



## FUNDAMENTALS OF BAYESIAN DATA ANALYSIS IN R

**Welcome to the  
course!**

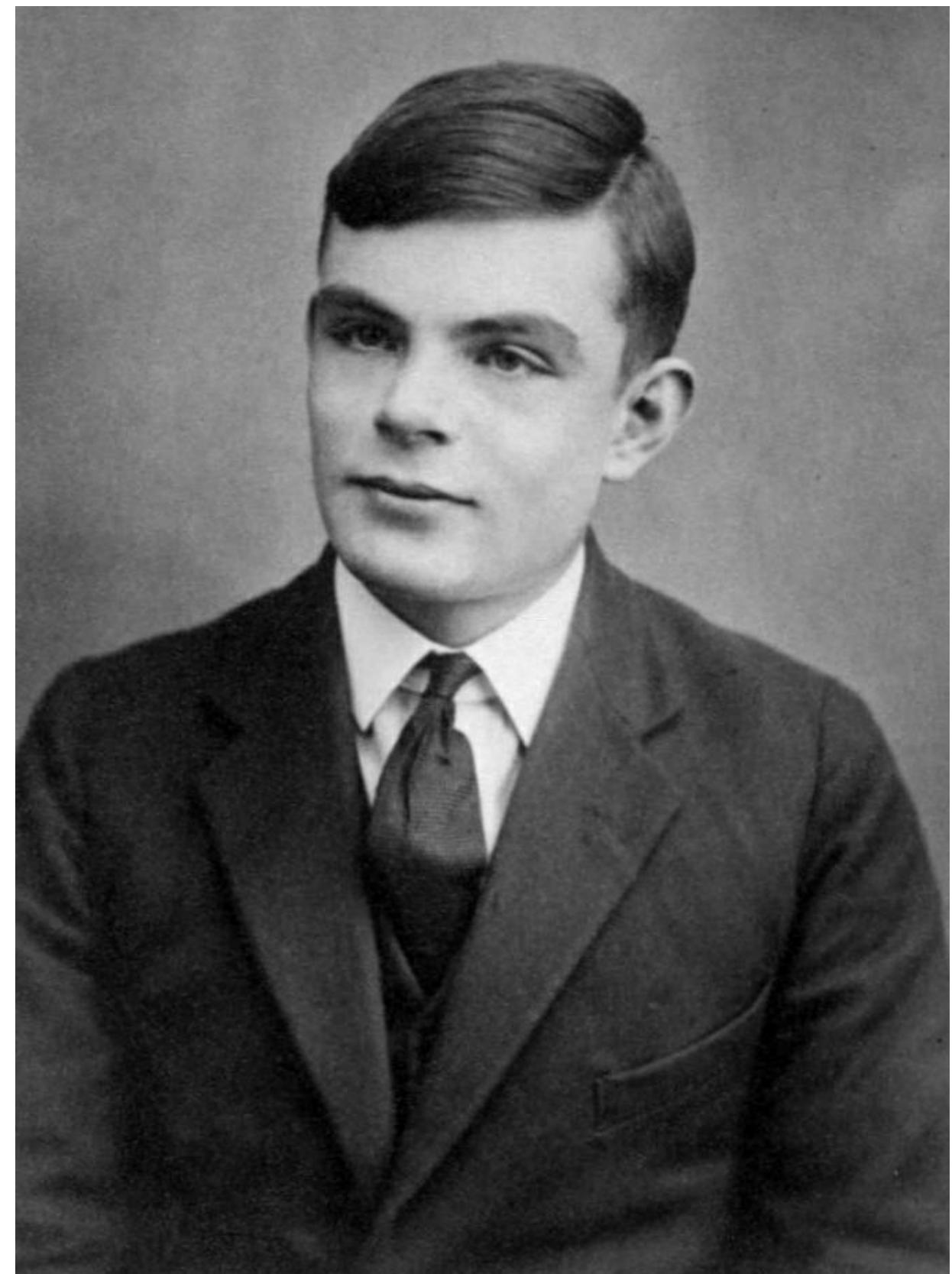
Rasmus Bååth  
Data Scientist

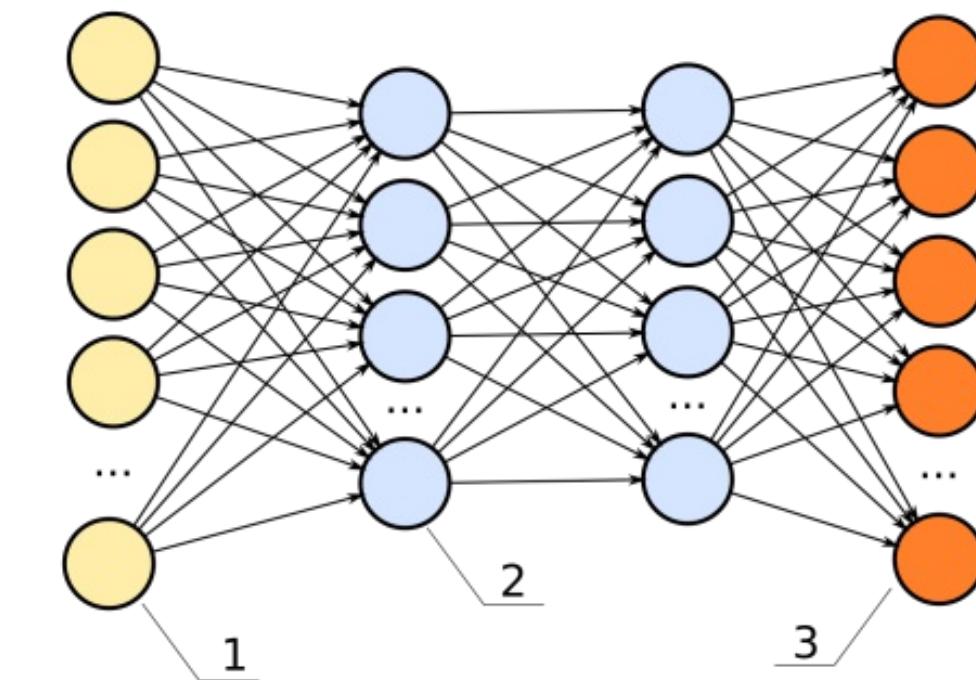
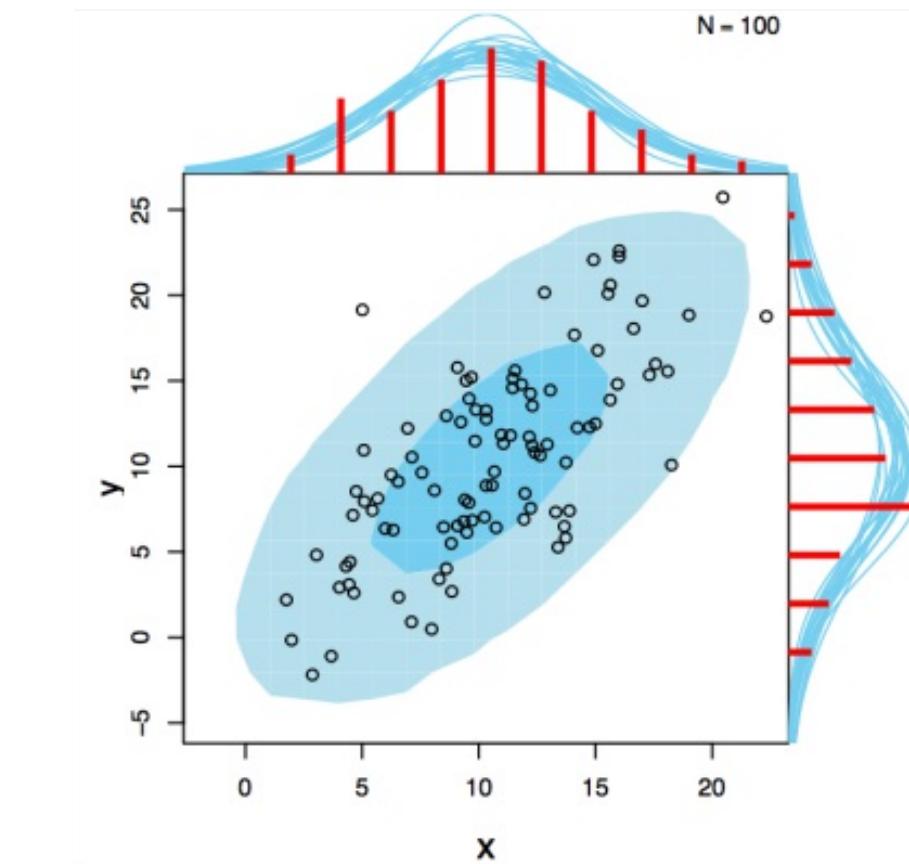
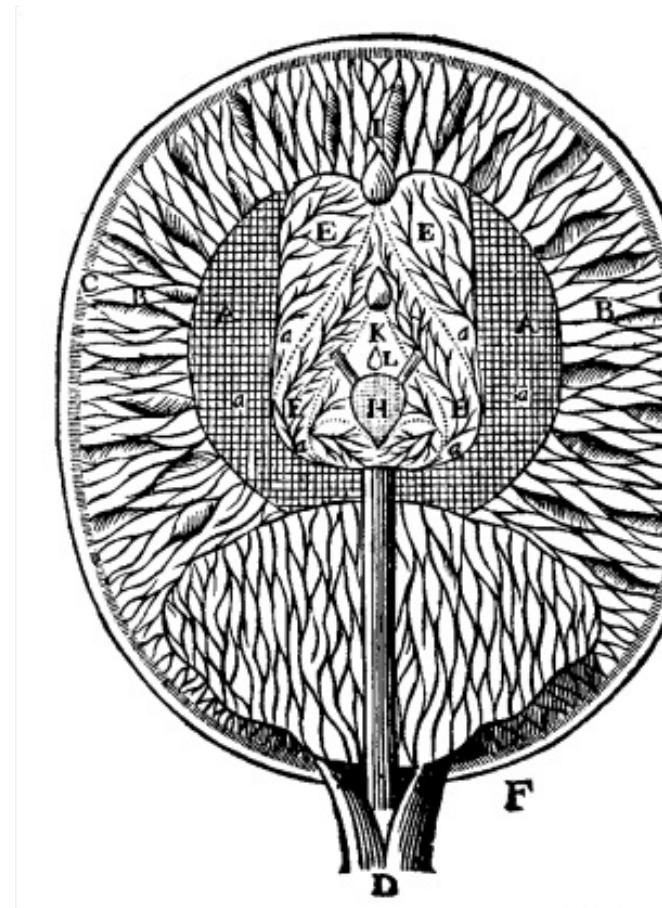






