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Poisson Ridge Regression for Multicollinearity Data: Case Study of the Number of Maternal Deaths in Lampung Province, Indonesia

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ABSTRACT: Poisson regression is a regression analysis used to determine the relationship between the dependent variable in the form of discrete data which is assumed to have a Poisson distribution and the independent variables. This method uses Maximum Likelihood parameter estimation which must meet the assumption of multicollinearity between independent variables. Violation of the multicollinearity assumption can cause the parameter estimation results to have non-minimum variance. Therefore, multicollinearity in Poisson distribution data needs to be overcome. This study aims to apply the Poisson Ridge regression method to multicollinearity Poisson data on the number of maternal deaths in Lampung Province, Indonesia using several Ridge penalty parameters. The results obtained in this study show that the Poisson Ridge regression method can handle multicollinearity well. Apart from that, it was also found that the Poisson Ridge regression method with the penalty parameter k_1=0.1498 was the best estimator because it gave the smallest MSE (18.6087) value compared to the other penalty parameter formulas. This shows that Poisson Ridge regression with Ridge penalty parameters k_1 is the best parameter estimate compared to other Ridge penalty parameter estimates. The results of the analysis on the number of maternal deaths in Lampung Province, Indonesia using the Poisson Ridge regression model with the best Ridge penalty parameter (k_1) show that the number of maternal deaths is influenced by the number of postpartum mothers who receive complete services (x_2) and the number of pregnant women who consume blood supplement tablets (x_3).

KEYWORDS: Poisson Ridge Regression, Ridge penalty parameters, Multicollinearity, Maternal deaths**,** MSE,

I. INTRODUCTION

Regression analysis is one of the data analysis methods used for modeling and analyzing the relationship between independent variables with dependent variable. If in a case where the dependent variable is discrete data so a good regression method to use is Poisson regression analysis. Regression analysis used to analyze and determine the relationship between the dependent variable in the form of discrete data and the independent variable in the form of mixed data, both continuous and discrete, is the Poisson regression model [1]. Poisson regression uses *Maximum Likelihood* parameter estimates which must meet the assumption of multicollinearity between the independent variables [2]. Basically, data often violates the multicollinearity assumption, causing one of the classical assumptions to not be fulfilled and parameter estimates that have non-minimum variance. So that with this multicollinearity problem, the Poisson Ridge Regression (PRR) method is used to overcome this problem. The Poisson Ridge Regression method was developed by [3], they modified the Ridge regression method to overcome multicollinearity which was originally introduced by [4].

The maternal mortality rate is an indicator that determines the level of welfare of a country. According to the World Health Organization (WHO) the maternal mortality rate is the number of women who die during pregnancy, childbirth or die within 42 days after pregnancy, which are caused by interruptions in pregnancy or its management, not due to injury or an accident [5]. Maternal mortality rate illustrates as one of the indicators that can improve society towards Indonesia's health development goals in 2025, namely by reducing the maternal mortality rate in Indonesia. Maternal mortality rate is also an indicator for launching progress in improving maternal health care in a country, identifying health problems, and designing a plan or program to reduce the number of maternal deaths. Therefore, Maternal

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mortality rate is one of the targets of the Sustainable Development Goals (SDG) in 2030 by reducing the maternal mortality rate to 70 per 100,000 live births.

There are several previous studies that discuss the problem of multicollinearity violations in Poisson regression such as research by [6] Poisson Ridge Regression (PRR) Modeling on Many Infant Mortality in Central Java with the conclusion that the Poisson Ridge Regression method can be used on these data which have a Poisson distribution. Furthermore, research conducted by [7] analyzed the Poisson Ridge Regression estimator using simulated data with the conclusion that the Poisson Ridge Regression model is good for use on data that has multicollinearity problems in Poisson regression. Based on the description above, the author is interested in conducting research using the Poisson Ridge Regression method to control the problem of multicollinearity in Poisson data on factors that influence the number of maternal deaths in Lampung province, Indonesia using different formulas of penalty Ridge parameter.

