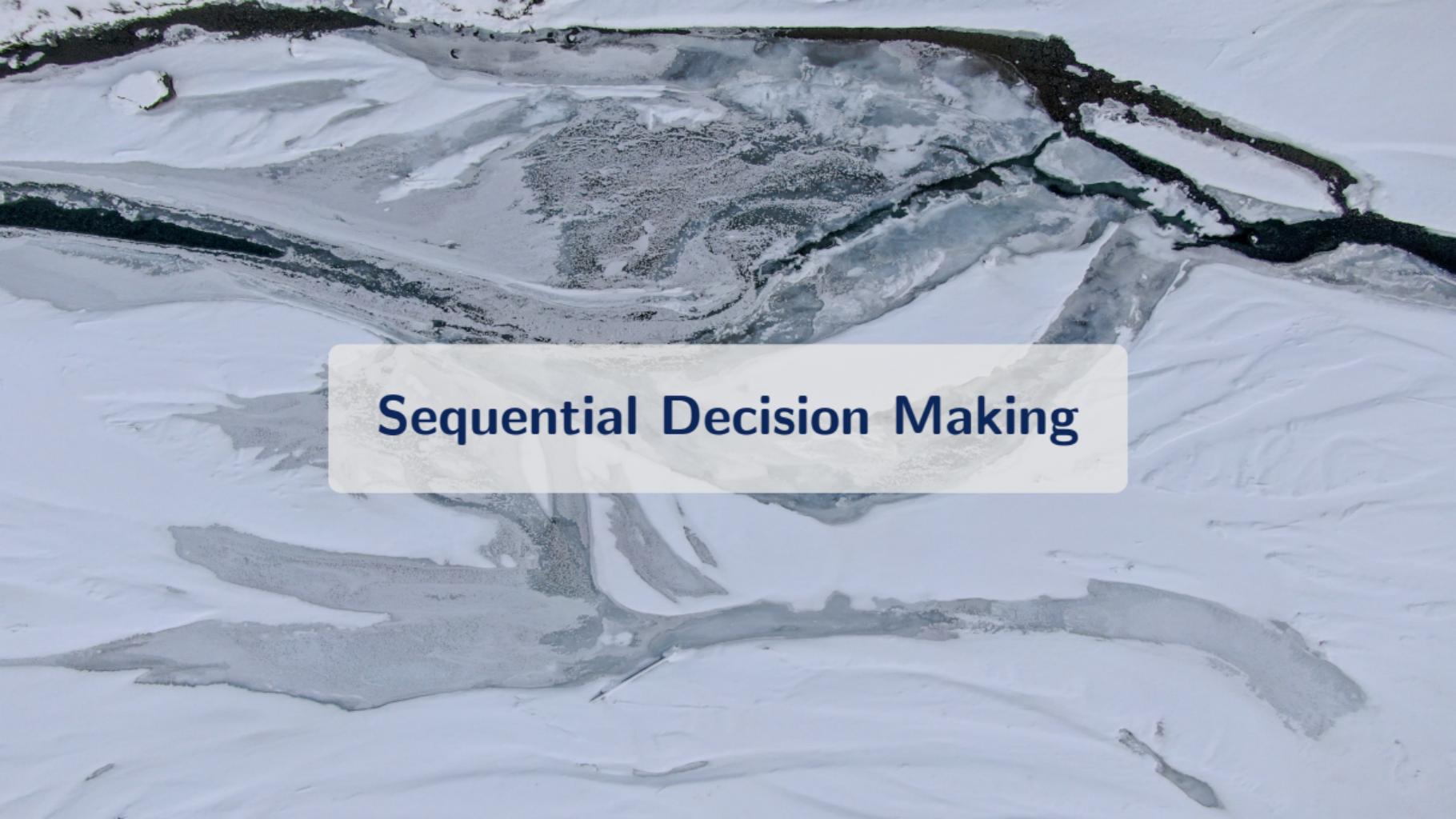


Modern Algorithmic Game Theory

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The background image shows a vast, frozen landscape, possibly a glacier or a large lake covered in ice. Dark, winding paths through the white snow and ice suggest the presence of water bodies like rivers or lakes beneath the surface.

