

Planning and Optimization

E5. Cost Partitioning

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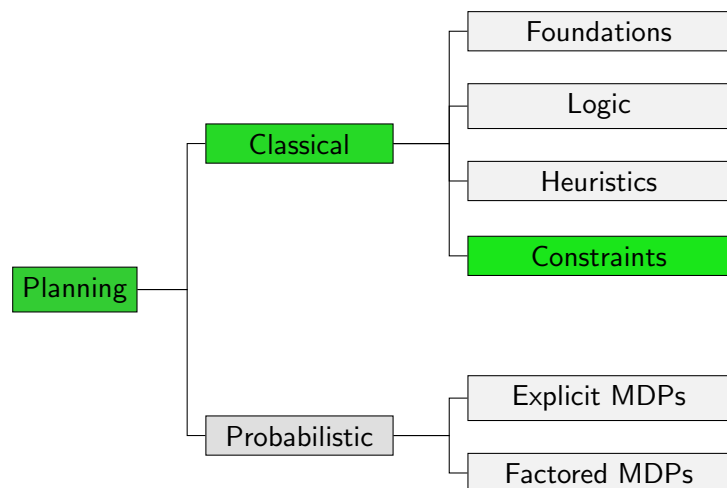
E5.1 Introduction

E5.2 Cost Partitioning

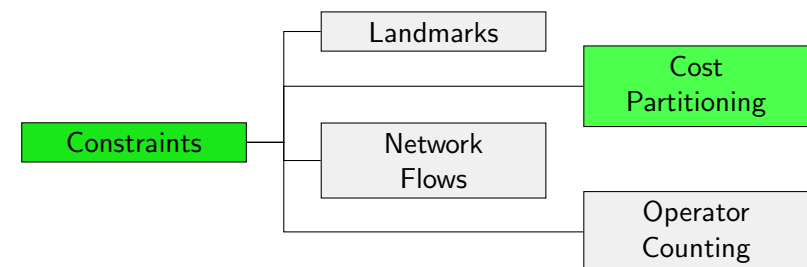
E5.3 Saturated Cost Partitioning

E5.4 Summary

Content of this Course



Content of this Course: Constraints



E5.1 Introduction

Exploiting Additivity

- ▶ Additivity allows to add up heuristic estimates admissibly. This gives better heuristic estimates than the maximum.
- ▶ For example, the canonical heuristic for PDBs sums up where addition is admissible (by an additivity criterion) and takes the maximum otherwise.
- ▶ **Cost partitioning** provides a more general additivity criterion, based on an adaption of the operator costs.

Additivity

When is it impossible to sum up abstraction heuristics admissibly?

- ▶ Abstraction heuristics are consistent and goal-aware.
- ▶ Sum of goal-aware heuristics is goal aware.
- ▶ \Rightarrow Sum of consistent heuristics not necessarily consistent.

Combining Heuristics Admissibly: Example

Example

Consider an FDR planning task $\langle V, I, \{o_1, o_2, o_3, o_4\}, \gamma \rangle$ with $V = \{v_1, v_2, v_3\}$ with $dom(v_1) = \{A, B\}$ and $dom(v_2) = dom(v_3) = \{A, B, C\}$, $I = \{v_1 \mapsto A, v_2 \mapsto A, v_3 \mapsto A\}$,

