

Econ 311: Behavioral and Experimental Economics

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Borrowing from Psychology

Psychology and Economics

- ▶ Behavioral and experimental economics owe much to the psychology literature
- ▶ Many of the foundation papers we will read in each section are from major branches of psychology:
 - ▶ social psychology
 - ▶ cognitive psychology
 - ▶ judgement and decision-making
- ▶ Many groundbreaking researchers in behavioral economics were trained as psychologists:
 - ▶ Amos Tversky, PhD in Cognitive Psychology
 - ▶ Daniel Kahneman, PhD in Psychology
 - ▶ Dan Ariely, PhD in Cognitive Psychology

Discussion Questions

- ▶ What ideas and concepts are shared between psychology and economics? Do they have the same names or different?
- ▶ What methods to the two areas share? What methods are distinct?
- ▶ How is theory in economics different than theory in psychology?

Two Systems Model

- ▶ System 1: fast, associative
 - ▶ Make connections from similarity
 - ▶ Processing occurs automatically
 - ▶ Good at: pattern completion, emotional reactions, repetitive tasks
- ▶ System 2: slow, deliberative
 - ▶ Uses symbols and rules
 - ▶ Processing occurs with conscious awareness
 - ▶ Good at one-shot learning, formal logic, educational knowledge, abstract theories
- ▶ May interact alternatively or simultaneously
- ▶ Moderated by mood, energy level, difficulty of problem, type of judgement

Probability

Why Do We Need Probability?

1. Social scientists are interested in making predictions about future behavior
 - ▶ Sometimes the best prediction we can give is a likelihood of a certain event of interest happening
2. We need a benchmark to talk about rationality of behavior
 - ▶ Probability judgement: Process of assigning a number to an event that represents one's strength of belief that that event will occur
 - ▶ The rules of probability come from very general assumptions but still give powerful restrictions on how probability judgement should behave

Probability Basics

- ▶ Let Ω be the space of all possible outcomes
 - ▶ Eg if we are rolling a single die, $\Omega = \{1, 2, 3, 4, 5, 6\}$
- ▶ A collection of one or more outcomes is an *event*, eg $E \in \Omega$
 - ▶ The event “roll a 3 or greater” is $E = \{3, 4, 5, 6\}$
- ▶ A probability function is a function P that assigns numbers between 0 and 1 (inclusive) to every possible event in Ω
 - ▶ $P(\{1\}) = \frac{1}{6}$
 - ▶ $P(\{3, 4, 5, 6\}) = \frac{2}{3}$

Axioms of Probability

- ▶ An axiom is a mathematical rule that is assumed to be true
- ▶ We have just two axioms in probability theory:
 1. $P(\Omega) = 1$
 - ▶ You can think of this as “something is guaranteed to happen”
 - ▶ Eg $P(\{1, 2, 3, 4, 5, 6\}) = 1$ in dice example
 2. $P(A \text{ or } B) = P(A) + P(B)$ for any two mutually exclusive events A and B
 - ▶ Called the *addition axiom*
 - ▶ Eg $P(\{1\}) + P(\{3, 4, 5, 6\}) = \frac{1}{6} + \frac{2}{3} = \frac{5}{6}$
- ▶ These rules may not uniquely determine the probability function for a given context
- ▶ But they do still allow us to make testable predictions about what a (possibly subjective) probability function should look like

Where Do These Probabilities Come From?

