Different Strokes in Randomised Strategies: Revisiting Kuhn's Theorem Under Finite-memory Assumptions

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Introduction

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- In general, these two classes of strategies are not comparable.
- Kuhn's theorem [Aum64]¹: in games of perfect recall any mixed strategy has an equivalent behavioural strategy and vice-versa.

Focus of this talk

A Kuhn-inspired classification of finite-memory strategies.

¹Aumann, "28. Mixed and Behavior Strategies in Infinite Extensive Games".

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- 2 Finite-memory strategies
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- 4 Differences between classes
- 5 Extending the classification

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Setting: finite stochastic games

We consider two-player stochastic games.



Essential characteristics

- Finite state space $S = S_1 \uplus S_2$ and action space A.
- Probabilistic transition function $\delta \colon S \times A \to \mathcal{D}(S)$.
- No deadlocks.

Strategies

Definition

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Outcome-equivalence

Given two strategies σ_1 and σ_2 , and an initial state $s_{\text{init}} \in S$, we define a probability distribution on the set of plays in the usual way: for any history $h = s_0 a_0 s_1 \dots s_n$ with $s_0 = s_{\text{init}}$, we set

$$\mathbb{P}_s^{\sigma_1,\sigma_2}(\mathsf{Cyl}(h)) = \prod_{k=0}^{n-1} \sigma_{i(k)}(s_0 a_0 \dots s_k) \cdot \delta(s_k, a_k, s_{k+1})$$

where Cyl(h) is the set of plays with h as a prefix, and i(k) = 1 if $s_k \in S_1$ and 2 otherwise.

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where ${\rm Cyl}(h)$ is the set of plays with h as a prefix, and i(k)=1 if $s_k\in S_1$ and 2 otherwise.

Outcome-equivalence

Two strategies σ_1 and τ_1 of \mathcal{P}_1 are outcome-equivalent if for all strategies σ_2 of \mathcal{P}_2 and all initial states $s_{\text{init}} \in S$, we have

$$\mathbb{P}^{\sigma_1,\sigma_2}_{s_{\text{init}}} = \mathbb{P}^{\tau_1,\sigma_2}_{s_{\text{init}}}.$$

J. C. A. Main, M. Randour

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Randomised finite-memory strategies

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Definition

A strategy σ_i of \mathcal{P}_i is finite-memory if it is induced by a stochastic Mealy machine $\mathcal{M} = (M, \mu_{\text{init}}, \alpha_{\text{next}}, \alpha_{\text{up}})$ where

- M is a finite set of memory states;
- $\mu_{\text{init}} \in \mathcal{D}(M)$ is an initial distribution;
- $\alpha_{\text{next}} \colon M \times S_i \to \mathcal{D}(A)$ is a stochastic next-move function;
- $\alpha_{up} \colon M \times S \times A \to \mathcal{D}(M)$ is a stochastic memory update function.

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- $\alpha_{up} \colon M \times S \times A \to \mathcal{D}(M)$ is a stochastic memory update function.
- We can classify Mealy machines following whether their initialisation, updates and outputs are randomised or deterministic.

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- Some classes of Mealy machines allow richer behaviours than others.
- For instance, the strategy illustrated on the right cannot be emulated with randomisation only in the outputs.



Our results

We use acronyms to define classes of Mealy machines: we use XYZ where X, Y, Z \in {D, R} where D stands for deterministic and R for random, and

- X characterises initialisation,
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Illustrating a finite-memory strategy

In the sequel, we will illustrate fragments of Mealy machines for \mathcal{P}_i as follows.



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$RDD \subseteq DRD$: trading random initialisation for outputs

We fix an RDD Mealy machine $\mathcal{M} = (M, \mu_{\text{init}}, \alpha_{\text{next}}, \alpha_{\text{up}}).$

- We use an adaptation of the subset construction to go from *M* to a DRD Mealy machine.
- State space of functions $f: \operatorname{supp}(\mu_{\operatorname{init}}) \to (M \cup \{\bot\})$:
 - We simulate the strategy from each initial state.
 - If an action is inconsistent with one of the simulations, we stop it (symbolised by \perp).

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$RRR \subseteq DRR$: determinising initialisation

We fix an RRR Mealy machine $\mathcal{M} = (M, \mu_{\text{init}}, \alpha_{\text{next}}, \alpha_{\text{up}}).$

- To derive a DRR Mealy machine from \mathcal{M} , we add a new initial state m_{new} to the memory state space.
- We use stochastic updates to return to \mathcal{M} from m_{new} . Transition probabilities are chosen so the distribution over memory states is the same in \mathcal{M} and the DRR Mealy machine after the first step.

