An Automated Credit Intelligence Learning System

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Abstract

To accelerate the financial service, microfinance need a tool and technology to provide an automated dynamic credit decision which provides an accountable and efficient system. Taking case on loan disbursement in the micro-business sector, this study presents a vary comprehensive innovation, namely Credit Intelligence Learning System (ACILES) which consist of dynamic credit scoring (CS) and optimal dynamic credit pricing: derived from tenor, rate, installment, and plafond (TRIP). While credit pricing is obtained by the profit based pricing and simulation process, the credit scoring is developed by modeling not only the borrowers data profile but also psychometric analysis of both borrower and surveyor’s perception via Item Response model which combined with Multivariate Adaptive Regression Splines (MARS) model and Structural Equation Modeling (SEM), respectively. Based on our experiment, it can be seen clearly that ACILES can be implemented in order to augment microfinance business capacity.

Keywords: Automated, Credit Pricing, Credit Scoring, Dynamic, Learning System
1 Introduction

Microfinance serves as an avenue of providing financial access to low-income individuals or groups in order to encourage economic development in a given area. According to the World Economic Forum (2015), governments, state agencies and international organizations have made many attempts to improve the current economic situation by acknowledging the importance of small businesses [25]. Therefore, with a group-based lending system that facilitates loan disbursements in micro-business (group liability), microfinance has successfully solved multiple financial constraints. Furthermore, microfinance allows others to become independent, which is imperative when managing one’s own business.

While emphasizing the need for financial inclusion, it is important to understand that traditional microfinance methodologies do not serve the best approach to accelerate process of loan disbursement to people in rural areas anymore. After measuring the impact of microfinance institutions, it is interesting to observe several obstacles such as accessibility, time and cost efficiency and area coverage. This financial disbursement challenge has triggered microfinance institutions to transform their movement, from conventional to technology-based method of financial distribution.

The process of financial technology has omitted several constraints of conventional lending process with financial service enhancement and integrated connections throughout peers and institutions such as finding new customers and deepening customer relationships. It also provides access to build a store-of-value with peer-to-peer lending solution using data analytics to develop products. Therefore, the concept of financial technology for micro-business is becoming increasingly more relevant.

Through credit scoring (CS) and credit pricing information such as tenor, rate, installment and plafond (TRIP) derived from peer-to-peer lending, we can implement a higher demand of access acceleration and immediate disbursement. The main differences between conventional and technology-based systems are in the usage of data. An effective online lending system via machine learning leverages a psychometric method during its credit scoring analysis and risk assessment. to understand how to efficiently tackle the difficulties that exist among the borrowers. Additionally, online loan applications with CS-TRIP avoid the challenges in-person services face by carrying out the process remotely.

This proposed system combines qualitative and quantitative method dynamically in order to configure the appropriate strategies. Investors can rely on the results of the CS-TRIP to help them choose a more reliable borrowers to invest in and decrease their overall risk profile. Investors can also observe their business growth in real-time without any additional constraints. This proposed automated system is far more effective than one based purely on subjectivity and human judgement. In the
light of this fact, it becomes important to develop an automated and dynamic credit scoring system to accelerate the loan disbursement process.

2 Related works

Credit scoring (CS) is a system to predict borrower compatibility to earn disbursement, which is useful to determine whether an applicant is creditworthy or not. The measurement of this system is based on the financial obligation likelihood of loan defaulting on its financial obligation. CS becomes one of the most important technologies that may affect performance management in handling microfinance business. It indicates a borrower’s compatibility to get a loan or not based on their credit history. This system has the same role with formal financial institutions, whose the measurement refers to the likelihood of loan defaulting by its financial obligations [19].

An experiment in Bolivia showed that the configuration of credit scoring in microfinance improved the judgement of credit risk [22]. In addition, the operational cost of lending can also be reduced into its significant amount. Hence, the implementation of credit system in microfinance has successfully resulted in several benefits, such as enhancement in efficiency, profitability and market share, reduction of cost as well as losses, and professional image management [24].

