### **Testing utility of model -** *F***-test**

- Testing the utility of the model to predict y by conducting individual t-tests on each of the  $\beta$ 's is not a good idea.
- Why? Even if we conduct each test at the  $\alpha = 0.05$  level, the *overall* probability of incorrectly rejecting  $H_0$  (the probability of a Type I error) is larger than 0.05.
- Even if we begin with an  $\alpha$  level of, for example, 0.05 on each individual test for  $\beta$ 's, the overall probability of an error will always be larger than the probability of Type I error on individual tests.
- The larger the number of predictors in the model, the higher the probability that at least one of those hypotheses tests will lead to the wrong conclusion.

• Illustration: suppose we conduct tests on two parameters  $\beta_1, \beta_2$  and we use  $\alpha = 0.05$  on each test. See what may happen:

	Correct decision for $eta_1$	Incorrect decision for $eta_1$
Correct decision for $eta_2$	$0.95 \times 0.95$	$0.95 \times 0.05$
Incorrect decision for $\beta_2$	$0.95 \times 0.05$	$0.05 \times 0.05$

- The probability of a correct decision on *both parameters* is only 0.95
  × 0.95 = 0.90! So our individual Type I error rate (α) is *eroded* in multiple tests.
- In general, for an individual Type I error rate of  $\alpha$ , the overall error rate on k tests is  $(1 \alpha)^k$ . For example, for k = 4 and  $\alpha = 0.05$ , the probability that we will reach the correct conclusion for all four  $\beta$ 's is only  $0.95^4 = 0.81$ , so the experiment-wise  $\alpha$  is really 0.19.

• Rather than testing each  $\beta$  individually, we use a *global test* that encompasses all  $\beta$ 's and test the following overall hypothesis:

 $H_0 : \beta_1 = \beta_2 = \dots = \beta_k = 0$  $H_a : \text{ at least one } \beta_j \neq 0.$ 

• The **test statistic** to test this hypothesis is called *F*-statistic and is calculated as:

$$F = \frac{(SS_{yy} - SSE)/k}{MSE} = \frac{R^2/k}{(1 - R^2)/[n - (k+1)]}$$

- The F statistic is the ratio of
  - the explained variability (as reflected by  $R^2$ ) and
  - the unexplained variability (as reflected by  $1 R^2$ ),

each divided by the corresponding degrees of freedom.

• The larger the F statistic, the more useful the model.

- <u>Critical value</u> for the test:  $F_{\alpha,numdf,denomdf}$  (three subscripts:  $\alpha$ , numerator degrees of freedom and denominator degrees of freedom).
- We use an F-table (pages 763-770 in book).
- Each table corresponds to a different  $\alpha$ : 0.1, 0.05, 0.025 and 0.01.
- We search the table using the numerator degrees of freedom (column) and the denominator degrees of freedom (rows):

Numerator d.f. = kDenominator d.f. = n - (k + 1)

• For example, if  $\alpha = 0.1$ , n = 20 and k = 4,  $F_{0.1,4,15} = 2.36$ .

- Critical region: reject  $H_0$  at level  $\alpha$  if  $F \geq F_{\alpha,numdf,denomdf}$ .
- How do we interpret the result?
  - If we fail to reject  $H_0$ : there is no evidence that any of the predictors are linearly associated to the response.
  - If we reject  $H_0$ : At least one of the predictors is linearly associated to the response.
- Note that if we reject  $H_0$ , all we know is that one of the predictors is associated to y but we do not know which.
- The next step is to conduct individual t-tests on the  $\beta$ 's, but keeping in mind the confidence erosion discussed earlier.

- The F statistic for the model is given by both SAS and JMP directly on the output. SAS calls it "'F Value"' and JMP calls it "'F Ratio"'.
- Both SAS and JMP compute the F-statistic as:

$$F = \frac{\text{Model Mean Square}}{\text{Error Mean Square}}$$

and the degrees of freedom are:

Numerator df = Model df = k  
Denominator df = Error df = 
$$n - (k + 1)$$
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