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► **To cite this version:**

Laurent Alfandari, Jérôme Monnot. A note on the Clustered Set Covering Problem. *Discrete Applied Mathematics*, 2014, 164, Part 1, pp.13-19. 10.1016/j.dam.2011.11.030 . hal-01508784

HAL Id: hal-01508784

<https://hal.science/hal-01508784>

Submitted on 14 Apr 2017

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A note on the Clustered Set Covering Problem*

Laurent Alfandari[†]

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Abstract

We define an **NP**-hard clustered variant of the Set Covering Problem where subsets are partitioned into K clusters and a fixed cost is paid for selecting at least one subset in a given cluster. We show that the problem is approximable within ratio $(1+\epsilon)(e/e-1)H(q)$, where q is the maximum number of elements covered by a cluster and $H(q) = \sum_{i=1}^q \frac{1}{i}$.

Key-words: Integer Programming, Set Covering, Maximal Coverage, Approximation.

1 Problem statement

In the classical Set Covering Problem (SCP), we are given a set of elements $C = \{1, \dots, n\}$, a collection $\mathcal{S} = \{S_1, \dots, S_m\} \subseteq 2^C$ of subsets of C covering C and a non-negative weight $c(S_j) \geq 0$ for each set $S_j \in \mathcal{S}$. The goal is to find a *set cover* $\mathcal{S}' = \{S_{j_1}, \dots, S_{j_t}\} \subseteq \mathcal{S}$, verifying $\cup_{i=1}^t S_{j_i} = C$, and minimizing $c(\mathcal{S}') = \sum_{i=1}^t c(S_{j_i})$. This problem has been widely studied by the computer science community and the main results given on it are the following: SCP is **NP**-hard, even in the unweighted case, i.e., $c(S_j) = 1 \forall j = 1, \dots, m$ [8]. SCP is $H(\Delta)$ -approximable where $H(\Delta) = \sum_{i=1}^{\Delta} \frac{1}{i}$ and Δ is the maximum size of a set of \mathcal{S} , i.e., $\Delta = \max_{j \leq m} |S_j|$ [4]; this gives a $(1 + \ln n)$ -approximation for SCP since $\Delta \leq n$ and $H(n) \leq 1 + \ln n$. On the other hand, SCP is not $(1 - \epsilon) \ln n$ -approximable for every $\epsilon > 0$ [7] closing the gap between positive and negative results on this problem. Finally, the restriction of SCP where Δ and δ are upper bounded by some constants is **APX**-complete [12]; here δ is the maximum number of sets of \mathcal{S} containing a given element of C , i.e., $\delta = \max\{p : \exists S_{j_1}, \dots, S_{j_p} \text{ such that } \cap_{i=1}^p S_{j_i} \neq \emptyset\}$.

We define the following variant of SCP, called Clustered Set Covering Problem (Clustered-SCP). Let $C = \{1, \dots, n\}$ be a set of elements and $\mathcal{S} = \{S_1, \dots, S_m\}$ be a collection of subsets of C . A positive cost $c_j = c(S_j)$ is associated with every subset $S_j \in \mathcal{S}$. Moreover, we assume that the index set $J = \{1, \dots, m\}$ is partitioned into K disjoint subsets $\mathcal{J} = \{J_k : k = 1, \dots, K\}$, i.e., $\cup_{k=1}^K J_k = J$ and $J_k \cap J_{k'} = \emptyset$ for $k \neq k'$. For $k = 1, \dots, K$, cluster $\mathcal{F}_k \subset \mathcal{S}$ is defined by $\mathcal{F}_k = \{S_j \in \mathcal{S} : j \in J_k\}$, and a fixed-cost $f_k \geq 0$ is paid as soon as at least one subset is selected within cluster \mathcal{F}_k for $k = 1, \dots, K$. The Clustered Set Covering Problem is to cover all elements of C by a collection of subsets $\mathcal{S}' \subset \mathcal{S}$ minimizing the sum of the costs of the selected subsets and the fixed costs. In other words, we want to find a set cover \mathcal{S}' minimizing $c(\mathcal{S}')$ plus the cost of the clusters used in \mathcal{S}' , i.e.,

*Research supported by the French Agency for Research under the DEFIS program TODO, ANR-09-EMER-010.

