

Problem statement

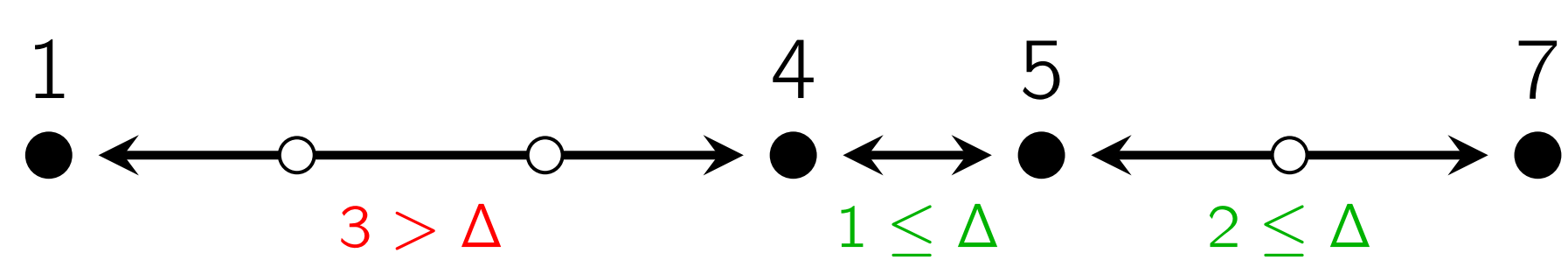
Knapsack with compactness constraints: extension of the classical minimization knapsack: n items $i \in \llbracket n \rrbracket$ with costs c_i and weights w_i .

• **Goal:** find $S \subseteq \llbracket n \rrbracket$ minimizing the total cost while ensuring that the total weight exceeds a given threshold q .

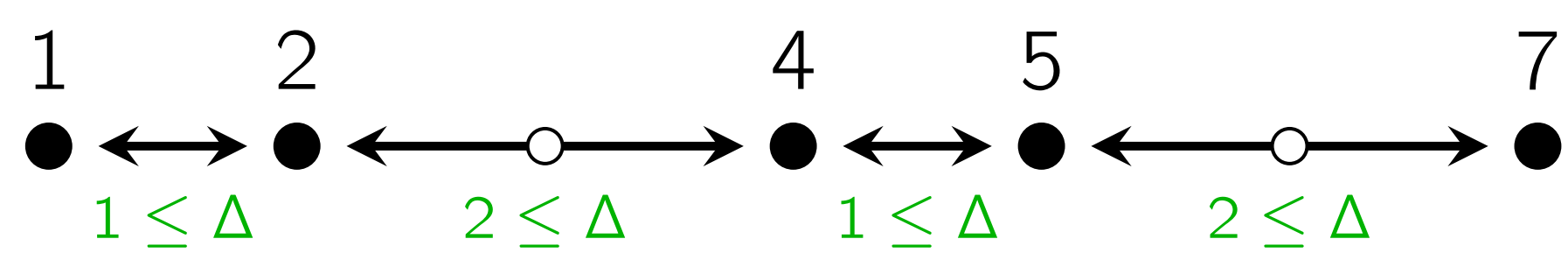
• **Compactness:** the selected items must remain grouped together.

There must not have gaps of more than $\Delta \geq 1$ in between two consecutive selected items. [3]

For example, with $\Delta = 2$:



(Fig 1: *non-compact* selection)



(Fig 2: *compact* selection)

The problem has applications in statistics, e.g. **detecting changes in time series** [1].

