

- » Introduction
- » Language:
'Prediction' is retrospective
- » Definitions:
'Prediction' is correlation
- » Validity:
Correlations can overfit
- » Paradox:
'Truth' may not predict
- » Summary
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» What Everybody Needs to Know About 'Prediction' in Machine Learning

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3 December 2018

Slides: <https://mominmalik.com/cfi.pdf>

► Existential threats, or myths?

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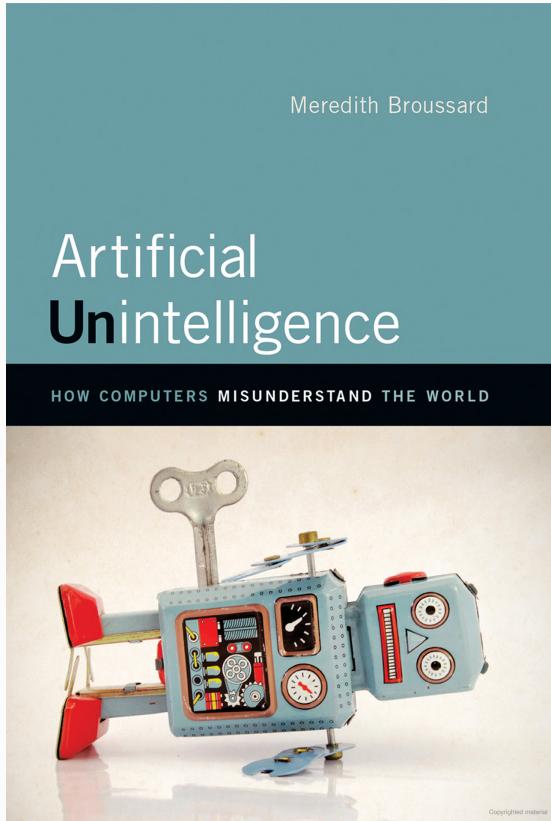
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› Solid general resource



'Prediction' in machine learning

- › Chapter 7: "Machine Learning: The DL on ML"
 - (Two mistakes, see https://github.com/momin-malik/guides/blob/master/Broussard_DL_on_ML.ipynb)
- › Chapter 3: "Hello, AI"
 - "So, it's not real AI?" he asked.
 - "Oh, it's real," I said. "And it's spectacular. But you know, don't you, that there's no simulated person inside the machine? Nothing like that exists. It's computationally impossible."
 - His face fell. "I thought that's what AI meant," he said. "I heard about IBM Watson, and the computer that beat the champion at Go, and self-driving cars. I thought they invented real AI."
- › Then, the rest of Part II

➤ The things everybody needs to know

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- Language: ‘Prediction’ (technical term) is not prediction (colloquial term); prediction is prospective, ‘prediction’ is retrospective.
- Definitions: ‘Prediction’ is based on correlations
- Validity: Correlations can *overfit*, and cross-validation only partially addresses
- Paradox: The *bias-variance tradeoff* (a consequence of the definition) makes it possible for a ‘false’ model to predict better than a ‘true’ one



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► Language: 'Prediction' is not prediction

➤ Lots of “predict...”

