



Unsupervised bias scan tool

A quantitative method to inform qualitative bias testing

NGO Algorithm Audit

Feb 26th 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:



Audit commissions

Advising on ethical issues emerging in concrete algorithmic practices



Technical tooling

Implementing and testing technical tools to detect and mitigate bias



Advocacy

Contributing to public debate on responsible use of algorithms



Knowledge sharing

Sharing techno-ethical insights with society, policy makers and others

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EUROPEAN
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NL AI Coalition

SIDNfonds

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)

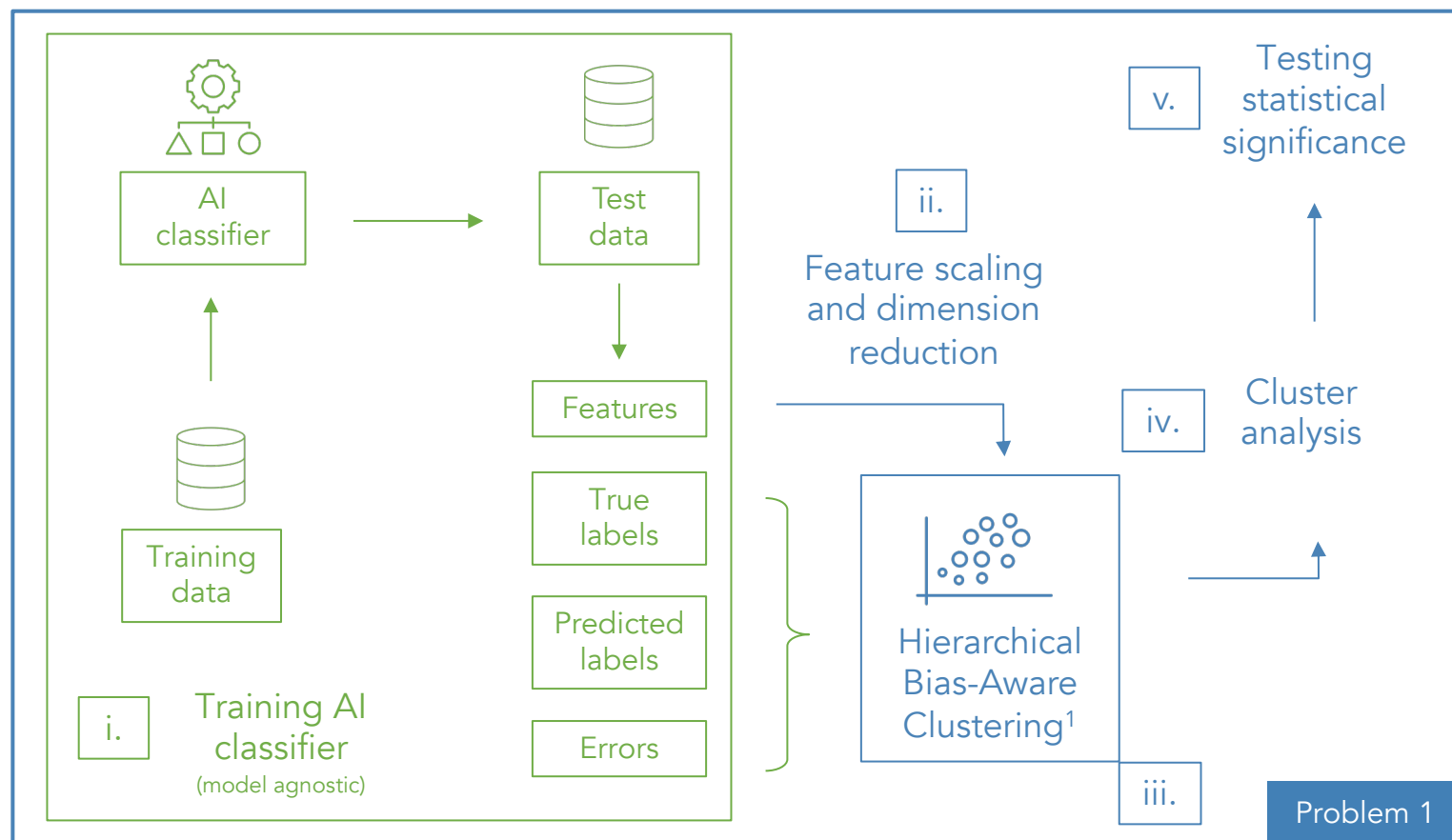
Quantitative reasoning paradigm

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

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

Over time a case repository emerges from which data scientists and public authorities can distill 'techno-ethical' best-practices

