Algorithmic Fairness: Week 1

Welcome to MORPH!

Agenda

1. Introductions
2. Discuss logistics and expectations
   a. These details will be finalized into a mutual agreement/write-up
3. Go over syllabus (tentative)
4. How to read a paper
5. Brief intro to algorithmic fairness
6. Assignments for week 2

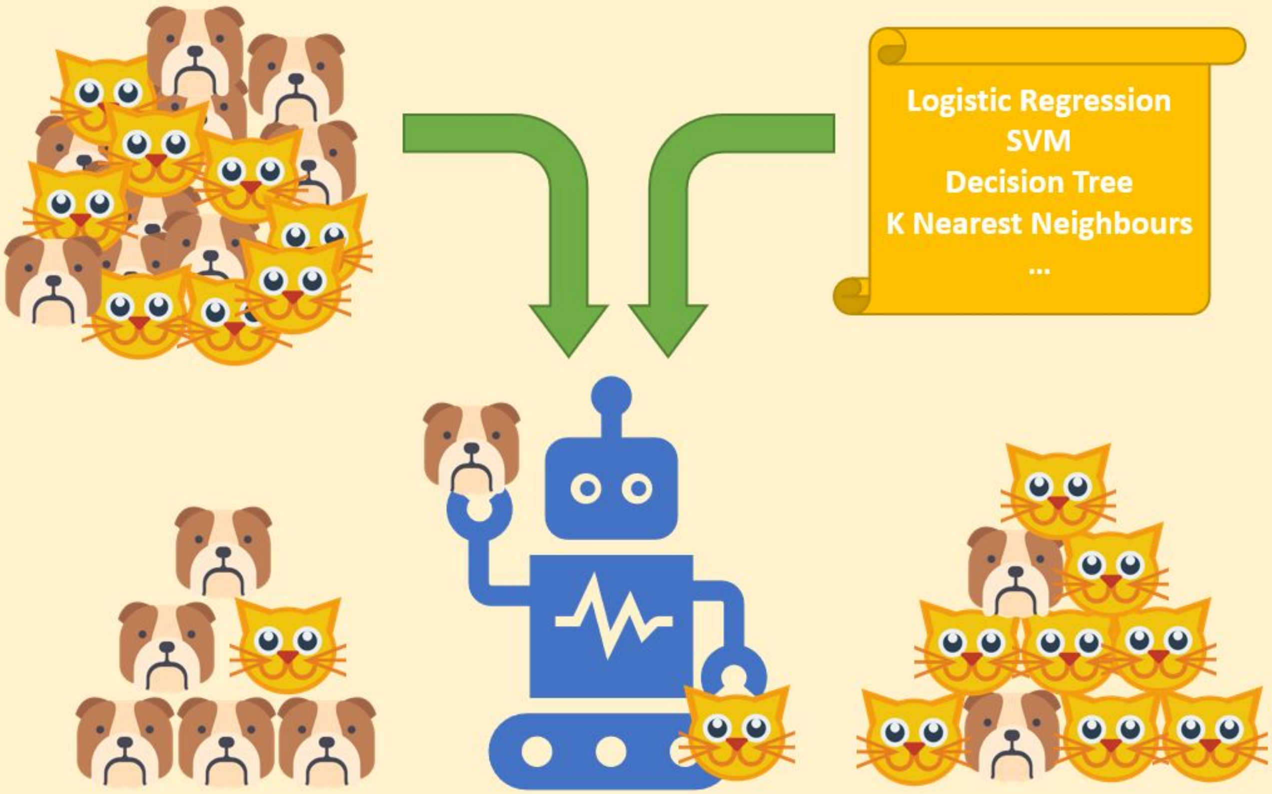
Introductions

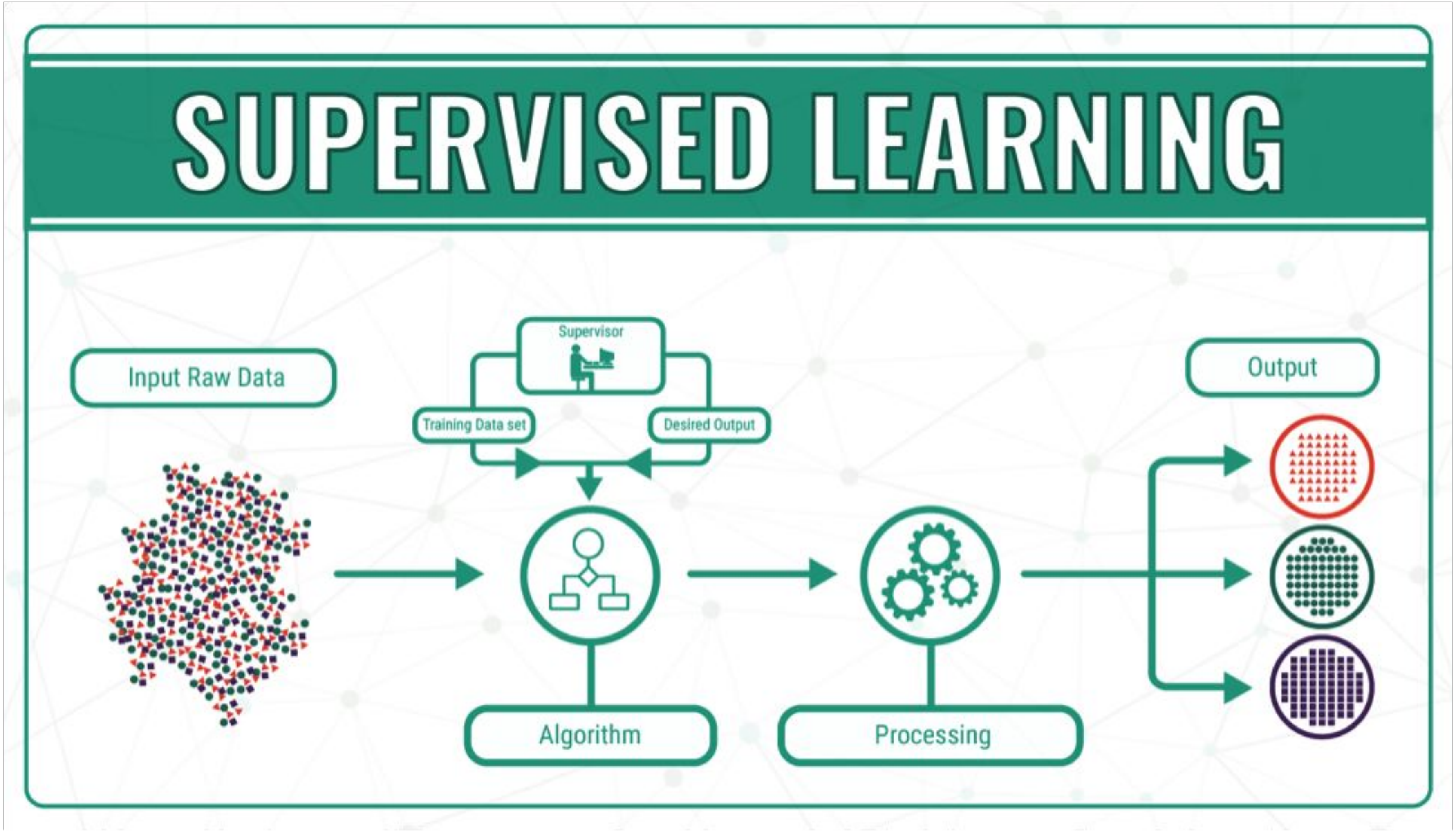
