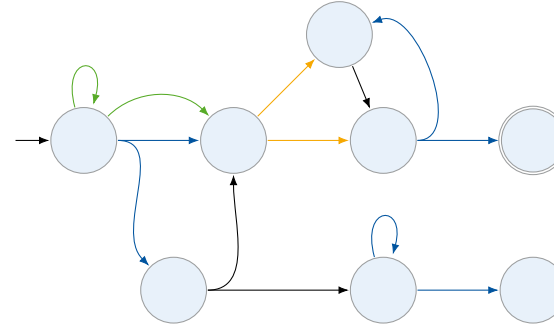
Learning Generalized Policies for Fully Observable Non-Deterministic Planning Domains

IJCAI 2024



Till Hofmann, Hector Geffner

August 6, 2024

Chair of Computer Science 6 (Machine Learning and Reasoning)

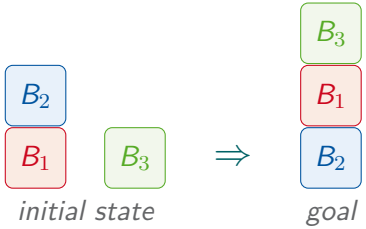
RWTH AACHEN UNIVERSITY

Generalized Policies for Classical Planning

Classical planning:

- Given: action model + initial state + goal
- Task: find a (concrete) policy $\pi_P : S \rightarrow 2^A$ that maps each state s to a set of actions $\pi_P(s)$

```
(:action pickup :parameters (?x)
 :precondition (and
   (clear ?x) (ontable ?x) (handempty))
 :effect (and (not (ontable ?x))
   (not (clear ?x)) (not (handempty))
   (holding ?x)))
(:action putdown ...)
(:action stack ...)
(:action unstack ...)
```



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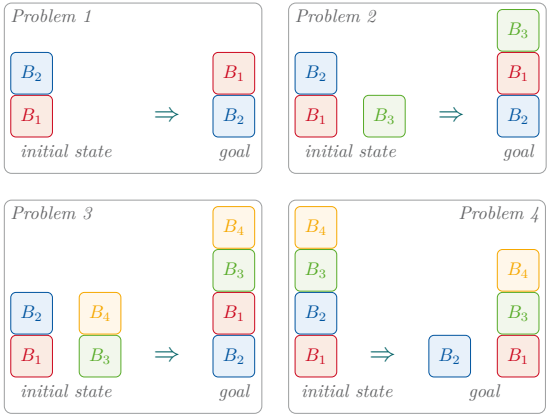
Generalized planning:

- Given: action model + **class of problems** $\mathcal{Q}$
- *Each* problem: initial state + goal
- Task: find a general policy that maps each problem $P \in \mathcal{Q}$ to a concrete policy $\pi(P) = \pi_P$

Example (Blocks World)

General policy:

1. Unstack all misplaced blocks
2. Stack them in the correct order



Generalized Policies for Classical Planning

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Generalized planning:

assumed to be *closed*

- Given: action model + **class of problems** $\mathcal{Q}$
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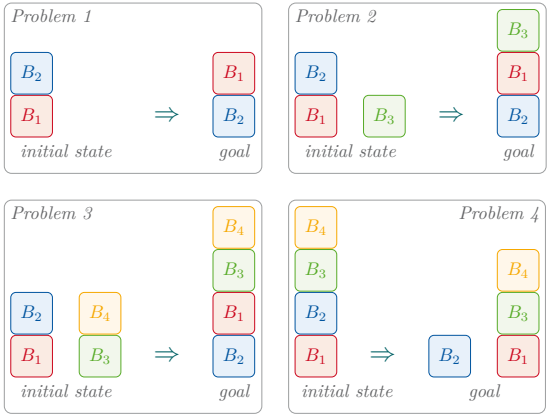

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Expressing and Learning Generalized Policies

Rule-based general policies (Bonet and Geffner 2018):

- Express a policy as a set of rules of the form $C \mapsto E_1 \mid \ldots \mid E_k$ over a feature space Φ
- Features: Boolean and numerical features, e.g., *# clear blocks*
- Learnable from a set of small problems (Bonet et al. 2019; Francès et al. 2021)

Example

General policy for clearing a one block x:

$$r_1 : \{\neg H, n > 0\} \mapsto \{H, n\downarrow\}$$
$$r_2 : \quad \{H\} \mapsto \{\neg H\}$$

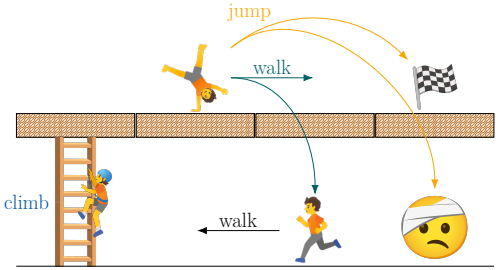
where

$H \triangleq$ true if holding a block

$n \triangleq$ number of blocks on top of x

Generalized Policies for FOND Planning

- FOND: action a may have multiple outcomes $a_1, a_2, \ldots$ not under the agent's control
- *Fairness:* for an infinitely occurring action a, all outcomes $a_1, a_2, \ldots$ occur infinitely often
- *Strong-cyclic:* all max. fair trajectories reach goal