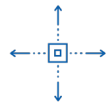
Benefits of our quantitative-qualitative approach



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



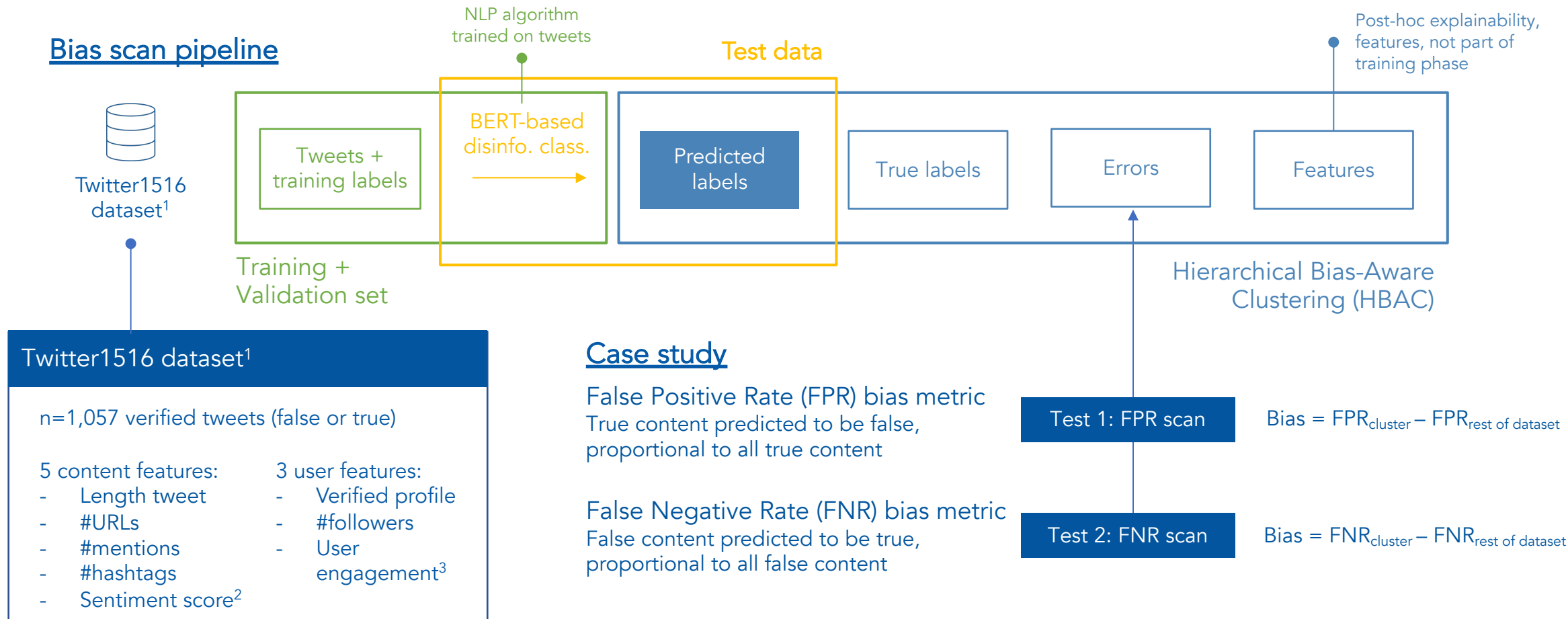
Allowing the wider AI auditing ecosystem, e.g., data scientists, journalists, policy makers, public- and private auditors, to use quantitative methods to detect potential bias. Source code is available on [GitHub](#).



