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When Correlation Clustering Meets Fairness Constraints

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Today’s Menu

- Intro to the context
- Background on Correlation Clustering
- The Fair-CC Problem
- Proposed approach
- Fairness-aware evaluation metrics
- Experimental methodology and results
- Conclusions and Future Work

Introduction

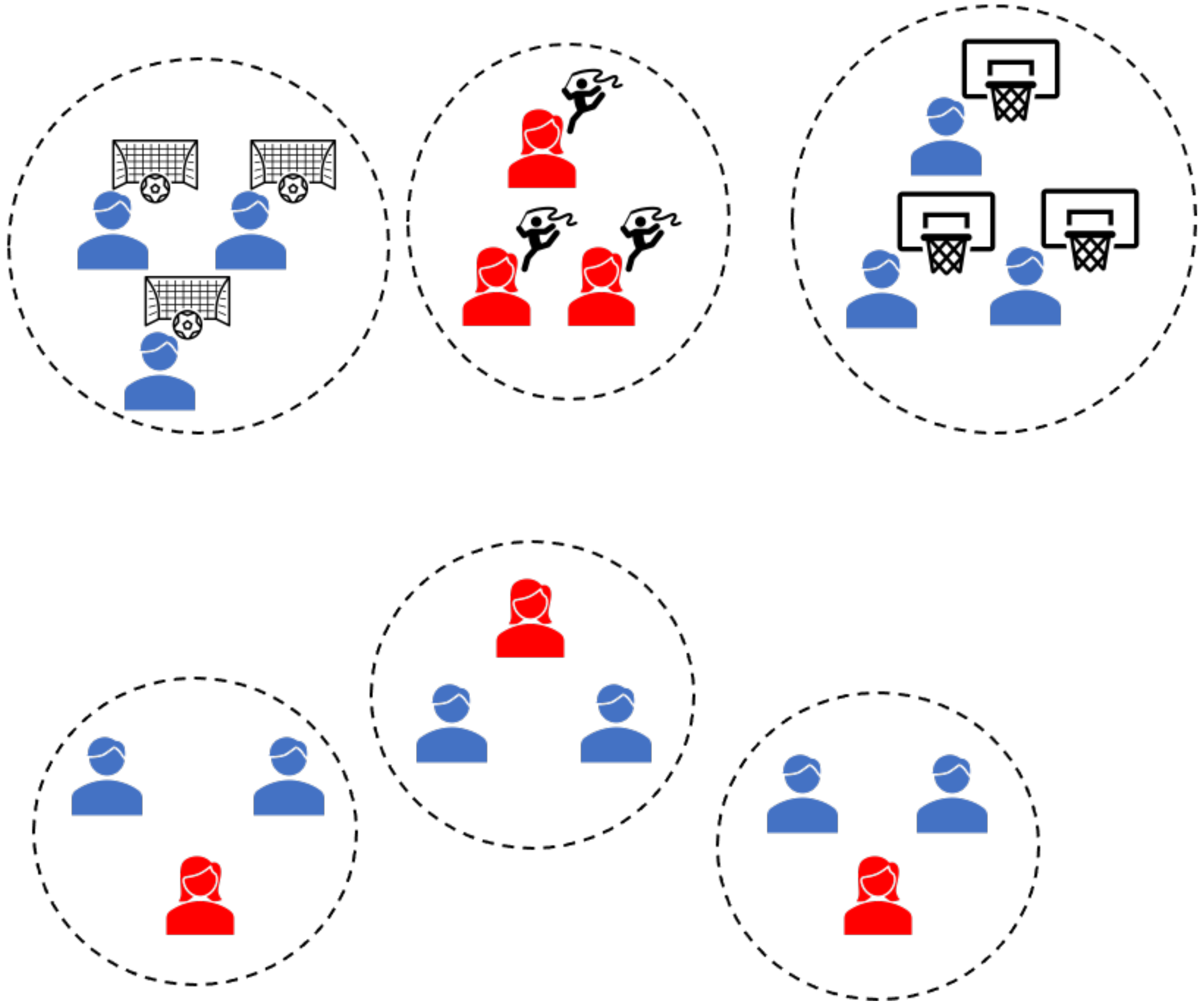
- Machine Learning (ML) systems achieved decision-making power in our lives (shall we entrust them?)
- Input data is often (intrinsically) biased
- ML algorithms must avoid amplifying input data bias
- Disparate impact must be removed
  - *no group of individuals should (even indirectly) be discriminated by a decision-making system* [1]

