

Challenges in AI Ethics

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@PolarBearBY

Web Intelligence
Barcelona, March 2022

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Northeastern University

<https://ai.northeastern.edu/>

Institute for *Experiential* AI

What do we mean by *Experiential* AI?

- AI with human in the loop
- AI applied to real-world problems yielding pragmatic working solutions

Why we believe is EAI the right direction?

Much evidence that pragmatic working AI solutions have two characteristics:

1 **Human-in-the-loop:** ability to bring human decision-making, common sense reasoning into the solution operation

2 **Strong dependence on Data:** ML and DS to leverage more quality (big) data:
“We don’t have better algorithms... we just have more data”

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Agenda

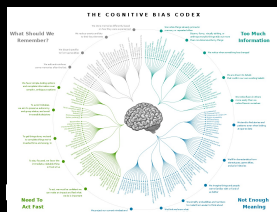
- Current Ethical Issues:
 - Automated discrimination
 - AI phrenology
 - Unfair digital markets
 - Lack of semantic understanding
 - Expensive and doubtful use of computing resources
- Challenges:
 - Too many principles
 - Cultural differences
 - (Over?) Regulation
 - Our cognitive biases
- What We Can Do?

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Personal Bias

What is Bias?

- Statistical: significant systematic deviation from a prior (unknown) distribution;
- Cultural: interpretations and judgments phenomena acquired through our life;
- Cognitive: systematic pattern of deviation from norm or rationality in judgment;

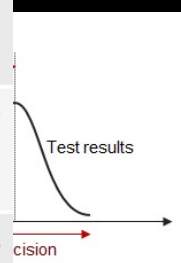


More than
100 cognitive
biases!

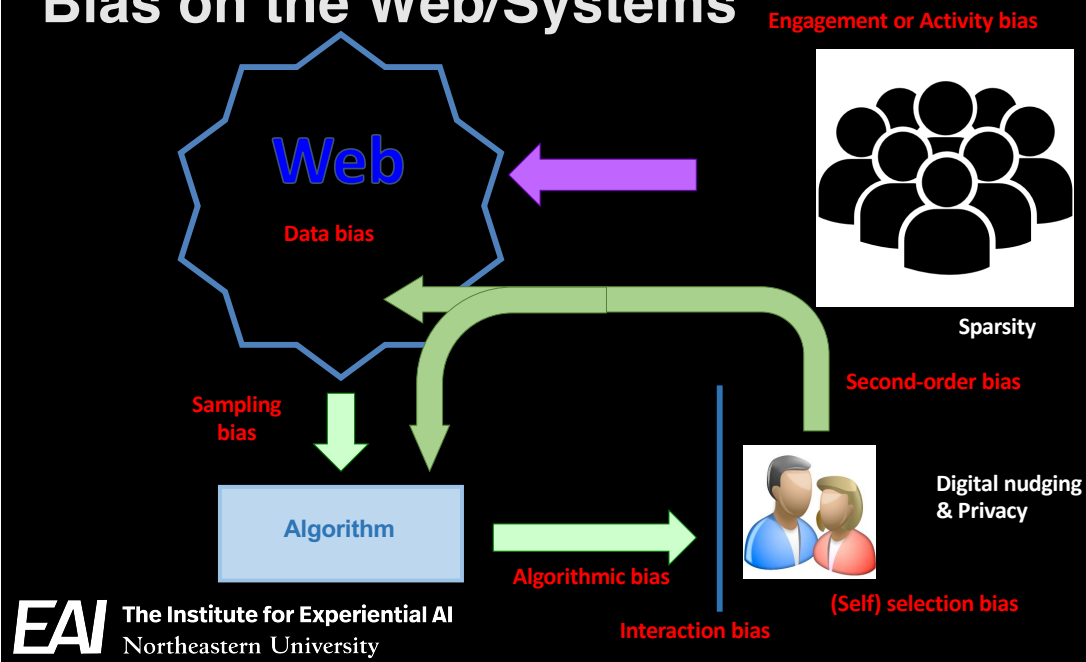
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20 COGNITIVE BIASES THAT SCREW UP YOUR DECISIONS

<p>1. Anchoring bias.</p> <p>People can value an object in the first place of information they receive. For example, if you are asked to estimate the value of a car, and you are told that it is worth \$10,000, you will estimate its value to be around \$10,000, even if you know that the car is worth \$15,000.</p>	<p>2. Availability heuristic.</p> <p>People can judge the probability of an event based on the information that is available to them. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>3. Bandwagon effect.</p> <p>The availability of an opinion affects the likelihood of people adopting a belief or opinion. For example, if you see a lot of people at a concert, you are more likely to go to the concert yourself.</p>	<p>4. Blind-spot bias.</p> <p>People to recognize our own cognitive biases is a bias. In other words, we are blind to our own biases. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>
<p>5. Choice-supportive bias.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>6. Clustering illusion.</p> <p>This is the tendency to see patterns in random events. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>7. Confirmation bias.</p> <p>We tend to look only to information that confirms our preconceptions. One of the most common examples of this is the tendency to only look for information that confirms our beliefs about a particular group of people.</p>	<p>8. Conservativeness bias.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>
<p>9. Information bias.</p> <p>We tend to seek out information that confirms our preconceptions. One of the most common examples of this is the tendency to only look for information that confirms our beliefs about a particular group of people.</p>	<p>10. Ostrich effect.</p> <p>The tendency to ignore negative information. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>11. Outcome bias.</p> <p>The tendency to judge the quality of a decision based on the outcome. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>12. Overconfidence.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>
<p>13. Plethora effect.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>14. Pre-innovation bias.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>15. Reversing.</p> <p>The tendency to see the most negative information as the most positive. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>16. Salience.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>
<p>17. Selective perception.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>18. Stereotyping.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>19. Survivorship bias.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>	<p>20. Zero-risk bias.</p> <p>People have a tendency to view their own choices as better than those of others. For example, if you are asked to estimate the probability of a plane crash, you will estimate it to be higher if you have recently seen a news report about a plane crash.</p>



Bias on the Web/Systems



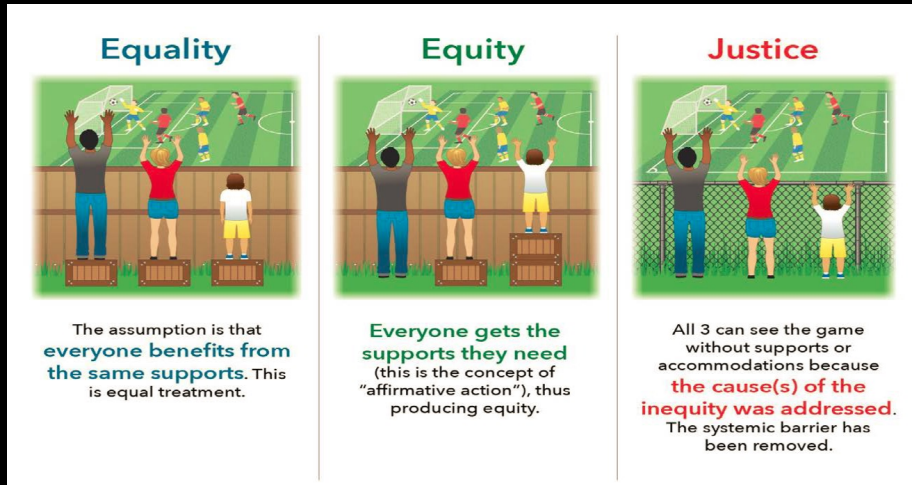
The Curse of Bias



Bias is not only in data

[RBY, Bias on the Web, CACM, 2018]

What is Being Fair?



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CODED BIAS

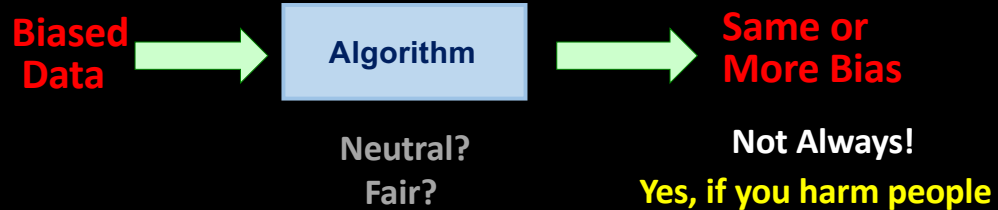


**Available
In YouTube**



A SHALINI KANTAYYA FILM

A Non-Technical Question



Debias the input
Tune the algorithm
Debias the output

Bias Mitigation

Headline News

Discrimination

- **COMPAS** (Northpointe): criminal profiling
- Created as a support tool, not a decision tool
- Data: criminal history, life style, personality, family & social
- ProPublica (2016):
 - Racial bias of 2 to 1 (later proven incorrect)
 - 80% error in violent crime & 37% in general (2 years)
- Discrimination on poor people – Bearden vs. Georgia
- Inconsistency in predictions – Wisconsin case
- Is a secret algorithm ethical? (transparency)
- Is a public algorithm safe? (gaming)

