Experiments and Causality

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Chapter 1

Live Session Introduction

This is the live session work space for the course. Our goal with this repository, is that we're able to communicate *ahead of time* our aims for each week, and that you can prepare accordingly.

1.1 Bloom's Taxonomy

An effective rubric for student understanding is attributed to Bloom (1956). Referred to as *Bloom's Taxonomy*, this proposes that there is a hierarchy of student understanding; that a student may have one *level* of reasoning skill with a concept, but not another. The taxonomy proposes to be ordered: some levels of reasoning build upon other levels of reasoning.

In the learning objective that we present in for each live session, we will also identify the level of reasoning that we hope students will achieve at the conclusion of the live session.

1. **Remember** A student can remember that the concept exists. This might require the student to define, duplicate, or memorize a set of concepts or facts.
2. **Understand** A student can understand the concept, and can produce a working technical and non-technical statement of the concept. The student can explain why the concept *is*, or why the concept works in the way that it does.
3. **Apply** A student can use the concept as it is intended to be used against a novel problem.
4. **Analyze** A student can assess whether the concept has worked as it should have. This requires both an understanding of the intended goal, an application against a novel problem, and then the ability to introspect or reflect on whether the result is as it should be.

5. **Evaluate** A student can analyze multiple approaches, and from this analysis evaluate whether one or another approach has better succeeded at achieving its goals.
6. **Create** A student can create a new or novel method from axioms or experience, and can evaluate the performance of this new method against existing approaches or methods.

Chapter 2

Importance of Experimentation

> Why do we conduct experiments?
>
> What is the value of making a causal statement?
>
> This is a data science program, with enough data and a savvy enough model, can't we just generate a causal statement that will be right? Can't I generate a statement that converges in probability to the *correct* value?

2.1 Learning Objectives

At the end of this live session, students will be able to

1. *Remember* (or find) the goals of the course, the assessment structure, and the learning model.
2. *Define*, in non-technical language, what it means for an action to cause an outcome.
3. *Understand* the difference between a causal statement, and an association statement.
4. *Apply* the framework of causal thinking against a series of studies to determine whether the study has achieved the goal that it intends.

2.2 Class Introductions

In no more than 2 minutes, could each student please:

- Introduce themselves, announcing their name as they would like it to be pronounced;
- Tell us where in the world they are studying;
- State what semester they are in the program;
- Any descriptive features that they would like the class to know about them (for example, gender pronouns); and,
- [Instructor's choice]

2.3 Course Plan

The course is built out into three distinct phases

- **Part 1** Develops causal theory, potential outcomes, and a permutation-based uncertainty measurement
- **Part 2** Further develops the idea of a treatment effect, and teaches how the careful design of experiments can improve the efficiency, and easy of analysis
- **Part 3** Presents practical considerations when conducting an experiment, including problems that may arise, and how to design an experiment in anticipation of those problems.

2.4 Course Logistics

- bCourses
  - Learning Modules attached to weeks
  - Modules contain async lectures, coding exercises, and quizzes
- GitHub
  - All the course materials are available in a GitHub repository
  - We have protected the `main` branch, so you can't do anything destructive
  - Use that as empowerment! This is your class, propose changes that you would like to see!
- Github Classroom
  - Assignments will all be applied programming assignments against simulated and real data
  - All assignment code will be distributed through GitHub Classroom
- Gradescope
  - All assignments will be submitted to Gradescope where we'll read your solutions and provide scores and feedback

2.4.1 Learning model for the class

The course assignments are designed to put what we have learned in reading, async, and live session into practice in code. In our ideal version of your studying, we would have you working hard together with your classmates in a study group on the assignments, coming to office hours to talk candidly about what is and isn't working, and then *every single student* arriving at a full solution.

2.4.2 Feedback model for the class

We want to get you feedback *very* quickly after you turn your assignments.

1. We will release a solution set the day that you turn your assignment in
2. We will hold a problem set debrief office hour the Friday (i.e. next day) after the problem set it submitted
3. We will have light-feedback on your assignments within 7 days of when you submitted them.
4. You should bring your assignment to office hours after you have turned it in so that we can talk about any differences between your approach, and the instructors approach.

2.4.3 Office hour model for the class

- We will hold office hours Sunday through Thursday at 5:30.
- We will hold more than 10 hours of office hours every week; they will all be recorded, and any student is welcome in any office hour

2.5 Article Discussion

2.5.1 Predict or Cause

- What are a few examples that Athey raises of causal questions masquerading as prediction questions?

    1.
    2.
    3.

