

# HW2 Solutions

## STAT 431 Spring 2019

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## 1 Bayesian inference on Binomial $\pi$

We observe  $X = 6$  successes in our sample of size  $N = 70$ , where we assume  $X \sim \text{Binomial}(N = 70, \pi)$ , where the success probability  $\pi$  is unknown. The likelihood of this model is given by

$$P(X | \pi, N) = \binom{N}{X} \pi^X (1 - \pi)^{N-X} \quad (1)$$

## 1.1 A - Posterior densities

### 1.1.1 I - Uniform prior

$$P(\pi \mid X) \propto P(X \mid \pi, N)P(\pi) \quad (2)$$

$$= P(X \mid \pi, N) \quad (3)$$

$$= \binom{N}{X} \pi^X (1 - \pi)^{N-X} \quad (4)$$

$$= \binom{70}{6} \pi^6 (1 - \pi)^{64} \quad (5)$$

The posterior distribution for  $\pi$  (under a uniform prior) is  $P(\pi \mid X) = \text{Beta}(X + 1, N - X + 1) = \mathbf{Beta}(7, 65)$ . The full density is then:

$$P(\pi \mid X) = \frac{\Gamma(72)}{\Gamma(7)\Gamma(65)} \pi^6 (1 - \pi)^{64}, \quad 0 < \pi < 1 \quad (6)$$

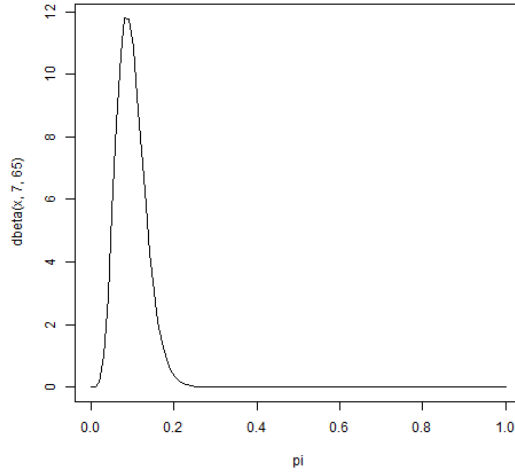


Figure 1: Posterior distribution of  $\pi$  under a uniform prior for  $\pi$ .

### 1.1.2 II - Informative Beta prior

*A priori*  $\pi \sim \text{Beta}(100, 100)$ . Then the form of the posterior is given as follows

$$P(\pi | X) \propto P(X | \pi, N)P(\pi) \quad (7)$$

$$= \pi^X (1 - \pi)^{N-X} (\pi^{99} (1 - \pi)^{99}) \quad (8)$$

$$= \pi^{X+99} (1 - \pi)^{N-X+99} \quad (9)$$

$$= \pi^{105} (1 - \pi)^{163} \quad (10)$$

The posterior distribution for  $\pi$  is  $P(\pi | X) = \text{Beta}(X+100, N-X+100) = \text{Beta}(106, 164)$ . The full density is:

$$P(\pi | X) = \frac{\Gamma(270)}{\Gamma(106)\Gamma(164)} \pi^{105} (1 - \pi)^{163}, \quad 0 < \pi < 1 \quad (11)$$

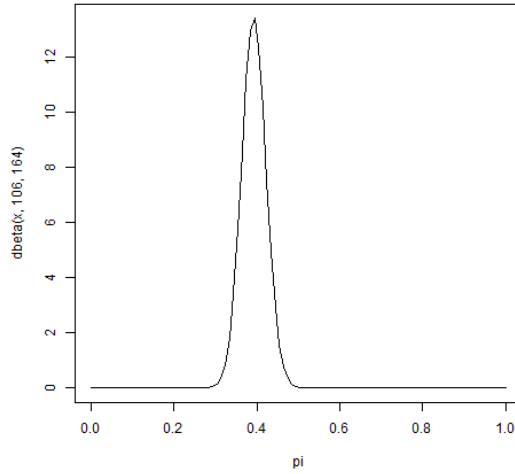


Figure 2: Posterior distribution of  $\pi$  under a  $\text{Beta}(100, 100)$  prior for  $\pi$ .

