Exploring Fairness of Ranking in Online Job Marketplaces

Shady Elbassuoni[1] Sihem Amer-Yahia[2] Ahmad Ghizzawi[1*] Christine El Atie[1]

[1]American University of Beirut, Lebanon [2]CNRS, Univ. Grenoble Alpes, France

Motivation

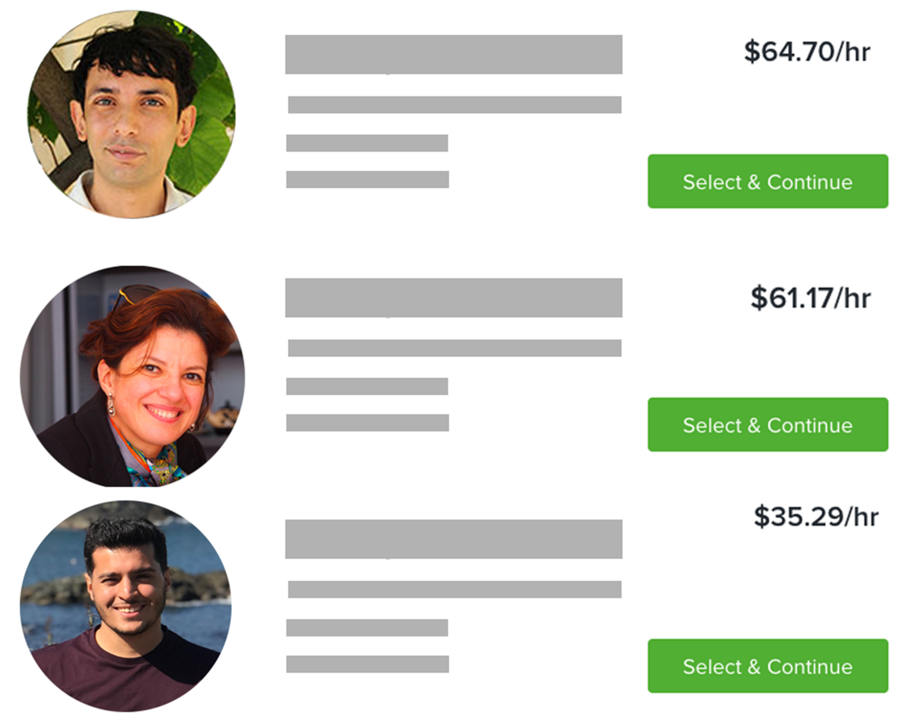
Online job marketplaces are more popular than ever..

People are being ranked by an algorithm

User	Gender	Country	Test	Approval	f(u)
	Protected Attributes		*Observed Attributes*		
U1	Female	America	0.76	0.56	0.620
U2	Female	India	0.50	0.20	0.290
U3	Male	America	0.89	0.92	0.911
U4	Male	India	0.65	0.65	0.650
U5	Male	Other	0.64	0.76	0.724
U6	Female	India	0.85	0.90	0.885
U7	Male	America	0.42	0.20	0.266
U8	Female	America	0.95	0.98	0.971
U9	Male	Other	0.30	0.15	0.195
U10	Male	Other	0.32	0.25	0.271

+

$$f(u) = 0.3 \times LanguageTest(u) + 0.7 \times ApprovalRate(u)$$



Objective

Unfairness in Online Job Marketplaces

*Unequal treatment of people by a scoring function based on their **protected** attributes (gender, ethnicity, etc..)*

*Inline with **group unfairness**[3]*

Goal

Given a set of workers W and a scoring function $f: W \rightarrow R$:

Identify the subgroups that exhibit the highest unfairness with respect to f

Quantify the amount of unfairness that a scoring function f on W

Positioning

Most previous work have assumed that groups are predefined.[4,5]

We consider groups of people defined with any combination of protected attributes (the so-called subgroup fairness[6])

Problem Definition

Most Unfair Partioning Problem

Given W and f, find partitioning $P = \{p_1, p_2, \ldots, p_k\}$ such that:

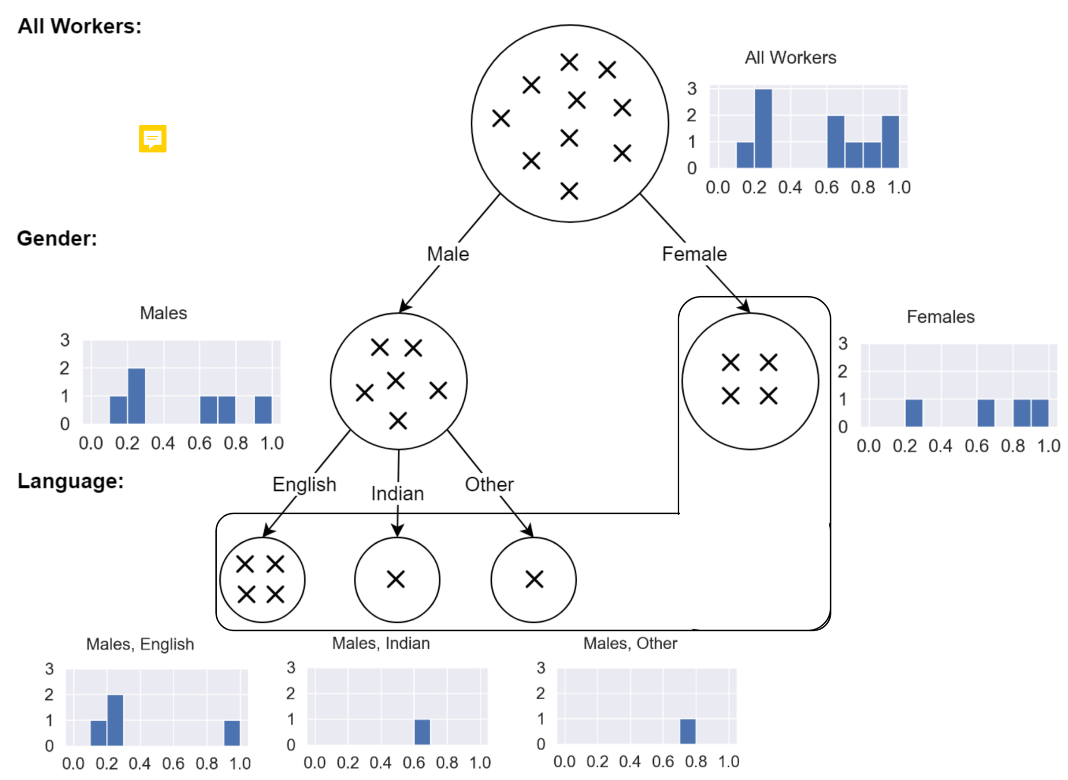
$$\underset{P}{\text{argmax}} \quad unfairness(P, f)$$

