University of Trieste Architecture and Engineering Department

Master Degree in Computer Science

Model-based Algorithms for the 0-1 Time-Bomb Knapsack Problem

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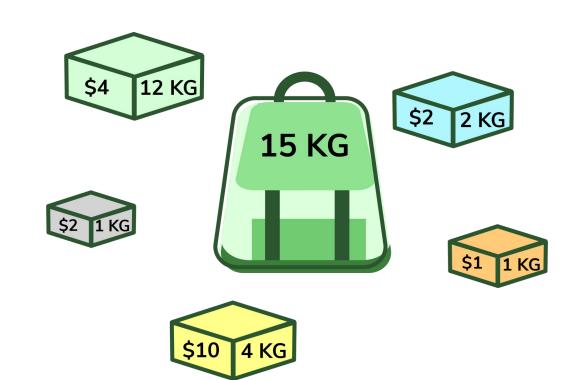
Introduction

0-1 Knapsack Problem:

- Classic problem in combinatorial optimization
- We have a fixed knapsack capacity
- A set of items
- Each item has a weight and a profit
- Maximize the profits without exceeding the capacity
- The problem is NP-hard

0-1 Time-Bomb Knapsack Problem

- Variant of the 01-KP
- Some items are time-bombs
- The objective is the maximization of the expected profit



A non-linear model

The 01-TB-KP can be fully defines by the following non-linear model

$$(NL) \max\left(\sum_{k\in N} p_k x_k\right) \left(\prod_{k\in K} q_k x_k\right) \tag{2}$$

$$s.t. \sum w_k x_k \le c \tag{3}$$

$$x_i \in \{0, 1\} \qquad i \in N \tag{4}$$

Linearization

The proposed methods are iterative and based on the following property.

This property allows the solution of the 01-TB-KP as a sequence of integer linear programming models

$$\prod_{k \in K} \alpha_k = \beta \Longleftrightarrow \sum_{k \in K} \log(\alpha_k) = \log(\beta)$$

Optimization of Profits

BestHeuValue: current best solution value LastExactProfit: objective function value of the last problem

$$(P^{(j)}) \max_{k \in \mathcal{N}} p_k x_k \tag{6}$$

$$s.t. \sum_{k \in N} w_k x_k \le c \tag{7}$$

$$\sum_{k \in N} \log(q_k) x_k \ge \log\left(\frac{BestHeuValue}{LastExactProfit}\right)$$
 (8)

$$\sum_{k \in N: \hat{x}_k^{(i)} = 1} x_k + \sum_{k \in N: \hat{x}_k^{(i)} = 0} (1 - x_k) \le n - 1 \qquad i = 1, 2, \dots, j - 1$$
 (9)

$$x_i \in \{0, 1\} \qquad \qquad i \in N \tag{10}$$

Optimization of Probabilities

BestHeuValue: current best solution value LastExactProbability: survival probability of the last solution

$$\left(S^{(j)}\right) \max \sum_{k \in N} \log(q_k) x_k \tag{11}$$

$$s.t. \sum_{k \in N} w_k x_k \le c \tag{12}$$

$$\sum_{k \in N} p_k x_k \ge \frac{BestHeuValue}{LastExactProbability} \tag{13}$$

$$\sum_{k \in N: \hat{x}_k^{(i)} = 1} x_k + \sum_{k \in N: \hat{x}_k^{(i)} = 0} (1 - x_k) \le n - 1 \qquad i = 1, 2, \dots, j - 1$$
 (14)

$$x_i \in \{0; 1\} \qquad \qquad i \in N \qquad (15)$$

IterativeAlgorithmP

Algorithm 1: IterativeAlgorithmP

```
Data: A 01-TB-KP instance
  Result: A solution and an upper bound for the optimal solution
           value
1 BestHeuSol=Ø;
2 BestHeuValue=0;
3 LastExactProfit=+∞;
4 j = 0;
5 Build model P^{(0)};
6 while BestHeuValue<LastExactProfit and computational time <
    MT do
       Solve model P^{(j)} with a maximum computation time of ML
       seconds;
      if P^{(j)} has been solved to optimality then
          if P^{(j)} is feasible then
              LastExactProfit=Value of the optimal solution of
10
               P^{(j)};
          else
11
              LastExactProfit=BestHeuValue;
12
          end
13
       end
14
       if BestHeuValue<LastExactProfit then
15
          \hat{x}^{(j)} = Retrieved solution of P^{(j)};
16
          if Eq. (2) evaluated on \hat{x}^{(j)} > BestHeuValue then
17
              BestHeuSol=\hat{x}^{(j)};
18
              BestHeuValue=Value(\hat{x}^{(j)});
19
          end
20
          j = j + 1;
21
          Build model P^{(j)};
22
23
       end
24 end
25 return BestHeuSol, LastExactProfit;
```

IterativeAlgorithmS

Algorithm 2: IterativeAlgorithmS

```
Data: A 01-TB-KP instance
   Result: A solution and a value indicating whether the solution
            is optimal or heuristic
1 BestHeuSol=Ø;
2 BestHeuValue=0;
3 LastExactProbability=1;
4 \ j = 0;
5 Build model S^{(0)};
 6 while Computational time < MT < MaxTime do
      Solve model S^{(j)} with a maximum computation time of ML
        seconds;
      if S^{(j)} has been solved to optimality then
           if P^{(j)} is feasible then
               LastExactProbability=Value of the optimal solution
10
                of S^{(j)};
           else
11
               return BestHeuSol, "exact";
12
           end
13
       end
14
       \hat{x}^{(j)}=Optimal solution of S^{(j)};
15
       \hat{y}^{(j)}=Optimal solution of the deterministic Knapsack
        problem with non-bomb unselected items and residual
        capacity;
       \hat{z}^{(j)} = \hat{x}^{(j)} \vee \hat{v}^{(j)}:
17
       if Eq. (2) evaluated on \hat{z}^{(j)} > BestHeuValue then
18
           BestHeuSol=\hat{z}^{(j)};
19
           BestHeuValue=Value(\hat{z}^{(j)});
20
       end
21
       j = j + 1;
      Build model S^{(j)};
23
24 end
25 return BestHeuSol, "heuristic";
```

