The European Commission's science and knowledge service

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Why machine learning may lead to unfairness

Songül Tolan[1], **Marius Miron[1]**, Emilia Gomez[1,2], Carlos Castillo[2]

[1]European Commission's Joint Research Centre
[2]Universitat Pompeu Fabra

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Machine learning for decision making

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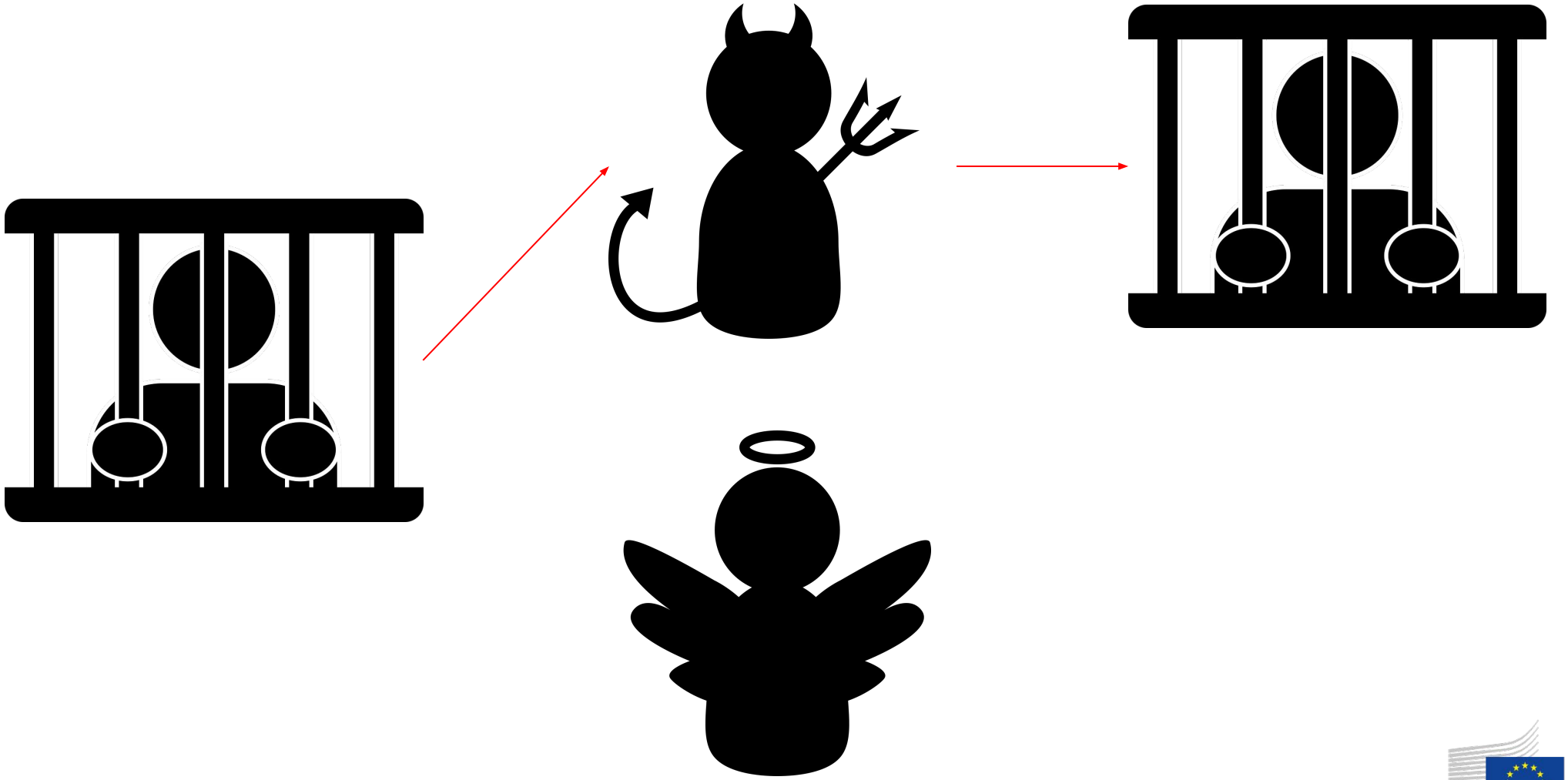
The criminal justice case

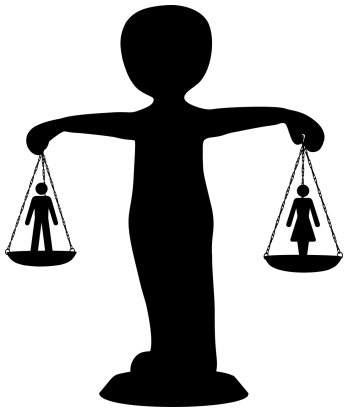
Trade-off: predictive performance vs fairness

Criminal recidivism



Criminal recidivism prediction

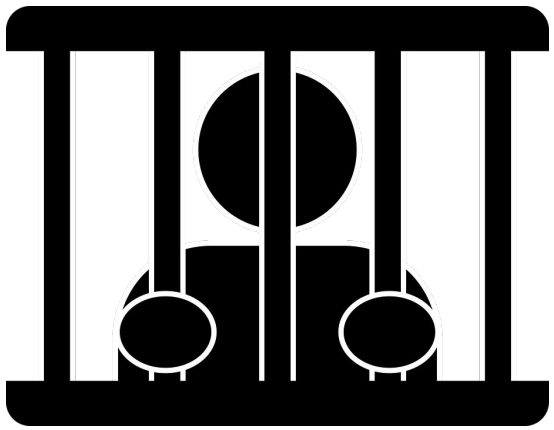
Prisoner



Human expert

Decision / Sentence

Criminal recidivism prediction



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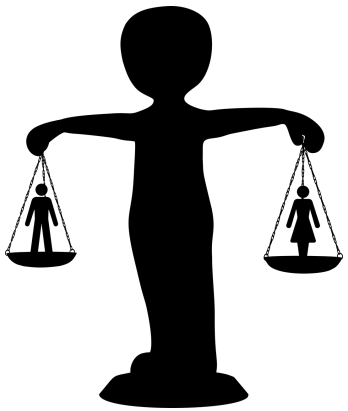

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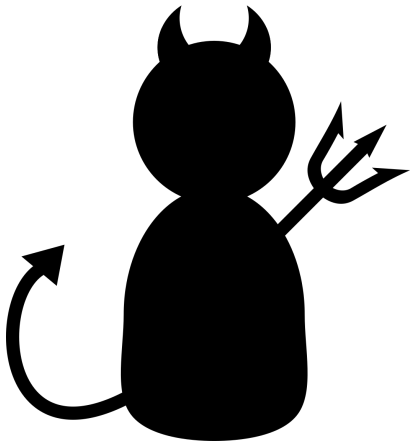
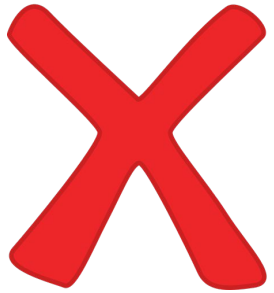
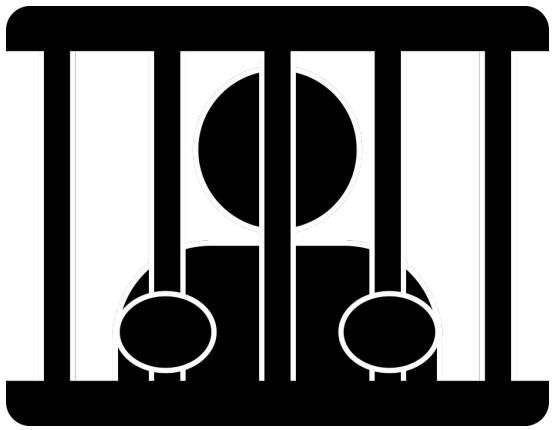


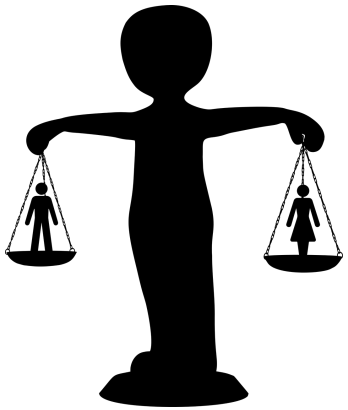
Outcome



Criminal recidivism prediction



Prisoner



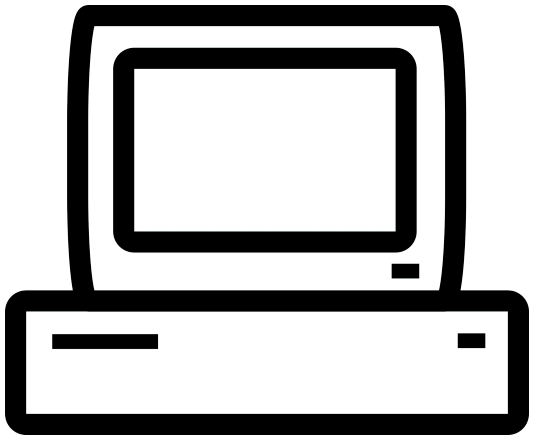
Human expert

Decision / Sentence

Outcome

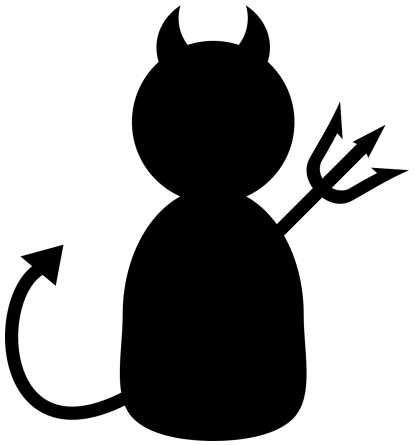
Criminal recidivism prediction

Features



Machine learning model

Prediction



Outcome

Criminal recidivism prediction

Examples of static features:

- **Age at crime**
- **Sex**
- **Nationality**
- **Previous number of crimes**
- **Sentence**
- **Year of crime**
- **Probation**

