

## LECTURE 6 - INFORMATIVE PRIORS

- WE HAVE PRIOR KNOWLEDGE ON  $\theta$

OUR JOB TRANSLATE PRIOR INFO INTO  $P(\theta)$  ["PRIOR ELICITATION"]

ELICITATION ERRORS  $\begin{cases} \textcircled{1} \text{ FITTING ERROR} \\ \textcircled{2} \text{ SPECIFICATION ERROR} \end{cases}$

$P(\theta)$  IS OFTEN DERIVED  
VIA AN ITERATIVE PROCESS

- 1 • INITIAL DISCUSSION
- 2 • DERIVATION OF A  $P(\theta)$
- 3 • PRESENT PRIOR TO EXPERT(S)
- 4 • IF EXPERT(S) HAPPY THEN STOP; OTHERWISE START DISCUSSION AGAIN

### ⑤ SENSITIVITY ANALYSIS

TRY DIFFERENT PRIORS  
AND REPORT EFFECT ON  
POSTERIOR

EXAMPLE : "HIDDEN FIGURES" - ESTIMATING # STUDENTS CHEATING  
IN EXAMS IN SCOTLAND DURING 2020

TASK CREATE A PRIOR  $P(\theta)$

PRIOR INFO  $\left\{ \begin{array}{l} \bullet \text{ N° OF CHEATERS CAUGHT } 480 \\ \bullet \text{ DISCOVERY RATE ESTIMATE } 0.535 [0.293, 0.974] \text{ 95\% CI} \end{array} \right.$

→ ESTIMATED #  $\hat{\theta} = 897 [493, 1638]$  95% CI  
OF CHEATERS

⇒ POSSIBLE WAYS TO FIND SUITABLE  $P(\theta)$  :

A • SET  $P(\theta)$  ASYMMETRIC  $\rightarrow$  GAMMA ( $a, b$ )  
e.g.

B • CONSIDER A TRANSFORMATION  
 $\phi = \log \theta$

$\phi = 6.8 [6.2, 7.4]$  95% CI

$6.8 \pm 1.96 \sigma = [6.2, 7.4]$   
 $\sigma = 0.306$

$\phi \sim N(6.8, 0.306^2)$

$\Rightarrow \theta \sim \log N(6.8, 0.306^2) \rightarrow \exp(6.8)$   
 $\underline{897}$

$\left\{ \begin{array}{l} \frac{a}{b} = 897 \quad a = 897b \\ \text{FIND } a, b \text{ SUCH THAT} \\ \text{LOWER \& UPPER 2.5\% QUANTILES} \\ \text{ARE } [493, 1638] \end{array} \right.$

→ WE CAN FORMALLY JUSTIFY DIFFERENT AVERAGES WITHIN A DECISION THEORY APPROACH

•  $\theta \in \Theta$  = PARAMETER

•  $L(\theta, a)$  = ASSOCIATED LOSS FOR ESTIMATE  $a$  WHEN TRUE VALUE IS  $\theta$

$$\left\{ \begin{array}{l} \bullet L(\theta, a) = |\theta - a| \\ \hat{\theta} = M_{\pi}(\theta) \\ \bullet L(\theta, a) = \begin{cases} 1 & \text{if } a \neq \theta \\ 0 & \text{if } a = \theta \end{cases} \\ \hat{\theta} = M_{0, \pi}(\theta) \end{array} \right.$$

⇒ BAYES ESTIMATE  $\hat{\theta}$  = VALUE  $a$  THAT MINIMISES THE POSTERIOR EXPECTED LOSS

$$\hat{\theta} = \min_{a \in \Theta} E_{\pi}(L(\theta, a)) = \min_{a \in \Theta} \left[ \int_{\Theta} L(\theta, a) \pi(\theta | x) d\theta \right]$$

(1)  $L(\theta, a) = (\theta - a)^2 \Rightarrow \hat{\theta} = E_{\pi}(\theta)$  = POSTERIOR MEAN

$$E_{\pi}[(\theta - a)^2] = E_{\pi}[(\theta - E_{\pi}(\theta) + E_{\pi}(\theta) - a)^2] = E_{\pi}[\underbrace{(\theta - E_{\pi}(\theta))^2}_{\text{VAR}_{\pi}(\theta)} + \underbrace{(E_{\pi}(\theta) - a)^2}_{\text{constant}} + \underbrace{2(E_{\pi}(\theta) - a)E_{\pi}[\theta - E_{\pi}(\theta)]}_{=0}]$$

$$\min_a \left[ \text{VAR}_{\pi}(\theta) + (E_{\pi}(\theta) - a)^2 \right]$$

→  $a = E_{\pi}(\theta)$  ✗