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An Alternative Method for Regression Modelling: Algorithm for Weighted Robust Regression

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Abstract: This report supplied a comprehensive method of an alternative fuzzy weighted robust linear regression as a technique for analysis through SAS algorithm. This alternative method is a manipulation technique for the small data set and give the researcher an options to launch the analysis even there is not enough data set.

Key words: Bootstrap · Weighted · SAS algorithm and robust regression

INTRODUCTION

Thus, this paper provides a road map of the practical approach for regression modeling and an illustration using fisheries dataset. The parametric bootstrap method is recommended for sample size between 50 and 100 for a reliable performance [1, 2]. A recent approach to analyse data with missing values in the covariates is weighted estimating equations and this technique appear to be highly efficient [3, 4]. Data of this study is a sample which composed of six variables. Namely variables are as in Table 1.

Multiple fuzzy with weighted regression technique was used in the analysis of relationship between variables. The algorithm is given as follows:

Figure 1 showed the flow chart of an alternative method of fuzzy weighted regression procedure.

Table 1: Description of Data

Num.	Code	Explanation of user variables
1.	Y	Standard Length of the fish
2.	X1	Total Length of the fish
3.	X2	Fish Weight (g)
4.	X3	Turbidity
5.	X4	Temperature
6	X5	Dissolved Oxygen (mg/l)

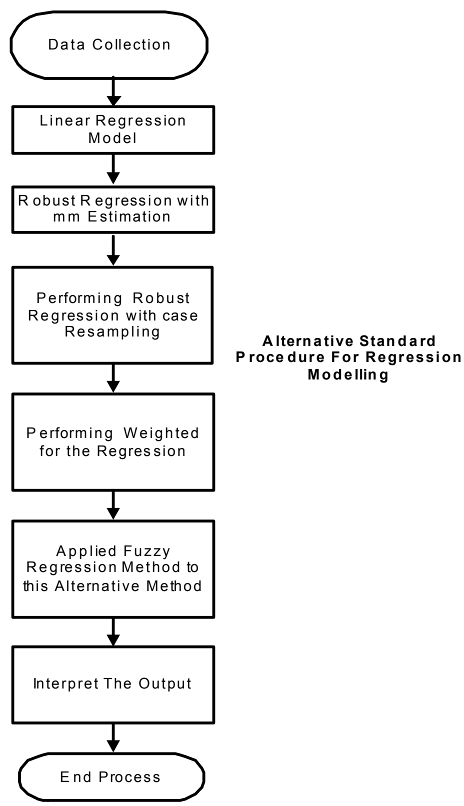

Fig. 1: Flow Chart of an Alternative Analysis

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```
/*Title 'alternatif linear programming with combining robust and bootstrap'*/

Data fish;
Input y x1 x2 x3 x4 x5;
Datalines;
```

31.00	52.00	2.00	19.70	26.08	5.43
32.00	42.00	2.00	1.420	29.75	3.58
32.00	41.00	2.00	6.100	26.39	7.06
33.00	42.00	1.00	1.420	29.75	3.58
33.00	42.00	2.00	17.80	28.36	6.56
34.00	44.00	2.00	1.420	29.75	3.58
34.00	45.00	10.00	1.730	29.35	3.54
35.00	45.00	1.00	12.63	30.44	4.03
35.00	43.00	1.00	1.420	29.75	3.58

```
;
run;
Ods rtf style=journal;

/*performing the procedure of modeling linear regression model*/
Ods graphics on;
Proc reg data=fish;
Model y=x1 x2 x3 x4 x5;
run;
Ods graphics off;

/*robust regression for mm-estimation*/
Ods graphics on;
Proc robustreg method=mm fwls data=fish plots=all;
Model y=x1 x2 x3 x4 x5 / diagnostics itprint;
Output out=resids out=robout r=residual weight=weight outlier=outlier sr=stdres;
run;

Ods graphics off;

/*using bootstrap with case resampling*/
Proc surveyselect data=fish out=boot1 method=urs samprate=1 outhits rep=100;
run;

/*robust regression for mm-estimation+bootstrap*/
Ods graphics on;
Proc robustreg method=m(wf=huber(c=1.345))fwls data=boot1 plots=all;
Model y=x1 x2 x3 x4 x5 / diagnostics itprint;
Output out=resids out=robout r=residual weight=weight outlier=outlier sr=stdres;
run;
Ods graphics off;

/*combining bootstrap technique with fuzzy regression*/
Proc optmodel;
Set j= 1..30;
Number y{j}, x1{j}, x2{j}, x3{j}, x4{j}, x5{j};
Read data boot1 into [_n_] y x1 x2 x3 x4 x5;

/*print y x1 x2 x3 x4 x5*/
Print y x1 x2 x3 x4 x5;

Number n init 30; /*total of observation*/

/*decision variable bounded or not bounded*/
Var aw{1..6}>=0; /*these six variables are bounded*/
Var ac{1..6}; /*these six variables are not bounded*/

/*objective function*/
Min z1= aw[1] * n + sum{i in j} x1[i] * aw[2]+sum{i in j} x2[i] * aw[3]+sum{i in j} x3[i] * aw[4]+sum{i in j} x4[i] * aw[5]+sum{i in j} x5[i] * aw[6];

/*linear constraints*/
Con c{i in 1..n}:
Ac[1]+x1[i]*ac[2]+x2[i]*ac[3]+x3[i]*ac[4]+x4[i]*ac[5]+x5[i]*ac[6]-aw[1]-x1[i]*aw[2]-x2[i]*aw[3]-x3[i]*aw[4]-x4[i]*aw[5]-x5[i]*aw[6]<=y[i];

Con c1{i in 1..n}:
Ac[1]+x1[i]*ac[2]+x2[i]*ac[3]+x3[i]*ac[4]+x4[i]*ac[5]+x5[i]*ac[6]+aw[1]+x1[i]*aw[2]+x2[i]*aw[3]+x3[i]*aw[4]+x4[i]*aw[5]+x5[i]*aw[6]>=y[i];

Expand; /*this provides all equations*/
Solve;
Print ac aw;
Quit;

Ods rtf close;
```

RESULT AND DISCUSSION

This paper explained on how an alternative programming method of fuzzy bootstrap weighted regression procedure using SAS software can be applied for the small sample size which the data is very difficult to collect. By resampling (using bootstrap method), it provides the pleminary comprehensive information and also give the general overview on how the data behaviour even though the original data is not enough (small sample size).

In our case, smaller standard error of the estimate parameter will tell us how accurate our estimate parameter is likely to be.

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