

Compact Knapsack: a Semidefinite Approach

Hubert Villuendas

✉: `hubert.villuendas@univ-grenoble.fr`

Laboratoire d'Informatique de Grenoble
Université Grenoble Alpes

February 26th, 2025

Items $i \in \{1, \dots, n\}$, with costs c_i and weights w_i .

- **min-Knapsack:** find a selection $S \subseteq \{1, \dots, n\}$ that minimizes the total cost and verifies

$$\sum_{i \in S} w_i \geq q$$

- **Compactness:** [*Santini and Malaguti, 2024*]
 S contains no gap that exceed Δ .

Items $i \in \{1, \dots, n\}$, with costs c_i and weights w_i .

- **min-Knapsack:** find a selection $S \subseteq \{1, \dots, n\}$ that minimizes the total cost and verifies

$$\sum_{i \in S} w_i \geq q$$

- **Compactness:** [*Santini and Malaguti, 2024*]
 S contains no gap that exceed Δ .



Example with $n = 7$ and $\Delta = 2$

Items $i \in \{1, \dots, n\}$, with costs c_i and weights w_i .

- **min-Knapsack:** find a selection $S \subseteq \{1, \dots, n\}$ that minimizes the total cost and verifies

$$\sum_{i \in S} w_i \geq q$$

- **Compactness:** [*Santini and Malaguti, 2024*]
 S contains no gap that exceed Δ .



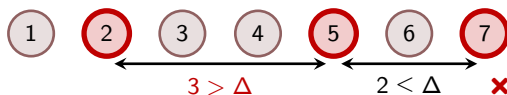
A non-compact example with $n = 7$ and $\Delta = 2$

Items $i \in \{1, \dots, n\}$, with costs c_i and weights w_i .

- **min-Knapsack**: find a selection $S \subseteq \{1, \dots, n\}$ that minimizes the total cost and verifies

$$\sum_{i \in S} w_i \geq q$$

- **Compactness**: [*Santini and Malaguti, 2024*]
 S contains no gap that exceed Δ .



A **non-compact** example with $n = 7$ and $\Delta = 2$

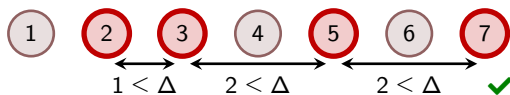
Problem statement

Items $i \in \{1, \dots, n\}$, with costs c_i and weights w_i .

- **min-Knapsack:** find a selection $S \subseteq \{1, \dots, n\}$ that minimizes the total cost and verifies

$$\sum_{i \in S} w_i \geq q$$

- **Compactness:** [*Santini and Malaguti, 2024*]
 S contains no gap that exceed Δ .



A **compact** example with $n = 7$ and $\Delta = 2$

Items $i \in \{1, \dots, n\}$, with costs c_i and weights w_i .

- **min-Knapsack:** find a selection $S \subseteq \{1, \dots, n\}$ that minimizes the total cost and verifies

$$\sum_{i \in S} w_i \geq q$$

- **Compactness:** [*Santini and Malaguti, 2024*]
 S contains no gap that exceed Δ .



Example with $n = 7$ and $\Delta = 2$

$$\left[\begin{array}{ll} \text{minimize} & c^\top x \\ \text{subject to} & w^\top x \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad x_i + x_j - 1 \leq \sum_{k=i+1}^{j-1} x_k \\ & x \in \{0, 1\}^n \end{array} \right.$$

Problem statement

Items $i \in \{1, \dots, n\}$, with costs c_i and weights w_i .

- **min-Knapsack**: find a selection $S \subseteq \{1, \dots, n\}$ that minimizes the total cost and verifies

$$\sum_{i \in S} w_i \geq q$$

- **Compactness**: [*Santini and Malaguti, 2024*]
 S contains no gap that exceed Δ .



Example with $n = 7$ and $\Delta = 2$

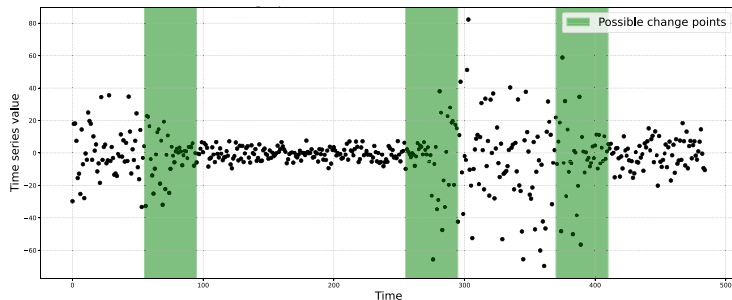
$$\left[\begin{array}{ll} \text{minimize} & c^\top x \\ \text{subject to} & w^\top x \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor (x_i + x_j - 1) \leq \sum_{k=i+1}^{j-1} x_k \\ & x \in \{0, 1\}^n \end{array} \right.$$

Strengthening coefficient

Given a time series $\{y_1, \dots, y_n\}$, how to detect changes?

Method [*Cappello and Padilla, 2022*] focuses **most probable** change point:

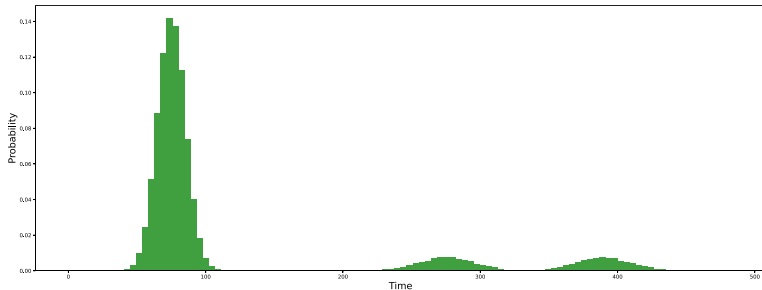
→ Each point gets a probability of being the change point.



Given a time series $\{y_1, \dots, y_n\}$, how to detect changes?

