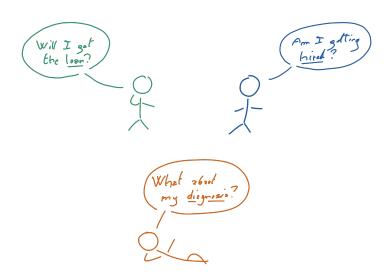
FAST AND ACCURATE FAIR k-CENTER CLUSTERING IN DOUBLING METRICS

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Joint work with Andrea Pietracaprina and Geppino Pucci



Disparate impact

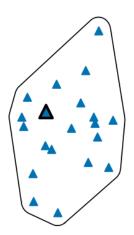
People in different protected classes should not experience disproportionally different outcomes.

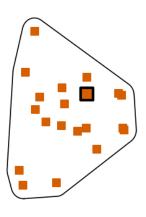
Disparate impact

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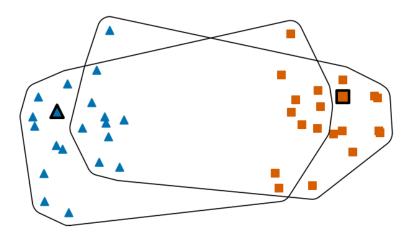
Unawareness does not help

Blindly ignoring protected attributes is no solution: correlated features (e.g. height which correlates with sex) can leak information about the protected attributes and thus lead to *unfair* solutions.





Classic k-center assigns each point to the closest center.

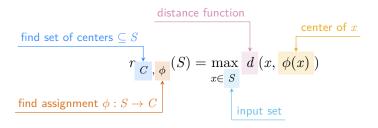


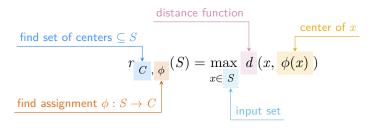
If we want to balance the colors in each cluster, we possibly have to assign points to farther away centers.

- ▶ Metric space (\mathcal{X}, d)
- ightharpoonup Set of points S
- \blacktriangleright Each point has one (or more) colors out of a set Γ
- ▶ Parameter *k*

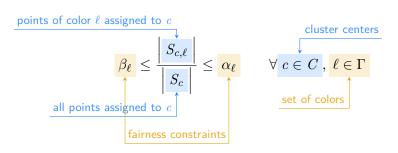
Goal

Build a clustering such that the *proportion* of points from each protected group is the same as the proportion in the entire dataset.





Minimize the above, where the assignment is subject to



- ightharpoonup Find a set of k centers, ignoring fairness
- Build the assignment function by means of linear programming, imposing fairness

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- ▶ 3 approximation [Ber+19; HL20]
- ▶ 9 approximation in MapReduce, $7 + \varepsilon$ in Streaming [Ber+22]
- ▶ large linear program of size $O(k \cdot n)$

Our contribution

$3+\varepsilon$ approximation algorithms

- ▶ **Sequential**: Linear time in the input size
- **Streaming**: 2 passes and memory $O\left(\log \frac{d_{max}}{d_{min}}\right)$
- ▶ **MapReduce**: 5 rounds and memory $O(\max\{|S|/p, p\})$, where p is the number of processors

Build a coreset

- ightharpoonup Set $T \subseteq S$
- $ightharpoonup |T| \ll |S|$
- ▶ Proxy function $\pi: S \to T$
- ightharpoonup Weight function $w:T\to\mathbb{N}$

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Solve the problem on the coreset

Still use linear programming

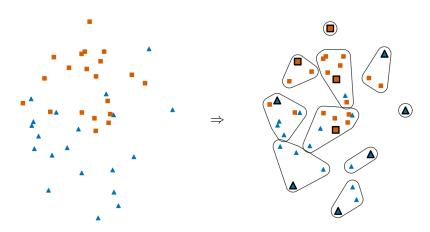
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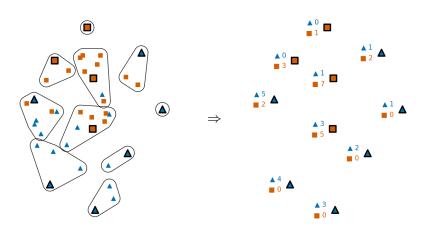
- Still use linear programming
- ▶ Less data ⇒ much faster!

