

## Tutorial, Part 2

### Example 1

Derivation of  $b$  done at the lecture.

Application of  $b = (X^T X)^{-1} X^T y$ :

System of normal equations (expressions 6 and 7):

$$\begin{array}{rclcl}
 n & \Sigma x_2 = n \cdot \bar{x}_2 & \Sigma x_3 = n \cdot \bar{x}_3 & \Sigma y = n \cdot \bar{y} & \\
 10 & b_1 + (10 \cdot 0.4) b_2 + (10 \cdot 0.8) b_3 = 10 \cdot 2.4 & & & \\
 4 & b_1 & + 10 b_2 & - 2 b_3 = 40 & \\
 8 & b_1 & - 2 b_2 & + 12 b_3 = -2 & 
 \end{array}$$

$$X^T X = \begin{bmatrix} 10 & 4 & 8 \\ 4 & 10 & -2 \\ 8 & -2 & 12 \end{bmatrix} \quad X^T y = \begin{bmatrix} 24 \\ 40 \\ -2 \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

symmetry

Determinant:

$$\begin{aligned}
 \det(X^T X) &= 10 \cdot 10 \cdot 12 + 4(-2)8 + 8 \cdot 4(-2) - \\
 &\quad - 8 \cdot 10 \cdot 8 - 10(-2)(-2) - 4 \cdot 4 \cdot 12 = \\
 &= 200
 \end{aligned}$$

Cofactors:

$$c_{11} = \begin{vmatrix} 10 & -2 \\ -2 & 12 \end{vmatrix} = 116$$

$$c_{12} = \begin{vmatrix} 4 & -2 \\ 8 & 12 \end{vmatrix} = 64$$

$$c_{13} = \begin{vmatrix} 4 & 10 \\ 8 & -2 \end{vmatrix} = -88$$

$$c_{21} = c_{12} = 64$$

symmetry

$$c_{22} = \begin{vmatrix} 10 & 8 \\ 8 & 12 \end{vmatrix} = 56$$

$$c_{23} = \begin{vmatrix} 10 & 4 \\ 8 & -2 \end{vmatrix} = -52$$

$$c_{31} = c_{13} = -88$$

symmetry

$$c_{32} = c_{23} = -52$$

symmetry

$$c_{33} = \begin{vmatrix} 10 & 4 \\ 4 & 10 \end{vmatrix} = 84$$

$$(X^T X)^{-1} = \frac{1}{\underset{\neq 0}{200}} \cdot \begin{bmatrix} 116 & -64 & -88 \\ -64 & 56 & +52 \\ -88 & +52 & 84 \end{bmatrix}^T =$$

$$= \begin{bmatrix} 0.58 & -0.32 & -0.44 \\ -0.32 & 0.28 & 0.26 \\ -0.44 & 0.26 & 0.42 \end{bmatrix}$$

$$b = (X^T X)^{-1} \cdot X^T y =$$

$$= \begin{bmatrix} 0.58 & -0.32 & -0.44 \\ -0.32 & 0.28 & 0.26 \\ -0.44 & 0.26 & 0.42 \end{bmatrix} \cdot \begin{bmatrix} 24 \\ 40 \\ -2 \end{bmatrix} = \begin{bmatrix} 1 \\ 3 \\ -1 \end{bmatrix} \begin{matrix} b_1 \\ b_2 \\ b_3 \end{matrix}$$

## Example 2

Properties on **Slide 20**. Proofs:

$$S(b_1, b_2, b_3) = \sum_{i=1}^n e_i^2 = \sum_{i=1}^n (y_i - \hat{y}_i)^2 =$$

**min criterion function**

$$= \sum_{i=1}^n (y_i - b_1 - b_2 x_{2i} - b_3 x_{3i})^2$$

**composite function**

$$\bullet \frac{\partial S}{\partial b_1} = -2 \sum_{i=1}^n (y_i - b_1 - b_2 x_{2i} - b_3 x_{3i}) = 0$$

