Introducing Counterfactual Causal Inference

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What might “cause” **mean**?: Definitions and Conceptualization

Why randomize?

Overview of Statistical Inference for Causal Quantities

Later: Weaknesses of randomized experiments.

Some of my recent causal questions

Did a new Hausa television station in northern Nigeria change attitudes about violence, the role of women in society, or the role of youth in society?

Will adding education counselors to public housing in the USA increase the numbers of low income youth enrolled in post-secondary education (like university) and receiving financial aid for their education?

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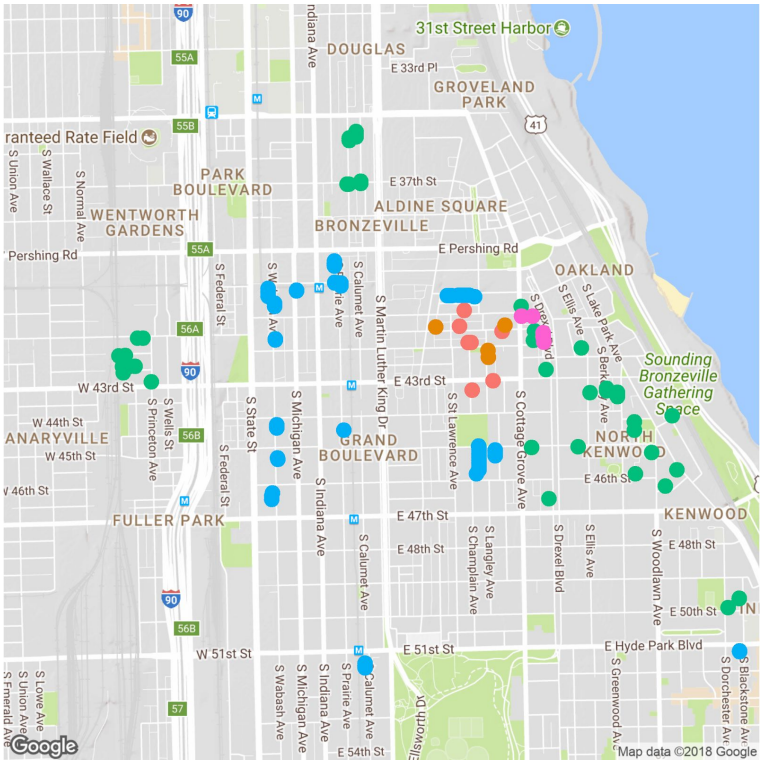
Figure 1: Example of overlapping AMPs in Chicago



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What does "cause" mean?

When someone says "X causes Y" they might mean:

Persistent association "We always/mostly see $Y = 1$ when $X = 1$ and $Y = 0$ when $X = 0$."

Counterfactual Difference "If X had not been this value, then Y would not have been that value."

Difference after manipulation "When we change X from one value to another value, then Y changes from one value to another value." (establishes causal priority of X over Y).

Difference after operation of a mechanism "Once upon a time A changed X, and then one day X changed B, and because of that B changed C, and finally C changed Y."

other...

Extra: If you want to dig into this see Brady (2008). http://egap.org/resources/guides/causality/

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Difference research designs help us **make the case** for a **claim** that "X causes Y" more or less strongly given different conceptualizations.

Often, **experiments** aim to **manipulate** (**by randomization**) parts of expected/theoretical mechanisms to reveal counter-factuals rather than aim to document persistent and wide-spread association.

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Why randomize?

Overview of Statistical Inference for Causal Quantities

Later: Weaknesses of randomized experiments.

Observational studies vs. Randomized studies

Discuss in small groups: Help me design the next project to answer this question (or one of your own causal questions):

Did a new Hausa television station in northern Nigeria change attitudes about violence, the role of women in society, or the role of youth in society?

