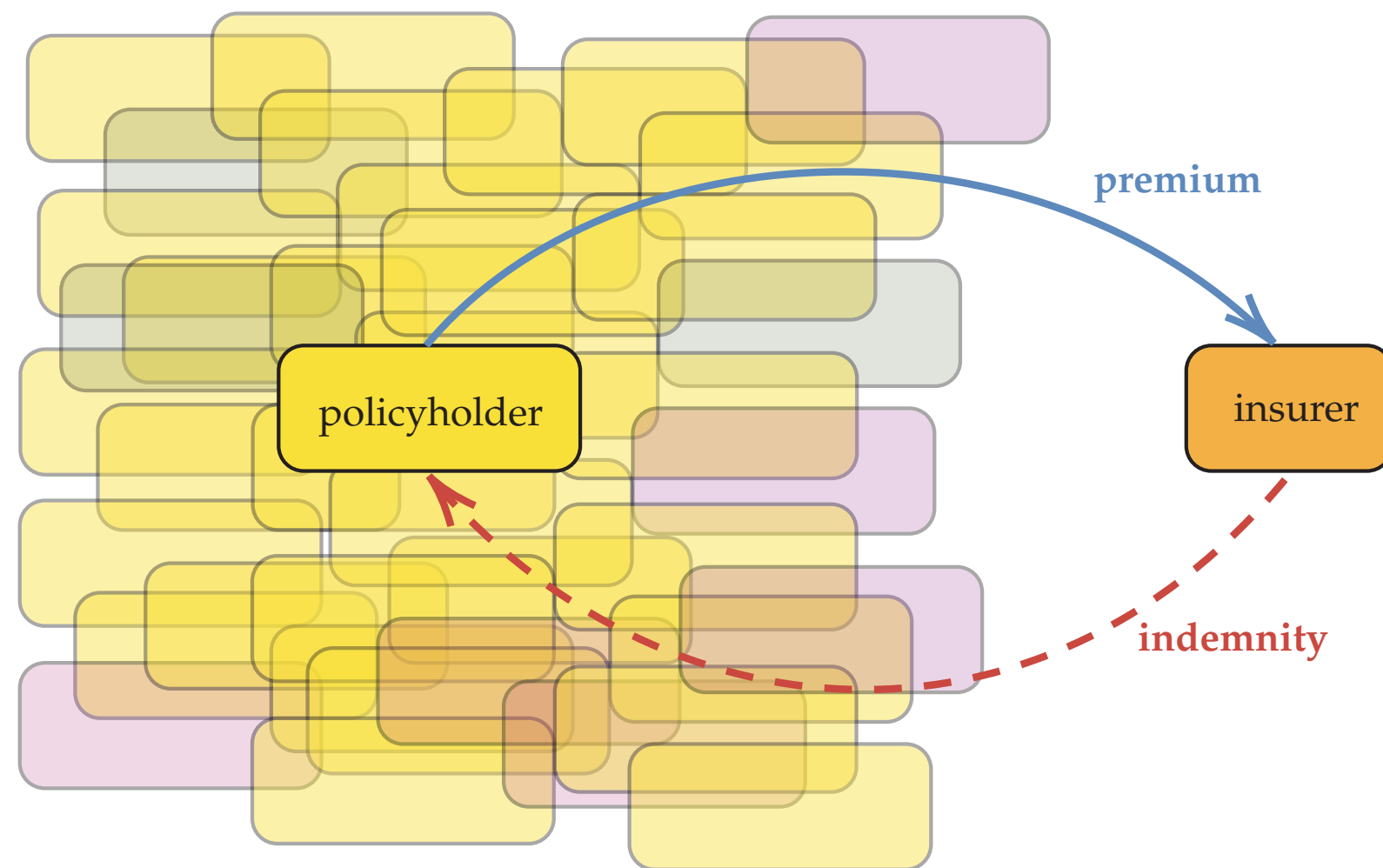




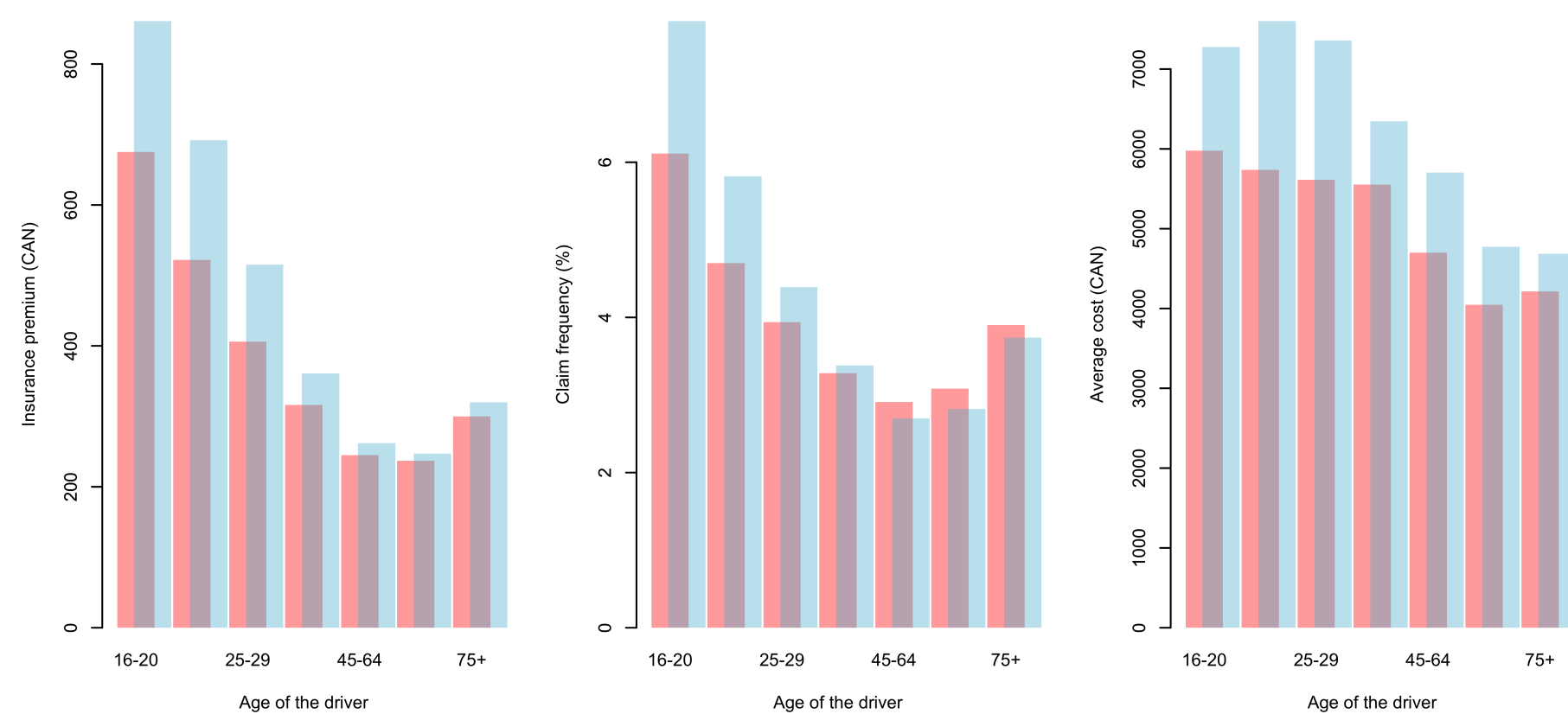
## INTRODUCTION

“Insurance is the contribution of the many to the misfortune of the few”, Bénéplanc et al. (2022). “at the core of insurance business lies discrimination between risky and non-risky insureds”, Avraham (2017), to ask for an **actuarially fair premium**.



By looking into earlier debates on discrimination, we show that some algorithmic biases are a renewed version of older ones, while others show a reversal of the previous order. Paradoxically, while the insurance practice has not deeply changed nor are most of these biases new, the machine learning era still deeply shakes the conception of insurance fairness.

