Dissertation Proposal

Discoverability and Interpretability of Spurious Associations in Data-Driven Decisions

Xian Teng

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Committee

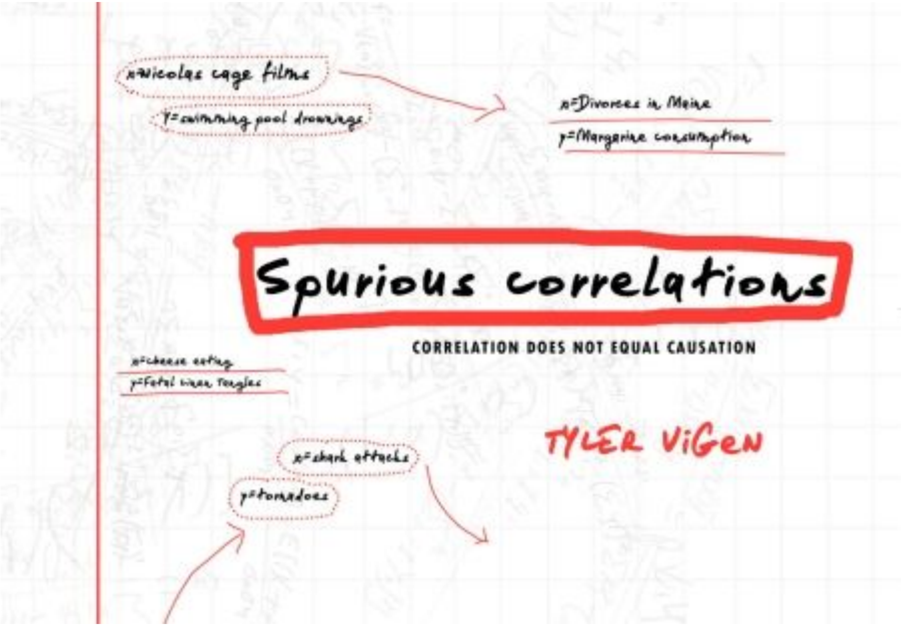
- Dr. Yu-Ru Lin (Chair), School of Computing and Information, University of Pittsburgh
- Dr. Rosta Farzan, School of Computing and Information, University of Pittsburgh
- Dr. Peter Brusilovsky, School of Computing and Information, University of Pittsburgh
- Dr. Gregory Cooper, Department of Biomedical Informatics, University of Pittsburgh School of Medicine

Outline

- Motivation and challenge
- Overview of my proposal
- Preliminaries
- Proposed research (incl. preliminary studies)
- Contribution and implication
- Timeline

Motivation and challenge

11 min



http://www.tylervigen.com/spurious-correlations

An example of COVID-19 vaccine effectiveness

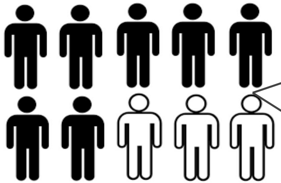
Nearly 60% of hospitalized COVID-19 patients in Israel fully vaccinated, data shows

Twitter user said "**Vaccines DO NOT stop transmissions!**"

https://www.beckershospitalreview.com/public-health/nearly-60-of-hospitalized-covid-19-patients-in-israel-fully-vaccinated-study-finds.html

% of people who are vaccinated (unvaccinated)

# of hospitalized patients per 100K among those who are Vax (Not-Vax)



Young <50yr

~ 70% → ~ 0.3

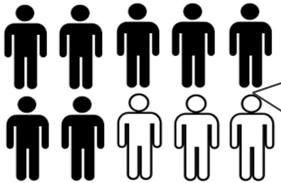
~ 30% → ~ 3.9

Old >50yr

~ 90% → ~ 13.6

~ 10% → ~ 91.9

https://www.covid-datascience.com/post/israeli-data-how-can-efficacy-vs-severe-disease-be-strong-when-60-of-hospitalized-are-vaccinated

