

Selected Topics in Network Optimization: Aligning BDDs for a Facility Location Problem and a Search Tree Method for DSPI.

Dissertation defense

Alexey Bochkarev

2021-11-02 Tue, 08-30, Zoom / Freeman Hall 129



Thanks for joining in the morning!

Presentation outline

1 TODO Aligning BDDs

- On BDD representations
- BDD alignment (“original”) problem
- The simplified problem
- Numerical experiments

2 A BDD-based approach to a Facility Location Problem

- Problem description
- BDD representation
- Solving the CPP
- Numerical experiments

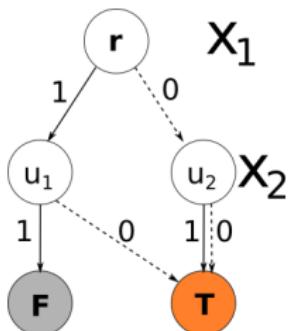
3 Monte Carlo Tree Search for DSPI

- Problem formulation
- MCTS framework
- Numerical experiments
- On correctness

What is an (O)BDD?

In a nutshell:

- A (maybe weighted) layered (D)AG
- Two outgoing arcs from each node
- One root, two terminals



Applications:

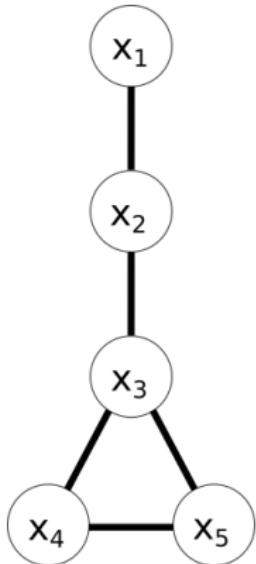
- Can encode a Boolean function
- ...
- ... or a combinatorial opt problem.

How it works:

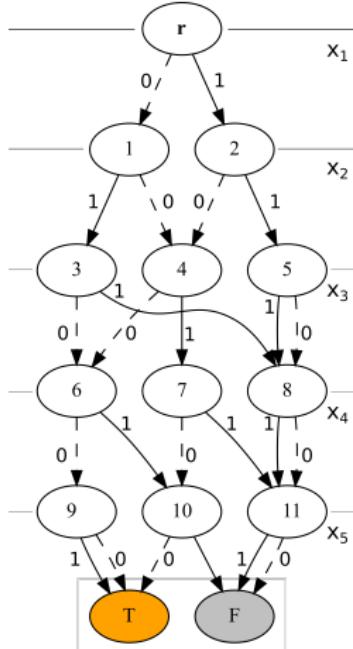
- A layer corresponds to a “decision” (binary variable),
- **one-arc** (or yes-arc) – $x_i = 1$,
- **zero-arc** (or no-arc) – $x_i = 0$.
- A **path** from root to terminal corresponds to an assignment of all variables.

Order of variables matters: a MIS example

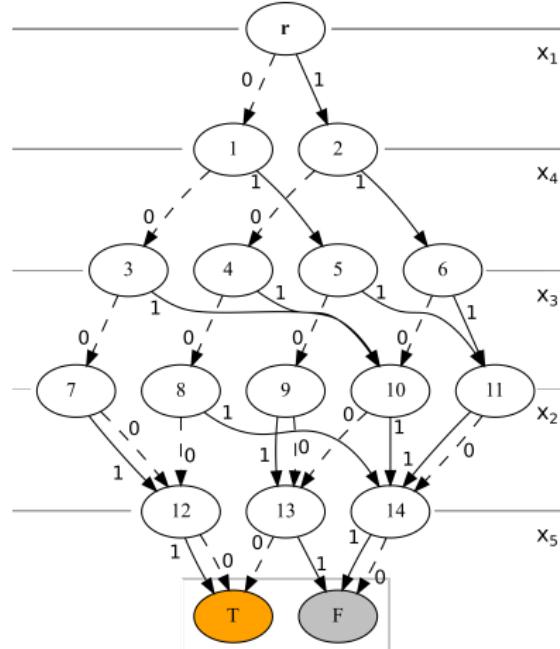
Original graph:



14 nodes:



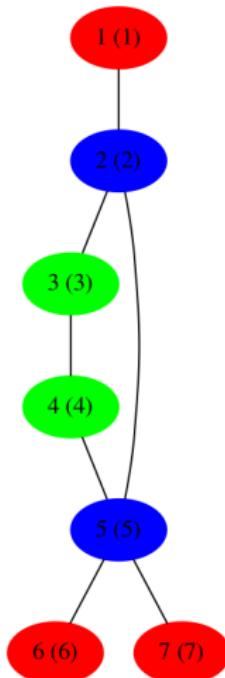
17 nodes



The **same** order of variables also matters

- Many problems can be reformulated as a set of (connected) instances over a collection of BDDs.
 - If we have the same order of variables:
[Lozano et al.(2020)Lozano, Bergman, and Smith] proposed an algorithm how to tackle such instances.
 - So, finding a good shared order of variables might be desirable.

A motivating example: t-UFLP



Assume:

- A graph; can **locate** a facility at any point,
 - A located facility **covers** all neighboring points.

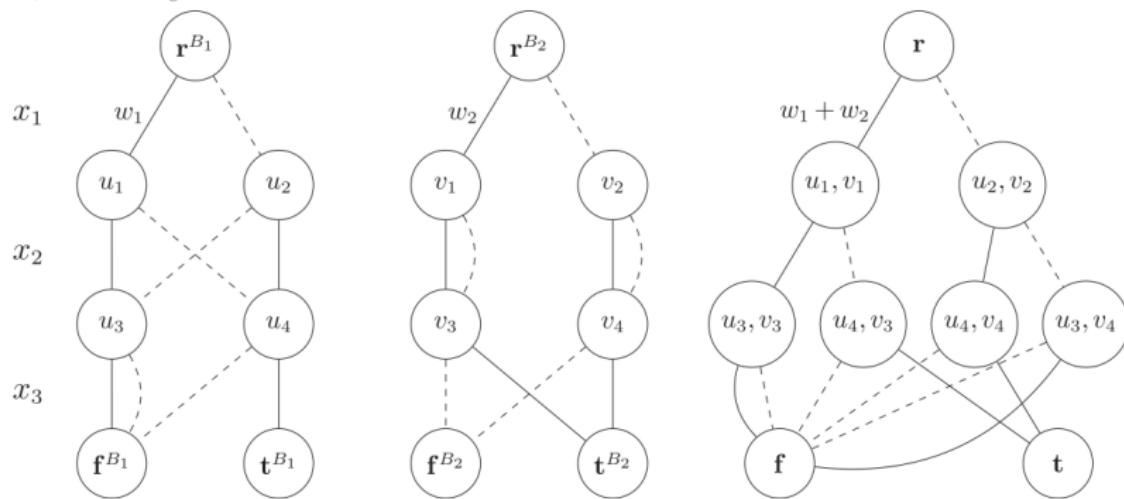
Objective: cover all points at min cost.

Constraints:

- Each point implies a facility “*type*”,
 - There is a limit on number of facilities by type.

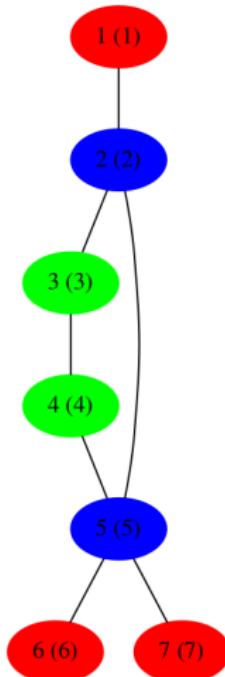
How to merge two diagrams?

Figure 4. Building an Intersection BDD



Source: [Lozano et al.(2020)Lozano, Bergman, and Smith]

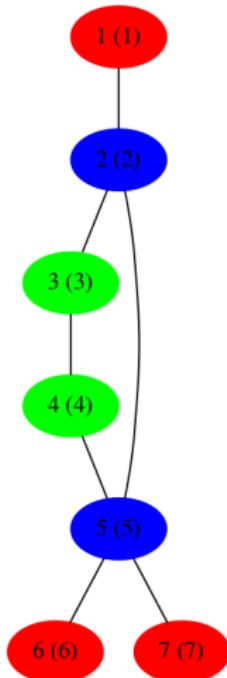
A motivating example: t-UFLP



Plan of attack:

- Formulate the problem with two BDDs,
- Enforce the shared order of variables,
- Merge (“intersect”) the two diagrams into one*
- Solve a shortest-path in the intersection DD.

