

# Mathematical Statistics II

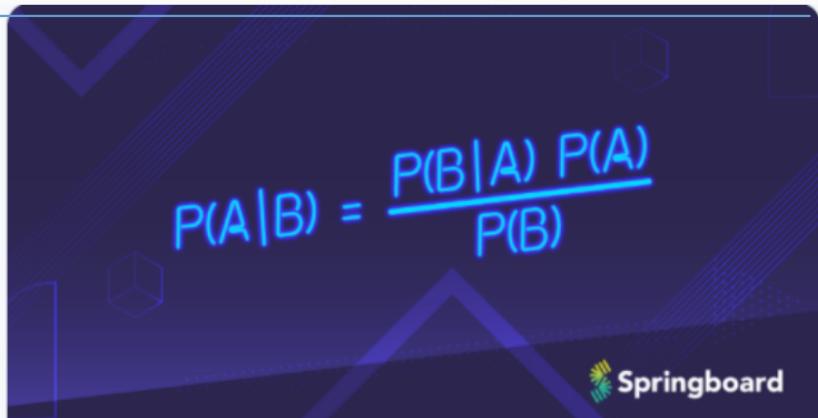
STA2212H S LEC9101

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Week 6

February 24 2021

Start recording!



Become a Data Scientist in 6 Months  
[springboard.com](http://springboard.com)

STA 2212S: Mathematical Statistics II  
Syllabus

Spring 2021

Updated Feb 3

Week	Date	Methods	References
1	Jan 13/15	Review of parametric inference	AoS Ch 9
2	Jan 20/22	Significance testing Hypothesis testing	AoS Ch 10.1,2, <del>6,7</del> ; SM Ch 7.3.2, <a href="#">4</a>
3	Jan 27/29	Significance testing	AoS Ch 10.2, 6; SM Ch 7.3.1, Ch 4
4	Feb 3/5	Goodness of fit testing, <a href="#">Intro to multiple testing</a>	AoS Ch 10.3,4,5,8; <a href="#">SM p.327-8 (hard)</a>
5	Feb 10/12	Multiple testing and FDR	AoS Ch 10.7, EH Ch 15.1,2
6	Feb 17/19	Break	
7	Feb 24/26	Bayesian Inference	AoS Ch 11.1-4; SM Ch 11.1,2; EH Ch 3, 13
8	Mar 3/5	Bayesian Inference	AoS Ch 11.5-9; SM Ch 11.4
9	Mar 10/12	Empirical Bayes	EH Ch 6
10	Mar 17/19	Statistical Decision theory	AoS Ch 12
11	Mar 24/26	Multivariate Models	AoS Ch 14; SM Ch 6.3
12	Mar 31	Causal Inference	AoS Ch 16
13	Apr 7	Recap	

1. HW 5 updated
2. Bayesian inference Part I
3. Friday: Solutions re HW 4, especially careful analysis re bonus question;  
if time, Proof of B-H FDR control

- Toronto Workshop on Reproducibility Feb 25-26
- Mar 1 3.00 pm EST Rebecca Barter  
“Teaching Data Science in the Real World” [Link](#)  
[Data Science ARES](#)
- Feb 25 1.00 pm EST [Dylan Small](#)  
[CANSSI National Seminar Series \(Journal Club; Slack\)](#)



version 1.  $P(A | B) = \frac{P(A, B)}{P(B)} = \frac{P(B|A) P(A)}{P(B)}$   $P(B) > 0$   
 cond'l prob.

version 2.  $A_1, \dots, A_k$  partition the sample space

$$P(A_j | B) = \frac{P(B|A_j) P(A_j)}{P(B)} = \frac{P(B|A_j) P(A_j)}{\sum_{i=1}^k P(B|A_i) P(A_i)}$$
 "discrete"

version 3. random variables  $Y, Z$ ,

$$f_{Z|Y}(z | y) = \frac{f_{Y|Z}(y|z) f_z(z)}{\int f_{Y|Z}(y|z) f_z(z)} = \frac{f_{Y|Z}(y|z) f_z(z)}{f_y(y)}$$
 if  $f_y(y) > 0$   
 on support  $y$

