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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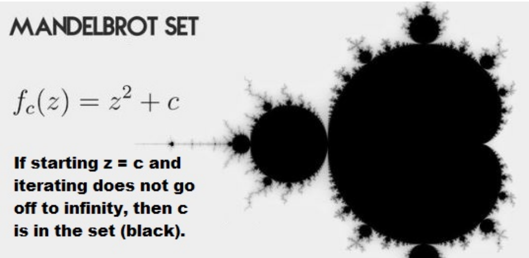

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- Whether the info and inferences are **true** is secondary!

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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- The Internet Archive Wayback Machine has indexed over **866 billion** webpages.

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

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- Many data centers are augmented with **server farms** to do the processing.

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- **Doing so front-loads material for both this week's activity and next week's homework.**

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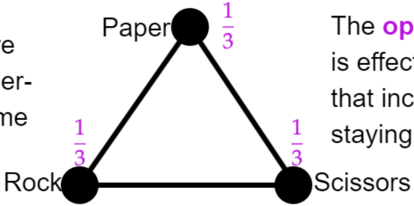
- Only foolproof way: a **completely random** strategy. Here: roll a die and play Rock on 1 or 2, Paper on 3 or 4, and Scissors on 5 or 6.
- But since this is a **fair game**, you can’t expect to win either.

Graph picture of Rock-Paper-Scissors game



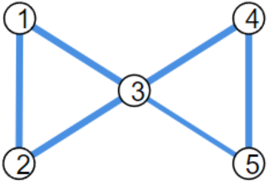
The **optimal random strategy** is effected by a **random walk** that includes the option of staying on your **current node**.

Another Single-Matrix Game

Imagine hunting a polar bear on ice floes in Arctic fog. When fog lifts:

- If hunter and bear are on adjacent floes, hunter shoots bear: $\rightarrow$ **+1**.
- If the bear is 2 or more floe-jumps away, the hunter misses: $\rightarrow$ **0**.
- If they find themselves on the same floe, $\rightarrow$ **?**.

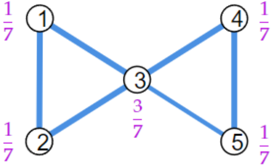
The network of adjacent floes can be represented as both a discrete graph and a matrix. Here is a picture of the game when five floes are arranged in a "bowtie" pattern:



You \ Bear	1	2	3	4	5
1	?	1	1	0	0
2	1	?	1	0	0
3	1	1	?	1	1
4	0	0	1	?	1
5	0	0	1	1	?

Bowtie Graph Game—Continued

If **? = 0** then the hunter achieves **expected value** $v = \frac{4}{7}$ by adopting the randomized strategy shown.



$$\begin{array}{c|ccccc|}
 & 1 & 2 & 3 & 4 & 5 \\
\hline
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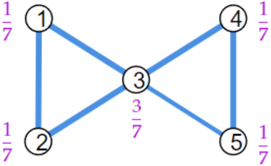

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- Note that *both* choose the central floe (3) less than half the time.

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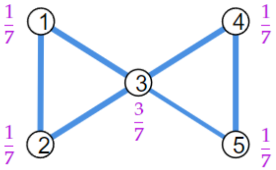

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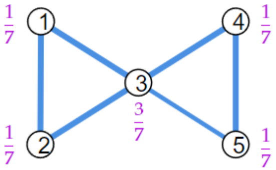

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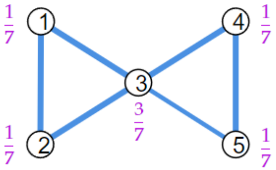

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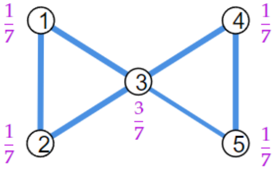

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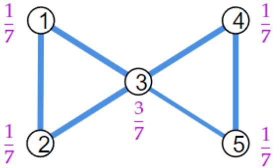
- Weird answer: $3 - \frac{16}{7-\sqrt{17}} = -2.56155...$

Bowtie Graph Game—Continued

If **?** $=$ **0** then the hunter achieves **expected value** $v = \frac{4}{7}$ by adopting the randomized strategy shown.



$$\begin{array}{c|ccccc|}
 & 1 & 2 & 3 & 4 & 5 \\
\hline
1 & 0 & 1 & 1 & 0 & 0 \\
2 & 1 & 0 & 1 & 0 & 0 \\
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\hline
\end{array}$$

The “same” strategy by the bear assures losing no worse than $v = \frac{4}{7}$.

- Note that *both* choose the central floe (3) less than half the time.
- If **?** $=$ **+1** then the hunter **dominates** by always choosing (3).
- If **?** is negative the bear sometimes wins. What negative value makes the game *fair*—that is, both have expected value 0?
- Weird answer: $3 - \frac{16}{7-\sqrt{17}} = -2.56155...$
- If **?** $=$ **-1** then $v = \frac{1}{3}$ and both hunter and bear play (3) one-third of the time—same frequency as in a **random walk** of the graph.

