

Solving Medium-Density Subset Sum Problems in Expected Polynomial Time: An Enumeration Approach

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Abstract. The subset sum problem (SSP) can be briefly stated as: given a target integer E and a set A containing n positive integer a_j , find a subset of A summing to E . The *density* d of an SSP instance is defined by the ratio of n to m , where m is the logarithm of the largest integer within A . Based on the structural and statistical properties of subset sums, we present an improved enumeration scheme for SSP, and implement it as a complete and exact algorithm (EnumPlus). The algorithm always equivalently reduces an instance to be low-density, and then solve it by enumeration. Through this approach, we show the possibility to design a sole algorithm that can efficiently solve arbitrary density instance in a uniform way. Furthermore, our algorithm has considerable performance advantage over previous algorithms. Firstly, it extends the density scope, in which SSP can be solved in expected polynomial time. Specifically, It solves SSP in expected $O(n \log n)$ time when density $d \geq c \cdot \sqrt{n}/\log n$, while the previously best density scope is $d \geq c \cdot n/(\log n)^2$. In addition, the overall expected time and space requirement in the average case are proven to be $O(n^5 \log n)$ and $O(n^5)$ respectively. Secondly, in the worst case, it slightly improves the previously best time complexity of exact algorithms for SSP. The worst-case time complexity of our algorithm is proved to be $O(n \cdot 2^{n/2} - c \cdot 2^{n/2} + n)$, while the previously best result is $O(n \cdot 2^{n/2})$.

1 Introduction

Let us denote \mathbb{N}_+ as the set of positive integers. The subset sum problem is a classical NP-complete problem, in which one asks, given a set $A = \{a_1, a_2, \dots, a_n\}$ with $a_j \in \mathbb{N}_+$ ($1 \leq j \leq n$) and $E \in \mathbb{N}_+$, if there exists a subset $A' \subseteq A$ such that the sum of all elements of A' is E . More formally, the subset sum problem can be formulated as an integer programming problem:

$$\begin{aligned} & \text{Maximize } z = \sum_{j=1}^n a_j x_j \\ & \text{Subject to } \sum_{j=1}^n a_j x_j \leq E; \forall j, x_j = 0 \text{ or } 1. \end{aligned}$$

Extensive study has been conducted on SSP and its related problems: knapsack problem [1] and integer partition problem [2]. Many noticeable results have been achieved. For example, the hardness distribution of those problems are carefully investigated in [2] [3] [4] [5] et al., and it is now known that the hardness of SSP varies greatly with density d (see [6]).

Low-density: an instance with density $0 < d < c$, for some constant c , can be efficiently solved by lattice reduction based algorithms, e.g., [7] [8] [9]. However, these algorithms have two main limits. Firstly, they cannot solve instance with $d \geq c$ efficiently, though the bound of constant c is recently extended from 0.6463 to 0.9408. Secondly, they are not complete, i.e., they may fail to find any solution of an instance when the instance actually has solution.

High-density: an instance with density $d > c \cdot n / \log n$ can be efficiently solved by various techniques such as branch-and-bound, dynamic programming, and number theory analysis. Specifically, the algorithm YS87 [10] adopts branch-and-bound technique; NU69 [11] and HS74 [12] adopt dynamic programming technique; ST02 [13] adopts both branch-and-bound and dynamic programming; CFG89 [14] and GM91 [15] utilize number theory analysis. However, these algorithms have two main limits. Firstly, they cannot solve instance with $d \leq c \cdot n / \log n$ efficiently. Secondly, their average-case complexity is expected to increase with n , thus they have difficulty in handling large size instance.

Medium-density: an instance with density $c \leq d$ and $d \leq c \cdot n / \log n$ is usually hard to solve. As far as we know, the algorithm DenseSSP [6] is the only previous algorithm that works efficiently in part of this density scope. It solves uniformly random instances with density $d \geq 16n/(\log n)^2$ in expected polynomial time $O(n^{3/2})$.

