Dissecting Scorpion:
Ablation Study of an Optimal Classical Planner

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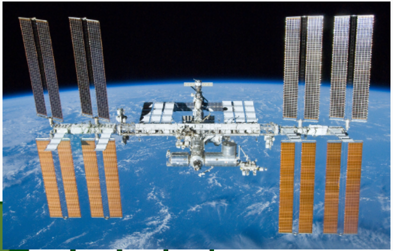
AI Planning



Given a compact task model, find a sequence of actions that achieves the goal.

Optimal Classical Planning

setting:

- deterministic
- fully observable
- cost-optimal plans

main approaches:

- (explicit) A^* search [e.g., Helmert et al. 2008]
- symbolic search [e.g., Edelkamp et al. 2015]
- planning as SAT/maxSAT/QBF/CP [e.g., Rintanen 2012]

related fields:

- path finding, model checking, petri nets, ...

Scorpion: Optimal Classical Planner

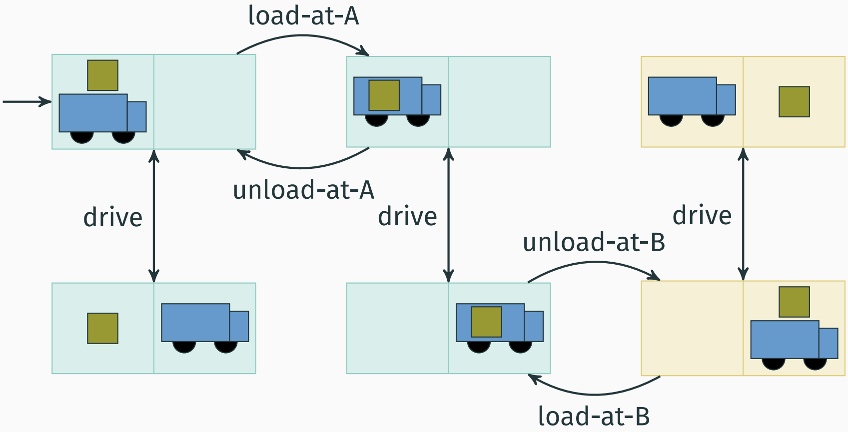
- winner of IPC 2023
- A^* search + admissible heuristic
  - abstractions: pattern databases and Cartesian abstractions
  - cost partitioning: saturated cost partitioning
- ECAI 2024 paper: literature overview and ablation study

