

stat151A HW1

$$1. \hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x}) y_i}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

(a)

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} = \bar{y} - \frac{\sum_{i=1}^n (x_i - \bar{x}) y_i}{\sum_{i=1}^n (x_i - \bar{x})^2} \bar{x}$$

$$(b) E(y_i | x_i) = \hat{\beta}_0 + \hat{\beta}_1 x_i$$

$$E(x_i | y_i) = \frac{1}{\hat{\beta}_1} y_i - \frac{\beta_0}{\hat{\beta}_1} = \alpha_1 y_i + \alpha_0$$

$$\text{thus. } \alpha_1 = \frac{1}{\hat{\beta}_1} = \frac{\sum (x_i - \bar{x})^2}{\sum (x_i - \bar{x}) \cdot y_i}$$

(c) yes, As can be seen in (b) $\alpha_1 = \frac{1}{\hat{\beta}_1}$

(d). See R code.

$$3. (b) \text{meth10} = \beta_0 + \beta_1 \log(\text{expand}) + \varepsilon$$

if expand increases by 10%.

$$\begin{aligned} \text{meth10} &= \beta_0 + \beta_1 \log_{10}(1.1 \cdot \text{expand}) + \varepsilon \\ &= \text{meth10} + 0.1 \beta_1 \end{aligned}$$

$$\begin{aligned}
 4. (a) \quad \hat{\beta}_0 + \hat{\beta}_1 a &= \frac{\sum_{i=1}^n (x_i - \bar{x}) y_i}{\sum_{i=1}^n (x_i - \bar{x})^2} a + \bar{y} - \hat{\beta}_1 \bar{x} \\
 &= \bar{y} - \hat{\beta}_1 \bar{x} + \hat{\beta}_1 a \\
 &= \bar{y} - \hat{\beta}_1 (a - \bar{x}) = \frac{\sum x_i}{n} + \frac{\sum (a - \bar{x})(x_i - \bar{x}) y_i}{\sum (x_i - \bar{x})^2}
 \end{aligned}$$

$$\begin{aligned}
 (b) \quad \text{var}(\hat{\beta}_0 + \hat{\beta}_1 a) &= \text{var} \left(\sum_{i=1}^n y_i \left(\frac{1}{n} + \frac{(a - \bar{x})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \right) \right) \\
 &= \sum_{i=1}^n \text{var}(y_i) \left(\frac{1}{n} + \frac{(a - \bar{x})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \right)^2 \\
 &= \sum_{i=1}^n \sigma^2 \left(\frac{1}{n} + \frac{(a - \bar{x})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \right)^2 \\
 &= \sum_{i=1}^n \left(\frac{1}{n^2} + \frac{2(a - \bar{x})(x_i - \bar{x})}{n \sum_{i=1}^n (x_i - \bar{x})^2} + \frac{(a - \bar{x})^2 (x_i - \bar{x})^2}{\sum_{i=1}^n (x_i - \bar{x})^4} \right) \\
 &= \sigma^2 \sum_{i=1}^n \left(\frac{1}{n^2} + 0 + \frac{(a - \bar{x})^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right) \\
 &= \frac{\sigma^2}{n} + \frac{\sigma^2 (a - \bar{x})^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad \text{thus proved.}
 \end{aligned}$$

$$(c). \quad \text{let } \tau = \text{var}(\hat{\beta}_0 + \hat{\beta}_1 a)$$

when $a = \bar{x}$, $\text{var}(\hat{\beta}_0 + \hat{\beta}_1 a)$ can achieve its smallest value since $\frac{\sigma^2 (a - \bar{x})}{\sum (x_i - \bar{x})^2} = 0$.

