

Data, AI, and Society

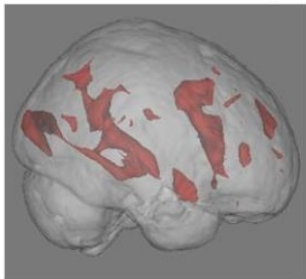
Resources and Dangers and Opportunities

Kenneth W. Regan

(Includes material from Kenny A. Joseph and some other past CSE199 units. Note new UB [Department of AI and Society](#))

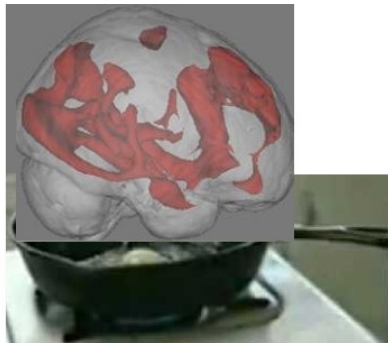
CSE199, Fall 2025

Main Problem...



**THIS IS YOUR
BRAIN**

Any Questions?



**THIS IS YOUR BRAIN
ON THE INTERNET**

(Brain scan source, 1987 PSA source)

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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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- Try Google “2025 incidents like the CrowdStrike crash.”



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- Does “Kasparov's Law” hold now? In the future?

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

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Before we can talk about **Misinformation**, we must note how **Claude Shannon** in 1947 essentially defined *information* merely as *data*.

The information $I(x)$ in a datum x equals the minimum length of a program that **generates** x .

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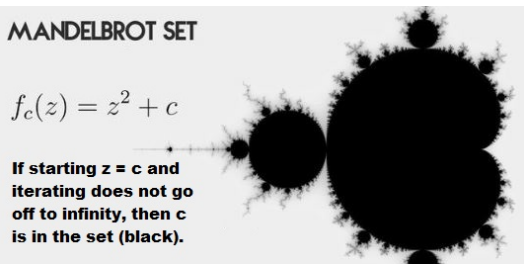
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- Queries are formulated using Boolean logic, numerics, and other built-in or user-created predicates.

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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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- Chicago Lakeside Technology Center, former champ at 1.1M sq. ft.

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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- Poker is a zero-sum game of **imperfect information**—you don't know what cards others have.
- **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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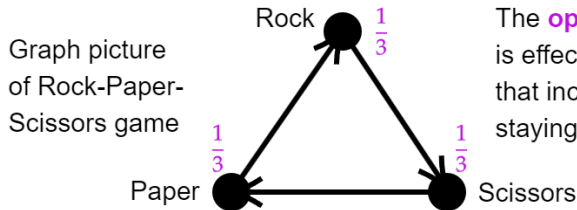
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- Only foolproof way: a **completely random** strategy. Here: roll a die and play Rock on 1 or 2, Paper on 3 or 4, and Scissors on 5 or 6.
- But since this is a **fair game**, you can’t expect to win either.



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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- 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.

The Internet as a Graph

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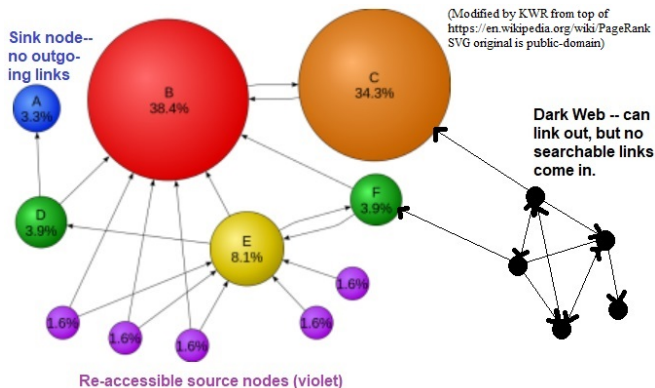
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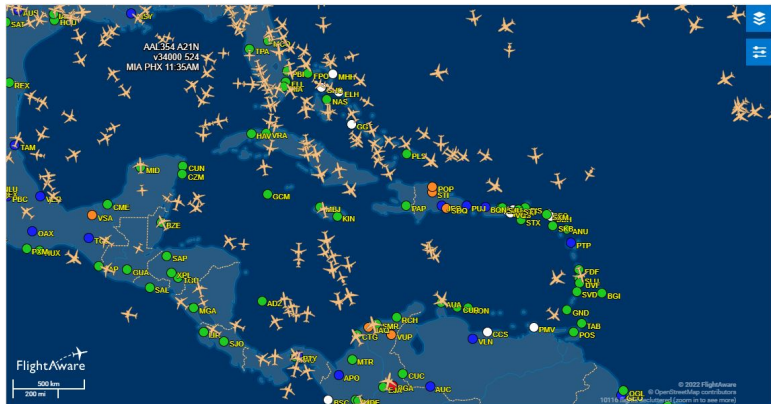
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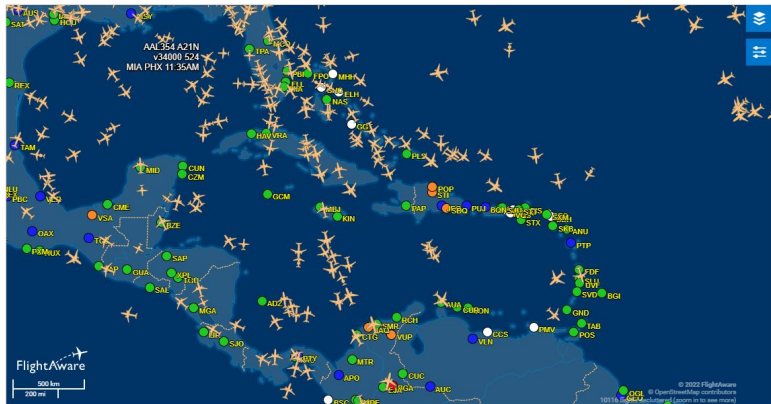
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Hurricane Tracking—Helene By NOAA



Note **error bars** around the forecasted track. Was spot-on.

