Data and Society

Resources and Dangers and Opportunities

Kenneth W. Regan

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

CSE199, Fall 2024

Main Problem...

Any Questions?

(Brain scan source, 1987 PSA source)

...And Problems

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

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

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

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

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

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

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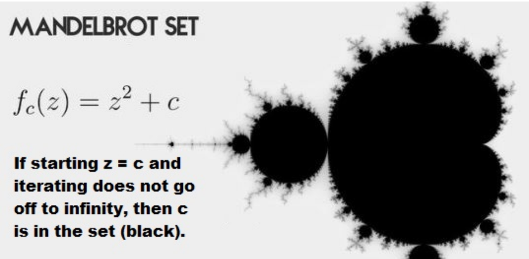

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- Whether the info and inferences are **true** is secondary!

Outline For Remaining Lectures

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

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

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

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

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

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

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

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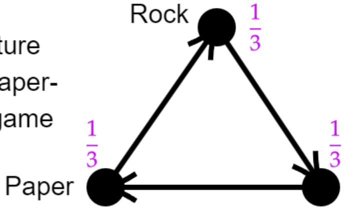
- Only foolproof way: a **completely random** strategy. Here: roll a die and play Rock on 1 or 2, Paper on 3 or 4, and Scissors on 5 or 6.
- But since this is a **fair game**, you can't expect to win either.

Graph picture of Rock-Paper-Scissors game



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

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

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- **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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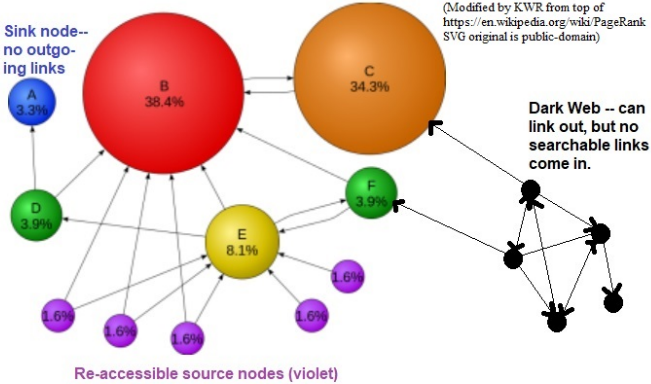

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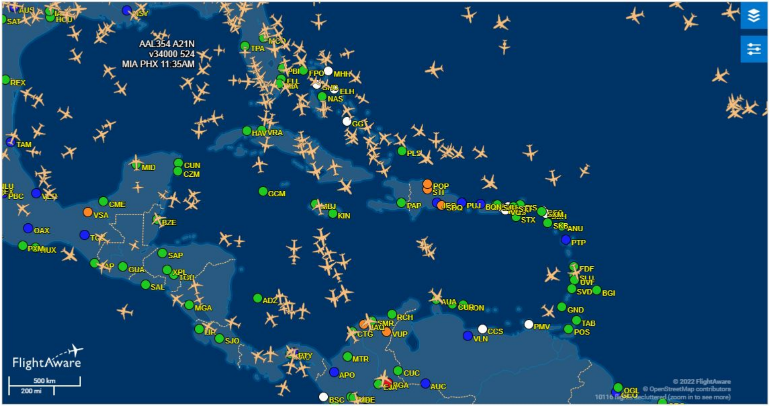
A “Semi-Structred” Example (of Inferencing)

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



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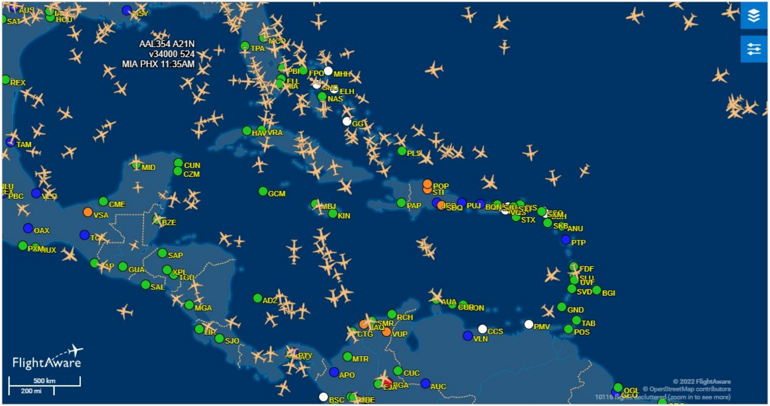