Method [*Cappello and Padilla, 2022*] focuses **most probable** change point:

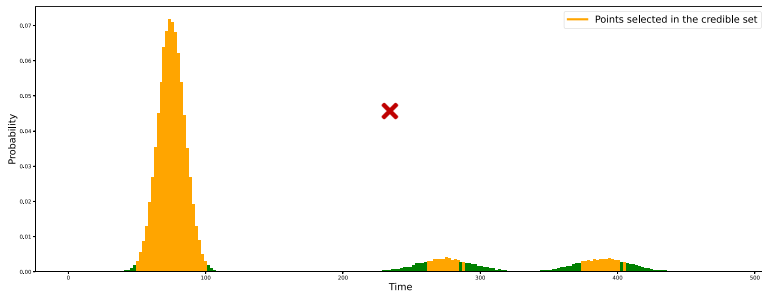
→ Each point gets a probability of being the change point.



Given a time series $\{y_1, \dots, y_n\}$, how to detect changes?

Method [*Cappello and Padilla, 2022*] focuses **most probable** change point:

→ Each point gets a probability of being the change point.

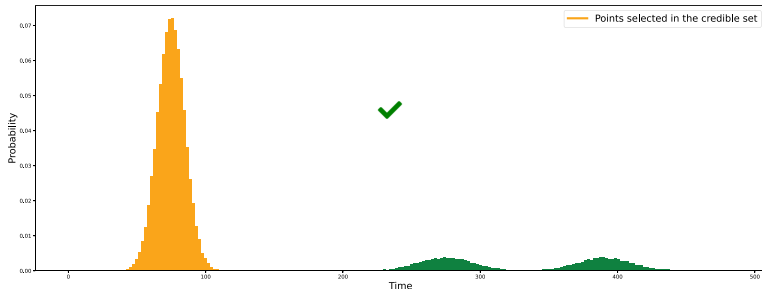


Credible set relative to the first change point

Given a time series $\{y_1, \dots, y_n\}$, how to detect changes?

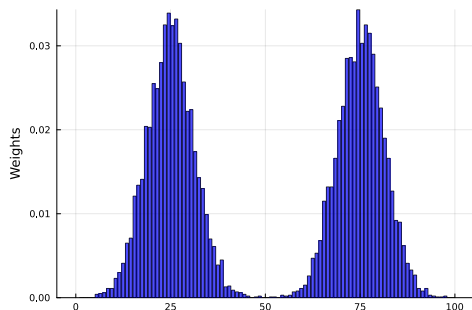
Method [*Cappello and Padilla, 2022*] focuses **most probable** change point:

→ Each point gets a probability of being the change point.



Credible set relative to the first change point with the compactness constraint

$$\left[\begin{array}{ll} \text{minimize} & c^\top x \\ \text{subject to} & w^\top x \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor (x_i + x_j - 1) \leq \sum_{k=i+1}^{j-1} x_k \\ & x \in \{0, 1\}^n \end{array} \right.$$



$$\left[\begin{array}{ll} \text{minimize} & c^\top x \\ \text{subject to} & w^\top x \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor (x_i + x_j - 1) \leq \sum_{k=i+1}^{j-1} x_k \\ & x \in \{0, 1\}^n \end{array} \right.$$

Substitute $X = xx^\top$. Then $X_{ij} = x_i x_j$ and $X_{ii} = x_i^2 = x_i$.

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & X \text{ has coefficients in } \{0, 1\} \\ & \text{rank}(X) = 1 \\ & X \succeq 0 \end{array} \right.$$

Substitute $X = xx^\top$. Then $X_{ij} = x_i x_j$ and $X_{ii} = x_i^2 = x_i$.

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & X \text{ has coefficients in } \{0, 1\} \\ & \text{rank}(X) = 1 \\ & X \succeq 0 \end{array} \right.$$

Theorem (Classical, see e.g. *De Meijer and Sotirov, 2024*)

Let $\bar{X} = \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0$, $X \neq 0$. The following are equivalent:

- $\text{rank}(X) = 1$
- $X = xx^\top$ with $x \in \{0, 1\}^n$
- X has coefficients in $\{0, 1\}$.

Substitute $X = xx^\top$. Then $X_{ij} = x_i x_j$ and $X_{ii} = x_i^2 = x_i$.

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0 \\ & \text{rank}(X) = 1 \end{array} \right.$$

Theorem (Classical, see e.g. *De Meijer and Sotirov, 2024*)

Let $\bar{X} = \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0$, $X \neq 0$. The following are equivalent:

- $\text{rank}(X) = 1$
- $X = xx^\top$ with $x \in \{0, 1\}^n$
- X has coefficients in $\{0, 1\}$.

Substitute $X = xx^\top$. Then $X_{ij} = x_i x_j$ and $X_{ii} = x_i^2 = x_i$.

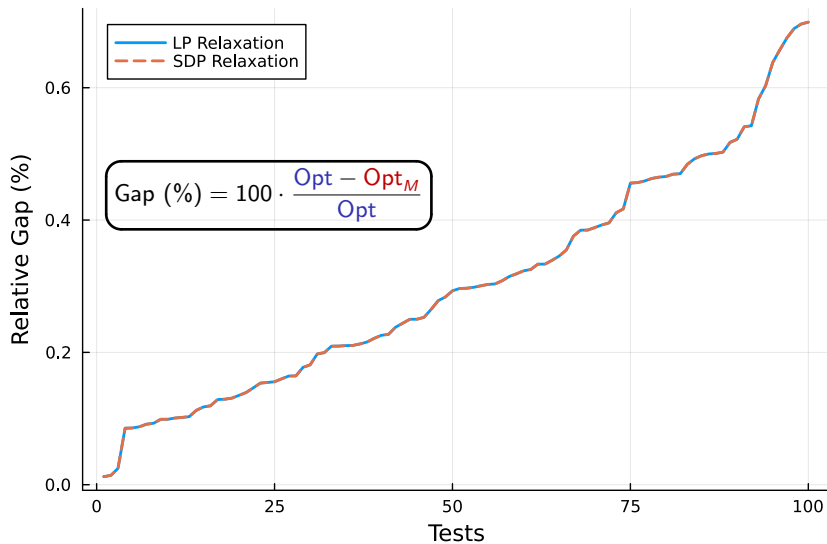
Relaxation!