[1] Feldman, M., Friedler, S.A., Moeller, J., Scheidegger, C., Venkatasubramanian, S.: Certifying and removing disparate impact. In: Proc. ACM KDD Conf. pp. 259–268 (2015)

The Fair Clustering Problem

Clustering a set of data objects s.t.:

- ➡ Similar objects are assigned to the same cluster, whereas dissimilar objects are assigned to different clusters
- ➡ Clusters should not be dominated by a specific type of sensitive data class (e.g., people having the same sex)



Can we tackle this problem through a
correlation clustering framework?

Min-Disagreement Correlation Clustering (MIN-CC)

Given an undirected graph $G = \langle V, E \rangle$ with vertex set V and edge set $E \subseteq V \times V$, and weights $w^+_{uv}, w^-_{uv} \in \mathbf{R}^+_0$, for all edges $(u, v) \in E$, find a clustering $\mathscr{C} : V \longrightarrow \mathbf{N}^+$ that minimizes:

$$\sum_{(u,v) \in E, \mathscr{C}(u) = \mathscr{C}(v)} w^-_{uv} \quad + \sum_{(u,v) \in E, \mathscr{C}(u) \neq \mathscr{C}(v)} w^+_{uv}$$

where w^+_{uv}, resp. w^-_{uv}, denote the benefit of clustering u and v together, resp. separately.

Problem Statement - Notation

Let $\mathscr{X} = \{X_1, \cdots, X_n\}$ be a set of n objects defined over a set of attributes $\mathscr{A}$ divided into two sets:

- $\mathscr{A}^F$ containing *fairness-aware* (or *sensitive*) attributes (e.g., those identifying sex, race, religion, relationship status in a citizen database);
- $\mathscr{A}^{\neg F}$ containing *non-sensitive* attributes (e.g., user preferences).

Both can include numerical (N) and categorical (C) attributes:

$$\mathscr{A}^F = \mathscr{A}^F_N \cup \mathscr{A}^F_C, \qquad \mathscr{A}^{\neg F} = \mathscr{A}^{\neg F}_N \cup \mathscr{A}^{\neg F}_C$$

Problem Statement - Fair-CC

Given a set of objects $\mathcal{X}$, two sets of attributes $\mathcal{A}^F$ and $\mathcal{A}^{\neg F}$, and an object similarity function $sim_S(\cdot)$ defined over the subspace S of the attribute set, find a clustering $\mathcal{C}^*$ to minimize:

$$\sum_{u,v \in \mathcal{X}, \mathcal{C}(u)=\mathcal{C}(v)} sim_{\mathcal{A}^F}(u,v) \quad + \sum_{u,v \in \mathcal{X}, \mathcal{C}(u)\neq\mathcal{C}(v)} sim_{\mathcal{A}^{\neg F}}(u,v)$$

This corresponds to solving a complete Min-CC instance:

- The set of vertices corresponds to the objects in $\mathcal{X}$ and,
- For each pair of vertices u and v, the positive-type (resp. negative-type) correlation-clustering weight corresponds to the similarity score between the two vertices according to the non-sensitive (resp. sensitive) attributes.

Utility functions

$$sim_{\mathscr{A}^{\neg F}}(u,v) := \psi^{+}\left(\alpha_N^{\neg F} \cdot sim_{\mathscr{A}_N^{\neg F}}(u,v) + (1-\alpha_N^{\neg F}) \cdot sim_{\mathscr{A}_C^{\neg F}}(u,v)\right)$$

$$sim_{\mathscr{A}^{F}}(u,v) := \psi^{-}\left(\alpha_N^{F} \cdot sim_{\mathscr{A}_N^{F}}(u,v) + (1-\alpha_N^{F}) \cdot sim_{\mathscr{A}_C^{F}}(u,v)\right)$$

