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Preface

ICSIIT 2017

This proceedings volume contains papers presented at the fifth International Conference on Soft Computing, Intelligent System and Information Technology (the 5th ICSIIT) held in Bali, Indonesia, 26-29 September 2017. Main theme of this international conference is “Building Intelligence through IoT and Big Data”, and it was organized and hosted by Informatics Engineering Department, Petra Christian University, Surabaya, Indonesia.

The Program Committee received 106 submissions for the conference from across Indonesia and around the world. After peer-review process by at least two reviewers per paper, 64 papers were accepted and included in the proceedings. The papers were divided into ten groups: Classification and Correlation Techniques, Feature Extraction and Image Recognition Methods, Algorithms for Intelligent Computation, Distributed Systems and Computer Networks, Mobile and Pervasive IoT Applications, Assessments of Integrated IS/IT, Simulation and Virtual Reality Applications, Smart Assistive Technologies, Smart Mobile Applications, Case Studies of Knowledge Discovery and Management.

We would like to thank all Program Committee members for their effort in providing high-quality reviews in a timely manner. We thank all the authors of submitted papers and the authors of selected papers for their collaboration in preparation of the final copy.

Compared to the previous ICSIIT conferences, the number of participants of the 5th ICSIIT 2017 is not only increasing, but also the research papers presented at the conference are improved both in quantity and quality. On behalf of the organizing committee, once again, we would like to thank all participants of this conference, who contributed enormously to the success of the conference.

We hope all of you enjoy reading this volume and that you will find it inspiring and stimulating for your research and future work.

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Credit Scoring Refinement Using Optimized Logistic Regression

2
Author(s)

Hendri Sutrisno ; Siana Halim

View All Authors

Abstract:
A poor credit scoring model will give a poor power for predicting defaulted loan. There are many approaches for modeling the default prediction, such as classical logistic regression and Bayesian logistics regression. In this paper, we applied both classical logistic regression and AUC (Area under Curved) optimized using Nelder-Mead Algorithm for refining a credit scoring model that has already been used for several years by an International bank in Indonesia. Both classical logistics regression and AUC optimized method perform well in improving the model, but logistic regression still better in some aspects. AUC Optimized model has higher AUC than logistic regression model but has lower Kolmogorov-Smirnov Score.

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I. Introduction

In Indonesia, SMEs (Small and Medium Enterprises) constantly contribute more than 57% in Gross Domestic Product since 2006 [1]. Until 2013, there were more than 57 million SMEs in Indonesia [2]. Every year, Bank X receives thousands of SMEs loan applicant and, as a result, it needs a tool that can process the loans faster and provide low risk. Credit scoring helps lenders take faster, cheaper, and more objective decisions in terms of providing loans [3]. Every classification technique for credit scoring data gives different results, where neutral networks and least-squares support vector machines yield good results, but the classical logistic regression is still performing well for credit scoring [4]. Until now, logistic regression remains the main method applied in the banking sector to develop the scoring models. Since the market is changing rapidly, new methods are required for optimizing the scoring problem. In recent years, many quantitative techniques have been used to examine predictive power in credit scoring [5]. Credit scoring models are usually evaluated using power curve such as the Receiver Operating Characteristic (ROC) curves [6].

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Keywords

IEEE Keywords
Predictive models, Logistics, Sociology, Statistics, Optimization, Computational modeling, Mathematical model

Author Keywords
Credit scoring; logistics regression; Nelder-Mead algorithm; AUC optimization.

Authors

Hendri Sutrisno

Siana Halim

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Credit Scoring Refinement

using Optimized Logistic Regression

Hendri Sutrisno
Industrial Engineering Department
Petra Christian University
Surabaya, Indonesia
hensoee@yahoo.com

Siana Halim
Industrial Engineering Department
Petra Christian University
Surabaya, Indonesia
halim@petra.ac.id

