

EquiPy: A Python Package implementing Sequential Fairness with Optimal Transport

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1 Introduction

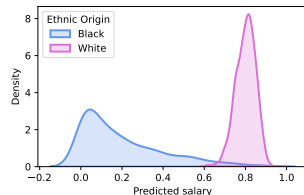
2 Fairness evaluation

3 Unfairness Mitigation

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Algorithmic Fairness

Context Consider a Machine Learning (ML) model f , its salary predictions on test set \hat{Y} and one sensitive attribute to which we have access in our dataset, **ethnic origin** (White/Black).



Potential source of discrimination

- 1 **Statistical bias** in the data: reproduction of past injustices, under-represented minority in an unbalanced data set,
- 2 **Explanatory variables** of the model: proxy variables (correlation between a sensitive attribute and other explanatory variables),
- 3 **Intentional bias**: bias can be the result of deliberate choices, which can be benevolent or malicious.

Motivations

Legislation

- AI Act (Europe, 2024) aims to ban or limit AI systems in production that present an “**unacceptable level of risk.**”
- **Motor insurance** regulation (Zebra, 2022).

| | United States | | | | | | | | | Canada | | | | |
|--------------------|---------------|----|----|----|----|----|----|----|----|--------|----|----|----|----|
| | 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 | • | • | • | • | • | • | • | • | • | • | • | • |
| 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 | • | • | • |

• Permitted attribute x Prohibited attribute * with conditions

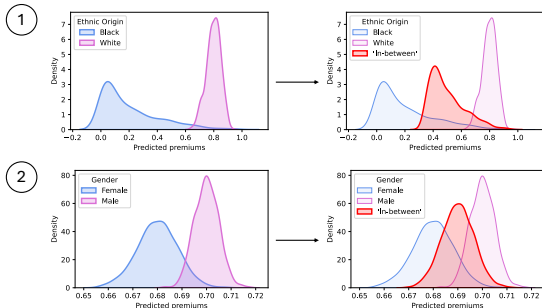
Proxy variables (Upton and Cook, 2014) Simply **eliminating the sensitive attributes** from predictive models does not guarantee fair premiums (Feller and Goel, 2016).

Single Sensitive Attribute Multiple **mitigation** approaches exist (Chzhen et al., 2020; Gouic et al., 2020; Hardt et al., 2016).

→ Approach to **evaluate and mitigate unfairness** in model predictions regarding **Multiple Sensitive Attributes** (MSA)

Objective

Consider an **insurance pricing model** f , its predicted premiums \hat{Y} and two sensitive attributes, **ethnic origin** A_1 (White/Black) and **gender** A_2 (Male/Female).



We avoid selecting a **reference category** (White/Black and Male/Female) because:

- if “Black” and “Female” are the references, the total premiums would fall short of the planned amount needed to cover claims,
- if “White” and “Male” are the references, the premiums would exceed the planned amount, leading to higher costs for the insureds.

Context of Multiple Sensitive Attributes

Intersectional Fairness

MSA \rightarrow Single sensitive attribute (SSA), by intersection:

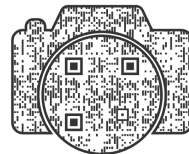
| | |
|----------------|----------------|
| Female & White | Female & Black |
| Male & White | Male & Black |

Sequential Fairness (Hu et al., 2024)

$\hat{Y} \longrightarrow \hat{Y}$ fair for $A_1 \longrightarrow \hat{Y}$ fair for A_1, A_2

- **Interpretability** accross MSA,
- Easily adding sensitive attributes (SA) to meet changing **regulatory demands**.

