

Date

## HW 10

$$Q1 \quad (1) \quad L(\mu) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - \mu)^2}{2\sigma^2}\right)$$

$$= \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n \exp\left(-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}\right)$$

$$L(\mu) = -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2.$$

$$(2) \quad \frac{\partial L(\mu)}{\partial \mu} = \frac{1}{\sigma^2} \left( \sum_{i=1}^n x_i - n\mu \right) = 0$$

$$\text{So } \mu = \frac{\sum_{i=1}^n x_i}{n} = \bar{x}$$

Since  $\mu > \mu_0$ 

$$\arg \max_{\mu \geq \mu_0} L(\mu) = \max(\mu_0, \bar{x})$$

$$(3) \quad \lambda = \frac{\sup_{\mu \geq \mu_0} L(\mu)}{\sup_{\mu < \mu_0} L(\mu)} \quad L(\bar{x}) = \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2\right)$$

$$L(\max(\bar{x}, \mu_0)) = \left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \max(\bar{x}, \mu_0))^2\right)$$

$$\text{So } \lambda = \exp\left(-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \max(\bar{x}, \mu_0))^2\right) = \frac{1}{\lambda} \quad \text{where } \sum_{i=1}^n (x_i - \max(\bar{x}, \mu_0))^2 = \sum_{i=1}^n x_i^2 - 2n\bar{x}\max(\bar{x}, \mu_0)$$

$$\text{So } \lambda = \exp\left(-\frac{1}{2\sigma^2} [n(\bar{x} - \max(\bar{x}, \mu_0))^2] + n\max(\bar{x}, \mu_0)^2\right)$$

$$\text{So } -\frac{1}{2\sigma^2} n(\bar{x} - \max(\bar{x}, \mu_0))^2 \leq \ln \lambda \quad = \sum_{i=1}^n (x_i - \bar{x})^2 + n(\bar{x} - \max(\bar{x}, \mu_0))^2$$

$$(\bar{x} - \max(\bar{x}, \mu_0))^2 \geq -\frac{2\sigma^2 \ln \lambda}{n}$$

$$\bar{x} > \mu_0, \max(\bar{x}, \mu_0) = \bar{x} \rightarrow -\frac{n(\bar{x} - \mu_0)^2}{2\sigma^2} \leq \ln \lambda \Leftrightarrow \bar{x} \leq \mu_0 + \sqrt{\frac{2\sigma^2 \ln \lambda}{n}}$$

$$\rightarrow \bar{x} < c$$

$$(4) \quad P\left(\frac{1}{n} \sum_{i=1}^n x_i < c \mid H_0\right) = \alpha \quad \bar{x} \sim N(\mu_0, \frac{\sigma^2}{n})$$

$$Z = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}} \sim (0, 1)$$

$$P(\bar{x} < c \mid H_0) = P(Z < \frac{c - \mu_0}{\sigma/\sqrt{n}}) = \alpha$$

$$\rightarrow c = Z\alpha \cdot \frac{\sigma}{\sqrt{n}} + \mu_0$$

$$Q2.0. \quad f(Y; \beta_0, \beta_1, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(Y_i - x_i\beta_1 - \beta_0)^2}{2\sigma^2}\right)$$

$$L(\beta_0, \beta_1, \sigma^2) = -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (Y_i - x_i\beta_1 - \beta_0)^2.$$

$$\text{So } L(\beta_0, \beta_1) = -\frac{1}{2\sigma^2} \sum_{i=1}^n (Y_i - x_i\beta_1 - \beta_0)^2.$$

$$(2) \quad \frac{\partial L(\beta_0, \beta_1)}{\partial \beta_0} = -\frac{1}{2\sigma^2} \cdot (-2) \sum_{i=1}^n (Y_i - x_i\beta_1 - \beta_0) = 0. \quad (*)$$

$$\frac{\partial L(\beta_0, \beta_1)}{\partial \beta_1} = -\frac{1}{2\sigma^2} \sum_{i=1}^n x_i(Y_i - x_i\beta_1 - \beta_0) = -\frac{1}{2\sigma^2} \sum_{i=1}^n x_i(Y_i - x_i\beta_1 - (\bar{Y} - \beta_1\bar{x})) = 0.$$

$$\text{So } \sum_{i=1}^n x_i(Y_i - \bar{Y}) = \sum_{i=1}^n x_i(x_i - \bar{x})(Y_i - \bar{Y}) \rightarrow \hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(Y_i - \bar{Y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

Substitute  $\hat{\beta}_1$  into  $(*) \quad \hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{x}$ .

