

Data and Society

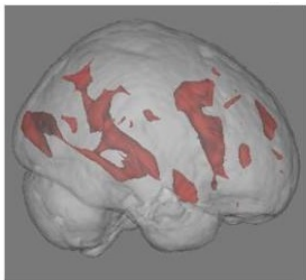
Resources and Dangers and Opportunities

Kenneth W. Regan

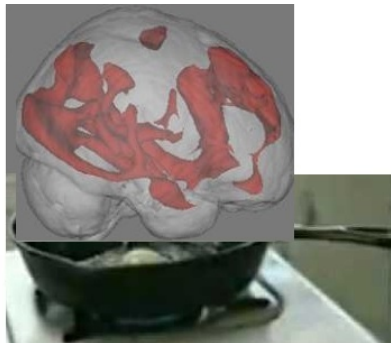
(Includes material from Kenny A. Joseph and some other past
CSE199 units.)

CSE199, Fall 2024

Main Problem...



**THIS IS YOUR
BRAIN**



**THIS IS YOUR BRAIN
ON THE INTERNET**

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.**

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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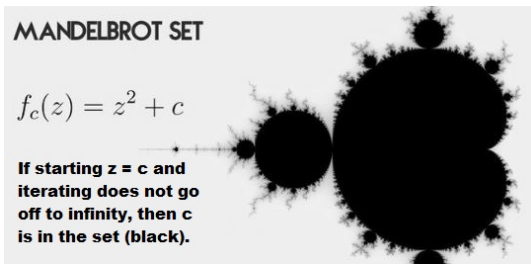
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- Internet **search**, on the other hand, can address the whole **searchable web**

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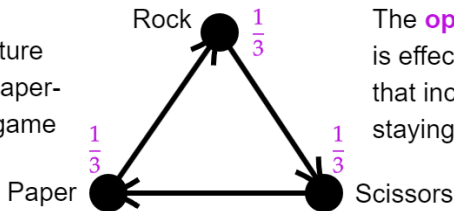
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- Only foolproof way: a **completely random** strategy. Here: roll a die and play Rock on 1 or 2, Paper on 3 or 4, and Scissors on 5 or 6.
- But since this is a **fair game**, you can’t expect to win either.

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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- Upshot is that **random walk** on G is often (near-)optimal strategy.

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- **Internet Search** is a solitaire game where the payoff to you is the *non-quantified* usefulness of the found pages to you.

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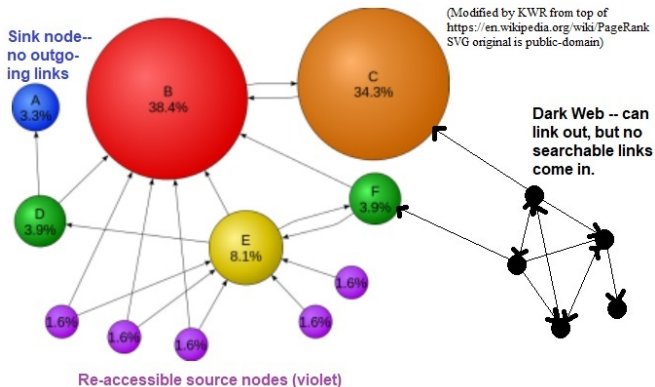
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A “Semi-Structured” Example (of Inferencing)