Fairness

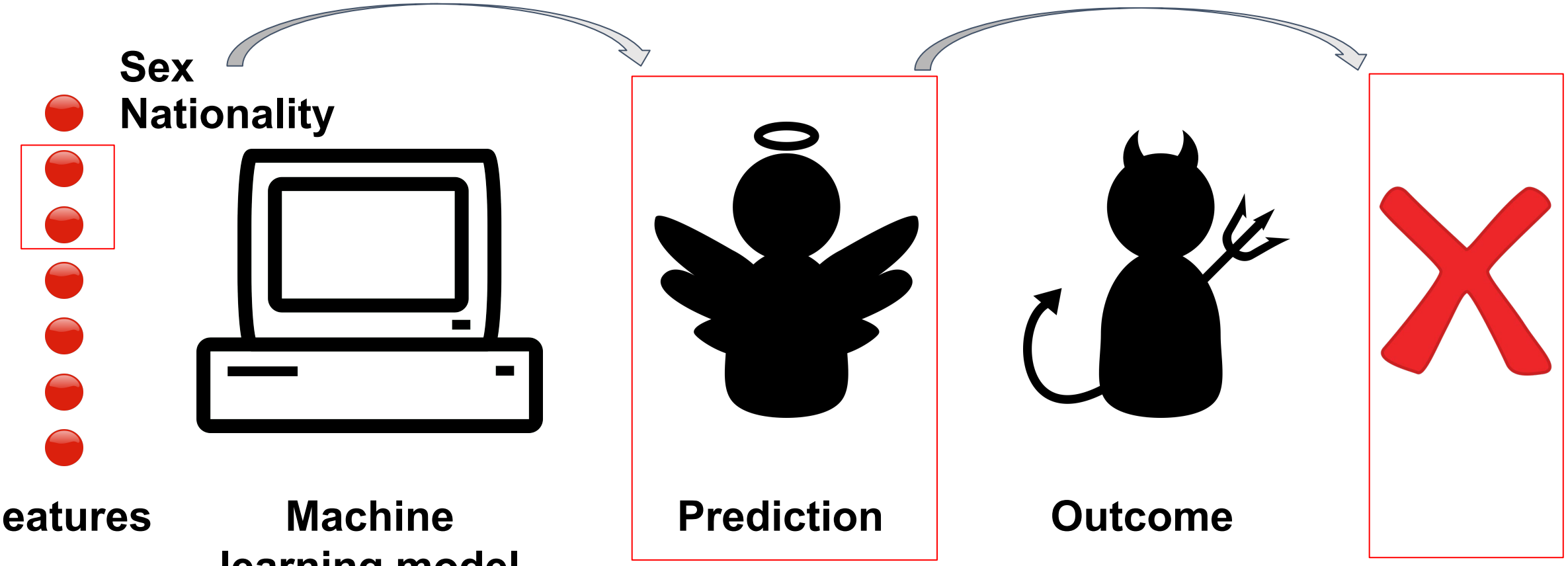
A decision is fair if it does not discriminate against people based on their membership to a protected group

Fairness

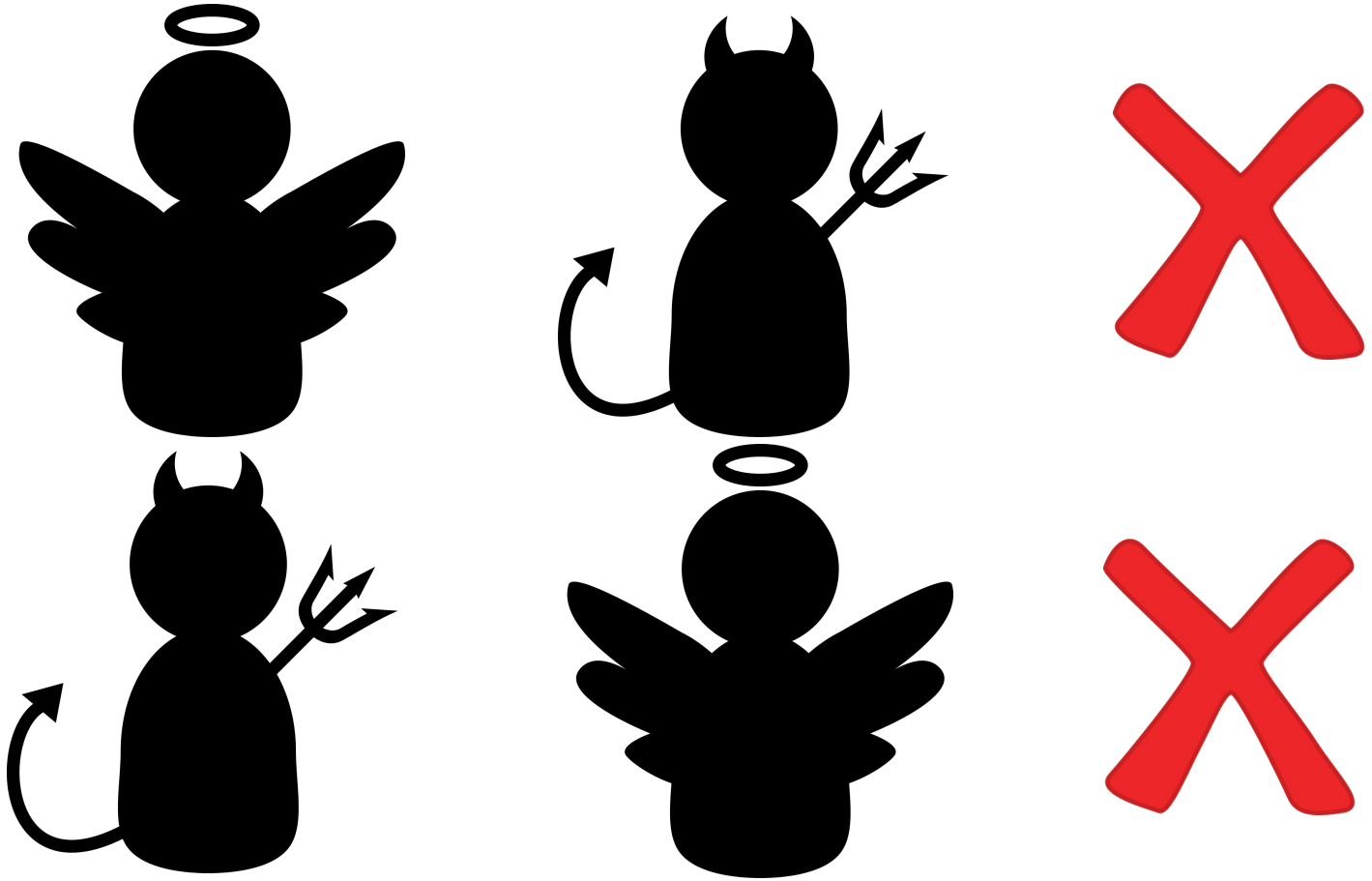
Example of protected features:

- **Age at crime**
- **Sex**
- **Nationality**
- **Previous number of crimes**
- **Sentence**
- **Year of crime**
- **Probation**

Measuring unfairness



Measuring unfairness



Prediction

Outcome

False negative

False positive

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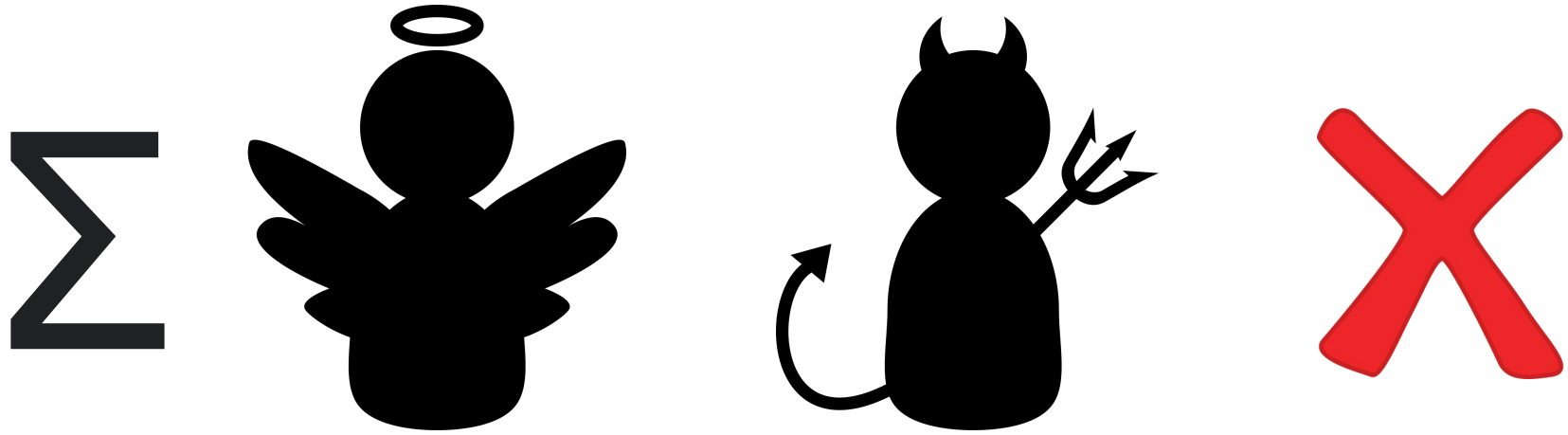
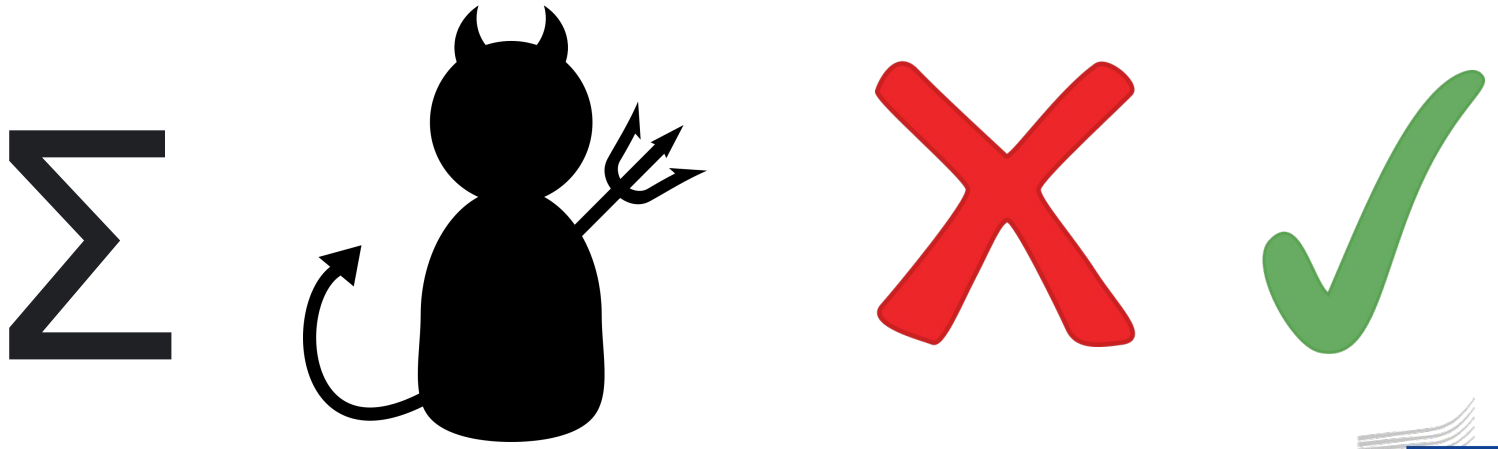
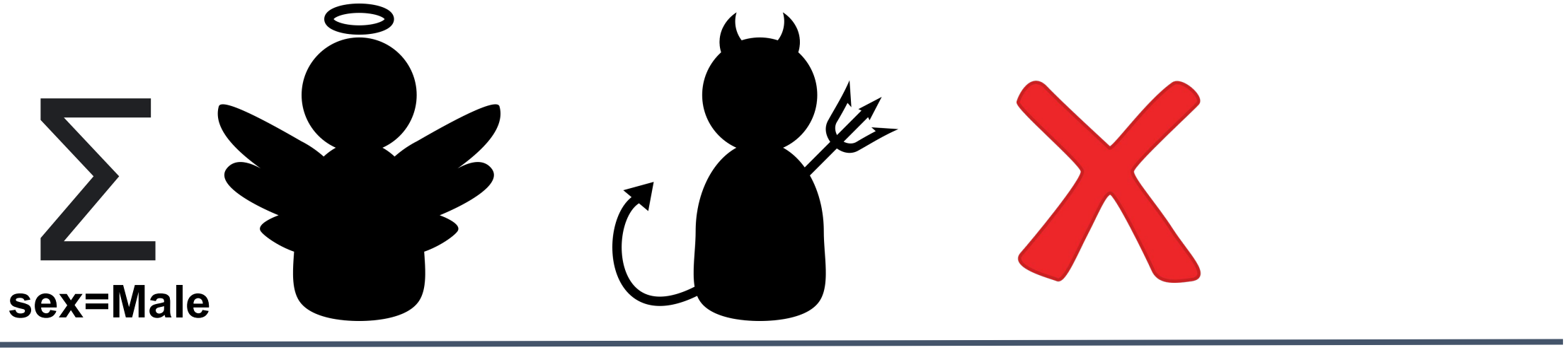
False negative rate = Miss rate





