

Parameter estimation in linear regression

THA4267 L9

14.02.2017

$$\underset{n \times 1}{\vec{y}} = \underset{n \times p}{\vec{X}} \underset{p \times 1}{\beta} + \underset{n \times 1}{\vec{\epsilon}}, \quad E(\vec{\epsilon}) = 0, \quad \text{Cov}(\vec{\epsilon}) = \sigma^2 \mathbf{I}$$

Estimate β by minimizing $LS(\beta)$

$$\begin{aligned} \text{(i)} \quad LS(\beta) &= (y - X\beta)^T (y - X\beta) \leftarrow \sum_{i=1}^n (y_i - x_i^T \beta)^2 \\ &= y^T y - 2y^T X\beta + \beta^T X^T X \beta \end{aligned}$$

$$\text{(ii)} \quad \frac{\partial LS(\beta)}{\partial \beta} = 0$$

$$\frac{\partial}{\partial \beta} (y^T y - 2y^T X\beta + \beta^T X^T X \beta) = 0$$

Rules (see slides)

$$\vec{d} = -2y^T X$$

$$D = X^T X$$

$$0 - 2X^T y + 2X^T X \beta = 0$$

$X^T y = X^T X \beta$	normal equations
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iii) Solving the normal equations (substitute $\hat{\beta}$ with β)

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

iv) min or max

$$\frac{\partial^2}{\partial \beta^2} LS(\beta) = \frac{\partial}{\partial \beta} (-2X^T y - 2X^T X \beta) \Big|_{\beta = \hat{\beta}}$$

$$= 2X^T X$$

If this matrix has only positive eigenvalues this will be the minimum.

Questions on slide:

X rank p : $X^T X$ $p \times p$ matrix
symmetric
positive definite
inverse exists

If $v^T X^T X v > 0$ for all $v \neq 0$ then $X^T X$ positive definite.

$$v^T X^T X v = (Xv)^T (Xv) \geq 0$$

Assume that $v^T X^T X v = 0$ then $Xv = 0$.

If X has full rank then $Xv = 0$ only has $v = 0$ as solution.

$\Rightarrow$ then $X^T X$ must be positive definite.

$\hat{\beta} = (X^T X)^{-1} X^T Y$ is the least squares estimator of β . If we assume a normal linear model then $\hat{\beta}$ is also the maximum likelihood estimator.

Ex: Acid rain: fit in R using lm

$$\hat{\beta}_0 = \text{"Estimate Intercept"} = 5.67$$

= estimate of the pH in a lake when

$$x_1 = 0, x_2 = 0, \dots, x_7 = 0.$$

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Telework

$$\beta_3 = 0.975$$

$\uparrow$
 C_a if C_a increase by one unit, and all the other concentrations are kept constant, then we predict that pH will increase by $\beta_3 = 0.975$.

St. Error: $\hat{SD}(\hat{\beta})$

Properties of $\hat{\beta}$

$$\hat{\beta} = \underbrace{(X^T X)^{-1} X^T}_{\substack{C \\ \parallel \\ \text{constants}}} Y \quad \begin{matrix} \uparrow \\ \text{RV} \end{matrix}$$

$$\text{and } E(Y) = X\beta \\ \text{Cov}(Y) = \sigma^2 I$$

$$Y = X\beta + \varepsilon \quad \begin{matrix} \nwarrow \\ E(\varepsilon) = 0 \\ \swarrow \\ \text{Cov}(\varepsilon) = \sigma^2 I \end{matrix}$$

Find $E(\hat{\beta})$ and $\text{Cov}(\hat{\beta})$:

$$E(\hat{\beta}) = E(CY) = \underbrace{C E(Y)}_{\parallel X\beta} = \underbrace{(X^T X)^{-1} X^T X}_{\substack{I \\ \text{unbiased}}} \beta = \underline{\underline{\beta}}$$

$$\text{Cov}(\hat{\beta}) = \text{Cov}(CY) = C \underbrace{\text{Cov}(Y)}_{\sigma^2 I} C^T$$

$$= (X^T X)^{-1} X^T \sigma^2 I [(X^T X)^{-1} X^T]^T$$

$$= \sigma^2 (X^T X)^{-1} \underbrace{X^T X (X^T X)^{-1}}_I$$

$\frac{X^T X}{(X^T X)^{-1}}$ is symmetric

$$= \underline{\underline{\sigma^2 (X^T X)^{-1}}}$$

In a normal model: $\hat{\beta} \sim N_p(\beta, \sigma^2 (X^T X)^{-1})$

Ex: Acid rain: What is $\text{Var}(\hat{\beta}_3)$?