Outline

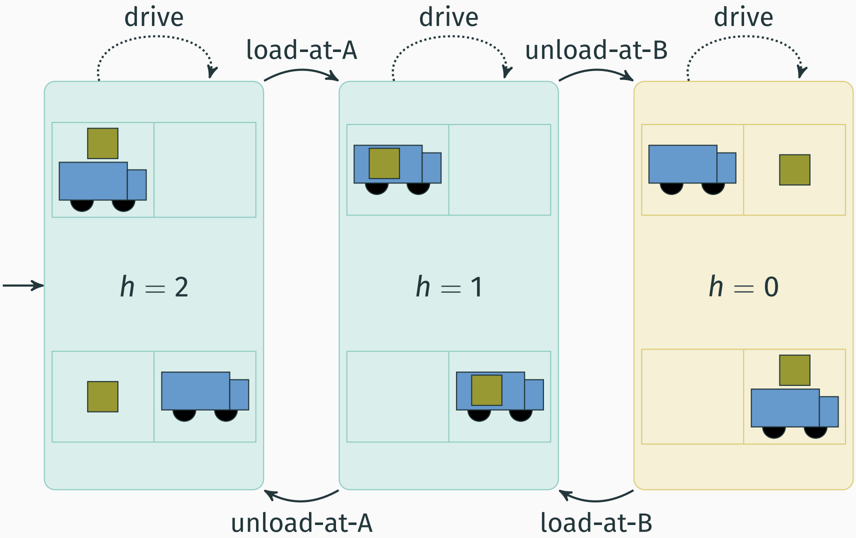
- Abstractions
- Cost Partitioning

Abstractions

Example Task



Example Abstraction

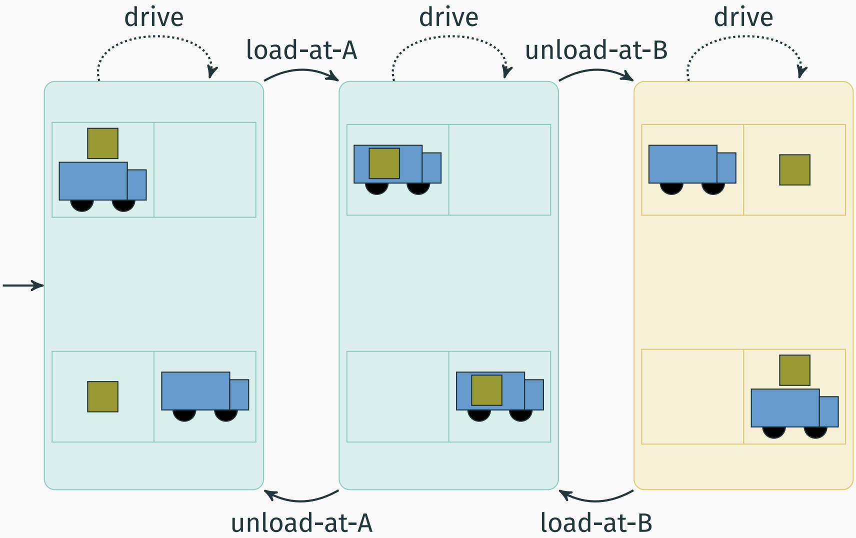


Abstraction Heuristics

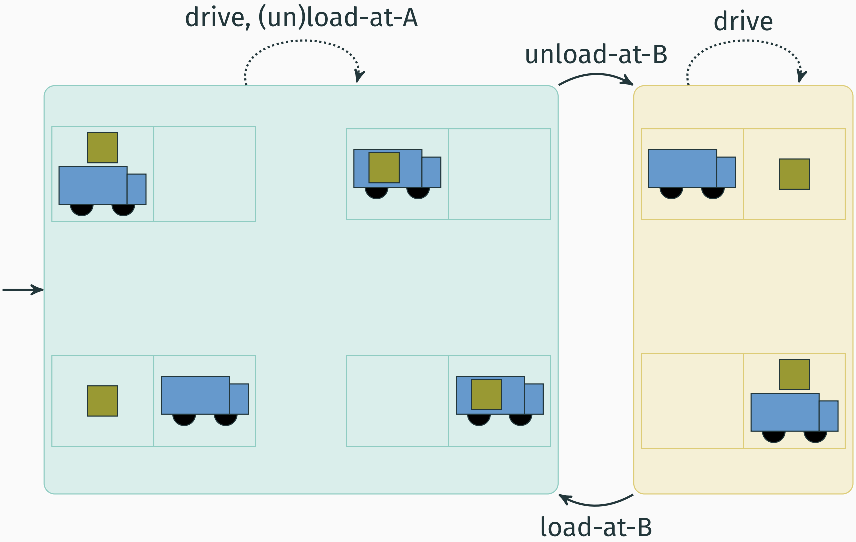
- abstractions preserve all plans $\rightarrow$ admissible
- higher accuracy $\rightarrow$ better guidance
- granularity vs. resource usage

$\rightarrow$ four main classes of abstractions

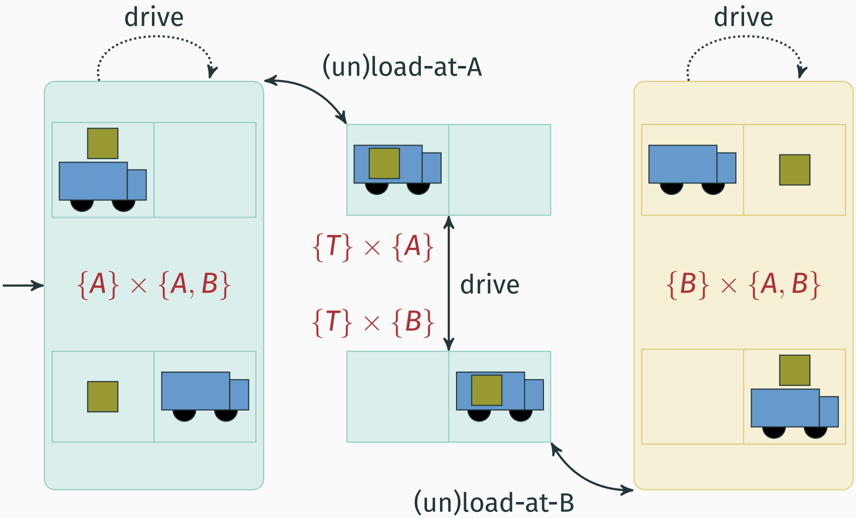
Projection (Pattern Database)



