

Achieving Group Fairness through Independence in Predictive Process Monitoring

Jari Peepkorn & Simon De Vos

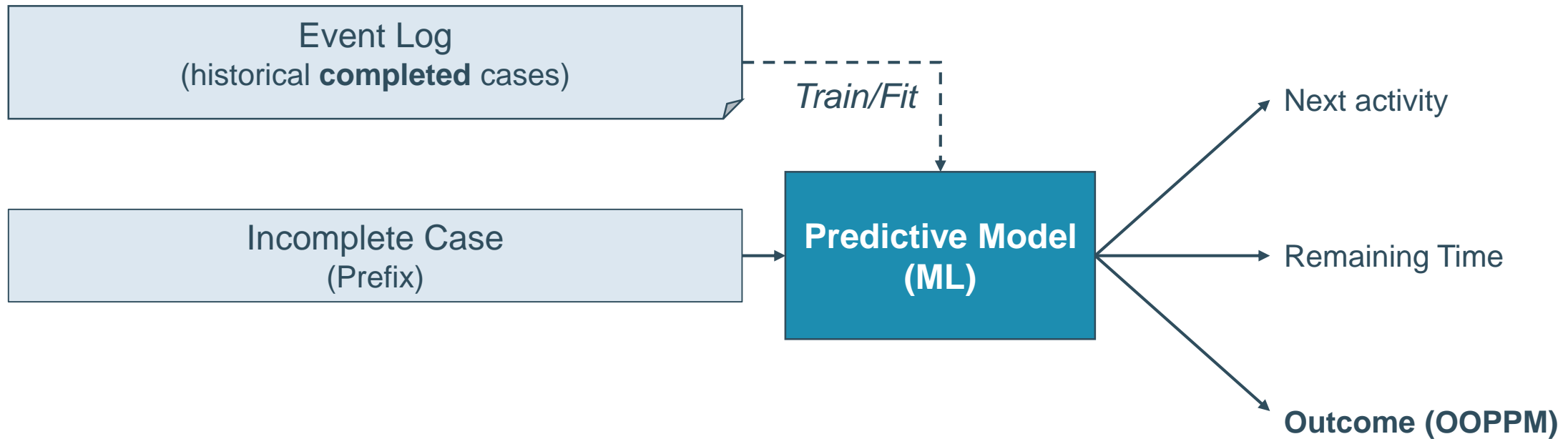
KU Leuven, LIRIS research group

CAiSE - 2025

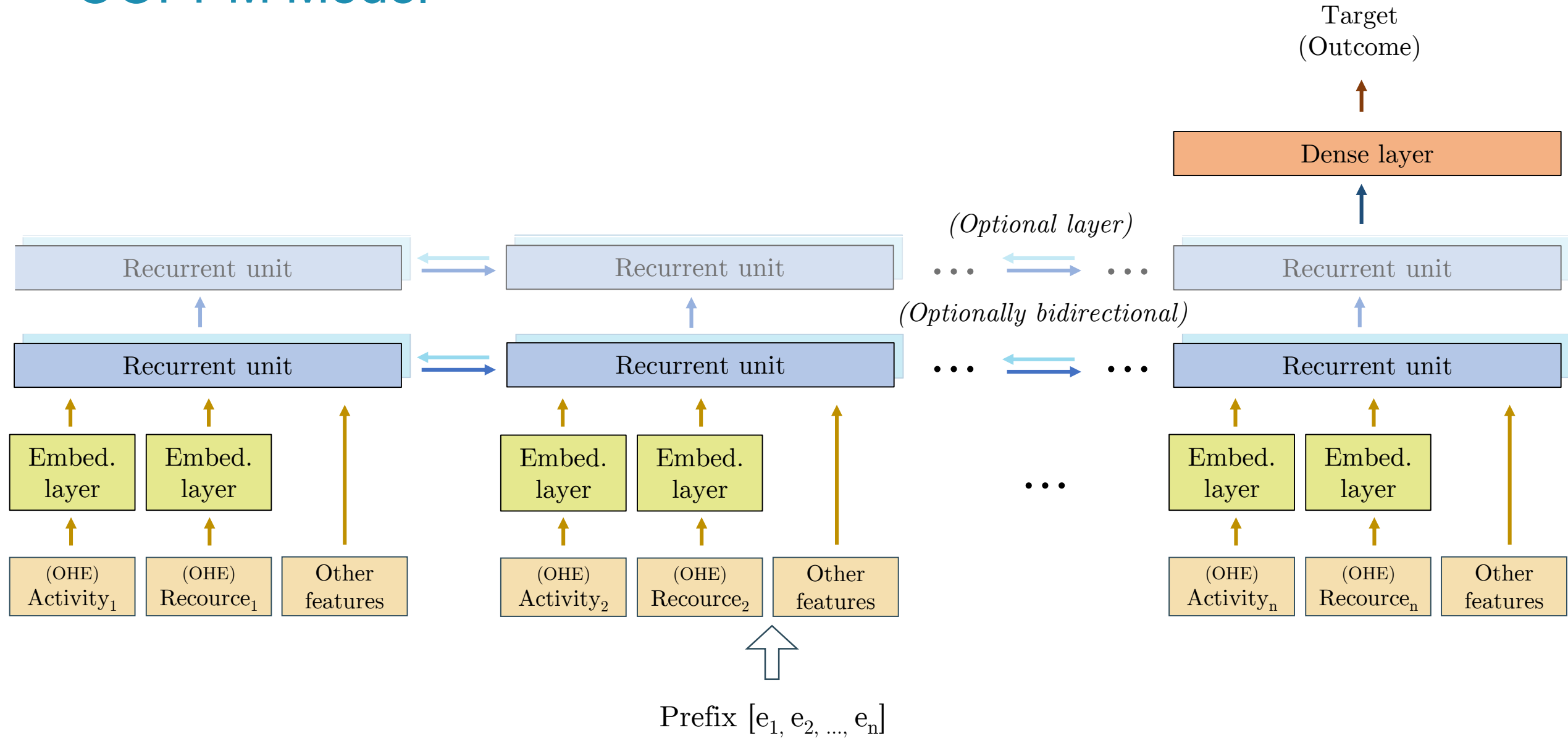


Predictive Process Monitoring

- Predicting future elements of ongoing cases

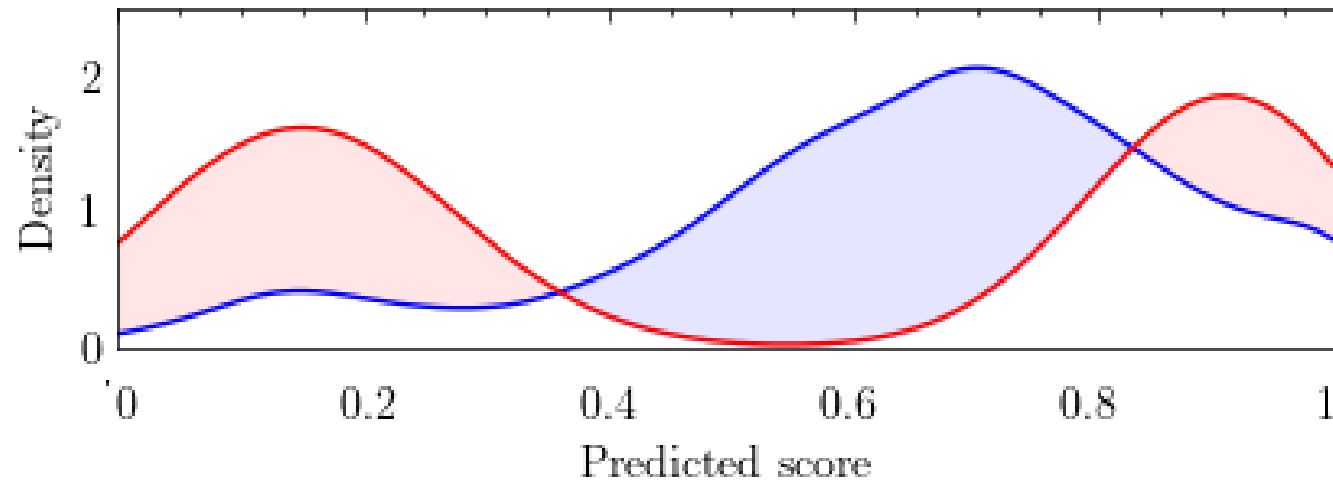


OOPPM Model



Output density plots

- An OOPPM model takes a prefix and outputs a value $[0, 1]$
→ Propensity $P(\hat{Y})$
- Take propensities of all prefixes → plot a density plot
→ Used to globally compare results on different groups



Fairness in Predictive Analytics (in general)

- Group fairness or individual fairness
 - We do train models for individual predictions
- Independence, Separation, Sufficiency
 - Equal predictive outcomes across protected groups