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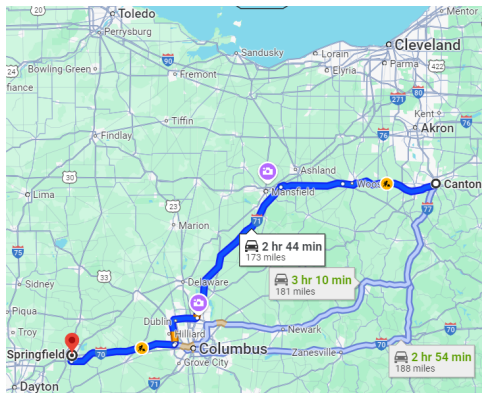
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- Look at all these **public datasets**!

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- (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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A rough working definition of **metadata** is:

Data in XML headers and in `<tag ATTR=...>` attributes

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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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- 1998 *DMCA*: Internet providers not responsible.
- For misuse of Bram Cohen’s *BitTorrent*—not so clear. Cut deal in 2005 with Motion Picture Association of America to follow DMCA.

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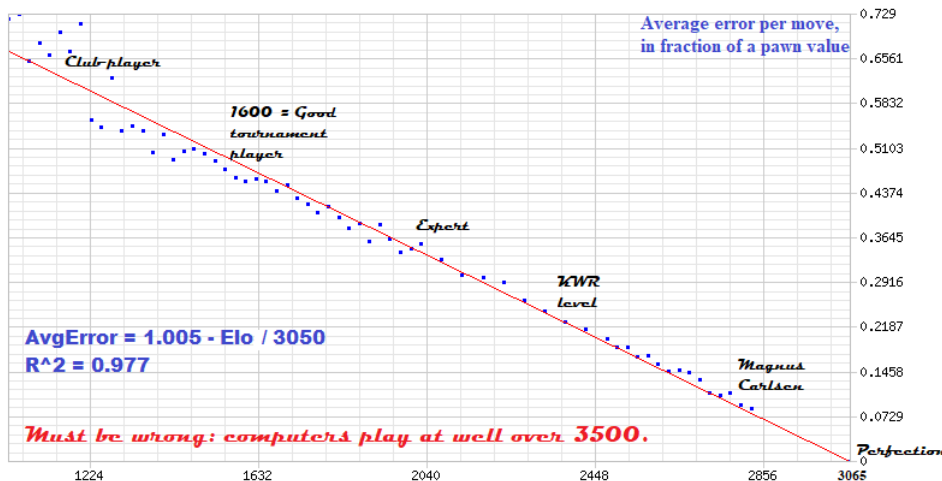
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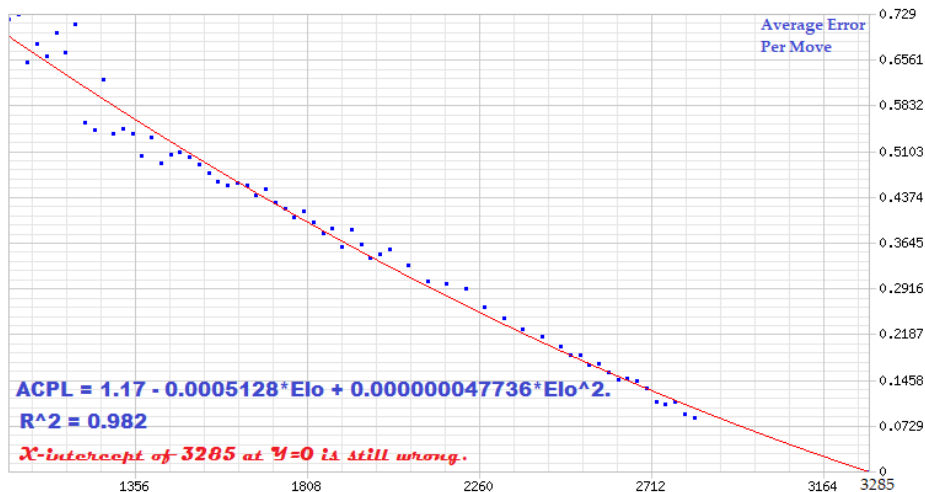
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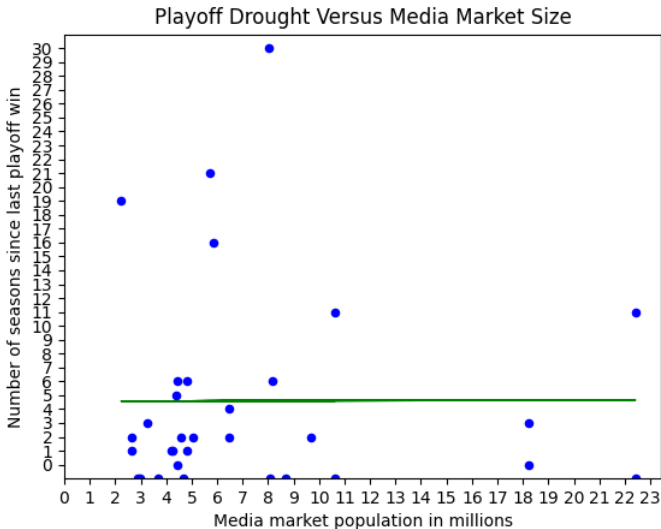
Linear Model: $ACPL = a + b \cdot \text{Elo Rating}$



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.

