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Journal of Modern Applied Statistical Methods

Volume 16 | Issue 2 Article 27

December 2017

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Recommended Citation

Shafiq, M., Amir, W. M., & Zafakali, N. S. (2017). JMASM 46: Algorithm for Comparison of Robust Regression Methods In Multiple Linear Regression By Weighting Least Square Regression (SAS). Journal of Modern Applied Statistical Methods, 16(2), 490-505. doi: 10.22237/jmasm/1509496020

Journal of Modern Applied Statistical Methods
November 2017, Vol. 16, No. 2, 490-505.
doi: 10.22237/jmasm/1509496020

ISSN 1538 − 9472

JMASM 46: Algorithm for Comparison of Robust Regression Methods In Multiple Linear Regression By Weighting Least Square Regression (SAS)

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The aim of this study is to compare different robust regression methods in three main models of multiple linear regression and weighting multiple linear regression. An algorithm for weighting multiple linear regression by standard deviation and variance for combining different robust method is given in SAS along with an application.

Keywords: Multiple linear regression, robust regression, M, LTS, S, MM estimation

Introduction

Multiple linear regression (MLR) is a statistical technique for modeling the relationship between one continuous dependent variable from two or more independent variables. A typical data template is compiled in Table 1.

Table 1. Data template for multiple linear regression

i	y_i	x_{i0}	x_{i1}	x_{i2}	..	x_{ip}
1	y_1	1	x_{11}	x_{12}	…	x_{1p}
2	y_2	1	x_{21}	x_{22}	…	x_{2p}
.	.	.	.	.		.
.	.	.	.	.		.
n	y_n	1	x_{n1}	x_{n2}	…	x_{np}

***Sources*:** Ahmad et al., 2016a; 2016b

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It is used when there are two or more independent variables and a single dependent variable where the equation below shows the model population information:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + L + \beta_k x_{ki} + \varepsilon_i \tag{1}$$

where

β_0 is the intercept parameter, and
$\beta_0, \beta_1, \beta_2, \ldots, \beta_{k-1}$ are the parameters associated with $k - 1$ predictor variables.

The dependent variable Y is written as a function of k independent variables, $x_1, x_2, \ldots, x_k$. A random error term is added to equation as to make the model more probabilistic rather than deterministic. The value of the coefficient β_i determines the contribution of the independent variables x_i, and β_0 is the y-intercept (Ahmad et al., 2016a; 2016b). The coefficients $\beta_0, \beta_1, \ldots, \beta_k$ are usually unknown because they represent population parameters. Below is the data presentation for multiple linear regression. A general linear model in matrix form can be defined by the following vectors and matrices as:

$$\mathbf{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}, \mathbf{X} = \begin{bmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1,p-1} \\ 1 & X_{21} & X_{22} & \cdots & X_{2,p-1} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & X_{n1} & X_{n2} & \cdots & X_{n,p-1} \end{bmatrix}, \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{p-1} \end{bmatrix} \text{ and } \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

Robust Regression

Robust regression is a method used when the distribution of the residual is not normally distributed and there are some outliers which affect the model (Susanti et al., 2014). It detects the outliers and provides better results (Chen, 2002). A common method of robust regression is the M estimate, introduced by Huber (1973), which is as efficient as Ordinary Least Square (OLS), and is considered the simplest approach. The Least Trimmed Squares (LTS) estimation was introduced by Rousseeuw (1984), and is a high breakdown value method. So, too, is the S estimation, another high breakdown value method with a higher statistical efficiency than LTS estimation (Rousseeuw & Yohai, 1984). The S estimation is used to minimize the dispersion of residuals. The MM estimation, a special type of M estimation introduced by Yohai (1987), combines high breakdown value estimation and efficient estimation. The M estimation has a higher breakdown value and greater statistical efficiency than the S estimation.

