Lecture 19: Experiments

Criminology 250

Prof Maria Cuellar

University of Pennslyvania

Experiments

Table 2.1

	A	Y	Y^0	Y^1
Rheia	0	0	0	?
Kronos	0	1	1	?
Demeter	0	0	0	?
Hades	0	0	0	?
Hestia	1	0	?	0
Poseidon	1	0	?	0
Hera	1	0	?	0
Zeus	1	1	?	1
Artemis	0	1	1	?
Apollo	0	1	1	?
Leto	0	0	0	?
Ares	1	1	?	1
Athena	1	1	?	1
Hephaestus	1	1	?	1
Aphrodite	1	1	?	1
Cyclope	1	1	?	1
Persephone	1	1	?	1
Hermes	1	0	?	0
Hebe	1	0	?	0
Dionysus	1	0	?	0

- **Goal**: Calculate the difference $P(Y^{a=1} = 1) - P(Y^{a=0} = 1) = 0$ (or ratio, or odds ratio).
- **Fundamental problem**: In a real world study we will not know both of Zeus's potential outcomes $Y^{a=1}$ under treatment and $Y^{a=0}$ under no treatment. Rather, we can only know his observed outcome Y under the treatment value A that he happened to receive.
- **Missing data**: Only one of the two counterfactual outcomes is known for each individual: the one corresponding to the treatment level that he actually received. The data are missing for the other counterfactual outcomes.

How does randomization work?

- Idealized example: Suppose the population represented by a diamond in Figure 1.1 was near-infinite, and that we flipped a coin for each individual in such population.
- We assigned the individual to the white group if the coin turned tails, and to the grey group if it turned heads. (Note that this was not a fair coin because the prob. of heads was <50%).
- Next we ask our research assistants to administer the treatment of interest (A=1) to individuals in the white group and a placebo (A=0) to those in the grey group.
- Causal effects: Five days later, at the end of the study, we computed the mortality risks in each group, $Pr[Y = 1|A = 1] = 0.3$ and $Pr[Y = 1|A = 0] = 0.6$. The associational risk ratio was $0.3/0.6 = 0.5$ and the associational risk difference was $0.3 - 0.6 = -0.3$. i.e., the treatment reduces changes of dying.

Ethical implications of randomization

- Costs: Randomized experiments are usually very costly and time-consuming.
- Field differences: They are commmon in medicine, agriculture, now economics, but not in criminology.
- Complaints: In almost every randomized experiment people might complain that it's unethical. If this medicine could save someone's life, why wouldn't you give it to someone who has the disease? How could you give them a placebo for the sake of getting a causal answer, and think that's ethical?
- Do they work? It would be unethical *not* to know whether the medicine works properly. Think of the manure fertilizer example: Fisher studied data from many years, and they just didn't know what worked. Instead of continuing to give people treatments we don't know work, let's first figure out if they work.
- Sometimes the comparison is not between treatment and placebo, but instead treatment 1 and treatment 2. There has to be a reasonable doubt (not sure what they call it) about the outcome.
- IRB's think about this every day.
- Good source of data: MIT Poverty Action Lab (JPAL): https://www.povertyactionlab.org/catalog-administrative-data-sets

Exchangeability

- Now imagine what would have happened if the research assistants had misinterpreted our instructions and had treated the grey group rather than the white group.
- How does this reversal of treatment status affect our conclusions? Not at all. We would still find that the risk in the treated (now the grey group) $Pr[Y = 1|A = 1]$ is 0.3 and the risk in the untreated (now the white group) $Pr[Y = 1|A = 0]$ is 0.6.
- When group membership is randomized, which particular group received the treatment is irrelevant.
- Formally, we say the groups are exchangeable. Exchangeability means that the **risk of death in the white group would have been the same as the risk of death in the grey group had individuals in the white group received the treatment given to those in the grey group**.

$$P(Y^a = 1|A = 1) = P(Y^a = 1|A = 0) = P(Y^a = 1).$$

- Another way of saying this is that

$$Y^a \perp\!\!\!\perp A, \text{ for all values of } a.$$

Note, this is not the same as $Y \perp\!\!\!\perp A$. If there's a causal effect then we want Y and A to be dependent on each other!

Why does randomization give us causation?

- Missing at random: Randomization ensures that the missing values in Table 2.1 occurred by chance. As a result, effect measures can be consistently estimated in randomized experiments despite the missing data.
- Exchangeability: When the treated and the untreated are exchangeable, we sometimes say that treatment is exogenous, and thus exogeneity is commonly used as a synonym for exchangeability.
- Go from potential outcomes to outcomes: Randomization gives us that the counterfactual risk under treatment is:

$$P(Y^{a=1} = 1) = P(Y = 1|A = 1).$$

In ideal randomized experiments, association is causation.

Does exchangeability hold in the Zeus example?

Table 1.1

	$Y^{a=0}$	$Y^{a=1}$
Rheia	0	1
Kronos	1	0
Demeter	0	0
Hades	0	0
Hestia	0	0
Poseidon	1	0
Hera	0	0
Zeus	0	1
Artemis	1	1
Apollo	1	0
Leto	0	1
Ares	1	1
Athena	1	1
Hephaestus	0	1
Aphrodite	0	1
Cyclope	0	1
Persephone	1	1
Hermes	1	0
Hebe	1	0
Dionysus	1	0

- We need to check whether $Y^a \perp\!\!\!\perp A$ holds for both $a = 0$ and $a = 1$.
- For $a = 0$, $P(Y^{a=0} = 1|A = 1) = 7/13$ and $P(Y^{a=0} = 1|A = 0) = 3/7$. Since 7/13 > 3/7, we conclude that the treated have a worse prognosis than the untreated, that is, that the treated and the untreated are **not** exchangeable. It's similar for $a = 1$: exchangeability does not hold.
- But only data from table 2.1 is available in the real world, and it's insufficient to compute counterfactual risks.
- We are generally unable to determine whether exchangeability holds in our study. If there is randomization (and a large enough sample), then we can assume there is exchangeability.

Table 1.2 from last class

Table 1.2

	A	Y
Rheia	0	0
Kronos	0	1
Demeter	0	0
Hades	0	0
Hestia	1	0
Poseidon	1	0
Hera	1	0
Zeus	1	1
Artemis	0	1
Apollo	0	1
Leto	0	0
Ares	1	1
Athena	1	1
Hephaestus	1	1
Aphrodite	1	1
Cyclope	1	1
Persephone	1	1
Hermes	1	0
Hebe	1	0
Dionysus	1	0

Conditional randomization

Table 2.2

	L	A	Y
Rheia	0	0	0
Kronos	0	0	1
Demeter	0	0	0
Hades	0	0	0
Hestia	0	1	0
Poseidon	0	1	0
Hera	0	1	0
Zeus	0	1	1
Artemis	1	0	1
Apollo	1	0	1
Leto	1	0	0
Ares	1	1	1
Athena	1	1	1
Hephaestus	1	1	1
Aphrodite	1	1	1
Cyclope	1	1	1
Persephone	1	1	1
Hermes	1	1	0
Hebe	1	1	0
Dionysus	1	1	0

- Table 2.2 also contains data on prognostic factor L (1 if the individual was in critical condition, 0 otherwise), which was measured before the treatment was assigned.
- We can now consider two mutually exclusive designs and discuss whether the data in Table 2.2 could have arisen from either of them.
- In this design, we would have classified all individuals as being in either critical ($L=1$) or noncritical ($L=0$) condition. Then we would have randomly selected 65%

Final project

Draw a DAG of the mechanism you are studying in your project.