$e_i$

$$-2 \sum_{i=1}^n e_i = 0$$

$$\sum_{i=1}^n e_i = 0 \quad \text{P4}$$

**INTERCEPT**

$$\bullet \frac{\partial S}{\partial b_2} = -2 \sum_{i=1}^n \underbrace{(y_i - b_1 - b_2 x_{2i} - b_3 x_{3i})}_{e_i} x_{2i} = 0$$

$$\begin{aligned} -2 \sum_{i=1}^n e_i x_{2i} &= 0 \\ \sum_{i=1}^n e_i x_{2i} &= 0 \end{aligned}$$

$$\frac{\partial S}{\partial b_3} = -2 \sum_{i=1}^n \underbrace{(y_i - b_1 - b_2 x_{2i} - b_3 x_{3i})}_{e_i} x_{3i} = 0$$

$$\begin{aligned} -2 \sum_{i=1}^n e_i x_{3i} &= 0 \\ \sum_{i=1}^n e_i x_{3i} &= 0 \end{aligned}$$

Generalize:  $\sum_{i=1}^n e_i x_{ji} = 0$  or  $X^T e = 0$  P1 ALWAYS

$$\begin{aligned} \bullet \sum_{i=1}^n \hat{y}_i \cdot e_i &= \sum_{i=1}^n (b_1 + b_2 x_{2i} + b_3 x_{3i}) \cdot e_i = \\ &= \sum_{i=1}^n b_1 e_i + \sum_{i=1}^n b_2 x_{2i} e_i + \sum_{i=1}^n b_3 x_{3i} e_i = \\ &= b_1 \underbrace{\sum_{i=1}^n e_i}_{=0 [P4]} + b_2 \underbrace{\sum_{i=1}^n x_{2i} e_i}_{=0 [P1]} + b_3 \underbrace{\sum_{i=1}^n x_{3i} e_i}_{=0 [P1]} = 0 \end{aligned}$$

or  $\hat{y}^T e = 0$  P2 ALWAYS

$$\begin{aligned}
 \bullet \quad y_i &= b_1 + b_2 x_{2i} + \dots + b_k x_{ki} + e_i \quad / \sum_i \\
 \sum_i y_i &= nb_1 + b_2 \sum_i x_{2i} + \dots + b_k \sum_i x_{ki} + \sum_i e_i \quad | : n \\
 \frac{1}{n} \sum_i y_i &= b_1 + b_2 \frac{1}{n} \sum_i x_{2i} + \dots + b_k \frac{1}{n} \sum_i x_{ki} \quad \sum_i e_i = 0 \text{ (P4)}
 \end{aligned}$$

$$\begin{aligned}
 \bar{y} &= b_1 + b_2 \bar{x}_2 + \dots + b_k \bar{x}_k \\
 \bar{y} &= \bar{y} \quad \text{P3} \\
 \underline{\underline{\bar{y}}} &= \text{INTERCEPT}
 \end{aligned}$$

Finally, we calculate  $a$  and  $b$ :

$$\begin{aligned}
 \sum_{i=1}^{10} e_i &= 0 \quad \text{(P4)} \\
 0.5 + b &= 0 \\
 b &= \underline{\underline{-0.5}}
 \end{aligned}$$

$$\begin{aligned}
 \sum_{i=1}^{10} \hat{y}_i \cdot e_i &= 0 \quad \text{(P2)} \\
 -7.375 + 1 \cdot a &= 0 \\
 a &= \underline{\underline{7.375}}
 \end{aligned}$$

## Tutorial, Part 3

### Example 1

We continue E1 from Tutorial, Part 2.

Variance estimators:

$$s_e^2 = \frac{y^T y - y^T X b}{n-k} = \frac{\sum_{i=1}^n y_i^2 - b^T X^T y}{n-k}$$

$$y^T X \cdot b = b^T \cdot X^T y = [2 \ 3 \ -1] \cdot \begin{bmatrix} 24 \\ 40 \\ -2 \end{bmatrix} = 170$$

$$s_e^2 = \frac{184 - 170}{10-3} = 2 \quad \text{variance estimate of the disturbances}$$

$$\text{var-cov}(b) = s_e^2 \cdot (X^T X)^{-1} =$$

$$= 2 \cdot \begin{bmatrix} 0.58 & -0.32 & -0.44 \\ -0.32 & 0.28 & 0.26 \\ -0.44 & 0.26 & 0.42 \end{bmatrix} =$$

variance estimates

$$= \begin{bmatrix} 1.16 & -0.64 & -0.88 \\ -0.64 & 0.56 & 0.52 \\ -0.88 & 0.52 & 0.84 \end{bmatrix}$$

variance-covariance matrix estimate of the regression coefficient estimates

## Hypothesis testing:

- $H_0: \beta_1 = 0$   
 $H_1: \beta_1 \neq 0$   
two-tailed test

$$t_1 = \frac{b_1 - \beta_1}{\sqrt{\text{var}(b_1)}} = \frac{2 - 0}{\sqrt{1.16}} = \underline{\underline{1.86}}$$