Sequential Decision Making

Extensive-Form Games

- We will model sequential decision making as an **extensive-form game**
- EFGs use a tree-like structure similar to perfect information game trees
- However, we need to deal with imperfect information, e.g. a player cannot see their opponent's hand in Poker
- Consider these two situations in Heads Up Texas Hold'em Poker:
 - Player 1 has ($A\spades, 8\clubsuit$) and Player 2 has ($K\hearts, K\clubsuit$)
 - Player 1 has ($A\spades, 8\clubsuit$) and Player 2 has ($2\hearts, 7\hearts$)
- Even though these two situations are different, Player 1 cannot distinguish them
- We will model these situations by combining groups of indistinguishable states from each player's point of view
- This forces each player to use the same strategy in each state they cannot tell apart

Extensive-Form Games Formalization

Extensive-form game is a tuple consisting of:

- a finite set of players $\mathcal{N} = \{1, 2, \dots, n\}$
- a finite set of action sequences \mathcal{H} . Each sequence $h \in \mathcal{H}$ is called a **history**. The empty sequence \emptyset is in \mathcal{H} and every prefix of a history is also a history, i.e.
 $(h, a) \in \mathcal{H} \implies h \in \mathcal{H}, h'a \sqsubseteq h$ denotes that h' is a prefix of h
- $\mathcal{Z} \subseteq \mathcal{H}$ is the set of terminal histories
- a finite set of actions available in every non-terminal history $\mathcal{A}(h) = \{a : (h, a) \in \mathcal{H}\}$
- a function $p: \mathcal{H} \setminus \mathcal{Z} \rightarrow \mathcal{N} \cup \{c\}$ that assigns each non-terminal history $h \in \mathcal{H} \setminus \mathcal{Z}$ an **acting player** (either $i \in \mathcal{N}$ or the chance player c)
- a function f_c that assigns every history h : $p(h) = c$, a probability measure over $\mathcal{A}(h)$
- a partition \mathcal{S}_i of histories $h \in \mathcal{H}$: $p(h) = i$ where player i is to act. A set $s_i \in \mathcal{S}_i$ is an **information state** of player i and $\mathcal{H}(s_i)$ is a set of histories belonging to s_i
- a **utility function** $u_i: \mathcal{Z} \rightarrow \mathbb{R}$ for every player $i \in \mathcal{N}$

