

REGRESSION TWO VARIABLES CASE

$$y_i = \beta_1 + \beta_2 x_i + \varepsilon_i, \quad \varepsilon_i \stackrel{iid}{\sim} (0, \sigma^2)$$

$i = 1, 2, \dots, n$

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \beta_1 + \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \beta_2 + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

$$Y = X \underbrace{\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}}_b + \varepsilon, \quad X = \begin{bmatrix} 1 & x_1 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix}$$

$$\hat{\beta} = (X'X)^{-1} X'y$$

$$X'X = \begin{pmatrix} 1 & 1 & \dots & 1 \\ x_1 & x_2 & \dots & x_n \end{pmatrix} \begin{pmatrix} 1 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} =$$

$$= \begin{pmatrix} n & \sum_{i=1}^n x_i \\ \sum_{i=1}^n x_i & \sum_{i=1}^n x_i^2 \end{pmatrix}$$

$$(X'X)^{-1} = \frac{1}{n} \frac{1}{\sum (x_i - \bar{x})^2} \begin{pmatrix} \sum x_i^2 & -\sum x_i \\ -\sum x_i & n \end{pmatrix}$$

$$X'Y = \begin{pmatrix} 1 & 1 & \dots & 1 \\ x_1 & x_2 & \dots & x_n \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n y_i x_i \end{pmatrix}$$

$$\sum (x_i - \bar{x})^2 = \sum x_i^2 - n\bar{x}^2$$

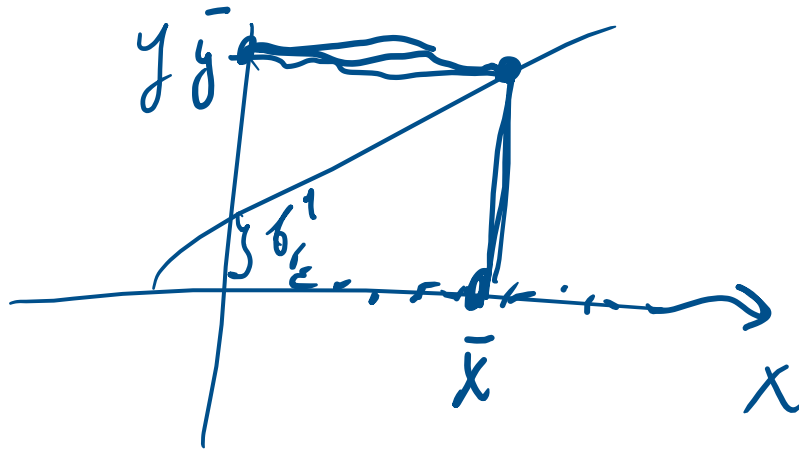
$$\sum (x_i - \bar{x})(y_i - \bar{y}) = \sum x_i y_i - n\bar{x}\bar{y}$$

$$b_2 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$b_1 = \bar{y} - \bar{x} b_2$$

$$\bar{x} = \frac{1}{n} \sum x_i$$
$$\bar{y} = \frac{1}{n} \sum y_i$$

→



$$X' \varepsilon^1 = 0 \quad \text{v. (0?)}$$

$$X' M \varepsilon = \underbrace{X' M}_{\varepsilon^1} \varepsilon = \underbrace{X' M}_{\mathbf{0}} \varepsilon = 0 \cdot \varepsilon = 0.$$

$$\hat{\beta}^1 = (X'X)^{-1} X'y, \quad \varepsilon^1 = y - \hat{y}^1 = y - X\hat{\beta}^1$$

$$\left[\hat{y}^1 \right]' \varepsilon^1 = (X\hat{\beta}^1)' \varepsilon^1 = \hat{\beta}^1' X' \varepsilon^1 = \hat{\beta}^1' \cdot 0 = 0.$$

$$\hat{\varepsilon} = y - \hat{y} \Rightarrow y = \hat{y} + \hat{\varepsilon}$$

$$y' y = (\hat{y} + \hat{\varepsilon})' (\hat{y} + \hat{\varepsilon}) \Rightarrow$$

$$\Rightarrow y' y = \hat{y}' \hat{y} + \hat{\varepsilon}' \hat{y} + \hat{y}' \hat{\varepsilon} + \hat{\varepsilon}' \hat{\varepsilon}$$

