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Super-Human AI for Strategic Reasoning

Tuomas Sandholm

Angel Jordan Professor of Computer Science, Carnegie Mellon University

Founder and Director, Electronic Marketplaces Laboratory

Co-Director, CMU AI

Founder, President, and CEO, Strategic Machine, Inc.

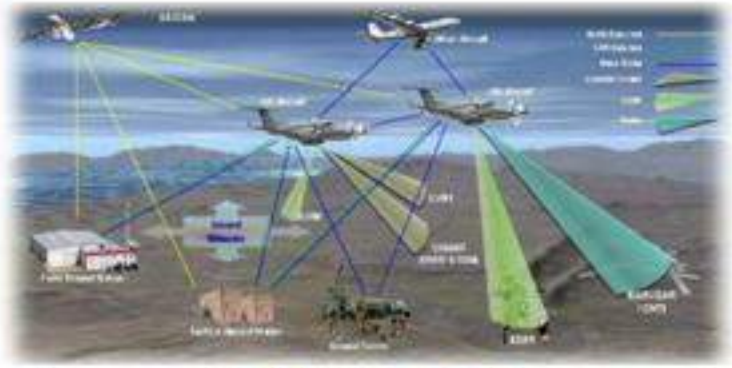
Founder, President, and CEO, Strategy Robot, Inc.

Founder, President, and CEO, Optimized Markets, Inc.

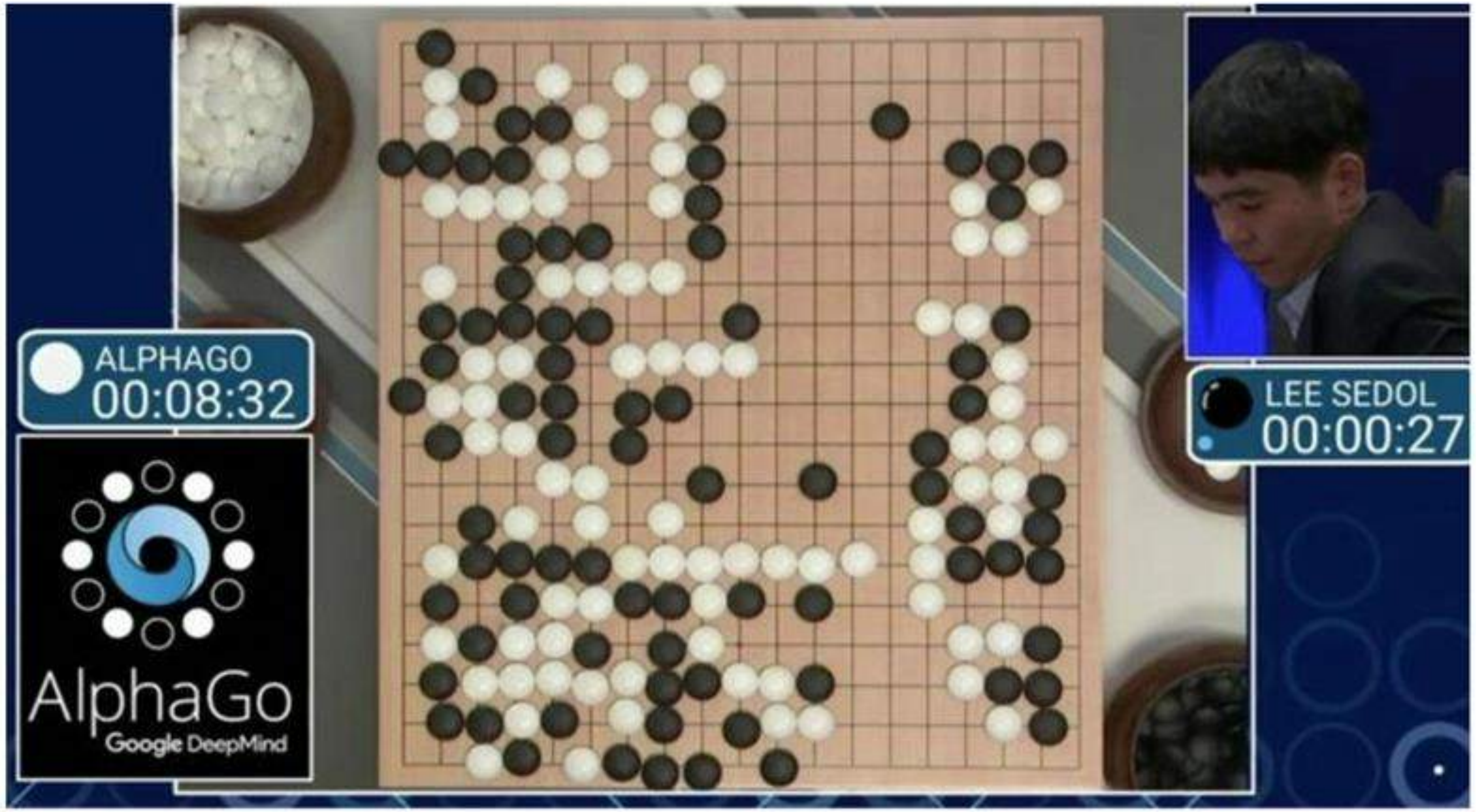
Paper in *Science* (Dec. 2017), joint work with my PhD student **Noam Brown**

Imperfect-information games




AlphaGo & AlphaZero



Those techniques extend to other **perfect-information** games

Perfect-information games

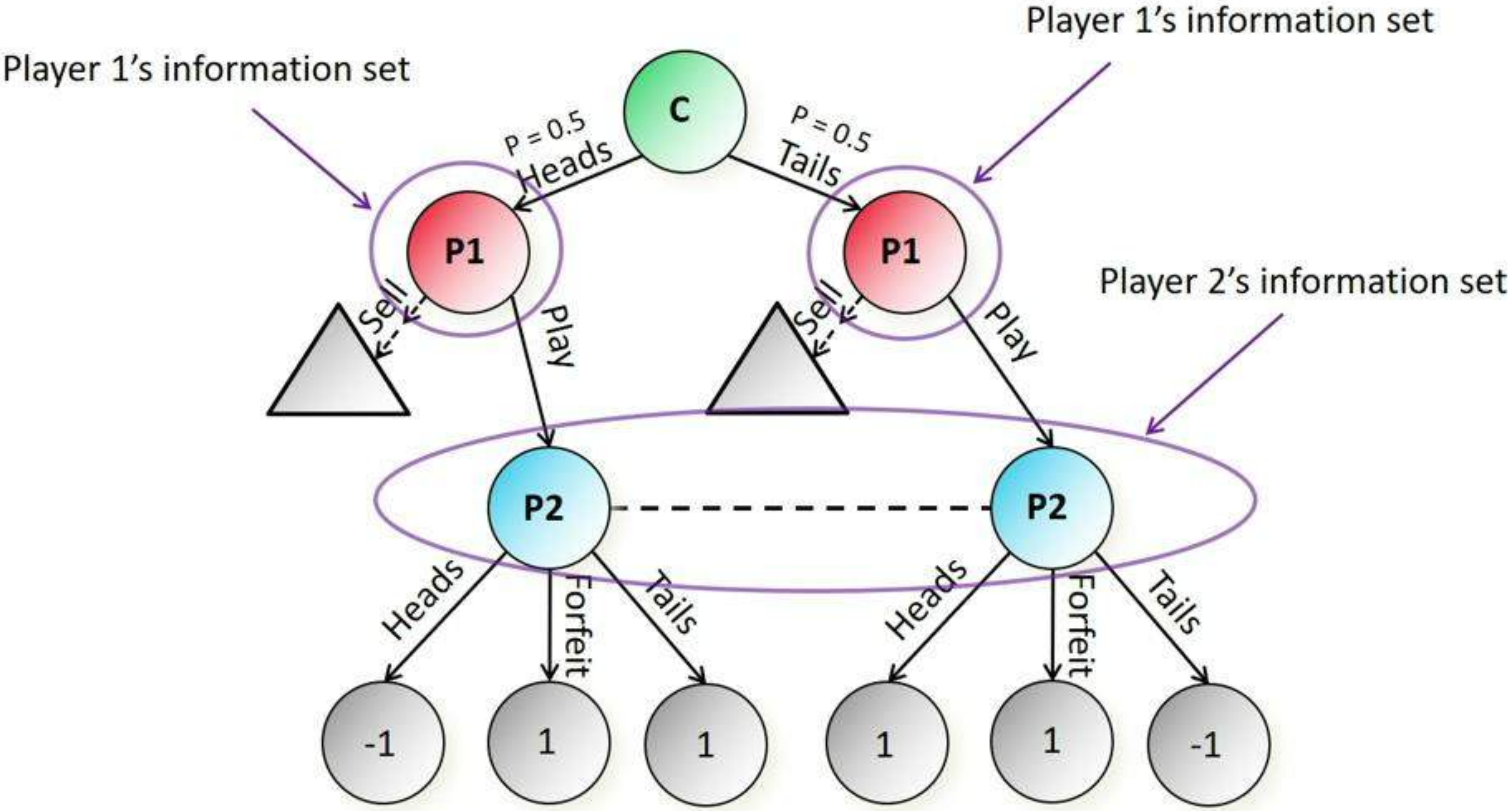
Sicilian Defense

Queen's Gambit

- Subgames can be solved with information from the subgame only
- This is **not true** in imperfect-information games

Imperfect-information games

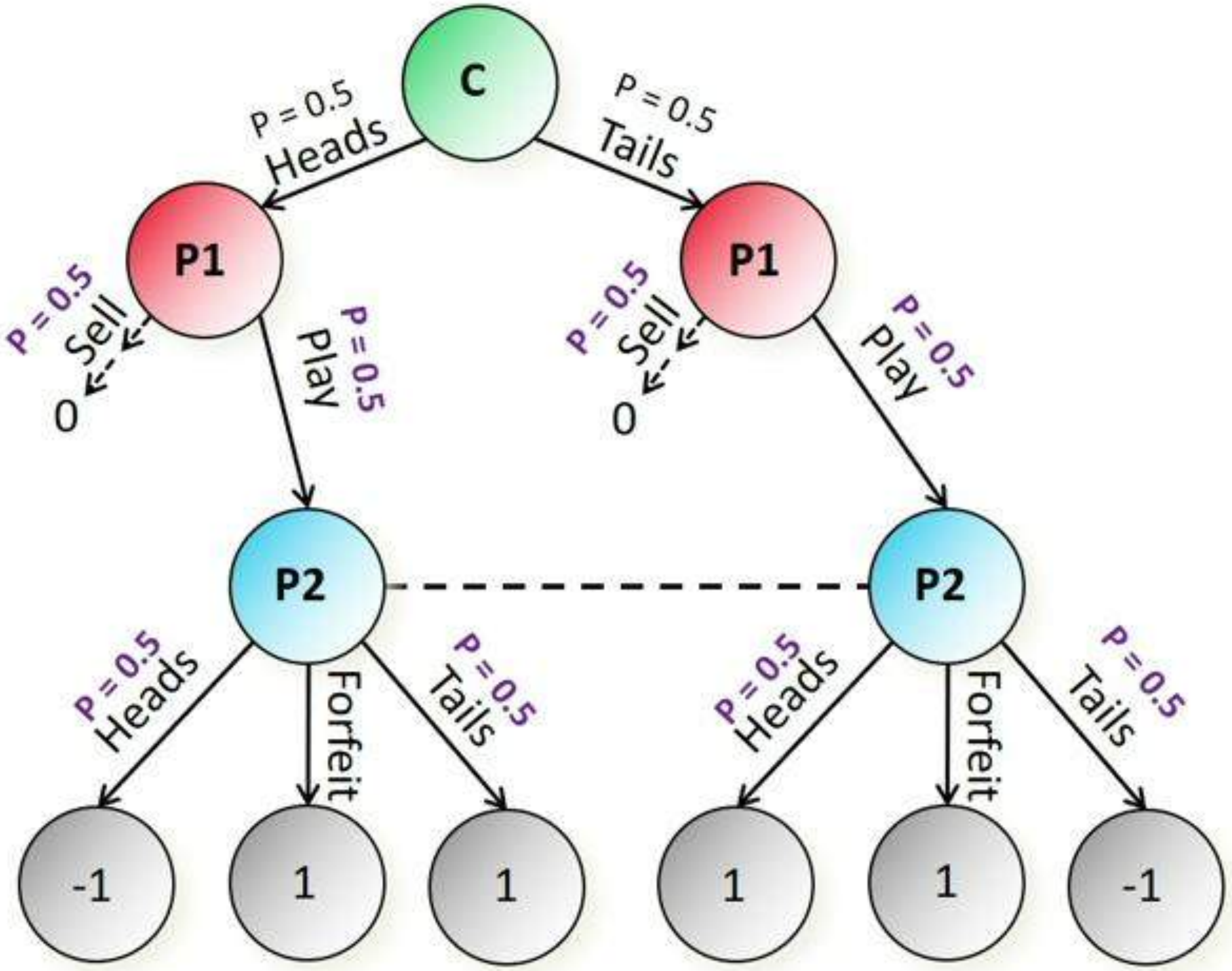
Example game: "Coin toss"

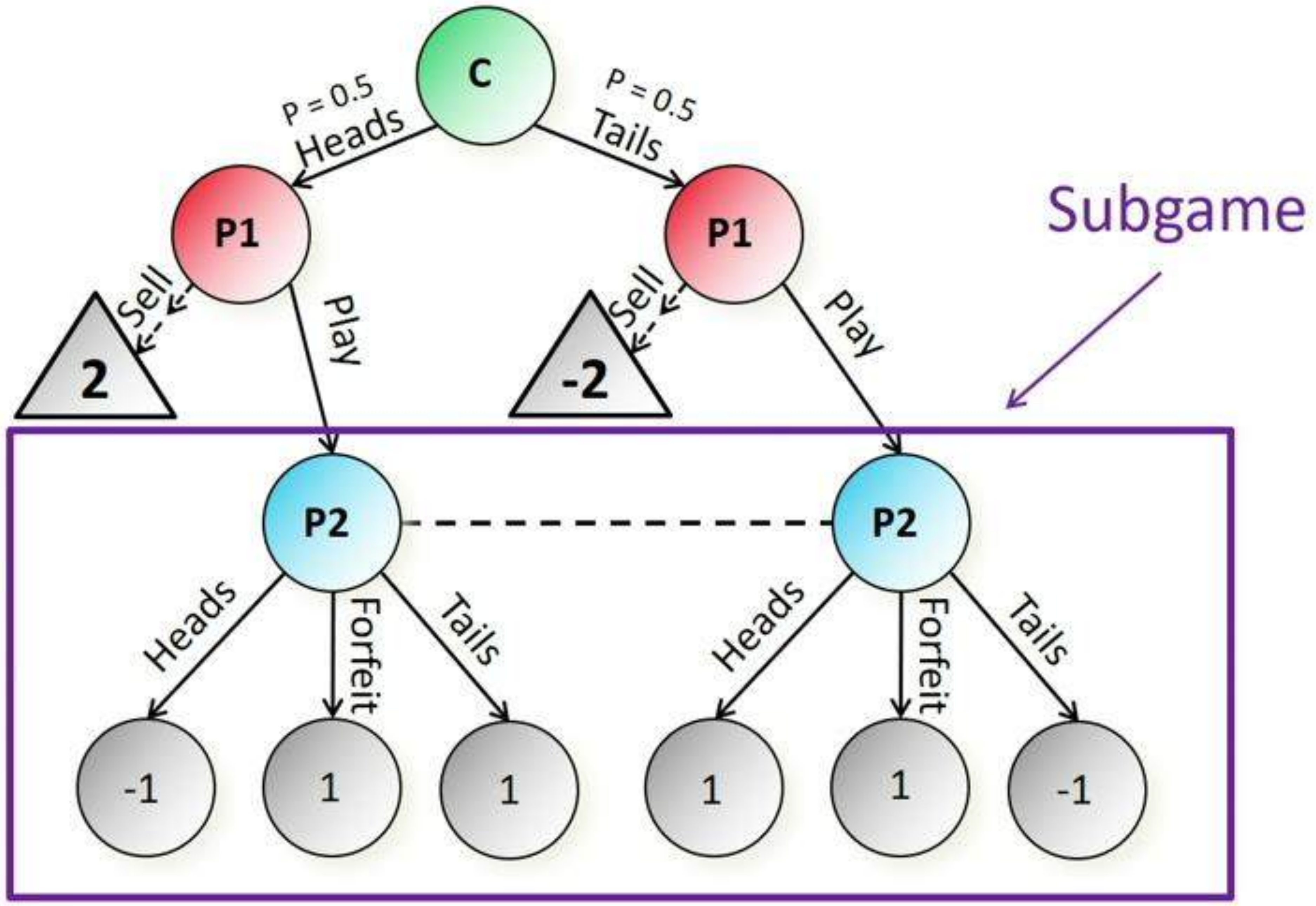


What is rational play?

