Revisiting 'ALL MODELS ARE WRONG': Addressing Limitations in Big Data, Machine Learning, and Computational Social Science

Momin M. Malik
Data Science Postdoctoral Fellow
Berkman Klein Center for Internet & Society at Harvard University

Wednesdays@NICO, 05 February 2020
Northwestern Institute on Complex Systems
Northwestern University, Evanston, Illinois

model elaboration is in any case not a plac

because this road is endless*.

ALL MODELS ARE WRONG BUT SOME ARE USEFUL

Now it would be very remarkable if any
in the real world could be <u>exactly</u> represen
model. However, cunningly chosen parsimoni

---

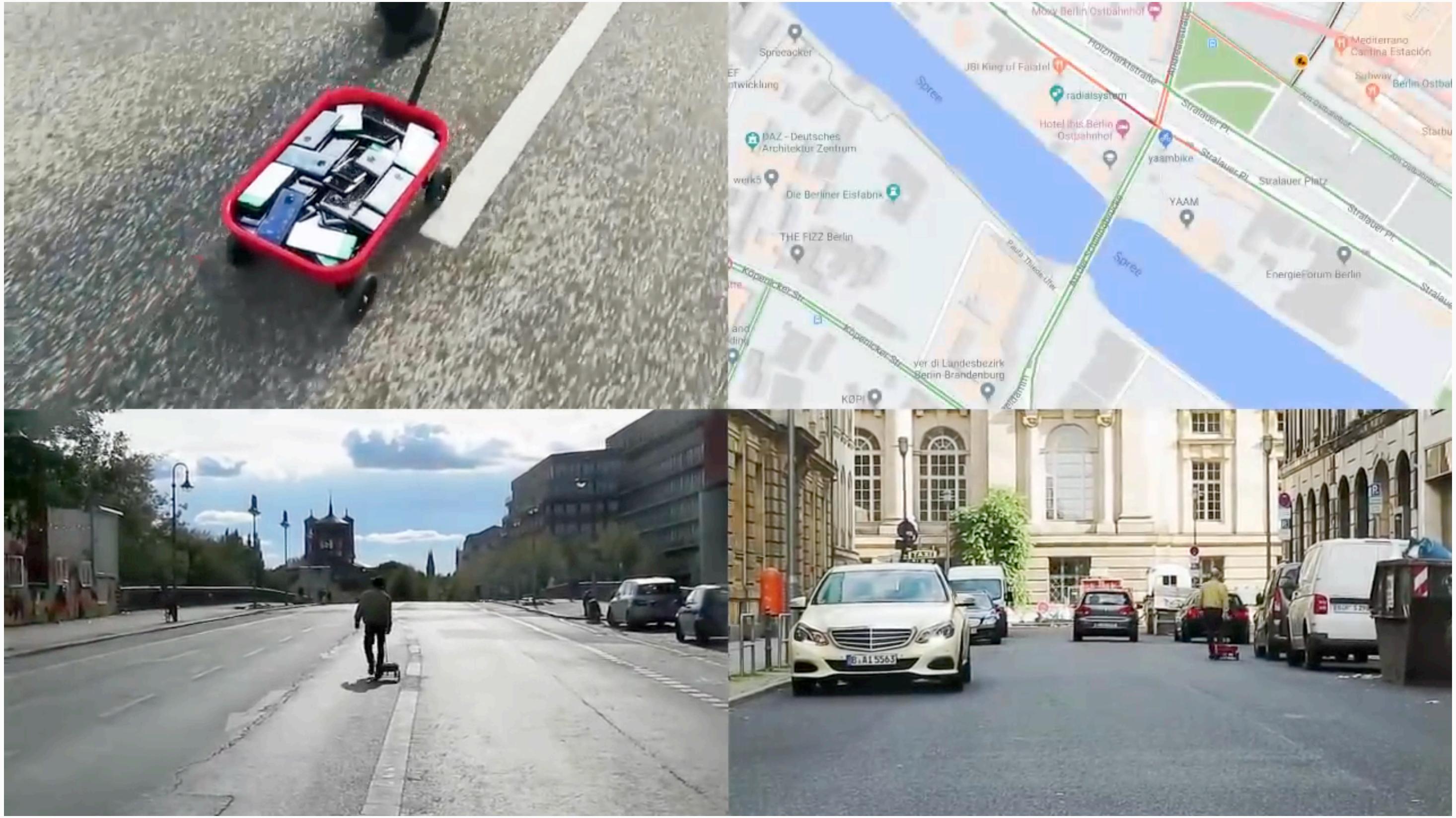
* Suppose for example that in advance of any
a model of the form of (1) with the usual no
Then it might be objected that the distribut

*"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**."*

David Lazer et al. 2009. Computational social science. *Science* 323 (5915), 721-723.
Eric Fisher. 2011. European detail map of Flickr and Twitter locations, https://flic.kr/p/a1vp4W

- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Simon Weckert, “Google Maps Hack”



- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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?'.*"

BERKMAN KLEIN CENTER
FOR INTERNET & SOCIETY
AT HARVARD UNIVERSITY

- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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

Outline

- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Trade-offs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion

BERKMAN KLEIN CENTER
FOR INTERNET & SOCIETY AT HARVARD UNIVERSITY

- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

About me

- Department of the History of Science, Harvard University
- Berkman — The Berkman Center for Internet & Society at Harvard University
- Oxford Internet Institute — University of Oxford
- Carnegie Mellon University School of Computer Science
- Data Science For Social Good Summer Fellowship
- Berkman Klein Center for Internet & Society at Harvard University

Carnegie Mellon University Societal Computing

ML Machine Learning Department

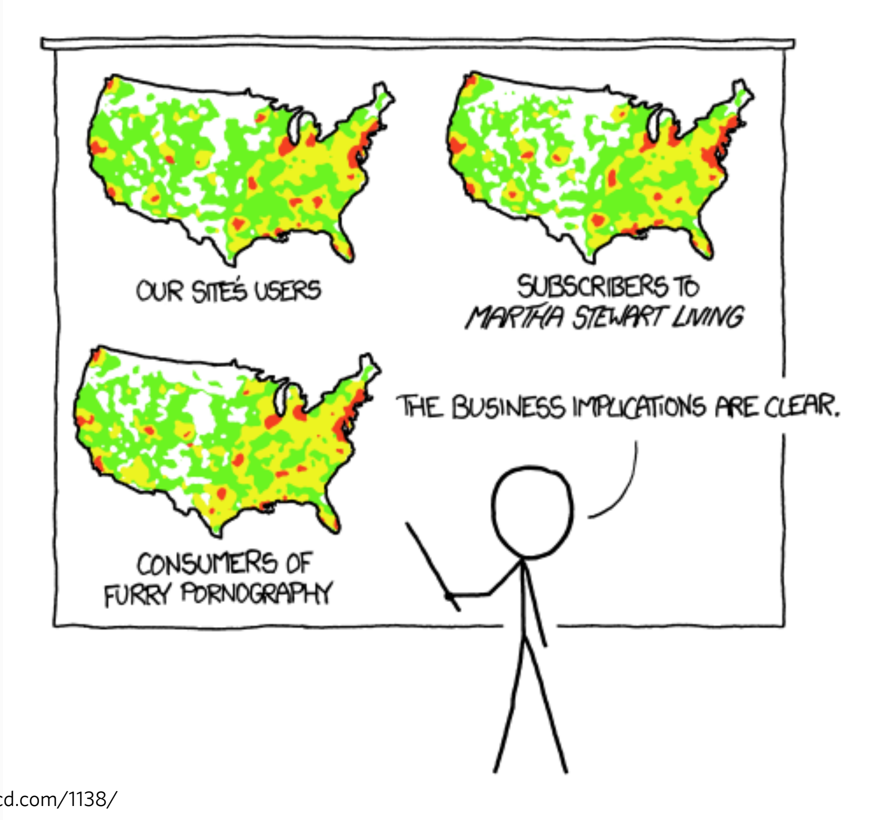
- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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

Introduction
Bias in geotagged tweets
Platform effects in social media
Tradeoffs in types of modeling
Dependencies and cross validation
Discussion and conclusion
References

