

Flexible Group Fairness Metrics for Survival Analysis

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Summary

- ← Biased survival models can lead to discrimination and disadvantage between groups of people in healthcare treatment.
- ← How to detect model bias in survival analysis is unclear.
- We evaluate metrics for model-agnostic bias assessment.
- We show which survival metrics recover biases.

Caring about survival model fairness

- Survival models can infer risk of event (e.g., death) or predict remaining survival time.
 - Decision makers use survival models in healthcare to diagnose patients and set future treatment courses.
- Biased survival models disadvantage individuals, groups of people, or the intersection of multiple groups of people.

Existing Gap

- How to assess bias in survival models is unclear.
 - Existing metrics are limited to evaluating Cox PH models.
- Need for model-agnostic survival fairness metrics.

Which metrics Φ capture group bias?

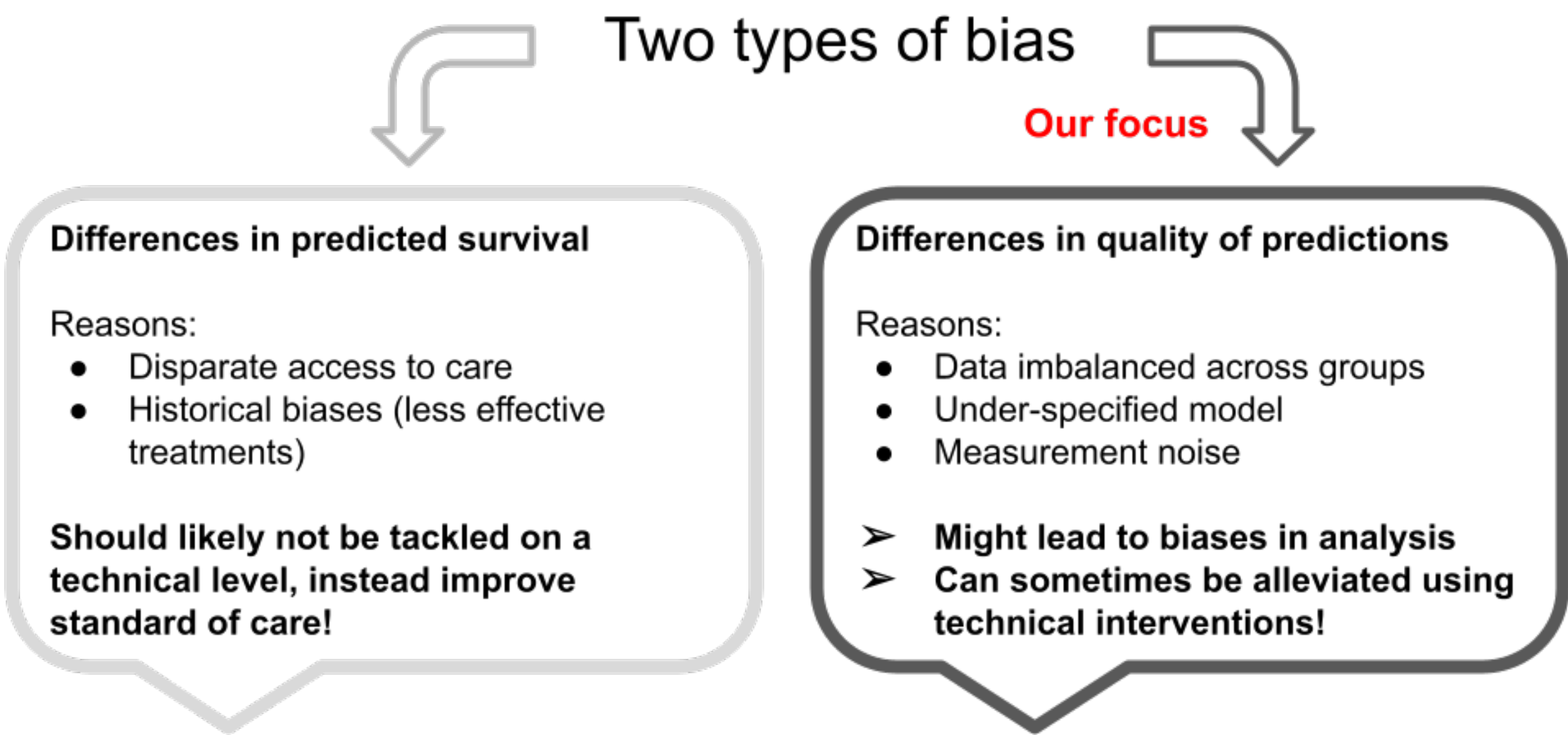
We simulate two sources of bias: (1) **Measurement error** by permuting covariates in a fraction, σ , of the disadvantaged population; and (2) **Representation bias** by undersampling a fraction, σ , of the disadvantaged population. We assess which Φ recover simulated biases over varying σ . Across 29 datasets we fit the regression model $\Delta_\Phi = \alpha + \sigma\beta$ and calculate the Spearman rank correlation $\rho(\Delta_\Phi, \sigma)$. We say Φ recovers bias if β and ρ are significant ($p \leq 0.05$) after Holm’s correction.

