

extra
notes
18 Jan 13

①



$C < V$

population
size

when $n \ll N$, SRS = IID

sample
size

is a lot
smaller
than

has nuclear report (nuclear
power
safety)

$P(A_1 \text{ and } A_2 \text{ and } \dots \text{ and } A_k)$

$$= P(A_1) P(A_2 | A_1) P(A_3 | A_1, A_2) \dots$$

naive
Bayes

$$= P(A_1) P(A_2) P(A_3) \dots P(A_k)$$

independence: slippery frequentist ⁽²⁾
 concept

at design time (before data): freq $\mathcal{I}_1, \mathcal{I}_2$ indep iff

$$P_{\mathcal{I}_1, \mathcal{I}_2}(y_1, y_2) = P_{\mathcal{I}_1}(y_1) \cdot P_{\mathcal{I}_2}(y_2)$$

after data? frequentist story unclear

| | before data | after data | | | | | | | | |
|---------------|--|----------------|---------------|---|-----------------------|---|----------|---|---------------|----------|
| | fixed "random" | fixed "random" | | | | | | | | |
| freq | <table border="1" style="display: inline-table; vertical-align: middle;"> <tr><td>θ</td><td>\mathcal{I}</td></tr> <tr><td>-</td><td>θ, \mathcal{I}</td></tr> </table> | θ | \mathcal{I} | - | θ, \mathcal{I} | <table border="1" style="display: inline-table; vertical-align: middle;"> <tr><td>θ</td><td>?</td></tr> <tr><td>\mathcal{I}</td><td>θ</td></tr> </table> \mathcal{I} ? | θ | ? | \mathcal{I} | θ |
| θ | \mathcal{I} | | | | | | | | | |
| - | θ, \mathcal{I} | | | | | | | | | |
| θ | ? | | | | | | | | | |
| \mathcal{I} | θ | | | | | | | | | |
| Bayes | | | | | | | | | | |
| | θ unknown | | | | | | | | | |
| | \mathcal{I} data | | | | | | | | | |

$$\{y_1, \dots, y_n, \dots\} = P$$

extending exd \leftrightarrow

thinking of y_1, \dots, y_n
as like a random
sample from P

$$P(A|D) = \frac{P(A) \cdot P(D|A)}{P(D)} \leftarrow$$

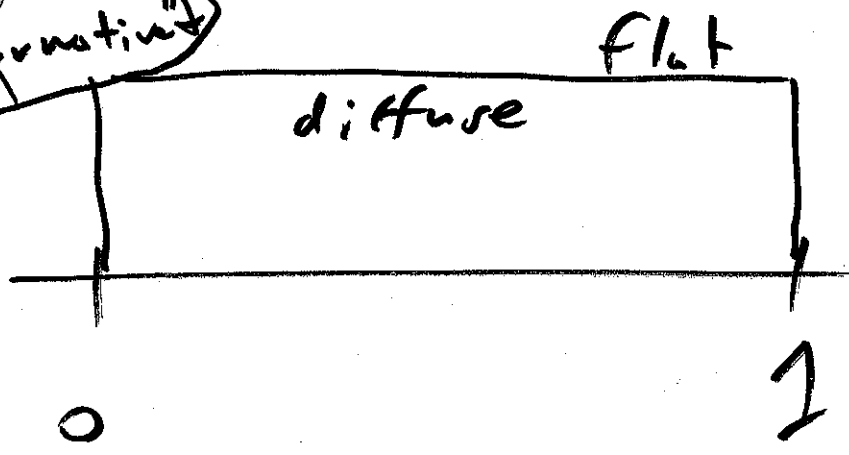


$P(D) = ?$
 \leftarrow ELISA +

$$\begin{aligned}
 P(D) &= P(D \text{ and } A) + P(D \text{ and } \text{not } A) \\
 &= \underset{.01}{P(A)} \underset{.95}{P(D|A)} + \underset{.99}{P(\text{not } A)} \underset{(1-.98)}{P(D|\text{not } A)}
 \end{aligned}$$

