

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

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 $\theta \in \Theta$

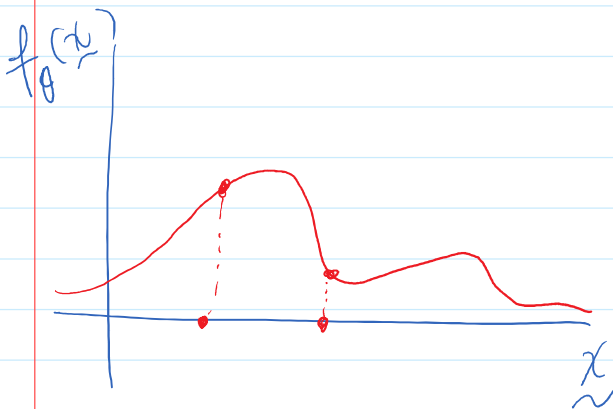
Recall: joint dist of my data

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

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

Way 1:

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

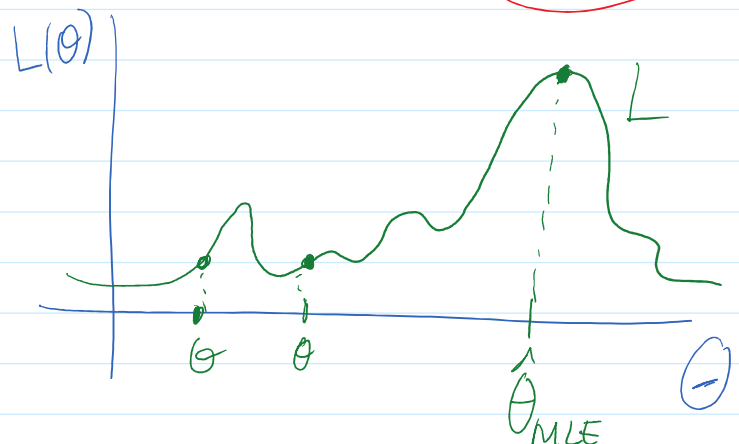


$$L: \Theta \rightarrow \mathbb{R}$$

Way 2:

think of as a fn of θ
call it: the likelihood fn

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



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

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

Defn: Maximum Likelihood Estimator (MLE)

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

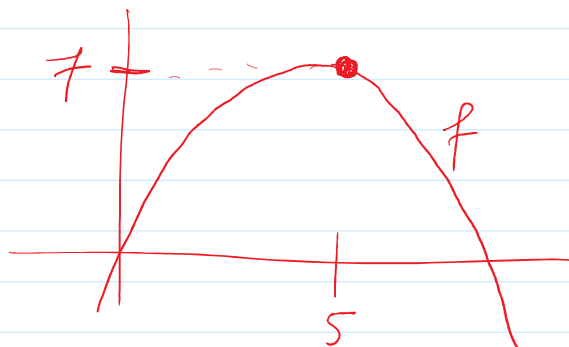
$$\hat{\theta}_{MLE} = \arg \max_{\theta \in \Theta} L(\theta)$$

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

Ex.

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

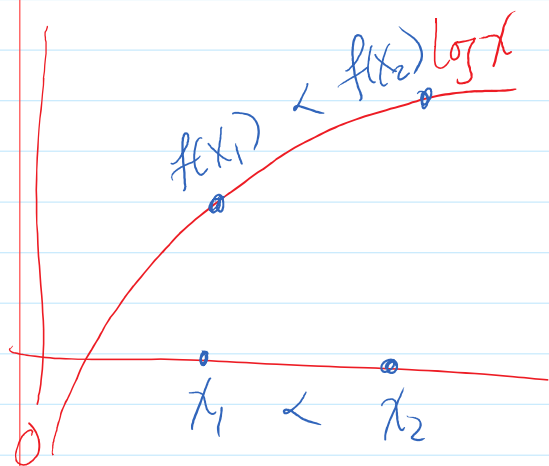
$$\operatorname{argmax}_x f(x) = 5$$



Alt. defn

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

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



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 θ ?

① Find $\ell(\theta)$

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

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

② take a derivative

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

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

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

Theorem: MLEs are based on Suff. Stats.

$$\hat{\theta}_{MLE} = \text{function}(T) \\ \uparrow \text{S.S. for } \theta.$$

pf. Factorization theorem

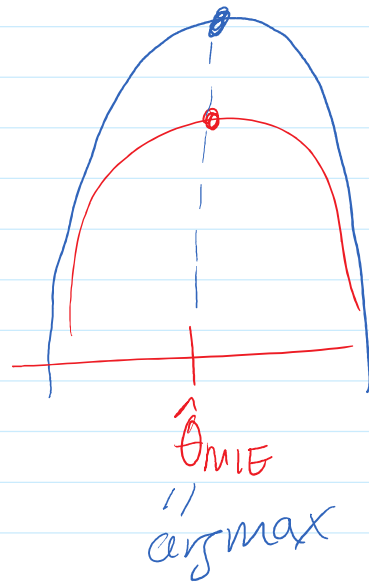
$$L(\theta) = f_{\theta}(x) = \underline{h(x)} g(\theta, t)$$

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

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

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



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 $l(p)$

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

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

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

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

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

$$+ \log \left(\prod_n \mathbb{1}(x_n = 0, 1) \right)$$

② ^{set} derivative to zero

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

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

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

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

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

Continue ex

$$\eta = \frac{p}{1-p} \quad \leftarrow \text{odds}$$

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

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

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

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

$$\Rightarrow \boxed{p = \frac{\eta}{1 + \eta}}$$

① Likelihood

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

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

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

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

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

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

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

$$\textcircled{2} \quad \boxed{\frac{\partial \ell}{\partial \eta} = 0}$$

$$\frac{\partial \ell}{\partial \eta}$$

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

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

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

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

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

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

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

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

Theorem Transformation for MLEs

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