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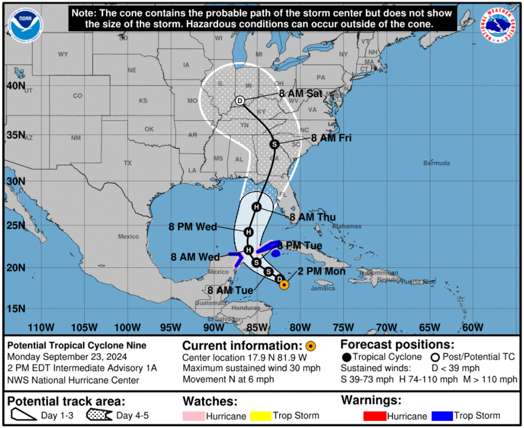
And what about north of the Black Sea?

Hurricane Tracking—Helene By NOAA



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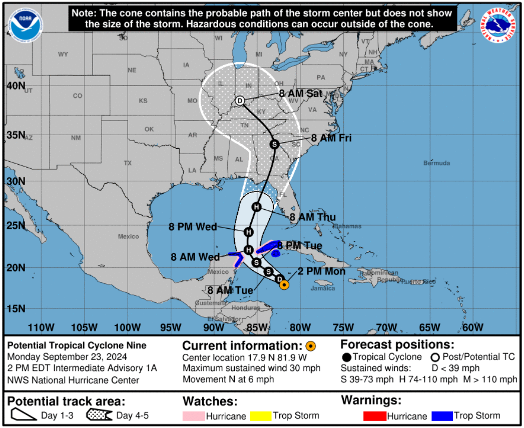

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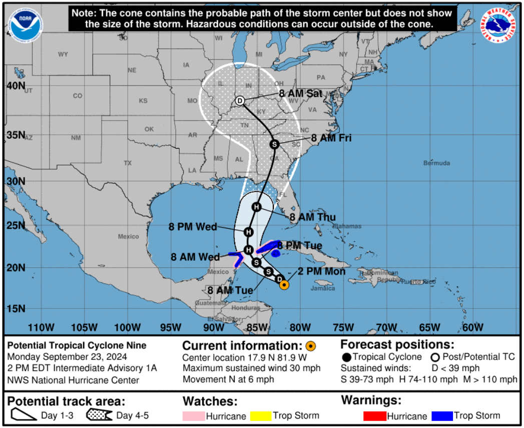

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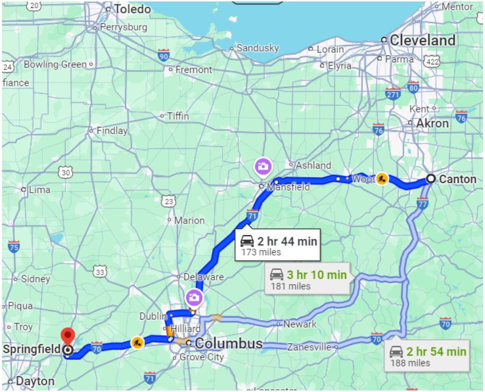

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- (Silly new example of correlation-versus-causation: do the KC Chiefs lose when Taylor Swift isn't at the game? Madden '24)

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[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. **But may do half-and-half with "Part V" because next Monday is fall break.**

