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On Algorithmic Fairness and Bias Mitigation in Recidivism Prediction

An econometric view on observed tradeoffs between conflicting definitions of fairness, and the applicability of post-processing methods for bias correction of criminal sentencing algorithms

By Lennert Jansen, under the supervision of dr. Paul Bouman (EUR) and Benjamin Timmermans (IBM)

Erasmus University Rotterdam

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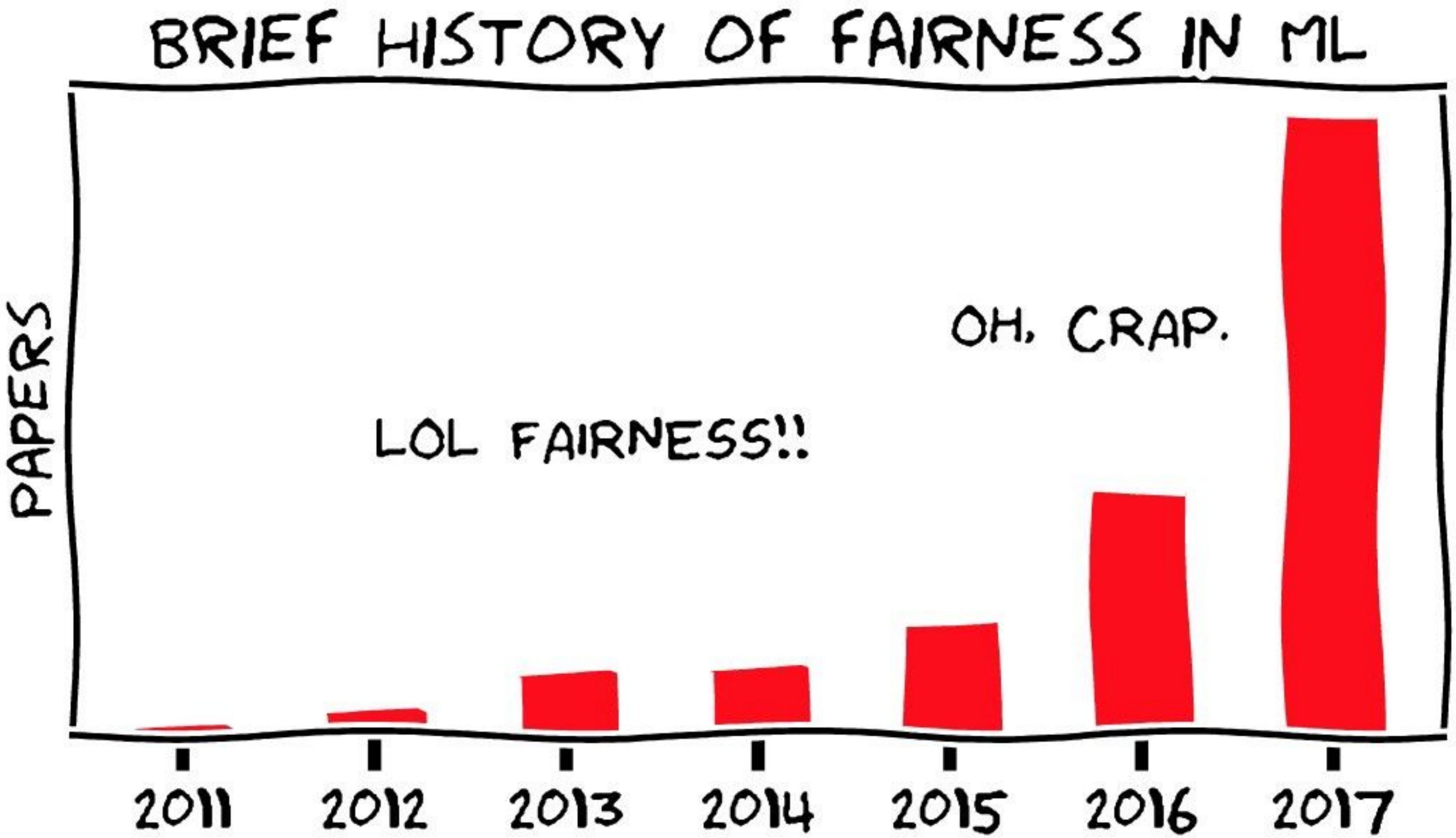
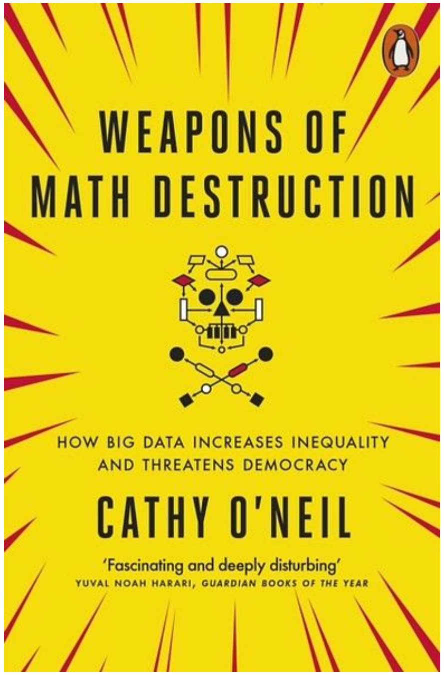
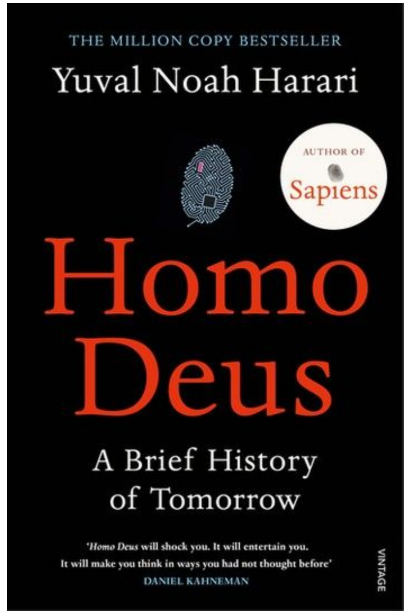
Acknowledgements

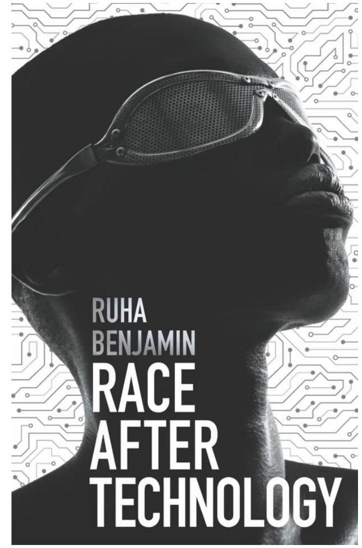
To my supervisors, family, and friends.

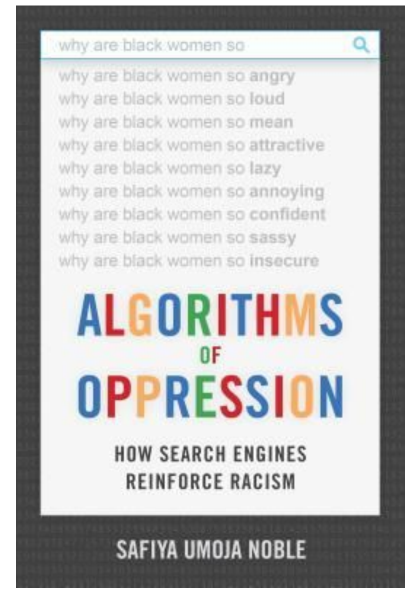


Source: https://towardsdatascience.com/a-tutorial-on-fairness-in-machine-learning-3ff8ba1040cb









Fairness and machine learning

Limitations and Opportunities

Solon Barocas, Moritz Hardt, Arvind Narayanan

This online textbook is an incomplete work in progress. Essential chapters are still missing. In the spirit of open review, we solicit broad feedback that will influence existing chapters, as well as the development of later material.

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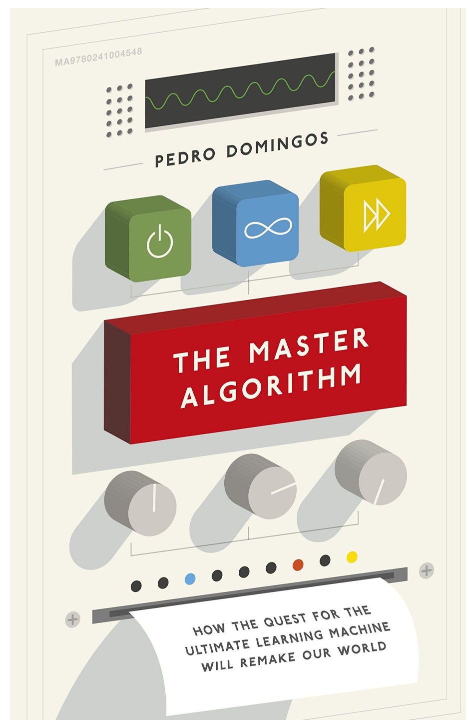

Theoretical background

Fairness in Machine Learning

"In the context of decision-making, fairness is the absence of any prejudice or favouritism towards an individual or group based on their inherent or acquired characteristics." (**)

(**)... on the basis of which discrimination is prohibited or frowned upon.

-Mehrabi et al. (2019)

Fairness in Machine Learning

Why should we care?