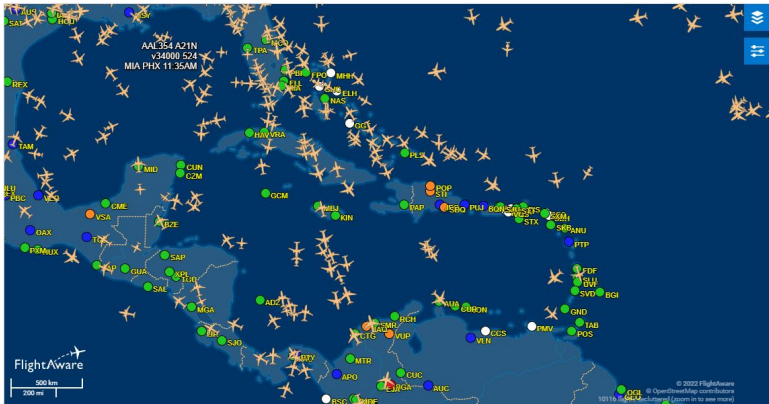
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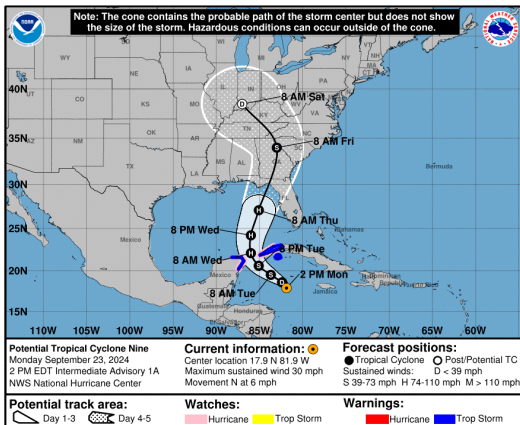
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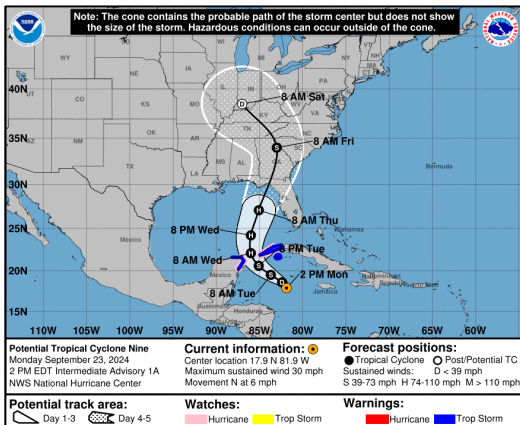
And what about north of the Black Sea?

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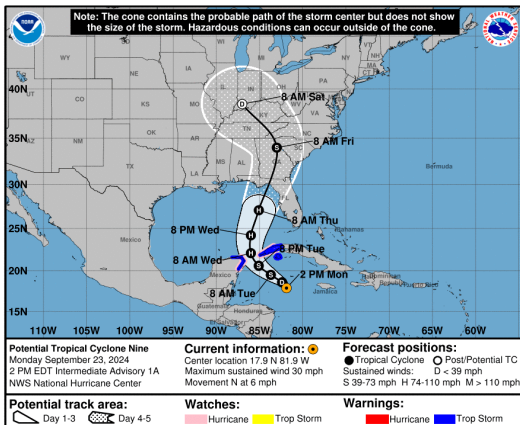
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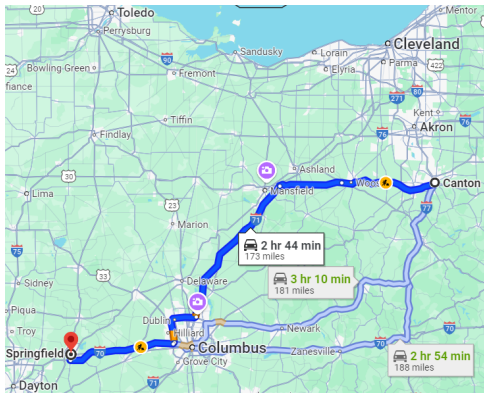
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- **Center For Open Science**—emphasizes rigor and replication in social, medical, and environmental studies.
- Impetus to be public—except mainly for *privacy* concerns.
- Tension over *proprietary* aspects, especially for NSF grants, public universities. . .
- Look at all these **public datasets!**

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- Example: “**Binge-Watching TV Is Killing Us.**”
- 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**)

