

# Homework 1.

# **Theory**

1. Show that  $\beta_0$  is unbiased

$$y_{i} = \beta_{0} + \beta_{1}x_{i} + \epsilon_{i}$$

$$E(\beta_{0}) = E(y_{i} - \beta_{1}x_{i} - \epsilon_{i})$$

$$E(\beta_{0}) = E(y_{i}) - \beta_{1} E(x_{i}) - E(\epsilon_{i})$$

$$E(\beta_{0}) = \overline{y} - \beta_{1}\overline{x} - 0$$

$$E(\beta_{0}) = \overline{y} - \beta_{1}\overline{x}$$

$$E(\beta_{0}) = \beta_{0}$$

$$\beta_{0} = \overline{y} - \beta_{1}\overline{x}$$

$$E(\hat{\beta}_{0}) = E(\overline{y} - \hat{\beta}_{1}\overline{x})$$

$$E(\hat{\beta}_{0}) = E(\overline{y}) - E(\hat{\beta}_{1}\overline{x})$$

$$E(\hat{\beta}_{0}) = \overline{y} - \overline{x} E(\hat{\beta}_{1})$$

$$E(\hat{\beta}_{1}) = \beta_{1} \qquad \text{(we showed this in class)}$$

$$E(\hat{\beta}_{0}) = \overline{y} - \beta_{1}\overline{x}$$

$$E(\hat{\beta}_{0}) = \beta_{0}$$

#### 2. Determine the variance of $\beta_0$

$$\operatorname{Var}(X+Y) = \operatorname{Var}(X) + \operatorname{Var}(Y) + 2\operatorname{Cov}(X,Y)$$

$$\hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \overline{x} \qquad \text{(from class)}$$

$$\operatorname{Var}(\hat{\beta}_0) = \operatorname{Var}(\overline{y} - \hat{\beta}_1 \overline{x})$$

$$\operatorname{Var}(\hat{\beta}_0) = \operatorname{Var}(\overline{y}) + \operatorname{Var}(\hat{\beta}_1 \overline{x}) + 2\operatorname{Cov}(\overline{y}, -\hat{\beta}_1 \overline{x})$$

$$\overline{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

$$\operatorname{Var}(\overline{y}) = \operatorname{Var}(\frac{1}{n} \sum_{i=1}^n y_i)$$

$$\operatorname{Var}(\overline{y}) = (\frac{1}{n})^2 \sum_{i=1}^n \operatorname{Var}(y_i)$$

$$\operatorname{Var}(\overline{y}) = (\frac{1}{n})^2 \sum_{i=1}^n \operatorname{Var}(\beta_0 + \beta_1 x_i + \epsilon_i)$$

$$\operatorname{Var}(\overline{y}) = (\frac{1}{n})^2 \sum_{i=1}^n \operatorname{Var}(\beta_0) + \operatorname{Var}(\beta_1 x_i) + \operatorname{Var}(\epsilon_i)$$

$$\operatorname{Var}(\overline{y}) = (\frac{1}{n})^2 \sum_{i=1}^n 0 + 0 + \sigma^2$$

$$\operatorname{Var}(\overline{y}) = (\frac{1}{n})^2 \cdot (n\sigma^2)$$

$$\operatorname{Var}(\overline{y}) = \frac{\sigma^2}{n}$$

$$\operatorname{Var}(-\beta_1 \overline{x}) = (-\overline{x})^2 \operatorname{Var}(\hat{\beta}_1)$$

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$$\operatorname{Var}(-\beta_1 \overline{x}) = (-\overline{x})^2 \frac{\sigma^2}{\sum_{i=1}^n (x_i - \overline{x})} \qquad \text{(we showed this in class)}$$