Models

• **Input:** costs $c \in \mathbf{R}_+^n$, weights $w \in \mathbf{R}_+^n$, threshold $q \in \mathbf{R}_+$

• **Variables:** \mathbf{x}_i binary, ($\mathbf{x}_i = 1 \Leftrightarrow$ item i is selected).

$$\begin{cases} \text{minimize} & c^\top \mathbf{x} \\ \text{subject to} & w^\top \mathbf{x} \geq q \\ & \text{compactness constraints} \\ & \mathbf{x} \in \{0, 1\}^n \end{cases}$$

Two expressions for the compactness constraints: $i, j \in \llbracket n \rrbracket$ with $j - i > \Delta$:

$$\mathbf{x}_i + \mathbf{x}_j - 1 \leq \sum_{k=i+1}^{j-1} \mathbf{x}_k \quad (1a)$$

(Linear compactness constraint - [3] approach)

$$\mathbf{x}_i \mathbf{x}_j \leq \sum_{k=i+1}^{j-1} \mathbf{x}_k. \quad (1b)$$

(Quadratic compactness constraint - our approach)

Semidefinite relaxation: with the matrix \mathbf{X} as variable, $c^\top \text{diag}(\mathbf{X})$ for the objective function, the knapsack constraint $w^\top \text{diag}(\mathbf{X}) \geq q$ and the constraints:

$$\left[\frac{j-i-1}{\Delta} \right] \mathbf{x}_{ij} \leq \sum_{k=i+1}^{j-1} \mathbf{x}_{kk} \quad (1b)_{\text{SDP}} \quad \left(\begin{array}{cc} 1 & \text{diag}(\mathbf{X})^\top \\ \text{diag}(\mathbf{X}) & \mathbf{X} \end{array} \right) \succeq 0. \quad (2)$$

Our approach: penalized model

The compactness is enforced in the objective rather than in the constraints: for a penalization parameter $\lambda \in \mathbf{R}_+$, the objective function becomes

$$c^\top \text{diag}(\mathbf{X}) + \lambda \sum_{\substack{1 \leq i < j \leq n \\ j-i > \Delta}} \left(\left[\frac{j-i-1}{\Delta} \right] \mathbf{x}_{ij} - \sum_{k=i+1}^{j-1} \mathbf{x}_{kk} \right).$$

Strengthening inequalities

Valid quadratic inequality, *linearize* and *lift* to the matrix space:

$$\begin{aligned} \mathbf{x}_i \mathbf{x}_j &\leftrightarrow \mathbf{X}_{ij} & \mathbf{x}_i^2 &\leftrightarrow \mathbf{X}_{ii} \\ \mathbf{X}_{ij} &\leftrightarrow \mathbf{X}_{ji} & \mathbf{X}_{ii}^2 &\leftrightarrow \mathbf{X}_{ii} \end{aligned}$$

• **Sherali-Adams inequalities:** $\forall i, j \in \llbracket n \rrbracket$
 $\mathbf{x}_i \mathbf{x}_j \geq 0 \quad \mathbf{x}_i(1 - \mathbf{x}_j) \geq 0 \quad (1 - \mathbf{x}_i)(1 - \mathbf{x}_j) \geq 0$

• **Quadratic knapsack constraints:** $\forall i \in \llbracket n \rrbracket$
 $w^\top \mathbf{x} \mathbf{x}_i \geq q \mathbf{x}_i \quad w^\top \mathbf{x} (1 - \mathbf{x}_i) \geq q (1 - \mathbf{x}_i)$

→ Strengthens SDP models.

Maximal Insufficient Subsets

Maximal Insufficient Subset: $S \subseteq \llbracket n \rrbracket$

$$\forall j \in \llbracket n \rrbracket \setminus S \quad q - w_j \leq \sum_{i \in S} w_i < q.$$

Valid inequality: $\sum_{i \notin S} \mathbf{x}_{ii} \geq 1. \quad (\text{MISC})$

Let X^* : optimal solution of SDP model. Then

$$\begin{cases} \text{minimize} & \text{diag}(X^*)^\top (1 - \mathbf{a}) \\ \text{subject to} & w^\top \mathbf{a} \leq q - \epsilon \\ & \mathbf{a} \in \{0, 1\}^n \end{cases} \quad (3)$$

Separation algorithm

For a SDP model M :

