Ethics in AI A Challenging Task

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@PolarBeaRBY

Digital Humanism Initiative, May 2021



Institute for Experiential Al

What do we mean by Experiential AI?

- Al with human in the loop
- Al 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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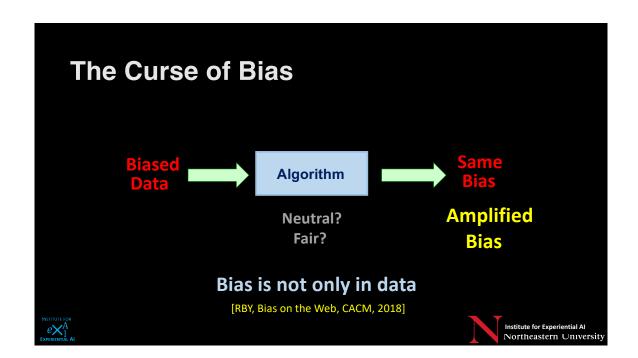
Agenda

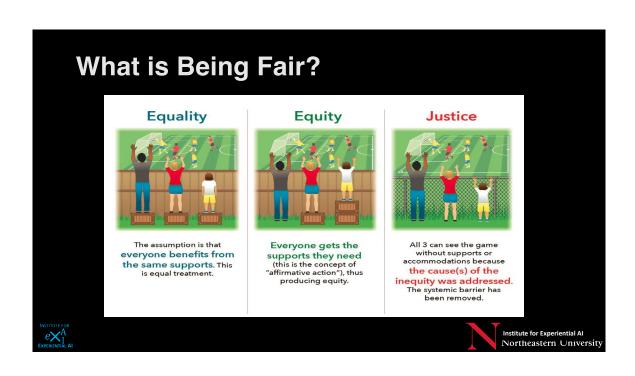
- Current Ethical Issues:
 - Automated discrimination
 - Physiognomy based on facial biometrics
 - Unfair digital commerce
 - Models stupidity
 - Expensive and doubtful use of computing resources
- Generic Issues:
 - Too many principles
 - Cultural differences
 - Regulation
 - Our cognitive biases
- Epilogue



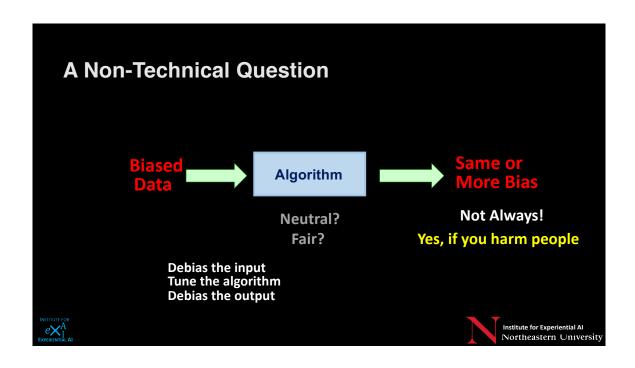


Personal Bias









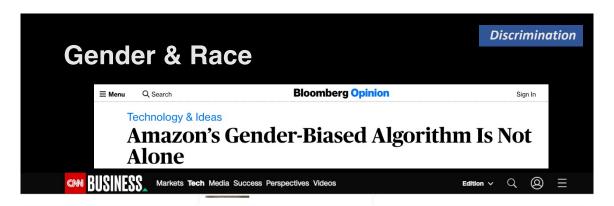
ACM US TPC Statement (1/2017) on Algorithm Transparency and Accountability

- 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

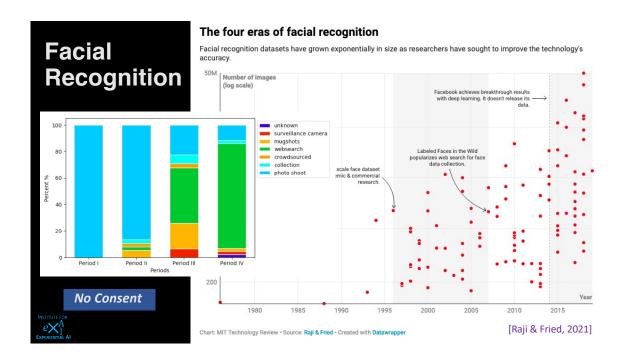






Facial recognition systems show rampant racial bias, government study finds





Discrimination Suspension of Facial Recognition



Discrimination Suspension of Facial Recognition

MOTHERBOARD

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

Michael Oliver is the second Black man found to be wrongfully arrested by Detroit police because of the technology-and his lawyers suspect there are many more.