A motivating example: t-UFLP



Plan of attack:

- Formulate the problem with two BDDs,
- Enforce the shared order of variables, ← this part
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TODO Aligning BDDs

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On BDD representations

BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

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TODO Conclusion

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In this section:

- BDD alignment problem,
- A simplified model / heuristic,
- Numerical experiments on aligning BDDs.

BDD alignment problem

Let us denote $T^*[D, \mathbf{v}]$ – a “transformed” version of BDD D to variable order $\mathbf{v} = (v_1, \dots, v_N)$. Then:

BDD Alignment Problem / “original” problem

$$s^* = \min_{\mathbf{v}} \left\{ |T^*[A, \mathbf{v}]| + |T^*[B, \mathbf{v}]| \right\},$$

where $|D|$ is the number of nodes in diagram D . The problem is NP-hard (because the min single BDD is NP-hard).

Research context

- Vast literature on minimizing single BDD.
- One of the central ideas: “Dynamic variable reordering” / **Sifting** algorithm (we will use it as a baseline).
- Limited consideration of the multi-BDD version, and all working with BDDs (obviously).

The purpose of this work

Try to avoid manipulations with BDD as much as possible, by introducing a “simpler” auxiliary problem.

TODO Aligning BDDs

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The simplified problem

BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

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TODO Conclusion

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How the BDDs are transformed?

TODO Aligning BDDs

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The simplified problem

BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

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TODO Conclusion

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The simplified problem

TODO Aligning BDDs

The simplified problem

BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Plan of attack with the simplified problem

TODO Aligning BDDs

The simplified problem

BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

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TODO Conclusion

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How to solve it now? Key properties

TODO Aligning BDDs

A horizontal row of 15 small circles. The 13th circle from the left is filled black, while all other circles are unfilled.

The simplified problem

BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Branch...

TODO Aligning BDDs

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The simplified problem

BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

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TODO Conclusion

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... and bound.

Numerical experiments: strategy

- First: consider the simplified problem in detail.
- Then: solve the original problem, benchmark vs the baseline and consider scaling.
- Analyze the solutions: original vs. simplified, problem structure.

TODO Aligning BDDs

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Numerical experiments

BDDs for t-UFLP

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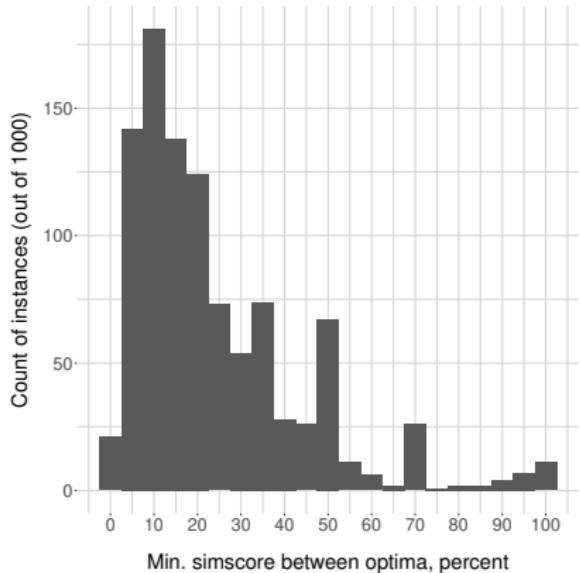
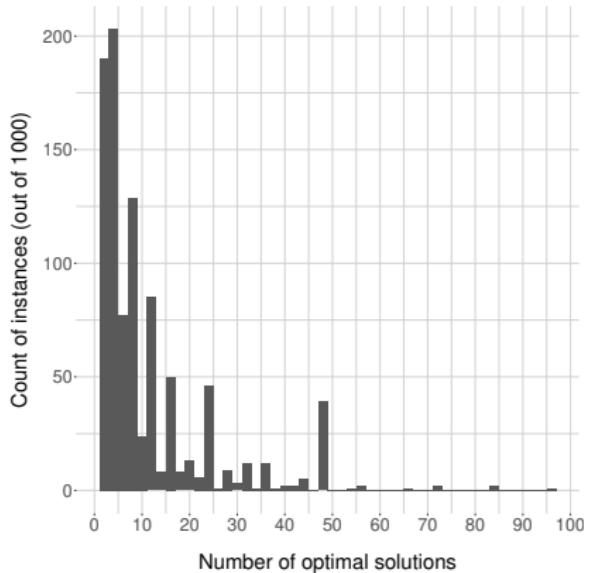
Monte Carlo Tree Search for DSPI

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Simplified problem: optima



TODO Aligning BDDs

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Numerical experiments

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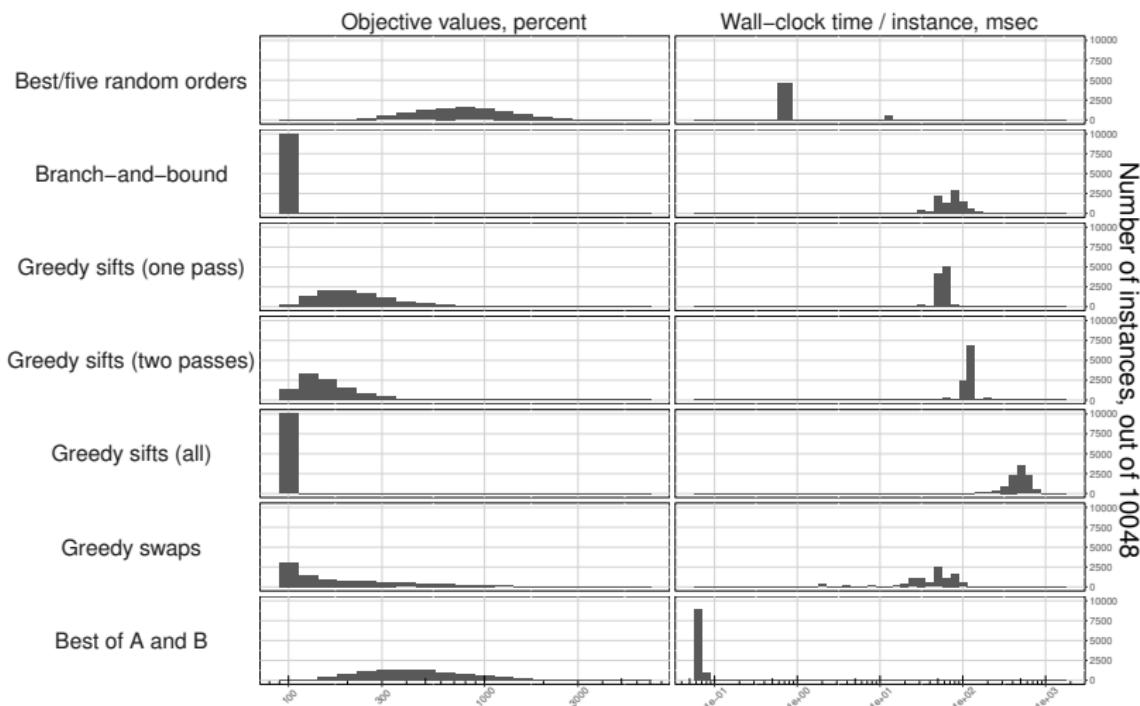
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Simplified problem: heuristics



TODO Aligning BDDs

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Numerical experiments

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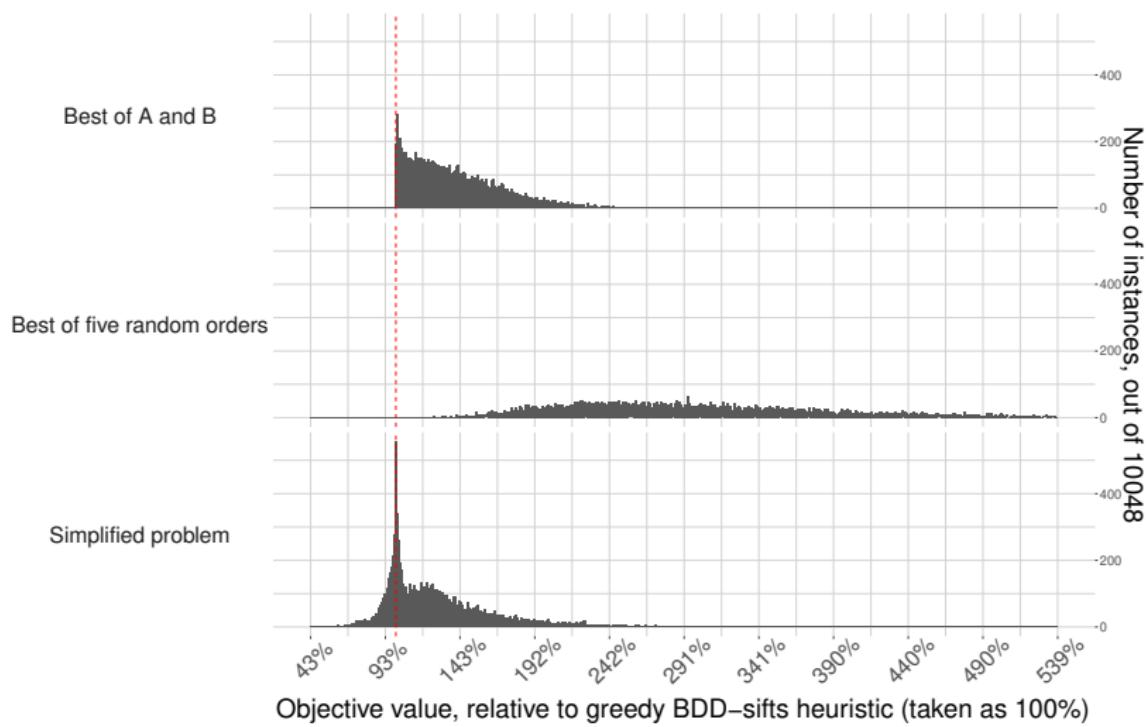
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Objectives relative to the “greedy sifts”



