Ling/CSC 439/539 Introduction to Probability Theory

Fall 2017

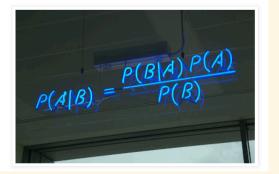
Take-away

Probability Theory Summary

- Representing conditional probabilities using contingency tables and probability trees
- ► The chain rule
- Bayes rule
- ► The law of total probability (aka the partition rule)
- Independent events

Motivation

Eleven Equations True Computer Science Geeks Should (at Least Pretend to) Know



http://www.elegantcoding.com/2011/11/ eleven-equations-true-computer-science.html

How juries are fooled by statistics

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http://www.ted.com/talks/lang/eng/peter_donnelly_shows_how_stats_fool_juries.html?
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Outline

Examples of Conditional Probabilities

Conditional Probability

Bayes' Rule

Independence

► How would you define "probability"?

O, A, B, and AB.

► Human blood is classified by the presence or absence of two antigens, called A and B. This gives rise to four types:

		Antigen B		
		Absent	Present	Marginal
Antigen A	Absent	0.44	0.10	0.54
	Present	0.42	0.04	0.46
	Marginal	0.86	0.14	1.00

Table: Probability Estimates for U.S. Blood Types

► Let *A* be the event "presence of antigen A" and *B* be the event "presence of antigen B"

Example: Blood Types

		Antigen B		
		Absent	Present	Marginal
Antigen A	Absent	0.44	0.10	0.54
	Present	0.42	0.04	0.46
	Marginal	0.86	0.14	1.00

Table: Probability Estimates for U.S. Blood Types

► Exercise!

		Child		
		Buck.	Unbuck.	Marginal
Parent	Buck.	0.48	0.12	0.60
	Unbuck.	0.10	0.30	0.40
	Marginal	0.58	0.42	1.00

Table: Probability Estimates for Seat Belt Status

► What is the (estimated) probability of the event "Child is Buckled"?

		Child		
		Buck.	Unbuck.	Marginal
Parent	Buck.	0.48	0.12	0.60
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Table: Probability Estimates for Seat Belt Status

- ▶ What is the (estimated) probability of the event "Child is Buckled"?
- ▶ What should our new estimate be if we know that ("given that") "Parent is Buckled"?

- A store owner discovers that some of her employees have taken cash. She decides to use a lie detector to discover
- Suppose that 10% of employees stole, but 100% say they didn't.
- ➤ The lie detector buzzes 80% of the time that someone lies, and 20% of the time that someone is telling the truth.
- If the detector buzzes, what's the probability that the person was lying?

who they are.

		Lie Detector Result		
		Pass	Buzz!!	Marginal
Employee	Honest			
	Dishonest!!			
	Marginal			

- ▶ 10% of employees are dishonest.
- ▶ The lie detector has the correct response 80% of the time in both cases.

		Lie Detector Result		
		Pass	Buzz!!	Marginal
Employee	Honest			0.9
	Dishonest!!			0.1
	Marginal			1.0

		Lie Detector Result		
		Pass	Buzz!!	Marginal
Employee	Honest	$0.8 \times ?$	0.2 × ?	0.9
	Dishonest!!	$0.2 \times ?$	$0.8 \times ?$	0.1
	Marginal			1.0

		Lie Detector Result		
		Pass	Buzz!!	Marginal
Employee	Honest	0.8×0.9	0.2×0.9	0.9
	Dishonest!!	0.2×0.1	0.8×0.1	0.1
	Marginal			1.0

		Lie Detector Result		
		Pass	Buzz!!	Marginal
Employee	Honest	0.72	0.18	0.9
	Dishonest!!	0.02	0.08	0.1
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Employee	Honest	0.72	0.18	0.9
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Table: Lie Detector Probabilities

What is the probability of the detector buzzing?

		Lie Detector Result		
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Employee	Honest	0.72	0.18	0.9
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- ► What is the probability of the detector buzzing?
- ► If the detector buzzes, what's the probability that the person was lying?

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Conditional Probability

- ▶ After we know *B* happened, we are only choosing from within *B*.
- ► The set *B* becomes our new sample space, with an updated probability of 1!
- ▶ Instead of asking "In what proportion of *S* is *D* true?", we now ask "In what proportion of *B* is *D* true?"

- ▶ We calculate conditional *proportions* from frequencies by restricting attention to ("conditioning on") a particular category, and dividing the joint frequency by the restricted total.
- Conditional probability is defined in exactly the same way, replacing proportions with probabilities.

Conditional Probability

To find the probability of *A given B*, consider the ways *A* can occur *in the context of B* (i.e., $A \cap B$), out of all the ways *B* can occur.

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Joint Probability from Conditional Probability

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► We can easily derive this:

Joint Probability from Conditional Probability

▶ We can rearrange the formula for conditional probability.