$$\begin{aligned} &\operatorname{Cov}(\bar{y},\hat{\beta}_1\bar{x}) = \bar{x}\operatorname{Cov}(\bar{y},\hat{\beta}_1) \\ &\operatorname{Cov}(\bar{y},\hat{\beta}_1\bar{x}) = \bar{x}\operatorname{Cov}(\frac{1}{n}\sum_{i=1}^n y_i, \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}) \end{aligned} \qquad \text{(definition from class notes)} \\ &\operatorname{Cov}(\bar{y},\hat{\beta}_1\bar{x}) = \bar{x} \cdot \frac{1}{n\sum_{i=1}^n (x_i - \bar{x})^2}\operatorname{Cov}(\sum_{i=1}^n y_i, \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})) \\ &\operatorname{Cov}(\bar{y},\hat{\beta}_1\bar{x}) = \bar{x} \cdot \frac{1}{n\sum_{i=1}^n (x_i - \bar{x})^2}\operatorname{Cov}(\sum_{i=1}^n y_i, \sum_{i=1}^n (x_i - \bar{x})(y_i) - \bar{y}\sum_{i=1}^n (x_i - \bar{x})) \\ &\operatorname{Cov}(\bar{y},\hat{\beta}_1\bar{x}) = \bar{x} \cdot \frac{1}{n\sum_{i=1}^n (x_i - \bar{x})^2}\operatorname{Cov}(\sum_{i=1}^n y_i, \sum_{i=1}^n (x_i - \bar{x})(y_i)) \qquad \text{(special zero from class)} \\ &\operatorname{Cov}(\bar{y},\hat{\beta}_1\bar{x}) = \bar{x} \cdot \frac{1}{n\sum_{i=1}^n (x_i - \bar{x})^2}\sum_{i=1}^n (x_i - \bar{x})\sum_{i=1}^n \operatorname{Cov}(y_i, y_i) \\ &\sum_{i=1}^n (x_i - \bar{x}) = 0 \\ &\operatorname{Cov}(\bar{y},\hat{\beta}_1\bar{x}) = 0 \end{aligned}$$

$$ext{Var}(\hat{eta}_0) = ext{Var}(ar{y}) + ext{Var}(\hat{eta}_1ar{x}) + ext{Cov}(ar{y},\hat{eta}_1ar{x}) \ ext{Var}(\hat{eta}_0) = ext{Var}(ar{y}) + ext{Var}(\hat{eta}_1ar{x}) + 0 \ ext{Var}(\hat{eta}_0) = rac{\sigma^2}{n} + ar{x}^2 rac{\sigma^2}{\sum_{i=1}^n (x_i - ar{x})} \ ext{Var}(\hat{eta}_0)$$

3(a). Show that  $\sum_{i=1}^n \hat{y}_i \cdot e_i = 0$ 

$$\sum_{i=1}^{n} \hat{y}_i \cdot e_i = 0$$

$$\sum_{i=1}^{n} (\hat{\beta}_0 + \hat{\beta}_1 x_i)(e_i) = 0$$

$$\sum_{i=1}^{n} \hat{\beta}_0(e_i) + \hat{\beta}_1(x_i)(e_i) = 0$$

$$\sum_{i=1}^{n} \hat{\beta}_0(e_i) + \sum_{i=1}^{n} \hat{\beta}_1(x_i)(e_i) = 0$$

$$\hat{\beta}_0 \sum_{i=1}^{n} (e_i) + \hat{\beta}_1 \sum_{i=1}^{n} (x_i)(e_i) = 0$$

$$\sum_{i=1}^{n} (e_i) = 0 \qquad \text{(from property 1)}$$

$$\hat{\beta}_0 \cdot 0 + \hat{\beta}_1 \cdot 0 = 0$$

$$0 = 0$$

3(b). Show that regression line passes through  $(\bar{x}, \bar{y})$ 

$$\hat{y}_i = \hat{eta}_0 + \hat{eta}_1 x_i$$
let  $x_i = \overline{x}$ 
 $\hat{y}_i = \hat{eta}_0 + \hat{eta}_1 \overline{x}$ 
 $\hat{y}_i = \overline{y} - eta_1 \overline{x} + \hat{eta}_1 \overline{x}$  (from normal equations)
 $\hat{y}_i = \overline{y}$ 