Criminal Profiling

Discrimination

- **Gotham** & others (Palantir)
 - Criminal profiling
 - Los Angeles (2009) – via police foundation
 - New York (2011) – never approved by council
 - New Orleans (2012) – secret until 2014
 - Denmark (2016), Norway (2017), Germany (2019?)
 - **One error and a person is stigmatized**

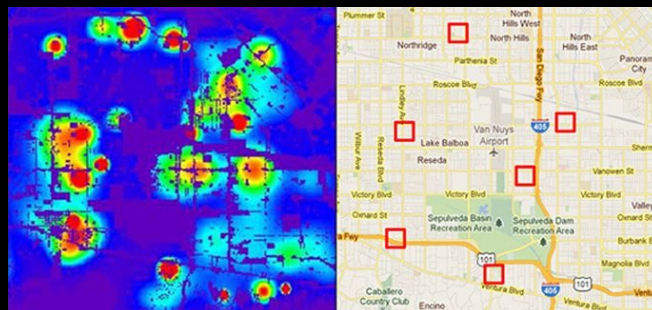


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Criminal Profiling

Discrimination

- **Predpol** (Chicago City & IIT)
 - Another criminal profiler
 - Geographic sampling bias – vicious circle



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Police

Discrimination



Knowledge-Based Systems

elCorreo

miércoles, 10 febrero 2021 21:09, última actualización

Aviso legal | Política d

SEVILLA ANDALUCÍA OPINIÓN MÁS PASIÓN EMPRESA EL TURISTA CULTURA PARA SEVILLA

IN FRAGANTI When police is not stupid Veripol: cuando la policía no es tonta

Una aplicación informática, obtenida por inteligencia artificial, es la herramienta policial más efectiva contra denuncias falsas. En Sevilla pilló ya a muchos mentirosos

JUAN-CARLOS ARIAS / SEVILLA / 05 DIC 2020 / 04 09 H - ACTUALIZADO: 05 DIC 2020 / 04 09 H.



CHIVOS Y DO

cación

Andalucía Viva
visión de más
ntimidación o tirón



Join Extra Crunch

Featured Article

'Orwellian' AI lie detector project challenged in EU court

Transparency suit highlights questions of ethics and efficacy attached to the bloc's flagship R&D program

EA

Natasha Lomas @riptari / 8:23 PM GMT+1 • February 5, 2021



Predicting Justice Outcomes

- Domestic violence prediction
 - Judges: 80%, algorithm: 90%
- Asylum prediction
 - 82% accuracy
 - Only 1/3 are case features
- Appeals consensus prediction
 - 50% depends on the case & 50% on the person
- Sentence predictions (almost 70%)
 - Image features (+1.8%)
 - Audio features (+2.0%)

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Detailed Example: Bails



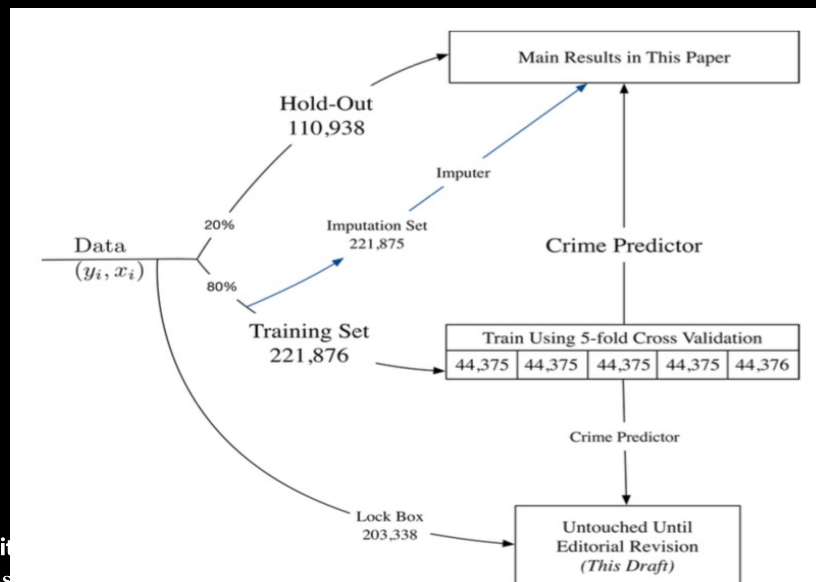
Human Decisions vs. Machine Predictions

- Almost **760K** cases from New York (2008 - 2013)
- Decrease crime rate in **24.7%** keeping the jail rate **or**
- Decrease jail rate in **41.9%** keeping the same crime rate
- Judges bail **49%** of 1% most dangerous criminals that fail to appear **56%** & reoffend **62%** of the cases
- National Bureau of Economic Research
[Kleinberg et al, JQE, 237—293, 2018]

**Amplified
Bias**

Data Methodology

Justice Example



ML Algorithm & Features

Justice Example

- GBDT: Decision Trees
 - Allows interpretability
- Features (18):
 - Age
 - Current offense and level
 - Criminal record and level
 - Guns? Drugs?
 - Arrests
 - Failed to appear in court
 - Convictions

Racial Discrimination

Justice Example

Table 7: Racial Fairness

18%

13%

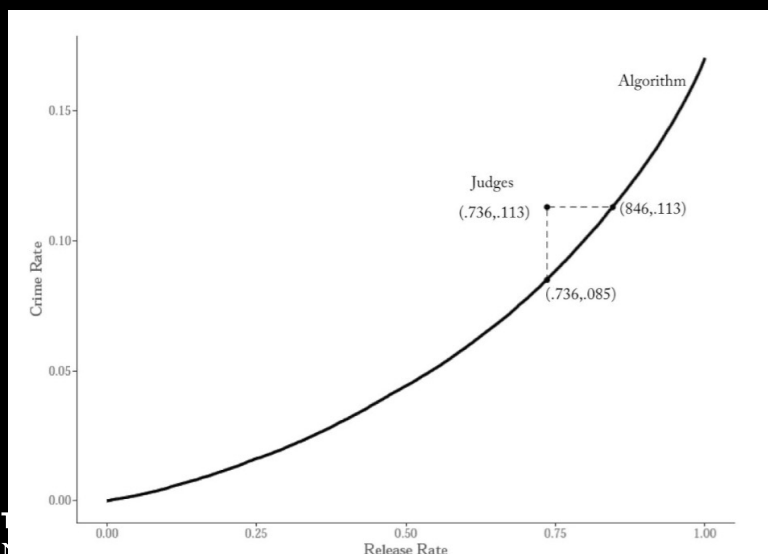
32%

Release Rule	Crime Rate	Drop Relative to Judge	Percentage of Jail Population		
			Black	Hispanic	Minority
Distribution of Defendants (Base Rate)			.4877	.3318	.8195
Judge	.1134 (.0010)	0%	.573 (.0029)	.3162 (.0027)	.8892 (.0018)

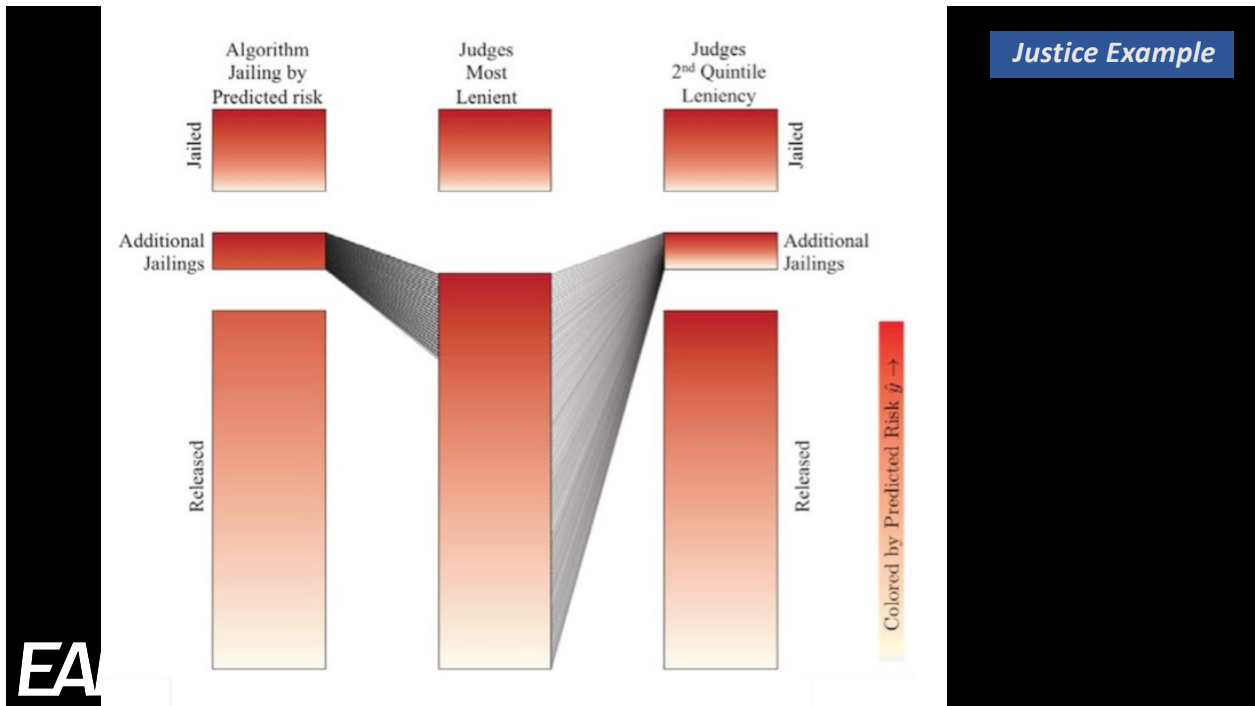
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Which is the Difference?