[1] [https://commons.wikimedia.org/wiki/File:Enigma\\_08.jpg](https://commons.wikimedia.org/wiki/File:Enigma_08.jpg)



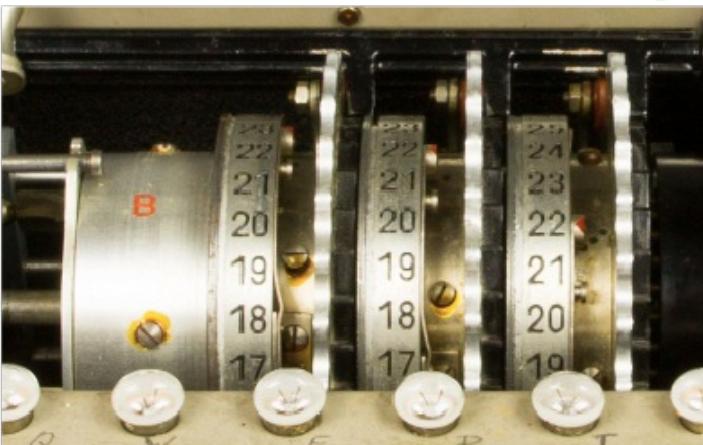


# Bayesian inference in a nutshell

A method for figuring out unobservable quantities given known facts that uses probability to describe the uncertainty over what the values of the unknown quantities could be.



# Wheel settings

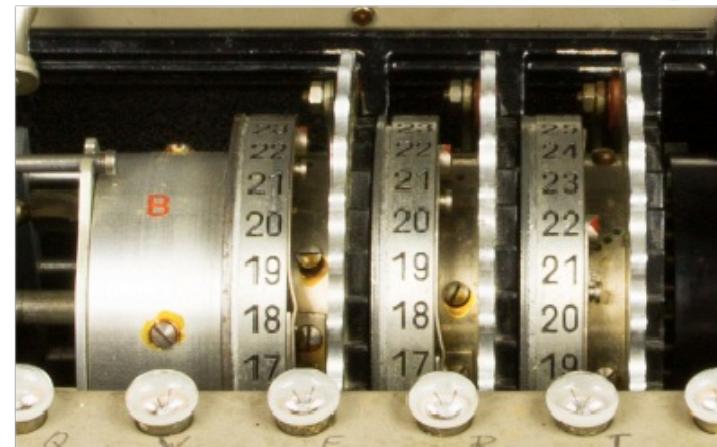


Enigma  
model



JAZSFOXRQERSPXEIYUA  
PARHCWSMYXCJIMFGVOAH  
SJPQJYYKEOABSAUZYNQL

# Wheel settings



Enigma  
model

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PARHCWSMYXCJIMFGVOAH  
SJPQJYYKEOABSAUZYQNQL

Bayesian Inference

# Bayesian data analysis

- The use of Bayesian inference to learn from data.
- Can be used for hypothesis testing, linear regression, etc.
- Is flexible and allows you to construct problem-specific models.

# Course overview

- **Chapter 1:** A small Bayesian analysis.
- **Chapter 2:** How Bayesian inference works.
- **Chapter 3:** Why you would want to use Bayesian data analysis?
- **Chapter 4:** Bayesian inference with Bayes theorem.
- **Chapter 5:** Wrapping up + a practical tool for Bayesian Data Analysis in R.



## FUNDAMENTALS OF BAYESIAN DATA ANALYSIS IN R

**Bayesian Data  
analysis: a tool to  
make sense of your  
data.**



## FUNDAMENTALS OF BAYESIAN DATA ANALYSIS IN R

**A little bit of  
background**

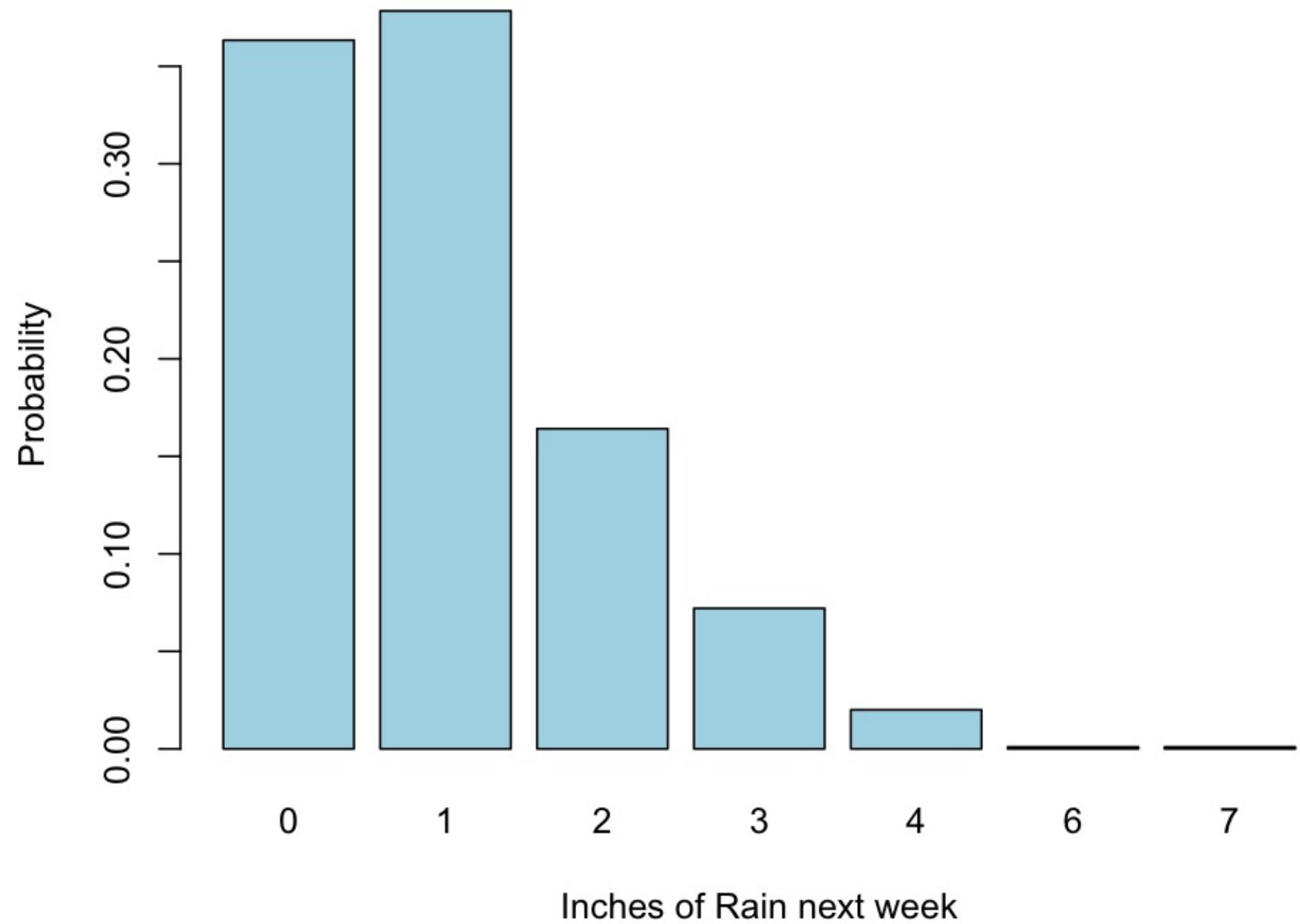
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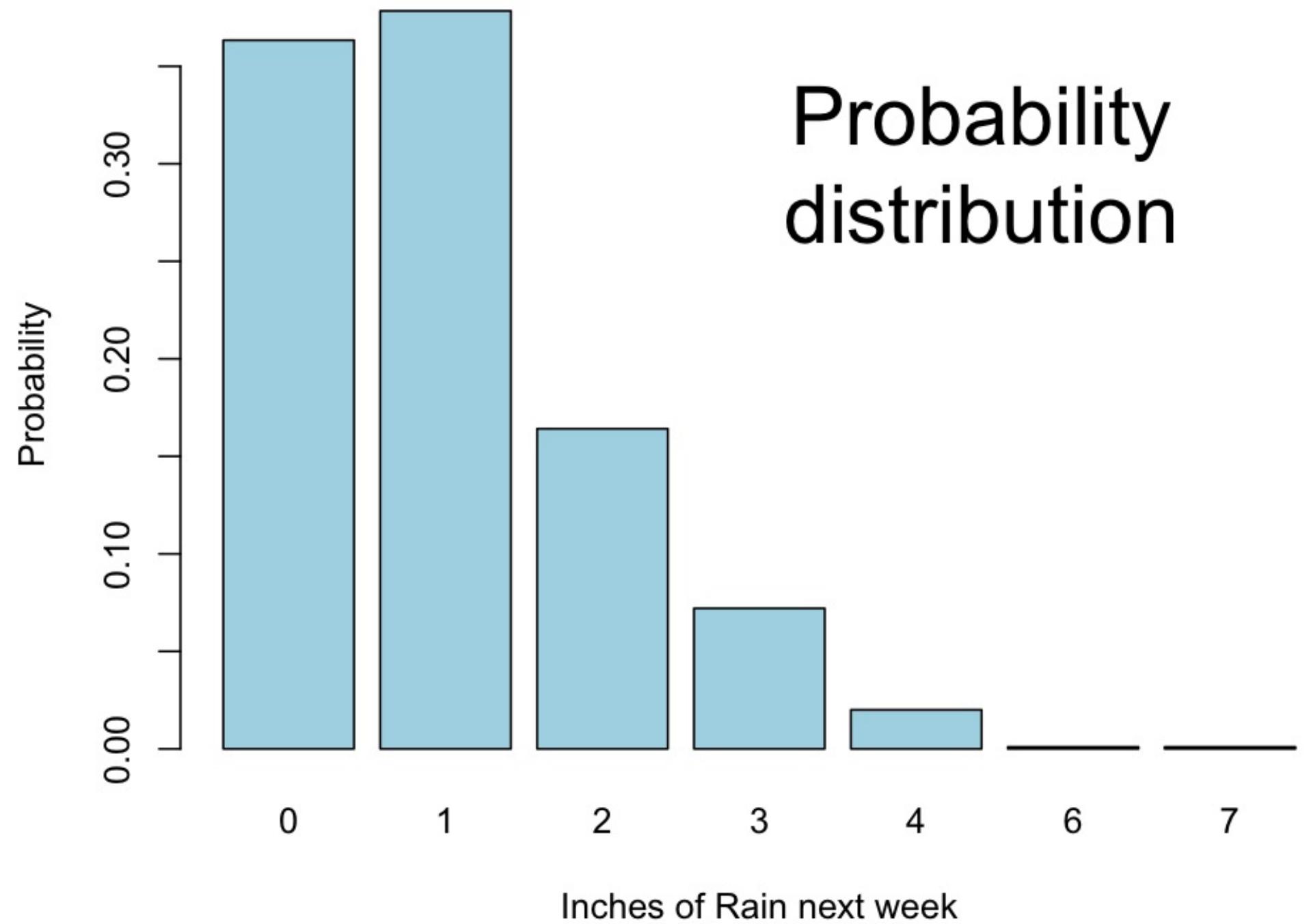