TODO Aligning BDDs

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BDDs for t-UFLP

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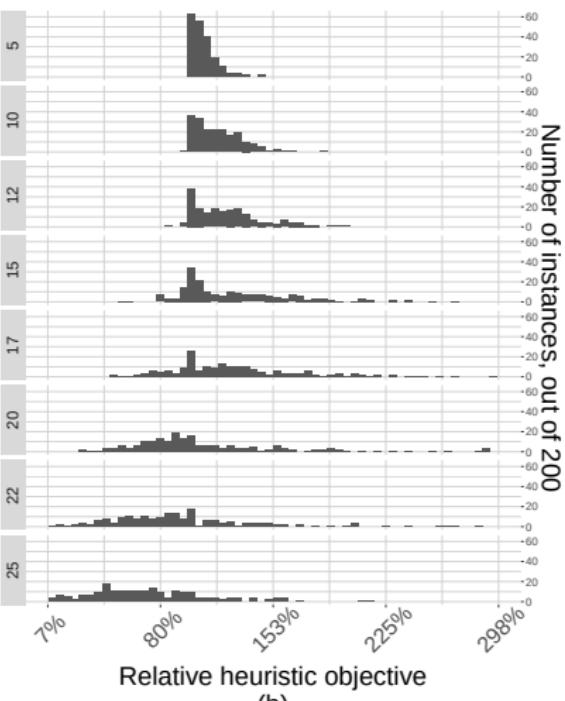
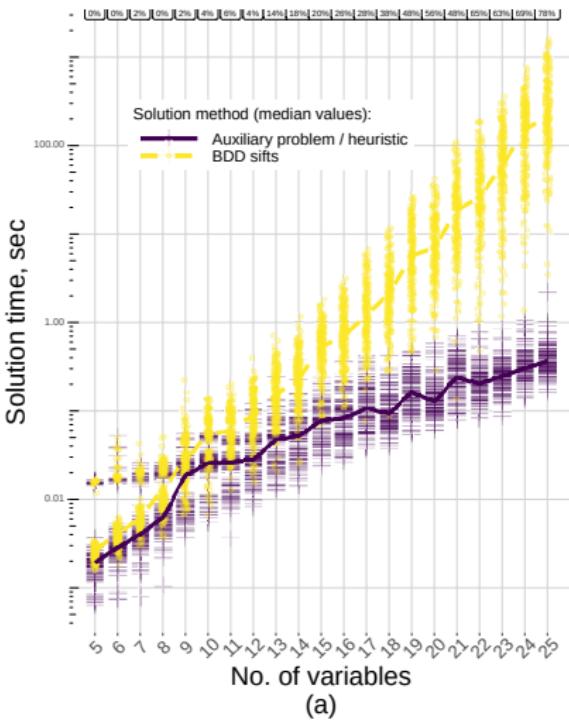
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Scaling with the problem size



TODO Aligning BDDs

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Numerical experiments

BDDs for t-UFLP

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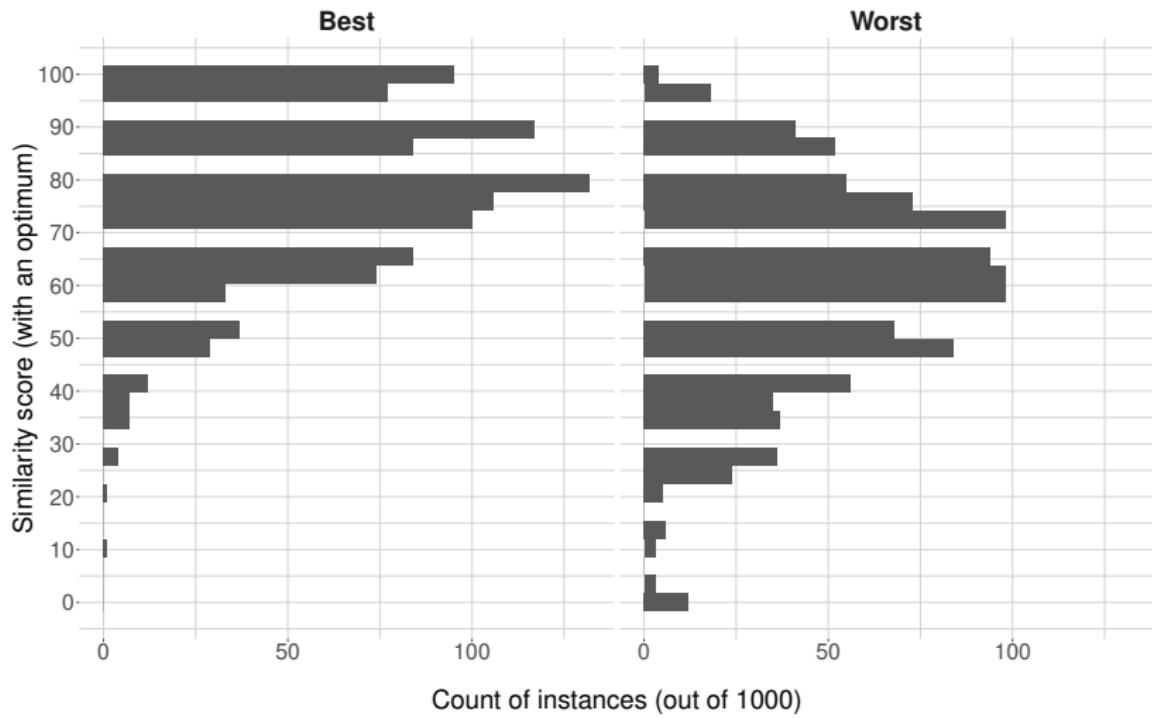
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Simplified vs. Original problem solutions



TODO Aligning BDDs

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Numerical experiments

BDDs for t-UFLP

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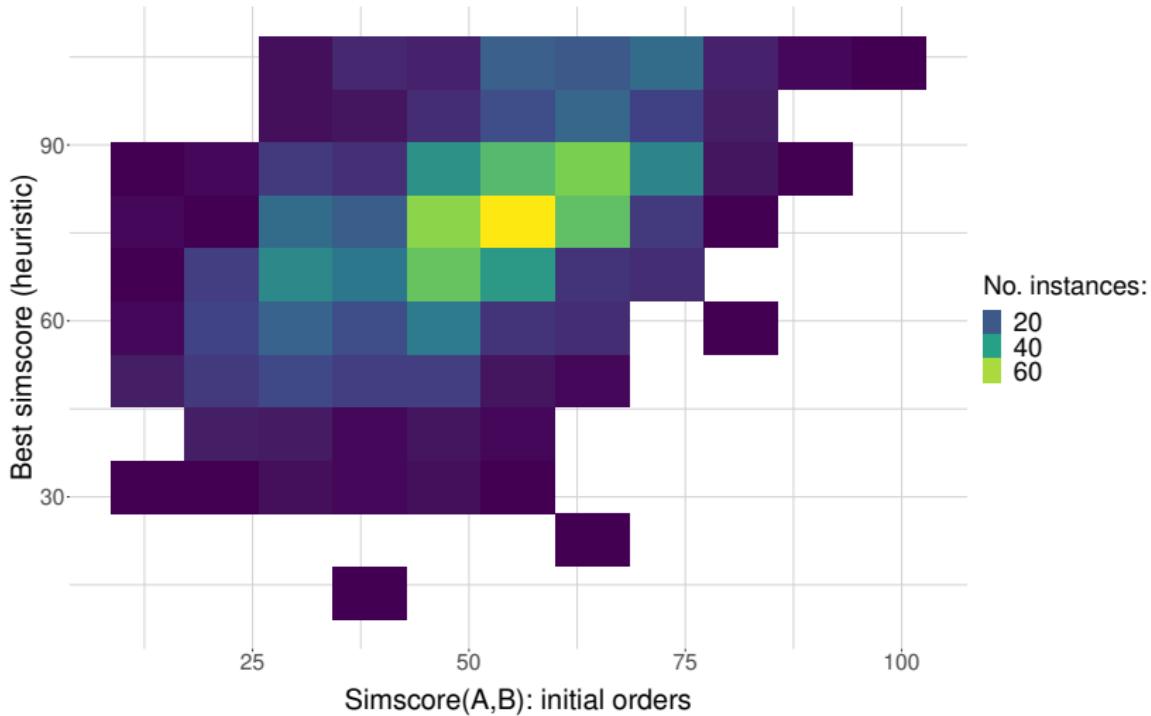
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Effects of the problem structure