False positive rate = False alarm rate

Group fairness - sex



False negative rate disparity

$$FNR_{disparity} = \frac{FNR_{female}}{FNR_{male}}$$

How likely it is for a member of a group to be wrongfully labeled as non-recidivist.

Headache?

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Too complicated?

The fairness in machine learning literature comprises at least 21 disparity metrics.

Juvenile recidivism

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Risk assessment tools

Structured Assessment of Violence Risk in Youth (SAVRY)

- high degree of involvement from human experts
- open and interpretable (in comparison with COMPAS)
- 24 risk factors scored low, medium or high

SAVRY

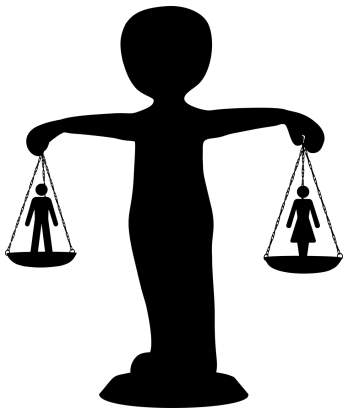
Examples of SAVRY features:

- **Early violence**
- **Self-harm history**
- **Home violence**
- **Poor school achievement**
- **Stress and poor coping**
- **Substance abuse**
- **Criminal parent/caregiver**

Criminal recidivism prediction

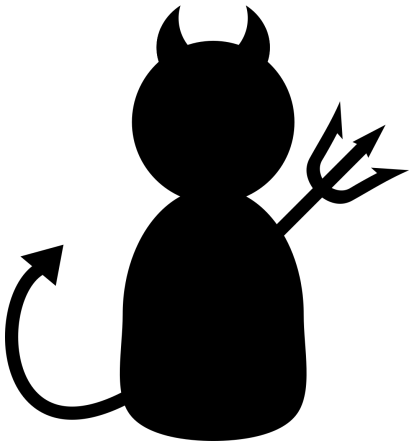
SAVRY features

SAVRY sum



Expert

Final expert evaluation



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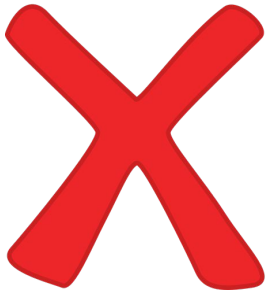

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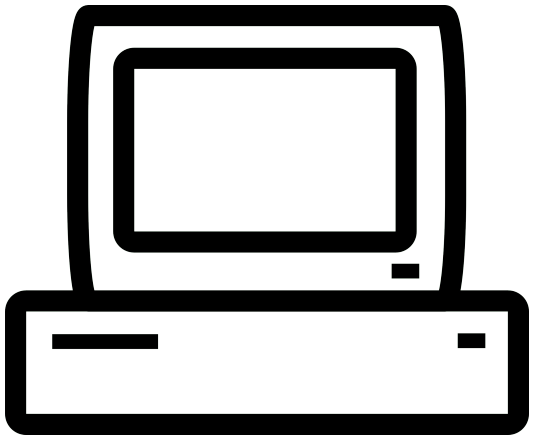
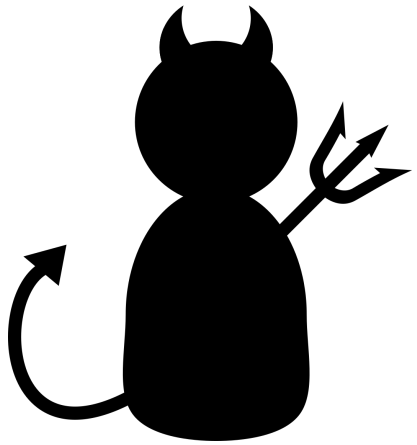
Static ML

Features



Machine learning model

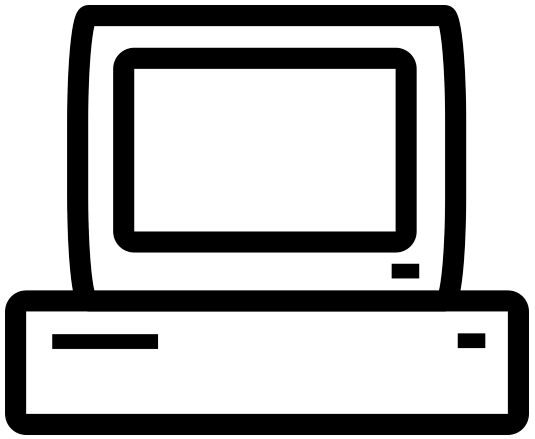
Prediction



Outcome

SAVRY ML

SAVRY features



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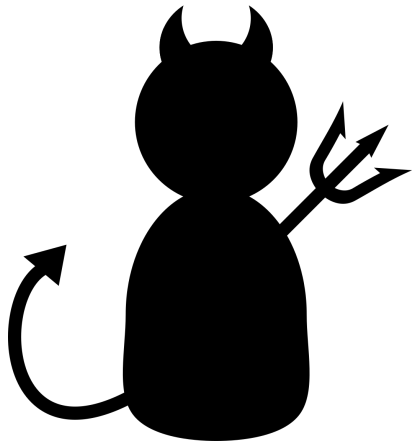
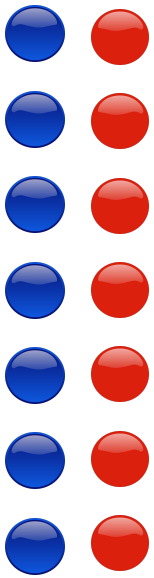
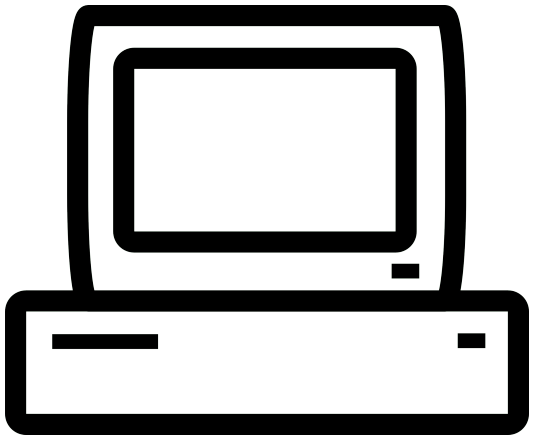


Outcome

Static + SAVRY ML

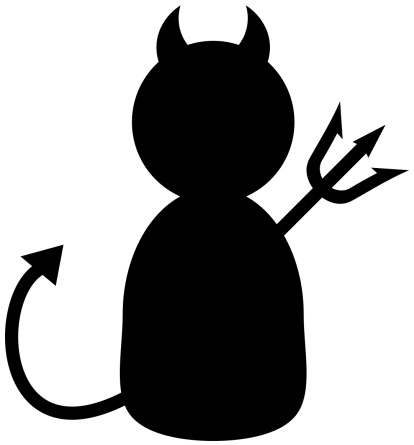


Features



Machine learning model

Prediction



Outcome

Dataset

Juvenile offenders in Catalonia[1]

- 855 people
- crimes between 2002 -2010, release in 2010
- age at crime between 12 and 17 years old
- status followed up on 2013 and 2015