Schervish text

## Bayes' theorem: Example

EH §3.1

Sonogram shows:

		Same sex	Different
		a	b
Twins are:	Identical	1/3	0
	Fraternal	1/3	1/3
Physicist			

1/3      2/3

Doctor

Figure 3.1 Analyzing the twins problem.

$$\begin{aligned} P(\text{ident} \mid \text{s.s.}) &= \frac{P(\text{s.s.} \mid \text{id}) \cdot P(\text{id})}{P(\text{ss} \mid \text{id})P(\text{id}) + P(\text{ss} \mid \overline{\text{id}})P(\overline{\text{id}})} \\ &= \frac{\frac{1}{2} \cdot \frac{1}{3}}{\frac{1}{3} \cdot \frac{1}{2} + \frac{1}{2} \cdot \frac{2}{3}} = \frac{1}{2} \end{aligned}$$

Sonogram shows twin boys. What is the probability they are **identical twins**?

## Example: diagnostic tests

ASI Sep 17; SM Ex. 11.2

		test negative	test positive	
		TN	FP	N
truth	C19 neg			
	C19 pos	FN	TP	P

link

( number )

↓ prevalence  
"in pop"

PPV =  $\Pr(C19 \text{ pos} | \text{test pos}) = \frac{\Pr(\text{true +} | C19) \cdot P(C19)}{\Pr(\text{true +} | C19) P(C19) + \Pr(\text{true} | \overline{C19}) P(\overline{C19})}$

↑  
positive predictive  
value

$\Pr(\text{true +} | C19) P(C19)$        $\Pr(\text{true} | \overline{C19}) P(\overline{C19})$

TP/P      FP/N

model  $X \sim f_{x|\theta}(x|\theta) \quad \theta \in \Theta \subseteq \mathbb{R}^k$  st. model

prior  $\theta \sim \pi_{\Theta}(\theta)$   $\oint \pi(\theta) d\theta = 1$  (maybe)  
proper

posterior  $f(\theta|x) = \frac{f(x|\theta)\pi(\theta)}{\int f(x|\theta)\pi(\theta)d\theta} = \frac{f(x|\theta)\pi(\theta)}{f(x)}$  or  
 $\underbrace{m(x)}$

sample  $X_1, \dots, X_n$   $f(\theta|z) = \frac{f(z|\theta)\pi(\theta)}{f(z)}$   
 ~~$\propto L(\theta; z)\pi(\theta)$~~

is "everything"

AoS box in §11.2

$f(\underline{z}) > 0$

## Example: Binomial

SM Ex.11.1; AoS Ex.11.2

$X_1, \dots, X_n$  i.i.d. Bernoulli ( $p$ )

$$f(\underline{x}|p) = \prod_{i=1}^n p^{x_i} (1-p)^{1-x_i} = p^s (1-p)^{n-s} \quad s = \sum x_i$$

$$f(s|p) = \binom{n}{s} p^s (1-p)^{n-s}, \quad 0 \leq p \leq 1; \quad 0 \leq s \leq n \\ L(p|s) = p^s (1-p)^{n-s}$$

$$f(s|p) = \binom{n}{s} p^s (1-p)^{n-s} \cdot \pi(p) / \int \binom{n}{s} p^s (1-p)^{n-s} dp$$

$$\pi(p) = \frac{p^{a-1} (1-p)^{b-1}}{B(a, b)} \quad 0 \leq p \leq 1 \quad \text{Beta}(a, b)$$

$$B(a, b) = \frac{\Gamma(a) \Gamma(b)}{\Gamma(a+b)}$$

$$\pi(p|s) \propto \frac{p^s (1-p)^{n-s} \cdot p^{a-1} (1-p)^{b-1}}{\int_{-\infty}^{\infty} \dots dp}$$

$$\pi(p|s) = \frac{p^{s+a-1} (1-p)^{n-s+b-1}}{\int_{-\infty}^{\infty} \dots dp}$$

