

New Avenues in Inductive Synthesis of Finite-State Controllers for POMDPs

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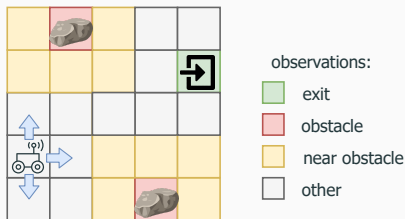
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First part of this presentation is based on paper: *Andriushchenko et al. Inductive Synthesis of Finite-State Controllers for POMDPs. In UAI'22.*

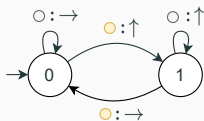
Inductive Synthesis of Finite-State Controllers for POMDPs

- partially observable Markov decision processes (**POMDPs**)
- indefinite-horizon specifications (no discounting)
- finite-state controllers (**FSCs**): compact automata-based representation of policies
- goal:** quickly find a (small) admissible FSC and incrementally improve it by increasing its size

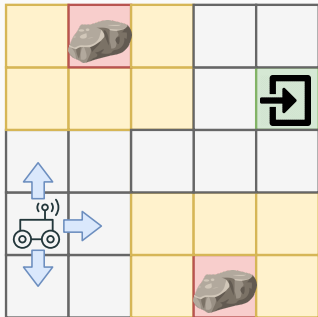
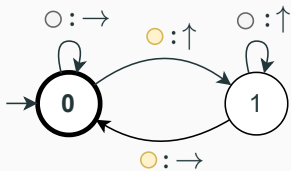


constraint: $\mathbb{P}_{\leq 0.1} [F \text{ crash}]$

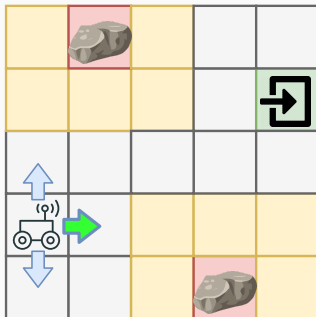
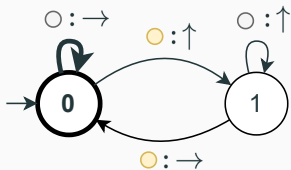
objective: minimize $\mathbb{R}^{\text{steps}} [F \text{ exit}]$



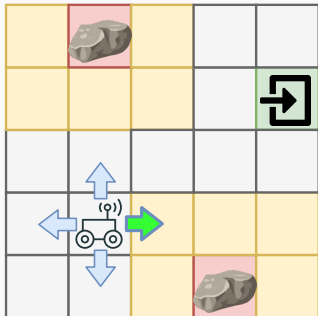
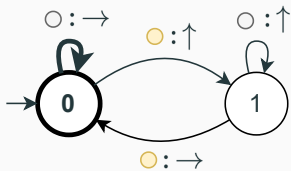
Finite-State Controller



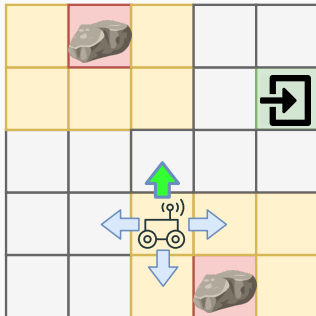
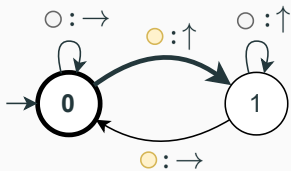
Finite-State Controller



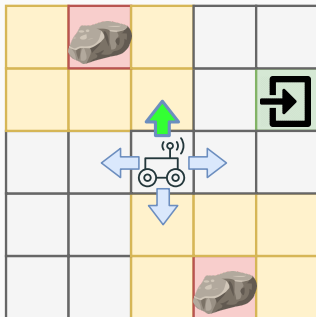
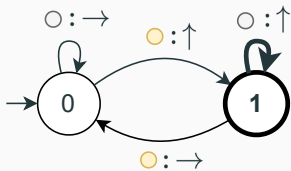
Finite-State Controller



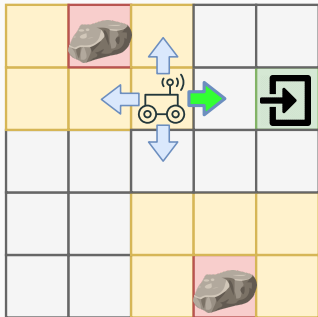
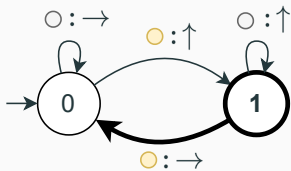
Finite-State Controller