CS has an important role to quantify the credit risk factor. In order to evaluate the accuracy of this method, various prediction techniques have been formulated and introduced. Several measurement methods such as expert systems, econometric models, artificial intelligence (AI) techniques and hybrid form [26] have different techniques. The expert system is used as a basic method to assess credit risk by its subjective analysis, which is highly depend on its subjective judgement. Equally, econometric models are the quantitative method of data analysis and prediction based on mathematics, statistic, and computer science. Hereinafter, with its popular method viz Artificial Neural Networks (ANN) and Support Vector Machines (SVM), AI becomes the most powerful computational learning to configure the human intelligence process. ANN itself, is the most popular method that been used to measure credit score. Hybrid form is a combination of two or more methods to measure the strengths and minimize the weaknesses of each method.

Many researchers have conducted an accurate comparison of several CS methods. Desai et. al. used a multilayer perceptron neural for credit scoring and found that neural network models outperform linear discriminant analysis (LDA) and logistic regression models [8]. Lee et. al. found that the Classification and Regression Tree (CART) and Multivariate Adaptive Regression Splines (MARS) outperform traditional LDA, logistic regression (LR), Neural Networks (NN), and SVM perform in terms of CS accuracy [14].
To its development, Lee et al. proposed an integration between credit scoring model using Back Propagation Neural Networks (BNN) with a traditional DA approach and implied that the proposed hybrid approach converged much faster than the conventional NN model [12]. They also outperformed traditional DA and logistic regression methods. While, Lee and Chen proposed a two-stage hybrid credit scoring model employing ANN and MARS [13]. They find that this hybrid model successfully outperformed LDA, LR, single ANNs and single MARS. However, research regarding to the accuracy of CS models is still wide open.

To solve the credit classification problems, several studies have focused their models on decreasing errors of type I and II. These models switch the rejected good credit applicants and reassign them to a conditionally accepted class. In order to evaluate this model, Chen and Huang proposed a hybrid methodology with applying NN and Genetic Algorithm (GA) [6]. By this model, they stated that the proposed hybrid model was a potentially effective tool to reassign the rejected applicants to the preferable accepted class, which using customer balance adjustments between costs and preferences.

On the other hand, Chuang and Lin presented a reassigning credit scoring model (RCSM) to solve classification problems and decrease the error of type I [7]. They develop an ANN and Case-Based Reasoning (CBR) based on CS model for reassignment of the rejected good credit applicants to the conditionally accepted class. By this experiment, the proposed hybrid model was more accurate compared to the other CS methods that are commonly used. This experiment also contributed to the reduction of error by type I in the scoring system. Furthermore, Li and Zhong used various techniques for credit scoring to maximizing revenue by decreasing the type I and type II errors [15]. They compare several statistical models such as LDA, LRA, MARS, Bayesian Model, and Decision Tree. Other than that, they also compare several AI models such as ANN, GA, and SVM. The other method was also applied in this experiment, such as Hybrid Method and Ensemble Method.

Try to convince on this view, Mark Schreiner has analyzed that CS for microfinance is able to be done [21]. The main differences of microfinance compared to formal financial institutions are on the flow of information, where microfinance usually used qualitative method and informal approach. In his further analysis, Schreiner suggests that the quantitative method is able to help microfinance using credit score, but is still less powerful compared to the scoring created in formal financial institution products [22]. Thus, the knowledge of information by qualitative method is still needed. By using information in qualitative methods, microfinance can predict and measure credit risk based on repayment behavior. This repayment behavior analysis can be done with psychometric tools.

Klinger et al. carried out a pilot test on the innovative psychometric tool [11]. This pilot test is aimed to evaluate credit risk of business owners in Peru who seek for a loan to develop their business. With this approach, the psychometric tool compared the behavior of business owners with the ones in other countries which apply the
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same psychometric tool. The results of this comparison shows that, despite the differences of personality by business owners among countries, the dimensions of business performance and their credit risk are common. The psychometric CS was discovered for the first time by Arraiz et. al. [3]. Their findings show that the psychometric test can lower the risk of the loan portfolio for bankable entrepreneur, which is classified from their credit history. This mechanism serves as the secondary screening platform for their credit. In addition, according to Entrepreneurial Finance Lab, the use of psychometric tests increased access to credit for unbanked entrepreneurs without any risk that probably affect the loan portfolio.

