

Data and AI and Society

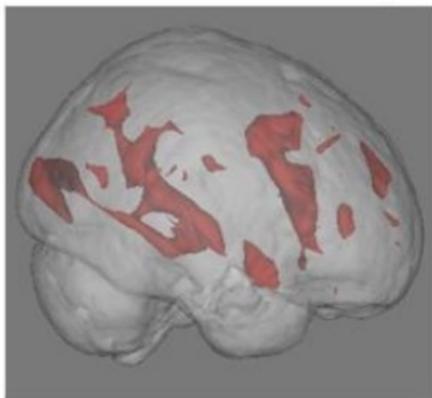
Resources and Dangers and Opportunities

Kenneth W. Regan

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

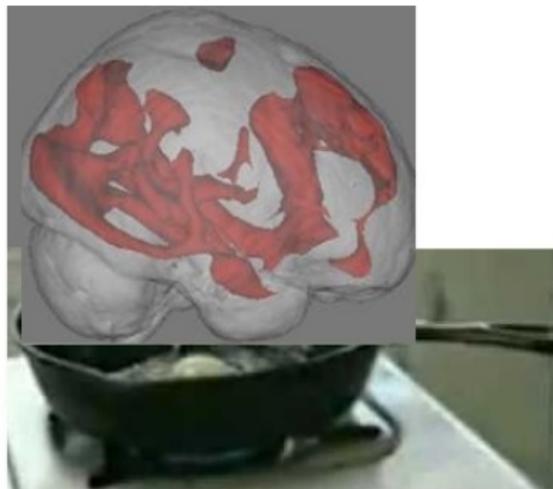
CSE199, Fall 2025

Main Problem...



**THIS IS YOUR
BRAIN**

Any Questions?



**THIS IS YOUR BRAIN
ON THE INTERNET**

(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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- Now: 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.**

The Ocean of Language Information Data

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

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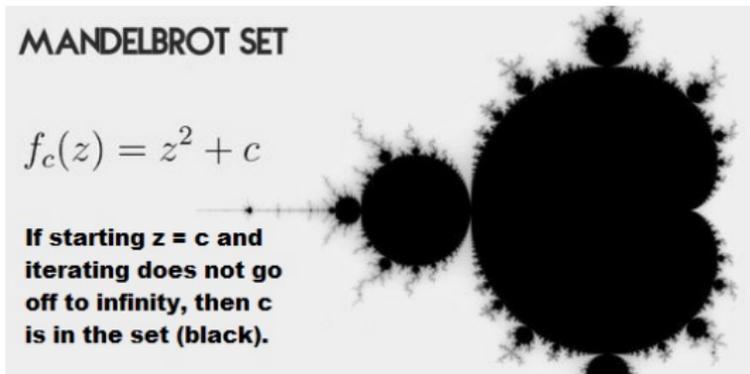
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- Apps built atop the **Structured Query Language** (SQL, pronounced that way or as “Sequel”) allow interactive queries.

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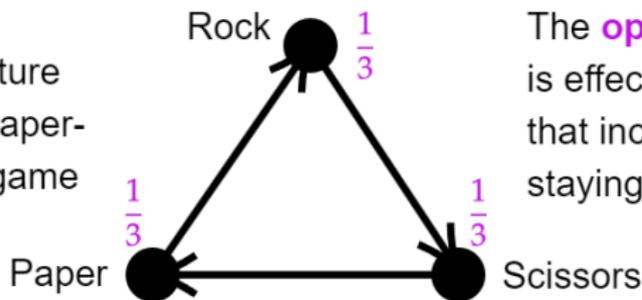
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- Only foolproof way: a **completely random** strategy. Here: roll a die and play Rock on 1 or 2, Paper on 3 or 4, and Scissors on 5 or 6.
- But since this is a **fair game**, you can’t expect to win either.

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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- **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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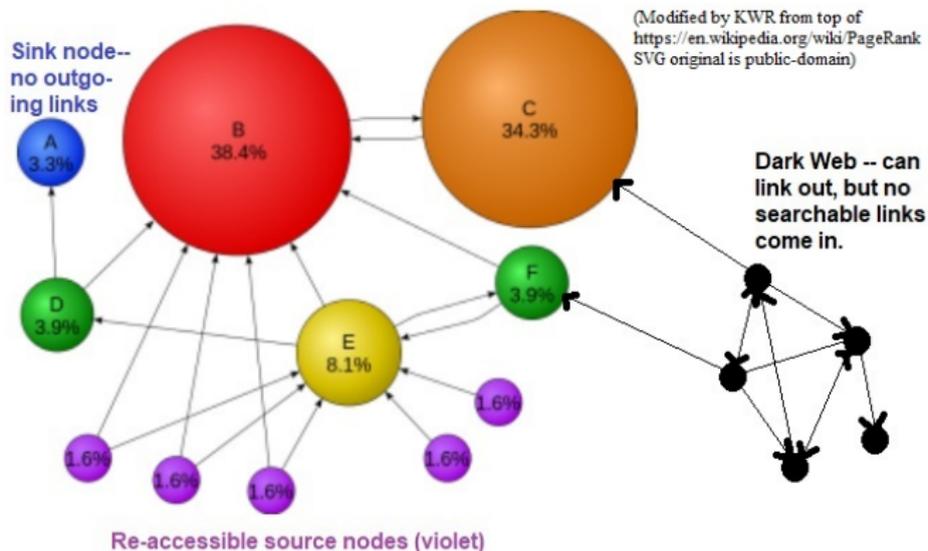
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Why almost no planes over Puerto Rico and the Dominican Republic + Haiti?

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Hurricane Tracking—Helene By NOAA



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

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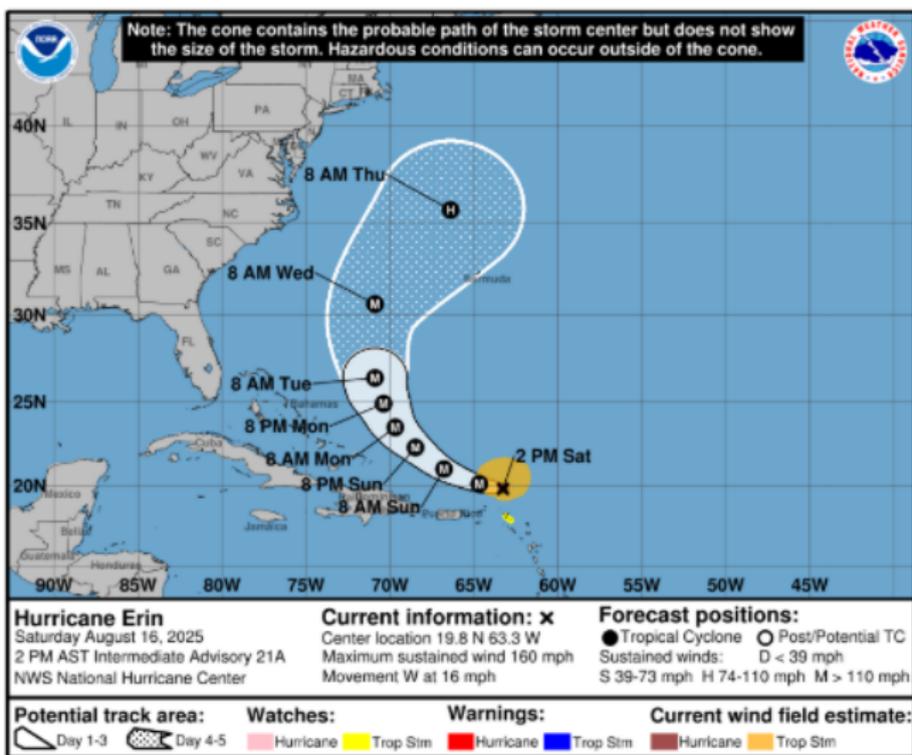
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Note **error bars** around the forecasted track. Was spot-on. (But, **Otis 2023** was a forecasting failure.) **Still remnants.** **Track of power outages.**

We Were Quite Sure Erin Would Stay Away



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- Tension over *proprietary* aspects, especially for NSF grants, public universities. . .
- Look at all these [public datasets](#)!

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- Or do already sick and less-active people watch more TV?
- 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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[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*.

Part III: Data Analytics

Friend-of-the-newsletter **Matt Glassman** asks:

Where do you stand on teaching statistics, data analysis, and game theory in public schools? My view is that prioritizing this over pre-calculus and calculus would on balance be better for most students, though there's certainly a trade-off.

I'm not sure whether I'm the perfect person to answer this question or I'm hopelessly biased because I use probability and statistics nearly every day in my work, while I basically never ² directly use any sort of calculus (although techniques like linear regression are **derived from calculus**). But I'm also not alone. Claude estimates that 1-3 percent of Americans use calculus daily in their work, while 8-15 percent use statistics

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 3. Probabilistic Modeling...to 4. Predictive Modeling
 5. Preference Aggregation: Voting, Ranking and Rating, **Polling**.
 6. Internet Search. (already covered last week; AI tie-in on Wed.)
 7. Sentiment Analysis. (this week's recitation, will say more Wed.)
- (More topics we could cover, but these give a foundation.)