***Abstract*—A poor credit scoring model will give a poor power for predicting defaulted loan. There are many approaches for modeling the default prediction, such as classical logistic regression and Bayesian logistics regression. In this paper, we applied both classical logistic regression and AUC (Area under Curved) optimized using Nelder-Mead Algorithm for refining a credit scoring model that has already been used for several years by an International bank in Indonesia. Both classical logistics regression and AUC optimized method perform well in improving the model, but logistic regression still better in some aspects. AUC Optimized model has higher AUC than logistic regression model but has lower Kolmogorov-Smirnov Score (KS-Score)**

Keywords*— *Credit scoring, logistics regression, Nelder-Mead Algorithm, AUC optimization

I. INTRODUCTION

In Indonesia, SMEs (Small and Medium Enterprises) constantly contribute more than 57% in Gross Domestic Product since 2006 [1]. Until 2013, there were more than 57 million SMEs in Indonesia [2]. Every year, Bank X receives thousands of SMEs loan applicant and, as a result, it needs a tool that can process the loans faster and provide low risk. Credit scoring helps lenders take faster, cheaper, and more objective decisions in terms of providing loans [3]. Every classification technique for credit scoring data gives different results, where neutral networks and least-squares support vector machines yield good results, but the classical logistic regression is still performing well for credit scoring[4]. Until now, logistic regression remains the main method applied in the banking sector to develop the scoring models. Since the market is changing rapidly, new methods are required for optimizing the scoring problem. In recent years, many quantitative techniques have been used to examine predictive power in credit scoring [5]. Credit scoring models are usually evaluated using power curve such as the Receiver Operating Characteristic (ROC) curves [6].

AUC is an area under the ROC curve and a good ROC should have high AUC value. Higher AUC mean the model better in predict bad debtors. Both the ROC curve and the AUC do not depend on the proportion of defaulters in the credit portfolio, therefore they could be used to monitor the performance of credit models over time [7]. Kraus [8], tried to optimize AUC it seems to be a reasonable procedure for estimating the parameters for credit scoring case besides logistic regression. This research will focus on how to validate current credit scoring model of an International Bank in Indonesia. When the model has already been validated, another interesting problem is how to develop a better classifier. So this research also focusses on developing the credit scoring model using AUC Optimization.

II. METHODS

A. Logistics Regression

Logistic regression is a statistical method for analyzing dataset in which there are one or more independent variables that determine outcome, which is only have two outcomes [9]. In retail banking, logistic regression is the most widely used method for classifying applicants into risk classes because of its good interpretability and simple explanation [10]. Logistic regression model is built with a modification of linear regression.

$$\mathrm{Y_i} = \beta_0 + \beta_1 \mathrm{X_{i1}} + \beta_2 \mathrm{X_{i2}} + \cdots + \beta_p \mathrm{X_{ip}} + \epsilon_i \tag{1}$$

Equation (1) considers n observation of one dependent variable and p independent variables. Thus, $\mathrm{Y_i}$ is the $\mathrm{i^{th}}$ observation of the dependent variable**,** *variable* $\mathrm{X_{ij}}$ *is* $\mathrm{i^{th}}$ *observation of the* $\mathrm{j^{th}}$ *independent variable***,** j *start from 1 to* p. The values of β_j represent parameters to be estimated. The value of $\mathrm{Y_i}$ will be between -∞ and +∞ depends on the value of independent variables. In order to make the value of $\boldsymbol{Y_i}$ always positive, the value will only range between 0 and +∞. To transfer the value of $\mathrm{Y_i}$ into a range between 0 and 1, then the binary logistic regression is used as the transferred function

$$\pi(\mathrm{x}) = \frac{\exp \mathrm{Y_i}}{1+\exp \mathrm{Y_i}} \tag{2}$$

Therefore, the formula of logit transformation would become as below.

$$\mathrm{g(x)} = \ln\left[\frac{\pi(\mathrm{x})}{1-\pi(\mathrm{x})}\right] \tag{3}$$

Using the logit transformation formula, we can turn back the logistic regression to linear regression

B. AUC Optimization – Nelder Mead Algorithm

Default customers are customers who fail to pay installments for the loan, and Non-Default customers are customers who pays regular installments for the loan. These classes are used for the description of the ROC graph. If a default is correctly classified and predicted as a default, it is a true positive(tp); while a non-default wrongly predicted as a default is counted as a false positive (fp).

