

## How $F$ Relates to $t$

Since the  $t$ -test is more intuitive than the  $F$ -test, it may help to see what the relationship is between the two tests. First, suppose we do the  $F$ -test with  $p_0 = 1$ . Then both tests are testing whether  $\beta_p = 0$  (we are taking the last column,  $X^{[p]}$ , for convenience as the one we are testing), so they have the very same null hypothesis. Let  $W_{p-1}$  denote the column space of the first  $p - 1$  columns of  $X$ . Define  $Z := X^{[p]} - P_{W_{p-1}}X^{[p]}$  to be the part of  $X^{[p]}$  that is orthogonal to  $W_{p-1}$ . Then

$$\hat{Y} = X\hat{\beta} = \sum_{k=1}^{p-1} X^{[k]}\hat{\beta}_k + X^{[p]}\hat{\beta}_p = \sum_{k=1}^{p-1} X^{[k]}\hat{\beta}_k + (P_{W_{p-1}}X^{[p]} + Z)\hat{\beta}_p = \hat{Y}^{(s)} + Z\hat{\beta}_p \quad (1)$$

since all terms but the last belong to  $W_{p-1}$  and the last term is  $\perp W_{p-1}$ . Equation (1) shows that the numerator of  $F$  is  $\|\hat{Y}\|^2 - \|\hat{Y}^{(s)}\|^2 = \|Z\hat{\beta}_p\|^2 = \|Z\|^2\hat{\beta}_p^2$ , whence  $F = \|Z\|^2\hat{\beta}_p^2/\hat{\sigma}^2$ . Equation (1) also shows that  $\hat{\beta}_p$  is the same for  $X$  as for the matrix  $V$  all of whose columns are the same as those of  $X$  except for the last one, which is changed to  $Z$ . You should check that since  $Z$  is orthogonal to the other columns of  $V$ , we have that all the entries of the last row and column of  $V'V$  are 0 except for the  $(p, p)$ -entry, and that entry is  $\|Z\|^2$ . You should also check that this means that the  $(p, p)$ -entry of  $(V'V)^{-1}$  is  $1/\|Z\|^2$ . Thus, we deduce that the SE of  $\hat{\beta}_p$  is  $\hat{\sigma}^2/\|Z\|^2$ . This shows that  $t = \hat{\beta}_p/(\hat{\sigma}/\|Z\|) = \hat{\beta}_p\|Z\|/\hat{\sigma}$ . Therefore,  $F = t^2$ .

That was for  $p_0 = 1$ . Now we derive a formula relating  $F$  to *several*  $t$ -statistics when  $p_0 > 1$ . Write  $\hat{Y}^{(s,k)}$  for the fitted value of  $Y$  in the small model consisting of the first  $k$  columns of  $X$ . In this notation,  $Y^{(s)} = Y^{(s,p_0)}$ . Then we have a telescoping sum for the numerator of the numerator of  $F$ :

$$\begin{aligned} \|\hat{Y}\|^2 - \|\hat{Y}^{(s)}\|^2 &= (\|\hat{Y}\|^2 - \|\hat{Y}^{(s,p-1)}\|^2) + (\|\hat{Y}^{(s,p-1)}\|^2 - \|\hat{Y}^{(s,p-2)}\|^2) \\ &\quad + (\|\hat{Y}^{(s,p-2)}\|^2 - \|\hat{Y}^{(s,p-3)}\|^2) + \dots + (\|\hat{Y}^{(s,p-p_0+1)}\|^2 - \|\hat{Y}^{(s)}\|^2). \end{aligned}$$

Each of these terms can be treated as above where we had  $p_0 = 1$ . However, since we are using  $\|e\|$  from the big model in the denominator of  $F$ , i.e., we are estimating  $\sigma$  from the big model (which makes sense since it gives us the most information about  $\sigma$ ), the terms don't quite match those of the squares of the corresponding  $t$ -statistics, which are from various smaller models. But it makes sense to consider modified  $t$ -statistics, where we use the same  $\hat{\sigma}$  always. Thus, let  $t_{(s,k)} := \hat{\beta}_k^{(s,k)}/\widehat{SE}_k$ , where the numerator is the estimated coefficient of  $X^{[k]}$  in the model from the first  $k$  columns of  $X$  and the denominator is the estimated SE of the numerator, using our fixed  $\hat{\sigma} = \|e\|/\sqrt{n-p}$ . This gives  $F = (1/p_0) \sum_{k=p-p_0+1}^p t_{(s,k)}^2$ . Thus,  $F$  is an *average* of modified  $t$ -statistics. It is possible to rederive the distribution of  $F$  from this formula.