

# Fairness, Accountability, Transparency and Ethics in Machine Learning.

Introduction to Computational Modelling. Degree in Computer  
Engineering. University of Cordoba. 2025-2026

Javier Sánchez Monedero (Universidad de Córdoba)

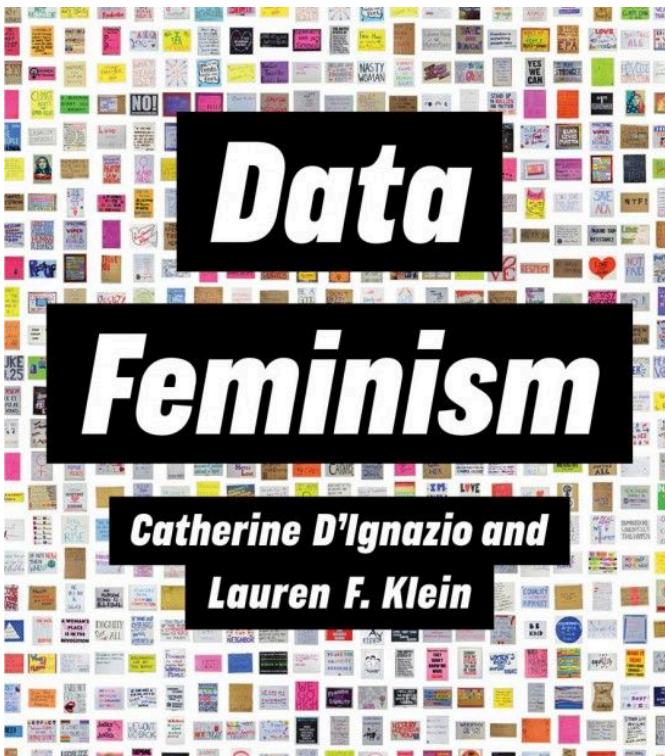
# Objectives

- Introduction and motivation to FATE in artificial intelligence
- Quantifying and mitigating bias: [FairLearn](#)



# Introduction and motivation to FATE

# Where to start? Books



## FAIRNESS AND MACHINE LEARNING

Limitations and Opportunities

Solon Barocas, Moritz Hardt, Arvind Narayanan

### CONTENTS

#### PREFACE

#### ACKNOWLEDGMENTS

- 1 [INTRODUCTION](#) [PDF](#)

- 2 [WHEN IS AUTOMATED DECISION MAKING LEGITIMATE?](#) [PDF](#)

We explore what makes automated decision making a matter of normative concern, situated in bureaucratic decision making and its mechanical application of formalized rules.

- 3 [CLASSIFICATION](#) [PDF](#)

We introduce formal non-discrimination criteria in a decision-theoretic setting, establish their relationships, and illustrate their limitations.

- 4 [RELATIVE NOTIONS OF FAIRNESS](#) [PDF](#)

We introduce formal non-discrimination criteria in a decision-theoretic setting, establish their relationships, and illustrate their limitations.

- 5 [CAUSALITY](#) [PDF](#)

We dive into the rich technical repertoire of causal inference and how it helps articulate and address shortcomings of the classification paradigm, while raising new conceptual and normative questions.

# Where to start? Video

- Documentary [Coded Bias](#)
- TED Talk by Joy Buolamwini  
[How I'm fighting bias in algorithms](#)

CODED BIAS

THERE IS NO ALGORITHM FOR TRUTH



A SHALINI KANTAYYA FILM



# FATE

- Fairness
- Accountability
- Transparency
- Ethics

[facctconference.org](http://facctconference.org)

[facctconference.org/network](http://facctconference.org/network)



# Seminar objectives

Discrimination in **systems/models** that make/support decisions with human consequences.

- This does not consider other forms of discrimination or injustice.
- Discrimination/equality issues need other kinds of non-technical interventions (see recommended books)

**Discrimination is not a general concept, it depends:**

- Domain of the problem
- Social group

# Protected Groups

Protected classes (not in all contexts):

- USA: "race", colour, gender, religion, religion, citizenship, pregnancy, age....
- Spain: gender, pregnancy, "race" (equal treatment law)...

The definition of protected groups goes further and includes the following categories **non-binary** and **intersectionality**

There's No Scientific Basis for Race—It's a Made-Up Label. National Geographic. 2018, March 12.



# Law on equal treatment and non-discrimination

Artículo 23 Ley 15/2022, de 12 de julio:

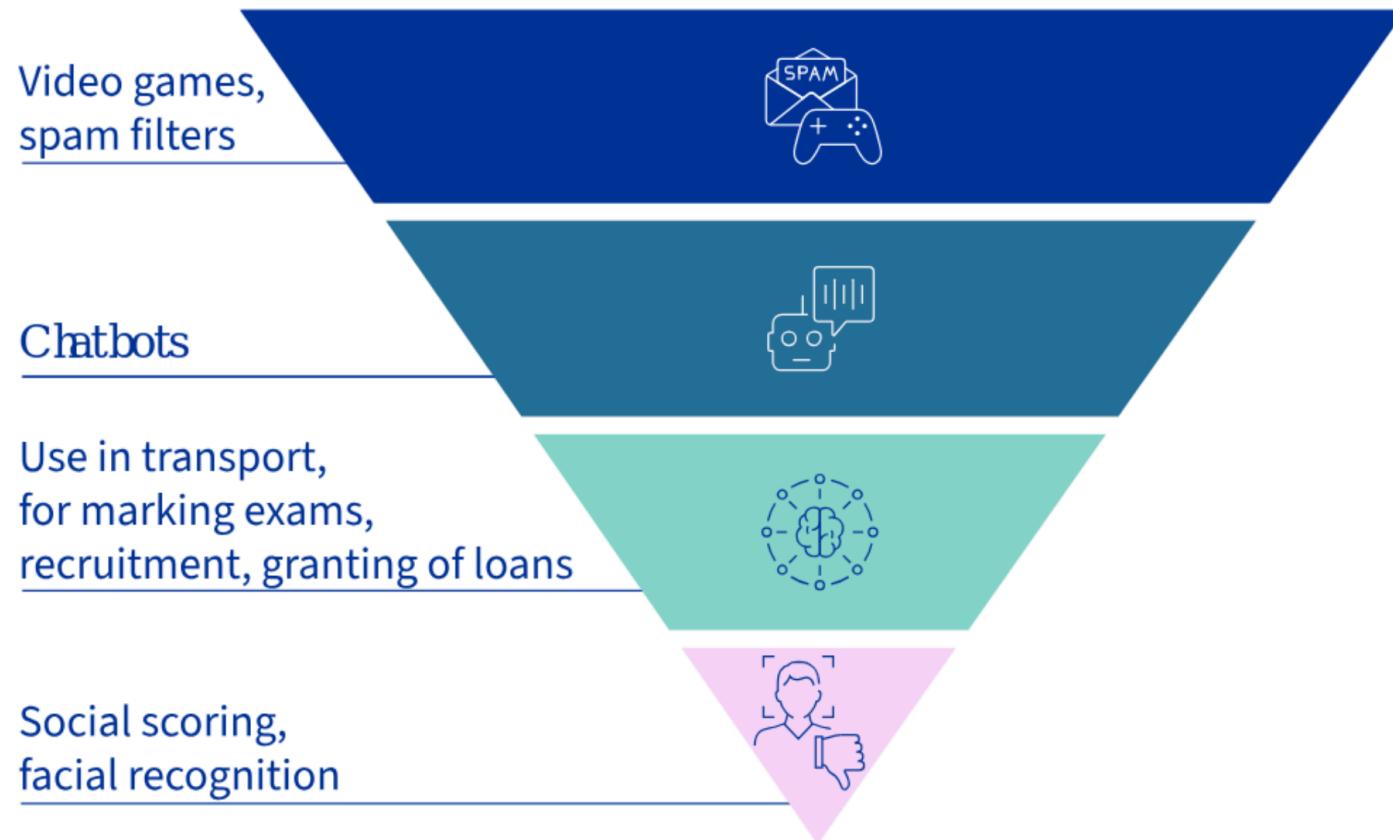
Artículo 23. *Inteligencia Artificial y mecanismos de toma de decisión automatizados.*

1. En el marco de la Estrategia Nacional de Inteligencia Artificial, de la Carta de Derechos Digitales y de las iniciativas europeas en torno a la Inteligencia Artificial, las administraciones públicas favorecerán la puesta en marcha de mecanismos para que los algoritmos involucrados en la toma de decisiones que se utilicen en las administraciones públicas tengan en cuenta criterios de minimización de sesgos, transparencia y rendición de cuentas, siempre que sea factible técnicamente. En estos mecanismos se incluirán su diseño y datos de entrenamiento, y abordarán su potencial impacto discriminatorio. Para lograr este fin, se promoverá la realización de evaluaciones de impacto que determinen el posible sesgo discriminatorio.

2. Las administraciones públicas, en el marco de sus competencias en el ámbito de los algoritmos involucrados en procesos de toma de decisiones, priorizarán la transparencia en el diseño y la implementación y la capacidad de interpretación de las decisiones adoptadas por los mismos.

3. Las administraciones públicas y las empresas promoverán el uso de una Inteligencia Artificial ética, confiable y respetuosa con los derechos fundamentales,

# Risk based approach of AI Act



## Level of risk: minimal

Solutions with minimal risk (the vast majority of AI systems) will not be regulated and be available as before.

## Level of risk: limited

Systems with limited risk will be allowed, but will have to fulfill certain transparency obligations, so users will have to be aware that they interact with AI.

## Level of risk: high

High-risk systems will have to meet strict criteria before they can be put on the EU market.

## Level of risk: unacceptable

Systems considered as threat to people's safety, livelihoods and individual rights will be banned.

## Definición de IA del RIA (AI Act)

The EU Artificial Intelligence Act: "*'AI system' means a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments;*" (Article 3.1)

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European Commission, [Guidelines on the definition of an artificial intelligence system established by the AI Act](#) 2024/1689 (AI Act), Brussels, 29.7.2025 (C(2025) 5053 final).

# ...but people also have biases



Differences (O'Neil 2016):