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0 \\ & \text{rank}(X) = 1 \end{array} \right.$$

Theorem (Classical, see e.g. *De Meijer and Sotirov, 2024*)

Let $\bar{X} = \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0$, $X \neq 0$. The following are equivalent:

- $\text{rank}(X) = 1$
- $X = xx^\top$ with $x \in \{0, 1\}^n$
- X has coefficients in $\{0, 1\}$.



Opt is the optimal integer solution and Opt_M is the optimal solution returned by model M ; here for the linear (—) and semidefinite (—) relaxations

$$\begin{array}{ll}
 \text{minimize} & c^\top \text{diag}(X) \\
 \text{subject to} & w^\top \text{diag}(X) \geq q \\
 & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\
 & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0
 \end{array}$$

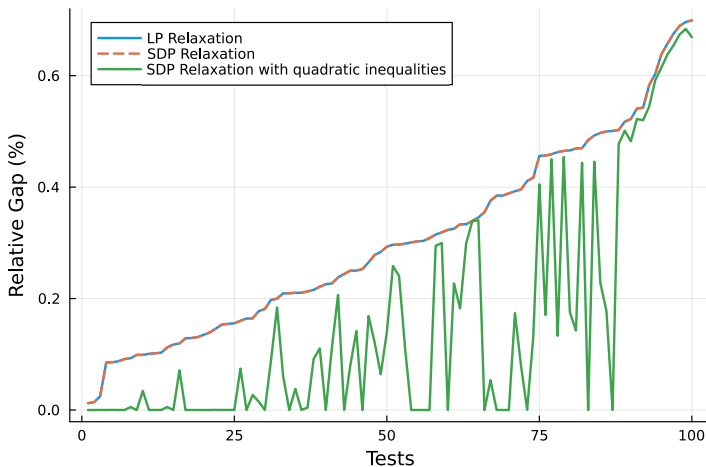
$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & \left(\begin{array}{cc} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{array} \right) \succeq 0 \\ & \left. \begin{array}{rcl} 0 & \leq & X_{ij} \\ X_{ij} & \leq & X_{ii} \\ X_{ii} + X_{jj} - 1 & \leq & X_{ij} \\ X_{ik} + X_{jk} & \leq & X_{kk} + X_{ij} \\ X_{ii} + X_{jj} + X_{kk} & \leq & X_{ik} + X_{jk} + X_{ij} \end{array} \right\} \forall i, j, k \in \llbracket n \rrbracket \end{array} \right.$$

$$\left[\begin{array}{ll}
 \text{minimize} & c^\top \text{diag}(X) \\
 \text{subject to} & w^\top \text{diag}(X) \geq q \\
 & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\
 & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0 \\
 & \left. \begin{array}{l}
 0 \leq X_{ij} \\
 X_{ij} \leq X_{ii} \\
 X_{ii} + X_{jj} - 1 \leq X_{ij} \\
 X_{ik} + X_{jk} \leq X_{kk} + X_{ij} \\
 X_{ii} + X_{jj} + X_{kk} \leq X_{ik} + X_{jk} + X_{ij}
 \end{array} \right\} \forall i, j, k \in \llbracket n \rrbracket \\
 & \text{tr}(\text{Diag}(w)^\top X)^2 \leq \|\text{Diag}(w)\|^2 \cdot \|X\|^2
 \end{array} \right.$$

$$\begin{aligned}
 & \text{minimize} && c^\top \text{diag}(X) \\
 & \text{subject to} && w^\top \text{diag}(X) \geq q \\
 & && \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j-i-1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\
 & && \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0 \\
 & && \left. \begin{aligned} 0 &\leq X_{ij} \\ X_{ij} &\leq X_{ii} \\ X_{ii} + X_{jj} - 1 &\leq X_{ij} \\ X_{ik} + X_{jk} &\leq X_{kk} + X_{ij} \\ X_{ii} + X_{jj} + X_{kk} &\leq X_{ik} + X_{jk} + X_{ij} \end{aligned} \right\} \forall i, j, k \in \llbracket n \rrbracket \\
 & && \sum_{i=1}^n w_i^2 X_{ii} + 2 \sum_{1 \leq i < k \leq n} w_i w_k X_{ik} \leq \left(\sum_{i=1}^n w_i^2 \right) \left(\sum_{1 \leq i, k \leq n} X_{ik} \right)
 \end{aligned}$$

Quadratic Inequalities

With the added quadratic inequalities



Relative gap for the semidefinite relaxation without (- - -)
vs. with (—) the quadratic inequalities

$$\begin{aligned}
 & \left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & \left(\begin{array}{cc} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{array} \right) \succeq 0 \\ & \left. \begin{array}{rcl} 0 & \leq & X_{ij} \\ X_{ij} & \leq & X_{ii} \\ X_{ii} + X_{jj} - 1 & \leq & X_{ij} \\ X_{ik} + X_{jk} & \leq & X_{kk} + X_{ij} \\ X_{ii} + X_{jj} + X_{kk} & \leq & X_{ik} + X_{jk} + X_{ij} \end{array} \right\} \forall i, j, k \in \llbracket n \rrbracket \\ & \sum_{i=1}^n w_i^2 X_{ii} + 2 \sum_{1 \leq i < k \leq n} w_i w_k X_{ik} \leq \left(\sum_{i=1}^n w_i^2 \right) \left(\sum_{1 \leq i, k \leq n} X_{ik} \right) \end{array} \right]
 \end{aligned}$$