1. Open data: http://cejfe.gencat.cat/en/recerca/opendata/jjuvenil/reincidencia-justicia-menors/index.html

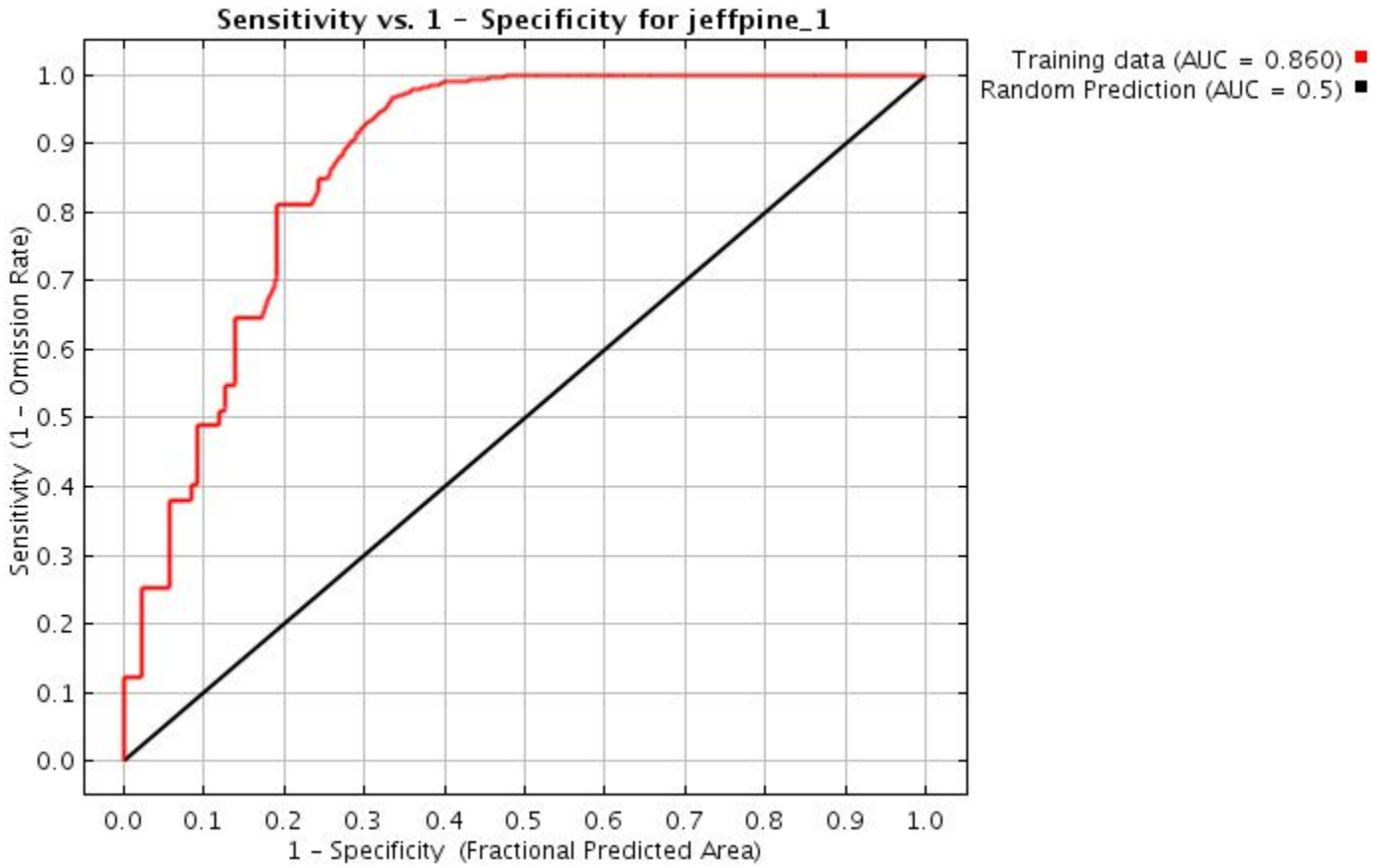
Experimental setup

Training a set of ML methods

- logistic regression (logit), multi-layer perceptron (mlp), support vector machines (lsvm), k-nearest neighbors (knn), random forest (rf), naive bayes (nb)
- k-fold cross validation with k=10 (10% test, 10% validation, 80% training)
- we run 50 different experiments with different initial conditions
- we compute feature importance with LIME[1]

1. LIME https://github.com/marcotcr/lime

Predictive performance - AUC ROC



Results, predictive performance AUC

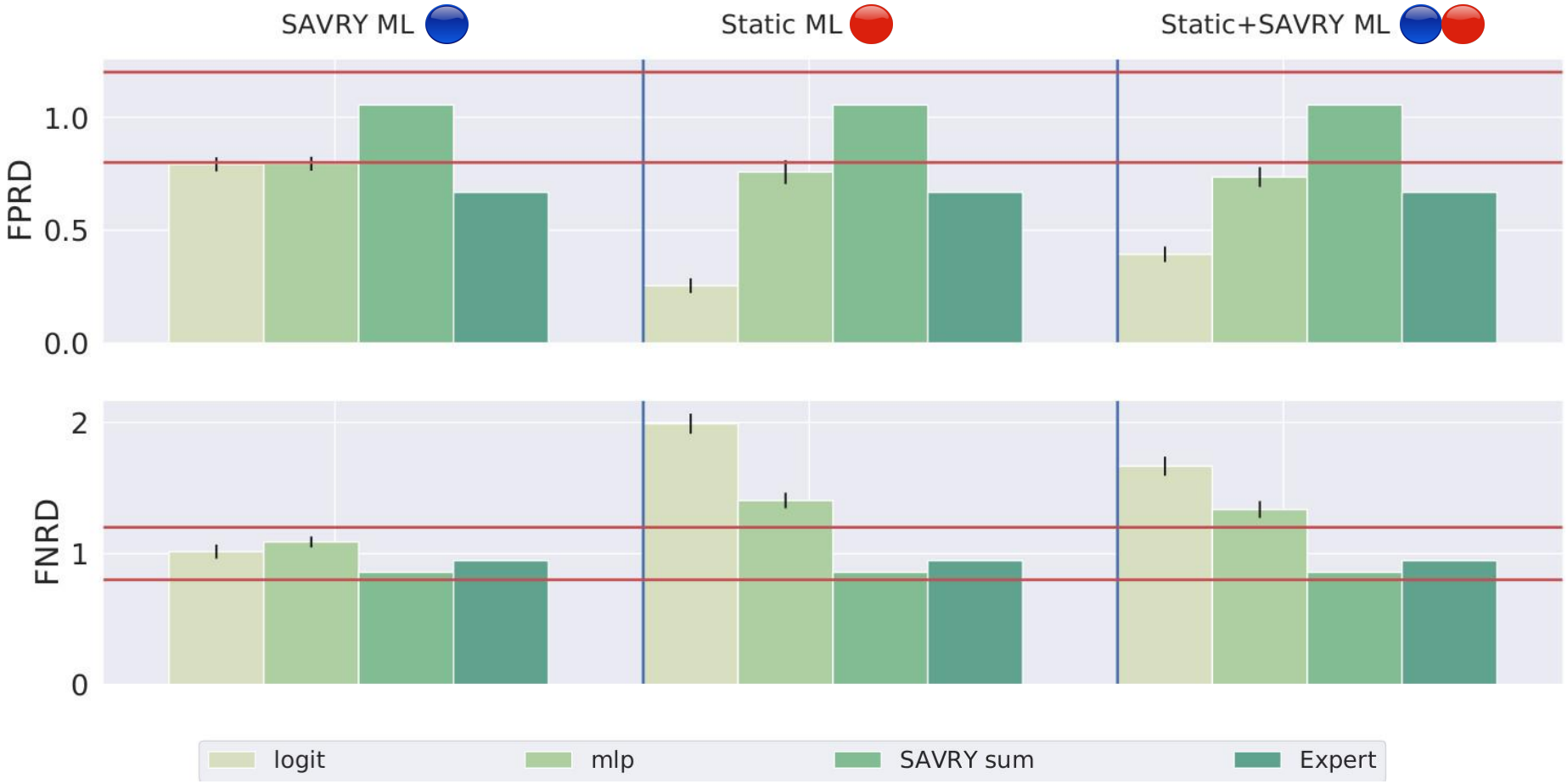
	logit		mlp		knn		lsvm		rsvm		nb		rf	
	mean	std.dev.	mean	std.dev.	mean	std.dev.	mean	std.dev.	mean	std.dev.	mean	std.dev.	mean	std.dev.
SAVRY ML	**.66**	.0058	**.66**	.0058	.60	.0121	.65	.0082	.52	.0197	.65	.0015	.65	.0110
Static ML	**.70**	.0055	**.70**	.0068	.62	.0122	.61	.0119	.56	.0149	.69	.0040	.66	.0110
Static+SAVRY ML	**.71**	.0064	**.70**	.0053	.64	.0129	**.71**	.0074	.50	.0058	.69	.0018	.69	.0121

