Pattern Selection for Optimal Classical Planning with Saturated Cost Partitioning

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August 14, 2019

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Setting

- optimal classical planning
- A^* search + admissible heuristic
- pattern databases

How to select patterns?

- bin packing (Edelkamp 2001)
- genetic algorithms (Edelkamp 2006)
- hill climbing (Haslum et al. 2007)
- CPC (Franco et al. 2017)
- CEGAR (Rovner et al. 2019)
- systematic (Pommerening et al. 2013)

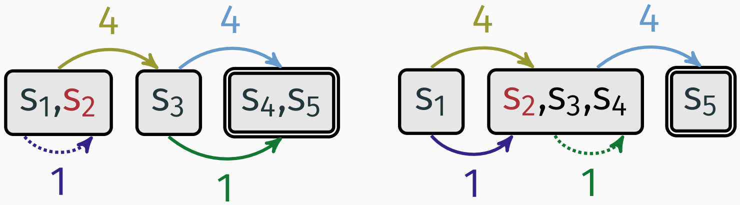
How to combine multiple PDB heuristics?

- maximize
- cost partitioning
- saturated cost partitioning

Saturated cost partitioning

Saturated cost partitioning algorithm

- 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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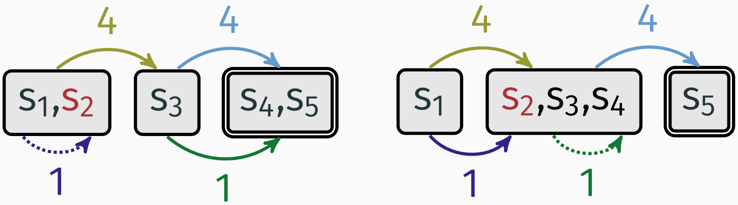

$\max(h_1(s_2), h_2(s_2)) = \max(5, 4) = 5$

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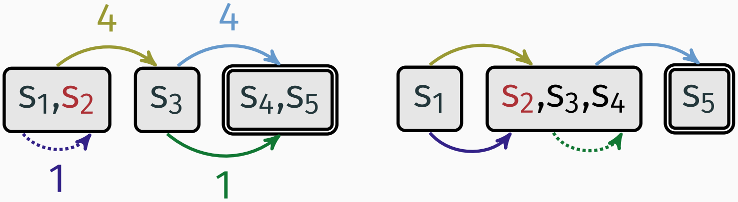

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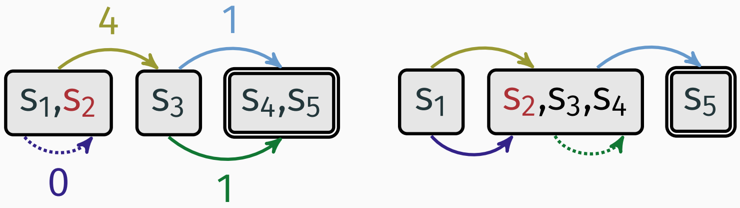

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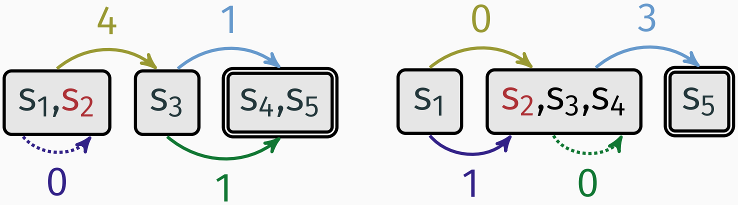

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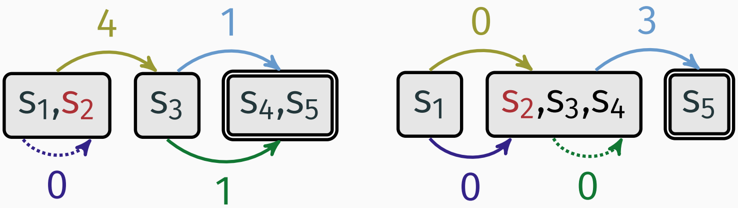

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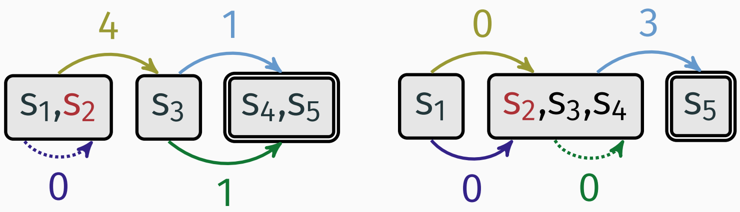

$$h^{\mathrm{SCP}}_{\langle h_1,h_2\rangle}(s_2) = 5 + 3 = 8$$

Diverse orders for saturated cost partitioning

Diversification algorithm

- sample 1000 states $\hat{S}$
- start with empty set of orders
- for 200 seconds:
    - sample a new state s
    - find a greedy order for s
    - if a sample in $\hat{S}$ profits from it, keep it
    - otherwise, discard it

Idea

- select patterns
- compute diverse saturated cost partitionings over PDBs

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- select patterns with saturated cost partitioning
- compute diverse saturated cost partitionings over PDBs

SYS-SCP: a new pattern selection algorithm

One SYS-SCP iteration

- start with empty pattern sequence σ
- for each pattern $P \in \textsc{Order}(\textsc{Sys})$:
  - add P to σ if $h^{SCP}_{\sigma}(s) < h^{SCP}_{\sigma \oplus P}(s) < \infty$ for any state s

- repeat until hitting time limit
- return all selected patterns

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- return all selected patterns
- problem: testing every state is infeasible

Evaluating a pattern using its projection

Theorem

$$
\begin{aligned}
&\exists s \in S(\mathcal{T}) : h^{\mathrm{SCP}}_{\sigma}(\mathrm{cost}, s) < h^{\mathrm{SCP}}_{\sigma \oplus P}(\mathrm{cost}, s) < \infty \\
\Leftrightarrow\ &\exists s' \in S(\mathcal{T}_P) : \qquad\qquad\qquad 0 < h^{*}_{\mathcal{T}_P}(\mathrm{rem}, s') \quad < \infty
\end{aligned}
$$

Using the theorem

- keep track of the remaining cost function
- select a PDB if it has positive finite goal distances

Pattern orders

order by increasing pattern size, break ties by:

- random
- states in projection
- active operators
- Fast Downward variable order:
  - up: [7, 5], [8, 2], [8, 5]
  - down: [8, 5], [8, 2], [7, 5]

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Systematic patterns with limits

LIM: 2M states per PDB, 20M states in collection, 100 seconds

Max pattern size	1	2	3	4	5
SYS	840	986	1057	922	731
SYS-LIM	840	985	1088	1050	1035

SYS-SCP vs. other pattern selection algorithms

	HC	SYS-3-LIM	CPC	CEGAR	SYS-SCP
Coverage	966	1088	1055	1098	1168
#domains SYS-SCP better	28	23	21	21	–
#domains SYS-SCP worse	3	2	3	3	–

Future work

- test patterns on samples

Summary

- new pattern selection algorithm based on saturated cost partitioning
- outperforms all previous pattern selection algorithms