Machine Learning & Society

Daniela Huppenkothen

DIRAC, University of Washington

Tiana_Athriel

dhuppenkothen

dhuppenk@uw.edu

Can you think of a situation where machine learning has played a role in your life? Was that interaction a positive or negative experience?

1 minute: think quietly
2 minutes: share with partner
5 minutes: share with group

Can you think of situations where an algorithm should not be used to support human decision making?

Technochauvinism (n): a mindset that says that algorithms are superior to human judgment. The same mindset argues using technology is always the best strategy.

Algorithms are designed by people, and people embed unconscious biases in algorithms, data collection and interpretation of results.

Meredith Broussard: Artificial Unintelligence

Automated Inference on Criminality using Face Images

Xiaolin Wu, Xi Zhang • Published in ArXiv 2016

We study, for the first time, automated inference on criminality based solely on still face images. Via supervised machine learning, we build four classifiers (logistic regression, KNN, SVM, CNN) using facial images of 1856 real persons controlled for race, gender, age and facial expressions, nearly half of whom were convicted criminals, for discriminating between criminals and non-criminals. All four classifiers perform consistently well and produce evidence for the validity of automated face... CONTINUE READING

https://www.semanticscholar.org/paper/Automated-Inference-on-Criminality-using-Face-Wu-Zhang/1cd357b675a659413e8abf2eafad2a463272a85f

see also: https://callingbullshit.org/case_studies/case_study_criminal_machine_learning.html

Automated Inference on Criminality using Face Images

Xiaolin Wu, Xi Zhang • Published in ArXiv 2016

We study, for the first time, automated inference on criminality based solely on still face images. Via supervised machine learning, we build four classif using facial images of 1856 real persons controlled fo nearly half of whom were convicted criminals, for disc criminals. All four classifiers perform consistently wel automated face... CONTINUE READING

VIEW PDF SAVE TO LIBRARY CREATE ALERT CITE

Is this a good idea?

https://www.semanticscholar.org/paper/Automated-Inference-on-Criminality-using-Face-Wu-Zhang/1cd357b675a659413e8abf2eafad2a463272a85f

see also: https://callingbullshit.org/case_studies/case_study_criminal_machine_learning.html

Automated Inference on Criminality using Face Images

Xiaolin Wu, Xi Zhang • Published in ArXiv 2016

We study, for the first time, automated inference on criminality based solely on still face images. Via supervised machine learning, we build four classif
using facial images of 1856 real persons controlled fo
nearly half of whom were convicted criminals, for disc
criminals. All four classifiers perform consistently wel
automated face... CONTINUE READING

VIEW PDF SAVE TO LIBRARY CREATE ALER

Is this a good idea?

Could this go wrong in some way?

https://www.semanticscholar.org/paper/Automated-In
1cd357b675a659413e8abf2eafad2a463272a85f

see also: https://callingbullshit.org/case_studies/case_study_criminal_machine_learning.html

“Unlike a human examiner/judge, a computer vision algorithm or classifier has absolutely no subjective baggages [sic], having no emotions, no biases whatsoever due to past experience, race, religion, political doctrine, gender, age, etc., no mental fatigue, no preconditioning of a bad sleep or meal. The automated inference on criminality eliminates the variable of meta-accuracy (the competence of the human judge/examiner) all together.”

(Wu & Zhang, 2016)

“Unlike a human examiner/judge, a computer vision algorithm or classifier has absolutely no subjective baggages [sic], having no emotions, no biases whatsoever due to past experience, race, religion, political doctrine, gender, age, etc., no mental fatigue, no preconditioning of a bad sleep or meal. The automated inference on criminality eliminates the variable of meta-accuracy (the competence of the human judge/examiner) all together.”

(Wu & Zhang, 2016)

Do you agree?

The Data

- 1856 Chinese men
- ages between 18 and 55
- no facial hair, scars or other markings
- non-criminals: photos acquired from the internet using web crawler (e.g. from company websites)
- criminals: ID photos published as wanted subjects, provided by police department
- algorithm classifies data set with 90% accuracy

The Data

Is this data set unbiased? In what ways could it be biased?

