

Information(?) ~~Data~~ \wedge Ethics

Dwight Barry, PhD

Principal Data Scientist

Seattle University, May 2019



Request for survey responses (*voluntary*)

<https://is.gd/techethics>

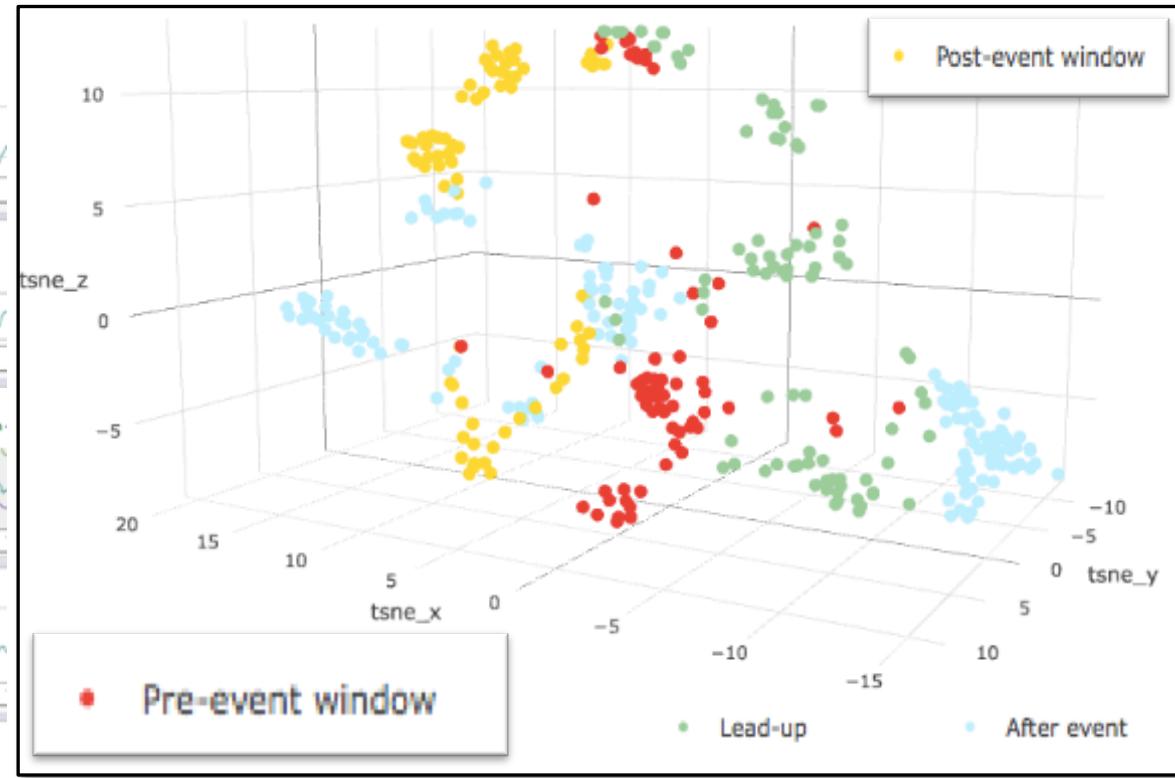
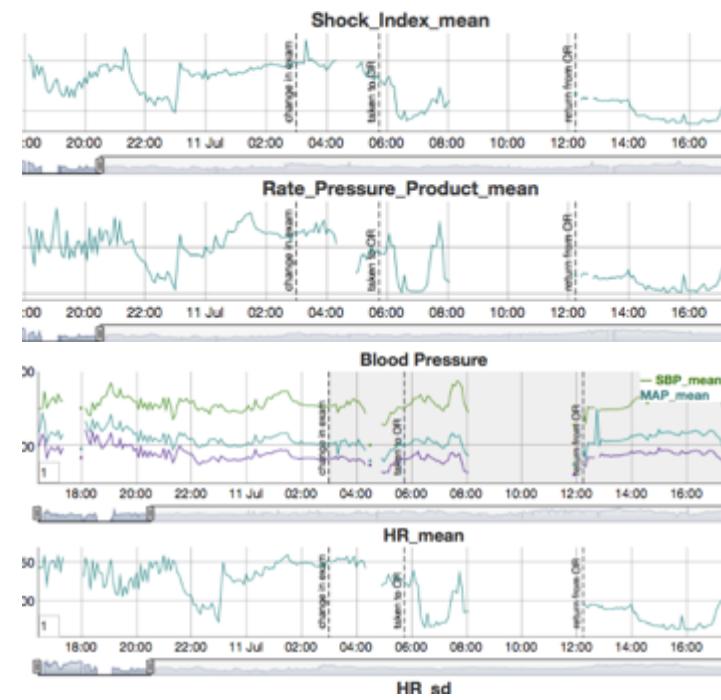


Serves a population of **2.8 million children**
\$2.3 billion USD annual revenue
10k clinicians & employees



A medical ICU scene featuring a patient in a bed connected to various monitoring devices. In the foreground, a Philips monitor displays two large numbers: (188) in green and (170) in red. Above it, a larger monitor shows a multi-parameter ECG strip with values like 112, 100, 104/76 (83), and 14. To the right, another monitor shows a heart rate of 77. A man with glasses and a beard is visible on the left, looking at the equipment. The room is filled with medical apparatus, including infusion pumps and a ventilator.

1,000
data points
per patient
per minute



Goal: Real-time analysis of organ function to prevent critical incidents & assist best possible long-term outcome by supporting brain health

9:51 ↗



Unit

All

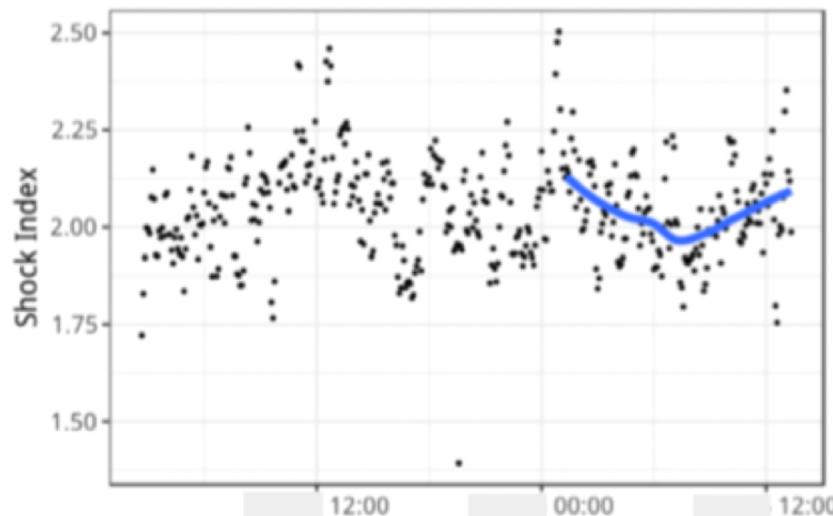
Unit

CICU-F6

Last Name:

Room

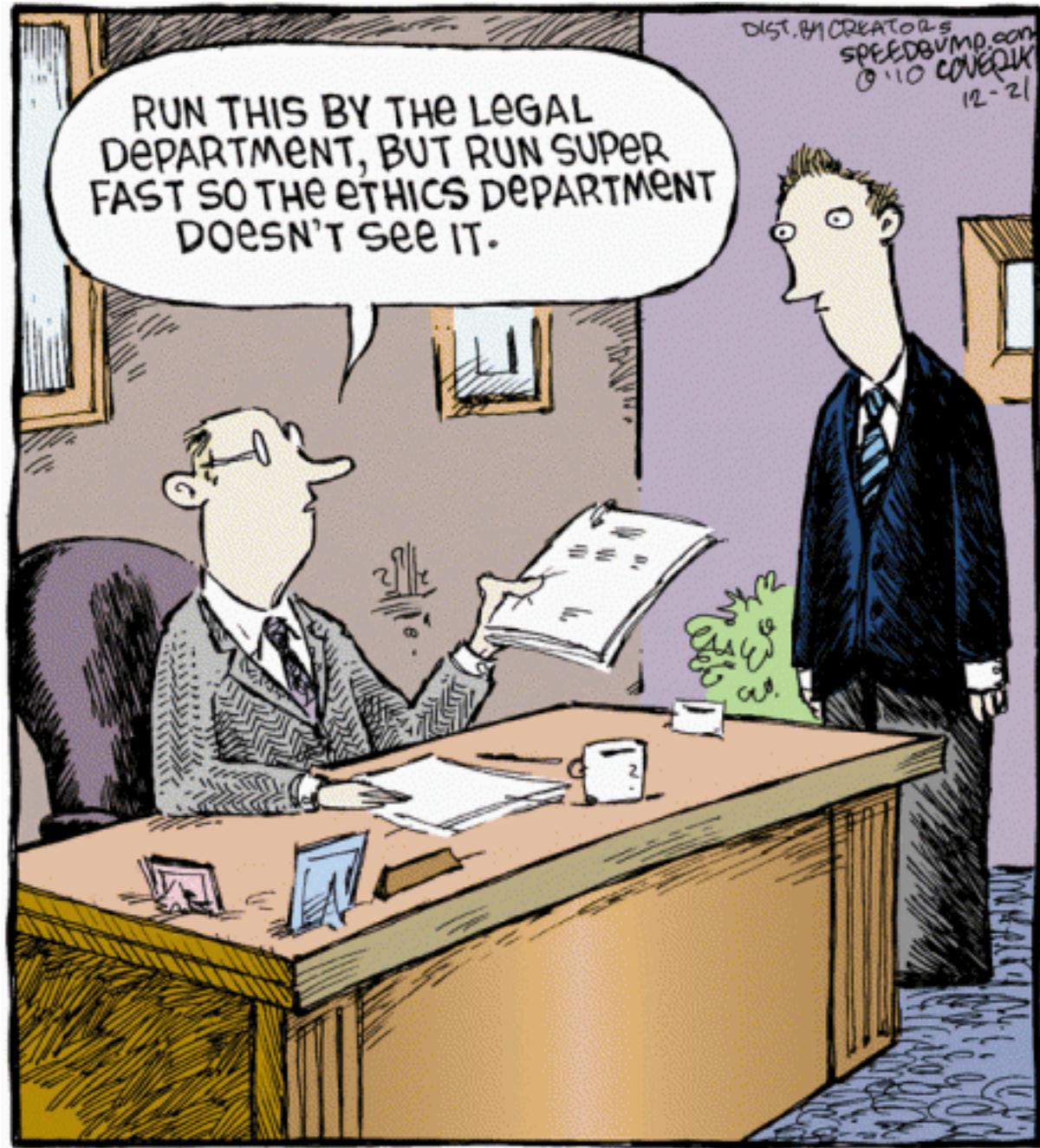
FA.6.



