

Big Data and Security

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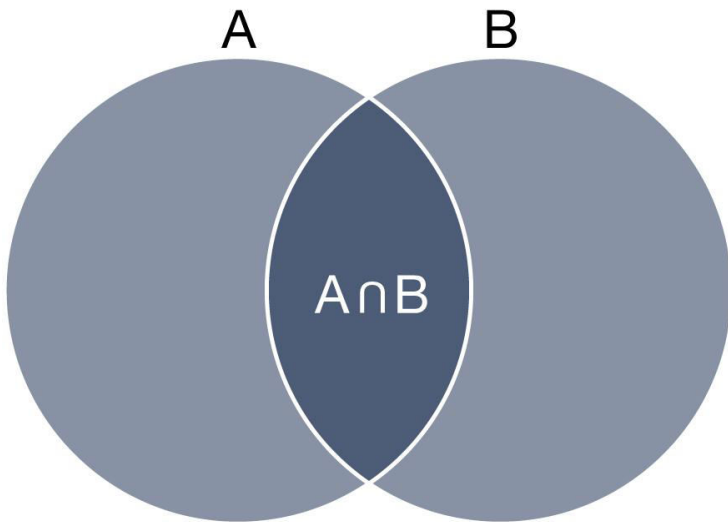
Lecturer

Sam Nunn School of International Affairs

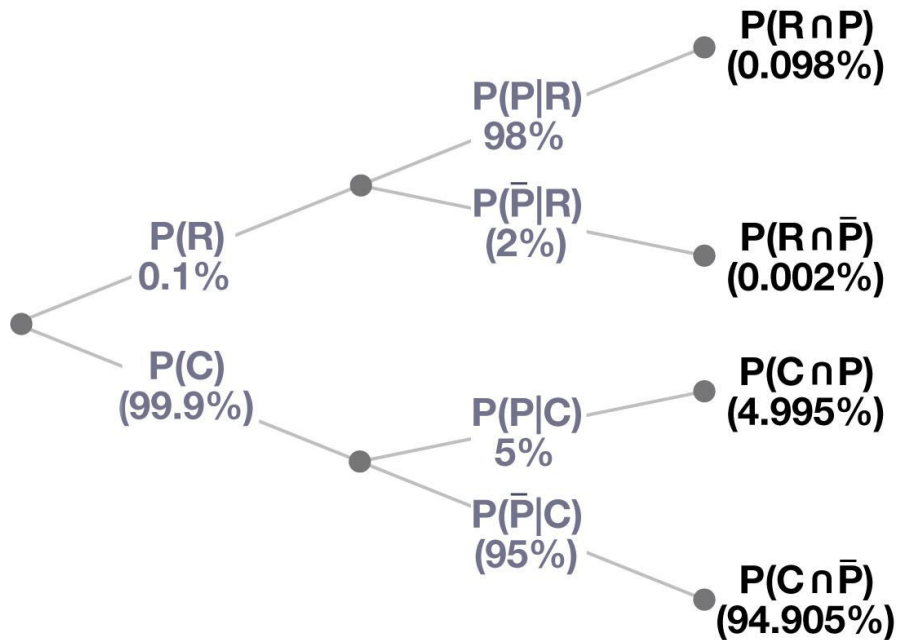
Probability and Bayes' Rule

Total Probability

- There are two ways to make A:
 - A and B
 - A and B^C



Conditional Probability



Bayes' Rule

- Bayes' rule provides a way to incorporate new information into existing prior beliefs to form updated beliefs
- What are the chances that B will happen, given that A happened.
- Rule:

$$P(B|A) = \frac{P(A|B) \cdot P(B)}{P(A)} = \frac{P(A|B) \cdot P(B)}{P(A|B)P(B) + P(A|B^C)P(B^C)}$$

Bayes' Rule Example: Context Clues

- There's an incoming Georgia Tech undergrad, and we're trying to predict his or her major
- Somebody mentions that the person is really interested in liberal arts
 - What do you think he or she will major in?

