

# Fighting Bias in AI: Can Ordinary People Make a Difference?

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Tübingen Days of Digital Freedom 2025

Omri Ben-Dov

ACT I

# AI: Artificial Intelligence

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Or: Intro to machine learning

Is this person wearing glasses?



Is this person smiling?



Does this person have short hair?



StyleGAN2 (Karras et al.)

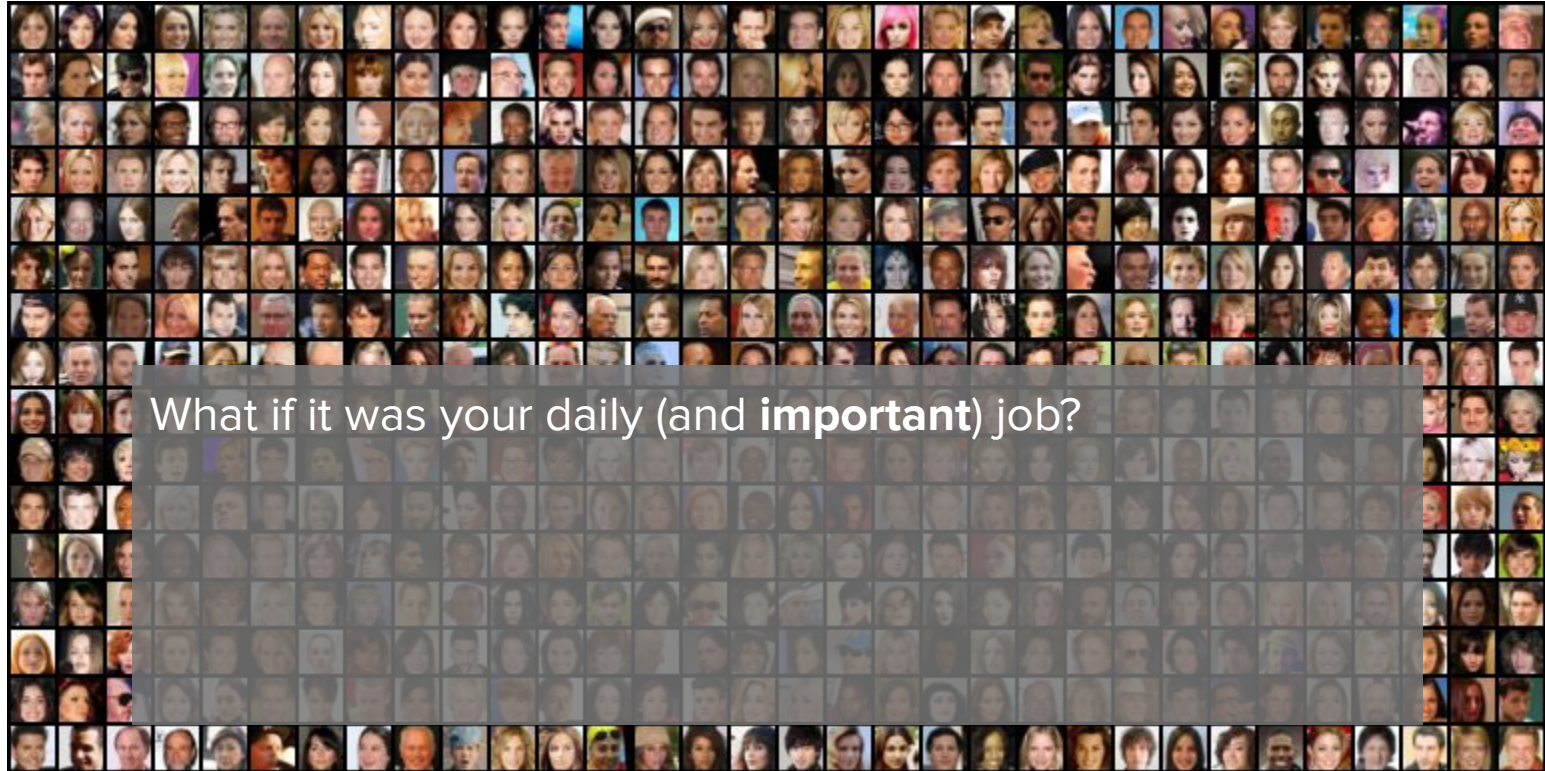
Is this person good looking?



Ready for hundreds of more rounds?

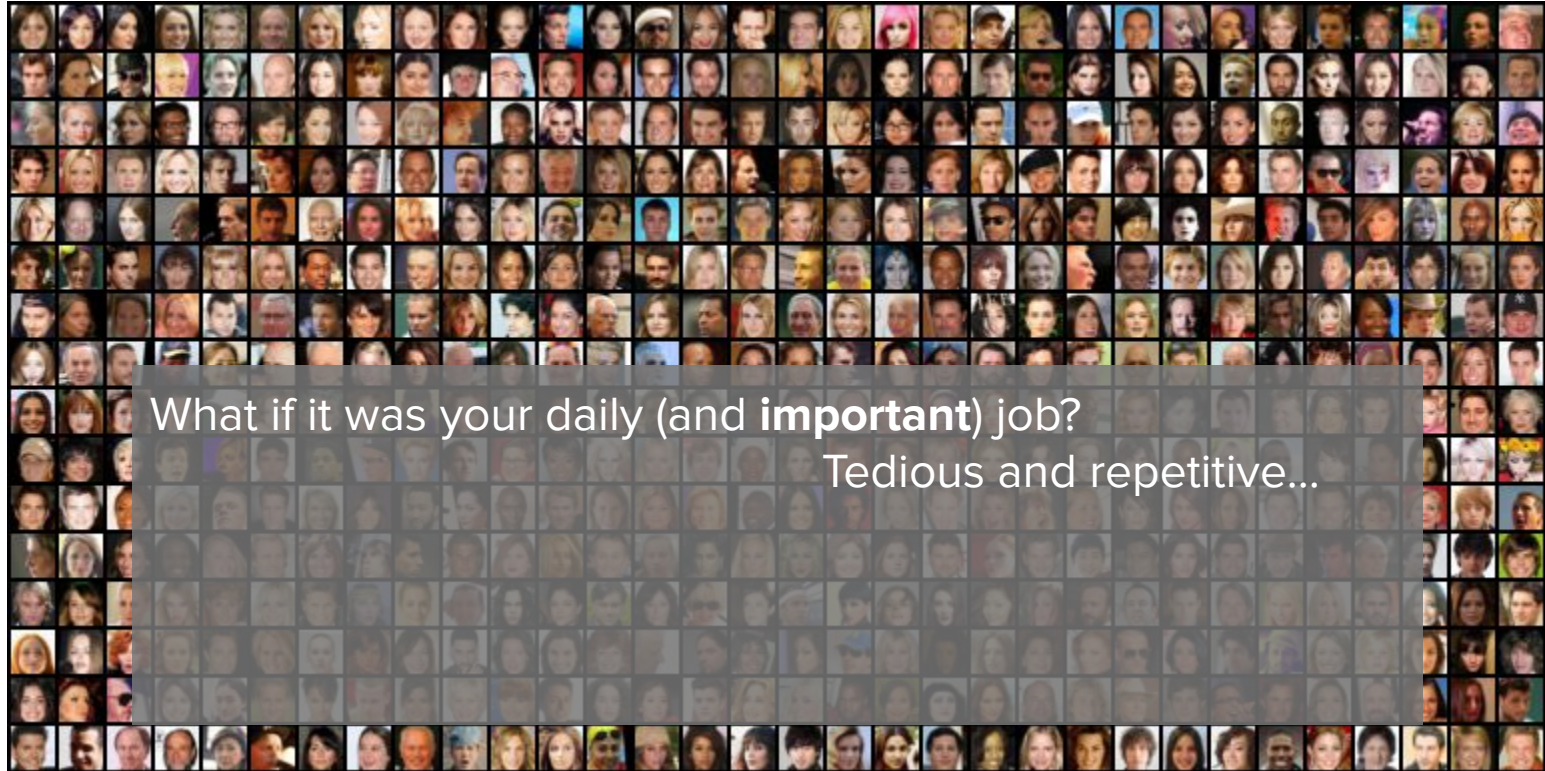


Ready for hundreds of more rounds?