Data, Metadata, and Privacy

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

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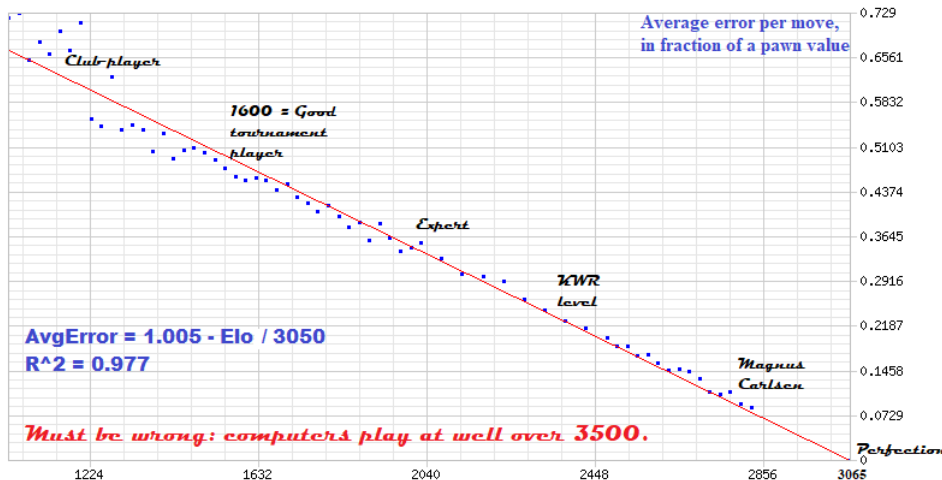
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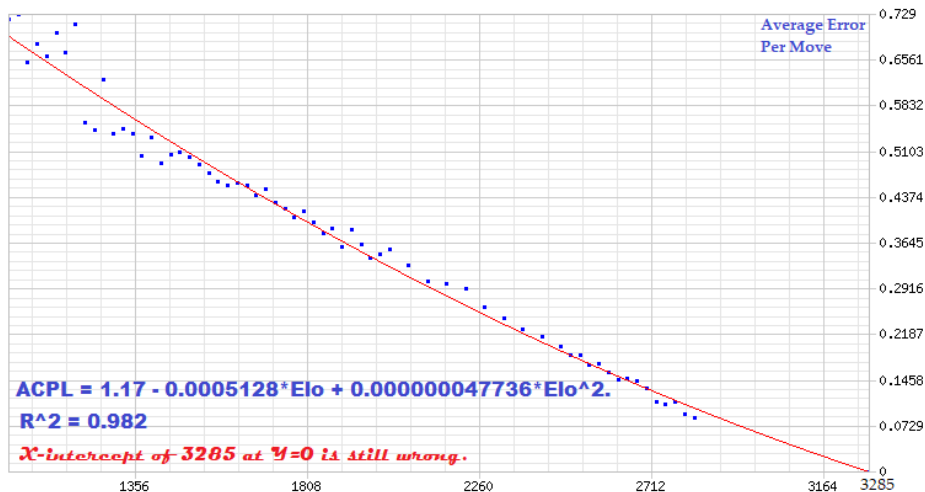
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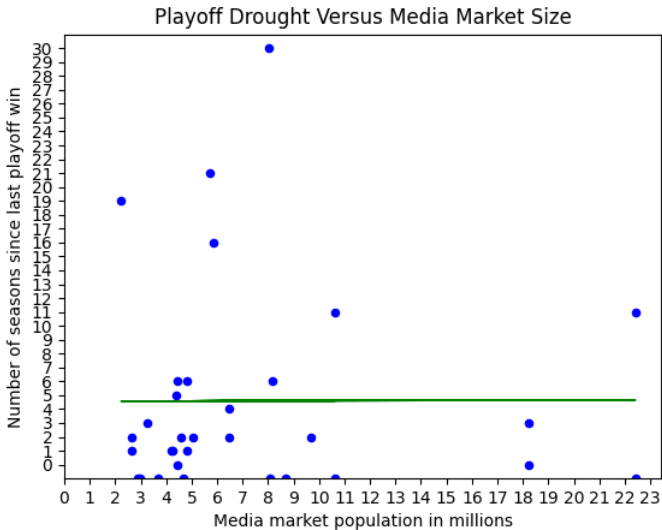
Linear Model: $ACPL = a + b \cdot \text{Elo Rating}$



Quadratic Fit—Only Marginally Better



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



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- E.g., does ACPL = the **skill** of a chess *performance*? Does ACPL=0 mean perfect play?
 - The corresponding Elo rating is only **3065** in the linear model, **3285** in the quadratic fit—both well short of perfection.

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

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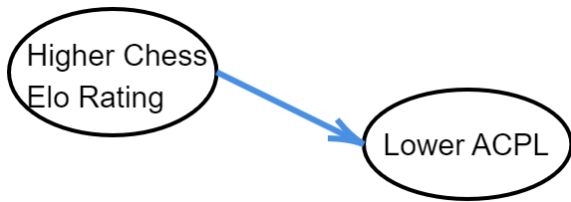
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- They can help ascertain
 - which are genuine causes—as opposed to mere correlations or null effects, and
 - which variables in the system can helpfully be **regressed** or **conditioned on**.

