

Bayes

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1.1 Let us consider a medical diagnostic test with 90% sensitivity and 80% specificity for a disease with incidence equal to 1 in 10,000 individuals. Use the Bayes theorem to calculate the probability that an individual has the disease when the test is positive and when the test is negative.

Solution

Given;

- i) Sensitivity 90% i.e if one has the disease(D) the test is positive with probability 0.9 otherwise the test will be negative with probability 0.1.
- ii) Specificity 80% i.e if one is healthy(H) the test will be negative with probability 0.8 otherwise the test will be positive with probability 0.2.

$$P(D) = 1/10000, P(H) = 1 - P(D) = 0.9999, P(+/D) = 0.9, \text{and } p(-/D) = 0.1, P(+/H) = 0.2, \text{and } P(-/H) = 0.8$$

a) the probability that an individual has the disease when the test is positive

$$p(D/+) = \frac{P(+/D)P(D)}{\sum_{k=1}^n P(D) + P(+/H)P(H)} = \frac{0.90 * 0.0001}{(0.90 * 0.0001) + (0.2 * 0.9999)} = 0.0004$$

b) the probability that an individual has the disease when the test is negative

$$p(D/-) = \frac{P(-/D)P(D)}{\sum_{k=1}^n P(-/D_k)P(D_k)} = \frac{P(-/D)P(D)}{P(-/D)P(D) + P(-/H)P(H)} = \frac{0.10 * 0.0001}{(0.10 * 0.0001) + (0.8 * 0.9999)} = 0.0000125$$

1.2 Let us consider the exponential distribution with density function $f(y/\theta) = \theta e^{-\theta y}$ and an i.i.d. sample $Y_i \sim \text{exponential}(\theta)$ for $i = 1, \dots, n$.

- a) Show that a gamma prior distribution is conjugate for θ .

Solution

i) Finding likelihood for the exponential distribution.

$$\prod_{i=1}^n f(y/\theta) = \prod_{i=1}^n \theta e^{-\theta y_i} = \theta^n e^{-\theta \sum_{i=1}^n y_i}$$

ii) The pdf of gamma distribution.

$$\frac{1}{\gamma\alpha\beta^\alpha} e^{-\frac{\theta}{\beta}} \theta^{\alpha-1}$$

iii) The posterior distribution

$$\theta^n e^{-\theta \sum y} \times \frac{1}{\gamma\alpha\beta^\alpha} e^{-\frac{\theta}{\beta}} \theta^{\alpha-1}$$

Collecting the like terms the result is as follows:

$$f(\theta/y) = e^{-n\bar{y}\theta - \frac{\theta}{\beta}} \times \theta^{n+(\alpha-1)}$$

$$f(\theta/y) = \gamma(n + \alpha, n\bar{y} + \beta)$$

b) Calculate the posterior mean and variance under this conjugate prior.

posterior mean

$$n + \alpha \times n\bar{y} + \beta = n + \alpha \times n\bar{y} + \beta$$

posterior variance

$$n + \alpha \times (n\bar{y} + \beta)^2 = n + \alpha \times (n\bar{y} + \beta)^2$$

c) For the following data

0.4 0.0 0.2 0.1 2.1 0.1 0.9 2.4 0.1 0.2

use the exponential distribution and (i) Plot the posterior distribution for gamma prior parameters a = b = 0.001

From the data given we need to obtain the mean so as to calculate the posterior parameters.

