

Stat 133: Bayesian Statistical Inference

Problem Set 2

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Problem 1

Recall our example about the reports of number of sexual partners. Using the same dataset and assuming that the number of sexual partners are a random sample from $\text{Poisson}(\lambda)$, suppose we infer about the average number of sexual partners for women λ in the population. Use the four different vague priors for λ used in that example.

```
# Creating a data frame with the counts of sex partners
srsp <- data.frame(
  Count = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 14),
  Men = c(44, 195, 20, 3, 3, 5, 3, 1, 1, 0, 0, 1),
  Women = c(102, 233, 18, 9, 2, 1, 0, 0, 0, 0, 0, 0)
)
print(srsp)
```

```
##      Count Men Women
## 1         0  44  102
## 2         1 195  233
## 3         2  20   18
## 4         3   3    9
## 5         4   3    2
## 6         5   5    1
## 7         6   3    0
## 8         7   1    0
## 9         8   1    0
## 10        9   0    0
## 11       10   0    0
## 12       14   1    0
```

```
# Creating a data frame with the prior hyperparameters
gamma <- data.frame(
  a = c(0.1, 0.5, 1, 2),
  b = c(0.1, 0.5, 1, 2)
)
# Updating the priors using the data
gamma <- gamma %>%
  mutate(total_count = sum(srsp$Count * srsp$Women),
         n = sum(srsp$Women),
```

```

a.star = a + total_count,
b.star = b + n)
print(gamma)

```

```

##      a    b total_count    n a.star b.star
## 1 0.1 0.1          309 365  309.1  365.1
## 2 0.5 0.5          309 365  309.5  365.5
## 3 1.0 1.0          309 365  310.0  366.0
## 4 2.0 2.0          309 365  311.0  367.0

```

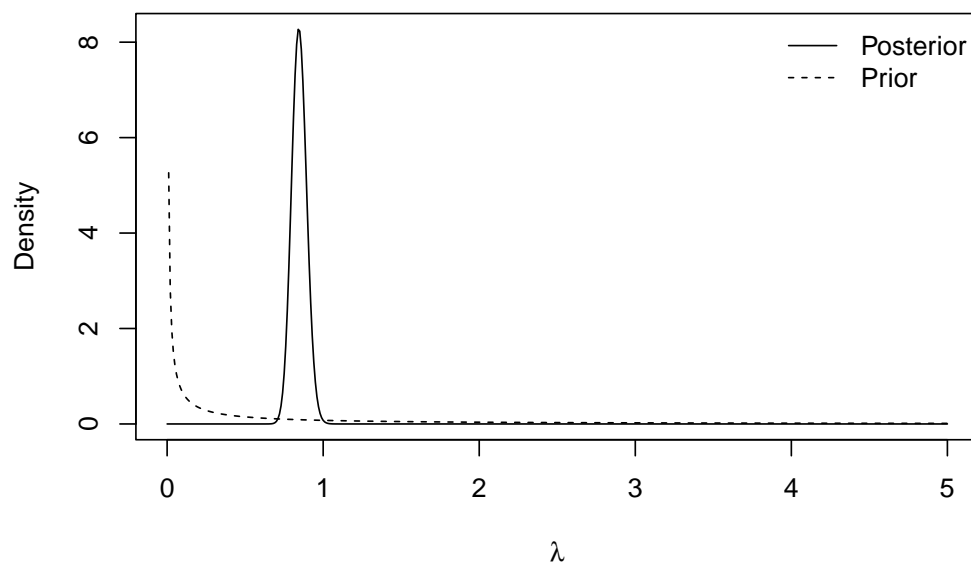
1. Graph each prior and corresponding posterior distribution using R.

```

# Plotting the Gamma (0.1,0.1) prior along with its posterior distribution
lambda <- seq(0.00,5.00,0.01)
prior1 <- dgamma(lambda, shape = 0.1, rate = 0.1)
post1 <- dgamma(lambda, shape = 309.1, rate = 365.1)
plot(lambda, post1, xlab = expression(lambda), ylab = "Density",
     type = "l", main = "Gamma (0.1,0.1) Prior and its Posterior")
lines(lambda, prior1, lty = 2)
legend("topright", legend = c("Posterior", "Prior"),
     lty = c(1, 2),
     col = c("black", "black"),
     bty = "n")