Φ	α	β	ρ	α	β	ρ
	Permutation			Undersampling		
RSBS	0.049	0.078*	0.976*	0.035	0.066*	0.855*
RISL	0.045	0.063*	0.976*	0.033	0.058*	0.891*
SNL	0.018	0.001	0.248	0.014	0.083*	1.000*
RCLL	0.018	0.009	0.879*	0.022	0.088*	1.000*
C_H	0.024	0.129*	1.000*	0.017	0.083*	1.000*
C_U	0.031	0.124*	1.000*	0.024	0.078*	0.976*
CalA	0.027	0.011*	0.891*	-0.015	0.197*	0.952*
CalD	2.686	0.487	0.721*	2.861	0.646	0.612

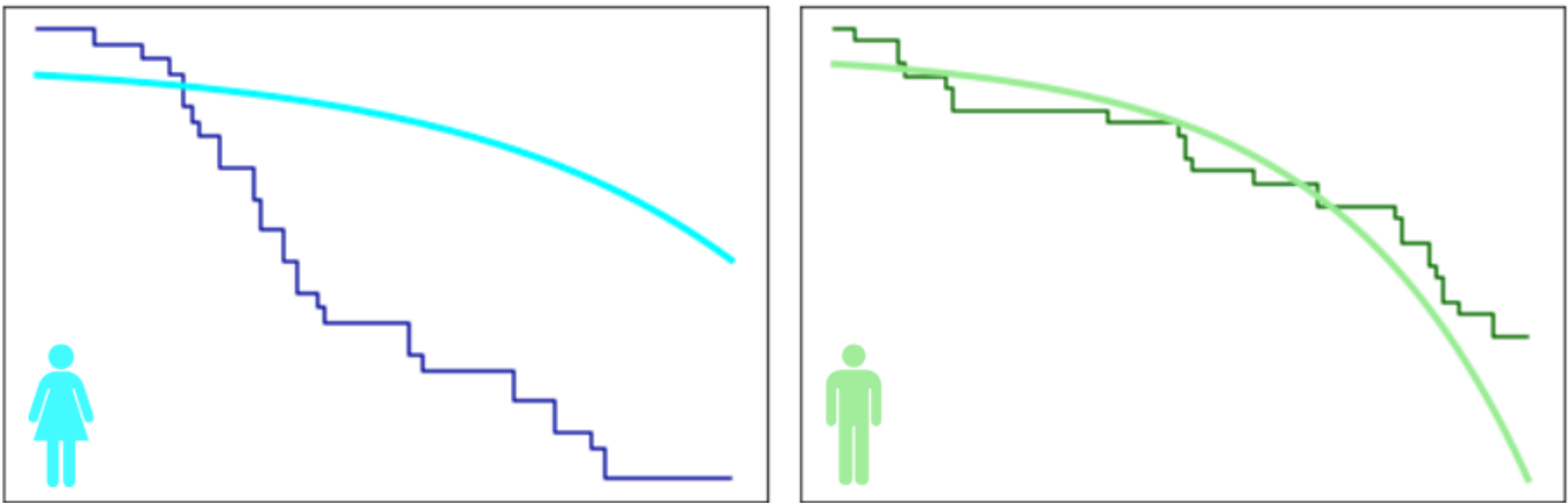
Table: Let $\Delta_\Phi = \alpha + \sigma\beta$ be our regression model. Table shows intercept, α , slope, β , and Spearman rank correlation (ρ) for each Φ and permutation (left) and undersampling (right) biasing methods. ‘*’ indicates $p \leq 0.05$ after Holm’s correction.

What is bias?

Definitions of bias depend on the required application. We focus on biases that describe a *difference in predictability* between groups. Such biases are often overlooked in practice.



Defining model-agnostic survival fairness metrics We define a class of fairness metrics, Δ_Φ , which depends only on the choice of survival metric, Φ . Let $Y_{A=i}$ be the hypothetical survival outcome for patient Y in protected group $A=i$ (e.g., gender=male), let $\hat{Y}_{A=i}$ be the survival prediction for this individual, and let $\Phi(\cdot, \cdot)$ be a survival metric:



$$\Delta_\Phi(Y, \hat{Y}) = \left| \Phi(Y_{A=0}, \hat{Y}_{A=0}) - \Phi(Y_{A=1}, \hat{Y}_{A=1}) \right|$$

Conclusions

- Survival analysis requires strong ethical consideration. But the literature around survival fairness is in its infancy.
- We have demonstrated how existing survival measures can be utilised to audit bias in algorithmic fairness.
- We found existing discrimination, calibration, and scoring rule measures for capturing model-agnostic bias but these depend on bias type and still require expert knowledge.
- Key research areas remaining: (1) understanding individual, intersectional, and counterfactual error-based fairness; (2) metrics for model-agnostic prediction-based fairness; (3) making survival fairness more accessible; (4) understanding how decision makers think about and utilise fairness.

More Information

<https://arxiv.org/abs/2206.03256>

https://github.com/Vollmer-Lab/survival_fairness

