Lecture *Hierarchical Planning*

Chapter:
Heuristics for (Non-Hierarchical) Planning Problems

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Overview:

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What's a heuristic in planning?

- The same as in search! (See respective lecture.)

So, what's covered here?

- We discuss *planning-specific* problem relaxations.
- We investigate some of the easiest/most fundamental heuristics for classical and POCL planning.

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- They should be *easier* than the original problem: either in terms of computational complexity or in the problem size.
- Ordinarily *safe* (cf. search: unsolvable in relaxation implies unsolvable in original).

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Further reading: Malte Helmert and Carmel Domshlak. "Landmarks, Critical Paths and Abstractions: What's the Difference Anyway?" In: *Proc. of the 19th Int. Conf. on Automated Planning and Scheduling (ICAPS 2009)*. AAAI Press, 2009, pp. 162–169

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  - Used for relaxed reachability analysis (“Given a state *s*, is there (maybe) a course of actions that enables the application of action *a* afterwards?”)
  - Basis for heuristics. $\rightarrow$ Both for classical and POCL planning!

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Further reading: Avrim L. Blum and Merrick L. Furst. "Fast Planning Through Planning Graph Analysis". In: *Artificial Intelligence* 90 (1997), pp. 281–300. DOI: 10.1016/S0004-3702(96)00047-1

Definitions, Delete Relaxation

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$\rightarrow$ h^+ refers to the perfect heuristic (h^*) for $\mathcal{P}^+$.

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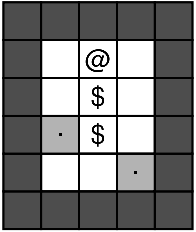
Consider Sokoban:



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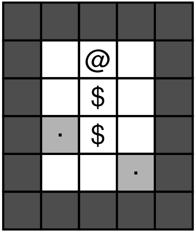

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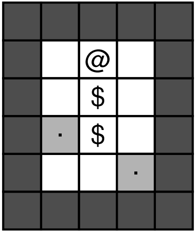

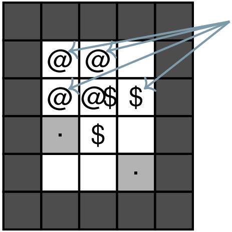

These positions are also *free!* (Since they were free before or have become so.)

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Let $\langle V, A, s_I, g\rangle$ be a (delete-free) planning problem.

Then, a *relaxed planning graph (rPG)* is a graph $\langle \bar{V}, \bar{A}\rangle$ consisting of:

- $\bar{V} = V^0 \dots V^n$, $V^i \subseteq V$, $0 \leq i \leq n$, a sequence of *variable layers*.

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Questions:

- Why is “delete-free” in the problem description put in parentheses?
- Why is n chosen as is? Is there a bound on n?
- What happens if we choose $n = i$, such that $V^i = V^{i+1}$ holds?

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Formal definition thereof:
Exercise!

Example – Exercise!

Draw the rPG with edges for the Cranes in the Harbor domain.

s_I: $\{CrateAtLoc1, TruckAtLoc2\}$ g: $\{CrateInTruck, TruckAtLoc2\}$

take
- pre: {CrateAtLoc1}
- add: {HoldCrate}
- del: {CrateAtLoc1}

put
- pre: {HoldCrate}
- add: {CrateAtLoc1}
- del: {HoldCrate}

moveLeft
- pre: {TruckAtLoc2}
- add: {TruckAtLoc1}
- del: {TruckAtLoc2}

moveRight
- pre: {TruckAtLoc1}
- add: {TruckAtLoc2}
- del: {TruckAtLoc1}

load
- pre: {HoldCrate, TruckAtLoc1}
- add: {CrateInTruck}
- del: {HoldCrate}

unload
- pre: {CrateInTruck, TruckAtLoc1}
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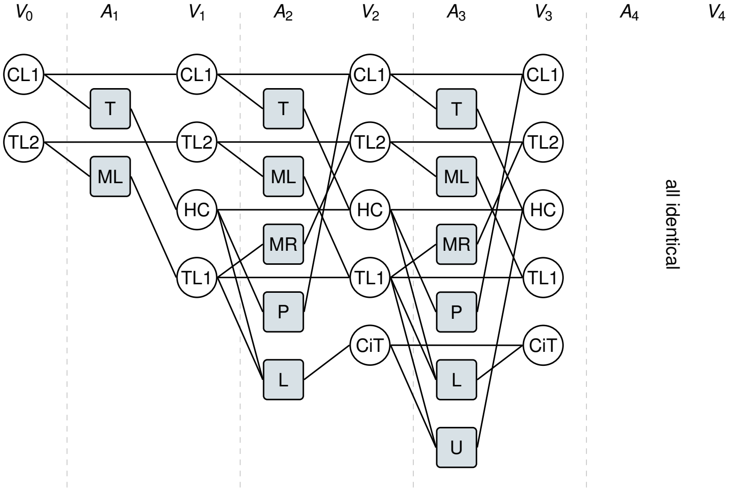
- del: {CrateInTruck}

Example – Exercise! cont'd

Solution:



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Let $\mathcal{P} = \langle V, A, s_I, g \rangle$ be a STRIPS planning problem and $\mathcal{G} = \langle \bar{V}, \bar{A} \rangle$ its rPG.

