

# Statistics for Machine Learning and Big Data

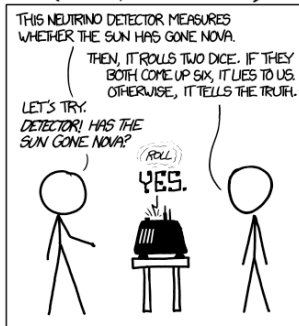
An Introduction

Part 4: Bayesians and frequentists

Jeff Abrahamson

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## DID THE SUN JUST EXPLODE? (IT'S NIGHT, SO WE'RE NOT SURE.)



### FREQUENTIST STATISTICIAN:



### BAYESIAN STATISTICIAN:



# Frequentists vs. Bayesians

*<https://xkcd.com/1132/>*

# Frequentists

# Flipping coins

You have a coin that when flipped ends up head with probability  $p$  and ends up tail with probability  $1 - p$ . (The value of  $p$  is unknown.)

Trying to estimate  $p$ , you flip the coin **14** times. It ends up heads **10** times.

Then you have to decide on the following event: “In the next two tosses we will get two heads in a row.”

Would you bet that the event will happen or that it will not happen?

*<http://www.behind-the-enemy-lines.com/2008/01/are-you-bayesian-or-frequentist-or.html>*

## Flipping coins, frequentist view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

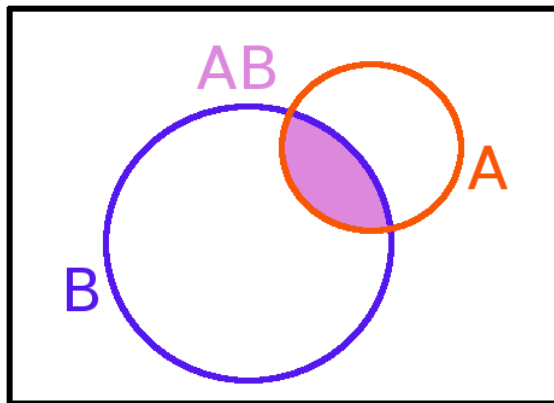
$$p = \frac{10}{14} \approx .714$$

$$\Pr(HH) = p^2 \approx .51$$

# Bayesians

# Review: conditional probability

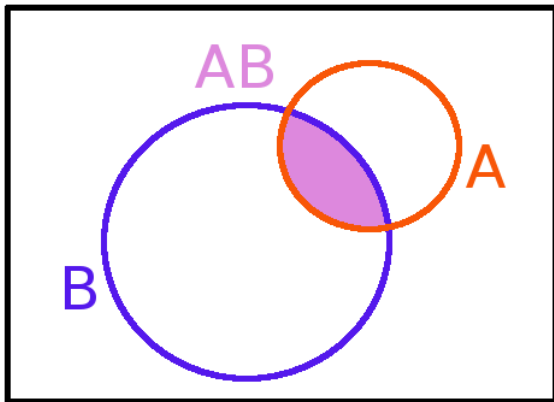
$$\Pr(A \mid B)$$





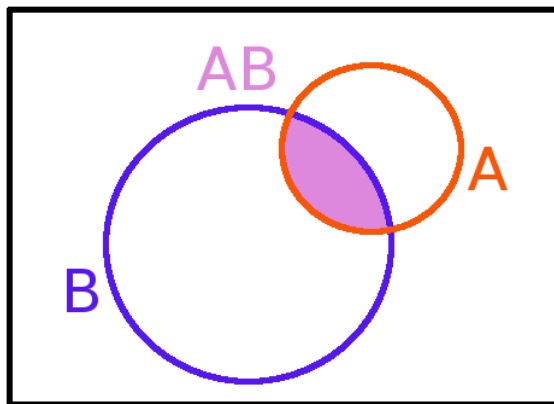
# Review: conditional probability

$$\Pr(A \mid B) = \frac{\Pr(A \cap B)}{\Pr(B)}$$



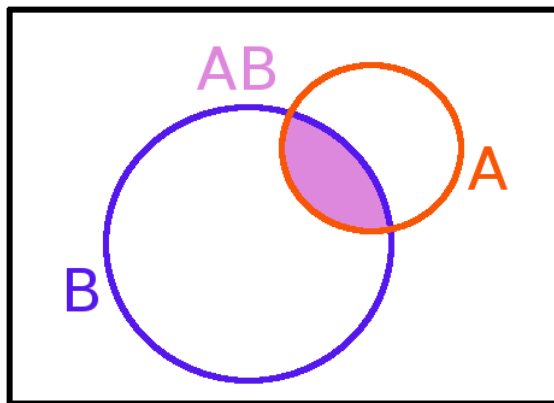
# Review: conditional probability

$$\Pr(A \mid B) \Pr(B) = \Pr(A \cap B)$$



# Review: conditional probability

$$\begin{aligned}\Pr(A \mid B) \Pr(B) &= \Pr(A \cap B) \\ &= \Pr(B \mid A) \Pr(A)\end{aligned}$$



## Review: Bayes theorem

$$\begin{aligned}\Pr(A \mid B) &= \frac{\Pr(A \cap B)}{\Pr(B)} \\ &= \frac{\Pr(B \mid A) \Pr(A)}{\Pr(B)}\end{aligned}$$

