit	Spain	0,1	-61%	Not available
MYC4	Denmark	0,2	0%	-26%
Pret d'Union	France	9,2	12%	127%
Prosper	USA	169,4	30%	242%
Ratesetter	The UK	41,2	19%	194%
Rebuilding Soc.	The UK	0,5	121%	50%
Saving Stream	The UK	3,8	182%	Not available
Smava	Germany	0,9	13%	50%
ThinCats	The UK	4,9	3%	-25%
Unilend	France	0,6	-45%	245%
Wellesley	The UK	27,7	-3%	Not available
Zencap	Germany	1,1	10%	Not available
Zopa	The UK	28,3	-8%	69%

Table 2: P2P Lending volumes in December 2014 (P2P Banking 2014)

Table 2 clearly shows that the US and the UK are leading markets in P2P lending and the market in Europe is comparatively smaller than in the US. In addition, it is clearly visible that the market is very volatile. Most of the platforms are growing while for some, there is decline in the market value and the reason could be the growing competition.

1.2 Research Objectives and Research Questions

This study attempts to build a credit risk model based on soft computing techniques to guide the investors in P2P lending for profitable investments. Ghatge and Halkarniakar (2013) state that an intelligent information system based on artificial intelligence can assist lenders in reducing the uncertainty related to the investment return. The thesis applies the latest studies using data mining techniques to evaluate credit risk to support investors in taking credit decisions. Data mining in general is a process of extracting meaningful value from a database. Data mining is most commonly used in classifying data into groups through pattern recognition (Singh & Chauhan, 2009). Sophisticated data analysis tools are employed in the data mining process to discover valuable hidden knowledge and compelling patterns and relationships from a large dataset (Gaur, 2013).

The objective of the thesis is to conduct an empirical study on the borrowers' behavior in P2P market in order to guide investors in making correct investment decisions. The thesis attempts to study the credit risk of Bondora, a leading P2P platform in Europe, and propose a solution for credit risk management from the investor's perspective. Artificial neural network has been employed as a data mining method to study the borrowers' behavior from the available dataset and derive a solution to predict borrowers' creditworthiness.

Furthermore, the thesis focuses on applying a credit scoring approach to support investors in decision making by classifying borrowers as good or bad customers. Good and bad customers are identified with relation to the probability of being default. Keramati and Yousefi (2011) recognize credit scoring as a statistical model that has been extensively applied for predicting default risk of individuals or companies. The study aims to employ neural networks for credit scoring to evaluate the credit risk in P2P lending and propose a credit risk model to minimize the future credit risk of the investors. Artificial neural networks are biologically-inspired methodologies that offer capabilities for classification, prediction and pattern recognition and have been successfully applied in different fields (Stahl & Jordanov, 2012).

The study aims at developing a credit scoring model for predicting default probability of future credit loans in assisting investors to select profitable investments. Several modeling approaches have been applied in the past years for constructing credit scoring

models. The most commonly used methods are logistic regression, classification trees, linear programming approaches and neural networks (Rezac & Rezac, 2011). The thesis illustrates the use of neural networks to construct a credit scoring model to assess the credit risk of borrowers. The aim of this thesis is to train and implement neural networks to tackle the problem of default by classifying the customers into good and bad customer groups. In addition, the study intends to identify the importance of the individual attributes in the classification process. In relation to the thesis objectives, the thesis attempts to answer the following research questions:

1. How can risk levels of future credit loans be predicted by using neural networks?

i. Which customers belong to good and bad customer groups?

ii. What are the borrowers' characteristics that have an impact on identifying the default risk?

By discovering the answers to the research questions the study aims at successfully guiding the investors for future investments in P2P lending. The study aims at supporting the investors in screening the loan applications made by the borrowers to identify creditworthy loans. Furthermore, the study intends to assist the investors to identify the profitable and non-profitable loans by classifying the borrowers into good and bad customer groups based on the historical loan data available. In addition, the research intends to make investors familiar with the characteristics of borrowers that have significant consequences for the default probability of loans.

The rest of the text in the thesis is arranged as follows. The second chapter is the presentation of P2P lending that includes its concept, process, benefits and challenges. The chapter concludes with the introduction to the case company Bondora. Chapter 3 is the literature review that contains all the necessary theoretical knowledge to support the research process. It also includes the previous related studies that support the suitability of the study. In chapter 4, the research methods and the research process are described. In addition, the chapter includes the description of the data used in the research and the data preparation process.

After describing the research methods and data in chapter 4, the model development process is explained in chapter 5. Chapter 6 presents the results obtained from the

developed model. The results are analyzed and some practical suggestions are included in the chapter. Finally, the thesis is concluded with the chapter that summarizes the entire study process and indicates limitations of the study and suggestions for future research.

2 PEER TO PEER LENDING

Peer-to-peer lending, also called online social lending is a form of micro-financing that allows individuals to lend or borrow directly from each other, without financial intermediaries, through an internet based platform (Luo et al., 2011). P2P lending came into existence in 2005 after the success and the ability of online markets to bring buyers and sellers together and since then it has been experiencing a significant growth (Lin et al., 2013).

The internet has enabled the existence of P2P lending as an alternative to traditional banking credit business, bringing together non-institutional borrowers and lenders (Mild et al., 2014). The market of P2P lending is currently hundreds of times smaller compared to the traditional finance and credit markets, but the growth has been enormous and is expected to increase in the future. In addition, individual investors and borrowers being the original focus of the business, institutional investors, such as community banks have also been attracted to P2P lending (Demyanyk & Kolliner, 2014).

According to Klafft (2008), P2P lending is similar to an auction process, where borrowers place requests for loans and lenders bid to fund the loans through an online platform. Chen et al. (2014) perceive P2P lending as an essential financial system for small and micro enterprises. Although P2P lending appears to be similar to crowd funding and microfinance, P2P lending differs from crowd funding and microfinance fundamentally in execution and purpose. P2P loans are more often used as a complementary to credit cards than bank debts (Gonzalez & Loureiro, 2014).

Everett (2010) mentions that most online borrowers make use of the loan for the purpose of small business, and for the simple reason that they have easier access and reasonable rates than bank loans. P2P lending eliminates the presence of traditional financial intermediaries and, hence, allows lenders to select borrowers for financing directly (Wang & Greiner, 2011). Larrimore et al. (2011) observe P2P lending as a single interaction between borrowers and lenders, which involves risks for both of the parties and the decision for funding a loan is almost entirely determined by the borrower's profile and request.

Most of the P2P loans have a life period of three years and do not include prepayment penalty. Borrowers may request a loan amounting up to $25,000. Usually, borrowers in P2P lending borrow from multiple lenders and the lenders have their investments spread among hundreds of borrowers (Verstein, 2011). Unlike the traditional auction, the duration in P2P lending is usually several days and this higher auction duration provides lenders the opportunity to review more auctions without rush. In addition, the longer auction duration helps in receiving more bidders (Puro et al., 2010).

2.1 Peer-to-Peer Lending Process

The P2P lending process begins with borrowers creating a listing that includes the amount of loan requested, the maximum rate they are willing to pay and their personal data. Borrowers, when making a loan request are required to describe the purpose of their loan and their financial condition, which determines the interest rate on the loan. P2P lending offers borrowers an opportunity to obtain a loan without the involvement of financial institutions in the decision process and the likelihood of better conditions than in traditional banking systems (Bachmann et al., 2011).

Individuals and companies can present their planned projects in P2P platforms for financing from private investors and the credit amount ranges from small to medium, with a payback period of less than three years (Mild et al., 2014). In most of the P2P lending platforms, borrowers have the choice to either select a closed or an open auction format when making a loan request. In the closed auction format, the bid is closed immediately after the amount requested is funded, while in the open format lenders can continue to bid even after the amount requested has been fully funded (Zhang et al., 2014).

P2P borrowers are scanned twice before the final decision is made on their loan application, first by the platform and then by the lenders. The platforms initially determine the borrowers that can apply for a loan by performing underwriting activities, such as evaluating credit history and the ability to repay the loan. The selected borrowers are then assigned to a credit class by the platforms based on the available credit and employment information. The platforms also determine the possible losses

from the loan being default for each credit class. Lenders now can select from the potential borrowers individually or they can invest in the list of loans selected by the platform based on the lenders' expressed criteria (Verstein, 2011).

Lenders in P2P lending have to make their decision based on the information provided by borrowers, and select the loan to fund and the amount to invest in it. Lenders choose to bid on the loan listings made by borrowers and the winners get the opportunity to fund the loan for the interest rate determined by the auction (Puro et al., 2010). Mild et al. (2014) perceive that lenders are fascinated by the high return advertised by P2P lending due to the absence of banking intermediaries.

According to Puro et al. (2010), lenders behave differently and use different bidding strategies in funding a loan. Lee and Lee (2012) mention that last minute bidding is often seen in P2P lending and investors are attracted at the last moment when the loan becomes fully funded. The lenders are usually influenced by other investors' decision when bidding for a loan and are attracted to a loan offer that already has many bidders. Some P2P platforms, such as Prosper.com encourage its borrowers and lenders to develop a social network by creating online groups and friendship with other members. The group leaders then can endorse specific listings and highlight certain listings to the group members and friends (Freedman & Jin, 2008).

Lee and Lee (2012) mention that P2P lenders tend to show a herding behavior due to the fear of selecting an unfavorable bid because they lack the institutional knowledge and have to face unknown borrowers over the internet. Herzenstein et al. (2010) explain that the herding behavior reduces lenders' search and opportunity cost, since herding increases the probability of a loan being fully funded and one of the bidders will be the winning one.

To summarize, P2P lending generally differs from the traditional banking in terms of purpose and operation. P2P lending operates online, without physical location, while traditional banking operates from a physical site. P2P loans are more often used as a complementary to credit cards, whereas bank loans are used for multiple purposes. P2P loans are short term loans, whereas banking loans can be both short term or long terms. There are no financial intermediaries in P2P lending, but traditional banking goes through financial intermediaries for loan approval. The loan processing time is quicker in P2P lending compared to traditional banking. P2P lending does not require any

collateral and are unsecured, whereas traditional banking requires collateral and are secured. Information asymmetry exists in P2P lending, but in traditional banking there is no (or very low) information asymmetry.

2.2 Benefits and Challenges of Peer to Peer Lending

P2P lending is favorable for individuals with short credit history for improving their access to credit. Furthermore, P2P lending allows consumers access to credit at a lower rate than the traditional lending models (Demyanyk & Kolliner, 2014). According to Malekipirbazari and Aksakalli (2015), P2P lending provides a high possibility of mutual benefits to borrowers and lenders. Borrowers can receive loans at a lower interest rate and lenders have the possibility to lend money at better interest rates that the rate they would get from banks.

P2P lending saves the transaction cost and provides an alternative to borrowers and lenders for financing and investing. Verstein (2011) states that P2P lending reduces the cost of providing the credit by unbundling unnecessary or unwanted services that are coupled with traditional intermediaries. Absence of a physical location in P2P lending eliminates the cost of hiring a teller and other overhead costs related to maintaining a physical location. Furthermore, since P2P lending is operated through the Internet, it allows quick connections of individuals and communities for the purpose of borrowing and lending (Malekipirbazari & Aksakalli, 2015).

The information asymmetry in P2P lending is a big challenge that creates the possibility of misrepresentation of borrowers (Yum et al., 2012). *The Economist* (2014) reports that lack of a clear regulation could be a significant issue for the investors. Furthermore, the unsecured and uninsured nature of P2P loans increases the risk for lenders. In addition, the growth in cross-border P2P lending is less addressed by domestic rules and hence creates tricky legal issues. Furthermore, with P2P lending being in its early stage, the trust in this type of e-commerce is still low among people (Zhang et al., 2014).

2.3 Bondora

Bondora, established in 2009, is the leading investment platform for investing in European personal loans. Since its establishment, Bondora has successfully attracted more than 7000 investors from 36 countries. Its investors range from individual investors investing a few thousand euros to sophisticated investors investing hundreds of thousands of euros. The interested investors must be above 18 years of age and a residence of the European Union or Switzerland or have businesses registered in the EU.

All the borrowers in Bondora are risk-assessed and are assigned a credit group that carries an interest rate appropriate to its risks. Bondora applies rigorous credit criteria for approving loan applications to secure the most creditworthy borrowers. Borrowers' financial and credit information are scanned through various data sources, including credit bureaus and pay slips. Furthermore, after borrowers are approved for a loan, they are required to verify their bank account details, mobile number, email address, postal address, personal details and ID document details. The majority of borrowers applying for loans in Bondora use the received amount for the settlement of high interest loans, such as credit card debts.