What comes to mind when
you think about ethics?

DIST. BY CREATORS
SPEEDBUMP.COM
© 10 COVERDIX
12-21

RUN THIS BY THE LEGAL
DEPARTMENT, BUT RUN SUPER
FAST SO THE ETHICS DEPARTMENT
DOESN'T SEE IT.



Why *data* ethics?



**DATA SCIENCE IS RESHAPING
THE HEALTHCARE INDUSTRY**

PS Ops: Home

System State

Housewide

		Inpatient		Psychiatry		
		Staffing	Capacity	Staffing	Capacity	Mitigation
Today	Night	2				
	Day	1				
		2				
	Evening	1				
		2				
	Night	1				
4/2/2016						
4/3/2016						
4/4/2016						
4/5/2016						
4/6/2016						
4/7/2016						
1-2 Weeks						
3-4 Weeks						
5-6 Weeks						

Unit: **PICU**

		Staffing	Capacity	State of Unit
Today	Night	2		
	Day	1		
		2		
	Evening	1		
		2		
	Night	1		
4/2/2016				
4/3/2016				
4/4/2016				
4/5/2016				
4/6/2016				
4/7/2016				
1-2 Weeks				
3-4 Weeks				
5-6 Weeks				

Reports

[Daily Summary](#) [IP Microsystem](#) [Staffing](#) [Patient](#) [Forecasts](#) [Utilization](#) [Events](#) [System](#) [Manuals](#)

Events

Event Type	Impact Level	Start	End	Description
Open Overflow	Critical	3/30/2016	4/1/2016	open B6400 Pod
Open Overflow	Critical	3/31/2016	4/1/2016	Opening B6 500 Pod for critical care
Renovation	High	3/7/2016	6/13/2016	Location B Entrance Renovation

System Update Times

0230, 0430, 0600, 0930, 1030, 1130,
1230, 1430, 1530, 1830, 2030, 2230

[New Version](#)

My Version: TV0.04

Current Version: V0.03

Test Version: TV0.04

System Messages: **No Message.**

PS Ops: Housewide Requests

[Save!](#)
[Exit](#)

[Home](#)

Date: 4/1/2016 Shift: Day 2

[Refresh](#)
[RN](#) [MHS/MHF](#) [PCA](#) [PCA 1:1](#) [HUC](#) [Psych](#) [PTO HL](#) [PCA 1:1 Requests](#) [Reports](#)

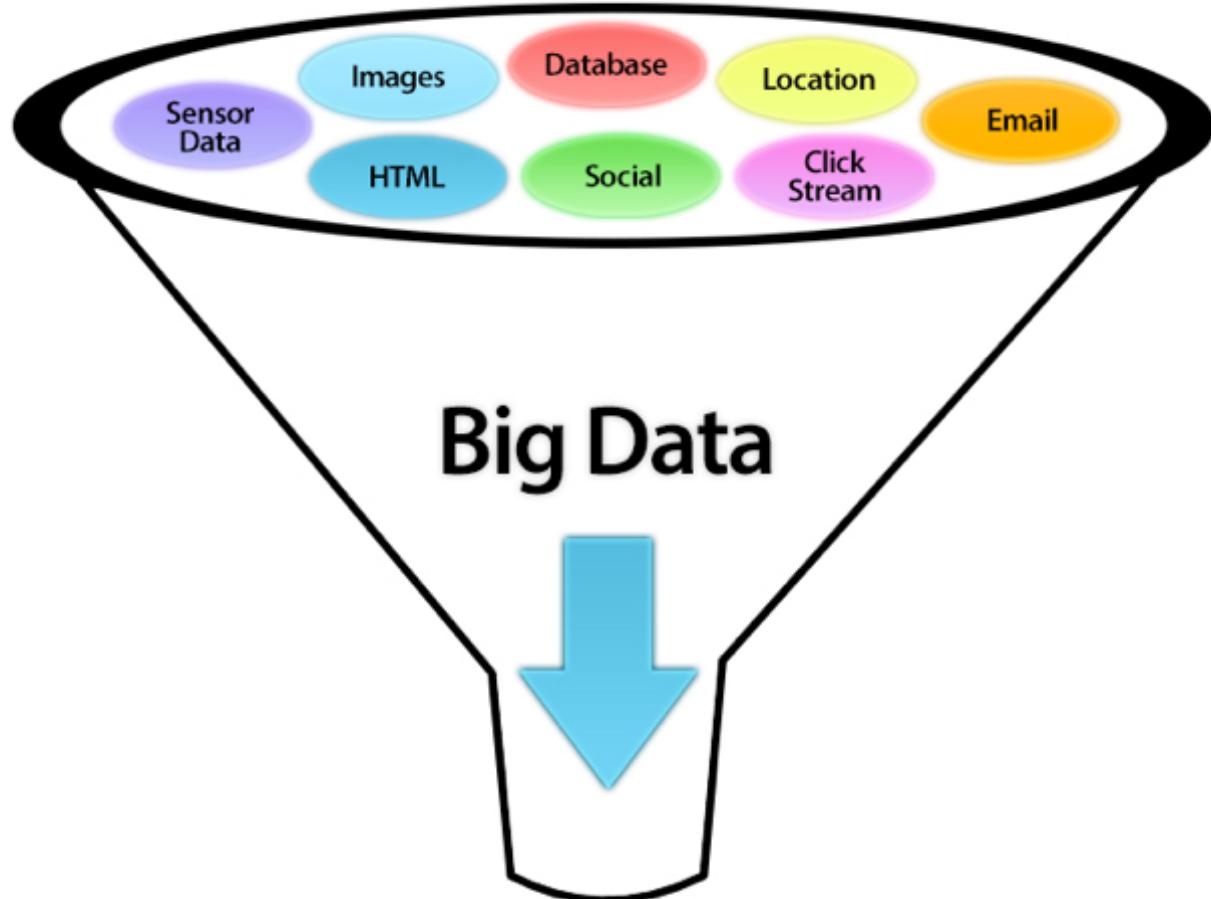
RN (POC)

[Copy Last Shift](#)

Filter: All Main Psych Liberty Sort: Unit Priority

Department												Schedule		Request				Mitigate						
Req	Unit	Occupancy	Acuity	Call Offs	Kro Data	Target	Variance	Request	Extra	Comment	CN UA p A	Pickup	Sent	Rec.	Rec. Dept	Return	Canc.	Var	Comment					
Adol Med	A6N	21	88% █	10.8	0	1	7	8	-1	0	0	0	0	0	0	0	0	-1						
BMT	ASS/ASN	34	94% █	16.0	2	1	17	22	-5	0	0	0	0	0	0	0	0	-4						
CICU	B6HI	22	88% █	16.8	0	2	16	18	-2	0	0	0	0	0	0	0	0	-2						
Comp Pulm	A7C1	8	73% █	11.3	0	1	4	3	1	0	0	0	0	0	0	0	0	0	1					
Complex Airway	B5CA	9	82% █	10.8	2	1	2	4	-2	1	0	511	0	0	1	0	0	-1						
CST	CST	0	0.0	0	0	0	0	0	0	0	0	0	0	2	0	LIB A4N, BSC	0	0	-2					
ED	B1	0	0.0	3	1	16	0	17	1	0	0	0	0	0	0	0	0	0	17					
Endocrine	A7C2	8	89% █	10.7	0	1	2	3	-1	0	0	0	0	0	0	0	0	-1						
Gen Surg	A3N	22	100% █	11.5	0	1	7	8	-1	0	0	0	0	0	0	0	0	-1						
GI Liver	A4N	23	96% █	13.5	2	1	8	11	-2	0	0	0	0	0	1	0	0	-1						
GI Lumen	A4S	17	71% █	9.9	0	1	8	6	2	0	1	0	0	0	0	0	1	1						
H/O	ASC/ASN	30	94% █	13.0	0	2	15	15	0	0	0	0	0	0	0	0	0	0						
Hosp Med	A6S	20	83% █	10.2	1	1	6	7	-1	0	0	PTAT 635.6	0	0	0	0	0	-1						
IP OF	IPU2	10	100% █	10.3	0	0	0	0	0	0	0	0	0	2	0	0	0	0	2					
Neuro/Trauma	A7NS	32	78% █	11.0	0	2	13	12	1	0	0	0	0	0	0	0	0	0	1					
NICU	B4	52	88% █	13.7	0	3	30	33	-3	2	0	0	0	0	2	0	0	-1						
PICU	B5CC	33	94% █	16.8	2	3	23	28	-5	5	0	includes ove	0	0	5	0	0	0						
Rehab	A4C1	9	90% █	10.4	0	1	3	3	0	0	0	470, 474	0	0	0	0	0	0						
SRU-RN	SRU-RN	0	0.0	0	0	9	0	9	0	0	0	0	0	9	0	0	0	0						
TCC	A3S	22	92% █	21.1	0	1	10	11	-1	0	0	MHS 342; 1	0	0	0	0	0	-1						
Tele	A6C	12	71% █	12.7	0	1	8	6	2	0	0	0	0	1	0	B4	0	0	1					