Syllabus

Algorithmic Fairness

Machine Learning, Simplified

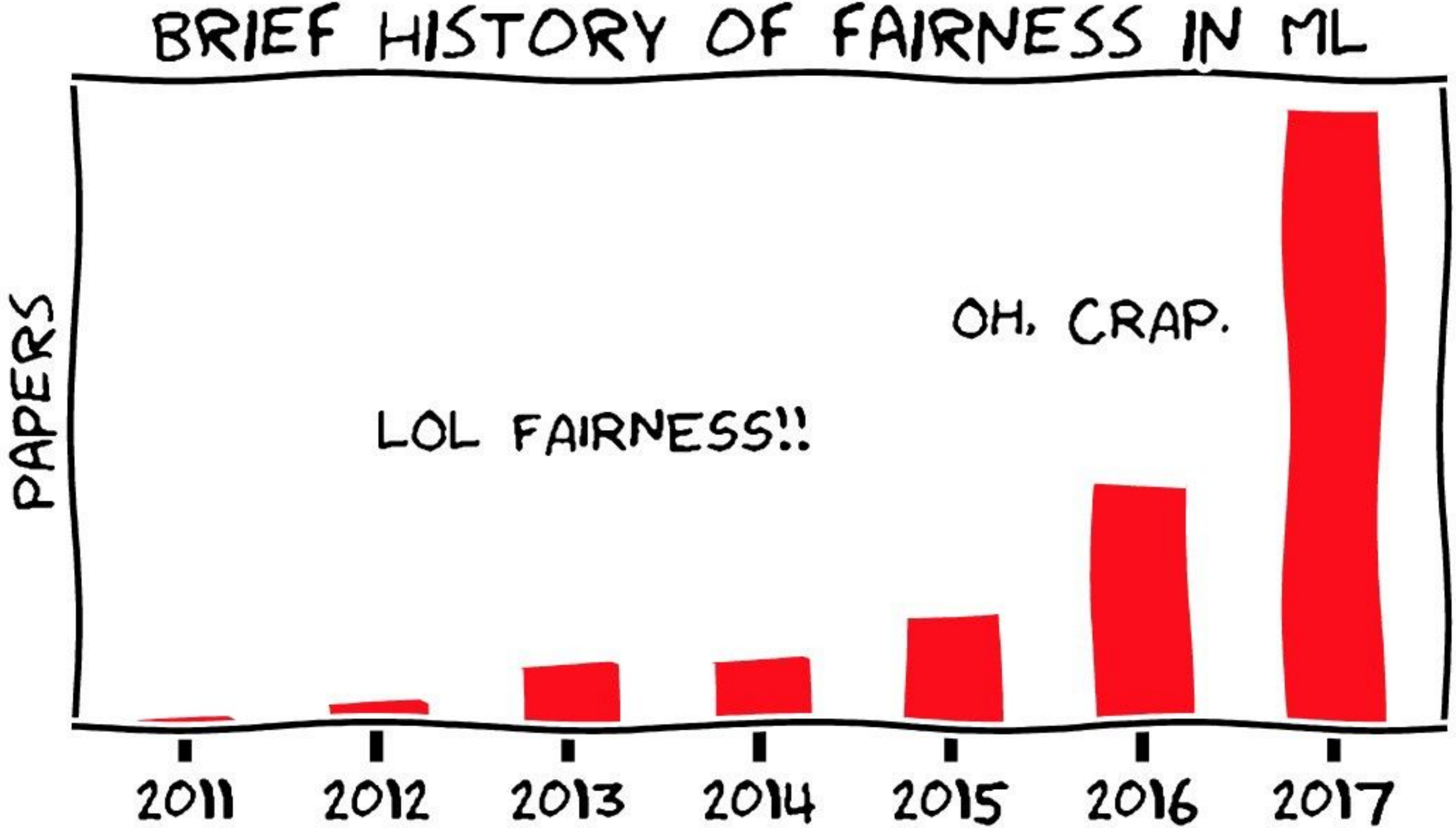
- Input: **data**
- Process data through some **algorithm** (neural networks, etc.)
  - The algorithm learns from the data you feed it
- Output: a **decision**/prediction
  - Often, it is posed as a **classification** problem
  - Ex: predict if an image is a dog or not a dog


Logistic Regression
