

**The Matrix-Based Approach to the General Linear Model -  
continued more**

**Back to the Least-Squares Approach: Statistical Inference for Several Coefficients**

If we have  $k$  covariates in our model, suppose we wish to test if  $q$  of them are not important. Suppose they are the first  $q$  coefficients, so we wish to test  $H_0 : \beta_1 = \beta_2 = \cdots = \beta_q = 0$ . Recall that we can express the null hypothesis in terms of the constraint  $\mathbf{L}\boldsymbol{\beta} = \mathbf{c}$ , and that the estimator under this constraint is

$$\mathbf{b}_0 = \mathbf{b} + (\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}'[\mathbf{L}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}']^{-1}(\mathbf{c} - \mathbf{L}\mathbf{b}).$$

The estimator  $\mathbf{b}_0$  is both the least-squares and maximum-likelihood estimator of  $\boldsymbol{\beta}$  under the constraint  $\mathbf{L}\boldsymbol{\beta} = \mathbf{c}$ . To test  $H_0 : \beta_1 = \beta_2 = \cdots = \beta_q = 0$  with this approach, we can calculate the reduction in regression sums of squares under  $H_0$ , which is equivalent to calculating the increase in error sums of squares. Again using the notation that model 0 is constrained under  $H_0$ , and  $RSS$  and  $\hat{\mathbf{y}}_1$  are from the unconstrained model, we have:

$$RSS_0 - RSS = (\mathbf{y} - \hat{\mathbf{y}}_0)'(\mathbf{y} - \hat{\mathbf{y}}_0) - (\mathbf{y} - \hat{\mathbf{y}}_1)'(\mathbf{y} - \hat{\mathbf{y}}_1).$$

We can identify  $\hat{\mathbf{y}}_0$  as  $\hat{\mathbf{y}}_0 = \mathbf{X}\mathbf{b}_0$  using the constrained least-squares solution above (with  $\mathbf{c} = \mathbf{0}$  under  $H_0$ ), to get

$$\begin{aligned} \hat{\mathbf{y}}_0 &= \mathbf{X}\mathbf{b}_0 = \mathbf{X}\mathbf{b} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}'[\mathbf{L}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}']^{-1}\mathbf{L}\mathbf{b} \\ &= \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}'[\mathbf{L}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}']^{-1}\mathbf{L}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} \\ &= (\mathbf{P} - \mathbf{P}_C)\mathbf{y} = \mathbf{P}_0\mathbf{y}, \end{aligned}$$

where  $\mathbf{P} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$  and  $\mathbf{P}_C = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}'[\mathbf{L}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{L}']^{-1}\mathbf{L}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$ . It can be verified that  $\mathbf{P}$ ,  $\mathbf{P}_C$ , and  $\mathbf{P}_0$  are all idempotent, and further that  $\mathbf{P}\mathbf{P}_C = \mathbf{P}_C\mathbf{P} = \mathbf{P}_C$ . Thus we have

$$(\mathbf{y} - \hat{\mathbf{y}}_0) = \mathbf{y} - \mathbf{P}_0\mathbf{y} = (\mathbf{I}_n - \mathbf{P}_0)\mathbf{y},$$

and recalling that  $(\mathbf{y} - \hat{\mathbf{y}}_1) = \mathbf{y} - \mathbf{P}\mathbf{y} = (\mathbf{I}_n - \mathbf{P})\mathbf{y}$ , so

$$\begin{aligned}
RSS_0 - RSS &= (\mathbf{y} - \widehat{\mathbf{y}}_0)'(\mathbf{y} - \widehat{\mathbf{y}}_0) - (\mathbf{y} - \widehat{\mathbf{y}}_1)'(\mathbf{y} - \widehat{\mathbf{y}}_1) \\
&= [(\mathbf{I}_n - \mathbf{P}_0)\mathbf{y}]'[(\mathbf{I}_n - \mathbf{P}_0)\mathbf{y}] - [(\mathbf{I}_n - \mathbf{P})\mathbf{y}]'[(\mathbf{I}_n - \mathbf{P})\mathbf{y}] \\
&= \mathbf{y}'(\mathbf{I}_n - \mathbf{P}_0)'(\mathbf{I}_n - \mathbf{P}_0)\mathbf{y} - \mathbf{y}'(\mathbf{I}_n - \mathbf{P})'(\mathbf{I}_n - \mathbf{P})\mathbf{y} \\
&= \mathbf{y}'(\mathbf{I}_n - \mathbf{P}_0)\mathbf{y} - \mathbf{y}'(\mathbf{I}_n - \mathbf{P})\mathbf{y} \\
&= \mathbf{y}'\mathbf{y} - \mathbf{y}'\mathbf{P}_0\mathbf{y} - (\mathbf{y}'\mathbf{y} - \mathbf{y}'\mathbf{P}\mathbf{y}) \\
&= \mathbf{y}'\mathbf{P}\mathbf{y} - \mathbf{y}'\mathbf{P}_0\mathbf{y} \\
&= \mathbf{y}'(\mathbf{P} - \mathbf{P}_0)\mathbf{y}
\end{aligned}$$

Also, since  $RSS = \mathbf{y}'(\mathbf{I}_n - \mathbf{P})\mathbf{y}$  and  $(\mathbf{I}_n - \mathbf{P})(\mathbf{P} - \mathbf{P}_0) = \mathbf{P} - \mathbf{P}_0 - \mathbf{P}^2 + \mathbf{P}\mathbf{P}_0 = \mathbf{P} - \mathbf{P}_0 - \mathbf{P} + \mathbf{P}_0 = \mathbf{0}$ , we know from Result 5 that the reduction in error sum of squares  $RSS_0 - RSS$  is independent of  $RSS$ , so the ratio of these two quadratic forms divided by their degrees of freedom leads to:

$$F_0 = \frac{(RSS_0 - RSS)/q}{RSS/(n - k - 1)},$$

which is distributed as an  $F$  statistic with  $q$  and  $n - k - 1$  degrees of freedom.