1. What would be an ideal observational study design? (no randomization) What questions would critical readers ask when you claim that your results reflect a causal relationship?
2. What would be an ideal experimental study design? (including randomization) What questions would critical readers ask when you claim that your results reflect a causal relationship?

Why randomize?

Randomization produces **fair** comparisons (ex. impersonal, no systematic differences between groups).

Randomization helps us reason about information/uncertainty:

> *Q: "What does this p-value mean?"*
>
> *A: "It is the probability of seeing a result as extreme as this in the world of the null hypothesis."*
>
> *Q: "What do you mean by probability or 'world of the null hypothesis'"?*

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Counterfactual Causal Inference

How can we use what we **see** to learn about what we want to **know**)?

			Turnout				
City	Pair	Treatment	Baseline	Outcome	Newspaper	y_1	y_0
Saginaw	1	0	17	16		?	16
Sioux City	1	1	21	22	Sioux City Journal	22	?
Battle Creek	2	0	13	14		?	14
Midland	2	1	12	7	Midland Daily News	7	?
Oxford	3	0	26	23		?	23
Lowell	3	1	25	27	Lowell Sun	27	?
Yakima	4	0	48	58		?	58
Richland	4	1	41	61	Tri-City Herald	61	?

Design and outcomes in the Newspapers Experiment. The Treatment column shows treatment randomized within pair with the newspaper ads as 1 and lack of treatment as 0. The potential outcomes are y_1 for treatment and y_0 for control. Panagopoulos (2006) provides more detail on the design of the experiment.

Counterfactual Causal Inference

How can we use what we **see** to learn about **potential outcomes** (causal effect$_i = f(y_{i,1}, y_{i,0})$)?

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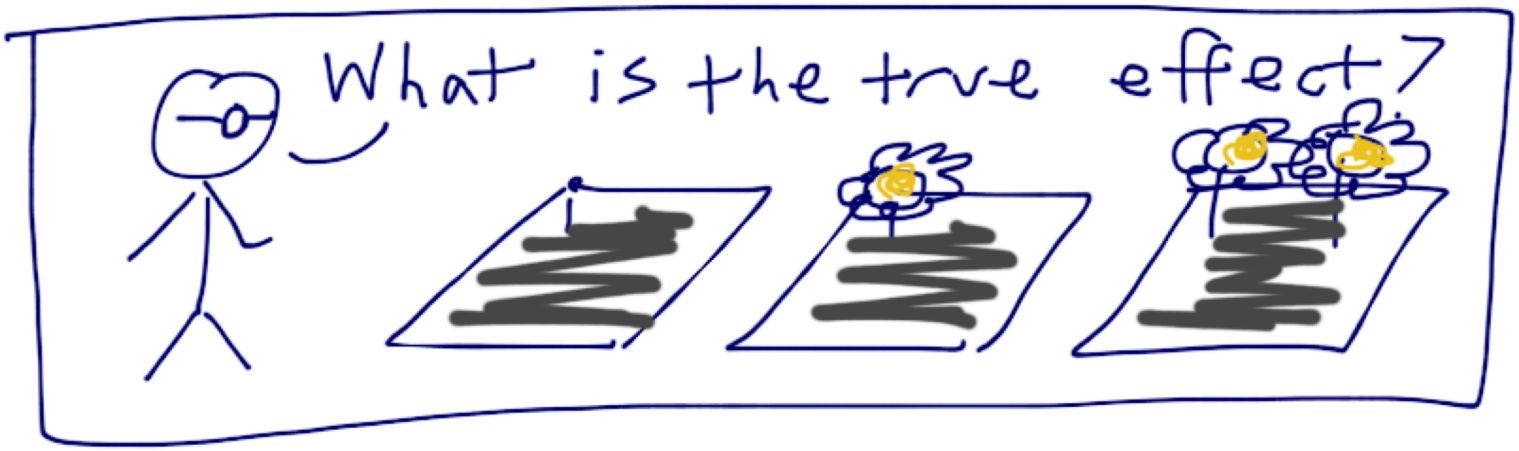
Small group exercise: **Can you think of more than one way to learn about the counterfactual causal effect of treatment using what we observe from an experiment?**

What is the true effect of the treatment assignment?



