Libratus & Pluribus

Artificial Intelligence Seminar – 184.068 – 2022W

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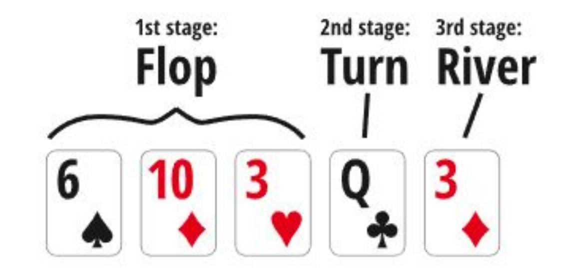
Basics of Texas Hold'em Poker

- Minimum of 2 players
- Standard deck of cards (no Jokers Included)



- 2 ***hole*** cards for each player (private)
- 5 ***community*** cards are (eventually) dealt face up

- Rounds of betting take place before the flop is dealt and after each subsequent deal
- The ***pot*** is the accumulation of all the **money/chips** betted and it's given to the winner
- In **each** round, players have **3 betting options**:
    - call
    - raise
    - fold

Basics of Texas Hold'em Poker

In the end, players who have not folded form the **best five-card poker hand**

- using all the available cards **(hole + community)**

The winner is the one with **highest-ranking** five-card poker hand.

Basics of Texas Hold’em Poker

If the betting causes **all but one** player to **fold**

- that player wins the pot
- he doesn’t need to show his cards

Players don’t need to have the best hand to win the pot

- they can try to get others to **fold better hands**

Bluff **-** To make other players believe that he has a better hand than they might have

- by betting or raising

Poker is a psychological game!

Libratus: The Superhuman AI for No-Limit Poker

Libratus was developed by **Noam Brown and Tuomas Sandholm of Carnegie Mellon University** and it was designed to play the game of poker, requiring 100 CPUs to run.

First AI agent to beat professional players in Heads-up no-limit Texas hold ’em, defeating 4 professional poker players in a tournament (2017).
Libratus played **120000 hands** in **20 days**, **winning $1.8 million**.

Libratus plays **no-limit heads up Texas Hold'em poker**

- **imperfect-information**, **extensive-form**, **zero-sum** finite game

Imperfect-information game

A game in which one or more players **do not have complete information** about the state of the game.

Poker is an imperfect information game

- the cards that each player holds in their hand are hidden to the others

Extensive form game

Poker is a **sequential game -** only one player acts a time
Sequential games can be represented in what is called **extensive-form**, also known as a **game tree**

graph with **nodes that represent positions** in a game and **lines that represent potential actions**

The **poker game tree** is an abstract concept to better understand the best ways to develop strategies.

- allows them to capture more expected value than their opponents

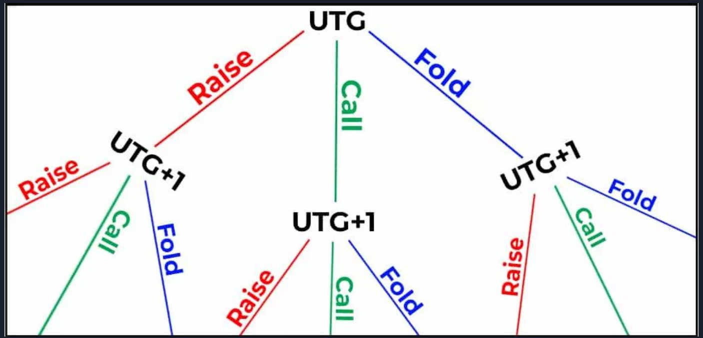
Game Tree

<u>Game Tree</u>
The tree starts from the **first preflop** decision

- A player (**UTG**) has 3 possible decisions: fold, call or raise.
- The next player (**UTG+1**) then makes his decision.

The deeper we go into the tree, the possibilities multiply exponentially!

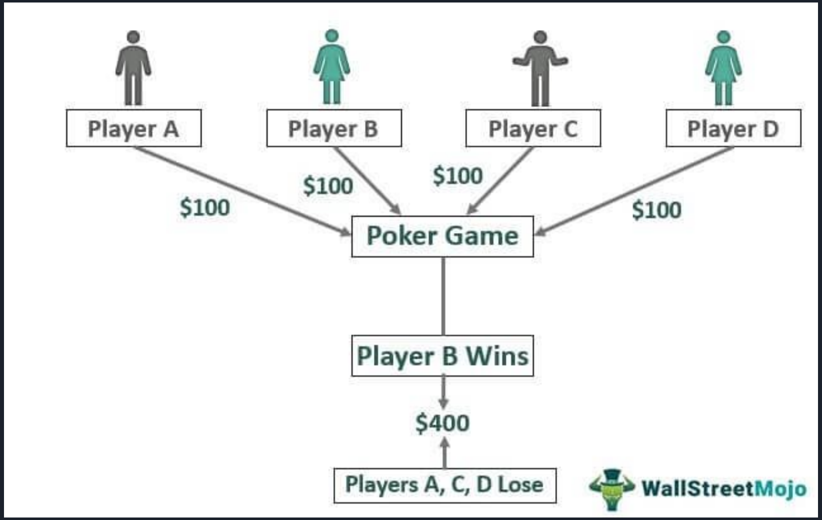
- When you add in the possibility of **multiple bet sizes**, then the tree becomes exponentially bigger once more.



Zero-sum game

One player's reward is the **negative** of their opponent(s)

- r1 + r2 + … + rN = 0



	Start	End	Profit
Player A	100	0	-100
Player B	100	400	+300
Player C	100	0	-100
Player D	100	0	-100
Total	400	400	0

Poker AI

- Rhode Island Hold'em: 10^9 decisions

  -> Solved with LP [Gilpin and Sandholm 2005]

- Limit Texas Hold'em: 10^{13} decisions

  -> Essentially solved with Counterfactual regret minimization+ [Zinkevich et al. 2007, Bowling et al. 2015, Tammelin et al. 2015]

  -> Required size compression (262TB -> 11TB)

- No-limit Texas Hold'em: 10^{161}

  -> Too big for the same approach

Libratus game plan

Uses **game theory** to make strategic decisions while playing poker.

branch of mathematics that studies decision-making in strategic situations, where the outcome of a decision is affected by the actions of other players

Libratus uses a technique called **Counterfactual regret minimization (CFR)** to determine its strategy in the game, producing an approximation of a **strategy profile** called **Nash Equilibrium**

Strategy profile

Set of strategies for all players involved in a game.

Given a **strategy profile** it's possible to emulate playing poker between players.

A single game play is a sequence of actions drawn from probability distributions given by players strategies. Once a game play is over, **players gain their utilities.**

Probabilistic framework → **expected** utilities

We can evaluate strategies and strategy profiles via expected utilities

Nash Equilibrium

Strategy profile such that no single player has incentive to deviate.

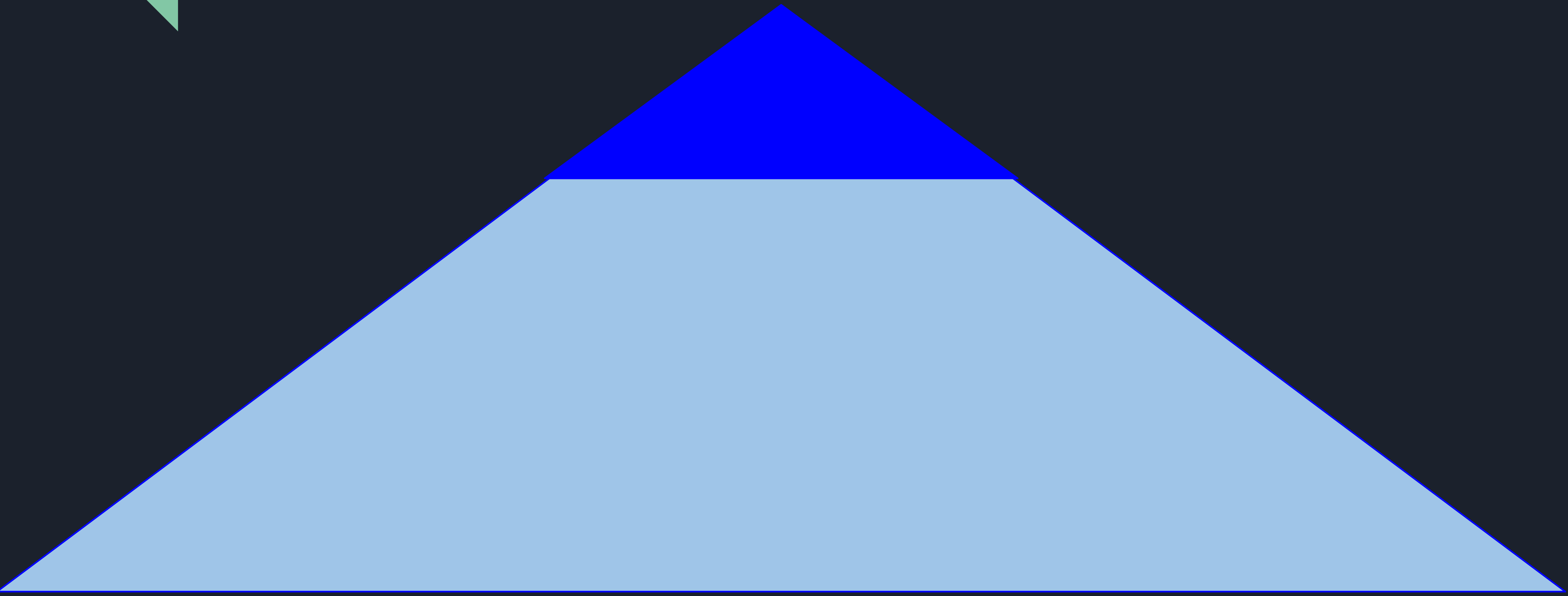
In 2 player zero-sum games, playing a Nash equilibrium ensures you will not lose in expectation.

A game reaches a state of **equilibrium** when no player in a game can improve their outcome by changing their strategy, assuming that all other players keep their strategies unchanged.

