

ANYTIME TREE SEARCH FOR COMBINATORIAL OPTIMIZATION

THESIS DEFENSE

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supervised by: **Louis Esperet, Thibault Honegger, Vincent Jost**

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EXAMPLE OF A COMBINATORIAL OPTIMIZATION PROBLEM

the Traveling Salesman Problem



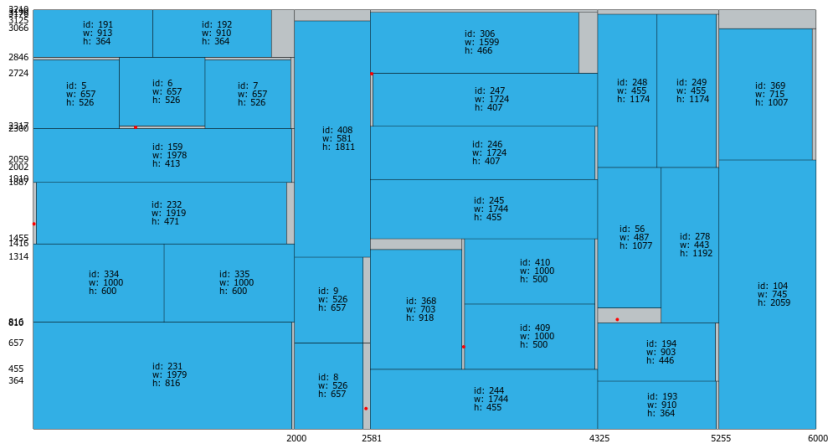
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ANOTHER EXAMPLE (GLASS WINDOW FACTORY)

Given some items, minimize the wasted area (bin packing variant)



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examples:

tabu search, evolutionary algorithms
ant colony optimization

from heuristic search / AI planning communities

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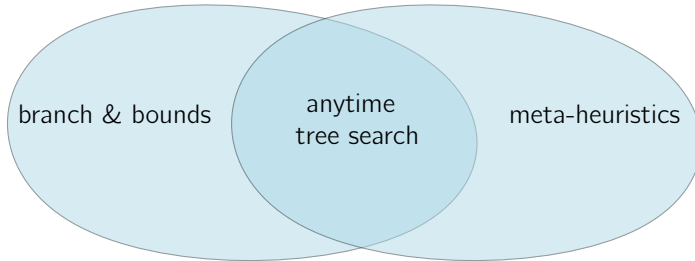
ANYTIME TREE SEARCH ALGORITHMS

from **heuristic search / AI planning** communities

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ANYTIME TREE SEARCH ALGORITHMS (CONT.)



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- and **guidance** strategies from meta-heuristics

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Not present in Operations Research

We study anytime tree search algorithms for classical OR problems

Anytime tree search algorithms

About the implementation

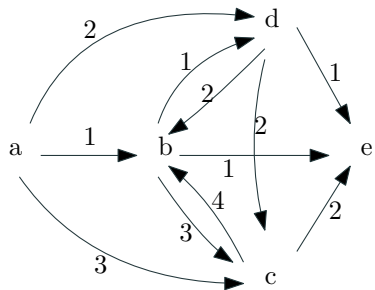
The sequential ordering problem

EURO/ROADEF challenge 2018

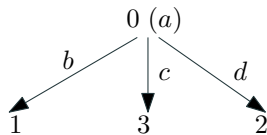
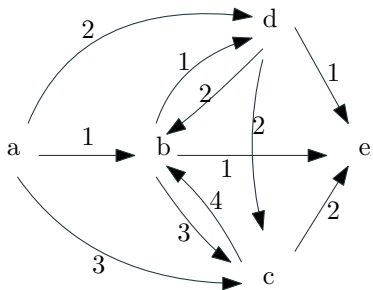
ANYTIME TREE SEARCH ALGORITHMS

EXAMPLE OF A BRANCH & BOUND

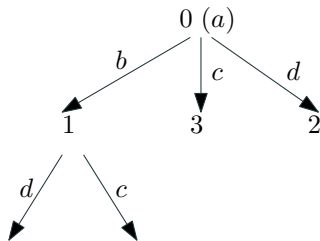
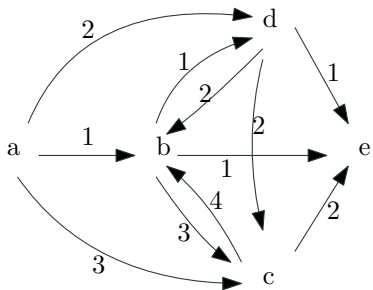
0 (a)



