Deep Counterfactual Regret Minimization

Noam Brown*[12], Adam Lerer*[1], Sam Gross[1], Tuomas Sandholm[23]

*Equal Contribution
[1]Facebook AI Research
[2]Carnegie Mellon University
[3]Strategic Machine Inc., Strategy Robot Inc., and Optimized Markets Inc.

Counterfactual Regret Minimization (CFR)

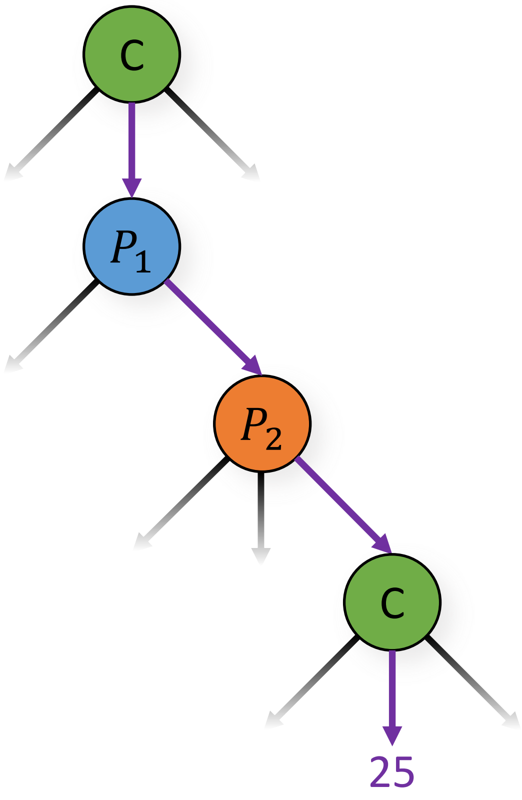
[Zinkevich et al. NeurIPS-07]

- **CFR** is the leading algorithm for solving partially observable games
  - Iteratively converges to an equilibrium
  - Used by ***every*** top poker AI in the past 7 years, including *Libratus*
  - ***Every single one*** used a **tabular** form of CFR

- This paper introduces a **function approximation** form of CFR using deep neural networks
  - Less domain knowledge
  - Easier to apply to other games

Example of Monte Carlo CFR [Lanctot et al. NeurIPS-09]

- Simulate a game with one player designated as the **traverser**



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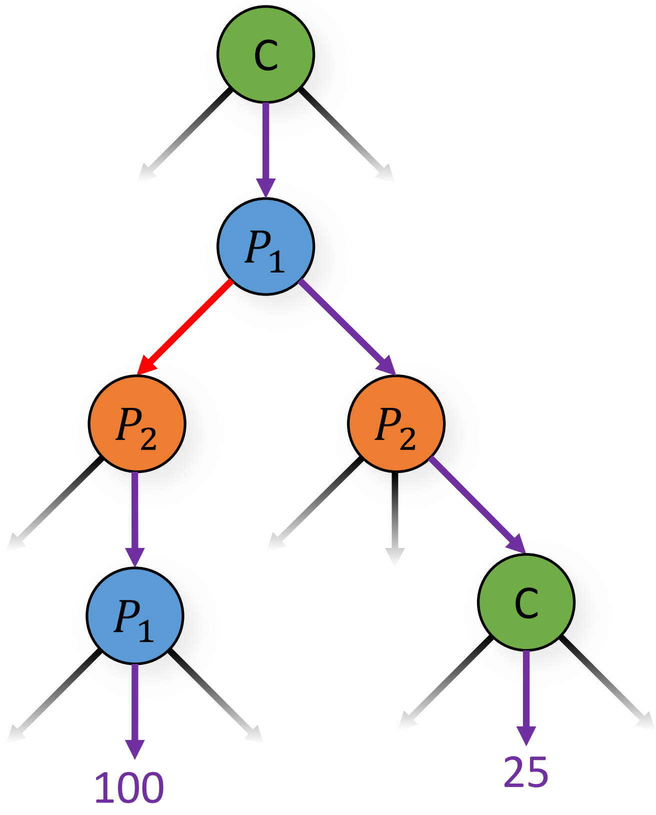
- After game ends, traverser sees how much better she could have done by choosing other actions