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$\bar{c}(\mathcal{S}') = c(\mathcal{S}') + \sum_{k: \mathcal{S}' \cap \mathcal{F}_k \neq \emptyset} f_k$; to simplify, such a value $\bar{c}(\mathcal{S}')$ will be called the *clustered set value* of \mathcal{S}' . The problem can be formulated as the following Integer Linear Program:

$$\text{Minimize } \sum_{k=1}^K f_k y_k + \sum_{j=1}^m c_j x_j \quad (1)$$

$$\text{s.t. } \sum_{j=1}^m a_{ij} x_j \geq 1 \quad \text{for } i = 1, \dots, n \quad (2)$$

$$y_k \geq x_j \quad \text{for } k = 1, \dots, K, j \in J_k \quad (3)$$

$$x_j, y_k \in \{0, 1\} \quad (4)$$

where binary data $a_{ij} = 1$ iff $i \in S_j$. Various minimum-cost multi-commodity flow problems in transportation planning can be formulated as Clustered-SCP. This is the case for the Crew Pairing problem in air transportation when crews are partitioned into clusters $k = 1, \dots, K$ according to their assigned airport basis for example ([6, 2]), or for fleet scheduling problems when vehicles or planes are of different types $k = 1, \dots, K$ ([2]), and a fixed cost is paid for using a given resource type. Also consider the labeled weighted Vertex Cover problem defined as follows: given a simple graph $G = (V, E)$ where each vertex $v \in V$ has a weight $w(v) \geq 0$ and a label $\mathcal{L}(v) \in \{c_1, \dots, c_K\}$ (ie., a color) and each label c_i has a cost $f_i \geq 0$, we want to find a vertex cover V' minimizing its weight $w(V') = \sum_{v \in V'} w(v)$ plus the cost of the labels used by V' ie $\sum_{c_i \in \mathcal{L}(V')} f_i$ where $\mathcal{L}(V') = \{\mathcal{L}(v) : v \in V'\}$. Recall that a vertex cover of a graph $G = (V, E)$ is a subset of vertices $V' \subseteq V$ such that $\forall e = (u, v) \in E, V' \cap \{u, v\} \neq \emptyset$. Labeled optimization has been investigated for many graph problems [3, 11, 9]. Clearly, the labeled weighted Vertex Cover problem is a particular case of the Clustered Set Covering Problem.

As SCP is a particular case of the Clustered SCP where $f_k = 0$ for all $k = 1, \dots, K$ (or Clustered SCP is equivalent to solve SCP when J are the trivial partitions, i.e., either $K = m$ and $J_i = \{i\}$ or $K = 1$ and $J_1 = \{1, \dots, m\}$), then the Clustered SCP is also **NP**-hard. The approximation approach proposed in this paper extends in some way the master-slave approach of [1] to more general fixed-charge covering problems.

2 Some complexity results

It is well known that SCP can be solved in polynomial time when $\Delta = \max_{i \leq m} |S_i| \leq 2$ (see for instance comment of problem [SP5] page 222 in [8]). For Clustered SCP, it is not the case. It also depends on the structure of the clusters. For instance, Clustered SCP is **NP**-hard even if $\Delta = 1$.

Lemma 1. *Clustered SCP is **NP**-hard even if $\Delta = 1$.*

Proof. The reduction is done from SCP. From an instance $I = (C, \mathcal{S}, c)$ of SCP where $\mathcal{S} = \{S_1, \dots, S_m\}$ and $C = \{1, \dots, n\}$, we build an instance $I_0 = (C_0, \mathcal{S}_0, c_0, K, \mathcal{J}, f)$ of Clustered-SCP by setting $C_0 = C$, $K = m$, and replacing $S_k = \{i_1, i_2, \dots, i_{|S_k|}\} \in \mathcal{S}$, for $k = 1, \dots, m$, by $|S_k|$ sets $S_{(k, i_j)} = \{i_j\}$ for $j = 1, \dots, |S_k|$ in the Clustered-SCP instance. Moreover, we set $J_k = \{(k, i_j) : i_j \in S_k\}$; Hence, the cluster set \mathcal{F}_k is defined by $\mathcal{F}_k = \{S_{(k, i_j)} : i_j \in S_k\}$. Finally, we set $c_0 = 0$ and $f_k = c(S_k)$. Thus, the clusters play the role of the sets of the SCP instance. In I_0 , each set contains only one element and any set

cover \mathcal{S}'_0 of I_0 with clustered set value $\bar{c}_0(\mathcal{S}'_0)$ can be converted into a set cover \mathcal{S}' of I with same value $\bar{c}_0(\mathcal{S}'_0)$, which completes the proof. \square

When the size of each cluster is upper bounded by a constant, we first prove that Clustered-SCP is equivalent to SCP.

