Fairness, Accountability, Transparency and Ethics in Machine Learning.

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

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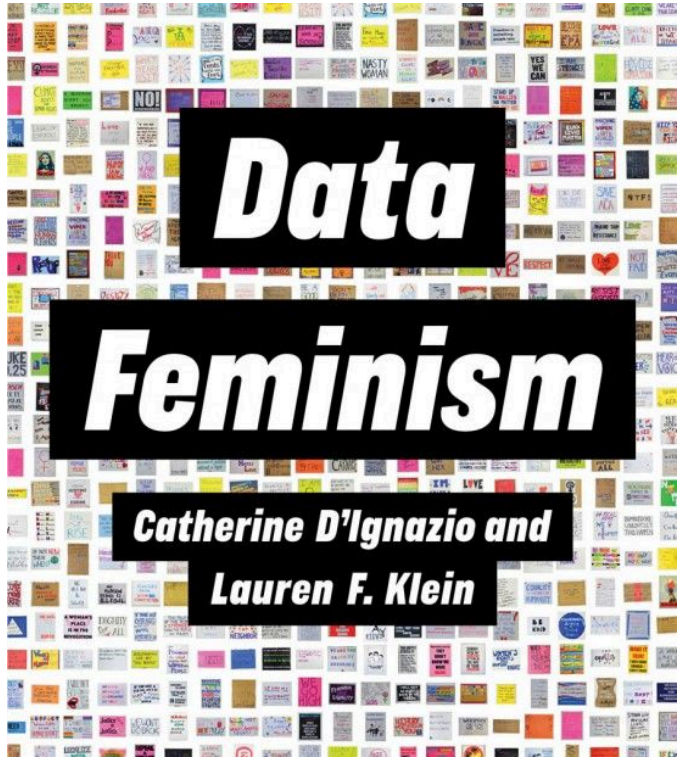
Objectives

- 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

Where to start? Video

- Documentary Coded Bias
- TED Talk dy Joy Buolamwini How I'm fighting bias in algorithms

FATE

- **Fairness**
- **Accountability**
- **Transparency**
- **Ethics**

facctconference.org

facctconference.org/network

Seminar objectives

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

- 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:

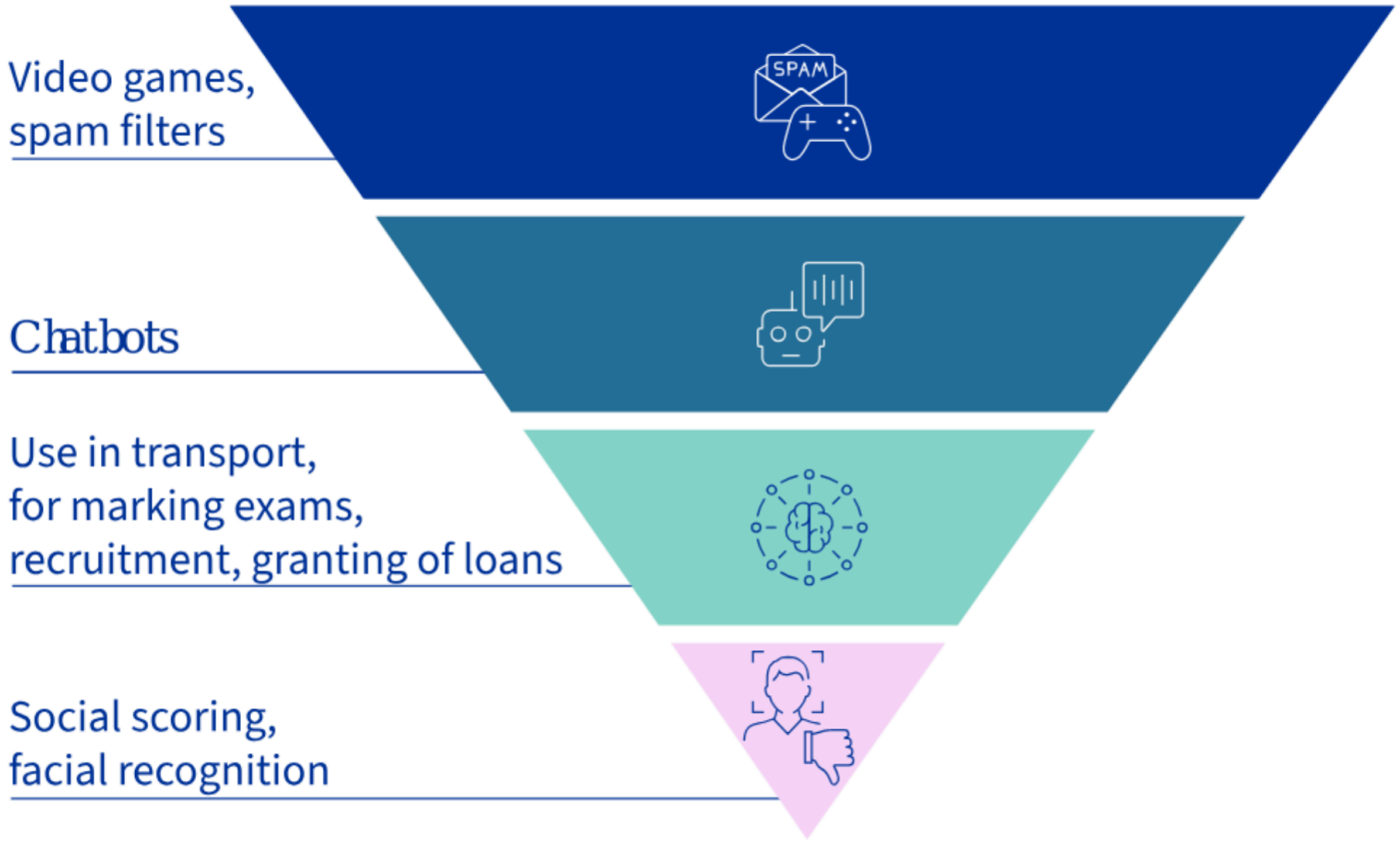
Artículo 23. *Inteligencia Artificial y mecanismos de toma de decisión automatizados.*

