## Unit 2: Probability and distributions

1. Probability and conditional probability

GOVT 3990 - Spring 2020

Cornell University

#### Outline

#### 1. Main ideas

- 1. Disjoint and independent do not mean the same thing
- 2. Application of the addition rule depends on disjointness of events
- 3. Probability trees are useful for conditional probability calculations
- 4. Bayesian inference: start with a prior, collect data, calculate posterior, make a decision or iterate
  - 5. Posterior probability and p-value do not mean the same thing

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- ▶ If A and B are *independent events*, having information on A does not tell us anything about B (and vice versa)
  - If A and B are independent:
    - $P(A \mid B) = P(A)$
    - $P(A \text{ and } B) = P(A) \times P(B)$

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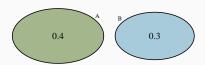
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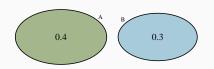
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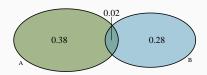
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=  $0.4 + 0.3 - 0 = 0.7$ 



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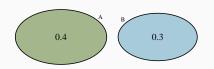
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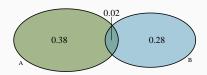
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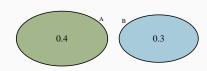
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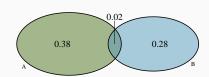
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$$P(A \text{ or } B)$$
  
=  $P(A) + P(B) - P(A \text{ and } B)$   
=  $0.4 + 0.3 - 0.02 = 0.68$ 



Application exercise: 2.1 Probability and conditional probability

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#### 1. Probability trees are useful for conditional probability calculations

- ► Probability trees are useful for organizing information in conditional probability calculations
- ► They're especially useful in cases where you know P(A | B), along with some other information, and you're asked for P(B | A)

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- ► These new beliefs are called posterior beliefs (or posterior probabilities), because they are post-data.
- ▶ You can iterate this process.

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- ▶ Ultimate goal: come to a class consensus about whether the die on the cellphone or the die on the computer is the "good die"
- ▶ We will start with priors, collect data, and calculate posteriors, and make a decision or iterate until we're ready to make a decision

## Prior probabilities

- $\blacktriangleright$  At each roll I tell you whether you won or not (win  $= \geq 4)$ 
  - P(win | 6-sided die) =  $0.5 \rightarrow bad$  die
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► Since initially you have no idea which is true, you can assign equal *prior probabilities* to the hypotheses

 $P(H_1 \text{ is true}) = 0.5$ 

 $P(H_2 \text{ is true}) = 0.5$ 

#### Rules of the game

- ➤ You won't know which die I'm holding in which hand, left (Computer) or right (Cellphone). left = YOUR left
- You pick die (L or R), I roll it, and I tell you if you win or not, where winning is getting a number ≥ 4. If you win, you get a piece of candy. If you lose, I get to keep the candy.
- ▶ We'll play this multiple times with different contestants.
- ▶ I will not swap the sides the dice are on at any point.
- You get to pick how long you want play, but there are costs associated with playing longer.

#### Hypotheses and decisions

	Truth	
Decision	L good, R bad	L bad, R good
Pick L	You get candy!	You lose all the candy :(
Pick R	You lose all the candy :(	You get candy!

## Sampling isn't free!

At each trial you risk losing pieces of candy if you lose (the die comes up < 4). Too many trials means you won't have much candy left. And if we spend too much class time and we may not get through all the material.

## Data and decision making

	Choice (L or R)	Result (win or loss)
Roll 1		
Roll 2		
Roll 3		
Roll 4		
Roll 5		
Roll 6		
Roll 7		

What is your decision? How did you make this decision?

#### Bayesian probability and updating our priors

Most companies drug test their employees before they start employment, and sometimes regularly during their employment as well. Suppose that a drug test for an illegal drugs is 97% accurate in the case of a user of that drug, and 92% accurate in the case of a non-user for that drug. Suppose also that 5% of the entire population uses that drug.

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  - $P(drug\ user) = 0.05$

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