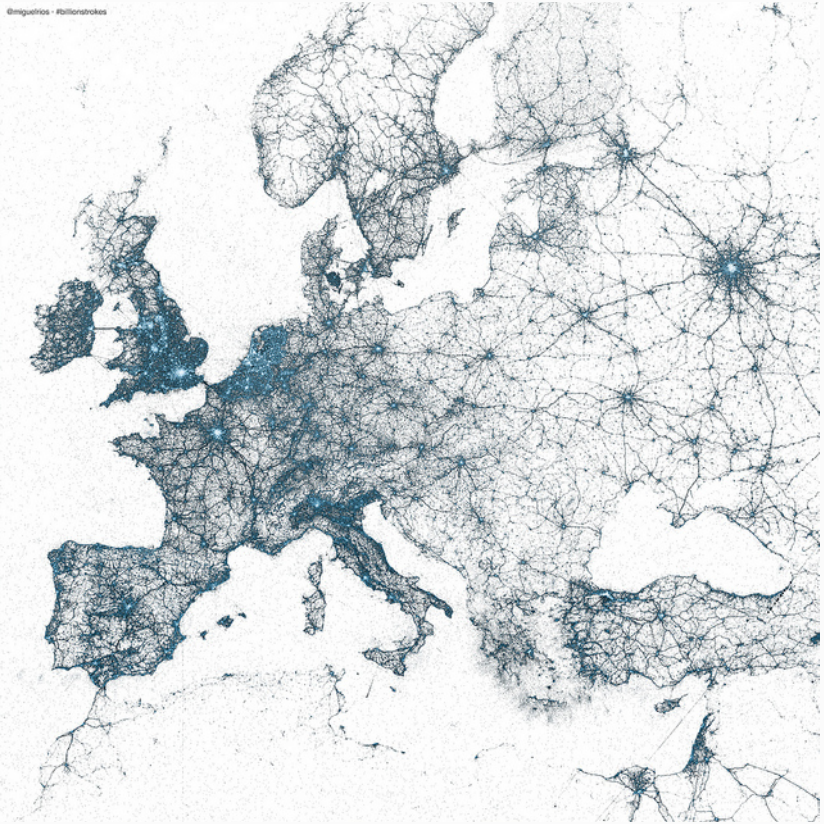
Many maps just show population

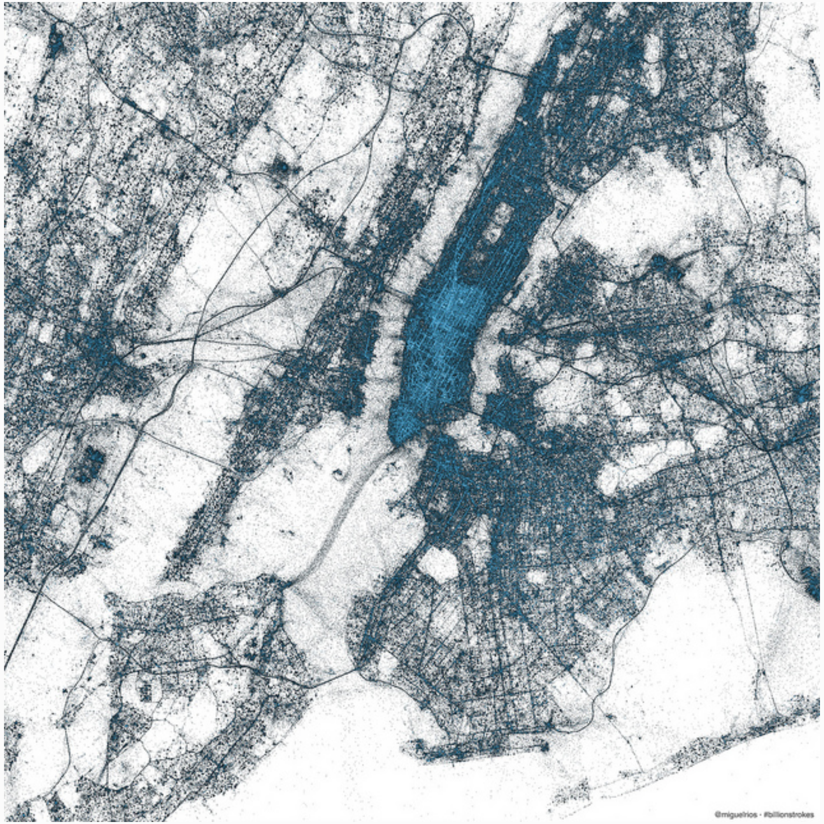


Randall Munroe. 2012. Heatmap. https://xkcd.com/1138/

- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

But maybe we can use this?

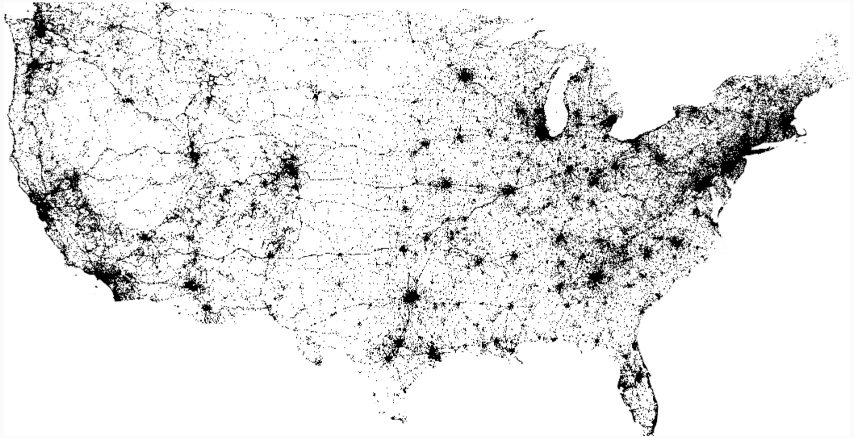




- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

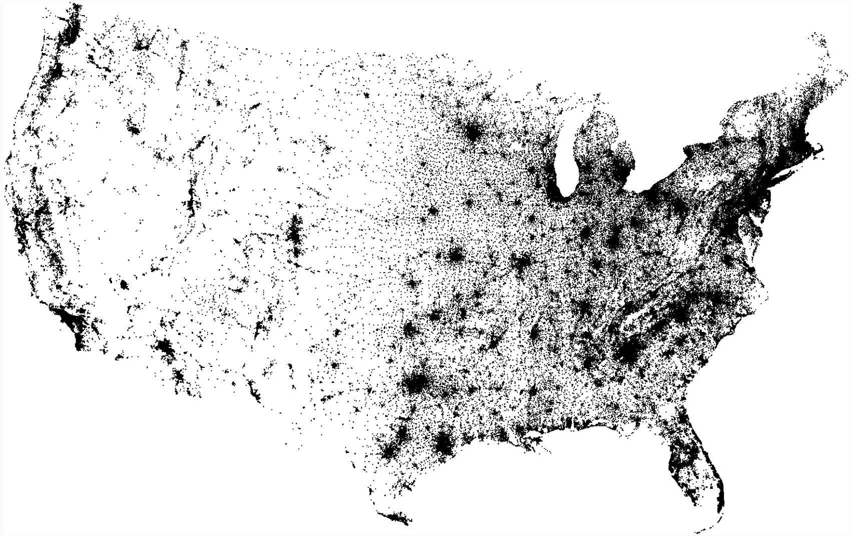
Do tweets measure population?

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:

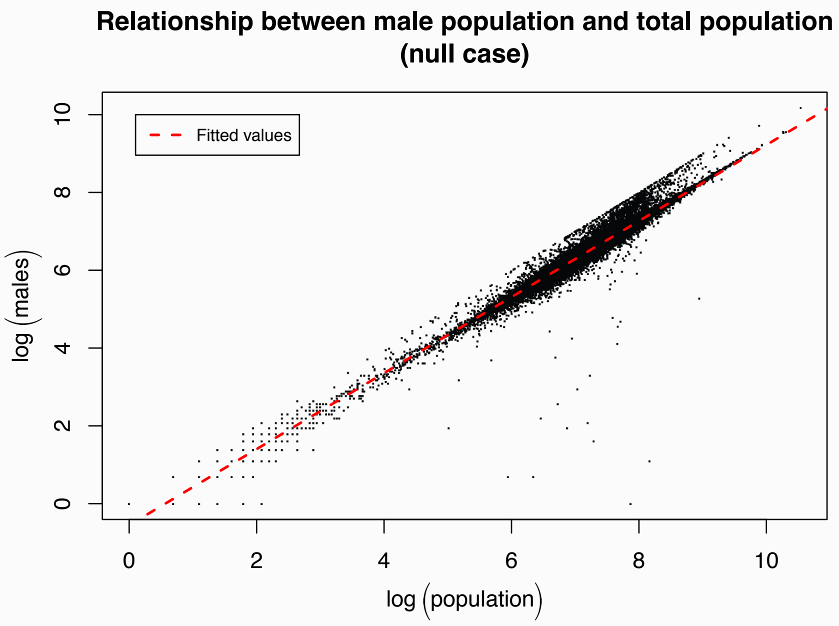
$$\log U_i = \beta_0 + \beta_1 \log P_i + \varepsilon_i'$$

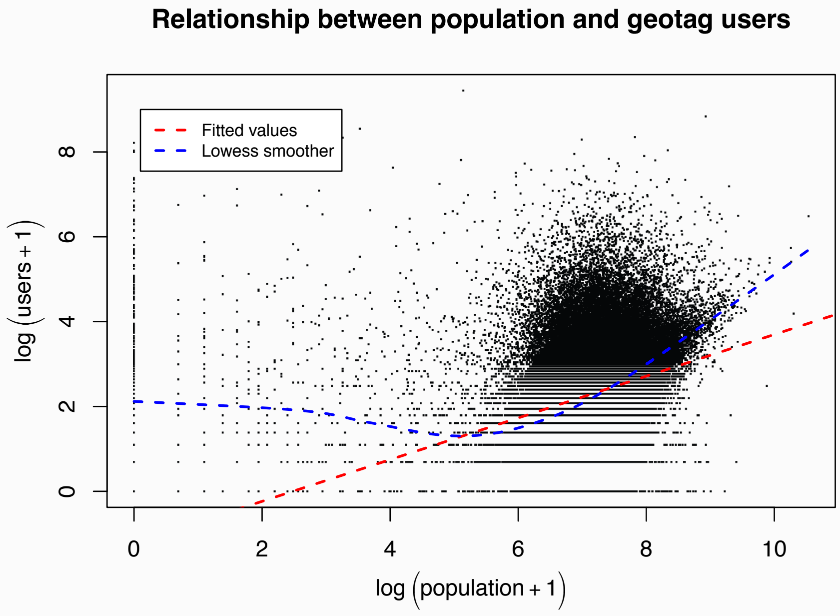
- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Result: Not proportional

(Each dot is a Census *block group*)





- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Identifying specifics

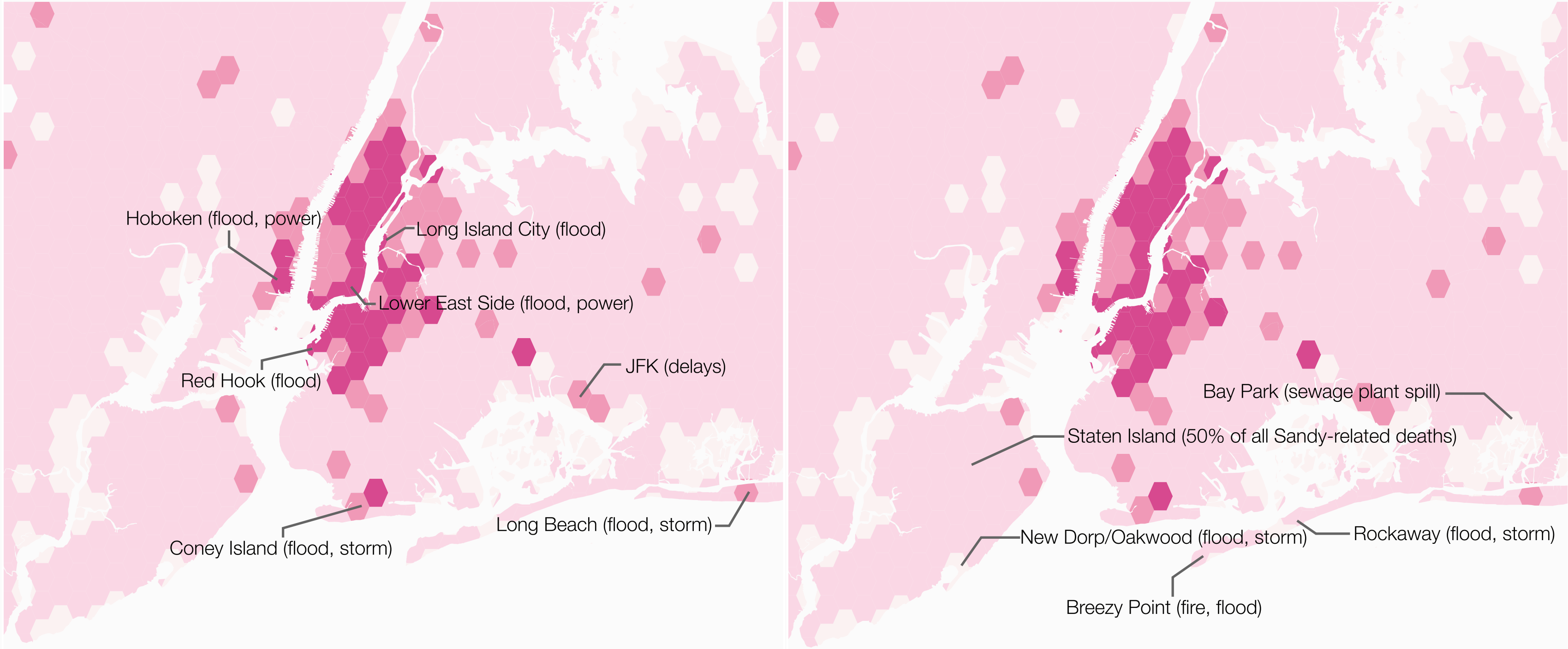
- Spatial multivariate modeling of biases

  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

- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Why it matters: Some uses are bad

Hurricane Sandy, tweets vs. damage/deaths



Shelton et al., 2014.

