

# Use of Extra Sums of Squares for Testing Hypotheses about

Context: Assume we have  $Y, \tilde{X}_1, \dots, \tilde{X}_{p-1}$ , we're assuming

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \varepsilon_i \quad \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$$

\* Testing whether multiple  $\beta_2, \beta_3$  are jointly equal to 0

$$\text{Null, } H_0: \beta_2 = \beta_3 = 0$$

$$\text{Alternative, } H_a: \beta_2 \neq 0 \text{ or } \beta_3 \neq 0$$

Compute

$$F^* = \left( \frac{SSR(X_2, X_3 | \cdot, X_1)}{2} \right) \div \left( \frac{SSE(X_1, X_2, X_3)}{n-4} \right)$$

Decision Rule for a level  $\alpha$ -test will be:

\* If  $F^* \leq F(1-\alpha; 2, n-4)$  conclude  $H_0$

\* If  $F^* > F(1-\alpha; 2, n-4)$  conclude  $H_a$

p-value given by  $\Pr(F \geq F^*)$ , where  $F \sim F_{2, n-4}$

# Use of Extra Sums of Squares for Testing Hypotheses about $\beta_k$

Context: Assume we have  $Y, X_1, \dots, X_{p-1}$ , we're assuming  $Y_i = \beta_0 + \sum_{k=1}^{p-1} X_{ik} \tilde{\beta}_k + \varepsilon_i$ ,  $\varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$

\* Testing whether multiple  $\beta_k, k \in S$  are jointly equal to 0  
set of  $q$  indices

Null,  $H_0: \beta_k = 0$  for all  $k \in S$

Alternative,  $H_a: \beta_k \neq 0$  for at least one  $k \in S$

Compute

$$F^* = \left( \frac{SSR(X_k, k \in S | X_m, m \notin S)}{q} \right) \div \left( \frac{SSE(X_1, \dots, X_{p-1})}{n-p} \right)$$

Decision Rule for a level  $\alpha$ -test will be:

\* If  $F^* \leq F(1-\alpha; q, n-p)$  conclude  $H_0$

\* If  $F^* > F(1-\alpha; q, n-p)$  conclude  $H_a$

$p$ -value given by  $\Pr(F \geq F^*)$ , where  $F \sim F_{q, n-p}$

# Use of Extra Sums of Squares for Testing Hypotheses about $\beta_k$

Context: Assume we have  $Y, X_1, \dots, X_{p-1}$ , we're assuming

$$Y_i = \beta_0 + \sum_{k=1}^{p-1} X_{ik} \tilde{\beta}_k + \varepsilon_i, \quad \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$$

\* Testing whether multiple  $\beta_k = \beta_l$ ,  $l \neq k$  are jointly equal to 0

Null,  $H_0: \beta_k = \beta_l$   
Alternative,  $H_a: \beta_k \neq \beta_l$

Under the null, we assume a reduced model

$$Y_i = \beta_0 + \beta_k (X_{ik} + X_{il}) + \sum_{m=1, m \neq k \text{ and } m \neq l}^{p-1} \beta_m X_{im} + \varepsilon_i, \quad \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$$

Test this null by fitting original model, computing the  $SSE(\text{full})$  and fitting the reduced model, computing  $SSE(\text{reduced})$

Construct our  $F^* = \frac{SSE(\text{reduced}) - SSE(\text{full})}{1} / \frac{SSE(\text{full})}{n-p}$

Perform a level  $\alpha$  test with decision rule based on  $F(1-\alpha, 1, n-p)$   
if  $F^* \leq F(1-\alpha, 1, n-p)$  conclude  $H_0$  if  $F^* > F(1-\alpha, 1, n-p)$  conclude  $H_a$

- \* Standardizing the multiple regression model
- \* Correlated predictors

Multiple lin. reg. model

$$y_i = \beta_0 + \sum_{k=1}^{p-1} \beta_k x_{ik} + \varepsilon_i, \quad \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$$

