Data and Society

Resources and Dangers and Opportunities

Kenneth W. Regan

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

CSE199, Fall 2024

Main Problem...

Any Questions?

(Brain scan source, 1987 PSA source)

...And Problems

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5. **What tools enable us to understand it?** We will cover some: probabilistic modeling, regression, simulation, preference aggregation, causal graphs, other data analytics...

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- How does that compare (in speed and mass) to "Memes" and viral content today?

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- Even nearer term: Elon Musk's **Neuralink** brain implant as used to play chess.

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- **Actual reality**: the July 19, 2024 CrowdStrike Crash.

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- Your further CS education will show how to build systems from the ground up.

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- **Datasets from the past have large racial and socioeconomic biases.**

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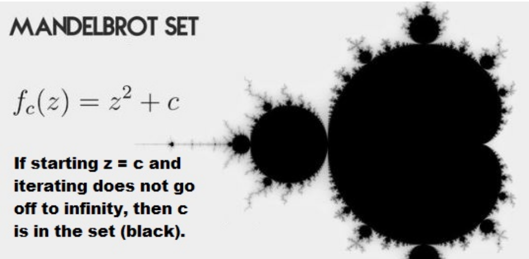

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- Whether the info and inferences are **true** is secondary!

Outline For Remaining Lectures

1. Some further remarks about Data as time allows in this lecture.
2. Our Global Data Village
3. Data Analytics, Search, and AI
4. AI, continued—Project Ideas
5. Societal Computing and Fairness
6. Synthesis.

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- How can the Net's architecture absorb this expansion?

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But for many users, where it lives virtually is in the Cloud.

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- **Nontrivial portion of world energy consumption**. (Segue to next unit.)

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- Graphs can be **directed** with arrows or **undirected**.

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- Rock-Paper-Scissors is a simpler example with *simultaneous play*.
- Describable as a **single-matrix game** like so:

You\Oppt.	Rock	Paper	Scissors
Rock	0	-1	1
Paper	1	0	-1
Scissors	-1	1	0

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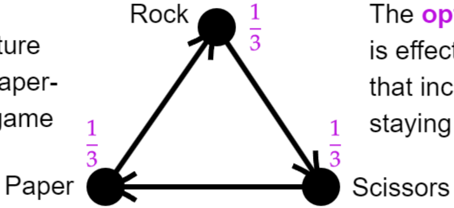
- Only foolproof way: a **completely random** strategy. Here: roll a die and play Rock on 1 or 2, Paper on 3 or 4, and Scissors on 5 or 6.
- But since this is a **fair game**, you can't expect to win either.

Graph picture of Rock-Paper-Scissors game



The **optimal random strategy** is effected by a **random walk** that includes the option of staying on your **current node**.

The walk is on the corresponding **undirected** graph.

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- Can have $N > 2$ players or as *solitaire*—

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- Upshot is that **random walk** on G is often (near-)optimal strategy.
- Can have $N > 2$ players or as *solitaire*—like vs. house at blackjack.

Non-Zero-Sum and Multiplayer Games

- Could play with rule that Paper+Scissors wins for *both* players.
- **Non-zero-sum** games use separate **payoff matrix** for each player.
- Could **pre-arrange** choices—but then the Paper player could **defect** by choosing Rock.
- Similar games can be played on any graph G, not just the triangle.
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- Upshot is that **random walk** on G is often (near-)optimal strategy.
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- **Internet Search** is a solitaire game where the payoff to you is the *non-quantified* usefulness of the found pages to you.

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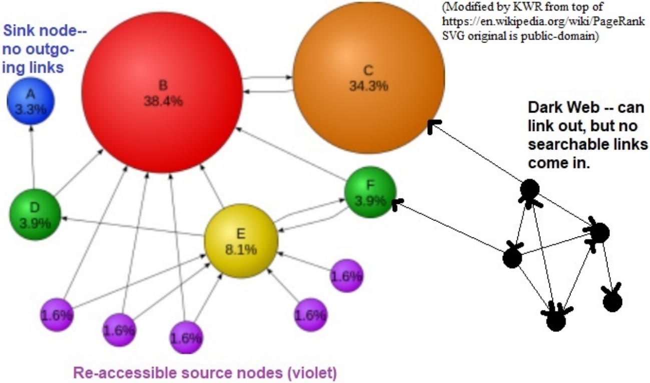

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Computing the walk probabilities gives weights $w_Q(P)$ on pages in G_Q. Return them in that order. (Alternative: in order of $w'_Q(P) \cdot r(P, Q)$.)

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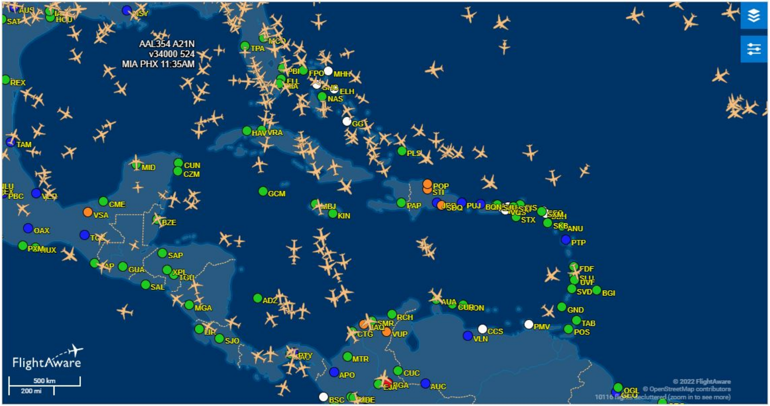
A “Semi-Structured” Example (of Inferencing)