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- The **NFElo odds tool** says **-7.5** means **73.8%** chance to win.

I use one or more of the following as **proxy** variables for skill:

- The frequency **T1** of P playing an engine's 1st-listed move.

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- The **average error** per move, measured as **ACPL** for "average centipawn loss."

Chess Example

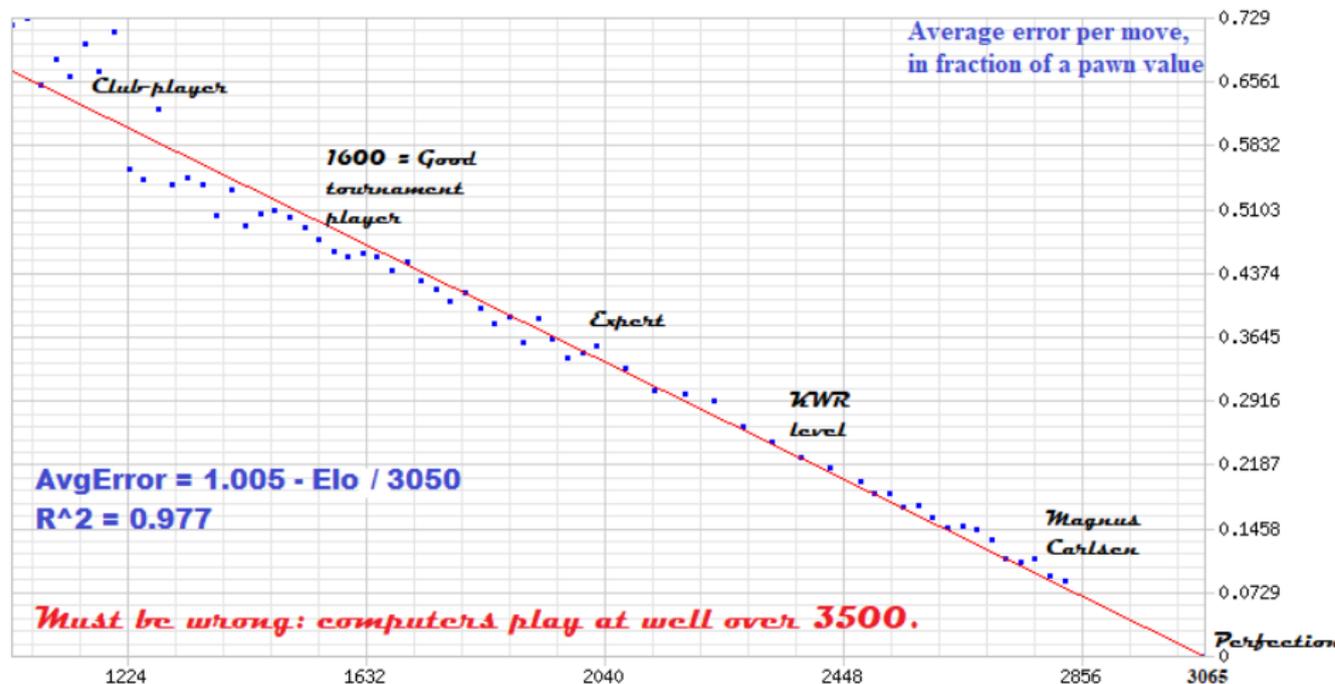
My chess cheating work starts with a player P 's **Elo rating** as the main independent variable giving P 's skill level.

- E.g. **1000** = bright beginner, **1600** = good club player, **2200** = master, **2800** = world championship caliber.
- Computer **engines** are far higher, e.g.: **Stockfish 16 = 3544**, **Torch 1.0 = 3531**, **Komodo Dragon 3.3 = 3529**.
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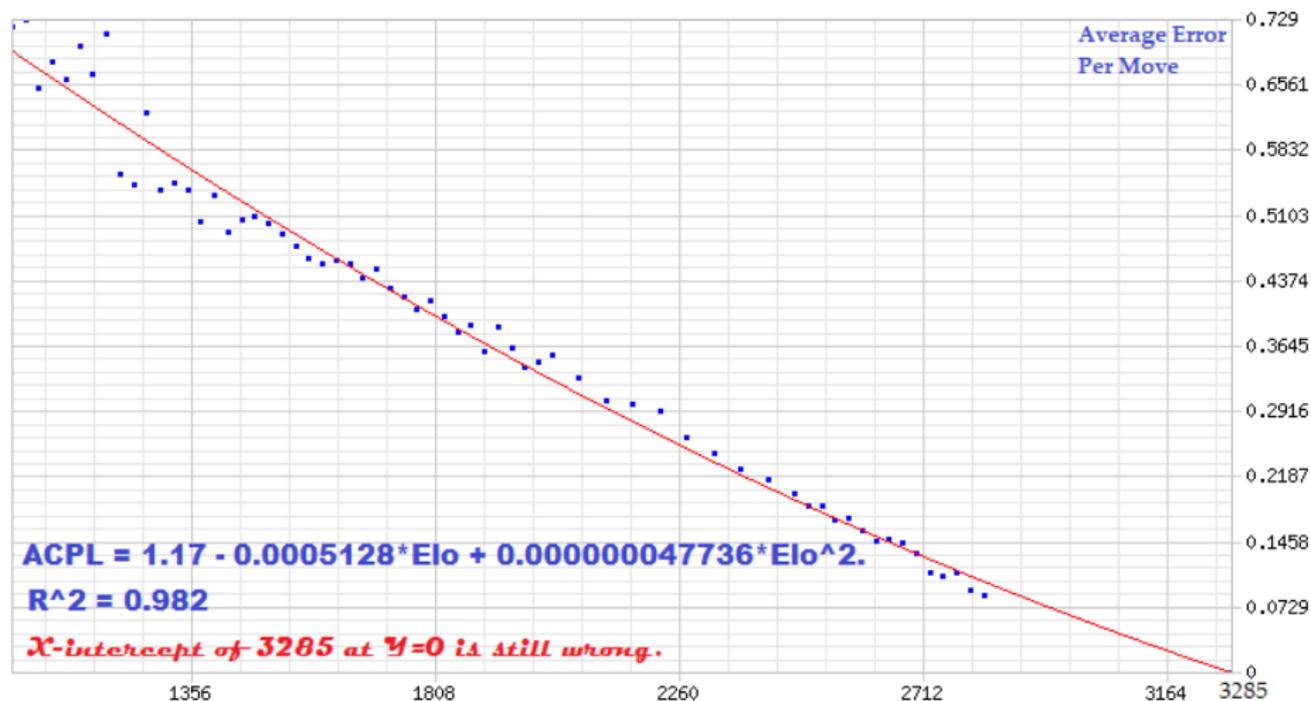
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Linear Model: $ACPL = a + b \cdot \text{Elo Rating}$



Quadratic Fit—Only Marginally Better



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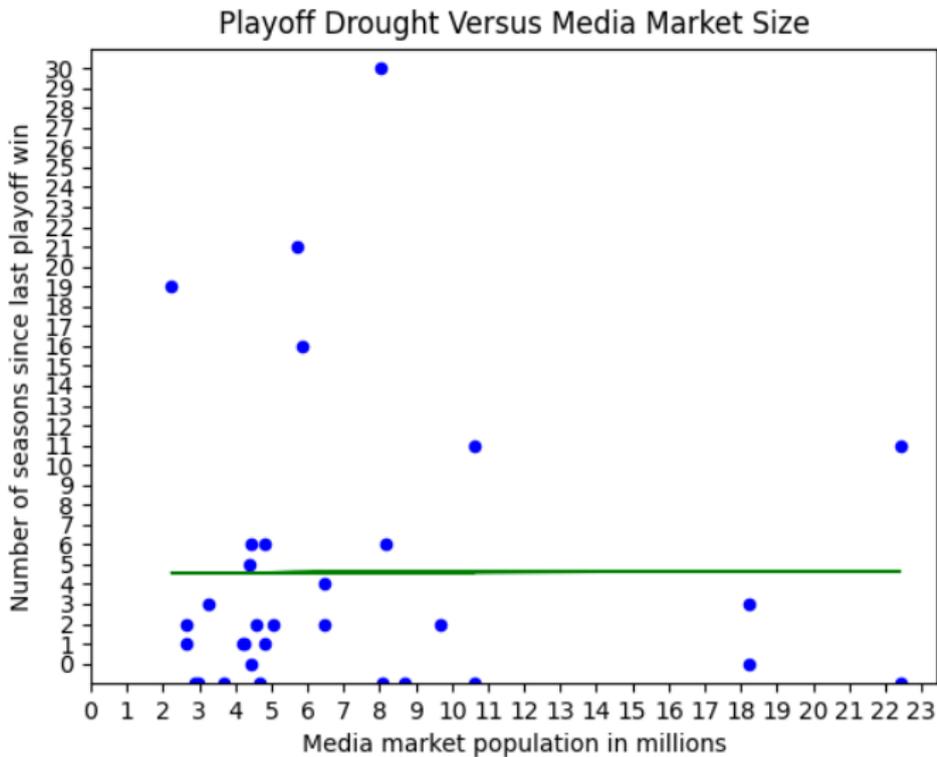
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- I can tell the raw data is [still too skewed](#) to do reliable science for finer purposes.

