Fair Set Cover

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DRSA'25 KDD 2025 1/16

Motivation

2 Problem Formulation

3 Unweighted Fair Set Cover

4 Experiments



DRSA'25 KDD 2025 2 / 16

Motivation

Set Cover Problem

- Given:
 - A universe of n elements $U = \{e_1, e_2, \dots, e_n\}$
 - A family of μ sets $S = \{S_1, S_2, \dots, S_{\mu}\}$, where $\bigcup_{i=1}^{\mu} S_i = U$
- Goal: Find the smallest sub collection $X \subseteq S$ such that $\bigcup_{s_i \in X} = U$.

Set Cover Applications

- classic applications: airline crew scheduling, facility location, computational biology, network security, etc.
- problems with societal impact: business license distribution, team formation, fair clustering, etc.
 - Prevent biased selection.

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3 / 16

Motivation Example

Team of Experts Assembly

The HR of a company wants to form a team of data scientists.

- Form a minimal-size team that collectively satisfies a set of skills (e.g., {python, sql, data-visualization, statistics, deep-learning, ...}).
- Historical Biases + solely optimizing for the team size ⇒ selection bias: mostly selecting from privileged groups.
- Societal Requirement: Equal (or proportionate) representation of various demographic groups.

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DRSA'25 KDD 2025 4 / 16

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- 3 Unweighted Fair Set Cover
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DRSA'25 KDD 2025 5 / 16

(Group) Fairness Notion: Demographic Parity

General Definition

- Given: non-negative coefficients $\{f_1, \dots, f_k\}$, where $\sum_{h=1}^{\kappa} f_h = 1$
- For all groups $\mathbf{g}_h \in \mathcal{G}$: $|X \cap \mathcal{S}_h| = f_h |X|$.

Customized Definitions

- Count-parity when $f_h = \frac{1}{k}$, $\forall \mathbf{g}_h \in \mathcal{G}$: equal number from each group.
- Ratio-parity when $f_h = \frac{m_h}{\mu}$, $\forall \mathbf{g}_h \in \mathcal{G}$: maintains the original group ratios.

ε -unfairness

If, for each group $\mathbf{g}_h \in \mathcal{G}$, it holds that $1 - \varepsilon \leq \frac{|X \cap \mathcal{G}_h|}{f_k|X|} \leq 1 + \varepsilon$.

Problem Definition

Generalize Fair Set Cover

- Given:
 - A universe of *n* elements $U = \{e_1, e_2, \dots, e_n\}$
 - A family of m sets $S = \{S_1, S_2, \dots, S_m\}$, where $\bigcup_{i=1}^m S_i = U$.
 - A set of k groups $\mathcal{G} = \{\mathbf{g}_1, \dots, \mathbf{g}_k\}$. Each $S \in \mathcal{S}$ is associated with a group $\mathbf{g}(S) \in \mathcal{G}$
 - A fraction f_h for each $\mathbf{g}_h \in \mathcal{G}$ such that their sum is equal to 1
 - A weighted function $w: \mathcal{S} \to \mathbb{R}^+$.
- Goal: Find a fair cover X_w such that $\sum_{S \in X_w} w(S)$ is minimized.
- Under count parity, we call the problem Fair Set Cover (FSC).
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Hardness

- FSC is NP-complete.
- \bullet FSC cannot be approximated with a sublinear approximation factor unless $\mathsf{P} = \mathsf{NP}.$

Key Aspects of Proposed Algorithms

Table: Summary of Algorithms for Zero-unfairness

Fairness	Setting	Algorithm	Approx. Factor	Runtime
Count Parity	Unweighted	Baseline	$k(\ln n + 1)$	$\mathcal{O}(mkn)$
		GreedyAlg	$\ln n + 1$	$\mathcal{O}(\operatorname{poly}(n,m,k))$
		FasterAlg	$\frac{e}{e-1}(\ln n+1)$	$\mathcal{O}(X^* nm\log n)$
	Weighted	Baseline	$k\Delta(\ln n + 1)$	$\mathcal{O}(mkn)$
		GreedyAlg	$\Delta(\ln n + 1)$	$\mathcal{O}(m^k n)$
		FasterAlg	$\frac{e}{e+1}\Delta(\ln n+1)$	$\mathcal{O}(mn\mathcal{L}+mkn^3)$
Ratio Parity	Unweighted	GreedyAlg	$\ln n + 1$	$\mathcal{O}(m^p n)$
		FasterAlg	$\frac{e}{e+1}(\ln n+1)$	$\mathcal{O}(m(p+\mathcal{L}))^{1}$

2025 8 / 16

 $^{^{1}\}mathcal{L}=$ time to solve an LP with n+k variables and 2n+2mk constraints.