Other than exact algorithms, it is worth to mention that highly efficient approximation methods (e.g., [16] [17]) can solve SSP at polynomial time and space cost. However, they cannot guarantee the exactness of their solutions. In this paper, we concentrate on solving SSP through exact methods, and we propose a complete and exact algorithm, which we call EnumPlus. The two main ingredients of EnumPlus are a new pruning mechanism and a new heuristic. Based on the structural property of subset sums, the pruning mechanism allows to dynamically partition the integer set into two parts and to prune branches in the search tree. Based on the statistical property of subset sums, the heuristic predicts which branch of the tree is more likely to contain the solution (and this branch is explored first by the algorithm).

1.1 Contributions

The main contribution of this work is two-fold. First, by equivalently reducing an instance to be low-density in linear time (see Section 4 and 6.2), we show the possibility to design a sole algorithm that can efficiently solve arbitrary density instance in a uniform way. Second, we propose a complete and exact algorithm that has considerable advantage over previous exact algorithms. Specifically, it extends the density scope, in which SSP can be solved in expected polynomial

time, and it slightly improves the previously best worst-case time complexity of exact algorithms for SSP.

1.2 Notation and Conventions

If it is not specifically mentioned, we assume that the elements of A are sorted in decreasing order ($a_1 > a_2 > \dots > a_n$), and use S to denote the sum of A . Following the notation and description style of [1], we denote some basic notations that are used for the algorithm description as follows:

A_k denotes the subset $\{a_k, a_{k+1}, \dots, a_n\}$ of A ;
 S_k denotes the sum value of A_k ($= \sum_{j=k}^n a_j$);
 d_k denotes the density of A_k ($= \frac{n-k+1}{\log \max\{a_j | a_j \in A_k\}}$);
 $W(E)$ denotes the number of solutions for a given target E and integer set A ;
 \hat{x}_k denotes current partial solution $\{x_j = 0, 1 | 1 \leq j \leq k\}$;
 \hat{z}_k denotes current partial solution value ($= \sum_{j=1}^k a_j x_j$);
 \hat{c}_k denotes current residual capacity ($= E - \hat{z}_k$);
 $\neg \hat{c}_k$ denotes current residual opposite capacity ($= S_{k+1} - \hat{c}_k$);
 $b_{MAX}|(A_k, \hat{c}_k)$ denotes the maximum subset sum of A_k while $b_{MAX} \leq \hat{c}_k$;
 $b_{MIN}|(A_k, \hat{c}_k)$ denotes the minimum subset sum of A_k while $b_{MIN} \geq \hat{c}_k$.

2 Motivation

There are two main causes of performance discrepancy of different enumeration (searching) scheme. In the first place, the efficiency to prune infeasible solutions contributes to the performance both in the worst case and in the average case. In the second place, proper search strategy contributes to the performance in the average case. Specifically, algorithm HS74 has the best time complexity $O(n \cdot 2^{n/2})$ in the worst case. It enumerates all possible solutions following breadth first strategy; it prunes redundant branches by dividing the original problem into two sub-problems and considering all equal subset sums as one state. However, HS74 does not work well in two situations. Firstly, when processing low-density instance, almost all subset sums are different to each other, thus few pruning can be made. Secondly, because of its breadth-first search strategy, HS74 is slow to approach solutions when the size, i.e. breadth, of an instance is considerable large.

The central idea of our approach is dynamically partitioning the original instance $A[1..n]$ to two sub-instances $A[1..k]$ and $A[k+1..n]$, $1 < k < n$. We treat the whole enumeration space as a binary tree (like the route colored by red in Figure 1) that is stemmed from $A[1]$ and ended by $A[n]$. During the enumeration of $A[1..n]$, all enumerated subset sums of $A[k+1..n]$ are organized as “block bounds”, which serve as block barriers that can prevent further expanding of the k -th level nodes. Therefore, for any partition point k , both $A[1..k]$ and $A[k+1..n]$ are incrementally and simultaneously enumerated by enumerating $A[1..n]$ as a

binary tree. In addition, a heuristic is utilized to accelerate the searching for global solution. The heuristic predicts which branch of the tree is more likely to contain the answer. Therefore, a large problem is recursively reduced into a smaller one in linear time, and it has high possibility that the two problems have at least one common solution. To clarify the description of our algorithm, we present the main phases separately.