FlightAware Live Tracker, Monday 9/19/22, about 11am:



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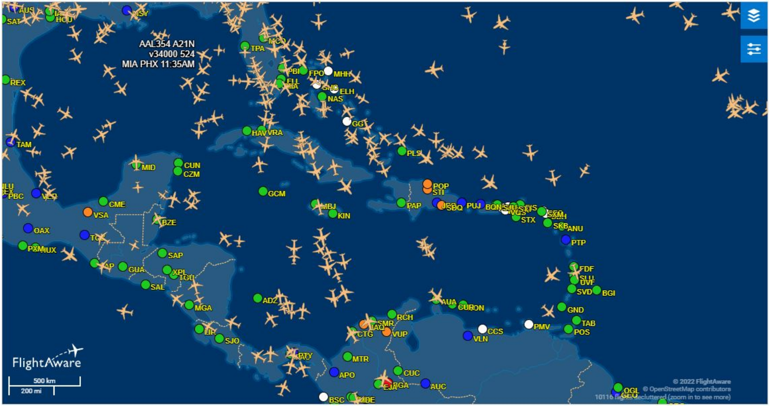

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And what about north of the Black Sea?

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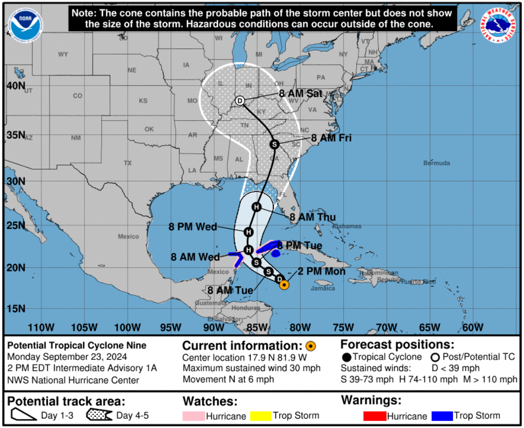

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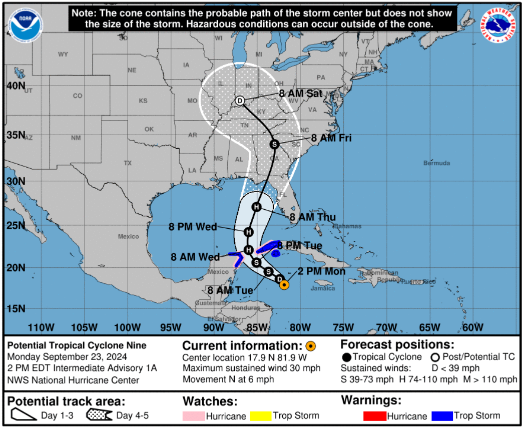

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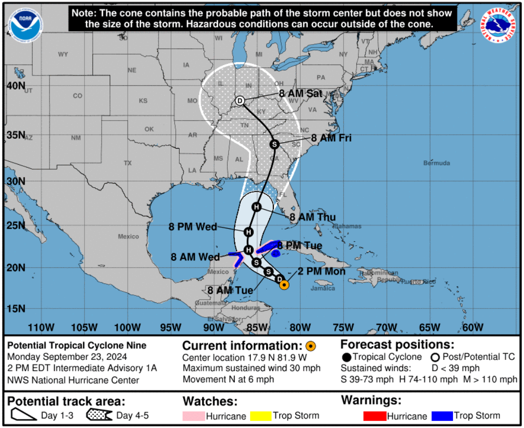

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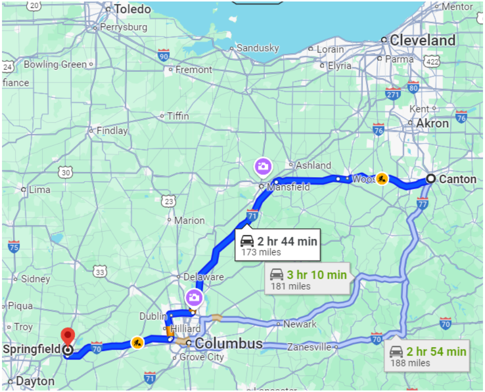
- Reports of lost pets in Springfield coming now—more than usual?



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- Either way, can insert targeted ads...
- (Silly new example of correlation-versus-causation: do the KC Chiefs lose when Taylor Swift isn't at the game? Madden '24)

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E.g. time and duration (and recipient??) of cell phone calls.
[Discuss 2010 French chess cheating case and civil vs. criminal law.]

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• Major controversy over gathering metadata by law enforcement and intelligence.

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- Has been a special research topic at UB CSE.

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- For misuse of Bram Cohen's BitTorrent—not so clear. Cut deal in 2005 with Motion Picture Association of America to follow DMCA.

Important CSE199 Items

- Regrade requests are due 11/22 for grades before 11/16
  - All materials except Cohort Survey 2 have been graded.
  - If you think something is wrong, request a regrade.
  - See the course announcements for instructions
  - Course Instructor Email addresses are in the syllabus!
  - Any regrade request that does not follow the instructions will be ignored
- No class next Monday (11/25)
- But otherwise, come to class!
  - Every 3 missed lectures/recitations is a half-letter drop in your grade!
- Nominate yourself to be a 199 TA next fall
  - Fill in the nomination form you'll get as a course announcement
- Reminder: All of this is in a course announcement on UBLearns that you got this morning.