$$t_c (n = n - k = 7, \alpha/2 = 0.025) = 2.365$$

$|t_1| < t_c$ , do not reject  $H_0$  at  $\alpha = 0.05$

- $H_0: \beta_2 = 0$   
 $H_1: \beta_2 \neq 0$

$$t_2 = \frac{b_2 - \beta_2}{\sqrt{\text{var}(b_2)}} = \frac{3 - 0}{\sqrt{0.56}} = \underline{\underline{4.01}}$$

$$t_c (n = n - k = 7, \alpha/2 = 0.025) = 2.365$$

$|t_2| > t_c$ , reject  $H_0$  at  $\alpha = 0.05$  and  
 conclude from  $H_1$   
What, in this case?

- $H_0: \beta_3 = 0$   
 $H_1: \beta_3 \neq 0$

$$t_3 = \frac{b_3 - \beta_3}{\sqrt{\text{var}(b_3)}} = \frac{-1 - 0}{\sqrt{0.84}} = \underline{\underline{-1.05}}$$

$$t_c (n = n - k = 7, \alpha/2 = 0.025) = 2.365$$

$|t_3| < t_c$ , do not reject  $H_0$  at  $\alpha = 0.05$

## Measures of fit of the model:

•  $s_e = \sqrt{s_e^2} = \sqrt{2} = \underline{\underline{1.414}}$  std. error of regression

•  $KV = \frac{s_e}{\bar{y}} = \frac{1.414}{2.4} = \underline{\underline{0.589}}$  estimate of the  
coef. of variation

•  $\overset{\text{total}}{TSS} = \overset{\text{explained}}{ESS} + \overset{\text{residual}}{RSS}$   
 $\sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n (\hat{y}_i - \bar{y}_i)^2 + \sum_{i=1}^n \underbrace{(y_i - \hat{y}_i)}_{e_i}^2$

$RSS = s_e^2 \cdot (n - k) = 2 \cdot (10 - 3) = \underline{\underline{14}}$

$ESS = b^T X^T y - n \bar{y}^2 = 170 - 10 \cdot 2.4^2 = \underline{\underline{112.4}}$

$TSS = ESS + RSS = \underline{\underline{126.4}}$

•  $R^2 = \frac{ESS}{TSS} = \frac{112.4}{126.4} = \underline{\underline{0.889}}$  estimate of the  
multiple  
determination coeff.

$\bar{R}^2 = R^2_{adj} = 1 - (1 - R^2) \cdot \frac{n-1}{n-k} =$   
 $= 1 - (1 - 0.889) \cdot \frac{9}{7} = \underline{\underline{0.857}}$   
adjusted  $R^2$

•  $H_0: \beta_j = 0, \forall j = 2, 3$   
 $H_1: \beta_j \neq 0, \exists j = 2, 3$

$F = \frac{R^2 / (k - 1)}{(1 - R^2) / (n - k)} = \frac{0.889 / 2}{(1 - 0.889) / 7} = \underline{\underline{28.1}}$

$F_c(m_1 = k - 1 = 2, m_2 = n - k = 7, \alpha = 0.05) = 4.74$

$F > F_c$ , reject  $H_0$  at  $\alpha = 0.05$  and conclude from  $H_1$   
What, in this case?



## Elasticity estimates:

$$\bullet \hat{\epsilon}_{\bar{y}, \bar{x}_2} = b_2 \cdot \frac{\bar{x}_2}{\bar{y}} = 3 \cdot \frac{0.4}{2.4} = \underline{\underline{0.5}}$$

$$\bullet \hat{\epsilon}_{\bar{y}, \bar{x}_3} = b_3 \cdot \frac{\bar{x}_3}{\bar{y}} = -1 \cdot \frac{0.8}{2.4} = \underline{\underline{-0.33}}$$

## Representation of the model:

$$y_i = \beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + u_i \quad (\text{PRM})$$

$$\hat{y}_i = \overset{b_1}{2} + \overset{b_2}{3} x_{2i} - \overset{b_3}{1} x_{3i} \quad (\text{SRM})$$

$$t_j: (1.86) \quad (1.01) \quad (-1.05) \quad [3 \text{ possibilities}]$$

$$n = 10$$

$$s_e = 1.414$$

$$R^2 = 0.889$$

$$F = 28.1$$

$$\bar{R}^2 = 0.857$$