The COMPAS debate

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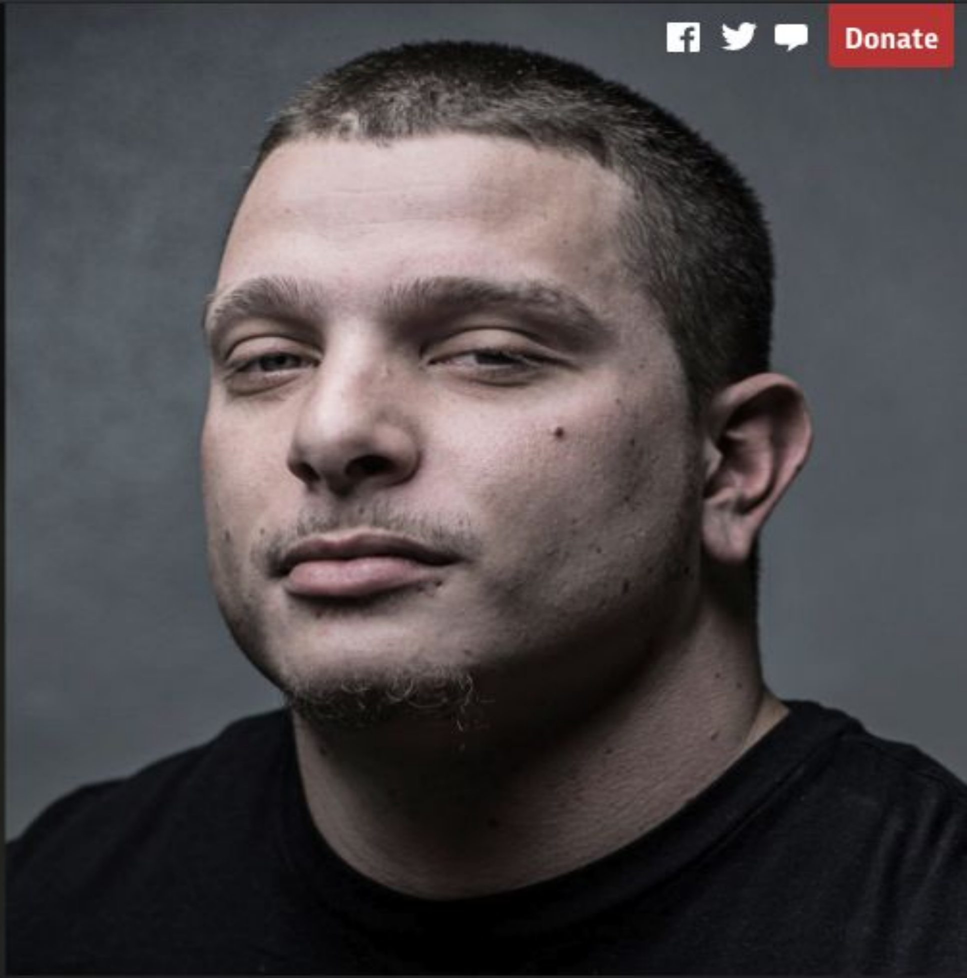
Donate



Bernard Parker, left, was rated high risk; Dylan Fugett was rated low risk. (Josh Ritchie for ProPublica)

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

The COMPAS debate

- **COMPAS** is a Recidivism Prediction Instrument
    - **(Correctional Offender Management Profiling for Alternative Sanctions)**
- ProPublica:
    - COMPAS violates error rate parities between groups → COMPAS is unfair
- COMPAS' developer:
    - COMPAS is well-calibrated by group → COMPAS is fair

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Who is right?

The COMPAS debate

They are both right and wrong, because:

- The two definitions of fairness in question are mutually exclusive
  - (in non-trivial cases)
- *“Neither calibration nor equality of false negative rates rule out blatantly unfair practices.”*

- Corbett-Davies et al. (2017)

Research objectives, methods, and data

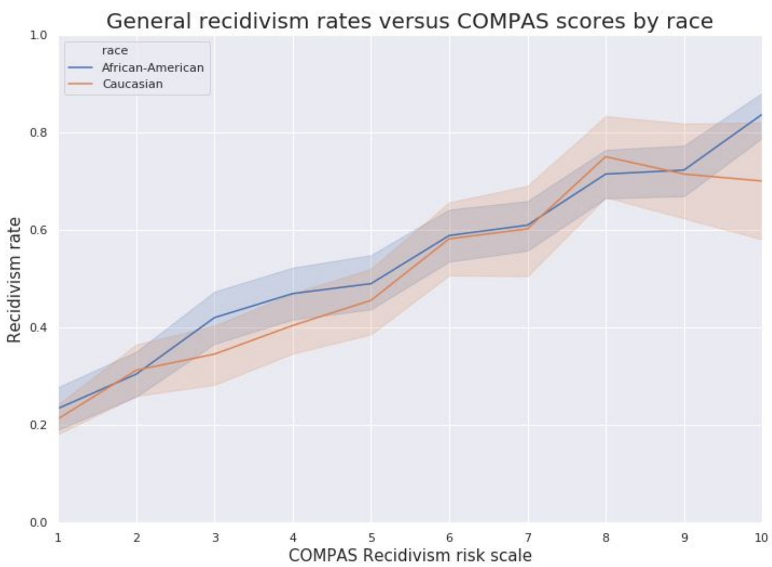
Research objectives and methods

- I aimed to investigate...
  - ...the extent to which COMPAS can be accused of being unfair with respect to race and / or gender, using...
    - ...machine learning / econometric methods.
    - ...fairness analysis methods.
  - ...the applicability of various bias mitigation methods, using...
    - ...IBM's new fair machine learning Python library, AIF360.
- Data
  - Criminal records of more than 6000 defendants
  - Broward County, Florida, U.S.A.

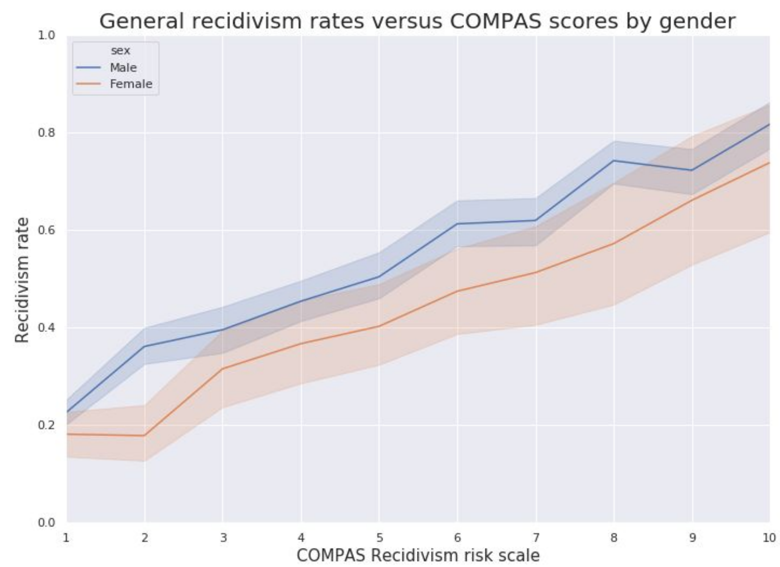
Results

Calibration by group

Well-calibrated by race

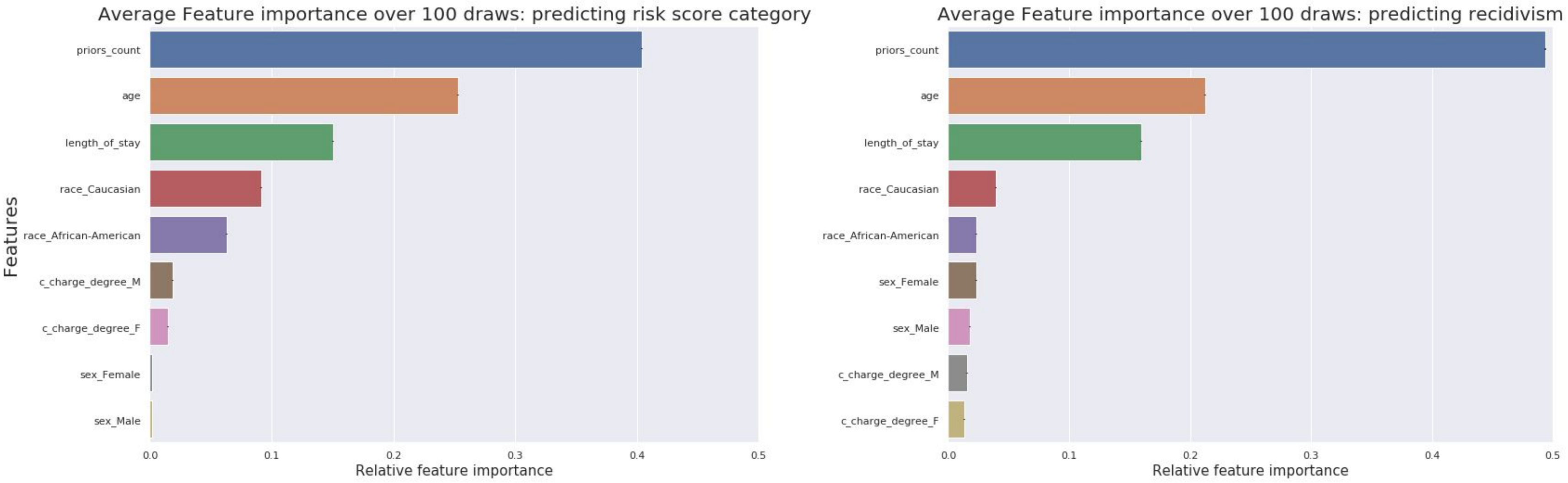


Uncalibrated by sex



Women are being held to the same standard as men, despite women recidivating significantly less

Random forest: relative feature importance



Race is about 2.5 as important for predicting score category than for predicting actual recidivism.

Logistic regression: main findings

- Score category vs. observed recidivism
  - African-Americans are 1.6 times more likely than Caucasians to receive high risk scores*
  - While <u>no</u> significant relationship is found between being African-American and actually recidivating**
- Error types
  - African-Americans are 1.72 times more likely to be misclassified as high-risk...
  - ...and 0.66 times as likely to me misclassified as low-risk **

*holding all other variables constant
** after controlling for relevant factors

Bias mitigation algorithms

- Equalised odds post-processing (EOPP)
- Calibrated equalised odds post-processing (CEOPP)
- Reject option based classification (RObC)

Bias mitigation algorithms

- Equalised odds post-processing (EOPP)
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Bias mitigation results

