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A Tight Approximation for Submodular Maximization with Mixed Packing and Covering Constraints

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Abstract
Motivated by applications in machine learning, such as subset selection and data summarization, we consider the problem of maximizing a monotone submodular function subject to mixed packing and covering constraints. We present a tight approximation algorithm that for any constant \( \varepsilon > 0 \) achieves a guarantee of \( 1 - \frac{1}{e} - \varepsilon \) while violating only the covering constraints by a multiplicative factor of \( 1 - \varepsilon \). Our algorithm is based on a novel enumeration method, which unlike previously known enumeration techniques, can handle both packing and covering constraints. We extend the above main result by additionally handling a matroid independence constraint as well as finding (approximate) pareto set optimal solutions when multiple submodular objectives are present. Finally, we propose a novel and purely combinatorial dynamic programming approach. While this approach does not give tight bounds it yields deterministic and in some special cases also considerably faster algorithms. For example, for the well-studied special case of only packing constraints (Kulik et al. [Math. Oper. Res. ‘13] and Chekuri et al. [FOCS ‘10]), we are able to present the first deterministic non-trivial approximation algorithm. We believe our new combinatorial approach might be of independent interest.

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Mixed Packing Covering Submodular Maximization

1 Introduction

The study of combinatorial optimization problems with a submodular objective has attracted much attention in the last decade. A set function $f : 2^\mathcal{N} \to \mathbb{R}_+$ over a ground set $\mathcal{N}$ is called submodular if it has the diminishing returns property: $f(A \cup \{i\}) - f(A) \geq f(B \cup \{i\}) - f(B)$ for every $A \subseteq B \subseteq \mathcal{N}$ and $i \in \mathcal{N} \setminus B$.\footnote{An equivalent definition is: $f(A) + f(B) \geq f(A \cup B) + f(A \cap B)$ for every $A, B \subseteq \mathcal{N}$.} Submodular functions capture the principle of economy of scale, prevalent in both theory and real world applications. Thus, it is no surprise that combinatorial optimization problems with a submodular objective arise in numerous disciplines, e.g., machine learning and data mining \cite{4, 5}, algorithmic game theory and social networks \cite{13, 22, 25, 27, 39}, and economics \cite{2}. Additionally, many classical problems in combinatorial optimization are in fact submodular in nature, e.g., maximum cut and maximum directed cut \cite{20, 21, 24, 26, 28}, maximum coverage \cite{15, 29}, generalized assignment problem \cite{8, 10, 14, 16}, maximum bisection \cite{3, 17}, and facility location \cite{1, 11, 12}.

In this paper we consider the problem of maximizing a monotone submodular function given mixed packing and covering constraints. In addition to being a natural problem in its own right, it has further real world applications.

As a motivating example consider the subset selection task in machine learning \cite{18, 19, 30} (also refer to Kulesza and Taskar \cite{31} for a thorough survey). In the subset selection task the goal is to select a diverse subset of elements from a given collection. One of the prototypical applications of this task is the document summarization problem \cite{30, 34, 35}: given textual units the objective is to construct a short summary by selecting a subset of the textual units that is both representative and diverse. The former requirement, representativeness, is commonly achieved by maximizing a submodular objective function, e.g., graph based \cite{34, 35} or log subdeterminant \cite{30}. The latter requirement, diversity, is typically tackled by penalizing the submodular objective for choosing similar textual units (this is the case for both of the above two mentioned submodular objectives). However, such an approach results in a submodular objective which is not necessarily non-negative thus making it extremely hard to cope with. As opposed to penalizing the objective, a remarkably simple and natural approach to tackle the diversity requirement is by the introduction of covering constraints. For example, one can require that for each topic that needs to appear in the summary, a sufficient number of textual units that refer to it are chosen. Unfortunately, to the best of our knowledge there is no previous work in the area of submodular maximization that incorporates general covering constraints.\footnote{There are works on exact cardinality constraints for non-monotone submodular functions, which implies a special, uniform covering constraint \cite{6, 33, 41}.}

Let us now formally define the main problem considered in this paper. We are given a monotone submodular function $f : 2^\mathcal{N} \to \mathbb{R}_+$ over a ground set $\mathcal{N} = \{1, 2, \ldots, n\}$. Additionally, there are $p$ packing constraints given by $P \in \mathbb{R}^{p \times n}_+$, and $c$ covering constraints given by $C \in \mathbb{R}^{c \times n}_+$ (all entries of $P$ and $C$ are non-negative). Our goal is to find a subset $S \subseteq \mathcal{N}$ that satisfies all packing and covering constraints that maximizes the value of $f$:

\begin{equation}
\max \{ f(S) : S \subseteq \mathcal{N}, P1_S \leq 1_p, C1_S \geq 1_c \}. \tag{1}
\end{equation}

In the above $1_S \in \mathbb{R}^n$ is the indicator vector for $S \subseteq \mathcal{N}$ and $1_k \in \mathbb{R}^k$ is a vector of dimension $k$ whose coordinates are all 1. We denote this problem as PACKING-COVERING SUBMODULAR MAXIMIZATION (PCSM). It is assumed we are given a feasible instance, i.e., there exists $S \subseteq \mathcal{N}$ such that $P1_S \leq 1_p$ and $C1_S \geq 1_c$.\footnote{\textit{Note:} We use \texttt{1} as a shorthand for \textit{indicator} vectors.}
As previously mentioned, (PCSM) captures several well known problems as a special case when only a single packing constraint is present \((p = 1 \text{ and } c = 0)\): maximum coverage \([29]\), and maximization of a monotone submodular function given a knapsack constraint \([40, 42]\) or a cardinality constraint \([37]\). For all of these special cases an approximation of \((1 - 1/e)\) is achievable and known to be tight \([38]\) (even for the special case of a coverage function \([15]\)).

When a constant number of knapsack constraints is given \((p = O(1) \text{ and } c = 0)\) Kulik et al. \([32]\) presented a tight \((1 - 1/e - \varepsilon)\)-approximation for any constant \(\varepsilon > 0\). An alternative algorithm with the same guarantee was given by Chekuri et al. \([9]\).