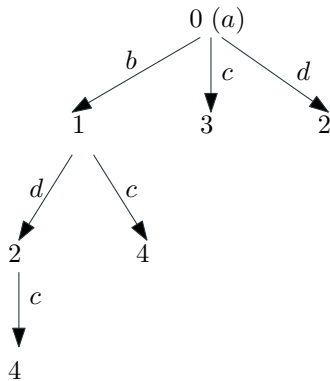
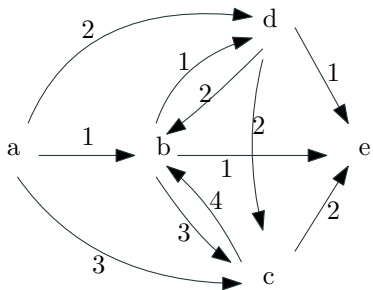
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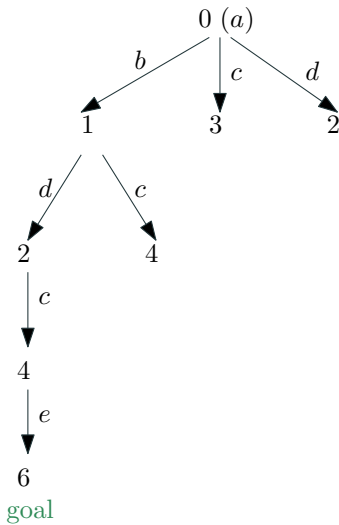
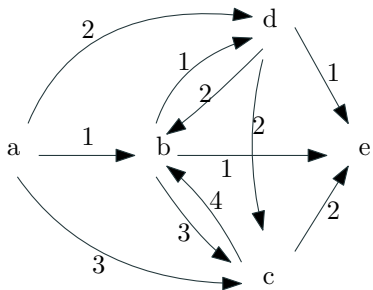
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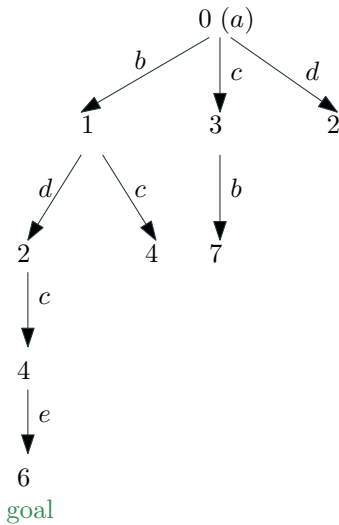
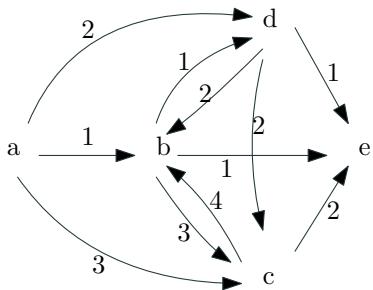
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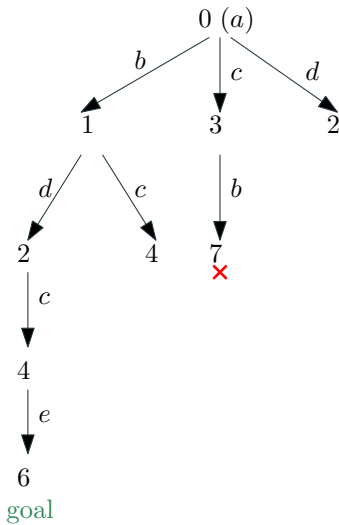
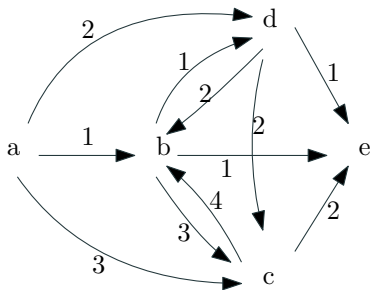
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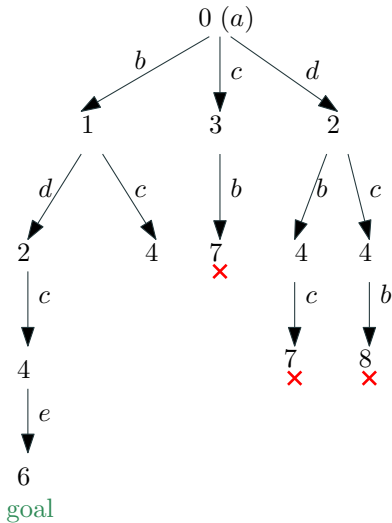
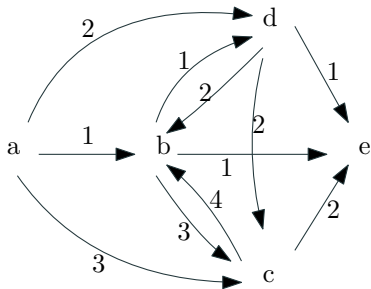
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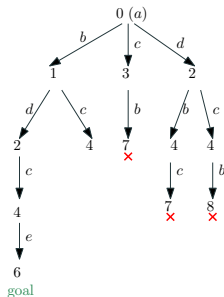
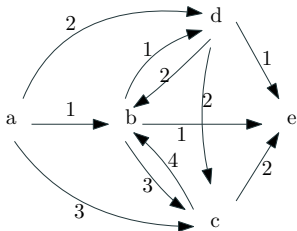
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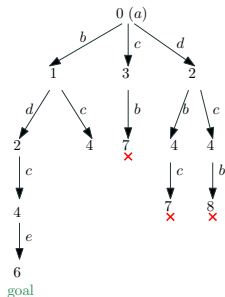
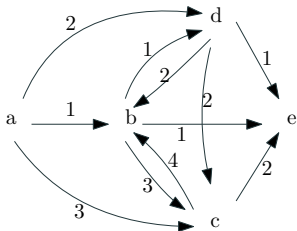


