Counterexample-guided Cartesian Abstraction Refinement and Saturated Cost Partitioning for Optimal Classical Planning

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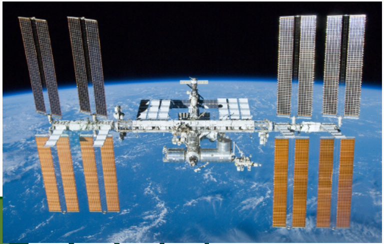
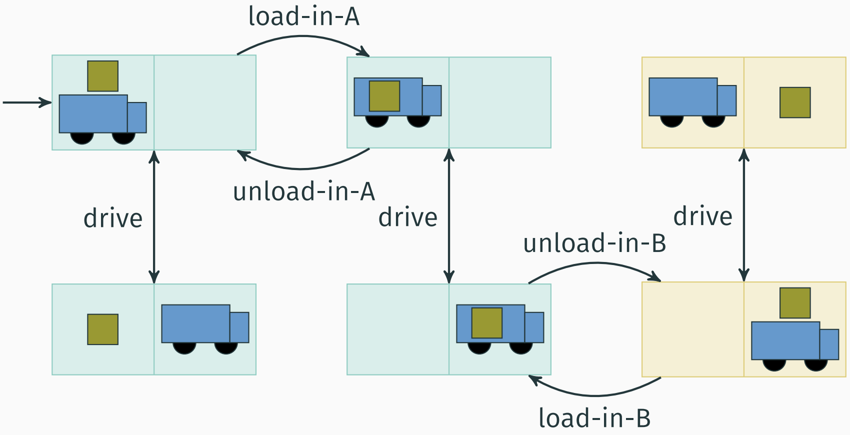
February 28, 2018

University of Basel

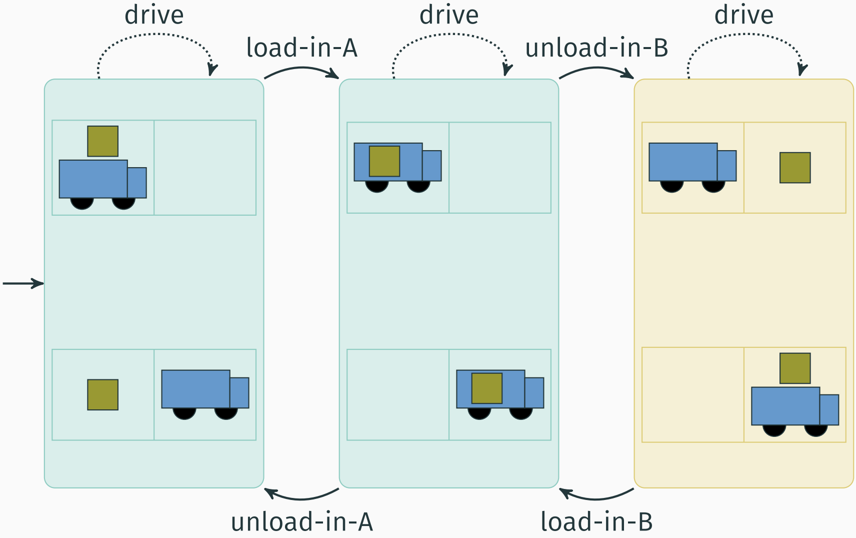
Planning



Find a sequence of actions that achieves a goal.


load-in-A
unload-in-A
drive
drive
drive
unload-in-B
load-in-B

Optimal Classical Planning: Example Abstraction



Abstraction Heuristics

- abstraction heuristics never overestimate $\rightarrow$ admissible
- A^* + admissible heuristic $\rightarrow$ optimal plan
- higher accuracy $\rightarrow$ better guidance

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- how to create abstractions?

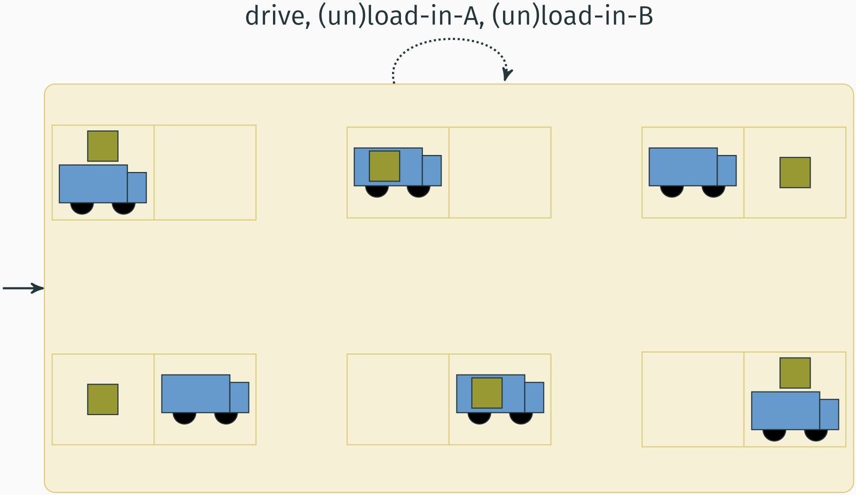
Counterexample-guided
Cartesian Abstraction Refinement

Counterexample-guided Abstraction Refinement (CEGAR)

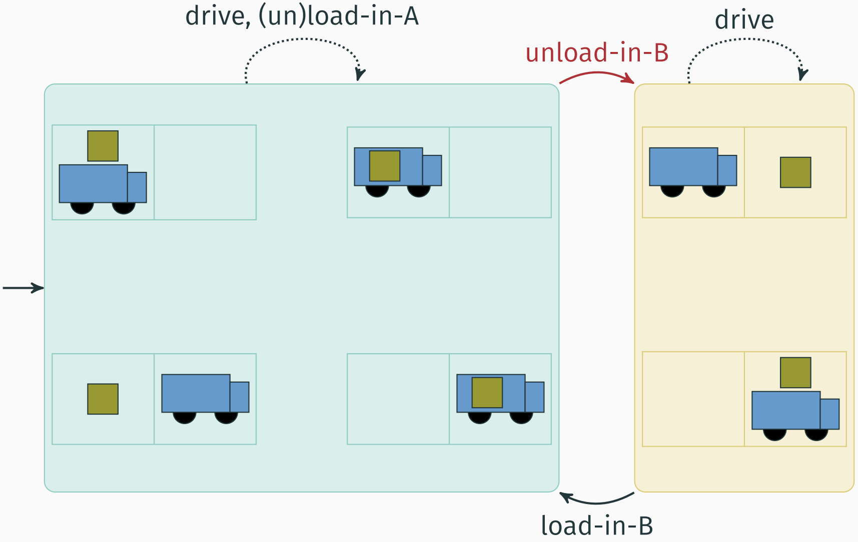
CEGAR Algorithm

- start with coarse abstraction
- until finding concrete solution or running out of time:
    - find abstract solution
    - check if and why it fails in the real world
    - refine abstraction