- Systematisation
- Scale
- New "digital" groups discriminated against

# Cases: NLP + Computer Vision

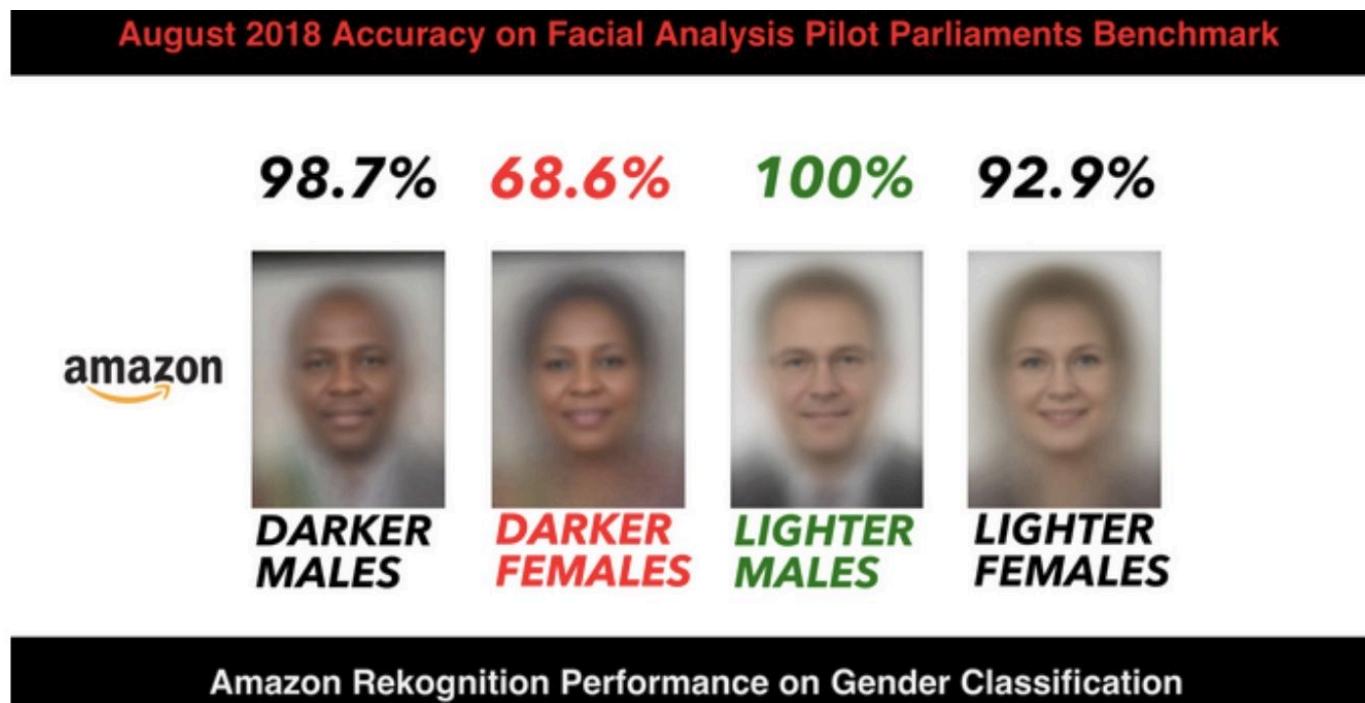
Algorithmic Bias in Grounded Setting



Zhao, J. et. al (2017). [Men Also Like Shopping: Reducing Gender Bias Amplification using Corpus-level Constraints](#).

# Case: facial recognition

Intersectional analysis of Amazon Rekognition face recognition performance. The lowest hit rate is for dark-skinned women.

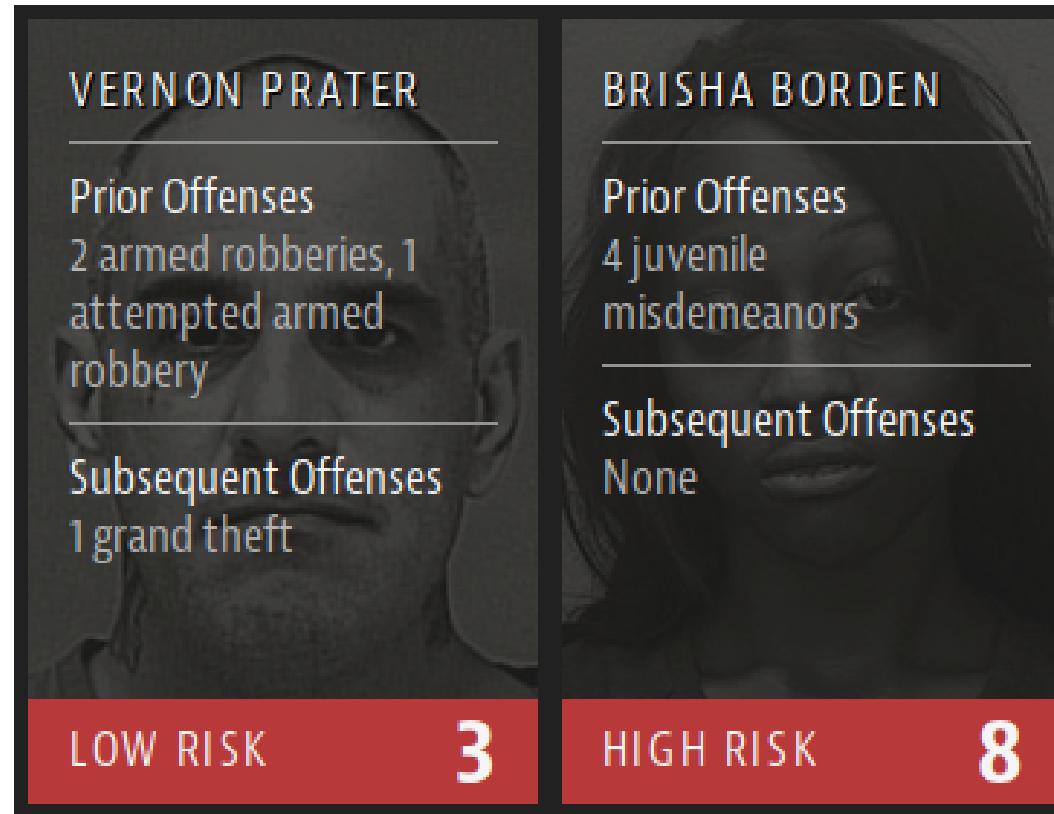


Fuente Buolamwini (2019). [Response: Racial and Gender bias in Amazon Rekognition — Commercial AI System for Analyzing Faces.](#)

# Case: justice

- **COMPAS** (*Correctional Offender Management Profiling for Alternative Sanctions*): tool for calculating recidivism risk scores for a person awaiting trial
- Uses ML to train a **risk estimation model from historical records**.
- **Input variables**: criminal history, type of charges, gender, ethnicity, age, environmental questions...
- **Dependent variable**: degree of risk, high degrees go to pre-trial detention.

# Case: justice



Angwin, J., & Larson, J. (2016, May 23). [Machine Bias](#). ProPublica.