II. POISSON RIDGE REGRESSION

Poisson distribution is a discrete probability distribution with events that have a small probability of occurrence or also called rare events, where an event occurs at a certain time interval or in a certain area. The Poisson distribution is included in the theoretical distribution that uses discrete random variables. According to [2], the Poisson distribution has a probability function for the random variable Y with the parameter μ as follows:

$$p(y,\mu) = \frac{e^{-\mu}\mu^{y}}{y!}$$

The probability function above shows that Poisson regression is a nonlinear regression method that models the relationship between the dependent variable (Y) in the form of a discrete random variable that has a Poisson distribution with the independent variable (X). In Poisson regression, it begins with the dependent variable having to follow the Poisson distribution, where the Poisson distribution of the dependent variable is in the exponential family which is a component in the Generalized Linear Model (GLM) so that Poisson regression is part of the GLM. In Poisson regression, the variance does not require homogeneity or constancy. Model of Poisson regression is

$$y_i = \mu_i + \varepsilon_i$$

$$y = e^{\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+\cdots+\beta_p x_{pi}} + \varepsilon_i$$

In estimating parameters in the Poisson regression model $\beta_0, \beta_1, \ldots \beta_n$ using the Maximum Likelihood Estimation (MLE) method by maximizing the likelihood function [8]. The likelihood function in Poisson regression is as follows:

$$L(y;\mu) = \prod_{i=1}^{n} P(y_i;\mu) = \frac{\left\{\left(\prod_{i=1}^{n} \mu_i^{\,y_i}\right)\left(e^{(-\sum_{i=1}^{n}\mu_i)}\right)\right\}}{\prod_{i=1}^{n}(y_i!)}$$

So that the above equation can be solved easily, the log likelihood function is formed as follows:

$$\log L(y;\beta)) = \log \frac{\left\{\left(\prod_{i=1}^{n} \mu_i^{\,y_i}\right)\left(e^{(-\sum_{i=1}^{n}\mu_i)}\right)\right\}}{\prod_{i=1}^{n}(y_i!)} = \sum\nolimits_{i=1}^{n} y_i\left(\boldsymbol{x}_i^T\boldsymbol{\beta}\right) - \sum\nolimits_{i=1}^{n} e^{(x_i^T\boldsymbol{\beta})} - \sum\nolimits_{i=1}^{n} \log y_i!$$

Then the first derivative of $\log L(y;\beta))$ is performed on β to obtain the Maximum Likelihood estimator value $\hat{\beta}$ as follows:

$$\frac{\partial \log L(y;\beta))}{\partial\beta} = \sum\nolimits_{i=1}^{n}\left(y_i - e^{(x_i^T\boldsymbol{\beta})}\right)\boldsymbol{x}_i^T = 0$$

Because the β parameter of the equation above is a non-linear equation, it is difficult to obtain explicitly, so the Iterative Weighted Least Square (IWLS) algorithm is used to obtain the estimated value of the Poisson regression parameters.

$$\widehat{\boldsymbol{\beta}}_{ML} = \left[\boldsymbol{X}^T\widehat{\boldsymbol{W}}\boldsymbol{X}\right]^{-1}\boldsymbol{X}^T\widehat{\boldsymbol{W}}\hat{\boldsymbol{s}}$$

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The biased MSE estimator $\widehat{\boldsymbol{\beta}}_{ML}$ to β is

$$\begin{aligned} MSE(\widehat{\boldsymbol{\beta}}_{ML}) &= E(\widehat{\boldsymbol{\beta}}_{ML} - \boldsymbol{\beta})^T(\widehat{\boldsymbol{\beta}}_{ML} - \boldsymbol{\beta}) \\ &= trace\left[(\boldsymbol{X}^T\widehat{\boldsymbol{W}}\boldsymbol{X})^{-1}\right] = \sum_{j=1}^{p}\frac{1}{\lambda_J} \end{aligned}$$

According to [9, 10], in examining the role of regression coefficients for individual independent variables, this can be done by making a comparison between the estimator and various estimators. One of the tests used is the Wald. The Wald test statistical formula can be written in the following equation:

$$W_j = \left(\frac{\hat{\beta}_j}{SE(\hat{\beta}_j)}\right)^2$$

To examine the significance of the regression coefficients simultaneously, it is carried out by simultaneously testing the significance of the parameters simultaneously. One test that is often used is the Likelihood Ratio Test, with statistical tests as follows:

$$G = -2\ln(L_0 - L_1)$$

Poisson regression requires standardization or standardization of variables. This can be done by centering and scaling variables to minimize rounding errors. Centering and scaling transformations are also useful in making it easier if the data we have has different units. The centering and scaling methods are only applied to the independent variable, because the dependent variable is discrete and non-negative data [11]. Let $X = (x_i, \dots x_p)$ where x_i column vector of matrix X of size $n \times 1$ and p is an independent variable. For a standardized matrix X it is denoted by X^*

$$X_{ij}^* = \frac{X_{ij} - \bar{X}_j}{\sqrt{\sum_{i=1}^{n}(X_{ij} - \bar{X}_j)^2}}$$