```

Gamma (0.1,0.1) Prior and its Posterior



```

# Plotting the Gamma (0.5,0.5) prior along with its posterior distribution
lambda <- seq(0.00,5.00,0.01)
prior2 <- dgamma(lambda, shape = 0.5, rate = 0.5)
post2 <- dgamma(lambda, shape = 309.5, rate = 365.5)
plot(lambda, post2, xlab = expression(lambda), ylab = "Density",
     type = "l", main = "Gamma (0.5,0.5) Prior and its Posterior")
lines(lambda, prior2, lty = 2)

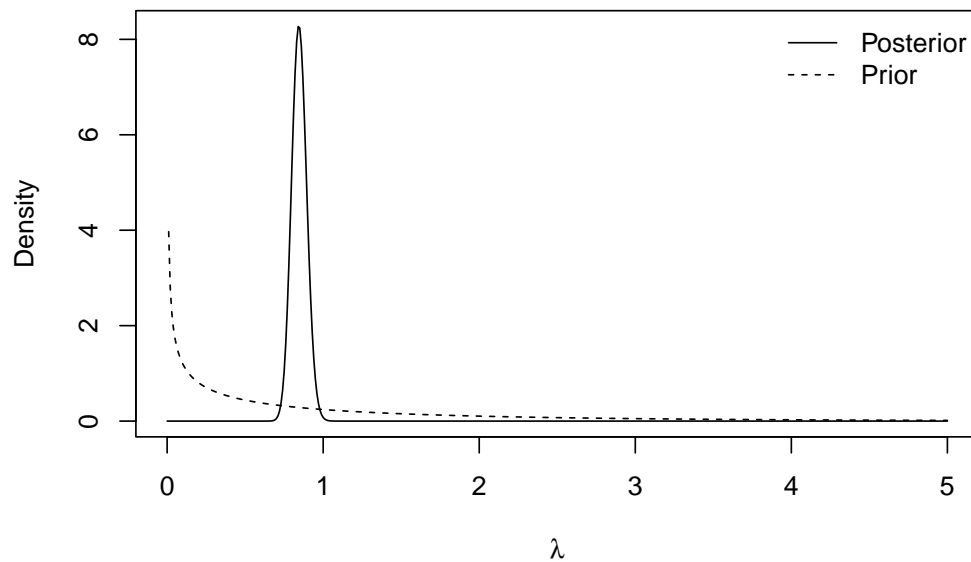
```

```

legend("topright", legend = c("Posterior", "Prior"),
      lty = c(1, 2),
      col = c("black", "black"),
      bty = "n")