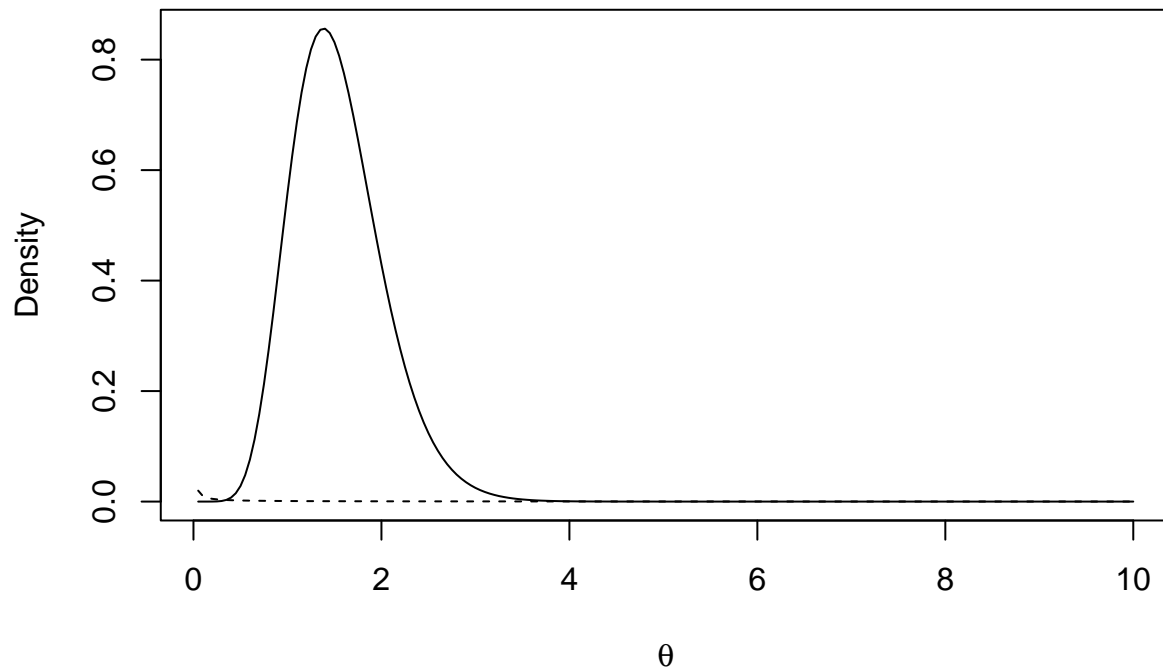
```
data<-c(0.4,0.0,0.2,0.1,2.1,0.1,0.9,2.4,0.1,0.2)
y_bar=mean(data)
y_bar
```

```
## [1] 0.65
```

$$\text{Posterior alpha} = n + \alpha \text{posterior beta} = n\bar{y} + \beta$$

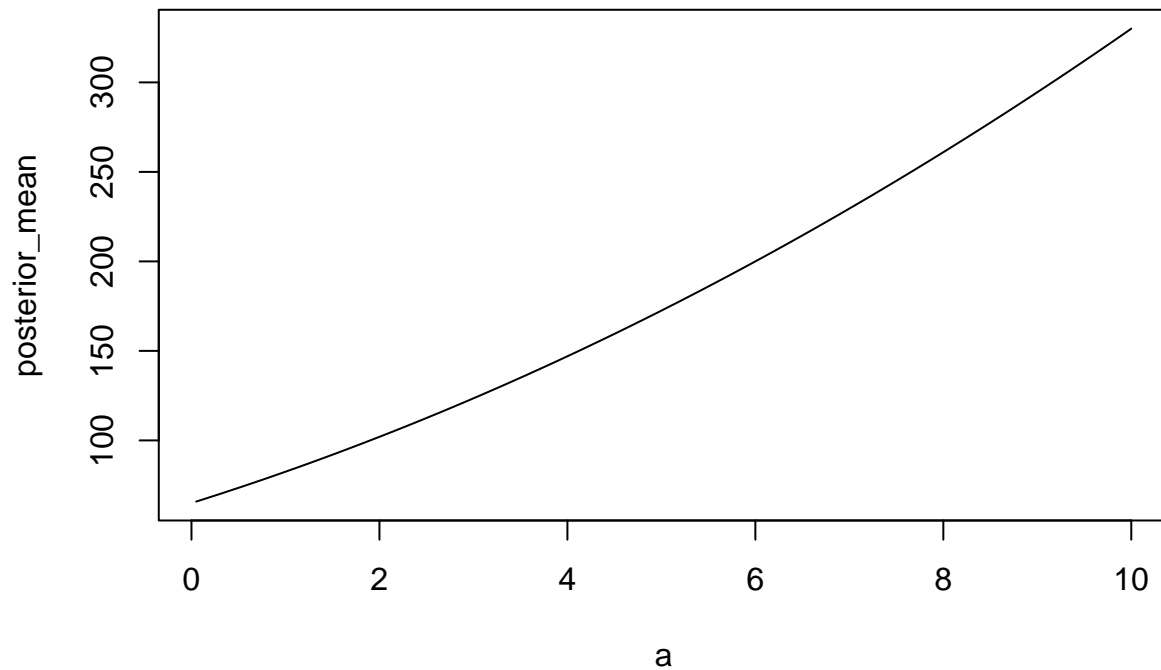
$$\text{Posterior alpha} = 10 + 0.001 = 10.001 \text{posterior beta} = 10 * 0.65 + 0.001 = 6.501$$

```
theta<-seq(0.05,10.0,0.05)
prior<-dgamma(theta,0.001,0.001)
posterior<-dgamma(theta,10.001,6.501)
plot(theta,posterior,xlab=expression(theta),ylab="Density",type="l")
lines(theta,prior,lty=2)
```

