Chapter 3: Multiple Linear Regression

Regression

$$y = \underset{n \times 1}{x} \times \underset{p \times 1}{\beta} + \underset{n \times 1}{\epsilon}$$

where p = k + 1

p is the total number of betas (or parameters), k is the number of regressor variables. $\epsilon \sim N(0, \sigma^2 I)$ where I is the identity matrix of whatever size it needs to be.

$$E[y] = x\beta$$

$$V[y] = V[\epsilon] = \sigma^2 I$$

$$y \sim N(x\beta, \sigma^2 I)$$

Least Square Estimate for β and σ^2

$$\hat{\beta} = (x'x)^{-1}x'y$$

$$\begin{split} \mathbf{E}[\hat{\boldsymbol{\beta}}] &= \boldsymbol{\beta} \\ \mathbf{V}[\hat{\boldsymbol{\beta}}] &= (\mathbf{x}'\mathbf{x})^{-1}\boldsymbol{\sigma}^2 = \mathbf{c}\boldsymbol{\sigma}^2 \\ \mathbf{V}[\hat{\boldsymbol{\beta}}_j] &= \mathbf{c}_{jj}\boldsymbol{\sigma}^2 \\ \mathbf{E}[\boldsymbol{\beta}_j] &= \boldsymbol{\beta}_j \\ \hat{\boldsymbol{\beta}}_i \sim &\mathbf{N}(\boldsymbol{\beta}_j, \mathbf{c}_{ij}\boldsymbol{\sigma}^2) \end{split}$$

$$\hat{y} = x\hat{\beta} = x(x'x)^{-1}x'y = Hy$$

$$\begin{array}{ll} \mathrm{E}[\hat{y}] &= \mathrm{E}[\mathrm{x}\hat{\beta}] &= \mathrm{x}\beta \\ \mathrm{V}[\hat{y}] &= \mathrm{V}[\mathrm{x}\hat{\beta}] &= \mathrm{x}\mathrm{V}[\hat{\beta}]\mathrm{x}' = \mathrm{x}(\mathrm{x}'\mathrm{x})^{-1}\mathrm{x}'\sigma^2 = \mathrm{H}\sigma^2 \\ \hat{y} \sim &\mathrm{N}(\mathrm{x}\beta \ , \, \mathrm{H}\sigma^2) \\ \hat{y}_{j} \sim &\mathrm{N}(\mathrm{x}_{j}\beta \ , \, \mathrm{h}_{jj}\sigma^2) \text{ where} \end{array}$$

$$h_{jj} = x'_j (x'x)^{-1} x_j$$

 $x_j = [x_{j0}, x_{j1}, ... x_{jk}]$

and

$$\hat{\epsilon} = y - \hat{y} = y - Hy = (I - H)y$$

where $\hat{\epsilon}$ is the estimated error.

$$\hat{\sigma^2} = \frac{SS_{res}}{n-p} = MS_{res}$$

where p = k + 1 = the number of parameters (i.e. β 's: β_0 , β_1 , ... β_k)

Confidence Intervals

$$\hat{\beta}_j \sim N(\beta_j, c_{jj}\sigma^2) \longrightarrow \frac{\hat{\beta}_j - \beta_j}{\sqrt{c_{jj}\sigma^2}} \sim N(0, 1)$$

or, if variance is unknown,

$$\hat{\beta}_j \sim N(\beta_j, c_{jj}MS_{res}) \longrightarrow \frac{\hat{\beta}_j - \beta_j}{\sqrt{c_{jj}MS_{res}}} or \frac{\hat{\beta}_j - \beta_j}{se(\hat{\beta}_j)} \sim t_{n-p}$$

variance:

$$\hat{\sigma^2} = MS_{res} = \frac{SS_{res}}{n-p} \sim \chi_{n-p}^2$$

So, the (1 - α) confidence interval for β $_j$ is

$$\hat{\beta}_j \pm t_{\frac{\alpha}{2},n-p} se(\hat{\beta}_j)$$

$$\hat{y}_j \sim \! \mathrm{N}(\mathbf{x}_j \boldsymbol{\beta} \; , \, \mathbf{h}_{jj} \sigma^2)$$

$$\frac{\hat{y}_j - x_j \beta}{\sqrt{h_{jj}\sigma^2}} \sim N(0, 1) \longrightarrow \frac{\hat{y}_j - x_j \beta}{\sqrt{h_{jj}MS_{res}}} \sim t_{n-p}$$

where $\sigma^2 = MS_{res}$

A 1 - α confidence interval for $\mathrm{E}[\mathrm{y}_0|\mathrm{x}_0]$ is:

$$\hat{y}_0 \pm t_{\frac{\alpha}{2}, n-p} \sqrt{x'_0(x'x)^{-1} x_0 \hat{\sigma}^2}$$

or

$$\hat{y}_0 \pm t_{\frac{\alpha}{2}, n-p} \sqrt{x_0'(x'x)^{-1} x_0 M S_{res}}$$

Analysis of Variance (ANOVA)

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Regression	p - 1 (or k)	SS_{Reg}	MS_{Reg}	$\frac{MS_{Reg}}{MS_{res}}$	n/a
Residuals	n - p or n - (k + 1)	SS_{res}	MS_{res}		
Total	n - 1	SS_{total}			

$$R^2 = \frac{SS_{Reg}}{SS_{Tot}}$$

$$R^2_{adi} = ?$$