Probability

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Math 141, 3/26/21

Outline

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- Discuss the Law of Total Probability and Bayes' Rule
- Define and investigate Random Variables

Section 1

Conditional Probability

The Law of Total Probability

Recall the **conditional probability** of an event A given another event B is

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One useful trick for computing probabilities is the following:

Theorem (The Law of Total Probability)

Let A and B be events. Then

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

• We can often represent the Law of Total Probability using a Tree Diagram:

Tree Diagrams



Lost Marbles

Two boxes contain a different number of red and blue marbles. The first box contains 20% red marbles while the second contains 80% red marbles. Suppose we select a marble from box 1 25% of the time and a marble from box 2 75% of the time. What is the probability that a red marble is selected?

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 - What is P(A|B) in this case?

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- Express each of these in terms of the *p*-value and conditional probabilities.

Let H denote a hypothesis and O denote some observation.

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 - P(H) is very, very low compared to P(O).
- By the principle of hypothesis testing, we might see that P(O|H) is high and favor the monster hypothesis H.
- Hypothesis testing just tells us about consistency of data with the null hypothesis. It doesn't give us the probability that the null is true.

Section 2

Random Variables

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- We use equation to express events associated to random variables.
 - Let X = 5 denotes the event "The random variable X takes the value 5".
- Events associated to variables have probabilities of occurring.
 - P(X = 5) = .5 means X has 50% probability of taking the value 5.

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- Examples of continuous variables:
 - The temperature of my office at a particular time of the day.
 - The amount of time it takes a radioactive particle to decay.
- Some discrete variables can be well-described by continuous variables:
 - The height of a random person selected from a large population.
 - The proportion of heads in a long sequence of coin flips.

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• Calculate $P(X \le 1)$. Then find x so that $P(X \le x) \ge .75$.

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The **expected value** (or mean) of a discrete random variable X is

$$E[X] = x_1 P(X = x_1) + x_2 P(X = x_2) + \dots + x_n P(X = x_n) = \sum_{i=1}^n x_i P(X = x_i)$$

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But also notice that

$$E[X] = \frac{1}{10} (1 \cdot 2 + 2 \cdot 4 + 3 \cdot 1 + 4 \cdot 1 + 5 \cdot 2)$$
$$= \frac{1}{10} (1 + 1 + 2 + 2 + 2 + 2 + 3 + 4 + 5 + 5)$$

The Law of Large Numbers, again

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This is a generalization:

Theorem (The Law of Large Numbers)

Let X be a random variable whose value depends on a random experiment. Suppose the experiment is repeated n times and let \bar{x}_n denote the arithmetic mean of the values of X in each trial. As n gets larger, the arithmetic mean \bar{x}_n approaches the expected value E[X] of that variable.

Gambler's Ruin

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• Assuming each wedge has equal probability, what is the expected value of the bet?

• Suppose a gambler begins with \$10,000. What will the gambler's fortune look like after 1000 plays?