IJCAI workshop on Generalization in Planning (GenPlan 22)

Learning Generalized Policy Automata for Relational Stochastic Shortest Path Problems

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Motivation

- A planetary rover needs to transport rocks back to the base for analysis.
  - The rover has a slippery gripper that can hold a single rock.
  - It is possible to reach any location from any given location.
- Actions have certain predictable, but stochastic elements.
  - Given the nature of the mission, good models of the effects of actions are available.

Image credit: https://mars.nasa.gov/msl/mission/overview/

How do we represent states and actions?

Image-based

- Some aspects of the state are not visible *eg. power, coeff. friction*
- Many problems cannot be naturally described using images.

Logic-based

$$s = \{\texttt{rock}(r_1), \texttt{loc}(l_1), \texttt{rock-at}(r_1, l_1)\}$$

- Many problems well-suited to such representations.
- Good heuristics available.

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How do we efficiently solve such problems?

Image credit: https://mars.nasa.gov/msl/mission/overview/

Generalized Relational Stochastic Shortest Path Problems (GSSPs)

- A domain D consisting of predicates **P** and actions **A**.

- A GSSP problem for a domain D is a tuple <O, S, A, s_0, G, T, C>
    - **O** is a set of objects.
    - **S** and **A** are sets of states and actions instantiating using **O** and **D**..
    - $\mathbf{s_0}$ is the initial state and **G** is a set of goal states.
    - **T** is the transition function and **C** is the cost function.

- We chose GSSPs over SSPs since they allow deadends to exist.

Solution to GSSPs

- Solutions are expressed as policies π: S →A

- GSSP solvers compute policies by iteratively solving Bellman equations over states reachable from the initial state.

$$v^i(s) = \min_a \sum_{s' \in S} t(s,a,s')[c(s,a,s') + v^{i-1}(s')]$$

- Many solvers typically initialize values with heuristic estimates; $v^0(s) = h(s)$

The Need for Generalization

- State spaces grow exponentially as state variables increase.

- Most of the existing solvers are “stateless”.

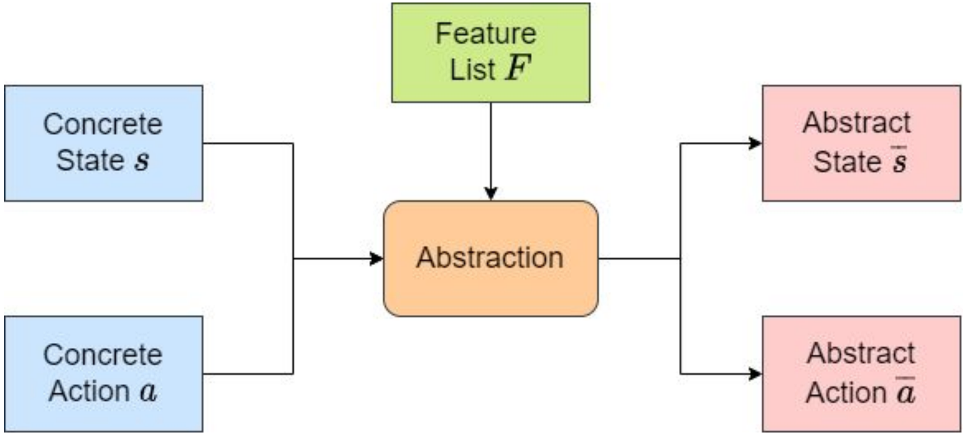
Example

1. Planetary rover problem with 1 rock across 1 location.
2. Planetary rover problem with 10 rocks across 10 locations.

Our Approach: GPA-accelerated SSP Solvers

- We use abstraction to create Generalized Policy Automata (GPA): abstract hypergraphs that encode partial policies.
- GPAs can be used to prune away large parts of the search space.
- SSP solvers operate over this reduced search space to quickly find solutions.
- Theoretical guarantees of hierarchical optimality and completeness.

Abstraction



- Given a list of features, we usefeature kernels that convert concrete states and actions into abstract states and actions.
- We use Canonical Abstraction [Sagiv et al.; 2002] to automatically generate features and feature kernels in a domain-independent fashion.

Learning GPAs

Given a set of solution policies $\pi_1, \ldots, \pi_n$, we learn GPAs by using abstraction to iteratively merge GPAs.

Learning GPAs

1. We represent the solution policy as a directed hypergraph.
2. We convert each directed hypergraph to a GPA using abstraction.
3. We iteratively merge each GPA one by one.

