

# Bayes' Rule

Foundations of Data Analysis

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## Brain Teaser: Trick Coin

I have four coins. Three are normal, one side heads, one side tails. One is a trick coin where both sides are heads. I pick one coin at random and flip it. If it shows heads, what is the probability that it is the trick coin?

# Bayes' Rule

Let's us “flip” a conditional:

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)}$$

# Deriving Bayes' Rule

Multiplication rule:

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

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

But these two equations are equal, so:

$$P(B \mid A)P(A) = P(A \mid B)P(B)$$

Dividing both sides by  $P(A)$  gives us:

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)}$$

# Trick Coin Example

$A$  = “heads”,  $B$  = “trick coin”

$$P(A \mid B) = 1.0$$

$$P(B) = 0.25$$

$$\begin{aligned} P(A) &= P(A \mid B)P(B) + P(A \mid B^c)P(B^c) \\ &= 1.0 \times 0.25 + 0.5 \times 0.75 = \frac{5}{8} \end{aligned}$$

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)} = \frac{1.0 \times 0.25}{5/8} = \frac{2}{5} = 0.4$$

# Random Variables

## Definition

A **random variable** is a function defined on a sample space,  $\Omega$ . Notation:  $X : \Omega \rightarrow \mathbb{R}$

- ▶ A random variable is neither random nor a variable.
- ▶ Just think of a random variable as assigning a number to every possible outcome.
- ▶ For example, in a coin flip, we might assign “tails” as 0 and “heads” as 1:

$$X(T) = 0, \quad X(H) = 1$$

# Dice Example

Let  $(\Omega, \mathcal{F}, P)$  be the probability space for rolling a pair of dice, and let  $X$  be the random variable that gives the sum of the numbers on the two dice. So,

$$X[(1, 2)] = 3, \quad X[(4, 4)] = 8, \quad X[(6, 5)] = 11$$

# Even Simpler Example

Most of the time the random variable  $X$  will just be the identity function. For example, if the sample space is the real line,  $\Omega = \mathbb{R}$ , the identity function

$$\begin{aligned} X : \mathbb{R} &\rightarrow \mathbb{R}, \\ X(s) &= s \end{aligned}$$

is a random variable.



# Defining Events via Random Variables

Setting a real-valued random variable to a value or range of values defines an event.

$$[X = x] = \{s \in \Omega : X(s) = x\}$$

$$[X < x] = \{s \in \Omega : X(s) < x\}$$

$$[a < X < b] = \{s \in \Omega : a < X(s) < b\}$$

# Joint Probabilities

Two binary random variables:

$C$  = cold / no cold = (1/0)

$R$  = runny nose / no runny nose = (1/0)

Event  $[C = 1]$ : “I have a cold”

Event  $[R = 1]$ : “I have a runny nose”

Joint event

$[C = 1] \cap [R = 1]$ : “I have a cold and a runny nose”

Notation for joint probabilities:

$$P(C = 1, R = 1) = P([C = 1] \cap [R = 1])$$

# Cold Example: Probability Tables

Two binary random variables:

$C$  = cold / no cold = (1/0)

$R$  = runny nose / no runny nose = (1/0)

Joint probabilities:

		$C$	
		0	1
$R$	0	0.40	0.05
	1	0.30	0.25

## Cold Example: Marginals

		$C$	
		0	1
$R$	0	0.50	0.05
	1	0.20	0.25

Marginals:

$$P(R = 0) = 0.55, \quad P(R = 1) = 0.45$$

$$P(C = 0) = 0.70, \quad P(C = 1) = 0.30$$

## Cold Example: Conditional Probabilities

		$C$		
		0	1	
$R$	0	0.50	0.05	0.55
	1	0.20	0.25	0.45
		0.7	0.3	

Conditional Probabilities:

$$P(C = 0 \mid R = 0) = \frac{P(C = 0, R = 0)}{P(R = 0)} = \frac{0.50}{0.55} \approx 0.91$$

$$P(C = 1 \mid R = 1) = \frac{P(C = 1, R = 1)}{P(R = 1)} = \frac{0.25}{0.45} \approx 0.56$$

# **Probabilistic Logic**

# Deductive Logic

How about *modus tollens*?

$A \Rightarrow B$

If it's raining, then the sidewalk is wet.

$B$  is false

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The sidewalk is not wet.

---

$A$  is false

It is not raining.

# Conditional Probability as Logic

Logic	Probability
$A, B$ are propositions	$A, B$ are events
$A \Rightarrow B$	$P(B   A) > P(B)$

Weak form of *modus ponens*:

If  $A$  is true,  $B$  becomes more likely.

$A$  is true.

---

$B$  is more likely.



# Bayesian Logic

Unlike Boolean logic, we can *flip* the implication!

$$P(B \mid A) > P(B) \quad \text{given}$$

$$\frac{P(A)P(B \mid A)}{P(B)} > P(A) \quad \text{multiply by } \frac{P(A)}{P(B)}$$

$$P(A \mid B) > P(A) \quad \text{Bayes' Rule}$$

## Flipping the implication: $P(B \mid A) > P(B)$

If  $A$  is true,  $B$  becomes more likely.

$B$  is true.

---

$A$  is more likely.

If it's raining, then the sidewalk is more likely to be wet.

The sidewalk is wet.

---

It's more likely to be raining.

## Exercise for You

Given that  $P(B \mid A) > P(B)$ , show that:

1. If  $\bar{B}$  happens,  $A$  becomes less likely.  
(weak form of *modus tollens*)
2. If  $\bar{A}$  happens,  $B$  becomes less likely.

# Final Bayesian Logic Rules

Given that  $P(B \mid A) > P(B)$ , analagous to  $A \Rightarrow B$ , we have four rules:

1. If  $A$ , then  $B$  is more likely (weak *modus ponens*)
2. If  $\bar{B}$ , then  $A$  is less likely (weak *modus tollens*)
3. If  $B$ , then  $A$  is more likely (no logical equivalent)
4. If  $\bar{A}$ , then  $B$  is less likely (no logical equivalent)

## Cold Example

		$C$		
		0	1	
$R$	0	0.50	0.05	0.55
	1	0.20	0.25	0.45
		0.7	0.3	

Remember:

$$P(C) = 0.3$$

$$P(C | R) = 0.56$$

What if I didn't give you the full table, but just:

$$P(R | C) = 0.83 \quad > \quad P(R) = 0.45$$

What can you say about the increase

$$P(C | R) > P(C)?$$

## Cold Example

Notice, having a cold *increases* my chance for a runny nose by the factor,

$$\frac{P(R \mid C)}{P(R)} = \frac{0.83}{0.45} = 1.85$$

How does such a ratio increase if I flip the conditional?

$$\begin{aligned}\frac{P(C \mid R)}{P(C)} &= \frac{P(C \cap R)}{P(R)P(C)} \\ &= \frac{P(R \mid C)}{P(R)} \\ &= 1.85\end{aligned}$$