A Desired Null Result? (data from before 2023 season—yes it's tiny but 32 teams are all there is)



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- We need a stronger **probabilistic model** that individuates moves.

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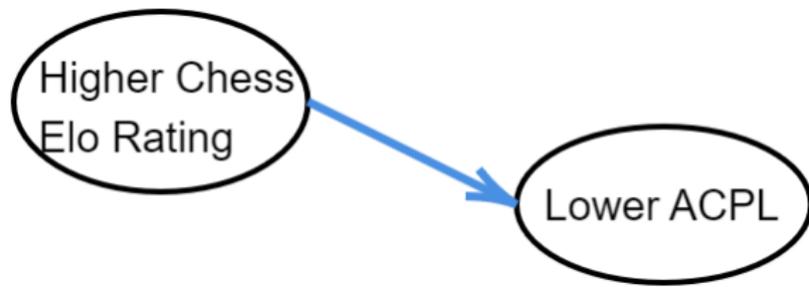
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- They can help ascertain
 - which are genuine causes—as opposed to mere correlations or null effects, and
 - which variables in the system can helpfully be **regressed** or **conditioned on**.

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



Transitive and Confounding Causes

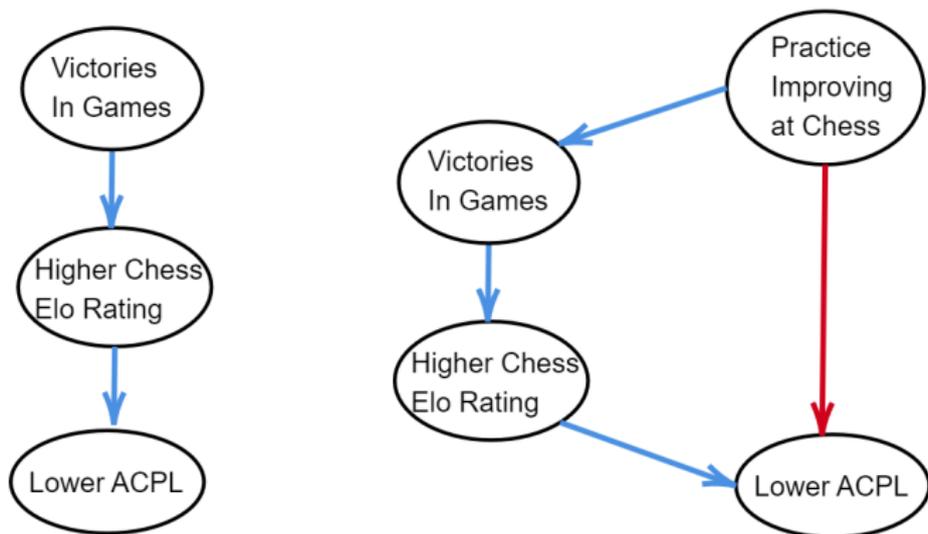
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- But if we have a lurking *common cause* D of both our *source* and *intended target*, then it can **confound** the smaller-scale analysis.
- I faced this when the pandemic caused official chess ratings to **lag** true skill. **Case of wrongly accused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

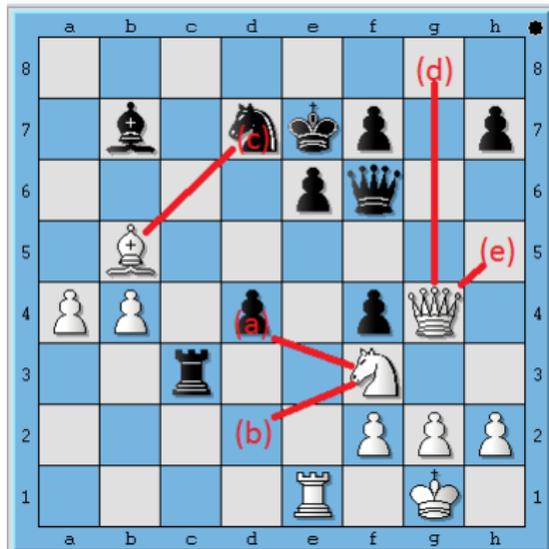
Chess and Tests—With Partial Credits (Or LLMs?)

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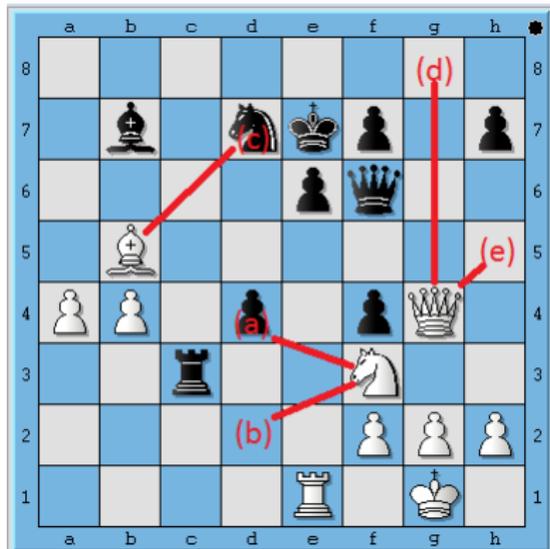
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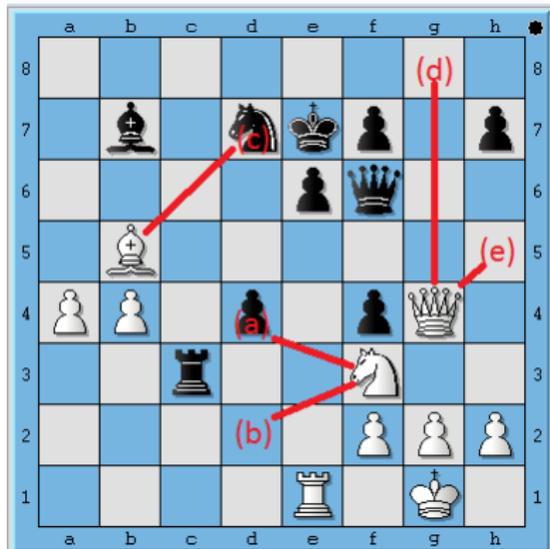
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Gaussian math yields confidence intervals that can enable **rejecting the null hypothesis of fair play** with high confidence.

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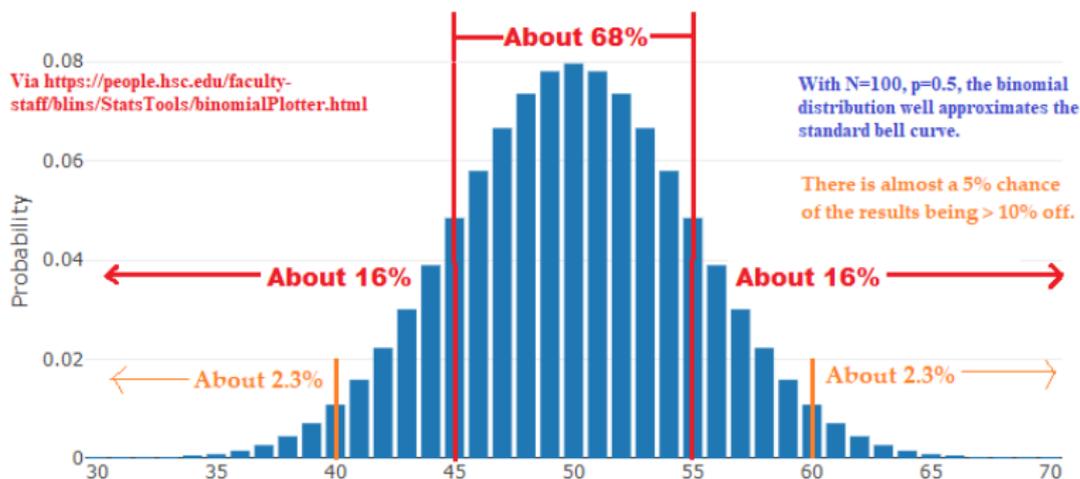
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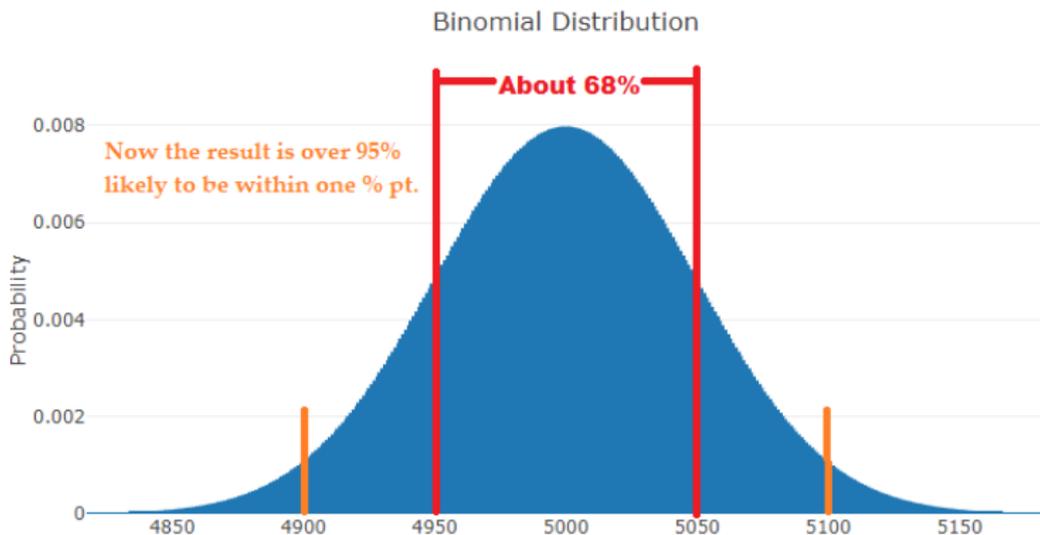
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- Almost **one-third** chance poll results will be **< 45%** or **> 55%**.