## A1. How would you quantify bias in the above problems?

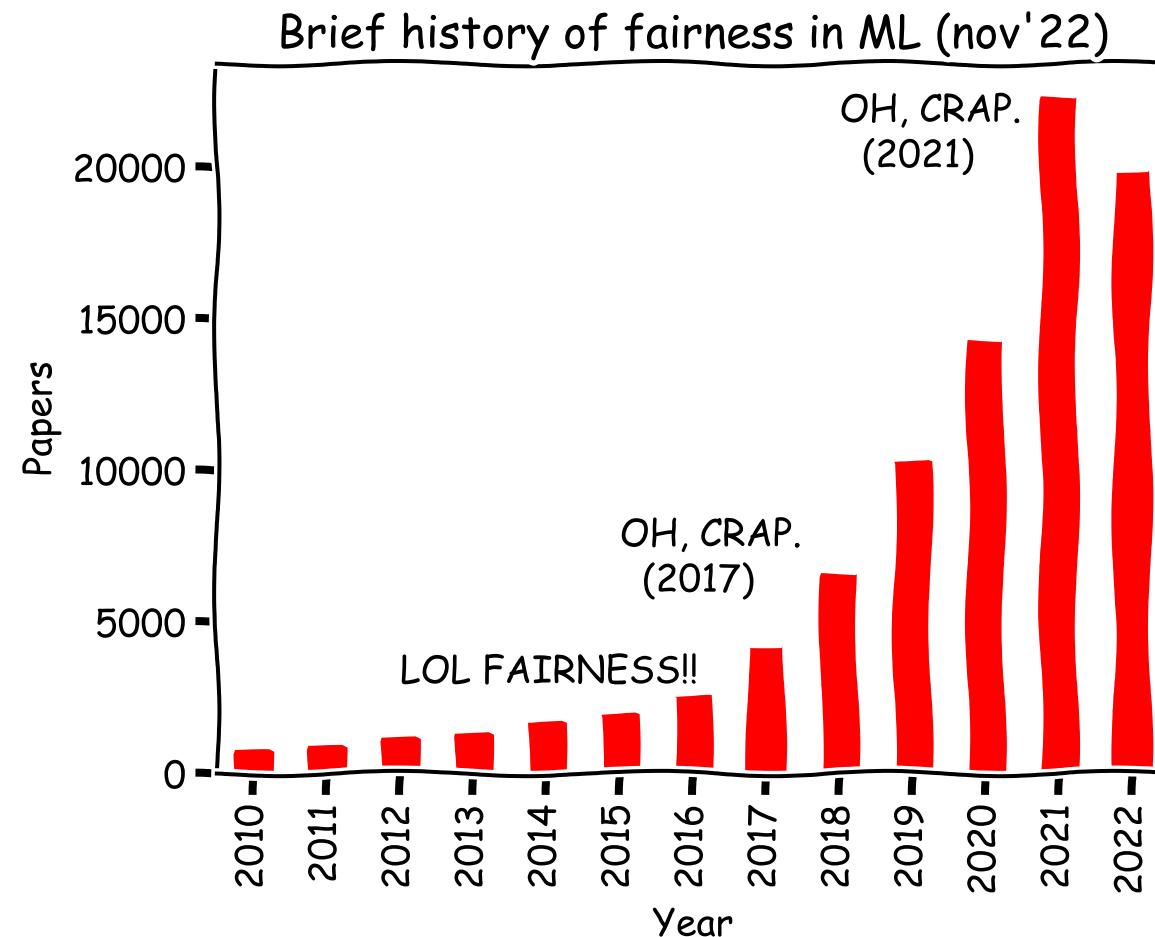
- **Facial recognition:** the model is less accurate in identifying women with dark skin.
- **Justice:** the model overestimates the risk of recidivism for African-Americans
- **Natural language processing:** system reproduces gender stereotypes associated with professions



# Quantifying and mitigating bias

# How to measure and mitigate bias?

Fairness through *unawareness*

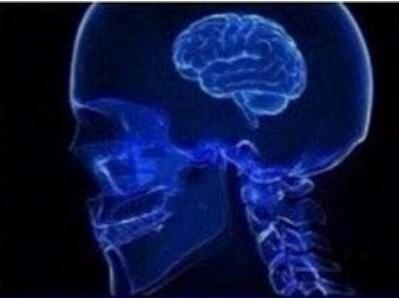


# Exploratory analysis

- Check distribution (prevalence/prior) class label
- Check distribution (prevalence/priority) class label by groups
- Check:
  - Visual
  - Descriptive statistics
  - Hypothesis testing

An excellent example can be found in Straw, I., & Wu, H. (2022).

**MIRAR  
LOS DATOS**



**MIRAR EL  
HISTOGRAMA**



**ESTADÍSTICA  
DESCRIPTIVA**



**CONTRASTE  
DE HIPÓTESIS**



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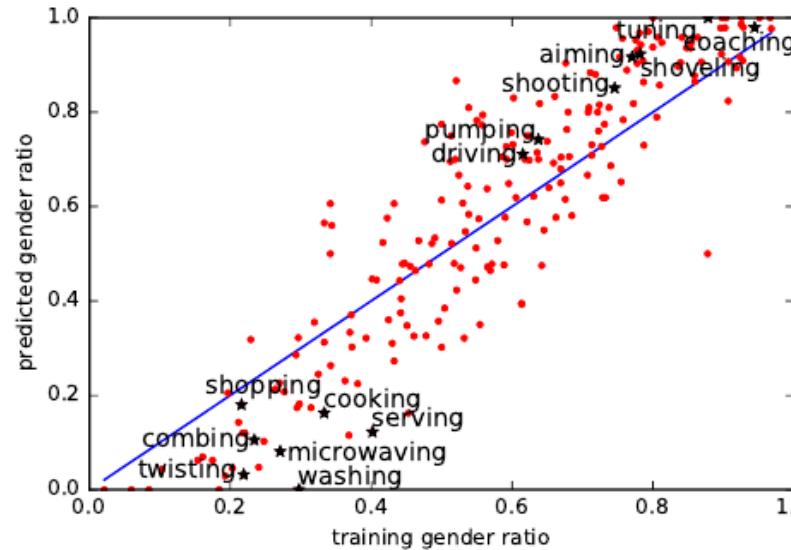
# The "zoo" of fairness metrics (for classification)