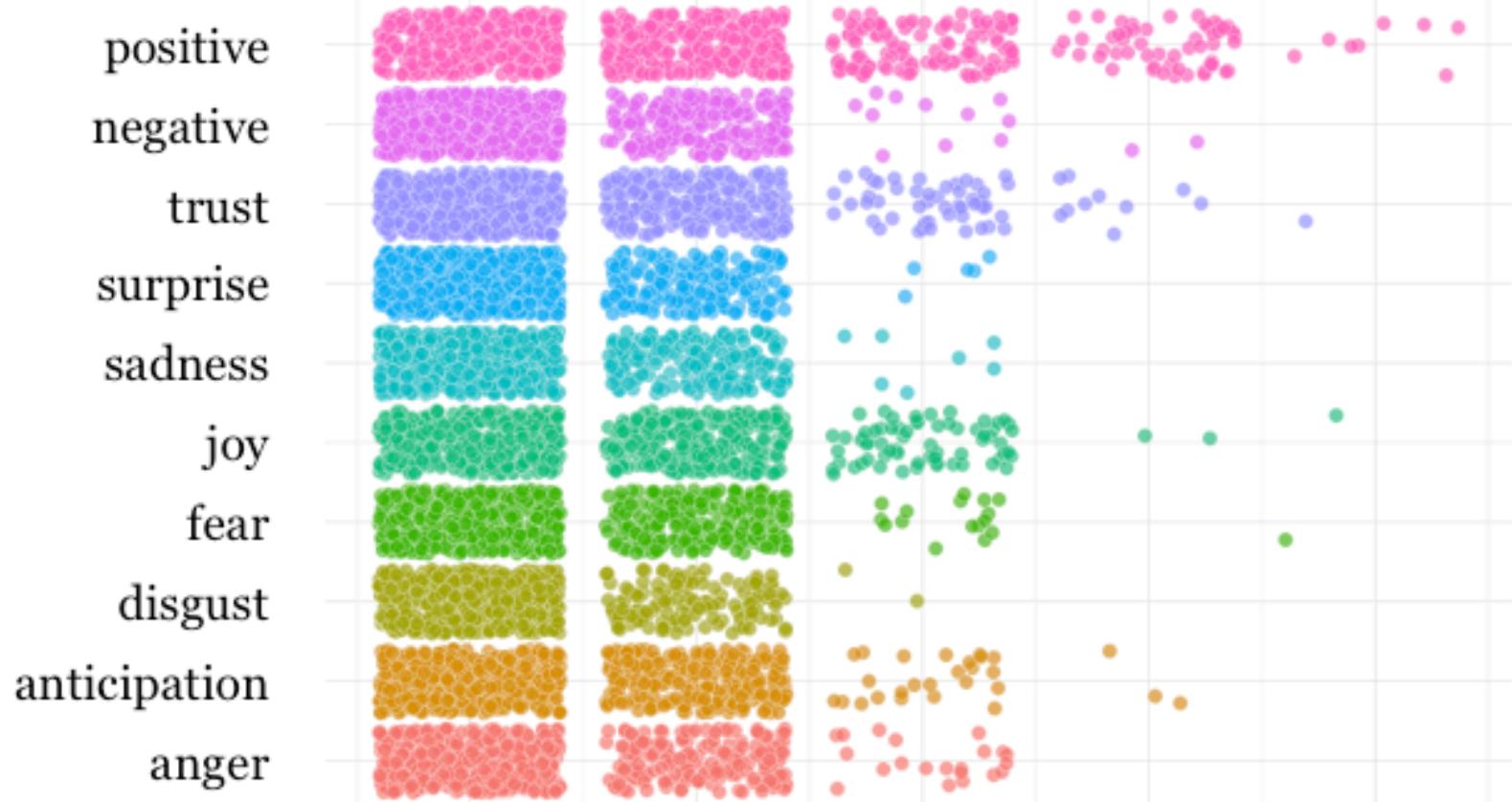
Total	384	█	12	198	198	8	9	1				0	12	12			0	1	-1
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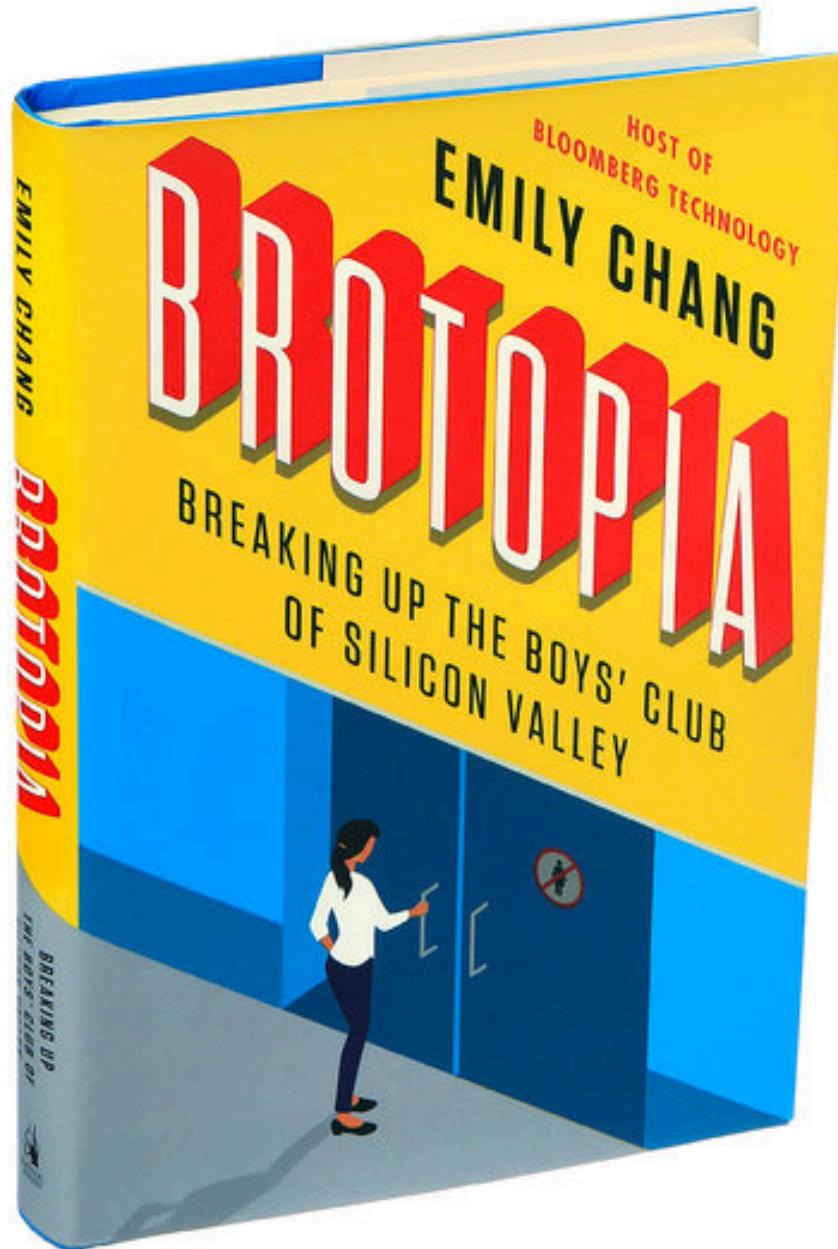


Actionable Intelligence



Tweets about Seattle Children's





BuzzFeed News

Game of Thrones Constance Wu Amazon

TECH

A Multimillion-Dollar Startup Hid A Sexual Harassment Incident By Its CEO — Then A Community of Outsiders Dragged It Into the Light

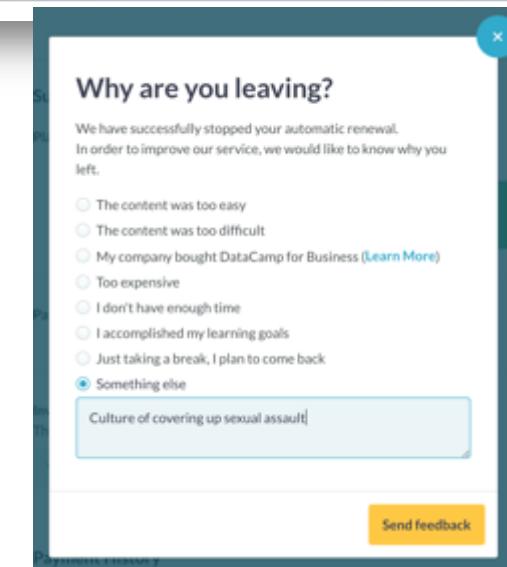
"Sexual misconduct happens everywhere. But DataCamp was dealing with a community with abnormally high standards and support for each other."

By Davey Alba

Posted on May 13, 2019, at 9:30 a.m. ET



The screenshot shows the DataCamp website's "Community" section. On the left, there's a sidebar with "News" (BETA), "Tutorials", "Cheat Sheets", "Open Courses", and "Podcast - DataFramed". The main content area has a heading "A note to our community" and some text below it. At the bottom, a browser's developer tools "Elements" tab is open, showing the page's HTML structure. A yellow circle highlights a specific line of code: "". The entire screenshot is framed by a thick black border.



R

Clinical Bioethics Consult Note

Big data predictive modeling on hospital staff



Treuman Katz Center
for Pediatric Bioethics

Patient Name:**DOB:****MR#:****Consult Date:** 12/09/2016**Attending Consultant:** Shah, Seema**Secondary Consultant:** Tate, Tyler**Requester:** Barry, Dwight**Requester's Service:** Enterprise Analytics

Reason for Consult:

To address the ethics of using predictive analytics (or "big data") as an evaluative and predictive tool within a healthcare organization.

Other Issues Identified:

None

Background:

Dwight Barry, lead data scientist at Seattle Children's Hospital, requested an ethics consult to help him understand and evaluate the ethical aspects of what he calls "people analytics," or using data to predict things about individuals within the organization. A more common term for this is "big data," which is defined by the Oxford English Dictionary as "Extremely large."

4. Training

Both the methodology/mechanics and the ethics of Big Data use are rapidly developing and constantly changing. Those working in data analysis may not have the ethics training to identify emerging issues or know when to call for a consult. Others within the organization may lack the technical training to understand what efforts are being undertaken and what potential issues might arise. It could therefore be beneficial to have planned seminars or lectures that could train large numbers of people to be able to both understand how big data actually works and to train data analysts in how to identify ethical issues that may arise in their work. One way to do this may be to have lectures or seminars open to the Seattle Children's community on the types of ethical issues that may arise, such as an ethics grand rounds presentation with an invited speaker. Another possibility is for a joint effort between an ethicist and data analyst to create a short annual training course for analysts and data-oriented employees on predictive modeling ethics. We are also happy to continue to be involved in training efforts or if further consultation is necessary.