	% of people who are vaccinated (unvaccinated)	# of hospitalized patients per 100K among those who are Vax (Not-Vax)	**Efficacy**
 Young <50yr	~ 70%	~ 3.9	91.8% (= 1-0.3/3.9)
	~ 30%	~ 0.3	
 Old >50yr	~ 90%	~ 91.9	85.2% (= 1-13.6/91.9)
	~ 10%	~ 13.6	

https://www.covid-datascience.com/post/israeli-data-how-can-efficacy-vs-severe-disease-be-strong-when-60-of-hospitalized-are-vaccinated

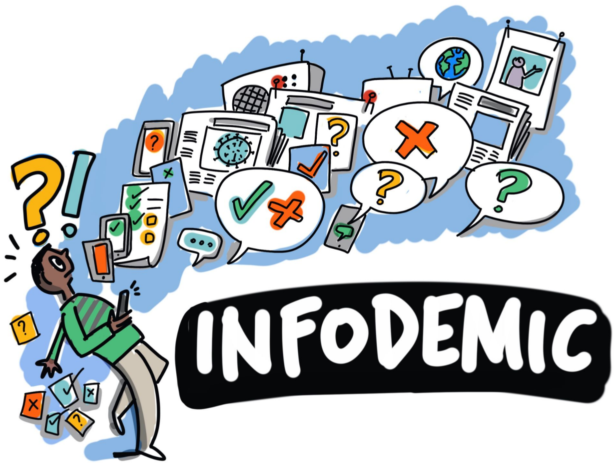
Simpson's paradox (SP)

A scenario where the marginal (or aggregated) association between a pair of variables – a cause variable X and an outcome variable Y – is different or strictly reversed from the conditional (or subgroup-level) associations.

The answer is simple -- older people like to be vaccinated, meanwhile they are more likely to get severe illness thus hospitalized.

Data can’t be lying!
Well... but data can be **misleading** if people do not see the whole story, and interpret data incorrectly

An example of COVID-19 misinformation debunking app

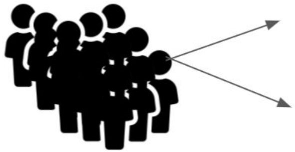


https://www.who.int/news-room/spotlight/let-s-flatten-the-infodemic-curve

Suppose a COVID-19 misinformation debunking APP is developed, an observational study shows that:

- 62% of users who have used this APP recognize misinformation, but this number is only 38% for those who didn't

Can we suggest to launch this APP?



n=100 (50%) → n=62 (62%)

n=100 (50%) → n=38 (38%)

What we observed

of users who have (haven't) used the debunking APP

# of users among those who have (haven't) used the APP disbelieve in falsehood

educated

n=80 (80%) → n=58 (72.5%)

n=20 (20%) → n=16 (80%)

-7.5%

less-educated

n=20 (20%) → n=4 (20%)

n=80 (80%) → n=22 (27.5%)