Thomas Bayes (1702-1761)

# Probability

- A number between 0 and 1.
- A statement about certainty / uncertainty.
- 1 is complete certainty something is the case.
- 0 is complete certainty something is *not* the case.
- Not only about yes/no events.





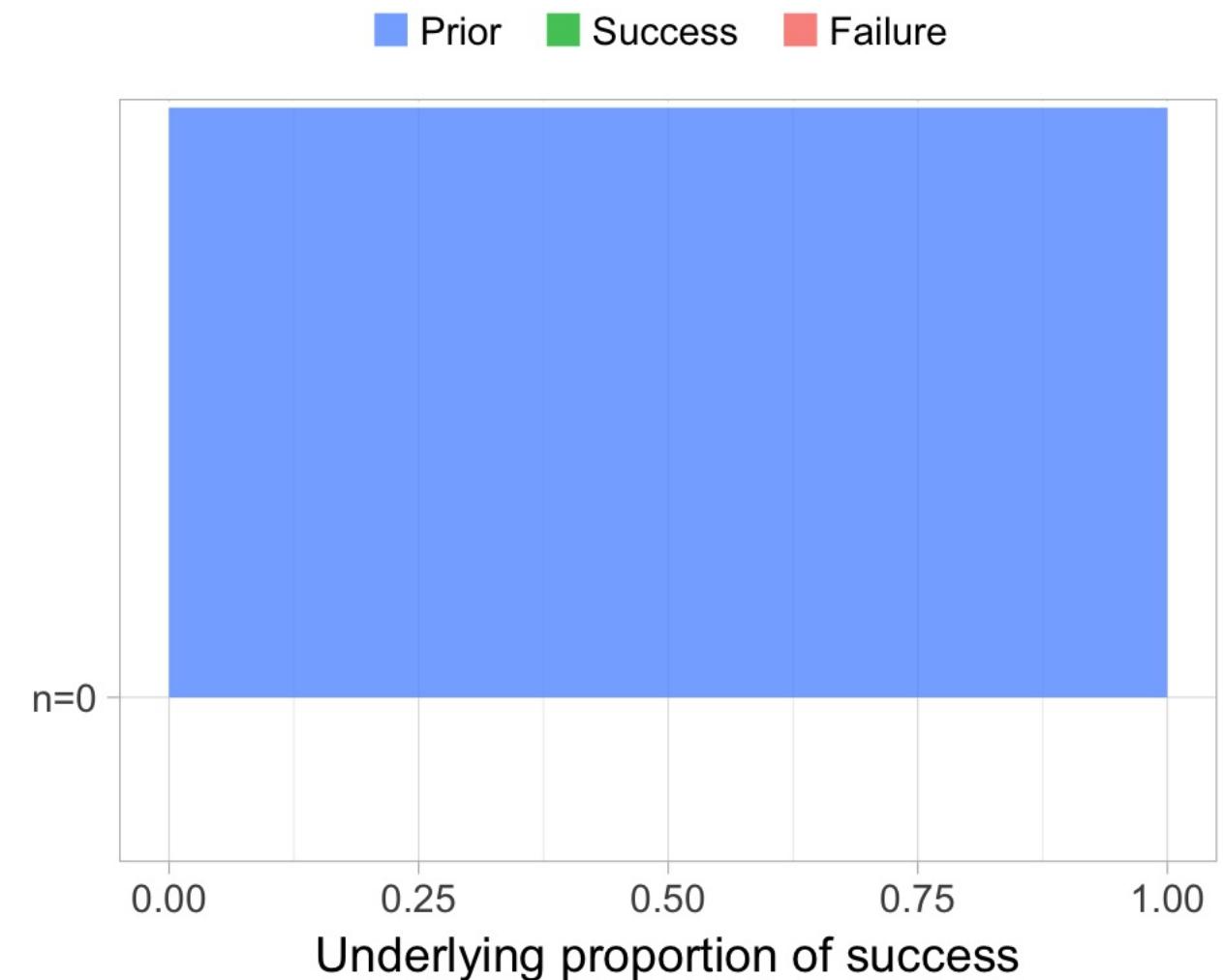
*The role of probability distributions in Bayesian data analysis is to represent uncertainty, and the role of Bayesian inference is to update probability distributions to reflect what has been learned from data.*

# A Bayesian model for the proportion of success

- `prop_model(data)`
- The data is a vector of successes and failures represented by 1s and 0s.
- There is an unknown underlying *proportion of success*.
- If data point is a success is only affected by this proportion.
- Prior to seeing any data, any underlying proportion of success is equally likely.
- The result is a probability distribution that represents what the model knows about the underlying proportion of success.

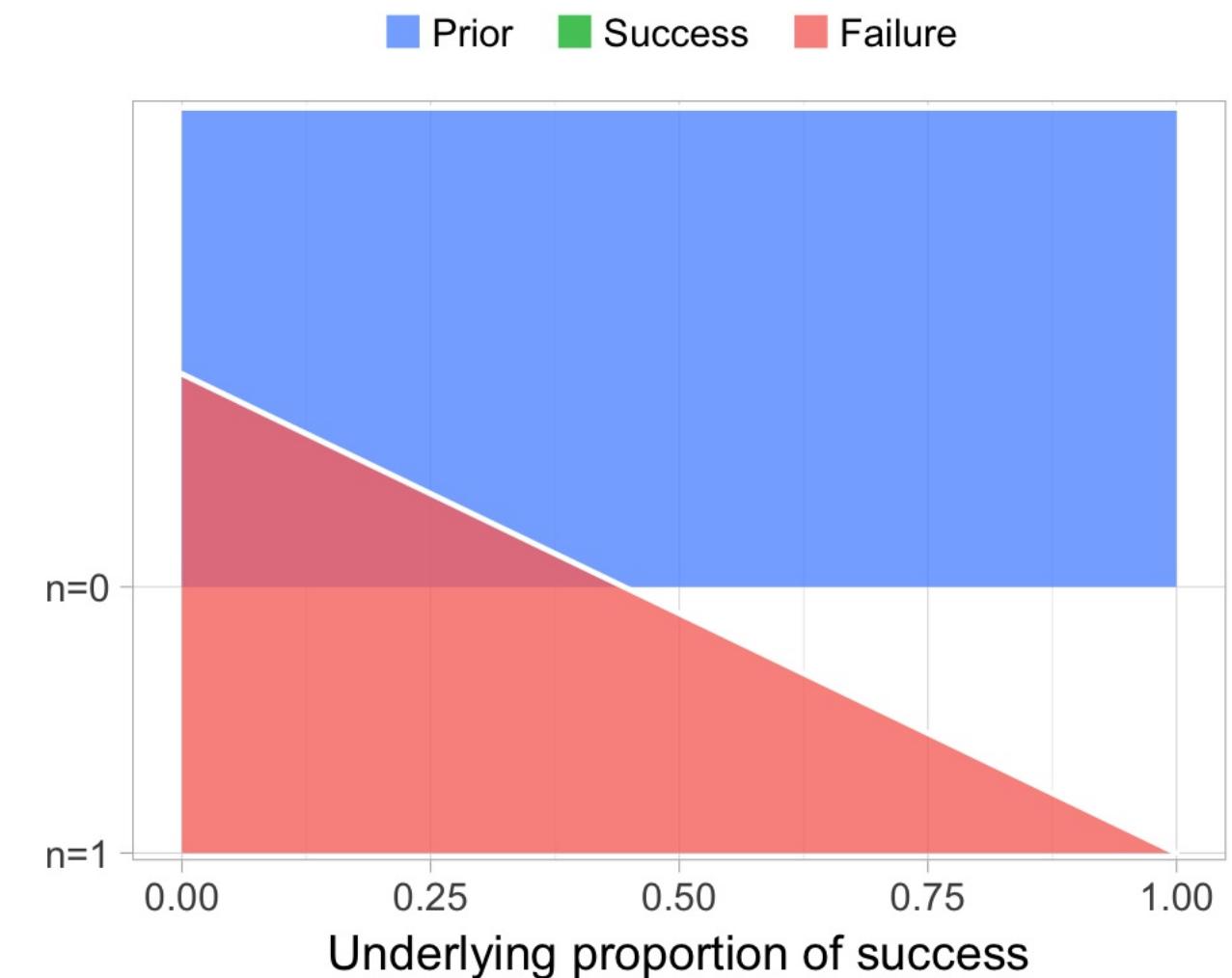
# Trying out prop\_model

```
data <- c()  
prop_model(data)
```