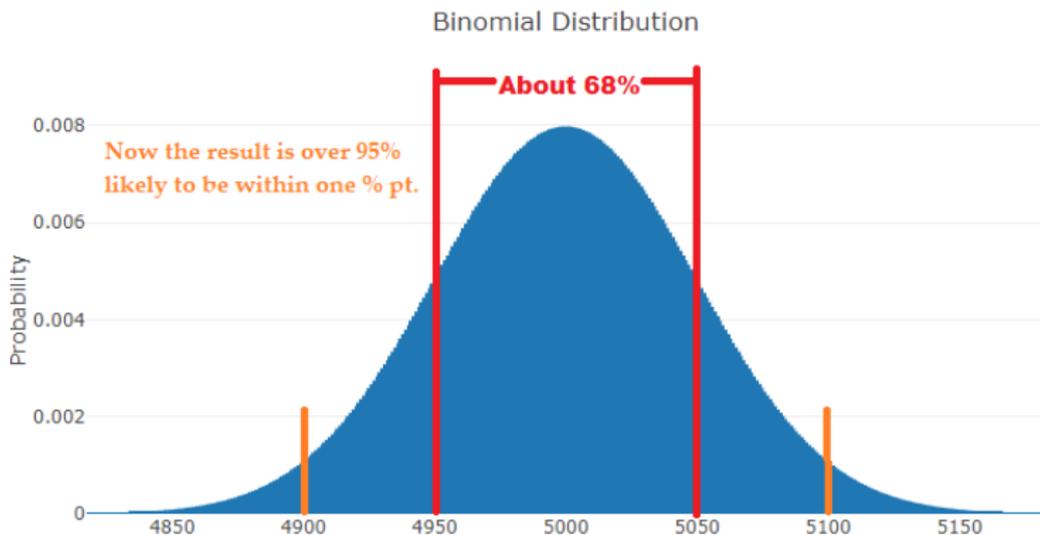


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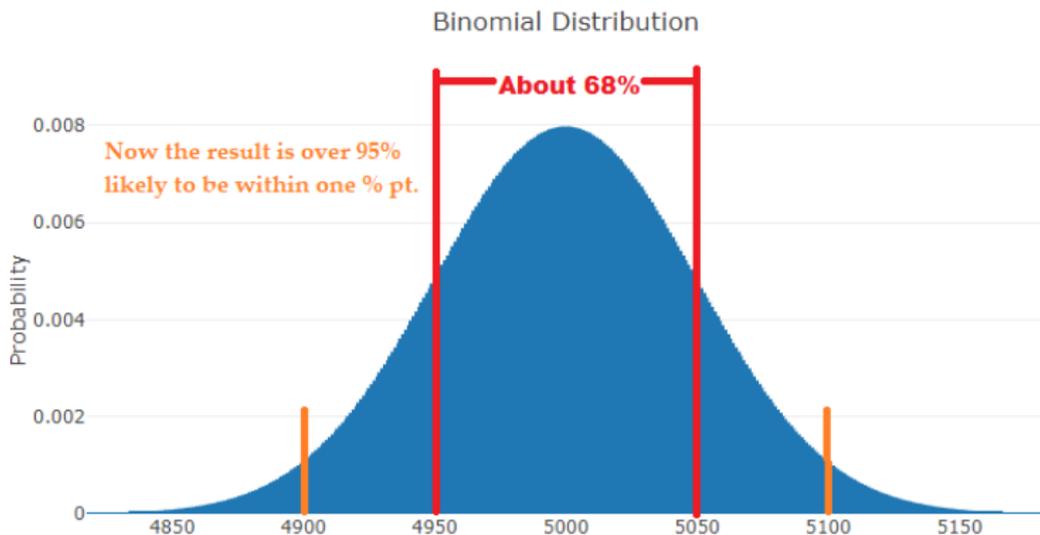
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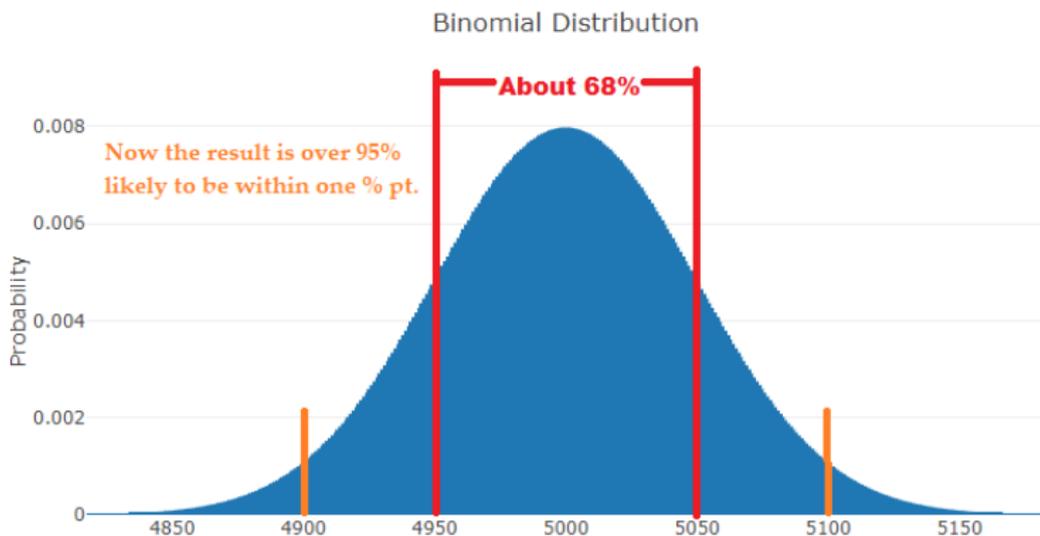
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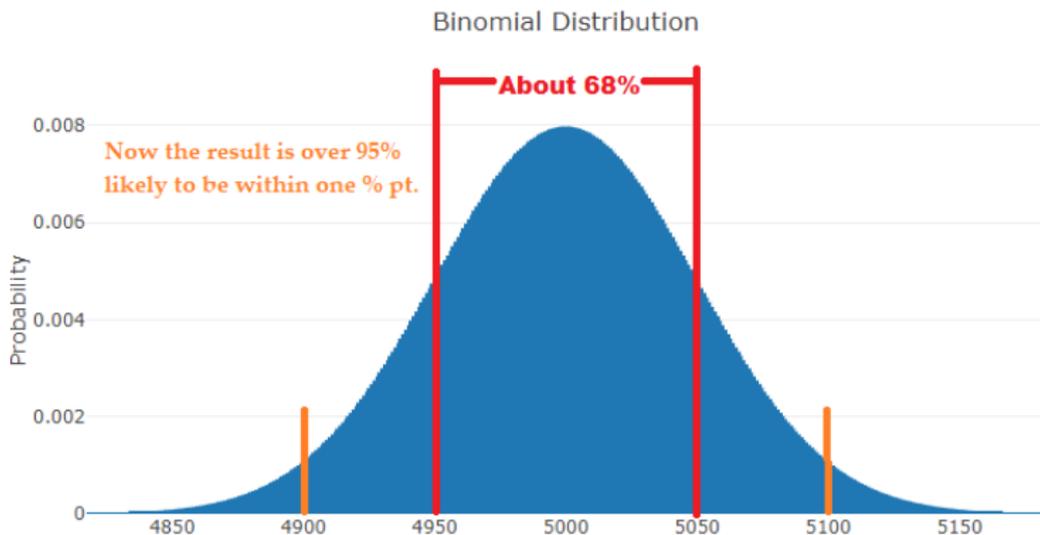
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- So results 47%-to-53% count as “statistically tied” (yuck).

