

Problem Set 5.1

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```
library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse 1.3.1 --
```

```
## v ggplot2 3.3.5      v purrr  0.3.4
## v tibble  3.1.6      v dplyr  1.0.7
## v tidyr   1.2.0      v stringr 1.4.0
## v readr   2.1.2      v forcats 0.5.1
```

```
## -- Conflicts ----- tidyverse_conflicts() --
```

```
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
```

```
library(janitor)
```

```
##
```

```
## Attaching package: 'janitor'
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
##      chisq.test, fisher.test
```

```
library(rstan)
```

```
## Loading required package: StanHeaders
```

```
## rstan (Version 2.21.3, GitRev: 2e1f913d3ca3)
```

```
## For execution on a local, multicore CPU with excess RAM we recommend calling
## options(mc.cores = parallel::detectCores()).
```

```
## To avoid recompilation of unchanged Stan programs, we recommend calling
## rstan_options(auto_write = TRUE)
```

```
## Do not specify '-march=native' in 'LOCAL_CPPFLAGS' or a Makevars file
```

```
##
```

```
## Attaching package: 'rstan'
```

```
## The following object is masked from 'package:tidyr':
##
##   extract

library(bayesplot)

## This is bayesplot version 1.8.1

## - Online documentation and vignettes at mc-stan.org/bayesplot

## - bayesplot theme set to bayesplot::theme_default()

##   * Does _not_ affect other ggplot2 plots

##   * See ?bayesplot_theme_set for details on theme setting

library(bayesrules)
```

Exercise 6.5

Part A

```
# Step 1: Define a grid of 6 pi values
grid_data <- data.frame(pi_grid = seq(from = 0, to = 1, length = 5))

# Step 2: Evaluate the prior & likelihood at each pi
grid_data <- grid_data %>%
  mutate(prior = dbeta(pi_grid, 3, 8),
         likelihood = dbinom(2, 10, pi_grid))

# Step 3: Approximate the posterior
grid_data <- grid_data %>%
  mutate(unnormalized = likelihood * prior,
         posterior = unnormalized / sum(unnormalized))

# Confirm that the posterior approximation sums to 1
grid_data %>%
  summarize(sum(unnormalized), sum(posterior))

##   sum(unnormalized) sum(posterior)
## 1          0.8765603           1

sum(grid_data['unnormalized'])

## [1] 0.8765603
```

```
sum(grid_data['posterior'])
```

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

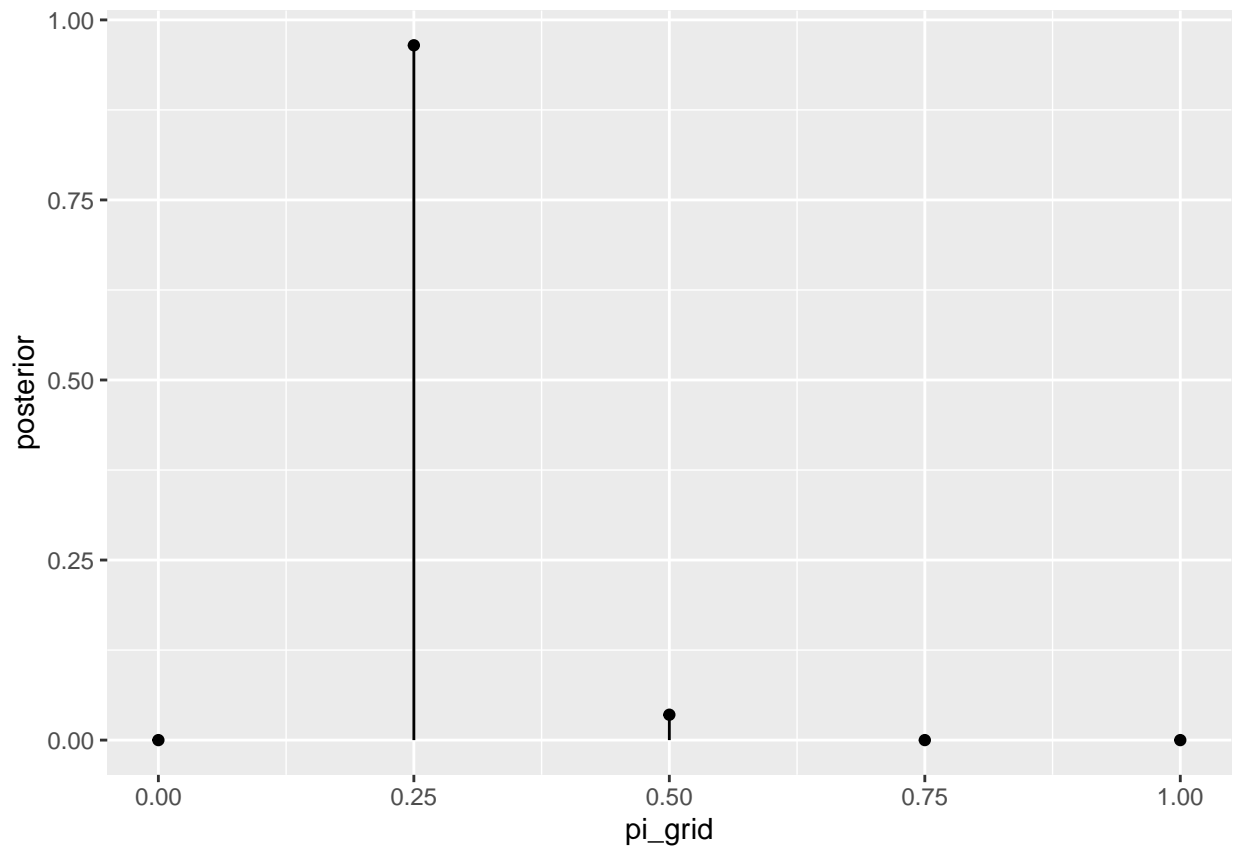
```
#Table
```

```
round(grid_data, 2)
```

```
##   pi_grid prior likelihood unnormalized posterior
## 1    0.00  0.00      0.00      0.00      0.00
## 2    0.25  3.00      0.28      0.85      0.96
## 3    0.50  0.70      0.04      0.03      0.04
## 4    0.75  0.01      0.00      0.00      0.00
## 5    1.00  0.00      0.00      0.00      0.00
```

```
# Plot the grid approximated posterior
```

```
ggplot(grid_data, aes(x = pi_grid, y = posterior)) +  
  geom_point() +  
  geom_segment(aes(x = pi_grid, xend = pi_grid, y = 0, yend = posterior))
```



Part B

```
# Step 1: Define a grid of 6 pi values
```

```
grid_data <- data.frame(pi_grid = seq(from = 0, to = 1, length = 201))
```

```

# Step 2: Evaluate the prior & likelihood at each pi
grid_data <- grid_data %>%
  mutate(prior = dbeta(pi_grid, 3, 8),
         likelihood = dbinom(2, 10, pi_grid))

# Step 3: Approximate the posterior
grid_data <- grid_data %>%
  mutate(unnormalized = likelihood * prior,
         posterior = unnormalized / sum(unnormalized))

# Confirm that the posterior approximation sums to 1
grid_data %>%
  summarize(sum(unnormalized), sum(posterior))

```

```

##      sum(unnormalized) sum(posterior)
## 1           41.79567           1

```

```
sum(grid_data['unnormalized'])
```

```
## [1] 41.79567
```

```
sum(grid_data['posterior'])
```

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