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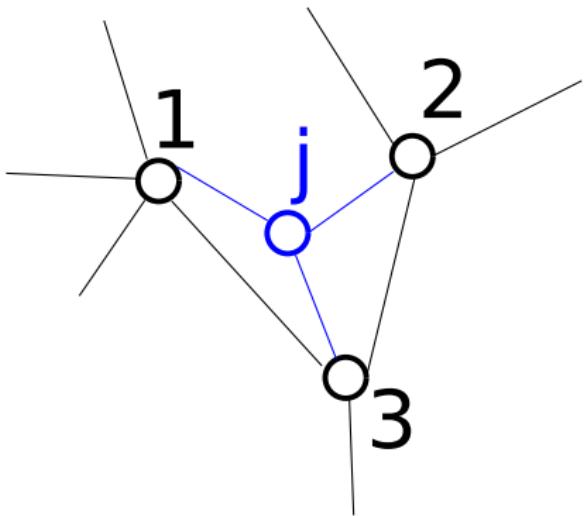
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A variant of the Facility Location Problem



- Locate facilities in a cheapest way, ...
- ... to cover all points, ...
- ... respecting the budget constraints, by facility "type".

Problem formulation

$$\begin{aligned}
 & \min \sum_{i=1}^M f_i x_i \\
 \text{s.t. } & \sum_{j \in S_i} x_j \geq 1 \quad i = 1, \dots, M, \\
 & \sum_{j \in T_t} x_j \leq k_t \quad t = 1, \dots, K, \\
 & x_i \in \{0, 1\} \quad i = 1, \dots, M.
 \end{aligned}$$

Here:

- S_j – adjacency lists,
- k_t – budgets,
- f_i – location costs,
- x_i – location decisions.

Problem formulation

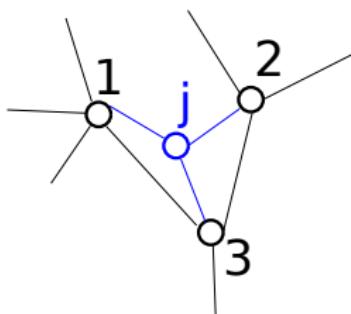
$$\begin{aligned}
 & \min \sum_{i=1}^M f_i x_i \\
 \text{s.t. } & \sum_{j \in S_i} x_j \geq 1 \quad i = 1, \dots, M, \rightarrow \text{“Cover” BDD} \\
 & \sum_{j \in T_t} x_j \leq k_t \quad t = 1, \dots, K, \rightarrow \text{“Type” BDD} \\
 & x_i \in \{0, 1\} \quad i = 1, \dots, M.
 \end{aligned}$$

Here:

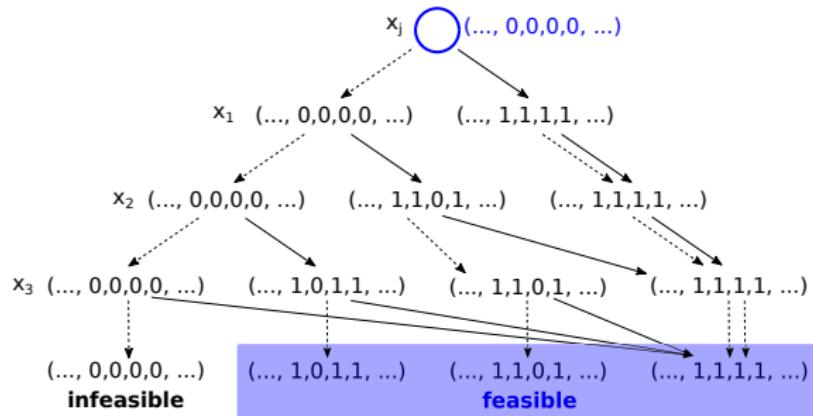
- S_j – adjacency lists,
- k_t – budgets,
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- x_i – location decisions.

How to build the cover BDD

Original graph:



Cover BDD:

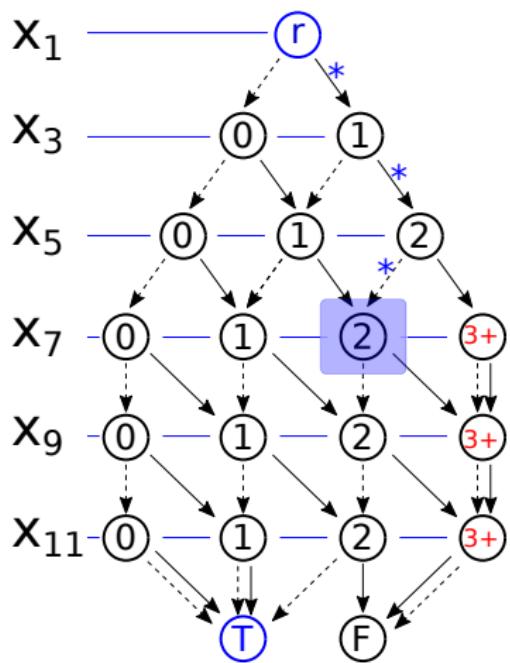


Building the diagram:

- Pick next point with the least “uncertainty”: # of neighbors to be added to the BDD,
- Process its adjacency list,
- Repeat.

How to build the type BDD

Part of Type BDD:



- Consider: $\sum_{j \in T} x_j \leq k$ for $T = \{1, 3, 5, 7, 9, 11\}$ and $k = 2$.
- Stack such blocks vertically.
- Minimize the number of inversions with the Cover BDD by choosing the order of variables within each block.
- Randomize the order of blocks.

Consistent Path Problem for t-UFLP

$$\begin{aligned}
 & \min \sum f_i v_{i, \text{HI}(i)}^C, \\
 \text{s.t.} \quad & \sum_{i: \text{HI}(i)=u \text{ or } \text{LO}(i)=u} v_{iu}^C = \sum_{j: \text{HI}(u)=j \text{ or } \text{LO}(u)=j} v_{uj}^C \text{ for all } u \in L_2^C \cup \dots \cup L_{(M-1)}^C, \\
 & \sum_{j: \text{HI}(r)=j \text{ or } \text{LO}(r)=j} v_{rj}^C = 1, \\
 & \sum_{j: \text{HI}(j)=u \text{ or } \text{LO}(j)=u} v_{ju}^C = 1 \text{ for } u \in \{\mathbf{T}^C, \mathbf{F}^C\}, \\
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 & v_{pq} \geq 0 \text{ for all valid } p, q; \quad x_i \in \{0, 1\}.
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Consistent Path Problem for t-UFLP

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 \end{aligned}$$

Approaches to solve the problem

- Simple MIP (with $x_i \in \{0, 1\}$ as decision variables),
- CPP + MIP (with continuous BDD flows + x_i as variables),
- CPP → Align-BDD → shortest-path (no binary variables!)