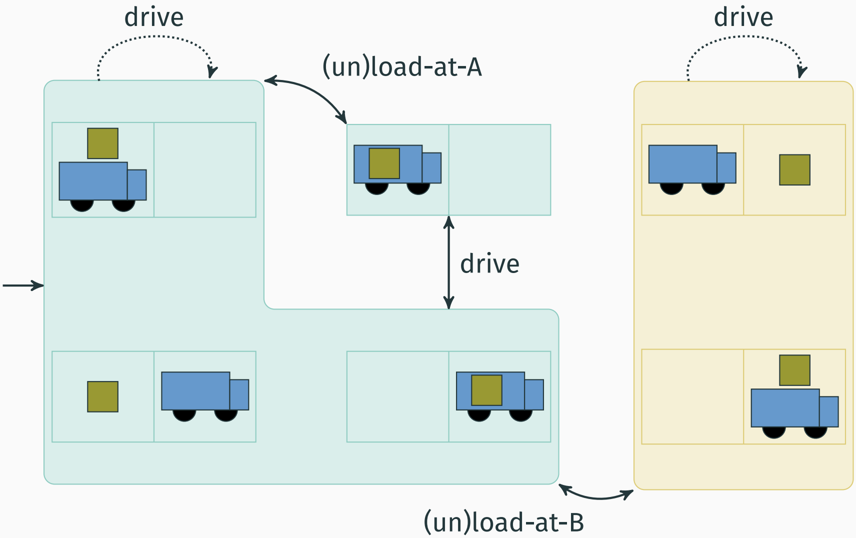
Domain Abstraction



Cartesian Abstraction



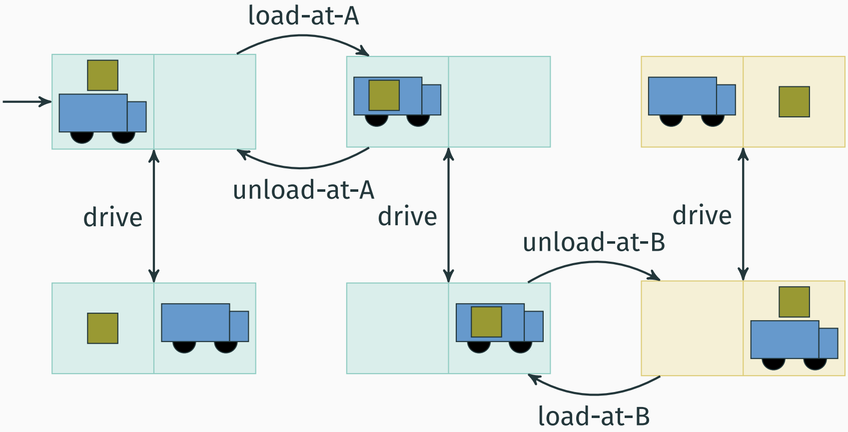
Merge-and-shrink Abstraction



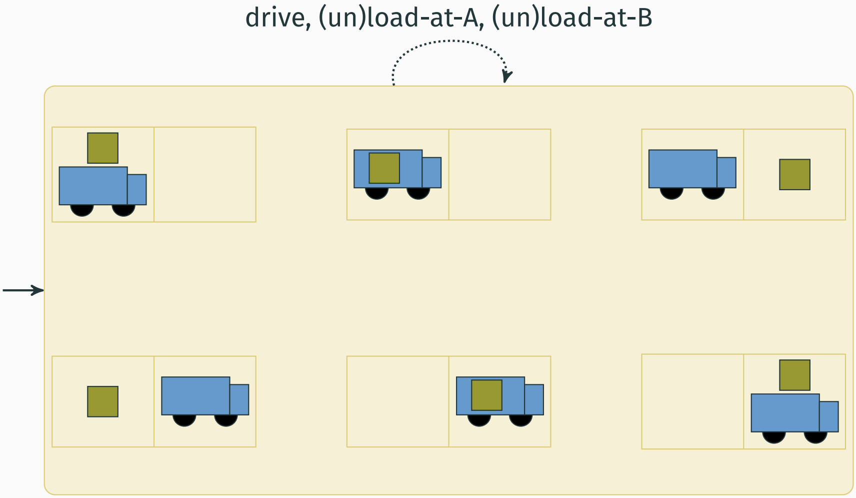
How to Generate an Abstraction?

- Projections (Pattern Databases)
  - bin packing [Edelkamp 2001]
  - genetic algorithms [Edelkamp 2006]
  - hill climbing [Haslum et al. 2007]
  - systematic [Pommerening et al. 2013]
  - CPC [Franco et al. 2017]
  - CEGAR [Rovner et al. 2019]
  - sys-SCP [Seipp 2019]
- Domain Abstractions
  - CEGAR [Kreft et al. 2023]
- Cartesian Abstractions
  - CEGAR [Pozo et al. 2024a; Seipp and Helmert 2018]
- Merge-and-shrink Abstractions
  - operations on factors [Sievers and Helmert 2021]

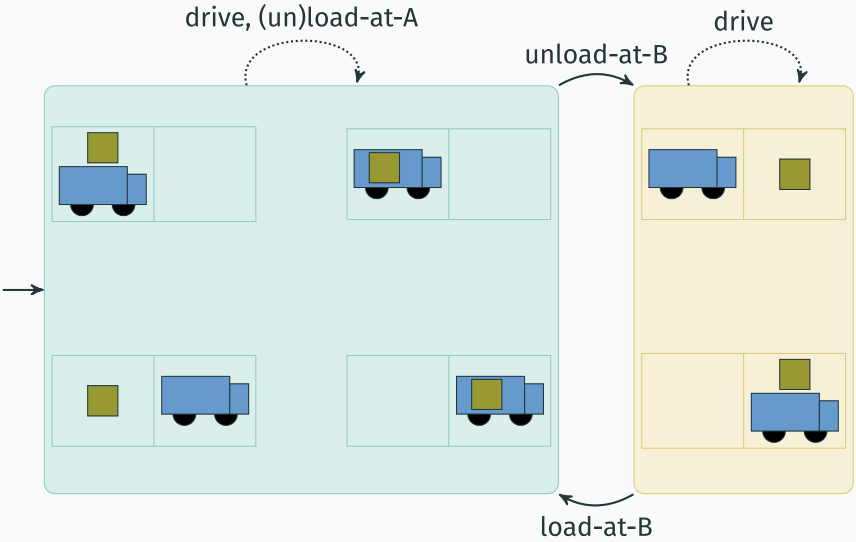
Cartesian CEGAR: Concrete Transition System



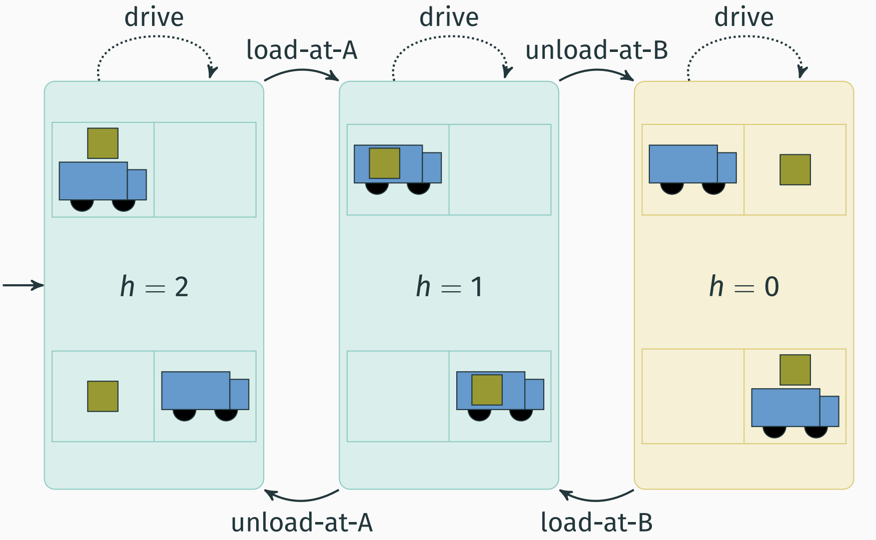
Cartesian CEGAR: Trivial Abstraction



Cartesian CEGAR: First Refinement



Cartesian CEGAR: Second Refinement



Multiple Abstractions

Generating Multiple Heuristics

- Pattern databases: use different patterns ([P1], [P1, T], [P2, T], ...)
- Domain/Cartesian abstractions: one abstraction per goal fact (P1=B, P2=C, ...)
- Merge-and-shrink: different merge/shrink strategies