- Protected feature s : gender, ethnicity, religion, ...

$$P(\hat{Y} | s = 0) = P(\hat{Y} | s = 1)$$

- Fairness through unawareness?
- Important due to
 - Ethical reasons
 - Legal reasons

Fairness in Predictive Process Monitoring

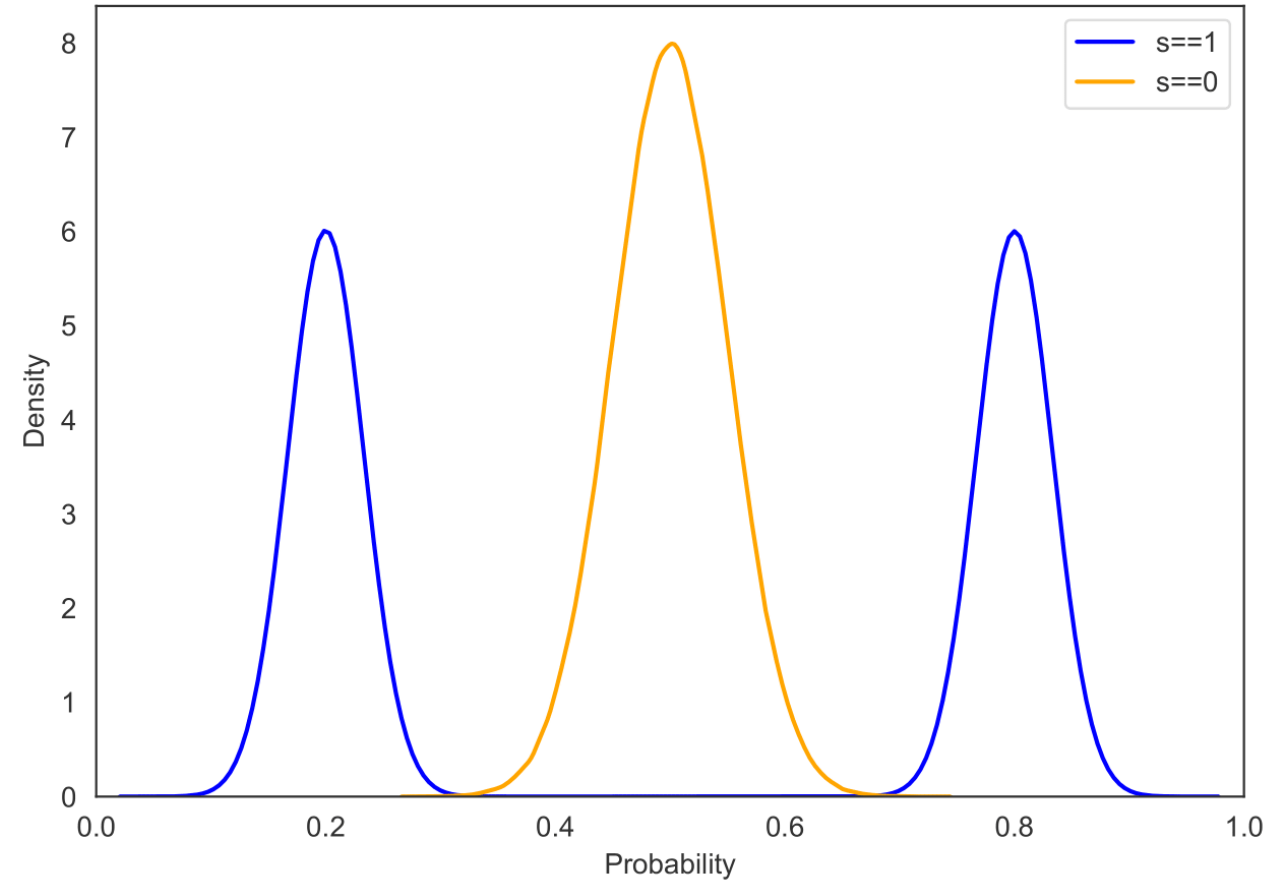
- A process might have been executed *unfairly*
 - A predictive model would reflect this
- If we use these early predictions for interventions
 - Enforce unfair behavior
- For example: a hiring process
 - The model would be trained on historically biased data
 - PPM would be used for early intervention → remove candidates before doing all screening
 - The historical bias could be reflected in the PPM algorithm
- This work focuses on
 - Outcome prediction (binary)
 - Independence
 - Possible trade-off with predictive performance