$$o_1 = \langle v_1 = A, v_1 := B, 1 \rangle$$

$$o_2 = \langle v_2 = A \wedge v_3 = A, v_2 := B \wedge v_3 := B, 1 \rangle$$

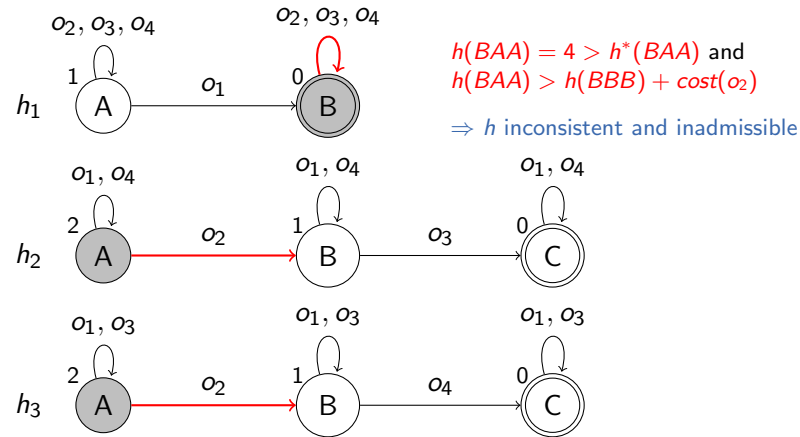
$$o_3 = \langle v_2 = B, v_2 := C, 1 \rangle$$

$$o_4 = \langle v_3 = B, v_3 := C, 1 \rangle$$

and $\gamma = (v_1 = B) \wedge (v_2 = C) \wedge (v_3 = C)$.

Combining Heuristics Admissibly: Example

Let $h = h_1 + h_2 + h_3$. Where is consistency constraint violated?



Consider solution $\langle o_1, o_2, o_3, o_4 \rangle$

Solution: Cost partitioning

h is not admissible because $cost(o_2)$ is considered in h_2 and h_3

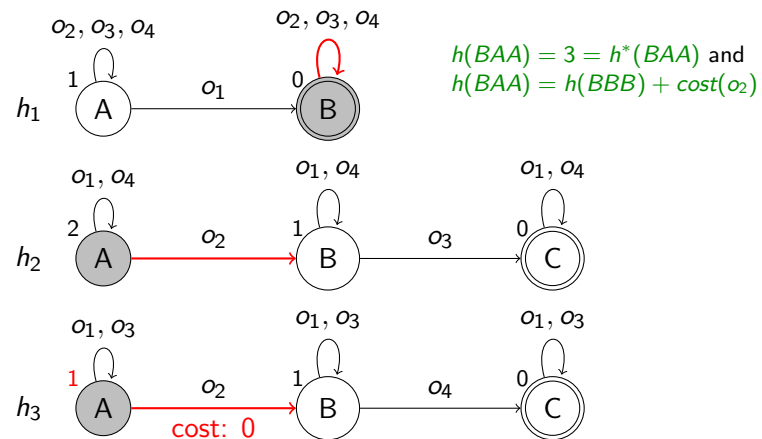
Is there anything we can do about this?

Solution 1:

We can ignore the cost of o_2 in h_2 or h_3 by setting its cost to 0.

Combining Heuristics Admissibly: Example

Assume $cost_3(o_2) = 0$



Consider solution $\langle o_1, o_2, o_3, o_4 \rangle$

Solution: Cost partitioning

h is not admissible because $cost(o_2)$ is considered in h_2 and h_3

Is there anything we can do about this?

Solution 1:

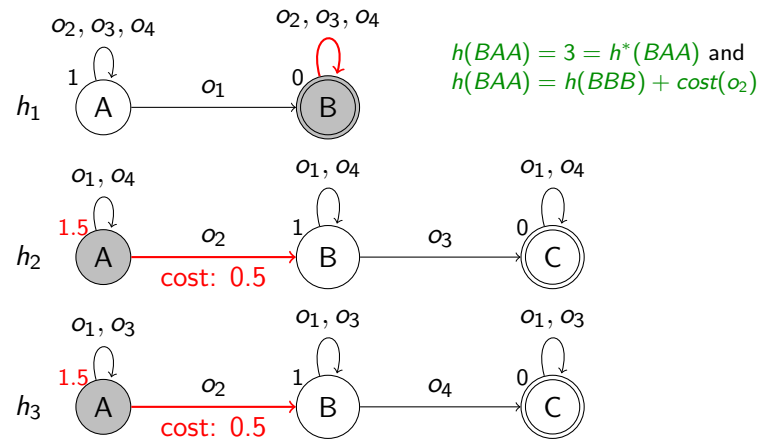
We can ignore the cost of o_2 in h_2 or h_3 by setting its cost to 0.

This is called a **zero-one cost partitioning**.

Solution 2: Consider a cost of $\frac{1}{2}$ for o_2 both in h_2 and h_3 .