- 1856 Chinese men
- ages between 18 and 55
- no facial hair, scars or other markings
- non-criminals: photos acquired from the internet using web crawler (e.g. from company websites)
- criminals: ID photos published as wanted subjects, provided by police department
- algorithm classifies data set with 90% accuracy

One possible bias: attractive defendants are less likely convicted, or with less severe sentences, than unattractive defendants.

e.g. Gunnell + Ceci, 2010

Examples

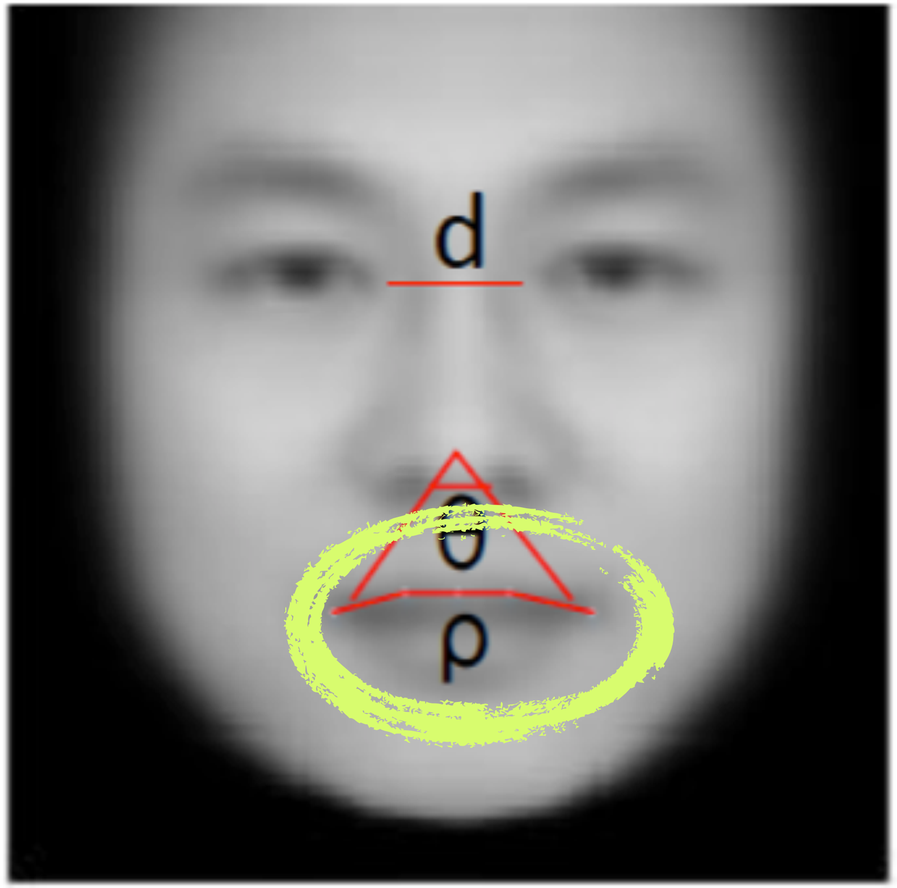
(a) Three samples in criminal ID photo set S_c.

criminal

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

non-criminal

What features in an image are discriminative?



Examples

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

criminal

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

non-criminal

Examples

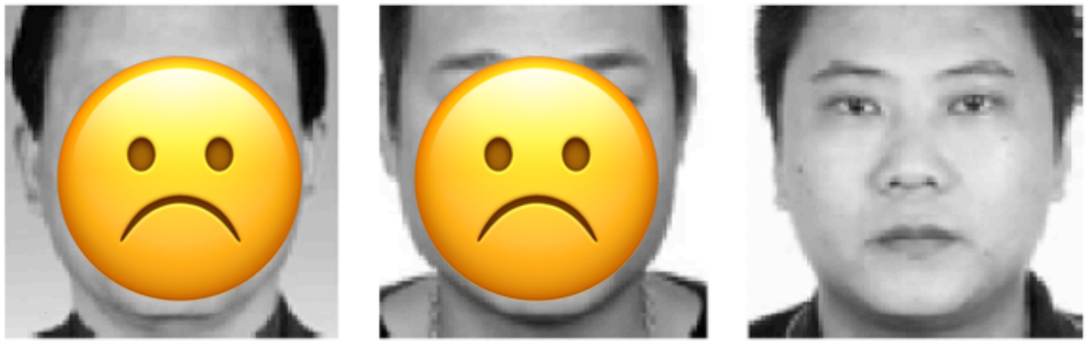
(a) Three samples in criminal ID photo set S_c.