Paper: **Sequential Fairness**



Python package: **EquiPy**



Roadmap

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Measuring Unfairness via Optimal Transport

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Notations

- $\mathbf{X} \in \mathcal{X}$: 'non-sensitive' features,
- $\mathbf{A} = (A_1, \dots, A_r) \in \mathcal{A}_1 \times \dots \times \mathcal{A}_r$: r sensitive features,
- \hat{Y} : response variable (continuous or score from a binary classifier)
- f : predictive model on (\mathbf{X}, \mathbf{A}) , with f^* the optimal Bayes estimator $\mathbb{E}[Y|\mathbf{X}, \mathbf{A}]$,
- ν_f : distribution of $f(\mathbf{X}, \mathbf{A})$ with cumulative distribution function F_f and quantile function Q_f ,
- $\nu_{f|a_i}$: conditional distribution of $f(\mathbf{X}, \mathbf{A})|A_i = a_i$ with $F_{f|a_i}$ and $Q_{f|a_i}$,
- $\mathcal{R}(f) = \mathbb{E}[(Y - f(\mathbf{X}, \mathbf{A}))^2]$: risk metric.

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Demographic Parity for Group Fairness

Demographic Parity requires that the predictions made by a model be **independent** of a specific sensitive attribute A (such as race, gender, or age).

Strong Demographic Parity $\forall a_i, a'_i \in \mathcal{A}_i, \nu_{f|a_i} = \nu_{f|a'_i}$ or $\text{distance}(\nu_{f|a_i}, \nu_{f|a'_i}) = 0$.

- ① f is strongly fair regarding **a single sensitive attribute** (SSA) A_i , if and only if:

$$\mathcal{U}_i(f) = \max_{a_i \in \mathcal{A}_i} \text{distance}(\nu_f, \nu_{f|a_i}) = 0$$

- ② f is strongly fair regarding **MSA**, if and only if:

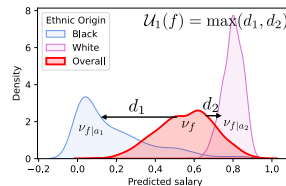
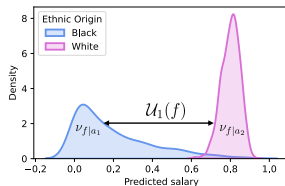
$$\mathcal{U}(f) = \mathcal{U}_1(f) + \dots + \mathcal{U}_r(f) = 0$$

→ **Wasserstein distance** from Optimal Transport (OT) theory is employed to compute the distance between distributions.

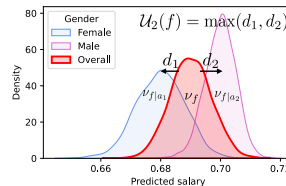
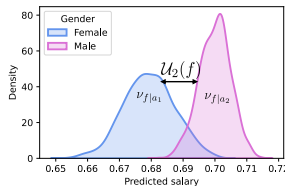
Example

Strong Demographic Parity for MSA: **ethnic origin** (A_1) and **gender** (A_2).

1



2



$$\mathcal{U}(f) = \mathcal{U}_1(f) + \mathcal{U}_2(f)$$

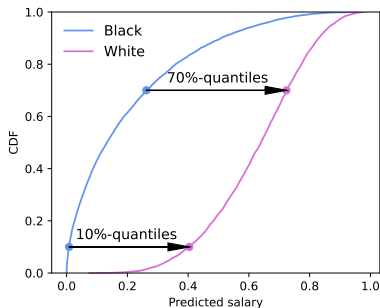
Optimal Transport

The objective of OT is to minimize the overall cost of moving one mass distribution (ν_A) onto another one (ν_B). We are searching for the most efficient mapping T to move mass between ν_A and ν_B , s.t. $\nu_B = T_{\#}\nu_A$, by solving (Monge, 1781)

$$\inf_{T_{\#}\nu_A=\nu_B} \int_{\mathcal{A}} c(x, T(x)) d\nu_A(x)$$

For some strictly convex ‘cost’ c , such as quadratic cost, and univariate distributions ν_A and ν_B , the **optimal transport map** T^* is (Santambrogio, 2015)

$$T^* = Q_B \circ F_A$$

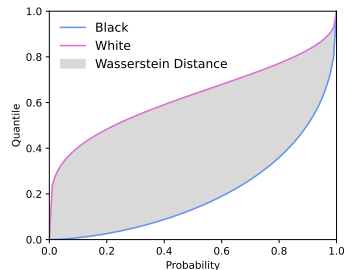


Optimal Transport and Wasserstein distance

For univariate distributions ν_A and ν_B , p -**Wasserstein distance** ($p \geq 1$) corresponds to the value of the minimum 'cost' required to transform ν_A into ν_B (Wasserstein, 1969):

$$\mathcal{W}_p(\nu_A, \nu_B) = \left(\int_{u \in [0,1]} |Q_A(u) - Q_B(u)|^p du \right)^{1/p}$$

→ **Fairness criterion**: $\mathcal{U}_i(f) = \max_{a_i \in \mathcal{A}_i} \mathcal{W}_1(\nu_f, \nu_{f|a_i})$.



