

# Bi-Objective Lexicographic Optimization in Markov Decision Processes with Related Objectives

Damien Busatto-Gaston<sup>1</sup> Debraj Chakraborty<sup>2</sup> Anirban Majumdar<sup>3</sup> Sayan Mukherjee<sup>3</sup>  
Guillermo A. Pérez<sup>4</sup> Jean-François Raskin<sup>3</sup>

1-Université Paris-Est Créteil, LACL, France

2-Masaryk University, Czech Republic

3-Université Libre de Bruxelles, Belgium

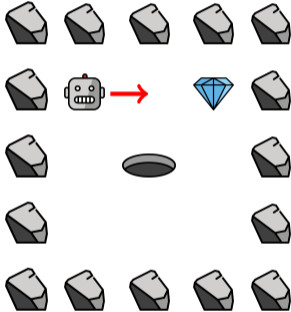
4-University of Antwerp, Belgium

Automated Technology for Verification and Analysis  
Singapore, 2023

# Example: Frozen lake



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▶  slips to different direction with some probability



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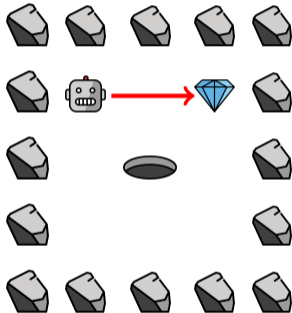
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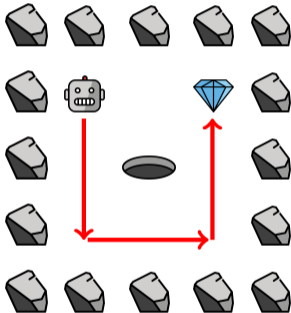
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- ▶ Maximize  $\mathbb{P}(\text{robot} \rightsquigarrow \text{diamond})$
  - ▶ Reach  as fast as possible

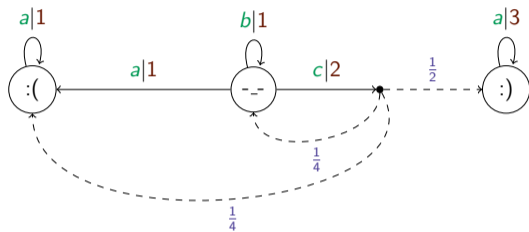




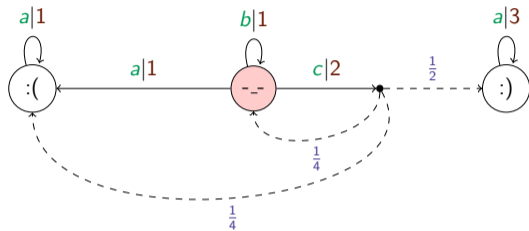
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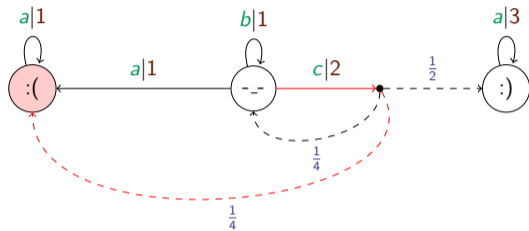


► Path :  $:($

Reward: 0



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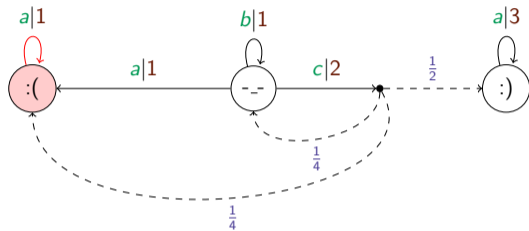


► Path :  $:- \xrightarrow{c} :)$

Reward: 2



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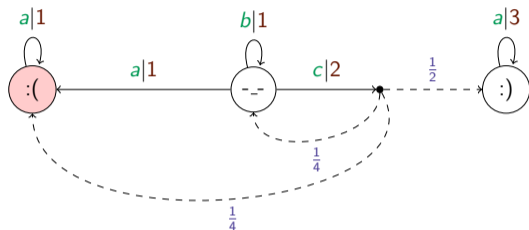


► Path :  $:( \xrightarrow{c} -- \xrightarrow{a} :($

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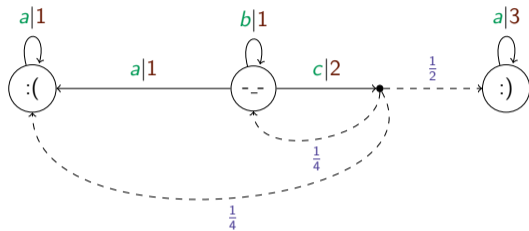


▶ Path :  $:- \xrightarrow{c} :( \xrightarrow{a} :( \dots$

Reward: 3

▶ **Mean-payoff** (MP): Average reward at limit :  $\rho \mapsto \lim_{n \rightarrow \infty} \frac{1}{n} \text{Reward}(\rho_n)$

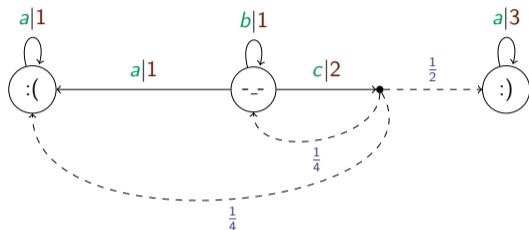
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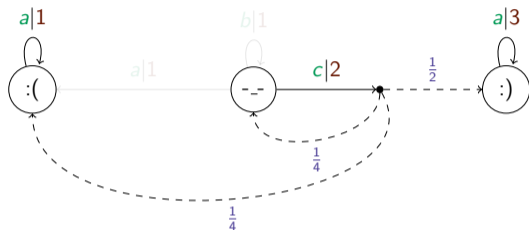
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- Fixing a strategy creates a **Markov chain**