Demographic Parity

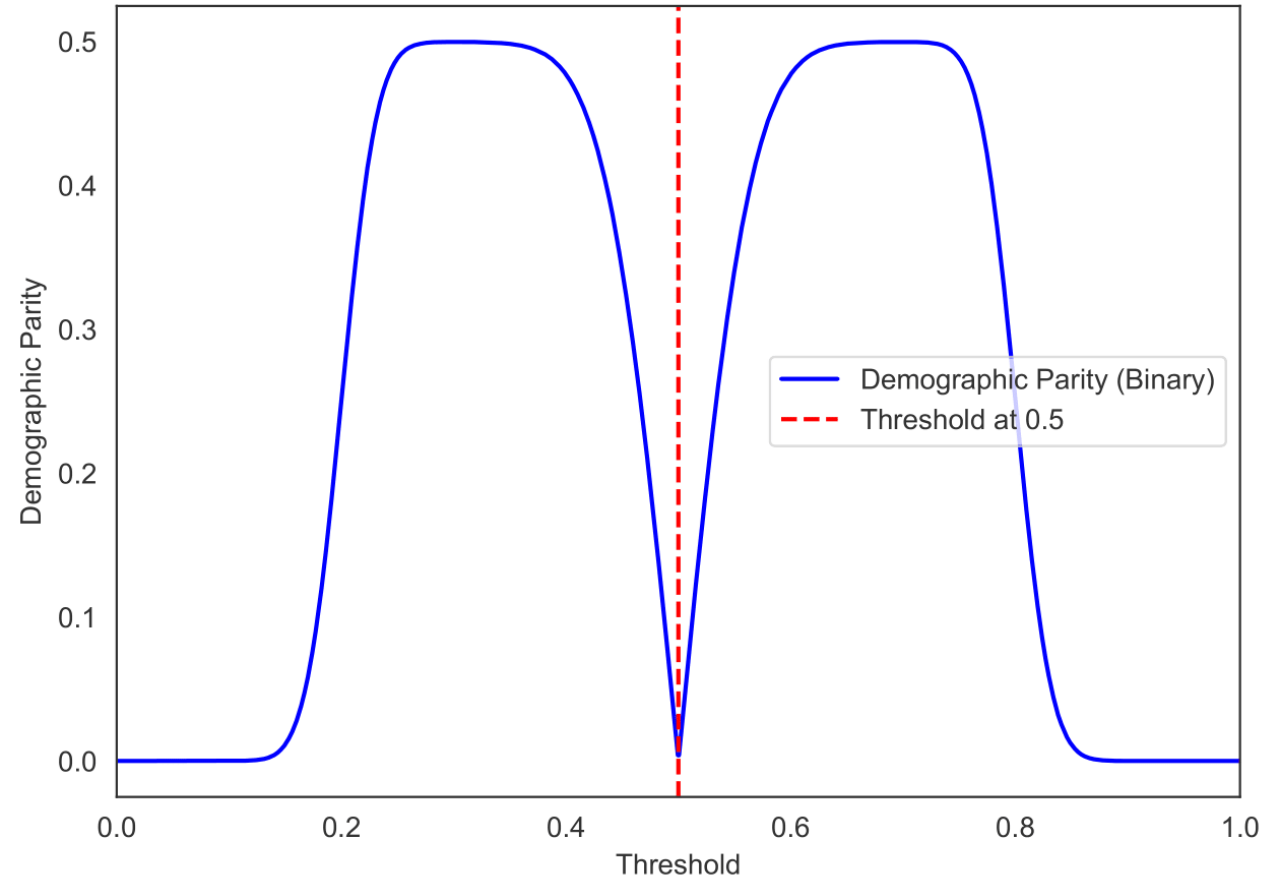
- Independence on group-level (here 2 groups)
- Most common metric in classification $\rightarrow \Delta DP$
 - Continuous version ΔDP_c
 \rightarrow Difference between average model output propensity
 - Binary version ΔDP_b^t
 \rightarrow Difference between fraction of samples classified as positive (> threshold t)

Limitations ΔDP

Probability Distribution of $s = 0$ and $s = 1$.



Demographic Parity (binary) for different threshold values



$$\Delta DP_C = 0$$

Distribution-based Metrics

- Take the whole distribution into account
 - Based on work by Han et al. (2023)

Xiaotian Han, Zhimeng Jiang, Hongye Jin, Zirui Liu, Na Zou, Qifan Wang, Xia Hu, “Retiring ΔDP : New Distribution-Level Metrics for Demographic Parity”, *Transactions on Machine Learning Research* (2023)

