

# The Many Faces of Strategy Complexity

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Based on joint work with

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# Talk overview

**Strategies** are at the center of game-theoretic approaches to reactive synthesis.

## Goal of this talk

Motivate and explain a **multifaceted vision** of strategy complexity.

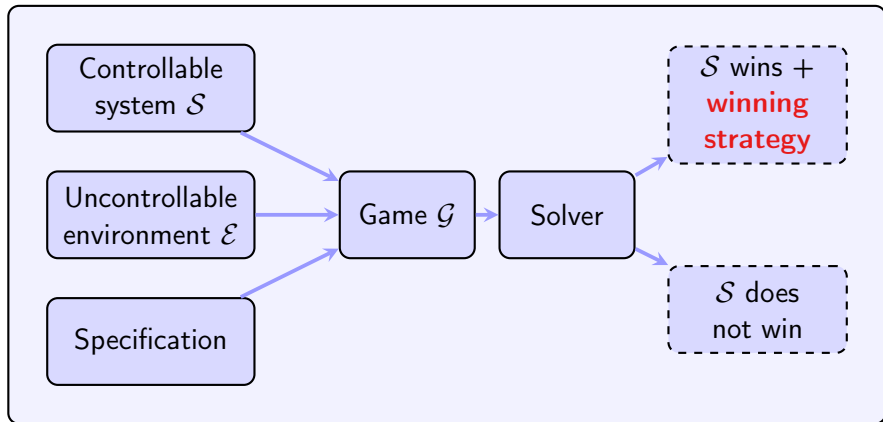
In the second part of this talk, we will focus on:

- **randomised** strategies;
- **alternative** representations of strategies.

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# Reactive synthesis through game theory

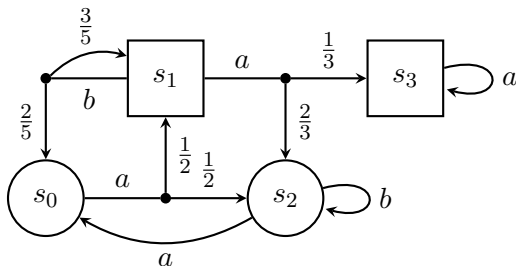


A **strategy** is a formal blueprint for a **controller of the system**.

# Turn-based stochastic games

## Turn-based stochastic game $\mathcal{G}$

- **Finite or countable** state space  $S = S_1 \uplus S_1$ .
- **Finite** action space  $A$ .
- **Randomised** transition function  $\delta: S \times A \rightarrow \mathcal{D}(S)$ .



**Plays** are sequences in  $(SA)^\omega$  coherent with transitions.

$\rightsquigarrow$  **Example:**  $s_0 a s_1 b s_1 \dots$

# Strategies

A **history** is a prefix  $h$  of a play ending in a **state**.

## Strategy

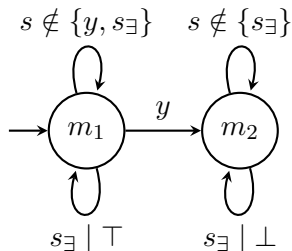
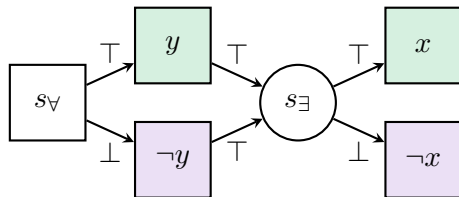
A **behavioural strategy** of  $\mathcal{P}_i$  is a function  $\sigma_i: \text{Hist}_i(\mathcal{G}) \rightarrow \mathcal{D}(A^{(i)})$ .

- Two strategies  $\sigma_1, \sigma_2$  and an initial state  $s \rightsquigarrow$  **distribution**  $\mathbb{P}_s^{\sigma_1, \sigma_2}$  over plays.
- A strategy  $\sigma_i$  is **pure** if  $\sigma_i: \text{Hist}_i(\mathcal{G}) \rightarrow A$ .
- A strategy is **memoryless** if  $\sigma_i: S_i \rightarrow \mathcal{D}(A)$ .

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## Strategies and memory



## Representation of strategies via Mealy machines with randomisation

- Set of **memory states**  $M$ ;
- initial **memory distribution**  $\mu_{\text{init}}$ ;
- **next-move** function  $\text{nxt}_{\mathcal{M}}: M \times S_i \rightarrow \mathcal{D}(A)$ ;
- memory **update** function  $\text{up}_{\mathcal{M}}: M \times S \times A \rightarrow \mathcal{D}(M)$ .



