Available online at www.worldscientificnews.com

World Scientific News

An International Scientific Journal

WSN 140 (2020) 1-11 EISSN 2392-2192

Parameter Estimation Using LU Decomposition in the Logistic Regression Model for Credit Scoring Analysis

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ABSTRACT

Banking is a financial institution that has a very important role in economic and trade activities which is useful for channeling funds in the form of loans to the public who need fresh funds for business in the hope of helping to improve the people's economy. In the loan process, banks are often exposed to risks known as credit risk or non-performing loans. Therefore, a credit analysis is performed by estimating the parameters using LU Decomposition in the Logistic Regression model. In this paper, the data used are data about cooperative financial services in Indonesia. Variables taken in the study are including the age of debtors (X_1), family dependents (X_2), the amount of savings (X_3), the value of collateral (X_4), the amount of income per month (X_5), given the credit limit (X_6), take home pay (X_7), and the loan term (X_8).

***Keywords*:** Credit Scoring, Logistic Regression, LU Decomposition, Problem Loans

1. INTRODUCTION

Banking is a financial institution that has a very important role in economic and trade activities. One of the benefits of banks is channeling funds in the form of credit to the public who need fresh funds for business or for consumptive needs [Agresti, A., 2002]. So, you could

(Received 08 December 2019; Accepted 24 December 2019; Date of Publication 27 December 2019)

say that banks are the core of every country's financial system. In the implementation of credit, in addition to helping improve the people's economy, banks also get a source of income in the form of revenue sharing. However, the process of channeling bank credit is often faced with a risk known as credit risk or problem loans. At present, the banking sector faces several risks.

According to [Tan, H., 2015], the risks encountered in the banking sector are credit risk, market risk, operational risk, interest risk, liquidity risk, and exchange rate risk. The concept of credit risk fails to meet the obligations of borrowers or signatories to people. More precisely, banks face risks as a result of declining credit quality. Market risk is defined that assets held by banks in the market are risk of loss due to market movements and changes in market prices [Turan, H., 2016]. One of the causes of the problem loans is the failure of the bank in conducting credit analysis of prospective debtors. Credit risk in the form of bad credit, is one of the main factors contributing to the banking crisis, this risk can be overcome using a scoring system that is owned by every bank [U. Rahmani et al, 2019].

In determining the decision to provide loans depends on the model and algorithm owned by each financial service to reduce the risk in their operations [Wang, D et al. 2017]. Empirical studies [Pagano et al., 1993], [Doblas-Madrid et al. 2013]; [P.Jakubik et al. 2015], [Kusi et al. 2017] show that sharing credit information reduces adverse bank selection, moral hazard and serves as a motivation for loan repayment which turns out to reduce bank bad loans and improve asset quality bank. In this study parameters will be estimated using LU Decomposition. [F. Serre et al 2016] Optimal circuit design for certain streaming streaming classes using LU Decomposition. Applying the LU decomposition concept to the Cholesky QR algorithm, that is, the idea is to use the LU-factor of the matrix given as a prerequisite before applying Cholesky decomposition.

A good credit rating model must be able to correctly rank customers from low to high probability of default, which is the basis of the approval strategy [Fang, F., et al, 2018]. Studying credit risk in commercial banks from Pakistan using credit rating models using credit assessment techniques such as credit rating models for individuals, logistic regression and discriminant analysis [Asia Semreen, 2012]. [Koh et al. 2006], conducted research on the establishment of a credit rating model conducted for financial institutions in German banks. [Lahsasna, et al. 2010], analyzing credit assessment models using soft computing methods. The establishment of a credit rating model conducted by Koh, et al. use a data mining approach for analysis.

[Wu, 2008] built a credit rating model using multiple linear regression models. Learn about assessing optimal credit growth from the perspective of financial stability based on the functional relationship between the square deviation of quarterly credit growth from the desired level and changes in provisioning fees one year later [Jakubik, P., et al. 2015]. Examining the private credit information section and its effect on bank credit risk in low and high income countries in Africa [Kusi, B. A et al. 2017]. The method of approach has been widely carried out by researchers about credit rating. However, credit valuation analysis has not been widely applied to financial services. [Bartolozzi et al. 2008], conduct research on credit assessment in the retail banking sector.