```

#Table
round(grid_data, 2)

```

```

##      pi_grid prior likelihood unnormalized posterior
## 1      0.00 0.00      0.00      0.00      0.00
## 2      0.00 0.01      0.00      0.00      0.00
## 3      0.01 0.03      0.00      0.00      0.00
## 4      0.01 0.07      0.01      0.00      0.00
## 5      0.02 0.13      0.02      0.00      0.00
## 6      0.03 0.19      0.02      0.00      0.00
## 7      0.03 0.26      0.03      0.01      0.00
## 8      0.04 0.34      0.04      0.01      0.00
## 9      0.04 0.43      0.05      0.02      0.00
## 10     0.04 0.53      0.06      0.03      0.00
## 11     0.05 0.63      0.07      0.05      0.00
## 12     0.06 0.73      0.09      0.06      0.00
## 13     0.06 0.84      0.10      0.08      0.00
## 14     0.06 0.95      0.11      0.11      0.00
## 15     0.07 1.06      0.12      0.13      0.00
## 16     0.07 1.17      0.14      0.16      0.00
## 17     0.08 1.29      0.15      0.19      0.00
## 18     0.09 1.40      0.16      0.22      0.01
## 19     0.09 1.51      0.17      0.26      0.01
## 20     0.10 1.62      0.18      0.30      0.01
## 21     0.10 1.72      0.19      0.33      0.01
## 22     0.10 1.83      0.20      0.37      0.01

```

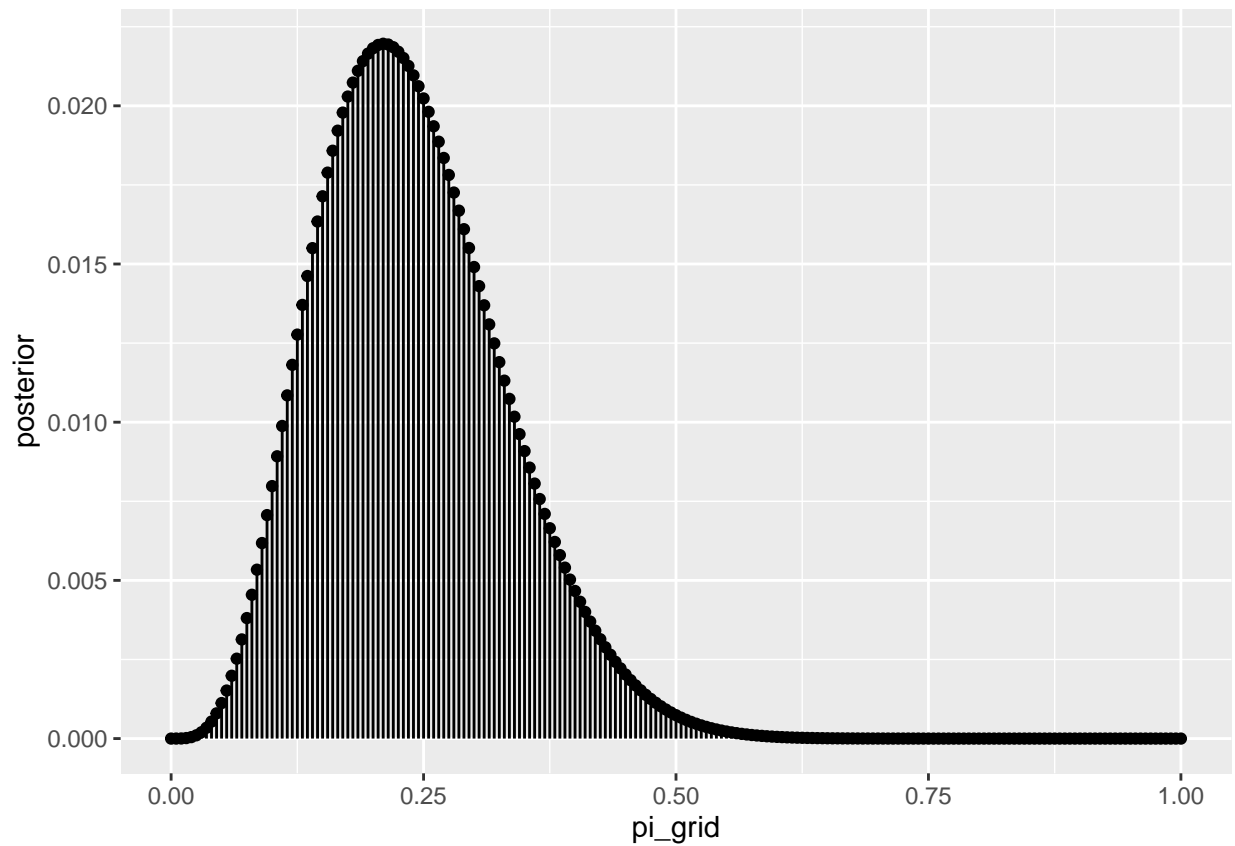
## 23	0.11	1.93	0.21	0.41	0.01
## 24	0.12	2.02	0.22	0.45	0.01
## 25	0.12	2.12	0.23	0.49	0.01
## 26	0.12	2.21	0.24	0.53	0.01
## 27	0.13	2.30	0.25	0.57	0.01
## 28	0.14	2.38	0.26	0.61	0.01
## 29	0.14	2.45	0.26	0.65	0.02
## 30	0.14	2.53	0.27	0.68	0.02
## 31	0.15	2.60	0.28	0.72	0.02
## 32	0.16	2.66	0.28	0.75	0.02
## 33	0.16	2.72	0.29	0.78	0.02
## 34	0.16	2.77	0.29	0.80	0.02
## 35	0.17	2.82	0.29	0.83	0.02
## 36	0.18	2.87	0.30	0.85	0.02
## 37	0.18	2.91	0.30	0.87	0.02
## 38	0.18	2.94	0.30	0.88	0.02
## 39	0.19	2.97	0.30	0.89	0.02
## 40	0.20	3.00	0.30	0.90	0.02
## 41	0.20	3.02	0.30	0.91	0.02
## 42	0.21	3.04	0.30	0.92	0.02
## 43	0.21	3.05	0.30	0.92	0.02
## 44	0.22	3.06	0.30	0.92	0.02
## 45	0.22	3.06	0.30	0.91	0.02
## 46	0.22	3.06	0.30	0.91	0.02
## 47	0.23	3.06	0.29	0.90	0.02
## 48	0.24	3.05	0.29	0.89	0.02
## 49	0.24	3.04	0.29	0.88	0.02
## 50	0.24	3.02	0.29	0.86	0.02
## 51	0.25	3.00	0.28	0.85	0.02
## 52	0.26	2.98	0.28	0.83	0.02
## 53	0.26	2.96	0.27	0.81	0.02
## 54	0.26	2.93	0.27	0.79	0.02
## 55	0.27	2.90	0.26	0.77	0.02
## 56	0.28	2.87	0.26	0.74	0.02
## 57	0.28	2.83	0.25	0.72	0.02
## 58	0.29	2.79	0.25	0.70	0.02
## 59	0.29	2.75	0.24	0.67	0.02
## 60	0.30	2.71	0.24	0.65	0.02
## 61	0.30	2.67	0.23	0.62	0.01
## 62	0.30	2.62	0.23	0.60	0.01
## 63	0.31	2.58	0.22	0.57	0.01
## 64	0.32	2.53	0.22	0.55	0.01
## 65	0.32	2.48	0.21	0.52	0.01
## 66	0.32	2.43	0.20	0.50	0.01
## 67	0.33	2.38	0.20	0.47	0.01
## 68	0.34	2.32	0.19	0.45	0.01
## 69	0.34	2.27	0.19	0.43	0.01
## 70	0.35	2.22	0.18	0.40	0.01
## 71	0.35	2.16	0.18	0.38	0.01
## 72	0.36	2.11	0.17	0.36	0.01
## 73	0.36	2.05	0.16	0.34	0.01
## 74	0.36	2.00	0.16	0.32	0.01
## 75	0.37	1.94	0.15	0.30	0.01
## 76	0.38	1.89	0.15	0.28	0.01

## 77	0.38	1.83	0.14	0.26	0.01
## 78	0.38	1.78	0.14	0.24	0.01
## 79	0.39	1.72	0.13	0.23	0.01
## 80	0.40	1.67	0.13	0.21	0.01
## 81	0.40	1.61	0.12	0.19	0.00
## 82	0.41	1.56	0.12	0.18	0.00
## 83	0.41	1.51	0.11	0.17	0.00
## 84	0.42	1.45	0.11	0.15	0.00
## 85	0.42	