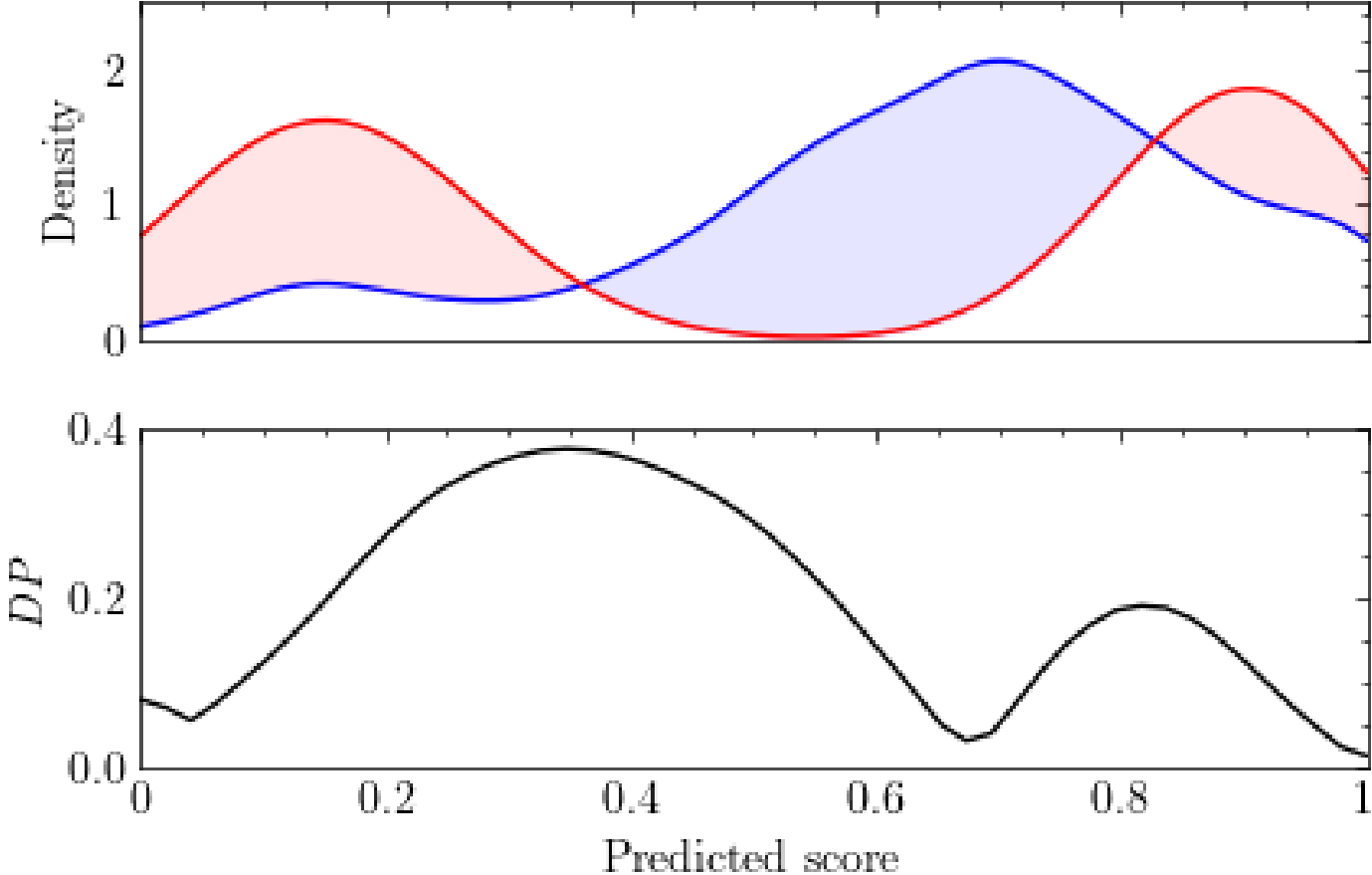
- Area between probability (propensity) density function curves (ABPC)

$$\text{ABPC} = \int_0^1 |f_0(x) - f_1(x)| dx$$

- Area between cumulative density function curves (ABCC)

$$\text{ABCC} = \int_0^1 |F_0(x) - F_1(x)| dx$$

Distribution-based Metrics



ABPC

Decision-centric fairness: Evaluation and optimization for resource allocation problems
Simon De Vos, Jente Van Belle, Andres Algaba, Wouter Verbeke, Sam Verboven

Integral Probability Metric Loss

- Incorporating independence into the learning process

- Composite loss function

Trade-off

$$\mathcal{L}_{\text{total}} = (1 - \lambda) \cdot \mathcal{L}_{\text{BCE}} + \lambda \cdot \mathcal{L}_{\text{IPM}}$$

1. Binary Cross Entropy
2. Integral Probability Metric Loss
 - Used to balance output densities of the groups (on that batch)
 - Wasserstein distance (Earth Mover's Distance)
(Sinkhorn approximation)

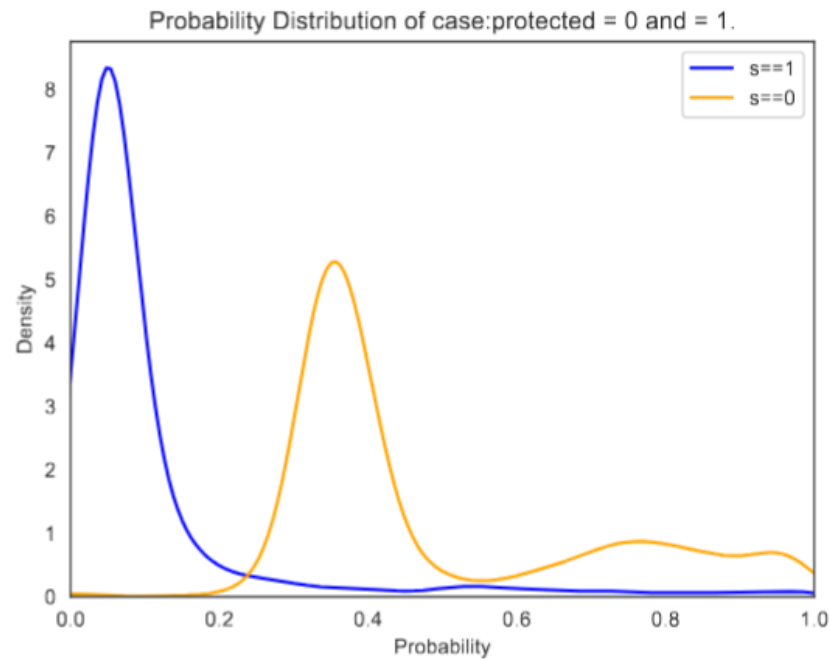
Experimental Setup

- We use (artificial) event logs used in fair process mining research
 - Pohl, T., Berti, A., Qafari, M.S., van der Aalst, W.M.P.: A collection of simulated event logs for fairness assessment in process mining (2023).
 - Three distinct processes (+ outcome definitions)
 - Each process: three distinct event logs = different levels of demographic imparity (*low – medium - high*)
 - Different sensitive features (gender, religion, ...)
 - Also combined into one feature *protected*
- Experiment 1: demonstrate the metrics by evaluating models trained with (regular) BCE loss
- Experiment 2: evaluate the performance-fairness trade-off of the composite loss function

