Lecture *Hierarchical Planning*

Chapter: *Heuristics for (Non-Hierarchical) Planning Problems*

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Overview:

Overview

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.

What are Heuristics?

Recap: How to come up with heuristics in a *domain-independent* way?

- Perform a *problem relaxation*.
- Solve the relaxed problem.
- Use the relaxation's solution cost as approximation (i.e., heuristic) of the actual (original, non-relaxed) problem.

What is a problem relaxation?

- Sometimes *special cases of planning problems* (e.g., ignore all delete lists).
- Sometimes *specialized calculations* (that might, however, still be interpreted as special cases of standard planning problems).
- 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).

Problem Relaxations for Planning

How to relax a STRIPS planning problem?

- Ignore the delete effects. → *Delete-relaxation heuristics*.
- Ignore an entire set of state variables. → *Abstraction heuristics*.
- Compute and exploit state variables (or actions) that have to be part of (or are contained in) any solution at some point. → *Landmark-based heuristics*.
- Estimate plan length by making relaxed assumptions on when a set of variables is regarded reachable. → *Critical path heuristics*.
- And many more!

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

Motivation

- The planning graph is a relaxed representation of the state and action space.
- It exists with varying degrees of constraints (mutexes, representing which state variables may be true at the same time) making it more or less informed.
- Here, we only cover the most relaxed form, which can be computed in polynomial time.
- Its main purpose today:
  - Use it to ground a domain (covered later).
  - 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. → Both for classical and POCL planning!

Historical Remarks

The *planning graph* is a data structure that was invented for a planning system called *GraphPlan*.

That planning system is *not* relevant for this course.

Note:
Do not think of a pink elephant right now!
Rephrased: Please *do not* confuse *GraphPlan* with the *planning graph*!
The first is a *planning system* – the latter a *data structure*.

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

Definition (Delete-free and -relaxed Planning Problems)

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

- It is called delete-free if for all $a \in A$, $del(a) = \emptyset$.
- Its delete-relaxation is the (delete-free) problem $\langle V, A', s_I, g \rangle$, where $A' = \{(pre, add, \emptyset, c) \mid (pre, add, del, c) \in A\}$.

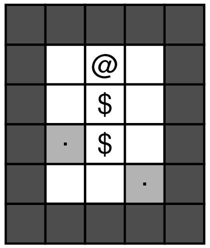
→ $\mathcal{P}^+$ refers to the delete-relaxation of $\mathcal{P}$ and

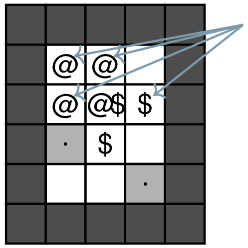
→ h^+ refers to the perfect heuristic (h^*) for $\mathcal{P}^+$.

Definitions, Delete Relaxation

What's the core idea behind delete relaxation?
$\rightarrow$ What's true once stays true!

Consider Sokoban: ...after moving left, down, right...





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

@ = the figure $ = a crate   · = a goal position

Definitions, Relaxed Planning Graph

Definition (Relaxed Planning Graph)

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*.
- $\bar{A} = A^1 \dots A^n$, $A^i \subseteq A$, $1 \leq i \leq n$, a sequence of *action layers*.
- $V^0 = s_I$.
- $A^i = \{a \in A \mid pre(a) \subseteq V^{i-1}\}$, $1 \leq i \leq n$.
- $V^i = V^{i-1} \cup \bigcup_{a \in A^i} add(a)$, $1 \leq i \leq n$.
- Choose $n = i$, such that $V^{i-1} = V^i$ holds.

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?