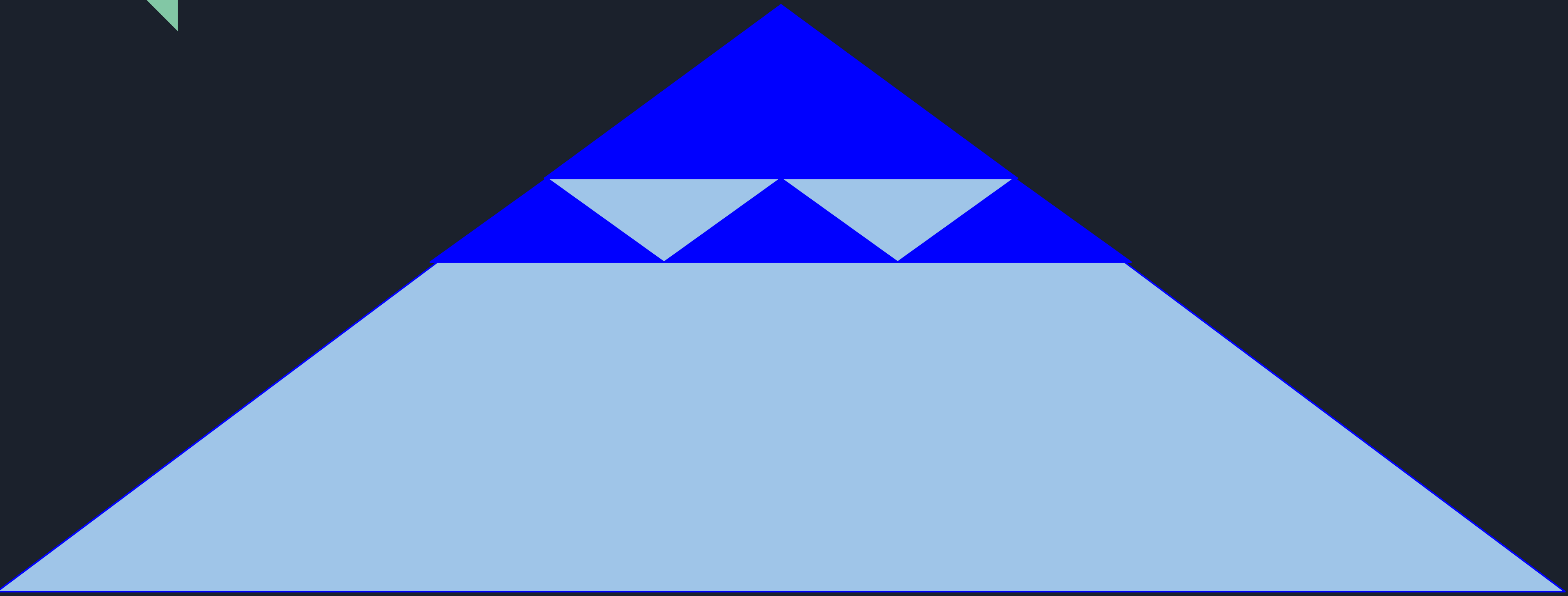
The goal is to find the Nash Equilibrium

Libratus

Libratus



Libratus



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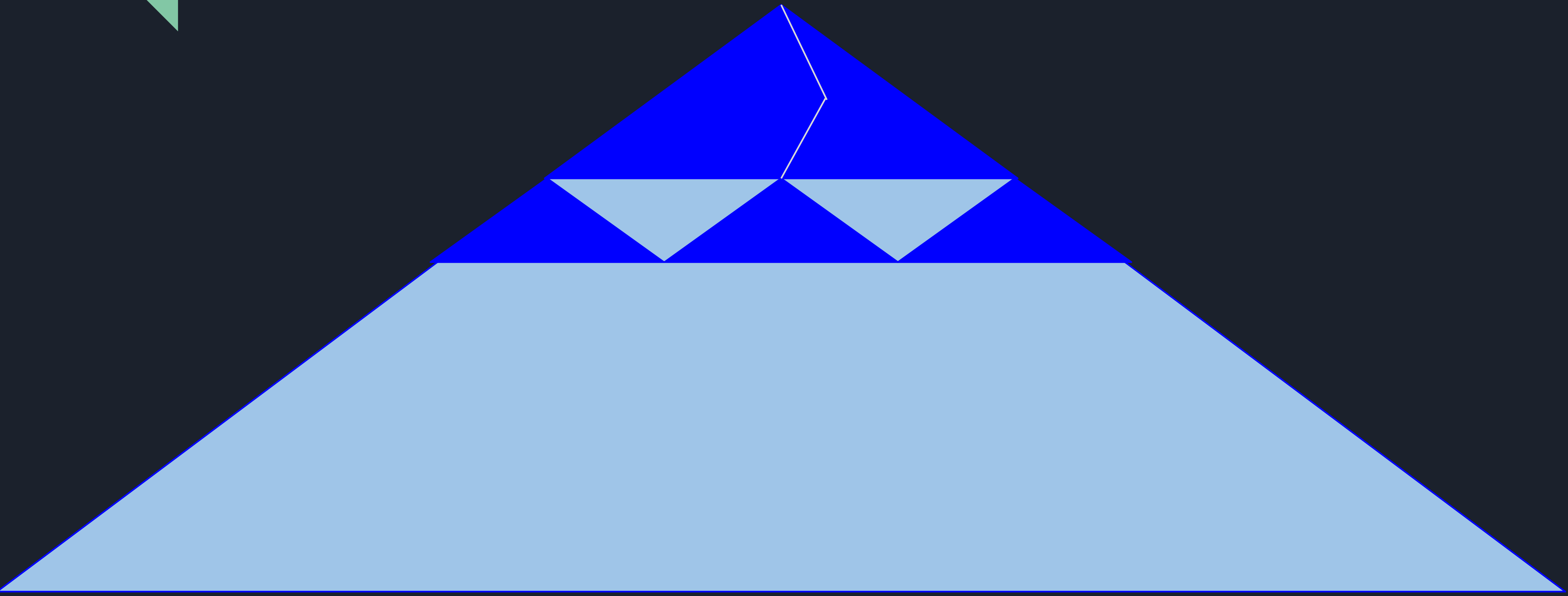
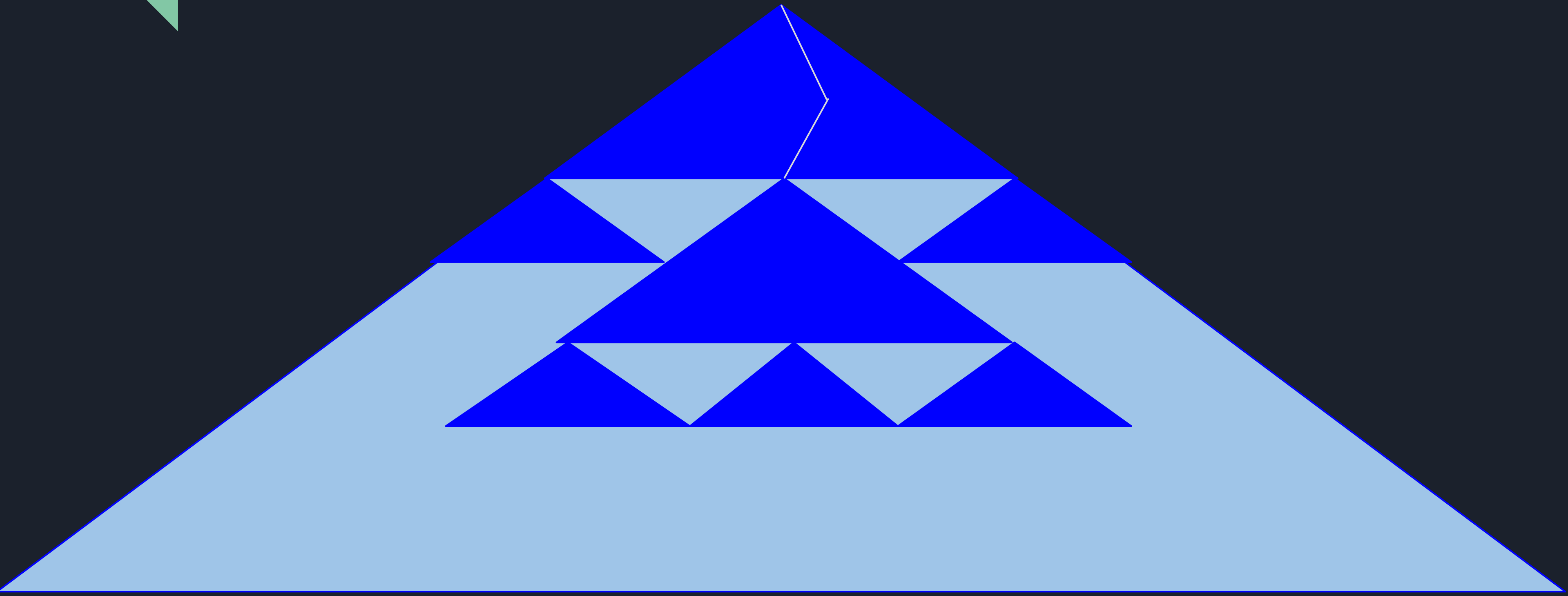


Libratus



Game abstraction

10^{161}

No-limit → **no restrictions on bets** → **number of possible actions is enormous**

It is costly and wasteful to construct a new betting strategy for a single-dollar difference in the bet.

