STAC67H: Regression Analysis Fall, 2014

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October 1, 2014

- Graphic analysis of residual is inherently subjective.
- There are occasions when one wishes to put specific questions to a test.

- Tests for Randomness: Durbin-Watson test will be covered in Chapter 12.
- Tests for Outliers: Will be covered in Chapter 10.
- Tests for Normality: Normal-probability plot has good reputation regarding test for normality.

Breusch-Pagan Test

- A large sample test: this test assumes that the error terms are independent and normally distributed.
- ② The variance of the error term ϵ_i , denoted by σ_i^2 , is related to the level of X

$$\log_e \sigma_i^2 = \gamma_0 + \gamma_1 X_i.$$

3 The variance σ_i^2 either increases or decreases with the level of X, depending on the sign of γ_1 .

Breusch-Pagan Test

- The constancy of error variance holds when $\gamma_1 = 0$.
- ② Fit a simple linear regression model regressing e_i^2 (response) against X_i (predictor) and obtain the *regression sum of squares* SSR^* .
- Ompute the test statistic as follows

$$\chi^2_{BP} = \frac{SSR^*}{2} / \left(\frac{SSE}{n}\right)^2$$

where SSE is the error sum of squares when regressing Y on X.

Breusch-Pagan Test

The hypotheses to be tested are

$$H_0: \gamma_1 = 0$$
 vs $H_A: \gamma_1 \neq 0$

- ② Under H_0 and for large n, the approximate distribution of χ^2_{BP} is χ^2 with 1 degrees of freedom.
- **3** Reject H_0 at α level of significance if

$$\chi^2_{BP} \ge \chi^2(1-\alpha,1)$$

Breusch-Pagan Test: In our airfreight breakage problem (n = 10)

The error sum of squares is

$$SSE = 17.6$$

② The regression sum of squares by regressing e_i^2 using X_i , we get

$$SSR^* = 6.4$$

Hence, the Breusch-Pagan test statistic is

$$\chi^{2}_{BP} = \frac{SSR^{*}}{2} / \left(\frac{SSE}{n}\right)^{2} = 1.033058$$

Breusch-Pagan Test: In our airfreight breakage problem (n = 10)

① At $\alpha = 0.05$ level of significance

$$\chi^2(0.95, 1) = 3.841459$$

4 Here,

$$\chi^2_{BP} \le \chi^2(0.95, 1) = 3.841459$$

3 Decision: We don't have enough evidence to reject $H_0: \gamma = 0$.

If the simple linear regression model ($Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$) is not appropriate for a data set, there are two basic choices:

- Abandon the regression model and develop and use a more appropriate model.
- Employ some transformation on the data so that the above regression model is appropriate for the transformed data.

Box-Cox Transformations

- It is often difficult to determine from diagnostic plots which transformation of Y is appropriate for correcting skewness of the distributions of error terms, unequal error variances, and nonlinearity of the regression function.
- 2 The Box-Cox procedure automatically identifies a transformation from the family of power transformations on *Y*.

Box-Cox Transformations

The family of power transformation is of the form

$$Y^* = Y^{\lambda}$$

A few examples of this power transformations

$$\begin{array}{ll} \lambda=2 & Y^*=Y^2 \\ \lambda=0.5 & Y^*=\sqrt{Y} \\ \lambda=0 & Y^*=\log_e Y \quad \text{(by definition)} \\ \lambda=-0.5 & Y^*=\frac{1}{\sqrt{Y}} \\ \lambda=-1.0 & Y^*=\frac{1}{Y} \end{array}$$

Box-Cox Transformations

With this power transformation, the normal error regression model becomes

$$Y_i^{\lambda} = \beta_0 + \beta_1 X_i + \epsilon_i$$

where the additional parameter λ needs to be estimated from the data using maximum likelihood method.

An Alternative to Maximum Likelihood

• Conduct a numerical search in a grid of potential λ values; for example,

$$\lambda = -2, \lambda = -1.75, \cdots, \lambda = 1.75, \lambda = 2.$$

② For each λ , standardize Y_i^{λ} using W_i so that the magnitude of the error sum of squares does not depend on the value of λ

$$W_i = \begin{cases} K_1(Y_i^{\lambda} - 1) & \lambda \neq 0 \\ K_2(\log_e Y_i) & \lambda = 0 \end{cases}$$

An Alternative to Maximum Likelihood

where

$$K_2 = \left(\prod_{i=1}^n Y_i\right)^{1/n}$$

the geometric mean of the Y_i observations,

and

$$K_1 = \frac{1}{\lambda K_2^{\lambda - 1}}$$

15/30

③ Fit regression model with response W_i and predictor variable X_i , and get SSE_{λ} .

Box-Cox Transformations

An Alternative to Maximum Likelihood

• The maximum likelihood estimate $\hat{\lambda}$ is that value of λ for which SSE_{λ} is a minimum.

Box-Cox Transformations

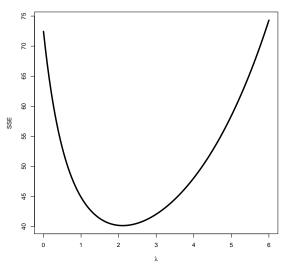


Figure: Plot of SSE against λ to determine appropriate transformation from the Box-Cox power transformations.

Box-Cox Transformations

Comments

- After a transformation has been selected, residual plots and other described analysis need to be employed to ascertain that the simple linear regression model is appropriate for the transformed data.
- When transformed models are employed, the estimators b_0 and b_1 obtained by least squares have the least squares properties with respect to the transformed observations, not the original ones.
- **3** The error sum of squares SSE is often fairly stable in a neighborhood around the estimate. It is therefore often reasonable to use a nearby λ value for which the power transformation is easy to understand.
- When the Box-Cox procedure leads to a λ value near 1, no transformation of Y may be needed.