Therefore, in this paper expanded the discussion of credit appraisal for financial services cooperatives using estimates of LU decomposition with the Logistic regression model. As the object is taken from one of the financial services in Indonesia. Credit assessment analysis is carried out to minimize credit risk or non-performing loans.

2. MATERIAL AND METHOD

2. 1. Logistic Regression Model

a. Logistic Regression

Logistic regression is a prediction model used in classification aimed at determining a causal relationship between a variable and other variables [Bekhet et al. 2014]. The variable "cause" can be called an explanatory variable an independent variable (X). While the "effect" variable is the variable that is affected the dependent variable (Y) [Agresti, 2002].

Regression Analysis or called logistic model or logit model is one part of Regression Analysis which is used to analyze data with response variables consisting of qualitative data [Hosmer, 2013]. Logistic Regression Analysis is used to predict the probability of an event occurring, by matching the data to the logit function. This method is a general linear model used for binomial regression. Logistic regression does not require the assumption of normality, heteroscedasticity, and autocorrelation, because the dependent variable is dichotomic / binary. Variables that only have two categories, namely the category that states the success event 0 and the category that states the failure event 1.

The parameters of the Binary Logistic Regression model are estimated by the Maximum Likelihood (MLE) method which is then solved by the LU Decompositon. The binary logistic regression equation used in this study are:

$$\pi(x_i) = \frac{\exp(\beta_0 + \beta_1 x_{1i} + \ldots + \beta_i xi)}{1 + \exp(\beta_0 + \beta_1 x_{1i} + \ldots + \beta_i x_{ii})} \qquad i = 1,2,\ldots,N \qquad (1)$$

with $\pi(x_i)$ is the chance of a successful event with probability values $0 \le \pi(x_i) \le 1$ and β_i are parameter values with $i = 1,2,\ldots,p$. $\pi(x_i)$ is a non-linear function, so it needs to be transformed into a logit form to obtain linear functions so that the relationship between independent variables and non-independent variables can be seen.

Transformation of logit $\pi(x_i)$ is done, so the simpler equation is obtained, namely:

$$g(x) = \ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = (\beta_0 + \beta_1 x_1 + \ldots + \beta_i x_i) \qquad (2)$$

The essential assumptions of logistic regression are independence between the successive observations and the existence of a linear relationship between logit (x) and the predictors $X_1, X_2, \ldots, X_i$. One of the necessary considerations before applying the logistic regression model is to determine whether the relationship between the independent variable and the probability of the event changes its sense or direction, or not.

b. Estimation of Logistic Regression Parameters

The purpose of logistic regression is to estimate the parameter $\beta_i (i = 0,1,\ldots,p)$ which has an effect on equation (2) [Sohn et al. 2016]. Suppose there are independent variables

$X_1, X_2, \ldots, X_i$, the conditional density function Y to β follows the Bernoulli Distribution as follows [Montrenko et al, 2014]:

$$f(y|\beta) = \prod_{i=1}^{N} \pi_i^{y_i} (1-\pi_i)^{1-y_i} \qquad y_i = 0{,}1 \tag{3}$$

The Y_i variable is given a code 0 and 1 for each pair $(X_i Y_i)$. If $Y_i = 1$, the contribution to the likelihood function is $\pi(X_i)$, and if $Y_i = 0$ then the contribution to the likelihood function is $1 - \pi(X_i)$, where $\pi(X_i)$ denotes the value of π (x) on x_i. So that the contribution to the likelihood function of the pair (x_i, y_i) can be written as follows [Feelders, 2000]:

$$L(\beta) = \prod_{i=1}^{N} \pi_i^{y_i} (1-\pi_i)^{1-y_i} \qquad y_i = 0{,}1 \tag{4}$$

Substitute equation (1) to equation (4)

$$L(\beta) = \prod_{i=1}^{N} \left(e^{\sum_{i=0}^{p} \beta_i x_{ii}} \right)^{Y_i} \left(1 + e^{\sum_{i=0}^{p} \beta_i x_{ii}} \right)^{-1} \tag{5}$$

from equation (5) is logically fed with natural logarithms, so the log likelihood function is obtained as follows [Dellin et al, 2005]:

$$l(\beta) = \sum_{i=1}^{N} \left\{ y_i \sum_{i=0}^{p} \beta_i x_{ii} - \ln\left(1 + e^{\sum_{i=0}^{p} \beta_i x_{ii}} \right) \right\} \tag{6}$$

The vector element β in equation (6) is estimated to use LU Dekomposition.