Method 1: CEOPP

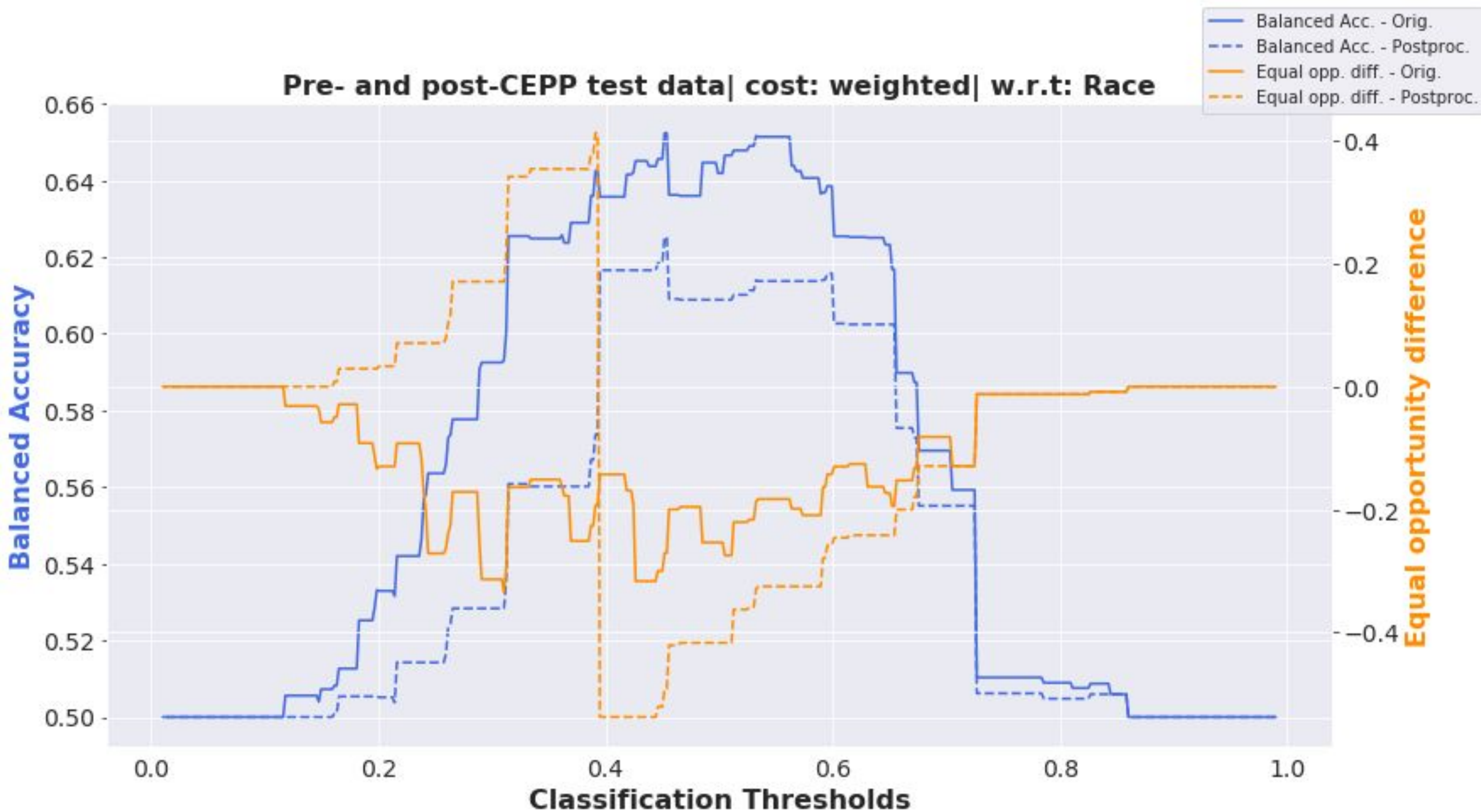
- Randomness
- Acceptable performance
- Satisfies calibration
- Moderately worsens accuracy
- Negligible improvement of between-group fairness
- Cases of notable improvements of within-group fairness

Method 2: RObC

- Deterministic
- Best performance by far
- Satisfies parity
- Preservation of accuracy
- Near-optimal between-group fairness
- Slight decrease in within-group fairness

N.B.: both methods performed considerably worse for sex

Bias mitigation results: observed trade-offs



Discussion and conclusions

Points of discussion

- Calibration or parity?
  - i.e., hold different people to different standards
  - Or “arbitrarily” switch labels just to satisfy quota
  - Consult domain experts
- Both bias mitigation methods are ethically debatable
  - Affirmative action in RObC
  - Randomness in CEOPP

Conclusions

- Accusations COMPAS confirmed
- You can’t have it all
- Reject option based classification achieves ‘fair’ outcome, while preserving utility
    - Affirmative action-style approach ethically dubious
- Trade-offs
    - Within- and between-group fairness
    - Fairness and accuracy

Recommended reading, viewing, and listening material

Popular science

- Domingos, P. (2015). *The master algorithm: How the quest for the ultimate learning machine will remake our world*. Basic Books.
- Harari, Y. N. (2016). *Homo Deus: A brief history of tomorrow*. Random House.
- Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan.
- O'neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Broadway Books.

Textbooks

- Barocas, S., Hardt, M. & Narayanan, A (2019). Fairness and Machine Learning. *Limitations and Opportunities.* (INCOMPLETE WORKING DRAFT)
- Pearl, J. (2009). *Causality*. Cambridge university press.

Scientific papers

- Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016). Machine bias. *ProPublica, May, 23, 2016*.
- Barocas, S., & Selbst, A. D. (2016). Big data's disparate impact. *Calif. L. Rev.*, *104*, 671.
- Verma, S., & Rubin, J. (2018, May). Fairness definitions explained. In *2018 IEEE/ACM International Workshop on Software Fairness (FairWare)* (pp. 1-7). IEEE.

Lectures & Tutorials

- The Emerging Theory of Algorithmic Fairness, Cynthia Drowk
- Tutorial: 21 fairness definitions and their politics, by Arvind Narayanan
- Inherent trade-offs in algorithmic fairness, by Jon Kleinberg
- Tutorial on Fairness in Machine Learning, by Solon Barocas & Moritz Hardt

Slides and code available on GitHub

- Jupyter Notebooks (WIP) & Slides available at
  - https://github.com/lennertjansen/msc_econometrics_thesis
- IBM's fairness analysis toolkit
  - https://github.com/IBM/AIF360
- Various beginner-level resources on fairness in AI
  - https://aif360.mybluemix.net/

References

1. Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2019). Machine bias: There's software used across the country to predict future criminals. and it's biased against blacks. 2016. *URL https://www. propublica. org/article/machine-bias-risk-assessments-in-criminal-sentencing.*
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4. Bellamy, R. K., Dey, K., Hind, M., Hoffman, S. C., Houde, S., Kannan, K., ... & Nagar, S. (2019). AI Fairness 360: An extensible toolkit for detecting and mitigating algorithmic bias. *IBM Journal of Research and Development*, 63(4/5), 4-1.
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6. Dieterich, W., Mendoza, C., & Brennan, T. (2016). Compas risk scales: Demonstrating accuracy equity and predictive parity. Northpoint Inc.
7. Kleinberg, J., Mullainathan, S., & Raghavan, M. (2016). Inherent trade-offs in the fair determination of risk scores. *arXiv preprint arXiv:1609.05807*.
8. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2019). A survey on bias and fairness in machine learning. *arXiv preprint arXiv:1908.09635*.
9. Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners. *OpenAI Blog*, *1*(8), 9.
10. Speicher, T., Heidari, H., Grgic-Hlaca, N., Gummadi, K. P., Singla, A., Weller, A., & Zafar, M. B. (2018, July). A unified approach to quantifying algorithmic unfairness: Measuring individual & group unfairness via inequality indices. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 2239-2248).

Thank you for your time and attention

Questions

Appendix

Discrimination...

- ...is <u>domain</u> specific

- ...is <u>feature</u> specific

Two types of discrimination

Disparate treatment

- Formal or intentional differential treatment

- Intention > outcome

Disparate impact

- Avoidable or unjustified disadvantageous outcome

- Outcome > intention

Algorithmic fairness: terminology

- Bias
  - An unwanted systematic error that systematically places certain groups at a disadvantage
- Bias mitigation algorithm
  - A set of procedures to make a decision-making model fair with respect to a certain characteristic (e.g., race, gender, age, etc.)

On the origin of biases

- Biased data
  - Unfair examples from an unjust past
- Features
  - Focussing on characteristics that are unfair towards a group
- Proxies
  - Using seemingly harmless variables as an approximation for protected attributes
- Sample size disparity
- Skewed sample

Strongly recommend the work of <u>Solon Barocas</u> (see references)

Algorithmic fairness: conventions

- Positive → favourable label or outcome
  - Labelled as low risk, not committing a crime, etc.
- Negative → *un*favourable label or outcome
  - Labelled as high risk, committing a crime (i.e., recidivating), etc.
- Error types
  - False positive: falsely being labelled as low risk, while re-committing a crime
  - False negative: falsely being labelled as high risk, while not becoming a recidivist

Fairness metrics

- Between-group fairness metrics
  - Is the overall outcome of group A comparable to that of group B?
- Within-group fairness metric
  - Are the outcomes of members of group A far from or close to the average outcome of group A?

Fairness metrics: group-fairness

- Statistical parity difference
  - Difference in rates of receiving the *favourable* label between the unprivileged and privileged group
- Disparate impact ratio
  - Ratio between rates of receiving the *favourable* label between the unprivileged and privileged group
- Equal opportunity difference
  - TPR_u - TPR_p = ... = FNR_p - FNR_u
- Average odds difference
  - Mean of absolute difference between FPR's and TPR's

Fairness metrics: within-group inequality

- Why the Theil index?
  - Special case of Generalised Entropy Indices
  - Sensitivity w.r.t. Within-group dispersion measured by alpha
  - Alpha = 1 for Theil index, i.e., neutral weight given
  - Theil index has a history of being applied to measurements of racial inequality
    - https://www.urban.org/research/data-methods/data-analysis/quantitative-data-analysis/segregation-measures
    - https://www.policymap.com/2015/07/racial-and-ethnic-segregation-in-the-news-and-on-policymap/
  - Bonus reason: Henri Theil also studied Econometrics at Erasmus
  - Further research as to the optimal GEI is needed, however

Three fundamental principles

- Independence
- Separation
- Sufficiency

Three fundamental principles: Separation

- Intuition
  - Prediction model and protected attribute (e.g., race) must be <u>independent, conditional on</u> target variable
- Examples
  - Equalised odds, equality of opportunity
- Pros
  - Optimality compatible, penalizes laziness
- Cons
  - Requires a reliable predictor or data

Three fundamental principles: Independence

- Intuition
  - Prediction model and protected attribute (e.g., race) must be <u>independent</u>
- Examples
  - Demographic parity, statistical parity, the four-fifths rule
- Pros
  - Simple, intuitive, easily compatible with legal notions
- Cons
  - Ignores possible correlation, laziness

Three fundamental principles: Sufficiency

- Intuition
  - Target variable is <u>independent</u> of the sensitive attribute, <u>given</u> the prediction score
- Examples
  - Calibration
- Pros
  - The risk score is *sufficient* for equitable prediction
- Cons
  -

Three fundamental principles: Trade-offs

These three fairness criteria are mutually exclusive
(except in degenerate cases)

Three fundamental principles: Exceptions

Some fairness criteria outside of these three categories:

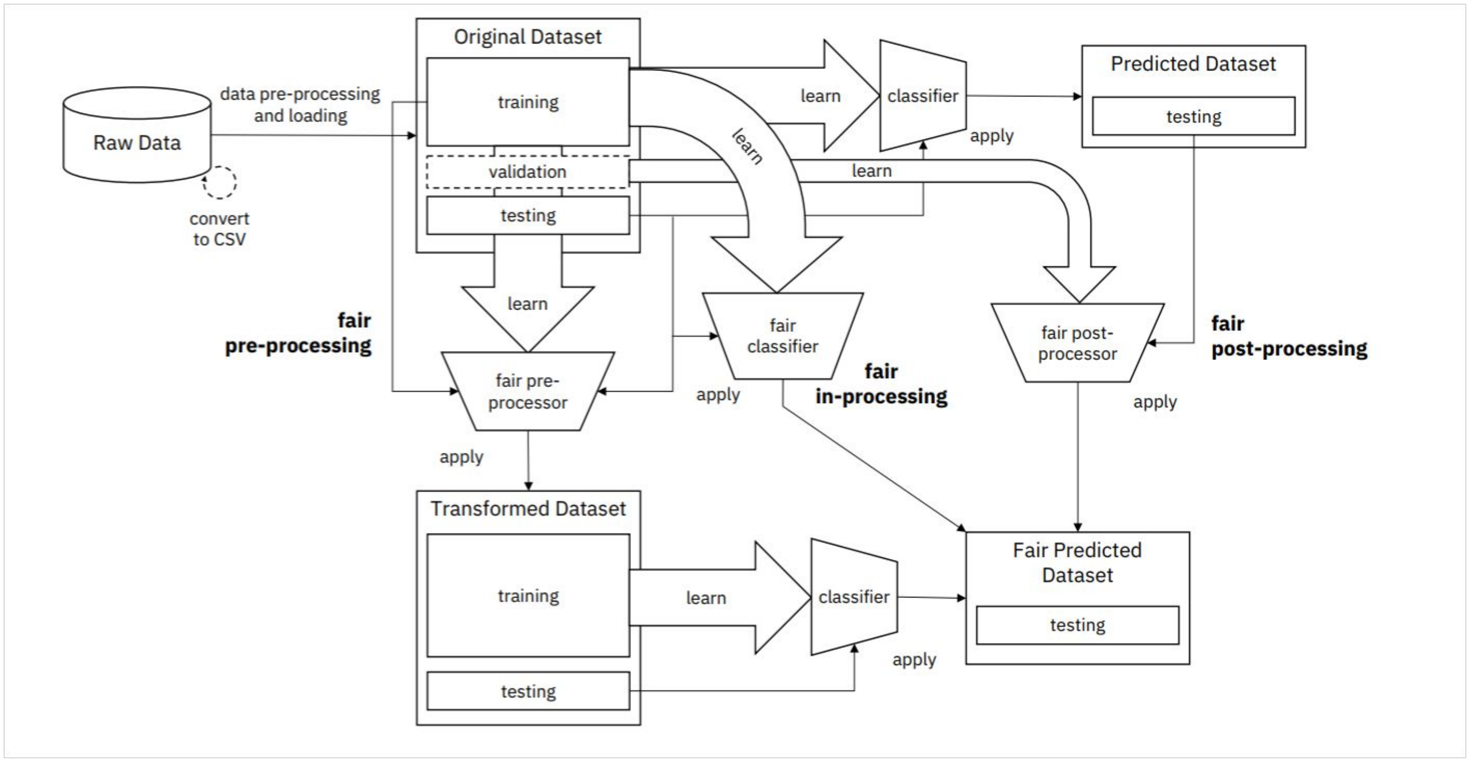
- Unawareness
- Individual fairness
- Counterfactual fairness

Achieving fairness

Three types of bias mitigation algorithms

- Pre-processing
- In-processing
- Post-processing

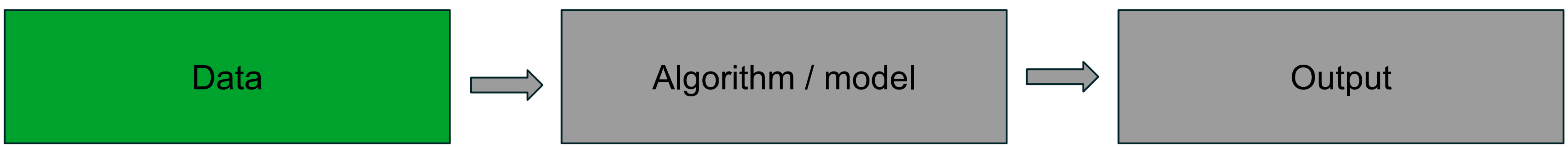
Achieving fairness: the ML pipeline (extended)



Achieving fairness: the machine learning pipeline

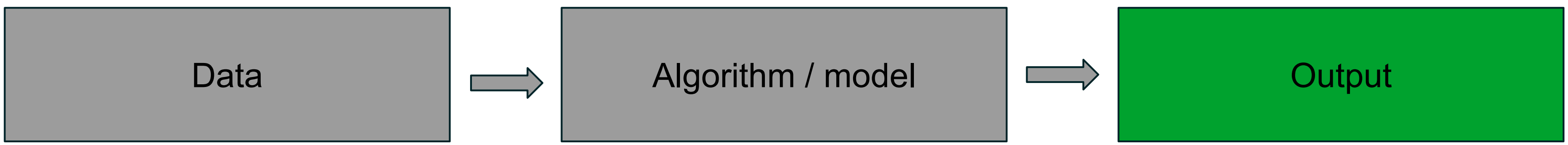
Data → Algorithm / model → Output

Achieving fairness: pre-processing

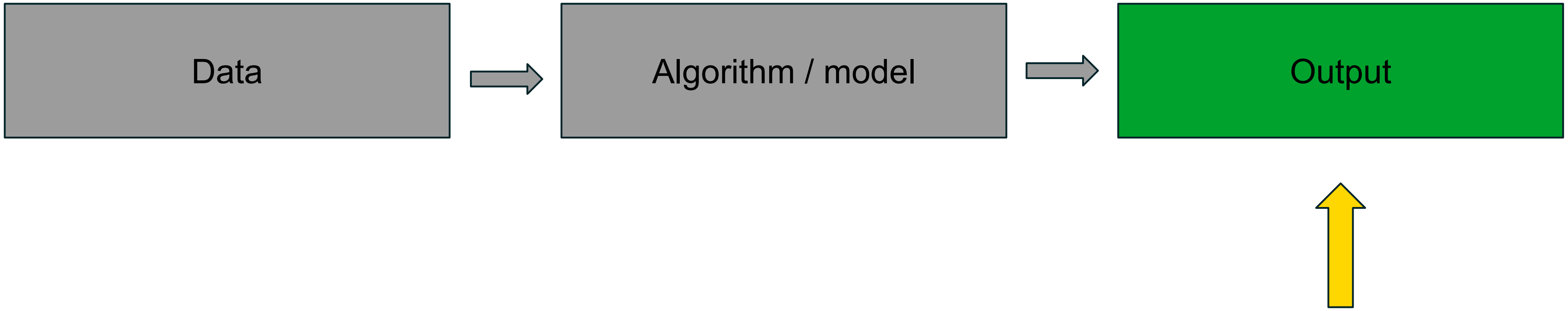


Achieving fairness: in-processing

Achieving fairness: post-processing



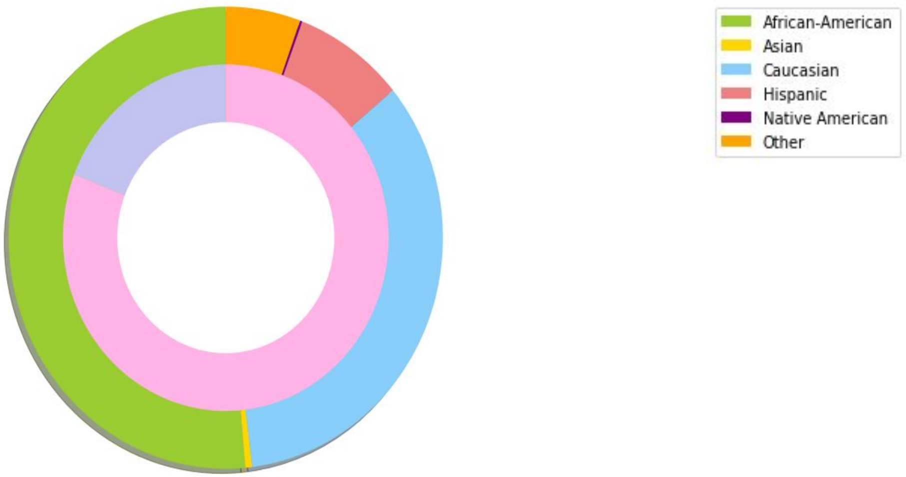
Achieving fairness: post-processing



Econometric methods

- Random forest
  - Natural framework to determine relative variable importance
- Logistic regression
  - Provides insights about the direction of statistical relationships, after controlling for relevant variables