Conditional Probability

Knowing that

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

We can easily derive this:

The "Chain Rule" of Probability

For any events, *A* and *B*, the joint probability $P(A \cap B)$ can be computed as

$$P(A \cap B) = P(A|B) \times P(B)$$

Or, since $P(A \cap B) = P(B \cap A)$

$$P(A \cap B) = P(B|A) \times P(A)$$

Example: Lie Detector

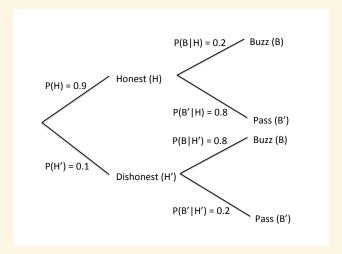
▶ A store owner discovers that some of her employees have taken cash. She decides to use a lie detector to discover who they are.

Conditional Probability

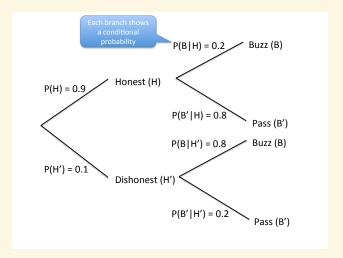
- Suppose that 10% of employees stole, but 100% say they didn't.
- ► The lie detector buzzes 80% of the time that someone lies, and 20% of the time that someone is telling the truth.
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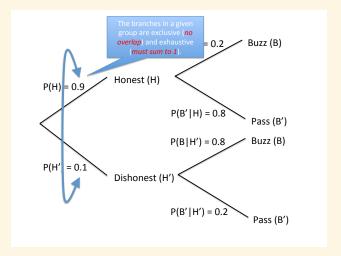
Probability tree == decision tree with probabilities attached to each decision

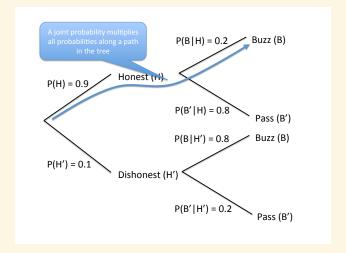
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Conditional Probability







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- \blacktriangleright What is P(Dishonest|Buzz)?

Let's View These Rules Using Probability Trees

- ▶ What is $P(Pass \cap Dishonest)$?
- ▶ What is *P*(Buzz)? Hint: which branches end up with the Buzz event?

- \blacktriangleright What is P(Dishonest|Buzz)?
- Computing conditional probabilities going against the flow of the tree is a bit tricky. We will see a better way next!

Suppose I want to sample a student. 16% of the students are Nutrition Science majors. Of the Nutrition Science majors, 54% are female.

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- What's the probability that I select a female Nutrition Science major?
- ▶ Let *N* be the event of selecting a Nutrition Science major. Let *F* be the event of selecting a female. What probabilities can I write down?
- What is the probability tree for this problem?

▶ Duncan's Donuts are looking into the probabilities of their customers buying donuts *and* coffee. Build the probability tree for them knowing that P(Donuts) = 3/4, P(Coffee|Donuts') = 1/3 and $P(Donuts \cap Coffee) = 9/20$.

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- ▶ *P*(*Donuts*|*Coffee*)?

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So altogether, I have

$$P(N|F) = \frac{P(N)P(F|N)}{P(F)} = \frac{0.54 \times 0.16}{0.55}$$

We can reverse conditional probabilities using Bayes' Rule

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- Remember: use Bayes Rule to reverse conditional probabilities.
- ▶ Useful to infer causes from effects (inferential statistics)!
- Very easy to derive from the chain rule, so remember that first.

Bayes' Rule

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

- ► The **prior** (baseline) probability of having Lycanthropy is 1 in 1000.
- ▶ A test has been developed which gives a positive result for 9 in 10 werewolves and 1 in 20 non-werewolves.
- What's the conditional probability of having Lycanthropy, given a positive test result?

Bayes' Rule

For any two events, A and B, we have

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- ▶ What's the conditional probability of having Lycanthropy, given a positive test result: P(L|T) = ?

Bayes' Rule for Werewolves

We have

$$P(L|T) = \frac{P(L)P(T|L)}{P(T)}$$

▶ Do we have everything we need?

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Bayes' Rule for Werewolves

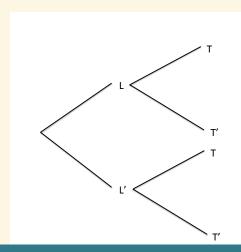
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- Do we have everything we need?
- We know P(L) = 1/1000, P(T|L) = 9/10. We're missing P(T).
- We also have P(T|L'), which we haven't used yet...
- Can we find P(T) from what we have?

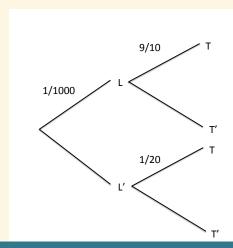
- Two equivalent ways of doing it:
 - Contingency tables
 - Probability trees
- Use whichever is easiest for you.
 - In this course we will use probability trees

$$P(L) = 1/1000, P(T|L) = 9/10, P(T|L') = 1/20$$



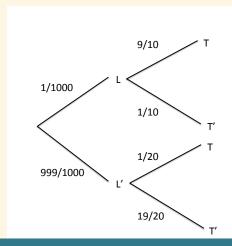
To the Probability Tree!

