

01/29/2020

Class # 2

We observe "data"

$x = \langle 0, 0, 1, 0, 1, 0 \rangle$ realization from a random process, Assume a parametric process

$$\mathcal{F} = \text{iid Bernoulli} = \{ \underbrace{p(x; \theta)}_{\text{PMF}} : \theta \in \mathbb{H} \} = \{ \theta^x (1-\theta)^{1-x} : \theta \in (0, 1) \}$$

$\underbrace{p(x; \theta)}_{\text{PMF}} = p(x; \theta)$ \leftarrow constant θ need to compare the probability i.e. $f(x) = f(x; a) = \sin(ax)$

We'd like to learn about θ (inference) \mathcal{F}

$$p(x; \theta) = p(\langle 0, 0, 1, 0, 1, 0 \rangle; \theta) = (\theta^0 (1-\theta)^{1-0}) \cdot (\theta^0 (1-\theta)^{1-0}) \cdots (\theta^1 (1-\theta)^{1-1})$$

$$= \theta^2 (1-\theta)^4$$

what if $\theta = 0.5$ $p(x; \theta) = 0.5^2 (1-0.5)^4 = 0.0156$

what if $\theta = 0.25$ $p(x; \theta) = 0.25^2 (1-0.25)^4 = 0.0198$

"likelihood function"

"probability"

$$\underset{\substack{\uparrow \\ \text{input}}}{\mathcal{L}(\theta; x)} = \underset{\substack{\uparrow \\ \text{input}}}{p(x; \theta)} \underset{\substack{\uparrow \\ \text{constant}}}{=} \Rightarrow \underset{\substack{\uparrow \\ \text{input}}}{p(x; \theta)} \underset{\substack{\uparrow \\ \text{constant}}}{\in (0, 1)}$$

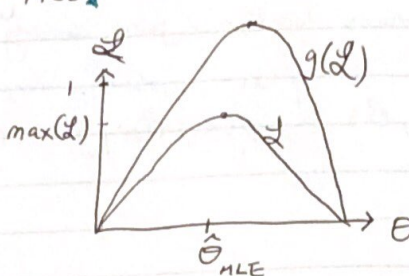
$$\mathcal{L}(x; \theta) \in (0, 1)$$

$$\operatorname{argmax}_{\theta \in \Theta} \{ \mathcal{L}(\theta; x) \} := \hat{\theta}_{MLE} \quad \text{"maximum likelihood estimate"}$$

↑
argument that results in the maximum

↙ consider g is a strictly increasing function.

$$= \operatorname{argmax}_{\theta \in \Theta} \{ g(\mathcal{L}(\theta; x)) \}$$

$$= \operatorname{argmax}_{\theta \in \Theta} \{ \mathcal{L}(\theta; x) \}$$


$$\mathcal{L}(\theta; x) := \ln(\mathcal{L}(\theta; x)) = \ln\left(\prod_{i=1}^n \theta^{x_i} (1-\theta)^{1-x_i}\right)$$

↑ "log-likelihood" ↑ monotonically increasing function

$$= \sum_{i=1}^n \ln(\theta^{x_i} (1-\theta)^{1-x_i})$$

$$= \sum_{i=1}^n x_i \ln(\theta) + (1-x_i) \ln(1-\theta)$$

$$= \ln(\theta) \sum_{i=1}^n x_i + \ln(1-\theta) \sum_{i=1}^n (1-x_i)$$

$$\text{let } \bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$$

$$\Rightarrow \sum x_i = n\bar{x}$$

sample arg

$$= \ln(\theta) (n\bar{x}) + \ln(1-\theta) (n(1-\bar{x})) = \mathcal{L}(\theta; x)$$

$$= n(\ln(\theta)\bar{x} + \ln(1-\theta)(1-\bar{x}))$$

① Find $\mathcal{L}(\theta; x)$

② Find $\frac{d}{d\theta} [\mathcal{L}(\theta; x)] = \mathcal{L}'(\theta; x)$

③ set $\mathcal{L}'(\theta; x) = 0$

④ solve for θ_{MLE}

$$\mathcal{L}'(\theta; x) = n \left(\frac{\bar{x}}{\theta} - \frac{1-\bar{x}}{1-\theta} \right) \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \frac{\bar{x}}{\theta} = \frac{1-\bar{x}}{1-\theta} \Rightarrow \bar{x}(1-\theta) = (1-\bar{x})\theta \Rightarrow \bar{x} - \bar{x}\theta = \theta - \bar{x}\theta \Rightarrow \hat{\theta}_{MLE} = \bar{x}$$

$$x = \langle 0, 0, 1, 0, 1, 0 \rangle \Rightarrow \bar{x} = \frac{1}{3} = \hat{\theta}_{MLE}$$

$$\bar{x} = \frac{1}{6} \sum_{i=1}^6 x_i = \frac{0+0+1+0+1+0}{6}$$

$$x_1, \dots, x_n \mid \theta \stackrel{iid}{\sim} \text{Bernoulli}(\theta)$$

$$\Rightarrow \hat{\theta}_{MLE} = \bar{x}$$

MLE is not the only point estimation strategy but it is common as it has nice properties.

