



WHAT WILL BECOME OF US

↳ HOW TECHNOLOGY IS
CHANGING WHAT IT MEANS TO BE HUMAN.

NOVEMBER 18, 2018



- ▶ Introduction
- ▶ "AI" is not AI
- ▶ "Prediction" is not prediction
- ▶ "Prediction" is not causation
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► "AI" is a Lie: Getting to the Real Issues

► *Momin M. Malik, PhD <momin_malik@cyber.harvard.edu>*
Data Science Postdoctoral Fellow
Berkman Klein Center for Internet & Society at Harvard University

AGTech Forum, 13 December 2018

Slides: <https://mominmalik.com/agtech2018.pdf>

► 3-point summary

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- Rule of thumb: Any place you see "AI" or "machine learning," substitute with "statistics"
- And any time you see "X predicts Y," read, "X correlates with Y"
- Only real-world testing (not simulated testing, nor real-world deployment) will tell if correlations will predict

>About me

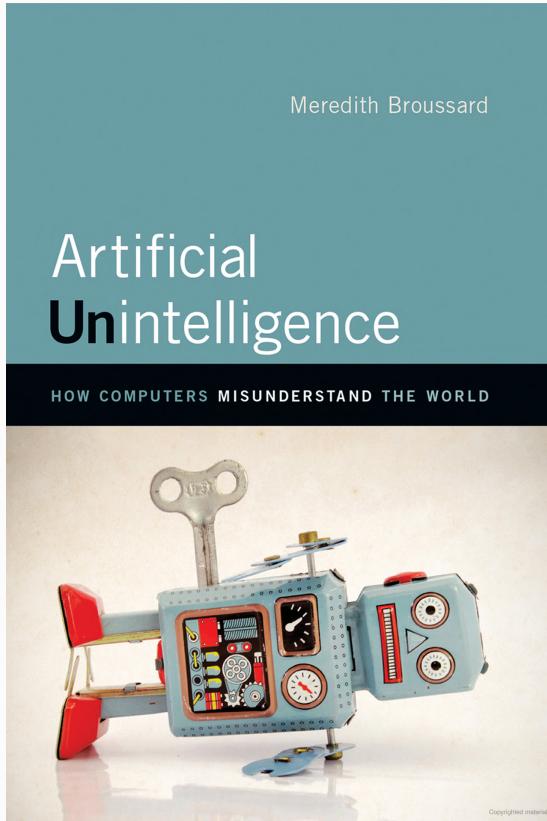
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FOR INTERNET & SOCIETY AT HARVARD UNIVERSITY

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► "AI" is not AI, but statistics

➤ “So, it’s not real AI?”



“AI” is a Lie

- “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.”

➤ Internally, joking about mismatch

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 **Baron Schwartz** 
@xaprb 

When you're fundraising, it's AI
When you're hiring, it's ML
When you're implementing, it's linear regression
When you're debugging, it's printf()

12:52 AM - 15 Nov 2017

5,545 Retweets 12,654 Likes

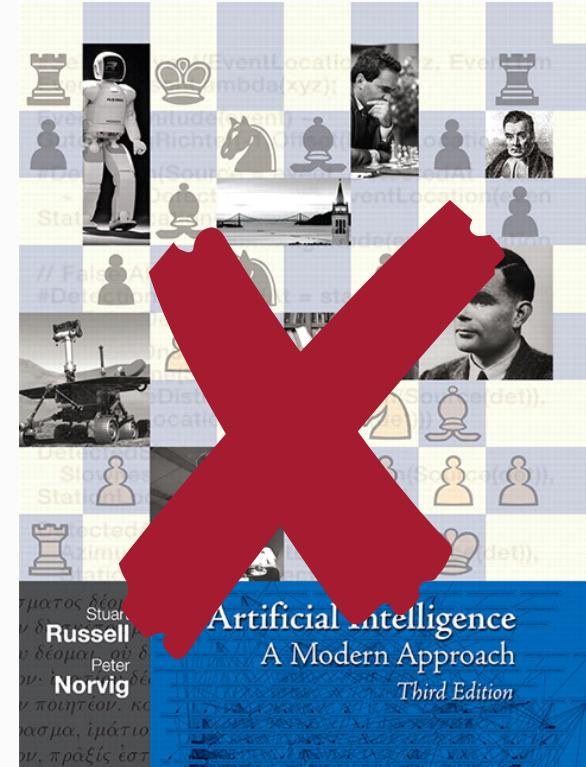
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➤ AI changed, but kept the same name!