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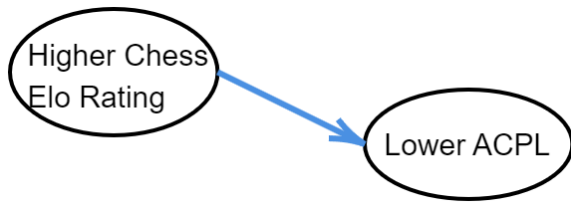
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- They can help ascertain
 - which are genuine causes—as opposed to mere correlations or null effects, and
 - which variables in the system can helpfully be **regressed** or **conditioned on**.

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



Transitive and Confounding Causes

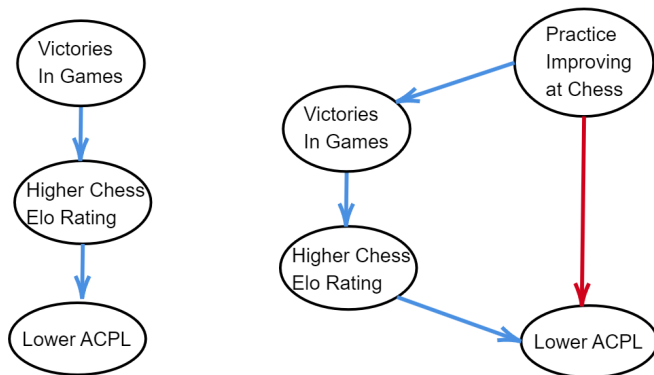
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- But if we have a lurking *common cause* D of both our *source* and *intended target*, then it can **confound** the smaller-scale analysis.
- I faced this when the pandemic caused official chess ratings to **lag** true skill. **Case of wrongly accused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

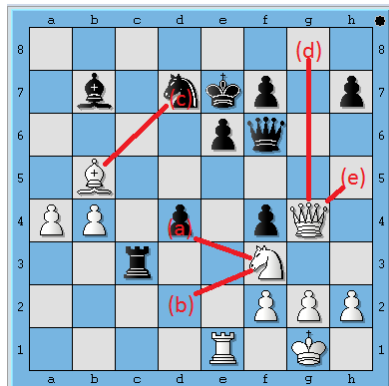
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(source: itunes.apple.com)

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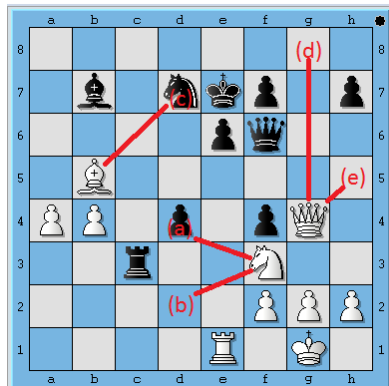
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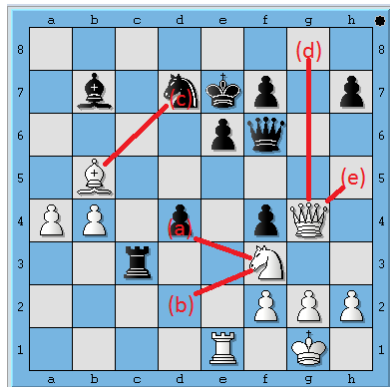
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Validate the model on millions of randomized trials involving “Frankenstein Players” to ensure conformance to the standard bell curve at all rating levels. This is also an example of **Simulation**.

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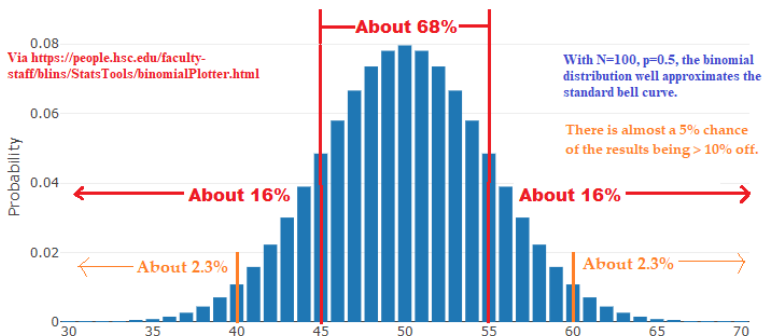
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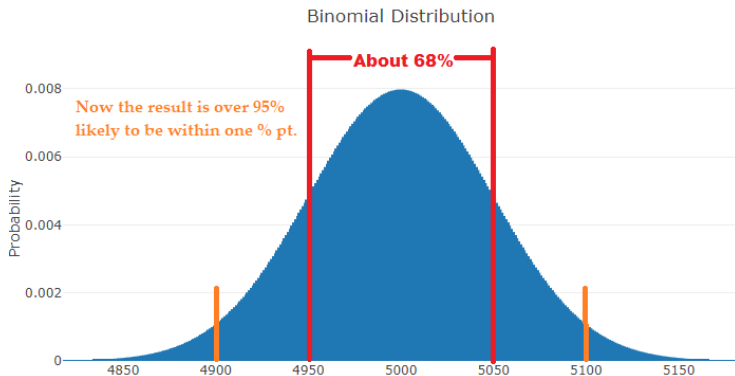
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- Almost **one-third** chance poll results will be **< 45%** or **> 55%**.

