

# Bi-response Poisson Regression Model based on Local Linear for Modelling Effect of Early Marriage on The Child-Girl to Maternal and Infant Mortality in East Java



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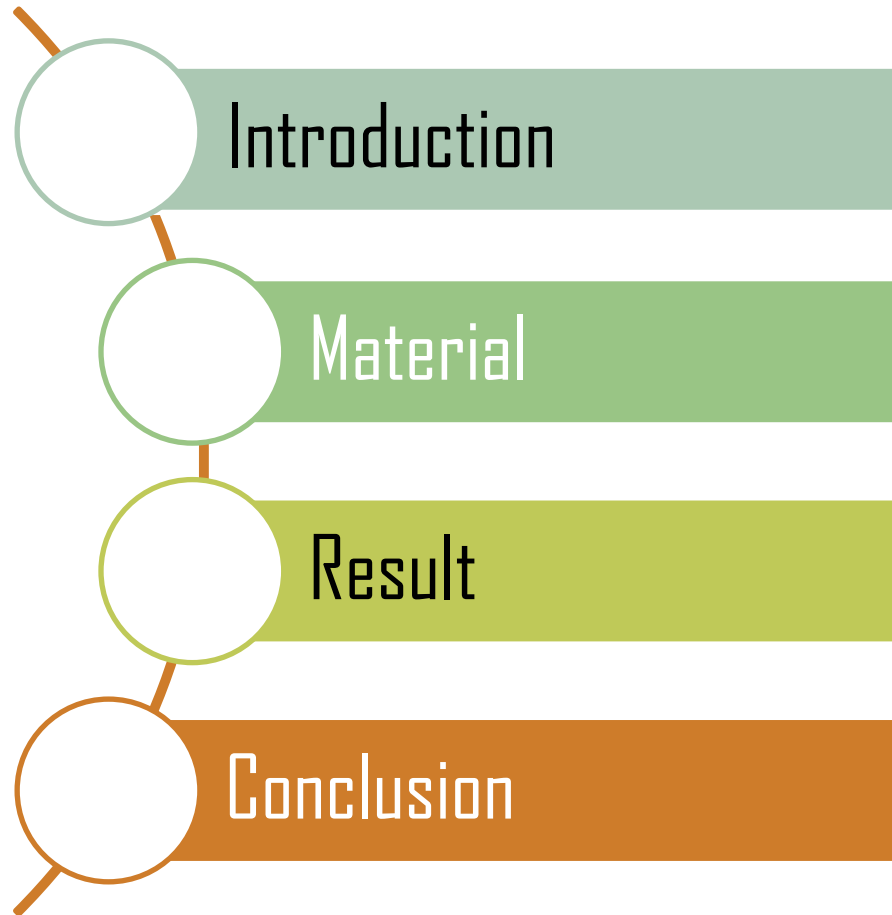
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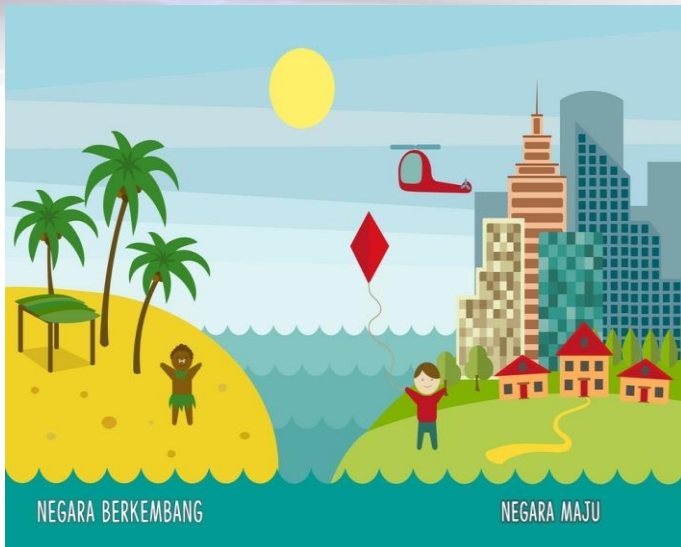
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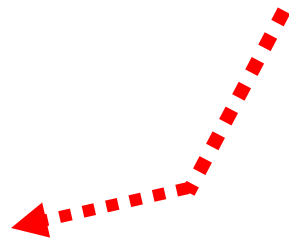
Developing countries



Early Marriage on The Child-Girl



Serious consequences for their health





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Early Marriage on The Child-Girl is defined as a marriage of a girl or boy before the age of 18 (UNICEF, 2001).





