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last time :  $P(X_1, \dots, X_n; \theta) \rightarrow$  fix parameter ( $\theta$ ) and calculate the probability of stuff happening

$\mathcal{L}(\theta; X_1, \dots, X_n) \rightarrow$  Try to figure out the model  
Try to infer the parameter  
Try all values and see which is best

$$\begin{aligned}\hat{\theta}_{MLE} &= \underset{\theta \in \mathcal{H}}{\operatorname{argmax}} \{ \mathcal{L}(\theta; X_1, \dots, X_n) \} \\ &= \underset{\theta \in \mathcal{H}}{\operatorname{argmax}} \{ \ell(\theta; X_1, \dots, X_n) \}\end{aligned}$$

EX :  $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bernoulli}(\theta)$

data = 0, 0, 1, 0, 1, 0  $\xi$  we know  $\theta = \frac{1}{3}$ . *Let's prove it.*

$$\begin{aligned}\ell(\theta; X) &= \ln \left( \prod_{i=1}^n \theta^{x_i} (1-\theta)^{1-x_i} \right) = \sum_{i=1}^n \ln(\theta^{x_i} (1-\theta)^{1-x_i}) \\ &= \sum_{i=1}^n [x_i \ln(\theta) + (1-x_i) \ln(1-\theta)] \\ &= \ln(\theta) \sum_{i=1}^n x_i + (n - \sum_{i=1}^n x_i) \ln(1-\theta)\end{aligned}$$

*Def:*  $\bar{X} = \frac{1}{n} \sum X_i \Rightarrow \sum X_i = n\bar{X}$

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

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

Trying to find  
Maximum so  
take derivative  
set = 0

$$\frac{d}{d\theta} (\leftarrow) = n \left( \frac{\bar{X}}{\theta} - \frac{1-\bar{X}}{1-\theta} \right) \stackrel{\text{set}}{=} 0$$

$$(1-\theta) \bar{X} - \theta(1-\bar{X}) = 0$$

$$\bar{X} - \theta \bar{X} - \theta + \theta \bar{X} = 0$$

$$\bar{X} - \theta = 0$$

$$\bar{X} = \theta$$

$$\boxed{\hat{\theta}_{MLE} = \bar{X}} \quad \boxed{W}$$

\* To move from  $\Pi \rightarrow \Sigma$  makes taking derivative easier.

EX:  $X_1, X_2, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Geo}(\theta) \stackrel{\text{pmf}}{:=} (1-\theta)^x \theta$  alternative parametrization of geometric

:  $X = \#$  of failures before the stopping success

:  $\text{Supp}(X) = \{0, 1, \dots\} = \mathbb{N}_0$

:  $\Theta = (0, 1)$   
param. space.

$$P(x_1, \dots, x_n; \theta) = \mathcal{L}(\theta; x_1, \dots, x_n) = \prod_{i=1}^n (1-\theta)^{x_i} \theta =$$

$$l(\theta; x) = \sum \ln((1-\theta)^{x_i} \theta)$$

$$= \ln(1-\theta) \sum x_i + n \ln(\theta)$$

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

$$l'(\theta; x) = \frac{n}{\theta} - \frac{n \bar{x}}{1-\theta} = 0$$

$$= n \left( \frac{1}{\theta} - \frac{\bar{x}}{1-\theta} \right) = 0$$

$$\frac{1}{\theta} - \frac{\bar{x}}{1-\theta} = 0$$

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

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

$$\boxed{\hat{\theta}_{MLE} = \frac{1}{\bar{x} + 1}} \quad \boxed{\checkmark}$$

## Properties of MLE

1. Consistency:  $\hat{\theta}_{MLE} \xrightarrow{P} \theta$  (true  $\theta$ )

$$: \forall \varepsilon > 0 \lim_{n \rightarrow \infty} P(|\hat{\theta}_{MLE} - \theta| \geq \varepsilon) = 0$$

: Whatever you demand of closeness from  $\theta$  to  $\hat{\theta}_{MLE}$ , add more data and you'll get there.



