Aishik Pyne
Harshavardhan Abhichandani
Niharika Shrivastava

Deceptive Poker

Team ID: 8

**Agents learn to <u>cheat</u> via collaboration
in a competitive multi-agent RL environment**

Introduction

Problem Statement

Introduction

Problem Statement

Texas Hold'em Poker

A popular skill and luck based gambling game

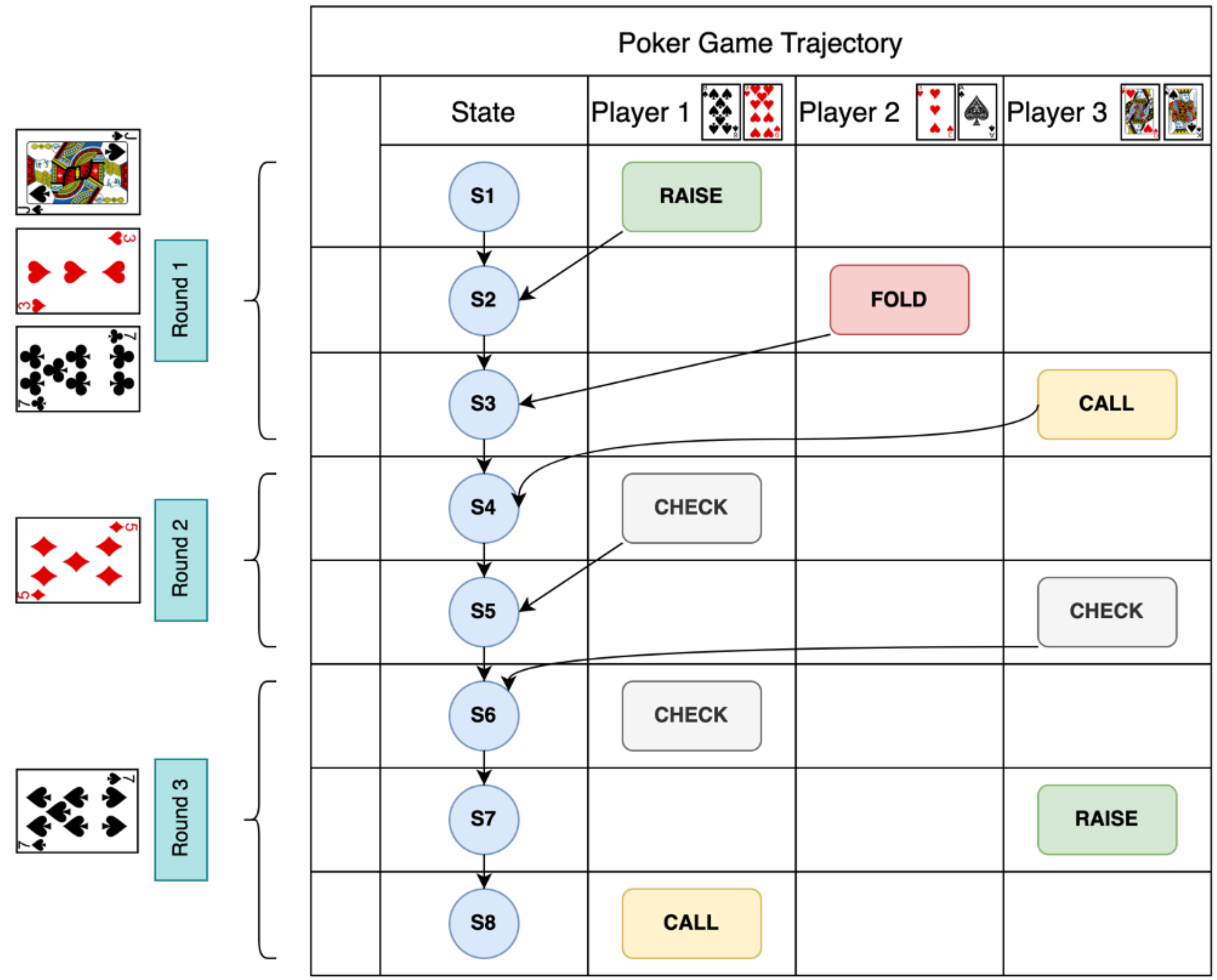
Introduction

Problem Statement

Texas Hold'em Poker

A popular skill and luck based gambling game

One Game of Poker



Winner gets all chips

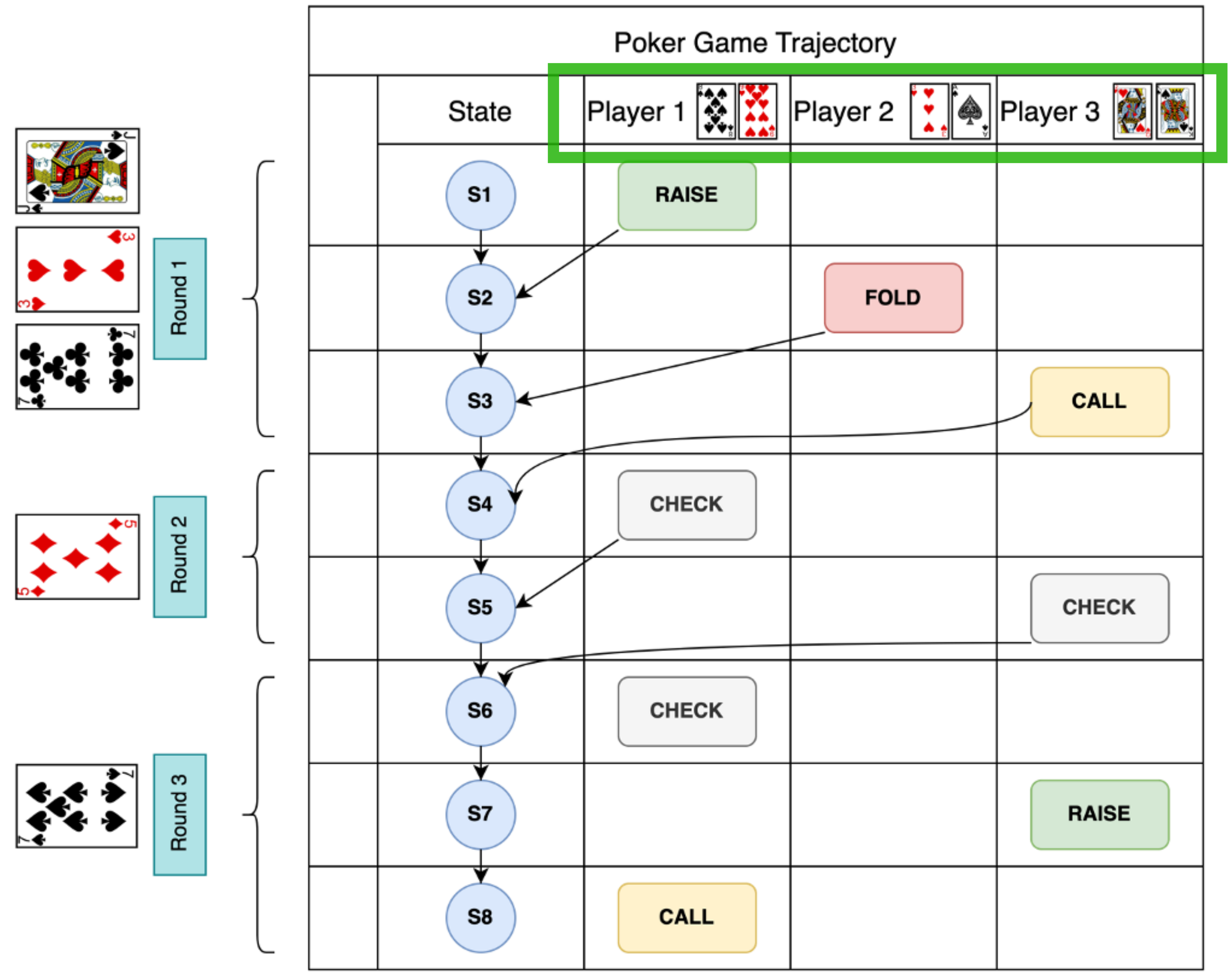
Introduction

Problem Statement

Texas Hold'em Poker

A popular skill and luck based gambling game

One Game of Poker



Winner gets all chips

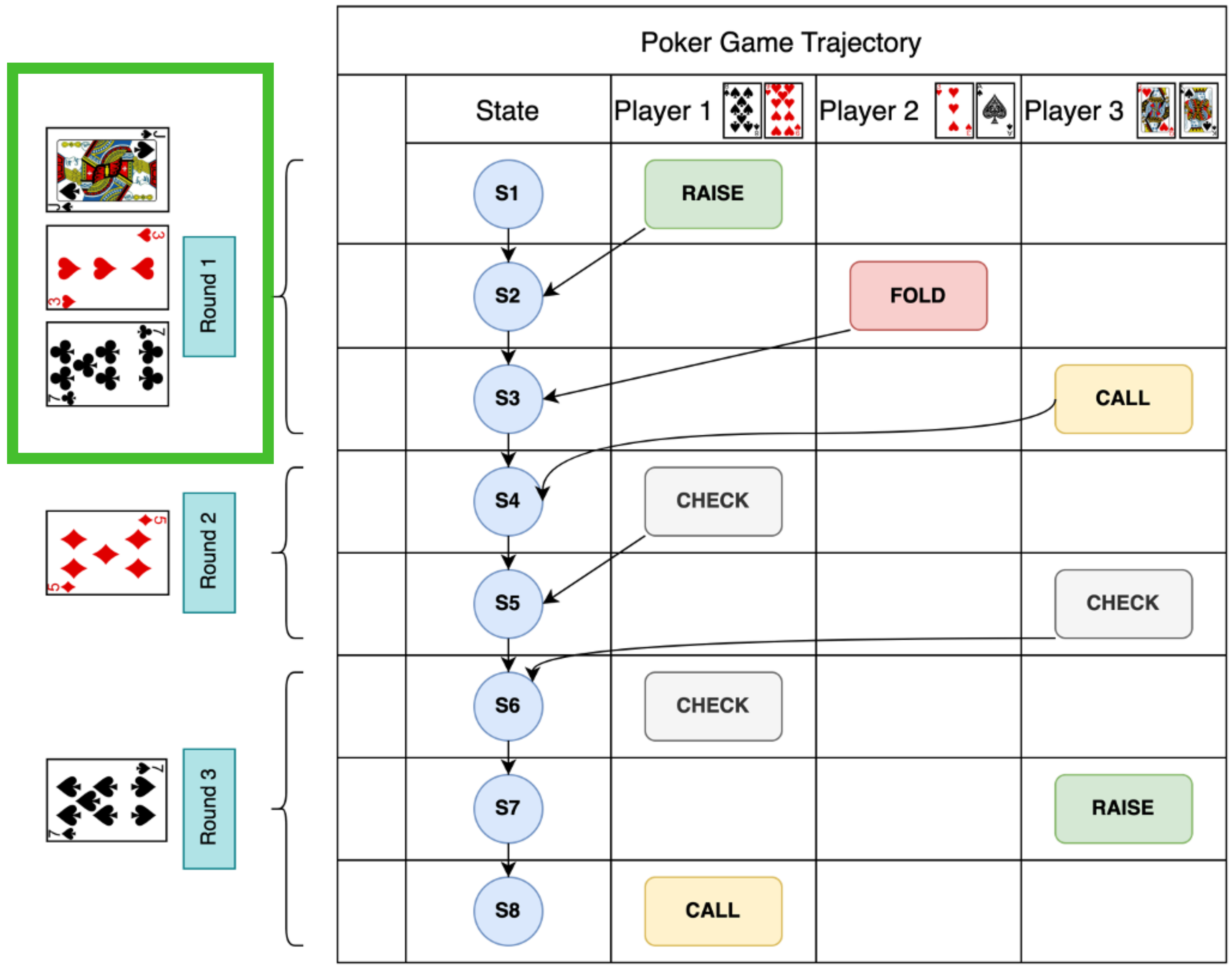
Introduction

Problem Statement

Texas Hold'em Poker

A popular skill and luck based gambling game

One Game of Poker



Winner gets all chips

Introduction

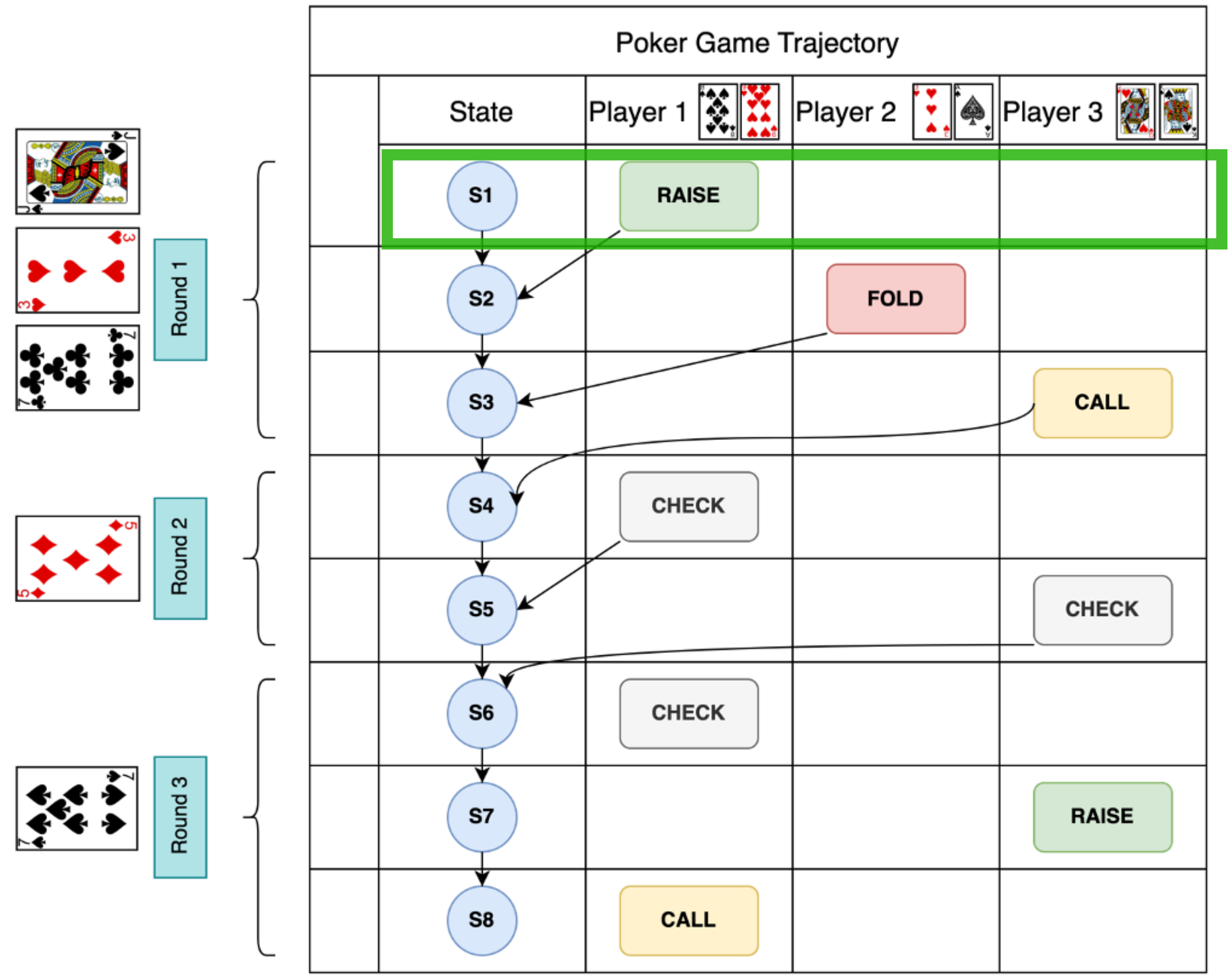
Problem Statement

CALL RAISE CHECK FOLD

One Game of Poker

Texas Hold'em Poker

A popular skill and luck based gambling game



Winner gets all chips

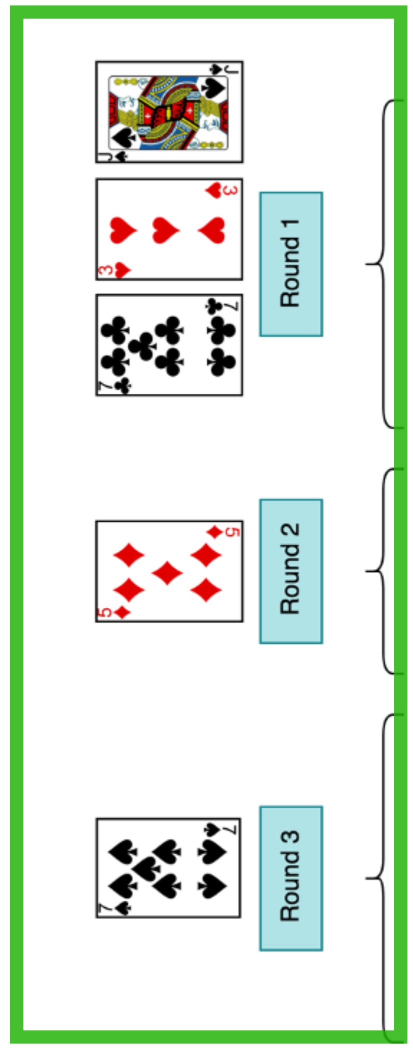