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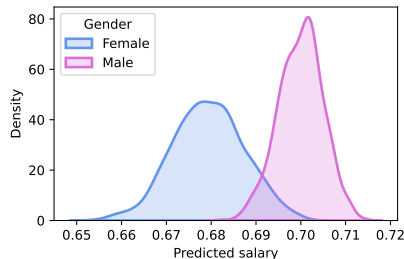
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Multiple methods

Objective: Transform model predictions $f(\mathbf{X}, \mathbf{A}) \in \mathbb{R}$ into fair ones $f_B(\mathbf{X}, \mathbf{A})$, while **preserving good performance** $\mathcal{R}(f)$.

- Pre-processing: transform multivariate distribution of \mathbf{X} ,
- In-processing: add a 'fairness' penalty in the objective function,

- **Post-processing:** transform univariate distribution of $\hat{Y} = f(\mathbf{X}, \mathbf{A})$.



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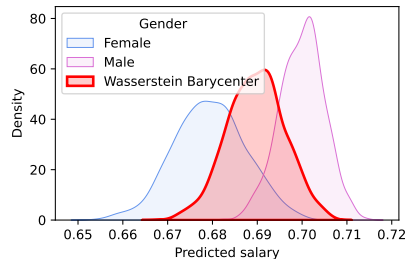
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Wasserstein barycenter

The **Wasserstein Barycenter** finds a representative distribution that lies between K given distributions (ν_1, \dots, ν_K) , and weights $(w_1, \dots, w_K) \in \mathbb{R}_+^K$. The \mathcal{W}_2 -Barycenter is the minimizer:

$$\text{Bar}\{(w_k, \nu_k)_{k=1}^K\} = \underset{\nu}{\operatorname{argmin}} \sum_{k=1}^K w_k \cdot \mathcal{W}_2^2(\nu_k, \nu)$$



Constructing f_B with Wasserstein barycenter, Gouic et al. (2020) prove $f_B = \operatorname{arginf}_f \{\mathcal{R}(f) : \mathcal{U}(f) = 0\}$.

Achieving Fairness via Optimal Transport

Single Sensitive Attribute ($r = 1$) (Chzhen et al., 2020)

$$\nu_{f_B} = \mu_{\mathcal{A}_1}(\nu_{f^*}) = \inf_f \sum_{a_1 \in \mathcal{A}_1} \mathbb{P}(A_1 = a_1) \cdot \mathcal{W}_2^2(\nu_{f^*|a_1}, \nu_f)$$

$$f_B(\mathbf{x}, a_1) = \left(\sum_{a'_1 \in \mathcal{A}_1} \mathbb{P}(A_1 = a'_1) Q_{f^*|a'_1} \right) \circ F_{f^*|a_1}(f^*(\mathbf{x}, a_1))$$

$$\forall (\mathbf{x}, a_1) \in \mathcal{X} \times \mathcal{A}_1.$$

→ **EquiPy**: This approach is implemented in the function **FairWasserstein** of **fairness** module.

Example

Consider ML model predictions $\hat{y} = \hat{f}(\mathbf{x}, a_1)$ where $a_1 \in \mathcal{A}_1$ corresponds to the observations of the SSA, A_1 : **ethnic origin** (White/Black).