Two-Matrix Games: Not Zero-Sum

Change the same-floe case to be: bear knocks the gun away but raids the hunter's lunch for **+3** value rather than kill em. Meanwhile the hunter videos the bear, for **+0.5** value. And in the two-floes-away case, let's penalize both of them **-0.5**, for missing and being inadvisably close. Now we need a separate **payoff matrix** for each:

H	1	2	3	4	5
1	0.5	1	1	−0.5	−0.5
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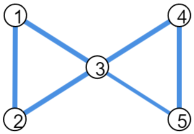

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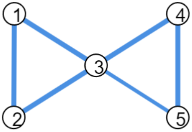

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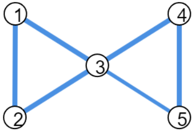

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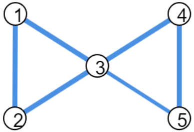

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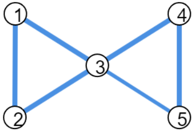

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- You will play a simpler(?) example game in recitations.

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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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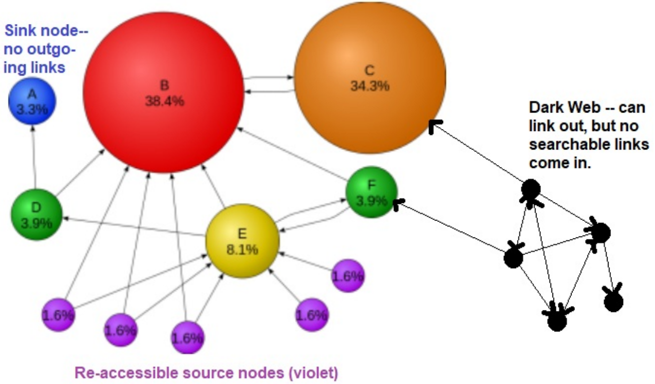

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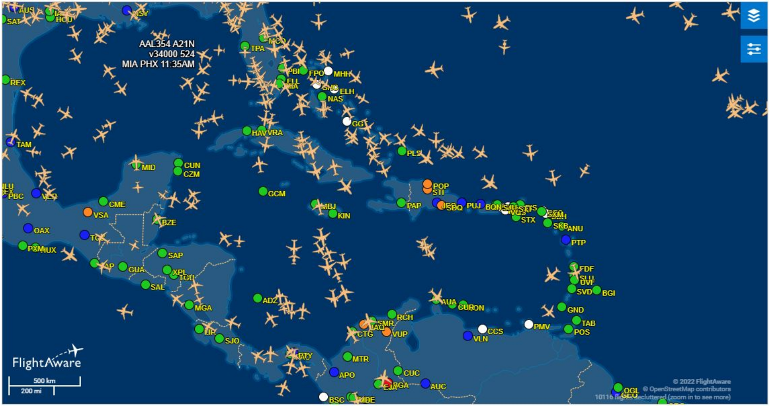
A "Semi-Structred" Example (of Inferencing)

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



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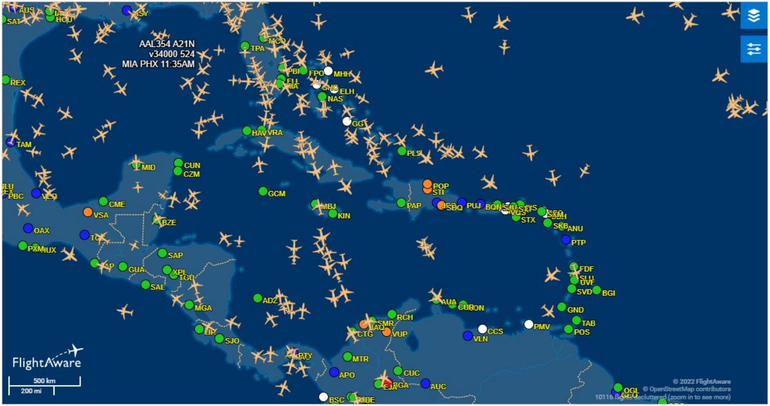

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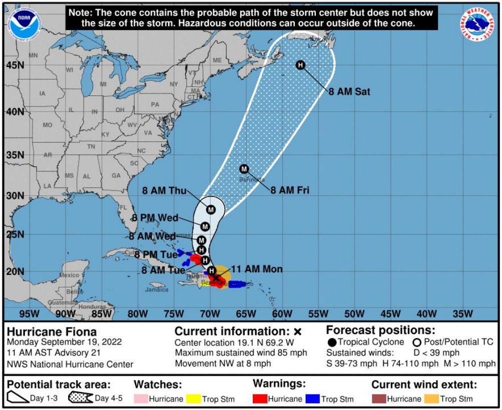
And what about north of the Black Sea?

Hurricane Tracking

NOAA (picture of Hurricane Fiona in 2022)



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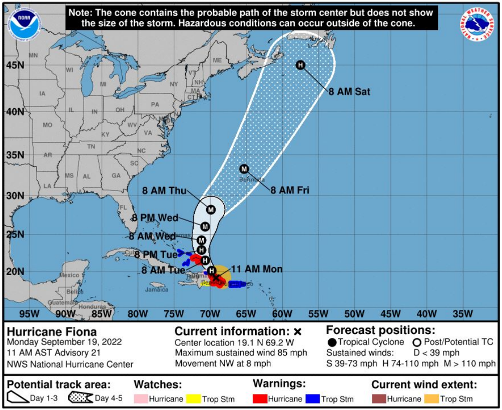

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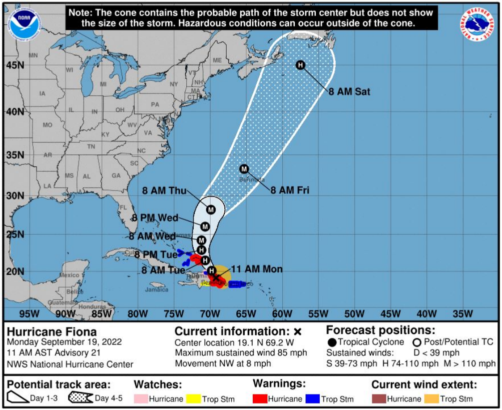