Locate a set of proxy points



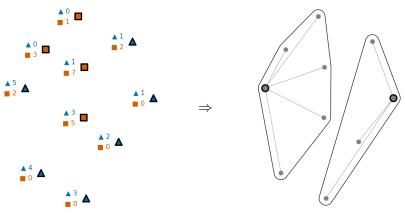
Goal: find a good compact representation of the input

Assign weights to coreset points



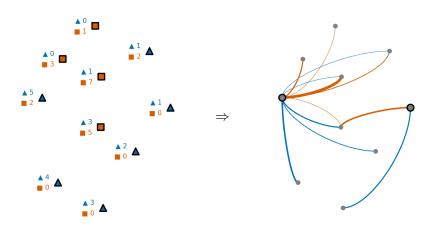
Goal: enable addressing fairness later

Find an unfair k-center clustering on the coreset



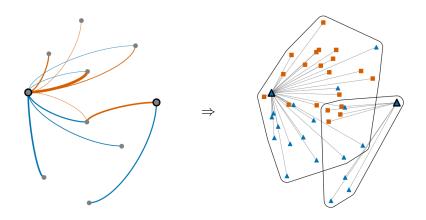
Goal: optimize the placement of centers

Distribute weight to centers



Goal: address fairness

Assign original points



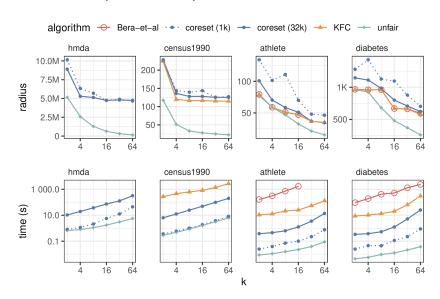
Goal: compute the solution

Is this any good?

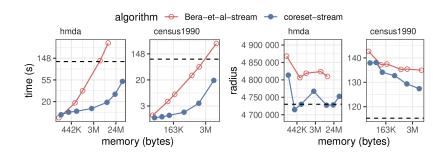
Is this any good?



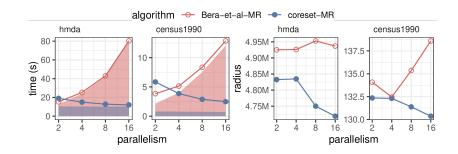
Experiments (sequential)



Experiments (Streaming)



Experiments (MapReduce)



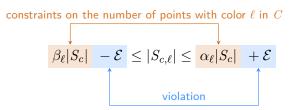
Thank you!



Appendix

Additive violation

The additive violation of an assignment, w.r.t. the fairness constraints $\alpha_{\ell}, \beta_{\ell}$, is the minimum \mathcal{E} s.t. $\forall c \in C, \ell \in \Gamma$



Our algorithm provides an additive violation of $4\Delta+3$, where Δ is the maximum number of colors per point.

Preliminaries: GMM

Classic algorithm for *unfair* k-center.

```
Input: Set S, parameter k C \leftarrow \{ \text{arbitrary point from } S \}; while |C| < k \text{ do} \qquad \qquad c \leftarrow \arg\max_{x \in S} d(x,C); \qquad \qquad C \leftarrow C \cup \{c\}; return C:
```

Provides a 2-approximation in time $O(k \cdot n)$

Starting point [Ber+19; HL20]

Algorithm

- 1. Find a set C of centers with the GMM algorithm
- 2. Do a binary search on guesses over the possible clustering radii
- 3. Instantiate a linear program and find a fractional solution (if any)
- 4. If the linear program has a feasible solution, then iteratively round it.