Similarity according to the set of non-sensitive and sensitive attributes

$$\alpha_N^F = |\mathscr{A}_N^F|/(|\mathscr{A}_N^F| + |\mathscr{A}_C^F|)$$

$$\alpha_N^{\neg F} = |\mathscr{A}_N^{\neg F}|/(|\mathscr{A}_N^{\neg F}| + |\mathscr{A}_C^{\neg F}|)$$

Weight similarities proportionally to the number of involved attributes

$$\psi^{+} = exp(|\mathscr{A}^F|/(|\mathscr{A}^F| + |\mathscr{A}^{\neg F}|) - 1)$$

$$\psi^{-} = exp(|\mathscr{A}^{\neg F}|/(|\mathscr{A}^F| + |\mathscr{A}^{\neg F}|) - 1)$$

Smoothing factors to penalize weights that are computed on a small number of attributes

Solving Fair-CC

The CC-Bounds algorithm: [2]

Input: Set of objects $\mathscr{X}$, sensitive attributes $\mathscr{A}^F$, non-sensitive attributes $\mathscr{A}^{\neg F}$, Min-CC algorithm A

Output: Clustering $\mathscr{C}$ of $\mathscr{X}$

1. Compute $sim_{\mathscr{A}^{\neg F}}(u, v), sim_{\mathscr{A}^F}(u, v) \ \forall u, v \in \mathscr{X}$

2. Build the instance
$I = \langle G = (\mathscr{X}, \mathscr{X} \times \mathscr{X}), \{sim_{\mathscr{A}^{\neg F}}(u, v), sim_{\mathscr{A}^F}(u, v)\}_{u,v \in \mathscr{X} \times \mathscr{X}} \rangle$

3. $\mathscr{C} \leftarrow$ run A on I

[2] Mandaglio, D., Tagarelli, A., Gullo, F.: Correlation clustering with global weight bounds. In: Proc. ECML-PKDD Conf. pp. 499–515 (2021)

Theoretical remarks

Let $T_{\mathsf{A}}(\mathscr{X})$ the running time of the algorithm A on the set of data objects $\mathscr{X}$

➡ The time complexity of CCBounds is $\mathcal{O}(|\mathscr{X}|^2|\mathscr{A}| + T_{\mathsf{A}}(\mathscr{X}))$

- Compute similarities over $\mathscr{A}$ attributes, for each pair of objects in $\mathscr{X}$, then solve the resulting Min-CC instance through A

➡ The space complexity of CC-Bounds is $\mathcal{O}(|\mathscr{X}|^2)$

- In-memory similarity storing

The Min-CC algorithm A used in CC-Bounds is the one proposed in [3], as it proposes constant-factor approximation guarantees (under certain conditions), s.t. $T_{\mathsf{A}}(\mathscr{X}) = \mathcal{O}(|\mathscr{X}|^2)$.

✓ The time complexity of CCBounds become $\mathcal{O}(|\mathscr{X}|^2|\mathscr{A}|)$.

[3] Ailon, N., Charikar, M., Newman, A.: Aggregating inconsistent information: ranking and clustering. In: Proc. ACM STOC Symp. pp. 684–693 (2005)

Theorem 1 [2]

If the condition

$$\binom{|\mathcal{X}|}{2}^{-1}\left(sim_{\mathcal{A}^{\neg F}}(u,v) + sim_{\mathcal{A}^{F}}(u,v)\right) \geq \max_{u,v\in\mathcal{X}} |sim_{\mathcal{A}^{\neg F}}(u,v) - sim_{\mathcal{A}^{F}}(u,v)|$$

holds on the similarity scores and the oracle A is an α-approximation algorithm for Min-CC, CCBounds is α-approximation algorithm for Fair-CC.