**Our Results.** We present a tight approximation guarantee for (PCSM) when the number of constraints is constant. Recall that we assume we are given a feasible instance, i.e., there exists \(S \subseteq N\) such that \(P1_S \leq 1_p\) and \(C1_S \geq 1_c\). The following theorem summarizes our main result. From this point onwards we denote by \(O\) some fixed optimal solution to the problem at hand.

\[\textbf{Theorem 1.}\] For every constant \(\varepsilon > 0\), assuming \(p\) and \(c\) are constants, there exists a randomized polynomial time algorithm for (PCSM) running in time \(n^{\text{poly}(1/\varepsilon)}\) that outputs a solution \(S \subseteq N\) that satisfies: (1) \(f(S) \geq (1 - 1/e - \varepsilon) f(O)\); and (2) \(P1_S \leq 1_p\) and \(C1_S \geq (1 - \varepsilon)1_c\).

We note four important remarks regarding the tightness of Theorem 1:

1. The loss of \(1 - 1/e\) in the approximation cannot be avoided, implying that our approximation guarantee is (virtually) tight. The reason is that no approximation better than \(1 - 1/e\) can be achieved even for the case where only a single packing constraint is present \([38]\).
2. The assumption that the number of constraints is constant is unavoidable. The reason is that if the number of constraints is not assumed to be constant, then even with a linear objective (PCSM) captures the maximum independent set problem. Hence, no approximation better than \(n^{-(1-\varepsilon)}\), for any constant \(\varepsilon > 0\), is possible \([23]\).
3. No true approximation with a finite approximation guarantee is possible, i.e., finding a solution \(S \subseteq N\) such that \(P1_S \leq 1_p\) and \(C1_S \geq 1_c\) with no violation of the constraints. The reason is that one can easily encode the subset sum problem using a single packing and a single covering constraint. Thus, just deciding whether a feasible solution exists, regardless of its cost, is already NP-hard.
4. Guaranteeing one-sided feasibility, i.e., finding a solution which does not violate the packing constraints and violates the covering constraint only by a factor of \(1 - \varepsilon\), cannot be achieved in time \(n^{o(1/\varepsilon)}\) unless the exponential time hypothesis fails (see \([36]\) for details).

Therefore, we can conclude that our main result (Theorem 1) provides the best possible guarantee for the (PCSM) problem. We also note that all previous work on the special case of only packing constraints \([9, 32]\) have the same running time of \(n^{\text{poly}(1/\varepsilon)}\).

We present additional extensions of the above main result. The first extension deals with (PCSM) where we are also required that the output is an independent set in a given matroid \(M = (N, I)\). We denote this problem by **Matroid Packing-Covering Submodular Maximization** (MatroidPCSM), and it is defined as follows:

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4 If the number of packing constraints \(p\) is super-constant then approximations are known only for special cases with “loose” packing constraints, i.e., \(P_{1,\ell} \leq O(\varepsilon^2/\ln p)\) (see, e.g., \([9]\)).
max \{ f(S) : S \subseteq \mathcal{N}, P_1S \leq 1_p, C_1S \geq 1_c, S \in \mathcal{I} \}$. As in (PCSM), we assume we are given a feasible instance, i.e., there exists $S \subseteq \mathcal{N}$ such that $P_1S \leq 1_p$, $C_1S \geq 1_c$, and $S \in \mathcal{I}$. Our result is summarized in the following theorem.

▶ **Theorem 2.** For every constant $\varepsilon > 0$, assuming $p$ and $c$ are constants, there exists a randomized polynomial time algorithm for (MATROIDPCSM) that outputs a solution $S \in \mathcal{I}$ that satisfies: (1) $f(S) \geq (1 - \frac{1}{e} - \varepsilon) f(O)$; and (2) $P_1S \leq 1_p$ and $C_1S \geq (1 - \varepsilon)1_c$.

The second extension deals with the multi-objective variant of (PCSM) where we wish to optimize over several monotone submodular objectives. We denote this problem by PACKING-COVERING MULTIPLE SUBMODULAR MAXIMIZATION (MULTIPCSM). Its input is identical to that of (PCSM) except that instead of a single objective $f$ we are given $t$ monotone submodular functions $f_1, \ldots, f_t : 2^\mathcal{N} \rightarrow \mathbb{R}_+$. As before, we assume we are given a feasible instance, i.e., there exists $S \subseteq \mathcal{N}$ such that $P_1S \leq 1_p$ and $C_1S \geq 1_c$. Our goal is to find pareto set solutions considering the $t$ objectives. To this end we prove the following theorem.

▶ **Theorem 3.** For every constant $\varepsilon > 0$, assuming $p$, $c$ and $t$ are constants, there exists a randomized polynomial time algorithm for (MULTIPCSM) that for every target values $v_1, \ldots, v_t$ either: (1) finds a solution $S \subseteq \mathcal{N}$ where $P_1S \leq 1_p$ and $C_1S \geq (1 - \varepsilon)1_c$ such that for every $1 \leq i \leq t$: $f_i(S) \geq (1 - \frac{1}{e} - \varepsilon) v_i$; or (2) returns a certificate that there is no solution $S \subseteq \mathcal{N}$, where $P_1S \leq 1_p$ and $C_1S \geq 1_c$ such that for every $1 \leq i \leq t$: $f_i(S) \geq v_i$.

We also note that Theorems 2 and 3 can be combined such that we can handle (MULTIPCSM) where a matroid independence constraint is present, in addition to the given packing and covering constraints, achieving the same guarantees as in Theorem 3.

All our previously mentioned results employ a continuous approach and are based on the multilinear relaxation, and thus are inherently randomized. We present a new combinatorial greedy-based dynamic programming approach for submodular maximization that enables us, for several well studied special cases of (PCSM), to obtain deterministic and considerably faster algorithms. Perhaps the most notable result is the first deterministic non-trivial algorithm for maximizing a monotone submodular function subject to a constant number of packing constraints (previous works $[9, 32]$ are randomized).

▶ **Theorem 4.** For every constants $\varepsilon > 0$ and $p \in \mathbb{N}$, there exists a deterministic algorithm for maximizing a monotone submodular function subject to $p$ packing constraints, that runs in time $O(n^{poly(1/\varepsilon)})$ and achieves an approximation of $\frac{1}{e} - \varepsilon$.

The interesting special case of (PCSM) is when a single packing and a single covering constraints are present ($p = c = 1$) is summarized in the following theorem.

