

model elaboration is in any case not a pleasure
because this road is endless*.

ALL MODELS ARE WRONG BUT SOME ARE USEFUL

Now it would be very remarkable if any model in the real world could be exactly represented by a mathematical model. However, cunningly chosen parsimonious

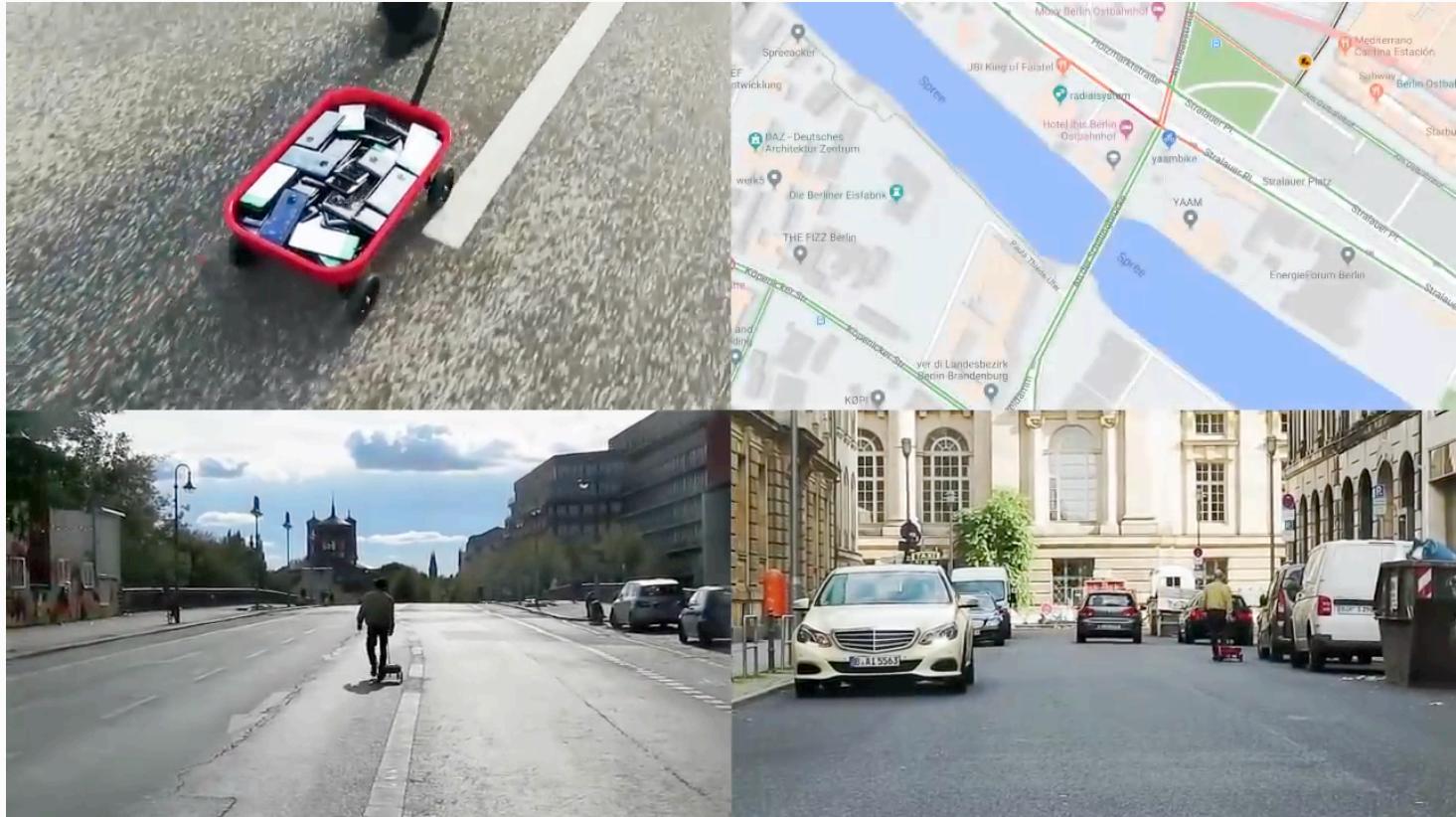
* Suppose for example that in advance of any model of the form of (1) with the usual normal distribution it might be objected that the distribution

*"We check our **e-mails** regularly, make **mobile phone calls**... We may post **blog entries** accessible to anyone, or maintain friendships through **online social networks**. Each of these transactions leaves **digital traces** that can be compiled into comprehensive pictures of both individual and group behavior, with the **potential to transform our understanding of our lives, organizations, and societies.**"*



› Simon Weckert, "Google Maps Hack"

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➤ This shows larger themes

- Available data are often only a *proxy*
- So long as the proxy is never the thing itself, it can fail
- Models of relationships and processes, too, are not the things themselves
- Box: “[For] a model there is no need to ask the question ‘Is the model true?’. If ‘truth’ is to be the ‘whole truth’ the answer must be ‘No’. The only question of interest is ‘Is the model illuminating and useful?’.”

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- **When, how data/models are *wrong***
- **When and how it matters**
- **What we can do**

> Outline

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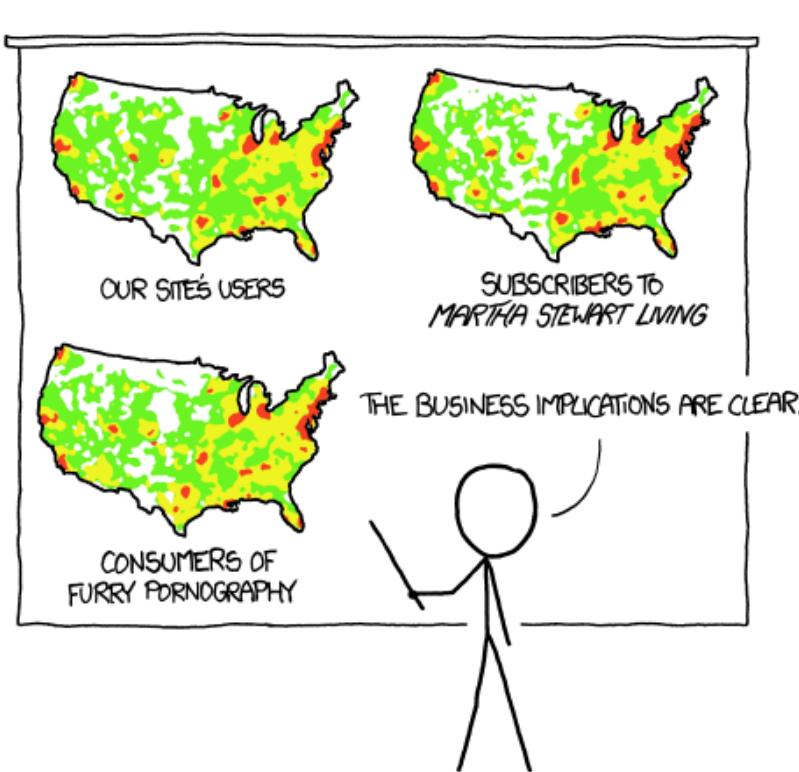
➤ Bias in geotagged tweets

Momin M. Malik, Hemank Lamba, Constantine Nakos, and Jürgen Pfeffer. 2015. Population bias in geotagged tweets. In *Papers from the 2015 ICWSM Workshop on Standards and Practices in Large-Scale Social Media Research* (ICWSM-15 SPSM), pages 18–27. May 26, 2015, Oxford, UK.

https://www.mominmalik.com/malik_chapter1.pdf

► Many maps just show population

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Randall Munroe. 2012. Heatmap. <https://xkcd.com/1138/>

