

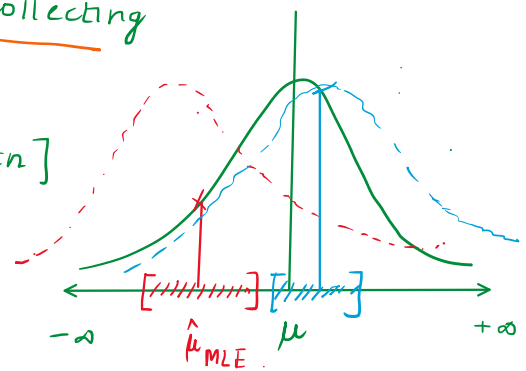
## Bayesian Inference

Classical Inference [Axiomatic Inference]  
vs Bayesian Inference.

Recall:  $X_1, X_2, \dots, X_n \stackrel{iid}{\sim} f_\theta(x)$  [ $\theta$  = unknown popln parameter].

Classical: Assume that  $\theta$  is a constant given value (unknown).  
Estimate/Infer about this fixed value based on sample obs,  
using different techniques.

Bayesian: Assume that  $\theta$  is a random variable.  
Begin with assuming that before collecting  
any sample obs, we have some  
distrn of  $\theta$ , say  $\pi(\theta)$ . [Prior distrn]



Eg:  $X_1, X_2, \dots, X_n \stackrel{iid}{\sim} N(\theta, \sigma^2)$   
[ $\theta$  = unknown,  $\sigma^2$  = known].

(i) Begin with a prior distrn of  $\theta$ , say  $\theta \sim \pi(\theta) = N(\mu, \tau^2)$   
( $\mu, \tau^2$  are known),  $\mu$  = prior belief about the unknown  
popln parameter,  $\tau^2$  = variance of prior mean indicates  
the strength of our belief in  $\mu$ . Larger  $\tau^2 \Rightarrow$  less sure are  
we about  $\mu$  being the exp value of  $\theta$ .

Alternatively,  $\theta \sim \pi(\theta) = \text{Uniform}[a, b]$ .

$\therefore$  Choice of Prior distribution is "subjective".

$\therefore$  Prior distrn  $\pi(\theta)$ : Prob distrn of the unknown popln parameter  
that captures the initial belief about  $\theta$ .

Let  $\Omega$ : Parameter space.

∴ If  $\theta$  is a discrete r.v.: condition for  $\pi(\theta)$  to be a valid pmf will  $\sum_{\theta \in \Omega} \pi(\theta) = 1$ .

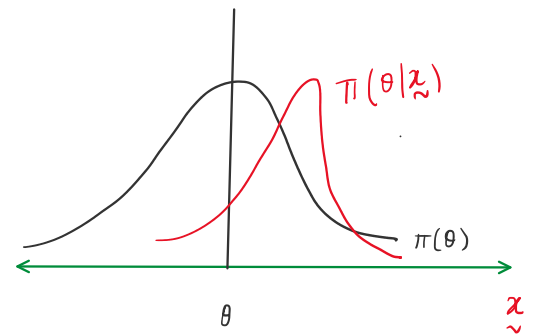
∴ If  $\theta$  is a continuous r.v.: condition for  $\pi(\theta)$  to be a valid pdf will  $\int_{\theta \in \Omega} \pi(\theta) = 1$ .

(ii) Let  $\underline{x} = \{x_1, x_2, \dots, x_n\}$  set of observed sample values.

Once the sample data is collected from the popln, we "update" our belief about  $\theta$ . This updated belief is captured the "posterior distn" of  $\theta$ . Denote as  $\pi(\theta | \underline{x})$ .

Posterior distn  $\pi(\theta | \underline{x})$  is used in Bayesian inference about  $\theta$ .

Define: The posterior distn as follows:



Case I: If  $\theta$  is discrete r.v.

$$\pi(\theta | \underline{x}) = \frac{f(\underline{x} | \theta) \cdot \pi(\theta)}{\sum_{\theta \in \Omega} f(\underline{x} | \theta) \cdot \pi(\theta)}$$

Case II: If  $\theta$  is a continuous r.v.

$$\pi(\theta | \underline{x}) = \frac{f(\underline{x} | \theta) \cdot \pi(\theta)}{\int_{\theta \in \Omega} f(\underline{x} | \theta) \cdot \pi(\theta)}$$

normalizing constant.

For  $\pi(\theta | \underline{x})$  to be a valid pmf:

$$\sum_{\theta \in \Omega} \pi(\theta | \underline{x}) = 1$$

For  $\pi(\theta | \underline{x})$  to be a valid pdf:

$$\int_{\theta \in \Omega} \pi(\theta | \underline{x}) = 1$$

Check: LHS:  $\int_{\theta \in \Omega} \pi(\theta | \underline{x})$

$$= \int_{\theta \in \Omega} \frac{f(\underline{x} | \theta) \cdot \pi(\theta)}{\int_{\theta \in \Omega} f(\underline{x} | \theta) \cdot \pi(\theta) d\theta} \cdot d\theta$$

Eg:  $X \sim \text{Poi}(\lambda)$ .

$$f(x) = e^{-\lambda} \frac{\lambda^x}{x!}$$

Eg:  $X \sim N(\mu, \sigma^2)$ .

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

HW.  $\pi(\theta|x) = f(x|\theta) \cdot \pi(\theta)$ .

$\therefore$  To make it a valid pdf:  $\pi(\theta|x) = c \cdot f(x|\theta) \pi(\theta)$ .

To find 'c',  $\int \pi(\theta|x) d\theta = 1$ .

$$= \int_{\theta \in \Omega} \left( \int_{\theta \in \Omega} f(x|\theta) \cdot \pi(\theta) d\theta \right) d\theta$$

constant

$$= \frac{\int f(x|\theta) \cdot \pi(\theta) \cdot d\theta}{\int f(x|\theta) \cdot \pi(\theta) \cdot d\theta} = 1.$$

(Proved)