

# Chapter 7.5 Bayesian Inferences with Continuous Priors

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Chapter 7 Learning About a Binomial Probability

# Introduction

- ▶ All Bayesian inferences about the proportion  $p$  are based on various summaries of this posterior beta distribution
- ▶ We will focus on three types of inference
  - ▶ Bayesian hypothesis testing: assess the likelihood of some values of  $p$
  - ▶ Bayesian credible interval: find an interval that is likely to contain  $p$
  - ▶ Bayesian prediction: learn about new observation(s) in the future.
- ▶ The use of simulation

# Bayesian hypothesis testing

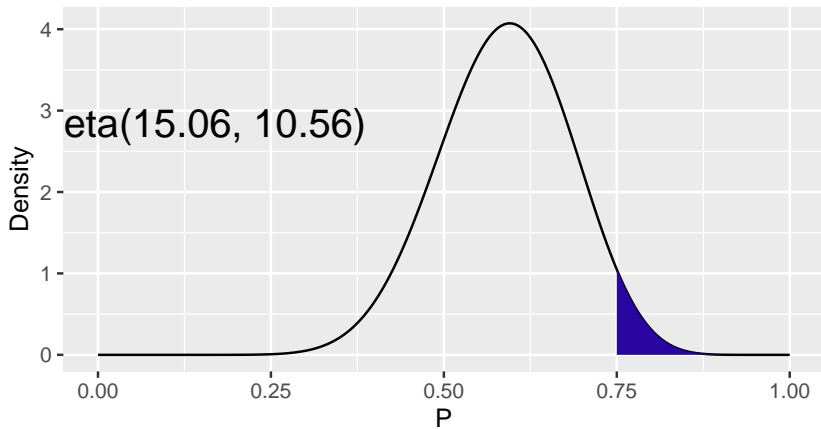
- ▶ Suppose one of the restaurant workers claims that at least 75% of the students prefer to eat out on Friday. Is this a reasonable claim?
- ▶ Test the hypothesis  $H : p \geq 0.75$
- ▶ Bayesian viewpoint: find the posterior probability that  $p \geq 0.75$  and make a decision based on the probability

## Bayesian hypothesis testing cont'd

- The exact solution: the `beta_area()` function

```
beta_area(lo = 0.75, hi = 1.0,  
          shape_par = c(15.06, 10.56), Color = "blue")
```

$$P(0.75 < P < 1) = 0.04$$



## Bayesian hypothesis testing cont'd

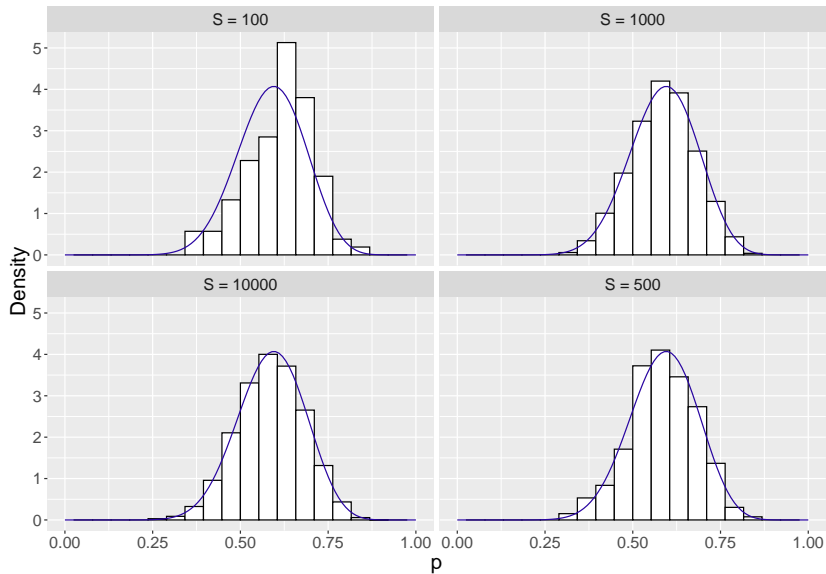
- ▶ The simulation solution:
  - ▶ generate a large number of random values from the beta posterior
  - ▶ summarize the sample of simulated draws to obtain the probability of  $p \geq 0.75$

```
S <- 1000  
BetaSamples <- rbeta(S, 15.06, 10.56)
```

```
sum(BetaSamples >= 0.75) / S
```

```
## [1] 0.051
```