THE INCONSENTABILITY OF FACIAL SURVEILLANCE

Evan Selinger* and Woodrow Hartzog**



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

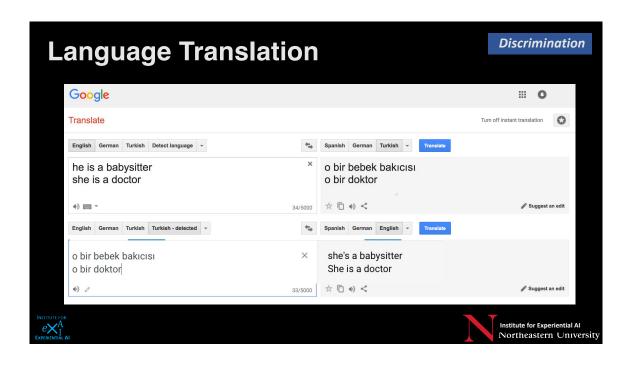


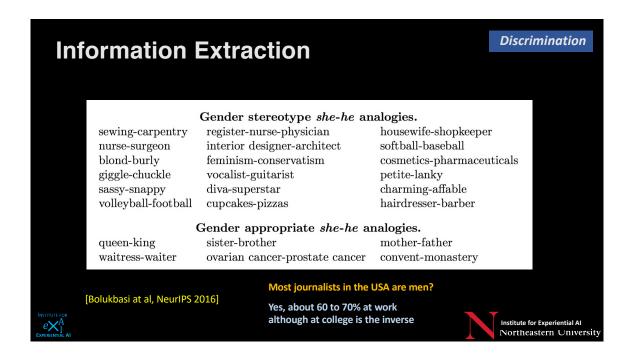


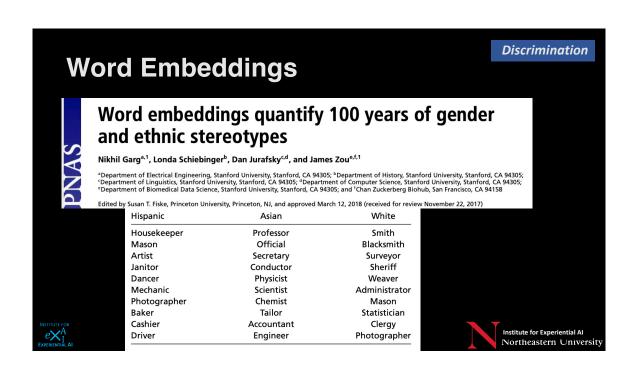


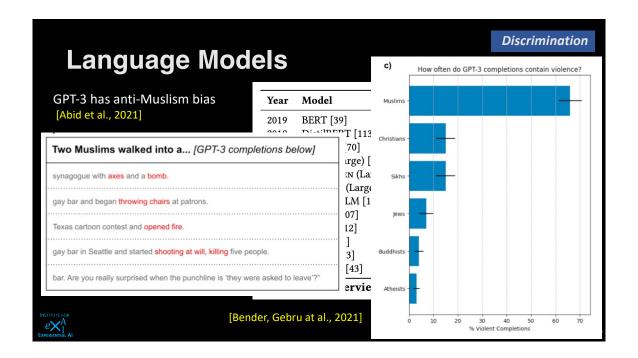


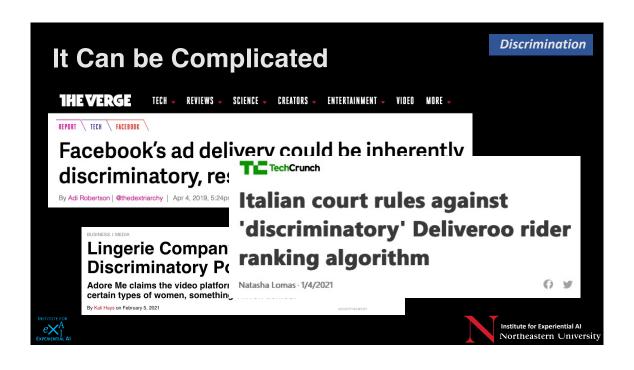


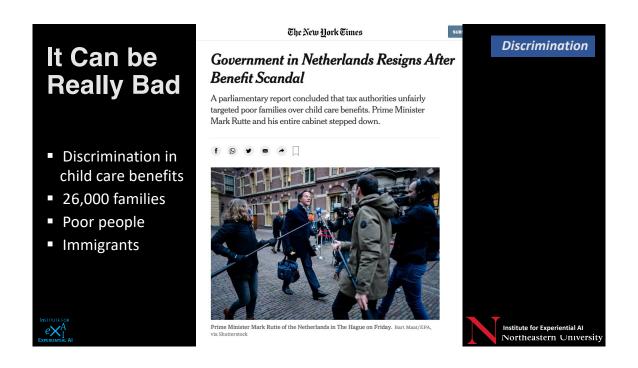












Justice

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
 - 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)





Police