Theorem 2. *Assume that the size of each cluster is upper bounded by a constant, i.e., $\forall k \leq K, |J_k| \leq a$. Then, Clustered-SCP is equivalent to approximate SCP.*

Proof. Let $I = (C, \mathcal{S}, c)$ be an instance of SCP where $\mathcal{S} = \{S_1, \dots, S_m\}$. We build an instance $I_0 = (C_0, \mathcal{S}_0, c_0, K, \mathcal{J}, f)$ of Clustered-SCP by setting $C_0 = C$, $\mathcal{S}_0 = \mathcal{S}$, $c_0 = c$, $K = m$, $\mathcal{J} = \{J_1, \dots, J_m\}$ where $J_k = \{k\}$ (hence, the corresponding cluster set is given by $\mathcal{F}_k = \{S_k\}$) and fixed costs $f_k = 0$ for $k = 1, \dots, K$. Clearly, I_0 is computed from I in polynomial time and each cluster is upper bounded by a constant ($a = 1$). It is easy to see that \mathcal{S}' is a set cover of I with value $c(\mathcal{S}')$ iff \mathcal{S}' is a set cover of I_0 with clustered set value $\bar{c}_0(\mathcal{S}') = c(\mathcal{S}')$.

Now, let us prove that we can polynomially reduce Clustered-SCP when each cluster is upper bounded by a constant to SCP. Let $I = (C, \mathcal{S}, c, K, \mathcal{J}, f)$ be an instance of Clustered-SCP where $\mathcal{S} = \{S_1, \dots, S_m\}$, $\mathcal{J} = \{J_1, \dots, J_K\}$ and $\forall k \leq K, |J_k| \leq a$ for some constant a . We build an instance $I_0 = (C_0, \mathcal{S}_0, c_0)$ of SCP as follows: $C_0 = C$ and for each $J_k \in \mathcal{J}$, we build $2^{|J_k|} - 1$ sets $S_A = \cup_{j \in A} S_j$ for $A \subseteq J_k$, $A \neq \emptyset$, with weight $c_0(S_A) = f_k + \sum_{j \in A} c(S_j)$. In other words, we generate all non-empty subset subsets induced by a cluster, for every cluster. Thus, $\mathcal{S}_0 = \{S_A : \exists J_k \in \mathcal{J} \text{ and } A \subseteq J_k \text{ with } A \neq \emptyset\}$. This instance I_0 of SCP can be constructed within $2^a m = O(m)$ time. \square

Note that Theorem 2 also holds when $a = \text{poly}(\log m)$ (i.e., $\forall k \leq K, |J_k| \leq \text{poly}(\log m)$) where poly is any polynomial. We recall that $\delta = \max\{j : \exists S_{i_1}, \dots, S_{i_j} \text{ such that } \cap_{p=1}^j S_{i_p} \neq \emptyset\}$ and $\Delta = \max_{i \leq m} |S_i|$.

Corollary 3. *Assume that each cluster is upper bounded by a constant. Then, Clustered-SCP is **APX**-complete when Δ and δ are upper bounded by constants.*

Proof. The **APX**-completeness of SCP when Δ and δ are upper bounded by constants (for instance, when $\Delta = 3$ and $\delta = 2$) is known from [12]. Hence, the result follows from Theorem 2. \square

Before introducing in section 4 the main result of the paper, i.e. the log-approximability of Clustered-SCP, we first need to approximate in section 3 another **NP**-hard problem, that we call Minimum Cover-Ratio Problem (MCRP), which appears as a subproblem in the general approximation algorithm for Clustered-SCP.

3 Approximation of the Minimum Cover-Ratio Problem

The Minimum Cover-Ratio Problem (MCRP) that appears as a subproblem in the Clustered-SCP approximation algorithm is defined as follows.