$$\pi(p|s) = \frac{p^{s+a-1} (1-p)^{n-s+b-1}}{B(a+s, b+n-s)}$$

special case  $a=b=1$   $\boxed{\pi(p)=1} \quad 0 \leq p \leq 1$

$$\begin{aligned}\pi_{sp}(p|s) &= \frac{p^s (1-p)^{n-s}}{B(s+1, n-s+1)} \quad 0 \leq p \leq 1 \\ &= \frac{P(s+1) P(n-s+1)}{P(n+2)} \cdot p^s (1-p)^{n-s} = \frac{B(a,b)}{\Gamma(a)\Gamma(b)}\end{aligned}$$

$$E\{B(a,b)\} = \frac{a}{a+b} \quad E(p|s) = \frac{s+1}{n+2}$$

$$\hat{p} = \frac{s}{n}$$

E.g. if we decide to estimate  $p$  by

$$E(p|s), \text{ then } \tilde{p}_B = \hat{p}w + (1-w) \cdot \frac{1}{2}$$

$$\tilde{p}_B = \overset{\uparrow}{\hat{p} \cdot w} + \overset{\uparrow}{\frac{1}{2}(1-w)} \quad w = \frac{n}{n+2} \simeq 1$$

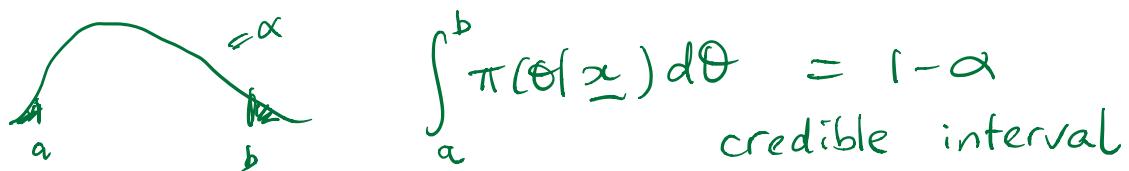
$\uparrow$  sample mean     $\uparrow$  prior mean     $E\{U(0,1)\}$

~~get~~  $\pi(\theta | \underline{x})$  ( $\theta \in \mathbb{R}$ )

→ est.  $\theta$  by  $E(\theta | \underline{x})$

est.  $\theta$  by  $\arg \sup_{\theta} \pi(\theta | \underline{x})$

→ posterior interval



## Example: Bivariate normal

EH §3.1

**Table 3.1** Scores from two tests taken by 22 students, mechanics and vectors.

	1	2	3	4	5	6	7	8	9	10	11
mechanics	7	44	49	59	34	46	0	32	49	52	44
vectors	51	69	41	70	42	40	40	45	57	64	61
	12	13	14	15	16	17	18	19	20	21	22
mechanics	36	42	5	22	18	41	48	31	42	46	63
vectors	59	60	30	58	51	63	38	42	69	49	63

Table 3.1 shows the scores on two tests, mechanics and vectors, achieved by  $n = 22$  students. The sample correlation coefficient between the two scores is  $\hat{\theta} = 0.498$ ,

$$\hat{\theta} = \frac{\sum_{i=1}^{22} (m_i - \bar{m})(v_i - \bar{v})}{\left[ \sum_{i=1}^{22} (m_i - \bar{m})^2 \sum_{i=1}^{22} (v_i - \bar{v})^2 \right]^{1/2}}, \quad (3.10)$$

with  $m$  and  $v$  short for mechanics and vectors,  $\bar{m}$  and  $\bar{v}$  their averages. We wish to assign a Bayesian measure of posterior accuracy to the true correlation coefficient  $\theta$ , “true” meaning the correlation for the hypothetical population of all students, of which we observed only 22.