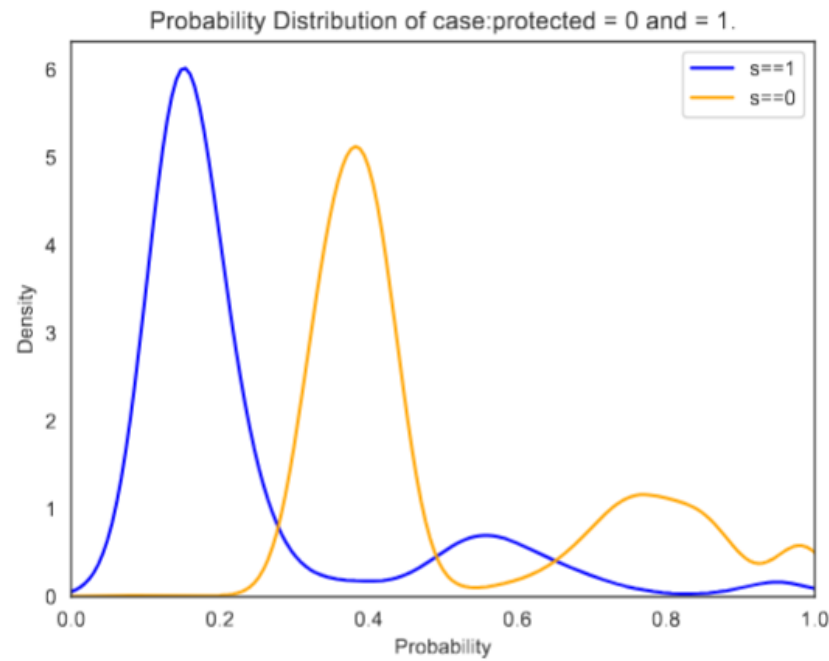
Experiment 1: Assessing Fairness Metrics

- Demographic disparity in the data reflected in predictive models
- Binary ΔDP_b^t less sensitive to pick this up → difference with other metrics

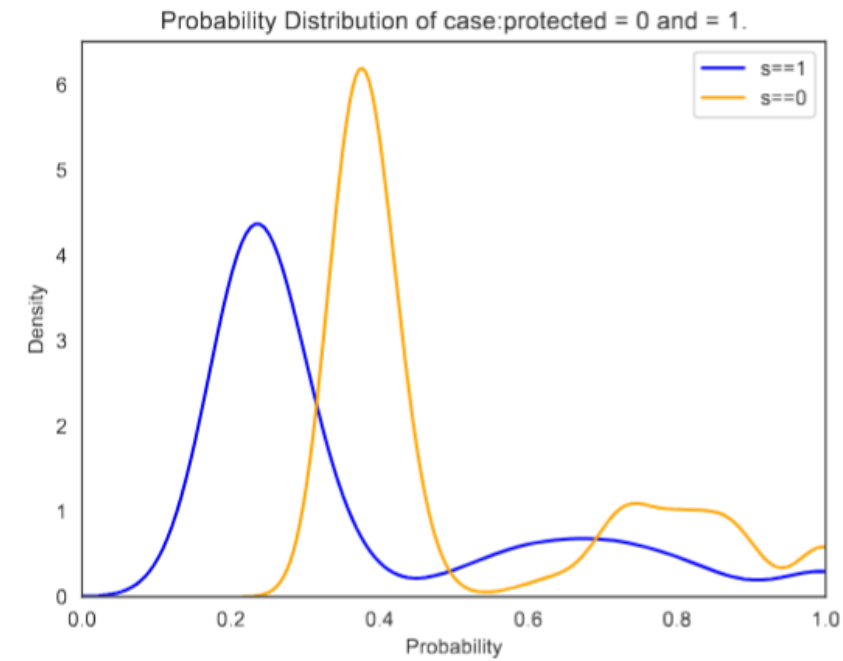
Sensitive feature: “protected”



