

# PROBLEM 1

$$E(\hat{\beta}_0) = E(\bar{y} - \beta_1 \bar{x})$$

Remember  $\beta_1$  &  $\bar{x}$  are constants  
so

$$\begin{aligned} E(\bar{y} - \beta_1 \bar{x}) &= E(\bar{y}) - \beta_1 \bar{x} \\ &= E\left(\sum_{i=1}^n \frac{y_i}{n}\right) - \beta_1 \bar{x} \\ &= \frac{1}{n} E\left(\sum_{i=1}^n y_i\right) - \beta_1 \bar{x} \end{aligned}$$

Since  $y_i, i=1, \dots, n$  are independent

$$E\left(\sum_{i=1}^n y_i\right) = \sum_{i=1}^n E(y_i) = \sum_{i=1}^n [\beta_0 + \beta_1 x_i]$$

$\Rightarrow$

$$\begin{aligned} E(\hat{\beta}_0) &= E(\bar{y} - \beta_1 \bar{x}) = \frac{1}{n} \sum_{i=1}^n [\beta_0 + \beta_1 x_i] - \beta_1 \bar{x} \\ &= n\beta_0/n + \beta_1 \frac{\sum x_i}{n} - \beta_1 \bar{x} \end{aligned}$$

Now you finish it!

(SEE ATTACHED)

## PROBLEM 1 Continued

$$\begin{aligned} E(\hat{\beta}_1) &= E\left(\frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}\right) \\ &= \frac{1}{\sum_{i=1}^n (x_i - \bar{x})^2} E\left(\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})\right) \\ &= \frac{1}{\sum_{i=1}^n (x_i - \bar{x})^2} \sum_{i=1}^n (x_i - \bar{x}) E(y_i - \bar{y}) \end{aligned}$$

$$\begin{aligned} E(y_i - \bar{y}) &= E(y_i) - \frac{1}{n} \sum_{i=1}^n E(y_i) \\ &= \beta_0 + \beta_1 x_i - \frac{1}{n} \sum_{i=1}^n [\beta_0 + \beta_1 x_i] \\ &= \beta_1 (x_i - \bar{x}) \end{aligned}$$

Now you finish it!

(SEE ATTACHED)

## PROBLEM 1, Part 1

$$\begin{aligned} \text{given } E(\hat{\beta}_0) &= \frac{n\beta_0}{n} + \frac{\beta_1 \sum x_i}{n} - \beta_1 \bar{x} \\ &= \beta_0 + \frac{\beta_1 \sum x_i}{n} - \beta_1 \bar{x} \end{aligned}$$

$$\text{given } \bar{x} = \sum \frac{x_i}{n}$$

$$E(\hat{\beta}_0) = \beta_0 + \beta_1 \bar{x} - \beta_1 \bar{x}$$

$$\boxed{E(\hat{\beta}_0) = \beta_0}$$

## Problem 1, Part 2

$$\text{given } E(\hat{\beta}_1) = \frac{1}{\sum (x_i - \bar{x})^2} E(x_i - \bar{x}) E(y_i - \bar{y})$$

$$\text{also that } E(y_i - \bar{y}) = \beta_1 (x_i - \bar{x})$$

$$E(\hat{\beta}_1) = \frac{1}{\sum (x_i - \bar{x})^2} \sum (x_i - \bar{x}) \beta_1 (x_i - \bar{x})$$

$$\boxed{E(\hat{\beta}_1) = \beta_1} \quad \text{UNBIASED}$$

## PROBLEM 2

$$l(\beta) = -n \log(\sqrt{2\pi\sigma^2}) - \frac{\sum_{i=1}^n (y_i - \beta x_i)^2}{2\sigma^2}$$

$$\frac{dl(\beta)}{d\beta} = -\frac{2}{2\sigma^2} \sum_{i=1}^n x_i (y_i - \beta x_i)$$

Since  $\sigma^2$  is constant we have the minimization results in

$$\sum_{i=1}^n x_i (y_i - \beta x_i) = 0$$

Now you finish it!

$$\sum_{i=1}^n x_i y_i - \sum_{i=1}^n \beta x_i^2 = 0$$

$$\beta \sum_{i=1}^n x_i^2 = \sum_{i=1}^n x_i y_i$$

$$\boxed{\beta = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}}$$

### PROBLEM 3

$$\hat{S} = \frac{\sum (x_i - \bar{x})^2}{n-1}$$

Assume  $X_i \sim N(\mu, \sigma^2)$

$$E(\hat{S}) = \frac{1}{n-1} E \left[ \sum_{i=1}^n (x_i^2 - 2x_i \bar{x} + \bar{x}^2) \right]$$

Now You Finish IT!

HINT: USE THE SLIDES

\* CALCULATING BIAS

\* VARIANCE

for help on this

(SEE ATTACHED)

### Problem 3

$$\text{use } \bar{X} = \sum_{i=1}^n \frac{X_i}{n}$$

$$\text{or } n\bar{X} = \sum_{i=1}^n X_i$$

$$E(\hat{S}) = \frac{1}{n-1} E\left[\sum_{i=1}^n X_i^2 - 2\bar{X} \sum_{i=1}^n X_i + n\bar{X}^2\right]$$

$$= \frac{1}{n-1} E\left[\sum_{i=1}^n X_i^2 - 2n\bar{X}^2 + n\bar{X}^2\right]$$

$$= \frac{1}{n-1} E\left[\sum_{i=1}^n X_i^2 - n\bar{X}^2\right]$$

$$= \frac{1}{n-1} \left[ \sum_{i=1}^n E(X_i^2) - nE(\bar{X}^2) \right]$$

since  $\text{Var}(X) = \sigma^2$  and  $X \sim N(\mu, \sigma^2)$

$$\sigma^2 = E(X^2) - 2E(X)E(X) + E(X)^2$$

$$= E(X^2) - 2\mu E(X) + \mu^2$$

$$= E(X^2) - 2\mu^2 + \mu^2$$

$$E(X^2) = \sigma^2 + \mu^2$$

(over)

### Problem 3 (CONT.)

given  $\bar{X} \sim N(\mu, \sigma^2/n)$  or  $\text{Var}(\bar{X}) = \frac{\sigma^2}{n}$

$$\text{so, } \text{Var}(\bar{X}) = \frac{\sigma^2}{n} = E(\bar{X}^2) - 2E(\bar{X}E(\bar{X})) + E(\bar{X})^2$$

$$\frac{\sigma^2}{n} = E(\bar{X}^2) - 2\mu^2 + \mu^2$$

$$\therefore E(\bar{X}^2) = \frac{\sigma^2}{n} + \mu^2$$

substituting the values:

$$E(\hat{S}) = \frac{1}{n-1} \left[ \sum_{i=1}^n E(X_i^2) - nE(\bar{X}^2) \right]$$

$$= \frac{1}{n-1} \left[ n\sigma^2 + \cancel{n\mu^2} - \frac{n\sigma^2}{n} - \cancel{n\mu^2} \right]$$

$$= \frac{1}{n-1} [\sigma^2(n-1)]$$

$$\boxed{E(\hat{S}) = \sigma^2}$$

$\therefore$  the sample variance = estimated variance. It is unbiased