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➤ “After about 14 years of trying to get language models to work using logical rules, I started to adopt probabilistic approaches.” (Peter Norvig, “On Chomsky,” 2010)



➤ Aspirational naming misleads

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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

I am not sure if I can do it 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.



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➤ “Prediction” is not prediction, but retrospective

► Prediction seems scary powerful



Topics+ The Download Magazine Events

Intelligent Machines

Software Predicts Tomorrow's News by Analyzing Today's and Yesterday's

Prototype software can give early warnings of disease or violence outbreaks by spotting clues in news reports.

by Tom Simonite February 1, 2013

A method of using online information to predict the future could transform many industries.

► Predict... the future?

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Mar 2010

Predicting the Future With Social Media

Sitaram Asur
Social Computing Lab
HP Labs
Palo Alto, California
Email: sitaram.asur@hp.com

Bernardo A. Huberman
Social Computing Lab
HP Labs
Palo Alto, California
Email: bernardo.huberman@hp.com

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

1216

N ENGL J MED 375;13 NEJM.ORG SEPTEMBER 29, 2016

The New England Journal of Medicine

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predict *verb*

pre-dict | \pri-dikt \v

predicted; predicting; predicts

Definition of *predict*

transitive verb

: to declare or indicate **in advance**

especially : foretell on the basis of observation, experience, or scientific reason

intransitive verb

: to make a *prediction*

↓ Other Words from *predict*

↓ Synonyms

↓ Choose the Right Synonym

➤ Prediction is not prediction

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- “*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.” (Daniel Gayo-Avello, 2012)

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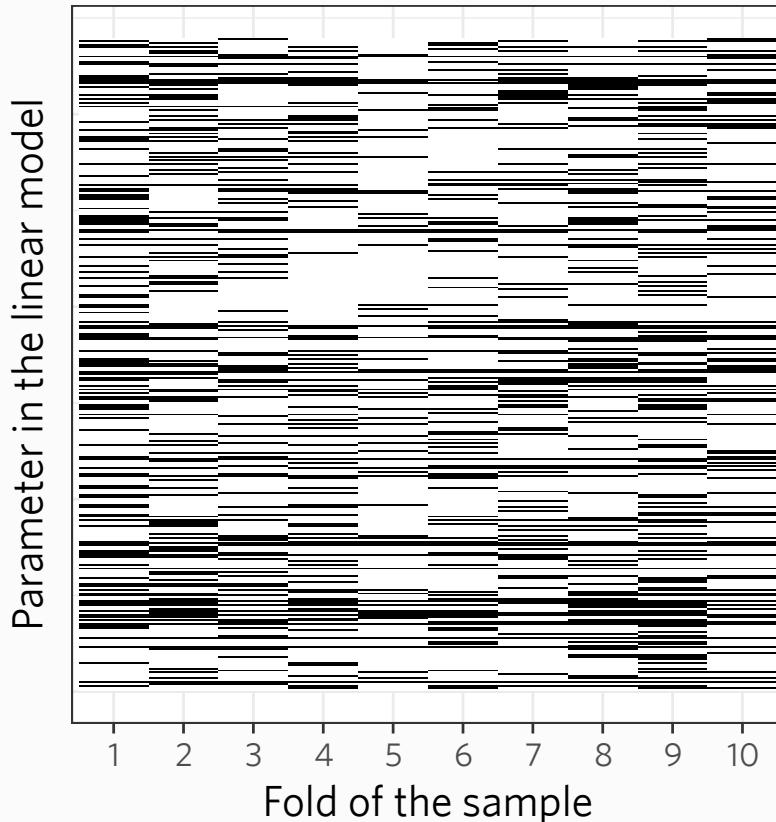
► Prediction is correlation, not causation

➤ Prediction is correlation

- Spurious (non-causal) correlations can fit the data really well!
- Google Flu Trends: half flu detector, half winter detector