After successfully undergoing the credit analysis process, all the eligible borrowers are offered suitable credit loans based on the rating. Borrowers then can choose from the offered lists after which Bondora's portfolio managers try to fund the loan on behalf of the investors, according to matching criteria of the loan. If the is not fully funded by the portfolio managers, it is sent to the market for investors to make manual bids. Investors can invest in the loan until it is fully funded or cancelled or the bidding time is closed.

Bondora does not apply any hidden fees and charges to its customers. A small and transparent fee is charged to the borrowers on their application being funded as well as a fixed monthly account fee which is added to the interest to be paid to the investors. Investors are not charged any fee, but a small fee is charged for investing in already issued loans on the platform.

Similarly to all investments, Bondora also carries some amount of risks, such as operational risk, credit risk or borrower's failure to pay back the loan and currency risk.

To safeguard the investor's investment from a borrower's failure to pay back the loan, Bondora has developed a standardized largely automated collection process. The process, in the situation of a delay of payment from borrowers, sends reminders to the borrowers through emails, text messages, and letters by post. The borrowers are also notified for the possibility of legal actions and possible charges. In the extreme case, the borrowers are published to the local credit bureau and a court case is filed in a local court.

Figure 1 illustrates the current statistics of Bondora, as of 20th February, 2015. Figure 1 describes the general statistics of Bondora.

CUSTOMERS	178,602	APPROVED LOANS	70,341,815.01€
INVESTORS	9,200	LOAN ISSUED	34,665,600.79€
BORROWERS	146,683	INVESTMENT BIDS MADE	43,415,403.32€
NUMBER OF LOAN APPLICATIONS	28,693	INVESTMENTS	1,662,996€
NUMBER OF LOANS ISSUED	15,981	AVERAGE INVESTMENT	26.11€
		AVERAGE LOAN APPLICATION	2,451.53€
		AVERAGE LOAN	2,169.18€

Figure 1: General statistics of Bondora (Bondora.fi, 2015)

The general statistics of Bondora shows that out of its total customers, more than 80% are borrowers, while the number of investors is only around 5%. The low number of investors compared to borrowers gives an idea of investors' unwillingness to invest due to lack of knowledge and the risk associated with the business. The difference between the approved loans and the investments made also justifies the idea of investors' unwillingness to invest. Furthermore, only around half, nearly 55% of the applied loans are funded by the investors.

The borrowers in Bondora apply for a loan for several purposes, such as loan consolidation, property, business, redecorating, travel and transportation. Figure 2 describes the details of the purpose of borrowers in Bondora.

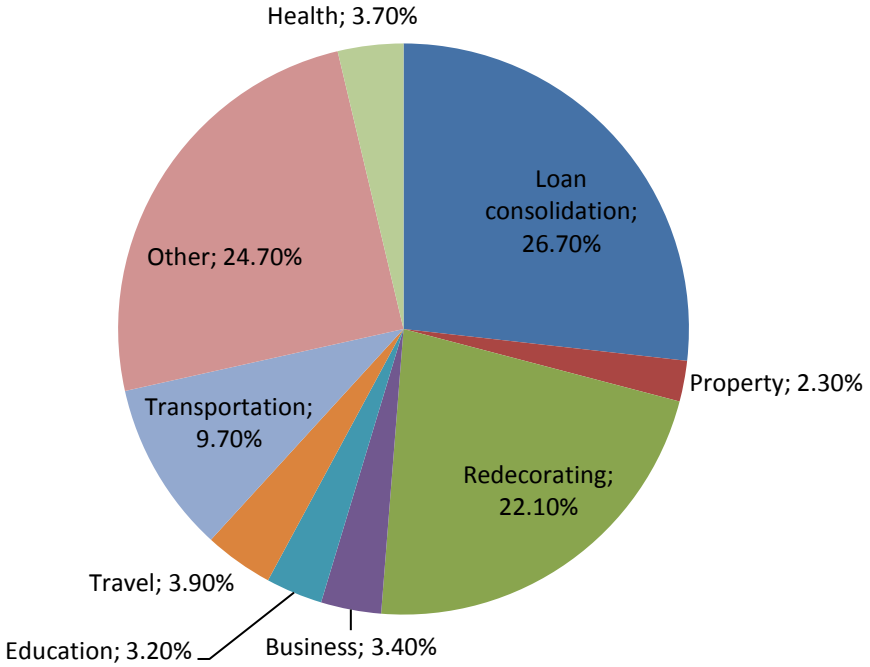

Figure 2: Loan Distribution in Bondora (Bondora.fi)

Loan consolidation, as clearly seen in Figure 2, is the main purpose of applying for loans in Bondora. Most borrowers plan to repay their credit cards debts and other loans. Following loan consolidation, redecorating is another area for which most of the borrowers apply for a loan. Loans applied for transportation, travel, education, business and health are comparatively low. Furthermore, 24.7% of the loan application are made for other purposes, such as working capital financing, purchase of machinery equipments, acquisition of stocks, and other business.

Bondora has been sucessfully attracting a high number of customers in the recent years and the amount of loans issued is also increasing with a good growth rate. Figure 3 gives a detailed veiw of the growth of customers and loans issued by Bondora from the start to the current period.

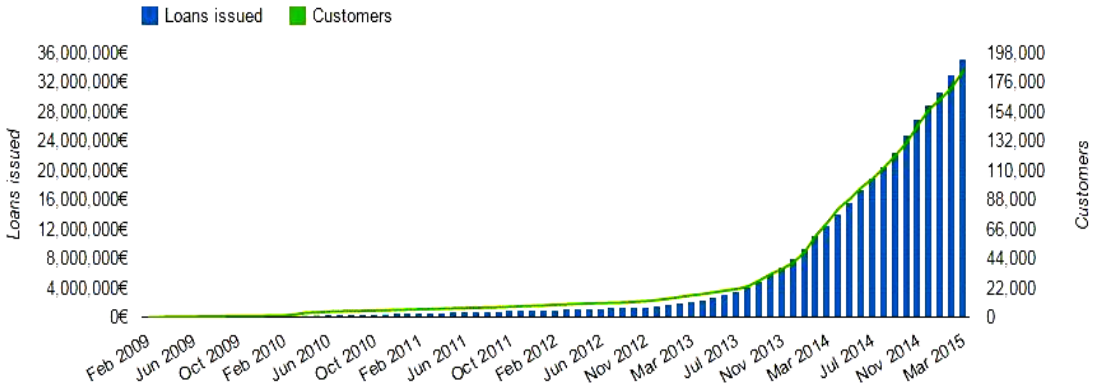

Figure 3: Loan volume and number of users (Bondora.fi, 2015)

In Figure 3, it can be seen clearly that the growth of the number of customers and loans issued are in proportion to each other. There was a steady and low growth in number of customers and loans issued in the beginning, until 2013. The growth rate has accelerated from 2013 and as a result the increase in customers and loans issued have been drastic.

3 LITERATURE REVIEW

This chapter is a detailed presentation of theories and ideas on the topics selected for the study. Different views of multiple researchers are presented to support the selection of the topics in the study. Furthermore, the chapter includes a brief description of previous studies relevant for the study topics.

3.1 Previous Studies in Peer to Peer Lending

In this section, previous studies that have been conducted in the context of the P2P lending markets are presented. In addition, the selection of the studies presented in this section is based on the thesis's objective of supporting the decision process from the lenders' perspective. The section covers observations and findings of several researchers on P2P lenders that contribute to constructive ideas for the research.

Mild et al. (2014) demonstrate that investors fail to make accurate investment decisions in P2P lending due to the absence of hard and quantifiable banking data. Hence, they developed a decision support tool using linear regression for investors to correctly predict the default risk. Through a posteriori experiment, they demonstrate that the decision support tool improves the decision quality and, hence, converts investors' losses into profits.

Lee and Lee (2012) studied the herding behavior of lenders from the largest P2P platform in Korea through an empirical study and discovered strong evidence of herding behavior in P2P lenders, i.e. lenders tend to bid for the loans that have more bids. However, they discovered that the herding behavior has a diminishing marginal effect, as the bidding advances. Similar to Lee and Lee (2012), Herzenstein et al. (2010) agree on the presence of the herding behavior in P2P lending and its diminishing effect, as the bidding progresses. They further state that strategic herding behavior benefits both lenders and borrowers. Their study further reveals that the herding behavior is beneficial to lenders, in the long run.

Zhang et al. (2014) developed a trust model to recognize the factors influencing the trust building process of an individual lender in P2P lending in China. Their results established that trust in borrowers positively effects lenders' willingness to invest, but trust in the lending intermediary platform has no effect on lenders' willingness to invest. However, Chen et al. (2014), in a similar study of developing a trust model, demonstrate that trust in both borrowers and intermediaries has a significant effect on lenders' intention to invest, but trust in borrowers is more crucial.

In their study of the bidding behavior of lenders on Prosper.com, Puro et al. (2011) revealed that lenders use heterogeneous bidding strategies. However, their findings highlight three main strategies most commonly used, the most widely used being the evaluator strategy followed by late biding and multi-bidding. In the evaluator bidding strategy, bidders make an early bid with a rate well below the current rate. The bidders using the late bidding strategy only make a bid when the auction is nearly closed because they do not want their information on their valuations to be disclosed to other bidders, until the last minute. The multi-bidding strategy followers use a blend of other strategies, where they make early bidding to signal other bidders, but they still make bids at the last moment.

Iyer et al. (2009) studied the P2P market of Prosper.com to evaluate lenders' ability to use borrowers' information to infer creditworthiness. The results show that lenders are partly able to use the rich information provided in P2P lending for deducing borrowers' creditworthiness. In addition, lenders mostly rely on borrowers' credit score and standard banking variables to determine the creditworthiness of borrowers, but non-banking variables or soft sources of information are also considered during the screening process. The results further show the greater lender inference from credible information and, hence, suggest that the modification of information to credible signals can improve screening from subjective information.

In his study of the P2P platform Prosper.com, Klafft (2008) discusses that return on investment has not been satisfactory to lenders. In his paper, he demonstrates that investors can increase their profitability with careful selection of borrowers with respect to easy to observe selection criteria. He then proposes three simple rules for lenders to apply when investing in P2P lending; his findings prove that following the rules could increase lenders' profitability. The rules proposed by Klafft are:

- *Rule 1: Only invest in borrowers which do not have any delinquent accounts.*
- *Rule 2: Only invest in borrowers which do not have any delinquent accounts AND a debt to income ratio below 20%.*
- *Rule 3: Only invest in borrowers which do not have any delinquent accounts AND a debt to income ratio below 20% AND where no credit inquiries have been reported during the last 6 months.*

The above mentioned previous studies have shown that investors in P2P lending are prone to high risk and, hence, more studies are necessary to guide the investors in selecting the low risk investments. Researchers have studied the lending behavior of investors from different aspects to assist them in estimating the credit risk. The studies further justify the need for sophisticated information systems to accurately study P2P borrowers' behavior for determining their creditworthiness.

3.2 Previous studies on applying neural networks in building a credit score

This section of the thesis presents the previous studies conducted in developing credit score using neural networks. The studies listed in this section are in relation to the objective of the thesis to create a credit risk model to identify good and bad customers.

West (2000), in his study investigated the credit scoring accuracy of five neural networks and compared the results with the traditional linear methods. He shows that neural network credit scoring models can outperform linear models in obtaining credit scoring accuracy by fractional improvement. However, he mentions that neural network credit scoring models require modeling skills to build topologies and develop superior training methods.

The study conducted by Malhotra and Malhotra (2003) compare neural networks with multiple discriminant analysis to identify potential loans. They cross-validated their results across seven different data samples. The results clearly indicate the robustness and supremacy of neural networks over multiple discriminant analysis, in identifying potential loan defaulters.

Angelini et al. (2007), in their work describe the case of successful application of neural networks in credit risk evaluation. They developed two neural network systems, one based on classical feed forward architecture and another with special purpose architecture, to estimate the default tendency of borrowers. Real data from Italian small business has been used to train the system. The results from both systems prove the effectiveness of neural networks in correctly classifying inputs with low error rate.

Khashman (2009) presented in his study a credit risk evaluation system using neural network model based on the back propagation learning algorithm. Using real world cases from an Australian credit approval database, he trained the neural network to either accept or reject a credit application. The experimental outcome from the study suggested that neural networks demonstrate effective results in automatic processing of credit applications. The study further compared the performance of single hidden layer neural network and double hidden layer neural network and the results show that single hidden layer neural network yields higher correct evaluations rate and reduced time cost.

