Data and Society Parts IV+V Mix

Kenneth W. Regan

(Includes material from Kenny A. Joseph and some other past CSE199 units.)

CSE199, Fall 2024

Precision, Accuracy, and a “Murphy’s Law”

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Thus using 100× more people brought only 10× more precision, but would keep percentage error—which is $\frac{skew}{N}$—at the same rate. Your 10× narrower confidence intervals would give you misplaced confidence in a wrong result. **(Your HW will emphasize detecting possible sources of bias/inaccuracy and how to manage them.)**

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- Aggregating tournaments checks my formulas for accuracy and bias.

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- Last, let's talk briefly about Sentiment Analysis.

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- "Joy" is an express term of the Harris-Walz campaign. Does it show?

Part VI: AI (part)

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The **Church-Turing Thesis** is primarily stated in terms of the class of *computable functions*, but here is Turing's angle:

> **Anything that human beings can consistently deduce or classify can also be achieved by computers acting alone.**

The **Turing Test** involves computers trying to be indistinguishable from humans in ordinary life communications and transactions.

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Also defies the logical **contrapositive** of Turing's Principle:

If it is really hard for computers then it should be hard for humans.

What we fear when worrying that AI will take away our jobs is:

Stuff that is hard for humans but easy for computers.

The logical **converse** of Turing's Principle acts as a brake, however:

If X is hard for humans—insofar as we can't consistently agree on answers—then X is hard for computers too.

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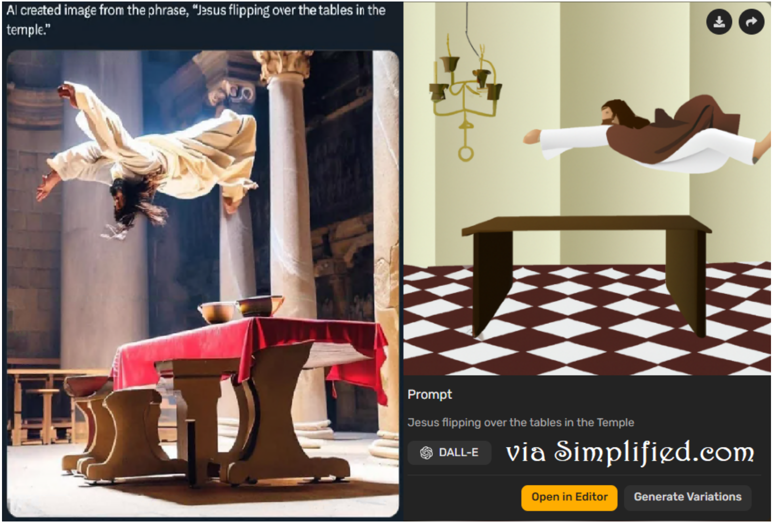
- But subject to **hallucinations** and other foibles—some shown by me here and here and here.

AI Art Adventure

"Jesus flipping over the tables in the Temple." From the movie *Jesus Christ Superstar*—then try it on Cutout or NightCafe or Simplified:

Two Results—one famous, one mine



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- Given that ChatGPT has already processed the data and rules to write grammatical and cogent Latvian, a minimal threshold on the way to *sentience*, IMHO, is that a non-Latvian speaker like myself, giving examples of high-quality limericks in English and with no further Latvian data of any kind, should be able to get it to write superb limericks in Latvian.

ChatGPT Is Made of Us ("Pogo" Quote)

- *We* are the training data for ChatGPT and other Large Language Models (LLMs).
- (Up to date only thru 2021, however.)
- Example: Writing a Limerick (in Latvian!). [show]
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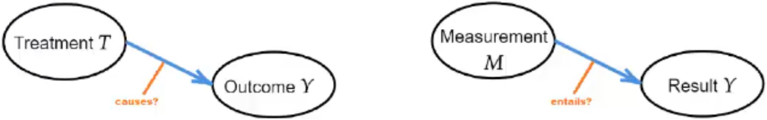
- (But possibly I already pushed it to the limits of its current data.)

Part V: Societal Computing and Fairness

Studies in medicine, psychology, and other sciences have enabled us to gauge significant causes and effects. Two typical notations for the objects of these studies:



- Often Y is a binary choice: does a desired outcome happen? does the result go one way or the other way?
- The math for determining whether there is a significant causal relationship then resembles a simple poll.
- For a targeted value Y, the study's findings can be phrased as whether Y is significantly ahead.
- I.e., is Y beyond the *margin of error* for the **null hypothesis** of no causation?

The Replication Crisis

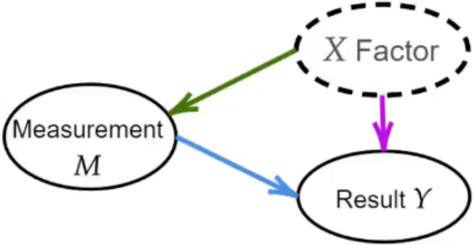
- Means that findings of significant causality in one published paper are not found when another team re-creates the study.
- A Simple Mechanism:
    - Something like Covid brings fresh Big Ideas in medicine and psychology (etc.).
    - More than 50 of the world's major institutions launch a study... privately.
    - The ground truth is "no effect"—analogous to our 50-50 election.
    - But $\sim$ our poll analogy, one study randomly gets results outside the margin of error, i.e., "$> 2\sigma$."
    - This is the academic threshold to publish, so they do.
    - The others who get "$< 2\sigma$" (or even $< -2\sigma$ or other forms of "no effect") stay silent.
- Just like if I focused on one high player in the Chess Olympiad—ignoring that there were almost 1,000 other players.
- When others try to replicate the study, the ground truth proves out.
- Can happen with 50 different big ideas, too (see this).

