

MoM examples

Ex.  $X_n \stackrel{iid}{\sim} U(0, \theta)$

Get MoM estimator:

$$E[X_n] = \mu_1 = m_1 = \frac{1}{N} \sum_{n=1}^N X_n = \bar{X}$$

$$E[X_n] = \frac{\theta + 0}{2} = \theta/2$$

Sys. of eqn.  $\frac{\theta}{2} = \bar{X}$

Solve for  $\theta$ :  $\hat{\theta}_{\text{MoM}} = 2\bar{X}$

Ex.  $X_n \stackrel{iid}{\sim} \text{Beta}(\alpha, 1)$

①  $\mu_1 = EX_n = \frac{\alpha}{\alpha+1}$

②  $m_1 = \bar{X}$

③  $\frac{\alpha}{\alpha+1} = \bar{X} \Rightarrow \alpha = \alpha\bar{X} + \bar{X}$

$$\Rightarrow \alpha - \alpha\bar{X} = \bar{X}$$

$$\Rightarrow \alpha(1 - \bar{X}) = \bar{X}$$

$$\Rightarrow \hat{\alpha} = \frac{\bar{X}}{1 - \bar{X}}$$

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## Maximum Likelihood Estimation (MLE)

If  $X_n \stackrel{iid}{\sim} f_\theta$  and  $\theta \in \Theta$

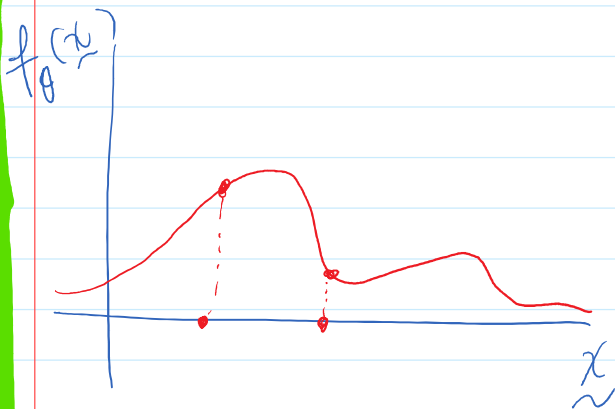
Recall: joint dist of my data

$$f_\theta(\underline{x}) = \prod_{n=1}^N f_\theta(x_n)$$

Typ. we think of this as a fn of  $\underline{x}$

Way 1:

$$f_\theta: \mathbb{R}^N \rightarrow \mathbb{R}$$

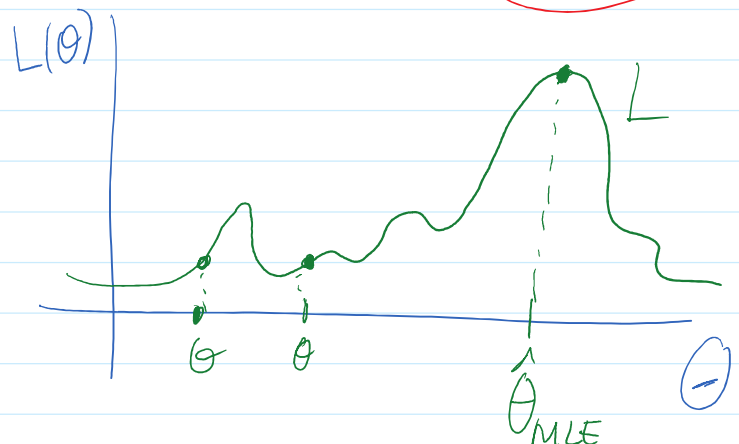


$$L: \Theta \rightarrow \mathbb{R}$$

Way 2:

think of as a fn of  $\theta$   
call it: the likelihood fn

$$L(\theta) = f_\theta(\underline{x})$$



Often it is useful to work with the

Often it is useful to work with the log-likelihood function

$$\ell(\theta) = \log L(\theta)$$

Defn: Maximum Likelihood Estimator (MLE)

Idea: want to estimate  $\theta$  as value  $\hat{\theta}$  with the largest likelihood

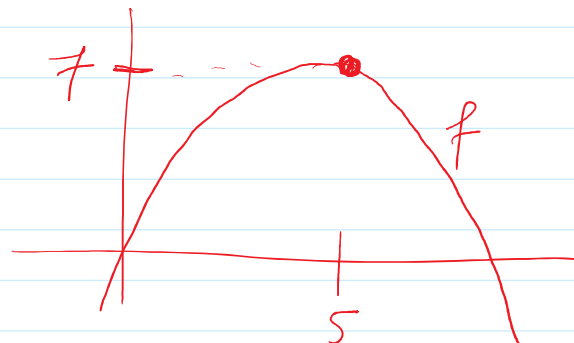
$$\hat{\theta}_{MLE} = \arg \max_{\theta \in \Theta} L(\theta)$$

the value of  $\theta$  that makes  $L(\theta)$  as large as possible.