The study conducted by Blanco et al. (2013) also reveals the supremacy of neural networks for credit scoring. The study used a database of 5500 borrowers from a Peruvian microfinance institution to build a credit scoring model based on the multilayer perceptron approach. In addition, the study also benchmarked the performance of the neural network credit scoring model against the traditional methods: linear discriminant analysis, quadratic discriminant analysis and logistic regression. The results of the study indicate that neural network credit scoring is suitable for microfinance institutions and it provides a higher accuracy in performance and a lower misclassification cost compared to the traditional methods.

Bekhet and Eletter (2014) have studied the use of neural networks for developing a credit score model to support the credit decisions for the Jordan commercial banks. Their results indicate that neural networks perform better than logistic regression in screening rejected applicants, which helps in identifying potential defaulters.

3.3 Neural Networks

Neural networks are considered to be one of the most efficient algorithms used for data mining because of the capability of resistance to strong noise, self learning, flexibility and usability (He & Liu, 2009). Wang and Sui (2007) claim that neural networks possess significant ability to detect meaningful knowledge from complex data to generate trends that are beyond the capability of humans or other computer techniques. Khashman (2011) points out that neural networks are considered to be accurate tools among the other existing tools in analyzing the credit risk in the credit industry.

An artificial neural network, generally termed just neural network is a mathematical or computational model (Singh & Chauhan, 2009). Artificial neural networks emulate biological nervous systems and brain structure and are computational modeling tools. Artificial neural networks can generally be viewed as information processing systems that use learning and generalization capabilities (Bahrammirzaee, 2010). According to Ince and Aktan (2009), a neural network is an algorithmic procedure that converts inputs into desired outputs using highly interconnected networks. Malhotra and Malhotra (2003) state that neural networks are non-linear models that use pattern recognition capabilities for classification. They further add that neural networks have been highlighted in multiple studies for the purpose of financial analysis, such as detecting fraudulent activities, credit evaluation and improving forecasting. A neural network can be used in modeling a complex relationship between inputs and outputs in discovering patterns from a data (Gaur, 2013).

Similar to biological nervous systems, a neural network is composed of neurons or nodes, which are the processing elements that process inputs and deliver a single output. Therefore, a neural network is a collection of neurons that are divided into three types of layers, the input layer, the hidden layer(s), and the output layer (Malhotra & Malhotra, 2003). According to Singh and Chauhan (2009), artificial neurons in neural networks are interconnected and a connectionist approach to computation is used for information processing.

A neural network is fundamentally comprised of three parts, the architecture or model, the learning algorithm and the activation functions (Gaur, 2013). A neural network is made up of nodes, the network topology that describes the connection between the

nodes and the training algorithm that determines the values of network weights for a particular network. The nodes in the network are interconnected and output from one node is transferred to another as an input, where a transfer function exists for nodes to transform input to an output (Ince & Aktan, 2009). According to Nazari et al. (2013), a hidden layer consists of two processes: the weighted summation function and the transformation function. The two functions transmit the values from the input layer to the output layer. First, in each neuron a weighted sum is calculated and then the transformation function is applied to the weighted sum that determines the output value of the neuron (West, 2000).

The following diagram in Figure 4 shows a simplified neural network.

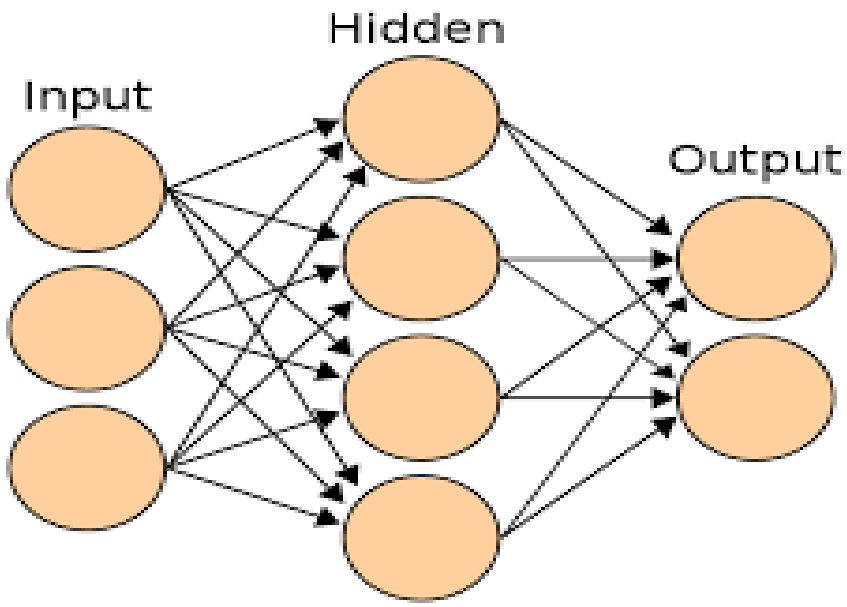

Figure 4: A simplified Neural Network

The input layer is provided with the data from the outer world, which then is weighted and proceeds further through the connections. The hidden layer takes the inputs from the input layer and distributes values to each neuron in it. The number of hidden layers and hidden neurons in a model can vary according to the complexity of the problem and the accuracy required, whereas the number of neurons in input and output layers depends on the input and output units. The number of neurons in the input layer is equivalent to the number of variables used in the dataset. A neural network is trained with a set of known input-output data, processed by a suitable learning method to

perform the model building. During the process, the values of weight coefficients between the processing neurons are adjusted and the training process continues until the model output matches (or sufficiently close to) the desired output (Mohanraj et al., 2015; Stahl & Jordanov, 2012; West, 2000). Most neural networks have the ability to change the structure in accordance to internal and external information that is supplied to the network during the learning phase (Singh & Chauhan, 2009).

A neural network learning process is generally composed of training, validation and testing phases. The dataset is divided into two subsets, training subset and test subset for the purpose of training and testing the model. The training subset data is used in the training phase, where the weights of the neural network are adjusted. Then the test subset data is used to examine how correctly the neural network has learned and the ability of the trained network to generalize, i.e. to correctly classify, fit, map and recognize inputs that were not used in the training process. The training of a neural network can either be supervised or unsupervised. In the supervised learning, both input and outputs are known beforehand and, hence, the output from the network is compared to the desired outcome to adjust the weights, whereas in the unsupervised learning only the inputs are known and the weights are adjusted by the network itself to match the inputs to the outcome (Stahl & Jordanov, 2012; Khashman, 2009). A common neural network process is summarized in Figure 5.

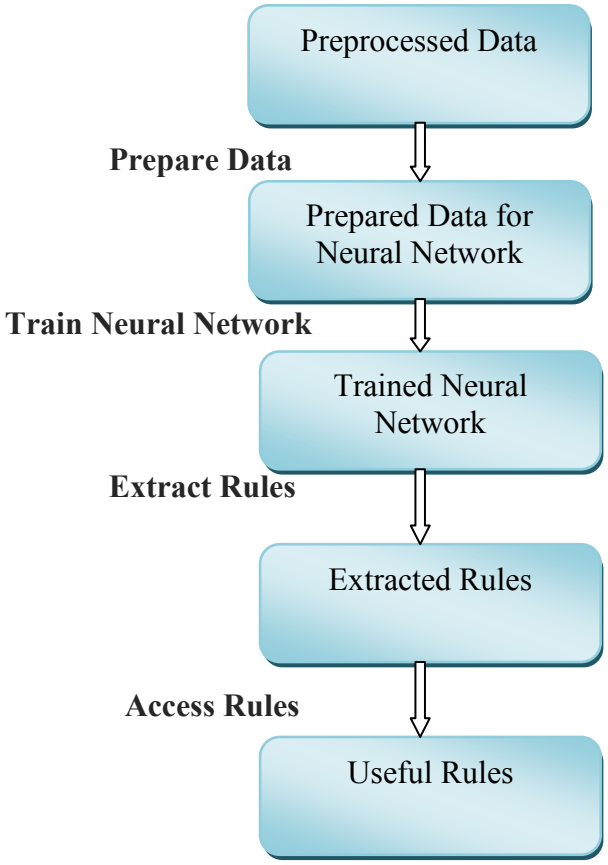

Figure 5: Neural Network Process

Ghatge and Halkarnikar (2013) mention that feed-forward back propagation neural networks are widely used and are popular for predicting the credit defaults. A feed-forward back propagation neural network is a fully connected network, which is trained in a supervised manner and is provided with input and output patterns. According to Rajkamal and Ranjan (2014), in a feed forward network, neurons are only connected forward, from one layer to another, but there are no connections backward, while in a feed forward back propagation network, the connections are in both forward and backward directions and the weights of the connections are altered to reduce the error. Fang et al. (2009) state that back propagation models are mostly applied in the areas of prediction and pattern recognition.

3.4 Application of Neural Networks in Credit Risk Evaluation

Neural networks are typically deployed for efficiently and effectively performing tasks, such as classification, recognizing patterns and prediction (Angelini et al., 2008). Neural networks are applied in developing credit scoring models as an alternative to linear methodologies. Khashman (2011) mentions that application of neural networks for credit scoring has been effective in the past decade due to the way neural networks operate and the availability of the training data. Neural networks usually perform better than linear methodologies, especially in situations where the relationship between dependent and independent variables is complex (Pacelli & Azzollini, 2010). Neural networks have been used in various business applications by researchers and the results reveal that in the credit industry neural networks are proven to be accurate tools for credit risk analysis (Khashman 2009).

Malhotra and Malhotra (2003) have listed the studies that made use of neural networks in the financial industry and the studies have shown neural networks to perform better and more robust than other models, such as logistic regression and linear multiple discriminant models. Blanco et al. (2013) suggest microfinance institutions to employ neural networks for setting up a credit scoring model instead of traditional linear methods. Ince and Aktan (2009), in their study of comparing the performance of credit scoring using different data mining techniques, conclude that neural networks have better overall credit scoring capabilities than discriminant analysis, logistic regression and decision trees. Similarly, the results of the study by West (2000) suggest that neural network credit scoring models are more accurate with 0.5 to 3% improvements in credit scoring accuracy.

3.5 Credit Scoring

Lahsasna et al. (2010) recognize credit scoring as one of the most generally practiced techniques in assessing the creditworthiness of credit applicants, with respect to applicants' certain features, such as age, income, gender and marital status. Similarly,

Khashman (2009) mentions credit scoring as one of the prominent analytical techniques used by financial institutions in credit risk evaluation. Ghatge and Halkarnikar (2013) 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 and also help in determining the probability of funding a loan. A credit scoring model is developed by using various statistical and data mining models, such as the data envelopment model, the scorecard model, neural networks, logistic regression and decision trees.

Bahrammirzaee (2010) 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 (2003), credit scoring systems that are developed using historical loan data with analytical models to determine creditworthiness of a borrower, use the probability of default as a basis of classification. Credit scoring approaches take into consideration the credit profile of individual loan applicants in order to classify the applicants into good or bad risk categories (Karamongikar & Pradhan, 2014).

Marques et al. (2012) state that the aim of credit scoring models is to distinguish between good and bad loans depending on the likelihood of customers to default with their repayments. The objective of credit scoring is to compute and manage financial risks by providing a precise and quick lending process to lenders. Credit scoring not only increases the speed and consistency of loan application; it also reduces the need for human involvement in credit evaluation and the cost of delivering the credit (Ghatge & Halkarnikar, 2013). Ince and Aktan (2009) describe credit scoring as a system to model the potential risk of loan applications that has the ability to process a large volume of credit applications in less time and with minimal labor.

Credit scoring models are built based on historical information of thousands of customers over a fixed period and identify the relationship between historical information and future credit performance. Mathematically the relationship can be represented as

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

where each customer is described by m attributes denoted by $x_1, x_2, \ldots\ldots x_m$ and y_i indicates the type of customer. In addition, f represents the function or credit scoring

model that determines the relation between customers' features (inputs) and their creditworthiness as the output (Lahsasna et al., 2010).

The growth in the credit industry and large loan portfolios has directed the financial industry to develop and use more accurate credit scoring models and artificial neural networks are being viewed as a suitable alternative (Bahrammirzaee, 2010). According to Khashei et al. (2013), accuracy of a credit scoring model is one of the most important criteria for its popularity among the researchers. The growing rate of credit defaults in the financial industry leading to financial crisis has enlarged the significance of credit scoring.

3.6 Credit risk in peer-to-peer lending

Khashman (2009) observes the credit risk analysis as an important issue in financial risk management and it has been in the focus for the financial and banking industry. Credit risk for any financial institution is a big threat in managing credits. Risk evaluation is a vital part of credit decisions and its precision has a significant consequence for credit management (Bekhet & Eletter, 2014). Emekter et al. (2014) view P2P lending to possess a higher inbuilt risk compared to traditional financing, although there are measures imposed to minimize the risk.