(a) hiring_high



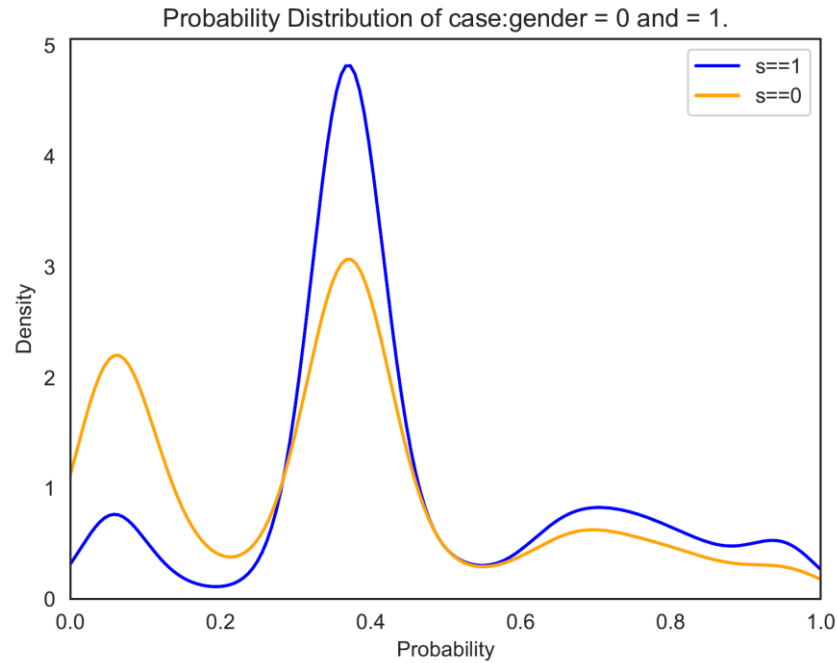
(b) hiring_medium



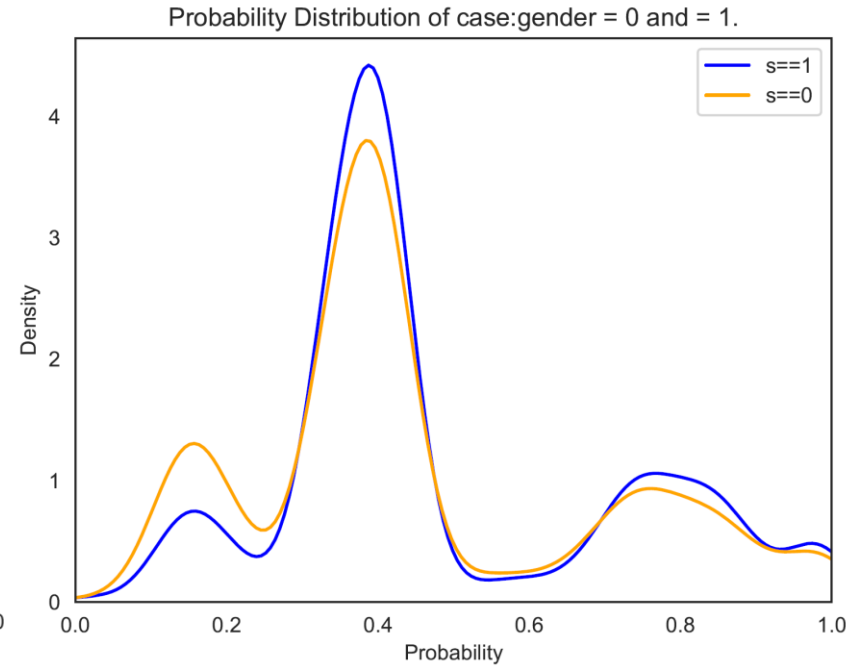
(c) hiring_low

Experiment 1: Assessing Fairness Metrics

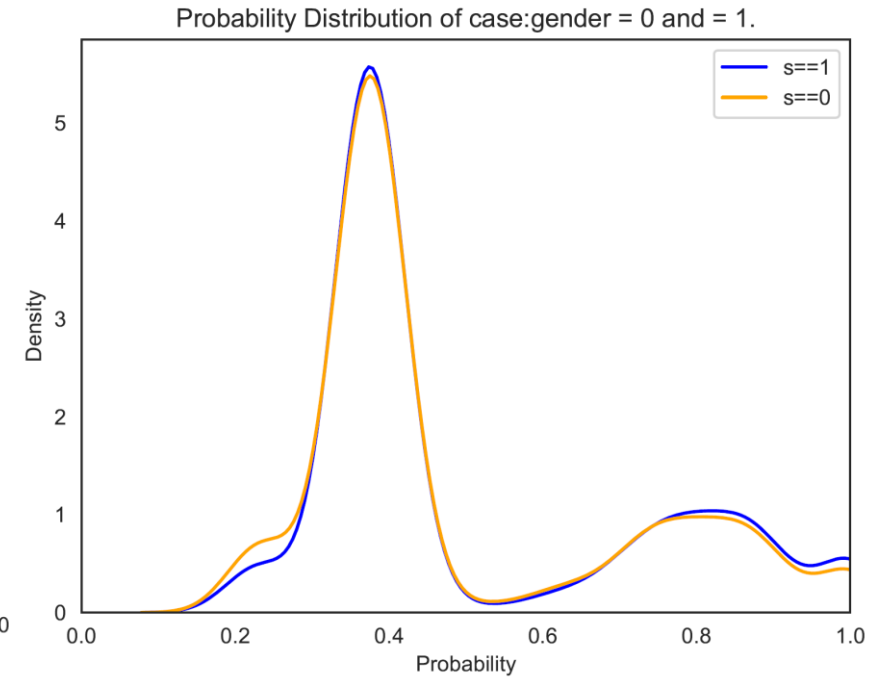
Sensitive feature: "gender"