- Which of these examples is the most surprising to you?
- Is there something that is common to each of these examples? Is this a general phenomenon, or is Athey very clever in picking examples? Said differently, is Athey making a clever argument or is a lot of what we do as data scientists actually causal work in disguise?

2.5.2 Do the suburbs make you fat?

1. What is the causal claim being made in this article?
2. If you had to draw out this causal claim, using arrows, what would it look like?
3. Do you acknowledge the association that the authors present? Is there *actually* a difference between the BMI of people who live in cities and the suburbs?
4. If you acknowledge the association, does that compel you to believe the causal claim? Why or why not?
5. Name, and draw, five alternative *confounding* variables that might make you skeptical that the claimed relationship exists.
6. (Optional) Name, and draw two *mechanisms* that might exist between suburbs and BMI. Why does the existence (or not) of these mechanisms *not* pose a fundamental problem to the causal claim that the authors make?
7. At the conclusion of reading this paper, do you believe that there is a causal relationship between location and BMI? If so, what compels you to to believe this; if not, why are you not compelled to believe this?

2.5.3 Nike Shoes

1. What is the causal claim being made in this article?
2. If you had to draw out this causal claim, using arrows, what would it look like?
3. Do you acknowledge the association that the authors present? Is there actually a difference in the finish time between people who are running with the Nike shoes vs. other shoes?
4. If you acknowledge the association, does that compel you to believe the causal claim? Why or why not?
5. What are some of the confounding relationships that the authors identify? (Can you name four?) How do they adjust their analyses once they acknowledge the confounding problem?
6. At the conclusion of reading this paper, do you believe that there is a causal relationship between shoes and finish time? If so, what compels you to to believe this; if not, why are you not compelled to believe this?

2.5.4 What is Science: Feynman's View

In *Cargo Cult Science*, Richard Feynman poses a view of science that is about a seeking of the truth.

1. What is Feynman's view of science? What does he think makes something *scientific*?

2. What are ways that individuals fool themselves when they are working as scientists? What are ways that individuals fool themselves when they are working as data scientists?
3. How can we as (data) scientists, train ourselves not to be fooled?[1]

[1]This is a footnote, rendered into an html document.

Chapter 3

Apples to Apples

3.1 Learning Objectives

At the conclusion of this week's live session, student will be able to:

1. *Describe*, using the technical language of potential outcomes, what it means for an input to *cause* an output.
2. *Describe* the fundamental problem of causal inference.
3. *Apply* iid sampling as a method of producing an unbiased, consistent estimator of a population.
4. *Proove* that the average treatment effect estimator produces an unbaised, consistent estimator for the average treatment effect.

3.2 This Causes That

What does it mean for an action to cause an outcome? Don't worry about conducting the experiment, or any measurement concerns at this point, just engage with the concepts.

3.2.1 Damn fine coffee

Suppose that you're getting ready for class, and you want to make sure that you're at your best. So, you drink a cup of water, eat a small snack, and brew a small pot of coffee for while you're in class.

> Why do you do this?

Presumably, you're doing this because you like each of these things, but also because you're interested in these things causing you to have a better class. If you framed this as as causal question, you might ask:

> If I drink a cup of coffee before class, will it cause me to be more alert?

What does it mean for coffee to cause alertness?

- Does coffee cause everyone to become more alert?
- Does coffee have to affect everyone equally in order for you to say it causes alertness?
- Could coffee have no effect for some people, and you would still say it causes alertness?

3.2.2 Meditation for focus

Suppose that you're getting ready for class, and you want ensure that you're at your best. So, you find a quiet place, and set your mind at ease with whatever form of meditation you think might be helpful.

> If I meditate before class, will it cause me to be more focused?

What does it mean for meditation to cause focus?

- Does meditation cause everyone to become more focused?
- Does meditation have to affect everyone equally?
- Some people are frustrated by not being able to quiet their thoughts, and actually find meditation frustrating. Can this be true, and still believe that meditation causes focus?

3.2.3 Selling coffee and meditation

Suppose that you're an enterprising soul, and you want to sell a book about brewing coffee as a meditation. You reason that there must be a niche for this approach. To get the word out, you place a few flyers with tear off phone-numbers at the local yoga studios and tech incubators (good intuition to find those MIDS students).

> If shown a flyer for coffee-meditatin, will it cause someone to take my training?

What does it mean for for flyers to cause people to sign-up for the training?

- Does the flyer cause everyone to take the training?
- Does the flyer affect everyone equally?

3.2.4 Reflecting on Causes

Does anything unify questions of causes?

