

Lab 2: Intro to Bayes

Olivier Binette

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Agenda

1. Introduction :)
2. Solution to Lab 2
3. Some tips for homework 1
4. Questions

Introduction

Olivier Binette

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Office hours: Wednesday 9am-10am EST

My job:

- ▶ Help you with the labs, homeworks, and content of the course.
 - ▶ Please email questions and/or come to office hours!
- ▶ Advocate for you.
 - ▶ Let me know if you have any issue, if you're not satisfied with grading, or if there's anything else.
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Task 1

Reminder:

If you have independent variables $Y_i \sim \text{Bernoulli}(\theta)$, then

$$X = \sum_{i=1}^n Y_i \sim \text{Binomial}(\theta, n).$$

Example:

- ▶ Y_i : indicator variable that individual i gets sick in a certain period of time.
- ▶ X : total number of people getting sick in the given period of time among the individuals $i = 1, 2, \dots, n$.

Task 1

Assume that

$$\begin{aligned}X \mid \theta &\sim \text{Binomial}(\theta, n), \\ \theta &\sim \text{Beta}(a, b).\end{aligned}$$

Derive the posterior distribution of θ given X .

Solution to Task 1

$$\begin{aligned} p(\theta | X) &= \frac{p(X | \theta)p(\theta)}{p(X)} \\ &\propto p(X | \theta)p(\theta) \\ &= \binom{n}{X} \theta^X (1 - \theta)^{(n-X)} \times \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{(a-1)} (1 - \theta)^{(b-1)} \\ &\propto \theta^X (1 - \theta)^{(n-X)} \times \theta^{(a-1)} (1 - \theta)^{(b-1)} \\ &\propto \theta^{X+a-1} (1 - \theta)^{(n-X+b-1)} \end{aligned}$$

Therefore

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

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Task 2

Simulate some data using the `rbinom` function of size $n = 100$ and probability equal to 1%. Remember to `set.seed(123)` so that you can replicate your results.

The data can be simulated as follows:

```
# set a seed
set.seed(123)
# create the observed data
obs.data <- rbinom(n = 100, size = 1, prob = 0.01)
head(obs.data)

## [1] 0 0 0 0 0 0

length(obs.data)

## [1] 100
```

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```
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```

```
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```

Task 3

1. Write a function with:

- ▶ **input:** simulated data and sequence of θ values.
- ▶ **output:** binomial likelihood of the data corresponding to each θ value.

```
theta = c(0.01, 0.1)
N = length(obs.data)
X = sum(obs.data)
LH = choose(N, X) * theta^(X) * (1-theta)^(N-X)
LH

## [1] 0.3697296376 0.0002951267

likelihood <- function(obs.data, theta) {
  N = length(obs.data)
  X = sum(obs.data)
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  return(LH)
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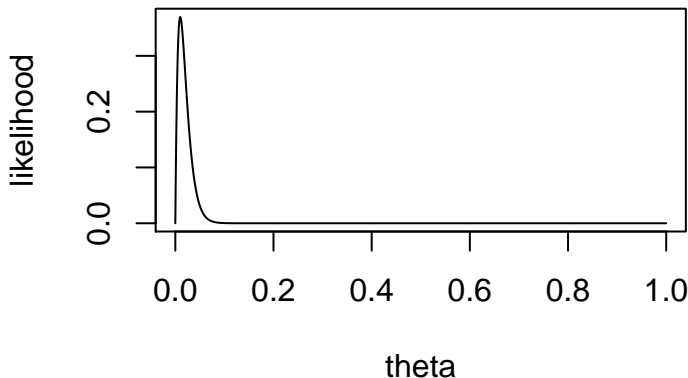
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}
```


Task 3

2. Plot the likelihood over a grid of θ values

```
theta = seq(0,1, length.out = 1000)
plot(theta, likelihood(obs.data, theta), type="l",
      ylab="likelihood", xlab="theta")
```



Task 4

1. Write a function with:

- ▶ **input:** prior parameters a , b , and the observed data.
 - ▶ **output:** parameters of the Beta posterior distribution of θ .
- takes as its inputs prior parameters a and b for the Beta-Bernoulli model and the observed data, and produces the posterior parameters you need for the model.

```
post_parameters <- function(a, b, obs.data) {  
  N = length(obs.data)  
  X = sum(obs.data)  
  a.post = a + X  
  b.post = N - X + b  
  return(c(a.post, b.post))  
}
```

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Task 4

2. **Generate and print** the posterior parameters for a non-informative prior i.e. $(a,b) = (1,1)$ and for an informative case $(a,b) = (3,1)$.

```
post_parameters(1,1, obs.data)
```

```
## [1]    2 100
```

```
post_parameters(3,1, obs.data)
```

```
## [1]    4 100
```

Task 4

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```
## [1]    2 100
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```
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```

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```

Task 5

Create two plots, one for the informative and one for the non-informative case to show the posterior distribution and superimpose the prior distributions on each along with the likelihood. What do you see?

Task 5

I'll only do the non-informative prior part with you.

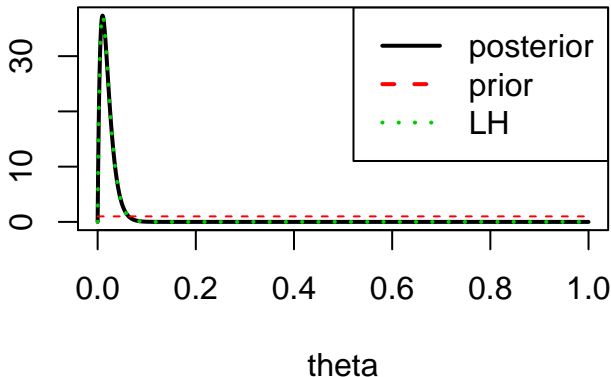
```
params1 = post_parameters(1,1, obs.data)

# Plot posterior distribution
theta = seq(0,1, length.out=1000)
plot(theta, dbeta(theta, shape1=params1[1], shape2=params1[2]),
      type="l", xlab="theta", ylab="")
# Plot prior
lines(theta, dbeta(theta, shape1=1, shape2=1), col=2, lty=2)
# Plot likelihood
LH = likelihood(obs.data, theta)
lines(theta, 1000*LH/sum(LH), col=3, lty=3)

legend("topright", legend=c("posterior", "prior", "LH"),
      lty=c(1,2,3), col=c(1,2,3))
```

Task 5

Here's the result:

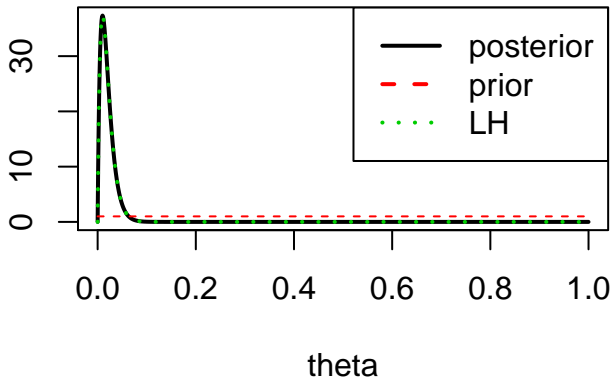


Observation: The posterior is almost the same as the normalized likelihood.

Interpretation: With a non-informative prior, the *likelihood* drives inference.

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Interpretation: With a non-informative prior, the *likelihood* drives inference.

Questions

- ▶ Questions?