Example Refinement



Example Refinement



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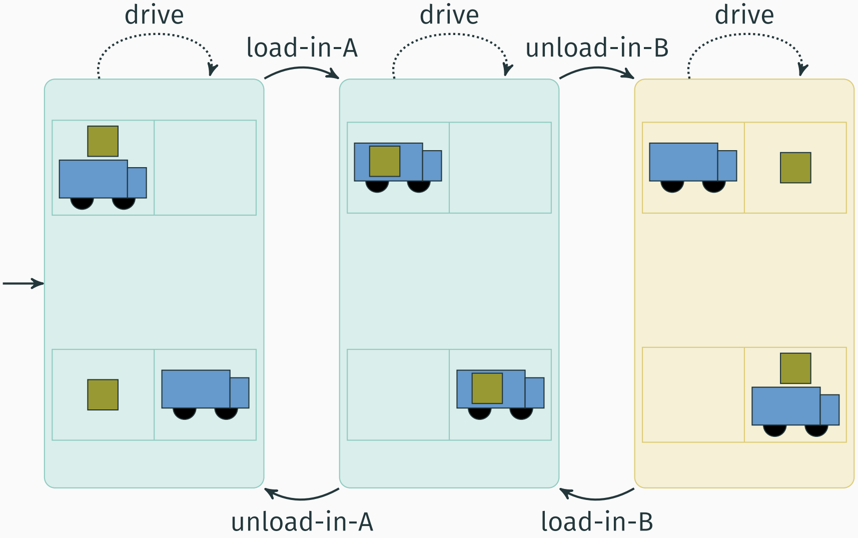
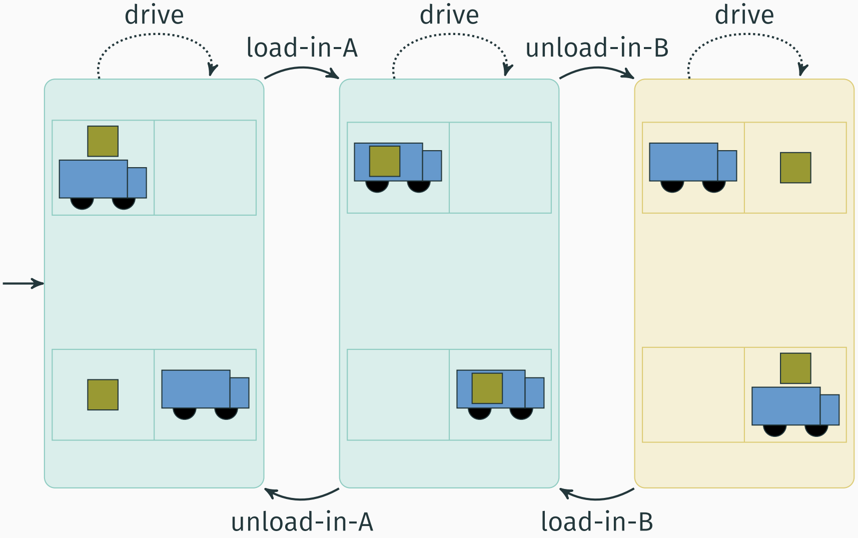


Classes of Abstractions

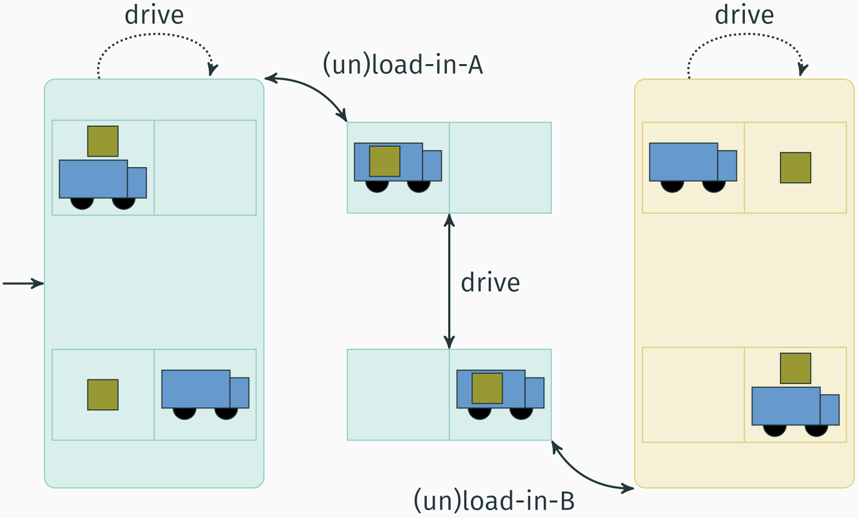
Cartesian Abstractions

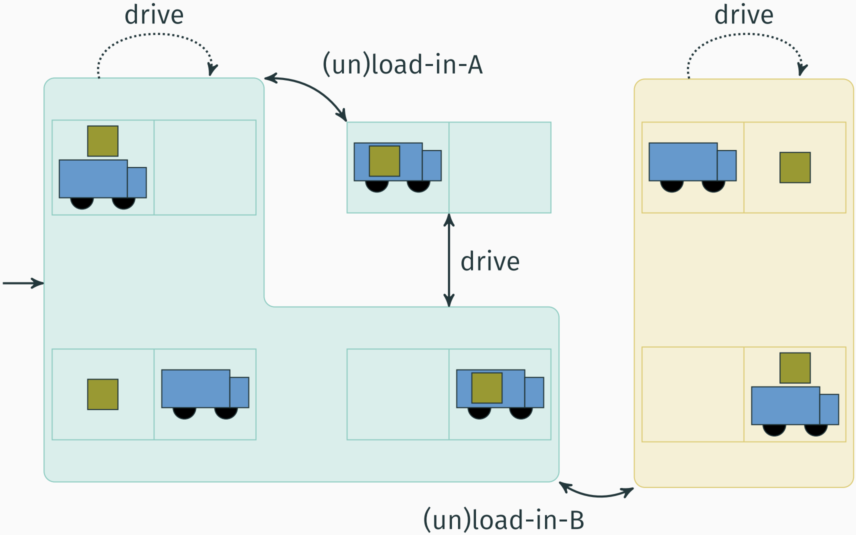
- relation to other classes of abstractions?