criminal

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

non-criminal

Examples



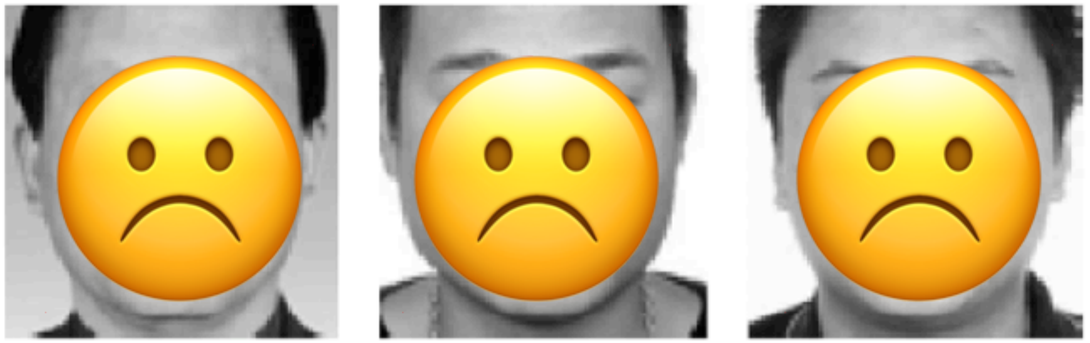
(a) Three samples in criminal ID photo set S_c.

criminal

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

non-criminal

Examples



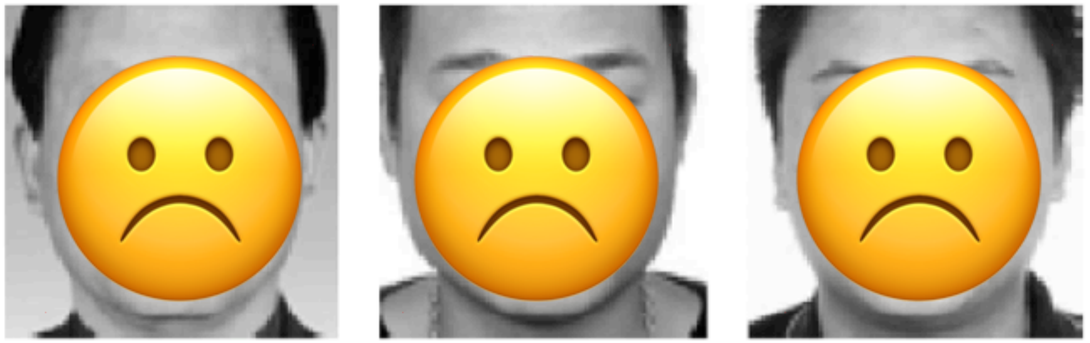
(a) Three samples in criminal ID photo set S_c.

criminal

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

non-criminal

Examples



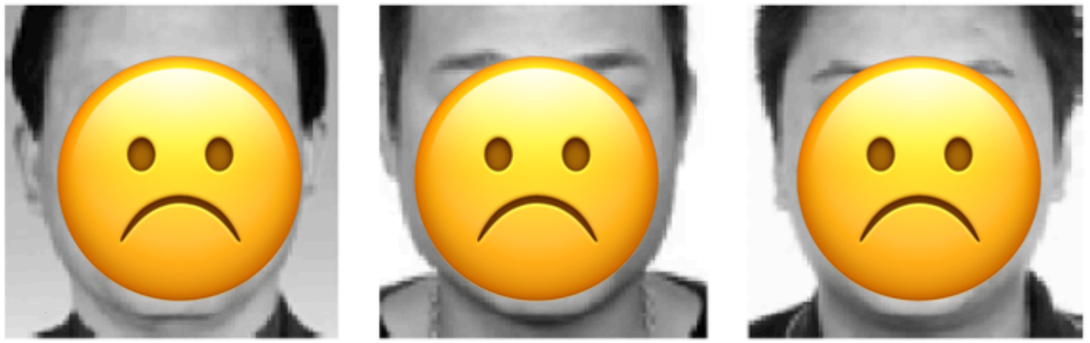
(a) Three samples in criminal ID photo set S_c.

criminal

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

non-criminal

Examples



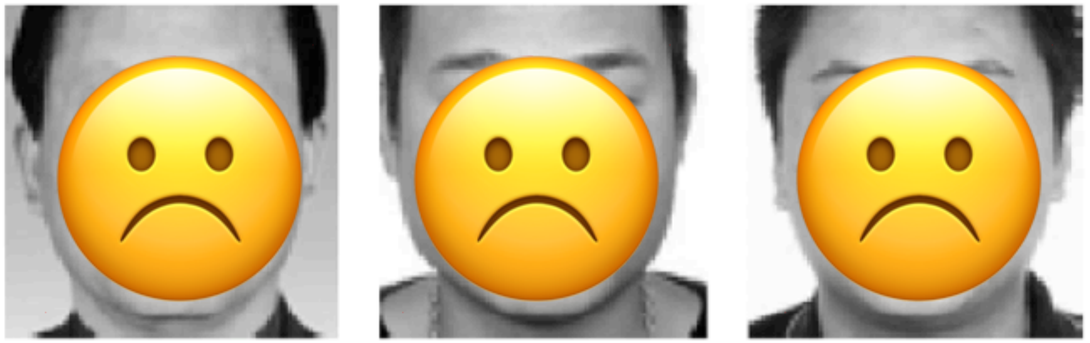
(a) Three samples in criminal ID photo set S_c.