Calculation for linear Regression using SAS

```
/* First do a simple linear regression */
     proc reg data = temp1;
     model y = x;
     run;

/* Compute the absolute and squared residuals*/
     data temp1.resid;
     set temp1.pred;
     absresid=abs(residual);
     sqresid=residual**2;

/* Run a Regression with the absolute residuals and squared residuals */
/* to get estimated standard deviation and estimated variance */
     proc reg data=temp1.resid;
     model absresid=x;
     output out=temp1.s_weights p=s_hat;

     model sqresid=x;
     output out=temp1.v_weights p=v_hat;

/* Compute weight using standard deviation */
     data temp1.s_weights;
     set temp1.s_weights;
     s_weight=1/(s_hat**2);
     label s_weight = "weights using absolute residuals";

/* Compute weight using variances */
     data temp1.v_weights;
     set temp1.v_weights;
     v_weight=1/v_hat;
```

```
     label v_weight = "weights using squared residuals";

/* Run a Weighted Least Square using estimated Standard Deviation */
/* and Variances */
     proc reg data=temp1.s_weights;
     weight s_weight;
     model y = x;
     run;

     proc reg data=temp1.v_weights;
     weight v_weight;
     model y = x;
     run;

/* Approach the Estimation Method Procedure for Robust Regression */
/* in this case, using the four methods LTS, M, MM and S-estimation */
     proc robustreg data = temp1 method =LTS;
     model y = x;
     run;
```

An Illustration of a Medical Case

A case study of triglycerides will illustrate the different methods for robust regression.

Table 1. Description of the variables

Variables	Code	Description
Triglycerides	Y	Triglycerides level of patients (mg/dl)
Weight	X1	Weight (kg)
Total Cholesterol	X2	Total cholesterol of patients (mg/dl)
Proconvertin	X3	Proconvertin (%)
Glucose	X4	Glucose level of patients (mg/dl)
HDL-Cholesterol	X5	High density lipoprotein cholesterol (mg/dl)
Hip	X6	Hip circumference (cm)
Insulin	X7	Insulin level of patients (IU/ml)
Lipid	X8	Taking lipid lowering medication (0 = no, 1= yes)