▶ **Theorem 5.** For every constant $\varepsilon > 0$ and $p = c = 1$, there exists a deterministic algorithm for (PCSM) running in time $O(n^{1/\varepsilon})$ that outputs a solution $S \subseteq \mathcal{N}$ that satisfies: (1) $f(S) \geq 0.353 f(O)$; and (2) $P_1S \leq (1 + \varepsilon)1_p$ and $C_1S \geq (1 - \varepsilon)1_c$. For the case when the packing constraint is a cardinality constraint, i.e., $P = 1_f/k$, we can further guarantee that $P_1S \leq 1_p$ and a running time of $O(n^{1/e}/k)$.

**Our Techniques.** Our main result is based on a continuous approach: first a continuous relaxation is formulated, second it is (approximately) solved, and finally the fractional solution is rounded into an integral solution. Similarly to the previous works of $[9, 32]$, which

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5 Known techniques to efficiently evaluate the multilinear extension are randomized, e.g., $[7]$. 
focus on the special case of only packing constraints, the heart of the algorithm lies in an
enumeration preprocessing phase that chooses and discards some of the elements prior to
formulating the relaxation. The enumeration preprocessing step of [9, 32] is remarkably
simple and elegant. It enumerates over all possible collections of large elements the optimal
solution chooses, i.e., elements whose size exceeds some fixed constant in at least one of the
packing constraints and are chosen by the optimal solution.\footnote{An additional part of the preprocessing involves enumerating over collections of elements whose marginal
value is large with respect to the objective $f$, however this part of the enumeration is not affected by
the presence of covering constraints and thus is ignored in the current discussion.} All remaining large elements
not in the guessed collection are discarded. This enumeration terminates in polynomial time
and ensures that no large elements are left in any of the packing constraints. Thus, once
no large elements remain concentration bounds can be applied. For the correct guess, any
of the several known randomized rounding techniques can be employed (alongside a simple
rescaling) to obtain an approximation of $1 - 1/e - \varepsilon$ (here $\varepsilon > 0$ is a constant that is used to
determine which elements are considered large). Unfortunately, this approach fails in the
presence of covering constraints since an optimal solution can choose many large elements in
any given covering constraint. One can naturally adapt the above known preprocessing by
enumerating over all possible collections of covering constraints that the optimal solution $O$
covers using only large elements. However, this leads to an approximation of $1 - 1/e - \varepsilon$
while both packing and covering constraints are violated by a multiplicative factor of $1 \pm \varepsilon$.
We aim to obtain one sided violation of the constraints, i.e., only the covering constraints
are violated by a factor of $1 - \varepsilon$ whereas the packing constraints are fully satisfied.

Avoiding constraint violation is possible in the presence of pure packing constraints [9, 32].
Known approaches for the latter are crucially based on removing elements in a pre-processing
and post-processing step in order to guarantee that concentration bounds hold. For mixed
constraints, these known removal operations may, however, arbitrarily violate the covering
constraints. Our approach aims at pre-processing the input instance via partial enumeration
so as to avoid discarding elements by ensuring that the remaining elements are “locally”
small relatively to the residual constraints. If this property would hold scaling down the
solution by a factor $1/(1 + \varepsilon)$ would be sufficient to avoid violation of the packing constraints.
Unfortunately, we cannot guarantee this to hold for all constraints. Rather, for some critical
constraints locally large elements may still be present. We introduce a novel enumeration
process that detects these critical constraints, i.e., constraints that are prone to violation.
Such constraints are given special attention as the randomized rounding might cause them
to significantly deviate from the target value. Unlike the previously known preprocessing
method, our enumeration process handles covering constraints with much care and it takes
into account the actual coverage of the optimal solution $O$ of each of the covering constraints.
Combining the above, alongside a postprocessing phase that discards large elements from
critical packing constraints, suffices to yield the desired result.

We also independently present a novel purely combinatorial greedy-based dynamic
programming approach that yields deterministic and in some special cases considerably faster
algorithms. Previously, greedy algorithms were known for one cardinality constraint [37] and
one packing constraint [40]. But in the presence multiple constraints, it is not clear how
to design a rule to greedily pick the next element. In fact, we tried several natural greedy
strategies but all of them failed. This holds even when some oracle gives us the set of vectors
of packing and covering values from an optimum solution and the algorithm follows any fixed
sequence of these values.
In our approach we maintain a table that contains greedy approximate solutions for all possible packing and covering values. Using this table we extend the simple greedy process by populating each table entry with the most profitable extension of the previous table entries. In this way we are able to simulate (in a certain sense) all possible sequences of packing and covering values for the greedy algorithm, ultimately leading to a good feasible solution. Our result implies that there exists one sequence (depending on the instance) where greedy performs well. To estimate the approximation factor we employ a factor-revealing linear program. To the best of our knowledge, this is the first time a dynamic programming based approach is used for submodular optimization. We believe our new combinatorial dynamic programming approach is of independent interest.

2 Preliminaries

In this paper we assume the standard value oracle model, where the algorithm can only access the given submodular function $f$ with queries of the form: what is $f(S)$ for a given $S$? The running time of the algorithm is measured by the total number of value oracle queries and arithmetic operations it performs. Additionally, let us define $f_A(S) \triangleq f(A \cup S) - f(A)$ for any subsets $A, S \subseteq \mathcal{N}$. Furthermore, let $f_A(\emptyset) \triangleq f_A(\{\}).$

The multilinear extension $F : [0,1]^\mathcal{N} \to \mathbb{R}_+$ of a given set function $f : 2^\mathcal{N} \to \mathbb{R}_+$ is:

$$F(x) \triangleq \sum_{R \subseteq \mathcal{N}} f(R) \prod_{e \in R} x_e \prod_{\ell \not\in R} (1 - x_\ell) \quad \forall x \in [0,1]^\mathcal{N}.$$  

Additionally, we make use of the following theorem that provides the guarantees of the continuous greedy algorithm of [7].

\begin{theorem}[Chekuri et al. [7]]
We are given a ground set $\mathcal{N}$, a monotone submodular function $f : 2^\mathcal{N} \to \mathbb{R}_+$, and a polytope $\mathcal{P} \subseteq [0,1]^\mathcal{N}$. If $\mathcal{P} \neq \emptyset$ and one can solve in polynomial time argmax $\{w^T x : x \in \mathcal{P}\}$ for any $w \in \mathbb{R}^\mathcal{N}$, then there exists a polynomial time algorithm that finds $x \in \mathcal{P}$ where $F(x) \geq (1 - 1/e) F(x^*)$. Here $x^*$ is an optimal solution to the problem: max $\{F(y) : y \in \mathcal{P}\}$.
\end{theorem}