$$\begin{aligned}
 & \left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \forall i, j \in \llbracket n \rrbracket, j - i > \Delta, \quad \left\lfloor \frac{j - i - 1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & \left(\begin{array}{cc} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{array} \right) \succeq 0 \\ & \left. \begin{array}{l} 0 \leq X_{ij} \\ X_{ij} \leq X_{ii} \\ X_{ii} + X_{jj} - 1 \leq X_{ij} \\ X_{ik} + X_{jk} \leq X_{kk} + X_{ij} \\ X_{ii} + X_{jj} + X_{kk} \leq X_{ik} + X_{jk} + X_{ij} \end{array} \right\} \forall i, j, k \in \llbracket n \rrbracket \\ & \sum_{i=1}^n w_i^2 X_{ii} + 2 \sum_{1 \leq i < k \leq n} w_i w_k X_{ik} \leq \left(\sum_{i=1}^n w_i^2 \right) \left(\sum_{1 \leq i, k \leq n} X_{ik} \right) \end{array} \right]
 \end{aligned}$$

Let $(\lambda_{ij})_{1 \leq i < j \leq n} \in \mathbf{R}^{n(n-1)/2}$

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) + \sum_{1 \leq i < j \leq n} \lambda_{ij} \left(\left\lfloor \frac{j-i-1}{\Delta} \right\rfloor X_{ij} - \sum_{k=i+1}^{j-1} X_{kk} \right) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \left(\begin{array}{cc} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{array} \right) \succeq 0 \\ & \left. \begin{array}{rcl} 0 & \leq & X_{ij} \\ X_{ij} & \leq & X_{ii} \\ X_{ii} + X_{jj} - 1 & \leq & X_{ij} \\ X_{ik} + X_{jk} & \leq & X_{kk} + X_{ij} \\ X_{ii} + X_{jj} + X_{kk} & \leq & X_{ik} + X_{jk} + X_{ij} \end{array} \right\} \forall i, j, k \in \llbracket n \rrbracket \\ & \sum_{i=1}^n w_i^2 X_{ii} + 2 \sum_{1 \leq i < k \leq n} w_i w_k X_{ik} \leq \left(\sum_{i=1}^n w_i^2 \right) \left(\sum_{1 \leq i, k \leq n} X_{ik} \right) \end{array} \right]$$

Let $x \in [0, 1]^n$ be the solution vector for the min-KPC.

- **Parsimony**

$$\frac{c^\top x}{c^\top \mathbf{1}}$$

Let $x \in [0, 1]^n$ be the solution vector for the min-KPC.

- **Parsimony**

$$\frac{c^\top x}{c^\top \mathbf{1}}$$

- **Compacity**

$$\frac{1}{n} \max \left\{ j - i - 1 \mid \begin{array}{l} i, j \text{ consecutive} \\ \text{selected items} \end{array} \right\} \quad \left(\text{theoretically } \leq \frac{\Delta}{n} \right)$$

Let $x \in [0, 1]^n$ be the solution vector for the min-KPC.

- **Parsimony**

$$\frac{c^\top x}{c^\top \mathbf{1}}$$

- **Compacity**

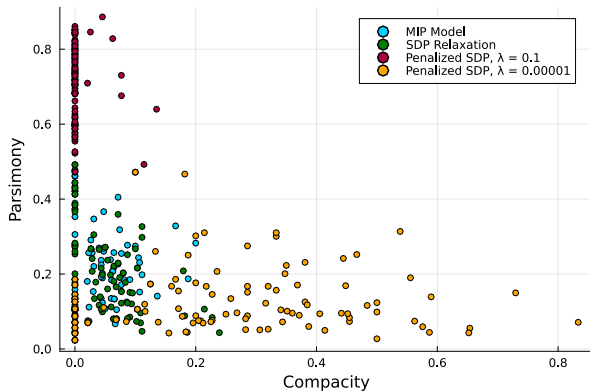
$$\frac{1}{n} \max \left\{ j - i - 1 \mid \begin{array}{l} i, j \text{ consecutive} \\ \text{selected items} \end{array} \right\} \quad \left(\text{theoretically } \leq \frac{\Delta}{n} \right)$$

- **Fractionnality**

$$\frac{2}{\sqrt{n}} \cdot \left\| x - \left\lfloor x + \frac{1}{2} \right\rfloor \right\|_2$$

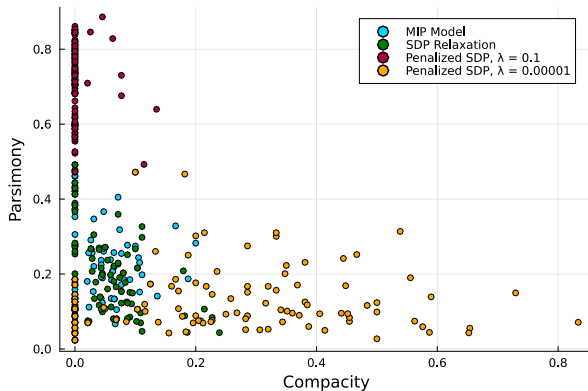
Measuring the quality of a solution

Benchmark: 100 instances; 4 models.



Measuring the quality of a solution

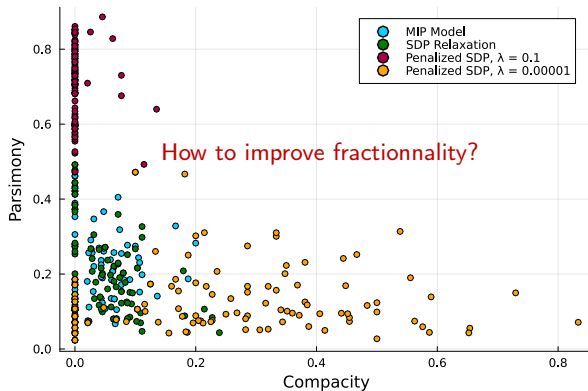
Benchmark: 100 instances; 4 models.



