

1) Suppose $Y_i = x_i^T \beta + \epsilon_i$ with $Q(\beta) \geq 0$. Let c_n be a constant that does not depend on β or σ^2 . Suppose the likelihood function is

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w/ or OLS

$$L(\beta, \sigma^2) = c_n \frac{1}{\sigma^n} \exp\left(\frac{-1}{2\sigma^2} Q(\beta)\right).$$

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a) Suppose that $\hat{\beta}_Q$ minimizes $Q(\beta)$. Show that $\hat{\beta}_Q$ is the MLE of β .

For fixed $\sigma > 0$, $L(\beta, \sigma^2)$ is maximized by minimizing $Q(\beta)$.

so $\hat{\beta}_Q$ maximizes $L(\beta, \sigma^2)$ regardless of the value

of σ^2 . so $\hat{\beta}_Q$ is the MLE of β .

→ b) Then find the MLE $\hat{\sigma}^2$ of σ^2 .

B instead of $\hat{\beta}$, -1

$$\log L_p(\sigma^2) = d - \frac{n}{2} \log(\sigma^2) - \frac{Q}{2\sigma^2}$$

$$\frac{d \log L_p(\sigma^2)}{d\sigma^2} = -\frac{n}{2\sigma^2} + \frac{Q}{2\sigma^4} \stackrel{\text{set}}{=} 0 \text{ or } \sigma^2 = \frac{Q}{n} \quad \text{unique } \sigma^2$$

$$\frac{d^2 \log L_p(\sigma^2)}{d(\sigma^2)^2} = \frac{n}{2\sigma^4} - \frac{2(\sigma^2)^{-3} Q}{2} \Big|_{\sigma^2} = \frac{n}{2\sigma^4} - \frac{n\sigma^2}{\sigma^6} = \frac{-n}{2\sigma^4} < 0$$

$$\frac{-n^3}{2Q^2}$$

or $\log L_p(\tau) = d - \frac{n}{2} \log(\tau) - \frac{Q}{2\tau}$

$$\frac{d \log L_p(\tau)}{d\tau} = -\frac{n}{2\tau} + \frac{Q}{2\tau^2} \stackrel{\text{set}}{=} 0 \text{ or } -n\tau + Q = 0 \text{ or } \tau = \sigma^2 = \frac{Q}{n} \quad \text{unique}$$

$$\frac{d^2 \log L_p(\tau)}{d\tau^2} = \frac{n}{2\tau^2} - \frac{2Q}{2\tau^3} \Big|_{\tau} = \frac{n}{2\tau^2} - \frac{2nQ}{2\tau^3} = \frac{-n}{2\tau^2} < 0$$

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so $\hat{\sigma}^2 = \frac{Q}{n}$ is the MLE $Q = Q(\hat{\beta})$

$\underline{a}^T \underline{\beta}$ is estimable if $\underline{a} \in C(\underline{X})$

if $E(\underline{b}^T \underline{Y}) = \underline{a}^T \underline{\beta}$

full full rank $\underline{a}^T \underline{\beta}$ is estimable by $\underline{a}^T \underline{\hat{\beta}}$

2) Let $\underline{Y} = \underline{X}\underline{\beta} + \underline{\epsilon}$ where $E(\underline{\epsilon}) = \underline{0}$, $Cov(\underline{\epsilon}) = \sigma^2 \underline{I}_n$, and \underline{X} has full rank. Note that $Y_i = \underline{x}_i^T \underline{\beta} + \epsilon_i$.

ASSUME \underline{X} is a constant matrix

a) Find $E(Y_i)$. = $\boxed{\underline{x}_i^T \underline{\beta}}$

$\underline{X} = \begin{bmatrix} \underline{x}_1^T \\ \vdots \\ \underline{x}_n^T \end{bmatrix}$

\underline{x}_i rowspace(\underline{X})

so $\underline{X}^T = \begin{bmatrix} \underline{x}_1 & \dots & \underline{x}_n \end{bmatrix}$

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$\underline{Y} = \underline{X}\underline{\beta} + \underline{\epsilon}$

b) Is $E(Y_i)$ estimable? Explain briefly. yes by $\underline{x}_i^T \underline{\hat{\beta}}$

or $\underline{x}_i \in C(\underline{X}')$ since \underline{x}_i is a column of \underline{X}^T

or $\underline{b} = (0, \dots, 0, 1, 0, \dots, 0)^T$ since $\underline{b}^T \underline{Y} = Y_i$
in position

or $\underline{x}_i^T \underline{\hat{\beta}} = \underline{x}_i^T (\underline{X} \underline{X}^T)^{-1} \underline{X}^T \underline{Y} = d^T \underline{Y}$ with

$E(d^T \underline{Y}) = E(Y_i)$

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3) Let $\underline{Y} = \underline{X}\underline{\beta} + \underline{\epsilon}$ where $\underline{\epsilon} \sim N_n(\underline{0}, \sigma^2 \underline{I}_n)$. Assume \underline{X} has full rank and that the first column of $\underline{X} = \underline{1}$ so that a constant is in the model. Let \underline{e} be the vector of residuals. Then the residual sum of squares $RSS = \underline{e}^T \underline{e} = \|(\underline{I} - \underline{P})\underline{Y}\|^2$. The sample mean $\bar{Y} = \frac{1}{n} \underline{1}^T \underline{Y}$. Prove that $\underline{e}^T \underline{e}$ and \bar{Y} independent (or dependent).