Extensive-Form Tree Example

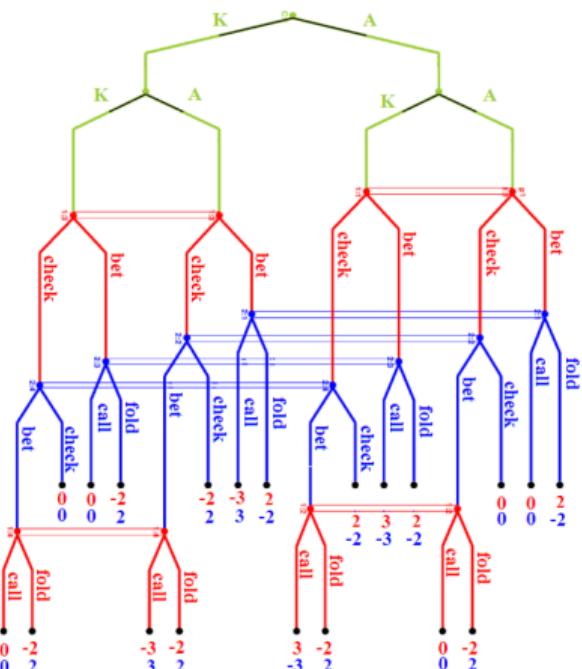
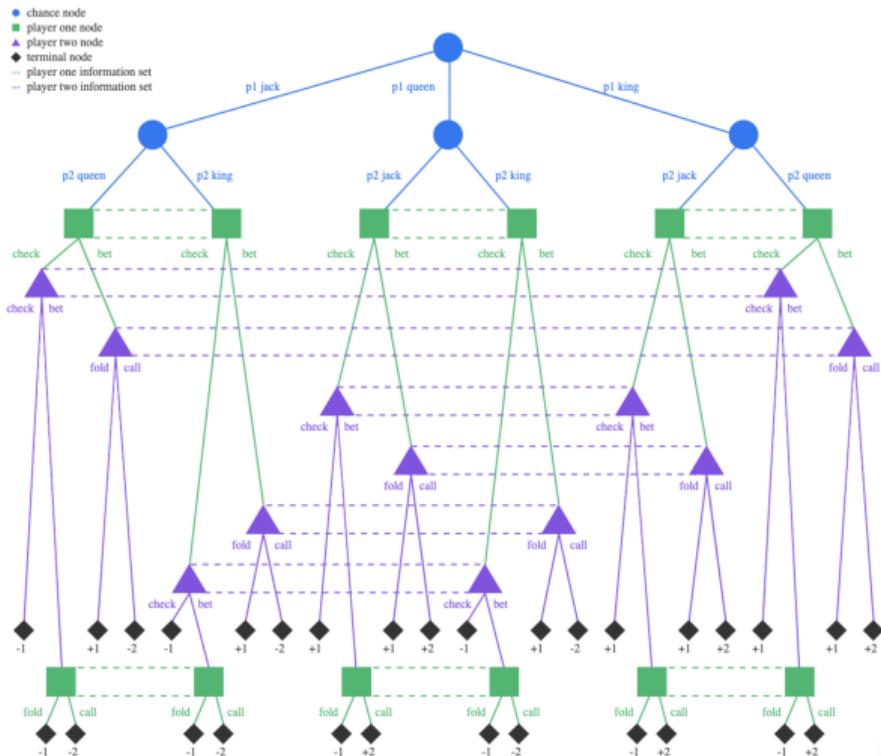


Figure: A game tree of a simple Poker-like game

Kuhn Poker Game Tree



Kuhn Poker Formalization Example

- $\mathcal{N} = \{1, 2\}$, plus the chance player denoted by c
- $\mathcal{H} = \{(\emptyset), (J), (J, Q), (J, Q, \text{bet}), (J, Q, \text{bet}, \text{call}), \dots\}, |\mathcal{H}| = 58$
- $\mathcal{Z} \subseteq \mathcal{H}, \mathcal{Z} = \{(J, Q, \text{bet}, \text{call}), (Q, J, \text{bet}, \text{fold}), \dots\}, |\mathcal{Z}| = 30$
- $\mathcal{A}(K, J) = \{\text{check}, \text{bet}\}, \mathcal{A}(K, J, \text{bet}) = \{\text{fold}, \text{call}\}$
- $p(\emptyset) = c, p(K) = c, p(K, J) = 1, p(K, J, \text{check}) = 2$
- $f_c(\emptyset) = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3}), f_c(J) = (0, \frac{1}{2}, \frac{1}{2})$
- $\mathcal{S}_1 = \{\{(K, J), (K, Q)\}, \{(K, J, \text{check}), (K, Q, \text{check})\}, \dots\}, |\mathcal{S}_1| = 6$
 $\mathcal{S}_2 = \{\{(J, K), (Q, K)\}, \{(J, K, \text{check}), (Q, K, \text{check})\}, \dots\}, |\mathcal{S}_2| = 6$
- $u_1(K, J, \text{bet}, \text{call}) = 2, u_2(K, Q, \text{bet}, \text{fold}) = -1$

Perfect Recall

- Extensive-form games is a powerful model of sequential decision making
- Unfortunately, it allows us to capture some non-realistic properties when we allow grouping arbitrary histories into information states, e.g. a history and its prefix both being in the same information state
- For example, rational players do not forget information they already know, e.g. what actions they played in previous rounds
- **Perfect recall** formalizes this property; we say that an extensive-form game satisfies perfect recall, if all players can recall their previous actions and the corresponding information states
- This is a critical property as in games with imperfect recall even basic operations (e.g. best response calculation) become hard

