

Data Science: Jordan Boyd-Graber

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SLIDES ADAPTED FROM DAVE BLEI AND LAUREN HANNAH

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### Context

- Data science is often worried about "if-then" questions
  - If my e-mail looks like this, is it spam?
  - If I buy this stock, will my portfolio improve?
- Since data science uses the language of probabilities, we need conditional probabilities (continuing probability intro)
- Also need to combine distributions

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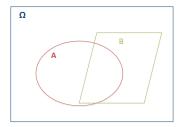
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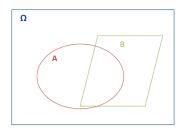
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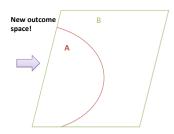
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### Independence (Reminder)

Random variables X and Y are independent if and only if P(X = x, Y = y) = P(X = x)P(Y = y). How does this interact with conditional probabilities?

Conditional probabilities equal unconditional probabilities with independence:

- P(X = x | Y) = P(X = x)
- Knowing Y tells us nothing about X

# Example

What is the probability that the sum of two dice is six given that the first is greater than three?

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# Example

- A ≡ First die
- $B \equiv$  Second die

	B=1	B=2	B=3	B=4	B=5	B=6
		3	4	5	6	7
A=2	3	4	5	6	7	8
A=3	4	5	6	7	8	9
A=4	5	6	7	8	9	10
A=5	6	7	8	9	10	11
A=6	7	8	9	10	11	12

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$$P(A > 3 \cap B + A = 6) =$$
  
 $P(A > 3) =$   
 $P(A > 3 \mid B + A = 6) =$ 

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$$P(A > 3 \cap B + A = 6) = \frac{2}{36}$$
  
 $P(A > 3) =$   
 $P(A > 3 | B + A = 6) =$ 

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$$P(A > 3) = \frac{3}{6}$$

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- B ≡ Second die

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	B=1	B=2	B=3	B=4	B=5	B=6	$B(4 > 2) = \frac{3}{2}$
A=1	2	3	4	5	6	7	$- \qquad P(A > 3) = \frac{3}{6}$
A=2	3	4	5	6	7	8	2 2 4
A=3	4	5	6	7	8	9	$P(A > 3   B + A = 6) = \frac{\frac{2}{36}}{\frac{3}{6}} = \frac{2}{3}$
A=4	5	6	7	8	9	10	6
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# Example

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- B ≡ Second die

$$P(A > 3 \cap B + A = 6) = \frac{2}{36}$$

	B=1	B=2	B=3	B=4	B=5	B=6	$P(A > 3) = \frac{3}{6}$
A=1	2	3	4	5	6	7	0
A=2	3	4	5	6	7	8	$P(A > 3   B + A = 6) = \frac{\frac{2}{36}}{\frac{3}{6}} = \frac{2}{36} \frac{6}{3}$
A=3	4	5	6	7	8	9	$F(A > 5 B + A = 0) = \frac{3}{\frac{3}{6}} = \frac{36}{36} = \frac{3}{3}$
A=4	5	6	7	8	9	10	1
A=5	6	7	8	9	10	11	$=\frac{1}{9}$
A=6	7	8	9	10	11	12	Ť

### **Combining Distributions**

- Somtimes distributions you have aren't what you need
  - □ Conditional → joint (chain)
  - Reverse conditional direction (Bayes')

#### The chain rule

 The definition of conditional probability lets us derive the chain rule, which let's us define the joint distribution as a product of conditionals:

$$P(X,Y) = P(X,Y)\frac{P(Y)}{P(Y)}$$

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- For example, let Y be a disease and X be a symptom. We may know P(X|Y) and P(Y) from data. Use the chain rule to obtain the probability of having the disease and the symptom.
- In general, for any set of *N* variables

$$P(X_1,...,X_N) = \prod_{n=1}^N P(X_n|X_1,...,X_{n-1})$$

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

- 1. Start with P(A|B)
- Change outcome space from B to  $\Omega$
- Change outcome space again from  $\Omega$  to A

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- 1. Start with P(A|B)
- Change outcome space from B to  $\Omega$ : P(A|B)P(B)
- Change outcome space again from  $\Omega$  to A:  $\frac{P(A|B)P(B)}{P(A)}$