3 Branch and Prune

The pruning mechanism is inspired by the partition operation of HS74. In HS74, the original instance is divided into two sub-instances, and their subset sums are separately computed and stored in two lists. For any subset sum s_i in a list, if a subset sum s_j can be found in the other list such that $s_i + s_j = E$, a feasible solution is located. While HS74 explicitly partitions the the oriental instance only one time before enumeration, our algorithm implicitly performs partition multiple times during enumeration.

A “block bound” of an integer set A is defined as a two elements structure $[b_{MAX}, b_{MIN}]$, in which b_{MAX} and b_{MIN} are subset sums of A . Furthermore, a block bound must conform two constraints: (1) $b_{MAX} < b_{MIN}$; (2) no subset sum of A falls between b_{MAX} and b_{MIN} . Block bounds are recursively calculated as follows:

$$\begin{aligned} & \text{If } \hat{c}_k \geq S_k, \quad b_{MIN}|(A_k, \hat{c}_k) = S, b_{MAX}|(A_k, \hat{c}_k) = S_k. \\ & \text{If } \hat{c}_k \leq 0, \quad b_{MIN}|(A_k, \hat{c}_k) = 0, b_{MAX}|(A_k, \hat{c}_k) = -a_{k+1}. \\ & \text{If } S_k > \hat{c}_k > 0, \quad b_{MIN}|(A_k, \hat{c}_k) = \min \left\{ \begin{aligned} & b_{MIN}|(A_{k+1}, \hat{c}_k), \\ & a_k + b_{MIN}|(A_{k+1}, \hat{c}_k - a_k) \end{aligned} \right\}, \\ & \quad b_{MAX}|(A_k, \hat{c}_k) = \max \left\{ \begin{aligned} & b_{MAX}|(A_{k+1}, \hat{c}_k), \\ & a_k + b_{MAX}|(A_{k+1}, \hat{c}_k - a_k) \end{aligned} \right\}. \end{aligned}$$

Let us consider a sorted integer array $A[1..n]$, we create an n elements list $V[1..n]$. Each element $V[k]$ of $V[1..n]$ is a collection of block bounds of the integer set A_k . Therefore, if there is an integer $s = b_{MAX}$ (or b_{MIN}), $[b_{MAX}, b_{MIN}] \in V[k+1]$, and $s + \hat{z}_k = E$, a feasible solution for target integer E is located. If there is a block bound $[b_{MAX}, b_{MIN}] \in V[k+1]$ such that $b_{MAX} < \hat{c}_k < b_{MIN}$, we can determine that there is no subset sum s of A_{k+1} such that $s + \hat{z}_k = E$. In this way, a block bound $[b_{MAX}, b_{MIN}]$ of A_k acts as a bounded block that prevents all attempts to find target E in A_k when $b_{MAX} \leq E \leq b_{MIN}$. To describe the mechanism of block bound, a case that has an integer set $A[1..4] = \{52, 40, 30, 16\}$ and the target value $E = 69$ is illustrated in Figure 1.

As we can see in Figure 1, the first node $\hat{c}_1 = 69$ is expended to two nodes $\hat{c}_2 = \{69, 17\}$, i.e., finding $E = 69$ and 17 in subset $A[2..4]$. Suppose the node having larger E is always expended first, the first block bound $[16, 138]$ is generated when finding $E = 69$ in subset $A[4..4]$. Therefore, later finding of $E = 39, 29$ in subset $A[4..4]$ is blocked by the block bound $[16, 138]$. In the same way, let us observe the case of $k = 3$, the searching for $\hat{c}_3 = 29$ is finished with the generation of a block bound $[16, 30]$, and the later searching for $\hat{c}_3 = 17$ will be