Part III: Data Analytics

We will cover the following tools and some of their societal implications:

1. Linear Regression: $Y = a + bX$, $Z = a + bX + cY$, and so on.
2. Causal Inference, Graphs, and Caveats.
3. Probabilistic Modeling.
4. Predictive Modeling.
5. Preference Aggregation:
   - Voting.
   - Ranking and Rating.
   - Polling and Poll Aggregation.
6. Internet Search. (already covered last week)

Many topics are left uncovered. Search will reappear in Wednesday's coverage of machine learning, sentiment analysis, and AI.

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- But whether this amounts to **causation** may remain problematic.

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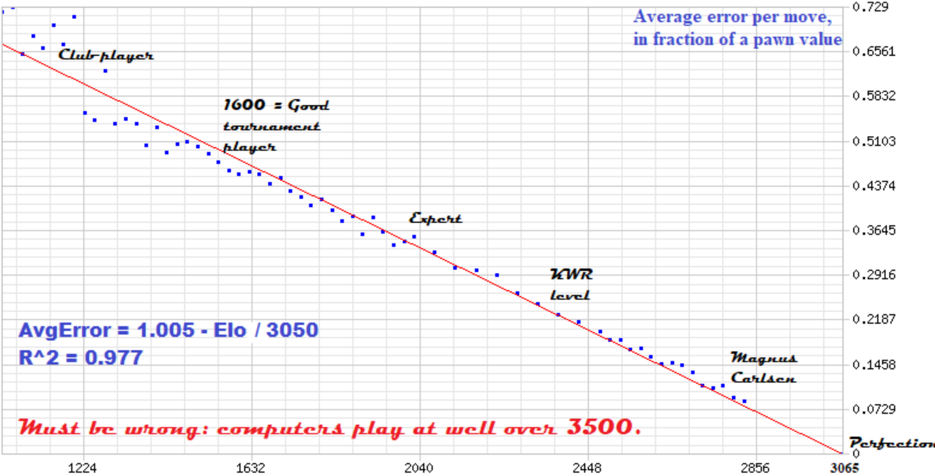
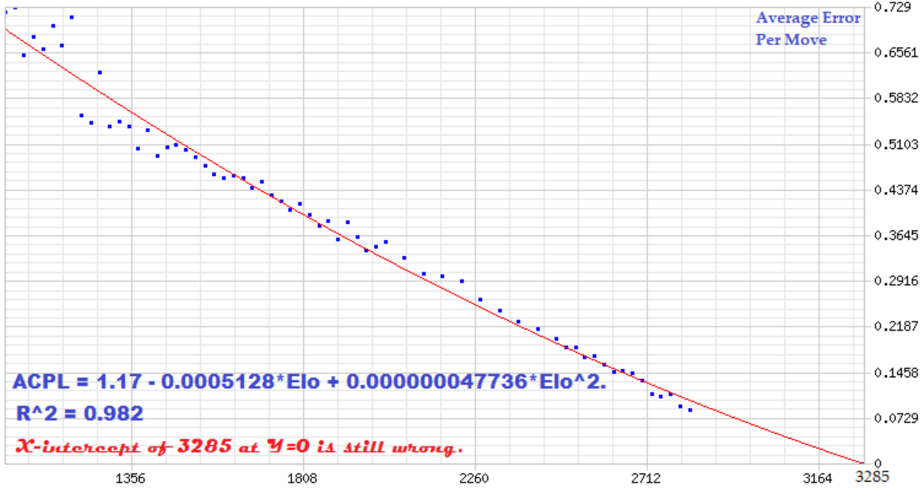
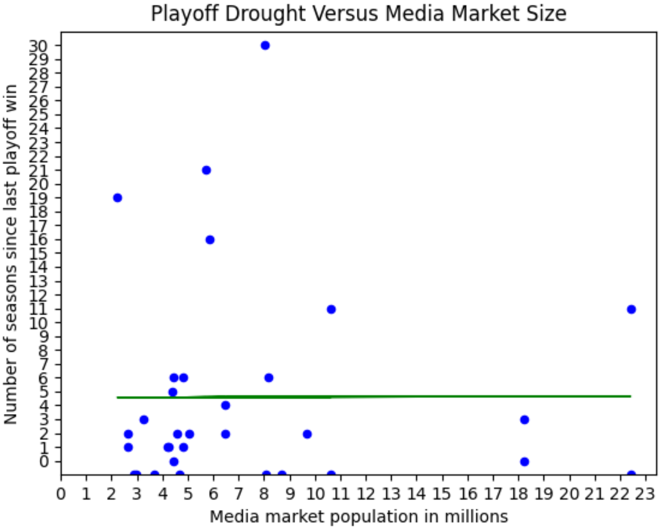
Linear Model: ACPL = $a + b \cdot$Elo Rating



Quadratic Fit—Only Marginally Better



A Desired Null Result? (data from a year ago)



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- Regression by itself says little about what **judgments** it supports:

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- We need a stronger **probabilistic model** that individuates game positions.

2. Causal Inference and Causal Graphs

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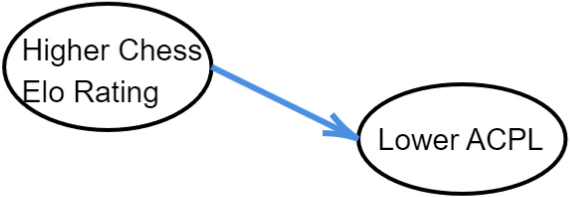
- Causal graphs have nodes—black or red for conditioning—and arrows.
- They can help ascertain
  - which are genuine causes—as opposed to mere correlations or null effects,and
  - which variables in the system can helpfully be **regressed** or **conditioned on**.