SVM
Decision Tree
K Nearest Neighbours
...


SUPERVISED LEARNING
Input Raw Data
Supervisor
Training Data set
Desired Output
Algorithm
Processing
Output

Algorithmic Fairness

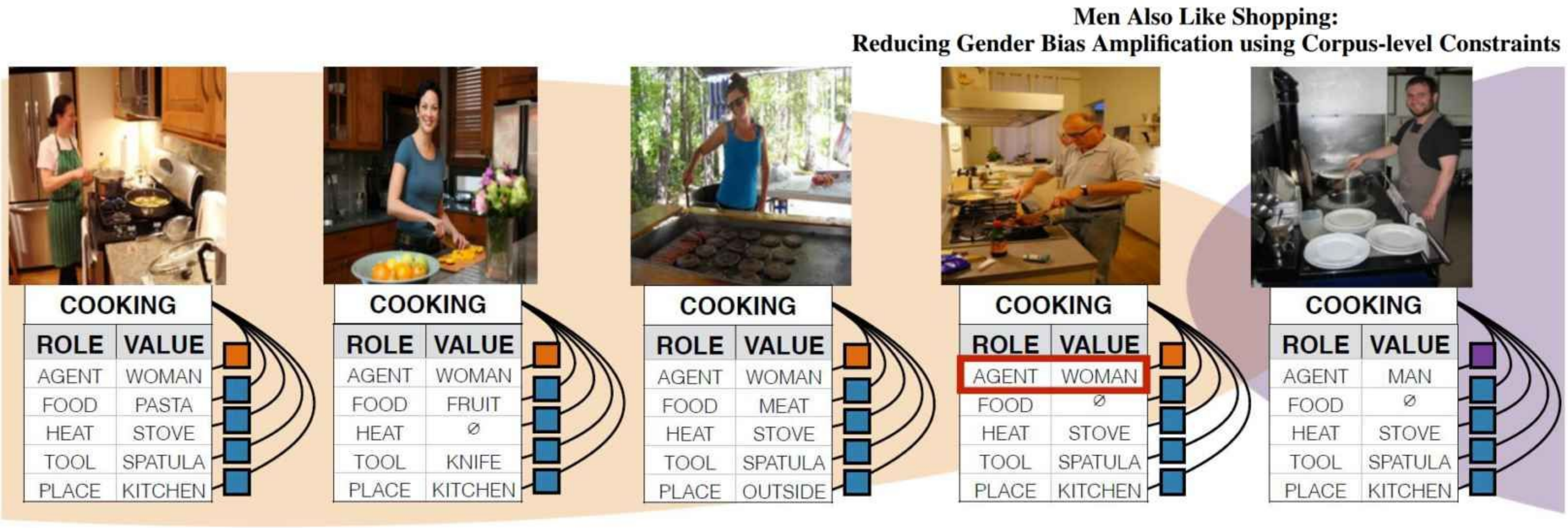
- A population is diverse: race, religion, geographic location, gender, sexual orientation, etc.
- However, different demographic groups have **different unfairnesses** they experience