Combining Multiple Heuristics

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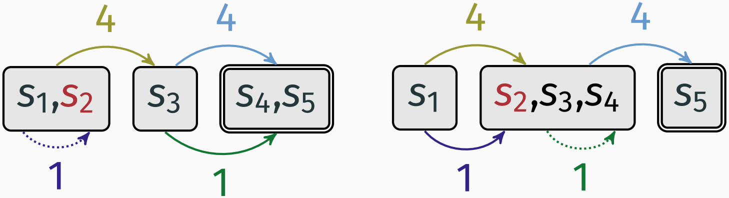

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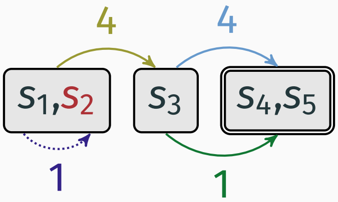
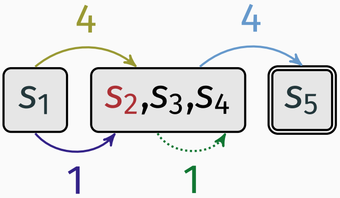
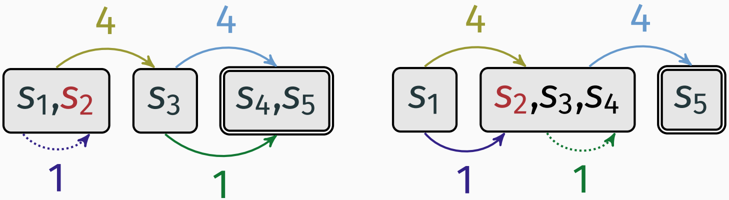




$h_1(s_2) = 5$ $h_2(s_2) = 4$

Combining Multiple Heuristics



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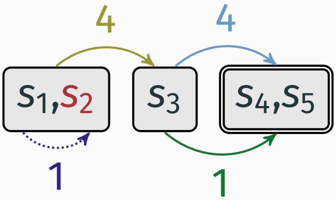
maximize over estimates:

- $h(s_2) = 5$

Combining Multiple Heuristics



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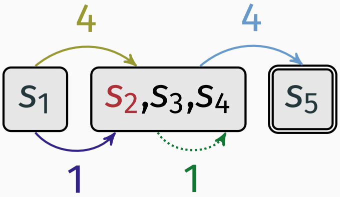


$h_2(s_2) = 4$

maximize over estimates:

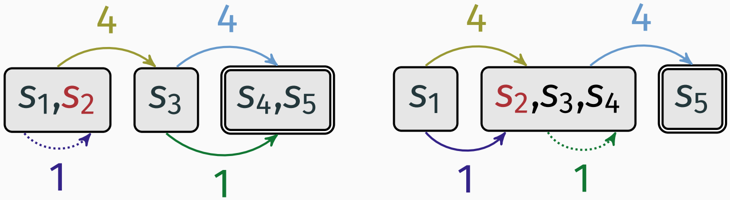
- $h(s_2) = 5$
- only selects best heuristic
- does not combine heuristics

Cost Partitioning

Multiple Heuristics: Cost Partitioning

Cost Partitioning

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



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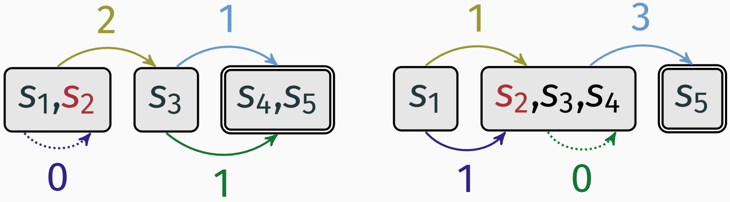

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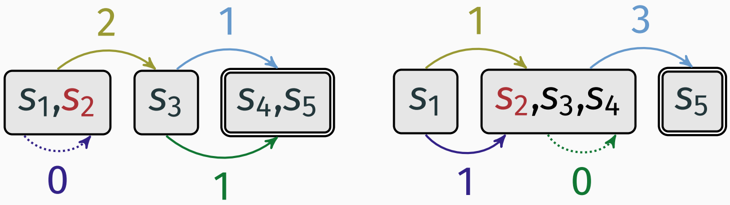


$$h(s_2) = 3 + 3 = 6$$

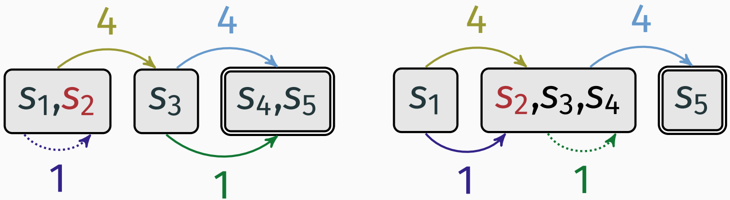
Optimal Cost Partitioning

Linear Program for state s [Katz and Domshlak 2010; Pommerening et al. 2015]

$$\text{maximize } \sum_i h_i(s) \text{ subject to}$$

$$\sum_i c_i(o) \leq cost(o) \quad \text{for all operators } o$$

$$h_i = \text{heuristic } i \text{ under cost } c_i \quad \text{for all heuristics } i$$



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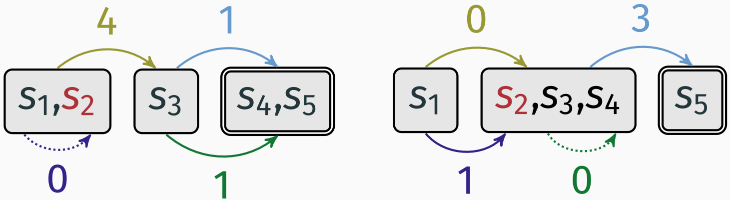