Nash Equilibrium: a profile of strategies in which no player can improve by deviating (beliefs derived from strategies using Bayes rule). **Robust**

ϵ-Nash Equilibrium: No player can improve by more than ϵ




C
P = 0.5
Heads
P = 0.5
Tails
P1
P1
Sell
Play
Sell
Play
2
-2
Subgame
P2
P2
Heads
Forfeit
Tails
Heads
Forfeit
Tails
-1
1
1
1
1
-1

Tackling imperfect-info games

- Techniques for perfect-info games don't apply
- Application-independent techniques that algorithmically create the strategy
- Challenges
  – Uncertainty about what others and chance will do
  – Hidden state => need to interpret signals
  => use game theory

Poker

- Recognized challenge problem in game theory, OR, and AI
  - [Nash 1950]
  - [Kuhn 1950]
  - [Newman 1959]
  - [Waterman 1970]
  - [Zadeh 1977]
  - [Caro 1984]
  - [Pfeffer & Koller 1995]
  - [Billings *et al.* 1998]
  - [Schaeffer *et al.* 1999]
  - [Shi & Littman 2001]
  - [Billings *et al.* 2003]
- Tremendous progress in the last 14 years
  - Rhode Island Hold'em solved (10^9 nodes) [Gilpin & Sandholm 2005]
  - Annual Computer Poker Competition started in 2006
  - Limit Texas Hold'em near-optimally solved (10^{13} decisions) [Bowling *et al.* 2015]

Heads-up no-limit Texas hold'em

- Has become the main ***benchmark and challenge problem*** in AI for imperfect-information games
- 10^{161} situations
- Mostly played on the Internet
  - Also in World Series of Poker, NBC Heads-Up Championship, etc.
  - Featured in *Casino Royale* and *Rounders*
- "Purest form of poker"
- No prior AI has beaten top humans

Texas hold'em

- Chance deals 2 cards to each player
- Round of betting
- Chance deals 3 shared cards
- Round of betting
- Chance deals 1 shared card
- Round of betting
- Chance deals 1 shared card
- Round of betting

Brains vs AI Rematch

- *Libratus* (= our AI) against four of the ***best*** heads-up no-limit Texas Hold'em specialist pros



- 120,000 hands over 20 days in January 2017
- $200,000 divided among the pros based on performance
- Conservative experiment design


POKER NIGHT
WE'LL BE
BACK SHORTLY

Final result [Brown & S. *Science*]

Libratus beat the top humans in this game by a lot

- Statistical significance 99.98%, i.e., 0.0002
- 147 mbb/hand
- Each human lost to Libratus
- "Science breakthrough of the year 2017", 2017 Supercomputing Award, …

Lengpudashi vs humans event

- 36,000 hands against 6 Chinese poker players
  - WSOP bracelet winner
  - Expertise in computer science & ML
  - Studied Libratus's hand histories in advance

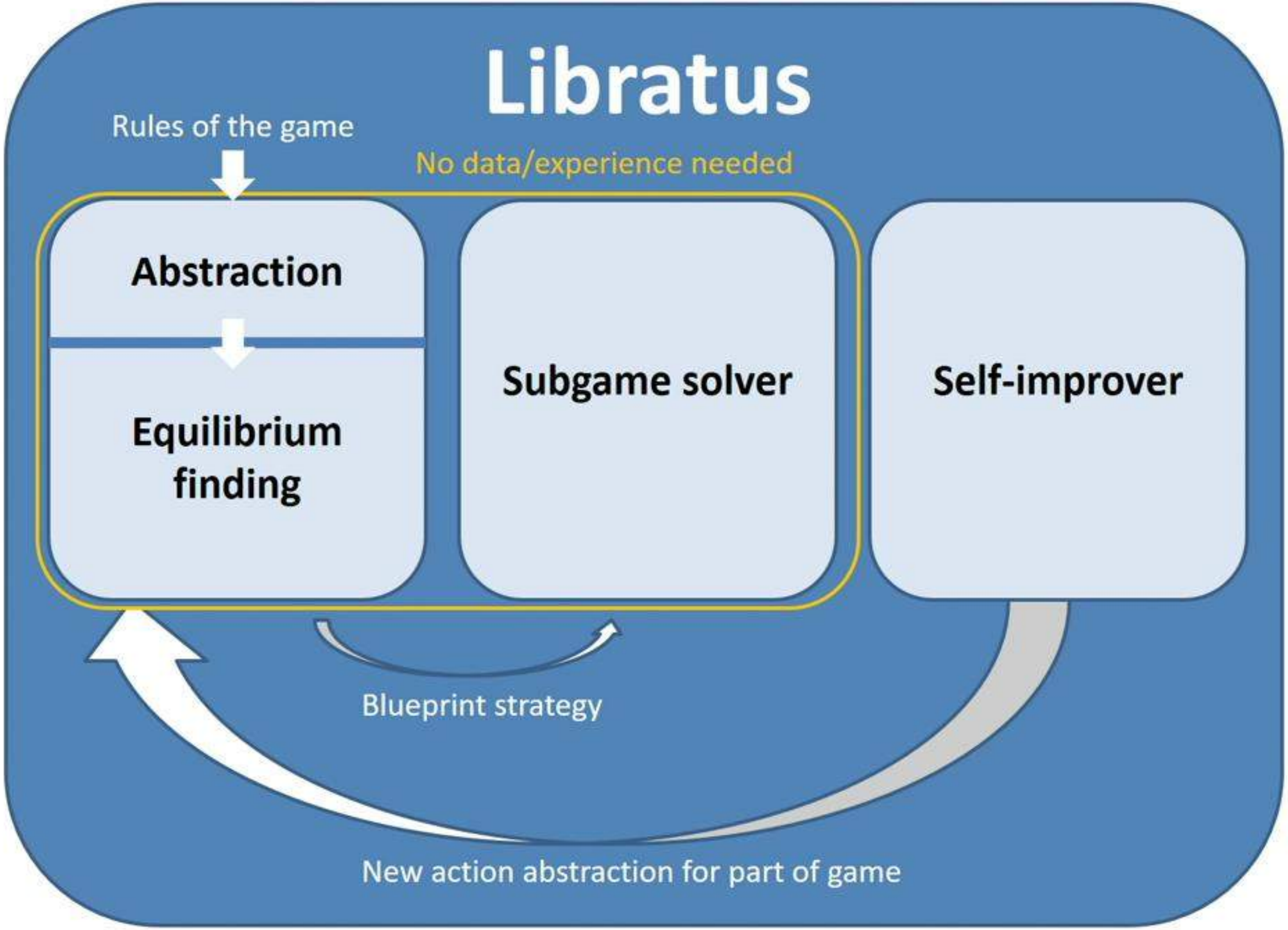
Lengpudashi vs humans event

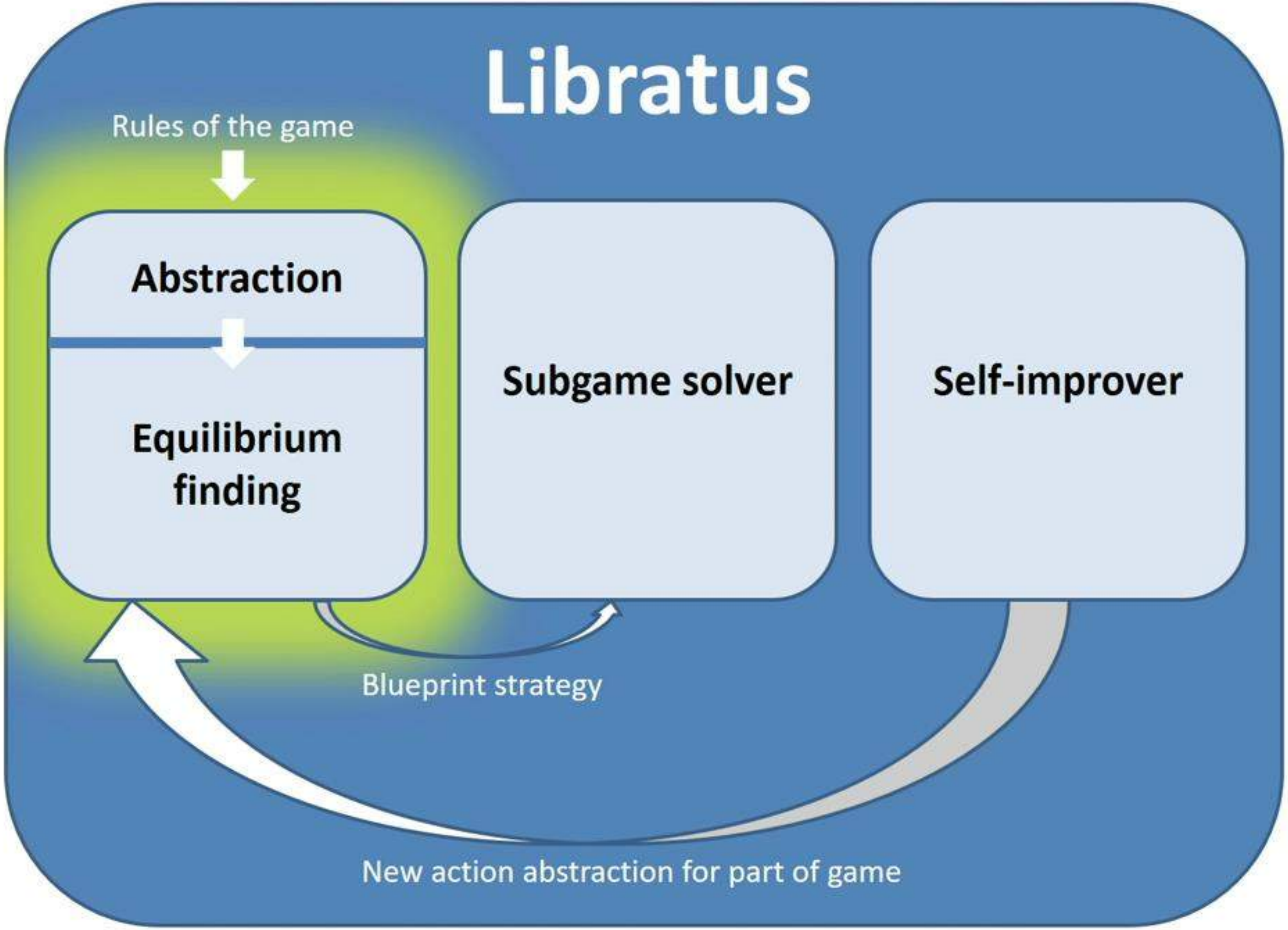
- 36,000 hands against 6 Chinese poker players
  - WSOP bracelet winner
  - Expertise in computer science & ML
  - Studied Libratus's hand histories in advance
- Lengudashi won by 220 mbb/hand
  - Won each of the 9 sessions
  - Also beat each human individually
- Demonstrated that this approach is not frail
  - Unlike what has been found with ML approaches (e.g., for Go and DOTA2)

How does *Libratus* work?

Provably correct techniques


Bridges supercomputer


Libratus
Rules of the game
No data/experience needed
Abstraction
Equilibrium finding
Subgame solver
Self-improver
Blueprint strategy
New action abstraction for part of game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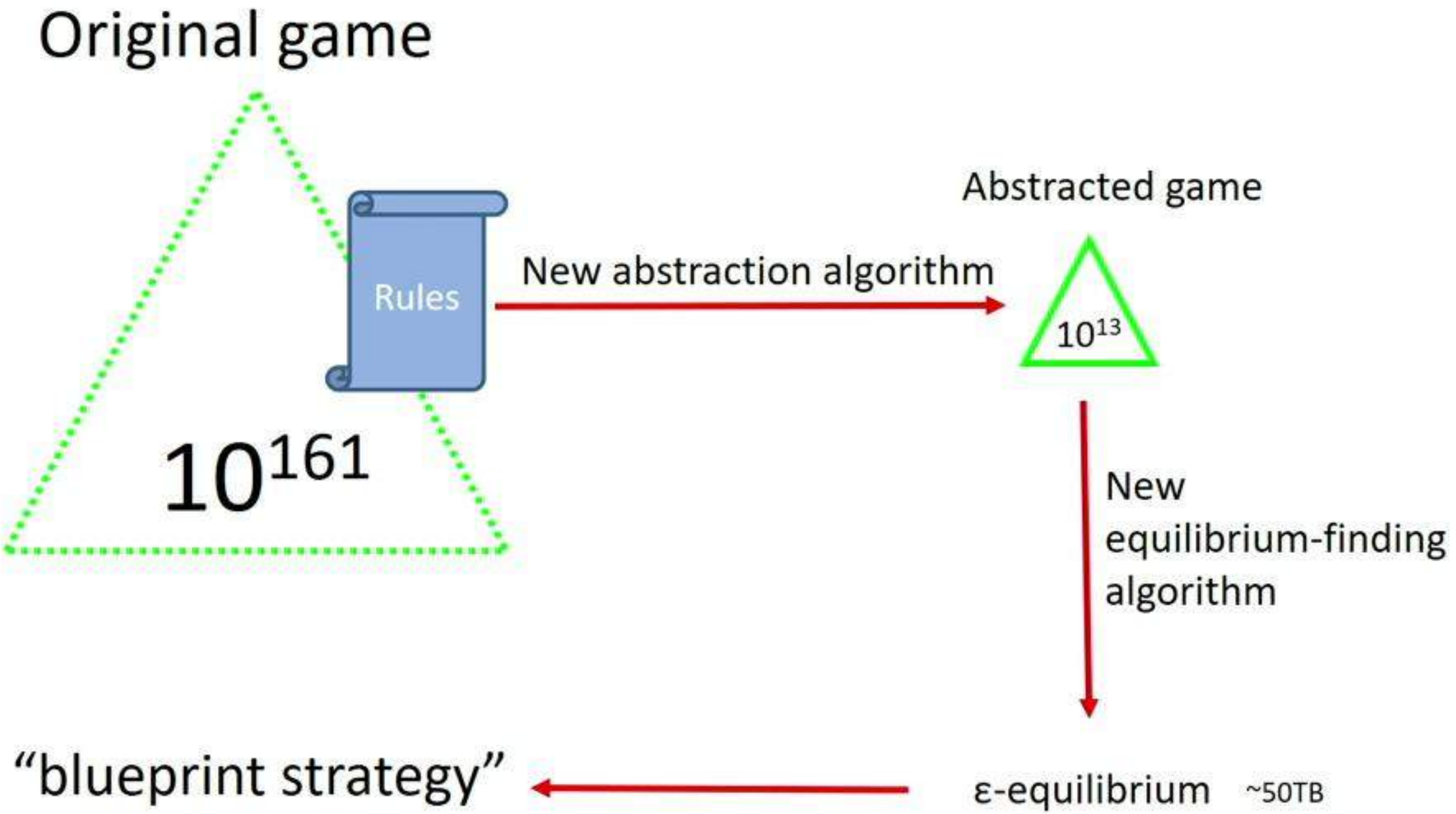
Abstraction [Gilpin & Sandholm EC-06, *J. of the ACM* 2007…]