Scalability Analysis

Experiment steps

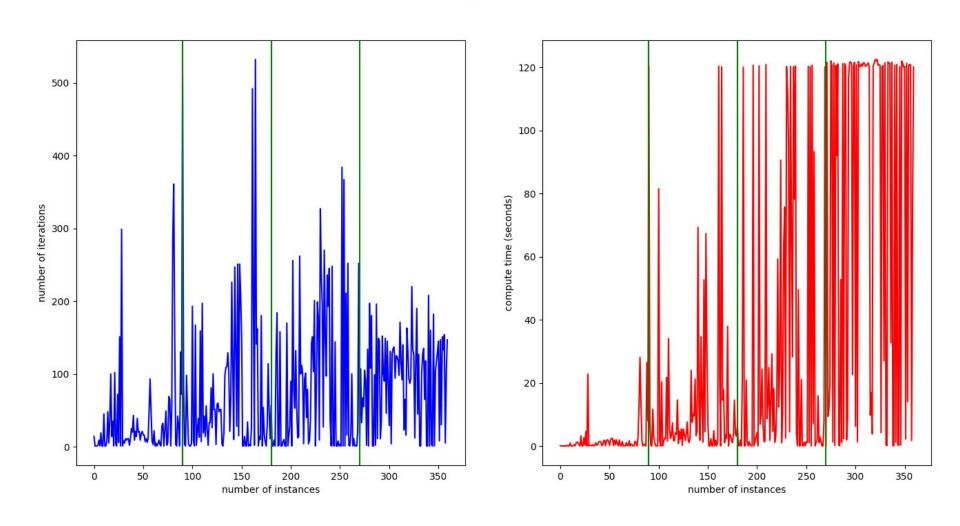
- Python 3.12.6
- Gurobi 12.0.1
- Testing on small instance (size 4)
- Scalability analysis
 - MT=120 seconds
 - ML = 1 second
 - 360 instances
 - instances of increasing size [100, 500, 1000, 5000]
 - generated by alberto-santini on GitHub

Testing Instance

```
Testing Instance
        number of items: 4
        knapsack's capacity: 5
        items weights : [2, 3, 1, 4]
        items profits : [10, 20, 15, 40]
        items survival probabilities : [0.9, 1, 0.8, 1]
IterativeAlgorithmP
        solution : [0.0, 0.0, 1.0, 1.0]
        expected profit: 44.0
        upper bound : 55.0
        number of iterations : 1
        computational time : 0.025 seconds
IterativeAlgorithmS
        solution : [0, 0, 1.0, 1.0]
        expected profit: 44.0
        solution type : exact
        number of iterations: 3
        computational time : 0.007 seconds
```

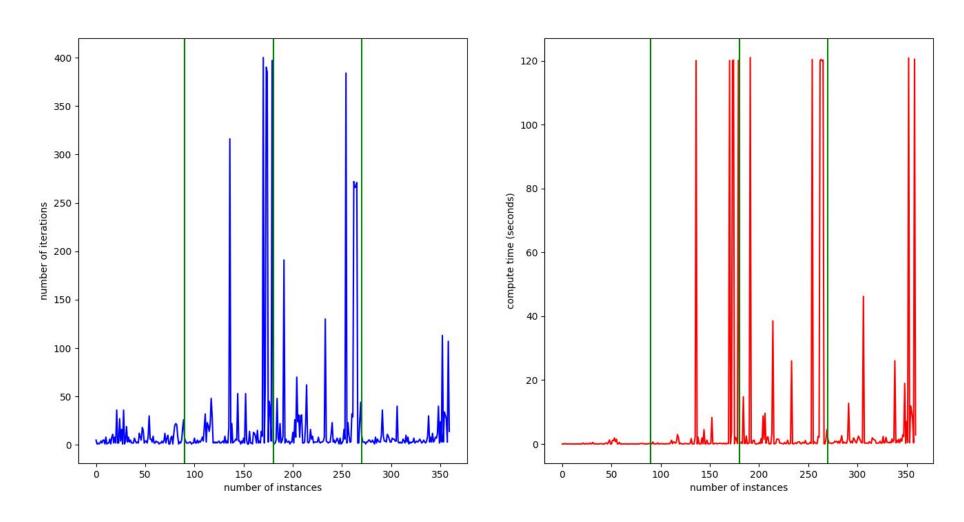
Scalability Algorithm P

Algorithm P



Scalability Algorithm S

Algorithm S



Final Comparison

		Size 100	Size 500	Size 1000	Size 5000	Total
Algorithm P	Avg. N iterations	33.58	75.06	83.72	91.81	71.04
	Avg. Comp time (seconds)	1.90	12.89	29.22	78.57	30.64
Algorithm S	Avg. N iterations	6.88	29.63	29.07	9.47	18.76
	Avg. Comp time (seconds)	0.15	7.17	9.62	4.99	5.48



Thank You for your attention