Improved Pattern Selection for PDB Heuristics in Classical Planning (Extended Abstract)

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iPDB (Haslum et al. 2007)

- State-of-the-art pattern selection algorithm
- Selects patterns (sets of variables) using hill-climbing search in the space of pattern collections
- Canonical heuristic of resulting pattern collection used in A*-search

Local Maxima in iPDB

- Hill-climbing can terminate early in local maximum
 - ▶ No extension with one variable has sufficient improvement
 - Well-known but unaddressed problem (already pointed out by) Haslum et al. (2007))

iPDB with Variable Neighborhood Search

- Addresses the problem of local maxima
- Based on variable neighborhood search (Mladenovic) and Hansen 1997)
- Looks for successor collections of increasing size
- Extends existing candidate patterns by further causally related variables
- Resets candidate collection once an improving candidate is found
- Anytime algorithm: runs as long as resources are available
 - We limit resources to stop the hill-climbing

Pseudocode (iPDB)

function generate-candidates(\mathcal{P}) : Candidates $:= \emptyset$ for $P \in \mathcal{P}$: for $V \in P$: for $V' \in causally-related(V) \setminus P$: Candidates := Candidates $\cup \{P \cup \{V'\}\}$ return Candidates

function iPDB() : $\mathcal{P} := \{\{V_q\} \mid V_q \text{ is a goal variable}\}$ Candidates := generate-candidates(\mathcal{P}) while True : S := generate-samples(1000) for $P_C \in$ Candidates : $\mathsf{improvement}[P_C] := |\{s \in \mathsf{S} \mid h^{\mathcal{P} \cup \{P_C\}}(s) > h^{\mathcal{P}}(s)\}|$ *P*_{best} := Candidate with highest improvement if improvement $[P_{\text{best}}] > \text{threshold}$: $\mathcal{P} := \mathcal{P} \cup \{ \mathcal{P}_{\mathsf{best}} \}$ Candidates := generate-candidates(\mathcal{P}) else : return $h^{\mathcal{P}}$

Pseudocode (iPDB-VNS)

function generate-candidates(\mathcal{P}) : Candidates := \emptyset for $P \in \mathcal{P}$: for $V \in P$: for $V' \in causally-related(V) \setminus P$: Candidates := Candidates $\cup \{P \cup \{V'\}\}$ return Candidates

function iPDB-VNS() : $\mathcal{P} := \{\{V_g\} \mid V_g \text{ is a goal variable}\}$ Candidates := generate-candidates(\mathcal{P}) while True : S := generate-samples(1000) for $P_C \in$ Candidates : $\mathsf{improvement}[P_C] := |\{s \in \mathsf{S} \mid h^{\mathcal{P} \cup \{P_C\}}(s) > h^{\mathcal{P}}(s)\}|$ *P*_{best} := Candidate with highest improvement if improvement $[P_{\text{best}}] > \text{threshold}$: $\mathcal{P} := \mathcal{P} \cup \{ \mathcal{P}_{\mathsf{best}} \}$ Candidates := generate-candidates(\mathcal{P}) else : Candidates := *generate-candidates*(Candidates) if time or memory limit exceeded : return $h^{\mathcal{P}}$

Experimental Evaluation

- Evaluated on IPC tasks
 - optimal tracks 1998–2011
- Resource limits
 - Very important to limit both time and memory
- Robust to parameter changes iPDB-VNS improves iPDB
 - Heuristic quality
 - Number of solved tasks
- iPDB-VNS is competitive with LM-cut

Heuristic Quality

#Expansions during A* search



Solved Tasks

	$oldsymbol{h}_{\infty,\infty}^{iPDB}$	hiPDB 900s,400M	hiPDB-VNS 900s,400M	μ_{LM-cut}
Airport (50)	25	38	38	28
Depot (22)	8	8	11	7
Elevators (50)	36	36	43	40
Floortile (20)	2	2	4	7
Miconic (150)	55	55	55	141
Parcprinter (50)	22	28	28	31
TPP (30)	6	6	8	7
Transport (50)	17	17	24	17
Trucks (30)	8	8	10	10
Woodworking (50)	13	23	23	29
Sum (502)	192	221	244	317
Sum in other domains (894)	474	473	481	452
Total sum (1396)	666	694	725	769
Coverage score (in %)	50.72	52.68	55.45	53.60