Projection (PDB)



Cartesian Abstraction

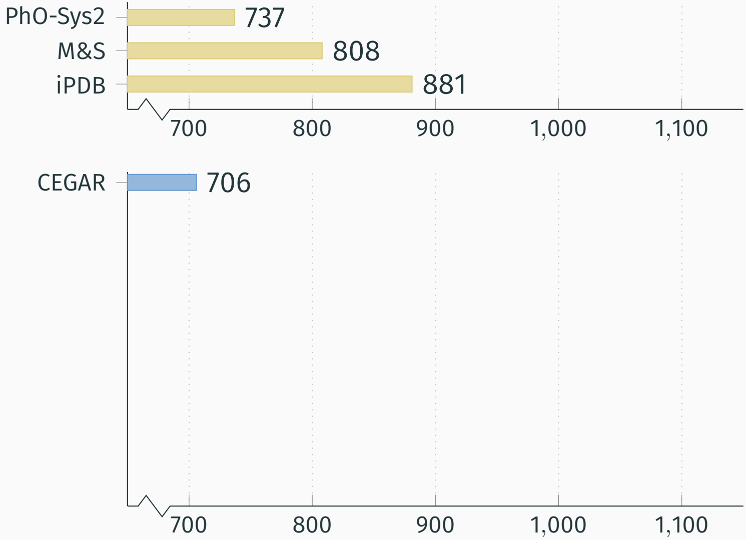



drive
(un)load-in-A
drive
drive
(un)load-in-B

Classes of Abstractions

- Projections (PDBs)
  refinement at least doubles number of states
- Cartesian Abstractions
  allow efficient and fine-grained refinement
- Merge-and-shrink Abstractions
  refinement complicated and expensive

Solved Tasks



CEGAR Drawbacks

Diminishing Returns

- finding solutions takes longer
- heuristic values only increase logarithmically

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Diminishing Returns

- finding solutions takes longer
- heuristic values only increase logarithmically

$\rightarrow$ multiple smaller abstractions

Task Decomposition by Goals

- build abstraction for each goal fact

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- problem: tasks with single goal fact

Task Decomposition by Landmarks

- build abstraction for each fact landmark

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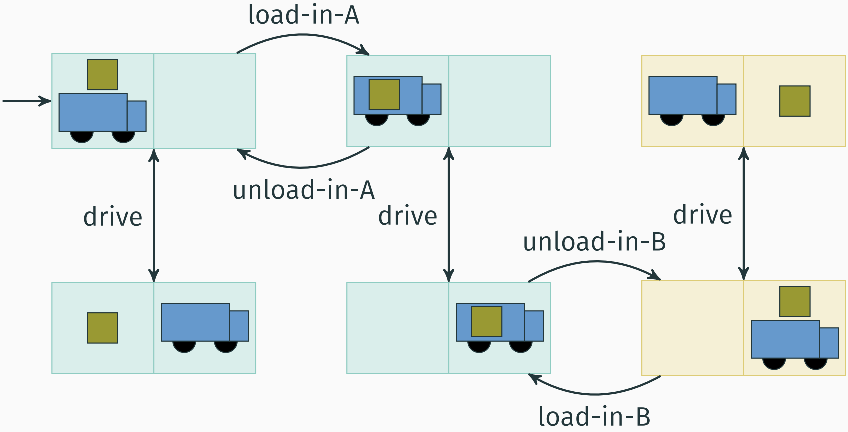

how to combine multiple heuristics?

Multiple Heuristics

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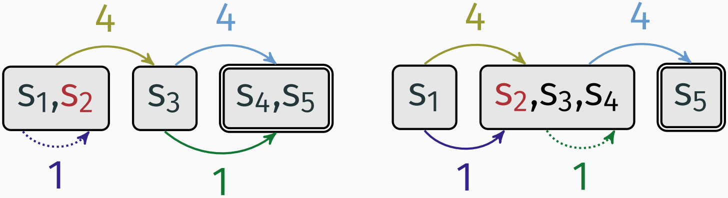
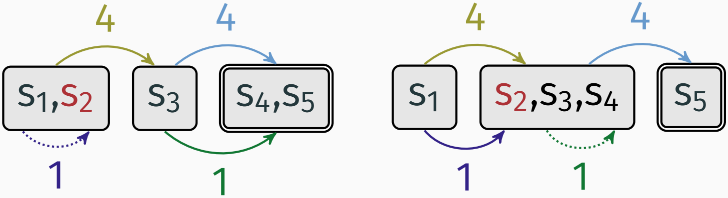


Multiple Heuristics

how to combine multiple heuristics?

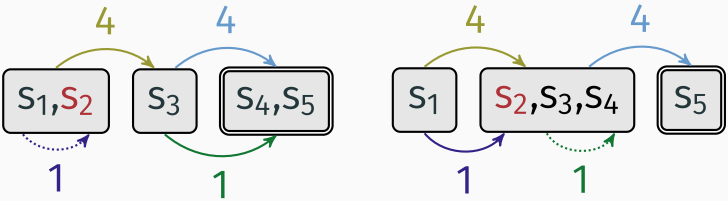


$h_1(s_2) = 5$

$h_2(s_2) = 4$

Multiple Heuristics

how to combine multiple heuristics?

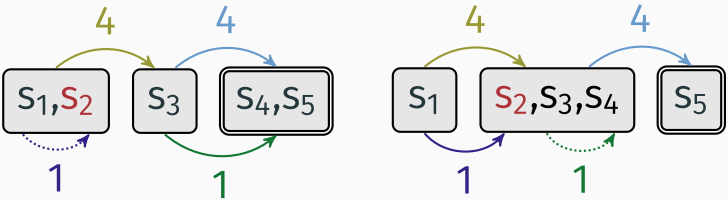


$h_1(s_2) = 5$ $h_2(s_2) = 4$

maximize over estimates:

- $h(s_2) = 5$

how to combine multiple heuristics?



$h_1(s_2) = 5$

$h_2(s_2) = 4$

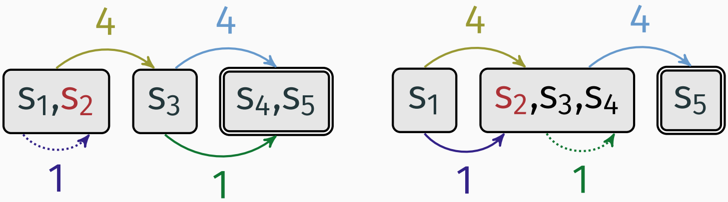
maximize over estimates:

- $h(s_2) = 5$
- only selects best heuristic
- does not combine heuristics

Multiple Heuristics: Cost Partitioning

Cost Partitioning

- split operator costs among heuristics
- sum of costs must not exceed original cost



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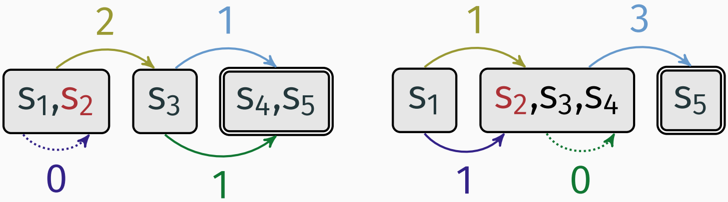