(I) $\hat{\theta}_{MLE} \xrightarrow{P} \theta$ "consistency" i.e. it converges to the value in n .
standard error = $\sqrt{\text{var}}$

(II) $\hat{\theta}_{MLE} \approx N(\theta, SE[\hat{\theta}_{MLE}]^2)$ "Asymptotic Normality"

(III) Among all consistent estimates, $\hat{\theta}_{MLE}$ has lowest variance. "Efficiency".

$T = \text{iid Geometric}$ $X \sim \text{Geom}(\theta) = (1-\theta)^x \theta$

$$L(\theta; x) = \prod_{i=1}^n (1-\theta)^{x_i} \theta$$

more convenient $\Rightarrow l(\theta; x) = \sum_{i=1}^n \ln((1-\theta)^{x_i} \theta) = \sum_{i=1}^n x_i \ln(1-\theta) + \ln(\theta) = n(\bar{x} \ln(1-\theta) + \ln(\theta))$

$$l'(\theta; x) = \left(-\frac{\bar{x}}{1-\theta} + \frac{1}{\theta} \right) \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \frac{1}{\theta} = \frac{\bar{x}}{1-\theta} = 1-\theta = \theta \bar{x}$$

$$\Rightarrow 1 = \theta + \theta \bar{x}$$

$$\Rightarrow 1 = \theta (1 + \bar{x})$$

$$\Rightarrow \hat{\theta}_{MLE} = \frac{1}{1 + \bar{x}}$$

example: $\bar{x} = 99$

$$\hat{\theta}_{MLE} = \frac{1}{1+99} = 1\%$$

$$\bar{x} = 1$$

$$\hat{\theta}_{MLE} = \frac{1}{1+1} = 50\%$$

$T = \text{iid Bernoulli}$ $\hat{\theta}_{MLE} = \bar{X}$

$$\hat{\theta}_{MLE} \stackrel{d}{\approx} N(\theta, SE[\hat{\theta}_{MLE}]^2) \stackrel{(I)}{\approx} N(\hat{\theta}_{MLE}, SE[\hat{\theta}_{MLE}]^2) \Big|_{\theta = \hat{\theta}_{MLE}} \approx N(\bar{x}, \frac{\bar{x}(1-\bar{x})}{n})$$

$$SE[\hat{\theta}_{MLE}] = SE[\bar{X}] = \sqrt{\frac{\sigma^2}{n}} = \sqrt{\frac{\theta(1-\theta)}{n}}$$

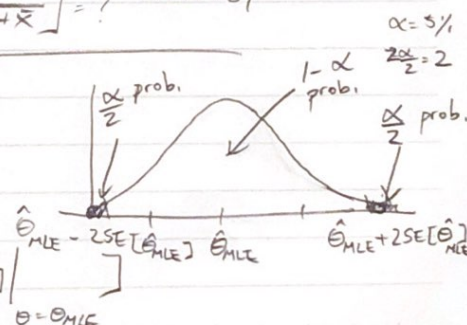
$T = \text{iid Geometric}$ $\hat{\theta}_{MLE} = \frac{1}{1+\bar{x}}$, $SE[\hat{\theta}_{MLE}] = SE[\frac{1}{1+\bar{x}}] = ?$ MATH 369

2nd Goal of inference "Confidence sets"

i.e. provide a range of plausible values of θ .

$$CI_{\theta, 1-\alpha} := [\hat{\theta}_{MLE} \pm z_{\frac{\alpha}{2}} SE[\hat{\theta}_{MLE}]] \Big|_{\theta = \hat{\theta}_{MLE}}$$

Confidence interval for θ of size $1-\alpha$



Third Goal of Inference: "Testing" also called "Hypothesis Testing"

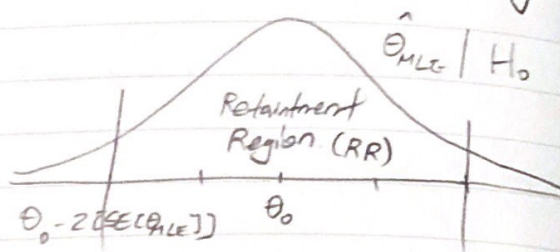
"null hypothesis" $H_0: \theta = \theta_0$ \leftarrow some specific value.

alternative hypothesis $H_a: \theta \neq \theta_0$

Assume my theory is true and let the data tell me if I'm right or wrong

$$\Rightarrow \hat{\theta}_{MLE} \approx N(\theta_0, SE[\hat{\theta}_{MLE}] \Big|_{\theta = \hat{\theta}_{MLE}}^2)$$

$$RR_{\theta_0, 1-\alpha} := [\theta_0 \pm z_{\frac{\alpha}{2}} SE[\hat{\theta}_{MLE}] \Big|_{\theta = \theta_0}]$$



If $\hat{\theta}_{MLE} \in RR \Rightarrow$ Retains H_0

If $\hat{\theta}_{MLE} \notin RR \Rightarrow$ Rejects H_0 / Accept H_a

We have a strategy for all 3 informal goals, We have done "frequentist inference" which is historically classic