[2] Mandaglio, D., Tagarelli, A., Gullo, F.: Correlation clustering with global weight bounds. In: Proc. ECML-PKDD Conf. pp. 499–515 (2021)

Evaluating Fairness

Focus on algorithm-independent evaluation metrics following a *group-level* approach under the *disparate impact* doctrine [4]

$$balance(\mathscr{C}) \overset{[5,6]}{=} \min_{C \in \mathscr{C}, b \in [m]} \min \left\{ R_{C,b}, \frac{1}{R_{C,b}} \right\} \in [0,1]$$

$$AE_A(\mathscr{C}) \overset{[7]}{=} \frac{\sum_{C \in \mathscr{C}} |C| \times ED(C_A, \mathscr{X}_A)}{\sum_{C \in \mathscr{C}} |C|}$$

[4] Feldman, M., Friedler, S.A., Moeller, J., Scheidegger, C., Venkatasubramanian, S.: Certifying and removing disparate impact. In: Proc. ACM KDD Conf. pp. 259–268 (2015)

[5] Chierichetti, F., Kumar, R., Lattanzi, S., Vassilvitskii, S.: Fair clustering through fairlets. In: Proc. NIPS Conf. pp. 5029–5037 (2017)

[6] Bera, S.K., Chakrabarty, D., Flores, N., Negahbani, M.: Fair algorithms for clustering. In: Proc. NIPS Conf. pp. 4955–4966 (2019)

[7] Abraham, S.S., P, D., Sundaram, S.S.: Fairness in clustering with multiple sensitive attributes. In: Proc. EDBT Conf. pp. 287–298 (2020)

Competing methods

- *Fair Clustering through Fairlets* [5]
- *HST-based Fair Clustering* [8]
- *Fair Correlation Clustering* [9]

- Based on *fairlets decomposition* (direct or via correlation clustering)
- The first two can just handle a single sensitive attribute

[5] Chierichetti, F., Kumar, R., Lattanzi, S., Vassilvitskii, S.: Fair clustering through fairlets. In: Proc. NIPS Conf. pp. 5029–5037 (2017)
[8] Backurs, A., Indyk, P., Onak, K., Schieber, B., Vakilian, A., Wagner, T.: Scalable fair clustering. In: Proc. ICML Conf. pp. 405–413 (2019)
[9] Ahmadian, S., Epasto, A., Kumar, R., Mahdian, M.: Fair correlation clustering. In: Proc. AISTATS Conf. pp. 4195–4205 (2020)

Data

- Publicly available real-world relational datasets
- Focus on a smaller subset of the original attributes

	#objs.	*sensitive* attribute	*non-sensitive* attributes
Adult	48 842	sex	age, fnlgwt, education_num, capital_gain, hours_per_week
Bank	40 004	marital	age, balance, duration
CreditCard	10 127	sex	customer_age, dependent_count, avg_utilization_ratio, total_relationship_count
Diabetes	101 763	sex	age, time_in_hospital
Student	649	sex	age, study_time, absences

Evaluation goals

$$inter(\mathscr{A}^{\neg F}) = \frac{1}{|\Theta|} \sum_{u,v \in \Theta} sim_{\mathscr{A}^{\neg F}}(u, v)$$

$$inter(\mathscr{A}^{F}) = \frac{1}{|\Theta|} \sum_{u,v \in \Theta} sim_{\mathscr{A}^{F}}(u, v)$$

$$intra(\mathscr{A}^{\neg F}) = \frac{1}{|\Omega|} \sum_{u,v \in \Omega} sim_{\mathscr{A}^{\neg F}}(u, v)$$

$$intra(\mathscr{A}^{F}) = \frac{1}{|\Omega|} \sum_{u,v \in \Omega} sim_{\mathscr{A}^{F}}(u, v)$$

Running times were measured while executing on the *Cresco6* cluster*

$$\Omega = \{u, v \in \mathscr{X} \mid \mathscr{C}(u) = \mathscr{C}(v)\}, \Theta = \{u, v \in \mathscr{X} \mid \mathscr{C}(u) \neq \mathscr{C}(v)\}$$