## 1.2 B - Posterior mean and standard deviations

### 1.2.1 I - Uniform prior

The posterior mean is  $\frac{X+1}{X+1+N-X+1} = \frac{X+1}{N+2} = \frac{7}{72} = \mathbf{0.09722}$ , and the posterior standard deviation is  $\sqrt{\frac{(X+1)*(N-X+1)}{(X+1+N-X+1)^2(X+1+N-X+1+1)}} = \sqrt{\frac{455}{72^2*73}} = \mathbf{0.03467}$ .

### 1.2.2 II - Informative Beta prior

The posterior mean is  $\mathbf{0.3925}$ , and the posterior standard deviation is  $\mathbf{0.02966}$ .

### 1.3 C - 95% Equal-tailed credible intervals

#### 1.3.1 I - Uniform prior

We obtain our 95% posterior credible interval for  $\pi$  under a uniform prior for  $\pi$  using the following R commands:

```
qbeta(c(0.025, 0.975), 7, 65) %>% round(3)
```

Our credible interval is **(0.041, 0.175)**.

#### 1.3.2 II - Informative Beta prior

Our credible interval is **(0.335, 0.451)**.

### 1.4 D - Posterior inference

#### 1.4.1 I - Uniform prior

Under a uniform prior for  $\pi$ ,

$$P(\pi \geq 0.2 \mid X, N) = \mathbf{0.007} \quad (12)$$

$$P(\pi < 0.2 \mid X, N) = \mathbf{0.993} \quad (13)$$

Where we found the first probability using the following R command:

```
(1-pbeta(0.2, 7, 65)) %>% round(3)
```

#### 1.4.2 II - Informative Beta prior

Under a Beta(100, 100) prior for  $\pi$ ,

$$P(\pi \geq 0.2 \mid X, N) = \mathbf{1} \quad (14)$$

$$P(\pi < 0.2 \mid X, N) = \mathbf{0} \quad (15)$$

## 2 Cowles, Problem 5.3

**Prompt:** If  $\phi = g(\pi) = \text{logit}(\pi)$ , show that a uniform prior on  $\pi$  induces the following density for  $\phi$ :

$$P_{\phi}(\phi) = \frac{e^{\phi}}{(1 + e^{\phi})^2} \quad (16)$$

**Solution:**

$$P_\phi(\phi) = P_\pi(g^{-1}(\phi)) \left| \frac{d\pi}{d\phi} \right| \quad (17)$$

$$= P_\pi \left( \frac{e^\phi}{1 + e^\phi} \right) \left( \frac{d}{d\phi} \frac{e^\phi}{1 + e^\phi} \right) \quad (18)$$

$$= P_\pi(\pi) \frac{(e^\phi)'(1 + e^\phi) - (e^\phi)(1 + e^\phi)'}{(1 + e^\phi)^2} \quad (19)$$

$$= \frac{(e^\phi)(1 + e^\phi) - (e^\phi)(e^\phi)}{(1 + e^\phi)^2} \quad (20)$$

$$= \frac{e^\phi}{(1 + e^\phi)^2} \quad (21)$$

In line 15 we apply the quotient rule. Going from line 15 to line 16,  $P_\pi(\pi) = 1$  as  $P_\pi$  is the uniform distribution.

### 3 GRADUTE SECTION ONLY

Continuing Problem 1, suppose that we encounter  $N = 20$  new individuals, who we assume are a random sample from a population of "people like us".

#### 3.1 Frequentist inference

The frequentist estimate for  $\pi$  is simply what we observe, i.e.  $\hat{\pi} = \frac{6}{70} = 0.0857$ . The probability that *at least* 4 individuals have played Euchre before  $P(X \geq 4 \mid \pi, N = 20)$  can be equivalently written as  $1 - P(X < 4 \mid \pi, N = 20)$ .

We evaluate this in R using the following command:

```
1 - pbinom(3, 20, 6/70)
```

and we find that  $P(\tilde{X} \geq 4 \mid \hat{\pi}, \tilde{N} = 20) = \mathbf{0.08639}$ .

#### 3.2 Posterior predictive probabilities

Using the *LearnBayes* package in R, with the following commands,

```
library(LearnBayes)
1 - (pbetap(c(7, 65), 20, 0:3) %>% sum)
```

We find that  $P(\tilde{X} \geq 4 \mid X, \tilde{N} = 20) = \mathbf{0.1459}$ .