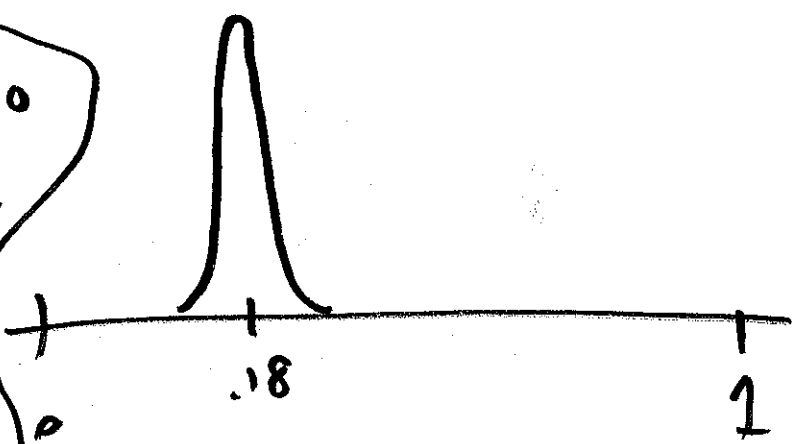
don't know much about θ

~~"non-informative"~~

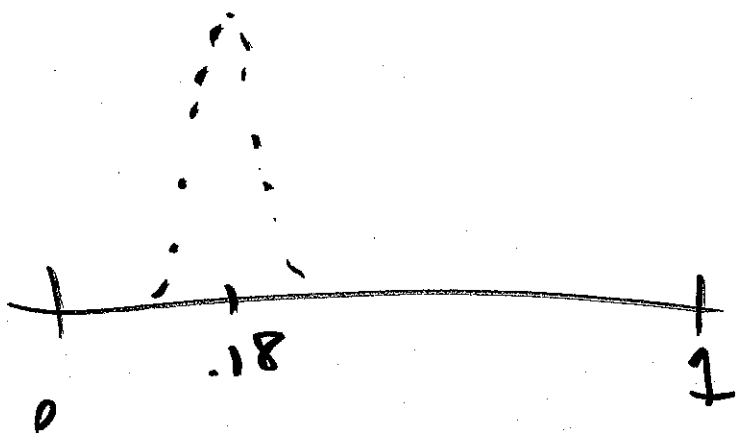


Fisher
"fiducial
inference"

$n = 400$
 $s = 72$
 $\bar{y} = \frac{s}{n}$
 $= 0.18$



$$\begin{aligned}
 \ell(\theta | y) &= \\
 & c \cdot p(y | \theta)
 \end{aligned}$$



$$p(\theta | y)$$

$$p(\gamma_{n+1}, \dots, \gamma_n | \gamma_1, \dots, \gamma_m) =$$

$$= \int_0^1 p(\gamma_{n+1}, \dots, \gamma_n, \theta | \gamma_1, \dots, \gamma_m) d\theta$$

$$= \int_0^1 p(\gamma_{n+1}, \dots, \gamma_n | \theta, \cancel{\gamma_1, \dots, \gamma_m}) \cdot \boxed{p(\theta | \gamma_1, \dots, \gamma_m)} d\theta$$

$$= \int_0^1 \underbrace{p(\gamma_{n+1}, \dots, \gamma_n | \theta)}_{\text{sampling dist for } \gamma_{n+1}, \dots, \gamma_n} \underbrace{p(\theta | \gamma_1, \dots, \gamma_m)}_{\text{part dist for } \theta \text{ given } \gamma_1, \dots, \gamma_m} d\theta$$

sampling dist
for $\gamma_{n+1}, \dots, \gamma_n$

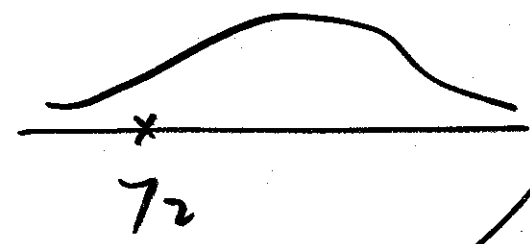
part dist
for θ
given
 $\gamma_1, \dots, \gamma_m$