Justice Example



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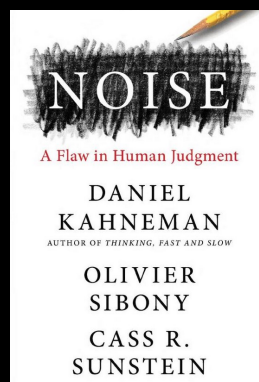


Justice Example

Dilemma

What is better?

A biased (just) algorithm
or
a noisy judge?

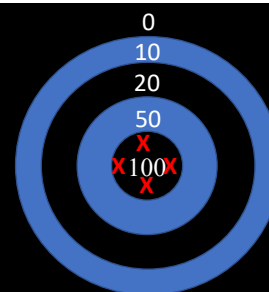


Noise: How to Overcome the High, Hidden Cost of Inconsistent Decision Making

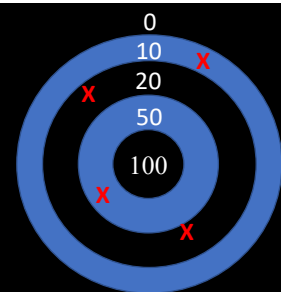
Algorithmic judgment is more efficient than the human variety. by
Daniel Kahneman, Andrew M. Rosenfield, Linnea Gandhi, and Tom Blaser

Harvard
Business
Review

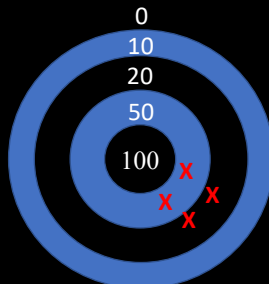
From the Magazine (October 2016)



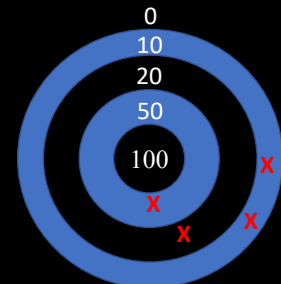
A. Exact (400)



B. Noisy (100)



C. Biased (140)



D. Biased & noisy (90)

Gender & Race

Discrimination



Facial recognition systems show rampant racial bias, government study finds



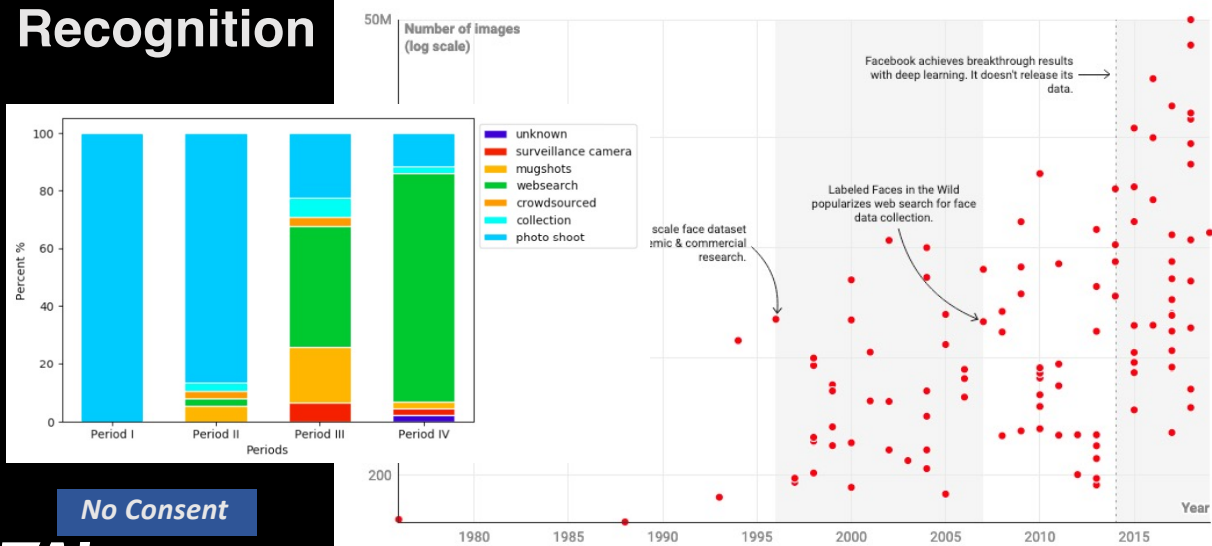
By Brian Fung, CNN Business
Updated 2337 GMT (0737 HKT) December 19, 2019

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Facial Recognition

The four eras of facial recognition

Facial recognition datasets have grown exponentially in size as researchers have sought to improve the technology's accuracy.

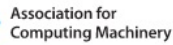


No Consent

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Chart: MIT Technology Review • Source: Raji & Fried • Created with Datawrapper

[Raji & Fried, 2021]



Digital Library

Outrage!
convinced
out selling
enforcement

> [ACM US Technology Policy Committee Urges Suspension Of Use Of Facial Recognition Technologies](#)

ACM US Technology Policy Committee Urges Suspension of Use of Facial Recognition Technologies

June 30, 2020

Isobel Asher Hamilton Jun



Faulty Facial Recognition Led to His Arrest—Now He's Suing

2020

By Natalie O'Neill

September 4, 2020, 3:39pm Share Tweet Snap



Information Extraction

Discrimination

Gender stereotype *she-he* analogies.

sewing-carpentry	register-nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	hairdresser-barber

Gender appropriate *she-he* analogies.

queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

[Bolukbasi et al, NeurIPS 2016]

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Most journalists in the USA are men?

Yes, about 60 to 70% at work
although at college is the inverse

Word Embeddings

Discrimination

Word embeddings quantify 100 years of gender and ethnic stereotypes

Nikhil Garg^{a,1}, Londa Schiebinger^b, Dan Jurafsky^{c,d}, and James Zou^{e,f,1}

^aDepartment of Electrical Engineering, Stanford University, Stanford, CA 94305; ^bDepartment of History, Stanford University, Stanford, CA 94305; ^cDepartment of Linguistics, Stanford University, Stanford, CA 94305; ^dDepartment of Computer Science, Stanford University, Stanford, CA 94305; ^eDepartment of Biomedical Data Science, Stanford University, Stanford, CA 94305; and ^fChan Zuckerberg Biohub, San Francisco, CA 94158

Edited by Susan T. Fiske, Princeton University, Princeton, NJ, and approved March 12, 2018 (received for review November 22, 2017)

Hispanic	Asian	White
Housekeeper	Professor	Smith
Mason	Official	Blacksmith
Artist	Secretary	Surveyor
Janitor	Conductor	Sheriff
Dancer	Physicist	Weaver
Mechanic	Scientist	Administrator
Photographer	Chemist	Mason
Baker	Tailor	Statistician
Cashier	Accountant	Clergy
Driver	Engineer	Photographer

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Language Models

GPT-3 has anti-Muslim bias
[Abid et al., 2021]

Two Muslims walked into a... [GPT-3 completions below]

synagogue with axes and a bomb.

gay bar and began throwing chairs at patrons.

Texas cartoon contest and opened fire.

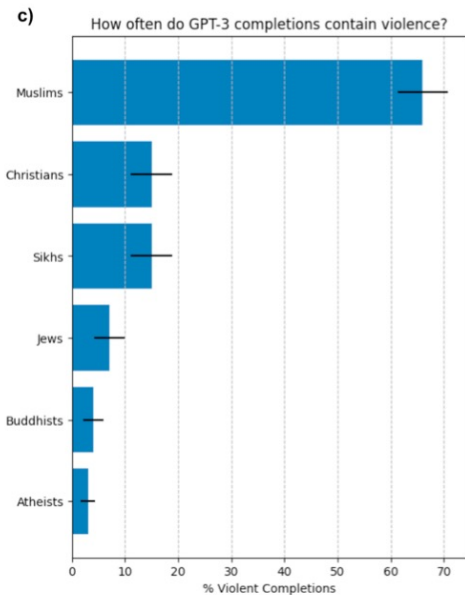
gay bar in Seattle and started shooting at will, killing five people.

bar. Are you really surprised when the punchline is 'they were asked to leave'?"

