

Meet Your Expectations With Guarantees: Beyond Worst-Case Synthesis in Quantitative Games

V. Bruyère (UMONS) E. Filiot (ULB)
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Highlights of Logic, Games and Automata



Context

- Verification and synthesis:
 - ▷ a reactive **system** to *control*,
 - ▷ an *interacting* **environment**,
 - ▷ a **specification** to *enforce*.

- Focus on *quantitative properties*.

Context

- Verification and synthesis:
 - ▷ a reactive **system** to *control*,
 - ▷ an *interacting* **environment**,
 - ▷ a **specification** to *enforce*.
- Focus on *quantitative properties*.
- Several ways to look at the interactions, and in particular, *the nature of the environment*.

Beyond worst-case synthesis

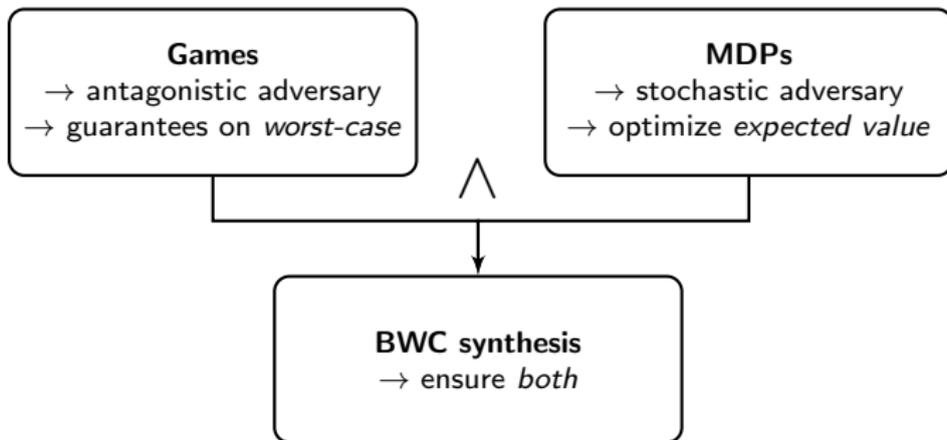
Games

- antagonistic adversary
- guarantees on *worst-case*

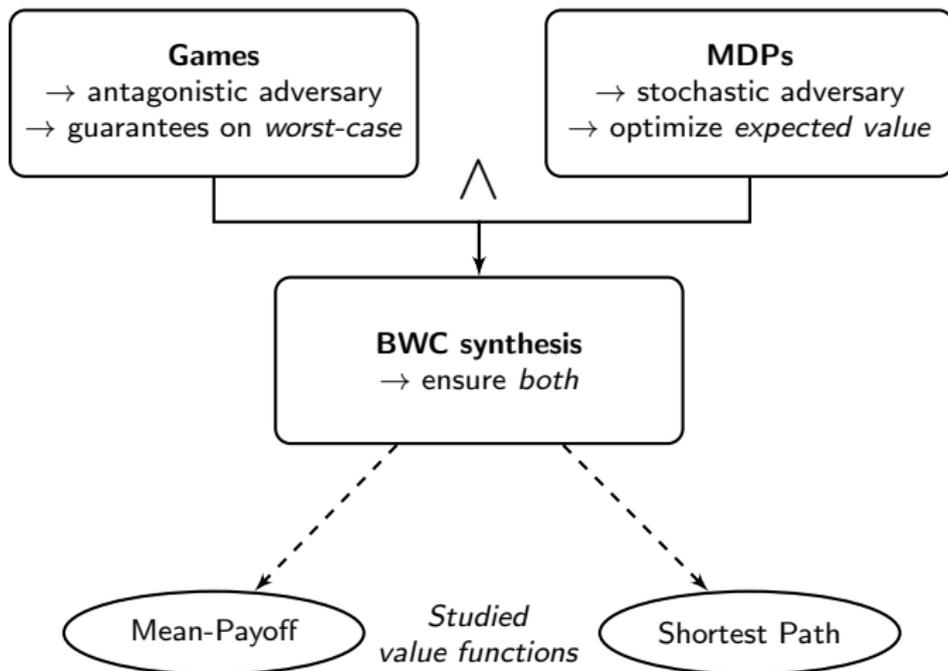
MDPs

- stochastic adversary
- optimize *expected value*

Beyond worst-case synthesis



Beyond worst-case synthesis



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Featured in STACS'14 [BFRR14]