T
$t(s_0, a_0, s_0) \rightarrow 0.8$
$t(s_0, a_0, s_1) \rightarrow 0.2$
$\ldots$

π
$s_0 \rightarrow a_0$
$s_1 \rightarrow a_1$
$s_2 \rightarrow a_2$
$s_g \rightarrow \emptyset$

Given a solution policy
for a problem

Learning GPAs

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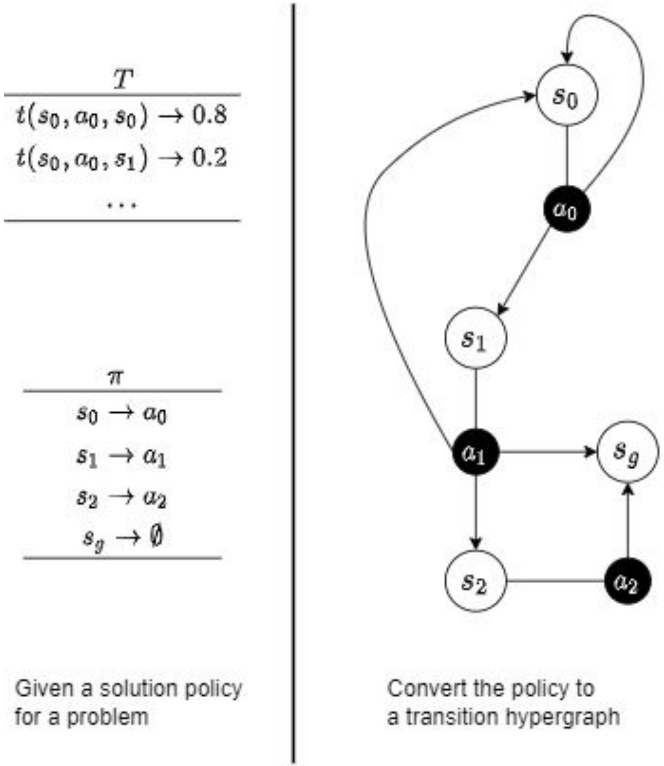

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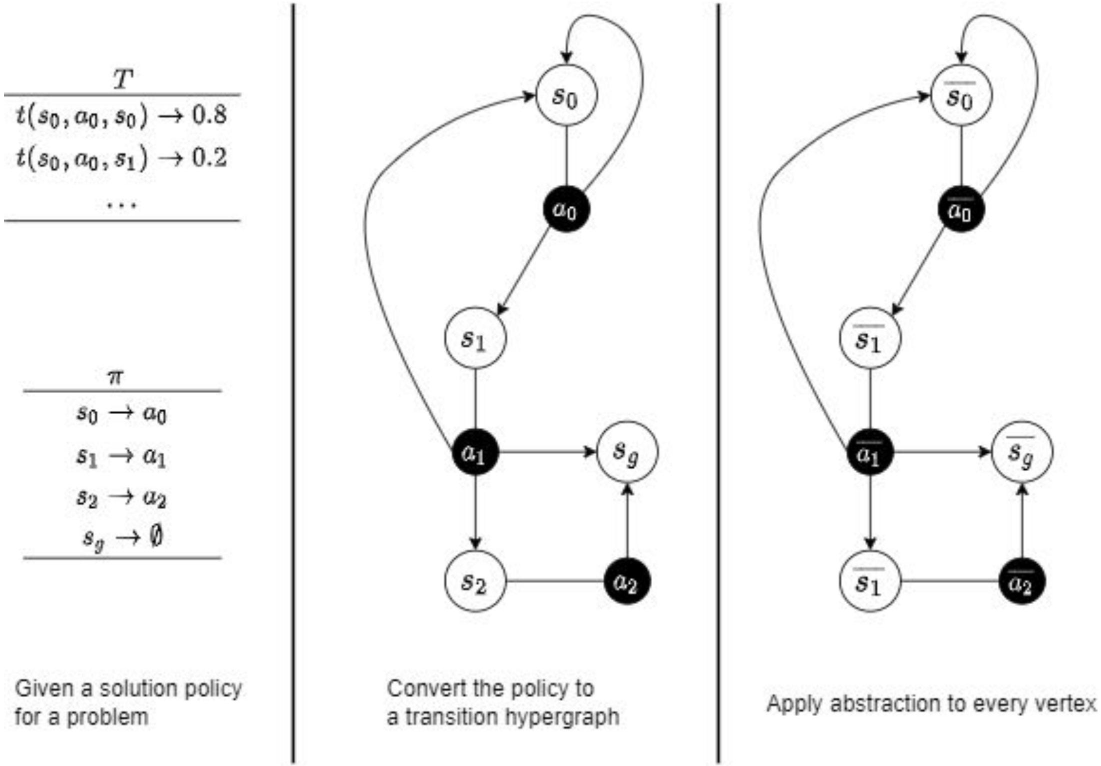