1.40	0.10	0.14	0.00
## 86	0.42	1.35	0.10	0.13	0.00
## 87	0.43	1.30	0.09	0.12	0.00
## 88	0.44	1.25	0.09	0.11	0.00
## 89	0.44	1.20	0.08	0.10	0.00
## 90	0.44	1.16	0.08	0.09	0.00
## 91	0.45	1.11	0.08	0.08	0.00
## 92	0.46	1.06	0.07	0.08	0.00
## 93	0.46	1.02	0.07	0.07	0.00
## 94	0.47	0.98	0.07	0.06	0.00
## 95	0.47	0.93	0.06	0.06	0.00
## 96	0.48	0.89	0.06	0.05	0.00
## 97	0.48	0.85	0.06	0.05	0.00
## 98	0.48	0.81	0.05	0.04	0.00
## 99	0.49	0.78	0.05	0.04	0.00
## 100	0.50	0.74	0.05	0.03	0.00
## 101	0.50	0.70	0.04	0.03	0.00
## 102	0.50	0.67	0.04	0.03	0.00
## 103	0.51	0.64	0.04	0.02	0.00
## 104	0.52	0.60	0.04	0.02	0.00
## 105	0.52	0.57	0.03	0.02	0.00
## 106	0.52	0.54	0.03	0.02	0.00
## 107	0.53	0.51	0.03	0.02	0.00
## 108	0.54	0.48	0.03	0.01	0.00
## 109	0.54	0.46	0.03	0.01	0.00
## 110	0.54	0.43	0.02	0.01	0.00
## 111	0.55	0.41	0.02	0.01	0.00
## 112	0.56	0.38	0.02	0.01	0.00
## 113	0.56	0.36	0.02	0.01	0.00
## 114	0.57	0.34	0.02	0.01	0.00
## 115	0.57	0.32	0.02	0.01	0.00
## 116	0.58	0.30	0.02	0.00	0.00
## 117	0.58	0.28	0.01	0.00	0.00
## 118	0.58	0.26	0.01	0.00	0.00
## 119	0.59	0.24	0.01	0.00	0.00
## 120	0.60	0.23	0.01	0.00	0.00
## 121	0.60	0.21	0.01	0.00	0.00
## 122	0.60	0.20	0.01	0.00	0.00
## 123	0.61	0.18	0.01	0.00	0.00
## 124	0.62	0.17	0.01	0.00	0.00
## 125	0.62	0.16	0.01	0.00	0.00
## 126	0.62	0.15	0.01	0.00	0.00
## 127	0.63	0.14	0.01	0.00	0.00
## 128	0.64	0.13	0.01	0.00	0.00
## 129	0.64	0.12	0.01	0.00	0.00
## 130	0.64	0.11	0.00	0.00	0.00

## 131	0.65	0.10	0.00	0.00	0.00
## 132	0.66	0.09	0.00	0.00	0.00
## 133	0.66	0.08	0.00	0.00	0.00
## 134	0.66	0.08	0.00	0.00	0.00
## 135	0.67	0.07	0.00	0.00	0.00
## 136	0.68	0.06	0.00	0.00	0.00
## 137	0.68	0.06	0.00	0.00	0.00
## 138	0.69	0.05	0.00	0.00	0.00
## 139	0.69	0.05	0.00	0.00	0.00
## 140	0.70	0.04	0.00	0.00	0.00
## 141	0.70	0.04	0.00	0.00	0.00
## 142	0.70	0.03	0.00	0.00	0.00
## 143	0.71	0.03	0.00	0.00	0.00
## 144	0.72	0.03	0.00	0.00	0.00
## 145	0.72	0.03	0.00	0.00	0.00
## 146	0.72	0.02	0.00	0.00	0.00
## 147	0.73	0.02	0.00	0.00	0.00
## 148	0.74	0.02	0.00	0.00	0.00
## 149	0.74	0.02	0.00	0.00	0.00
## 150	0.74	0.01	0.00	0.00	0.00
## 151	0.75	0.01	0.00	0.00	0.00
## 152	0.76	0.01	0.00	0.00	0.00
## 153	0.76	0.01	0.00	0.00	0.00
## 154	0.76	0.01	0.00	0.00	0.00
## 155	0.77	0.01	0.00	0.00	0.00
## 156	0.78	0.01	0.00	0.00	0.00
## 157	0.78	0.01	0.00	0.00	0.00
## 158	0.78	0.00	0.00	0.00	0.00
## 159	0.79	0.00	0.00	0.00	0.00
## 160	0.80	0.00	0.00	0.00	0.00
## 161	0.80	0.00	0.00	0.00	0.00
## 162	0.80	0.00	0.00	0.00	0.00
## 163	0.81	0.00	0.00	0.00	0.00
## 164	0.82	0.00	0.00	0.00	0.00
## 165	0.82	0.00	0.00	0.00	0.00
## 166	0.83	0.00	0.00	0.00	0.00
## 167	0.83	0.00	0.00	0.00	0.00
## 168	0.84	0.00	0.00	0.00	0.00
## 169	0.84	0.00	0.00	0.00	0.00
## 170	0.84	0.00	0.00	0.00	0.00
## 171	0.85	0.00	0.00	0.00	0.00
## 172	0.86	0.00	0.00	0.00	0.00
## 173	0.86	0.00	0.00	0.00	0.00
## 174	0.86	0.00	0.00	0.00	0.00
## 175	0.87	0.00	0.00	0.00	0.00
## 176	0.88	0.00	0.00	0.00	0.00
## 177	0.88	0.00	0.00	0.00	0.00
## 178	0.88	0.00	0.00	0.00	0.00
## 179	0.89	0.00	0.00	0.00	0.00
## 180	0.90	0.00	0.00	0.00	0.00
## 181	0.90	0.00	0.00	0.00	0.00
## 182	0.90	0.00	0.00	0.00	0.00
## 183	0.91	0.00	0.00	0.00	0.00
## 184	0.92	0.00	0.00	0.00	0.00