SAVRY Sum has 0.64 AUC
Expert has 0.66 AUC

Results: disparity, sex

False alarm rates

Miss rates



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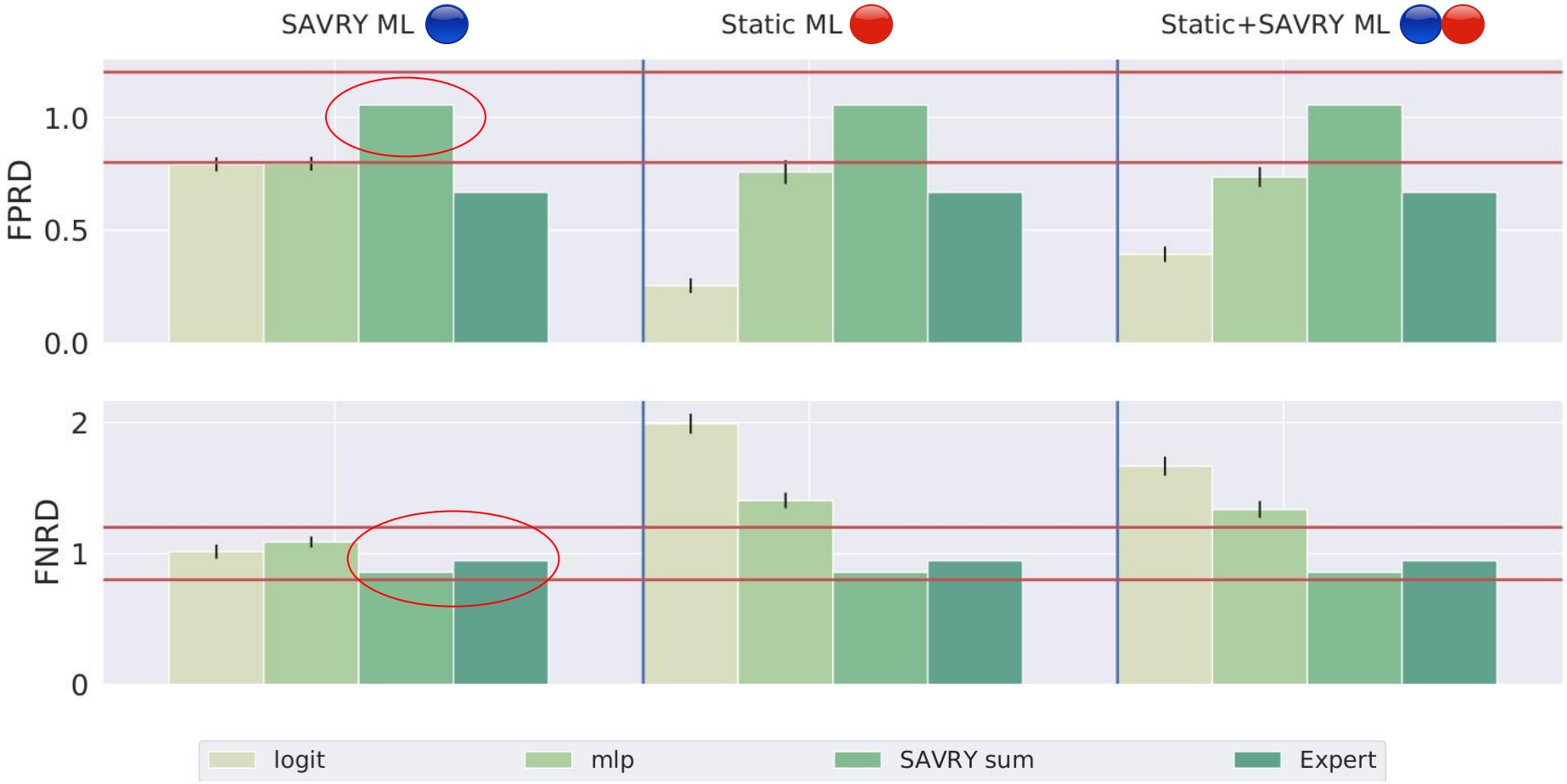

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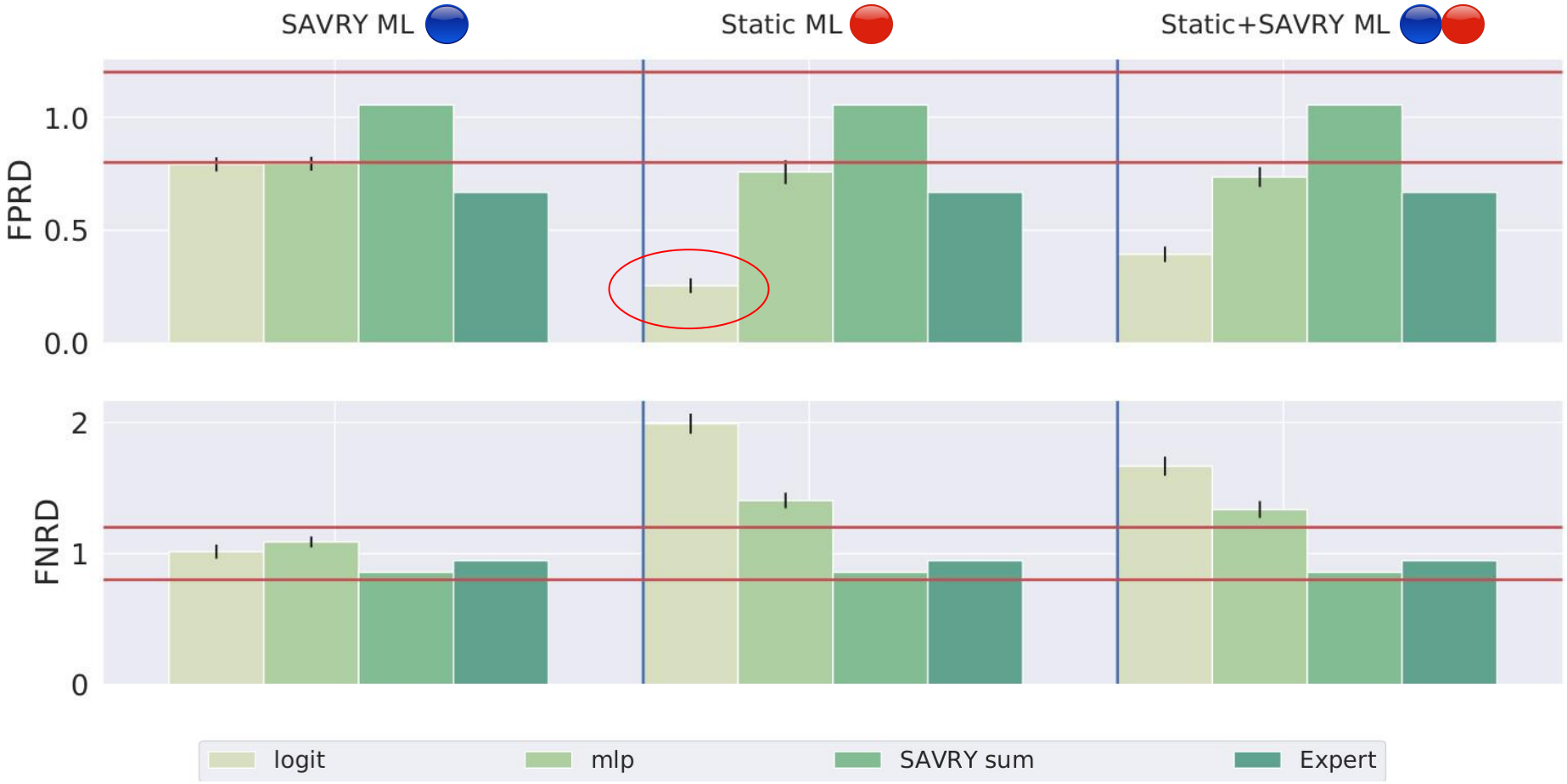

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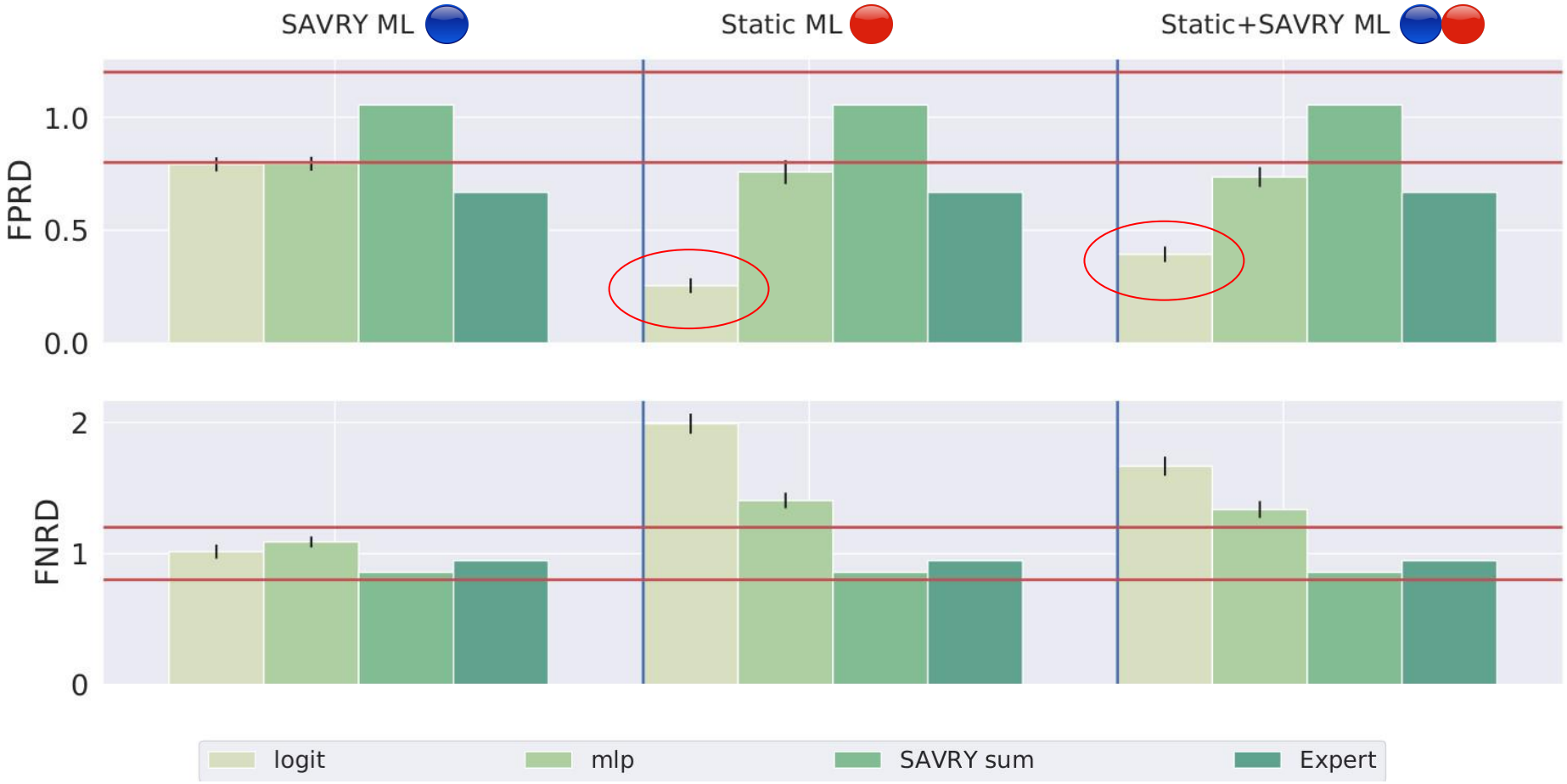

