

Module 1: Introduction to Bayesian Statistics

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Agenda

- ▶ Motivations
- ▶ Traditional inference
- ▶ Bayesian inference
- ▶ Bernoulli, Beta
- ▶ Posterior of Bernoulli-Beta
- ▶ Conjugacy
- ▶ Example with 2012 election data
- ▶ Marginal likelihood
- ▶ Posterior Prediction
- ▶ Additional problems at the end of lecture (derivation + applied)

What should you learn?

- ▶ You should learn the main principles of Bayesian inference/prediction and how to apply these to real data analysis.
- ▶ You will continue with this in lab/homework to make sure that you understand these key principles.

Traditional inference

You are given **data** X and there is an **unknown parameter** you wish to estimate θ

How would you estimate θ ?

- ▶ Find an unbiased estimator of θ .
- ▶ Find the maximum likelihood estimate (MLE) of θ by looking at the likelihood of the data.
- ▶ Please review unbiased estimation and finding an MLE.
- ▶ Please also review other background material such as likelihoods, sufficient statistics, basic probability concepts, etc. Most of this material can be reviewed in Chapters 1-3 in Hoff.

Bayesian inference

Bayesian methods trace its origin to the 18th century and English Reverend Thomas Bayes, who along with Pierre-Simon Laplace discovered what we now call **Bayes' Theorem**

- ▶ $p(x | \theta)$ likelihood
- ▶ $p(\theta)$ prior
- ▶ $p(\theta | x)$ posterior
- ▶ $p(x)$ marginal distribution

How can we derive $p(\theta | x)$?

Derivation of $p(\theta \mid x)$

Bernoulli distribution

The Bernoulli distribution is very common due to binary outcomes.

- ▶ Consider flipping a coin (heads or tails).
- ▶ We can represent this a binary random variable where the probability of heads is θ and the probability of tails is $1 - \theta$.

Consider $X \sim \text{Bernoulli}(\theta) \mathbb{1}(0 < \theta < 1)$

The likelihood is

$$p(x | \theta) = \theta^x (1 - \theta)^{(1-x)} \mathbb{1}(0 < \theta < 1).$$

- ▶ Exercise: what is the mean and the variance of X ?

Bernoulli distribution

- Suppose that $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bernoulli}(\theta)$. Then for $x_1, \dots, x_n \in \{0, 1\}$ what is the likelihood?

Notation

- ▶ \propto : means “proportional to”
- ▶ $x_{1:n}$ denotes x_1, \dots, x_n

Likelihood

$$\begin{aligned} p(x_{1:n}|\theta) &= \mathbb{P}(X_1 = x_1, \dots, X_n = x_n \mid \theta) \\ &= \prod_{i=1}^n \mathbb{P}(X_i = x_i \mid \theta) \\ &= \prod_{i=1}^n p(x_i|\theta) \\ &= \prod_{i=1}^n \theta^{x_i} (1 - \theta)^{1-x_i} \\ &= \theta^{\sum x_i} (1 - \theta)^{n - \sum x_i}. \end{aligned}$$

Beta distribution

Given $a, b > 0$, we write $\theta \sim \text{Beta}(a, b)$ to mean that θ has pdf

$$p(\theta) = \text{Beta}(\theta|a, b) = \frac{1}{B(a, b)} \theta^{a-1} (1 - \theta)^{b-1} \mathbb{1}(0 < \theta < 1),$$

i.e., $p(\theta) \propto \theta^{a-1} (1 - \theta)^{b-1}$ on the interval from 0 to 1.

► Here,

$$B(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$$

.

- Parameters a, b control the shape of the distribution.
- This distribution models random behavior of percentages/proportions.

Posterior of Bernoulli-Beta

Let's derive the posterior of $\theta \mid x_{1:n}$

Conjugacy

What do you notice about the prior and the posterior from the Bernoulli-Beta example that we just considered?

