

AMS206
7 Feb 19

this exchangeability
time:
next conjugate
time: modeling

hypothesis / significance testing (soon)

Frequentist inference point &

	Neyman	Fisher/...	interval estimates
small-sample	Quiz (3) exact CIs	?	bootstrapping
large-sample	(CS 2) Confidence intervals based on (CIs) & "CLT & conf. tricks"	internals based on MLE & Fisher information	

Frank Ramsey
(- 1927)
died age 26

CS1

$$P(\theta = 1 | y_1 = 1, B) =$$

$$\frac{P(\theta = 1 | B) \cdot P(y_1 = 1 | \theta = 1, B)}{P(y_1 = 1 | B)}$$

T/E prop.

$$P(A|B) \in (0, 1)$$

$$P(y_1 = 1 | B)$$

CS2) $\theta \in (0, 1)$ ^{cont. r.v.}
 ~~\mathbb{R}~~ ^{space of possible θ}

$p(\theta | \gamma, \mathcal{B}) = f_{\theta | \gamma, \mathcal{B}}$ ^{post. dist. θ} (2)

$\gamma = (\gamma_1, \dots, \gamma_n)$
 $\gamma_i \in \{0, 1\}$
 $\mathcal{B} = \{B_1, \dots, B_b\}$

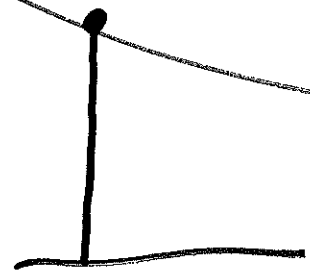
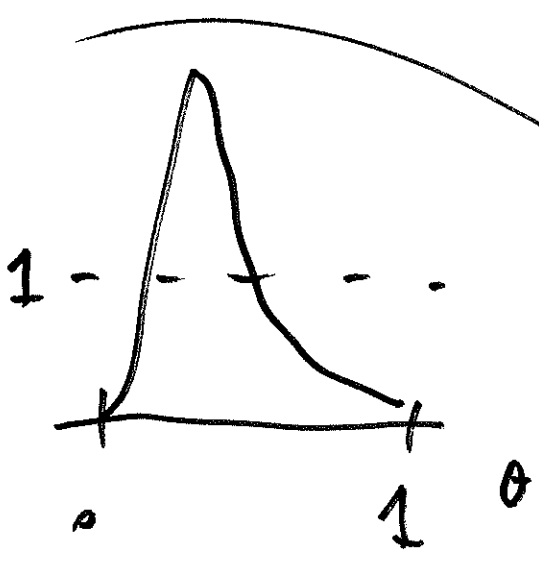
$p(\theta | \mathcal{B})$ $p(\gamma | \theta, \mathcal{B})$

 $p(\gamma | \mathcal{B})$
 \downarrow
 $f_{\Sigma | \mathcal{B}}(\gamma | \mathcal{B})$

$\Sigma = (\Sigma_1, \dots, \Sigma_n)$
 $f_{\Theta | \mathcal{B}}(\theta | \mathcal{B})$

$f_{\Sigma | \Theta, \mathcal{B}}(\gamma | \theta, \mathcal{B})$

$f_{\Theta | \Sigma, \mathcal{B}}(\theta | \gamma, \mathcal{B})$



$$p(\theta | y, \mathcal{B}) = \frac{p(\theta | \mathcal{B}) \cdot p(y | \theta, \mathcal{B})}{p(y | \mathcal{B})} \quad (3)$$

↑

post. dist.

for θ given y & \mathcal{B}

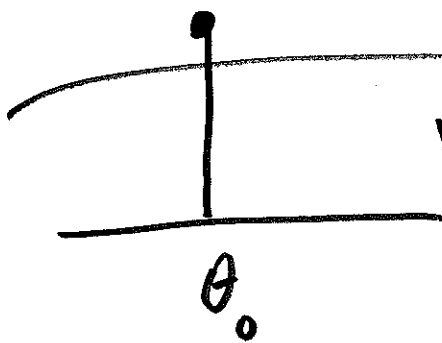
(thm)

Math fact:

under plausible Axioms (assumptions),

the optimal action a^* maximizes

$$E_{(\theta | y, \mathcal{B})} \underline{U(a, \theta | \mathcal{B})} = \text{Expected Utility}$$



$p(\theta | y, \mathcal{B})$

find a to max.

$$U(a, \theta_0 | \mathcal{B})$$

MEU

$$SE(\bar{Y}) = \sqrt{\frac{\sigma^2}{n}} = \frac{\sigma}{\sqrt{n}}$$

$$(\mathcal{Y}_i | \mu, \sigma^2) \stackrel{\text{iid}}{\sim} N(\mu, \sigma^2)$$

$(i=1, \dots, n)$

$$\mathcal{Y} = (\mathcal{Y}_1, \dots, \mathcal{Y}_n)$$

$$\bar{\mathcal{Y}} = \frac{1}{n} \sum_{i=1}^n \mathcal{Y}_i$$

$$\hat{\sigma}_{\text{MLE}}^2 = \frac{1}{n} \sum_{i=1}^n (\mathcal{Y}_i - \bar{\mathcal{Y}})^2$$

$$\hat{\sigma}_{\text{unbiased}}^2 = \frac{1}{n-1} \sum_{i=1}^n (\mathcal{Y}_i - \bar{\mathcal{Y}})^2$$

$$(\theta = \sigma^2)$$

$$\text{bias}(\hat{\theta}_{\text{MLE}}) = E(\hat{\theta}_{\text{MLE}}) - \theta$$

$$= \underline{\underline{O\left(\frac{1}{n}\right)}}$$

a function is

$O\left(\frac{1}{n}\right)$ if when $n \uparrow \infty$, the

function goes to 0 at a

$\frac{1}{n}$ rate

$$\text{SE}(\hat{\theta}_{\text{MLE}}) = \underline{\underline{O\left(\frac{1}{\sqrt{n}}\right)}}$$