```

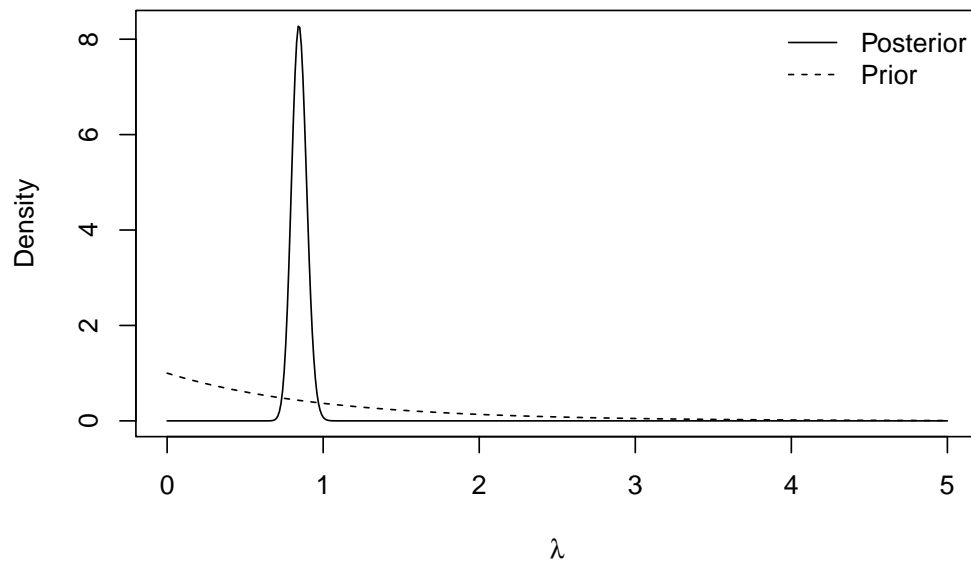
Gamma (0.5,0.5) Prior and its Posterior



```

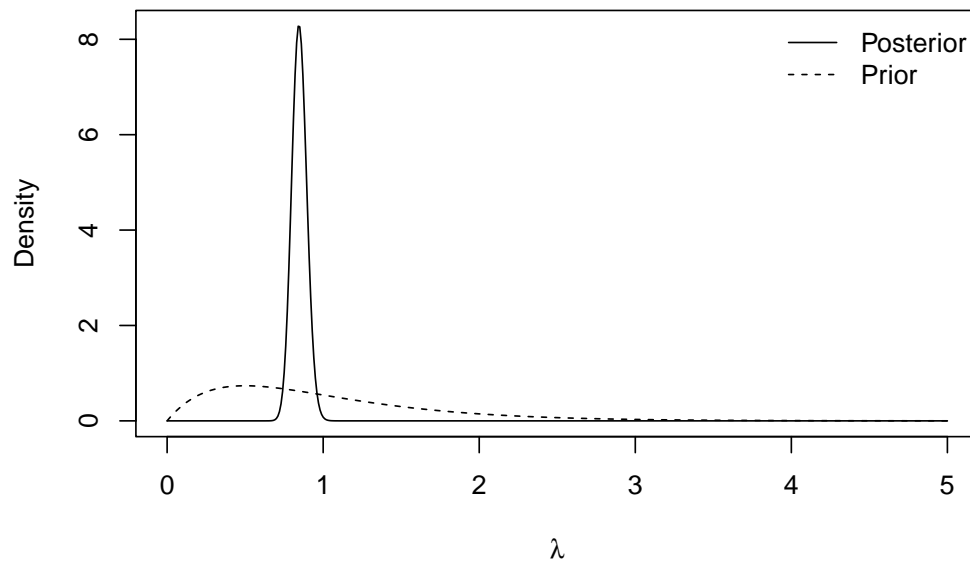
# Plotting the Gamma (1,1) prior along with its posterior distribution
lambda <- seq(0.00,5.00,0.01)
prior3 <- dgamma(lambda, shape = 1, rate = 1)
post3 <- dgamma(lambda, shape = 310, rate = 366)
plot(lambda, post3, xlab = expression(lambda), ylab = "Density",
      type = "l", main = "Gamma (1,1) Prior and its Posterior")
lines(lambda, prior3, lty = 2)
legend("topright", legend = c("Posterior", "Prior"),
      lty = c(1, 2),
      col = c("black", "black"),
      bty = "n")

```

Gamma (1,1) Prior and its Posterior

```
# Plotting the Gamma (2,2) prior along with its posterior distribution
lambda <- seq(0.00,5.00,0.01)
prior4 <- dgamma(lambda, shape = 2, rate = 2)
post4 <- dgamma(lambda, shape = 311, rate = 367)
plot(lambda, post4, xlab = expression(lambda), ylab = "Density",
      type = "l", main = "Gamma (2,2) Prior and its Posterior")
lines(lambda, prior4, lty = 2)
legend("topright", legend = c("Posterior", "Prior"),
      lty = c(1, 2),
      col = c("black", "black"),
      bty = "n")
```