2. 2. LU Decomposition

LU decomposition is a method of solving linear equations introduced by Alan Tu ring, a mathematician. LU decomposition is a procedure for simplifying a matrix. LU decomposition is often used in solving linear problems on computers.

Suppose there is a matrix A, a lower triangular matrix and an upper triangle matrix are formed so that,

$$A = LU$$

where L = lower triangle and U = upper triangle [K.R. Goodearl et al. 2012]. Because it must form the upper triangular matrix and the lower triangular matrix, then in LU decomposition, the completed matrix must be square. In the LU Decomposition method uses elementary row operations, but it is not allowed to swap rows between matrices because if swapped lines between matrices are not returned to the original matrix [Kumar. J et al. 2018].

The upper triangle (U) is obtained from elementary row operations without changing the order of the matrix rows. In LU Decomposition, there is no unique solution from the upper triangle matrix and the lower triangle matrix.

However, if the diagonal matrix of the bottom triangle is 1, then there will be a unique solution of the upper triangle matrix (U) and the bottom triangle matrix (L) [Al-Kurdi, A. et al. 2006]. This makes it easier to solve using the LU Decomposition method. In addition, in solving problems of linear equations using LU Decomposition can be resolved faster than LU decomposition in general [Pan. P, 2000]. This method uses a specific matrix in the lower triangle, where all the diagonal elements are worth 1.

The upper triangle (U) is derived from the operation of the elementary row without changing the order of the matrix row, and the value of the other L elements is obtained from the multiplication opponent in making the U matrix.

Decomposition Method LU has a weakness, because not all matrices can be factored. However, LU Decomposition Algorithm is more often used in the system of solving linear equations. Suppose that the system of linear equations $Ax = b$ is known. If A can be decomposed into LU, then $ULx = b$, the following is an illustration of LU Decomposition steps [J. W. Demmel et al. 1992]:

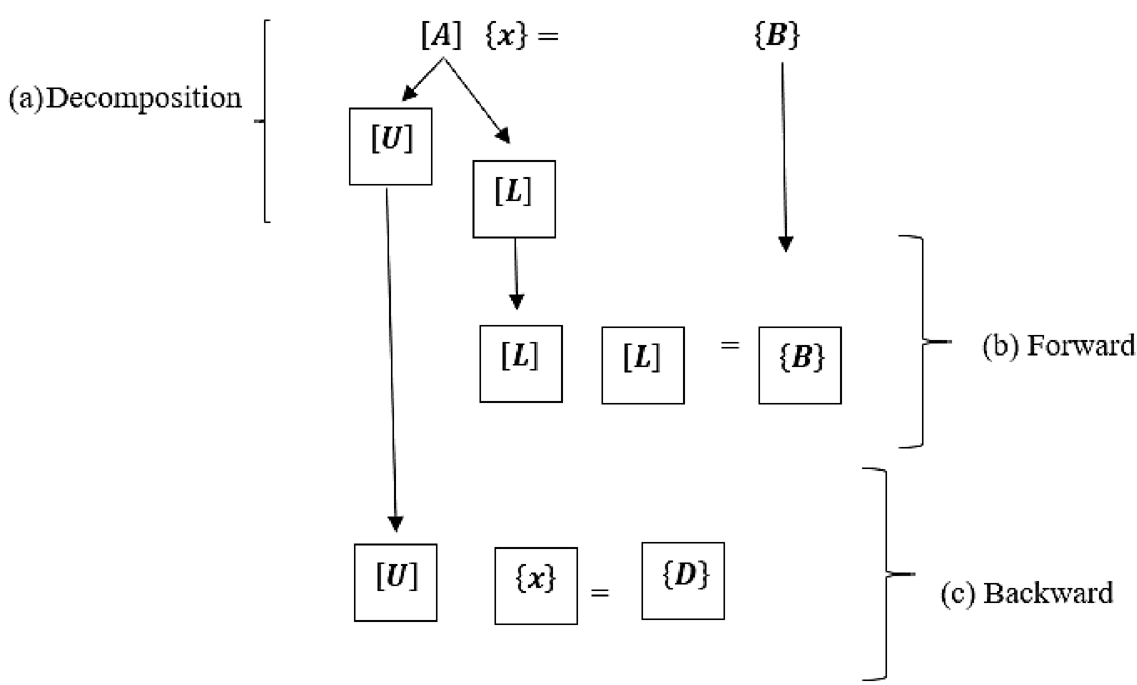

Figure 1. Illustration of LU Decomposition steps

In the first part, it is a step for the decomposition of matrix A into the upper triangle matrix (L) and the bottom triangle matrix (U). Then the next step is forward subtitles at Lx = b and backward subtitles at $Ux = b$

2. 3. Estimated Significance Test Parameters

Estimation is estimating certain characteristics of a particular population or it can be called the estimated population value (parameter) using the sample value. The way to draw conclusions about parameters relates to ways of estimating parameter prices. So, the unknown price of the actual parameter will be estimated based on sample statistics taken from the population concerned. In this paper, a significance test is carried out from a logistic model in order to see which significant independent variables are. The significance test of the logistic regression model in this paper was carried out with several statistical tests, namely: Likelihood Ratio Test, Wald Test, Hosmer & Lemeshow Test, and R-Square $\left(R^2\right)$.

2. 3. 1. Test of Likelihood Ratio

Maximum Likelihood is a method that can be used to estimate a parameter in a regression in order to get an estimator for unknown parameters from a population with a maximum Likelihood function. Before forming a logistic regression model, a significant parameter test was first carried out.

The first test conducted to test the effect of the role of parameters in the overall model, namely the hypothesis as follows: Maximum Likelihood is a method that can be used to estimate a parameter in a regression with the aim of obtaining an estimator for unknown parameters from a population with a maximum probability function.

According to Hosmer and Lameshow (1989; 2013), the Likelihood Ratio test is to test the significance of all the coefficients of the independent variables in the model shown by the G statistics, whose equations are as follows:

$H_0 : \beta_1 = \beta_2 = \ldots \beta_i = 0$ (the model has no significant effect)

$H_1 : \exists \beta_1 \neq \beta_2 \neq \ldots \beta_i \neq 0$ (the model has a significant effect on the model)

where i = 0, 1, …., p

According to Hosmer and Lameshow (1989), the Likelihood Ratio test is to test the significance of all the coefficients of the independent variables in the model shown by the G statistics, whose equations are as follows:

$$G = 2\left[\sum_{i=1}^{n} y_i \ln \hat{\pi}_i + \sum_{i=1}^{n}(1 - y_i)\ln(1 - \hat{\pi}_i) - n_1 \ln n_1 - n_0 \ln n_0 + n \ln n\right] \qquad (7)$$

The hypothesis for the Likelihood ratio test is $H_0 : \beta_0 = \beta_1 = \ldots = \beta_i = 0$, with alternatives $H_1 : \exists \beta_0 \neq \beta_1 \neq \ldots \neq \beta_i \neq 0 \quad (i = 0,1,\ldots, p)$. Because the statistic G follows the Chi-Square distribution with the degree of freedom equal to the number of independent variables. The criteria used are: if $G \geq \chi^2_{(1-\alpha)(df)}$ then H_0 rejected and if $G < \chi^2_{(1-\alpha)(df)}$ then H_0 be accepted. Where α is the significant level specified, and $df = m - 1$ with m number of model parameters.

2. 3. 2. Wald Test

According to Hosmer and Lemeshow (1989; 2013), to test the significance of $\beta_i\left(i=0,1,\ldots,p\right)$ parameters, the Wald test is used individually. The Wald test uses Z statistics, where this Z statistic follows the Raw Normal distribution.

