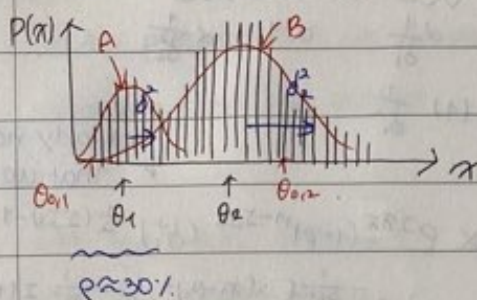


Consider the following data.



[theory]

$$f(x) = p N(\theta_1, \sigma_1^2) + (1-p) N(\theta_2, \sigma_2^2)$$

How many parameters are in this model?

↳ 5

[posterior]

$$P(\theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p | x) \propto P(x | \theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p) \cdot P(\theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p)$$

$$P(x_1, \dots, x_n | \theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p) = \prod_{i=1}^n \left( p \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{1}{2\sigma_1^2}(x_i - \theta_1)^2} + (1-p) \frac{1}{\sqrt{2\pi}\sigma_2} e^{-\frac{1}{2\sigma_2^2}(x_i - \theta_2)^2} \right)$$

→ we're in trouble because we can't simplify this product of  $(a_i + b_i)$

Introduce  $B$

$$P(A|x) = \int P(A, B|x) dB$$

"Data Argumentation" or "parameter Argumentation" We introduce parameters:

$$I_1 := \mathbb{I}_{x_1 \text{ comes from distribution A}} = \begin{cases} 1, & \text{if } x_1 \text{ from distr A} \\ 0, & \text{if } x_1 \text{ from distr B} \end{cases}$$

$$I_2 := \mathbb{I}_{x_2}$$

⋮

$$I_n := \mathbb{I}_{x_n}$$

New Bayesian Setup:

$$P(\theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p, I_1, \dots, I_n | x) \propto P(x | \theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p, I_1, \dots, I_n)$$

$$\begin{aligned} P(x | \dots) &= \prod_{i=1}^n \left( \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{1}{2\sigma_1^2}(x_i - \theta_1)^2} \right)^{I_i} \left( \frac{1}{\sqrt{2\pi}\sigma_2} e^{-\frac{1}{2\sigma_2^2}(x_i - \theta_2)^2} \right)^{1-I_i} \\ &= \left( \frac{1}{\sqrt{2\pi}\sigma_1} \right)^{\sum I_i} e^{-\frac{1}{2\sigma_1^2} \sum I_i (x_i - \theta_1)^2} \left( \frac{1}{\sqrt{2\pi}\sigma_2} \right)^{n - \sum I_i} e^{-\frac{1}{2\sigma_2^2} \sum (1-I_i)(x_i - \theta_2)^2} \end{aligned}$$

$$P(\theta_1, \sigma_1^2, \theta_2, \sigma_2^2, p, I_1, \dots, I_n) = P(I_1, \dots, I_n | p, \theta_1, \sigma_1^2, \theta_2, \sigma_2^2) \cdot P(p, \theta_1, \sigma_1^2, \theta_2, \sigma_2^2)$$

$$= \underbrace{P(I_1, \dots, I_n | p)}_{\prod_{i=1}^n P(I_i | p)} \underbrace{P(p)}_{U(0,1)} \underbrace{P(\theta_1 | \delta_1^2)}_{\propto 1} \underbrace{P(\delta_1^2)}_{\propto \frac{1}{\delta_1^2}} \underbrace{P(\theta_2 | \delta_2^2)}_{\propto 1} \underbrace{P(\delta_2^2)}_{\propto \frac{1}{\delta_2^2}}$$

\*Jeffreys' priors

$$= \prod_{i=1}^n P(I_i | p) \quad U(0,1) \quad \propto 1 \quad \propto \frac{1}{\delta_1^2} \quad \propto 1 \quad \propto \frac{1}{\delta_2^2}$$

$$= p^{I_{1:n}} (1-p)^{n-I_{1:n}} (1) (1) \frac{1}{\delta_1^2} (1) \frac{1}{\delta_2^2}$$

clearly not a kernel  
↓ that we know

$$P(\theta, \delta_1^2, \theta_2, \delta_2^2, p, I_1, \dots, I_n | x) \propto p^{I_{1:n}} (1-p)^{n-I_{1:n}} (\delta_1^2)^{-\frac{1}{2}(I_{1:n}-1)} (\delta_2^2)^{-\frac{1}{2}(n-I_{1:n}-1)} \\ \cdot e^{-\frac{1}{2\delta_1^2} I_{1:n}(\bar{x}_1 - \theta_1)^2} \cdot e^{-\frac{1}{2\delta_2^2} I(1-I_{1:n})(\bar{x}_1 - \theta_2)^2}$$

Create a Gibbs Sampler:

$$P(p | -) \propto p^{I_{1:n}+1-1} (1-p)^{n-I_{1:n}+1-1} \propto \text{Beta}(I_{1:n}+1, n-I_{1:n}+1)$$

$$P(\theta_1 | -) \propto e^{-\frac{1}{2\delta_1^2} I_{1:n}(\bar{x}_1 - \theta_1)^2}$$

$$\propto e^{-\frac{I_{1:n} \bar{x}_1^2}{2\delta_1^2}} e^{+\frac{I_{1:n} \bar{x}_1 \theta_1}{\delta_1^2}} e^{-\frac{I_{1:n} \theta_1^2}{2\delta_1^2}}$$

$$\propto e^{\frac{I_{1:n} \bar{x}_1}{\delta_1^2} \theta_1 - \frac{I_{1:n}}{2\delta_1^2} \theta_1^2} \quad a = \frac{I_{1:n} \bar{x}_1}{\delta_1^2}, \quad b = \frac{I_{1:n}}{2\delta_1^2}$$

$$\propto \mathcal{N}\left(\frac{I_{1:n} \bar{x}_1}{I_{1:n}}, \frac{\delta_1^2}{I_{1:n}}\right)$$

let  $n_A = I_{1:n}$  : # of first distr.