Gamma (2,2) Prior and its Posterior



2. Provide the Bayes estimates for λ under the quadratic, symmetric linear, and binary losses.

```
gamma <- gamma %>%
  mutate(mean.post = a.star / b.star,
         median.post = qgamma(p = 0.5, shape = a.star, rate = b.star),
         mode.post = (a.star - 1) / b.star) %>%
  # Rounding off values of decimals to 4 decimal places
  mutate(across(where(is.numeric), round, 4)) %>%
  print()
```

##	a	b	total_count	n	a.star	b.star	mean.post	median.post	mode.post
## 1	0.1	0.1	309	365	309.1	365.1	0.8466	0.8457	0.8439
## 2	0.5	0.5	309	365	309.5	365.5	0.8468	0.8459	0.8440
## 3	1.0	1.0	309	365	310.0	366.0	0.8470	0.8461	0.8443
## 4	2.0	2.0	309	365	311.0	367.0	0.8474	0.8465	0.8447

3. Generate the 95% HPD interval for each posterior distribution.

```
# HPD interval for posterior of Gamma (0.1,0.1) prior
hpd1 <- round(hpd(posterior.icdf = qgamma, shape = 309.1, rate = 365.1),
             digits = 4)

# HPD interval for posterior of Gamma (0.5,0.5) prior
hpd2 <- round(hpd(posterior.icdf = qgamma, shape = 309.5, rate = 365.5),
             digits = 4)

# HPD interval for posterior of Gamma (1,1) prior
hpd3 <- round(hpd(posterior.icdf = qgamma, shape = 310, rate = 366),
             digits = 4)

# HPD interval for posterior of Gamma (2,2) prior
```

```
hpd4 <- round(hpd(posterior.icdf = qgamma, shape = 311, rate = 367),
  digits = 4)

hpd_intervals <- data.frame(
  hpd.lower95 = c(hpd1[1], hpd2[1], hpd3[1], hpd4[1]),
  hpd.upper95 = c(hpd1[2], hpd2[2], hpd3[2], hpd4[2]))

gamma %>%
  bind_cols(hpd_intervals) %>%
  select(-mean.post, -median.post, -mode.post)
```

##	a	b	total_count	n	a.star	b.star	hpd.lower95	hpd.upper95
## 1	0.1	0.1	309	365	309.1	365.1	0.7531	0.9417
## 2	0.5	0.5	309	365	309.5	365.5	0.7533	0.9418
## 3	1.0	1.0	309	365	310.0	366.0	0.7536	0.9420
## 4	2.0	2.0	309	365	311.0	367.0	0.7541	0.9423

4. Assess the evidence about $H_0 : \lambda \leq 1$ and $H_1 : \lambda > 1$ for each posterior distribution using Bayes factor.

```
gamma %>%
  select(a, b, a.star, b.star) %>%
  mutate(
    p.h1.prior = 1 - pgamma(q = 1, shape = a, rate = b),
    p.h1.post = 1 - pgamma(q = 1, shape = a.star, rate = b.star)) %>%
  mutate(
    bf.10 = (p.h1.post)/(1-p.h1.post)/(p.h1.prior/(1-p.h1.prior)),
    bf.01 = 1/bf.10) %>%
  select(-p.h1.prior, -p.h1.post) %>%
  # Rounding off values of decimals to 4 decimal places
  mutate(across(where(is.numeric), round, 4)) %>%
  print()
```

##	a	b	a.star	b.star	bf.10	bf.01
## 1	0.1	0.1	309.1	365.1	0.0059	169.9986
## 2	0.5	0.5	309.5	365.5	0.0027	376.9806
## 3	1.0	1.0	310.0	366.0	0.0021	468.6151
## 4	2.0	2.0	311.0	367.0	0.0018	542.4913

For all four Gamma priors, the Bayes factor for H_1 is less than 1, meaning there is negative evidence for the alternative hypothesis, based on the scale suggested by Jeffreys (1961). Moreover, the Bayes factor for H_0 , $B_{01} > 10^2$ for all four Gamma priors, indicating that there is **decisive evidence in support of the null hypothesis** that the average number of sexual partners for women is less than 1.