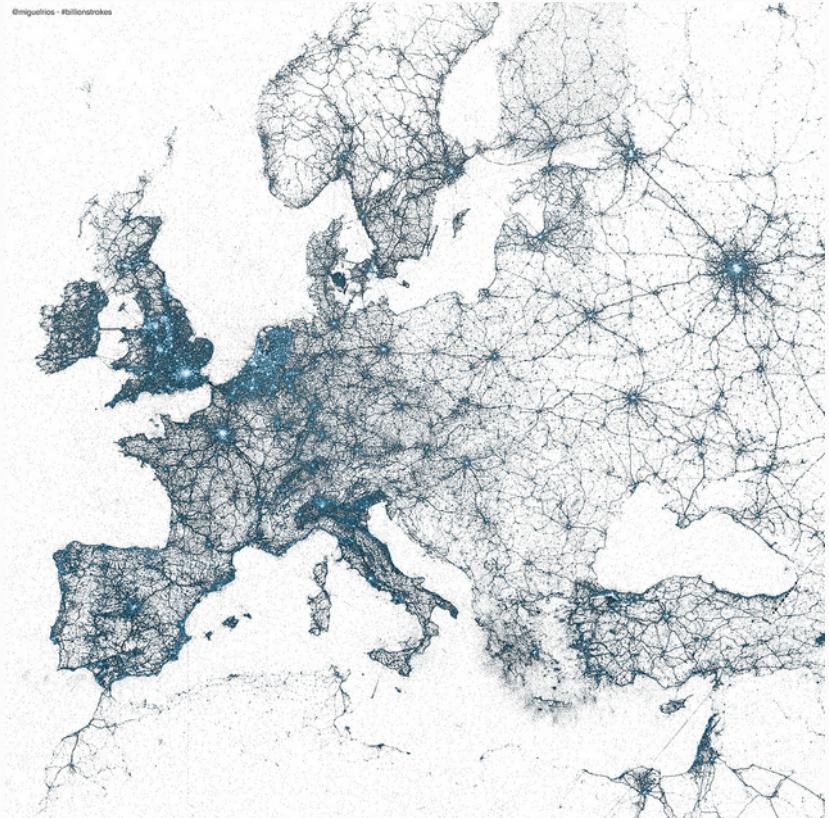
Revisiting “All Models are Wrong”

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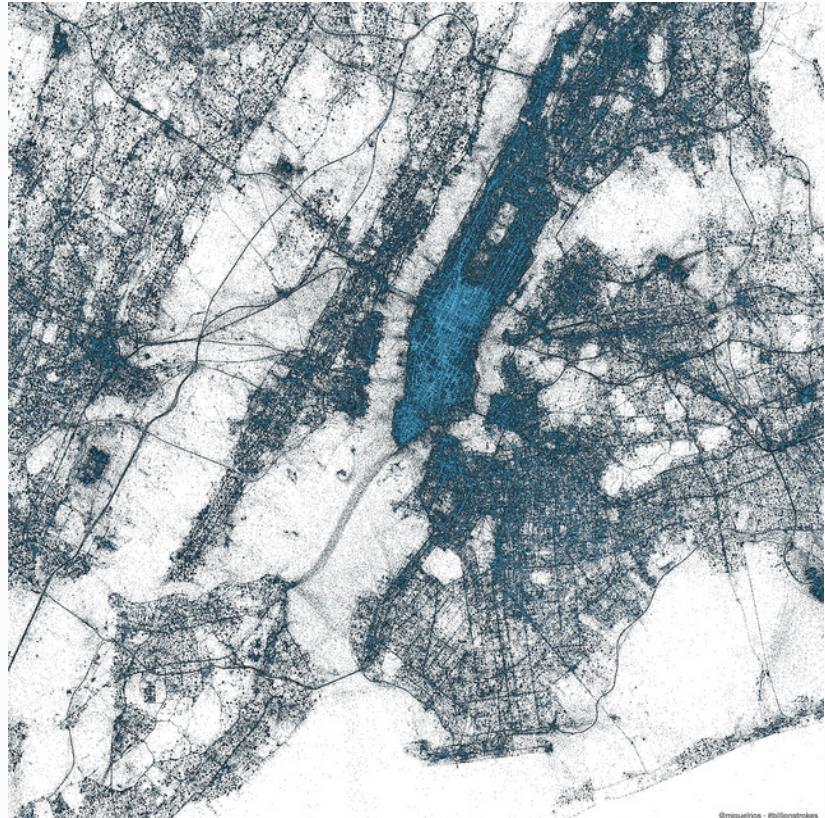
<https://MominMalik.com/nico2020.pdf>

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➤ But maybe we can use this?



Revisiting "All Models are Wrong"



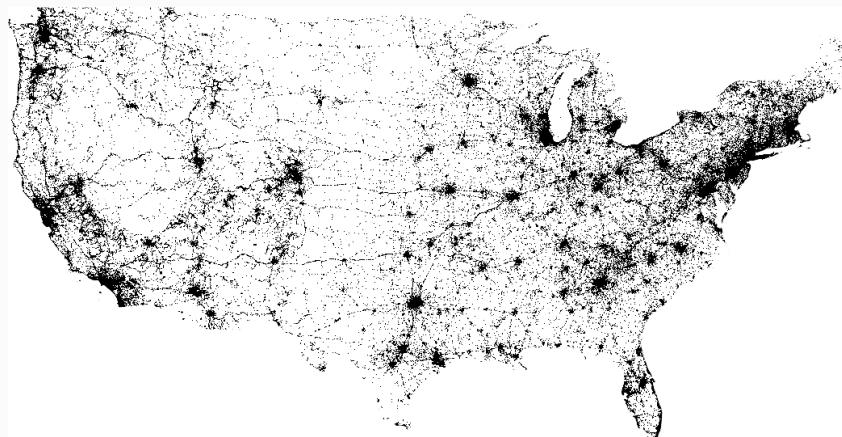
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<https://MominMalik.com/nico2020.pdf>

► Do tweets measure population?

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Geotagged tweets



Adapted from Eric Fischer, 2009, Contiguous United States geotag map. <https://flic.kr/p/a7WMWS>.

Population



Population density in 2010 US Census. Each square represents 1,000 people. Adapted from Geography Division, U.S. Department of Commerce / Economics and Statistics Administration / U.S. Census Bureau, Nighttime Population Distribution Wall Map.

› Modeling population vs. users

› Users proportional to population:

$$U_i = \alpha P_i + \varepsilon_i P_i$$

› Take a log transformation:

$$\log U_i = \log \alpha + \log P_i + \varepsilon'_i$$

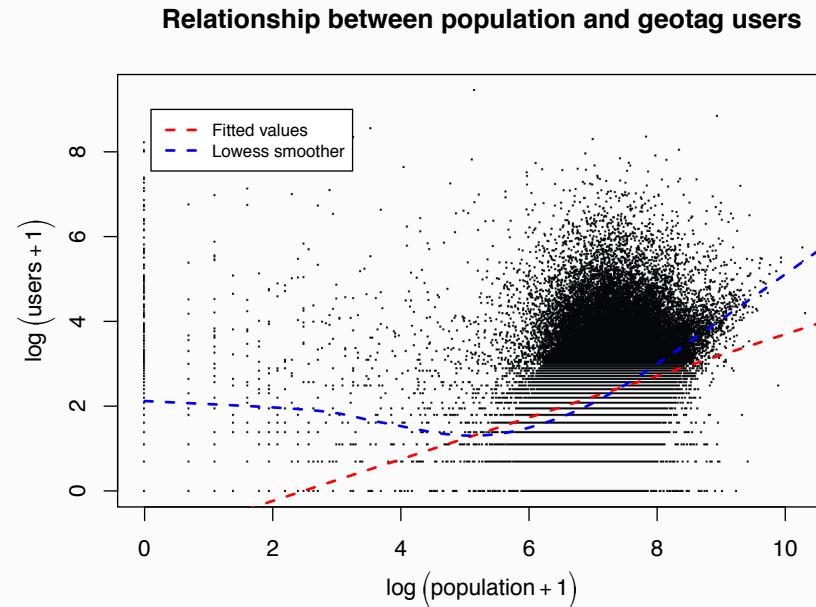
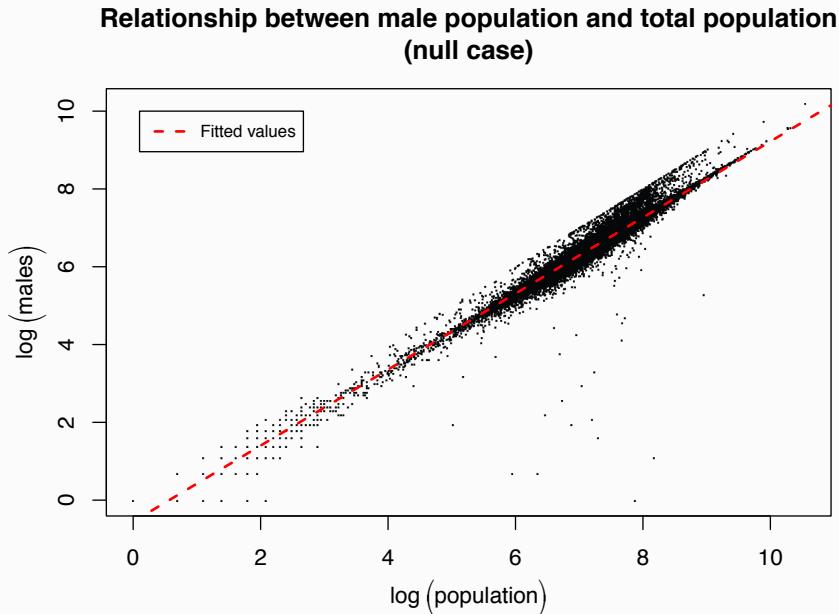
› Compare to a linear model:

$$\log U_i = \beta_0 + \beta_1 \log P_i + \varepsilon'_i$$

Result: Not proportional

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(Each dot is a Census *block group*)



