

Discrimination-Free Insurance Pricing

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Programme SAV Block Course

- Refresher: Generalized Linear Models (THU 9:00-10:30)
- Feed-Forward Neural Networks (THU 13:00-15:00)
- Discrimination-Free Insurance Pricing (THU 17:15-17:45)
- LocalGLMnet (FRI 9:00-10:30)
- Convolutional Neural Networks (FRI 13:00-14:30)
- Wrap Up (FRI 16:00-16:30)

Contents: Discrimination-Free Insurance Pricing

- Direct discrimination
- Indirect discrimination
- Unawareness price
- Discrimination-free price

- **Direct Discrimination**

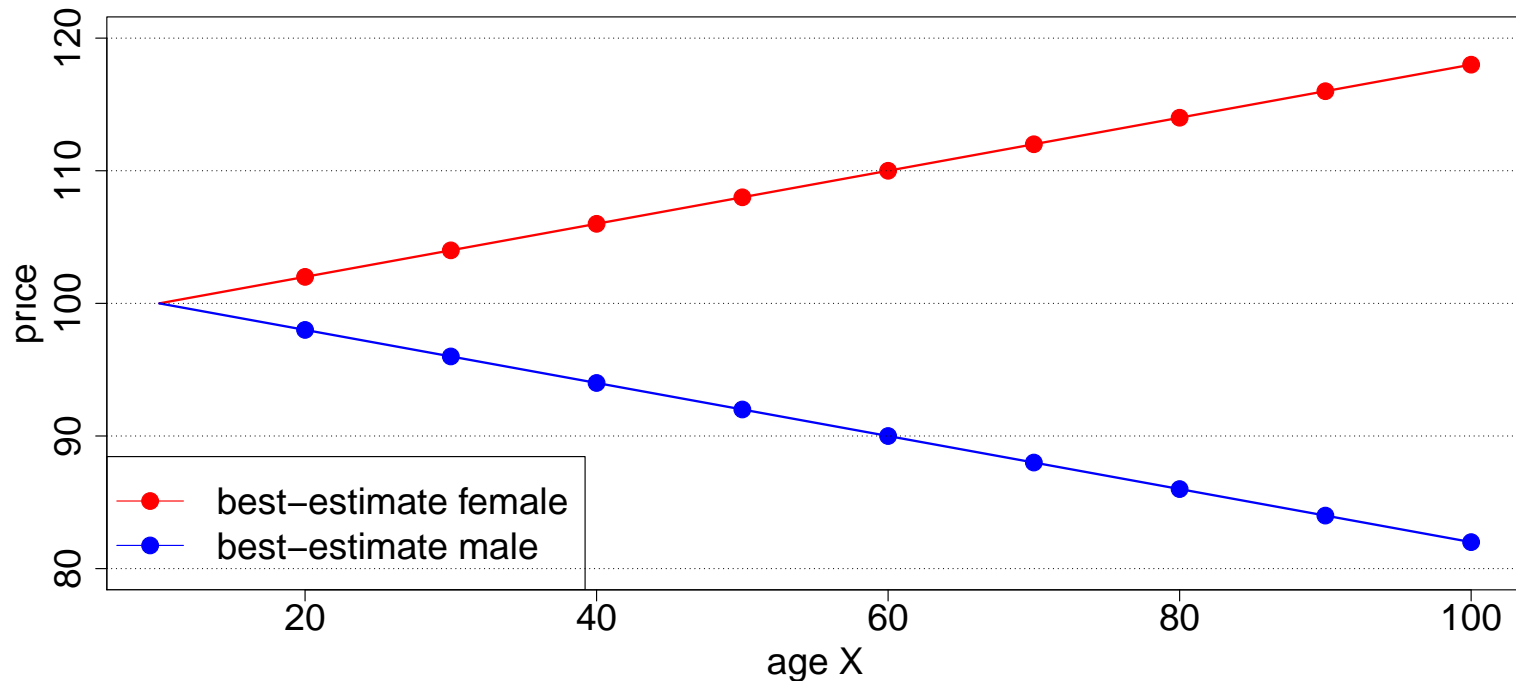
Best-Estimate Pricing

- Basic pricing setup is given by
 - ★ Y denotes the claim costs;
 - ★ X denotes non-discriminatory covariates;
 - ★ D denotes discriminatory covariates.
- Develop regression model for Y using covariates X and D as explanatory variables.
- This motivates best-estimate price for Y