Full paper available on arXiv: [abs/1309.5439](https://arxiv.org/abs/1309.5439)

Meet Your Expectations With Guarantees: Beyond Worst-Case Synthesis in Quantitative Games

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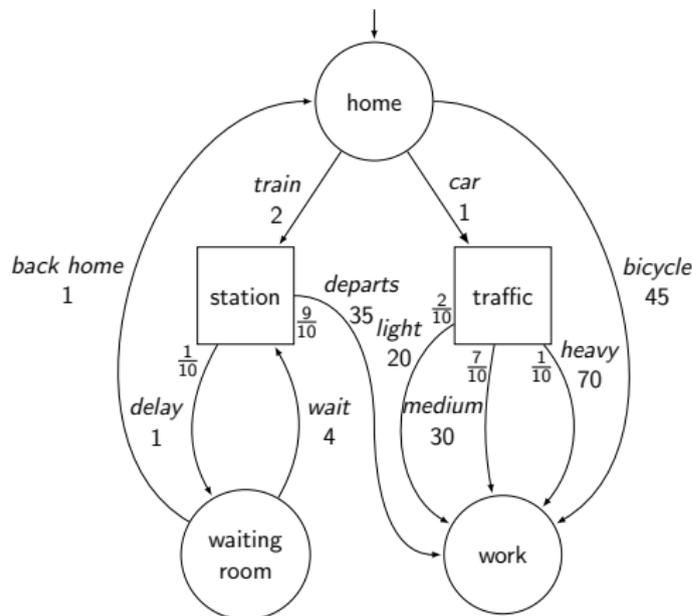
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Abstract. We extend the quantitative synthesis framework by going beyond the worst-case. On the one hand, classical analysis of two-player games involves an adversary (modeling the environment of the system) which is purely antagonistic and asks for strict guarantees. On the other hand, stochastic models like Markov decision processes represent situations where the system is faced to a purely randomized environment: the aim is then to optimize the expected payoff, with no guarantee on individual outcomes. We introduce the beyond worst-case synthesis problem, which is to construct strategies that guarantee some quantitative requirement in the worst-case while providing a higher expected value against a particular stochastic model of the environment given as input. This problem is relevant to produce system controllers that provide nice expected performance in the everyday situation while ensuring a strict (but relaxed) performance threshold even in the event of very bad (while unlikely) circumstances. We study the beyond worst-case synthesis problem for two important quantitative settings: the mean-payoff and the shortest path. We show how to decide the existence of finite-memory strategies satisfying the problem and how to establish algorithms and we study complexity bounds and memory requirements.

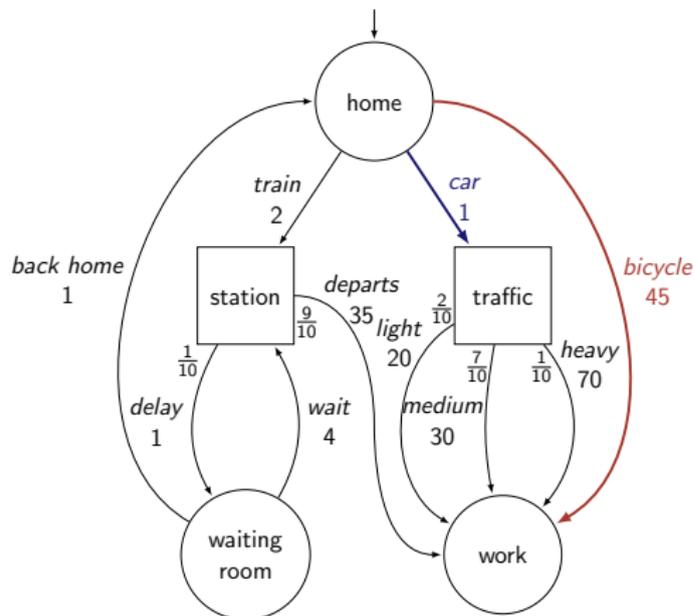
21 Sep 2013

Example: going to work (shortest path)