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Thus using $100\times$ more people brought only $10\times$ more precision, but would keep percentage error—which is $\frac{skew}{N}$ —at the same rate. Your $10\times$ 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.)**

Part IV: AI and Machine Learning

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

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- Can we use it to predict elections? [Brexit 2016](#), [Canada 2015](#), [USA 2016 \(paper\)](#), [USA 2016 \(BrandsEye\)](#).

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- Simplistic idea: if the electorate is (un-)happy that's (bad) good news for the incumbent.

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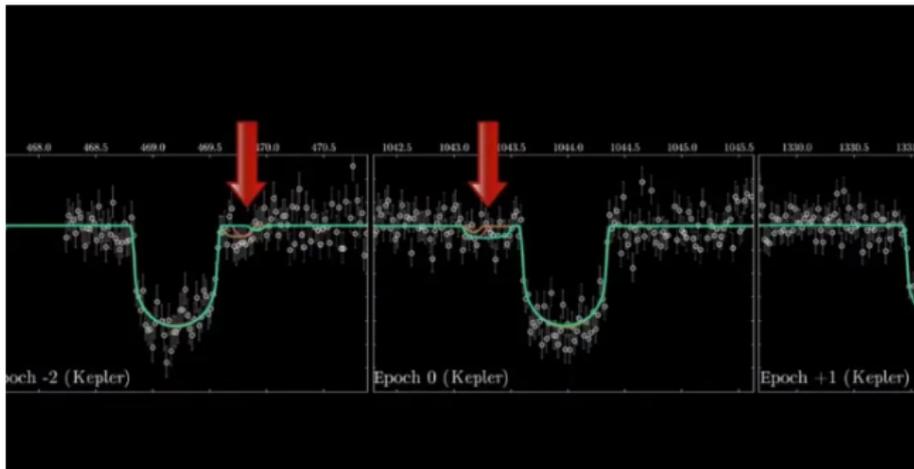
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- Stops recognizably short of trying to be [AGI](#): Artificial General Intelligence.

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**.

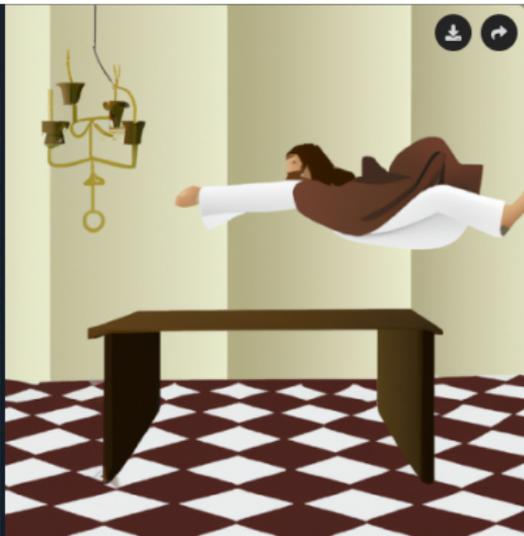
AI Art Adventure

“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

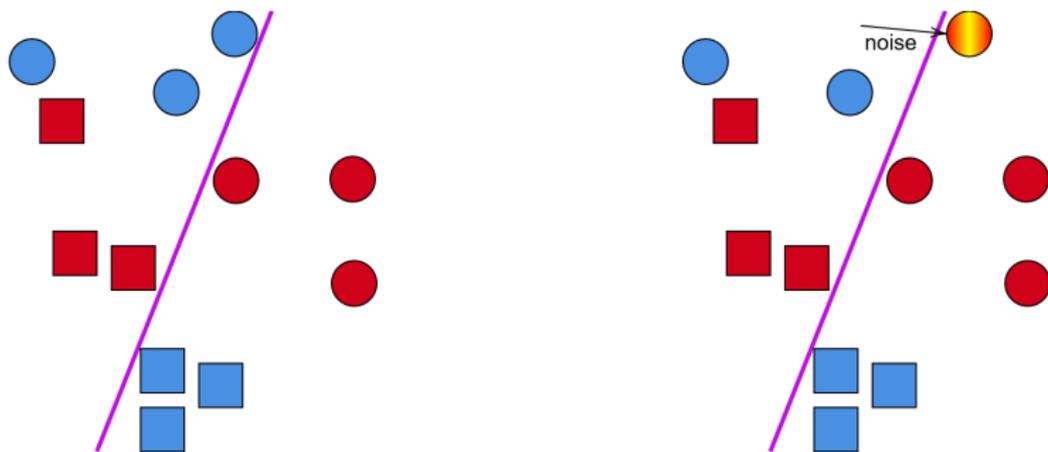
via [Simplified.com](https://www.simplified.com)

Open in Editor

Generate Variations

How AI Can Be Fragile

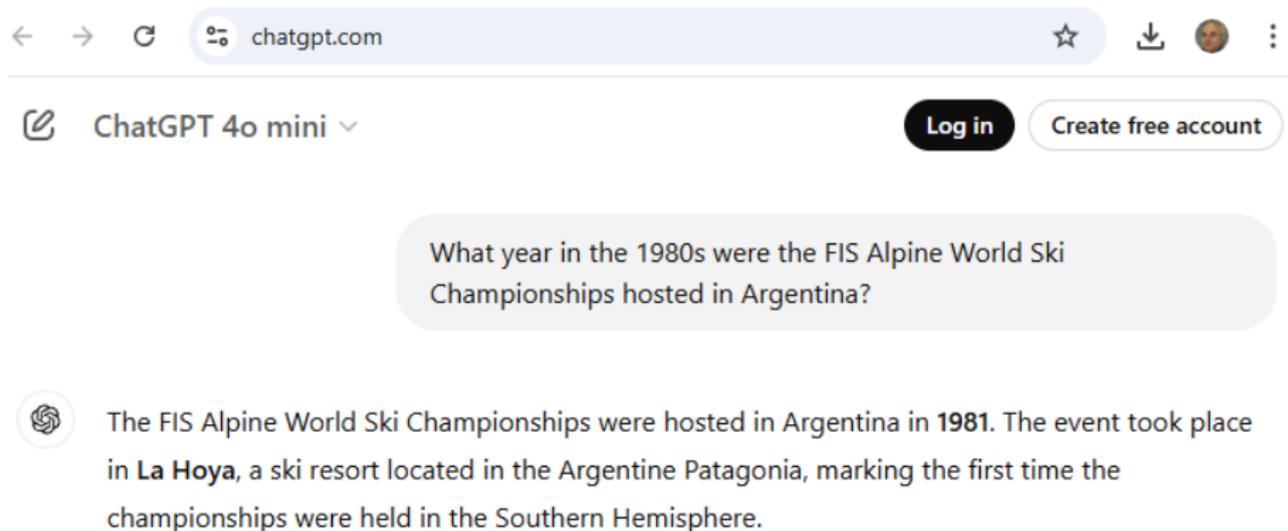
We gain *encoding advantage* by needing just one line to separate both the red shapes and the blue shapes.



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

How AI Can Be “Truthy”

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



The screenshot shows the ChatGPT 4o mini web interface. At the top, there is a browser address bar with the URL "chatgpt.com". Below the address bar, the text "ChatGPT 4o mini" is displayed with a dropdown arrow. To the right of this text are two buttons: "Log in" and "Create free account". The main content area contains a user question in a light gray rounded rectangle: "What year in the 1980s were the FIS Alpine World Ski Championships hosted in Argentina?". Below the question, the AI's response is shown, starting with the OpenAI logo icon. The response text is: "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."

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) (Today)



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?