3 Algorithms for the (PCSM) Problem

Preprocessing – Enumeration with Mixed Constraints. We define a guess $D$ to be a triplet $(E_0, E_1, c')$, where $E_0 \subseteq \mathcal{N}$ denotes elements that are discarded, $E_1 \subseteq \mathcal{N}$ denotes elements that are chosen, and $c' \in \mathbb{R}_+$ represents a rough estimate (up to a factor of $1 + \epsilon$) of how much an optimal solution $O$ covers each of the covering constraints, i.e., $C_1$. Let us denote by $\mathcal{N} \triangleq \mathcal{N} \setminus (E_0 \cup E_1)$ the remaining undetermined elements with respect to guess $D$.

We would like to define when a given fixed guess $D = (E_0, E_1, c')$ is consistent, and to this end we introduce the notion of critical constraints. For the $i^{th}$ packing constraint the residual value that can still be packed is: $(r_D)_i \triangleq 1 - \sum_{e \in E_1} \mathbb{P}_{i,e}$, where $r_D \in \mathbb{R}$. For the $j^{th}$ covering constraint the residual value that still needs to be covered is: $(s_D)_j \triangleq \max \{0, c'_j - \sum_{e \in E_1} C_{i,e}\}$, where $s_D \in \mathbb{R}$. A packing constraint $i$ is called critical if $(r_D)_i \leq \delta$, and a covering constraint $j$ is called critical if $(s_D)_j \leq \delta c'_j$ ($\delta \in (0,1)$ is

\textsuperscript{7} We note that the actual guarantee of the continuous greedy algorithm is $(1 - 1/e - o(1))$. However, for simplicity of presentation, we can ignore the $o(1)$ term due to the existence of a loss of $\epsilon$ (for any constant $\epsilon$) in all of our theorems.
a parameter to be chosen later). Thus, the collections of critical packing and covering constraints, for a given guess $D$, are given by: $Y_D \triangleq \{i = 1, \ldots, p : (r_D)_i \leq \delta\}$ and $Z_D \triangleq \{j = 1, \ldots, c : (s_D)_j \leq \delta c_j\}$. Moreover, elements are considered large if their size is at least some factor $\alpha$ of the residual value of some non-critical constraint ($\alpha \in (0, 1)$ is a parameter to be chosen later). Formally, the collection of large elements with respect to the packing constraints is defined as $P_D \triangleq \{\ell \in \bar{N} : \exists i \notin Y_D \text{ s.t. } P_{i,\ell} \geq \alpha (r_D)_i\}$, and the collection of large elements with respect to the covering constraints is defined as $C_D = \{\ell \in \bar{N} : \exists j \notin Z_D \text{ s.t. } C_{j,\ell} \geq \alpha (s_D)_j\}$. It is important to note, as previously mentioned, that the notion of a large element is with respect to the residual constraint, as opposed to previous works [9, 32] where the definition is with respect to the original constraint. Let us now formally define when a guess $D$ is called consistent.

**Definition 1.** A guess $D = (E_0, E_1, c')$ is consistent if: (1) $E_0 \cap E_1 = \emptyset$; (2) $c' \geq 1_c$; (3) $P_{1, E_1} \leq 1_p$; and (4) $P_D = C_D = \emptyset$.

Intuitively, requirement (1) states that a variable cannot be both chosen and discarded, (2) states that the each covering constraint is satisfied by an optimal solution $O$, (3) states the chosen elements $E_1$ do not violate the packing constraints, and (4) states that no large elements remain in any non-critical constraint.

Finally, we need to define when a consistent guess is correct. Assume without loss of generality that $O = \{o_1, \ldots, o_\gamma\}$ and the elements of $O$ are ordered greedily: $f_{o_1,\ldots,o_{\gamma-1}}(o_{\gamma}) \leq f_{o_1,\ldots,o_{\gamma-1}}(o_i)$ for every $i = 1, \ldots, k - 1$. In the following definition $\gamma$ is a parameter to be chosen later.

**Definition 2.** A consistent guess $D = (E_0, E_1, c')$ is called correct with respect to $O$ if: (1) $E_1 \subseteq O$; (2) $E_0 \subseteq \bar{O}$; (3) $\{o_1, \ldots, o_\gamma\} \subseteq E_1$; and (4) $c' \leq C_{1, O} \leq (1 + \delta)c'$.

Intuitively, requirement (1) states that the chosen elements $E_1$ are indeed elements of $O$, (2) states that no element of $O$ is discarded, (3) states that the $\gamma$ elements of largest marginal value are all chosen, and (4) states that $c'$ represents (up to a factor of $1 + \delta$) how much $O$ actually covers each of the covering constraints.

We are now ready to present our preprocessing algorithm (Algorithm 1), which produces a list $\mathcal{L}$ of consistent guesses that is guaranteed to contain at least one guess that is also correct with respect to $O$. Lemma 7 summarizes this, its proof appears in [36].

**Algorithm 1:** Preprocessing.

1. $\mathcal{L} \leftarrow \emptyset$
2. foreach $j_1, \ldots, j_c \in \{0, 1, \ldots, \lceil \log_{1+\delta} m \rceil \}$ do
3. | Let $c' = ((1 + \delta)^{j_1}, \ldots, (1 + \delta)^{j_c})$
4. | foreach $E_1 \subseteq \bar{N}$ such that $|E_1| \leq \gamma + (p+\gamma)/(\alpha \delta)$ do
5. | | Let $H = (\emptyset, E_1, c')$
6. | | Let $E_0 = \{\ell \in N \setminus E_1 : f_{E_1}(\ell) > (\gamma^{-1}) f(E_1)\} \cup P_H \cup C_H$
7. | | Set $D = (E_0, E_1, c')$
8. | | If $D$ is consistent according to Definition 1 add it to $\mathcal{L}$.
9. Output $\mathcal{L}$.