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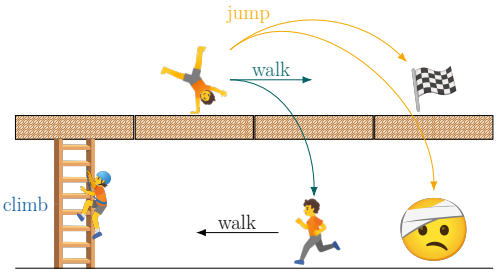
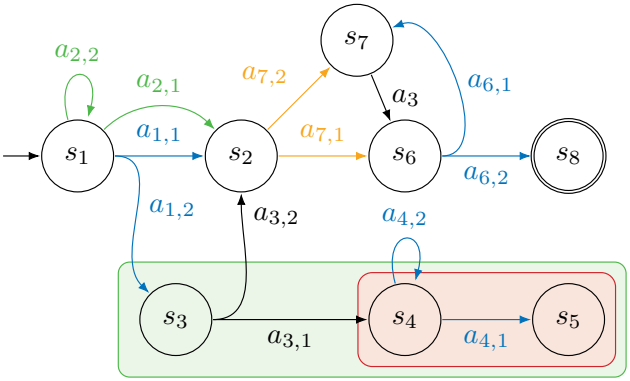
Questions

1. How do we express general policies for FOND domains?
2. How can we learn FOND general policies?



From Classical to FOND General Policies



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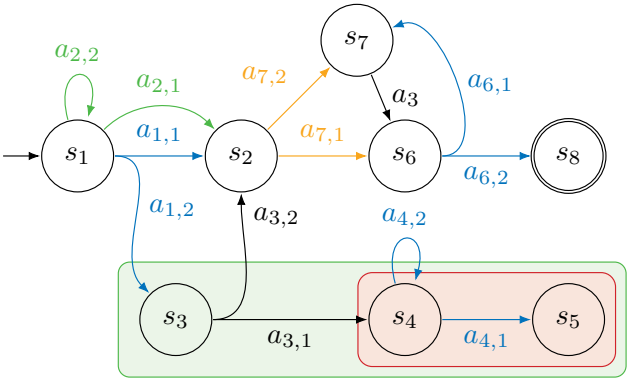
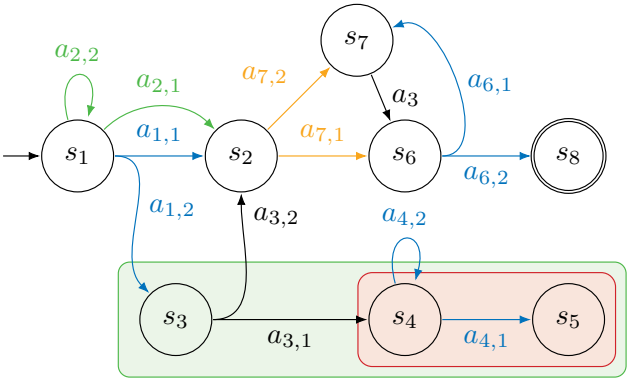


All-outcome relaxation: agent can choose action outcome → classical planning

From Classical to FOND General Policies

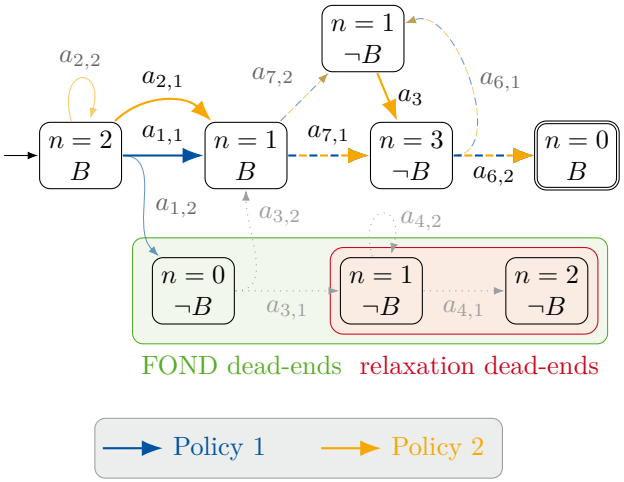


All-outcome relaxation: agent can choose action outcome $\rightarrow$ classical planning

Observation

A general policy for the *all-outcome relaxation* is also a general policy for the original FOND problem if it avoids FOND dead-ends