Poisson regression also assumes the fulfillment of multicollinearity among the independent variables. Multicollinearity is the existence of a strong linear relationship between some or all of the independent variables in the regression model [2]. In multicollinearity the presence of strong correlation can cause the estimated value to be unstable so that the results of the regression analysis become inappropriate. Multicollinearity can also cause large standard deviations of the regression coefficient estimates. In dealing with multicollinearity problems in Poisson data, one must use different method. One method that can be used to deal with correlation between independent variables in Poisson data is Poisson Ridge Regression. Poisson Ridge regression is a combination of the Ridge regression method and Poisson regression model which can be used to analyze data that has multicollinearity problems or experiences high correlation in the independent variables [3, 4]. The problem of multicollinearity in Ridge regression can be overcome by adding the penalty parameter (k) to reduce the value of the variance of the estimator. Even though Ridge regression provides a biased regression coefficient estimator, this method can give estimated parameter closer to the actual estimated parameter values. To apply Ridge regression, the first thing to do is to transform the centering and scaling methods. The following is an equation model by carrying out the transformation as follows:

$$\ln(\hat{\mu}) = \beta_1{}^*X_{1i}{}^* + \beta_2{}^*X_{2i}{}^* + \cdots + \beta_p{}^*X_{pi}{}^*$$

The same method is applied when Poisson Ridge Regression model is used to estimate the parameters. It begins with transforming the data using the centering and scaling method on the independent variables. In addition, maximum likelihood estimates is also used to minimized the sum of squares of the residual Weighted Sum of Square Error (WSSE) [11]. The $\widehat{\boldsymbol{\beta}}_{ML}$ estimator obtained will be seen as the optimal estimator in Weighted Sum of Square Error (WSSE). Using the Lagrange method, the estimated parameters of Poisson Ridge Regression model is

$$\widehat{\boldsymbol{\beta}}_{PRR} = (\boldsymbol{kI} + \boldsymbol{X}^T\widehat{\boldsymbol{W}}\boldsymbol{X})^{-1}\boldsymbol{X}^T\widehat{\boldsymbol{W}}\hat{\boldsymbol{s}}$$

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According to [12] there is a matrix **G** with size $p \times p$ with eigen vector elements $\boldsymbol{X^T \widehat{W} X}$, where $\boldsymbol{\Lambda_{PRR}}$ matrix diagonal of $(\lambda_{1PR}, \lambda_{2PR}, \dots \lambda_{pPR,})$ corresponds to matrix **G**.

$$\boldsymbol{\Lambda_{PRR} = G^T X^T \widehat{W} X G = Z^T \widehat{W} Z}$$

Based on the above equation, where $\boldsymbol{Z} = \boldsymbol{XG}$ has size $n \times n$.

$$\boldsymbol{\hat{\gamma}_{ML} = \left(Z^T \widehat{W} Z\right)^{-1} Z^T \widehat{W} \hat{s} = \Lambda_{PRR}^{-1} Z^T \widehat{W} \hat{s}}$$

The following is an estimator for the Poisson Ridge Regression which can be written by adding the penalty paramter k, where $k > 0$ and $\boldsymbol{B} = (\boldsymbol{\Lambda_{PRR}} + \boldsymbol{kI})$:

$$\boldsymbol{\hat{\gamma}_{PRR} = (I - kB^{-1})\hat{\gamma}_{ML}}$$

and mean square error of the Poisson Ridge Regression estimator is

$$\begin{aligned}\boldsymbol{MSE_{PRR}} &= \boldsymbol{Var(\hat{\gamma}_{PRR})} + \left(\left(\boldsymbol{Bias(\hat{\gamma}_{PRR})}\right)\left(\boldsymbol{Bias(\hat{\gamma}_{PRR})}\right)^{\boldsymbol{T}}\right) \\ &= \left(\boldsymbol{(I - kB^{-1})\Lambda_{PRR}^{-1}(I - kB^{-1})}\right) + \left(\boldsymbol{(-kB^{-1}\gamma)(-kB^{-1}\gamma)^T}\right)\end{aligned}$$