## Review: Bayes theorem

$$\begin{aligned}\Pr(A_j \mid B) &= \frac{\Pr(A_j \cap B)}{\Pr(B)} \\ &= \frac{\Pr(B \mid A_j) \Pr(A_j)}{\Pr(B)}\end{aligned}$$

*if  $A = \cup_j A_j$  covers  $A \cup B$  and is a non-overlapping cover of  $A$*

## Review: Bayes theorem

$$\begin{aligned}\Pr(A_j | B) &= \frac{\Pr(A_j \cap B)}{\Pr(B)} \\&= \frac{\Pr(B | A_j) \Pr(A_j)}{\Pr(B)} \\&= \frac{\Pr(B | A_j) \Pr(A_j)}{\sum_i \Pr(B \cap A_i)} \\&= \frac{\Pr(B | A_j) \Pr(A_j)}{\sum_i \Pr(B | A_i) \Pr(A_i)}\end{aligned}$$

*if  $A = \cup_i A_i$  covers  $A \cup B$  and is a non-overlapping cover of  $A$*

## Review: Bayes theorem

$$\begin{aligned}\Pr(A \mid B) &= \frac{\Pr(A \cap B)}{\Pr(B)} \\ &= \frac{\Pr(B \mid A) \Pr(A)}{\Pr(B)}\end{aligned}$$

## Review: Bayes theorem

$$\Pr(H \mid E) = \frac{\Pr(E \mid H) \Pr(H)}{\Pr(E)}$$



## Review: Bayes theorem

$$\Pr(H \mid E) = \frac{\Pr(E \mid H) \Pr(H)}{\Pr(E)} = \frac{\Pr(E \mid H)}{\Pr(E)} \cdot \Pr(H)$$

Here  $H$  is the hypothesis and  $E$  is evidence.

# Review: Bayes theorem

$$\Pr(H \mid E) = \frac{\Pr(E \mid H)}{\Pr(E)} \cdot \Pr(H)$$

*Prior probability of  $H$*

# Review: Bayes theorem

$$\Pr(H \mid E) = \frac{\Pr(E \mid H)}{\Pr(E)} \cdot \Pr(H)$$

Impact of  $E$  on  $H$

## Review: Bayes theorem

$$\Pr(H \mid E) = \frac{\Pr(E \mid H)}{\Pr(E)} \cdot \Pr(H)$$

Likelihood of observing  $E$  given  $H$

## Review: Bayes theorem

$$\Pr(H \mid E) = \frac{\Pr(E \mid H)}{\Pr(E)} \cdot \Pr(H)$$

*Marginal likelihood or model evidence*

# Review: Bayes theorem

$$\Pr(H \mid E) = \frac{\Pr(E \mid H)}{\Pr(E)} \cdot \Pr(H)$$

*Posterior probability of  $H$*

# Using Bayes theorem

If the evidence  $E$  doesn't fit  $H$ , we reject  $H$ .