	notion	use of $Y$	condition
group fairness	Demographic Parity	-	equal acceptance rate across groups
	Conditional Demographic Parity	-*	equal acceptance rate across groups in any strata
	error parity	✓	equal accuracy across groups
		✓	equal FPR and FNR across groups
		✓	equal precision across groups
individual fairness	FTU/Blindness	-	no explicit use of sensitive attributes
	Fairness Through Awareness	-*	similar people are given similar decisions
causality-based fairness	Counterfactual Fairness	-	an individual would have been given the same decision if she had had different values in sensitive attributes
	path-specific Counterfactual Fairness	-	same as above, but keeping fixed some specific attributes

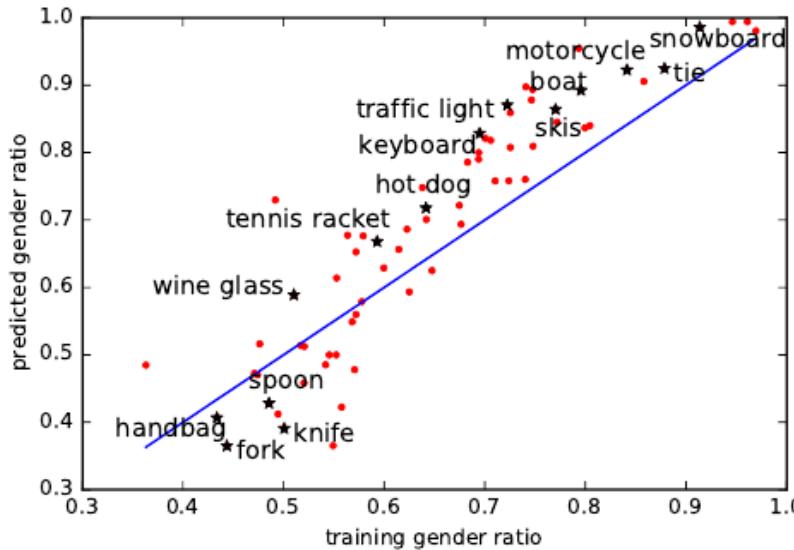
\* there are exceptions to these cases where  $Y$  is actually employed, e.g. CDP conditioning on  $Y$  becomes Equality of Odds, and there are notions of individual fairness that use a similarity metric defined on the target space (Berk et al., 2017).

Castelnovo, A., Crupi, R., Greco, G. et al. A clarification of the nuances in the fairness metrics landscape. Sci Rep 12, 4209 (2022).  
<https://doi.org/10.1038/s41598-022-07939-1>

# Bias visualization



(a) Bias analysis on imSitu vSRL



(b) Bias analysis on MS-COCO MLC

Figure 2: Gender bias analysis of imSitu vSRL and MS-COCO MLC. (a) gender bias of verbs toward man in the training set versus bias on a predicted development set. (b) gender bias of nouns toward man in the training set versus bias on the predicted development set. Values near zero indicate bias toward woman while values near 0.5 indicate unbiased variables. Across both datasets, there is significant bias toward males, and significant bias amplification after training on biased training data.

## A3. Judicial case

- Suppose a generic test (with or without statistical techniques) to estimate the risk of recidivism. What errors should we minimise?
- Regarding the class: what metrics are we interested in?
- What if the test involves loss of freedom?

## Cases: COMPAS

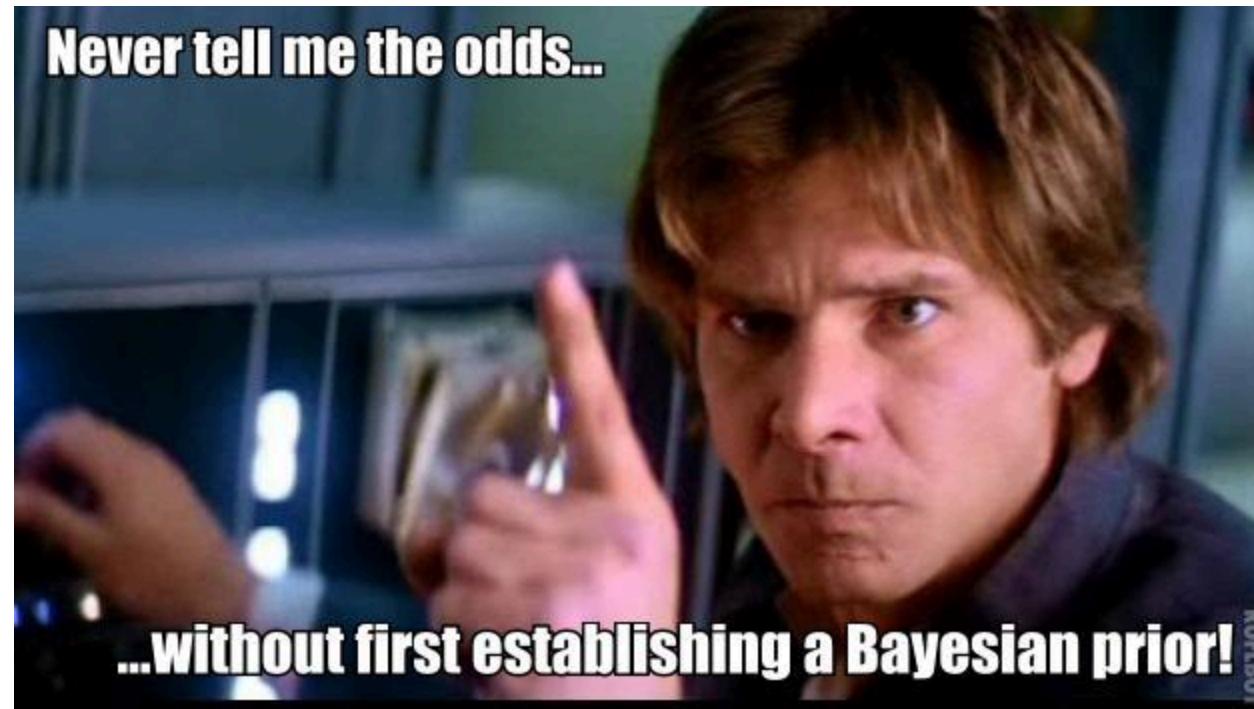
- **ProPublica:** the system discriminates because it overestimates the risk for African Americans (different false positive for the groups: 44.8% vs 23.4%).
- **Northpointe:** system does not discriminate because it classifies high risk equally (similar true positives for all ethnic groups: 63% vs. 59%)