There are several Ridge penalty parameters (k) that can be used in the Poisson Ridge regression model. For example, research in [13] suggests using the Ridge penalty estimator value $\hat{k}_1 = \frac{1}{\hat{\alpha}_{max}^2}$. In addition, [14], proposed the optimal value of k with the formula $\hat{k}_2 = max(\, s_i)$ and $\hat{k}_3 = \text{median}\,(\, s_i)$. Furthermore, [15] recommends the optimal k value with the formula $\hat{k}_4 = \text{median}\,(q_i)$ and $\hat{k}_5 = \max\,(q_i)$. Meanwhile, [16] uses the optimal k value as follows:

$$\hat{k}_6 = \max\left(\frac{1}{m_i}\right) \qquad \hat{k}_7 = \text{median}\left(\frac{1}{m_i}\right)$$

$$\hat{k}_8 = \text{median}\,\left(\frac{\lambda_i}{(n-p) + \lambda_i \alpha_i^2}\right)$$

In this research, the results of using all these penalty parameters will be compared and will see which one has the smallest mean square value as the best penalty estimator method.

III. METHODOLOGY

This research used case data on the number of maternal deaths in each district of Lampung Province, Indonesia with a total of 15 observations using 6 independent variables and 15 observations. The variables are the number of pregnant women (x_1), the number of postpartum mothers who receive complete services (x_2), the number of pregnant women taking blood supplement tablets (x_3), the number of pregnant women carrying out immunizations (x_4), the number of active integrated health posts (x_5),, and the number public health canter (x_6), The analysis begins by testing whether the data follows a Poisson distribution or not using the one-sample Kolmogorov-Smirnov test statistic. Next, checking for multicollinearity problems in the data is carried out by looking at the variance inflation factor (VIF) value. Then the data was analysed using the Poisson Ridge regression model. However, before applying the Poisson Ridge regression model, the penalty value of Ridge penalty parameter (k) has to be determined first and the best k value obtained is used to obtain the Poisson Ridge Regression estimator. The selection of the best k values is done by comparing the smallest MSE with formula:

$$MSE = \sum_{i=1}^{n} \frac{\left(\hat{Y}_t - Y_t\right)^2}{n}, \qquad i = 1,2,3, \dots n$$

for eight penalty Ridge parameters $(\boldsymbol{k_1}, \boldsymbol{k_{2,}}, \dots, \boldsymbol{k_{8,}})$ used in the Poisson Ridge Regression estimator.

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IV. EXPERIMENTAL RESULTS

The first analysis carried out was to test whether the data followed a Poisson distribution or not using the one-sample Kolmogorov-Smirnov test statistic (H_o: Data is distributed Poisson vs H_1: Data is not distributed Poisson). The results of the analysis can be seen in Table 1 below.

Table1. Kolmogorov-Smirnov test

N	15
D_{count}	0.2316
P-value	0.3969

Based on Table 1 above, it can be seen that the p-value in the Kolmogorov test above is 0.3969, where the p-value$= 0.3969 > \alpha = 0.05$ then accept H_0. Because H_0 is accept, it can be concluded that data used is distributed Poisson..

Next, checking whether or not there is correlation between the independent variables in the data is done by looking at the variance inflation factor (VIF) value whether it is greater or less than 10. If it is greater than 10, it means there is a correlation between the independent variables and this indicates the presence of multicollinearity. The result is shown in Table 2.

Table 2. VIF value

Variable	VIF
X_1	10.411595
X_2	42.025961
X_3	132.711452
X_4	5.790547
X_5	9.799327
X_6	2.126600

From Table 2, it can be seen that some varibles are having value of VIF > 10 indicating the existence of multicollinearity. Those variables arex_1, x_2, and x_3 which have VIF values > 10. From these results it can be ascertained that there is a correlation between the independent variables in the data used and clearly shows the detection of multicollinearity in the data.

Because there is multicollinearity between independent variables, Poisson Ridge Regression is used. To apply this model, before applying the model, a centering and scaling transformation is carried out on the independent variables so that variable X data is obtained as a result of the transformation to make it easier to carry out the analysis. Next, Poisson Ridge regression analysis was carried out using several Ridge penalty estimators (k_1, k_2, …, k_8). The obtained parameter estimates are presented in Table 4.

Based on Table 4 below, it can be understood that using the Poisson Ridge Regression method with several Ridge parameter k penalties used results in biased regression coefficients, but this bias estimate can usually be used as a bias tolerance. This bias tolerance does not guarantee that the bias will always be small, but the bias in the Poisson Ridge Regression method can be close to the actual estimated parameter values. In this method, the use of the appropriate Ridge penalty parameter (k) can reduce the variance value of the Poisson Ridge Regression estimator. In selecting the best model, this research uses the Mean Square Error (MSE) estimator in Poisson Ridge Regression for the 8 different penalty parameters used.