› Identifying specifics

› Spatial multivariate modeling of biases

Geotagged tweet users associated with:

-  Rural, poor, elderly, non-coastal
-  Asian, Hispanic, black

› ...but these are only the demographics we can access. E.g., harassment of women on Twitter likely discourages geotag use

> Why it matters: Some uses are bad

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Hurricane Sandy, tweets vs. damage/deaths



Taylor Shelton, Ate Poorthuis, Mark Graham, and Matthew Zook. 2014. Mapping the data shadows of Hurricane Sandy. *Geoforum* 52, 167-179.

› Responses to demographic bias

- › Model the biases!
- › Calibration and weighting
- › Use data for appropriate questions
 - “Postcards, not ticket stubs” (Tasse et al., 2017)
- › Find clever study designs or data comparisons, establish *panels*, etc.

Dan Tasse, Zichen Liu, Alex Sciuto, and Jason I. Hong. 2017. State of the geotags: Motivations and recent changes. *Proceedings of the Eleventh International AAAI Conference on Web and Social Media (ICWSM 2017)*, pp. 250-259.

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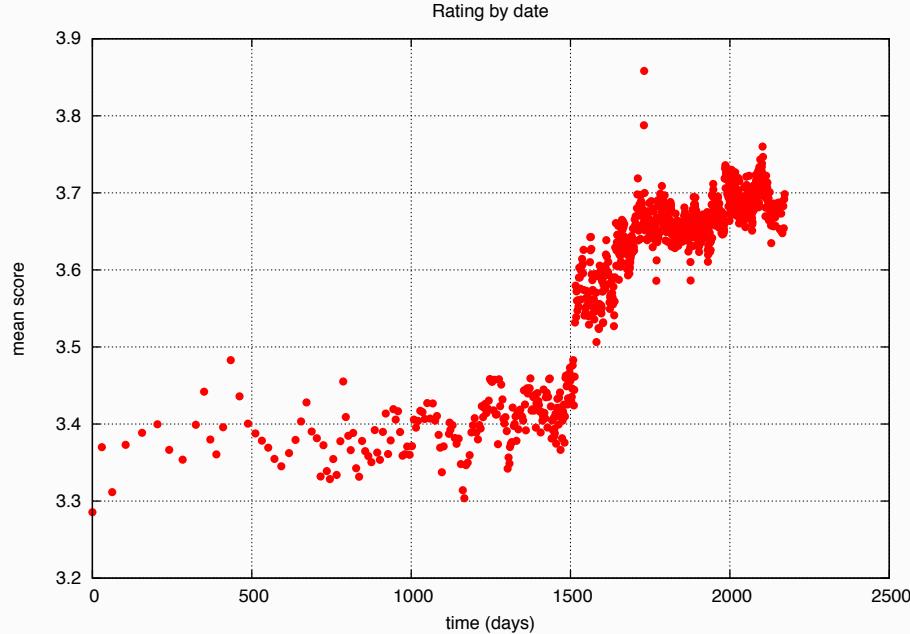
› References

› Platform effects in social media

Momin M. Malik and Jürgen Pfeffer. 2016. Identifying platform effects in social media data. In *Proceedings of the Tenth International AAAI Conference on Web and Social Media (ICWSM-16)*, pages 241-249. May 18-20, 2016, Cologne, Germany. https://www.mominmalik.com/malik_chapter2.pdf

➤ Design can cause/change behavior

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Average Netflix movie ratings over time. Each point averages 100,000 rating instances.

Yehuda Koren. (2009). Collaborative filtering with temporal dynamics.

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› Social media platforms are businesses



- › Not neutral utilities or research environments
- › Platform engineers try to shape user behavior towards desirable ends

► Sites try to grow their users' networks

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The image is a composite of two screenshots from social networking platforms. On the left, a LinkedIn interface is shown with a prominent 'People You May Know' section highlighted by a pink rectangular box. Below this, several user profiles are displayed. On the right, a Twitter interface is shown with a 'Who to follow' section. This section includes a search bar, a 'Follow' button, and three individual profiles with their names, bios, and 'Follow' buttons.

LinkedIn Screenshot:

- Section: People You May Know
- Profile 1: Joseph Randall (Software engineer at Evergreen, Greater New York City)
- Profile 2: Dan Cleveland (Quant analyst at Partners San Francisco Bay Area)
- Profile 3: Irene Baoter (Investment analyst at Panhandle Management Greater Boston Area)
- Profile 4: Heather Considine (Designer San Francisco Bay Area)
- Profile 5: Andrew Kornbluth (Law Professor at Stanford Law School San Francisco Bay Area)

Twitter Screenshot:

- Keton Kakkar @KetonKakkar**
Afghan American / Child of Immigrants | @PhillipsAcademy / @Swarthmore | formerly @BKCHarvard | Editor @swatgazette
Followed by Frank Pasquale and monicabulger.
- William Bumpas @wwbumpas**
Now in DC, prev @oioxford. Likes data, ethnography, tech, policy, media, critical theory, China, rural US, subversive memes. Loves any combo thereof.
he/they
Followed by Prof Gina Neff and Oxford Internet Institute.
- Rich Boroff @boroff**
Running (a minor part of) the computing infrastructure for a major university in the Boston, MA area, and trying to keep the bad guys at bay.
Followed by Berkman Klein Center for Internet & Society.

> Recommending “friend-of-a-friend”

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Screenshot of a Facebook "People you may know" section. The interface includes a search bar, user profile "Dann", and a sidebar for searching friends by name, location, and high school.

People you may know

- Sara Anderson Severance**
Denver, Colorado
Rachelle Albright and 10 other mutual friends
- Anne Walker (Anne Anderson)**
Sarah Frederick and 6 other mutual friends
- Paul Dube**
Ryan Dube is a mutual friend.
- Mark Rieder**
Lord Beaverbrook High School
Justin Pot is a mutual friend.

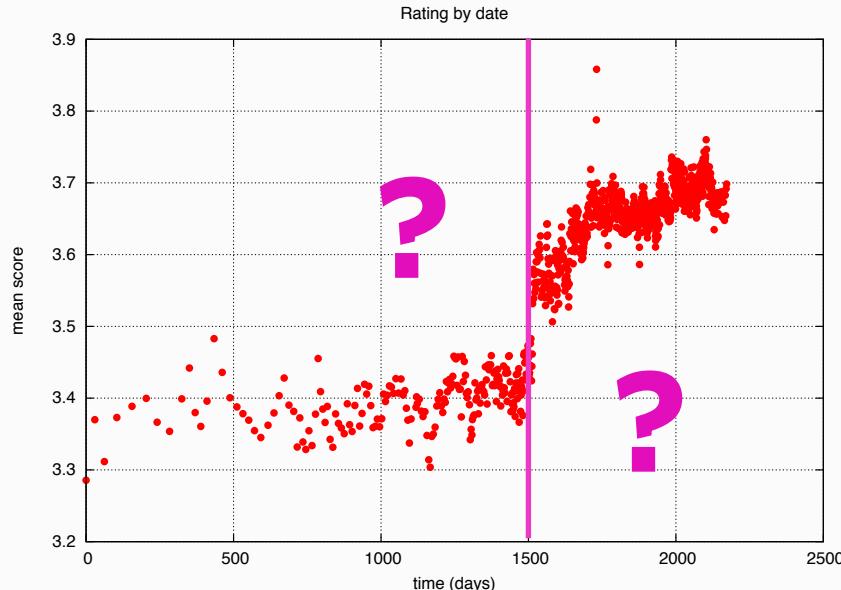
Dann Albright, makeuseof.com

Add Friend Remove Add Friend Remove Add Friend Remove Add Friend Remove

Search for Friends
Find friends from all
Name
Search for someone
Home Town
 Prescott, Wisconsin
Enter another city
Current location
 Denver, Colorado
Enter another city
High School
 Prescott High School
Enter another high school

➤ Behavior, or platform effects?