Luo et al. (2011) perceive aligning the right information with the right people as a key challenge in P2P lending that may lead to a credit loss for investors. Although P2P markets are growing, lenders in this market are not professional and, in addition, they are embraced with big risks as the loans are granted without collaterals (Lee & Lee, 2012). Verstein (2011) mentions that P2P lenders often fail to value the risk of investing in P2P lending. Furthermore, lenders are at a high risk of becoming victims to fraud by dishonest borrowers' fraudulent behavior. In addition, P2P lenders may encounter the risk by considering inappropriate factors in selecting borrowers.

It is clear with the growing number of P2P lending platforms that more borrowers are attracted to the micro financing system and, at the same time, this generates a new investment platform for the lenders. However, Klafft (2008) identifies the necessity for investors to know whether investing in P2P lending platforms is as beneficial as it is

claimed to be. He further states that since the risk of credit default is on P2P lenders and most of them are not experts in risk management, it is difficult for P2P lenders to review the quality of the deal offered. Similar to Klafft (2008), Yum et al. (2012) also state that P2P lenders may misinterpret the creditworthiness of borrowers as compared to financial institutions; additionally, information asymmetry between lenders and borrowers is sharper compared to other financial markets.

The lack of a collateral in P2P lending impels lenders to critically assess the credit default risk. Most lenders during assessment of loans tend to suffer from various biases and inability to take smart investment decisions (Mild et al., 2014). Information asymmetry between lenders and borrowers in P2P lending is one of the key problems that obstruct lenders in knowing borrowers' credibility (Emekter et al., 2014). In addition to providing necessary technological structure and friendly interface, P2P lending platforms should also be responsible for ensuring the information provided by borrowers to be valid and verified to reduce the loan defaults (Zhang et al., 2014).

According to Gonzalez and Loureiro (2014), the lending decisions of investors in the presence of information asymmetry are not only affected by their perceptions and judgments of borrowers, but lenders' characteristics and circumstances also affect the decision. Berger and Gleisner (2009) suggest that recommendation from P2P platforms after a careful screening of borrowers leads to a better credit condition by generating healthier information on creditworthiness.

According to Herzenstein et al. (2008), there are no explicit rules that guide lenders to make a decision on how to lend their money. In such circumstances, lenders use certain variables as a base to make decisions for funding a loan. Such variables are demographic characteristics, financial strength, effort indicators, loan amount, initial interest rate and duration of loan request. In the absence of adequate measurable data, to increase the trust factor between lenders and borrowers, P2P lending platforms facilitate the exchange of messages between borrowers and lenders for additional information. Some platforms also allow borrowers to post pictures to present their identification to assist lenders in speeding the decision making process (Gonzalez & Loureiro, 2014).

Iyer et al. (2009) state that lenders rely on verified financial information while making decisions, such as borrowers' number of current defaults, debt-to-income ratio, amount of default and the number of credit inquiries, in the last six months. Hence, Iyer et al.

(2009) indicate that the capability of lenders to judge financial risk and information is pivotal to the feasibility of these markets.

Credit scores are considered to be the best measures of default probability, even though they may not include all the aspects of creditworthiness (Iyer et al., 2009). Klafft (2008) also notices credit score to be a strong decisive factor in evaluating a loan bid and further mentions that debt-to-income ratio has a smaller but impactful influence. Most P2P platforms assist lenders in taking precise decisions by administering financial impression of borrowers, which are aggregated into a credit score that is often determined by external rating agencies (Bachmann et al., 2011). According to Lin et al. (2013), unlike traditional banks P2P lenders are decentralized and lack sophisticated risk assessment tools and, hence, they tend to rely on social networks or online community to supervise the risk associated with the deals. Mild et al. (2014) suggest that in order to develop P2P lending as a sincere and secured alternative for a broader population, investors' risk needs to be compensated.

3.7 Summary to Findings from Literature Review

Neural network, as a data mining technique processes an input data to provide an output through interconnected networks. Neural networks use a pattern recognition approach in classifying inputs into desired outputs. Due to their efficiency and accuracy, neural networks have been widely utilized in research related to credit risk evaluation. Credit scoring is a widely used data mining technique to evaluate credit risk in the financial sector. It classifies credit applicants into predefined groups based on the historical data available. It identifies the possibility of default for an application, guiding investors to select profitable investments. Credit scoring increases the speed of processing an application with less human effort.

P2P lenders are clearly seen to lack expertise in risk evaluation, resulting in high risk of loss on investment. The lenders rely on certain information of borrowers to make a decision, which is affected by the presence of information asymmetry. The above mentioned previous studies in P2P lending have shown that investors in P2P lending are prone to high risk and hence, more studies are necessary to guide the investors in

selecting the low risk investments. Researchers have studied the lending behavior of investors from different perspectives to assist them in estimating the credit risk. The studies further justify the need for sophisticated information systems to accurately study P2P borrowers' behavior to determine their creditworthiness.

The previous studies on using neural networks to develop a credit score model demonstrate the suitability of using neural networks for credit risk assessment. The studies have revealed that neural networks are capable of correctly classifying input data with low error rates. Neural networks work effectively in screening loan applications and in identifying the probable default loans, saving time consumption and lowering the investment risk of investors. The results of the studies have successfully exhibited the effectiveness and accuracy of neural networks over traditional linear methods. Hence, the studies evidently prove the appropriateness of selecting neural network for constructing a credit score model for this study.

4 RESEARCH METHODS

The study applies quantitative research methods to achieve the desired research objectives. There have been different quantitative methods proposed in recent years to evaluate credit risk. Data mining technique has been used as the quantitative method in this research. Keramati and Yousefi (2011) indicate that data mining methods have gained more popularity than other methods because of their ability to discover realistic information from the database and transforming them into useful knowledge. The knowledge obtained from data mining allows users to observe interesting patterns and regularities from hidden information in data that are supportive in decision making (Beniwal & Arora, 2012). Data mining tools have the ability to resolve traditional problems in less time by frequently browsing in the database and producing useful information unnoticed by experts (Fang et al., 2009).

Data mining techniques are used for extracting rules and predicting behavior patterns in several fields of science, such as information technology, human resources, education, biology and medicine (Al-Radaideh & Al Nagi, 2012). The hidden knowledge extracted from data can be beneficial for financial institutions in reducing the risk and henceforth increasing the profit (Khashei et.al, 2013). Singh and Chauhan (2009) emphasize four factors for an effective data mining: the high-quality data, the "right" data, adequate sample size and the right tool. According to Stahl and Jordanov (2012), data mining includes several intelligent methods, among which neural networks are more often used in data mining tasks related to classification and cluster analysis. Some popular data mining tools, which are extensively used in many studies to evaluate credit accurately are artificial neural networks, genetic algorithms, genetic programming, support vector machines and some hybrid models (Bekhet & Eletter, 2014).

This research also focuses on classification as a data mining technique for classifying the borrowers into good and bad groups. Classification is one of the most useful data mining techniques that can help build models from an input dataset so as to classify observations into predefined classes. Classification techniques are supervised learning techniques generally used for building classification models to predict a class for a given data based on information learned from historical data (Al-Radaideh & Al Nagi, 2012). Khashei et al. (2013) recognize classification models to be widely used data

mining approaches in helping decision makers and managers to take credit decisions with condensed credit risk. In addition, they mention that classification techniques have been widely acknowledged in credit scoring and bankruptcy applications.

In addition to classification, neural network and credit scoring are also an integral part of the research methods applied in this thesis. Neural network has been used in the research to develop a credit score model to identify credit risks of the borrowers for supporting investors in making smart decisions. Neural network has been utilized in the research because of its growing use and popularity in different fields of study, as well as its accuracy compared to other linear methods. Maholtra and Malhotra (2003) mention that neural networks have been highlighted in many studies for various financial purposes, such as detecting fraudulent activities, running credit evaluation, and engaging in securities trading. Sing and Chauhan (2009) see neural network to be of efficient use in financial areas because of the capability of neural network to mine valuable information from huge amounts of historical data. Similarly, credit scoring is selected as a method to evaluate creditworthiness of the borrowers, as it is extensively used in financial industry to evaluate credit risk.

4.1 Research Process

A number of systematic steps were followed during the research process for the successful completion of the study. Each of the stages in the process was performed with close consideration of the research outcomes. Figure 6 describes the general processes involved in the research.

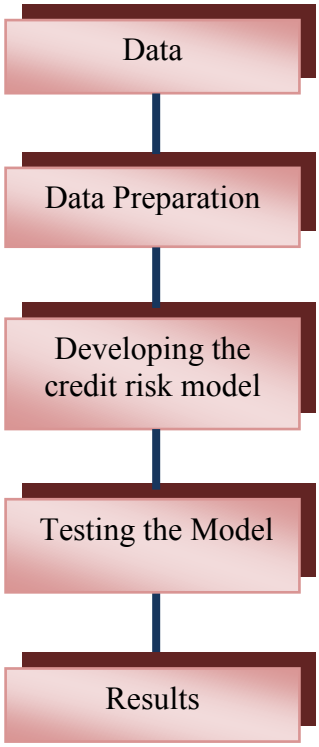

Figure 6: Research Process

The objective of the thesis, as mentioned in the introduction chapter, is assessing the credit risk of borrowers to support investors in credit decision in P2P lending. For the purpose of assessing the credit risk of borrowers, an online publicly available dataset of a European P2P lending platform, Bondora has been selected. The dataset contains the historical information on borrowers' loan transactions along with their demographic and financial data. The detailed illustration of the variables in the dataset can be found in Bondora's website[1]. As mentioned earlier, a quantitative research method has been selected for conducting the research that includes neural network and credit scoring as the main data mining tools.

The data, as the core of the research for obtaining the desired research objectives, has been studied attentively. According to Gaur (2013), data preparation is the first important step in a data mining process that prepares data to fit into the specific data mining method. Preparing a suitable dataset for a data mining process plays a decisive role in the entire process. Hence, a data preparation process was applied to the original data extracted from Bodora's website to abstract only meaningful data.

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

The variables were selected on the basis of their suitable impact on the outcome. Previous research on the topic and relevant literature were studied for selecting the meaningful variables. Furthermore, other necessary data preprocessing, such as replacing the missing data and transforming data values were performed.

The successful preprocessing of the data provided the input data set to be used in the further research process. As mentioned above, a data mining method is applied to the data set to retrieve rules and behavior patterns of the borrowers to identify the credit risk associated with the loans. Neural network is chosen as the data mining tool considering its effectiveness, accuracy and growing popularity in analyzing the credit risk. A feed forward back propagation neural network has been developed for studying the historical data of borrowers to generate meaningful rules and behavior patterns in supporting investors in choosing less risky investments. The neural network has been developed using the R program. After completion of the development and the validation of the system, a careful analysis is carried out in order to provide constructive suggestions and guidance for the investors to make smart investment decisions.

4.2 Data and Data Preparation

In this section, a detailed explanation of the data used is presented. The explanation includes the data types included in the dataset and some basic statistics of the data. In addition, the measures taken in the data preprocessing phase are illustrated.

4.2.1 Data

The dataset used in the study is a publicly available dataset from the P2P lending website, Bondora[2]. The dataset contains a large amount of information related to borrowers' loan history. The data include information of 27,825 borrowers and has the information classified under 171 variables. The data set has been generated on 15th

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

February 2015 and it includes loan characteristics and the complete transaction history of the participants from 1st of March 2009 to 15th February 2015.

The dataset consists of demographic information of borrowers, such as age, gender, marital status, country of residence, and employment status. In addition to the demographic information, information on borrowers' financial status, such as income sources, total income, liabilities, debts, debt to income ratio, and other financial agreements are included. The data further exhibits loan information of borrowers, such as loan amount applied, application date, credit history, loan period, interest rate, late charges and payments, and default loans. Furthermore, it reveals the loan status and payment information of the accepted loans and details of the rejected loans.

The data set consists of 24,092 accepted loan applications and 3732 rejected loan applications, which is decided based on the credit decision taken by the company. Among the applied loans, 16,036 were funded by the investors while 11,788 were not funded. However, it was surprising to see that the investors had also funded loan applications that were rejected by the company. Among the total borrowers, 11,570 were female and 14,697 were male, but 140 borrowers did not mention their gender information, which leads to information asymmetry.

About 87% of the total borrowers, i.e. 24,227 borrowers, did not have any previous credit history with the company. The number of borrowers that had a previous credit history of at least 3 months with the company were 3597. Hence, the large number of new customers gives an explanation for the growth in P2P lending. In addition, most of the loans, i.e 27,685, were normal loans while only 141 loans were business loans.