To maximize profitability, business owners need to understand price elasticity from customer’s demand. Thus, the idea of profit based pricing is based on profit maximization with the combination of cost, risk, and the elasticity of price from customers [9]. Profit based pricing is used to determine optimal prices from any given segment, using objective function that combines the net interest income with price elasticity [18].

As mentioned above, price based segment is derived from credit risk strategy; which did not provide any numerical result. Try to answering this challenge, Oliver and Oliver successfully found a numerical algorithm of price based segment [16]. This algorithm is used to find optimal prices to maximize return on equity by considering price response and default risk, based on the solution of nonlinear differential equations.

The main purpose of adopting an analytical approach to credit pricing is for increasing profitability. Reported by Boyd et. al. that a UPS package shipper earned an increase in profit, which more than $100 million per year by using Target Pricing System (TPS) [5]. Another case, the profitability of the sub-prime auto lender AmeriCredit is also increased about $4 million in three months by implementing this credit pricing optimization system [17]. TPS itself, is a bid pricing system that takes cost, price sensitivity, and competitive environment factors.

Those three main elements of TPS functioned as a measurement variable when generating bids of goods portfolio or service which to be performed in a contract period. Understandably, this is the reason that many companies utilize credit pricing to improve both the processes and the systems that they use to set the prices.

3 An Automated Credit Intelligence Learning System

Due to the challenge to accelerate loan disbursement on microfinance, an Automatic Credit Intelligence Learning System (ACILES) is created to assist arduous conditions between lender and borrower on the process of lending. ACILES itself, is a machine that has the capacity to gather and analyze loan
disbursement by micro-business through data aggregation from its loan portfolio. This system has also become a platform to integrate the communication process between the systems used. Based on the configuration of machine learning, these systems are also able to adapt with recent data within a second, which allow business owners to monitor business performance and also perform the managerial process remotely.

In its process, ACILES combines dynamic credit scoring (CS) process to assess the creditworthiness of the applicant and its risks as well as the process of determining automatic credit pricing. We construct a credit score based on qualitative and quantitative data, in order to improve the measurement of credit risk in microfinance business. Subsequently, we construct a machine to determine the credit pricing for each risk. Therefore, ACILES aims to accelerate the process of credit analysis, so that the process of loan disbursement becomes faster and safer, which improves microfinance business sustainability.

ACILES process is divided into two stages (Figure 1). The first is automated model construction process. In this stage, the machine learning creates a dynamic CS and optimal credit pricing models which consist of four variables: tenor, rate, installment and plafond (TRIP). The CS model consists of two components: Item Response model, which combined Multivariate Adaptive Regression Splines (MARS) models based on the borrower’s qualitative and qualitative data; Structural Equation Modeling (SEM), which is aggregated by psychometric analysis of both borrower and surveyor’s perception. This machine will run automatically and periodically in order to accommodate data that grow rapidly. In the learning process, the machine will study the risks based on existing data and determine the credit price to maximize profitability, which corresponds to each risk. In this process, the score that was updated regularly will allow the same borrower to obtain different pricing and credit score for any given period.

The second stage is real-time CS-TRIP simulation process. Based on the model in the first stage, the output from this second stage process will deliver a prediction of the CS-TRIP. This prediction includes a degree of risk and pricing that will be given to the loan applicant. Section 3.1-3.3. describes each process in figure 1 in more details.
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Figure 1: An Automatic Credit Intelligence Learning System
3.1 Dynamic Credit Scoring

CS models are initiated in order to measure creditworthiness aspect of borrowers. According to the data in Figure 1 at Dynamic CS part, the process is divided into three main parts.

The first, creation of borrower portfolio using Item Response model that is combined with MARS model.

MARS model is chosen to configure this system because of its flexibility to handle continuous and categorical data, compared with a linear regression model. In addition, linear relationship between dependent and independent variables are not required in MARS model. Furthermore, compared to artificial intelligence methods, MARS is more superior because of its short training time and compatibility to interpret [15].

MARS is nonlinear and nonparametric regression method with high-dimensional data, which is introduced by Friedman [10] with the following equation:

$$\hat{f}(x) = a_0 + \sum_{m=1}^{M} a_m \prod_{k=1}^{K_m} \left[ s_{km}(x_{v(k,m)} - t_{km}) \right]_+$$

(1)

where $a_0$ and $a_m$ are parameters, $M$ is the number of basis functions, $K_m$ is the number of knots, $s_{km}$ takes on values of either -1 or 1 and indicates the right/left sense of the associated step function, $v(k,m)$ is the label of the independent variable, and $t_{km}$ indicates the knot location. Subscript + indicates a value of zero for negative value of the argument.