- When we measure behavior, what are we really measuring? People's behavior, or platform effects?
- How, as outsiders, can we find out?



Average Netflix movie ratings over time. Each point averages 100,000 rating instances.

› *Data artifacts can reveal inner workings*

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The Matrix (1999) "déjà vu" scene

› Data artifacts as natural experiments

- › Regression Discontinuity (RD) Design (technically, Interrupted Time Series, ITS) estimates causality

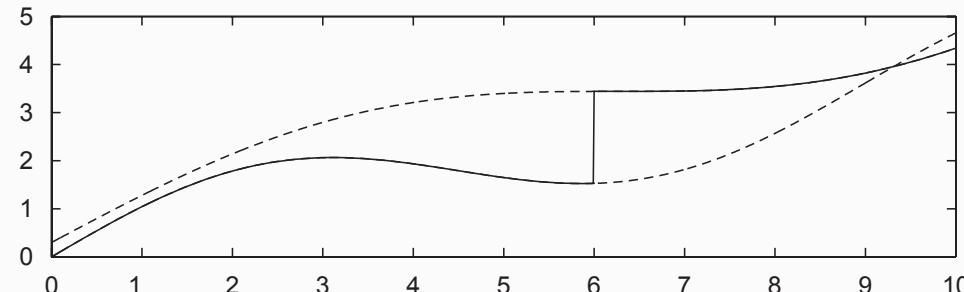


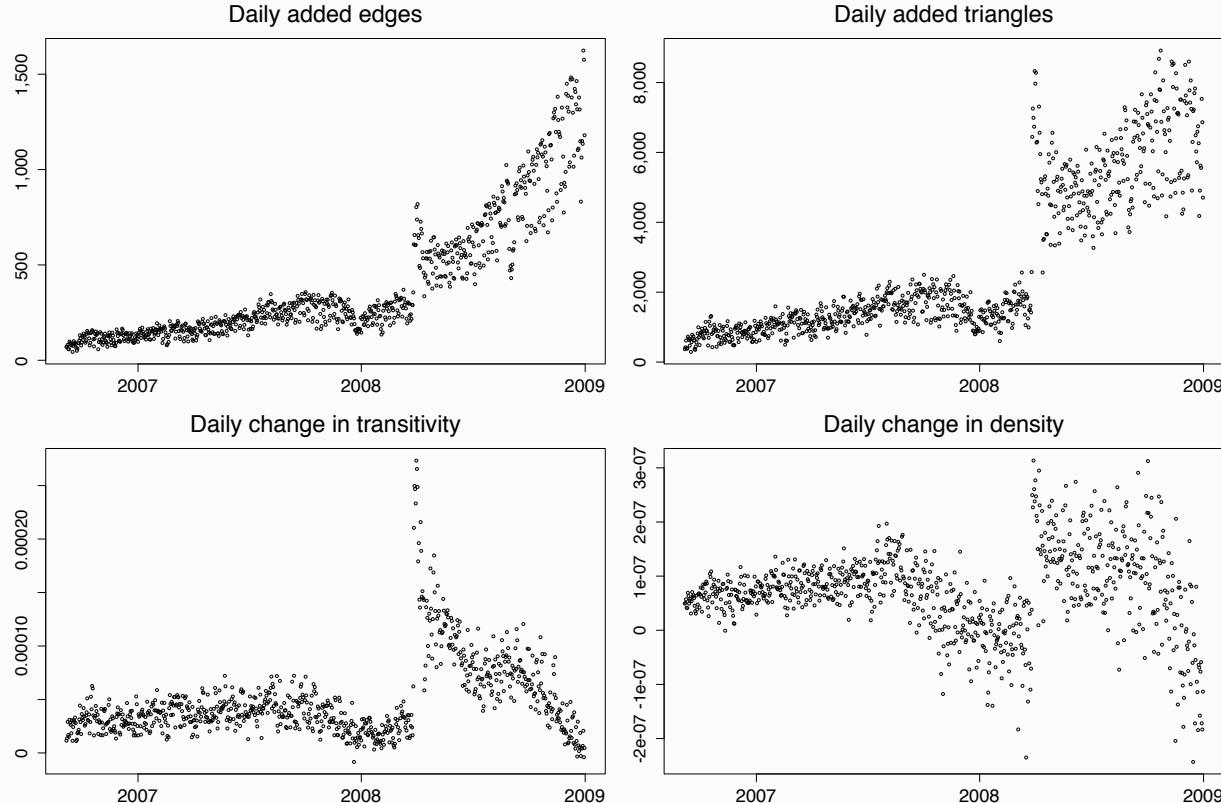
Fig. 2 from Imbens and Lemieux (2008): Potential and observed outcome regression functions.

- › The difference between “before” and “after” estimates the *local average treatment effect*

Guido W. Imbens and Thomas Lemieux. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2): 615–635.

Case: Facebook's "People You May Know"

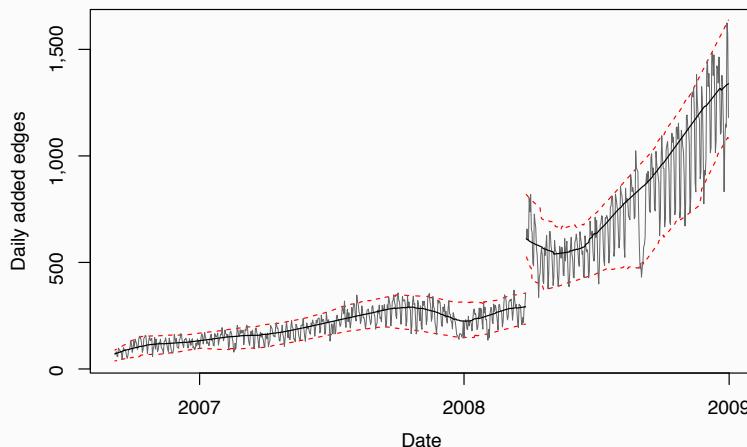
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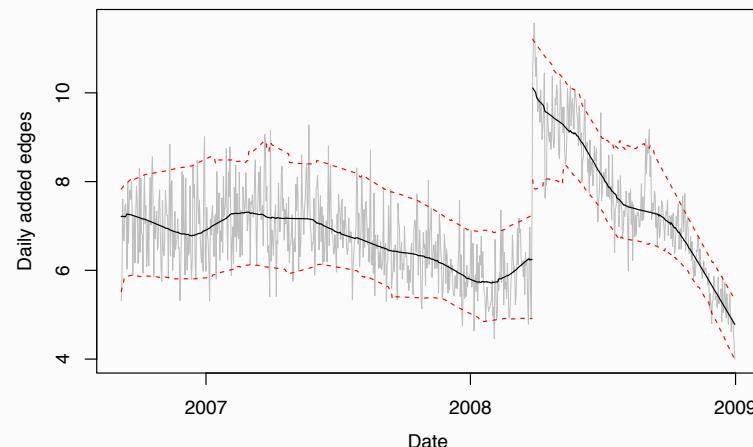
› PYMK changed the Facebook network!

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› Facebook links: +300 new edges per day (x2)



› Triangles: +3.8 triangles per edge (x1.62)



› Responses to platform effects

- › Investigate: how do Facebook “friendship” fail to generalize? What about the Facebook social network?
- › Platform effects are phenomena to study in themselves!
- › Data artifacts as natural experiments

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► Data well-studied; *models*, not yet



Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries

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Social data in digital form—including user-generated content, expressed or implicit relations between people, and behavioral traces—are at the core of popular applications and platforms, driving the research agenda of many researchers. The promises of social data are many, including understanding “what the world thinks” about a social issue, brand, celebrity, or other entity, as well as enabling better decision-making in a variety of fields including public policy, healthcare, and economics. Many academics and practitioners have warned against the naïve usage of social data. There are biases and inaccuracies occurring at the source of the data, but also introduced during processing. There are methodological limitations and pitfalls, as well as ethical boundaries and unexpected consequences that are often overlooked. This paper recognizes the rigor with which these issues are addressed by different researchers varies across a wide range. We identify a variety of menaces in the practices around social data use, and organize them in a framework that helps to identify them.