$$\mu(X, D) = \mathbb{E}[Y | X, D].$$

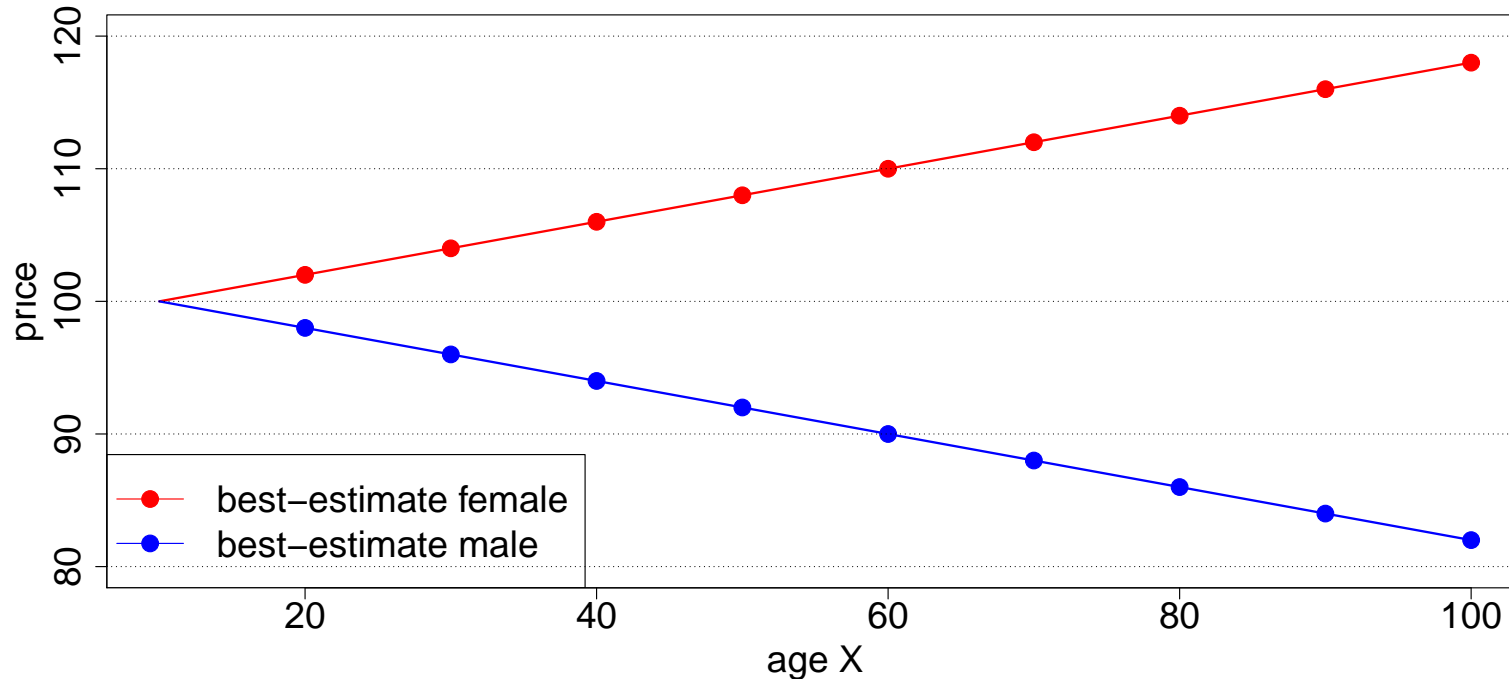
- The best-estimate price
 - ★ uses maximal available information X and D ;
 - ★ minimizes prediction uncertainty (in an L^2 -sense);
 - ★ is discriminatory w.r.t. D .