Problem 2

Recall our exercise about the proportion of voters who will support each of the 66 senatorial candidates. Suppose that we model the number of voters who will vote for the i th candidate from the February 2025 *Pulso ng Bayan* Pre-Electoral national survey using $\text{Binomial}(n = 2400, \theta_i)$. Use the posterior distribution for each candidate from our exercise as the prior distribution for each candidate.

```
# Importing the results of the PnB survey for Jan 2025
pnb.jan <- read_excel(
  path = "C:/Users/amore_6ou078y/OneDrive/Documents/Pulso ng Bayan.xlsx",
  sheet = "Jan 2025")
head(pnb.jan)
```

```
## # A tibble: 6 x 5
##   candidate      party aware vote rank
##   <chr>         <chr> <dbl> <dbl> <chr>
## 1 TULFO, ERWIN  LAKAS    99  62.8  1
## 2 GO, BONG GO  PDPLBN    99  50.4  2-3
## 3 SOTTO, TITO  NPC       99  50.2  2-4
## 4 TULFO, BEN BITAG IND       97  46.2  3-8
## 5 CAYETANO, PIA NP        98  46.1  4-8
## 6 BONG REVILLA, RAMON, JR. LAKAS    98  46    4-8
```

```
# Importing the results of the PnB survey for Feb 2025
pnb.feb <- read_excel(
  path = "C:/Users/amore_6ou078y/OneDrive/Documents/Pulso ng Bayan.xlsx",
  sheet = "Feb 2025")
head(pnb.feb)
```

```
## # A tibble: 6 x 5
##   candidate      party aware vote rank
##   <chr>         <chr> <dbl> <dbl> <chr>
## 1 GO, BONG GO  PDPLBN   100  58.1  1-2
## 2 TULFO, ERWIN LAKAS    98  56.6  1-2
## 3 SOTTO, TITO  NPC      100  49    3-4
## 4 BONG REVILLA, RAMON, JR. LAKAS   100  46.1  3-6
## 5 DELA ROSA, BATO PDPLBN   100  44.3  4-7
## 6 REVILLAME, WILLIE WIL IND      98  42.3  4-9
```

```
# Updating pnb.jan with the posterior parameters computed in our class exercise
pnb.jan <- pnb.jan %>%
  mutate(count = ceiling(vote/100*2400),
         a.star = 1 + count,
         b.star = 1 + 2400 - count)
# Creating a new column in pnb.feb for the no. of votes per candidate
pnb.feb <- pnb.feb %>%
  mutate(count= ceiling(vote/100*2400))
head(pnb.jan)
```

```
## # A tibble: 6 x 8
##   candidate      party aware vote rank count a.star b.star
##   <chr>         <chr> <dbl> <dbl> <chr> <dbl> <dbl> <dbl>
## 1 TULFO, ERWIN  LAKAS    99  62.8  1    1508  1509    893
## 2 GO, BONG GO  PDPLBN    99  50.4  2-3  1210  1211   1191
## 3 SOTTO, TITO  NPC       99  50.2  2-4  1205  1206   1196
## 4 TULFO, BEN BITAG IND       97  46.2  3-8  1109  1110   1292
## 5 CAYETANO, PIA NP        98  46.1  4-8  1107  1108   1294
## 6 BONG REVILLA, RAMON, JR. LAKAS    98  46    4-8  1104  1105   1297
head(pnb.feb)
```

```
## # A tibble: 6 x 6
##   candidate      party aware vote rank count
##   <chr>         <chr> <dbl> <dbl> <chr> <dbl>
```

```
## 1 GO, BONG GO          PDPLBN    100  58.1 1-2    1395
## 2 TULFO, ERWIN         LAKAS      98   56.6 1-2    1359
## 3 SOTTO, TITO          NPC        100   49   3-4    1176
## 4 BONG REVILLA, RAMON, JR. LAKAS    100  46.1 3-6    1107
## 5 DELA ROSA, BATO       PDPLBN    100  44.3 4-7    1064
## 6 REVILLAME, WILLIE WIL IND        98  42.3 4-9    1016
```

```
# Merging pnb.jan and pnb.feb
pnb.feb <- pnb.feb %>%
  left_join(pnb.jan %>% select(candidate, a.star, b.star),
            by = "candidate",
            suffix = c("", "_jan")) %>%
  mutate(
    a_prior = ifelse(!is.na(a.star), a.star, 1),
    b_prior = ifelse(!is.na(b.star), b.star, 1),

    # Computing new a.star and b.star using priors
    a.star_new = a_prior + count,
    b.star_new = b_prior + (2400 - count)
  ) %>%
  select(-party, -aware, -vote, -rank, -a.star, -b.star)
head(pnb.feb)
```

```
## # A tibble: 64 x 6
##   candidate          count a_prior b_prior a.star_new b.star_new
##   <chr>              <dbl>   <dbl>   <dbl>     <dbl>     <dbl>
## 1 GO, BONG GO        1395    1211    1191     2606     2196
## 2 TULFO, ERWIN       1359    1509     893     2868     1934
## 3 SOTTO, TITO        1176    1206    1196     2382     2420
## 4 BONG REVILLA, RAMON, JR. 1107    1105    1297     2212     2590
## 5 DELA ROSA, BATO     1064     990    1412     2054     2748
## 6 REVILLAME, WILLIE WIL 1016    1007    1395     2023     2779
## 7 TULFO, BEN BITAG     977    1110    1292     2087     2715
## 8 PACQUIAO, MANNY PACMAN  958     976    1426     1934     2868
## 9 LAPID, LITO         946     906    1496     1852     2950
## 10 BINAY, ABBY        903     988    1414     1891     2911
## # i 54 more rows
```