Definitions, Relaxed Planning Graph, cont'd

We can extend this definition of rPGs to add information about reachability, i.e.,

- Which variable(s) enable which action precondition?
- Which variable(s) get added by which action(s)?
- How variables "remain valid" (due to the absence of deletions). (That is, all variables v in V^i and V^{i+1} share an edge)

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}

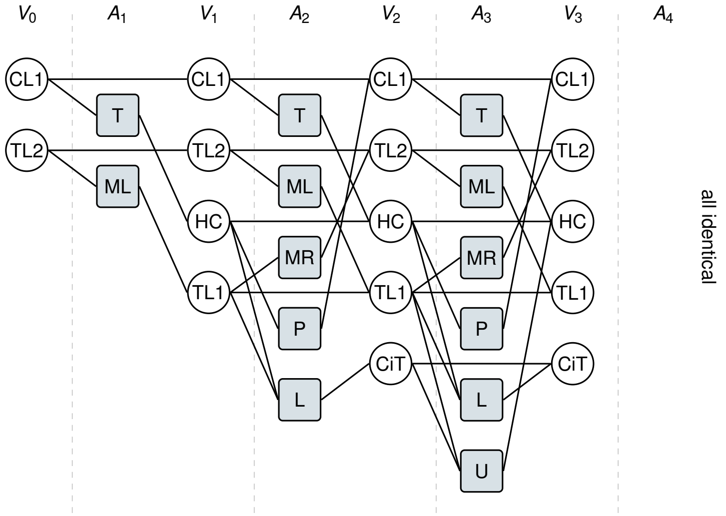
moveRight
pre: {TruckAtLoc1}
add: {TruckAtLoc2}
del: {TruckAtLoc1}

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

unload
pre: {CrateInTruck, TruckAtLoc1}
add: {HoldCrate}
del: {CrateInTruck}

Example – Exercise! cont'd

Solution:



h^{max} for Classical Planning

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.

- $h^{max}(s)$ returns the first layer number in which all goal variables hold. Meaning: Number of action layers required in $\mathcal{P}^+$ to make the hardest variable in g true (starting in some $s \in S$, e.g., s_I).
- Formally, h^{max} can be calculated as follows:

action vertex The cost of an action vertex $a \in A^i$ is 1 plus the maximum of the predecessor vertex costs.

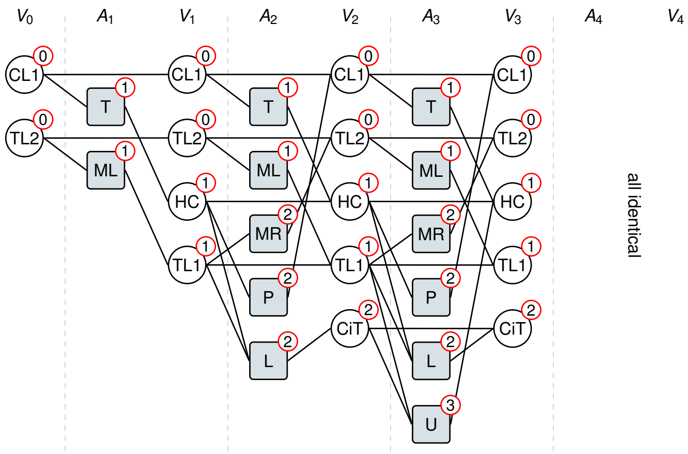
variable vertex
- The cost of a variable vertex v is 0 if $v \in V^0$.
- For all $v \in V^i$, $i > 0$, the cost of v equals the minimum cost of all predecessor vertices (these might be either action or variable vertices).

vertex set For a set of state variables $\bar{v} \subseteq V$, the cost equals the most expensive variable in $\bar{v}$.

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

Example – Exercise!

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



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

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

Admissibility

Is h^{max} admissible?

Yes. (trivial)

h^{add} for Classical Planning

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.

- $h^{add}(s)$ calculates the cost reaching g from $s \in S$ via adding the costs of the actions' preconditions. Implicit assumption: "subgoal independence".
- Formally, h^{add} can be calculated as follows:

action vertex The cost of an action vertex $a \in A^i$ is $c(a)$ plus the sum of the predecessor vertex costs.