# Using Bayes theorem

If the evidence  $E$  doesn't fit  $H$ , we reject  $H$ .

If the evidence  $E$  is extremely unlikely, we also reject  $H$ .



## Example: a baby!

A friend had a baby, but we don't know more.

A mutual friend says it's a boy and shows us a picture of a baby boy.

*[http://en.wikipedia.org/wiki/Bayesian\\_inference](http://en.wikipedia.org/wiki/Bayesian_inference)*

## Example: a baby!

A friend had a baby, but we don't know more.

A mutual friend says it's a boy and shows us a picture of a baby boy.

$E$ : picture of a baby boy

$H$ : the baby is a boy

$$\begin{aligned}\Pr(H \mid E) &= \frac{\Pr(E \mid H) \Pr(H)}{\Pr(E)} \\ &= \frac{(1)(\frac{1}{2})}{\frac{1}{2}} \\ &= 1\end{aligned}$$

## Example: a baby!

A friend had a baby, but we don't know more.

A mutual friend says it's a dog and shows us a picture to prove it.

## Example: a baby!

A friend had a baby, but we don't know more.

A mutual friend says it's a dog and shows us a picture to prove it.

$E$ : picture of a puppy

$H$ : the baby is a boy

$$\begin{aligned}\Pr(H \mid E) &= \frac{\Pr(E \mid H) \Pr(H)}{\Pr(E)} \\ &= \frac{(1)(0)}{\epsilon} \\ &= 0\end{aligned}$$

## Example: medical testing

A disease affects 0.1% of the population.  
The test is not perfect:

	+	-
Sick	.95	.05
Healthy	.01	.99

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## Exercise

## Example: medical testing

A disease affects 0.1% of the population.  
The test is not perfect:

	+	-
Sick	.95	.05
Healthy	.01	.99

$\Pr(S \mid -)$	.005%
$\Pr(S \mid +)$	8.6%
$\Pr(H \mid -)$	99.9%
$\Pr(H \mid +)$	91.3%

## Example: medical testing

A disease affects 0.1% of the population.

The test is not perfect:

	+	-
Sick	.95	.05
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$$\begin{aligned}\Pr(S \mid -) &= \frac{\Pr(- \mid S) \Pr(S)}{\Pr(-)} \\&= \frac{\Pr(- \mid S) \Pr(S)}{\Pr(- \mid H) \Pr(H) + \Pr(- \mid S) \Pr(S)} \\&= \frac{(.05)(.001)}{(.95)(.999) + (.05)(.001)} = .005\%\end{aligned}$$



## Example: medical testing

A disease affects 0.1% of the population.

The test is not perfect:

	+	-
Sick	.95	.05
Healthy	.01	.99

$$\begin{aligned}\Pr(S \mid +) &= \frac{\Pr(+ \mid S) \Pr(S)}{\Pr(+)} \\&= \frac{\Pr(+ \mid S) \Pr(S)}{\Pr(+ \mid H) \Pr(H) + \Pr(+ \mid S) \Pr(S)} \\&= \frac{(.95)(.001)}{(.01)(.999) + (.95)(.001)} = 8.6\%\end{aligned}$$

## Example: medical testing

A disease affects 0.1% of the population.

The test is not perfect:

	+	-
Sick	.95	.05
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$$\begin{aligned}\Pr(H \mid -) &= \frac{\Pr(- \mid H) \Pr(H)}{\Pr(-)} \\&= \frac{\Pr(- \mid H) \Pr(H)}{\Pr(- \mid H) \Pr(H) + \Pr(- \mid S) \Pr(S)} \\&= \frac{(.99)(.999)}{(.99)(.999) + (.05)(.001)} = 99.9\%\end{aligned}$$

## Example: medical testing

A disease affects 0.1% of the population.

The test is not perfect:

	+	-
Sick	.95	.05
Healthy	.01	.99

$$\begin{aligned}\Pr(H \mid +) &= \frac{\Pr(+ \mid H) \Pr(H)}{\Pr(+)} \\&= \frac{\Pr(+ \mid H) \Pr(H)}{\Pr(+ \mid H) \Pr(H) + \Pr(+ \mid S) \Pr(S)} \\&= \frac{(.01)(.999)}{(.01)(.999) + (.95)(.001)} = 91.3\%\end{aligned}$$

# Flipping coins

You have a coin that when flipped ends up head with probability  $p$  and ends up tail with probability  $1 - p$ . (The value of  $p$  is unknown.)