# Strategy complexity via memory

- The complexity of strategies is traditionally measured by the size of their **memory**.
- Memory requirements for optimal strategies in games have been thoroughly studied.

## A glimpse into known results on memory

- Characterisations and one-to-two player lifts (e.g., [GZ05; Bou+22]).
- Refining memory bounds/computing optimal bounds (e.g., [Bou+23; Mai24]).
- Trading memory for **randomisation** (e.g., [CAH04; CRR14]).

# Strategy complexity in general

- Memory size does **not fully describe** the complexity of strategies.
- Other aspects also play a role in the complexity of strategies.
- **Major question**: what makes a strategy complex?

## Our vision

Strategy complexity is **multifaceted**: various factors contribute to the complexity of a strategy.

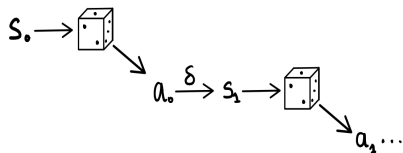
- **Next step**: a brief look into **randomisation**.

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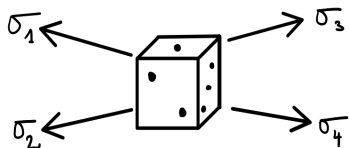
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# Mixed and behavioural strategies

- There exist different definitions of **randomised strategies**.



Behavioural strategies



Mixed strategies

- In general, these two classes of strategies are **not comparable**.
- Kuhn's theorem [Aum64]: in **games of perfect recall** any mixed strategy has an equivalent behavioural strategy and vice-versa.

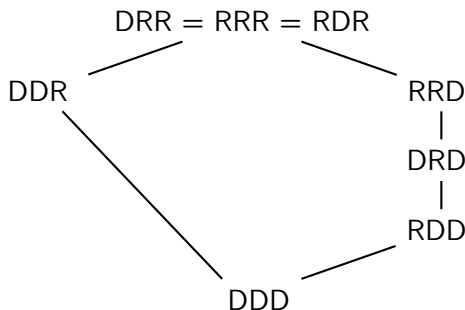
What happens with finite-memory strategies?

Are all models of **finite-memory randomised strategies equivalent**?

## Randomisation and finite memory [MR24]

A class of Mealy machines is denoted by  $XYZ$  where  $X, Y, Z \in \{D, R\}$  where  $D$  stands for deterministic and  $R$  for random, and

- $X$  characterises initialisation,
- $Y$  characterises the next-move function,
- $Z$  characterises updates.



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# Random strategies and multiple objectives

- We study one-player games, i.e., **Markov decision processes**, with **multiple payoffs**.
- In general, the satisfaction of multi-objective queries requires **randomised strategies**.

## Main questions

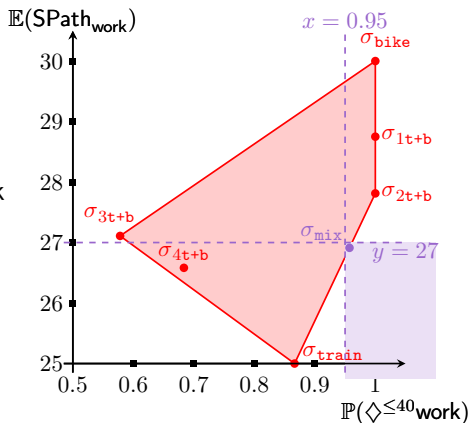
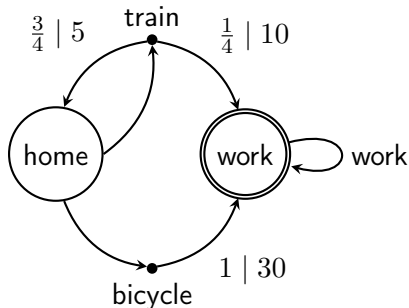
- What is the relationship between expected payoffs of **pure strategies** and expected payoffs of **general strategies**?
- What **type of randomisation** do we need for multi-objective queries?

→ **Goal**: results for the **broadest possible class of payoffs**.

# Multi-objective Markov decision processes

We consider **two goals**:

- reaching work under 40 minutes with **high probability**;
- minimising the **expected** time to reach work.





# Payoffs

- A **payoff** is a measurable function  $f: \text{Plays}(\mathcal{M}) \rightarrow \bar{\mathbb{R}}$ .
- We let  $\mathbb{E}_s^\sigma(f) = \int_{\pi \in \text{Plays}(\mathcal{M})} f(\pi) d\mathbb{P}_s^\sigma(\pi)$ .