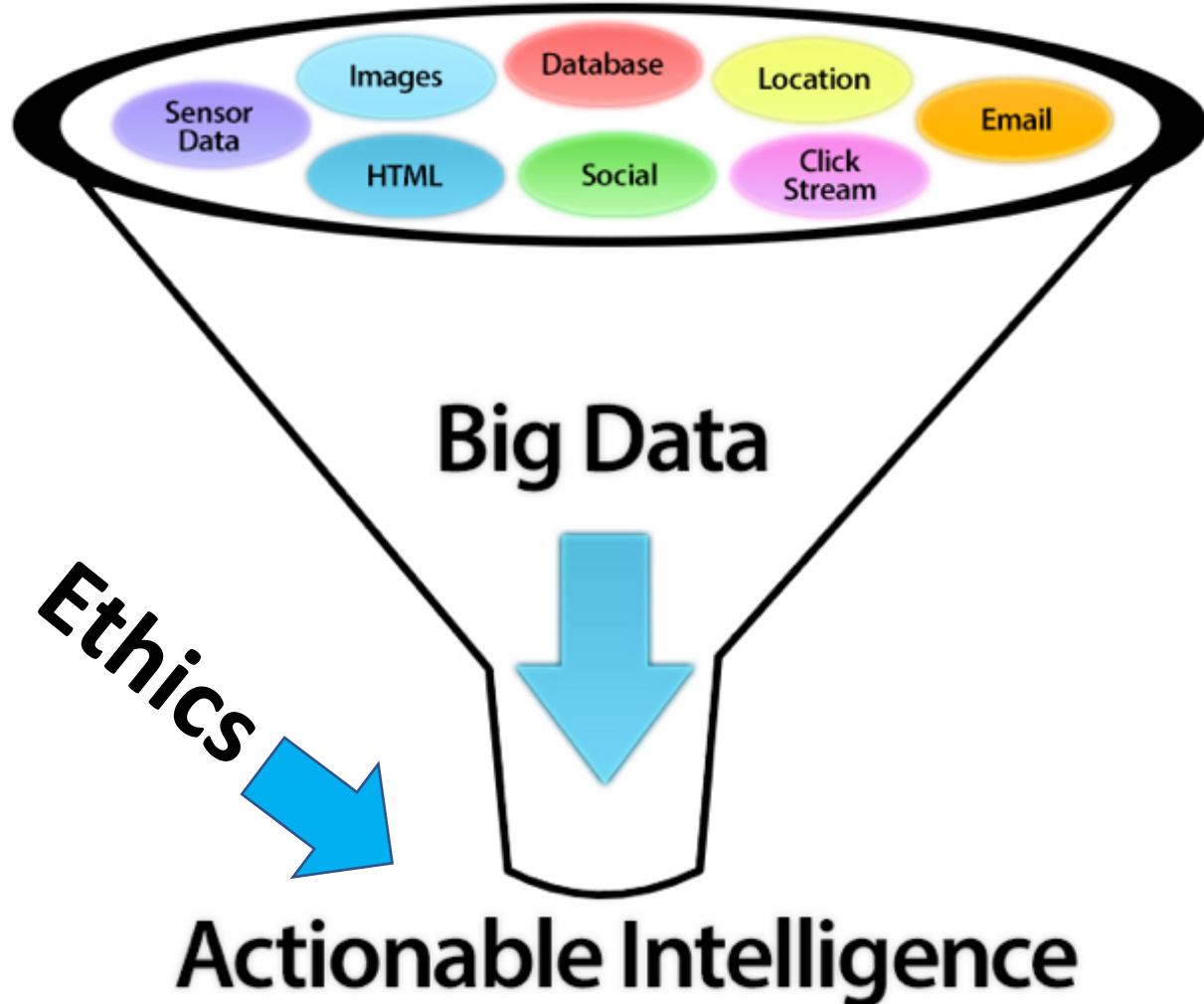
organization.

Other Issues Identified:

None

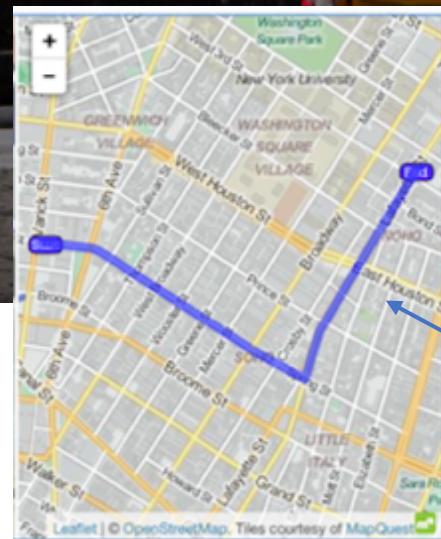
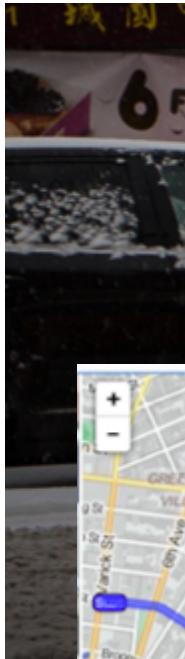
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Dwight Barry, lead data scientist at Seattle Children's Hospital, requested an ethics consult to help him understand and evaluate the ethical aspects of what he calls "people analytics," or using data to predict things about individuals within the organization. A more common term for this is "big data," which is defined by the Oxford English Dictionary as "Extremely large



NYC Taxi Database

20GB+ of uncompressed data comprising more than **173 million individual trips** that provided ...

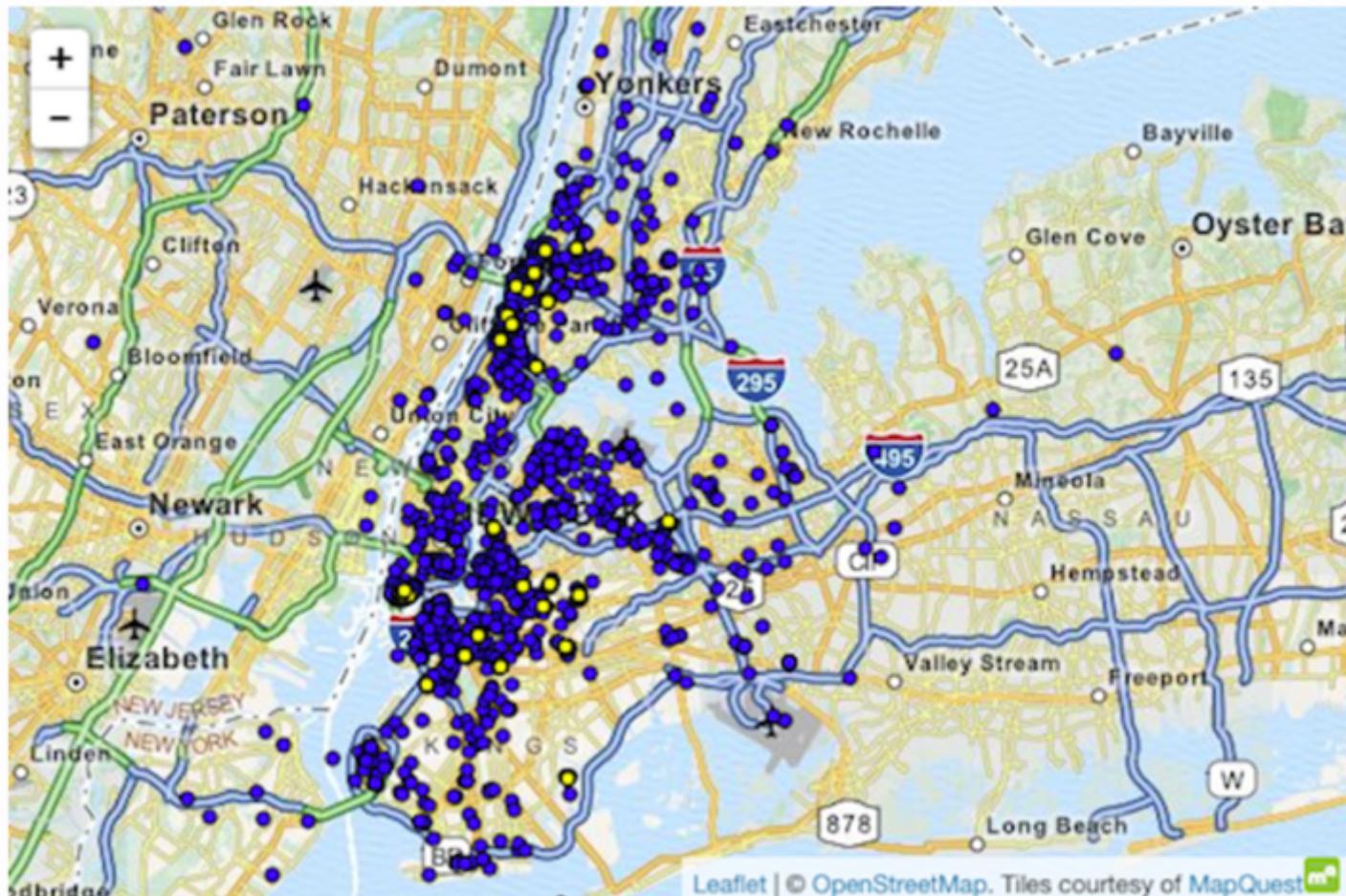


...anonymized version of the
taxi's unique id number,

pickup and drop off location,

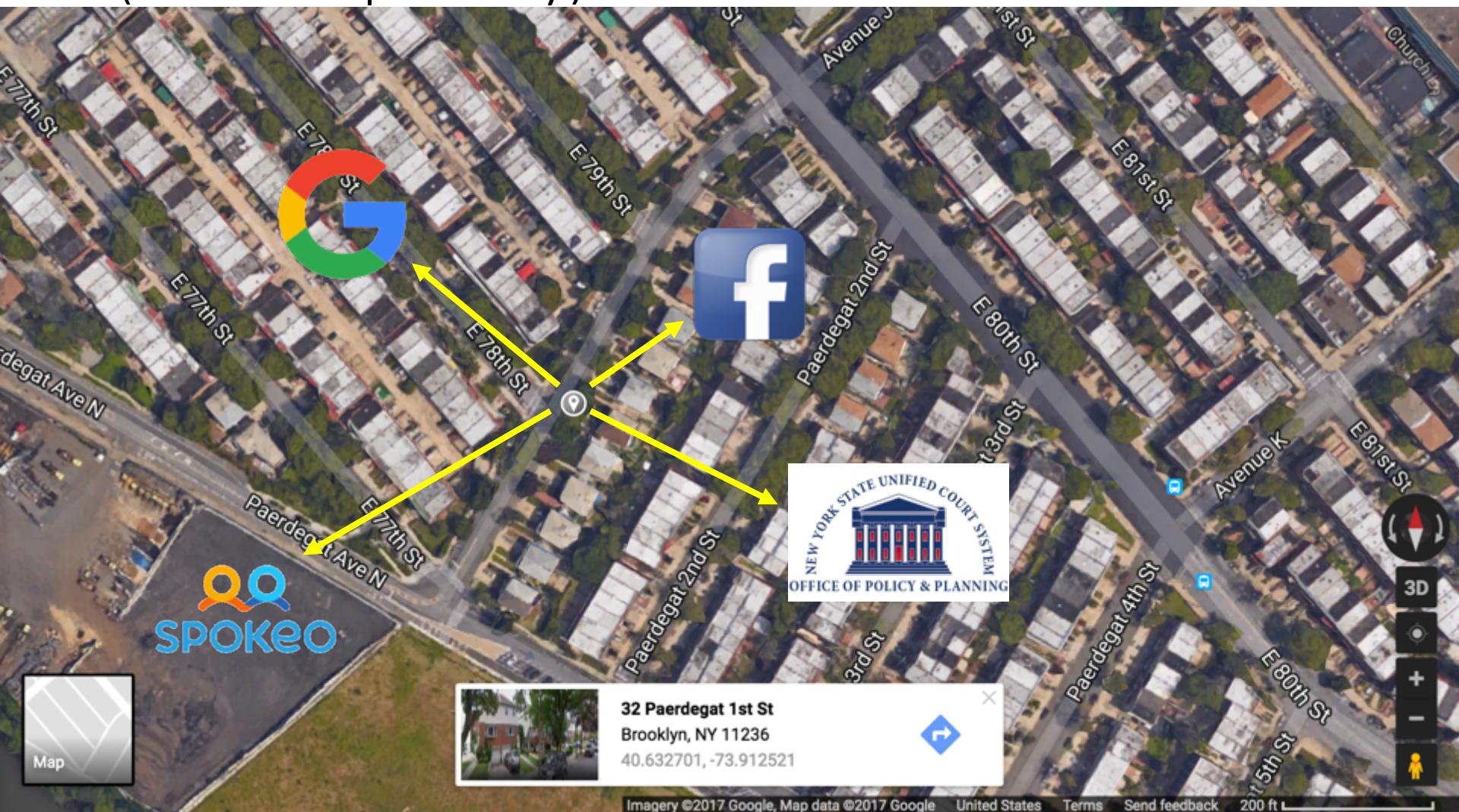
and other metadata.