5 The New Algorithm

Based on the “block bound” and “heuristic search” techniques, we propose a complete and exact algorithm EnumPlus for SSP. In this algorithm, the whole search space is enumerated as a binary tree T . For any given target value v at a branch node, the algorithm try to find both $b_{MAX}|(A_k, v)$ and $b_{MIN}|(A_k, v)$ in the sub-tree T_k that has x_k as root node. If the block bound is already existed in the block bound list $V[k]$, the existed block bound will be returned. Otherwise, T_k is expended to find the block bound $[b_{MAX}|(A_k, v), b_{MIN}|(A_k, v)]$, and the newly found block bound is inserted into $V[k]$ as a new element. The enumeration procedure terminates in 2 cases: 1) a feasible solution is found, 2) it is backtracked to the root of T . At each branch node (x_k) of T , if the target value v is more possible to be found when $x_k = 0$, then the branch $x_k = 0$ is enumerated first, otherwise the branch $x_k = 1$ is enumerated first.

The pseudo-code of EnumPlus and SetSum are given in Algorithm 1 and Algorithm 2 respectively, while the concrete implements of sub-algorithms QBB and UBB are not given since they can be implemented by simply adopting some classic data structures/algorithms (e.g., AVL-balance tree and Red-Black-balance tree).

Algorithm 1 EnumPlus($A[1..N], E$)

Input: an integer set $A[1..N]$; target value E .

Output: the maximum subset sum $b1 \leq E$; the minimum subset sum $b2 \geq E$.

- 1: allocate the vector of block bound sets $V[1..N]$;
 - 2: $S \leftarrow$ sum value of $A[1..N]$;
 - 3: $[b1, b2] \leftarrow$ SetSum(1, E);
 - 4: destroy the vector of block bound sets $V[1..N]$;
 - 5: **return** $[b1, b2]$;
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6 Performance Analysis

Before analyzing the complexity of our algorithm, we assume that the requirement of time and space of our algorithm is maximized when target value $E = S/2$. The assumption is reasonable because our algorithm simultaneously search both E and $S - E$ in the answer space. Moreover, $E = S/2$ is the hardest case for the dynamic programming algorithm (see [15]). Therefore, all our following analysis will be provided in case of that $S/2$ is chosen as target value E .

6.1 Worst-Case Complexity

Before the presentation of our results about the worst-case complexity of EnumPlus, we first introduce a lemma as follows:

Algorithm 2 SetSum(k, v)

Input: k = start position of residual subset $A[k..n]$;

v = residential capacity \hat{c} .

Output: $[b_{MAX}, b_{MIN}]$ = block bound of $A[k..N]$ for $\hat{c} = v$.

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1: if  $v \geq S_k$  return  $[S_k, S]$ ;
2: if  $v \leq 0$  return  $[-a_{k+1}, 0]$ ;
3:  $[b_{MAX}, b_{MIN}] \leftarrow \text{QBB}(V[k], v)$ ; // query block bound  $[b_{MAX}, b_{MIN}]$  in  $V[k]$  such
   that  $b_{MAX} \leq v \leq b_{MIN}$ .
4: if  $b_{MAX} \leq v \leq b_{MIN}$  then
5:   if  $v = b_{MAX}$  or  $v = b_{MIN}$  then
6:     identify solution; halt; // found solution
7:   else
8:     return  $[b_{MAX}, b_{MIN}]$ ;
9:   end if
10: else if inequation 1 holds then
11:    $[b3, b4] \leftarrow \text{SetSum}(k+1, v)$ ;
12:    $[b1, b2] \leftarrow \text{SetSum}(k+1, v - A[k])$ ;  $b1+ = A[k]$ ;  $b2+ = A[k]$ ;
13: else
14:    $[b1, b2] \leftarrow \text{SetSum}(k+1, v - A[k], v2)$ ;  $b1+ = A[k]$ ;  $b2+ = A[k]$ ;
15:    $[b3, b4] \leftarrow \text{SetSum}(k+1, v)$ ;
16: end if
17:  $b_{MAX} \leftarrow \max\{b1, b3\}$ ;  $b_{MIN} \leftarrow \min\{b2, b4\}$ ;
18:  $\text{UBB}(V[k], b_{MAX}, b_{MIN})$ ; // insert  $[b_{MAX}, b_{MIN}]$  into  $V[k]$ 
19: return  $[b_{MAX}, b_{MIN}]$ ;
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Lemma 1. For a certain subset $A[k..n]$ of A , the number of block bounds generated by SetSum is less than $\min\{2^{k-1}, 2^{n-k+1}\}$.

