Criminal Machine Learning

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Privacy, Security and ethical aspects of data

Université Cote d'Azur

Criminal Machine Learning

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

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

The following slides are from the instructors Carl T. Bergstrom and Jevin West
Course: INFO 198 / BIOL 106B. University of Washington
Available online:
- https://www.youtube.com/watch?v=rga2-d1oi30
- https://www.youtube.com/watch?v=4u6HGaXx90A

Are you a criminal based on your face?

Automated Inference on Criminality using Face Images

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Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=rga2-d1oi30

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

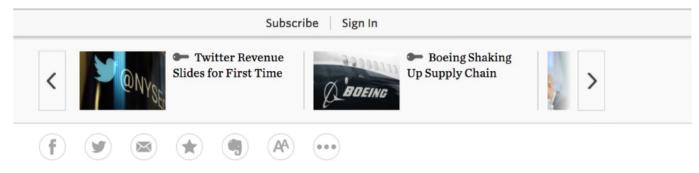(b) Three samples in non-criminal ID photo set S_n

4

Algorithms are as biased as the training data coming from humans!

" 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(2017)

One possible reason: your attractiveness influences your chance of being convicted...

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LAW BLOG

U-G-L-Y, You Might Have an Alibi, But You're Guilty, You're Guilty!

By ASHBY JONES

May 17, 2010 1:25 pm ET

A new study from Cornell reveals something rather disturbing: physically unattractive criminal defendants are 22 percent more likely to be convicted and hit with longer sentences than physically attractive defendants. Click here for the story from the Cornell Chronicle; here for a story from the Cornell Daily Sun.

Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=rga2-d1oi30

Criminals have smaller angle θ, larger curvature ρ than non-criminals.
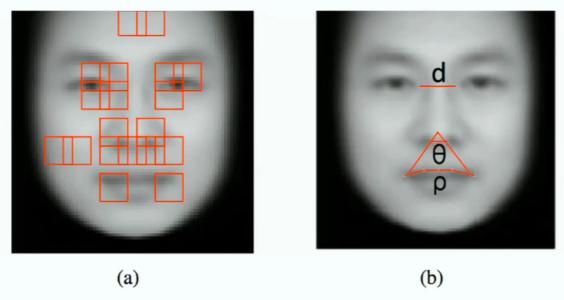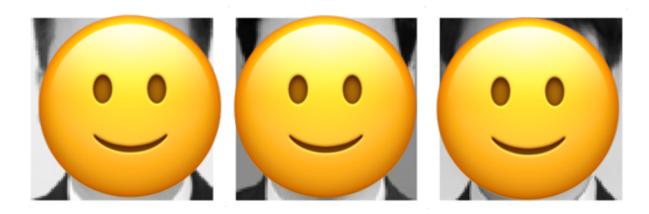

(a)   (b)

Figure 8. (a) FGM results; (b) Three discriminative features ρ, d and θ.
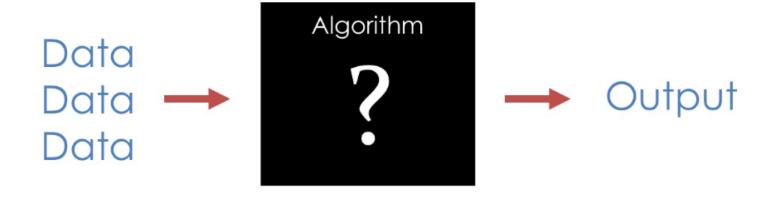
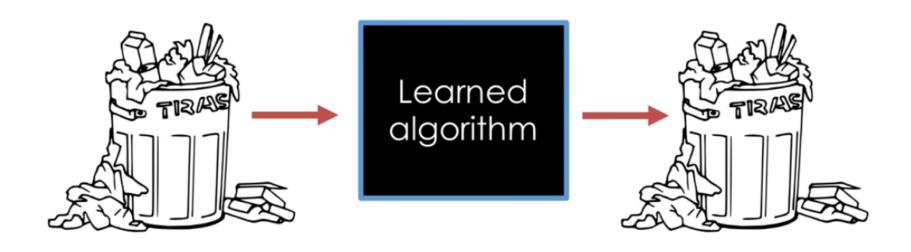# Because they are smiling!

