

Single-Parameter Models

Previous Example: ① parameter Space is Discrete with
(generic status; finite possibilities
spell correction) ② observations - - - Discrete - - -

e.g. parameter {
woman
carrier, not}
observation {
son
healthy, disease}

$$P(\theta|y) = \frac{P(\theta) P(y|\theta)}{\sum_{\theta^*} P(\theta^*) P(y|\theta^*)}$$

Now: the parameter space can be continuous
observation can be anything

Example 1. estimating the bias of a coin:

◦ Observation: $\{y_1, y_2, y_3, y_4, \dots\}_{i=1, \dots, n}^{y_i \in \{0, 1\}}$,
a sequence of binary variable.

◦ Quantity of interest (parameters): bias of a coin θ

◦ inference objective: $P(\theta | y_1, y_2, \dots, y_n)^{(0,1)}$
(posterior distribution)

$$= \frac{P(\theta) P(y_1, y_2, \dots, y_n | \theta)}{P(y_1, y_2, \dots, y_n)}$$

① Specify a Model \rightarrow Likelihood

$y_i \stackrel{\text{iid}}{\sim} \text{Bernoulli}(\theta)$ (Model)
 $i = 1, \dots, n$

$$\begin{aligned} \text{So } P(y_1, y_2, \dots, y_n | \theta) &= \prod_{i=1}^n P(y_i | \theta) \\ &= \prod_{i=1}^n \theta^{y_i} (1-\theta)^{(1-y_i)} \\ &= \theta^{\left| \sum_{i=1}^n y_i \right|} (1-\theta)^{\left| n - \sum_{i=1}^n y_i \right|} \end{aligned}$$

Bernoulli probability

#head *#tail*

② Prior distribution:

$$\theta \sim \text{Uniform}(0, 1)$$

$$P(\theta) = 1 \in \theta \in (0, 1)$$

$$\begin{aligned}
 ③^* \quad p(y_1, y_2, \dots, y_n) &= \int_0^1 P(y_1, y_2, \dots, y_n | \theta) p(\theta) d\theta \\
 &= \int_0^1 \theta^{\sum_{i=1}^n y_i} (1-\theta)^{n-\sum_{i=1}^n y_i} d\theta \quad \because \theta \text{ now is a continuous variable.} \\
 &= \text{Beta} \left(\sum_{i=1}^n y_i + 1, n - \sum_{i=1}^n y_i + 1 \right)
 \end{aligned}$$

$$\theta \sim \text{Beta}(\alpha, \beta)$$

$$p(\theta) = \frac{\theta^{\alpha-1} (1-\theta)^{\beta-1}}{\text{Beta}(\alpha, \beta)}$$

$$\begin{aligned}
 \int p(x) dx &= 1 \\
 x &\sim N(0, 1) \\
 \int \frac{e^{-x^2/2}}{\sqrt{2\pi}} dx &= 1
 \end{aligned}$$

④ posterior:

$$p(\theta | y_1, y_2, \dots, y_n) = \frac{\theta^{\sum_{i=1}^n y_i} (1-\theta)^{n-\sum_{i=1}^n y_i}}{\text{Beta} \left(\sum_{i=1}^n y_i + 1, n - \sum_{i=1}^n y_i + 1 \right)}$$

$$[\theta | y_1, \dots, y_n] \sim \text{Beta} \left(\sum_{i=1}^n y_i + 1, n - \sum_{i=1}^n y_i + 1 \right)$$

distribution

$$\text{IE}[\theta | y_1, \dots, y_n] = \frac{\sum_{i=1}^n y_i + 1}{n+2} \left(\frac{p}{p+q} \right)$$

(in future might need to do approximation here)

$\left(\frac{\sum_{i=1}^n y_i}{n} \right) * \left(\frac{n}{n+2} \right) + \left(\frac{1}{2} \right) * \left(\frac{2}{n+2} \right)$

Sample mean (data only)

prior mean

Since $P(\theta) = 1$

So posterior mean

$$= \frac{n}{n+2} * \text{Data part}$$

$$+ \frac{2}{n+2} * \text{prior part}$$

(prior only)

what does '2' here?

→ degree of freedom from Beta

if prior info is sufficient \Rightarrow assign a large

weight to prior part

$$P(\theta) = 1 = \theta^{1-1} (1-\theta)^{1-1}$$

$\sim \text{Beta}(1, 1)$

(Specify how strong our prior is)



Review: what is Beta Distribution?

△ What Happen when $n \rightarrow \infty$? $\left(\frac{n}{n+2}\right) \approx 1$

→ effect from prior will disappear.

only the data part explains

$$\begin{cases} E(\theta | y_1, \dots, y_n) \approx \frac{\sum y_i}{n} \\ \text{Var}(\theta | y_1, \dots, y_n) = \frac{(\sum y_i + 1)(n - \sum y_i + 1)}{(n+2)^2(n+3)} \\ \leq \frac{\frac{1}{4} \left(\sum_{i=1}^n y_i + 1 + n - \sum_{i=1}^n y_i + 1 \right)^2}{(n+2)^2(n+3)} \\ = \frac{1}{4} * \frac{1}{n+3} < \frac{1}{12} \end{cases}$$

Variance of uniform dis'

$\sqrt{\eta}$
prior variance

Posterior \rightarrow Variance reduction to the prior.

Beta distribution:

$$f(x) = \frac{(x-a)^{p-1} (b-x)^{q-1}}{B(p,q) (b-a)^{p+q-1}}, \quad a \leq x \leq b; p,q > 0$$

$$B(\alpha, \beta) = \int_0^1 t^{\alpha-1} (1-t)^{\beta-1} dt$$

$$\text{mean} = \frac{p}{p+q}, \quad \text{standard deviation}$$

$$= \sqrt{\frac{pq}{(p+q)^2 (p+q+1)}}$$