THE ALGORITHM-DESIGN METHODOLOGY



1. define the **search tree**
2. define a **bound** (or **guidance strategy**)

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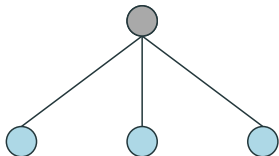


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3. **search** the resulting tree (generic part)

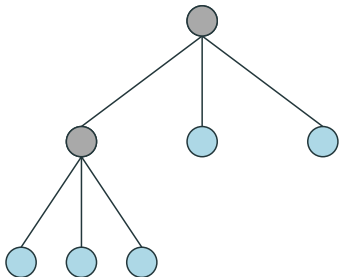
DEPTH FIRST SEARCH



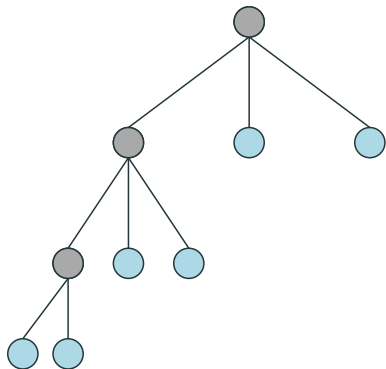
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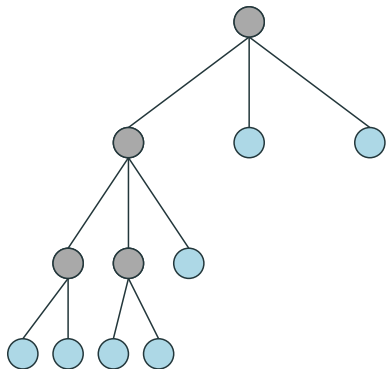
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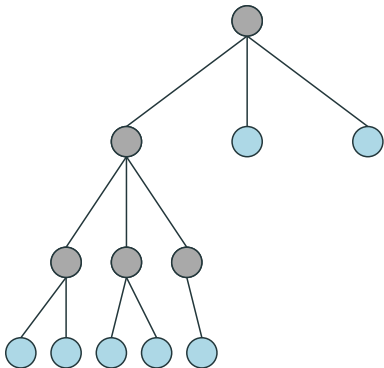
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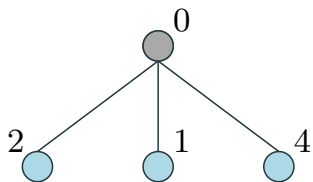
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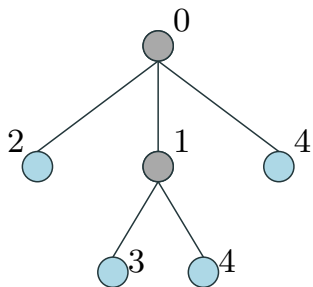