## Which payoffs $f$ are relevant?

- $f$  is **good** if  $\mathbb{E}_s^\sigma(f)$  is well-defined for all strategies  $\sigma$  and all  $s \in S$ .
- $f$  is **universally integrable** payoffs:  $\mathbb{E}_s^\sigma(|f|) \in \mathbb{R}$  if for all strategies  $\sigma$  and all  $s \in S$ .

For a **multi-dimensional payoff**  $\bar{f} = (f_1, \dots, f_d)$  and  $s \in S$ , we let:

- $\text{Pay}_s(\bar{f}) = \{\mathbb{E}_s^\sigma(\bar{f}) \mid \sigma \text{ strategy}\}$ ;
- $\text{Pay}_s^{\text{pure}}(\bar{f}) = \{\mathbb{E}_s^\sigma(\bar{f}) \mid \sigma \text{ pure strategy}\}$ .

## Universally integrable payoffs

In the introductory example, we had  $\text{Pay}_{\text{home}}(\bar{f}) = \text{conv}(\text{Pay}_{\text{home}}^{\text{pure}}(\bar{f}))$ .

**When does this generalise?**

**Theorem ((M., Randour))**

Let  $\bar{f} = (f_1, \dots, f_d)$  be **universally integrable**. Then, for all states  $s$ ,

$$\text{Pay}_s(\bar{f}) = \text{conv}(\text{Pay}_s^{\text{pure}}(\bar{f})).$$

*In particular, to match the expected payoff of any strategy, it suffices to:*

- **mix  $d + 1$  pure strategies;**
- *consider strategies use **randomisation at most  $d$**  along any play.*

**Sequel: proof of a weaker result**

If  $\bar{f}$  is universally integrable, then  $\text{cl}(\text{Pay}_s(\bar{f})) = \text{cl}(\text{conv}(\text{Pay}_s^{\text{pure}}(\bar{f})))$ .

# Universally integrable payoffs

A simpler proof

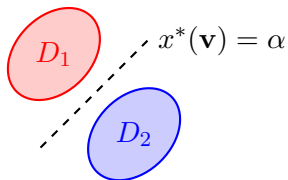
**Non-direct inclusion:**  $\text{Pay}_s(\bar{f}) \subseteq \text{cl}(\text{conv}(\text{Pay}_s^{\text{pure}}(\bar{f})))$ .

Let  $\sigma$  be a strategy and  $\mathbf{q} = \mathbb{E}_s^\sigma(\bar{f})$ . Assume  $\mathbf{q} \notin \text{cl}(\text{conv}(\text{Pay}_s^{\text{pure}}(\bar{f})))$ .

**Main idea:** reduction to a **one-dimensional** payoff.

## Theorem (Hyperplane separation theorem)

Let  $D_1, D_2 \subseteq \mathbb{R}^d$  be **disjoint convex** sets. If  $D_1$  is **closed** and  $D_2$  is **compact**, then there exists a **linear form**  $x^*: \mathbb{R}^d \rightarrow \mathbb{R}$  and  $\varepsilon > 0$  such that for all  $\mathbf{p}_1 \in D_1$  and  $\mathbf{p}_2 \in D_2$ ,  $x^*(\mathbf{p}_1) + \varepsilon < x^*(\mathbf{p}_2)$ .



# Universally integrable payoffs

A simpler proof

**Non-direct inclusion:**  $\text{Pay}_s(\bar{f}) \subseteq \text{cl}(\text{conv}(\text{Pay}_s^{\text{pure}}(\bar{f})))$ .

Let  $\sigma$  be a strategy and  $\mathbf{q} = \mathbb{E}_s^\sigma(\bar{f})$ . Assume  $\mathbf{q} \notin \text{cl}(\text{conv}(\text{Pay}_s^{\text{pure}}(\bar{f})))$ .

**Main idea:** reduction to a **one-dimensional** payoff.

- There exists a linear form  $x^*$  such that, for all **pure strategies**  $\tau$ ,

$$x^*(\mathbb{E}_s^\tau(\bar{f})) < x^*(\mathbf{q})$$

- By linearity, we obtain that for all pure strategies  $\tau$ ,

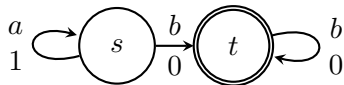
$$\mathbb{E}_s^\tau(x^*(\bar{f})) < \mathbb{E}_s^\sigma(x^*(\bar{f}))$$

## Lemma

Let  $f$  be **universally integrable**. For all strategies  $\sigma$ , there exists a **pure strategy**  $\tau$  such that  $\mathbb{E}_s^\sigma(f) \leq \mathbb{E}_s^\tau(f)$ .