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heuristic For a state $s \in S$, $h^{max}(s)$ equals the cost of g.

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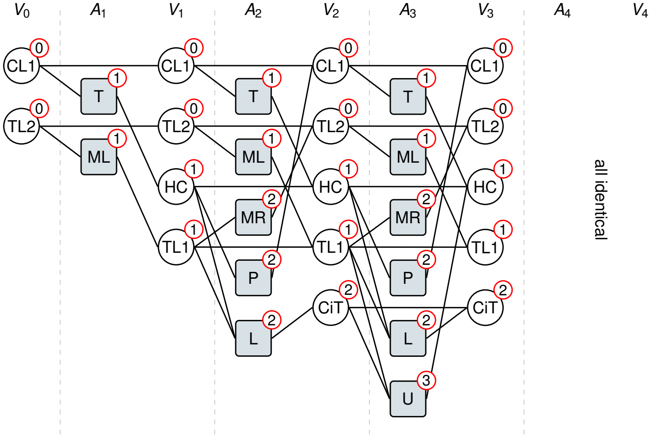

$s_I = \{CrateAtLoc1, TruckAtLoc2\}$ $g = \{CrateInTruck, TruckAtLoc2\}$

$h^{max}(s_I) = 2$ $h^*(s_I) = 4$ $h^*_{makespan}(s_I) = 3$

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Yes. (trivial)

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Calculate h^{add} for the Cranes in the Harbor domain.

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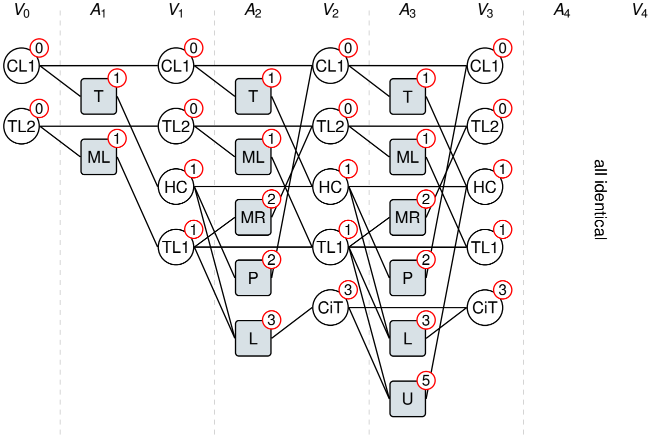

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Admissibility

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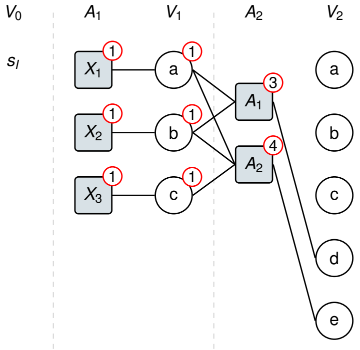
Heuristic assumes subgoal independence, which is normally not given:



$$s_I = \emptyset \quad g = \{d, e\} \quad h^{add}(s_I) = 7 \quad h^*(s_I) = 5$$

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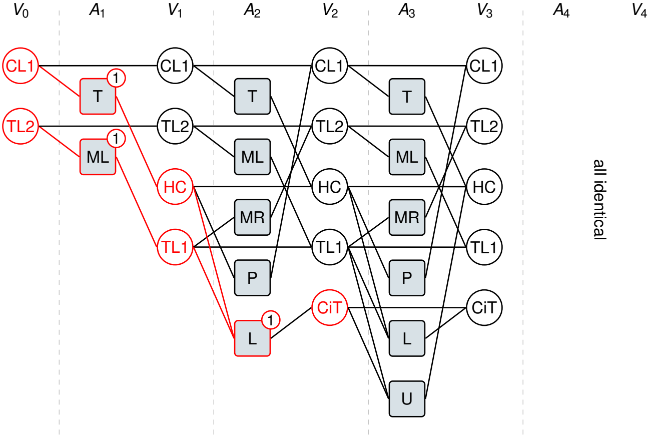

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- Now, guess a sequence of b actions and verify in linear time whether it's applicable.
- Return true or false (depending on whether all goals hold in the final state).