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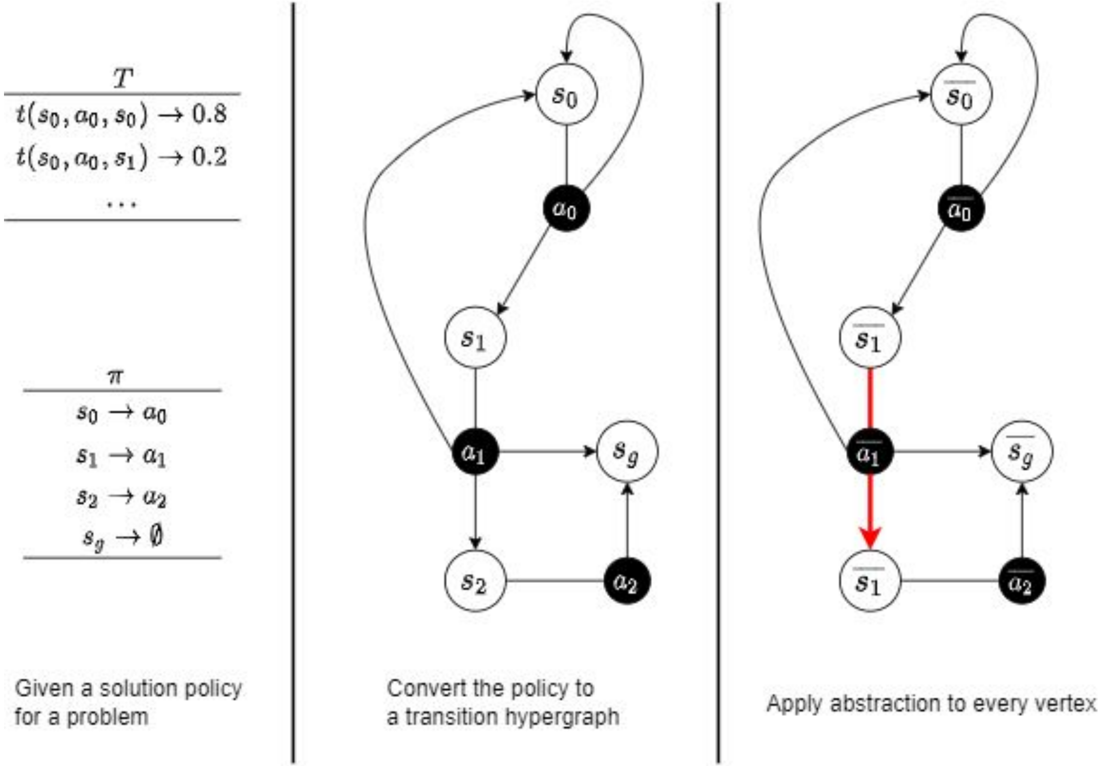

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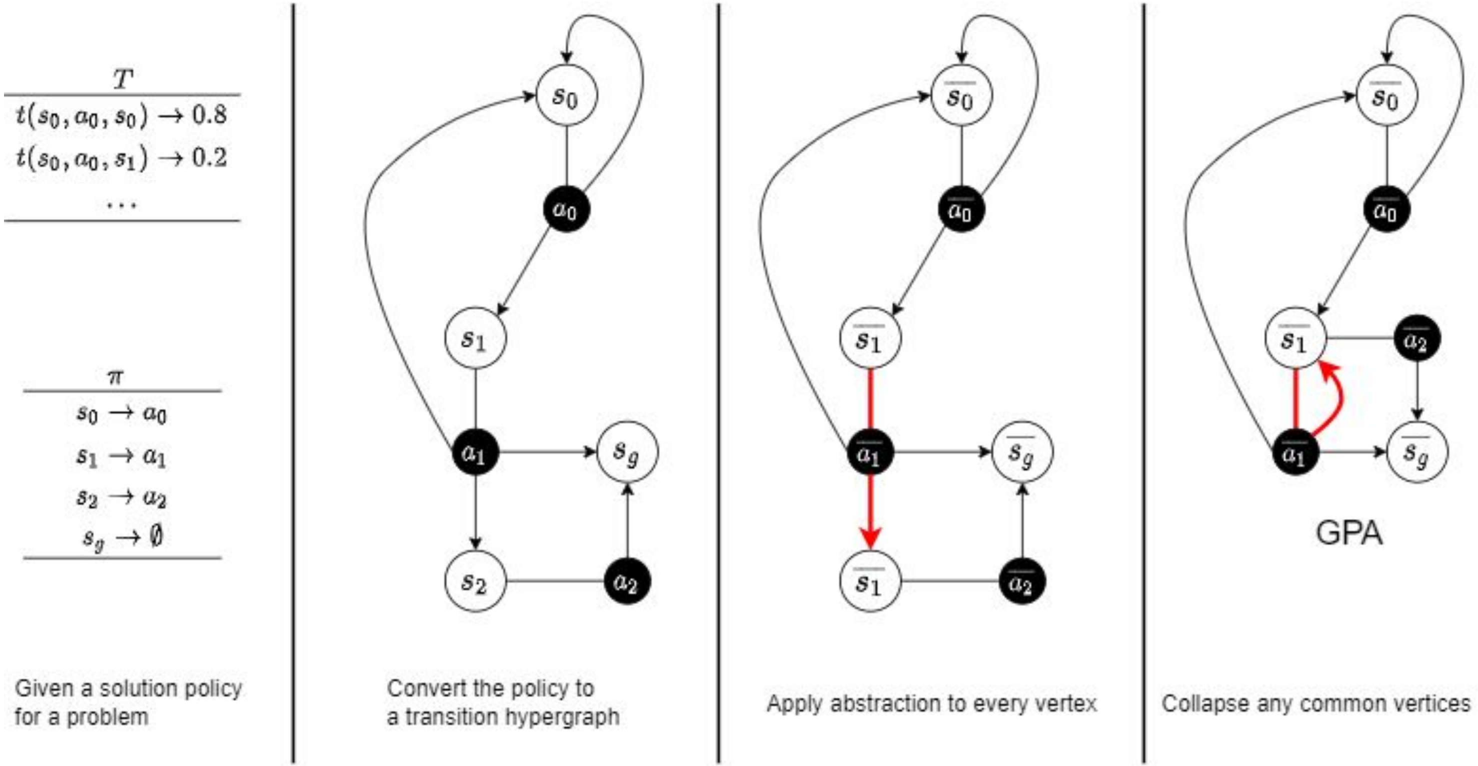

