

## Chapter 3: Multiple Linear Regression

### Regression

$$\underset{n \times 1}{y} = \underset{n \times (k+1)}{x} \times \underset{(k+1) \times 1}{\beta} + \underset{n \times 1}{\epsilon}$$

or

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

$\epsilon \sim N(0, \sigma^2 I)$  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 $\beta$ and $\sigma^2$

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

$$E[\hat{\beta}] = \beta$$

$$V[\hat{\beta}] = (x'x)^{-1}\sigma^2 = c\sigma^2$$

$$V[\hat{\beta}_j] = c_{jj}\sigma^2$$

$$E[\beta_j] = \beta_j$$

$$\hat{\beta}_j \sim N(\beta_j, c_{jj}\sigma^2)$$

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

$$E[\hat{y}] = E[x\hat{\beta}] = x\beta$$

$$V[\hat{y}] = V[x\hat{\beta}] = xV[\hat{\beta}]x' = x(x'x)^{-1}x'\sigma^2 = H\sigma^2$$

$$\hat{y} \sim N(x\beta, H\sigma^2)$$

$$\hat{y}_j \sim N(x_j\beta, h_{jj}\sigma^2) \text{ where}$$

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

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

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.  $\beta$ 's:  $\beta_0, \beta_1, \dots, \beta_k$ )

### 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,

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

variance:

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

So, the  $(1 - \alpha)$  confidence interval for  $\beta_j$  is

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

$$\hat{y}_j \sim N(x_j\beta, h_{jj}\sigma^2)$$

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

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

A  $1 - \alpha$  confidence interval for  $E[y_0|x_0]$  is:

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

or

$$\hat{y}_0 \pm t_{\frac{\alpha}{2}, n-p} \sqrt{x_0'(x'x)^{-1}x_0MS_{res}}$$

## 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		$SS_{total}$			

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

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