

To compare the variance of regression coefficients by using  
different resampling techniques

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## 1 Introduction

Consider the following regression models

$$y_i = \alpha + \beta x_i + \epsilon_i, i = 1, \dots, n$$

$$y_i = \alpha + \beta x_i + x_i \epsilon_i, i = 1, \dots, n$$

where  $\alpha=1.5$ ,  $\beta=7.5$ ,  $n=15$ ,  $x_i$ 's are generated from *Uniform*(0, 20) distribution, and  $\epsilon_i$ 's are generated from one of the following distribution

let  $\hat{\beta}$  be the OLS estimator of  $\beta$ . For each of the above cases, compare

- The true variance of  $\hat{\beta}$  (estimated)
- The estimated variance using delete-1 jackknife
- The estimated variance using residual bootstrap
- The estimated variance using paired bootstrap

## 2 Results

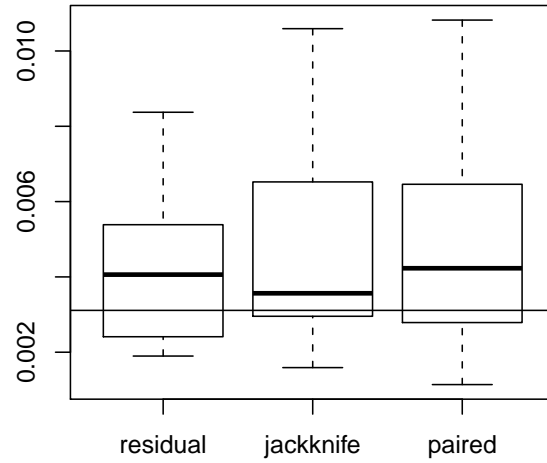
Table 1: Results of model 1

Distribution	standard normal	Double exponential	t-distribution with d.f 2	Logistic
Estimated Variance of beta - hat by simulation	.054100064	.08149226	.05461763	.07262628
Estimated Variance of beta - hat by jackknife sampling	.05205357	.08352675	.0497562	.07139115
Estimated Variance of beta - hat by residual bootstrap	.05365725	.09632952	.05114177	.06413493
Estimated Variance of beta - hat by paired bootstrap	.05222555	.08326425	.04760964	.05591118

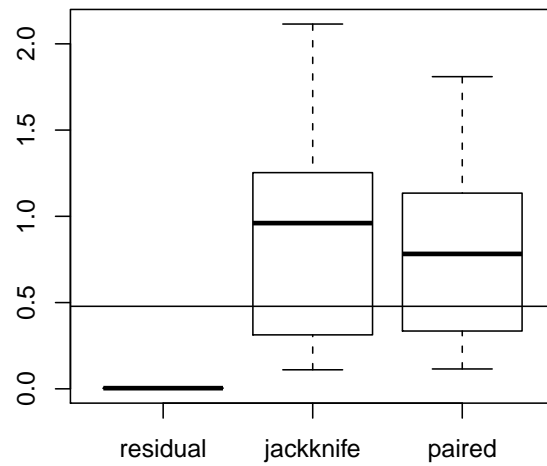
Table 2: Result of model 2

Distribution	standard normal	Double exponential	t-distribution with d.f 2	Logistic
Estimated Variance of beta - hat by simulation	.04227235	.86834482	.6635769	1.22626803
Estimated Variance of beta - hat by jackknife sampling	.02731309	.07073187	.4044742	.08270864
Estimated Variance of beta - hat by residual bootstrap	.03903361	.52648465	.03214410	.03903361
Estimated Variance of beta - hat by paired bootstrap	.03479961	.57495839	.3733652	.03479961

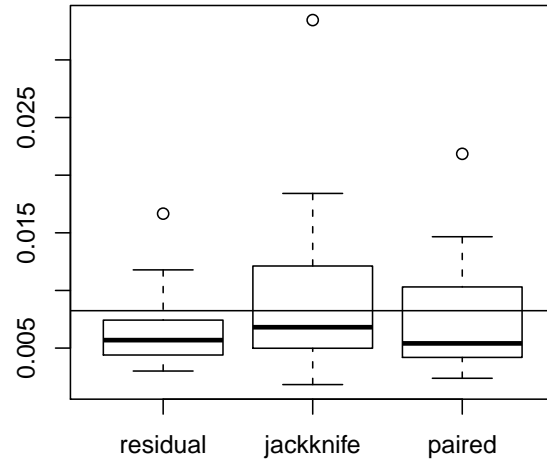
**Figure 1** : Boxplot for double exponential ( **model 1** )



