

Stat 543

2-4-05

"the" method of moments

last time:

$$\gamma(\theta) = h(\mu_1(\theta), \dots, \mu_r(\theta))$$

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

another view: where I can write

$$\mu_1(\theta) = h_1^*(\theta)$$

$$\mu_2(\theta) = h_2^*(\theta)$$

⋮

$$\mu_r(\theta) = h_r^*(\theta)$$

I could define a method of moments estimator of  $\theta$  to be a solution to

$$(h_1^*(\theta), h_2^*(\theta), \dots, h_r^*(\theta)) = (\hat{\mu}_{1n}, \hat{\mu}_{2n}, \dots, \hat{\mu}_{rn})$$

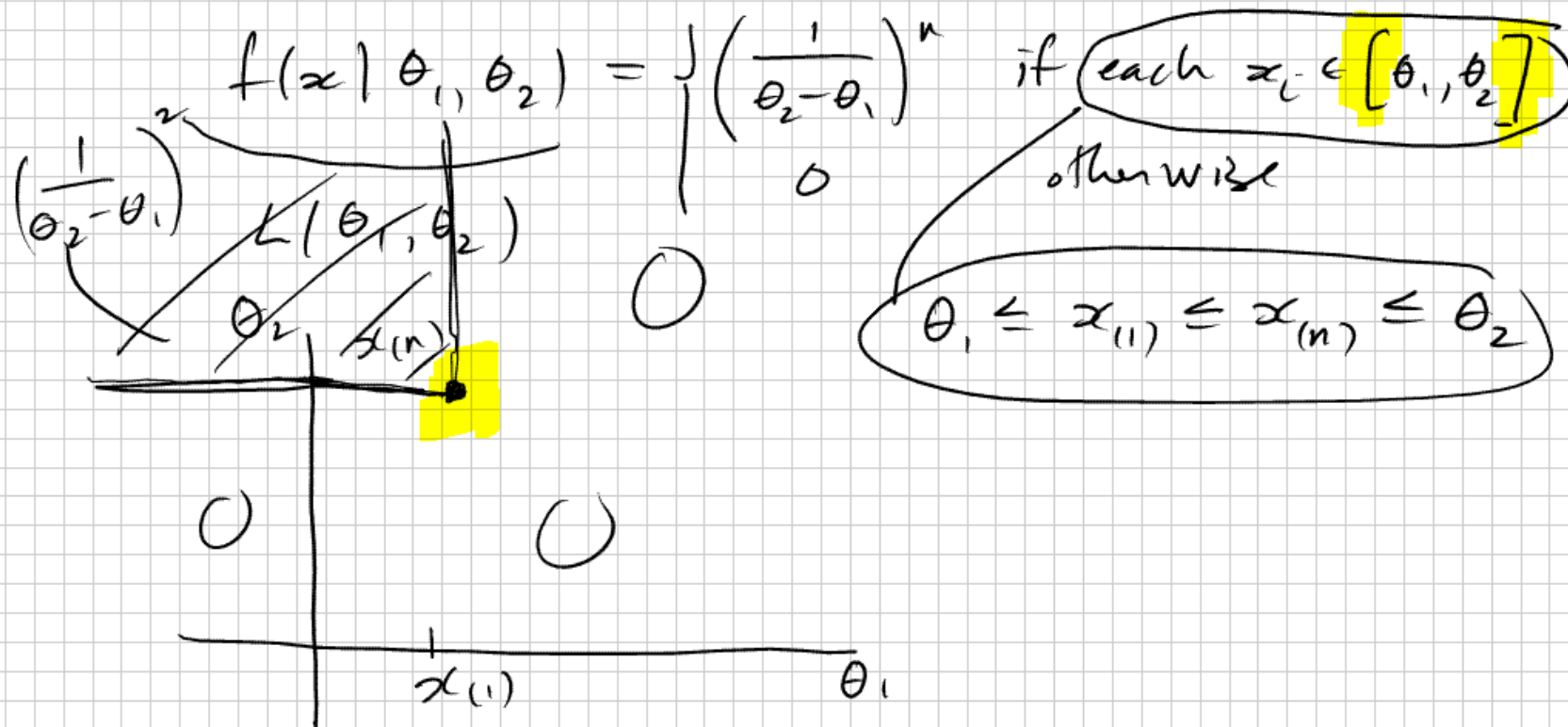
(this version is what we used in the truncated Poisson example)

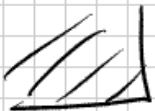
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Def If  $\hat{\theta}$  is a value of  $\theta$  maximizing  $L(\theta)$  then we will call  $\hat{\theta}$  a maximum likelihood estimate of  $\theta$

