Online Saturated Cost Partitioning for Classical Planning

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Setting

- optimal classical planning
- A* search + admissible heuristic
- multiple abstraction heuristics
- cost partitioning

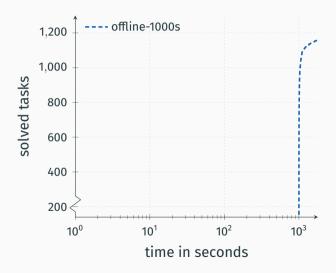
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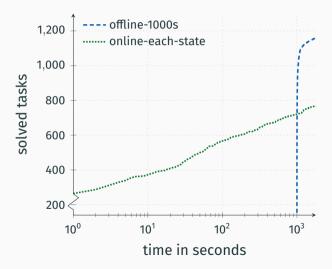
- optimal classical planning
- A* search + admissible heuristic
- multiple abstraction heuristics
- saturated cost partitioning

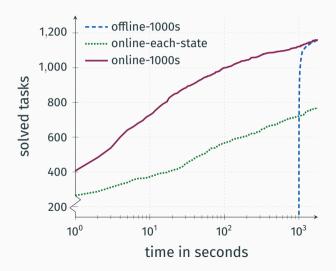
Problem

different states need different cost partitionings:

- precompute cost partitionings
- $\,
 ightarrow\,$ no good stopping criterion, search starts late
 - compute cost partitioning for each state
- $\rightarrow \ too \ expensive$



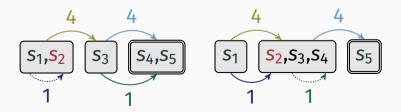




Cost partitioning

• split action costs among heuristics such that: sum of costs \leq original cost

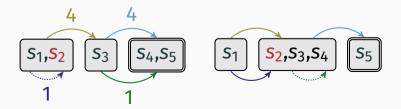
- order heuristics, then for each heuristic *h*:
 - use minimum costs preserving all estimates of h
 - use remaining costs for subsequent heuristics



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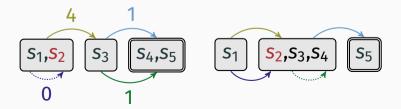
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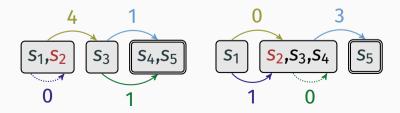
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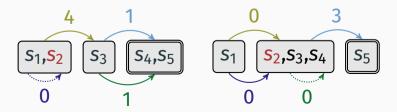
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Order matters:

•
$$h^{\text{SCP}}_{\rightarrow}(s_2) = 8$$

•
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 $\,\rightarrow\,$ use multiple orders and maximize over estimates

Offline diversification

- sample 1000 states
- · start with empty set of orders
- until time limit is reached:
 - · compute order for new sample
 - · store order if a sample profits from it

Online diversification

COMPUTEHEURISTIC(S)

- if Select(s) and not time limit reached
 - · compute order for s
 - · store order if s profits from it
- return maximum over all stored orders for s

Offline vs. online diversification

Offline

- compute orders for samples for T seconds
- store order if one of 1000 samples profits from it

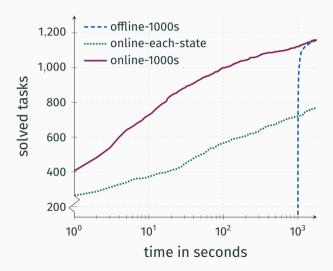
Online

- compute orders for subset of evaluated states for at most T seconds
- store order if single evaluated state profits from it

Selection strategies

SELECT

- Bellman (Eifler and Fickert 2018)
- Novelty (Lipovetzky and Geffner 2012)
- Interval



Summary

Offline diversification	Online computation	Online diversification
long precomputation	no precomputation	no precomputation
samples	states	states
fast evaluations	slow evaluations	fast evaluations
high coverage	low coverage	high coverage