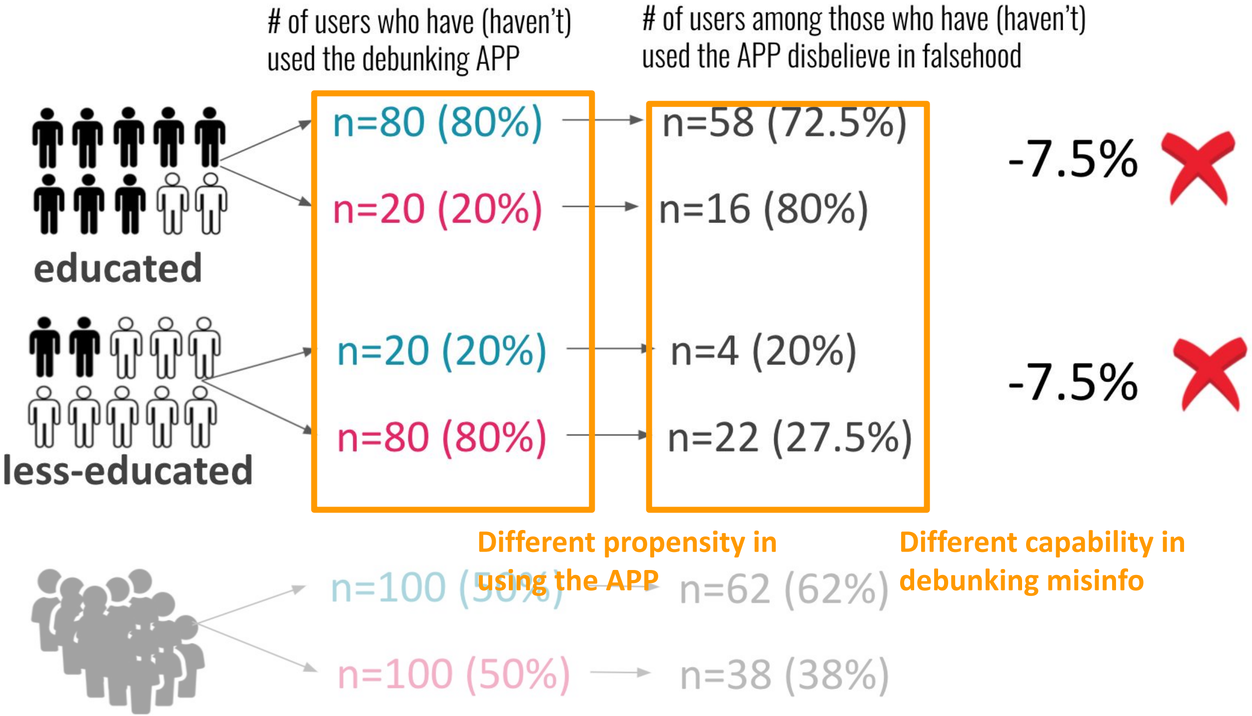
-7.5%

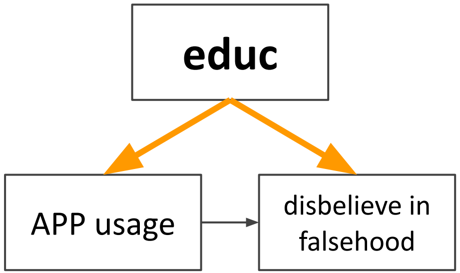
Hidden

n=100 (50%) → n=62 (62%)

n=100 (50%) → n=38 (38%)