What if it was your daily (and **important**) job?

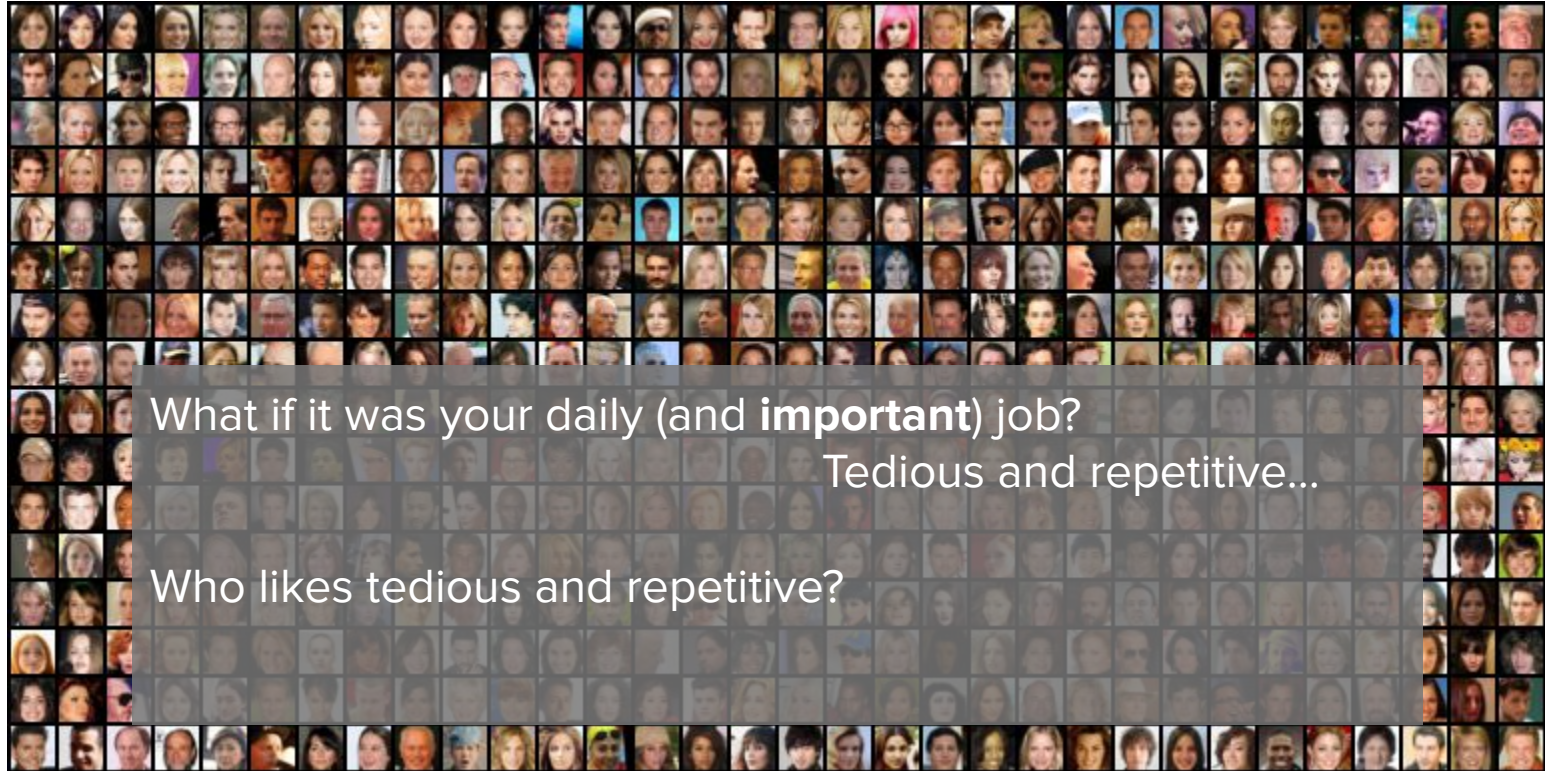
# Ready for hundreds of more rounds?



What if it was your daily (and **important**) job?

Tedious and repetitive...

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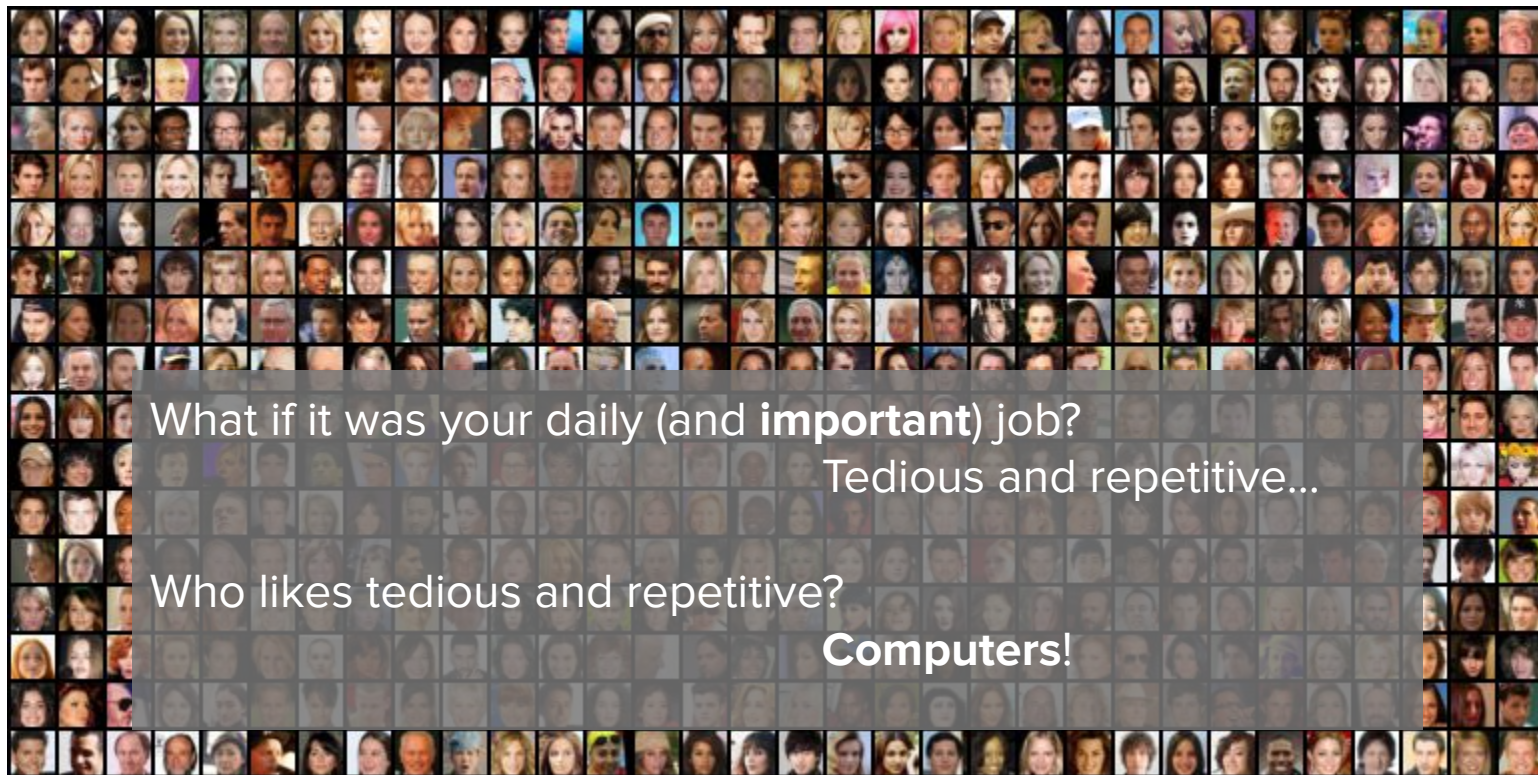


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Tedious and repetitive...

