

MATH 392 Problem Set 2

Sam D. Olson

Time Spent on PS 2: 7 hours

Exercises from the book

7.2.1

$$f(\mathbf{x} \mid \theta) = \theta^n e^{-\theta y}$$

Where $y = \sum_{i=1}^n x_i$

As Example 7.2.8 provides five observed values, we have

$$y = x_1 + x_2 + \dots + x_5 = 16,178$$

If we believe, as the question supposes, that the prior distribution of θ is the gamma distribution with parameters 1 and 5000, we then have a new posterior distribution of θ , $\xi(\mathbf{x} \mid \theta)$ as the gamma distribution with parameters $\alpha_{new} = \alpha_{prior} + 1 = 5 + 1 = 6$ and $\beta_{new} = \beta_{prior} + 5000 = 16178 + 5000 = 21178$

When we evaluate the conditional joint p.d.f., we have

$$f(x_n \mid \mathbf{x}) = \int_{\Omega} \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^\alpha e^{-\theta y} \theta^{\alpha-1} e^{-\beta \theta} d\theta$$

We thus have

$$f(x_6 \mid \mathbf{x}) = \int_0^\infty (7.518 \cdot 10^{23}) \beta^6 e^{-\theta(21178+x_6)} d\theta$$

For $x_6 > 0$, we may simplify this expression by evaluating this integral, yielding:

$$f(x_6 \mid \mathbf{x}) = (7.518 \cdot 10^{23}) \frac{\Gamma(7)}{(21178 + x_6)^7} = \frac{5.413 \cdot 10^{26}}{(21178 + x_6)^7}$$

We may now compute $Pr(X_6 > 3000 \mid \mathbf{x})$ using the above, integrating from 3000 to ∞ with respect to x_6 . Once we simplify the integral, we may substitute $x_6 = 3000$ and write:

$$Pr(X_6 > 3000 \mid \mathbf{x}) = \int_{3000}^{\infty} \frac{5.413 \cdot 10^{26}}{(21178 + x_6)^7} dx_6 = \int_{3000}^{\infty} 5.413 \cdot 10^{26} \cdot (21178 + x_6)^{-7} dx_6 = 0.4516$$

7.2.2

Note: via Equation 7.2.11: $f_n(x | \theta) = \theta^y(1 - \theta)^{n-y}$

For $n = 8, y = 2$ we then have:

$$f_n(x | \theta \text{ right}) = \theta^2(1 - \theta)^6$$

Given, $\xi(0.1) = 0.7$ and $\xi(0.2) = 0.3$

$$\begin{aligned}
\xi(0.1 | x) = Pr(\theta = 0.1 | x) &= \frac{\xi(0.1)f_n(x | 0.1)}{\xi(0.1)f_n(x | 0.1) + \xi(0.2)f_n(x | 0.2)} \\
&= \frac{(0.7)(0.1)^2(0.9)^6}{(0.7)(0.1)^2(0.9)^6 + (0.3)(0.2)^2(0.8)^6} \\
&= 0.5418
\end{aligned}$$

Note: $\xi(0.2 | x) + \xi(0.1 | x) = 1$

Hence:

$$\begin{aligned}
\xi(0.2 | x) &= 1 - \xi(0.1 | x) \\
&= 1 - \frac{(0.7)(0.1)^2(0.9)^6}{(0.7)(0.1)^2(0.9)^6 + (0.3)(0.2)^2(0.8)^6} \\
&= 1 - 0.5418 \\
&= 0.4582
\end{aligned}$$

Thus, the posterior pdf of θ is

$$\xi(0.1) = 0.5418$$

$$\xi(0.2) = 0.4582$$

Intuitively, given the information we are less sure the rate of defective items is 0.1 and more sure the rate is 0.2.

7.2.3

Let X denote the number of defects on the roll of tape.

For λ , the p.f. of X , we have, for $x \in \mathbb{Z}^{\geq 0}$:

$$f(x | \lambda) = \frac{e^{-\lambda}\lambda^x}{x!}$$

$$\begin{aligned}
\xi(1.0 | x = 3) &= Pr(1.0 | x = 3) \\
&= \frac{\xi(1.0)f(3 | 1.0)}{\xi(1.0)f(3 | 1.0) + \xi(1.5)f(3 | 1.5)}
\end{aligned}$$

Note, using the Poisson table in the back of the book, we have:

$$f(3 | 1.0) = 0.0613$$

$$f(3 | 1.5) = 0.1255$$

We then note: $\xi(1.0 | 3) + \xi(1.5 | 3) = 1$

Hence: $\xi(1.5 | 3) = 1 - \xi(1.0 | 3)$

Evaluating yields: $\xi(1.0 | 3) = 0.2456$

$$\xi(1.5 | 3) = 0.7544$$

Thus the posterior p.f. of λ is given by: $\xi(1.0) = 0.2456$ and $\xi(1.5) = 0.7544$

Intuitively, we're now more sure $\lambda = 0.6$ and less sure $\lambda = 0.4$.