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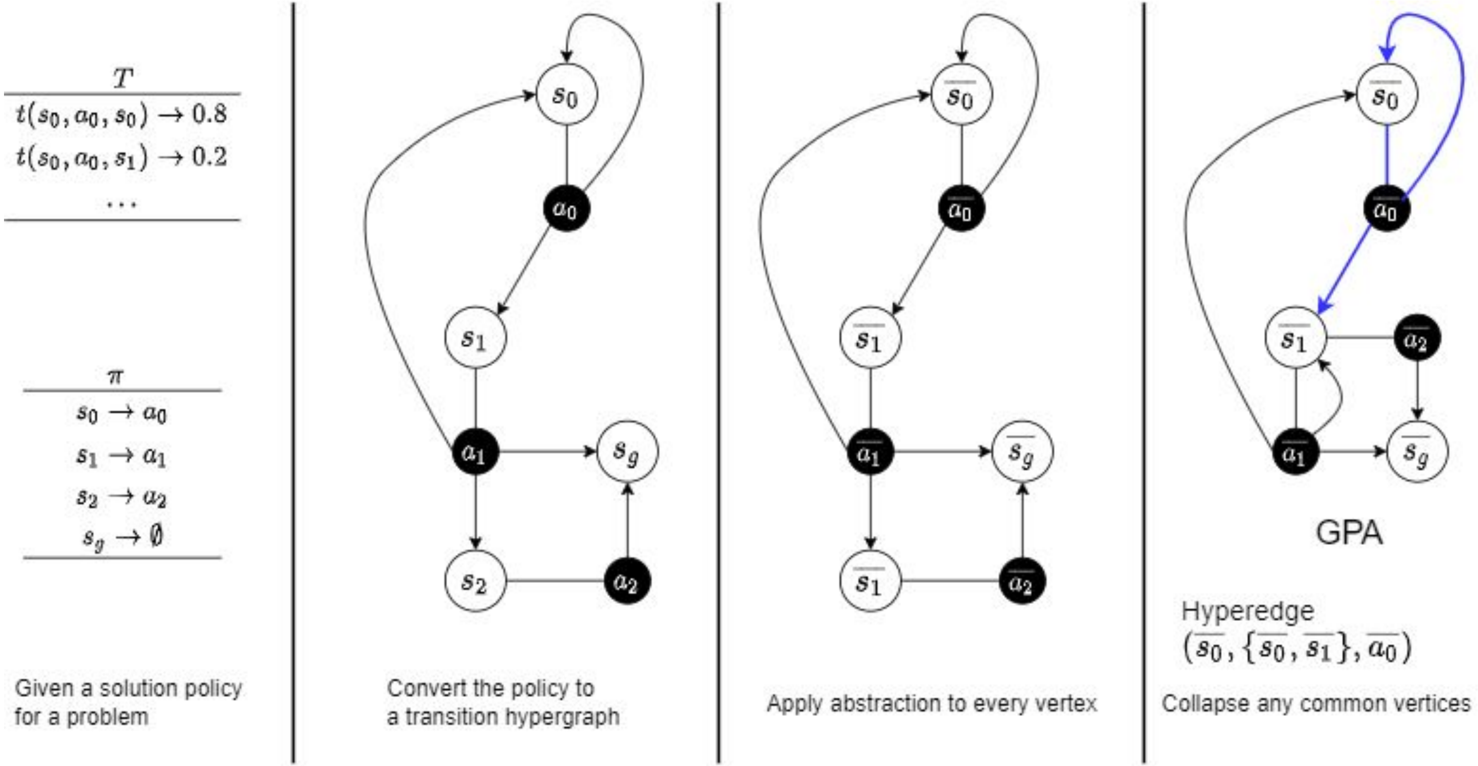

