

Learning Generalized Unsolvability Heuristics for Classical Planning

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Introduction

- Recent interest in detecting unsolvable states, i.e., there is no plan to any goal state
- Some methods are unsolvability heuristics tailored to the given problem
- We approach the problem from a generalized planning perspective: problem-independent characterization of unsolvable states
- We learn formulas of Boolean features based on description logic
- The problem is cast as a self-supervised classification task
- The input is small instances that are labeled through exhaustive search

Questions

- Can unsolvable states be characterized using only the predicates defined in the domain?
- If so, are the characterizations concise?
- Can they be learned efficiently?
- Are they fast to evaluate?
- Can they compete against existing methods?
- Can they complement existing methods?

Methods

The pipeline for learning formulas is roughly:

- Label states as either solvable or unsolvable
- Enumerate concepts and evaluate them on said states
- Derive Boolean features from concepts
- Find a DNF formula of Boolean features that satisfies some criteria, we consider:
 - Perfect: Holds for all and only unsolvable states
 - Safe: Holds for only unsolvable states
 - DecisionTree: Maximize F1 score

These two learned formulas are perfect:

- Hiking: $|\exists at_person.(\exists at_car^{-1}.T)| = 0$
- Spanner: $|loose \sqcup \exists at.(\exists link^+.(\exists at^{-1}.man))| > |usable|$

Conclusions

With respect to the questions:

- Yes, and many unsolvable states can be decided in polynomial time
- Yes, furthermore the formulas are interpretable
- Primary bottleneck is enumeration and evaluation of Boolean features, this prevents us from learning features of higher complexity
- Time polynomial in the number of objects
- Yes, the learned formulas sometimes dominate
- This is especially clear for Spanner where existing methods struggle, and we learn an exact characterization

Experimental Results

	h^{CG}	h^{CEA}	h^{SEQ}	h^1	h^2	h^3	k -consistency			T-PERFECT					T-SAFE					DECISIONTREE							
							k=1	k=2	k=3	prec	rec	C	L	k	t	prec	rec	C	L	k	t	prec	rec	C	L	k	t
Barman	0.00	0.88	0.39	0.88	1.00	1.00	0.00	0.00	0.00	-	-	-	-	-	0.97	0.36	11	18	9	5h	0.97	0.99	28	56	8	6s	
Childsnack	0.58	0.58	0.09	0.58	0.94	1.00	0.00	0.27	0.27	-	-	-	-	-	1.00	1.00	7	9	11	1h	0.91	0.98	16	32	11	10s	
Hiking	0.00	1.00	0.00	1.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	1	1	8	27m	1.00	1.00	1	1	8	1m	1.00	1.00	1	1	8	1s
Nomystery	0.00	0.53	0.00	0.31	0.91	1.00	0.00	0.00	0.83	-	-	-	-	-	0.87	0.12	22	39	17	5h	0.65	0.92	1	1	12	1s	
Spanner	0.05	0.05	0.00	0.05	0.13	0.31	0.00	0.00	0.01	1.00	1.00	1	1	13	5m	1.00	1.00	1	1	13	4m	1.00	1.00	1	1	13	1s
Woodworking	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1	1	8	50s	0.98	1.00	1	1	8	2m	0.98	1.00	1	1	9	6s