(a) hiring_high



(b) hiring_medium

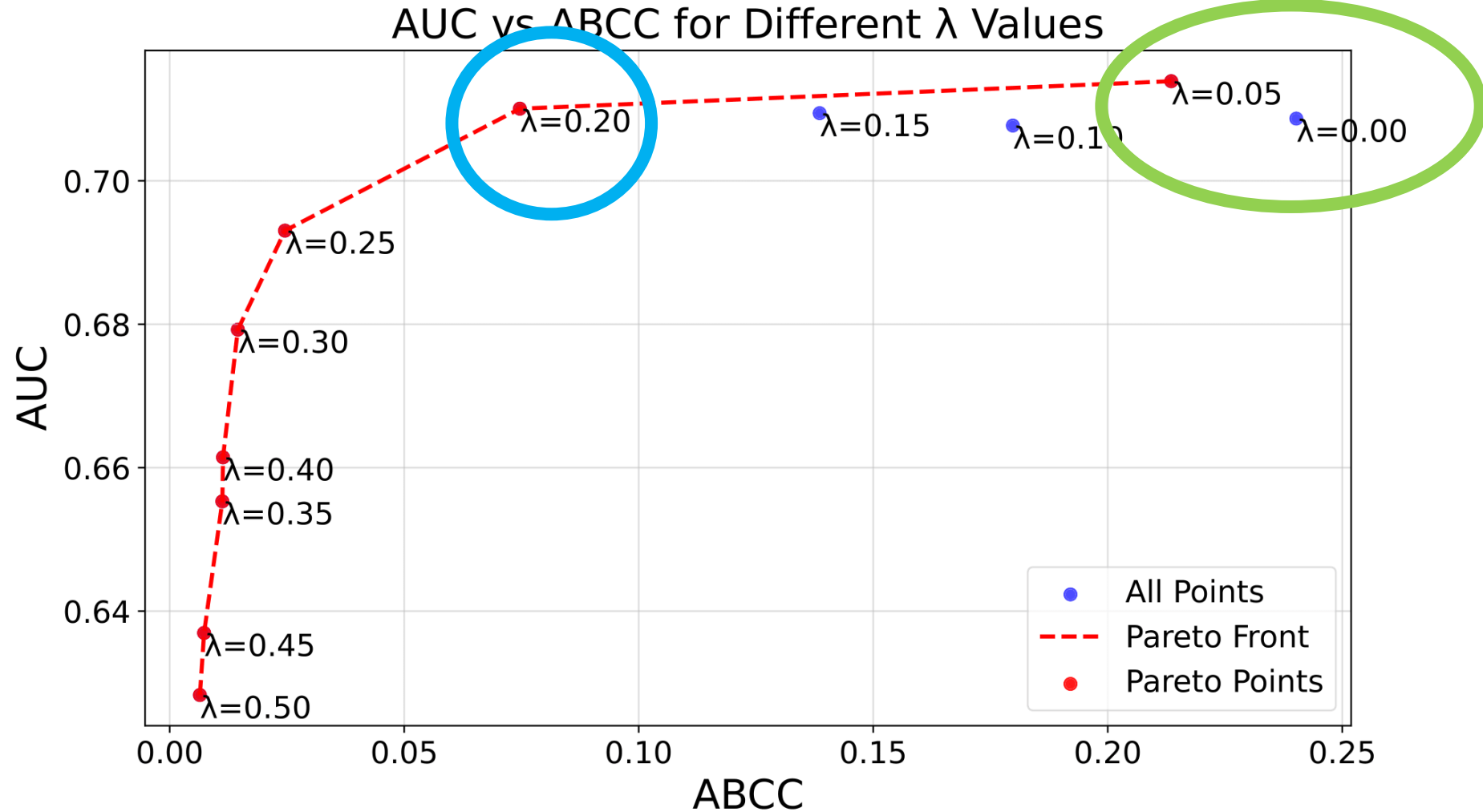


(c) hiring_low

Experiment 2: Testing IPM Loss

$$\mathcal{L}_{\text{total}} = (1 - \lambda) \cdot \mathcal{L}_{\text{BCE}} + \lambda \cdot \mathcal{L}_{\text{IPM}}$$

- Use different values for λ



Considerations

- *Propensity* \neq *probability*
- This does not fix unfair process execution
- Possible conflict with other fairness metrics (*separation*)
- Experiments done on artificial data

Conclusion & Future Work

- Introduced group independence and demographic parity violation in PPM
 - ✓ Robust and flexible density-based metrics
 - ✓ Use of a composite loss function to decrease DP violation
 - Allowing end-users to customize an optimal trade-off
- Future work
 - Other forms of (group) fairness
 - Multiclass tasks (next event prediction)
 - Non-binary sensitive features
 - More explicitly look at decision-making
 - ...

Questions?

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Achieving Group Fairness through Independence in Predictive Process Monitoring

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https://link.springer.com/chapter/10.1007/978-3-031-94569-4_11



Table 1: Information on the event logs [26], sensitive feature is “protected”.

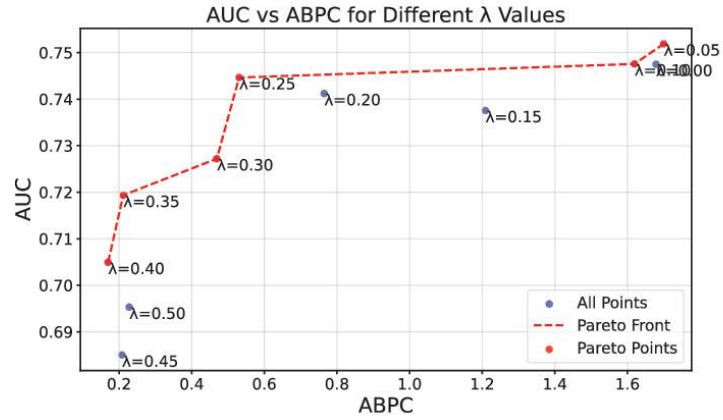
Name	Training (& Validation) Set					Test Set				
	#Pref.	%+	% \mathcal{S}_1	% \mathcal{S}_0^+	% \mathcal{S}_1^+	#Pref.	%+	% \mathcal{S}_1	% \mathcal{S}_0^+	% \mathcal{S}_1^+
hiring_high	40268	41.24	19.94	48.86	10.66	10090	40.58	20.46	48.02	11.68
hiring_medium	43753	46.05	15.71	50.61	21.58	10983	46.04	16.59	50.54	23.44
hiring_low	45633	50.01	9.24	51.44	35.97	11566	50.07	9.43	51.27	38.50
lending_high	36999	24.51	30.44	32.33	6.63	9196	25.13	32.11	33.69	7.04
lending_medium	36582	27.64	21.16	31.51	13.23	9101	28.48	21.02	32.62	12.91
lending_low	37994	30.52	9.78	31.73	19.35	9480	30.75	9.48	31.33	25.25
renting_high	40516	28.91	25.67	34.49	12.78	10132	30.72	26.32	36.33	15.04
renting_medium	42089	42.21	9.68	43.56	29.66	10533	41.37	10.29	43.17	25.65
renting_low	41723	34.87	18.06	37.91	21.08	10413	34.50	18.79	37.54	21.41

Table 2. Results Exp. 1, sensitive feature is *protected* (no removal).

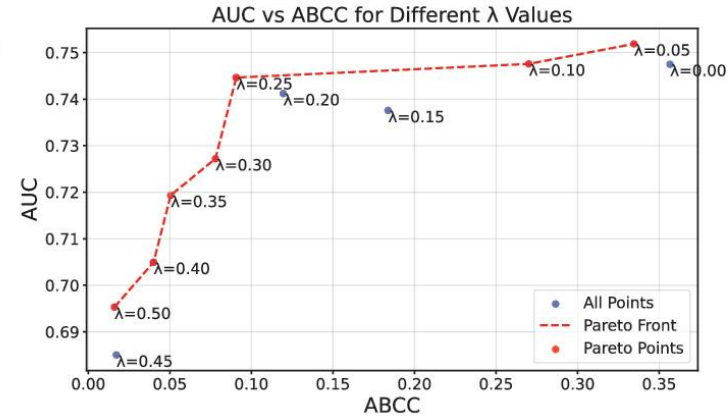
Log	AUC	F1 _{0.5}	F1 _{Opt.}	Acc. _{0.5}	Acc. _{Opt.}	$\Delta DP_b^{0.5}$	$\Delta DP_b^{\text{opt.}}$	ΔDP_c	ABPC	ABCC
hiring_high	0.75	0.56	0.64	0.71	0.57	0.25	0.90	0.38	1.71	0.38
hiring_medium	0.72	0.58	0.66	0.69	0.55	0.17	0.80	0.27	1.66	0.27
hiring_low	0.70	0.59	0.67	0.67	0.53	0.05	0.69	0.14	1.30	0.14
lending_high	0.71	0.00	0.53	0.75	0.60	0.00	0.89	0.24	1.85	0.24
lending_medium	0.65	0.00	0.52	0.72	0.53	0.00	0.89	0.18	1.81	0.18
lending_low	0.59	0.07	0.51	0.68	0.43	0.02	0.22	0.11	1.02	0.11
renting_high	0.65	0.12	0.53	0.69	0.55	0.06	0.81	0.22	1.70	0.22
renting_medium	0.61	0.28	0.61	0.59	0.52	0.17	0.42	0.13	1.51	0.13
renting_low	0.63	0.00	0.55	0.65	0.53	0.00	0.86	0.13	1.66	0.13

Table 3: Results Exp. 1, sensitive feature is *protected* (with removal).