When you think about *{this}* causing *{that}*, do you think about it at a population level, a smaller group level, or at the individual level?

3.3 Potential Outcomes

Potential outcomes are a system of reasoning, and a corresponding notation, that allow us to talk about observable and un-observable characteristics of the world.

> What is your position on *ontology*? What does it mean for something to exist?

- Does *Field Experiments*, as a textbook, exist?
- Do Don Green and Alan Gerber, the authors of the textbook that we're reading, exist?
- Does David Reiley, the slower-talking Davids in the async, exist?
- Do I, your section, instructor, exist (or am I a deep fake in this room with you)?
- Can a concept exist, even if you can't hold it? Even if you haven't seen it?

3.3.1 Defining Potential Outcomes

For each of the following sets of notation: (1) Read the notation aloud, not as "Y sub i zero," but instead as "The potential outcome to control . . . ."

- $Y_i(0)$:
- $Y_i(1)$:

- $E[Y_i(0)]$:
- $E[Y_i(1)]$:
- $E[Y_i(0)|D_i = 0]$:
- $E[Y_i(1)|D_i = 1]$:
- $E[Y_i(0)|D_i = 1]$:
- $E[Y_i(1)|D_i = 0]$:

- Which of these concepts that you have just read aloud exist?
- Can a concept exist, even if you can't hold it? Even if you can't see it?

3.4 Using Independence

Suppose that you have a random variable that is defined as the function,

$$Y = \begin{cases} \frac{1}{10} & , 0 \leq y \leq 10 \\ 0 & , \text{otherwise} \end{cases}$$

- What is the expected value of this function?

$$\begin{aligned} E[Y] &= \int_0^{10} y \cdot f_y(y)\ dy \\ &= \int_0^{10} y \cdot \frac{1}{10}\ dy \\ &= \frac{1}{10} \int_0^{10} y\ dy \\ &= \frac{1}{10} \cdot \frac{1}{2} y^2 \Big|_0^{10} \\ &= \frac{1}{20} y^2 \Big|_0^{10} \\ &= \frac{1}{20} \cdot [(100) - (0)] \\ &= \frac{1}{20} \cdot 100 \\ &= \mathbf{5} \end{aligned}$$

- Why is the expected value a good characterization of a random variable?
- If you wanted to write down an estimator to produce a summary statistic for Y given a sample of data, what properties do the following estimators possess:
- $\hat{\theta}_1 = y_1$
- $\hat{\theta}_2 = \frac{1}{2} \sum_{i=1}^{2} y_i$

- $\hat{\theta}_3 = \frac{1}{n-1} \sum_{i=1}^{N} y_i$
- $\hat{\theta}_4 = \frac{1}{n} \sum_{i=1}^{N} y_i$

```
population_function <- function(sample_size) {
  runif(n=sample_size, min=0, max=10)
}
```

```
theta_1 <- function(data) {
  # take the first element

}

theta_2 <- function(data) {
  # sum the first two elements and divide by two

}

theta_3 <- function(data) {
  # sum the sample, and divide by 1 less than the sample size

}

theta_4 <- function(data) {
  # sum the sample, and divide by the sample size
  # honestly, just use the mean call.
  # clearly, this is a silly function to write, since you're just
  # providing an alias, without modification, to an existing function.

}

theta_4 <- function(data) {
  mean(data)
  }
```

```
theta_4(population_function(100))
```

```
## [1] 4.85391
```

Chapter 4

Quantifying Uncertainty

4.1 Learning Objectives

1.
2.
3.

Chapter 5

Blocking and Clustering

5.1 Learning Objectives

1.
2.
3.

Chapter 6

Covariates and Regression

6.1 Learning Objectives

1.
2.
3.

Chapter 7

Regression and Multifactor Experiments

7.1 Learning Objectives

1.
2.
3.

Chapter 8

Heterogeneous Treatment Effects

8.1 Learning Objectives

1.
2.
3.

Chapter 9

Treatment Noncompliance

9.1 Learning Objectives

1.
2.
3.

Chapter 10

Spillover and Interference

10.1 Learning Objectives

1.
2.
3.

Chapter 11

Causality from Observational Data

11.1 Learning Objectives

1.
2.
3.

Chapter 12

Problems and Diagnostics

12.1 Learning Objectives

1.
2.
3.

Chapter 13

Attrition, Mediation, and Generalizability

13.1 Learning Objectives

1.
2.
3.

Chapter 14

Applications of Experiments

14.1 Learning Objectives

1.
2.
3.

Chapter 15

Review of the Course

15.1 Learning Objectives

1.
2.
3.