7.2.5

Note, the mean and variance of the beta distribution is respectively given by the following:

$$\text{Mean: } \frac{\alpha}{\alpha+\beta} = \frac{1}{3}$$

$$\text{Variance: } \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} = \frac{1}{45}$$

Given the formula for the mean, we have:

$$\alpha + \beta = 3\alpha$$

Hence,

$$\beta = 2\alpha$$

It follows, then

$$\frac{\alpha}{\alpha+\beta} = \frac{2}{3}$$

We may then rewrite the variance as:

$$\frac{2}{9(\alpha+\beta+1)} = \frac{1}{45}$$

Thus:

$$90 = 9(\alpha + \beta + 1)$$

And

$$10 = (\alpha + \beta + 1)$$

$$9 = (\alpha + \beta)$$

As

$$\beta = 2\alpha$$

$$9 = (3\alpha)$$

Hence

$$\alpha = 3, \beta = 6$$

As we have established the parameters of the prior p.d.f. of θ , it follows:

$$\theta \sim \text{Beta}(\alpha = 3, \beta = 6)$$

Or, alternatively, the prior p.d.f. of θ , is:

$$\begin{aligned} \xi(\theta) &= \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha-1} (1 - \theta)^{\beta-1} \\ &= \frac{\Gamma(9)}{\Gamma(3)\Gamma(6)} \theta^{3-1} (1 - \theta)^{6-1} \\ &= \frac{\Gamma(9)}{\Gamma(3)\Gamma(6)} \theta^2 (1 - \theta)^5 \end{aligned}$$

7.2.8

Per 7.2.14:

$$\xi(\theta | x_1) \propto f(x_1 | \theta)\xi(\theta)$$

Extending this to x_2 via 7.2.15, we have

$$\xi(\theta | x_1, x_2) \propto f(x_2 | \theta)\xi(\theta | x_1) = f(x_2 | \theta)f(x_1 | \theta)\xi(\theta)$$

Per 7.2.16, this holds for x_1, x_2, \dots, x_n , written

$$\xi(\theta | \mathbf{x}) \propto f(x_n | \theta)\xi(\theta | x_1, x_2, \dots, x_{n-1})$$

Via Eq. 7.2.4, we note:

$$f_{n-1}(x_1, x_2, \dots, x_n) = f(x_1 | \theta)f(x_2 | \theta)\dots f(x_{n-1} | \theta)$$

Thus,

$$\xi(\theta | \mathbf{x}) \propto f(x_n | \theta)f(x_{n-1} | \theta)\dots f(x_1 | \theta)\xi(\theta)$$

As $\mathbf{x} = x_1, x_2, \dots, x_n$

$$\xi(\theta | \mathbf{x}) \propto f(\mathbf{x} | \theta)\xi(\theta)$$

However, as this is proportional, to make this an equality we must add an appropriate factor.

Let: $\psi = g_n(\mathbf{x})^{-1}$, where $g_n(\mathbf{x}) = \int_{\Omega} f_n(\mathbf{x} | \theta)\xi(\theta)d\theta$

Thus, per 7.2.7, we have:

$$\xi(\theta | \mathbf{x}) = f(\mathbf{x} | \theta)\xi(\theta)\psi = \frac{f(\mathbf{x}|\theta)\xi(\theta)}{g_n(\mathbf{x})}$$

7.2.10

Note, $f(x | \theta) = 1$ for $\theta - \frac{1}{2} < x < \theta + \frac{1}{2}$ and 0 otherwise.

And similarly, $\xi(\theta) = \frac{1}{10}$ for $10 < \theta < 20$ and 0 otherwise.

If we observe $x = 12$, we then have

$$\xi(\theta | x = 12) \text{ is positive for } 11.5 < \theta < 12.5$$

Additionally, given X is taken from the uniform distribution, and as θ is similarly taken from a uniform distribution, the posterior prior distribution is from the uniform distribution.

