Lab 5

Name here

Suppose you have been hired as a statistical consultant by a NBA expansion team that will be moving to Big Sky, MT. Your goal is to help identify basketball players to bring to Montana.

Specifically, the team has one more spot to fill and is looking to add a free throw shooting specialist. Here are two options:

- Bugs Bunny. Bugs Bunny is a shooting guard that was 2 for 7 on free throws last year.
- Tasmanian Devil. Tasmanian Devil is a center that was 25 for 40 on free throws last year.

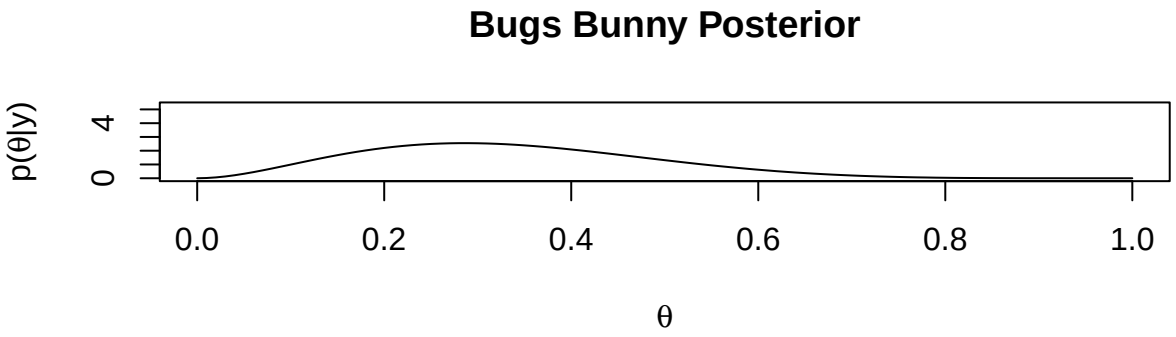
1.

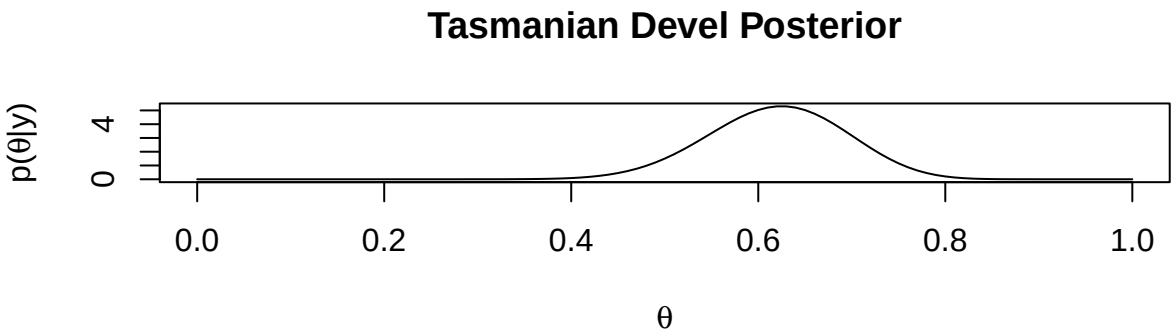
Use a binomial model, along with uniform prior of the probability parameter, to model the free throw shooting for Bugs Bunny and Tasmanian Devil.

a (4 points)

Plot and summarize the posterior distribution for each player.

```
par(mfcol=c(2,1))
x <- seq(0,1, by=.01)
y.max <- max(dbeta(x,26,16))
plot(x,dbeta(x,3,6), main='Bugs Bunny Posterior', type='l', ylim=c(0,y.max),ylab=expression(paste('p(',
plot(x,dbeta(x,26,16), main='Tasmanian Devel Posterior', type='l', ylim=c(0,y.max),ylab=expression(paste
```





b (4 points)

Using the posteriors above, compute the probability that Bugs Bunny has a higher shooting percentage (θ parameter in the binary setting).

```
num.sims <- 5000
bugs <- rbeta(num.sims, 3, 6)
td <- rbeta(num.sims, 26, 16)
bugs.better <- mean(bugs > td)
```

In this setting, the probability that Bugs Bunny has a higher shooting percentage is 0.049

c (2 points) If both players had 25 free throws, who do you think will make more free throws? Why?

I'd think that Tasmanian Devil would have a better outcome, but with 25 free throws it would be possible that Bugs Bunny does better, but highly unlikely.