Introduction

Problem Statement

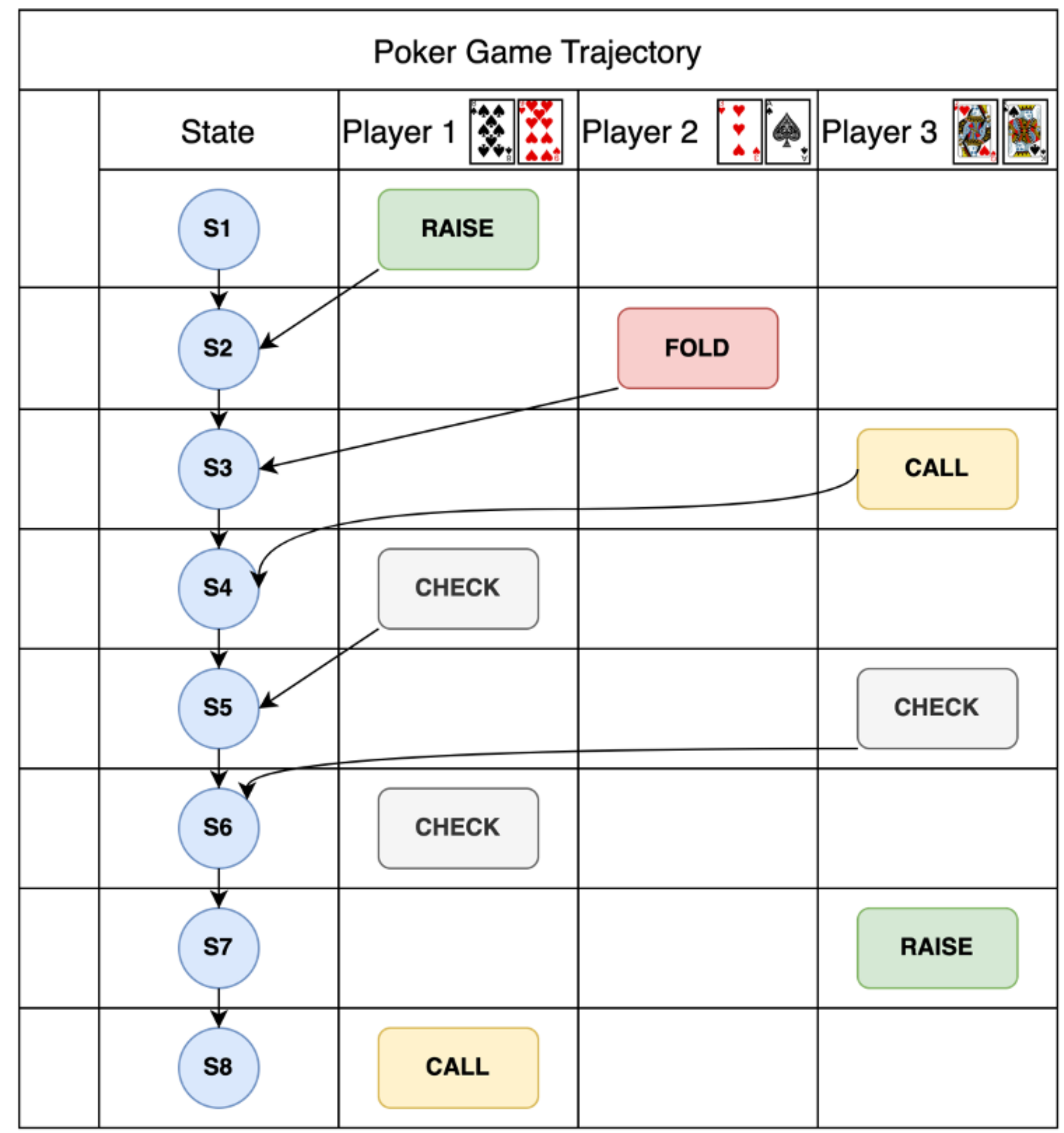
CALL RAISE CHECK FOLD

Texas Hold'em Poker

A popular skill and luck based gambling game



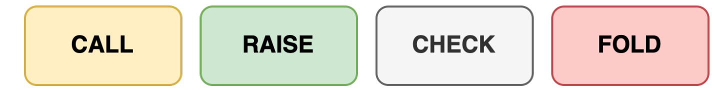
One Game of Poker



Winner gets all chips

Introduction

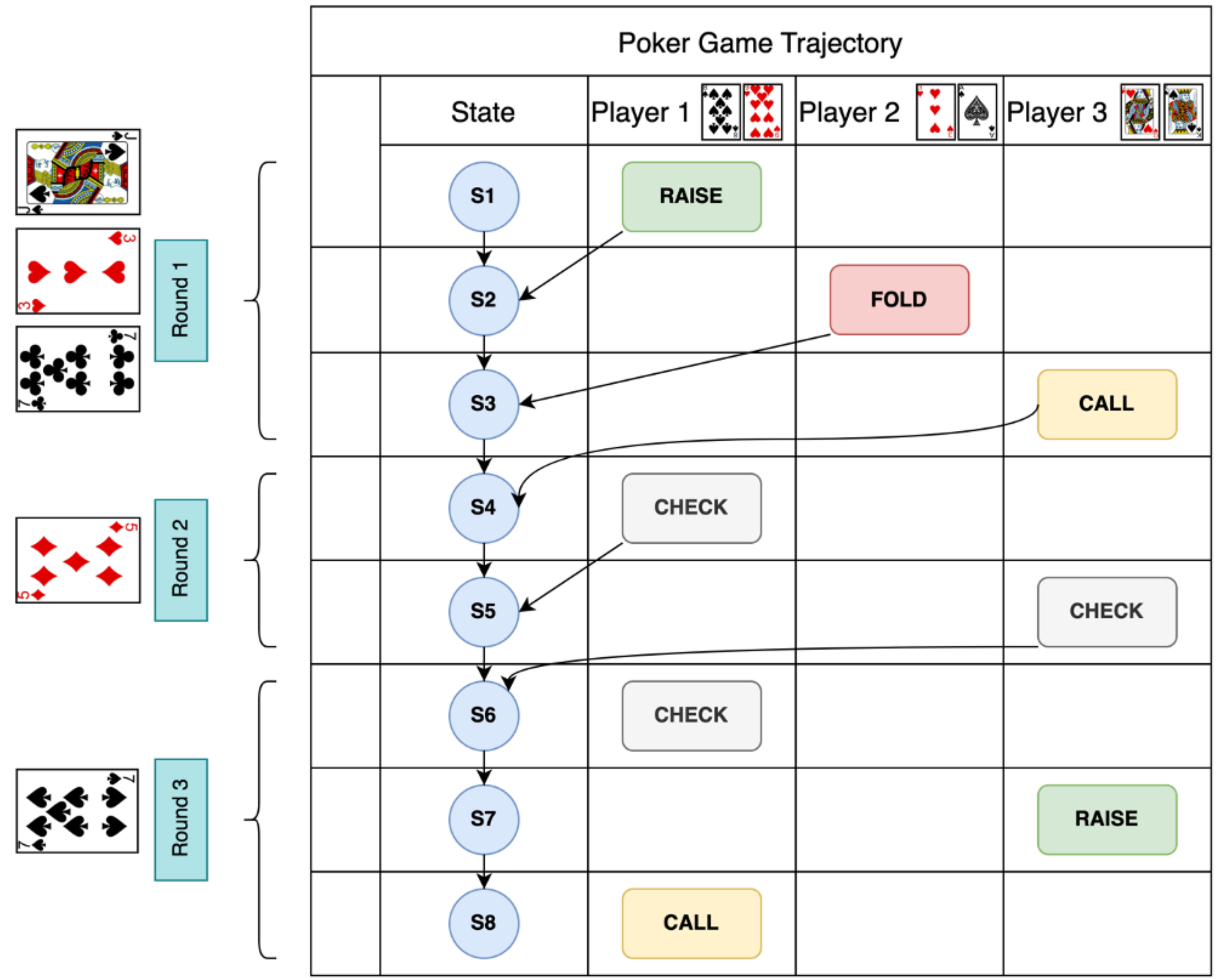
Problem Statement



Texas Hold'em Poker

A popular skill and luck based gambling game

One Game of Poker



Winner gets all chips

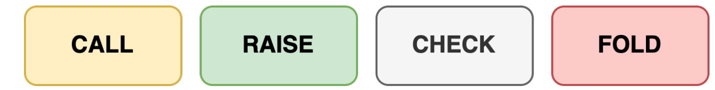
Introduction

Problem Statement

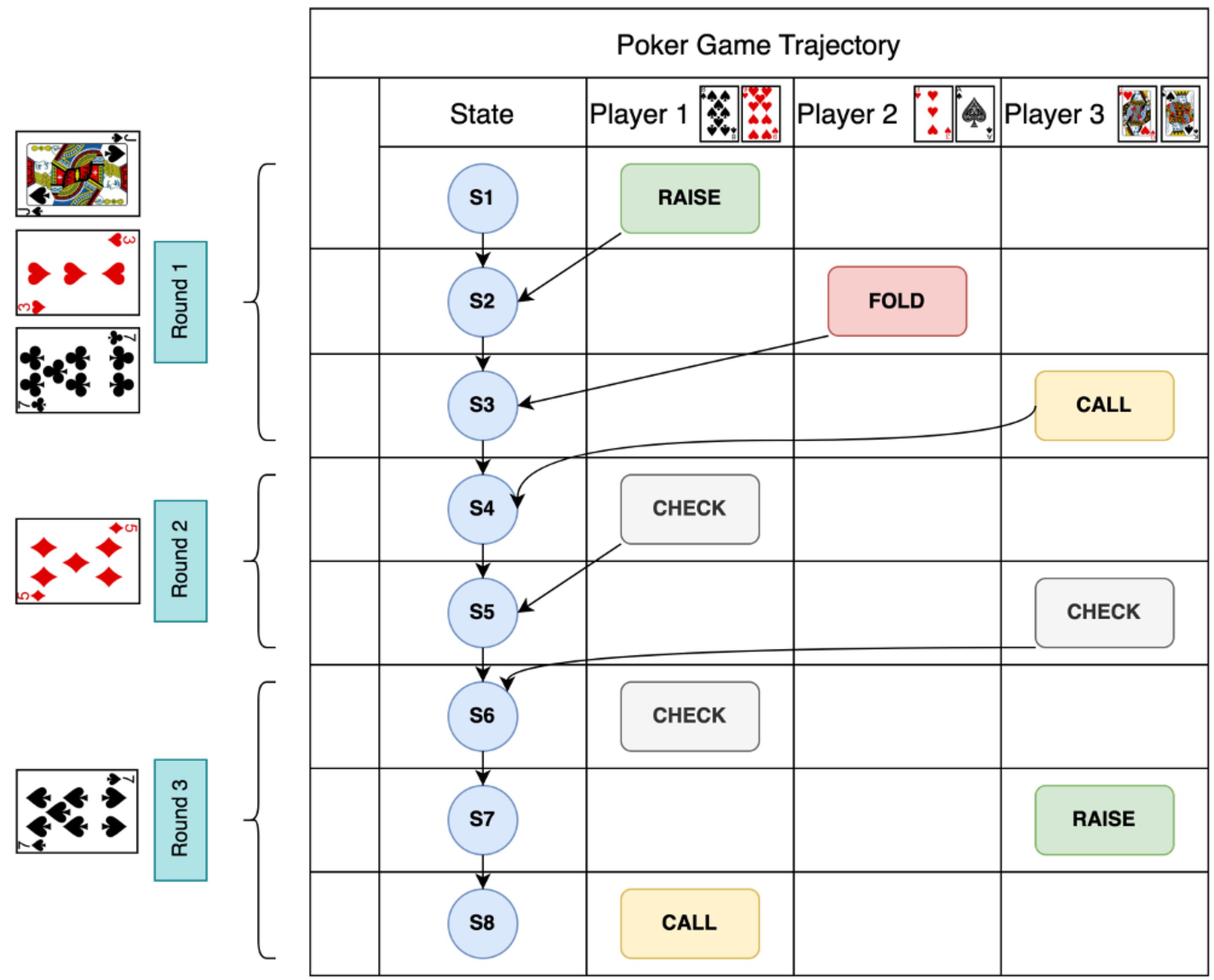
Texas Hold'em Poker

A popular skill and luck based gambling game

Modelling Poker in RL Setting



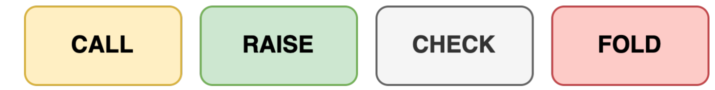
One Game of Poker



Winner gets all chips

Introduction

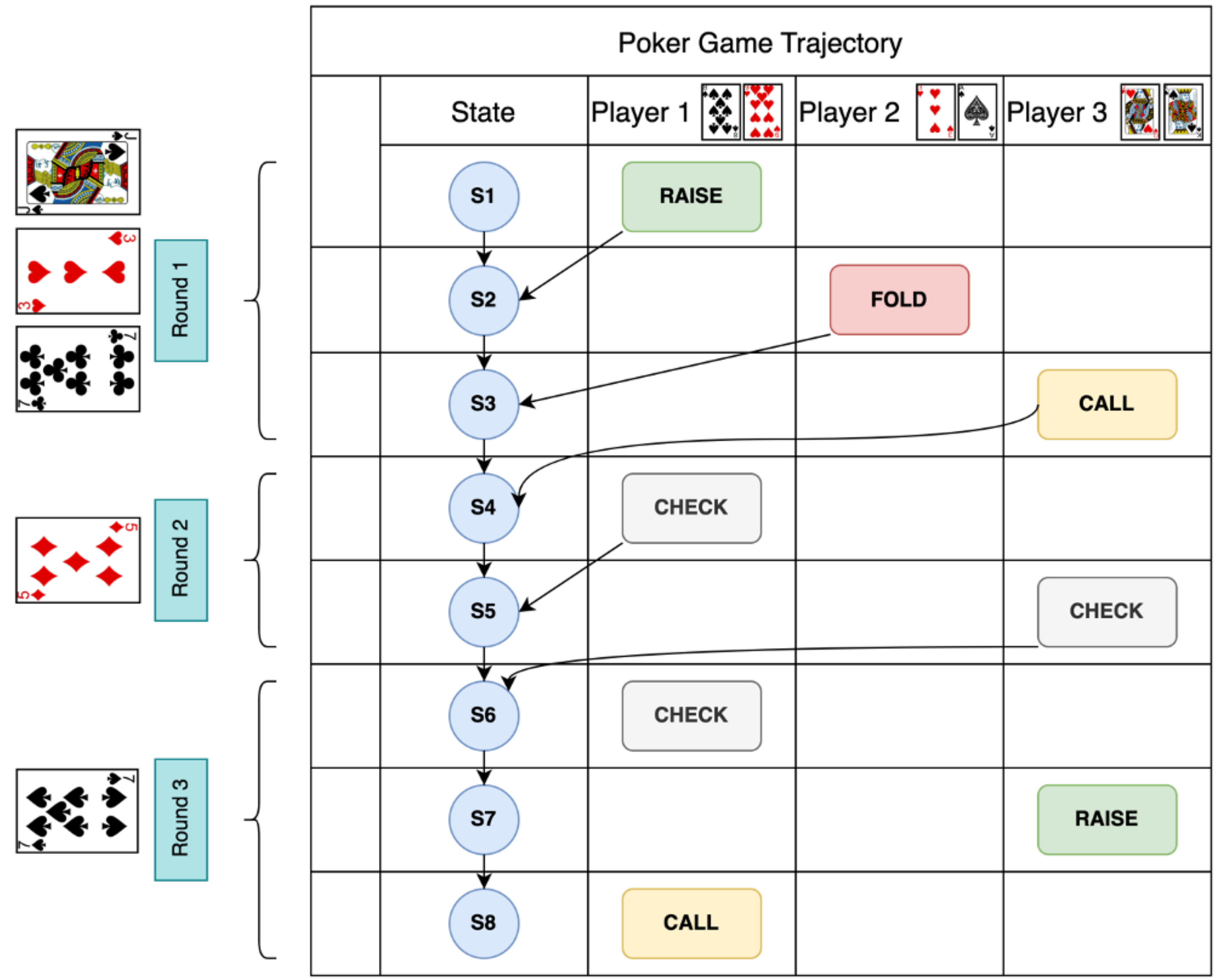
Problem Statement



One Game of Poker

Texas Hold’em Poker

A popular skill and luck based gambling game



Winner gets all chips

Modelling Poker in RL Setting

- Partially Observable

Introduction

Problem Statement

Texas Hold'em Poker

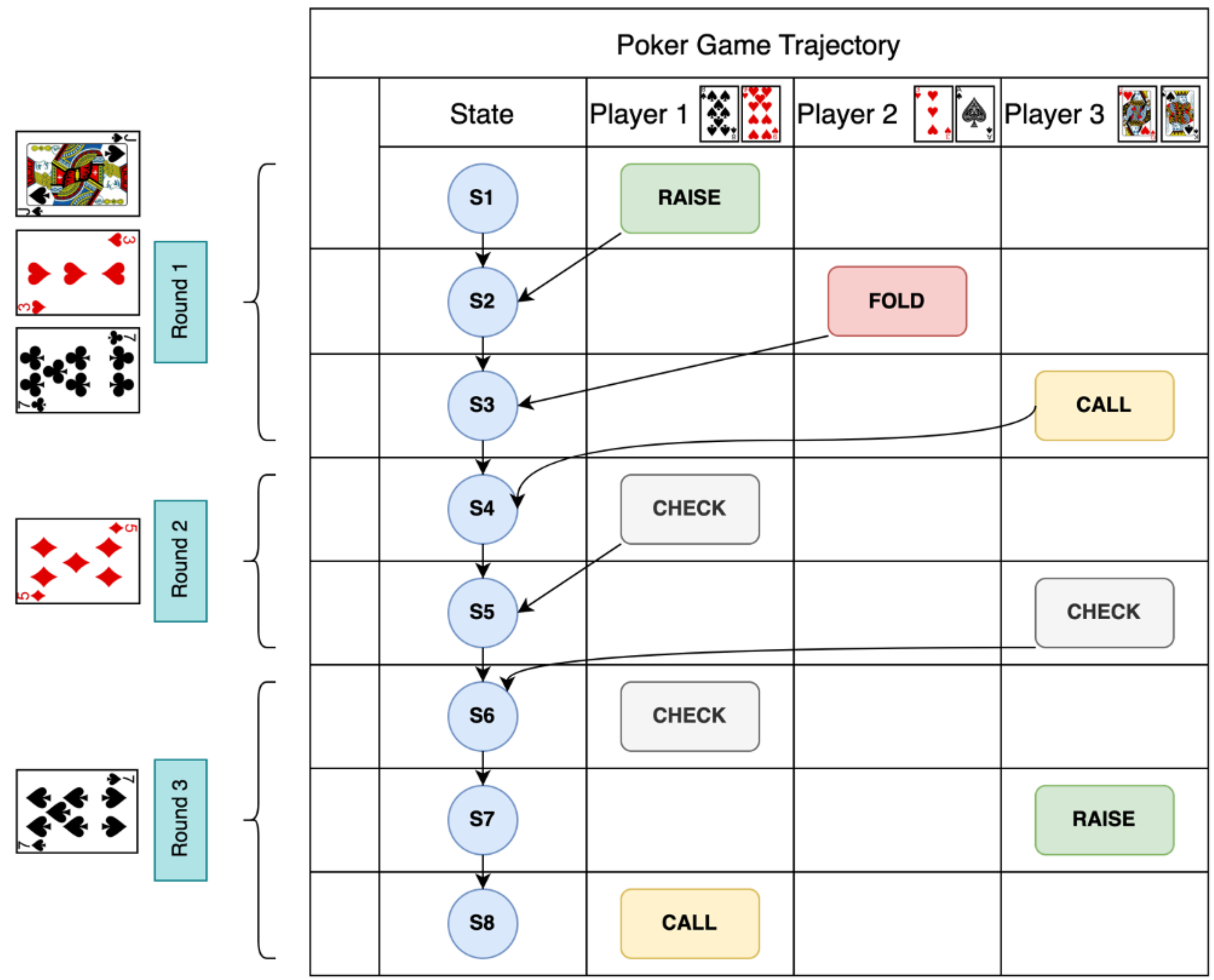
A popular skill and luck based gambling game