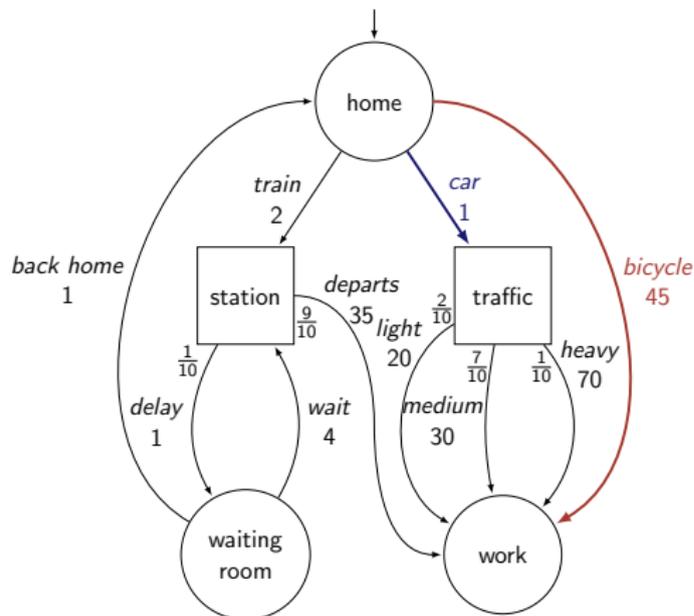
- ▷ Weights = minutes
- ▷ Goal: minimize our **expected time** to reach “work”
- ▷ **But**, important meeting in one hour! Requires **strict guarantees on the worst-case** reaching time.

Example: going to work (shortest path)



- ▷ Optimal **expectation** strategy: take the car.
 - $\mathbb{E} = 33$, $WC = 71 > 60$.
- ▷ Optimal **worst-case** strategy: bicycle.
 - $\mathbb{E} = WC = 45 < 60$.

Example: going to work (shortest path)



- ▷ Optimal **expectation** strategy: take the car.
 - $\mathbb{E} = 33$, $WC = 71 > 60$.
- ▷ Optimal **worst-case** strategy: bicycle.
 - $\mathbb{E} = WC = 45 < 60$.
- ▷ **Sample BWC strategy**: try train up to 3 delays then switch to bicycle.
 - $\mathbb{E} \approx 37.56$, $WC = 59 < 60$.
 - Optimal \mathbb{E} under WC constraint
 - Uses finite **memory**

Beyond worst-case synthesis

Definition

Given a game $G = (S_1, S_2, E, w)$, an initial state $s_{\text{init}} \in S$, a finite-memory stochastic model $\lambda_2^{\text{stoch}} \in \Lambda_2^F$ of the adversary, a measurable value function $f: \text{Plays}(G) \rightarrow \mathbb{R} \cup \{-\infty, \infty\}$, and two rational thresholds $\mu, \nu \in \mathbb{Q}$, the *beyond worst-case (BWC) problem* asks to decide if \mathcal{P}_1 has a finite-memory strategy $\lambda_1 \in \Lambda_1^F$ such that

$$\begin{cases} \forall \lambda_2 \in \Lambda_2, \forall \pi \in \text{Outs}_G(s_{\text{init}}, \lambda_1, \lambda_2), f(\pi) > \mu & (1) \\ \mathbb{E}_{s_{\text{init}}}^{G[\lambda_1, \lambda_2^{\text{stoch}}]}(f) > \nu & (2) \end{cases}$$

and the *BWC synthesis problem* asks to synthesize such a strategy if one exists.

Beyond worst-case synthesis

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Notice the **highlighted** parts!

Related work

Common philosophy: avoiding outlier outcomes

- 1 Our strategies are *strongly risk averse*
 - ▶ avoid risk at all costs and optimize among safe strategies

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- 1 Our strategies are *strongly risk averse*
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- 2 Other notions of risk ensure low probability of risked behavior [WL99, FKR95]
 - ▷ without worst-case guarantee
 - ▷ without good expectation

Related work

Common philosophy: avoiding outlier outcomes

- 1 Our strategies are *strongly risk averse*
 - ▷ avoid risk at all costs and optimize among safe strategies
- 2 Other notions of risk ensure low probability of risked behavior [WL99, FKR95]
 - ▷ without worst-case guarantee
 - ▷ without good expectation
- 3 Trade-off between expectation and variance [BCFK13, MT11]
 - ▷ statistical measure of the stability of the performance
 - ▷ no strict guarantee on individual outcomes