Definition 1. *Given two subsets I and J of elements, a cost function $c : J \rightarrow \mathbb{N}$, a positive number f and binary data $a_{ij} \in \{0, 1\}$ for $(i, j) \in I \times J$, the Minimum Cover-Ratio Problem*

(MCRP) formulates as follows:

$$\begin{aligned} \text{Minimize } r(x) &= \frac{f + \sum_{j \in J} c_j x_j}{\sum_{i \in I} \text{cov}_i(x)} \\ x_j &\in \{0, 1\} \end{aligned}$$

where $\text{cov}_i(x) = \min(1; \sum_{j \in J} a_{ij} x_j)$ is equal to 1 if x covers element i , 0 otherwise.

To our knowledge, the MCRP has never been studied before. If the fixed cost f is equal to zero, then the problem is trivial since it suffices to select index j with minimum ratio $c_j / \sum_{i \in I} a_{ij}$, set $x_j = 1$ and all other variables to zero for obtaining the optimal solution. The general problem is **NP**-hard as shown in the following proposition 4.

Proposition 4. *MCRP is NP-hard.*

Proof. The reduction is from the Set Covering Problem (SCP). Consider an instance of SCP such that the element set $C = \{1, \dots, n\}$ is to be covered by $\mathcal{S} = \{S_1, \dots, S_m\}$. Construct the MCRP instance by setting $I = C$, $J = \{1, \dots, m\}$, $a_{ij} = 1$ if and only if $i \in S_j$, and $f = n \sum_{j=1}^m c_j$. Let \bar{x} (resp. \underline{x}) denote an arbitrary MCRP solution covering exactly all n (resp. at most $n - 1$) elements of $I = C$. We have

$$\begin{aligned} r(\underline{x}) &\geq \frac{n \sum_{j=1}^m c_j + c \cdot \underline{x}}{n - 1} \\ &= \sum_{j=1}^m c_j + \frac{\sum_{j=1}^m c_j}{n - 1} + \frac{c \cdot \underline{x}}{n - 1} \\ &\geq \sum_{j=1}^m c_j + \frac{\sum_{j=1}^m c_j}{n} \\ &= \frac{f + \sum_{j=1}^m c_j}{n} \\ &\geq r(\bar{x}) \end{aligned}$$

Thus, an MCRP optimal solution necessarily satisfies that $\sum_{i \in I} \text{cov}_i(x) = n$, i.e. all elements of $I = C$ are covered, which means that an optimal SCP solution is found. \square

For approximating MCRP, we use existing approximation results for the Budgeted Maximum Coverage Problem (BMCP) defined in [10].

Definition 2. [10] *Given two subsets I and J of elements, a cost function $c : J \rightarrow \mathbb{N}$, a budget $B > 0$ and binary data $a_{ij} \in \{0, 1\}$ for $(i, j) \in I \times J$, the Budgeted Maximum Coverage Problem (BMCP) is formulated as follows:*

$$\begin{aligned} &\text{Maximize } \sum_{i \in I} \text{cov}_i(x) \\ &\text{s.t. } \sum_{j \in J} c_j x_j \leq B \\ &\quad x_j \in \{0, 1\} \end{aligned}$$

where, again, $\text{cov}_i(x) = \min(1; \sum_{j \in J} a_{ij} x_j)$.

In [10], it is proved that there exists a polynomial-time algorithm APPROX-BMCP(B) approximating BMCP with input budget bound B within performance ratio $1 - 1/e$. We derive from this result the following approximation result for MCRP.

Theorem 5. *MCRP is approximable within performance ratio $(1 + \epsilon)(e/e - 1)$ in time polynomial in both n and $1/\epsilon$.*

Proof. Let $c_{min} = \min\{c_j : j \in J\}$, and

$$T = \left\lceil \frac{\ln(\sum_{j \in J} c_j / c_{min})}{\ln(1 + \epsilon)} \right\rceil$$

Set $B_t = (1 + \epsilon)^t c_{min}$ for $t = 0, 1, \dots, T$, and remark that $B_0 = c_{min}$, $B_t = (1 + \epsilon)B_{t-1}$, and

$$\begin{aligned} B_T &= c_{min} \exp\left(\left\lceil \frac{\ln(\sum_{j \in J} c_j / c_{min})}{\ln(1 + \epsilon)} \right\rceil \ln(1 + \epsilon)\right) \\ &\geq c_{min} \exp\left(\frac{\ln(\sum_{j \in J} c_j / c_{min})}{\ln(1 + \epsilon)} \ln(1 + \epsilon)\right) \\ &= \sum_{j \in J} c_j \end{aligned}$$