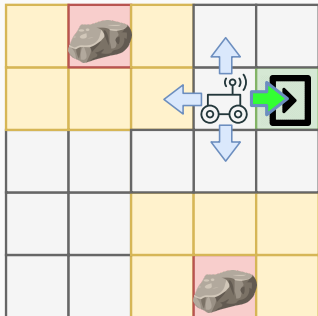
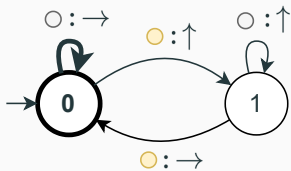
Finite-State Controller



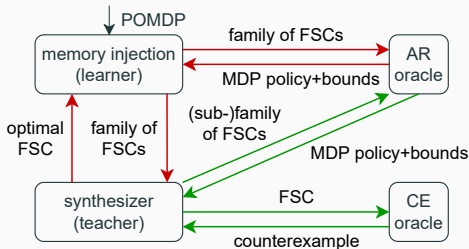
Finite-State Controller



Finite-State Controller



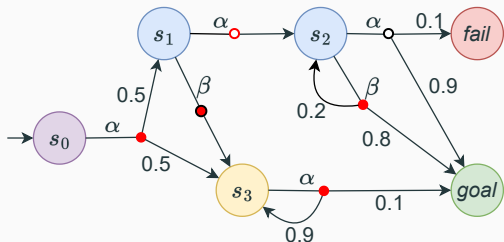
Inductive Synthesis of Finite-State Controllers for POMDPs



- **the inner synthesis loop** explores the given family of FSCs using two oracles and identifies the optimal solution
- **the outer synthesis loop** iteratively increases the size of the families explored in the inner loop by adding memory to the FSCs
- **abstraction refinement (AR) oracle** over-approximates all FSCs in the given (sub-)family using a quotient MDP
- **counterexample-based (CE) oracle** provides a counterexample in the form of a subfamily of unsatisfiable FSCs

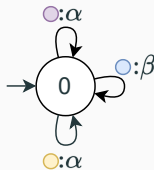
Inductive Synthesis of Finite-State Controllers for POMDPs

- simple POMDP example
- colors encode **observations**, blue states s_1 and s_2 are indistinguishable
- F_1^* represents 1-state FSC, π_1^* represents the optimizing policy for the fully-observable MDP
- 1-state FSC can only choose one action for each observation
- optimal 1-state FSC and the optimizing policy choose different actions in blue states

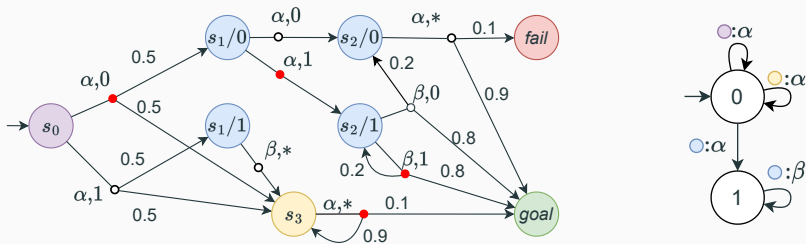


constraint: $\mathbb{P}_{\leq 0} [F \text{ fail}]$

minimize $\mathbb{R}^{steps} [F \text{ goal}]$



Inductive Synthesis of Finite-State Controllers for POMDPs



- to find an optimal FSC we have to add memory node for the blue observation
- adding a memory node creates a new family of FSCs
- in our example the family \mathcal{F}_2 is represented by the **quotient MDP** shown above (left figure)
- the FSC F_2^* (right figure) represents the optimal policy

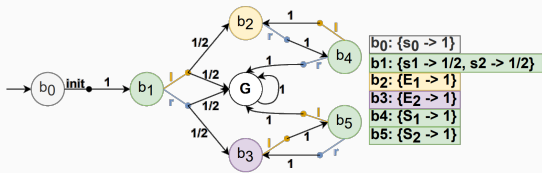
The inductive synthesis is implemented in a tool called PAYNT