Conjugacy

A class P of prior distributions for θ is called **conjugate** for the likelihood $p(x | \theta)$ if

$$p(\theta) \in P \implies p(\theta | x) \in P.$$

Tip: In practice, we check to see if the posterior has an updated form of the prior.

Conjugacy

Benefits

- ▶ We do minimal or often no math. In fact, https://en.wikipedia.org/wiki/Conjugate_prior provides many conjugate families.
- ▶ We have an exact posterior distribution. No approximations are needed.
- ▶ Computation is fast and simple!

Downside

- ▶ Sometimes an unrealistic assumption, however, might provide guidance to us.

Approval ratings of Obama

What is the proportion of people that approve of President Obama in PA?

- ▶ We take a random sample of 10 people in PA and find that 6 approve of President Obama. **Likelihood**
- ▶ The national approval rating (Zogby poll) of President Obama in mid-September 2015 was 50%. We'll assume that in PA his approval rating is also 50%. **Prior**
- ▶ Based on this prior information, we'll use a Beta prior for θ and we'll choose a and b .

Let's consider choosing a prior distribution that is skewed and see what happens.

Obama Example

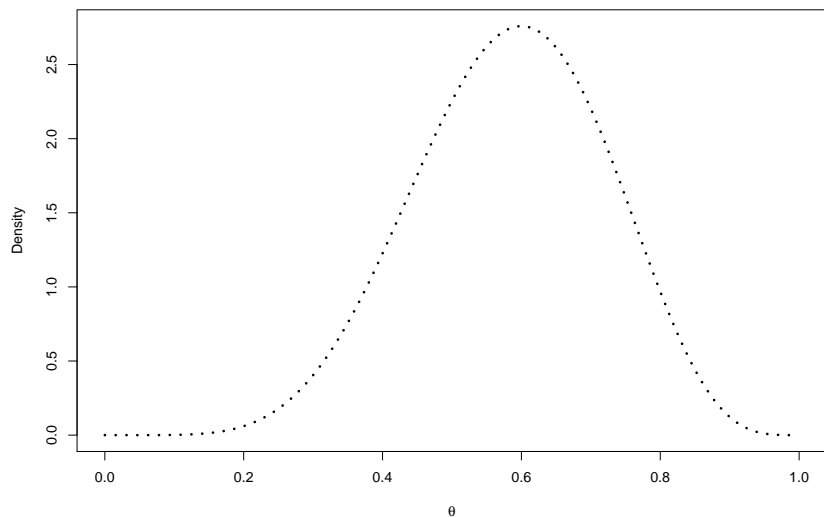
```
n <- 10
# Fixing values of a,b. Chosen skewed Beta.
# a = 21/8
# b = 0.04
a <- 0.25
b <- 0.25
th <- seq(0, 1, length = 500)
x <- 6
# we set the likelihood, prior, and posteriors with
# THETA as the sequence that we plot on the x-axis.
# Beta(c,d) refers to shape parameter
like <- dbeta(th, x + 1, n - x + 1)
prior <- dbeta(th, a, b)
print(a / (a + b))
```

```
## [1] 0.5
```

```
post <- dbeta(th, x + a, n - x + b)
```