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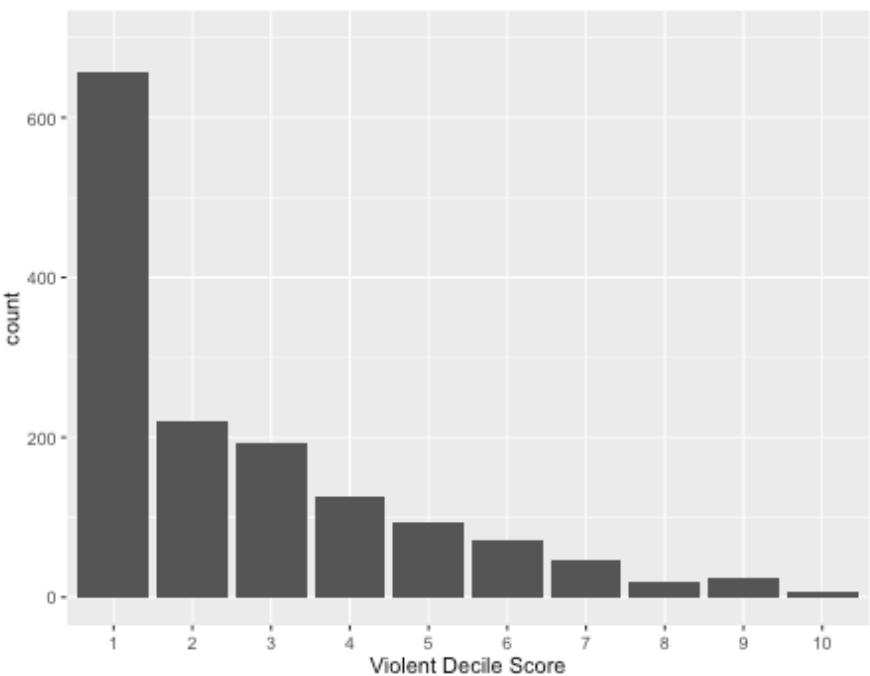
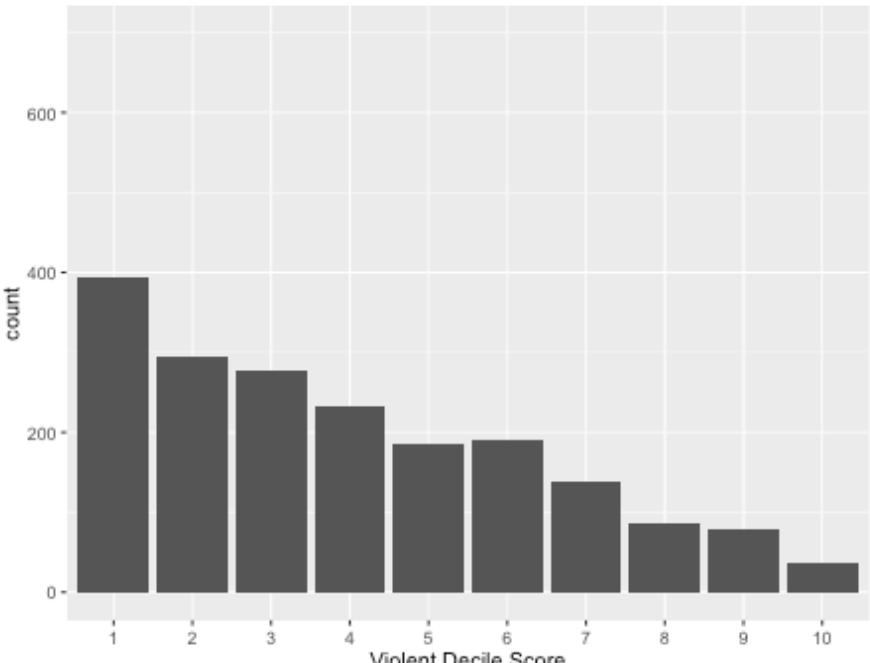
Larson, J., & Angwin, J. (2016, May 23). [How We Analyzed the COMPAS Recidivism Algorithm](#). ProPublica.

## Cases: COMPAS

How can ProPublica's and Northpointe's mathematical definitions of fairness be compatible?