The second part, the psychometric data will be processed using SEM model to identify borrower’s perception. The third part is the same with the second, but to identify surveyor’s perception.

SEM is used to describe the pattern of the relationship or correlation between the set of variables in the model. SEM is a collection of statistical techniques to examine relations between one or more independent and dependent variable. Both independent and dependent variables can be used to measure unobserved latent variable, which is not directly observed. This form of SEM is separated by two forms: continuous and discrete [23]. In its fundamental base, SEM can be viewed as combination of factor analysis and linear regression or part analysis. These relationships between latent variables are represented by regression. Furthermore, relationship between observed variable can be examine by covariance structure modeling.

Data of borrowers consist of variables, where data redundancy is likely to happen. If the data is directly used in the regression model, the multicollinearity of emergence will be allowed in this process. The variables are grouped in such a way of data so that there are no redundant variables. This condition is purposed to reduce multico. We call this category as the combination of variables. This combination is used as an initial variable selection in the modeling process in order to get the best
models that are parsimonious. Based on its objectives, the credit can be divided into two main parts: productive and consumptive credit [20]. Productive credit are the loans that are used to finance the working capital needs of borrowers such as to facilitate the production, whether in agriculture, industry, trade and other productive sectors. Conversely, consumer credits are the loans that are granted in order to fulfill the consumptive needs of borrowers, such as the financing of education and house renovation. The credit objectives from borrowers will affect credit ratings on credit analysis process. Therefore, a different model is required to answer each different purpose.

Modeling process using MARS method begins with dividing the data based on credit objectives. This data will be modeled from a combination of variables that have been formed in each part. Therefore, the optimal MARS model is selected in a two-stage process. In the first place, a very large number of basis functions are applied to fit the initial data. In the second stage, the basic function is deleted based on their level of contribution. This backward stepwise process is using criteria by generalized cross validation (GCV). From GCV validation, the best model (the greatest $R^2$) of variable combination will be chosen. On the whole, it can clearly be seen that each credit objective has its different MARS models.

At the same time, SEM models the psychometric data on borrower and surveyor’s perception, separately. The process of modeling is summarized in four stages: model specification, model estimation, model evaluation, and model modification. The first, model specification consists of stating the hypotheses to be tested in both diagram and equation form. Statistical identification and evaluation is also used to evaluate the underlying assumption regarding to the model. The second, the relation in the diagram is also translated into equations in order to estimate the model. To illustrate, one of the method in model specification is in the Bentler-Weeks method [4]. At the third stage, we use model evaluation to assess the suitable model in SEM and to interpret parameter estimation. The last stage is model modification. We use this model to test hypotheses in the theoretical work and to improve the analysis transitions from confirmatory to exploratory. If the parameter in regression part of SEM is positive, the result of SEM model is compatible to be used to improve credit score predictions. Furthermore, the results of MARS and SEM model are combined with a certain measurement scoring to build a decent credit score. Hierarchical clustering (HC) process is used to obtain the credit grade, because of its easiness to handle in any form, either of similarity or distance, which embedded flexibility regarding a level of granularity, also more versatile [1].

### 3.2 Optimal Credit Pricing

Differences in risk of borrowers cause many lenders not to offer the same price of credit. There are two reasons to charge different prices to its different segment [18]. First, incremental cost and risk vary by each segment. Most of the lenders
differentiate prices, according to product and borrower characteristics as well as channel. Second, borrower price sensitivity is different for each segment. In this paper, we will try to separate the borrower based on their amount of plafond, tenor, credit scoring, and the k-funding.

The main problem on price optimization is to determine the exact rate of APR (Annual Percentage Rate) to be charged for each segment. This price should be updated regularly in order to respond market changes cost of funds or competitive action. Therefore, price optimization involves a probability for loan funding with incremental profitability to lenders. An increase in rate for potential borrower reduces the likelihood of the customer receives a loan, but it increases profits when the customer accepts it. This loan profitability is measured by Net Interest Income (NII). On the other hand, Present Value Net Interest Income (PVNII) measures the expected present value after tax payment of the loan or benefit entirely from lending.

