# Deep CFR for HUNL

Nima Chitsazan
Foad Khoshouei
Ridhi Mahajan

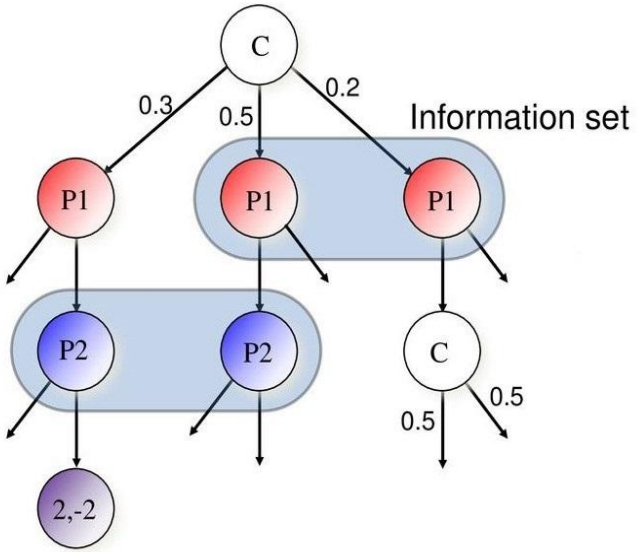
(Team 6)

# Imperfect Information Games

- Information available to the agent is limited (Meyerson 1997)
- Applications: Negotiation, Managing Online Auction, Navigating Traffic
- Poker has been widely used for testing
- Solving the game is to find Nash Equilibrium
- No improvement by deviating from the equilibrium

# Related Work

- Counter-Factual Regret Minimization (CFR) (Zinkevich 2007)
- CFR+, Discounted CFR, Monte Carlo CFR (MCCFR)
- Deep CFR, Single Deep CFR
- Deep Reinforcement Learning- Neural Fictitious Self Play (NSFP) (Heinrich 2016)
- Deep Stack (Bowling 2017)
- Libratus (Brown 2018)
- Pluribus (Brown 2019)



# CFR, Deep CFR Methods

- CFR finds the Nash Equilibrium by minimizing Counter Factual Regret
- By iteratively updating the weights, it converges to Nash
- CFR is computationally expensive
- Deep CFR uses Neural Network to approximate the Regret

