

# A polynomial-time exact algorithm for the Subset Sum problem

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## 1.0 Definition of the problem.

Subset sum problem (SSP) can be defined as follow :

given a set  $W$  of  $n$  positive integers and a integer  $c$ , (capacity of the knapsack),

find

$$\max z = \sum x(i)w(i) \quad 1.0$$

s.t.

$$\sum x(i)w(i) \leq c \quad 1.1$$

$$x(i) = 0 \text{ or } 1; i = 1, \dots, n \quad 1.2$$

$$0 < w(i) \leq c; i = 1, \dots, n \quad 1.3$$

In the present paper it will be always assumed that  $W$  is sorted in ascending order, i.e.,  $w(i+1) \geq w(i)$ ,  $i = 0, \dots, n-2$ .

Subset sum problem is a well known problem in operations research and it can be proved that it belongs to complexity class NP-Hard, therefore finding an algorithm that solves SSP in polynomial-time prove that  $P=NP$ .

## 1.1 Exploring solutions.

A trivial way to solve SSP is to enumerate all possible binary combination for x and chose the optimal one, requiring in the worst case  $2^n$  iterations.

The basic idea of the presented algorithm derive from the following question :

“does exist a way to explore all binary combination of x in a more efficient way ?”

the answer is : yes it do, and the complexity of this way is polynomial.

Let's consider the following table that enumerates all binary combination of x for n=5 :

x	base	x	base
00000	5	10000	5
00001	5	10001	5
00010	5	10010	5
00011	2	10011	2
00100	5	10100	5
00101	3	10101	3
00110	3	10110	3
00111	3	10111	3
01000	5	11000	5
01001	4	11001	5
01010	4	11010	5
01011	2	11011	2
01100	4	11100	5
01101	4	11101	5
01110	4	11110	5
01111	4	11111	5

Table 1.0

**Definition 1.1.0 : base of a binary number**

The base of a binary number x is defined by following code :

```
int base(int x[], int n)
{
    int i;

    i=0;
    while(x[i]==0 && i<n)
        i++;
    // i is the position of first "1" bit

    i++;
    // "1" skipped

    while(x[i]==0 && i<n)
        i++;
    // all "0" skipped

    // i is the position of the second "1" bit
    while(x[i]==1 && i<n)
        i++;

    return i;
}
```

As you can see from table 1.0 and from code definition the base of a binary number x is the position of the at least second "1" bit whit successor "0" starting from less significant bit (rightmost bit).

We can obtain all binary numbers of base k starting from 0 adding "1" and shifting one by one until k then again adding "1" and shifting this last until k-1 and so on until all bit from 1 to k are "1".

**Definition 1.1.1** The base  $k$  of a binary number  $x$  is *pure* if  $x(i)=0$  for all  $i>k$ .

Examples for  $n=5$  :

$x = 00011$	base=2	pure.
$x = 10011$	base=2	not pure.
$x = 00101$	base=3	pure.
$x = 10101$	base=3	not pure.

Cardinality of set of all numbers in a given pure base  $pb$  can be easily computed as to be  $O(\sum_{i=1, \dots, pb} (pb-i))$ .

**Definition 1.1.2** We denote with “ $x$  inc  $k$ ” the increment of  $x$  by  $k$  positions in the same base of  $x$ , and similarly we denote with “ $x$  dec  $k$ ” the decrement of  $x$  by  $k$  positions in the same base of  $x$ .

Examples for  $n=5$  :

$x$	$x$ inc 1	$x$ dec 1
00001	00010	00000
00100	01000	00010
01100	01101	01010
01101	01110	01100

**Proposition 1.1.0** Solutions  $z=x*w$  whit all  $x$  of the same base are monotone if  $W$  is monotone.

*Proof.* At each increment of  $x$  in the given base we add an item  $w[h]$  and eventually subtract an item  $w[k] \leq w[h]$ .

**Proposition 1.1.1** Searching the maximum of  $z=x*w$  not exceeding  $c$  in all possible  $x$  of the same base can be performed in  $O(\log(n))$  time.

*Proof.* Binary search of a value in a sorted array of values.

## 1.2 Improving ideas.

Let be “ $x_a$ ” a general feasible solution vector of pure base “ $b_a$ ” and let be “ $a$ ” the corresponding sum, i.e.,  $a = x_a * w$ .

**Proposition 1.2.0** if  $a \geq a'$  for all possible  $a'$  with  $a$  and  $a'$  of any pure base  $b=2, \dots, n$ , let be  $b_a$  the base of  $a$ , then there exist at least an optimal solution of value  $o_{sa}$  such that  $x_{osa} \leq x_a$  and  $x_{osa} > (2^{b_a})^{-1}$ , i.e., there exists an optimal solution vector  $x_{osa}$  less than or equal to solution vector  $x_a$  and greater than  $(2^{b_a})^{-1}$ . (base of  $(2^{b_a})^{-1}$  is  $b_a' = b_a - 1$ , therefore greater feasible solution of pure base  $b_a'$  is, for definition, less than or equal to  $a$ )

*Proof.* If  $a=c$  proof is obvious. Let's consider a capacity  $c = a+k$ ,  $k > 0$ . Let be  $x_{osa}$  the optimal solution vector obtainable under condition  $x_{osa} \leq x_a$  and  $x_{osa} > (2^{b_a})^{-1}$ , let be  $o_{sa}$  it's solution value, i.e.,  $o_{sa} = x_{osa} * w$ , we can write  $o_{sa} = a + \alpha$ ,  $\alpha \geq 0$ .