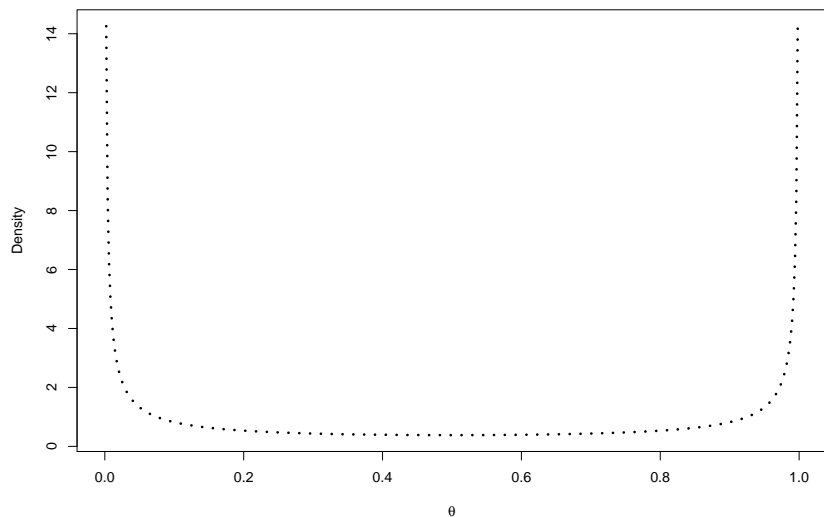
Likelihood

```
plot(th, like, type = "l", ylab = "Density",  
      lty = 3, lwd = 3, xlab = expression(theta))
```



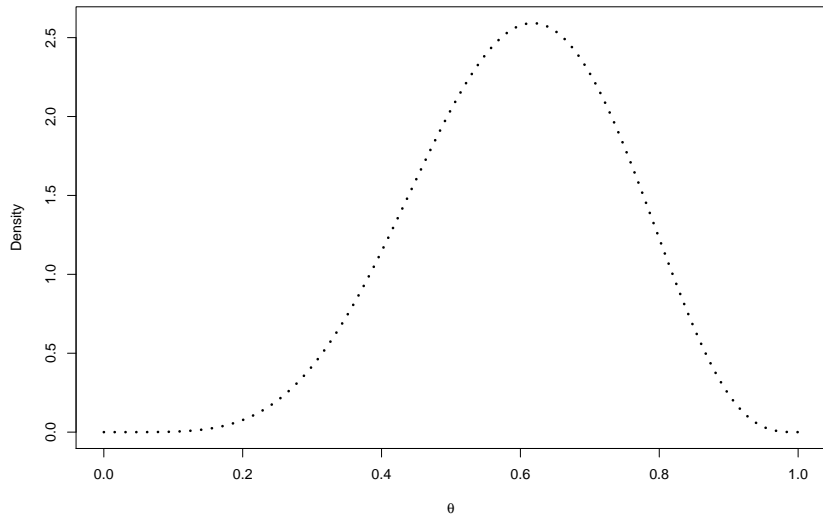
Prior

```
plot(th, prior, type = "l", ylab = "Density",  
      lty = 3, lwd = 3, xlab = expression(theta))
```

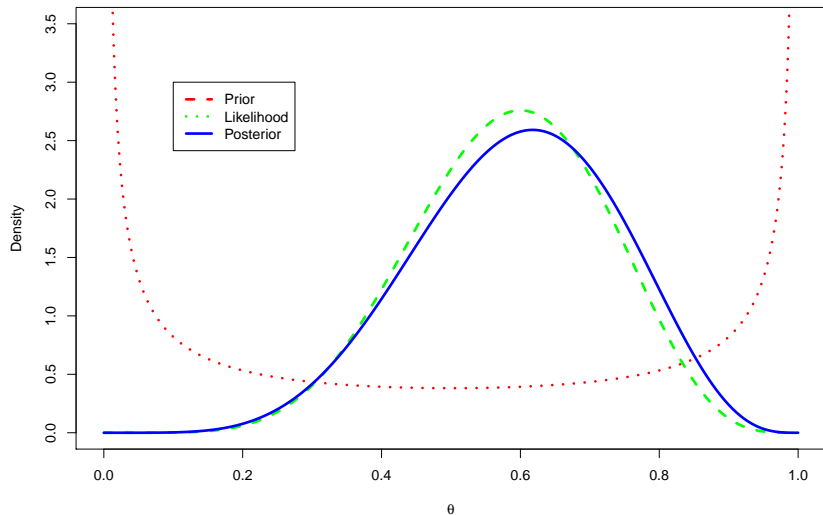


Posterior

```
plot(th, post, type = "l", ylab = "Density",  
      lty = 3, lwd = 3, xlab = expression(theta))
```



Likelihood, Prior, and Posterior



Back to the Prior

- ▶ We choose the prior here two different ways. What happened?
- ▶ In the supplemental material (end of lecture), find an example where we have more information and can set a, b from in a more subjective and principled manner.