From Classical to FOND General Policies



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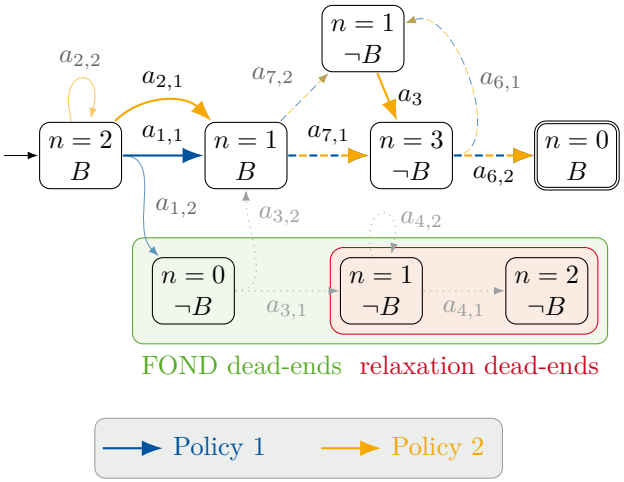


All-outcome relaxation: agent can choose action outcome → classical planning

Observation

A general policy for the *all-outcome relaxation* is also a general policy for the original FOND problem if it avoids FOND dead-ends

Learning:

- Select features that describe the FOND dead-ends
- Learn a general policy for the relaxation that avoids dead-ends

⇒ Combinatorial optimization problem

more details on poster

Example: Learned Policy for Acrobatics

Selected features:

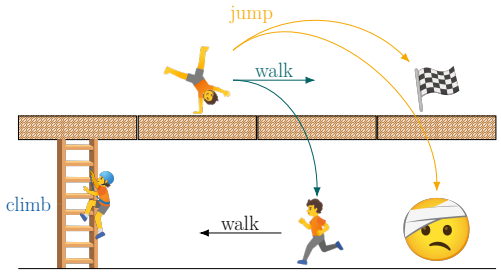
1. Distance $d \equiv \mathrm{dist}(\mathit{position}, \mathit{next\text{-}fwd}, \mathit{position}_G)$ between the current position and the goal position
2. Boolean feature $U \equiv |\mathit{up}|$ which is true if the agent is currently on the beam
3. Boolean feature $B \equiv |\mathit{broken\text{-}leg}|$ which is true if the agent's leg is broken

Learned policy rules:

$$r_1 : \quad \{U, d > 0, \neg B\} \mapsto \{d\downarrow\}$$
$$r_2 : \quad \{\neg B, \neg U\} \mapsto \{U\} \mid \{d\uparrow\}$$

Learned state constraint:

$$b_1 : \quad \{B, \neg U\}$$



Evaluation

$\mathcal{Q}$	# problems	# solved	# training p.	# obj (train)	# obj (all)	t_{solve}/s	# features	# sel. features	# constraints	max complex.	policy cost
acrobatics	18	18	3	3	9	0.12	23	3	1	4	6
beam-walk	9	9	2	3	9	0.05	22	2	0	4	5
blocks3ops	95	95	4	4	20	3:44	194	3	0	5	11
blocks-clear	95	95	2	3	20	1.5	34	2	0	4	6
blocks-on	190	190	2	3	20	1:56	704	3	0	6	11
doors	19	19	5	7	33	1:18	625	4	1	10	19
islands	300	300	4	32	83	1h	1182	4	1	7	13
first-resp	99	**15**$^{\mathsf{M}}$	2	5	36	33:40	332	5	2	7	20
miner	69	**13**$^{\mathsf{I}}$	2	9	184	297h	1073	8	4	6	28
spiky-tire	170	**36**$^{\mathsf{I}}$	3	6	23	1h	479	8	5	8	36
tireworld	980	**7**$^{\mathsf{C}}$	1	3	100	0.11	27	5	4	4	12
triangle-tire	10	**1**$^{\mathsf{I}}$	1	6	231	0.29	27	3	1	4	9

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proven to generalize to all instances

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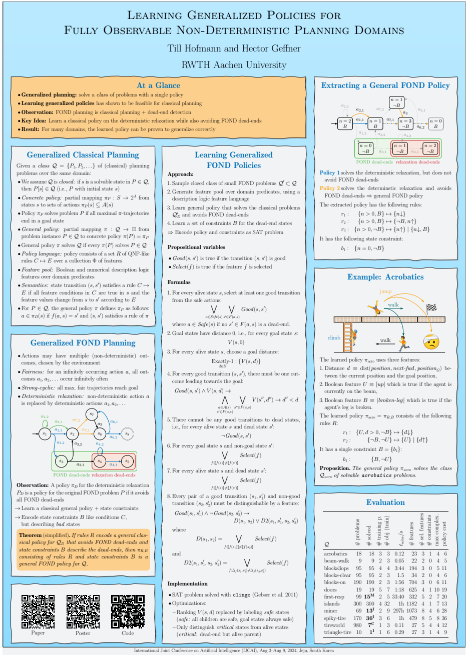

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Paper

Appendix

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