

Stat 543

4-8-05

Example Stat 101 "Fact"

For  $\hat{p}_n$  = a sample fraction of "type A" items from a large dichotomous population

$$Z = \frac{\hat{p}_n - p}{\sqrt{\frac{\hat{p}_n(1-\hat{p}_n)}{n}}} \quad \text{is "approximately std normal"}$$

So approximate confidence limits for  $p$  are

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

How / Why?

Define

$$Y_i = \begin{cases} 1 & \text{if the } i\text{th sampled object is of type A} \\ 0 & \text{otherwise} \end{cases}$$

$Y_i \sim \text{Bernoulli}(p)$  population fraction of type A  
and "if the population

is large in comparison to sample then these are  
'approximately independent' "

$$X_n = \sum_{i=1}^n Y_i \quad (\text{This is } \text{Bi}(n, p))$$

$$\hat{p}_n = \frac{X_n}{n} = \bar{Y}_n$$

CLT says for  $p \in (0, 1)$

$$\sqrt{n} (\bar{Y}_n - p) = \sqrt{n} (\hat{p}_n - p) \xrightarrow{\mathcal{L}_P} N(0, \text{Var } Y_i)$$

$p(1-p)$

Since  $\hat{p}_n = \bar{Y}_n \xrightarrow{P} EY_1 = p$  (Weak law of large numbers)

I'll be able to "replace  $p(1-p)$  with  $\hat{p}_n(1-\hat{p}_n)$ ". . .

$$\begin{pmatrix} \sqrt{n}(\hat{p}_n - p) \\ \hat{p}_n \end{pmatrix} \xrightarrow{L_p} \begin{pmatrix} N(0, p(1-p)) \\ p \end{pmatrix}$$

$g(u, v) = \frac{u}{\sqrt{v(1-v)}}$  is cont<sup>s</sup> except where

$v=0$  or  $v=1$  so as long as  $p \in (0, 1)$

$$g(\sqrt{n}(\hat{p}_n - p), \hat{p}_n) \xrightarrow{L_p} g(N(0, p(1-p)), p)$$

That is

$$\frac{\sqrt{n}(\hat{p}_n - p)}{\sqrt{\hat{p}_n(1-\hat{p}_n)}} \xrightarrow{L_p} N(0,1)$$

The most important large sample theory for inference at this level concerns ML and the behavior of LRT statistics — regarding the 1st

- Thm 5.2.2 "Often" MLE's are
- 1) consistent
  - 2) approximately normal with variance at the approximate dsu  $I^{-1}(\theta)$
- for exponential families

Def A sequence of estimators  $\{\delta_n\}$  of  $\theta$  is **consistent** (weakly consistent / consistent in probability) at  $\theta_0 \in \Theta$  provided

$$\delta_n \xrightarrow{P_{\theta_0}} \theta_0$$

Aside:

Recall an earlier comment about MoM estimation... in an iid model

Provided  $E|X_1|^r < \infty$

$$\frac{1}{n} \sum_{i=1}^n X_i^s = \hat{\mu}_{sn} \xrightarrow{P_{\theta}} \mu_s(\theta) = E_{\theta} X_1^s \quad \forall s \leq r$$

(by WLLN)

Then if  $h(\cdot, \dots, \cdot)$  is cont<sup>s</sup> at  $(\mu_1(\theta), \mu_2(\theta), \dots, \mu_r(\theta))$

and

$$J_n = h(\hat{\mu}_{1n}, \hat{\mu}_{2n}, \dots, \hat{\mu}_{rn})$$

is consistent for  $J(\theta) = h(\mu_1(\theta), \dots, \mu_r(\theta))$

i.e. MOM estimators are typically consistent

Thy for "MLE's" — In class IID theory  
(mostly for  $\Theta \subset \mathbb{R}^1$ ) — handout is somewhat more  
general + B+D results are for multi-dimensional  $\eta$   
exponential families (iid)

Suppose  $X_1, X_2, \dots$  are iid with pdf or pmf  $f(x|\theta)$

Let

$$l_n(\theta) = \sum_{i=1}^n \ln f(X_i | \theta)$$

be the  $n$ th likelihood - what can be said in general?

Thm 1 (handout) If  $\Theta \subset \mathbb{R}^1$  under appropriate regularity conditions if  $\epsilon > 0$

$$P_{\theta_0} \left[ \begin{array}{l} \text{The equation } l'_n(\theta) = 0 \\ \text{has a root within } \epsilon \\ \text{of } \theta_0 \end{array} \right] \rightarrow 1$$

(The  $\theta_0$  probability that the score function has a 0 close to  $\theta_0$  goes to 1)

Corollary 2 (on handout)