## Maternal Mortality



# I N T R O D U C T I O N

The death of woman while pregnant or within 42 days of termination of pregnancy, irrespective of the duration and site of the pregnancy, from any cause related to or aggravated by the pregnancy or its management but not from accidental causes.

(Dinkes Jatim, 2016)



## Infant Mortality



# I N T R O D U C T I O N

The death of an infant before his or her first birthday or infant under one year of age.  
(Dinkes Jatim, 2016).





Maternal Mortality & Infant Mortality

Quality of Implementation Health Service

Prosperity Level

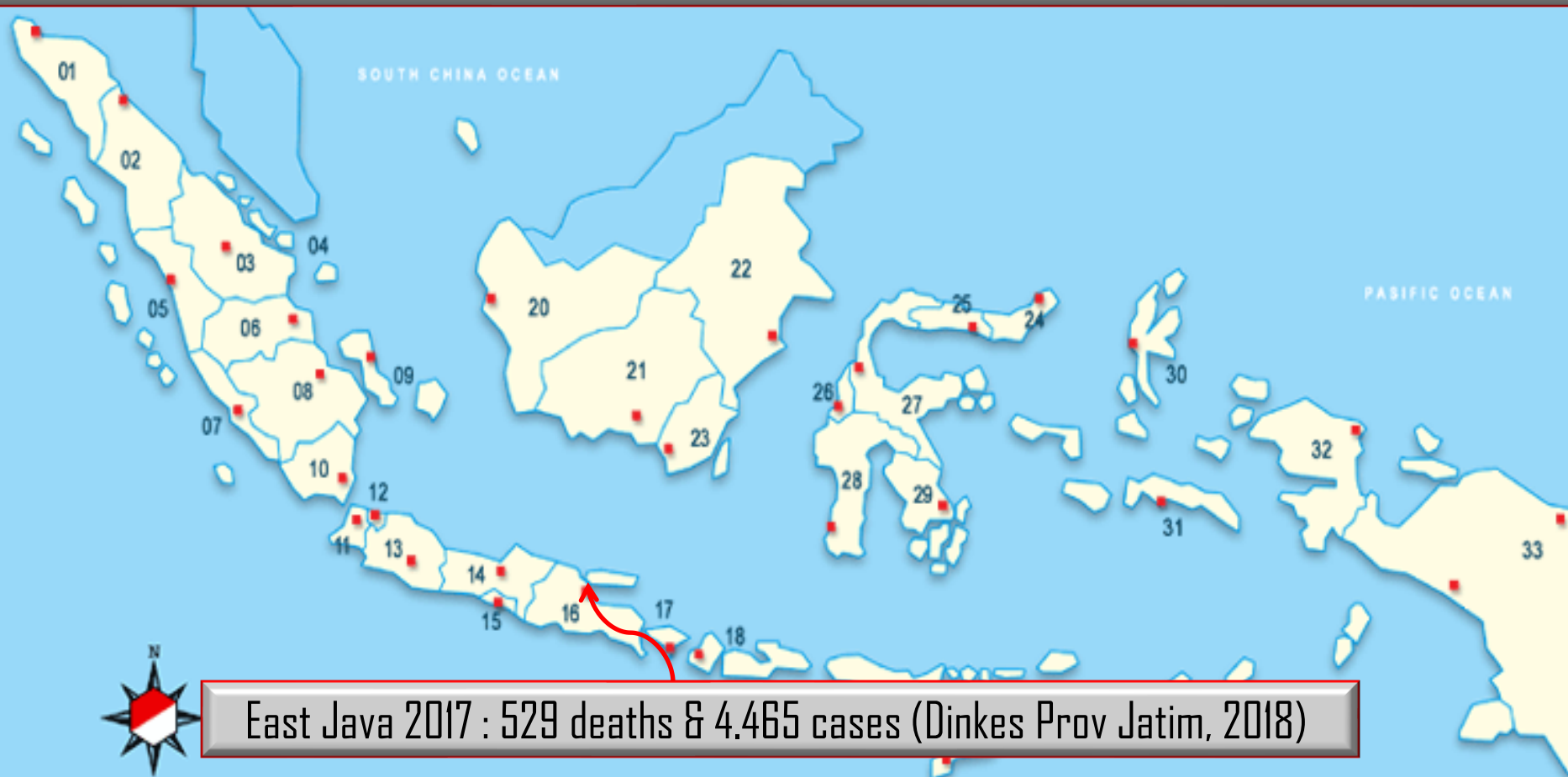


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## Maternal Mortality and Infant Mortality

Indonesia : 359 deaths per 100. 000 live births & 40 deaths per 1.000 live births (BPS, 2017)