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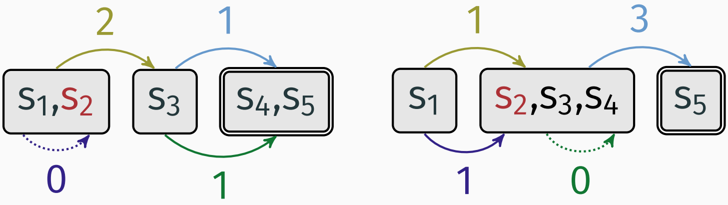
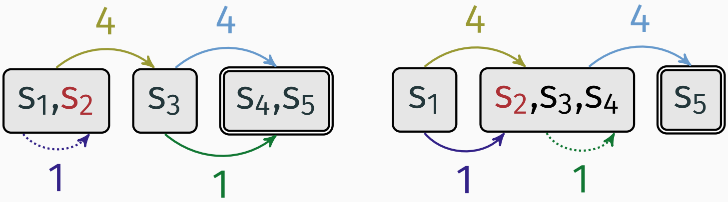


$$h(s_2) = 3 + 3 = 6$$

Saturated Cost Partitioning

Saturated Cost Partitioning Algorithm

- order heuristics, then for each heuristic h:
    - use minimum costs preserving all estimates of h
    - use remaining costs for subsequent heuristics



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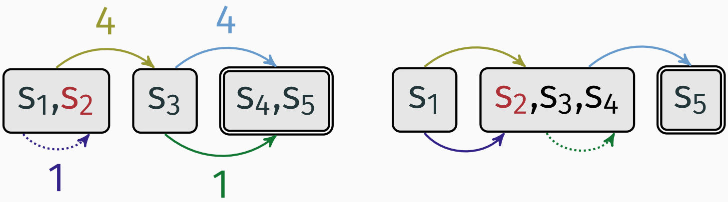

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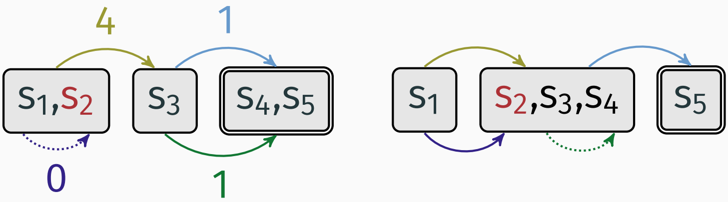

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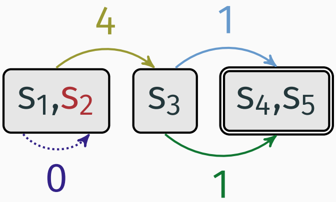

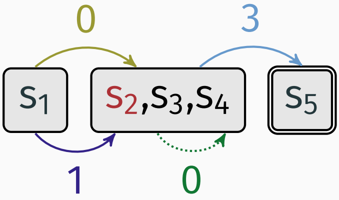

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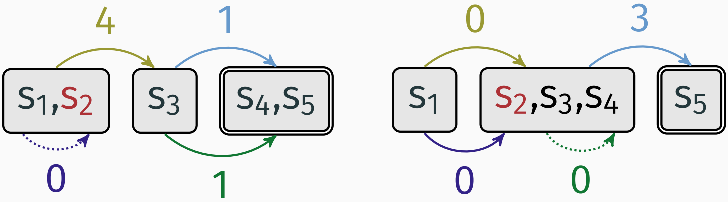

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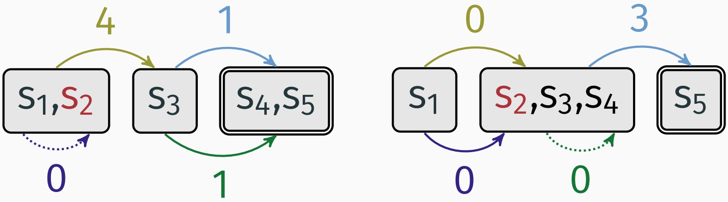
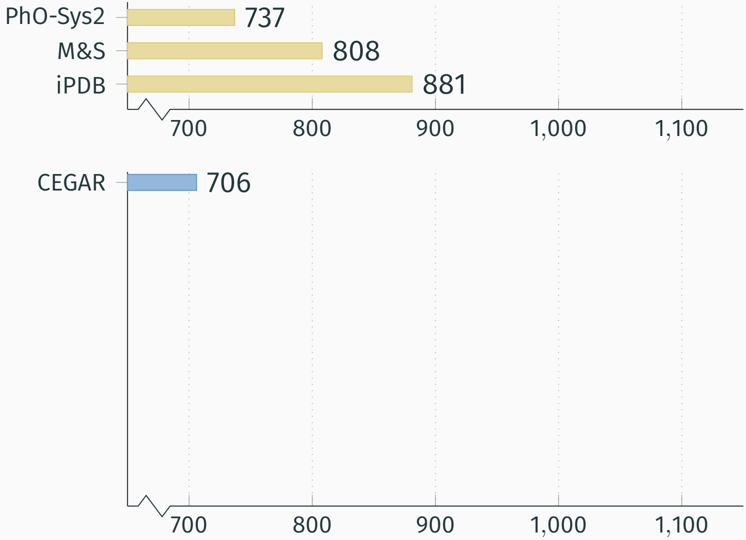


$$h(s_2) = 5 + 3 = 8$$

Solved Tasks



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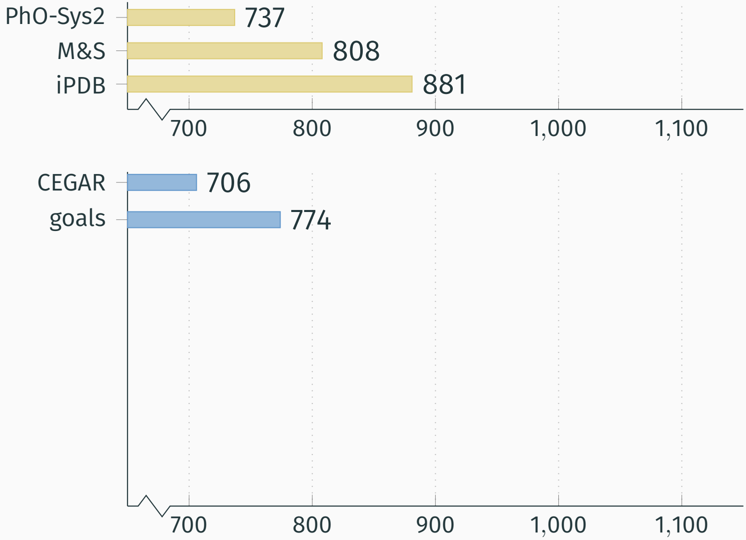

