

Math 6010

Partial solutions to homework 5

1. We have a linear model with $p = 2$, parameter vector $\beta = (\beta_1, \beta_2)'$ and design matrix,

$$\mathbf{X} = \begin{pmatrix} a_1 & b_1 \\ \vdots & \vdots \\ a_n & b_n \end{pmatrix}.$$

Note that

$$\mathbf{X}'\mathbf{X} = \begin{pmatrix} \sum_{i=1}^n a_i^2 & \sum_{i=1}^n a_i b_i \\ \sum_{i=1}^n a_i b_i & \sum_{i=1}^n b_i^2 \end{pmatrix},$$

so that

$$(\mathbf{X}'\mathbf{X})^{-1} = \frac{1}{(\sum_{i=1}^n a_i^2)(\sum_{i=1}^n b_i^2) - (\sum_{i=1}^n a_i b_i)^2} \begin{pmatrix} \sum_{i=1}^n b_i^2 & -\sum_{i=1}^n a_i b_i \\ -\sum_{i=1}^n a_i b_i & \sum_{i=1}^n a_i^2 \end{pmatrix},$$

provided that \mathbf{X} has full rank.¹ Since

$$\hat{\beta} \sim N_2(\beta, \sigma^2(\mathbf{X}'\mathbf{X})^{-1}),$$

we can read off the following:

$$\text{Cov}(\hat{\beta}_1, \hat{\beta}_2) = -\frac{\sigma^2 \sum_{i=1}^n a_i b_i}{(\sum_{i=1}^n a_i^2)(\sum_{i=1}^n b_i^2) - (\sum_{i=1}^n a_i b_i)^2}.$$

This is zero if and only if $\sum_{i=1}^n a_i b_i = 0$. Because $\hat{\beta}_1$ and $\hat{\beta}_2$ are jointly normal, they are independent if and only if they are uncorrelated; that is, if and only if $\sum_{i=1}^n a_i b_i = 0$.

2. See page 65 of Lecture 9 in my lecture notes.
5. Since $\text{Var}(\hat{Y}) = \mathbf{X} \text{Var}(\hat{\beta}) \mathbf{X}' = \sigma^2 \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'$, the variance of \hat{Y}_i is the (i, i) th element of the preceding variance/covariance matrix; that is,

$$\text{Var}(\hat{Y}_i) = \sigma^2 \sum_{j=1}^p \sum_{k=1}^p X_{i,j} [(\mathbf{X}\mathbf{X}')^{-1}]_{j,k} X_{i,k}.$$

¹In this case, this means that $(\sum_{i=1}^n a_i^2)(\sum_{i=1}^n b_i^2) \neq (\sum_{i=1}^n a_i b_i)^2$. According to the Cauchy-Schwarz inequality, $(\sum_{i=1}^n a_i^2)(\sum_{i=1}^n b_i^2) \geq (\sum_{i=1}^n a_i b_i)^2$. Therefore, \mathbf{X} has full rank if and only if the Cauchy-Schwarz inequality is a strict inequality. This turns out to mean that $z_i := a_i b_i$ is not a linear function of i .

Because

$$\sum_{i=1}^n X_{i,j} X_{i,k} = [\mathbf{X}' \mathbf{X}]_{j,k},$$

it follows that

$$\sum_{i=1}^n \text{Var}(\hat{Y}_i) = \sigma^2 \sum_{j=1}^p \sum_{k=1}^p [(\mathbf{X} \mathbf{X})^{-1}]_{j,k} [\mathbf{X}' \mathbf{X}]_{j,k} = \sigma^2 \text{tr}((\mathbf{X}' \mathbf{X})^{-1} (\mathbf{X}' \mathbf{X})).$$

Because $(\mathbf{X}' \mathbf{X})^{-1} (\mathbf{X}' \mathbf{X}) = \mathbf{I}_{p \times p}$, its trace is p ; this does the job.