$X^* \leftarrow \text{argmin}(M)$; solve (3)

if $\text{Opt}(3) \geq 1$ **then** (\mathcal{A} (MISC) separating X^*)

return X^*

else

$S \leftarrow \text{correct}(\bar{S} = \{i \text{ s.t. } \mathbf{a}_i^* = 1\}) \quad (\star)$

return $\text{argmin}(M \text{ with (MISC)})$

end if

(\star) **while** $\sum_{i \in \bar{S}} w_i < q$

$\bar{S} \leftarrow \bar{S} \cup \{\text{argmin}_j w_j\}$

while end; remove the last item added

Metrics

Imprecision

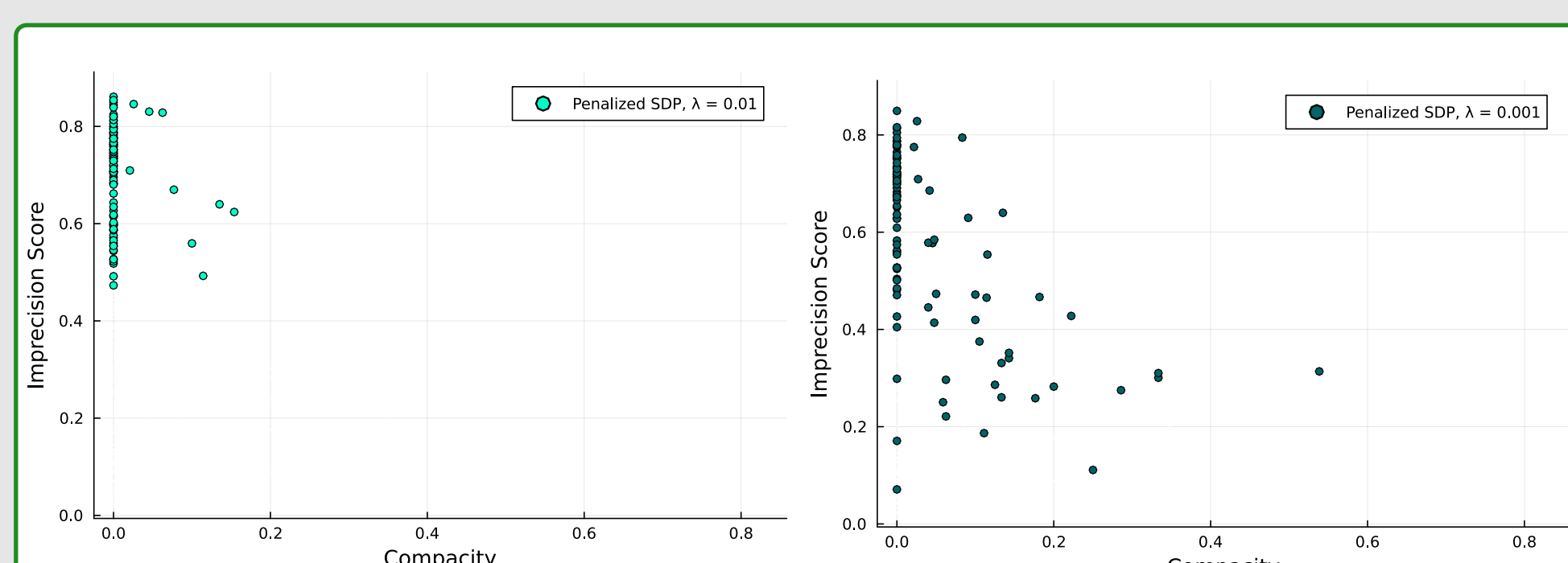
$$\text{imp}(\mathbf{x}) = \frac{c^\top \mathbf{x}}{\|c\|_1}$$