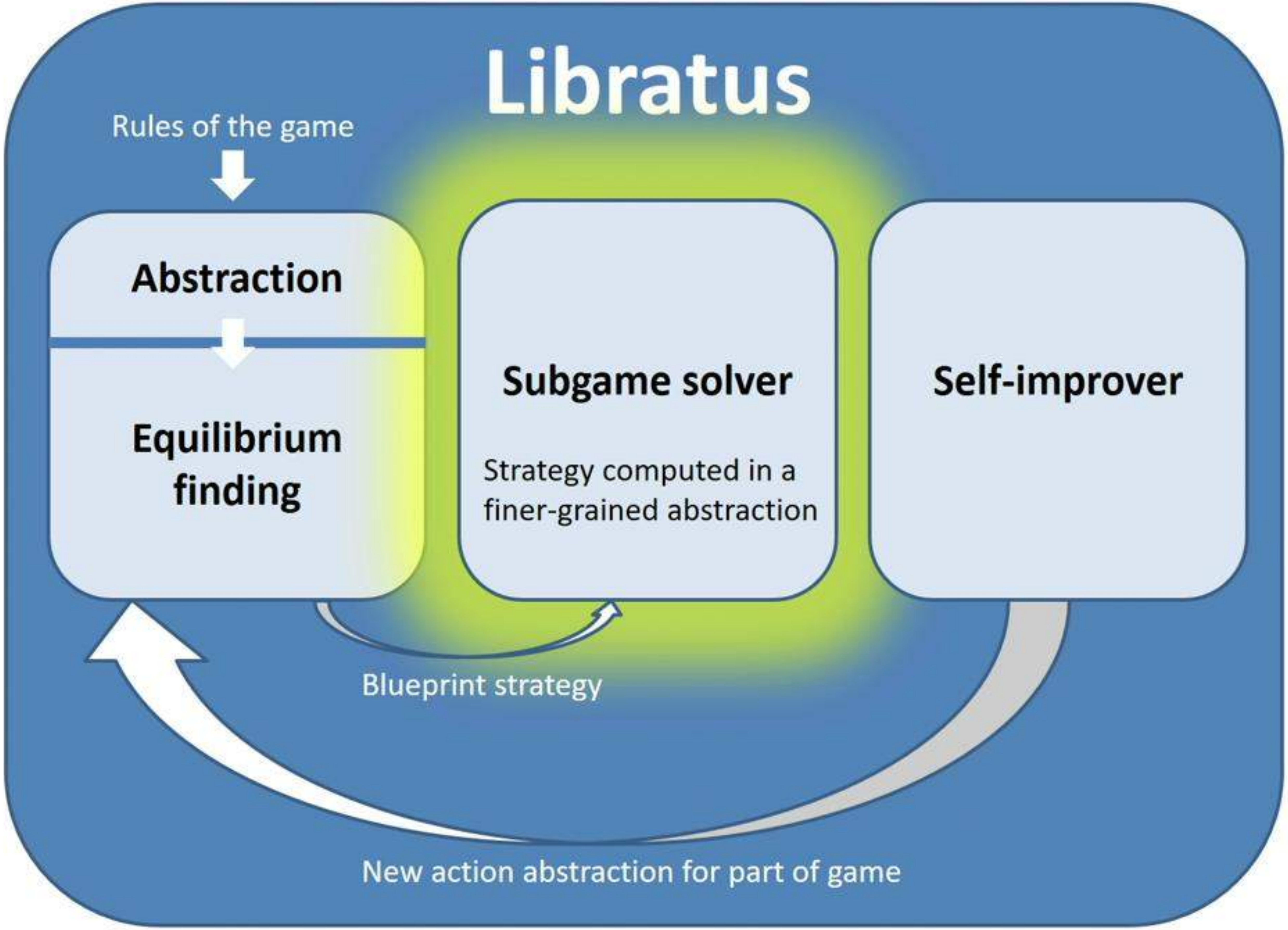
Foreshadowed by Shi & Littman 01, Billings et al. IJCAI-03

Abstraction in Libratus

- Abstracting chance's action (cards in poker)
  - Same algorithm that we used in *Tartanian8* [Brown, Ganzfried & Sandholm AAMAS-15]
  - But much finer abstraction
    - 1st and 2nd betting round: no abstraction
    - 3rd betting round: 55M card histories -> 2.5M buckets
    - 4th betting round: 2.4B card histories -> 1.25M buckets
- Abstracting player's actions (bet sizes in poker)
  - Largely based on what top humans and AIs do
  - Added radical bet sizes
  - Optimized some of the bet sizes in the early parts of the tree [Brown & Sandholm AAAI-14]

Our equilibrium-finding algorithm

- Improvement on Monte-Carlo Counterfactual Regret Minimization [Lanctot *et al.* *NIPS*-09]
- Starts visiting less often paths where our own actions don't look promising (similar to Brown & Sandholm NIPS-15 paper and AAAI-17 workshop paper)
  => Speedup => can solve larger abstractions
- Also, the imperfect-recall abstraction, in effect, becomes finer grained
  => Better solution quality
- Distributed across 1 + 195 compute nodes
  - Distribution along game tree, not "embarrassingly parallel"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New ideas in subgame solver

NIPS-17 best paper award

- Provably *safe* subgame solving taking into account opponent's mistakes in the hand so far
- Off-tree actions & nested subgame solving
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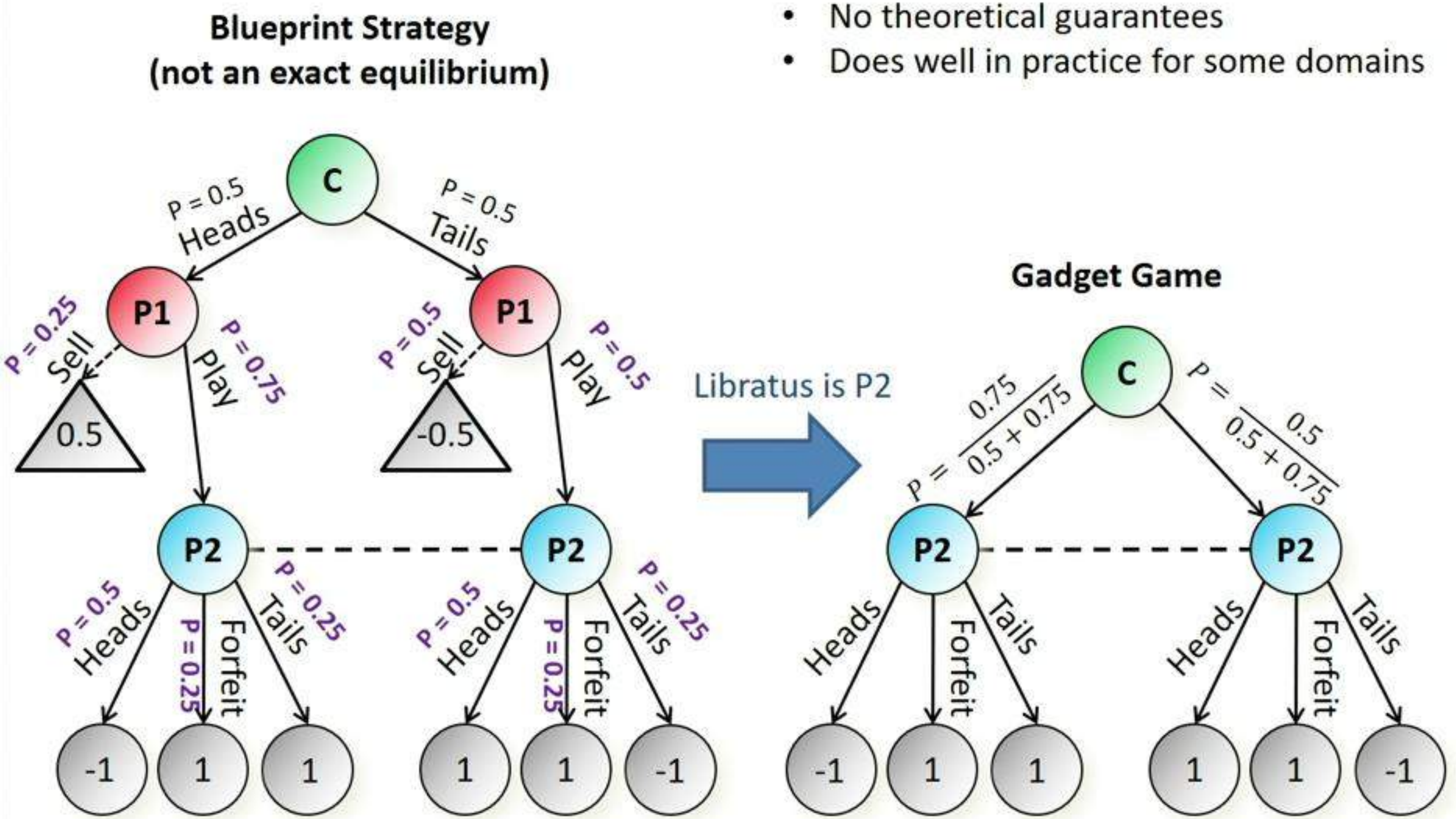
Unsafe subgame solving

[Ganzfried & Sandholm AAAMAS 2015]

- No theoretical guarantees
- Does well in practice for some domains



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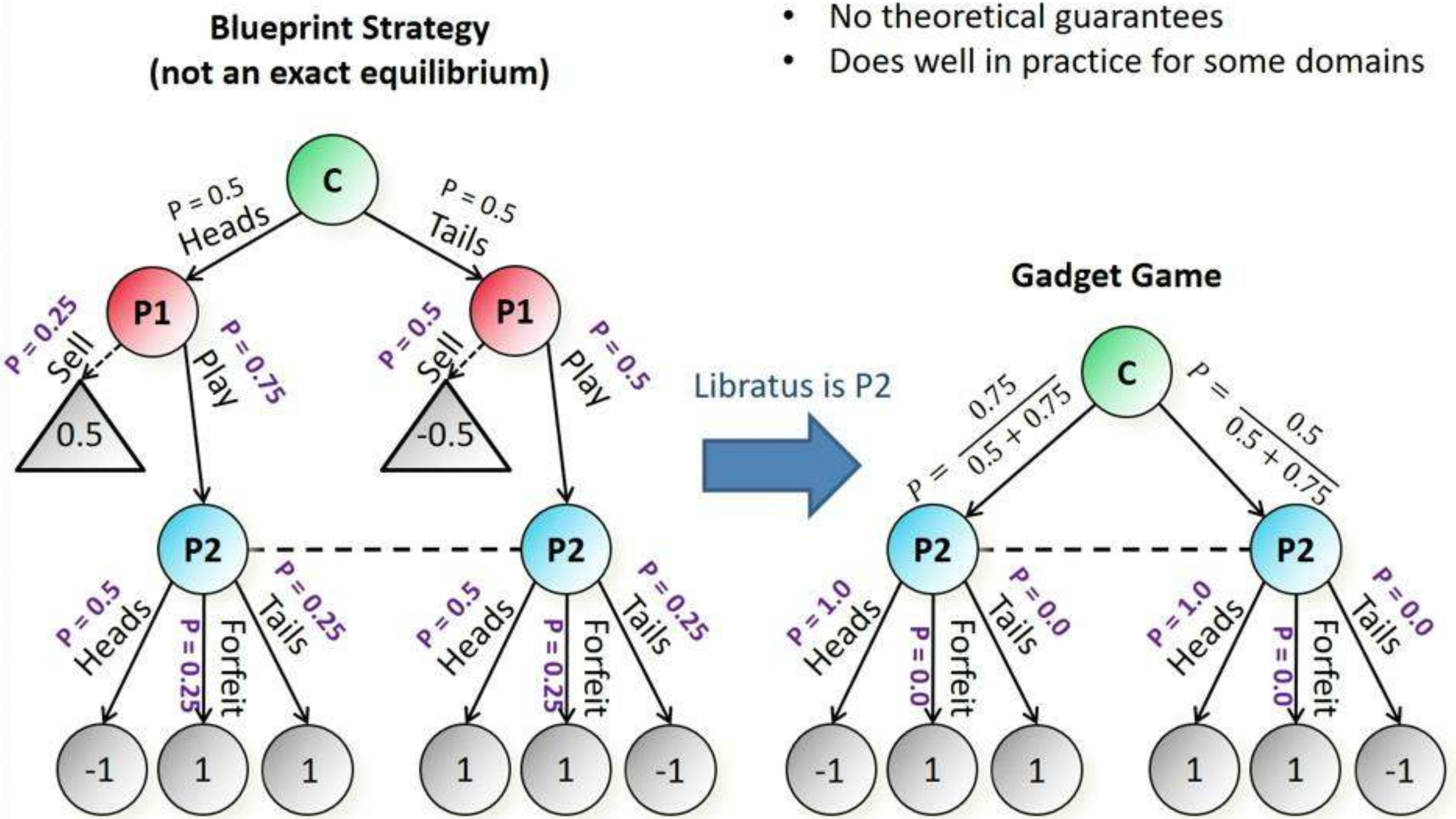
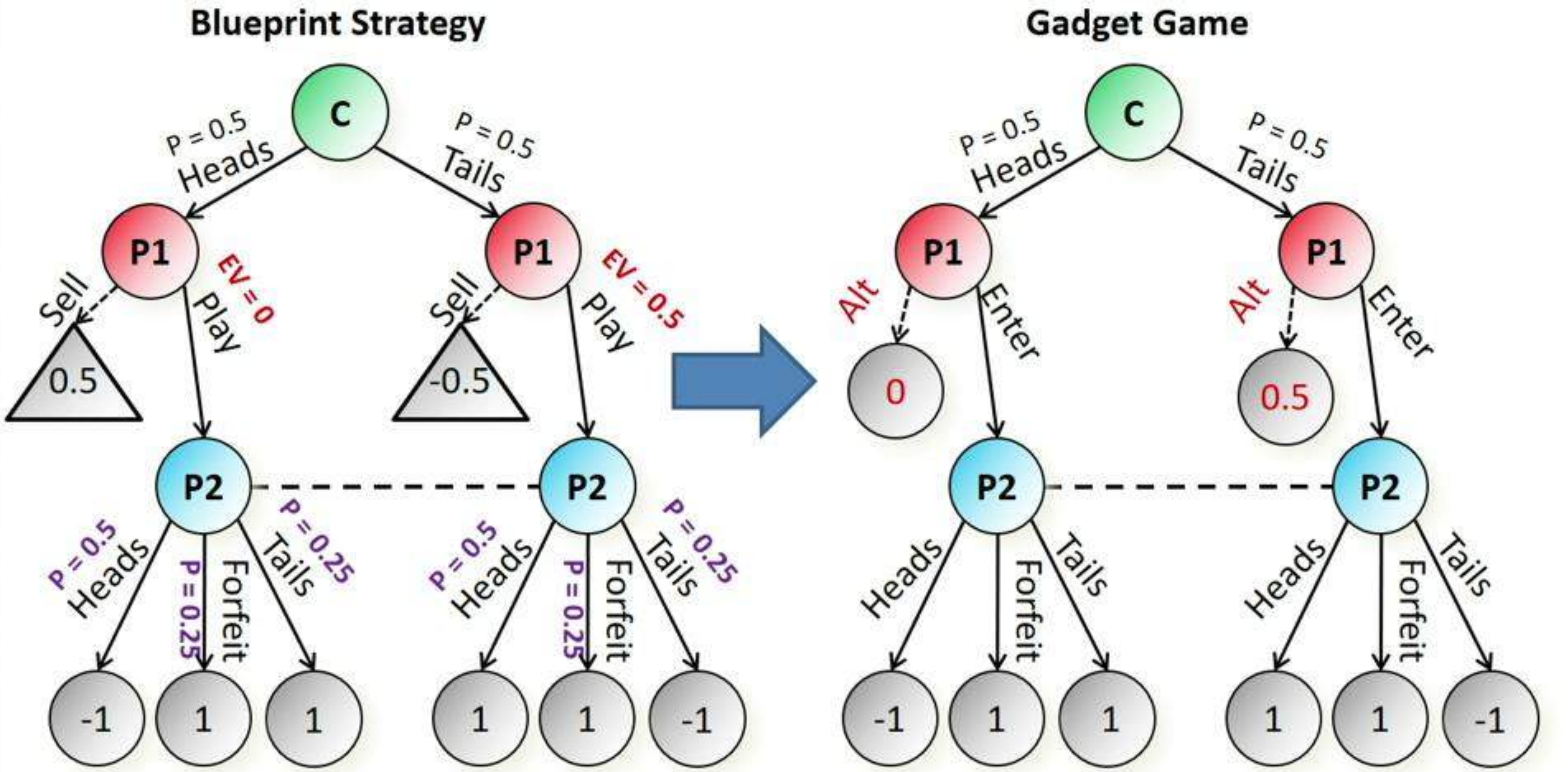