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		FasterAlg	$\frac{e}{e+1}(\ln n+1)$	$\mathcal{O}(m(p+\mathcal{L}))^2$

KDD 2025 9/16

 $^{^{2}\}mathcal{L}=$ time to solve an LP with n+k variables and 2n+2mk constraints. DRSA'25

- Motivation
- 2 Problem Formulation
- 3 Unweighted Fair Set Cover
- 4 Experiments



DRSA'25 KDD 2025 10 / 16

Unweighted Fair Set Cover – Binary Groups

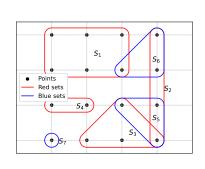
FSC Greedy (binary groups)

Let $U^- = U$ be the set of uncovered elements. Repeat until $U^- = \emptyset$:

- find the pair of sets (S_{Red}, S_{Blue}) from the unselected sets that covers the max # uncovered elements.
- move S_{Red} and S_{Blue} to the selected set X.
- update the uncovered elements: $U^- \leftarrow U^- \setminus (S_A \cup S_B)$

Analysis

- Always Fair (0-unfairness)
- Approximation Ratio: $\log n$
- Time Complexity: $O(m^2n)$



Standard Greedy:

- selects $\{S_1, S_2, S_3, S_4, S_7\}$
- unfair: 4 red sets and 1 blue set

FSC Greedy selects $\langle (S_1, S_5), (S_3, S_6), (S_4, S_1) \rangle$.

Unweighted Fair Set Cover – General Grouping

Extension of Greedy to non-binary groups

- \bullet Extending beyond binary groups: at every iteration select k sets, one from each group that maximally cover the uncovered elements.
- Time complexity: $O(m^k n)$ (exponential to the number of groups)

Instead, at every iteration, the Faster alg. finds the k sets approximately:

Max k-color Cover Problem

- Given the uncovered U^- and non-selected sets \mathcal{S}^- , and k colors
- select k sets $X \subseteq \mathcal{S}^-$, one from each color, such that $|X \cap U^-|$ is maximized.

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12 / 16

Max k-color Cover – A $(1-\frac{1}{e})$ -Approximation Algorithm

The LP-Relaxtion Algorithm

- Model the problem as IP
- 2 Relax to LP and Solve
- **③** Rounding: For every group $\mathbf{g}_h \in \mathcal{G}$, sample exactly one set from \mathcal{S}_h^- , using the probabilities $\{x_i^* \mid S_i \in \mathcal{S}_h^-\}$.

Analysis

- Approximation factor: $(1 \frac{1}{e})$.
- Time Complexity: $O(\mathcal{L}(n+k,2(n+m))).$

IP Formulation

 $\max \sum_{j} y_{j}$ s.t. $\sum_{i:S_{i} \in \mathcal{S}_{h}^{-}} x_{i} = 1,$

 $\sum_{:S_i \in \mathcal{S}_h^-} x_i = 1, \qquad \forall \mathbf{g}_h \in \mathcal{G}$ $\sum_{i:S_h} x_i \ge y_j, \qquad \forall e_j \in U^-$

 $i: e_j \in S_i$ $x_i \in \{0, 1\},$

 $\forall S_i \in \mathcal{S}^-$

 $y_j \in \{0,1\},$

 $\forall e_i \in U^-$

13 / 16

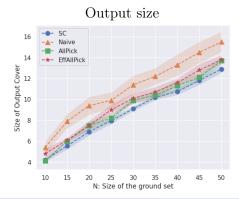
- Motivation
- 2 Problem Formulation
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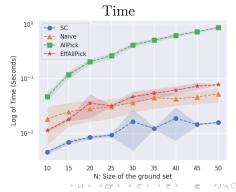


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Highlighted Experiments – Resume Skills

${\bf Algorithm}$	Avg. Fairness Ratio	Avg. Cover Size
OPT-SC	0.48	3.32
Greedy-SC	0.55	3.42
Opt-FSC	1.00	3.75
EffAllPick	1.00	3.90





DRSA'25 KDD 2025 15 / 16

Thank you!

Question?

16 / 16