Strategies

- In extensive-form games players do not choose a row/column, but instead an edge in the game tree
- Since we need to ensure the players cannot distinguish states merged into information sets, we allow the players to choose an action only in information states in contrast to histories/states
- This way, the players must play the same strategy in all histories grouped in an information state
- We distinguish among three types of strategies in extensive-form games – **pure**, **mixed** and **behavioral**

Strategies

- A **pure** strategy is a complete plan of actions, one for each possible information state in a game, chosen **once** at the start of a game
- A **mixed** strategy is a probability distribution over pure strategies
- A **behavioral** strategy is a mapping from an information state to a distribution over the available actions $s_i \rightarrow \Delta(\mathcal{A}(s_i))$
- In other words, a behavioral strategy is a collection of independent probability distributions $\pi_i(s_i)$ over actions $\mathcal{A}(s_i)$, one for each information state s_i
- In games with perfect recall, it can be shown that mixed and behavioral strategies are **realization equivalent**, i.e. any outcome that is achievable using one strategy is also achievable using the other and vice versa
- This equivalence is known as **Kuhn's theorem**

Reach Probabilities

- Given a strategy profile π , we define the **reach probability of a history** $h \in \mathcal{H}$ as

$$P^\pi(h) = \prod_{h' a \sqsubseteq h} \pi(h', a)$$

- $P^\pi(h)$ can also be rewritten as the product of individual player's contribution $P_i^\pi(h)$
- Naturally, the **reach probability of an information state** $s_i \in \mathcal{S}_i$ is defined as

$$P^\pi(s) = \sum_{h \in \mathcal{H}(s_i)} P^\pi(h)$$

- Note that, for brevity, we overload the notation $P^\pi(\cdot)$ for both the histories and information states. The same applies to $\pi(\cdot, a)$.

Strategy Evaluation

- Expected utility $u_i(\pi)$ of player i given a strategy profile π is a weighted sum over the terminal histories $h \in \mathcal{Z}$
- Mathematically, this is defined as

$$u_i(\pi) = \sum_{h \in \mathcal{Z}} P^\pi(h) u_i(h)$$

- Similarly to reinforcement learning, we define the **history value function** $v_i^\pi(h)$ as the expected utility of player i when starting in $h \in \mathcal{H}$ and following strategy π
- The **history-action value function** $q_i^\pi(h, a)$ is defined analogously, except that player i first takes action $a \in \mathcal{A}(h)$ and then follows their policy π