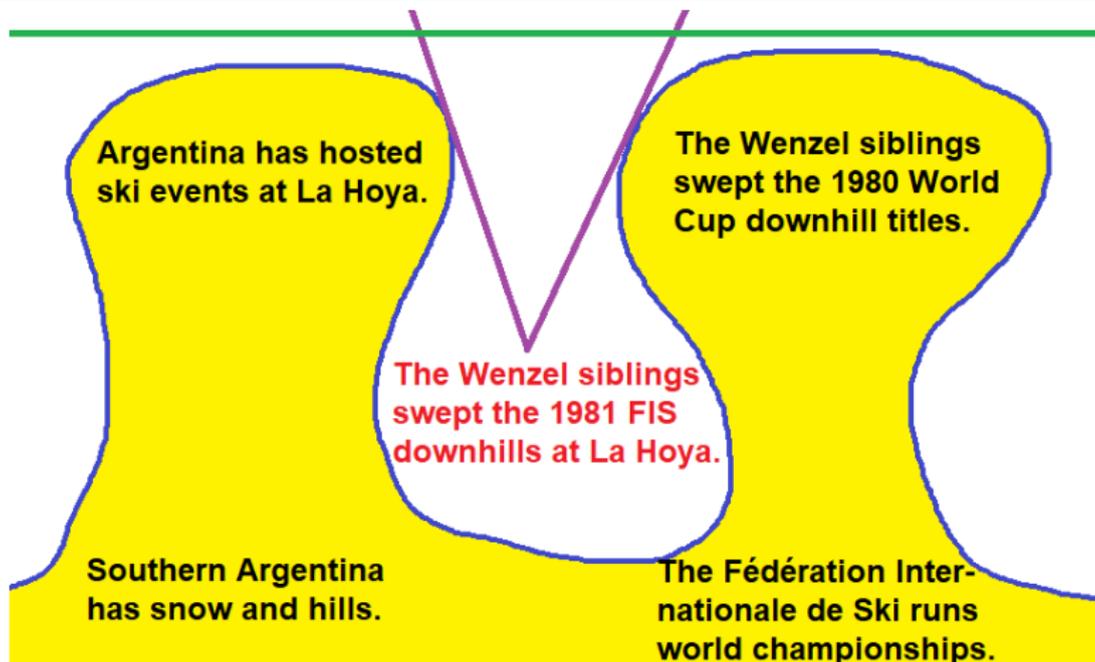


At the 1981 FIS Alpine World Ski Championships in Argentina, the winners of the women's and men's downhill races were:

- **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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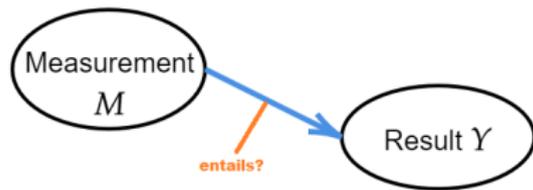
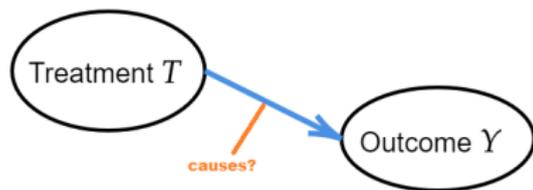
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- 9 Selection Bias:** Domain might be OK overall but if you condition on, say, games played in late evening you may get more youngsters.

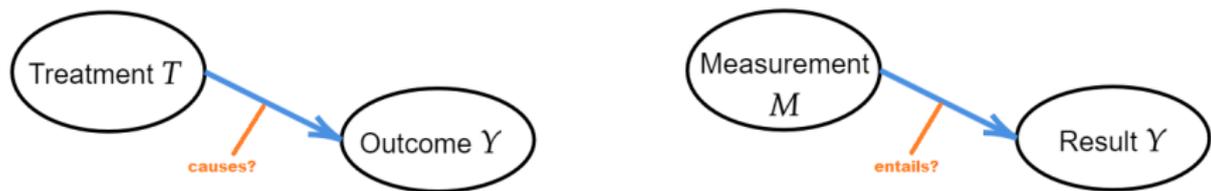
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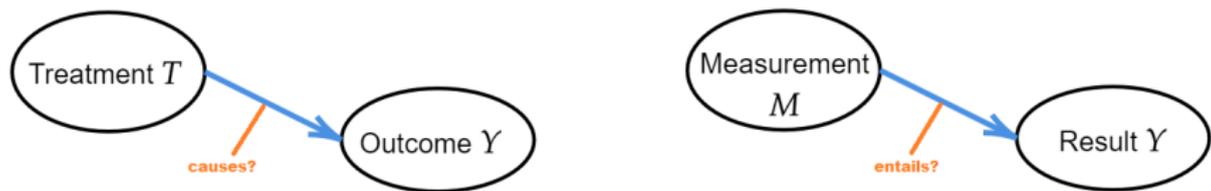
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- Often Y is a binary choice: does a desired outcome happen? does the result go one way or the other way?

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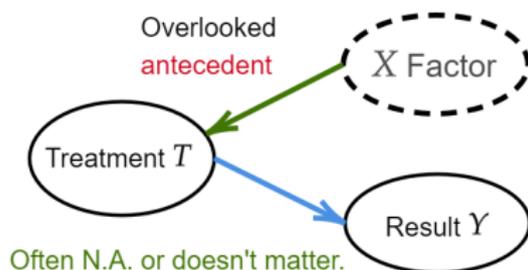
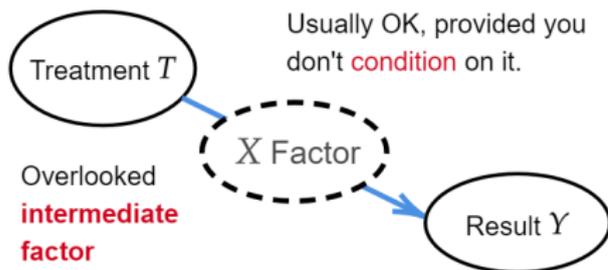
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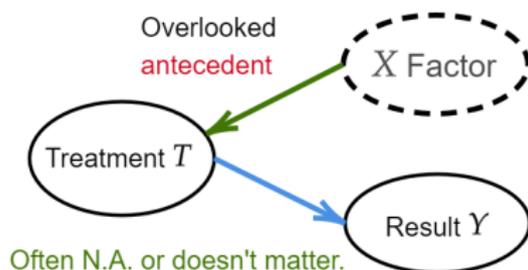
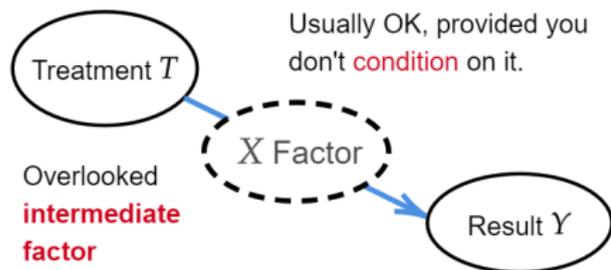
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- Can we make a tight enough relation between our measurements M and the results Y we are trying to capture?

Missing Factors in Studies—When Benign and...

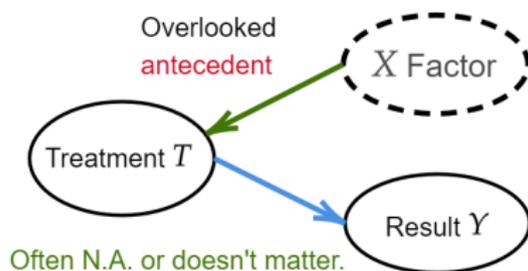
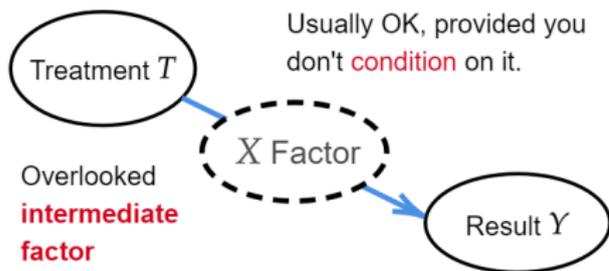


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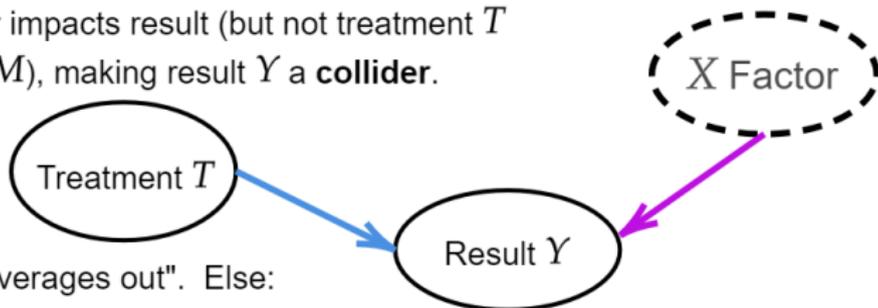
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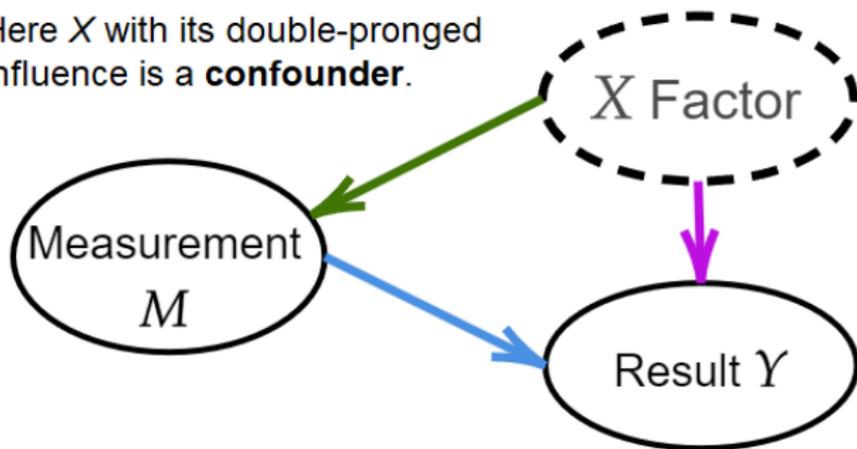
Overlooked factor impacts result (but not treatment T or measurement M), making result Y a **collider**.