* https://www.eneagrid.enea.it

Hyper-params and Configurations

- Random sampling of the original data
  - 1k/10k tuples which preserve some desired ratio between the protected classes
- Specification of *p* and *q* parameters
  - *p/q* represents the minimum balance required by each cluster
- Minimum shared requirements, e.g., single and binary sensitive attribute
- Number of clusters *k* as the (rounded) avg. number of clusters returned by CCBounds in ten iterations

	p, q	split ratio	k_{avg}	k
Adult-1k	1,2	650/350	3.12	3
Bank-1k	1,2	650/350	3.48	3
Credit-Card-1k	1,6	800/200	5.6	6
Diabetes-1k	1,2	540/460	5.2	5
Student-1k	1,2	266/383	3.88	4
Adult-10k	1,2	6 500/3 500	2.96	3
Bank-10k	1,2	6 500/3 500	3.28	3
Credit-Card-10k	1,6	4 769/5 358	6.32	6
Diabetes-10k	1,2	5 400/4 600	6.44	6
Adult-Full	2,5	32 650/16 192	3.64	4
Bank-Full	2,5	12 790/27 214	3.64	4
Diabetes-Full	1,2	47 055/54 708	OOM	6

Results - Balance

		#clust.	balance ↑	AE ↓	$intra(\mathcal{A}^{\neg F})$ ↑	$intra(\mathcal{A}^{F})$ ↓	$inter(\mathcal{A}^{\neg F})$ ↓	$inter(\mathcal{A}^{F})$ ↑	time (s) ↓
Adult-1k	CCBounds	3.12	0.565	**0.007**	**0.685**	0.524	**0.415**	**0.334**	< **1**
	FAIRLETS	3	0.805	**0.004**	0.585	**0.319**	0.596	**0.335**	< **1**
	HST-FC	3	**0.971**	0.01	0.616	0.335	0.599	**0.336**	< **1**
	SIGNED	41	0.66	0.03	0.59	**0.32**	0.60	**0.33**	240
Adult-10k	CCBounds	2.96	0.52	0.03	**0.65**	0.43	**0.43**	**0.33**	3.86
	FAIRLETS	3	0.82	**0.003**	0.60	**0.32**	0.615	**0.33**	< 1
	HST-FC	3	**0.98**	**0.006**	0.626	0.336	0.618	**0.336**	3.03
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
Adult-Full	CCBounds	3.64	0.56	**0.003**	**0.69**	0.47	**0.42**	0.24	75.5
	FAIRLETS	4	0.66	0.02	0.59	**0.32**	0.62	**0.34**	**6.5**
	HST-FC	4	**0.96**	**0.008**	0.63	0.34	0.62	**0.34**	72.86
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
Bank-1k	CCBounds	3.48	0.565	**0.006**	**0.727**	0.587	**0.441**	**0.369**	< **1**
	FAIRLETS	3	0.828	**0.002**	0.606	**0.354**	0.613	**0.364**	< **1**
	HST-FC	3	**0.968**	**0.007**	0.621	0.365	0.617	**0.365**	< **1**
	SIGNED	41	0.7	0.03	0.61	**0.35**	0.63	**0.36**	224
Bank-10k	CCBounds	3.28	0.52	**0.0007**	**0.78**	0.63	**0.45**	**0.36**	4.74
	FAIRLETS	3	0.7	0.001	0.59	**0.32**	0.63	**0.36**	< **1**
	HST-FC	3	**0.969**	0.004	0.656	0.365	0.656	**0.365**	3.07
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
Bank-Full	CCBounds	3.64	0.55	**0.0004**	**0.72**	0.55	**0.45**	**0.37**	51.1
	FAIRLETS	4	0.68	0.001	0.62	**0.34**	0.65	0.36	**5.3**
	HST-FC	4	**0.94**	0.008	0.66	0.37	0.66	**0.37**	28
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h

- "Fairness-native" methods yield better balance scores
- CCBounds is aligned with its direct competing method in most cases
- On small yet heavily unbalanced datasets (i.e., CreditCard-1k with an 80:20 ratio), CCBounds achieves the second-best score, while other competing methods struggle
- Overall, the balance obtained by CCBounds in all evaluation scenarios ranges from 0.45 to 0.613