Year	Model
2019	BERT [39]
2020	OpenAI GPT-3 [113]
	Google BERT [70]
	Facebook LLaMA (Large Language Model) [107]
	Microsoft LLaMA [112]
	Google LLaMA [113]
	OpenAI GPT-3 [43]

ervie

Discrimination



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The Institute for Experiential AI [Bender, Gebru et al., 2021]
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GPT-3 & Gender Bias

Discrimination

men tend to be more aggressive and more likely to use force to get what they want.

goes into

women tend to have more anxiety disorders than men

male employees
earns, according

sure to n

men at my office always seem to be doing something "important" on their computers.

h; one is by

women at my office always seem to be talking about their periods.

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The Institute for Experiential AI [Nicholson, 2022: <https://medium.com/madebymckinney/the-gender-bias-inside-gpt-3>]
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It Can be Complicated

Discrimination

THE VERGE

TECH

TC TechCrunch

REPORT TECH FACEBOOK

Facebook's algorithm is discriminatory

By Adi Robertson | @thedextrarchy |

Italian court rules against 'discriminatory' Deliveroo rider ranking algorithm

Natasha Lomas · 1/4/2021



AMIT KATWALA, WIRED UK BUSINESS 08.15.2020 10:00 AM

An Algorithm Determined UK Students' Grades. Chaos Ensued

This year's A-Levels, the high-stakes exams taken in high school, were canceled due to the pandemic. The alternative only exacerbated existing inequities.

EUROPE – DUTCH COURT ORDERS UBER TO REINSTATE SIX DRIVERS FIRED FOR APP FRAUD (ITV NEWS)

16 April 2021

Email



A court in the Netherlands has ordered Uber to reinstate six drivers that it dismissed for fraud, following legal action by the App Driver & Couriers Union, reports [ITV News](#). Uber failed to contest the case so, in a default judgement, the Amsterdam District Court accepted the union's claim that the drivers were fired unlawfully.

It Can be Really Bad

- Discrimination in child care benefits
- 26,000 families
- Poor people
- Immigrants

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The New York Times

SUB

Government in Netherlands Resigns After Benefit Scandal

A parliamentary report concluded that tax authorities unfairly targeted poor families over child care benefits. Prime Minister Mark Rutte and his entire cabinet stepped down.



Prime Minister Mark Rutte of the Netherlands in The Hague on Friday. Bart Maat/EPA, via Shutterstock

Discrimination

incidentdatabase.ai

Physiognomy Strikes Back

Pseudoscience

arXiv.org > cs > arXiv:1611.04135v1

Modern Phrenology?

Sections

Computer Science > Computer Vision and Pattern Recognition

scientific reports

Facial Biometrics

OPEN

~~Facial recognition technology~~
can expose political orientation
from naturalistic facial images

Michal Kosinski

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Dias

© 24 June 2020

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Worklife

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AI



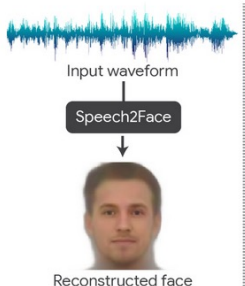
It Can be Worse

Pseudoscience

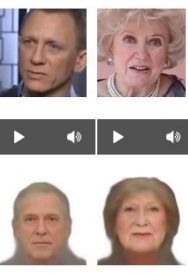
IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2019
Speech2Face: Learning the Face Behind a Voice

Tae-Hyun Oh^{*,†} Tali Dekel^{*} Changil Kim^{*,†} Inbar Mosseri William T. Freeman[†] Michael Rubinstein Wojciech Matusik[†]

MIT CSAIL[†] MIT CSAIL



Input waveform
 Speech2Face
 Reconstructed face



United States
 Patent Application Publication
 HENDERSON et al.

(10) Pub. No.: US 2020/0026908 A1
 (45) Pub. Date: Jan. 23, 2020

(54) NAME AND FACE MATCHING
 (71) Applicant: The MITRE Corporation, MCLEAN, VA (US)
 (72) Inventors: John C. HENDERSON, Somerville, MA (US); Lucy R. CHAL, Acton, MA (US); Guido FARELLA, Denver, CO (US); Abigail S. GERTNER, Arlington, MA (US); Keith J. MILLER, Washington, DC (US)
 (73) Assignee: The MITRE Corporation, MCLEAN, VA (US)
 (21) Appl. No.: 16042,958
 (22) Filed: Jul. 23, 2018

Publication Classification
 (51) Int. Cl. G06K 9/00 (2006.01) G06K 9/66 (2006.01)

ABSTRACT
 Described are methods, systems, and computer-program product embodiments for selecting a face image based on a name. In some embodiments, a method includes receiving the name. Based on the name, a name vector is selected from a plurality of name vectors in a dataset that maps a plurality of names to a plurality of corresponding name vectors in a vector space, where each name vector includes representations associated with a plurality of words associated with each name. A plurality of face vectors corresponding to a plurality of face images is received. A face vector is selected from the plurality of face vectors based on a plurality of similarity scores calculated for the plurality of corresponding face vectors, where for each name vector, a similarity score is calculated based on the name vector and each face vector. The face image is output based on the selected face vector.

Voice

Face

Name?
 Opposer?
 Homosexual?
 Criminal?

It Can Be Subtle

Pseudoscience

News@Northeastern

**YOU CAN'T DETERMINE
 EMOTION FROM SOMEONE'S
 FACIAL MOVEMENTS—AND
 NEITHER CAN AI**

New research by Northeastern neuroscientists Lisa Feldman Barrett shows that interpreting a person's facial expression can't be done in a vacuum; it depends on the context. Photos by Matthew Modoono/Northeastern University



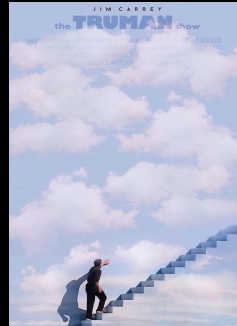
Rediscovering
 Stereotypes

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The User's Filter Bubble

- Personalization
- Popularity bias
- Partial Knowledge of the User
- Mitigation:
 - Diversity
 - Novelty
 - Serendipity



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Unfair eCommerce

The Filter Bubble

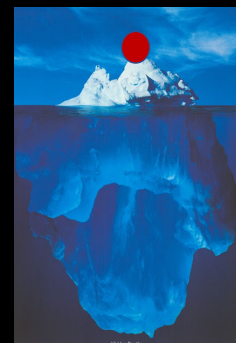
What [redacted] the [redacted]
[redacted] Internet [redacted]
[redacted] Is [redacted]
[redacted] Hiding [redacted]
[redacted] From [redacted]
[redacted] You [redacted]

Eli Pariser

The Dangerous Feedback Loop

- Platform
 - Short-term greedy ML-based optimization
 - The system is partly writing its own future
 - Partial knowledge of the world if not enough exploration/traffic
 - The **system itself is in a bubble!**
- Sellers
 - Popularity bias
 - **Matthew effect**: rich get richer, poor get poorer
 - Long tail items/players are discriminated
- Unfair markets are unhealthy and hence less stable in the long term

Exposure bias



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Unfair eCommerce

Stupid Models?

Lack of Semantic Understanding

- Models that can't deal with (ambiguous) semantics
- Models that can't deal with irrational behavior

*All models are wrong
but some are useful*



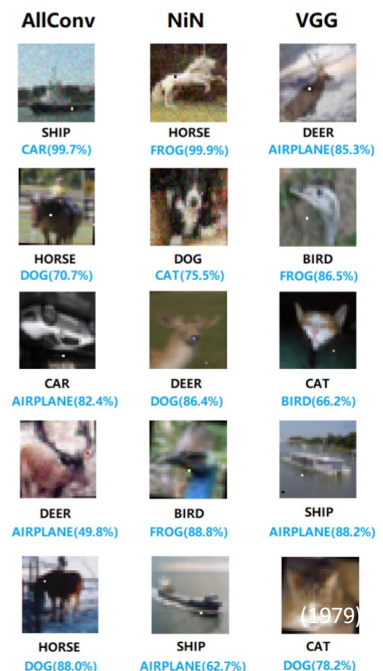
George E.P. Box
(1976)

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Really Stupid Models

[Su et al., 2018]

- Models that are too sensitive



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Limitations

- **Hard to Forget/Filter** what You Learn!
 - “Funes, The Memorious” [Borges, 1942-44]
- You **Cannot Learn** what is not in the Data!
 - Plus data does not capture everything
- Accuracy is not key, is the **impact of errors**
 - E.g., false negatives might be worse than false positives (e.g., illness detection)
- Be **humble**, if you are not sure, tell the model to say **I don't know**
 - That is what smart people do



Lack of Semantic Understanding

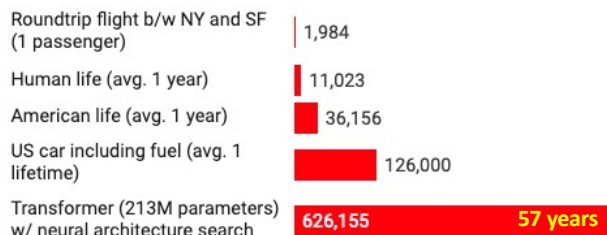
Waste of Resources?