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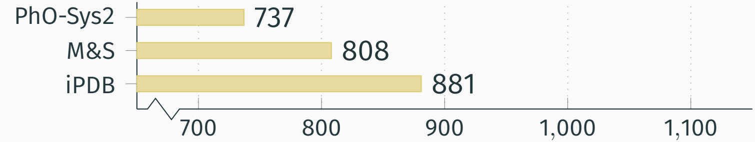

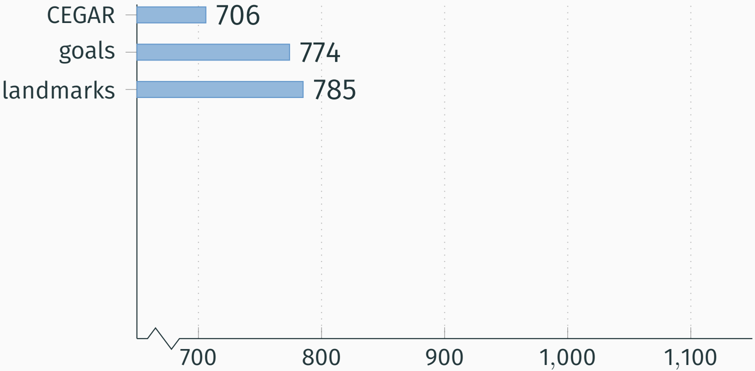

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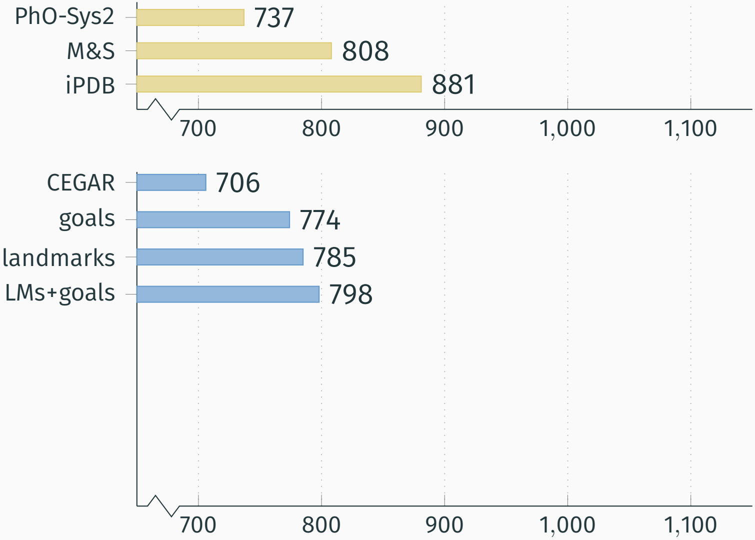
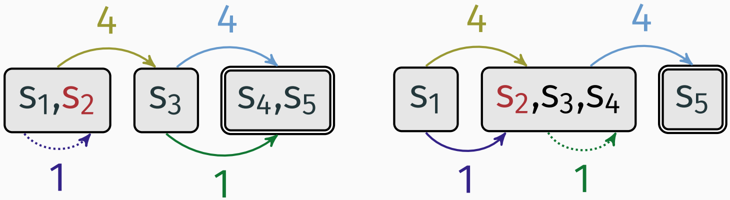


Order of Heuristics Is Important



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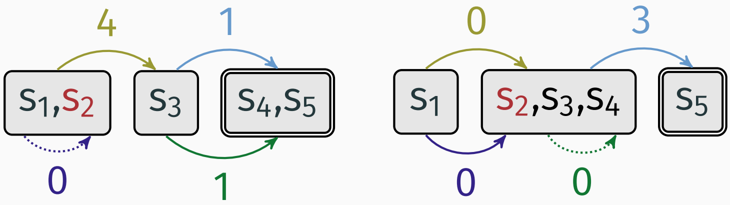
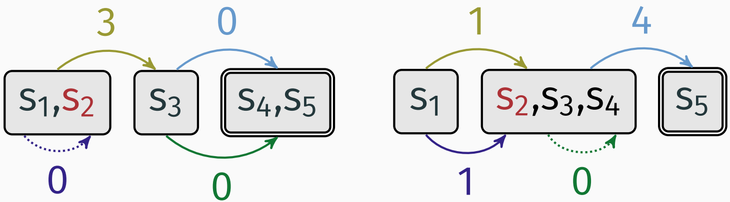


$$h^{\mathrm{SCP}}_{\rightarrow}(s_2) = 5 + 3 = 8$$

Order of Heuristics Is Important



$$h^{\mathrm{SCP}}_{\rightarrow}(s_2) = 5 + 3 = 8$$

$$h^{\mathrm{SCP}}_{\leftarrow}(s_2) = 3 + 4 = 7$$

Finding a Good Order

- n heuristics $\rightarrow$ n! orders

Finding a Good Order

- n heuristics $\rightarrow$ n! orders

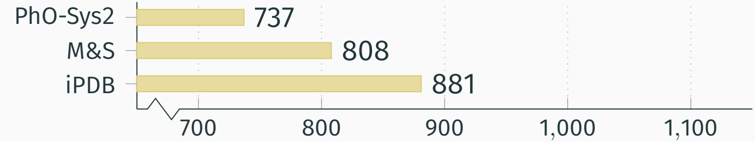
$\rightarrow$ search for good order: greedy initial order + optimization

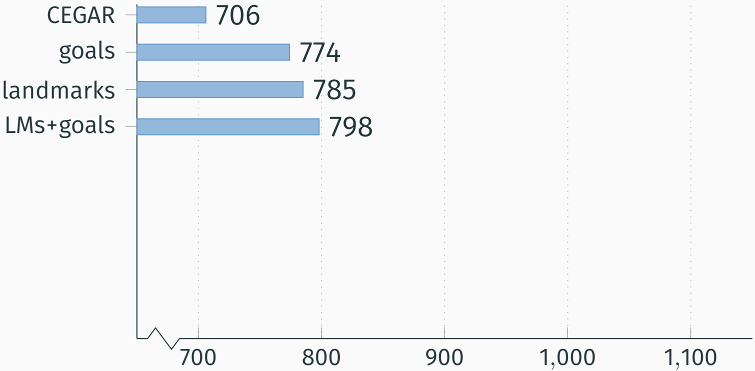
Goal: high estimates and low costs

Greedy Orders

Goal: high estimates and low costs
$\rightarrow$ order by heuristic/costs ratio

Solved Tasks





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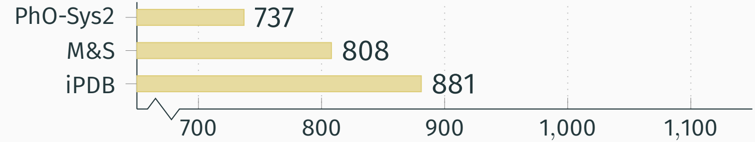
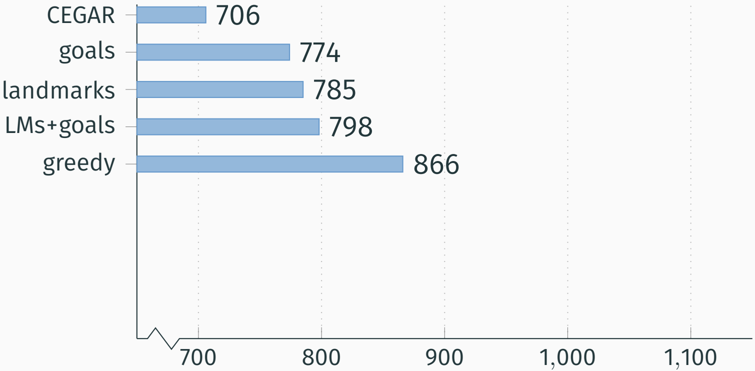