Compacity

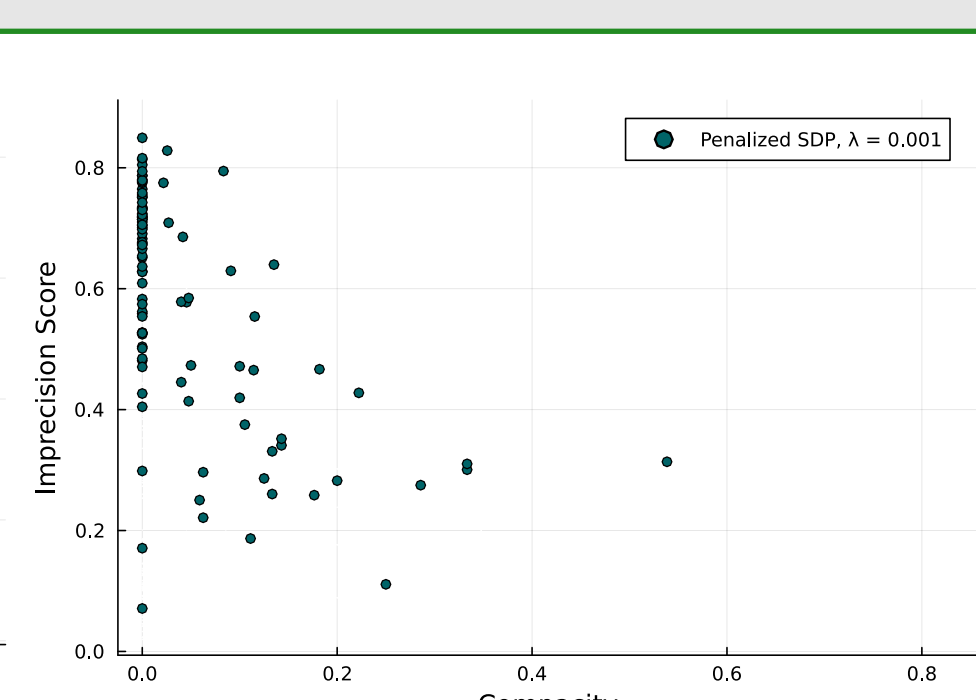
$$\text{comp}(S) = \frac{1}{n} \max_{i,j \in S} \left\{ j - i - 1 \mid \begin{array}{c} i, j \\ \text{consecutive} \end{array} \right\}$$

Fractionnality

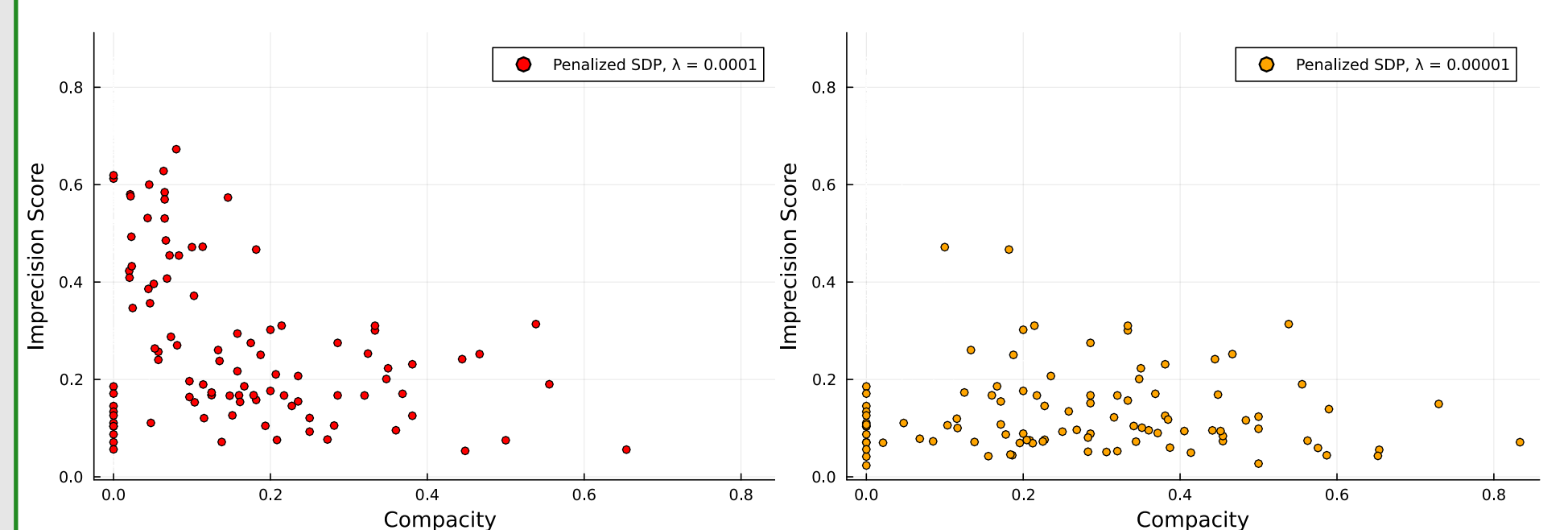
$$\text{frac}(\mathbf{x}) = \frac{2}{\sqrt{n}} \left\| \mathbf{x} - \left[\mathbf{x} + \frac{1}{2} \cdot \mathbf{1} \right] \right\|_2$$