Proof. In case of $2^{k-1} \geq 2^{n-k+1}$, the number of all possible subset sums of $A[k..n]$ is less than $(2^{n-k+1} - 1)$, therefore the number of all possible block bounds of $A[k..n]$ is less than 2^{n-k+1} , i.e. $\min\{2^{k-1}, 2^{n-k+1}\}$. In case of $2^{k-1} < 2^{n-k+1}$, the search tree has at most 2^{k-1} nodes at level k . Because each node generates at most one block bound, the number of all possible block bounds of $A[k..n]$ is less than 2^{k-1} , i.e. $\min\{2^{k-1}, 2^{n-k+1}\}$.

About the worst-case complexity of EnumPlus, there are 2 propositions given as follows:

Proposition 2. The worst-case space complexity of EnumPlus is $O(2^{n/2})$.

Proof. For a subset A_k , the number of block bounds generated by SetSum is less than $\min\{2^{k-1}, 2^{n-k+1}\}$, therefore the total number Num(n) of generated block bounds is

$$\text{Num}(n) \leq \sum_{k=1}^n \min\{2^{k-1}, 2^{n-k+1}\} \leq 2 \times \sum_{k=1}^{n/2} 2^{k-1} \leq 2^{n/2+1}.$$

Thus the worst-case space complexity of EnumPlus is $O(2^{n/2})$.

Proposition 3. *The worst-case time complexity of EnumPlus is $O(n \cdot 2^{n/2} - c \cdot 2^{n/2} + n)$.*

Proof. As we proved in the proposition 2, there are at most $2^{n/2+1}$ block bounds are generated, and each recursive call for SetSum generates one block bound. The main time cost of each block bound is to search and insert it in a collection $V[k]$. There are some classic data structures/algorithms, such as AVL-balance tree and Red-Black-balance tree, can efficiently manage the search and insert operations on storable data collection. The worst-case time cost of these algorithms to search or insert in the n elements collection is $\log n$. Therefore we have the worst-case time cost $\text{Time}(n)$ of EnumPlus as follows:

$$\begin{aligned} \text{Time}(n) &= 2 \times \sum_{k=1}^{n/2} \sum_{i=1}^{2^{k-1}} [\log i] = 2 \times \sum_{k=1}^{n/2} \sum_{i=1}^k ((i-1) \times 2^{i-2}) \\ &= 2 \times \sum_{k=1}^{n/2} ((k-2) \times 2^{k-1} + 1) \\ &\leq (n-6) \times 2^{n/2} + n + 8 \end{aligned}$$

Thus the worst-case time complexity of algorithm EnumPlus is $O(n \cdot 2^{n/2} - c \cdot 2^{n/2} + n)$.

6.2 Average-Case Complexity

Before analyzing the average-case complexity of our algorithm, 2 lemmas are introduced as follows:

Lemma 4. *EnumPlus always reduces an instance A_1 with $\hat{c}_1 = S_1/2$ to A_k with \hat{c}_k , $|\hat{c}_k - S_k/2| \leq a_{k-1}/2$, in linear time.*

Proof. **[Induction]** We first consider $k = 2$. Because of the heuristic search strategy, EnumPlus first expands the branch that leads to a sub-problem, in which $|\hat{c}_k - S_k/2|$ is smaller. Then we have

$$\hat{c}_2 = \begin{cases} S_1/2, & \text{if } |S_1 - S_2| \leq |S_1 - 2a_1 - S_2| \\ S_1/2 - a_1, & \text{if } |S_1 - S_2| > |S_1 - 2a_1 - S_2|. \end{cases}$$

Therefore,

$$\hat{c}_2 - S_2/2 = \begin{cases} a_1/2, & \text{if } |S_1 - S_2| \leq |S_1 - 2a_1 - S_2| \\ -a_1/2, & \text{if } |S_1 - S_2| > |S_1 - 2a_1 - S_2|. \end{cases}$$

Thus EnumPlus reduces A_1 with $\hat{c}_1 = S_1/2$ to A_2 with \hat{c}_2 , $|\hat{c}_2 - S_2/2| \leq a_1/2$, in 1 step.