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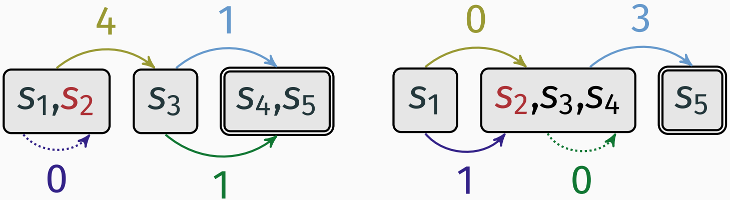
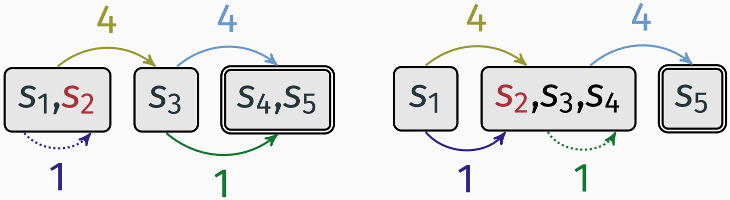


$$h(s_2) = 5 + 3 = 8$$

SCP Algorithm [Seipp et al. 2020a]

- 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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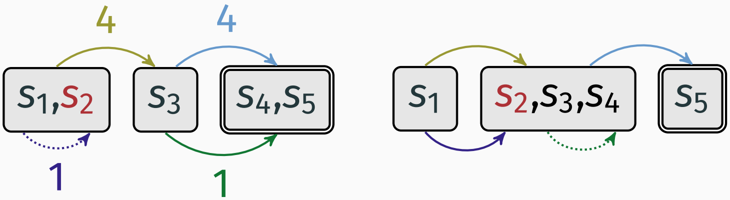

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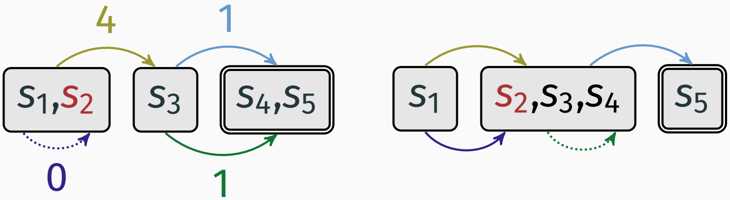

Saturated Cost Partitioning

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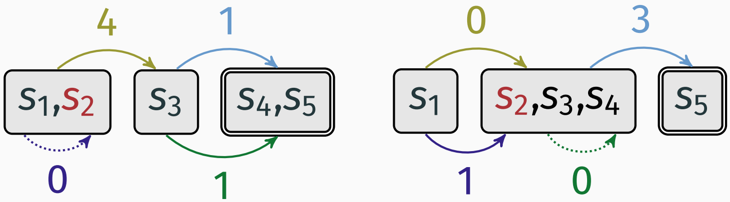

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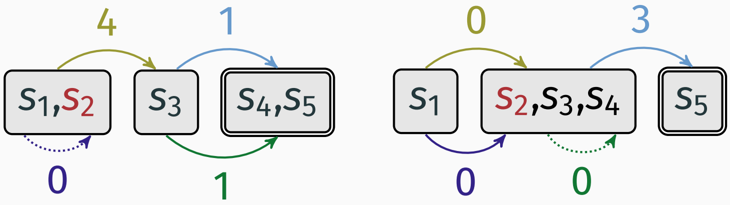

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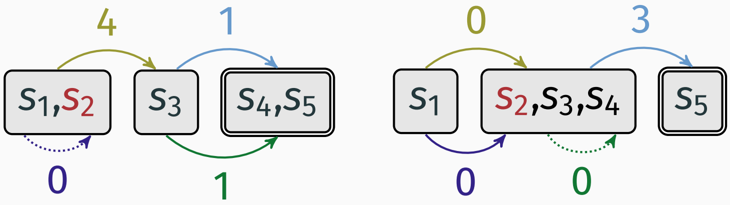
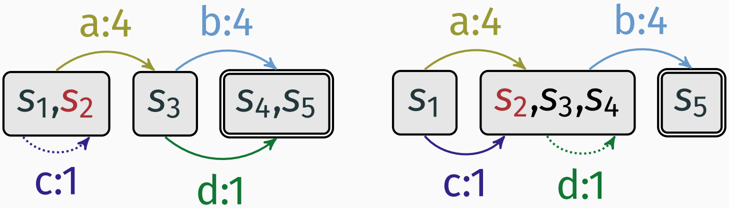


$$h(s_2) = 5 + 3 = 8$$

Post-hoc Optimization [Pommerening et al. 2013]



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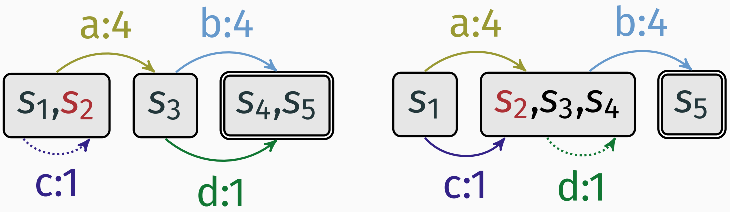
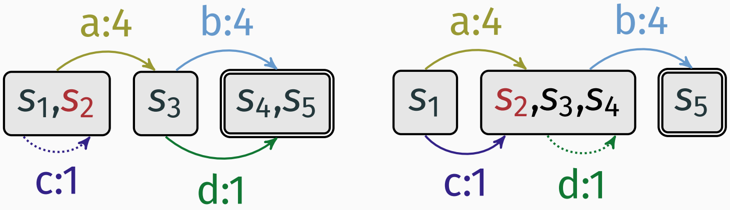


- a, b, d active $\quad h_1(s_2) = 5$

Post-hoc Optimization [Pommerening et al. 2013]



- a, b, d active $h_1(s_2) = 5 \quad \rightarrow \quad 4A + 4B + 1D \geq 5$

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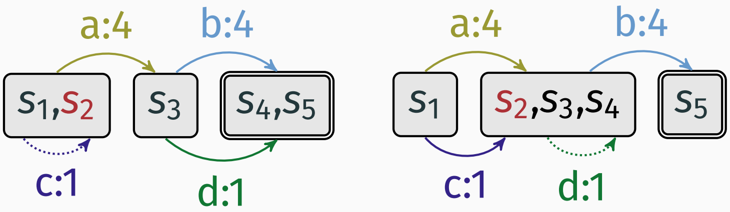

