

Learning to Correct Mistakes: Backjumping in Long-Horizon Task and Motion Planning



*Equal contribution

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Challenges in long-horizon planning:

- Long-horizon search in TAMP problems is intractable due to a large depth and branching factor
- Early actions may make future actions infeasible, leading to many backtracking steps

Research question:

- How can we identify a culprit variable to improve planning efficiency?

Two learning models with two sampling methods:

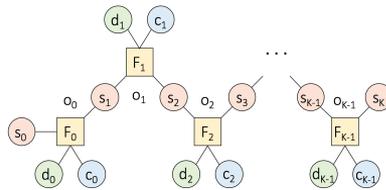
- Imitation learning: directly predicting a culprit variable by leveraging access to the true culprit in training data
- Plan feasibility prediction: counterfactual approach for binary prediction
- Sampling methods: batch sampling and forgetting

Contributions:

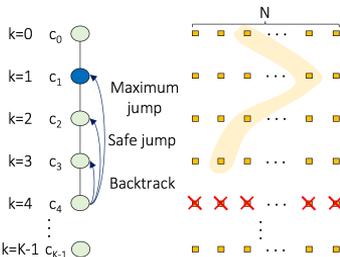
- We exploit long-horizon dependency in TAMP and propose to learn a backjumping policy for planning efficiency
- Our models empirically outperform baselines (e.g., backtracking) in two representative domains

Dirty laundry:

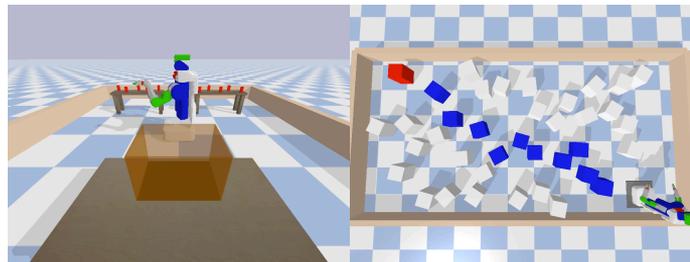
- Generalization is tested in similar tasks only: what is good representation?
- Several assumptions (perfect action and observation), but other work exists addressing them
- A really long horizon of hundred of actions has yet to be evaluated



[TAMP as constraint satisfaction]

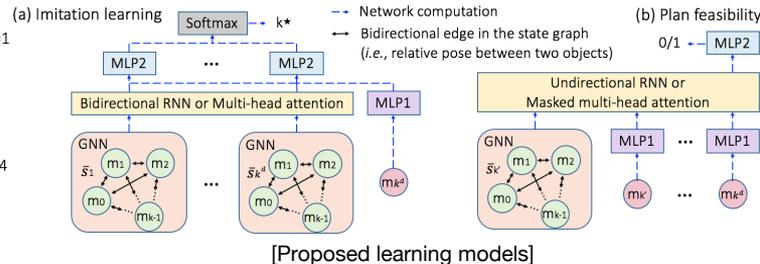


[Search tree example]



[Pick-and-place task]

[NAMO task]



[Proposed learning models]

Task	Backtracking	IL RNN	IL Attn	PF RNN	PF Attn
Packing	4414 ± 879	2464 ± 464	2638 ± 602	2205 ± 313	2062 ± 297*
NAMO	(21 ± 10) × 10 ⁴	543 ± 187	425 ± 153*	529 ± 188	2614.7 ± 709.5
Packing (11)	12098 ± 2518	5350 ± 1094*	7044 ± 1481	6142 ± 767	7109 ± 809
Packing (12)	34719 ± 6514	15139 ± 3080*	16339 ± 3971	22377 ± 3244	31824 ± 3925
Packing (BS)	13541 ± 4205	4464 ± 1160	7073 ± 2040	4556 ± 749	4311 ± 690*

[Main result: the number of nodes visited in the search tree obtained by solving 100 problems]