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



Transitive and Confounding Causes

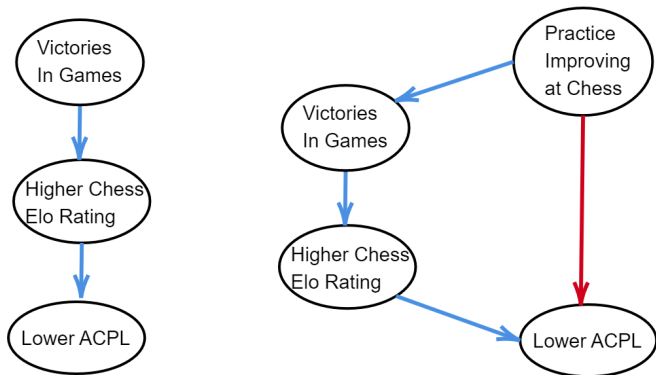
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- But if we have a lurking *common cause* D of both our *source* and *intended target*, then it can **confound** the smaller-scale analysis.
- I faced this when the pandemic caused official chess ratings to **lag** true skill. **Case of wrongly accused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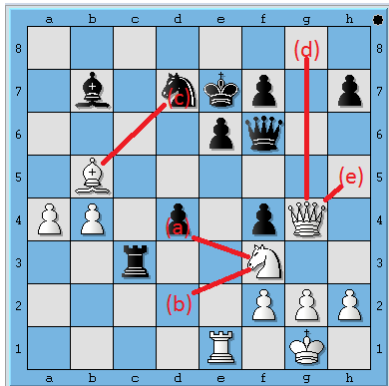
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(source: itunes.apple.com)

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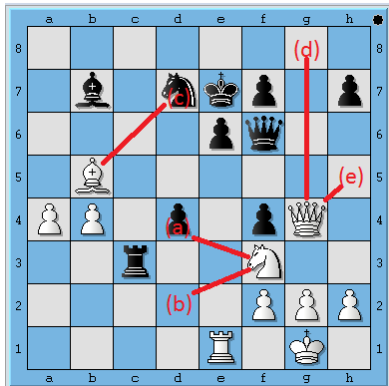
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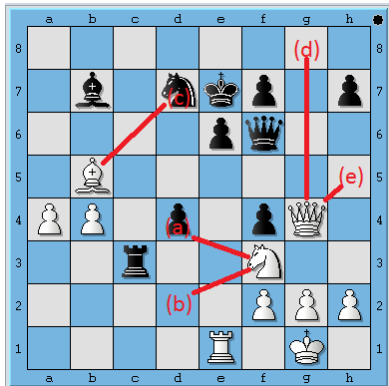
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Gaussian math yields confidence intervals that can enable **rejecting the null hypothesis** of *fair play* with high confidence.

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

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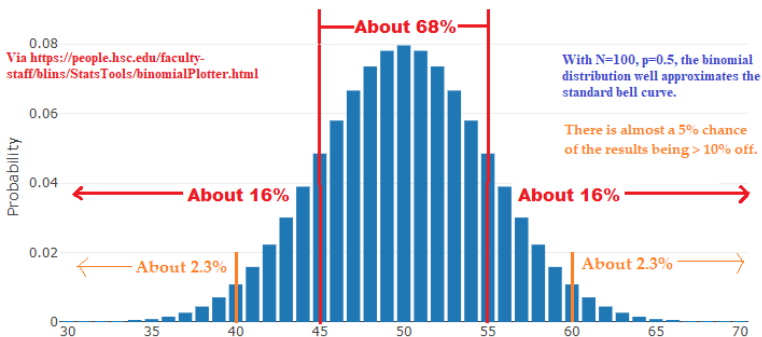
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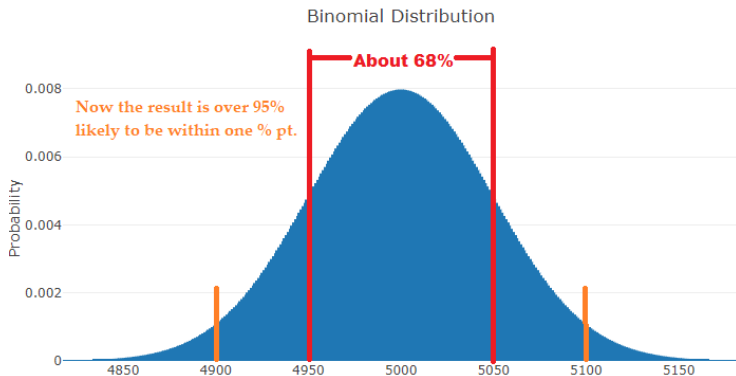
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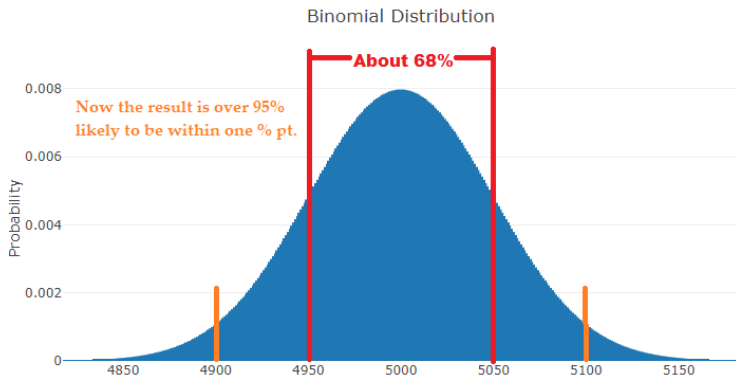