Figure 7 depicts the age distribution of borrowers in the dataset. The age range of the borrowers, as seen in the data, is between 18 and 80 years, where 18 is the minimum age limit for applying for a loan. The average age of borrowers is 37.21 years. In Figure 7, it can be seen that most of the borrowers are from the young age group, moe specifically from the age range of 23 and 48 years.

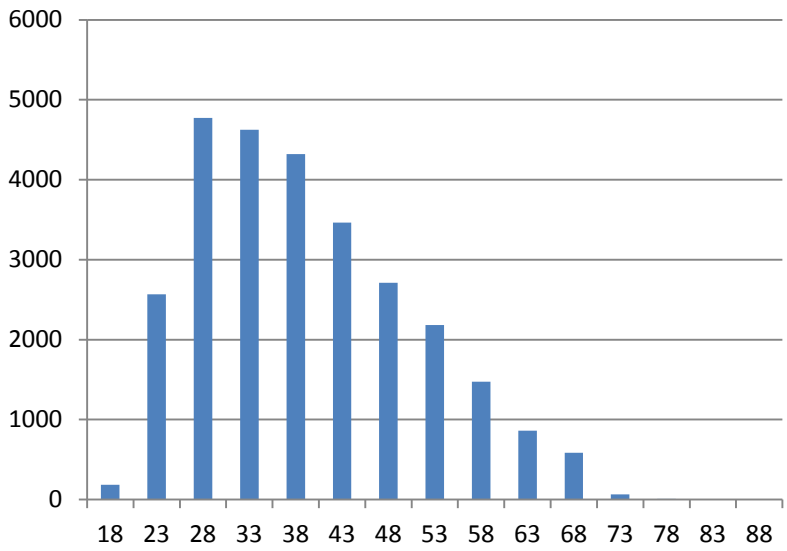

Figure: 7 Age Distribution of Borrowers

The dataset consists of borrowers from four different countries. Half of the borrowers are Estonian, while other borrowers are from Spain, Finland and Slovakia. Spain represents the second largest number of borrowers with 27%, followed by Finland with 21%. Borrowers from Slovakia are very few, i.e. 2% of the total borrowers. Although Bondora has attracted investors from 36 European countries, the data shows that currently Bondora is facilitating loans to borrowers from only four countries. Figure 8 depicts the nationality of the borrowers.

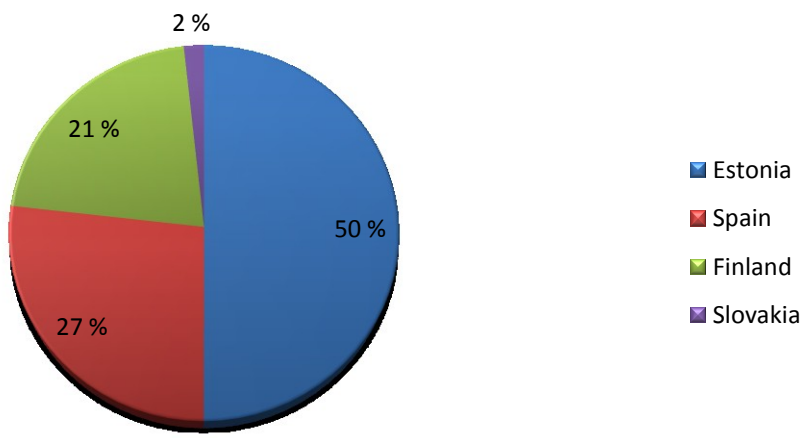

Figure 8: Nationality of Borrowers

The borrowers in the dataset are classified into three credit groups: A, B and C, where the risk level is in the increasing order from A to C. As seen in Figure 9, most of the borrowers fall in the risk category A, with 23,197 borrowers. The number of borrowers in the risk category B and C are 3072 and 1545, respectively.

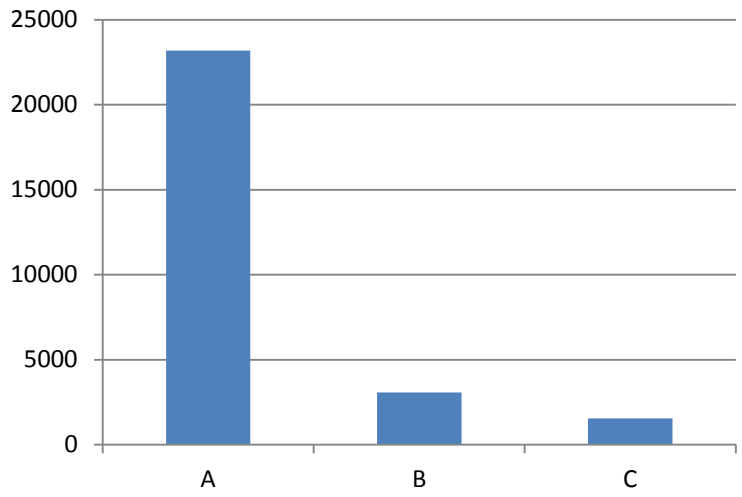

Figure 9: Risk Categories of Borrowers

The loans have been applied for various purposes, which are mainly classified into eight categories in the dataset. Figure 10 shows the distribution of the loan purposes of the borrowers. Loan consolidation is the major purpose of loan application for borrowers; 24% of the borrowers have applied for the loan for loan consolidation. Similarly, 21% of the borrowers have applied for the loans for home improvement purposes. The number of borrowers applying for a loan for other purposes, such as travel, education, vehicle, health, business and real estate is comparatively lower than loan consolidation and home improvement. Furthermore, 27% of the borrowers had applied for loans for other purposes besides the above mentioned ones.

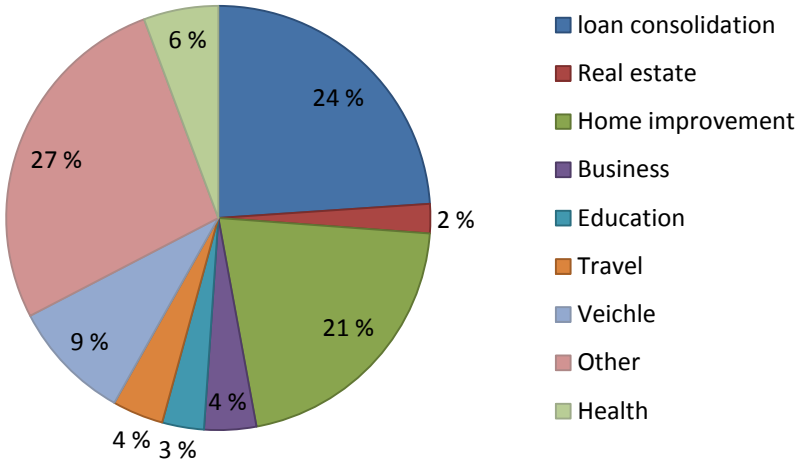

Figure 10: Loan purposes of Borrowers

The borrowers, as shown in Figure 11, are mostly of single status, which accounts for 34% of the total borrowers. Married people account for 30% of the total borrowers. Similarly, 24% of the borrowers have cohabitant status while 10% of them are divorced and 2% are widows. The high number of single borrowers applying for the loans could be seen as the attraction of young borrowers towards P2P lending.

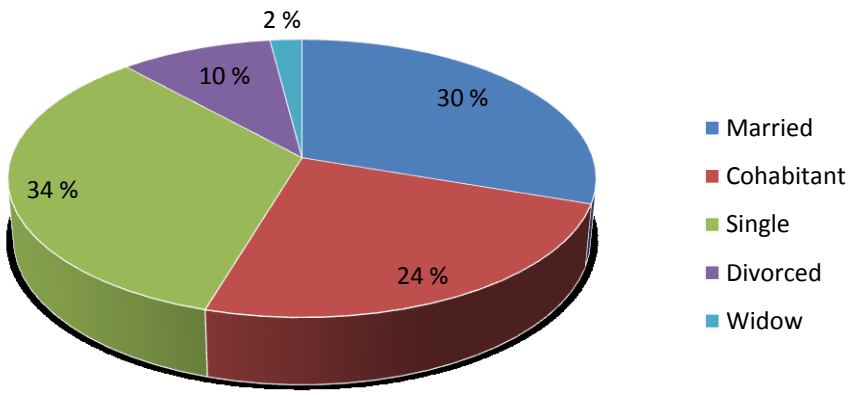

Figure 11: Marital Status of Borrower

The number of defaulted loans were 2544, which is comparatively smaller than the total number of loans, but significantly demonstrates the credit risk. Figure 12 describes the number of defaulted loans in each of the risk categories.

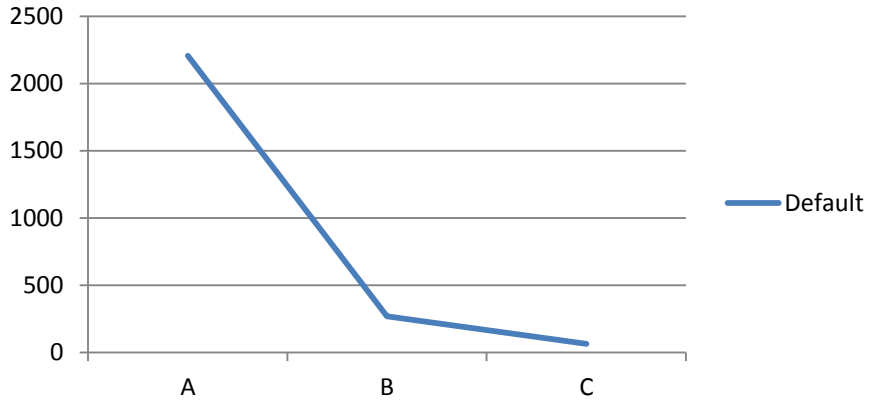

Figure 12: Loan defaults in Risk Categories

The number of default loans is highest in risk category A, i.e. 2207, while the loan defaults in risk categories B and C are 269 and 66, respectively. The high number of loan defaults in risk category A could be explained by the high number of borrowers, compared to risk categories B and C. However, A being the category with the least risk, the high number of default loans in the category signals that risk category cannot only be considered when investing in the loans.

Table 3 gives a general view of the loan description of borrowers in the dataset.

	Minimum	**Maximum**	**Average**
Applied Amount	31.9558€	40,000€	2432.041€
Funded Amount	6.39€	10,000€	2173.996€
Duration	1month	60 months	39.816 months

Table 3: Loan Description of Borrowers

The maximum amount of loan applied by the borrowers is 40,000 Euros, while the average amount applied is 2432.041 Euros. A borrower, in average, is funded 2173.996

euros, the lowest funded amount is 6.39 Euros and the highest is 10,000 Euros. The duration of the loans ranges from 1 month to 60 months.

4.2.2 Data Preparation

Data preparation is the process of selecting and processing data to make them fit the designed data mining model. Data preparation has a decisive role in the successful outcome of the data mining process. It generally includes four phases: data cleaning, data option, data preprocessing and data expression. Data cleaning refers to eliminating the misrelated data points, filling vacant data and correct inconsistency in the data (Fang et al., 2009). Due to its huge size, the real world dataset can be noisy and may contain missing and inconsistent data. Hence, data preprocessing before a data mining can significantly improve the quality of the data that consequently increases the efficiency and reduces the time for the data mining process. The data selected for data mining should be converted into an acceptable form to be processed by the system, as most neural networks only accept numerical data. Hence, all symbolic data should be converted to numerical and should be expressed between 0 and 1 or -1 and 1 (Wand & Sui, 2007).

The dataset, as mentioned above in section 4.2.1, consists of 175 variables and it is not possible to include all of them in the model development process. According to Beniwal and Arora (2012), the dataset chosen for data mining may contain irrelevant attributes and they need to be removed. In addition, most data mining algorithms do not perform well with a large set of features or attributes. The main objective of selecting attributes is to prevent over fitting and improve model performance with regards to cost and time effectiveness. From the large dataset, only 19 variables were proposed to be used in the model development process. The selection of the variables was based on previous related studies and literature. In addition, the relativity of the variables' effect on the outcome was considered during the selection of the variables. Furthermore, the variables that represented information after the loan is funded were not included, as the interest of the study focuses on qualities of borrowers before the loan is funded. The selected variables, their type and description are shown in Table 4.