$$\Rightarrow y' y = \hat{y}' \hat{y} + \hat{\varepsilon}' \hat{\varepsilon}$$

$$\bar{y} = \bar{y} \quad \text{δυσωπ},$$

$X' \varepsilon = 0$ ΑΝ ΥΠΑΡΧΕΙ ΣΤΑΘΕΡΑ

ΣΤΗΝ ΠΛΑΝΩΔΡΟΜΗΣΗ $X = \begin{pmatrix} 1 & & & \\ & 1 & & \\ & & \dots & \\ & & & 1 \end{pmatrix}$

$$X' \varepsilon = 0 \Rightarrow \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{pmatrix} = 0 \Rightarrow$$

$$\sum_{i=1}^n \varepsilon_i = 0$$

$$y_i = \bar{y} + \varepsilon_i$$

$$\frac{1}{n} \sum y_i = \frac{1}{n} \sum \bar{y} + \frac{1}{n} \sum \varepsilon_i$$

$$\bar{y} = \bar{y}$$

RSS = RESIDUALS SUM OF SQUARES

$$\underbrace{y' y}_{\sum_{i=1}^n y_i^2} = \underbrace{y' \hat{y}}_{\sum_{i=1}^n \hat{y}_i^2} + \underbrace{\varepsilon' \varepsilon}_{\sum_{i=1}^n \varepsilon_i^2}$$

$n \bar{y}^2$

$$\Rightarrow y' y - n \bar{y}^2 = y' \hat{y} - n \bar{y}^2 + \varepsilon' \varepsilon$$

$$\Rightarrow \underbrace{\sum_{i=1}^n (y_i - \bar{y})^2}_{TSS} = \underbrace{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}_{ESS} + \underbrace{\sum_{i=1}^n \varepsilon_i^2}_{RSS}$$

TSS = TOTAL SUM OF SQUARES (ANAKRISION AMO TOY MESO)
 ESS = EXPLAINED

$R^2 = \frac{ESS}{TSS} =$ ΠΟΣΟΣΤΟ ΤΟΥ VARIABILITY
ΤΟΥ Y ΜΟΥ ΕΞΗΓΕΙΤΑΙ ΑΠΟ ΤΟ
VARIABILITY ΤΩΝ X

$$\Rightarrow R^2 = \frac{TSS - RSS}{TSS} \Rightarrow R^2 = 1 - \frac{RSS}{TSS}$$

$$\bar{R}^2 \text{ (ADJUSTED } R^2) = 1 - \frac{RSS/n-k}{TSS/n-k} \leftarrow \text{NO OF X'S VARIABLES}$$

$$H_0: R\beta = q \text{ v.s. } H_1: R\beta \neq q$$

$k = \text{NO. EXPLAN. VAR.}$
 $v = \text{NO. RESTRICTIONS}$

$$F = \frac{(R\hat{\beta} - q)' \left[R (X'X)^{-1} R' \right]^{-1} (R\hat{\beta} - q) / v}{\frac{\sum \varepsilon_i^2}{n-k}} \underset{H_0}{\sim} F$$

$$F(v, n-k)$$

$$AN \quad \varepsilon \sim N(0, \sigma^2 I_n)$$

$$Y = X\beta + \varepsilon \Rightarrow \hat{\beta} = (X'X)^{-1}X'Y \Rightarrow \hat{\varepsilon} = Y - X\hat{\beta}$$

Εστω $\hat{\beta}$ η ΕΚΤΙΜΗΤΡΙΑ ΤΟΥ β
 ΑΦΟΥ ΕΧΩ ΕΝΣΘΜΑΤΩΣΕΙ ΤΟΥΣ
 ΠΕΡΕΘΡΙΣΜΟΥΣ $\Rightarrow \hat{\varepsilon} = Y - X\hat{\beta}$

$$F = \frac{(\hat{\varepsilon}'\hat{\varepsilon} - \hat{\varepsilon}'\hat{\varepsilon})/v}{\hat{\varepsilon}'\hat{\varepsilon}} \stackrel{H_0}{\sim} F(v, n-k)$$

$$\rightarrow \frac{(RSS - \frac{RSS}{n-k})/v}{RSS/n-k} \stackrel{H_0}{\sim} F(v, n-k)$$