We can say that  $k \geq \alpha$  because  $o_{sa} = a + \alpha \leq c$ , but  $a = c - k$  therefore  $c - k + \alpha \leq c$  therefore  $k \geq \alpha$ .

Suppose that a solution vector  $x_{os} > x_a$  or  $x_{os} \leq (2^{b_a})^{-1}$  exists such that  $o_s > o_{sa}$ , then we can write  $o_s = a' + \alpha' > o_{sa} = a + \alpha$ , but  $a = c - k$  therefore  $a' + \alpha' > c - k + \alpha \geq c - k + k$ , therefore,  $a' + \alpha' > c$  that, for definition, is impossible.

It's important to note that it's not excluded the presence of an optimal solution  $x_{os} > x_a$  or  $x_{os} \leq (2^{b_a})^{-1}$ , but simply if such solution exists then the same solution value do exists for  $x \leq x_a$  and  $x > (2^{b_a})^{-1}$ .

**Proposition 1.2.1** Finding  $a \geq a'$  for all possible  $a'$  with  $a$  and  $a'$  of any pure base  $b=2, \dots, n$ , can be performed in  $O(n \cdot \log(n))$  time.

*Proof.* It will be shown the  $O(n \cdot \log(n))$  algorithm `maxABase`.

```

int maxABase(int[] w, int n, int c)
{
    int k,k1,lsb1,lsb2,lsbmax,lsbmin,i,amax,basemax,base;

    i=n-1;
    k=0;
    while(k<c && i>=0)
    {
        if (k+w[i]<=c)
        {
            k+=w[i];
            lsb1=i;
        }
        else
            break;
        i--;
    }
    lsbmin=0;
    lsbmax=lsb1-1;
    lsb2=binarySearch(w,c-k,lsbmin,lsbmax);
    if (lsb2>-1)
        k+=w[lsb2];

    amax=0;
    basemax=n;
    base=n;

    while(base>1)
    {
        if (lsb2>-1)
            k-=w[lsb2];
        i=base-1;
        k-=w[i];
        base--;
        i=lsb1-1;
        while(k<c && i>=0)
        {
            if (k+w[i]<=c)
            {
                k+=w[i];
                lsb1=i;
            }
            else
                break;
            i--;
        }
    }
}

```

```

lsbmin=0;
lsbmax=lsb1-1;
lsb2=binarySearch(w,c-k,lsbmin,lsbmax);
if (lsb2>-1)
    k+=w[lsb2];

if (k>amax)
{
    amax=k;
    basemax=base;
}
base--;
}

return basemax;
}

```

binarySearch is a function that searches for an item  $w(\text{lsb2}) = \max w(i) \leq c-k, i = \text{lsbmin}, \dots, \text{lsbmax}$ , which can be performed in  $O(\log(n))$  time.

**Proposition 1.2.2** given  $a \geq a'$  for all possible  $a'$  with  $a$  and  $a'$  of any pure base  $pb=2, \dots, n$ , then finding optimal solution  $x \text{ s.t. } \sum x_i w_i \leq c$  and  $x \text{ s.t. } \sum x_i w_i > (2^{ba}) - 1$ , can be performed in  $O(n^2 \log(n))$  time.

*Proof.* We consider SSP', i.e., finding  $\sum x(i)w(i) \leq c-a$  with items  $w(i), i < \text{lsb}$  (less significant bit), then SSP'', i.e., finding  $\sum x(i)w(i) \leq c - (a \text{ dec } 1)$  with items  $w(i), i < \text{lsb}$ , until finding  $\sum x(i)w(i) \leq c - (a \text{ dec } z)$  with items  $w(i), i < \text{lsb}$ , where  $a \text{ dec } z$  is the first available binary number of base  $a$ .

Cardinality of set of all numbers in a given pure base  $pb$  can be easily computed as to be  $O(\sum_{i=1}^{pb} (pb-i))$ .

### **Worst-case time complexity of algorithm.**

We can now summarize steps of algorithm for a global worst-case time complexity evaluation :

STEP	COST
1 – Sort of weights array $w$ in ascending order.	$O(n \cdot \log(n))$
2 – Search of max pure base $a$ .	$O(n \cdot \log(n))$
3 – Search of optimal solution vector $x \leq x_a, x > (2^{ba}) - 1$ .	$O(n^2 \cdot \log(n))$

worst case time complexity of algorithm :  **$O(n^2 \cdot \log(n))$** .

expected time complexity of algorithm :  **$O(n \cdot \log(n))$** .



**References.**

[1] Silvano Martello, Paolo Toth, 1990. Knapsack Problems Algorithms And Computer implementations.

[2] Hans Kellerer, Ulrich Pferschy, David Pisinger, 2004. Knapsack Problems.

[3] Michael R. Garey, David S. Johnson WH Freeman, 1979. Computers and Intractability: A guide to the theory of NP-completeness.