Discrimination

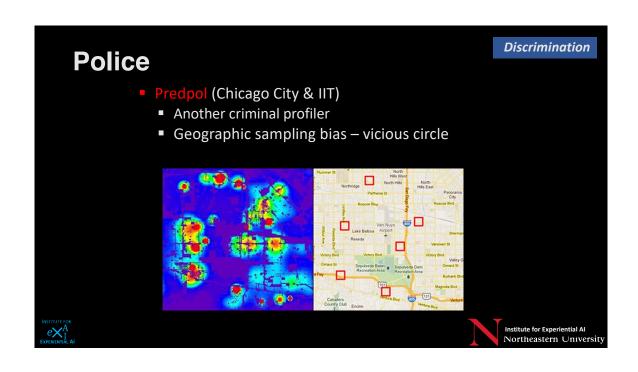
- Gotham & others (Palantir)
 - Criminal profiling
 - Los Angeles (2009) via police foundation
 - New York (2011) never approved by council
 - New Orleans (2012) secret until 2014
 - Denmark (2016), Norway (2017), Germany (2019?)
 - One error and a person is stigmatized

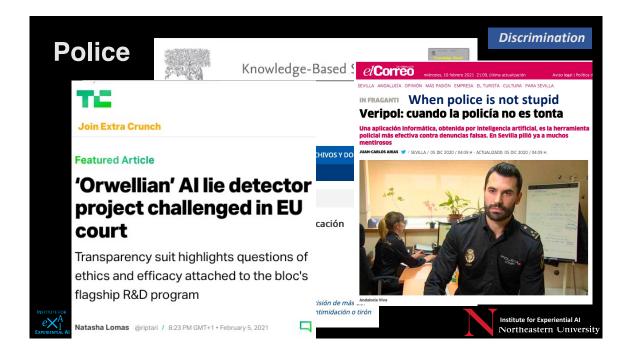


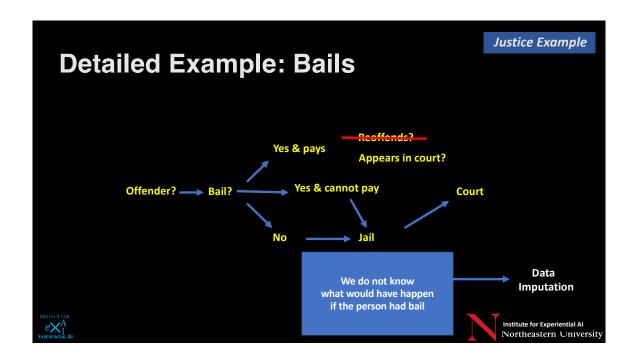












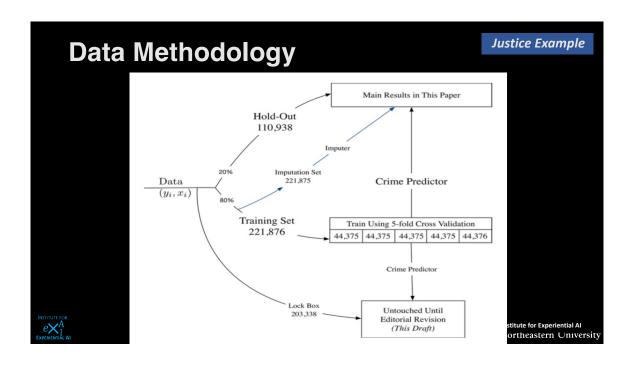
Justice Example

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]