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

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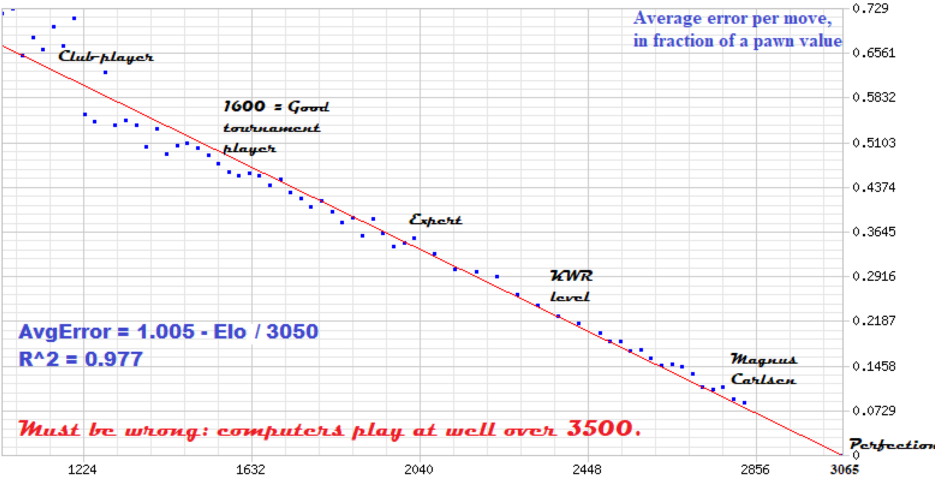
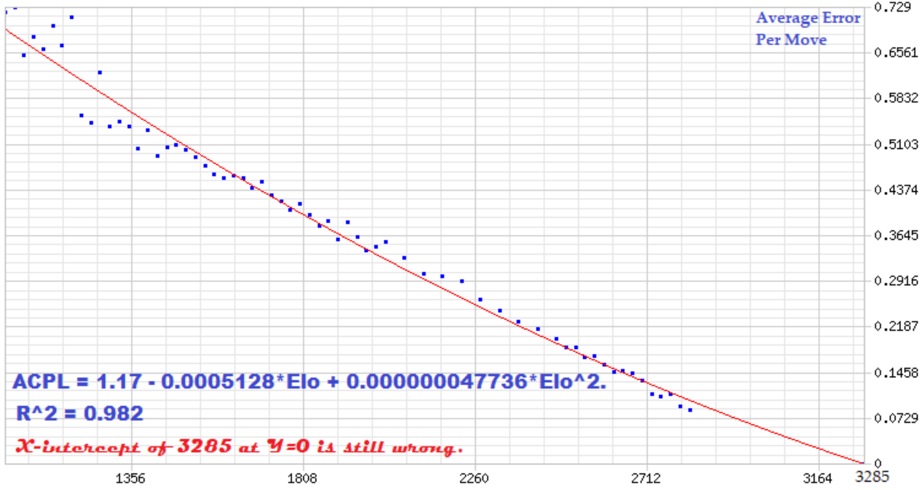
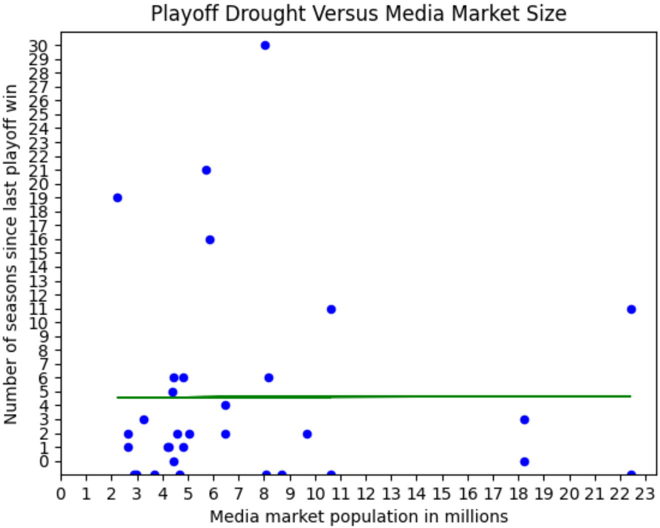
Linear Model: ACPL $= a + b \cdot$Elo Rating



Quadratic Fit—Only Marginally Better



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



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

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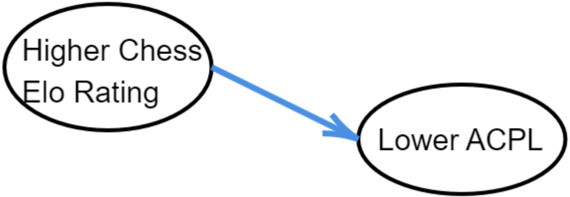
- Causal graphs have nodes—black or red for conditioning—and arrows.
- They can help ascertain
  - which are genuine causes—as opposed to mere correlations or null effects,and
  - which variables in the system can helpfully be **regressed** or **conditioned on**.

