



# Unsupervised bias scan tool

A quantitative method to inform qualitative bias testing

NGO Algorithm Audit

January 4th 2023

## Overview of Algorithm Audit's bias scan tool

1.

### Problem description

- Problem 1 (quantitative) – Detecting (higher-dimensional) forms of differentiation
- Problem 2 (qualitative) – A persistent gap between general legal requirements and concrete AI practice

2.

### Solution

- Unsupervised bias scan tool to *detect* differentiation (quantitative)
- A deliberative approach to *establish* unfair treatment (qualitative)

3.

### Case study

- Disparities in a BERT-based Twitter disinformation classifier (quantitative)
- Audit commission: Assessing potentially unfair treatment by an AI classifier (qualitative)

4.

### Conclusion + contributors and endorsements

#### Work of NGO Algorithm Audit:



#### i) Audit commissions

Advising on ethical issues emerging in concrete algorithmic practices



#### ii) Technical tooling

Implement and tests technical tools to detect and mitigate bias in practice



#### iii) Advocacy

Sharing techno-legal knowledge with society and policy makers

#### Supported by:

EUROPEAN  
ARTIFICIAL  
INTELLIGENCE  
FUND

NL AI Coalition

**SIDN**fonds

# Problem 1: The human mind is not equipped to detect higher-dimensional forms of algorithmic differentiation

The quantitative reasoning paradigm of AI...

Exploiting higher-dimensional correlations

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \dots & a_{1,n} \\ a_{2,1} & \ddots & & \\ \vdots & & & \\ a_{n,1} & & & a_{n,n} \end{pmatrix}$$

$n \times n$  matrices are used to represent and perform computations with  $n$ -dimensional data

...poses challenges to assess fair treatment.

1.

How to detect disparities in the sheer data volume AI outputs?

2.

How to detect differentiation upon new categories of people defined by a mixture of many data points (*ad hoc bias*)?

3.

How to detect unfair differentiation when protected attributes are not available to compute group fairness metrics?

## Problem 2: If differentiation is detected, a persistent gap remains between quantitative fairness metrics and qualitative interpretation

### Qualitative reasoning paradigm

Legal requirements  
Non-discrimination  
Equal treatment

Ethical requirements  
Unfair, but lawful  
differentiation



Battle of numbers  
(e.g., COMPAS algorithm)

