



Fairness assessment & unfairness mitigation

1. Measurement

2. Quantitative definition

3. Practical application

4. References

1. Definition

Fairness as unobservable theoretical construct.

Measurement model from quantitative social sciences as a framework for understanding fairness in computational systems.

$$\begin{aligned} q_{tjkl} &= \mu_{jkl} + \sum_{i} \tau_{ijklt} \\ y_{ijkl} &= \mu_{jkl} + \left(\sum_{k^* < = k}^{} \sum_{t=1}^{} T_{ijk^*l^*} w_{ijk^*l^*t} \tau_{ijk^*l^*t} \right), \end{aligned}$$

2. Individual and group fairness

Individual fairness, which requires that similar people be treated similarly, and **group fairness**, which requires that different groups of people, such as groups defined in terms of different demographic factors, be treated similarly.

```
selection_rates = MetricFrame(
    metrics=selection_rate, y_true=y_true, y_pred=y_true, sensitive_features=sensitive)
```



2. Quantitative definition

→ Statistical or demographic parity

The prediction should be independent of the protected attribute. It is invoked to address disparity under the US Equal Employment Opportunity Comission's "four-fifths rule".

→ Bounded group loss

It formalizes the requirement that the predictor's loss remain below some acceptable level for each protected group.

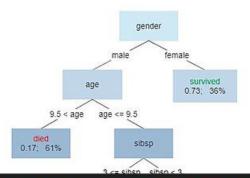
2. Parity constraints



Group fairness is typically formalized by a set of constraints on the behaviour of the predicator called parity constraints.

Demographic parity in Binary classification

$$E[h(X) \mid A = a] = E[h(X)] \forall a$$



```
classifier = DecisionTreeClassifier(min_samples_leaf=10, max_depth=4)
mitigator = ExponentiatedGradient(classifier, constraint)
```

2. Parity constraints

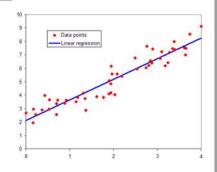


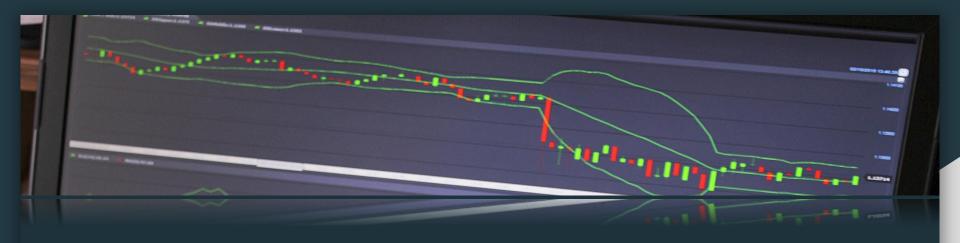
Bounded group loss in Regression.

$$\min_{f \in \mathcal{F}} \mathbb{E} \big[\ell(Y, f(X)) \big]$$

such that
$$\forall a \in \mathcal{A}$$
: $\mathbb{E}[\ell(Y, f(X)) \mid A = a] \leq \zeta_a$.

CDF f of predictions vector, A sensitive feature, C bound.





3. Practical Application

2. Toward job recommendation

This paper presents a job recommendation algorithm designed and validated in the context of the French Public Employment Service.

It focuses on e-recruitment, i.e. the design and exploitation of recommender systems selecting job ads best suited for job seekers.

- Sensitivity of the data.
- E- recruitment involves rival goods.

Datasets:

- Recsys chanllenge 2017
- CareerBuilder public dataset.

2. MUSE

This paper presents an e-R system called MUlti-head Sparse E-recruitment learned from proprietary data of French public employment service Pôle emploi.

MUSE. 0

It models the main 3 facets relevant to job recommendations such as geographical and skills.

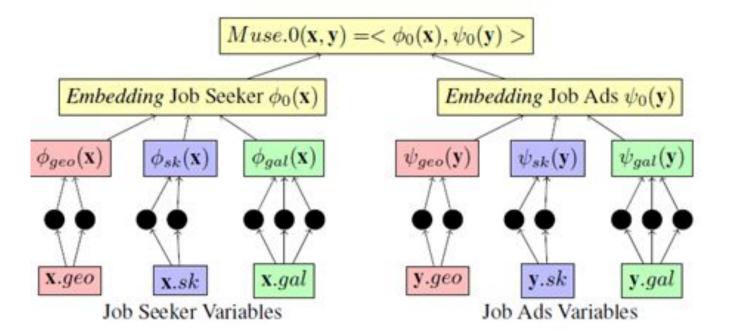
$$s(\mathbf{x}, \mathbf{y}) = \langle \phi_0(\mathbf{x}), \psi_0(\mathbf{y}) \rangle$$

Loss function

$$\mathcal{L}(\phi_0, \psi_0) = \sum_{(x, y, y')} [\langle \phi_0(\mathbf{x}), (\psi_0(\mathbf{y}) - \psi_0(\mathbf{y}')) \rangle + \eta]_+$$

Guillaume Bied, Solal Nathan, Elia Perennes, Morgane Hoffmann, Philippe Caillou, et al.. Toward Job Recommendation for All. IJCAI 2023 - The 32nd International Joint Conference on Artificial Intelligence, Aug 2023, Macau, China. pp.5906-5914, <10.24963/ijcai.2023/655>. <hacheology contact the second se

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