Bayes' Rule Example: Context Clues

- There's an incoming Georgia Tech undergrad, and we're trying to predict his or her major
- Somebody mentions that the person is really interested in liberal arts
 - What do you think he or she will major in?
- We want to calculate the probability of majoring in liberal arts at Georgia Tech given an interest in liberal arts
 - A = person is interested in liberal arts
 - B = person majors in liberal arts
- Assume event probabilities:
 - $P(B) = 622/14,558 = .042$
 - $P(A|B) = .95$
 - $P(A|B^C) = .1$

Bayes' Rule Example

$$P(B|A) = \frac{P(A|B) \cdot P(B)}{P(A|B)P(B) + P(A|B^c)P(B^c)}$$

$$= \frac{(.95) \cdot (.042)}{(.95) \cdot (.042) + (.1) \cdot (.958)}$$

$$P(B|A) = .29$$

- Now it is more likely (.29 instead of .042) that this student will major in liberal arts
- But it's still more likely they won't major in liberal arts

How Does This Help Us Modeling?

- First, we have a model for the data
- We form **prior distribution** assumptions about our parameters of interest: $p(\text{parameters})$
 - This takes into account our prior beliefs about how likely particular things are to be true
- We observe data, so we can use Bayes' rule to calculate:

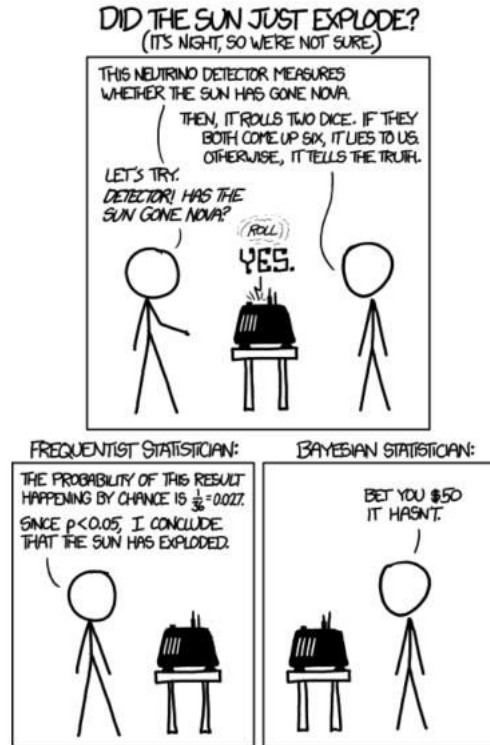
$$p(\text{parameters}|\text{data}) = \frac{p(\text{data}|\text{parameters}) \cdot p(\text{parameters})}{p(\text{data})}$$

- $p(\text{parameters})$ is just our prior probability distribution
- $p(\text{data}|\text{parameters})$ is just plugging in each data point to our probability distribution
- $p(\text{data})$ is all the different ways the data could have been generated

Frequentists vs. Bayesians

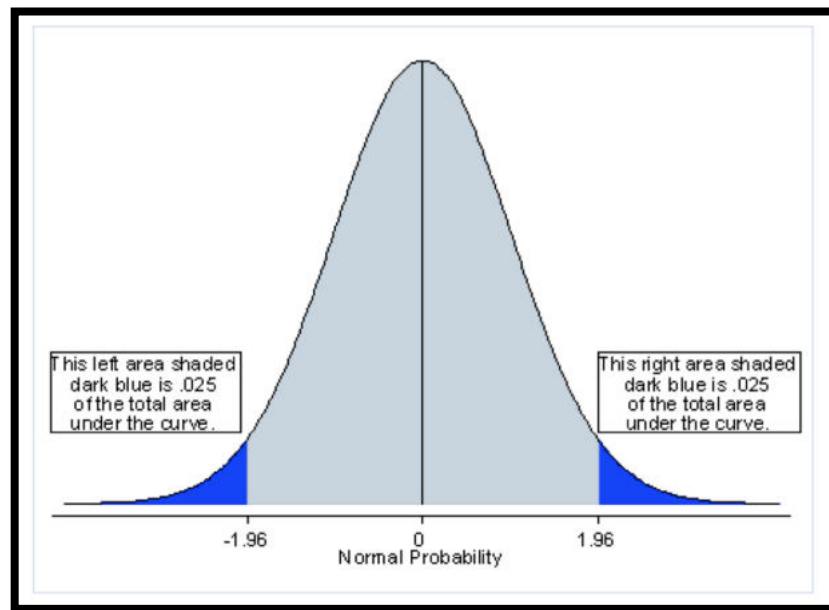
- Think about estimating β as the mean of a sample
 - Frequentists
 - β is a fixed, unknown parameter
 - When we estimate the mean, this depends on the data and is drawn from a distribution
 - So our estimate is a random variable
 - We think about our estimate as if it is drawn from a distribution
 - Bayesians
 - Before starting, we have some beliefs about the distribution of β
 - Once we see our data, we have a new belief, incorporating the data
 - E.g. We used to think β was normally distributed with mean 1, standard deviation 3, now we think it's normally distributed with mean 2, standard deviation 1.5