- a, b, d active $h_1(s_2) = 5 \quad \rightarrow \quad 4A + 4B + 1D \geq 5$
- a, b, c active $h_2(s_2) = 4$

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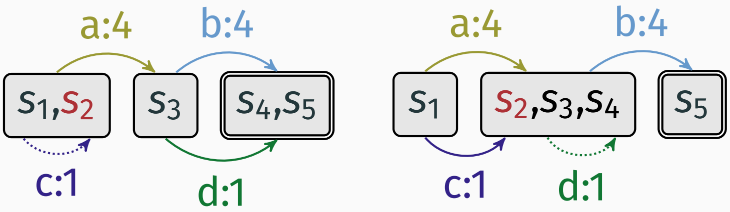

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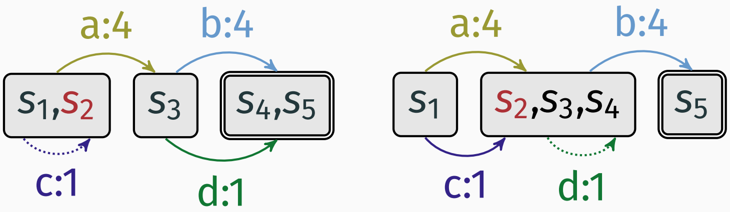
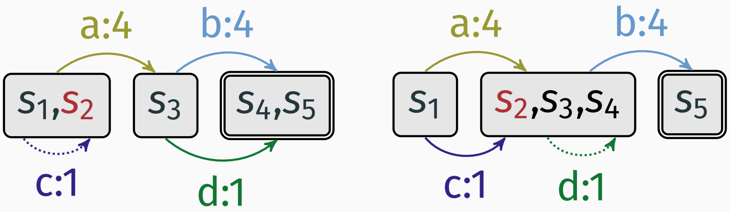


- a, b, d active $\quad h_1(s_2) = 5 \quad \rightarrow \quad 4A + 4B + 1D \geq 5$
- a, b, c active $\quad h_2(s_2) = 4 \quad \rightarrow \quad 4A + 4B + 1C \geq 4$
- $A \geq 0, B \geq 0, C \geq 0, D \geq 0$

Post-hoc Optimization [Pommerening et al. 2013]



minimize $4A + 4B + 1C + 1D$ **such that**

$$4A + 4B + 1D \geq 5$$

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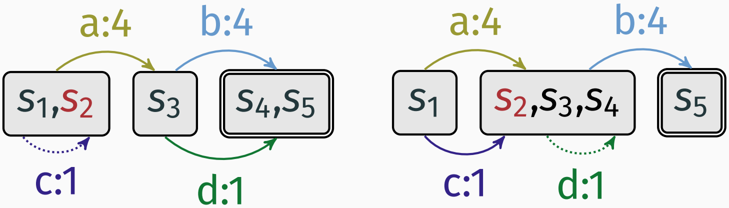
Post-hoc Optimization [Pommerening et al. 2013]



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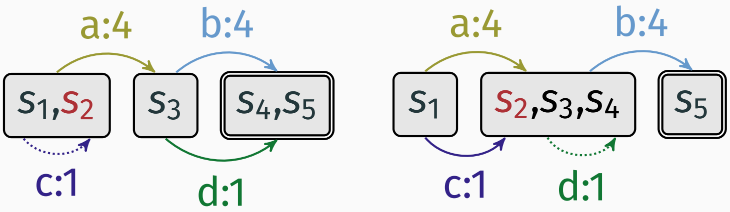
$$h(s_2) = 5$$

Saturated Post-hoc Optimization [Seipp et al. 2021]



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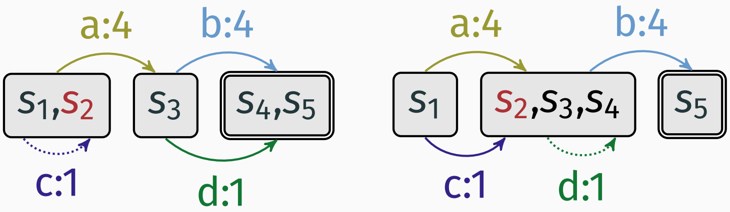

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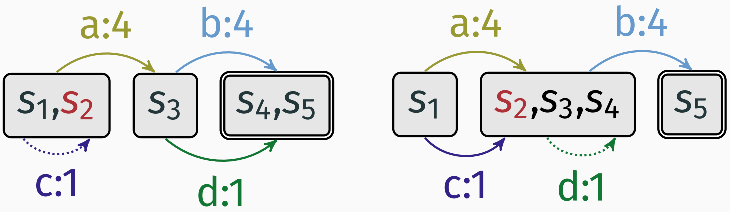

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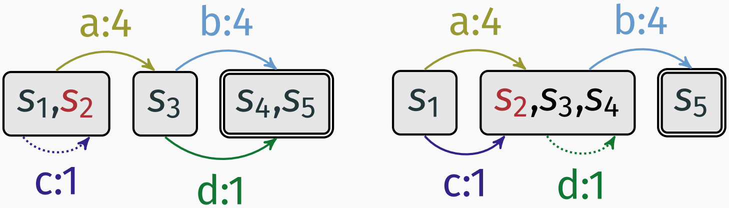

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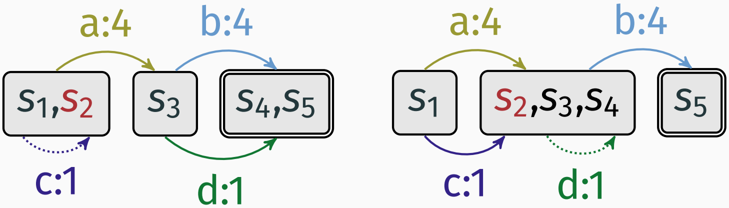