Sources: Ahmad & Shafiq, 2013; Ahmad et al., 2014

Algorithm for Weighting Multiple Linear Model Regression by different Robust Regression Methods

```
Title ‘Alternative Modeling on Weighting Multiple linear regression’;
Data Medical;
input  Y  X1  X2 X3  X4  X5  X6  X7  X8;
Datalines;

168    85.77  209    110    114    37     130.0  17     0
304    58.98  228    111    153    33     105.5  28     1
72     33.56  196    79     101    69     88.5   6      0
119    49.00  281    117    95     38     104.2  10     1
116    38.55  197    99     110    37     92.0   12     0
87     44.91  184    131    100    45     100.5  18     0
136    48.09  170    96     108    37     96.0   13     1
78     69.43  163    89     111    39     103.0  8      0
223    47.63  195    177    112    39     95.0   15     0
200    55.35  218    108    131    31     104.0  33     1
159    59.66  234    112    174    55     114.0  14     0
181    68.97  262    152    108    44     114.5  20     1
134    51.49  178    127    105    51     100.0  21     0
162    39.69  248    135    92     63     93.0   9      1
96     56.58  210    122    105    56     103.4  6      0
117    63.48  252    125    99     70     104.2  10     0
106    66.70  191    103    101    32     103.3  16     0
120    74.19  238    135    142    50     113.5  14     1
119    60.12  169    98     103    33     114.0  13     0
116    36.60  221    113    88     60     94.3   11     1
109    56.40  216    128    90     49     107.1  13     0
105    35.15  157    114    88     35     95.0   12     0
88     50.13  192    120    100    54     100.0  11     0
241    56.49  206    137    148    79     113.0  14     1
175    57.39  164    108    104    42     103.0  15     0
146    43.00  209    116    93     64     97.0   13     0
199    48.04  219    104    158    44     97.0   11     0
85     41.28  171    92     86     64     95.4   5      0
90     65.79  156    80     98     54     98.5   11     1
87     56.90  247    128    95     57     106.3  9      0
103    35.15  257    121    111    69     89.5   13     0
```

```
121    55.12  138    108    104    36     109.0  13     0
223    57.17  176    112    121    38     114.0  32     0
76     49.45  174    121    89     47     101.0  8      0
151    44.46  213    93     116    45     99.0   10     1
145    56.94  228    112    99     44     109.0  11     0
196    44.00  193    107    95     31     96.5   12     0
113    53.54  210    125    111    45     105.5  19     0
113    35.83  157    100    92     55     95.0   13     0
;
Run;

ods rtf file='result_ex1.rtf' ;

/* This first step is to make the selection of the data that have a
significant impact on triglyceride levels. The next step is to perform
the procedure of modeling linear regression model and run the regression
to get the residuals*/
     proc reg data= Medical;
     model Y =  X1  X2 X3  X4  X5 X6  X7 X8;
     output out=work.pred r=residual;
     run;

/* Compute the Absolute and Squared Residuals*/
     data work.resid;
     set work.pred;
     absresid=abs(residual);
     sqresid=residual**2;

/* Run a Regression Compute the Absolute and Squared Residuals to Get
Estimated Standard Deviation and Variances*/
     proc reg data=work.resid;
     model absresid=X1  X2 X3  X4  X5  X6  X7  X8;
     output out=work.s_weights p=s_hat;

     model sqresid=X1  X2 X3  X4  X5  X6  X7  X8;
     output out=work.v_weights p=v_hat;
     run;
```

```
/* Compute the Weight Using Estimated Standard Deviation and Variances*/
     data work.s_weights;
     set work.s_weights;
     s_weight=1/(s_hat**2);
     label s_weight = "weights using absolute residuals";

     data work.v_weights;
     set work.v_weights;
     v_weight=1/v_hat;
     label v_weight = "weights using squared residuals";

/* Do a Weighted Least Squares Using the Weight from the Estimated
Standard Deviation*/
     proc reg data=work.s_weights;
     weight s_weight;
     model Y = X1  X2 X3  X4  X5  X6  X7  X8;
     run;

/* Do a Weighted Least Squares Using the Weight from the Estimated
Variances*/
     proc reg data=work.v_weights;
     weight v_weight;
     model Y = X1  X2 X3  X4  X5  X6  X7  X8;
     run;

/* Do Robust Regression, a Four Estimation Method to compare which are
LTS, M, MM and S-Estimation For Weighted Least Square using estimated
Standard Deviation*/
     proc robustreg method=LTS data=work.s_weights;
     weight s_weight;
     model Y = X1  X2 X3  X4  X5  X6  X7  X8 / diagnostics leverage;
     run;

/* Do a Robust Regression, a Four Estimation Method compare which are
LTS, M, MM and S-Estimation For Weighted Least Square using estimated
Variances*/
     proc robustreg method=LTS data=work.v_weights;
     weight v_weight;
```

```
model Y = X1  X2 X3  X4  X5  X6  X7  X8 / diagnostics leverage;
run;
```

Results

Compiled in Table 2 are the results from the multiple regression analysis using the original data. Compiled in Table 3 are the results for the weighted least square by standard deviation and weighted least square by variance. The residual plots do not indicate any problem with the model, as can be seen in Figures 1-3. A normal distribution appears to fit the sample data fairly well. The plotted points form a reasonably straight line. In our case, the residual plots bounce randomly around the 0 line (residual vs. predicted value). This supports the reasonable assumption that the relationship is linear.