Modelling Poker in RL Setting

- Partially Observable
- Multi-Agent Zero-Sum

CALL RAISE CHECK FOLD

One Game of Poker



Winner gets all chips

Introduction

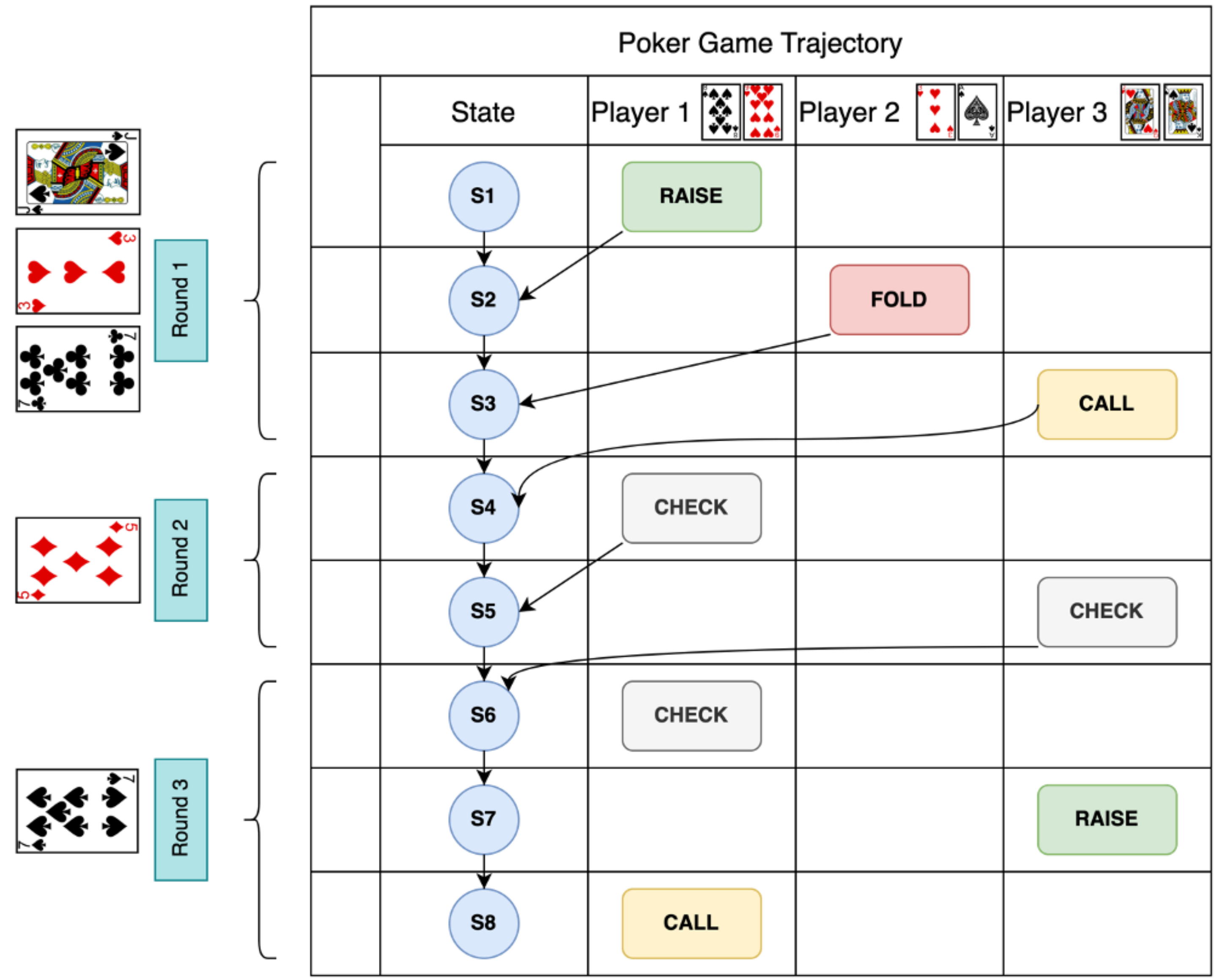
Problem Statement

CALL RAISE CHECK FOLD

One Game of Poker

Texas Hold'em Poker

A popular skill and luck based gambling game



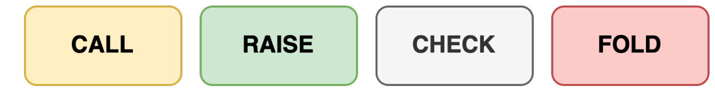
Winner gets all chips

Modelling Poker in RL Setting

- Partially Observable
- Multi-Agent Zero-Sum
- Extensive Form game

Introduction

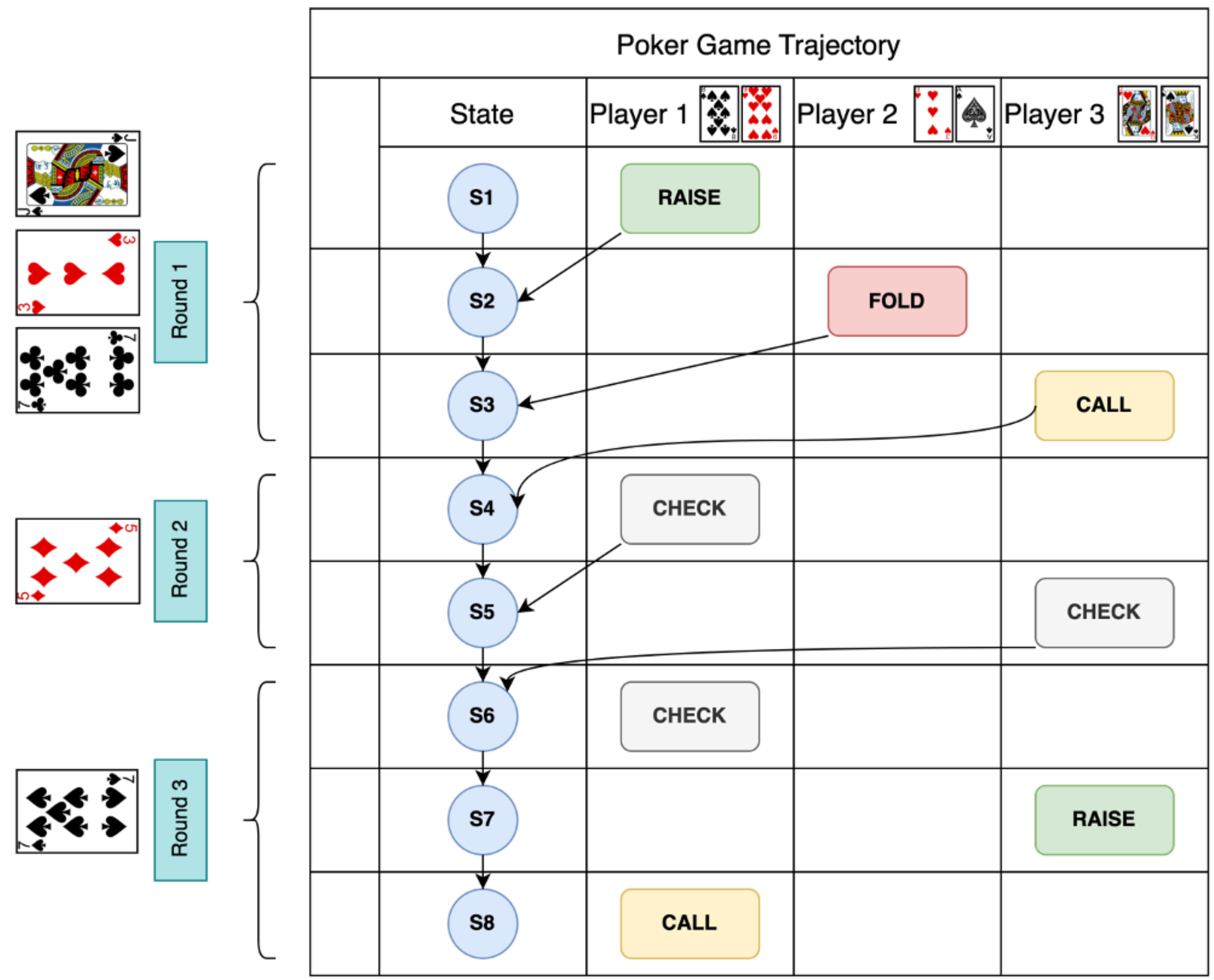
Problem Statement



One Game of Poker

Texas Hold’em Poker

A popular skill and luck based gambling game



Winner gets all chips

Modelling Poker in RL Setting

- Partially Observable
- Multi-Agent Zero-Sum
- Extensive Form game
- Intractable State-Space: 10^{14}

Introduction
Objectives

Introduction

Objectives

- Train fully competitive agent to play poker.

Training Brain 1

Introduction

Objectives

- Train fully competitive agent to play poker.
- Train agents that learn to cheat via collaboration.

Training Brain 1

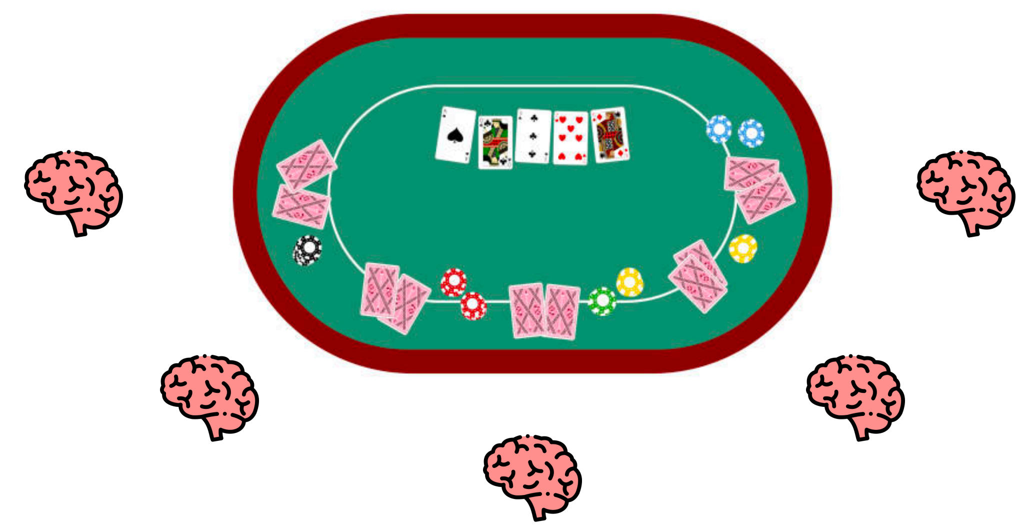
Training Brain 2

Introduction

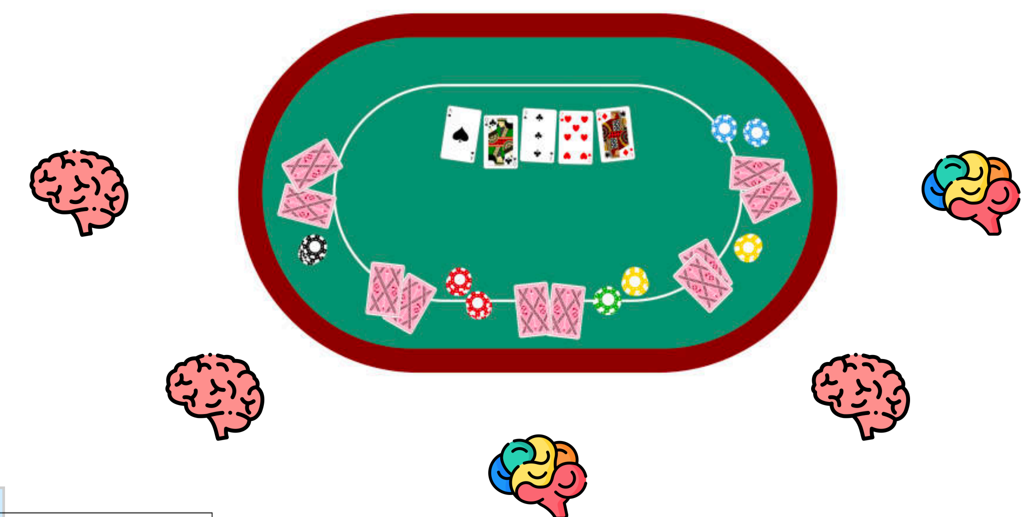
Objectives

- Train fully competitive agent to play poker.
- Train agents that learn to cheat via collaboration.
- Create a classifier which can detect agents that are cheating.