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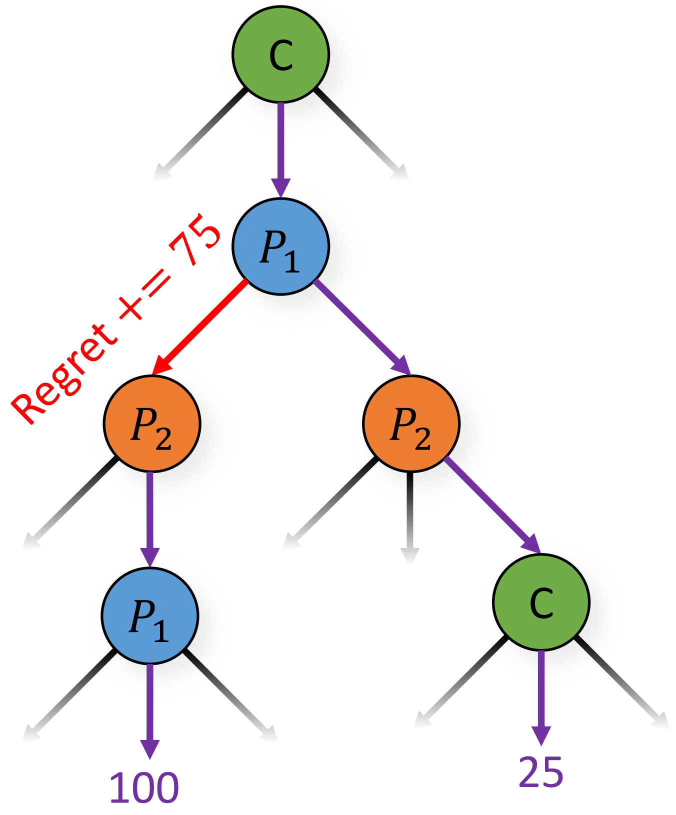
- This difference is added to the action's **regret**. In future iterations, actions with higher regret are chosen with higher probability



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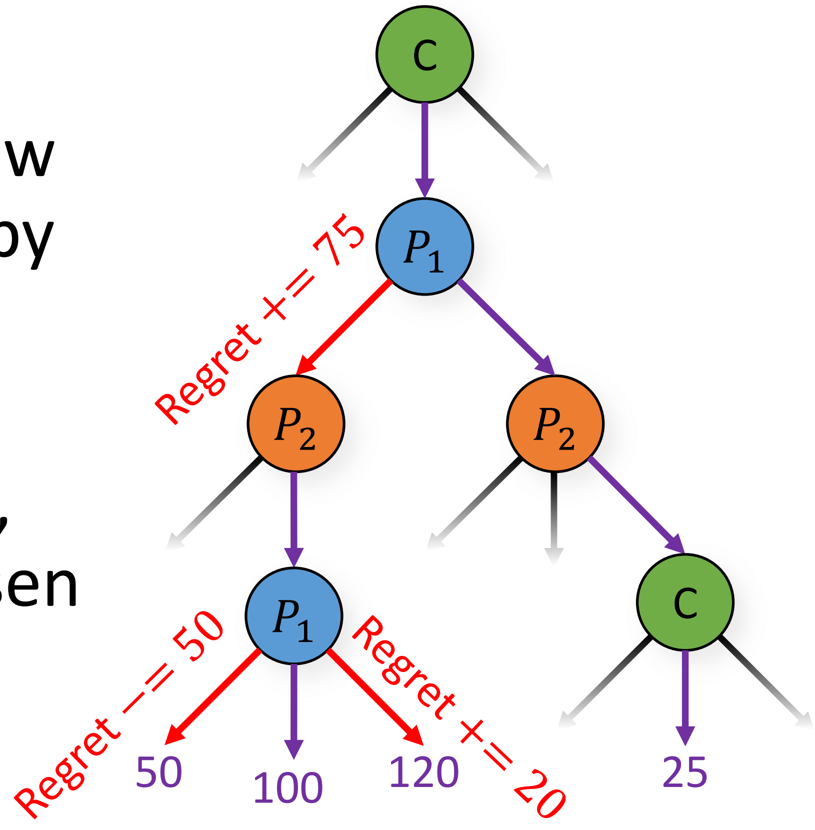
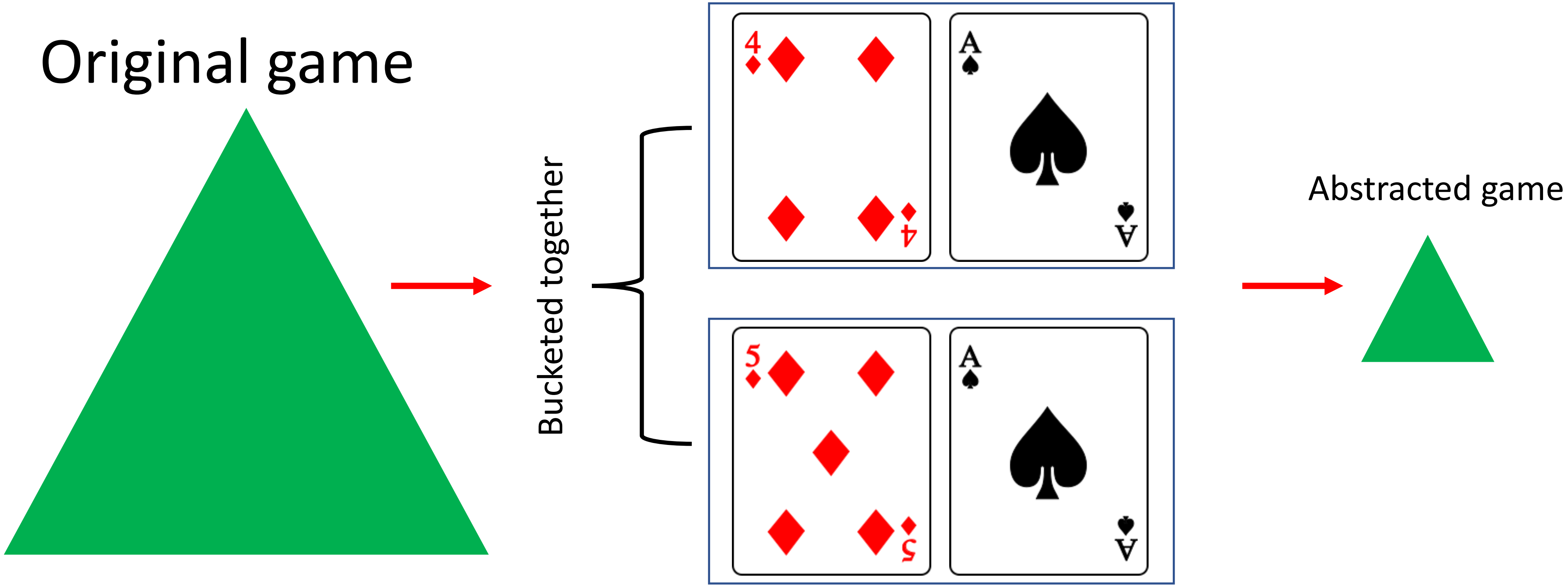
- Process repeats even for hypothetical decision points