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



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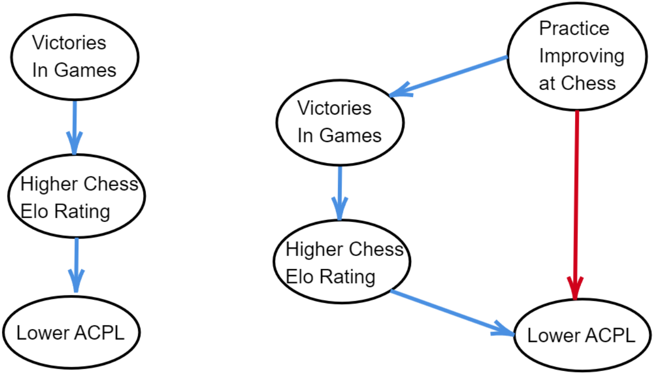
- But if we have a lurking *common cause* D of both our *source* and *intended target*, then it can **confound** the smaller-scale analysis.
- I faced this when the pandemic caused official chess ratings to lag true skill. Case of wrongly accused player.



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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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- 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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(b) feebleness . . dashed

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(source: itunes.apple.com)

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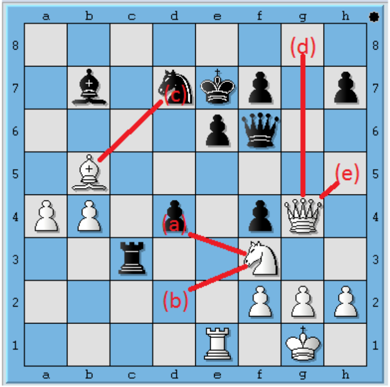

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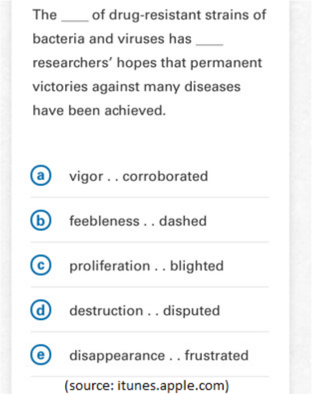

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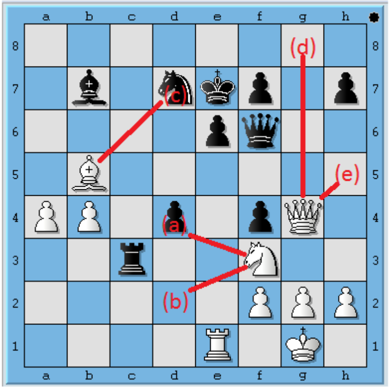

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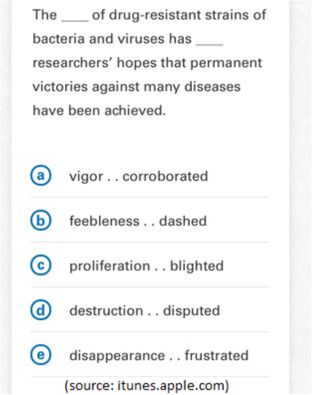
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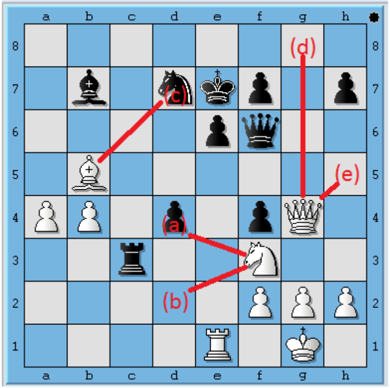

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Validate the model on millions of randomized trials involving "Frankenstein Players" to ensure conformance to the standard bell curve at all rating levels. This is also an example of **Simulation.**

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

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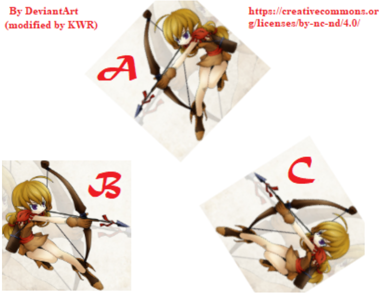
- Early study by mathematicians: Jean-Charles de Borda, Nicolas de Condorcet (1700s), Charles Dodgson (= Lewis Carroll!, 1800s).

