# **Unit 2: Probability and distributions**

# 2. Bayes' theorem and Bayesian inference

Sta 101 - Spring 2015

Duke University, Department of Statistical Science

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#### 2. Main ideas

- Probability trees are useful for conditional probability calculations
- 2. Bayesian inference: start with a prior, collect data, calculate posterior, make a decision or iterate
- Posterior probability and p-value do not mean the same thing

# 3. Summary

#### Announcements

Review Project 1 assignment and start thinking about data you might want to find / collect for your project

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#### 2. Main ideas

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# 3. Summary

# 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)

#### 2. Main ideas

- Probability trees are useful for conditional probability calculations
- 2. Bayesian inference: start with a prior, collect data, calculate posterior, make a decision or iterate
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# 3. Summary

2. Bayesian inference: start with a prior, collect data, calculate posterior, make a decision or iterate

We'll play a game to demonstrate this approach...

# Dice game

- ▶ Two dice: 6-sided and 12-sided
  - I keep one die in my left hand and one die on the right

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- Ultimate goal: come to a class consensus about whether the die on the left or the die on the right 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

- ▶ At each roll I tell you whether you won or not (win =  $\geq 4$ )
  - P(win on 6-sided die) = 0.5 → bad die
  - P(win on 12-sided die) = 0.75 → good die

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- The two competing claims are
  - H<sub>1</sub>: Good die is in left hand H<sub>2</sub>: Good die is in right hand
- Since initially you have no idea which is true, you can assign equal prior probabilities to the hypotheses

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P(H_1 \text{ is true}) = 0.5
P(H_2 \text{ is true}) = 0.5
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- ▶ 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.

	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?

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$$P(hypothesis data) = \frac{P(hypothesis and data)}{P(data)}$$

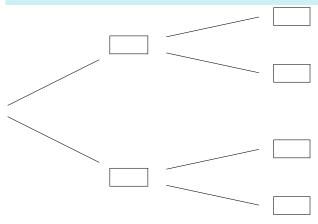
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$$P(\text{hypothesis data}) = \frac{P(\text{hypothesis and data})}{P(\text{data})}$$

$$= \frac{P(\text{data} | \text{hypothesis}) \times P(\text{hypothesis})}{P(\text{data})}$$

Calculate the posterior probability for the hypothesis chosen in the first roll, and discuss how this might influence your decision for the next roll.



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# Summary

# 3. Posterior probability and p-value do not mean the same thing

- p-value : P(observed or more extreme outcome | null hypothesis is true)
  - This is roughly P(data | hypothesis)
- posterior : P(hypothesis | data)
- Bayesian approach avoids the counter-intuitive Frequentist p-value for decision making, and more advanced Bayesian techniques offer flexibility not present in Frequentist models
- ► Watch out!

A good prior helps, a bad prior hurts, but the prior matters less the more data you have.

### Application exercise: 2.2 Bayesian inference for drug testing

See the course website for instructions.

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