Then we assume that EnumPlus reduces A_1 with $\hat{c}_1 = S_1/2$ to A_k with \hat{c}_k , $|\hat{c}_k - S_k/2| \leq a_{k-1}/2$, in $k-1$ steps.

Consider A_{k+1} and \hat{c}_{k+1} , we have

$$\hat{c}_{k+1} = \begin{cases} \hat{c}_k, & \text{if } |\hat{c}_k - S_{k+1}| \leq |\hat{c}_k - 2a_{k+1} - S_{k+1}| \\ \hat{c}_k - a_k, & \text{if } |\hat{c}_k - S_{k+1}| > |\hat{c}_k - 2a_{k+1} - S_{k+1}|. \end{cases}$$

Combine the above definition of \hat{c}_{k+1} and the assumption that $|\hat{c}_k - S_k/2| \leq a_{k-1}/2$, we have that $|\hat{c}_{k+1} - S_{k+1}/2| \leq a_k/2$. Thus EnumPlus reduces A_1 with $\hat{c}_1 = S_1/2$ to A_{k+1} with \hat{c}_{k+1} , $|\hat{c}_{k+1} - S_{k+1}/2| \leq a_k/2$, in k steps.

Lemma 5. *Let $M = 2^m$ and the n elements of A is uniformly random in $[1..M]$, the number of distinct subset sums of A is expected to be $O(n^4)$.*

Proof. We use S_1, \dots, S_M to denote the sequence of all subsets of A listed in non-decreasing order of their sums. Let the sum of subset S_u be $P_u = \sum_{j \in S_u} a_j$. For any $2 \leq u \leq M$, define $\Delta_u = P_u - P_{u-1} \geq 0$, then P_u is a distinct subset sum if $\Delta_u > 0$, and P_1 is always a distinct subset sum. Let every element a_j of A be a non-negative random variable with density function $f_j : [1..M] \rightarrow [0, 1]$, i.e., $f_j(t) = \Pr(a_j = t), t \in [1..M]$. We notice that there is a theorem, which is proved by [18] for general discrete distributions, shows that:

Suppose $\pi = \max_{j \in [1..n]}(\max_{x \in [1..M]}(f_j(x)))$ and $\mu \geq \max_{j \in [1..n]}(\mathbf{E}[a_j])$. Then the expected number of dominating sets is $\mathbf{E}[q] = O(\mu n^2(1 - e^{-\pi n^2})) = O(\mu \pi n^4)$.

Because a distinct subset sum is a special case of dominating set on condition that weight w_j and profit p_j are both equal to a_j , the number of distinct subset sums is equal to the number of dominating sets on this condition. Since a_j is uniformly random in $[1..M]$, we have $\pi = 1/M$, $\mu = M/2$. Therefore, the number of distinct subset sums is expected to be

$$\mathbf{E}[q] = O\left(\frac{M}{2} \cdot \frac{1}{M} \cdot n^4\right) = O(n^4).$$

Assume that the elements of A is uniformly random in $[1..M]$, we have 2 propositions about the complexity of EnumPlus in the average case:

Proposition 6. *Given an integer set A whose elements are uniformly distributed, the overall expected time and space requirement of EnumPlus in the average case are $O(n^5 \log n)$ and $O(n^5)$.*

Proof. According to Lemma 5, the number of distinct subset sums of A is expected to be $O(n^4)$. Therefore the expected space cost is $O(n \cdot n^4) = O(n^5)$, and the expected time cost is $O(n \cdot n^4 \cdot \log(n^4)) = O(n^5 \log n)$. Thus the overall time and space complexity of EnumPlus are expected to be $O(n^5 \log n)$ and $O(n^5)$ respectively.