Mean-payoff

- $$\text{MP}(\pi) = \liminf_{n \rightarrow \infty} \left[\frac{1}{n} \cdot \sum_{i=0}^{i=n-1} w((s_i, s_{i+1})) \right]$$
- Sample play $\pi = 2, -1, -4, 5, (2, 2, 5)^\omega$
 - ▷ $\text{MP}(\pi) = 3$
 - ▷ long-run average weight \rightsquigarrow *prefix-independent*

Mean-payoff

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	worst-case	expected value	BWC
complexity	$\text{NP} \cap \text{coNP}$	P	NP \cap coNP
memory	memoryless	memoryless	pseudo-polynomial

- ▷ [LL69, EM79, ZP96, Jur98, GS09, Put94, FV97]
- ▷ Additional modeling power **for free!**

Shortest path

- Strictly positive integer weights, $w: E \rightarrow \mathbb{N}_0$
- \mathcal{P}_1 wants to minimize its total cost up to target
 - ▷ inequalities are reversed

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	worst-case	expected value	BWC
complexity	P	P	pseudo-poly. / NP-hard
memory	memoryless	memoryless	pseudo-poly.

- ▷ [BT91, dA99]
- ▷ Problem **inherently harder** than worst-case and expectation.
- ▷ NP-hardness by K^{th} largest subset problem [JK78, GJ79]

Beyond BWC synthesis?

Possible future works include

- study of other quantitative objectives,
- extension of our results to more general settings (multi-dimension [CDHR10, CRR12], decidable classes of games with imperfect information [DDG⁺10], etc),
- other related strategies,
- application of the BWC problem to various practical cases.

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Thanks!

Do not hesitate to discuss with us!

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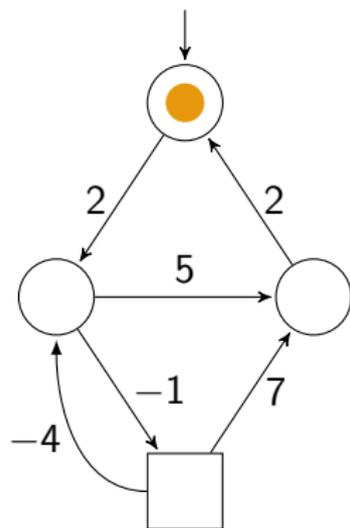
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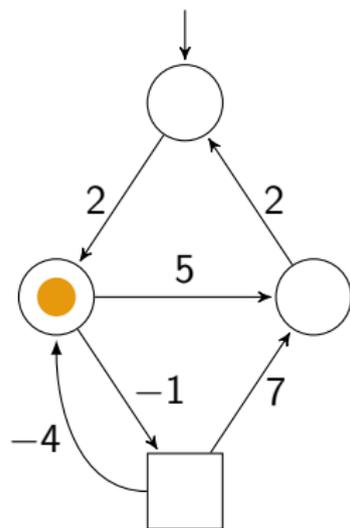
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Quantitative games on graphs



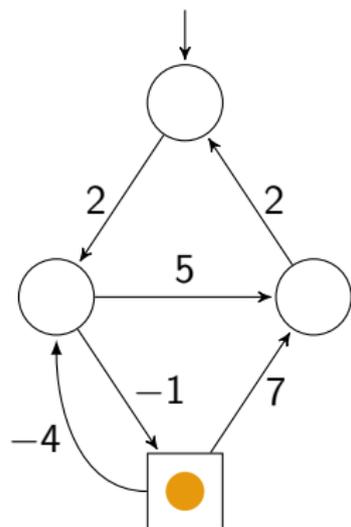
- Graph $\mathcal{G} = (S, E, w)$ with $w: E \rightarrow \mathbb{Z}$
- Two-player *game* $G = (\mathcal{G}, S_1, S_2)$
 - ▷ \mathcal{P}_1 states = \bigcirc
 - ▷ \mathcal{P}_2 states = \square
- Plays have values
 - ▷ $f: \text{Plays}(\mathcal{G}) \rightarrow \mathbb{R} \cup \{-\infty, \infty\}$
- Players follow *strategies*
 - ▷ $\lambda_i: \text{Prefs}_i(G) \rightarrow \mathcal{D}(S)$
 - ▷ Finite memory \Rightarrow stochastic output Moore machine $\mathcal{M}(\lambda_i) = (\text{Mem}, m_0, \alpha_u, \alpha_n)$

