



FairER: Entity Resolution with Fairness Constraints

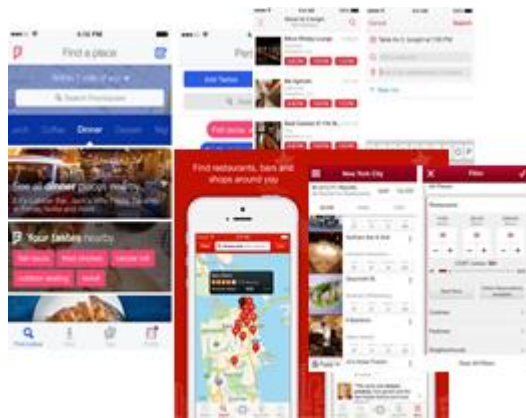
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Decision-making AI systems

We live in a world where decisions are assisted or taken by algorithmic systems driven by large amounts of data

Where to eat?



Who to date?



What are the news?



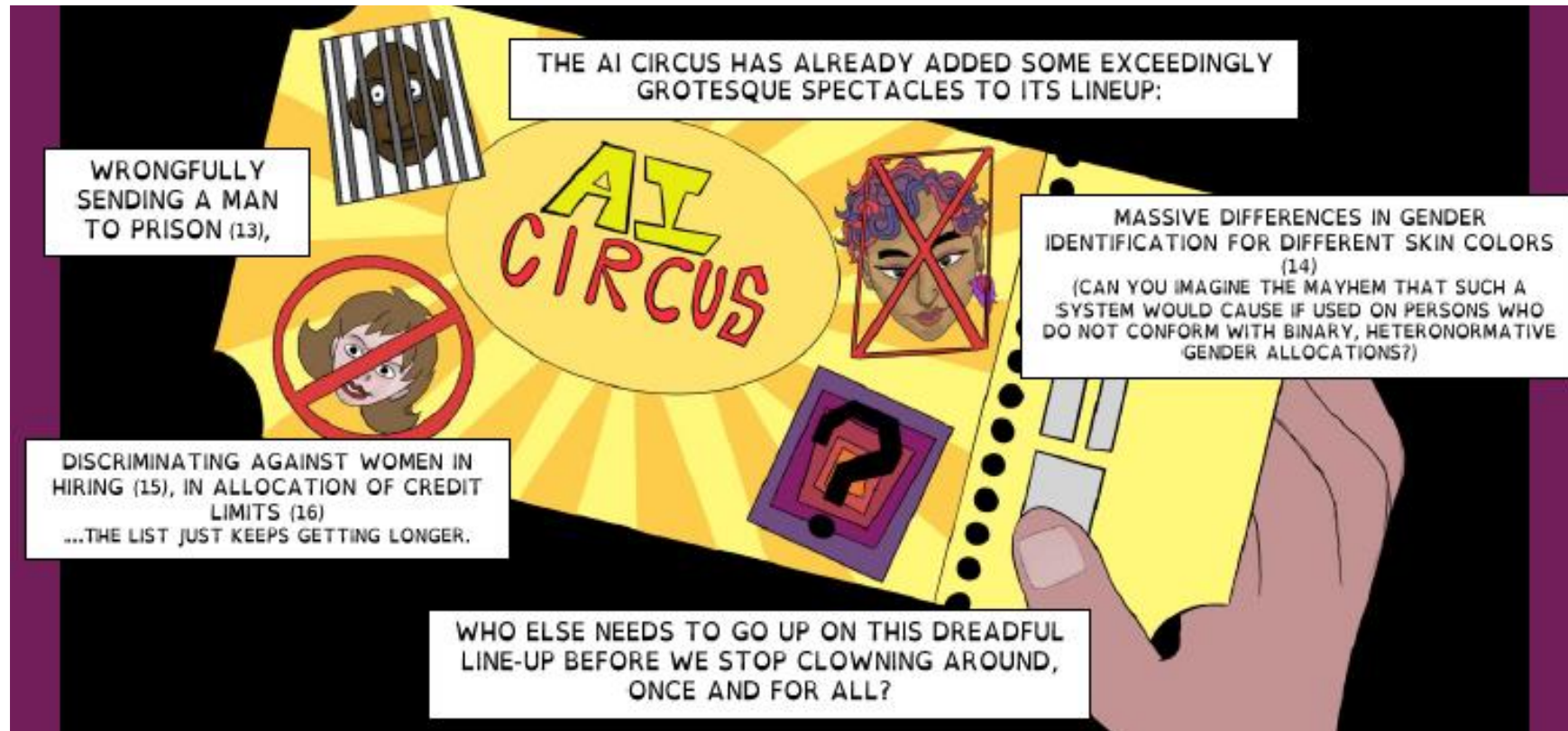
What to read, watch, buy..?



Pitoura, Stefanidis, Koutrika. "Fairness in Rankings and Recommenders: Models, Methods and Research Directions". ICDE 2021

FairER: Entity Resolution with Fairness Constraints

Some serious AI fairness issues...