Table 2. Parameter Estimates for Original Data

Variables	Parameter Estimate	Standard Error	*P* value
Intercept	-86.56544	102.93662	0.4070
x_1	-1.08598	0.95288	0.2634
x_2	-0.06448	0.21973	0.7712
x_3	0.61857	0.36615	0.1015
$\mathbf{x_4}$	**1.10882**	**0.33989**	**0.0028**
x_5	-0.52289	0.57119	0.3673
x_6	0.81327	1.38022	0.5601
$\mathbf{x_7}$	**2.77339**	**1.25026**	**0.0343**
x_8	22.40585	14.51449	0.1331

Table 3. Parameter Estimates for Weighted Multiple Linear Regression

	Weighted Least Square MLR (SD)			Weighted Least Square MLR (V)		
Variables	Parameter Estimate	Standard Error	*P* value	Parameter Estimate	Standard Error	*P* value
Intercept	-150.25787	90.05385	0.1056	-139.33900	90.60374	0.1353
x_1	**-1.30694**	**0.59423**	**0.0357**	-1.19482	0.68833	0.0936
x_2	-0.01586	0.17670	0.9291	0.05784	0.19730	0.7716
x_3	0.44460	0.35706	0.2227	0.36626	0.44451	0.4169
x_4	**0.89106**	**0.38240**	**0.0267**	**1.01359**	**0.37253**	**0.0111**
x_5	-0.23352	0.44853	0.6064	-0.24328	0.52342	0.6457
x_6	1.74405	1.10677	0.1256	1.35688	1.20057	0.2680
x_7	**2.81731**	**1.29607**	**0.0377**	**3.17543**	**1.31793**	**0.0228**
x_8	16.87506	10.34963	0.1135	15.78743	12.16151	0.2048