Cast of characters

- ▶ Observed data: x
- ▶ This often involves many data points, e.g.,
 $x = x_{1:n} = (x_1, \dots, x_n)$.

likelihood	$p(x_{1:n} \theta)$
prior	$p(\theta)$
posterior	$p(\theta x_{1:n})$
marginal likelihood	$p(x_{1:n})$
posterior predictive	$p(x_{n+1} x_{1:n})$

Marginal likelihood

The **marginal likelihood** is defined as

$$p(x) = \int p(x|\theta)p(\theta) d\theta$$

Example: Back to the Bernoulli-Beta

$$X_1, \dots, X_n \mid \theta \stackrel{iid}{\sim} \text{Bernoulli}(\theta)$$

and

$$\theta \sim \text{Beta}(a, b).$$

What is the marginal likelihood for the Bernoulli-Beta?

Marginal Likelihood: Bernoulli-Beta

Then the marginal likelihood is

$$\begin{aligned} p(x_{1:n}) &= \int p(x_{1:n}|\theta)p(\theta) d\theta \\ &= \int_0^1 \theta^{\sum x_i} (1-\theta)^{n-\sum x_i} \frac{1}{B(a,b)} \theta^{a-1} (1-\theta)^{b-1} d\theta \\ &= \frac{1}{B(a,b)} \int_0^1 \theta^{\sum x_i + a - 1} (1-\theta)^{n - \sum x_i + b - 1} d\theta \\ &= \frac{B(a + \sum x_i, b + n - \sum x_i)}{B(a,b)} \int_0^1 \frac{\theta^{\sum x_i + a - 1} (1-\theta)^{n - \sum x_i + b - 1}}{B(a + \sum x_i, b + n - \sum x_i)} d\theta \\ &= \frac{B(a + \sum x_i, b + n - \sum x_i)}{B(a,b)}, \end{aligned}$$

by the integral definition of the Beta function.

Posterior predictive distribution

- ▶ At times, we may wish to find the **conditional distribution of x_{n+1} given $x_{1:(n+1)}$** .
- ▶ **Assumption 1:** Assume that $x_{1:(n+1)}$ are independent given θ

$$\begin{aligned} p(x_{n+1}|x_{1:n}) &= \int p(x_{n+1}, \theta|x_{1:n}) d\theta \\ &= \int \frac{p(x_{n+1}, \theta, x_{1:n})}{p(x_{1:n})} d\theta \quad (\text{Conditional probability}) \\ &= \int \frac{p(x_{n+1}|\theta, x_{1:n})p(\theta|x_{1:n})p(x_{1:n})}{p(x_{1:n})} d\theta \quad (\text{Product rule}) \\ &= \int p(x_{n+1}|\theta, x_{1:n})p(\theta|x_{1:n}) d\theta \\ &= \int p(x_{n+1}|\theta)p(\theta|x_{1:n}) d\theta \quad \text{By Assumption 1.} \end{aligned}$$

Posterior predictive distribution: Bernoulli-Beta

$$X_1, \dots, X_n \mid \theta \stackrel{iid}{\sim} \text{Bernoulli}(\theta)$$

and

$$\theta \sim \text{Beta}(a, b).$$

The posterior distribution can be shown to be

$$p(\theta \mid x_{1:n}) = \text{Beta}(\theta \mid a_n, b_n), \text{ where } a_n = a + \sum x_i \text{ and } b_n = b + n - \sum x_i.$$