Drop off locations for ...



NOT AN ACTUAL DROP OFF!

(for example only)



Unique in the shopping mall: On the reidentifiability of credit card metadata

Yves-Alexandre de Montjoye,^{1,*} Laura Radaelli,² Vivek Kumar Singh,^{1,3} Alex “Sandy” Pentland¹



Fig. 1 Financial traces in a simply anonymized data set such as the one we use for this work.

Arrows represent the temporal sequence of transactions for user 7abc1a23 and the prices are grouped in bins of increasing size (29).

Exploring ADINT: Using Ad Targeting for Surveillance on a Budget – or – How Alice Can Buy Ads to Track Bob

Paul Vines, Franziska Roesner, and Tadayoshi Kohno

Paul G. Allen School of Computer Science & Engineering, University of Washington
plvines@cs.washington.edu,franzi@cs.washington.edu,yoshi@cs.washington.edu

...we find that — for \$1000 USD — **we can track the location of individuals who are using apps served by that advertising network**, as well as infer whether they are using potentially sensitive applications (e.g., certain religious or sexuality-related apps)

What Women Know About the Internet

The digital world is not designed to keep women safe. New regulations should be.

By Emily Chang

Ms. Chang, an anchor at Bloomberg TV, is the author of “Brotopia.”

April 10, 2019



The Department of Justice reports that about 75 percent of the victims of stalking and cyberstalking are women.

And so women look over our shoulders online, just as we do in real life.

REGULATION

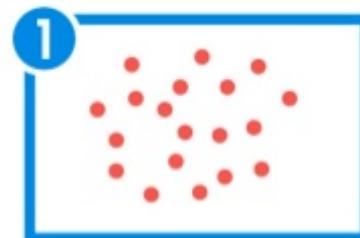
There's No Such Thing as Anonymous Data

by Scott Berinato

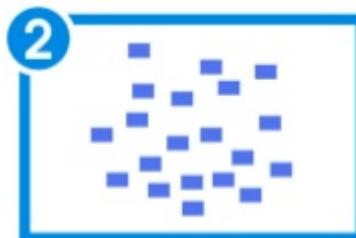
FEBRUARY 09, 2015

Harvard
Business
Review

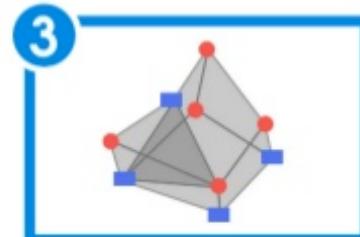
Data Set Correlation



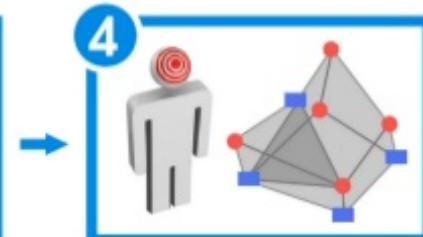
Anonymous Data Set #1
For IP Address 172.16.253.1



Anonymous Data Set #2
For IP Address 172.16.253.1



172.16.253.1 Data Sets Are
Combined & Correlated



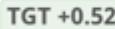
You Are Personally
Identified For Targeting

How Target Figured Out A Teen Girl Was Pregnant Before Her Father Did



Kashmir Hill, FORBES STAFF

Welcome to *The Not-So Private Parts* where technology & privacy collide [FULL BIO ▾](#)

Every time you go shopping, you share intimate details about your consumption patterns with retailers. And many of those retailers are studying those details to figure out what you like, what you need, and which coupons are most likely to make you happy. **Target**  , for example, has figured out how to determine its way into your womb, to figure out whether you have a baby on the way long before you need to start buying diapers.



TARGET

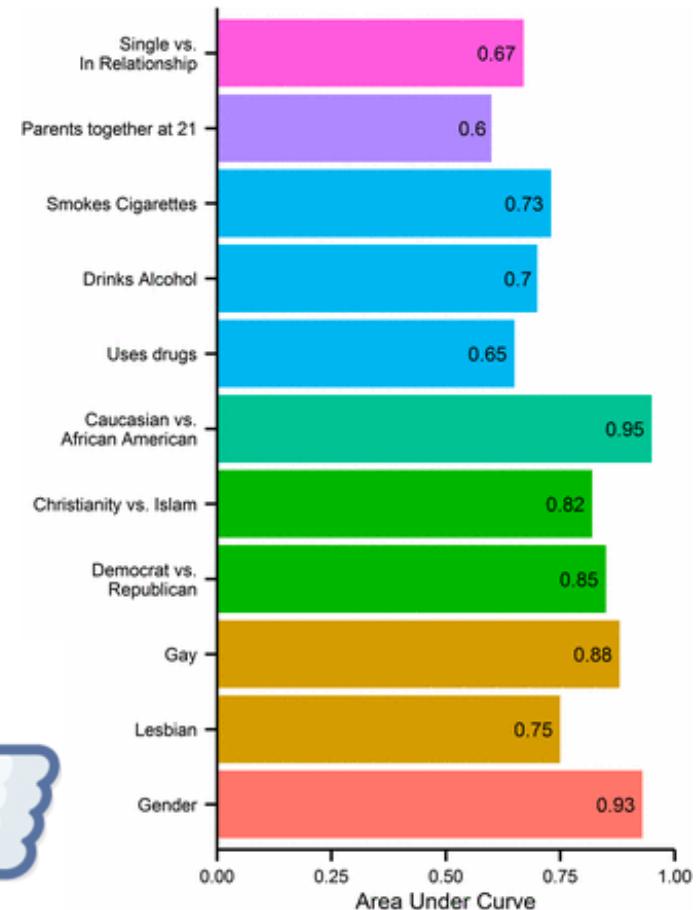
Target has got you in its aim

Private traits and attributes are predictable from digital records of human behavior

Michal Kosinski^{a,1}, David Stillwell^a, and Thore Graepel^b

^aFree School Lane, The Psychometrics Centre, University of Cambridge, Cambridge CB2 3RQ United Kingdom; and ^bMicrosoft Research, Cambridge CB1 2FB, United Kingdom

Abstract: We show that easily accessible digital records of behavior, **Facebook Likes**, can be used to automatically and accurately predict a range of highly sensitive personal attributes including: sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender.



Identifying Relevant Users and Groups in the Context of Credit Analysis Based on Data from Twitter

Danyollo W. A., Alisson V. B., Alexandre N. D.
Moacir L.M. J., Jansepetrus B. P.

Center of Informatics – Federal University of Paraiba.
João Pessoa, PB – Brazil.
danyellowagneralbuquerque, alisson.brito,
alexandrend, moacir.lopes.jr, jansebp}@gmail.com

Roberto Felício Oliveira

Department of Informatics – State University of Goias.
Posse, GO - Brazil
Prof.roberto.posse@gmail.com

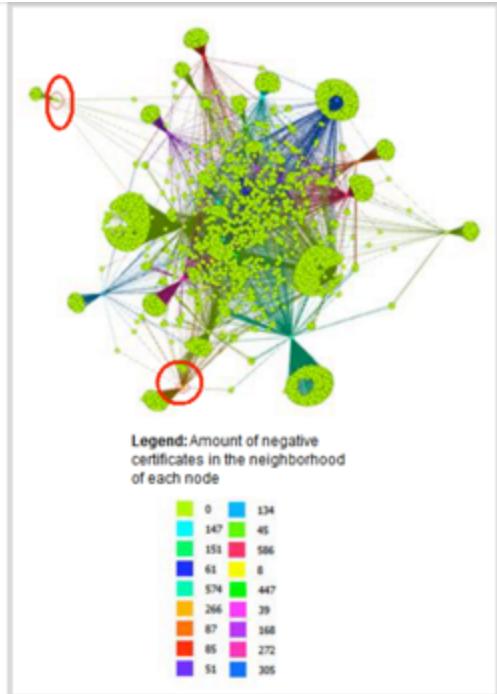


Fig. 6. Amount of negative certificates from the neighborhood of 26 users.

Abstract: ... this study collected data from the social network Twitter, and compared them with data from a financial institution in order to model the network and analyze their similarities. Three thousand users from Twitter were analyzed and 504 matched with the database from company for credit analysis. The results demonstrated that most of those users have more credit restriction than their neighbors, and users with no restrictions normally have also neighborhoods with no credit restriction as well.

Preliminary conclusions in this study indicate that among the 26 found communities (the 26 initial users and their followers), those with the highest number of people with credit restrictions are communities where the central node has some constraint credit associated.

TIME

93% of hiring managers
will review a candidate's
social profile before
making a hiring decision.

October 2014

YOUR ENGINEERING
EXPERIENCE LOOKS
GREAT, BUT YOUR
SOCIAL MEDIA SCORE
IS NEARLY ZERO.



BECAUSE
I FOCUS
ON MY
WORK!