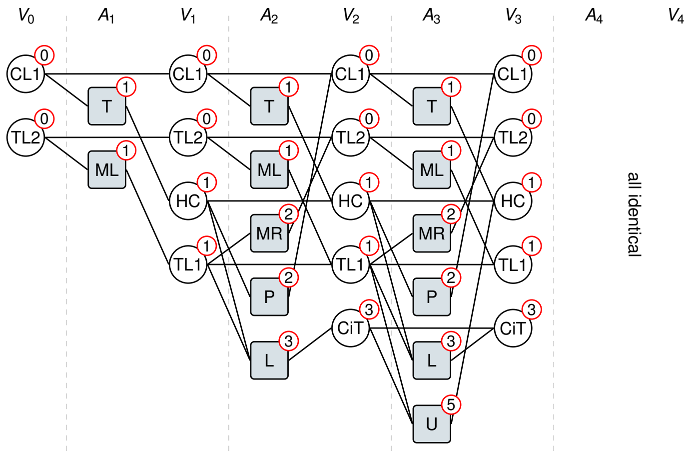
variable vertex
- The cost of a variable vertex v is 0 if $v \in V^0$.
- For all $v \in V^i$, $i > 0$, the cost of v equals the minimum cost of all predecessor vertices (these might be either action or variable vertices).

vertex set For a set of state variables $\bar{v} \subseteq V$, the cost equals the sum of costs of the variables in $\bar{v}$.

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

Example – Exercise!

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



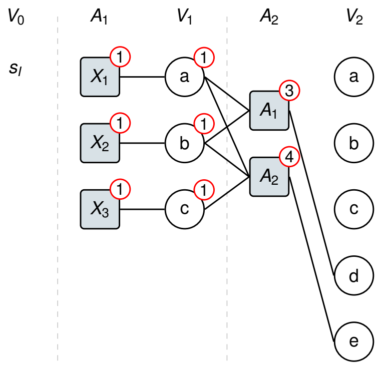
$s_I = \{CrateAtLoc1, TruckAtLoc2\}$ $g = \{CrateInTruck, TruckAtLoc2\}$

$h^{add}(s_I) = 3$ $h^*(s_I) = 4$

Admissibility

Is h^{add} admissible? No.

Heuristic assumes subgoal independence, which is normally not given:



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

h^{FF} for Classical Planning

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.

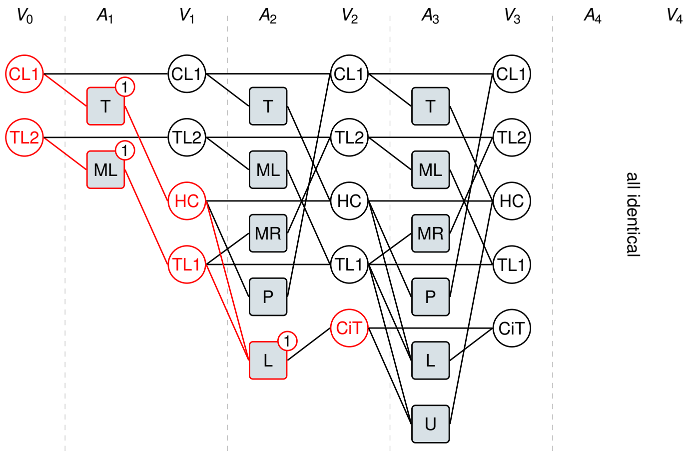
- h^{FF} calculates some (delete-relaxed) plan for $\mathcal{P}^+$.
- Formally, h^{FF} is defined as follows:
  - Compute rPG until the goals are reached.
  - For making a set of state variables true (starting with the goals), select a set of actions that achieve them.
  - For each selected action, repeat the process for their preconditions.

Tie-Breaking Always select an "easy" action first – easy meaning small $\sum_{v \in pre(a)} \min\{i \mid v \text{ is in fact layer } i\}$ value.

heuristic For a state $s \in S$, $h^{FF}(s)$ equals the cost of the extracted plan (selected actions).

Example – Exercise!

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



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

$h^{FF}(s_I) = 3$ $h^*(s_I) = 4$

Admissibility

Is h^{FF} admissible? No (except for the practice).

If the *original* planning problem $\mathcal{P}$ happens to be delete-free already, it might (easily) happen that a suboptimal set of actions is selected.

Theorem

Computing h^+ is $\mathbb{NP}$-complete.

Hardness of Solving $\mathcal{P}^+$ Optimally

Theorem

Computing h^+ is $\mathbb{NP}$-complete.