If we assume that the joint  $(m, v)$  distribution is bivariate normal (as

$$(x_{ni}, y_{ni}) \sim \mathcal{N}_2 \left( \begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix}, \Sigma \right)$$

$$\Sigma = \begin{pmatrix} \sigma_x^2 & \rho \sigma_x \sigma_y \\ \rho \sigma_x \sigma_y & \sigma_y^2 \end{pmatrix}$$

$$\pi(\theta)$$

$$\pi(\theta | x, y)$$

$$\hat{\theta}_{\text{MLE}} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

bb

$$\pi(\rho | x, y) = f(\hat{\rho} | \rho) \cdot \pi(\rho) / \left( f(\hat{\rho} | \rho) \pi(\rho) d\rho \right)$$
$$-1 \leq \rho \leq 1$$

$$\propto \frac{1}{\pi} (n-2)(1-\rho^2)^{(n-1)/2} (1-\hat{\rho}^2)^{(n-4)/2} \cdot \int_0^\infty \frac{dw}{(\cosh w - \rho \hat{\rho})^{n-1}} \pi(w)$$

$$\pi_1(\rho) = \frac{1}{2} \quad -1 \leq \rho \leq 1 \quad -1 \leq \rho \leq 1$$

$$\pi_2(\rho) = \frac{1}{1-\rho^2} \quad -1 \leq \rho \leq 1$$

$$\pi_3(\rho) = 1 - |\rho|, \quad -1 \leq \rho \leq 1$$

## Example: Bivariate normal

EH §3.1

$n=22$

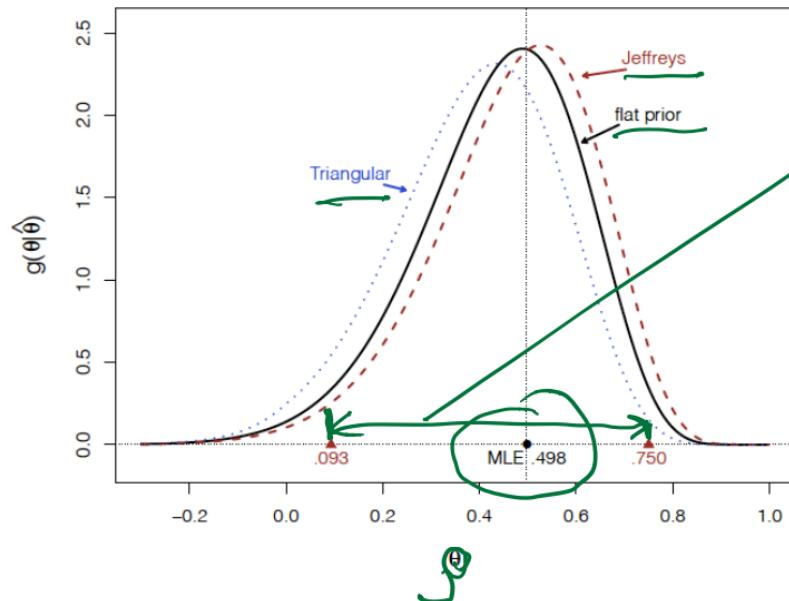


Figure 3.2 Student scores data; posterior density of correlation  $\theta$  for three possible priors.

credible interval  
Jeffreys prior

← each

$$\int \pi_k(\rho | \hat{\rho}) d\rho = 1$$

$k = 1, 2, 3$

are "normalized"

$$\pi_k(\rho | \hat{\rho}) \propto L(\hat{\rho}; \rho) \pi(\rho)$$

## 11.2 · Inference

579

**Table 11.2** Mortality rates  $r/m$  from cardiac surgery in 12 hospitals (Spiegelhalter *et al.*, 1996b, p. 15). Shown are the numbers of deaths  $r$  out of  $m$  operations.

A	0/47	B	18/148	C	8/119	D	46/810	E	8/211	F	13/196
G	9/148	H	31/215	I	14/207	J	8/97	K	29/256	L	24/360

provided the mode lies inside the parameter space. Here  $\tilde{J}(\theta)$  is the second derivative matrix of  $\tilde{\ell}(\theta)$ . This expansion corresponds to a posterior multivariate normal