Mitigation approach

$$\begin{aligned}\hat{f}_{B_1}(\mathbf{x}, a_1 = \text{White}) &= \mathbb{P}[A_1 = \text{White}] \cdot \hat{f}(\mathbf{x}, a_1 = \text{White}) \\ &\quad + \mathbb{P}[A_1 = \text{Black}] \cdot Q_{\text{Black}} \circ F_{\text{White}}(\hat{f}(\mathbf{x}, a_1 = \text{White}))\end{aligned}$$

$$\begin{aligned}\hat{f}_{B_1}(\mathbf{x}, a_1 = \text{Black}) &= \mathbb{P}[A_1 = \text{Black}] \cdot \hat{f}(\mathbf{x}, a_1 = \text{Black}) \\ &\quad + \mathbb{P}[A_1 = \text{White}] \cdot Q_{\text{White}} \circ F_{\text{Black}}(\hat{f}(\mathbf{x}, a_1 = \text{Black}))\end{aligned}$$

Sequential fairness

Multiple Sensitive Attributes ($r \geq 1$) (Hu et al., 2024)

$$f_B(\mathbf{x}, \mathbf{a}) := f_{B_1} \circ f_{B_2} \circ \cdots \circ f_{B_r}(\mathbf{x}, \mathbf{a})$$
$$f_{B_i} \circ f_{B_j}(\mathbf{x}, \mathbf{a}) = \left(\sum_{a'_i \in \mathcal{A}_i} \mathbb{P}(A_i = a'_i) Q_{f_{B_j}|a'_i} \right) \circ F_{f_{B_j}|a_i}(f_{B_j}(\mathbf{x}, \mathbf{a}))$$

$\forall (\mathbf{x}, \mathbf{a}) \in \mathcal{X} \times \mathcal{A}_{1:r}$, with the i -th component of \mathbf{a} denoted a_i .

Hu et al. prove the **associativity** of Wasserstein barycenters:

$\mu_{\mathcal{A}_1} \circ \mu_{\mathcal{A}_2}(\nu_{f^*}) = \mu_{\mathcal{A}_2} \circ \mu_{\mathcal{A}_1}(\nu_{f^*})$. Fairness mitigation remains **unaffected by the order** of $\mathcal{A}_{1:r}$.

→ **EquiPy**: This approach is implemented in the function **MultiWasserstein** of **fairness** module.

Example

Consider transformed model predictions fair regarding **ethnic origin** $\hat{f}_{B_1}(\mathbf{x}, \mathbf{a})$ where $\mathbf{a} = (a_1, a_2) \in \mathcal{A}_1 \times \mathcal{A}_2$ corresponds to the observations of the MSA, A_1 and A_2 : **ethnic origin** and **gender** (Male/Female).

Mitigation approach

$$\begin{aligned}\hat{f}_{B_2}(\mathbf{x}, a_1, a_2 = \text{Male}) &= \mathbb{P}[A_2 = \text{Male}] \cdot \hat{f}_{B_1}(\mathbf{x}, a_1, a_2 = \text{Male}) \\ &\quad + \mathbb{P}[A_2 = \text{Female}] \cdot Q_{\text{Female}} \circ F_{\text{Male}}(\hat{f}_{B_1}(\mathbf{x}, a_1, a_2 = \text{Male}))\end{aligned}$$

$$\begin{aligned}\hat{f}_{B_2}(\mathbf{x}, a_1, a_2 = \text{Female}) &= \mathbb{P}[A_1 = \text{Female}] \cdot \hat{f}_{B_1}(\mathbf{x}, a_1, a_2 = \text{Female}) \\ &\quad + \mathbb{P}[A_2 = \text{Male}] \cdot Q_{\text{Male}} \circ F_{\text{Female}}(\hat{f}_{B_1}(\mathbf{x}, a_1, a_2 = \text{Female}))\end{aligned}$$

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Life insurance dataset

- Public SEER dataset: <https://seer.cancer.gov>,
- Prediction of **one-year mortality** of US individuals with melanoma skin cancer,
→ Utilizing the methodology presented in Sauce et al. (2023), we convert the dataset into survival data, by accounting for **exposure** over a given time interval.
- Sample size $n = 547,878$ from 2004 to 2018,
- Explanatory variables: 16 features describing patient characteristics (age, **gender** male/female, **ethnic origin**) and cancer attributes (tumor size, extent).

→ **MSA** framework: use of the function **MultiWasserstein**.