Re-solve refinement

[Burch *et al*. AAAI 2014]

- P1 can choose between entering the subgame or taking the EV (according to the blueprint) of the subgame
- Makes sure opponent's EV for entering the subgame is no higher than in the blueprint strategy
  => Strategy provably no worse than blueprint strategy
- But may miss obvious opportunities for improvement (e.g., not forfeiting)



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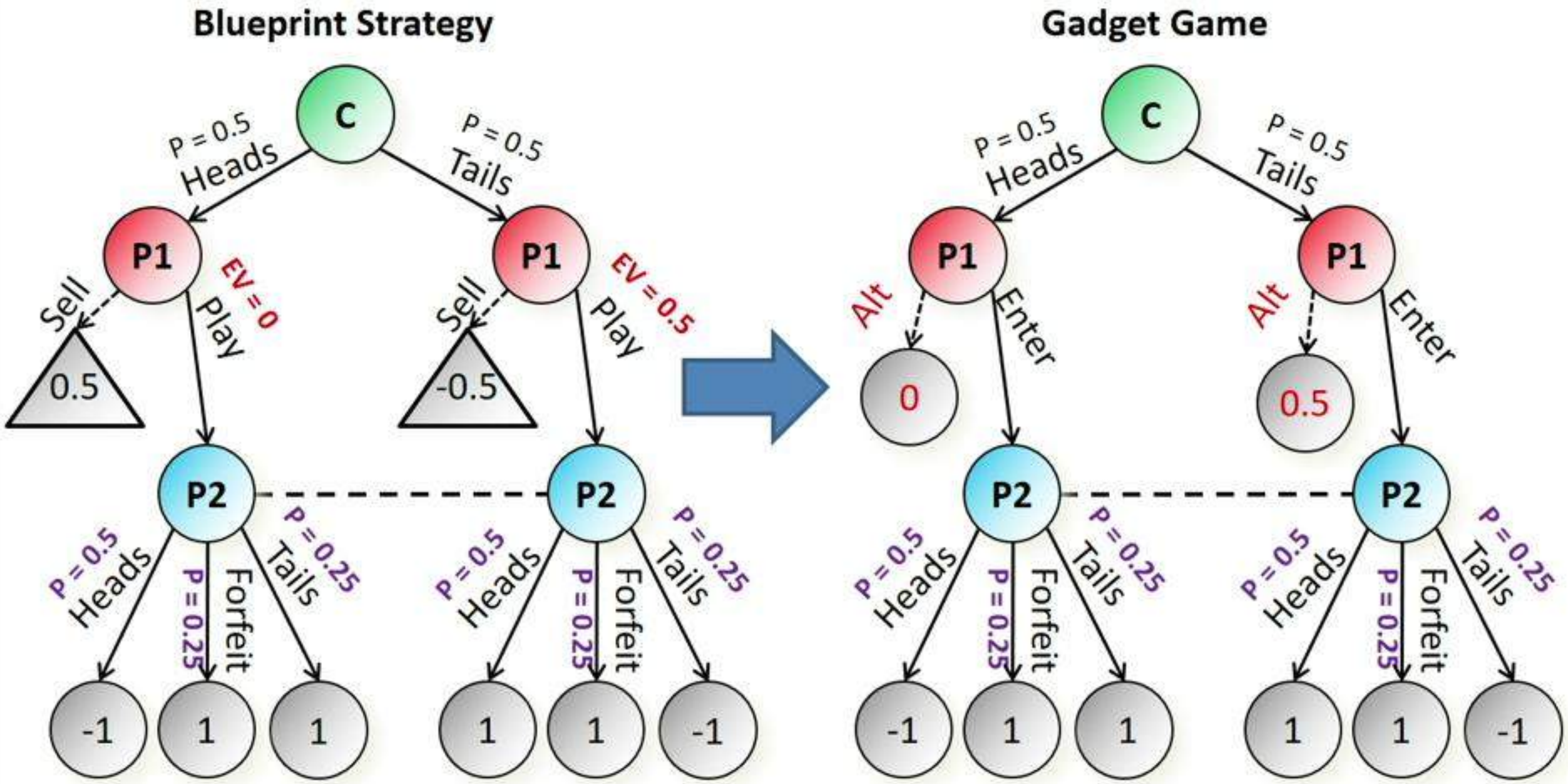
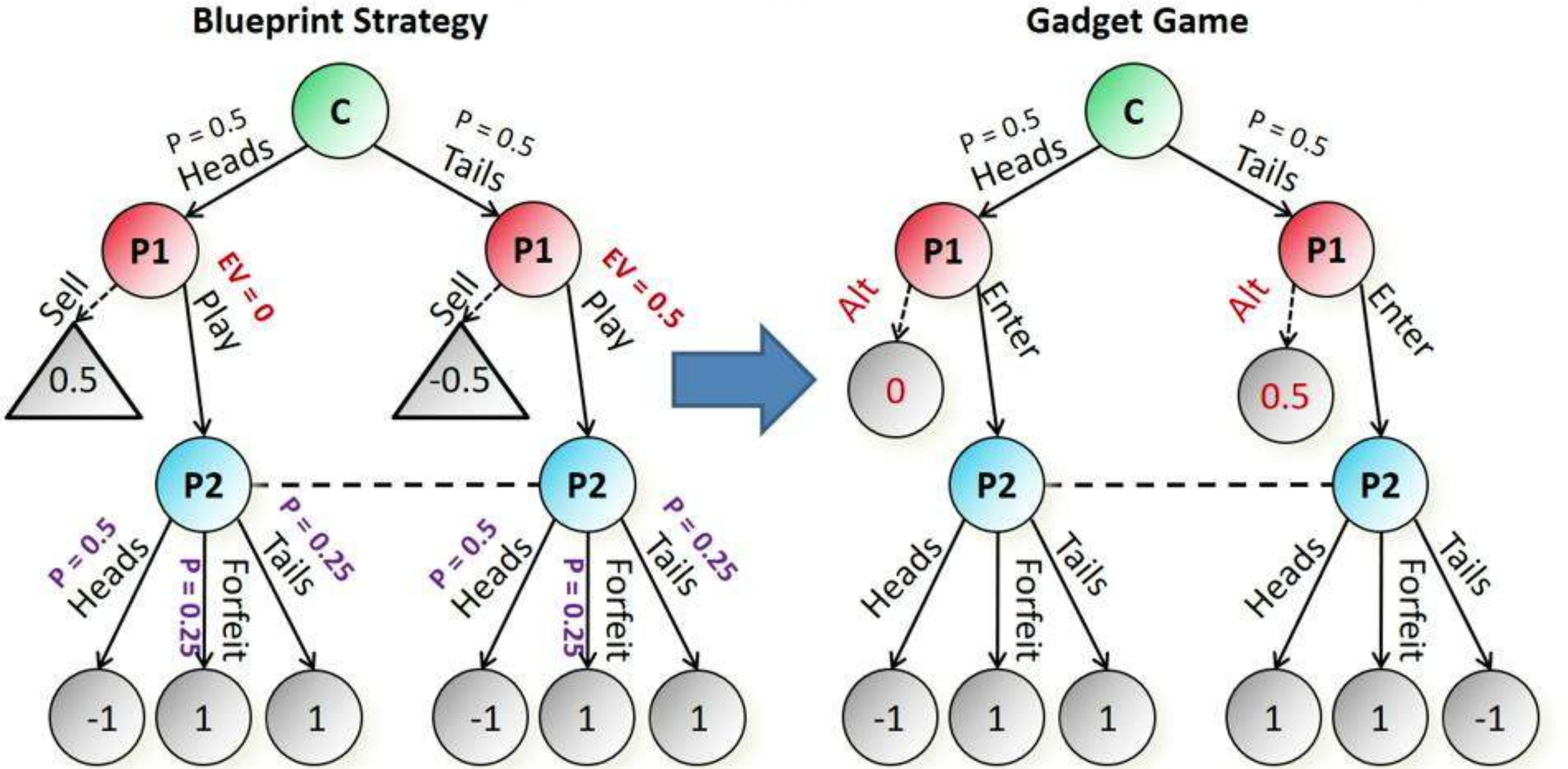


Maxmargin refinement [Moravcik et al. AAAI 2016]

Similar to Re-solve, but punishes P1 as much as possible for choosing Enter rather than Alt

$Margin_{Heads} = EV[Alt_{Heads}] - EV[Enter_{Heads}]$

Maximizes the minimum margin (Re-solve simply attempts to make all margins nonnegative)



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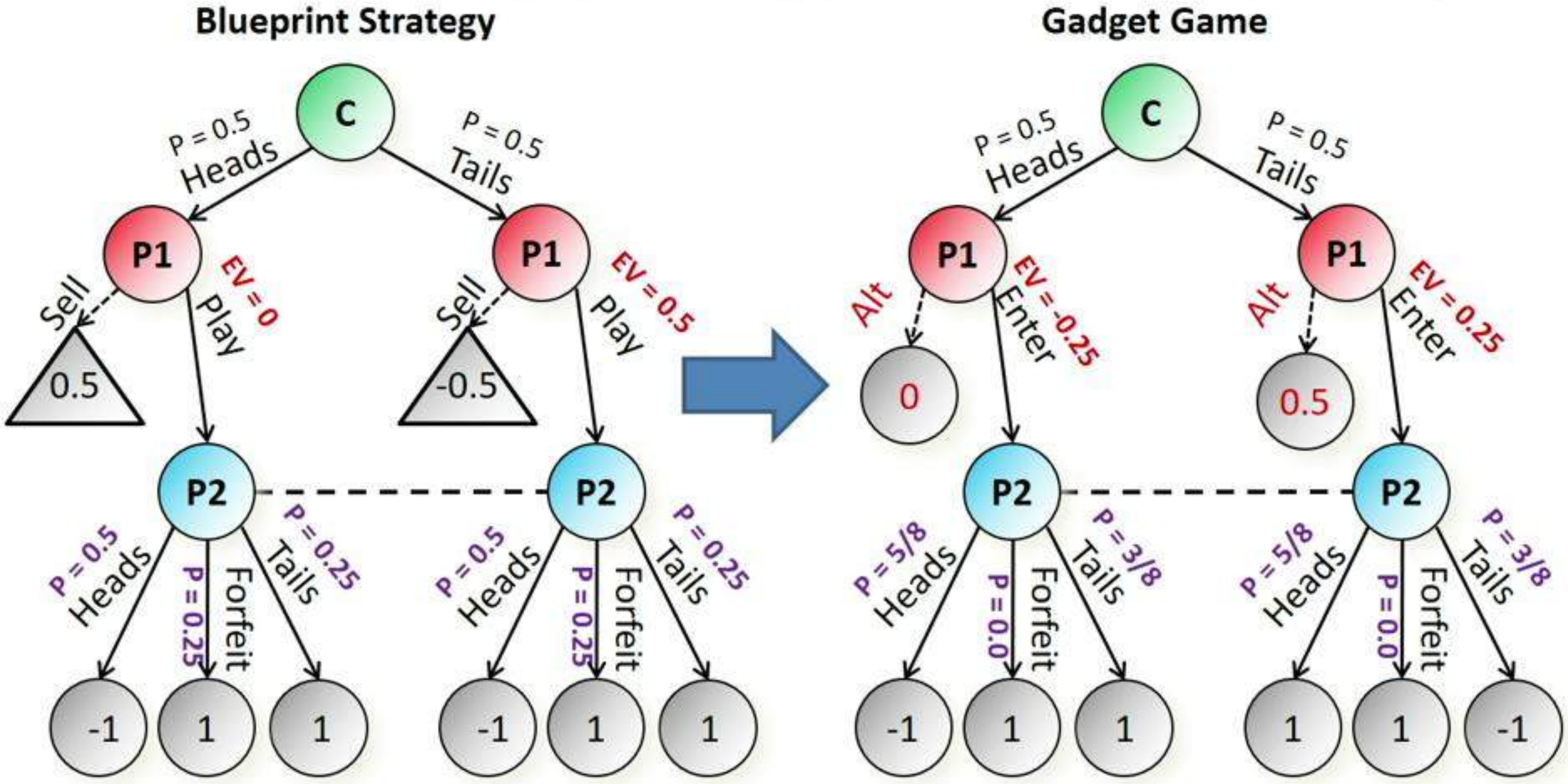