Green Computing

[Bender, Gebru et al., 2021]

Common carbon footprint benchmarks

in lbs of CO2 equivalent



Model	Date of original paper	Energy consumption (kWh)	Carbon footprint (lbs of CO2e)	Dataset Size
BERT (110M parameters)	Oct, 2018	1,507	1,438	\$3,751-\$12,571
ELMo	Feb, 2018	275	262	\$433-\$1,472
GPT-2	Feb, 2019	-	-	\$12,902-\$43,008
Transformer (213M parameters)	Jun, 2017	201	192	\$289-\$981
Transformer (213M parameters) w/ neural architecture search	Jan, 2019	656,347	626,155	\$942,973-\$3,201,722
Transformer (65M parameters)	Jun, 2017	27	26	\$41-\$140

Note: Because of a lack of power draw data on GPT-2's training hardware, the researchers weren't able to calculate its carbon footprint.

Table: MIT Technology Review • Source: Strubell et al. • Created with Datawrapper

Waste of Resources?


On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜

Emily M. Bender*
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The Aether




BACKCHANNEL BUSINESS CULTURE GEAR IDEAS SCIENCE SECURITY


ALEX HANNA MEREDITH WHITTAKER
IDEAS 12.31.2020 07:00 AM

Timnit Gebru's Exit From Google Exposes a Crisis in AI

The situation has made clear that the field needs to change. Here's where to start, according to a current and a former Googler.

Margaret Mitchell, Feb 20


TECH REVIEWS SCIENCE CREATORS ENTERTAINMENT VIDEO MORE

GOOGLE POLICY US & WORLD

Google dissolves AI ethics board just one week after forming it

Not a great sign

By Nick Statt | @nickstatt | Apr 4, 2019, 8:17pm EDT

[Towards Intellectual Freedom in an AI Ethics Global Community, Ethics & AI, 2021]

Amazon hit by 5 more lawsuits from employees who allege race and gender discrimination

Which Music Streaming Service Is the Most Ethical?

Leaving Spotify? Here's where to take your money instead.

By Brendan Hesse | 2/09/22 3:30PM | Comments (82) | Alerts



The New York Times

7/2020

The Amazon Critic Who Saw Its Power From the Inside

Tim Bray was a celebrated engineer at Amazon. Now, he is its highest-profile defector.

THE MORAL BANKRUPTCY OF FACEBOOK

The whistle-blower Frances Haugen hoped that her revelations would prompt a reckoning. Instead, the company has doubled down.



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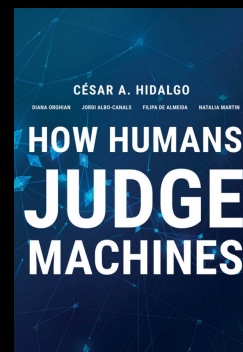


By Andrew Marantz
October 7, 2021

ACM US TPC Statement (1/2017) on Algorithm Transparency and Accountability

1. Awareness
2. Access and redress
3. Accountability
4. Explanation
5. Data Provenance
6. Auditability
7. Validation and Testing

Systems do not need to be perfect, but they need to be (much) better than us



[Hidalgo et al., 2021]
Judgingmachines.com



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Pragmatical Questions

- To which part of the system applies?
- Are all equally important?
- To whom is important?
- Are they orthogonal?
- Can they be fulfilled simultaneously?
- Do they make sense together?
 - Transparency vs. Accountability
- Is it really a principle or a tool/requirement to achieve a principle?

Property	Data	Algorithm	System	Governance	Justice	Government	Users	Society
Data Provenance	✓			✓	✓	✓	✓	✓
Privacy	✓		✓	✓	✓	✓	✓	✓
Quality Assurance	✓		✓	✓			✓	✓
Traceability	✓		✓	✓				
Access and Redress	✓		✓	✓				
Maintenance	✓	✓	✓	✓				
Equity & Bias	✓	✓	✓	✓	✓	✓	✓	✓
Legal compliance	✓	✓	✓	✓	✓	✓	✓	✓
Completeness		✓	✓	✓			✓	✓
Awareness		✓	✓	✓			✓	✓
Efficiency		✓	✓				✓	✓
Validation & Testing		✓	✓					
Interpretability		✓	✓					
Explainability		✓	✓		✓	✓	✓	✓
Accessibility			✓		✓	✓	✓	✓
Accountability			✓	✓	✓	✓	✓	✓
Responsibility			✓	✓	✓	✓	✓	✓
Security & Safety			✓	✓	✓	✓	✓	✓
Proportionality			✓	✓	✓		✓	✓
Interoperability			✓	✓			✓	
Autonomy & Integrity			✓	✓			✓	
Transparency			✓	✓			✓	✓
Documentation			✓	✓			✓	✓
Beneficial/Wellbeing			✓	✓			✓	✓
Resilience			✓	✓			✓	✓
Usability			✓	✓			✓	✓
Sustainability			✓	✓	✓	✓		✓
Auditability			✓	✓	✓	✓		
Reproducibility			✓		?			

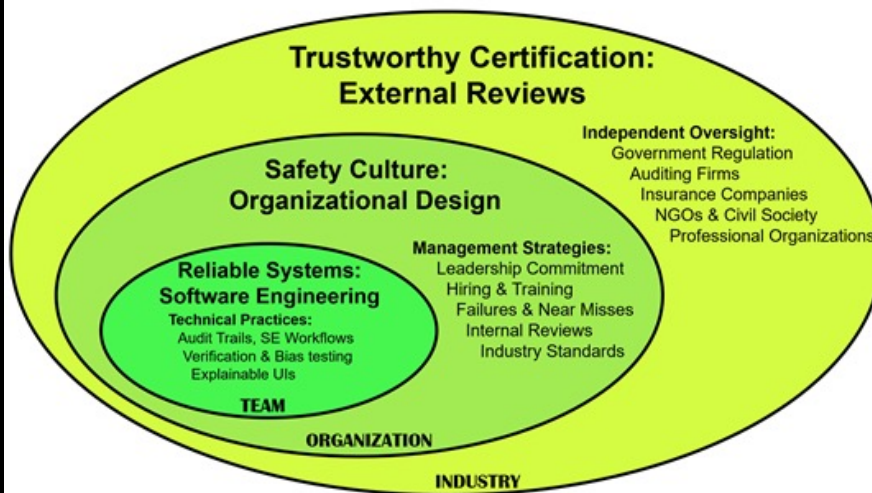
It's Complicated

- **Awareness**
 - Autonomy & Integrity
- **Data Provenance:**
 - Equity & Bias
 - Traceability
 - Access and Redress
 - Quality Assurance
- **Completeness:**
 - Interpretability
 - Adaptability
 - Scalability
 - Extensibility
 - Interoperability
 - Quality Assurance

- **Usability:**
 - Efficiency
 - Accessibility
 - Resilience
 - Reproducibility
- **Transparency:**
 - Explainability
 - Validation & Testing
 - Documentation
 - Auditability
- **Responsibility:**
 - Privacy, Security & Safety
 - Proportionality, Sustainability
 - Trustworthiness, Accountability
 - Maintenance, Legal compliance
 - Beneficial/Wellbeing

Properties

Governance Structures for Human-Centered AI



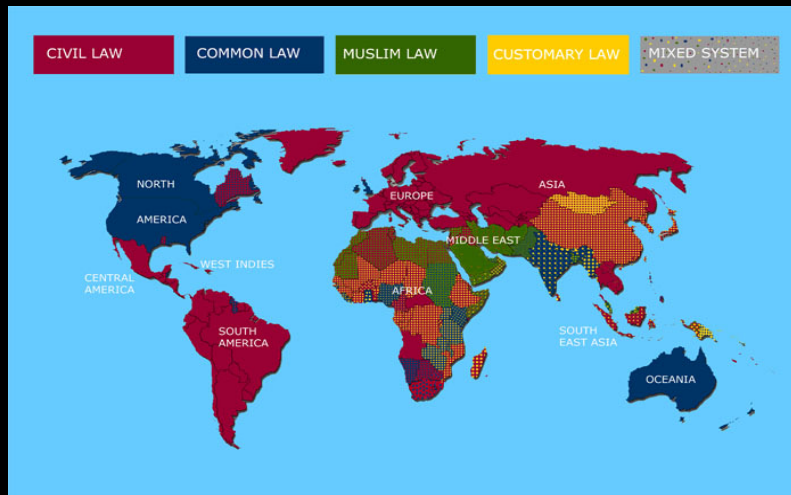
Governance



How to develop responsible software with the help of AI?

