Combining Policies and Heuristics for Classical Planning

In this project, we aim to leverage the strengths of both learning and planning paradigms while mitigating their weaknesses. We follow one of the earliest works (Yoon et al. 2008) in this line of research and propose a combination of policy-guided heuristic search with unsolvability detection. Since our policies are prone to misclassification, the use of heuristics together with policies allows to mitigate the imperfections of the statistical learning. To decrease the impact of inaccurate heuristic estimates, we use the policy for unsolvable transitions as an unsolvability detection.





Good transition decreases the distance to the goal state.

 p_1

Bad transition increases or does not change the distance to the goal state.

 p_2

An example of applying policyguided search to an instance with an infinitely large state space:

S₃

 \mathcal{S}_1

 \mathcal{S}_2

 \mathcal{S}_4

The policy fails to

predict good transition

 S_1 S_3 p_3 p_n

Unsolvable transition leads to the state from which the goal state can never (inf) be reached.

initial state

goal state

Always follow a good 2 transition predicted by a policy. Add all successor states along the trajectory to the open list.



From the planning perspective, heuristics help: 1) to select the next state for policy execution if the policy fails; 2) to select the "good" transition" with the smallest heuristic estimate if there are multiple.

 \mathcal{S}_7 \mathcal{S}_3 0 10 \mathcal{S}_{5} Unsolvability detection helps to avoid expanding S_5 before S₇.

Our preliminary results support the main motivation that the fields of learning and planning can complement each other rather than one superseding the other.



Machine **Reasoning Lab**

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