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.

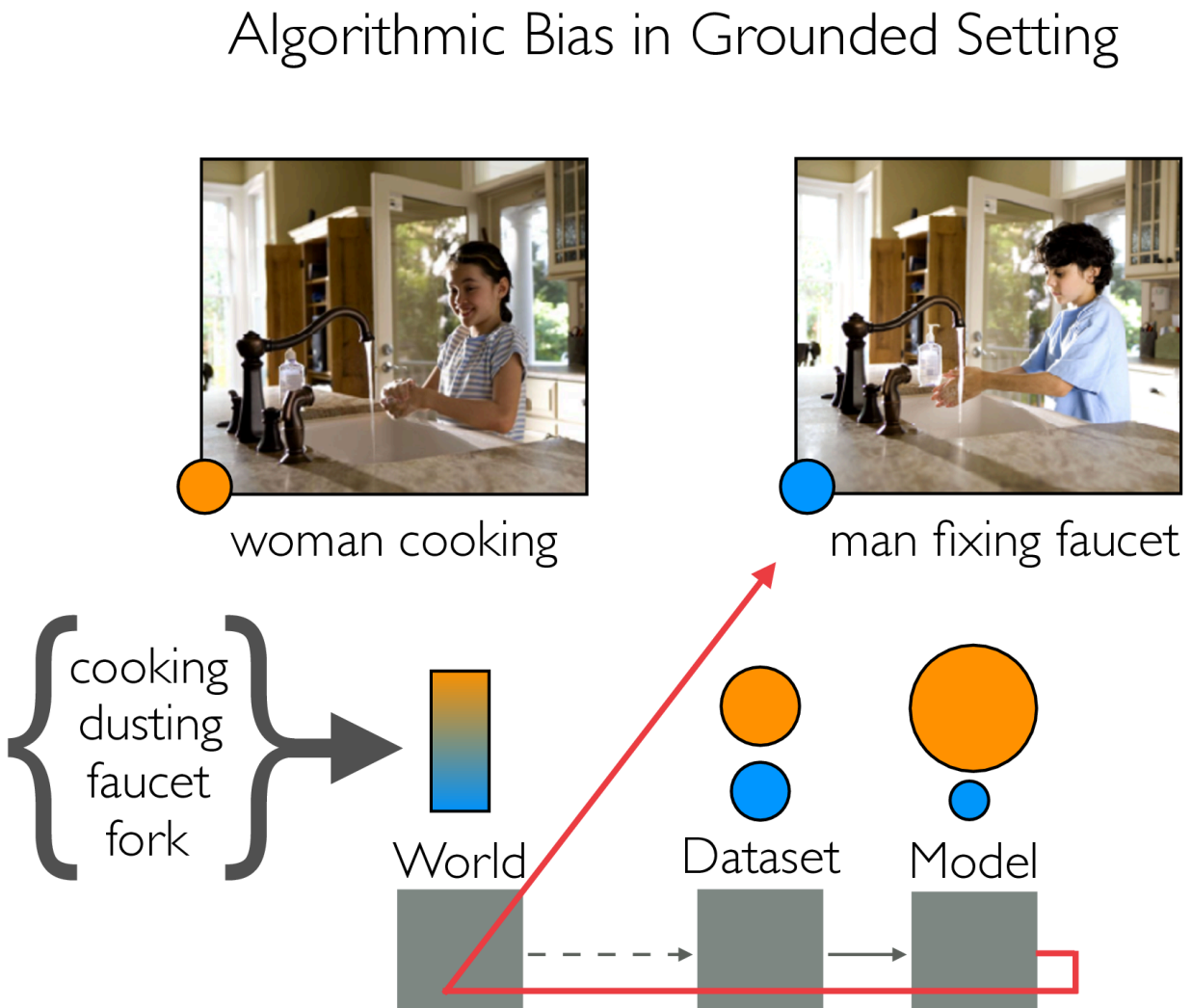
Source Artificial intelligence act

...but people also have biases

Differences (O'Neil 2016):