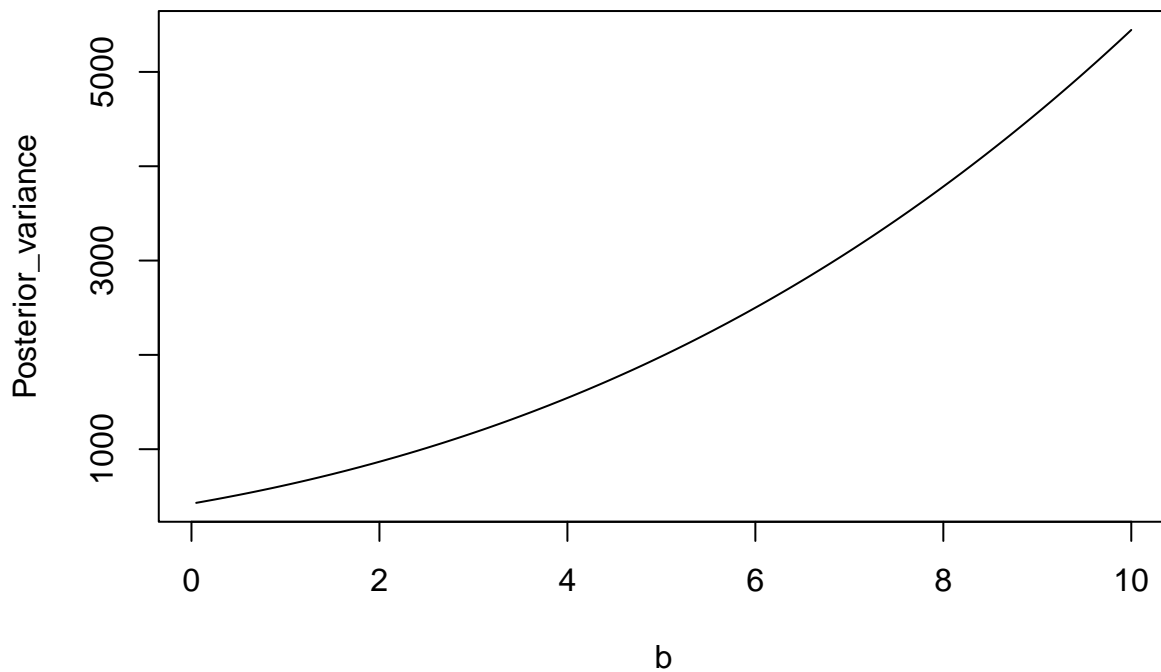


- (ii) Perform sensitivity analysis for various values of a and b . Produce related plots depicting changes on the posterior mean and variance.

```
#prior parameters
set.seed(2455)
a=seq(0.05,10,0.05)
b=seq(0.05,10,0.05)
n<-10
y_bar=0.65
#Posterior mean
prior_mean=a*b
posterior_mean=(n+a)*(n*y_bar+b)
plot(posterior_mean~a,type="l")# similar to b since the sequence is the same.
```



```
#Posterior variance
Posterior_variance=(n+a)*(n*y_bar+b)^2
prior_variance=a*b^2
plot(Posterior_variance~b,type="l")
```



1.3

In the exponential distribution, consider directly the mean parameter $\mu = \frac{1}{\theta}$

In the exponential distribution i.e

$$f(y|\theta) = \theta e^{-\theta y}$$

We consider directly that $\mu = \frac{1}{\theta}$

a) What is the conjugate prior for μ ?

$$\mu = \frac{1}{\theta}$$

Consider μ for Gamma distribution as the prior for μ in exponential distribution

$$\mu^{Gamma} = \alpha\beta$$

$$\mu^{Exp} = \frac{1}{\theta}$$

The posterior ;

$$\alpha\beta \times \frac{1}{\theta} \equiv \alpha\beta$$

$$\mu^{Gamma \text{ pos}} = \alpha\beta$$

Therefore conjugate prior for μ is μ Gamma distribution

b) What is the posterior distribution for μ and θ under this setup?

The posterior distribution for μ and $\theta = \text{Gamma}$

c) Is the posterior analysis under this approach equivalent to the corresponding one in Problem 1.2?

Posterior mean in Q1.2 = $(n + \alpha)(n\bar{y} = \beta)$ whereas in this case posterior mean = $\alpha\beta$

The analysis under this approach is not equivalent to that in Q1.2

1.4 For $Y_i \sim \text{gamma}(v, \theta)$ assuming that V is known