Results

Benchmark		Size		PRISM	Storm		Inductive synthesis		Upper- bounds
Model	Spec.	S/Act	Z		first	best	fastest	best	
Grid-av 4-0.1	P_{\max}	17 59	4	[0.21,1] < 1s	0.82 < 1s	0.85 124s	0.92 (4) < 1s	0.93 (5f) 53s*	≤ 0.99
Grid 30-sl	R_{\min}	900 3587	37	TO/MO	121 1s	- -	119 (6) 150s*	- -	≥ 116.1
Maze sl	R_{\min}	15 54	8	[7.09,7.09] 2s	7.67 < 1s	- -	7.14 (3) < 1s	7.09 (3f) 1s*	≥ 7.08
Crypt 4	P_{\max}	1972 4612	510	[0.33,0.79] 6s	0.33 < 1s	- -	0.33 (0) < 1s	- -	≤ 0.33
Nrp 8	P_{\max}	125 161	41	[0.13,0.24] 3s	0.13 < 1s	- -	0.13 (0) < 1s	- -	≤ 0.13
Hallway	R_{\min}	61 301	23	TO/MO	19.3 < 1s	19.2 < 1s	16.3 (1) < 1s	14.9 (4f) 218s*	≥ 12.4
Drone 4-2	P_{\max}	1226 3026	761	TO/MO	0.86 < 1s	0.91 138s	0.94 (0) < 1s	0.97 (2) 326s	≤ 0.97
Refuel 6	P_{\max}	208 565	50	[0.67,0.72] 136s	0.67 < 1s	- -	0.44 (2) < 1s	0.67 (2f) 45s*	≤ 0.69
Netw-p 2-8-20	R_{\max}	$2 \cdot 10^4$ $3 \cdot 10^4$	4909	[557,557] 1099s	537 < 1s	- -	540 (0) 105s	- -	≤ 558
Rocks 12	R_{\min}	6553 $3 \cdot 10^4$	1645	TO/MO	38 < 1s	20 47s	42 (0) 1s	- -	≥ 20

Belief-Based Methods

- most of the state-of-the-art approaches use **beliefs**
- probabilistic model checker **Storm**
- constructing **Belief MDP**
- construction techniques: **cut-offs, clipping**
- they provide good bounds, but the results are not as easy to interpret as **FSCs**
- can we use them to enhance the synthesis loop?



- finding **memoryless** scheduler in **Belief MDP** gives us **observation-based** scheduler for the initial POMDP

Belief-Based Methods Integration

- **what** information should we extract from the Belief MDP and its scheduler?
 - can we use the extracted information to enhance both inner and outer synthesis loop? And **how**?
 - **when** should we use the extracted information?
-
- actions taken in belief MDP scheduler, bound values, belief MDP structure
 - **inner synthesis loop**: improved exploration of the family of FSCs, using bounds to prune the design space
 - **outer synthesis loop**: memory injection improvement based on belief MDP scheduler
 - proof of concept experiments show promising results

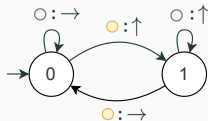
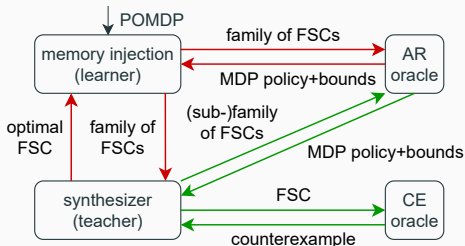
Integration experiments

Benchmark		Storm			PAYNT	PAYNT + Storm
Model	Spec.	clipping	cut-offs	over-app		
Grid-av 4-0.1	P_{max}	0.85	0.93	0.94	0.92	0.93
		124s	66s		< 1s	78s
Network 2-8-20	R_{min}	6.56	3.2	3.2	4.24	4.19
		3s	13s		188s	183s
Network 3-8-20	R_{min}	11.88	11.15	6.26	11.01	10.91
		403s	62s		188s	256s
Rocks 12	R_{min}	20	33.24	20	42	20
		51s	66s		< 1s	51s
Rocks 16	R_{min}	26	43.06	25.88	46	26
		86s	68s		2s	94s
drone 4-1	P_{max}	0.79	0.86	0.97	0.87	0.81
		1044s	64s		254s	160s

Time differences are not important here as we are trying to find small FSCs, which represent the solution more efficiently compared to belief-based approach!

Thank You for Your Attention!

- novel learning framework to obtain finite-state controllers (**FSCs**) for **POMDPs**
- enhancing the inductive synthesis loop by extracting information from belief-based methods
- future research: **online analysis, discounting**



See: *Andriushchenko et al. Inductive Synthesis of Finite-State Controllers for POMDPs*