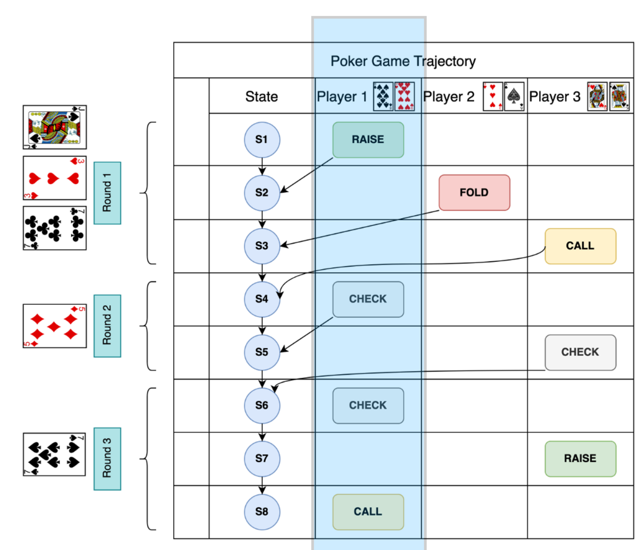
Training Brain 1



Training Brain 2



$$p(\{B_1, B_2\} \mid \tau)$$



Brain 1:
Training Fully Competitive Agents

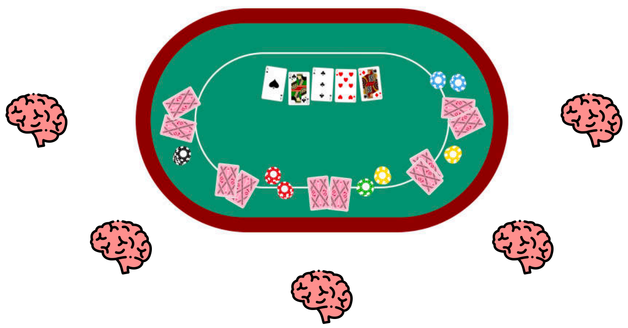
Brain 1: Competitive Agents

Algorithm

Brain 1: Competitive Agents

Algorithm

Training Brain 1



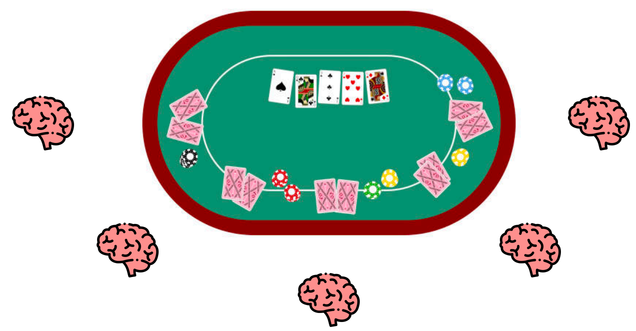
State Space

- Hand Cards
- Community Cards
- History of Raises

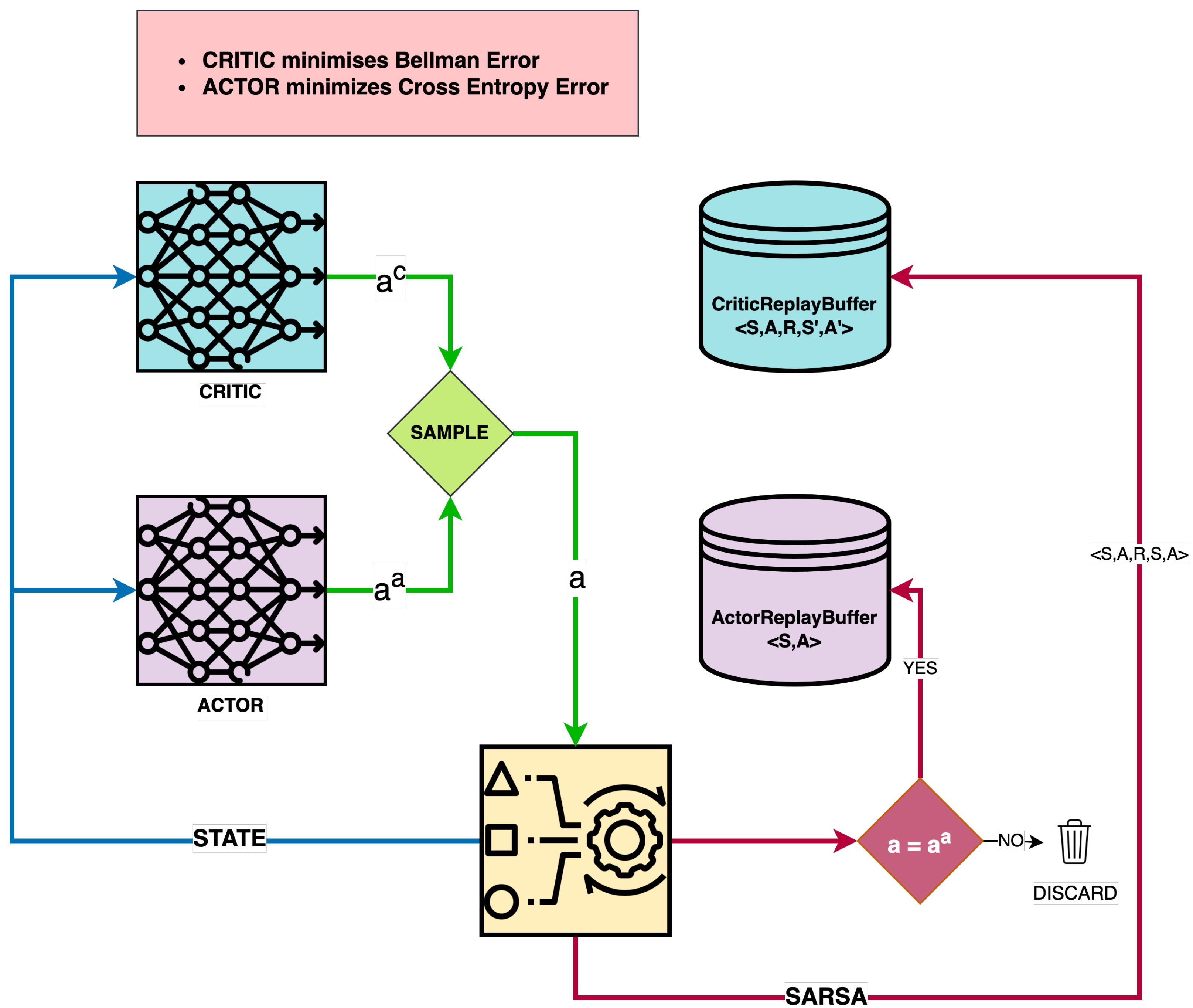
Brain 1: Competitive Agents

Algorithm

Training Brain 1



Neural Fictitious Self Play



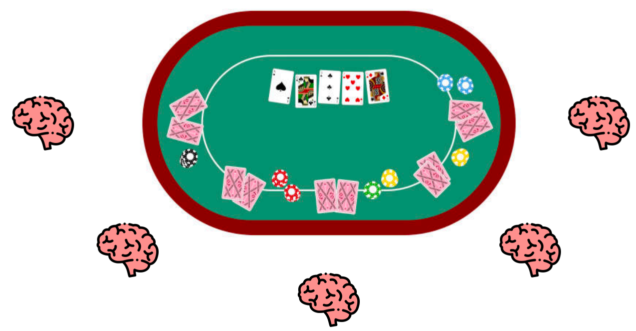
State Space

- Hand Cards
- Community Cards
- History of Raises

Brain 1: Competitive Agents

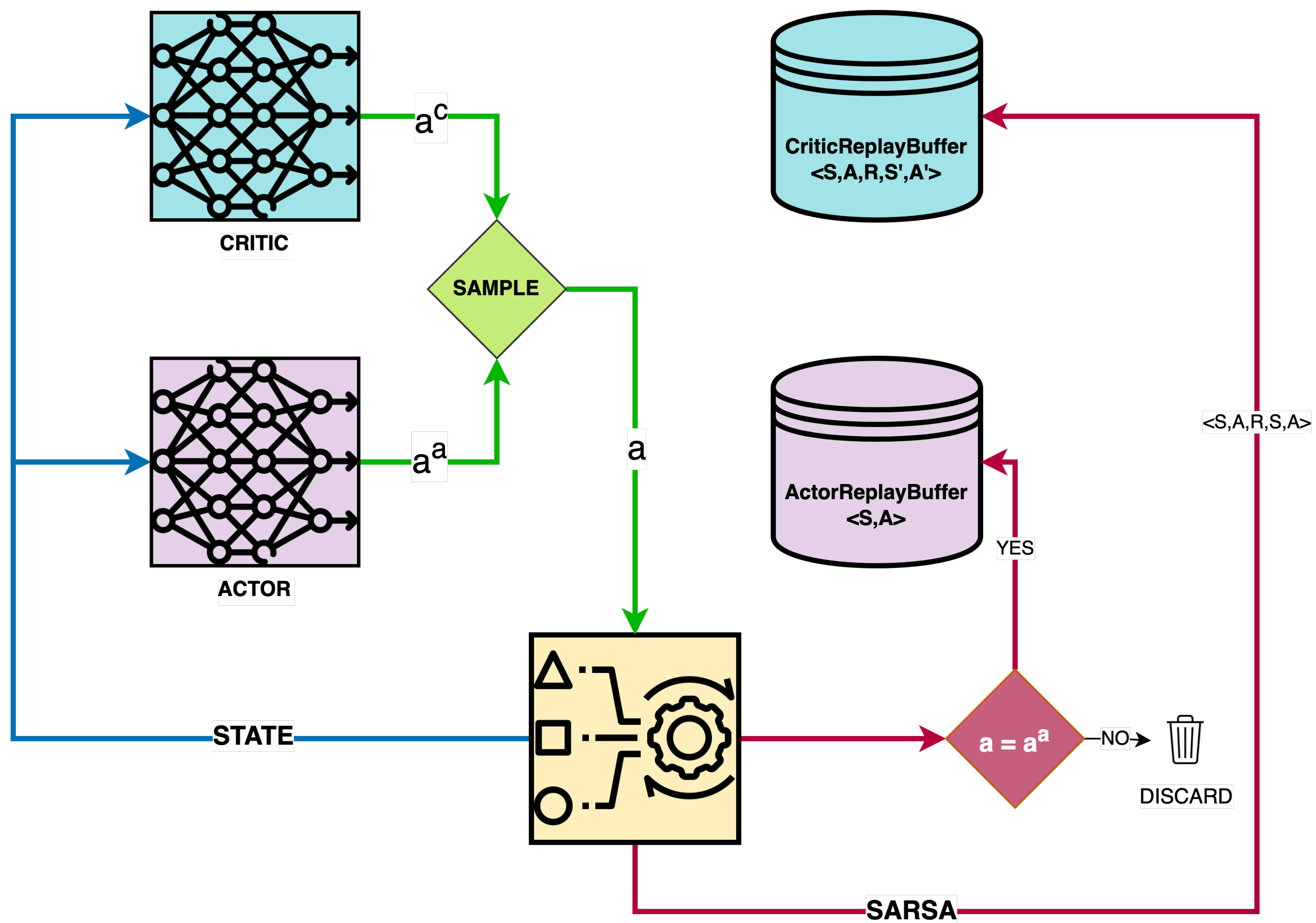
Algorithm

Training Brain 1



Neural Fictitious Self Play

- CRITIC minimises Bellman Error
- ACTOR minimizes Cross Entropy Error



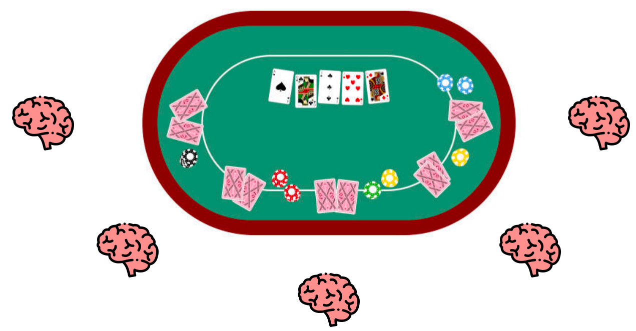
State Space

- Hand Cards
- Community Cards
- History of Raises

Brain 1: Competitive Agents

Algorithm

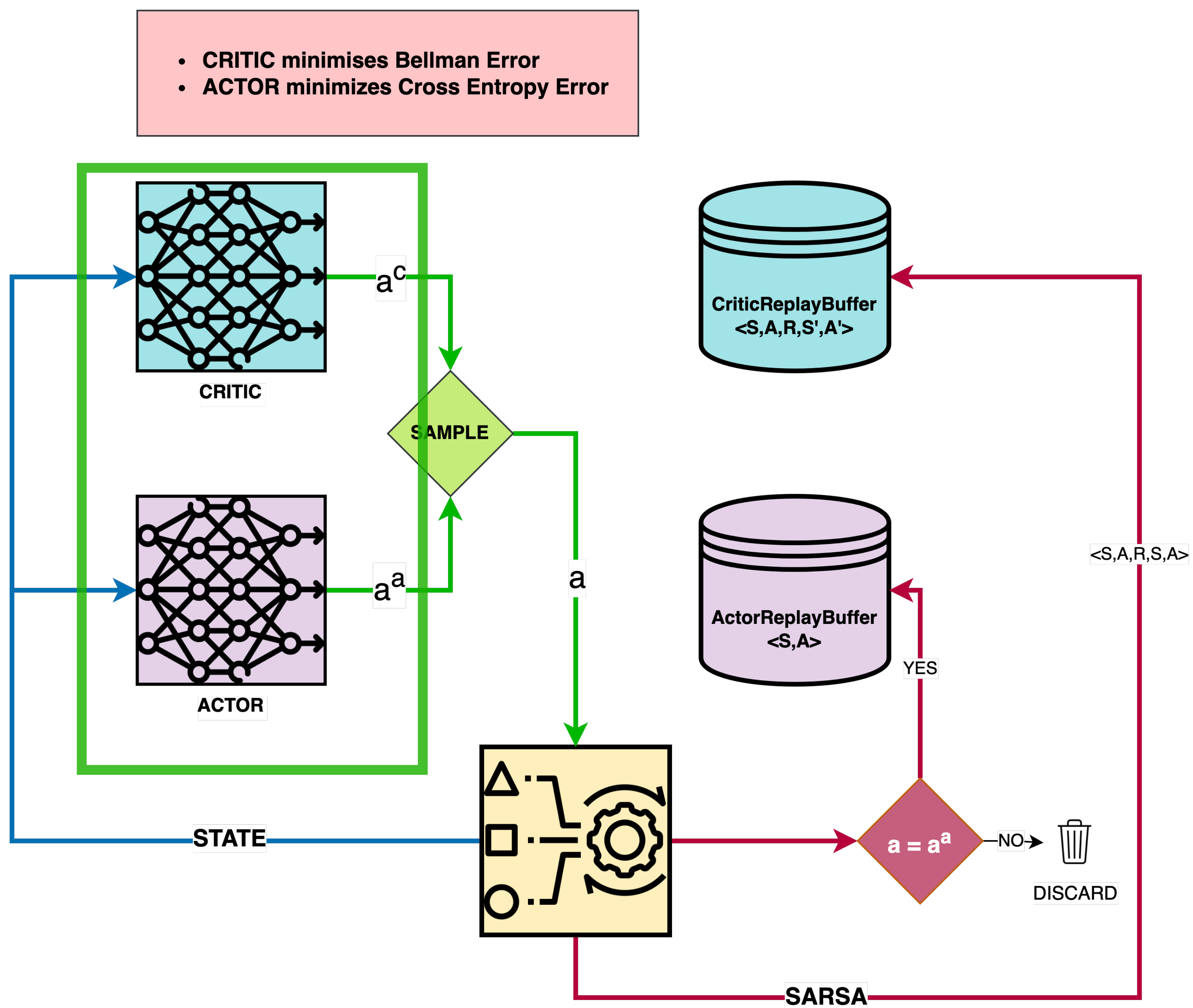
Training Brain 1



State Space

- Hand Cards
- Community Cards
- History of Raises

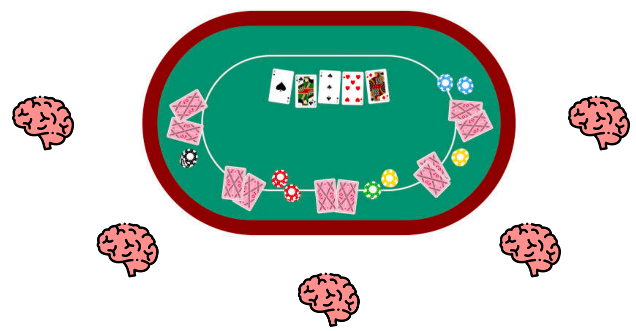
Neural Fictitious Self Play



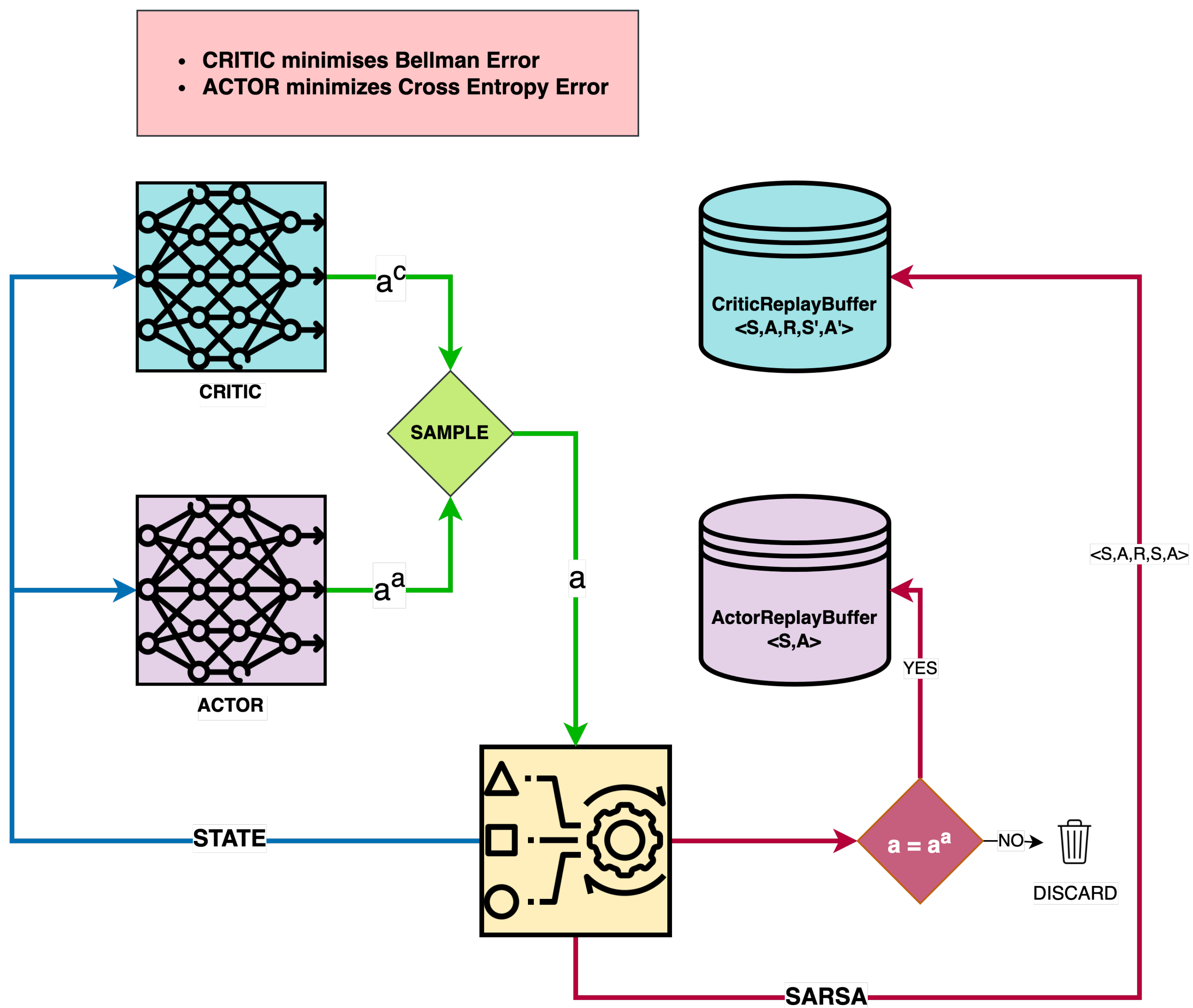
Brain 1: Competitive Agents

Algorithm

Training Brain 1



Neural Fictitious Self Play



State Space

- Hand Cards
- Community Cards
- History of Raises

Evaluation

- NSFP consistently beats a Rule Based agent with **win-ratio** 3.65

Brain 2: Training Collaborative Agents

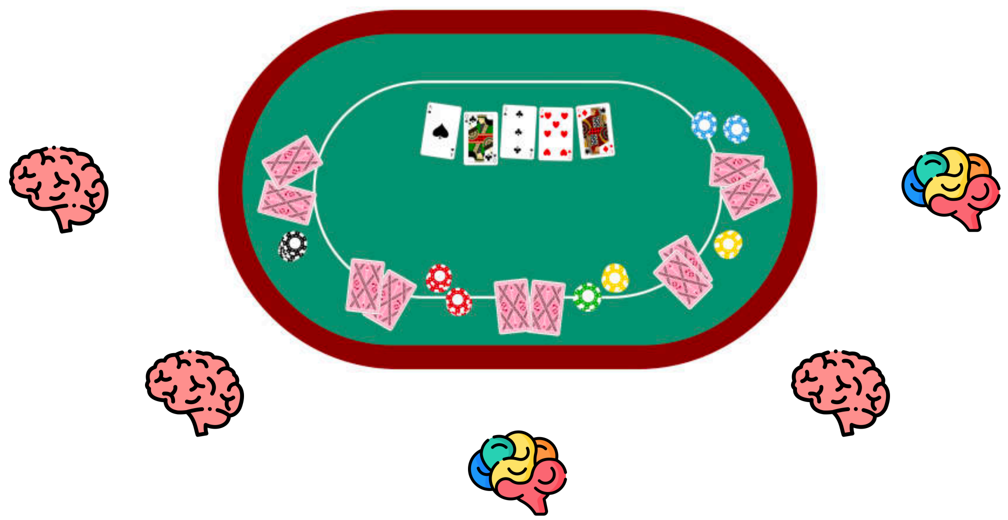
Brain 2: Collaborative Agents

Setup

Brain 2: Collaborative Agents

Setup

Training Brain 2

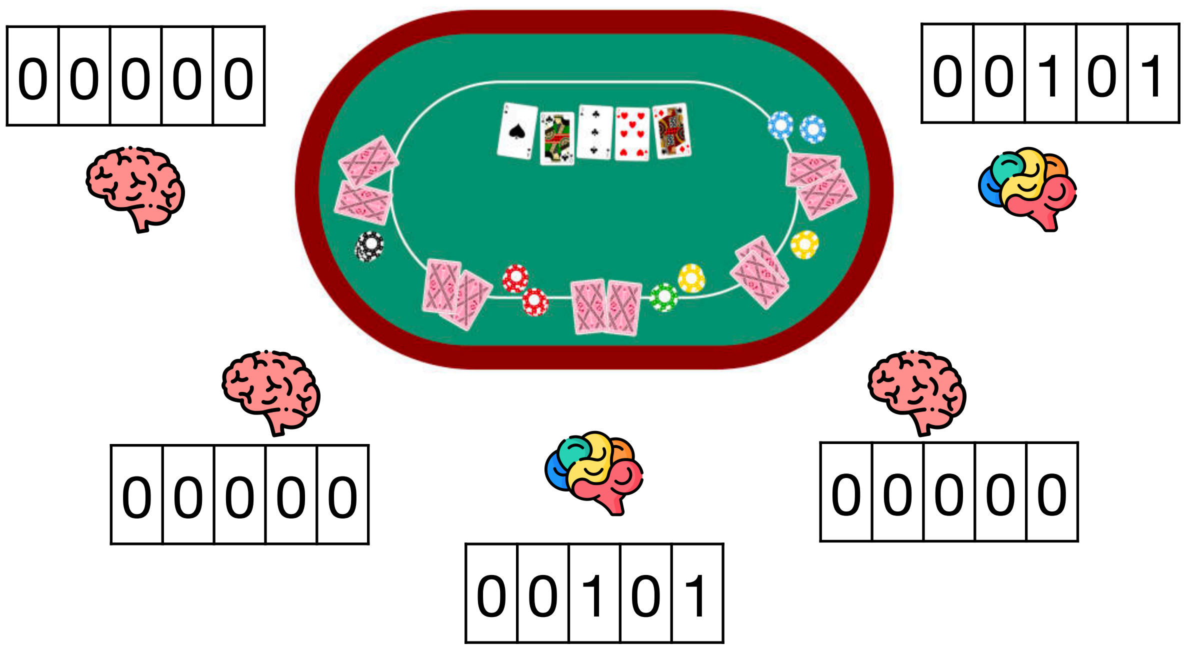


Brain 2: Collaborative Agents

Setup

- Add context to the agents as to who their partner is by indicating which historical raises were made by the agent's partner