Who likes tedious and repetitive?

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**Computers!**

# Can we explain the task to a computer?

How do you tell a computer what glasses are?

What if the question is ambiguous?

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We were not born with knowledge of glasses, but learned it...

Can a computer learn to answer a single yes/no question about different people?

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Machine learning:

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Machine learning:

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Yes, even ChatGPT answers a single question

# Basic Machine Learning - “Is the person wearing glasses?”

The data:  
People and the  
corresponding answer



yes



no

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X 1000 (or some other large number)

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Learning



The learning algorithm:  
Turn the data into a machine  
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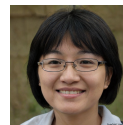
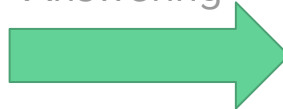
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Answering



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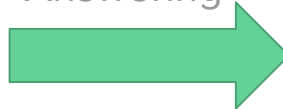
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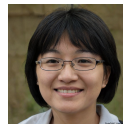
The learning algorithm:  
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Answering



The “algorithm” (inference):  
Answer about new people



yes



no



Is the machine always correct?

**NO!**

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**NO!**

Data quality



yes



no



no



Is the machine always correct?

**NO!**



yes



yes



no

# Is the machine always correct?

# NO!

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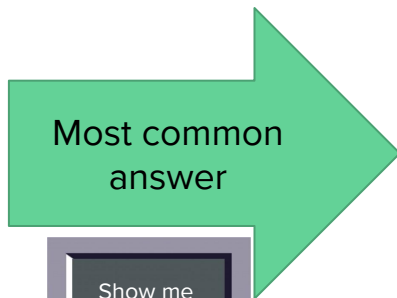
yes



yes



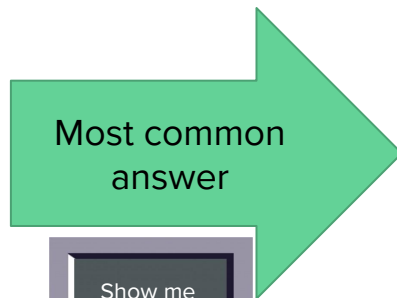
no



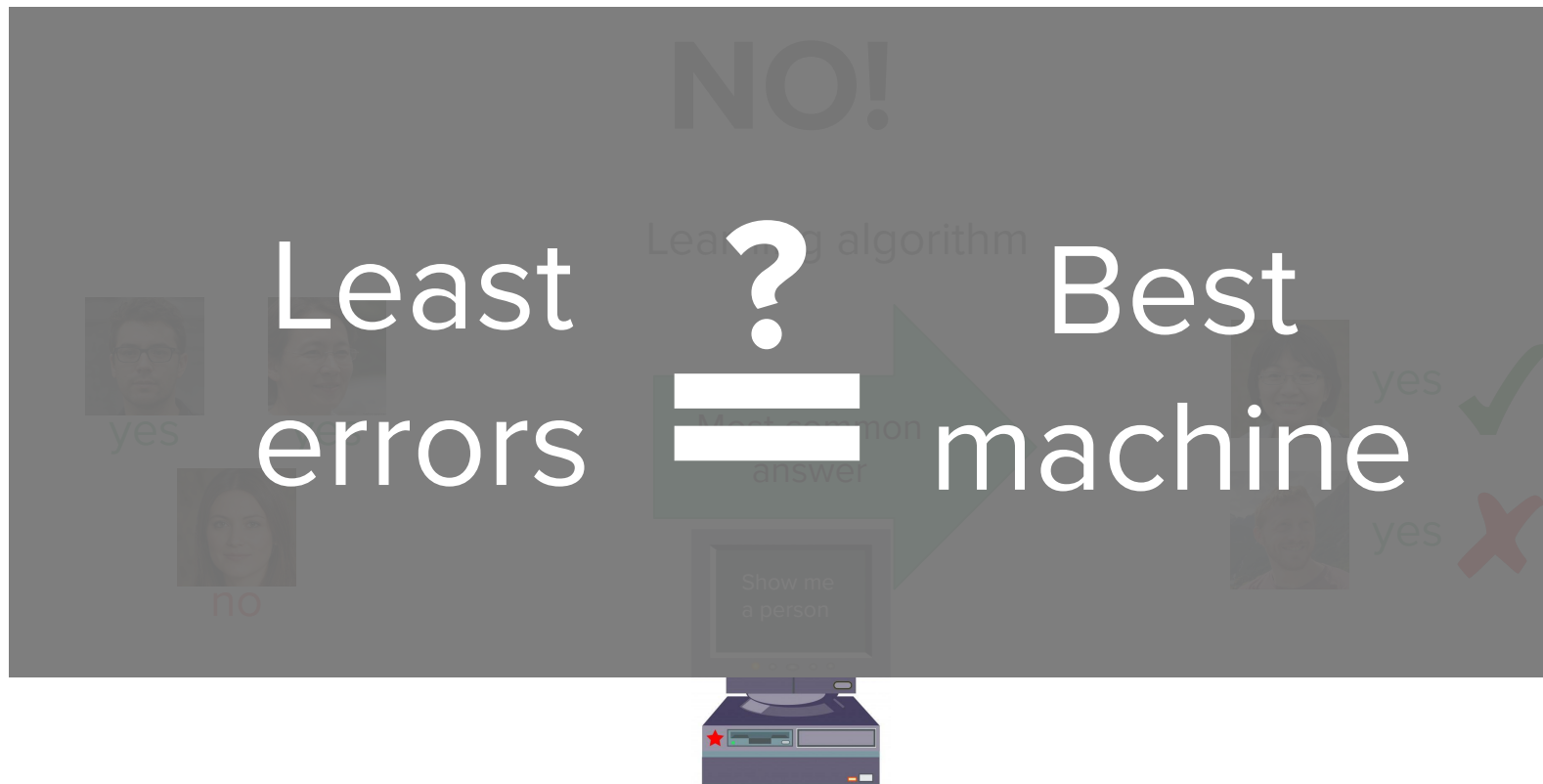
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Is the machine always correct?



ACT II

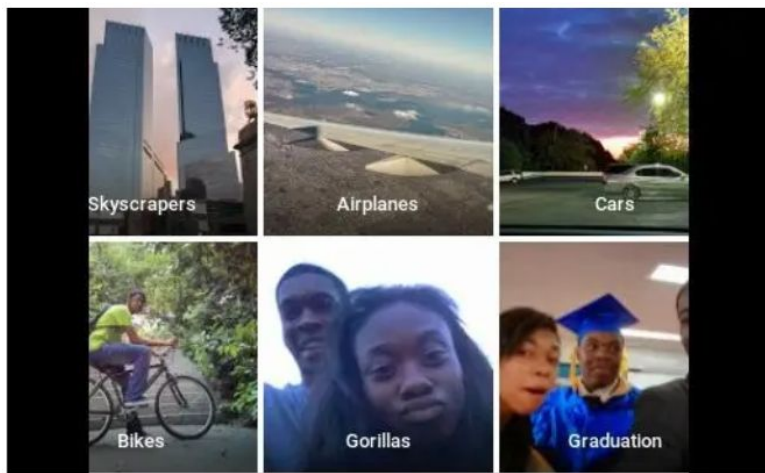
# Bias in AI

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Or: The Paradox of Fairness in Machine Learning

# How good is the learning machine?

Do we want the machine to answer correctly for most people?



diri noir avec banan @jackyalcine · Jun 29  
Google Photos, y'all [redacted] My friend's not a gorilla.