Example  $X_1, \dots, X_n$  iid  $U(\theta_1, \theta_2)$

$X = (X_1, \dots, X_n)$  with jt pdf



on   $L(\theta_1, \theta_2)$  increases in  $\theta_1$  up to  $x_{(1)}$  and increases in  $\theta_2$  down to  $x_{(n)}$  — so the MLE of  $(\theta_1, \theta_2)$  is  $(x_{(1)}, x_{(n)})$

Example  $X_1, X_2, \dots, X_n$  iid Poisson( $\lambda$ )

$$L(\lambda) = f(x|\lambda) = \prod_{i=1}^n \frac{e^{-\lambda} \lambda^{x_i}}{x_i!} \quad \text{on } \{0, 1, 2, \dots\}^n$$

$$\text{So } \log L(\lambda) = -n\lambda + (\sum x_i) \log \lambda - \sum \log x_i!$$

If  $\sum x_i = 0$  this is maximized by  $\lambda = 0$   
i.e. a maximum likelihood estimate is 0

If  $\sum x_i \geq 1$

$$\frac{d}{d\lambda} \log L(\lambda) = -n + \frac{\sum x_i}{\lambda} = 0$$

implies  $\lambda = \frac{\sum x_i}{n}$

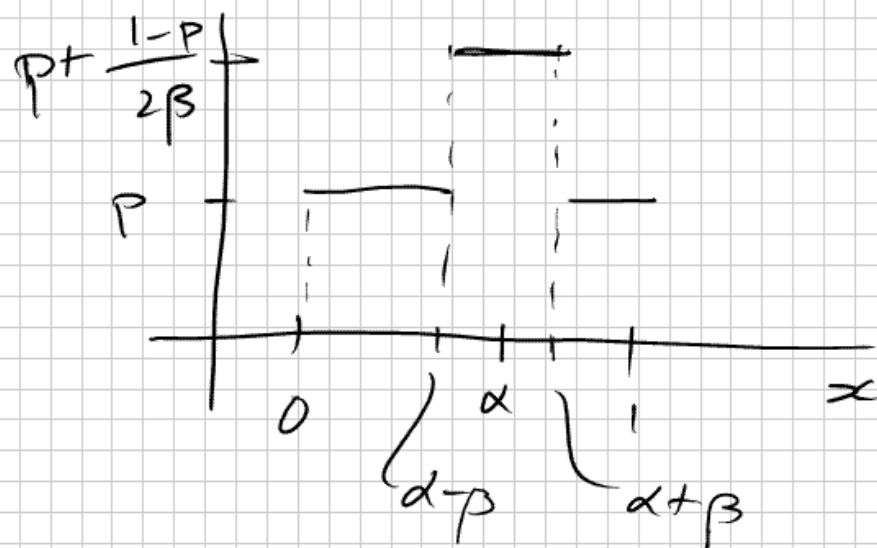
i.e.  $\bar{X}$  is the MLE of the Poisson mean  $\lambda$  — (I really should check that  $\bar{X}$  is a maximizer and not just a place where  $L(\lambda) = 0$ ) —

note that  $\frac{d}{d\lambda} \log L(\lambda) < 0$  if  $\lambda > \bar{x}$   
 $> 0$  if  $\lambda < \bar{x}$

For a given model and observation  
 There need not be a maximizer of  $f(x|\theta)$   
 ... and if there is one there is nothing  
 that guarantees uniqueness — in the  
 case that  $f(x|\theta)$  is a density the  
 likelihood can be unbounded — even when  
 it is bounded the sup of  $L(\theta)$  may not  
 be attained

Example  $X_1, X_2, \dots, X_n$  iid with marginal  
 pdf

$$f(x|p, \alpha, \beta) = p \mathbb{I}[0 \leq x \leq 1] + \frac{1-p}{2\beta} \mathbb{I}[\alpha - \beta \leq x \leq \alpha + \beta]$$



with probability 1 (for any  $p, \alpha, \beta$ )

$$0 < x_{(1)} \leq x_{(n)} < 1$$

and for example with  $\alpha = x_{(1)}$  and  $\beta < \min(x_{(1)}, x_{(2)} - x_{(1)})$  and  $p > 0$

The likelihood (jt density of  $n$  observations)

is

$$L(p, \alpha, \beta) = p^{n-1} \left( p + \frac{1-p}{2\beta} \right) \quad \text{as } \beta \rightarrow 0$$

$\uparrow$   
 $x_{(1)}$

So there really is no MLE here ... ☹️

— a "fix" to this might be to replace densities with pmf's admitting that observations are really only good to some number of decimal places ...

unfortunately, even if  $\mathbb{I}$  "fix" the problem of potential unboundedness there is still no guarantee that  $L(\theta)$  can be maximized

Example  $X_1, \dots, X_n$  iid  $N(\mu, \sigma^2)$

$Y_i = X_i$  rounded to the nearest integer

Suppose all  $y_i = 13$