Best-Estimate Price: Example



- Best-estimate prices $\mu(X, D)$ using all available information
 - ★ with non-discriminatory age information X ;
 - ★ with discriminatory gender information D .

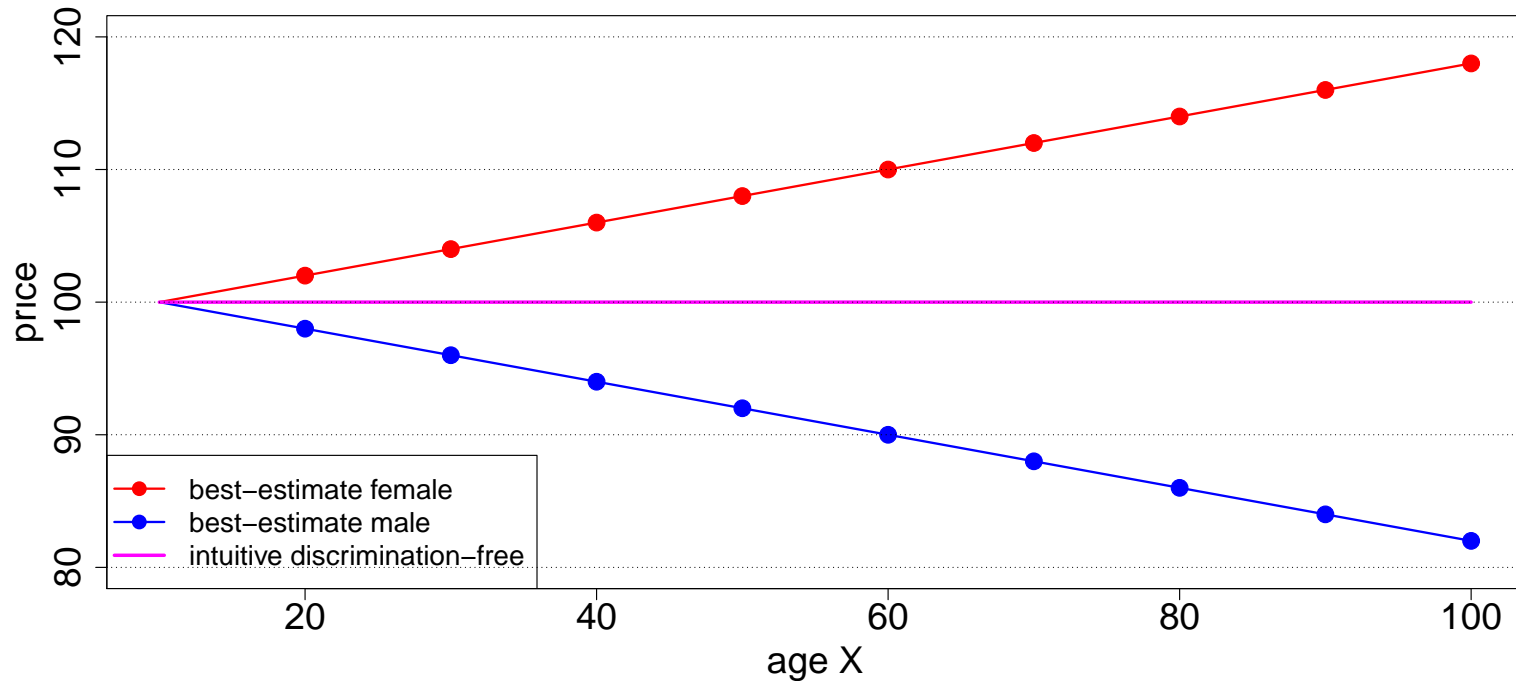
Best-Estimate Price: Direct Discrimination



- Article 2(a):¹ “direct discrimination: where one person is treated less favourably, on grounds of sex...”
- Intuitive guess for discrimination-free price?