$$\text{TP rate} = \frac{\text{default correctly classified (tp)}}{\text{total default (p)}} \tag{4}$$

$$\text{FP rate} = \frac{\text{non−default incorrectly classified (fp)}}{\text{total non−default (p)}} \tag{5}$$

ROC curve is created by plotting TPR (true positive rate) versus FPR (false positive rate). Figure 1 shows an example of ROC Curve. AUC is an area under the ROC curve. A good ROC should have high AUC. Higher AUC mean the model better in predict bad debtors. When the AUC is equal to 1, it becomes the ideal model, which means the model leads to zero FPR or, in other words, there is no non-default debtor that is incorrectly classified.

AUC is computed with the following formula [8] [11]:

$$AUC = \frac{1}{n_{nd} \cdot n_d} \sum_1^{n_{nd}} \sum_1^{n_d} S(x_{nd}, x_d) \tag{6}$$

Eguchi and Copas [11] started AUC optimization with linear scores by dealing with a complex calculating method for the AUC. Kraus [8] has proposed a recent method for building credit scoring model, which is called AUC optimization, with Wilcoxon Mann-Whitney procedure as method of calculation and Nelder-Mead method as the optimization algorithm. The outcomes are compared using different performance measures, and DeLong's test for analyze the significance of the different AUC measures. Extending the definition of equation (6); β^t is introduced as a vector of coefficients, while n_{nd} and n_d denote the scores as vectors of explanatory variables:

$$AUC(\beta) = \frac{1}{n_{nd} \cdot n_d} \sum_1^{n_{nd}} \sum_1^{n_d} S(\beta^t(x_{nd}, x_d)) \tag{7}$$

The aim is to optimize the β-coefficients by maximizing $AUC(\beta)$:

$$\hat{\beta}_{AUC} = \underset{\beta}{\arg\max} \frac{1}{n_{nd} \cdot n_d} \sum_1^{n_{nd}} \sum_1^{n_d} S(\beta^t(x_{nd}, x_d)) \tag{8}$$

III. Results and Discussions

A. Model 2.0

Model 2.0 consider 31 predictor variables. The dataset has 14,700 responses which consist of 14,290 non-default and 4,410 default. It will be separated randomly into train and test dataset with 70:30 proportions. Training dataset has 248 defaults and 10,042 non-defaults, while testing dataset has 98 defaults and 4,312 non-defaults.

Only good Predictor Variables will be selected for the model. Pearson's Chi-Square Test for Independence is used to filter the good predictor variables. The Alpha of the test is 0.1., with the hypothesis test as the follow:

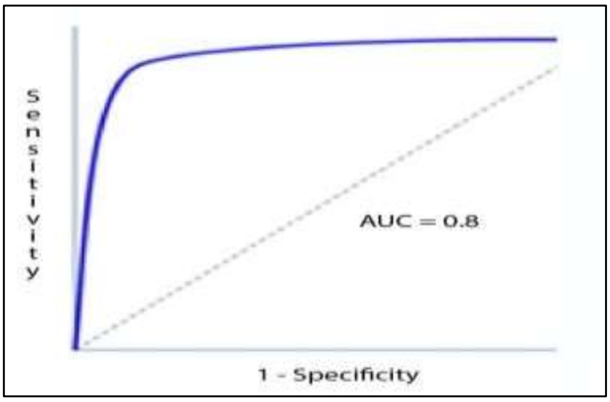


Fig 1. Example of ROC curves

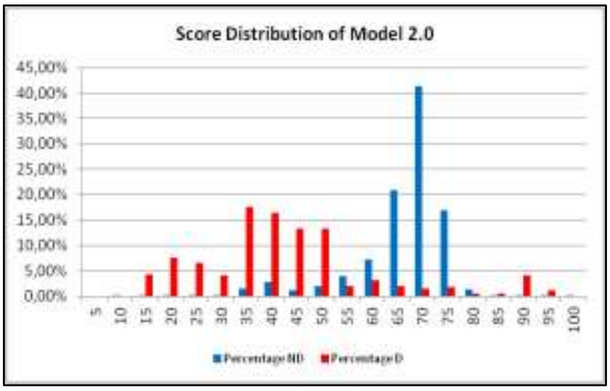


Fig 2. Model 2.0 score distribution

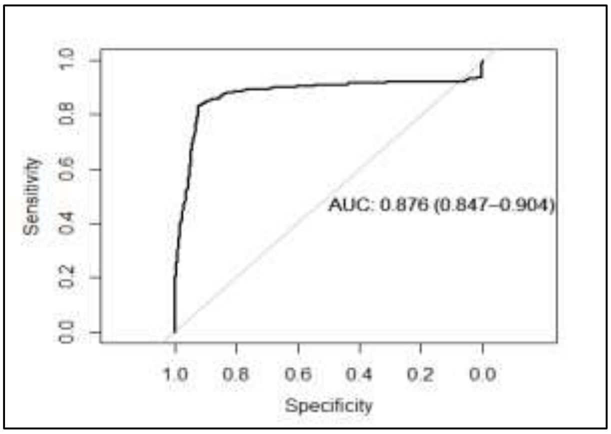


Fig 3. Receiver operating characteristic curve of Model 2.0

H_0: Response Variable is dependent with Predictor Variable.
H_1: Response Variable is not dependent with Predictor Variable.

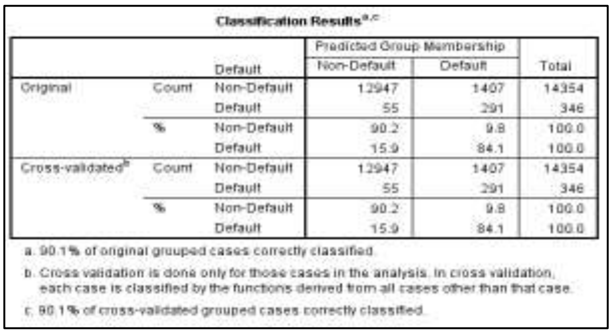
As the result of the test, there are 11 predictors variable that can predict default variable with error of 10% (Table 1). Not all good predictor variables are significant to the model of the model. Only significant predictor variables will be selected for the model. These selected variables should not have multi-collinearity with the others. The predictor variables should not have VIF value more than 5, which indicates that these variables are not multi-collinear with the others (Table 2).

Table 1. Pearson's Chi-Square Test for Independence in Variables Selection

Factors	Sig. test	Explanation	Factors	Sig. test	Explanation
RP1	0.283686	Bad	SC5	0.715114	Bad
RP2	0.019249	Good	FC1	0.029199	Good
RF1	0.367032	Bad	TI	0.175191	Bad
QM1	0.089796	Good	T2	0.216289	Bad
QM2	0.554222	Bad	TI	0.610069	Bad
QM3	0.740063	Bad	T3	0.622519	Bad
QM4	0.075396	Good	TI	0.844008	Bad
QM5	0.067597	Good	OC1	0.945753	Bad
QM7	0.683416	Bad	CR1	0.936653	Bad
QM8	0.443678	Bad	CR2	0.048498	Good
QM9	0.427229	Bad	AA1	0.085696	Good
YO1	0.665467	Bad	AA2	5.00E-05	Good
SC1	0.297085	Bad	LQ1	0.00125	Good
SC2	0.017499	Good	LR1	5.00E-05	Good
SC3	0.898905	Bad	PR1	0.934503	Bad
SC4	0.934353	Bad			

Table 2. Model 2.0 Summary

Factors	Est. value	Std. error	Z value	Pr (>|z|)	VIF
(Intercept)	-4.93731	0.552664	-8.93366	4.12E-19	0
QM5	-0.24278	0.149042	-1.62897	0.103319	1.002843
SC2	-1.07421	0.332101	-3.2346	0.001218	1.006764
FC1	0.567436	0.26886	2.11053	0.034813	1.00573
CR2	0.813105	0.436951	1.860862	0.062764	1.003276
AA2	-2.21651	0.176919	-12.5284	5.22E-36	1.040163
LQ1	-0.70768	0.177591	-3.98492	6.75E-05	1.011919
LR1	6.380752	0.271464	23.50493	3.6E-122	1.051683