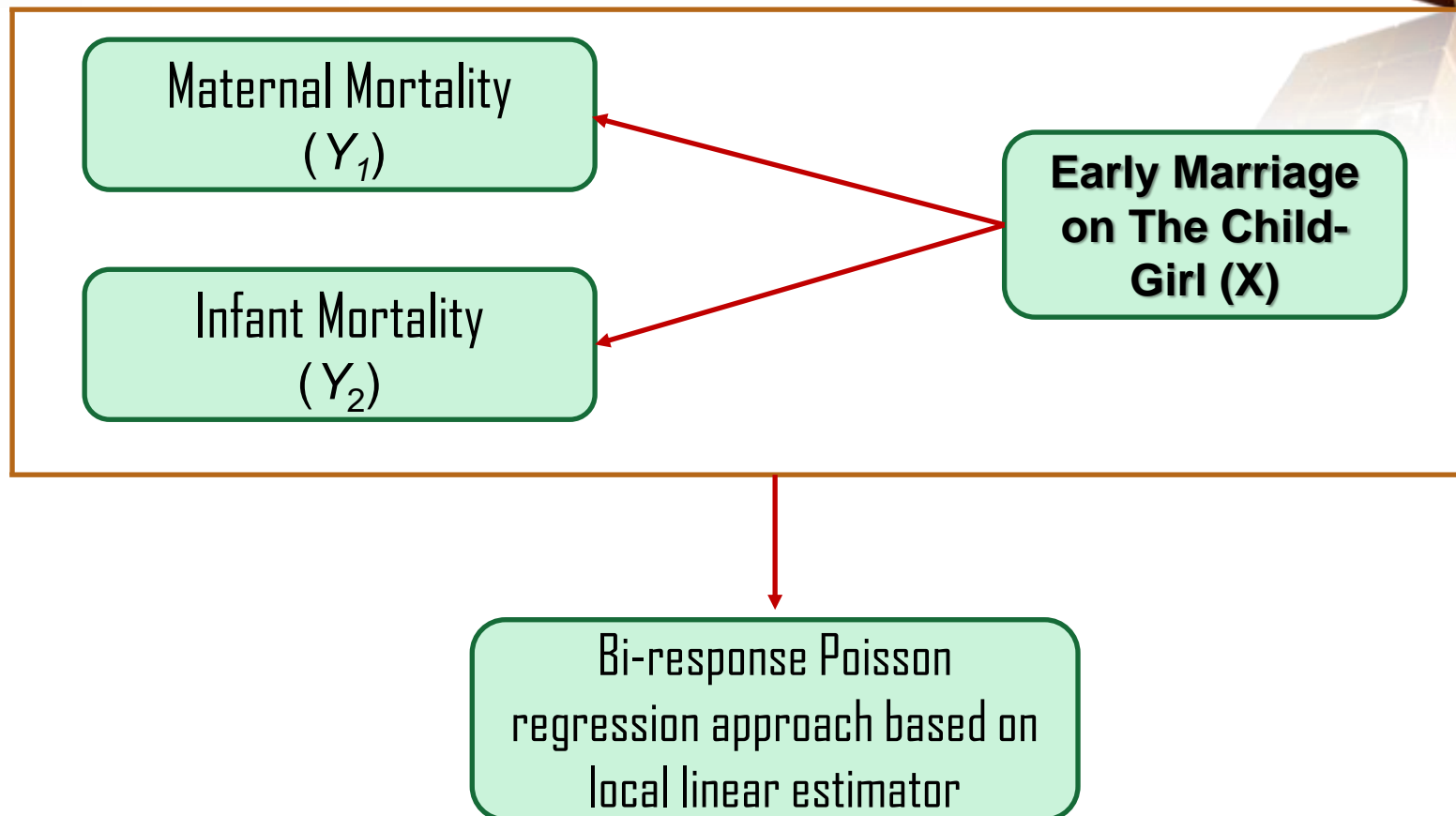


East Java 2017 : 529 deaths & 4.465 cases (Dinkes Prov Jatim, 2018)





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## Local Linear Estimator



# I N T R O D U C T I O N

Simple and easy to apply.  
(Liang & Zeng, 2005)

Every differentiable function can be approximated locally by a straight line (Loader, 1999)

Does not require large amounts of data for model estimation.  
(Nottingham & Cook, 2001)

Fits well to boundaries.  
(Nottingham & Cook, 2001)



## PDF for Bivariate Poisson Distribution

Let the random variables  $V_1$ ,  $V_2$ , and  $U$  be independently Poisson distributed with parameters are  $\theta_1, \theta_2$ , dan  $\gamma$ . New random variable  $Y_1$  and  $Y_2$  can be constructed by:  $Y_1 = V_1 + U$ ;  $Y_2 = V_2 + U$