RSS = $\tilde{\varepsilon}' \tilde{\varepsilon}$ = RESTRICTED RESID. SUM. SQ.
 URSS = $\varepsilon' \varepsilon$ = UNRESTRICTED $\gg \gg \gg$

$$y_i = b_1 + b_2 x_{i2} + b_3 x_{i3} + \dots + b_k x_{ik} + \varepsilon_i$$
$$i = 1, 2, \dots, n$$

$H_0: b_2 = b_3 = \dots = b_k = 0$ v.s. $H_1: \text{AT LEAST ONE } \neq 0$
RESTRICTED MODEL

$$y_i = b_1 + \varepsilon_i \Rightarrow \tilde{y}_i = \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \theta_1 + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

$$y = x\theta_1 + \varepsilon$$

$$\hat{\theta}_1 = (x'x)^{-1} x'y = \left(\begin{pmatrix} 1 & 1 & \dots & 1 \end{pmatrix} \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \right)^{-1} \begin{pmatrix} 1 & \dots & 1 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$$

$$= n^{-1} \sum_{i=1}^n y_i = \frac{1}{n} \sum y_i = \bar{y}$$

$$F = \frac{\left(\frac{\sum \tilde{\varepsilon}^2 - \frac{(\sum \tilde{\varepsilon})^2}{n-k}}{k-1} \right)}{\frac{\sum \hat{\varepsilon}^2}{n-k}} \sim F(k-1, n-k)$$

ΤΥΠΩΝΕΤΑΙ ΑΠΟ ΘΛΑΤΑ ΟΙΚΟΝΟΜ. ΜΑΚΕΤΑ
 ΕΙΝΑΙ F STATISTIC ΓΙΑ ΤΗΝ ΥΠΟΘΕΣΗ
 ΟΤΙ ΟΛΕΣ ΟΙ ΜΕΤΑΒΛΗΤΕΣ ΠΛΗΝ ΤΗΣ
 ΣΤΑΘΕΡΑΣ ΕΙΝΑΙ ΜΗΔΕΝ. ΓΙΑ ΔΙ
 ΕΛΕΓΧΟ ΤΗΝ ΣΤΑΤΙΣΤΙΚΗ ΣΥΜΑΝΤΙΚΟΤΗΤΑ
 ΟΛΩΝ ΤΩΝ ΜΕΤΑΒΛΗΤΩΝ (ΓΛΗΡ ΣΤΑΘΕΡΑΣ)
 ΑΠΟ ΚΟΙΝΟΥ,

$H_0: b_1 = b_5 = 0$ v.s. $H_1: \text{AT least one } \neq 0$

$$F = \frac{(RSS - URSS) / q}{\frac{URSS}{n-k}}$$

$$= \frac{(1655.775 - 1655.006) / 2}{\frac{1655.006}{528-5}} \stackrel{H_0}{\sim} F(2, 523)$$

Reject H_0 iff $F > F(2, 523)_{5\%}$

INFO. CRITERIA

$n = \text{NO. OF OBS.}$
 $k = \text{NO. OF EXPLAN. VAR.}$

$$\text{AKAIKE INFO.} = \text{AIC} = \ln \frac{\sum \hat{\epsilon}^2}{n} + \frac{2k}{n}$$

$$\text{SCHWARZ INFO.} = \text{SC} = \ln \frac{\sum \hat{\epsilon}^2}{n} + \frac{k}{n} \ln n$$

$$\text{HANNAN-QUINN-HQ} = \ln \frac{\sum \hat{\epsilon}^2}{n} + \frac{k}{n} \ln(\ln n)$$

Σ ΥΓΚΡΙΝΟΝΤΑΣ ΜΟΝΤΕΛΑ (ΠΑΛΙΝΔΡΟΜΗΣΕΙΣ)
ΔΙΑΓΕΝΟΥΜΕ ΤΟ ΜΟΝΤΕΛΟ ΜΕ ΤΑ
ΜΙΚΡΟΤΕΡΑ INFO. CRIT.