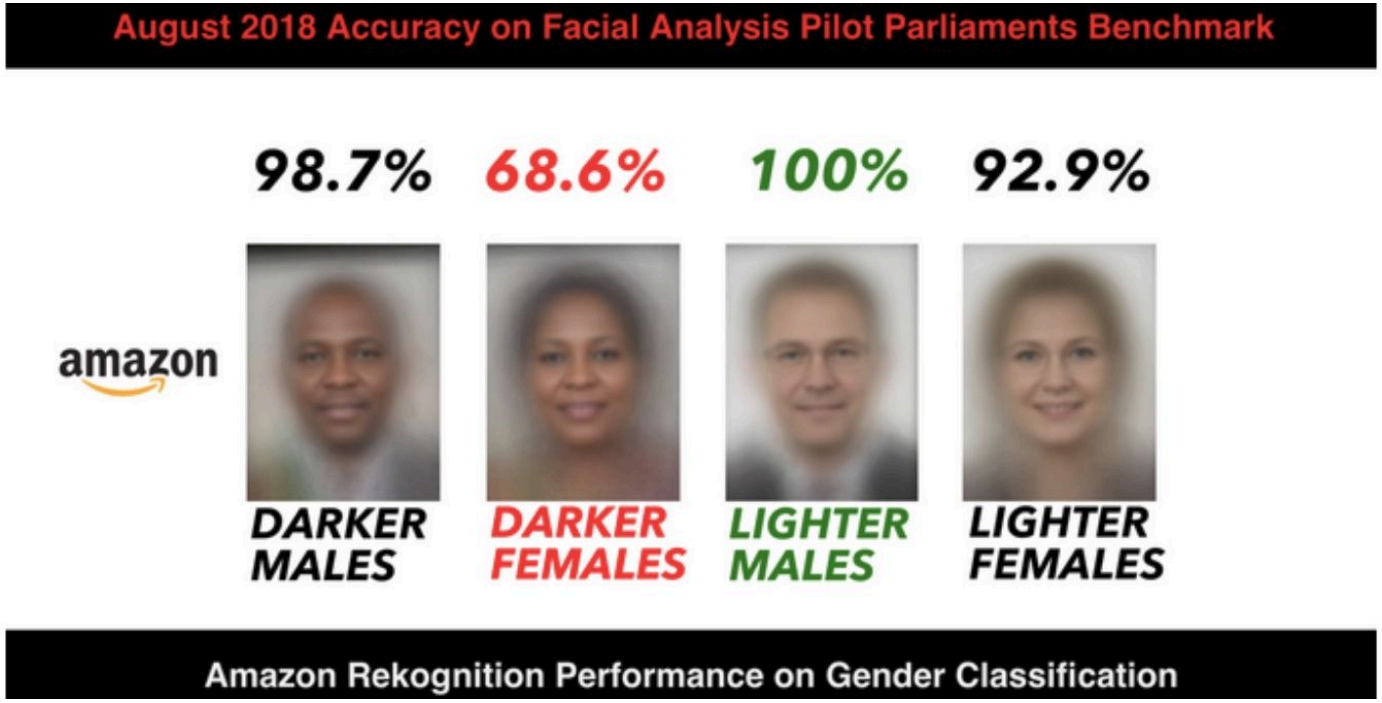
- Systematisation
- Scale

Cases: NLP + Computer Vision



Case: facial recognition

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

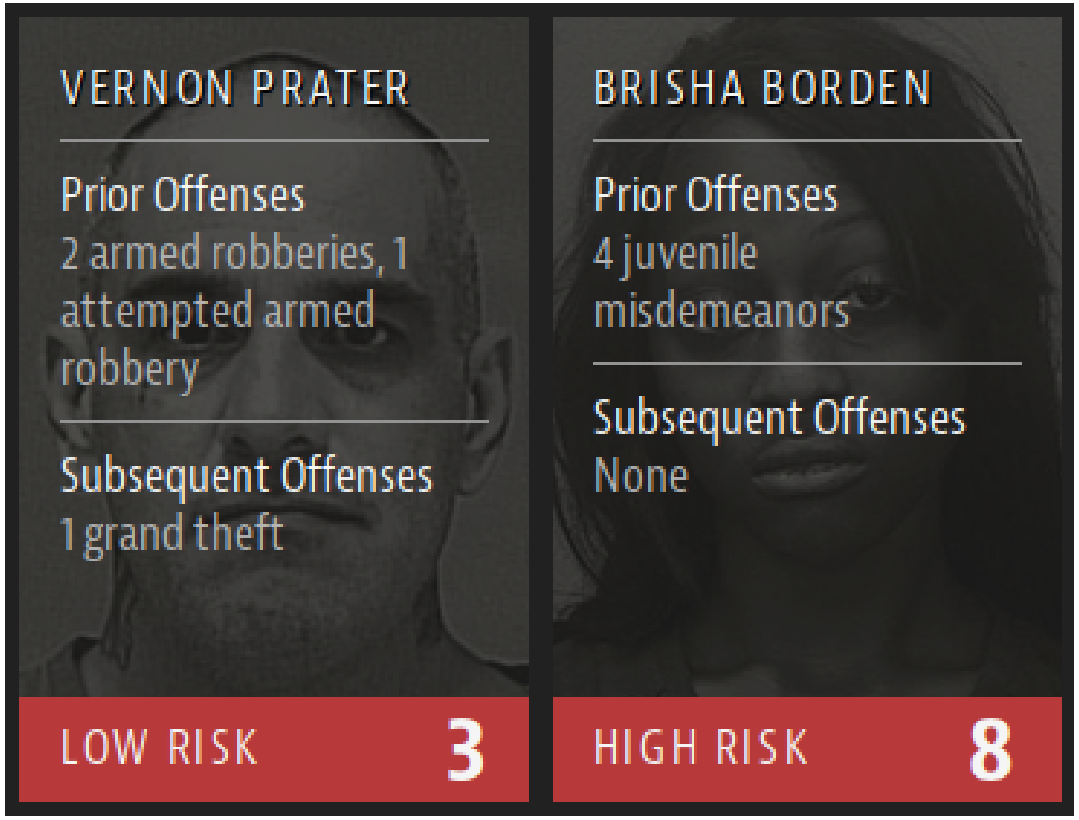