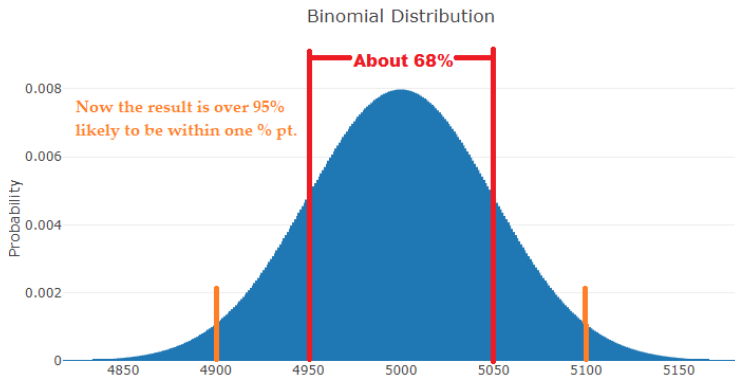


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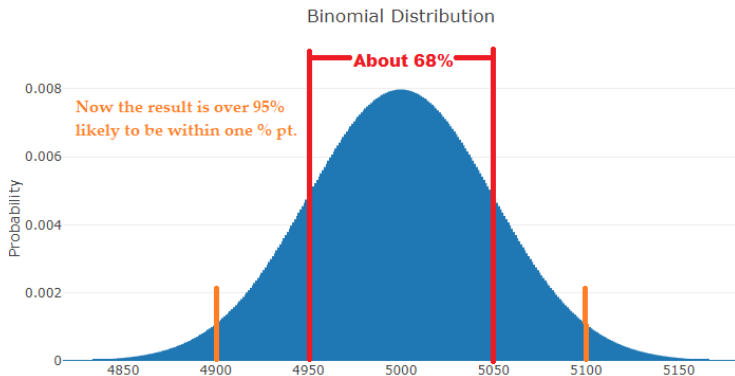
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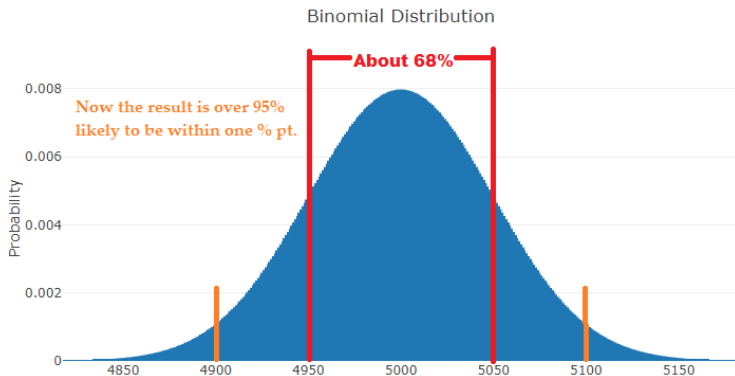
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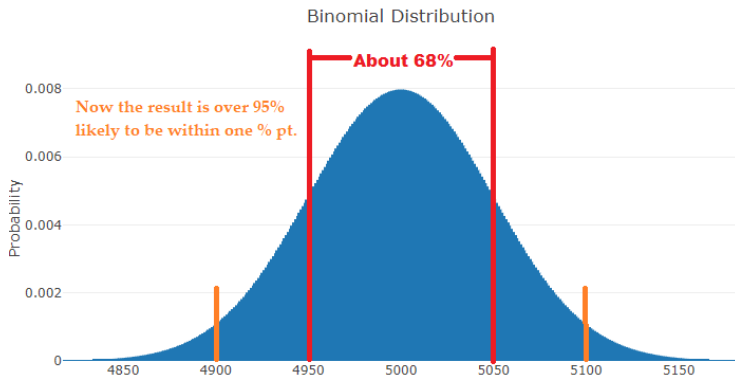
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- So results 47%-to-53% count as “statistically tied” (yuck).

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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.

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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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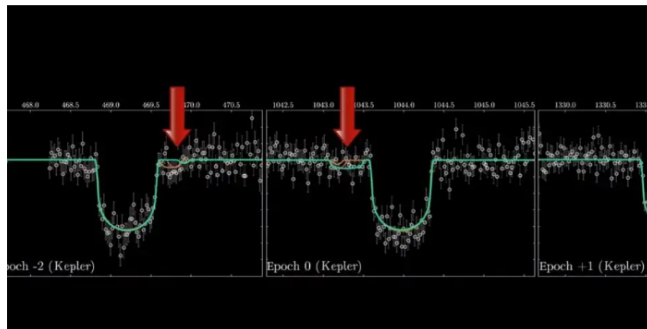
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- In general, “smart interface to database” is a near-term boon...not subject to truth/falsehood issues that arise in what I’ll call “unattached” use.
- Stops recognizably short of trying to be [AGI](#): Artificial General Intelligence.