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

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

Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=rga2-d1oi30

Even when you don't know how an algorithm or statistical test works, you can spot bullshit by looking carefully at what goes in and what comes out.

Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=4u6HGaXx90A

Garbage In, Garbage Out

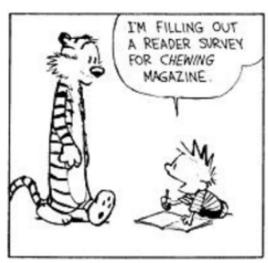Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=4u6HGaXx90A
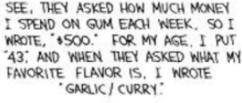
Algorithms are as biased as the training data coming from humans!

" 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."
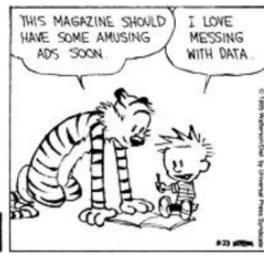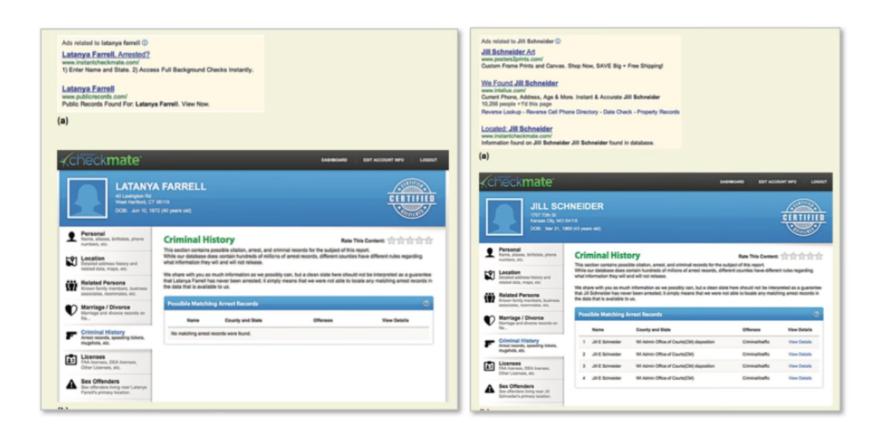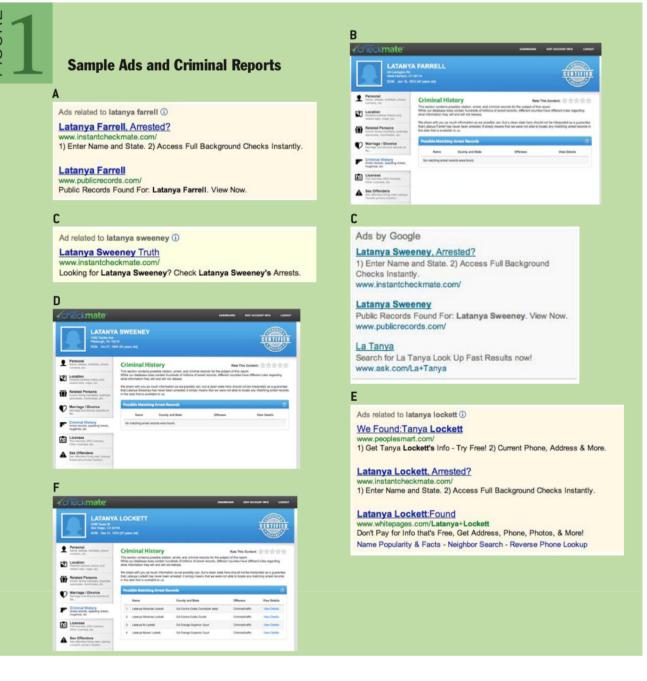
—Wu & Zhang(2017)

Algorithmic Bias

Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=4u6HGaXx90A

Ad Discrimination

Sweeney, Latanya. "Discrimination in online ad delivery." *Queue* 11.3 (2013): 10.