$$(3) \quad E(\hat{\beta}_1) = E\left(\frac{\sum_{i=1}^n (x_i - \bar{x})(X_i + \beta_1 + \beta_0 + \epsilon_i) - (\bar{Y}\beta_1 + \beta_0 + \bar{\epsilon})}{\sum_{i=1}^n (x_i - \bar{x})^2}\right) < Y \text{ is } N(X\beta_1 + \beta_0, \sigma^2) \\ \text{any linear combination of } Y_i \text{ is also normal}$$

$$E(\hat{\beta}_0) = E(\bar{Y} - \hat{\beta}_1 \bar{x}) = \bar{Y} - \beta_1 \bar{x} = \beta_0$$

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

$$\text{Var}(\hat{\beta}_0) = \text{Var}(\bar{Y} - \hat{\beta}_1 \bar{x}) = \frac{\sigma^2}{n} + \bar{x}^2 \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$\rightarrow \hat{\beta}_1 \sim N(\beta_1, \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}) \quad \hat{\beta}_0 \sim N(\beta_0, \frac{\sigma^2}{n} + \bar{x}^2 \frac{\sigma^2}{\sum_{i=1}^n (x_i - \bar{x})^2}) \quad \sigma = (\frac{1}{n})^{1/2} \text{ (ii.)}$$

① For  $H_0: \beta_0 = 0$ ,  $H_1: \beta_0 > 0$ .

$$T_0 = \frac{\hat{\beta}_0}{\sqrt{\text{Var}(\hat{\beta}_0)}} \sim N(0, 1)$$

$$\text{P-value } p = P(Z > T_0)$$

② For  $H_0: \beta_1 = 0$ ,  $H_1: \beta_1 > 0$

$$T_1 = \frac{\hat{\beta}_1}{\sqrt{\text{Var}(\hat{\beta}_1)}} \sim N(0, 1)$$

$$\text{P-value } p = P(Z > T_1)$$

$$t = \frac{\beta_1}{\sqrt{\frac{\sigma^2}{n} + \frac{\bar{x}^2}{\sum_{i=1}^n (x_i - \bar{x})^2}}}$$

$$P_1 = P(T > t) = 1 - P(T \leq t) \quad T \sim t_{n-2}$$

$$P_2 = P(T < t) \quad T \sim t_{n-2}$$

Q3.

$$(i) f(Y|\beta, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2\sigma^2}(Y - X\beta)^T(Y - X\beta)\right)$$

$$\ell(\beta, \sigma^2) = -\frac{n}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}(Y - X\beta)^T(Y - X\beta)$$

We minimize  $(Y - X\beta)^T(Y - X\beta)$

$$(Y - X\beta)^T(Y - X\beta) = Y^T Y - 2\beta^T X^T Y + \beta^T X^T X \beta$$

$$\nabla \beta = -2X^T Y + 2X^T X \beta$$

$$\rightarrow X^T X \beta = X^T Y$$

$$\rightarrow \hat{\beta} = (X^T X)^{-1} X^T Y$$

(ii)  $H_0: \beta_1 = 0$ ,  $H_1: \beta_1 > 0$ . Denote first row of  $(X^T X)^{-1}$  by  $(v_1, \dots, v_p)$

$$\hat{\beta}_1 = (1, 0, \dots, 0) \hat{\beta} \quad \text{Var}(\hat{\beta}_1) = \sigma^2 (1, 0, \dots, 0) (X^T X)^{-1} (1, 0, \dots, 0)^T = \sigma^2 v_1$$

$$T = \frac{\hat{\beta}_1}{\sqrt{\sigma^2 v_1}}$$

Under  $H_0$ ,  $T$  follows  $t$ -distribution with  $n-p$  degrees of freedom

$$\text{P-value} = P(T > t_{\text{obs}})$$

Q4

$$(i) f(Y_i|\beta, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(Y_i - (\beta_0 + \beta_1 x_i + \beta_2 x_i^2))^2}{2\sigma^2}\right)$$

$$\ell(\beta, \sigma^2) = -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (Y_i - (\beta_0 + \beta_1 x_i + \beta_2 x_i^2))^2$$

$$X = \begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 \end{bmatrix} \quad \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} \quad Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}$$

and  $\hat{\beta} = (X^T X)^{-1} X^T Y$ .

$$(ii) \hat{\beta} \sim N(\beta, \sigma^2 (X^T X)^{-1})$$

$$(ii) \text{Var}(\hat{\beta}) = \sigma^2 (X^T X)^{-1}, \quad \hat{\beta} \sim N(\beta, \sigma^2 (X^T X)^{-1})$$

$$\hat{\beta}_1 \sim N(\beta_1, V_{\beta_1})$$

So 1- $\alpha$  confidence interval is  $\hat{\beta}_1 \pm Z_{1-\frac{\alpha}{2}} \sqrt{V_{\beta_1}}$

where  $Z_{1-\frac{\alpha}{2}}$  is critical value from standard normal distribution

$$(iii) z = \frac{\hat{\beta}_1 - \beta_1}{\sqrt{V_{\beta_1}}} \quad z \sim N(0, 1)$$