```
## 185    0.92 0.00    0.00    0.00    0.00
## 186    0.92 0.00    0.00    0.00    0.00
## 187    0.93 0.00    0.00    0.00    0.00
## 188    0.94 0.00    0.00    0.00    0.00
## 189    0.94 0.00    0.00    0.00    0.00
## 190    0.95 0.00    0.00    0.00    0.00
## 191    0.95 0.00    0.00    0.00    0.00
## 192    0.96 0.00    0.00    0.00    0.00
## 193    0.96 0.00    0.00    0.00    0.00
## 194    0.96 0.00    0.00    0.00    0.00
## 195    0.97 0.00    0.00    0.00    0.00
## 196    0.98 0.00    0.00    0.00    0.00
## 197    0.98 0.00    0.00    0.00    0.00
## 198    0.98 0.00    0.00    0.00    0.00
## 199    0.99 0.00    0.00    0.00    0.00
## 200    1.00 0.00    0.00    0.00    0.00
## 201    1.00 0.00    0.00    0.00    0.00
```

```
# Plot the grid approximated posterior
ggplot(grid_data, aes(x = pi_grid, y = posterior)) +
  geom_point() +
  geom_segment(aes(x = pi_grid, xend = pi_grid, y = 0, yend = posterior))
```



problem 6.13

a)

```
# STEP 1: DEFINE the model
bb_model <- "
  data {
    int<lower = 0, upper = 10> Y;
  }
  parameters {
    real<lower = 0, upper = 1> pi;
  }
  model {
    Y ~ binomial(10, pi);
    pi ~ beta(3, 8);
  }
"

# STEP 2: SIMULATE the posterior
bb_sim <- stan(model_code = bb_model, data = list(Y = 2),
              chains = 3, iter = 12000, seed = 1)

##
## SAMPLING FOR MODEL '2d032ece7c158ae32f246bd4866ed7ab' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:      1 / 12000 [ 0%] (Warmup)
## Chain 1: Iteration: 1200 / 12000 [ 10%] (Warmup)
## Chain 1: Iteration: 2400 / 12000 [ 20%] (Warmup)
## Chain 1: Iteration: 3600 / 12000 [ 30%] (Warmup)
## Chain 1: Iteration: 4800 / 12000 [ 40%] (Warmup)
## Chain 1: Iteration: 6000 / 12000 [ 50%] (Warmup)
## Chain 1: Iteration: 6001 / 12000 [ 50%] (Sampling)
## Chain 1: Iteration: 7200 / 12000 [ 60%] (Sampling)
## Chain 1: Iteration: 8400 / 12000 [ 70%] (Sampling)
## Chain 1: Iteration: 9600 / 12000 [ 80%] (Sampling)
## Chain 1: Iteration: 10800 / 12000 [ 90%] (Sampling)
## Chain 1: Iteration: 12000 / 12000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.1 seconds (Warm-up)
## Chain 1:           0.128 seconds (Sampling)
## Chain 1:           0.228 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL '2d032ece7c158ae32f246bd4866ed7ab' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
```

```

## Chain 2:
## Chain 2:
## Chain 2: Iteration:      1 / 12000 [ 0%] (Warmup)
## Chain 2: Iteration:    1200 / 12000 [ 10%] (Warmup)
## Chain 2: Iteration:    2400 / 12000 [ 20%] (Warmup)
## Chain 2: Iteration:    3600 / 12000 [ 30%] (Warmup)
## Chain 2: Iteration:    4800 / 12000 [ 40%] (Warmup)
## Chain 2: Iteration:    6000 / 12000 [ 50%] (Warmup)
## Chain 2: Iteration:    6001 / 12000 [ 50%] (Sampling)
## Chain 2: Iteration:    7200 / 12000 [ 60%] (Sampling)
## Chain 2: Iteration:    8400 / 12000 [ 70%] (Sampling)
## Chain 2: Iteration:    9600 / 12000 [ 80%] (Sampling)
## Chain 2: Iteration:   10800 / 12000 [ 90%] (Sampling)
## Chain 2: Iteration:   12000 / 12000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.097 seconds (Warm-up)
## Chain 2:           0.113 seconds (Sampling)
## Chain 2:           0.21 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL '2d032ece7c158ae32f246bd4866ed7ab' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:      1 / 12000 [ 0%] (Warmup)
## Chain 3: Iteration:    1200 / 12000 [ 10%] (Warmup)
## Chain 3: Iteration:    2400 / 12000 [ 20%] (Warmup)
## Chain 3: Iteration:    3600 / 12000 [ 30%] (Warmup)
## Chain 3: Iteration:    4800 / 12000 [ 40%] (Warmup)
## Chain 3: Iteration:    6000 / 12000 [ 50%] (Warmup)
## Chain 3: Iteration:    6001 / 12000 [ 50%] (Sampling)
## Chain 3: Iteration:    7200 / 12000 [ 60%] (Sampling)
## Chain 3: Iteration:    8400 / 12000 [ 70%] (Sampling)
## Chain 3: Iteration:    9600 / 12000 [ 80%] (Sampling)
## Chain 3: Iteration:   10800 / 12000 [ 90%] (Sampling)
## Chain 3: Iteration:   12000 / 12000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.071 seconds (Warm-up)
## Chain 3:           0.081 seconds (Sampling)
## Chain 3:           0.152 seconds (Total)
## Chain 3:

```

b)

```

as.array(bb_sim, pars = "pi") %>%
  head(4)

```

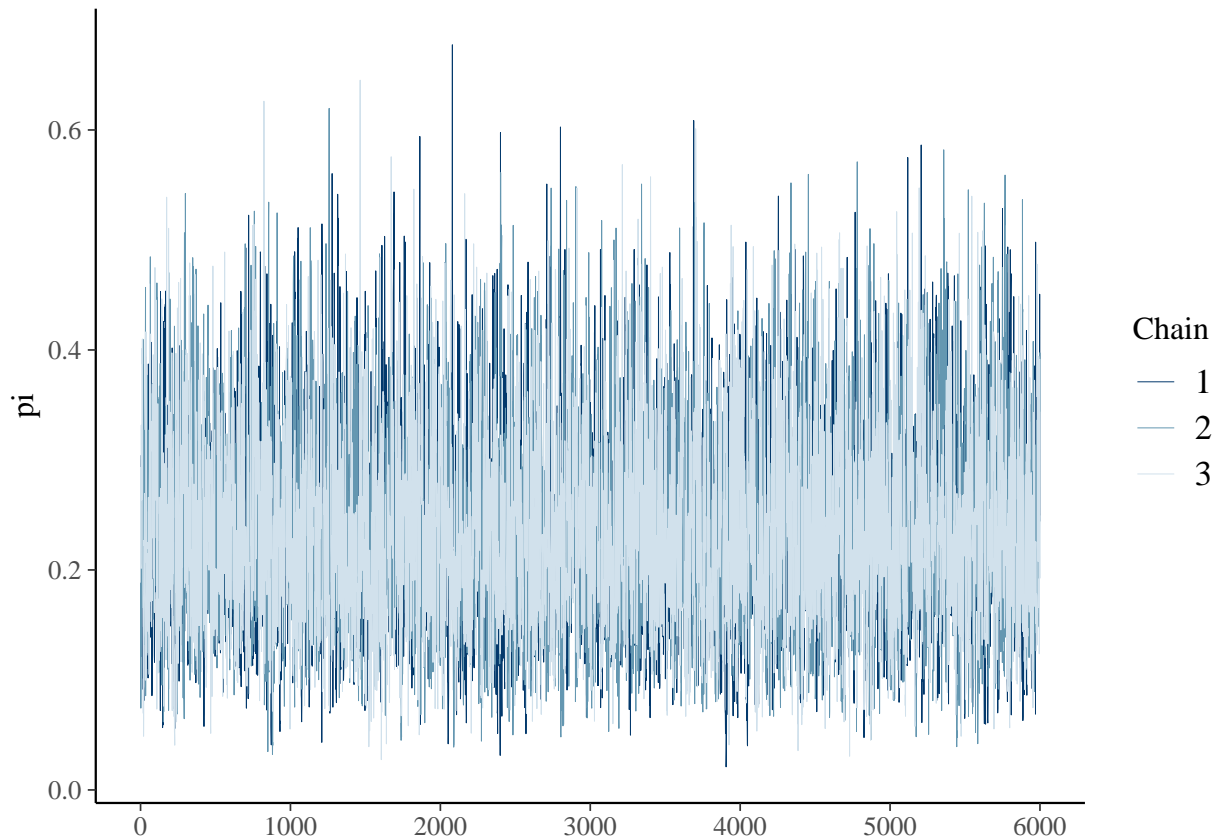
```