# Beyond universally integrable payoffs

## Example



## Payoffs

1 reaching  $t \rightsquigarrow f_1 = \mathbb{1}_{\diamond t}$ ;

2 sum of weights  $\rightsquigarrow f_2 = \sum_{\ell=0}^{\infty} w(c_{\ell})$ .

- $\mathbb{E}_s^{\sigma_a}(f_2) = +\infty \implies f_2$  is **not universally integrable**.
- $\text{Pay}_s^{\text{pure}}(\bar{f}) = \{(0, +\infty)\} \cup \{(1, \ell) \mid \ell \in \mathbb{N}\}$ .  
 $\implies \text{conv}(\text{Pay}_s^{\text{pure}}(\bar{f})) = (\{1\} \times \mathbb{R}_{\geq 0}) \cup ([0, 1[ \times \{+\infty\})$ .
- We have  $(1, +\infty) \in \text{Pay}_s(\bar{f})$  via  $\sigma$  such that for all  $\ell \in \mathbb{N}$ :

$$\sigma(s(as)^{\ell})(a) = \begin{cases} \frac{1}{2} & \text{if } \ell \in 2^{\mathbb{N}} \\ 1 & \text{if } \ell \notin 2^{\mathbb{N}} \end{cases}$$

**→ The theorem and the key lemma do not generalise.**

# Beyond universally integrable payoffs

## Theorem (M., Randour)

Let  $\bar{f}$  be a good payoff and  $s \in S$ . Let  $\mathbf{q} \in \text{Pay}_s(\bar{f})$ .  
All neighbourhoods of  $\mathbf{q}$  (in  $\bar{\mathbb{R}}$ ) intersect  $\text{conv}(\text{Pay}_s^{\text{pure}}(\bar{f}))$ . In other words,  
 $\mathbf{q}$  can be approximated by **finite-support mixed strategies**.

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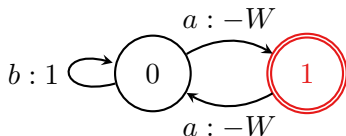
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# Memory does not tell the whole story (1/2)

## Counter-based strategies

**Memory** and **randomisation** do **not fully reflect** the complexity of a strategy.

- We consider a game with an **energy-Büchi** objective [CD12], where  $W \in \mathbb{N}$ .



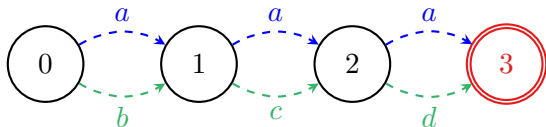
- Need memory **exponential** in the binary encoding of  $W$  to satisfy the energy-Büchi objective.
- **Polynomial** representation with a **counter**-based approach.



## Memory does not tell the whole story (2/2)

Action choices influence simplicity

**Memory** and **randomisation** do **not fully reflect** the complexity of a strategy.



→ Strategy  $\sigma_1$  is **simpler to represent** than  $\sigma_2$

- The **action choices** can impact how concise the strategy can be made.

### Related challenge

How to represent and analyse **memoryless strategies** when the state space is **infinite**?

# Memoryless strategies in one-counter MDPs

- We study **one-counter Markov decision processes**.
- We consider counter-based strategies with a **compact representation** that we call **interval strategies**.

## Our contribution (Ajdarów, M., Novotný, Randour)

- PSPACE **verification** algorithms for interval strategies.
- PSPACE **realisability** algorithms for **structurally-constrained** interval strategies.
- Our algorithms are based on a **finite abstraction** of an **infinite system**.

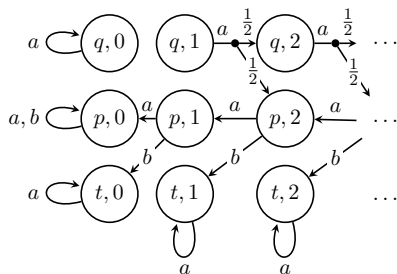
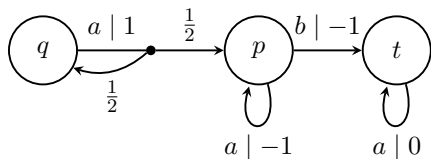
# One-counter Markov decision processes

## One-counter MDP (OC-MDP) $\mathcal{Q}$

- **Finite** MDP  $(Q, A, \delta)$ .
- **Weight function**  
 $w: Q \times A \rightarrow \{-1, 0, 1\}$ .