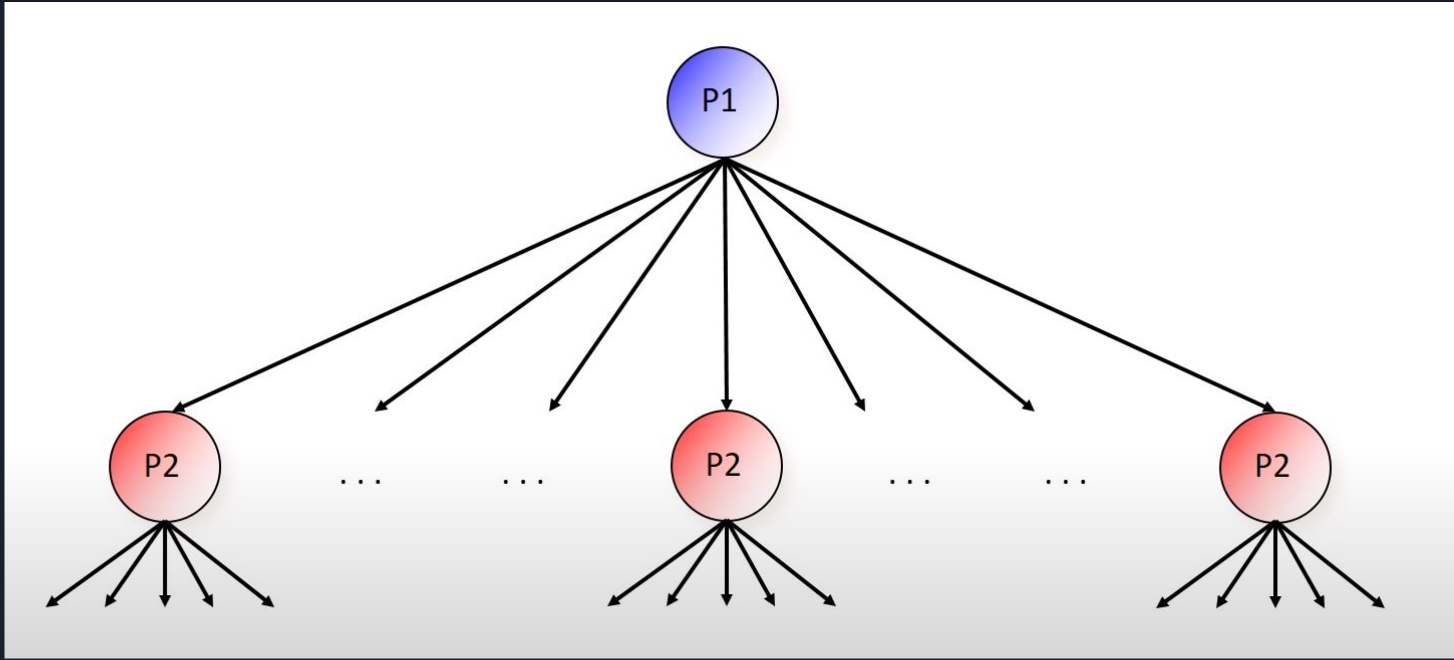
Libratus abstracts the game using a technique - **Blueprinting**

- by grouping similar bets (**action abstraction**) and card combinations (**card abstraction**)

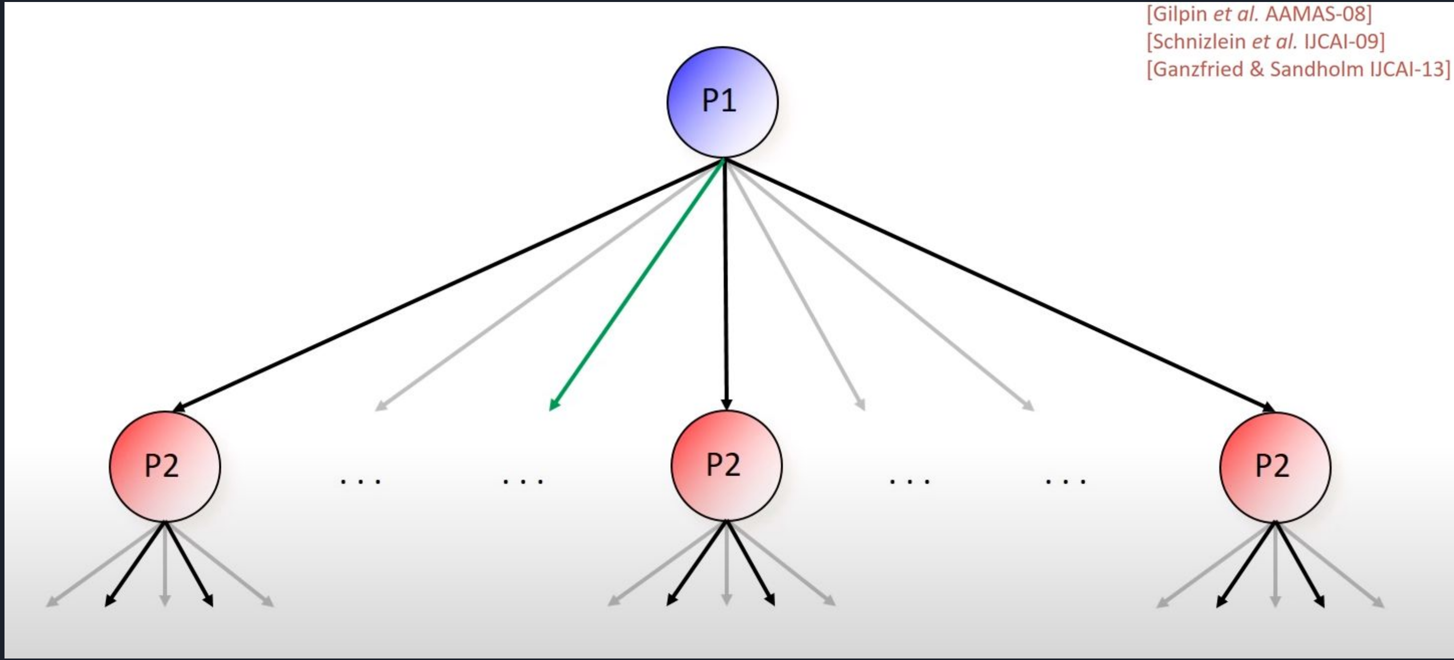
↓

This allows the AI to consider a **smaller number of possible actions**, making the decision-making process more **efficient**.