Membership Proof:

- Each action needs to be applied at most once.
- Thus, the maximum *required* plan length (to achieve any goal description) is bounded by $b \leq |A|$.
- 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).

Hardness of Solving $\mathcal{P}^+$ Optimally

Theorem

Computing h^+ is $\mathbb{NP}$-complete.

Hardness Proof: Reduction from CNF-SAT:

- Let $\varphi = \underbrace{\{C_1, \ldots, C_n\}}_{\text{clauses}}$, $C_j = \underbrace{\{\varphi_{j_1}, \ldots, \varphi_{j_k}\}}_{\text{literals}}$, and $V = \underbrace{\{x_1, \ldots, x_m\}}_{\text{variables}}$.
- For each boolean variable $x_i \in V$ add two actions to A:
  $[x_i \mapsto \top]$ with effects $x_i{-}\top$, $x_i{-}set$ $\quad$ $[x_i \mapsto \bot]$ with effects $x_i{-}\bot$, $x_i{-}set$
- For each *positive* $\varphi_{j_i} = x_{j_i}$ or *negative* $\varphi_{j_i} = \neg x_{j_i}$ add
  $x_{j_i}{-}\top$ $[$"$x_{j_i} = \top$" $C_j \mapsto \top]$ $C_j{-}\top$ or $x_{j_i}{-}\bot$ $[$"$x_{j_i} = \bot$" $C_j \mapsto \top]$ $C_j{-}\top$
- $g = \{x_i{-}set \mid 1 \leq i \leq m\} \cup \{C_j{-}\top \mid 1 \leq j \leq n\}$
- 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

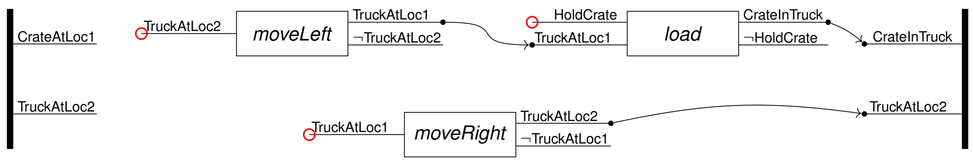
Classical vs. POCL Heuristics

Reminder Classical Planning:

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

POCL Planning:

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



Classical vs. POCL Heuristics

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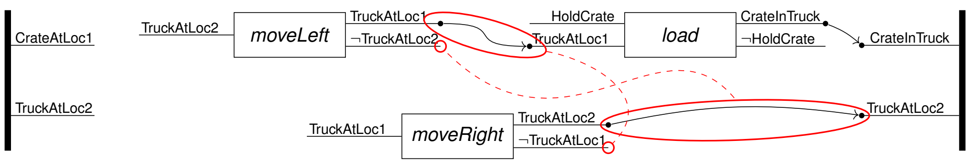


POCL Heuristics

So, how to compute heuristics for partial plans?

- Count *all* flaws.
- Count a *subset* of all flaws, e.g. the open preconditions – called the *OC* heuristic (see Nguyen and Kambhampati).
- Via compilation:
  - Translate each search node into a linear program (see Bylander).
  - Translate each search node into a (new/altered) *classical* problem and use standard classical heuristics (see Bercher et al.).
- Directly *adapt* heuristics for classical planning:
  - FF heuristic → *Relax* heuristic (see Nguyen and Kambhampati).
  - Add heuristic → *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

Adapting Classical Heuristics for POCL Planning

Again:

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

POCL Planning:

Here, there is neither a *current state* nor a goal description – but a partial plan with flaws.

Now what?

- What do we do? How to bring both worlds together?

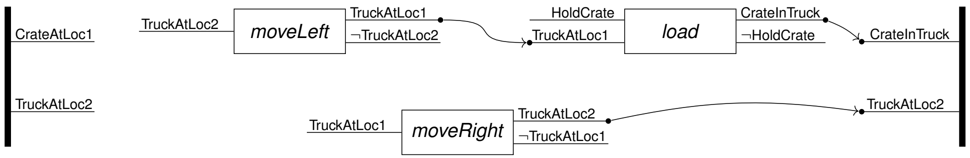
→ Use the partial plan's initial state as initial state of heuristic.