a) Prove that the gamma distribution is a conjugate prior for θ

Solution

$$p(Y_i|\theta) = \frac{\beta^v \theta^{v-1} e^{-\beta\theta}}{\Gamma v}$$

$$\theta \sim \text{gamma}(v, \theta) = \frac{\beta^v \theta^{v-1} e^{-\beta\theta}}{\Gamma v}$$

Posterior \propto likelihood \times prior

Likelihood

$$\prod \frac{\beta^v \theta^{v-1} e^{-\beta\theta}}{\Gamma v} \propto \theta^{n(v-1)} e^{-n\beta\theta}$$

$$\propto \theta^{n(v-1)} e^{-n\beta\theta} \theta^{v-1} e^{-\beta\theta}$$

collecting similar terms

$$\propto \theta^{nv-n+v-1} e^{-n\beta\theta-\beta\theta}$$

$$\propto \theta^{nv-n+v-1} e^{-\beta\theta(n+1)}$$

$$\sim \text{gamma}(nv - n + v, \theta(n+1))$$

b) Find the posterior mean and variance for θ

Mean

$$= \frac{nv - n + v}{\theta(n + a)}$$

Variance

$$= \frac{nv - n + v}{(\theta(n + 1))^2}$$

c) Examine the effect on the posterior density of θ

(i) Of the known parameter v

$$= \frac{nv - n + v - v}{\theta} = \frac{n(v - 1)}{\theta}$$

(ii) Of the sample size n

$$\begin{aligned} &= \frac{\theta(n + 1) - \theta}{\sqrt{\frac{(n-1)\theta + (n-1)\theta(n+1)}{n+n-2}}} \\ &= \frac{\theta(n + 1 - 1)}{\left(\frac{\theta(n-1)(1+n+1)}{2n-2}\right)^{\frac{1}{2}}} \\ &= \frac{\theta n}{\left(\frac{\theta(n+2)}{2}\right)^{\frac{1}{2}}} \end{aligned}$$

(iii) Of the prior parameters

v proportion

$$\frac{nv - n + v}{V}$$

θ proportion

$$\frac{\theta(n + 1)}{\theta} = n + 1$$

1.5. Let us consider Y_i (for $i = 1, \dots, n$) be an i.i.d. sample of categorical variables with n categories.

a. Show that a Dirichlet prior is conjugate for the probability of each category.