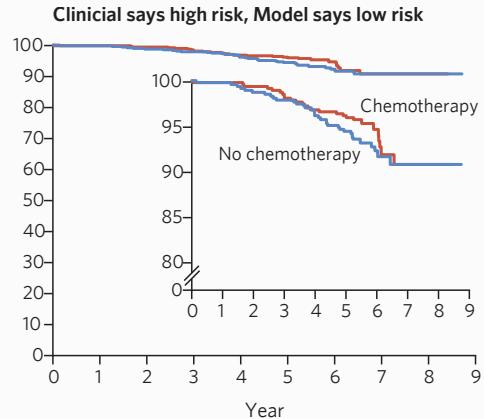
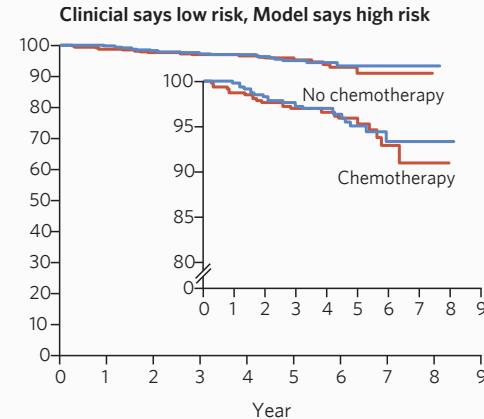
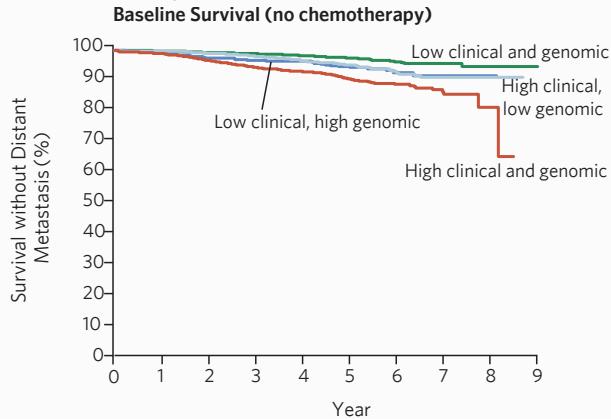
► Intervention requires causality



- › Very different sets of correlations can “predict” equally well
- › But they suggest very different interventions

► At a minimum, demand real-world experimental testing

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- Breast cancer: when a machine learning model said "high risk" but clinical risk was low, chemo made things worse!
- (But can help avoid unnecessary chemo)

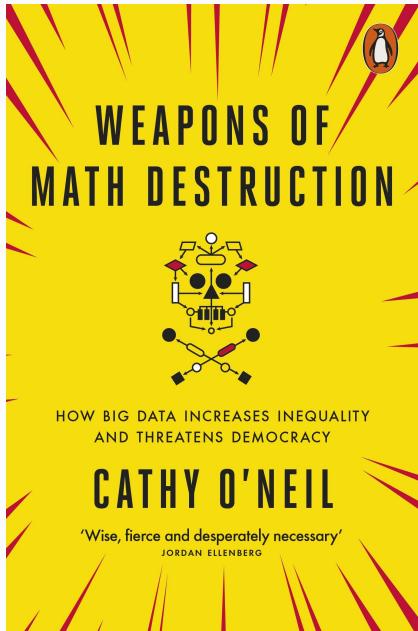
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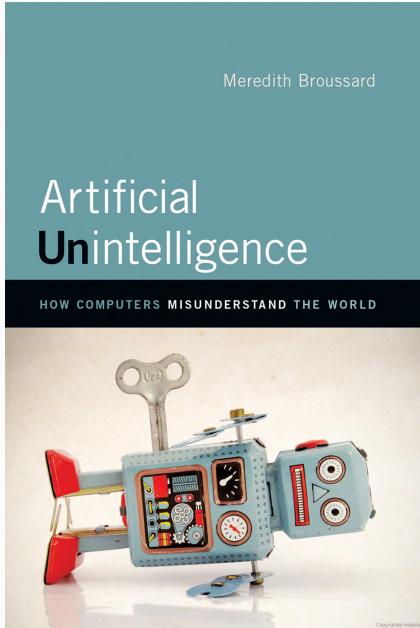
- There's lots of misleading language. Don't believe the hype, or everything you hear.
- Anything using “artificial intelligence” or “machine learning” is going to be statistical
- AI, ML are based on *correlations*. Among other issues, they can go wrong in every way that correlations can go wrong.