## , , parameters = pi
##
##           chains

```

```
## iterations   chain:1   chain:2   chain:3
##      [1,] 0.2249787 0.18837278 0.2935260
##      [2,] 0.2764489 0.07439545 0.2059931
##      [3,] 0.2323178 0.16303609 0.2013071
##      [4,] 0.2869850 0.12158335 0.3316874
```

```
mcmc_trace(bb_sim, pars = "pi", size = 0.1)
```

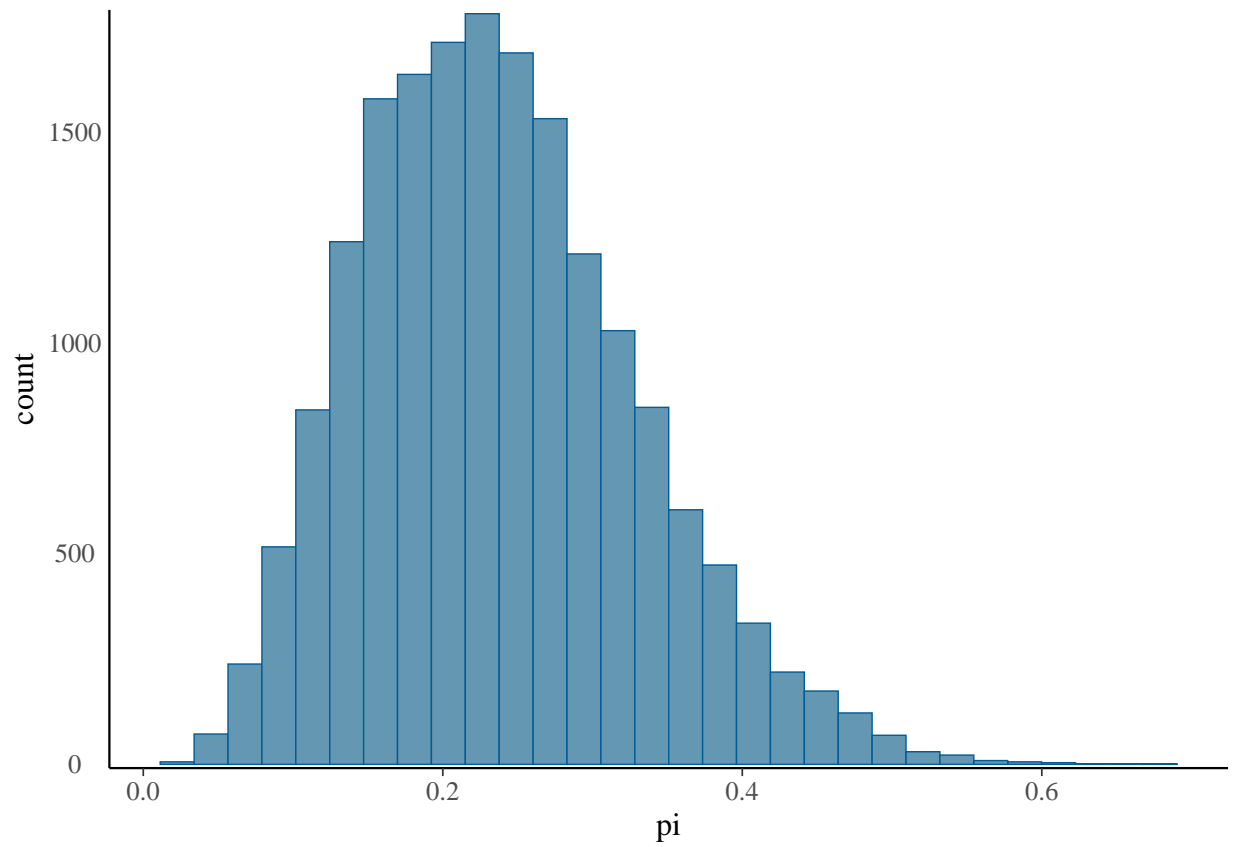


c) The first 50% of the MCMC process there are always remove known as “burn-in” or “warm-up” samples. The second half are kept as the final Markov chain sample. that is the reason why there are only 6,000. (12,000/2)

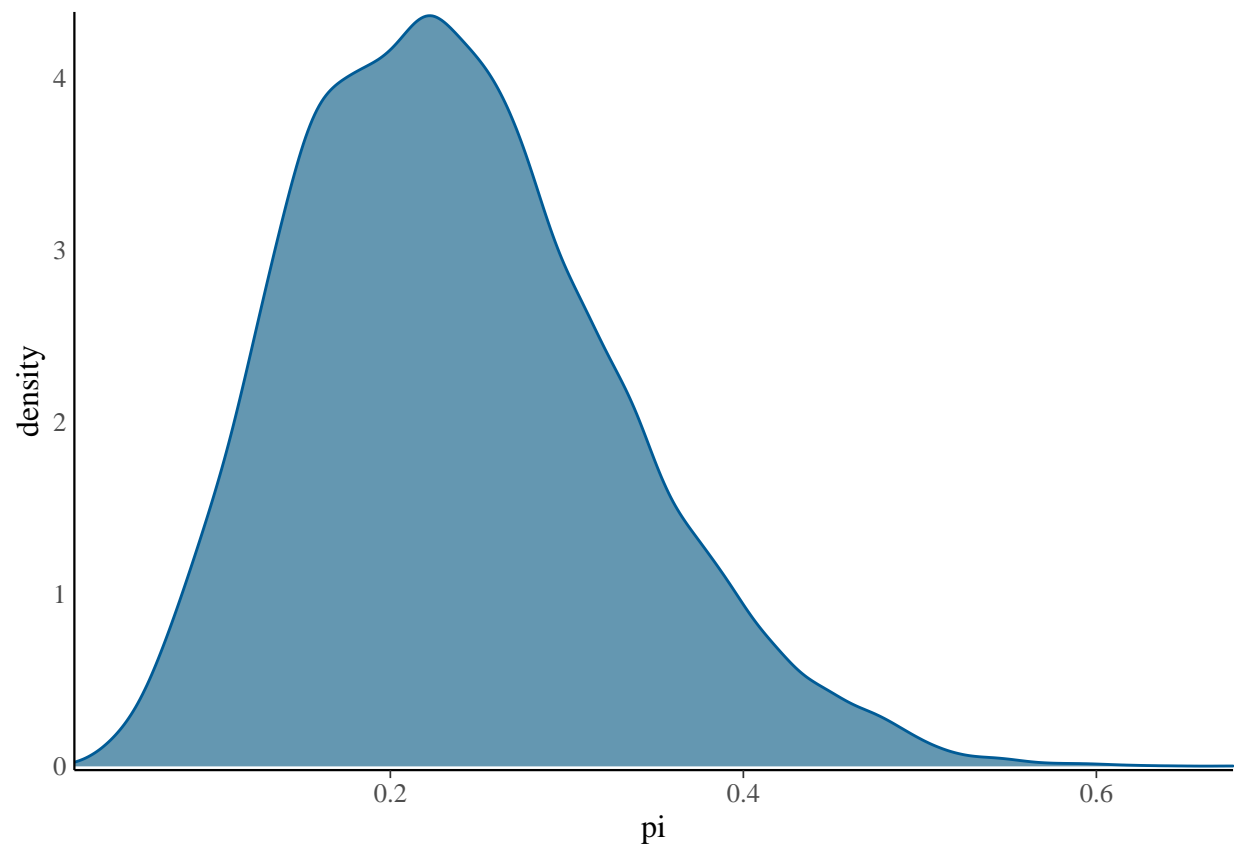
d)