1. Visualize the 95% HPD intervals for senatorial candidates with the corresponding posterior median using `geom_pointrange`. Order the candidates by increasing posterior median.

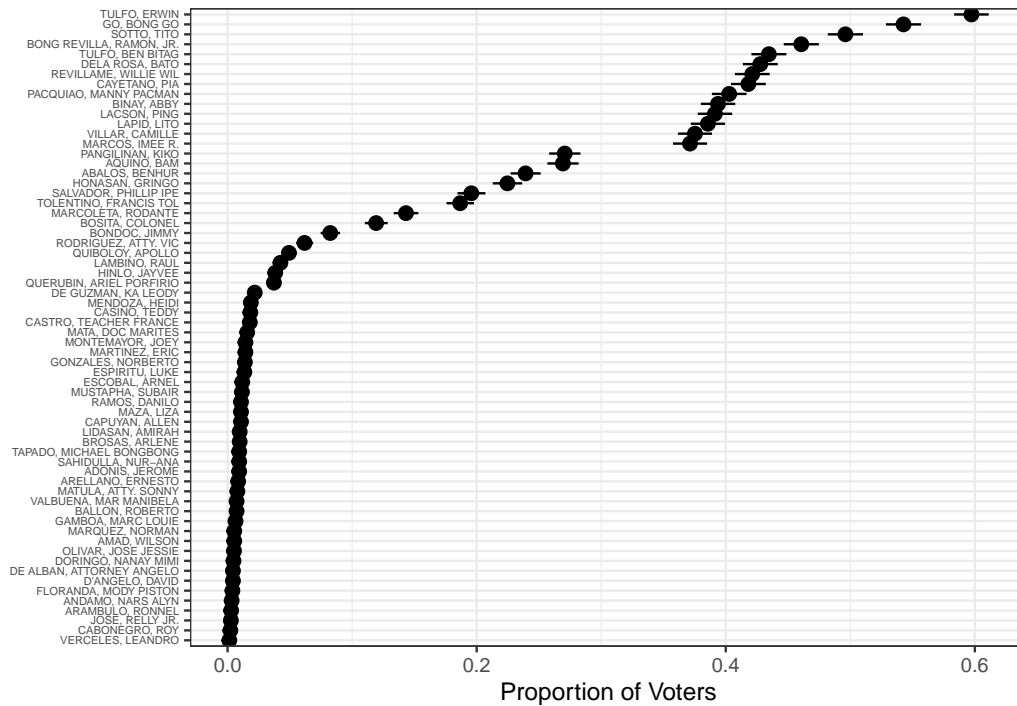
```
pnb.feb %>%
  mutate(median = qbeta(p = 0.5, shape1 = a.star_new, shape2 = b.star_new)) %>%
  rowwise() %>%
  mutate(hpd.lower95 = hpd(posterior.icdf = qbeta,
                           shape1 = a.star_new,
                           shape2 = b.star_new,
                           conf = 0.95)[1],
         hpd.upper95 = hpd(posterior.icdf = qbeta,
                           shape1 = a.star_new,
                           shape2 = b.star_new,
                           conf = 0.95)[2]) %>%
  ggplot() +
  geom_pointrange(aes(xmin = hpd.lower95,
                     xmax = hpd.upper95,
                     x = median,
```



```

y = reorder(candidate, median))) +
xlab("Proportion of Voters") +
theme_bw() +
theme(axis.title.y = element_blank())