$$= \mathcal{N}(\bar{x}_A, \frac{\delta_1^2}{n_A})$$

$$P(\theta_2 | -) \propto \mathcal{N}\left(\frac{I(1-I_{1:n}) \bar{x}_1}{n-I_{1:n}}, \frac{\delta_2^2}{n-I_{1:n}}\right) \quad \text{let } n_B = n-I_{1:n}$$

$$= \mathcal{N}(\bar{x}_B, \frac{\delta_2^2}{n_B})$$

$$P(\delta_1^2 | -) \propto (\delta_1^2)^{-\frac{1}{2}(I_{1:n}-1)} e^{-\frac{I_{1:n}(\bar{x}_1 - \theta_1)^2}{2\delta_1^2}}$$

$$\propto \text{InvGamma}\left(\frac{I_{1:n}}{2}, \frac{I_{1:n}(\bar{x}_1 - \theta_1)^2}{2}\right)$$

$$= \text{InvGamma}\left(\frac{n_A}{2}, \frac{n_A \bar{\sigma}_1^2}{2}\right)$$

$$P(\delta_2^2 | -) \propto \text{InvGamma}\left(\frac{n-I_{1:n}}{2}, \frac{I(1-I_{1:n})(\bar{x}_1 - \theta_2)^2}{2}\right)$$

$$= \text{InvGamma}\left(\frac{n_B}{2}, \frac{n_B \bar{\sigma}_2^2}{2}\right)$$

$$P(I_{1:n} | -) \propto \left( p \frac{1}{\sqrt{2\pi\delta_1^2}} e^{-\frac{1}{2\delta_1^2}(\bar{x}_1 - \theta_1)^2} \right)^{I_{1:n}} \left( (1-p) \frac{1}{\sqrt{2\pi\delta_2^2}} e^{-\frac{1}{2\delta_2^2}(\bar{x}_1 - \theta_2)^2} \right)^{1-I_{1:n}}$$

$$\propto A^{I_{1:n}} B^{1-I_{1:n}}$$

$$\propto \underbrace{\left(\frac{A}{A+B}\right)^{I_{1:n}}}_{p} \underbrace{\left(\frac{B}{A+B}\right)^{1-I_{1:n}}}_{1-p}$$

$$\propto \text{Bern}(p) = \text{Bern}\left(\frac{A}{A+B}\right)$$



We can now build a Gibbs Sampler to have inference for all  $n$  parameters. We do need to be careful to specify a good starting location though.

Set  $\theta_{0,1} = 25\%$  of data  $\sigma_{0,1}^2, \sigma_{0,2}^2 = 1$  (don't matter)

$\theta_{0,2} = 75\%$  of data

$I_1, \dots, I_{n/2} = 1$  and  $I_{n/2+1}, \dots, I_n = 0$ .

This will force the first group to be  $\theta_1$  and the upper group to be centered at  $\theta_2$ .

Bayes Factors (B) AKA "ratio of evidences". We want to compare two models

$M_1 = \langle \mathcal{F}_1, P_1(\theta) \rangle$  model 1 is likelihood 1 and prior 1

$M_2 = \langle \mathcal{F}_2, P_2(\theta) \rangle$  model 2 " " " "

$$B = \frac{P_{M_1}(x)}{P_{M_2}(x)} = \frac{\int_{\Theta_1} P_1(x|\theta) P_1(\theta) d\theta}{\int_{\Theta_2} P_2(x|\theta) P_2(\theta) d\theta} \quad \text{If } > 1 \Rightarrow M_1 \text{ better}$$

$$\quad \quad \quad \text{If } < 1 \Rightarrow M_2 \text{ better}$$

marginal  
probability  
averaged  
over all  $\theta$  for  $P_j(x|\theta)$  and  $P_j(\theta)$   
for both models.

Often Bayes Factors compare  $H_0$  to  $H_a$ .  $H_0$  and  $H_a$  differ on  $\Theta$ .

Imagine  $n=100$  coin flips and  $x=61$  heads. Want to test if coin is unfair.

$H_0: \theta = 0.5$

• Frequentist Test

$H_a: \theta \neq 0.5$

$$\text{Retention Region} = \left[ \theta_0 \pm z_{\alpha/2} \sqrt{\frac{\theta_0(1-\theta_0)}{n}} \right]$$

$\alpha = 5\%$

$$= \left[ 0.5 \pm 2 \cdot \sqrt{\frac{0.5(1-0.5)}{100}} \right]$$

$\hat{\theta} = 61/100 = 0.61$

$$= [0.40, 0.60]$$

$\hat{\theta} \notin \text{Ret. Region} \Rightarrow \text{Reject } H_0$

Bayesian Test using CR method

let  $\theta \sim U(0,1)$

$$CR_{0.95} = [q_{\text{beta}}(0.025, 61+1, 39+1), q_{\text{beta}}(0.975, 61+1, 39+1)]$$

$$= [0.511, 0.700]$$

$\theta_0 = 0.5 \notin CR_{0.95} \Rightarrow \text{Reject } H_0$