## MDP $\mathcal{M}^{\leq \infty}(\mathcal{Q})$ induced by $\mathcal{Q}$

- **Countable** MDP over  
 $S = Q \times \mathbb{N}$ .
- State transitions via  $\delta$ .
- Counter updates via  $w$ .



# Interval strategies

We study a restricted class of **memoryless strategies** of  $\mathcal{M}^{\leq \infty}(Q)$ .

## Open-ended interval strategies (OEIS)

$\sigma$  is an OEIS if  $\exists k_0 \in \mathbb{N}$  s.t.  $\forall q \in Q$  and  $\forall k \geq k_0$ ,  $\sigma(q, k) = \sigma(q, k_0)$ .

$\mathbb{N}_0$	1	2	...	$k_0 - 1$	$k_0$	$k_0 + 1$	...
$Q$	$\sigma_1$	$\sigma_2$	...	$\sigma_{k_0-1}$	$\sigma_{k_0}$	$\sigma_{k_0}$	...

Group counter values  
in intervals

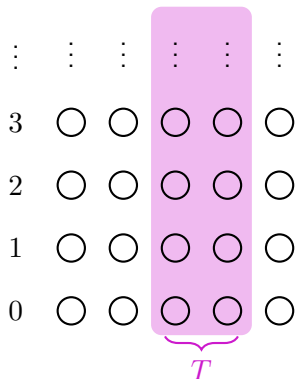


Inter.	$I_1$	$I_2$	...	$I_d = \llbracket k_0, \infty \rrbracket$
$Q$	$\tau_1$	$\tau_2$	...	$\tau_d = \sigma_{k_0}$

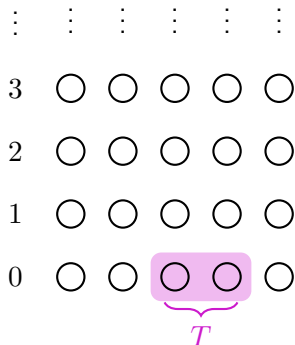
$\rightsquigarrow$  **Finite partition of**  
 $\mathbb{N}_0$  into **intervals**

# Objectives

- An **objective** is a measurable set of plays.
- Let  $T \subseteq Q$  be a **target**.
- We study variants of **reachability objectives**.



**State reachability**  $\text{Reach}(T)$



**Selective termination**  $\text{Term}(T)$

# Interval strategy verification problem

## Interval strategy verification problem

Decide whether  $\mathbb{P}_{\mathcal{M}^{\leq \infty}(Q), s_{\text{init}}}^{\sigma}(\Omega) \geq \theta$  given an **OEIS**  $\sigma$ , an **objective**  $\Omega \in \{\text{Reach}(T), \text{Term}(T)\}$ , a **threshold**  $\theta \in \mathbb{Q} \cap [0, 1]$  and an **initial configuration**  $s_{\text{init}} \in Q \times \mathbb{N}$ .

- We construct a finite **compressed Markov chain**  $\mathcal{C}_{\mathcal{I}}^{\sigma}$ .
- We have formulae (in the signature  $\{0, 1, +, -, \cdot, \leq\}$ ):
  - $\Phi_{\delta}^{\mathcal{I}}(\mathbf{x}, \mathbf{z}^{\sigma})$  for **transition probabilities** of  $\mathcal{C}_{\mathcal{I}}^{\sigma}$ ;
  - $\Phi_{\Omega}^{\mathcal{I}}(\mathbf{x}, \mathbf{y})$  for **termination probabilities** from configurations of  $\mathcal{C}_{\mathcal{I}}^{\sigma}$ .
- We can solve the verification problem by checking if

$$\mathbb{R} \models \forall \mathbf{x} \forall \mathbf{y} (\Phi_{\delta}^{\mathcal{I}}(\mathbf{x}, \mathbf{z}^{\sigma}) \wedge \Phi_{\Omega}^{\mathcal{I}}(\mathbf{x}, \mathbf{y})) \implies y_{s_{\text{init}}} \geq \theta.$$

# Conclusion

**Strategy complexity** can be analysed through different approaches:

- memory requirements;
- randomisation requirements;
- the existence of small strategy representations.

## In a nutshell

We are interested in developing deeper insight on **strategy complexity** and studying **alternative strategy models**.

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