➤ Further reading

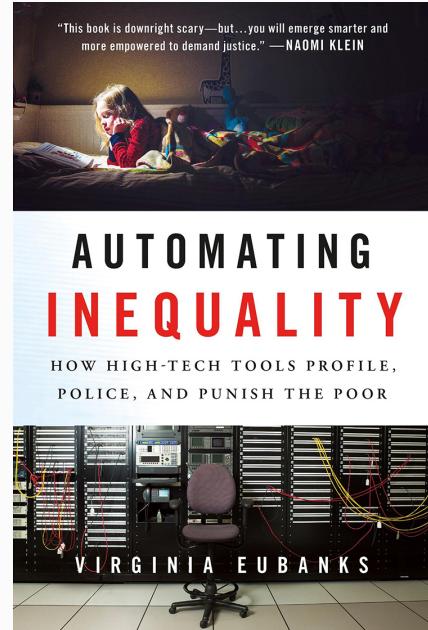
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➤ One of the earliest, still one of the best!



➤ Chapter 7: best machine learning overview for lay audience
(But, two subtle mistakes: see mominmalik.com/broussard)



➤ Stories showing that *implementation is key*. The best intentions, and most careful technical work, can go awry.



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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>.

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Summary

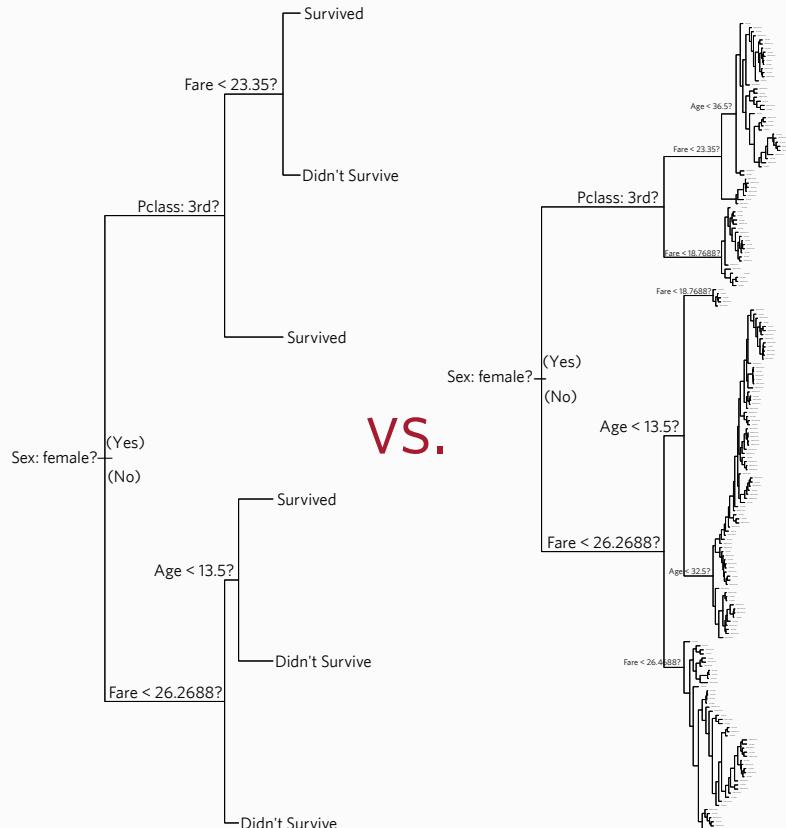
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➤ Correlations can “overfit”

- *Overfitting*: Model finds correlation to random ‘noise’ (“memorizes the data”)
- (Overfitting is simpler than “*p*-hacking,” but similar)
- Existing solution: split the data (e.g., 1:1, 4:1, 9:1). “Hold out” one part. Idea: *The signal should be the same, but not the noise*. Testing on held out data (cross-validation) should reveal overfitting



➤ But cross-validation can fail

- Re-using the test set can overfit to the test set! E.g., Kaggle competitions
- 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"!