ML Algorithm & Features

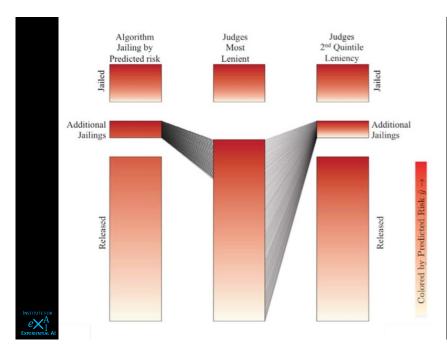
Justice Example

- 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

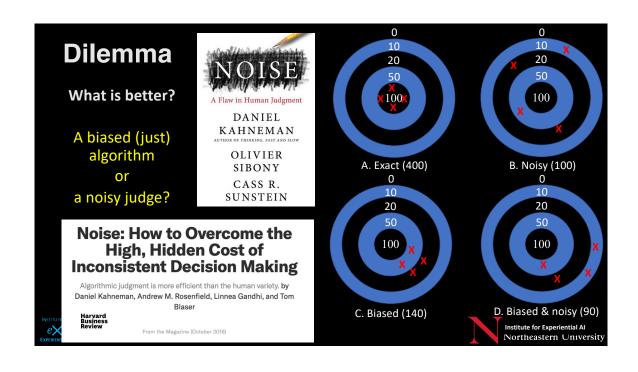




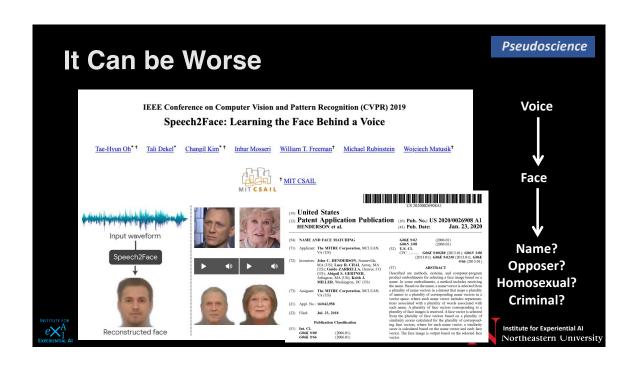
Racial Discrimination 18% Table 7: Racial Fairness 13% 32% Drop Relative Percentage of Jail Population Crime Rate Release Rule to Judge Black Hispanic Minority Distribution of Defendants (Base Rate) Judge .1134 .573 .3162 .8892 0% (.0010)(.0029)(.0027)(.0018)Algorithm .0854 .5984 .3023 .9007 Usual Ranking -24.68% (.0008)(.0029)(.0027)(.0017)Match Judge on Race .0855 .573 .3162 .8892 -24.64% (.0008)(.0029)(.0027)(.0018)Equal Release Rates .0873 .4877 .3318 .8195 -23.02% (.0008) (.0023)for all Races (.0029)(.0028).0876 .4877 .3162 .8039 Match Lower of -22.74% Experiential Al Base Rate or Judge (.0008)(.0027)(.0029)(.0023)stern University

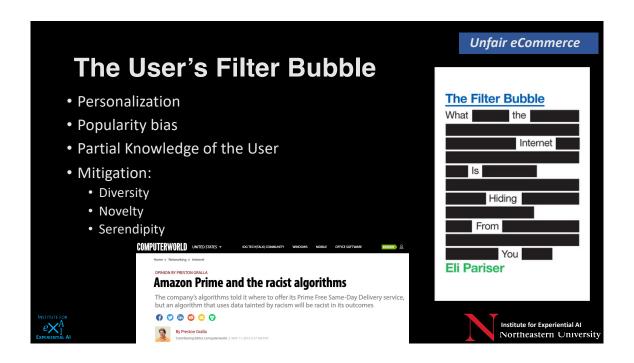












The Dangerous Feedback Loop

Evnosure hia

Unfair eCommerce

- 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
 - Long tail items/players are discriminated
 - Matthew effect: rich get richer, poor get poorer
- Unfair markets are unhealthy and hence less stable in the long term





Stupid Models?