Falaah Arif Khan and Julia Stoyanovich. "Mirror, Mirror". Data, Responsibly Comics, Volume 1 (2020)

https://dataresponsibly.github.io/comics/vol1/mirror_en.pdf

Entity Resolution (ER)

Identify entity descriptions from different data sources that refer to the same real-world entity (called *matches*)

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

Traditional ER (*aka 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'
 - common scoring function types:
 - heuristics (e.g., MinoanER)
 - agglomerative clustering (e.g., SiGMa)
 - binary classifiers (e.g., DeepMatcher, DeepER)

Traditional ER: Example

E

id	Name	Location	Employer	Rep	Sex
e ₁	Danny Barber	LA	UCLA	600	M
e ₂	Susan Doe	Texas	UT Austin	7,000	F
e ₃	Peter Simons	NY	NYU	4	M
e ₄	M. Anderson	Denmark	Aarhus Univ.	8	M
e ₅	Julia Rondo	France	CNRS, Paris	460	F
e ₆	J. Parker	California	UC Berkeley	381	M



E'

id	Full-name	Affiliation	h-index	Sex
e' ₁	Doe, S.	UT	14	F
e' ₂	J. Parker	UCSC	5	M
e' ₃	Simons, Pete	NYU	11	M
e' ₄	M. Anderson	Aarhus	15652	M
e' ₅	J. Rondo	CNRS	4653	F
e' ₆	Juliana Rondo	CNRS	25	F

desc.
score
↓

Traditional ER	R[4]
e ₃ -e' ₃	e ₃ -e' ₃
e ₄ -e' ₄	e ₄ -e' ₄
e ₆ -e' ₂	e ₆ -e' ₂
e ₅ -e' ₆	e ₅ -e' ₆
e₅-e'₅	
e₅-e'₁	
e ₂ -e' ₁	

3 male

1 female

Fairness-aware ER: Intuition

- Retrieved results: not only the most likely matches, but also satisfy some *fairness constraint*
- *Fairness in ER decisions*: equal decision measures that allow us to examine the allocation of benefits and harms across **groups** by looking at the decision alone
 - group-based fairness: disjoint groups (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 position

Fairness-aware ER: Definition

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

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

s.t. $R[k]$ satisfies F ,

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

FairER: a simple, yet highly efficient fairness-aware ER method

Targets one instance of fairness-aware ER

▪ Fairness criterion F: $\left| \frac{|R_p|}{k} - \frac{|R_n|}{k} \right| = \varepsilon^*,$

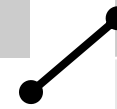
where $\frac{|R_p|}{k}$ (resp. $\frac{|R_n|}{k}$) is the ratio of protected (resp. non-protected) group members in the first k results and ε^* is the smallest possible ratio for a given k

- $\varepsilon^* = 0$, if k is even, otherwise $\varepsilon^* = 1/k$

FairER: Example

E

id	Name	Location	Employer	Rep	Sex
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e ₂	Susan Doe	Texas	UT Austin	7,000	F
e ₃	Peter Simons	NY	NYU	4	M
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id	Full-name	Affiliation	h-index	Sex
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e' ₄	M. Anderson	Aarhus	15652	M
e' ₅	J. Rondo	CNRS	4653	F
e' ₆	Juliana Rondo	CNRS	25	F

E'

desc.
score



FairER Q _p	FairER Q _n	R[4]	
e ₅ -e' ₆	e ₃ -e' ₃	e ₅ -e' ₆	female
e₅-e'₅	e ₄ -e' ₄	e ₃ -e' ₃	male
e₅-e'₁	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	e₃-e'₂		