¹COUNCIL DIRECTIVE 2004/113/EC of 13 December 2004, Official Journal of the European Union L 373/37

Best-Estimate Price: Direct Discrimination



- Article 2(a): “**direct discrimination**: where one person is treated less favourably, on grounds of sex...”
- **Intuitive guess for discrimination-free price.**

- **Unawareness Price and Indirect Discrimination**

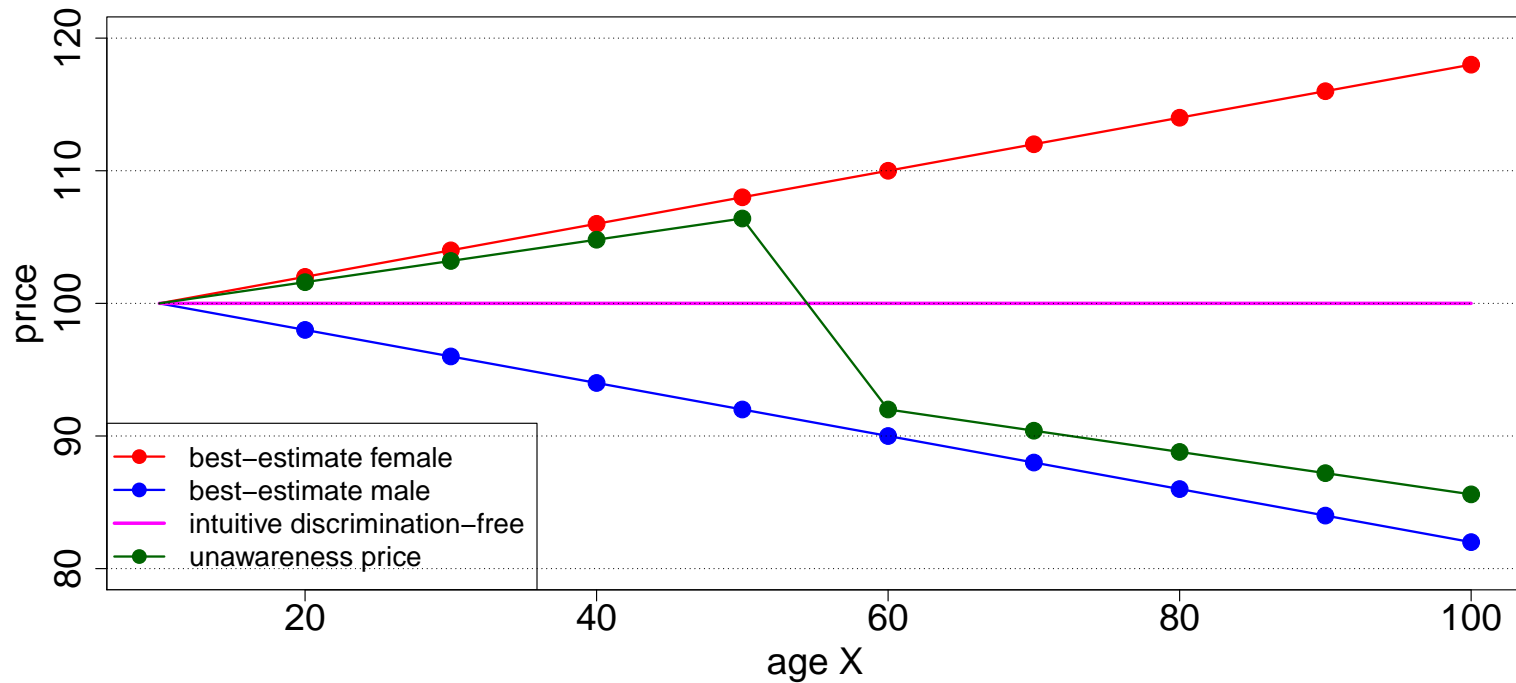
Unawareness Price

- Direct discrimination can be avoided by dropping discriminatory information D .
- This provides unawareness price for Y