Let's start with a simple example and see how considerations can mushroom:



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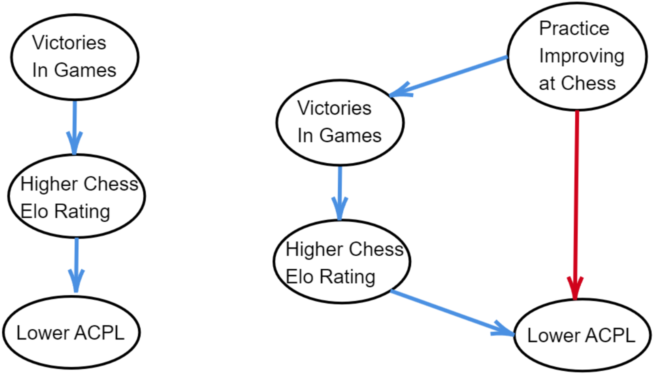
- But if we have a lurking *common cause* D of both our *source* and *intended target*, then it can **confound** the smaller-scale analysis.
- I faced this when the pandemic caused official chess ratings to lag true skill. Case of wrongly accused player.



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- The factor defining each segment is **conditioned on** and shows in **red**.

Conditioning on the middle node of a causal chain can sever the "A causes C" inference. A and C may even show as **independent** in the conditioned slices---here, because lower error (higher accuracy) might not imply more wins when players of the same rating are in action. Some players may even win more *via* higher ACPL if it tempts their opponents into playing wildly.

(We will do more causal graph examples next week.)

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  - It helps to be *confident* that the class won't just bomb your exam.

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- My chess model's probability forecasts are similarly accurate within $\sim 5\%$.

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In my model, the m_j are possible moves in chess positions.

Chess and Tests—With Partial Credits (Or LLMs?)

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(source: itunes.apple.com)

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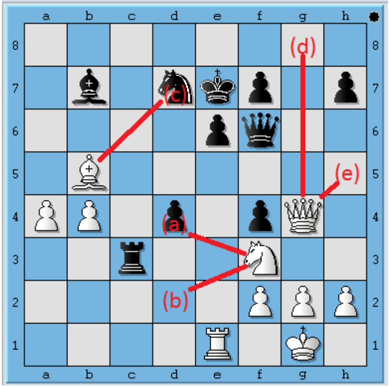

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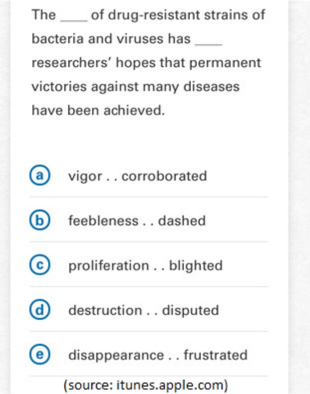

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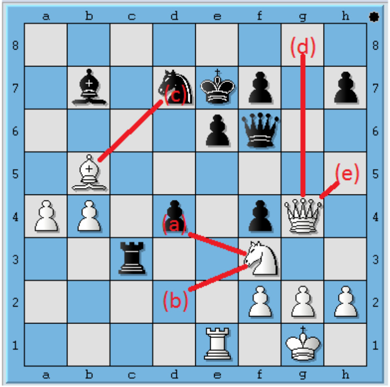

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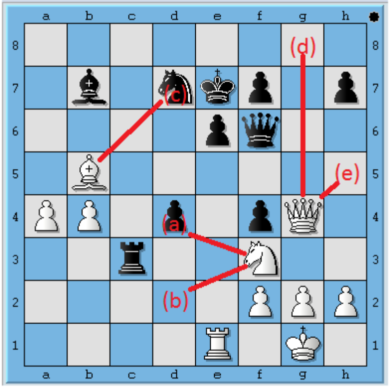

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Gaussian math yields confidence intervals that can enable **rejecting the null hypothesis** *of fair play* with high confidence.

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- Rating numbers convert into **rankings**. E.g. chess players by Elo.

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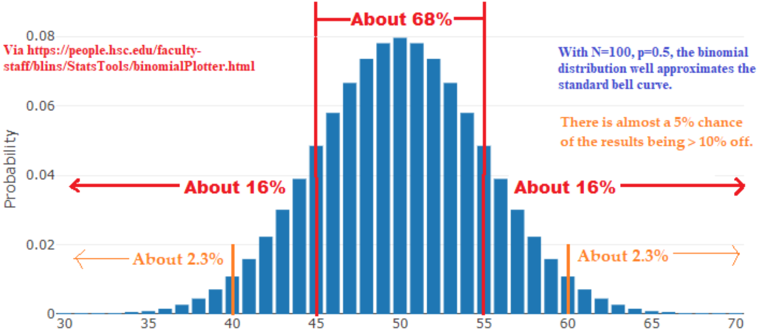
- Almost **one-third** chance poll results will be $<$ **45%** or $>$ **55%**.