Merging GPAs

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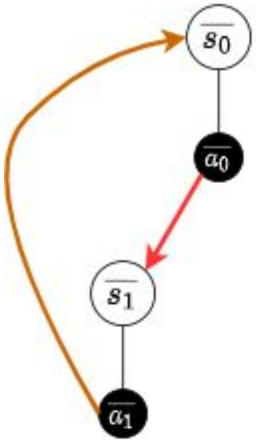
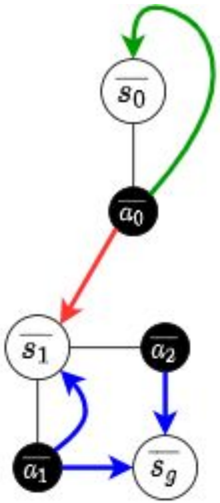


GPA 1



GPA 2

Merging GPAs

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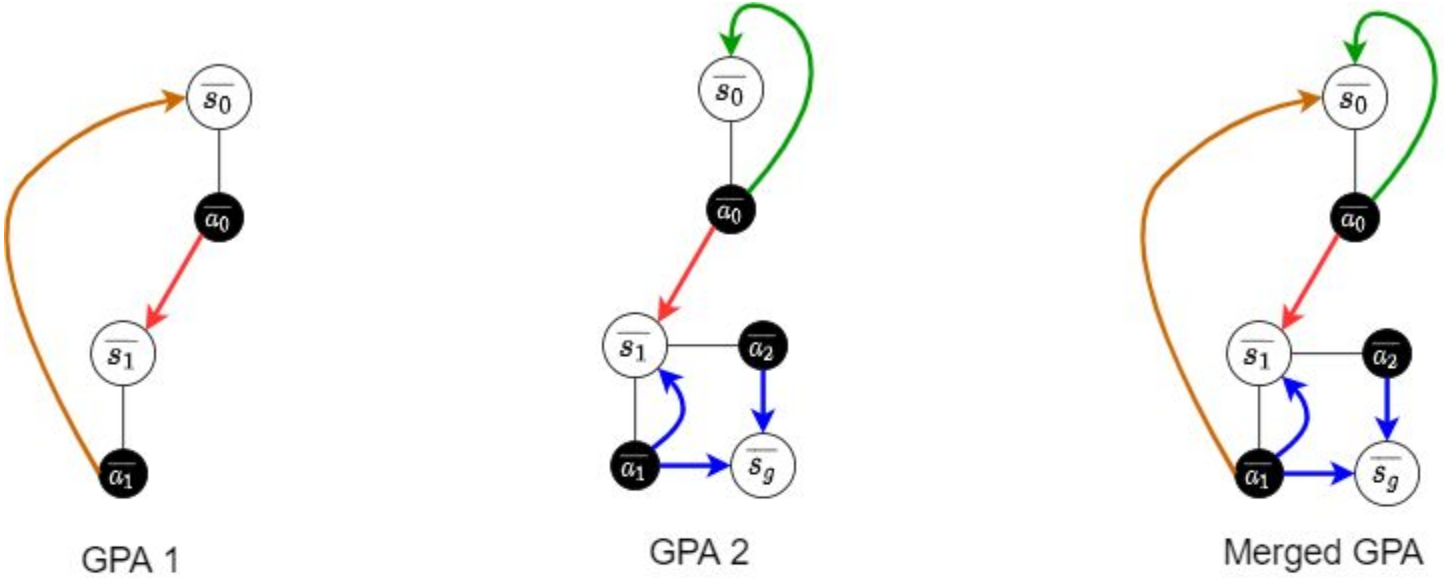


Using GPAs for solving SSPs

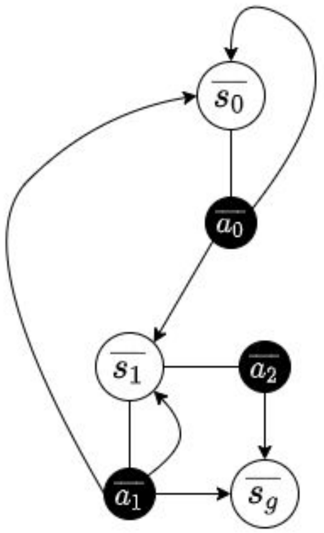
Intuitively, we modify the cost function for transitions that do not appear in the GPA to prune the search space.