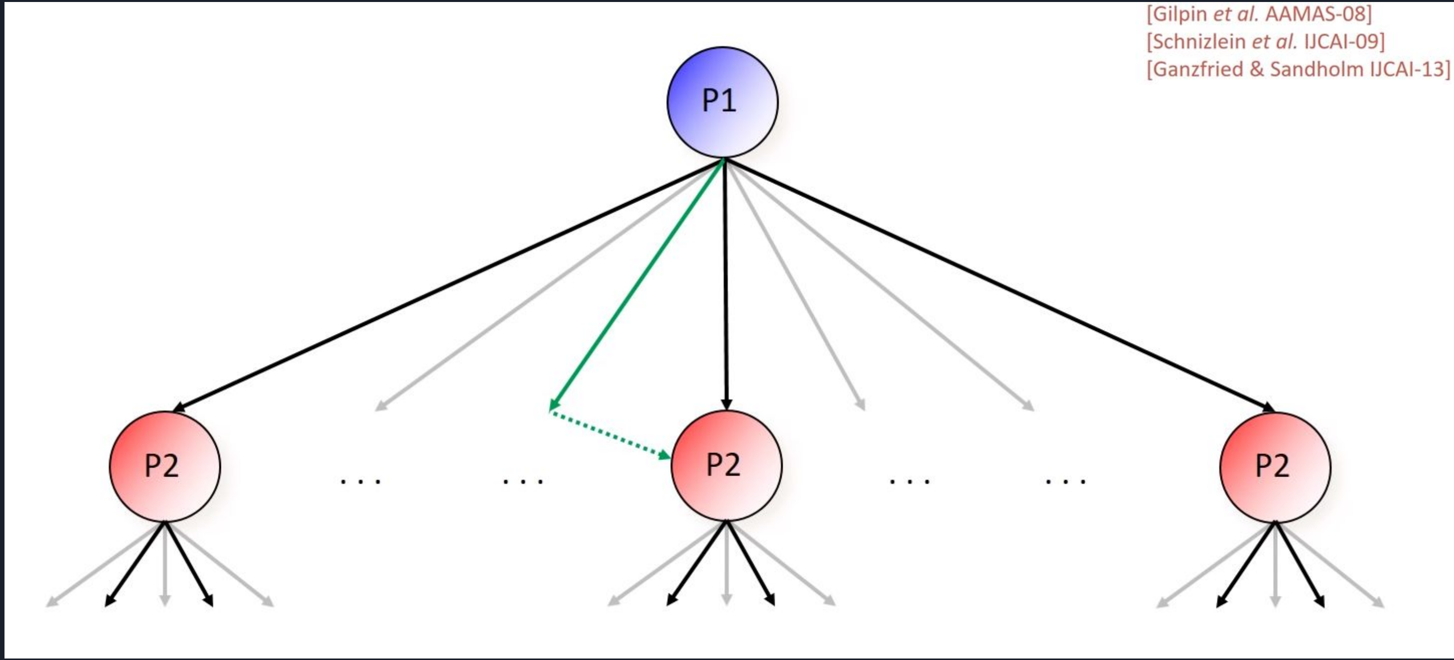
Action abstraction



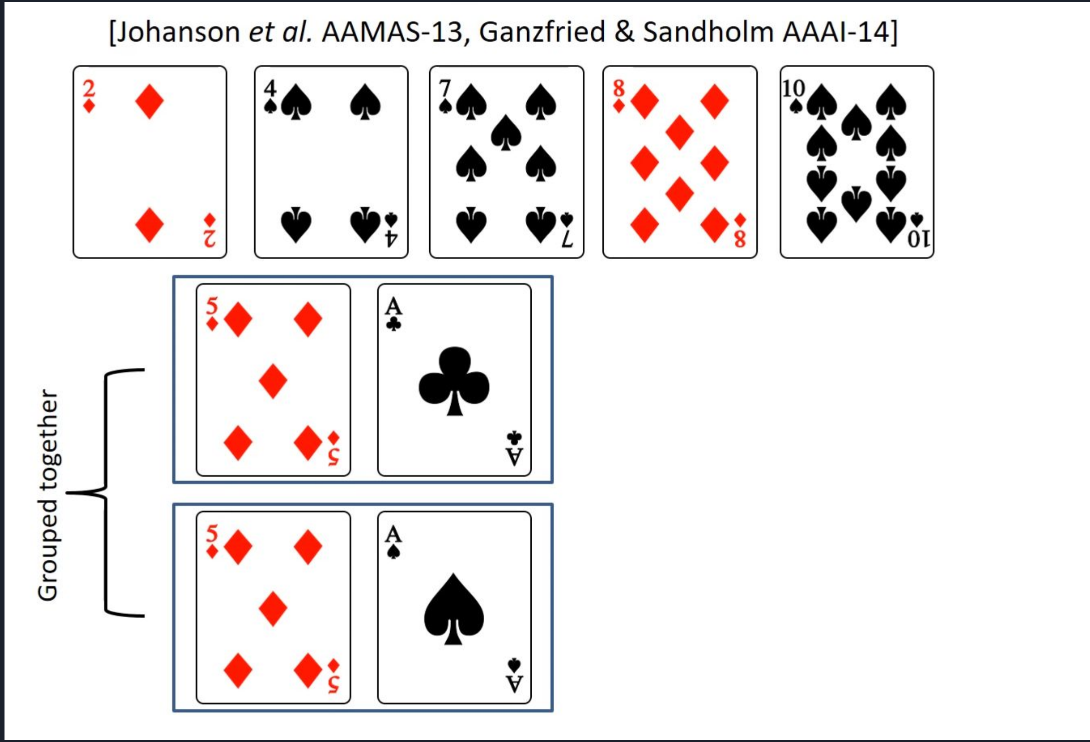
Action abstraction



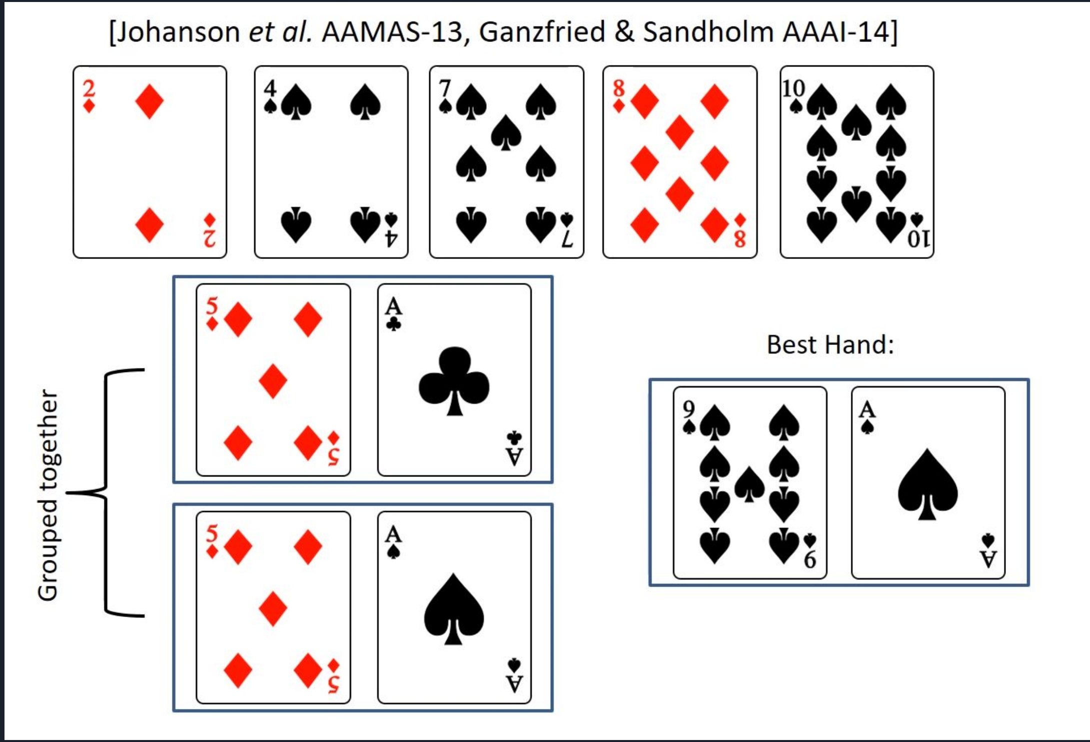
Action translation



Card abstraction



Card abstraction



Libratus abstraction

Libratus does not use any card abstraction on the **first (preflop)** and **second (flop)** betting rounds

The **last two betting rounds**, which are exponentially larger, are more coarsely abstracted.

Third round: **55 million** different hand possibilities are grouped into **2.5 million buckets**

Fourth round: **2.4 billion** different possibilities are grouped into **1.25 million buckets**

Counterfactual regret minimization

Regret

- To update the strategy profile for each player
- Keeps track of the **regrets** at **each decision point**
    - uses them to adjust the probability of each action in the strategy profile

Counterfactual regret - The **difference in expected utility** between

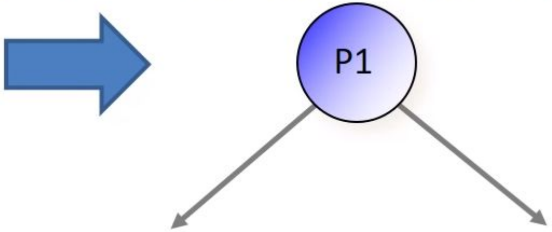
- the decision that was actually made
- the **best decision** that could have been made

given the information available at the time

Monte Carlo CFR

[Zinkevich *et al.* NIPS-07, Lanctot *et al.* NIPS-12]

Regrets = [0,0]



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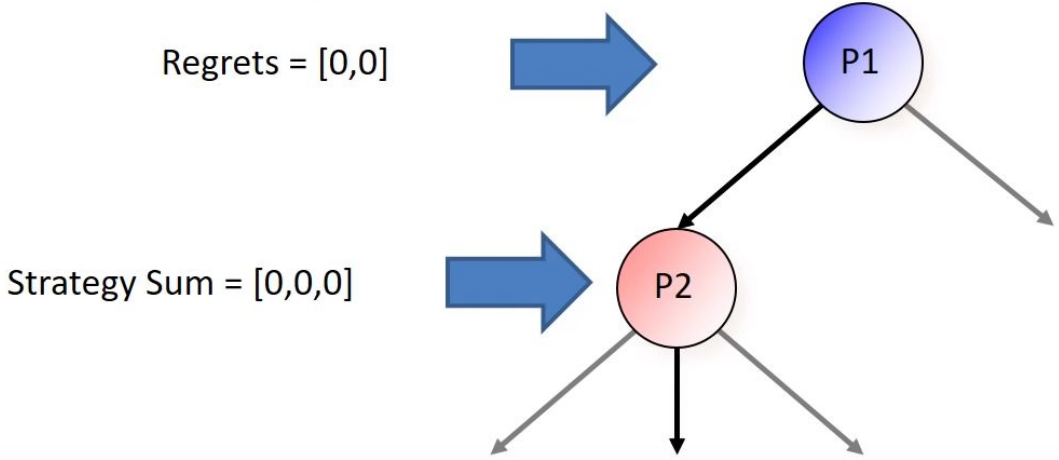

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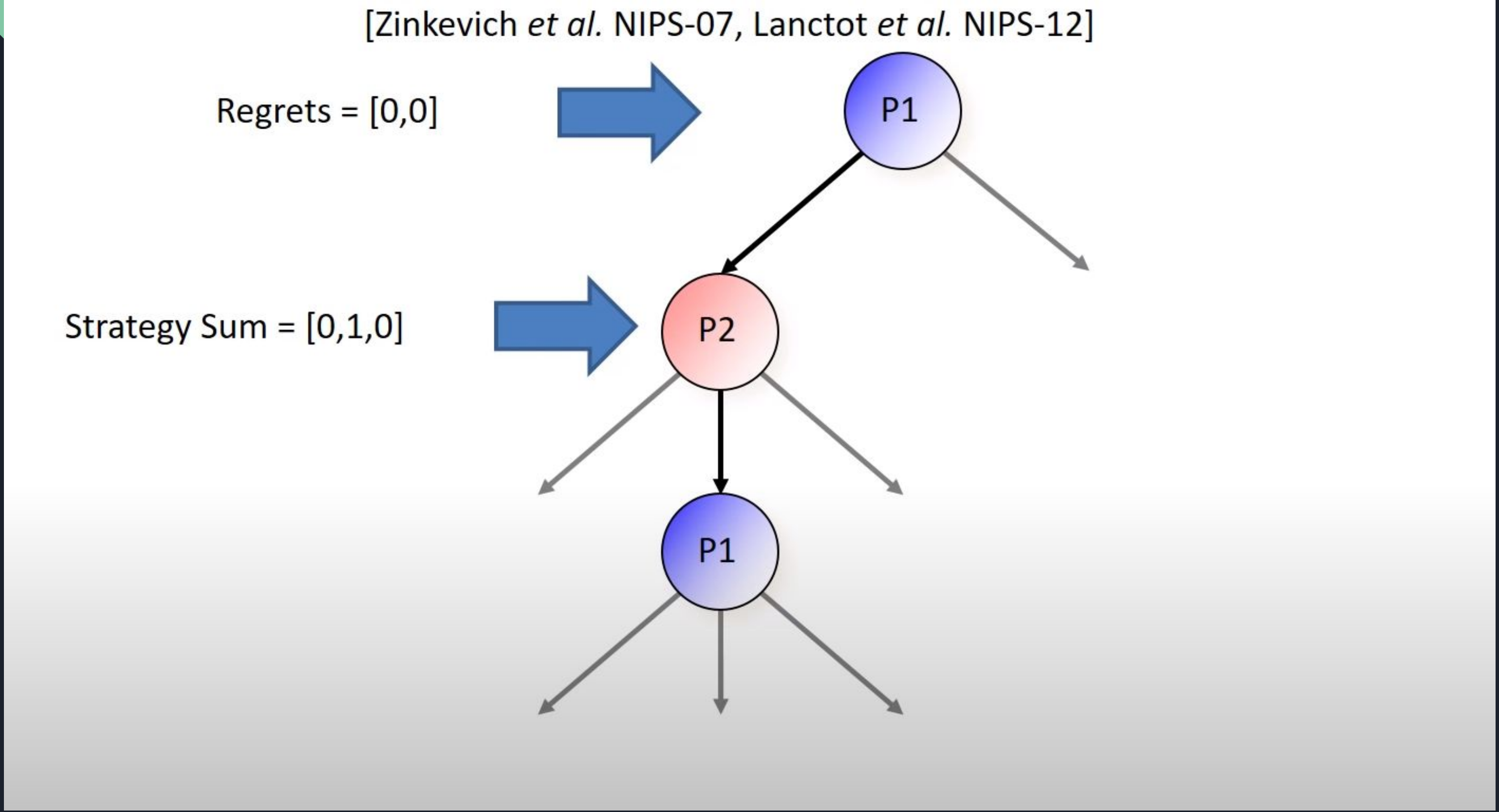