this shows that the regression line passes through  $(\bar{x}, \bar{y})$ 

### 4. Derive the MLE of $\sigma^2$

$$y_{i} = \beta_{0} + \beta_{1}x_{i} + \varepsilon_{i},$$

$$\varepsilon_{i} = y_{i} - \beta_{0} - \beta_{1}x_{i},$$

$$\varepsilon_{i} \sim \mathcal{N}(0, \sigma^{2}),$$

$$y_{i} - \beta_{0} - \beta_{1}x_{i} \sim \mathcal{N}(0, \sigma^{2})$$

$$L(\beta_{0}, \beta_{1}, \sigma^{2} \mid \{(x_{i}, y_{i})\}_{i=1}^{n}) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^{2}}} \exp\left(-\frac{(y_{i} - \beta_{0} - \beta_{1}x_{i})^{2}}{2\sigma^{2}}\right)$$

$$L = (2\pi\sigma^{2})^{-n/2} \exp\left(-\frac{1}{2\sigma^{2}} \sum_{i=1}^{n} (y_{i} - \beta_{0} - \beta_{1}x_{i})^{2}\right)$$

$$\ln L = -\frac{n}{2} \log(2\pi\sigma^{2}) - \frac{1}{2\sigma^{2}} \sum_{i=1}^{n} (y_{i} - \beta_{0} - \beta_{1}x_{i})^{2}$$

$$\frac{\partial \ln L}{\partial \sigma^{2}} = -\frac{n}{2\sigma^{2}} + \frac{1}{2(\sigma^{2})^{2}} \sum_{i=1}^{n} (y_{i} - \beta_{0} - \beta_{1}x_{i})^{2}$$

$$\frac{\partial \ln L}{\partial \sigma^{2}} = 0$$

$$0 = -\frac{n}{2\sigma^{2}} + \frac{1}{2(\sigma^{2})^{2}} \sum_{i=1}^{n} (y_{i} - \beta_{0} - \beta_{1}x_{i})^{2}$$

$$\frac{n}{2\sigma^{2}} = \frac{1}{2(\sigma^{2})^{2}} \sum_{i=1}^{n} (y_{i} - \beta_{0} - \beta_{1}x_{i})^{2}$$

$$n = \frac{1}{\sigma^{2}} \sum_{i=1}^{n} (y_{i} - \beta_{0} - \beta_{1}x_{i})^{2}$$

$$\sigma^{2} = \frac{\sum_{i=1}^{n} (y_{i} - \beta_{0} - \beta_{1}x_{i})^{2}}{n}$$

 $i=1,\ldots,n,$ 

### **Methods**

Inference and result

· Linear model fit:

$$\widehat{\text{RTEN}} = -0.593 + 1.097 \cdot \text{PREP}$$

Estimates:

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Residuals:
    Min
              1Q Median
                               30
                                      Max
-0.90625 -0.20008 0.06453 0.21065 0.60091
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.59257 0.42265 -1.402
Χ
           1.09742
                      0.05615 19.543 <2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.347 on 41 degrees of freedom
Multiple R-squared: 0.9031,
                           Adjusted R-squared: 0.9007
F-statistic: 381.9 on 1 and 41 DF, p-value: < 2.2e-16
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- Interpretation: A 1 unit increase in the preparedness rating of the judge increases their retention score by 1.10 on average.
- · Inference:

To see whether trial preparation (PREP) is a statistically significant predictor of retention ratings (RTEN), we test the hypotheses below:

$$H_0:eta_1=0 \qquad ext{vs.} \qquad H_a:eta_1
eq 0.$$

The linear model we fit gives the resutls below:

$$\hat{eta}_1 = 1.097, \quad SE(\hat{eta}_1) = 0.056, \quad t = 19.54, \quad p < 2 imes 10^{-16}.$$

Since the p-value is significantly less than 0.05, we reject  $H_0$  and conclude that trial preparation is a statistically significant predictor of retention ratings at the 5% confidence

level.

A 95% confidence interval for the slope is given by

$$1.097 \pm 2.02 \times 0.056 = (0.985, \ 1.209),$$

so, for a one-unit increase in trial preparation rating, we expect that the retention rating would increase by between 0.99 and 1.21 points.