Combining Heuristics Admissibly: Example

Assume $cost_2(o_2) = cost_3(o_2) = \frac{1}{2}$



Consider solution $\langle o_1, o_2, o_3, o_4 \rangle$

Solution: Cost partitioning

h is not admissible because $cost(o_2)$ is considered in h_2 and h_3

Is there anything we can do about this?

Solution 1:

We can ignore the cost of o_2 in h_2 or h_3 by setting its cost to 0. This is called a **zero-one cost partitioning**.

Solution 2: Consider a cost of $\frac{1}{2}$ for o_2 both in h_2 and h_3 . This is called a **uniform cost partitioning**.

General solution: satisfy **cost partitioning constraint**

$$\sum_{i=1}^n cost_i(o) \leq cost(o) \text{ for all } o \in O$$

What about o_1, o_3 and o_4 ?

E5.2 Cost Partitioning

Cost Partitioning

Definition (Cost Partitioning)

Let Π be a planning task with operators O .

A **cost partitioning** for Π is a tuple $\langle cost_1, \dots, cost_n \rangle$, where

- ▶ $cost_i : O \rightarrow \mathbb{R}_0^+$ for $1 \leq i \leq n$ and
- ▶ $\sum_{i=1}^n cost_i(o) \leq cost(o)$ for all $o \in O$.

The cost partitioning induces a tuple $\langle \Pi_1, \dots, \Pi_n \rangle$ of planning tasks, where each Π_i is identical to Π except that the cost of each operator o is $cost_i(o)$.

Cost Partitioning: Admissibility (1)

Theorem (Sum of Solution Costs is Admissible)

Let Π be a planning task, $\langle cost_1, \dots, cost_n \rangle$ be a cost partitioning and $\langle \Pi_1, \dots, \Pi_n \rangle$ be the tuple of induced tasks.

Then the sum of the solution costs of the induced tasks is an admissible heuristic for Π , i.e., $\sum_{i=1}^n h_{\Pi_i}^* \leq h_{\Pi}^*$.

Cost Partitioning: Admissibility (2)

Proof of Theorem.

If there is no plan for state s of Π , both sides are ∞ . Otherwise, let $\pi = \langle o_1, \dots, o_m \rangle$ be an optimal plan for state s of Π . Then

$$\begin{aligned} \sum_{i=1}^n h_{\Pi_i}^*(s) &\leq \sum_{i=1}^n \sum_{j=1}^m cost_i(o_j) && (\pi \text{ plan in each } \Pi_i) \\ &= \sum_{j=1}^m \sum_{i=1}^n cost_i(o_j) && (\text{comm./ass. of sum}) \\ &\leq \sum_{j=1}^m cost(o_j) && (\text{cost partitioning}) \\ &= h_{\Pi}^*(s) && (\pi \text{ optimal plan in } \Pi) \end{aligned}$$

□

Cost Partitioning Preserves Admissibility

In the rest of the chapter, we write h_{Π} to denote heuristic h evaluated on task Π .

Corollary (Sum of Admissible Estimates is Admissible)

Let Π be a planning task and let $\langle \Pi_1, \dots, \Pi_n \rangle$ be induced by a cost partitioning.

For admissible heuristics h_1, \dots, h_n , the sum $h(s) = \sum_{i=1}^n h_{i, \Pi_i}(s)$ is an admissible estimate for s in Π .

Cost Partitioning Preserves Consistency

Theorem (Cost Partitioning Preserves Consistency)

Let Π be a planning task and let $\langle \Pi_1, \dots, \Pi_n \rangle$ be induced by a cost partitioning $\langle cost_1, \dots, cost_n \rangle$.

If h_1, \dots, h_n are consistent heuristics then $h = \sum_{i=1}^n h_{i, \Pi_i}$ is a consistent heuristic for Π .

Proof.

