

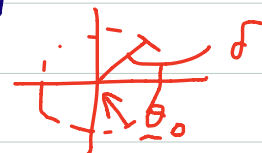
## Maximum likelihood estimators - summary

1. Under weak conditions on  $f(y; \theta)$ , but strong conditions on  $\Theta$  (finite),

$\hat{\theta} \xrightarrow{p} \theta_0$  using Jensen's & WLLN

2. Under more smoothness conditions on  $f(y; \theta)$ , and  $\theta_0 \in \omega \subset \Theta$ ,  $\exists$  local max of  $l(\theta; y)$  in  $\omega$ , & the one closest to  $\theta_0 \xrightarrow{p} \theta_0$

3. This local max is a solution of the score equation  $l'(\theta; y) = 0$ .



Pf.: use TPE ; see also SM  $\S$  123  
 $\theta \in \mathbb{R}$

4. Under more smoothness conditions on  $f(y; \theta)$ , including bdd 3<sup>rd</sup> derivs,

$$\hat{\theta} - \theta_0 = \frac{1}{i_+^{-1}(\theta_0)} U(\theta_0) + o_p(1)$$

## TPE Theorem 6.3.7

$Y_1, \dots, Y_n$  satisfy A0-A3 & a.a.  $y$ ,  
 $\frac{\partial f(y; \theta)}{\partial \theta}$  exists in  $\omega$ . Then w.p.1 as  
 $n \rightarrow \infty$ ,  $\frac{\partial}{\partial \theta} \ell(\theta; y) = 0$

has a sol<sup>n</sup>  $\hat{\theta}_n(y)$  s.t.  $\hat{\theta}_n \rightarrow \theta_0$ .

Pf.  $\exists a$  s.t.  $\theta_0 \pm a \in \omega$ . Define

$$S_n = \left\{ y : \ell(\theta_0; y) > \ell(\theta_0 - a; y) \text{ and} \right. \\ \left. \ell(\theta_0; y) > \ell(\theta_0 + a; y) \right\}$$

use Wald pf. to show  $P_{\theta_0}(S_n) \rightarrow 1$ .

$\therefore$  for any  $y \in S_n$ ,  $\exists \theta_0 - a < \hat{\theta}_n < \theta_0 + a$   
where  $\ell(\cdot)$  has a local max., therefore

$\ell'(\hat{\theta}_n) = 0$ . Hence for any  $a$   
suff'tly small,  $\exists \hat{\theta}_n = \hat{\theta}_n(a)$  s.t.

$$P_{\theta_0} \{ |\hat{\theta}_n(a) - \theta_0| < a \} \rightarrow 1.$$

Let  $\theta_n^*$  be the root closest to  $\theta_0$   
( $\exists$  by continuity of  $\ell(\theta)$ ).

$$\text{Then } P_{\theta_0} \{ |\theta_n^* - \theta_0| < a \} \rightarrow 1.$$

A0-A3: - Dist<sup>s</sup>  $P_\theta$  are distinct

$$f(y; \theta) = f(y; \theta') \text{ iff } \theta = \theta'$$

- Common rt

- $Y_1, \dots, Y_n$  iid  $f(y; \theta_0)$
- $\Theta$  contains open set  $\omega$  &  $\theta_0$  is interior pt. of  $\omega$

Vector:  $\exists \omega \subset \Theta$  (open), w.  $\theta_0 \in \omega$

Define  $\mathcal{Q}_a$  sphere centered at

$\theta_0$ , radius  $a$ . Want to show

$a \rightarrow 1, l(\underline{\theta}) < l(\theta_0) \forall \underline{\theta}$  on surface of  $\mathcal{Q}_a$ .

$$\frac{1}{n} l(\underline{\theta}) - \frac{1}{n} l(\theta_0) = \frac{1}{n} \sum_j (\theta_j - \theta_j^0) l'(\theta_j^0; y) \quad S_1$$

$$+ \frac{1}{2n} \sum_{jk} (\theta_j - \theta_j^0)(\theta_k - \theta_k^0) l_{jk}(\theta_j^0, y) \quad S_2$$

$$+ \frac{1}{6n} \sum_{jkl} (\theta_j - \theta_j^0)(\theta_k - \theta_k^0)(\theta_l - \theta_l^0) l_{jkl}(\theta_j^0, y) \quad S_3$$

$$\frac{1}{n} l'(\underline{\theta}; y) \rightarrow 0 ; \quad \frac{1}{n} l''(\underline{\theta}; y) \rightarrow -I_1(\theta_0)$$

etc.