criminal

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

non-criminal

Examples



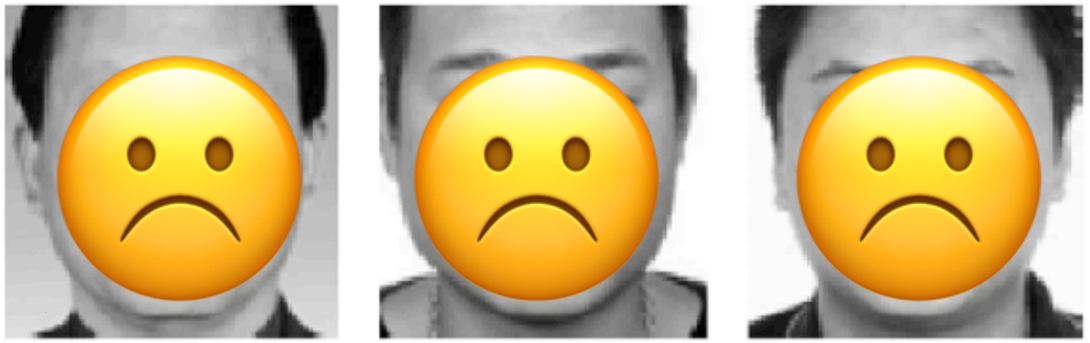
(a) Three samples in criminal ID photo set S_c.

criminal

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

non-criminal

Examples



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

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

This is a bad interpretation of a bad training data set!

Machine learning is only as good as its **training data set.**

Machine learning is only as good as its **training data set.**

In most cases, you can identify a **faulty application** of an algorithm solely by looking at the **training data** used and the **interpretation** of the results.

What makes the application of machine learning ethical?

Why is this important at all?

What can we do to ensure that we are applying machine learning ethically and responsibly?

Checklists help eliminate basic mistakes

https://etherpad.wikimedia.org/p/ata-ml-ethics

- ❑ Have we listed how this technology can be attacked or abused?
- ❑ Have we tested our training data to ensure it is fair and representative?
- ❑ Have we studied and understood possible sources of bias in our data?
- ❑ Does our team reflect diversity of opinions, backgrounds, and kinds of thought?
- ❑ What kind of user consent do we need to collect to use the data?
- ❑ Do we have a mechanism for gathering consent from users?
- ❑ Have we explained clearly what users are consenting to?
- ❑ Do we have a mechanism for redress if people are harmed by the results?
- ❑ Can we shut down this software in production if it is behaving badly?
- ❑ Have we tested for fairness with respect to different user groups?
- ❑ Have we tested for disparate error rates among different user groups?
- ❑ Do we test and monitor for model drift to ensure our software remains fair over time?
- ❑ Do we have a plan to protect and secure user data?

Mason, Loukides, Patil: Ethics and Data Science (2018)

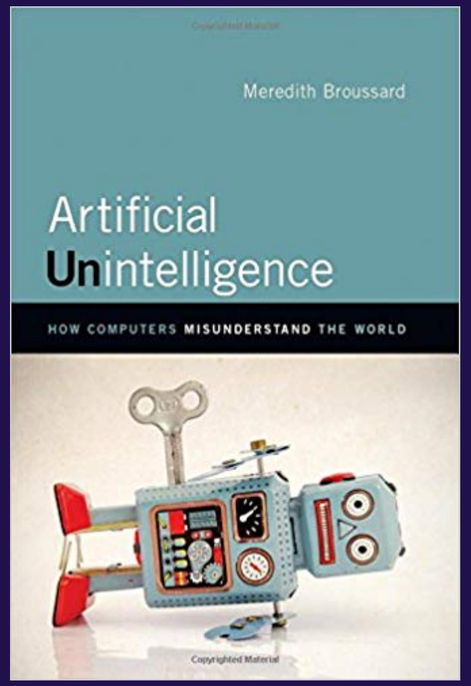
But we are astronomers! Why should we care?