> Fuente Buolamwini (2019). Response: Racial and Gender bias in Amazon Rekognition — Commercial AI System for Analyzing Faces.

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.

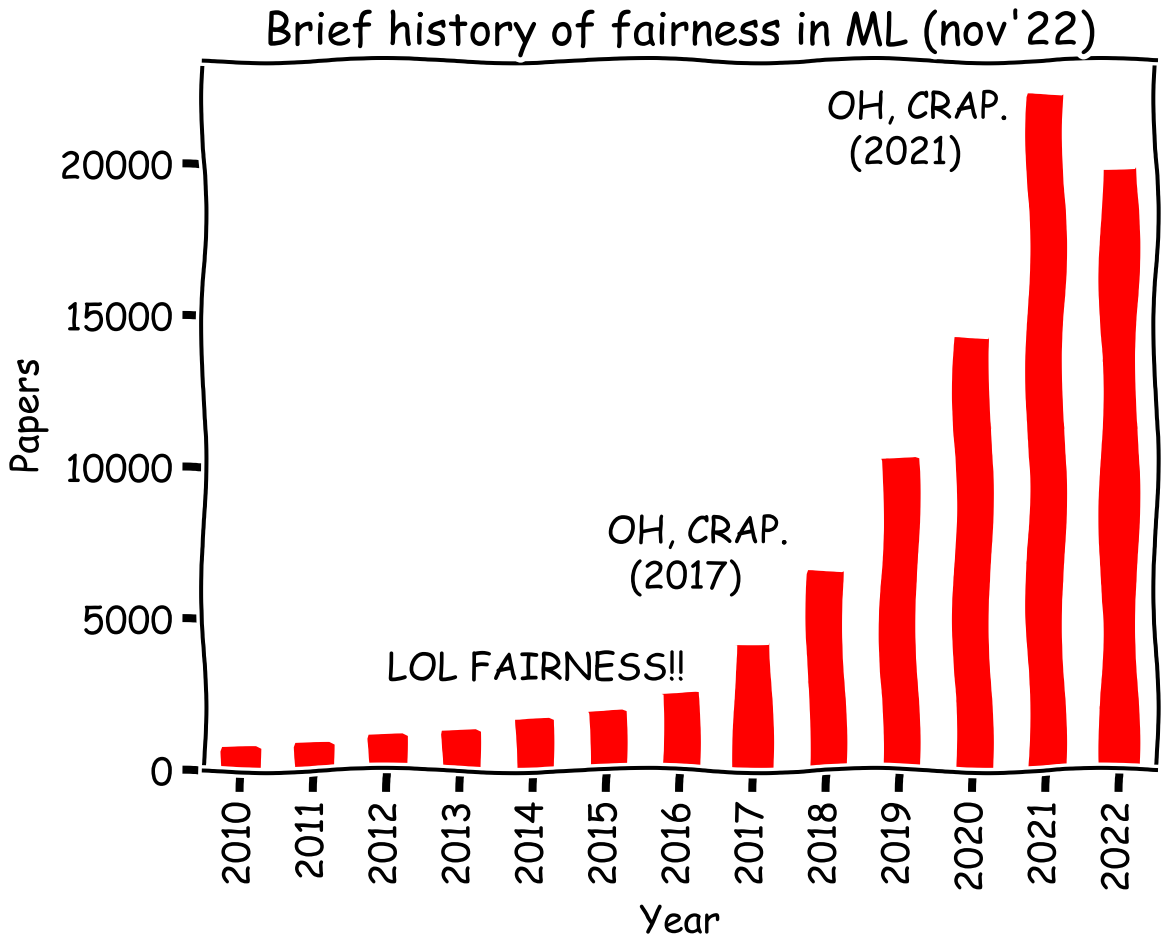
A1. How would you quantify bias in the above problems?

