Counterexample-Guided Abstraction Refinement for Pattern Selection in Optimal Classical Planning

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Motivation

- Pattern databases (PDB) for optimal planning:
 - Based on pattern collections (single PDBs don't scale)
 - Combining PDBs: e.g., canonical PDBs, cost partitioning
 - Pattern selection: e.g., hill climbing, genetic optimization

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- This work: pattern selection (fixed combination: SCP)
 - Observation: existing algorithms relatively slow
- Contribution: pattern selection based on the counterexample-guided abstraction refinement principle
 - Fast method
 - Only select useful patterns
 - Convergence

Outline







Disjoint Pattern Collections with CEGAR ○● Multiple CEGAR Runs

Experimental Results

Schematic Algorithm

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- Initialize pattern collection C with one pattern per goal
- Repeat:
 - For each $P \in C$, compute abstract plan π_P
 - For each $P \in C$, look for flaws v of π_P
 - Select flaw (P, v) and refine C by adding v to C: add v to P or merge P with P' containing v

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Multiple CEGAR Runs

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Multiple CEGAR

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Multiple CEGAR

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- Diversification:
 - Restrict each iteration to single goal: ⇒ single pattern
 - Randomly forbid variables for selection (blacklisting)
 - Keep track of progress (stagnation)

Outline







Coverage (SCP Heuristic) on IPC Benchmarks

Competitors				
	SYS2	HC (900s)	CPC (100s)	
Coverage	981	965.4	1033.5	
Constr. t.	0.05	4.97	103.82	

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Coverage	946.6	6	1063.2	1087.2	
Constr. t.	0.48	B	51.81	39.65	

Conclusions

- CEGAR for pattern selection: fast algorithm
- State-of-the-art pattern selection (for explicit PDBs & until IJCAI)
- Future work: interleave pattern selection with cost partitioning

Competitors						
	SYS	HC1	CPC1	HC9	CPC9	G
Cov. C.t.	981 0.05	946.4 3.05	1033.5 103.82	965.4 4.97	1021.1 876.21	839 5.49

	CE			
	single	multiple	sRCG	mRCG
Cov.	946.6	1087.2	758.8	1018.7
C.t.	0.48	39.65	0.07	10.07