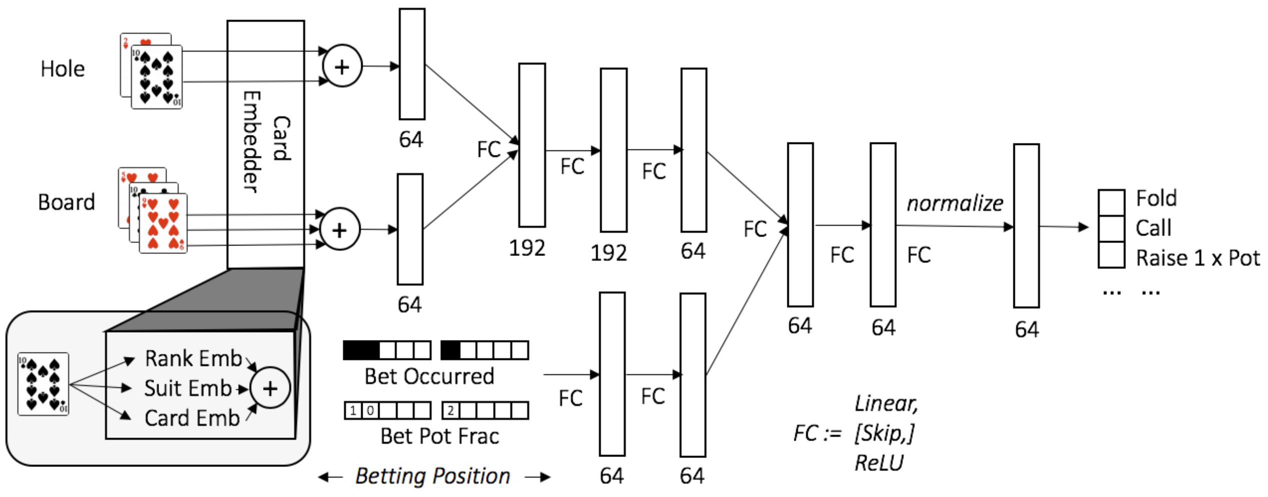
Prior Approach: Abstraction in Games



- Requires extensive domain knowledge
  - Several papers written on how to do abstraction just in poker
  - Difficult to extend to other games

Deep CFR

- **Input:** low-level features (visible cards, observed actions)
- **Output:** estimate of action regrets
- On each iteration:
  1. Collect samples of action regrets, add to a buffer
  2. Train a network to predict regrets
  3. Use network's regret estimates to play on next iteration



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- **Theorem:** With arbitrarily high probability, Deep CFR converges to an ϵ-Nash equilibrium in two-player zero-sum games, where ϵ is determined by prediction error

Experimental results in limit Texas hold'em

- Deep CFR produces superhuman performance in heads-up limit Texas hold'em poker
  - ~ 10 trillion decision points
  - Once played competitively by humans
- Deep CFR outperforms Neural Fictitious Self Play (NFSP), the prior best deep RL algorithm for partially observable games [Heinrich & Silver arXiv-15]
  - Deep CFR is also much more sample efficient
- Deep CFR is competitive with domain-specific abstraction algorithms

Conclusions

- Among algorithms for non-tabular solving of partially-observable games, Deep CFR is the **fastest, most sample-efficient, and produces the best results**

- Uses less domain knowledge than abstraction-based approaches, making it easier to apply to other games