ΠΡΟΣΟΧΗ: ΤΑ INFO CRITERIA ΧΡΗΣΙΜΟΠΟΙΟΥΝΤΑΙ
ΑΝ ΤΑ ΜΟΝΤΕΡΑ ΕΙΝΑΙ

NON-NESTED

(A) $y_i = \beta_1 + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \varepsilon_i$

(B) $y_i = \beta_1 + \beta_2 x_{i2} + \beta_3 x_{i3} + \eta_i$

ΑΝ ΣΤΟ (A) ΙΣΧΥΕΙ $\beta_4 = 0 \implies$ (B)

ΑΡΑ (B) IS NESTED INTO (A)
(ΕΜΦΩΛΕΥΕΙ)

ΓΕΝΙΚΩΣ

ENA ΜΟΝΤΕΝΟ (A) IS NESTED
IN TO (B) ΑΝΝ ΜΕ ΜΗΔΕΝΙΚΟΥΣ
ΠΕΡΙΟΡΙΣΜΟΥΣ ΤΩΝ ΣΥΝΤΕΛΕΣΤΩΝ
ΤΟΥ (B) ΕΧΩ ΤΟ (A)

ΣΤΑ NESTED MODELS ΕΑΝ ΧΡΗΣΗ
ΤΟΥ F (ΑΝ ΕΧΩ 2 Η ΠΕΡΙΣΣΟΤΕΡΟΥΣ ΠΕΡΙΟΡΙΣΜΟΥΣ)
Η ΤΟΥ t (ΑΝ ΕΧΩ 1 ΠΕΡΙΟΡΙΣΜΟ).

AN TA MODELS ARE NON-NESTED
XPHEH TON INFO. CRIT.

AHAAH AIAHEMO TO MONTEHO
ME TA MIKROTEPA INFO. CRITER.

$$(A) y_i = \beta_1 + \beta_2 x_{i2} + \beta_3 x_{i3} + \varepsilon_i$$

$$(B) y_i = \gamma_1 + \gamma_2 x_{i2} + \gamma_3 z_i + \eta_i$$

(A), (B) NON-NESTED. (TOTE INFO. CRITER.)

$$Y = X\beta + \varepsilon \rightarrow \hat{\beta} = (X'X)^{-1}X'Y$$

$n \times 1$ $n \times k$ $k \times 1$ $n \times 1$

$\hat{\beta}$ MINIMIZES $\varepsilon'\varepsilon = \min_{\beta} (Y - X\beta)'(Y - X\beta)$

$\hat{\beta}$ OLS

$x_i \stackrel{i.i.d.}{\sim} N(\mu, \sigma^2)$
(JOINT DENSITY)

$i = 1, 2, \dots, n$

$$f(x_1, x_2, \dots, x_n) \stackrel{\text{INDEP.}}{=} f(x_1) f(x_2) \dots f(x_n)$$

$$= \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_1 - \mu)^2}{2\sigma^2}} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_2 - \mu)^2}{2\sigma^2}} \dots \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_n - \mu)^2}{2\sigma^2}}$$

$$= f(x_1, x_2, \dots, x_n; \underbrace{\mu, \sigma^2})$$

$$= L(\underbrace{\mu, \sigma^2} \mid x_1, x_2, \dots, x_n)$$

↑

LIKELIHOOD.

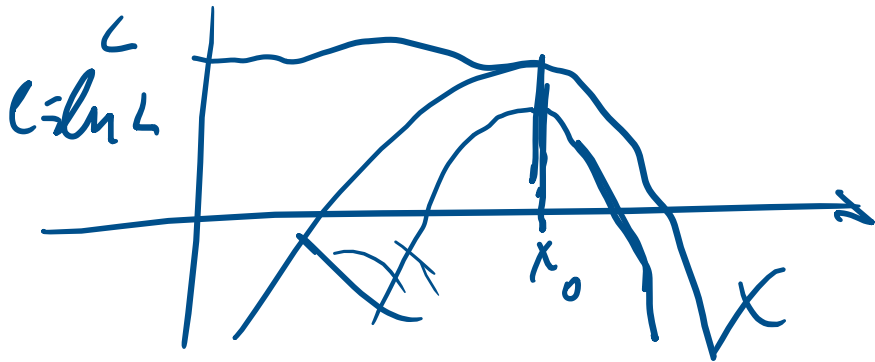
JOINT DENSITY $\stackrel{\text{IND.}}{\iff}$ PRODUCT MARGINAL

$$f(x_1, x_2, \dots, x_n) \stackrel{\text{IND.}}{\iff} f(x_1) f(x_2) \dots f(x_n)$$