As $c_{min} \leq B_t \leq \sum_{j \in J} c_j$ there exists at least one $t \in \{0, \dots, T\}$ such that $B_t \geq \sum_{j \in J} c_j x_j^*$, where $x^* = (x_j^*)$ is an optimal MCRP solution. Let \hat{t} denote the smallest index t verifying the above condition, i.e.

$$\hat{t} = \arg \min_{t \in \{0, \dots, T\}} \{t : (1 + \epsilon)^t c_{min} \geq \sum_{j \in J} c_j x_j^*\}$$

By definition of \hat{t} , we have:

$$\sum_{j \in J} c_j x_j^* \leq (1 + \epsilon)^{\hat{t}} c_{min} \leq (1 + \epsilon) \sum_{j \in J} c_j x_j^* \quad (5)$$

Now, consider the following algorithm.

Begin / Algorithm APPROX-MCRP /
For $t = 0, 1, \dots, T$
 $B_t \leftarrow (1 + \epsilon)^t c_{min}$
 $x^t \leftarrow \text{APPROX-BMCP}(B_t)$
EndFor
Return $\bar{x} \leftarrow \min_{t=0, \dots, T} \frac{f + \sum_{j \in J} c_j x_j^t}{\sum_{i \in I} cov_i(x^t)}$
End

We obtain from the fact that APPROX-BMCP(B_t) is a $(1 - \frac{1}{e})$ -approximation for BMCP ([10]):

$$\begin{aligned} \sum_{i \in I} cov_i(x^{\hat{t}}) &\geq (1 - \frac{1}{e}) \sum_{i \in I} cov_i(x^*) \\ \Rightarrow \frac{f + c \cdot x^{\hat{t}}}{\sum_{i \in I} cov_i(x^{\hat{t}})} &\leq \left(\frac{e}{e-1}\right) \frac{f + (1 + \epsilon)^{\hat{t}} c_{min}}{\sum_{i \in I} cov_i(x^*)} \\ \Rightarrow r(\bar{x}) \leq r(x^{\hat{t}}) &\leq (1 + \epsilon) \frac{e}{e-1} r(x^*) \quad \text{using (5)} \end{aligned}$$

which concludes the proof of Theorem 5. \square

Based on the above approximation result for MCRP, we can now introduce the main result for Clustered-SCP in next section.

4 Approximation of Clustered-SCP

The approximation algorithm for Clustered-SCP is based on an iterative approximate solving of the Minimum Cover-Ratio Problem (MCRP) introduced in section 3. The main principle of the algorithm is to solve at each iteration K subproblems: for each cluster k , we find a collection of subsets within \mathcal{F}_k minimizing the ratio of the total cost of that collection (including fixed cost) by the number of new elements covered by that collection. Each subproblem is obviously a Minimum Cover-Ratio Problem and can be approximated as shown in section 2. Then the best collection with minimum ratio among all clusters k is added to the solution in a greedy way. The fixed cost of the chosen cluster is set to zero and the process is iterated until all elements of C are covered.

Begin / Algorithm APPROX-CLUSTERED-SCP /
 $U \leftarrow C$ (subset of elements that remain to cover)
 $\mathcal{S}^h \leftarrow \emptyset$ (current solution)
Repeat
For $k = 1, \dots, K$ **do**
 $\mathcal{S}_k \leftarrow$ collection of subsets returned by APPROX-MCRP for the MCRP subproblem:
 $\min\{r_k(\mathcal{S}') = \frac{f_k + c(\mathcal{S}')}{|(\cup_{S_j \in \mathcal{S}'} S_j) \cap U|} : \mathcal{S}' \subseteq \mathcal{F}_k\}$
Endfor
 $l \leftarrow \arg \min_{1 \leq k \leq K} r_k(\mathcal{S}_k)$
 $\mathcal{S}^h \leftarrow \mathcal{S}^h \cup \{\mathcal{S}_l\}$
 $f_l \leftarrow 0$
 $U \leftarrow U \setminus (\cup_{S_j \in \mathcal{S}_l} S_j)$
Until $U = \emptyset$
Output \mathcal{S}^h
End

An example of application of the above algorithm when the minimum-ratio subproblem is solved to optimality, is given in figure 1.