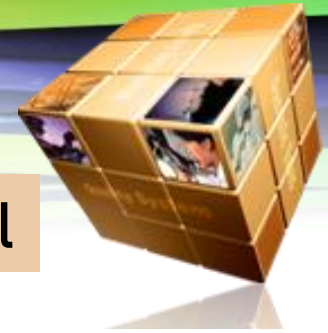
The probability function is

$$P(Y_1 = y_1, Y_2 = y_2) = f(y_1, y_2) = \exp[-(\theta_1 + \theta_2 + \gamma)] \sum_{k=0}^s \frac{\gamma^k}{k!} \frac{\theta_1^{y_1-k}}{(y_1-k)!} \frac{\theta_2^{y_2-k}}{(y_2-k)!} \quad (2)$$

where  $y_1, y_2 = 0, 1, 2, \dots$  and  $s = \min(y_1, y_2)$

$$E(Y_1) = \theta_1 + \gamma \quad Cov(Y_1, Y_2) = \gamma \quad Corr(Y_1, Y_2) = \frac{\gamma}{\sqrt{(\theta_1 + \gamma)(\theta_2 + \gamma)}}$$

$$E(Y_2) = \theta_2 + \gamma$$



## Local Birespon Poisson Regression Model

For data points  $x_{ij}$  in neighborhood  $x_{0j}$ , we approximate  $m_r(x_{ij})$  via a Taylor expansion by a polynomial of a degree 1:

$$m_r(x_{ij}) \approx \beta_{0i}^{(r)}(x_{0j}) + \beta_{1i}^{(r)}(x_{0j})(x_{ij} - x_{0j}); r = 1, 2, j = 1, 2, \dots, p.$$

$$x_{ij} \in (x_{0j} - h, x_{0j} + h)$$

or

$$m_r(x_{ij}) = \mathbf{X}_r(x_0) \tilde{\beta}(x_0); r = 1, 2.$$

$$\theta_{ri} = \exp\left(\sum_{j=1}^p m_r(x_{ij})\right); r = 1, 2, i = 1, 2, \dots, n, \text{ and } j = 1, 2, \dots, p.$$

(Darnah, 2019)





## Local Biresponse Poisson Regression Model

Local linear estimator for  $\tilde{\beta}^{(1)}(x_0)$ ,  $\tilde{\beta}^{(2)}(x_0)$ , and  $\gamma$  in biresponse Poisson regression is the solution equation:

$$\frac{\partial L}{\partial \gamma} = \sum_{i=1}^n \prod_{j=1}^p K_{hj}(x_{ij} - x_{0j}) \left\{ 1 - \sum_{k=0}^s \left( \frac{k \exp[\mathbf{X}_{1i}^T(x_0) \tilde{\beta}^{(1)}(x_0)] - \gamma y_{1i}}{\gamma \exp[\mathbf{X}_{1i}^T(x_0) \tilde{\beta}^{(1)}(x_0)] - \gamma^2} + \frac{k - y_{2i}}{\exp[\mathbf{X}_{2i}^T(x_0) \tilde{\beta}^{(2)}(x_0)] - \gamma} \right) \right\} = 0$$

$$\frac{\partial L}{\partial \tilde{\beta}^{(1)}(x_0)} = \sum_{i=1}^n \prod_{j=1}^p K_{hj}(x_{ij} - x_{0j}) \left\{ -\exp[\mathbf{X}_{1i}^T(x_0) \tilde{\beta}^{(1)}(x_0)] \mathbf{X}_{1i}(x_0) + \sum_{k=0}^s \frac{(y_{1i} - k) \exp[\mathbf{X}_{1i}^T(x_0) \tilde{\beta}^{(1)}(x_0)] \mathbf{X}_{1i}(x_0)}{\exp[\mathbf{X}_{1i}^T(x_0) \tilde{\beta}^{(1)}(x_0)] - \gamma} \right\} = 0$$

$$\frac{\partial L}{\partial \tilde{\beta}^{(2)}(x_0)} = \sum_{i=1}^n \prod_{j=1}^p K_{hj}(x_{ij} - x_{0j}) \left\{ -\exp[\mathbf{X}_{2i}^T(x_0) \tilde{\beta}^{(2)}(x_0)] \mathbf{X}_{2i}(x_0) + \sum_{k=0}^s \frac{(y_{1i} - k)(y_{2i} - k) \exp[\mathbf{X}_{2i}^T(x_0) \tilde{\beta}^{(2)}(x_0)] \mathbf{X}_{2i}(x_0)}{\exp[\mathbf{X}_{2i}^T(x_0) \tilde{\beta}^{(2)}(x_0)] - \gamma} \right\} = 0$$