Check:  $l'(\hat{\theta}) = 0 = \underbrace{l'(\theta)} + (\hat{\theta} - \theta) \underbrace{l''(\theta)} + \underbrace{R_n}$

$\rightarrow \frac{-l'(\theta) - R_n}{l''(\theta)} = (\hat{\theta} - \theta)$

$\rightarrow \frac{\frac{1}{\sqrt{n}}(l'(\theta) + R_n)}{-\frac{1}{n}l''(\theta)} = \sqrt{n}(\hat{\theta} - \theta)$

$\sqrt{n}(\hat{\theta} - \theta) = \frac{\frac{1}{\sqrt{n}}\{u(\theta) + R_n\}}{\frac{i_1(\theta)}{-\frac{1}{n}l''(\theta)}}$

$= \left\{ \frac{\frac{1}{\sqrt{n}}u(\theta)}{\frac{i_1(\theta)}{\sqrt{n}i_1(\theta)}} + \frac{R_n}{\sqrt{n}i_1(\theta)} \right\} (1 + o_p(1))$

$= \frac{\frac{1}{\sqrt{n}}u(\theta)}{\frac{i_1(\theta)}{\sqrt{n}i_1(\theta)}} + \frac{R_n}{\sqrt{n}i_1(\theta)} + \{o_p(1)\}$

$\frac{1}{\sqrt{n}} R_n = \frac{1}{2}(\hat{\theta} - \theta)^2 l'''(\theta_n^*) \frac{1}{\sqrt{n}}$

$= \frac{1}{2} n(\hat{\theta} - \theta)^2 \cdot \frac{\frac{1}{n} l'''(\theta_n^*)}{i_3(\theta)} \cdot i_3(\theta) \frac{1}{\sqrt{n}}$

$= O_p(1) (1 + o_p(1)) O(1) \frac{1}{\sqrt{n}}$

$= \underline{\underline{O_p\left(\frac{1}{\sqrt{n}}\right) = o_p(1)}}$

n+bc

$$\sqrt{n}(\hat{\theta} - \theta) = \boxed{\frac{1}{\sqrt{n}} U(\theta)} + o_p(1) + \left\{ \uparrow \right\} o_p(1)$$

CLT  $\uparrow$   $O_p(1) + o_p(1)$

$$\hat{\theta} - \theta = \frac{U(\theta)}{ni,(\theta)} + o_p(1)$$

$$= \frac{U(\theta)}{i_+(\theta)} + o_p(1)$$

Vector version

$$\underline{\hat{\theta}} - \underline{\theta} = i_+^{-1}(\underline{\theta}) \underline{U}(\underline{\theta}) + o_p(1)$$

$$\underline{l}'(\underline{\hat{\theta}}) = \underline{0} = \underbrace{l'(\underline{\theta})}_{p \times 1} + \underbrace{l''(\underline{\theta})}_{p \times p} (\underline{\hat{\theta}} - \underline{\theta}) + \underbrace{R_n}_{p \times 1}$$

$$\underbrace{i_+^{-1}(\underline{\theta}) \{l''(\underline{\theta})\}}_{1 + o_p(1)} (\underline{\hat{\theta}} - \underline{\theta}) = i_+^{-1}(\underline{\theta}) \underline{U}(\underline{\theta})$$

$$R_n = (\underline{\hat{\theta}} - \underline{\theta})^T \underbrace{l'''(\underline{\theta}_n^*)}_{p \times p \times p} (\underline{\hat{\theta}} - \underline{\theta})$$

$\frac{\partial^3 l(\theta)}{\partial \theta_1 \partial \theta_2 \partial \theta_3}$

$$1 \times p \quad p \times p \times p \quad p \times 1$$

$$(1 \times p \times p) \cdot (p \times 1) \rightarrow p \times p \times p \times 1 = p \times 1$$

Vector version

$$l(\underline{\theta}) = l(\hat{\underline{\theta}}) - (\underline{\theta} - \hat{\underline{\theta}})' l'(\hat{\underline{\theta}}) - \frac{1}{2} (\underline{\theta} - \hat{\underline{\theta}})' l''(\hat{\underline{\theta}}) (\underline{\theta} - \hat{\underline{\theta}})$$

$$- \frac{1}{6} \sum_{r,s,t} (\theta_r - \hat{\theta}_r)(\theta_s - \hat{\theta}_s)(\theta_t - \hat{\theta}_t) \frac{\partial^3 l(\theta)}{\partial \theta_r \partial \theta_s \partial \theta_t} \Big|_{\theta = \hat{\theta}}$$

$$2\{l(\hat{\theta}) - l(\theta)\} = (\hat{\theta} - \theta)' i_+(\theta) (\hat{\theta} - \theta) + o_p(1)$$

$$\xrightarrow{d} \chi^2_1$$

$$\xrightarrow{d} \chi^2_1$$

$$X_n \xrightarrow{d} X \quad a_n \not\rightarrow 0 \Rightarrow X_n + a_n \xrightarrow{d} X$$

etc.