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Tabel 4. Estimated Value, Variance and Bias of Poisson Ridge Regression

Penalty parameter (k)	Parameter	Estimated Values	Variance	Bias
k_1 = 0.1498	Υ_1	-0.91809347	5.468714	14.31975
	Υ_2	0.04625582		
	Υ_3	1.90410789		
	Υ_4	-0.64842062		
	Υ_5	-0.26899440		
	Υ_6	-0.15222899		
k_2=0.4943	Υ_1	-0.86916331	1.933293	16.67546
	Υ_2	0.03415268		
	Υ_3	1.23936948		
	Υ_4	-0.38834208		
	Υ_5	-0.11427734		
	Υ_6	-0.04746465		
k_3 = 0.0380	Υ_1	-0.93519214	13.57227	11.12173
	Υ_2	0.05227213		
	Υ_3	2.30576036		
	Υ_4	-0.82866162		
	Υ_5	-0.48009683		
	Υ_6	-0.53763052		
k_4 = 0.0078	Υ_1	-0.93992287	45.83691	4.668231
	Υ_2	0.05417642		
	Υ_3	2.44514790		
	Υ_4	-0.89596682		
	Υ_5	-0.60932566		
	Υ_6	-1.70237977		
k_5=0.00803	Υ_1	-0.93988674	44.78238	4.788309
	Υ_2	0.05416143		
	Υ_3	2.44402519		
	Υ_4	-0.89541417		
	Υ_5	-0.60808188		
	Υ_6	-1.67480800		
k_6 = 0.2843	Υ_1	-0.89834692	3.270105	15.51022
	Υ_2	0.04063334		
	Υ_3	1.57439514		
	Υ_4	-0.51400998		
	Υ_5	-0.17597114		
	Υ_6	-0.08176365		
k_7=0.2127	Υ_1	-0.90875588	4.174969	14.95893
	Υ_2	0.04344566		
	Υ_3	1.73432533		
	Υ_4	-0.57779296		
	Υ_5	-0.21569418		
	Υ_6	-0.10851320		
k_8=0.0449	Υ_1	-0.93411015	12.16667	11.63585
	Υ_2	0.05185268		
	Υ_3	2.27590225		
	Υ_4	-0.81457912		
	Υ_5	-0.45775431		
	Υ_6	-0.46449231		

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Table 5 gives the mean square error values for different Ridge penalty parameters. From table 5, it can be seen that if there is multicollinearity in the Poisson distribution data, then if data analysis it is best to use the Poisson Ridge regression model to produce a small error. Because if the error is high it will affect the parameter estimates and the conclusions that will be drawn. Therefore, if the data contains multicollinearity, Poisson Ridge regression should be used. Apart from that, in Table 5 it can also be seen that when using Poisson Ridge regression one must also pay attention to the Ridge penalty method that will be used because mean square error of Poisson Ridge regression is very dependent on the value of the Ridge penalty parameter. By using eight different formulas for the Ridge penalty parameter in the Poisson Ridge regression model, the smallest MSE value of the model was obtained when using the Ridge penalty parameter using the k_1 method with an MSE value = 19.03561.

Tabel 5. MSE for different penalty parameters

Poisson Ridge Regression with different *k*	MSE
k_1	19.0356
k_2	20.8201
k_3	21.0176
k_4	33.0818
k_5	32.6624
k_6	19.6483
k_7	19.2556
k_8	20.5140

Based on the best Ridge penalty parameters in the Poisson Ridge regression model above, an analysis was carried out to determine which independent variables influence the number of maternal deaths in Lampung Province, Indonesia using the Wald test. The results of the study showed that the number of postpartum mothers who receive complete services (x_2), the number of pregnant women taking blood supplement tablets (x_3) both had p-value <0.05, which means x_2 and x_3 have a significant influence on the number of maternal deaths in Lampung Province, Indonesia.

V. CONCLUSION

Based on the results of research on handling multicollinearity using Poisson Ridge regression, it can be concluded that the use of the Ridge penalty parameter value greatly influences the MSE value. In a case study of the number of maternal deaths in Lampung Province, Indonesia, it was found that the Ridge k1 penalty parameter was the best to use. It can also be concluded that the number of maternal deaths in Lampung Province, Indonesia is influenced by the number of postpartum mothers who receive complete services (x_2) and the number of pregnant women who consume blood supplement tablets (x_3).

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