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- $g = \{x_i - set \mid 1 \leq i \leq m\} \cup \{C_j - \top \mid 1 \leq j \leq n\}$

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- $g = \{x_i - set \mid 1 \leq i \leq m\} \cup \{C_j - \top \mid 1 \leq j \leq n\}$
- φ is satisfiable if and only if a plan of size $n + m$ exists.

Classical Heuristics, Literature

Heuristics h^{add} and planner HSP:

- Blai Bonet and Héctor Geffner. "Planning as Heuristic Search: New Results". In: *Proc. of the 5th Europ. Conf. on Planning: Recent Advances in AI Planning (ECP 1999)*. Springer, 1999, pp. 360–372
- Patrik Haslum and Héctor Geffner. "Admissible Heuristics for Optimal Planning". In: *Proc. of the 5th Int. Conf. on Artificial Intelligence Planning Systems (AIPS 2000)*. AAAI Press, 2000, pp. 140–149

Heuristics h^{max}, h^{m} (not shown here), h^{add} (recap)

- Patrik Haslum and Héctor Geffner. "Admissible Heuristics for Optimal Planning". In: *Proc. of the 5th Int. Conf. on Artificial Intelligence Planning Systems (AIPS 2000)*. AAAI Press, 2000, pp. 140–149

Heuristic h^{FF}, planner FF, and *relaxed* planning graph:

- Jörg Hoffmann and Berhard Nebel. "The FF Planning System: Fast Plan Generation Through Heuristic Search". In: *Journal of Artificial Intelligence Research (JAIR)* 14 (2001), pp. 253–302

Classical vs. POCL Heuristics

Reminder Classical Planning:

Classical planning heuristics take the *current state* as input and estimate the goal distance to some *goal state*.

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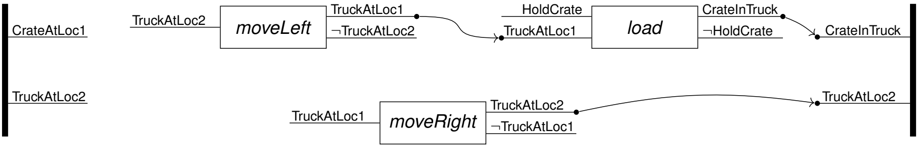
Here, there is neither a *current state* nor a goal description (it might be satisfied already). Instead, what do we have?



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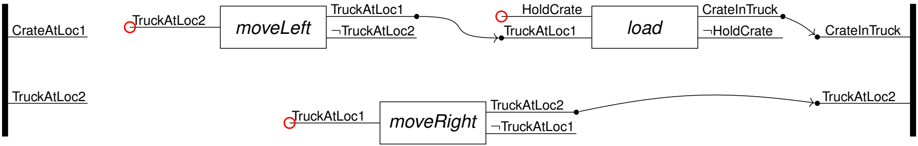

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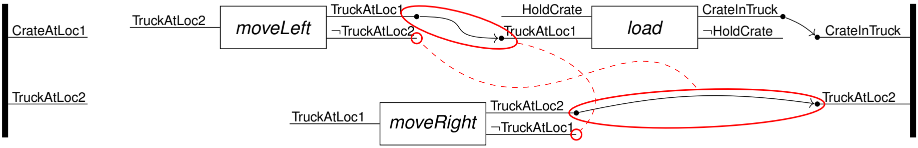

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  - Add heuristic $\rightarrow$ *Add heuristic for POCL planning* (see Younes and Simmons).

POCL Heuristics, Literature

Nguyen and Kambhampati — XuanLong Nguyen and Subbarao Kambhampati. "Reviving Partial Order Planning". In: *Proc. of the 17th Int. Joint Conf. on Artificial Intelligence (IJCAI 2001)*. Morgan Kaufmann, 2001, pp. 459–466

Bercher et al. — Pascal Bercher et al. "Using State-Based Planning Heuristics for Partial-Order Causal-Link Planning". In: *Advances in Artificial Intelligence, Proc. of the 36th German Conf. on Artificial Intelligence (KI 2013)*. Springer, 2013, pp. 1–12

Bylander — Tom Bylander. "A Linear Programming Heuristic for Optimal Planning". In: *Proc. of the 14th National Conf. on Artificial Intelligence (AAAI 1997)*. AAAI Press, 1997, pp. 694–699

Younes and Simmons — Håkan L. S. Younes and Reid G. Simmons. "VHPOP: Versatile heuristic partial order planner". In: *Journal of Artificial Intelligence Research (JAIR)* 20 (2003), pp. 405–430

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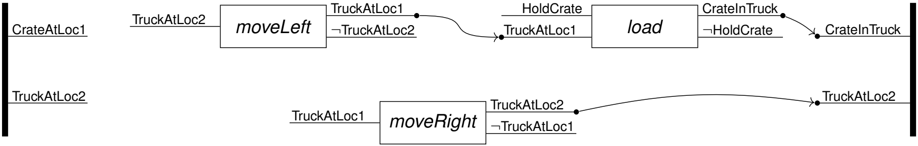

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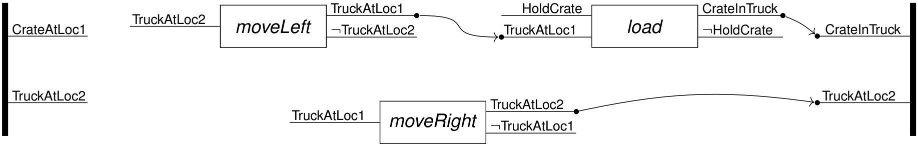

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- This ignores negative effects and the causal links' pruning power.