ΕΚΤΙΜΗΤΡΙΕΣ ΜΕΓΙΣΤΗΣ ΠΙΘΑΝΟΦΑΝΕΙΑΣ
= ΟΙ ΕΚΤΙΜΗΤΡΙΕΣ ΜΕΓΙΣΤΟΠΟΙΟΥΝ
ΤΗΝ ΑΠΟ-ΚΟΙΝΟΥ ΣΥΝΑΡΤΗΣΗ ΚΑΤΑΝΟΜΗΣ
ΤΟΥ ΔΕΙΓΜΑΤΟΣ ΔΕΔΟΜΕΝΩΝ ΤΩΝ
ΠΑΡΑΤΗΡΗΣΕΩΝ.

$$L(\mu, \sigma^2 | \mathbf{x}) = \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right)^n e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2}$$

$$Q(\mu, \sigma^2 / x_1, \dots, x_n) = \ln L(\mu, \sigma^2 / x_1, x_2, \dots, x_n)$$



$$Q(\theta) = \ln L(\theta)$$

$$\frac{\partial Q}{\partial \theta} = \frac{1}{L(\theta)} \frac{\partial L}{\partial \theta}$$

\Downarrow \Downarrow
 0 0

$$\max_{\mu, \sigma^2} \ell(\mu, \sigma^2, x_1, x_2, \dots, x_n)$$

$$\ell(\mu, \sigma^2) = -\frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \sigma^2$$

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

$$\frac{\partial \ell}{\partial \mu} = 0 \Rightarrow -\frac{1}{\sigma^2} \sum_{i=1}^n -2(x_i - \hat{\mu}) = 0 \Rightarrow$$

$$\sum (x_i - \hat{\mu}) = 0 \Rightarrow \sum x_i - \sum \hat{\mu} = 0 \Rightarrow$$
$$\Rightarrow \sum x_i = n \hat{\mu} \Rightarrow \hat{\mu} = \frac{1}{n} \sum x_i = \bar{x}$$

$$\frac{\partial \mathcal{L}}{\partial \sigma^2} = 0 \Rightarrow -\frac{n}{2} \frac{1}{\sigma^2} + \frac{1}{2\sigma^4} \sum (x_i - \mu)^2 = 0$$

$$\Rightarrow \sigma^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2$$

$$= \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \neq s^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$$

$$y_i = b_1 + b_2 x_{i2} + b_3 x_{i3} + \dots + b_k x_{ik} + \varepsilon_i$$

$\varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2)$

$$E(y_i) = b_1 + b_2 x_{i2} + \dots + b_k x_{ik} + E(\varepsilon_i)$$
$$= b_1 + b_2 x_{i2} + \dots + b_k x_{ik} + 0$$

$$V(y_i) = E[(y_i - E(y_i))^2] = E(\varepsilon_i^2) = \sigma^2$$

$$y_i = f(x_i) + \varepsilon_i \sim N$$

$$y_i \stackrel{iid}{\sim} N(b_1 + b_2 x_{i2} + \dots + b_k x_{ik}, \sigma^2)$$

$$f(y_i) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i - \beta_1 - \beta_2 x_{i2} - \dots - \beta_k x_{ik})^2}{2\sigma^2}}$$

$$f(y_1, \dots, y_n) \stackrel{\text{IND.}}{=} f(y_1) \cdot \dots \cdot f(y_n)$$

$$l(\beta_1, \beta_2, \dots, \beta_k, \sigma^2 | y_1, y_2, \dots, y_n) =$$

$$= -\frac{n}{2} \ln 2\pi - \frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_1 - \beta_2 x_{i2} - \dots - \beta_k x_{ik})^2$$

$$= -\underbrace{\frac{1}{2} \ln \pi}_{\text{constant}} - \underbrace{\frac{1}{2} \ln \sigma^2}_{\text{constant}} - \frac{1}{2\sigma^2} (Y - X\beta)' (Y - X\beta)$$

$$\max_{\beta} \ell = \max_{\beta} \quad \searrow \quad =$$

$$= \min_{\beta} (Y - X\beta)' (Y - X\beta) \rightarrow$$

$$\Rightarrow \hat{\beta}_{OLS} = (X'X)^{-1} X'Y \equiv \hat{\beta}_{MLE}$$

$$\frac{\partial \ell}{\partial \sigma^2} = 0 \Rightarrow -\frac{n}{2} \frac{1}{\sigma^2} + \frac{1}{2\sigma^4} (Y - X\hat{\beta})' (Y - X\hat{\beta}) = 0$$