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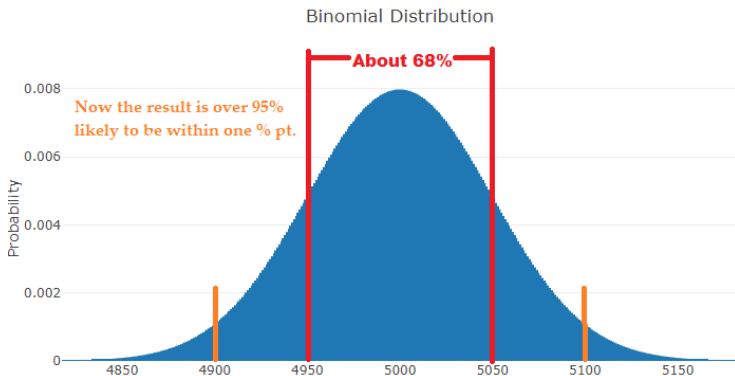
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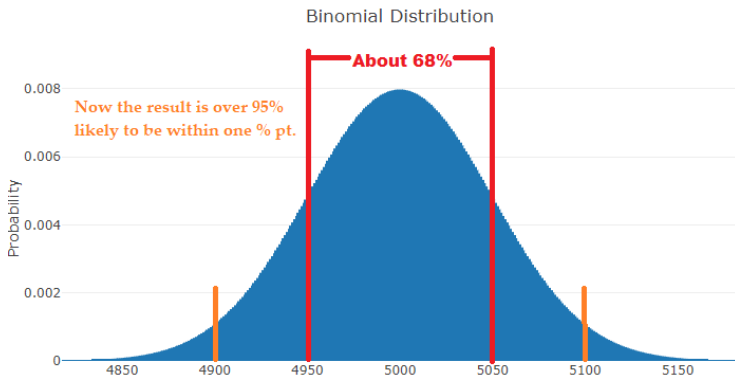
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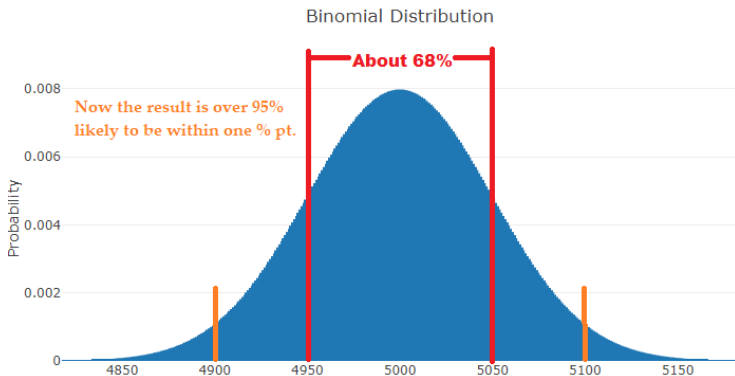
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- So results 47%-to-53% count as “statistically tied” (yuck).

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- 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

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

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- E.g. [paper](#), “Vehicle defect discovery from social media.”
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- Can we use it to predict elections? [Brexit 2016](#), [Canada 2015](#), [USA 2016 \(paper\)](#), [USA 2016 \(BrandsEye\)](#).
- ([show Python 3 Trinkets web app and activity code.](#))
- Simplistic idea: if the electorate is (un-)happy that’s (bad) good news for the incumbent.
- “Joy” is an express term of the Harris-Walz campaign. [Does it show?](#)

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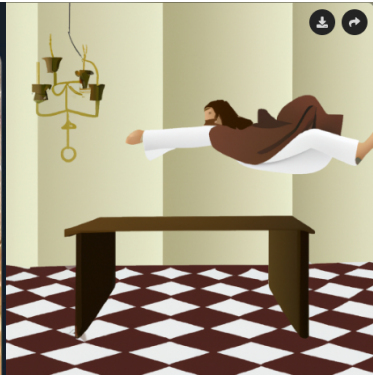
AI Art Adventure

“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

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



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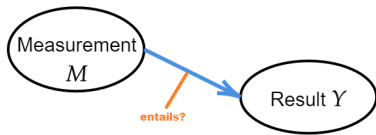
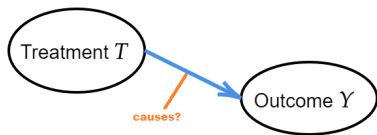
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- This *may* foster adapting my chess model for a “simple frequentist” kind of cheating detection.