What we observed



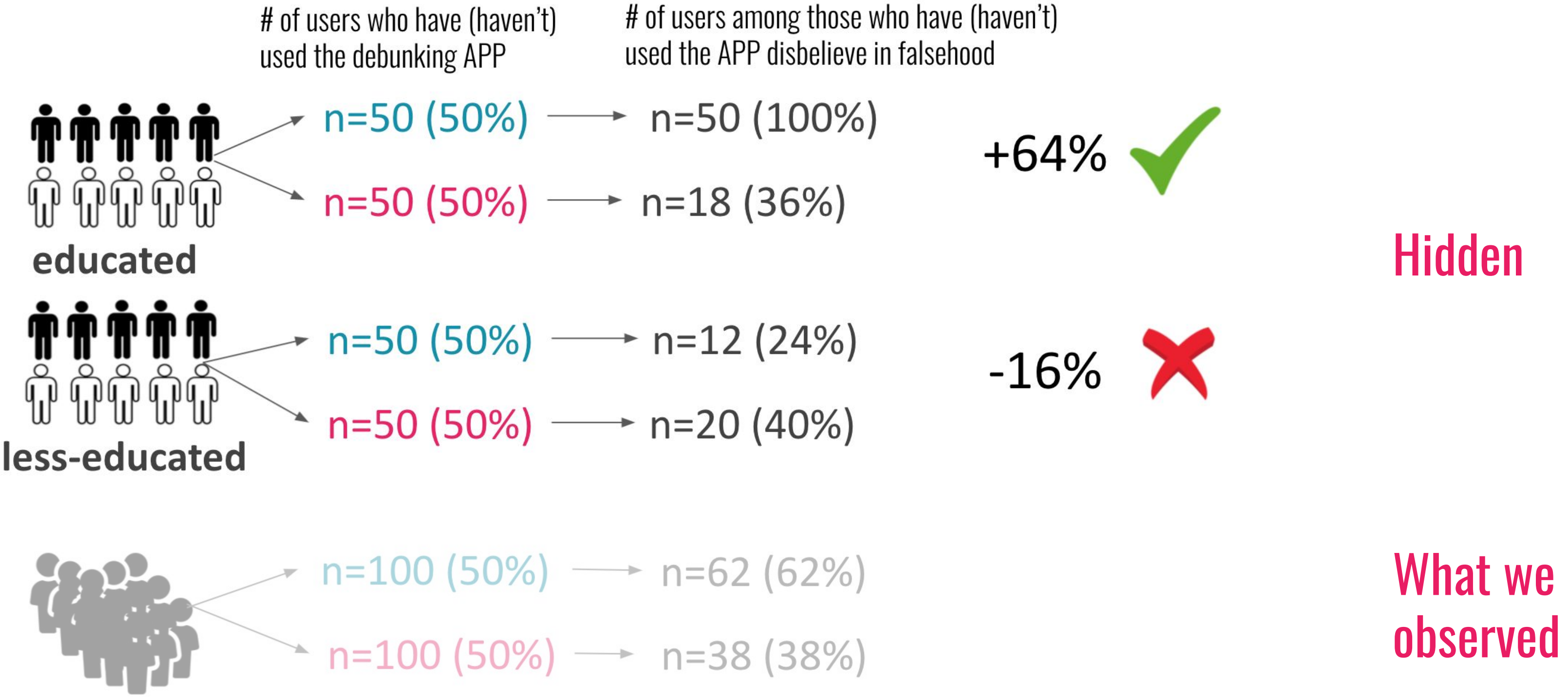


Confounding bias: a scenario where an aggregated X-Y relation is "distorted" by the presence of other hidden variables that are simultaneously influence both X and Y.

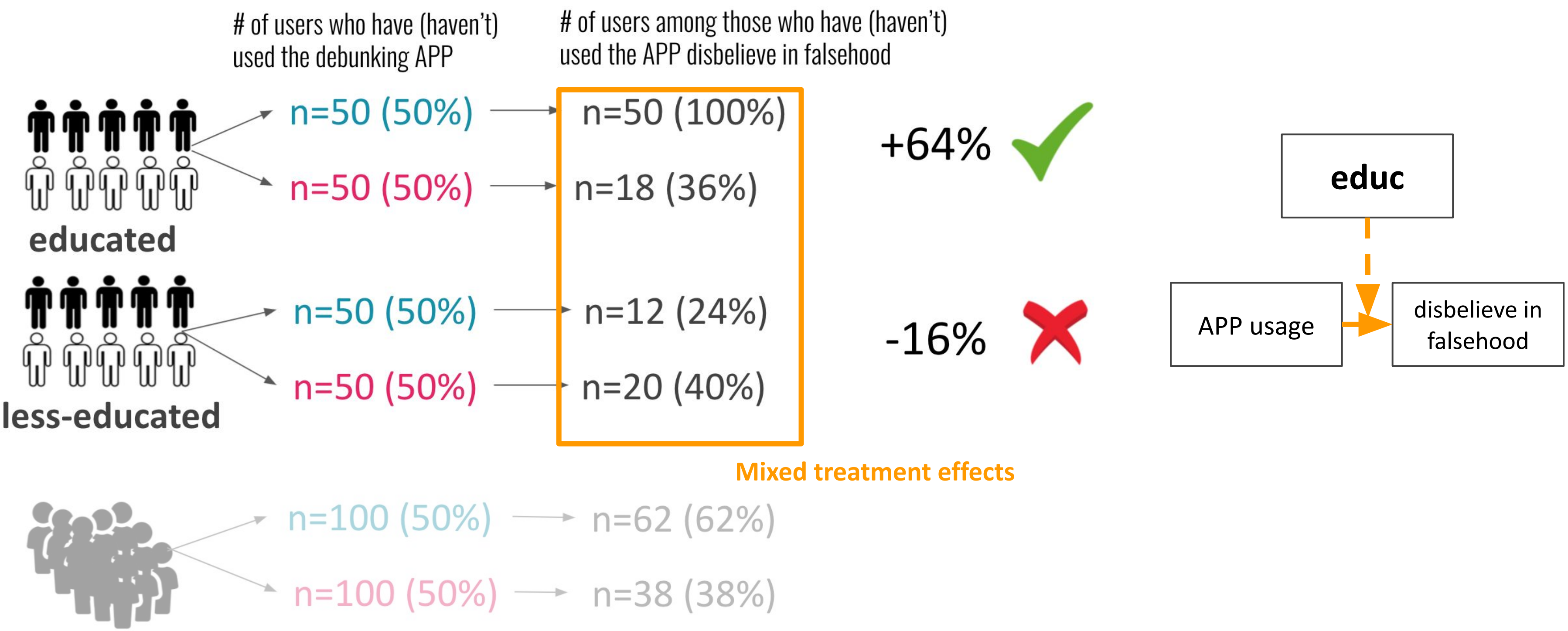
n=100 (50%) → n=62 (62%)