$$\Rightarrow \hat{\sigma}_{OLS}^2 = \frac{1}{n} (Y - X\hat{\beta})' (Y - X\hat{\beta})$$

$$= \frac{1}{n} \hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n \hat{\varepsilon}_i^2$$

$$\hat{\sigma}_{OLS}^2 = \frac{1}{n-k} \sum_{i=1}^n \hat{\varepsilon}_i^2$$

$$\hat{\beta}_{MLE} = \hat{\beta}_{OLS} = (X'X)^{-1} X'y$$

$$\hat{\sigma}_{MLE}^2 = \frac{1}{n} \varepsilon' \varepsilon$$

$$\varepsilon = y - X\hat{\beta}$$

$$\hat{\sigma}_{OLS}^2 = \frac{1}{n-k} \varepsilon' \varepsilon$$

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

Q ΘΕΤΙΚΑ ΟΡΙΣΜΕΝΗ ΣΥΜΜΕΤΡΙΚΗ
ΜΗΤΡΑ

$$V(\varepsilon_i) = \sigma^2 w_{ii}, \quad \text{cov}(\varepsilon_i, \varepsilon_j) = \sigma^2 w_{ij}$$

$$V(\varepsilon_i) = \sigma^2 \quad \forall i \quad \Delta \in N \quad 1 \leq X \leq E_1$$

$$\text{cov}(\varepsilon_i, \varepsilon_j) = 0 \quad \forall i \neq j \quad \Delta \in N \quad 1 \leq X \leq E_1$$

$$E(Y) = X\beta + E(\varepsilon) = X\beta$$

$$V(Y) = E[(Y - E(Y))(Y - E(Y))'] =$$
$$= E(\varepsilon \varepsilon') = \sigma^2 \Omega$$

$$Y \sim N(X\beta, \sigma^2 \Omega)$$

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

$$\frac{\partial \ell}{\partial \beta} = 0 \Rightarrow \frac{1}{\sigma^2} (X' \underline{\sigma}^{-1} Y - X' \underline{\sigma}^{-1} X \beta^{\uparrow}) = 0$$

$$\Rightarrow \beta_{MLE}^{\uparrow} = (X' \underline{\sigma}^{-1} X)^{-1} X' \underline{\sigma}^{-1} Y$$

$$\frac{\partial \ell}{\partial \sigma^2} = 0 \Rightarrow \hat{\sigma}_{MLE}^2 = \frac{1}{n} (Y - X \hat{\beta}^{\uparrow})' (Y - X \hat{\beta}^{\uparrow})$$

Q ΣΕΤΙΚΑ ΟΡΙΣΜΕΝΗ ΜΗΤΡΑ \Rightarrow

$$Q^{-1} \gg \gg \gg \gg \gg \Rightarrow$$

$$\exists P : |P| \neq 0 : Q^{-1} = P'P$$

$$\hat{\beta}_{MLE} = (X'Q^{-1}X)^{-1}X'Q^{-1}Y =$$

$$= (X'P'PX)^{-1}X'P'PY =$$

$$= [(PX)'PX]^{-1}(PX)'PY =$$

$= \hat{\beta}_{OLS}$ THE ΠΑΛΙΝΔΡΟΜΗΣΗ

PY ON PX

$$PY = PX\beta + P\varepsilon \quad \rightarrow \quad \hat{\beta}_{OLS} = \left((PX)'PX \right)^{-1} (PX)'PY$$

$$Y^* = X^*\beta + \varepsilon^*$$

$$\hat{\beta}_{OLS} = \left(X^{*'}X^* \right)^{-1} X^{*'}Y^* \Rightarrow BLUE$$

$$\text{iff } V(\varepsilon^*) = \sigma^2 I_n$$

$$\begin{aligned}
V(\varepsilon^*) &= V(P\varepsilon) = P V(\varepsilon) P' = \\
&= P \sigma^2 Q P' = \sigma^2 P (P'P)^{-1} P' = \\
&= \sigma^2 \underbrace{P P^{-1}}_I \underbrace{(P')^{-1} P'}_I = \sigma^2 I_n.
\end{aligned}$$

$$V(\varepsilon) = \sigma^2 Q \neq \sigma^2 I_n$$

$$\hat{\beta}_{MLE} = (X' Q^{-1} X)^{-1} X' Q^{-1} y = \hat{\beta}_{GLS}$$

GLS = GENERALISED LEAST SQUARES