



FairER: Entity Resolution with Fairness Constraints



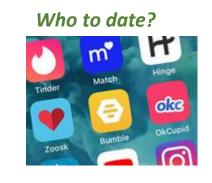
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Motivation

Data-driven decision-making AI systems...



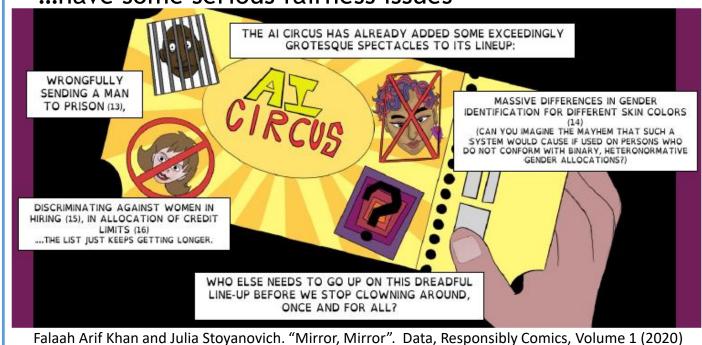


What to read, watch, buy..?



...have some serious fairness issues

https://dataresponsibly.github.io/comics/vol1/mirror en.pdf



Entity Resolution

Identify data records from different sources that refer to the same real-world entities (matches)

	E									
d	Name	Location	Employer	Rep	Sex		id	Full-name	Affiliation	h-index
9₁	Danny Barber	LA	UCLA	600	М		●e′ ₁	Doe, S.	UT	14
2	Susan Doe	Texas	UT Austin	7,000	F		e' ₂	J. Parker	UCSC	5
3	Peter Simons	NY	NYU	4	М	•	●e′ ₃	Simons, Pete	NYU	11
1	M. Anderson	Denmark	Aarhus Univ.	8	М	•	●e′₄	M. Anderson	Aarhus	15652
5	Julia Rondo	France	CNRS, Paris	460	F	•—	• e′ ₅	J. Rondo	CNRS	4653
6	J. Parker	California	UC Berkeley	381	М		e' ₆	Juliana Rondo	CNRS	25

Traditional (fairness-agnostic) ER

- Goal: Discover as many matches as possible
- Matching decision process for (e,e'): Relies on a scoring function s assessing the similarity of the attribute values and names used to describe e and e'
 - scoring function types: heuristics, aggl. clustering, supervised

Definition 2.1 (Fairness-agnostic ER). Given a set of candidate matches $C \subseteq E \times E'$ and a scoring function $s : E \times E' \to \mathbb{R}$, produce a subset $R \subseteq C$ of matches that maximizes the cumulative scores:

$$R = \underset{R^* \subseteq C}{\operatorname{argmax}} \sum_{(e_i, e'_j) \in R^*} s(e_i, e'_j).$$

- Matching pairs ranked according to their scores
- Additional constraints may be imposed to R
 - e.g., 1-to-1 constraint (clean-clean ER)
- <u>Issue</u>: ignores the qualitative features of the results

Fairness-aware ER

- Retrieved results: not only the most likely matches, but also satisfy some *fairness constraint*
- to examine the allocation of benefits and harms across groups by looking at the decision alone
 - group-based fairness: protected vs non-protected
 - all groups should receive similar treatment, i.e., have similar chances to be resolved
- Ranked group fairness: a fairness constraint should be satisfied when considering the results within a given rank

Definition 2.2 (Fairness-aware ER). Given a set of candidate matches $C \subseteq E \times E'$, a scoring function $s: E \times E' \to \mathbb{R}$, and a fairness criterion F, produce a ranking of matches $R \subseteq C$ that for any given rank position k, maximizes the cumulative scores:

$$R = \underset{R^* \subseteq C}{\operatorname{argmax}} \sum_{(e_i, e'_i) \in R^*} s(e_i, e'_j)$$

s.t. R[k] satisfies F,

where R[k] are the k first results of R.