Posterior predictive distribution: Bernoulli-Beta

The posterior predictive can be derived to be

$$\begin{aligned}\mathbb{P}(X_{n+1} = 1 \mid x_{1:n}) &= \int \mathbb{P}(X_{n+1} = 1 \mid \theta) p(\theta \mid x_{1:n}) d\theta \\ &= \int \theta \text{Beta}(\theta \mid a_n, b_n) d\theta \\ &= \frac{a_n}{a_n + b_n} \quad (\text{Mean of Beta distribution}).\end{aligned}$$

Similarly,

$$\mathbb{P}(X_{n+1} = 0 \mid x_{1:n}) = 1 - \mathbb{P}(X_{n+1} = 1 \mid x_{1:n}) = \frac{b_n}{a_n + b_n}.$$

Posterior predictive distribution (continued)

This implies that

$$p(x_{n+1}|x_{1:n}) = \begin{cases} \frac{a_n}{a_n+b_n} = \frac{(a+\sum_i x_i)}{a+b+n} & \text{if } x_{n+1} = 1 \\ \frac{b_n}{a_n+b_n} = \frac{b+\sum_i (1-x_i)}{a+b+n} & \text{if } x_{n+1} = 0 \end{cases}$$

More formally,

$$\begin{aligned} p(x_{n+1}|x_{1:n}) &= \frac{a_n^{x_{n+1}} b_n^{1-x_{n+1}}}{a_n + b_n} \mathbb{1}(x_{n+1} \in \{0, 1\}) \\ &= \frac{(a + \sum_i x_i)^{x_{n+1}} (b + \sum_i (1 - x_i))^{1-x_{n+1}}}{(a + b + n)} \mathbb{1}(x_{n+1} \in \{0, 1\}) \end{aligned}$$

Either solution above is correct. (See page 40 of Hoff for a similar derivation of this result).

Posterior predictive distribution

Observe that the posterior predictive distribution:

1. Does not depend on unknown parameters.
2. The predictive distribution depends on the observed data.

Posterior Predictive Function

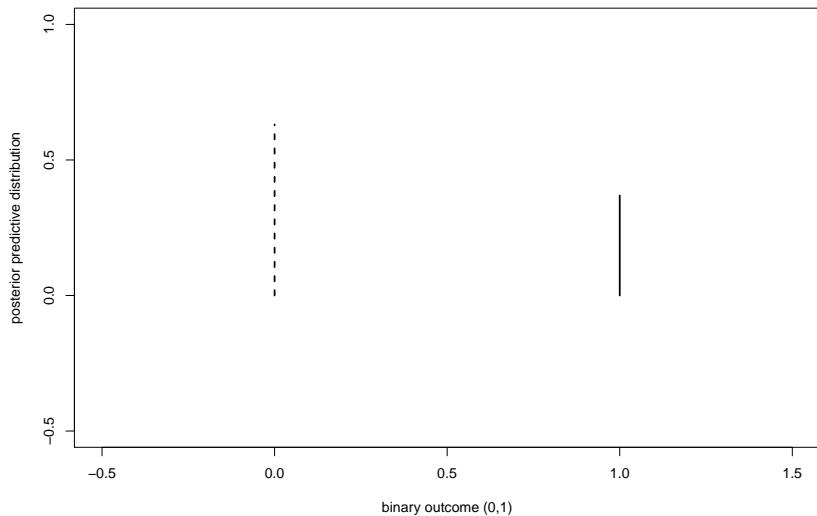
```
posterior_pred <- function(a = 1, b = 1,  
                           x = x, n = 100, new_point) {  
  if (new_point == 1) {  
    return((a + x)/(a + b + n))  
  } else {  
    return(b + (n - x)/(a + b + n))  
  }  
}  
  
new_value <- posterior_pred(a = a, b = b, x = x,  
                           n = n, new_point = 0)  
print(new_value)
```

```
## [1] 0.6309524
```

```
print(1-new_value)
```

```
## [1] 0.3690476
```