➤ Introduction

➤ Language:
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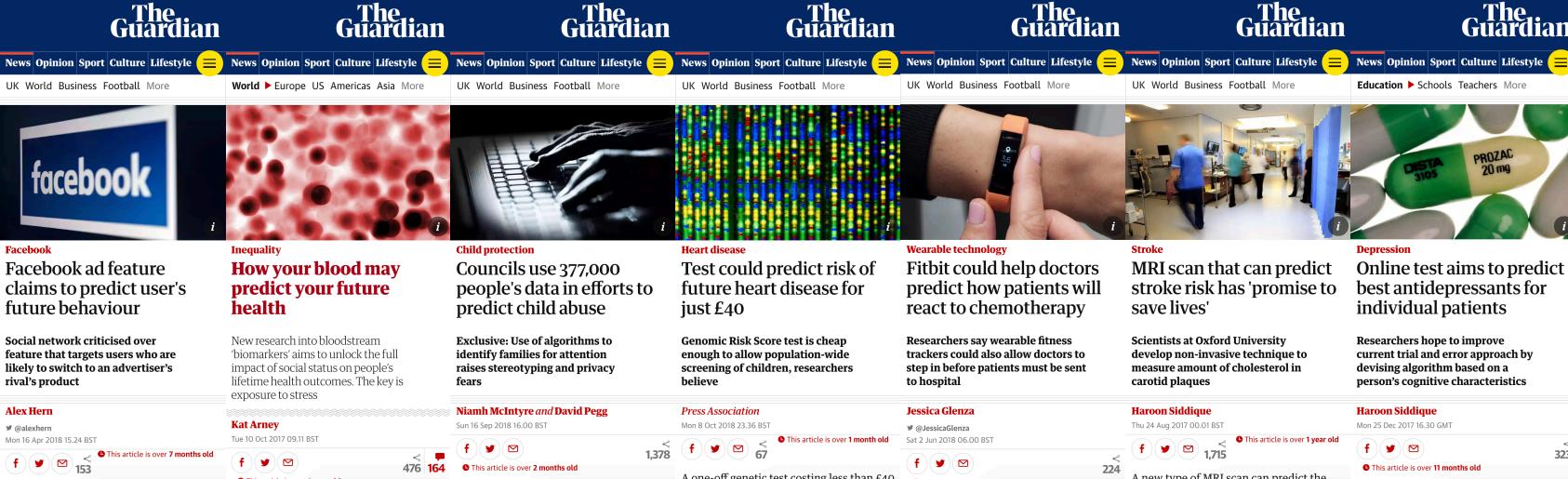
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The Guardian headlines include:

- Facebook**: Facebook ad feature claims to predict user's future behaviour
- Inequality**: How your blood may predict your future health
- Child protection**: Councils use 377,000 people's data in efforts to predict child abuse
- Heart disease**: Test could predict risk of future heart disease for just £40
- Wearable technology**: Fitbit could help doctors predict how patients will react to chemotherapy
- Stroke**: MRI scan that can predict stroke risk has 'promise to save lives'
- Depression**: Online test aims to predict best antidepressants for individual patients

Each article includes a small image, the author's name, the publication date, social sharing icons, and a 'This article is over [X] months old' badge.

➤ If you relied on *The Guardian*, what sort of picture might you get?

► Predict... the future?

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Mar 2010

Predicting the Future With Social Media

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Abstract—In recent years, social media has become ubiquitous and important for social networking and content sharing. And yet, the content that is generated from these websites remains largely untapped. In this paper, we demonstrate how social media content can be used to predict real-world outcomes. In particular, we use the chatter from Twitter.com to forecast box-office revenues for movies. We show that a simple model built from

This paper reports on such a study. Specifically we consider the task of predicting box-office revenues for movies using the chatter from Twitter, one of the fastest growing social networks in the Internet. Twitter¹, a micro-blogging network, has experienced a burst of popularity in recent months leading to a huge user-base, consisting of several tens of millions of

Predicting the Future — Big Data, Machine Learning, and Clinical Medicine

Ziad Obermeyer, M.D., and Ezekiel J. Emanuel, M.D., Ph.D.

By now, it's almost old news: Big data will transform medicine. It's essential to remember, however, that data by themselves are useless. To be useful, data must be analyzed, interpreted, and acted on. Thus, it is algorithms —

not data sets — that will prove transformative. We believe, therefore, that attention has to shift to new statistical tools from the field of machine learning that will be critical for anyone practicing medicine in the 21st century.

First, it's important to understand what machine learning is not. Most computer-based algorithms in medicine are "expert systems" — rule sets encoding knowledge on a given topic, which are applied to draw conclusions

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The New England Journal of Medicine

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English
Oxford Living Dictionaries

predict

British & World English > predict

Definition of *predict* in English:

predict 

VERB

[WITH OBJECT]

Say or estimate that (a specified thing) will happen in the future or will be a consequence of something.