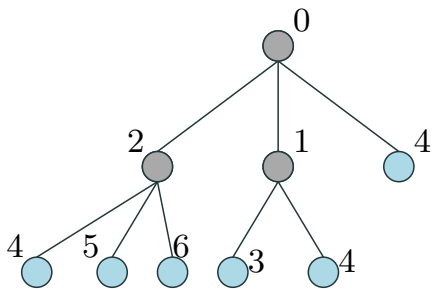
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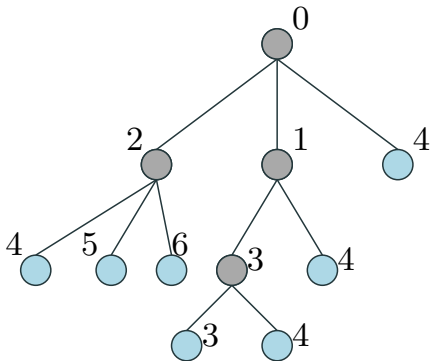




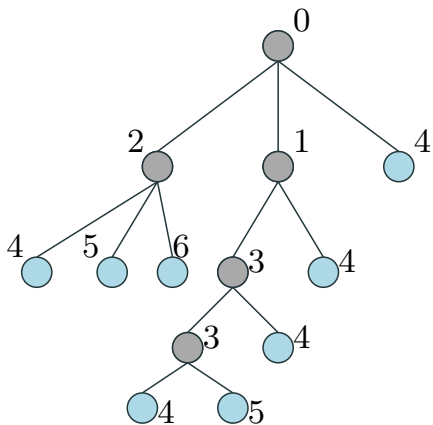




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ADVANTAGES AND DRAWBACKS

	Depth First Search	A*/Best First
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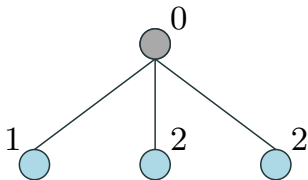
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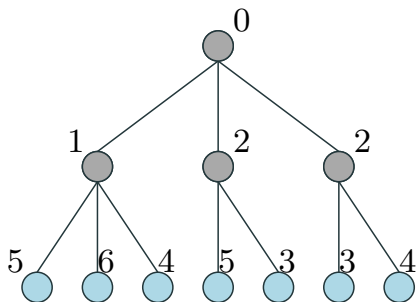
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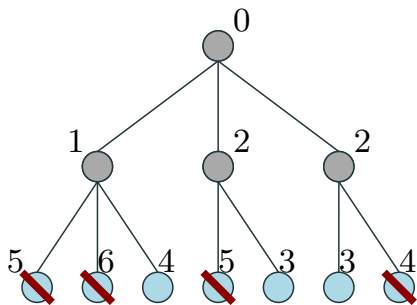
BEAM SEARCH (D=3)



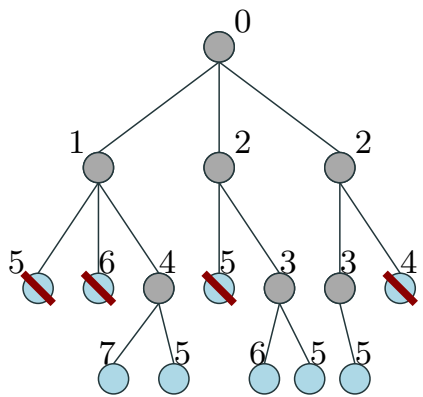
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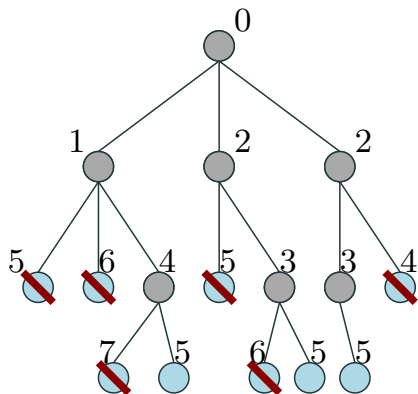
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- the algorithm may **open a node multiple times...**
- **but not that much** given some conditions (theorem)
- in average a node is reopened only once

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Thus, we believe it is an efficient strategy

ABOUT THE IMPLEMENTATION

Collaboration with Abdel-Malik Bouhassoun

A LARGE NUMBER OF TREE SEARCH ALGORITHMS

DFS, A*, Beam Search and many others...