n=100 (50%) → n=38 (38%)

What we observed



# of users who have (haven't) used the debunking APP
# of users among those who have (haven't) used the APP disbelieve in falsehood
n=50 (50%)
n=50 (100%)
n=50 (50%)
n=18 (36%)
+64%
educated
n=50 (50%)
n=12 (24%)
n=50 (50%)
n=20 (40%)
-16%
less-educated
n=100 (50%)
n=62 (62%)
n=100 (50%)
n=38 (38%)
Hidden
What we observed



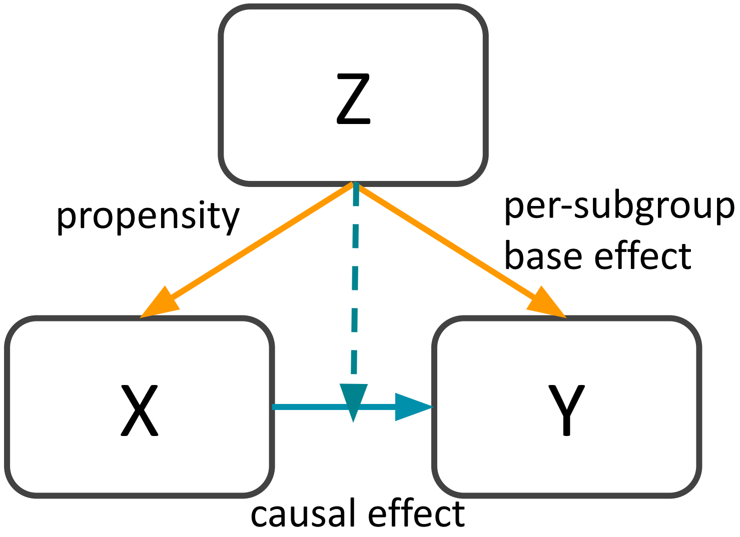
Causal effect heterogeneity: a "biological" phenomenon where the causal effect is different across different subgroups.

SP might lead to harmful consequences

Anti-vaccine sentiment spread on social platform, bad for battling this pandemic

Harmful for less-education people (fairness/equity issues)

Causal explanations of SP



M1. Confounding bias involves

- the Z-X link, the propensity of receiving a certain type of treatment
- the Z-Y link, the base effect characterizing the basic likelihood of getting an outcome of interest without any treatment

M2. Effect heterogeneity involves

- the X-Y link, the direct causal effect
- the Z-(X-Y) link, the effect-modifying effect

Research question

How can we **solve SP-related spurious associations in practical observational studies** as well as to **support people to make reliable decisions**.