Variables	Type	Description	Reference
CreditDecision	Binary	Credit decision taken by Bondora 0 Application rejected 1 Application approved EMPTY No approval process	Bekhet and Eletter, 2014
NewCreditCustomer	Binary	Did the customer have prior credit history in Bondora 0 Customer had at least 3 months of credit history in Bondora 1 No prior credit history in Bondora	West, 2000
Age	scale	Age of the borrower (years)	Blanco et al., 2013; Bekhet and Eletter, 2014
Gender	Binary	0 Male 1 Woman	Blanco et al., 2013; Bekhet and Eletter, 2014
Country	Nominal	Residency of the borrower	Bekhet and Eletter, 2014
CreditGroup	Nominal	Credit Group of the borrower	
AppliedAmount	Scale	Amount applied	West, 2000
Interest	Scale	Maximum interest rate accepted in the loan application	Blanco et al., 2013
LoanDuration	Scale	The loan term	Blanco et al., 2013
UseOfLoan	Nominal	0 Loan consolidation 1 Real estate 2 Home improvement 3 Business 4 Education 5 Travel 6 Vehicle 7 Other 8 Health	Bekhet and Eletter, 2014; West, 2000
ApplicationType	Nominal	1 Timed funding (loan will be paid out after auction time runs out) 2 Quick funding (loan will be paid out as soon as the amount is fu	
NewOfferMade	Binary	Underwriters restructured the initial application and either offered longer term, higher/lower loan amount or higher interest rate 0 No 1 Yes	
marital_status_id	Nominal	1 Married 2 Cohabitant 3 Single 4 Divorced 5 Widow	Blanco et al., 2013
employment_status_id	Nominal	1 Unemployed 2 Partially employed 3 Fully employed 4 Self-employed 5 Entrepreneur 6 Retiree	West, 2000
Employment_Duration_Current_Employer	Scale	Employment time with the current employer	West , 2000; Bekhet and Eletter, 2014
income_total	Scale	Total income	Bekhet and Eletter, 2014
DebtToIncome	Scale	Debt to income ratio	Klafft, 2008; Malhotra

			and Malhotra, 2003
BondoraCreditHistory	Nominal	A categorical variable with three values: “No credit history” The applicant is a new credit customer for Bondora or a customer with less than 3 months of credit history in Bondora “Good credit history” The applicant is an existing credit customer for Bondora and has not had Bondora loans past due “Bad credit history” The applicant is an existing credit customer for Bondora and has had Bondora loans at least 14 days overdue	
AD	Binary	Actual default; A loan is been considered to be in default after missing 3 consecutive payments 0 No 1 Yes	

Table 4: Proposed variables for Credit Scoring Model

A preliminary analysis was performed with the proposed variables in order to obtain a valuable result. During the preliminary analysis, the DebtToIncome variable was removed because there were many missing data points, as the data for the variable was only available for Estonian borrowers. In addition, the objective of the study was to develop a model that could be generalized to all borrowers. Hence, considering the study objective, the DebtToIcome variable was removed. Furthermore, the Gender variable was also noticed to have less effect in constructing the model. From the preliminary analysis, the Gender variable was observed to have no significant effect on the outcome of a loan being default, as all the classes of gender: male, female and unidentified had an almost equal amount of defaulted loans.

Employment_Duration_Current_Employer variable was also ignored after the preliminary analysis, even though it was given importance in previous similar researches, because of the large number of missing data points. In addition, the variables NewCreditCustomer and BondoraCreditHistory were realized to exhibit a similar description of a borrower's credit history with the company. Hence, only one of the variables was chosen. NewCreditCustomer was considered to be favorable over BondoraCreditHistory, even though BondoraCreditHistory offered a higher level of description of a borrower's credit history with Bondora, classifying borrowers into no credit history, good credit history and bad credit history groups. However, the variable

BondoraCreditHistory exhibited mostly no credit, since most of the borrowers were new and, thus, the rest of the two classes did not add a good meaning to the data.

In the preliminary analysis, a correlation test was also performed, where the correlation of the numeric variables was calculated in order to see if any of the variables were close to each other, which may lead to a similar effect in the outcome. The correlation calculated is shown in Table 5.

	Age	**AppliedAmount**	**Interest**	**LoanDuration**	**income_ total**
Age	1.00000000				
AppliedAmount	0.0811257	1.0000000			
Interest	0.02440348	-0.07469480	1.00000000		
LoanDuration	0.1838068	0.4231193	0.1808917	1.0000000	
income_total	0.16203812	0.35929868	0.09116227	0.27494082	1.000000

Table 5: Correlation of the numeric variables

In Table 5, it is seen that there is no significant correlation among the numeric variables, meaning that data in one of the variables does not have larger effect on the increase or decrease in the value of data in any other variable. In addition, two of the variables AppliedAmount and Interest have a negative correlation, which states that they are inversely related to each other, but the inverse relation, as seen in Table 5 is very low. Increase in value of one of the variables results in a decrease in the value of the other variable and vice versa. Since there was no presence of significant correlation between the variables, all the above numeric variables were considered to be suitable to be used as the input variables for the model development.

The preliminary analysis resulted in eliminating four of the variables from the proposed variables. Hence, the final set of input variables consisted of 15 variables, which are shown in Table 6.

Variables	Type	Description
CreditDecision	Binary	Credit decision taken by Bondora 0 Application rejected 1 Application approved EMPTY No approval process
NewCreditCustomer	Binary	Did the customer have prior credit history in Bondora 0 Customer had at least 3 months of credit history in Bondora 1 No prior credit history in Bondora
Age	Scale	Age of the borrower (years)
Country	Nominal	Residency of the borrower
CreditGroup	Ordinal	Credit Group of the borrower
AppliedAmount	Scale	Amount applied
Interest	Scale	Maximum interest rate accepted in the loan application
LoanDuration	Scale	The loan term
UseOfLoan	Nominal	0 Loan consolidation 1 Real estate 2 Home improvement 3 Business 4 Education 5 Travel 6 Vehicle 7 Other 8 Health
ApplicationType	Nominal	1 Timed funding (loan will be paid out after auction time runs out) 2 Quick funding (loan will be paid out as soon as the amount is fu
NewOfferMade	Binary	Underwriters restructured the initial application and either offered longer term, higher/lower loan amount or higher interest rate 0 No 1 Yes
marital_status_id	Nominal	1 Married 2 Cohabitant 3 Single 4 Divorced 5 Widow
employment_status_id	Nominal	1 Unemployed 2 Partially employed 3 Fully employed 4 Self-employed 5 Entrepreneur 6 Retiree
income_total	Scale	Total income
AD (Actual default)	Binary	Actual default; A loan is been considered to be in default after missing 3 consecutive payments 0 No 1 Yes

Table 6: Final Input Variables

The variables are of four different data types: binary, scale, ordinal and nominal. CreditGroup is the only variable with ordinal data type. The variables CreditDecision, NewCreditCustomer, NewOfferMade and AD are binary data types. Similarly, the variables Country, UseOfLoan, ApplicationType, marital status id, and employment status id are nominal data types and the rest of the variables have scale data types. Among the variables, the variable AD(actual default) is the output variable that describes whether a loan is default or not and the rest of the variables are independent variables, describing borrowers' characteristics that include demographic and financial features.

The dataset included loan data of both funded and non-funded loans. The non-funded loans were considered to be unsuitable for the study, since all the non-funded loans were treated as default loans. Hence, including non-funded loans would give a wrong understanding of defaulted loans and, thus, they were excluded from the study. The total number of observations in the dataset after removing the non-funded loans were 16,037. However, the loans that were not fully matured were included in the dataset, since for the loans to be considered as default required only three consecutive missed payments. Hence, in order to ensure that all the defaulted loans were included in the dataset, both matured and non-matured loans were included.

5 DEVELOPING THE MODEL

The data prepared in the data preparation stage is used as the input data for constructing the credit risk model to identify the credit risk of borrowers and classify them as default and non-default customers. The model was developed using the programming language R. R is widely used by data miners for data analysis. In addition, it is a freely available programming software. Hence, it was considered to be a suitable option for the purpose of the study (RCore Team, 2014). The packages of R used in developing the model are nnet, NeuralNetTools, caTools, and ROCR. The R script composed for the model development is presented in the Appendix. The caTools package was used to split the dataset into training and testing dataset, while the nnet package was applied for training the model. Similarly, NeuralNetTools was used for plotting the model and the ROCR package was used for evaluating the model.

The final dataset included 16,037 loan observations, and the number of loan observations without any missing data were 15,799. Hence, there were 238 loan observations that had some missing data, which is a very low number compared to the total observations. Therefore, they were not replaced and no adjustments were made for the missing data, considering that the implementation of the neural network algorithm in the nnet package of R can integrate the missing data with the dataset. All the variables were treated as numeric during the process of developing the model. Two of the variables, Country and CreditGroup, were converted to numeric, while all the other variables were already in the numeric form.

The dataset was then divided into two parts for training and testing in the ratio 70%:30%. Hence, 70% of the data was used for training the model, while 30% of the data was used for testing the model. The data was randomly split in a way that both the training and testing sets contain default cases of approximately the same percentage. Table 7 shows the summary of the data used in the model development process.

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

Table 7: Data partition summary

5.1 Choosing the Neural Network Topology

The next process in the model development was to select a suitable topology for neural network. A feed forward back propagation neural network model was applied for developing the credit risk model, with three layers: input, hidden and output layers. As mentioned in Chapter 3.3, Ghatge and Halkarnikar (2013) state that the feed forward back propagation model has been widely used for predicting credit defaults. Hence, it was applied for the model building, taking into consideration its relativity to the study objectives. The model was initially constructed with an input layer having 14 neurons, which equals the number of input variables and the output layer with 1 neuron. The number of nodes in the hidden layer was chosen to be 5. However, the effectiveness of the number of nodes in the hidden layer was evaluated and adjusted accordingly later.

The neural network with the selected topology is then provided with the training data set, for training the model. Figure 13 represents the topology and description of the model composed.

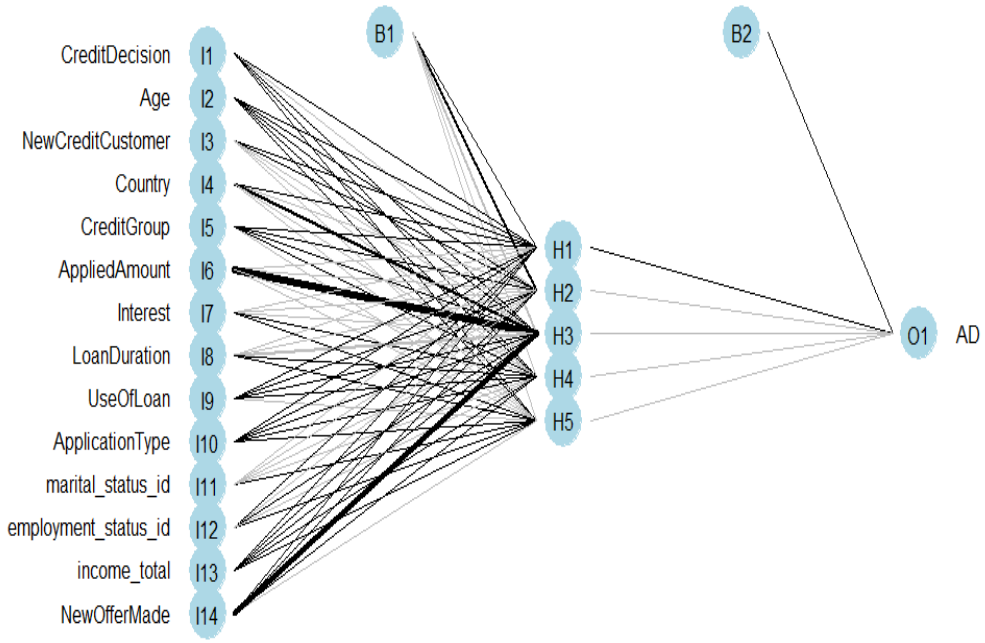

Figure 13: Neural Network Topology

As seen in Figure 13, the model, as per feed forward back propagation approach, has a fully connected network and follows an iterative process. It is trained in a supervised manner by feeding the input variables and defining the output patterns. During the training process, the input data is first fed to the input layer, where they are then processed and then passed as an input to the hidden layer. The hidden layer then sums and transforms the inputs and sends them to the output layer, where the final processing occurs and the result is produced. Since the model is trained with the feed forward back propagation approach, the training follows an iterative process that compares the output during each process, until the desired output is obtained.

The model went through 100 iterations to complete the training process. The required output for the model should be represented as a factor that classifies the result as default or not, where 0 is non-default and 1 is default. In practice, neural network provides an estimation of a loan being default as a value between 0 and 1. Accordingly, we need to specify a threshold value that determines who is considered to be predicted as default. The straightforward choice in applications for the threshold value is 0.5, but as

described later in the chapter, as per the study objective, a different threshold value was selected.