**Lemma 7.** The output $\mathcal{L}$ of Algorithm 1 contains at least one guess $D$ that is correct with respect to some optimal solution $O$.
Proof. Fix any optimal solution $O$. At least one of the vectors $c'$ enumerated by Algorithm 1 satisfies property (4) in Definition 2 with respect to $O$. Let us fix an iteration in which such a $c'$ is enumerated. Define the “large” elements $O$ has with respect to this $c'$:

$$O_L \triangleq \{ \ell \in O : \exists \delta \ s.t. \ P_{\ell, \ell} \geq \alpha \delta \} \cup \{ \ell \in O : \exists j \ s.t. \ C_{j, \ell} \geq \alpha \delta c'_j \}. \tag{2}$$

Denote by $O_\gamma \triangleq \{o_1, \ldots, o_\gamma\}$ the $\gamma$ elements of $O$ with the largest marginal (recall the ordering of $O$ satisfies: $f_{(o_1, \ldots, o_\gamma)}(o_{\gamma+1}) \leq f_{(o_1, \ldots, o_{\gamma-1})}(o_\gamma)$). Let us fix $E_1 \triangleq O_\gamma \cup O_L$ and choose $H \triangleq (\emptyset, E_1, c')$. Clearly, $|E_1| \leq \gamma + (p+\delta)/(\alpha \delta)$ since $|O_\gamma| = \gamma$ and $|O_L| \leq (p+\delta)/(\alpha \delta)$. Hence, we can conclude that $H$ is considered by Algorithm 1.

We fix the iteration in which the above $H$ is considered and show that the resulting $D = (E_0, E_1, c')$ of this iteration is correct and consistent (recall that Algorithm 1 chooses $E_0 = \{\ell \in \mathcal{N} \setminus E_1 : f_{E_1}(\ell) > (\gamma^{-1})f(E_1)\cup P_H \cup C_H)$. The following two observations suffice to complete the proof:

Observation 1: $\forall \ell \in O \cup (\mathcal{N} \setminus E_0): f_{E_1}(\ell) \leq \gamma^{-1}f(E_1)$.

Observation 2: $O \cap P_H = \emptyset$ and $O \cap C_H = \emptyset$.

Clearly properties (1) and (3) of Definition 2 are satisfied by construction of $E_1$, $H$, and subsequently $D$. Property (2) of Definition 2 requires the above two observations, which together imply that no element of $O$ is added to $E_0$ by Algorithm 1. Thus, all four properties of Definition 2 are satisfied, and we focus on showing that the above $D$ is consistent according to Definition 1. Property (1) of Definition 1 follows from properties (1) and (2) of Definition 2. Property (2) of Definition 1 follows from the choice of $c'$. Property (3) of Definition 1 follows from the feasibility of $O$ and property (1) of Definition 2. Lastly, property (4) of Definition 1 follows from the fact that $P_D \subseteq P_H$ and that $P_H \subseteq E_0$, implying that $P_D = \emptyset$ (the same argument applies to $C_D$). We are left with proving the above two observations.

We start with proving the first observation. Let $\ell \in O \cup (\mathcal{N} \setminus E_0)$. If $\ell \in \mathcal{N} \setminus E_0$ then the observation follows by the construction of $E_0$ in Algorithm 1. Otherwise, $\ell \in O$. If $\ell \in O_\gamma$ then we have that $f_{E_1}(\ell) = 0$ since $O_\gamma \subseteq E_1$. Otherwise $\ell \in O \setminus O_\gamma$. Note:

$$f_{E_1}(\ell) \leq f_{O_\gamma}(\ell) \leq \gamma^{-1}f(O_\gamma) \leq \gamma^{-1}f(E_1).$$

The first inequality follows from diminishing returns and $O_\gamma \subseteq E_1$. The third and last inequality follows from the monotonicity of $f$ and $O_\gamma \subseteq E_1$. Let us focus on the second inequality, and denote $O = \{o_1, \ldots, o_k\}$ and the sequence $a_1 \triangleq f_{(o_1, \ldots, o_k)}(o_k)$. The sequence of $a_i$s is monotone non-increasing by the ordering of $O$ and the monotonicity of $f$ implies that all $a_i$s are non-negative. Note that $a_1 + \ldots + a_{\gamma} = f(O_\gamma)$, thus implying that $f_{O_\gamma}(\ell) \leq \gamma^{-1}f(O_\gamma)$ for every $\ell \in \{o_{\gamma+1}, \ldots, o_k\}$ (otherwise $a_1 + \ldots + a_{\gamma} > f(O_\gamma)$). The second inequality above, i.e., $f_{O_\gamma}(\ell) \leq \gamma^{-1}f(O_\gamma)$, now follows since $\ell \in O \setminus O_\gamma = \{o_{\gamma+1}, \ldots, o_k\}$.

Let us now focus on proving the second observation. Let us assume on the contrary that there is an element $\ell$ such that $\ell \in O \cap P_H$. Recall that $P_H = \{\ell \in \mathcal{N} \setminus E_1 : \exists i \notin Y_H \ s.t. \ P_{i, \ell} \geq \alpha(r_H)i\}$ where $Y_H = \{i : (r_H)i \leq \delta\}$. This implies that $\ell \in O \setminus E_1$, namely that $\ell \notin O_L$, from which we derive that for all packing constraint $i$ we have that $P_{i,\ell} < \alpha \delta$. Since $\ell \in P_H$ we conclude that there exists a packing constraint $i$ for which $(r_H)i \leq \alpha \delta$. Combining the last two bounds we conclude that $(r_H)i < \delta$, which implies that the $i$th packing constraint is critical, i.e., $i \notin Y_H$. This is a contradiction, and hence $O \cap P_H = \emptyset$. A similar proof applies to $C_H$ and the covering constraints. \hfill \Box

**Randomized Rounding.** Before presenting our main rounding algorithm, let us define the residual problem we are required to solve given a consistent guess $D$. First, the residual objective $g : 2^\mathcal{N} \rightarrow \mathbb{R}_+$ is defined as: $g(S) \triangleq f(S \cup E_1) - f(E_1)$ for every $S \subseteq \mathcal{N}$. Clearly, $g$
is submodular, non-negative, and monotone. Second, let us focus on the feasible domain and denote by $\mathbf{P}(\mathbf{C})$ the submatrix of $\mathbf{P}$ (C) obtained by choosing all the columns in $\bar{N}$. Hence, given $D = (E_0, E_1, E')$ the residual problem is:

$$\max \{ g(S) + f(E_1) : S \subseteq \bar{N}, \mathbf{P}1_S \leq \mathbf{r}_D, \mathbf{C}1_S \geq \mathbf{s}_D \}. \quad (3)$$