- Introduction
- Bias in geotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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.

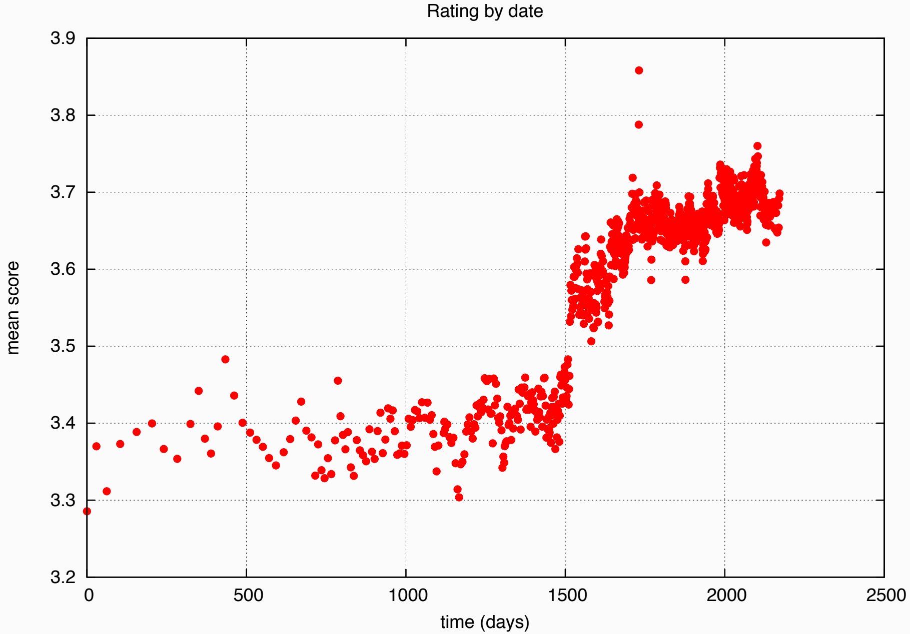
- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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

Introduction
Bias in eotagged tweets
Platform effects in social media
Tradeoffs in types of modeling
Dependencies and cross validation
Discussion and conclusion
References

Design can cause/change behavior



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

Koren, 2009.

BERKMAN KLEIN CENTER FOR INTERNET & SOCIETY AT HARVARD UNIVERSITY
- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

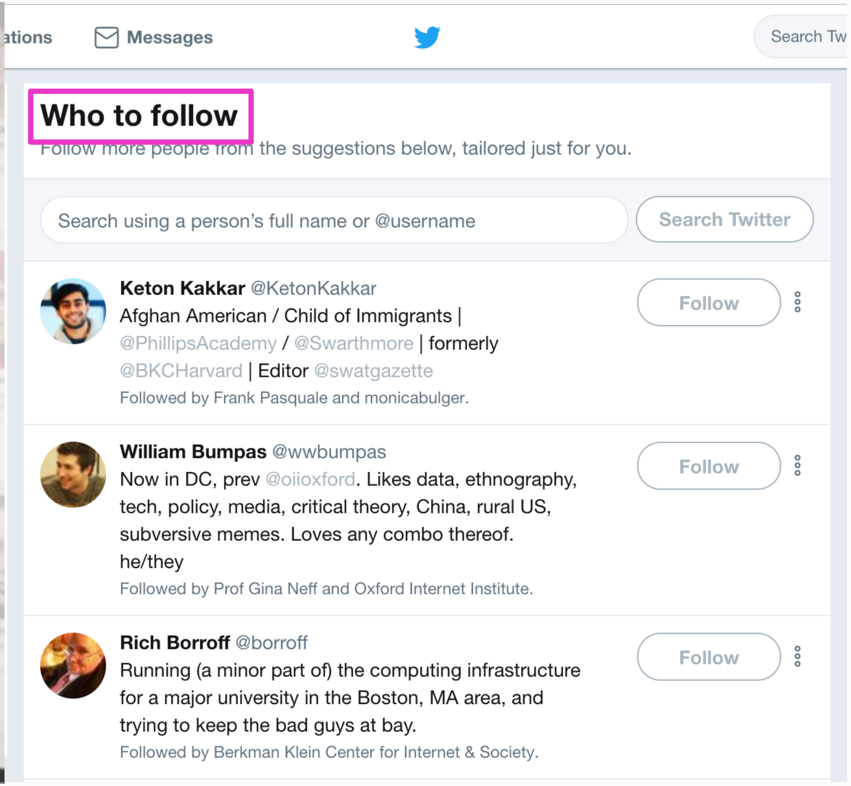
Social media platforms are businesses

Markets Insider, Business Insider (2018)

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

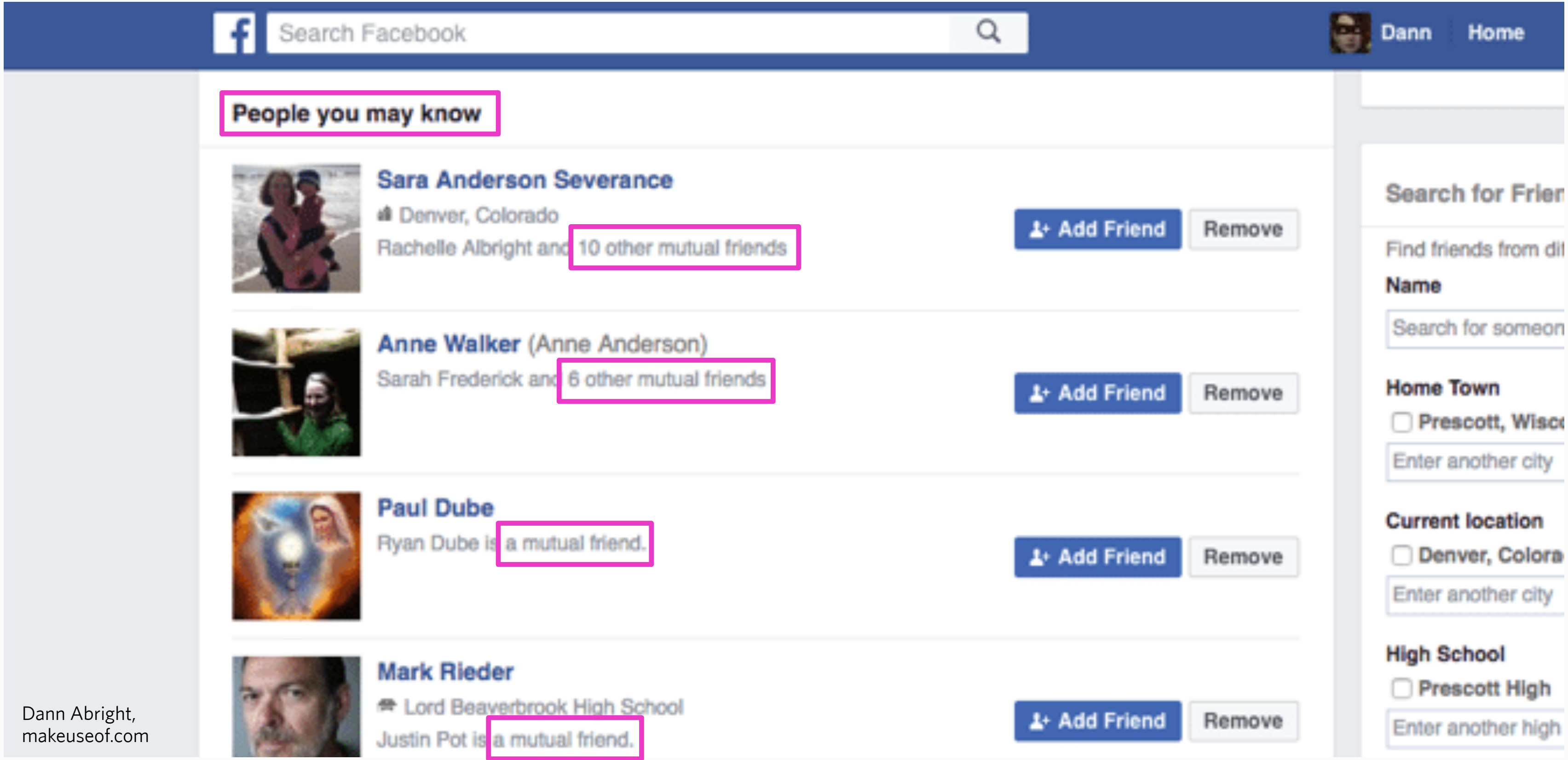
Sites try to grow their users' networks

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References



- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Recommending “friend-of-a-friend”

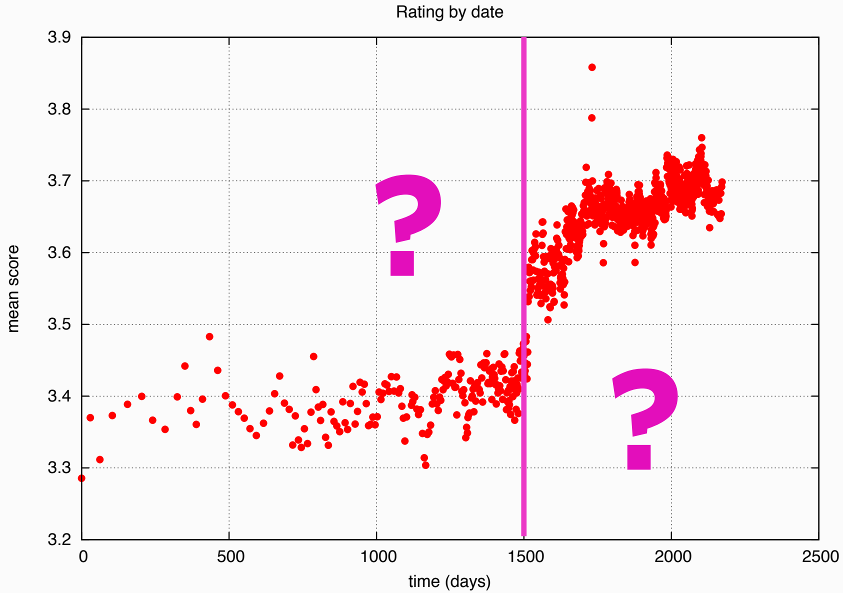


Dann Abright, makeuseof.com

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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.