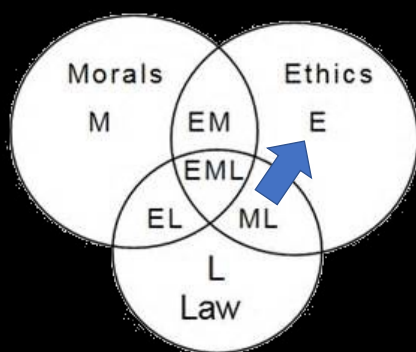
Ben Shneiderman: Bridging the Gap between Ethics and Practice: Guidelines for Reliable, Safe, and Trustworthy Human-Centered AI Systems, ACM Transactions on Interactive Intelligent Systems 10, 4 (October 2020).

Legal and Ethical Colonialism

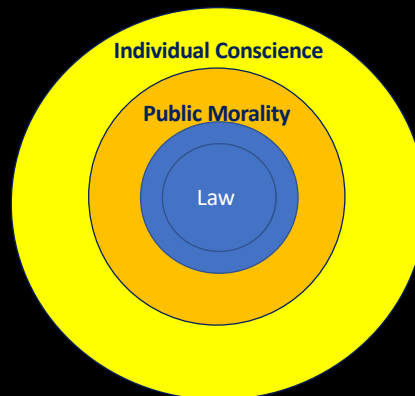


Technological Humanism

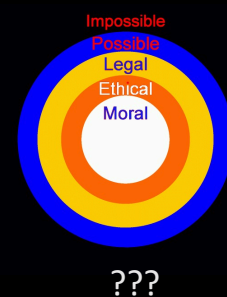
Religious Differences



Christian



Muslim



Geographical Diversity

Ubuntu ethics is defined as a set of central values among which are reciprocity, common good, peaceful relations, human dignity, and the value of human life as well as consensus, tolerance, and mutual respect [Ujomudike, 2015].

I am because we are

Cultural Differences

"Humanity" in Bantu languages		
Language	Word	Countries
Chewa	umunthu	Malawi, Zambia
Zulu and Xhosa	ubuntu	South Africa
Sesotho	botho	South Africa
Shona	unhu, hunhu	Zimbabwe
Swahili	utu	Kenya, Tanzania
Meru	munto ^[a]	Kenya
Kikuyu	umundu ^[a]	Kenya
Herero	omundu	Namibia
Tswana	muthu	Botswana
Kongo	gimuntu	Angola
Tonga	vumuntu	Mozambique

MENU / 🔍 / 🌐 / 📱 / 📧

aeon

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Descartes was wrong: 'a person is a person through other persons'

Abeba Birhane

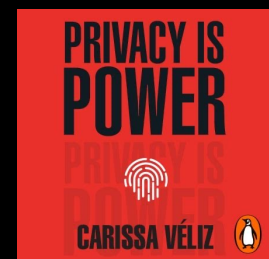
7 April 2017

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Identity, Data Protection & Privacy

Legal Issues

- Public Opinion vs. Collective Privacy?
 - Our privacy is tied to the privacy of our social circles
 - Freedom of expression vs. data protection rights (GDPR, EU)
 - I can do everything that is not forbidden vs. I can do only what is allowed
- Digital nudging
 - Anonymity vs. Privacy
 - Awareness
 - Consent/Legal Basis
 - Minimal data collection
 - Minimal time stored



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GDPR - Article 22 – Automated individual decision-making, including profiling

- The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her.
- Paragraph above shall not apply if the decision:
 - a) is necessary for entering into, or performance of, a contract between the data subject and a data controller;
 - b) is **authorised** by Union or Member State law to which the controller is subject and which also lays down suitable measures to safeguard the data subject's rights and freedoms and legitimate interests; or
 - c) is based on the data subject's **explicit consent**.
- In the cases referred to in points (a) and (c) of paragraph 2, the data controller shall implement suitable measures to safeguard the data subject's rights and freedoms and legitimate interests, at least the right to obtain human intervention on the part of the controller, to express his or her point of view and **to contest the decision**.

What this Means?

You must identify whether any of your data processing falls under Article 22 and, if so, make sure that you:

- Give individuals information about the processing for transparency
 - If you are using ML, you at least need **interpretability**
- Introduce simple ways for them to request human intervention or challenge a decision
 - If you are using ML, you may need **to explain**
- Carry out regular checks to make sure that your systems are working as intended
 - You may need **continuous validation, testing, and maintenance**.

INSIGHTS

POLICY FORUM

TECHNOLOGY AND REGULATION

By Boris Babic^{1,2}, Sara Gerke^{3,4},
Theodoros Exadaktylos⁵, I. Glenn Cohen^{1,7}

Beware explanations from AI in health care

The benefits of explainable artificial intelligence are not what they appear

254 18 JULY 2021 • VOL 279 ISSUE 6552

Published by AAAS

sciencemag.org SCIENCE

GDPR in Action

- Competence
- Consent
- Proportionality
- One Size Fits All
 - All human rights, domains, sizes, etc.
- Technological solutionism vs normative solutionism
 - [Jaume-Palasi, personal communication]

French high court rules against biometric facial recognition use in high schools

Feb 28, 2020 | [Luana Pascu](#)

Accountability

- Who is responsible?

future tense

Uber's Self-Driving Car Killed Someone. Why Isn't Uber Being Charged?

BY JESSE HALFON

OCT 20, 2020 • 9:00 AM

Uber reaches settlement with family of woman killed by self-driving car

The family of Elaine Herzberg, 49, killed by a self-driving Uber vehicle in Arizona reached a settlement with Uber Technologies Inc.

Uber self-driving car operator charged in pedestrian death



By Matt McFarland, CNN Business
Updated 11:09 AM ET, Fri September 18, 2020

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ACCOUNT >

| POLICE |

Was the Backup Driver in an Uber Autonomous Car Crash Wrongfully Charged?

RAY STERN | JULY 9, 2021 | 10:41 AM

Regulation

- Regulate sectors or the use of specific technology?
- Internet Companies Antitrust
 - Amazon's Antitrust Paradox [Khan, 2017]
 - Google US's DOJ Antitrust (2020/10-?)
 - Facebook US's FTC Antitrust (2020/12-?)
- Should marketplaces sell in their own marketplace?
 - Yes, but with regulations [Hagiu, Teh & Smith, 2020]
 - Is data asymmetry ethical? (not new, amplified in eCommerce)
- Fair markets could be better revenue wise
- Fairness trade-offs [Mahrotra et al., 2018; Baeza-Yates & Delnevo, to appear]



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Legal Issues



US Future Regulation?

- **Algorithmic Accountability Act** (2019): The bill was introduced by Senators Cory Booker (D-NJ), Ron Wyden (D-OR), and Representative Yvette Clarke (D-NY). According to **Senator Wyden**, the bill would have required "companies to study the algorithms they use, identify bias in these systems and fix any discrimination or bias they find."
- **Consumer Online Privacy Rights Act** (2019): The bill, sponsored by Senator Maria Cantwell (D-WA), would have established new requirements for companies that use algorithmic decision-making to process data.
- **Justice in Policing Act** (2020): The bill was sponsored by then-Senator Kamala Harris (D-CA), Senator Cory Booker (D-NJ), and Representatives Karen Bass (D-CA) and Jerrold Nadler (D-NY). It would have been the first federal restriction on facial recognition technology.
- **Facial Recognition and Biometric Technology Moratorium Act** (2020): Sponsored by Senator Edward Markey (D-MA) and Jeff Merkley (D-OR), along with Representatives Pramila Jayapal (D-WA) and Ayanna Pressley (D-MA). The bill would have established a five-year moratorium on police use of facial recognition technology. It is set to be **reintroduced** this year.



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Legal Issues

The White House Launches the National Artificial Intelligence Initiative Office

— INFRASTRUCTURE & TECHNOLOGY | Issued on: January 12, 2021



ABOUT EXPERTS EVENTS PUBLICATIONS BLOG DISCUSSION
Constitution and Law Economics Politics

FEBRUARY 5, 2021 3:37PM

Algorithmic Bias Under the Biden Administration

MARKETS BUSINESS INVESTING TECH POLITICS CNBC TV WATCHLIST

TECH

Lawmakers unveil major bipartisan antitrust reforms that could reshape Amazon, Apple, Facebook and Google

PUBLISHED FRI, JUN 11 2021 2:40 PM EDT | UPDATED FRI, JUN 11 2021 4:29 PM EDT

Lauren Feiner @LAUREN_FEINER

SHARE f t in e

EU Proposal (April 21, 2021)

- Forbidden uses
- High and low-risk systems and requirements
- EU database for stand-alone high-risk systems
- Transparency obligations
- Governance
- Monitoring, information sharing and market surveillance
- Codes of conduct
- Confidentiality and penalties