Quantitative games on graphs



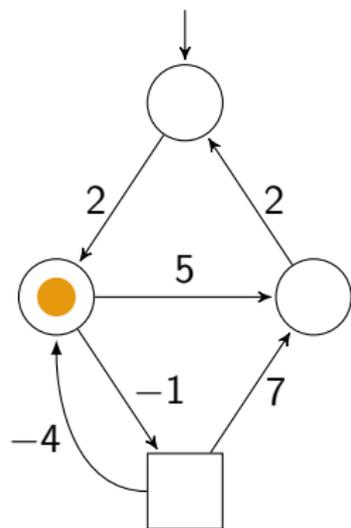
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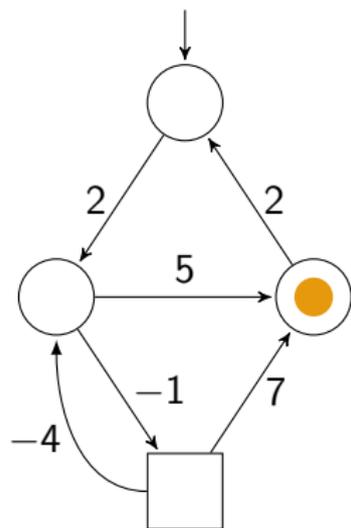
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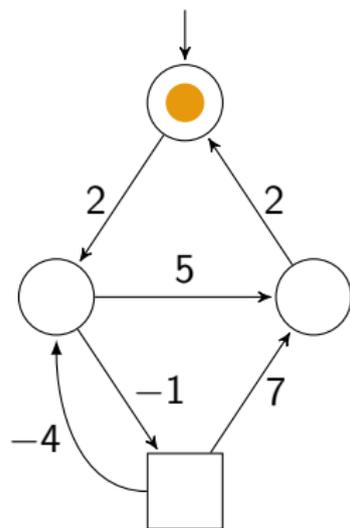
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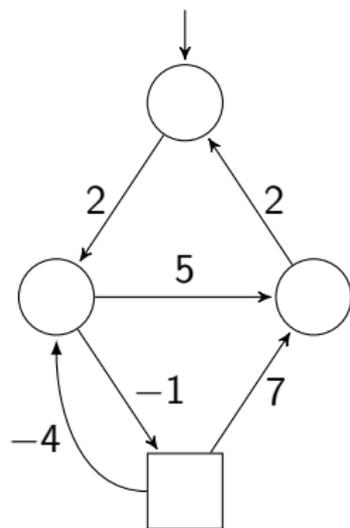
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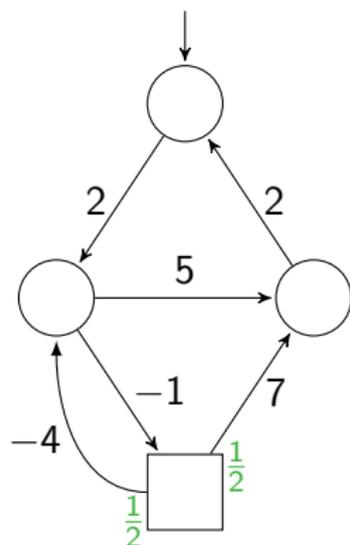
Quantitative games on graphs



Then, $(2, 5, 2)^\omega$

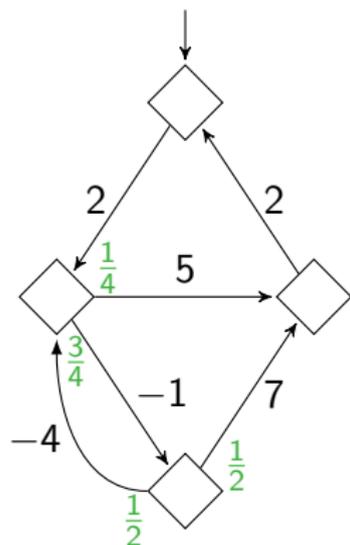
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Markov decision processes