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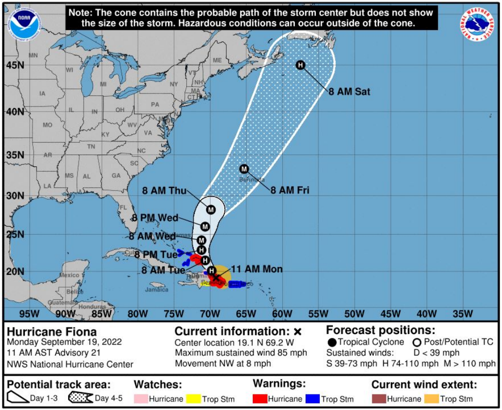

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Hurricane Francine today.

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- For our purposes, we can say they can map the front within a mile or two of accuracy, also based on reports (when confirmed).
- Real-time location of individual units and large equipment is dicier...if *we* could do it, the other army could.

Mapping and Geolocation

- *Google Maps* and similar services—lack of them was cited often in the "8 Hours Without Internet" essays.
- Fire Information for Resource Management System (FIRMS).
  - Originally built by NASA for fighting wildfires.
  - But now used for war tracking.
- Daily mapping of the front in Ukraine: ISW, LiveUAMap, DefMon3.
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- Part of **OSINT**: Open-Source Intelligence.)

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- Definitely August 16 arrest of US citizen for eating cat in Canton.
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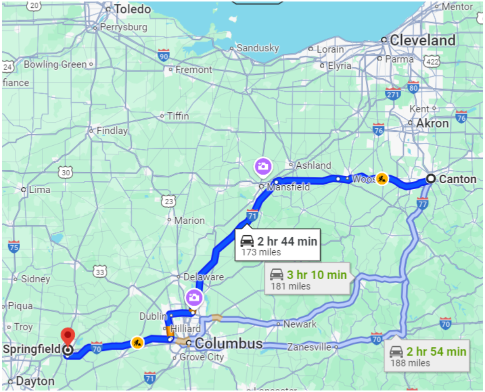
- Reports of lost pets in Springfield coming now—more than usual?



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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

In our previous `<recipe>` example this would include:

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[Discuss 2010 French chess cheating case and civil vs. criminal law.]

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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

We will cover the following tools and some of their societal implications (after covering some leftover Part II slides):

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. (covered last week)

There are many left uncovered. The last will lead in to Wednesday's coverage of machine learning, sentiment analysis, and AI.

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- [show graphs from FanGraphs article, bottom of page. And this.]
- Goal is to fit the **coefficients** $a, b, \ldots$ by **linear regression** on available data for the modeled variables.

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

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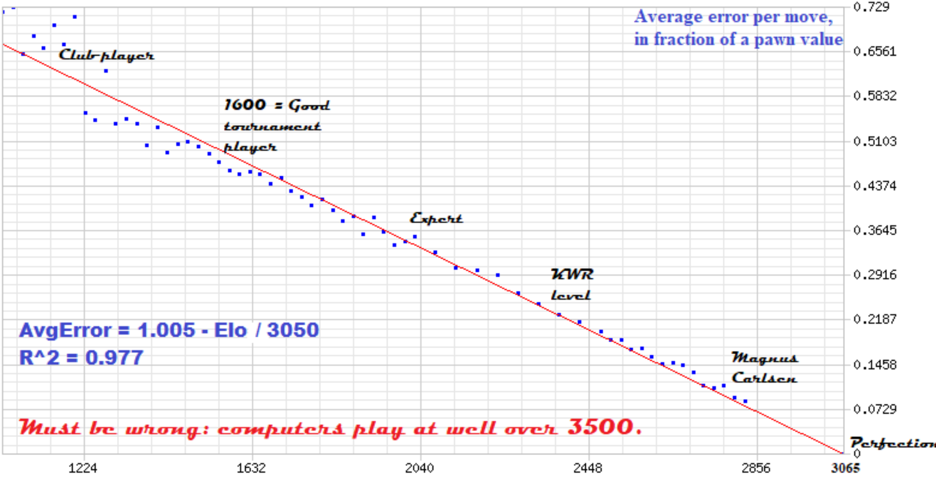
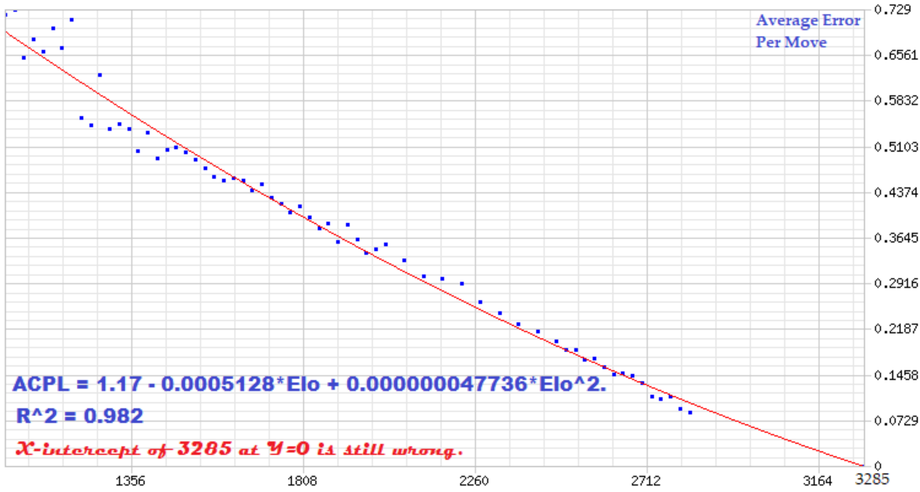
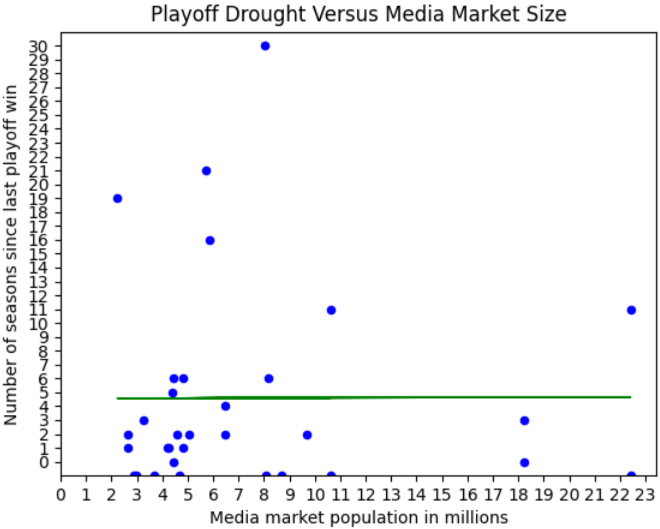
Linear Model: ACPL = $a + b$·Elo Rating