• Models that can't deal with ambiguous semantics
• Models that are too sensitive

Prace
Life's a Bitche: Facebook says sorry for shutting down town's page

Ville de Bitche in north-east Prance had fallen foul of social network's algorithm

A IRPLANE(42,8%)

DEER
AIRPLANE(42,8%)

DOG (66,4%)

BIRD
CAT
AIRPLANE(42,8%)

FROG(88,8%)

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Limitations

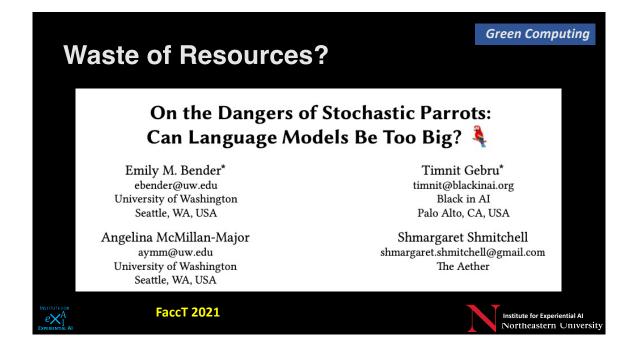
- Hard to Forget what You Learn!
 - "Funes, The Memorious" [Borges, 1942-44]
- You Cannot Learn what is not in the Data!
- Accuracy is not key, is the impact of errors
 - Usually false negatives are worse than false positives (e.g., illness detection)
 - Many errors are $\operatorname{not-human} \rightarrow \operatorname{large}$ negative impact
- Be humble, if you are not sure, tell the model to say I don't know

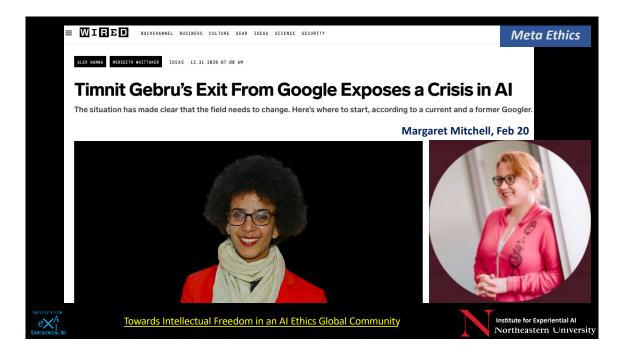




Stupid Models

Green Computing Waste of Resources? # of Parameters Carbon Date of Energy Common carbon footprint benchmarks original paper Cloud compute cost (kWh) CO2e) in lbs of CO2 equivalent BERT (110M Oct, 2018 1,507 1,438 \$3,751-\$12,571 ELMo Feb. 2018 \$433-\$1,472 275 262 Roundtrip flight b/w NY and SF 1,984 (1 passenger) GPT-2 \$12,902-\$43,008 Transformer Human life (avg. 1 year) 11,023 (213M parameters) Jun, 2017 201 192 \$289-\$981 American life (avg. 1 year) 36,156 Transformer US car including fuel (avg. 1 (213M parameters) w/ neural 126,000 \$942,973-\$3,201,722 architecture Transformer (213M parameters) search w/ neural architecture search Transformer (65M \$41-\$140 Jun, 2017 parameters) [Bender, Gebru at al., 2021]





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?





Principles

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:

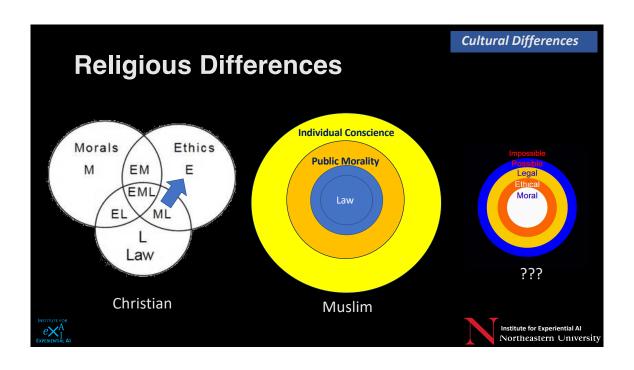
- Privacy, Security & Safety
- Proportionality, Sustainability
- Trustworthiness, Accountability
- Maintenance, Legal compliance
- Beneficial/Wellbeing

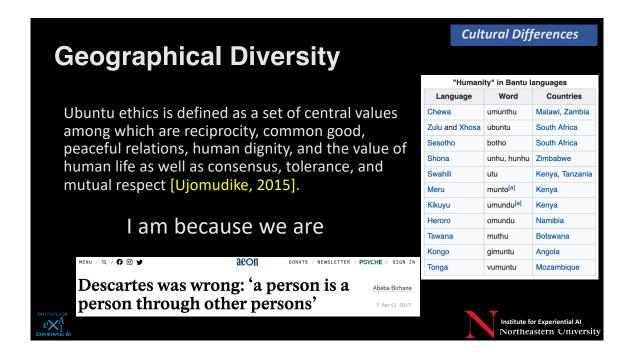


Principles





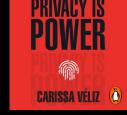




Legal Issues

Identity, Data Protection & Privacy

- 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







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
 - 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;
 - 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.