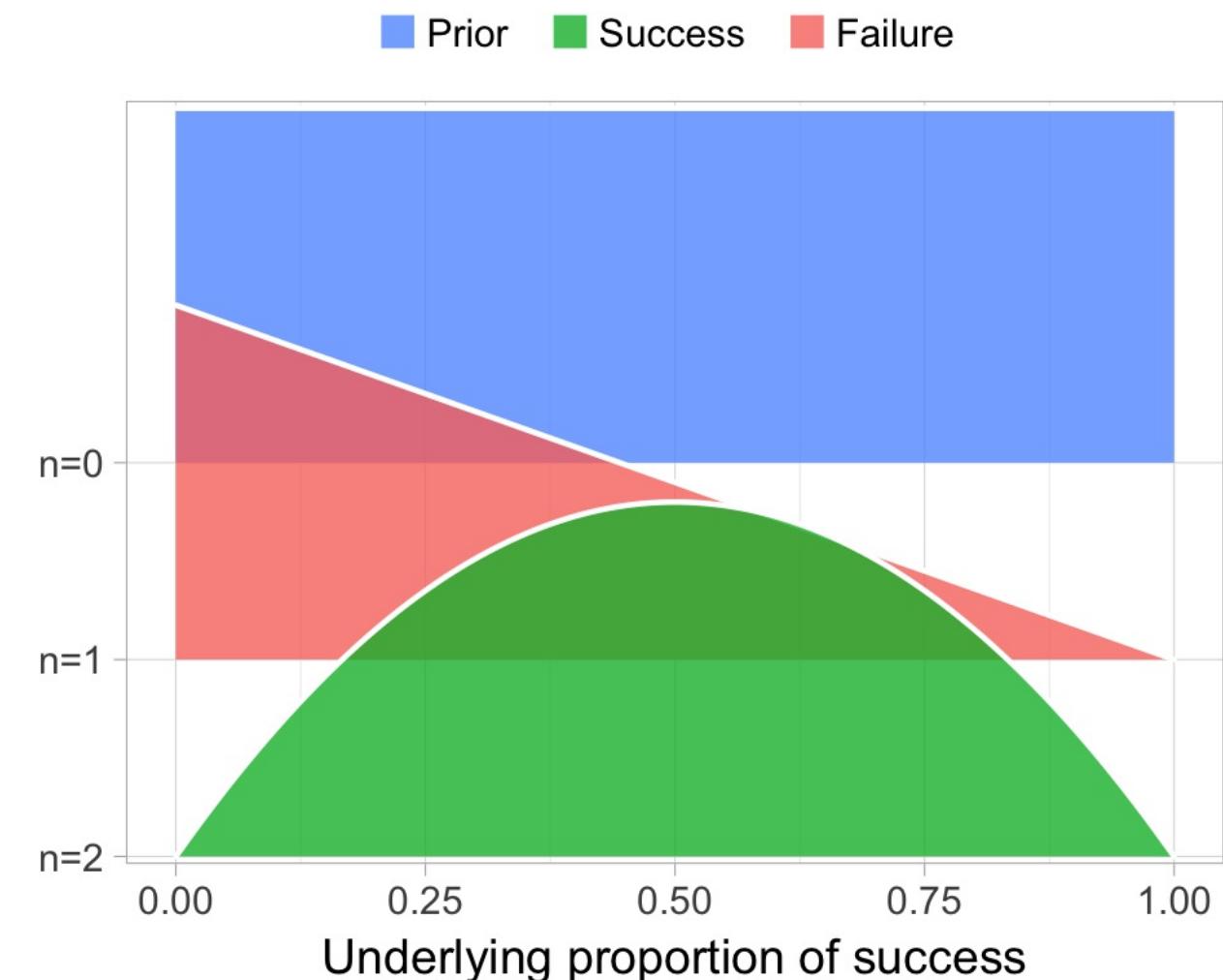
# Trying out prop\_model

```
data <- c(0)
prop_model(data)
```



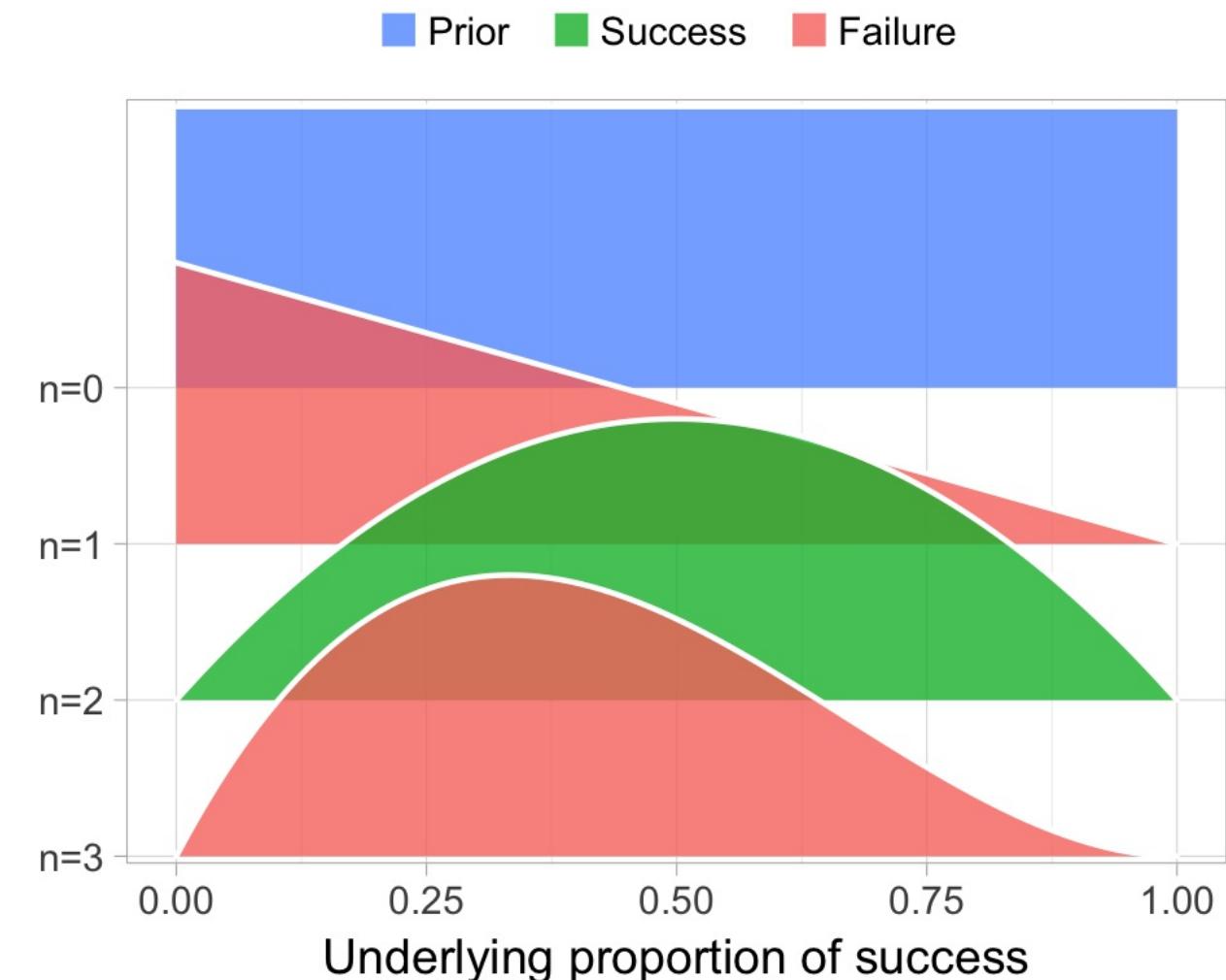
# Trying out prop\_model

```
data <- c(0, 1)  
prop_model(data)
```



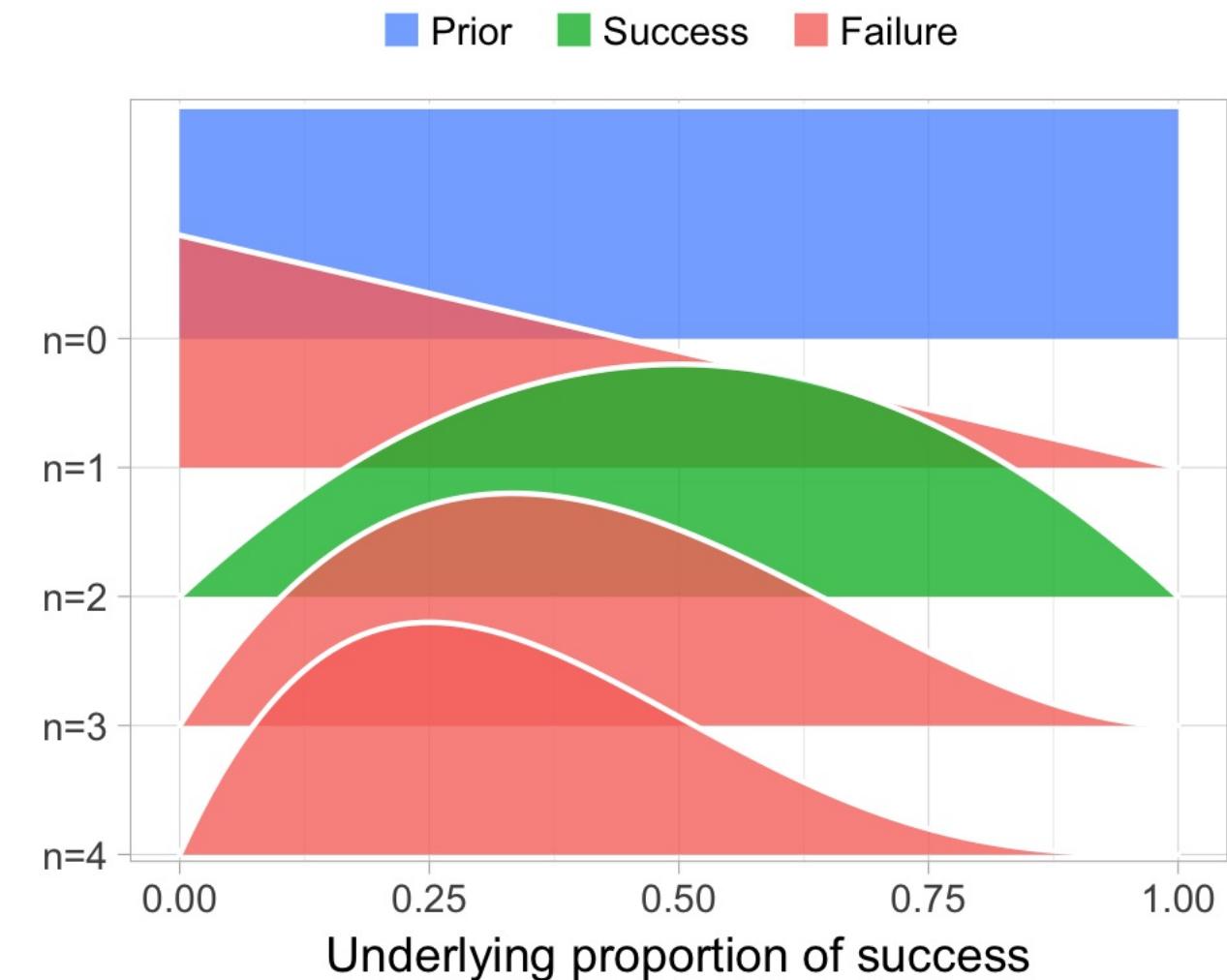
# Trying out prop\_model

```
data <- c(0, 1, 0)  
prop_model(data)
```