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

...When Not: I. Confounding Factors

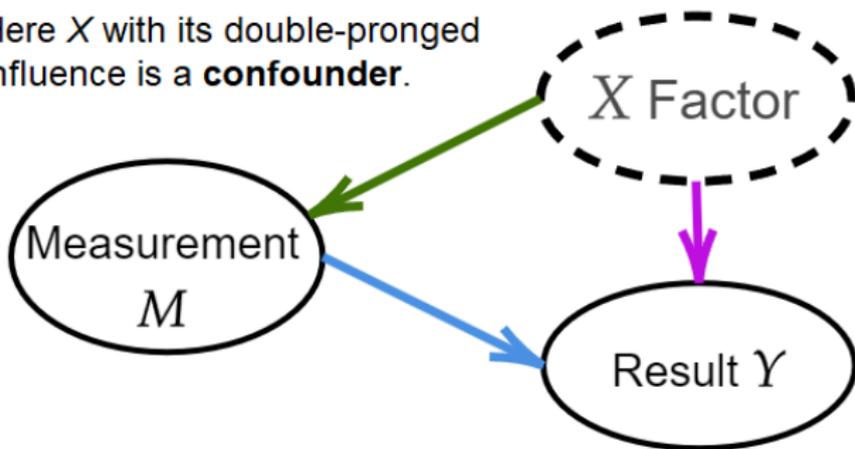
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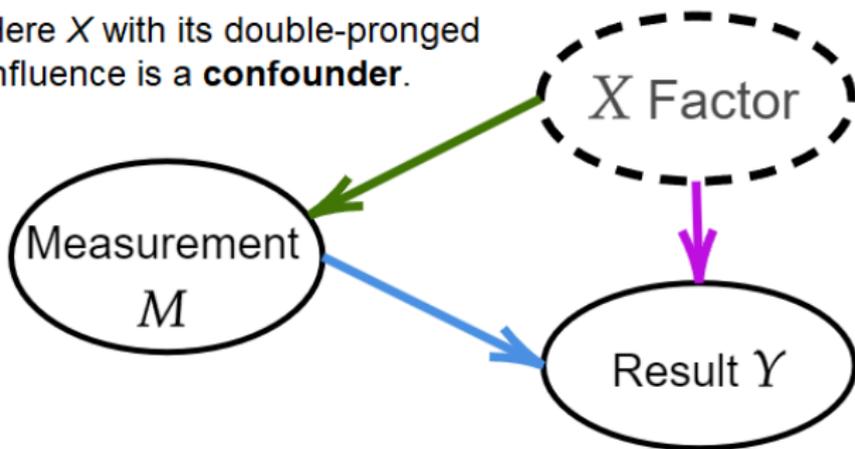


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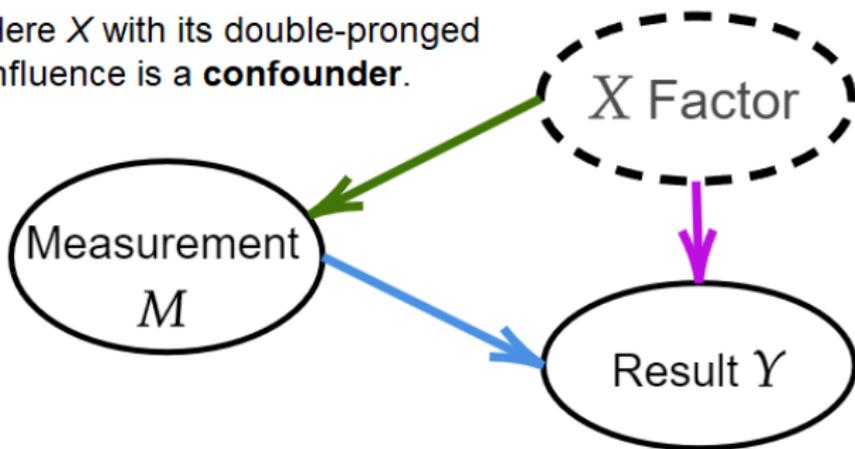


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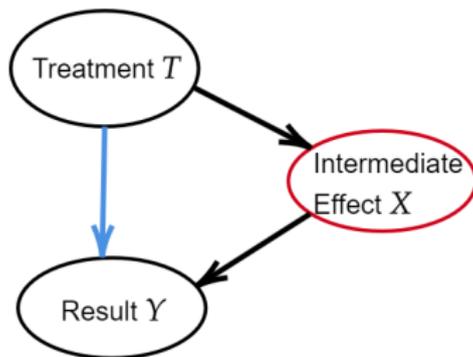
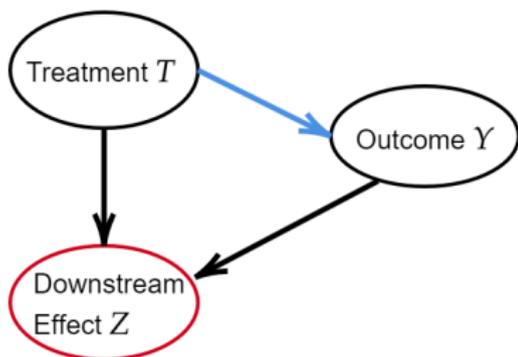


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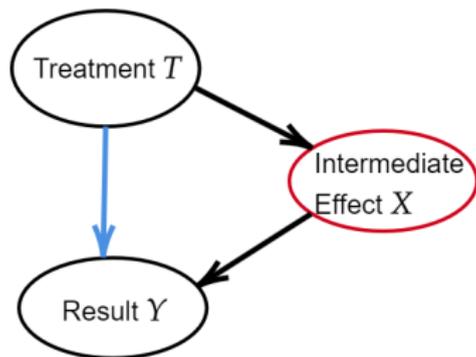
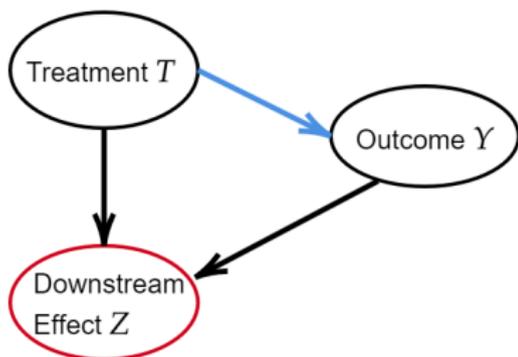
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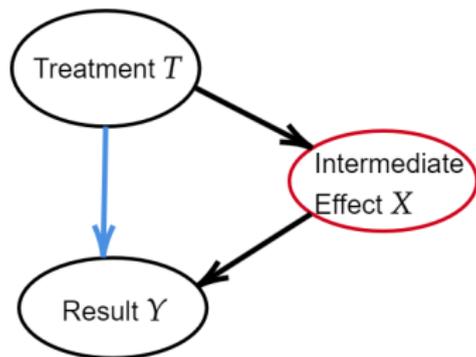
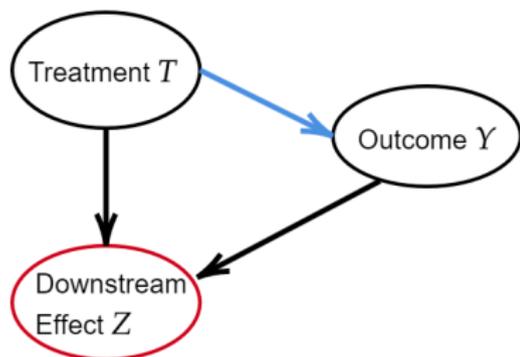
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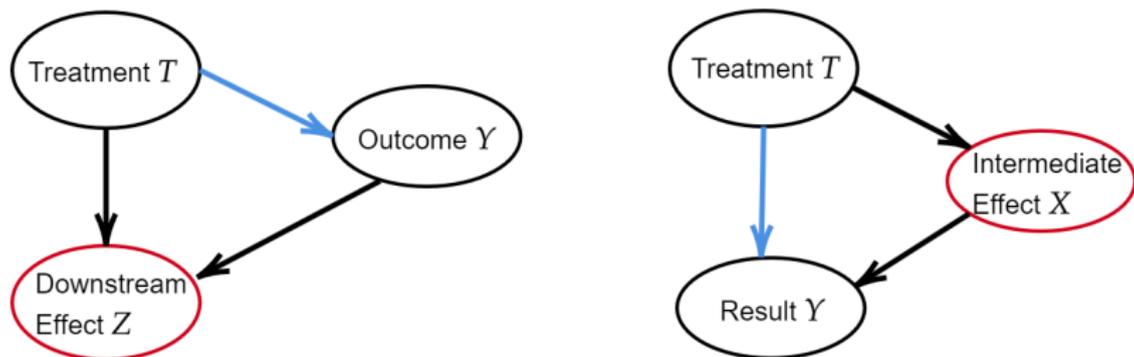
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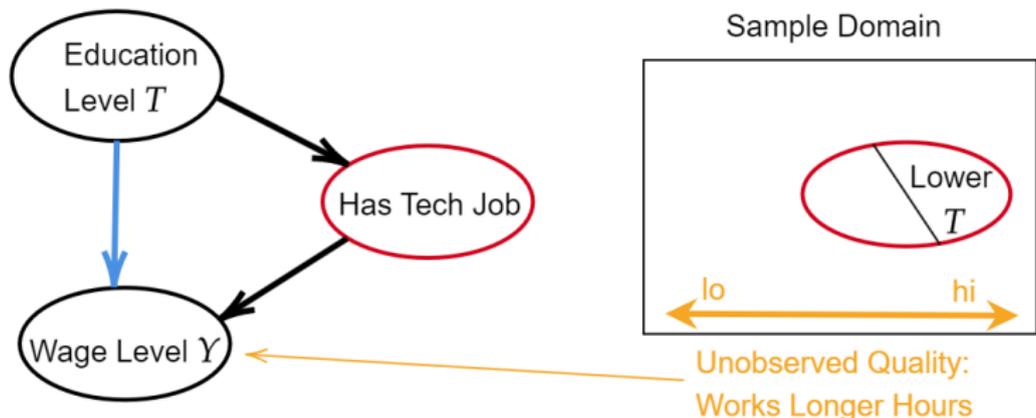
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- Each way, conditioning on Z or X **selects** a **subsample** that may be skewed relative to the whole domain.