Thus, as:

$$\xi(\theta | x = 12) \propto f(x | \theta)\xi(\theta)$$

We know the posterior distribution $\xi(\theta | x = 12)$ is uniform for $11.5 < \theta < 12.5$

7.3.10

For the random sample taken from the normal distribution with θ unknown, and standard deviation, $\sigma = 2$, $\sigma^2 = 4$.

Similarly, as the prior distribution of θ is a normal distribution with standard deviation $v = 1$, $v^2 = 1$.

Note the variance of the posterior distribution, τ^2 which also follows the normal distribution, is given by the following equation:

$$\tau^2 = \frac{\sigma^2 v^2}{\sigma^2 + nv^2} = \frac{4}{4+n}$$

For $\tau = 0.1$, we have:

$$\tau^2 = 0.01 = \frac{4}{4+n}$$

Solving for n , we have $n = 396$. Thus, we need at least 396 observations to reduce the standard deviation of the posterior distribution of θ , τ to the value 0.1.

7.3.21

We know the posterior distribution of θ with the p.d.f. of the prior distribution of θ given by $\frac{1}{\theta}$ (for $\theta > 0$) is proportional to:

$$\xi(\theta | \mathbf{x}) \propto \theta^n e^{-\theta \sum_{i=1}^n x_i} \frac{1}{\theta} \propto \theta^{n-1} e^{-\theta \bar{x}_n n}$$

Note the posterior distribution of θ is proportional to the Gamma distribution with parameters n and $n\bar{x}_n$. Hence:

$$\xi(\theta | \mathbf{x}) \sim \text{Gamma}(\alpha = n, \beta = n\bar{x}_n).$$

Note, the mean of the Gamma distribution is $\frac{\alpha}{\beta}$, thus the mean of the posterior distribution of θ is:

$$\frac{\alpha}{\beta} = \frac{n}{n\bar{x}_n} = \frac{1}{\bar{x}_n}$$

7.4.5

Per Ex. 5 of Section 7.3, specifically with note of Thm. 7.3.2,

The posterior distribution of θ is the Gamma distribution with parameters $\alpha + y$ and $\beta + n$.

Thus:

$$\alpha = 3 + \sum_{i=1}^n x_i = 3 + 2 + 2 + 6 + 0 + 3 = 16$$

and

$$\beta = 1 + n = 1 + 5 = 6$$

As we now know the parameters of the posterior distribution of θ , we note the Bayes estimate is the mean of the posterior distribution. As such, we note the mean of the Gamma distribution is given by:

$$\frac{\alpha}{\beta} = \frac{16}{6} = \frac{8}{3}.$$

7.4.12

Prior to finding the posterior distribution of θ for each statistician, note, for $0 < \theta < 1$:

Statistician A: $\xi_A(\theta) = 2\theta \rightarrow$ A's prior distribution for $\theta \sim \text{Beta}(2, 1)$

Statistician B: $\xi_B(\theta) = 4\theta^3 \rightarrow$ B's prior distribution for $\theta \sim \text{Beta}(4, 1)$

A. Note Thm. 7.3.4 such that the posterior distribution of θ is as follows for statisticians A and B respectively.

$$(A): \xi(\theta | \mathbf{x}) \sim \text{Beta}(\alpha + y, \beta + n - y) = \text{Beta}(2 + 710, 1 + 290) = \text{Beta}(712, 291)$$

$$(B): \xi(\theta | \mathbf{x}) \sim \text{Beta}(\alpha + y, \beta + n - y) = \text{Beta}(4 + 710, 1 + 290) = \text{Beta}(714, 291)$$

B. Now that we know the parameters of the posterior distribution of θ for each statistician, note the Bayes estimate for each statistician is equal to the mean of the posterior distribution.

Thus, for the mean of the Beta distribution, $\frac{\alpha}{\alpha + \beta}$, we have:

$$(A): \frac{\alpha}{\alpha + \beta} = \frac{712}{712 + 291} = \frac{712}{1003}$$

$$(B): \frac{\alpha}{\alpha + \beta} = \frac{714}{714 + 291} = \frac{714}{1005}$$

C. The difference between the Bayes estimates of statisticians A and B are given by the following equation:

$$(A): \frac{2+y}{2+y+1+1000-y} = \frac{2+y}{1003}$$

$$(B): \frac{4+y}{4+y+1+1000-y} = \frac{4+y}{1005}$$

$$\text{Difference, (A)-(B): } \frac{2+y}{1003} - \frac{4+y}{1005} = \frac{1003(4+y) - 1005(2+y)}{1003(1005)} = \frac{2002-2y}{1003(1005)} = \frac{2(1001-y)}{1003(1005)}$$

Note, we maximize the difference between the Bayes estimates of A and B when $y = 0$, i.e. no one votes in favor of the proposition. For $y = 0$, we have:

$$\frac{2002}{1003(1005)} = 0.001986 \approx 0.002$$

It follows that the Bayes estimates of statisticians A and B could not differ by more than 0.002

Additional Exercise

For 7.4.12, use the `prop_model()` function in the slides to visualize the prior and posterior distributions of statisticians A and B.

