THE MULTIPLE LINEAR REGRESSION MODEL

Notation:

p predictors $x_1, x_2, \ldots, x_p$

(Some might be values of indicator variables for categorical variables.)

k-1 *non-constant* terms $u_1, u_2, \ldots, u_{k-1}$

Each u_j is a function of $x_1, x_2, \ldots, x_p$:

$$u_j = u_j(x_1, x_2, \ldots, x_p)$$

For convenience, we often set $u_0 = 1$ (constant function/term)

The Basic Multiple Linear Regression Model:

Two assumptions:

1. $E(Y|\underline{x})$ (or $E(Y|\underline{u}) = \eta_0 + \eta_1 u_1 + \ldots + \eta_{k-1}u_{k-1}$
   (Linear Mean Function)

2. $Var(Y|\underline{x})$ (or $Var(Y|\underline{u}) = \sigma^2$
   (Constant Variance)

Assumption (1) in vector notation:

$$\underline{u} = \begin{bmatrix} u_0 \\ u_1 \\ \cdot \\ \cdot \\ \cdot \\ u_{k-1} \end{bmatrix} = \begin{bmatrix} 1 \\ u_1 \\ \cdot \\ \cdot \\ \cdot \\ u_{k-1} \end{bmatrix}, \qquad \underline{\eta} = \begin{bmatrix} \eta_0 \\ \eta_1 \\ \cdot \\ \cdot \\ \cdot \\ \eta_{k-1} \end{bmatrix}$$

Then

$$\underline{\eta}^T = [\eta_0 \;\; \eta_1 \; \ldots \;\; \eta_{k-1}]$$

and

$$\underline{\eta}^T\underline{u} = \eta_0 + \eta_1 u_1 + \ldots + \eta_{k-1}u_{k-1},$$

so (1) becomes:

(1') $E(Y|\underline{x}) = \underline{\eta}^T\underline{u}$

Data:

i^{th} observation $x_{i1}, x_{i2}, \dots, x_{ip}, y_i$

Recall

$$\underline{x}_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ \cdot \\ \cdot \\ \cdot \\ x_{ip} \end{bmatrix} = [x_{i1}, x_{i2}, \dots, x_{ip}]^T$$

Define similarly

$$u_{ij} = u_j(x_{i1}, x_{i2}, \dots, x_{ip})$$

= the value of the j^{th} term for the i^{th} observation,

and

$$\underline{u}_i = \begin{bmatrix} u_{i0} \\ u_{i1} \\ \cdot \\ \cdot \\ \cdot \\ u_{i,k-1} \end{bmatrix}$$

So in particular, the model says: $E(Y|\underline{x}_i) = \underline{\eta}^T\underline{u}_i$

Estimation of Parameters: Analogous to simple linear regression:

Consider functions of the form

$$y = h_0 + h_1u_1 + \dots + h_{k-1}u_{k-1} = \underline{h}^T\underline{u}.$$

(The graph of such an equation is a "hyperplane.")

The *least squares estimate* of $\underline{\eta}$ is the vector

$$\hat{\underline{\eta}} = \begin{bmatrix} \hat{\eta}_0 \\ \hat{\eta}_1 \\ \cdot \\ \cdot \\ \cdot \\ \hat{\eta}_{k-1} \end{bmatrix}$$

that minimizes the "objective function"

$$RSS(\underline{h}) = \sum_{i=1}^{n} (y_i - \underline{h}^T\underline{u}_i)^2$$

Recall:

In simple linear regression, the solution for $\hat{\eta}_1$ had

$$SXX = \sum_{i=1}^{n}(x_i - \bar{x})^2$$

in the denominator. So the formula for $\hat{\eta}_1$ won't work if all x_i's = $\bar{x}$. In that case, there is not a unique solution to the least squares problem. (Draw a picture in the case n = 2!)

In multiple regression:

There is a unique solution $\underline{\hat{\eta}}$ *provided* both:

i) k < n (i.e., the number of terms is less than the number of observations)

ii) no u_j is (as a function) a linear combination of the other u_j's

If there is a unique solution, it is called the *ordinary least squares (OLS) estimate* of the (vector $\underline{\eta}$ of) coefficients.

Examples where there is not a unique solution:

1. When k = 2 (simple linear regression) and there is only one data point.

2. k = 2 and both data points have the same x value.

3. Similar examples for larger k.

4. Two predictors, three terms with
   $u_1 = x_1$, $u_2 = x_2$, $u_3 = x_1 + x_2$

   e.g., Scholastic Aptitude Test Scores (SAT) with terms SATM, SATM, SATM + SATV

Multicollinearity:

When condition (ii) is violated, we say there is (*strict*) *multicollinearity*. (e.g., example 4 above.)

A situation close to strict multicollinearity is typically called *multicollinearity*. Technically, there is a solution, but

a. The solutions involved small denominators, which can make calculation virtually impossible. (e.g., if $p = 1$ and if x is close to constant, then SXX is very small.)

b. The variances will be large, making inference virtually useless.