- **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).

Straw, I., & Wu, H. (2022). Investigating for bias in healthcare algorithms: A sex-stratified analysis of supervised machine learning models in liver disease

The "zoo" of fairness metrics

	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	✓	equal accuracy across groups
		Equality of Odds	✓	equal FPR and FNR across groups
		Predictive Parity	✓	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

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?

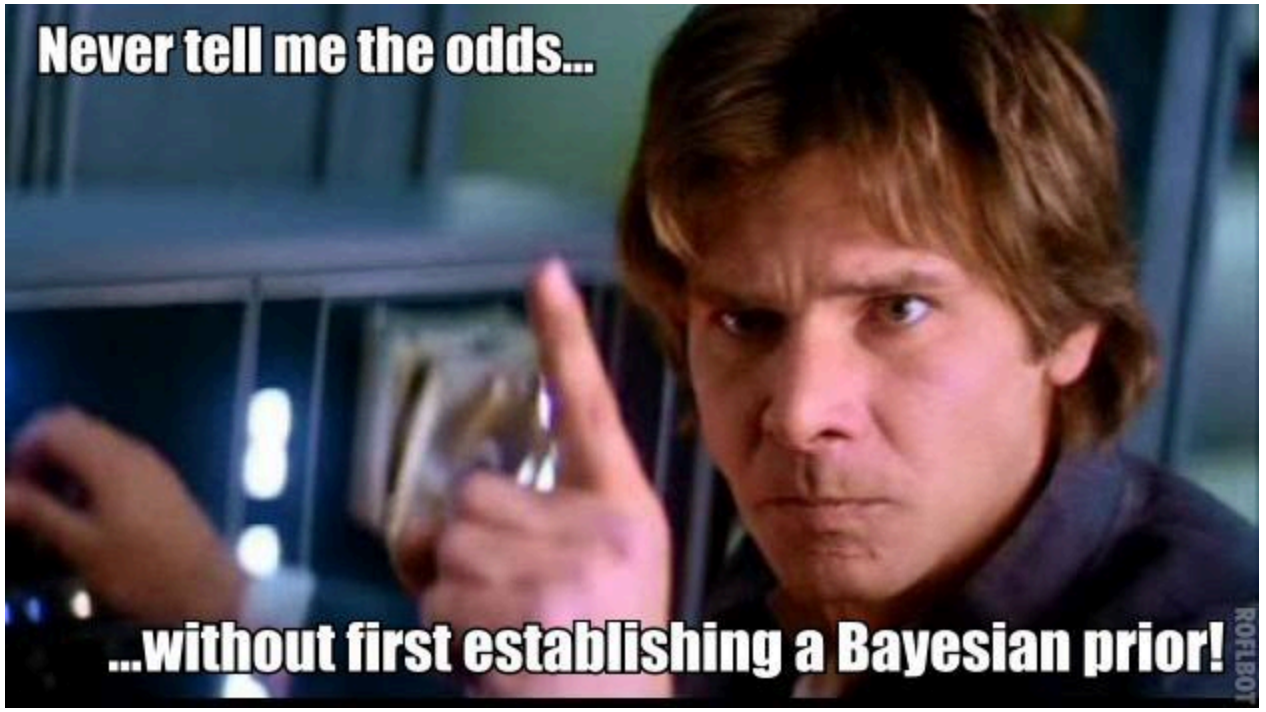
Cases: COMPAS

- **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%)