**For your own sanity, you have to remember that not all problems can be solved. Not all problems can be solved, but all problems can be illuminated.* – Ursula Franklin³

Keywords: social media, user data, biases, evaluation, ethics

1. INTRODUCTION

We use *social data* as an umbrella concept for all kind of digital traces produced by or about users, with an emphasis on content explicitly written with the intent of communicating or interacting with others. Social data typically comes from *social software*, which provides an intermediary or a focus for a social relationship between users. It includes a variety of platforms—for social media and communication (e.g., Facebook), question and answering (e.g., Quora), or collaboration (e.g., Wikipedia)—and purposes from finding information (White, 2013) to keeping in touch with friends (Lampe et al., 2008). Social software enables the social web, a class of websites “in which user participation is the primary driver of value” (Gruber, 2008).

The social web enables access to social traces at a scale and level of detail, both in breadth and depth, impractical with conventional data collection techniques, like surveys or user

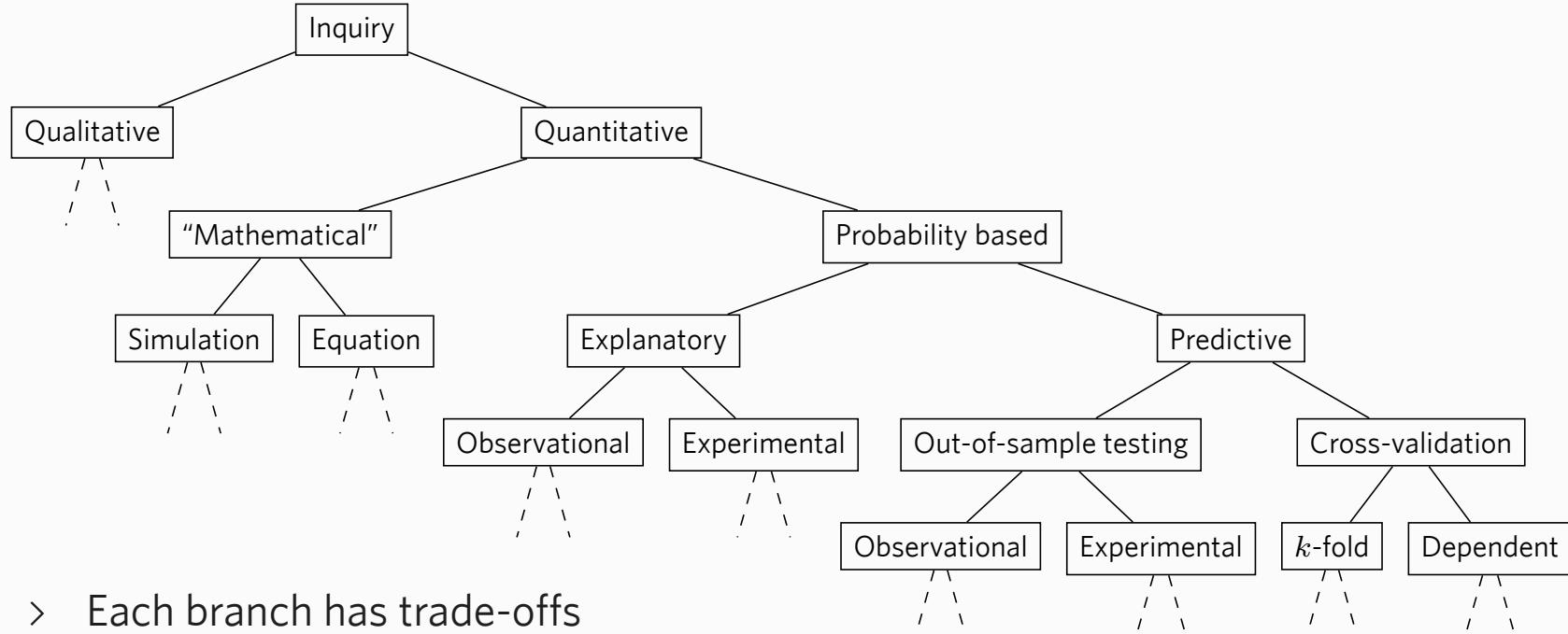
¹Received: 26 February 2019
 Accepted: 27 May 2019
 Published: 11 July 2019
 Citation: Oltanu A, Castillo C, Diaz F and Kiciman E (2019) Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries. *Front. Big Data* 2:10. doi: 10.3389/fdata.2019.00010

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➤ Tradeoffs in types of modeling

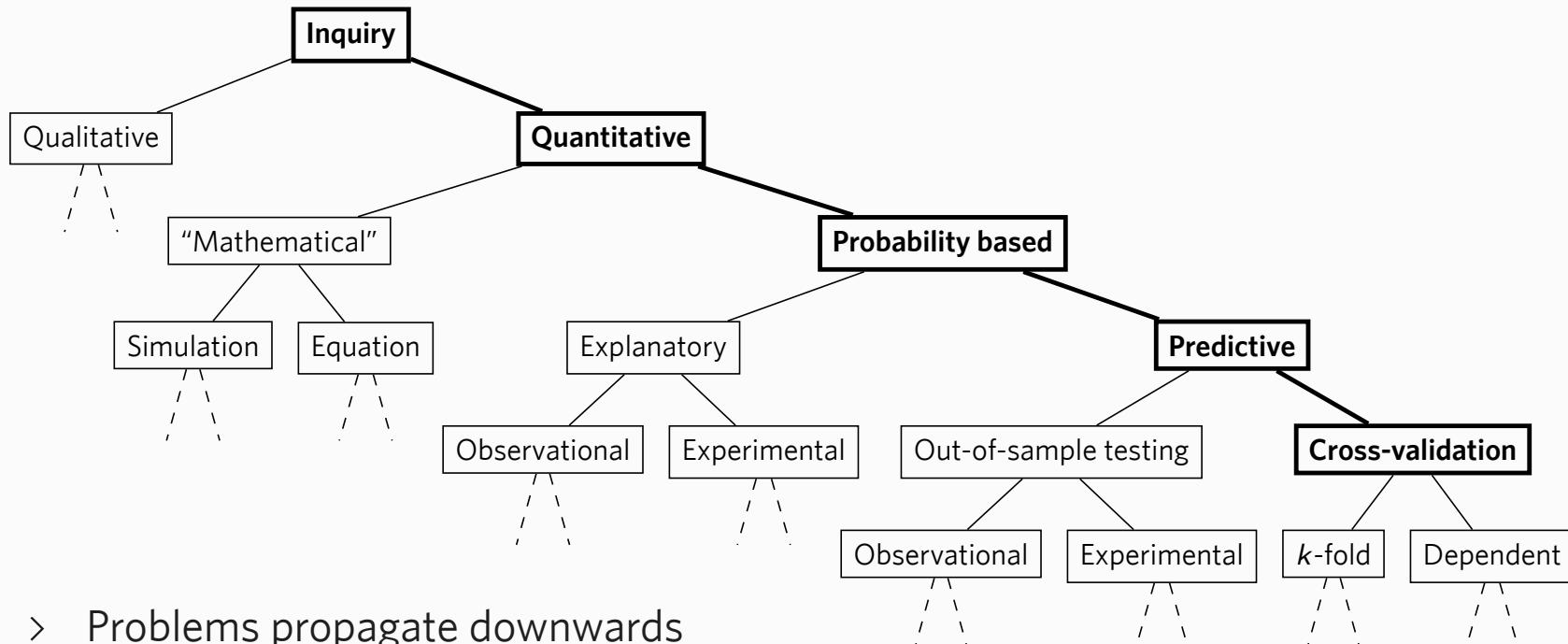
Momin M. Malik. 2020. A hierarchy of limitations in machine learning. In submission.
https://www.mominmalik.com/hierarchy_draft.pdf

> Approaches to research



- > Each branch has trade-offs
- > No one method is better any other
- > Mixed methods can combine