TODO Aligning BDDs

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BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

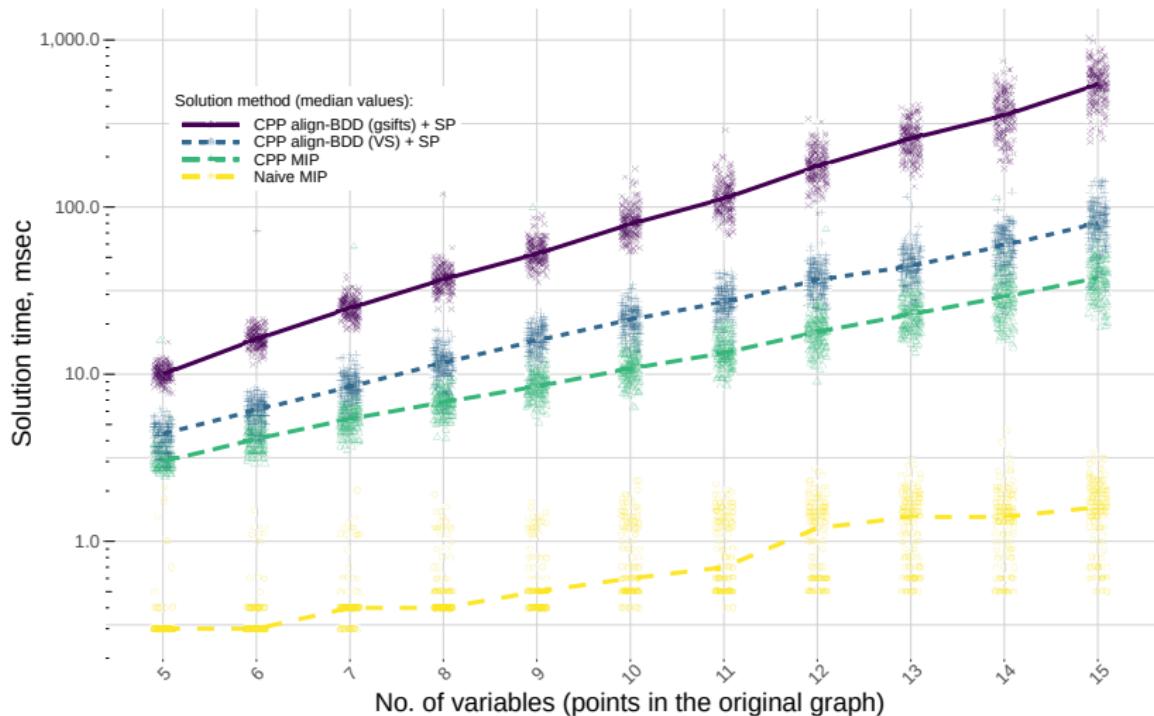
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TODO Conclusion

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Numerical experiments

Comparing runtimes (random instances)



TODO Aligning BDDs

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Numerical experiments

BDDs for t-UFLP

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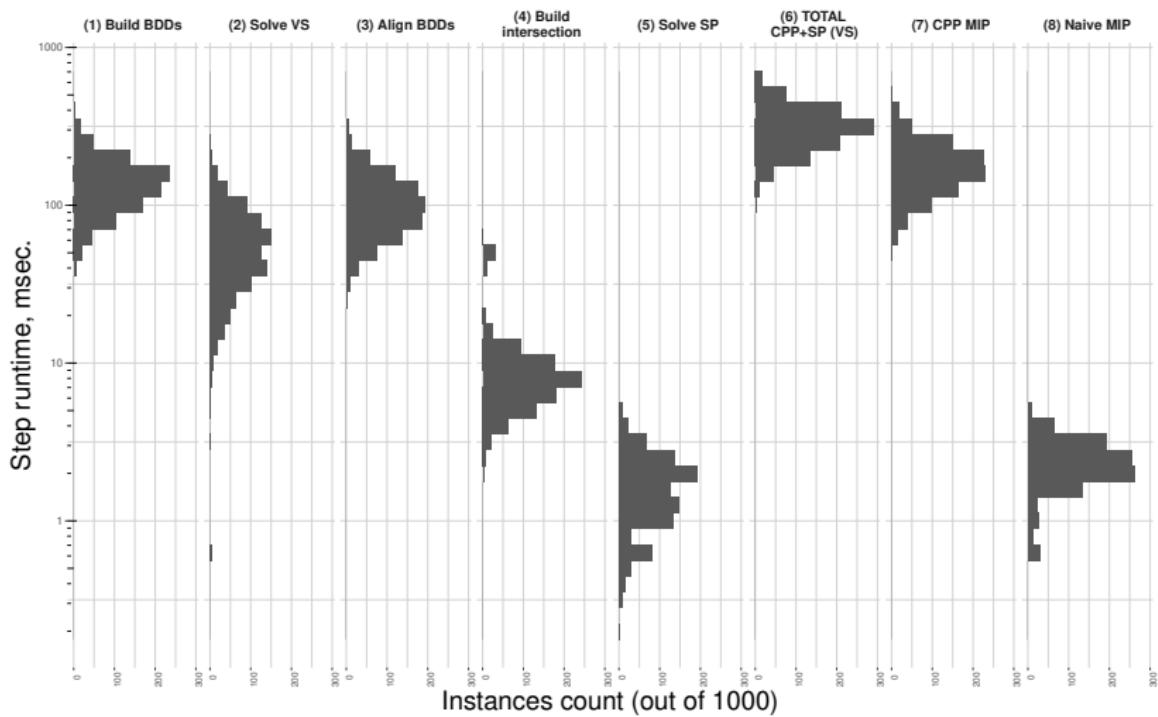
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Runtimes breakdown



TODO Aligning BDDs

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Numerical experiments

BDDs for t-UFLP

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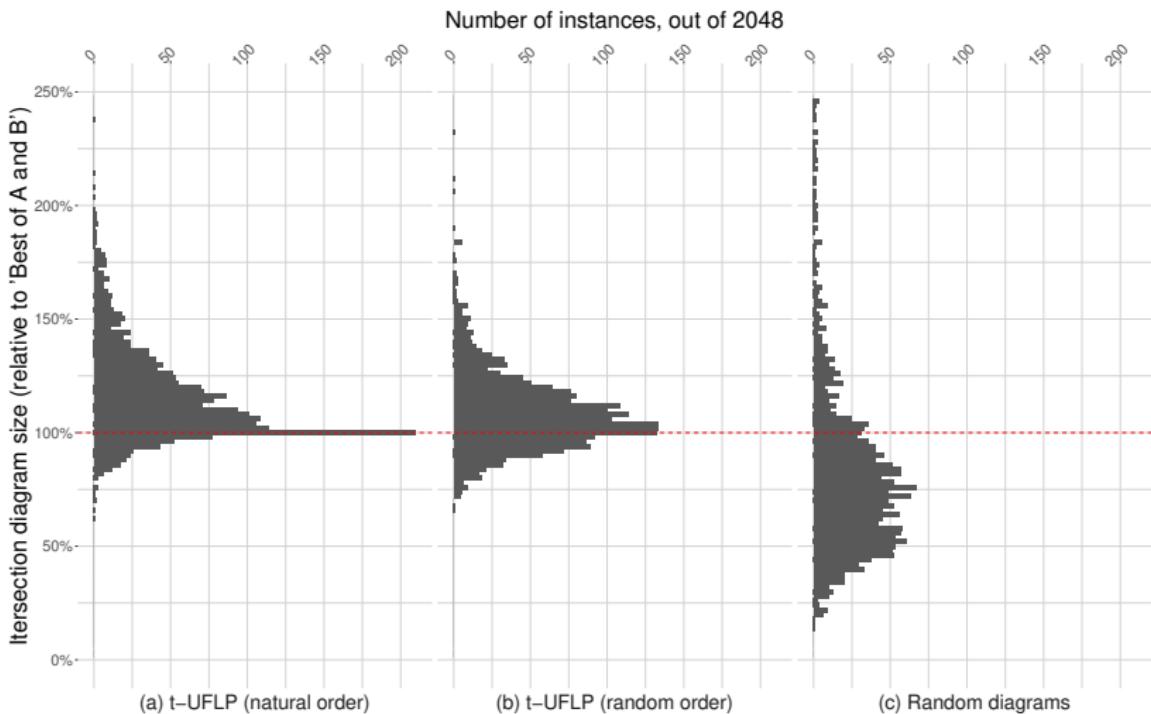
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Alignment heuristic performance vs. problem structure



Summary on t-UFLP

- present an illustration for the Align-BDD heuristic (simplified problem),
- introduce a problem, propose a CPP reformulation,
- apply the heuristic to align the diagrams and obtain an LP,
- demonstrate the runtimes in numerical experiments,
- highlight the limits / effects of the problem structure.

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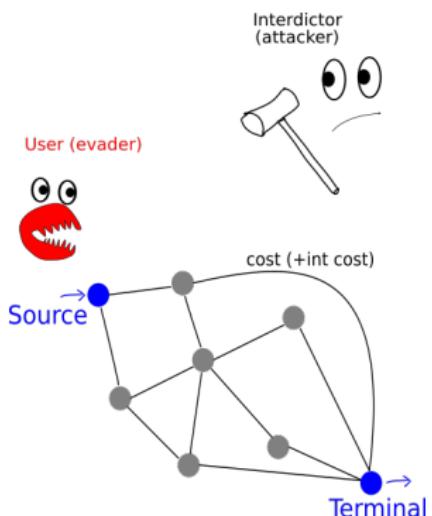
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A game of “interdiction”: intro



- **Network:** a directed graph with two special nodes (source \textcircled{S} and terminal \textcircled{T}), and a pair of "costs" associated to each edge.
- **User:** seeks to run through the graph, \textcircled{S} to \textcircled{T} , at min cost.
- **Attacker:** maximizes the User's cost by "attacking" the arcs, having a limited "budget".