→ Use the the open (i.e., unprotected) preconditions as goal state.

Adapting Classical Heuristics for POCL Planning, cont'd

Using classical heuristics in POCL planning:

- Use the partial plan's initial state as initial state of heuristic.
- Use the the open (i.e., unprotected) preconditions as goal state.



What problems could arise from doing this?

- This ignores negative effects and the causal links' pruning power.
- We get unreachable goals: $\{TruckAtLoc1, TruckAtLoc2\}$

Why – or more precisely: *when* – does this work?

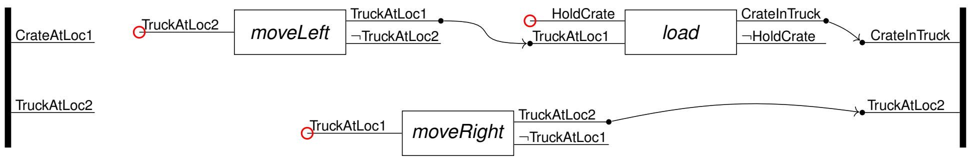
- We only use heuristics that rely on (full) delete relaxation!

Add Heuristic for POCL Planning

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

- Then, let $h^{add}_g(s)$ be the *classical* Add heuristic estimating the goal distance from some state $s \in S$ to the goals g. (In contrast to the last section, we now made the goals g explicit in the sub script.)
- Then, with $h^{add}_{POCL}(P)$ we refer to the *Add Heuristic for POCL Planning* that estimates the goal distance from some current partial plan P to some solution plan. It is defined as $h^{add}_G(s_I)$, where G is the set of open preconditions of P.

Add Heuristic for POCL Planning, Example

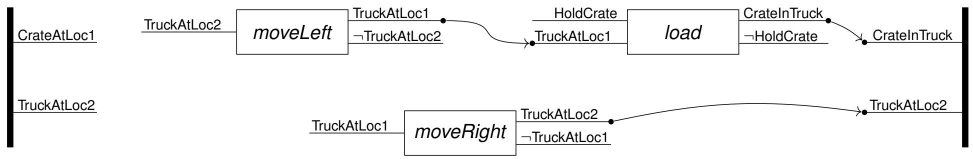


For $h^{add}_{POCL}(P)$, we use:

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

Accounting for Positive Interactions

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



Here, the precondition *TrackAtLoc2* 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.

Add Heuristic for POCL Planning Reusing Actions

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

- Then, let $h^{add}_g(s)$ be the *classical* Add heuristic estimating the goal distance from some state $s \in S$ to the goals g. (In contrast to the last section, we now made the goals g explicit in the sub script.)
- Then, with $h^{add-r}_{POCL}(P)$, $P = (PS, \prec, CL)$, we refer to the *Add Heuristic for POCL Planning Reusing Actions* that estimates the goal distance from some current partial plan P to some solution plan. It is defined as $h^{add}_G(s_I)$, where G is a subset of open preconditions of P, i.e., $G = \{v \mid (v, ps)$ is an open precondition of P and there is no plan step $ps' \in PS$ with $v \in add(ps')$ such that $\prec \cup \{(ps', ps)\}$ is a strict partial order$\}$.

Relax Heuristic

The FF heuristic for POCL planning – called *Relax heuristic* or h^{FF}_{POCL} – transfers the ideas of h^{add}_{POCL} to the FF heuristic:

- It relies on a rPG. (This is not *perfectly* true, but for the sake of simplicity we assume this here.)
- 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.

Summary

- Many heuristics base upon the relaxed planning graph (or an relaxed action model).
- h^{max} is admissible and can be computed in $\mathbb{P}$.
- h^{add} is inadmissible and can be computed in $\mathbb{P}$.
- h^{FF} is inadmissible (in theory, but often admissible in practice) and can be computed in $\mathbb{P}$.
- h^{+} is admissible and $\mathbb{NP}$-complete to compute.
- All these heuristics take the *current state* as input and estimate the goal distance to some *goal state*.
- But since they are delete-relaxed, they can be used for POCL planning as well.