# Chapter 7.2 Bayesian Inference with Discrete Priors

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Chapter 7 Learning About a Binomial Probability

## Example: students' dining preference

- ▶ A popular restaurant in a college town has been in business for about 5 years
- ► The restaurant owner wishes to learn more about his customers
- ► Interested in learning about the dining preferences of the students
- ► The owner plans to conduct a survey by asking students "what is your favorite day for eating out?"
- He wants to find out what percentage of students prefer to dine on Friday
- ► Let *p* denote the proportion of all students whose answer is Friday

# Discrete prior distributions for proportion p

► A set of plausible values of *p*:

$$p = \{0.3, 0.4, 0.5, 0.6, 0.7, 0.8\}$$

► A laymen's prior distribution for *p*:

$$\pi_I(p) = (1/6, 1/6, 1/6, 1/6, 1/6, 1/6)$$

► An expert's prior distribution for *p*:

$$\pi_e(p) = (0.125, 0.125, 0.250, 0.250, 0.125, 0.125)$$

# R for $\pi_e(p)$

► The ProbBayes R package

```
## p Prior
## 1 0.3 1
## 2 0.4 1
## 3 0.5 2
## 4 0.6 2
## 5 0.7 1
## 6 0.8 1
```

## R for $\pi_e(p)$ cont'd

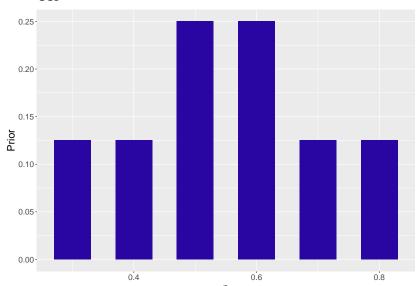
▶ Use the function mutate() to normalize these weights to obtain the prior probabilities in the Prior column

```
bayes_table %>%
  mutate(Prior = Prior / sum(Prior)) -> bayes_table
bayes_table
```

```
## p Prior
## 1 0.3 0.125
## 2 0.4 0.125
## 3 0.5 0.250
## 4 0.6 0.250
## 5 0.7 0.125
## 6 0.8 0.125
```

# R for $\pi_e(p)$ cont'd

► Plot the restaurant owner's prior distribution by use of ggplot2 functions



#### Likelihood

- ► The restaurant owner gives a survey to 20 student diners at the restaurant
- Out of the 20 student respondents, 12 say that their favorite day for eating out is Friday
- ► The likelihood is a function of the quantity of interest, the proportion *p*
- The owner has conducted an experiment 20 times
  - each experiment involves a "yes" or "no" answer from the respondent to the rephrased question "whether Friday is your preferred day to dine out"
  - the proportion p is the probability a student answers "yes"

## Review: binomial experiment

#### Four conditions for a binomial experiment:

- One is repeating the same basic task or trial many times
   let the number of trials be denoted by n
- On each trial, there are two possible outcomes called "success" or "failure"
- ► The probability of a success, denoted by p, is the same for each trial
- ► The results of outcomes from different trials are independent

#### The binomial likelihood function

► The probability of *y* successes in a Binomial experiment is given by

$$Prob(Y = y) = \binom{n}{y} p^{y} (1-p)^{n-y}, y = 0, \cdots, n$$

► The likelihood is the chance of 12 successes in 20 trials viewed as a function of the probability of success *p*:

Likelihood = 
$$L(p) = \binom{20}{12} p^{12} (1-p)^8$$

- generally use L to denote a likelihood function
- L is a function of p

#### R for the likelihood

- ▶ The likelihood function L(p) is efficiently computed using the dbinom() function in R
  - the sample size *n*: 20 in the dining survey
  - ightharpoonup the number of successes y: 12 in the dining survey
  - p: the list of 6 plausible values  $p = \{0.3, 0.4, 0.5, 0.6, 0.7, 0.8\}$