**Forbes**

## Google Photos Tags Two African-Americans As Gorillas Through Facial Recognition Software

By [Maggie Zhang](#), Forbes Staff. I write about technology, innovation, and startups.

Published Jul 01, 2015, 01:42pm EDT, Updated Jul 01, 2015, 02:35pm EDT

**The  
Guardian**

A beauty contest was judged by AI and  
the robots didn't like dark skin

**Sam Levin** in San Francisco

Fri 9 Sep 2016 00:42 CEST

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Do we want the machine to answer correctly for most people?



## Insight - Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin

October 11, 2018 2:50 AM GMT+2 · Updated October 10, 2018

The AP logo, consisting of the letters "AP" in a bold, black, sans-serif font, with a red horizontal bar underneath.

## The secret bias hidden in mortgage-approval algorithms

BY EMMANUEL MARTINEZ AND LAUREN KIRCHNER/THE MARKUP

Published 6:04 PM GMT+2, August 25, 2021

The Forbes logo, with the word "Forbes" in a blue, serif font.

## Google Photos Tags Two African-Americans As Gorillas Through Facial Recognition Software

By [Maggie Zhang](#), Forbes Staff. I write about technology, innovation, and startups.

Published Jul 01, 2015, 01:42pm EDT, Updated Jul 01, 2015, 02:35pm EDT

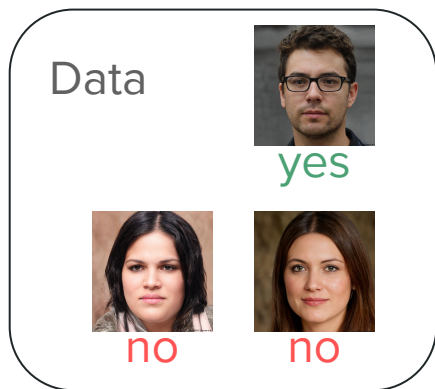
The Guardian logo, with "The" in a smaller font above "Guardian" in a large, bold, black, serif font.

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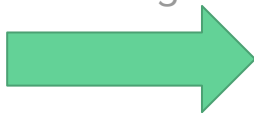
**Sam Levin** in San Francisco

Fri 9 Sep 2016 00:42 CEST

# Sources of unfairness



Learning

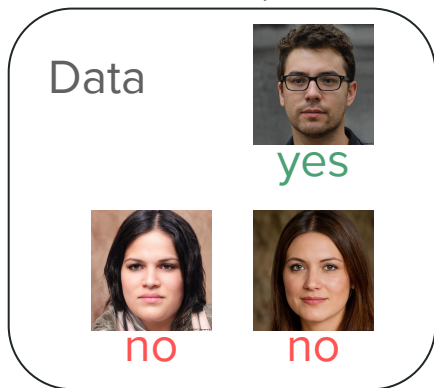


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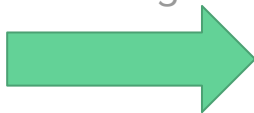
The data:

Is there bias in the data?

If the world is biased, the machine will be biased



Learning

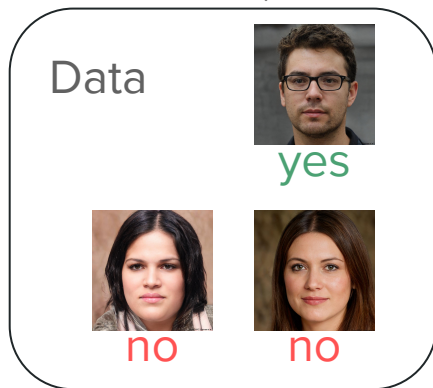


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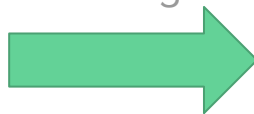
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Learning



The algorithm:

If we learn to answer correctly for the majority of people, it may be wrong for the minority

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- **Positive predicted value (PPV):** the fraction of positive cases which were correctly predicted out of all the positive predictions. It is usually referred to as [precision](#), and represents the [probability](#) of a correct positive prediction. It is given by the following formula:

$$PPV = P(actual = + | prediction = +) = \frac{TP}{TP + FP}$$

- **False discovery rate (FDR):** the fraction of positive predictions which were actually negative out of all the positive predictions. It represents the [probability](#) of an erroneous positive prediction, and it is given by the following formula:

$$FDR = P(actual = - | prediction = +) = \frac{FP}{TP + FP}$$

- **Negative predicted value (NPV):** the fraction of negative cases which were correctly predicted out of all the negative predictions. It represents the [probability](#) of a correct negative prediction, and it is given by the following formula:

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- **False omission rate (FOR):** the fraction of negative predictions which were actually positive out of all the negative predictions. It represents the [probability](#) of an erroneous negative prediction, and it is given by the following formula:

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- **True positive rate (TPR):** the fraction of positive cases which were correctly predicted out of all the positive cases. It is usually referred to as sensitivity or recall, and it represents the [probability](#) of the positive subjects to be classified correctly as such. It is given by the formula:

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### Definitions based on predicted outcome [\[ edit \]](#)

The definitions in this section focus on a predicted outcome  $R$  for various [distributions](#) of subjects. They are the simplest and most intuitive notions of fairness.

- **Demographic parity**, also referred to as **statistical parity**, **acceptance rate parity** and **benchmarking**. A classifier satisfies this definition if the subjects in the protected and unprotected groups have equal probability of being assigned to the positive predicted class. This is, if the following formula is satisfied:

$$P(R = + | A = a) = P(R = + | A = b) \quad \forall a, b \in A$$

- **Conditional statistical parity**. Basically consists in the definition above, but restricted only to a [subset](#) of the instances. In mathematical notation this would be:

$$P(R = + | L = l, A = a) = P(R = + | L = l, A = b) \quad \forall a, b \in A \quad \forall l \in L$$

### Definitions based on predicted probabilities and actual outcome [\[ edit \]](#)

These definitions are based in the actual outcome  $Y$  and the predicted probability score  $S$ .

- **Test-fairness**, also known as **calibration** or **matching conditional frequencies**. A classifier satisfies this definition if individuals with the same predicted probability score  $S$  have the same probability of being classified in the positive class when they belong to either the protected or the unprotected group:

$$P(Y = + | S = s, A = a) = P(Y = + | S = s, A = b) \quad \forall s \in S \quad \forall a, b \in A$$

- **Well-calibration** is an extension of the previous definition. It states that when individuals inside or outside the protected group have the same predicted probability score  $S$  they must have the same probability of being classified in the positive class, and this probability must be equal to  $S$ :

$$P(Y = + | S = s, A = a) = P(Y = + | S = s, A = b) = s \quad \forall s \in S \quad \forall a, b \in A$$

- **Balance for positive class**. A classifier satisfies this definition if the subjects constituting the positive class from both protected and unprotected groups have equal average predicted probability score  $S$ . This means that the expected value of probability score for the protected and unprotected groups with positive actual outcome  $Y$  is the same, satisfying the formula:

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### Definitions based on predicted and actual outcomes [\[ edit \]](#)

These definitions not only considers the predicted outcome  $R$  but also compare it to the actual outcome  $Y$ :

- **Predictive parity**, also referred to as **outcome test**. A classifier satisfies this definition if the subjects in the protected and unprotected groups have equal PPV. This is, if the following formula is satisfied:

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Mathematically, if a classifier has equal PPV for both groups, it will also have equal FDR, satisfying the formula:

$$P(Y = - | R = +, A = a) = P(Y = - | R = +, A = b) \quad \forall a, b \in A$$

- **False positive error rate balance**, also referred to as **predictive equality**. A classifier satisfies this definition if the subjects in the protected and unprotected groups have equal FPR. This is, if the following formula is satisfied:

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- When this definition is extended to a subset of the instances, it is referred to as **conditional test-fairness**. In this case, the group have the same predicted probability score  $S$  they must belong to the subset of the instances. In this case, this probability must be equal to  $S$ :

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# How to make machine learning fair?