Example

$$v^1(s) = \min_a \sum_{s' \in S} t(s, a, s')[c(s, a, s') + v^0(s')]$$

Consider the transition

$$t(s_0, a_0, s_2) = 1$$



GPA

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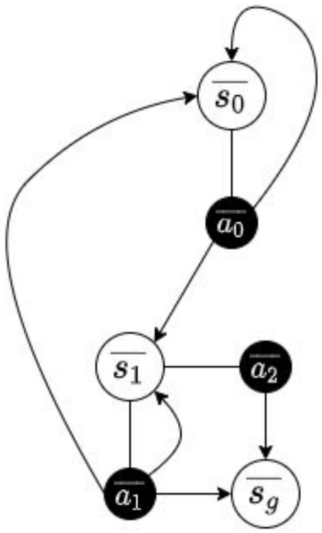

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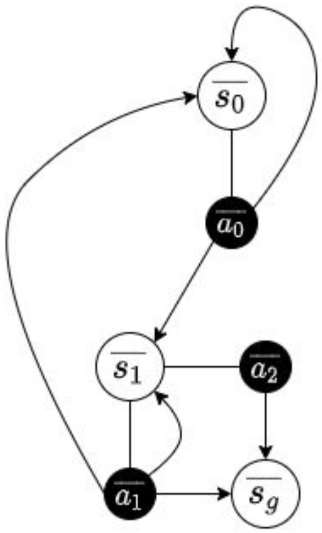
$v^1(s_0) =$	$c(s_0, a_0, s_2) + v^0(s_2)$
Apply Abstraction	$(\overline{s_0}, \overline{a_0}, \overline{s_2})$



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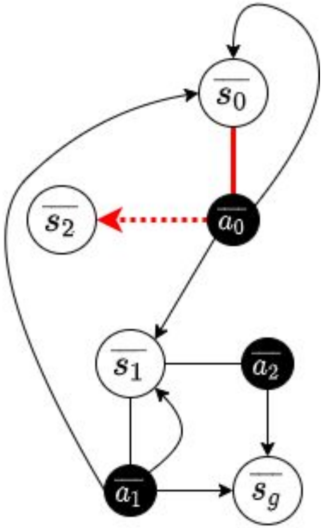

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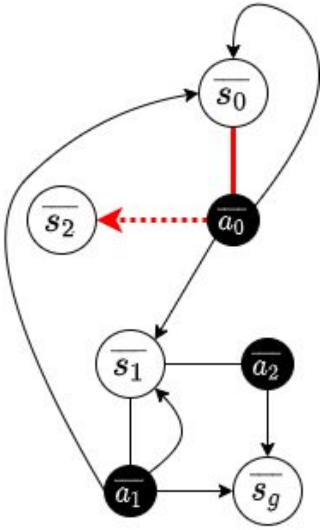

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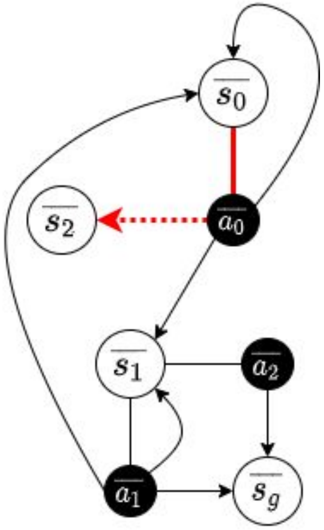

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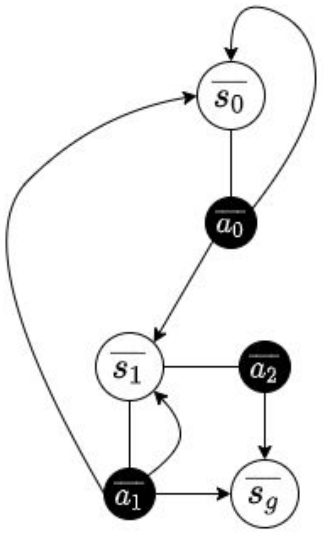

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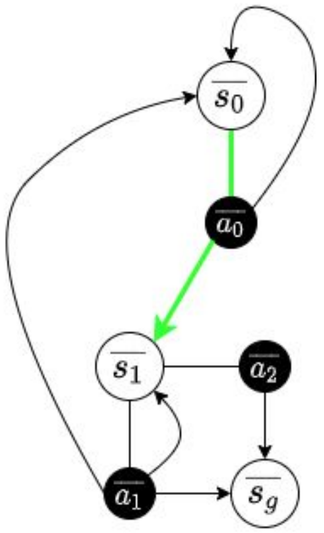

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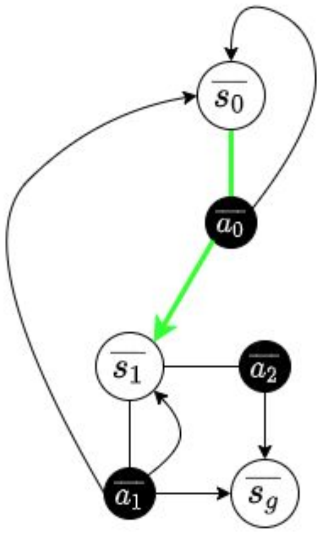

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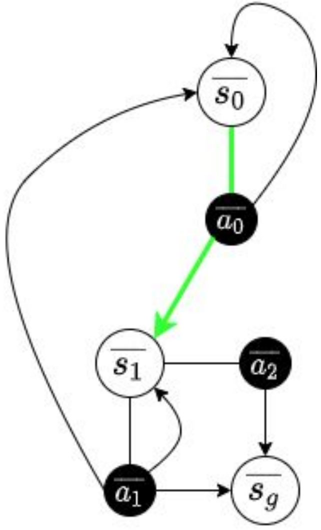
	Pruned	**Allowed**



GPA

Theoretical Analysis

- **Thm 3.1:** Our approach is complete.