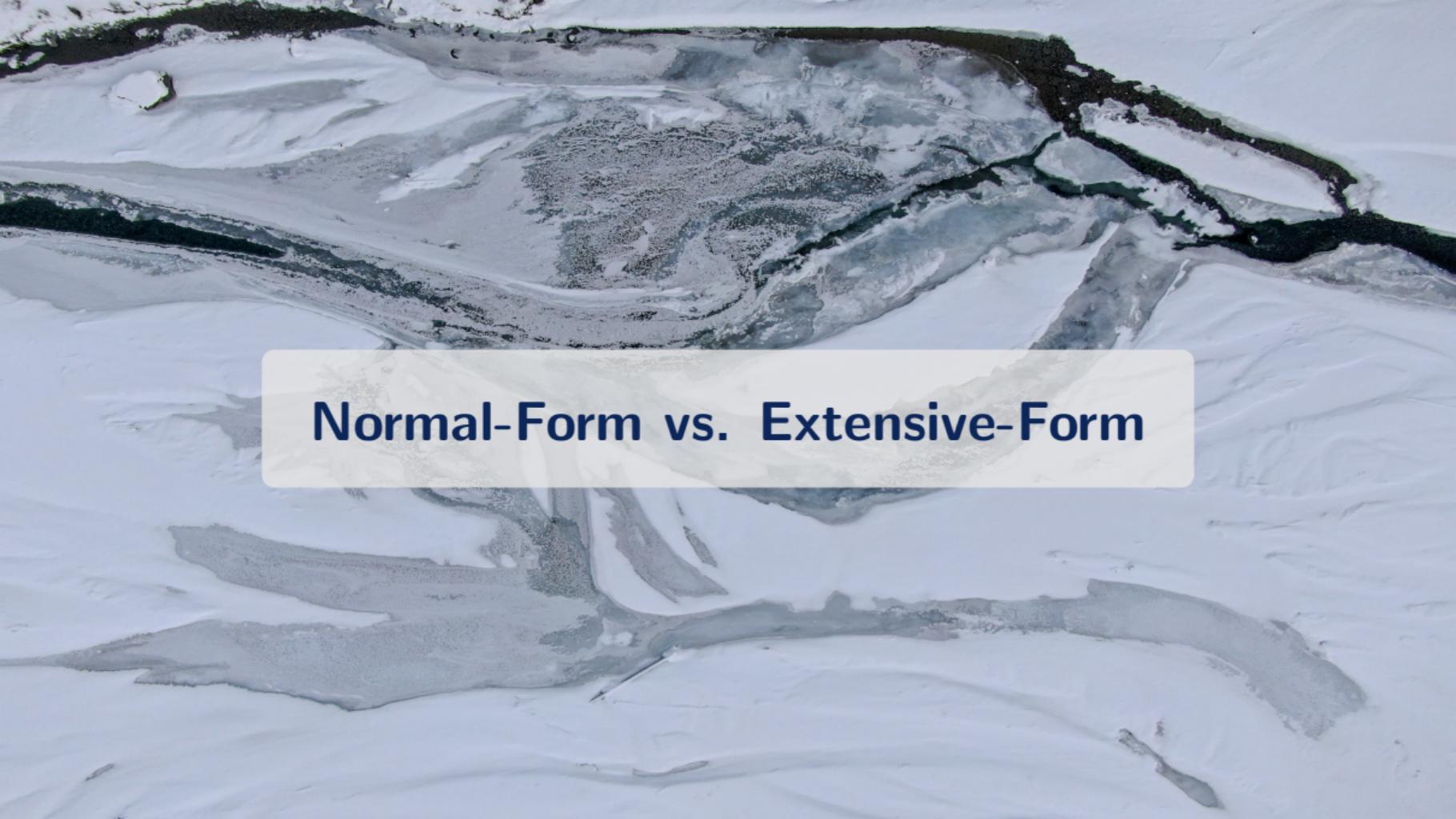
State & State-Action Value Functions

- Similarly to the reach probability of an information state, the value and action value functions of an information state are defined as sums over its histories
- However, compared to reinforcement learning, these values are not conditional on reaching a particular state, but instead depend on the reach probabilities
- The **state** value $v_i^\pi(s_i)$ of an information state $s_i \in \mathcal{S}_i$ is defined as

$$v_i^\pi(s_i) = \sum_{h \in \mathcal{H}(s_i)} P^\pi(h) v_i^\pi(h)$$

- Similarly, the **state-action** value $q_i^\pi(s_i, a)$ of an information state $s_i \in \mathcal{S}_i$ and an action $a \in \mathcal{A}(s_i)$ is defined as

$$q_i^\pi(s_i, a) = \sum_{h \in \mathcal{H}(s_i)} P^\pi(h) q_i^\pi(h, a)$$

The background image shows a wide, frozen body of water, likely a lake or a large river, covered in white snow and ice. Dark, winding channels of meltwater or rivers are visible, creating a complex network of grey and black streaks across the white surface.