$$\mu(\mathbf{X}) = \mathbb{E}[Y | \mathbf{X}].$$

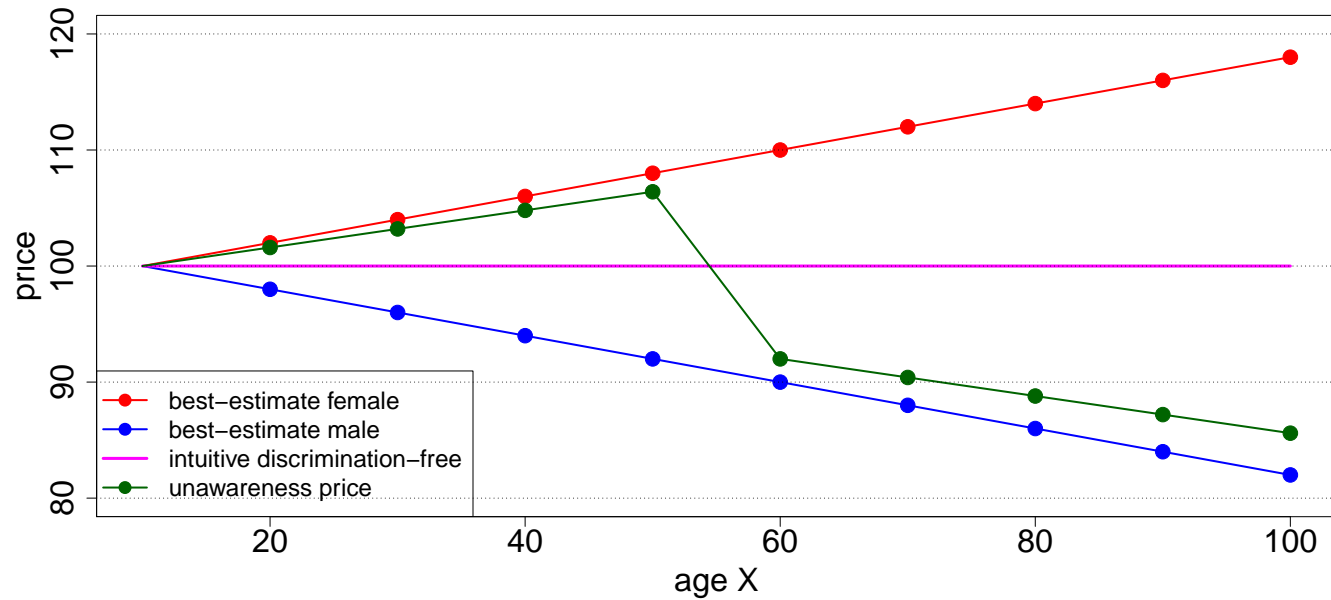
- The unawareness price
 - ★ uses maximal available non-discriminatory information \mathbf{X} ;
 - ★ minimizes prediction uncertainty (in an L^2 -sense w.r.t. \mathbf{X});
 - ★ is the best approximation to the best-estimate price $\mu(\mathbf{X}, D)$;
 - ★ avoids direct discrimination.