Study Size Matters

- Bookending this is that human-subject studies tend to be small.
- Landmark studies by Kahneman et al. were only $N \sim 100$ people.
- Even some of his famous book Thinking Fast and Slow has come under a cloud.
- Possible to get closed-world 95% or 99% confidence...
- ...but beyond that, the "Murphy's Law" that precision grows only as $\sqrt{N}$ while skew grows as N kicks in.
- Premise of my own Kahneman obit:
  - Get higher N from less-targeted situations.
  - Such as chess—in real competitions rather than simulations (such as your "Prisoner's Dilemma" activity).
- Mining social media is a major example.
- Can we make a tight enough relation between our measurements M and the results Y we are trying to capture?

Other Study Design Flaws To Beware

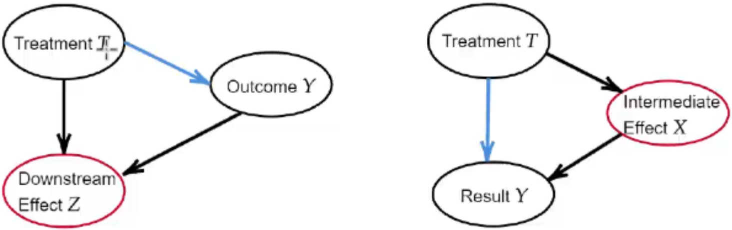
Confounding Factor(s):



- Possible example: X = a scandal, such as in North Carolina.
- Can both *stimulate* M (such as "heat") while *inhibiting* Y (such as "Challenger Wins").
- Even if impact is positive on both M and Y, X can dominate, drown out, or otherwise skew the effect we are trying to analyze.

Selection Bias From Conditioning

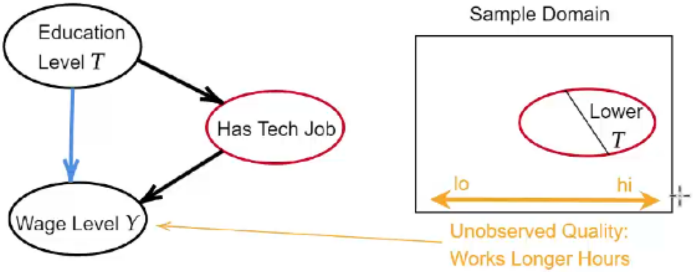
Conditioning on Other Effects



- Chess examples: (IIa) T = chess training, Y = more wins, Z = lower ACPL.
- (IIb): T = chess training, X = higher rating, Y = lower ACPL.
- Each way, conditioning on Z or X **selects** a **subsample** that may be skewed relative to the whole domain.

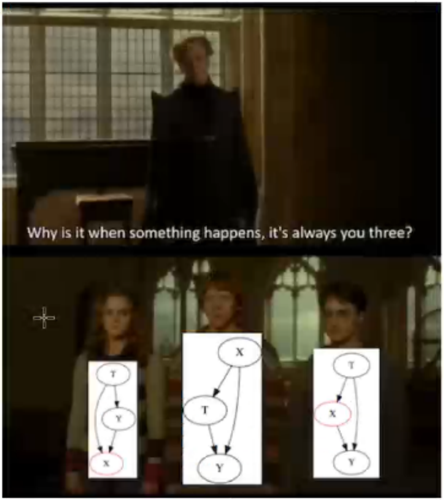
Non-Chess Example (adapted from here

Suppose we are doing a large-scale study of the effect of education on wages, but decide to condition on people having tech jobs:



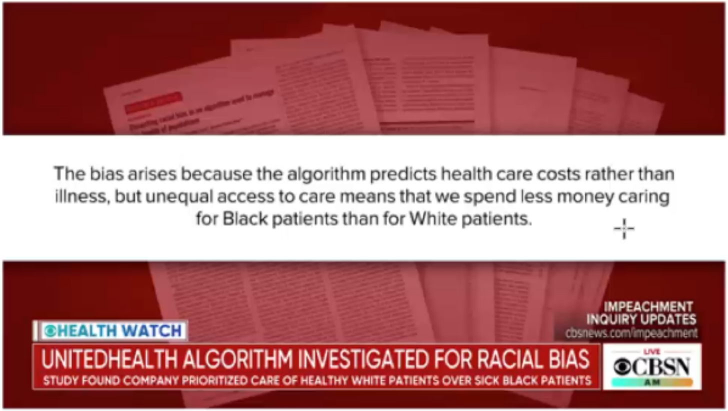
- Subsample from conditioned variable is skewed.
- (Source says "white-collar jobs" rather than "tech jobs.")
- Can also happen from choices of unrepresentative proxy variables.

Harry Potter Meme (also from here



Example of Bias From Proxy Variable (K. Joseph)

Here the variable Y' = health care costs used for Y = level of illness did implicit conditioning. Video.



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- Insofar as we are the training data for the Internet, the latter has baked in tangible amounts of racism and sexism.