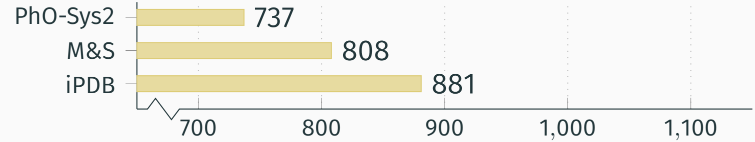
Optimized Orders

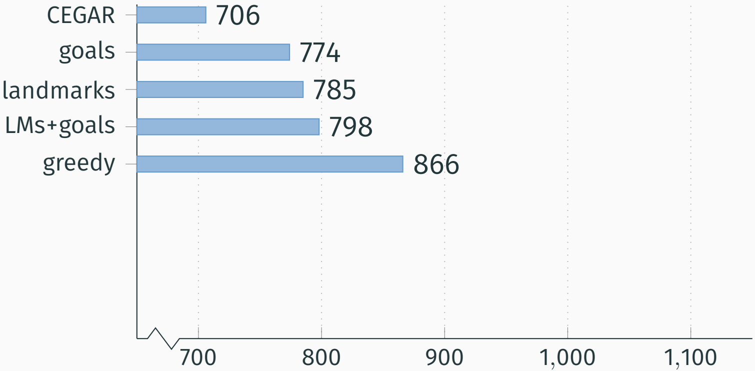
Optimization: finding initial order usually only first step

Hill-climbing Search

- start with initial order
- until no better successor found:
  - switch positions of two heuristics
  - commit to first improving successor

Solved Tasks





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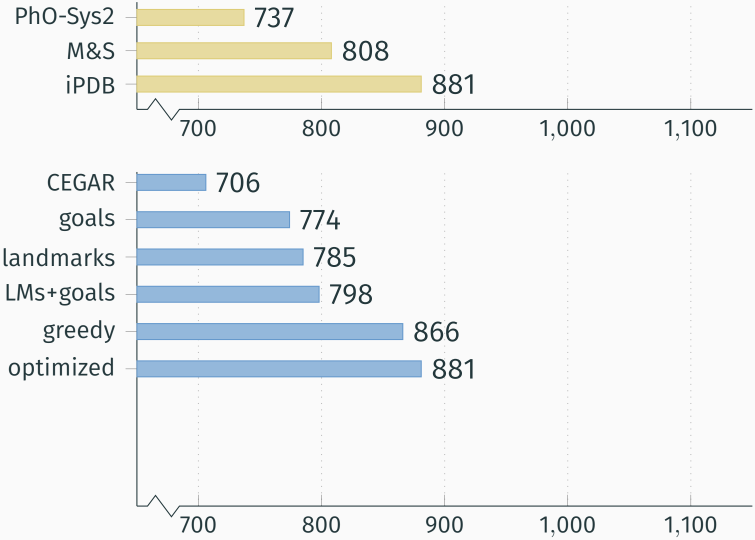
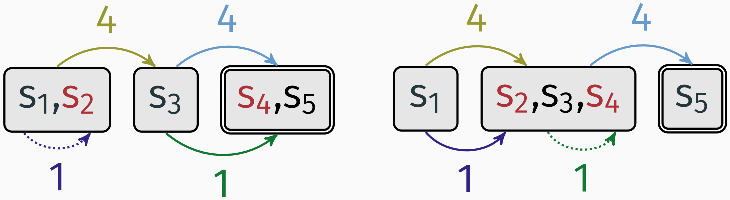


One Order Is Not Enough



$$h^{SCP}_{\rightarrow}(s_2) = 8$$
$$h^{SCP}_{\leftarrow}(s_2) = 7$$

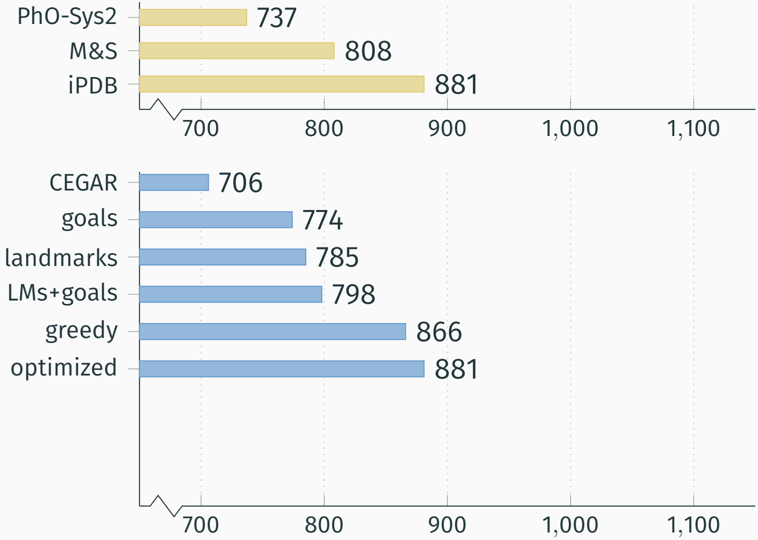
$$h^{SCP}_{\rightarrow}(s_4) = 3$$
$$h^{SCP}_{\leftarrow}(s_4) = 4$$

Multiple Orders

Approach:

- compute saturated cost partitioning for multiple orders
- maximize over heuristic estimates