'it is too early to predict a result'

[with clause] 'he predicts that the trend will continue'

[+ More example sentences](#)

[+ Synonyms](#)

Origin

Early 17th century: from Latin *praedict-* 'made known beforehand, declared', from the verb *praedicere*, from *prae-* 'beforehand' + *dicere* 'say'.

Pronunciation 

predict /prɪ'dɪkt/ 



English
Oxford Living Dictionaries

predict

Thesaurus > predict

Synonyms of *predict* in English:

predict

See definition of *predict*

VERB

1 *'it is difficult to predict what the outcome will be'*

SYNONYMS

forecast, foretell, foresee, prophesy, divine, prognosticate, anticipate, see, say, tell in advance, project, speculate, envision, envisage, imagine, picture, estimate, conjecture, guess, hazard a guess

archaic augur, previse, presage, foreshow

Scottish archaic spae

rare vaticinate, auspicate

➤ 'Prediction' is not prediction!

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*"I Wanted to Predict Elections with Twitter
and all I got was this Lousy Paper"*

A Balanced Survey on Election Prediction using Twitter Data

Daniel Gayo-Avello
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Department of Computer Science - University of Oviedo (Spain)

May 1, 2012

Abstract

Predicting X from Twitter is a popular fad within the Twitter research subculture. It seems both appealing and relatively easy. Among such kind of studies, electoral prediction is maybe the most attractive, and at this moment there is a growing body of literature on such a topic.

This is not only an interesting research problem but, above all, it is extremely difficult. However, most of the authors seem to be more interested in claiming positive results than in providing sound and reproducible methods.

"It's not prediction at all! I have not found a single paper predicting a future result. All of them claim that a prediction could have been made; i.e. they are post-hoc analysis and, needless to say, negative results are rare to find."

► “Wishful mnemonics” of AI

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ARTIFICIAL INTELLIGENCE MEETS NATURAL STUPIDITY

Drew McDermott
MIT AI Lab Cambridge, Mass 02139

As a field, artificial intelligence has always been on the border of respectability, and therefore on the border of crackpottery. Many critics <Dreyfus, 1972>, <Lighthill, 1973> have urged that we are over the border. We have been very defensive toward this charge, drawing ourselves up with dignity when it is made and folding the cloak of Science about us. On the other hand, in private, we have been justifiably proud of our ideas, because pursuing them is the only

Unfortunately, the necessity for s the culture of the hacker in computer to cripple our self-discipline. In a young field, self-discipline is not necessarily a virtue, but we are not getting any younger. In the past few years, our tolerance of sloppy thinking has led us to repeat many mistakes over and over. If we are to retain any credibility, this should stop.

This paper is an effort to ridicule some of these mistakes. Almost everyone I know should find himself the target at some point or other; if you don't, you are encouraged to write up your own favorite fault. The three described here I suffer from myself. I hope self-ridicule will be a complete catharsis, but I doubt it. Bad

though, if we can't

Wishful Mnemonics

Wishful Mnemonics

A major source of simple-mindedness in AI programs is the use of mnemonics like "UNDERSTAND" or "GOAL" to refer to programs and data structures. This practice has been inherited from more

Compare the mnemonics in Planner <Hewitt,1972> with those in Conniver <Sussman and McDermott, 1972>:

Planner	Conniver
GOAL	FETCH & TRY-NEXT
CONSEQUENT	IF-NEEDED
ANTECEDENT	IF-ADDED
THEOREM	METHOD
ASSERT	ADD

It is so much harder to write programs using the terms on the right! When you say (GOAL . . .), you can just feel the enormous power at your fingertips. It is, of course, an illusion.

When you say (GOAL . . .), you can just feel the enormous power at your fingertips. It is, of course, an illusion.

1965> What if atomic symbols had been called "concepts", or CONS had been called ASSOCIATE? As it is, the programmer has no debts to pay to the system. He can build whatever he likes. There are some minor faults; "property lists" are a little risky; but by now the term is sanitized.