# Choice of $S$



# Bayesian credible interval

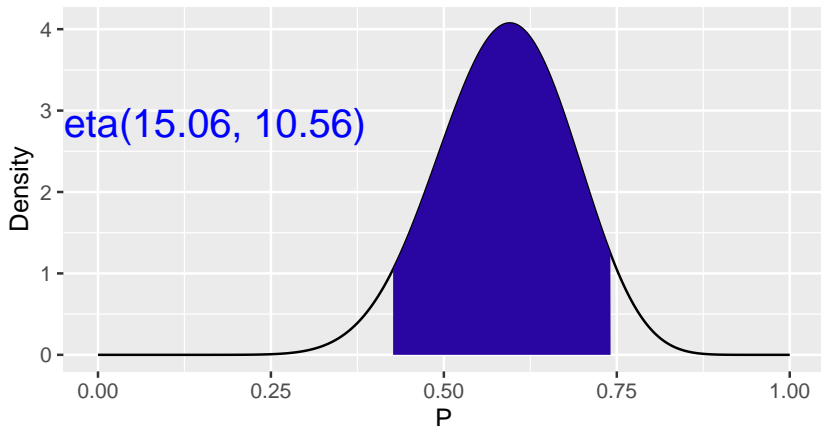
- ▶ An interval provides an uncertainty estimate for the parameter  $p$
- ▶ A 90% Bayesian credible interval is an interval that contains 90% of the posterior probability
- ▶ Different from the interpretation of a traditional confidence interval

## Bayesian credible interval cont'd

- ▶ A 90% “equal tails” interval: the `beta_interval()` function

```
beta_interval(0.9, c(15.06, 10.56), Color = crcblue)
```

$$P(0.427 < P < 0.741) = 0.9$$





# Bayesian credible interval cont'd

- ▶ A 90% “equal tails” interval: the `qbeta()` function

```
qbeta(c(0.05, 0.95), 15.06, 10.56)
```

```
## [1] 0.4266788 0.7410141
```

# Bayesian credible interval cont'd

- ▶ A 90% “equal tails” interval: simulation using the `quantile()` function

```
S <- 1000  
BetaSamples <- rbeta(S, 15.06, 10.56)  
quantile(BetaSamples, c(0.05, 0.95))
```

```
##           5%           95%  
## 0.4276337 0.7445882
```

- ▶ Choice of  $S$

# Bayesian prediction

- ▶ Random variable  $\tilde{Y}$ : the number of students preferring Friday to dine out out of the  $m$  respondents
- ▶  $\tilde{Y} \mid p \sim \text{Binomial}(m, p)$ , where  $p$  is the **posterior**
- ▶ Mathematically,

$$f(\tilde{Y} = \tilde{y}, p \mid Y = y) = f(\tilde{Y} = \tilde{y} \mid p)\pi(p \mid Y = y)$$

$$f(\tilde{Y} = \tilde{y} \mid Y = y) = \int f(\tilde{Y} = \tilde{y} \mid p)\pi(p \mid Y = y)dp$$

- ▶ The density of  $\tilde{Y}$  given  $p$  is Binomial with  $m$  trials and success probability  $p$ ,
- ▶ The posterior density of  $p$  is  $\text{Beta}(a + y, b + n - y)$

## Bayesian prediction cont'd

$$f(\tilde{Y} = \tilde{y} \mid Y = y) = \binom{m}{\tilde{y}} \frac{B(a + y + \tilde{y}, b + n - y + m - \tilde{y})}{B(a + y, b + n - y)}$$