NO, I'M
PRETTY
SURE
YOU'RE
DEAD.



Will My Next Car Be a **Libertarian** or a **Utilitarian**?

Who Will Decide?

Tom Fournier



GARRETTHAWK/WIKIMEDIA

Change is coming.

Experimental, self-driving cars are plying public roads in many U.S. states, heralding what some automotive industry experts and regulators see as a profound and imminent disruption in the transportation industry, and a change to our way of life. With this change, a large swath

<http://moralmachine.mit.edu/>



Home Judge Classic Design Browse About Feedback En



By Grendelkhan (Own work) [CC BY-SA 4.0 (<http://creativecommons.org/licenses/by-sa/4.0>)], via Wikimedia Commons

Welcome to the Moral Machine! A platform for gathering a human perspective on moral decisions made by machine intelligence, such as self-driving cars.

We show you moral dilemmas, where a driverless car must choose the lesser of two evils, such as killing two passengers or five pedestrians. As an outside observer, you **judge** which outcome you think is more acceptable. You can then see how your responses compare with those of other people.

Teaching A.I. Systems to Behave Themselves



Geoffrey Irving, left, and Dario Amodei demonstrate how simple video games are used to train A.I. bots.
CHRISTIE HEMM KLOK FOR THE NEW YORK TIMES

By CADE METZ

AUGUST 13, 2017

Automated Inference on Criminality using Face Images

Xiaolin Wu
McMaster University
Shanghai Jiao Tong University
xwu510@gmail.com

Xi Zhang
Shanghai Jiao Tong University
zhangxi_19930818@sjtu.edu.cn



(a) Three samples in criminal ID photo set S_c .



(b) Three samples in non-criminal ID photo set S_n

Figure 1. Sample ID photos in our data set.

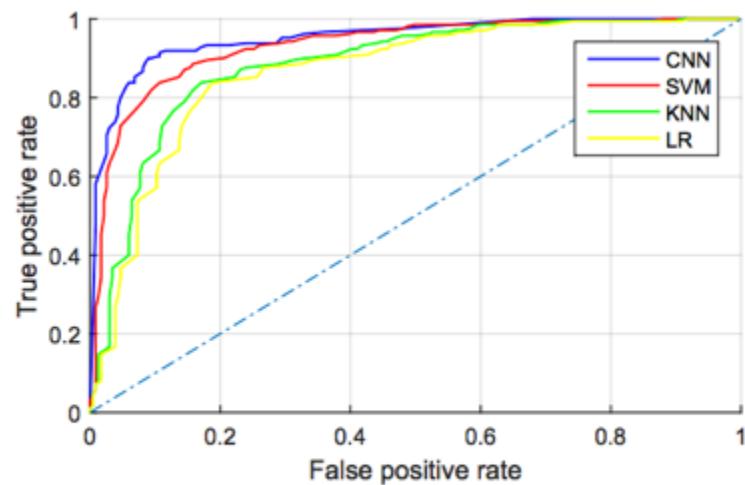


Figure 5. The ROC curves of the four tested binary face classifiers on criminality.

Automated Inference on Criminality using Face Images

Xiaolin Wu
McMaster University
Shanghai Jiao Tong University
xwu510@gmail.com

Xi Zhang
Shanghai Jiao Tong University
zhangxi_19930818@sjtu.edu.cn

“We are the first to study automated *face-induced inference on criminality* free of any biases of subjective judgments of human observers.”

Figure 1. Sample ID photos in our data set.

on criminality.

ssifiers



At the Kaiser Wilhelm Institute for Anthropology, Human Genetics, and Eugenics, **a racial hygienist** measures a woman's features in an attempt to determine her racial ancestry. Berlin, Germany, date uncertain.

— National Archives and Records Administration, College Park, Md.



Moritz Hardt

Follow

Researcher. Machine learning, optimization, privacy and social questions in computation.

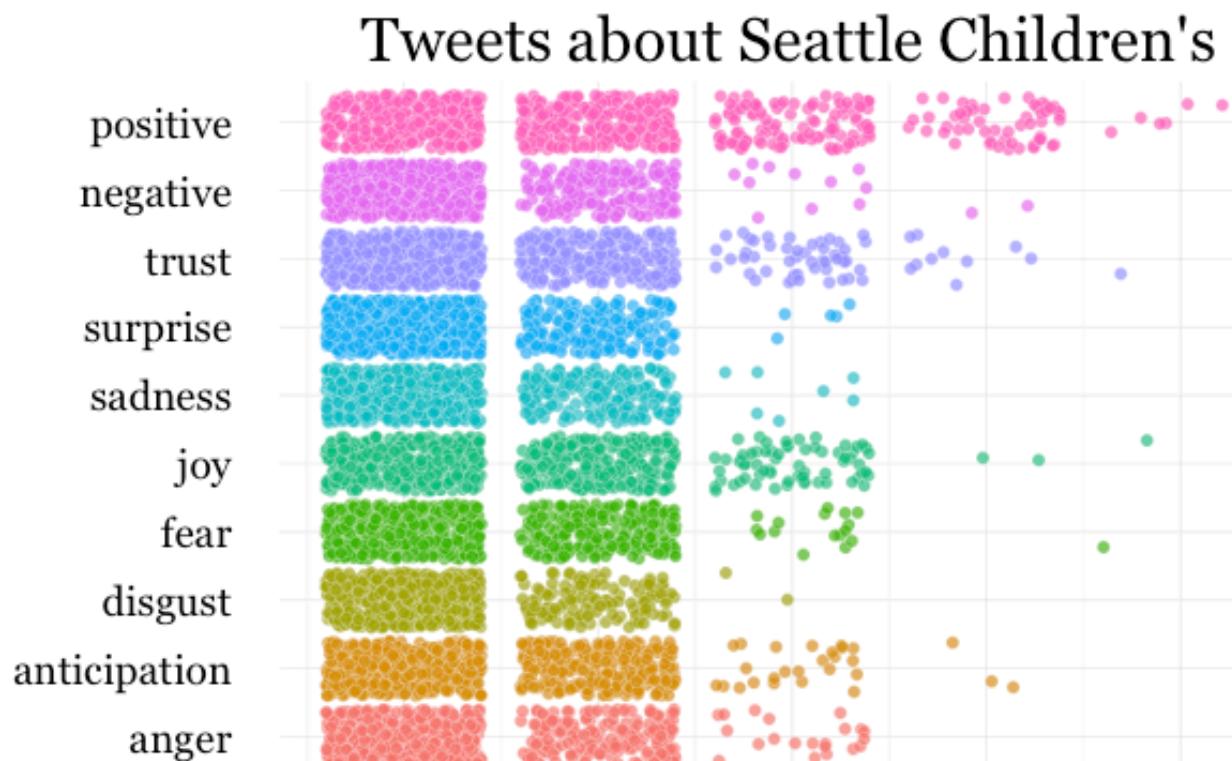
Sep 26, 2014 · 8 min read

How big data is unfair

Understanding unintended sources of unfairness in data driven decision making

As we're on the cusp of using machine learning for rendering basically all kinds of consequential decisions about human beings in domains such as education, employment, advertising, health care and policing, it is important to understand why *machine learning is not, by default, fair or just in any meaningful way*.

	sentiment
fidget	-9.931679
interrupt	-9.634706
staunchly	1.466919
imaginary	-2.989215
taxing	0.468522
world-famous	6.908561
low-cost	9.237223
disapointment	-8.737182
totalitarian	-10.851580
bellicose	-8.328674
freezes	-8.456981
sin	-7.839670
fragile	-4.018289
fooled	-4.309344
undecided	-2.816172
handily	2.339609
demonizes	-2.102152
easygoing	8.747150
unpopular	-7.887475
commiserate	1.790899



```
In [12]: text_to_sentiment("this example is pretty cool")
```

```
Out[12]: 3.889968926086298
```

```
In [13]: text_to_sentiment("this example is okay")
```

```
Out[13]: 2.7997773492425186
```

```
In [14]: text_to_sentiment("meh, this example sucks")
```

```
Out[14]: -1.1774475917460698
```

```
In [15]: text_to_sentiment("Let's go get Italian food")
```

```
Out[15]: 2.0429166109408983
```

```
In [16]: text_to_sentiment("Let's go get Chinese food")
```

```
Out[16]: 1.4094033658140972
```

```
In [17]: text_to_sentiment("Let's go get Mexican food")
```

```
Out[17]: 0.38801985560121732
```

```
In [18]: text_to_sentiment("My name is Emily")
```

```
Out[18]: 2.2286179364745311
```

```
In [19]: text_to_sentiment("My name is Heather")
```

```
Out[19]: 1.3976291151079159
```

```
In [20]: text_to_sentiment("My name is Yvette")
```

```
Out[20]: 0.98463802132985556
```

```
In [21]: text_to_sentiment("My name is Shaniqua")
```

```
Out[21]: -0.47048131775890656
```

Division of Criminal Justice Services
Office of Justice Research and Performance



Criminal Justice Research Report

Andrew M. Cuomo
Governor

Michael C. Green
Executive Deputy Commissioner

September 2012

New York State COMPAS-Probation Risk and Need Assessment Study: Examining the Recidivism Scale's Effectiveness and Predictive Accuracy

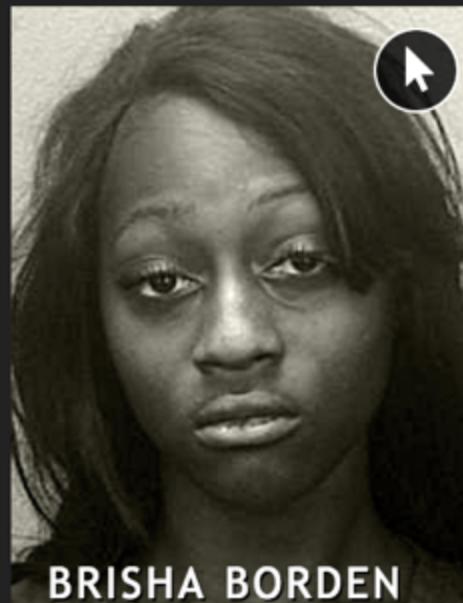
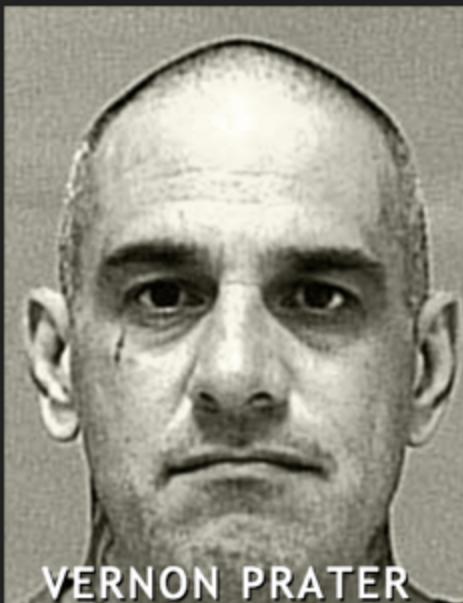
Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

Two Petty Theft Arrests



LOW RISK

3

HIGH RISK

8

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

Two Petty Theft Arrests

VERNON PRATER

Prior Offenses

2 armed robberies,
1 attempted armed
robbery

Subsequent Offenses

1 grand theft

LOW RISK

3

BRISHA BORDEN

Prior Offenses

4 juvenile
misdemeanors

Subsequent Offenses

None

HIGH RISK

8

RESPONSE TO PROPUBLICA: DEMONSTRATING ACCURACY EQUITY AND PREDICTIVE PARITY

The website ProPublica recently published a story that focused on the scientific validity of COMPAS, raising questions about racial bias. As a result of the article and the subsequent national attention that it garnered, Northpointe launched an in-depth analysis of the data samples used by ProPublica. Drawing from the [results of our analysis](#) of ProPublica's data, Northpointe unequivocally rejects the ProPublica conclusion of racial bias in the COMPAS risk scales.