How AI Extends Search

[show Tonito.]

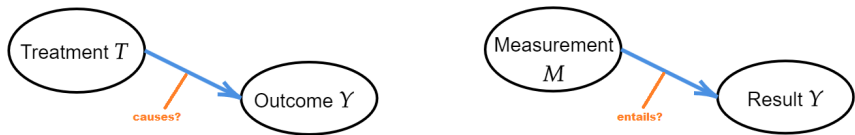
Part V: Societal Computing and Fairness

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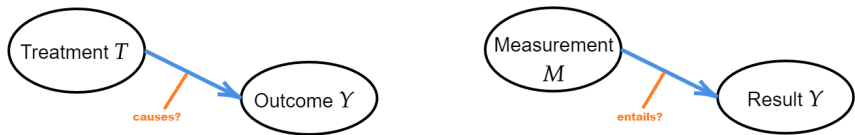
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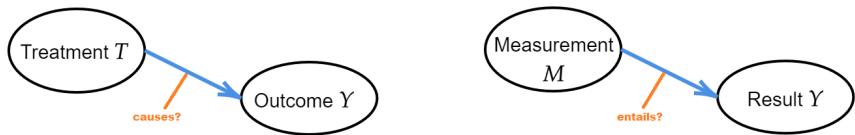
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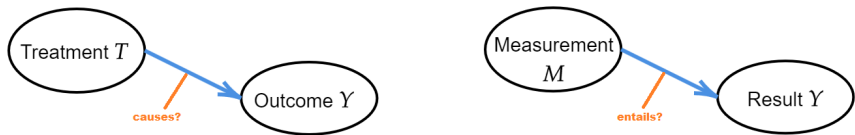
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- I.e., is Y beyond the *margin of error* for the **null hypothesis** of no causation?

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

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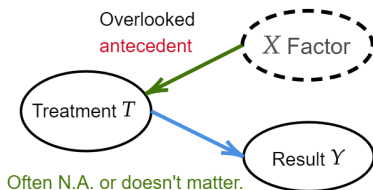
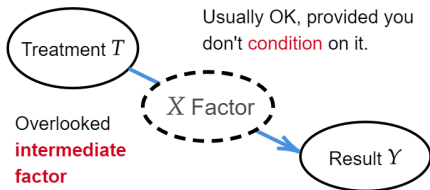
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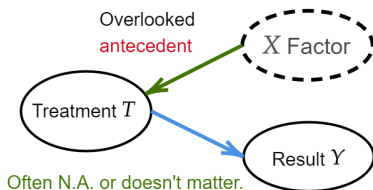
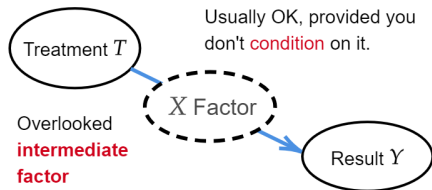
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- Can we make a tight enough relation between our measurements M and the results Y we are trying to capture?

Missing Factors in Studies—When Benign and...

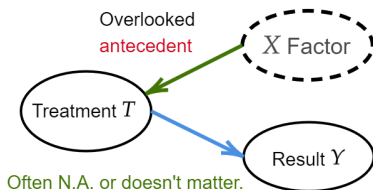
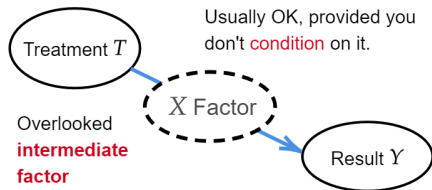


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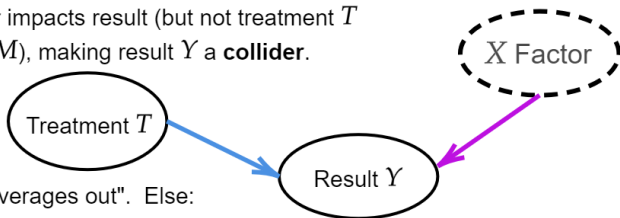
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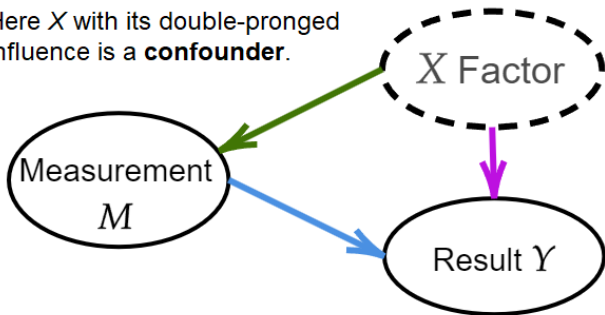
Overlooked factor impacts result (but not treatment T or measurement M), making result Y a **collider**.