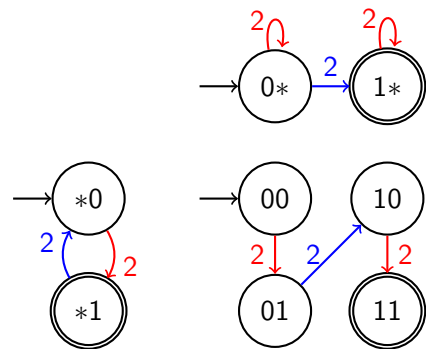
Let o be an operator that is applicable in state s .

$$\begin{aligned} h(s) &= \sum_{i=1}^n h_{i, \Pi_i}(s) \leq \sum_{i=1}^n (cost_i(o) + h_{i, \Pi_i}(s[o])) \\ &= \sum_{i=1}^n cost_i(o) + \sum_{i=1}^n h_{i, \Pi_i}(s[o]) \leq cost(o) + h(s[o]) \end{aligned}$$

□

Cost Partitioning: Example

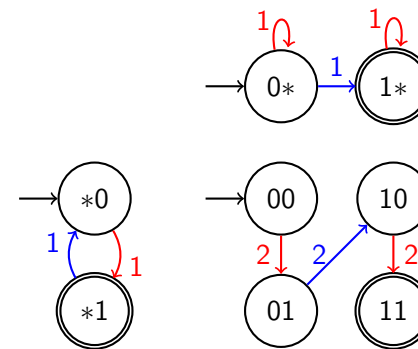
Example (No Cost Partitioning)



Heuristic value: $\max\{2, 2\} = 2$

Cost Partitioning: Example

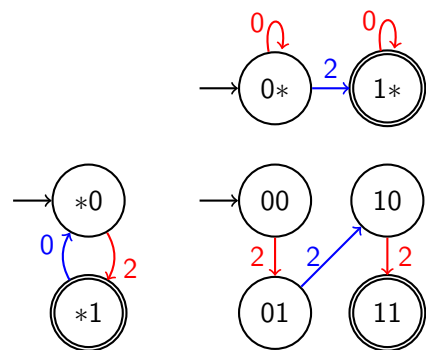
Example (Cost Partitioning 1)



Heuristic value: $1 + 1 = 2$

Cost Partitioning: Example

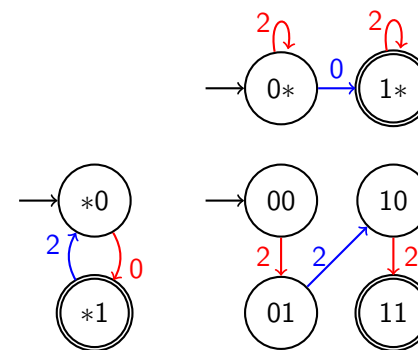
Example (Cost Partitioning 2)



Heuristic value: $2 + 2 = 4$

Cost Partitioning: Example

Example (Cost Partitioning 3)



Heuristic value: $0 + 0 = 0$

Cost Partitioning: Quality

- ▶ $h(s) = h_{1,\Pi_1}(s) + \dots + h_{n,\Pi_n}(s)$
can be **better or worse** than any $h_{i,\Pi}(s)$
→ depending on cost partitioning
- ▶ strategies for defining cost-functions
 - ▶ uniform
 - ▶ zero-one
 - ▶ saturated (now)
 - ▶ optimal (next chapter)

E5.3 Saturated Cost Partitioning

Idea

Heuristics do not always “need” all operator costs

- ▶ Pick a heuristic and use minimum costs **preserving all estimates**
- ▶ Continue with **remaining cost** until all heuristics were picked

Saturated cost partitioning (SCP) currently offers the **best tradeoff between computation time and heuristic guidance in practice.**

Saturated Cost Function

Definition (Saturated Cost Function)

Let Π be a planning task and h be a heuristic.
A cost function scf is **saturated** for h and $cost$ if

- ① $scf(o) \leq cost(o)$ for all operators o and
- ② $h_{\Pi_{scf}}(s) = h_{\Pi}(s)$ for all states s ,
where Π_{scf} is Π with cost function scf .

Minimal Saturated Cost Function

For abstractions, there exists a unique **minimal saturated cost function** (MSCF).