Quadratic Fit—Only Marginally Better



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



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

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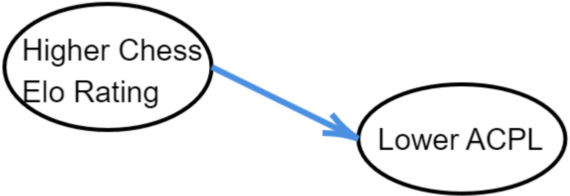
- Causal graphs have nodes—black or red for conditioning—and arrows.
- They can help ascertain
  - which are genuine causes—as opposed to mere correlations or null effects,and
  - which variables in the system can helpfully be **regressed** or **conditioned on**.

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



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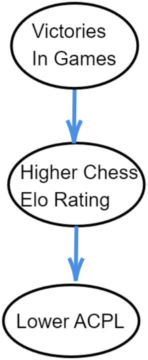
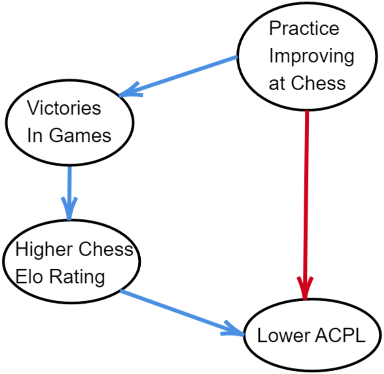
- But if we have a lurking *common cause* D of both our *source* and *intended target*, then it can **confound** the smaller-scale analysis.
- I faced this when the pandemic caused official chess ratings to lag true skill. Case of wrongly accused player.





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

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- (a) vigor . . corroborated
- (b) feebleness . . dashed
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(source: itunes.apple.com)

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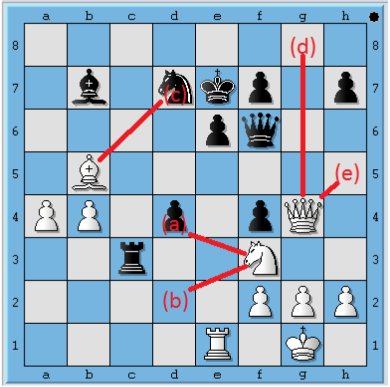

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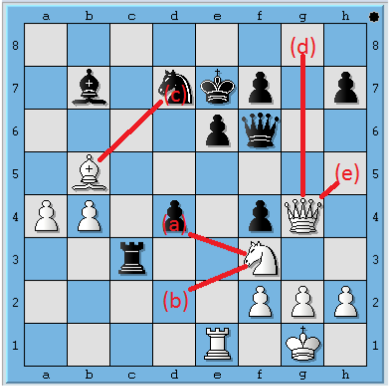

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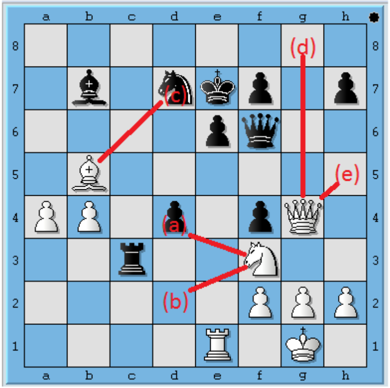

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Validate the model on millions of randomized trials involving "Frankenstein Players" to ensure conformance to the standard bell curve at all rating levels. This is also an example of **Simulation.**

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

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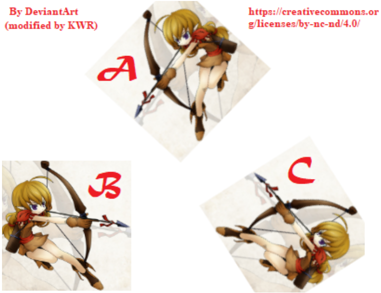
- What if there are more "candidates" than voters—such as when judging the Olympics?
- Early study by mathematicians: Jean-Charles de Borda, Nicolas de Condorcet (1700s), Charles Dodgson (= Lewis Carroll!, 1800s).