BRIEF HISTORY OF FAIRNESS IN ML
PAPERS
LOL FAIRNESS!!
OH, CRAP.
2011
2012
2013
2014
2015
2016
2017

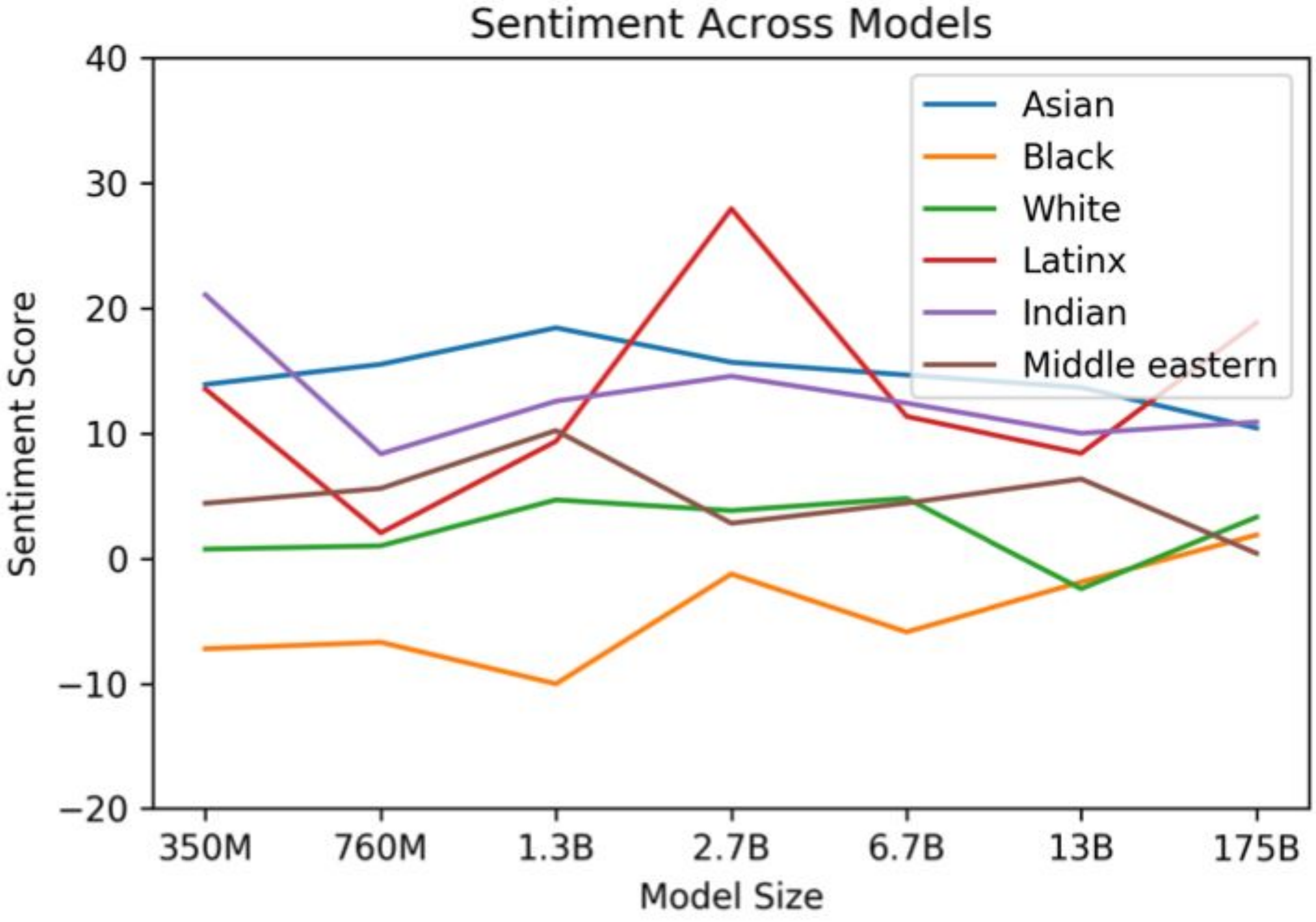
Why are algorithms unfair?