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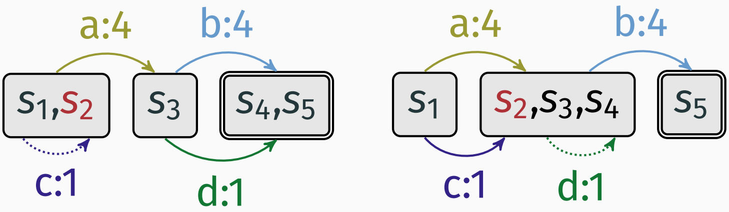

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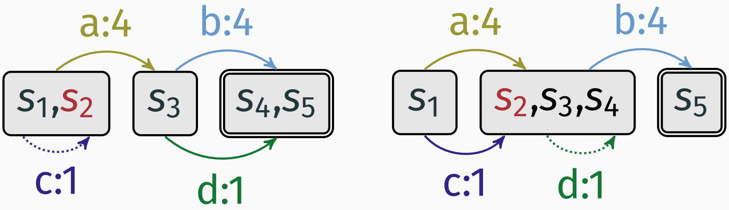

minimize $4A + 4B + 1C + 1D$ **such that**

- $4A + 1B + 1D \geq 5$
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- $A \geq 0, B \geq 0, C \geq 0, D \geq 0$

$$h(s_2) = 7.2$$

Theoretical Relationships

UCP

Uniform Cost Partitioning

distribute costs evenly among relevant heuristics

Theoretical Relationships

GZOCP

UCP

Greedy Zero-one Cost Partitioning

order heuristics and give full cost to first relevant heuristic

Theoretical Relationships

GZOCP

PhO

UCP

Post-hoc Optimization

Theoretical Relationships

GZOCP

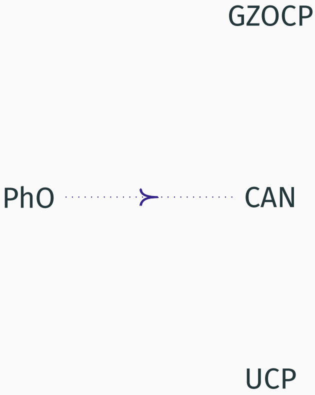
PhO CAN

UCP

Canonical Heuristic

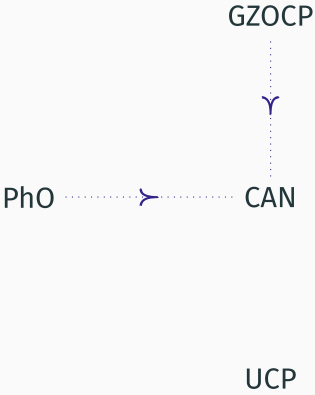
maximum over sums of independent heuristic subsets

Theoretical Relationships



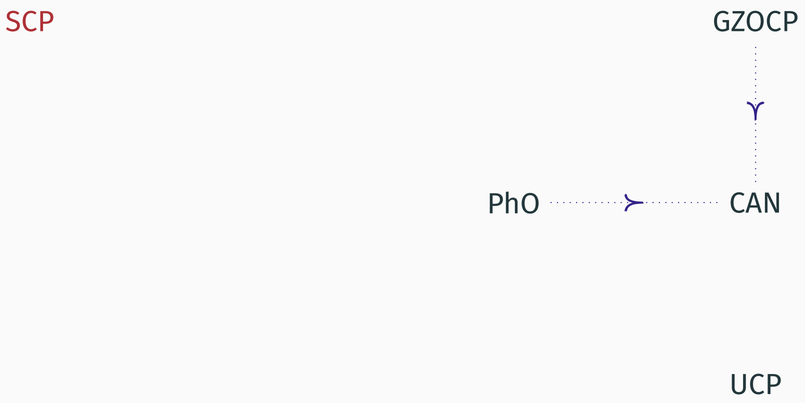
[Pommerening et al. 2013]

Theoretical Relationships

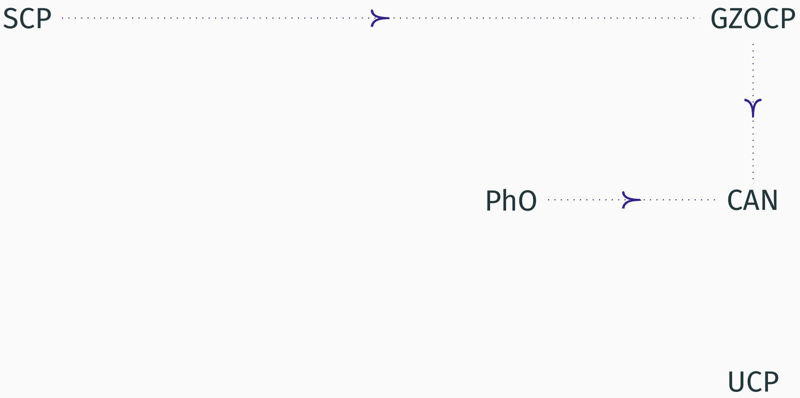


[Seipp et al. 2017]

Theoretical Relationships



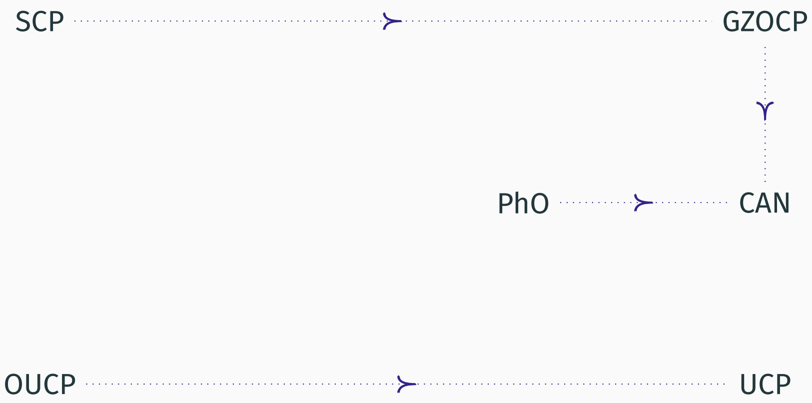
Theoretical Relationships



[Seipp et al. 2017]