After training the model with the training dataset, the created model is then evaluated with the testing dataset. The evaluation of the composed model was performed with the Receiver operating characteristics (ROC) curve. The evaluation was performed by changing the number of hidden nodes in the hidden layer in order to obtain the best possible model for the accurate results. Area under curve (AUC) was applied to select the optimal number of nodes in the hidden layer. AUC was calculated for the model with a different number of nodes in the hidden layer. The value of AUC ranges from 0.5 to 1, where the value 0.5 represents poor performance, while 1 signifies that the model performs perfectly. Hence, the objective of using the ROC curve is to find the AUC value for the model which is above 0.5 and close to 1. The calculations of the AUC value for the model with different number of nodes in the hidden layer is shown in Table 8.

No. of hidden layers	AUC value
1	0.4892827
2	0.6961792
3	0.6912217
4	0.7222599
5	***0.7511012***
6	0.7495214
7	0.7157632
8	0.744844
9	0.7464918
10	0.7454594

Table 8: AUC value with different number of nodes in the hidden layer

As shown in Table 8, the value for AUC was calculated for the model with 1 hidden node to 10 hidden nodes. Comparing the AUC values for the model with different hidden nodes, it is clear that the model with 5 hidden nodes has the highest value for AUC. Hence, according to the AUC approach, the model with 5 nodes in the hidden layer is considered to produce a higher accurate results. Furthermore, the model with a

hidden node 1 has AUC value below 0.5, which shows that the result from the model is equivalent to random guessing and, thus, it is ineffective. After the evaluation process, the initially proposed topology for the model with 14 input neurons, 5 hidden nodes and 1 output neuron was finalized, without any changes.

5.2 Choosing the Threshold Value

The next step in developing the model is choosing the threshold value for effectively classifying the loans as default and non-default. A classification threshold value increases the default classification rate and decreases the non-default classification rate and vice versa. Depending on the objective of a study, the threshold value can either be high or low. Hence, the model was tested with different threshold values for the accurate results.

The focus of the study is to identify more default borrowers correctly in order to minimize the investment risk of the lenders. Hence, the testing of the model was done by keeping a low threshold value for correctly classifying a higher number of the default borrowers. The tables below show the classification outcomes of the model with different threshold values.

Actual	Predicted		
	Non Default	Default	% Correct
Non Default	3962	52	98.70
Default	686	48	6.53

Table 9: Classification with threshold value 0.5

The classification results with the threshold value 0.5, as seen in Table 9, show that the model classifies 98.70% of the non-default loans correctly while it only classifies 6.53% of default correctly. Therefore, the result is not acceptable as per the study objectives, which is to identify a higher percentage of default loans correctly. Hence, the above result shows that the threshold value should be kept lower than 0.5 for the desired result of classifying more default loans correctly.

Actual	Predicted		
	Non Default	Default	% Correct
Non Default	2779	1235	69.23
Default	238	496	67.57

Table 10: Classification with threshold value 0.2

The classification with the threshold value 0.2, as shown in Table 10, classifies a higher number of default loans correctly compared to the threshold value of 0.5, with 67.57% correct classification. It also classifies 69.23% of non-default loans correctly. However, the objective of the study is to obtain higher classification rate for default loans and, thus, the search for the best threshold value is continued.

Actual	Predicted		
	Non Default	Default	% Correct
Non Default	1960	2054	48.82
Default	126	608	82.83

Table 11: Classification with threshold value 0.1

The classification with the threshold value 0.1, as seen in Table 11, has a good classification rate for default loans, which is 82.83 %. In contrast, the classification rate for non-default loans is less than 50%. Hence, many of the non-default loans are misclassified as default loans, which misleads the investors when selecting the borrowers. Thus, the model is considered unsuitable since the results have a high probability of misleading the investors, which is not the study objective. Therefore, the threshold value needs to be determined between 0.1 and 0.2.

Actual	Predicted		
	Non Default	Default	% Correct
Non Default	2436	1578	60.68
Default	177	557	75.88

Table 12: Classification with threshold value 0.15

Actual	Predicted		
	Non Default	Default	% Correct
Non Default	2517	1497	62.70
Default	188	546	74.38

Table 13: Classification with threshold value 0.16

Table 12 and Table 13 show the classification results with the threshold value 0.15 and 0.16, respectively. The results of the two classifications do not show much difference. However, the classification with the threshold value 0.16 gives a better classification rate for default loans with less misclassification of non-default loans. Hence, closely considering the study objectives, the threshold value 0.16 is considered to be better than the threshold value 0.15. Therefore, the threshold value of 0.16 is finalized for the model to classify the loan applications.

6 RESULTS AND DISCUSSION

The results obtained from the developed model for credit scoring of the borrowers are discussed in this chapter. The chapter presents the results and also includes the analysis of the results with respect to the desired study objectives. In addition, the chapter attempts to relate the obtained results to the literature and previous studies.

6.1 Results

The developed model was successful in classifying default and non-default loans. The model can be applied as a guiding tool for investors to judge the credit risk while selecting borrowers for investment. The model, as developed from the historical loan data of the borrowers, successfully recognizes the behavior pattern of borrowers and predicts the default probability of new loan applications. Hence, the lenders can reduce the risk of investment failure by selecting profitable borrowers after processing the loan applications through the model.

The summary of the outcome of the constructed model is highlighted in Table 14.

Sample	**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

Table 14: Classification Results

The model correctly classified 64.47% of non-default loans and 74.75% of 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. The classification results as seen in Table 14, clearly show that the model classifies a higher percentage of default loans correctly

compared to non-default loans. The purpose of identifying default loans with greater accuracy is to minimize the credit risk of lenders to the greatest extent possible. However, in the process, the focus was also to avoid a very low non-default classification rate in order to avoid high misclassification of non-default loans as default loans.

Figure 14 shows the relative importance of all the variables in the model. The importance of the variables signifies the extent to which the model's outcome can vary for different values of the independent variables.

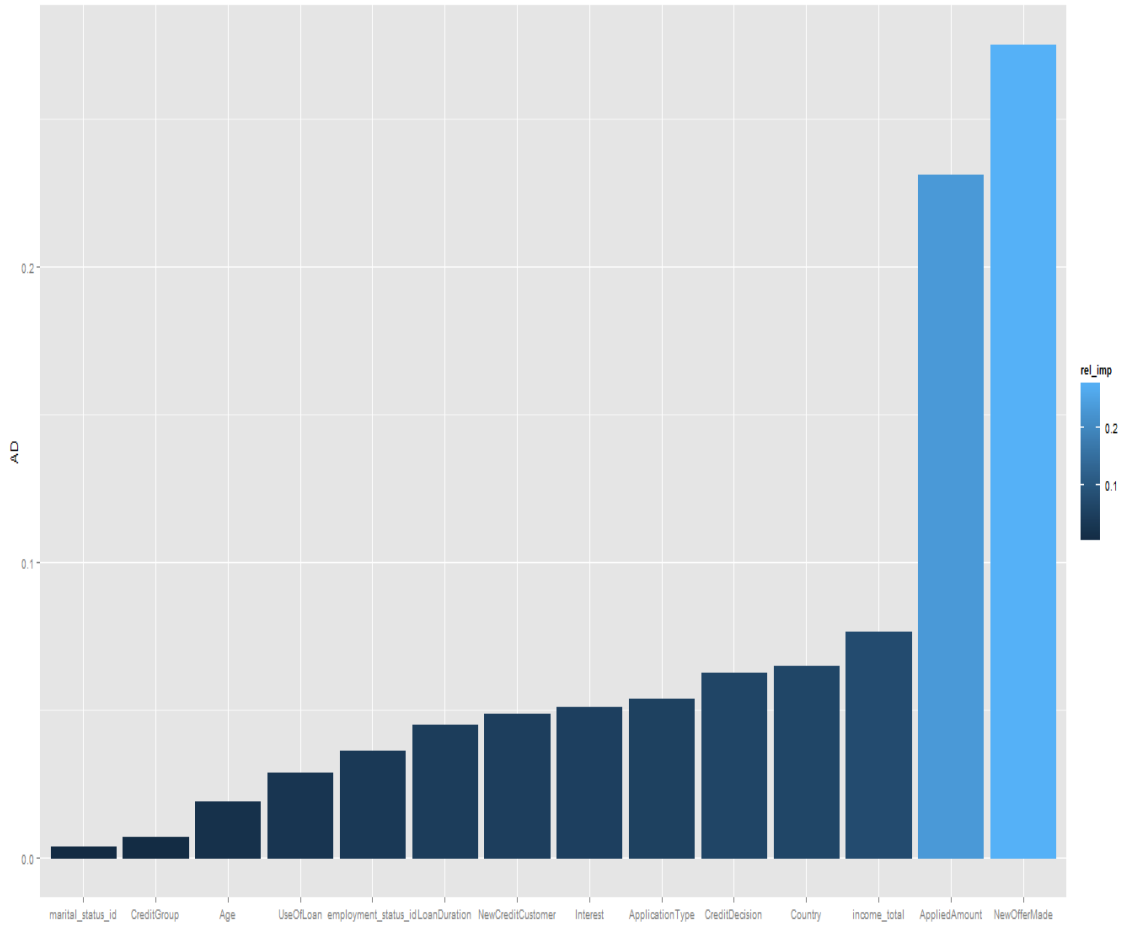

Figure 14: Relative Importance of the Variables

In Figure 14, it is evidently visible that NewOfferMade and AppliedAmount are the most important variables in the model that have bigger influence on the outcome. Furthermore, the NewOfferMade variable has the highest importance among all the variables in the model. In comparison to variables NewOfferMade and AppliedAmount, other variables seem to have less importance. After NewOfferMade and

AppliedAmount, variables income_total, Country, and CreditDecision have almost similar importance in the model. They are followed by the variables ApplicationType, Interest, NewCustomer and LoanDuration, which have nearly equal importance. Variables having the least importance are employment_status_id, UseOfLoan, Age, CreditGroup and marital_status_id. Among all the variables, marital_status_id has the least importance.

The results suggest that the variable marital_status_id has extremely low or no influence on the results predicted by the model. In contrast to marital_status_id, NewOfferMade scored the highest importance, which indicates that it strongly influences the predicted outcome of the model. Furthermore, the results indicate that NewOfferMade, AmountApplied, income_total, Country, CreditDecision, ApplicationType and Interest have a high effect on how the model classifies the loan applications.

As can be seen from the results, it is clear that some variables have higher influence on the model's outcome and some have very small influence. The effects of the more influential variables on the default probability are shown in the following tables. As seen in Table 15, there is a clear difference in the default rate between the loans that are funded directly and the loans that are funded after being restructured by underwriters. Only 11.42% of loans that are restructured are defaulted, while the default rate is 22.4% for the loans that have not been restructured are defaulted.

NewOfferMade	**Borrowers**	**Actual Default**	**Percentage (%)**
Yes	9693	1106	11.42
No	6344	1423	22.44

Table 15: Effect of NewOfferMade on Actual Default

Table 16 shows the effect of AppliedAmount on a loan being default. As seen in Table 16, loans with an applied amount of greater than 7000 Euros have a high rate of default, followed by a loan amount between 0 to 1000 Euros and 5000 to 6000 Euros. When the applied amount is between 3000 and 4000 Euros, it has the lowest default rate of 12.51%. However, the classification of loan amounts in more classes would have given better results for the default rates.

AppliedAmount(Euros)	Borrowers	Actual Default	Percentage (%)
0-1000	6205	1068	17.21
1000-2000	3881	547	14.01
2000-3000	2931	455	15.52
3000-4000	991	124	12.51
4000-5000	729	103	14.12
5000-6000	430	73	16.96
6000-7000	252	39	15.47
Greater than 7000	621	120	19.32

Table 16: Effect of AppliedAmount on Actual Default

The effect of Interest on default rates clearly shows that loans with higher interest rate have higher probability of being default than loans with lower interest rate. However, Table 17 also shows that there is not a single defaulted loan with an interest rate greater than 50%.

Interest	Borrowers	Actual Default	Percentage (%)
0-10	69	1	1.44
10-20	1689	149	8.82
20-30	7083	1265	17.85
30-40	6253	982	15.70
40-50	314	132	42.03
Greater than50	311	0	0

Table 17: Effect of Interest on Actual Default

As seen in Table 18, the default rate is highest for the Slovakian borrowers, 42.32%, followed by Spain with 20.21% and Estonia with 14.82%. The Finnish borrowers have the lowest default rate of 10.68%

Country	Borrowers	Actual Default	Percentage (%)
Estonia	10586	1568	14.82
Spain	2805	567	20.21
Finland	2294	245	10.68
Slovakia	352	149	42.32

Table 18: Effects of Country on Actual Default

Borrowers with a negative credit decision from the platform have a higher probability of default than borrowers with a positive credit decision. From Table 19, it is visible that

29.98% of borrowers with a negative credit decision have defaulted, while only 14.27% of borrowers with a positive credit decision have defaulted.