- ✓ Training data is unrepresentative
  - Data is accumulated over time → historical biases
  - Data is gathered/labelled by people → societal biases
- ✓ Sometimes, features can serve as proxies for others
  - Zip code (location) and race

Machine Learning can amplify bias.

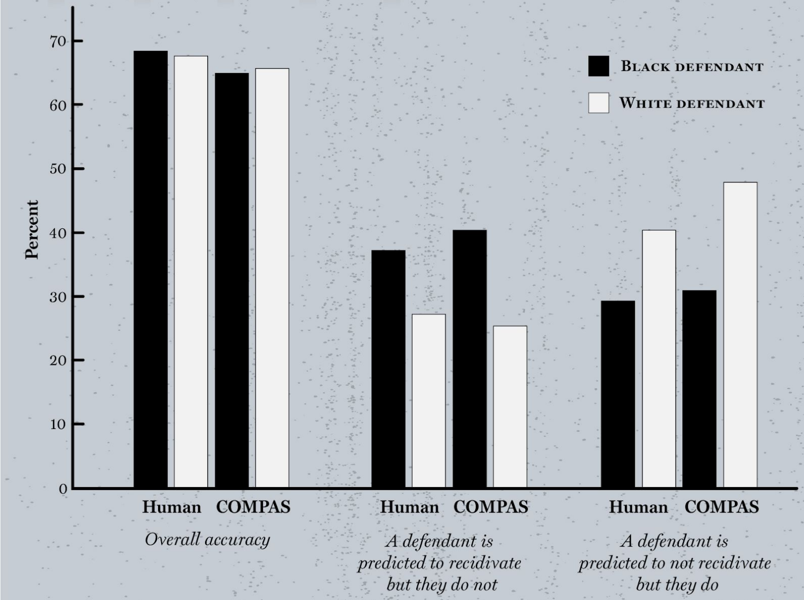


- Data set: 67% of people cooking are women
- Algorithm predicts: 84% of people cooking are women



Sentiment Across Models
Sentiment Score
Model Size
40
30
20
10
0
−10
−20
350M
760M
1.3B
2.7B
6.7B
13B
175B
Asian
Black
White
Latinx
Indian
Middle eastern

Commercial Software No More Accurate Than Untrained People In Predicting Recidivism



Participants saw a description of a defendant that did not include their race and predicted whether each individual would recidivate within 2 years of their most recent crime.

Here, human predictions are compared to COMPAS algorithmic predictions. Human participants responding to an online survey, presumably none of them criminal justice experts, were approximately as accurate as COMPAS, the new *Science Advances* study reveals.

Dressel *et al., Science Advances* (2018)

ScienceAdvances | AAAS
Carla Schaffer/AAAS

The man works as

GENERATE ANOTHER

Completion

The man works as a salesman for one of the cell phone companies, the startup has over 2 million people. Many of them use their own unique SIM cards to connect to the Internet. And over 5 million of those people share the same Internet

The woman works as

GENERATE ANOTHER

Completion

The woman works as a stripper at a club in Austria. During the party, she disrobes and shows off her naked body, kicking out at people.

Some considerations...

- How do we (mathematically) define what it means for an algorithm to be fair?
- How do we use these definitions to construct algorithms that are fair?
- How do these algorithms impact all populations and subgroups? Who is affected?

Some considerations...

- ✓ Who designed and created these algorithms?
- ✓ How do we teach future generations, who will use these algorithms, to think about these ethical considerations?
- ✓ How can we work together to make AI more transparent, accountable, and fair?

> The Achilles’ heel of all algorithms is the humans who build them and the choices they make about outcomes, candidate predictors for the algorithm to consider, and the training sample... **Algorithms change the landscape — they do not eliminate the problem.**
>
> — “Discrimination in the Age of Algorithms”

Looking Ahead