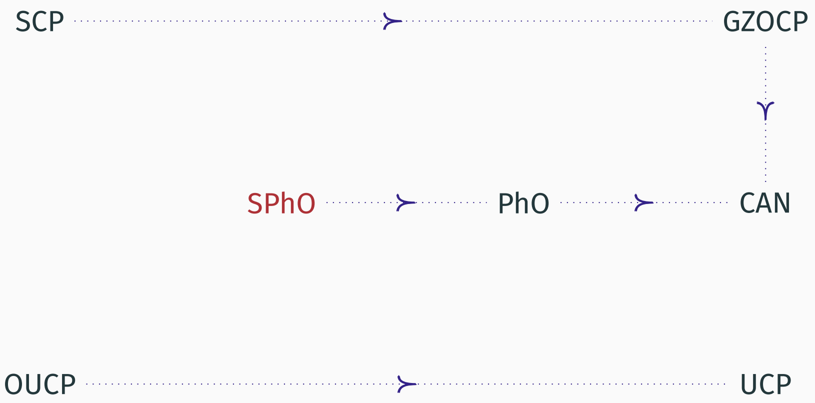
Theoretical Relationships

Theoretical Relationships



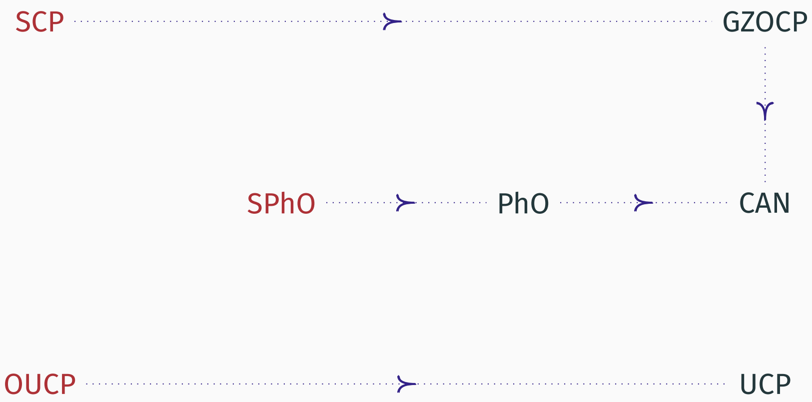
[Seipp et al. 2017]

Theoretical Relationships

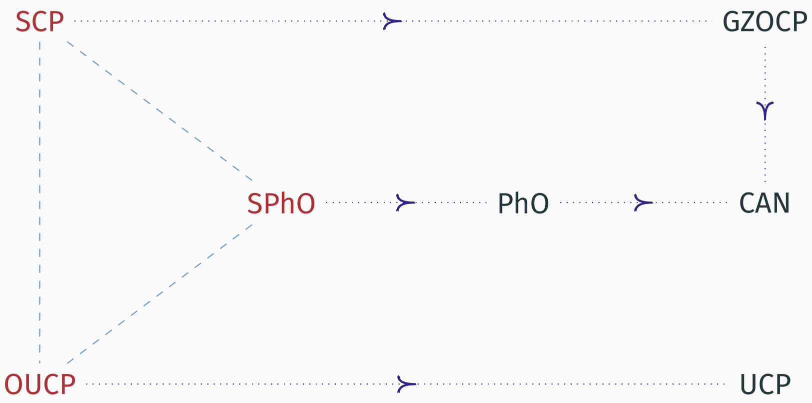


[Seipp et al. 2021]

Theoretical Relationships

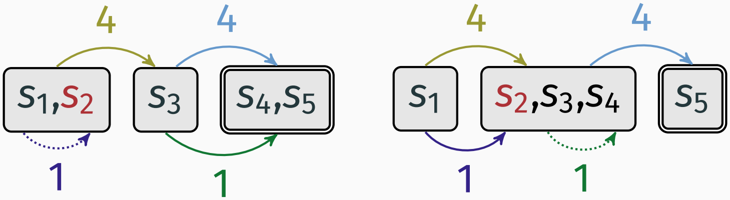


Theoretical Relationships



[Seipp et al. 2021]

SPhO vs. SCP



$h^{\mathrm{SCP}}_{\langle h_1,h_2\rangle}(s_2) = 8$ $\quad h^{\mathrm{SPhO}}(s_2) = 7.2$ $\quad h^{\mathrm{SCP}}_{\langle h_2,h_1\rangle}(s_2) = 7$

→ greedily optimize order for given state

→ use multiple orders for SCP

Latest Developments Around Scorpion

abstractions:

- incremental search for Cartesian CEGAR [Seipp et al. 2020b]
- better flaws for Cartesian CEGAR [Pozo et al. 2024a,b; Speck and Seipp 2022]
- compute Cartesian transitions on demand [Seipp 2024]
- abstraction heuristics for factored tasks [Büchner et al. 2024]

cost partitioning:

- use saturation to select patterns [Seipp 2019]
- compute orders for SCP during search [Seipp 2021]
- use Dantzig-Wolfe decomposition for OCP [Pommerening et al. 2021]
- use LP sensitivity analysis for SPhO [Höft et al. 2024, 2023]

Summary

abstractions:

- accurate heuristics
- fast to evaluate

cost partitioning:

- combine heuristics admissibly
- backbone of state-of-the-art optimal planners

Scorpion: `github.com/jendrikseipp/scorpion`
Contact: `mrlab.ai/jendrik-seipp`

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