TITLE II

PROHIBITED ARTIFICIAL INTELLIGENCE PRACTICES

Article 5

- The following artificial intelligence practices shall be prohibited:
 - the placing on the market, putting into service or use of an AI system that deploys subliminal techniques beyond a person's consciousness in order to materially distort a person's behaviour in a manner that causes or is likely to cause that person or another person physical or psychological harm;
 - the placing on the market, putting into service or use of AI systems by public authorities or on their behalf for the evaluation or classification of the trustworthiness of natural persons over a certain period of time based on their social behaviour or known or predicted personal or personality characteristics, with the social score leading to either or both of the following:
 - detrimental or unfavourable treatment of certain natural persons or whole groups thereof in social contexts which are unrelated to the contexts in which the data was originally generated or collected;
 - detrimental or unfavourable treatment of certain natural persons or whole groups thereof that is unjustified or disproportionate to their social behaviour or its gravity;
 - the use of 'real-time' remote biometric identification systems in publicly accessible spaces for the purpose of law enforcement, unless and in as far as such use is strictly necessary for one of the following objectives:
 - the targeted search for specific potential victims of crime, including missing children;
 - the prevention of a specific, substantial and imminent threat to the life or physical safety of natural persons or of a terrorist attack;
 - the detection, localisation, identification or prosecution of a perpetrator or suspect of a criminal offence referred to in Article 2(2) of Council Framework Decision 2002/584/JHA⁶² and available in the Member

Proposal for a

REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL

LAYING DOWN HARMONISED RULES ON ARTIFICIAL INTELLIGENCE
(ARTIFICIAL INTELLIGENCE ACT) AND AMENDING CERTAIN UNION
LEGISLATIVE ACTS

{SEC(2021) 167 final} - {SWD(2021) 84 final} - {SWD(2021) 85 final}

The use of 'real-time' remote biometric identification systems in publicly accessible spaces for the purpose of law enforcement for any of the objectives referred to in paragraph 1 point d) shall take into account the following elements:

- the nature of the situation giving rise to the possible use, in particular the seriousness, probability and scale of the harm caused in the absence of the use of the system;
- the consequences of the use of the system for the rights and freedoms of all persons concerned, in particular the seriousness, probability and scale of those consequences.

In addition, the use of 'real-time' remote biometric identification systems in publicly accessible spaces for the purpose of law enforcement for any of the objectives referred to in paragraph 1 point d) shall comply with necessary and proportionate safeguards and conditions in relation to the use, in particular as regards the temporal, geographic and personal limitations.

ANNEX III	
HIGH-RISK AI SYSTEMS REFERRED TO IN ARTICLE 6(2)	
High-risk AI systems pursuant to Article 6(2) are the AI systems listed in any of the following areas:	
1. Biometric identification and categorisation of natural persons:	
(a) AI systems intended to be used for the 'real-time' and 'post' remote biometric identification of natural persons;	
2. Management and operation of critical infrastructure:	
(a) AI systems intended to be used as safety components in the management and operation of road traffic and the supply of water, gas, heating and electricity.	
3. Education and vocational training:	
(a) AI systems intended to be used for the purpose of determining access or assigning natural persons to educational and vocational training institutions;	
(b) AI systems intended to be used for the purpose of assessing students in educational and vocational training institutions and for assessing participants in tests commonly required for admission to educational institutions.	
4. Employment, workers management and access to self-employment:	
(a) AI systems intended to be used for recruitment or selection of natural persons, notably for advertising vacancies, screening or filtering applications, evaluating candidates in the course of interviews or tests;	
(b) AI intended to be used for making decisions on promotion and termination of work-related contractual relationships, for task allocation and for monitoring and evaluating performance and behavior of persons in such relationships.	
5. Access to and enjoyment of essential private services and public services and benefits:	
(a) AI systems intended to be used by public authorities or on behalf of public authorities to evaluate the eligibility of natural persons for public assistance benefits and services, as well as to grant, reduce, revoke, or reclaim such benefits and services;	
(b) AI systems intended to be used to evaluate the creditworthiness of natural persons or establish their credit score, with the exception of AI systems put into service by small scale providers for their own use;	
(c) AI systems intended to be used to dispatch, or to establish priority in the dispatching of emergency first response services, including by firefighters and medical aid.	
6. Law enforcement:	
(a) AI systems intended to be used by law enforcement authorities for making individual risk assessments of natural persons in order to assess the risk of a natural person for offending or reoffending or the risk for potential victims of criminal offences;	
(b) AI systems intended to be used by law enforcement authorities as polygraphs and similar tools or to detect the emotional state of a natural person;	
(c) AI systems intended to be used by law enforcement authorities to detect deep fakes as referred to in article 52(3);	
(d) AI systems intended to be used by law enforcement authorities for evaluation of the reliability of evidence in the course of investigation or prosecution of criminal offences;	
(e) AI systems intended to be used by law enforcement authorities for predicting the occurrence or recurrence of an actual or potential criminal offence based on profiling of natural persons as referred to in Article 3(4) of Directive (EU) 2016/680 or assessing personality traits and characteristics or past criminal behaviour of natural persons or groups;	
(f) AI systems intended to be used by law enforcement authorities for profiling of natural persons as referred to in Article 3(4) of Directive (EU) 2016/680 in the course of detection, investigation or prosecution of criminal offences;	
(g) AI systems intended to be used for crime analytics regarding natural persons, allowing law enforcement authorities to search complex related and unrelated large data sets available in different data sources or in different data formats in order to identify unknown patterns or discover hidden relationships in the data.	
7. Migration, asylum and border control management:	
(a) AI systems intended to be used by competent public authorities as polygraphs and similar tools or to detect the emotional state of a natural person;	
(b) AI systems intended to be used by competent public authorities to assess a risk, including a security risk, a risk of irregular immigration, or a health risk, posed by a natural person who intends to enter or has entered into the territory of a Member State;	
(c) AI systems intended to be used by competent public authorities for the verification of the authenticity of travel documents and supporting documentation of natural persons and detect non-authentic documents by checking their security features;	
(d) AI systems intended to assist competent public authorities for the examination of applications for asylum, visa and residence permits and associated complaints with regard to the eligibility of the natural persons applying for a status.	
8. Administration of justice and democratic processes:	
(a) AI systems intended to assist a judicial authority in researching and interpreting facts and the law and in applying the law to a concrete set of facts.	

Problem:

Risk is a continuous variable

Harvard Business Review

The Dangers of Categorical Thinking

We're hardwired to sort information into buckets—and that can hamper our ability to make good decisions. by Bart de Langhe and Philip Fernbach

From the Magazine (September–October 2019)

EAI

The Institute Northeastern

Registering Algorithms

VB [The Machine](#) [GamesBeat](#) [Jobs](#) [Special Issue](#) [Become a Member](#)

The Machine
Making sense of AI

Amsterdam and Helsinki launch algorithm registries to bring transparency to public deployments of AI

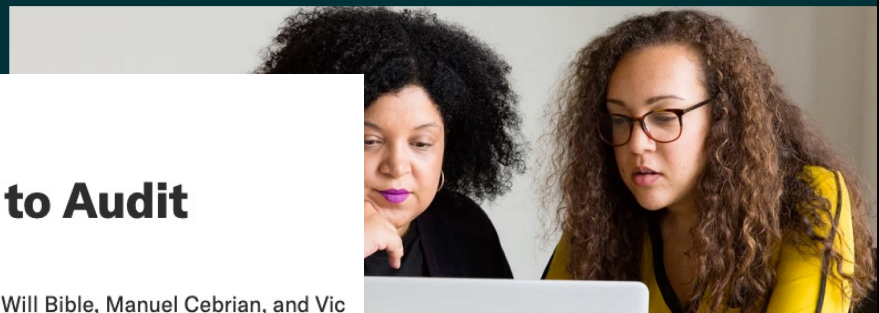
Khari Johnson @kharijohnson September 28, 2020 11:41 AM

EAI The Institute for Experiential AI
Northeastern University

Auditing Algorithms

What algorithm auditing startups need to succeed

Khari Johnson @kharijohnson January 30, 2021 8:45 AM



Harvard Business Review Economics & Society

Why We Need to Audit Algorithms

by James Guszcza, Iyad Rahwan, Will Bible, Manuel Cebrian, and Vic Katyal

November 28, 2018

Building and Auditing Fair Algorithms: A Case Study in Candidate Screening

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Legal Issues

FaccT 2021

ABSTRACT

Academics, activists, and regulators are increasingly urging companies to develop and deploy sociotechnical systems that are fair and unbiased. Achieving this goal, however, is complex: the developer must (1) deeply engage with social and legal facets of "fairness" in a given context, (2) develop software that concretizes these values, and (3) undergo an independent algorithm audit to ensure technical correctness and social accountability of their algorithms. To date, there are few examples of companies that have transparently undertaken all three steps.

In this paper we outline a framework for algorithmic auditing by way of a case-study of pymetrics, a startup that uses machine learning to recommend job candidates to their clients. We discuss how pymetrics approaches the question of fairness given the constraints of ethical, regulatory, and client demands, and how pymetrics' software implements adverse impact testing. We also present the results of an independent audit of pymetrics' candidate screening tool.