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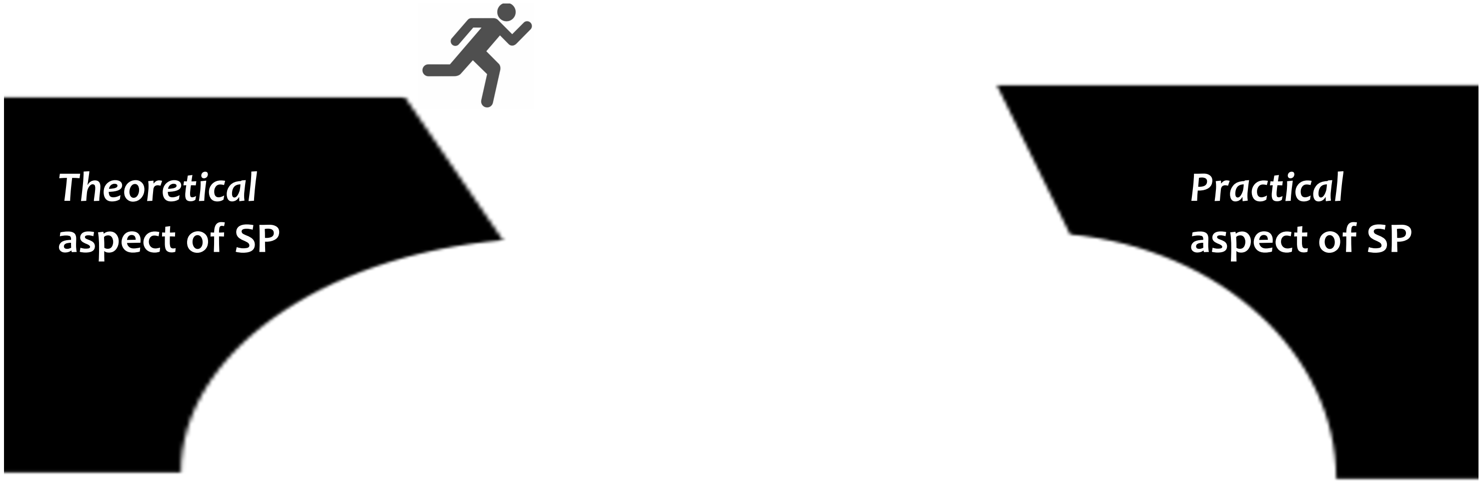
How can we **solve SP-related spurious associations in practical observational studies** as well as to **support people to make fairer and reliable decisions**.



Causal reasons causing SP (Lindley and Novick 1981; Hernán et al. 2011; Pearl 2000)

How to avoid it in practical settings?

Prior efforts to fill the gap

Types	Main idea	Limitations
T1. Statistical tests & clustering analysis (Kievit et al. 2013, Norton and Divine 2015)	Test the independence of each Z with X and Y; Take the learned clusters as possible subgroups	● No guidance of **population partition** ● **Unsupervised clusters might not invite SP**
T2. Partition algorithms (Alipourfard et al. 2018a,b, Correia et al 2020)	Divide samples into subgroups and check paradoxical associations (e.g., stratification)	● Unable to handle **high-dimensional Z** ● Neglect within-subgroup **confounding and effect heterogeneity** (nested SP)
T3. Visualization (Schneiter and Symanzik 2013, Armstrong and Wattenberg 2014, Friendly et al. 2013)	For the purpose of explanation	● **Not a general tool** in practical data analysis settings