Solved Tasks



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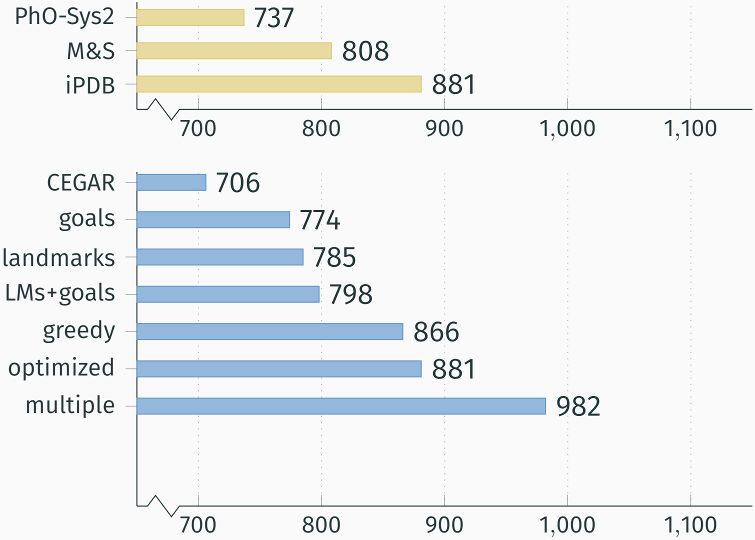


Multiple Orders

Problems:

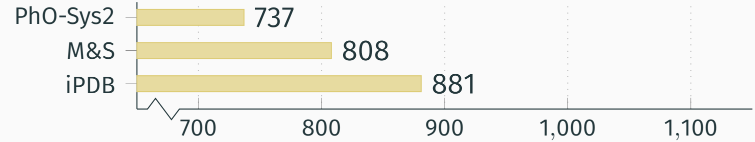
- many useless orders
- slow evaluation

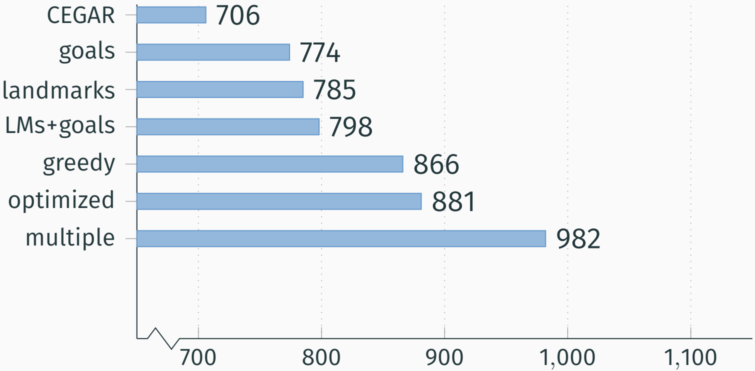
Diverse Orders

Diversification Algorithm

- sample 1000 states
- start with empty set of orders
- until time limit is reached:
    - generate an optimized order
    - if a sample profits from it, keep it
    - otherwise, discard it

Solved Tasks





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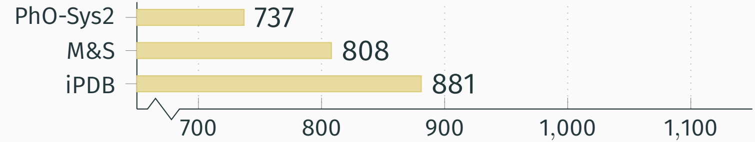
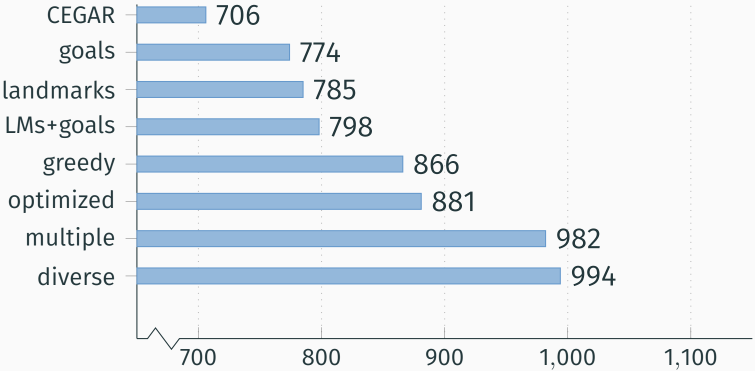




Comparison of Cost Partitioning Algorithms

Theoretical Comparison

UCP

Uniform Cost Partitioning

distribute costs evenly among relevant heuristics

GZOCP

UCP

Greedy Zero-one Cost Partitioning

order heuristics and give full cost to first relevant heuristic

Theoretical Comparison

GZOCP

PhO

UCP

Post-hoc Optimization

compute weight for each heuristic and return weighted sum

Theoretical Comparison

GZOCP

PhO

CAN

UCP

Canonical Heuristic

maximum over sums of independent heuristic subsets

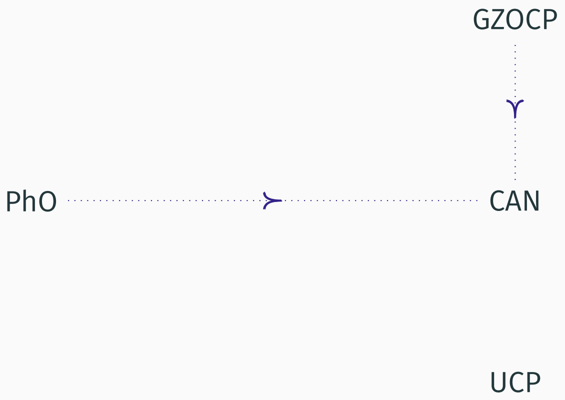
Theoretical Comparison

GZOCP

PhO $\succ$ CAN

UCP

Pommerening et al. 2013


GZOCP
PhO
CAN
UCP

$$
\begin{tikzcd}
\mathrm{SCP} & & \mathrm{GZOCP} \arrow[d, dash, dotted, "\curlyvee" description] \\
& \mathrm{PhO} \arrow[r, dash, dotted, "\succ" description] & \mathrm{CAN} \\
& & \mathrm{UCP}
\end{tikzcd}
$$

$$
\begin{tikzcd}
\mathrm{SCP} \arrow[rr, dotted, dash, "\succ" marking] & & \mathrm{GZOCP} \arrow[d, dotted, dash, "\curlyvee" marking] \\
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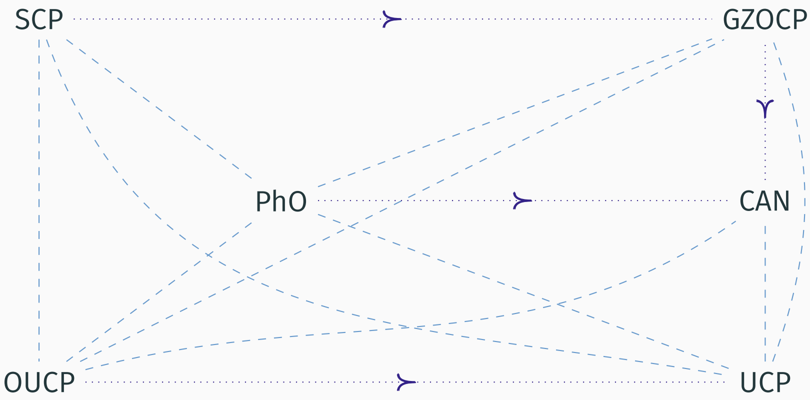
$$