Normal-Form vs. Extensive-Form

Normal-Form to Extensive-Form Games

- We can convert any normal-form game to an equivalent extensive-form game
- We simply let one player act first and group all subsequent histories into a single information state so that the opponent doesn't know what move the first player made

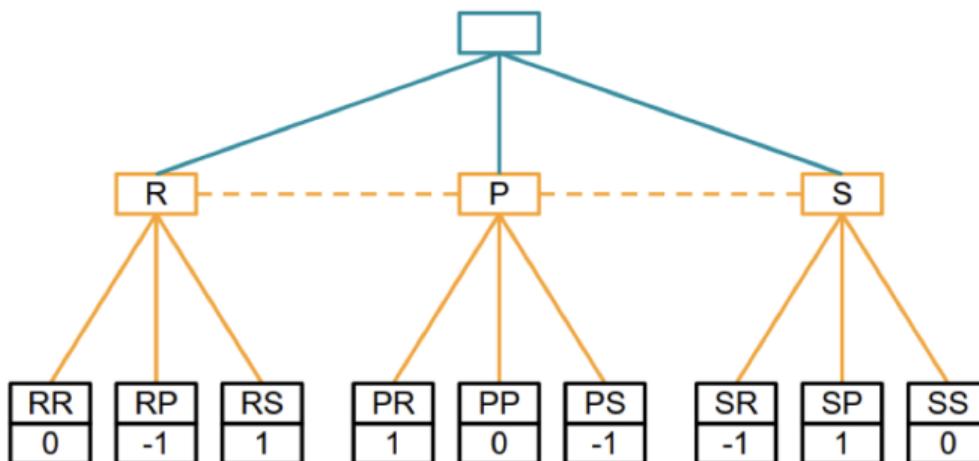
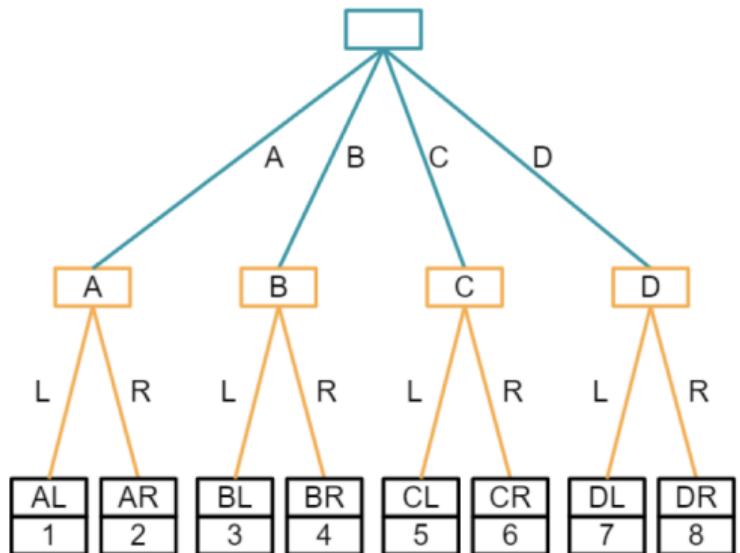


Figure: Sequential Rock-Paper-Scissors

Extensive-Form to Normal-Form Games

- Any extensive-form game that satisfies perfect recall, can be converted to an equivalent normal-form game
- Unfortunately, the resulting normal-form game can be exponentially larger than the original extensive-form game
- The set of each player's actions in the resulting normal-form game consists of all **pure strategies** in the original game
- The utility matrix consists of **expected payoffs** of the corresponding pure strategies in the original game

Extensive-Form to Normal-Form Games



	A	B	C	D
AL-BL-CL-DL	1	3	5	7
AL-BL-CL-DR	1	3	5	8
AL-BL-CR-DL	1	3	6	7
AL-BL-CR-DR	1	3	6	8
AL-BR-CL-DL	1	4	5	7
AL-BR-CL-DR	1	4	5	8
AL-BR-CR-DL	1	4	6	7
AL-BR-CR-DR	1	4	6	8
AR-BL-CL-DL	2	3	5	7
AR-BL-CL-DR	2	3	5	8
AR-BL-CR-DL	2	3	6	7
AR-BL-CR-DR	2	3	6	8
AR-BR-CL-DL	2	4	5	7
AR-BR-CL-DR	2	4	5	8
AR-BR-CR-DL	2	4	6	7
AR-BR-CR-DR	2	4	6	8