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

Cases: COMPAS

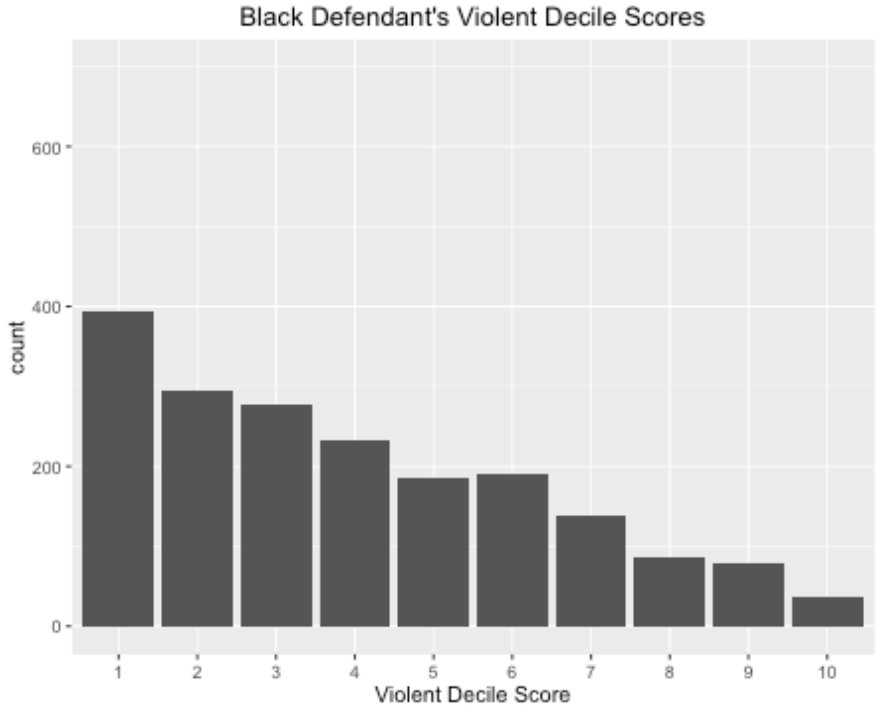
How can ProPublica's and Northpointe's mathematical definitions of fairness be compatible?