In order to formulate the multilinear relaxation of (3), consider the following two polytopes: $\mathcal{P} \triangleq \{ \mathbf{x} \in [0,1]^N : \mathbf{P} \mathbf{x} \leq \mathbf{r}_D \}$ and $\mathcal{C} \triangleq \{ \mathbf{x} \in [0,1]^N : \mathbf{P} \mathbf{x} \geq \mathbf{s}_D \}$. Let $G : [0,1]^N \to \mathbb{R}_+$ be the multilinear extension of $g$. Thus, the continuous multilinear relaxation of (3) is:

$$\max \left\{ f(E_1) + G(\mathbf{x}) : \mathbf{x} \in [0,1]^N, \mathbf{x} \in \mathcal{P} \cap \mathcal{C} \right\}. \quad (4)$$

Our algorithm performs randomized rounding of a fractional solution to the above relaxation (4). However, this is not enough to obtain our main result and an additional post-processing step is required in which additional elements are discarded. Since covering constraints are present, one needs to perform the post-processing step in great care. To this end we denote by $L_D$ the collection of large elements with respect to some critical packing constraint: $L_D \triangleq \{ \ell \in \bar{N} : \exists i \in Y_D \text{ s.t. } \mathbf{P}_{i,\ell} \geq \beta \mathbf{r}_D \}$ ($\beta \in (0,1)$ is a parameter to be chosen later). Intuitively, we would like to discard elements in $L_D$ since choosing any one of those will incur a violation of a packing constraint. We are now ready to present our rounding algorithm (Algorithm 2).

**Algorithm 2: $(f, \bar{N}, \mathbf{P}, \mathbf{C})$.**

1. Use Algorithm 1 to obtain a list of guesses $\mathcal{L}$.
2. foreach $D = (E_0, E_1, E') \in \mathcal{L}$ do
   3. Use Theorem 6 to compute an approximate solution $\mathbf{x}^*$ to problem (4).
   4. Scale down $\mathbf{x}^*$ to $\bar{\mathbf{x}} = \mathbf{x}^*/(1 + \delta)$
   5. Let $R_D$ be such that for every $\ell \in \bar{N}$ independently: $\Pr[\ell \in R_D] = \bar{\mathbf{x}}_{\ell}$.
   7. $S_D \leftarrow E_1 \cup R_D'$
   8. $S_{\text{alg}} \leftarrow \text{argmax} \{ f(S_D) : D \in \mathcal{L}, \mathbf{P} \cdot 1_{S_D} \leq 1_r, \mathbf{C} \cdot 1_{S_D} \geq (1 - \varepsilon)1_r \}$

We note that Line 6 of Algorithm 2 is the post-processing step where all elements of $L_D$ are discarded. Our analysis of Algorithm 2 shows that in an iteration a correct guess $D$ is examined, with a constant probability, $S_D$ satisfies the packing constraints, violates the covering constraint by only a fraction of $\varepsilon$, and $f(S_D)$ is sufficiently high.

The following lemma gives a lower bound on the value of the fractional solution $\bar{\mathbf{x}}$ computed by Algorithm 2 (for a full proof refer [36]).

**Lemma 8.** If $D \in \mathcal{L}$ is correct then in the iteration of Algorithm 2 it is examined the resulting $\bar{\mathbf{x}}$ satisfies: $G(\bar{\mathbf{x}}) \geq (1 - 1/e - \delta)f(O) - f(E_1)$.

Let us now fix an iteration of Algorithm 2 for which $D$ is not only consistent but also correct (the existence of such an iteration is guaranteed by Lemma 7). Intuitively, Algorithm 2 performs a straightforward randomized rounding where each element $\ell \in \bar{N}$ is independently chosen with a probability that corresponds to its fractional value in the solution of the multilinear relaxation (4). However, two key ingredients in Algorithm 2 are required in order to achieve an $\varepsilon$ violation of the covering constraints and no violation of the packing constraints: (1) scaling: prior to the randomized rounding $\mathbf{x}^*$ is scaled down by a factor $(1 + \delta)$ (line 4 in Algorithm 2); and (2) post-processing: after the randomized rounding all chosen large elements in a critical packing constraint are discarded (line 6 in Algorithm 2).
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The first ingredient above (scaling of $x^*$) allows us to prove using standard concentration bounds that with good probability all non-critical packing constraints are not violated. However, when considering critical packing constraints this does not suffice and the second ingredient above (discarding $L_D$) is required to show that with good probability even the critical packing constraints are not violated. While discarding $L_D$ is beneficial when considering packing constraints, it might have a destructive effect on both the covering constraints and the value of the objective. To remedy this we argue that with high probability only few elements in $L_D$ are actually discarded, i.e., $|R_D \cap L_D|$ is sufficiently small. Combining the latter fact with the assumption that the current guess $D$ is not only consistent but also correct, according to Definition 2, allows us to prove the following lemma (for a full proof refer to [36]).

Lemma 9. For any constant $\varepsilon > 0$, choose constants $\alpha = \delta^3$, $\beta = \delta^3/(3\varepsilon)$, $\gamma = 1/\delta^3$, and $
\delta < \min\{1/(15(p+c)), \varepsilon/(2+30(p+c)^2)\}$. With a probability of at least $1/2$ Algorithm 2 outputs a solution $S_{alg}$ satisfying: (1) $P1_{S_{alg}} \leq 1_p$; (2) $C1_{S_{alg}} \geq (1 - \varepsilon)1_c$; and (3) $f(S_{alg}) \geq (1 - 1/\alpha - \varepsilon)f(O)$.

The above lemma suffices to prove Theorem 1, as it immediately implies it.

4 Greedy Dynamic Programming

In this section, we present a novel algorithmic approach for submodular maximization that leads to deterministic and considerably faster approximation algorithms in several settings. Perhaps the most notable application of our approach is Theorem 4. To the best of our knowledge, it provides the first deterministic non-trivial approximation algorithm for maximizing a monotone submodular function subject to packing constraints. To highlight the core idea of our approach, we first present a vanilla version of the greedy dynamic programming approach applied to (PCSM) that gives a constant-factor approximation and satisfies the packing constraints, but violates the covering constraints by a factor of 2 and works in pseudo-polynomial time.