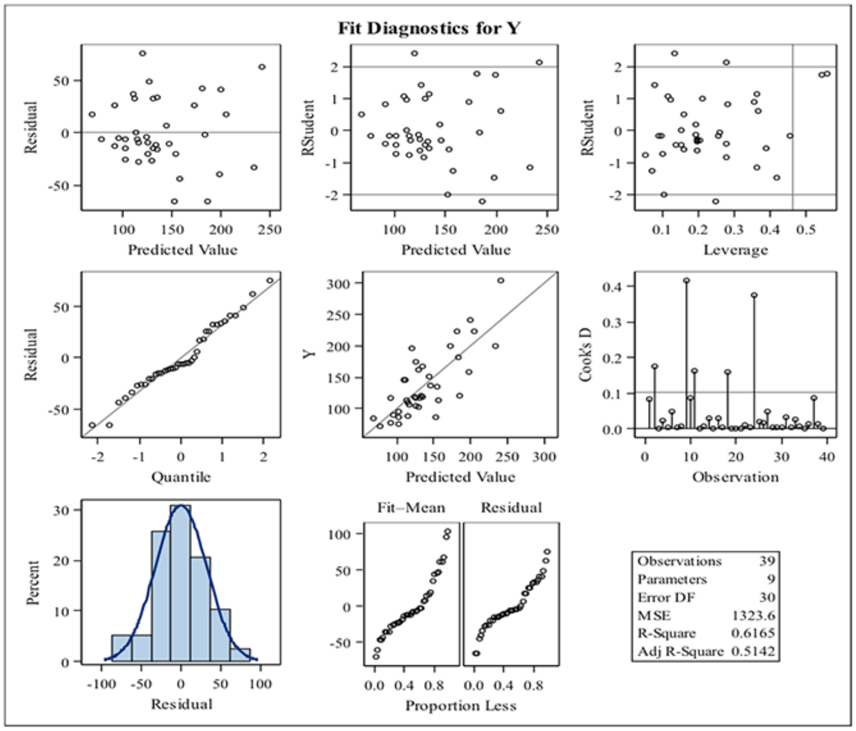

Figure 1. Fit Diagnostic for *y*

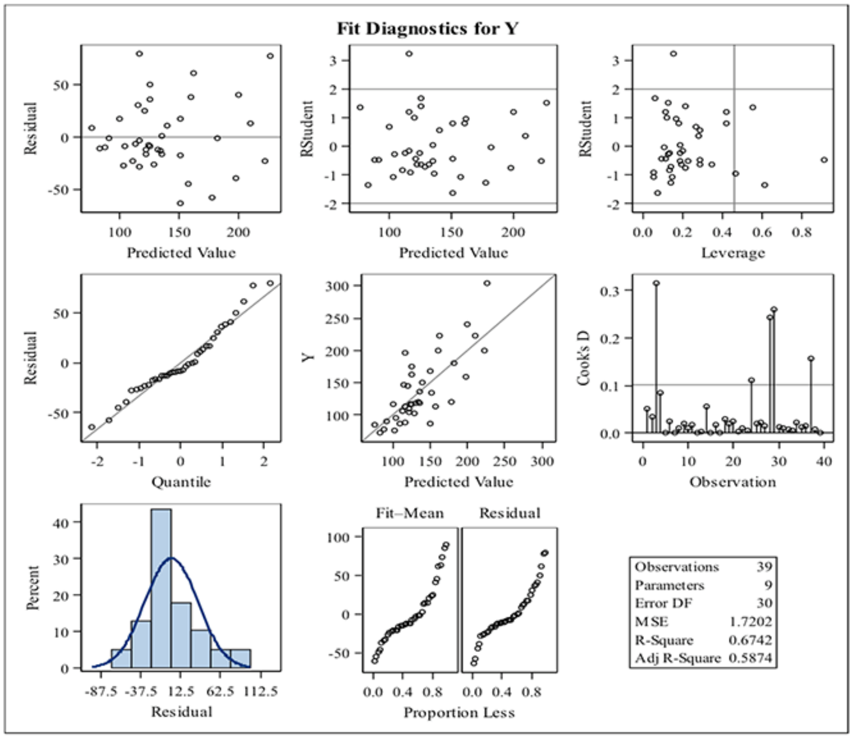

Figure 2. Fit Diagnostic for *y*-weighted least square using standard deviation

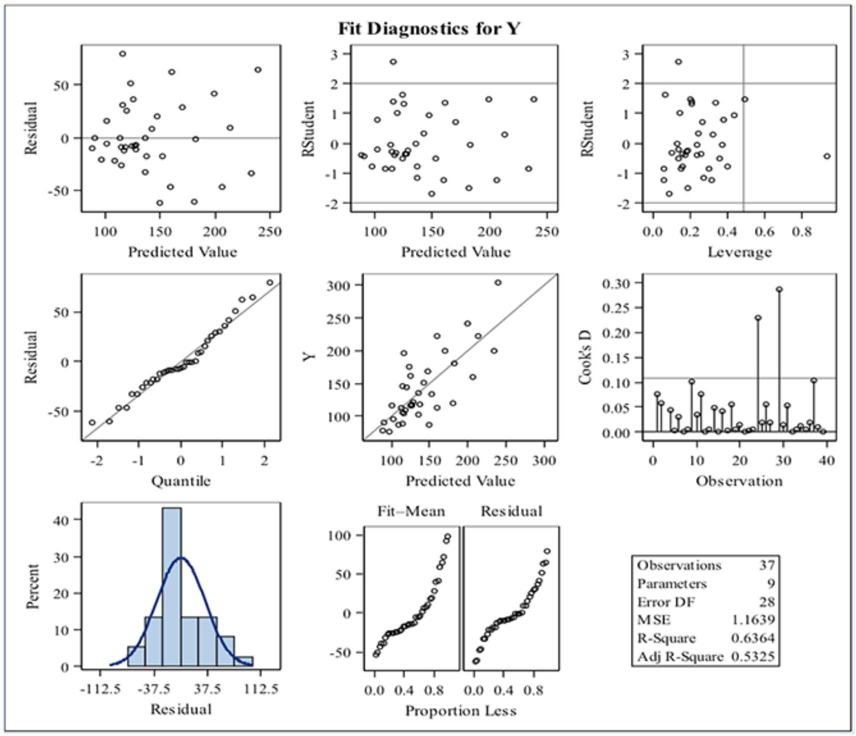

Figure 3. Fit Diagnostic for *y*-weighted least square using variances

---

Shown in Table 2 are the variables x_4 (p = 0.0028) and x_7 (p = 0.0343) were statistically significant for the multiple regression analysis. Shown in Table 3 are the variables x_1 (p = 0.0357), x_4 (p = 0.0267) and x_7 (p = 0.0377), which were statistically significant for weighted least square by standard deviation. The weighted least square by variance model shows the variable x_4 (p = 0.0111) and x_7 (p = 0.0028). RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data, which are to observe how close the data points are to the model predicted values. Lower value of RMSE indicated a better fit. The RMSE for weighted least square by variance (1.08) shows a lower value compared to the weighted least square standard deviation (1.31) and multiple regression (36.4). A higher R-squared value indicated how well the data fit the model and also indicates a better model. The model multiple regression analysis has R-squared of 0.62, weighted standard deviation multiple regression has R-squared of 0.67 and weighted variance multiple regression has R-squared of 0.63.