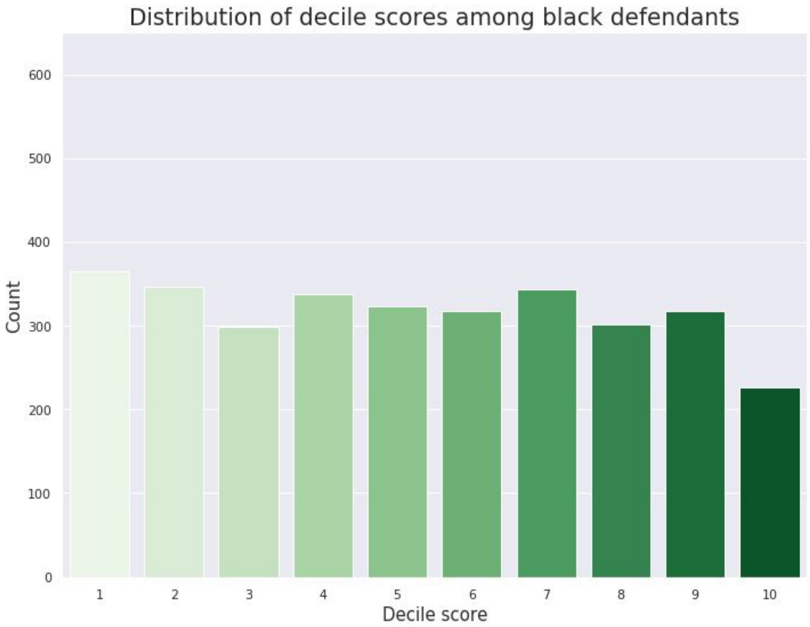
Demographic breakdown of dataset

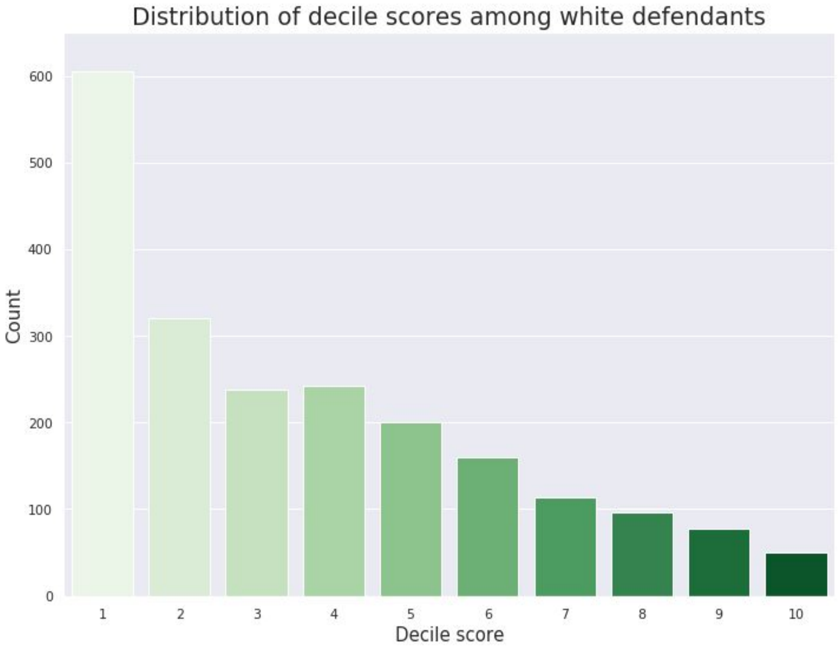


Race/ Sex	African-American	Asian	Caucasian	Hispanic	Native American	Other	All
Female	549	2	482	82	2	58	1175 (**19%**)
Male	2626	29	1621	427	9	285	4997 (**81%**)
All	3175	31	2103	509	11	343	6172
%	**51.4%**	**0.5%**	**34.1%**	**8.2%**	**0.2%**	**5.6%**	

Table 3: Racial and gender-based breakdown of the *general* recidivism dataset.

Exploratory data analysis: distribution of scores





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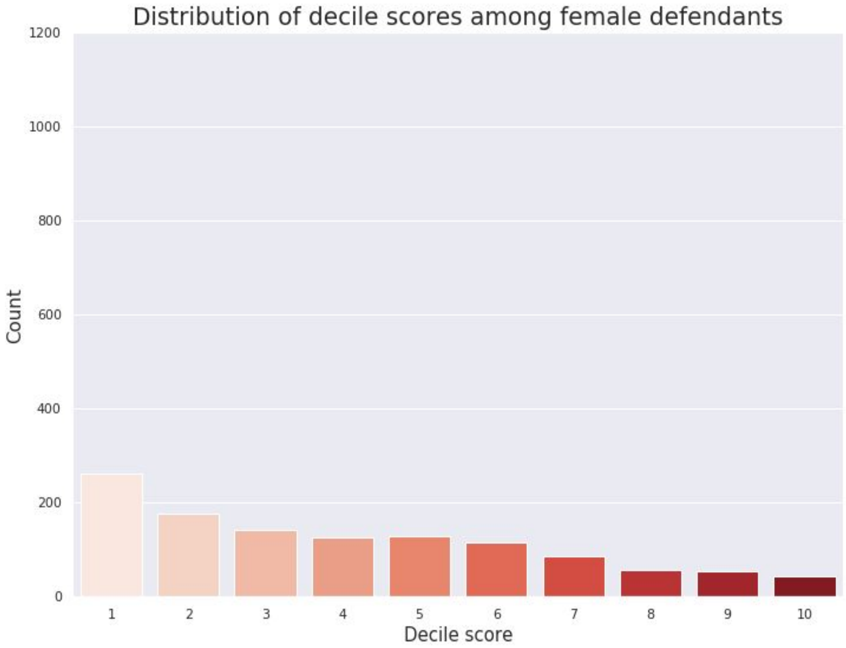
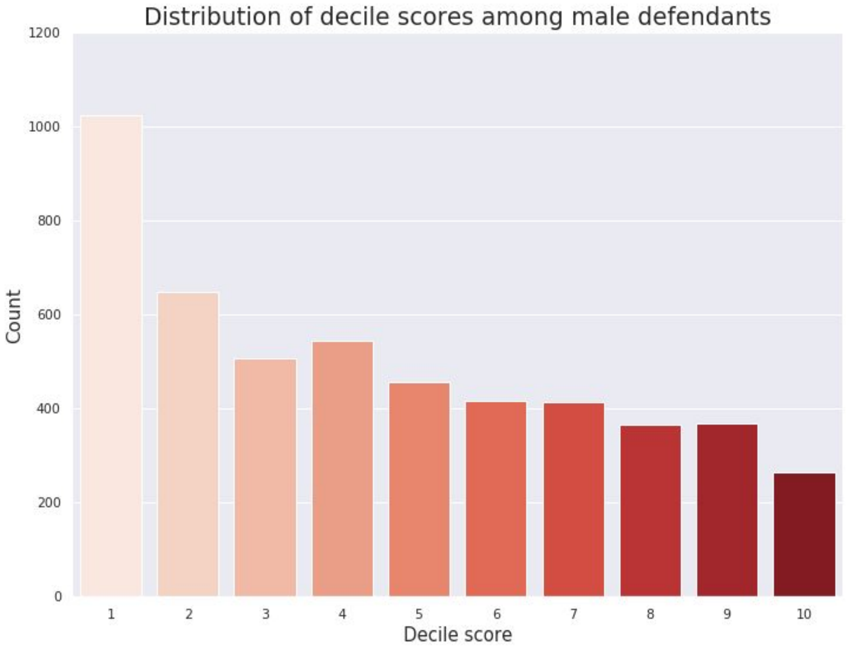
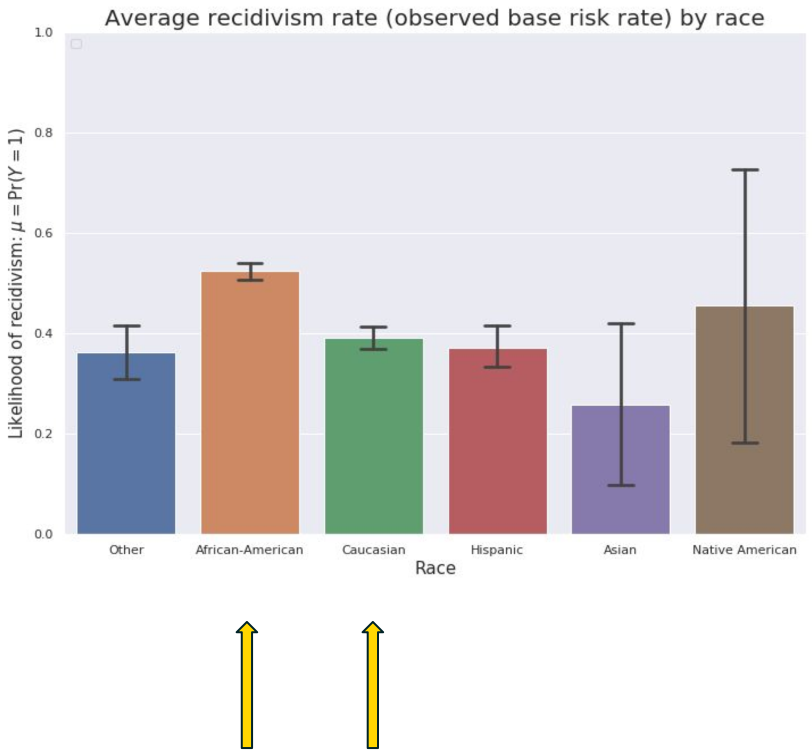
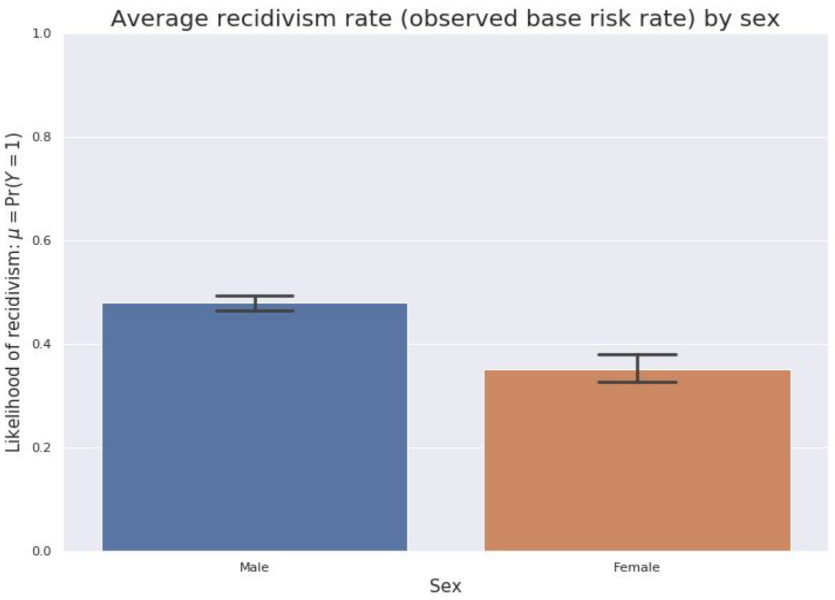




Exploratory data analysis: base rates





Logistic regression: score category

	coef	std err	z	p-value	[0.025	0.975]
const	-1.5248	0.078	-19.442	0.000	-1.679	-1.371
sex_female	0.2193	0.079	2.764	0.006	0.064	0.375
age_cat_greater_than_45	-1.3574	0.099	-13.711	0.000	-1.551	-1.163
age_cat_less_than_25	1.3063	0.076	17.231	0.000	1.158	1.455
race_african_american	0.4770	0.069	6.879	0.000	0.341	0.613
race_other2	-0.5410	0.105	-5.165	0.000	-0.746	-0.336
priors_count	0.2695	0.011	24.305	0.000	0.248	0.291
c_charge_degree_m	-0.3089	0.066	-4.646	0.000	-0.439	-0.179
two_year_recid	0.6821	0.064	10.671	0.000	0.557	0.807

Logistic regression: observed recidivism

	coef	std err	z	p-value	[0.025	0.975]
const	-0.6082	0.065	-9.430	0.000	-0.735	-0.482
sex_female	-0.3477	0.072	-4.840	0.000	-0.489	-0.207
age_cat_greater_than_45	-0.6695	0.076	-8.801	0.000	-0.819	-0.520
age_cat_less_than_25	0.7333	0.069	10.639	0.000	0.598	0.868
race_african_american	0.0959	0.063	1.529	0.126	-0.027	0.219
race_other2	-0.1780	0.088	-2.025	0.043	-0.350	-0.006
priors_count	0.1656	0.008	20.536	0.000	0.150	0.181
c_charge_degree_m	-0.2186	0.059	-3.721	0.000	-0.334	-0.103