Unawareness Price: Example

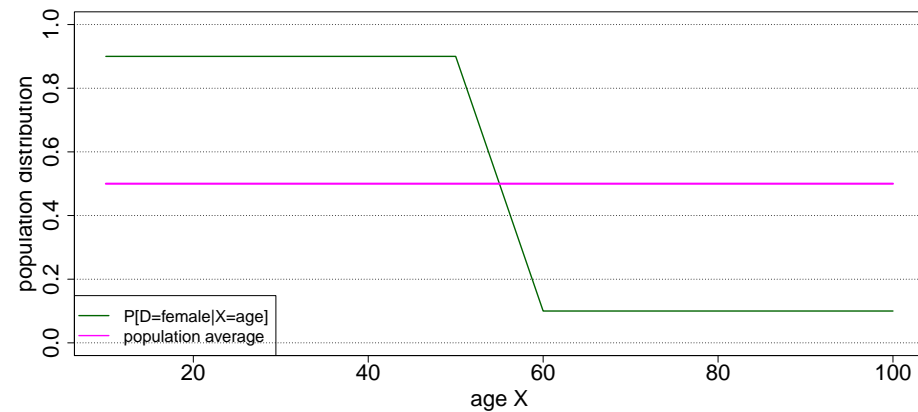


- What goes “wrong” here?

Unawareness Price: Example



- What goes “wrong” here?



What Goes “Wrong” with the Unawareness Price?

- The unawareness prices can be expressed as (tower property)

$$\begin{aligned}\mu(\mathbf{X}) &= \mathbb{E} [\mu(\mathbf{X}, \mathbf{D}) | \mathbf{X}] \\ &= \int_d \mu(\mathbf{X}, \mathbf{D} = d) \, d\mathbb{P}(\mathbf{D} = d | \mathbf{X}).\end{aligned}$$

- This shows that we infer \mathbf{D} from \mathbf{X} in the unawareness price.
- Article 2(b):² “indirect discrimination: where an apparently neutral provision... would put persons of one sex at a particular disadvantage compared with persons of the other sex, unless that provision... is objectively justified...”

²COUNCIL DIRECTIVE 2004/113/EC of 13 December 2004, Official Journal of the European Union L 373/37

- **Discrimination-Free Price**

Discrimination-Free Pricing

- The unawareness prices can be expressed as (tower property)

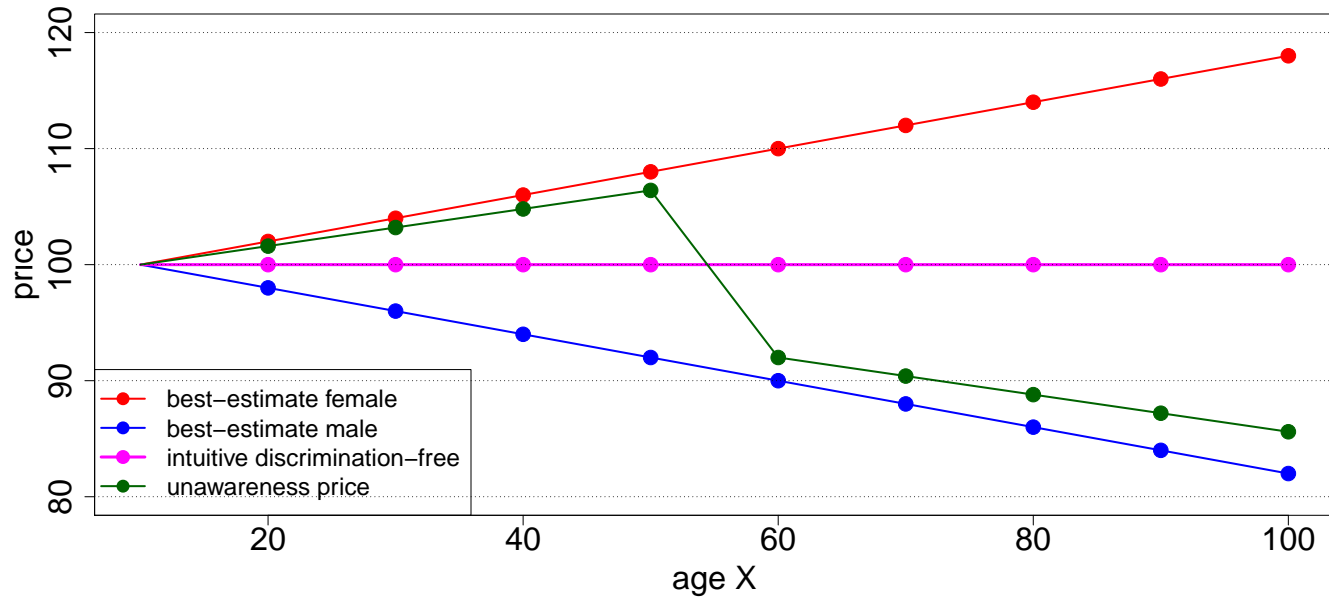
$$\begin{aligned}\mu(\mathbf{X}) &= \mathbb{E} [\mu(\mathbf{X}, \mathbf{D}) | \mathbf{X}] \\ &= \int_d \mu(\mathbf{X}, \mathbf{D} = d) \, d\mathbb{P}(\mathbf{D} = d | \mathbf{X}).\end{aligned}$$

