

# Bayesian Calculations: Simulation of Coin Flipping

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## 1 Background

Bayes Theorem allows us to state our *prior* beliefs, to calculate the *likelihood* of our data given those beliefs, and then to update those beliefs with data, thus arriving at a set of *posterior* beliefs. However, Bayesian calculations can be difficult to understand. This document attempts to provide a simple walkthrough of some Bayesian calculations.

## 2 Bayes Rule

A draft interactive version of these ideas can be found [here](#).

Mathematically Bayes Theorem is as follows:

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)}$$

In words, Bayes Theorem may be written as follows:

$$\text{posterior} = \frac{\text{likelihood} * \text{prior}}{\text{data}}$$

Our posterior beliefs are proportional to our prior beliefs, multiplied by the likelihood of those beliefs, given the data.

### 3 This Example

In this example, we provide an example of using Bayes Theorem to examine our conclusions about the proportion of heads when a coin is flipped 10 times.

Conventionally, we call this proportion that we are trying to estimate  $\theta$ .

For the sake of simplicity, this example uses a relatively simple set of prior beliefs about 3 possible values for the proportion  $\theta$ .

R code in this example is adapted and simplified from Kruschke (2011), p. 70

### 4 Prior

We set a simple set of prior beliefs, concerning 3 values of  $\theta$ , the proportion of heads.

```
theta1 <- c(0.25, 0.5, 0.75) # candidate parameter values
```

```
ptheta1 <- c(0.25, 0.5, 0.25) # prior probabilities
```

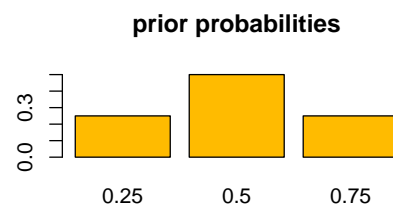
```
ptheta1 <- ptheta1/sum(ptheta1) # normalize
```

Our values of  $\theta$  are 0.25, 0.5 and 0.75, with probabilities  $P(\theta)$  of 0.25, 0.5 and 0.25.

```
barplot(names.arg = theta1, height = ptheta1,
        main = "prior probabilities", col = "#FFBB00") # graph
```

```
myBayesianEstimates <- tibble(theta1, ptheta1)
```

```
pander(myBayesianEstimates) # nice table
```



theta1	ptheta1
0.25	0.25
0.5	0.5
0.75	0.25

### 5 The Data

10 coin flips. 1 Heads. 9 Tails.

```
data1 <- c(1, 0, 0, 0, 0, 0, 0, 0, 0, 0) # the data
```

```
data1_factor <- factor(data1, levels = c(0, 1),
  labels = c("T", "H"))
```

```
n_heads <- sum(data1 == 1) # number of heads
```

```
n_tails <- sum(data1 == 0) # number of tails
```

```
plot(x = seq(1,10), # x from 1 to 10
  y = rep(1,10), # y = 1
  col = data1_factor, # color by data
  cex = 3, # size
  lwd = 2, # line width
  axes = FALSE,
  main = "10 Coin Tosses",
  xlab = " ",
  ylab = " ")
```

```
text(x = seq(1,10), # x from 1 to 10
  y = rep(1,10), # y = 1
  labels = data1_factor) # label with data1_factor
```

10 Coin Tosses

## 6 Likelihood

The likelihood is the probability that a given value of  $\theta$  would produce this number of heads.

The probability of multiple independent events  $A, B, C$ , etc. is

$$P(A, B, C, \dots) = P(A) * P(B) * P(C) * \dots$$

Therefore, in this case, the likelihood is proportional to  $[P(\text{heads})]^{\text{number of heads}}$  and multiply this by  $[P(\text{tails})]^{\text{number of tails}}$ .

Thus:

$$\mathcal{L}(\theta) \propto \theta^{\text{number of heads}} * (1 - \theta)^{\text{number of tails}}$$

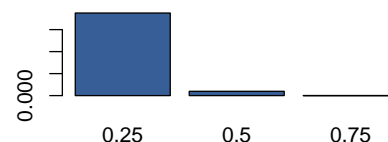
```
likelihood1 <- theta1^n_heads * (1 - theta1)^n_tails # likelihood
```

```
barplot(names.arg = theta1, height = likelihood1,
  main = "likelihood", col = "#375E97") # graph
```

At this point our estimates include not only a value of  $\theta$  and  $P(\theta)$ , but also the likelihood,  $\mathcal{L}(\theta)$ .

```
myBayesianEstimates <- tibble(theta1, ptheta1,
  likelihood1)
```

likelihood



```
pander(myBayesianEstimates) # nice table
```

theta1	ptheta1	likelihood1
0.25	0.25	0.01877
0.5	0.5	0.0009766
0.75	0.25	2.861e-06

## 7 Posterior

We then calculate the denominator of Bayes theorem:

$$\Sigma[\mathcal{L}(\theta) * P(\theta)]$$

```
pdata1 <- sum(likelihood1 * ptheta1) # normalize
```

We then use Bayes Rule to calculate the posterior:

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)}$$

```
posterior1 <- likelihood1 * ptheta1/pdata1 # Bayes Rule
```

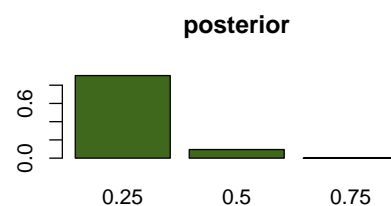
```
barplot(names.arg = theta1, height = posterior1,
        main = "posterior", col = "#3F681C") # graph
```

Our estimates now include  $\theta$ ,  $P(\theta)$ ,  $\mathcal{L}(\theta)$  and  $P(\theta|D)$ .

```
myBayesianEstimates <- tibble(theta1, ptheta1,
                              likelihood1, posterior1)
```

```
pander(myBayesianEstimates) # nice table
```

theta1	ptheta1	likelihood1	posterior1
0.25	0.25	0.01877	0.9056
0.5	0.5	0.0009766	0.09423
0.75	0.25	2.861e-06	0.000138



## 8 Credits

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Questions, comments and corrections are most welcome.