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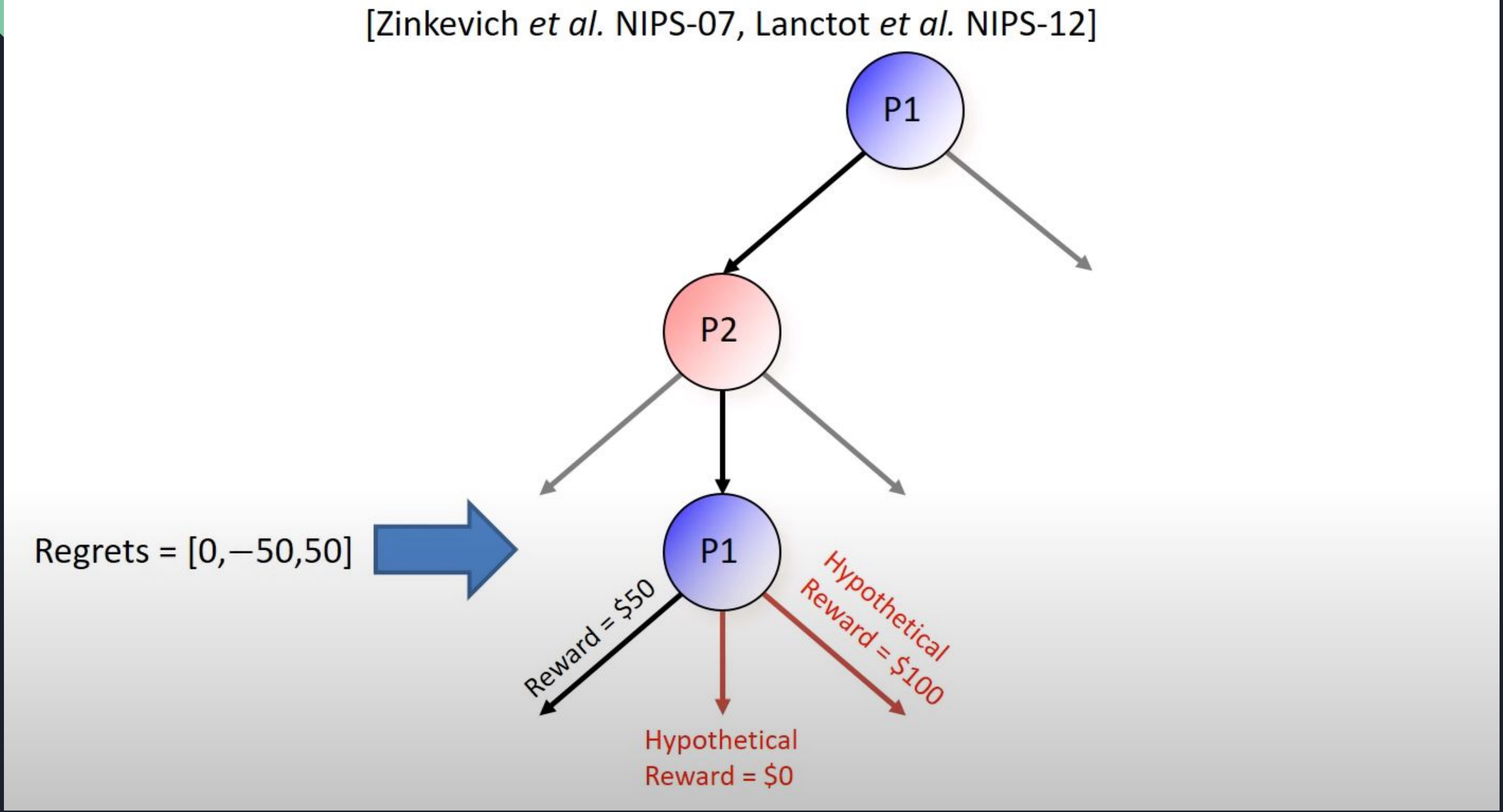

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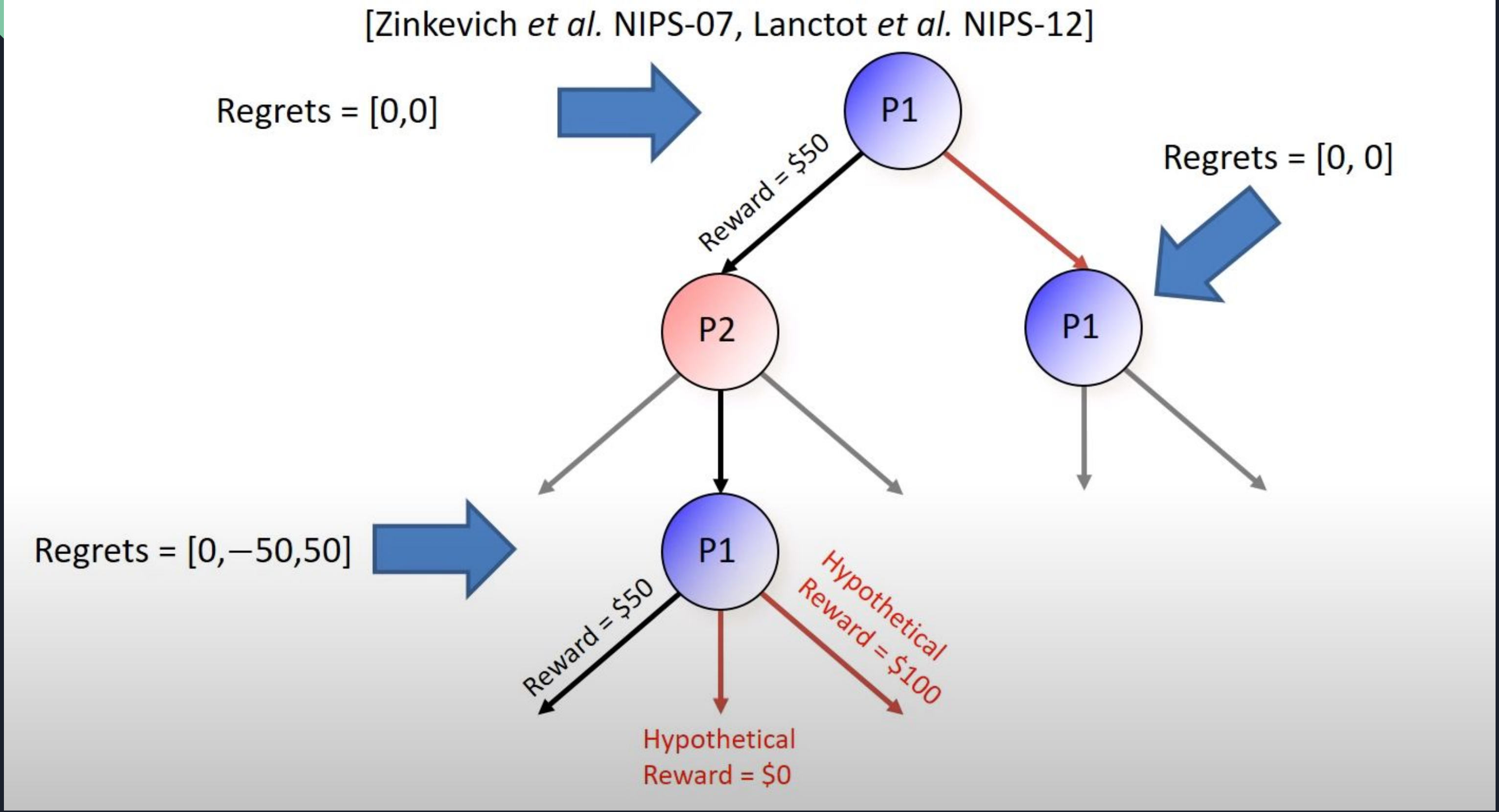
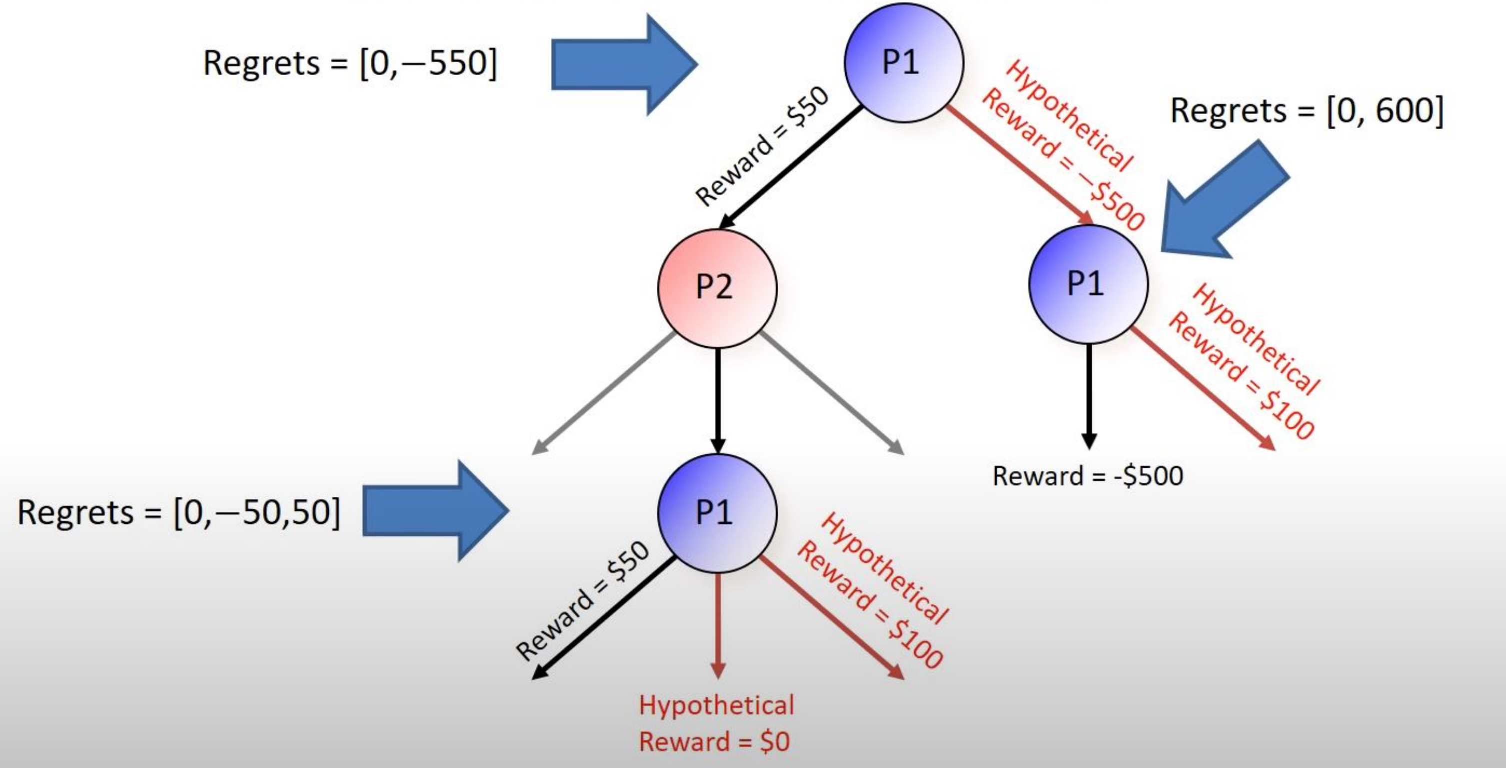