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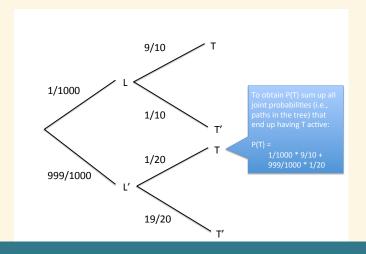
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 - 2. To find the joint probabilities, we multiplied a marginal by a conditional, according to the "chain rule".

The Law of Total Probability

For any events A and B, we have $P(B) = P(A \cap B) + P(A' \cap B)$. Together with two applications of the chain rule, this gives us

$$P(B) = P(A)P(B|A) + P(A')P(B|A')$$

Bayes' Rule Revisited

Incorporating the Law of Total Probability into Bayes' Rule, we get

Bayes Rule (version 2)

For any events *A* and *B*, we have

$$P(A|B) = \frac{P(A \cap B)}{P(A \cap B) + P(A' \cap B)}$$
$$= \frac{P(A)P(B|A)}{P(A)P(B|A) + P(A')P(B|A')}$$

Independence

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- ▶ 10% of employees are dishonest.
- ▶ There's a 5% chance of rain tomorrow.
- ▶ What's the probability an employee is dishonest if it rains tomorrow?
- Probably your intuition is that one conveys no information about the other. What does this mean about the relationship between the conditional probability of D given R, and the marginal probability of D?

Independent Events

We say that event *A* is **independent** of event *B* if conditioning on B does not change the probability of A, that is if

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We say that event *A* is **independent** of event *B* if conditioning on *B* does not change the probability of *A*, that is if

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▶ If the employee is dishonest, what's the probability that it will rain tomorrow?

Independent Events

We say that event *A* is **independent** of event *B* if conditioning on *B* does not change the probability of *A*, that is if

$$P(A|B) = P(A)$$

- ► If the employee is dishonest, what's the probability that it will rain tomorrow?
- ▶ It seems like independence should be symmetric. Is it?

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Probabilistic Independence

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▶ So independence is in fact symmetric.

▶ It turns out that if *A* and *B* are independent, then their joint probability has a particularly simple form

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$$= P(A)P(B)$$

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Independence (version 2)

If A and B are independent events, then

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Independence (version 2)

If A and B are independent events, then

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▶ What is $P(A \cup B)$ for independent events?

1. *E*: First coin comes up heads, *F*: Second coin comes up heads

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- 3. *E*: Sample a nutrition science major, *F*: Sample a female

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- 2. *E*: First coin comes up heads, *F*: First coin comes up tails
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- 2. *E*: First coin comes up heads, *F*: First coin comes up tails
- 3. *E*: Sample a nutrition science major, *F*: Sample a female
- 4. *E*: Draw a yellow ball on first pick, *F*: Draw a yellow ball on second pick (with replacement)
- 5. *E*: Draw a yellow ball on first pick, *F*: Draw a yellow ball on second pick (without replacement)

1. We remove socks from a drawer with black and white, one after another, until we get a match. Is the color of the first sock independent of the color of the second?

- 1. We remove socks from a drawer with black and white, one after another, until we get a match. Is the color of the first sock independent of the color of the second?
- 2. E_1 : it rains today. E_2 : today is Thursday.

In-class Exercise: the Case of the Two Classes

- ► The Health Club is wondering how best to market their new yoga class, and the Head of Marketing wonders if someone who goes swimming is more likely to go to a yoga class. "Maybe we could offer some sort of discount to the swimmers to get them to try our yoga."
- ► The CEO disagrees: "I think you're wrong. I think people who go swimming and people who go to yoga are independent. I don't think people who go swimming are more likely to do yoga than anybody else."
- ► They ask a group of 96 people whether they go to swimming or yoga classes. Out of this group, 32 go to yoga and 72 go swimming. 24 people go to both.
- Are the two classes dependent or independent?

Practice Exercise: the Absent-minded Diners

- Three friends decide to go out for a meal, but they forget where they're going to meet.
- ► Fred decides to throw a coin. If it lands heads, he'll go to the diner; tails, and he'll go to the Italian restaurant.
- George throws a coin, too: heads, it's the Italian restaurant; tails, it's the diner.
- Ron decides he'll just go to the Italian restaurant because he likes the food.
- ▶ What's the probability all three friends meet?
- ▶ What's the probability one of them eats alone?

Take-away

Probability Theory Summary

- Representing conditional probabilities using contingency tables and probability trees
- ► The chain rule
- Bayes rule
- ► The law of total probability (aka the partition rule)
- Independent events

For more see this course + textbook:

Math 363:

http://math.arizona.edu/~jwatkins/math363f15.htm