Proposition 7. *EnumPlus solves SSP in $O(n \log n)$ time when density $d \geq c \cdot \sqrt{n}/\log n$.*

Proof. Consider an integer set $A[1..n]$ whose elements are uniformly random in $[1..2^m]$. As the previous result shown by [3] and [2], if density $d > 1$, there is a high possibility that the instance with target value $S/2$ has many solutions. Thus it is expected that the sub-instance A_{n-m+1} with $S_{k-m+1}/2$ has many solutions, and it takes at most $O(m2^{m/2})$ time to locate these solutions. Furthermore, as we proved in Lemma 4, EnumPlus reduces instance $A[1..n]$ with $S/2$ to sub-instance A_k with $S_k/2$ in linear time. Thus the expected time complexity for

the problem A with $S/2$ is $O(m2^{m/2}) + O(n)$. If $n = O(2^{m/2l})$, $\frac{m}{2 \log m} > l \geq 1$, then the expected time complexity for instance $A[1..n]$ with $S/2$ is $O(n^l \log n)$, and $d = O(\sqrt[2l]{2^m/m}) = O(\sqrt[2l]{n}/\log n)$. Thus EnumPlus solves SSP in $O(n \log n)$ time when density $d \geq c \cdot \sqrt{n}/\log n$.

6.3 Comparison of Related Works

Among the previously exact algorithms for SSP, HS74 has the best time complexity $O(n \cdot 2^{n/2})$ in the worst case. EnumPlus is an overall improvement of HS74, its worst-case time complexity is $O(n \cdot 2^{n/2} - c \cdot 2^{n/2} + n)$. As we described in Section 2, HS74 always reduce the original instance to 2 half size sub-instances. As we know, if the density of sub-instance is larger than 1, a solution is expected to be found by solving one sub-instance whose size is half of the original instance. However, by using a new heuristic, EnumPlus reduce the original instance to a smaller sub-instance, in which the solution can be found (see the proof of Proposition 7). Thus the performance of EnumPlus is better than HS74 in average case, especially when handling large size instance. Specifically, EnumPlus solves SSP in $O(n \log n)$ time when density $d \geq c \cdot \sqrt{n}/\log n$. This density bound is better than the density bound $d \geq c \cdot n/(\log n)^2$ of DenseSSP, which is the only previous algorithm working efficiently beyond the magnitude bound of $O(n/\log n)$. However, it must be noticed that the performance of EnumPlus is still not good enough when handling low-density instance. When density $d < 0.9408$, some incomplete algorithms, which are based on lattice reduction, are expected to outperform EnumPlus.

7 Conclusions and Future Work

In this work, we proposed a new enumeration scheme that utilizes both structural property and statistical property of subset sums to improve the efficiency of enumeration. The improved enumeration scheme is implemented as a complete and exact algorithm (EnumPlus). The algorithm always equivalently reduces an instance to be low-density, and then solve it by enumeration. Through this approach, we show the possibility to design a sole algorithm that can efficiently solve arbitrary density instance in a uniform way. Furthermore, our algorithm has considerable performance advantage over previous exact algorithms. It slightly improves the previously best time complexity of exact algorithms for SSP in the worst case; it extends the density scope to $d \geq c \cdot \sqrt{n}/\log n$, in which SSP can be solved in polynomial time. In addition, the overall expected time and space requirements are proved to be $O(n^5 \log n)$ and $O(n^5)$ respectively in the average case.

As we previously described, arbitrary density SSP instance can be equivalently reduced to and solved as low density instance by our approach. Thus the efficiency of EnumPlus mainly relies on efficiently solving low density problem. Since the lattice reduction approach shows particular efficiency when dealing low density instance, the integration of the two approaches may be a potential way

to further improve the performance of our algorithm. Therefore, the relationship between lattice reduction and enumeration scheme is an important issue in our future work.

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