Model	Average fractionnality
SDP Relaxation	0.1904
Penalized SDP with $\lambda = 0.1$	0.0028
Penalized SDP with $\lambda = 0.00001$	0.0429

Measuring the quality of a solution

Benchmark: 100 instances; 4 models.



Model	Average fractionnality
SDP Relaxation	0.1904
Penalized SDP with $\lambda = 0.1$	0.0028
Penalized SDP with $\lambda = 0.00001$	0.0429

Definitions (Insufficient subset)

- We call $S \subseteq \{1, \dots, n\}$ *insufficient* if

$$\sum_{i \in S} w_i < q.$$

Definitions (Insufficient subset)

- We call $S \subseteq \{1, \dots, n\}$ *insufficient* if

$$\sum_{i \in S} w_i < q.$$

- We say that S is *maximal* if:

$$\forall j \notin S, \quad w_j + \sum_{i \in S} w_i \geq q.$$

Definitions (Insufficient subset)

- We call $S \subseteq \{1, \dots, n\}$ *insufficient* if

$$\sum_{i \in S} w_i < q.$$

- We say that S is *maximal* if:

$$\forall j \notin S, \quad w_j + \sum_{i \in S} w_i \geq q.$$

$$\sum_{i \notin S} x_i \geq 1$$

(MISC)

Definitions (Insufficient subset)

- We call $S \subseteq \{1, \dots, n\}$ *insufficient* if

$$\sum_{i \in S} w_i < q.$$

- We say that S is *maximal* if:

$$\forall j \notin S, \quad w_j + \sum_{i \in S} w_i \geq q.$$

$$\sum_{i \notin S} x_{ii} \geq 1 \quad (\text{MISC})$$

Question

Given X^* a fractionnal point, how to find S *maximal insufficient subset* such that (MISC) separates X^* ?

(MISC) separates X^* $\Leftrightarrow$ S M.I.S. such that $\sum_{i \notin S} X_{ii}^* < 1$

$$(\text{MISC}) \text{ separates } X^* \iff S \text{ M.I.S. such that } \sum_{i=1}^n (1 - \mathbb{1}_S(i)) X_{ii}^* < 1$$

(MISC) separates X^* $\Leftrightarrow$ S M.I.S. such that $\sum_{i=1}^n (1 - \mathbb{1}_S(i)) X_{ii}^* < 1$

$$\left[\begin{array}{ll} \text{minimize} & \sum_{i=1}^n (1 - \alpha_i) X_{ii}^* \\ \text{subject to} & \sum_{i=1}^n w_i \alpha_i < q \\ & \alpha \in \{0, 1\}^n \end{array} \right.$$

(MISC) separates X^* $\Leftrightarrow$ S M.I.S. such that $\sum_{i=1}^n (1 - \mathbb{1}_S(i)) X_{ii}^* < 1$

$$\left[\begin{array}{ll} \text{minimize} & \sum_{i=1}^n (1 - \alpha_i) X_{ii}^* \\ \text{subject to} & \sum_{i=1}^n w_i \alpha_i < q \\ & \alpha \in \{0, 1\}^n \end{array} \right.$$

```

S  $\leftarrow$   $\{i \in \llbracket n \rrbracket \mid \alpha_i^* = 1\}$ 
while  $\sum_{i \in S} w_i < q$  do
    Add  $j \in \llbracket n \rrbracket \setminus S$  of minimal weight to  $S$ 
end while
Remove the last item that was added
return  $S$ 
    
```

(MISC) separates X^* $\Leftrightarrow$ S M.I.S. such that $\sum_{i=1}^n (1 - \mathbb{1}_S(i)) X_{ii}^* < 1$

$$\left[\begin{array}{ll} \text{minimize} & \sum_{i=1}^n (1 - \alpha_i) X_{ii}^* \\ \text{subject to} & \sum_{i=1}^n w_i \alpha_i < q \\ & \alpha \in \{0, 1\}^n \end{array} \right.$$

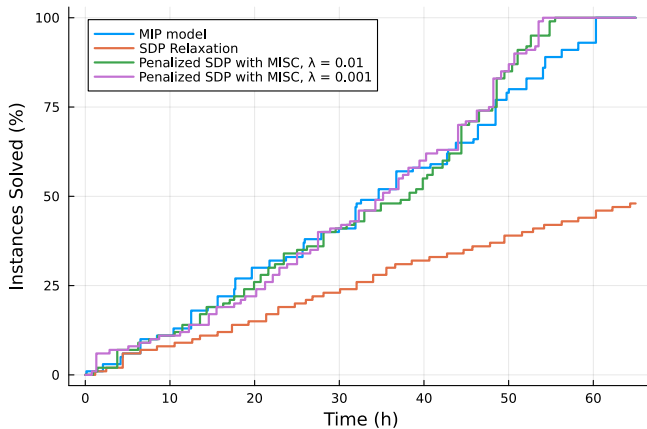
```

S  $\leftarrow \{i \in \llbracket n \rrbracket \mid \alpha_i^* = 1\}$ 
while  $\sum_{i \in S} w_i < q$  do
    Add  $j \in \llbracket n \rrbracket \setminus S$  of minimal weight to  $S$ 
end while
Remove the last item that was added
return  $S$ 
    
```

Proposition (adapted from knapsack literature)

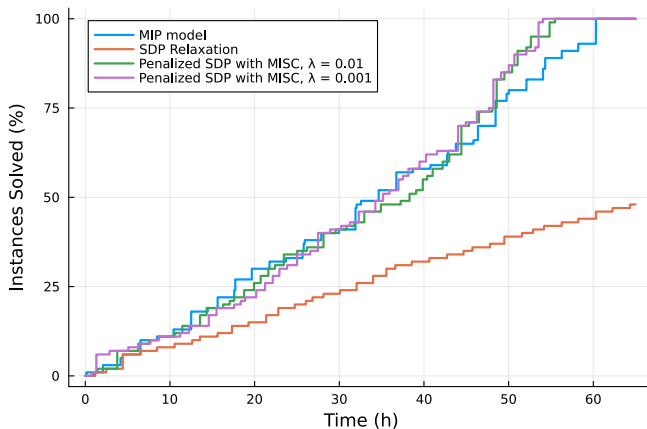
- S is a maximal insufficient subset
- If $\sum_{i=1}^n (1 - \alpha_i^*) X_{ii}^* < 1$, then $\sum_{i \notin S} X_{ii}^* < 1$
- If $\sum_{i=1}^n (1 - \alpha_i^*) X_{ii}^* \geq 1$, then no (MISC) separate X_{ii}^* .