Monte Carlo CFR

[Zinkevich *et al.* NIPS-07, Lanctot *et al.* NIPS-12]



Unsafe Subgame solving

- An **estimate of the opponent's strategy** is made

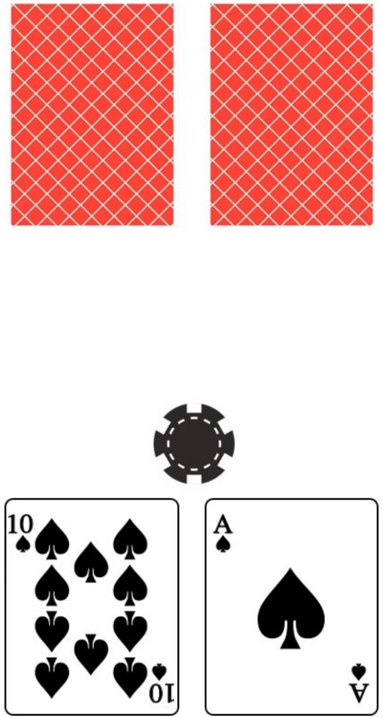
- This gives a **belief** distribution over states

- Update beliefs via **Bayes Rule -** mathematical formula for determining conditional probability. Conditional probability is the likelihood of an outcome occurring, based on a previous outcome having occurred in similar circumstances

May result in very high exploitability!

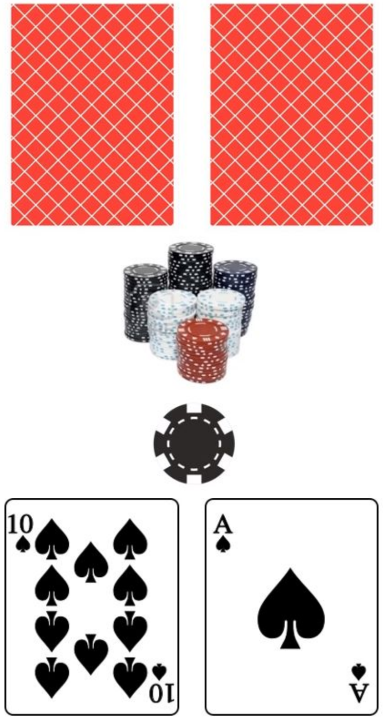
Unsafe Subgame solving

[Ganzfried & Sandholm AAMAS 2015]



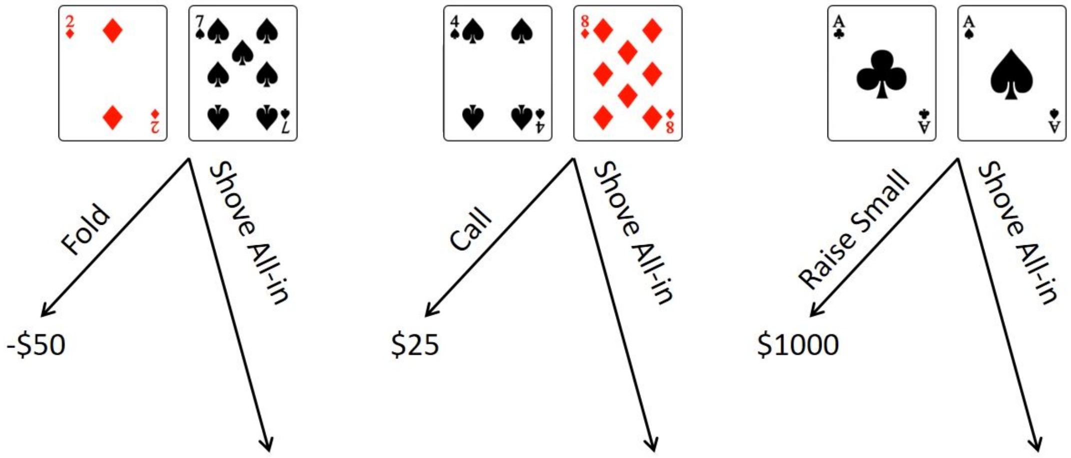
Unsafe Subgame solving

[Ganzfried & Sandholm AAMAS 2015]



Safe Subgame solving

[Burch et al AAAI-14, Moravcik et al AAAI-16, Brown & Sandholm NIPS-17]



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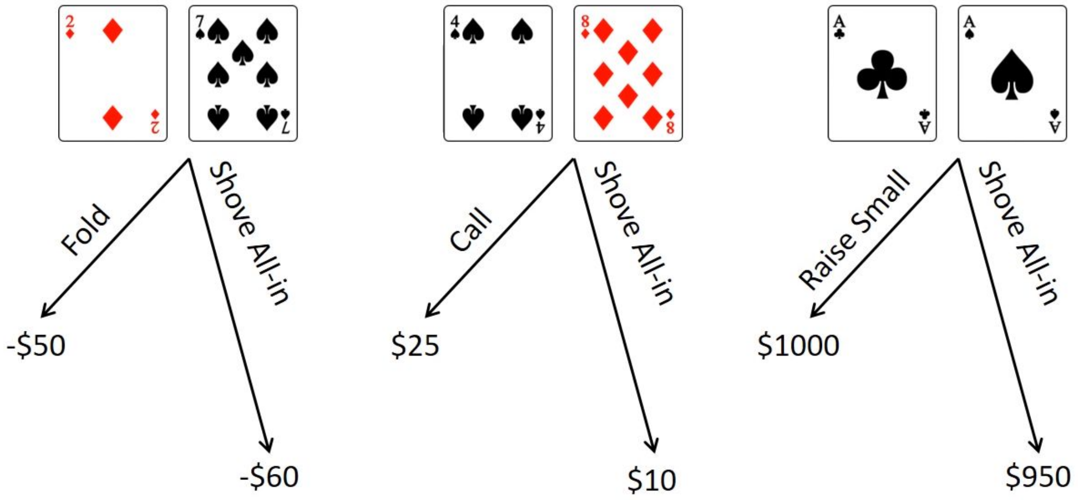