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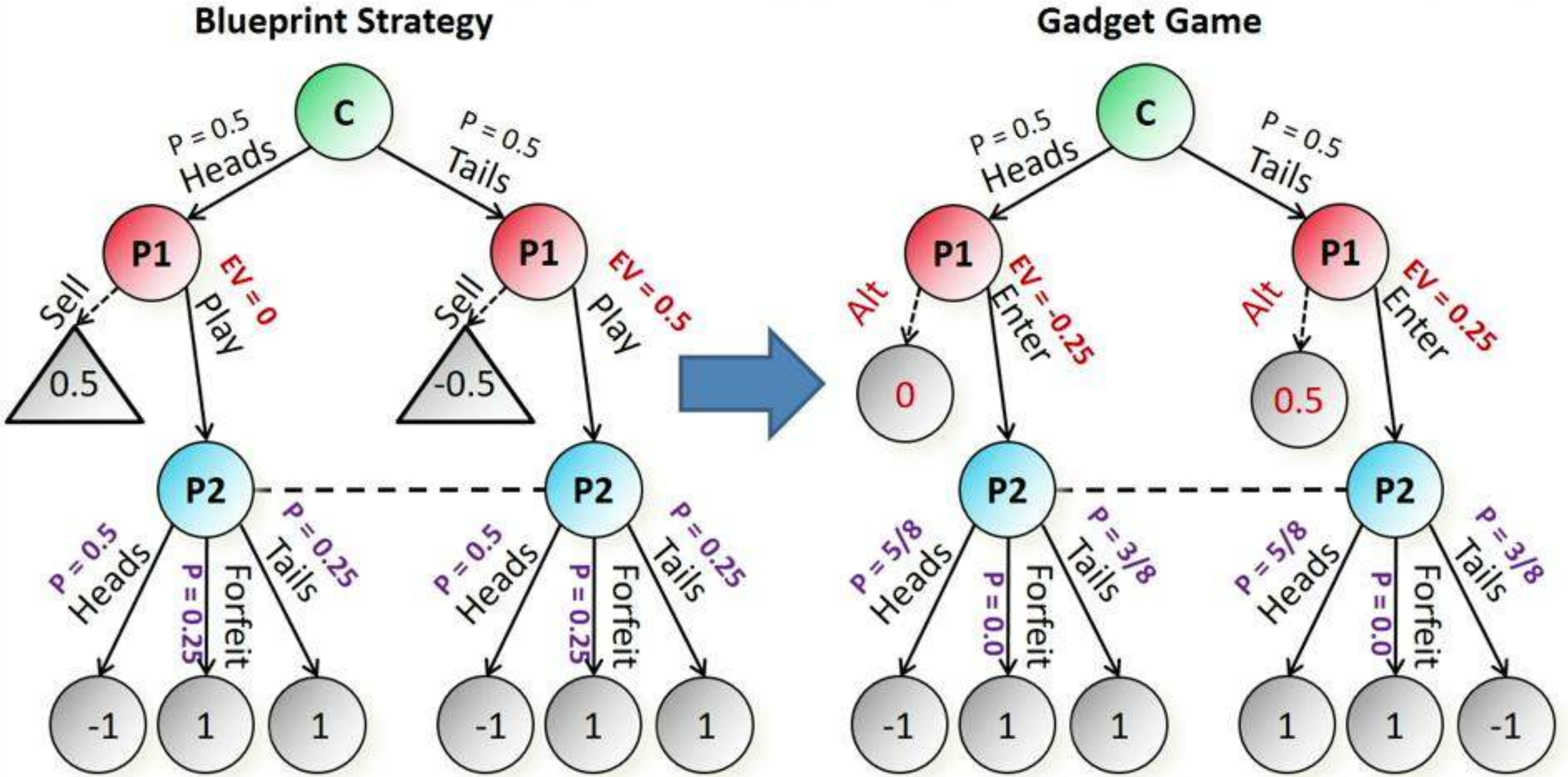
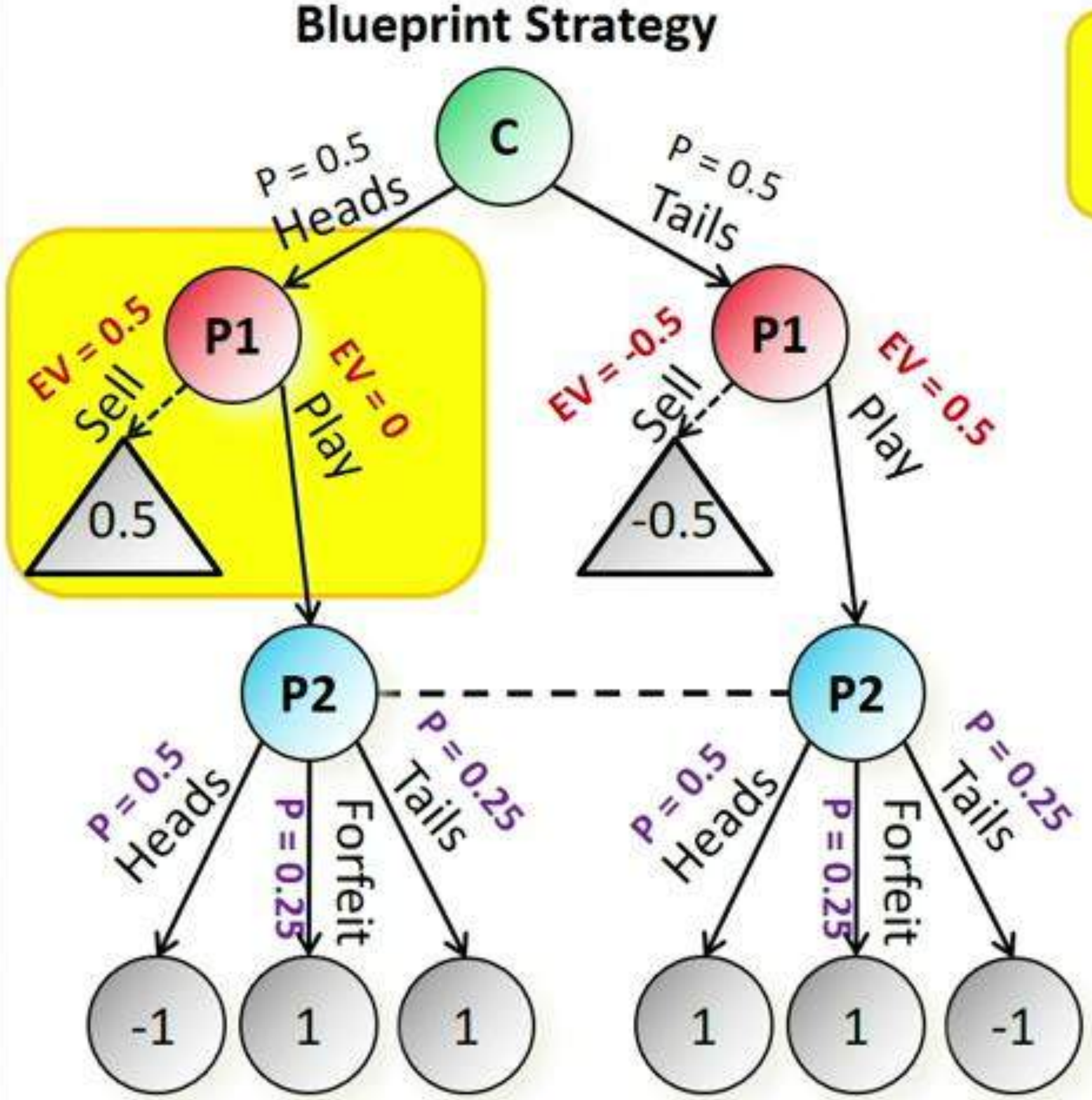


Problem: While we focus on reducing P1's EV for Heads in the subgame to -0.25, P1 can just Sell for 0.5 in Heads

Reach-maxmargin refinement:

(solving a single subgame here)

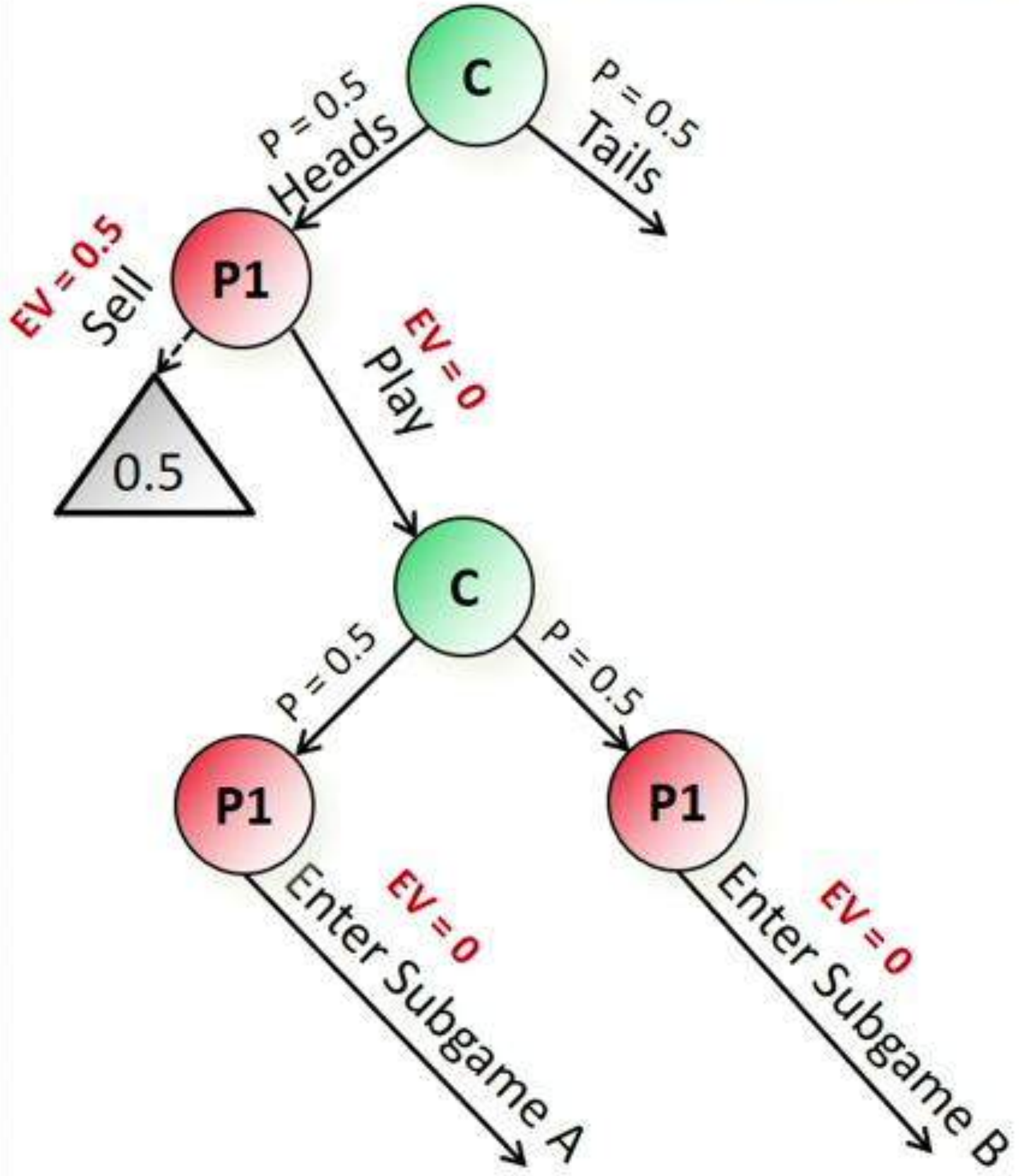
[Brown & Sandholm AAAI-17 workshop, NIPS-17, Science-17; related to Jackson AAAI-15 workshop]



- If P1 chooses Play following Heads, P1 is ***gifting*** us 0.5
- So, in Gadget Game we can increase the alternative payoff following Heads by 0.5, because choosing Play would still be a mistake for P1 there
- Thus the Gadget Game solver focuses on reducing P1's EV for other types she may have

Reach-maxmargin refinement: multiple subgames

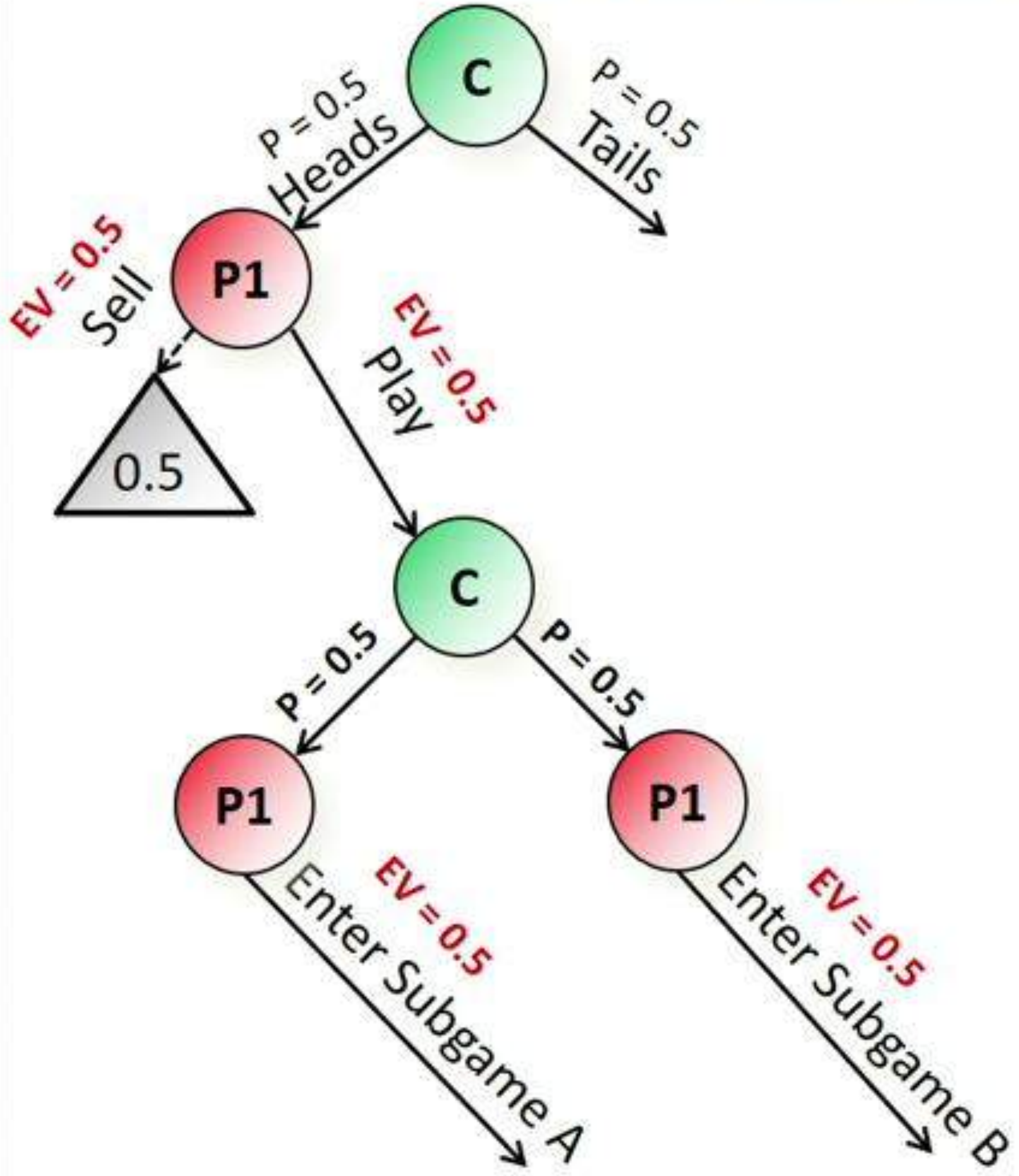
[Brown & Sandholm AAAI-17 workshop, NIPS-17, Science-17]



- If multiple subgames are refined, off-path EVs might not remain constant
- Solution: split gifts among subgames by probability subgame is reached

Reach-maxmargin refinement: multiple subgames

[Brown & Sandholm AAAI-17 workshop, NIPS-17, Science-17]



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Reach-maxmargin refinement: multiple subgames

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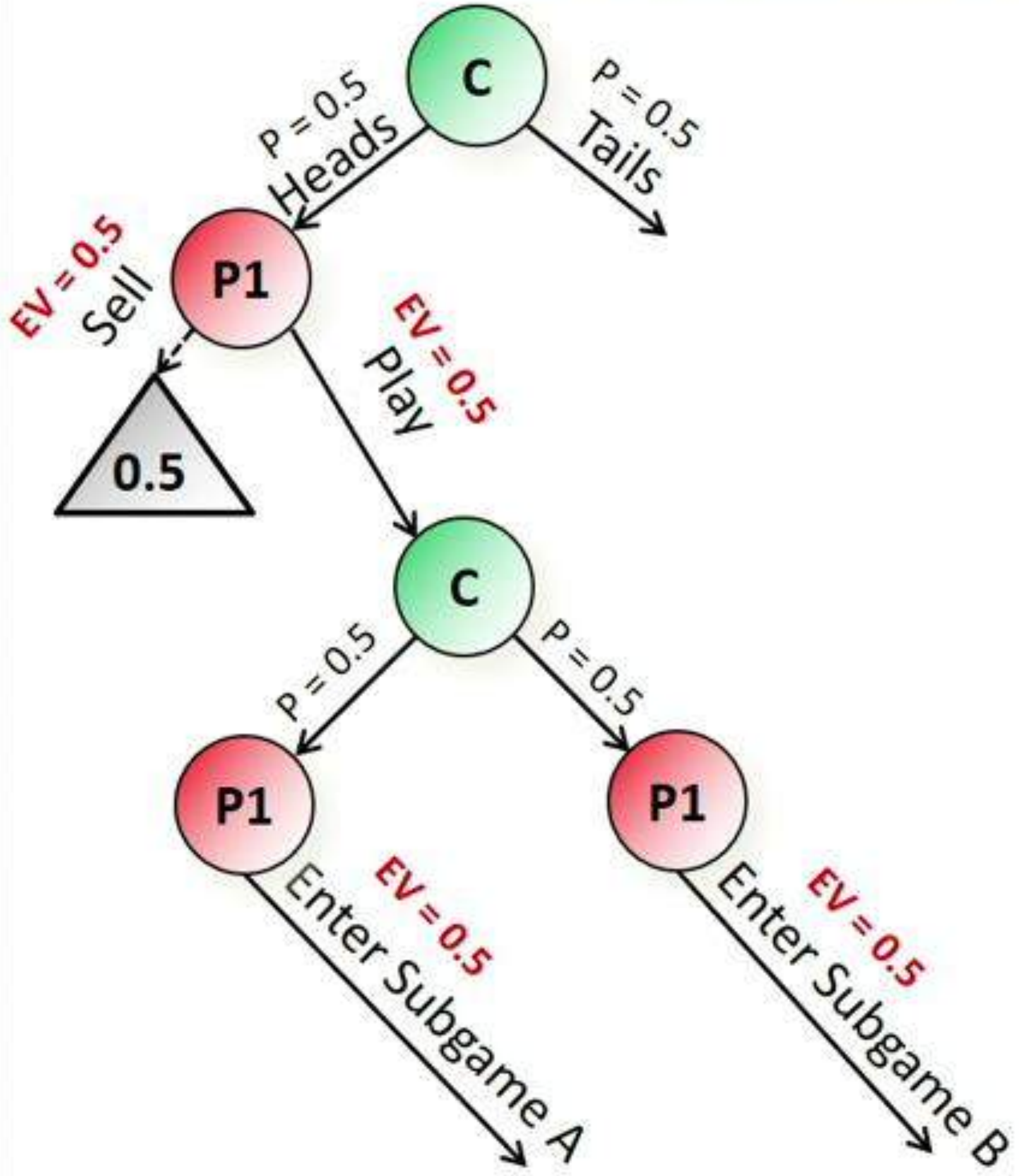