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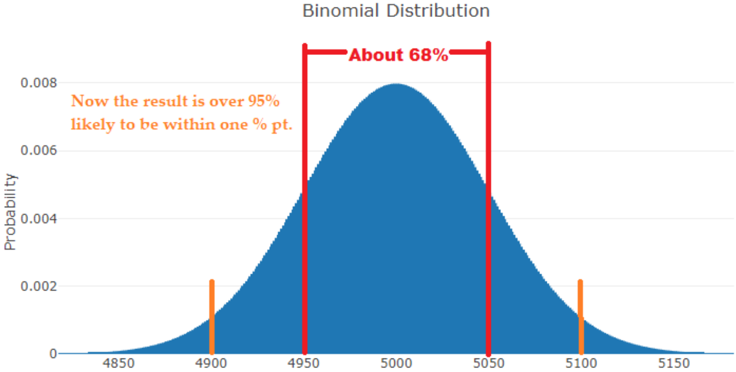

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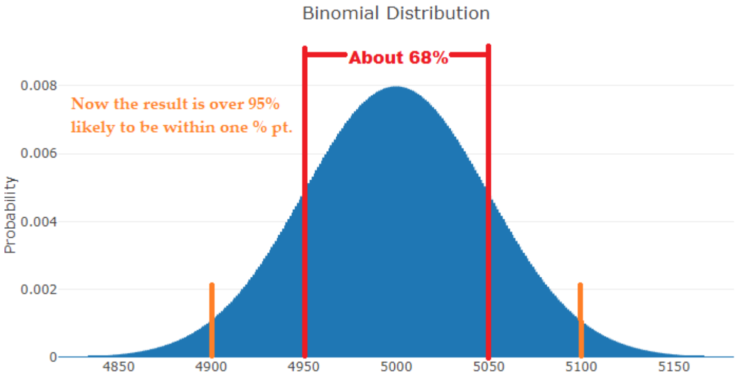

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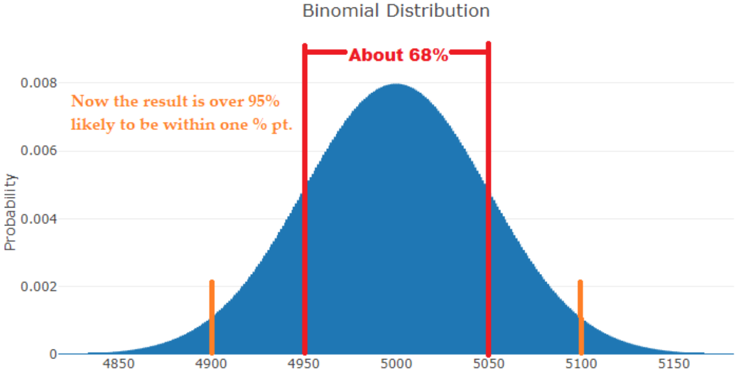

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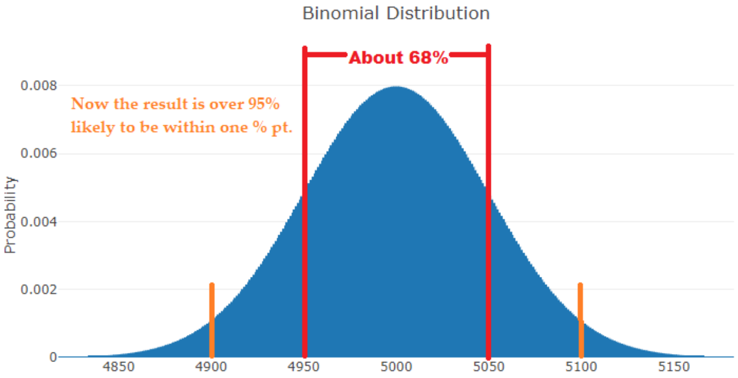

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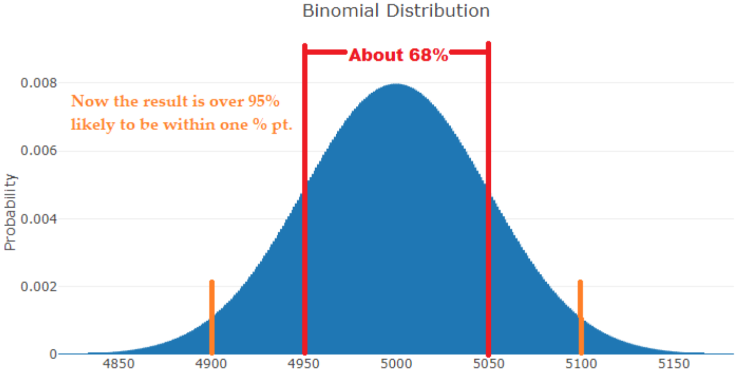

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- So results 47%-to-53% count as "statistically tied" (yuck).

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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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- Any Q&A about that? (Mention Sentiment Analysis if time allows.)

Part VI: AI and Machine Learning

Alan Turing: Besides his WWII work on the Enigma machine (featured in the movie *The Imitation Game*) and **Turing Machine** theory of computation in his 1936-38 PhD thesis under Alonzo Church, he is considered the **founder** of Artificial Intelligence.

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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.

Turing All the Possibilities

TP: If it is easy for humans then it will soon be easy for computers.

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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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- Using multiple **layers** of neural nets gives **deep learning**.

