

Group Work 03

```
library(bayesrules) # R package for our textbook
library(tidyverse) # Collection of packages for tidying and plotting data
library(janitor) # Helper functions like tidy and tabyl
library(rstan)
library(broom)
```

i Note

The Monday problems are a selection from BR Exercises 8.15-8.17, packaged in a different format

i Note

Make sure to remove `#l eval: false` from any code chunks if you copy the whole document using the “code” button

1 An exact analysis

This problem uses the `pulse_of_the_nation` data from slides13

```
data("pulse_of_the_nation")
pulse_of_the_nation %>%
  count(climate_change)
```

```
# A tibble: 3 x 2
  climate_change      n
  <fct>          <int>
1 Not Real At All    150
2 Real and Caused by People 655
3 Real but not Caused by People 195
```

- (a) Bayesians think of the entire $\text{Beta}(151,852)$ posterior pdf as an estimate for π . But for communication purposes, it can be useful to report what values of π are typical. Identify and calculate two possible posterior point estimates.
- (b) The posterior estimates above merely capture the typical posterior π value, thus miss the bigger picture. It's important to supplement these estimates with a posterior credible interval. (Bayesians use “credible” instead of “confidence”) Calculate a 95% posterior credible interval for π . Revisiting a plot of the posterior might spark some ideas, and you'll need some R code of the `rXXX`, `qXXX`, `dXXX`, `pXXX` variety.
- (c) How can we interpret this interval, (a,b)?
- (d) What would a strict frequentist say if you asked them “What's the probability that π lies within the Bayesian credible interval?”
- (e) A researcher claims that more than 13% of people don't believe in climate change. Using your interval from (b), what do you think about this claim?
- (f) Calculate and interpret a posterior probability that helps you test this claim. You'll need some R code of the `rXXX`, `qXXX`, `dXXX`, `pXXX` variety.
- (g) There's no common cut-off / threshold (eg: 0.05) for interpreting Bayesian posterior probabilities, hence no binary conclusion. Better yet, Bayesian conclusions are more holistic and nuanced. With this in mind, summarize your conclusions about our hypothesis.

2 Bayes Factor

i Posterior Odds

The **posterior odds** for a hypothesis test H_0 against H_a after observing data $Y = y$ is

$$\text{posterior odds} = \frac{P(H_a|Y = y)}{P(H_0|Y = y)}$$

i Posterior Odds

The **prior odds** for a hypothesis test H_0 against H_a is

$$\text{posterior odds} = \frac{P(H_a)}{P(H_0)}$$

Bayes Factor

In a hypothesis test of two competing hypotheses, H_a vs H_0 , the **Bayes Factor** is an odds ratio for H_a :

$$\text{Bayes Factor} = \frac{\text{posterior odds}}{\text{prior odds}} = \frac{P(H_a|Y)/P(H_0|Y)}{P(H_a)/P(H_0)}$$

Calculate the **prior odds**, **posterior odds**, and **Bayes Factor** for the researcher's claim that "more than 13% of people don't believe in climate change". What do these numbers tell you?

3 BR Exercise 8.21

Now, let's explore how we can do estimation and hypothesis testing with an approximate posterior sample from MCMC.

- (a) Load the following packages, and run the following R/stan code to fit an MCMC approximation for the same problem. Make sure you understand all of the pieces of the model fitting code.

```
library(rstan)
library(bayesrules)
library(bayesplot)
library(broom)

# Define the Beta-Binomial model in rstan notation
climate_model <- "
data {
  real<lower=0> alpha;
  real<lower=0> beta;
  int<lower=1> n;
  int<lower=0, upper=n> Y;
}

parameters {
  real<lower=0, upper=1> pi;
}

model {
  Y ~ binomial(n, pi);
  pi ~ beta(alpha, beta);
}
```

```
"

# Set the random number seed
set.seed(84735)

# SIMULATE the posterior
climate_sim <- stan(
  model_code = climate_model,
  data = list(alpha = 1, beta = 2, Y = 150, n = 1000),
  chains = 4, iter = 5000*2)

```

(b) Give the following plots a quick peak. Do you see any red flags?

```
mcmc_trace(climate_sim, pars = "pi")
mcmc_dens_overlay(climate_sim, pars = "pi")
mcmc_dens(climate_sim, pars = "pi")

```

(c) The four chains in `climate_sim` are currently stored as an array. Use the code below to store all the chains in a single data frame.

```
# Store the array of 4 chains in 1 data frame
climate_chains <- as.data.frame(
  climate_sim,
  pars = "lp__", include = FALSE)

# Check out the results
dim(climate_chains)
head(climate_chains)

```

(d) Recall your exact posterior point estimates of π from earlier. Estimate these posterior features using your MCMC simulation. (How accurate are these estimates?) NOTE: The `sample_mode()` function in `{bayesrules}` calculates the mode of a sample.

```
climate_chains %>%
  summarize(____)

```

- (e) Recall your exact 95% posterior credible interval for π from earlier. Estimate this interval using your MCMC simulation. (How accurate is this estimate?)
- (f) Recall your exact analysis of the claim that more than 13% of people don't believe in climate change, i.e. $\pi > 0.13$. Estimate the posterior probability of this claim using your MCMC simulation. (How accurate is this estimate?)
- (g) Play around with the following shortcut functions that can address some, but not all, of our posterior questions. These are applied directly to `climate_sim`, not `climate_chains`. Take notes what they do (leaving comments in your `.qmd` would be sufficient!)

```
# What is the estimate? The posterior mean, median, or mode?  
tidy(climate_sim, conf.int = TRUE, conf.level = 0.95)  
  
#  
mcmc_areas(climate_sim, pars = "pi", prob = 0.95)
```

4 TBA Wed

5 TBA Wed