Dirichlet - Categorical Model

$$Y_1, \dots, Y_n \sim \text{Cat}(\theta)$$

$$\theta \sim \text{Dir}(\alpha)$$

$$P(\theta|\alpha) \propto \prod_{j=1}^m \theta_j^{\alpha_j - 1}$$

let data be $D = (y_1 \dots y_n) \in \{1 \dots m\}$

$$P(D|\theta) = \prod_{i=1}^n P(Y_i = y_i|\theta) = \prod_{i=1}^n \theta_{y_i} = \prod_{i=1}^n \prod_{j=1}^m \theta_j^{I(y_i=j)}$$

$$P(D|\theta) = \prod_{j=1}^m \theta_j^{\sum I(y_i=j)}$$

Let the exponent be c

$$c = \sum I(y_i = j)$$

$$P(D|\theta) = \prod_{j=1}^m \theta_j^{c_j}$$

$$\text{Likelihood } P(D|\theta) = \prod_{j=1}^m \theta_j^{c_j}$$

$$\text{Prior } P(\theta) \propto \prod_{j=1}^m \theta_j^{\alpha_j - 1}$$

$$\text{Posterior distribution } P(D|\theta) \propto P(D|\theta) * (P(\theta))$$

$$\begin{aligned} &= \prod_{j=1}^m \theta_j^{c_j} * \prod_{j=1}^m \theta_j^{\alpha_j - 1} \\ &= \prod_{j=1}^m \theta_j^{c_j + \alpha_j - 1} \propto \text{Dir}(\theta|c + \alpha) \end{aligned}$$

This indicates that Dir is a conjugate Prior for categorical distribution

Predictive distribution

$$\begin{aligned} P(y|D) &= \int P(y|\theta, D) * P(\theta) d\theta = \int \theta_y P(\theta|D) = E(\theta_y|D) \\ &= \frac{c_y + \alpha_y}{n + \alpha_0} \text{ where } \alpha_0 = \sum_{x=1}^m \alpha_x \end{aligned}$$

b. Calculate the posterior mean and variance for the probability of each category.

In general

$$Y \sim \text{Dir}(\beta) \text{ where } \beta > 0$$

$$E(Y_i) = \frac{\beta_i}{\beta_0}$$

From the posterior distribution $P(\theta|D) \propto \text{Dir}(\theta|c + \alpha)$

$$\beta_i = c_y + \alpha_y$$

$$\begin{aligned} \therefore E(\theta_y|D) &= \frac{c_y + \alpha_y}{n + \alpha_0} \\ \sigma^2(Y_i) &= \frac{\beta_i(\beta_0 + \beta_i)}{\beta_0^2(\beta_0 + 1)} \\ &= \frac{(c_y + \alpha_y)(n + \alpha_0 - (c_y + \alpha_y))}{(n + \alpha_0)^2(n + \alpha_0 + 1)} \end{aligned}$$

c. Calculate the posterior correlations between the probabilities of two different categories

Covariance of β_j and β_k where $j \neq k$

$$\begin{aligned} \text{Cov}(\beta_j, \beta_k) &= -\frac{\beta_j \beta_k}{\beta_0^2(\beta_0 + 1)} \\ &= -\frac{(c_y + \alpha_y)^2}{(n + \alpha)^2(n + \alpha_0 + 1)} \end{aligned}$$