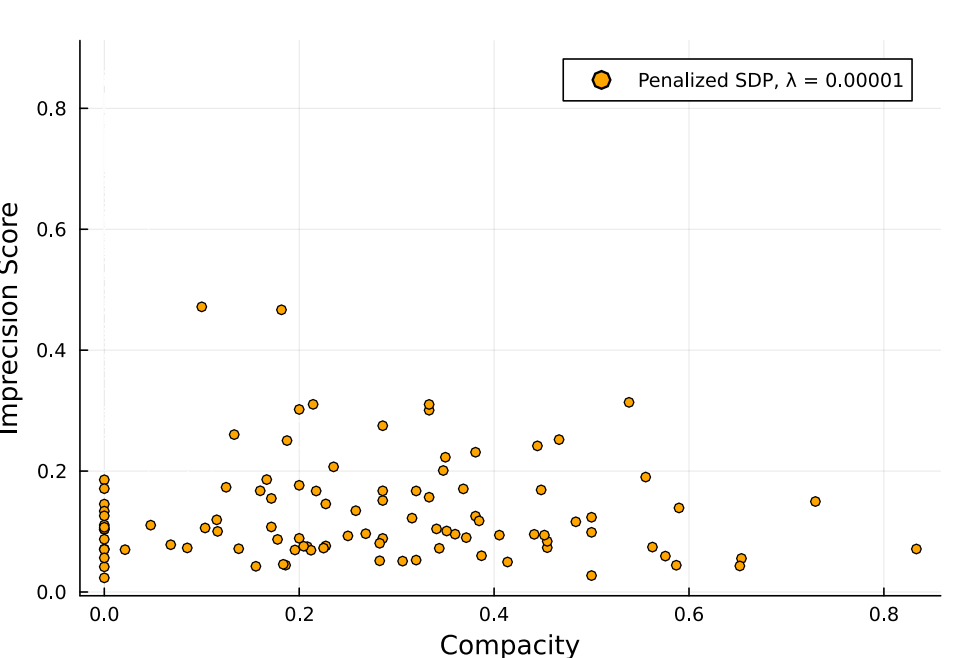
(Fig 3: $\lambda = 10^{-2}$)