Training Brain 2

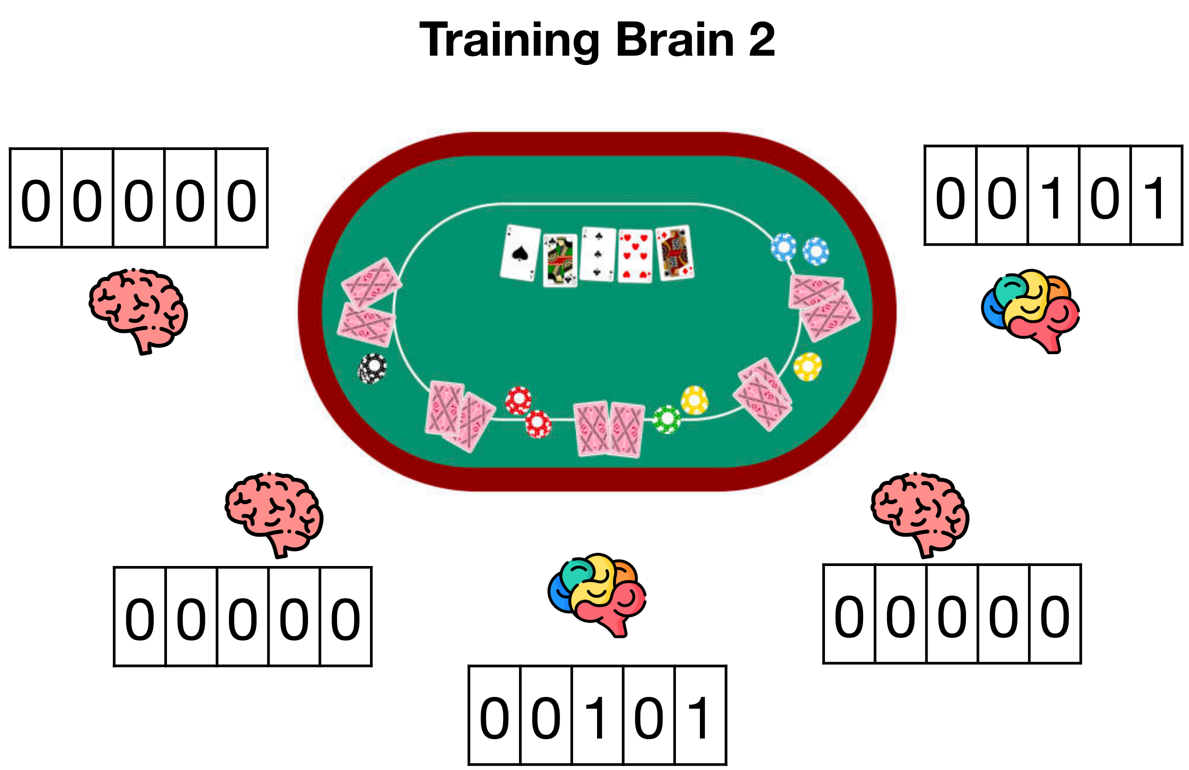


Brain 2: Collaborative Agents

Setup

- Add context to the agents as to who their partner is by indicating which historical raises were made by the agent's partner

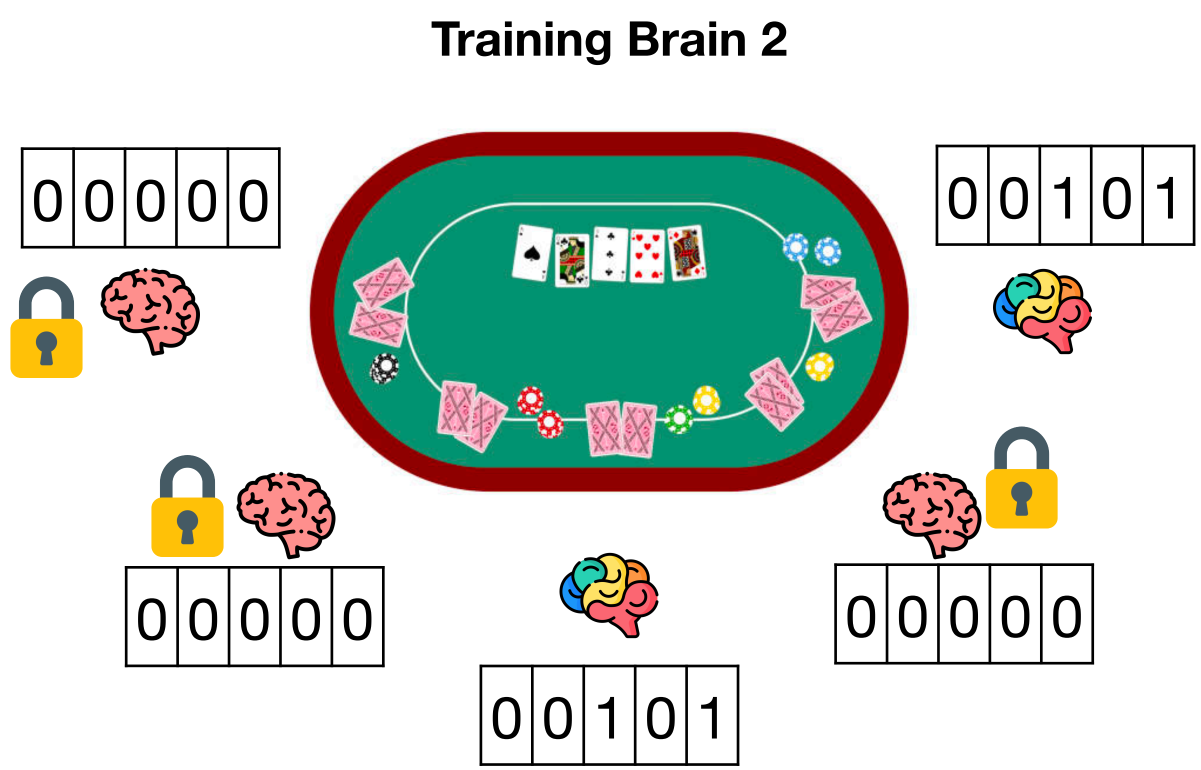
- Update the reward function:
  - Either agent wins: Max Winning
  - Both agents lose: Avg Loss



Brain 2: Collaborative Agents

Setup

- Add context to the agents as to who their partner is by indicating which historical raises were made by the agent's partner
- Update the reward function:
  - Either agent wins: Max Winning
  - Both agents lose: Avg Loss
- Freeze the competitive agents during training