Condorcet's Paradox and Arrow's Impossibility



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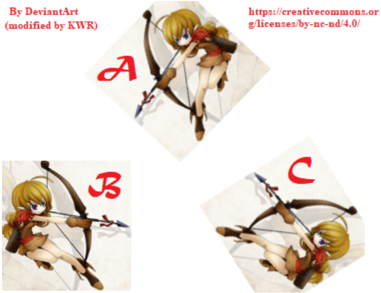

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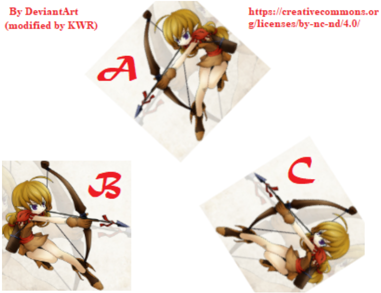

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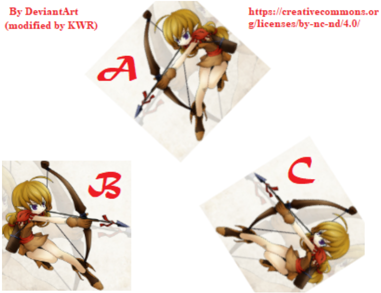

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- **Kenneth Arrow, 1950s:** No way to fix except to allow minority rule, dictatorship, or weighting votes unequally via **ratings**.
- "Least Bad"? (used in Maine and Alaska): Eliminate candidate with fewest first-place votes and repeat until a majority winner.

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- In gymnastics and other sports, $S = D + E$. The difficulty score D depends only on what you attempt; the execution score E tells how well you performed it.

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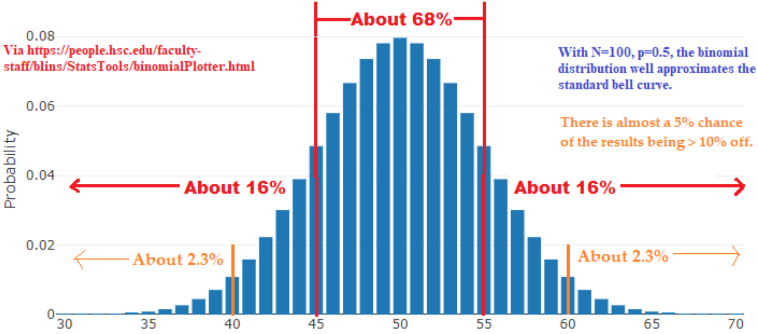
- Almost **one-third** chance poll results will be $<$ **45%** or $>$ **55%**.



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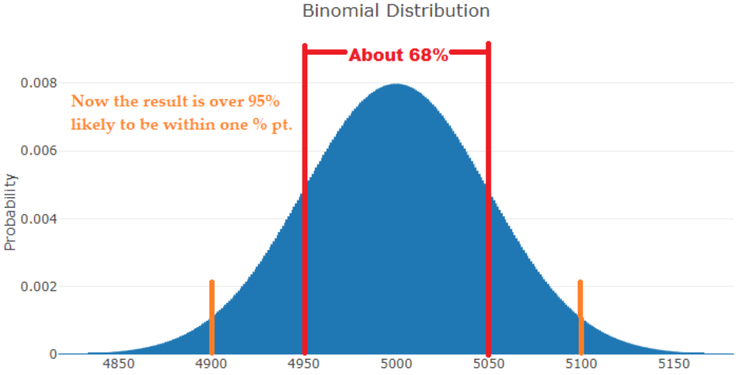

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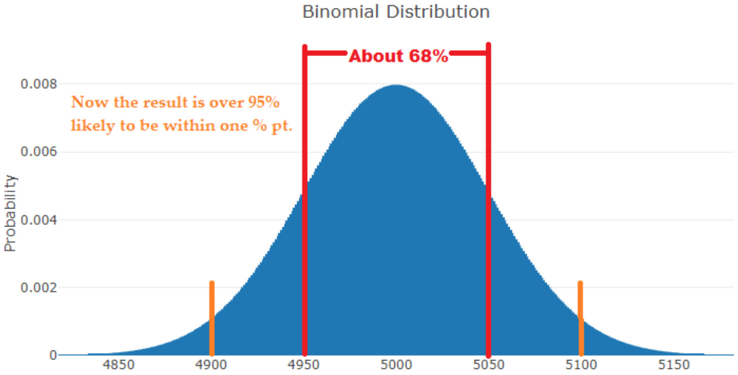

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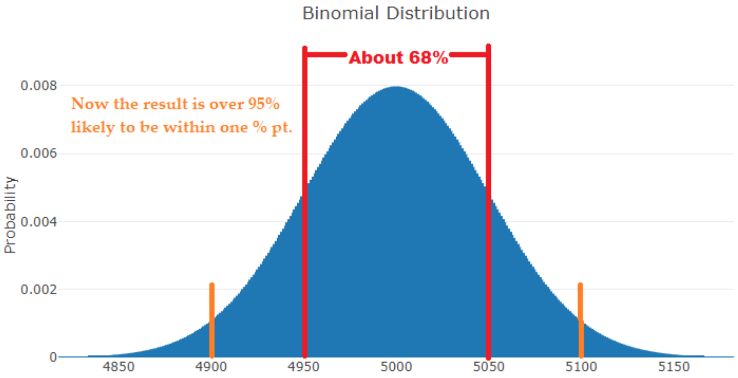