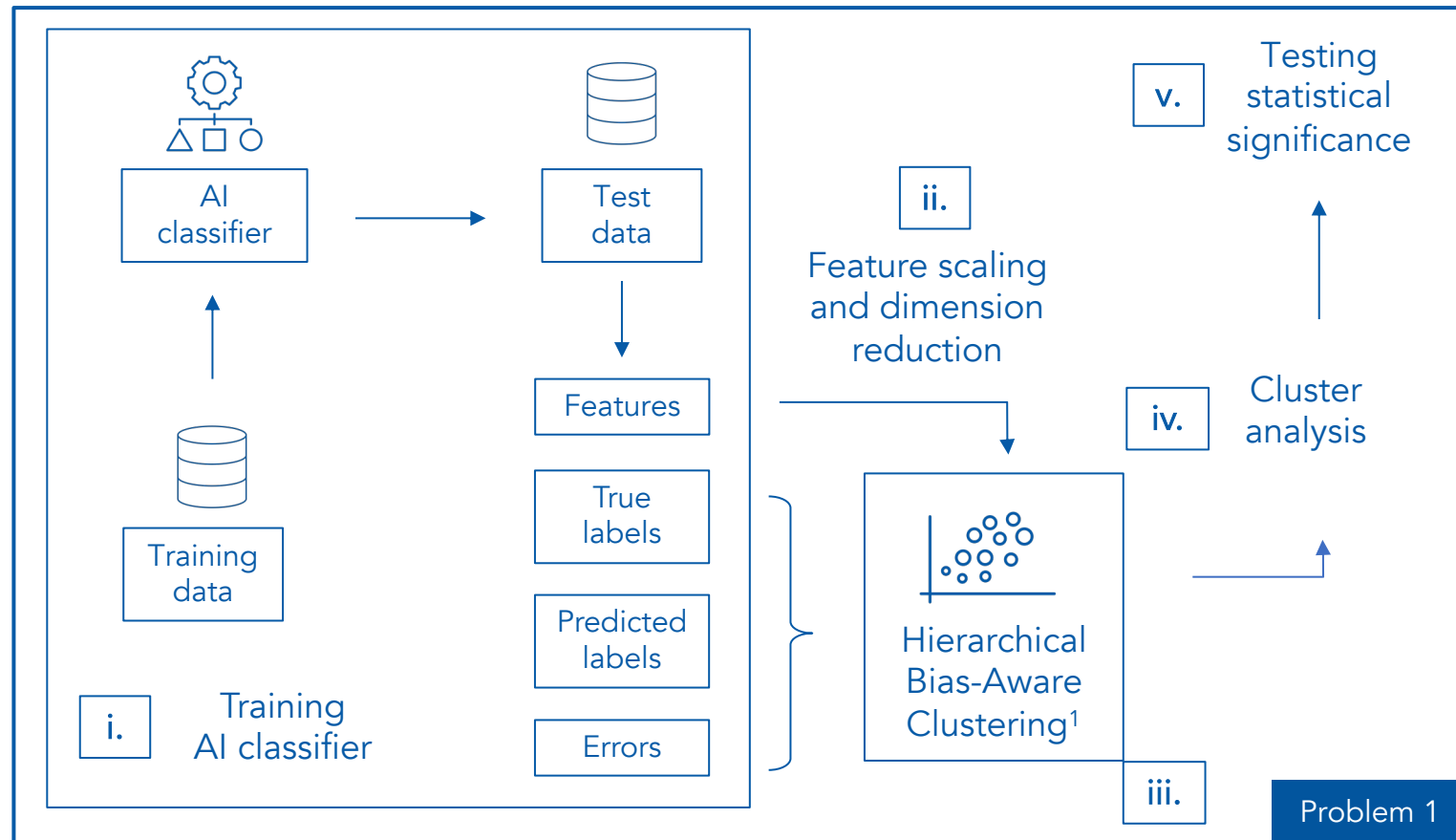
### Quantitative reasoning paradigm

AI practice  
Correlations  
Proxies  
Fairness metrics



## Solution: Quantitative method to *detect* differentiation (problem 1) Qualitative approach to *establish* unfair treatment (problem 2)

### Quantitative bias scan tool



### Qualitative expert-led deliberation

- 1. Identify issue**  
Identify a suspected disparity in an AI classifier.
- 2. Audit commission**  
Form an independent and diverse commission of experts.
- 3. Analysis**  
Independent review of issue by audit commission.
- 4. Advice**  
Advice by audit commission is published and shared online.

Problem 2

<sup>1</sup> Misztal, Indurkya, Bias-Aware Hierarchical Clustering for detecting the discriminated groups of users in recommendation systems, *Information Processing and Management* (2021)

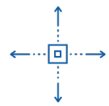
## Benefits of our quantitative-qualitative approach



Unsupervised machine learning



No data needed on protected characteristics of users.



Model agnostic



Works for all binary classification algorithms.



Bridging the quantitative and qualitative reasoning paradigm



Automated identification of potential bias allows human experts to assess observed disparities in a qualitative manner, subject to political, social and environmental traits.



Open-source and not for profit



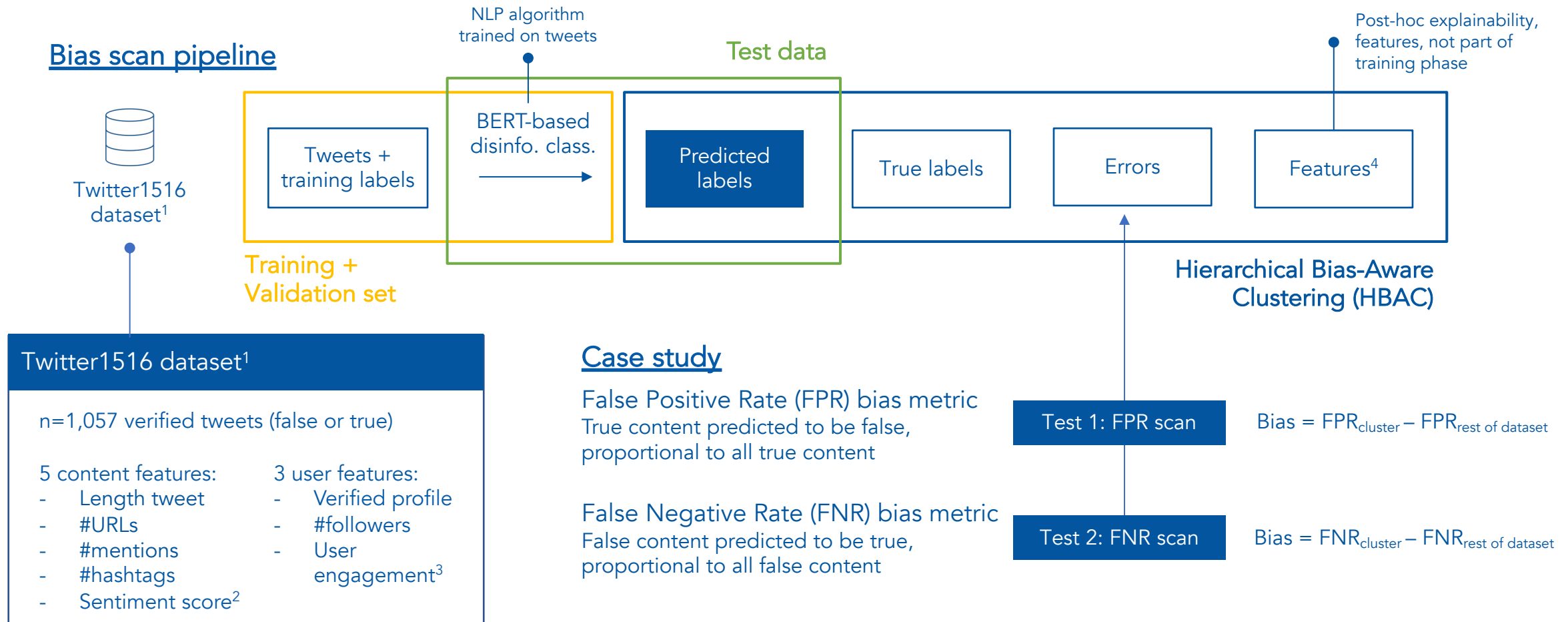
Allowing the wider AI auditing ecosystem, e.g., data scientists, journalists, policy makers, public- and private auditors, to use quantitative methods to detect potential bias. Source code is available on [GitHub](#).