Discrimination

GDPR in Action

- Competence
- Consent
- Proportionality

- One Size Fits All
 - All human rights, domains, sizes, etc.
- Technological solutionism vs normative solutionism
 - [Jaume-Palasi, to appear]

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

(E) Feb 28, 2020 | <u>Luana Pascu</u>







Legal Issues

Institute for Experiential AI
Northeastern University

EU Proposal (April 21, 2021)

- Forbidden uses
- High-risk systems and requirements
- EU database for stand-alone high-risk systems
- Transparency obligations

· At least 50% external

- Governance
- Monitoring, information sharing and market surveillance
- Codes of conduct
- Confidentiality and penalties





TITLE II

PROHIBITED ARTIFICIAL INTELLIGENCE PRACTICES

Article 5

- 1. The following artificial intelligence practices shall be prohibited:
 - (a) the placing on the market, putting into service or use of an AI system that
 - (b) 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;
 - (c) 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;
 - (d) 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;
 - (iii) the detection, localisation, identification or prosecution of a perpetrator or suspect of a criminal offence referred to in Article 2(2) of Council Experience Position 2003(584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle in the Article 2003 (584) IIIA 62 and particle 2

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:

- (a) 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;
- (b) 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.
- 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) Al 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.
- 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) Al 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
 - (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.

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) Al systems intended to be used by law enforcement authorities for predicting the occurrence or reoccurrence 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.
- Migration, asylum and border control management:
- (a) Al 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) Al 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.
- . 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.

al Al 11versity











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.

ACM Reference Format:

Christo Wilson, Avijit Ghosh, Shan Jiang, Janelle Szary, Kelly Trindel, and Frida Polli. ing Fair Algorithms: A Case Study in Candi ence on Fairness, Accountability, and Transpa 10, 2021, Virtual Event, Canada. ACM, New https://doi.org/10.1145/3442188.3445928

to be practical, independent, and construction have better incentive to participate in this shows



Using AI to Make Hiring Decisions? Prepare for EEOC

Cognitive Biases

Bad (Human) Practices

- · 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
- 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]



Cognitive Biases



Our Professional Biases

- - Our big data and deep learning bias: small data is more frequent & harder
 [Baeza-Yates, KD Nuggets, 2018]
- Design and Implementation
 - Do systems reflect the characteristics of the designers?
 - Do systems reflect the characteristics of the coders?
- Evaluation

Problems

[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





Epilogue

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
- Interaction
 - Make sure that the user is aware of the biases all the time
 - Give more control to the user
- 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
- Evaluation & Deployment
 - Do not fool yourself!
 - Error & sensibility analysis (e.g., synthetic data if possible)
 - Algorithms registration / Certification / External Auditing





Recommendations for Us

Epiloque

- 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 and Ethics Board and enforce a Code of Ethics
- Improve Explainability (repeat 100 times)
- 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





Final Take-Home Messages

- Epilogue
- 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**
- Who profits/suffers technology, transhumanism vs. humanism
- Ethics is **complicated**, do not underestimate it!
- Plenty of open research problems! (in small data even more!)

Can AI algorithms ever be ethical?

The perils of cyberspace and social media

4 FEBRUARY 2021, HAZEL HENDERSON

Al and Ethics (2021) 1:21–25
https://doi.org/10.1007/v43681-029-00013-4

OPINION PAPER

You cannot have Al ethics without ethics

Dave Lauer ©

Received: 2 September 2020 / Revised: 2 September 2020 / Accepted: 4 September 2020 / Published online: 6 October 2020 © Springer Nature Switzerland AG 2020

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Questions?

ASIST 2012 Book of the Year Award (Biased Ad) Modern Information Retrieval the concepts and technology behind search

New Conferences that started in 2018:

Tientale George Actes

Ricardo Baeza-Yates Berthier Ribeiro-Neto

Contact: rbaeza@acm.org www.baeza.cl @polarbeaRBY

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Biased Questions?

Conference on Fairness, Accountability, and Transparency

AAAI/ACM Conference on AI, Ethics, and Society

http://www.aies-conference.com

http://facctconference.org