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Data artifacts can reveal inner workings

The Matrix (1999) "déjà vu" scene

BERKMAN KLEIN CENTER
FOR INTERNET & SOCIETY AT HARVARD UNIVERSITY

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Data artifacts as natural experiments

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

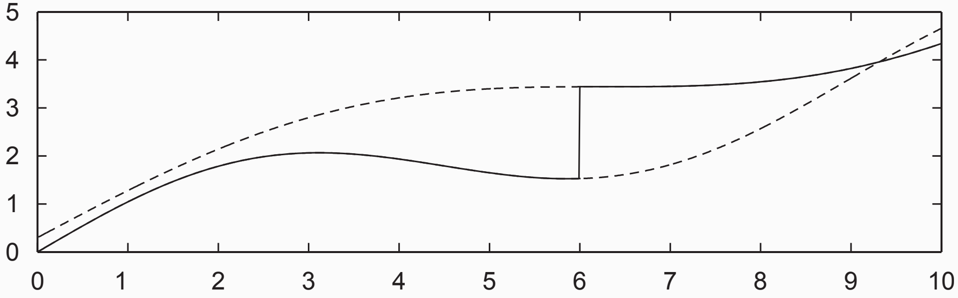


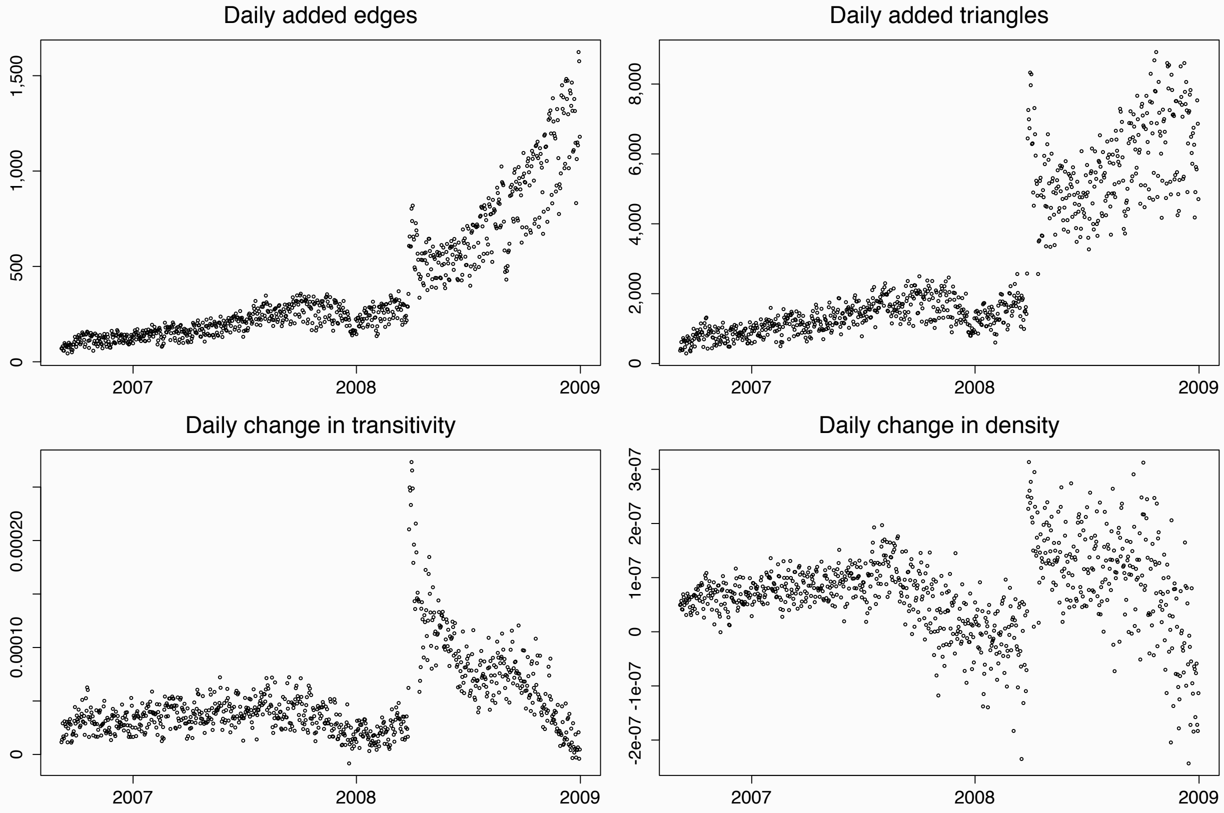
Fig. 2 from Imbens and Lemieux (2008): Potential and observed outcome regression functions.

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

BERKMAN KLEIN CENTER
FOR INTERNET & SOCIETY
AT HARVARD UNIVERSITY

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Case: Facebook's "People You May Know"

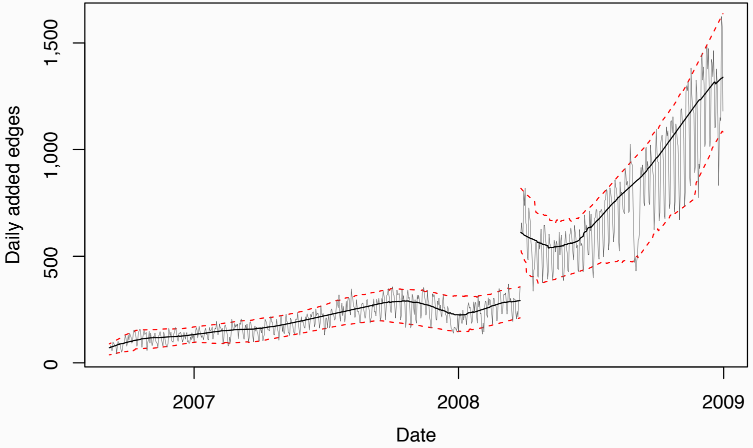


BERKMAN KLEIN CENTER FOR INTERNET & SOCIETY AT HARVARD UNIVERSITY

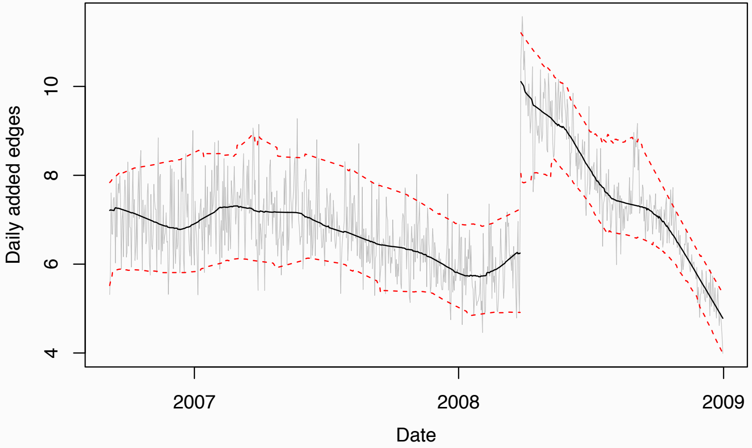
- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

PYMK changed the Facebook network!

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



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

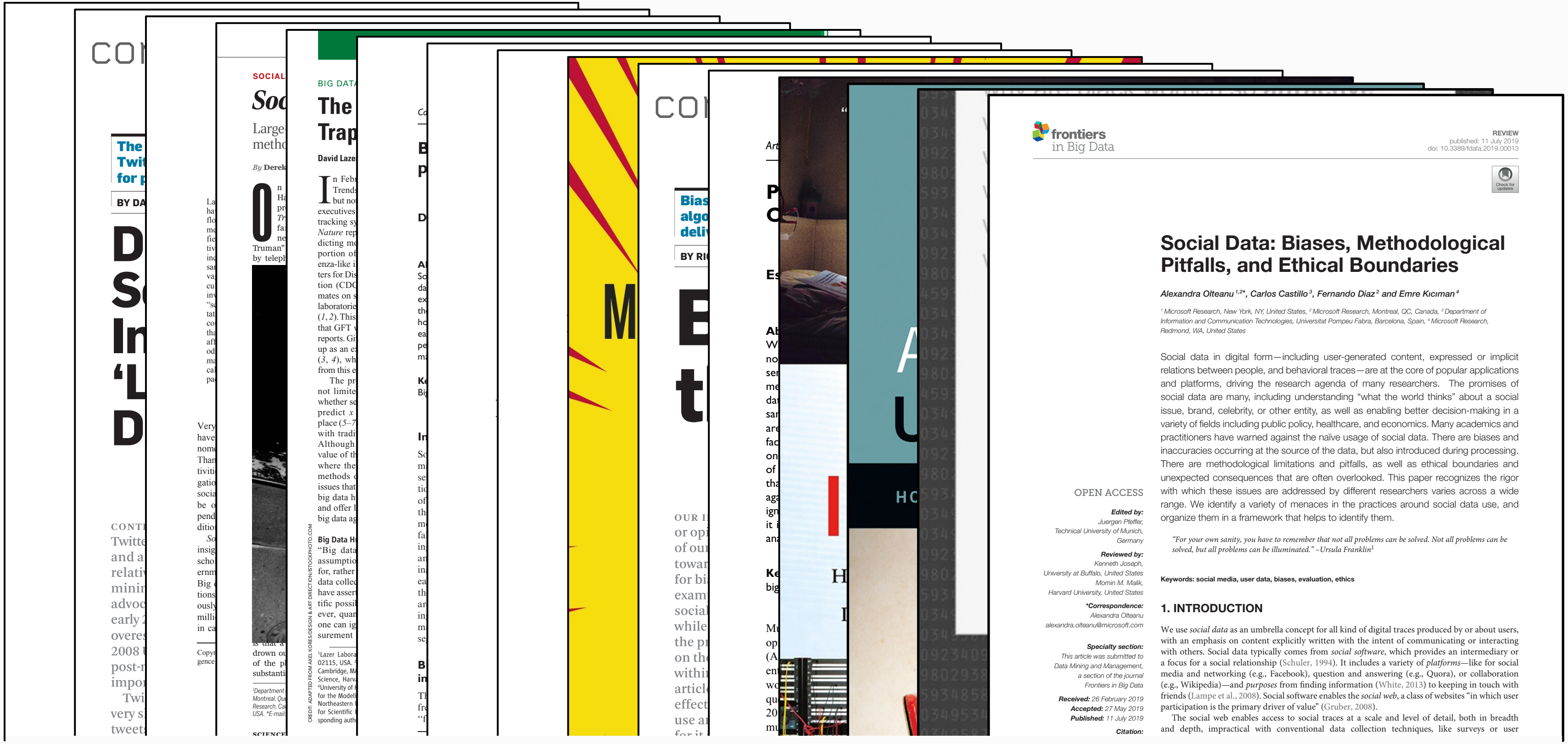


- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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