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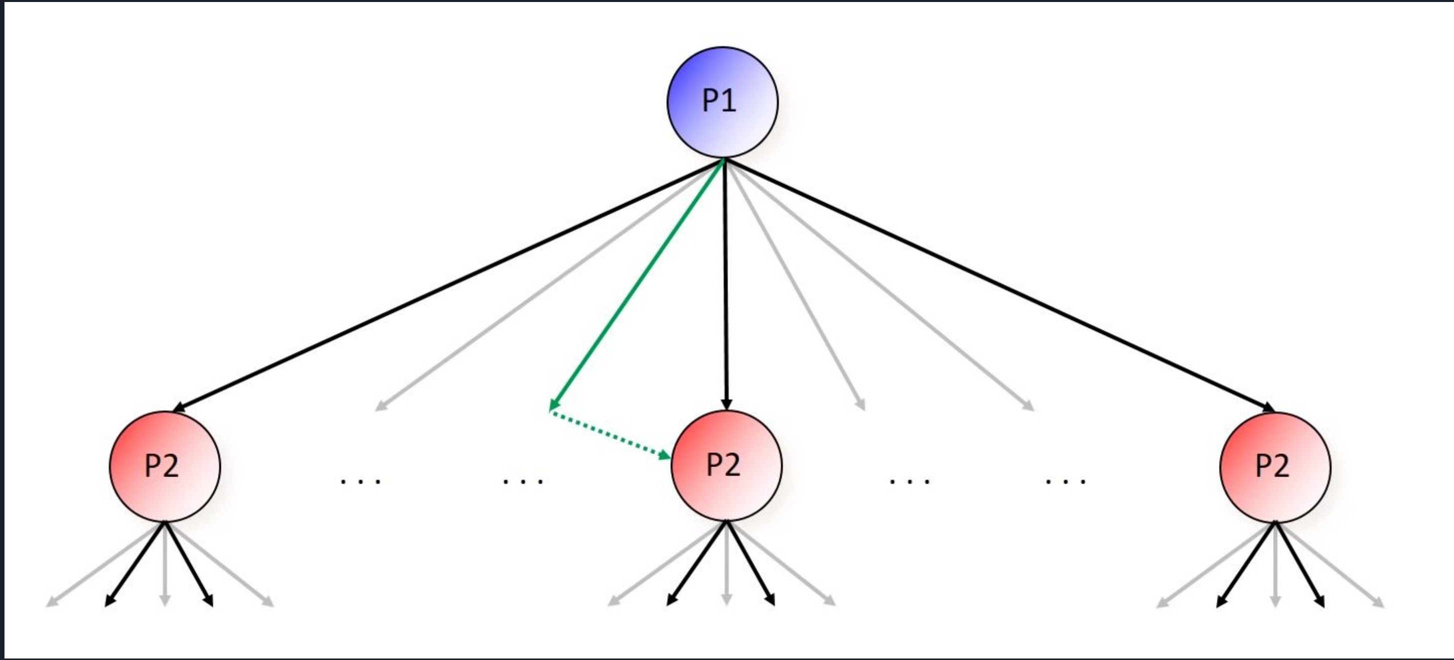
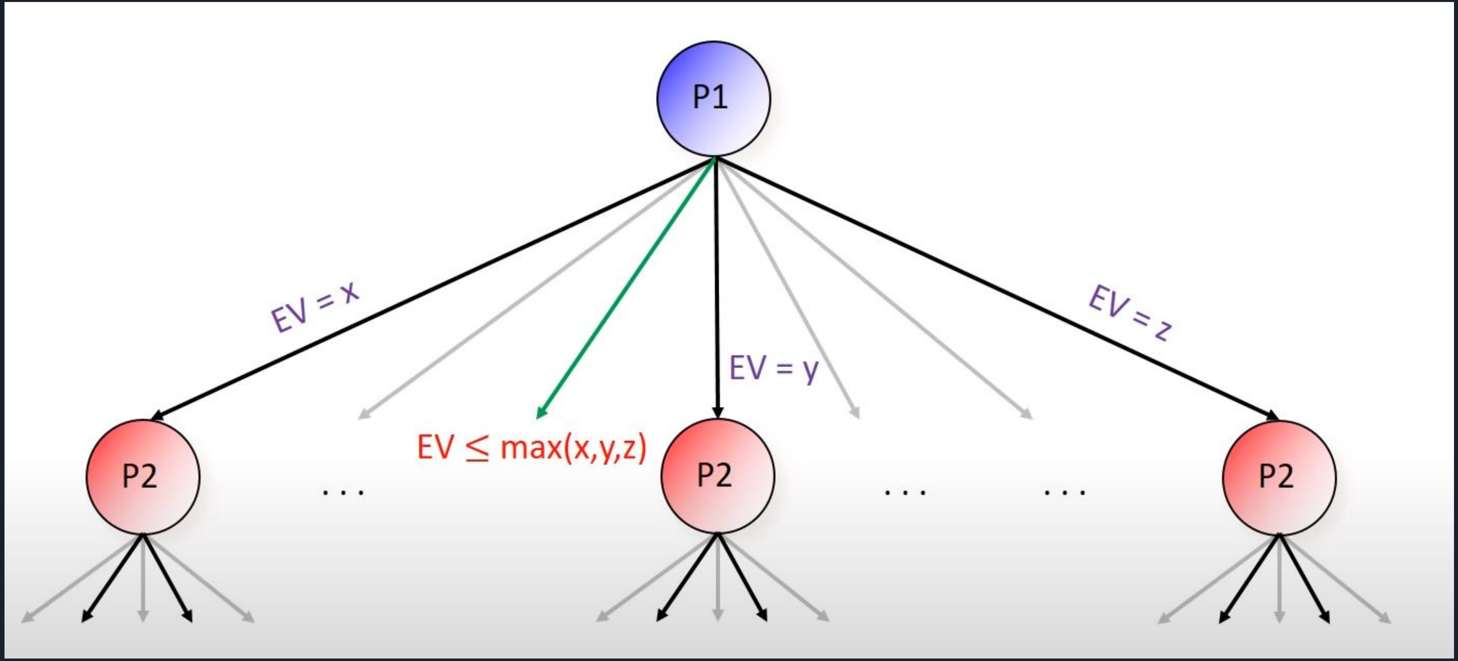
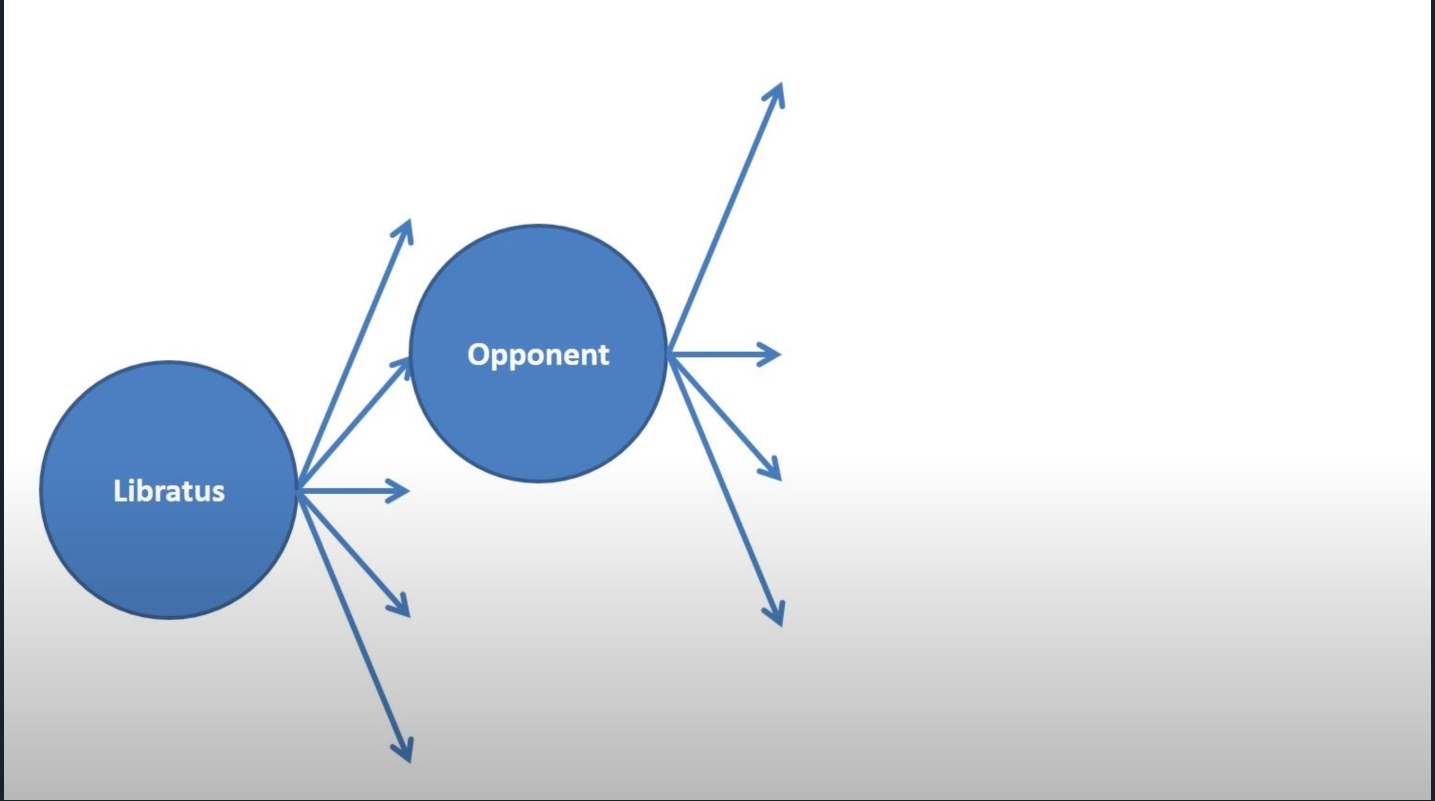