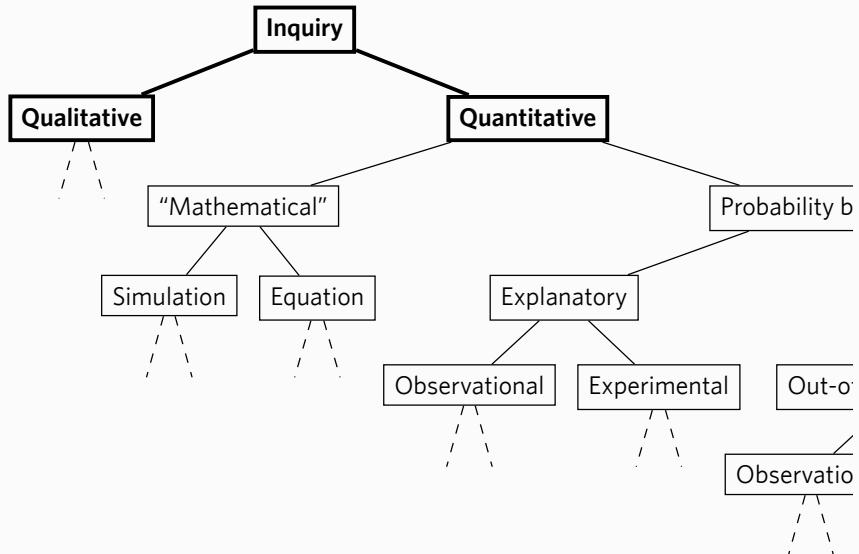
> Typical machine learning



- > Problems propagate downwards
- > E.g., quantification affects everything below

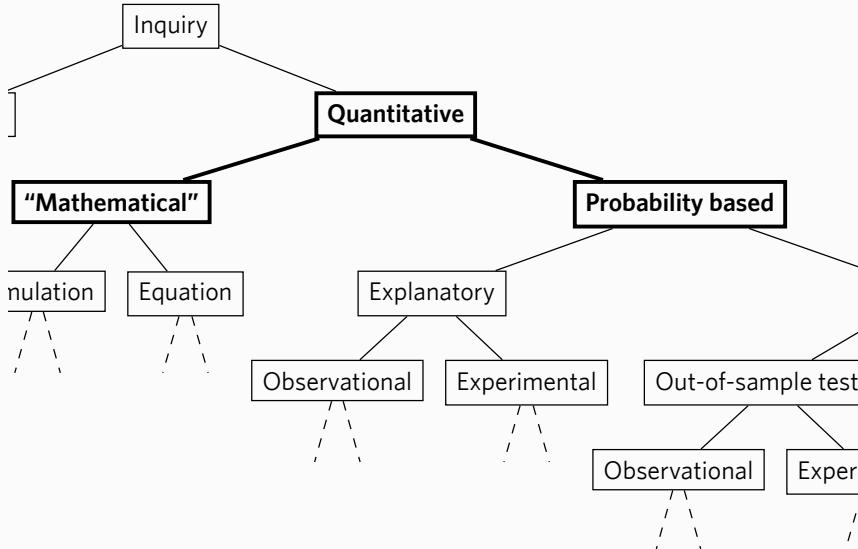
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› Quantification locks in meaning



- › Qualitative research can get directly at how things are multifaceted, heterogeneous, intersubjective
- › Quantification/measurements lock in one meaning; and frequently are *proxies*, which are imperfect

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- › Statistics and machine learning are the only option to both directly use data and account for variability
- › They do so via central tendency
- › This requires multiple observations, and independence assumptions

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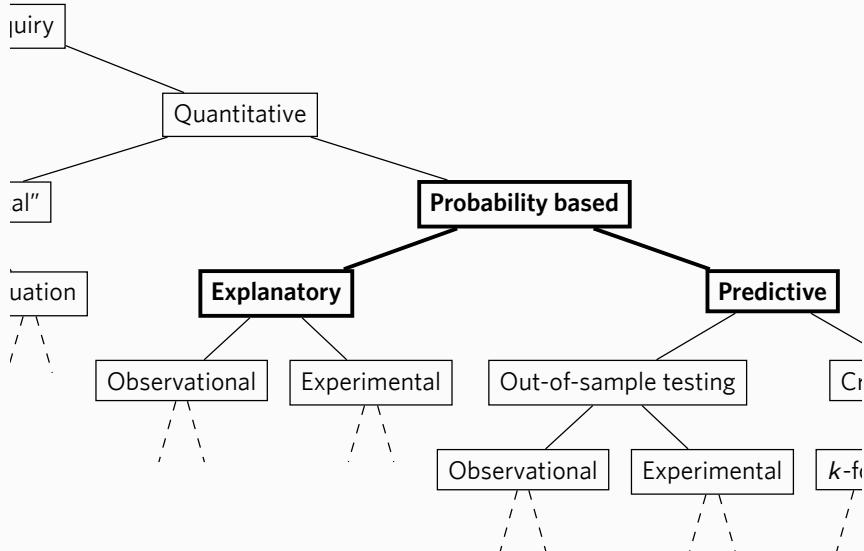
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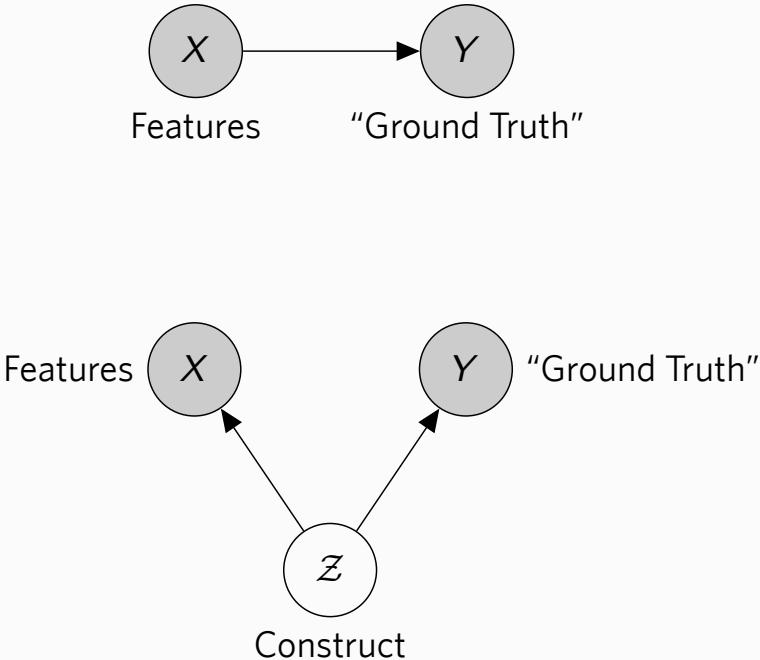
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› ML is “prediction” only



- › “Predictions” are defined as what minimizes loss
- › I.e., *correlations*
- › Non-causal correlations can sometimes predict well, but they frequently don’t explain, and can fail unexpectedly

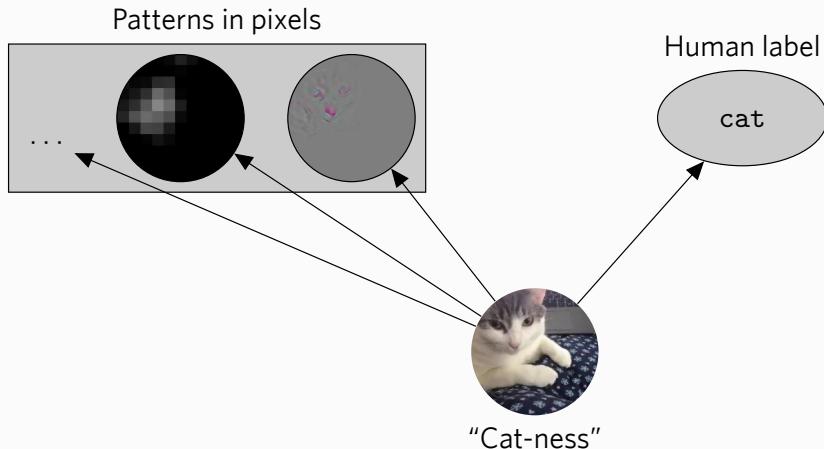
› Prediction misses constructs



- › Constructs: primitives of social science
 - What we care about
 - Often unobservable (and hypothetical/subjective, e.g. friendship)
 - Proxies always give errors (for binary constructs: false negatives and false positives)
 - E.g., Google maps usage is not traffic

