

Homework 02
Joseph Blubaugh
jblubau1@tamu.edu
STAT 608-720

1. For this to be true we must assume that the variance of $var(x_i) = 0$. Variance of constants are 0 as well so the variance of $var(Y_i) = var(e_i)$

$$Y_i = B_0 + B_1 X_i + e_i$$

$$var(Y_i) = var(B_0) + var(B_1 var(X_i)) + var(e_i)$$

$$var(Y_i) = var(e_i)$$

2. The sum of squares is calculated by squaring and summing the difference between the predicted value and actual value of y for each observation. The coefficients are set so that the total sum of squared errors are minimized.
3. a) Since there are not predictor variables there will only be a constant coefficient plus the error term. $B_0 = \bar{y}$ because the average value of y will minimize the RSS.

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ \dots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ \dots \\ 1 \end{bmatrix} + [B_0] + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ \dots \\ e_n \end{bmatrix}$$

$$Y_i = B_0 + e_i$$

b)

$$\text{For, } \hat{B} = (X'X)^{-1}X'Y$$

$$\begin{aligned} E(\hat{B}|X) &= (X'X)^{-1}X'Y|X \\ &= (X'X)^{-1}X'E(Y|X) \\ &= (X'X)^{-1}X'XB \\ &= B \end{aligned}$$

$$Y_i = B_0 n$$

$$\bar{Y} = B_0$$

4. a) i.

$$\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \dots & \dots \\ 1 & x_n \end{bmatrix} + \begin{bmatrix} B_0 \\ B_1 \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \dots \\ e_n \end{bmatrix} \rightarrow y_i = B_0 + B_1 x + e_i$$

ii.

$$Y_i = X_i B + e_i$$

$$e_i = Y - X_i B$$

$$\sum e_i^2 = e' e = \begin{bmatrix} e_1 & e_2 & \dots & e_i \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ \dots \\ e_i \end{bmatrix} = (Y - X_i B)'(Y - X_i B)$$

$$\frac{d}{dB} (Y - X_i B)'(Y - X_i B) = -2X'(Y - XB)$$

$$-2X'(Y - XB) = 0$$

$$X'Y = (X'X)B$$

$$B = (X'X)^{-1}X'Y$$

b)

$$\begin{aligned} E(\hat{B}|X) &= (X'X)^{-1}X'Y|X \\ &= (X'X)^{-1}X'E(Y|X) \\ &= (X'X)^{-1}X'XB \\ &= B \end{aligned}$$

$$\begin{aligned} Var(\hat{B}|X) &= Var((X'X)^{-1}X'Y) \\ &= (X'X)^{-1}X'Var(Y)X(X'X)^{-1} \\ &= (X'X)^{-1}X'Var(XB + e)X(X'X)^{-1} \\ &= (X'X)^{-1}X' \sum X(X'X)^{-1} \\ &= (X'X)^{-1}X'\sigma^2 I X(X'X)^{-1} \\ &= \sigma^2 (X'X)^{-1}X'X(X'X)^{-1} \\ \frac{\sigma^2}{\sum_{i=1}^n x_i^2} &= \sigma^2 (X'X)^{-1} \end{aligned}$$

c) For $\hat{B}|X \rightarrow N(B, \frac{\sigma^2}{\sum_{i=1}^n x_i^2})$

Since we know that the errors are normally distributed, the Y s and the sum of the Y s must be normally distributed so \hat{B} is a linear combination of the Y s. The distribution therefore must be normal.

5.

$$X'X = \begin{bmatrix} 1 & \bar{x} \\ \bar{x} & \frac{1}{n} \sum_{i=1}^n x_i^2 \end{bmatrix} \quad X'Y = \begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_i y_i \end{bmatrix} \quad (X'X)^{-1} = \frac{1}{SXX} \begin{bmatrix} \frac{1}{n} & -\bar{x} \\ -\bar{x} & 1 \end{bmatrix}$$

$$\begin{aligned} \hat{B} &= (X'X)^{-1} X'Y \\ &= \frac{1}{SXX} \begin{bmatrix} \frac{1}{n} & -\bar{x} \\ -\bar{x} & 1 \end{bmatrix} \begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_i y_i \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{n} \sum_{i=1}^n y_i & \sum_{i=1}^n x_i^2 - \bar{x} \sum_{i=1}^n x_i y_i \\ \sum_{i=1}^n x_i y_i & -\bar{x} \sum_{i=1}^n y_i \end{bmatrix} \\ &= \begin{bmatrix} \frac{\bar{y}SXX - \bar{x}SXY}{SXX} \\ \frac{SXY}{SXX} \end{bmatrix} \\ &= \begin{bmatrix} \bar{y} - \hat{B}\bar{x} \\ B \end{bmatrix} \end{aligned}$$

6.

$$\begin{aligned} Var(a'\hat{B}|X) &= Var(a'(X'X)^{-1}X'Y) \\ &= (X'X)^{-1}X'aVar(Y)Xa'(X'X)^{-1} \\ &= (X'X)^{-1}X'aVar(XB + e)Xa'(X'X)^{-1} \\ &= (X'X)^{-1}X' \sum Xa'(X'X)^{-1} \\ &= (X'X)^{-1}X'\sigma^2IXa'(X'X)^{-1} \\ &= \sigma^2(X'X)^{-1}X'Xa'(X'X)^{-1} \\ \frac{a'\sigma^2}{\sum_{i=1}^n x_i^2} &= a'\sigma^2(X'X)^{-1} \end{aligned}$$

7. Confidence Intervals are an indication of the mean of the prediction. A model that explains variance well could have a small confidence interval meaning there is high certainty that the mean of all values at that particular x is within that range. The prediction interval is the interval in which would expect 95 percent of predicted values to be for a particular x.
8. The line plotted over the data points is not least squares because it is not intersecting the averages of both x and y. Simple least squares regression will fit models through the averages of two vectors because that is the point where the sum of squared errors are minimized.