(Darnah, 2019)



## Kernel Function and Optimum Bandwidth Selection

$$K_h(x) = \frac{1}{h} K\left(\frac{x}{h}\right), \text{ untuk } -\infty < x < \infty \text{ dan } h > 0$$

(Wasserman, 2005)

For choosing optimum bandwidth, we use cross validation (CV) criterion that has minimum value.

$$CV(h_1, h_2, \dots, h_q) = \sum_{i=1}^n (y_i - \hat{y}_{-i}(x_i))^2; i = 1, 2, \dots, n$$

(Li & Racina, 2004)



## Index of Distribution Test (IB)

*Index of dispersion test (IB) for bivariate Poisson distribution:*

$$I_B = \frac{n(\bar{y}_2 s_{y_1}^2 - 2m_{11}^2 + \bar{y}_1 s_{y_2}^2)}{(\bar{y}_1 \bar{y}_2 - m_{11}^2)}$$

where:

$$s_{y_1}^2 = \frac{\sum_{i=1}^n (y_{1i} - \bar{y}_1)^2}{n}$$

$$s_{y_2}^2 = \frac{\sum_{i=1}^n (y_{2i} - \bar{y}_2)^2}{n}$$

$$m_{11} = \frac{\sum_{i=1}^n (y_{1i} - \bar{y}_1)(y_{2i} - \bar{y}_2)}{n}$$

$Y_1$  and  $Y_2$  are bivariate Poisson distribution if:

$$I_B < \chi_{(\alpha, 2n-3)}^2$$

Best (1999)



## Correlation Coefficient

$$r_{y_1y_2} = \frac{\sum_{i=1}^n (y_{1i} - \bar{y}_1)(y_{2i} - \bar{y}_2)}{\sqrt{\sum_{i=1}^n (y_{1i} - \bar{y}_1)^2} \sqrt{\sum_{i=1}^n (y_{2i} - \bar{y}_2)^2}}$$

The test statistics is:

$$t = \frac{r_{y_1y_2} \sqrt{n-2}}{\sqrt{1-r_{y_1y_2}^2}}$$

The null hypothesis is rejected if  $|t| > t_{\left(n-2, \frac{\alpha}{2}\right)}$

(Weisberg, 2005)

If  $r_{y_1y_2} \geq \pm 0,5$  strong correlation.

If  $r_{y_1y_2} < \pm 0,5$  weak correlation.

Gogtay & Thatte (2017)





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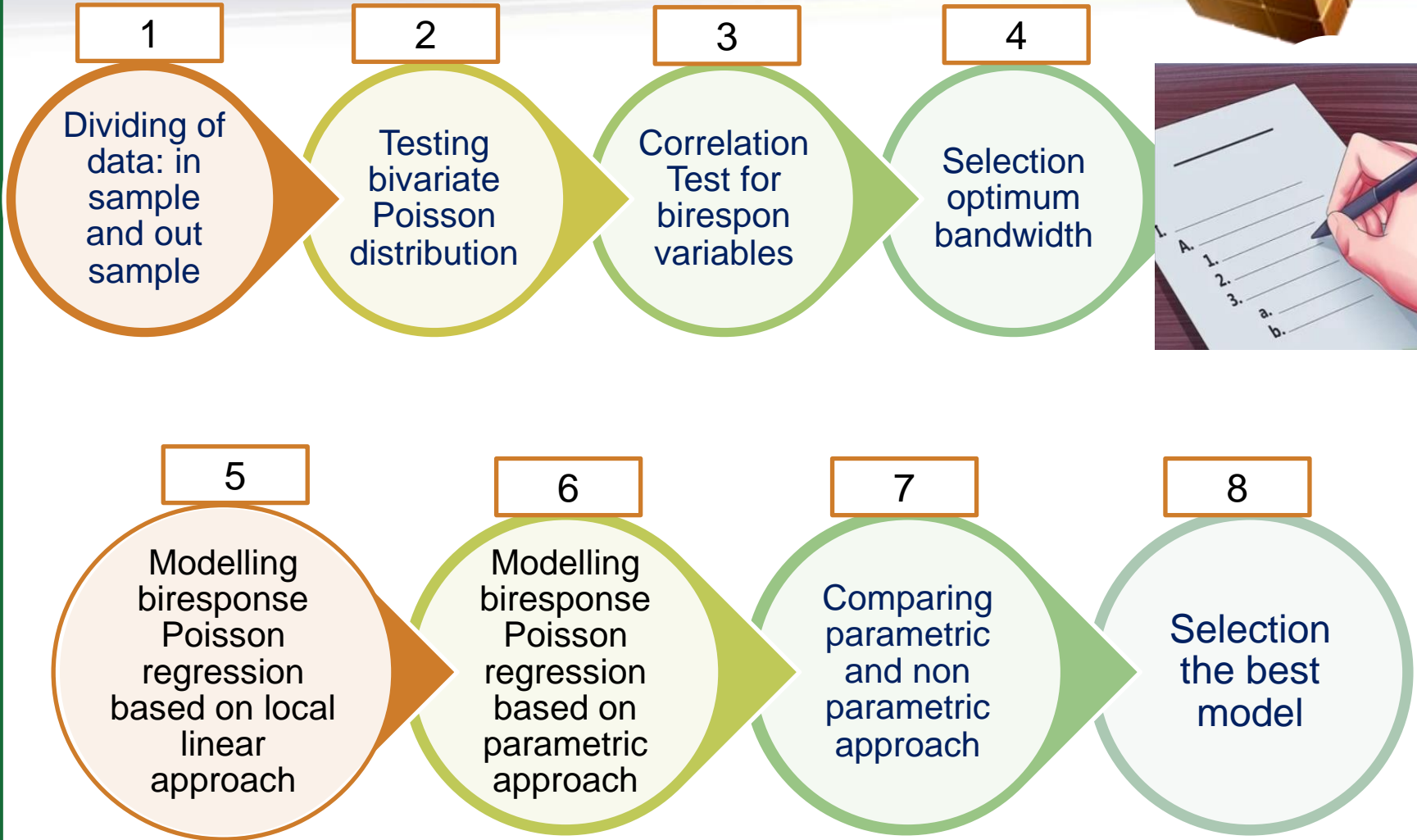
The response variables are the maternal mortality and the infant mortality cases in East Java 2017 were collected from the Health Service Province (Dinkes Provinsi) East Java.