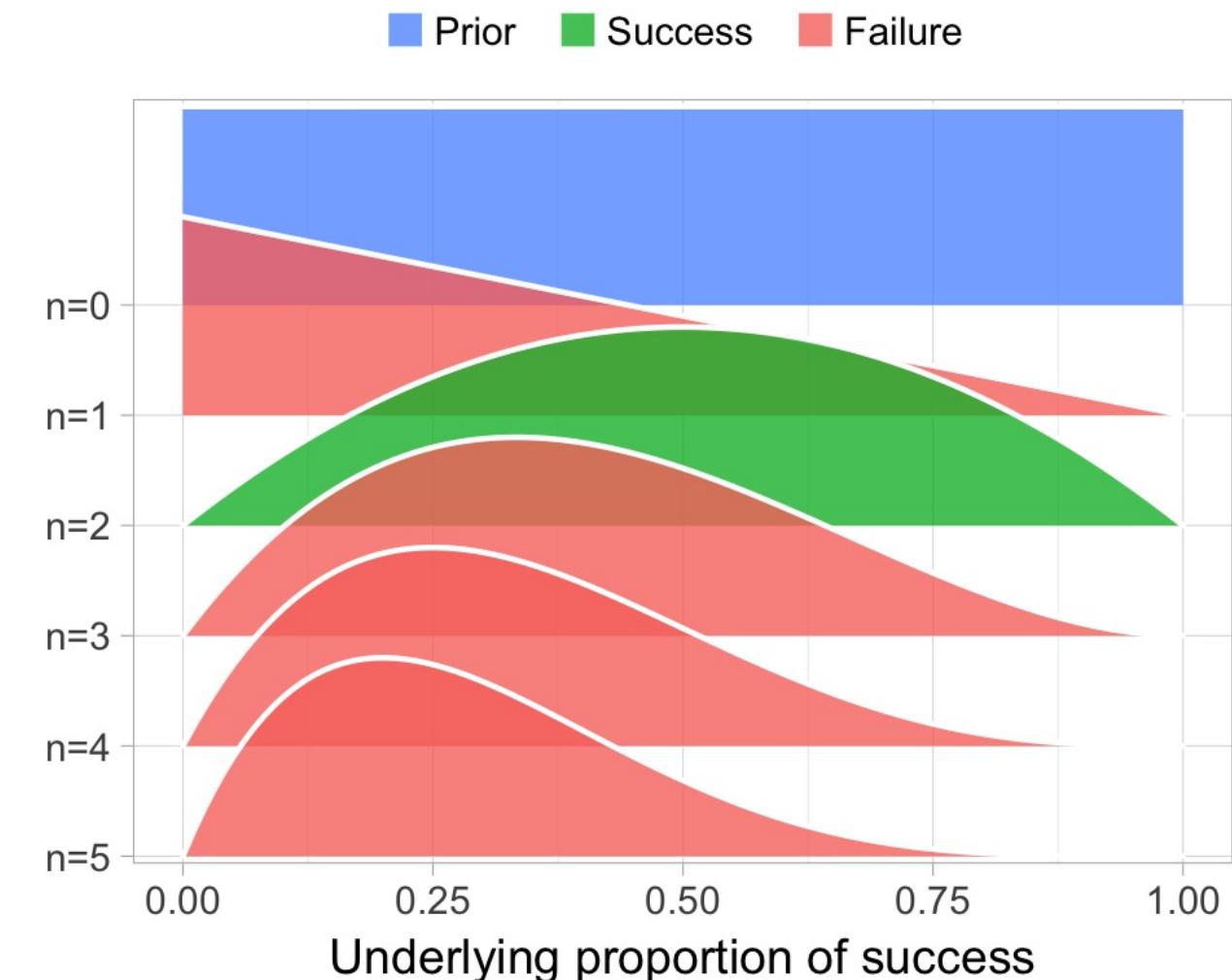
# Trying out prop\_model

```
data <- c(0, 1, 0, 0)  
prop_model(data)
```



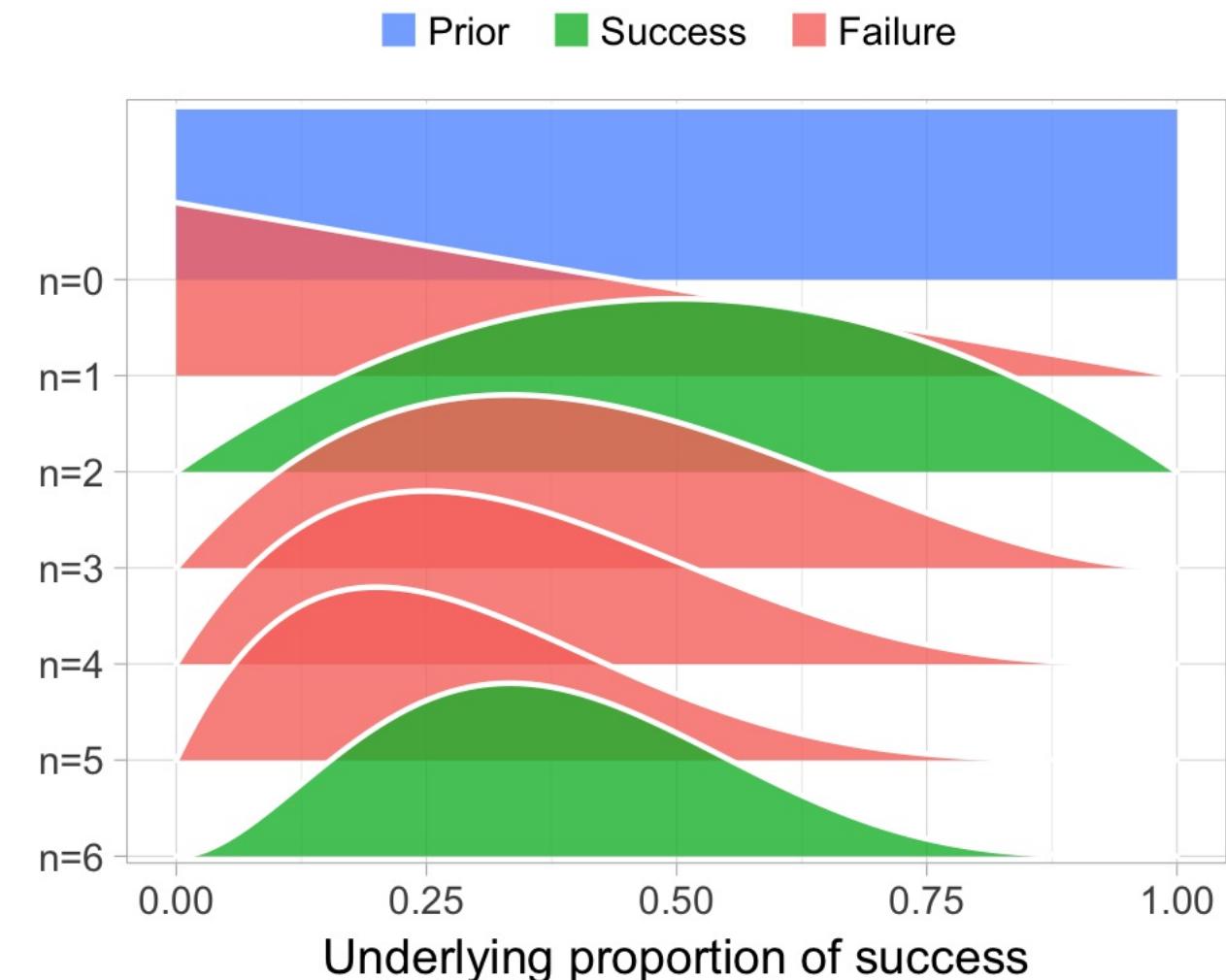
# Trying out prop\_model

```
data <- c(0, 1, 0, 0, 0)  
prop_model(data)
```