Inherent Trade-Offs in the Fair Determination of Risk Scores

Jon Kleinberg *

Sendhil Mullainathan †

Manish Raghavan ‡

Recent discussion in the public sphere about algorithmic classification has involved tension between competing notions of what it means for a probabilistic classification to be fair to different groups. **We formalize three fairness conditions** that lie at the heart of these debates, and we prove that except in highly constrained special cases, **there is no method that can satisfy these three conditions simultaneously.**

Attacking discrimination with smarter machine learning

As machine learning is increasingly used to make important decisions across core social domains, the work of ensuring that these decisions aren't discriminatory becomes crucial.

Here we discuss "threshold classifiers," a part of some machine learning systems that is critical to issues of discrimination. A threshold classifier essentially makes a yes/no decision, putting things in one category or another. We look at how these classifiers work, ways they can potentially be unfair, and how you might turn an unfair classifier into a fairer one. As an illustrative example, we focus on loan granting scenarios where a bank may grant or deny a loan based on a single, automatically computed number such as a credit score.

By Martin Wattenberg, Fernanda Viégas, and Moritz Hardt.

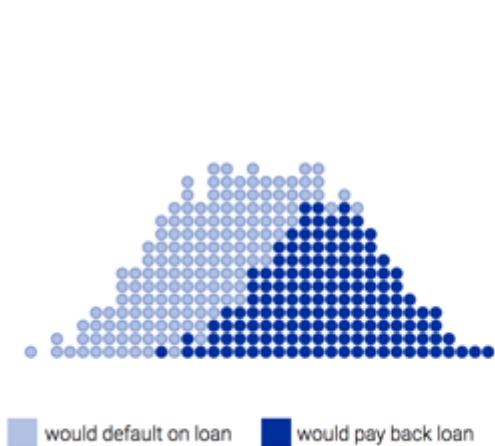
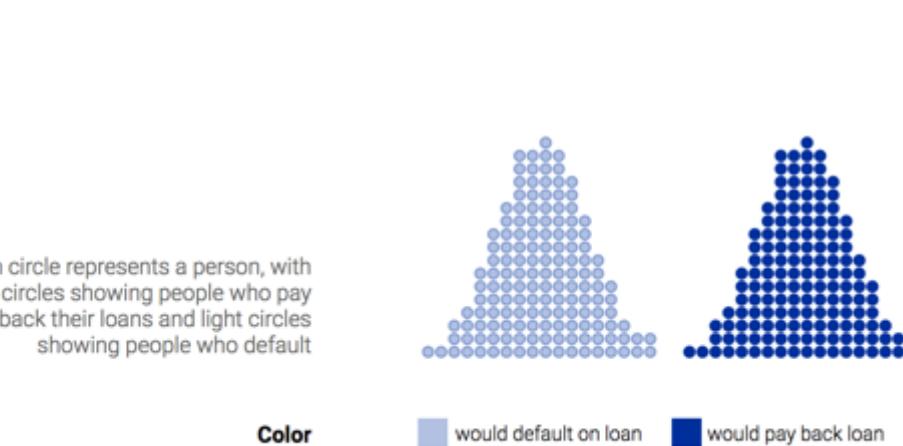
This page is a companion to a [recent paper by Hardt, Price, Srebro](#), which discusses ways to define and remove discrimination by improving machine learning systems.

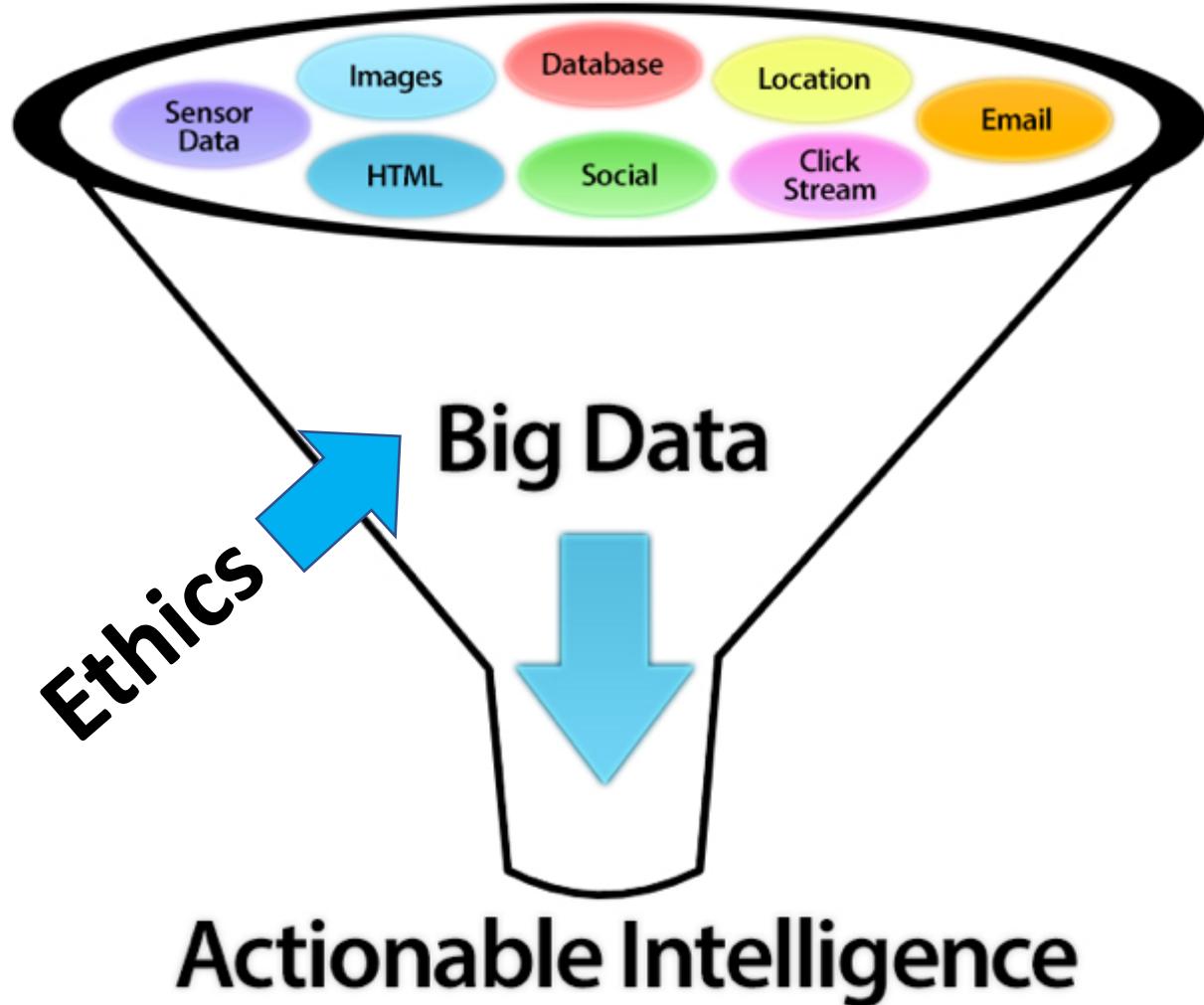
Loan applicants: two scenarios

A. Clean separation



B. Overlapping categories





Intelligible Models for HealthCare: Predicting Pneumonia Risk and Hospital 30-day Readmission

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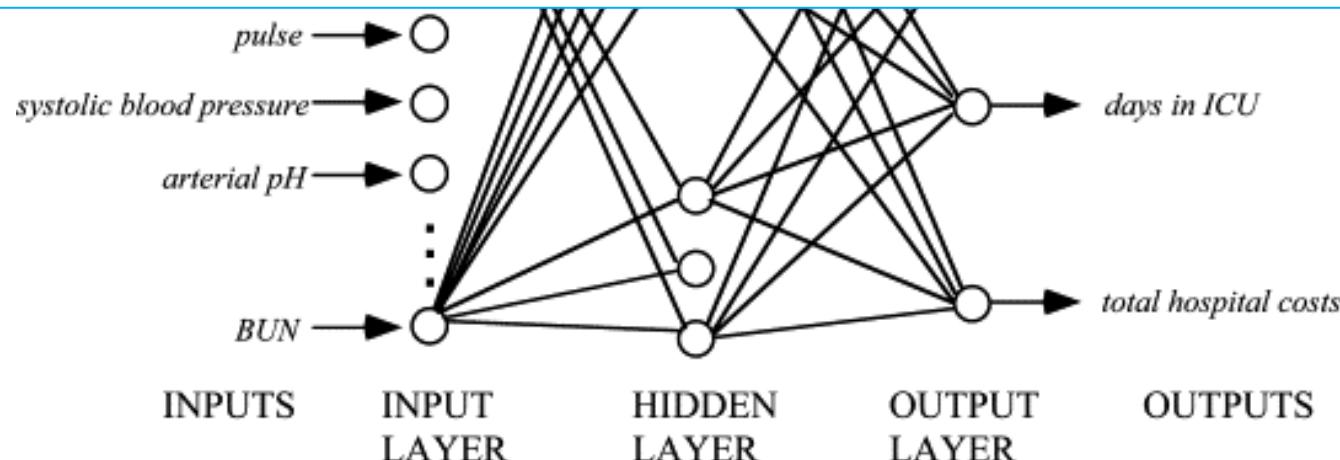
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$\text{HasAsthma}(x) \Rightarrow \text{LowerRiskofDeath}(x)$