```



2. Who among the senatorial candidates is supported by the majority of voters? Support your answer using Bayes factor.

```
# Computing for Bayes factor
```

```

pnb.feb %>%
mutate(
  p.h1.prior = 1 - pbeta(q = 0.5, shape1 = a_prior, shape2 = b_prior),
  p.h1.post = 1 - pbeta(q = 0.5, shape1 = a_star_new, shape2 = b_star_new),
  bf.10 = ifelse(p.h1.post == 0 | p.h1.post == 1, NA,
    (p.h1.post / (1 - p.h1.post)) / (p.h1.prior / (1 - p.h1.prior))),
  bf.01 = ifelse(is.na(bf.10), NA, 1 / bf.10)) %>%
select(candidate, p.h1.prior, p.h1.post, bf.10, bf.01) %>%
# Rounding off values of decimals to 4 decimal places
mutate(across(where(is.numeric), round, 4)) %>%
head()

```

```
## # A tibble: 6 x 5
```

##	candidate	p.h1.prior	p.h1.post	bf.10	bf.01
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
## 1	GO, BONG GO	0.658	1	3.24e+8	0
## 2	TULFO, ERWIN	1	1	NA	NA
## 3	SOTTO, TITO	0.581	0.292	2.97e-1	3.36
## 4	BONG REVILLA, RAMON, JR.	0	0	5e-4	1838
## 5	DELA ROSA, BATO	0	0	NA	NA
## 6	REVILLAME, WILLIE WIL	0	0	NA	NA

According to the scale suggested by Jeffreys (1961) for interpreting the Bayes factor, it is only for **Bong Go** that there is decisive evidence that the majority of voters supports his

candidacy, with a Bayes factor for H_1 of $B_{10} \approx 3.24e + 8$.

However, it is important to note that while the Bayes factor for H_1 for Erwin Tulfo cannot be assessed based on the scale, this is due to both his prior and posterior probability of H_1 being approximately equal to 1. As a result, the Bayes factor calculation leads to an indeterminate form (0/0), making it mathematically undefined and returning an NA. Despite this, the fact that the posterior probability remains virtually equal to 1 strongly suggests that **Erwin Tulfo** has decisive support from the majority of voters.

Problem 3

Suppose that MMDA is studying the number of traffic accidents per month occurring at a certain intersection. They collected data for the past two years, given as follows:

2 4 3 1 1 3 2 2 4 0 5 2 5 2 4 4 3 1 3 8 4 2 1 1

The researchers have prior information on the Poisson parameter and believe that the Poisson parameter is 3 on the average with a standard deviation of 3. A gamma conjugate prior is used to represent the prior information.