Classification Results[a,c]

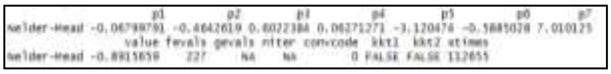
		Default	Predicted Group Membership: Non-Default	Predicted Group Membership: Default	Total
Original	Count	Non-Default	12947	1407	14354
		Default	55	291	346
	%	Non-Default	90.2	9.8	100.0
		Default	15.9	84.1	100.0
Cross-validated[b]	Count	Non-Default	12947	1407	14354
		Default	55	291	346
	%	Non-Default	90.2	9.8	100.0
		Default	15.9	84.1	100.0

a. 90.1% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 90.1% of cross-validated grouped cases correctly classified.

Fig 4. Model 2.0 score threshold



```
                    p1         p2        p3         p4        p5         p6       p7
Nelder-Mead -0.06799791 -0.4642619 0.6022384 0.06271271 -3.120474 -0.5885028 7.010125
                 value fevals gevals niter convcode  kkt1  kkt2 xtimes
Nelder-Mead -0.8915659    227     NA    NA        0 FALSE FALSE 112655
```

Fig 5. Model 2.1 summary

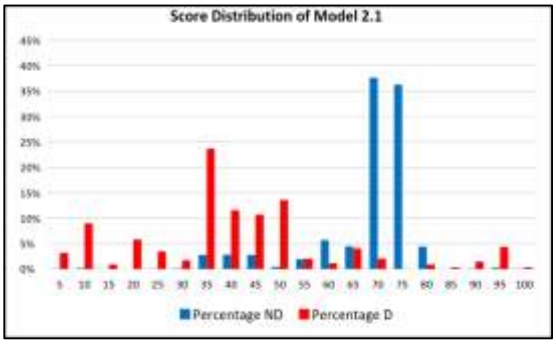


Fig 6. Model 2.1 score distribution

As seen on Fig 2 there is a significant difference scores between default and non-default applicants. Measuring the stability of a population aims to find out whether the population of testing dataset differs from the population of training dataset. Population Stability Index usually used as the indicator that still the development population perform as well as in the validation population. With a very low index of 0.008674917, there is an insignificant change between train and test dataset judged using Model 2.0 from its scores.

The ability of scorecard to separate between default and non-default can be measured by calculating the value of Kolmogorov-Smirnov Score. The KS Score of this model is 0.754. This means that Model 2.0 is good enough to separate the defaults and non-defaults. The model is very good in separation. The good separation of Model 2.0 also can be seen by the AUC (see Fig. 3).

Applicants with score lower than or equal to 52.3 will be predicted as default, while those with score higher than 52.3 will be predicted as non-default. The classification of Model 2.0 correctly predicts 84.1% the default and 90.2% the non-default (Fig 4). The next section will discuss how to improve the AUC with Nelder-Mead Algorithm.

B. Model 2.1: AUC Optimization

The objective of this optimization is to get a better AUC by changing the parameter value of predictor variables (Fig 5). The optimized model called Model 2.1. The score distribution of this model can be seen in Fig 6. In this figure we can figure out that there are some customers even though the score is only 35 but they were not defaulted,

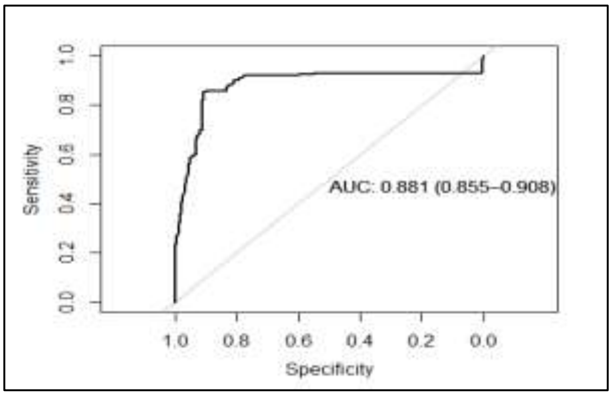


Fig 7. Model 2.1 receiver operating characteristic curve

Classification Results[a,c]