- Gifts might not be as large as we thought, because the subgames they come from will be improved
- Solution: substitute a lower bound on the gift
  - In practice, this can be an estimate

New ideas in subgame solver

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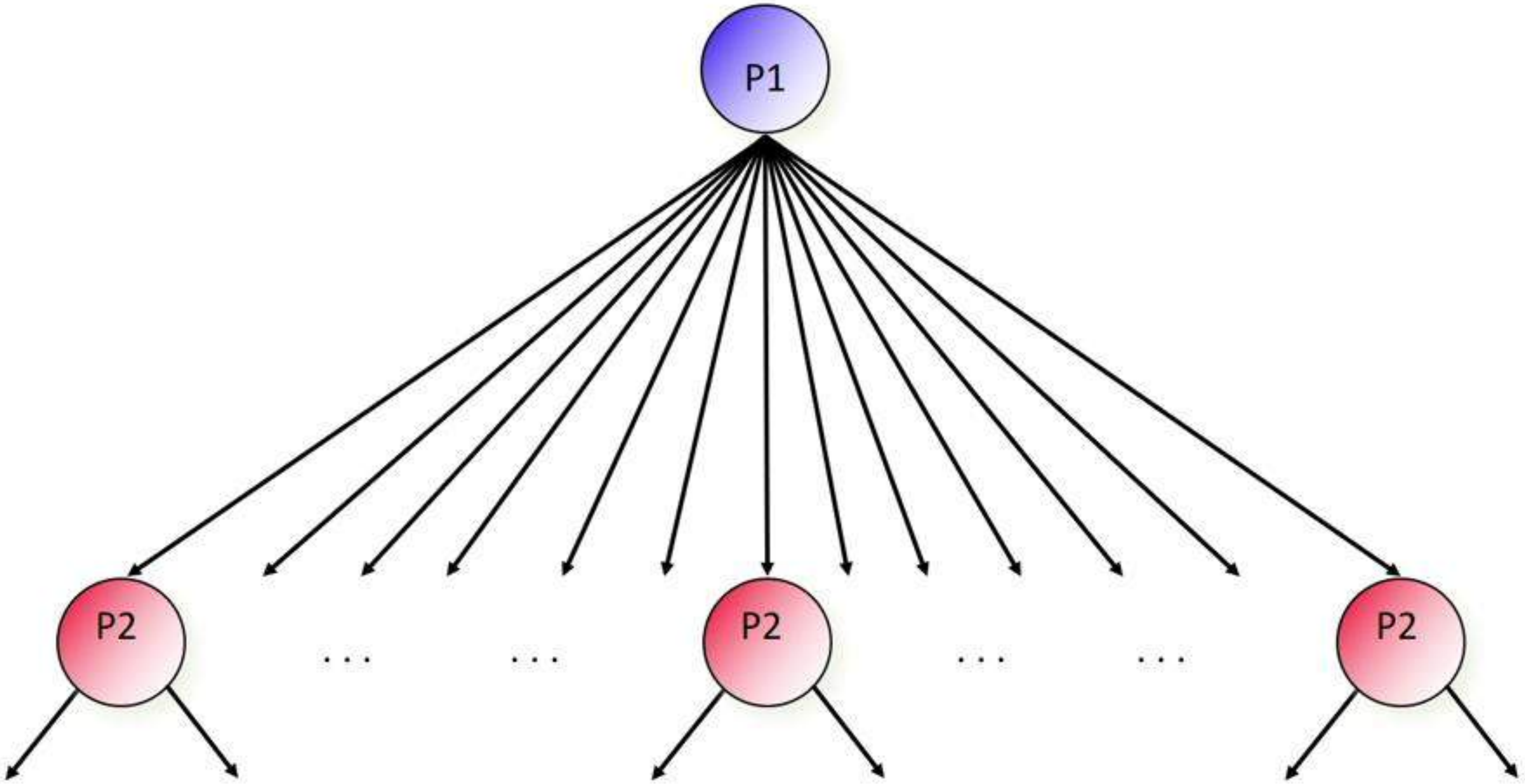
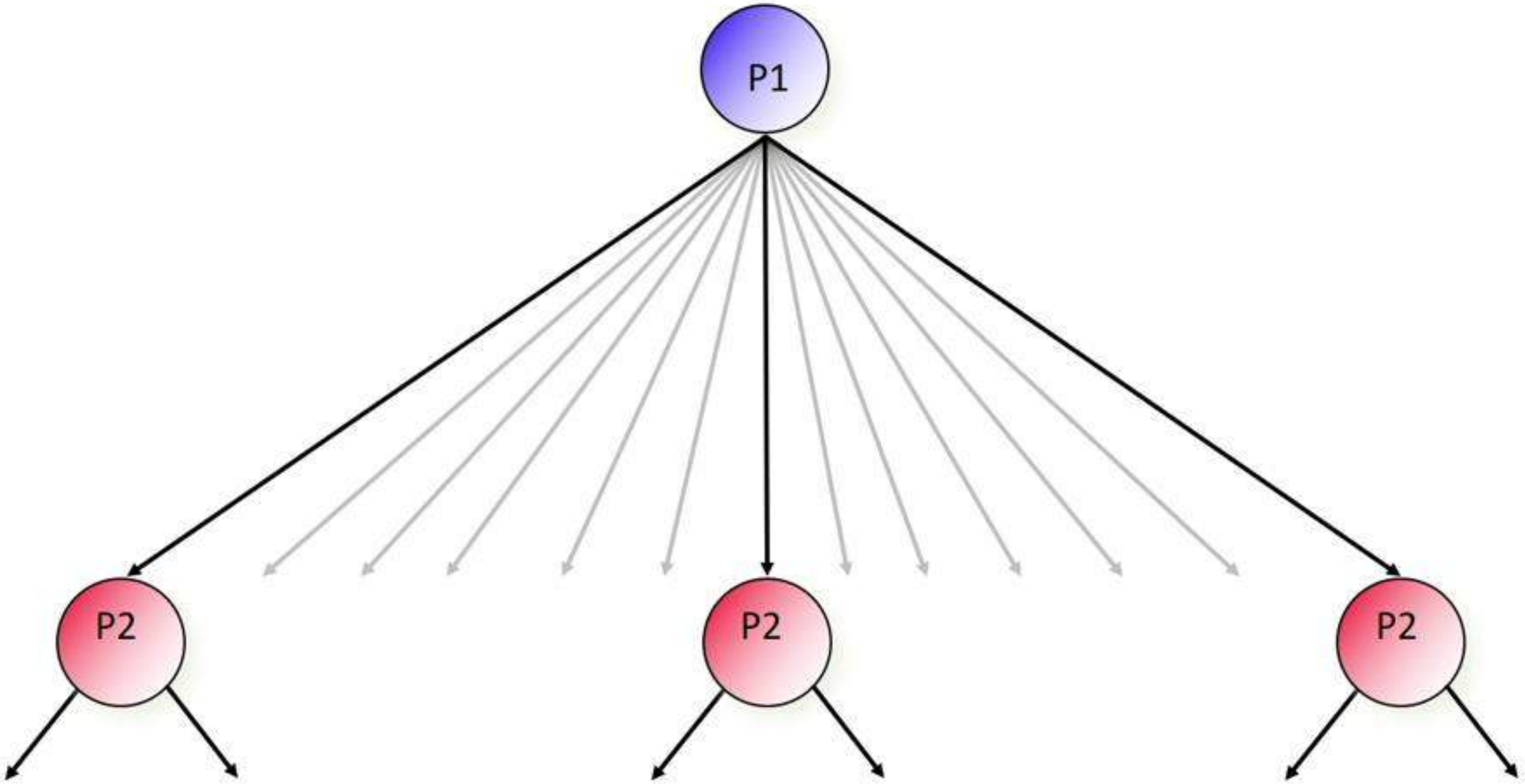
Action abstraction

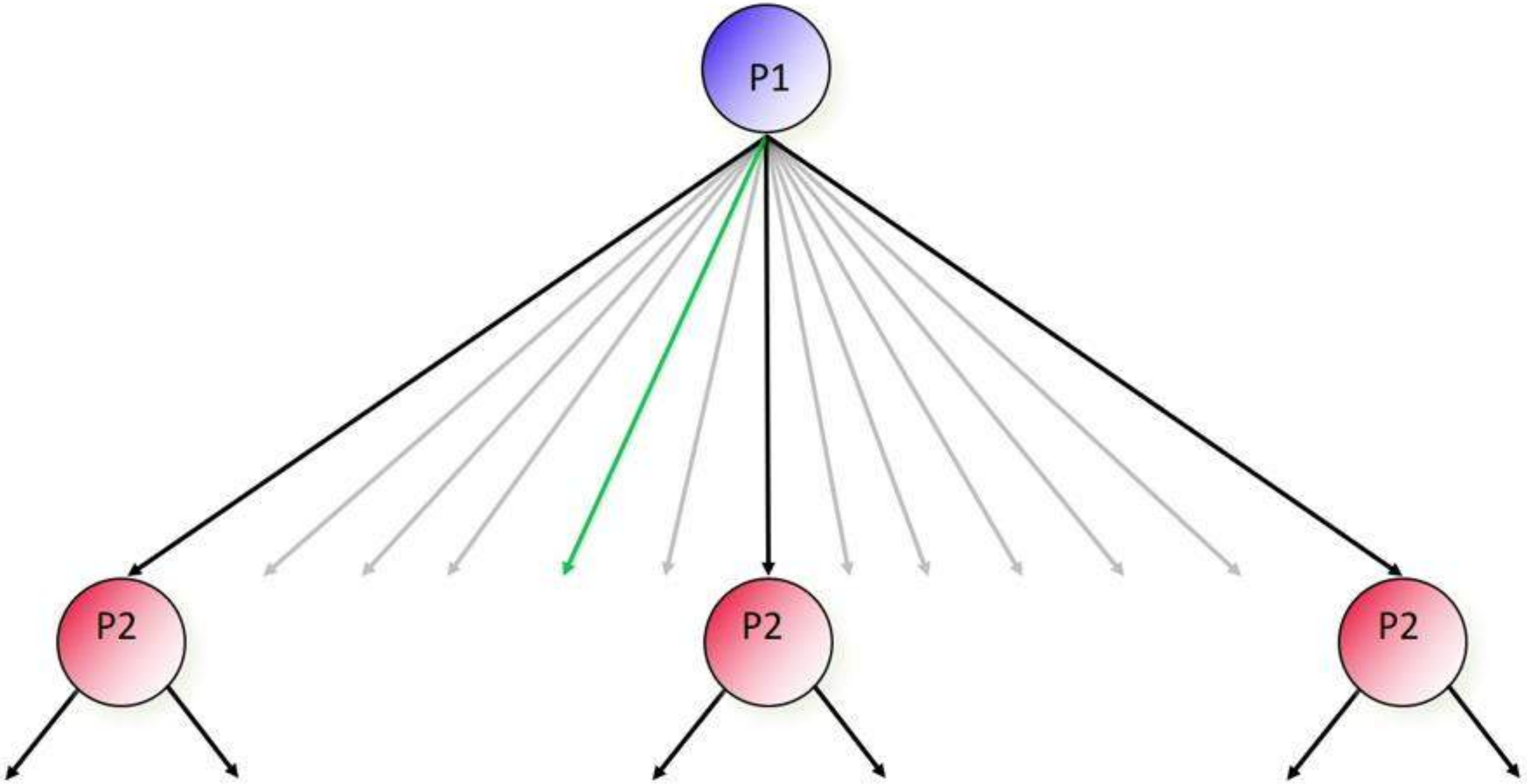


Action abstraction



[Gilpin et al. AAMAS-08], [Hawkin et al. AAAI-11, AAAI-12], [Brown & Sandholm AAAI-14]

Action translation

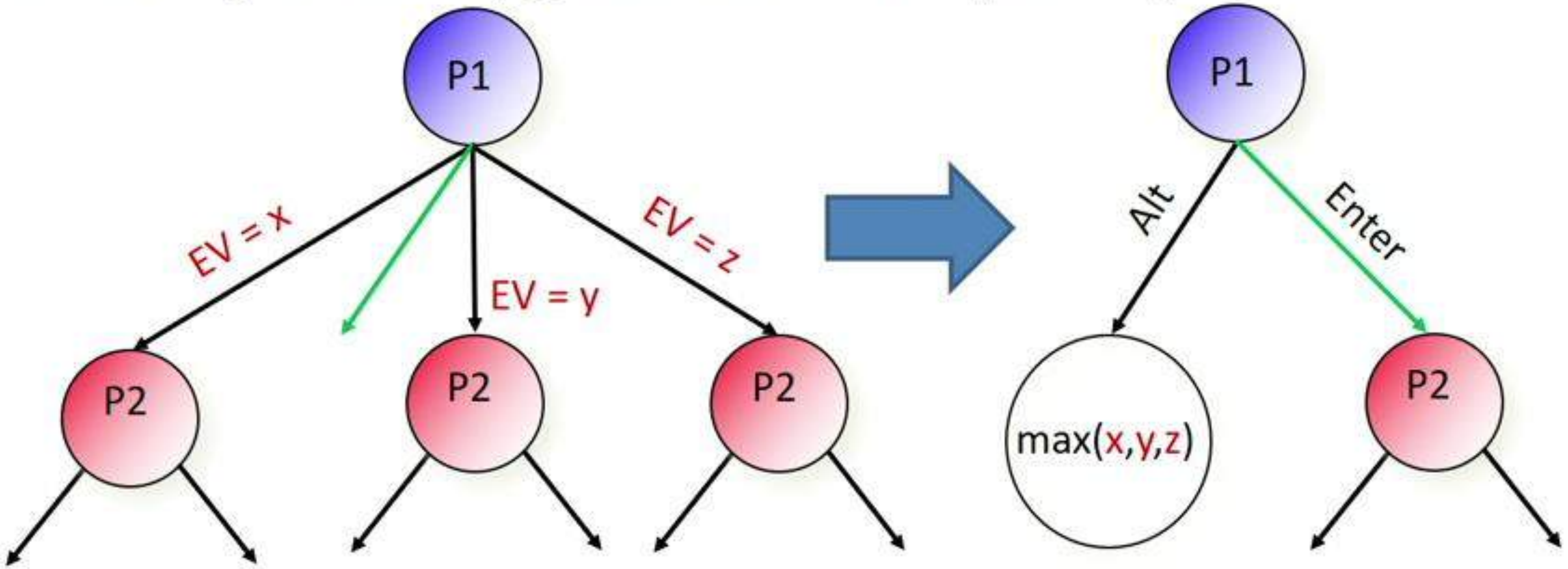


[Gilpin et al. AAMAS-08], [Schnizlein et al. IJCAI-09], [Ganzfried & Sandholm IJCAI-13]

Subgame solving even with "off-tree" actions

[Brown & Sandholm AAAI-17 workshop, arXiv, NIPS-17]

- Idea: Solve a subgame in real time (e.g., for the off-tree action that opponent took)



- **Theorem 1.** (even with hidden actions) Let Δ be such that there exists a Nash equilibrium where each alt payoff for Player 1 is within Δ of the Nash equilibrium EV at that point for Player 1. Then our Reach-Maxmargin subgame-solving technique yields a 2Δ-minmax strategy for Player 2 for the full game.
- **Theorem 2.** (even with hidden actions) If Player 1's alt payoffs are computed from a best response (in the full game) to Player 2's blueprint strategy, then the strategy formed by our Reach-Maxmargin subgame-solving technique has no greater regret for Player 2 in the full game than Player 2's blueprint strategy.
- ***"Nested subgame solving":*** can be reapplied for every subsequent opponent (e.g., off-tree) action
  - **Theorem 1'.** Player 2's strategy is a 2Δ * (number of reapplications within one play-through of the game)-minmax strategy.
  - **Theorem 2'.** Exactly like Theorem 2.