Approximations scalar

$$\sqrt{n} (\hat{\theta} - \theta) i_1^{1/2}(\theta) \xrightarrow{d} N(0, 1)$$

$$(\hat{\theta} - \theta) i_1^{1/2}(\theta) \sim N(0, 1)$$

To this order of approx<sup>n</sup>,

$$(\hat{\theta} - \theta) i_1^{1/2}(\hat{\theta}), (\hat{\theta} - \theta) j^{1/2}(\hat{\theta}), (\hat{\theta} - \theta) j^{1/2}(\theta)$$

$$\text{also } \sim N(0, 1)$$

$$\text{Also } u(\theta) / i_1^{1/2}(\theta) \sim N(0, 1) \text{ and}$$

$$u(\theta) / j^{1/2}(\hat{\theta}), \text{ etc. } \sim N(0, 1)$$

And

$$r(\theta) = \pm \sqrt{2 \{ \ell(\hat{\theta}) - \ell(\theta) \}} \sim N(0, 1)$$

$$Y \sim \text{Bin}(n, \theta) \quad \binom{n}{y} \theta^y (1-\theta)^{n-y}$$

$$\hat{\theta} = \frac{Y}{n}$$

$$l(\theta) = y \ln \theta + (n-y) \ln(1-\theta)$$

$$l'(\theta) = \frac{y}{\theta} - \frac{n-y}{1-\theta}$$

$$l''(\theta) = -\frac{y}{\theta^2} - \frac{(n-y)}{(1-\theta)^2}$$

$$l'(\hat{\theta}) = 0 \quad y(1-\hat{\theta}) - (n-y)\hat{\theta} = 0$$
$$y - y\hat{\theta} - n\hat{\theta} + y\hat{\theta} = 0 \quad \hat{\theta} = \frac{y}{n}$$

$$i(\theta) = E\{-l''(\theta)\} = \frac{n\cancel{\theta}}{\theta^2} + \frac{n(1-\cancel{\theta})}{(1-\theta)^2}$$
$$= \frac{n}{\theta(1-\theta)}$$



$$(\hat{\theta} - \theta) i^{1/2}(\theta) \sim \mathcal{N}(0, 1)$$

$$\left( \frac{y}{n} - \theta \right) \cdot \sqrt{n} \frac{1}{\sqrt{\theta(1-\theta)}} \sim \mathcal{N}(0, 1) \text{ using } i(\theta)$$

$$(\hat{\theta} - \theta) j^{1/2}(\hat{\theta}) \sim \mathcal{N}(0, 1)$$

$$\left( \frac{y}{n} - \theta \right) \cdot \sqrt{n} \frac{1}{\sqrt{\frac{y}{n}(1-\frac{y}{n})}} \sim \mathcal{N}(0, 1) \text{ } j(\hat{\theta})$$

$$\text{CI}_{\alpha} \quad \frac{y}{n} = \hat{p} \pm 1.96 \frac{\hat{p}(1-\hat{p})}{\sqrt{n}} \quad ]$$

CI<sub>1</sub> inverting (\*)

Bichel &  
Doksum

Using vector version  
 $\gamma_1, \dots, \gamma_n$  iid

$$\hat{\theta} - \theta = i^{-1}(\theta) U(\theta) + o_p(1)$$

$$(\hat{\theta} - \theta) \sim N_2(0, i_+^{-1}(\theta)) \quad (\psi, \lambda) \in \mathbb{R} \times \mathbb{R}$$

$$\begin{pmatrix} \hat{\psi} - \psi \\ \hat{\lambda} - \lambda \end{pmatrix} \sim N \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} i^{\psi\psi}(\theta) & i^{\psi\lambda}(\theta) \\ i^{\lambda\psi}(\theta) & i^{\lambda\lambda}(\theta) \end{pmatrix} \right]$$