- registering search statistics measuring

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- *etc.*

FOR A TOTAL OF...

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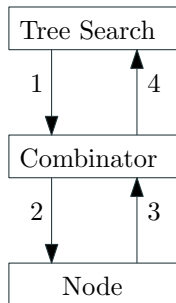
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we need a clever way to implement all of these variants

tree search algorithm



Problem specific tree





the CATS framework:
(COMBINATOR-BASED ANYTIME TREE SEARCH)



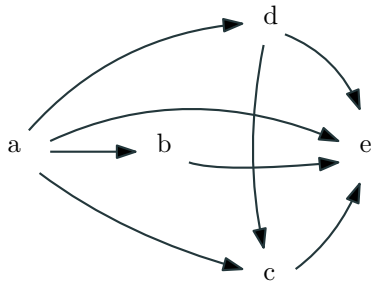
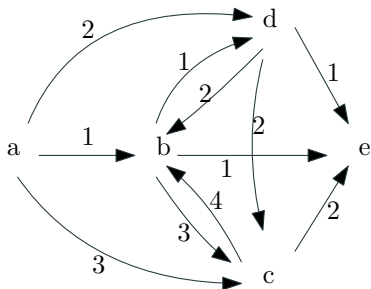
the CATS framework: (COMBINATOR-BASED ANYTIME TREE SEARCH)

- implemented in C++ (efficient)
- 15+ tree search algorithms
- 5 combinators
- GNU/GPL license

THE SEQUENTIAL ORDERING PROBLEM

Collaboration with Abdel-Malik Bouhassoun and Hadrien Cambazard

Asymmetric Traveling Salesman Problem with precedence constraints



- Standard benchmark, proposed in 2006 (“large” instances)

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- Some instances are almost precedence free
- Some are heavily constrained
- “in the middle” instances remain open (7 instances)

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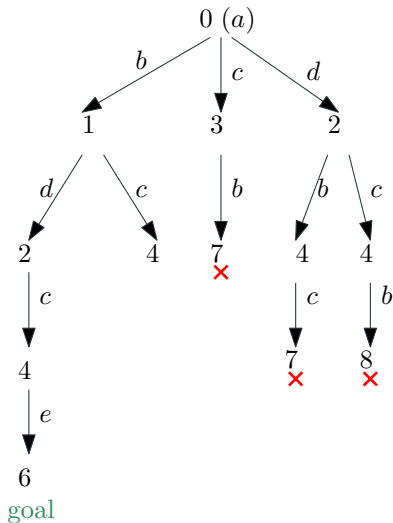
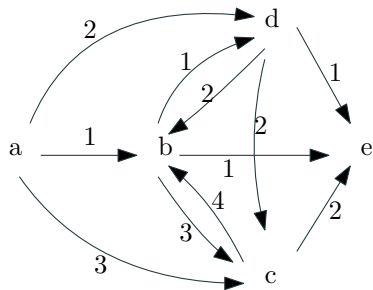
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- Exact methods tend to build stronger bounds
- meta-heuristics strongly rely on 3-opt (local search)

IMPLICIT TREE - FORWARD BRANCHING



Example, two equivalent partial solutions:

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2. **a,c,b,d** cost 12

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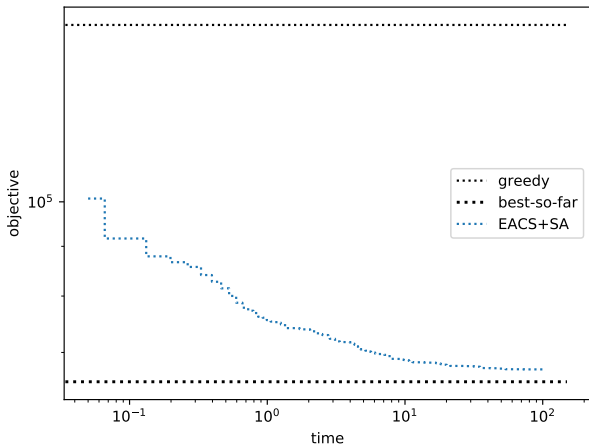
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Discard (2) as it is “dominated” by (1).