The predictor variable is the Early Marriage on The Child-Girl was collected from Central Agency on Statistics (BPS) East Java.

Once all the data was collected, we entered the data into the Open Source Software (OSS)-R for analysis.



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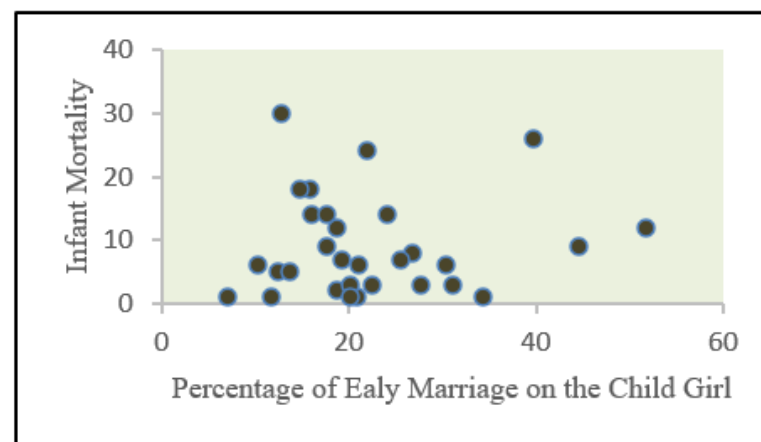
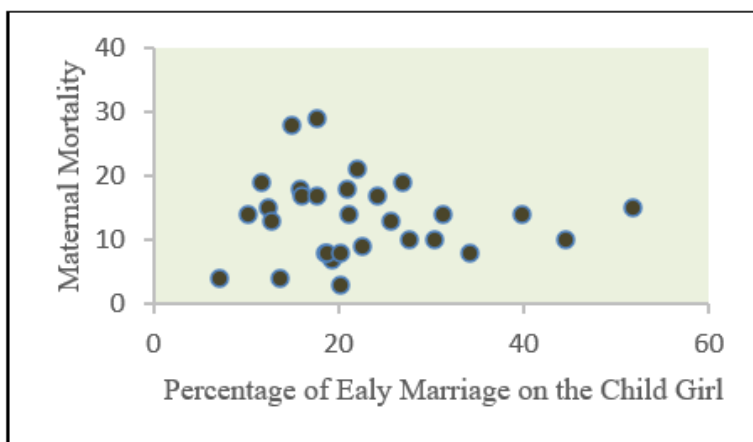
## Characteristics the Variables

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Variable	Mean	Standard Deviation	Minimum	Maximum
Maternal Mortality	13,9	10,1	0	49
Infant Mortality	10,9	14,7	0	65
Percentage of Early Marriage on The Child-Gird	20,9	10,4	6,8	51,7