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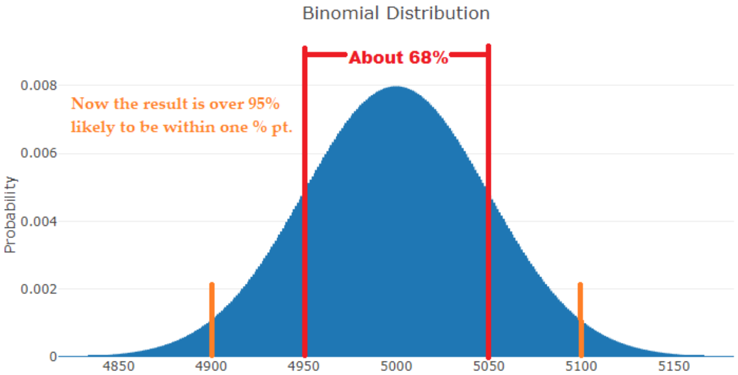

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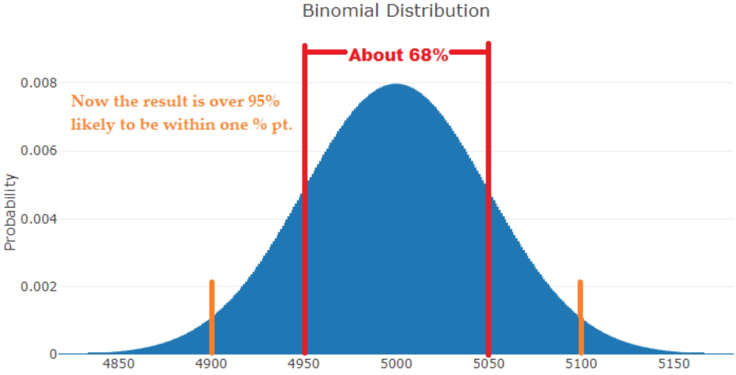

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- So results 47%-to-53% count as "statistically tied" (yuck).

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- Now let's talk about Sentiment Analysis.

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

Part VI: AI

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.

Part VI: AI

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

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

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

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

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

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

Stuff that is hard for humans but easy for computers.

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

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

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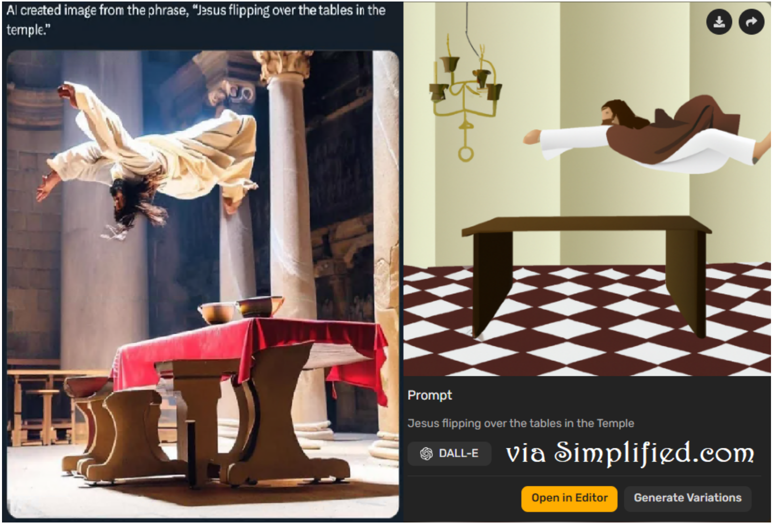
- But subject to **hallucinations** and other foibles—some shown by me here and here and here.

AI Art Adventure

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

Two Results—one famous, one mine



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

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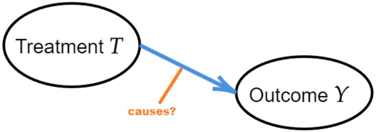
- This *may* foster adapting my chess model for a “simple frequentist” kind of cheating detection.

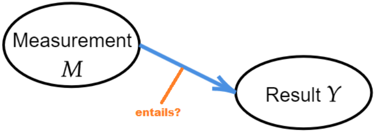
Large Language Models

[show Stephen Wolfram link as above.]

Part V: Societal Computing and Fairness

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





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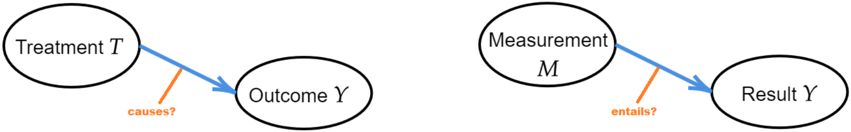

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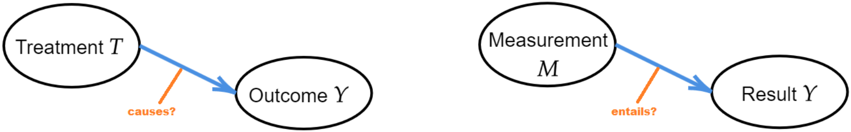

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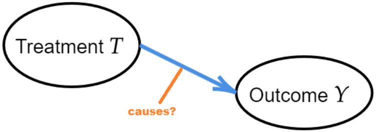

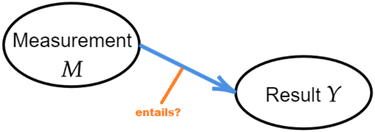

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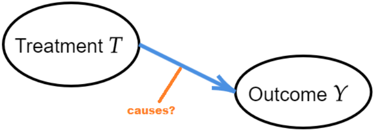

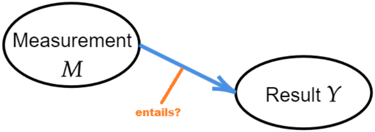

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- I.e., is Y beyond the *margin of error* for the **null hypothesis** of no causation?