RESULTS - PERFORMANCE PROFILES ON R.700.1000.15

state-of-the-art:

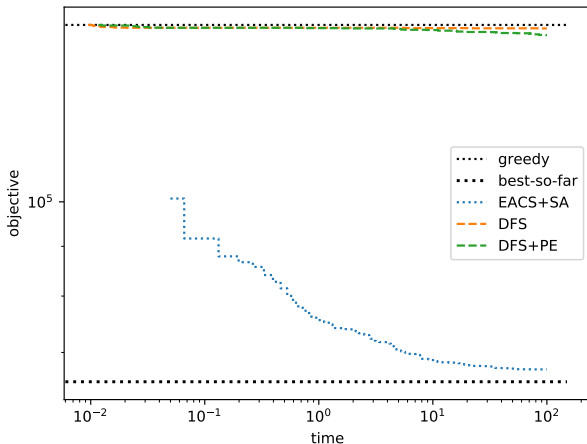
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- best-so-far LKH3 with 100.000 seconds run ($\approx 27\text{h}$)



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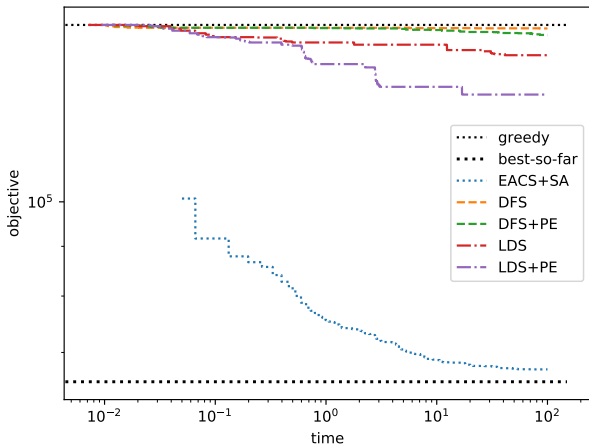
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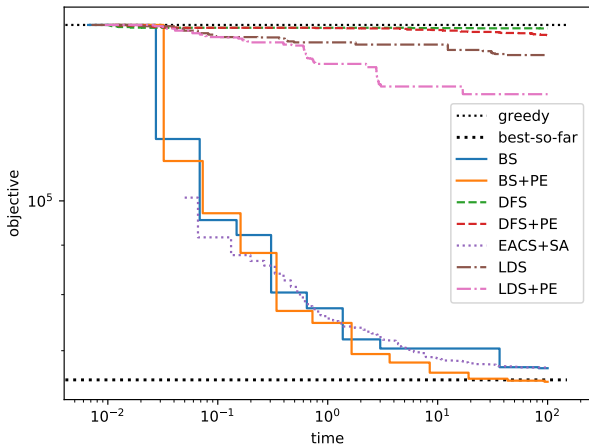
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RESULTS - NEW BEST-SO-FAR SOLUTIONS

6 over 7 new-best-so-far solutions
(the other one is probably optimal)

Instance	best known	BS+PE (600s)
R.500.100.15	5.284	5.261
R.500.1000.15	49.504	49.366
R.600.100.15	5.472	5.469
R.600.1000.15	55.213	54.994
R.700.100.15	7.021	7.020
R.700.1000.15	65.305	64.777

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1% precedence constraints: large search space and poor guidance

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The SOPLIB mainly contains heavily constrained instances:

- hard for MIPs and local searches
- but (relatively) easy for constructive algorithms
- **thus the need to consider anytime tree searches**

- The search-strategy choice is crucial

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- (cheap) search space reductions are useful

EURO/ROADEF CHALLENGE 2018

Collaboration with Florian Fontan

EURO/ROADEF CHALLENGE

Presented by the French and European *Operations Research* societies

International competition

A challenge every two years:

- 2012: Google
- 2014: SNCF
- 2016: Air Liquide

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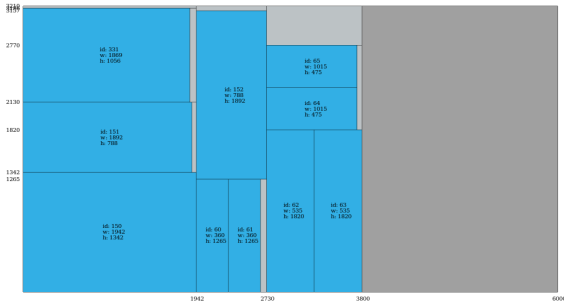
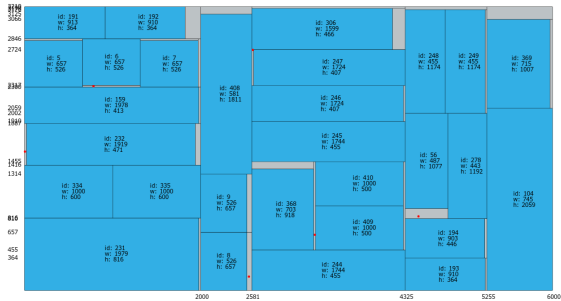
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ONE OF OUR SOLUTIONS



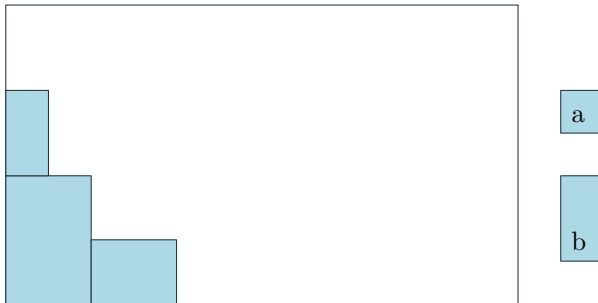
- Cutting & packing problem
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- with various constraints, some examples:
 - guillotine cuts
 - Defects
 - precedence constraints
- Large-size instances (up to 700 items)

PLACE ITEMS IN THE CORNER RULE

Called a “staircase” representation

Place a remaining item at a possible position



PLACE ITEMS IN THE CORNER RULE

Called a “staircase” representation

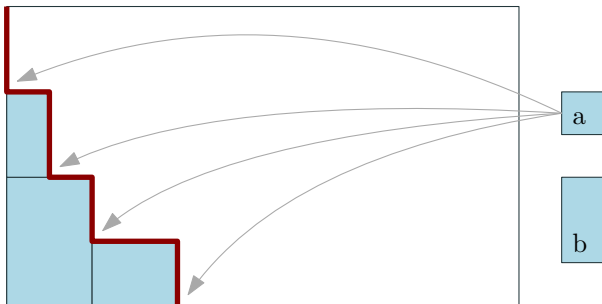
Place a remaining item at a possible position



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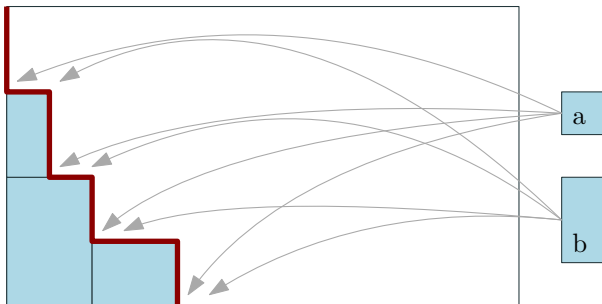
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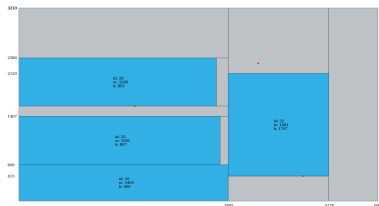
In this case, 8 children for this node

branch & bound ideas:

- (pseudo-)dominance rules
- symmetry-breaking rules

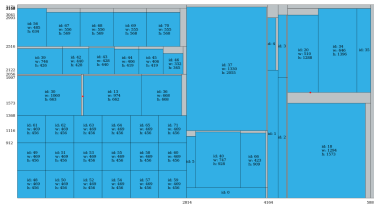
LET'S TALK ABOUT GUIDES (NODE GOODNESS MEASURE)

Which one should I keep?