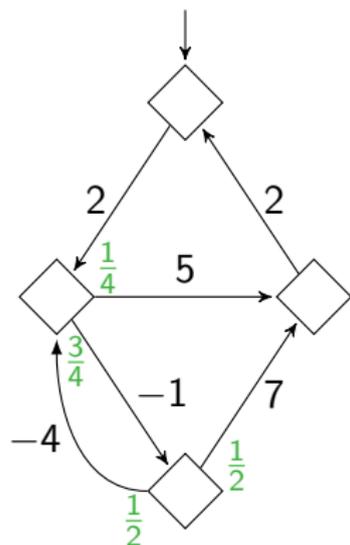
- MDP $P = (\mathcal{G}, S_1, S_\Delta, \Delta)$ with $\Delta: S_\Delta \rightarrow \mathcal{D}(S)$
 - ▷ \mathcal{P}_1 states = \bigcirc
 - ▷ stochastic states = \square
- MDP = game + strategy of \mathcal{P}_2
 - ▷ $P = G[\lambda_2]$

Markov chains



- MC $M = (\mathcal{G}, \delta)$ with $\delta: S \rightarrow \mathcal{D}(S)$
- MC = MDP + strategy of \mathcal{P}_1
= game + both strategies
 - ▷ $M = P[\lambda_1] = G[\lambda_1, \lambda_2]$

Markov chains



- MC $M = (\mathcal{G}, \delta)$ with $\delta: S \rightarrow \mathcal{D}(S)$
- MC = MDP + strategy of \mathcal{P}_1
= game + both strategies
 - ▷ $M = P[\lambda_1] = G[\lambda_1, \lambda_2]$
- Event $\mathcal{A} \subseteq \text{Plays}(\mathcal{G})$
 - ▷ probability $\mathbb{P}_{\text{Sinit}}^M(\mathcal{A})$
- Measurable $f: \text{Plays}(\mathcal{G}) \rightarrow \mathbb{R} \cup \{-\infty, \infty\}$
 - ▷ *expected value* $\mathbb{E}_{\text{Sinit}}^M(f)$

Classical interpretations

- **System** trying to ensure a specification = \mathcal{P}_1
 - ▷ whatever the actions of its **environment**

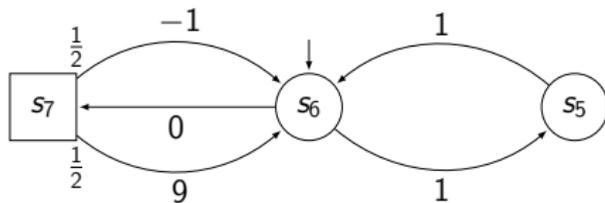
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- The environment can be seen as
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 - two-player game, *worst-case* threshold problem for $\mu \in \mathbb{Q}$
 - $\exists? \lambda_1 \in \Lambda_1, \forall \lambda_2 \in \Lambda_2, \forall \pi \in \text{Outs}_G(s_{\text{init}}, \lambda_1, \lambda_2), f(\pi) \geq \mu$

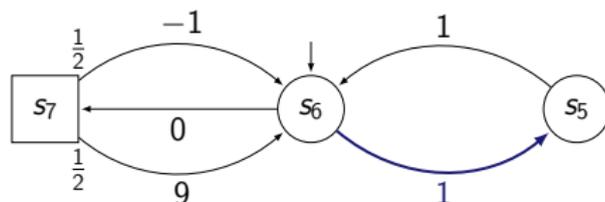
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 - ▷ *fully stochastic*
 - MDP, *expected value* threshold problem for $\nu \in \mathbb{Q}$
 - $\exists? \lambda_1 \in \Lambda_1, \mathbb{E}_{s_{\text{init}}}^{P[\lambda_1]}(f) \geq \nu$

An ideal situation



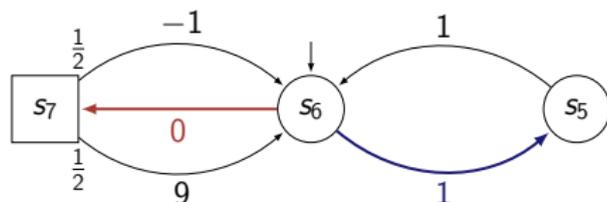
An ideal situation



Game interpretation

- ▶ Worst-case threshold is $\mu = 0$
- ▶ **All** states are winning: memoryless optimal worst-case strategy $\lambda_1^{wc} \in \Lambda_1^{PM}(G)$, ensuring $\mu^* = 1 > 0$

