Automated Planning F7. Optimal and General Cost Partitioning

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based on slides from the AI group at the University of Basel

[Optimal Cost Partitioning](#page-1-0)

Content of this Course

Optimal Cost Partitioning: General Approach

- Can we find a better cost partitioning than with the uniform or saturation strategy? Even an optimal one?
- \blacksquare Idea: exploit linear programming
	- Use variables for cost of each operator in each task copy
	- Express heuristic values with linear constraints
	- Maximize sum of heuristic values subject to these constraints

Optimal Cost Partitioning: General Approach

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LPs known for

- **abstraction heuristics (not covered in this course)**
- \blacksquare disjunctive action landmarks (now)

Optimal Cost Partitioning for Landmarks: Basic Version

- Use an LP that covers the heuristic computation and the cost partitioning.
- LP variable C_{Lo} for cost of operator *o* in induced task for disjunctive action landmark *L* (cost partitioning)
- LP variable Cost_L for cost of disjunctive action landmark *L* in induced task (value of individual heuristics)

Optimal Cost Partitioning for Landmarks: Basic LP

Variables

Non-negative variable Cost_l for each disj. action landmark $L \in \mathcal{L}$ Non-negative variable $C_{\ell,0}$ for each $L \in \mathcal{L}$ and operator *o*

Objective

Maximize $\sum_{\substack{\textbf{\textit{L}}}\in \textbf{\textit{\underline{L}}}}$ Cost_L

Subject to

$$
\sum_{L \in \mathcal{L}} C_{L,o} \le \text{cost}(o) \quad \text{for all operators } o
$$
\n
$$
\text{Cost}_{L} \le C_{L,o} \qquad \text{for all } L \in \mathcal{L} \text{ and } o \in L
$$

Optimal Cost Partitioning for Landmarks: Improved

■ Observation: Explicit variables for cost partitioning not necessary. ■ Use implicitly $cost_l(o) = Cost_l$ for all $o \in L$ and 0 otherwise.

Optimal Cost Partitioning for Landmarks: Improved LP

Variables

Non-negative variable Cost_L for each disj. action landmark $L \in \mathcal{L}$

Objective

Maximize $\sum_{\substack{L \in \mathcal{L}}} \mathsf{Cost}_L$

Subject to

$$
\sum_{L \in \mathcal{L}: o \in L} \text{Cost}_L \leq \text{cost}(o) \quad \text{for all operators } o
$$

Example (1)

Example

Let Π be a planning task with operators o_1, \ldots, o_4 and
 $cost(o_1) = 3$ $cost(o_2) = 4$ $cost(o_3) = 5$ and $cost(o_4)$. $cost(o_1) = 3, cost(o_2) = 4, cost(o_3) = 5$ and $cost(o_4) = 0$. Let the following be disjunctive action landmarks for Π:

$$
\mathcal{L}_1 = \{o_4\}
$$

\n
$$
\mathcal{L}_2 = \{o_1, o_2\}
$$

\n
$$
\mathcal{L}_3 = \{o_1, o_3\}
$$

\n
$$
\mathcal{L}_4 = \{o_2, o_3\}
$$

Example (2)

Optimal Cost Partitioning for Landmarks (Dual view)

Variables

Non-negative variable Applied*^o* for each operator *o*

Objective

```
Minimize Í
o Appliedo
· cost(o)
```
Subject to

$$
\sum_{o \in L} \text{Applied}_o \ge 1 \text{ for all landmarks } L
$$

Minimize "plan cost" with all landmarks satisfied.

Example: Dual View

Example: Dual View

This is equal to the LP relaxation of the MHS heuristic

Reminder: LP Relaxation of MHS heuristic

Example (Minimum Hitting Set)

minimize
$$
3X_{0_1} + 4X_{0_2} + 5X_{0_3}
$$
 subject to
\n $X_{0_4} \ge 1$
\n $X_{0_1} + X_{0_2} \ge 1$
\n $X_{0_1} + X_{0_3} \ge 1$
\n $X_{0_2} + X_{0_3} \ge 1$
\n $X_{0_1} \ge 0$, $X_{0_2} \ge 0$, $X_{0_3} \ge 0$, $X_{0_4} \ge 0$

 \rightarrow optimal solution of LP relaxation:

 $X_{o_4} = 1$ and $X_{o_1} = X_{o_2} = X_{o_3} = 0.5$ with objective value 6

 \rightarrow LP relaxation of MHS heuristic is admissible and can be computed in polynomial time

[General Cost Partitioning](#page-15-0)

Content of this Course

General Cost Partitioning

Cost functions are usually non-negative.

- \blacksquare We tacitly also required this for task copies
- Makes sense intuitively: original costs are non-negative
- But: not necessary for cost-partitioning! \Box

General Cost Partitioning

Definition (General Cost Partitioning)

Let Π be a planning task with operators *O*.

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

- $cost_i: 0 \rightarrow \mathbb{R}$ for $1 \leq i \leq n$ and
- $\sum_{i=1}^{n} cost_i(o) \le cost(o)$ for all $o \in O$.

General Cost Partitionings are Admissible

Theorem (Sum of Admissible Estimates is Admissible)

Let Π *be a planning task and let* ⟨Π¹ , . . . , ^Π*n*⟩ *be induced by a general cost partitioning.*

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

Heuristic value: $2 + 2 = 4$

Heuristic value: $4 + 2 = 6$

Heuristic value: $-\infty + 5 = -\infty$

[Summary](#page-25-0)

Summary

- For abstraction heuristics and disjunctive action landmarks, we know how to determine an optimal cost partitioning, using linear programming.
- Although solving a linear program is possible in polynomial time, the better heuristic guidance often does not outweigh the overhead (in particular for abstraction heuristics).
- In constrast to standard (non-negative) cost partitioning, general cost partitioning allows negative operators costs.
- General cost partitioning has the same relevant properties as non-negative cost partitioning but is more powerful.