2. Asymptotic Normality:  $\hat{\theta}_{MLE} \xrightarrow{\text{distribution}} N(\theta, SE(\hat{\theta}_{MLE})^2)$  Standard Error  
 : If you want a reasonable range (Confidence Interval)  
 : You're safe to perform testing hypothesis.

3. Efficiency:  $\hat{\theta}_{MLE}$  has the lowest standard error theoretically possible.

EX:  $\theta = 0.6 \pm 0.01$  \* MLE  
 $\theta = 0.6 \pm 17$

### Inference with MLEs

1. Point Estimate  $\hat{\theta}_{MLE}$
2. Confidence Set ( $I_{\theta, 1-\alpha} = [\hat{\theta}_{MLE} \pm Z_{\frac{\alpha}{2}} \text{S.E.}[\hat{\theta}_{MLE}]]$ )
3. Hypothesis testing: level  $\alpha$ 
 $H_0: \theta = \theta_0$  ( $\neq$  reject)  
 $H_1: \theta \neq \theta_0$  ( $=$  reject)  
 : retainment region =  $[\theta_0 \pm Z_{\frac{\alpha}{2}} \text{S.E.}(\hat{\theta}_{MLE})]$

So: Observe data  $\rightarrow$  Pick  $\mathbb{F}_{\text{model}} \rightarrow$  Do inference with your MLE.

### Holes/Problems in the System.

1. EX:  $\mathbb{F} \neq \text{Bernoulli}$ ,  $X = 0, 0, 0$ ,  $\hat{\theta}_{MLE} = \bar{X} = \frac{0+0+0}{3} = 0$

So the  $\text{S.E.}[\hat{\theta}_{MLE}] = \sqrt{\hat{\theta}_{MLE}(1-\hat{\theta}_{MLE})} = 0$ .

This tells us NOTHING. No inference can be made. XX

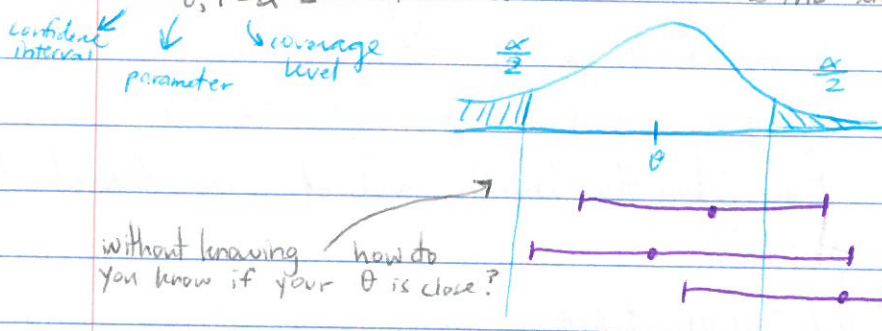
2. What if I have prior knowledge about  $\odot$ ? I can't use it.

EX: Guessing a professor's age.

You know, they're not 5 or 100 years old, but not a part of the testing - Can't use it.

### 3. Frequentist Confidence Interval Interpretation

C.I.  $0, 1-\alpha$  [0.42, 0.47] ← What does this likely mean?



(a) If the experiment is repeated "many" times, then you cover ( $\theta \in \text{interval}$ )  $1-\alpha$  proportion of the time.

\*Problem: You only want to do it once!

(b) Before I do my experiment,  $P(\theta \in \text{C.I.}) = 1-\alpha$

\*Problem: We don't care about before experiment  
: Can't tell me anything about interval

∴ largely unsatisfactory.