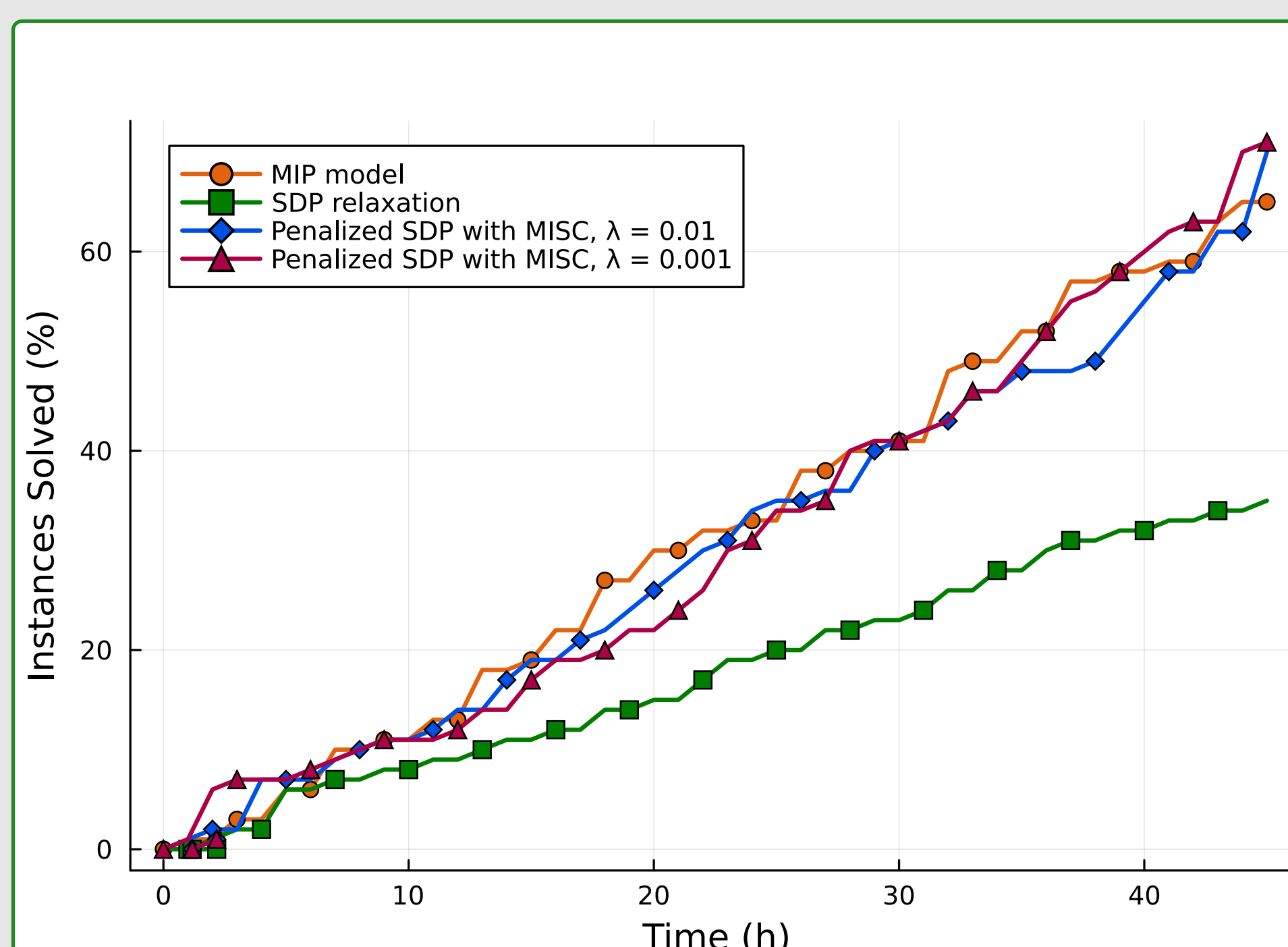
(Fig 4: $\lambda = 10^{-3}$)



(Fig 5: $\lambda = 10^{-4}$)



(Fig 6: $\lambda = 10^{-5}$)



(Fig 7: Computation time for the studied models on the benchmark of 100 hard instances)

λ	Average fractionnality (frac)	
	Penalized SDP	Separation Algorithm
$\lambda = 10^0$	$2.779 \cdot 10^{-3}$	$1.243 \cdot 10^{-5}$
$\lambda = 10^{-2}$	$2.339 \cdot 10^{-3}$	$1.311 \cdot 10^{-5}$
$\lambda = 10^{-4}$	$1.673 \cdot 10^{-2}$	$5.069 \cdot 10^{-5}$
$\lambda = 10^{-6}$	$4.326 \cdot 10^{-2}$	$8.510 \cdot 10^{-5}$

(Fig 8: Average fractionnality with the separation procedure)

References

- [1] Cappello & Padilla (2025). **Bayesian variance change point detection with credible sets**. IEEE Trans. on Pattern Analysis and Machine Intelligence.
- [2] Villuendas, Besançon & Malick (2025). **Knapsack with compactness: a semidefinite approach**. arXiv:2504.17543.
- [3] Santini & Malaguti (2024). **The min-knapsack problem with compactness constraints and applications in statistics**. European Journal of Operational Research.