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

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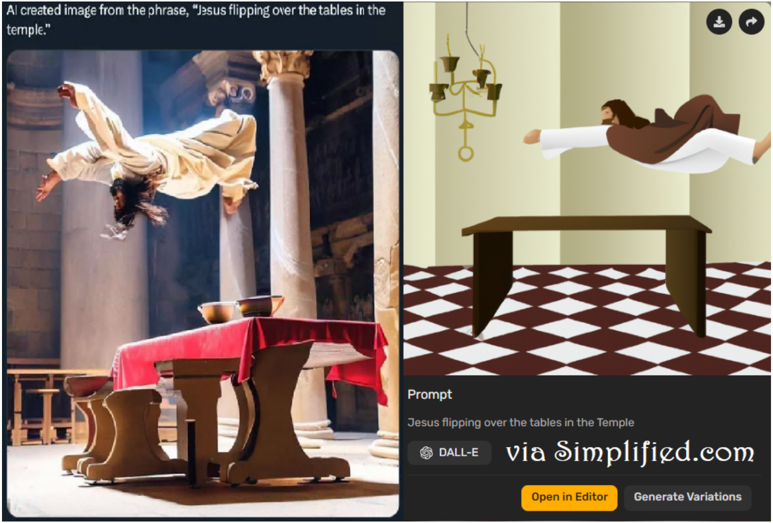
- But subject to **hallucinations** and other foibles—some shown by me here and here and here.

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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- (But possibly I already pushed it to the limits of its current data.)

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- This *may* foster adapting my chess model for a "simple frequentist" kind of cheating detection.

How AI Extends Search

[show Tonito.]

Part V: Societal Computing and Fairness

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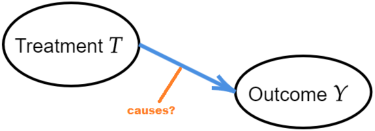

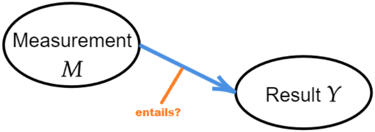

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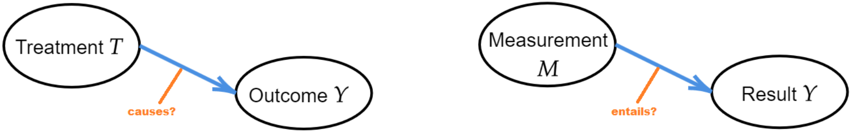

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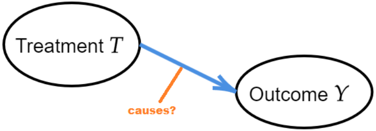

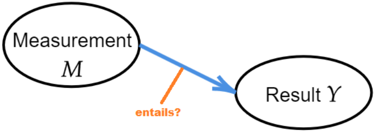

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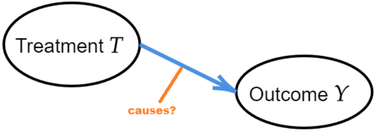

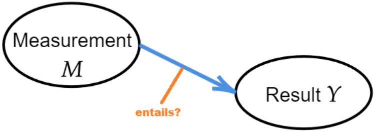

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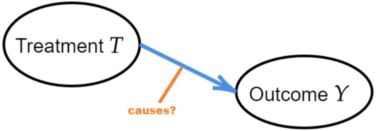

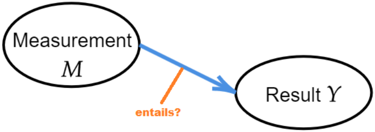

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- I.e., is Y beyond the *margin of error* for the **null hypothesis** of no causation?

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- Can happen with 50 different big ideas, too (see this).

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- Can we make a tight enough relation between our measurements M and the results Y we are trying to capture?

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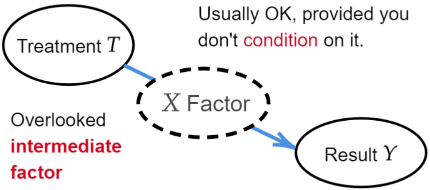

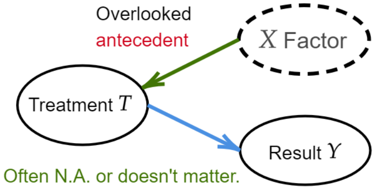

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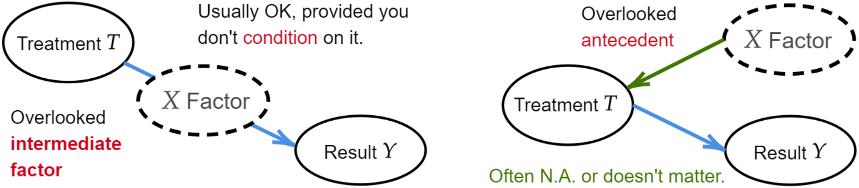

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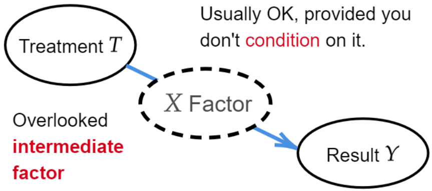

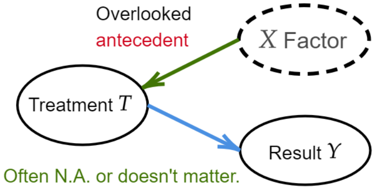

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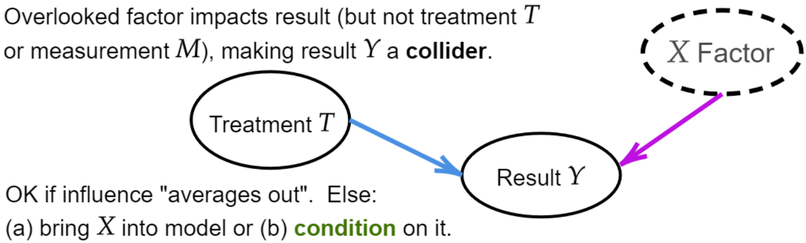
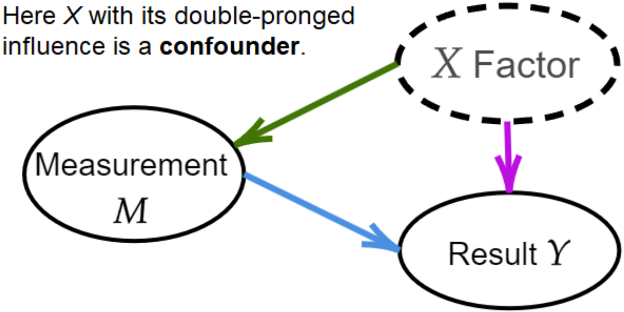


