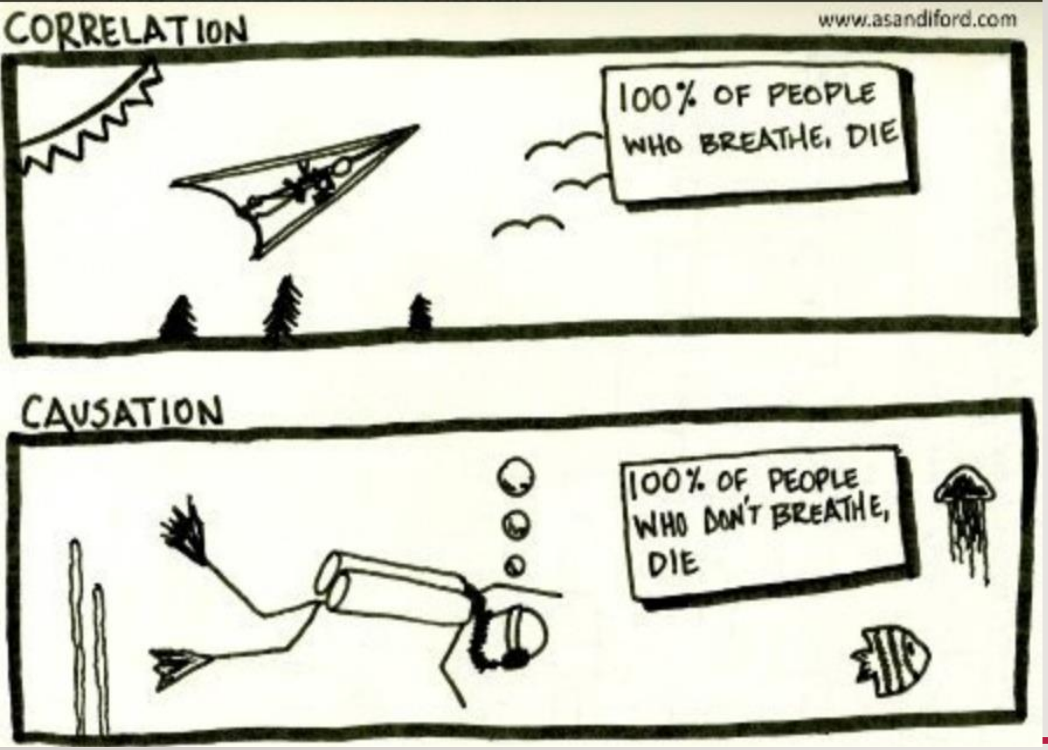

CAUSAL INFERENCE IN NATURAL LANGUAGE PROCESSING FOR ECONOMICS

WEEK 2: CAUSAL INFERENCE – TEXT AS OUTCOMES

SUMMER SEMESTER 22

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LOGISTICS

- Any questions with…
  - Group sign-ups? (groups of 2 to 3 students, in total 8 groups)
  - Research interests

https://docs.google.com/spreadsheets/d/1EEUJp1Srz05BwEUH2u3CbYwMykmqEUhZdn2SqrmeaRs/edit#gid=0

Group sign-up Deadline: TODAY Tuesday 19.04 @ 23.59 → If not yet in group by then, I'll randomize the rest of you into groups.

AGENDA

- CI with Text as Outcomes
  - Challenges
  - Applications

- Coding exercises:
  - [Stata]: Propensity Score Matching
  - [Python]: KDD Ceviche UberRide Data: CI with observational data

CENTRAL CAUSAL EQUATION OF INTEREST

$$Outcome_i = \beta_0 + \beta_1 Treatment_i + \boldsymbol{X}_i\theta + \varepsilon$$

A simple RCT with one treatment group and one control group in which the treatment and control have been perfectly randomized can be analyzed with a simple t-test.

Randomization can be checked by comparing the observables of the treatment group and control group prior to the experiment and after the experiment in a robustness check by including controls in a regression framework.

CENTRAL CAUSAL EQUATION OF INTEREST

If β_1 differs from the t-test difference, then either:

- the treatment and control groups are NOT perfectly balanced purely due to chance,

AND one or more of the observable characteristics are correlated with the outcome.

- OR, more concerning, the experiment may have a problem with internal validity.

THREATS TO INTERNAL VALIDITY?

1) Survey bias: having to answer to a survey alters the outcomes of the surveyed individuals.

- Survey biases generally occur with repeated samples.
  - E.g: administering a health survey might make you pay more attention to your health → improve it.

→Survey bias alters the measured impact of the treatment.

WHY? it alters the behavior of the control group.

→ Potentially biased estimated treatment effect.

THREATS TO INTERNAL VALIDITY?

2) <u>Experimenter bias</u>: any systematic errors in the research process or the interpretation of its results that are attributable to a researcher's behavior, preconceived beliefs, expectancies, or desires about results.

Examples?