We consider a **dynamic** version of the game, following [Sefair and Smith(2016)].
(NP-hard)

A game of “interdiction”: formulation

The Interdictor's optimal objective z^* can be expressed as:

$$z^*(S, i) = \max_{S' \subseteq \text{FS}(i) \setminus S : |S \cup S'| \leq b} \left\{ \min_{j \in \text{FS}(i)} \{z^*(S \cup S', j) + \tilde{c}_{ij}(S \cup S')\} \right\},$$

where:

- S : interdiction set,
- i : current Evader's node, $\text{FS}(i)$ – forward star of node i ,
- \tilde{c}_{ij} : arc traversal costs (given the interdiction),
- b : Interdictor's budget.

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Existing algorithms (by Sefair & Smith)

- polynomial DP algorithm for a DAG
- exact DP algorithm, exp time for general case.

Monte Carlo Tree Search

- Maintain the game tree,
- Try not to create all the nodes,
- Prune the definitely suboptimal ones,
- Drive the tree growth by a computationally cheap objective estimate (e.g., based on simulated games).

The “game tree”

Create a “game tree”, where **nodes** contain the following information.

- Current **status**

- $p(j) \in \mathcal{N}$: where is the Evader,
- $S_j \subseteq \mathcal{A}$: what is interdicted,
- $\tau(j)$: who's turn is it (Interdictor/Evader)

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- Possible further **development**
 - $\text{children}(j)$: child game tree nodes,
 - $\text{actions}(j)$: available actions.

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 - $\text{children}(j)$: child game tree nodes,
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 - Costs info, to drive the search and prune the tree
 - \hat{Q}_j : cost-to-go (starting from this node),
 - $LB(j)$, $UB(j)$: bounds on the true cost-to-go,
 - $N_j \in \mathbb{N}$: how many times the node was visited

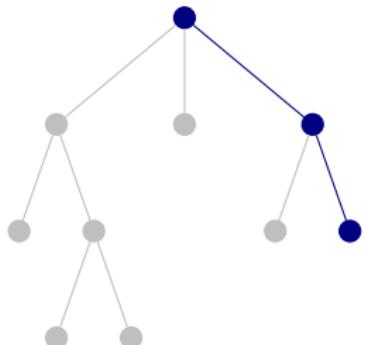
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So, we iterate through **episodes**, each one implying a “full cycle” of the game tree update in four **phases**.

Phase 1. Selection



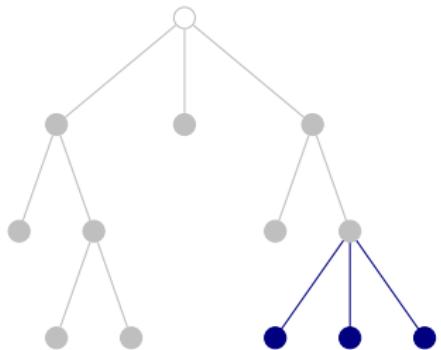
What's happening:

- Start at the root node,
- Use *tree policy* to choose the next node recursively...
- ... pruning nodes as we go, when possible ...
- ... until we reach a leaf.

What's updated:

- Nothing in the tree.
- Along the way: bounds for pruning (more momentarily!) + path costs.

Phase 2. Expansion



What's happening:

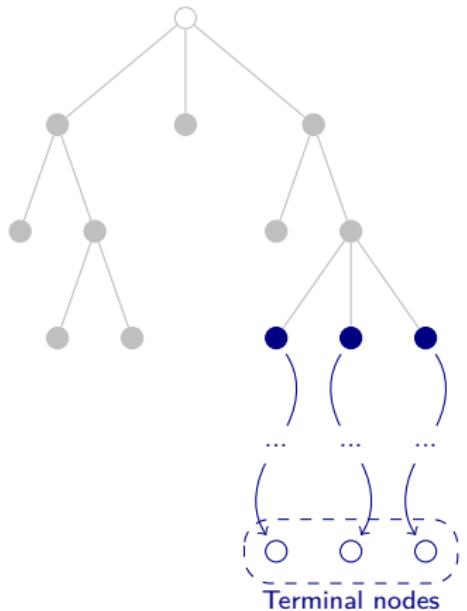
- Create child nodes for possible actions.

What's updated:

- New nodes are created,
- UBS and LBs are calculated

Note: Some inconsistencies can be introduced here, between child and parent nodes.

Phase 3. Roll-outs



What's happening:

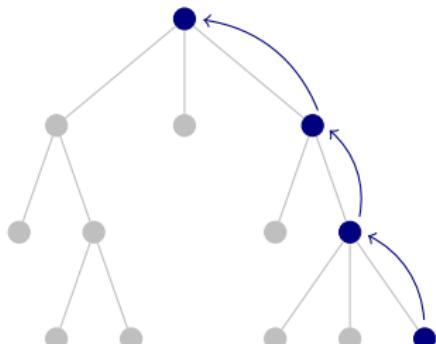
- Run a random simulated game from each node,
- Calculate cost-to-go estimate \hat{Q}_j as the simulated game cost.

What's updated

- Cost-to-go for each new node.

Note: We do not record the intermediate game states occurred during roll-outs!

Phase 4. Backpropagation



What's happening:

- Start at the selected node,
- Recursively update (“propagate”) node information for parents ...
- ... until we reach the root.

What's updated: Information in each parent node, using the child nodes:

- UBs and LBs
- Cost-to-go estimate: the best value (given the turn).

The Algorithm

The algorithm can perform actions for both players. Each turn involves two steps:

Step 1. THINK.

We iteratively improve the tree (while we have budget):

FOR $k = 1, \dots, K$ **DO**

- Selection
- Expansion
- Roll-outs
- Backpropagation

END.

Step 2. ACT.

... then pick an action corresponding to the “most attractive” child node of the root.

TODO Aligning BDDs

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MCTS framework

BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

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TODO Conclusion

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There are several secret ingredients



SI-1. How to select?

- **with probability** ε : choose at random;
- **otherwise**, a child node with the **best score**:

$$R_j = \underbrace{\sigma_i(\tilde{C}_{ij} + \hat{Q}_j)}_{\text{best cost-to-go}} + \underbrace{C_p \sqrt{\log(N_i)/N_j}}_{\text{encourage exploration}}, \quad \text{for all } j \in \text{children}(i)$$

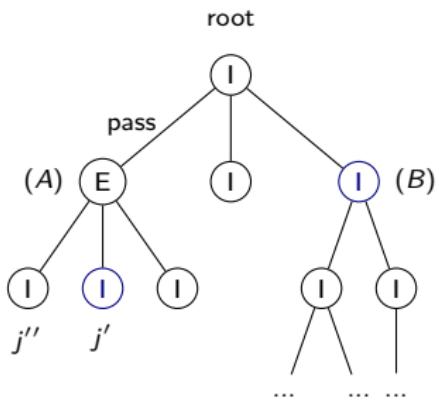
“Best” here depends on the turn (the Evader will choose the smallest cost estimate, the Interdictor — the largest).

SI-2. How to prune?

We leverage the classic idea of **alpha–beta pruning**:

Maintain two running numbers (bounds):

- α : the worst (minimum) alternative cost achievable by the Interdictor,
- β : the worst (maximum) alternative cost achievable by the Evader.



Pruning condition: $\beta \leq \hat{\alpha}_j$ or $\hat{\beta}_j \leq \alpha$, where

- $\hat{\alpha}_j = \pi_n + LB(j)$ (Interdictor's turns), and
- $\hat{\beta}_j = \pi_n + \widetilde{C}_{nj} + UB(j)$ (Evader's turns)

SI-3. How to back-propagate?