Shown in Table 4 is a comparison of the models—multiple linear regression (model 1), weighted least square by standard deviation (model 2) and weighted least square by variance (model 3)—using the four different robust methods, which are M estimation, LTS estimation, S estimation and MM estimation. The LTS estimation has high R-squared in three of the models compared to other robust methods. The S estimation also has high R-squared compared to MM and M estimation.

Table 4. Comparison of Model by using different Robust Method

	Model 1			Model 2			Model 3		
Method	*Outlier*	*Leverage*	R^2	*Outlier*	*Leverage*	R^2	*Outlier*	*Leverage*	R^2
M	0.0000	0.2051	0.4662	0.0769	0.2051	0.5761	0.1622	0.1892	0.5090
LTS	0.1282	0.2051	0.7289	0.1282	0.2051	0.7289	0.1351	0.1892	0.7032
S	0.0000	0.2051	0.5230	0.0000	0.2051	0.6079	0.0000	0.1892	0.5232
MM	0.0000	0.2051	0.4602	0.0000	0.2051	0.5843	0.0000	0.1892	0.5214

From Figure 4-6 there is a detection of outlier in observations. They present a regression diagnostics plot (a plot of the standardized residuals of robust regression LTS versus the robust distance). As indicated in Figure 4 and 5, observation 37 is identified as outlier. The observations of 2, 9, 24, and 27 are identified as outlier and leverage. Observations 10, 18 and 33 are identified as leverage point. In Figure 6, observation 35 is identified as outlier, observations 2, 8, 23, and 26 are identified as outlier and leverage, and observations 10, 17 and 27 are identified as leverage. The leverage plots available in SAS software are considered useful and effective in detecting multicollinearity, non-linearity, significance of the slope, and outliers (Lockwood & Mackinnon, 1998).

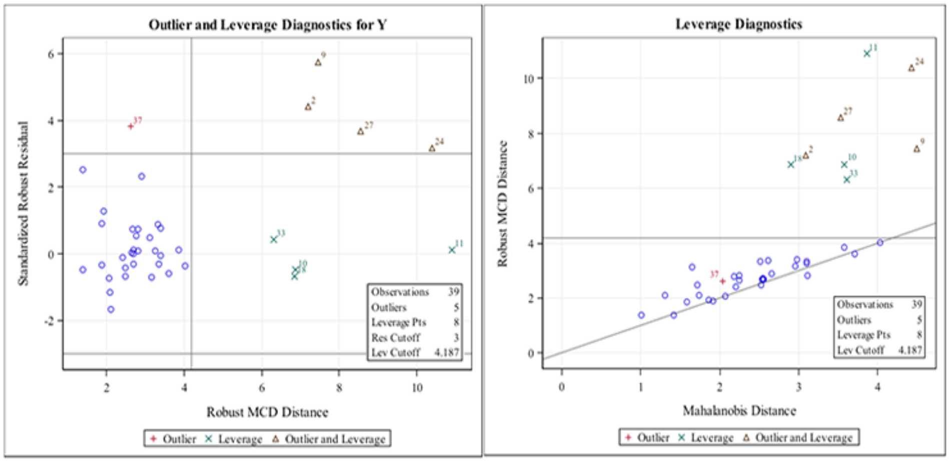

Figure 4. Outlier and Leverage Diagnostic for Y using LTS (Model 1)