The bias scan tool is available as a web application on our [website](#). Creating instant a bias scan report for binary classifier data.

# Detecting disparities on a self-trained BERT-based disinformation classifier, using the Twitter1516 dataset

## Bias scan pipeline



<sup>1</sup> Liu, Xiaomo and Nourbakhsh, Armineh and Li, Quanzhi and Fang, Rui and Shah, Sameena, in *Proceedings of the 24th ACM International on Conference on Information and Knowledge Management* (2015)

<sup>2</sup> Based on the VADER sentiment analysis tool, <https://github.com/cjhutto/vaderSentiment>

<sup>3</sup> Vosoughi, S., Roy, D., and Aral, S.: The spread of true and false news online. *Science* 359, 6380 (2018), 1146–1151.

<sup>4</sup> The Twitter1516 dataset and self-collected features scaled using Scikit's StandardScaler

## Results: Suspected disparities in the BERT-based Twitter misinformation classifier

More details  
on [GitHub](#)

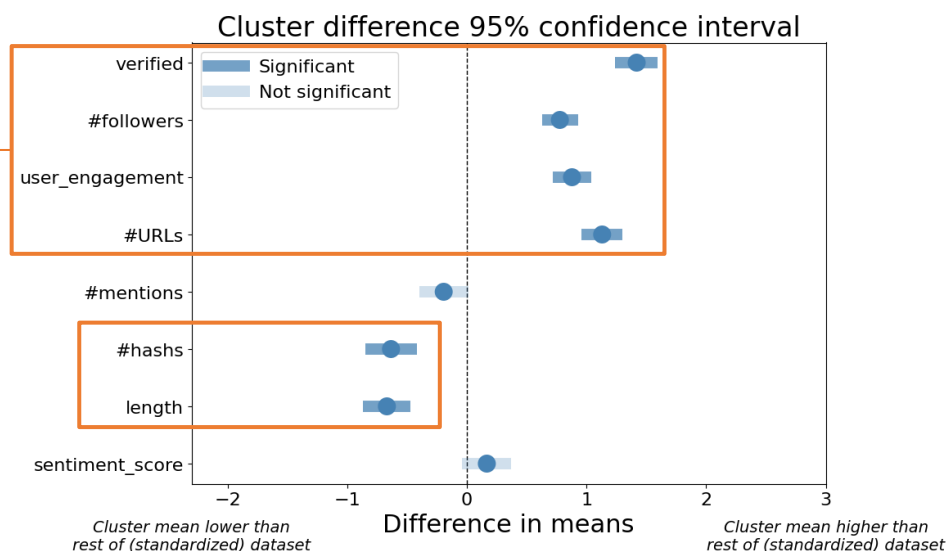


### FPR scan

Cluster with highest bias (FPR): 0.08  
#elements in cluster with highest bias<sup>1</sup>: 249

On average, users that:

- are **verified**, have higher **#followers**, **user engagement** and **#URLs**;
  - use less **#hashtags** and have lower **tweet length**
- have more true content classified as false (false positives).