12 hospitals  
mortality rate

1. hospital A only

$$m = 47 \quad r = 0 \quad \hat{p} = 0$$

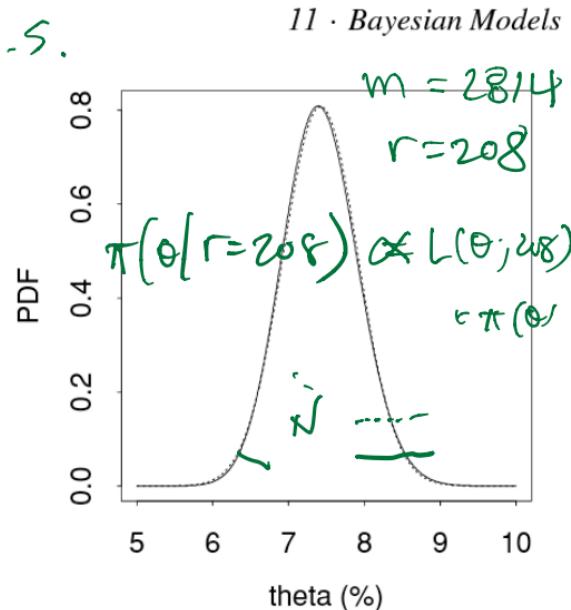
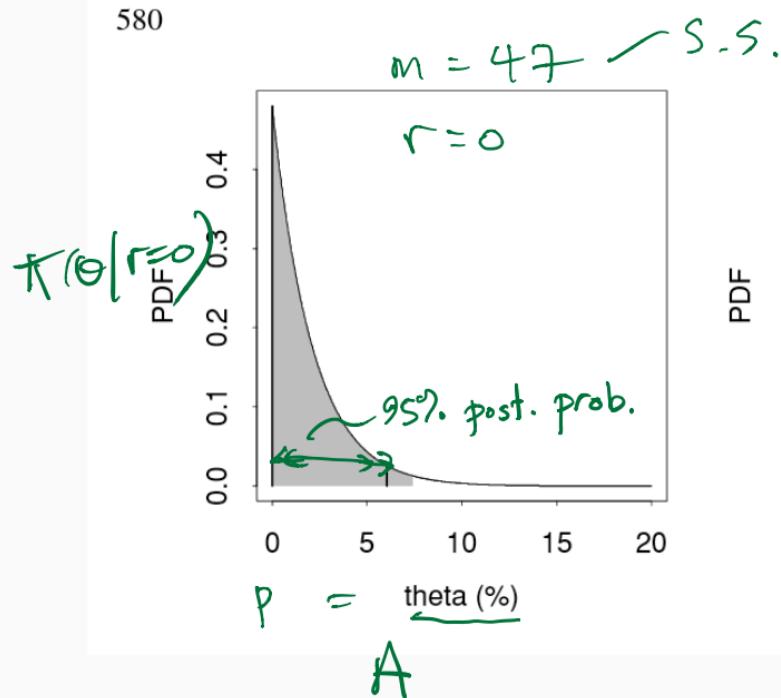
2. all hospitals together

$$r_H \sim \text{Bin}(m_H, p_H) \quad p \text{ same}$$

$$\pi(p) \sim U(0, 1): \quad p_{\text{Bayes}, A} = \frac{0+1}{47+2}$$

# Example: Binomial

SM Ex.11.11



**Figure 11.1** Cardiac surgery data. Left panel: posterior density for  $\theta_A$ , showing boundaries of 0.95 highest posterior credible interval (vertical lines) and region between posterior 0.025 and 0.975 quantiles of  $\pi(\theta_A | y)$  (shaded). Right panel: exact posterior beta density for overall mortality rate  $\theta$  (solid) and normal approximation (dots).

all fog.

$$r=208 \quad m=2814$$

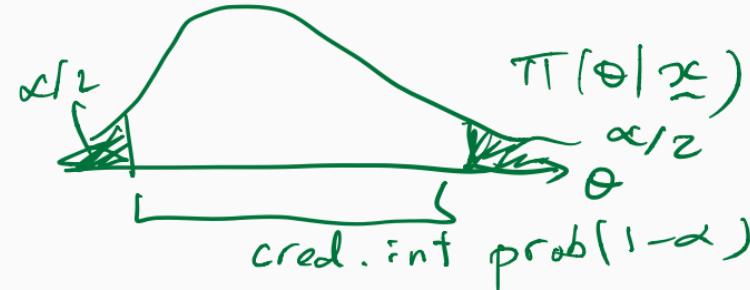
$$\tilde{P} = \frac{(208+1)}{(2814+2)} \approx \tilde{P} = \frac{208}{2814}$$