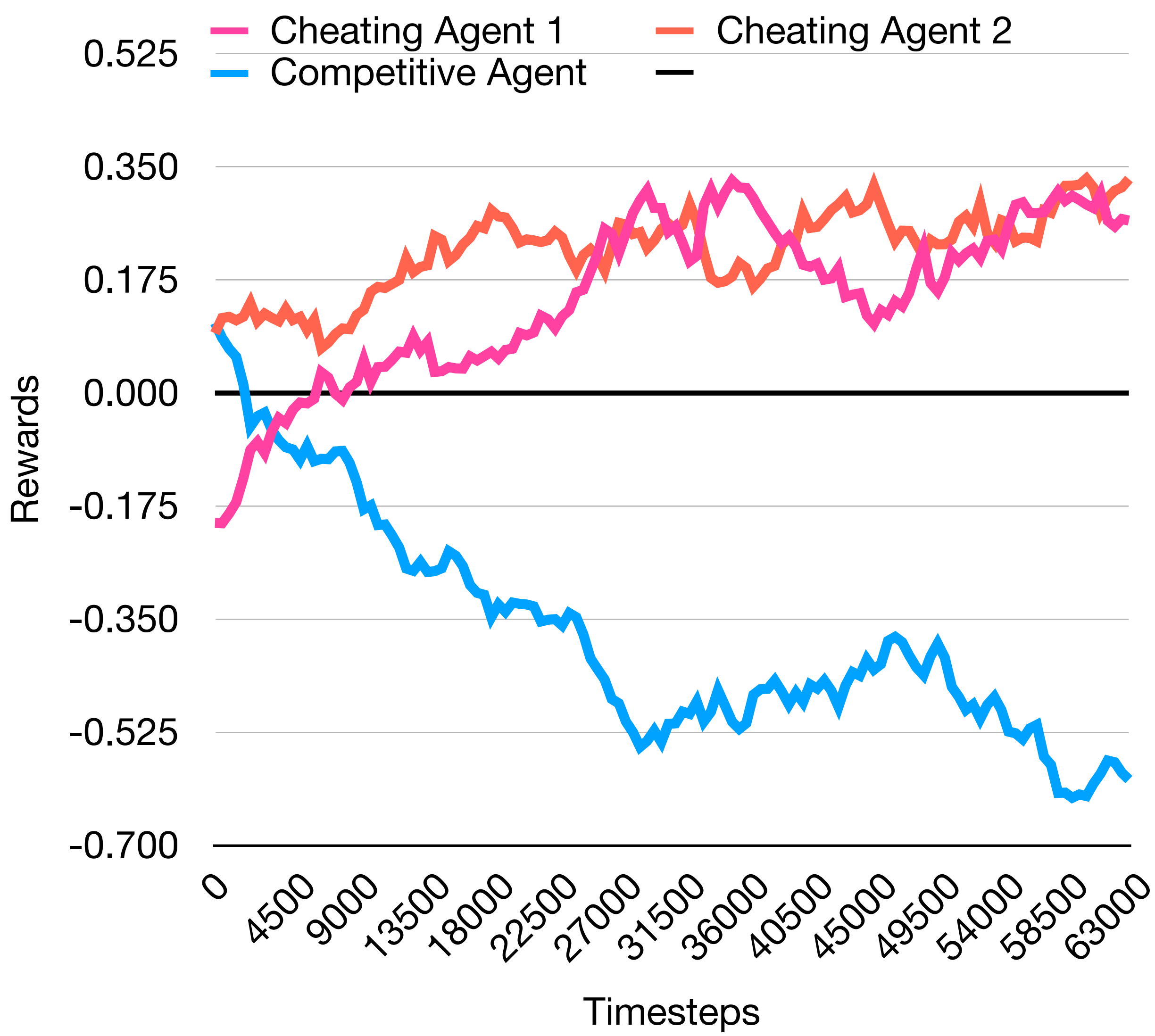


Brain 2: Collaborative Agents

Training and Results

Brain 2: Collaborative Agents

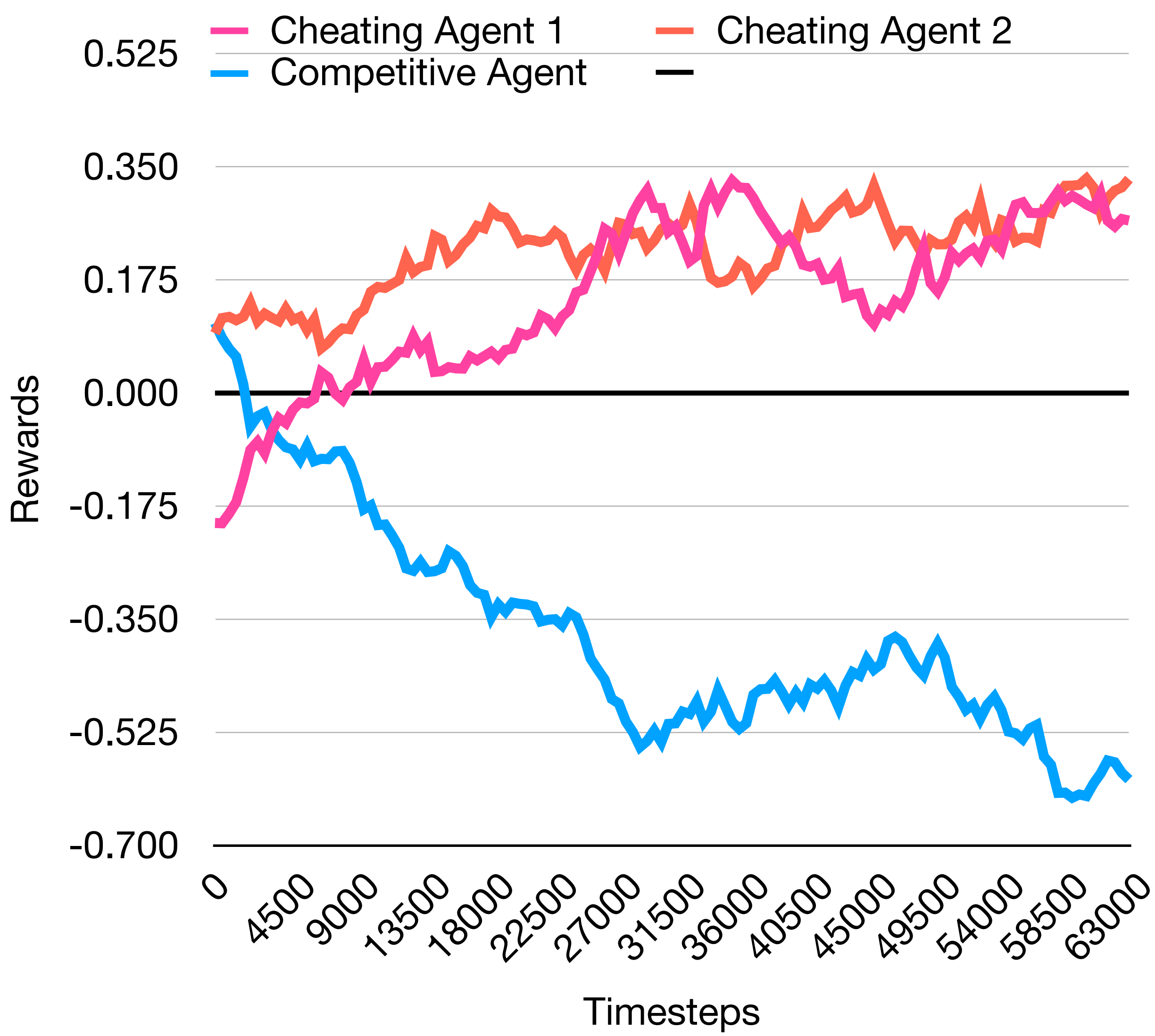
Training and Results



Training Brain 2

Brain 2: Collaborative Agents

Training and Results

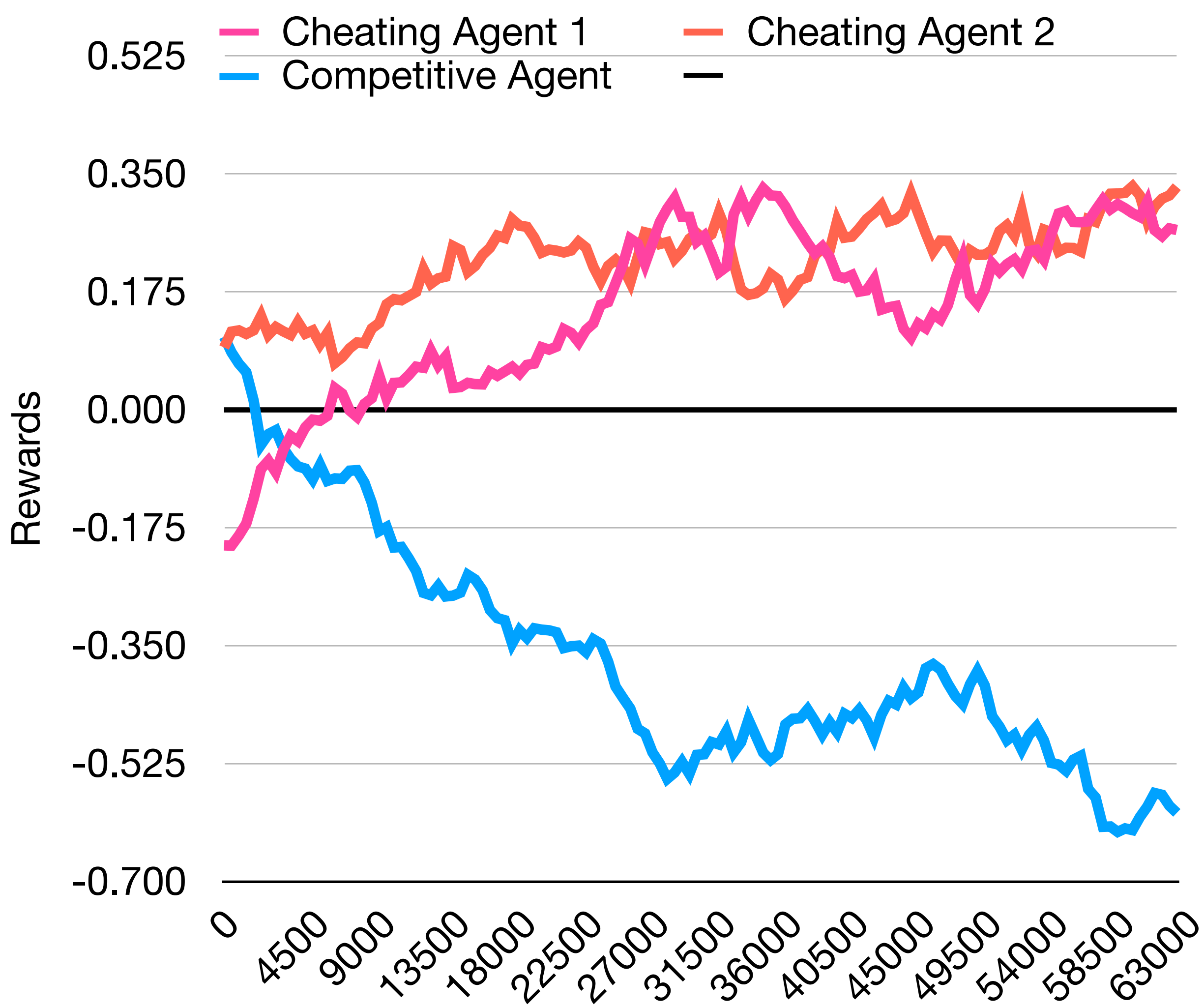


Training Brain 2

WinRatio(Cheater vs Fair) $= 1.14$

Brain 2: Collaborative Agents

Training and Results



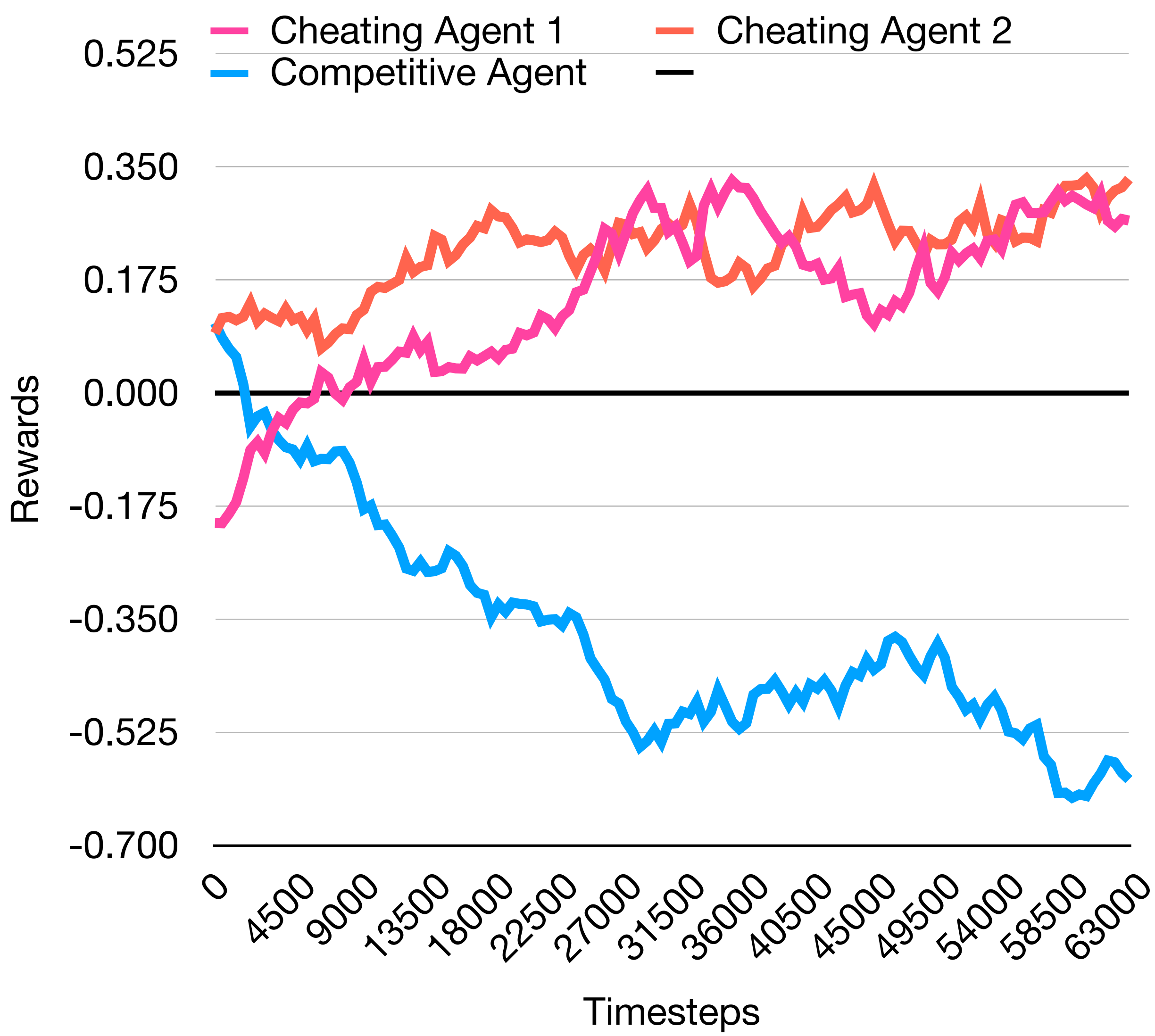
Training Brain 2

WinRatio(Cheater vs Fair) $= 1.14$

WinRatio(Cheater vs Fair(Same Epochs)) $= 1.09$

Brain 2: Collaborative Agents

Training and Results

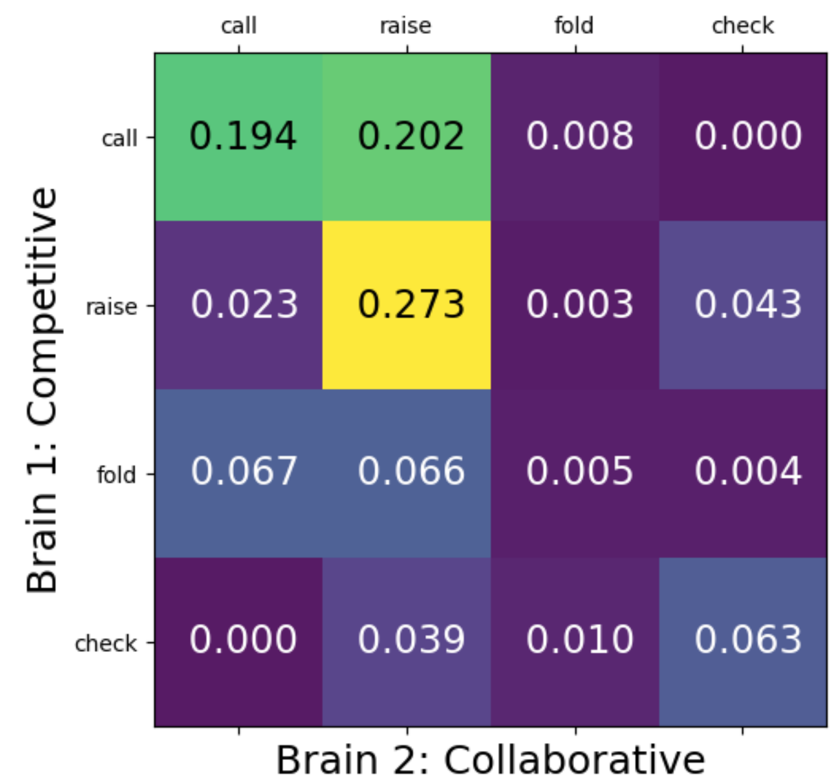


Training Brain 2

WinRatio(Cheater vs Fair) $= 1.14$

WinRatio(Cheater vs Fair(Same Epochs)) $= 1.09$

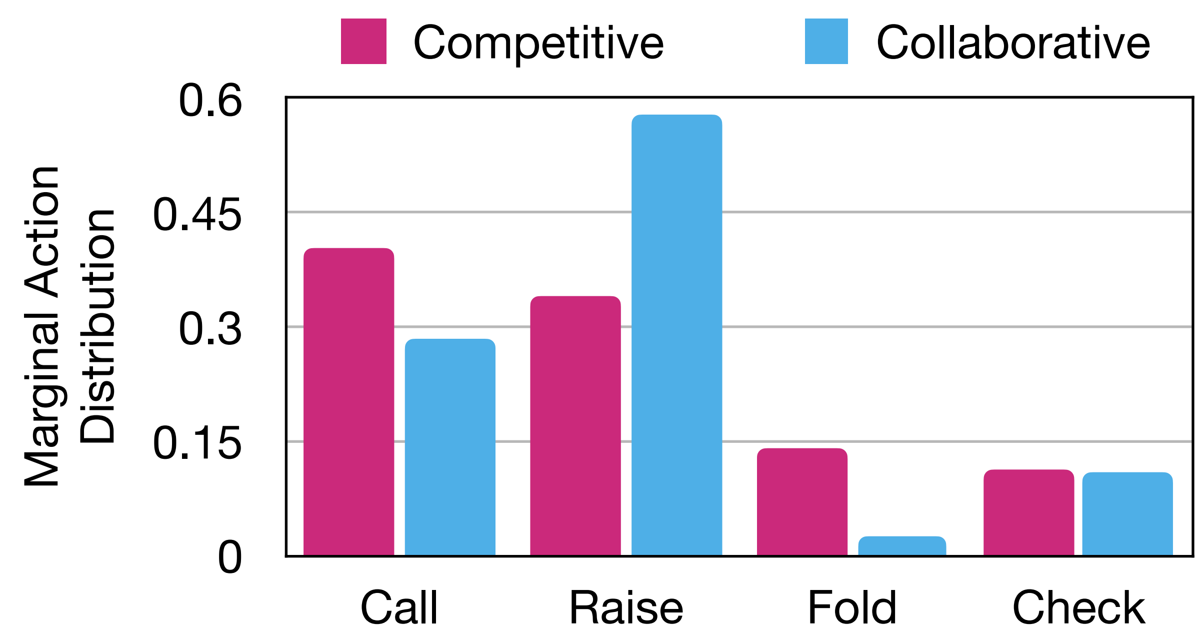
Action Distribution: $p(B_1, B_2)$



Probability of Action Similarity among the Brains

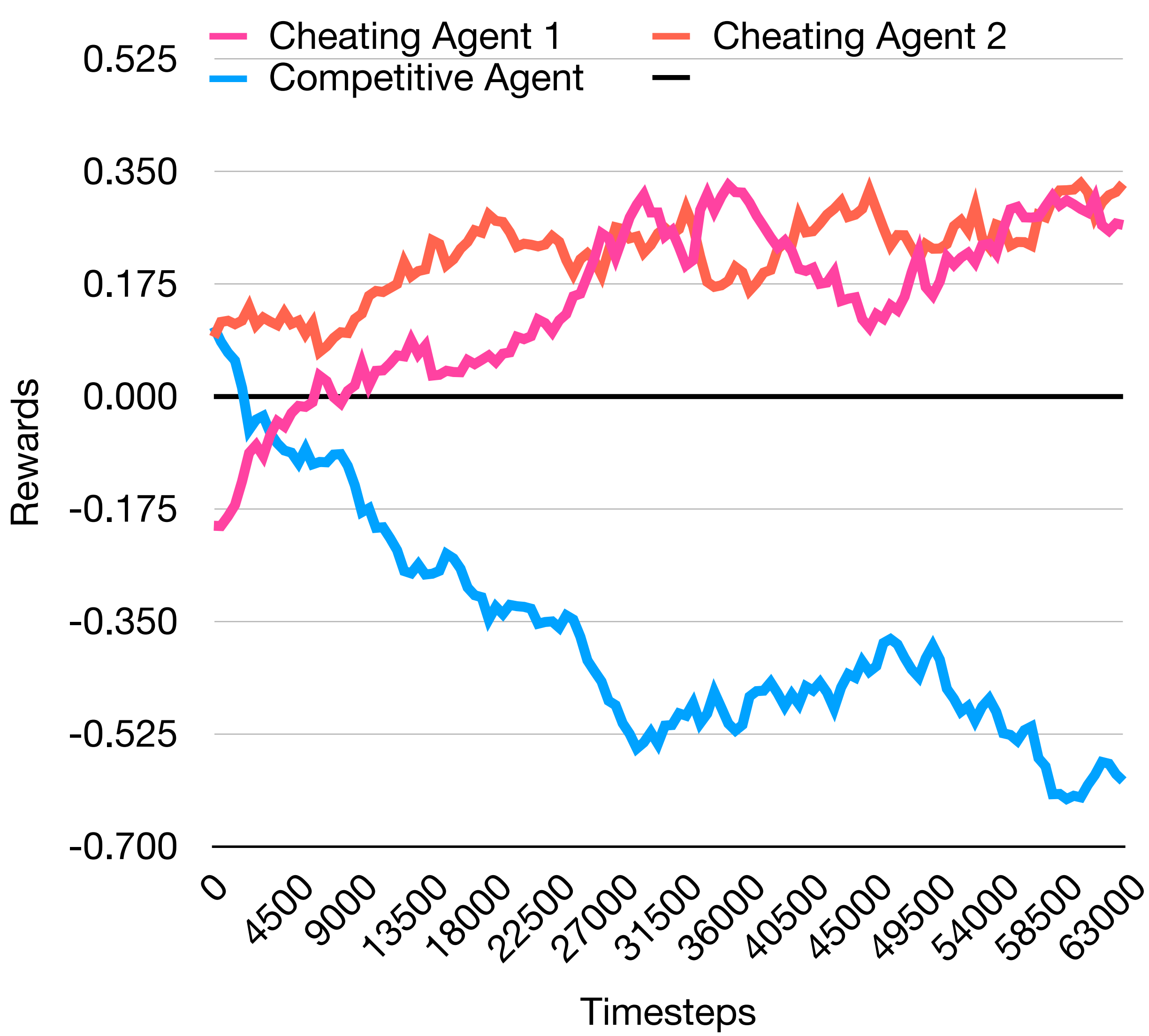
$$p(B_1 == B_2) = \frac{\sum_{i=j} A_{i,j}}{\sum A_{i,j}}$$

= 0.535



Brain 2: Collaborative Agents

Training and Results

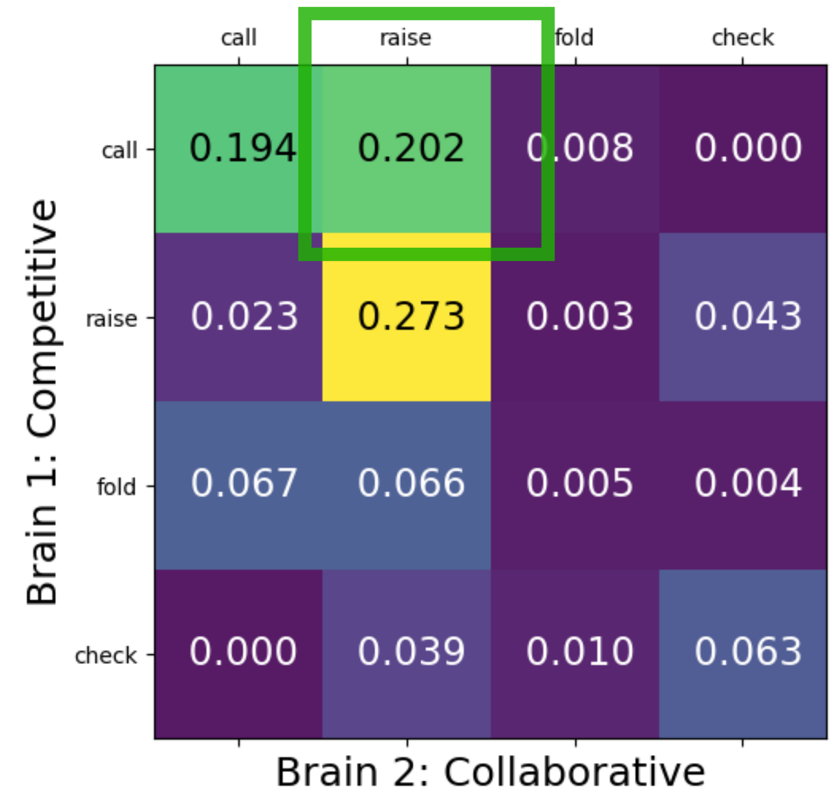


Training Brain 2

WinRatio(Cheater vs Fair) $= 1.14$

WinRatio(Cheater vs Fair(Same Epochs)) $= 1.09$

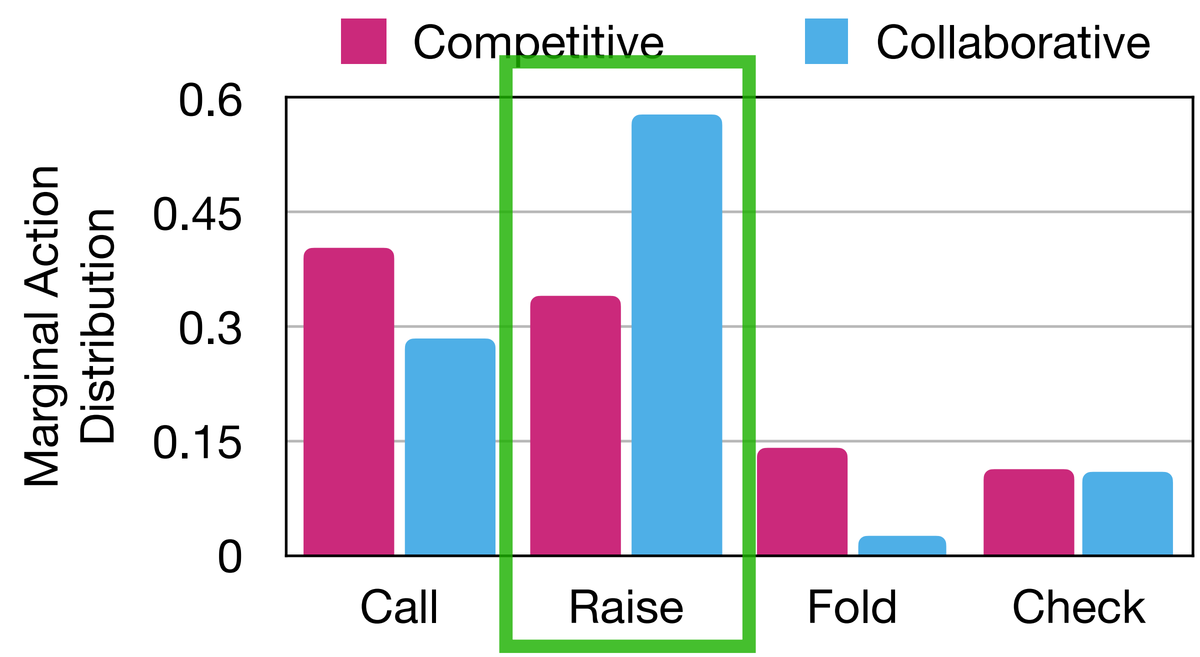
Action Distribution: $p(B_1, B_2)$



Probability of Action Similarity among the Brains

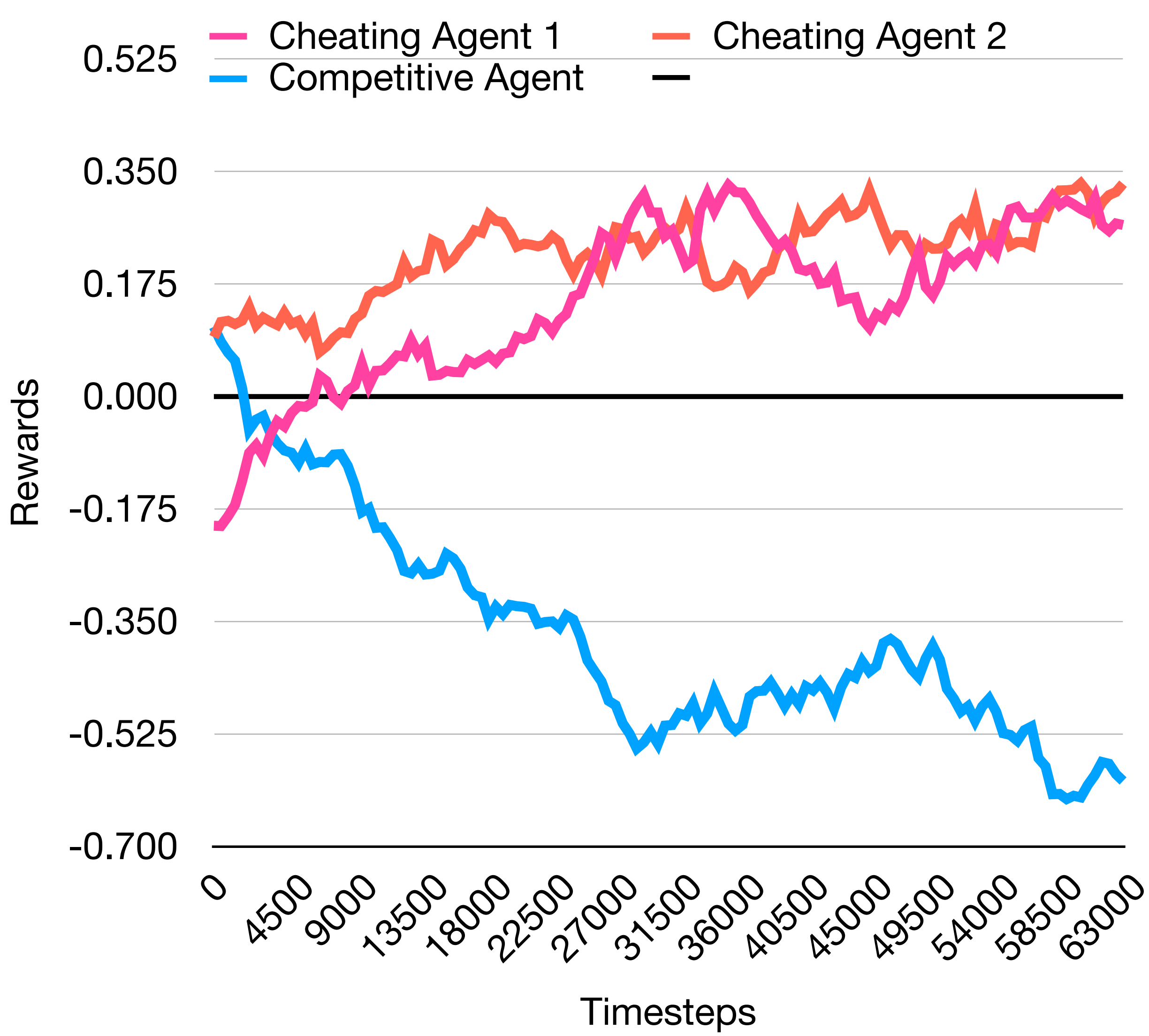
$$p(B_1 == B_2) = \frac{\sum_{i=j} A_{i,j}}{\sum A_{i,j}}$$