TEXT AS DATA IN THE CI FRAMEWORK

Discovery is central to text/audio/image-based causal inferences because such complex, high-dimensional data types ALWAYS need simplification before it can be used meaningfully.

E.g: Take a collection of e-mails, classify into 'spam' and 'not spam.'

Let $\boldsymbol{g}$ be the function which maps the documents into our measure of interest g.

→ $\boldsymbol{g}$ = a crucial codebook that tells us how to compress our documents into categories, topics, or dimensions.

TEXT AS DATA IN THE CI FRAMEWORK

- The need to discover and iteratively define measures and concepts from data is a fundamental component of social science research.
- (!) BUT the iterative discovery process poses problems for causal inference. WHY?
- We may not know $\boldsymbol{g}$ in advance of conducting our experiment.
- AND consequently, we may not know our outcome or treatment.

→ Identification problem!

TEXT AS OUTCOMES - LAB/FIELD EXPERIMENTS WITH TEXTS

Gold standard to obtain causal estimates. For instance:

- Subjects fill out open-ended survey responses before and after the experiment
- (!) In reality, lots of observation data is used to determine causal relationship (see application later)

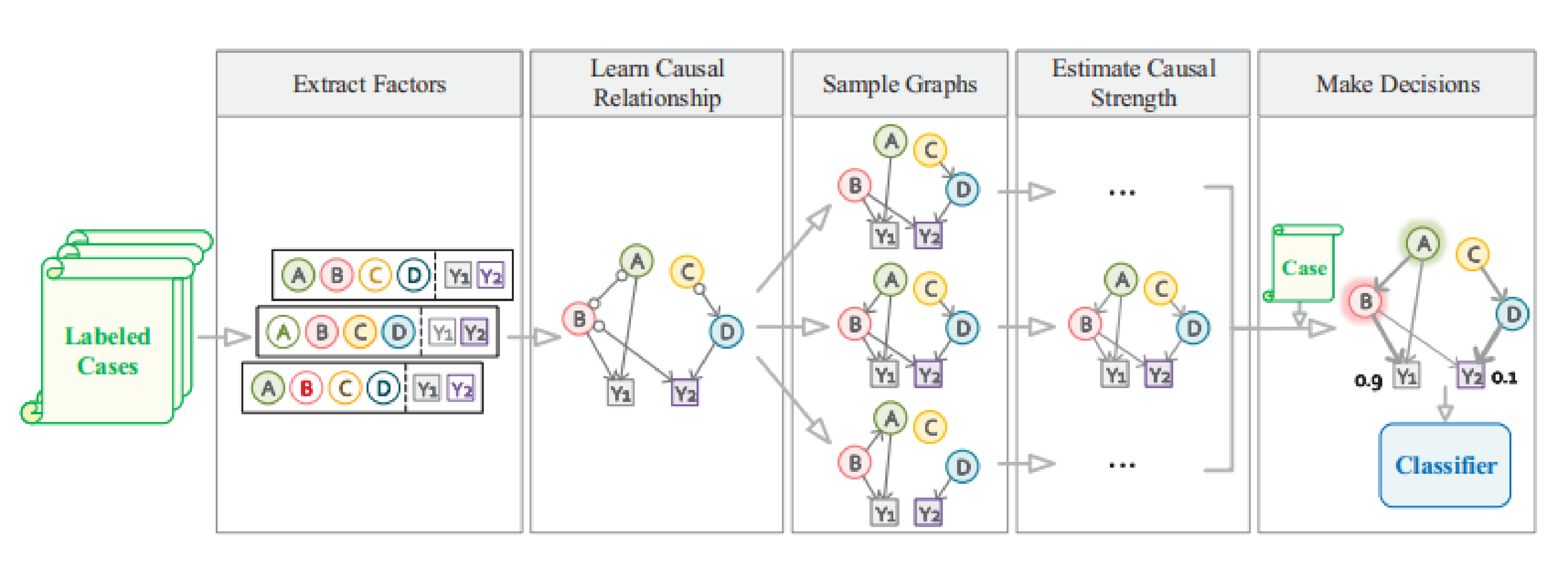
E.g: (1) group norm promotion and social sanctioning on a racist online harrassments (Munger, 2016)

How? collect a sample of Twitter users who have harassed other users and use "bots" to sanction the harassers.

Method? Vary the identity of the bots between in-group (white man) and out-group (black man) + the number of Twitter followers each bot has → subjects who were sanctioned by a high-follower white male significantly reduced their use of a racist slur.

CI MODEL WITH TEXT AS OUTCOME : OBSERVATIONAL DATA

- A legal AI system assists judges to deal with complicated cases that involve multiple parties and complex events, CI could help to figure out the exact distinguishable elements that are crucial for fair and impartial judgements (Liu et al., 2021, ACL)



EXERCISE TIME ☺

- Go to Github's course channel →Exercise folder to access these files.
- Open your Google Colab.