We don't Know.

What is the true effect of the treatment assignment?

I don't know the truth, but I can provide a good guess of the average causal effect.

i	Z_i	Y_i	y_{i1}	y_{i0}
A	0	16	?	16
B	1	22	22	?
C	0	7	?	7
D	1	14	14	?
			$\bar{y}_{i1}$	$\bar{y}_{i0}$

$$\widehat{ATE} = \bar{Y}_i | Z_i = 1 - \bar{Y}_i | Z_i = 0$$

$$= \frac{22+14}{2} - \frac{16+7}{2} = 6.5$$

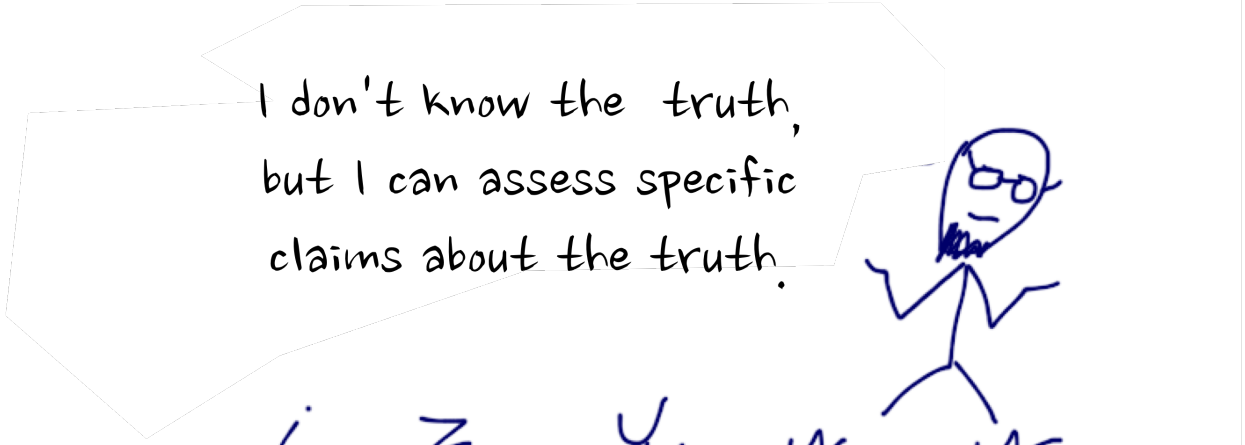
What is the true effect of the treatment assignment?

I dew nut knew thee truth,
but, given pryors, I cane
predikte itf
probabeeleetee.

i	Z_i	Y_i	y_{i1}	y_{i0}
A	0	16		16
B	1	22	22	
C	0	7		7
D	1	14	14	

$P(\boxed{}, f(y_{i1} - y_{i0})) =$

What is the true effect of the treatment assignment?



