

STAT 3008 Applied Regression Analysis

Tutorial 9.

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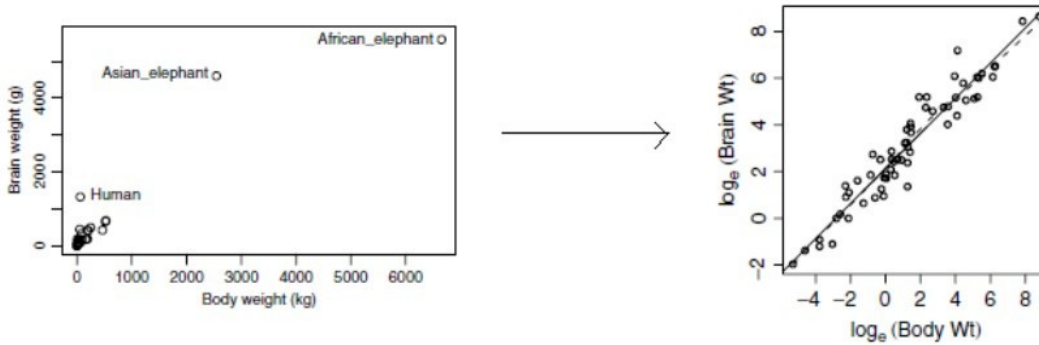
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1 Transformation

1.1 Why transformation?

♣ The assumption of linear relation does not hold.



We can transform:

- ★ The predictor
- ★ The response
- ★ Both

to achieve the linear relationship.

1.2 Transformation methods for simple linear regression

Power Transformation

$$\psi(X, \lambda) = \begin{cases} X^\lambda, & \text{if } \lambda \neq 0 \\ \log X, & \text{if } \lambda = 0 \end{cases}$$

♣ Log transformation is useful when

1. Observations are positive
2. Range of variable is huge (i.e. $Max(X) \gg Min(X)$)

♣ Continuation of the example in part 1.1

Both variables have large range. So we perform transformation on both the predictor and the response.

$$\psi(BrainWt, 0) = \alpha + \beta\psi(BodyWt, 0) + e$$

$$\begin{aligned} \Rightarrow \log(\text{BrainWt}) &= \alpha + \beta \log(\text{BodyWt}) + e \\ \Rightarrow \text{BrainWt} &= e^\alpha (\text{BodyWt})^\beta e^e = \tilde{\alpha} (\text{BodyWt})^\beta \delta \end{aligned}$$

δ is multiplicative error.

$$\widehat{\text{BrainWt}} = e^{\log(\widehat{\text{BrainWt}})} = e^{\hat{\alpha} + \hat{\beta} \log(\text{BodyWt})}$$

C.I. for $e^{\alpha + \beta \log(\text{BodyWt})} \leftarrow$ Delta method.

Scaled Power Transformation

$$\psi_s(X, \lambda) = \begin{cases} \frac{X^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0 \\ \log X, & \text{if } \lambda = 0 \end{cases}$$

♣ Advantages:

1. Continuous function of λ
2. Preserve the direction of association.

E.g. find transformation for X for true model $E(Y|X) = \beta X^{-\frac{1}{2}}$,

Power transformation,

Let $\psi(X, \lambda) = X^{-\frac{1}{2}}$ (i.e. $\lambda = -\frac{1}{2}$), then $E(Y|X) = \beta \psi(X, -\frac{1}{2})$.

Scaled power transform,

$$E(Y|X) = \tilde{\alpha} + \tilde{\beta} \psi_s(X, \lambda) = \beta X^{-\frac{1}{2}} \Rightarrow \tilde{\alpha} = \beta, \tilde{\beta} = -\frac{1}{2}\beta, \lambda = -\frac{1}{2}.$$

1.3 Transformation selection for simple linear regression

Remarks:

1. It is to choose λ ;
2. Suppose we only transform X now.

♣ Method 1: Draw many fitted curves

i.e. Plot (x, \hat{y}) for various λ .

♣ Method 2: Draw many scatter plots

i.e. Plot $(\psi(X, \lambda), y)$.

♣ Method 3: Plot λ against RSS of fitting y against $\psi(X, \lambda)$, then find the λ that minimizes RSS.

1.4 Methods for multiple regression

Method 1: Inverse fitted value plot

★ Plot \hat{Y} against Y .

★ Find transformation for Y . ← see if curve (Y, \hat{Y}_λ) matches the pattern of (Y, \hat{Y})

★ Match $\rightarrow \hat{\beta}_0 + \hat{\beta}_1 \psi_S(Y, \lambda) = \hat{Y}_\lambda \approx \hat{Y} = X\hat{\beta}$

\hat{Y} and $\psi_S(Y, \lambda)$ linearly related, while \hat{Y} and $X\hat{\beta}$ linearly related, so $\psi_S(Y, \lambda)$ and $X\hat{\beta}$ linearly related.

Which is the correct order of the steps in the Inverse fitted value plot?

[a]. Plot \hat{Y}_λ against Y .

[b]. Fit a linear regression between Y and X , obtaining \hat{Y} .

[c]. Specify a scaled-power transformation $\psi_S(Y; \lambda)$.

[d]. Fit \hat{Y} against $\psi_S(Y; \lambda)$, obtaining \hat{Y}_λ .

[e]. Plot \hat{Y} against Y .

Ans: b,e,c,d,a.

★ After the above steps, we have decided an λ . Then go back to the analysis and fit $\psi_S(Y, \lambda)$ against X .

Method 2: Modified Power transformation for all predictors

Use the modified power family:

$$\psi_M(Y, \lambda) = \begin{cases} (\sqrt[\lambda]{y_1 \cdots y_n})^{1-\lambda} \frac{Y^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0 \\ (\sqrt[\lambda]{y_1 \cdots y_n})^{1-\lambda} \log Y, & \text{if } \lambda = 0 \end{cases}$$

Transform predictors so that each pair of predictors in the scatterplot matrix have a linear relationship.

$$(X_1, X_2, \dots, X_p) \rightarrow (\psi_M(X_1, \lambda_1), \psi_M(X_2, \lambda_2), \dots, \psi_M(X_p, \lambda_p))$$

Method 3: Box Cox Transformation

Modified power family:

$$\psi_M(Y, \lambda) = \begin{cases} (\sqrt[\lambda]{y_1 \cdots y_n})^{1-\lambda} \frac{Y^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0 \\ (\sqrt[\lambda]{y_1 \cdots y_n})^{1-\lambda} \log Y, & \text{if } \lambda = 0 \end{cases}$$

♣ Advantage:

Unit of $\psi_M(Y, \lambda)$ is the same as Y for all λ .

♣ Selection of λ .

- ★ Fix a λ , fit model with transformed Y_λ and obtain $RSS(\lambda)$
- ★ Try various λ and find the one which minimizes $RSS(\lambda)$

2 Example

Thomas is analyzing a data set using the Box-Cox transformation. The minimum value of RSS occurs when $\lambda = -0.979$. Therefore, he transformed the response with

$$\left(\sqrt[n]{y_1 \cdots y_n}\right)^{1.979} \frac{Y^{-0.979} - 1}{-0.979}$$

Any comment?

$\lambda = -0.979$ seems to have no good interpretations or meanings. I would suggest $\lambda = -1$ as it may have a better interpretation.

3 Discussions on Exercise 8-10 solutions