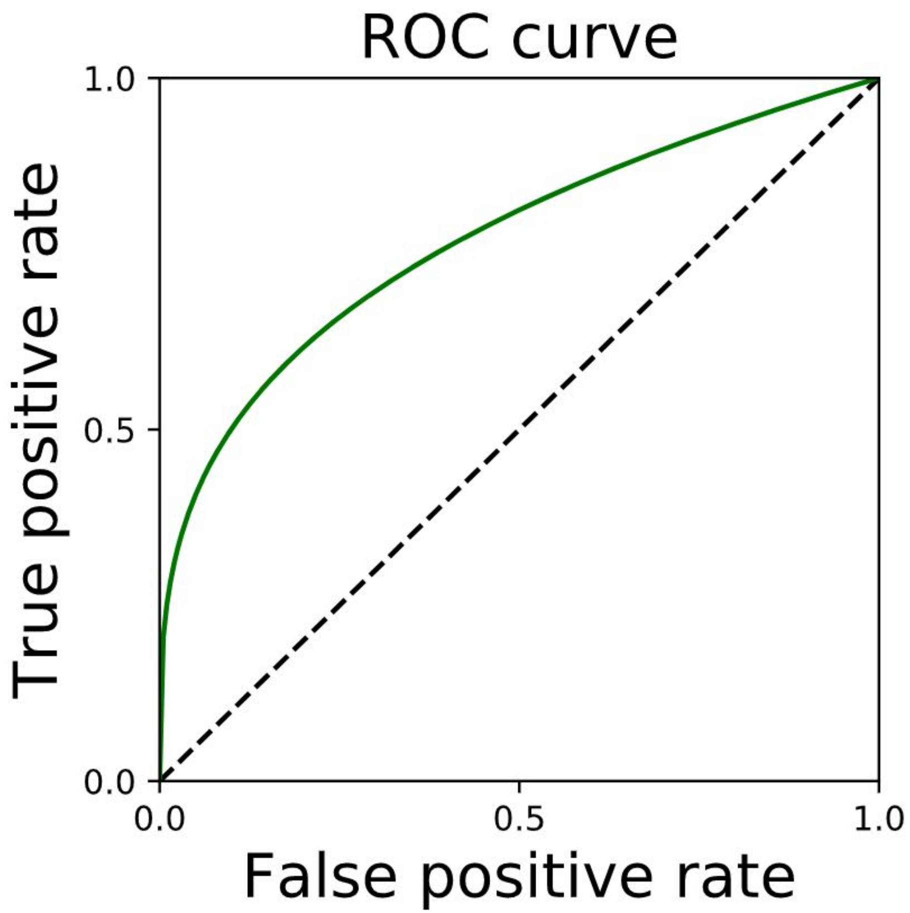
Logistic regression: false negatives

	coef	std err	z	p-value	[0.025	0.975]
const	-1.6686	0.102	-16.347	0.000	-1.869	-1.469
sex_female	0.1867	0.103	1.812	0.070	-0.015	0.389
age_cat_greater_than_45	-1.4005	0.136	-10.310	0.000	-1.667	-1.134
age_cat_less_than_25	1.3885	0.105	13.198	0.000	1.182	1.595
race_african_american	0.5431	0.096	5.669	0.000	0.355	0.731
race_other2	-0.4806	0.145	-3.309	0.001	-0.765	-0.196
priors_count	0.2884	0.017	17.150	0.000	0.255	0.321
c_charge_degree_m	-0.1601	0.091	-1.766	0.077	-0.338	0.018

Logistic regression: false positives

	coef	std err	z	p-value	[0.025	0.975]
const	0.6857	0.108	6.346	0.000	0.474	0.898
sex_female	-0.2483	0.127	-1.961	0.050	-0.496	-0.000
age_cat_greater_than_45	1.3046	0.146	8.940	0.000	1.019	1.591
age_cat_less_than_25	-1.2275	0.110	-11.189	0.000	-1.442	-1.012
race_african_american	-0.4137	0.102	-4.073	0.000	-0.613	-0.215
race_other2	0.6138	0.152	4.046	0.000	0.316	0.911
priors_count	-0.2536	0.015	-17.234	0.000	-0.282	-0.225
c_charge_degree_m	0.4759	0.097	4.883	0.000	0.285	0.667

How does EOPP work and why didn't it succeed?



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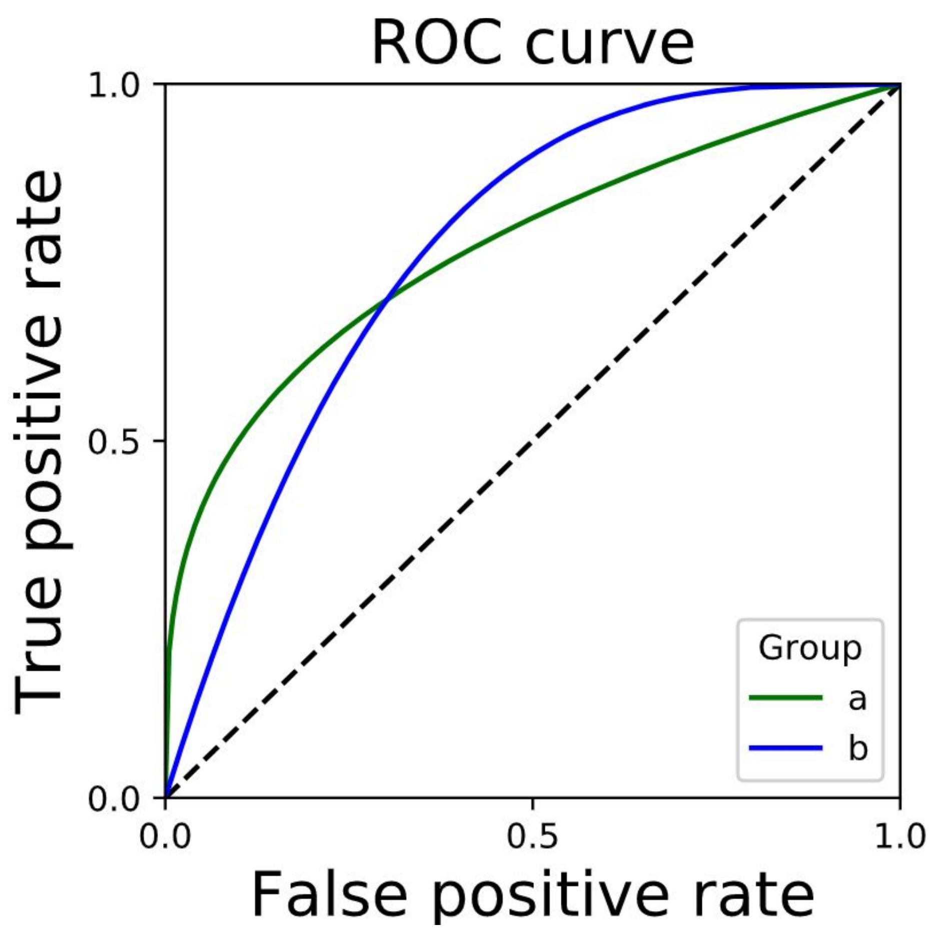
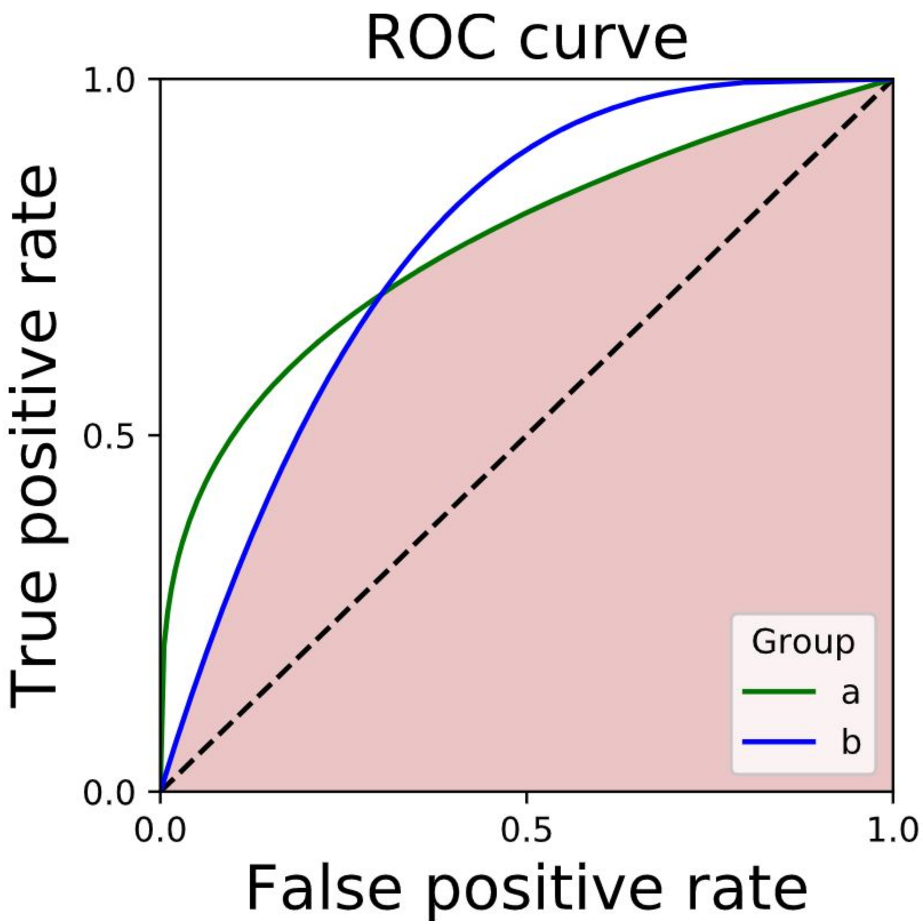
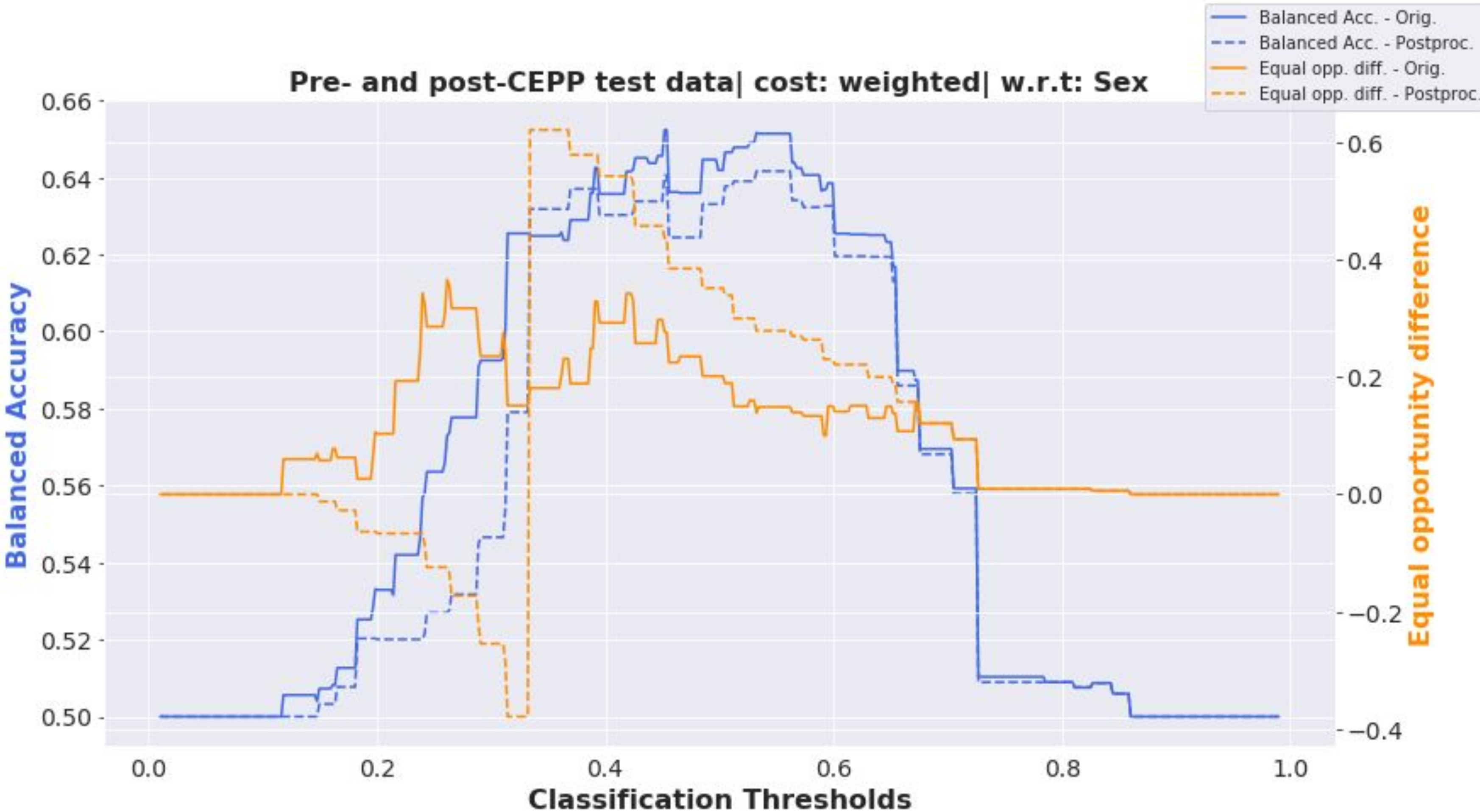