How AI Extends Research

Exoplanets note from Big Think [source](#)

Based on the Kepler lightcurve of the transiting exoplanet Kepler-1625b, we were able to infer the existence of a potential exomoon. The fact that the transits didn't occur with the exact same periodicity, but that there were timing variations, was our major clue that led researchers in that direction. With large enough exoplanet data sets, machine learning algorithms can now find additional exoplanet and exomoon candidates that were unidentifiable with human-written algorithms.



Credit: NASA GSFC/SVS/Katrina Jackson

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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

AI created image from the phrase, "Jesus flipping over the tables in the temple."



Prompt

Jesus flipping over the tables in the Temple



DALL-E

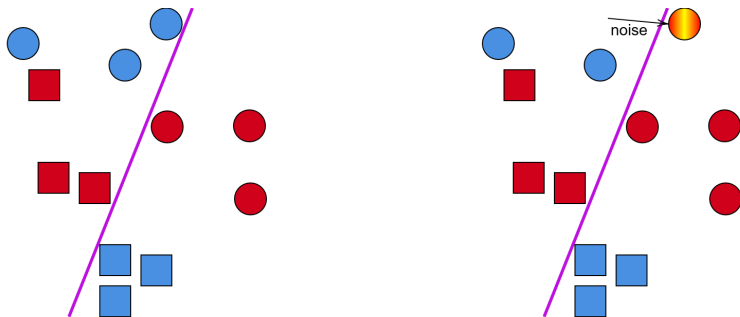
via [Simplified.com](https://www.simplified.com)

[Open in Editor](#)

[Generate Variations](#)

How AI Can Be Fragile

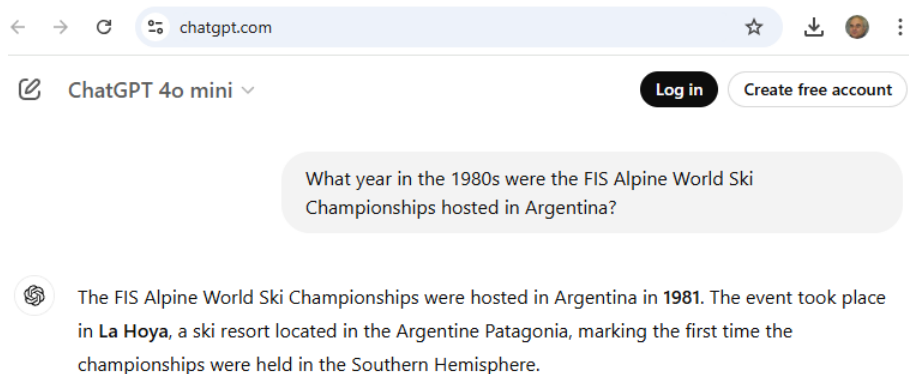
We gain *encoding advantage* by needing just one line to separate both the red shapes and the blue shapes.



But the line cuts things real close. A little noise could make a blue *Circle* be misread as a *Square*, as shown at right.

How AI Can Be “Truthy”

I reproduced an example in a Medium [article on AI hallucinations](#).



In the article, the response was, “The FIS Alpine World Ski Championships were hosted in Argentina in 1985.”

It Gets Worse (Fact Checks: FIS, Wenzels)



The FIS Alpine World Ski Championships were hosted in Argentina in **1981**. The event took place in **La Hoya**, a ski resort located in the Argentine Patagonia, marking the first time the championships were held in the Southern Hemisphere.

Who won the women's and men's downhill races at those championships?

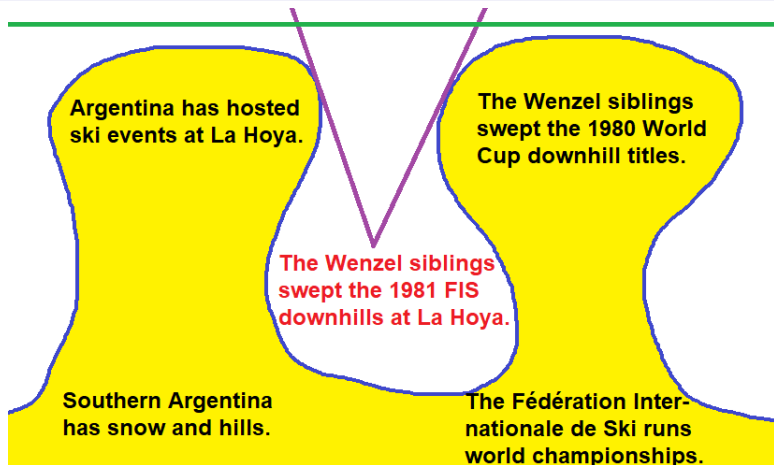


At the 1981 FIS Alpine World Ski Championships in Argentina, the winners of the women's and men's downhill races were:

- **Women's Downhill:** **Hanni Wenzel** (Liechtenstein) won the gold medal in the women's downhill.
- **Men's Downhill:** **Andreas Wenzel** (Liechtenstein) won the gold medal in the men's downhill.

The Wenzel siblings made history with their victories in both events.

Rough Diagram of What Could Have Happened



The red is a *positive linear combination* of the four true items in black. When combos sit in “truth pockets,” linear separators (in purple and green) cannot penetrate far enough to rope them off.