...When Not: I. Confounding Factors



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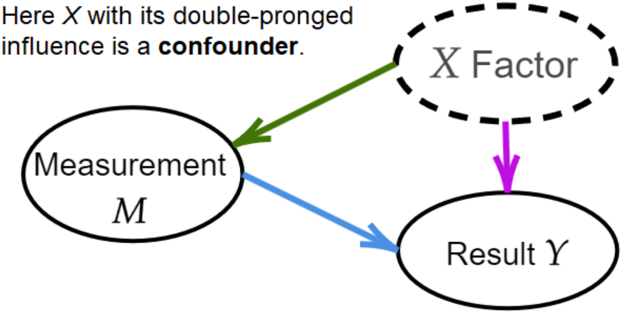

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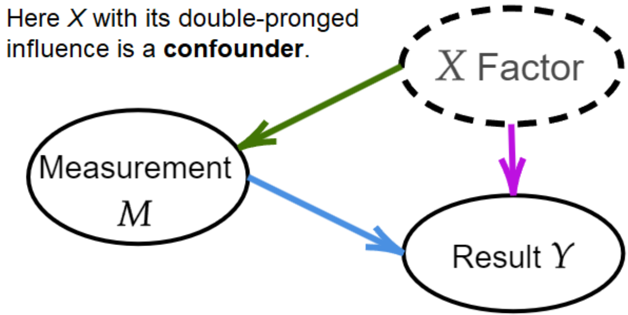

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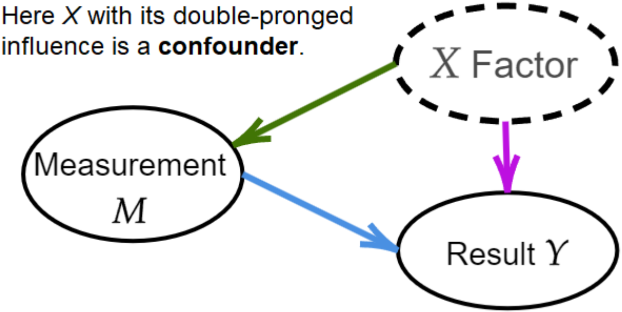

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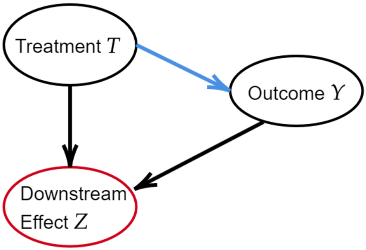
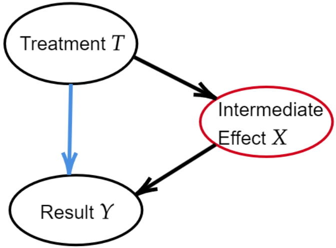
- Can both *stimulate* M (such as "heat") while *inhibiting* Y (such as "Challenger Wins").
- Even if impact is positive on both M and Y, X can dominate, drown out, or otherwise skew the effect we are trying to analyze.

II. Selection Bias From Conditioning

Conditioning on Other Effects





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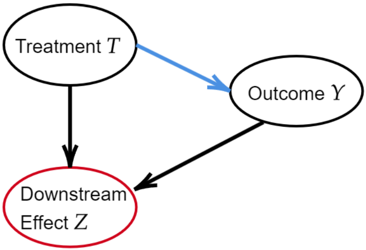

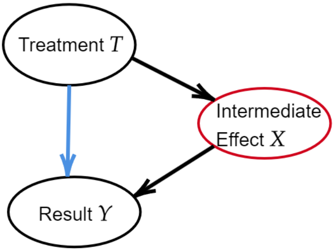

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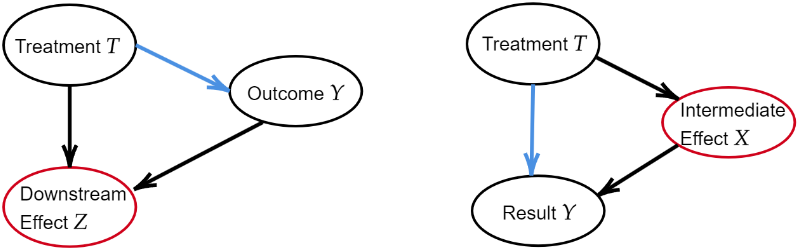

