

2.5: Multiple Linear Regression

Dr. Bean - Stat 5100

1 Why Multiple Linear Regression?

- Models that use a single explanatory variable to predict a response are very limited in terms of its capability.
- We are often interested in determining the effect of an explanatory variable on the response variable *after* accounting for the effects due to other explanatory variables.
 - Example: Is there a difference in the pay based on gender after accounting for job type and hours worked?

(Individual) Can you think of another scenario where using multiple predictors would be useful in predicting a single response variable?

2 What Changes from Simple Linear Regression?

1. Interpretation of coefficients

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_{p-1} X_{i,p-1} + \varepsilon_i$$

$$\beta_0 = E[Y | X_1 = X_2 = \dots = X_{p-1} = 0]$$

$$\beta_k = \begin{array}{l} \text{expected (or average) change in } Y \\ \text{for every unit increase in predictor } X_k, \\ \text{while holding all other predictors constant} \end{array}$$

β_k sometimes called “partial regression coefficient” because it reflects partial effect of X_k on Y after accounting for effects of other predictors

2. ANOVA table

- model $df = p - 1 = \#$ of predictor variables
- error $df = n - p$
 - we have to “spend” more degrees of freedom to calculate the additional coefficients

- model F-test more meaningful:

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_{p-1} = 0$$

$$H_a : \beta_k \neq 0 \text{ for at least one } k = 1, \dots, p-1$$

- R^2 called coefficient of multiple determination (still interpret as % variance in Y explained by model); $\sqrt{R^2}$ called coeff. of multiple correlation

3. Refer to regression “surface” instead of “line”

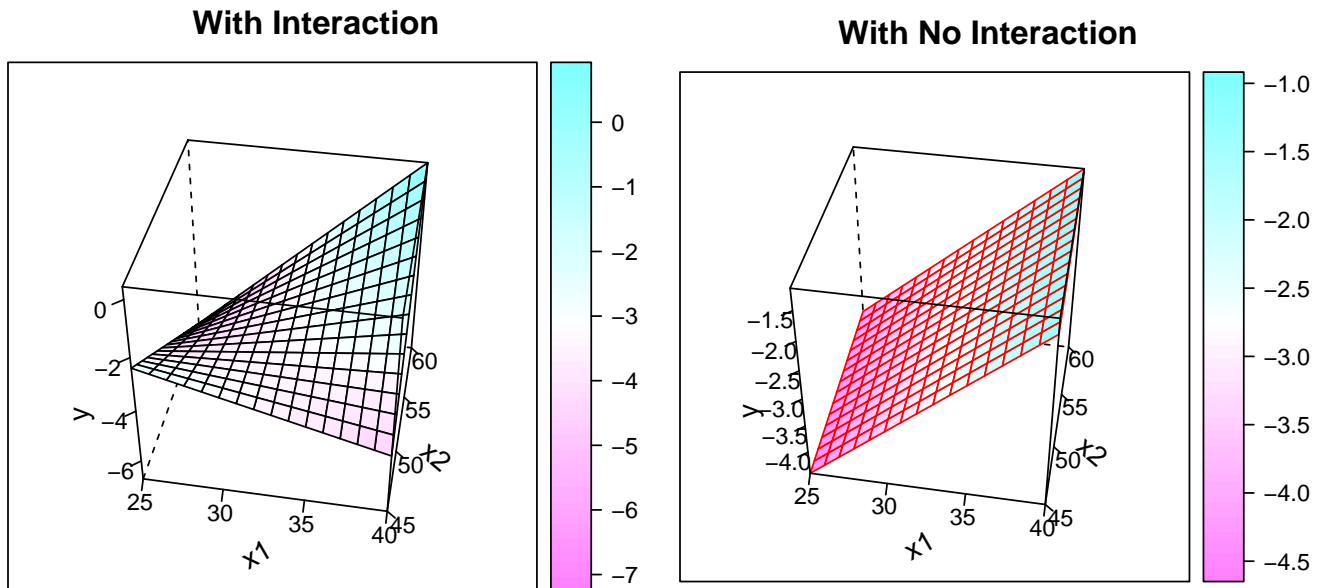


Figure 1: Regression surface using two X variables to predict Y . Harder to visualize when there are more than two predictor variables.

4. F-test for lack of fit less practical

- requires multiple observations at one or more X profiles, which is hard to achieve when the number of X 's is large.
- “ X -profile” or “covariate profile” refers to specific values for all predictors

5. More assumptions to check later – regarding inter-related predictors

- basically, if predictors are related to each other, the model becomes very hard to interpret

6. Other variable types can be included

(interactions, qualitative, higher-order) – (more in Module 3)

3 Matrix Approach to Multiple Linear Regression

When the number of X variables gets large, the matrix representation of linear regression models is easier to write and understand.

$$Y = (Y_1, \dots, Y_n)' = \text{vector of response variable}$$

$$\varepsilon = (\varepsilon_1, \dots, \varepsilon_n)' = \text{vector of error terms}$$

$$X_k = (X_{1k}, \dots, X_{nk})' = \text{vector of predictor variable \#k} \quad (k = 1, \dots, p-1)$$

$$X = \begin{bmatrix} 1 & X_1 & \dots & X_{p-1} \end{bmatrix} = \text{matrix with } p \text{ columns and } n \text{ rows}$$

$$\beta = (\beta_0, \beta_1, \dots, \beta_{p-1})' = \text{vector of coefficients}$$

$$b = (b_0, b_1, \dots, b_{p-1})' = \text{vector of coefficient estimates}$$

Then regression model is

$$Y = X\beta + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 I) \quad I = \text{"identity" matrix}$$

Estimates:

$$b = (X'X)^{-1}X'Y \quad \begin{array}{l} \text{Matrices with variance on} \\ \text{diag., covariance on off-diag.} \end{array}$$

$$\begin{array}{ll} \text{truth:} & Cov(b) = (X'X)^{-1}\sigma^2 \\ \text{estimated:} & s^2\{b\} = (X'X)^{-1} \cdot \text{MSE} \end{array} \quad \begin{array}{l} \sqrt{\text{diag. elements}} \text{ gives} \\ \text{SE's of } b_k\text{'s} \end{array}$$

We'll come back to this, but for now, note that

$$\begin{aligned} \hat{Y} &= Xb \\ &= X(X'X)^{-1}X'Y \\ &= HY \end{aligned}$$

H projects Y down to column space of X:

- Y = observed response values vector; is not
a [perfect] linear combination of predictor variables
- \hat{Y} = predicted response values vector; is
a [perfect] linear combination of predictor variables