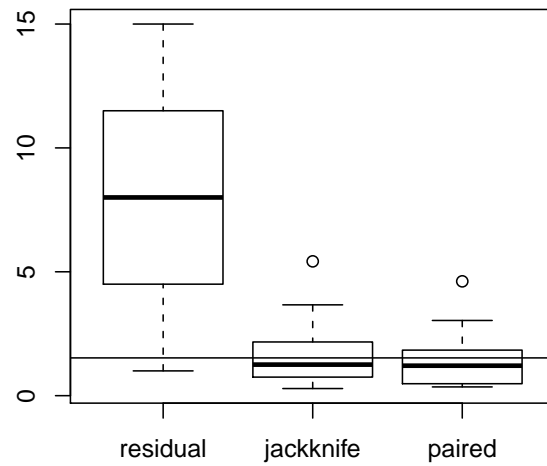
**Figure 2** : Boxplot for double exponential ( **model 2** )



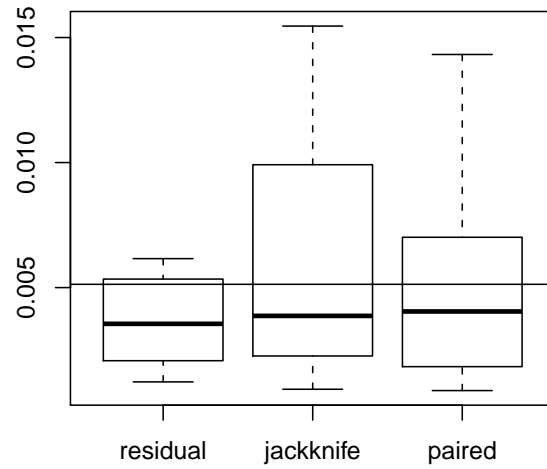
**Figure 3** : Boxplot for logistic with parameter 0,1 ( **model 1** )



**Figure 4** :Boxplot for logistic with parameter 0,1 ( **model 2** )



**Figure 5** :Boxplot for normal with parameter 0,1 ( **model 1** )



**Figure 6** :Boxplot for normal with parameter 0,1 ( **model 2** )

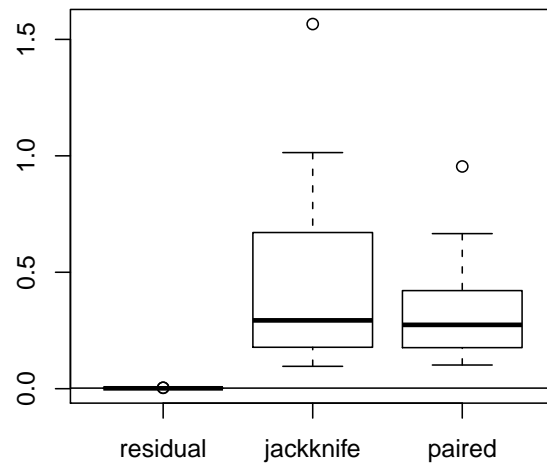


Figure 7 :Boxplot for t-distribution with d.f 2 ( **model 1** )

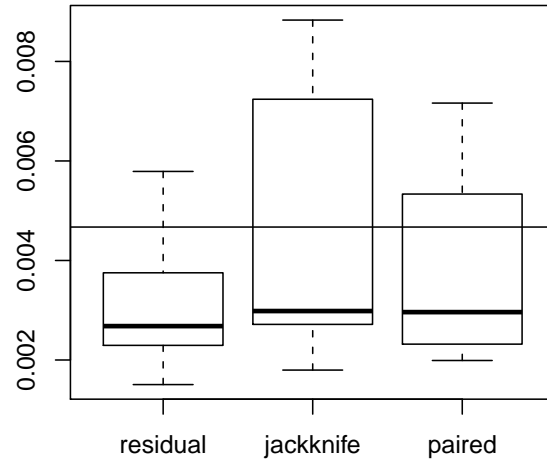
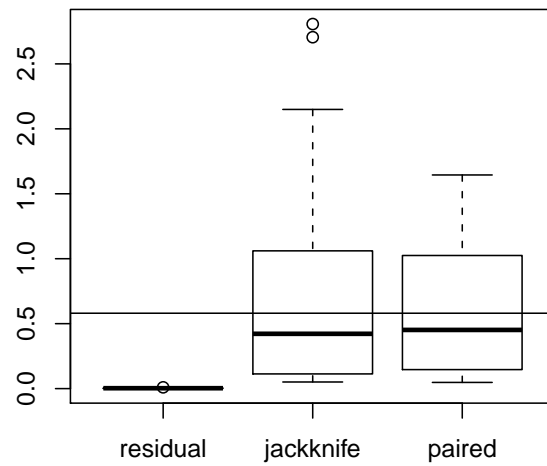