Challenges

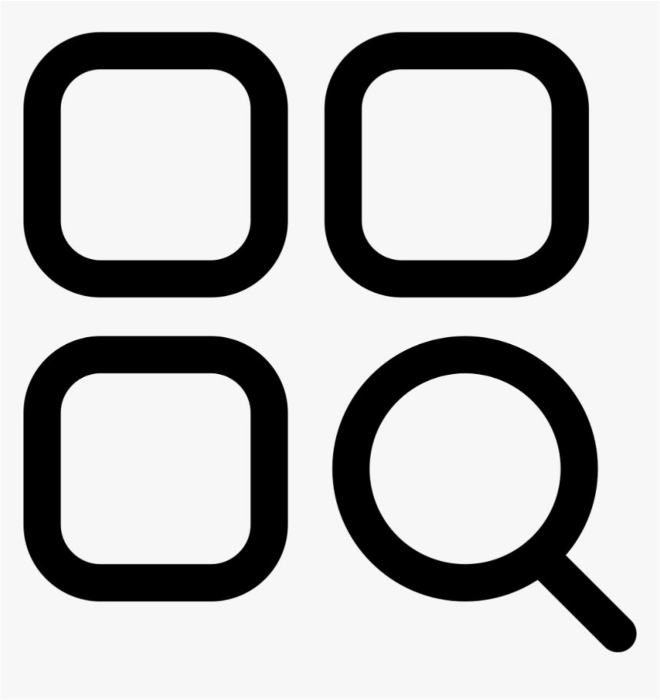
C1. Lack of automated discovery of population partition in a high dimensional covariate space.
(T1 - no automatic methods, T2- unable to deal with high-dimensional Z)

C2. Lack of an assessment of a candidate partition.
(T2 - neglect within-subgroup confounding and effect heterogeneity)

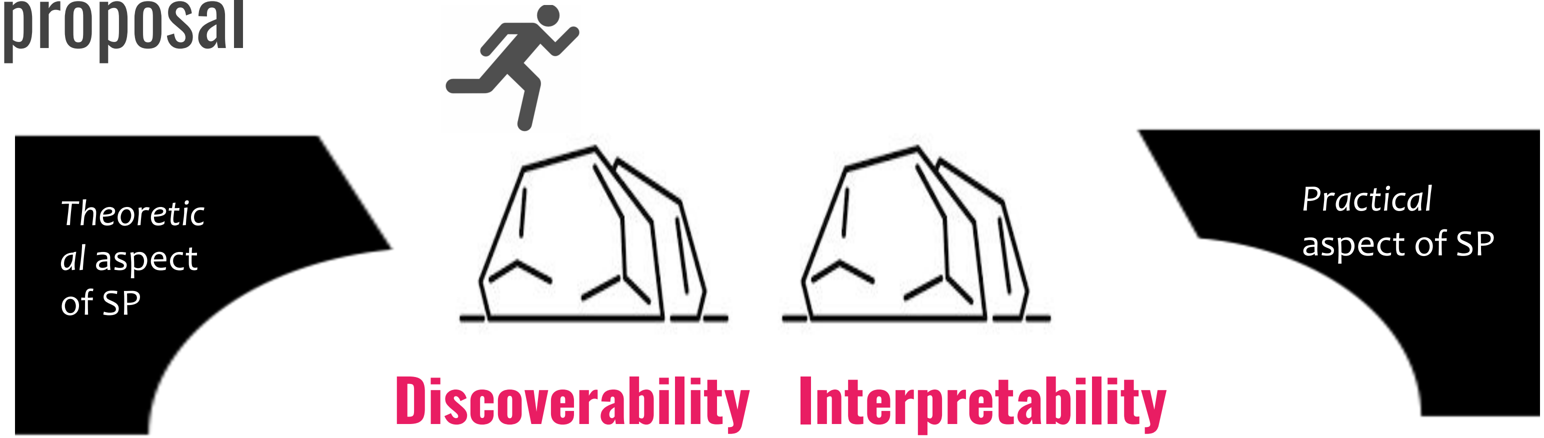
C3. Lack of an interpretable system in assisting data-driven decision making
(T3 - lack general and practical tools)

Overview of my proposal

1 min



My proposal



- **RC1. [Discoverability]** Detect and characterize subgroups wherein confounding bias is minimized and causal effect is homogeneous.
    - RC1a. Develop algorithms to perform population partitioning (Challenge C1)
    - RC1b. Propose assessment metrics to characterize a candidate partition (Challenge C2)
- **RC2. [Interpretability]** Design a visual analytic system to support visualization and interpretation of Simpson's paradox (Challenge C3).