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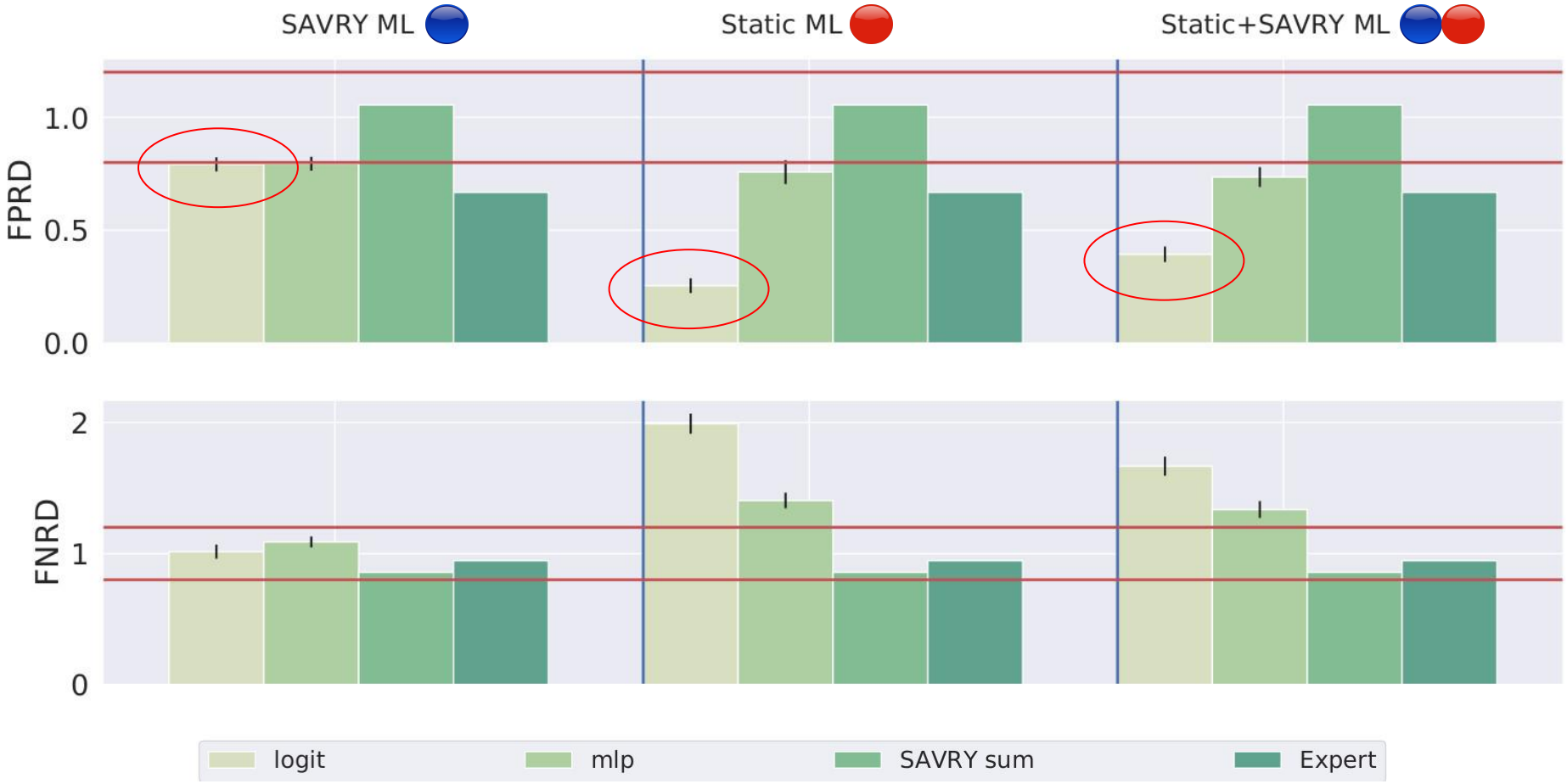

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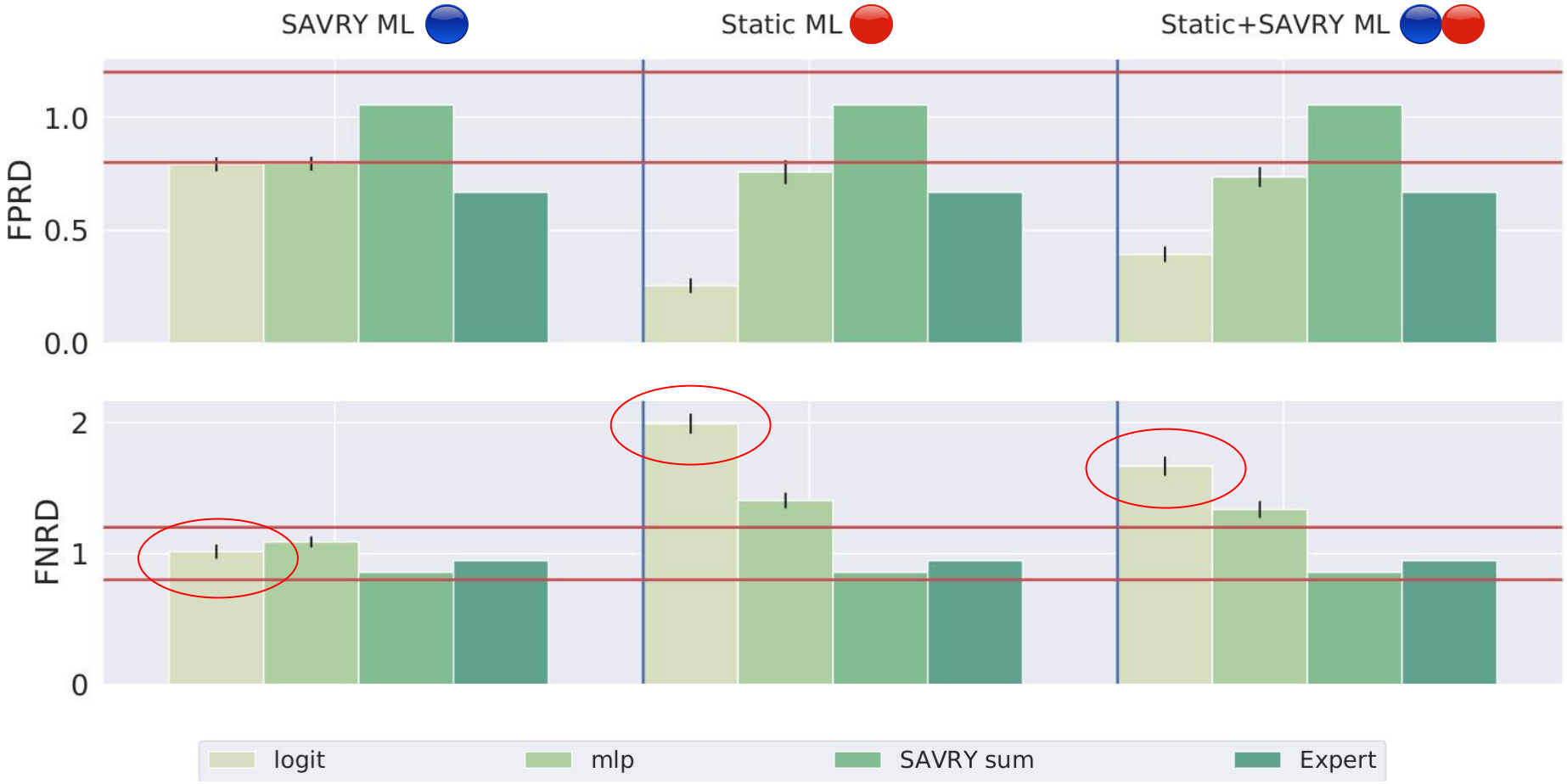

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Results: disparity, nationality

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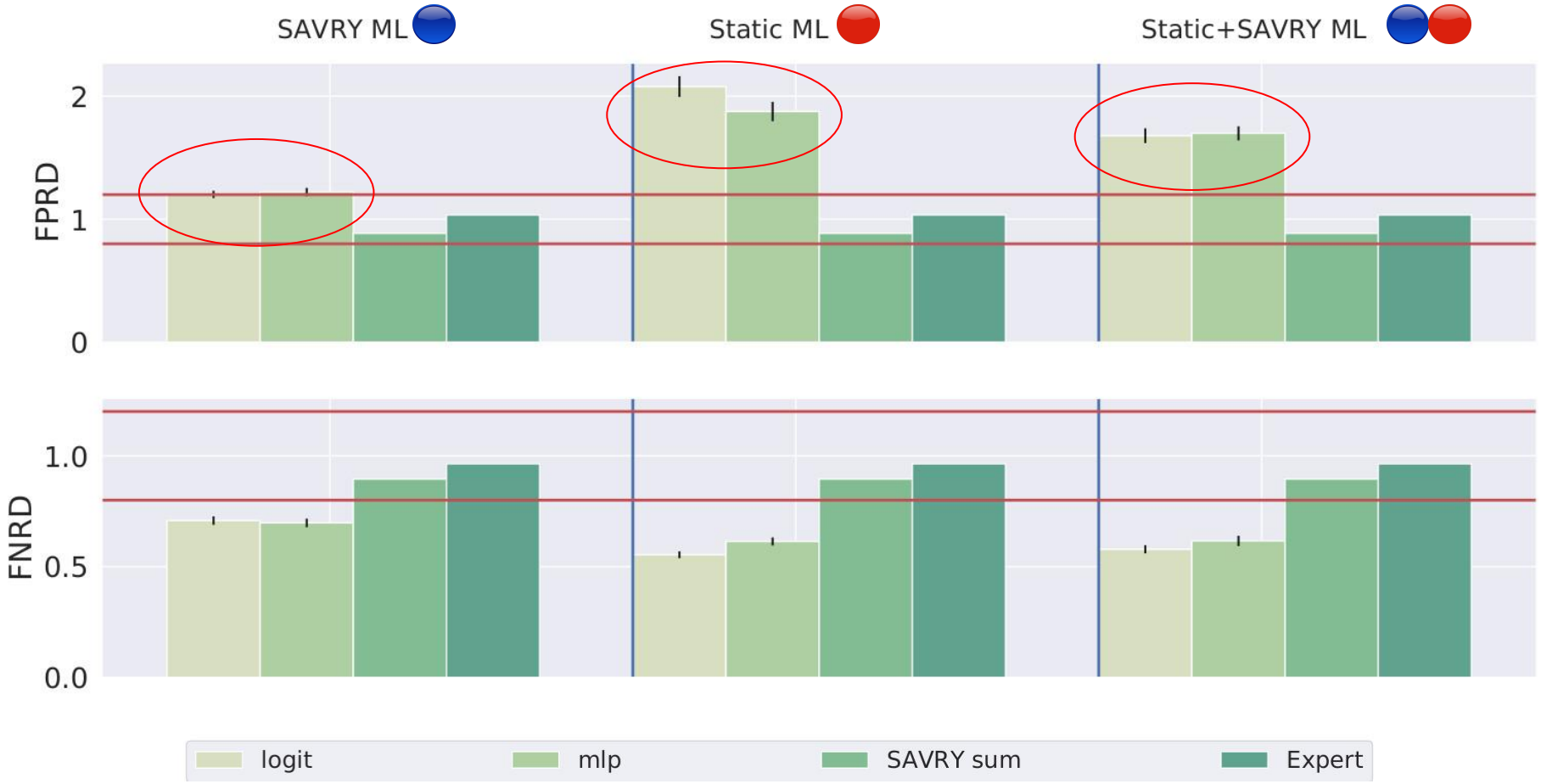
Miss rates