Source [Han Solo and Bayesian Priors](#)



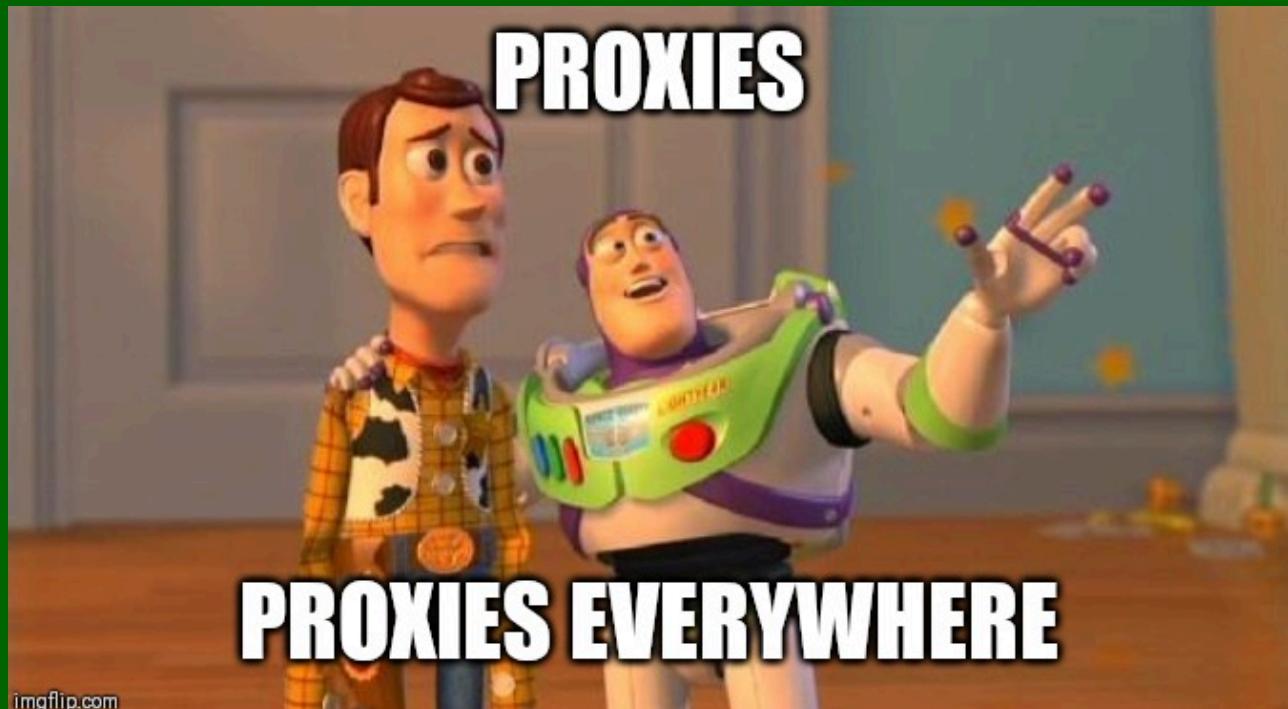
## Cases: COMPAS

It is mathematically compatible because the a priori prevalence/baseline frequency/probability of the two groups is different (see Chouldechova (2017)).

A. Chouldechova. Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments. *Big Data*, 5(2):153–163, 2017. <https://doi.org/10.1089/big.2016.0047>

## A4. How can we mitigate bias?

- We already have a measure of statistical bias.
- How could we mitigate?
- But first: Does a statistical/algorithmic intervention make sense?



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# Bias mitigation techniques

## UNDERSTANDING BIAS

### Socio-technical causes of bias

- Data generation
- Data collection
- Institutional bias

### Bias manifestation in data

- Sensitive features & causal inferences
  - Data representativeness
  - Data modalities

### Fairness definition

- Similarity-based
- Causal reasoning
- Predicted outcome
- Predicted & actual outcome
- Predicted probabilities & actual outcome

## MITIGATING BIAS

### Pre-processing

- Instance class modification
  - Instance selection
  - Instance weighting

### In-processing

- Classification model adaptation
- Regularization / Loss function s.t. constraints
  - Latent fair classes

### Post-processing

- Confidence/probability score corrections
- Promoting/demoting boundary decisions
- Wrapping a fair classifier on top of a black-box baselearner

Fuente Ntoutsi, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdl, W., Vidal, M.-E., ... Staab, S. (2020). Bias in data-driven artificial intelligence systems—An introductory survey. *WIREs Data Mining and Knowledge Discovery*, 10(3), e1356.  
<https://doi.org/10.1002/widm.1356>

# ML tools for mitigation and explainability



<https://fairlearn.org/>

Alternatives:

<https://ai-fairness-360.org/>

<https://pair-code.github.io/what-if-tool/>

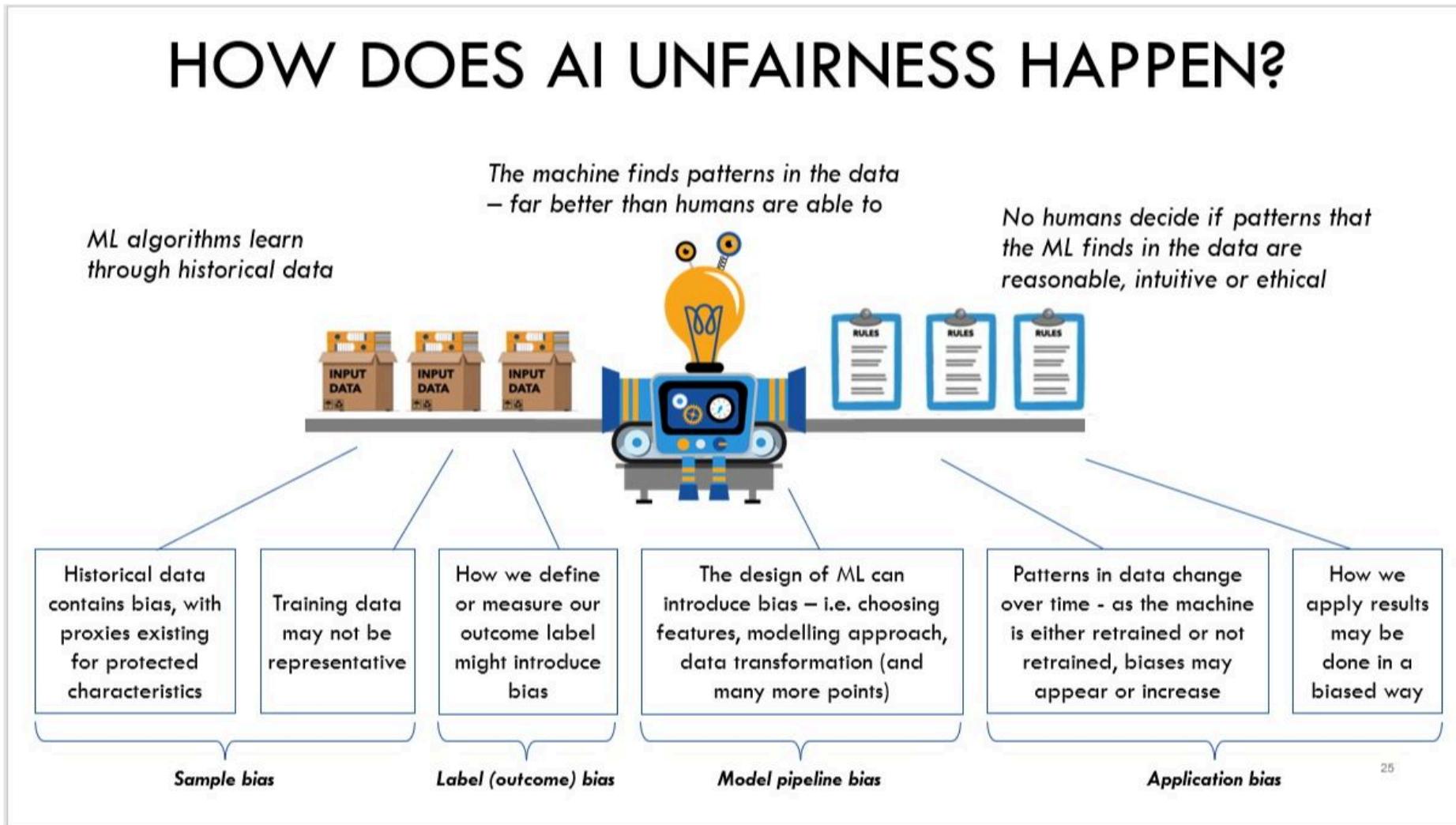
# Jupyter lab notebook with FairLearn and COMPAS

- COMPAS general recidivism data
- Simplified version of ProPublica experiments

<https://github.com/javism/seminariofate2025>

# Summary and Conclusions

# Recap: bias sources



# Summary

- The move from research prototypes to real applications of artificial intelligence has led to the emergence of many research lines
- Not only FATE: Robust AI, privacy in AI (federated learning, homeomorphic encryption...), human-machine interaction (HCI)...
- Areas involved according to context: ethics, law, politics -> **Socio-technical systems!**
- Regulation (IA Act, GDPR, Rider Act, AESIA...) and standards (IEEE, ISO)
- Learning opportunities and better understanding of statistical problems and concepts.

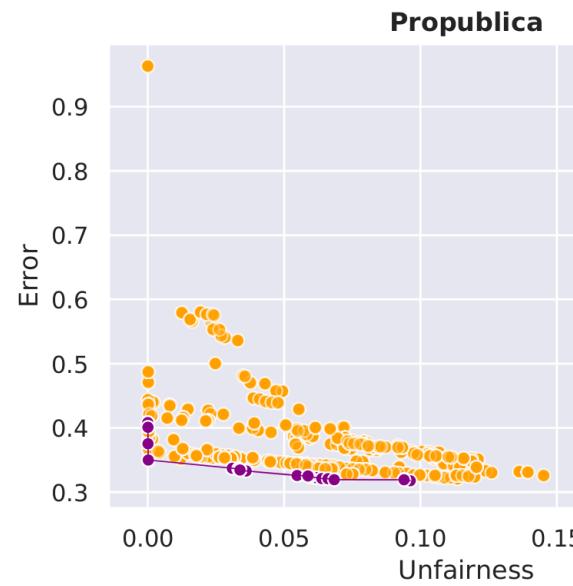
# Trabajos relacionados de AYRNA

## Explorar límites de precisión vs ecuanimidad

Valdivia, A., Sánchez-Monedero, J., & Casillas, J. (2021). How fair can we go in machine learning? Assessing the boundaries of accuracy and fairness. *Int J Intel Sys*, 36(4), 1619–1643. <https://doi.org/10.1002/int.22354>

## Gender-Equity model for Liver Allocation

El grupo AYRNA, IMIBIC y otros centros trabajan en alternativas al MELD que no discriminan por género como estimador de riesgo de mortalidad en trasplantes hepáticos.  
<https://gema-transplant.com/>



# Trabajos relacionados de AYRNA

## Desarrollo Ley Rider

Guía práctica y herramienta sobre la obligación empresarial de información sobre el uso de algoritmos en el ámbito laboral. *Ministerio de Trabajo y Economía Social. Gobierno de España.* 2022.

<https://prensa.mites.gob.es/WebPrensa/noticias/laboral/detalle/4125>

## Proyecto AlgoRace

Proyecto AlgoRace. Investigación sobre discriminación racial e inteligencia artificial. 2021-2024. <https://algorace.org/>

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<https://capitanswing.com/libros/armas-de-destruccion-matematica/>
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<https://mitpress.mit.edu/9780262044004/>
- Solon Barocas and Moritz Hardt and Arvind Narayanan (2019). *Fairness and Machine Learning: Limitations and Opportunities*. <http://www.fairmlbook.org>
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## Referencias (II)

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- Ntoutsi, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdl, W., Vidal, M.-E., ... Staab, S. (2020). Bias in data-driven artificial intelligence systems—An introductory survey. *WIREs Data Mining and Knowledge Discovery*, 10(3), e1356. <https://doi.org/10.1002/widm.1356>
- A. Valdivia, C. Hyde-Vaamonde, J. García-Marcos. Judging the algorithm: A case study on the risk assessment tool for gender-based violence implemented in the Basque country. <https://arxiv.org/abs/2203.03723>