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## 1) Pre-processing the data:

Change the data to be fair in the first place



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## 2) In-processing the algorithm:

Change the algorithm to be fair to minorities

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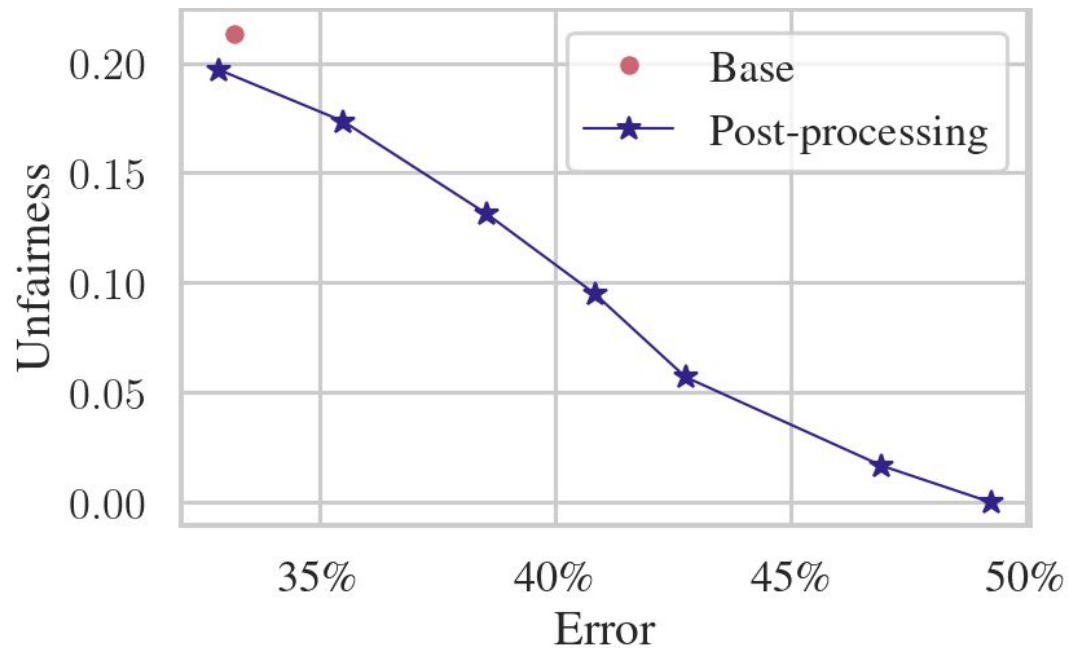
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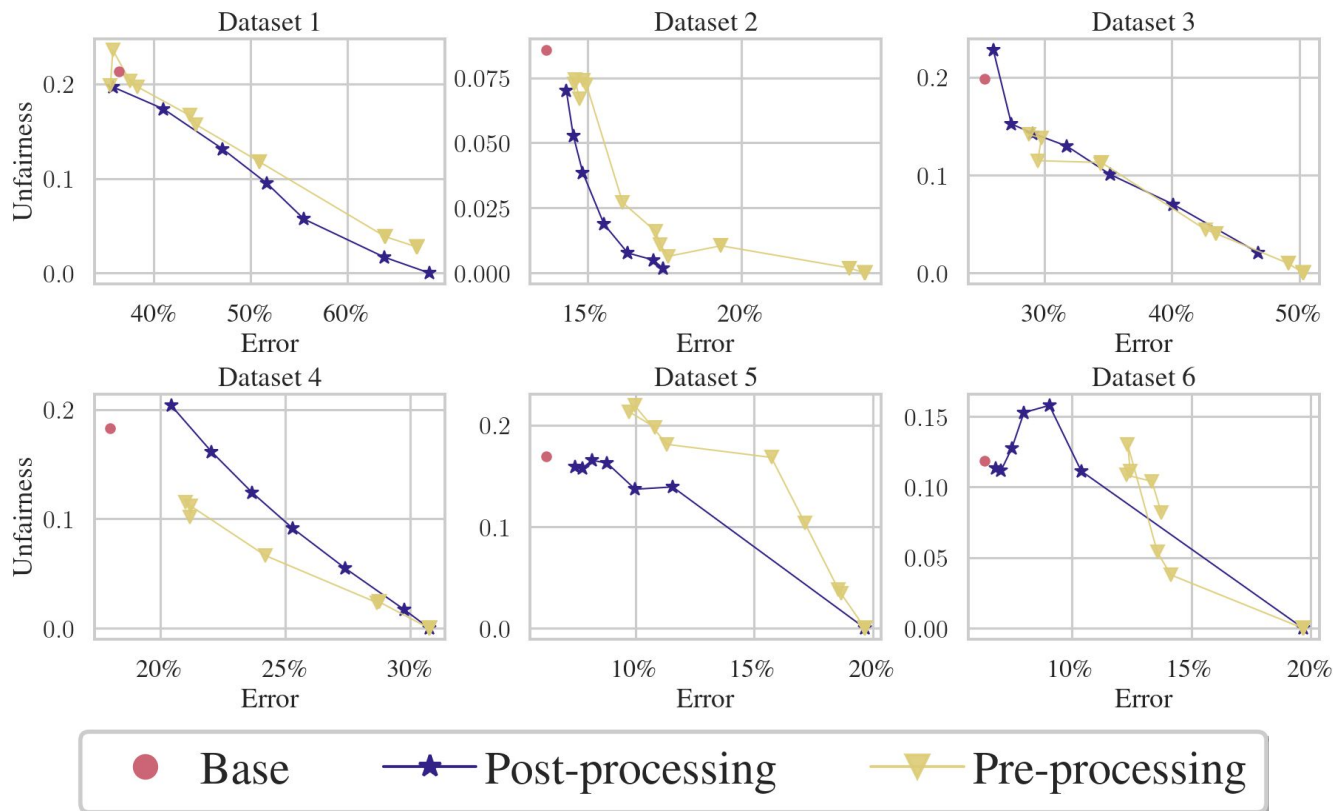
## 3) Post-processing the answers:

Change the answers to be fair

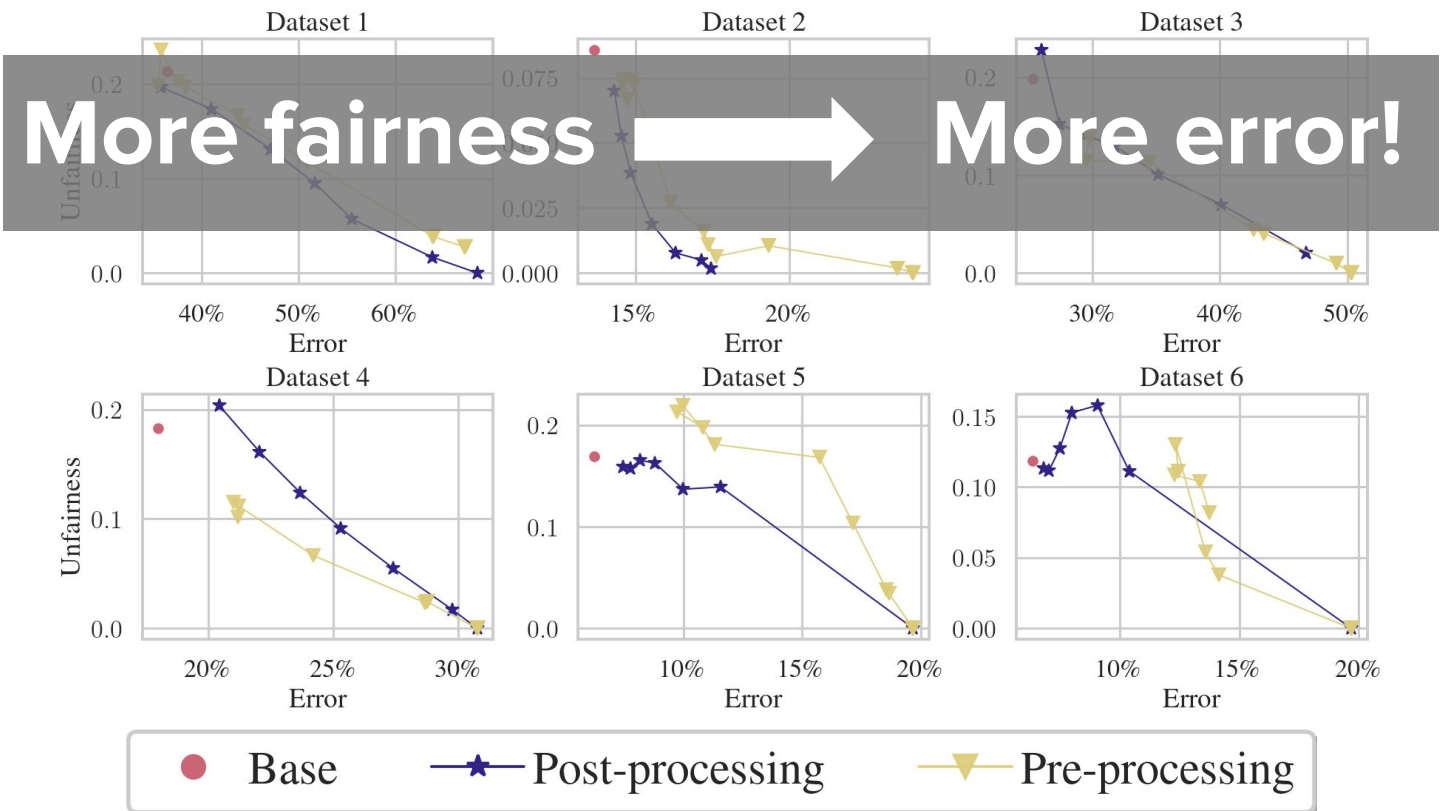
## The cost of fairness is error



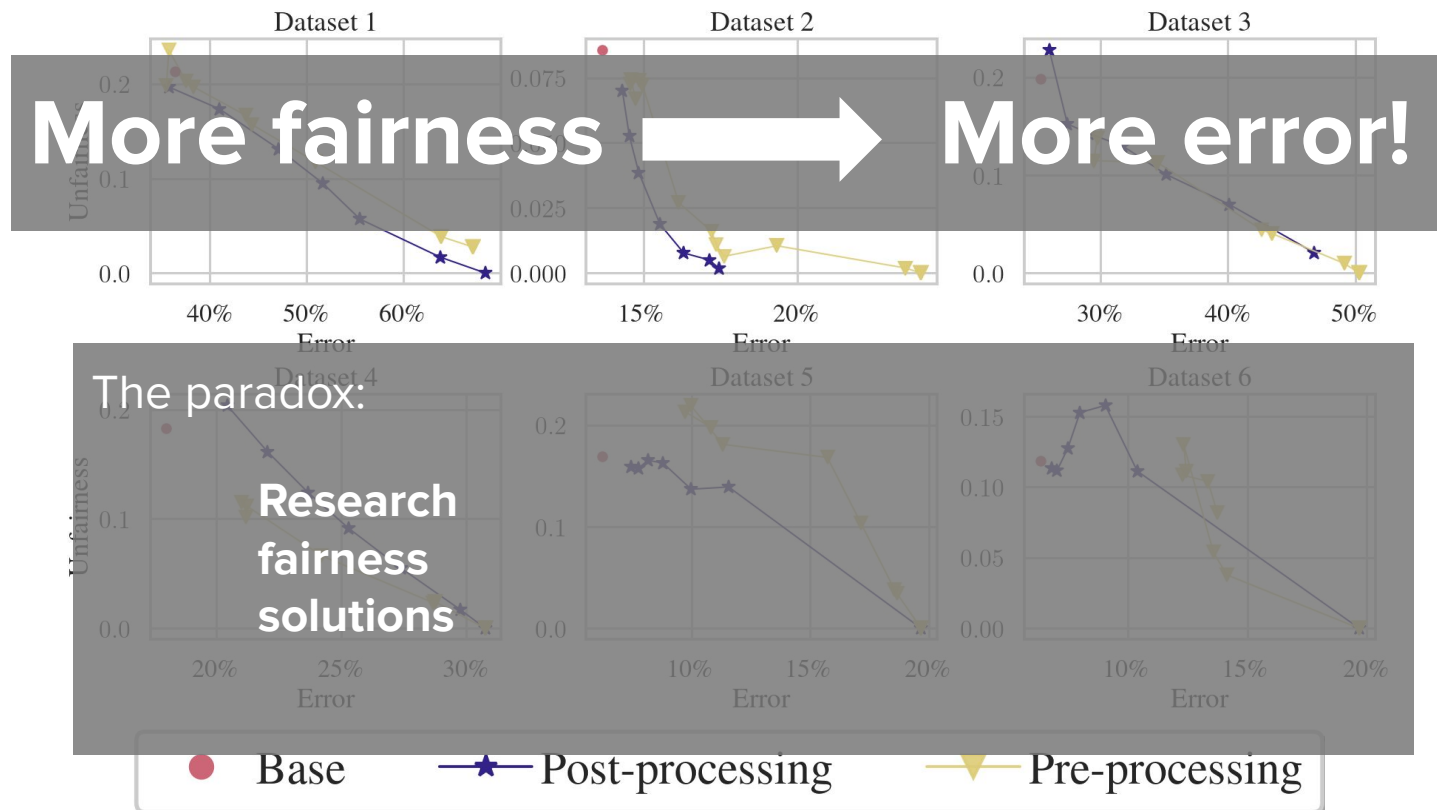
# The cost and the paradox



# The cost and the paradox



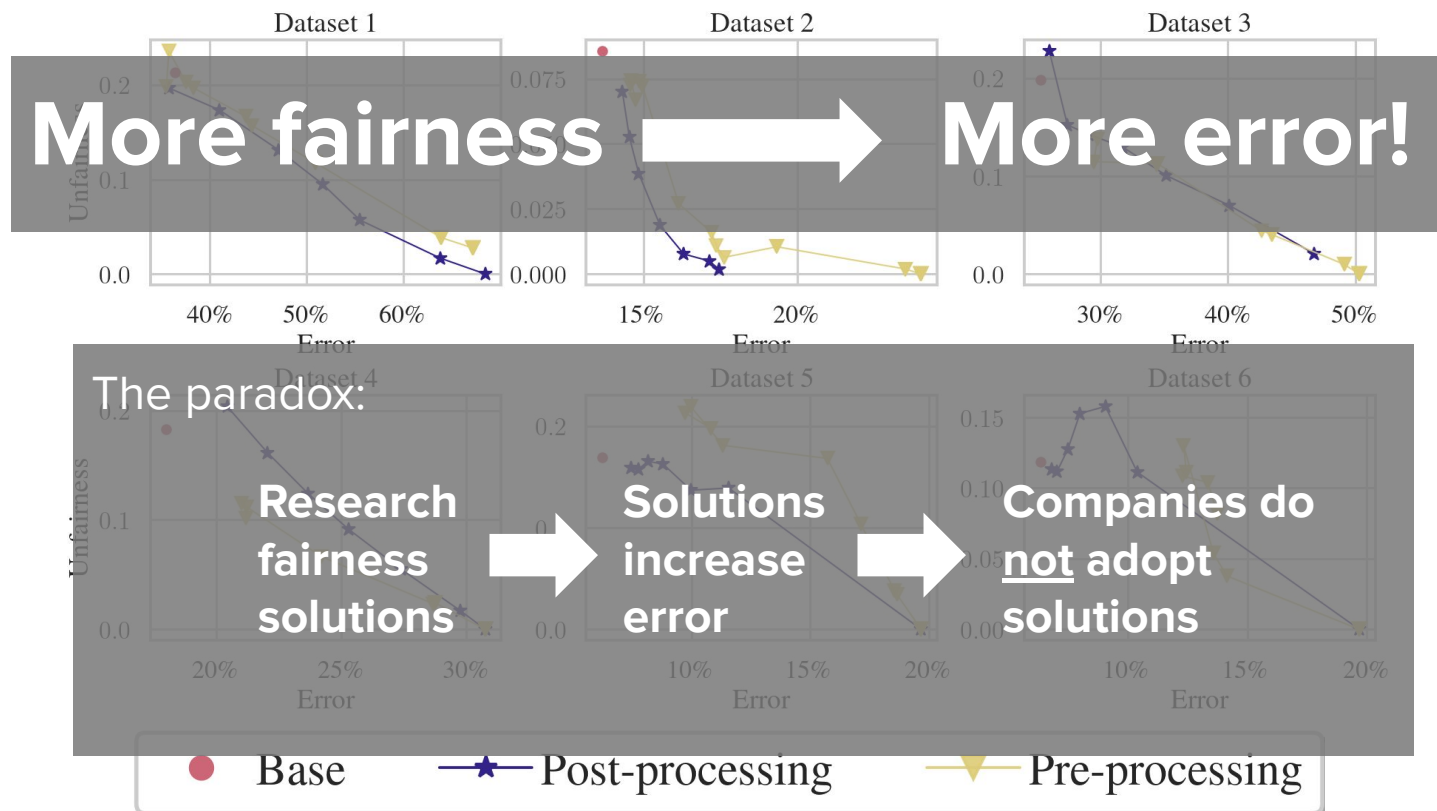
# The cost and the paradox



# The cost and the paradox



# The cost and the paradox



Give up on fairness?

If companies don't use fair learning,  
what can we do?

ACT III

# Fighting Bias in AI: Can Ordinary People Make a Difference?

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Or: Collective Action in Machine Learning

# One person is not enough, but together...



News > Business > Business News

## Uber drivers work together to create price surge and charge customers more, researchers find

Some drivers are deliberately going offline in unison so that prices surge and they can charge customers more when they log back into the app

Thrown under the bus and outrunning it! The logic of Didi and taxi drivers' labour and activism in the on-demand economy

[Julie Yujie Chen](#)  [View all authors and affiliations](#)

[Volume 20, Issue 8](#) | <https://doi.org/10.1177/1461444817729149>

## On-demand workers are protesting – using the apps they work for



By Sara Ashley O'Brien, CNN Business

 5 min read · Published 2:39 PM EDT, Fri June 14, 2019