## DISCRIMINATION & INSURANCE



	CA	HI	GA	NC	NY	MA	PA	FL	TX	AL	ON	NB	NL	QC
Gender	x	x	•	x	•	x	x	•	•	•	•	x	x	•
Age	x	x	•	x*	•	x	•	•	•	•*	•	x	x	•
Driving experience	•	x	•	•	•	x	•	•	•	•	•	•	•	•
Credit history	x	x	•	•	•	x	•	•	•	x*	x	•*	x	•
Education	x	x	x	x	x	x	•	•	•	•	•	•	•	•
Profession	x	x	x	•	x	x	•	•	•	•	•	•	•	•
Employment	x	x	x	•	x	x	•	•	•	•	•	•	•	•
Family	•	x	•	•	•	x	•	•	•	•	•	•	•	•
Housing	x	x	•	•	•	x	•	•	•	x	x	•	•	•
Address/ZIP code	•	•	•	•	•	•	•	•	•	x	x	•	•	•

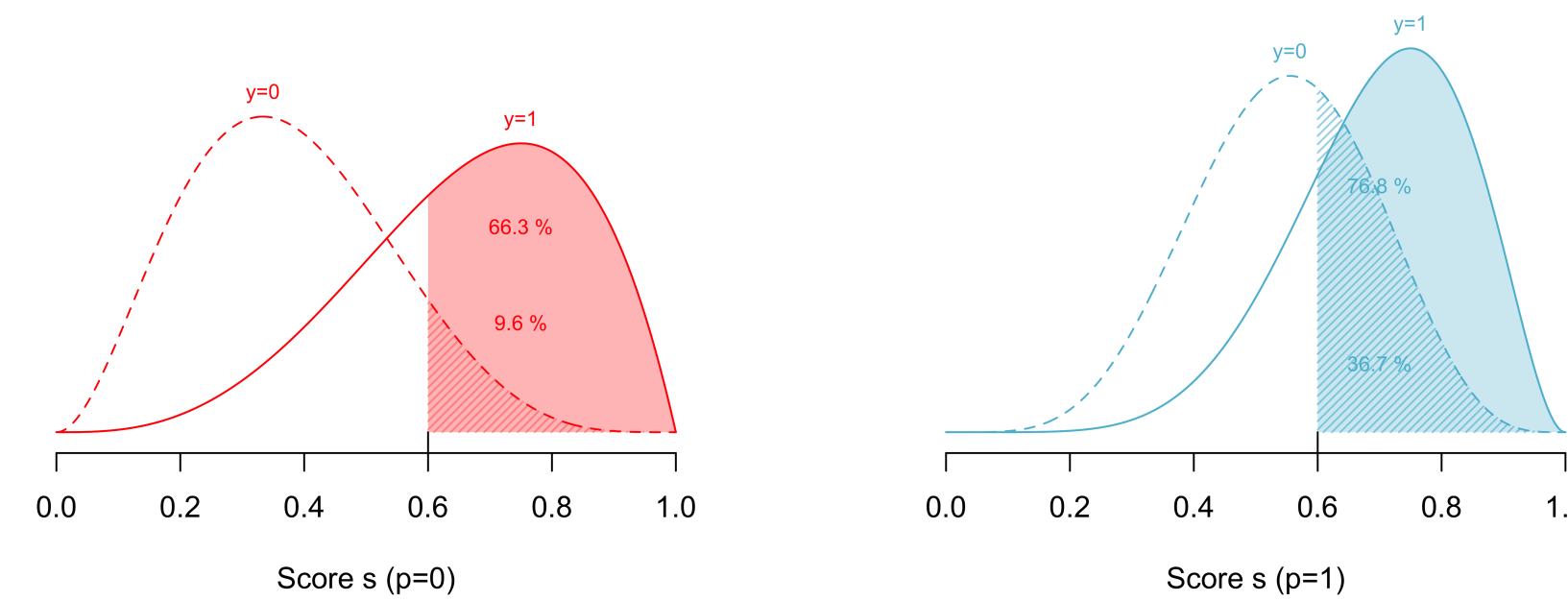
But not much on **proxy based discrimination** (standard in high dimension).

## GROUP FAIRNESS

Classically,  $y$  is the variable of interest, e.g. accident occurrence ( $\{0, 1\}$ ), frequency ( $\mathbb{N}$ ) or annual cost, time before invalidity recovery ( $\mathbb{R}_+$ ), etc),  $\mathbf{x}$  some covariates and  $p$  is a protected (sensitive) attribute (in  $\{0, 1\}$ ). Dwork et al. (2012), Hardt et al. (2016), Corbett-Davies et al. (2017), Berk et al. (2017) introduced various concepts of fairness