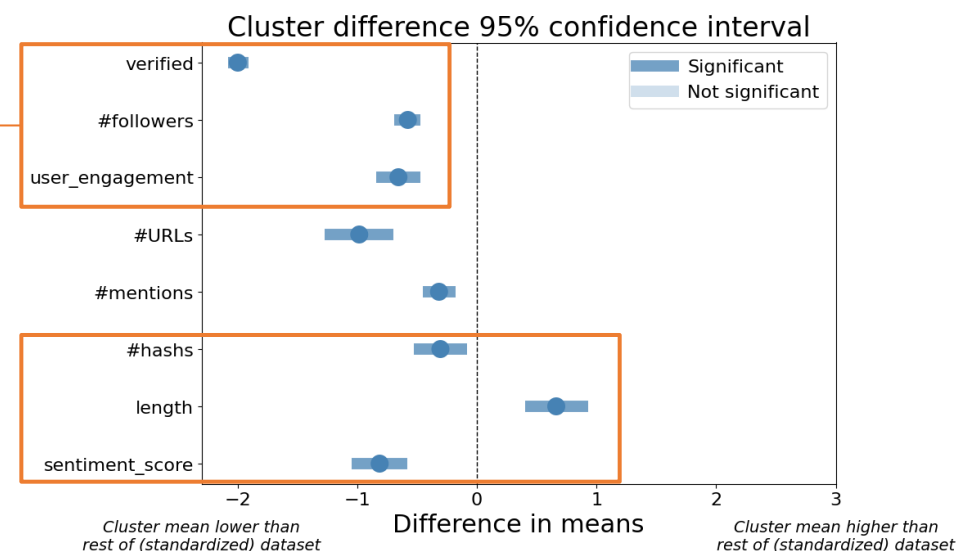


### FNR scan

Cluster with highest bias (FNR): 0.13  
#elements in cluster with highest bias<sup>1</sup>: 46

On average, users that:

- use more **#hashtags** and have higher **sentiment score**;
  - are **non-verified**, have less **#followers**, **user engagement** and **tweet length**
- have more false content classified as true (false negatives).





## Qualitative assessment of identified disparities by audit commission

### Questions to assess unfair treatment

1. Is there an indication that one of the statistically significant features, or a combination of the features, from Slide 8 are critically linked to one or multiple protected grounds?
2. In the context of disinformation detection, is it as harmful to classify true content as false (false positive) as false content as true (false negative)?
3. For a specific cluster of people, is it justifiable to have true content classified as false 8 percentage points more often? For a specific cluster of people, is it justifiable to have false content classified as true 13 percentage points more often?
4. Is it justifiable that the disinformation classification algorithm is too harsh towards users with verified profile, more #followers and higher user engagement and too lenient towards users with non-verified profile, less #followers and lower user engagement?

### Audit commission



Expert A



Expert B



Expert C



Expert D

## Conclusion: To be included once available

Audit commissions convenes  
in Jan-Feb 2023, to elaborate on the  
questions formulated in slide 9.

## This project is a collective effort of AI experts from a wide range of professional backgrounds

### 15+ endorsements from various parts of the AI auditing community

#### Algorithm Audit's bias scan tool team



Jurriaan Parie, Trustworthy AI consultant, Deloitte



Ariën Voogt, PhD-candidate in Philosophy, Protestant Theological University of Amsterdam



Joel Persson, PhD-candidate in Applied Data Science, ETH Zürich

#### Journalism

- Gabriel Geiger, Investigative Reporter Algorithms and Automated Decision-Making at Lighthouse Reports
- Hayden Field [to be confirmed], Senior Reporter, Emerging Tech at Morning Brew
- AA

#### Industry

- Selma Muhammed, Trustworthy AI consultant at Deloitte
- Laurens van der Maas, Data Scientist at Amazon Web Services
- BB

#### Academia

- Anne Meuwese, Professor in Public Law & Ai at Leiden University
- Marlies van Eck, Assistant Professor in Administrative Law & AI at Radboud University
- Emma Beauxis-Ausselet, Associate Professor Ethical Computing at University of Amsterdam
- Vahid Niamadpour, PhD-candidate in Linguistics at Leiden University
- Floris Holstege, PhD-candidate in Explainable Machine Learning at University of Amsterdam

#### Civil society organisations

- CC
- DD
- Simone Maria Parazzoli, Fellow at the OECD Observatory of Public Sector Innovation (OPSI)



Want to know more?  
**Get involved**  
Contact us!

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<https://www.linkedin.com/company/algorithm-audit/>



<https://github.com/NGO-Algorithm-Audit>