(Hint: If $\underline{Y} \sim N_n(\underline{\mu}, \underline{\Sigma})$, then $\underline{A}\underline{Y} \perp \underline{B}\underline{Y}$ iff $\underline{A}\underline{\Sigma}\underline{B}^T = \underline{0}$.)

So prove whether $(\underline{I} - \underline{P})\underline{Y} \perp \frac{1}{n} \underline{1}^T \underline{Y}$.

$\underline{P}\underline{X} = \underline{X}$ so $\underline{P}\underline{1} = \underline{1}$

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$(\underline{I} - \underline{P}) \sigma^2 \underline{I} \frac{1}{n} \underline{1} = \frac{\sigma^2}{n} (\underline{I} - \underline{1}\underline{1}^T) \underline{1} = \underline{0}$.

so $\frac{1}{n} \underline{1}^T \underline{Y} \perp (\underline{I} - \underline{P})\underline{Y}$.

(so $\underline{Y} \perp \perp \|(\underline{I} - \underline{P})\underline{Y}\|^2$)

$\frac{\underline{I} - \underline{P}}{n \times n}$ $\frac{1}{1 \times n}$ not conformable

or $\frac{1}{n} \underline{1}^T \sigma^2 \underline{I} (\underline{I} - \underline{P}) = \frac{\sigma^2}{n} (\underline{1}^T - \underline{1}^T) \underline{1} = \underline{0}$

$\underline{X}^T \underline{P} = \underline{X}^T$ so $\underline{1}^T \underline{P} = \underline{1}^T$

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4) Partition \mathbf{X} as $\mathbf{X} = [\mathbf{X}_1 \ \mathbf{X}_2]$, let \mathbf{P} be the projection matrix for $\mathcal{C}(\mathbf{X})$ and let \mathbf{P}_1 be the projection matrix for $\mathcal{C}(\mathbf{X}_1)$. Find $\mathbf{P}\mathbf{P}_1$.

$$= \mathbf{P}_1$$

$$\mathcal{C}(\mathbf{P}_1) = \mathcal{C}(\mathbf{X}_1) \subseteq \mathcal{C}(\mathbf{X})$$

5) Suppose that $Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \epsilon_i$. Testing $H_0: \beta_1 = \beta_3 = \beta_4 = 0$ is equivalent to testing $H_0: \mathbf{A}\boldsymbol{\beta} = \mathbf{0}$. What is \mathbf{A} ?

$$\boldsymbol{\beta} = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{pmatrix}$$

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\text{want } \mathbf{A}\boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \beta_3 \\ \beta_4 \end{pmatrix}$$

6) Suppose $\mathbf{Z}_n \xrightarrow{D} N_k(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. Let \mathbf{A} be a constant $r \times k$ matrix. Find the limiting distribution of $\mathbf{A}\mathbf{Z}_n$.

$$\mathbf{A}\mathbf{Z}_n \xrightarrow{D} N_r(\mathbf{A}\boldsymbol{\mu}, \mathbf{A}\boldsymbol{\Sigma}\mathbf{A}^T)$$

7) Let the linear model $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$ where \mathbf{X} has full rank p , $E(\boldsymbol{\epsilon}) = \mathbf{0}$ and $\text{Cov}(\boldsymbol{\epsilon}) = \sigma^2 \mathbf{I}$. Let \mathbf{A} be a conformable constant matrix. Then for a large class of iid error distributions, what is the limiting distribution of $\sqrt{n}\mathbf{A}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta})$? Let \mathbf{A} be $r \times p$.

$$\sqrt{n}\mathbf{A}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}) \xrightarrow{D} N_r(\mathbf{0}, \sigma^2 \mathbf{A}\mathbf{W}\mathbf{A}^T)$$

$$\left(\begin{array}{l} \text{by OLS CLT } \sqrt{n}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}) \rightarrow N_p(\mathbf{0}, \sigma^2 \mathbf{W}) \\ \text{where } \frac{\mathbf{X}^T \mathbf{X}}{n} \rightarrow \mathbf{W}^{-1} \end{array} \right)$$