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 disinformation classifier, using the Twitter1516 dataset

Bias scan pipeline



¹ 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)

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

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

⁴ 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](#)

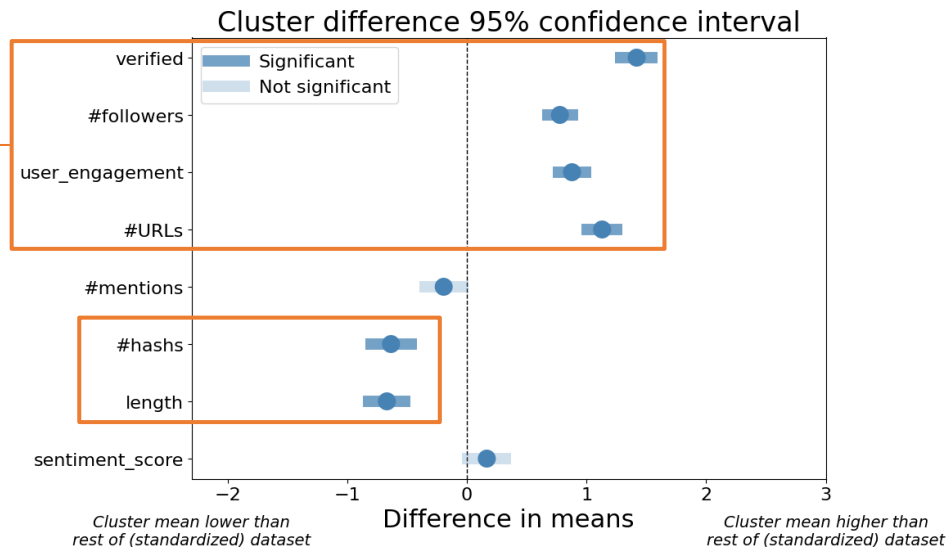


FPR scan

Cluster with highest bias (FPR): 0.08
#elements in cluster with highest bias¹: 249

On average, users that:

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

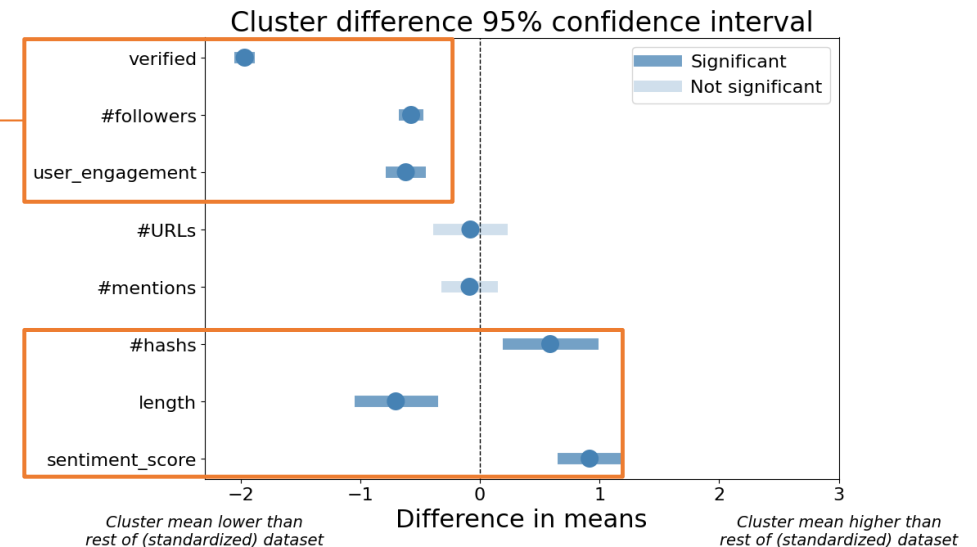


FNR scan

Cluster with highest bias (FNR): 0.13
#elements in cluster with highest bias¹: 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



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Expert E

Conclusion: To be included once available

Audit commission 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



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Civil society organisations

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Want to know more?
Get involved
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<https://www.linkedin.com/company/algorithm-audit/>



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