

Model  $Y_1, \dots, Y_n$  i.i.d.  $f(y; \theta)$   $\theta \in \mathbb{R}^p$

Likelihood  $L(\theta; y) = L(\theta; y_1, \dots, y_n)$

$$= \prod_{i=1}^n f(y_i; \theta)$$

Log-likelihood  $l(\theta; y) = \sum l(\theta; y_i)$

$$= \sum_{i=1}^n \log f(y_i; \theta)$$

Maximum likelihood estimate  $\hat{\theta} = \arg \sup_{\theta} l(\theta)$

Score function  $l'(\theta) = l'(\theta; y) = \frac{\partial l(\theta; y)}{\partial \theta}$   $p \times 1$  vector

- if  $l(\theta)$  is smooth, 'well-behaved', then  $\hat{\theta}$  is found by

$$l'(\hat{\theta}) = 0 \quad \hat{\theta} = \hat{\theta}(y)$$

- this is usually a nonlinear equation

- observed information function

$$j(\theta) = -l''(\theta; y)$$

- expected information function

$$i(\theta) \quad p \times p \text{ matrix} \\ = E j(\theta)$$

Example  $Y_i \sim \text{Gamma}(\beta, \mu)$

$$f(y_i; \beta, \mu) = \frac{1}{\Gamma(\beta) \left(\frac{\beta}{\mu}\right)^\beta} y_i^{\beta-1} e^{-y_i \beta / \mu}$$

$$l(\beta, \mu; y) =$$

$$\frac{\partial l}{\partial \beta} =$$

$$\frac{\partial l}{\partial \mu} =$$

Inference based on the likelihood function

$$\frac{1}{\sqrt{n}} \ell'(\theta; y) \xrightarrow{d} N(0, \dot{\ell}(\theta)) \quad \dot{\ell}(\theta) = \frac{\dot{\ell}(\theta)}{n}$$

leading to 3 approximations:

$$\ell'(\theta) \{ \dot{\ell}(\tilde{\theta}) \}^{-1/2} \sim N(0, I)$$

$$(\hat{\theta} - \theta) \{ \dot{\ell}(\tilde{\theta}) \}^{+1/2} \sim N(0, I)$$

$$2 \{ \ell(\tilde{\theta}) - \ell(\theta) \} \sim \chi^2_p$$

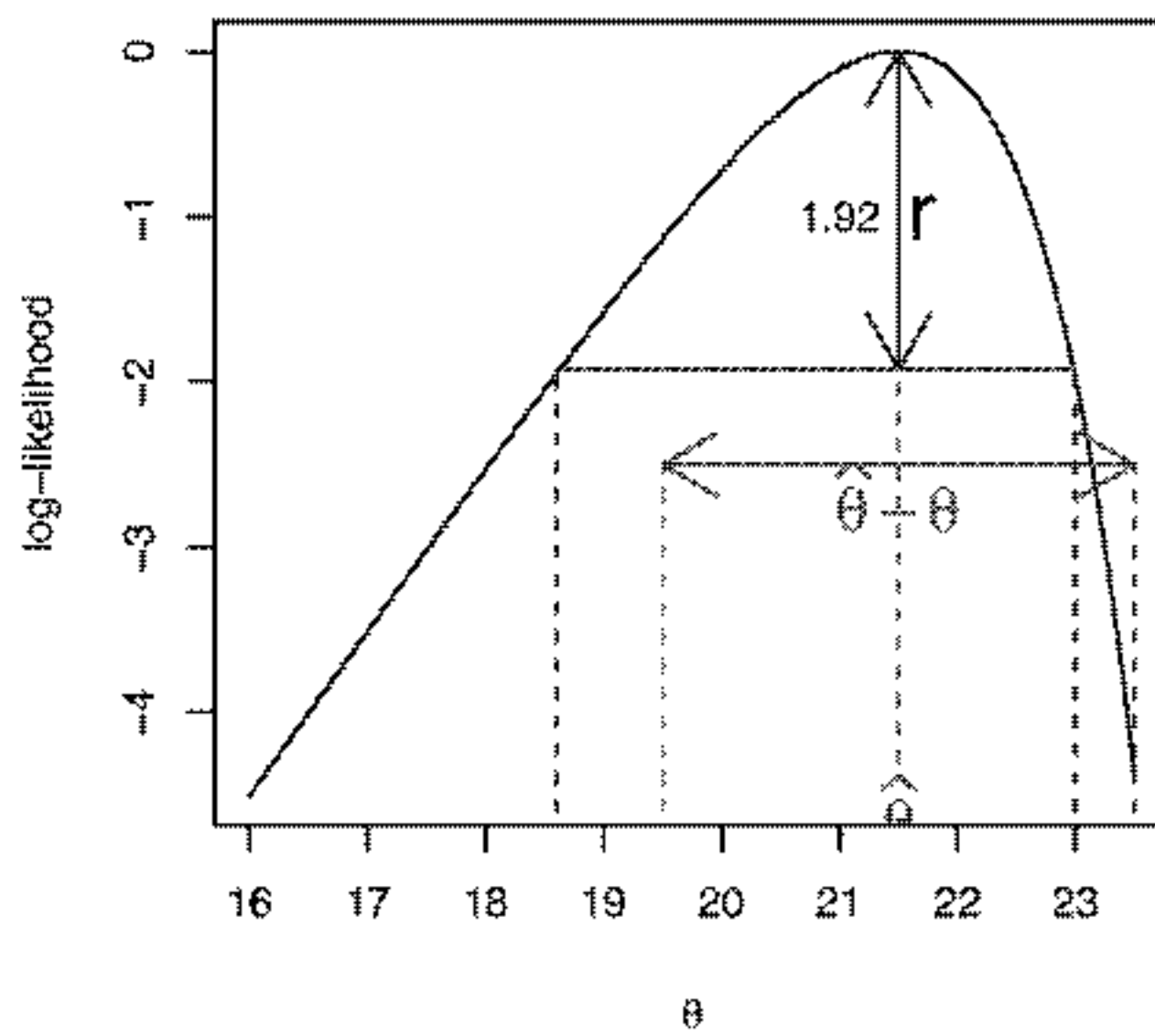
Special Case:  $p = 1$

Outline	Asymptotics and approximations	<b>Likelihood inference</b>	Continuous responses	Some theory	Summary
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## Likelihood inference

Parametric model:  $f(y; \theta)$  e.g.  $\exp\{-(y - \theta) - e^{-(y - \theta)}\}$