Results - Balance

		#clust.	balance ↑	AE ↓	$intra(\mathcal{A}^{\neg F})$ ↑	$intra(\mathcal{A}^{F})$ ↓	$inter(\mathcal{A}^{\neg F})$ ↓	$inter(\mathcal{A}^{F})$ ↑	time (s) ↓
CreditCard-1k	CCBounds	5.6	0.613	0.127	**0.6**	0.497	**0.46**	0.362	**< 1**
	FAIRLETS	6	0.4	0.042	0.485	**0.355**	0.486	**0.375**	**< 1**
	HST-FC	6	**0.756**	**0.026**	0.513	0.373	0.481	**0.377**	**< 1**
	SIGNED	171	0.56	0.1	0.56	0.41	0.49	**0.38**	173
CreditCard-10k	CCBounds	6.32	0.496	0.17	**0.6**	0.46	**0.46**	0.32	4.1
	FAIRLETS	6	0.94	**0.01**	0.497	**0.34**	0.49	**0.337**	< 1
	HST-FC	6	**0.955**	**0.013**	0.52	**0.337**	0.491	**0.337**	2.52
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
Diabetes-1k	CCBounds	5.2	0.45	0.33	**0.622**	0.519	**0.512**	0.352	< 1
	FAIRLETS	5	**0.92**	**0.015**	0.537	0.381	0.532	**0.385**	< 1
	HST-FC	5	0.872	0.05	0.585	0.386	0.529	**0.386**	< 1
	SIGNED	106	0.85	0.04	0.58	**0.36**	0.54	**0.38**	257
Diabetes-10k	CCBounds	6.44	0.48	0.22	**0.65**	0.54	**0.5**	0.36	4.72
	FAIRLETS	6	**0.92**	**0.01**	0.53	**0.38**	**0.53**	**0.39**	< 1
	HST-FC	6	0.799	0.065	0.59	**0.388**	**0.53**	**0.386**	2.84
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
Diabetes-Full	CCBounds	OOM	OOM	OOM	OOM	OOM	OOM	OOM	OOM
	FAIRLETS	6	**0.93**	**0.01**	OOM	OOM	OOM	OOM	**22.2**
	HST-FC	6	0.81	0.06	OOM	OOM	OOM	OOM	761.2
	SIGNED	OOM	OOM	OOM	OOM	OOM	OOM	OOM	OOM
Student-1k	CCBounds	3.88	0.51	0.10	**0.625**	0.463	**0.471**	0.224	**< 1**
	FAIRLETS	4	0.82	**0.013**	0.528	**0.339**	0.543	**0.357**	**< 1**
	HST-FC	4	**0.93**	0.024	0.563	0.357	0.541	**0.358**	**< 1**
	SIGNED	55	0.82	0.04	0.57	**0.34**	0.55	**0.36**	71

- "Fairness-native" methods yield better balance scores
- CCBounds is aligned with its direct competing method in most cases
- On small yet heavily unbalanced datasets (i.e., CreditCard-1k with an 80:20 ratio), CCBounds achieves the second-best score, while other competing methods struggle
- Overall, the balance obtained by CCBounds in all evaluation scenarios ranges from 0.45 to 0.613

Results - Average Euclidean Fairness

		#clust.	balance ↑	AE ↓	$intra(\mathcal{A}^{\neg F})$ ↑	$intra(\mathcal{A}^{F})$ ↓	$inter(\mathcal{A}^{\neg F})$ ↓	$inter(\mathcal{A}^{F})$ ↑	time (s) ↓
Adult-1k	CCBounds	3.12	0.565	**0.007**	**0.685**	0.524	**0.415**	**0.334**	< **1**
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	Signed	NA	NA	NA	NA	NA	NA	NA	> 48h

- CCBounds obtains very good scores under different scenarios
- Among the best-performing approaches for the *Adult-1k*, *Adult-Full* and *Bank-1k* datasets
- Outperforms all the other methods by an order of magnitude on *Bank-10k* and *Bank-Full*
- Performances worsen while considering the remaining datasets

Results - Average Euclidean Fairness

		#clust.	balance ↑	AE ↓	$intra(\mathcal{A}^{\neg F})$ ↑	$intra(\mathcal{A}^{F})$ ↓	$inter(\mathcal{A}^{\neg F})$ ↓	$inter(\mathcal{A}^{F})$ ↑	time (s) ↓
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	HST-FC	6	0.81	0.06	OOM	OOM	OOM	OOM	761.2
	SIGNED	OOM	OOM	OOM	OOM	OOM	OOM	OOM	OOM
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	FAIRLETS	4	0.82	**0.013**	0.528	**0.339**	0.543	**0.357**	< **1**
	HST-FC	4	**0.93**	0.024	0.563	0.357	0.541	**0.358**	< **1**
	SIGNED	55	0.82	0.04	0.57	**0.34**	0.55	**0.36**	71