For 7.4.12, use the `prop_model()` function in the slides to visualize the prior and posterior distributions of statisticians A and B. Note: for this exercise, the order of the 710 ‘TRUE’ values and 290 ‘FALSE’ values is arbitrary. To illustrate this point, the `prop_model` of Statistician A is illustrated with ‘TRUE’ values first in the first output, and ‘TRUE’ values last in the second output.

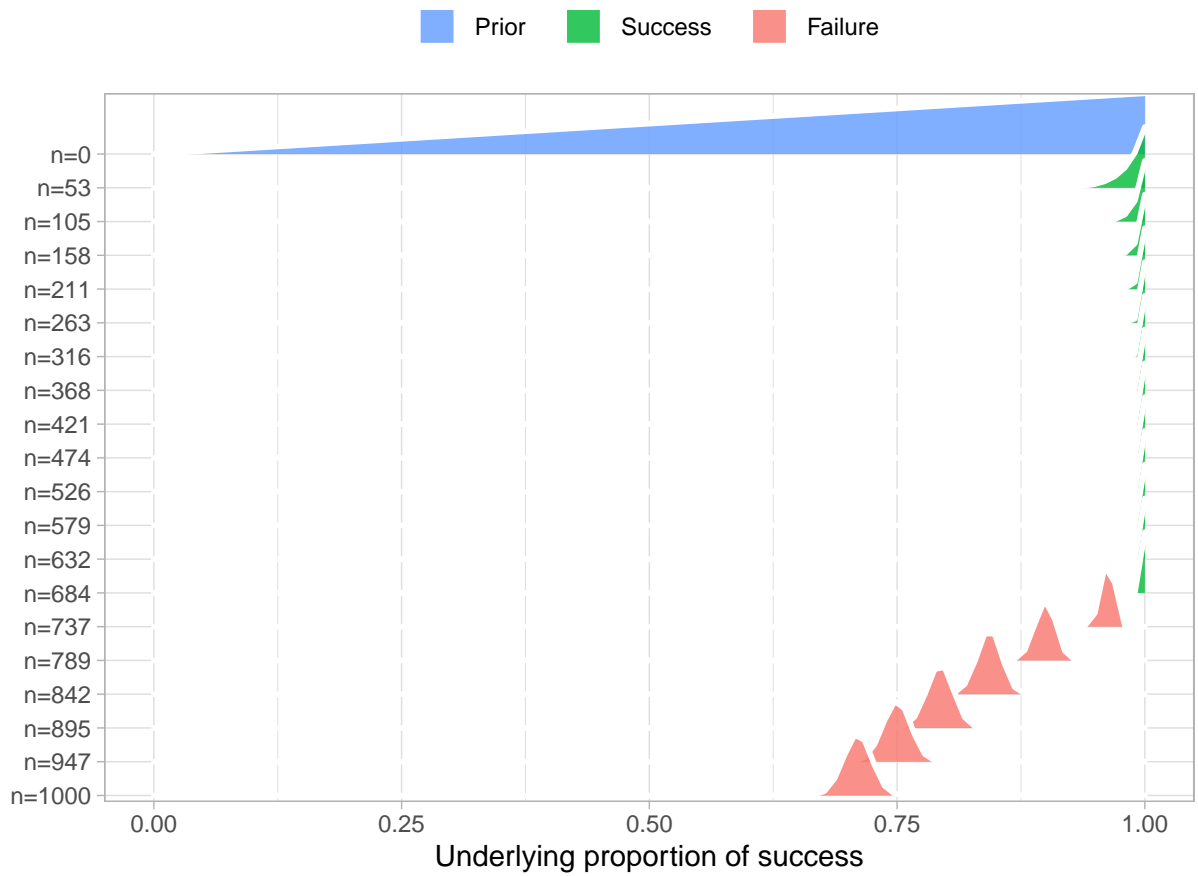
```
trues <- rep(TRUE, times=710)
falses <- rep(FALSE, times=290)
sampledata <- c(trues, falses)

prop_model(sampledata, prior_prop = c(2, 1))
```

