

1.

$$\begin{aligned} (a) \quad P(y) &= P(\theta=1) P(y|\theta=1) + P(\theta=2) P(y|\theta=2) \\ &= 0.5 N(y|1, 2^2) + 0.5 N(y|2, 2^2) \end{aligned}$$

See R code

$$\begin{aligned} (b) \quad P(\theta=1|y=1) &= \frac{P(\theta=1, y=1)}{P(\theta=1, y=1) + P(\theta=2, y=1)} \\ &= \frac{P(\theta=1) P(y=1|\theta=1)}{P(\theta=1) P(y=1|\theta=1) + P(\theta=2) P(y=1|\theta=2)} \\ &= \frac{0.5 N(1|1, 2^2)}{0.5 N(1|1, 2^2) + 0.5 N(1|2, 2^2)} \\ &= 0.53 \end{aligned}$$

(c) As $\sigma \rightarrow \infty$, the posterior density for θ approaches the prior (the data contain no information):

$$\begin{aligned} P(\theta=1|y=1) &= \frac{0.5 N(1|1, \sigma^2)}{0.5 N(1|1, \sigma^2) + 0.5 N(1|2, \sigma^2)} \\ &\rightarrow \frac{1}{2} \quad (\sigma \rightarrow \infty) \end{aligned}$$

As $\sigma \rightarrow 0$, the posterior density for θ becomes concentrated at 1:

$$P(\theta=1|y=1) \rightarrow 1$$

2.

$$\begin{aligned}\text{Use } P(GG) &= P(M)P(GG|M) + P(D)P(GG|D) \\ &= P(M)p + (1-P(M))p^2\end{aligned}$$

$$\Rightarrow P(M) = \frac{P(GG) - p^2}{p(1-p)}$$

3.

(a) $X \sim \text{NegBin}(r, \theta)$

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

$$\begin{aligned} P(\theta|X) &\propto \theta^r (1-\theta)^x \times \theta^{\alpha-1} (1-\theta)^{\beta-1} \\ &= \theta^{r+\alpha-1} (1-\theta)^{x+\beta-1} \end{aligned}$$

which is $\text{Beta}(r+\alpha, x+\beta)$.

Thus, the conjugate prior for θ in $\text{NegBin}(r, \theta)$ is $\text{Beta}(\alpha, \beta)$.

(b) $X \sim \text{Gamma}(\alpha, \beta)$, α is known

Let $\beta \sim \text{Gamma}(a, b)$.

Then

$$\begin{aligned} P(\beta|X) &\propto \beta^\alpha e^{-\beta x} \times \beta^{a-1} e^{-b\beta} \\ &= \beta^{\alpha+a-1} e^{-(x+b)\beta} \end{aligned}$$

which is $\text{Gamma}(\alpha+a, x+b)$.

(c) $X \sim \text{Gamma}(\alpha, \beta)$, β is known.

In this case, we cannot write the distribution of α .
So none is available.

4.

 $\theta \sim \text{beta}(\alpha, \beta)$ with $E(\theta) = 0.6$.

$$\text{Var}(\theta) = 0.3^2$$

$$(a) \quad E(\theta) = \frac{\alpha}{\alpha + \beta} = 0.6 \quad \text{--- } \textcircled{1}$$

$$\text{Var}(\theta) = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)} = 0.3^2 \quad \text{--- } \textcircled{2}$$

In $\textcircled{2}$,

$$\frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)} = \left(\frac{\alpha}{\alpha + \beta}\right) \left(\frac{\beta}{\alpha + \beta}\right) \frac{1}{\alpha + \beta + 1}$$

$$= \left(\frac{\alpha}{\alpha + \beta}\right) \left(1 - \frac{\alpha}{\alpha + \beta}\right) \left(\frac{1}{\alpha + \beta + 1}\right)$$

$$= (0.6)(1 - 0.6) \left(\frac{1}{\alpha + \beta + 1}\right) = 0.09$$

$$\Rightarrow \alpha + \beta + 1 = \frac{24}{9}$$

$$\Rightarrow \alpha + \beta = \frac{5}{3} \quad \text{--- } \textcircled{2'}$$

$$\text{In } \textcircled{1} \quad \alpha = 0.6\alpha + 0.6\beta$$

$$\Rightarrow 0.4\alpha = 0.6\beta$$

$$\Rightarrow \alpha = \frac{3}{2}\beta \quad \text{--- } \textcircled{1'}$$

From $\textcircled{1'}$, $\textcircled{2'}$

$$\alpha = 1, \beta = \frac{2}{3}$$

Thus, $\theta \sim \text{beta}(\alpha = 1, \beta = \frac{2}{3})$.

(b). $y_1, \dots, y_{1000} \stackrel{iid}{\sim} \text{Bernoulli}(\theta)$.

$$\Rightarrow \bar{y} = 0.65$$

$$\theta \sim \text{Beta}(1, \frac{2}{3})$$

$$\begin{aligned} P(\theta | y_1, \dots, y_{1000}) &\propto \theta^{\sum_{i=1}^{1000} y_i} (1-\theta)^{1000 - \sum_{i=1}^{1000} y_i} \theta^{1-1} (1-\theta)^{\frac{2}{3}-1} \\ &= \theta^{\sum_{i=1}^{1000} y_i} (1-\theta)^{1000 + \frac{2}{3} - \sum_{i=1}^{1000} y_i - 1} \\ &= \theta^{1000 \bar{y}} (1-\theta)^{1000 + \frac{2}{3} - 1000 \bar{y} - 1} \\ &= \theta^{650} (1-\theta)^{350 + \frac{2}{3} - 1} \end{aligned}$$

which is $\text{Beta}(651, 350 + \frac{2}{3})$ distribution.

The posterior mean and variance are given by

$$E(\theta | y_1, \dots, y_{1000}) = \frac{651}{651 + 350 + \frac{2}{3}} = 0.6499$$

$$\text{Var}(\theta | y_1, \dots, y_{1000}) = \frac{(651)(350 + \frac{2}{3})}{(651 + 350 + \frac{2}{3})^2 (651 + 350 + \frac{2}{3} + 1)} = 0.00023$$