**w241 Lecture 1 - Importance of Experimentation**

Two main bullets:

1. learn to see causal reasoning
2. Recognize the pitfalls of observational data

Case Study (NYT Article about Estrogen):

When the nurses health study results came back in the first place, why should the people who observed these results have been cautious? What if somebody said to you, but they followed these nurses over time didn’t they?

The nurses self selected into taking estrogen. There might be a factor that is unobservable that both causes fewer heart attacks and causes the nurse to take estrogen. Maybe people who take estrogen are more concerned about their health and therefore have a healthier lifestyle in general on top of taking the drug.

What is the counterfactual? If you look at the headline, it’s not clear that implies a linear additive causal effect (each additional sexual partner decreases the risk of cancer). Specify a reasonable counterfactual is important.

The point of the last exercise is focused mostly on the title of the article where it says “Sex with 21 women lowers risk of prostate cancer, academics find”

it says the number 21 but doesn’t tell us in comparison to what

that title can suggests a large amount of things. 1 of which is that with each new sexual partner, you have a lower risk of prostate cancer

another way of interpreting it is that 21 is a specific cut off point. once you reach that 21 number, you’ll be less likely to get prostate cancer.

another interpretation is simply, “21 is a high number” we are comparing a large number of sexual partners with a low number of sexual partners

**Lecture 2 - Comparing Apples to Apples**

How do we make sure our 2 groups only differ in the X variable and otherwise identical?

**Potential Outcomes as Theoretical Concepts**

Experimentation delivers much more reliable causal inference than any observational method.

Allows us to compare two identical populations in which all that varies is treatment of interest.

Potential Outcomes - Theoretical concepts useful for thinking about what an experiment could show

Notations

Yi(1) = potential outcome if you were to be in the treatment

Yi(0) = potential outcome if you were to be in control

tau i = Yi(1) - Yi(o) = treatment effect

In village (i) only, how many more budget percentage points would be devoted to water sanitation if you were in treatment versus control?

Not directly observable, but useful to think about hypothetically.

No Causation Without Manipulation

If you can’t imagine a manipulation that answers your question, it may not have a causal answer

What would the same person do if in one treatment versus another?

Intervention is required to generate needed data, but sometimes imagining an intervention is impossible.

Fundamentally Unanswerable Questions

Example: What is the effect on mortality rates of being born in Africa?

What does this mean for a particular person?

Yi(1) = outcome if person born in Africa

Yi(0) = outcome if same person born in the United States

Born in African hospital? Live entire life in Africa? <- Question is not well posed

What is the ideal experiment?

What is the implied manipulation?

di = treatment “dosage”

Di versus di

Realization of xi of a random variable Xi

**Lecture 2**

Excludability and Non-interference were violated.

Exclusion restriction - assignment of treatment affect. Not that only the treatment will drive outcome. Many other things affect outcome, but they’re not a threat. Without using a placebo in the control group can violate the exclusion restriction. Want to test the effect of a drug. Control group is a pure control that does not receive a placebo. People who takes drugs and those who receive nothing. There are many things that can affect the outcome of getting diabetes. But those things don’t matter if we use random assignment. But what if taking the drug introduces a placebo effect in the drug taking group. The drug taking group might be purely feeling better because of the placebo effect. That is an exclusion error. That’s why we should give the control group a placebo pill, to eliminate the effect of the placebo effect.

Exclusion restriction example 2. If you have person A handle for the control group and person B to handle the treatment group. In that case, person A and person B become factors that make the control group and treatment group different.

In the textbook, they sent out text messages encouraging women to run. It can violate the exclusion restriction and the non-interference restriction.

**Lecture 3**

Standard error - assume repeated experimentation in t.test (which we don’t observe in real life). In computing a standard error we pretend that we are observing this process over and over again. In experiments, we can imagine all the different ways that our treatments can be allocated to subjects. That’s called the randomization distribution.

Questions 3.1 a,b,c,e

a) Standard error = variability in the sampling

b) Randomization inference - mix treatment and control group, randomize, and calculate the tau. do this multiple times and get a distribution of the taus. Then compare the true sample tau to that tau <- This might be wrong

reading - bottom line, even the best research experiment had a result that has such a large variation between advertisement and ROI, that it doesn’t really tell us anything. Instead of getting, “increasing the advertisement can raise the ROI by x%” the results is like a large range.

3.5 a,b,d,e

Box 3.7 in page 65 with the in class Rmd file.

**Week 4**

It’s tempting to do blocking with everything. But they’re not the most important thing.

Statistical Power: Type 1 error we care most about. Type 2, fail to reject the null hypothesis when in fact it is false. Type 1 error, reject the null hypothesis when in fact it is true. Power = 1 - prob of type 2 error. (Probability that we correctly reject the null hypothesis). Clients and who ever pays for the test would care about power. Also, you care if you want to know if the experiment is worth your time.

Treatment effect size/ Practical significance

Sample size (overall) - not worth doing the experiment unless we have at least k subjects.

Underlying Variance of Outcomes

alpha level of significance

We make our best guess of what we think tau would be. Then we calculate the statistical power before we run the experiment.

Base like for statistical Power is 80%.

How is blocking different from controlling for covariance?

Different strategy. controlling for covariance is something like, make sure people meditate at certain times of the day. Or control for covariance is tied to regression? Blocking you do 2 experiments, one on women and one on men, then combine the 2 experiments and get a weighted average?

limitations of blocking - doesn’t hurt very much except you can waste time and resources doing unnecessary blocking.

**Lecture 5**

Compound vs Covariants: Covariants are other variables that we can add to our regression model to make it more accurate. Compound is a hypothetical connection between a third variable to our treatment and our outcomes.

Between subject design vs. Within subject design: within subject design is when you compare units expose to units not exposed. Team A with player and Team A without a player. Between subject design is if you randomly assigned the player to different teams for each game. Then the treatment group would be the results of the teams with the player and the control group would be the results of the teams without the player.

Robust standard errors are good : Robust to Heteroskedasticity (as our inputs change, the variance in the output increases or decreases)

Also talked about clustered Standard errors

**Lecture 6**

Two different ways you can get bad controls (post-treatment variables)

1. in a regression you can add an x that is in itself a consequence of your treatment.
2. If you do manipulation checks (Did these people react the way i expected to them?) and then I drop subjects that fail the manipulation check, then you have created a post-treatment situation.

If you have a variable that is impacted by the treatment you have post-treatment variable. Very simple consequence, it will cause a non-zero bias. Bias can be almost any size and any direction. We can possibly use the post-treatment variable as it’s own outcome variable in it’s own experiment and use suggested evidence that there is a chain of relation here.

Factorial design - multi factor experiments

**Lecture 7**

How is HTE different from blocking? Blocking is done before you run the regression as a part of experimental design during the allocation of the treatment. HTE is something you look for afterwards and you can do it whether you have blocking or not.

Treatment by covariate interaction. Control for that covariate, control for our treatment, and then we interact the two.

HTE does not tell us causal information. HTE provides us with noncausal information about our causal correlation. Puts together a more cohesive story about the causal relationship we are experimenting on.

keyby is the data table version of GroupBy in dplr.

Null model, short model, restricted model = lm(y ~ x + cov)

2SLS - 2 stage least squares