			Predicted Group Membership		
		Default	Non-Default	Default	Total
Original	Count	Non-Default	13034	1320	14354
		Default	55	291	346
	%	Non-Default	90.8	9.2	100.0
		Default	15.9	84.1	100.0
Cross-validated[b]	Count	Non-Default	13034	1320	14354
		Default	55	291	346
	%	Non-Default	90.8	9.2	100.0
		Default	15.9	84.1	100.0

a. 90.6% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 90.6% of cross-validated grouped cases correctly classified.

Fig 8. Model 2.0 score threshold

and some of them defaulted even though the score is 95.

The simulation value, AUC score is 0.891 after going through 227 times the function is called. Convcode is an integer code, which 0 indicates successful convergence. There is no significant difference in interpret Model 2.1 and Model 2.0 since there are no changes in the parameter value from true real positive to true real negative or otherwise (Fig 7).

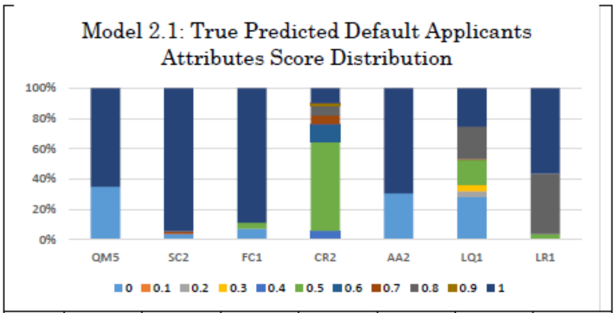
As seen on Fig 6 there is a significant difference scores between default and non-default applicants. With a very low index of 0.000456, there is an insignificant change between train and test dataset judged using Model 2.1 from its scores. With KS Score of 0.745, Model 2.1 is good enough to separate the defaults and non-defaults. The model is very good in separation. The defaults and non-defaults score distribution is quite good in separating the defaults and non-defaults. The good separation of Model 2.1 also can be seen by the AUC.

The AUC of Model 2.1 is 0.881. Model AUC is a very good model in separating defaults and non-defaults. There is a small improvement of AUC Score from Model 2.0 by 0.005. The model is very good in separation.

Applicants that have score lower than or equal to 52 will be predicted as default while those with score higher than 52 will be predicted as non-default. From all the 1,611 applicants that

Table 3. Model 2.0-Model 2.1 comparison

KS Score	0.754	0.745
Population Stabilit Index	0.008	0.001
Error Type I	1,407 applicants	1,320 applicants
Error Type II	55 applicants	55 applicants



Name	QM5	SC2	FC1	CR2	AA2	LQ1	LR1
Par	-0.07	-0.46	0.60	0.06	-3.12	-0.59	7.01
Dist.	0-1	0-1	1	0.5-1	0-1	0-1	0.8-1

Fig. 9 Model 2.1 true default predicted population

Fig. 10. Model 2.1 score below threshold groups

scored lower than or equal to 52, 291 were default while 1,320 are not. From all 13,089 applicants with score higher than 52, 13,034 were not default while only 50 default (see Fig 8).

C. Model 2.0 – Model 2.1 Comparison

There are differences between Model 2.0 and Model 2.1. To select the best one, we can compare those Models by some critical aspects. Table 3 shows the comparison.

The AUC value of Model 2.0 and Model 2.1 are good, which Model 2.1 has a better score. The KS Score of Model 2.0 and Model 2.1 are same good which Model 2.0 has higher value than Model 2.1. The Population Stability Index of Model 2.0 also higher than Model 2.1 where Model 2.1 almost considered that a little potential that the population of training dataset is different with the testing dataset. Model 2.0 give a higher type 1 error but have a same type 2 error with Model 2.1. Model 2.0 is not a bad model, but Model 2.1 perform better with the higher score of AUC, lower index of population stability and also a lower error in type I error.