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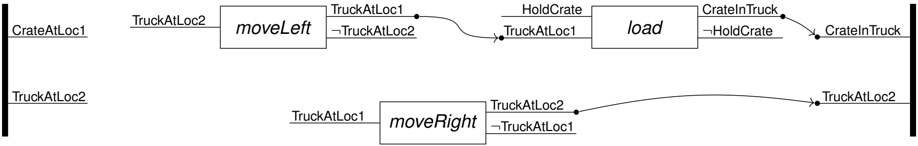

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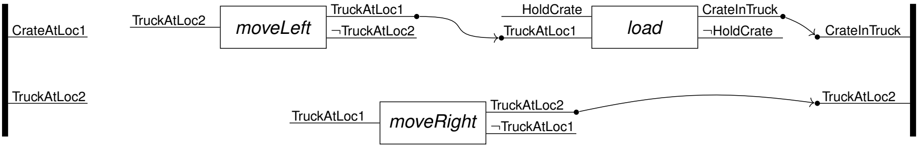

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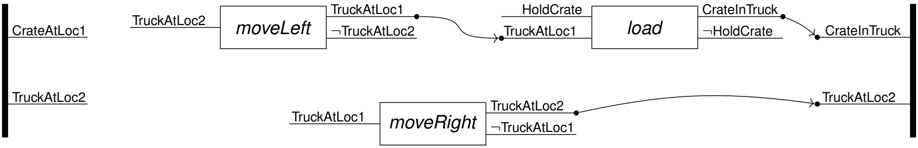

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- We only use heuristics that rely on (full) delete relaxation!

Add Heuristic for POCL Planning

Let $\langle V, A, s_I, g\rangle$ be a STRIPS planning problem.

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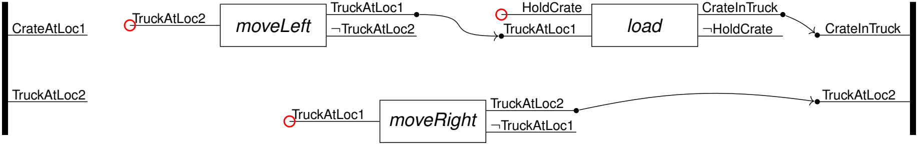
Add Heuristic for POCL Planning, Example

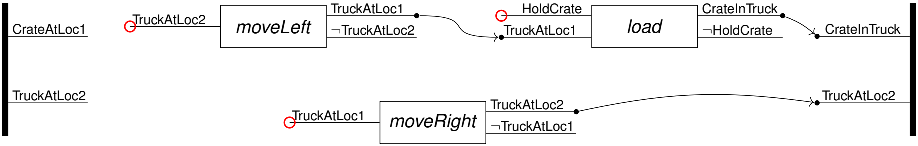


For $h^{add}_{POCL}(P)$, we use:

- $s_I = \{CrateAtLoc1, TruckAtLoc2\}$
- $G = \{TruckAtLoc1, TruckAtLoc2, HoldCrate\}$

Accounting for Positive Interactions

Estimating the goal distance to *all* open preconditions might be too pessimistic:



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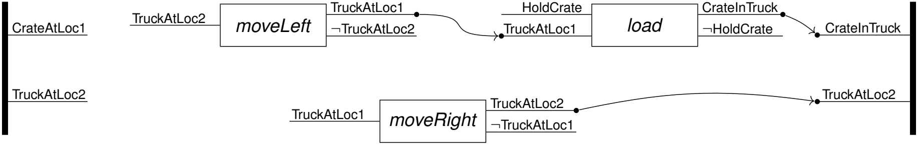

Here, the precondition *TrackAtLoc*2 might be accomplished by using the effect of *moveRight*.

Another example: Consider a (large) ”solution” plan in which (almost) all causal links are missing. $h^{add}_{POCL}(P)$ would be *highly* inaccurate.

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- As goal state we consider the set of open preconditions – just as h^{add}_{POCL} does.
- We than extract a plan from the rPG in the same way the FF heuristic does. However, the cost of an action a, $c(a)$ in that relaxed solution plan is only accounted for if a does not occur in the input plan P.

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- But since they are delete-relaxed, they can be used for POCL planning as well.