The Z statistics are:

$$Z=\frac{\beta_1}{SE\left(\beta_1\right)}\ ;\ i=0,1,\ldots,p \tag{8}$$

where β_1 is the estimator for parameters $\left(\beta_1\right)$and $SE\left(\beta_1\right)$= estimator of standard error for the coefficient β_1. The Wald test hypothesis is $H_0:\beta_i=0$. With alternatives $H_1:\beta_i\neq 0$ $\left(i=0,1,\ldots,p\right)$. The criteria used if $-Z_{\frac{1}{2}(1-\alpha)}<Z<Z_{\frac{1}{2}(1-\alpha)}$ then H_0 accepted and if $Z_{\frac{1}{2}(\alpha)}\leq Z\leq Z_{\frac{1}{2}(1-\alpha)}$ then H_0 rejected. Where $Z_{\frac{1}{2}(\alpha)}$ is the percentile of a standard normal distribution with level significance α .

2. 3. 3. Hosmer & Lemeshow Test

According to Hosmer and Lemeshow (1989; 2013), the Hosmer and Lemeshow test is known as the Logistic Regression Model compatibility test for data. The equation of this test is as follows:

$$C=\sum_{i=1}^{g}\frac{\left(o_i-n_i\bar{\pi}_i\right)^2}{n_i\bar{\pi}_i\left(1-\bar{\pi}_i\right)} \tag{9}$$

The hypothesis used is as follows:

H_0 :there is no difference between the results of observations with the model used

H_1 :there is a difference between the results of observations with the model used

This Hosmer and Lemeshow test will follow the Chi-Square distribution with degrees of freedom $df=\left(g-2\right)$. In general use $g=10$. Test the criteria used, namely: H_0 rejected if $C>\chi^2{}_{(1-\alpha)(g)}$ and H_0 accepted if $C<\chi^2{}_{(1-\alpha)(g)}$. Where the α level of significance is determined.

2. 3. 4. R-Squared Test R^2

According to Hosmer and Lemeshow (1989; 2013), the value of R^2 in the Logistic Regression analysis shows the strong relationship between independent variables and free variables. For the value of R^2 it is:

$$R^2 = 1 - \exp\left[-\left(\frac{L^2}{n} \right) \right] \tag{10}$$

where: L = log Likelihood value of the model and n = amount of data. If $R^2 \to 1$, then the relationship between the independent variable and the dependent variable is strong and if $R^2 \to 0$ then the relationship is weak.

3. RESULT AND DISCUSSION

Data analysis was carried out in the manner described in the chapter Before further data was performed, normality tests were carried out which apply to multivariate analysis. In a multivariate analysis the normality test aims to find out whether the data distribution approaches or follows normal distribution. Data that have patterns like the normal distribution are good data for multivariate analysis. Data can be used to estimate the parameters of the binary logistics model after the data is normally distributed. For this reason, data normality test is done using SPSS.

3. 1. Result

Estimator vector is determined using Binary Logistic Regression parameter estimation by maximizing the Likelihood function in equation (6). Estimation is carried out using LU Decomposition as described in section 2.4. Test the Significance aims to test the parameter estimator that affects the dependent variable $\pi(X)$. Parameter estimation using LU Decomposition is done using Maple. Significant parameter estimation results and Standrad Error are shown in Table 1.

Table 1. Significant Variable Parameter Estimates

Parameter Coefficient (X_i)	Parameter Estimator (β_i)	Significance
Family dependents (X_2)	0.786	Signifikance
The amount of savings (X_3)	2.154	Signifikance
The value of collateral (X_4)	0.910	Signifikance
Given the credit limit (X_6)	-1.097	Signifikance
The loan term (X_8)	0.5812	Signifikance

Maximum Likelihood value $\hat{\beta} = -26.84$

Table 1, the estimated parameter obtained for family dependents is 0.786, the amount of savings is 2.154, the collateral value 0.910, given the credit limit, the loan term is 0.5812 and the maximum value of the Likelihood is -26.84. Therefore, for parameter estimation using LU decomposition can be used in this credit data.

4. CONCLUSION

LU decomposition is used as a Logistic Regression estimator for the purpose of estimating parameters for variables. In this study, it was conducted on financial services. Consisting of eight factors analyzed, namely the age of debt, family dependents, the amount of savings, the value of the collateral, the amount of income per month, the credit limit, net income, and the term of the loan. The accuracy value obtained for LU decomposition using this logistic regression model is 94% with a significant variable consisting of), dependents of the family, the amount of savings, the value of the collection, credit limit, and time period loan.

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