## Knapsack Problem (KP01)

#### Given:

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n items, P_j "profit" of item j, j = 1, ..., n (P_j > 0), W_j "weight" of item j, j = 1, ..., n (W_j > 0), one container ("knapsack") with "capacity" C:
```

determine a subset of the n items so as to maximize the global profit, and such that the global weight is not larger than the knapsack capacity C.

#### KP01 is NP-Hard

## Knapsack Problem (KP01)

Determine a subset of items so as to maximize the global profit, and such that the global weight is not larger than the knapsack capacity *C*.

#### We assume:

$$n \geq 2$$
 $P_{j} > 0,$ 
 $J = 1, ..., n$ 
 $W_{j} > 0, W_{j} \leq C,$ 
 $J = 1, ..., n$ 
 $\sum_{j=1, n} W_{j} > C$ 

### **Mathematical Model KP01**

$$x_j = \begin{cases} 1 & \text{if item } j \text{ is inserted in the knapsack} \\ 0 & \text{otherwise} \end{cases}$$
  $(j = 1, ..., n)$ 

$$\sum_{j=1,n} P_j x_j$$

$$\sum_{j=1,n} W_j x_j \leq C$$

$$x_j \in \{0, 1\}$$
  $(j = 1, ..., n)$ 

or

$$0 \le x_j \le 1$$
 integer  $(j = 1, ..., n)$ 

**ILP Model (Binary Linear Programming Model)** 

## There exist items j with $P_j < 0$ and $W_j < 0$

Let 
$$N = \{j: P_j > 0 \text{ and } W_j > 0, j = 1, ..., n\};$$
Let  $R = \{j: P_j < 0 \text{ and } W_j < 0, j = 1, ..., n\}.$ 
Set  $y_j = x_j$ ,  $P'_j = P_j$ ,  $W'_j = W_j$   $j \in N$ 
Set  $y_j = 1 - x_j$ ,  $P'_j = -P_j$ ,  $W'_j = -W_j$   $(x_j = 1 - y_j)$   $j \in R$ 

$$Z = \sum_{j=1,n} P_j x_j = \sum_{j\in N} P_j y_j + \sum_{j\in R} P_j (1 - y_j) = \sum_{j\in N} P'_j y_j + \sum_{j\in R} P'_j y_j + \sum_{j\in R} P_j = \sum_{j=1,n} P'_j y_j + a$$
where  $a = \sum_{i\in R} P_j$ 

# There exist items j with $P_j < 0$ and $W_j < 0$

Let 
$$N = \{j: P_j > 0 \text{ and } W_j > 0, j = 1, ..., n\};$$
  
Let  $R = \{j: P_j < 0 \text{ and } W_j < 0, j = 1, ..., n\}.$   
Set  $y_j = x_j$ ,  $P'_j = P_j$ ,  $W'_j = W_j$   $j \in N$   
Set  $y_j = 1 - x_j$ ,  $P'_j = -P_j$ ,  $W'_j = -W_j$   $(x_j = 1 - y_j)$   $j \in R$   
 $Z = \sum_{j=1,n} P_j x_j = \sum_{j=1,n} P'_j y_j + a$  where  $a = \sum_{j \in R} P_j$   
 $\sum_{j=1,n} W_j x_j = \sum_{j=1,n} W'_j y_j + b$  where  $b = \sum_{j \in R} W_j$ 

# There exist items j with $P_j < 0$ and $W_j < 0$

$$x_j = y_j$$
  $j \in \mathbb{N}$ ;  $x_j = 1 - y_j$   $j \in \mathbb{R}$ 

# Computational Complexity of the Decision and Optimization Problems

- *Decision Problem*: given a problem, determine if at least a solution exists for this problem.
- Example: Feasibility Problem: determine if at least a feasible solution exists for the considered problem.
- Optimization Problem: determine a feasible solution that maximizes (or minimizes) the objective function of the considered problem.

# Computational Complexity of the Decision and Optimization Problems (2)

• Size of a problem R: number of "symbols" (bit, bytes, words, ...) needed to represent the input data of an instance of R (by neglecting the proportionality constants).

- Example: KP-01: input data:  $n, C, (P_i), (W_i)$ :
  - \*  $(P_i)$ : n values,  $(W_i)$ : n values
  - \* (2 n + 2) values (symbols): size = n

# Computational Complexity of the Decision and Optimization Problems (3)

• Given a problem *R*: Determine the *computing time* (number of *elementary operations*), expressed as a *function of the size* of *R*, to find the solution of *R* in the *worst case*.

• The theory of the *Computational Complexity* of the problems has been analyzed for the *Decision Problems*, but it can be applied to the *Optimization Problems* as well.

## **Polynomial Problems**

A *Problem R* is *Polynomial* if R can be solved through at least one algorithm whose computing time in the worst case grows according to a *polynomial function* of the size of R.

Examples:

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given an array A_j of n elements (j = 1, ..., n):
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- Determine the *minimum value* of the n elements: effective algorithm: O(n) time (in the worst case the computing time is proportional to n: "linear" in n).
- *Sort* the *n* elements according to non-decreasing (or non-increasing) values:

```
effective algorithm: O(n \log n) time.
```

### Classes P and NP

• CLASS P contains all the Polynomial Problems.

• CLASS NP contains all the problems that can be solved in polynomial time in the best case (through a "non deterministic Turing Machine").

### Class NP

From an operational point of view, a problem *R* belongs to *Class NP* if it can be solved through a *Decisional Tree* such that:

- 1) the number of "levels";
- 2) the number of "descendent nodes" of each node;
- 3) the computing time required to consider each node

are polynomial functions of the size of R.

Class P is contained in Class NP

Class P = Class NP ?

## Example of a Problem in Class NP

#### Knapsack Problem in Decision Version:

Given an instance of KP-01, determine if there exists at least one feasible solution whose profit is not smaller than a given value K: KP-01(K)

#### Binary Decision Tree

- \* at each level j (j = 1, 2, ..., n) consider item j and fix the value of  $x_i$  to 0 or to 1:
  - $^{\circ}$  *n* levels;
  - ° 2 descendent nodes for each node;
  - $^\circ$  constant computing time for each node.

$$KP-01(K) \in Class NP$$

# Knapsack Problem in Decision Version Binary Decision Tree for KP-01(K)

\* at each level j (j = 1, 2, ..., n) consider item j and fix the value of  $x_j$  to 0 or to 1.

In the worst case, the algorithm requires a computing time proportional to the global number of nodes of the binary decision tree (exponential time with respect to the size of KP-01(K)).

Also  $KP-01 \in Class NP$ 

## Complexity of the Problems

From a "practical" point of view, the Feasibility and Optimization Problems can be subdiveded in three main classes:

- 1) Polynomial Problems (Class P);
- 2) NP-Hard Problems (also called NP-Complete Problems): belong to Class NP, but no polynomial algorithm has been proposed for their solution in the worst case (example: KP-01);
- 3) Surely Difficult Problems: do not belong to Class NP (example: determine all the optimal solutions of KP-01; the number of such solutions could be exponential with respect to the size n).

#### NP-Hard Problems

A problem *R* is *NP-Hard* if:

1)  $R \in Class NP$ ;

2) There exists an *NP-Hard Problem T* which is "reducible" to R ( $T \propto R$ ):

for any instance t of T, it is possible to define, in a computing time polynomial in the size of t, an instance r of R such that, determined the solution of the instance r of R, the solution of the instance t of T can be obtained in a computing time polynomial in the size of t.

## Partition Problem (PP)

Given: m positive values:  $a_j$  (j = 1, ..., n), one positive value b

determine if there exists a subset of the m values whose sum is exactly equal to the given value b.

#### **Feasibility Problem**

Size: m + 2: m

**PP** is known to be **NP-Hard** 

(even if 
$$b = \sum_{j=1,m} a_j / 2$$
)

### KP-01 is NP-Hard

- 1)  $KP-01 \in Class NP$
- 2)  $PP \propto KP-01$

Given any instance of  $PP: m, (a_i), b:$ 

- 1) Define (in time O(m)) an instance  $(n, (P_j), (W_j), C)$  of KP-01:
  - \* n = m
  - \* C = b
  - \*  $P_i = a_i \quad (j = 1, ..., n),$
  - \*  $W_j = a_j \quad (j = 1, ..., n).$
- 2) Determine the optimal solution  $(x_1, x_2, ..., x_n, z)$  of *KP-01*.
- 3) If z = C: PP has a feasible solution  $(x_1, x_2, ..., x_n)$

If z < C: PP has no feasible solution

Computing time O(m)

## **Particular Cases of KP01**

a) Constant Profits: the Problem is Polynomial

$$P_{j} = K \quad (j = 1, ..., n)$$

- 1) Sort the n items according to non-decreasing values of the weights  $W_j$ :  $(O(n \log n) \text{ time})$ ;
- 2) Insert the items until the first item s is found such that:

$$\sum_{j=1,s} W_j > C$$
 (items  $s, s+1, ..., n$  are not inserted):
$$O(n) \text{ time.}$$

Global computing time:  $O(n \log n) + O(n)$ :  $O(n \log n)$ 

## Particular Cases of KP01 (2)

b) Constant Weights: the Problem is Polynomial

$$W_j = K \qquad (j = 1, ..., n)$$

- 1) Sort the n items according to non-increasing values of the profits  $P_i$ :  $(O(n \log n) \text{ time})$ ;
- 2) Insert the items until the first item s is found such that:

$$\sum_{j=1,s} W_j > C \quad \text{(items } s, s+1, ..., n \text{ are not inserted):}$$

$$O(n) \text{ time.}$$

Global computing time:  $O(n \log n) + O(n)$ :  $O(n \log n)$