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

...When Not: I. Confounding Factors

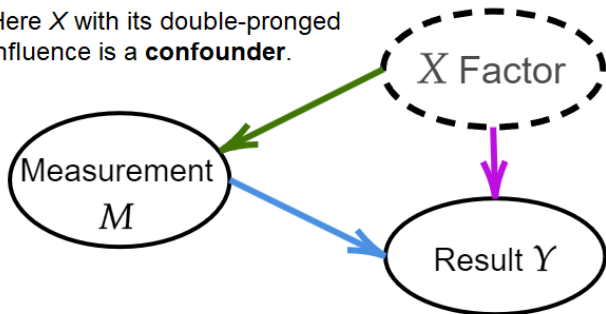
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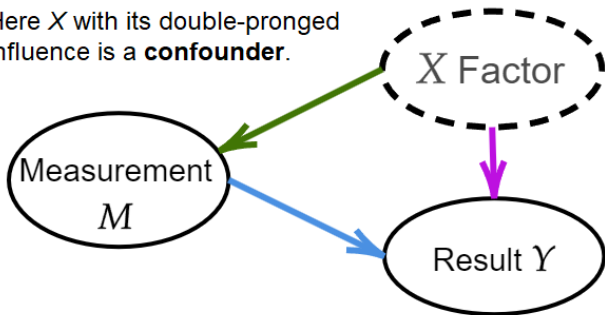


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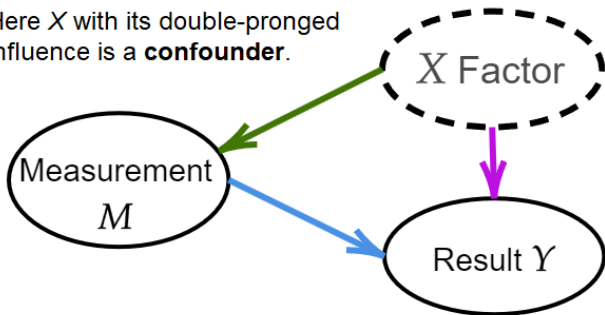


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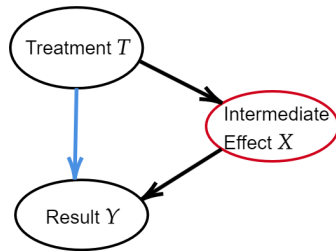
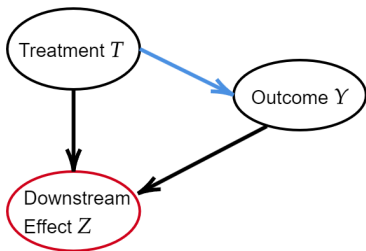


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- Even if impact is positive on both M and Y , X can dominate, drown out, or otherwise skew the effect we are trying to analyze.

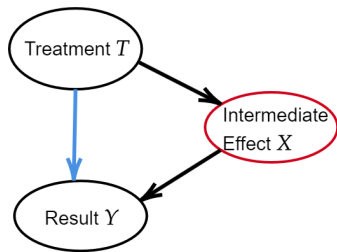
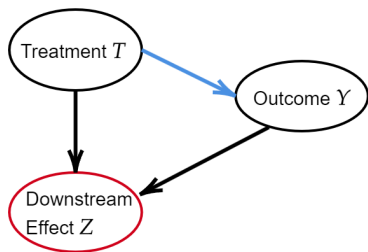
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Conditioning on Other Effects