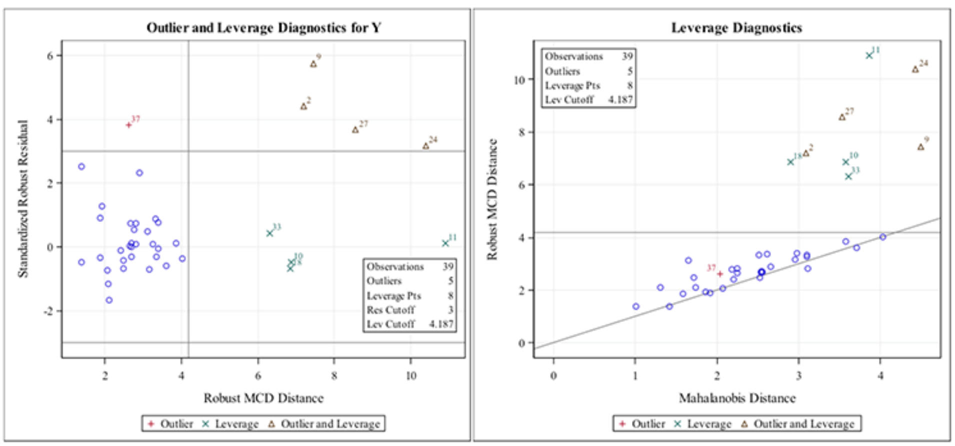

Figure 5. Outlier and Leverage Diagnostic for Y using LTS (Model 2)

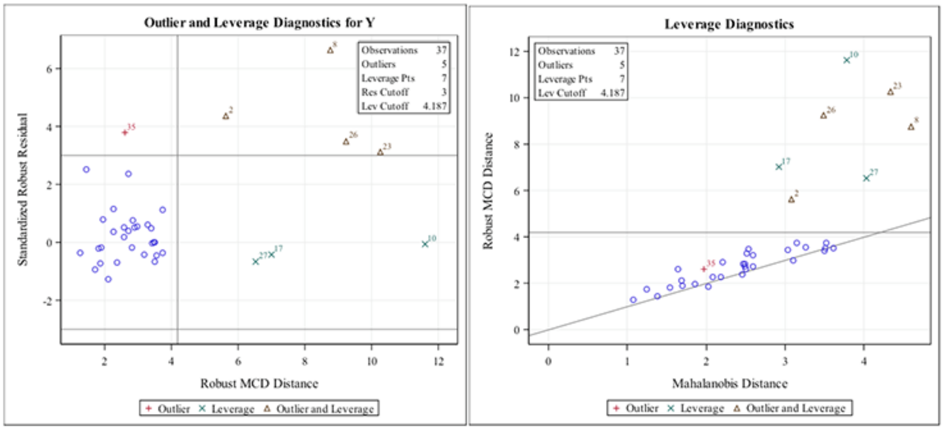

Figure 6. Outlier and Leverage Diagnostic for Y using LTS (Model 3)

Conclusion

SAS code for four different methods of robust regression was considered: M estimation, LTS estimation, S estimation, and MM estimation. They provide a better understanding of the weighted multiple linear regression and different robust method underlying of relative contributions.

Acknowledgements

The authors would like to express their gratitude to Universiti Sains Malaysia for providing research funding (Grant 304/PPSG/61313187, School of Dental Sciences, Universiti Sains Malaysia).

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