Posterior Predictive Plot



Overall Summary

- ▶ We covered the “cast of characters” needed to work with Bayesian models
- ▶ These include the likelihood, prior, posterior, marginal likelihood, and posterior predictive distribution
- ▶ We derived Bayes' Theorem
- ▶ Bernoulli-Beta
- ▶ Conjugacy

Background Knowledge

- ▶ Familiar with Discrete and Continuous Distributions
- ▶ Can calculate expectations and variances
- ▶ Change of variables
- ▶ Mean squared error
- ▶ Sufficiency
- ▶ Confident calculating the likelihood and log-likelihood
- ▶ Confident in working with partial derivatives
- ▶ Familiar maximizing or minimizing functions (and proving they are global max/min)

Detailed Summary for Exam

- ▶ Bayes Theorem
- ▶ Likelihood
- ▶ Prior
- ▶ Posterior derivation
- ▶ Marginal likelihood
- ▶ Posterior predictive distribution
- ▶ Conjugacy
- ▶ Proportionality
- ▶ Understanding when models are appropriate for data given to you (Ex: Approval ratings for Obama)
- ▶ What is an informative prior
- ▶ What is a non-informative prior
- ▶ Proper posterior
- ▶ How do you incorporate a pilot study into your posterior analysis (Ex: See sleep study)

Supplemental Material

Below you will find supplemental material, such as exercises to help you for the exam with solutions provided.

Exercise

We write $X \sim \text{Poisson}(\theta)$ if X has the Poisson distribution with rate $\theta > 0$, that is, its p.m.f. is

$$p(x|\theta) = \text{Poisson}(x|\theta) = e^{-\theta} \theta^x / x!$$

for $x \in \{0, 1, 2, \dots\}$ (and is 0 otherwise). Suppose $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Poisson}(\theta)$ given θ , and your prior is

$$p(\theta) = \text{Gamma}(\theta|a, b) = \frac{b^a}{\Gamma(a)} \theta^{a-1} e^{-b\theta} \mathbb{1}(\theta > 0).$$

What is the posterior distribution on θ ?

Solution

Since the data is independent given θ , the likelihood factors and we get

$$\begin{aligned} p(x_{1:n}|\theta) &= \prod_{i=1}^n p(x_i|\theta) \\ &= \prod_{i=1}^n e^{-\theta} \theta^{x_i} / x_i! \\ &\propto_{\theta} e^{-n\theta} \theta^{\sum x_i}. \end{aligned}$$

Solution

Thus, using Bayes' theorem,

$$\begin{aligned} p(\theta|x_{1:n}) &\propto p(x_{1:n}|\theta)p(\theta) \\ &\propto e^{-n\theta} \theta^{\sum x_i} \theta^{a-1} e^{-b\theta} \mathbb{1}(\theta > 0) \\ &\propto e^{-(b+n)\theta} \theta^{a+\sum x_i-1} \mathbb{1}(\theta > 0) \\ &\propto \text{Gamma}(\theta \mid a + \sum x_i, b + n). \end{aligned}$$

Therefore, since the posterior density must integrate to 1, we have

$$p(\theta|x_{1:n}) = \text{Gamma}(\theta \mid a + \sum x_i, b + n).$$

Module 1 Derivations

Class notes from Module 1 can be found below:

<https://github.com/resteorts/modern-bayes/blob/master/lecturesModernBayes20/lecture-1/notes-module1.pdf>

<https://github.com/resteorts/modern-bayes/blob/master/lecturesModernBayes20/lecture-1/notes-module1.pdf>

Additional Applied Example

Below, there is an additional applied example that you may find useful regarding this material.

How Much Do You Sleep Example

We are interested in a population of American college students and the proportion of the population that sleep at least eight hours a night, which we denote by θ .