► Constructs: Subjective, multifaceted

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› Responses to problems of proxy

- › Identify/define the underlying construct
- › How does the correlation work? Where does it fail?
- › Treat “ground truth” labels as *measurements*; investigate validity
- › Use machine learning for *scaling subjective human judgments*, rather than thinking it uncovers underlying “truth”



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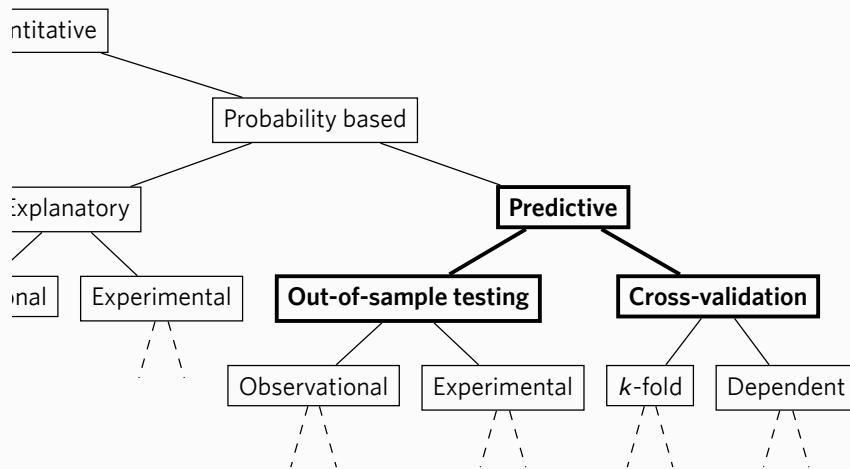
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► Performance claims are from cross-validation

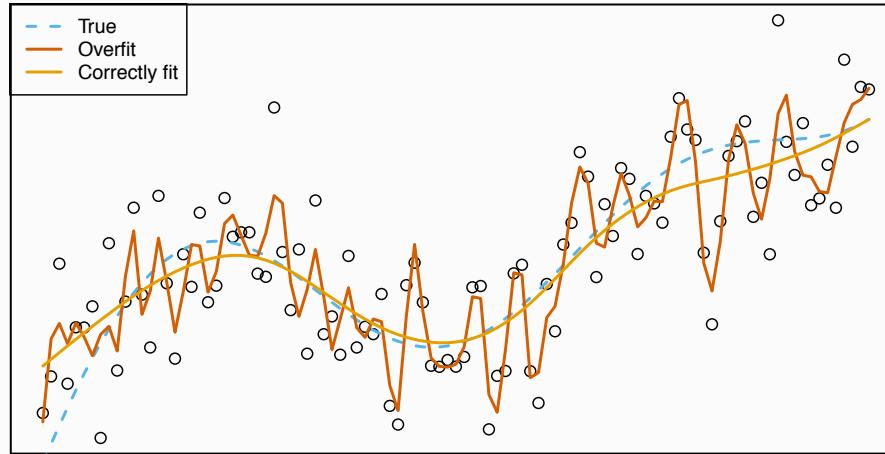


- Rescher (1998) notes every prediction involves a metaprediction: do we think the prediction works?
- Cross-validation is metaprediction for ML
- But, how well does cross-validation work?

Nicholas Rescher. 1998. *Predicting the future: An introduction to the theory of forecasting*. State University of New York Press.

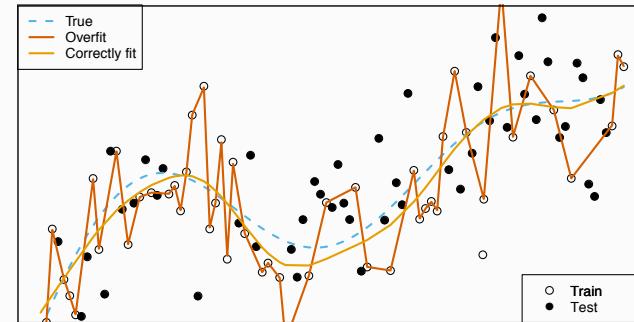
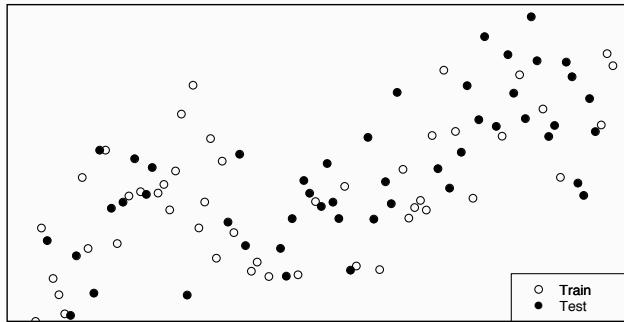
Revisiting “All Models are Wrong”

› Purpose of cross-validation



- › If we are no longer guided by theory, and use automatic methods, we risk overfitting: fitting to the noise, not the data

› Intuition for cross-validation



- › Idea: if we split data into two parts, the signal should be the same but the noise would be different
- › *Cross validation*: Fitting the model on one part of the data, and “testing” on the other

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➤ Classic argument for CV

$$\begin{aligned}
 \text{Err}(\hat{\mu}) &= \frac{1}{n} \mathbb{E}_f \|Y^* - \hat{Y}\|_2^2 \\
 &= \frac{1}{n} \left[\mathbb{E}_f \|Y^*\|_2^2 + \mathbb{E}_f \|\hat{Y}\|_2^2 - 2\mathbb{E}_f (Y^{*T} \hat{Y}) \right] \\
 &= \frac{1}{n} \left[\mathbb{E}_f \|Y^*\|_2^2 + \mathbb{E}_f \|\hat{Y}\|_2^2 - 2 \text{tr } \mathbb{E}_f (Y^* \hat{Y}^T) \right] \\
 &\quad + \frac{1}{n} \left[\mu^T \mu + \mathbb{E}_f (\hat{Y})^T \mathbb{E}_f (\hat{Y}) + 2 \text{tr } \mu \mathbb{E}_f (\hat{Y})^T \right] \\
 &\quad + \frac{1}{n} \left[-\mu^T \mu - \mathbb{E}_f (\hat{Y}) \mathbb{E}_f (\hat{Y})^T - 2\mu^T \mathbb{E}_f (\hat{Y}) \right] \\
 &= \frac{1}{n} \left[\text{tr } \Sigma + \|\mu - \mathbb{E}(\hat{Y})\|_2^2 + \text{tr } \text{Var}_f(\hat{Y}) - 2 \text{tr } \text{Cov}_f(Y^*, \hat{Y}) \right] \\
 &= \text{irreducible error} + \text{bias}^2 + \text{variance} - \text{optimism}
 \end{aligned}$$

› Apply this to non-iid data

- › Imagine we have, for $\Sigma_{ii} = \sigma^2$ and $\Sigma_{ij} = \rho\sigma^2$, $i \neq j$

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} \sim \mathcal{N} \left(\begin{bmatrix} \mathbf{X} \\ \mathbf{X} \end{bmatrix} \beta, \begin{bmatrix} \Sigma & \rho\sigma^2 \mathbf{1} \mathbf{1}^T \\ \rho\sigma^2 \mathbf{1} \mathbf{1}^T & \Sigma \end{bmatrix} \right)$$

- › Then, optimism in the training set is:

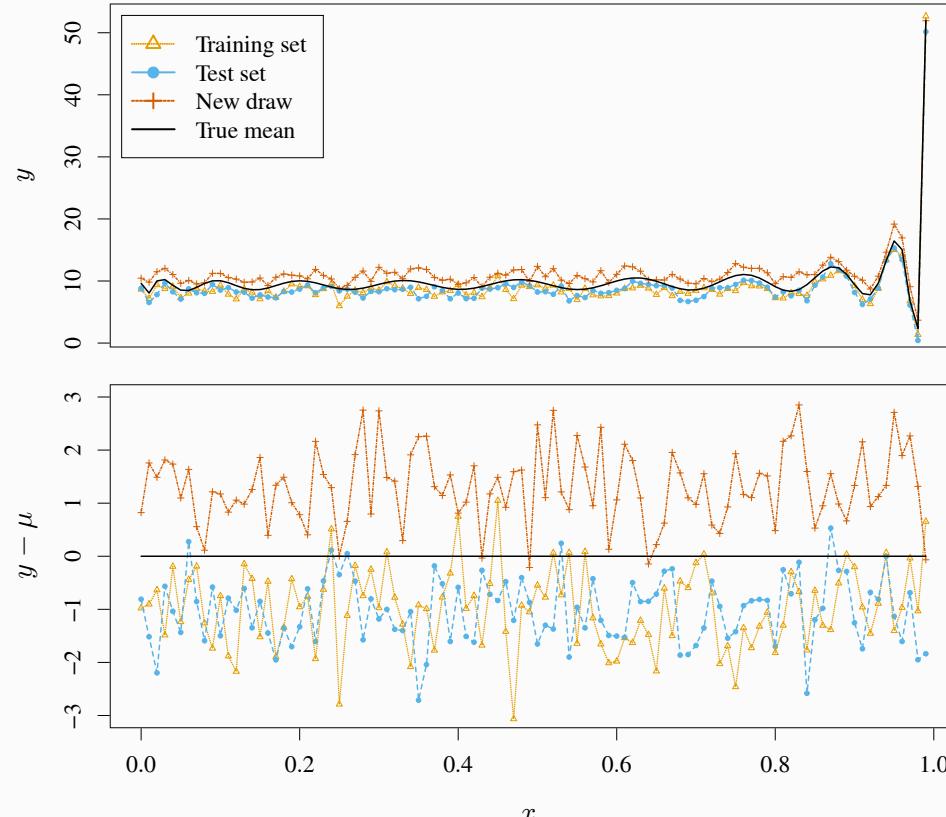
$$\frac{2}{n} \operatorname{tr} \operatorname{Cov}_f(Y_1, \hat{Y}_1) = \frac{2}{n} \operatorname{tr} \operatorname{Cov}_f(Y_1, \mathbf{H}Y_1) = \frac{2}{n} \operatorname{tr} \mathbf{H} \operatorname{Var}_f(Y_1) = \frac{2}{n} \operatorname{tr} \mathbf{H} \Sigma$$

- › But test set also has nonzero optimism!

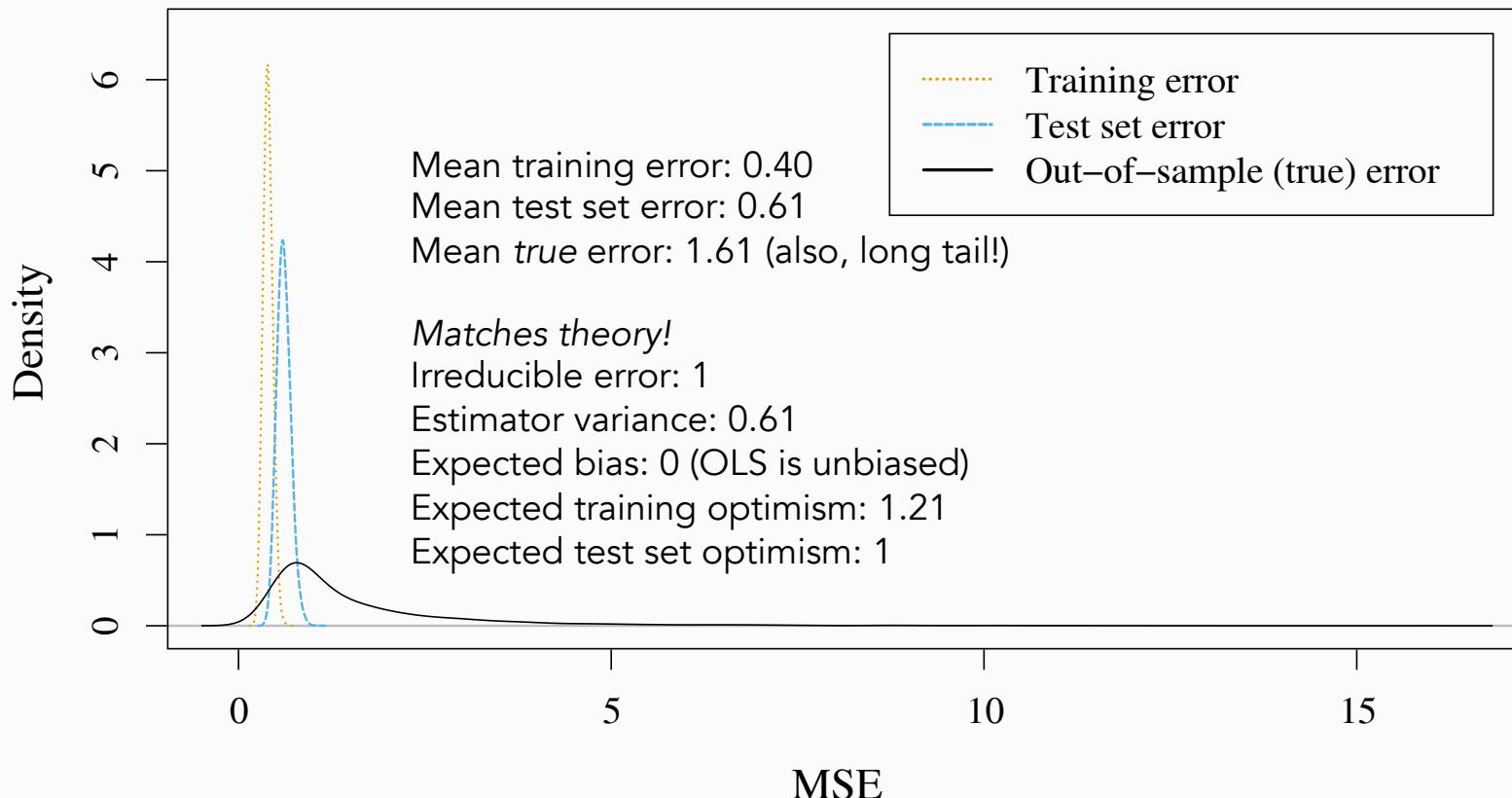
$$\frac{2}{n} \operatorname{tr} \operatorname{Cov}_f(Y_2, \hat{Y}_1) = \frac{2}{n} \operatorname{tr} \operatorname{Cov}_f(Y_2, \mathbf{H}Y_1) = \frac{2\rho\sigma^2}{n} \operatorname{tr} \mathbf{H} \mathbf{1} \mathbf{1}^T = 2\rho\sigma^2$$

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» Simulating the toy example



› Out-of-sample MSE: *much worse!*



➤ Many real-world examples

- There are indeed cases where cross-validation assessments of machine learning performance fail!
- Time series: do cross-validation in blocks
 - Otherwise, “time traveling,” gives great performance
- Activity recognition: “leave one subject out” cross validation performs far worse (i.e., more honestly)
- Necessary but not sufficient; underlying causal processes can introduce unobserved variance, destroying previously-holding correlations

› Responses to failures in CV

- › Do *true* out-of-sample testing
- › Do experimental testing if predictions used for decisions (Cardoso et al., 2014)
- › All performance claims are preliminary until such testing
- › Language: maybe use “retrodiction” and “back-testing,” or simply “correlation,” instead of “prediction” to not mislead
- › For robustness, maybe do statistics instead

Fatima Cardoso et al. 2016. 70-gene signature as an aid to treatment decisions in early-stage breast cancer. *New England Journal of Medicine* 375 (8): 717-729.



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► Discussion and conclusion

➤ Larger themes for this work

- “Confirmation holism,” and “experimenter’s regress”: if we don’t like a result, we can always find *something* to challenge
- We should do this even when we *do* like a result
- Box: “this road is endless...”
- Qualitative, critical, and theoretical social science can guide, especially around where and how claims of universalism and objectivity support injustice
- Data and models should *reflect* understandings of the world, not *define* them

➤ The work to be done

- We have a good idea of where biases are; but work remains in quantifying them
- Modelers should be trained with clear articulations of limitations of data and modeling
- Mixed methods probably the most promising way forward for research
 - Qualitative annotation for “ground truth” (Patton et al., 2019)
 - Experimental design for testing machine learning

Desmond U. Patton et al. 2019. Annotating social media data from vulnerable populations: Evaluating disagreement between domain experts and graduate student annotators. *Proceedings of the 52nd Hawaii International Conference on System Sciences (HICSS-52)*, pp. 2142–2151.

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