$$\text{subject to} \quad \forall i, j \; p_i \bigcap p_j = \phi$$

$$\bigcup_{i=1}^{k} p_i = W$$

$$unfairness(P, f) = \underset{i,j}{\text{avg}} \; EMD(h(p_i, f), h(p_j, f))$$

where $h(p_i, f)$ is a histogram of the scores of the individuals in p_i using f.



Algorithms

BALANCED(W, f, A)

```
a = worstAttribute(W, f, A)
A = A − a
current = split(W, a)
currentAvg = averageEMD(current, f)
while A ≠ ∅ do
    a = worstAttribute(current, f, A)
    A = A − a
    children = split(current, a)
    childrenAvg = averageEMD(children, f)
    if currentAvg ≥ childrenAvg then
        break
    else
        current = children
        currentAvg = childrenAvg
    end if
end while
Add current to output
```

***BALANCED** results in a partitioning of all individuals using the same set of attributes resulting in a balanced tree.*

UNBALANCED(current, siblings, f, A)

```
if A = ∅ then
    Add current to output
else
    currentAvg = averageEMD(current, siblings, f)
    a = worstAttribute(current, f, A)
    A = A − a
    children = split(current, a)
    childrenAvg = averageEMD(children, siblings, f)
    if currentAvg ≥ childrenAvg then
        Add current to output
    else
        for each partition p ∈ children do
            UNBALANCED({p}, children − {p}, f, A)
        end for
    end if
end if
```

***UNBALANCED** partitions the individuals in a non-homogenous manner by locally deciding for each partition whether to further split it or not resulting in an unbalanced tree.*

Evaluation

***Dataset**: simulated crowdsourcing platform of 20,000 users*

***Attributes**: gender, year of birth, language, ethnicity, years of experience, language test and approval rate*

***Functions**:*

$$f_i(u) = \alpha_i \times LanguageTest(u) + (1 - \alpha_i) \times ApprovalRate(u)$$

$$\text{where } 1 \le i \le 5 \text{ and } \alpha_i \in \{0.3,\ 0.7,\ 0.5,\ 1,\ 0\}$$

***Baselines**: R-BALANCED, R-UNBALANCED, and ALL-ATTRIBUTES*

***Table a:** Average EMD and runtime for 500 workers and random functions*

***Table b:** Average EMD and runtime for 7300 workers and biased functions*

Algorithm	Average EMD				
	f_1	f_2	f_3	f_4	f_5
UNBALANCED	0.195	0.191	**0.179**	**0.247**	**0.257**
R-UNBALANCED	0.193	0.193	0.177	0.243	0.253
BALANCED	**0.196**	**0.194**	0.177	0.246	0.253
R-BALANCED	0.195	**0.194**	0.177	0.246	0.253
ALL-ATTRIBUTES	0.195	0.193	0.177	0.246	0.253

(a)

Algorithm	Average EMD	
	Gender	Gender&Ethnicity
UNBALANCED	0.040	0.164
R-UNBALANCED	0.399	0.362
BALANCED	**0.800**	**0.427**
R-BALANCED	0.496	0.368
ALL-ATTRIBUTES	0.420	0.368

(b)

Conclusion and Future Work

Contributions

Formalized unfairness in Online Job Marketplaces

Proposed heuristics-based algorithms to find the most unfair partitioning

Findings

Our algorithms efficiently partition the individuals without exploring the full space of partitionings

Using fewer observed attributes increases the chance of unfairness

Future work

Investigating metrics and formulations other than EMD

Repairing bias in context of ranking in online job marketplaces

* ahg05@mail.aub.edu

[3]Friedler, Sorelle A., Carlos Scheidegger, and Suresh Venkatasubramanian. "On the (im) possibility of fairness." *arXiv preprint arXiv:1609.07236* (2016).

[4]Singh, Ashudeep, and Thorsten Joachims. "Fairness of exposure in rankings." Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. ACM, 2018.

[5]Hannák, Anikó, et al. "Bias in online freelance marketplaces: Evidence from taskrabbit and fiverr." *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*. ACM, 2017.

[6]Kearns, Michael, et al. "Preventing fairness gerrymandering: Auditing and learning for subgroup fairness." *arXiv preprint arXiv:1711.05144* (2017).