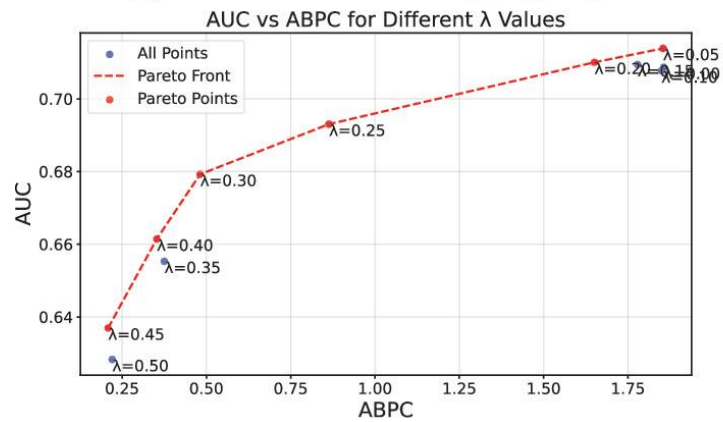
Log	AUC	F1 _{0.5}	F1 _{Opt.}	Acc. _{0.5}	Acc. _{Opt.}	$\Delta DP_b^{0.5}$	$\Delta DP_b^{opt.}$	ΔDP_c	ABPC	ABCC
hiring_high	0.73	0.56	0.62	0.71	0.57	0.23	0.61	0.22	1.11	0.22
hiring_medium	0.71	0.58	0.64	0.69	0.59	0.15	0.40	0.13	0.75	0.13
hiring_low	0.7	0.59	0.67	0.67	0.52	0.07	0.46	0.10	0.87	0.10
lending_high	0.66	0.00	0.46	0.75	0.54	0.00	0.49	0.09	0.99	0.09
lending_medium	0.62	0.00	0.49	0.72	0.49	0.00	0.45	0.04	0.84	0.04
lending_low	0.59	0.08	0.51	0.68	0.42	0.03	0.02	0.07	0.73	0.07
renting_high	0.60	0.02	0.49	0.69	0.43	0.00	0.06	0.03	0.40	0.03
renting_medium	0.61	0.29	0.61	0.59	0.51	0.14	0.25	0.07	0.93	0.07
renting_low	0.61	0.00	0.54	0.65	0.46	0.00	0.07	0.03	0.39	0.03



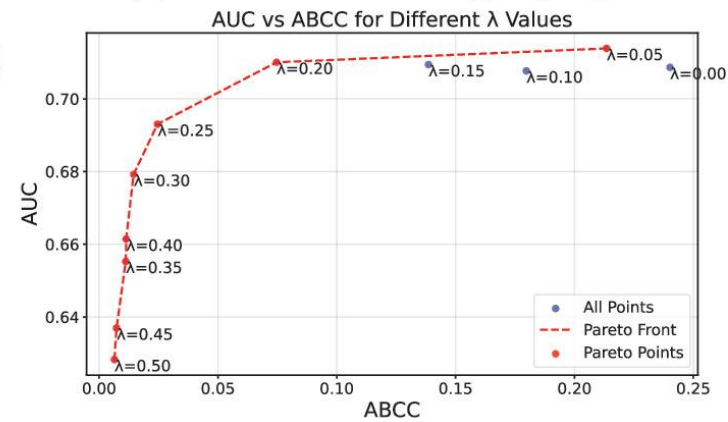
(a) AUC vs ABPC of hiring_high log.



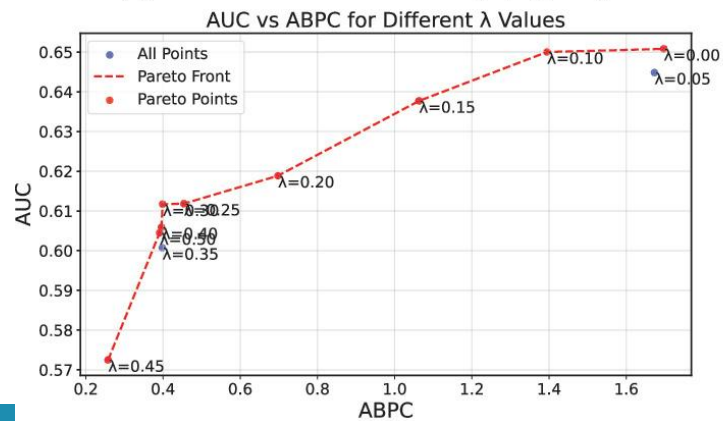
(b) AUC vs ABCC of hiring_high log.



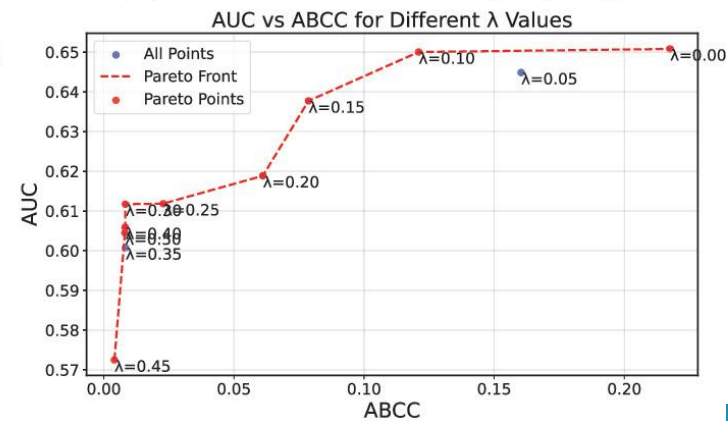
(c) AUC vs ABPC of lending_high log.



(d) AUC vs ABCC of lending_high log.



(e) AUC vs ABPC of renting_high log.



(f) AUC vs ABCC of renting_high log.