Jabed Tomal (U of T) Regression Analysis October 1, 2014 18 / 30

1 The $100(1-\alpha)\%$ confidence interval of β_0 is

$$b_0 \pm t(1 - \alpha/2; n-2)s\{b_0\}$$

② The 100(1 $-\alpha$)% confidence interval of β_1 is

$$b_1 \pm t(1 - \alpha/2; n-2)s\{b_1\}$$

What is the confidence coefficient of their joint intervals?

Bonferroni Joint Confidence Intervals

• Let A_1 denote the event that the first confidence interval does not cover β_0 . Then

$$P(A_1) = \alpha$$

2 Let A_2 denote the event that the second confidence interval does not cover β_1 . Then

$$P(A_2) = \alpha$$

③ Here $A_1^C \cap A_2^C$ is the event which indicates that both of the confidence intervals cover $β_0$ and $β_1$.

$$P(A_1^C \cap A_2^C) = ?$$

Here,

$$A_1^C\cap A_2^C=(A_1\cup A_2)^C$$

The probability theory of a complimentary event gives us

$$P(A_1^C \cap A_2^C) = 1 - P(A_1 \cup A_2) = 1 - P(A_1) - P(A_2) + P(A_1 \cap A_2)$$

After simplification, we write

$$P(A_1^C \cap A_2^C) = 1 - \alpha - \alpha + P(A_1 \cap A_2)$$

• Since $P(A_1 \cap A_2) \ge 0$, we get

$$P(A_1^C \cap A_2^C) \ge 1 - 2\alpha.$$

This inequality is called Bonferroni inequality.

Hence, the confidence coefficient of containing both of the parameters in their respective intervals could be as low as

$$1-2\alpha$$
.

Example: If both of the individual coefficients are 0.95, the joint confidence coefficient could be as low as 0.90.

- We use Bonferroni inequality to obtain a family confidence coefficient of at least 1α for estimating β_0 and β_1 .
- ② We do this by increasing the confidence coefficients for each β_0 and β_1 to

1 –
$$\alpha$$
/2.

3 This results to a Bonferroni bound of at least

$$1-\alpha$$
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- We use Bonferroni inequality to obtain a family confidence coefficient of at least 1α for estimating β_0 and β_1 .
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3 This results to a Bonferroni bound of at least

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Bonferroni Joint Confidence Intervals

• Thus, the 1 $-\alpha$ joint Bonferroni confidence limits for β_0 and β_1 for is

$$b_0 \pm Bs\{b_0\}$$
 $b_1 \pm Bs\{b_1\}$

where $B = t(1 - \alpha/4; n - 2)$.

Airfreight breakage problem:

The estimates are

$$b_0 = 10.2, \ b_1 = 4, \ \textit{MSE} = 2.2, \ s^2\{b_0\} = 0.44, \ s^2\{b_1\} = 0.22$$

2 For $\alpha = 0.05$

$$B = t(1 - 0.05/4; 10 - 2) = 2.751524.$$

ullet Hence, the 95% simultaneous confidence intervals for eta_0 and eta_1 are

$$8.374846 \le \beta_0 \le 12.025154$$

and

$$2.709421 \le \beta_1 \le 5.290579$$

- We consider the simultaneous predictions of g new observations on Y in g independent trials at g different levels of X.
- ② With the Bonferroni procedure, the 1 $-\alpha$ simultaneous prediction intervals are:

$$\hat{Y}_h \pm Bs\{pred\}$$

where $B = t(1 - \alpha/2g; n - 2)$.

Airfreight breakage problem:

• We want to get simultaneous prediction intervals for two new observations ($Y_{h1} = 18, X_{h1} = 2$) and ($Y_{h2} = 23, X_{h2} = 3$). The estimates are

$$\hat{Y}_{h1} = 18.2, \ \hat{Y}_{h2} = 22.2, \ \textit{MSE} = 2.2, \ s^2\{\hat{Y}_{h1}\} = 2.64, \ s^2\{\hat{Y}_{h2}\} = 3.3$$

② For $\alpha = 0.05$ and g = 2

$$B = t(1 - 0.05/4; 10 - 2) = 2.751524.$$

1 Hence, the 95% simultaneous confidence intervals for Y_{h1} and Y_{h2} are

$$13.7293 \le Y_{h1} \le 22.6707$$

 $17.20161 < Y_{h2} < 27.19839$

- We consider the simultaneous predictions of g new observations on Y in g independent trials at g different levels of X.
- 2 With the Scheffe procedure, the $1-\alpha$ simultaneous prediction intervals are:

$$\hat{Y}_h \pm Ss\{pred\}$$

where $S^2 = gF(1 - \alpha; g, n - 2)$.

Airfreight breakage problem:

• We want to get simultaneous prediction intervals for two new observations ($Y_{h1} = 18, X_{h1} = 2$) and ($Y_{h2} = 23, X_{h2} = 3$). The estimates are

$$\hat{Y}_{h1} = 18.2, \ \hat{Y}_{h2} = 22.2, \ \textit{MSE} = 2.2, \ s^2\{\hat{Y}_{h1}\} = 2.64, \ s^2\{\hat{Y}_{h2}\} = 3.3$$

② For $\alpha = 0.05$ and g = 2

$$S^2 = 2F(1 - 0.05; 2, 10 - 2) = 8.91794.$$

1 Hence, the 95% simultaneous confidence intervals for Y_{h1} and Y_{h2} are

$$13.34785 \le Y_{h1} \le 23.05215$$

 $16.77513 < Y_{h2} < 27.62487$