$n = 10$

$s = 5$

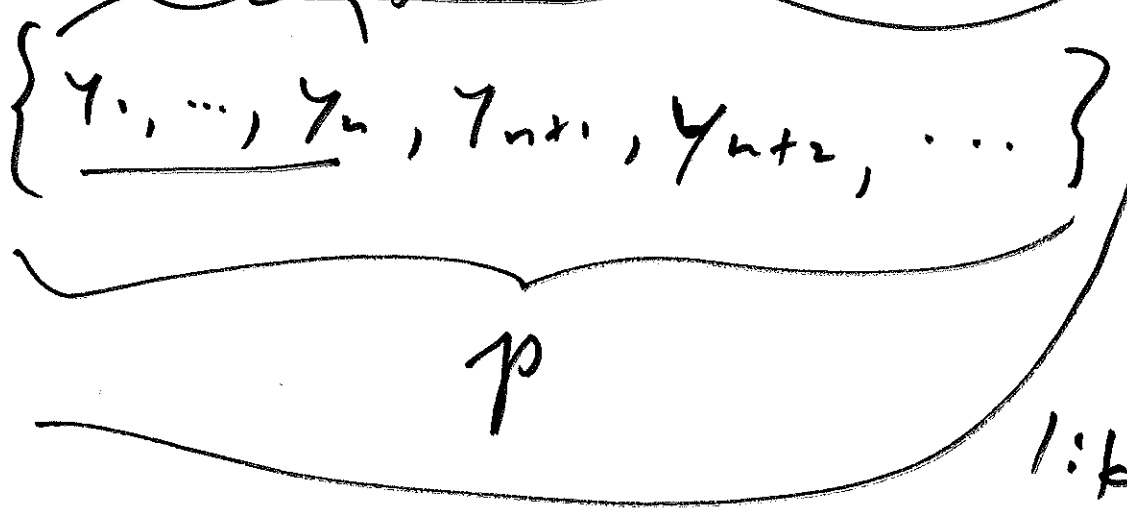
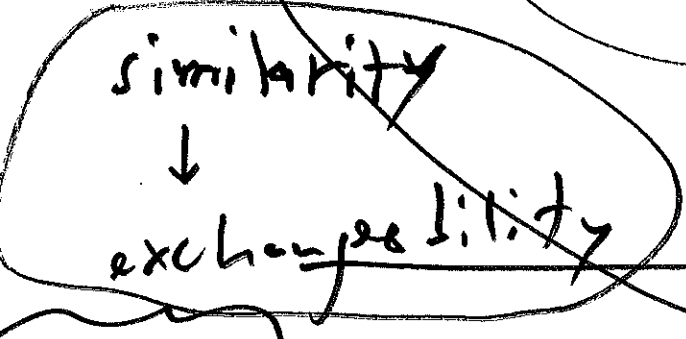
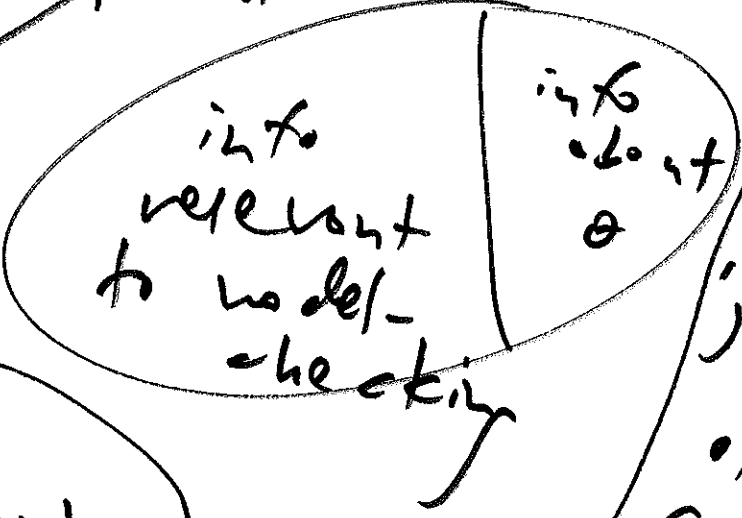
X	1	1	1	1	1	0	0	0	0	0
X	1	0	1	0	1	0	1	0	1	0
X	1	0	1	1	0	1	0	0	1	0

$(\mathbb{I}, \theta, \mathcal{B})$ IID

Bernoulli (θ)

$(i=1, \dots, n)$

total info



extending judgment of exch. from $(\gamma_1, \dots, \gamma_n)$ to $(\gamma_1, \gamma_2, \dots)$

is exactly like thinking

of $(\gamma_1, \dots, \gamma_n)$ as an IID sample from $\mathcal{P} = (\gamma_1, \gamma_2, \dots)$

exch \rightarrow

$$\underline{(Y_1, \dots, Y_n)} \rightarrow (Y_1, Y_2, \dots)$$

binary uncertainty
I judge exchangeable

$$\begin{aligned} \rightarrow & \left. \begin{array}{l} \text{prior} \\ \text{lik} \end{array} \right\} \begin{aligned} & (\theta | \mathcal{B}) \sim p(\theta | \mathcal{B}) \\ & (Y_i | \theta, \mathcal{B}) \stackrel{\text{IID}}{\sim} \text{Bernoulli}(\theta) \\ & (i=1, \dots, n) \end{aligned} \end{aligned}$$

(hierarchical model)