Condorcet's Paradox and Arrow's Impossibility



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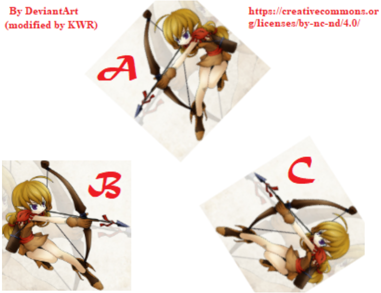

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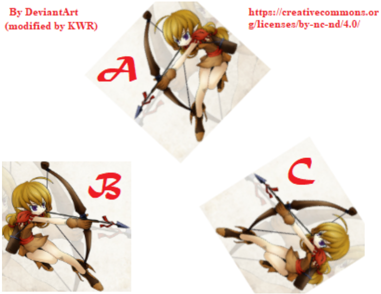

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- Then 2/3 prefer A to B, 2/3 prefer B to C, and 2/3 prefer C to A.
- **Kenneth Arrow, 1950s:** No way to fix except to allow minority rule, dictatorship, or weighting votes unequally via **ratings**.

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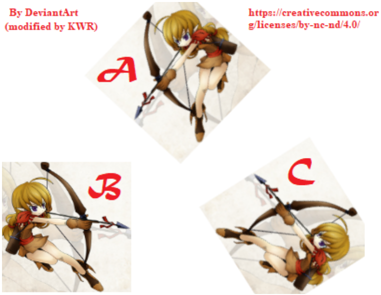

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- Then 2/3 prefer A to B, 2/3 prefer B to C, and 2/3 prefer C to A.
- **Kenneth Arrow, 1950s:** No way to fix except to allow minority rule, dictatorship, or weighting votes unequally via **ratings**.
- "Least Bad"? (used in Maine and Alaska): Eliminate 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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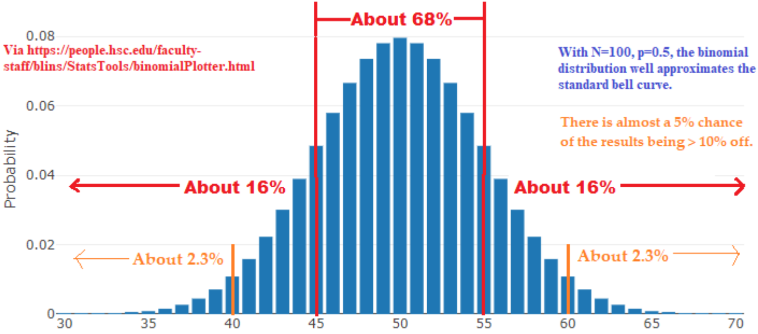
- Almost **one-third** chance poll results will be $< \mathbf{45\%}$ or $> \mathbf{55\%}$.



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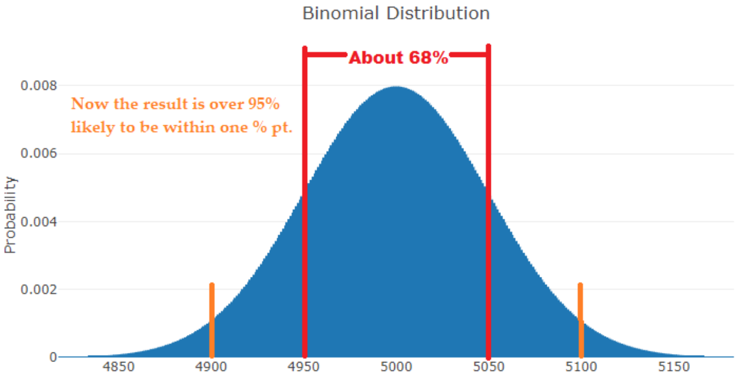

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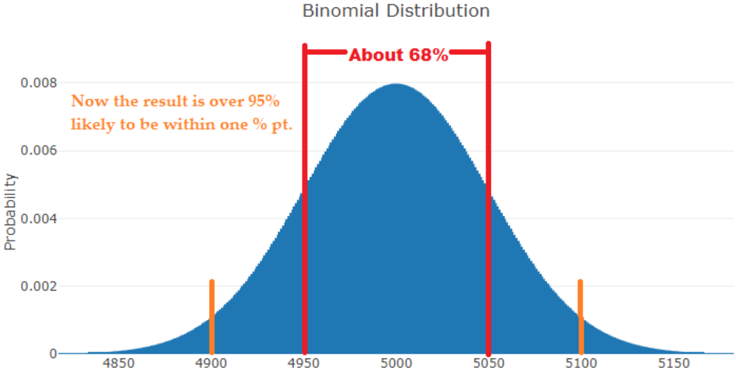