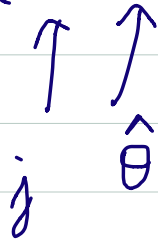
$$1) \quad \hat{\psi} - \psi \sim N(0, i^{\psi\psi}(\theta)) \quad \hat{\beta}_1 \text{ se } \hat{\beta}_1 = z$$

$$\hat{\lambda} - \lambda \sim N(0, i^{\lambda\lambda}(\theta)) \quad \hat{\beta}_2 \text{ se}$$

$$\vdots \quad \vdots \\ \hat{\beta}_j \text{ se}$$

$$(\hat{\psi} - \psi) \{i^{\psi\psi}(\hat{\theta})\}^{-1/2} \sim N(0, 1)$$

$$\hat{\psi} \pm 1.96 \{i^{\psi\psi}(\hat{\theta})\}^{-1/2} \sim 95\% \text{ CI}$$



$$r_e = (\hat{\psi} - \psi) \{j^{\psi\psi}(\hat{\psi}, \hat{\lambda})\}^{-1/2} \sim N(0, 1)$$

$$\begin{bmatrix} i_{\psi\psi}(\theta) & i_{\psi\lambda}(\theta) \\ i_{\lambda\psi}(\theta) & i_{\lambda\lambda}(\theta) \end{bmatrix}^{-1} = \frac{1}{i_{\psi\psi} i_{\lambda\lambda} - i_{\psi\lambda}^2} \begin{bmatrix} i_{\lambda\lambda} & -i_{\psi\lambda} \\ -i_{\lambda\psi} & i_{\psi\psi} \end{bmatrix}$$

$$\begin{matrix} \uparrow \\ E \frac{\partial^2 \ell}{\partial \lambda \partial \psi} \end{matrix} = \begin{bmatrix} i_{\lambda\lambda} & - \\ \dots & - \\ - & - \end{bmatrix}$$

$$\begin{bmatrix} i_{\psi\psi} & i_{\psi\lambda} \\ i_{\lambda\psi} & i_{\lambda\lambda} \end{bmatrix} = \begin{bmatrix} 1 & - \\ i_{\psi\psi} - i_{\psi\lambda}^2 i_{\lambda\lambda} & - \\ - & - \end{bmatrix}$$

In general

$$i_{\psi\psi} = i_{\psi\psi} - i_{\psi\lambda} i_{\lambda\lambda}^{-1} i_{\lambda\psi}$$

$$2) \begin{pmatrix} u_\psi \\ u_\lambda \end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} i_{\psi\psi} & i_{\psi\lambda} \\ i_{\lambda\psi} & i_{\lambda\lambda} \end{pmatrix} \right)$$

$$u_\psi(\psi, \lambda) \{i_{\psi\psi}(\theta)\}^{-\frac{1}{2}} \xrightarrow{d} \mathcal{N}(0, 1)$$

$$\tau_u = u_\psi(\psi, \hat{\lambda}_\psi) \{j_{\psi\psi}(\hat{\psi}, \hat{\lambda})\}^{-\frac{1}{2}}$$

$$3) \quad w(\theta) = 2 \{ \ell(\hat{\theta}) - \ell(\theta) \} \xrightarrow{d} \chi_2^2$$

$$\{ \underline{\theta} : w(\theta) < c_\alpha \} \quad 95\% \text{ c. reg.} \\ \text{for } \underline{\theta}$$

$$1) \quad (\hat{\underline{\theta}} - \underline{\theta})^T i_+(\underline{\theta}) (\hat{\underline{\theta}} - \underline{\theta}) \quad \text{also}$$

$$u(\underline{\theta})^T i_+^{-1}(\underline{\theta}) u(\underline{\theta}) \quad \text{als}$$

Example  $Y_1, \dots, Y_n$  iid  $N(\mu, \sigma^2)$

$$f(y; \underline{\theta}) = \frac{1}{(\sqrt{2\pi}\sigma)^n} e^{-\frac{1}{2\sigma^2} \sum (y_i - \mu)^2}$$

$$l(\mu, \sigma^2) = -\frac{n}{2} \ln \sigma^2 - \frac{1}{2\sigma^2} \sum (y_i - \mu)^2$$

$$l_{\mu} = -\frac{1}{2\sigma^2} 2 \sum (y_i - \mu)(-1)$$

$$= \frac{n\bar{y} - n\mu}{\sigma^2} \quad \hat{\mu} = \bar{y}$$

$$l_{\sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum (y_i - \mu)^2$$

$$0 = -\frac{n\hat{\sigma}^2}{2\hat{\sigma}^4} + \frac{1}{2\hat{\sigma}^4} \sum (y_i - \bar{y})^2$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum (y_i - \bar{y})^2 \quad \begin{array}{l} \text{m.l.e.} \\ \text{not unbiased} \end{array}$$