```
# Histogram of the Markov chain values
mcmc_hist(bb_sim, pars = "pi") +
  yaxis_text(TRUE) +
  ylab("count")
```

```
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
```

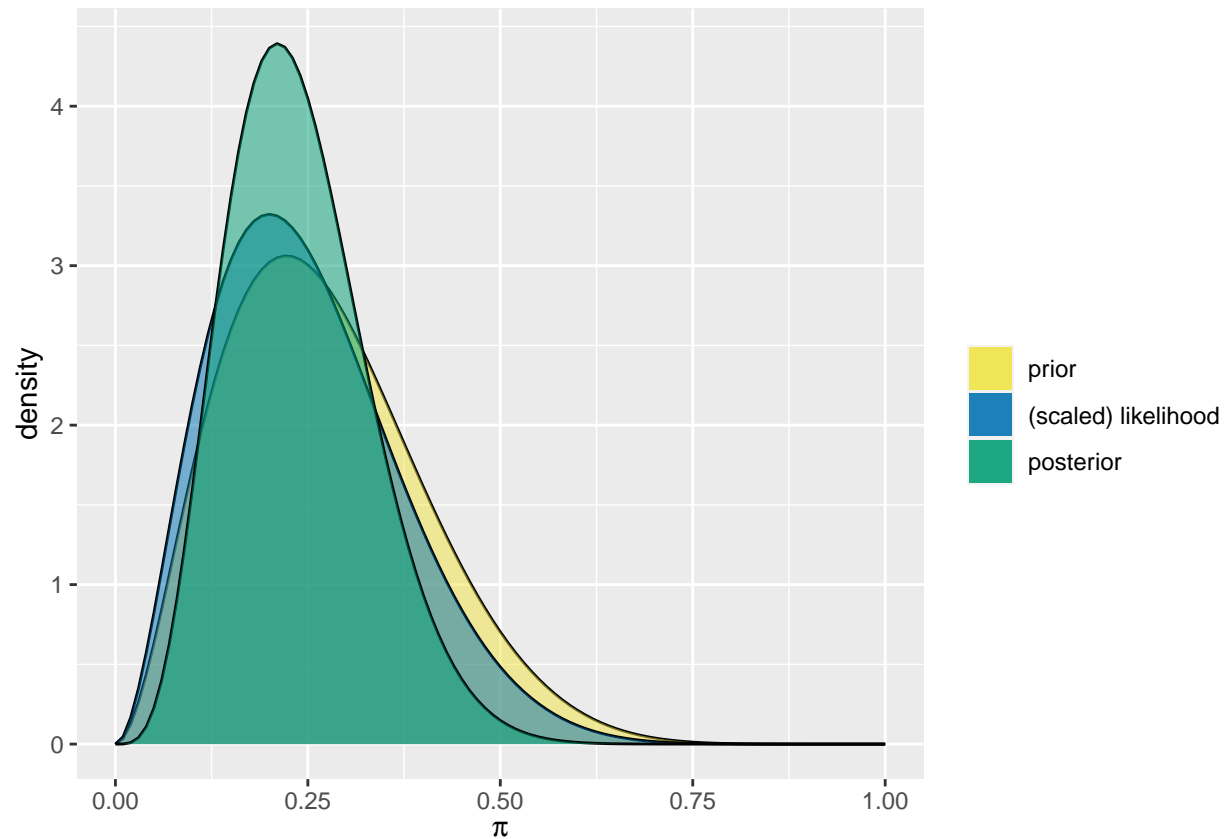


```
# Density plot of the Markov chain values
mcmc_dens(bb_sim, pars = "pi") +
  yaxis_text(TRUE) +
  ylab("density")
```



e)

```
plot_beta_binomial(alpha = 3, beta = 8, y = 2, n = 10)
```



They look similar, the majority of the pdf is around 0.2 and 0.24. So they look pretty similar

problem 6.14

```
# STEP 1: DEFINE the model
bb_model <- "
  data {
    int<lower = 0, upper = 12> Y;
  }
  parameters {
    real<lower = 0, upper = 1> pi;
  }
  model {
    Y ~ binomial(12, pi);
    pi ~ beta(4, 3);
  }
"

# STEP 2: SIMULATE the posterior
bb_sim <- stan(model_code = bb_model, data = list(Y = 4),
              chains = 3, iter = 12000, seed = 1)
```

```
##
## SAMPLING FOR MODEL 'b61b4553aa22e133ec03c9d7da030f7b' NOW (CHAIN 1).
```

```

## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:      1 / 12000 [ 0%] (Warmup)
## Chain 1: Iteration:    1200 / 12000 [ 10%] (Warmup)
## Chain 1: Iteration:    2400 / 12000 [ 20%] (Warmup)
## Chain 1: Iteration:    3600 / 12000 [ 30%] (Warmup)
## Chain 1: Iteration:    4800 / 12000 [ 40%] (Warmup)
## Chain 1: Iteration:    6000 / 12000 [ 50%] (Warmup)
## Chain 1: Iteration:    6001 / 12000 [ 50%] (Sampling)
## Chain 1: Iteration:    7200 / 12000 [ 60%] (Sampling)
## Chain 1: Iteration:    8400 / 12000 [ 70%] (Sampling)
## Chain 1: Iteration:    9600 / 12000 [ 80%] (Sampling)
## Chain 1: Iteration:   10800 / 12000 [ 90%] (Sampling)
## Chain 1: Iteration:   12000 / 12000 [100%] (Sampling)
## Chain 1:
## Chain 1: Elapsed Time: 0.073 seconds (Warm-up)
## Chain 1:                0.078 seconds (Sampling)
## Chain 1:                0.151 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'b61b4553aa22e133ec03c9d7da030f7b' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:      1 / 12000 [ 0%] (Warmup)
## Chain 2: Iteration:    1200 / 12000 [ 10%] (Warmup)
## Chain 2: Iteration:    2400 / 12000 [ 20%] (Warmup)
## Chain 2: Iteration:    3600 / 12000 [ 30%] (Warmup)
## Chain 2: Iteration:    4800 / 12000 [ 40%] (Warmup)
## Chain 2: Iteration:    6000 / 12000 [ 50%] (Warmup)
## Chain 2: Iteration:    6001 / 12000 [ 50%] (Sampling)
## Chain 2: Iteration:    7200 / 12000 [ 60%] (Sampling)
## Chain 2: Iteration:    8400 / 12000 [ 70%] (Sampling)
## Chain 2: Iteration:    9600 / 12000 [ 80%] (Sampling)
## Chain 2: Iteration:   10800 / 12000 [ 90%] (Sampling)
## Chain 2: Iteration:   12000 / 12000 [100%] (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 0.074 seconds (Warm-up)
## Chain 2:                0.072 seconds (Sampling)
## Chain 2:                0.146 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'b61b4553aa22e133ec03c9d7da030f7b' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 0 seconds.
## Chain 3: Adjust your expectations accordingly!

```

```

## Chain 3:
## Chain 3:
## Chain 3: Iteration:      1 / 12000 [ 0%] (Warmup)
## Chain 3: Iteration:  1200 / 12000 [10%] (Warmup)
## Chain 3: Iteration:  2400 / 12000 [20%] (Warmup)
## Chain 3: Iteration:  3600 / 12000 [30%] (Warmup)
## Chain 3: Iteration:  4800 / 12000 [40%] (Warmup)
## Chain 3: Iteration:  6000 / 12000 [50%] (Warmup)
## Chain 3: Iteration:  6001 / 12000 [50%] (Sampling)
## Chain 3: Iteration:  7200 / 12000 [60%] (Sampling)
## Chain 3: Iteration:  8400 / 12000 [70%] (Sampling)
## Chain 3: Iteration:  9600 / 12000 [80%] (Sampling)
## Chain 3: Iteration: 10800 / 12000 [90%] (Sampling)
## Chain 3: Iteration: 12000 / 12000 [100%] (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 0.072 seconds (Warm-up)
## Chain 3:           0.08 seconds (Sampling)
## Chain 3:           0.152 seconds (Total)
## Chain 3:

```