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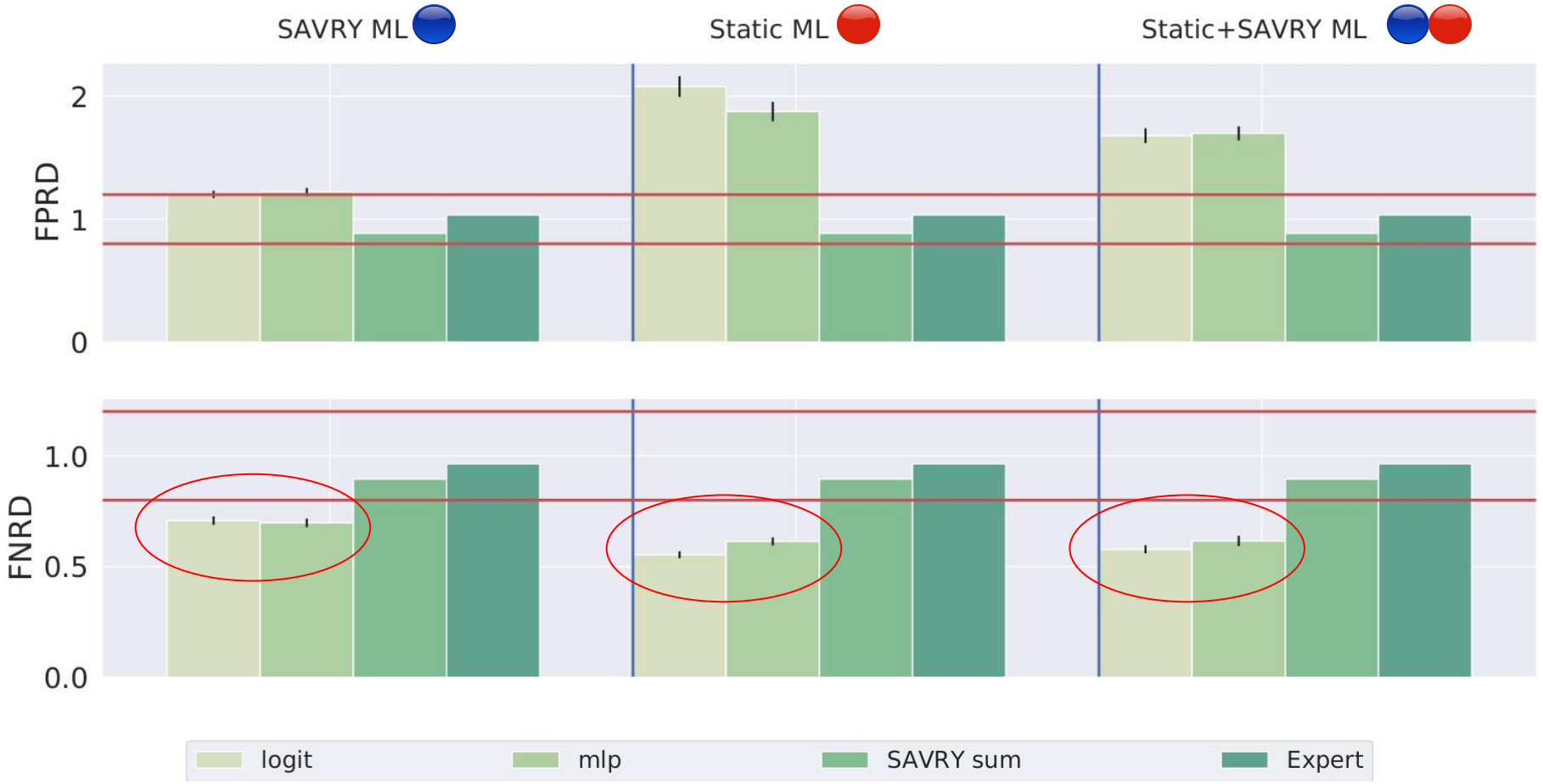

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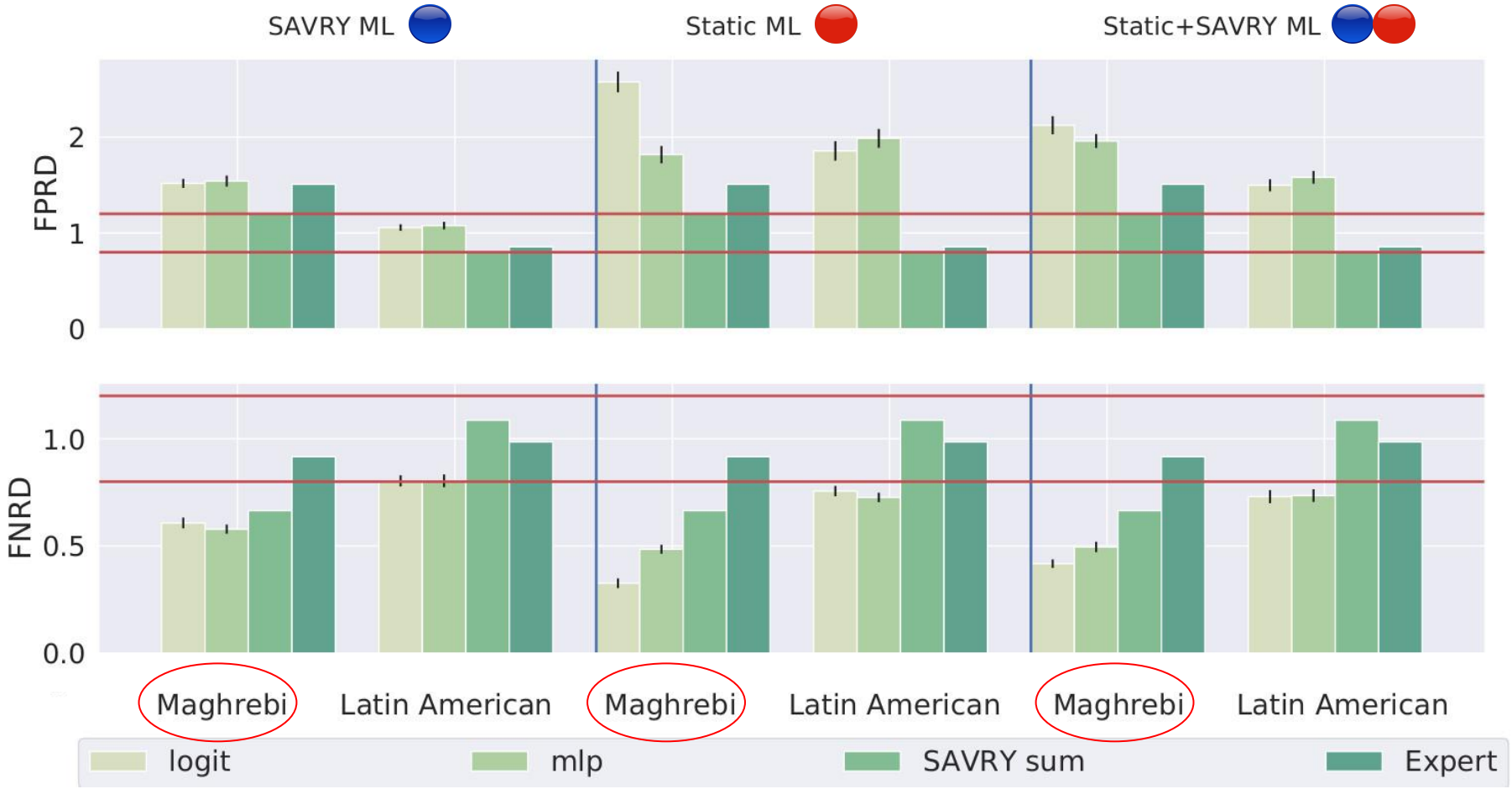