Benchmark: 100 instances with $n \in \{200, \dots, 400\}$.



Computational Results; computing times

Benchmark: 100 instances with $n \in \{200, \dots, 400\}$.



Model	Average fractionnality
SDP Relaxation	0.2509
Penalized SDP with $\lambda = 0.01$	1.3107e-5
Penalized SDP with $\lambda = 0.001$	6.7288e-6

- Compactness constraint brings a new layer of difficulties to the standard knapsack problem.

- Compactness constraint brings a new layer of difficulties to the standard knapsack problem.
- The penalized version provides high-quality heuristics and tight bounds for the problem.

- Compactness constraint brings a new layer of difficulties to the standard knapsack problem.
- The penalized version provides high-quality heuristics and tight bounds for the problem.
- The penalized version allows tuning the model to the appropriate balance between parsimony and compacity.

- Compactness constraint brings a new layer of difficulties to the standard knapsack problem.
- The penalized version provides high-quality heuristics and tight bounds for the problem.
- The penalized version allows tuning the model to the appropriate balance between parsimony and compacity.
- Future work is needed to strengthen the model and to improve numerical performance.



Cappello, L. and Padilla, O. H. M. (2022).

Bayesian variance change point detection with credible sets.
arXiv preprint arXiv:2211.14097.



De Meijer, F. and Sotirov, R. (2024).

On integrality in semidefinite programming for discrete optimization.
SIAM Journal on Optimization, 34(1):1071–1096.



Santini, A. and Malaguti, E. (2024).

The min-knapsack problem with compactness constraints and applications in statistics.

European Journal of Operational Research, 312(1):385–397.

Definition (Positive semidefinite matrix)

A symmetric matrix $X \in M_n(\mathbf{R})$ is *positive semidefinite* if for all $v \in \mathbf{R}^n$, $v^\top X v \geq 0$. We write $X \succeq 0$.

Properties

- $X \succeq 0 \iff X = \sum_{i=1}^r \lambda_i x_i x_i^\top$ with $\lambda_i \geq 0$ and $x_i \in \mathbf{R}^n$.
- $X \succeq 0 \iff$ all principal minors of X are nonnegative.

Proposition (Schur complement's lemma)

Let X be the symmetric matrix defined by

$$X = \begin{pmatrix} A & B^\top \\ B & C \end{pmatrix}$$

with A invertible. Then $X \succeq 0$ if and only if $C - BA^{-1}B^\top \succeq 0$.

With 10 items, costs $c_1 = 1$ for all $i \in \llbracket 10 \rrbracket$, $w_1 = w_{10} = 11$, $w_j = 1$ for all $j \neq 1, 10$, $q = 22$ and $\Delta = 2$.

$$\left[\begin{array}{ll} \text{minimize} & x_1 + \cdots + x_{10} \\ \text{subject to} & 11x_1 + x_2 + \cdots + x_9 + 11x_{10} \geq 22 \\ & \forall i, j \in \llbracket 10 \rrbracket, j - i > 2, \quad \left\lfloor \frac{j-i-1}{2} \right\rfloor (x_i + x_j - 1) \leq \sum_{k=i+1}^{j-1} x_k \\ & x \in [0, 1]^{10} \end{array} \right.$$

Set $\mathbf{X} = (x_{\text{LP}}^*)^\top x_{\text{LP}}^*$. Then $\mathbf{X}$ is not a solution of

$$\left[\begin{array}{ll} \text{minimize} & X_{11} + \cdots + X_{1010} \\ \text{subject to} & 11X_{11} + X_{22} + \cdots + X_{99} + 11X_{1010} \geq 22 \\ & \forall i, j \in \llbracket 10 \rrbracket, j - i > 2, \quad \left\lfloor \frac{j-i-1}{2} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0. \end{array} \right.$$

$$\left[\begin{array}{ll} \text{minimize} & x_1 + \cdots + x_{10} \\ \text{subject to} & 11x_1 + x_2 + \cdots + x_9 + 11x_{10} \geq 22 \\ & \forall i, j \in \llbracket 10 \rrbracket, j - i > 2, \quad \left\lfloor \frac{j-i-1}{2} \right\rfloor (x_i + x_j - 1) \leq \sum_{k=i+1}^{j-1} x_k \\ & x \in [0, 1]^{10} \end{array} \right.$$

$$x_{\text{LP}}^* = \left(1, \frac{3}{4}, \frac{119}{180}, 0, \frac{17}{135}, \frac{251}{540}, 0, \frac{107}{540}, \frac{11}{15}, \frac{11}{15} \right)$$

$$\left[\begin{array}{ll} \text{minimize} & X_{11} + \cdots + X_{1010} \\ \text{subject to} & 11X_{11} + X_{22} + \cdots + X_{99} + 11X_{1010} \geq 22 \\ & \forall i, j \in \llbracket 10 \rrbracket, j - i > 2, \quad \left\lfloor \frac{j-i-1}{2} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \\ & \begin{pmatrix} 1 & \text{diag}(X)^T \\ \text{diag}(X) & X \end{pmatrix} \succeq 0. \end{array} \right.$$

X does not verify the (2,9)-compactness constraint:

$$\left\lfloor \frac{9-2-1}{2} \right\rfloor X_{29} = \boxed{\frac{33}{20}} > \frac{29}{20} = \sum_{k=3}^8 X_{kk}$$

$$\text{Opt}(\text{SDP}) \approx 4.42 < 4.66 \approx \text{Opt}(\text{LP})$$

Focus on "hard" instances from [*Santini and Malaguti, 2024*]: TwoPeaks instances.