- **Demographic parity**,  $\mathbb{P}[\hat{Y} = 1 | P = p] = \text{cst}, \forall p$
- **Equalized odds**,  $\mathbb{P}[\hat{Y} = 1 | P = p, Y = y] = \text{cst}_y, \forall p, y$
- **Equalized opportunity**,  $\mathbb{P}[\hat{Y} = 1 | P = p, Y = 1] = \text{cst}, \forall p$
- **Predictive equality**,  $\mathbb{P}[\hat{Y} = 1 | P = p, Y = 0] = \text{cst}, \forall p$
- **conditional accuracy equality**  $\mathbb{P}[Y = y | P = p, \hat{Y} = y] = \text{cst}_y, \forall p, y$

Those notions are simply related to independence  $\hat{Y} \perp\!\!\!\perp P$ , or conditional independence  $\hat{Y} \perp\!\!\!\perp P | Y$  or  $Y \perp\!\!\!\perp P | \hat{Y}$ . Let  $s$  denote the score function,  $s(\mathbf{x}, p) = \mathbb{P}(Y = 1 | \mathbf{x}, p)$  so that  $\hat{Y} = \mathbf{1}(s > \text{threshold})$ .



Inspired by Goodfellow et al. (2018), to avoid un-fairness, penalize according to  $HGR(\hat{y}, p)$ , e.g.

$$\text{argmin}_{\theta, \omega} \{ \mathcal{L}(h_{\theta}(\mathbf{x}), y) + \lambda HGR_{\omega}(\hat{y}, p) \},$$

where  $HGR(U, V)$  is  $\max \{ \text{corr}[f(U), g(V)] \} = \max_{f \in \mathcal{S}_U, g \in \mathcal{S}_V} \{ \mathbb{E}[f(U)g(V)] \}$  and where  $\mathcal{S}_U = \{ f : U \rightarrow \mathbb{R} : \mathbb{E}[f(U)] = 0 \text{ and } \mathbb{E}[f(U)^2] = 1 \}$  and similarly  $\mathcal{S}_V$ . But a conditional version, can also be considered

$$HGR(U, V | Z) = \max_{f \in \mathcal{S}_U | Z, g \in \mathcal{S}_V | Z} \{ \mathbb{E}[f(U)g(V) | Z] \}.$$

## INDIVIDUAL FAIRNESS

Duivesteijn and Feelders (2008), Kusner et al. (2017)

- **Lipschitz property**,  $D(\hat{y}_i, \hat{y}_j)$  or  $D(s_i, s_j) \leq d(\mathbf{x}_i, \mathbf{x}_j), \forall i, j$
- **Counterfactual fairness**,

$$\mathbb{P}[Y_{P \leftarrow p'}^* = y | \mathbf{X} = \mathbf{x}] = \mathbb{P}[Y_{P \leftarrow p}^* = y | \mathbf{X} = \mathbf{x}], \forall p', \mathbf{x}, y.$$

If the prediction in the real world is the same as the prediction in the counterfactual world where the individual would have belonged to a different demographic group, we have counterfactual equity.

Black et al. (2020), Torous et al. (2021) or de Lara et al. (2021) suggested

- **Transport-based fairness**,  $\mathbb{P}_0[\mathcal{X}_F^-(m, T^*)] = \mathbb{P}_0[\mathcal{X}_F^+(m, T^*)]$

$$\begin{aligned} \mathcal{X}_F^+(m, T^*) &= \{ \mathbf{x} \in \mathcal{X} : m(\mathbf{x}, 0) > m(T^*(\mathbf{x}), 1) \} \\ \mathcal{X}_F^-(m, T^*) &= \{ \mathbf{x} \in \mathcal{X} : m(\mathbf{x}, 0) < m(T^*(\mathbf{x}), 1) \} \end{aligned}$$

where  $\mathbb{P}_0(\cdot) = \mathbb{P}(\cdot | p = 0)$ ,  $\mathbb{P}_1(\cdot) = \mathbb{P}(\cdot | p = 1)$ , and

$$T^* \in \text{argmin}_{T: T_{\#} \mathbb{P}_0 = \mathbb{P}_1} \int_{\mathbb{R}^k} \| \mathbf{x} - T(\mathbf{x}) \|^2 d\mathbb{P}(\mathbf{x}).$$

## TO GO FURTHER

The question we address is

- How to quantify properly price discrimination ?

but then, remaining questions are

- How to identify the source of the discrimination ?
- How to get a ratemaking formula that is “discrimination free” ?

with technical challenges, **continuous protected attribute**, Grari et al. (2022), **non-observed protected attribute**, Grari et al. (2021), Racicot et al. (2021) and connections with **causal-related fairness**, and prevention.

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