Vanilla Greedy Dynamic Programming. Let us start with a sketch of the algorithm’s definition and analysis. For simplicity of presentation, we assume in the current discussion relating to pseudo-polynomial time algorithms that $C \in \mathbb{N}^{n \times n}_+$ and $P \in \mathbb{N}^{p \times n}_+$. Let $p \in \mathbb{N}^n_+$ and $c \in \mathbb{N}^n_+$ be the packing and covering requirements, respectively. A solution $S \subseteq \mathcal{N}$ is feasible if and only if $C \cdot 1_S \geq c$ and $P \cdot 1_S \leq p$. We also use the following notations: $c_{max} = ||c||_\infty$, $p_{max} = ||p||_\infty$, and $[s]_0 = \{0, \ldots, s\}$ for every integer $s$.

We define our dynamic programming as follows: for every $q \in [n]\{0\}$, $c' \in [n \cdot c_{max}]_0$, and $p' \in [p_{max}]_0$ a table entry $T[q, c', p']$ is defined and it stores an approximate solution $S$ of cardinality $q$ with $C \cdot 1_S = c'$ and $P \cdot 1_S = p'$. For the base case, we set $T[0, 0, c, 0] \leftarrow \emptyset$. For populating $T[q, c', p']$ when $q > 0$, we examine every set of the form $T[q - 1, c' - C_\ell, p' - P_\ell] \cup \{\ell\}$, where $\ell$ satisfies $\ell \in \mathcal{N} \setminus T[q - 1, c' - C_\ell, p' - P_\ell]$, $c' - C_\ell \geq 0$, and $p' - P_\ell \geq 0$. Out of all these sets, we assign the most valuable one to $T[q, c', p']$. Note that this operation stores a greedy approximate solution in the table entry $T[q, c', p']$. The output of our algorithm is the best of the solutions $T[q, c', p']$, for $1 \leq q \leq n$, $c' \geq c/2$ and $p' \leq p$. See Algorithm 3 for pseudo code.

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8 We introduce a dummy solution $\bot$ for denoting undefined table entries, and initialize the entire table with $\bot$. For the exact details we refer to [36].
Algorithm 3: Vanilla Greedy Dynamic Program.
1. create a table $T$: $[n] \times [n \cdot c_{\text{max}}] \times [p_{\text{max}}] \rightarrow 2^N$ initialized with entries $\perp$
2. $T[0, 0, 0] \leftarrow \varnothing$
3. for $q = 0$ to $n$ do
   4. foreach $c' \in [n \cdot c_{\text{max}}]$ and $p' \in [p_{\text{max}}]$ do
      5. foreach $\ell \in N \setminus T[q, c', p']$ do
          6. $c'' \leftarrow c + C_\ell$, $p'' \leftarrow p + P_\ell$
          7. $T[q + 1, c'', p''] \leftarrow \arg \max \{f(T[q + 1, c'', p'']) \in T[q, c', p'] \cup \{\ell\}\}$
   8. Output $\arg \max_{q, c' \geq \epsilon/2, p' \leq p} f(T[q, c', p'])$.

Let us now sketch the analysis of the above algorithm. Let $O$ be an optimal set solution. We consider an arbitrary permutation of $O$, say $\{o^1, o^2, \ldots, o^k\}$. Let $O^i = \{o^1, \ldots, o^i\}$ be the set of the first $i$ elements in this permutation and let $O^i = \emptyset$. We introduce the function $g: O \rightarrow \mathbb{R}_+$ for denoting the marginal value of the elements in $O$. More precisely, let $g(o^i) = f_{O^i-1}(o^i)$. Note that $f(O) = \sum o g(o)$. Let us compute the marginal value sequence $c_1, \ldots, c_k$ of the elements in terms of the value $f(S_q)$ of the table entry $S_q := T[q, C_1q, P_1q]$ corresponding to $O_q$. The construction of the sequence $a_1, \ldots, a_k$ divides $[k]$ into $m$ phases where $m$ is a positive integer parameter. A (possibly empty) phase $i \in [m]$ is characterized by the following property. Consider a prefix $O_q$ and its corresponding table entry $S_q$. If $q$ is in phase $i$ then there exists an element $o_{q+1} \in O \setminus O_q$ such that adding $o_{q+1}$ to $S_q$ increases $f$ by at least an amount of $(1 - \epsilon/m)g(a_{q+1})$. We set $O_{q+1} = O_q \cup \{o_{q+1}\}$. Thus, in earlier phases we make more progress in the corresponding dynamic programming solution $S_q$ relative to $g(O_q)$ than in later phases. Additionally, we prove a complementing inequality. At the end of phase $i \in [m]$ all elements in $O \setminus O_q$ increase $f$ by no more than $(1 - \epsilon/m)g(a_{q+1})$. We prove that this implies that $f(S_q)$ is at least $i/m \cdot g(O \setminus O_q)$ and thus large relatively to the complement of $O_q$. We set up a factor-revealing linear program that constructs the worst distribution of the marginal values over the phases that satisfy the above inequalities. For the purpose of analysis, by scaling, we assume that $f(O) = \sum_o g(o) = 1$. The following lemma formalizes the above sketch. It is also the basis for the factor-revealing LP below (for its proof refer to [36]).

Lemma 10. Let $m \geq 1$ be an integral parameter. We can pick for each $i \in [m]$ a set $O_i = \{a_i^1, a_i^2, \ldots, a_i^k\} \subseteq O$ (possibly empty) such that the following holds. For $i \neq j$, we have that $O_i \cap O_j = \emptyset$. Let $L_i = \sum_{j=1}^i q_j$, $Q_i = \cup_{j=1}^i O_j$, $C_i = C_{Q_i}$, $P_i = P_{Q_i}$, and let $A_i := T[L_i, C_i, P_i]$ be the corresponding DP cell. Then $C_{A_m} \geq \epsilon/2$ and the following inequalities hold.

1. $f(A_0) = g(O_0)$ where $A_0 = O_0 = \emptyset$,
2. $f(A_i) \geq f(A_{i-1}) + (1 - \epsilon/m)g(O_i) \forall i \in [m]$ and
3. $f(A_i) \geq \frac{1}{m} \left(1 - \sum_{j=1}^i g(O_j) \right) \forall i \in \{0\} \cup [m]$.