Stat A Pre-Post (‘TRUE’ first) –

```
## Warning: `data_frame()` is deprecated, use `tibble()`.
## This warning is displayed once per session.
```

Binomial model – Data: 710 successes, 290 failures

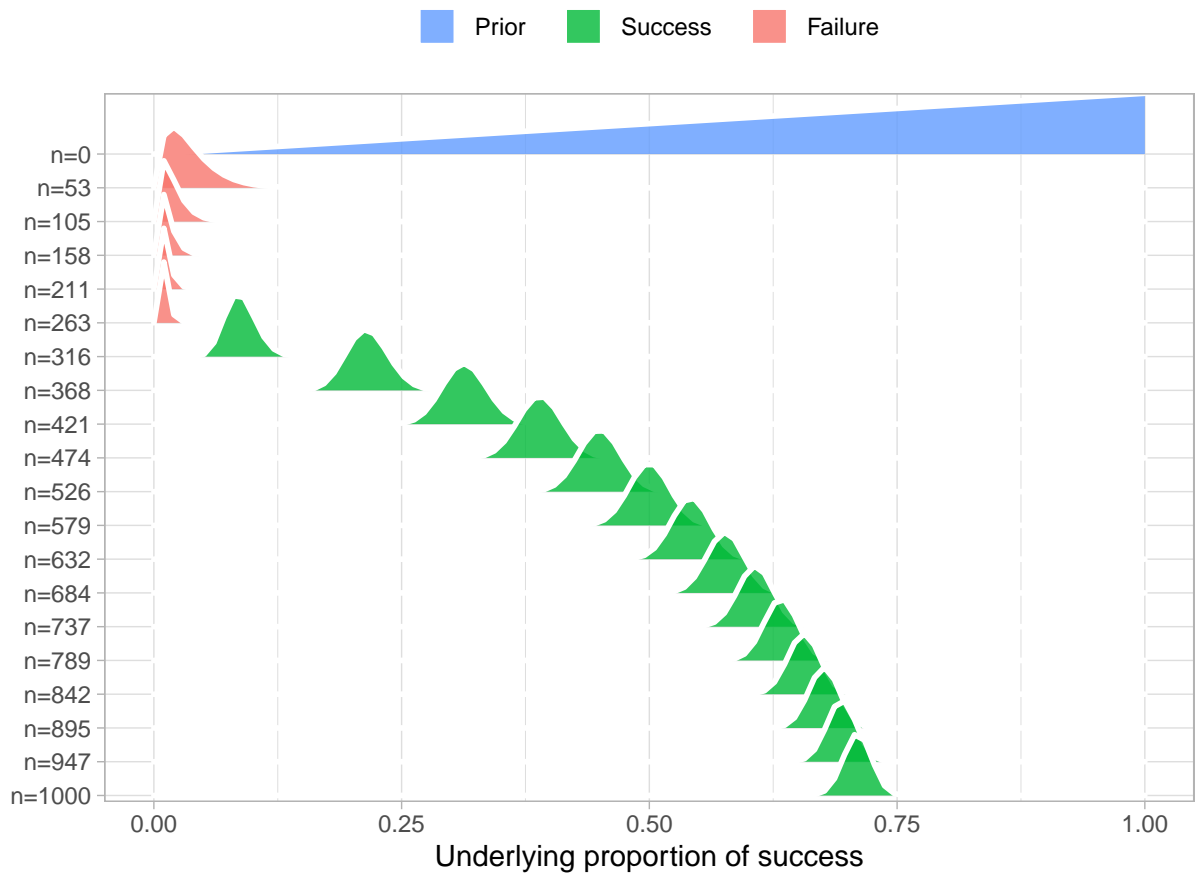


```
trues <- rep(TRUE, times=710)
falses <- rep(FALSE, times=290)
sampledata <- c(falses, trues)

prop_model(sampledata, prior_prop = c(2, 1))
```

Stat A Pre-Post ('TRUE' second) –

Binomial model – Data: 710 successes, 290 failures



Stat B Pre-Post –

```
trues <- rep(TRUE, times=710)
falses <- rep(FALSE, times=290)
sampledata <- c(trues, falses)

prop_model(sampledata, prior_prop = c(4, 1))
```


Binomial model – Data: 710 successes, 290 failures