$$\text{and } \text{var}(\hat{\beta}_0 + \hat{\beta}_1 a) = \frac{\sigma^2}{n}$$

6. (a) $\hat{y} = y = \hat{\beta}_1 x$

$$Q(\hat{\beta}_1) = \sum_{i=1}^n (y_i - \hat{\beta}_1 x_i)^2$$

$$\frac{\partial Q}{\partial \hat{\beta}_1} = -2 \sum_{i=1}^n (y_i - \hat{\beta}_1 x_i) x_i = 0$$

$$\Rightarrow \sum_{i=1}^n (y_i x_i - \hat{\beta}_1 x_i^2) = 0$$

$$\sum y_i x_i = \sum \hat{\beta}_1 x_i^2$$

$$\sum y_i x_i = \hat{\beta}_1 \sum x_i^2$$

$$\hat{\beta}_1 = \frac{\sum y_i x_i}{\sum x_i^2}$$

(b) To show $\hat{\beta}_1$ is unbiased. $E(\hat{\beta}_1 | x) = \beta_1$

$$E(\hat{\beta}_1 | x) = E\left(\frac{\sum y_i x_i}{\sum x_i^2}\right)$$

$$= \frac{\sum x_i E(y_i)}{\sum x_i^2} = \frac{\sum x_i E(\beta_1 x_i)}{\sum x_i^2} = \frac{\beta_1 \sum x_i^2}{\sum x_i^2}$$

$$= \frac{\sum x_i^2 \beta_1}{\sum x_i^2}$$

$$= \frac{\beta_1 \sum x_i^2}{\sum x_i^2} = \beta_1$$

thus proved.

(c) ~~var(y)~~ $\text{var}(y|x) = \sigma^2$ by assumption.

$$\text{var}(\hat{\beta}_1) = \text{var}(\hat{\beta}_1 | x) = \text{var}\left(\frac{\sum y_i x_i}{\sum x_i^2} \mid x\right)$$

$$= \frac{\sum x_i^2 \text{var}(y_i)}{(\sum x_i^2)^2} = \frac{\sum x_i^2}{(\sum x_i^2)^2} \cdot \sigma^2 = \frac{1}{\sum x_i^2} \cdot \sigma^2$$

$$7. (a). E(\hat{\beta}_0 | x) = E(\bar{y} - \hat{\beta}_1 \bar{x}).$$

$$E(\hat{\beta}_1 | x) = E\left(\frac{\sum (x_i - \bar{x}) y_i}{\sum (x_i - \bar{x})^2} \mid x\right) \\ = \frac{\sum (x_i - \bar{x}) E(y_i | x_i)}{\sum (x_i - \bar{x})^2}$$

$$E(y_i | x_i) = \beta_0 + \beta_1 x_i$$

$$E(\hat{\beta}_1 | x) = \frac{\sum (x_i - \bar{x})(\beta_0 + \beta_1 x_i)}{\sum (x_i - \bar{x})^2} = \beta_1$$

thus $\hat{\beta}_1$ is unbiased estimator.

$$E(\hat{\beta}_0 | x) = E\left(\frac{1}{n} \sum y_i\right) - \hat{\beta}_1 \bar{x} \\ = \frac{1}{n} \sum E(y_i) - \beta_1 \bar{x} \\ = \frac{1}{n} \sum (\beta_0 + \beta_1 x_i) - \beta_1 \bar{x} \\ = \beta_0 + \beta_1 \cdot \frac{1}{n} \sum x_i - \beta_1 \bar{x} \\ = \beta_0 + \beta_1 \cdot \frac{1}{n} \sum x_i - \beta_1 \cdot \frac{1}{n} \sum x_i = \beta_0.$$

thus $\hat{\beta}_0$ is unbiased estimator.

$$(c) \begin{cases} N(0, 25) & x_i \leq 65 \\ T_2(0, 10) & 65 < x_i \leq 70 \\ \text{uniform}[-8, 8] & x_i > 70 \end{cases}$$

variance from the three intervals are not consistent.

The assumption of homoskedasticity suggests that the variance is consistent for all x_i s. Thus in this case, the assumption of homoskedasticity is not valid.