= 0.535



Brain 2: Collaborative Agents

Training and Results

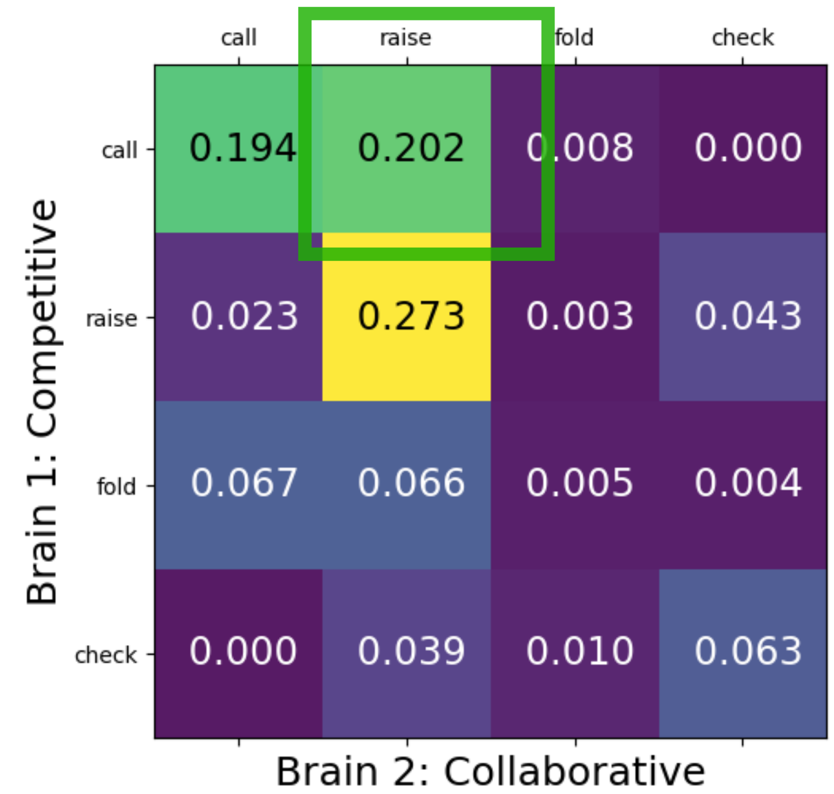


Training Brain 2

WinRatio(Cheater vs Fair) $= 1.14$

WinRatio(Cheater vs Fair(Same Epochs)) $= 1.09$

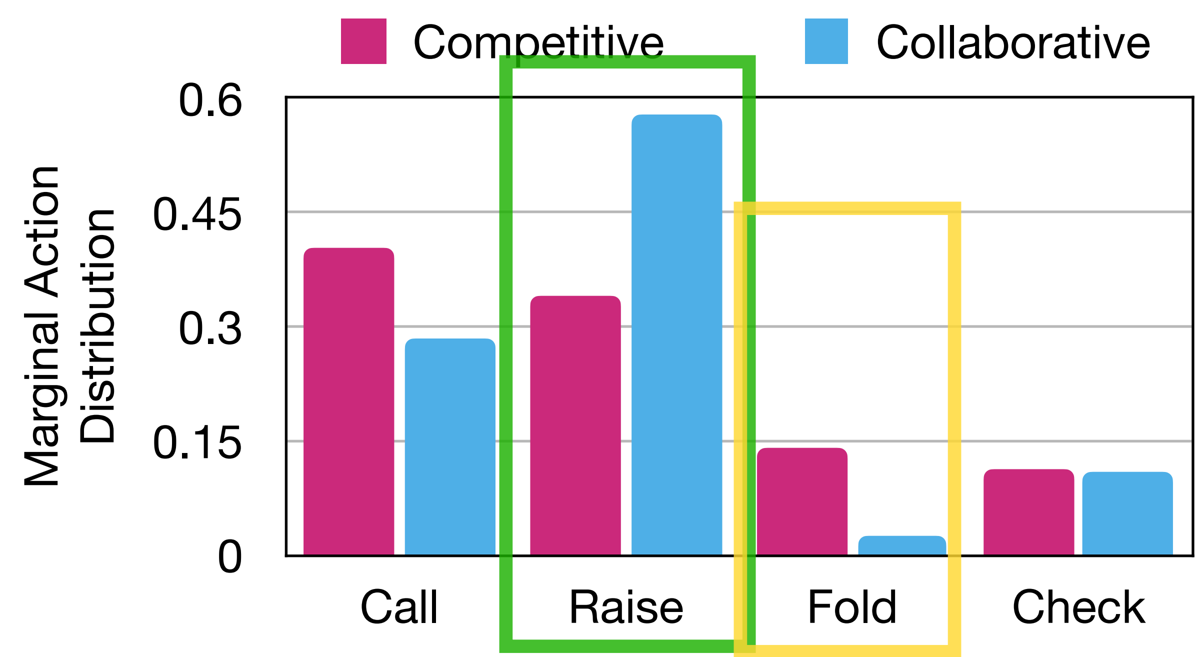
Action Distribution: $p(B_1, B_2)$



Probability of Action Similarity among the Brains

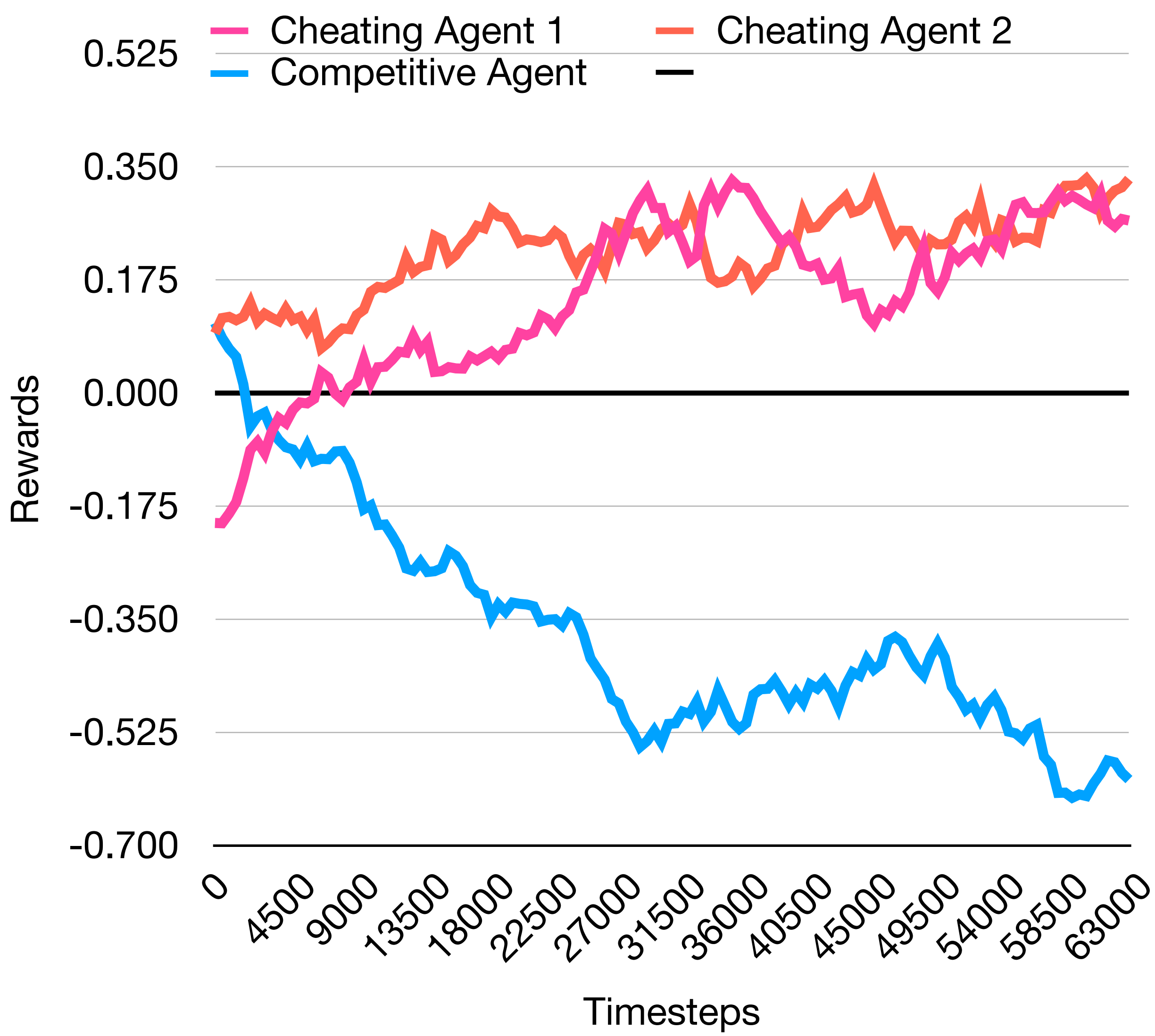
$$p(B_1 == B_2) = \frac{\sum_{i=j} A_{i,j}}{\sum A_{i,j}}$$

= 0.535



Brain 2: Collaborative Agents

Training and Results

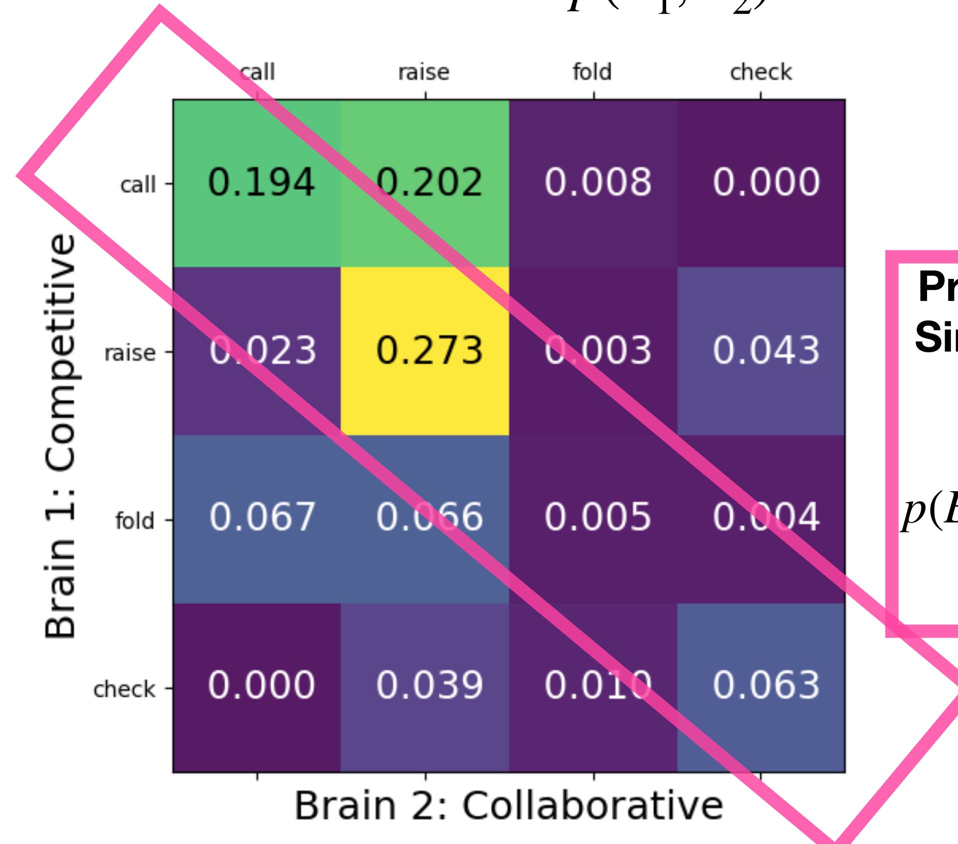


Training Brain 2

WinRatio(Cheater vs Fair) $= 1.14$

WinRatio(Cheater vs Fair(Same Epochs)) $= 1.09$

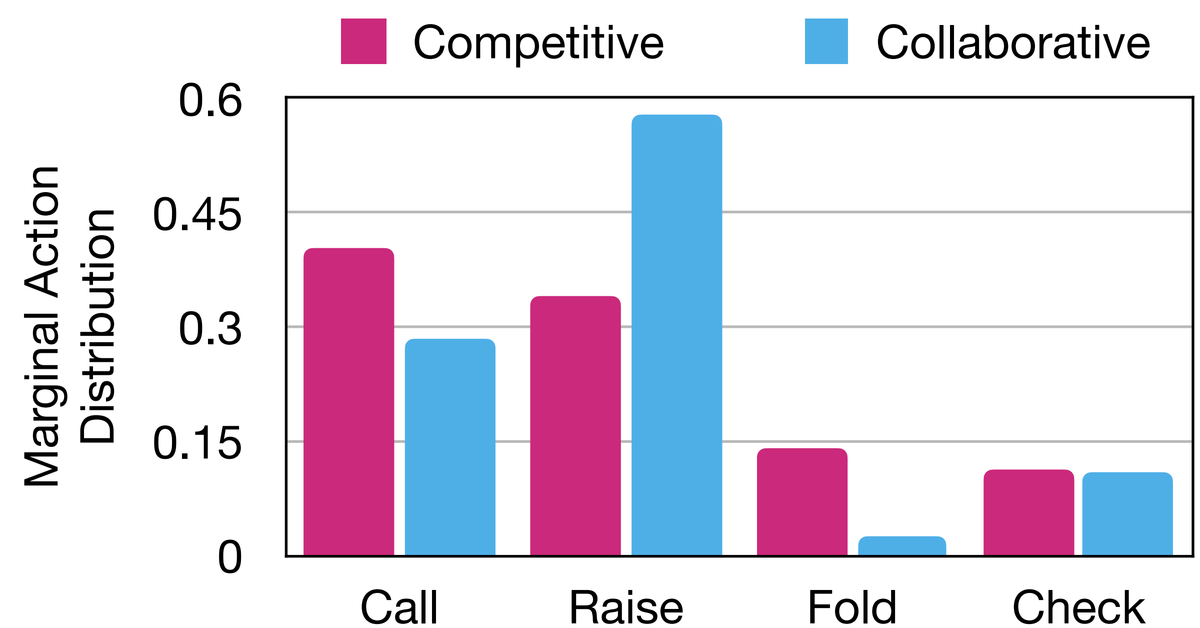
Action Distribution: $p(B_1, B_2)$



Probability of Action Similarity among the Brains

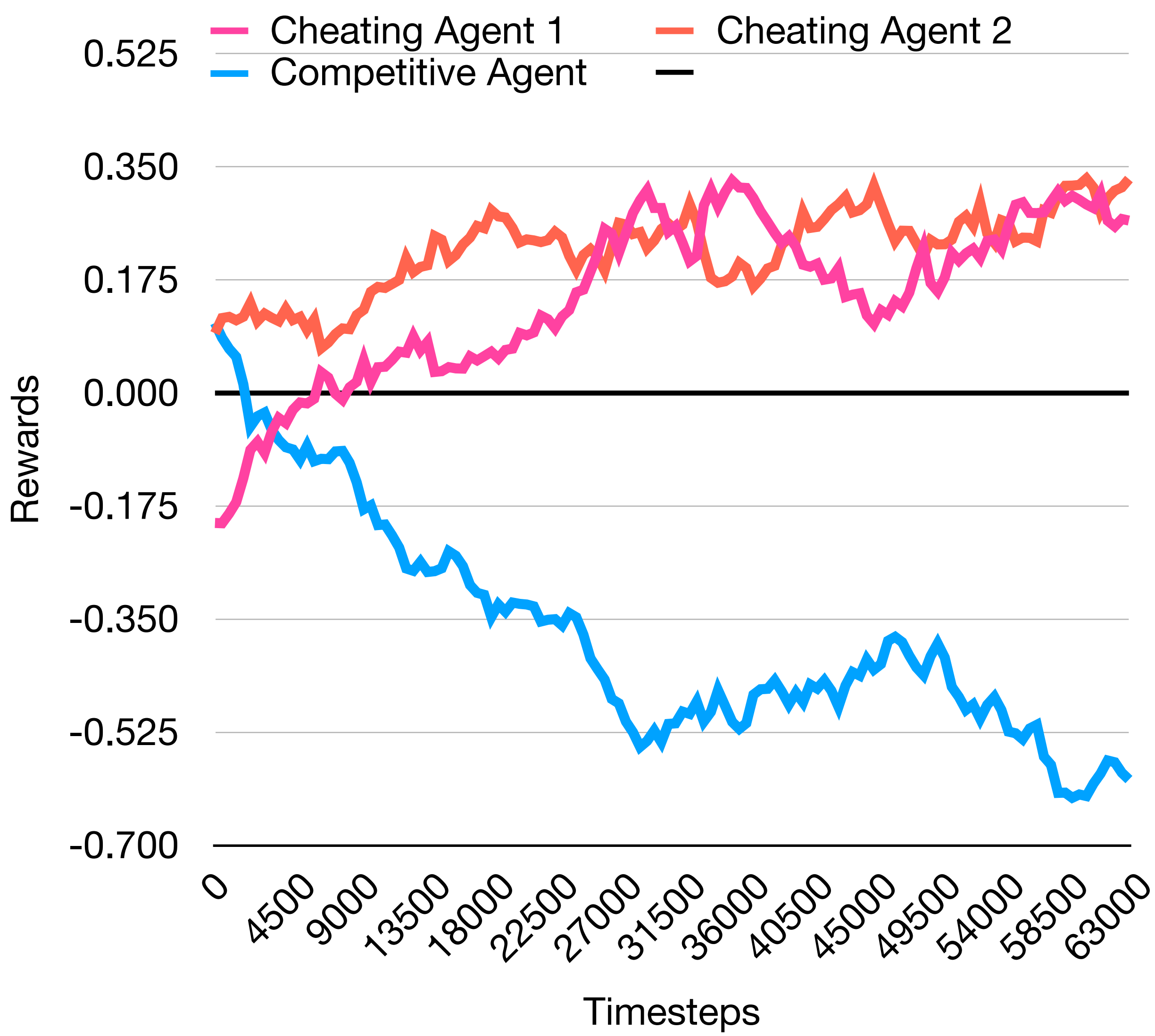
$$p(B_1 == B_2) = \frac{\sum_{i=j} A_{i,j}}{\sum A_{i,j}}$$