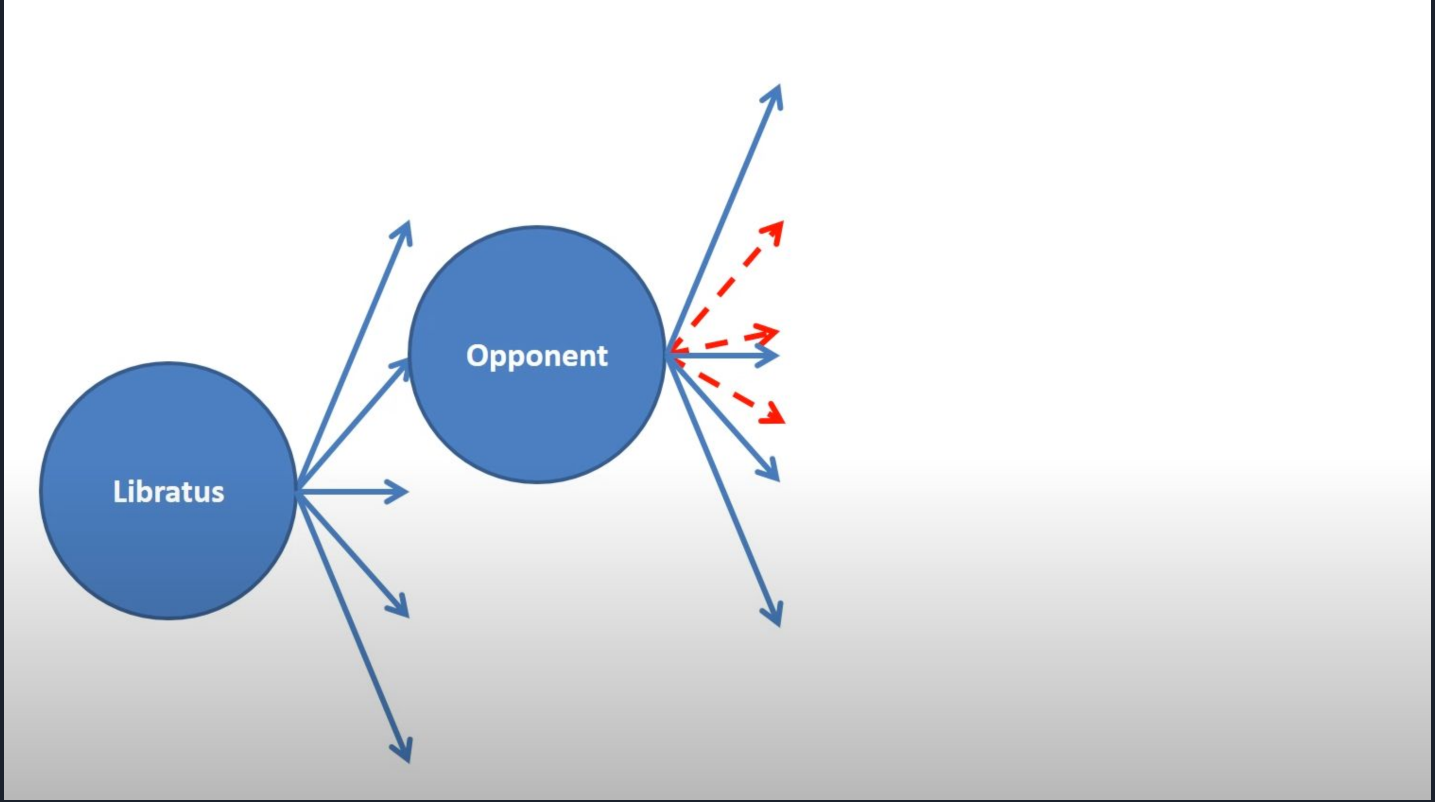
Subgame Solving – Off-tree actions



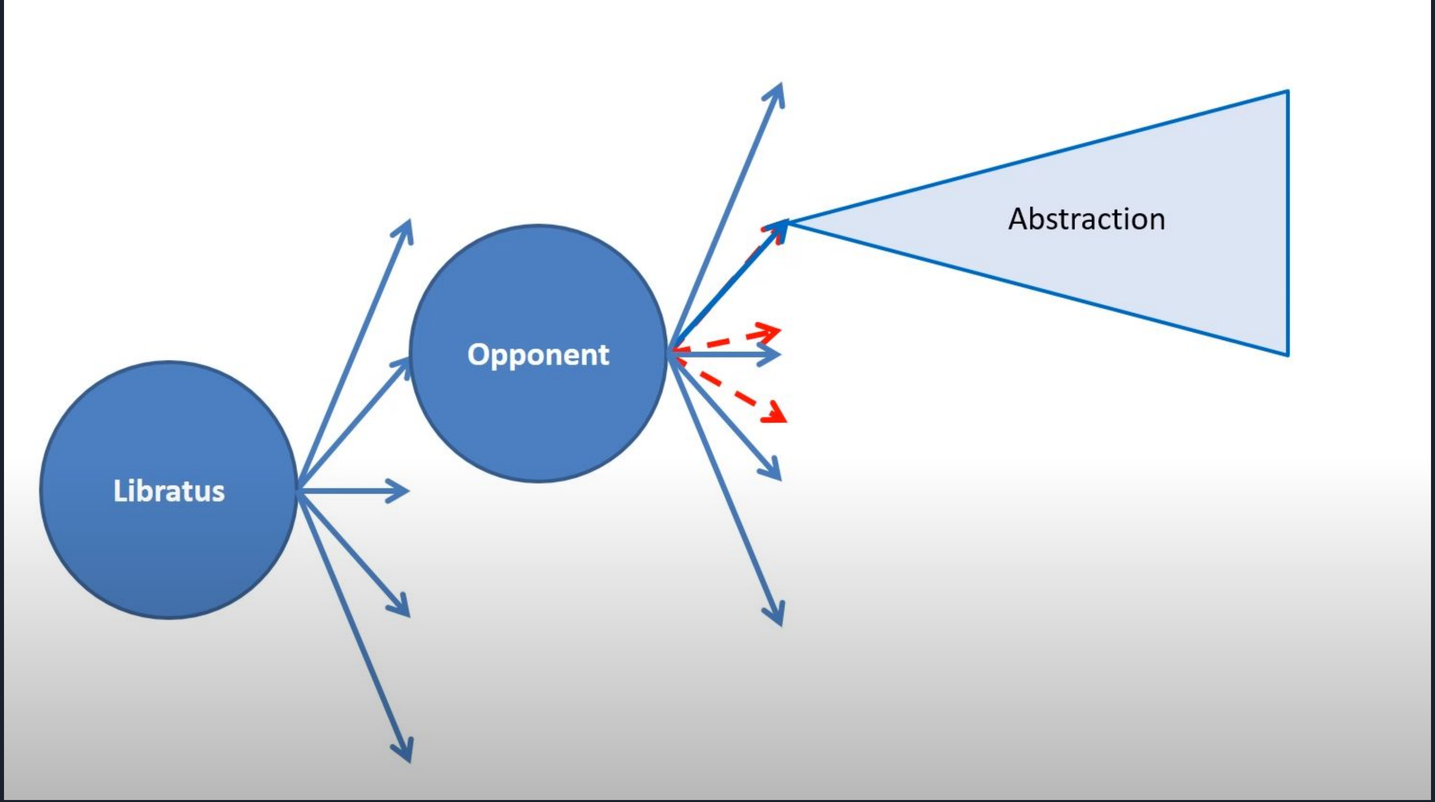
Self-Improvement



Self-Improvement



Self-Improvement



Pluribus

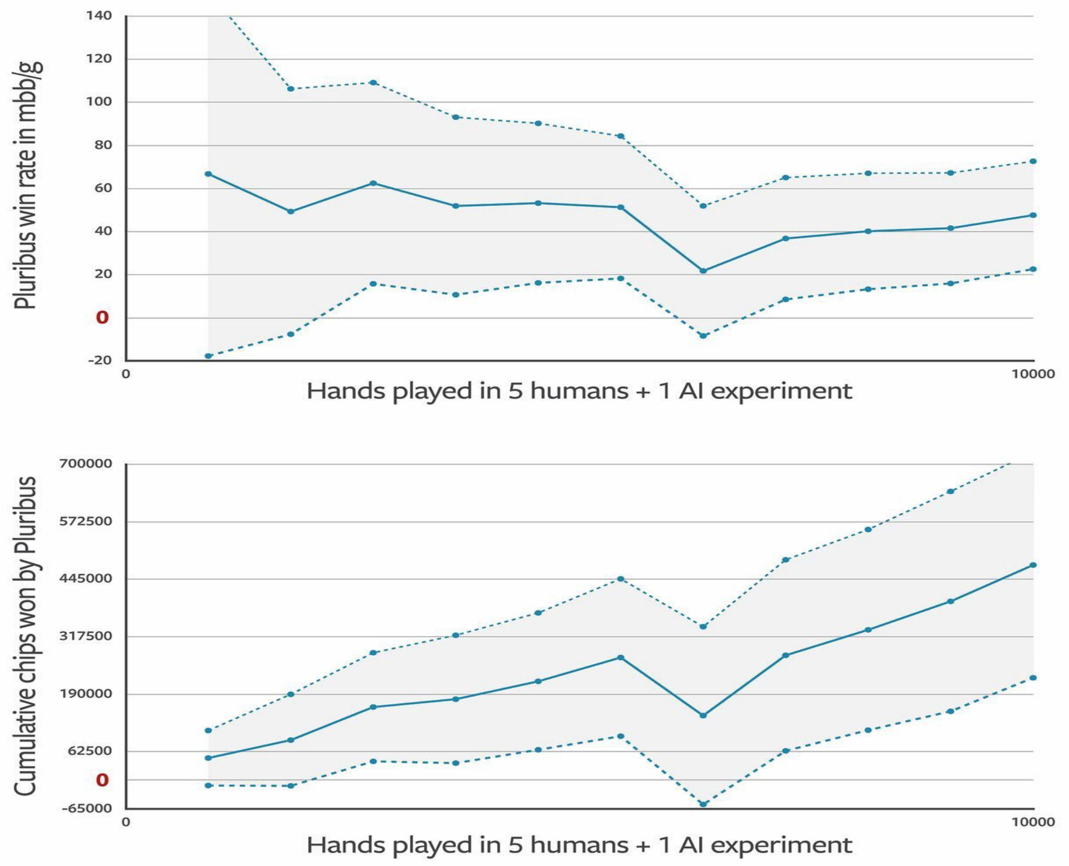
- Designed to play in a **multiplayer** environment (**3+ players**)
- Improvement from **Libratus**
- Team of AI researchers from Facebook in collaboration with Carnegie Mellon University

Was able to defeat **12** professional poker players (2019) in a **six-player** game, playing **10000 hands and winning on average $480** from its human competitors for **every 100 hands-on.**

Pluribus has to deal with a **higher level of uncertainty**, and has to take into account the different strategies and behaviors of multiple opponents at the same time.

Pluribus has the use of additional techniques like **fictitious play** and **abstract reasoning** which allows the AI to reason about the strategies of its opponents and the state of the actions **on the long run**. This allows the AI to make more accurate predictions about the actions of its opponents and make more strategic decisions.

Pluribus



[Brown and Sandholm 2019]

Observations

After talking to Poker professionals, they stated their main **strengths**:

- Many different bet sizes
- Huge overbets
- Near-perfect balance

The only **“weakness”** found was that there were no opponent exploitation

Both Pluribus and Libratus have the potential to be applied in other fields such as **finance, cybersecurity, and military strategy**.

Pluribus, due to its ability to play in a multi-player game, could have more potential applications in decision making in group dynamics.

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Thank you for your time!

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