RESULT



(a) (b)  
**FIGURE 1.** Plot of the Maternal Mortality Case (a) and Infant Mortality Case (b) by Percentage of Early Marriage on the Child Girl



## Corelation and Bi-variate Poisson Distribution Test on Response Variable

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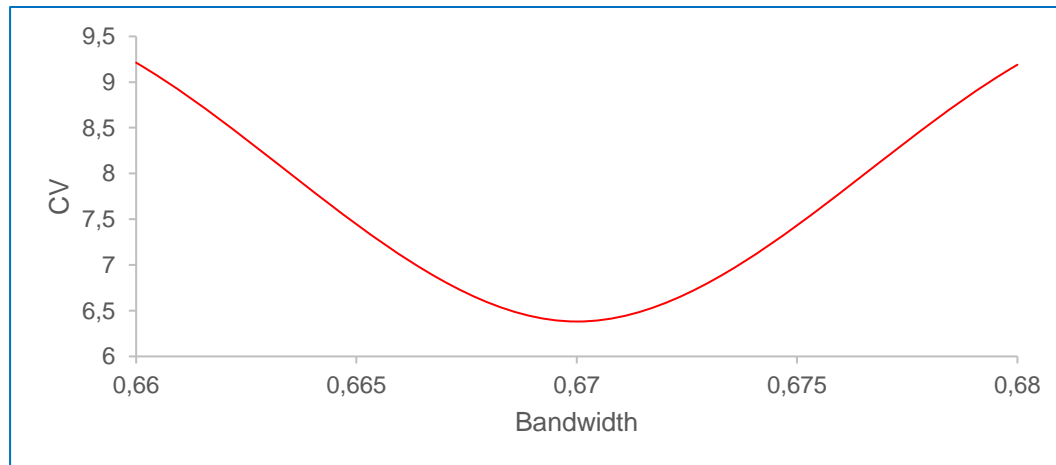
	<b>Value</b>	<b>Conclusion</b>
Index IB	-41,1	Bivarite Poisson Distribution
Chi Square	75,6	
t	2,7	Correlation is significant
t_table	2,0	
Coef.corelation	0,5	Strong correlation



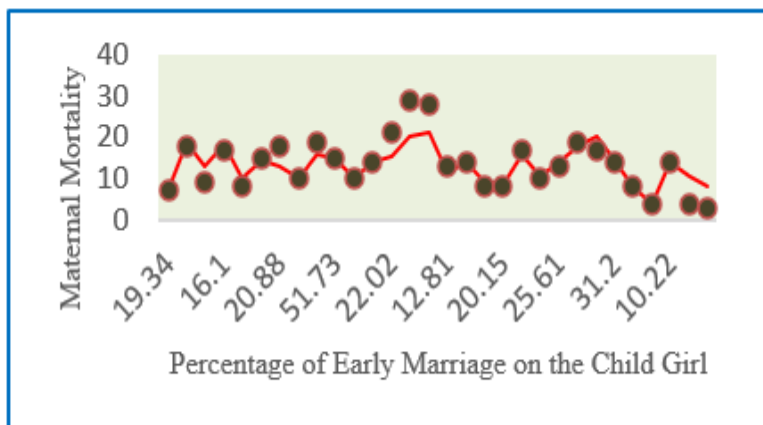
## Selection Optimum Bandwidth

Bandwidth (h)	0,65	0,66	0,67	0,68	0,69	0,70
CV	8,378115	9,212682	6,381427	9,190332	9,290435	11,06244

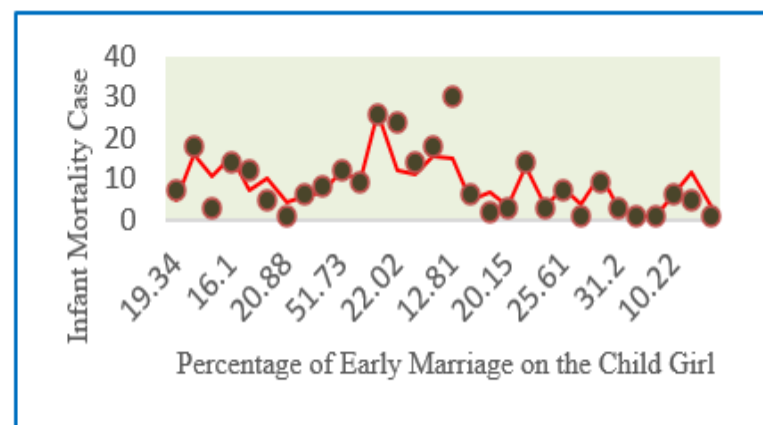
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**FIGURE 4.** Plot of CV with bandwidth value.



