

Stat 543

4-15-05

Recall :  $\delta_n(X)$  an "MLE"

$$\sqrt{n} (\delta_n(X) - \theta_0) \xrightarrow{L_{\theta_0}} N\left(0, \frac{1}{I_1(\theta_0)}\right)$$

$\Rightarrow$  (unusable) confidence limits for  $\theta$

$$\delta_n(X) \pm z \frac{1}{\sqrt{n I_1(\theta)}}$$

☹  $I(\theta)$  usually depends on  $\theta$

?? how to modify / extend this to provide something that's usable?

Corollary 7 of handout under appropriate  
regularity conditions ( $\delta_n(x)$  as before)

$$\sqrt{I_1(\delta_n(x))} \sqrt{n} (\delta_n(x) - \theta_0) \xrightarrow{L_{\theta_0}} N(0,1)$$

Why? above is

$$\left( \sqrt{\frac{I_1(\delta_n(x))}{I_1(\theta_0)}} \right) \left( \sqrt{n I_1(\theta_0)} (\delta_n(x) - \theta_0) \right)$$

$P_{\theta_0}$   
provided  $I_1(\cdot)$   
is cont<sup>s</sup>

$$\xrightarrow{L_{\theta_0}} N(0,1)$$

so the product  
converges in  
d<sub>sn</sub> to  $N(0,1)$

Example  $X_1, X_2, \dots, X_n$  iid Bernoulli  $p$

$$I_1(p) = \frac{1}{p(1-p)}$$

so replacing unusable confidence limits

$$\hat{p} \pm z \sqrt{\frac{1}{n I_1(p)}} \quad \text{i.e.} \quad \hat{p} \pm z \sqrt{\frac{p(1-p)}{n}}$$

by 
$$\hat{p} \pm z \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

This route to "fixing" the unusable confidence limits is sometimes called using the "Expected Fisher information"

A second route is to make use of the "sample Fisher information" — note that

$$I(\theta_0) = nI_1(\theta_0) = n \left( E_{\theta_0} \left[ -\frac{d^2}{d\theta^2} \log f(X, \theta) \right] \right) \Bigg|_{\theta = \theta_0}$$

a mean that can perhaps be approximated by a sample average

$$\frac{1}{n} l''_n(\theta_0) = \frac{1}{n} \sum_{i=1}^n \frac{d^2}{d\theta^2} \log f(X_i | \theta) \Bigg|_{\theta = \theta_0}$$

So by WLLN  $\frac{1}{n} l''_n(\theta_0) \xrightarrow{P_{\theta_0}} -I(\theta_0)$

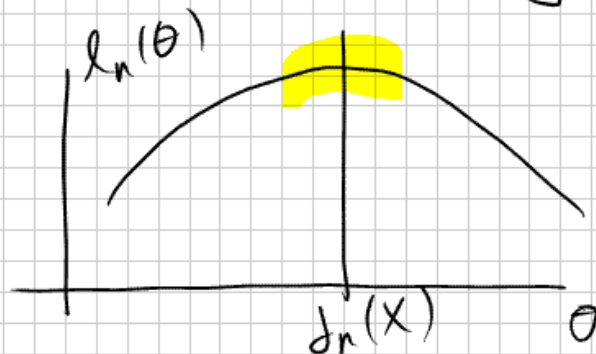
and if things are nice  $\frac{1}{n} l''_n(\theta_0) = \frac{1}{n} l''_n(\delta_n(X))$

goes to 0 in  $\theta_0$  probability ... and hopefully  
this makes plausible

Corollary 8 on handout under appropriate conditions

$$\sqrt{-l_n''(\delta_n(x))} (\delta_n(x) - \theta_0) \xrightarrow{L_{\theta_0}} N(0,1)$$

(I've replaced the FI evaluated at  $\delta_n(x)$   
with minus the curvature of loglikelihood evaluated  
at  $\delta_n(x)$ )



And this leads to confidence limits for  $\theta$

$$\hat{\theta}_n(x) \pm z \frac{1}{\sqrt{-l_n''(\hat{\theta}_n(x))}}$$

(this is called use of the "observed FI")

Example iid Bernoulli

$$l_n(p) = \sum X_i \ln p + (n - \sum X_i) \ln(1-p)$$

$$l_n'(p) = \frac{\sum X_i}{p} - \frac{n - \sum X_i}{1-p}$$

$$l_n''(p) = -\frac{\sum X_i}{p^2} - \frac{n - \sum X_i}{(1-p)^2}$$

$$\begin{aligned}
 \ell_n''(\hat{p}) &= -\frac{\sum X_0}{\left(\frac{\sum X_0}{n}\right)^2} - \frac{n - \sum X_0}{\left(\frac{n - \sum X_0}{n}\right)^2} \\
 &= -n \left( \frac{1}{\hat{p}} + \frac{1}{1 - \hat{p}} \right) \\
 &= \frac{-n}{\hat{p}(1 - \hat{p})}
 \end{aligned}$$

So we get approximate confidence limits

$$\hat{p} \pm z \frac{1}{\sqrt{-\ell_n''(\hat{p})}}$$

i.e.

$$\hat{p} \pm z \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}$$

!!! I get the same interval as when I used "Expected FI" — That always happens in exponential families — in other cases there can be a difference ... when there is the 2nd of these (according to folklore) does a better job of holding nominal coverage levels (for moderate  $n$ ) than the 1st —

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These results (Corollary 7+8) cover estimation of a one dimensional parameter ... what if  $\theta$  is  $k \times 1$  and I wish to do confidence set estimation of all or part of  $\theta$  — I can use the approximate MVN  $\hat{\theta}$  of an "MLE" —

How? Use a Stat 542 dsu fact

$$Y \sim N_k(\mu, \Sigma)$$

$$\Downarrow (Y - \mu)' \Sigma^{-1} (Y - \mu) \sim \chi_k^2$$

How? if  $c$  is the upper  $\alpha$  pt of  $\chi_k^2$  dsu

$$P[(Y - \mu)' \Sigma^{-1} (Y - \mu) < c] = 1 - \alpha$$

and  $\therefore$  if  $Y = y$

$$\left\{ \mu \in \mathbb{R}^k \mid (y - \mu)' \Sigma^{-1} (y - \mu) < c \right\}$$

is a  $(1 - \alpha) \times 100\%$  confidence set for  $\mu$