8) Let the full model be $Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5} + \epsilon_i$ and let the reduced model be $Y_i = \beta_0 + \beta_2 x_{i2} + \epsilon_i$ for $i = 1, \dots, n$. Write the full model as $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} = \mathbf{X}_1\boldsymbol{\beta}_1 + \mathbf{X}_2\boldsymbol{\beta}_2 + \boldsymbol{\epsilon}$, and consider testing $H_0 : \boldsymbol{\beta}_2 = \mathbf{0}$ where $\boldsymbol{\beta}_1$ corresponds to the reduced model. Let \mathbf{P}_1 be the projection matrix on $C(\mathbf{X}_1)$ and let \mathbf{P} be the projection matrix on $C(\mathbf{X})$.

$$\text{Then } F_R = \frac{n-p}{q} \frac{\mathbf{Y}'(\mathbf{P} - \mathbf{P}_1)\mathbf{Y}}{\mathbf{Y}'(\mathbf{I} - \mathbf{P})\mathbf{Y}}$$

Assume $\boldsymbol{\epsilon} \sim N_n(\mathbf{0}, \sigma^2 \mathbf{I})$. Assume H_0 is true.

a) What is q ? $= 6 - 2 = \boxed{4} = \# \text{ predictors in}$

full model but not in reduced model

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b) What is the distribution of $\mathbf{Y}'(\mathbf{P} - \mathbf{P}_1)\mathbf{Y}$?

$$\frac{\mathbf{Y}'(\mathbf{P} - \mathbf{P}_1)\mathbf{Y}}{\sigma^2} \sim \chi^2_4 \quad \text{so } \mathbf{Y}'(\mathbf{P} - \mathbf{P}_1)\mathbf{Y} \sim \sigma^2 \chi^2_4 = \boxed{\sigma^2 \chi^2_4}$$

c) What is the distribution of $\mathbf{Y}'(\mathbf{I} - \mathbf{P})\mathbf{Y}$? $\text{rank}(\mathbf{I} - \mathbf{P}) = n - p = n - 6$

$$\frac{\mathbf{Y}'(\mathbf{I} - \mathbf{P})\mathbf{Y}}{\sigma^2} \sim \chi^2_{n-p} \quad \text{so } \mathbf{Y}'(\mathbf{I} - \mathbf{P})\mathbf{Y} \sim \sigma^2 \chi^2_{n-p} = \boxed{\sigma^2 \chi^2_{n-6}}$$

d) What is the distribution of F_R ?

$$F_{q, n-p} \sim \boxed{F_{4, n-6}}$$

9) Let the model be $Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \epsilon_i$. The model in matrix form is $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$ where $\boldsymbol{\epsilon} \sim N_n(\mathbf{0}, \sigma^2 \mathbf{I})$. Let \mathbf{P} be the projection matrix on $C(\mathbf{X})$ where the $n \times p$ matrix \mathbf{X} has full rank p . What is the distribution of $\mathbf{Y}'\mathbf{P}\mathbf{Y}$?

Hint: If $\mathbf{Y} \sim N_n(\boldsymbol{\mu}, \mathbf{I})$, then $\mathbf{Y}'\mathbf{A}\mathbf{Y} \sim \chi^2(\text{rank}(\mathbf{A}), \boldsymbol{\mu}'\mathbf{A}\boldsymbol{\mu}/2)$ iff $\mathbf{A} = \mathbf{A}'$ is idempotent. $\mathbf{Y} \sim N_n(\mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{I})$, so $\frac{\mathbf{Y}}{\sigma} \sim N_n\left(\frac{\mathbf{X}\boldsymbol{\beta}}{\sigma}, \mathbf{I}\right)$.

$$\frac{\mathbf{Y}'\mathbf{P}\mathbf{Y}}{\sigma^2} \sim \chi^2 \left[\text{rank}(\mathbf{P}), \left(\frac{\mathbf{X}\boldsymbol{\beta}}{\sigma}\right)' \frac{\mathbf{P}}{2} \frac{\mathbf{X}\boldsymbol{\beta}}{\sigma} \right] \sim \chi^2 \left(\text{rank}(\mathbf{P}), \frac{(\mathbf{X}\boldsymbol{\beta})'\mathbf{P}\mathbf{X}\boldsymbol{\beta}}{2\sigma^2} \right)$$

$$\text{So } \underline{\mathbf{Y}'\mathbf{P}\mathbf{Y}} \sim \boxed{\sigma^2 \chi^2 \left(\overset{=5}{p}, \frac{\mathbf{B}'\mathbf{X}'\mathbf{X}\mathbf{B}}{2\sigma^2} \right)}$$

$$\mathbf{P}\mathbf{X}\mathbf{B} = \mathbf{X}\mathbf{B}$$

$$\left(\begin{aligned} \text{rank}(\mathbf{P}) &= \text{tr}(\mathbf{P}) = \text{tr}(\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}') \\ &= \text{tr}[\mathbf{X}'\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}] = \text{tr}(\mathbf{I}_p) = p = \text{rank}(\mathbf{X}) \end{aligned} \right)$$