Resolution theorists have been pretty good about wishful mnemonics. They thrive on hitherto meaningless words like RESOLVE and PARAMODULATE, which can only have their humble, technical meaning. There are actually quite few pretensions in the resolution literature. <Robinson, 1965> Unfortunately, at the top of their intellectual edifice stand the word "deduction". This is very wishful, but not entirely their fault. The logicians who first misused the term (e.g., in the "deduction" theorem) didn't have our problems; pure resolution theorists don't either. Unfortunately, too many AI researchers took them at their word and assumed that deduction, like payroll processing, had been tamed.

Of course, as in many such cases, the only consequence in the long run was that "deduction" changed in meaning, to become something narrow, technical, and not a little sordid.

➤ Proposal: More precise language

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- ~~Predict the risk, predict the likelihood~~: Calculate the risk, calculate the likelihood
- ~~Predict the probability~~: Estimate the probability
- ~~Prediction, predicted~~: Fitted value, fitted
- ~~We predict~~: We detect, we classify, we model
- ~~X predicts Y~~: X is correlated with Y
- ~~X predicts Y, ceteris paribus~~ (partial correlation): X is associated with Y

➤ Proposal: Use alternatives

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- Retrodiction
- Backtesting (retrodiction for testing)
- Hindcasting (backtesting for forecasting)
- In-sample vs. ➤ Out of-sample
- Interpolation vs. ➤ Extrapolation
- Diagnosis vs. ➤ Prognosis
- Retrospective vs. ➤ Prospective

➤ (Language not enough: *mechanics matter*)

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Pseudo-Mathematics and Financial Charlatanism: The Effects of Backtest Overfitting on Out-of-Sample Performance

*David H. Bailey, Jonathan M. Borwein,
Marcos López de Prado, and Qiji Jim Zhu*

Another thing I must point out is that you cannot prove a vague theory wrong. [...] Also, if the process of computing the consequences is indefinite, then with a little skill any experimental result can be made to look like the expected consequences

"training set" in the machine-learning literature). The OOS performance is simulated over a sample not used in the design of the strategy (a.k.a. "testing set"). A backtest is *realistic* when the IS performance

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► Definitions: 'Prediction' is correlation, not causation

► Prediction is correlation

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- > Prediction = "Fitted value" minimizing *loss*
- > $L(y, f(x)) = (y - f(x))^2$
- > Spurious (non-causal) correlations can *fit* really well!
- > But such fits fall apart if the context changes (Google Flu Trends)

POLICYFORUM

BIG DATA

The Parable of Google Flu: Traps in Big Data Analysis

David Lazer,^{1,2*} Ryan Kennedy,^{1,3*} Gary King,² Alessandro Vesagnani^{1,6,3}

In February 2013, Google Flu Trends (GFT) made headlines but not for a reason that Google executives or the creators of the flu tracking system would have hoped. *Nature* reported that GFT was predicting more than double the proportion of doctor visits for influenza-like illness (ILI) than the Centers for Disease Control and Prevention (CDC), which bases its estimates on surveillance reports from laboratories across the United States (1, 2). This happened despite the fact that GFT was built to predict CDC reports. Given that GFT is often held up as an exemplary use of big data (3, 4), what lessons can we draw from this error?

The problems we identify are not limited to GFT. Research on whether search or social media can predict x has become commonplace (5–7) and is often put in sharp contrast with traditional methods and hypotheses. Although these studies have shown the value of these data, we are far from a place where they can supplant more traditional methods or theories (8). We explore two issues that contributed to GFT's mistakes—big data hubris and algorithm dynamics—and offer lessons for moving forward in the big data age.

Big Data Hubris

"Big data hubris" is the often implicit assumption that big data are a substitute for, rather than a supplement to, traditional data collection and analysis. Elsewhere we



Large errors in flu prediction were largely avoidable, which offers lessons for the use of big data.

run ever since, with a few changes announced in October 2013 (10, 15).