- Choose peaks location $\lambda_1 \rightsquigarrow \mathcal{N}(n/3, n/6)$, $\lambda_2 \rightsquigarrow \mathcal{N}(2n/3, n/6)$.

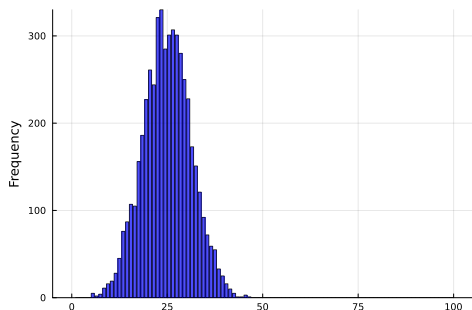
Appendix - How to generate instances?

Focus on "hard" instances from [*Santini and Malaguti, 2024*]: TwoPeaks instances.

- Choose peaks location $\lambda_1 \rightsquigarrow \mathcal{N}(n/3, n/6)$, $\lambda_2 \rightsquigarrow \mathcal{N}(2n/3, n/6)$.
- Histogramm 5000 samples for each peak

$$\text{1}^{\text{st}} \text{ peak} \quad w_1 \rightsquigarrow \mathcal{N}(\lambda_1, n/2k) \qquad \text{2}^{\text{nd}} \text{ peak} \quad w_2 \rightsquigarrow \mathcal{N}(\lambda_2, n/2k)$$

where $k \in \{8, 16, 32\}$.



Appendix - How to generate instances?

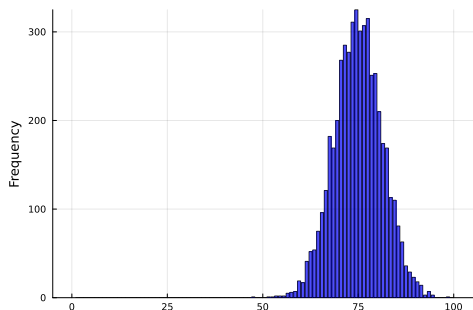
Focus on "hard" instances from [*Santini and Malaguti, 2024*]: TwoPeaks instances.

- Choose peaks location $\lambda_1 \rightsquigarrow \mathcal{N}(n/3, n/6)$, $\lambda_2 \rightsquigarrow \mathcal{N}(2n/3, n/6)$.
- Histogramm 5000 samples for each peak

1st peak $w_1 \rightsquigarrow \mathcal{N}(\lambda_1, n/2k)$

2nd peak $w_2 \rightsquigarrow \mathcal{N}(\lambda_2, n/2k)$

where $k \in \{8, 16, 32\}$.



Appendix - How to generate instances?

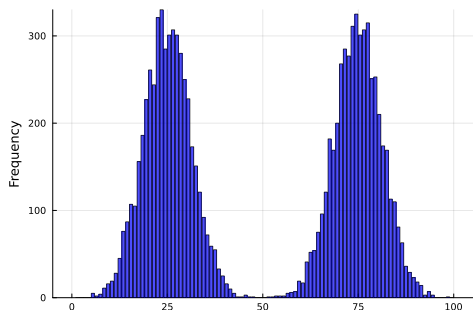
Focus on "hard" instances from [*Santini and Malaguti, 2024*]: TwoPeaks instances.

- Choose peaks location $\lambda_1 \rightsquigarrow \mathcal{N}(n/3, n/6)$, $\lambda_2 \rightsquigarrow \mathcal{N}(2n/3, n/6)$.
- Histogramm 5000 samples for each peak

$$\text{1}^{\text{st}} \text{ peak} \quad w_1 \rightsquigarrow \mathcal{N}(\lambda_1, n/2k) \qquad \text{2}^{\text{nd}} \text{ peak} \quad w_2 \rightsquigarrow \mathcal{N}(\lambda_2, n/2k)$$

where $k \in \{8, 16, 32\}$.

- Set $w \leftarrow w_1 + w_2$ and normalize.



For $\lambda \in \mathbf{R}^{n(n+1)/2}$:

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) + \varphi(\lambda, X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0 \\ & \text{Quadratic constraints} \end{array} \right.$$

For $\lambda \in \mathbf{R}^{n(n+1)/2}$:

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) + \varphi(\lambda, X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0 \\ & \text{Quadratic constraints} \end{array} \right.$$

Pay&Reward

$$\text{minimize} \quad c^\top \text{diag}(X) + \sum_{i < j} \lambda_{ij} \left(\left\lfloor \frac{j-i-1}{\Delta} \right\rfloor X_{ij} - \sum_{k=i+1}^{j-1} X_{kk} \right)$$

For $\lambda \in \mathbf{R}^{n(n+1)/2}$:

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) + \varphi(\lambda, X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0 \\ & \text{Quadratic constraints} \end{array} \right.$$

MaxGap

$$\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) + \tau \\ \text{subject to} & \tau \geq \lambda_{ij} \left(\left\lfloor \frac{j-i-1}{\Delta} \right\rfloor X_{ij} - \sum_{k=i+1}^{j-1} X_{kk} \right) \end{array}$$