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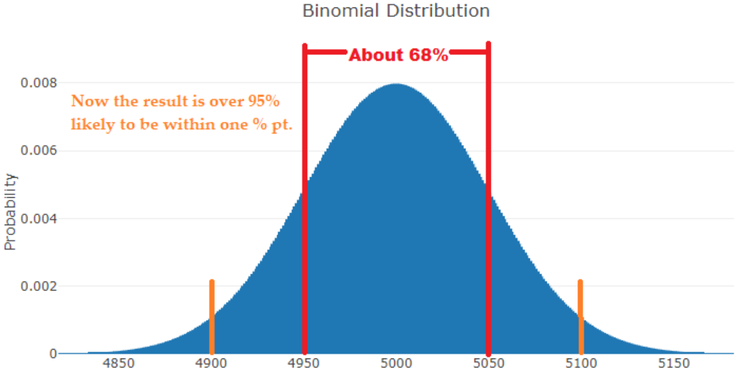

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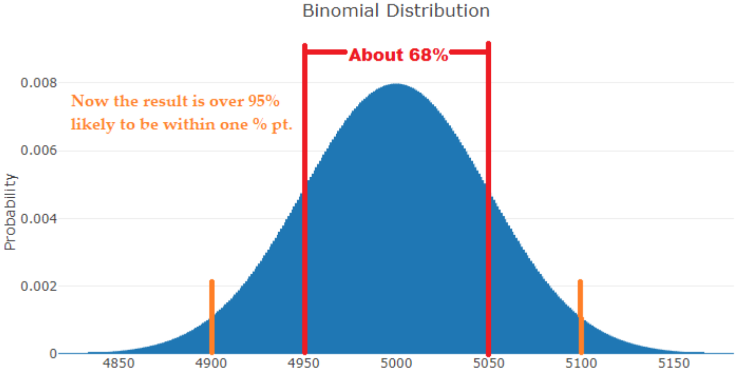

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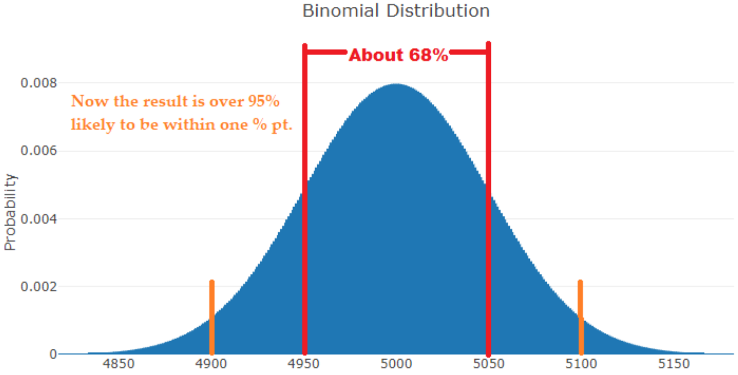

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- So results 47%-to-53% count as "statistically tied" (yuck).

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Thus using $100\times$ 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.)**

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- Last, let's talk briefly about Sentiment Analysis.

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

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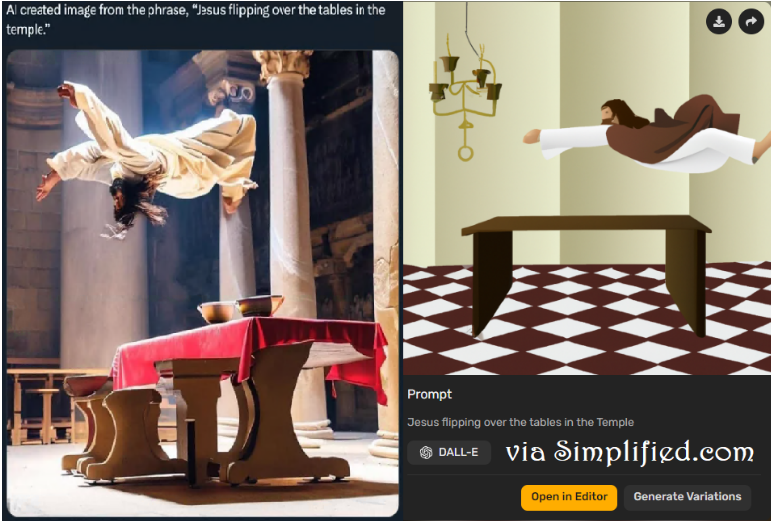
- But subject to **hallucinations** and other foibles—some shown by me here and here and here.

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.]

Toward AGI

Part V: Societal Computing and Fairness

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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.