Although not widely reported until 2013, the new GFT has been persistently overestimating flu prevalence for a much longer time. GFT also missed by a very large margin in the 2011–2012 flu season and has missed high for 100 out of 108 weeks starting with August 2011 (see the graph). These errors are not randomly distributed. For example, last week's errors predict this week's errors (temporal autocorrelation), and the direction and magnitude of error varies with the time of year (seasonality). These patterns mean that GFT overlooks considerable information that could be extracted by traditional statistical methods.

Even after GFT was updated in 2009, the comparative value of the algorithm as a stand-alone flu monitor is questionable. A study in 2010 demonstrated that GFT accuracy was not much better than a fairly simple projection forward using already available (typically on a 2-week lag) CDC data (4). The comparison has become even worse since that time, with lagged models significantly outperforming GFT (see the graph). Even 3-week-old CDC data do a better job of projecting current flu prevalence than GFT [see supplementary materials (SM)].

Considering the large number of approaches that provide inference on influenza activity (16–19), does this mean that

➤ (Caution: “Causation” is itself limited)

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- Critique 1: Causal inference (econometrics) can fail hopelessly
- Critique 2: Automated methods (from “causal learning”) have strong, unrealistic, and untestable assumptions
- Critique 3: Statistical expression of causation is short-range (Gene Richardson)

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A Cautionary Note on the Use of Matching to Estimate Causal Effects: An Empirical Example Comparing Matching Estimates to an Experimental Benchmark

Kevin Arceneaux¹, Alan S. Gerber², and Donald P. Green²

Abstract

In recent years, social scientists have increasingly turned to matching as a method for drawing causal inferences from observational data. Matching compares those who receive a treatment to those with similar background attributes who do not receive a treatment. Researchers who use matching frequently tout its ability to reduce bias, particularly when applied to data sets that contain extensive background information. Drawing on a randomized voter mobilization experiment, the authors compare estimates generated by matching to an experimental benchmark. The enormous sample size enables the authors to exactly match each treated subject to 40 untreated subjects. Matching greatly exaggerates the effectiveness of pre-election phone calls encouraging voter participation. Moreover, it can produce nonsensical results: Matching suggests that another pre-election phone

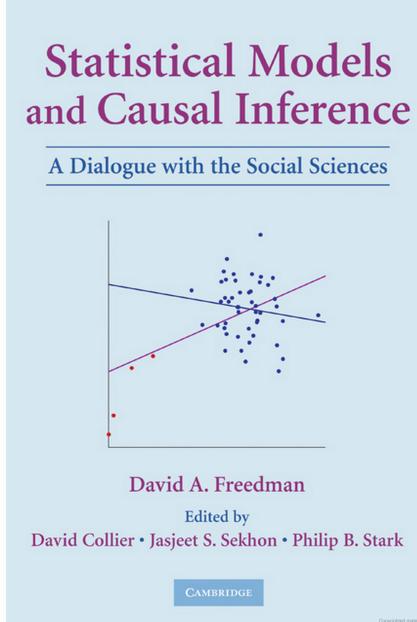
¹Temple University, Philadelphia, PA, USA