Definition (MSCF for Abstractions)

Let Π be a planning task and α be an abstraction for Π .
The **minimal saturated cost function** for α is

$$\text{mscf}(o) = \max_{\alpha(s) \xrightarrow{o} \alpha(t)} \max\{h^\alpha(s) - h^\alpha(t), 0\}$$

Algorithm

Saturated Cost Partitioning: Seipp & Helmert (2014)

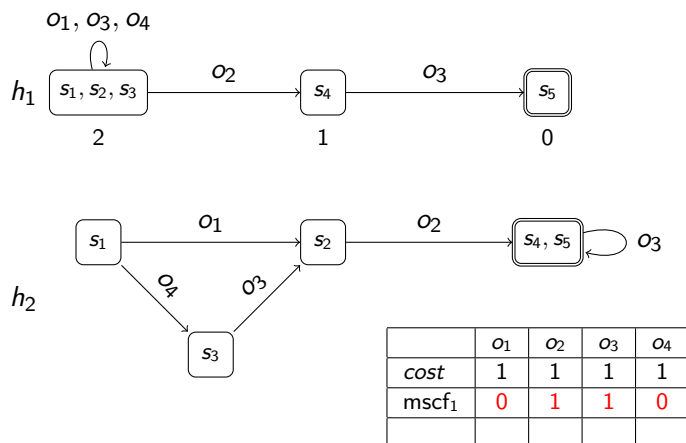
Iterate:

- 1 Pick a heuristic h_i that hasn't been picked before.
Terminate if none is left.
 - 2 Compute h_i given current *cost*
 - 3 Compute minimal saturated cost function mscf_i for h_i
 - 4 Decrease *cost*(o) by $\text{mscf}_i(o)$ for all operators o
- $\langle \text{mscf}_1, \dots, \text{mscf}_n \rangle$ is **saturated cost partitioning** (SCP)
for $\langle h_1, \dots, h_n \rangle$ (in pick order)

Example

Consider the abstraction heuristics h_1 and h_2

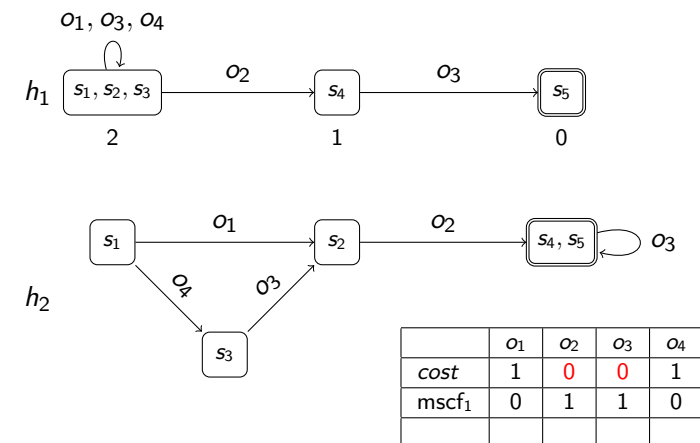
- 3 Compute minimal saturated cost function mscf_i for h_i



Example

Consider the abstraction heuristics h_1 and h_2

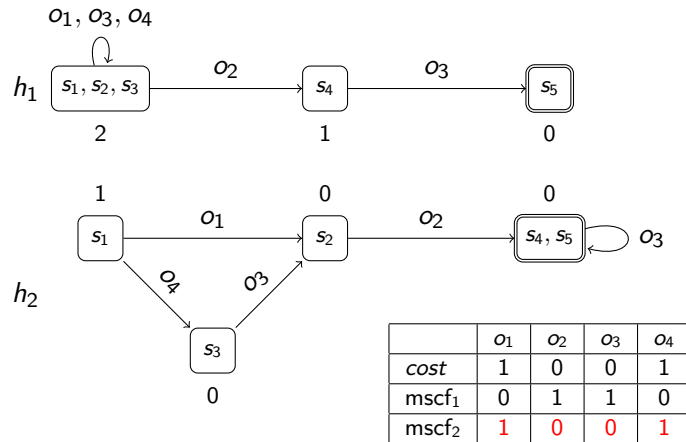
- 4 Decrease *cost*(o) by $\text{mscf}_i(o)$ for all operators o