point estimates

posterior mean, mode, median

posterior intervals 1

equi-tailed



posterior intervals 2

highest post.  
density intervals

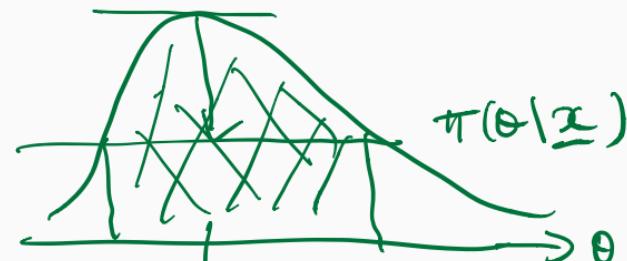
functions of the parameter

$$\pi(\theta|z) \propto L(\theta; z) \pi(\theta)$$

$$\alpha = \alpha(\theta)$$

$$\boxed{\pi(\alpha|z) = \pi(\theta|z) \left| \frac{d\theta}{d\alpha} \right|}$$

$\approx 1 - \alpha$



point estimates  $\pi(\theta|x)$  — mean, median, mode (posterior)

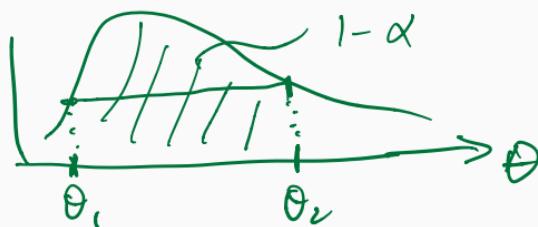
posterior intervals 1 —  $\tilde{\theta} \pm \text{s.e.} - z_{\alpha/2}$  ← approx.(normal)

$$\text{or find } \int_{-\infty}^{\theta_L} \pi(\theta|x) d\theta = \frac{\alpha}{2}; \int_{\theta_U}^{\infty} \pi(\theta|x) d\theta = \frac{\alpha}{2}$$

posterior intervals 2

functions of the parameter ↗ highest post. density (HPD)  $\Rightarrow (\theta_L, \theta_U)$  posterior credible int. of prob  $1-\alpha$

exact  $\rightarrow \pi(\theta|x)$



↑ exact

# Functions of the parameter

SM Ex.11.8; AoS §11.3

$$S \sim \text{Bin}(n, p)$$

$$\psi = \log\{p/(1-p)\}$$

parameter of interest

$$\pi(p|s) = \frac{p^s(1-p)^{n-s}}{B(s+1, n-s+1)} \quad 0 \leq p \leq 1 \quad \text{flat}$$

$$p = \frac{e^\psi}{1+e^\psi}; \quad \psi = \log \frac{p}{1-p}$$

$$\pi(p) = 1$$

$$\pi(\psi|s) \propto \frac{\left\{e^\psi/(1+e^\psi)\right\}^s \left\{1/(1+e^\psi)\right\}^{n-s} \cdot \frac{e^\psi}{(1+e^\psi)^2}}{\pi(\psi)}$$