# Trying out prop\_model

```
data <- c(0, 1, 0, 0, 0, 1)  
prop_model(data)
```





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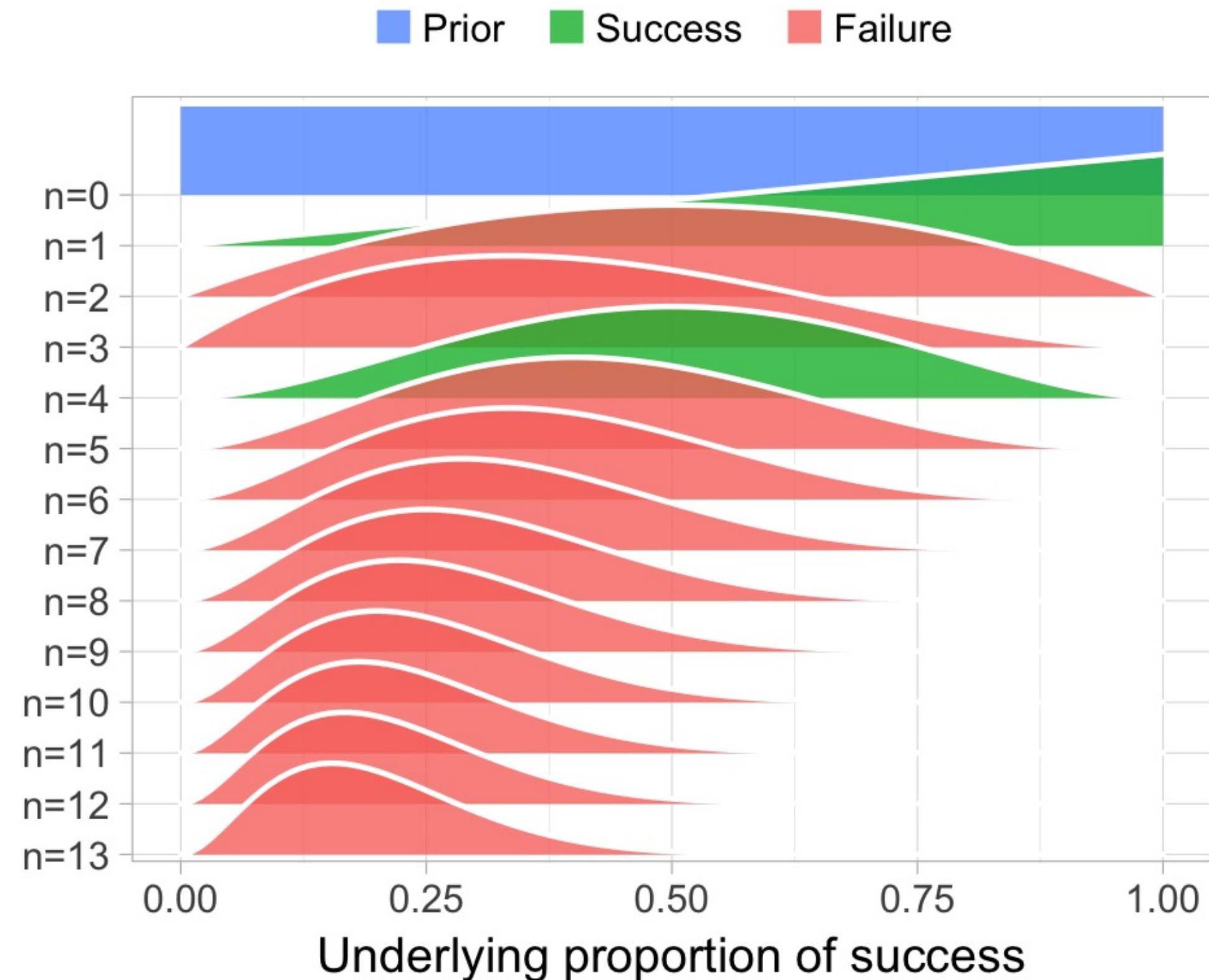
**Now, you try out  
prop\_model!**

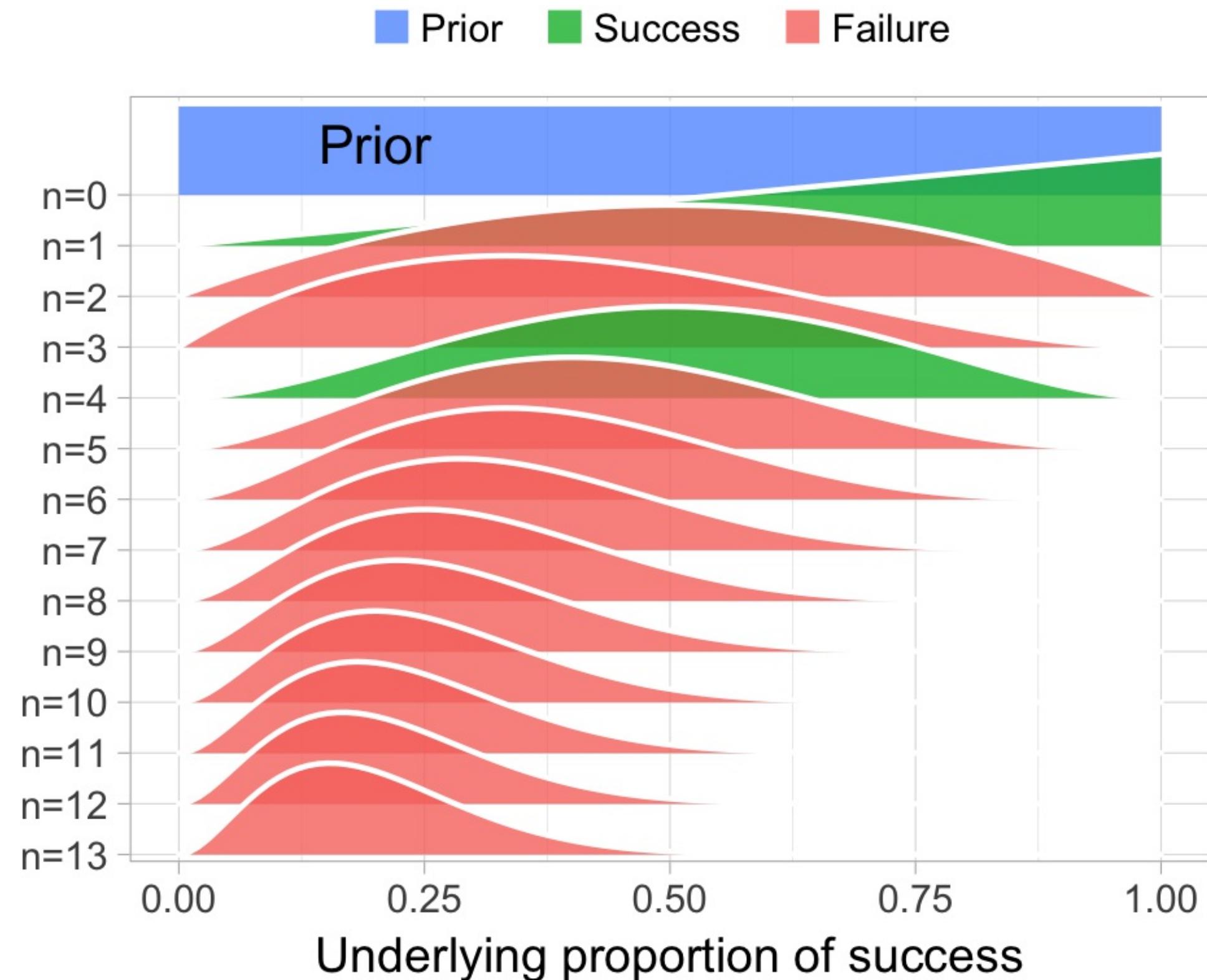


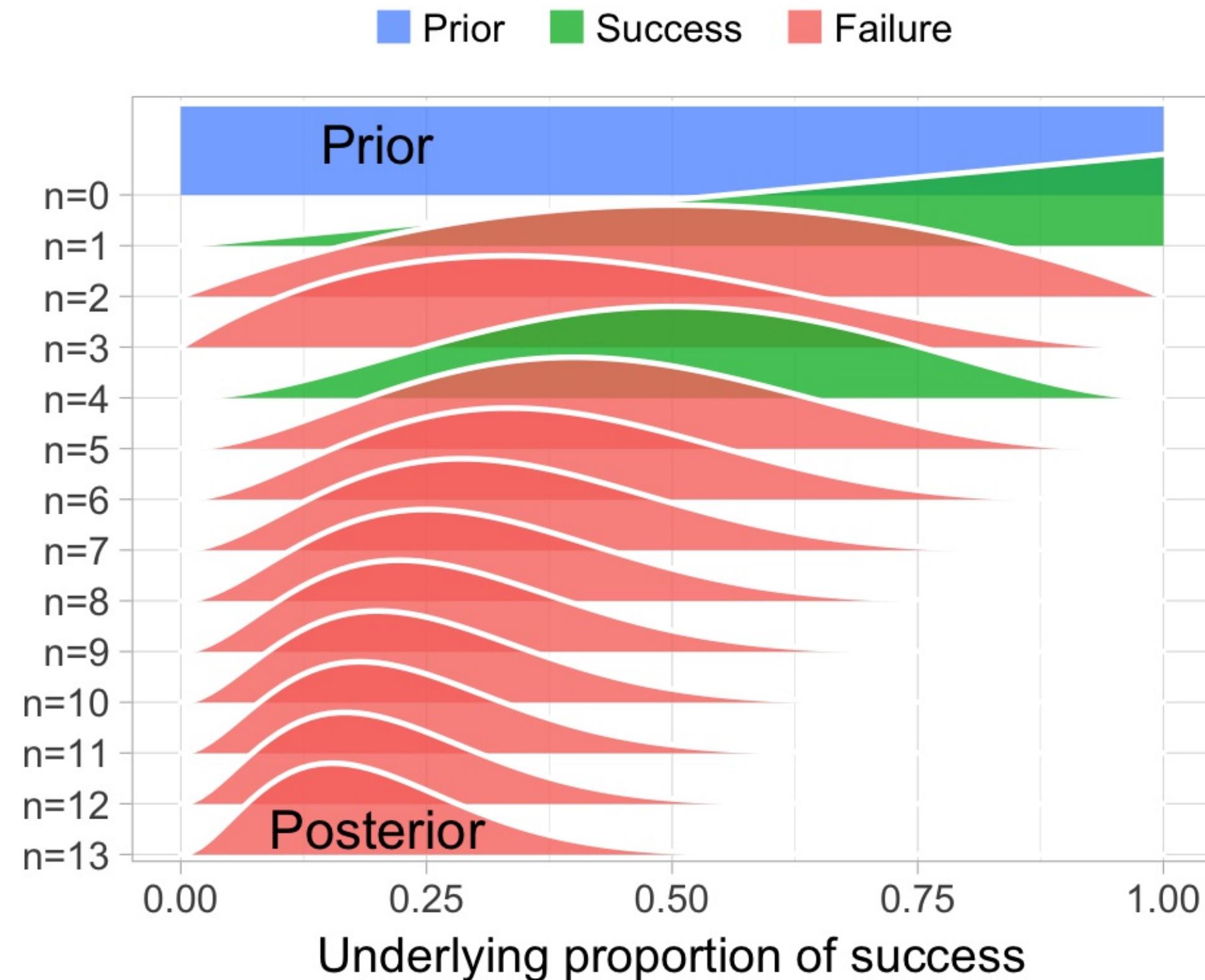
## FUNDAMENTALS OF BAYESIAN DATA ANALYSIS IN R