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  - The others who get "$< 2\sigma$" (or even $< -2\sigma$ or other forms of "no effect") stay silent.

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- A Simple Mechanism:
  - Something like Covid brings fresh Big Ideas in medicine and psychology (etc.).
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  - But $\sim$ our poll analogy, one study randomly gets results outside the margin of error, i.e., "$> 2\sigma$."
  - This is the academic threshold to publish, so they do.
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- Can happen with 50 different big ideas, too (see this).

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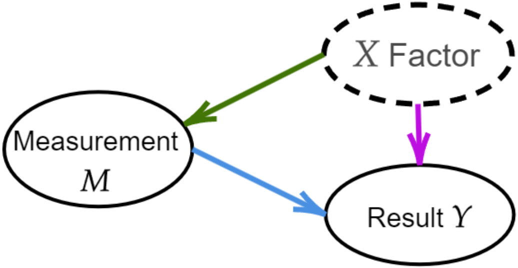
- Can we make a tight enough relation between our measurements M and the results Y we are trying to capture?

Other Study Design Flaws to Beware

Confounding Factor(s):



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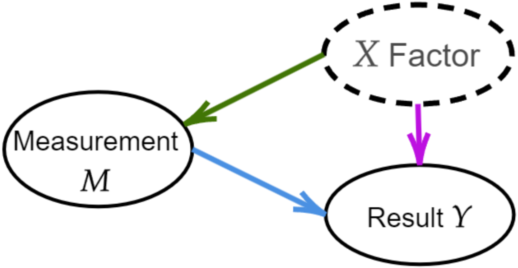

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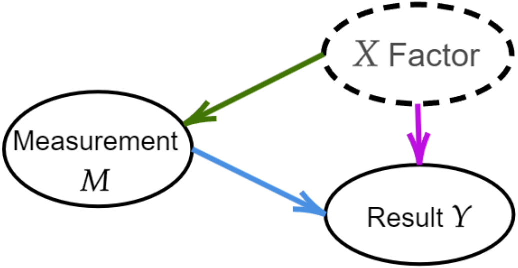

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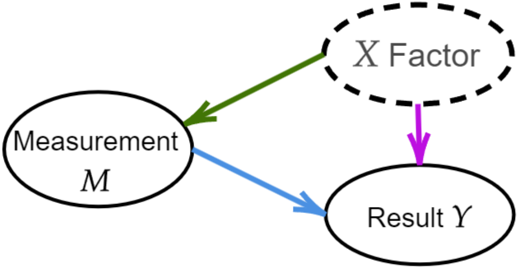
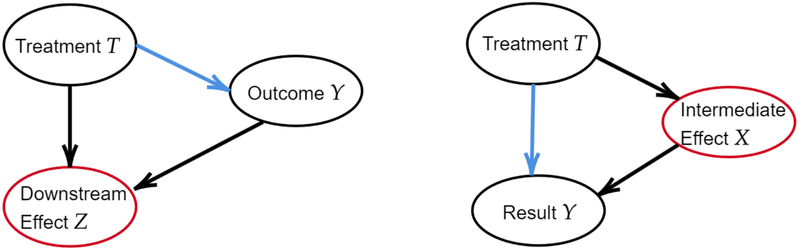


- Possible example: X = a scandal, such as in North Carolina.
- Can both *stimulate* M (such as "heat") while *inhibiting* Y (such as "Challenger Wins").
- Even if impact is positive on both M and Y, X can dominate, drown out, or otherwise skew the effect we are trying to analyze.

II. Selection Bias From Conditioning

Conditioning on Other Effects



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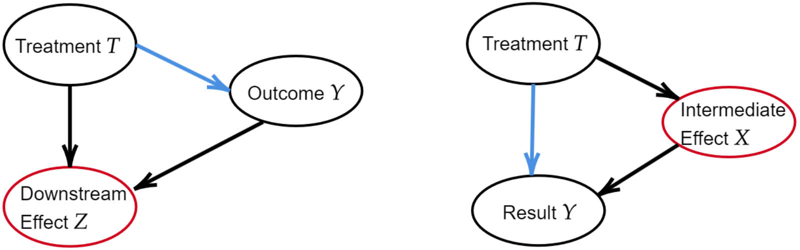

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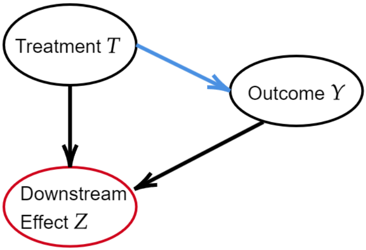