Trying to estimate  $p$ , you flip the coin **14** times. It ends up heads **10** times.

Then you have to decide on the following event: “In the next two tosses we will get two heads in a row.”

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# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

This is going to hurt.

# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

$p$  is now a distribution instead of a value.

Instead of ML estimate of  $p$ , we consider  $p$  as a random variable.

# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

$$\Pr(p \mid \text{data}) = \frac{\Pr(\text{data} \mid p) \Pr(p)}{\Pr(\text{data})}$$

# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

$$\Pr(p \mid \text{data}) = \frac{\Pr(\text{data} \mid p) \Pr(p)}{\Pr(\text{data})}$$



# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

$$\Pr(\text{data} \mid p) = \binom{14}{10} p^{10} (1 - p)^4$$

# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

Ignoring constants,

$$\Pr(p \mid \text{data}) \propto p^{10}(1 - p)^4 \Pr(p)$$

# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

What is  $\Pr(p)$ ?

Convenient to use the Beta distribution (a.k.a. the conjugate prior to the binomial distribution).

$$\text{Beta}(p; a, b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{a-1} (1-p)^{b-1}$$

For us, that means

$$\Pr(p) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{a-1} (1-p)^{b-1}$$

# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

$$\begin{aligned}\Pr(p \mid \text{data}) &\propto p^{10}(1-p)^4 p^{a-1}(1-p)^{b-1} \\ &\propto p^{10+a-1}(1-p)^{4+b-1} \\ &\propto \text{Beta}(p; a+10, b+4)\end{aligned}$$

# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

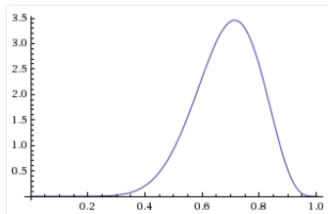
If we assume we know nothing about  $p$ , then let's say the prior is uniform, which is  $a = b = 1$ .

$$\Pr(p \mid \text{data}) \propto \text{Beta}(p; a + 10, b + 4) = \text{Beta}(p; 11; 5)$$

# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

We can at least plot  $\text{Beta}(p; 11; 5)$ .



# Flipping coins, Bayesian view

We saw 10 heads in 14 tosses. What's the probability of the next two tosses are both heads?

And let's just jump to the solution,

$$\begin{aligned}\Pr(HH \mid \text{data}) &= \int_0^1 \Pr(HH \mid p) \Pr(p \mid \text{data}) \, dp \\ &= \frac{B(13, 5)}{B(11, 5)} \approx .485\end{aligned}$$

# Summary

The frequentist bets on  $HH$ ,  $\Pr(HH) \approx .51$ .

The Bayesian bets against  $HH$ ,  $\Pr(HH) \approx .49$ .



# Fair coins

Suppose we flip 20 coins and get  $12H + 8T$ .

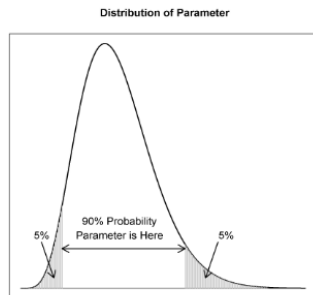
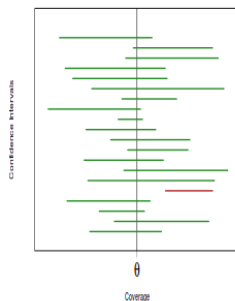
Exercise.

- What is the probability of being closer to the “truth” assuming the coin is fair?
- What if we got  $13H + 7T$ ?

# Confidence interval vs credible interval

## Interpretations of Confidence

- **Frequentist:** A collection of intervals with 90% of them containing the true parameter
- **Bayesian:** An interval that has a 90% chance of containing the true parameter.



# Break

# Questions?

`purple.com/talk-feedback`