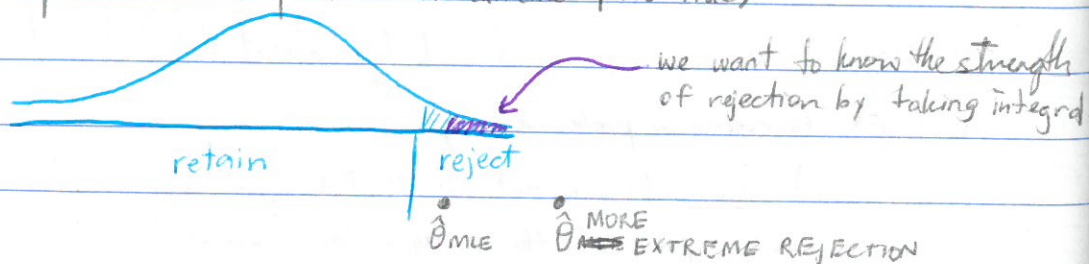
### 4. Hypothesis Testing : level $\alpha$ $H_0: \theta = \theta_0$

$H_1: \theta \neq \theta_0$

There are 2 outcomes (a)  $H_0$  : Retain

(b)  $H_0$  : Reject

p-value  $:= P(\text{this data or "more extreme" } | H_0 \text{ true})$





probability of null hyp given data.

Want to know:  $P(H_0 | X)$ ? (Want to know how good interval is)

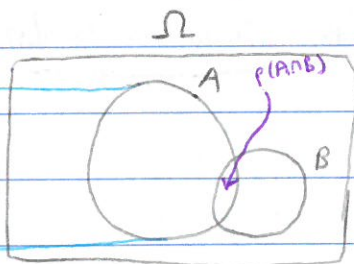
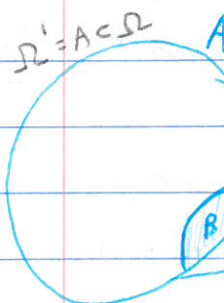
EX:  $X = 0, 0, 1, 0, 1, 0$ ,  $\hat{\theta} = \frac{1}{3}$

C.I.  $\theta, 95\% = \left[ \frac{1}{3}, \pm 2\sqrt{\frac{1}{3} \cdot \frac{2}{3}} \right] = [-0.60, 1.26]$  BUT, we can't get  $(-) \#s$  or  $\#s > 1$ !

used the 2 bc of 95% bc we assume the Normality distribution  
BUT Not converged yet.

\* Normal Asymptotic didn't kick in yet bc  $n=6$ . (not big enough)

Motivation for 341: To prove Bayesian > Frequentist approach.



$A = \text{smoking}$   $P(A) = 0.2$   
 $B = \text{lung cancer}$   $P(B) = 0.06$   
 $P(A \cap B) = 0.036$

Conditional Prob.  $P(B|A)$ .

look at shapes:

$\bigcirc \propto \bigcirc$

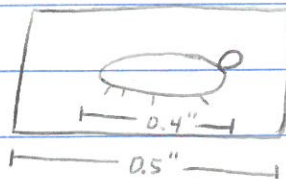
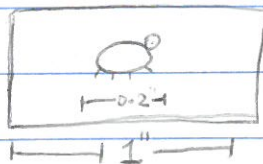
$P(A \cap B) \propto P(B|A)$

$P(A \cap B) = c P(B|A)$

\* The shapes are the same but the scale of the size are different.

$P(B|A) = \frac{P(\Omega)}{P(A)} \frac{P(A \cap B)}{P(A \cap B)} = \frac{P(A \cap B)}{P(A)}$  } Bayes Rule

Bug example:



Zoom =  $\frac{1''}{0.5''} = \frac{\text{Previous Zoom}}{\text{Current Zoom}}$

$$A = \text{comma}$$

$$P(A|B)$$

$B^c$

$$P(A) = P(A, B) + P(A, \bar{B}) = \text{Law of Total Probability}$$

||

$$P(A|B)P(B) + P(A|\bar{B})P(\bar{B}) \Rightarrow P(B|A) = \frac{P(A|B)P(B)}{P(A|B)P(B) + P(A|\bar{B})P(\bar{B})}$$

posterior prob.

likelihood/prob. of data

Prior Prob.

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)}$$

Lung Cancer  
target of Estimation

evidence/data

After

Before

So, Begin with  $P(B)$  with introduction to data  $(A) \rightarrow P(B|A)$

Bayesian  
Conditionalism