Extensive-Form to Normal-Form Games

- As any extensive-form game with perfect recall can be converted to an equivalent normal-form game, all theorems and results that hold in normal-form games also hold in extensive-form games
- Namely,
 - the existence of Nash equilibria,
 - the existence of a pure best response,
 - the collapse of Nash equilibria and Maximin strategies in zero-sum games,
 - not-so-nice properties of other games, such as the multiple equilibria problem
- For small enough games (think Kuhn Poker) we can even use the algorithms that we discussed in the previous lectures to find (converge to) Nash equilibria in these games

The background image shows a wide, frozen body of water, likely a lake or reservoir, covered in a thick layer of white snow. Dark, winding paths of ice, possibly from vehicles or animals, crisscross the surface. The lighting suggests it's either dawn or dusk, with long shadows cast across the snow.

Extensive-Form Fictitious Play

Extensive-Form Fictitious Play

- A generalization of normal-form Fictitious Play to extensive-form games
- First introduced by Johannes Heinrich, Marc Lanctot and David Silver in a paper named *Fictitious Self-Play in Extensive-Form Games*
- It follows the same structure as normal-form Fictitious Play where in each iteration:
 - We compute a best response to the average strategy of our opponent
 - We add the computed best response to the running average strategy
- However, each of these two steps is more involved than its normal-form counterpart

Best Response Computation

- Just like in perfect information games, we traverse the tree bottom-up and greedily select the action with the highest value, while propagating the values up the tree.
- However, in imperfect information games, action values in an information state depend on action values of each history in that particular information state
- Furthermore, these histories need to be weighted by their reach probabilities $P^\pi(h)$ which require knowing strategies of **all** players even in the preceding states
- How can we know our best-response strategy up the tree if we are computing it bottom-up?
- Perfect recall guarantees that our contribution to $P^\pi(h)$ is the same for all $h \in \mathcal{H}(s)$! Mathematically, $P_i^\pi(h) = P_i^\pi(h') \quad \forall h, h' \in \mathcal{H}(s)$
- Thus, when computing a best response, we can weigh the history-action values only using opponents' policies π_{-i}

Counterfactual Reach Probability

- The notion of excluding one player's policy when computing a reach probability leads to the notion of a **counterfactual reach probability**
- Given a strategy profile π , we define the counterfactual reach probability of history $h \in \mathcal{H}$ as

$$P_{-i}^{\pi}(h) = \prod_{j \in \mathcal{N} \setminus \{i\}} P_j^{\pi}(h) = \prod_{h' a \sqsubseteq h : p(h') \neq i} \pi(h', a)$$

- It is the probability of reaching history h when player i **attempts** to reach that particular history and all other players stick to their strategies.
- In other words, at every history h' that is a prefix of history h , where player i has to act, they place all of its probability mass on the particular action a that is on the path to h , i.e. $\pi_i(h', a) = 1$, where $h' a \sqsubseteq h$ and $p(h') = i$.

Counterfactual Value Functions

- Similarly, to state and state-action value functions, we define **counterfactually-weighted** state and state-action value functions
- The **counterfactual state-action** value $q_{i,c}^\pi(s_i)$ of an information state $s_i \in \mathcal{S}_i$ is defined as

$$q_{i,c}^\pi(s_i) = \sum_{h \in \mathcal{H}(s_i)} P_{-i}^\pi(h) q_i^\pi(h, a)$$

- The **counterfactual state** value $v_{i,c}^\pi(s_i)$ of an information state $s_i \in \mathcal{S}_i$ is defined as

$$v_{i,c}^\pi(s_i) = \sum_{a \in \mathcal{A}_i(s_i)} \pi_i(s_i, a) q_{i,c}^\pi(s_i, a)$$