D. Error Analysis

There are two categories of error of Model 2.1. The first is type I error, an error occurs when the prediction is default but actually non-default. This error will give a potential lost for Bank X. Bank had already rejected the applicant because of the poor score, but actually the applicant is not default, so Bank X will suffer loss by this error.

The second one is type II error in which the prediction is non-default but actually default. This kind of error can also cause the Bank to suffer, because the Bank had already accepted the applicant loan in prediction the applicant will not become default, but actually the applicant is default. For the banking perspective's, the type I error has to be as minimized as possible. Since, it is very hard to get a potential customer, once he or she is rejected. However, for the type II error, the bank still has opportunity to force those failed customers to pay their loan, e.g. by seizing the customer's collateral, sue the customer in court and black listed those customers.

The chance of type II error in Model 2.1 only about 0.42% (50 cases of 13,089 applicants but 81.93% for type I error (1,320 cases of 1,611 applicants).

Model 2.1 contains a very high type I error and offers many risk in its application. The risk of type I error is Bank X lose the potential income applicants which not default. Deep analysis is needed to reduce the risk of the implementation of Model 2.1. Some non-default applicants may have a lower attribute score in the selected variables which lead to score that below the threshold. These applicants are a potential applicant that can bring benefit for Bank X. We can know the applicants who truly default by their score attribute population. The population of the true predicted default applicants (applicant who is predicted as default and actually default) as in the Fig 9

The AUC of Model 2.0 is 0.876. Model AUC is a very good model in separating defaults and non-defaults. Using the discriminant analysis, we can know the threshold score for accepting or rejecting applicants (Fig 10).

After knowing the distribution of the true predicted default applicants, we can see the applicants in that population and its score. There are 772 of 1,611 applicants that categorized to this group. 30.05% applicants who match with the first group were default. 232 of 291 (79.7%) of true default predicted applicants were in this group.

The interesting point is only 7.03% from the second group were default. 92.97% applicants of this group were not default. This system make the Bank X easier to take further action for them who have score below the threshold. This system offers lower risk in accepting or rejecting the applicants who have score below the threshold than Model 2.1.

CONCLUSION

Recently there are many techniques in developing a good credit scoring model, such as AUC Optimization. AUC is a value that indicate how good a model in separating two different populations. Higher AUC value mean the model better in separating the populations.

By optimizing the AUC value, there is a possibility that the AUC value get higher. In term of optimizing, there are many techniques in optimizing, such as Nelder-Mead Algorithm.

The first used model in term of building a good model is Model 2.0 based on Logistic Regression Model. Model 2.0 performs well and is able to predict the default and the non-default applicants accurately with AUC value of 0.876. The second one is Model 2.1 based on AUC Optimization from Model 2.0. Model 2.1 has a 0.881 AUC value which is higher than Model 2.0's AUC value, but has a lower KS-Score. Although has a lower score, Model 2.1 still remain in the same class with Model 2.0 of their KS Score. Model 2.1 also has a lower type I error. Model 2.0 predict 1,407 applicants as default applicants but they are actually not going to default, while Model 2.1 only 1,320 applicants.

Even Model 2.1 performs better; the model still has a very large of errors. Model 2.1 can only predict 18.06% default applicants correctly which is mean that Model 2.1 also contain a lot of risk in its implementation. Model 2.1 rejected about 81.94% of all applicants with score below the threshold while they were not default. Bank X could lose many potential incomes. Deep analysis can provide some options to reduce the risks of the implementation of Model 2.1.

By knowing the true default applicants' population, we can filter the default predicted applicants into two groups. The first group is the default predicted applicant who have a similar population to the population of the true default applicants. The second one is another group except the first population in default predicted applicants.

With this separation, Model 2.1 has type I error of 69.95% for the first group and 92.97% for the second group. If the applicant has a score below the threshold and included to the second group, then Bank X has a lower risk in accepting the applicants from 18.06% to 7.03%. Bank X also has a lower risk in rejecting the applicants if the applicant matched with the first group. Model 2.1 can only predict the true default applicants with a rate of 18.06 and if we added the first group as additional filtering system, then Model 2.1 can predict the true default applicants with a rate of 30.05%.

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