Dissertation Abstract: Domain-Independent Heuristics in Probabilistic Planning

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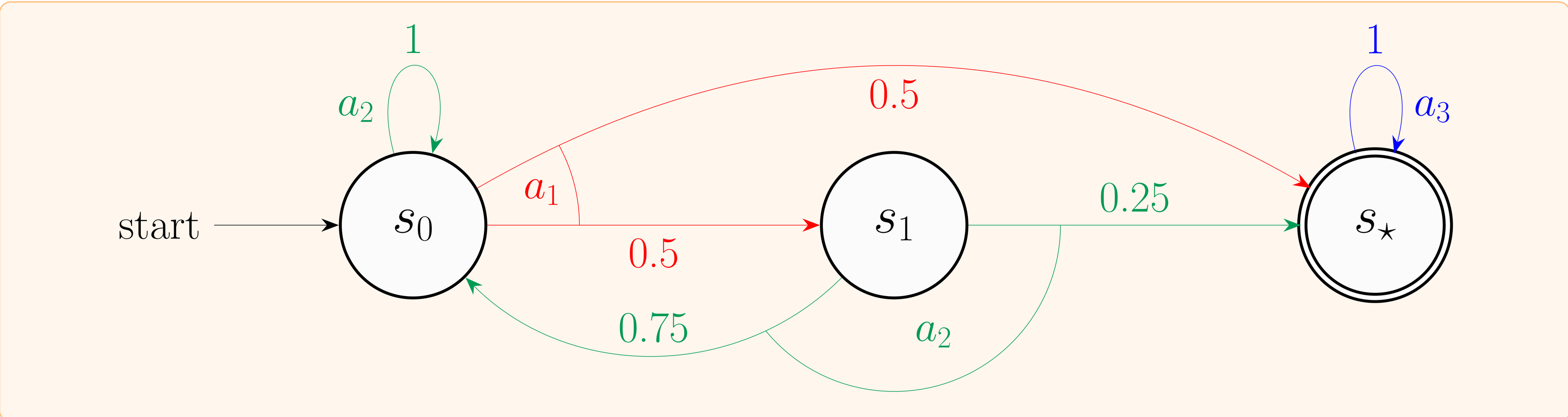
Probabilistic Planning

Probabilistic Planning considers decision-making in stochastic environments. The state space model typically assumed is a *Markov Decision Process* (MDP). For goal-oriented problems as considered here, an MDP consists of the following components:

- A finite set of *states* S
- A finite set of *actions* A
- A *transition probability function* $T : S \times A \times S \to [0, 1]$
  - For all $s \in S, a \in A$, either $T(s, a, \cdot)$ is a probability distribution or $T(s, a, \cdot) \equiv 0$
- An *initial state* $s_0 \in S$
- A set of *goal states* $S_\star \subseteq S$



Optimization Objectives

I consider two settings: *Goal-probability maximization* ("MaxProb") and *Stochastic Shortest Path Problems* (SSPs, Bertsekas and Tsitsiklis (1991)).

In these settings, behaviour is specified by a policy $\pi : S \to A$.

For MaxProb, π is optimal for state s if the probability to eventually reach the goal when starting in s and executing π is maximal among all policies.

The SSP setting also assumes a *cost function* $c : A \to \mathbb{R}^+$. π is optimal for a state s if:

- When starting in s and executing π the goal state is reached with certainty
- Among all such policies, π has the lowest expected cost-to-goal

$V^\star_{\mathrm{MP}}(s)$ is the optimal goal probability, $V^\star_{\mathrm{SSP}}(s)$ is the optimal expected cost-to-goal of s.

Heuristic Search

In both setting considered here, an optimal policy can be found with MDP heuristic search.

Requires an *admissible* heuristic $h : S \to \mathbb{R}$, i.e. h is optimistic w.r.t. the objective:

$$h(s) \leq V^\star_{\mathrm{MP}}(s) \qquad\qquad h(s) \leq V^\star_{\mathrm{SSP}}(s)$$

However, only few domain-independent admissible heuristics are known:

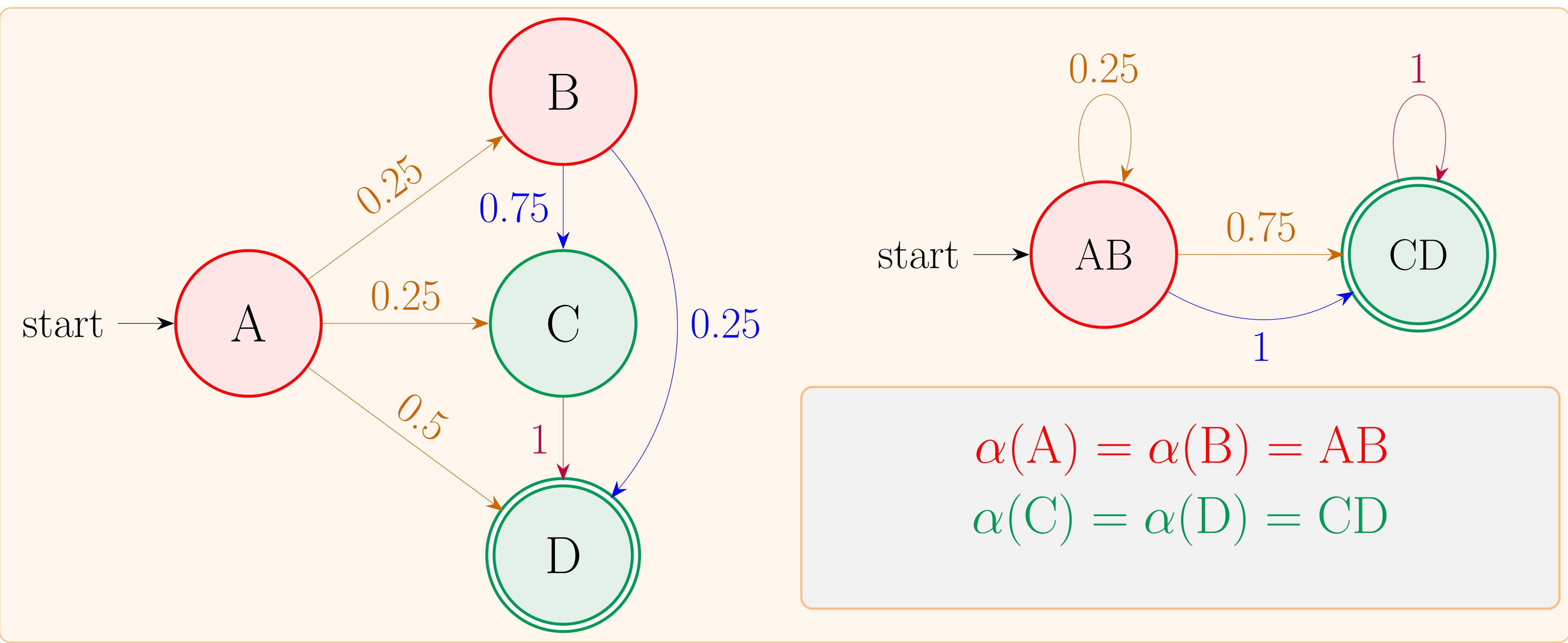
- Determinization-based Heuristics
- Occupation Measure Heuristics for SSPs (Trevizan, Thiébaux, and Haslum, 2017)

Thesis Goal: Development of new domain-independent admissible heuristics for MaxProb and SSPs with a focus on *abstraction heuristics*

Abstraction Heuristics

Abstractions are induced by a function $\alpha : S \to S_\alpha$, where S_α are the *abstract states*.

The *abstraction mapping* α induces an abstract SSP with reduced state set S_α.



Induces the admissible (for both objectives) *abstraction heuristic* h^α which maps state s to the optimal state value of the abstract state $\alpha(s)$ in the abstract state space.

Types of Abstraction Heuristics

How to instantiate the abstraction mapping α?

Multiple frameworks have been studied in classical planning, for example:

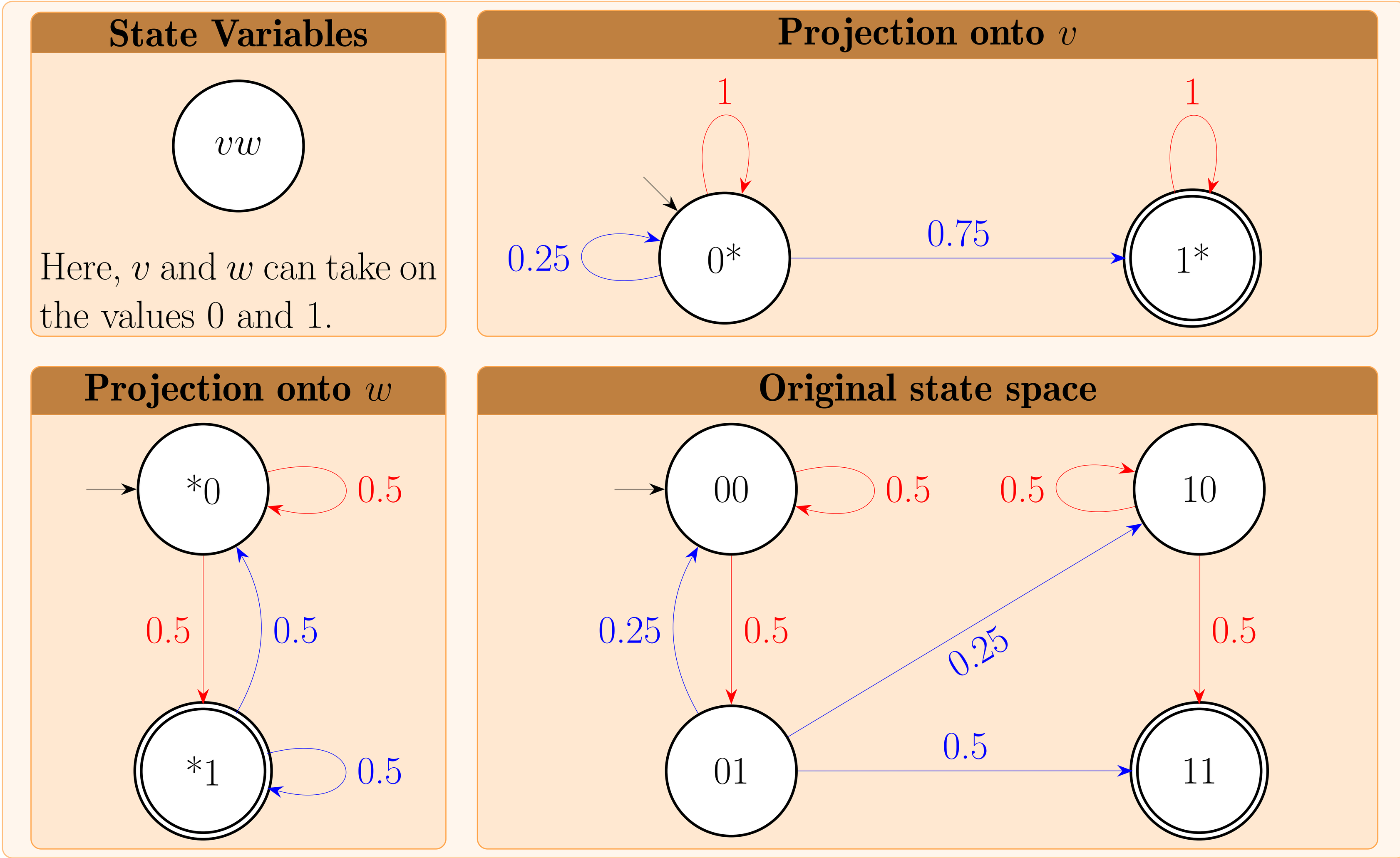
- Pattern Database Heuristics
- Cartesian Abstraction Heuristics
- Merge-and-Shrink Heuristics

Porting these to probabilistic planning could lead to strong admissible heuristics!

Pattern Database Heuristics

Pattern Databases (PDBs, Edelkamp (2001)) are based on *projections*.

For *factored state spaces*, where states consist of multiple *state variables* $\mathcal{V}$, a projection considers only a subset of variables $V \subseteq \mathcal{V}$, called a *pattern*.



A PDB stores the abstract state values of a projection in a precomputed lookup table. A PDB heuristic combines the estimates of multiple PDBs.

I already published research on PDB Heuristics for SSPs (Klößner and Hoffmann, 2021) and MaxProb (Klößner et al., 2021).

Results:

- Performs considerably better than the determinization-based PDB variant
- For SSPs, even competitive with occupation measure heuristics!
- For both settings, individual PDB estimates can even be added (SSP) or multiplied (MaxProb) under certain conditions without losing admssibility

Other Relevant Topics

Other topics that fall into the scope of this thesis are:

- Admissibility-Preserving Heuristic Combination
  - Cost Partitioning for SSPs (Partially addressed, Klößner et al. (2022))
- Other classes of admissible heuristics?

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