**You just did some  
Bayesian data analysis!**

Rasmus Bååth  
Data Scientist

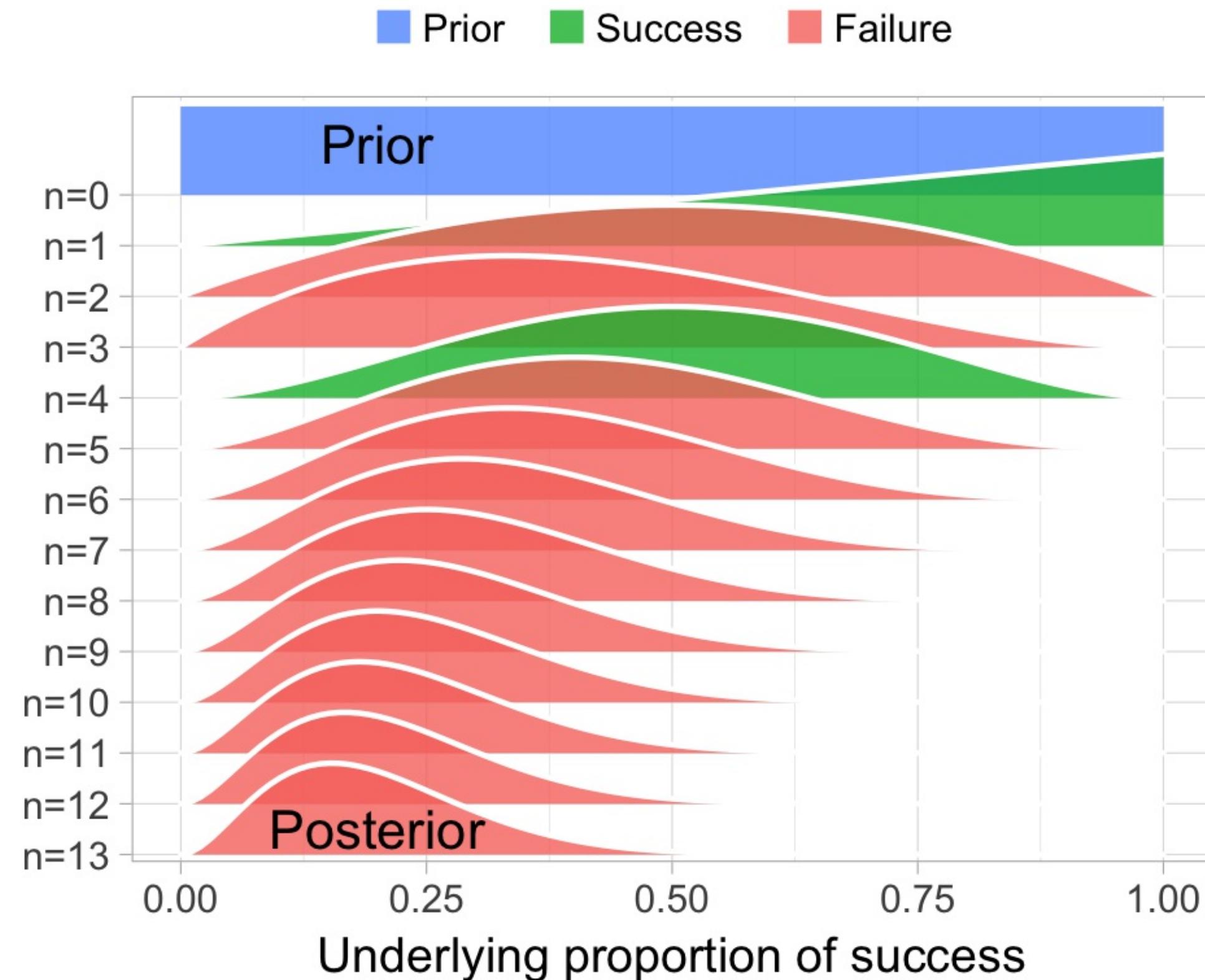




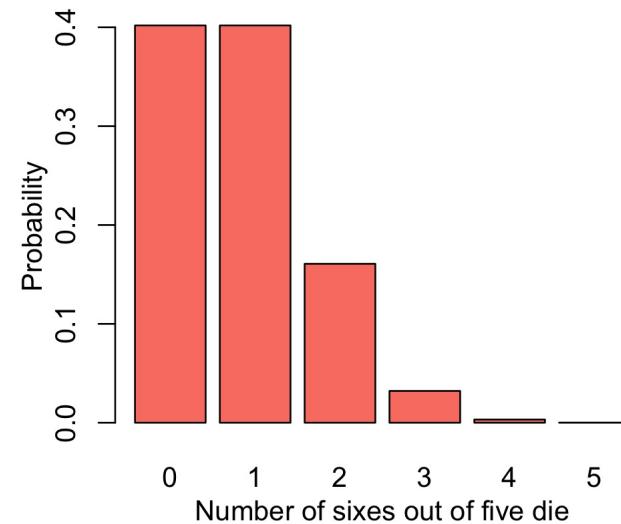


# Priors & Posteriors

- A **prior** is a probability distribution that represents what the model knows before seeing the data.
- A **posterior** is a probability distribution that represents what the model knows after having seen the data.



# The probability distribution over #? when rolling 5 dice



$$p(x) = \binom{5}{x} \left(\frac{1}{6}\right)^x \left(1 - \left(\frac{1}{6}\right)\right)^{5-x}$$

```
> number_of_sixes
[1] 1 1 0 0 1 0 1 2 0 1 0 0 1 0 0 0 0 0 1 1 1 1 0 0 2 0
[29] 0 1 0 0 1 0 0 1 0 1 2 0 1 0 0 0 1 2 1 2 0 0 1 1 3 3 0 0
[57] 1 1 1 1 1 0 0 1 2 0 1 3 1 1 1 0 1 0 1 2 0 1 1 0 1 1 1 0
[85] 2 1 0 4 0 1 2 1 1 1 2 0 1 0 1 1 0 0 2 0 0 0 0 0 1 1 0 1
[113] 0 0 0 0 2 0 0 0 0 0 1 1 0 0 2 1 1 1 0 2 1 1 1 0 0 1 1 1
...

```

```
> mean(number_of_sixes)
[1] 0.83
```

```
posterior <- prop_model(data)
print(posterior)
```

```
[1] 0.23 0.36 0.20 0.21 0.12
[6] 0.10 0.03 0.16 0.09 0.14
[11] 0.23 0.05 0.15 0.26 0.22
...
...
```