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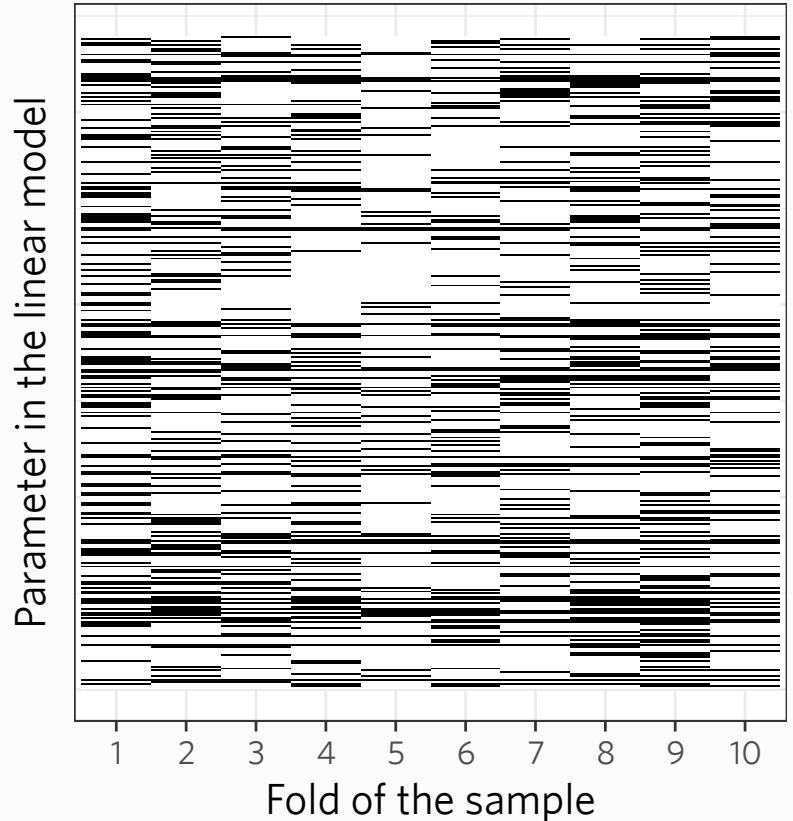
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➤ The problem with correlation

- Very different models will 'predict' equally well, and often better than any theory-driven model (Mullainathan & Spiess, 2017)
- For *intervention*, we need causality (or at least associations)
- Another problem: correlations can *overfit*



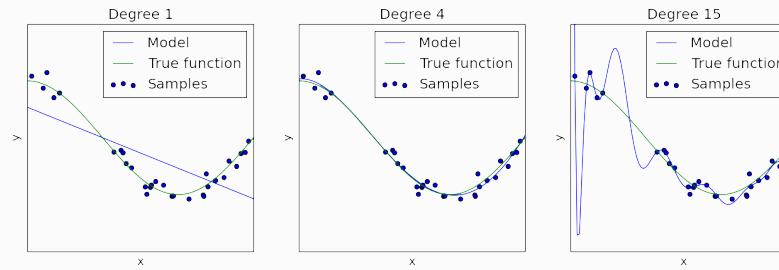
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➤ **Validity: Correlations can overfit, cross-validation doesn't fully address**

Overfitting and cross validation

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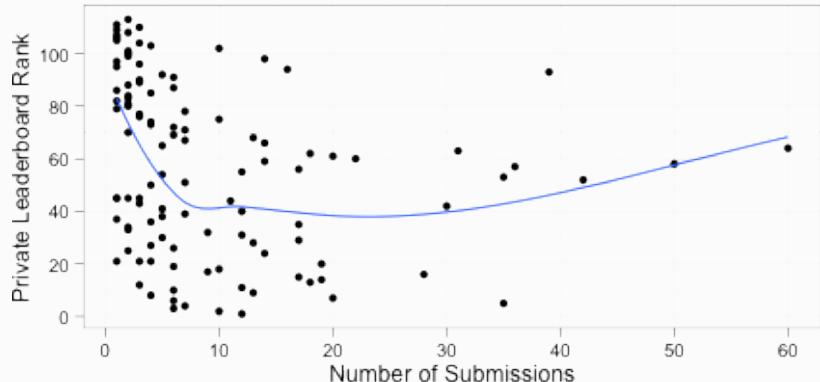
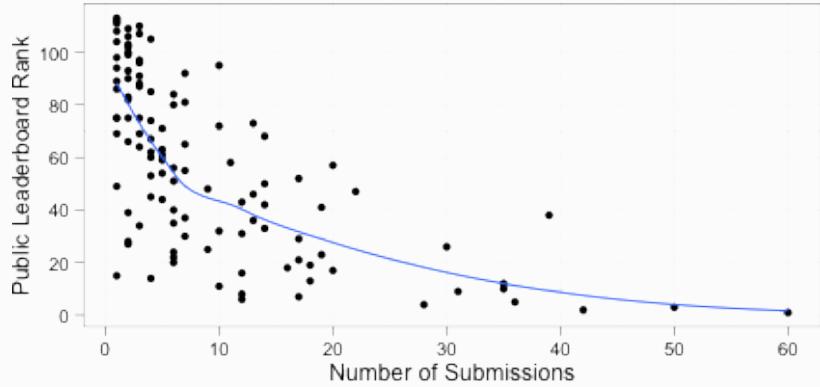
- ▶ Overfitting: Model correlates with the 'noise' rather than causes/*data-generating process*. Machine learning metaphor: "memorize the data."