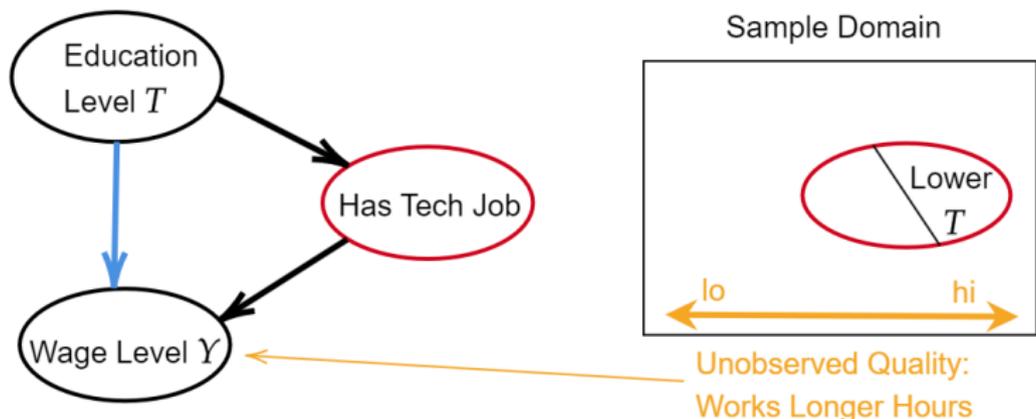
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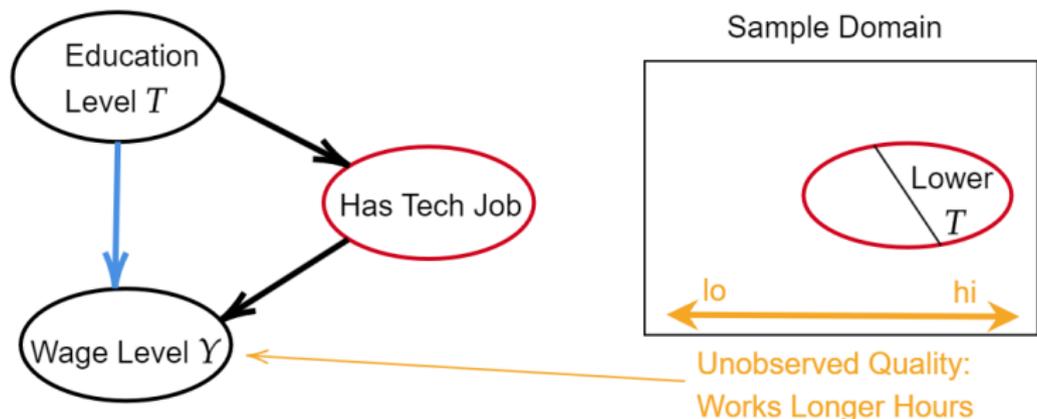
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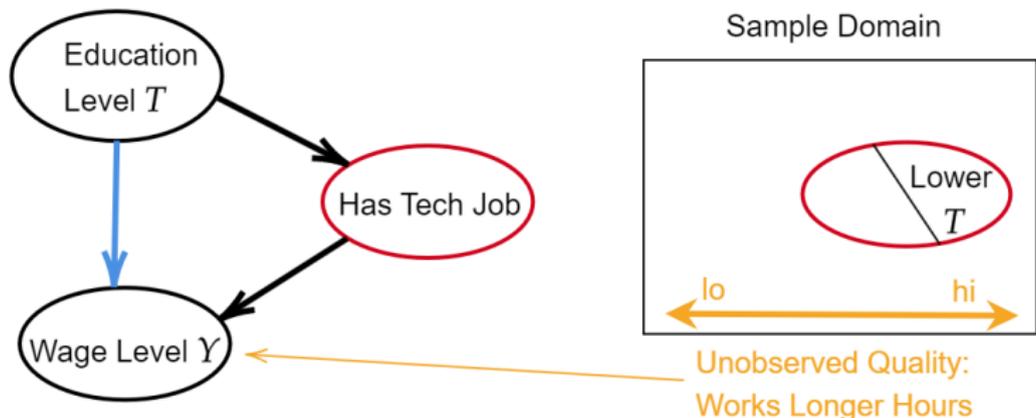
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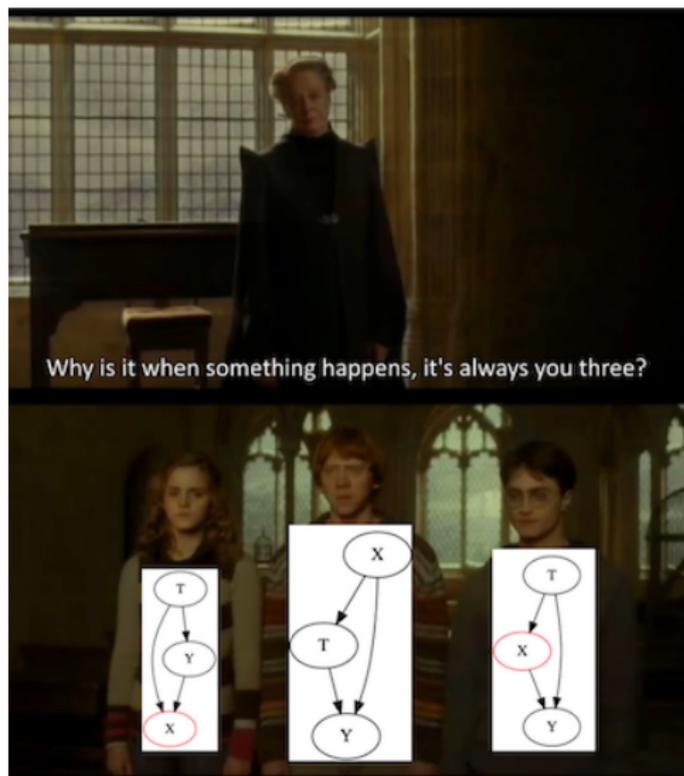
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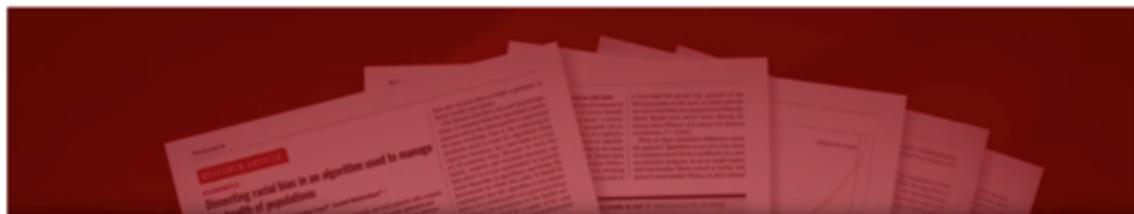
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- Can also happen from choices of unrepresentative proxy variables.

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.



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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.

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- Another “Murphy’s Law” situation: Minorities have **higher variance** in trained diagnoses simply because they comprise a minority in the datasets.

Bias in Datasets

- Article, “**How our data encodes systematic racism**” in Dec. 2020.
- Example from article: “Google Image search results for ‘healthy skin’ show only light-skinned women.”
- Same search in late 2025 gives results that are still horribly...**sexist!**
- (And maybe under-represents East- and South-Asians.)
- Amazon **resumé filter**: Trained on mostly male hiring data, perpetuated the same.
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