Example

Consider the abstraction heuristics h_1 and h_2

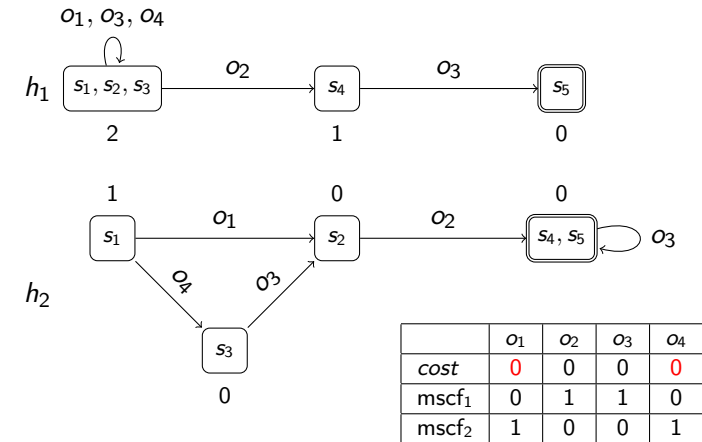
- ③ Compute minimal saturated cost function mscf_i for h_i



Example

Consider the abstraction heuristics h_1 and h_2

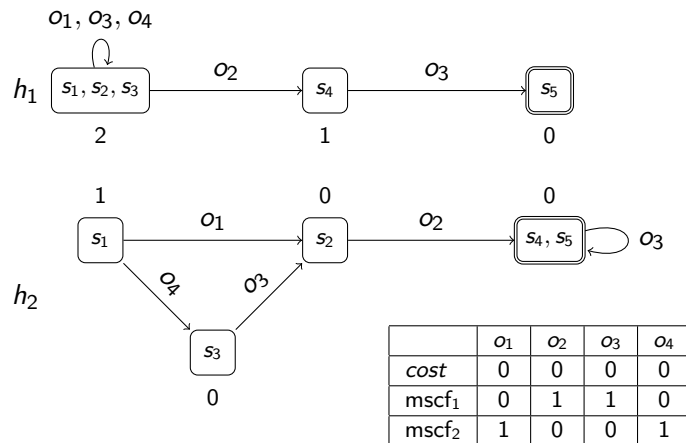
- ④ Decrease $\text{cost}(o)$ by $\text{mscf}_i(o)$ for all operators o



Example

Consider the abstraction heuristics h_1 and h_2

- ④ Pick a heuristic h_i . **Terminate if none is left.**

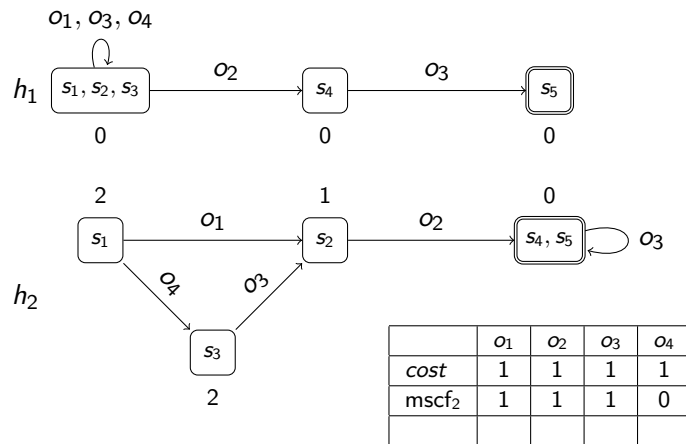


Influence of Selected Order

- ▶ quality highly susceptible to selected order
- ▶ there are almost always orders where SCP performs much better than uniform or zero-one cost partitioning
- ▶ but there are also often orders where SCP performs worse