Intelligible Models for HealthCare: Predicting Pneumonia Risk and Hospital 30-day Readmission

Opinion

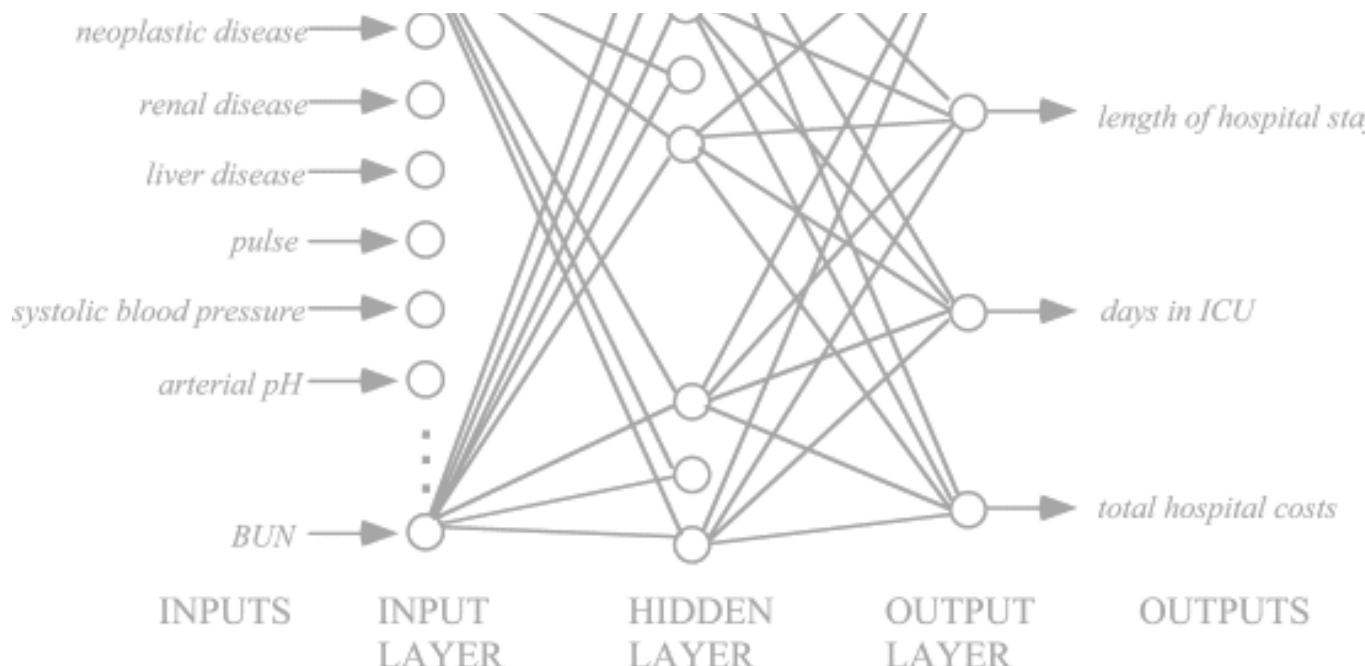
VIEWPOINT

Unintended Consequences of Machine Learning in Medicine

Federico Cabitza, PhD
Department of Informatics, University of Milano-Bicocca,

Over the past decade, machine learning techniques have made substantial advances in many domains. In health care, global interest in the potential of machine learning has increased. For example, a deep learning algorithm has

the expense of other elements that are more difficult or impossible to easily describe. Relying on ML-DSS requires considering digital data as reliable and complete representations of the phenomena that these data are



False-Positive Psychology: Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant

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Abstract

In this article, we accomplish two things. First, we show that despite empirical psychologists' nominal endorsement of a low rate of false-positive findings ($\leq .05$), flexibility in data collection, analysis, and reporting dramatically increases actual false-positive rates. In many cases, a researcher is more likely to falsely find evidence that an effect exists than to correctly find evidence that it does not. We present computer simulations and a pair of actual experiments that demonstrate how unacceptably easy

Hack Your Way To Scientific Glory

You're a social scientist with a hunch: **The U.S. economy is affected by whether Republicans or Democrats are in office.** Try to show that a connection exists, using real data going back to 1948. For your results to be publishable in an academic journal, you'll need to prove that they are "statistically significant" by achieving a low enough p-value.

1 CHOOSE A POLITICAL PARTY

Republicans

Democrats

2 DEFINE TERMS

Which politicians do you want to include?

- Presidents
- Governors
- Senators
- Representatives

How do you want to measure economic performance?

- Employment
- Inflation
- GDP
- Stock prices

Other options

Factor in power

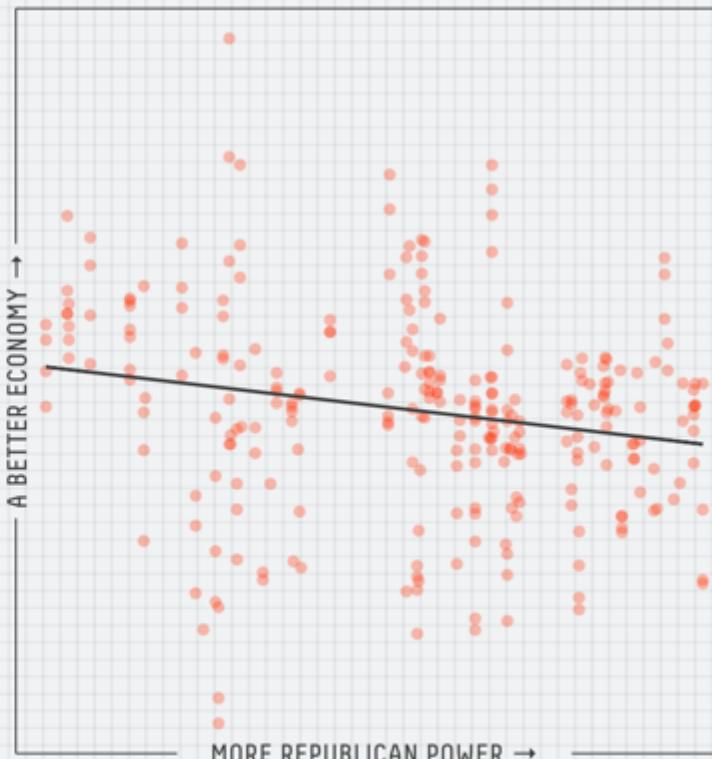
Weight more powerful positions more heavily

Exclude recessions

Don't include economic recessions

3 IS THERE A RELATIONSHIP?

Given how you've defined your terms, does the economy do better, worse or about the same when more Republicans are in power? Each dot below represents one month of data.



4 IS YOUR RESULT SIGNIFICANT?

If there were no connection between the economy and politics, what is the probability that you'd get results at least as strong as yours? That probability is your p-value, and by convention, you need a p-value of 0.05 or less to get published.



Result: Publishable

You achieved a p-value of **less than 0.01** and showed that **Republicans have a negative effect on the economy**. Get ready to be published!

If you're interested in reading real (and more rigorous) studies on the connection between politics and the economy, see the work of Larry Bartels and Alan Blinder and Mark Watson.

Data from The @unitedstates Project, National Governors Association, Bureau of Labor Statistics, Federal Reserve Bank of St. Louis and Yahoo Finance.

Misuse of statistics is unethical.

Douglas Altman, 1980

Biostatistician

British Medical Journal

Ethical Guidelines for Statistical Practice

*Prepared by the Committee on Professional Ethics of the American Statistical Association
Approved by the ASA Board in April 2016*

4 Running multiple tests on the same data set at the same stage of an analysis increases the chance of obtaining at least one invalid result. Selecting the one “significant” result from a multiplicity of parallel tests poses a grave risk of an incorrect conclusion. Failure to disclose the full extent of tests and their results in such a case would be highly misleading.

**A mistake in the operating room
can threaten the life of one patient;
a mistake in statistical analysis or
interpretation can lead to
hundreds of early deaths.**

Andrew Vickers

Biostatistician

Memorial Sloan Kettering Cancer Center

FDA Estimates Vioxx Caused 27,785 Deaths

The Food and Drug Administration (FDA) estimates that Vioxx may have contributed to 27,785 heart attacks

By Unknown Author

The Food and Drug Administration (FDA) estimates that Vioxx may have contributed to 27,785 heart attacks and sudden cardiac deaths between 1999 and 2003. The estimate is based on the number of prescriptions issued for Vioxx between 1999 and 2003.

Raw data is both an oxymoron
and a bad idea... data should be
cooked with care.

– Geoffrey Bowker 2005

A blurred background photograph of a man's profile, wearing dark sunglasses and a blue hoodie, looking down at his smartphone. The scene is set outdoors with a building visible in the background.

GOOGLE STALKING FOR BUSINESS

(IT'S A REAL THING, WE PROMISE)

MAXIMIZEDIGITALMEDIA.COM



Miles McBain
@MilesMcBain



Writing a formalish request for data to another gov department today and there was a para which was effectively a 'No AI' declaration. I am guessing this will become increasingly common.

9:51 PM · 5/13/19 · [Twitter Web App](#)



“Children’s is thoughtful
about how we use data.”

Data Ethics Checklist Tool

Consider a medium to large data product or project that you're currently working on, or have worked on recently. Fill out the 8-question data ethics checklist tool below to score your opinion about the extent to which ethical dimensions may be involved with this data project. Some examples have been provided that may provide more insight into the meanings of the questions.

After that, we would appreciate if you could complete the optional 8-question survey that asks your thoughts related to your use of this tool.

Finally, press "Submit" when you are ready to consent to having your results included in this research.

Potential Privacy Issues

Examples: People are frequently unaware that data can be aggregated across multiple sources, used to infer seemingly unrelated information, or otherwise go beyond "mere" records. For instance, an ETL process may integrate data that the family may not be aware is connected (demographics and health outcomes). These questions aim to help determine if those inferences are potentially problematic.

P1. Does this process/method/analysis use information that patient/families/employees are probably unaware that Seattle Children's has collected (or could integrate)?

* must provide value

- 0: Definitely not
- 1: In some situations
- 2: Definitely yes

reset

Roughly, did they "consent" to have their data used in this way, though think more broadly than "mere" legal consent.



What would you do?