Data well-studied; *models*, not yet



frontiers in Big Data

REVIEW
published: 11 July 2019
doi: 10.3389/fdata.2019.00013

Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries

Alexandra Olteanu[1,2], Carlos Castillo[3], Fernando Diaz[2] and Emre Kıcıman[4]*

[1] Microsoft Research, New York, NY, United States, [2] Microsoft Research, Montreal, QC, Canada, [3] Department of Information and Communication Technologies, Universitat Pompeu Fabra, Barcelona, Spain, [4] Microsoft Research, Redmond, WA, United States

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 Franklin[1]

OPEN ACCESS

Edited by:
Juergen Pfeffer,
Technical University of Munich,
Germany

Reviewed by:
Kenneth Joseph,
University at Buffalo, United States
Momin M. Malik,
Harvard University, United States

***Correspondence:**
Alexandra Olteanu
alexandra.olteanu@microsoft.com

Specialty section:
This article was submitted to
Data Mining and Management,
a section of the journal
Frontiers in Big Data

Received: 26 February 2019
Accepted: 27 May 2019
Published: 11 July 2019

Citation:

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 (Schuler, 1994). It includes a variety of *platforms*—like for social media and networking (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

Introduction

Bias in eotagged tweets

Platform effects in social media

Tradeoffs in types of modeling

Dependencies and cross validation

Discussion and conclusion

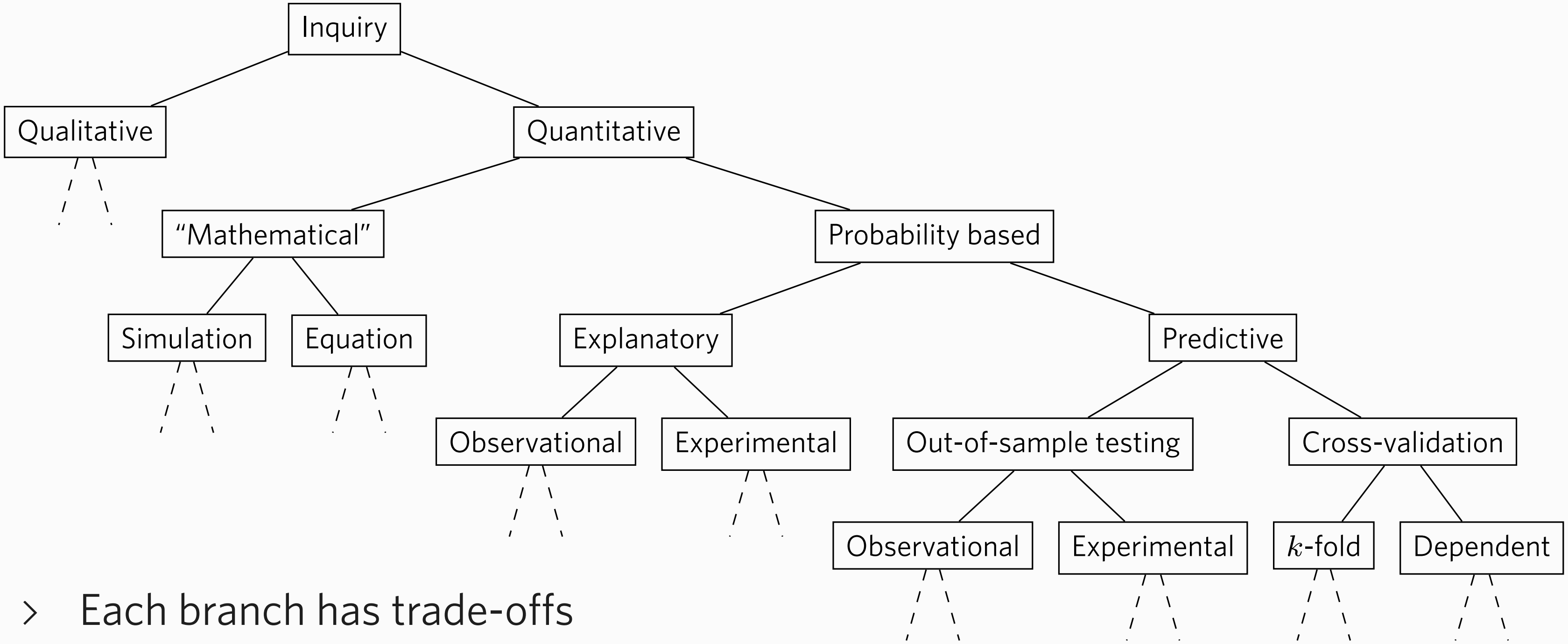
References

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

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Approaches to research

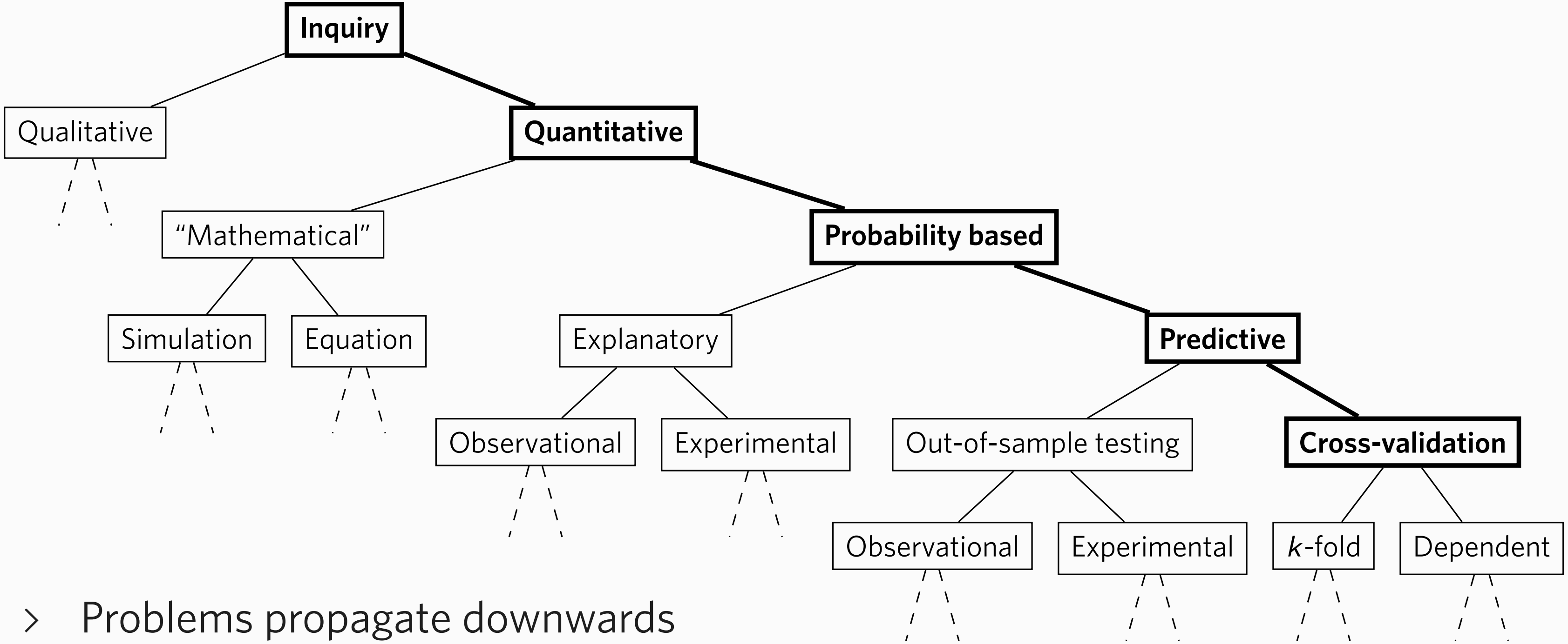


- Each branch has trade-offs
- No one method is better any other
- Mixed methods can combine