#### R for the likelihood cont'd

The values are placed in the Likelihood column of the bayes\_table data frame

```
## p Prior Likelihood

## 1 0.3 0.125 0.003859282

## 2 0.4 0.125 0.035497440

## 3 0.5 0.250 0.120134354

## 4 0.6 0.250 0.179705788

## 5 0.7 0.125 0.114396740

## 6 0.8 0.125 0.022160877
```

## Posterior distribution for proportion *p*

► Bayes' rule for a discrete parameter:

$$\pi(p_i \mid y) = \frac{\pi(p_i) \times L(p_i)}{\sum_j \pi(p_j) \times L(p_j)}$$

- $\blacktriangleright$   $\pi(p_i)$  is the prior probability of  $p=p_i$
- $\triangleright$   $L(p_i)$  is the likelihood function evaluated at  $p = p_i$
- $\pi(p_i \mid y)$  is the posterior probability of  $p = p_i$  given the number of successes y
- ▶ by the **Law of Total Probability**, the denominator gives the marginal distribution of the observation *y*.

# Bayes' rule

Bayes' rule can also be expressed as "prior times likelihood":

$$\pi(p_i \mid y) \propto \pi(p_i) \times L(p_i)$$

# Posterior probability calculation

► First, calculate the denominator and denote the value as *D*.

$$D = \pi(0.3) \times L(0.3) + \pi(0.4) \times L(0.4) + \dots + \pi(0.8) \times L(0.8)$$

▶ Then the posterior probability of p = 0.3 is given by

$$\pi(p = 0.3 \mid 12) = \frac{\pi(0.3) \times L(0.3)}{D} \approx 0.005$$

In a similar fashion, the posterior probability of p = 0.5 is calculated as

$$\pi(p = 0.5 \mid 12) = \frac{\pi(0.5) \times L(0.5)}{D} \approx 0.310$$

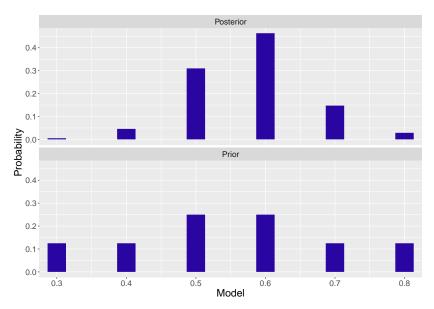
## R for posterior probability calculation

Use the bayesian\_crank() function to compute the posterior probabilities

```
bayesian_crank(bayes_table) -> bayes_table
bayes_table
```

```
## p Prior Likelihood Product Posterior
## 1 0.3 0.125 0.003859282 0.0004824102 0.004975901
## 2 0.4 0.125 0.035497440 0.0044371799 0.045768032
## 3 0.5 0.250 0.120134354 0.0300335884 0.309786454
## 4 0.6 0.250 0.179705788 0.0449264469 0.463401326
## 5 0.7 0.125 0.114396740 0.0142995925 0.147495530
## 6 0.8 0.125 0.022160877 0.0027701096 0.028572757
```

# Comparing prior and psoterior



## Inference: students' dining preference

- ▶ What is the posterior probability that over half of the students prefer eating out on Friday?
- ightharpoonup i.e. one is interested in the probability that p>0.5, in the posterior
- ▶ Looking at the table, this posterior probability is equal to

$$Prob(p > 0.5) \approx 0.463 + 0.147 + 0.029 = 0.639$$

➤ This means the owner is reasonably confident (with probability 0.639) that over half of the college students prefer to eat out on Friday

# Inference: students' dining preference cont'd

▶ Obtain the probability from the R output

```
sum(bayes_table$Posterior[bayes_table$p > 0.5])
```

```
## [1] 0.6394696
```

### Discussion: issues with discrete priors

- ▶ If a plausible value is not specified in the prior distribution, it will be assigned a probability of zero in the posterior
- lt generally is more desirable to have p to be any value in [0, 1] including less plausible values such as p = 1.0
- ➤ To make this happen, the proportion *p* should be allowed to take any value between 0 and 1, which means *p* will be a continuous variable
- i.e. it is necessary to construct a continuous prior distribution for p
- ▶ A popular class of continuous prior distributions for proportion is: the beta distribution