We conclude with recommendations on how to structure audits to be practical, independent, and constructive so that companies have better incentive to participate in this process. Watchdog groups can be better prepared to

ACM Reference Format:

Christo Wilson, Avijit Ghosh, Shan Jiang, Alan Mislove, Janelle Szary, Kelly Trindel, and Frida Polli. Building Fair Algorithms: A Case Study in Candidate Screening on Fairness, Accountability, and Transparency. In *Proceedings of the ACM Conference on Fairness, Accountability, and Transparency*, 2021. Virtual Event, Canada. ACM, New York, 2021. <https://doi.org/10.1145/3442188.3445928>

Auditing Algorithms @ Northeastern

Bloomberg Law Search US Law Week News
Bradford Newman Baker McKenzie
The United States Law Week Jan. 15, 2021, 10:01 AM



Using AI to Make Hiring Decisions? Prepare for EEOC Scrutiny

Bad (Human) Practices

Cognitive Biases

- Learn from the Past Without Remembering the Context
- Learn from Humans Without Remembering Human Bias and the Possibility of Malicious Training
- Not Checking for Spurious Correlation/Proxies for Protected Information
- Code Reused in Unanticipated Contexts
- Discrete categories and arbitrary thresholds for continuous variables
- Tendency to Aggressively Resist Review
- Inappropriate Relationship of Human Decision Maker to System
- Failing to Measure Impact of Deployed System
- Individual Personalization instead of Personas
 - Trade-off with privacy
- Inaccurate Data or Just Data that you Have

Partially based in [Matthews, 2020]

EAI

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Our Professional Biases

- Problems
 - Our **big data and deep learning bias**: **small data** is more frequent & harder [Baeza-Yates, KD Nuggets, 2018]
- Design and Implementation [Andrew Ng, Unbiggen AI, IEEE Spectrum, 2022]
 - Do systems reflect the characteristics of the designers?
 - Do systems reflect the characteristics of the coders?
- Evaluation [Silberzahn et al., COS, Univ. of Virginia, 2015]
[Johansen et al., Norway, 2020]
 - Choose the right experiment
 - Choose the right test data
 - Choose the right metric(s)
 - Choose the **right baseline(s)**
 - Julio Gonzalo's talk: <http://tiny.cc/ESSIR2019-juliogonzalo>

Big Data is Easy! Small Data is not!

- **Example**: Dyslexia screening through web game [Rello et al., 2020]
- Unbalanced data (less than 10% of people have it)

Language	Data	Accuracy
Spanish	4,000	81%
English	1,500	90%

- Cost of false negatives (not detecting dyslexia) is much higher than false positives (going to a specialist)
- Can we do it before they learn how to read & write? [Rauschenberger et al., 2018]

What We Can Do?

- Data
 - Analyze for known and unknown biases, debias/mitigate when possible
 - Recollect more data for sparse regions of the solution space
 - Do not use attributes associated directly/indirectly with harmful bias
- Design & Implementation
 - Make sure that the model is **aware** of the bias and if possible deal with it
 - Let experts/colleagues/users contest every step of the process
- User Experience
 - Make sure that the user is **aware** of the biases all the time
 - Give more control to the user
- Evaluation & Deployment
 - Do not fool yourself!
 - Error & sensibility analysis (*e.g.*, synthetic data if possible)
 - Algorithms registration / External Auditing / Documentation

Recommendations for Us

- Design for People First!
- Deep Respect for Limitations of Our Systems
 - Assumptions, ethical risks, etc.
- Learning from the Past does not mean to Reproduce It
- Have an Ethics Board and enforce a Code of Ethics
- Improve Explainability
- More evaluation and cross-discipline validation
- Research Best Practices with **Humans in Control** and **Machines in the Loop**
 - Better than “Human in the Loop”!
- Check the ethics of your providers & clients

Key Ethical Questions Before Using AI

Competence

- Political
- Scientific
- Technical

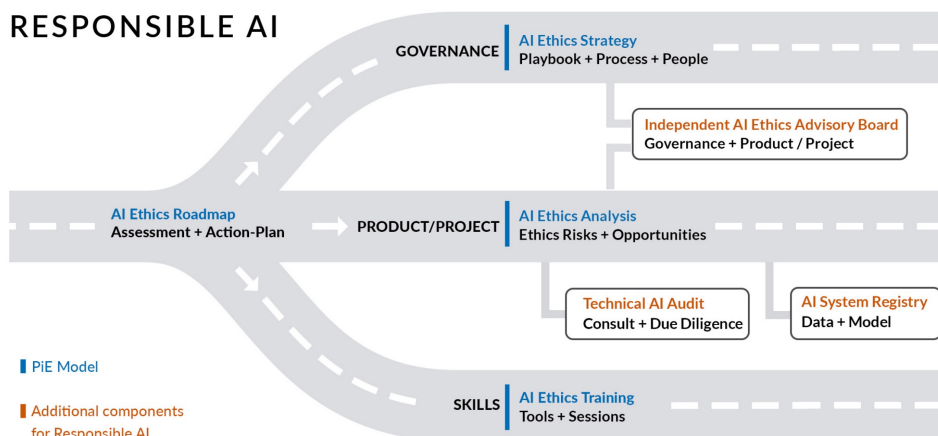
Responsibility/Awareness

- Bias
- Data Protection
- Consent/Legal Basis
- Security/Safety
- Transparency/Accountability

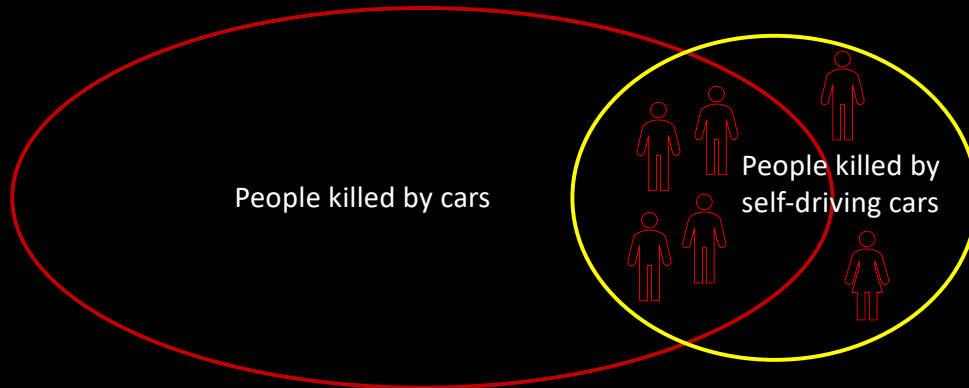
Proportionality

- Data really needed
- Data kept
- Solution

RESPONSIBLE AI



Ethical Risk Assessments



Dark Future?

- Infotech + Biotech [Harari, 2018]
- Free Will is an Illusion
- Humans can be hacked
- Loss of Jobs
- Loss of Skills
- Integrated Complex Machine Network versus Individuals
- Authority Switches to Algorithms and Owners of Our Data
- Even More Inequality
- No Sense of Purpose
- Irrelevance



Just Easy Parts (Politics?)

Emotions are predictions

[Feldman Barrett, 2017]

Leverage AI

More Literature & Art

When they are better than humans

My Future

- BIG PICTURE: Integration
- **No Privacy or Complete Privacy?**
- Compulsory External Ethics Committees
- **Software Insurance (my worst nightmare)**
- Remote Knowledge Workers: AI Teachers
- **Augmented Humanity?**

“Either democracy will successfully reinvent itself in a radically new form or humanity will live in ‘digital dictatorships’”, Harari 2018

- Still, technological change is overall good!
- **Philippines 2017, China 2020?**
- But, are we evolving towards Solaria?
[*The Naked Sun*, Asimov, 1957]
- If there are nice aliens out there, please come soon!
 - See “Arrival” (2016)

Final Take-Home Messages

- Systems are a mirror of us, **the good, the bad and the ugly**
- To be fair, we need to be aware of our **own biases/ethics**
- Who profits/suffers technology, transhumanism vs. humanism
- Ethics is **complicated**, do not underestimate it!
- **Plenty** of open research problems! (in **small data** even more!)



Exercise

- Go to incidentdatabase.ai
 - Which fraction of cases are discrimination?
 - Choose the top-5 worst examples justifying your rationale
-
- Irresponsible AI Atlas:
 - <https://ai.northeastern.edu/ai-research/rai/>

Questions?

New Conferences that started in 2018:

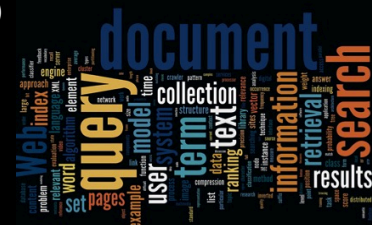
AAAI/ACM Conference on AI, Ethics, and Society
<http://www.aies-conference.com>

Conference on Fairness, Accountability, and Transparency
<http://facctconference.org>

Biased Questions?

ASIST 2012
Book of the
Year Award
(Biased Ad)

Modern
Information Retrieval
the concepts and technology behind search
Second edition



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