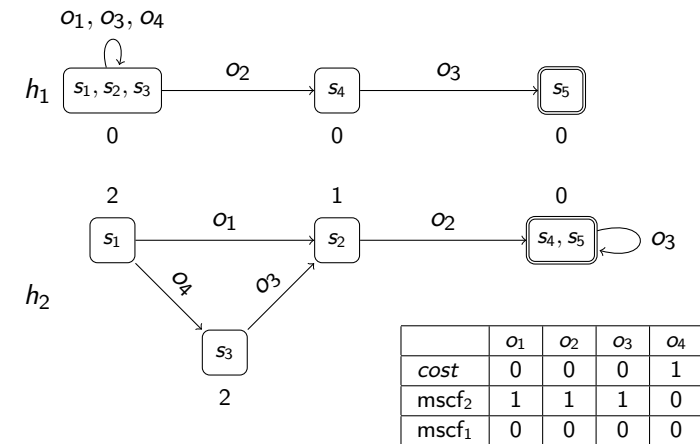
Saturated Cost Partitioning: Order

Consider the abstraction heuristics h_1 and h_2



Saturated Cost Partitioning: Order

Consider the abstraction heuristics h_1 and h_2



Influence of Selected Order

- ▶ quality highly susceptible to selected order
 - ▶ there are almost always orders where SCP performs much better than uniform or zero-one cost partitioning
 - ▶ but there are also often orders where SCP performs worse
- Maximizing over multiple orders good solution in practice

SCP for Disjunctive Action Landmarks

Same algorithm can be used for disjunctive action landmarks, where we also have a minimal saturated cost function.

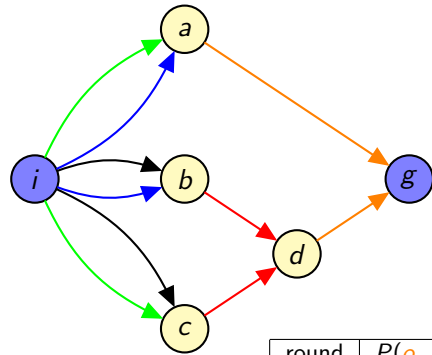
Definition (MSCF for Disjunctive Action Landmark)

Let Π be a planning task and \mathcal{L} be a disjunctive action landmark. The minimal saturated cost function for \mathcal{L} is

$$mscf(o) = \begin{cases} \min_{o \in \mathcal{L}} cost(o) & \text{if } o \in \mathcal{L} \\ 0 & \text{otherwise} \end{cases}$$

Does this look familiar?

Reminder: LM-Cut



$O_{\text{blue}} = \langle \{i\}, \{a, b\}, \{\}, 4 \rangle$
 $O_{\text{green}} = \langle \{i\}, \{a, c\}, \{\}, 5 \rangle$
 $O_{\text{black}} = \langle \{i\}, \{b, c\}, \{\}, 3 \rangle$
 $O_{\text{red}} = \langle \{b, c\}, \{d\}, \{\}, 2 \rangle$
 $O_{\text{orange}} = \langle \{a, d\}, \{g\}, \{\}, 0 \rangle$

round	$P(O_{\text{orange}})$	$P(O_{\text{red}})$	landmark	cost
1	d	b	$\{O_{\text{red}}\}$	2
2	a	b	$\{O_{\text{green}}, O_{\text{blue}}\}$	4
3	d	c	$\{O_{\text{green}}, O_{\text{black}}\}$	1
			$h^{\text{LM-cut}}(I)$	7

SCP for Disjunctive Action Landmarks

Same algorithm can be used for **disjunctive action landmarks**, where we also have a **minimal saturated cost function**.

Definition (MSCF for Disjunctive Action Landmark)

Let Π be a planning task and \mathcal{L} be a disjunctive action landmark. The **minimal saturated cost function** for \mathcal{L} is

$$\text{mscf}(o) = \begin{cases} \min_{o \in \mathcal{L}} \text{cost}(o) & \text{if } o \in \mathcal{L} \\ 0 & \text{otherwise} \end{cases}$$

Does this look familiar?

LM-Cut computes SCP over disjunctive action landmarks

E5.4 Summary

Summary

- ▶ **Cost partitioning** allows to admissibly add up estimates of several heuristics.
- ▶ This can be better or worse than the best individual heuristic on the original problem, depending on the cost partitioning.
- ▶ **Saturated cost partitioning** offers good tradeoff between computation time and heuristic guidance
- ▶ LM-Cut computes SCP over disjunctive action landmarks