BERKMAN KLEIN CENTER
FOR INTERNET & SOCIETY AT HARVARD UNIVERSITY

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

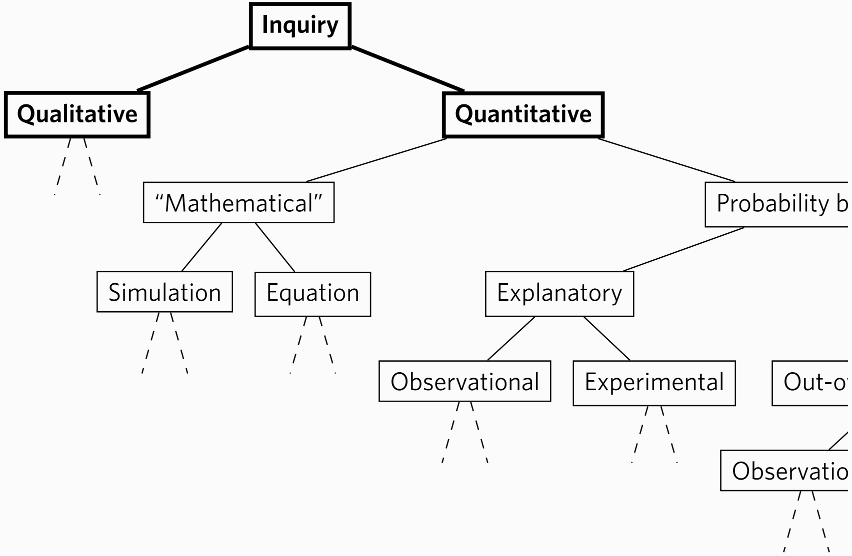
Typical machine learning



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

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

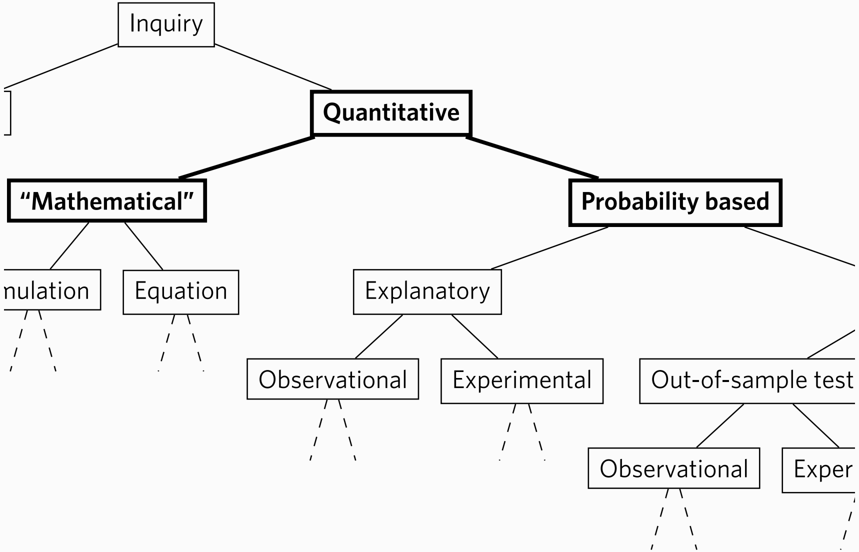
Quantification locks in meaning



- 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

Introduction
Bias in eotagged tweets
Platform effects in social media
Tradeoffs in types of modeling
Dependencies and cross validation
Discussion and conclusion
References

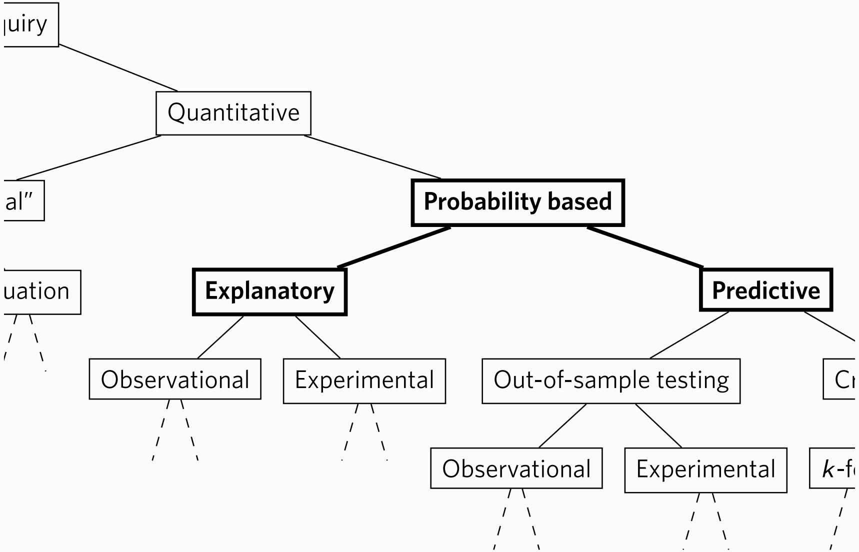
Stats and ML use central tendencies



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

Introduction
Bias in eotagged tweets
Platform effects in social media
Tradeoffs in types of modeling
Dependencies and cross validation
Discussion and conclusion
References

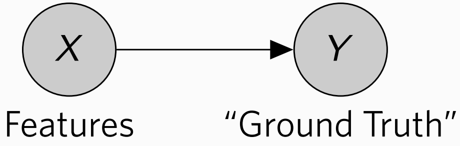
ML is "prediction" only

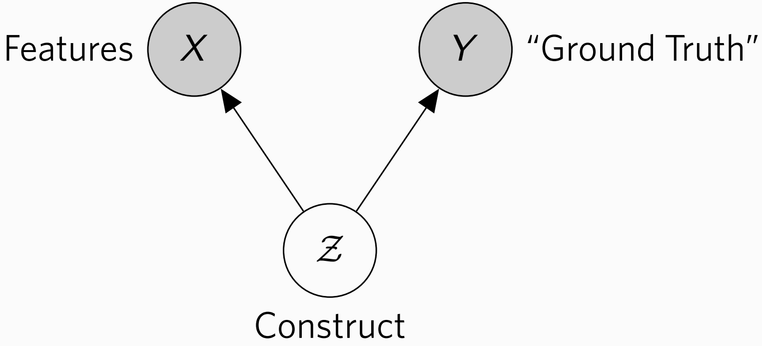


- "Predictions" are defined as what minimizes loss
- I.e., *correlations*
- Non-causal correlations can sometimes predict well, but they frequently don't explain, and can fail unexpectedly

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Prediction misses *constructs*

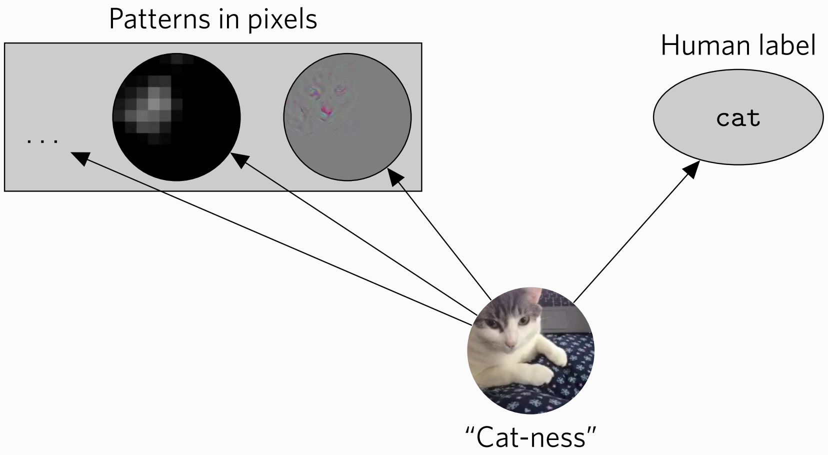




- *Constructs*: primitives of social science
  - What we care about
  - Often unobservable (and hypothetical/subjective, e.g. friendship)
  - Proxies always give errors (for binary constructs: false negatives and false positives)
  - E.g., Google maps usage is not traffic

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Constructs: Subjective, multifaceted



- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Responses to problems of proxy

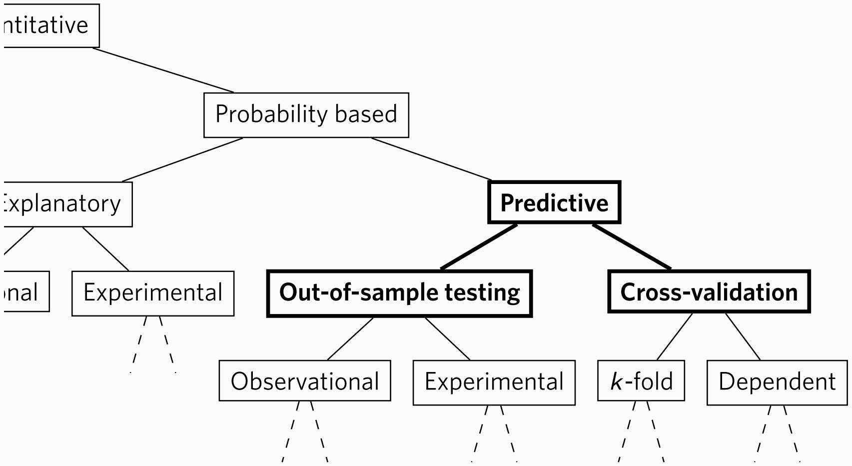
- Identify/define the underlying construct
- How does the correlation work? Where does it fail?
- Treat "ground truth" labels as *measurements*; investigate validity
- Use machine learning for *scaling subjective human judgments*, rather than thinking it uncovers underlying "truth"

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Dependencies and cross validation

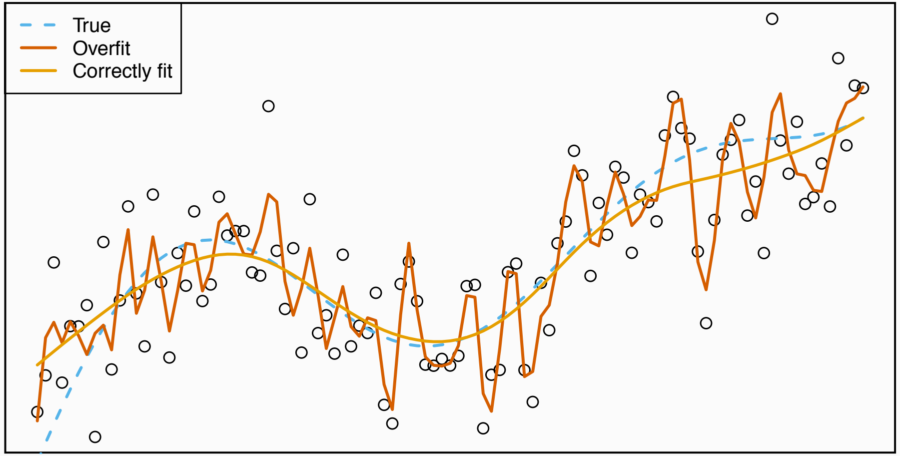
Momin M. Malik. 2020. A hierarchy of limitations in machine learning. In submission.
https://www.mominmalik.com/hierarchy_draft.pdf

Performance claims are from cross-validation



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

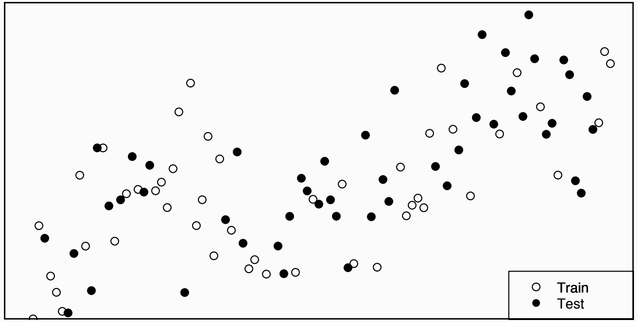
Purpose of cross-validation

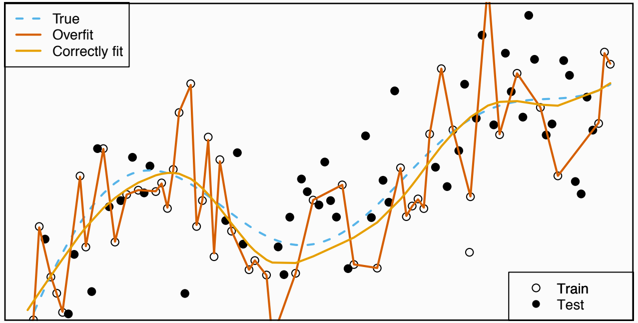


- If we are no longer guided by theory, and use automatic methods, we risk overfitting: fitting to the the noise, not the data