- We need to “break the structure” that allows to infer \mathbf{D} from \mathbf{X} .
- This motivates **discrimination-free price**

$$\mu^*(\mathbf{X}) = \int_d \mu(\mathbf{X}, \mathbf{D} = d) \, d\mathbb{P}^*(\mathbf{D} = d),$$

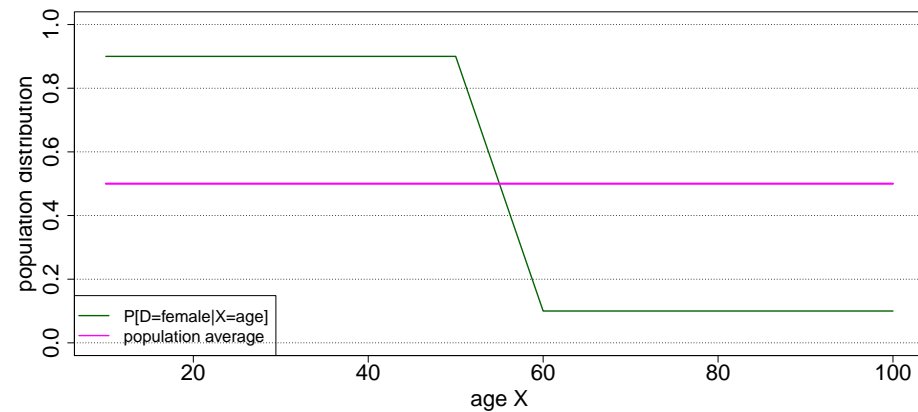
for some choice \mathbb{P}^* (there are infinitely many).

Discrimination-Free Price: Example



- For population distribution

$$\mathbb{P}^*(D) = \mathbb{P}(D).$$



Concluding Remarks

- We need to collect discriminatory information D , otherwise we cannot calculate discrimination-free prices, i.e. just knowledge of X is not good enough.
- Lindholm et al. (2020) give a mathematical definition of (in-)direct discrimination.
- For any given problem there are infinitely many choices \mathbb{P}^* , and henceforth there are infinitely many discrimination-free prices.
- Discrimination-free prices need to be made unbiased.
- Discrimination-free prices sacrifice predictive power relative to unawareness prices.
- Discrimination-free prices can be motivated by “do-operators” in causal statistics (confounders), see Pearl et al. (2016).
- Discrimination-free prices have same structure as partial dependence plots (PDPs), see Zhao–Hastie (2019) and Lorentzen–Mayer (2020).

- Definition of discrimination-free prices is independent of any model.
- Discrimination-free prices may induce unwanted economic side effects like adverse selection.
- Indirect discrimination can be explained by the fact that non-discriminatory covariates are used to predict discriminatory ones. The better information we have, the more accurately this can be done.
- We did not discuss fairness nor which variables are discriminatory (ethnicity, etc.).

References

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