Ad Discrimination

Google search for
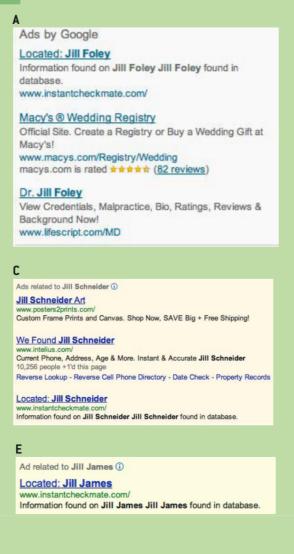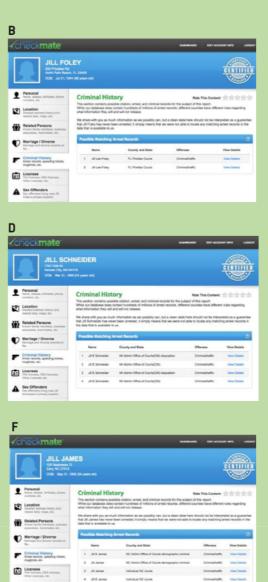*Latanya Farrell,
Latanya Sweeney, and
Latanya Lockett*

FIGURE 1

Sample Ads and Criminal Reports

Latanya Sweeney. Discrimination in Online Ad Delivery (2013). https://queue.acm.org/detail.cfm?id=2460278

Ad Discrimination

Google search for
Jill Foley,
Jill Schneider, and
Jill James

FIGURE 3

Sample Ads and Criminal Reports for Names that Include the First Name "Jill"

Latanya Sweeney. Discrimination in Online Ad Delivery (2013). https://queue.acm.org/detail.cfm?id=2460278 15
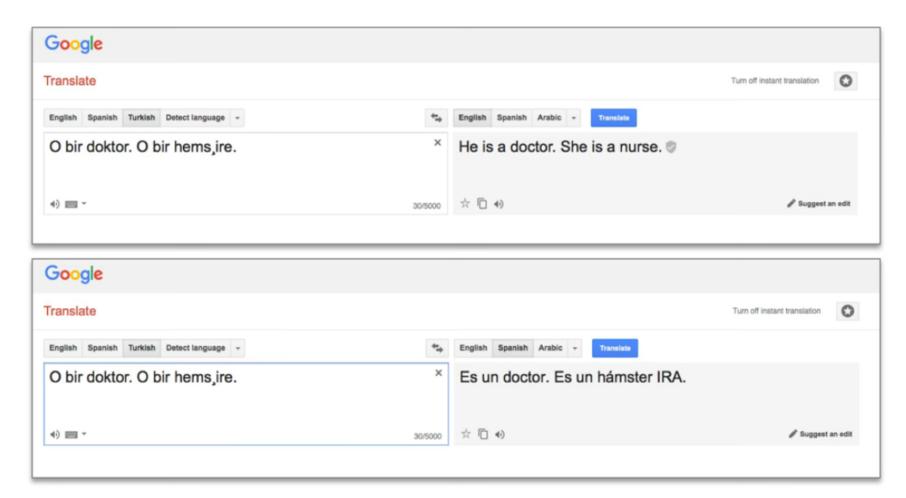
Gender Bias

Percentage of women in top 100 Google image search results for CEO: 11%
Percentage of U.S. CEOs who are women: 27%

Kay, Matthew, Cynthia Matuszek, and Sean A. Munson. "Unequal representation and gender stereotypes in image search results for occupations." *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems.* ACM, 2015.

Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=4u6HGaXx90A

Translation Bias

Caliskan, Aylin, Joanna J. Bryson, and Arvind Narayanan. "Semantics derived automatically from language corpora contain human-like biases." *Science* 356.6334 (2017): 183-186.

Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=4u6HGaXx90A

Calling Bullshit on Machine Injustice

Scientific method is not dead

Machines are NOT bias-free

Garbage in, Garbage out

Fallibility of machines

Algorithmic Ethics

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Source: lecture of Carl T. Bergstrom and Jevin West, https://www.youtube.com/watch?v=4u6HGaXx90A