mistake in AoS density

$$\pi(\psi) = \frac{e^\psi}{(1+e^\psi)^2} \text{ logistic dens.}$$



$$\pi(p) = 1 \quad 0 \leq p \leq 1$$

Jeffreys' prior

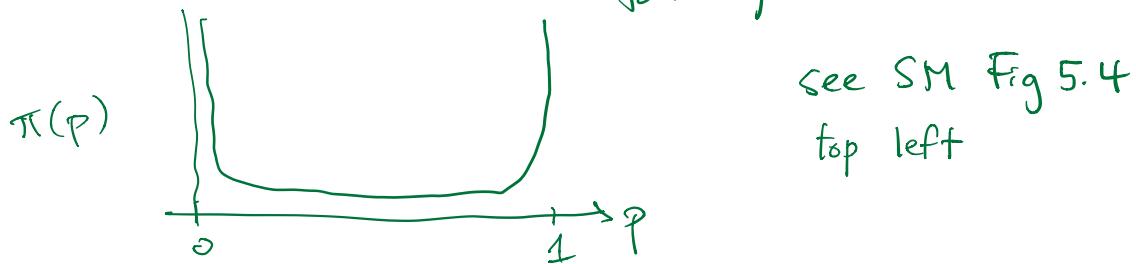
$$\Rightarrow \pi(\varphi) = \text{[bell curve]} \quad \varphi \in \mathbb{R}$$

$$\pi(\varphi) = 1, \quad -\infty \leq \varphi \leq \infty \quad \text{not}$$

$$\pi(\varphi|s) = \frac{\mathcal{L}(\varphi; s) \cdot \pi(\varphi)}{\int \mathcal{L}(\varphi; s) \cdot \pi(\varphi) d\varphi} \quad \begin{matrix} \text{proper} \\ \text{if } \int \pi(\varphi) d\varphi < \infty \end{matrix}$$

I think of  $\pi(\varphi) = 1$  on  $\mathbb{R}$  that  
 $\pi(\varphi|s)$  is proper ✓ yes (I checked)

if  $\pi(\varphi) = 1$  what's the implied prior  
 for  $p$ : it's  $\text{Beta}(\frac{1}{2}, \frac{1}{2})$



see SM Fig 5.4  
 top left

Priors of convenience can be "misleading"

$$\pi(\theta | \underline{x}) = \frac{L(\theta; \underline{x})\pi(\theta)}{\int L(\theta; \underline{x})\pi(\theta) d\theta} \quad \text{dist}^{\approx} \text{ of } \pi(\theta | \underline{x})$$


$$= e^{\tilde{l}(\theta; \underline{x})} / \int e^{\tilde{l}(\theta; \underline{x})} d\theta$$

r.v.  
 $\underline{x} \sim \prod_{i=1}^n f(x_i; \theta)$   
 $= \underline{f(\underline{x}; \theta)}$

$$\tilde{l}(\theta; \underline{x}) = \ell(\theta; \underline{x}) + b \rho \pi(\theta)$$

$$= \tilde{l}(\hat{\theta}; \underline{x}) + \cancel{\frac{(\theta - \hat{\theta}) \tilde{l}'(\hat{\theta})}{2}} + \frac{1}{2} (\theta - \hat{\theta})^2 \tilde{l}''(\hat{\theta}) + \dots$$

assume  $\tilde{l}'(\hat{\theta}) = 0$

$$\hat{\ell}(\tilde{\theta}) + \frac{1}{2}(\theta - \tilde{\theta})^2 \hat{\ell}''(\tilde{\theta}) + \frac{1}{3}(\theta - \tilde{\theta})^3 \hat{\ell}'''(\theta^*)$$

$$\pi(\theta | \underline{x}) = \frac{e^{\tilde{\ell}(\theta)}}{\int e^{\tilde{\ell}(\theta)} d\theta} = \frac{e^{\tilde{\ell}(\tilde{\theta})}}{e^{\tilde{\ell}(\tilde{\theta})} \int e^{-\frac{1}{2}(\theta - \tilde{\theta})^2 \hat{\ell}''(\theta)} d\theta} \xrightarrow{\substack{\theta \leq \theta^* \leq \tilde{\theta} \\ \rightarrow N}} \text{const.}$$

$$\pi(\theta | \underline{x}) \simeq N(\tilde{\theta}; \{-\hat{\ell}''(\tilde{\theta})\}^{-1})$$

(recall  $x \sim N(\mu, \sigma^2)$  :  $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}$ )