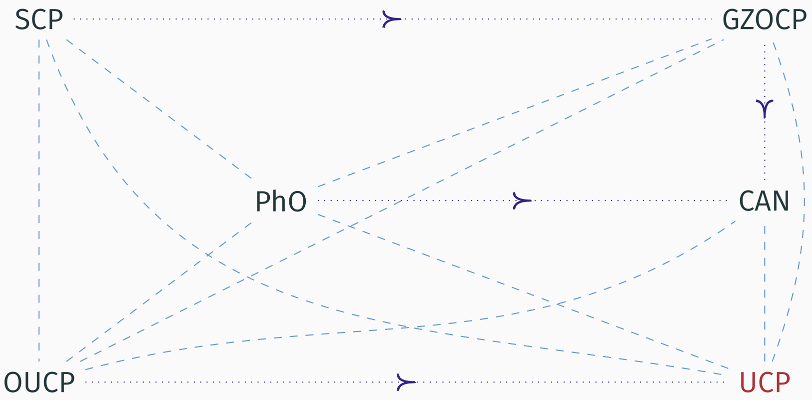
Theoretical Comparison



Experimental Comparison

- Heuristics: Cartesian abstraction heuristics + PDBs

Experimental Comparison



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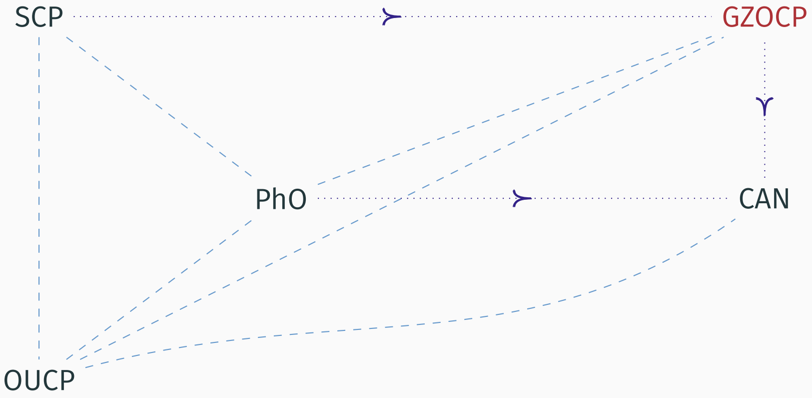

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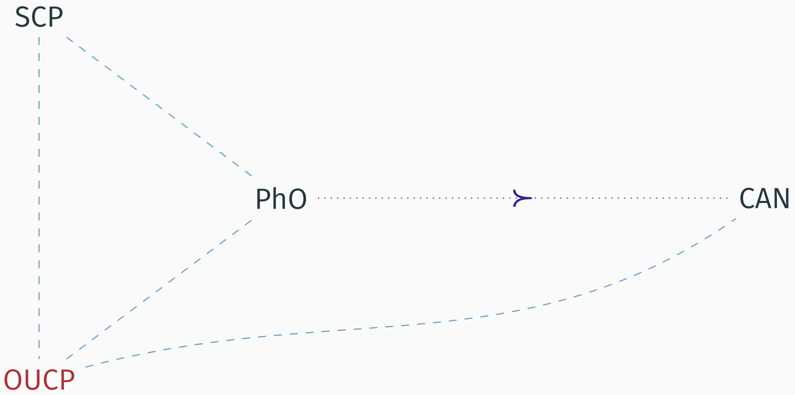


Experimental Comparison

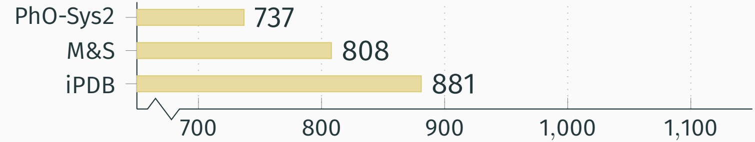
SCP

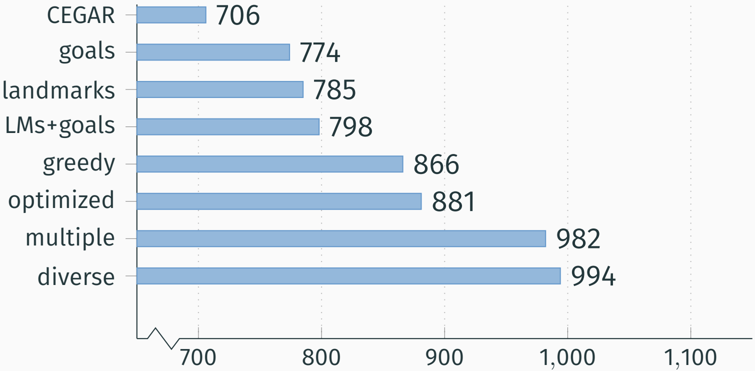
PhO $\succ$ CAN

Experimental Comparison

SCP

Solved Tasks





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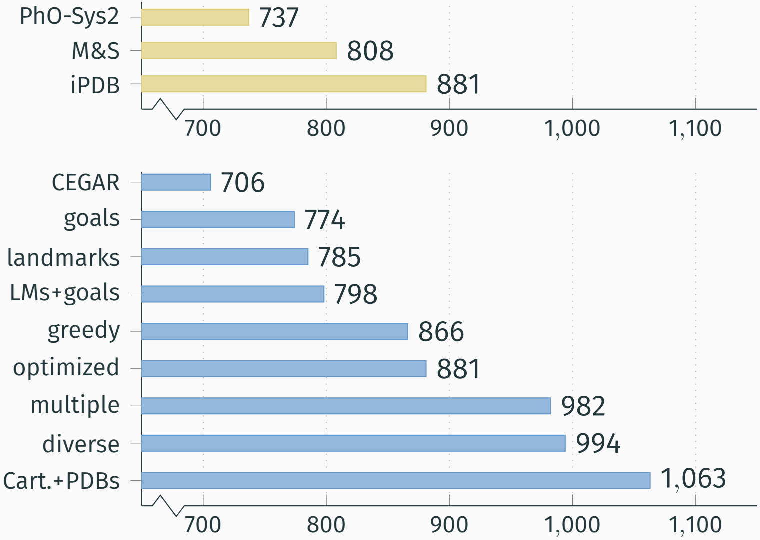

Conclusion

Counterexample-guided Cartesian Abstraction Refinement

- refines abstraction only where needed
- decompositions yield complementary heuristics

Conclusion

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- refines abstraction only where needed
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- assigns each heuristic only the costs it needs
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Comparison of Cost Partitioning Algorithms

- dominances and non-dominances
- saturated cost partitioning preferable in all settings