FairER property

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

Experiments

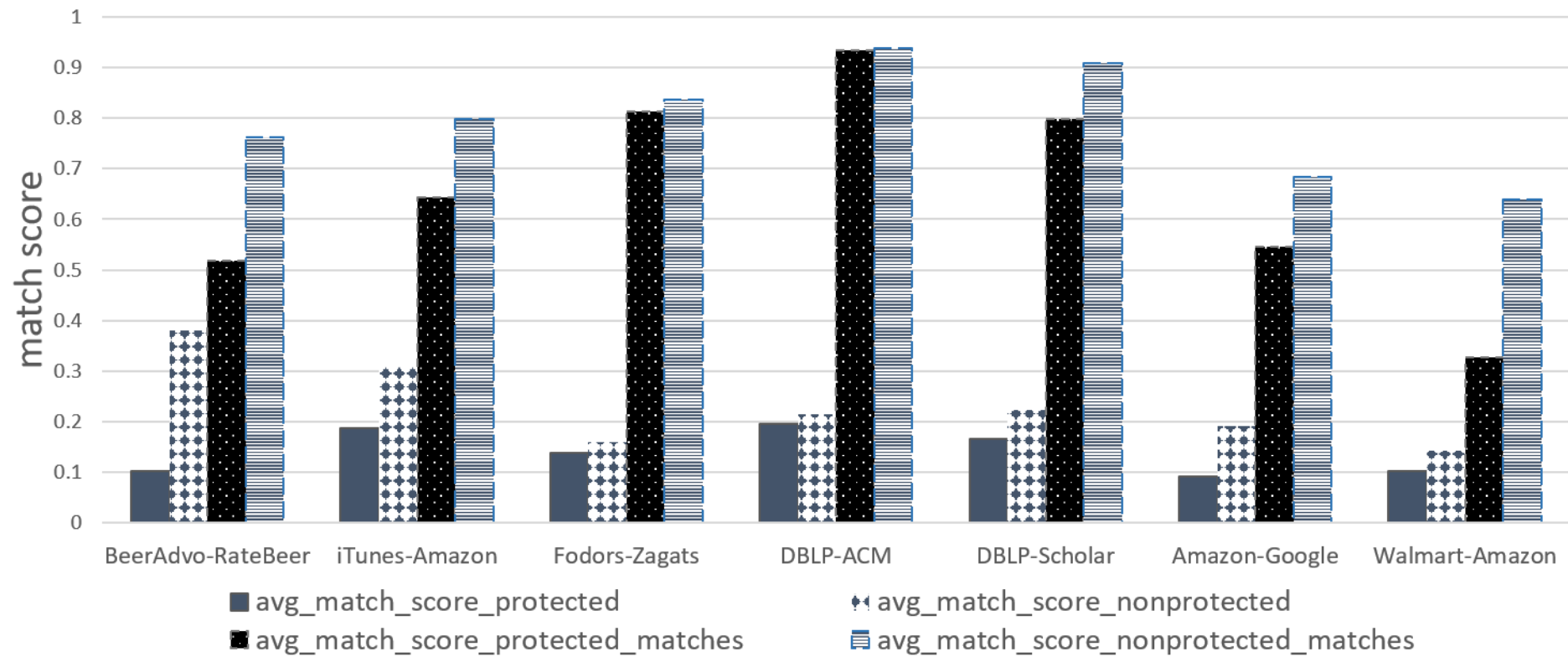
- Baselines:
 - Color-blind: traditional ER (DeepMatcher, 1-to-1 constraint)
 - FA*IR: use FA*IR, a fair ranking algorithm to re-rank original candidates
- Datasets: All seven datasets provided by DeepMatcher

- Protected group criterion:

- $|R_p^*|$: number of ground truth matches in protected group
- $|R_n^*|$: number of ground truth matches in non-protected group

Dataset	Pr. group criterion	$ R_p^* , R_n^* $
BeerAdvo-RateBeer (D1)	“Red” in beer name	5, 9
iTunes-Amazon (D2)	“Dance” in genre	11, 16
Fodors-Zagats (D3)	type = “asian”	3, 19
DBLP-ACM (D4)	female last author	39, 405
DBLP-Scholar (D5)	“vldb j” in venue	80, 990
Amazon-Google (D6)	“Microsoft” in manufacturer	12, 222
Walmart-Amazon (D7)	category = “printers”	11, 182

Avg scores of protected and non-pr. groups



Fairness scores (bias@k)

- F: $\left| \frac{|R_p|}{k} - \frac{|R_n|}{k} \right| = \varepsilon^*$
- bias@k: $\frac{|R_p|}{k} - \frac{|R_n|}{k}$

<0: favoring non-protected,
0: no bias,
>0: favoring protected

ε^* : minimum possible bias

Method	D1	D2	D3	D4	D5	D6	D7
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$k = 5 (\epsilon^* = 0.2)$

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
Fa*ir	-0.6	-0.4	-0.6	-0.6	-0.6	-0.6	-0.6
FairER	0	0	0	0	0	0	0

$k = 15 (\epsilon^* = 0.07)$

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

$k = 20 (\epsilon^* = 0)$

Color-blind	-0.4	-0.3	-0.7	-0.6	-0.9	-0.9	-0.9
Fa*ir	-0.4	-0.3	-0.4	-0.4	-0.4	-0.56	-0.4
FairER	0	0	0	0	0	0	0

Accuracy@k

Method	D1	D2	D3	D4	D5	D6	D7
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@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
Fa*ir	0.73	1	0.93	1	0.93	0.71	0.6
FairER	0.66	1	0.66	1	1	0.73	0.33
Accuracy@20							
Color-blind	0.65	1	1	1	0.95	0.75	0.65
Fa*ir	0.65	1	0.85	1	0.95	0.72	0.6
FairER	0.65	0.95	0.65	1	0.95	0.7	0.4

Conclusion

Summary:

- Introduced the problem of **fairness-aware ER**
 - proposed a general constraint-based formulation
- Presented **FairER algorithm**
 - solves an instance of this problem
 - fairness expressed as cardinality constraints of protected and non-protected group members in the output

Ongoing work:

- Extending FairER to more **complex protected group criteria**
- **Bias mitigation** in other ER tasks (blocking, clustering, fusion)
- Impact of **alternative fairness measures** on ER

Thanks!

Resources publicly available: <https://github.com/vefthym/fairER>



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