- ▶ Frequentist perspective
 - ▶ Probabilities represent *long run* averages
 - ▶ Eg, dice: $P(4) = \frac{1}{6}$ because if I roll a die a very large number of times, $\frac{1}{6}$ of the time I will roll a 4
- ▶ Counting perspective
 - ▶ Break event space into small enough pieces that they are be equally likely to happen
 - ▶ Probabilities of more complex events can then be built by addition rule, since pieces are mut
 - ▶ Example: what is the probability of flipping two heads in a row?
 - ▶ Break down into 4 equally likely events: HH, HT, TH, TT
 - ▶ Only 1 of these has two heads, so $P(HH) = \frac{1}{4}$

Conditional Probabilities

- ▶ We can define *conditional probability* $P(A|B) = \frac{P(A \text{ and } B)}{P(B)}$
 - ▶ This is the probability of A occurring given that we know B has occurred.
 - ▶ Example: $P(\text{winter}) = \frac{1}{4}$ but $P(\text{winter} \mid \text{snowed last weekend}) > \frac{1}{4}$
- ▶ We say two events A and B are *independent* if $P(A|B) = P(A)$
 - ▶ Dice example: Probability of rolling a six is independent of what you rolled previously
- ▶ Multiplication rule: For any two events A and B then $P(A \text{ and } B) = P(A|B)P(B)$
 - ▶ Comes from rearranging definition of conditional probability
 - ▶ Note that if A and B are independent, $P(A \text{ and } B) = P(A)P(B)$

Bayes' Rule: Intuition

- ▶ Suppose you have the following information:
 - ▶ The baseline breast cancer rate in women is 10%
 - ▶ If a patient has breast cancer, a mammogram will return positive with 90% probability
 - ▶ If a patient **does not** have breast cancer, a mammogram will return positive with 20% probability
- ▶ Question: What is the probability that a patient has cancer given that you see a positive mammogram result?
 - ▶ Consider 100 women, all of whom we test for breast cancer
 - ▶ 10 will have cancer (from the baseline rate)
 - ▶ Of these, 9 will return positive, 1 will return negative
 - ▶ 90 will not have cancer
 - ▶ Of these 72 (90×0.8) will return negative, 18 will return positive
 - ▶ So among the positive tests, only $\frac{9}{27} = \frac{1}{3}$ are true positives for cancer

Bayes' Rule: Formalization

- ▶ Suppose we are considering two events A_1 and B
- ▶ From the definition of conditional probability, we have
 - ▶ $P(A_1|B) = \frac{P(A_1 \text{ and } B)}{P(B)}$
 - ▶ $P(B|A_1) = \frac{P(B \text{ and } A_1)}{P(A_1)} = \frac{P(A_1 \text{ and } B)}{P(A_1)}$
- ▶ Substituting one into the other:

$$P(A_1|B) = \frac{P(B|A_1)P(A_1)}{P(B)}$$

- ▶ This is the most basic statement of Bayes' rule

Bayes' Rule: Alternate Formulations

- ▶ That $P(B)$ on the bottom is not very useful
- ▶ Suppose A_2 is the even that A_1 does not happen, ie $A_1 + A_2 = \Omega$
- ▶ Then

$$\begin{aligned}P(B) &= P(B \text{ and } A_1) + P(B \text{ and } A_2) \\&= P(B|A_1)P(A_1) + P(B|A_2)P(A_2)\end{aligned}$$

- ▶ This give us a more useful version of Bayes' rule:

$$P(A_1|B) = \frac{P(B|A_1)P(A_1)}{P(B|A_1)P(A_1) + P(B|A_2)P(A_2)}$$

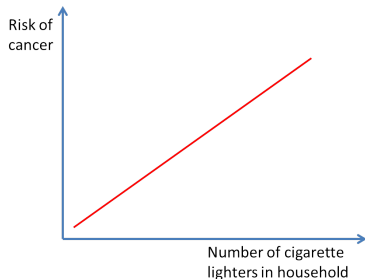
- ▶ Or more generally:

$$P(A_1|B) = \frac{P(B|A_1)P(A_1)}{\sum_i P(B|A_i)P(A_i)}$$

Experimental Design

Why Do We Need Experiments?