Experiments on medium-sized games

- Our best **reach subgame solving** technique has **3x** less exploitability than the best prior safe subgame-solving technique
- **Nested reach subgame solving** is **12x** less exploitable than best action-mapping technique

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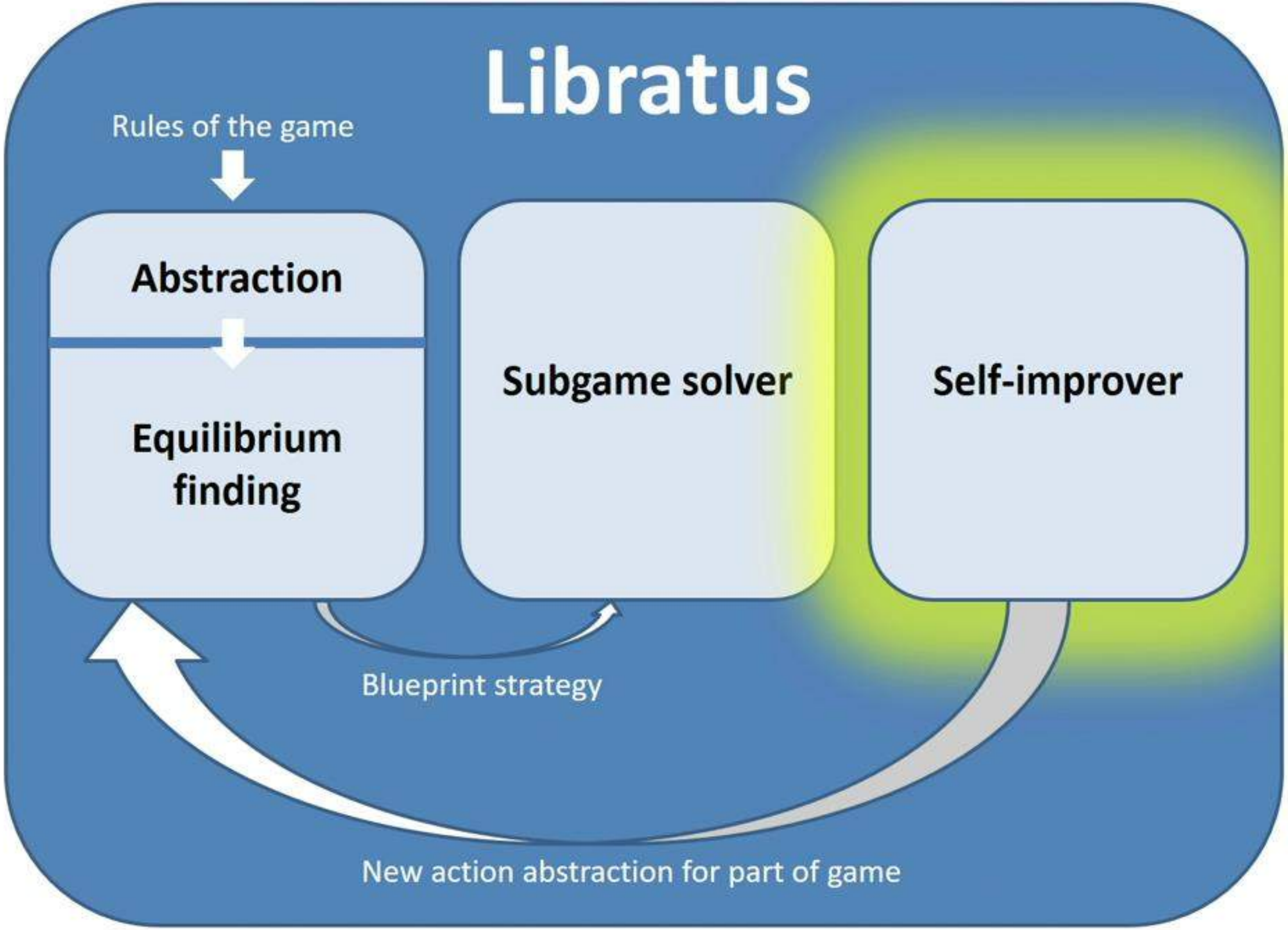
Libratus's "balance" and use of "blockers"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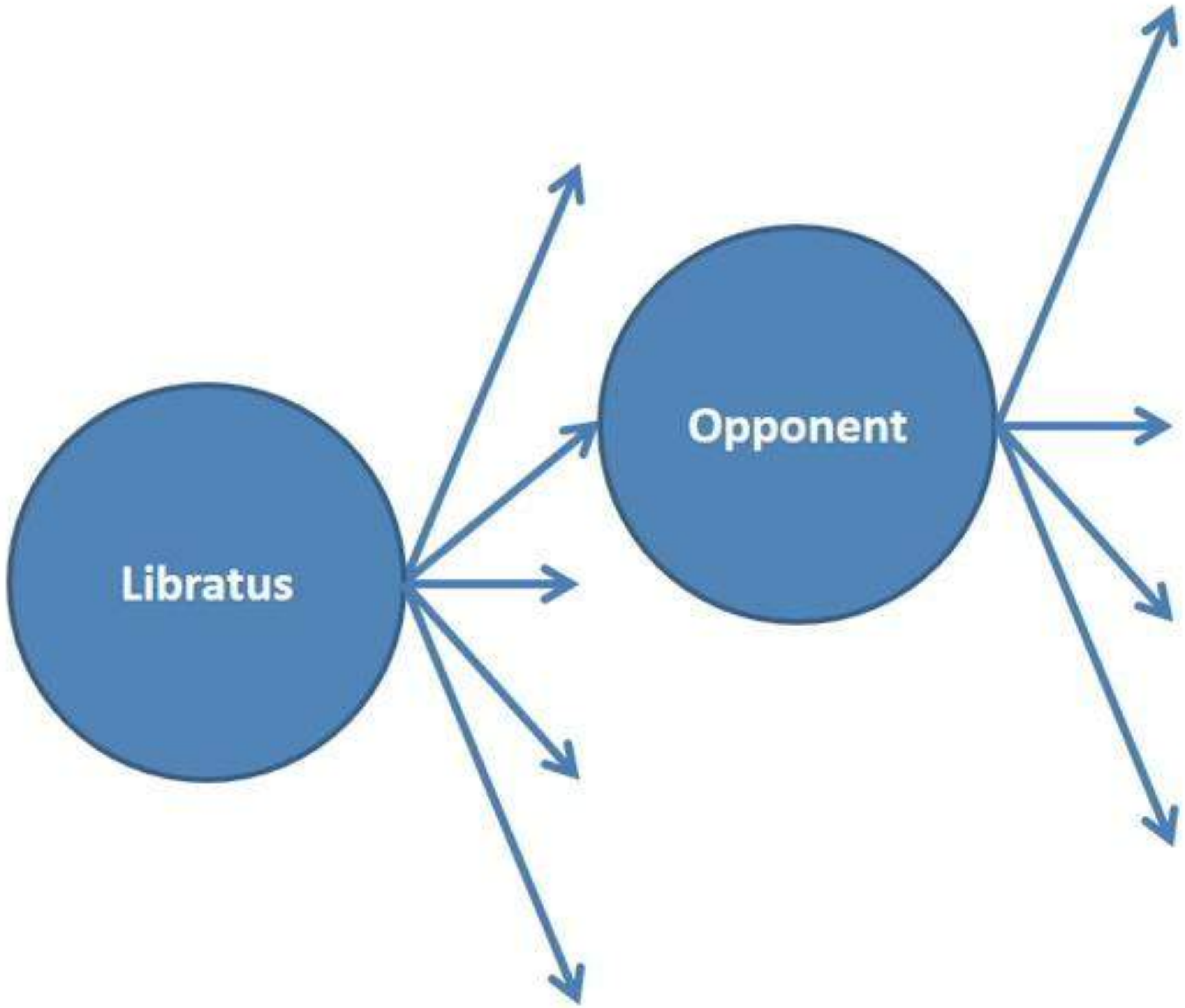
Filling holes in the action tree



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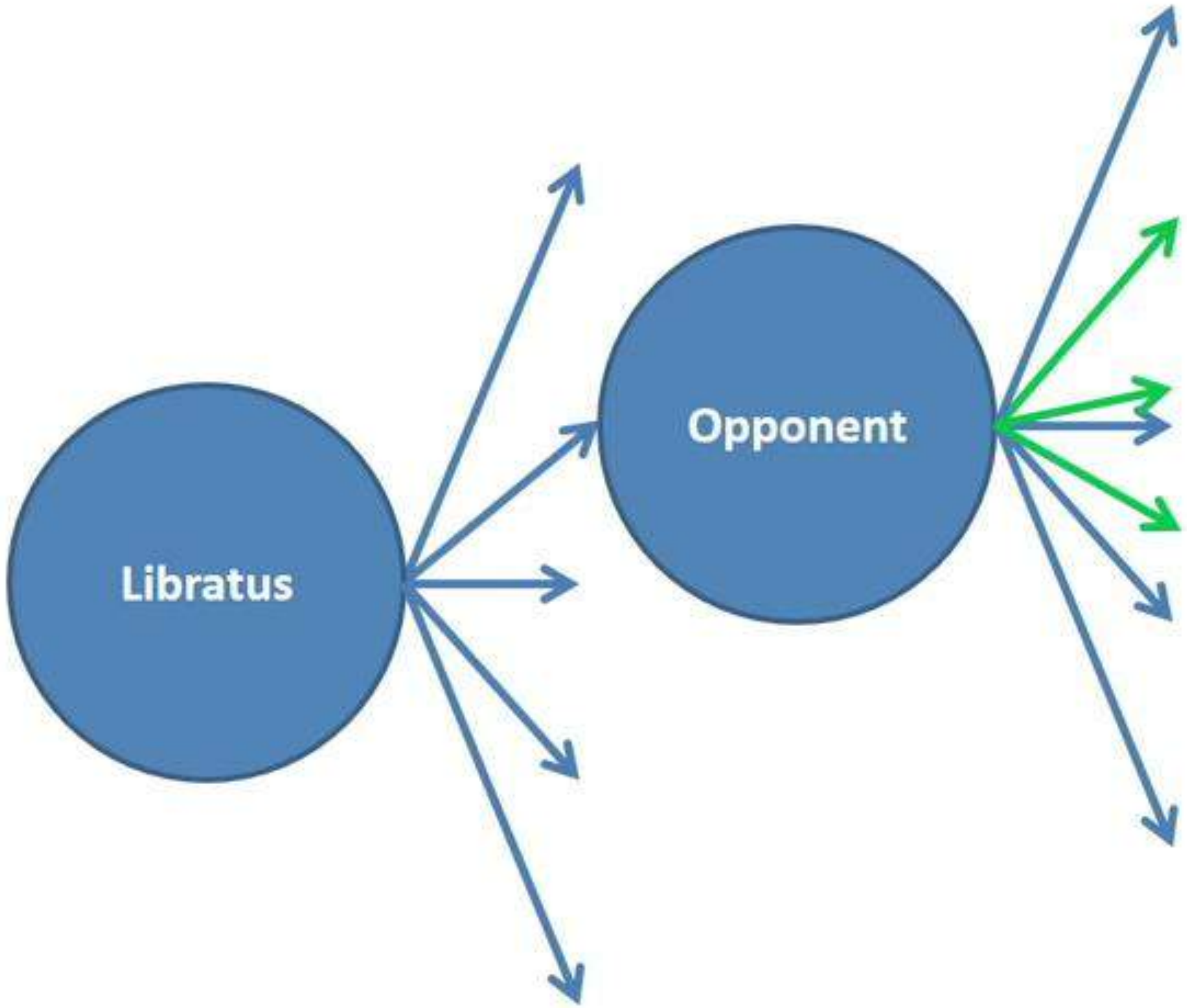

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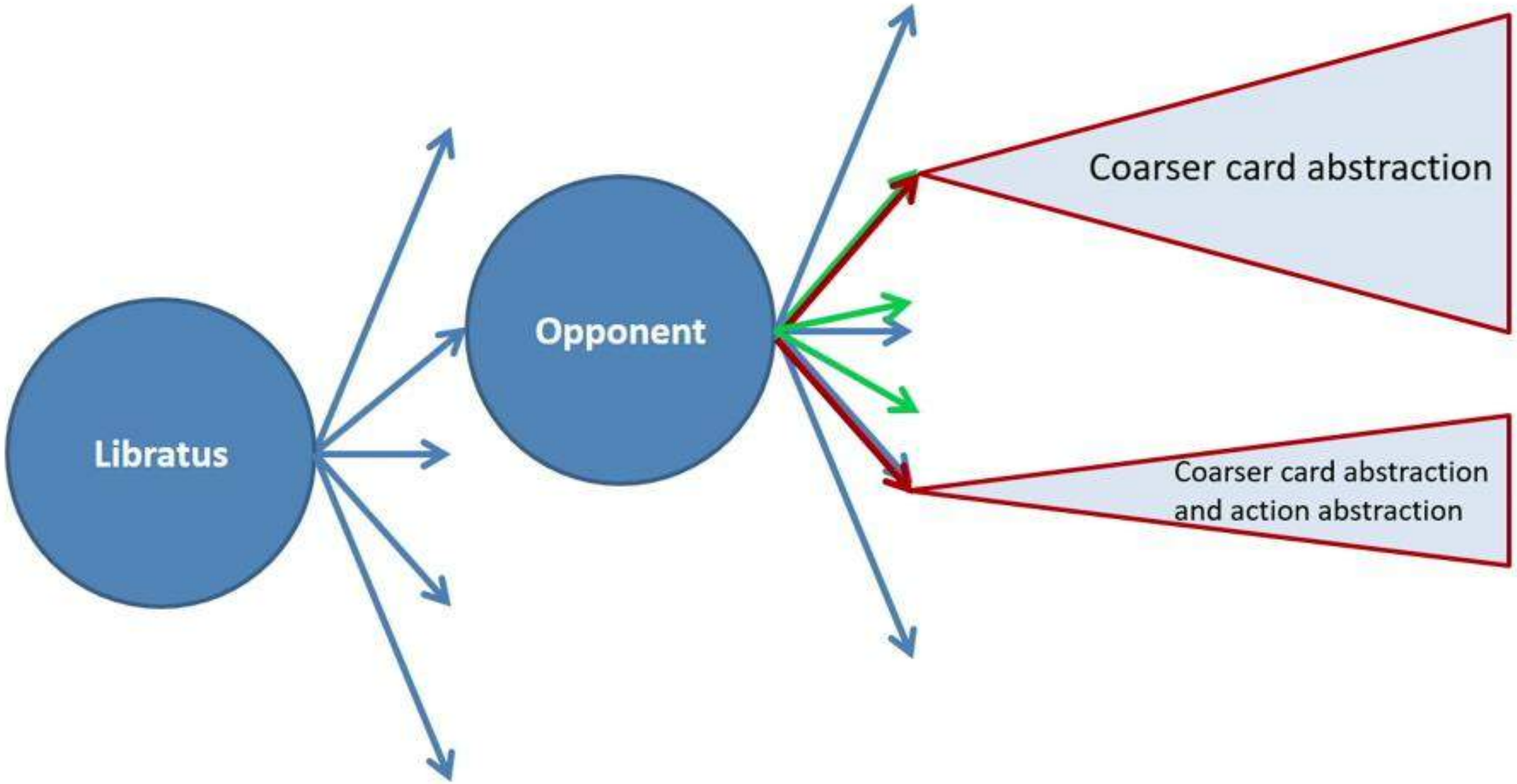