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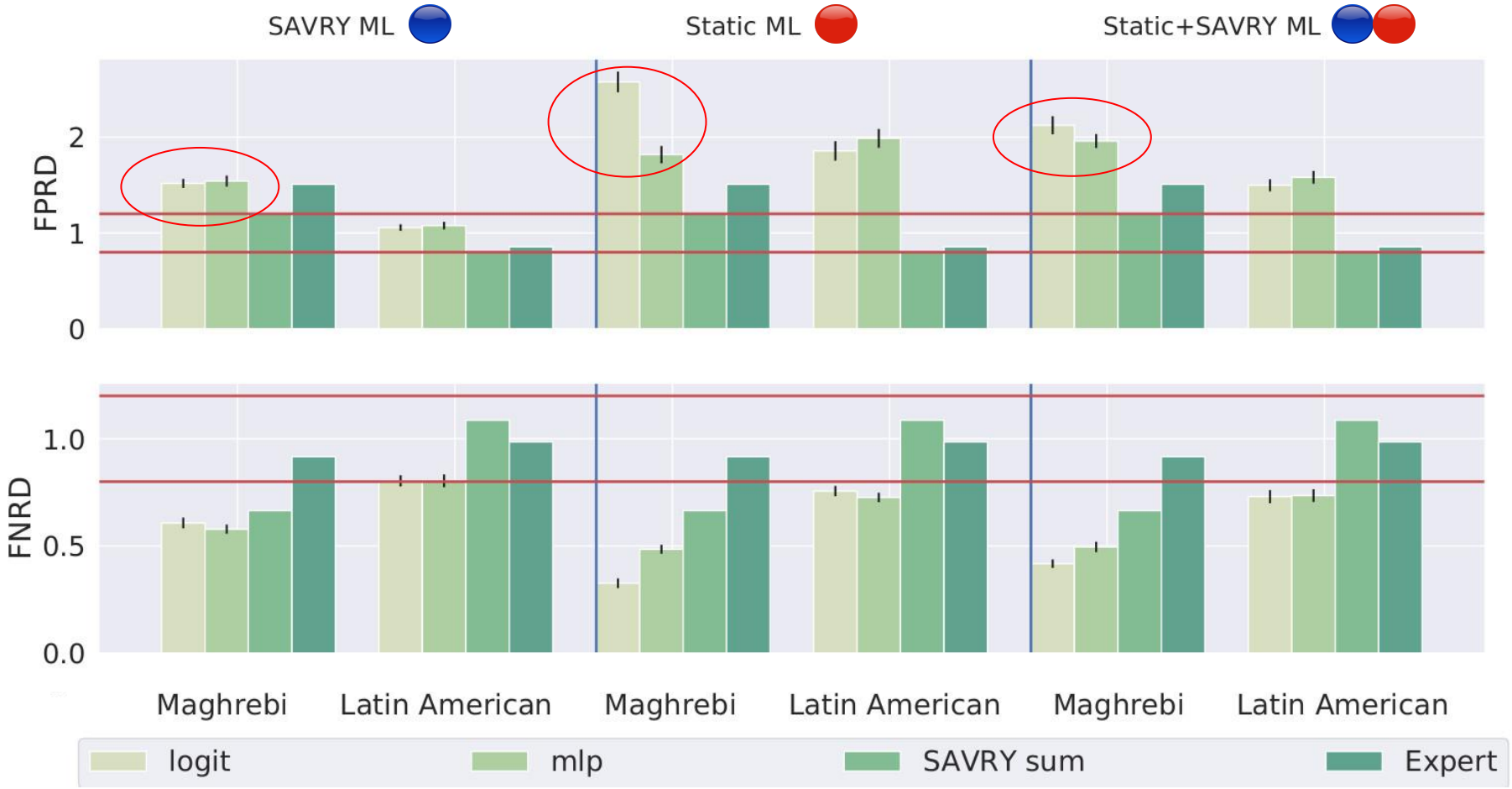

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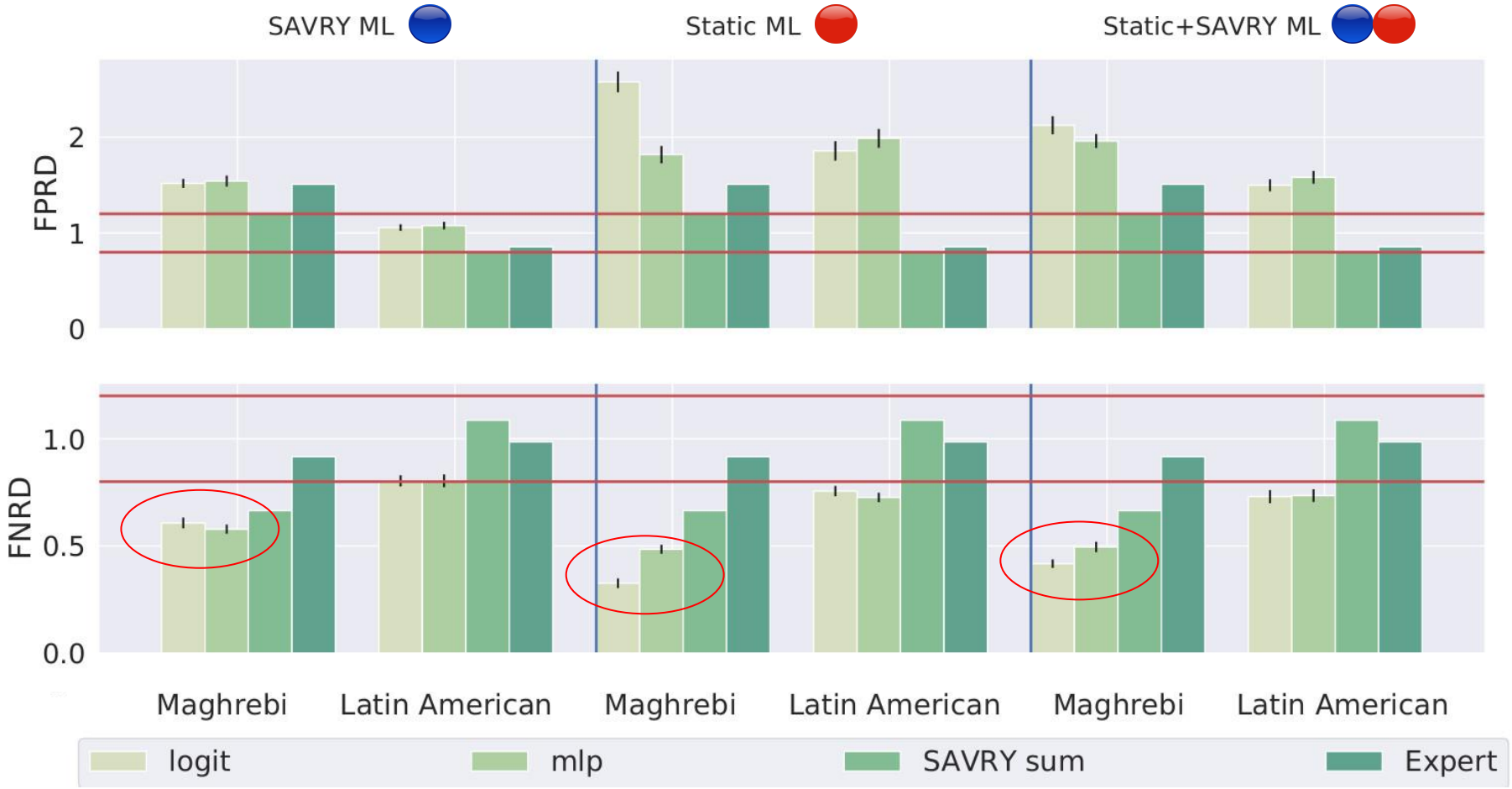

Results: feature importance for logit

SAVRY ML			Static			Static+SAVRY		
final expert evaluation	0.370***	(0.076)	✓crime in 07-08	-0.298**	(0.118)	✓crime in years 07-08	-0.272**	(0.133)
SAVRY sum	0.183	(0.910)	✓crime in year 09	-0.259**	(0.121)	✓crime in year 09	-0.255*	(0.132)
personality	-1.362	(7.061)	✓age maincrime	-0.109***	(0.021)	✓days to program start (norm)	-0.117***	(0.044)
treatment susceptibility	-1.340	(6.336)	✓days to program start (norm)	-0.105***	(0.040)	✓age maincrime	-0.115***	(0.022)
total score (social)	-0.141	(0.909)	✓crime in year 10	-0.275***	(0.098)	final expert evaluation	0.291***	(0.091)
total score (protective)	0.191	(0.902)	✓days in program (norm)	-0.087*	(0.048)	✓crime in year 10	-0.256**	(0.115)
previous violent offenses	-0.601	(2.533)	✓prog: enforcement measure	-0.248**	(0.103)	✓female	-0.196***	(0.053)
total score (historic)	0.056	(0.045)	✓prior crimes frequency	0.059*	(0.033)	✓enforcement measure	-0.206*	(0.122)
home violence	-0.543	(1.816)	✓female	-0.187***	(0.046)	✓Maghrebi	0.152**	(0.069)
past intervention failures	-0.598	(2.530)	✓Maghrebi	0.158***	(0.058)	✓Latin American	0.135**	(0.060)
			✓Latin American	0.105**	(0.052)			
			✓prog: mediation/reparation	-0.178*	(0.103)			

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Results: feature importance for mlp

SAVRY ML		Static ML		Static+SAVRY ML			
feature	importance	feature	importance	feature	importance		
	Mean	StdDev		Mean	StdDev		Mean	StdDev
probation/internment	147.43	24.85	✓province of residence	219.21	28.44	✓foreigner	199.80	11.37
total score (social)	117.93	9.71	✓age maincrime	202.83	25.72	✓sex	188.07	8.35
total score (personality)	117.63	9.83	✓foreigner	178.38	19.06	✓national group	117.40	23.09
total score (protective)	115.76	8.56	✓year of maincrime	168.96	13.86	✓maincrime category	150.90	16.44
total score (historic)	116.59	10.25	✓prior crimes	175.11	22.56	✓prior crimes frequency	151.53	18.26
history non-violent offending	112.17	7.44	✓national group	181.68	32.23	✓maincrime program sentence	143.29	10.50
positive/resilience characteristics	111.62	7.32	✓prior crimes frequency	156.15	20.98	✓year of maincrime	141.88	9
previous violence	113.22	8.93	✓maincrime category	144.27	18.26	✓maincrime violent	148.92	16.23
early violence	111.42	7.17	✓maincrime violent	137.20	14.95	✓province of execution	146.07	13.76
pro-social activities	109.82	5.57	✓prior crimes	131.53	12.66	✓prior crimes	146.97	14.71

Results: difference in base rates (prevalence)

	Base rate	Not Recidivated	Recidivated	Difference
protected features				
male	40.03%	0.839	0.931	0.093***
female	20.37%	0.161	0.069	-0.093***
Spanish	32.06%	0.667	0.523	-0.143***
foreign	46.22%	0.333	0.477	0.143**

Descriptive statistics of input features by recidivism status.

Results: difference in base rates

	Base rate	Not Recidivated	Recidivated	Difference
protected features				
male	40.03%	0.839	0.931	0.093***
female	20.37%	0.161	0.069	-0.093***
Spanish	32.06%	0.667	0.523	-0.143***
foreign	46.22%	0.333	0.477	0.143**

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Descriptive statistics of input features by recidivism status.

Conclusions

- ML models have better predictive performance
- ML models tend to discriminate more
- static features outweigh SAVRY features as importance
- preliminary study: the cause may be in the data (base rates)

Contributions

We propose a methodology and a ML framework[1]

- to easily train ML models on tabular data (csv files)
- to evaluate these models in terms of predictive performance and fairness
- to connect to interpretability frameworks
- to reproduce with ease results and research

1. Open framework: https://gitlab.com/HUMAINT/humaint-fatml

Thank you!

Any questions?

You can find me at @nkundiushuti & marius.miron@ec.europa.eu & mariusmiron.com

European Commission