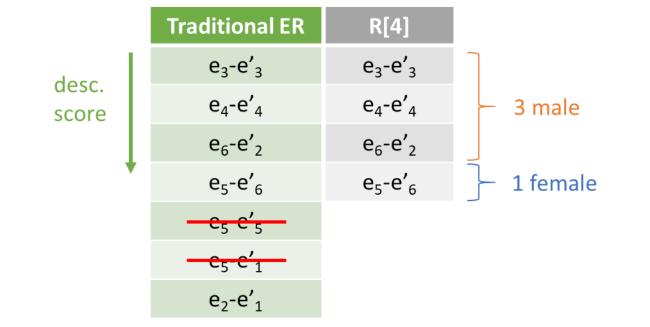
FairER

Fairness criterion F:

$$\left|\frac{|R_p|}{k} - \frac{|R_n|}{k}\right| = \varepsilon^*,$$

where $\frac{|R_p|}{k}$ (resp. $\frac{|R_p|}{k}$) is the ratio of protected (resp. non-protected) group members in the first k results and ε^* is the smallest possible ratio for a given k

Example



ı	FairER Q _p	FairER Q _n	R[4]	
desc.	e ₅ -e' ₆	e ₃ -e' ₃	e ₅ -e' ₆	female
score	-e₅ e'₅ -	e ₄ -e' ₄	e ₃ -e' ₃	male
ţ	<u>-e₅ e'₁ </u>	e ₆ -e' ₂	e ₂ -e' ₁	female
	e ₂ -e' ₁	e ₁ -e' ₂	e ₄ -e' ₄	male
	e ₂ -e' ₅			

Proposition: FairER is a 1-1/e approximation to the problem of fairness-aware ER, for F defined as $||R_p|/k-|R_n|/k|=\varepsilon^*$

Experimental Evaluation

Baselines: Color-blind (DeepMatcher, 1-to-1 constraint), FA*IR (fair ranking algorithm)

Datasets: All 7 datasets available from DeepMatcher

Accuracy@k

Fa*ir

FairER

0.73

Method	D1	D2	D3	D4	D5	D6	D 7		
Accuracy@5									
Color-blind	1	1	1	1	1	0.8	0		
Fa*ir	1	1	1	1	1	1	0		
FairER	1	1	1	1	1	0.8	0.4		
Accuracy@1	Accuracy@10								
Color-blind	0.9	1	1	1	1	0.7	0.4		
Fa*ir	0.9	1	1	1	1	0.6	0.4		
FairER	0.9	1	0.8	1	1	0.8	0.4		
Accuracy@15									
Color-blind	0.73	1	1	1	0.93	0.73	0.6		

 $as@k = \frac{|R_p|}{|R_p|} - \frac{|R_n|}{|R_n|}$ fav. non-pr. no bias fav. prot.

0.66

0.93

0.71

0.73

0.6

0.33

Method	D1	D 2	D3	D4	D5	D6	D7	
$k = 5 \ (\epsilon * = 0.2)$								
Color-blind	-0.6	-0.6	-1	-1	-1	-1	-0.6	
Fa*ir	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6	-0.6	
FairER	0.2	0.2	0.2	0.2	0.2	0.2	0.2	
$k = 10 \ (\epsilon * = 0)$								
Color-blind	-0.6	-0.4	-1	-0.6	-0.8	-0.8	-0.8	

Color-blind	-0.6	-0.4	-1	-0.6	-0.8	-0.8	-0.8		
Fa*ir	-0.6	-0.4	-0.6	-0.6	-0.6	-0.6	-0.6		
FairER	0	0	0	0	0	0	0		
$k = 15 \ (\epsilon * = 0.07)$									

FairER	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Fa*ir	-0.47	-0.33	-0.47	-0.47	-0.47	-0.57	-0.47
Color-blind	-0.6	-0.33	-0.73	-0.6	-0.87	-0.87	-0.87

https://github.com/vefthym/fairER