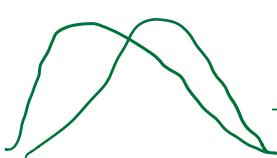
$$\begin{aligned} \pi(\theta | \underline{x}) &= \frac{e^{-\frac{1}{2}(\theta - \tilde{\theta})^2 \{-\hat{\ell}''(\tilde{\theta})\}}}{\sqrt{2\pi} \cdot [-\hat{\ell}''(\tilde{\theta})]^{1/2}} \\ &= \frac{\{-\hat{\ell}''(\tilde{\theta})\}^{1/2}}{\sqrt{2\pi}} e^{-\frac{1}{2}(\theta - \tilde{\theta})^2 \{-\hat{\ell}''(\tilde{\theta})\}} \end{aligned}$$

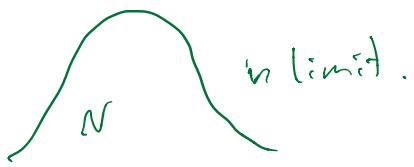
rigorous :  $\tilde{\theta} \xrightarrow{\text{not}} \theta$  is probability  
 $\sqrt{n}(\tilde{\theta} - \theta) \xrightarrow{\text{not}} \text{in dist} \approx N(0, 1)$

assume that  $\exists \tilde{\theta} = \tilde{\theta}(\underline{x})$  s.t.

$$\pi(\tilde{\theta} | \underline{x}) \geq \pi(\theta | \underline{x}) \quad \forall \theta \in \Theta$$

- that  $\tilde{\theta}$  also satisfies  $\frac{\partial}{\partial \theta} \pi(\tilde{\theta} | \underline{x}) = 0$
- that  $\pi(\theta)$  is proper.





in limit.

$$\begin{aligned} \frac{\partial}{\partial \theta} \log \pi(\tilde{\theta} | \underline{x}) &= 0 \\ &= \frac{\partial}{\partial \theta} l(\tilde{\theta}; \underline{x}) + \underbrace{\frac{\partial}{\partial \theta} \pi(\tilde{\theta})}_{\log} \\ \frac{\partial}{\partial \theta} l(\hat{\theta}; \underline{x}) + \underbrace{\frac{\partial}{\partial \theta} \pi(\hat{\theta})}_{\text{leave prior "down"}} &= 0 \end{aligned}$$

$$\pi(\theta | y) = \frac{e^{l(\theta; \underline{x})} \pi(\theta)}{\int e^{l(\theta; \underline{x})} \pi(\theta) d\theta} \quad \text{leave prior "down"}$$

$$l(\theta; \underline{x}) = l(\hat{\theta}; \underline{x}) + (\theta - \hat{\theta}) l'(\hat{\theta}; \underline{x}) + \frac{1}{2} (\theta - \hat{\theta})^2 l''(\hat{\theta}; \underline{x}) \quad \xrightarrow{\text{def. pdf}}$$

$$\begin{aligned} \pi(\theta | y) &\approx e^{-\frac{1}{2}(\theta - \hat{\theta})^2 \{-l''(\hat{\theta})\}} \cdot \frac{\pi(\hat{\theta}) + \frac{(\theta - \hat{\theta}) \pi'(\hat{\theta})}{\dots}}{\dots + \dots} \\ &\qquad \qquad \qquad \boxed{e^{\dots ?}} \end{aligned}$$

$$\approx e^{-\frac{1}{2}(\theta - \hat{\theta})^2 \{-l''(\hat{\theta})\}} \cdot \frac{1}{\sqrt{2\pi}} | -l'(\hat{\theta}) |^{1/2}$$

$$N(\hat{\theta}, j(\hat{\theta})) \quad j(\theta) = \text{F. info. fn.}$$

$$\hat{\theta} \pm z_{\alpha/2} \{ j(\hat{\theta}) \}^{1/2} \quad \begin{array}{l} \text{approx } 1-\alpha \\ \text{credible interval} \end{array}$$

$$\theta \sim N(\hat{\theta}, \hat{j}^{-1}) \quad (\theta - \hat{\theta}) \hat{j}^{1/2} \sim N(0, 1)$$

$$= 1-\alpha \text{ C.I. from } N \text{ approx to } \hat{\theta}$$

If  $\theta \in \mathbb{R}$ , and ... regularity ...

post-credible interval  $\approx$  conf. interval

as  $n \rightarrow \infty$ .

"prior is washed out by the data"