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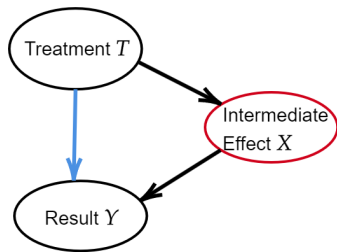
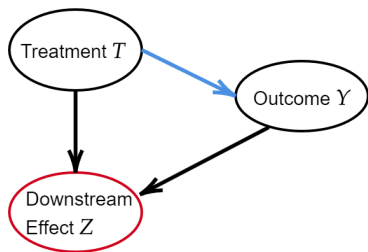
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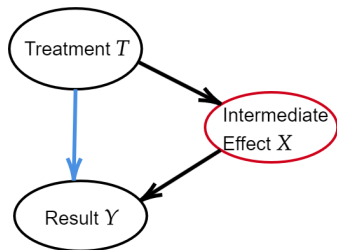
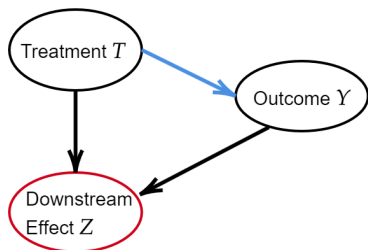
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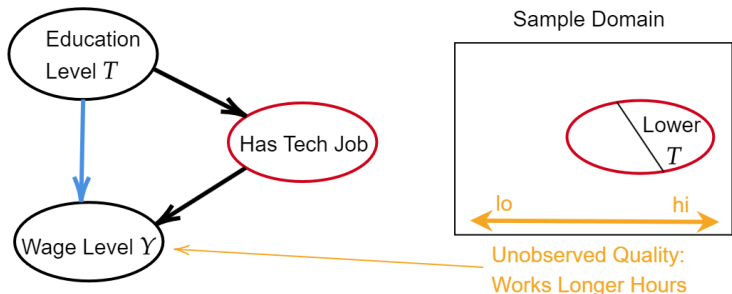
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- Each way, conditioning on Z or X **selects** a **subsample** that may be skewed relative to the whole domain.

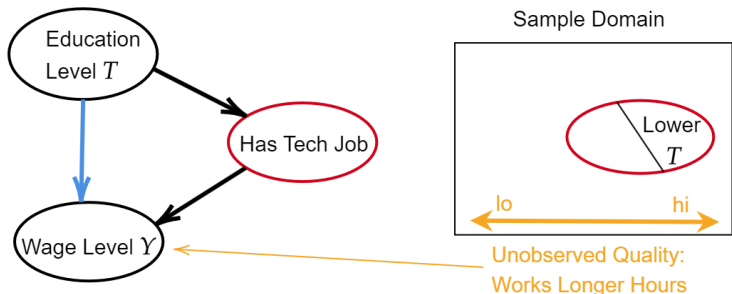
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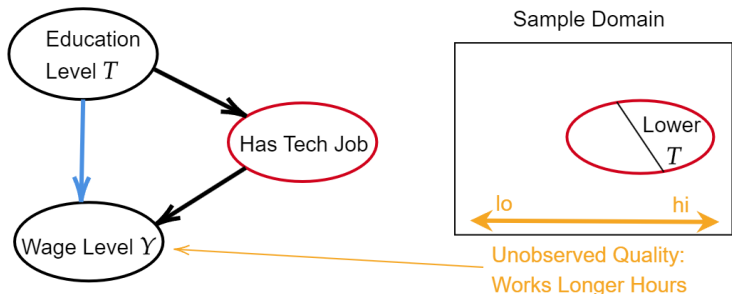
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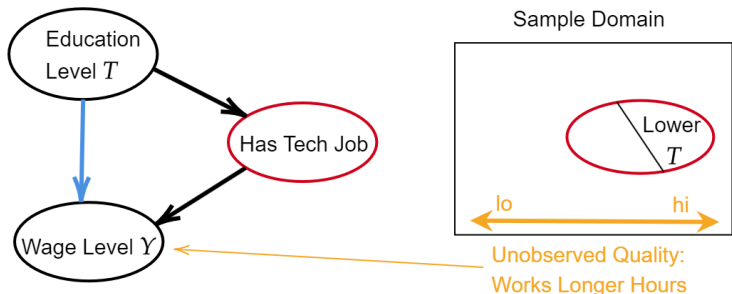
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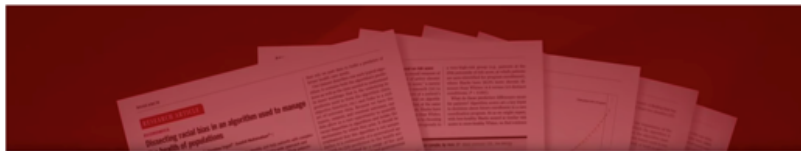
- Subsample from conditioned variable is skewed.
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- Can also happen from choices of unrepresentative proxy variables.

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 news banner with a red overlay. On the left is the 'HEALTH WATCH' logo. In the center, the 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 website 'cbsnews.com/impeachment' and the 'LIVE CBSN AM' logo.

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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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