Below we describe a factor-revealing LP that captures the above-described multi-phase analysis for the greedy DP algorithm. The idea is to introduce variables for the quantities in the inequalities in the previous lemma and determining the minimum ratio that can be
guaranteed by these inequalities.

\[
\begin{align*}
\min \ a_m \\
\text{s.t.} \\
\quad a_1 &\geq (1 - \frac{1}{m}) a_1; \\
\quad a_i &\geq a_{i-1} + (1 - \frac{1}{m}) a_i \quad \forall i \in [m] \setminus \{1\}; \\
\quad a_i &\geq \frac{1}{m} \left(1 - \sum_{j\leq i} o_j\right) \quad \forall i \in [m]; \\
\quad a_i &\geq 0, \ o_i \geq 0 \quad \forall i \in [m].
\end{align*}
\]

The variable \(o_i\) corresponds to the marginal value \(g(O_i)\) for the set \(O_i\) in our analysis. Variables \(a_i\) correspond to the quantities \(f(A_i)\) for the approximate solution \(A_i\) for each phase \(i = 1, 2, \ldots, m\). We add all the inequalities we proved in Lemma 10 as the constraints for this LP. Note that since \(f(O) = 1\), the minimum possible value of \(a_m\) will correspond to a lower bound on the approximation ratio of our algorithm.

The following is the dual for the above LP:

\[
\begin{align*}
\max \ \sum_{i=1}^{m} \frac{1}{m} y_i \\
\text{s.t.} \\
\quad x_i + y_i - x_{i+1} &\leq 0 \quad \forall i \in [m-1]; \\
\quad x_m + y_m &\leq 1; \\
\quad \frac{1}{m} \sum_{j\geq i} y_j - (1 - \frac{1}{m}) x_i &\leq 0 \quad \forall i \in [m]; \\
\quad x_i &\geq 0, \ y_i \geq 0 \quad \forall i \in [m].
\end{align*}
\]

This linear program gives for every \(m\) a lower bound on the approximation ratio. Analytically, we can show that if \(m\) tends to infinity the optimum value of the LP converges to \(1/e\). This leads to the following lemma (for its proof refer to [36]).

\[\blacktriangleright \text{Lemma 11. Assuming } p \text{ and } c \text{ are constants, the vanilla greedy dynamic programming algorithm for } (PCSM) \text{ runs in pseudo-polynomial time } O(n^2 p_{\max} c_{\max}) \text{ and outputs a solution } S \subseteq N \text{ that satisfies: (1) } f(S) \geq (1/e) \cdot f(O), \text{ (2) } P_1 S \leq p \text{ and } C_1 S \geq 1/2 \cdot c.\]

Applications and Extensions of Greedy Dynamic Programming Approach

We briefly explain the applications of the approach to the various specific settings and the required tailored algorithmic extensions to the vanilla version of the algorithm.

Scaling, guessing and post-processing for packing constraints. An immediate consequence of Lemma 11 is a deterministic \((1/e)\)-approximation for the case of constantly many packing constraints that runs in pseudo-polynomial time. We can apply standard scaling techniques to achieve truly polynomial time. This may, however, introduce a violation of the constraints within a factor of \((1 + \varepsilon)\). To avoid this violation, we can apply a pre-processing and post-processing by Kulik et al. [32] to achieve Theorem 4.

Forbidden sets for a single packing and a single covering constraints. In this setting we are able to ensure a \((1 - \varepsilon)\)-violation of the covering constraints by using the concept of forbidden sets. Intuitively, we exclude the elements of these set from being included to the dynamic programming table in order to be able to complete the table entries to solutions with only small violation.
Fix some $\epsilon > 0$. By guessing we assume that we know the set $G$ of all, at most $1/\epsilon$ elements $\ell$ from the optimum solution with $P_{\ell} > \epsilon \cdot p$. We can guess $G$ using brute force in $n^{O(1/\epsilon)}$ time. This allows us to remove all elements with $P_{\ell} \geq \epsilon \cdot p$ from the instance. Let $N'$ be the rest of the elements. (For consistency reasons, we use bold-face vector notation here also for dimension one.)

Fix an order of $N'$ in which the elements are sorted in a non-increasing order of $C_{\ell}/P_{\ell}$ values, breaking ties arbitrarily. Let $N_i$ be the set of the first $i$ elements in this order. For any $p' \leq p$, let $F_{p'}$ be the smallest set $N_i$ with $P_{1N_i} \geq p - p'$. Note that the profit of $F_{p'}$ is at least the profit of any subset of $N'$ with packing value at most $p - p'$ and that the packing value of $F_{p'}$ is no larger than $(1 + \epsilon)p - p'$. Also note that for any $0 \leq p' \leq p'' \leq p$, it holds that $F_{p''} \subseteq F_{p'}$.

Now we explain the modified Greedy-DP that incorporates the guessing and the forbidden sets ideas. Let $G$ be the set of the guessed big elements as described above. For the base case, we set $T[C_{1G}, P_{1G}]=G$ and $T[c', p] = \bot$ for all table entries with $c' \neq C_{1G}$ or $p' \neq P_{1G}$.

In order to compute $T[c', p']$, we look at every set of the form $T[c' - C_{\ell}, p' - P_{\ell}] \cup \{\ell\}$, where $\ell \in N' \setminus \{T[c' - C_{\ell}, p' - P_{\ell}] \cup F_{p'}\}$. $c' - C_{\ell} \geq 0$, and $p' - P_{\ell} \geq 0$. Notice that we forbid elements belonging to $F_{p'}$ to be included in any table entry of the form $T[c', p']$. Now out of all these sets, we assign the most valuable set to $T[c', p']$. The output of our algorithm is the best of the solutions $T[c', p'] \cup F_{p'}$, such that $c' + C_{1G} \geq c$.

By means of a more sophisticated factor-revealing LP, we obtain Theorem 5. Finally, if the packing constraint is actually a cardinality constraint we can assume that $\epsilon < 1/p$. Hence, there will be no violation of the cardinality constraint and also guessing can be avoided.

5 Extensions: Matroid Independence and Multi-Objective

Refer to [36] for the extensions that deal with a matroid independence constraint and with multiple objectives.

References

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