```

as.array(bb_sim, pars = "pi") %>%
  head(4)

```

```

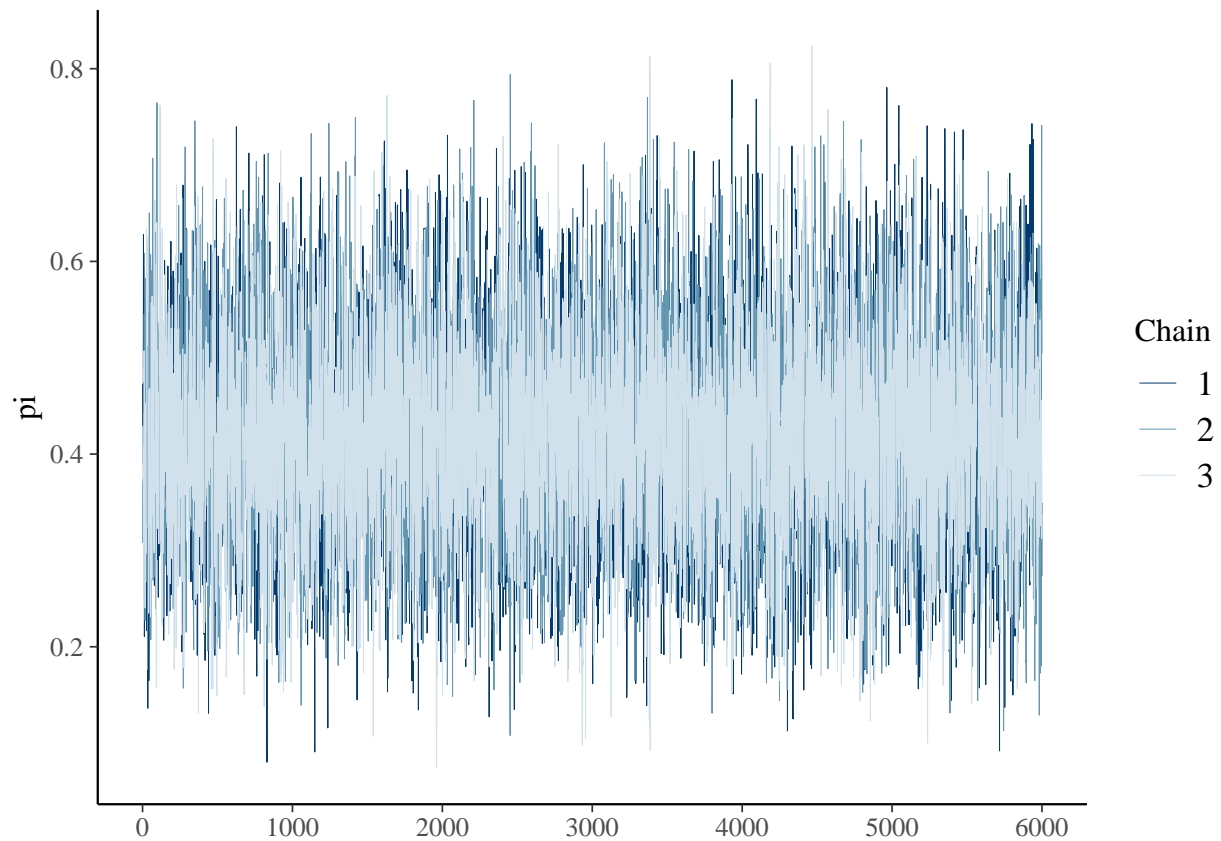
## , , parameters = pi
##
##           chains
## iterations chain:1 chain:2 chain:3
##      [1,] 0.4725206 0.3077464 0.4289977
##      [2,] 0.4688443 0.3743118 0.3724838
##      [3,] 0.4243136 0.3094735 0.3719880
##      [4,] 0.3904008 0.3302203 0.3719880

```

```

mcmc_trace(bb_sim, pars = "pi", size = 0.1)