**Algorithm 1** Deep Counterfactual Regret Minimization

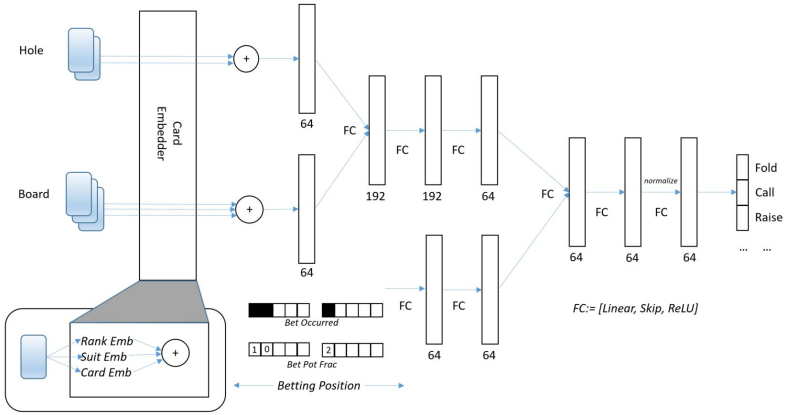
**function** DEEPCFR

Initialize each player's advantage network $V(I, a|\theta_p)$ with parameters $\theta_p$ so that it returns 0 for all inputs.
Initialize reservoir-sampled advantage memories $\mathcal{M}_{V,1}, \mathcal{M}_{V,2}$ and strategy memory $\mathcal{M}_\Pi$.
**for** CFR iteration $t = 1$ to $T$ **do**
  **for each** player $p$ **do**
    **for** traversal $k = 1$ to $K$ **do**
      TRAVERSE$(\emptyset, p, \theta_1, \theta_2, \mathcal{M}_{V,p}, \mathcal{M}_\Pi)$ ▷ Collect data from a game traversal with external sampling
    Train $\theta_p$ from scratch on loss $\mathcal{L}(\theta_p) = \mathbb{E}_{(I,t',\tilde{r}^{t'})\sim\mathcal{M}_{V,p}}\left[t' \sum_a \left(\tilde{r}^{t'}(a) - V(I, a|\theta_p)\right)^2\right]$
  Train $\theta_\Pi$ on loss $\mathcal{L}(\theta_\Pi) = \mathbb{E}_{(I,t',\sigma^{t'})\sim\mathcal{M}_\Pi}\left[t' \sum_a \left(\sigma^{t'}(a) - \Pi(I, a|\theta_\Pi)\right)^2\right]$
  **return** $\theta_\Pi$

Source: Deep Counterfactual Regret Minimization (Brown et al. 2019)

# Network Architecture

- Private cards and the community cards are embedded separately into two vectors with dimension 64.
- Followed by three dense layers with size 192 (Card Layers).
- Two dense layers of size 64 (Betting Layers). The information from the last betting layer and the last card layer are combined and conveyed through three (3) layers of size 64 (Comb- Layers).




Source: Deep Counterfactual Regret Minimization (Brown et al. 2019)

# Test Problem

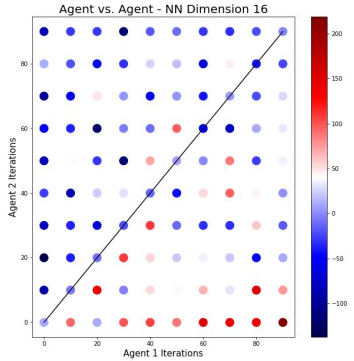
Leduc Poker:

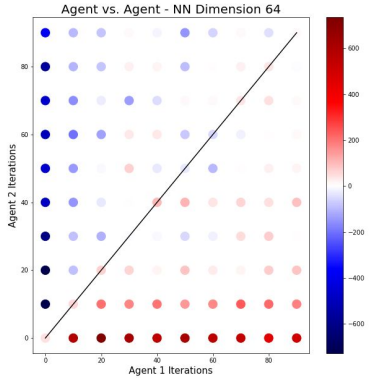
- 2 Suits, 3 Ranks of Each
- 1 Private Card
- 1 Community Card

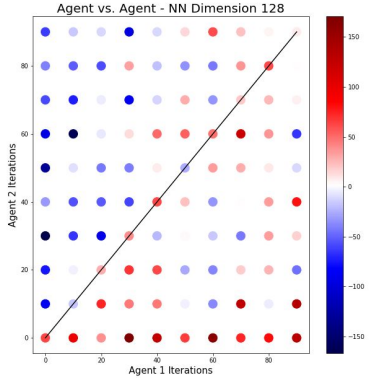
Heads-UP No Limit Holde'm (HUNL):

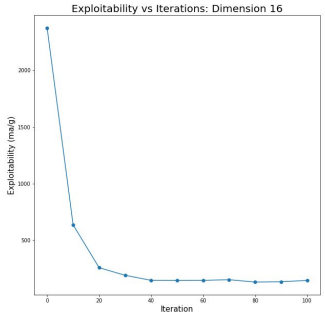
- 52 Cards
- 2 Private cards
- 5 Community Cards
- 4 Rounds of betting
- $10^{161}$ Game States