P-value,  $\geq P(z > \text{observed } z)$

$$(iv) \hat{\beta} = \begin{bmatrix} -1.262 \\ 9.355 \\ -0.980 \end{bmatrix}$$

95% CI for  $\beta_1$  (8.0954, 10.781)

T-statistic for  $H_0: \beta_1 = 0$ :  $T = 19.480$

P-value  $\approx 0$

We reject  $H_0$  and in favor of  $H_1$

Programme.

$$b: \hat{\beta}_0 = -0.02013735$$

$$\hat{\beta}_1 = 0.4426883$$

$$Y^T X^T X Y = 9$$

$$(9 - 1 = 8) \text{ degrees of freedom} \quad 0 < \beta_1 < 0.4426883$$

$$\sigma^2 = (\hat{\beta}_0 + \hat{\beta}_1 T)^T X^T X (\hat{\beta}_0 + \hat{\beta}_1 T) / 8 \quad \hat{\sigma}^2 = 1.8$$

$$T = 19.480$$

reject  $H_0$  if  $|T| > t_{\alpha/2}$

$$|T| > 19.480 \Rightarrow |T| > 9$$

$$E(Y^T X^T X Y) = 9 + \beta_1^2 T^2 + 2\beta_1 \beta_0 T + \beta_0^2$$

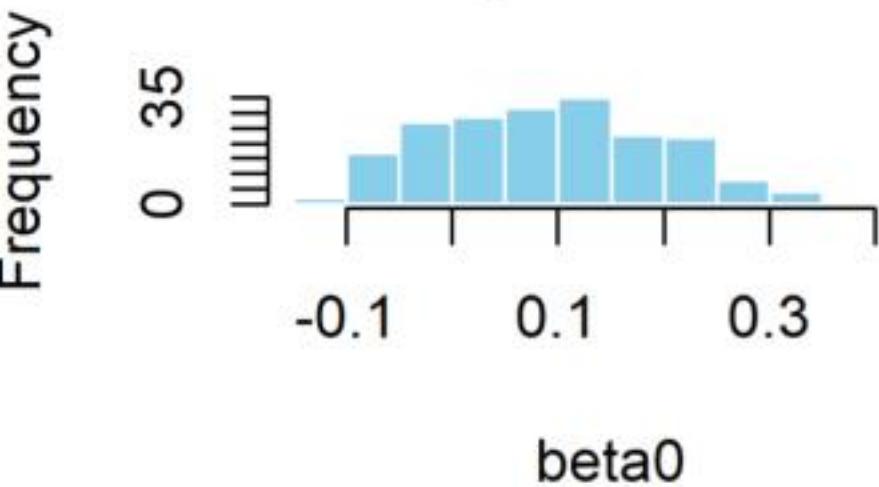
$$E((Y - \hat{Y})^T X^T X (Y - \hat{Y})) = E(Y^T X^T X Y) - E(\hat{Y}^T X^T X \hat{Y}) = 9 - \beta_1^2 T^2$$

$$E(Y^T X^T X Y) = 9 - \beta_1^2 T^2$$

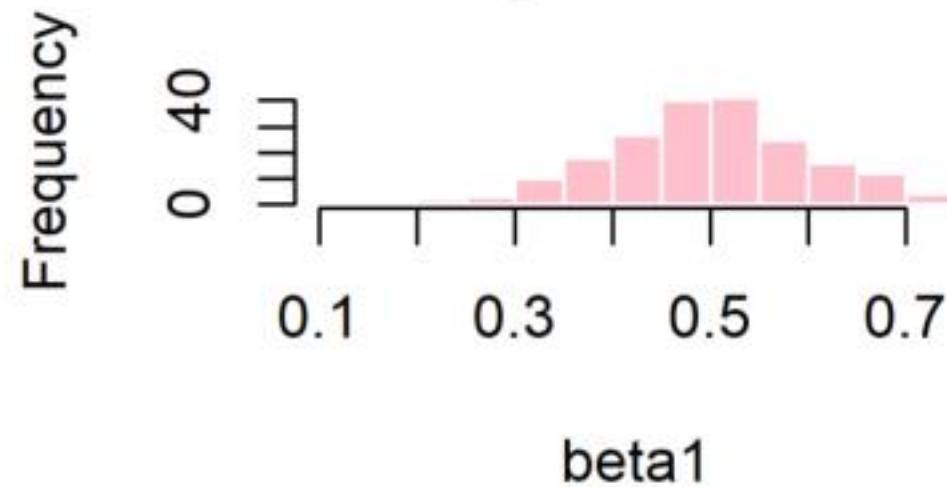
$$Y^T X^T X Y = 9 - \beta_1^2 T^2$$

$$E(Y^T X^T X Y) = 9 - \beta_1^2 T^2$$

### Histogram of beta0



### Histogram of beta1



### Histogram of P-values