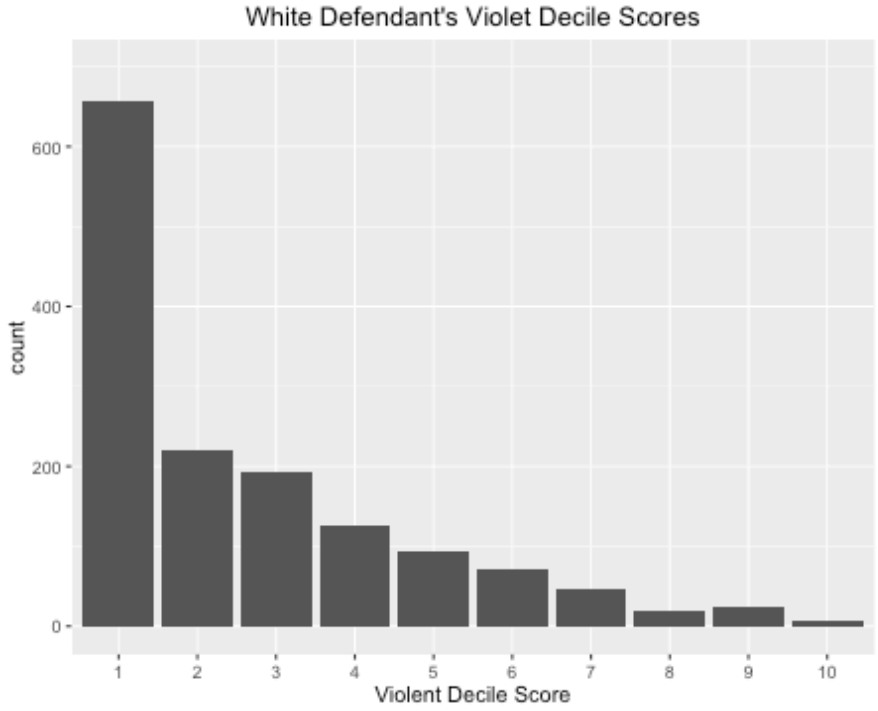


> Source Han Solo and Bayesian Priors

Cases: COMPAS

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

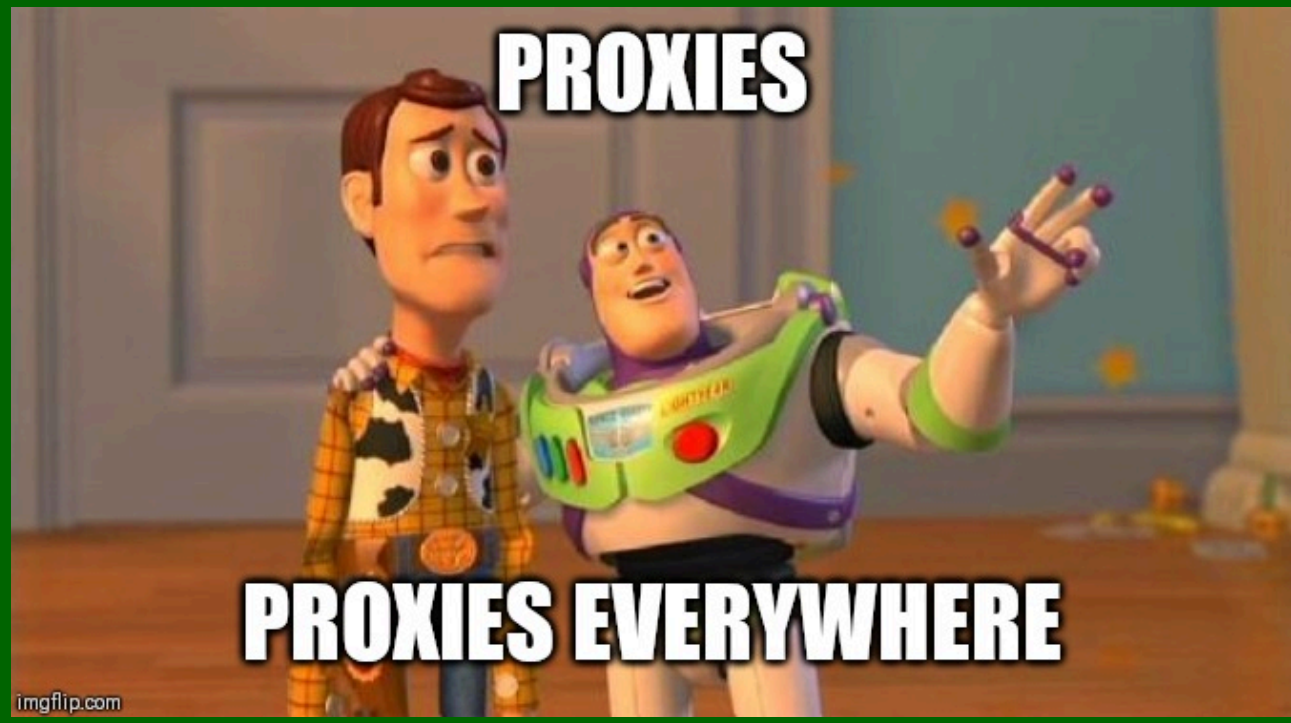




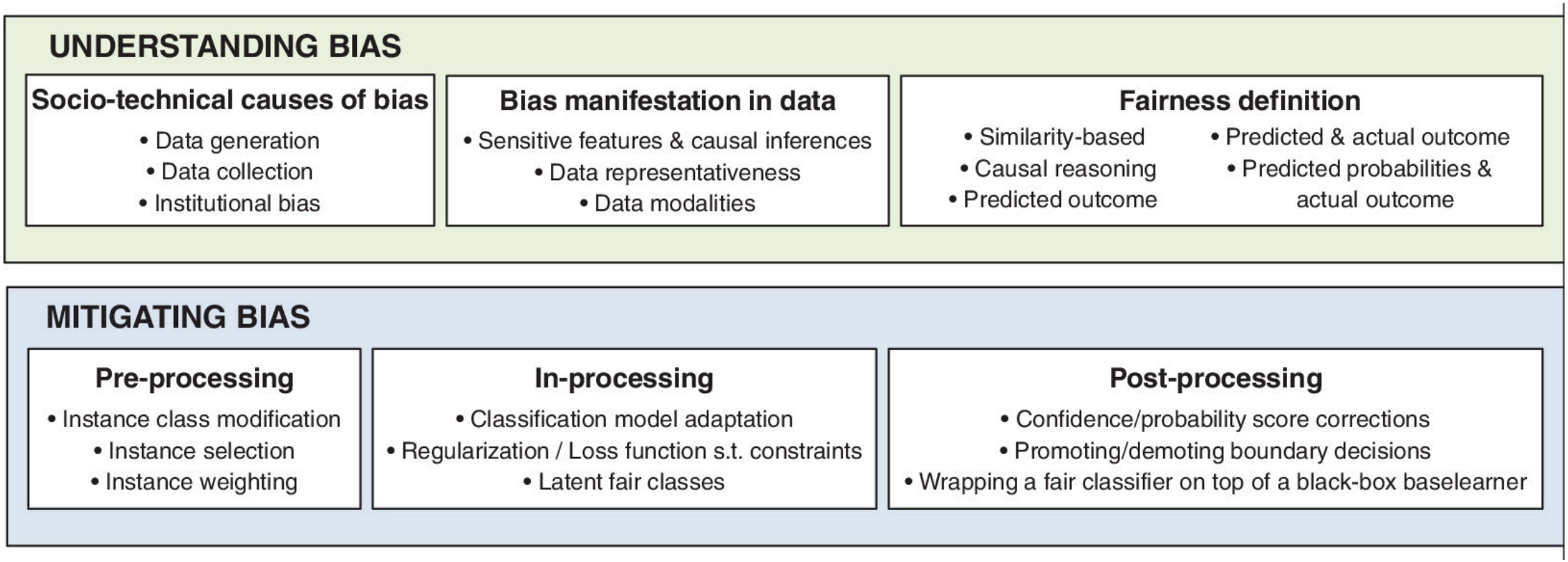
A. Chouldechova. Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments. Big Data, 5(2):153–163, 2017. https://doi.org/10.1089/big.2016.0047