- ▶ (A *p*-value compares fit and *uncertainty*; overfitting is simpler)
- ▶ Cross validation: split the data into two parts (e.g., 1:1, 4:1, 9:1). *The central tendency should be the same, but not the noise.* Error rate on the held-out "test" set should say how well correlations generalize

➤ But cross-validation can fail

- Re-using the test set can overfit to the test set!
Happens in Kaggle
- Or, if there are dependencies (temporal, network, group) between data splits, it “shares” information
- E.g., temporal: Fitting on values that come after test values is “time traveling”!



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➤ A 'false' model may predict better than a 'true' one

➤ The bias-variance tradeoff

- The bias-variance ‘decomposition’, a foundational result for machine learning and modern statistics:

$$\begin{aligned}\text{EPE}(x) &= \mathbb{E}[(Y - \hat{f}(x))^2 | X = x] \\ &= \text{Var}(Y) + \mathbb{E}[(\hat{f}(x) - f(x))^2 | X = x] + \mathbb{E}[(\hat{f}(x) - \mathbb{E}[\hat{f}(x)])^2 | X = x] \\ &= \sigma^2 + \text{bias}^2(\hat{f}(x)) + \text{Var}(\hat{f}(x))\end{aligned}$$

- Leads to a ‘tradeoff’: *Even if we have all the “right” variables, a biased model may be better*
- This is very strange!

► Simulation illustration: Setup

- A linear data-generating process.