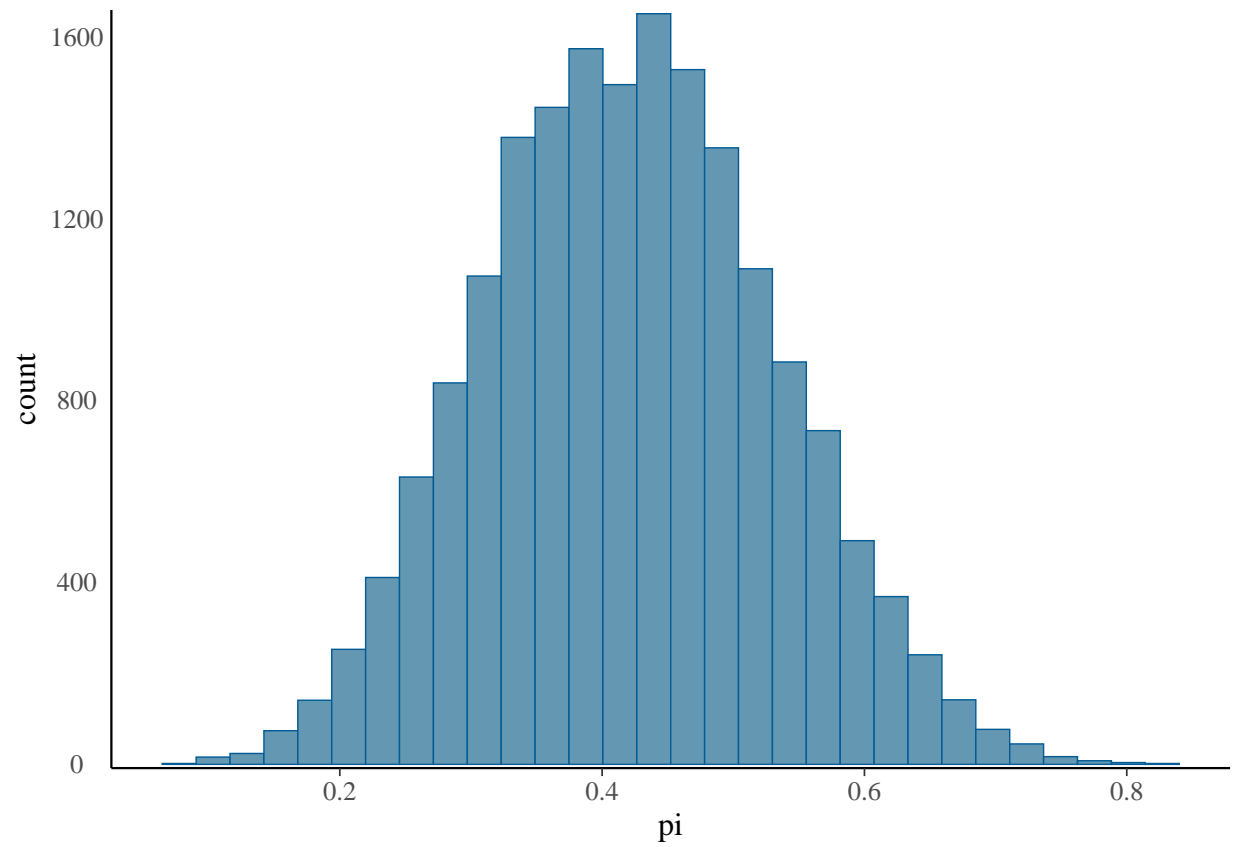
```

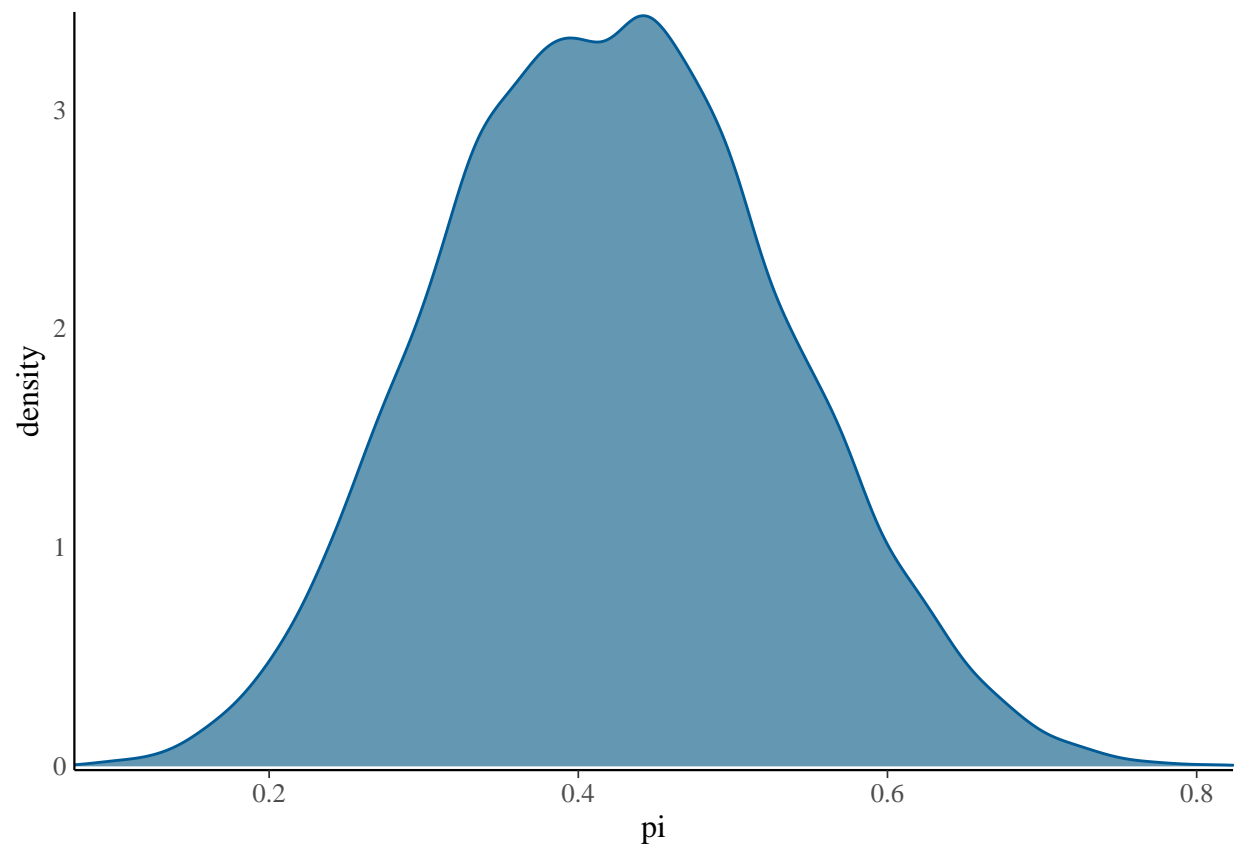
```
# Histogram of the Markov chain values
```

```
mcmc_hist(bb_sim, pars = "pi") +  
  yaxis_text(TRUE) +  
  ylab("count")
```

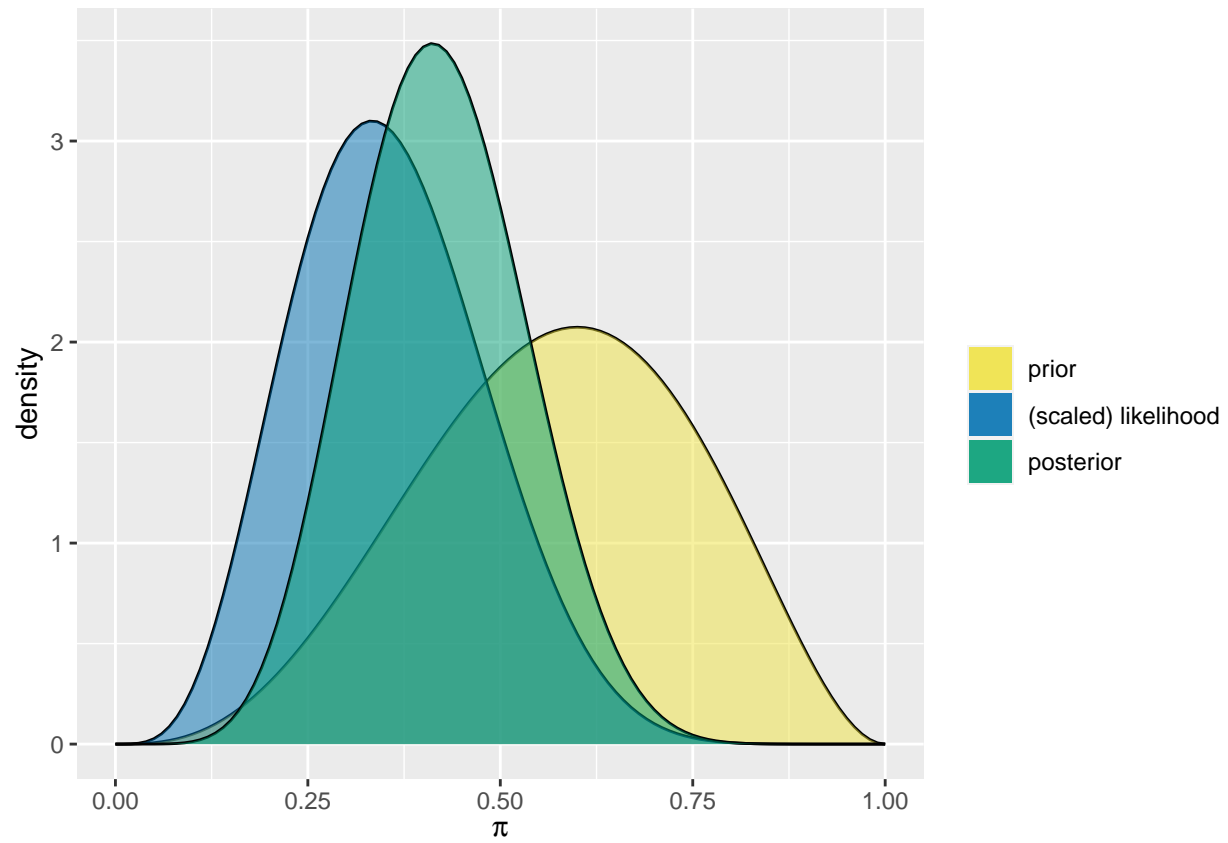
```
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
```



```
# Density plot of the Markov chain values
mcmc_dens(bb_sim, pars = "pi") +
  yaxis_text(TRUE) +
  ylab("density")
```



```
plot_beta_binomial(alpha = 4, beta = 3, y = 4, n = 12)
```



They look similar, the majority of the pdf is around 0.4 and 0.45. So they look pretty similar