Best Response Computation

- We have now seen that we only need to consider our opponent's strategies when computing a best response against them
- Thus, starting at the leaf nodes and moving upwards until we reach the root node, we perform the follow three steps at each information state s_i of player i :
 - compute the counterfactually-weighted action values $q_{i,c}^\pi(s_i, \cdot)$
 - choose the action a maximizing $q_{i,c}^\pi(s_i, \cdot)$
 - propagate the chosen action's value $q_{i,c}^\pi(s_i, a)$ up the tree
- On the other hand, at each information state s_{-i} of the opponent, we simply compute the expected value $v_{-i}(s_{-i})$ and propagate it up the tree

Policy Averaging

- Averaging in the space of behavioral strategies is not as straightforward and we need to exercise caution
- A common mistake is to simply average the strategies locally, in each individual information state
- This is incorrect as for $\pi_1^c = 0.5\pi_1^a + 0.5\pi_1^b$, we expect
 $u_1(\pi_1^c, \pi_2) = 0.5u_1(\pi_1^a, \pi_2) + 0.5u_1(\pi_1^b, \pi_2)$
- The issue is due to the dynamics being inherently sequential — the distribution over the terminal states $P^\pi(z)$ depends on the full sequence of actions leading to z
- Proper averaging in the behavioral strategy space must take into account reach probabilities of each information state

Policy Averaging Example

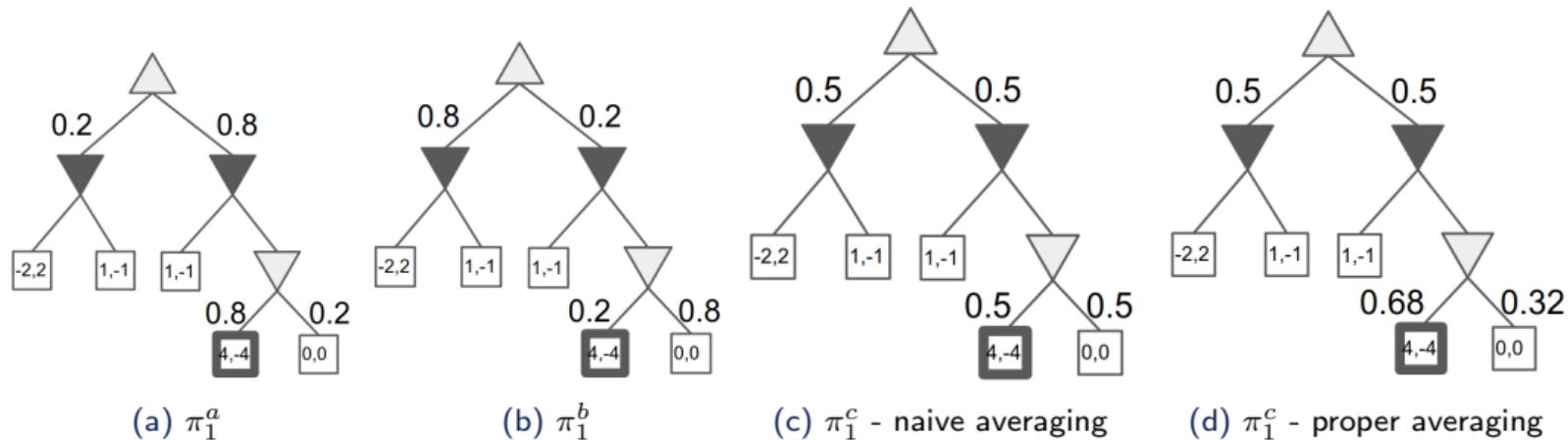


Figure: Consider the highlighted state s playing against an opponent who plays to reach that state, and its reach probability $P^\pi(s)$. a) $P^{\pi_1^a}(s) = 0.64$ b) $P^{\pi_1^b}(s) = 0.04$ c) Naive strategy averaging simply averages the strategies in isolation: $P^{\pi_1^c}(s) = 0.25 \neq 0.5 \cdot 0.64 + 0.5 \cdot 0.04$ d) Proper strategy averaging takes reach probabilities into consideration

Week 7 Homework

You can find more detailed descriptions of homework tasks in the GitHub repository.

1. Strategy profile evaluation
2. Best response calculation
3. Strategy averaging
4. Extensive-form Fictitious play