Assuming the Evader's turn, and i being the current game tree node:

- Update the bounds:

$$UB(i) \leftarrow \min_{j \in \text{children}(i)} \left\{ \tilde{C}_{ij}(S_i) + UB(j) \right\},$$

$$LB(i) \leftarrow \min_{j \in \text{children}(i)} \left\{ \tilde{C}_{ij}(S_i) + LB(j) \right\}.$$

- Update the cost-to-go estimate:

$$\hat{Q}_i \leftarrow \min_{j \in \text{children}(i)} \left\{ \tilde{C}_{ij}(S_i) + \hat{Q}_j \right\}.$$

SI-4. Bounds

Are inspired by Sefair & Smith 2016:

- **Lower bound:** restrict the **Attacker**. Make attacks “expire” after a single turn).
- **Upper bound:** restrict the **Interdictor**. Remove some arcs so that G is a DAG (\Rightarrow DSPI is simple to solve.) Repeat multiple times and choose the best bound.

Numerical experiments: strategy

- How does it perform on pre-defined instances? (relative to the known optimum, and to the bounds)
- How does it perform on randomly generated instances with different budgets?
- What's the dynamics of the tree construction? How does the algorithm work?
- What's the point of “playing out”, i.e., changing root nodes?

TODO Aligning BDDs

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Numerical experiments

BDDs for t-UFLP

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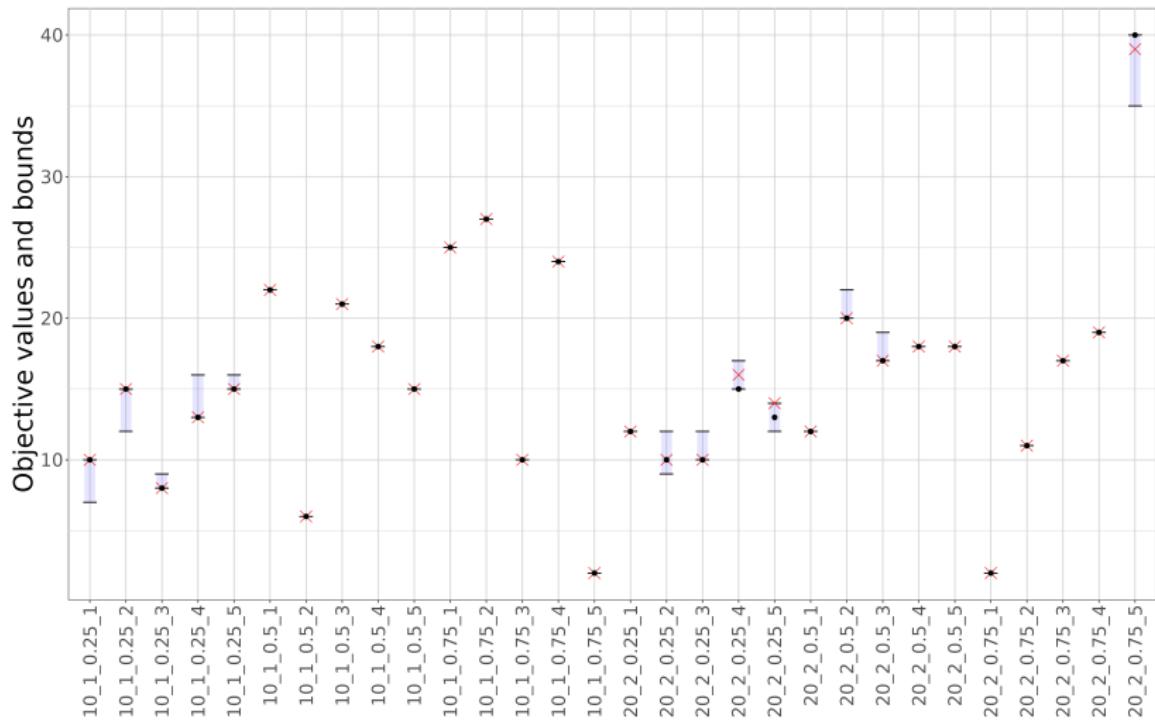
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Pre-defined instances



TODO Aligning BDDs

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BDDs for t-UFLP

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Monte Carlo Tree Search for DSPI

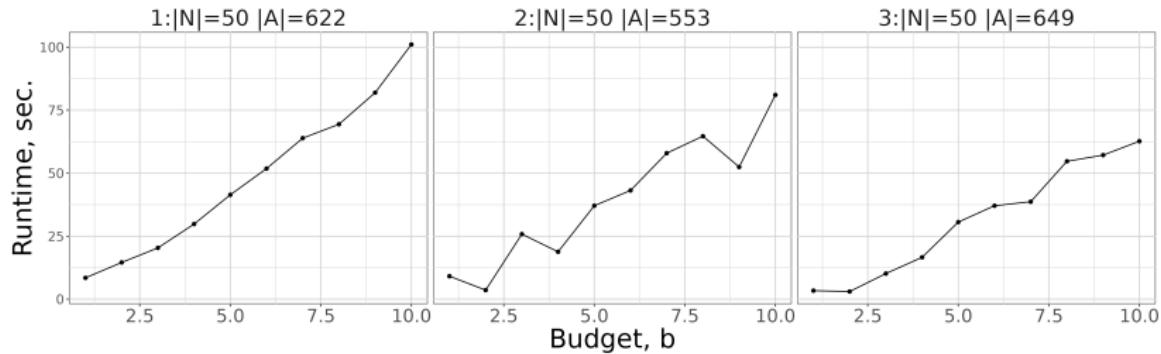
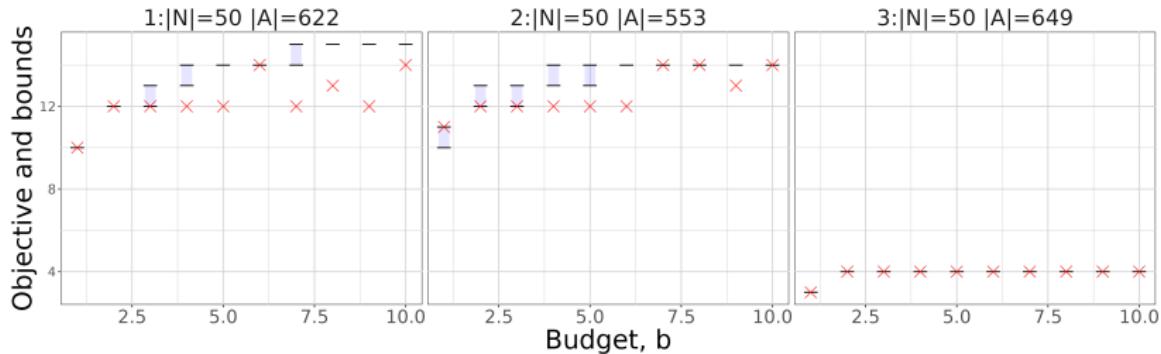
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TODO Conclusion

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Numerical experiments

Random instances (snapshot)



TODO Aligning BDDs

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Numerical experiments

BDDs for t-UFLP

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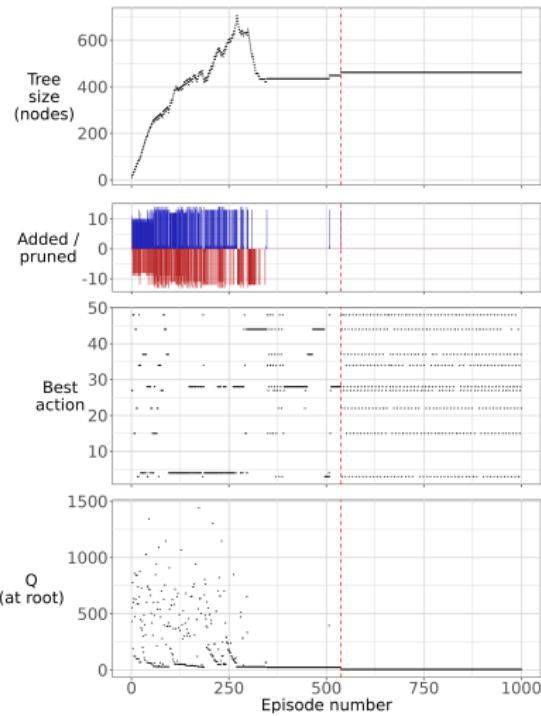
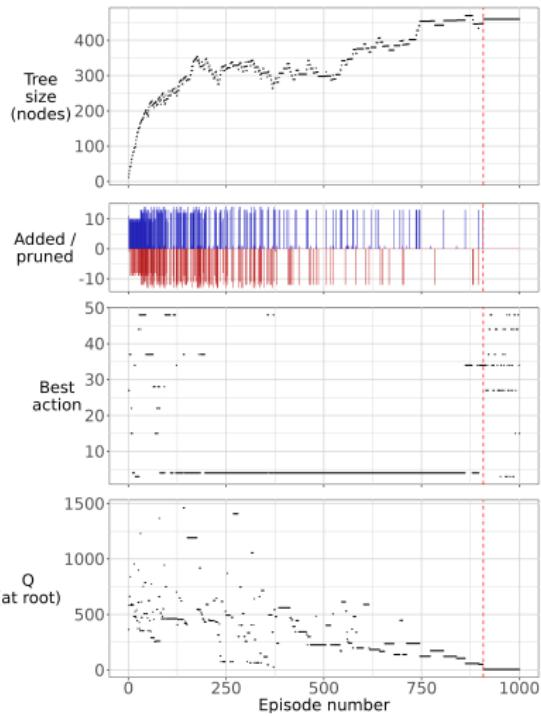
Monte Carlo Tree Search for DSPI