Model fitting

- ① Split the data into train and test sets,
- ② Fit **Logistic Regression*** f ,
- ③ Apply f on the test set to obtain \hat{y}_{test} .

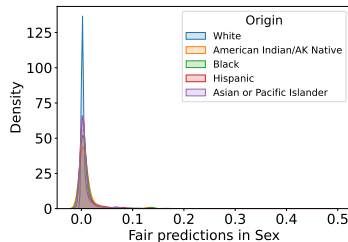
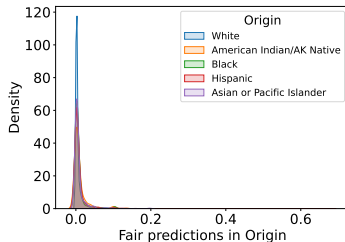
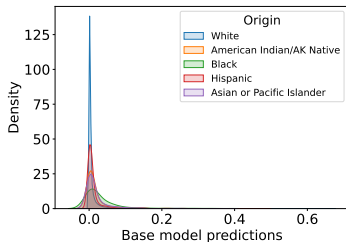
We consider different model fitting scenarios, in which we include or exclude sensitive attributes as explanatory variables:

| Ethnic origin | Gender | AUC | Unfairness |
|---------------|------------|------|------------|
| No | No | 0.87 | 0.22 |
| Yes | Yes | 0.87 | 0.24 |

* **Model-agnosticity** of EquiPy: f can be any ML model.

Transforming predictions

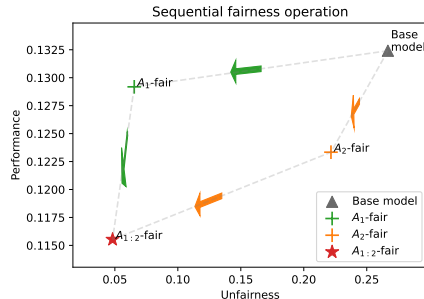
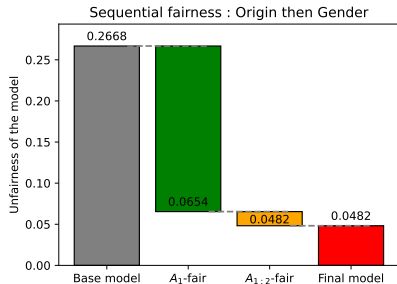
- 1 Split the test data into calibration and test sets,
- 2 Specify an order to sequentially correct: A_1 corresponds to **ethnic origin** and A_2 corresponds to **gender**,
- 3 Fit and transform your test predictions using MultiWasserstein from fairness module.



Visualizations

Unfairness and **metric** calculations with graphs module:

- `fair_waterfall_plot`: sequential gain in fairness for the specified order A_1 then A_2 ,
- `fair_multiple_arrow_plot`: fairness-performance relationship for all potential pathways.



Additional results: Approximate fairness

When correcting biases related to **gender**, we reduce fairness regarding **origin**:

| Fairness step | Unfairness in origin | Unfairness in gender |
|----------------------------|-----------------------------|-----------------------------|
| Base model | 0.2371 | 0.0297 |
| Origin | 0.0345 | 0.0309 |
| Origin & Gender | 0.0469 | 0.0013 |

We can **prioritize fairness accross attributes** by specifying $\epsilon = [0, 0.5]$ corresponding to exact fairness in A_1 and 0.5-approximate fairness in A_2 .

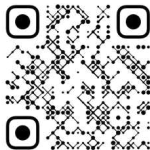
$$f_B = 0.5 \cdot (f_{B_2} \circ f_{B_1}) + 0.5 \cdot f_{B_1}$$

Wrap up

- The novel approach of **Sequential Fairness**, introduced in Hu et al. (2024), allows to mitigate unfairness regarding **Multiple Sensitive Attributes**.
- The Python package **EquiPy** implements the Sequential Fairness approach and is applicable to **any continuous Machine Learning predictions**.

Code available: https://github.com/fer-agathe/quantil_seminar
Comments are welcome: fernandes_machado.agathe@courrier.uqam.ca

Documentation **EquiPy**



5 Appendix

References I

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