- **Thm 3.2:** Our approach is guaranteed to find hierarchically optimal policies.
    - Hierarchically optimal **given** the training data.
    - Policy improvement is guaranteed when falling back to the original cost function.

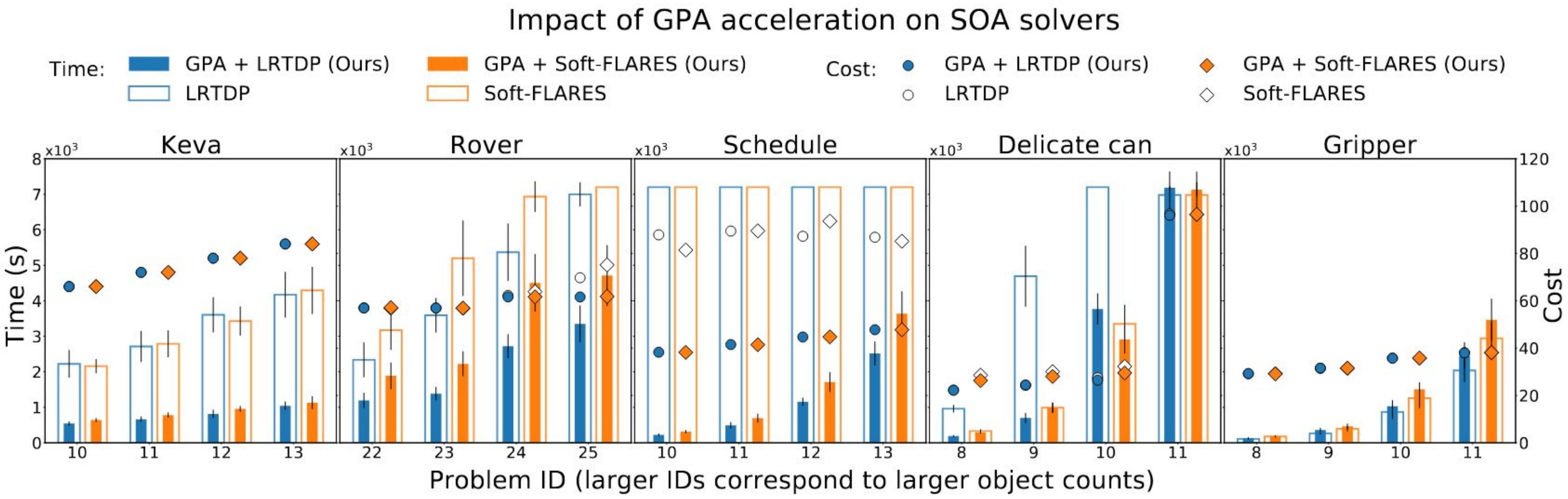
Empirical Evaluation

- 4 benchmark domains.
  - 1 from the International Probabilistic Planning Competition (IPPC)
  - 1 from robotics
  - 2 stochastic versions of International Planning Competition (IPC) domains.
- 2 baseline solvers.
  - LRTDP (Bonet and Geffner; 2003)
  - Soft-FLARES (Pineda et al.; 2019)
- Few-shot training.
  - Solution policies from less than 20 problems.
  - Training time was less than 10 seconds.
- Large test problems.
  - Test set consisted of problems that had more than 2x the object counts of the training set.

Evaluation Methodology

- Run a solver until convergence or 7200 seconds.
- Simulate policy computed 100 times with a horizon limit of 100.
- Report avg. cost incurred.
- 10 total runs.