How Much Do You Sleep Example

- ▶ *The Gamecock*, at the USC printed an internet article "College Students Don't Get Enough Sleep" (2004).
 - ▶ Most students spend six hours sleeping each night.
- ▶ 2003: University of Notre Dame's paper, *Fresh Writing*.
 - ▶ The article reported took random sample of 100 students:
 - ▶ "approximately 70% reported to receiving only five to six hours of sleep on the weekdays,
 - ▶ 28% receiving seven to eight,
 - ▶ and only 2% receiving the healthy nine hours for teenagers."

How Much Do You Sleep

- ▶ Have a random sample of 27 students is taken from UF.
- ▶ 11 students record that they sleep at least eight hours each night.
- ▶ Based on this information, we are interested in estimating θ .

How Much Do You Sleep

- ▶ From USC and UND, believe it's probably true that most college students get less than eight hours of sleep.
- ▶ Want our prior to assign most of the probability to values of $\theta < 0.5$.
- ▶ From the information given, we decide that our best guess for θ is 0.3, although we think it is very possible that θ could be any value in $[0, 0.5]$.

Our Model

Our model can be summarized by the Binomial-Beta distribution

$$X|\theta \sim \text{Binomial}(n, \theta) \quad (1)$$

$$\theta \sim \text{Beta}(a, b) \quad (2)$$

You can show that the posterior of

$$\theta \mid X \sim \text{Beta}(x + a, n - x + b)$$

Choice of a, b for Beta Prior

- ▶ Given this information, we believe that the median of θ is 0.3 and the 90th percentile is 0.5.
- ▶ Knowing this allows us to estimate the unknown values of a and b .
- ▶ How do we actually calculate a and b ?

Choice of a,b for Beta Prior

We would need to solve the following equations:

$$\int_0^{0.3} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1-\theta)^{b-1} d\theta = 0.5$$

$$\int_0^{0.5} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{a-1} (1-\theta)^{b-1} d\theta = 0.9$$

In non-calculus language, this means the 0.5 quantile (50th percentile) = 0.3. The 0.9 quantile (90th percentile) = 0.5.

The equations are written as percentiles above!

- ▶ We can easily solve this numerically in R using a numerical solver `BBsolve` using the `BB` package. .
- ▶ The documentation for this package is not great, so beware.

How Much Do You Sleep

```
## load the BB package
library(BB)

## using percentiles
myfn <- function(shape) {
  test <- pbeta(q = c(0.3, 0.5), shape1 = shape[1],
    shape2 = shape[2]) - c(0.5, 0.9)
  return(test) }
BBsolve(c(1, 1), myfn)
```

```
## Successful convergence.
```

```
## $par
```

```
## [1] 3.263743 7.185121
```

```
##
```

```
## $residual
```

```
## [1] 5.905161e-08
```

```
##
```

```
## $fn.reduction
```

How Much Do You Sleep

Using our calculations from the Beta-Binomial our model is

$$X \mid \theta \sim \text{Binomial}(27, \theta)$$

$$\theta \sim \text{Beta}(3.3, 7.2)$$

$$\theta \mid x \sim \text{Beta}(x + 3.3, 27 - x + 7.2)$$

$$\theta \mid 11 \sim \text{Beta}(14.3, 23.2)$$

How Much Do You Sleep

```
th <- seq(0,1,length=500)
a <- estimated$par[1]
b <- estimated$par[2]
n <- 27
x <- 11
prior <- dbeta(th, a, b)
like <- dbeta(th, x + 1, n - x + 1)
post <- dbeta(th, x + a, n - x + b)
plot(th, post, type = "l", ylab = "Density", lty = 2, lwd = 3,
      xlab = expression(theta))
lines(th, like, lty = 1, lwd = 3)
lines(th, prior, lty = 3, lwd = 3)
legend(0.7, 4, c("Prior", "Likelihood", "Posterior"),
      lty = c(3,1,2), lwd = c(3,3,3))
```



How Much Do You Sleep