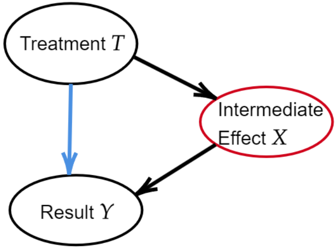

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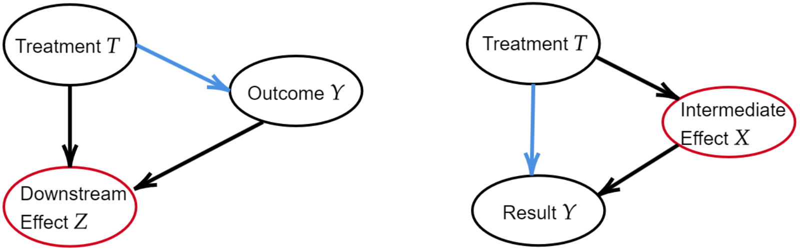

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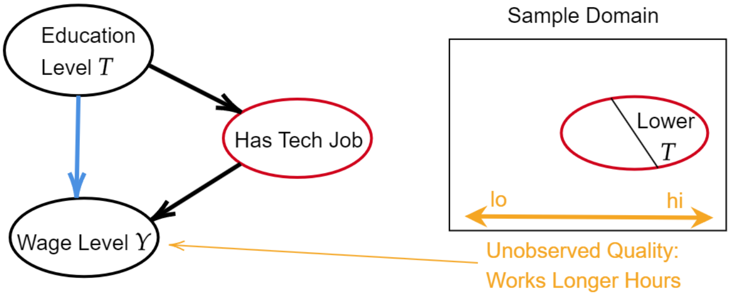
- (IIb): T = chess training, X = higher rating, Y = lower ACPL.
- Each way, conditioning on Z or X **selects** a **subsample** that may be skewed relative to the whole domain.

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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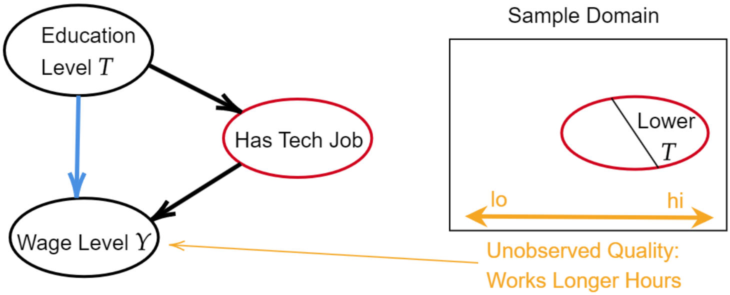

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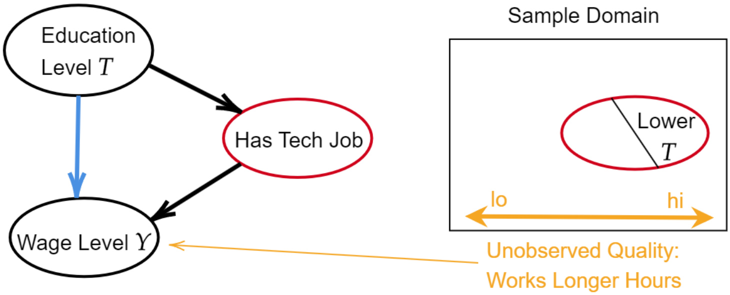

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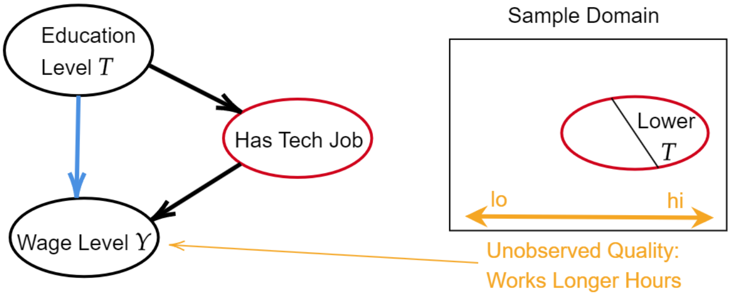

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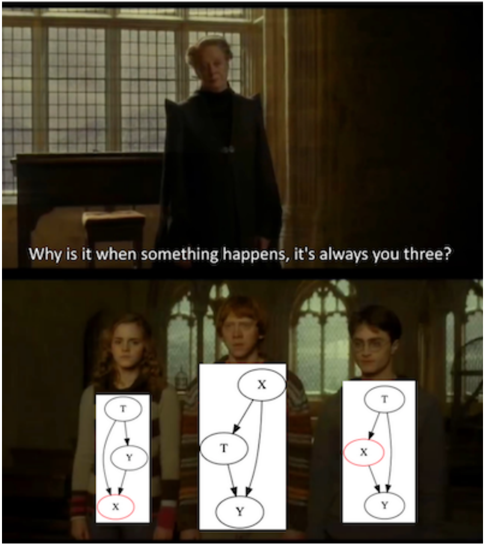
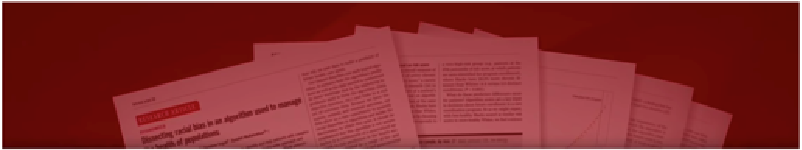
- (Source says "white-collar jobs" rather than "tech jobs.")
- Can also happen from choices of unrepresentative proxy variables.

Harry Potter Meme (also from here)



Example of Bias From Proxy Variable (K. Joseph)

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



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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