Empirical Evaluation



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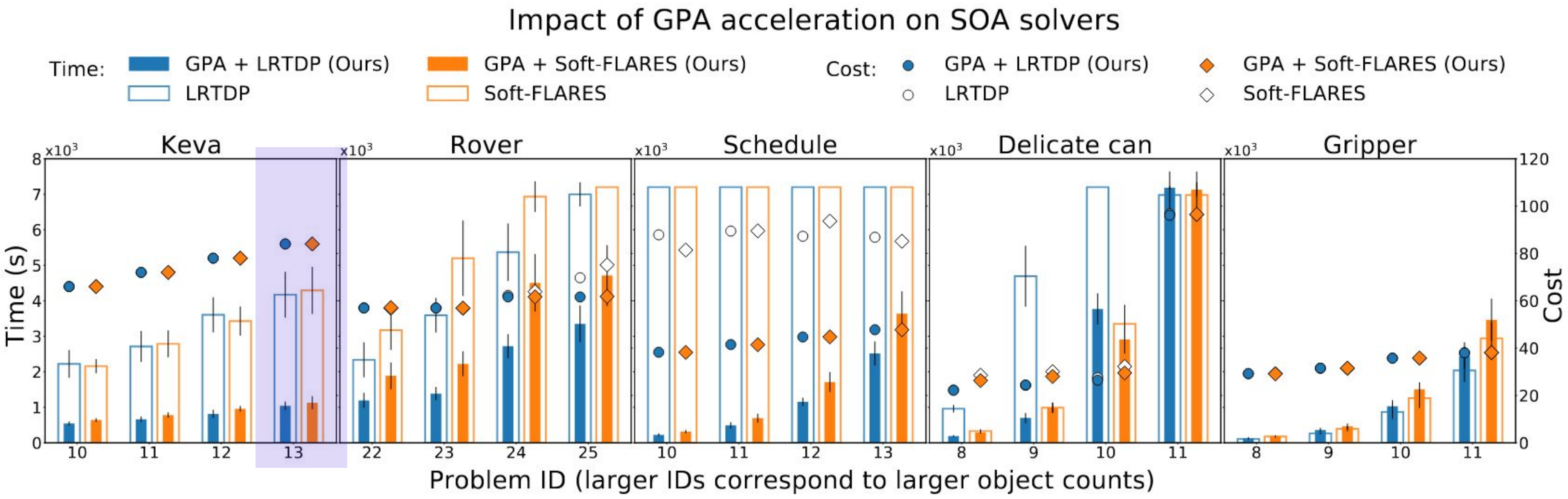
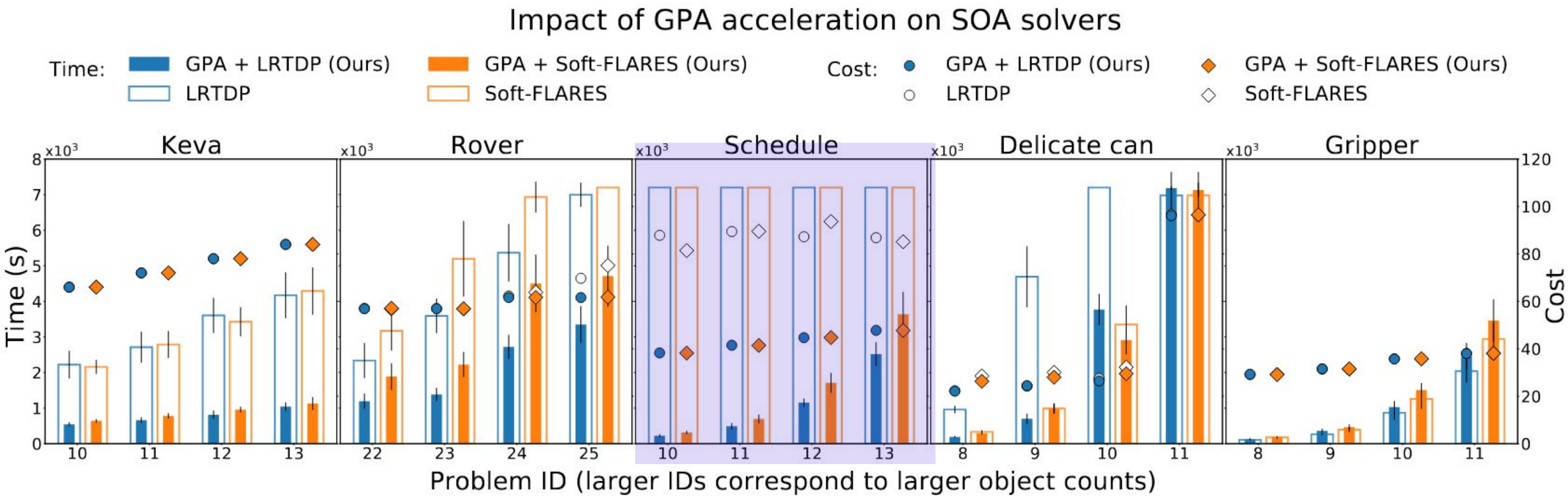


GPA accelerated solvers can solve problems much faster than baselines.

Empirical Evaluation



Sometimes baselines do find a policy that can yield equivalent cost, but they provide no convergence guarantees whereas our approach hierarchically converges in a fraction of the time.

Conclusions

- We introduced an approach that uses abstraction to synthesize GPAs.
- GPAs can be used to prune large parts of the search space.
- Our results show that embedding GPAs results in significant time savings.

Future Work

- Utilize description logic based abstractions.
- Add memory to the GPAs.

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- We introduced an approach that uses abstraction to synthesize GPAs.
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Future Work

- Utilize description logic based abstractions.

Thank you!