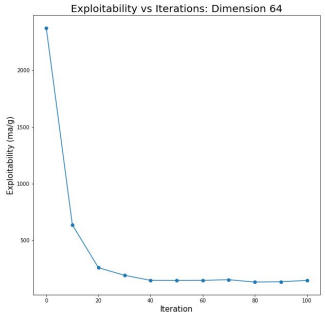
# Results For Leduc

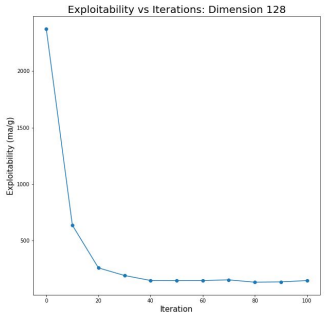


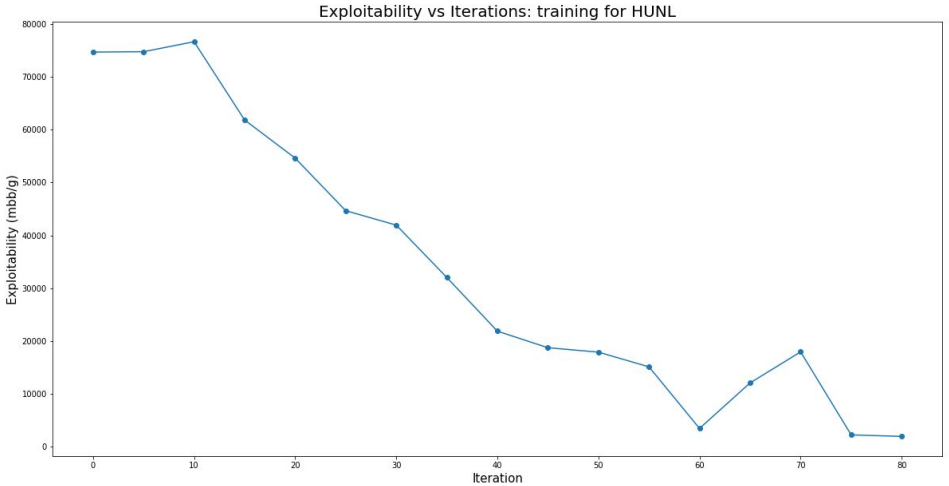



# Methods to Implement Deep-CFR for HUNL

| Issue | Solution | Implemented? |
|---|---|---|
| Large number of actions -- High branching factor | Action Abstraction | ✓ |
| High running time | Adaptive Traversals Per Iteration | ✓ |
| Costly function to compute | Local Best Response (LBR) | ✓ |
| Training the network from scratch at each iteration is slow | Warm Start -- Use weights from previous iteration | ✓ |
| Large number of states | Card Abstraction | ✗ |

# Results for HUNL

- Agent Trained on the game of HUNL
- Exploitability vs Iteration shown for HUNL
- Trained agent can play against humans reasonably

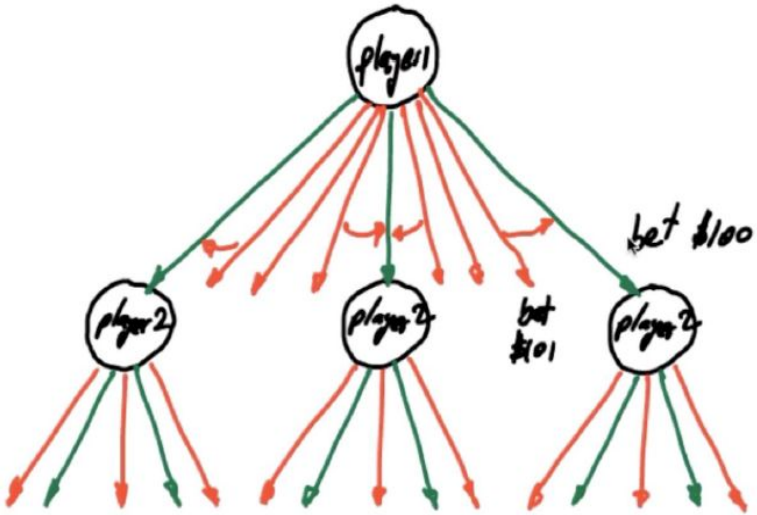


# Results for HUNL

# Conclusion and Future Work

- Adaptive Traversing
- Action Abstraction (Discretized Bets)

- Tree Pruning
- Card Abstraction




Source: Iddo Drori, Deep Learning Course, Summer 2019

Questions?