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \in \mathbb{R}^n$$

$$p(y_1 | y_2, \dots, y_n)$$

$$Y_{-k} = (y_1, \dots, y_{k-1}, y_{k+1}, \dots, y_n)$$

$$p(y_2 | Y_{-2})$$



$$f(\theta | y) = \theta^s (1-\theta)^{n-s}$$

$$p(\theta | y) = c p(\theta) \cdot \ell(\theta | y)$$

$$= c p(\theta) \theta^s (1-\theta)^{n-s}$$

$$\frac{\theta (1-\theta)}{\text{Beta}}$$

$$= \underbrace{c \theta^{s-1}}_{\text{Beta}} \underbrace{(1-\theta)^{n-1}}_{\text{Beta}}$$

prior
sample
size

$$\begin{bmatrix} 1 \\ \vdots \\ 1 \\ \hline 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\begin{matrix} \uparrow \\ \alpha = 4.5 \\ + \\ \uparrow \\ \beta = 25.5 \\ + \end{matrix}$$

Beta(α, β)
prior

$$n_0 = \text{mean} \frac{\alpha + \beta}{\alpha + \beta}$$

$$n_0 = 30$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

$$\begin{matrix} 5 \\ \parallel \\ 400 \end{matrix}$$

$$\begin{bmatrix} 1 \\ \vdots \\ 1 \\ \hline 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\begin{matrix} \uparrow \\ 5 \\ \downarrow \\ \uparrow \\ n-5 \\ \downarrow \end{matrix}$$

data

$$\text{mean } \frac{5}{5}$$

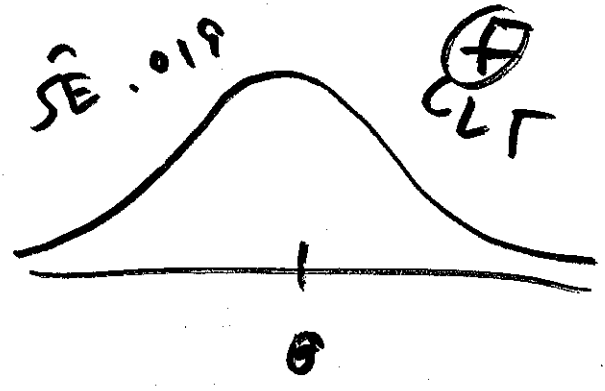
$$\text{mean } \frac{5}{5 + (n-5)} = \frac{5}{n}$$

Analysis 1: Beta(α, β) prior, Bayes likelihood,
Bayesian posterior

Analysis 2: merge prior, sample data, do likelihood analysis
or merged sample

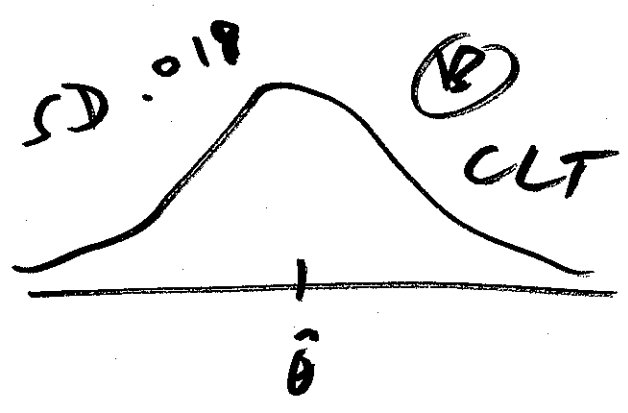
$$\text{Analysis 1} = \text{Analysis 2}$$

(F)



repeated-sampling
dist. of $\hat{\theta}$

(B)



post-dist for
 θ since γ
& relatively
diffuse prior-
info

(F)

$$c_1 e^{-c_2 (\hat{\theta} - \theta)^2}$$

(B)

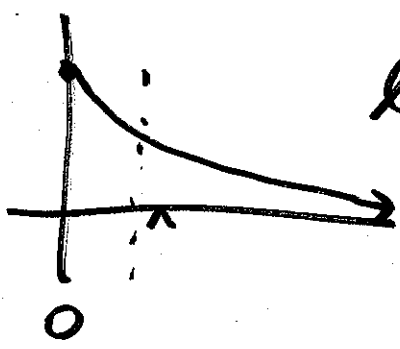
$$c_1 e^{-c_2 (\theta - \hat{\theta})^2}$$

$c_1 e$

=

$c_1 e$

Berstein - von Mises Thm.



$l(\theta^2 | D)$

$$\frac{\partial^2}{\partial \theta^2} \ln L = 0$$

variance
components
models