How does EOPP work and why didn't it succeed?



Bias mitigation results: observed trade-offs



Bias mitigation results: observed trade-offs

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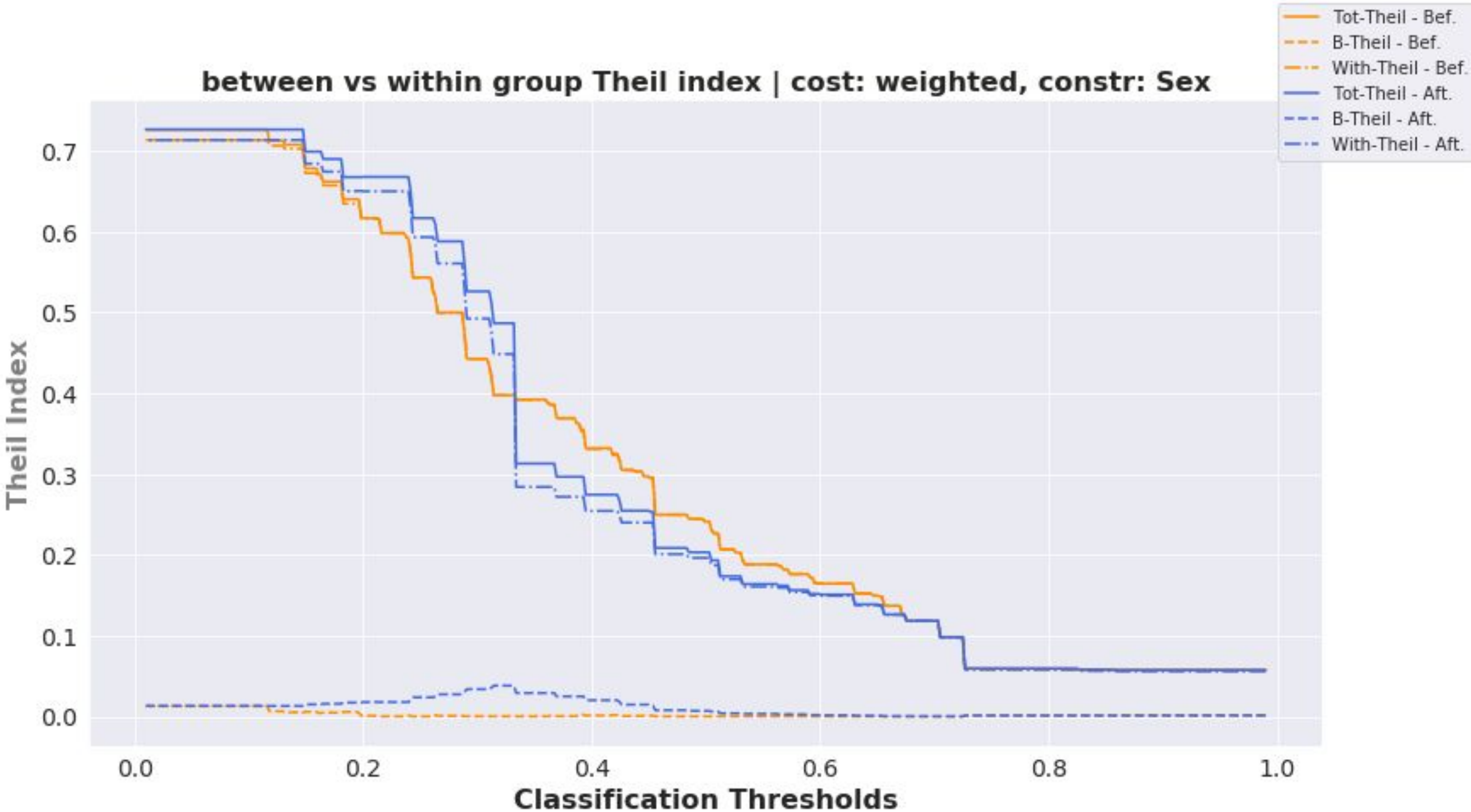
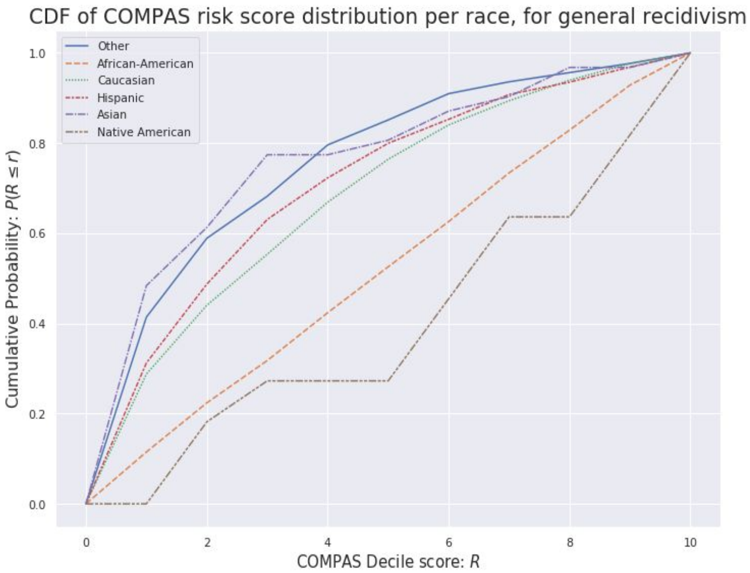
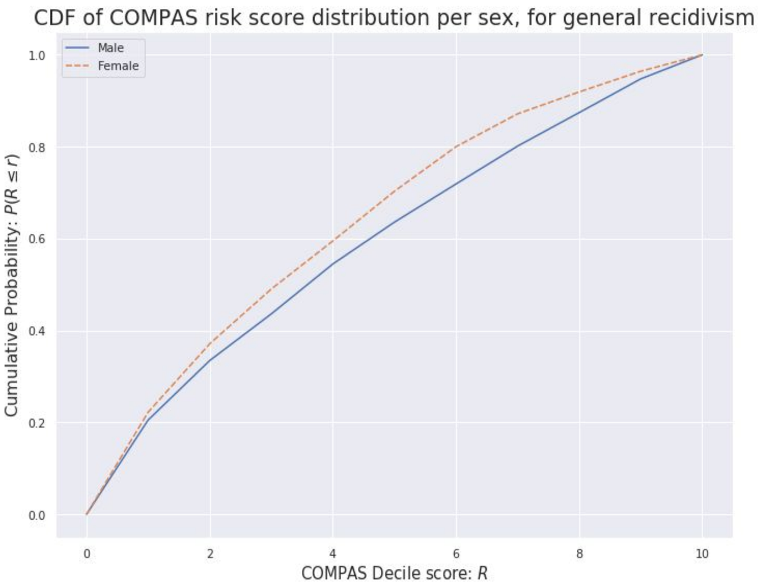