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$\text{len}_T : \rho \mapsto$  length of the shortest prefix of  $\rho$  reaching  $T$



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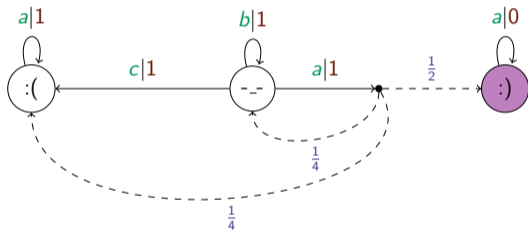
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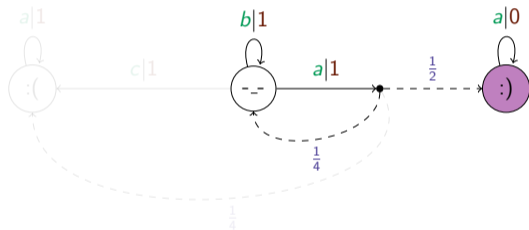
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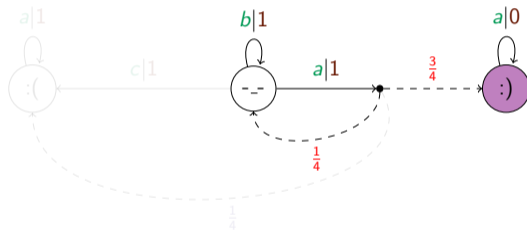
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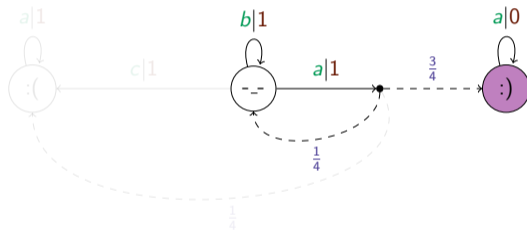
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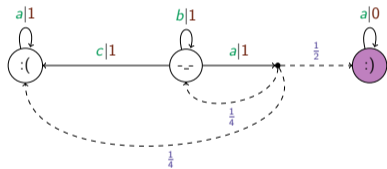


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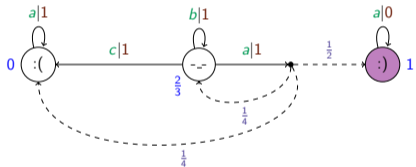


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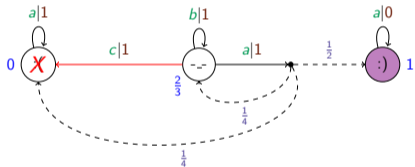


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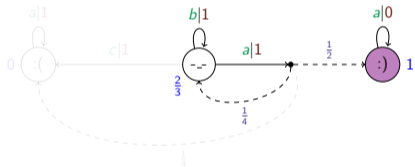


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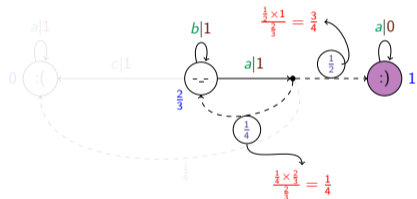
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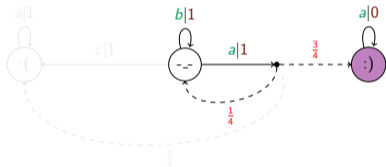
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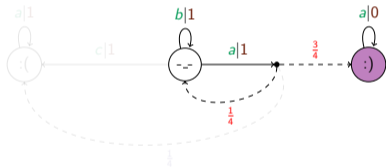
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- ▶ Find the strategy  $\arg \min_{\sigma'} \mathbb{E}_{\sigma'}(\text{len}(\odot))$  in  $M'$



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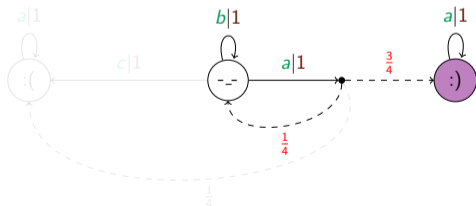
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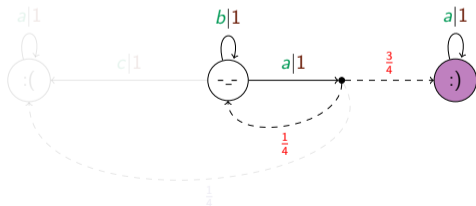
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$$\sigma \notin \arg \max_{\sigma'} \mathbb{P}_{\sigma'}^M(s_0 \models \diamond \odot)$$



$$\mathbb{E}_{\sigma}^{M'}(\text{len}_{\odot}) = \infty$$



## Experimental results

layouts	$P(\text{robot} \rightsquigarrow \text{diamond})$	$\min(\text{robot} \rightsquigarrow \text{diamond})$	$E_{opt}(\text{robot} \rightsquigarrow \text{diamond})$	$E_{storm}(\text{robot} \rightsquigarrow \text{diamond})$
1	0.66	9	76.48	76.48
2	0.52	18	299.75	629.16
3	1.00	2	2.40	12.12
4	1.00	3	3.44	34.47
5	1.00	6	7.71	137.56
6	0.68	10	264.04	9598.81
7	1.00	5	112.69	9367.02
8	0.91	10	11.49	5879.63
9	1.00	3	3.66	5711.76
10	0.91	5	12.89	149357.57

**Table:** Comparison of expected conditional distance to the target given by the strategy optimizing distance and the strategy given by model checker STORM



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safety	any measurable function

Thank You!