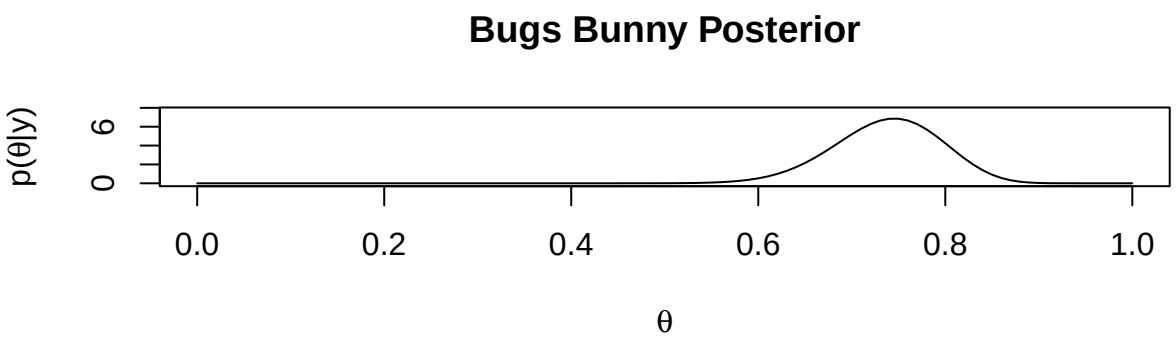
2.

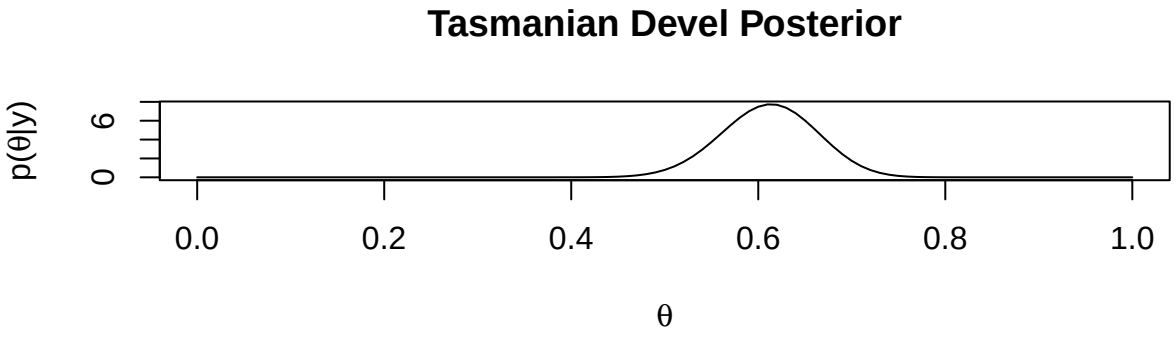
Now assume that we know that shooting guards, like Bugs Bunny, tend to make about 80 percent of free throws and centers, like Tasmanian Devil, tend to make about 60 percent of free throws. This information can be imparted by more informative priors: Use Beta(40,10) for Bugs Bunny and Beta(30,20) for Tasmanian Devil as the prior distributions.

a (4 points)

Plot and summarize the posterior distribution for each player.

```
par(mfcol=c(2,1))
x <- seq(0,1, by=.01)
y.max <- max(c(dbeta(x,42,17),dbeta(x,55, 35)))
plot(x,dbeta(x,42,15), main='Bugs Bunny Posterior', type='l', ylim=c(0,y.max),ylab=expression(paste('p(
plot(x,dbeta(x,55,35), main='Tasmanian Devel Posterior', type='l', ylim=c(0,y.max),ylab=expression(paste
```





b (4 points)

Using the posteriors above, compute the probability that Bugs Bunny has a higher shooting percentage (θ parameter in the binary setting).

```
num.sims <- 5000
bugs <- rbeta(num.sims, 42, 15)
td <- rbeta(num.sims, 55, 35)
bugs.better <- mean(bugs > td)
```

In this case, the probability that bugs bunny has a higher shooting percentage is 0.943

c (2 points)

If both players had 25 free throws, who do you think will make more free throws? Why?

Now I'd bet on Bugs Bunny making more free throws.

3. (4 points)

Reflect on the results from question a and question b. Which analysis, and associated prior, do you prefer, why?

The prior distribution can be highly influential for the posterior and that is not necessarily good or bad. Rather it depends on how reasonable the prior belief is and how much data is available to change or update the prior beliefs.

4. Bayesian Analysis on a continuous outcome

Let's model housing prices using our King County, WA dataset.

A normal distribution seems like a reasonable stating point, although we will see some potential issues.