- ▶ This is the beta-binomial distribution with parameters  $m$ ,  $a + y$  and  $b + n - y$

$$\tilde{Y} \mid Y = y \sim \text{Beta-Binomial}(m, a + y, b + n - y).$$

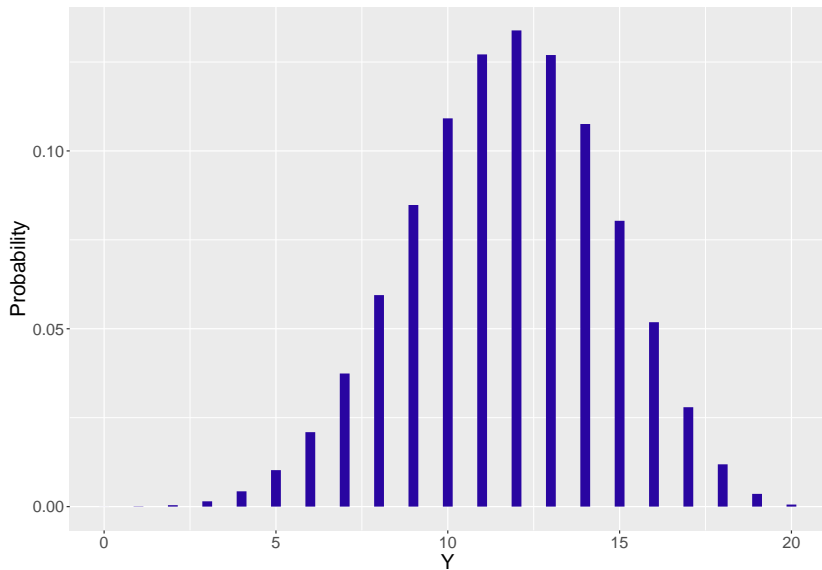
- ▶ Summary: Bayesian prediction of a new observation is a beta-binomial distribution where  $m$  is the number of trials in the new sample,  $a$  and  $b$  are shape parameters from the Beta prior, and  $y$  and  $n$  are quantities from the data/likelihood

## Bayesian prediction cont'd

- ▶ Compute the predictive probability that  $\tilde{y}$  students prefer Friday in a new survey of 20 students
- ▶ The exact solution
- ▶ The `pbetap()` function from the `ProbBayes` package. The inputs to `pbetap()` are the vector of Beta shape parameters  $(a, b)$ , the sample size 20, and the values of  $\tilde{y}$  of interest.

```
a <- 15.06
b <- 10.56
prob <- pbetap(c(a, b), 20, 0:20)
pred_distribution <- data.frame(Y = 0:20,
                                Probability = prob)
prob_plot(pred_distribution,
           Color = crcblue, Size = 4) +
  theme(text=element_text(size=18))
```

## Bayesian prediction cont'd



# Bayesian prediction cont'd

- The simulation solution

sample  $p \sim \text{Beta}(a + y, b + n - y)$

↓

sample  $\tilde{Y} \sim \text{Binomial}(m, p)$

## Bayesian prediction cont'd

- ▶ The `rbeta()` and `rbinom()` functions

```
a <- 3.06; b <- 2.56  
n <- 20; y <- 12  
pred_p_sim <- rbeta(1, a + y, b + n - y)  
(pred_y_sim <- rbinom(1, n, pred_p_sim))
```

```
## [1] 10
```

- ▶ Repeat this for  $S$  times



## Bayesian prediction cont'd

- ▶ `pred_p_sim` contains 1000 simulated draws from the posterior
- ▶ For each element of this posterior sample, the `rbinom()` function is used to simulate a corresponding value of  $\tilde{Y}$  from the binomial sampling density

```
a <- 3.06; b <- 2.56
n <- 20; y <- 12
S <- 1000
pred_p_sim <- rbeta(S, a + y, b + n - y)
pred_y_sim <- rbinom(S, n, pred_p_sim)
```

# Bayesian prediction cont'd

## ► Comparison