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

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“Cowboy closes barn door after the horse has left” via OpenAI API:



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

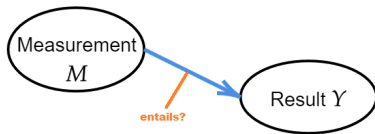
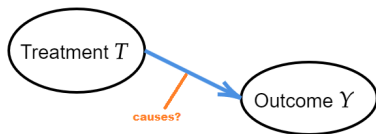
Announcement 12/2

Important CSE 199 Things

- CSE Cohort Survey #3 is now out, it is due next Monday!
- This is the last week of CSE 199! There is no final and no class next Monday. Thanks for being a great class!
- Nominate yourself to be a 199 TA next fall
 - Fill in the nomination form you got as a course announcement
- All of this is in a course announcement on UBLearns that you got this morning.

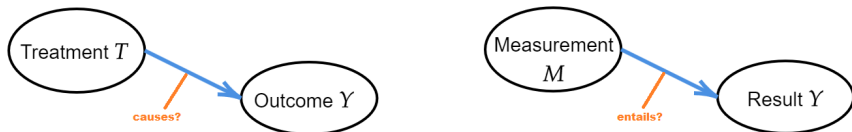
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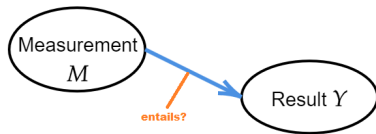
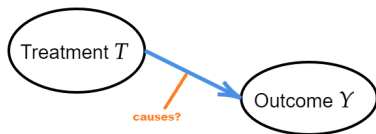
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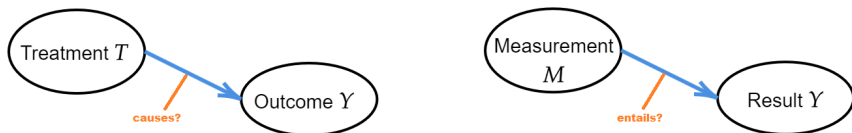
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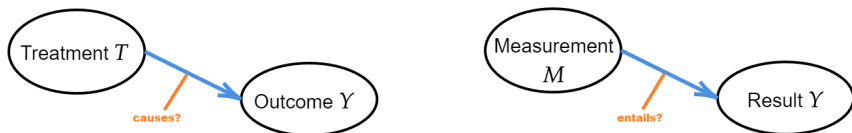
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- I.e., is Y beyond the *margin of error* for the **null hypothesis** of no causation?

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

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- 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.

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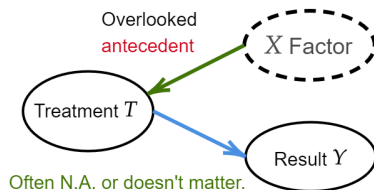
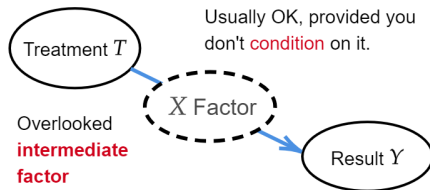
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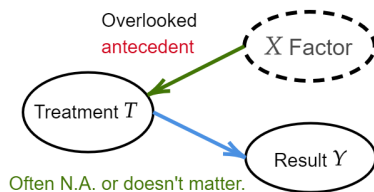
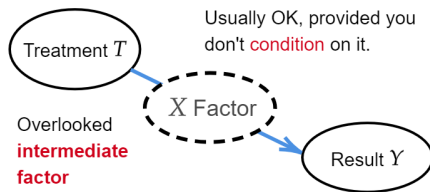
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- Can we make a tight enough relation between our measurements M and the results Y we are trying to capture?

Missing Factors in Studies—When Benign and...

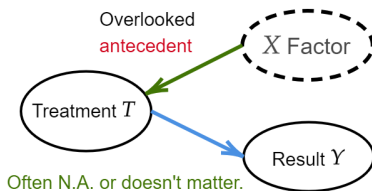
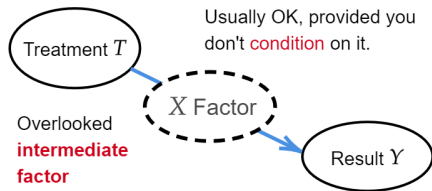


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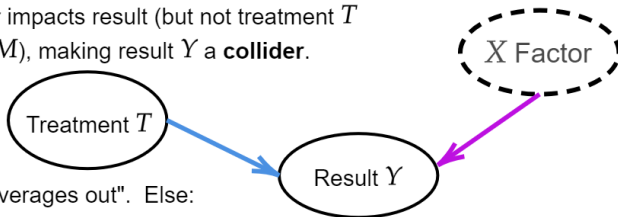
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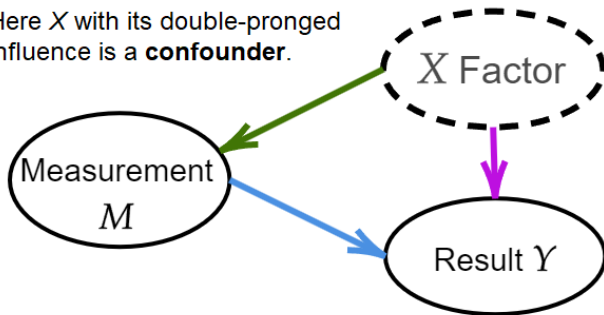
Overlooked factor impacts result (but not treatment T or measurement M), making result Y a **collider**.