$$price = \beta_0 + \epsilon \;\; \epsilon \sim N(0, \sigma^2)$$

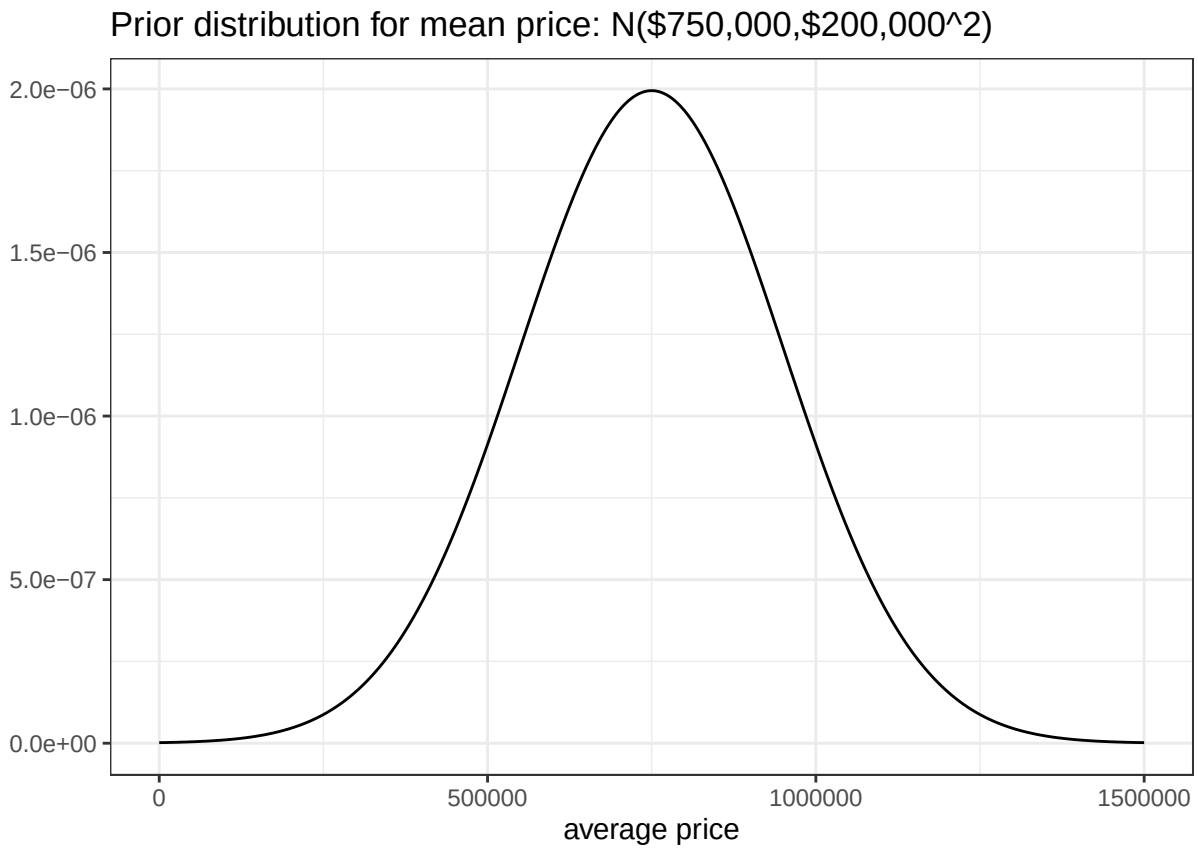
So we have two parameters in this model β_0 and σ^2

a. Specify and plot a prior distributions for β_0

```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.2 --
## v ggplot2 3.4.0      v purrr   1.0.1
## v tibble  3.1.8      v dplyr   1.0.10
## v tidyr   1.2.1      v stringr 1.5.0
## v readr   2.1.3      v forcats 0.5.2
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
temp_seq <- seq(0,1500000, length.out = 500)
tibble(vals = c(dnorm(temp_seq, 750000, 200000)),
       temperature = temp_seq) %>%
  ggplot(aes(x = temperature, y = vals)) +
  geom_line() + theme_bw() +
  ggtitle(paste('Prior distribution for mean price: N($750,000,$200,000^2)')) +
  xlab('average price') + ylab('')
```



b. (4 points)

Using your prior from part a, along with a prior such that $\sigma \sim Gamma(.00001, .00001)$, model the mean housing price in the Seattle dataset.

```
seattle <- read_csv('http://www.math.montana.edu/ahoegh/teaching/stat408/datasets/SeattleHousing.csv')
```

```
## Rows: 869 Columns: 14
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl (14): price, bedrooms, bathrooms, sqft_living, sqft_lot, floors, waterfr...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
y <- seattle$price
n <- nrow(seattle)
```

For reference, you should expect to get similar values to `summary(lm(price ~ 1, data=seattle))`

```
model_normal<- "model{
  # Likelihood
  for (i in 1:n){
    y[i] ~ dnorm(beta0, 1/sigma^2)
  }

  # Prior
  beta0 ~ dnorm(750000, 1/200000^2)
```

```
  sigma ~ dgamma(.00001, .00001)
}"
```

```
library(rjags)
```

```
## Loading required package: coda
```

```
## Linked to JAGS 4.3.0
```

```
## Loaded modules: basemod,bugs
```

```
dataList = list(y = y, n = n)

model <- jags.model(file = textConnection(model_normal), data = dataList)
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 869
##    Unobserved stochastic nodes: 2
##    Total graph size: 881
##
## Initializing model
```

```
update(model, n.iter = 5000) # warmup


# take samples
posterior_sample <- coda.samples(model,
                       variable.names = c("beta0", 'sigma'),
                       n.iter = 10000)

summary(posterior_sample)
```

```
##
## Iterations = 6001:16000
## Thinning interval = 1
## Number of chains = 1
## Sample size per chain = 10000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##         Mean    SD Naive SE Time-series SE
## beta0 634217 21348    213.5          213.5
## sigma 633056 15085    150.9          219.7
##
## 2. Quantiles for each variable:
##
##         2.5%    25%    50%    75%  97.5%
## beta0 592798 619641 634311 648788 676641
## sigma 604847 622729 632587 642932 664498
```