- CCBounds obtains very good scores under different scenarios
- Among the best-performing approaches for the *Adult-1k*, *Adult-Full* and *Bank-1k* datasets
- Outperforms all the other methods by an order of magnitude on *Bank-10k* and *Bank-Full*
- Performances worsen while considering the remaining datasets

Results - Similarities

		#clust.	balance ↑	AE ↓	$intra(\mathcal{A}^{\neg F})$ ↑	$intra(\mathcal{A}^{F})$ ↓	$inter(\mathcal{A}^{\neg F})$ ↓	$inter(\mathcal{A}^{F})$ ↑	time (s) ↓
Adult-1k	CCBounds	3.12	0.565	**0.007**	**0.685**	0.524	**0.415**	**0.334**	**< 1**
	Fairlets	3	0.805	**0.004**	0.585	**0.319**	0.596	**0.335**	**< 1**
	HST-FC	3	**0.971**	0.01	0.616	0.335	0.599	**0.336**	**< 1**
	Signed	41	0.66	0.03	0.59	**0.32**	0.60	**0.33**	240
Adult-10k	CCBounds	2.96	0.52	0.03	**0.65**	0.43	**0.43**	**0.33**	3.86
	Fairlets	3	0.82	**0.003**	0.60	**0.32**	0.615	**0.33**	**< 1**
	HST-FC	3	**0.98**	**0.006**	0.626	0.336	0.618	**0.336**	3.03
	Signed	NA	NA	NA	NA	NA	NA	NA	> 48h
Adult-Full	CCBounds	3.64	0.56	**0.003**	**0.69**	0.47	**0.42**	0.24	75.5
	Fairlets	4	0.66	0.02	0.59	**0.32**	0.62	**0.34**	**6.5**
	HST-FC	4	**0.96**	**0.008**	0.63	0.34	0.62	**0.34**	72.86
	Signed	NA	NA	NA	NA	NA	NA	NA	> 48h
Bank-1k	CCBounds	3.48	0.565	**0.006**	**0.727**	0.587	**0.441**	**0.369**	**< 1**
	Fairlets	3	0.828	**0.002**	0.606	**0.354**	0.613	**0.364**	**< 1**
	HST-FC	3	**0.968**	**0.007**	0.621	0.365	0.617	**0.365**	**< 1**
	Signed	41	0.7	0.03	0.61	**0.35**	0.63	**0.36**	224
Bank-10k	CCBounds	3.28	0.52	**0.0007**	**0.78**	0.63	**0.45**	**0.36**	4.74
	Fairlets	3	0.7	0.001	0.59	**0.32**	0.63	**0.36**	**< 1**
	HST-FC	3	**0.969**	0.004	0.656	0.365	0.656	**0.365**	3.07
	Signed	NA	NA	NA	NA	NA	NA	NA	> 48h
Bank-Full	CCBounds	3.64	0.55	**0.0004**	**0.72**	0.55	**0.45**	**0.37**	51.1
	Fairlets	4	0.68	0.001	0.62	**0.34**	0.65	0.36	**5.3**
	HST-FC	4	**0.94**	0.008	0.66	0.37	0.66	**0.37**	28
	Signed	NA	NA	NA	NA	NA	NA	NA	> 48h

- On the sensitive attributes, CCBounds tends to group a few more objects with the same sensitive attribute value than the other methods
- CCBounds is still able to properly separate the objects into clusters, when accounting for the sensitive attribute
- CCBounds achieves the best performance in all the considered evaluation scenarios when considering non-sensitive attributes