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Guarantees

- ▶ The algorithm provides a 3 approximation to the radius
- ▶ The solution has an additive violation up to $4\Delta + 3$

Outline of our approach

- 1. Build a weighted coreset T out of the input set S
- 2. Compute a fair k-center clustering on of T, whose centers are C
- 3. Build a fair assignment of S to C by using information from the solution on the coreset

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In MapReduce, steps 1. and 3. are carried out in a single parallel round each

In Streaming, steps 1. and 3. require each a pass on the data

```
\label{eq:continuous_section} \begin{split} & \textbf{Input: Set } S, \ \mathsf{parameter} \ k, \ \mathsf{parameter} \ \varepsilon \\ & T \leftarrow \{ \mathsf{arbitrary point from} \ S \}; \\ & \textbf{while} \ |T| < k \ \textbf{do} \quad T \leftarrow \ T \cup \{ \arg\max_{x \in S} d(x, \, T) \} \ ; \end{split}
```

```
\begin{split} & \textbf{Input: Set } S, \text{ parameter } k, \text{ parameter } \varepsilon \\ & T \leftarrow \{ \text{arbitrary point from } S \}; \\ & \textbf{while } |T| < k \text{ do } T \leftarrow T \cup \{ \arg \max_{x \in S} d(x,T) \} \;; \\ & r_k \leftarrow \max_{x \in S} d(x,T); \end{split}
```

```
\begin{array}{l} \text{Input: Set $S$, parameter $k$, parameter $\varepsilon$} \\ T \leftarrow \{\text{arbitrary point from $S$}\}; \\ \text{while } |T| < k \text{ do } T \leftarrow T \cup \{\arg\max_{x \in S} d(x,T)\} \;; \\ r_k \leftarrow \max_{x \in S} d(x,T); \\ \text{while } \max_{x \in S} d(x,T) > \frac{\varepsilon}{6} \cdot r_k \text{ do} \\ \  \  \  \  \  \, T \leftarrow T \cup \{\arg\max_{x \in S} d(x,T)\} \end{array}
```

```
Input: Set S, parameter k, parameter \varepsilon
T \leftarrow \{\text{arbitrary point from } S\};
while |T| < k do T \leftarrow T \cup \{\arg \max_{x \in S} d(x, T)\};
r_k \leftarrow \max_{x \in S} d(x, T);
while \max_{x \in S} d(x, T) > \frac{\varepsilon}{6} \cdot r_k do
 T \leftarrow T \cup \{\arg\max_{x \in S} d(x, T)\}
for t \in T do
 copy t for each color combination in \Gamma, with weight 0;
for x \in S do
return T, w, \pi;
```

Properties of the coreset

Proxy radius

Let T be a coreset on S constructed as above, and let π be its proxy function. Then

$$d(x, \pi(x)) \le \frac{\varepsilon}{3} OPT_{unf} \le \frac{\varepsilon}{3} OPT_{fair}$$

Size

If S belongs to a metric space with doubling dimension D, then

$$|T| \le |\Gamma| \cdot k \cdot \left(\frac{12}{\varepsilon}\right)^D$$

Properties of the coreset

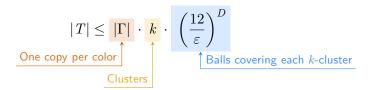
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A revised linear program, on the coreset

Let $C\subseteq T$ be a set of centers found by GMM on the coreset and a radius guess R

How much of the weight of
$$t$$
 is assigned to c
$$z_{t,c} \geq 0 \quad \text{Assign all the weight} \qquad \substack{t \in T \\ c \in C} \text{ if } d(t,c) \leq R$$

$$\sum_{c \in C} z_{t,c} = \boxed{w(t)} \qquad \qquad \forall t \in T$$

$$\beta_{\ell} \sum_{t \in T} z_{t,c} \leq \sum_{t' \in T_{\ell}} z_{t',c} \leq \alpha_{\ell} \sum_{t \in T} z_{t,c} \qquad \qquad \forall c \in C, \ell \in \Gamma$$