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?**



Bias mitigation techniques



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/

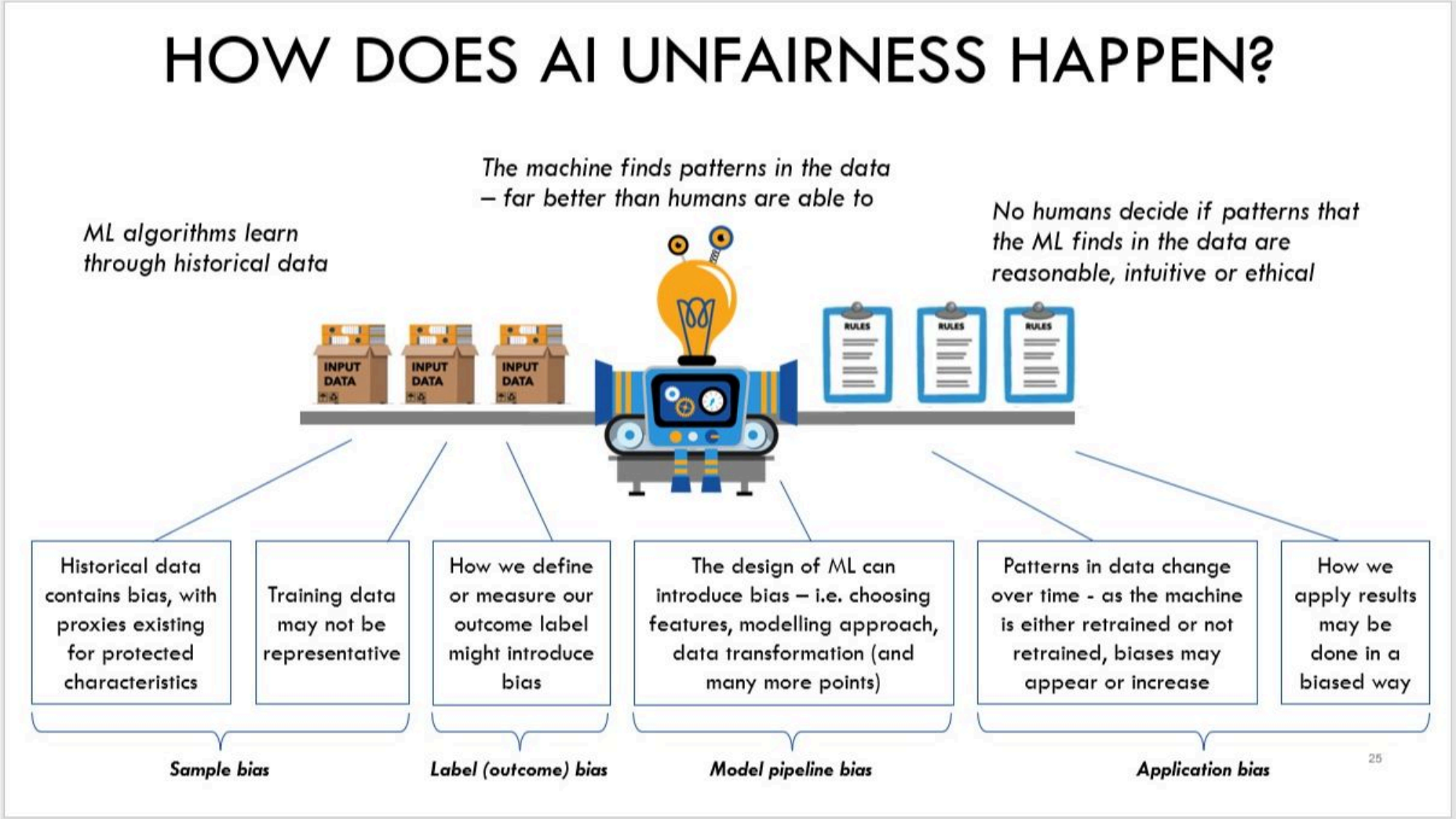
Jupyter lab notebook with FairLearn and COMPAS

- COMPAS general recidivism data
- Simplified version of ProPublica experiments

https://github.com/javism/seminariofate2025

Summary and Conclusions

Recap: bias sources



Source Luke Vilain

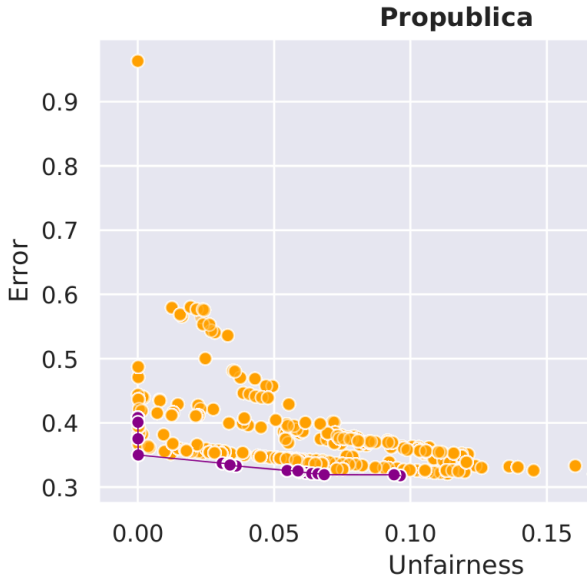
Summary

- 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 discriminen 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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