Ex.

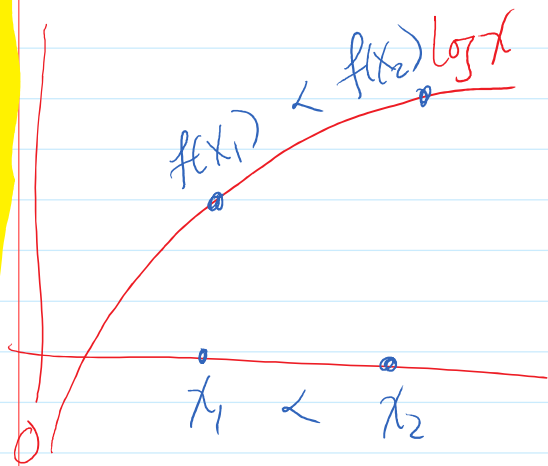
$$\max_x f(x) = 7$$

$$\arg \max_x f(x) = 5$$



Alt. defn

$$\hat{\theta}_{MLE} = \underset{\theta \in \Theta}{\operatorname{argmax}} \ell(\theta) = \underset{\theta \in \Theta}{\operatorname{argmax}} L(\theta)$$



equivalent  
b/c  $\log$  is increasing

$$x_1 < x_2 \text{ then } \log(x_1) < \log(x_2)$$

Ex.  $X_n \stackrel{\text{iid}}{\sim} N(\theta, 1)$  where  $\theta \in \mathbb{R}$

What's the MLE of  $\theta$ ?

① Find  $\ell(\theta)$

$$\begin{aligned} L(\theta) &= f_{\theta}(\underline{x}) = \prod_{n=1}^N f_{\theta}(x_n) = \prod_{n=1}^N \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(x_n - \theta)^2\right) \\ &= (2\pi)^{-N/2} \exp\left(-\frac{1}{2} \sum_{n=1}^N (x_n - \theta)^2\right) \end{aligned}$$

$$\begin{aligned} \ell(\theta) &= \log L(\theta) = \log((2\pi)^{-N/2}) - \frac{1}{2} \sum_{n=1}^N (x_n - \theta)^2 \\ &= -\frac{N}{2} \log(2\pi) - \frac{1}{2} \sum_{n=1}^N (x_n - \theta)^2 \end{aligned}$$

$$= -\frac{N}{2} \log(2\pi) - \frac{1}{2} \sum_{n=1}^N (\chi_n - \theta)$$

② take a derivative

$$\begin{aligned} \frac{\partial \ell}{\partial \theta} &= -\frac{1}{2} \sum_{n=1}^N 2(\chi_n - \theta)(-1) = \sum_{n=1}^N (\chi_n - \theta) \\ &= \sum_{n=1}^N \chi_n - N\theta \end{aligned}$$

critical pts where  $\frac{\partial \ell}{\partial \theta} = 0$

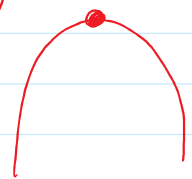
$$\text{so } \sum_{n=1}^N \chi_n - N\theta = 0 \Rightarrow \boxed{\hat{\theta}_{MLE} = \bar{X}}$$

Technically: Need to check  $\frac{\partial^2 \ell}{\partial \theta^2} < 0$

and need to check

$$\lim_{\theta \rightarrow \pm\infty} L(\theta) = 0$$

$-N$



Theorem: MLEs are based on Suff. Stats.

$$\hat{\theta}_{MLE} = \text{function}(T)$$

$\uparrow$  s.s. for  $\theta$ .

Pf. Factorization theorem

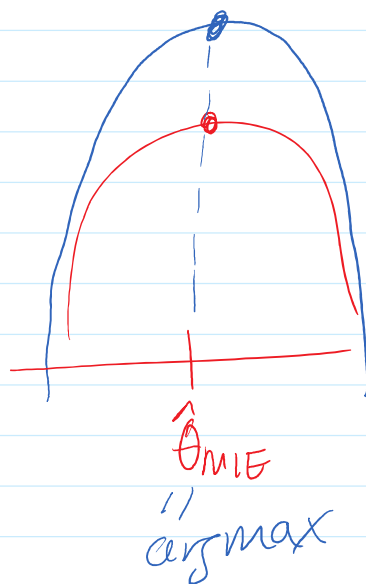
pf. Factorization theorem

$$L(\theta) = f_{\theta}(x) = \underline{h(x)g(\theta, t)}$$

$$\hat{\theta}_{MLE} = \arg \max_{\theta} L(\theta)$$

$$= \arg \max_{\theta} h(x)g(\theta, t)$$

$$= \arg \max_{\theta} g(\theta, t)$$



ex. let  $X_n \stackrel{iid}{\sim} \text{Bern}(p)$  ,  $p \in [0, 1]$

what is  $\hat{p}_{MLE}$ ?