$H_0: y_{i1} = y_{i0}$

i	Z_i	Y_i	y_{i1}	y_{i0}
A	0	16	?	16
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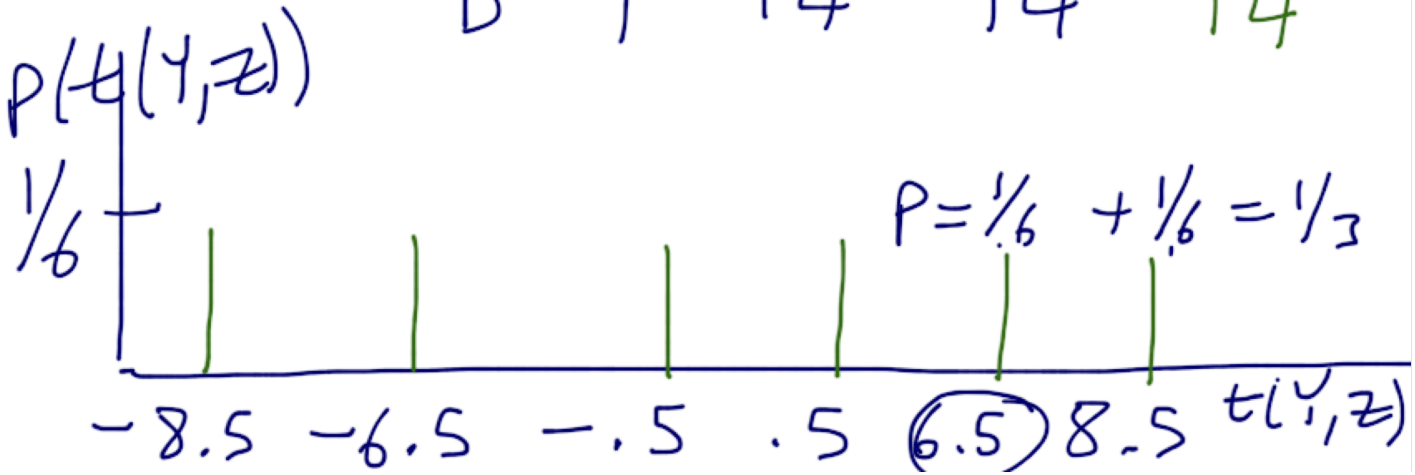

What is the true effect of the treatment assignment?

See also Pearl (2000) and also Richardson and Robins (2013). For more on the potential outcomes approach see Imbens and Rubin (2015).

Estimating an Average Treatment Effect

```
Z <- c(0,1,0,1)
Y <- c(16,22,7,14)
estate <- mean(Y[Z==1]) - mean(Y[Z==0]) ## same as coef(lm(Y~Z))["Z"]
estate

[1] 6.5
```

Testing the Sharp Null of No Effects

```
Om <- matrix(0,ncol=choose(4,2),nrow=length(Z)) ## All possible experiments
whotrted <- combn(1:4,2)
for(i in 1:choose(4,2)){ Om[cbind(whotrted[,i],i)]<-1 }
meandifftz <- function(y,z){ mean(y[z==1]) - mean(y[z==0]) }
thedist<-apply(Om,2, function(z){ meandifftz(Y,z) })
rbind(Om,thedist)

        [,1] [,2] [,3] [,4] [,5] [,6]
         1.0  1.0  1.0  0.0  0.0  0.0
         1.0  0.0  0.0  1.0  1.0  0.0
         0.0  1.0  0.0  1.0  0.0  1.0
         0.0  0.0  1.0  0.0  1.0  1.0
thedist  8.5 -6.5  0.5 -0.5  6.5 -8.5

table(thedist)

thedist
-8.5 -6.5 -0.5  0.5  6.5  8.5
   1    1    1    1    1    1

theobs <- meandifftz(Y,Z)
mean(thedist >= theobs)

[1] 0.3333333
```

What do we need to interpret our calculations as teaching about causal quantities?

For the sharp null test: Randomization occurred as reported.

What do we need to interpret our calculations as teaching about causal quantities?

For the sharp null test: Randomization occurred as reported.

For the average treatment effect: Randomization occurred as reported plus no interference between units.

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Brady, Henry E. 2008. "Causation and explanation in social science." *Oxford handbook of political methodology* pp. 217–270.

Imbens, Guido W and Donald B Rubin. 2015. *Causal Inference in Statistics, Social, and Biomedical Sciences.* Cambridge University Press.

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Richardson, Thomas S and James M Robins. 2013. "Single World Intervention Graphs (SWIGs): A unification of the counterfactual and graphical approaches to causality." *Center for the Statistics and the Social Sciences, University of Washington Series. Working Paper* 128(30):2013.