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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

Classic argument for CV

Introduction
Bias in eotagged tweets
Platform effects in social media
Tradeoffs in types of modeling
Dependencies and cross validation
Discussion and conclusion
References

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

BERKMAN KLEIN CENTER FOR INTERNET & SOCIETY AT HARVARD UNIVERSITY

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Apply this to non-iid data

- Imagine we have, for $\boldsymbol{\Sigma}_{ii} = \sigma^2$ and $\boldsymbol{\Sigma}_{ij} = \rho\sigma^2, \quad i \neq j$

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

- Then, optimism in the training set is:

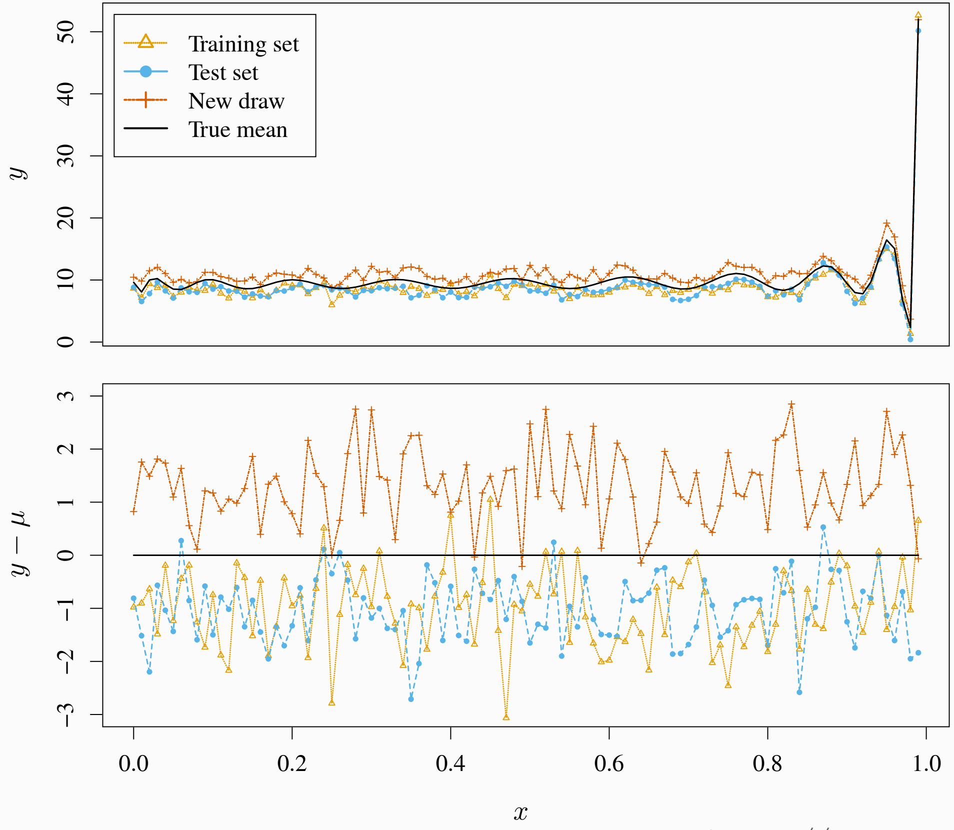
$$\frac{2}{n} \operatorname{tr} \operatorname{Cov}_f(Y_1, \widehat{Y}_1) = \frac{2}{n} \operatorname{tr} \operatorname{Cov}_f(Y_1, \mathbf{H} Y_1) = \frac{2}{n} \operatorname{tr} \mathbf{H} \operatorname{Var}_f(Y_1) = \frac{2}{n} \operatorname{tr} \mathbf{H}\boldsymbol{\Sigma}$$

- But test set also has nonzero optimism!

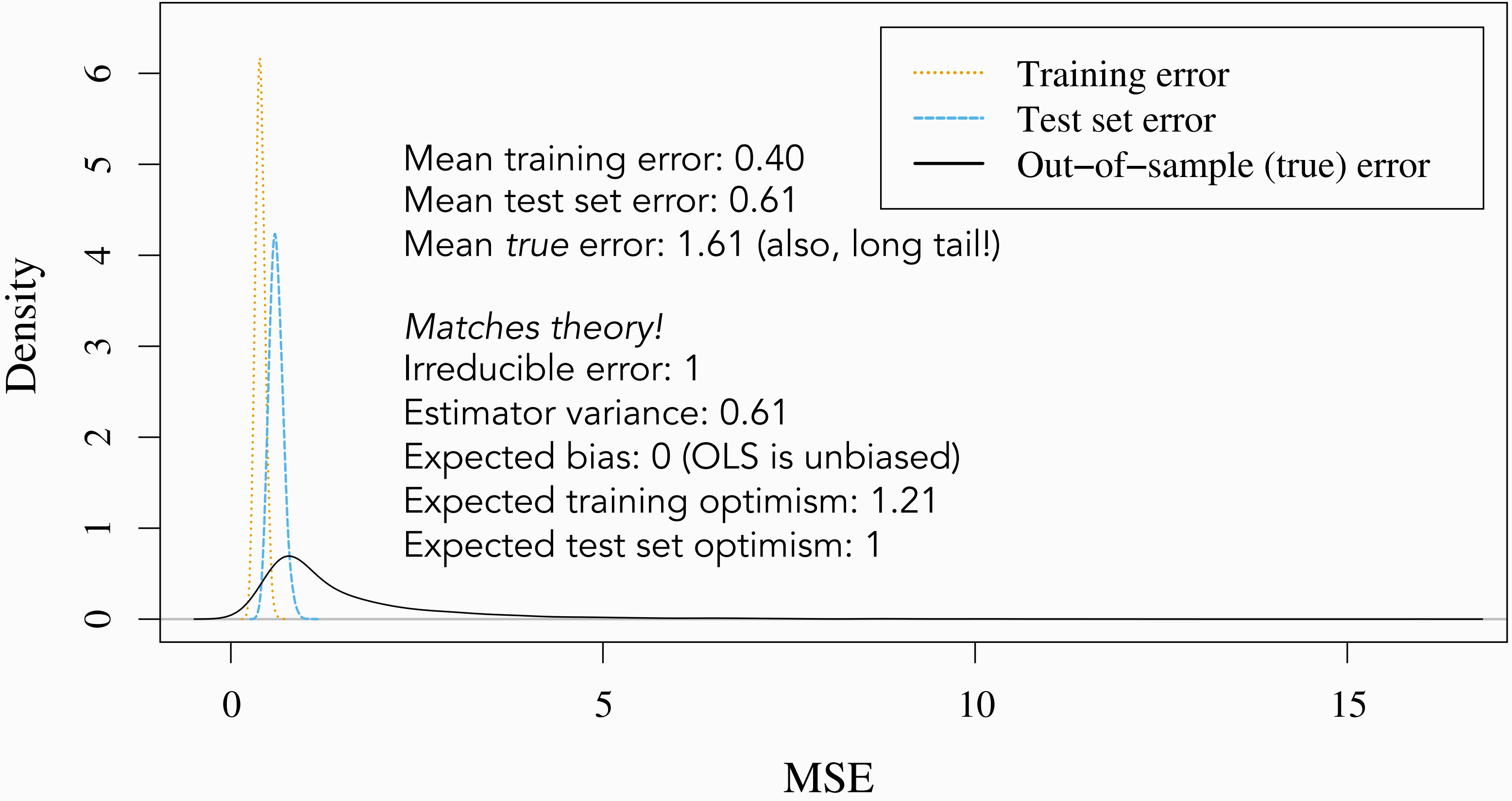
$$\frac{2}{n} \operatorname{tr} \operatorname{Cov}_f(Y_2, \widehat{Y}_1) = \frac{2}{n} \operatorname{tr} \operatorname{Cov}_f(Y_2, \mathbf{H} Y_1) = \frac{2\rho\sigma^2}{n} \operatorname{tr} \mathbf{H}\mathbf{1}\mathbf{1}^T = 2\rho\sigma^2$$

Introduction
Bias in eotagged tweets
Platform effects in social media
Tradeoffs in types of modeling
Dependencies and cross validation
Discussion and conclusion
References

Simulating the toy example



Out-of-sample MSE: *much* worse!



Mean training error: 0.40
Mean test set error: 0.61
Mean *true* error: 1.61 (also, long tail!)

Matches theory!
Irreducible error: 1
Estimator variance: 0.61
Expected bias: 0 (OLS is unbiased)
Expected training optimism: 1.21
Expected test set optimism: 1

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Discussion and conclusion

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

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

BERKMAN KLEIN CENTER FOR INTERNET & SOCIETY AT HARVARD UNIVERSITY

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

References (1/6)

Abbott, Andrew. 1988. Transcending general linear reality. *Sociological Theory* 6 (2): 169–186. https://dx.doi.org/10.2307/202114.

Agre, Philip E. 1997. Towards a critical technical practice: Lessons learned from trying to reform AI. In *Social science, technical systems, and cooperative work: Beyond the great divide*, edited by Geoffrey C. Bowker, Susan Leigh Star, Will Turner, and Les Gasser, 131–158. Lawrence Erlbaum Associates. https://web.archive.org/web/20040203070641/http://polaris.gseis.ucla.edu/pagre/critical.html.

Agre, Philip E. 2000, July 12. Notes on critical thinking, Microsoft, and eBay, along with a bunch of recommendations and some URL's. *Red Rock Eater Newsletter*. https://pages.gseis.ucla.edu/faculty/agre/notes/00-7-12.html.

Bailey, David H., Jonathan M. Borwein, Marcos López de Prado, and Qiji Jim Zhu. 2014. Pseudo-mathematics and financial charlatanism: The effects of backtest overfitting on out-of-sample performance. *Notices of the AMS* 61 (5): 458–471. https://dx.doi.org/10.1090/noti1105.