A revised linear program, on the coreset

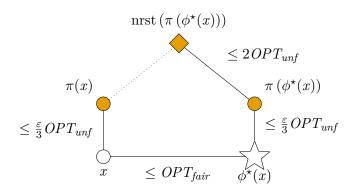
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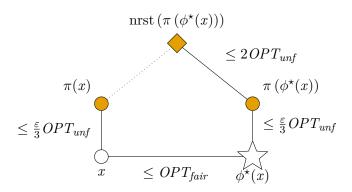
$$\begin{array}{c|c} & \text{How much of the weight of t is assigned to c} \\ \hline z_{t,c} \geq 0 & \text{Assign all the weight} & \substack{t \in T \\ c \in C} \text{ if } d(t,c) \leq R \\ \hline \sum_{c \in C} z_{t,c} = \boxed{w(t)} & \forall t \in T \\ \\ \beta_{\ell} \sum_{t \in T} z_{t,c} \leq \sum_{t' \in T_{\ell}} z_{t',c} \leq \alpha_{\ell} \sum_{t \in T} z_{t,c} & \forall c \in C, \ell \in \Gamma \\ \end{array}$$

Which radius guess R allows for a feasible solution?



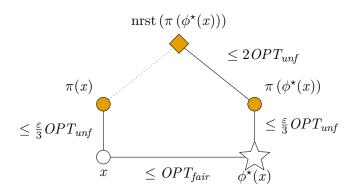






By the triangle inequality, we have that

$$d(\pi(x), \operatorname{nrst}(\pi(\phi^{\star}(x)))) \leq \frac{2\varepsilon}{3} OPT_{fair}$$



Is the assignment fair?

By a charging argument, we can build an assignment of coreset points to centers that respects the fairness constraints.

Summary

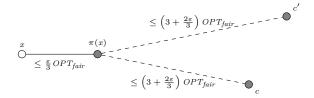
- ightharpoonup Set $T \subseteq S$
- ▶ Proxy function $\pi: S \to T$
- ightharpoonup Weight function $w: T \to \mathbb{N}$
- ▶ Weight assignment $\hat{\phi}\left(t,c\right)$, for $t\in T$ and $c\in C\subseteq T$ such that

$$\hat{\phi}(t,c) > 0 \implies d(t,c) \le \left(3 + \frac{2}{3}\varepsilon\right) OPT_{fair}$$

Building the final assignment

 $\begin{array}{ll} \textbf{Input:} & \text{The weight distribution } \hat{\phi}\left(t,c\right) \text{, the proxy function} \\ & \pi\left(\cdot\right) \text{, the set } S \text{, the coreset } T \text{, the coreset centers } C \\ \textbf{for } x \in S \textbf{ do} \\ & t \leftarrow \pi\left(x\right); \\ & c \leftarrow \text{arbitrary } c \in C : \hat{\phi}\left(t,c\right) > 0; \\ & \phi\left(x\right) \leftarrow c; \\ & \hat{\phi}\left(t,c\right) \leftarrow \hat{\phi}\left(t,c\right) - 1; \end{array}$

return C, ϕ



Summary

Approximation

$$3 + \varepsilon$$

Linear program size

$$\min\{2^{k-1}k|\Gamma|, k\cdot \left|\Gamma|\cdot k\cdot \left(\frac{12}{\varepsilon}\right)^D\}$$
 State of the art had n here

Datasets

dataset	n	d	$ \Gamma $
hmda	16 007 906	8	18
census1990	2 458 285	66	8
athlete	206 165	3	2
diabetes	89 782	9	5
4area	35 385	8	4
adult	32 561	5	7
creditcard	30 000	14	7
bank	4 5 2 1	9	3
victorian	4 500	10	45
reuter_50_50	2500	10	50