CreditDecision	Borrowers	Actual Default	Percentage (%)
Yes	14505	2070	14.27
No	1531	459	29.98

Table 19: Effects of CreditDecision on Actual Default

Table 20 shows that timed funding loans have higher default rates than quick funding loans. The default rate for timed funding loans is 28.50% while the default rate is 13.87% for the quick funding loans.

ApplicationType	Borrowers	Actual Default	Percentage (%)
Timed funding	2077	592	28.50
Quick funding	13959	1937	13.87

Table 20: Effect of ApplicationType on Actual Default

6.2 Discussion

The results presented in Chapter 6.1 accomplish the study objectives of classifying the borrowers in P2P lending as good and bad customers. As shown in Table 14, the model constructed is able to classify customers as default or non-default customers based on the selected features of the customers. Neural network as discussed in Chapter 3.1, to recognize patterns from data for classification and prediction, has been successfully applied in developing the model. In addition, the objective of a credit scoring approach has been productively obtained in classifying loans into predefined classes of default and non-default with respect to the loan profiles of the borrowers.

It has been mentioned in many studies that neural network is more effective than linear methods, such as logistic regression and linear discriminant model in predicting credit risk. The studies conducted by Malhotra & Malhotra (2003), Khashman (2009), Blanco et al. (2012), West (2000), Ince & Aktan (2009) have successfully shown that neural network models consistently perform better in identifying the default risk of borrowers.

The result obtained from the model was compared with the results from the logistic regression model with the same data set, under similar circumstances. The comparison of the results is presented in Table 21.

	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

Table 21: Comparison between Neural Network and Logistic Regression

The comparison of classification results obtained from neural network and logistic regression as seen in Table 21 distinctly signifies the efficiency of neural network for credit scoring. The model with neural network has a higher classification rate for default loans than logistic regression. Hence, the comparison results justify the superiority of neural network over linear methods in credit scoring as described in the Literature Review chapter.

The relative importance of the variables obtained from the model describes the influence of the variables in predicting the default risk of borrowers. Although there have not been many studies that have applied a similar method of research as in this study, some similar studies have pointed out important features of borrowers to consider in investment decision making. Studies performed by Mild et al. (2014), Iyer et al. (2011) and Klafft (2008) stress that financial data should be given more importance when making investment decisions. The studies assign importance to banking variables, such as deliquencies, debt to income ratio and credit score of borrowers.

The results, as shown in Figure 11, show that demographic features have less importance in influencing the model outcome than financial variables. Nevertheless, the model did not include the most used banking varibles, such as debt to income ratio and deliquencies of borrowers due to many missing data for the variables, which may have affected the effectivness of the result. However, variables such as NewOfferMade and CreditDecision considered for developing the model could be considered to be important, as they describe the creditworthiness of borrowers offered by the platform after studying the borrowers' credit history.

Credit scoring has been widely used in credit risk evaluation, but has been less applied in P2P lending. The successful implementation of credit scoring for predicting the default risk of loans is presented in the previous studies by Blanco et al. (2012), Bekhet & Eletter (2014) and Angelini et al. (2007). Bekhet & Eletter (2014) show that debt payment ratio has the highest importance in predicting default risk, which is not used in this study due to a large number of missing data points. Although Bekhet & Eletter (2014) performed their study in a different field of predicting the default risk of companies, their result shows similarity with the result from this study conducted in P2P lending. Similar to the results shown in Figure 14 for relative importance of variables, Bekhet & Eletter (2014) also pointed out applied amount, loan duaration, income, and interest rate to have greater influnece in the result . Hence, the similarities of the result of the study to the previous studies support the effectivenss of the study.

6.3 Suggestions

It is clear that lenders, as described in Chapter 3.3, are exposed to high risk as they are not professional investors and hence lack the knowledge of risk evaluation. Thus, the lenders face difficulty in selecting the loan applications to secure profitable investments and the chances of selecting bad applications are high. The model developed in this study can be a guiding tool for the lenders to screen the profitable loan applications. Since the model has been developed from the past behavior of borrowers, it is able to predict the default probability of borrowers based on historical data. Although the model does not provide a perfect classification of default and non-default loans, the results, as discussed in Chapters 6.1 and 6.2, justify the applicability and effectiveness of the model in predicting the default probability of loan applications.

Lenders who are willing to invest in P2P lending can use the model developed in this study to screen the loan applications. Lenders can supply the selected features of borrowers to the model to predict the default probability of borrowers. The model classifies the loan applications as default or non-default for the loan data supplied. Hence, based on the output provided by the model, lenders can select the potential loan applications to invest in. It is advisable for lenders not to invest in applications that have

default as model output, as they have a higher probability of defaulting. Similarly, applications with output non-default have a higher probability of being a profitable investment. However, if lenders are risk takers and would like to invest in loans classified as default, they are advisable to charge a high interest rate from borrowers, considering the risk associated with it being default.

From the results presented in Figure 14, it is noticeable that financial information of borrowers has a greater influence on the outcome of the model compared to the demographic information. Therefore, focusing on financial information of borrowers would give a better understanding of the probability of a loan being default. NewOfferMade having the highest influence in the model's outcome should be given more attention when selecting borrowers. As shown in Table 15, loans that are not offered any restructuring in either loan duration, loan amount or loan interest after underwriting have high default rate. Hence, comparing the default rate of the two types of loans, loans that have received a new offer are more likely to be profitable than the loans that have not received new offers.

Looking at the effect of the applied amount on the default rates, as seen in Table 16, it is not necessarily advisable to invest in the most secured range of loan amounts, as there is not much difference in the default rates for the different ranges of the applied amount. However, loans with an applied amount higher than 7000 Euros have high default rates and hence, it would be safe not to invest in loans with high applied amounts. The loans with high interest rates are more likely to be default compared to the loans with low interest rates, as seen in Table 17. Considering the results from Table 17, loans with low interest rate would be more secured in terms of investment and return.

Comparing the default rates of the borrowers from different countries, Slovakian borrowers are prone to higher default risk and hence, lenders are not advised to invest in them or invest with high interest rates. Similarly, considering the four nationalities, Finnish borrowers are more likely to be safe to invest in. In addition, the data set used in the study reveals that lenders have frequently invested in the loan applications that were rejected by the platform. The results in Table 19 clearly identify that borrowers with rejected credit decisions have a higher probability of being default than the accepted loan applications by the platform. Hence, lenders would have a higher probability of

securing their investments by investing in loan applications with positive credit decision from the platform.

7 CONCLUSION

The conclusion chapter includes a brief summary of the study performed. In addition, it includes a brief description of the findings. Finally, the chapter concludes with the limitations related to the study and a few suggestions for further research in the field.

7.1 Summary

The purpose of the thesis was to study the credit risk in P2P lending in order to guide lenders in screening loan applications to select profitable investments. P2P lending is an online market where lenders and borrowers meet virtually for funding a loan. P2P lending has been growing globally with an exceptional growth rate and more borrowers and investors are attracted to it because of easy access to credit and higher return compared to traditional banking. However, the lack of expertise of lenders in assessing the credit risk of borrowers has created a high risk of an investment failure. Hence, to secure the return on the investment, lenders need to carefully assess borrowers' credit risk.

The thesis applies data mining techniques to study the credit risk of a leading European P2P company, Bondora. Artificial neural network has been used to build a credit scoring model to evaluate the credit risk of borrowers and predict the credit risk of new loans. A feed forward back propagation neural network has been applied to study behavior pattern of borrowers from a historical data set to classify borrowers into predefined classes of default or non-default. The neural network applied for credit scoring has shown promising results in identifying the credit risk of borrowers. The results from the study are supportive in explaining the effectiveness of neural network and credit scoring in the field of credit evaluation.

The results from the study have been supportive in addressing the research questions proposed by the study.

1. How can risk levels of future credit loans be predicted by using neural networks?

The results from the study have clearly shown that data mining techniques can perform very well in assessing the credit risk. Artificial neural network, as described in Chapter 5, has been successfully applied to develop a credit scoring model in predicting the credit risk of future loans. The model developed with neural network effectively classified the borrowers into two predefined groups of default and non-default. The classification of borrowers into the two groups also identifies the risk associated to default of loans in the groups. The borrowers classified as the default group has a high risk of default, whereas the borrowers in the non-default group have a low risk of default.

i. Which customers belong to good and bad customer groups?

The customers are recognized to be good or bad, in relation to their probability of being default. Borrowers that are classified as default are considered to be bad customers who have very high chances of being default, while the borrowers who are classified as non-default are good customers who hold low risk of default.

ii. What are the borrowers' characteristics that have an impact on identifying the default risk?

The results from the study also identified the impact of borrowers' characteristics on the output of the model. The results, as described in Chapter 6.1, identified the relative importance of variables on the outcome. As shown in Figure 14, the model clearly identified financial characteristics to be more influential and demographic characteristics to be less influetial. NewOfferMade and AppliedAmount were identified to be the most influential variables while marital_status_id was the least influential variable.

7.2 Limitations and Further Research

The results of the study are promising for supporting lenders in screening creditworthy borrowers. However, the study has a few limitations that may affect the efficiency of the study results. Data limitation was one of the major limitations to the study. The lack of

some important variables in the input data set, such as debt to income ratio and liabilities of borrowers due to many missing data values, may have affected the results. In addition, the data set itself was a limitation in the research due to a considerably low number of default loan observations compared to the total number of observations.

Data composition was another important limitation to the study. The data set with a comparably high number of default loan observations to the total number of observations would have allowed the algorithm in the program to recognize more accurately the behavior patterns, and thus, producing better results. Moreover, the data set included many not matured loans, which means that the number of default loans is likely to be higher when all the loans have matured and also the inclusion of not matured loans may have misled the results.

Another limitation of the study is the generalization. Although the model could be used for similar studies, the results from the study cannot be generalized to all P2P lending companies, since they operate in different cultural environments and financial systems; they have different business models and mechanisms of operation. Similarly, the influencing variables can change over time with addition of more data, where borrowers can improve or decline their performance, which can affect the default rates and influencing factors for predicting the default risk.

For future research, the study can be performed by including additional variables or the missing variables in this study and the results can be compared. In addition, performing a similar study with a newer data set to compare the results performed with the old data set would be interesting in analyzing the change or similarity. Furthermore, it would be interesting to see the comparison of similar studies between two or more P2P companies to figure out the similarities in credit risk in P2P lending, operating in different environments.

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APPENDIX

R-script used for developing the model

```
# First, we convert non-numeric variables to numeric variables, standardize it and convert AD to
a categorical variable
credit.bondora$Country <- as.numeric (credit.bondora$Country)
credit.bondora$CreditGroup<- as.numeric (credit.bondora$CreditGroup)
credit.bondora[,1:14] <- scale(credit.bondora[,1:14])
credit.bondora[,15] <- as.factor(credit.bondora[,15])

# Next, we will separate data for train and test set
# As it is done by random partition, set.seed ensures
# that the next time it will be run, the same random
# separation is obtained, so the results will be exactly the same

set.seed(144)

# Now we split the dataset, 70% train and 30% test

split <- sample.split(credit.bondora$AD, SplitRatio = 0.7)

train <- subset(credit.bondora, split == TRUE)

test <- subset(credit.bondora, split == FALSE)

# In the following we train the neural network, this uses
# a function from the nnet package. Size is the number of nodes in the
# hidden layer

fitnn <- nnet(AD~., data = train, size = 5)

# We create the plot of the neural network

plotnet(fitnn)
```

```
# To see what are the most important input variables

garson(fitnn, 'AD')

# Here we evaluate the created model on the training set

TestPrediction <- predict(fitnn, newdata=test, type = "raw")

# Here we create a table where the rows (0-1) stand for the actual
# outcome, the colums show the prediction with a given threshold
# False is not default, True is default, and
# we have to find a good threshold that shows a good estimation.
# TestPrediction is a number for every observation between 0 and 1,
# Normally we classify cases by looking at the prediction
# and if it is above 0.5, the we classify it as 1 (True)
# if it is less than 0.5, the as 0 (False).

table(test$AD, TestPrediction >= 0.16)

# Finally there is an overall measure, the ROC curve
# It is calculated below. It is a value between 0.5
# and 1. 0.5 means that the model has the same performance as
# random guessing (so it is useless) and 1 means that
# the model is perfect, so we want high numbers for AUC
# (area under the ROC curve).

ROCRpredTest <- prediction(TestPrediction, test$AD)

auc <- as.numeric(performance(ROCRpredTest, "auc")@y.values)

auc

# Classification with logistic regression

fitlm = glm(AD ~ ., data=train, family=binomial)

TestPrediction = predict(fitlm, newdata=test, type="response")

table(test$AD, TestPrediction >= 0.16)
```