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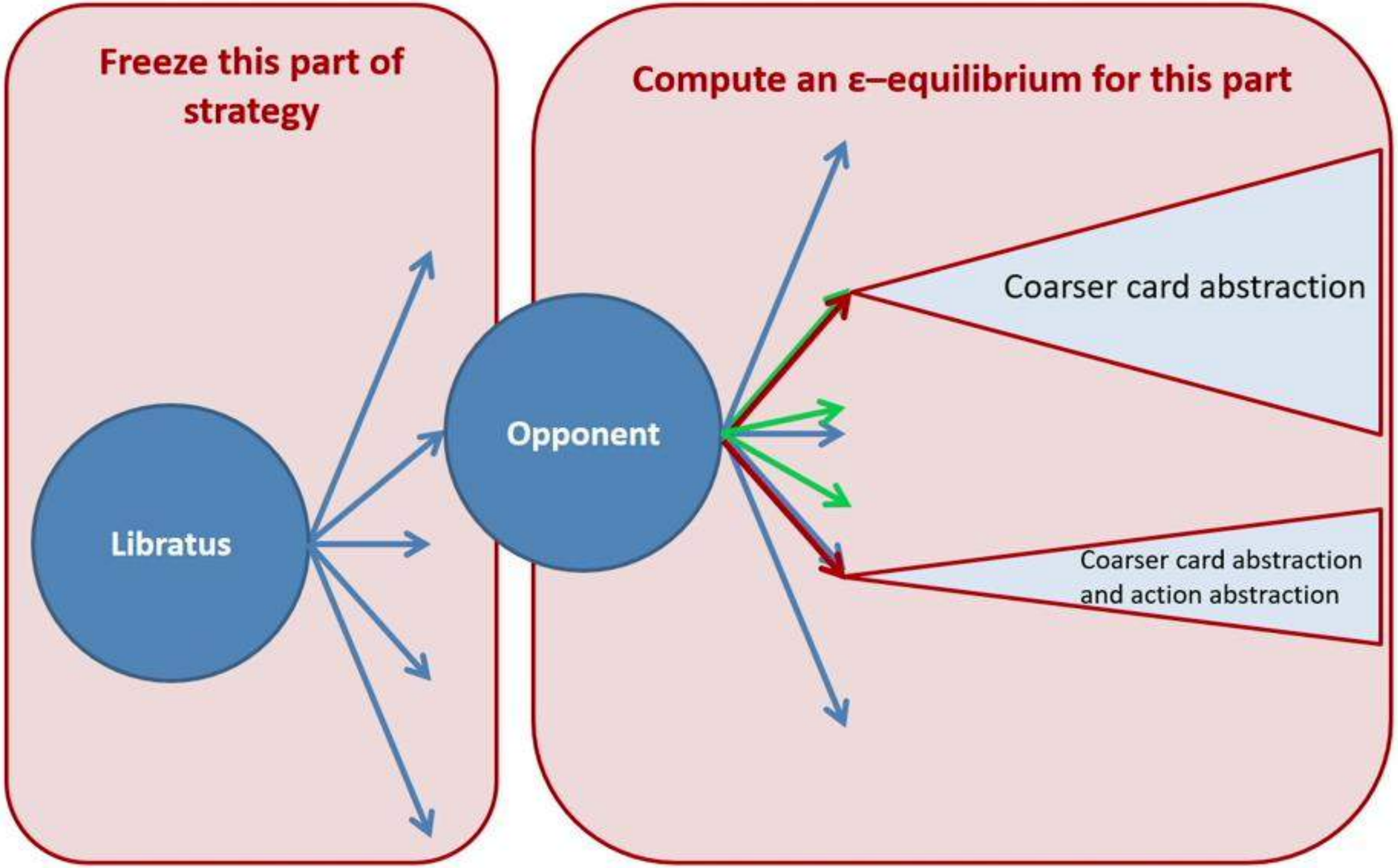

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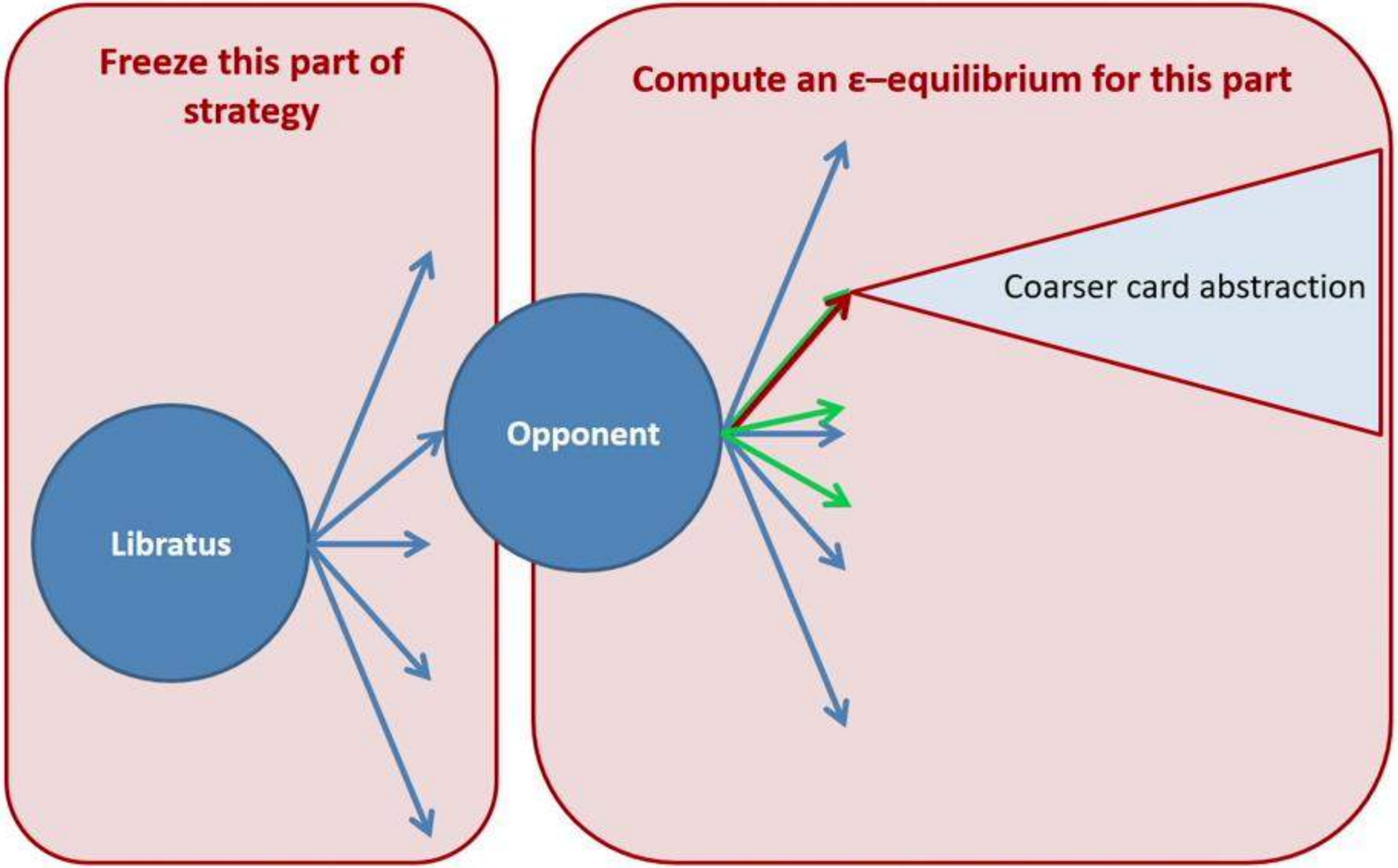
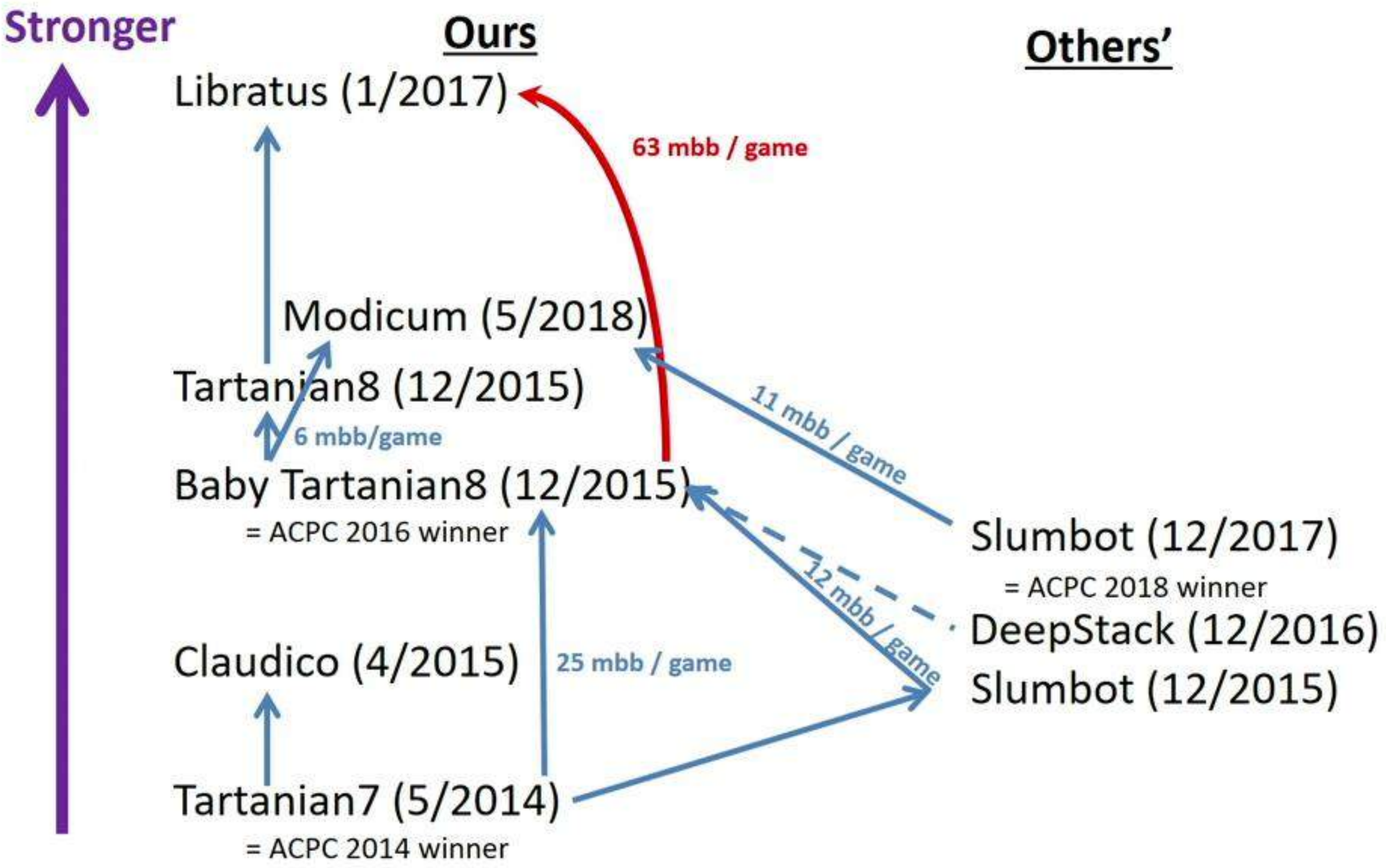


We do this for top *k* holes

Libratus fixing its own weaknesses

Head-to-head strength of top AIs



Observations about Libratus's play

- Strengths:
  - Small bets & huge bets & huge all-ins
  - Multiple bet sizes in any one situation
  - "Limping", "donk betting"
  - "Perfect balance"
  - Mixed strategy
  - Probability distributions over players' hands; not just "range-based"
  - Near-perfect subgame play; "great use of blockers"
  - Different bet sizings used in subgames
- Weaknesses?
  - No opponent exploitation

Is safe (equilibrium) play timid/boring?

Some current research on this topic in my lab

- Lossy abstraction algorithms with bounds [Kroer & Sandholm EC-14, EC-16, AI^3 2018]
  - They also apply to modeling
  - To do: Unify with our best practical abstraction algorithms
- Simultaneous abstraction & equilibrium finding [Brown & Sandholm AAAI-15]
- General warm starting for CFR algorithms [Brown & Sandholm AAAI-16]
- New, fastest algorithm in CFR family [Brown & Sandholm manuscript]
- Regret decomposition framework [Farina, Kroer, Sandholm manuscript]
- Equilibrium-finding algorithms by developing new theory of gradient-based techniques [Kroer *et al.* EC-15, EC-17, 2 manuscripts]
- Algorithms for equilibrium refinements [Farina, Kroer & Sandholm ICML-17], [Kroer, Farina & Sandholm IJCAI-17], [Farina, Gatti & Sandholm manuscript]
- Equilibrium finding for >2 agents [Berg & Sandholm AAAI-17]
- Exploration vs. exploitation vs. exploitability [Ganzfried & Sandholm TEAC-15]
- Depth-limited solving in imperfect-info games [Brown & Sandholm arXiv-18]

Applying this new technology capability

Most real-world settings are imperfect-information games

STRATEGIC MACHINE, INC.

Commercial applications:

- Strategic pricing & strategic product portfolio optimization
- Gaming (incl. video games), training, streams, bot detection, …
- Automated negotiation, negotiation support, other strategic augmentation
- Electricity markets
- Finance: Strategic execution of trades, trading large blocks, illiquid markets, OTC, strategic portfolio construction, …
- Investment banking
- Political campaigns (e.g., media spending)
- Business strategy
- Bidding & auction design
- Strategic market segmentation
- Interaction between vehicles & semi-autonomous fleets
- Acquisition strategy (e.g., movie rights: portfolio construction and negotiation strategy)
- Sports
- Steering evolution and biological adaptation [Sandholm 2012, AAAI-15 SMT Blue Skies]
  - E.g., for medical treatment planning [Kroer & Sandholm IJCAI-16] and synthetic biology

Government applications

STRATEGY ROBOT, INC.

For the first time, doesn't assume a naïve "Red".
Unlike in simulation and current war gaming, Red's strategy is not input but rather output!

- Strategic, operative, and tactical level planning in adversarial military settings
- Force planning & acquisition
- War gaming
- Training
- Intelligence
- National security, trade, and diplomatic strategies
- Next-generation cybersecurity
  - Wireless jamming [DeBruhl et al.]
  - Zero-day vulnerability discovery & play-out
  - Operating systems, sequential screening, honeypotting, …
- Physical security
- Automated negotiation & negotiation support
- Other strategic augmentation