Before analyzing the approximation ratio of the above algorithm, we introduce the following lemma. For every element $i \in C$, let $\rho_i = r_l(\mathcal{S}_l)$ where \mathcal{S}_l is the collection of subsets selected by the Clustered-SCP algorithm that covers element i for the first time at some iteration l (in other words, element i has not been covered during the $l - 1$ first iterations).

Lemma 6. *Let $\rho_i = r_l(\mathcal{S}_l)$ where \mathcal{S}_l is the first collection of subsets selected by the Clustered-SCP algorithm that covers element i , over all iterations. Then $\bar{c}(\mathcal{S}^h) = \sum_{i=1}^n \rho_i$.*

Proof. Let l_t (resp. U_t) denote selected index l (resp. set U) at iteration t of the algorithm, $t = 1, \dots, T$, and f_{l_t} the value of the fixed cost of cluster l at iteration t (ie., f_l or 0). We

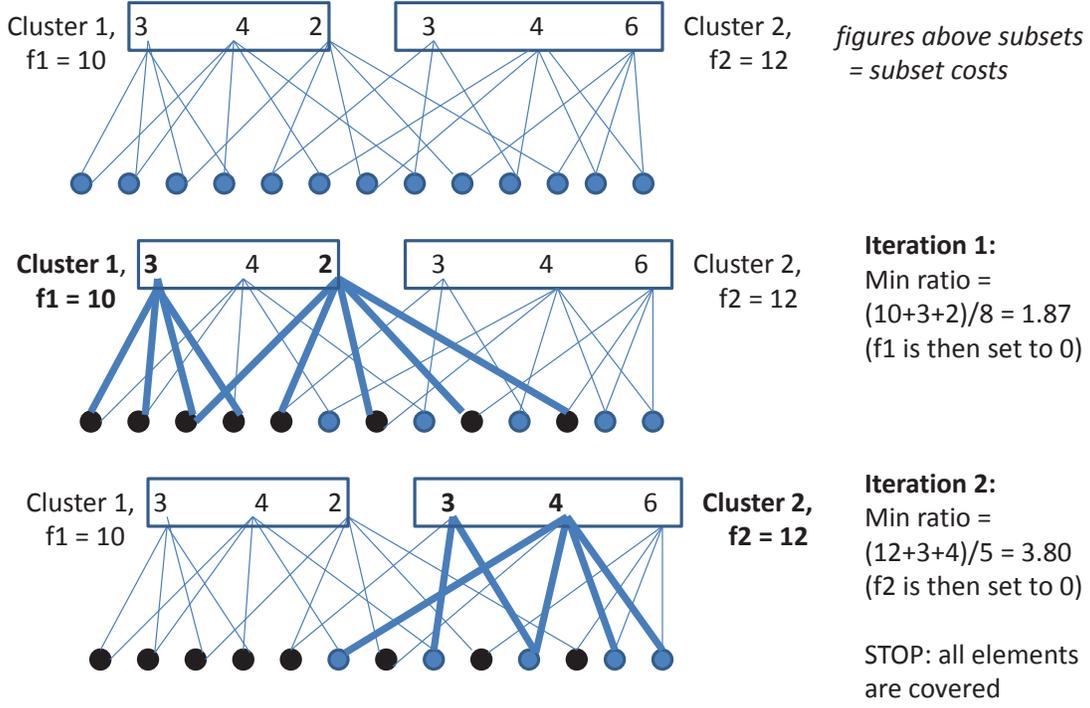


Figure 1: Example of application of APPROX-CLUSTERED-SCP algorithm with minimum-ratio MCRP subproblem solved to optimality.

have:

$$\begin{aligned}
\bar{c}(\mathcal{S}^h) &= \sum_{t=1}^T c(\mathcal{S}_{l_t}) + f_{l_t} \\
&= \sum_{t=1}^T r_{l_t}(\mathcal{S}_{l_t}) \times |\cup_{S_j \in \mathcal{S}_{l_t}} S_j \cap U_t| \\
&= \sum_{i=1}^n \{r_{l_t}(\mathcal{S}_{l_t}) : t \text{ is the first iteration where } i \text{ is covered}\} \\
&= \sum_{i=1}^n \rho_i
\end{aligned}$$

□

Theorem 7. Algorithm APPROX-CLUSTERED-SCP approximates the Clustered SCP within ratio $(1 + \epsilon) \frac{e}{e-1} H(q)$, where $q = \max_{1 \leq k \leq K} |\cup_{S_j \in \mathcal{F}_k} S_j|$ and $H(q) = \sum_{i=1}^q \frac{1}{i}$ is the q -th harmonic number (note that $q \leq n$).