An ideal situation



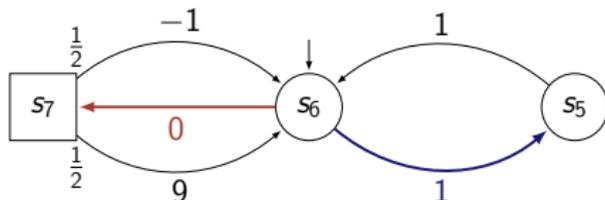
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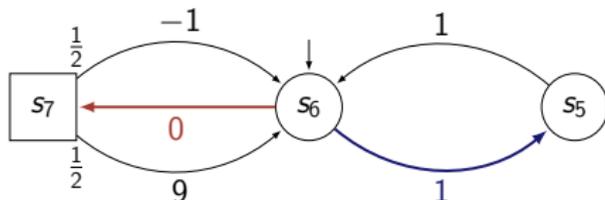
- ▶ Memoryless optimal expected value strategy $\lambda_1^e \in \Lambda_1^{PM}(P)$ achieves $\nu^* = 2$

A cornerstone of our approach



BWC problem: what kind of thresholds $(0, \nu)$ can we achieve?

A cornerstone of our approach



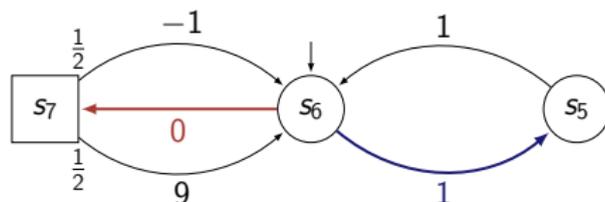
BWC problem: what kind of thresholds $(0, \nu)$ can we achieve?

Key result

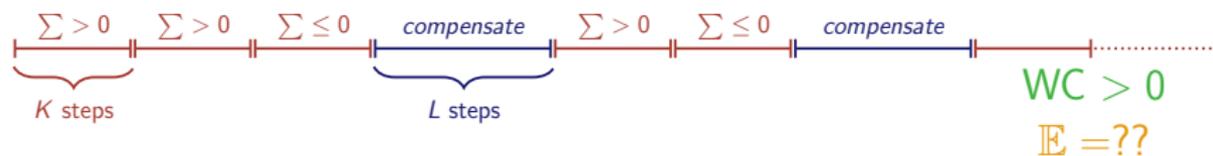
For all $\varepsilon > 0$, there exists a finite-memory strategy of \mathcal{P}_1 that satisfies the BWC problem for the thresholds pair $(0, \nu^* - \varepsilon)$.

- ▶ We can be **arbitrarily close to the optimal expectation** while ensuring the worst-case!

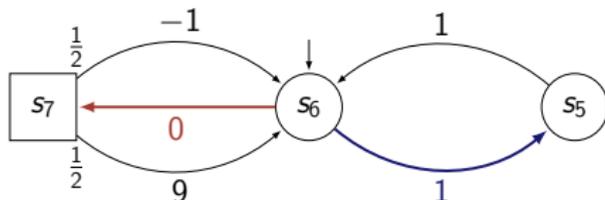
Combined strategy



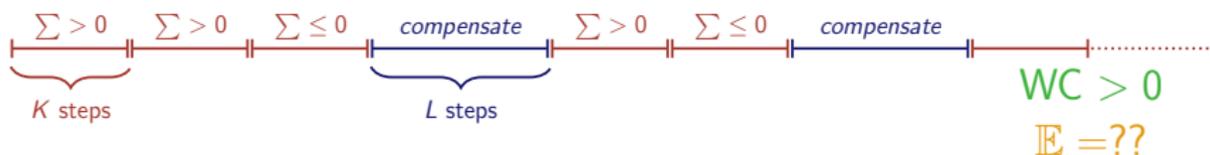
Outcomes of the form



Combined strategy



Outcomes of the form



What we want

$$K, L \rightarrow \infty$$

$$\mathbb{E} = \nu^* = 2$$

Combined strategy: crux of the proof

Precise reasoning on convergence rates using involved techniques

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 - ▷ application of Chernoff bounds and Hoeffding's inequality for Markov chains [Tra09, GO02]
- **Overall we are good**: $WC > 0$ and $\mathbb{E} > \nu^* - \varepsilon$ for sufficiently large K, L .