Frequentists vs. Bayesians



The Frequentist Approach: p-Values

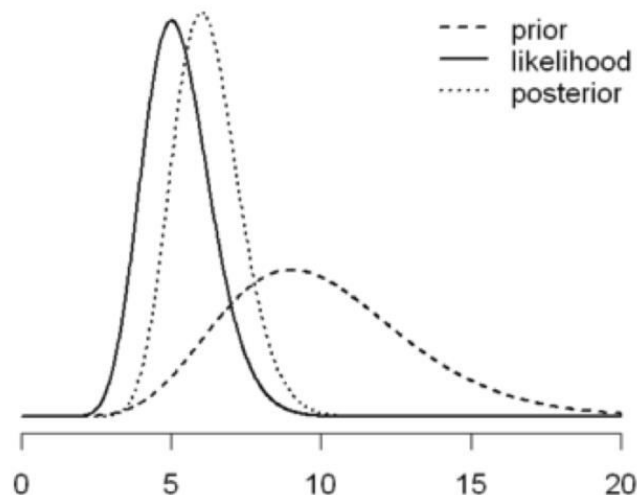
- Frequentists think about $\hat{\beta}$ compared to a specific **null hypothesis**, and reject if it's unlikely that this null hypothesis is true



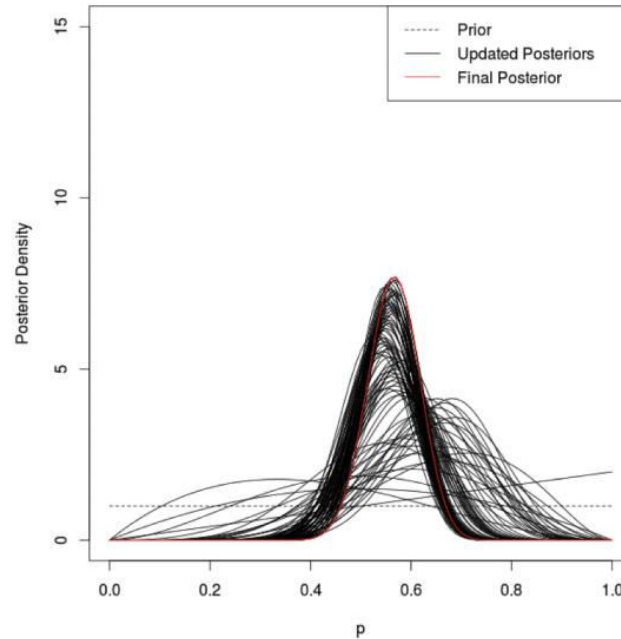
(n.d.). Retrieved from https://saylordotorg.github.io/text_introduutory-statistics/s09-04-areas-of-tails-of-distribution.html

Bayesian Methods: More Intuition

- Bayes rule provides a “compromise” between what you thought beforehand (the “priors”) and what you think now



Bayesian Methods: More Intuition



Lesson Summary

- Bayes' rule provides a way to incorporate new information into existing prior beliefs to form updated beliefs
- The rule is based on pure probability theory
- Bayesians have some beliefs about the distribution of β
 - Once seeing the data, we have a new belief, incorporating the data