$$l_{\mu\mu} = -\frac{n}{\sigma^2} \quad l_{\mu\sigma^2} = -\frac{n(\bar{y}-\mu)}{\sigma^4}$$

$$l_{\sigma^2\sigma^2} = \frac{n}{2\sigma^4} - \frac{2}{2\sigma^6} \sum (y_i - \mu)^2$$

$$j(\hat{\theta}) = \begin{bmatrix} \frac{n}{\hat{\sigma}^2} & 0 \\ 0 & \frac{n}{2\hat{\sigma}^4} \end{bmatrix} \quad j(\underline{\theta}) = \begin{bmatrix} \cdot \\ \cdot \end{bmatrix} ?$$

$$i(\theta) = \begin{bmatrix} \frac{n}{\sigma^2} & 0 \\ 0 & \frac{n}{2\sigma^4} \end{bmatrix}$$

$$\begin{pmatrix} \hat{\mu} - \mu \\ \hat{\sigma}^2 - \sigma^2 \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \frac{\sigma^2}{n} & 0 \\ 0 & \frac{2\sigma^4}{n} \end{pmatrix} \right)$$

$\bar{y} \sim N(\mu, \frac{\sigma^2}{n})$  in fact exact

$\hat{\sigma}^2 \sim N(\sigma^2, \frac{2\sigma^4}{n})$  not exact

(exact  $\propto$  to  $\chi_{n-1}^2$ )

$$\underline{l_p(\mu)} = l(\mu, \hat{\sigma}_\mu^2)$$

$$\frac{\partial l}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum (y_i - \mu)^2$$

$$\hat{\sigma}_\mu^2 = \frac{\sum (y_i - \mu)^2}{n} \quad (n+1 \text{ c})$$

↙  
+

$$\sqrt{\{l_p(\hat{\mu}) - l_p(\mu)\}} \sim \mathcal{N}(0, 1)$$

$$l(\mu, \hat{\sigma}_\mu^2) = -\frac{n}{2} \log \hat{\sigma}_\mu^2 - \frac{1}{2\hat{\sigma}_\mu^2} \sum (y_i - \mu)^2$$

$$l_p(\mu) = -\frac{n}{2} \log \left( \frac{\sum (y_i - \mu)^2}{n} \right) - \frac{n}{2}$$

$$= +\frac{n}{2} \log n - \frac{n}{2} \log \sum (y_i - \mu)^2 - \frac{n}{2}$$

$$\hat{\mu} = \bar{y}$$

$$2\{l_p(\hat{\mu}) - l_p(\mu)\}$$

$$= 2\left\{\frac{n}{2} \log \sum (y_i - \mu)^2 - \frac{n}{2} \log \sum (y_i - \bar{y})^2\right\}$$

$$= n \log \hat{\sigma}_\mu^2 - n \log \hat{\sigma}^2$$

$$= n \log \left( \frac{\hat{\sigma}_\mu^2}{\hat{\sigma}^2} \right) = n \log \left( \frac{\hat{\sigma}_\mu}{\hat{\sigma}} \right)^2$$

$$= 2n \log(\hat{\sigma}_\mu / \hat{\sigma})$$

$$\pm \sqrt{2\{l_p(\hat{\mu}) - l_p(\mu)\}} = \pm \sqrt{2n \log(\hat{\sigma}_\mu / \hat{\sigma})}$$

$$\hat{\sigma}_\mu^2 = \frac{1}{n} \sum (y_i - \mu)^2$$

$$= \frac{1}{n} \left\{ \sum (y_i - \bar{y})^2 + n(\bar{y} - \mu)^2 \right\}$$

$$= \hat{\sigma}^2 + (\bar{y} - \mu)^2$$



$$\frac{\hat{\sigma}_\mu^2}{\hat{\sigma}^2} = 1 + \frac{(\bar{y} - \mu)^2}{\hat{\sigma}^2} = 1 + \frac{(\bar{y} - \mu)^2}{s^2/n} \cdot \left(\frac{s^2/n}{\hat{\sigma}^2}\right)$$

$$= 1 + T^2 \cdot \left(\frac{n-1}{n}\right) \cdot \left(\frac{n}{n-1}\right)$$

↑