## Waze to go: residents fight off crowdsourced traffic... for a while

Residents on a formerly quiet street tried reporting bogus blockades, but it hasn't worked to stem the crowdsourced traffic tide.

Written by Lisa Vaas

JUNE 07, 2016



## Your quote tweets make bad tweets worse. Do this instead

Critics denouncing Parkland shooting conspiracy theories ended up fanning the flames on social media. Here's how you can criticize without amplifying.

## How Anitta megafans gamed Spotify to help create Brazil's first global chart-topper

Fans skirted terms and conditions, but a strategy from the singer's team came close to the streaming platform's limit.

The information age



Uber



NETFLIX

The information age



They all collect our data:

- Information
- Clicks
- History
- Likes
- Time
- Anything

And use machine learning



NETFLIX

The information age



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NETFLIX

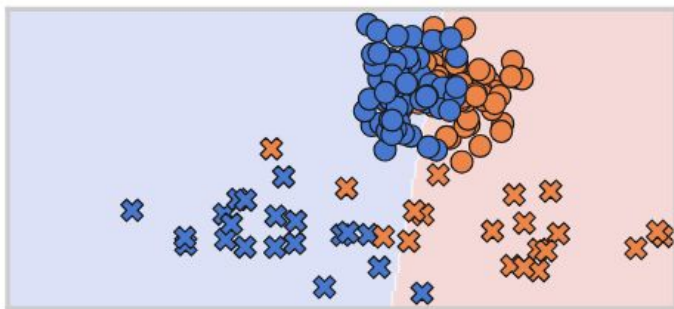
What can a minority do?

**Coordinate** how to change their  
**interaction** with the apps!

# Can a minority group collaborate for fairness?

What should the minority do? Change interaction....

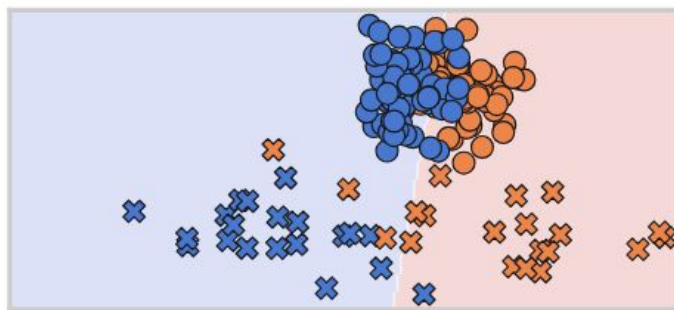
(a) Before collective action



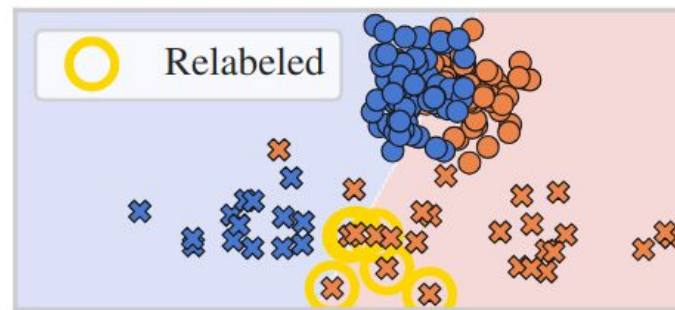
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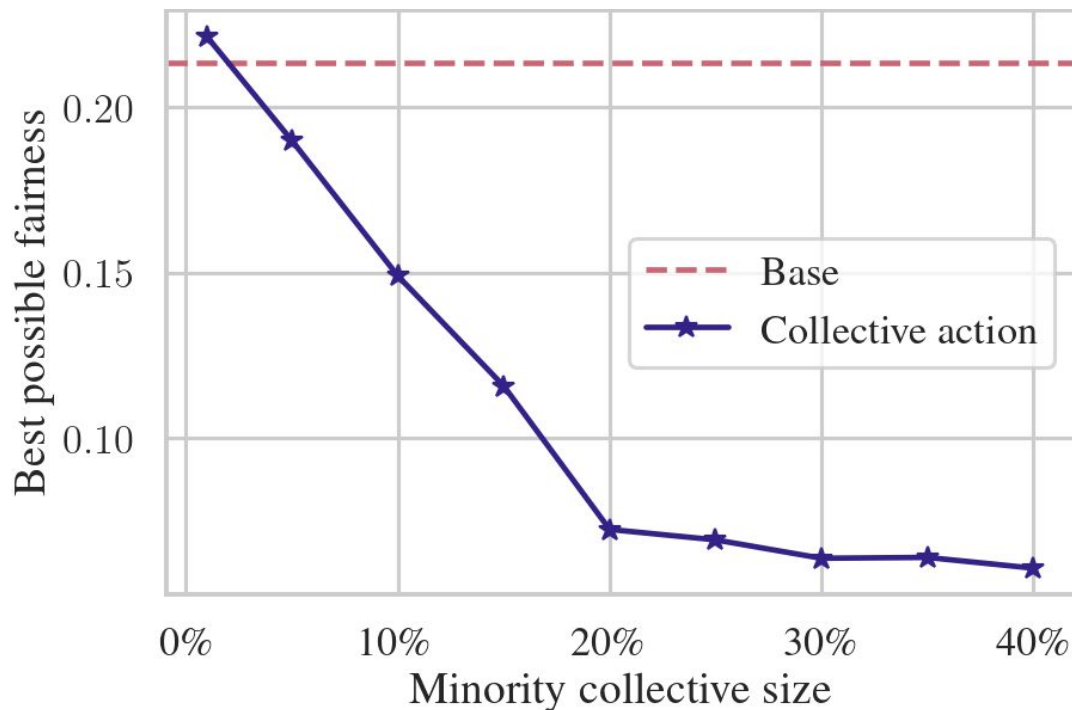