Exploratory data analysis: distribution of scores





Bias mitigation results

Equalised odds post-processing

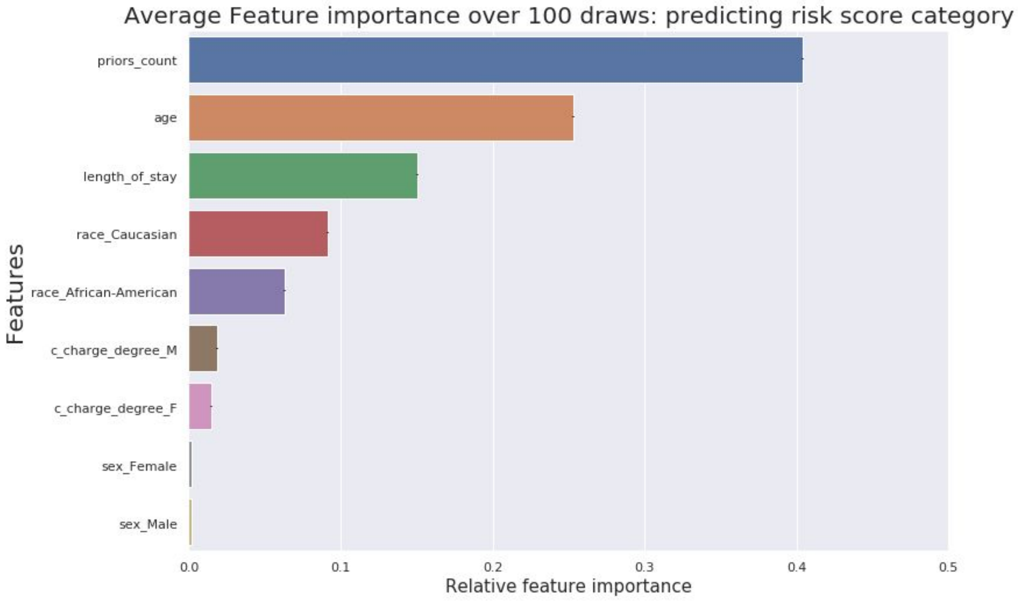
- Unsatisfactory performance
  - Returned either the unchanged unfair model, or a fair random guessing classifier
- Possible explanations
  - There exist only trivial intersection points in the combined problem-space*
  - Model misspecification

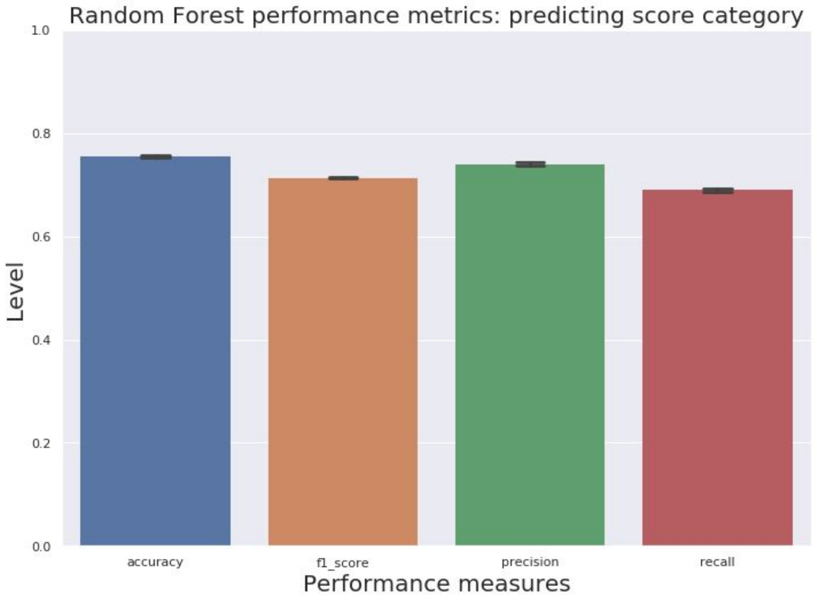
Bias mitigation results

Calibrated equalised odds post-processing

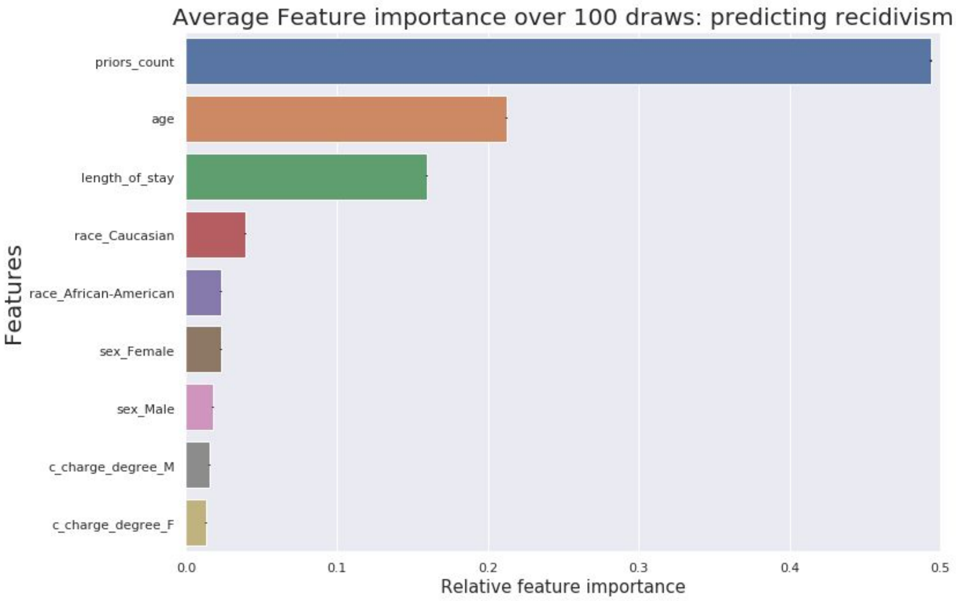
- Acceptable performance
    - Moderate decrease in prediction performance
    - Satisfies calibration
    - Fails to notably improve group-fairness
- Possible explanations
    - Incompatibility of calibration and error rate parity (Kleinberg's impossibility result)
    -

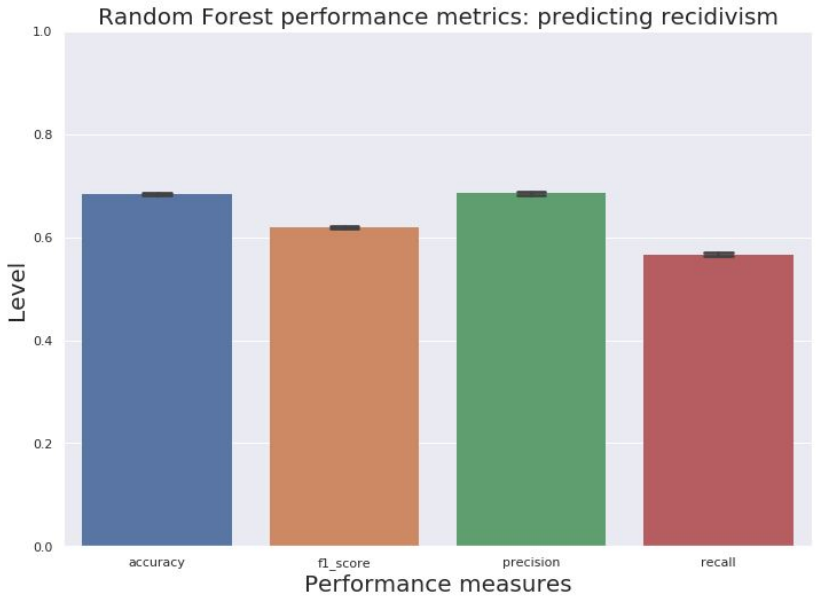
Random forest: relative feature importance





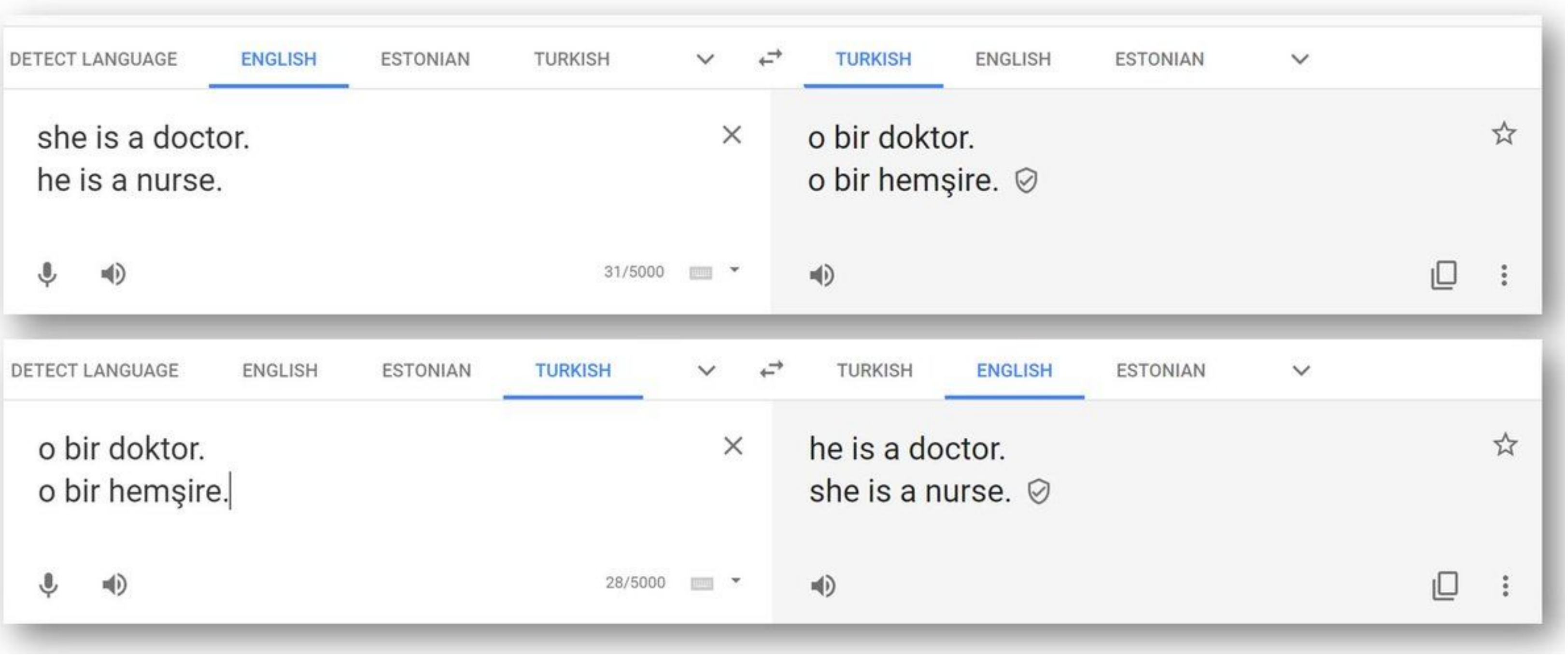
Random forest: relative feature importance





Further research

- Develop all-round optimised fairness metric using inequality indices (i.e., expand on the work of Speicher et al. 2018)
- Bias origin modelling (i.e., quantify the work of Barocas & Selbst 2016)
- Speculative
    - General purpose bias mitigation algorithm using more advanced deep learning models (inspired by Radford et al. 2019)


DETECT LANGUAGE
ENGLISH
ESTONIAN
TURKISH
TURKISH
ENGLISH
ESTONIAN
she is a doctor.
he is a nurse.
31/5000
o bir doktor.
o bir hemşire.
DETECT LANGUAGE
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