Results - Similarities

		$\#clust.$	balance ↑	AE ↓	$intra(\mathcal{A}^{\neg F})$ ↑	$intra(\mathcal{A}^{F})$ ↓	$inter(\mathcal{A}^{\neg F})$ ↓	$inter(\mathcal{A}^{F})$ ↑	time (s) ↓
CreditCard-1k	CCBounds	5.6	0.613	0.127	**0.6**	0.497	**0.46**	0.362	**< 1**
	FAIRLETS	6	0.4	0.042	0.485	**0.355**	0.486	**0.375**	**< 1**
	HST-FC	6	**0.756**	**0.026**	0.513	0.373	0.481	**0.377**	**< 1**
	SIGNED	171	0.56	0.1	0.56	0.41	0.49	**0.38**	173
CreditCard-10k	CCBounds	6.32	0.496	0.17	**0.6**	0.46	**0.46**	0.32	4.1
	FAIRLETS	6	0.94	**0.01**	0.497	**0.34**	0.49	**0.337**	**< 1**
	HST-FC	6	**0.955**	**0.013**	0.52	**0.337**	0.491	**0.337**	2.52
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
Diabetes-1k	CCBounds	5.2	0.45	0.33	**0.622**	0.519	**0.512**	0.352	**< 1**
	FAIRLETS	5	**0.92**	**0.015**	0.537	0.381	0.532	**0.385**	**< 1**
	HST-FC	5	0.872	0.05	0.585	0.386	0.529	**0.386**	**< 1**
	SIGNED	106	0.85	0.04	0.58	**0.36**	0.54	**0.38**	257
Diabetes-10k	CCBounds	6.44	0.48	0.22	**0.65**	0.54	**0.5**	0.36	4.72
	FAIRLETS	6	**0.92**	**0.01**	0.53	**0.38**	**0.53**	**0.39**	**< 1**
	HST-FC	6	0.799	0.065	0.59	**0.388**	**0.53**	**0.386**	2.84
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
Diabetes-Full	CCBounds	OOM	OOM	OOM	OOM	OOM	OOM	OOM	OOM
	FAIRLETS	6	**0.93**	**0.01**	OOM	OOM	OOM	OOM	**22.2**
	HST-FC	6	0.81	0.06	OOM	OOM	OOM	OOM	761.2
	SIGNED	OOM	OOM	OOM	OOM	OOM	OOM	OOM	OOM
Student-1k	CCBounds	3.88	0.51	0.10	**0.625**	0.463	**0.471**	0.224	**< 1**
	FAIRLETS	4	0.82	**0.013**	0.528	**0.339**	0.543	**0.357**	**< 1**
	HST-FC	4	**0.93**	0.024	0.563	0.357	0.541	**0.358**	**< 1**
	SIGNED	55	0.82	0.04	0.57	**0.34**	0.55	**0.36**	71

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Results - Running Times

		#clust.	balance ↑	AE ↓	$intra(\mathcal{A}^{\neg F})$ ↑	$intra(\mathcal{A}^{F})$ ↓	$inter(\mathcal{A}^{\neg F})$ ↓	$inter(\mathcal{A}^{F})$ ↑	time (s) ↓
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	FAIRLETS	3	0.805	**0.004**	0.585	**0.319**	0.596	**0.335**	< **1**
	HST-FC	3	**0.971**	0.01	0.616	0.335	0.599	**0.336**	< **1**
	SIGNED	41	0.66	0.03	0.59	**0.32**	0.60	**0.33**	240
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	FAIRLETS	3	0.82	**0.003**	0.60	**0.32**	0.615	**0.33**	< **1**
	HST-FC	3	**0.98**	**0.006**	0.626	0.336	0.618	**0.336**	3.03
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
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	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h
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	HST-FC	4	**0.94**	0.008	0.66	0.37	0.66	**0.37**	28
	SIGNED	NA	NA	NA	NA	NA	NA	NA	> 48h

- FAIRLETS, HST-FC and CCBounds guarantee reasonable running times
- CCBounds overcomes its direct competing method SIGNED
  - Parallelized pairwise similarity computation
  - Abnormal number of clusters for SIGNED

Results - Running Times

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Conclusions

- We assessed how correlation clustering can handle fair clustering
- Experimental evidence that CCBounds may serve as a good trade-off between the traditional and fairness-aware clustering conditions

Future Work

- Alternative definitions of the similarity functions
- Generalization of CCBounds to
  - Multiple protected values
  - Multiple sensitive attributes with many values

Thanks!

Any questions?

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