OK if influence "averages out". Else:
 (a) bring X into model or (b) **condition** on it.

...When Not: I. Confounding Factors

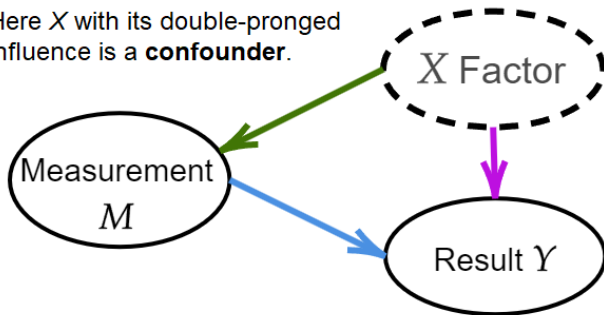
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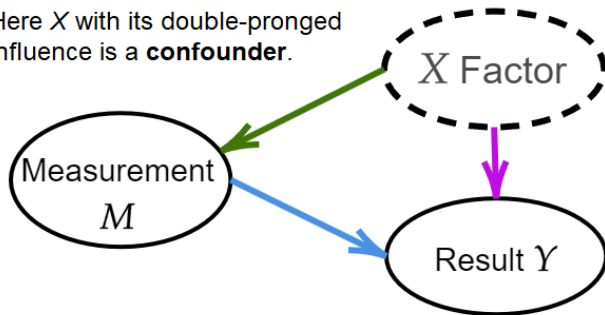


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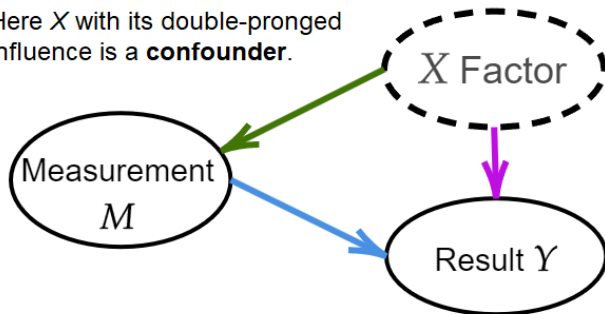


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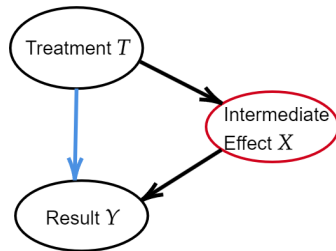
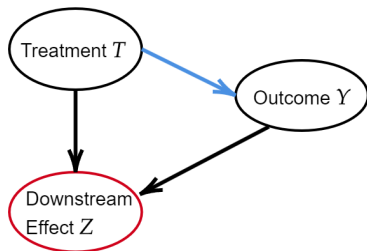


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- Even if impact is positive on both M and Y , X can dominate, drown out, or otherwise skew the effect we are trying to analyze.

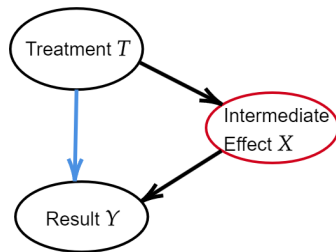
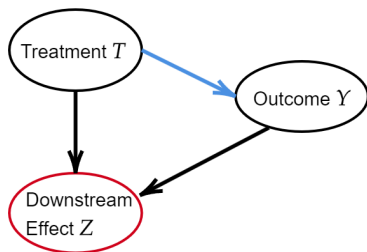
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Two main kinds: (a) **collider bias** (at left) and (b) **mediator bias**.



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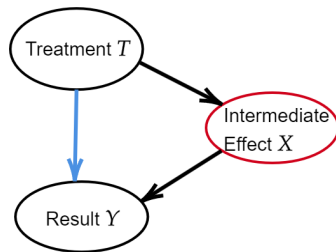
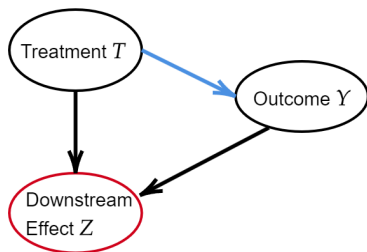
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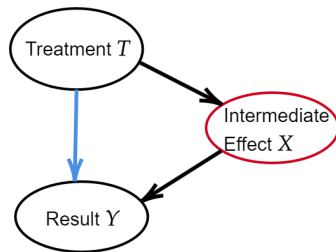
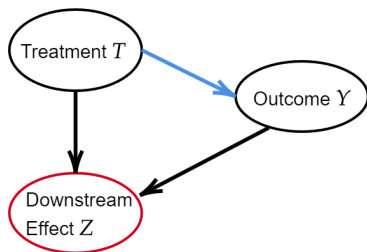
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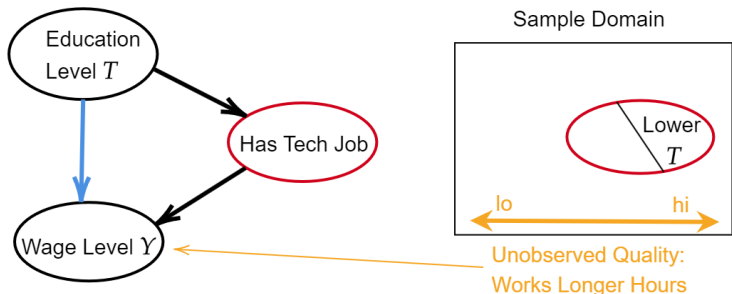
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- Each way, conditioning on Z or X **selects** a **subsample** that may be skewed relative to the whole domain.