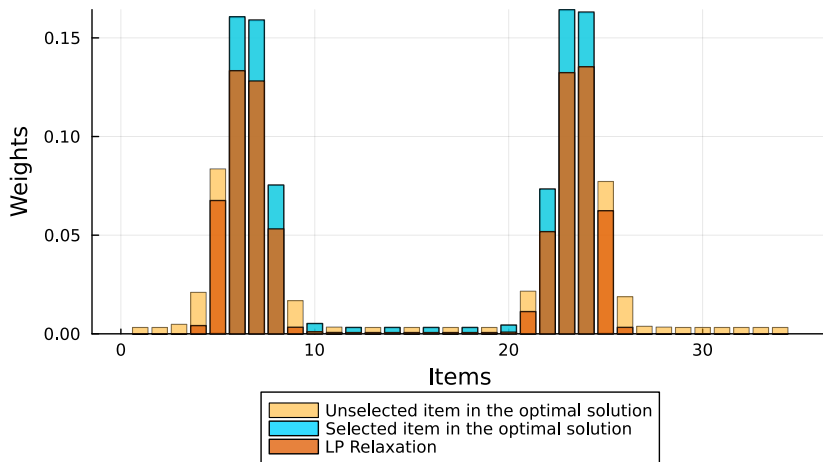
For $\lambda \in \mathbf{R}^{n(n+1)/2}$:

$$\left[\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) + \varphi(\lambda, X) \\ \text{subject to} & w^\top \text{diag}(X) \geq q \\ & \begin{pmatrix} 1 & \text{diag}(X)^\top \\ \text{diag}(X) & X \end{pmatrix} \succeq 0 \\ & \text{Quadratic constraints} \end{array} \right.$$

PayEachGap

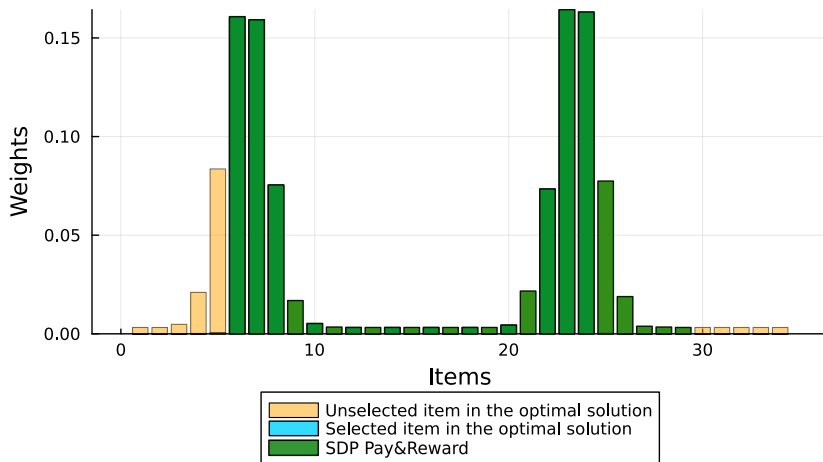
$$\begin{array}{ll} \text{minimize} & c^\top \text{diag}(X) + \sum_{i < j} \lambda_{ij} \left\lfloor \frac{j-i-1}{\Delta} \right\rfloor X_{ij} \\ \text{subject to} & \left\lfloor \frac{j-i-1}{\Delta} \right\rfloor X_{ij} \leq \sum_{k=i+1}^{j-1} X_{kk} \end{array}$$

Appendix - Effects of the different penalizations



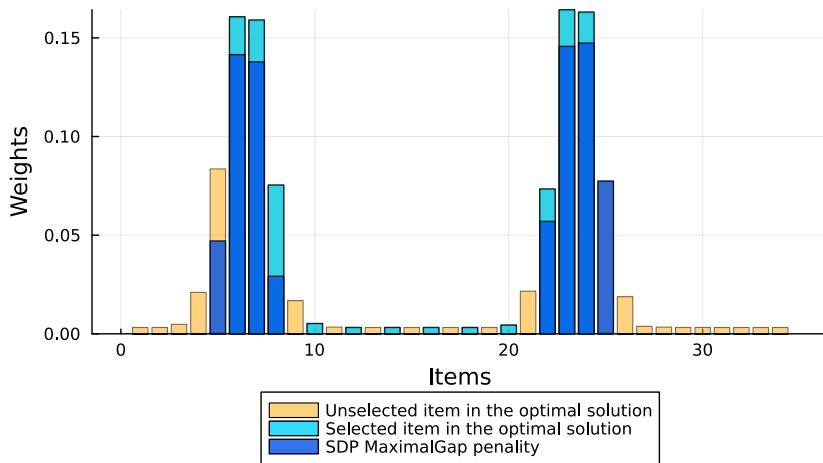
selected items for the linear relaxation, with $\Delta = 2$

Appendix - Effects of the different penalizations



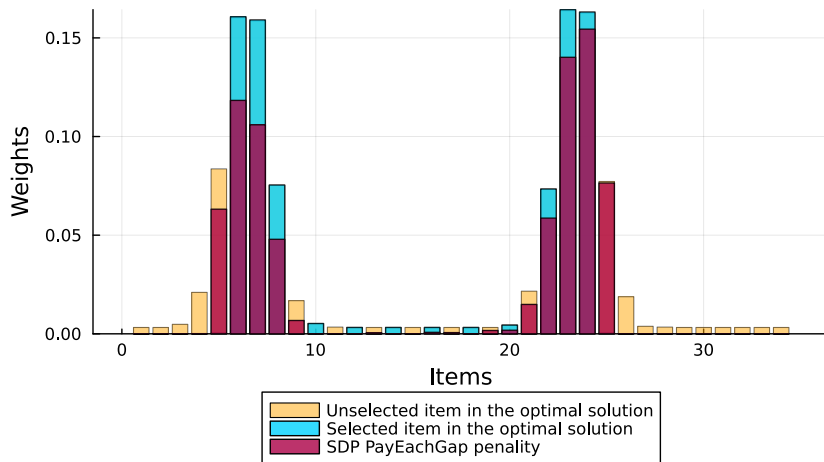
selected items for the Pay&Reward penalization, with $\Delta = 2$

Appendix - Effects of the different penalizations



selected items for the [MaxGap penalization](#), with $\Delta = 2$

Appendix - Effects of the different penalizations



selected items for the PayEachGap penalization, with $\Delta = 2$