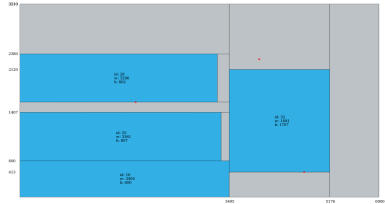
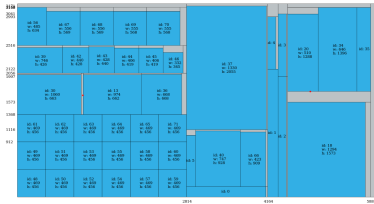


The less waste, the more attractive the partial solution

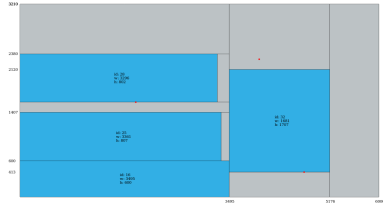
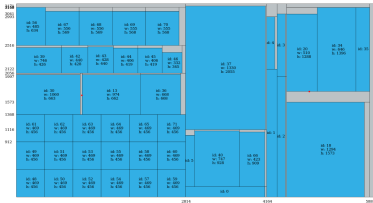
WHAT HAPPENS WHEN WE USE BOUNDS AS GUIDES



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Problem with waste:

- Small items at the beginning and big items at the end

HOW TO CORRECT THIS BIAS?

$$\frac{\text{waste percentage}}{\text{mean item area}}$$

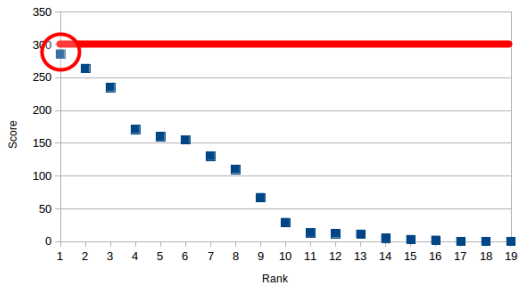
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cannot be used to prune nodes
Thus the need to separate the two concepts

- Variant of Iterative Beam Search
- replace the truncated BrFS by a truncated A*
- Called **Iterative MBA***

PERFORMANCE



- anytime tree search algorithm (IMBA*)
- combines exact-methods parts (dominances, *etc.*)
- **new “heuristic” guidance strategy**

These 3 components are required to provide a competitive algorithm.

- Study over many well-studied variants in the literature
- **large number of benchmarks (10+)**

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- and very competitive on other variants
- open-source software (PackingSolver)

BONUS

TREE SEARCH FOR OTHER PROBLEMS

Collaboration with Aurélien Secardin and Pablo Andres Focke

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- state-of-the-art (new best-known solutions on many instances)

Well studied problem ($F_m/permu/C_{max}$, and $F_m/permu/\sum C_j$)

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We present an **iterative beam search** (again):

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- **guidance strategy similar the LR greedy heuristic**
- state-of-the-art results on large VRF instances (makespan)
- state-of-the-art results on large Taillard instances (flowtime)

WRAPPING-UP

Benefits from a large variety of contributions:

- **exact methods** (search space reductions)
- **anytime tree search** (AI/planning)
- **meta-heuristics** (guide functions)

Simple and efficient anytime tree search algorithms applied on various problems:

- sequential ordering problem
- EURO/ROADEF challenge
- generalization to Cutting & packing
- longest common subsequence
- permutation flowshop

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- Learn guides automatically (ACO, Reinforcement Learning)

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- Learn guides automatically (ACO, Reinforcement Learning)
- More search-space reductions:
 - decision diagrams, ng-routes, etc.
 - MIP, CP

ANYTIME TREE SEARCH FOR COMBINATORIAL OPTIMIZATION

THESIS DEFENSE

presented by: **Luc Libralesso**

supervised by: **Louis Esperet, Thibault Honegger, Vincent Jost**

July, 24, 2020

G-SCOP, Grenoble, France

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Jan Gmys, Mohand Mezmaz, Nouredine Melab, and Daniel Tuyttens. A computationally efficient branch-and-bound algorithm for the permutation flow-shop scheduling problem. 284(3):814–833. ISSN 0377-2217. doi: 10.1016/j.ejor.2020.01.039. URL <http://www.sciencedirect.com/science/article/pii/S037722172030076X>.