(a)



(b)

**FIGURE 5.** Estimation of maternal mortality (a) and infant mortality (b).

In bi-response Poisson regression modeling with a linear local approach, the estimated regression curves obtained are local so the results are different for regencies in East Java.



## Example

Bojonegoro Regency:

$$\hat{\theta}_1(x) = \exp(2.775282 + 0.053417(x - 24.13)), \quad x \in (24.13 \pm 0.67) \quad (1)$$

$$\hat{\theta}_2(x) = \exp(2.570254 + 0.13352925(x - 24.13)), \quad x \in (24.13 \pm 0.67) \quad (2)$$

It can be interpreted that for the percentage of early marriage on the child-girl in between 23.5% to 24.8%, if the percentage of early marriage on the child-girl increased by 1 percent then the average maternal mortality and infant mortality in Bojonegoro regency will increase 1 person.

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Bi-response Poisson regression model based on parametric approach

$$\hat{\theta}_1(x) = \exp(2.664013 - 0.002877 X).$$

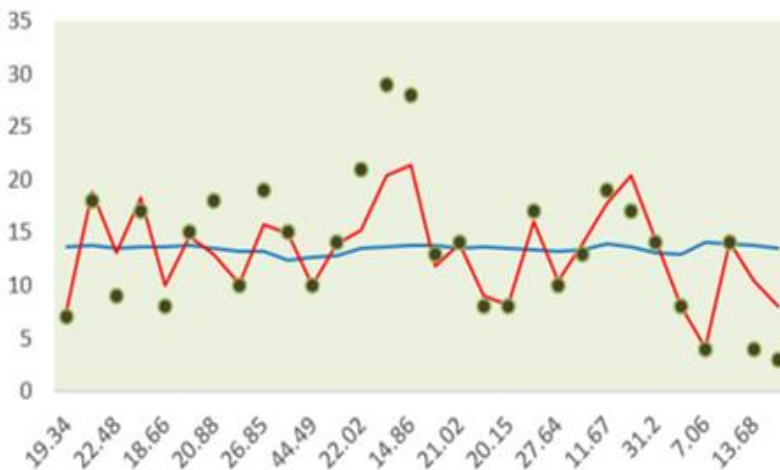
$$\hat{\theta}_2(x) = \exp(2.050035 - 0.006337 X).$$

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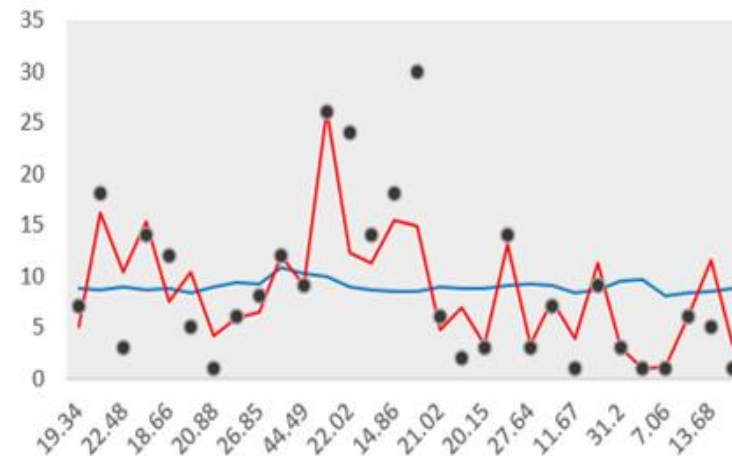
Deviance Value of Bi-response Poisson Regression

Parametric  
137.045

Local Linear  
42.29256



(a)



(b)

**FIGURE 6 .** Plot Observation and Estimation Data of maternal mortality (a) and infant mortality (b).

The black dot represents the observation response variable data, the red line represents the nonparametric approach y variable estimation data, and the blue line represents the parametric approach y variable estimation data.





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The scatter plot of total number of the maternal mortality and infant mortality case by the percentage of early marriage on the child-girl does not pattern. Variable who doesn't have a pattern can approach with nonparametric method and for smoothing used local linear estimator.

The optimum bandwidth is 0.67 and CV value is 6.381427. The optimum bandwidth used to get the best bi-response Poisson regression model.

Bi-response Poisson regression model based on local linear estimator provides a good model estimate of both the maternal mortality and infant mortality with deviance value is 42.29256, it is smaller than deviance value a parametric approach. Deviance value a parametric approach is 137.045.

In addition, further research can be carried out by considering other predictor variables that are considered to have a significant.



**Thank you**