(b) After collective action

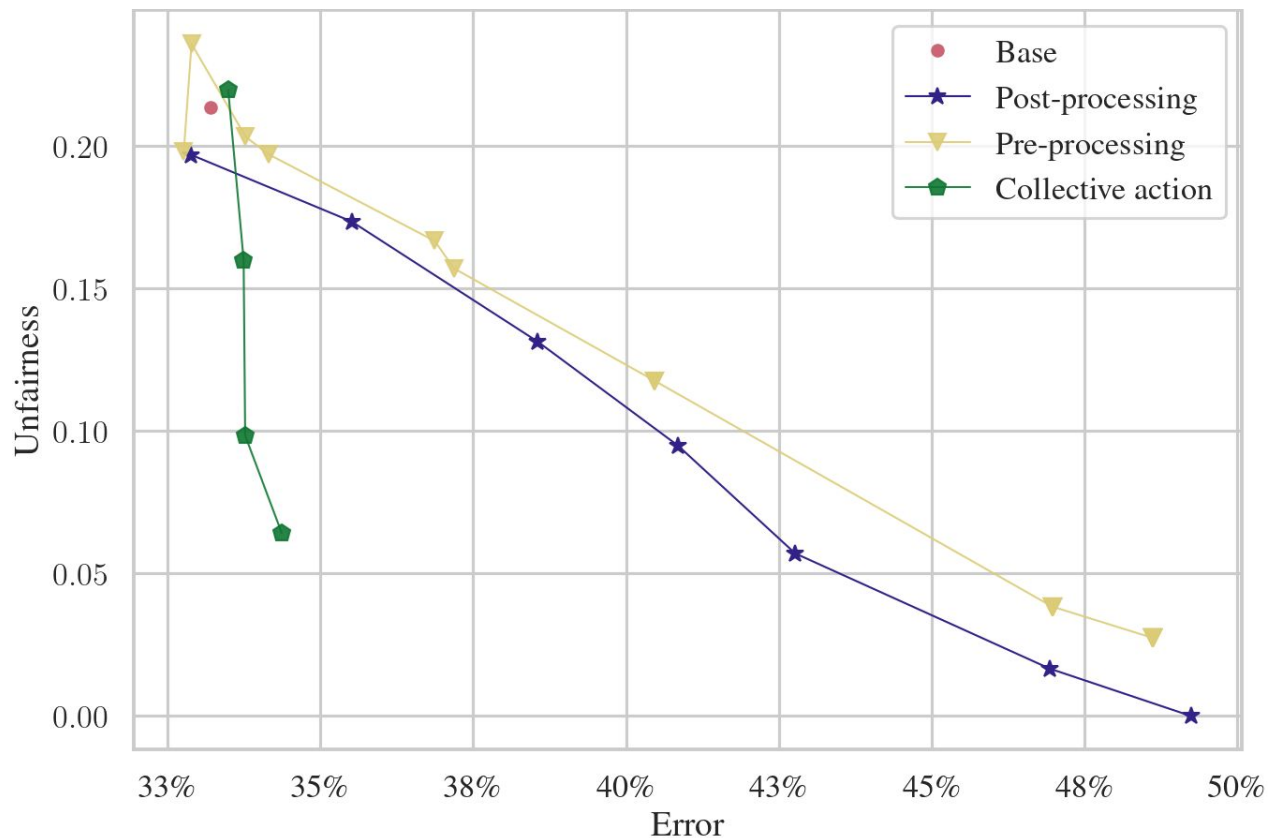


# Can a minority group collaborate for fairness?

Best fairness with less than 30% of the minority!



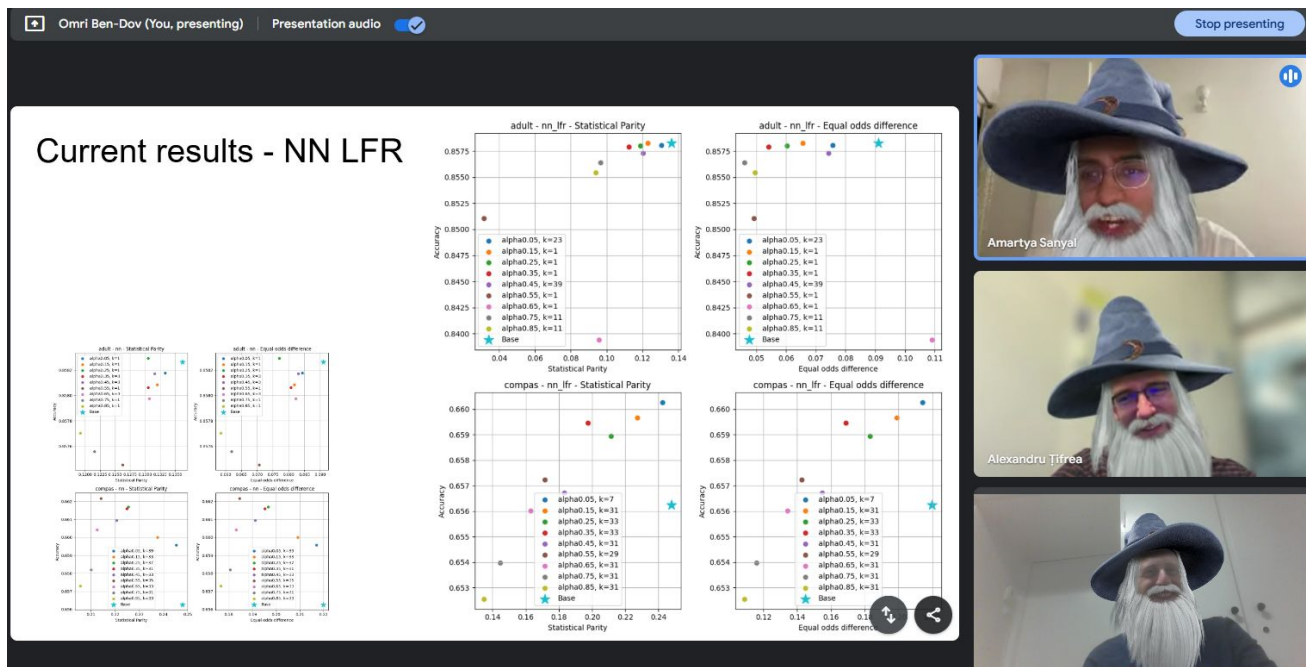
## Smaller error, but no “perfect” fairness



# Only first steps

- “Simple” fairness problems
  - Can be improved?
- How else can collective action contribute to social good?

# The team



# Recap

## 1. AI = Machine learning

- Use a lot of data to answer a simple question (including chatGPT)

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For the  
slides and  
more details