Figure 8 :Boxplot for t-distribution with d.f 2 ( **model 2** )



### 3 Methodology

We considered two linear models

$$y_i = \alpha + \beta x_i + \epsilon_i, i = 1, \dots, n \quad (1)$$

$$y_i = \alpha + \beta x_i + x_i \epsilon_i, i = 1, \dots, n \quad (2)$$

where  $\alpha=1.5$ ,  $\beta=7.5$ ,  $n=15$ ,  $x_i$ -s are generated from  $U(0,20)$  distribution, and  $\epsilon_i$ -s are generated from one of the following distribution.

- standard normal
- $t_5$
- double exponential with rate 1
- logistic (with location parameter 0 and scale parameter 1)

Now we want to estimate  $\beta$  for these models, and then to find variance of estimated  $\beta$  by these resampling techniques. We adopted 4 resampling plans to obtain  $\hat{\beta}$  and its variance.

#### 3.1 Simulation

In first techniques we fitted linear model and then calculated value of  $\beta$  and then simply simulated the process to find estimate variance of  $\hat{\beta}$ .

#### 3.2 Residual Bootstrap

We fitted a least square regression equation and define the usual residuals as

$$\epsilon_{in} = y_i - x_i' \beta_n, i = 1, \dots, n$$

We used

$$\tilde{\epsilon}_{in} = \epsilon_{in} - n^{-1} \sum_{i=1}^n \epsilon_{in}$$

Let  $F_n$  be the EDF that puts mass  $n^{-1}$  at each  $\{\tilde{\epsilon}_{in}\}, i = 1, \dots, n$

Now let  $\{\epsilon_1^*, \dots, \epsilon_n^*\}$  be i.i.d.  $F_n$  and

let

$$y_i^* = x_i' \beta_n + \epsilon_i^*, \quad i = 1, \dots, n.$$

where  $\{\epsilon_1^*, \dots, \epsilon_n^*\}$  is a random sample drawn with replacement from  $\{\tilde{\epsilon}_{1n}, \dots, \tilde{\epsilon}_{nn}\}$ . then using  $y^*$  instead of  $y$  in the linear model and we estimated beta .

### 3.3 Paired Bootstrap

Consider the ECDF  $F_n$  which puts mass  $n^{-1}$  at each pair  $\{y_i, x_i\}, i = 1, \dots, n$ . The bootstrap random samples are drawn with replacement from  $y_i, x_i$  and hence the pair  $y_i^*, x_i^*$  are i.i.d.  $F_n$ . then using these pairs we estimated  $\beta$  and its variance

### 3.4 delete-1 Jackknife

In this method we deleted 1 pair among  $\{y_i, x_i\}$  and using the remaining pairs we estimated  $\beta$ . Repeating this  $n$  times we calculated its variance, which is given by

$$V(\hat{\beta}) = n^{-1} \sum_{i=1}^n (\beta_i - \bar{\beta})^2$$

where  $\bar{\beta} = \frac{1}{n} \sum_{i=1}^n \beta_i$ .

### 3.5 Variance consistent

Any resampling plan, say  $R$  is said to be variance consistent if its variance estimates say  $V_R$ , satisfies  $V(\beta_n)/V_R \rightarrow 1$

## 4 Conclusion

### 4.1 Model 1

We see from our result that overall residual bootstrap is approximates our simulated result i.e residual bootstrap is *variance consistent*

### 4.2 Model 2

In model 2 where we have heteroscedasticity no resampling plans go near to simulated result of variance. But from theory we know that paired bootstrap resampling technique is robust, but our results deviate.