① Write  $L(p)$  and/or  $l(p)$

$$L(p) = \prod_n f_p(x_n)$$

$$= \prod_n p^{x_n} (1-p)^{1-x_n} \mathbb{1}(x_n=0,1)$$

$$= p^{\sum x_n} (1-p)^{N-\sum x_n} \prod_n \mathbb{1}(x_n=0,1)$$

$$f_p(x) = p^x (1-p)^{1-x} \mathbb{1}(x=0,1)$$

$$l(p) = \log L(p) = (\sum_n x_n) \log(p) + (N - \sum_n x_n) \log(1-p)$$

$$\ell(p) = \log L(p) = \left(\sum_n x_n\right) \log(p) + (N - \sum_n x_n) \log(1-p) \\ + \log\left(\prod_n \mathbb{1}(x_n = 0, 1)\right)$$

② <sup>set</sup> derivative to zero

$$\frac{\partial \ell}{\partial p} = \left(\sum_n x_n\right) \frac{1}{p} + (N - \sum_n x_n) \frac{-1}{1-p} = 0$$

$$\Rightarrow \left(\sum_n x_n\right)(1-p) - (N - \sum_n x_n)p = 0$$

$$\Rightarrow \underbrace{\left(\sum_n x_n\right)}_{N\bar{x}} - p \cancel{\left(\sum_n x_n\right)} - Np + p \cancel{\left(\sum_n x_n\right)} = 0$$

$$\Rightarrow N\bar{x} - Np = 0$$

$$\boxed{\hat{p} = \bar{x}}$$

Continue ex

$$\eta = \frac{p}{1-p}$$

← odds

$$\rightarrow \eta(1-p) = p$$

$$\Rightarrow \eta - \eta p = p$$

$$\Rightarrow \eta - \eta p = p$$

$$\Rightarrow \eta = (1 + \eta) p$$

$$\Rightarrow \boxed{p = \eta / (1 + \eta)}$$

① Likelihood

$$L(p) = p^{N\bar{X}} (1-p)^{N-N\bar{X}}$$

$$\boxed{L(\eta) = \left(\eta / (1 + \eta)\right)^{N\bar{X}} \left(1 - \eta / (1 + \eta)\right)^{N-N\bar{X}}}$$

$$\ell(\eta) = N\bar{X} \log(\eta / (1 + \eta)) + (N - N\bar{X}) \log(1 - \eta / (1 + \eta))$$

recall:  $\log(a/b) = \log a - \log b$

$$= N\bar{X} [\log \eta - \log(1 + \eta)] + (N - N\bar{X}) [-\log(1 + \eta)]$$

$$= N\bar{X} \log \eta - \cancel{N\bar{X} \log(1 + \eta)} - N \log(1 + \eta) + \cancel{N\bar{X} \log(1 + \eta)}$$

$$\ell(\eta) = N\bar{X} \log \eta - N \log(1 + \eta)$$

$$\frac{d}{d\eta} \ell(\eta)$$



$$(2) \left| \frac{\partial \ell}{\partial \eta} = 0 \right|$$

$$\frac{\partial \ell}{\partial \eta} = \frac{N\bar{X}}{\eta} - \frac{N}{1+\eta} = 0$$

$$\Rightarrow (1+\eta)N\bar{X} - \eta N = 0$$

$$\Rightarrow \cancel{N}\bar{X} + \eta\cancel{N}\bar{X} - \eta\cancel{N} = 0$$

$$\Rightarrow \bar{X} = \eta(1-\bar{X})$$

$$\Rightarrow \hat{\eta} = \frac{\bar{X}}{1-\bar{X}} = \frac{\hat{p}}{1-\hat{p}}$$

$$\eta = \frac{p}{1-p}$$

$$\hat{p} = \bar{X}$$

## Theorem Transformation for MLEs

If  $\hat{\theta}$  is the MLE for  $\theta$  then the MLE for  $g(\theta)$  is  $g(\hat{\theta})$ .