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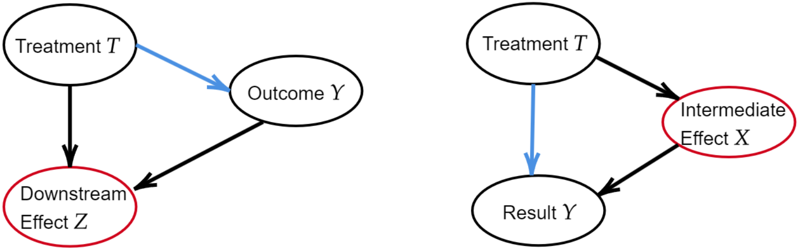
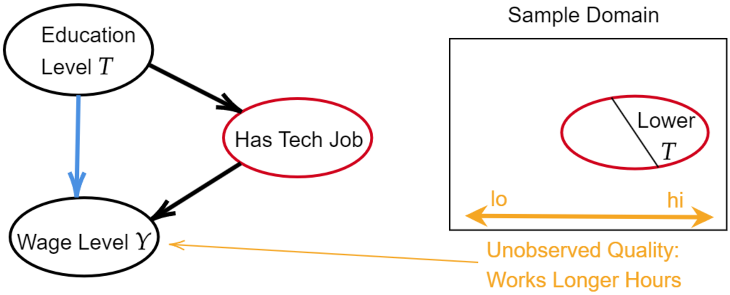


- Chess examples: (IIa) T = chess training, Y = more wins, Z = lower ACPL.
- (IIb): T = chess training, X = higher rating, Y = lower ACPL.
- Each way, conditioning on Z or X **selects** a **subsample** that may be skewed relative to the whole domain.

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:



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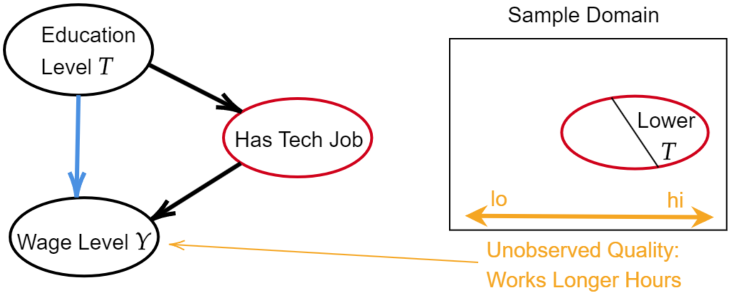

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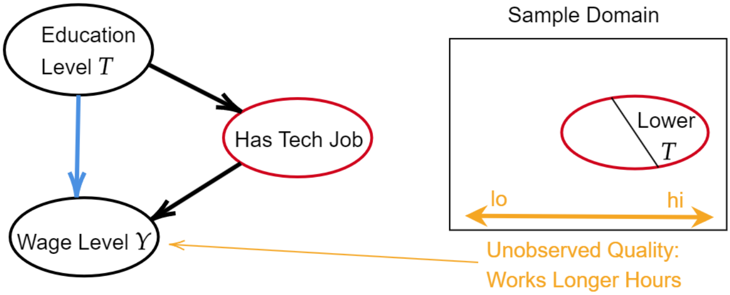

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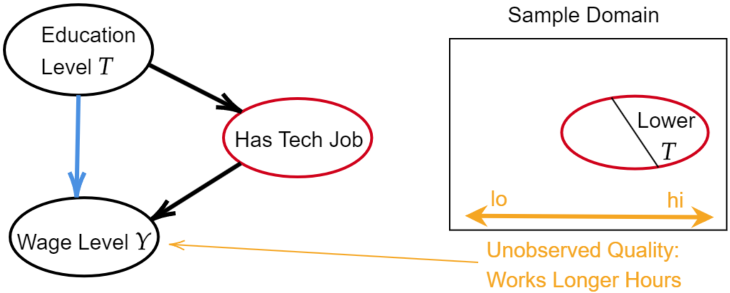

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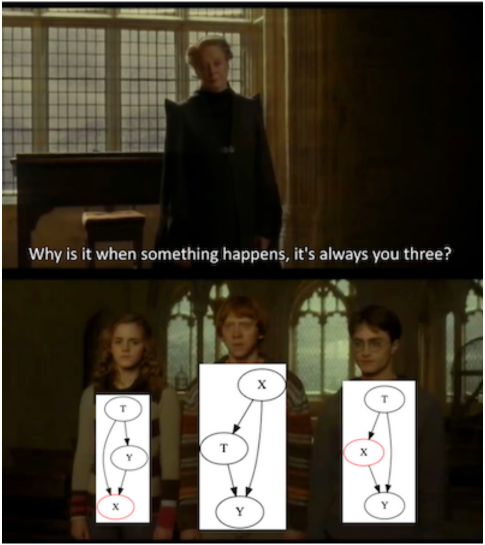
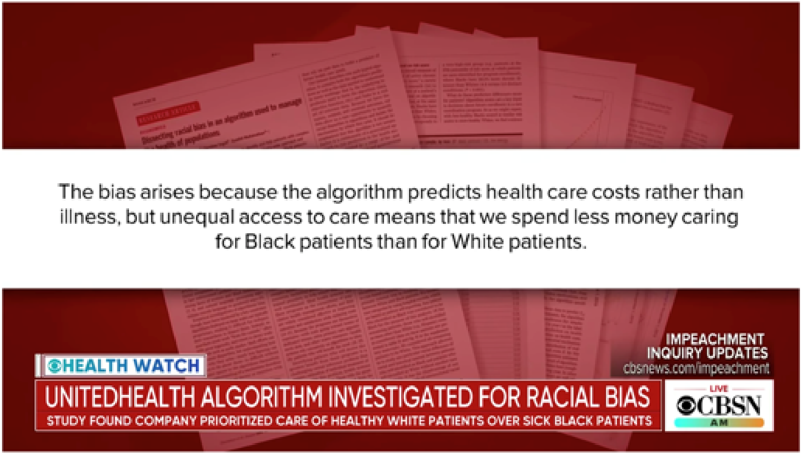
- Can also happen from choices of unrepresentative proxy variables.

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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