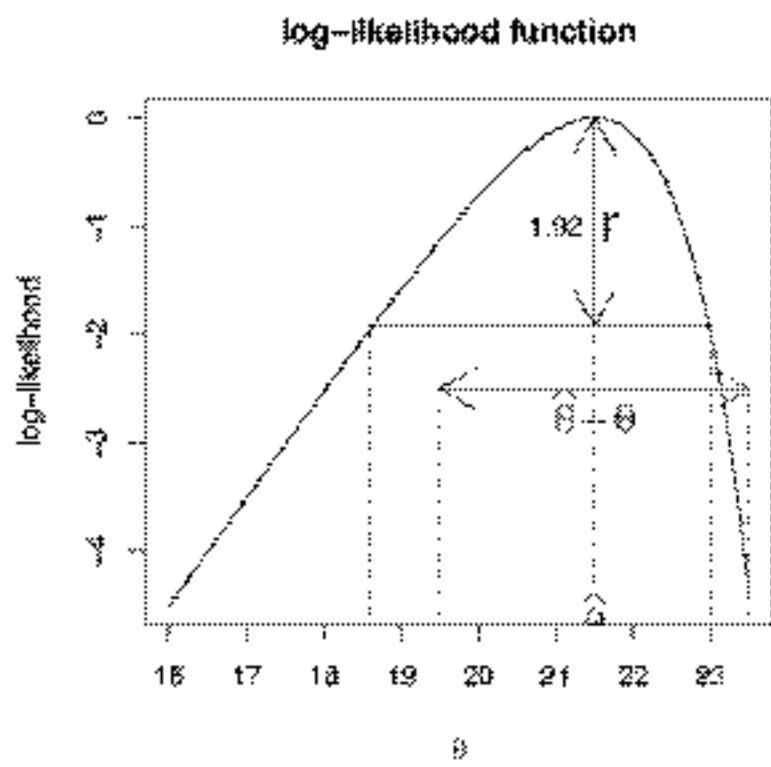
log-likelihood function



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## Likelihood inference

$$\ell(\theta; y) = \log f(y; \theta) \quad j(\hat{\theta}) = -\ell''(\hat{\theta})$$



standardized maximum likelihood est.:  $q(\theta) = (\hat{\theta} - \theta)\{j(\hat{\theta})\}^{1/2}$

likelihood root:  $r(\theta) = \sqrt{2\{\ell(\hat{\theta}) - \ell(\theta)\}}$

standardized score function:  $s(\theta) = \ell'(\theta)\{j(\hat{\theta})\}^{-1/2}$   
 $\xrightarrow{d} N(0, 1)$

If  $\theta = \theta_0$ ,  $\hat{\theta} - \theta_0 \sim N(0, j(\hat{\theta})^{-1})$

$$\frac{\hat{\theta} - \theta_0}{\sqrt{j(\hat{\theta}_0)^{-1}}} \sim N(0, 1)$$

p-value

$$\text{If } \theta = \theta_0 \quad 2 \{ \ell(\hat{\theta}) - \ell(\theta_0) \} \sim \chi_{p-1}^2$$

$$\text{OR } \hat{\theta} \pm z^{\alpha/2} \{ j(\hat{\theta}) \}^{-1/2}$$

is a  $1-\alpha$  CI for  $\theta$

$$\text{OR } \{ \theta : 2 \{ \ell(\hat{\theta}) - \ell(\theta) \} \leq 3.84 \}$$

is a 95% CI for  $\theta$

What about  $p > 1$ ?

$$\hat{\theta} - \theta \sim N_p(0, j^{-1}(\hat{\theta}))$$

- diagonal elements of  $j^{-1}(\hat{\theta})$  estimate  
asy. variance of components of  $\theta$

$$\hat{\theta}_5 \pm 1.96 \times \text{s.e.}(\hat{\theta}_5) \sim 95\% \text{ CI}$$

- this uses normal approx<sup>n</sup> to dist<sup>n</sup> of  $\hat{\theta}$

What is the likelihood ratio version of this?

$$\hat{\theta} = \text{MLE} = \underset{\theta}{\text{arg sup}} l(\theta; y)$$

$$\hat{\hat{\theta}} = \text{constrained MLE} = \underset{\theta \in \Theta_0}{\text{arg sup}} l(\theta; y)$$

1) e.g.  $\frac{1}{\Gamma(\beta)} \left(\frac{\beta}{\mu}\right)^{\beta} y_i^{\beta-1} e^{-\beta y_i/\mu}$

$$\theta = (\beta, \mu) \quad \hat{\theta} = (\hat{\beta}, \hat{\mu})$$

- want to test  $\beta = 1$   $\hat{\hat{\theta}} = (1, \hat{\mu})$

or  $\beta = \beta_0$   $\hat{\hat{\theta}} = (\beta_0, \hat{\mu})$

2) e.g.  $\theta = (\psi, \lambda)$ , want inference on  $\psi$

$$\hat{\hat{\theta}} = (\psi, \hat{\lambda}_{\psi}) \quad \text{constrained MLE}$$

$$2 \{ l(\hat{\psi}, \hat{\lambda}) - l(\psi, \hat{\lambda}_{\psi}) \} \xrightarrow{d} \chi^2_{\dim \psi}$$