## FUNDAMENTALS OF BAYESIAN DATA ANALYSIS IN R

**Finish off the Zombie  
drug analysis!**



## FUNDAMENTALS OF BAYESIAN DATA ANALYSIS IN R

# Wrapping up the zombie analysis

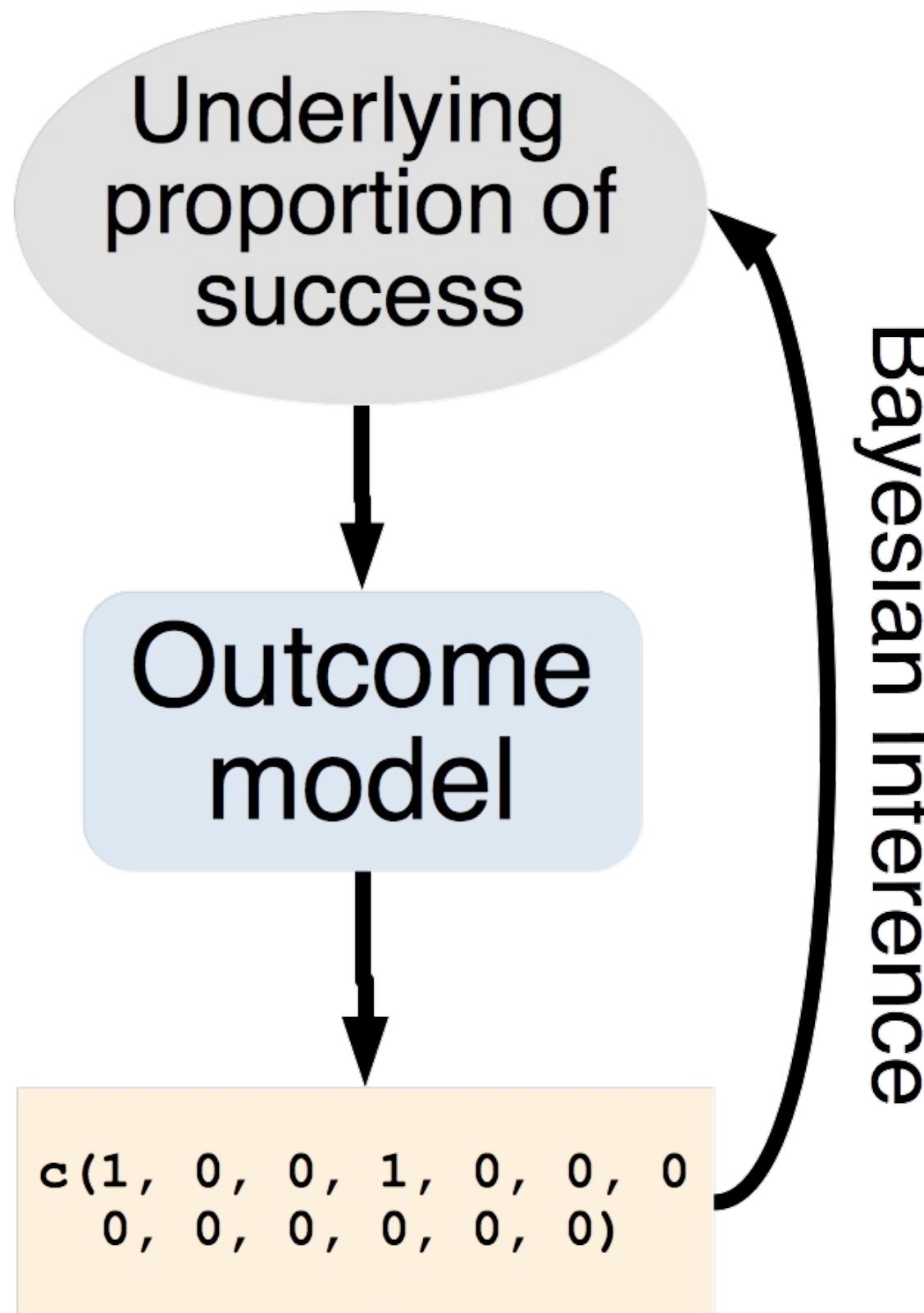
Rasmus Bååth  
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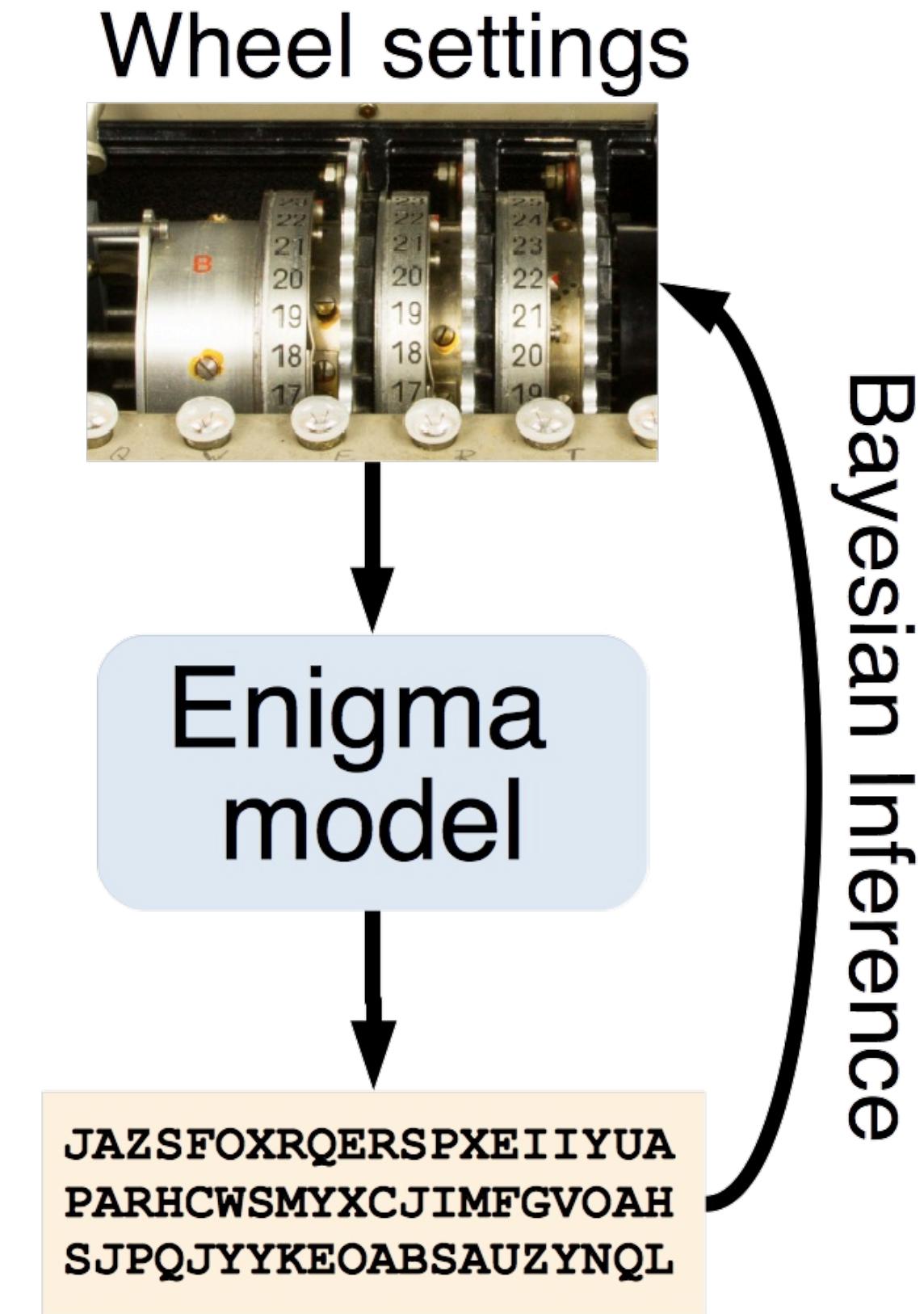
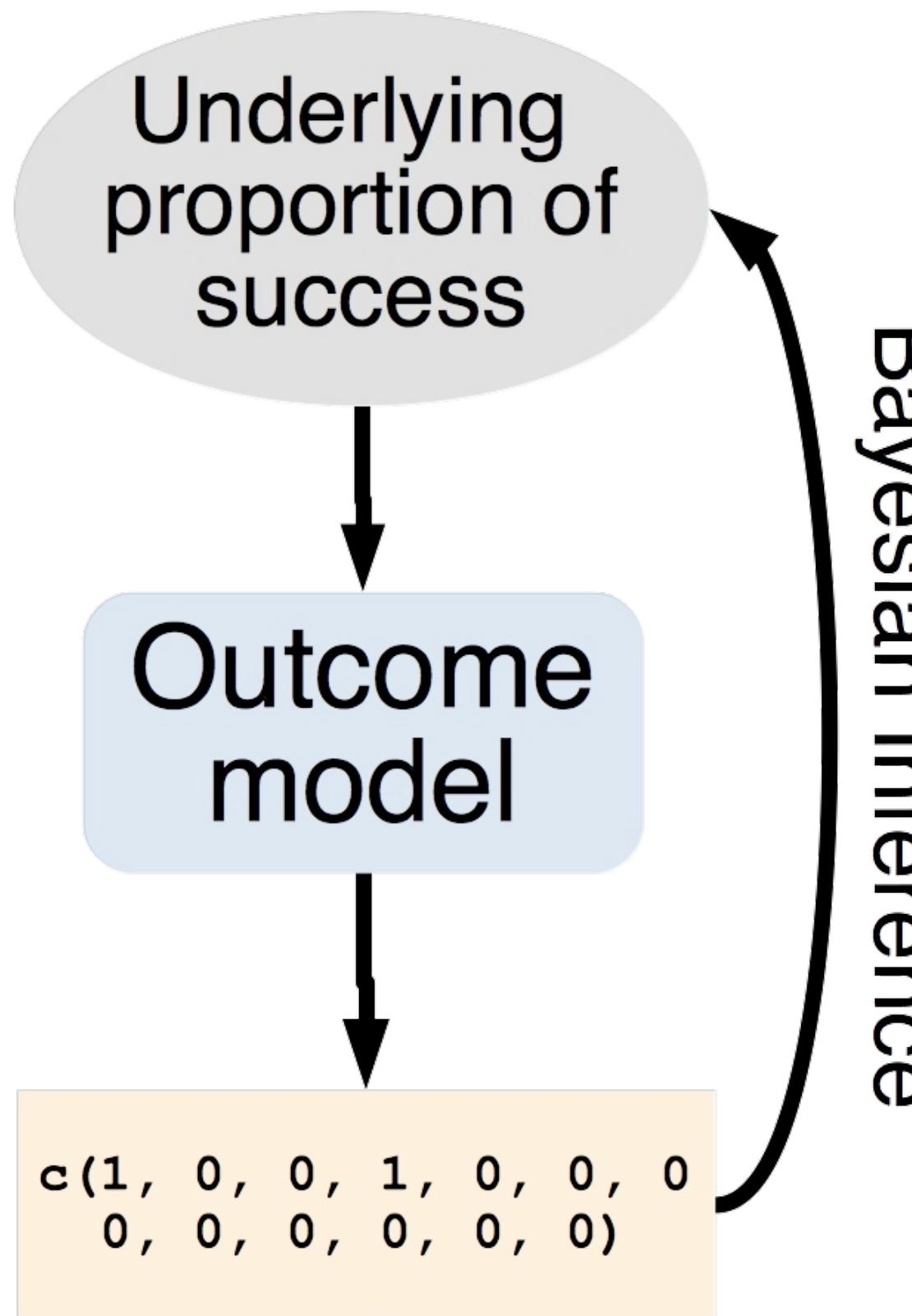
# The result of the zombie analysis

```
data = c(1, 0, 0, 1, 0, 0, 0,  
       0, 0, 0, 0, 0, 0)  
posterior <- prop_model(data)  
  
median(posterior)  
## 0.19  
quantile(posterior, c(0.05, 0.95))  
## 5%    95%  
## 0.06  0.39  
sum(posterior > 0.07) / length(posterior)  
## 0.93
```

# The result in a journal

Given the data of two cured and 11 relapsed zombies, and using the Bayesian model described before, there is a 90% probability that our drug cures between 6% and 39% of treated zombies. Further, there is 93% probability that our drug cures zombies at a higher rate than the current state of the art drug.







## FUNDAMENTALS OF BAYESIAN DATA ANALYSIS IN R

**Next up: How does  
Bayes work?**