In the funding process, there are possibilities that a borrower is default, which causes the payment obstructed. This condition mostly happens during the loan period. Assume that the lender pays a periodic rate $r_c$ for capital and has an internal discount rate $r_d$. Let $s_i$ become the probability of borrower to make a payment to period $i$. Then the expected value of net interest income from a risk loan is:

$$ PVNII_R(P, r, n) = P \left[ \sum_{i=1}^{n} \left( \frac{1}{(1+r_d)^i} \left( \frac{r(1+r)^n}{(1+r)^n-1} - \frac{r(1+r)^n}{(1+r)^n-1} \right) \right) \right] $$

(2)

where $s_i = \prod_{j=1}^{i} (1 - p_i)$ for $i = 1, 2, ..., n$. $p_i$ is the probability that the borrower default in period $i$.

The following is the price optimization problem that maximize expected total profitability [18]

$$ \max_r TR(r) = \sum_i D_i \tilde{F}_i(r_i)[PVNII(P_i, r_i, n_i) + v_i], \quad r_i \geq 0 $$

(3)

where $N$ is number of segment, $r = r_1, r_2, ..., r_N$ is the vector of rates offered to each segment, $D_i > 0$ is total demand (in number of loans) in segment $i$, $P_i > 0$ is average loan size in pricing segment $i$, $n_i \geq 1$ is typical term in segment $i$, $PVNII(P_i, r_i, n_i)$ is present value net interest income, $v_i$ is the present value of expected non-interest items (such as fees and operating cost) in segment $i$, $\tilde{F}_i(r_i)$ is the bid responses model, the fraction of successful applications who will accept the loan as a function of the rate $r_i$. $\tilde{F}_i(r_i)$ is a function such as the probit or logit that can be interpreted as complementary cumulative distribution function of a probability distribution.

The optimization problem can be solved using nonlinear programming. $PVNII(P_i, r_i, n_i)$ is log concave in $r$ and that is sufficient for existence and uniqueness of solution [18]. Log concavity is a weaker condition than concavity.
At this stage, this system is not only suitable to get the optimal rate, but also to generate plafond table that is used in the simulation process. The table is obtained by determining the most appropriate distribution of plafond for each segment. Each distribution of the segment generates a random number, which is quite large. At the end, we obtain a complete plafond table for each segment.

### 3.3 Simulation Process

The Simulation Process is used to measure the creditworthiness of a borrower and to determine the rate that will be given to new loan applications based on CS model and by the previous optimal credit pricing, i.e. TRIP. This process consists of five stages as seen in figure 1.

The process of this diagram starts with determining a borrower’s credit grade based on CS model and loan application data. At the second stage, determination to borrower segment is created based on the loan application, to apply the credit grade. At the third stage, in accordance with the rate of borrower segment, each plafond in the plafond table is determined. Corresponding to this process, at the fourth stage, installment is calculated to the given rate. At the final stage, the selection is processed based on this installment, which is the closest one with borrower’s willingness to pay.

Due to the obstacles to get a valid data of the borrower’s information, the amount that is given to the borrower is based on borrower's willingness to pay. In this stage, we also obtain the optimal TRIP in order to create a measurement of borrower’s ability to make a repayment. Therefore, the loan table contains a selection of the plafond and tenor, which plafond value is come near to optimal plafond. The table also displays installment to be paid according to the selected loans.

### 4 Results and Discussion

In this paper, we use the 2014-2016 panel data from PT. Amartha Mikro Fintek to implement ACILES for calculating credit scoring (CS) and credit pricing such as tenor, rate, installment and plafond (TRIP). This data are divided into several components: borrower profile, loan disbursement data, and credit dues. We also use psychometric data of borrower’s and surveyor’s perception, in order to improve the information about borrower. Therefore, the items of data used are based on the result by item response modeling. Item Response model is used to enhance conceptual toolkit and research technique by its researchers. This method is meant to gain a better level of understanding in psychometric measurement. Furthermore, we analyze the data with the same process described in figure 1, which runs automatically every week. The output from this credit score model is a form of mathematical equation, which is used to predict credit score from new borrowers.
Meanwhile, the other output of this credit pricing is optimal rate value for any given segment shown in table 1:

Table 1. Optimal rate per segment

<table>
<thead>
<tr>
<th>No</th>
<th>Plafond</th>
<th>Tenor (weeks)</th>
<th>Credit Grade</th>
<th>The k-funding</th>
<th>Weekly Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rp.6.500.00 - Rp.7.000.000</td>
<td>50</td>
<td>B</td>
<td>6</td>
<td>0.68%</td>
</tr>
<tr>
<td>2</td>
<td>Rp.6.500.00 - Rp.7.000.000</td>
<td>50</td>
<td>B</td>
<td>7</td>
<td>0.61%</td>
</tr>
<tr>
<td>3</td>
<td>Rp.6.500.00 - Rp.7.000.000</td>
<td>50</td>
<td>C</td>
<td>7</td>
<td>0.77%</td>
</tr>
<tr>
<td>4</td>
<td>Rp.5.500.00 - Rp.6.000.000</td>
<td>50</td>
<td>B</td>
<td>4</td>
<td>0.75%</td>
</tr>
<tr>
<td>5</td>
<td>Rp.5.500.00 - Rp.6.000.000</td>
<td>50</td>
<td>B</td>
<td>5</td>
<td>0.72%</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>49</td>
<td>Rp.5.500.00 - Rp.6.000.000</td>
<td>50</td>
<td>C</td>
<td>6</td>
<td>0.84%</td>
</tr>
</tbody>
</table>

On the other hand, the simulation process shown on figure 1 occurs in all new transactions. For a deep dive, considering Hartini proposed a loan in the amount of Rp. 3,500,000. For repayment, she commits to pay Rp. 100,000 every period. Based on loan filing provided, the ACILES will directly count Hartini's credit score and its optimal credit pricing. Figure 2 shows the loans that can be taken by Hartini as the output of the ACILES. In this case, the plafond recommended by system (*) is Rp. 3,800,000, which will be repaid within 50 period (weeks) with a repayment amount Rp. 99,000. The total rate for this case is 30.26%.

The system is set to recommend a loan, with the result that the loan repayment will be paid close to the value of the borrower's ability to pay. While loan will produce a maximum plafond, borrower can choose the loans beyond the recommendation. All rates generated in figure 2 are the optimal rate. However, the main obstacle of this system is the difficulties to get a valid data to measure a borrower’s ability to earn credit automatically. At the end, inputs from borrower are still required to validate the data.
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Figure 2: Loan Table (Simulation Model)

5 Conclusion and Future Works

This study presents a project of an Automatic Credit Intelligence Learning System (ACILES) to accelerate the financial access in microfinance. In the ACILES, we develop a machine learning for dynamic credit scoring (CS), which has the function to measure creditworthiness of a borrower and its risk, as well as the process of determining the overall credit pricing.

The credit pricing itself ranges from tenor, rate, installment and plafond (TRIP). We construct the scoring model using an Item Response model that is combined with Multivariate Adaptive Regression Splines (MARS) model and Structural Equation Modeling (SEM) to obtain a more detailed information to the borrower. Furthermore, a decent credit score is clustered by using Hierarchical Clustering (HC) to obtain a credit grade. We use the profit based pricing model to obtain optimal credit pricing. The results show that the CS-TRIP can be implemented to accelerate operational process in one of microfinance business in Indonesia, i.e. Amarta Mikro Fintek.

On the next project, the maintenance of ACILES becomes necessary. This maintenance includes validation to the current data, model evaluation by CS-TRIP, which includes several points such as model improvement, model alteration with the better accuracy. This idea is proposed in order to maintain and accelerate ACILES performance, therefore the system is able to analyze the borrower’s credit efficiently.

Most of microfinance business use group liability system to secure the borrowing process and gain the loan guarantees as implemented in Grameen Bank, including...
Amartha Mikro Fintek. Furthermore, in order to minimize the risk of greater losses, a predictive model of partial liability becomes more and more relevant to be used. This model will be used to maximize group rate transfer as proposed by Allen [2]. This model is eligible to predict default rate from group lending and to estimate extra funds in order to cover borrower’s default, which is known as a group reserve valuation.

References