1. What is the 95% HPD interval for the Poisson parameter?

$$y_1, y_2, \dots, y_{24} | \lambda \sim \text{Poisson}(\lambda)$$

$$\lambda \sim \text{Gamma}(a, b), \quad b > 0$$

To compute the hyperparameters of the prior Gamma distribution, note that the mean of the gamma distribution is $E(\lambda) = \frac{a}{b}$ and its variance is $\text{Var}(\lambda) = \frac{a}{b^2}$. Thus, based on the given,

$$E(\lambda) = 3 = \frac{a}{b} \tag{1}$$

$$\text{Var}(\lambda) = 3^2 = \frac{a}{b^2} \tag{2}$$

From (1), we can express a as $a = 3b$. Substituting this expression for a into (2),

$$\frac{3b}{b^2} = 9$$

$$\rightarrow b = \frac{1}{3}$$

$$\stackrel{(1)}{\rightarrow} a = 3 \left(\frac{1}{3} \right) = 1$$

```
accidents <- c(2, 4, 3, 1, 1, 3, 2, 2, 4, 0, 5, 2, 5, 2, 4, 4, 3, 1, 3, 8,
              4, 2, 1, 1)
n <- length(accidents)

# Prior Parameters
a_prior <- 1
b_prior <- 1/3

# Posterior Parameters
a_post <- a_prior + sum(accidents)
b_post <- b_prior + n

# 95% HPD Interval
hpd_interval <- hpd(qgamma, shape = a_post, rate = b_post, conf = 0.95)
```

```
cat(sprintf("95%% HPD Interval: (%.4f, %.4f)", hpd_interval[1],
            hpd_interval[2]))
```

```
## 95% HPD Interval: (2.1450 3.4673)
```

2. The researchers wanted to test whether the mean number of traffic accidents per month is equal to 3 or not at 5% level of significance. What is the conclusion when the hypothesis test is performed?

$$H_0 : \lambda = 3$$

$$H_1 : \lambda \neq 3$$

When dealing with a point null hypothesis, it suffices to check whether or not the hypothesized value of the parameter belongs in the HPD interval to decide if H_0 should be rejected. The computed 95% HPD interval for λ in the previous item was (2.1450, 3.4673). Since the interval contains 3, the hypothesized value of λ , we **do not reject** H_0 . There is insufficient evidence to say that the mean number of traffic accidents per month is not equal to 3 at 5% level of significance.

3. Consequently, the researchers wanted to test whether the mean number of traffic accidents per month is greater than 3 or not.

(a) At 5% level of significance, what is the conclusion when the hypothesis test is performed?

Testing $H_0 : \lambda \leq 3$ vs. $H_1 : \lambda > 3$ at $\alpha = 0.05$,

```
p.h0 = pgamma(q = 3, shape = a_post, rate = b_post)
reject.ho = ifelse(p.h0 < 0.05, "yes", "no")
cat("reject.ho:", reject.ho)
```

```
## reject.ho: no
```

At 5% level of significance, we do not reject H_0 . There is insufficient evidence to say that the mean number of traffic accidents per month is greater than 3.

(b) Using Bayes factor, what is the conclusion when the hypothesis test is performed?

```
# Computing for Bayes factor
p.h1.prior = 1 - pgamma(q = 3, shape = a_prior, rate = b_prior)
p.h1.post = 1 - pgamma(q = 3, shape = a_post, rate = b_post)
bf.10 = (p.h1.post / (1 - p.h1.post)) / (p.h1.prior / (1 - p.h1.prior))
cat("Bayes Factor:", round(bf.10, digits = 4))
```

```
## Bayes Factor: 0.6151
```

Since $B_{10} < 1$, we have negative evidence for the alternative hypothesis that $\lambda > 3$, i.e., the null hypothesis is supported and should not be rejected.