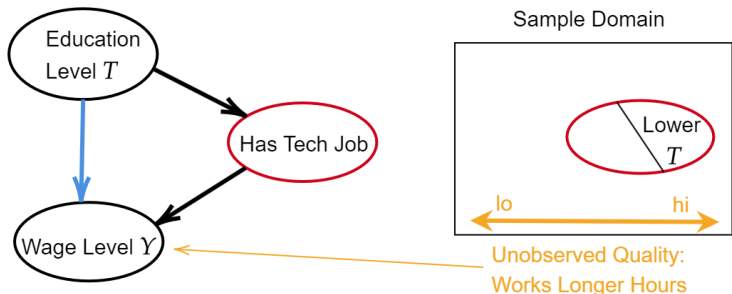
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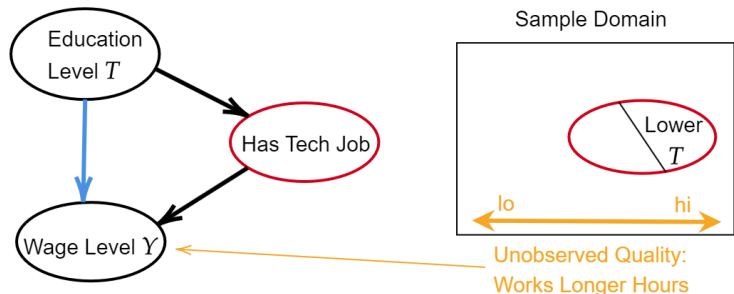
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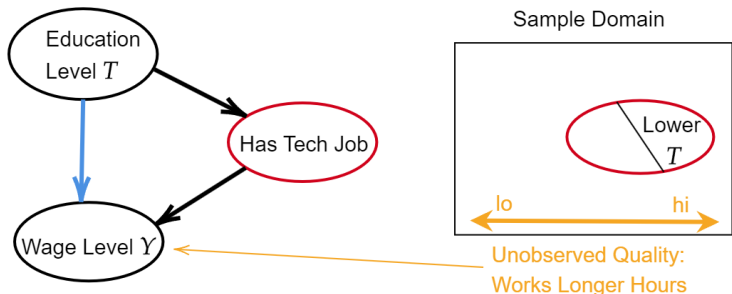
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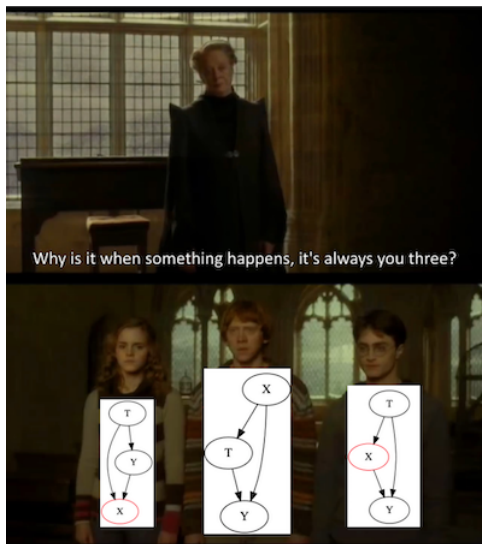
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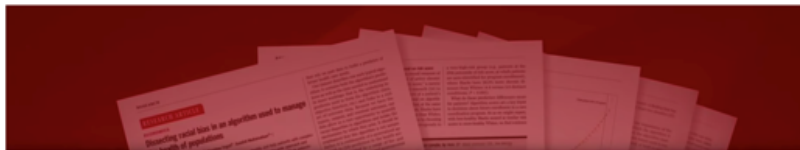
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- Can also happen from choices of unrepresentative proxy variables.

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](#).



The bias arises because the algorithm predicts health care costs rather than illness, but unequal access to care means that we spend less money caring for Black patients than for White patients.

A banner with a red background and white text. On the left is the "HEALTH WATCH" logo. The main text reads: "UNITEDHEALTH ALGORITHM INVESTIGATED FOR RACIAL BIAS" and "STUDY FOUND COMPANY PRIORITIZED CARE OF HEALTHY WHITE PATIENTS OVER SICK BLACK PATIENTS". On the right is the "IMPEACHMENT INQUIRY UPDATES" logo with the URL "cbsnews.com/impeachment" and the "LIVE CBSN AM" logo.

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- Another aspect is **model neutrality** (of input at least).
- **Revisit question of affirmatively de-biasing Google search.**
- Distinguish (a) bias from the model being **skewed** away from what should be true outputs given the inputs, from (b) true outputs that are biased in a **normative** sense by missing a target of fairness.
- Removing skew bias improves accuracy and can preserve neutrality.
- Removing normative bias may reduce accuracy and neutrality.
- **Sep. 2024 Women's Olympiad Chess Example:** Skewed outcomes on Captures, Advancing Moves, and Knight Moves.
- **Shows up for the men too.** *Should I remove this bias?*
- (Note my model's **high accuracy and precision overall.**)
- Doing so would make my model more predictive...but less neutral.

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- All best with the rest of term and your time at UB!