Bergmeir, Christoph, Rob J. Hyndman, and Bonsoo Koo. 2018. A note on the validity of cross-validation for evaluating autoregressive time series prediction. *Computational Statistics & Data Analysis* 120: 70–83. https://dx.doi.org/10.1016/j.csda.2017.11.003.

Borgatti, Steve. 2019. Types of validity. BA 762: Research Methods. Gatton College of Business & Engineering, University of Kentucky. https://sites.google.com/site/ba762researchmethods/materials/handouts/typesofvalidity.

Box, George E. P. 1979. Robustness in the strategy of scientific model building. Technical Report #1954, Mathematics Research Center, University of Wisconsin-Madison.

Breiman, Leo. 2001. Statistical modeling: The two cultures. *Statistical Science* 16 (3): 199–231. https://dx.doi.org/10.1214/ss/1009213726

References (2/6)

Cardoso, Fatima, Laura J. van't Veer, Jan Bogaerts, Leen Slaets, Giuseppe Viale, Suzette Delaloge, Jean-Yves Pierga, Etienne Brain, Sylvain Causeret, Mauro DeLorenzi, Annuska M. Glas, Vassilis Golfinopoulos, Theodora Goulioti, Susan Knox, Erika Matos, Bart Meulemans, Peter A. Neijenhuis, Ulrike Nitz, Rodolfo Passalacqua, Peter Ravdin, Isabel T. Rubio, Mahasti Saghatchian, Tineke J. Smilde, Christos Sotiriou, Lisette Stork, Carolyn Straehle, Geraldine Thomas, Alastair M. Thompson, Jacobus M. van der Hoeven, Peter Vuylsteke, René Bernards, Konstantinos Tryfonidis, Emiel Rutgers, and Martine Piccart. 2016. 70-gene signature as an aid to treatment decisions in early-stage breast cancer. *New England Journal of Medicine* 375 (8): 717–729. https://dx.doi.org/10.1056/NEJMoa1602253.

Chatfield, Chris. 1995. Model uncertainty, data mining and statistical inference. *Journal of the Royal Statistical Society. Series A (Statistics in Society)* 158 (3): 419–466. https://dx.doi.org/10.2307/2983440.

Cox, David R. 1990. Role of models in statistical analysis. *Statistical Science* 5 (2): 169–174. https://dx/doi.org/10.1214/ss/1177012165

Doshi-Velez, Finale and Been Kim. 2017. Towards a rigorous science of interpretable machine learning. https://arxiv.org/abs/1702.08608.

Dwork, Cynthia, Vitaly Feldman, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Aaron Roth. 2015. The reusable holdout: Preserving validity in adaptive data analysis. *Science* 349 (6248): 636–638. https://dx.doi.org/10.1126/science.aaa9375.

Efron, Bradley. 2004. The estimation of prediction error: covariance penalties and cross-validation. *Journal of the American Statistical Association* 99 (467): 619–632. https://dx.doi.org/10.1198/016214504000000692.

Fisher, R. A. 1922. On the mathematical foundations of theoretical statistics. *Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character* 222: 309–368. https://dx/doi.org/10.1098/rsta.1922.0009.

References (3/6)

Gayo-Avello, Daniel. 2012. "I wanted to predict elections with Twitter and all I got was this lousy paper": A balanced survey on election prediction using Twitter data. https://arxiv.org/abs/1204.6441.

Ginsberg, Jeremy, Matthew H. Mohebbi, Rajan S. Patel, Lynnette Brammer, Mark S. Smolinski, and Larry Brilliant. 2009. Detecting influenza epidemics using search engine query data. *Nature* 457: 1012–1015. https://dx.doi.org/10.1038/nature07634.

Hammerla, Nils Y., and Thomas Plötz. 2015. Let's (not) stick together: Pairwise similarity biases cross-validation in activity recognition. *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp '15), 1041–1051. https://dx.doi.org/10.1145/2750858.2807551.

Imbens, Guido W. and Thomas Lemieux. 2008. Regression discontinuity designs: A guide to practice. *Journal of Econometrics* 142 (2): 615–635. https://dx.doi.org/10.1016/j.jeconom.2007.05.001.

Jones, Matthew L. 2018. How we became instrumentalists (again): Data positivism since World War II. *Historical Studies in the Natural Sciences* 48 (5): 673–684. https://dx.doi.org/10.1525/hsns.2018.48.5.673.

Kass, Robert E. 2011. Statistical inference: The big picture. *Statistical Science* 26 (1): 1–9. https://dx.doi.org/10.1214/10-STS337.

Keyes, Os. 2018. The misgendering machines: Trans/HCI implications of automatic gender recognition. *Proceedings of the ACM on Human-Computer Interaction* (CSCW), 2, 88:1–88:22.

Kleinberg, Jon, Jens Ludwig, Sendhil Mullainathan, and Ziad Obermeyer. 2015. Prediction policy problems. *American Economic Review* 105 (5): 491–495. https://dx.doi.org/10.1257/aer.p20151023.

Koren, Yehuda. 2009. Collaborative filtering with temporal dynamics. *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (KDD '09), 447–456. https://dx.doi.org/10.1145/1557019.1557072.

References (4/6)

- Introduction
- Bias in eotagged tweets
- Platform effects in social media
- Tradeoffs in types of modeling
- Dependencies and cross validation
- Discussion and conclusion
- References

Lanius, Candice. 2015, January 15. Fact check: Your demand for statistical proof is racist. *Cyborgology*. https://thesocietypages.org/cyborgology/2015/01/12/fact-check-your-demand-for-statistical-proof-is-racist/.

Lazer, David, Ryan Kennedy, Gary King, and Alessandro Vespignani. 2014. The parable of Google Flu: Traps in big data analysis. *Science* 343 (6176): 1203–1205. https://dx.doi.org/10.1126/science.1248506.

Lipton, Zachary C. 2015. The myth of model interpretability. *KDnuggets* 15 (13). https://www.kdnuggets.com/2015/04/model-interpretability-neural-networks-deep-learning.html.

Lipton, Zachary C. and Jacob Steinhardt. 2018. Troubling trends in machine learning scholarship. https://arxiv.org/abs/1807.03341.

Messerli, Franz H. 2012. Chocolate consumption, cognitive function, and Nobel laureates. *The New England Journal of Medicine* 367: 1562–1564. https://dx.doi.org/10.1056/NEJMon1211064.

Mullainathan, Sendhil and Jann Spiess. 2017. Machine learning: An applied econometric approach. *Journal of Economic Perspectives* 31 (2): 87–106. https://dx.doi.org/10.1257/jep.31.2.87.

Olteanu, Alexandra, Carlos Castillo, Fernando Diaz, and Emre Kıcıman. 2019. Social data: Biases, methodological pitfalls, and ethical boundaries. *Frontiers in Big Data* 2. https://dx.doi.org/10.3389/fdata.2019.00013.

Opsomer, Jean, Yuedong Wang, and Yuhong Yang. 2001. Nonparametric regression with correlated errors. *Statistical Science* 16 (2): 134–153. https://dx.doi.org/10.1214/ss/1009213287.

Park, Greg. 2012. The dangers of overfitting: A Kaggle postmortem. http://gregpark.io/blog/Kaggle-Psychopathy-Postmortem/.

References (5/6)

Introduction
Bias in eotagged tweets
Platform effects in social media
Tradeoffs in types of modeling
Dependencies and cross validation
Discussion and conclusion
References

Patton, Desmond U., Philipp Blandfort, William Frey, Michael Gaskell, and Svebor Karaman. 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), 2142–2151. https://dx.doi.org/10.24251/HICSS.2019.260.

Patton, Michael Quinn. 2014. The nature, niche, value, and fruit of qualitative inquiry. In *Qualitative research & evaluation methods: Integrating theory and practice*, 4th edition, 2–44. SAGE Publications, Inc. https://uk.sagepub.com/sites/default/files/upm-binaries/64990_Patton_Ch_01.pdf.

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

Rose, Todd. 2016. *The end of average: How we succeed in a world that values sameness*. HarperOne. See excerpt at https://www.thestar.com/news/insight/2016/01/16/when-us-air-force-discovered-the-flaw-of-averages.html. Animated video: https://vimeo.com/237632676.

Rosset, Saharon, and Ryan J. Tibshirani. 2019. From fixed-X to random-X regression: Bias-variance decompositions, covariance penalties, and prediction error estimation. *Journal of the American Statistical Association*. https://dx.doi.org/10.1080/01621459.2018.1424632.

Santillana, Mauricio, Wendong Zhang, Benjamin M. Althouse, and John W. Ayers. 2014. What can digital disease detection learn from (an external revision to) Google Flu Trends? *American Journal of Preventive Medicine* 47 (3): 341–347. http://dx.doi.org/10.1016/j.amepre.2014.05.020.

Shapiro, Ian. 2014. Methods are like people: If you focus only on what they can't do, you will always be disappointed. In *Field experiments and their critics: Essays on the uses and abuses of experimentation in the social sciences*, edited by Dawn Langan Teele, 228–241. Yale University Press.

Introduction
Bias in eotagged tweets
Platform effects in social media
Tradeoffs in types of modeling
Dependencies and cross validation
Discussion and conclusion
References

References (6/6)

Shelton, Taylor, Ate Poorthuis, Mark Graham, and Matthew Zook. 2014. Mapping the data shadows of Hurricane Sandy: Uncovering the sociospatial dimensions of 'big data.' *Geoforum* 52: 167–179. http://dx.doi.org/10.1016/j.geoforum.2014.01.006.

Shmueli, Galit. 2010. To explain or to predict? *Statistical Science* 25 (3): 289–310. https://dx.doi.org/10.1214/10-STS330.

Spirtes, Peter and Kun Zhang. 2016. Causal discovery and inference: Concepts and recent methodological advances. *Applied Informatics* 3 (3): 1–28. https://dx.doi.org/10.1186/s40535-016-0018-x.

Tasse, Dan, 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)*, 250–259. https://aaai.org/ocs/index.php/ICWSM/ICWSM17/paper/view/15588.

Tibshirani, Robert. 2015, December 6. Recent advances in post-selection inference. Breiman Lecture, NeurIPS 2015. http://statweb.stanford.edu/~tibs/ftp/nips2015.pdf

Wallach, Hanna. 2018. Computational social science ≠ computer science + social data. *Communications of the ACM* 61 (3): 42–44. https://dx.doi.org/10.1145/3132698.

Wasserman, Larry A. 2013. Rise of the machines. In *Past, present, and future of statistical science*, 525–536. Chapman and Hall/CRC. http://www.stat.cmu.edu/~larry/Wasserman.pdf.