Proof. Let $I = (C, \mathcal{S}, c, K, \mathcal{J}, f)$ be an instance of Clustered-SCP where $\mathcal{S} = \{S_1, \dots, S_m\}$, $\mathcal{J} = \{J_1, \dots, J_K\}$. Let \mathcal{S}^* denote an optimal solution for the Clustered SCP, $K^* = \{k :$

$\mathcal{S}^* \cap \mathcal{F}_k \neq \emptyset$, $\mathcal{S}_k^* = \mathcal{S}^* \cap \mathcal{F}_k$, and $J_k^* = \{j : S_j \in \mathcal{S}_k^*\}$. Hence, $\mathcal{S}^* = \{S_j : j \in \cup_{k \in K^*} J_k^*\}$. Transform every subset $S_j \in \mathcal{S}^*$ into $S'_j \subset S_j$ such that no element i belongs to two different subsets S'_j and $S'_{j'}$ (if so, remove the element from other subsets until it appears only once in a subset). In other words, $\{S'_j : j \in \cup_{k \in K^*} J_k^*\}$ is a partition of C . Let $n_k = |\cup_{j \in J_k^*} S'_j|$ and re-order these n_k elements as $i_{k,1}, i_{k,2}, \dots, i_{k,n_k}$ so that there are picked in that order by algorithm APPROX-CLUSTERED-SCP. Recall that $\rho_{i_{k,s}}$ is the value of $r_k(\mathcal{S}_k)$ when element $i_{k,s}$ has been covered for the first time by algorithm APPROX-CLUSTERED-SCP. Since in the worst case, elements $i_{k,1}, \dots, i_{k,s-1}$ have been covered during some previous iterations, we have by Theorem 5,

$$\rho_{i_{k,s}} \leq (1 + \epsilon) \frac{e}{e-1} \frac{f_k + \sum_{j \in J_k^*} c_j}{n_k - s + 1} \quad \text{for } k \in K^*, s = 1, \dots, n_k \quad (6)$$

We deduce from lemma 6 that

$$\begin{aligned} \bar{c}(\mathcal{S}^h) &= \sum_{i=1}^n \rho_i \\ &= \sum_{k \in K^*} \sum_{j \in J_k^*} \sum_{i \in S'_j} \rho_i \\ &= \sum_{k \in K^*} \sum_{s=1}^{n_k} \rho_{i_{k,s}} \\ &\leq (1 + \epsilon) \frac{e}{e-1} \sum_{k \in K^*} \sum_{s=1}^{n_k} \frac{f_k + \sum_{j \in J_k^*} c_j}{n_k - s + 1} \quad \text{by (6)} \\ &= (1 + \epsilon) \frac{e}{e-1} \sum_{k \in K^*} H(n_k) \times (f_k + \sum_{j \in J_k^*} c_j) \\ &\leq (1 + \epsilon) \frac{e}{e-1} H(q) \sum_{k \in K^*} \left(f_k + \sum_{S_j \in J_k^*} c_j \right) \\ &= (1 + \epsilon) \frac{e}{e-1} H(q) \bar{c}(\mathcal{S}^*) \end{aligned}$$

which ends the proof. \square

5 Conclusion

We have designed a polynomial-time algorithm achieving a logarithmic approximation ratio of $(1 + \epsilon)(e/e - 1)H(q) \leq (1 + \epsilon)(e/e - 1)(1 + \ln q)$, with $q \leq n$, for the Clustered Set Covering Problem. As the Set Covering Problem is a particular case of Clustered Set Covering and SCP cannot be approximated within a better ratio than $(1 - \epsilon) \ln n$ [7], the achieved ratio is asymptotically tight. We believe this approach could be extended to various fixed-cost optimization problems, not only for covering problems. Finally, an open problem is to design classes of NP-hard optimization problems for which the fixed-cost variant conserves in some way the approximability properties of the original problem.

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