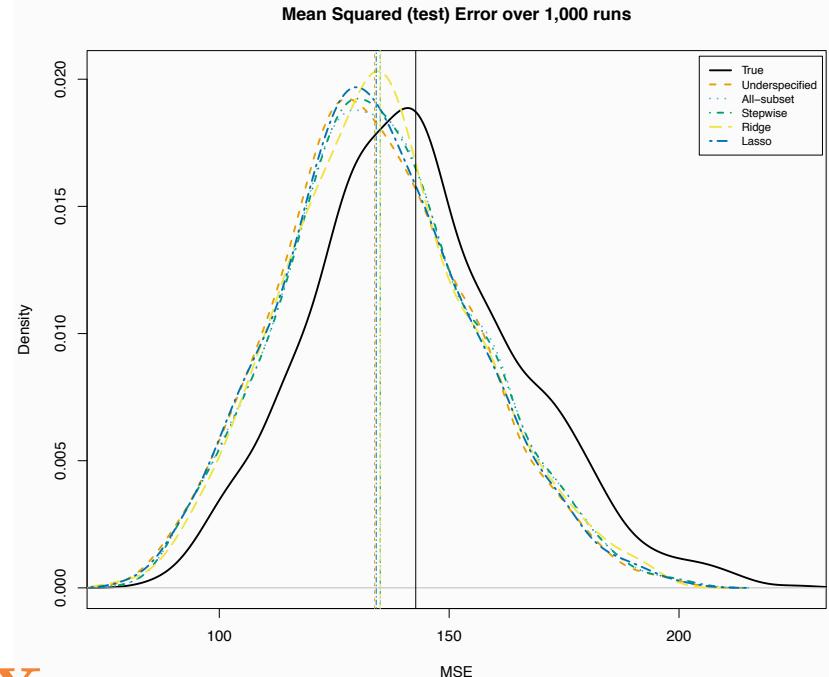
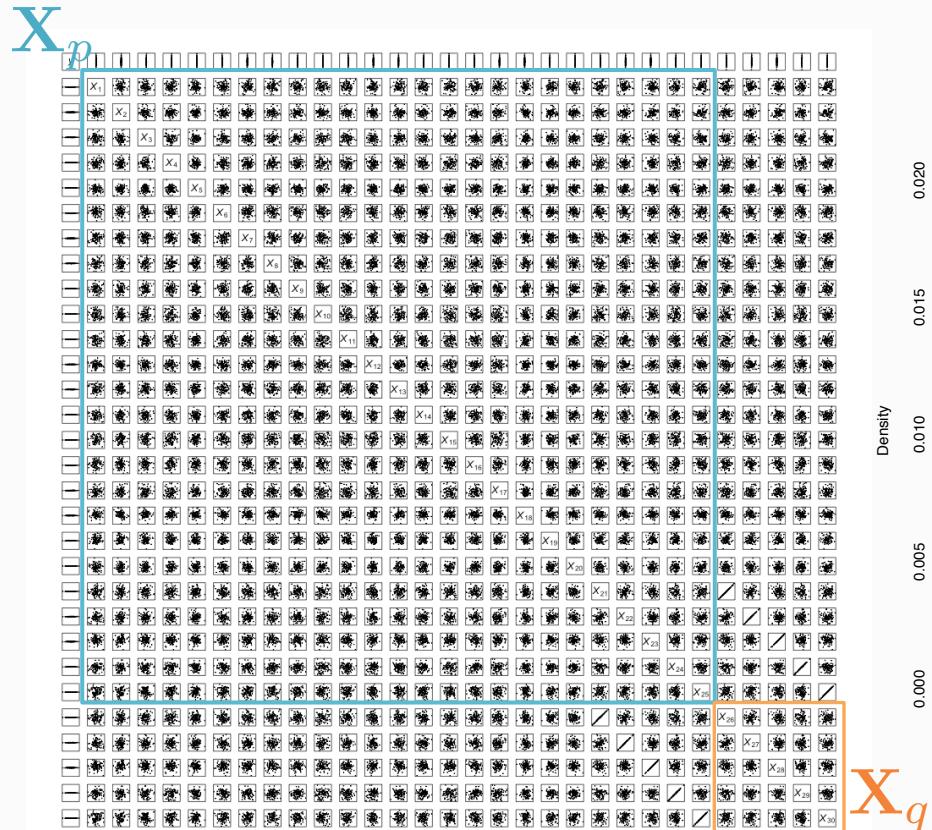
$$\mathbf{y} \sim \mathcal{N}(\beta_p \mathbf{X}_p + \beta_q \mathbf{X}_q, \sigma^2 \mathbf{I})$$

- Wu et al. (2007): Fitting only \mathbf{X}_p has lower expected MSE than fitting the model that generated the data when:

$$\beta_q^T \mathbf{X}_q^T (\mathbf{I}_n - \mathbf{H}_p) \mathbf{X}_q \beta_q < q\sigma^2$$

► The 'true' model predicts worse!

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- ‘Prediction’ is a metaphor used for fitted values, not (necessarily) actual prediction
- Spurious correlations count as ‘prediction’ and can do quite well in narrow terms, but are fragile and don’t help us intervene
- Correlations can overfit, and cross-validation doesn’t fully solve
- The bias-variance tradeoff means things are even more strange
- *I would argue: These are the pertinent issues*

➤ Thank you!

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Robot holding skull: Cover image of "What Will Become of Us?", *New York Times Magazine* (The Tech & Design issue), 14 November 2018. Concept by delcan & company. Photo illustration by Jamie Chung. Prop styling by Pink Sparrow. C.G. work by Justin Metz.
<https://www.nytimes.com/2018/11/14/magazine/behind-the-cover-what-will-become-of-us.html>.

Terminator skull: Nemesis Now Ltd, Terminator Skull Box T-800 (18CM). <https://www.menkind.co.uk/terminator-t800-skull-box>.

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