Standardized multiple regression model is

$$\frac{y_i - \bar{y}}{s_y} = \gamma_0 + \sum_{k=1}^{p-1} \gamma_k \left( \frac{x_{ik} - \bar{x}_k}{s_k} \right) + \delta_i, \quad \delta_i \stackrel{iid}{\sim} N(0, \omega^2)$$

$$s_y = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2}, \quad s_k = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_{ik} - \bar{x}_k)^2}, \quad \bar{x}_k = \frac{1}{n} \sum_{i=1}^n x_{ik}$$

$$\tilde{y}_i = \gamma_0 + \sum_{k=1}^{p-1} \gamma_k \tilde{x}_{ik} + \delta_i, \quad \delta_i \stackrel{iid}{\sim} N(0, \omega^2)$$

$$\frac{y_i - \bar{y}}{s_y} = \gamma_0 + \sum_{k=1}^{p-1} \gamma_k \left( \frac{x_{ik} - \bar{x}_k}{s_k} \right) + \delta_i, \quad \delta_i \stackrel{iid}{\sim} N(0, \omega^2)$$

same as saying

$$y_i - \bar{y} = s_y \gamma_0 + \sum_{k=1}^{p-1} s_y \gamma_k \left( \frac{x_{ik} - \bar{x}_k}{s_k} \right) + s_y \delta_i, \quad \delta_i \stackrel{iid}{\sim} N(0, \omega^2)$$

same as saying

$$y_i = \bar{y} + s_y \gamma_0 + \sum_{k=1}^{p-1} s_y \gamma_k \left( \frac{x_{ik} - \bar{x}_k}{s_k} \right) + s_y \delta_i, \quad \delta_i \stackrel{iid}{\sim} N(0, \omega^2)$$

$$y_i = \bar{y} + s_y \gamma_0 - \left( \sum_{k=1}^{p-1} \left( \frac{s_y}{s_k} \right) \gamma_k \bar{x}_k \right) + \sum_{k=1}^{p-1} \left( \frac{s_y}{s_k} \right) \gamma_k x_{ik} + s_y \delta_i, \quad \delta_i \stackrel{iid}{\sim} N(0, \omega^2)$$

$$\Rightarrow \beta_k = \frac{s_y}{s_k} \gamma_k, \quad \text{for } k \geq 1$$

$$\Rightarrow \beta_0 = \bar{y} - \sum_{k=1}^{p-1} \beta_k \bar{x}_k + \cancel{s_y \gamma_0} = 0$$

when we have subtracted off mean of  $y_i$ 's and  $x_{ik}$ 's, we don't need an intercept, so  $\gamma_0 = 0$

Relate  <sup>$g_1, \dots, g_{p-1}$</sup>  standardized to  <sup>$b_0, \dots, b_{p-1}$</sup>  non-standardized regression coefficient estimates

$$b_k = \left( \frac{s_y}{s_k} \right) g_k \text{ for } k \geq 1$$

and  $b_0 = \bar{y} - \sum_{k=1}^{p-1} b_k \bar{x}_k$

Why do we care about standardizing?

- \* Numerically, solving for the regression coefficients of the standardized model is more stable
- \* Interpretation! Can be helpful if we want to compare estimated regression coefficients

let's consider a problem where  $y$  measured in dollars  
 $x_1$  is measured in thousands  
 $x_2$  is measured in cents of dollars

let's consider a problem where  $Y$  measured in dollars  
 $X_1$  is measured in thousands  
 $X_2$  is measured in cents of dollars

We assume

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \varepsilon_i, \quad \varepsilon_i \stackrel{\text{iid}}{\sim} N(0, \sigma^2)$$

we get estimates  $b_0 = 200$   
 $b_1 = 20,000$   
 $b_2 = 0.2$

what is the interpretation of  $b_1$ ?

average change in  $Y$  in dollars when  $X_1$  increases by one unit  $\rightarrow$  one thousand dollars, holding  $X_2$  constant

what is the interpretation of  $b_2$ ?

average change in  $Y$  in dollars when  $X_2$  increases by one unit  $\rightarrow$  one cent, holding  $X_1$  constant

What if we assumed the standardized model, and got estimates  $g_1$  and  $g_2$  of the standardized regression coefficients?

Interpretation of  $g_1$  would be

average change in  $Y$  in standard deviations from  $\bar{Y}$  when  $X_1$  is increased by one standard deviation from its mean, holding  $X_2$  constant