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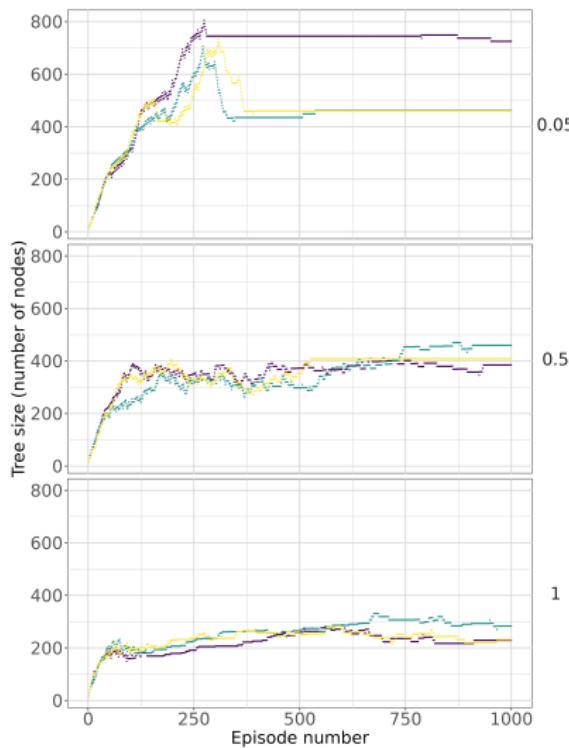
TODO Conclusion

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Convergence profiles

 $\varepsilon = 0.05$  $\varepsilon = 0.5$ 

A remark: that's not just different runs



For each value of ε (0.05, 0.5, and 1) we performed three runs, to confirm these are indeed different “modes” of the algorithm.

TODO Aligning BDDs

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Numerical experiments

BDDs for t-UFLP

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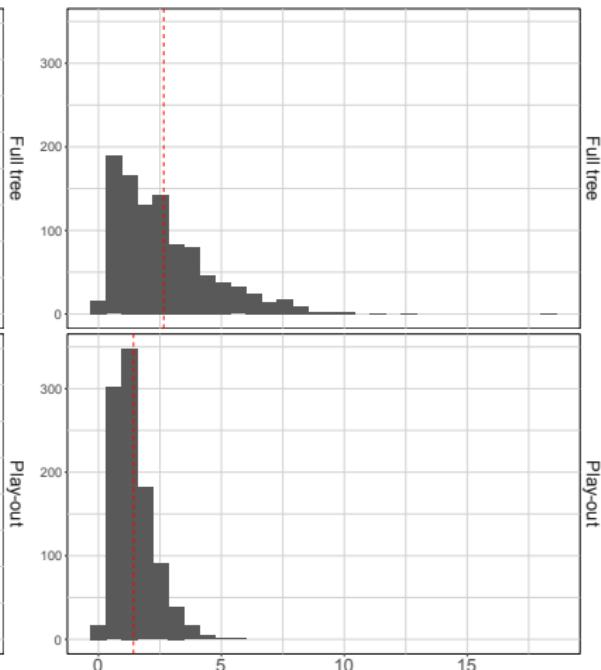
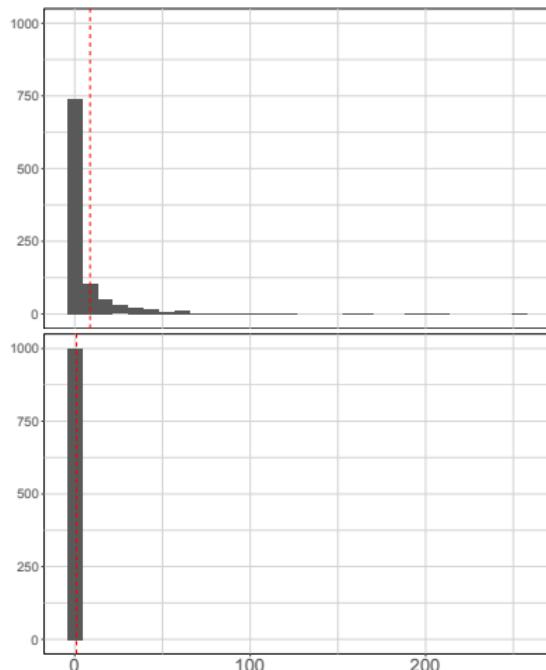
Monte Carlo Tree Search for DSPI

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TODO Conclusion

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Play-out vs. first-move strategy



Why does it work? (A sketch on “correctness”)

Theorem (Proposition)

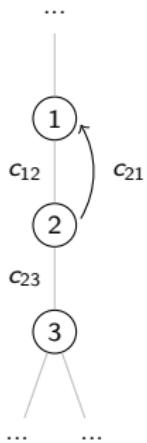
$$\lim_{k \rightarrow \infty} \mathbb{P}\{Q_{root}^k = \text{true optimum}\} = 1$$

A sketch of the proof:

- The game tree has finite number of nodes (there is a bound independent from K).
- We never cut off all the optima \Rightarrow the tree contains at least one.
- What is left is a finite-size minimax tree, containing an optimum.
- As $K \rightarrow \infty$, probability to select every node for expansion converges to 1.

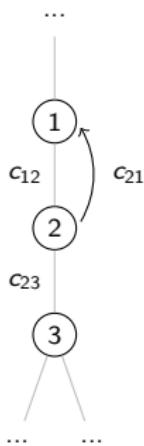
Why in the world the tree is finite?

Network:

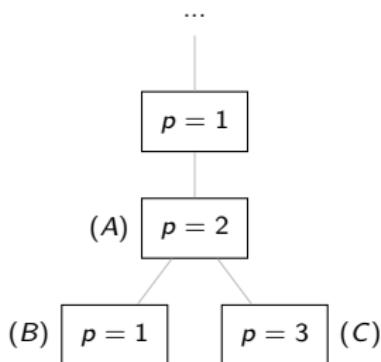


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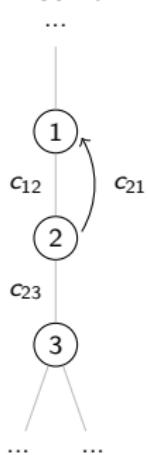
After the **first**
expansion:



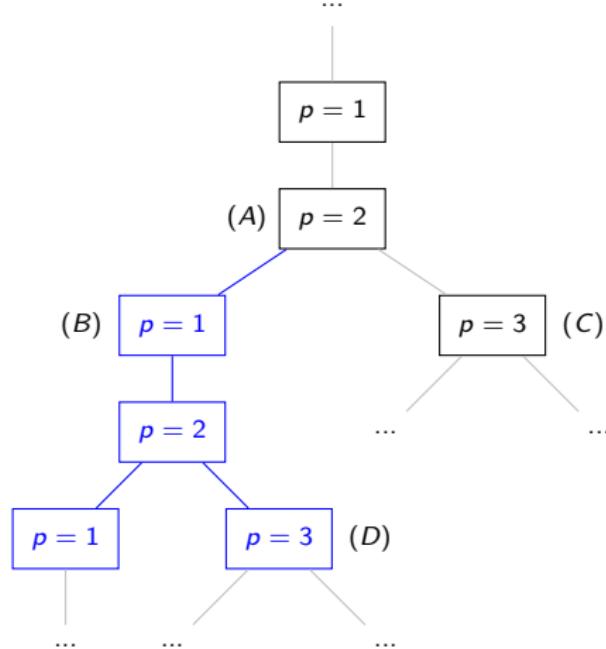
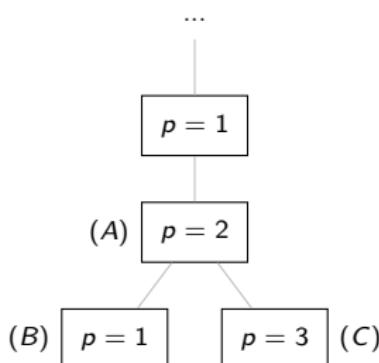
Why in the world the tree is finite?

After the **second** expansion:

Network:



After the **first** expansion:



Mentioned sources



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