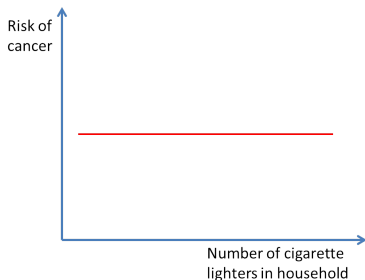
- Suppose we observe the following pattern in observational data:



- Can we conclude that cigarette lighters cause cancer?
 - No, correlation is not causation
 - More likely that there is a third variable (smoking) that causes the other two

Experiments Give Us Control

- ▶ Experiments allow the researcher to *control* all the variables (or at least control them more than in observational data)
- ▶ Experiments also the researcher to determine causality using *random assignment*
 - ▶ For example, if we randomly gave some people more cigarette lighters to have around the house, we would probably see that they have no *causal* relationship with cancer risk



Building Blocks

- ▶ Every experiment needs some *participants*, also known as *subjects* or *decision-makers*
- ▶ The most basic unit in an experiment is a *task* or *choice*
 - ▶ For example, deciding whether or not to buy a food item
- ▶ A *treatment* is a series of one or more similar tasks
 - ▶ For example, choosing whether or not to buy many food items, one at a time
- ▶ An *experiment* consists of one or more treatments
 - ▶ For example, could have one treatment where all food items are 25 cents, and another where all food items are at 75 cents

Treatment Variables

- ▶ Many experiments consist of only one treatment
- ▶ But many others have more than one treatment
 - ▶ The parts that differ between the treatments are called *treatment variables*
- ▶ A common experimental design is to have two treatment variables that can each take on two levels
 - ▶ This is called a *2-by-2* design
 - ▶ Example:
 - ▶ We are interested in responses to requests for donations to the local animal shelter
 - ▶ Vary whether a picture of a dog is included, and vary whether a specific amount of money is asked for

	Amount Specified	Amount Not Specified
Photo	Treatment A	Treatment B
No Photo	Treatment C	Treatment D

Within- vs Between-Subjects Design

- ▶ In a *between-subjects* design, each subject completes only one treatment
- ▶ In a *within-subjects* design, each subject completes multiple treatments
- ▶ Is one of these designs better than the other?
 - ▶ A within-subjects design can suffer from *order effects*: the order the subjects do the treatments in can matter
 - ▶ However, a within-subjects design needs less subjects and gives more control of subject characteristics

Incentives

- ▶ Choices in experiments are typically incentivized with some kind of material *incentive* or *payoff*
 - ▶ Incentives may be cash, consumption goods, social image
 - ▶ Important to calibrate the size of the *stakes* to the task
 - ▶ Eg, bad idea to only pay a few cents for correctly solving an entire crossword puzzle
- ▶ In some cases, hypothetical stakes may be appropriate

Context

- ▶ Generally want to avoid contexts that include unnecessary complications or distractions for subjects
- ▶ For example, consider food choice experiment
 - ▶ Primarily interested in testing the law of demand
 - ▶ Avoid confounds such as making decisions publicly observable
 - ▶ Unless, of course, this is the treatment variable I'm interested in
 - ▶ Controlling context is easier in lab experiments than field experiments
- ▶ Related issue: experimenter demand effect
 - ▶ Subjects may be influenced by what they think the experimenter wants them to do
 - ▶ Avoid using language that implies a value judgement or normative choice

Independence

- ▶ A famous (likely apocryphal) story:
 - ▶ Graduate student is studying how fast lacerations heal on the skin of mice, depending on whether or not mice have a certain genetic mutation
 - ▶ Advisor tells graduate student he should double his sample size for increased statistical power
 - ▶ Doubling the number of mice is very expensive and time-consuming
 - ▶ Graduate student is very clever: makes a second laceration on each mouse
- ▶ Has the number of observations doubled?
 - ▶ Not really: the two cuts on each mouse are probably not *independent* from another
 - ▶ For example, if one cut heals quickly, I can expect the other cut will heal quickly too
 - ▶ Thus the second cut does not add new information

Pitfalls of Experiment Design

- ▶ Changing two treatment variables at the same time
- ▶ Poor choice of context
- ▶ Order effects not considered
- ▶ Observations not fully independent
- ▶ Poor choice of incentives and stakes