$$\text{SD}(\hat{\beta}_3) = 0.144 : \sqrt{\hat{\sigma}^2 \cdot \underbrace{(X^T X)^{-1}_{24,42}}_{1.55}}$$

Need estimator for σ^2

Last information on $\hat{\beta}$: From part 1:

$$(\hat{\beta} - E(\hat{\beta}))^T \text{Cov}(\hat{\beta})^{-1} (\hat{\beta} - E(\hat{\beta})) \sim \chi_p^2$$

$$\frac{1}{\sigma^2} (\hat{\beta} - \beta)^T (X^T X) (\hat{\beta} - \beta) \sim \chi_p^2$$

$$\begin{aligned} \text{Cov}(\hat{\beta}) &= \sigma^2 (X^T X)^{-1} \\ \text{Cov}(\hat{\beta})^{-1} &= \frac{1}{\sigma^2} (X^T X) \end{aligned}$$

Estimator for σ^2 [F3.2.2]

$$Y = X\beta + \varepsilon, \quad \varepsilon \sim N_n(0, \sigma^2 I)$$

$$L(\beta, \sigma^2) = \left(\frac{1}{2\pi}\right)^{\frac{n}{2}} \left(\frac{1}{\sigma^2}\right)^{\frac{n}{2}} \exp\left\{-\frac{1}{2\sigma^2} (y - X\beta)^T (y - X\beta)\right\}$$

$$l(\hat{\beta}, \sigma^2) = \ln(L(\hat{\beta}, \sigma^2))$$

$$= -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} (y - X\hat{\beta})^T (y - X\hat{\beta})$$

$$\frac{\partial l}{\partial \sigma^2} = 0 \quad \Leftrightarrow$$

$$\frac{d(\ln x)}{dx} = \frac{1}{x}, \quad \frac{d\frac{1}{x}}{dx} = -\frac{1}{x^2}$$

$$0 = -\frac{n}{2} \frac{1}{\sigma^2} + \frac{1}{2} \frac{1}{\sigma^4} (y - X\hat{\beta})^T (y - X\hat{\beta}) = 0$$

$$\frac{n}{\sigma^2} = \frac{1}{\sigma^4} (y - X\beta)^T (y - X\beta)$$

$$\hat{\sigma}_{ML}^2 = \frac{1}{n} (Y - X\hat{\beta})^T (Y - X\hat{\beta}) = \frac{1}{n} \hat{E}^T \hat{E}$$

$\hat{E}^T \hat{E}$ = sum of squares of errors SSE

But, this estimator is rarely used, because it is biased (use tr-formula part 1 to find the mean)

However: $\hat{\sigma}^2$ is unbiased

$$\hat{\sigma}^2 = \frac{1}{n-p} \hat{E}^T \hat{E}$$

REML found by maximizing
↑
restricted

$$L(\sigma^2) = \int_p L(\beta, \sigma^2) d\beta$$

THA4295 Statistical Inference; more on this.

Ex: Acid rain

$$\hat{SD}(\hat{\beta}_0) = \sqrt{(X^T X)^{-1} [4.4] \cdot \hat{\sigma}^2}$$

$$\hat{\sigma}^2 = \frac{1}{n-p} \hat{E}^T \hat{E}$$

$$\hat{\sigma} = 0.1165$$

$\hat{\sigma}$ is residual standard error in printout

Predicted values and residuals [F3.2.1]

$$E(Y) = X\beta, \text{ so } E(\hat{Y}) = X\hat{\beta} \equiv \hat{Y} \leftarrow \text{prediction}$$

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

$$\hat{Y} = X\hat{\beta} = \underbrace{X(X^T X)^{-1} X^T}_H Y = HY$$

$H = \underbrace{X(X^T X)^{-1} X^T}_{n \times n}$ is called the "hat matrix" for putting the hat on Y .

$$\text{Residuals: } \hat{e} = Y - \hat{Y} = Y - HY = (I - H)Y$$

$\parallel$
 IY

Observe (see also RecEx3.P3a) that

H is symmetric
 $\swarrow$
 H is idempotent $H^2 = H$
has rank $p \Rightarrow$ show this

$(I - H)$ is also symmetric and idempotent,
 $\swarrow$
and $\text{rank}(I - H) = n - p. \Rightarrow$ show this

$\Rightarrow$ Work with RecEx3.P3 - and be ready for L10!
supervision Thurs. 16.15 at Smia.