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$RRR \subseteq RDR$: determinising outputs

We fix an RRR Mealy machine $\mathcal{M} = (M, \mu_{\text{init}}, \alpha_{\text{next}}, \alpha_{\text{up}}).$

- To derive a RDR Mealy machine from \mathcal{M} , we expand the state space by augmenting memory states with pure memoryless strategies $\sigma_i \colon S_i \to A$.
- We use stochastic initialisation and updates to integrate the randomisation over actions in the transitions.

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Naive construction \rightsquigarrow memory state space grows by a factor of $|A|^{|S_i|}$

 \hookrightarrow We can do better:

Theorem

There exists an RDR Mealy machine with $|M| \cdot |S_i| \cdot |A|$ states whose induced strategy is outcome-equivalent to \mathcal{M} .

• Consider a game such that $S_i = \{s_1, s_2, s_3\}$, and $A = \{a_1, a_2, a_3\}$. Assume that for a memory state $m \in M$, we have:

$$\alpha_{\text{next}}(m, s_1)(a_1) = \alpha_{\text{next}}(m, s_1)(a_2) = \frac{1}{2};$$

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$$a_{\mathsf{next}}(m, s_3)(a_1) = \frac{1}{3}, \ \alpha_{\mathsf{next}}(m, s_3)(a_2) = \frac{1}{6} \text{ and } \alpha_{\mathsf{next}}(m, s_3)(a_3) = \frac{1}{2}.$$

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We represent the actions in a table to derive the pure memoryless strategies and their probabilities.

s_1	a_1		a_2		
s_2	a_1	a_2		a_3	
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s_1	a_1	 		a_2			
s_2	a_1	a	2	a_3			
s_3	a_1	a_2		a_3			
σ_k	σ_1	σ_2	σ_3	σ_4			
$x_1 = 0$ $x_2 = \frac{1}{3} x_3 = \frac{1}{2} x_4 = \frac{2}{3}$ $x_5 = \frac{1}{3} x_5 = \frac{1}{3} x_$							

$RRR \subseteq RDR$: exploiting the memoryless strategies

- For each memory state $m \in M$, we determine pure memoryless strategies $\sigma_1^m, \ldots, \sigma_{\ell(m)}^m$ and their respective probabilities $p_1^m, \ldots, p_{\ell(m)}^m$.
- We split transitions that enter m into transitions that go to the states (m, σ_j^m) : a transition of probability q into m yields a transition with probability $q \cdot p_j^m$ into (m, σ_j^m) .



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Differences between classes

We discuss the following aspects:

- The chain of inclusions $DDD \subsetneq RDD \subsetneq DRD \subsetneq RRD \subsetneq RRR$ is strict.
- It holds that $DDR \nsubseteq RRD$ and $RDD \nsubseteq DDR$.



Strictness: $RDD \subsetneq DRD$

In a one-player deterministic game, RDD strategies have finitely many outcomes.

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- In a one-player deterministic game, RDD strategies have finitely many outcomes.
- The DRD strategy depicted below has no RDD equivalent.



Strictness: DDR \nsubseteq RRD

- The number of memory states in which we can find ourselves as a play goes on cannot increase for an RRD strategy..
- To have a positive probability of never using a, we must eventually be in a memory state m such that $\alpha_{next}(m, s)(a) = 0$ with positive probability.



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Taxonomy in settings of partial information

Up to now, we have discussed a classification of strategies in a setting of perfect information.

 \rightsquigarrow Can we weaken this hypothesis ?

- It is not necessary to see the states themselves.
- For the inclusion RDD ⊆ DRD, we rely on the visibility of actions in our subset construction.
- For the inclusion RRR ⊆ DRR, we also use the visibility of actions in conditional probabilities.

Partial information

The classification holds in games where \mathcal{P}_i can see their actions and distinguish the owner of states from their observations.

References I

Aumann, Robert J. "28. Mixed and Behavior Strategies in Infinite Extensive Games". In: Advances in Game Theory. (AM-52), Volume 52. Princeton University Press, 2016, pp. 627–650. DOI: doi:10.1515/9781400882014-029. URL: https://doi.org/10.1515/9781400882014-029. What happens to the lattice in full generality ? If we assume nothing on the visibility of actions ?

- Two inclusions of our lattice no longer hold. We have:
 - RDD⊈DRD;
 - RRR $\not\subseteq$ DRR (we even have RDD $\not\subseteq$ DRR).
- Intuitively, for a strategy with deterministic outputs (i.e., in a subclass of RDR), the output actions are encoded in the Mealy machine itself. ~> such strategies allow the same behaviours whether actions are visible or not.

General lattice: no hypotheses on actions



Subgame perfect equilibria and Kuhn's theorem

- In the statement of Kuhn's theorem and our classification, the output of the strategies along inconsistent branches histories are completely disregarded.
- In other words, our classification approach is not relevant for the study of subgame perfect equilibria, for which these inconsistent histories are nonetheless taken in account.
- However, the output of a finite-memory strategy along an inconsistent history is not well-defined.