- Technology and algorithms can be misused.
- There is a growing number of studies about the astronomy community
- You might have a future job or side project that is not in astronomy

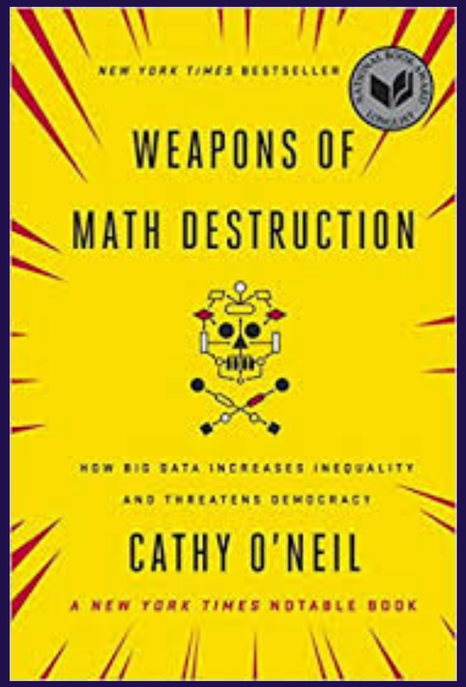
What can we do?

- keep up with the developments in data science and ethics
- think about the ethical implications of your project in advance
- make sure your team represents many different backgrounds and experiences
- take your university’s training in human subject research
- use check lists
- be open to feedback and criticism

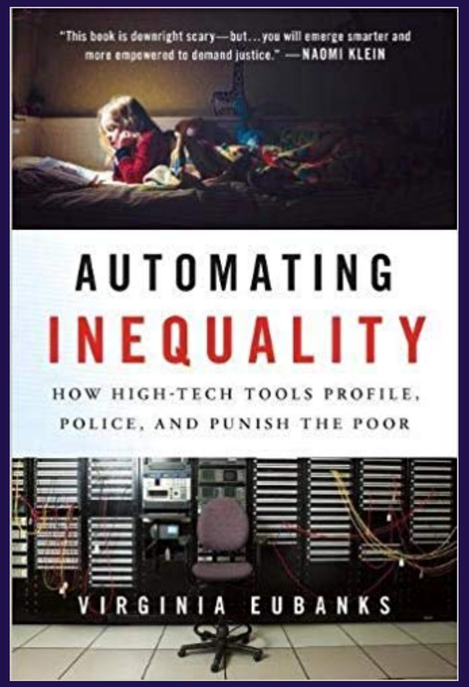
Resources



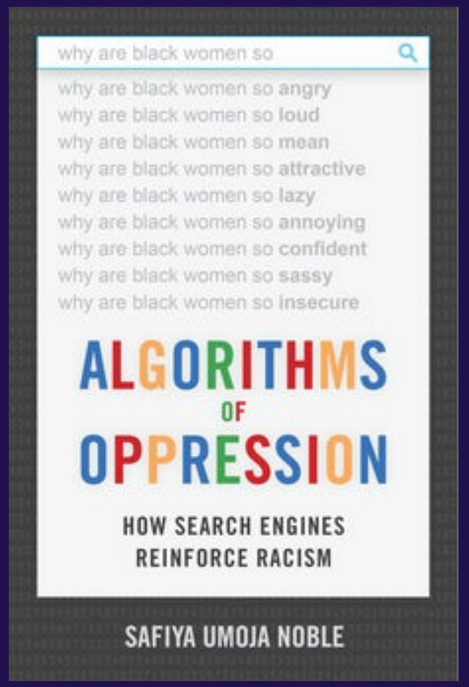
Meredith Broussard



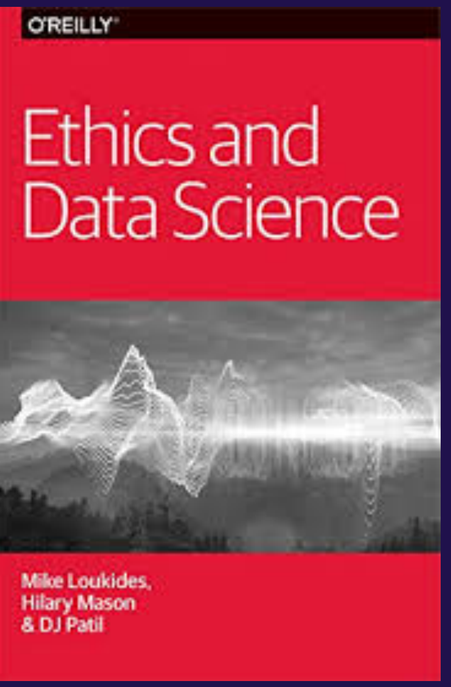
Cathy O'Neil



Virginia Eubanks



Safiya Umoja Noble



Mike Loudikes, Hilary Mason, DJ Patil

also: e.g. Data & Society