= 0.535



Brain 2: Collaborative Agents

Training and Results

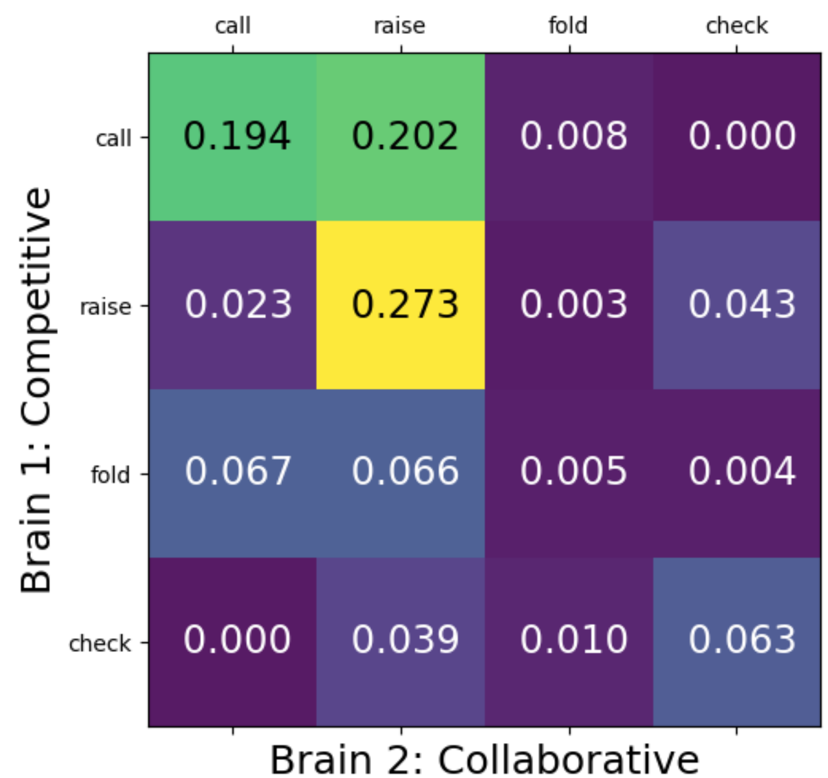


Training Brain 2

WinRatio(Cheater vs Fair) $= 1.14$

WinRatio(Cheater vs Fair(Same Epochs)) $= 1.09$

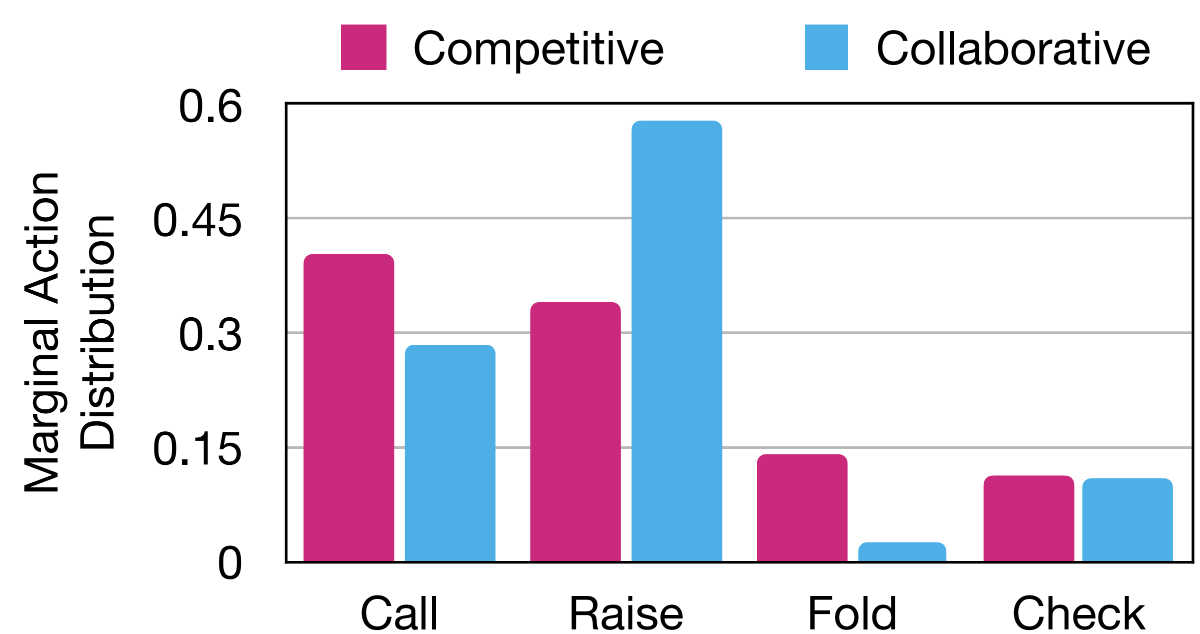
Action Distribution: $p(B_1, B_2)$



Probability of Action Similarity among the Brains

$$p(B_1 == B_2) = \frac{\sum_{i=j} A_{i,j}}{\sum A_{i,j}}$$

= 0.535



Discriminator: Detecting who is cheating

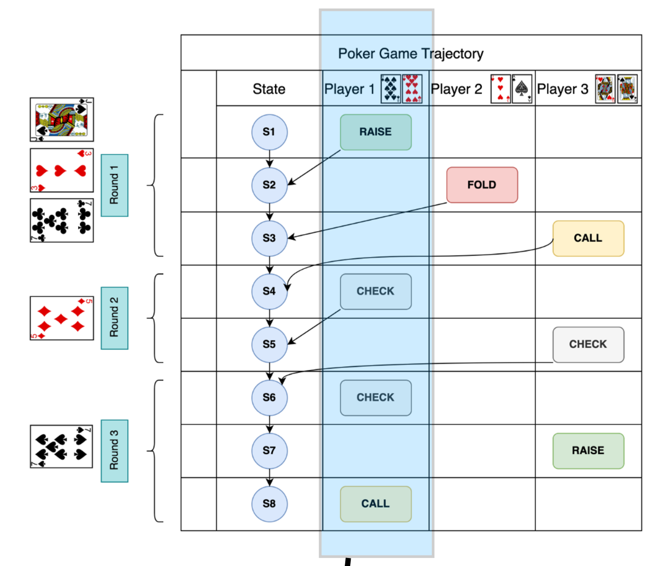
Discriminator

Setup and Challenges

Discriminator

Setup and Challenges

$$p(\{B_1, B_2\} \mid \tau)$$

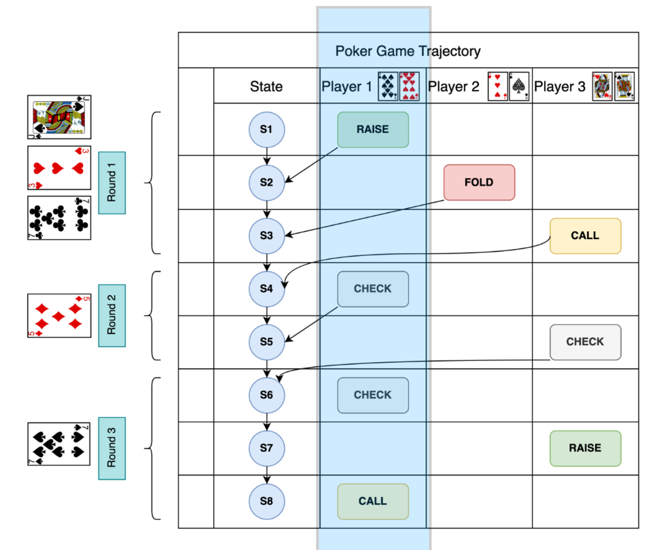


Discriminator

Setup and Challenges

- $f_{B_1}(s) \rightarrow a$
- $f_{B_2}(s) \rightarrow a$
- Action Space is small
- State Space is intractable

$$p(\{B_1, B_2\} \mid \tau)$$

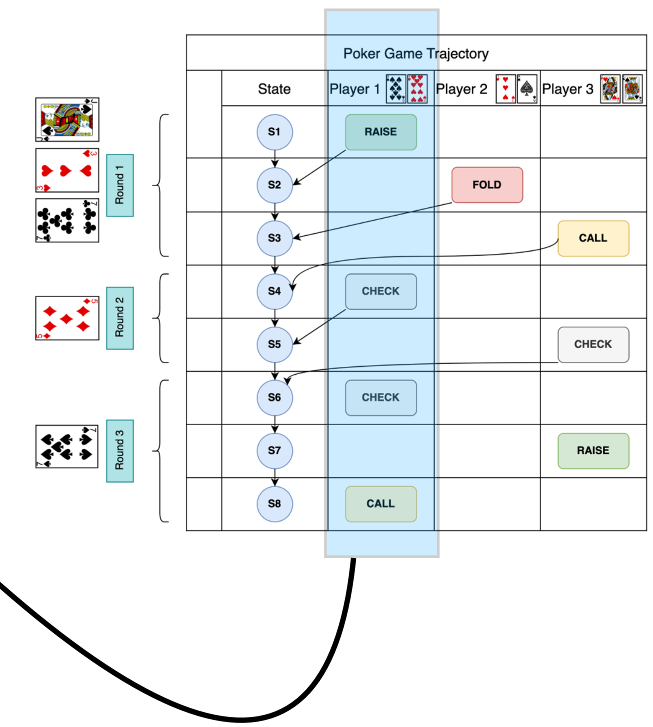


Discriminator

Setup and Challenges

- $f_{B_1}(s) \rightarrow a$
- $f_{B_2}(s) \rightarrow a$
- Action Space is small
- State Space is intractable

$$p(\{B_1, B_2\} \mid \tau)$$



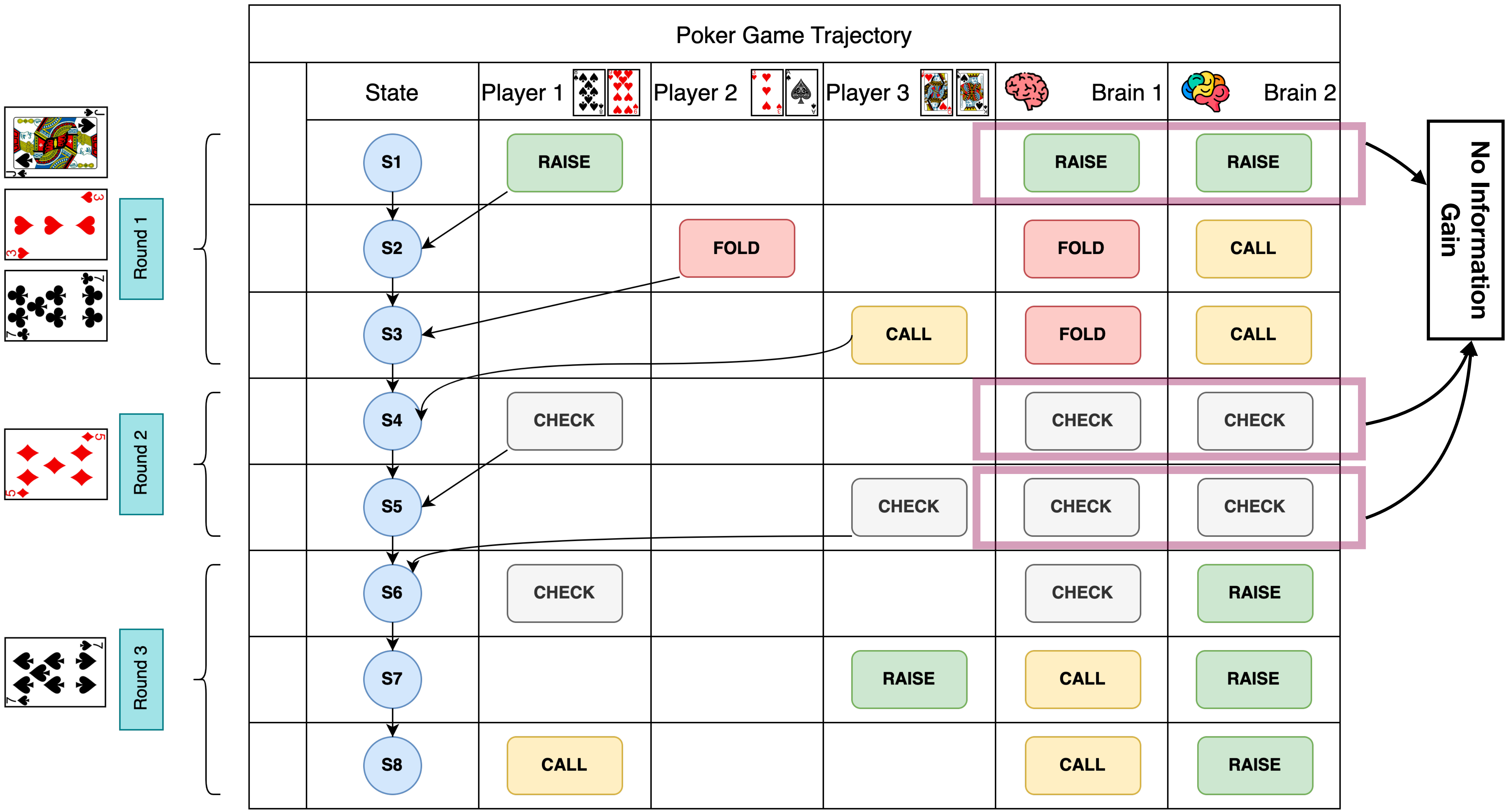
Can we take advantage of small action space to create a discriminator which doesn't enumerate the state space?

Discriminator Logic

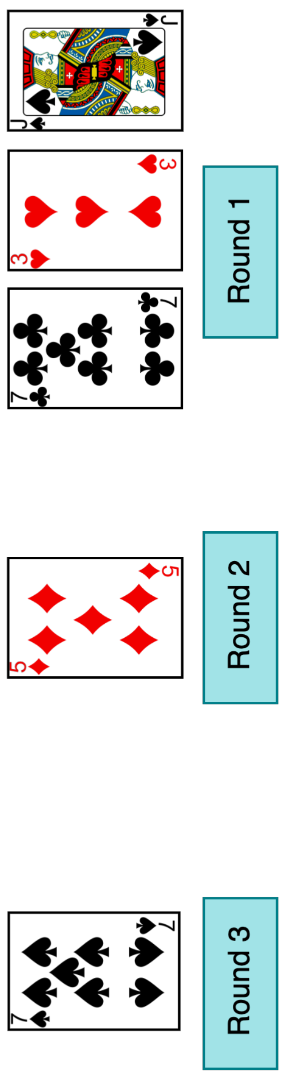
Discriminator Logic

Poker Game Trajectory						
	State	Player 1	Player 2	Player 3	Brain 1	Brain 2
Round 1	S1	RAISE			RAISE	RAISE
	S2		FOLD		FOLD	CALL
	S3			CALL	FOLD	CALL
Round 2	S4	CHECK			CHECK	CHECK
	S5			CHECK	CHECK	CHECK
Round 3	S6	CHECK			CHECK	RAISE
	S7			RAISE	CALL	RAISE
	S8	CALL			CALL	RAISE

Discriminator Logic



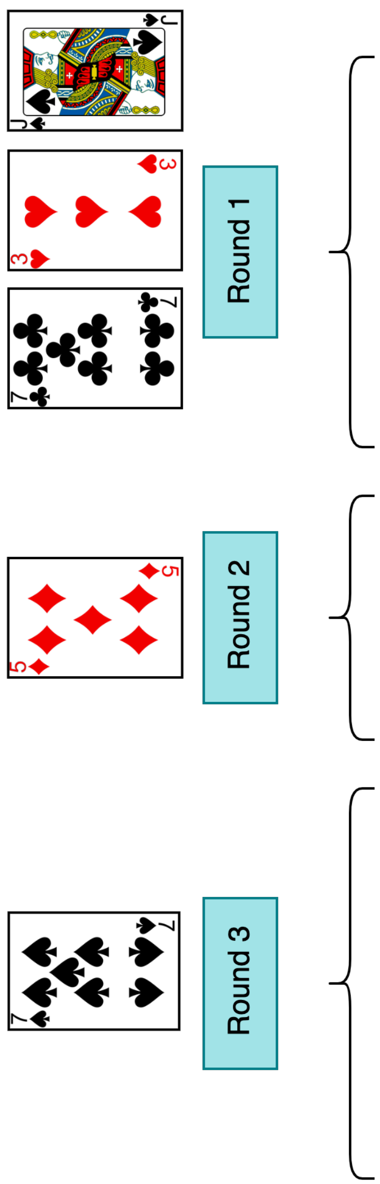
Discriminator Logic



Poker Game Trajectory						
	State	Player 1	Player 2	Player 3	Brain 1	Brain 2
	S1	RAISE			RAISE	RAISE
	S2		FOLD		FOLD	CALL
	S3			CALL	FOLD	CALL
	S4	CHECK			CHECK	CHECK
	S5			CHECK	CHECK	CHECK
	S6	CHECK			CHECK	RAISE
	S7			RAISE	CALL	RAISE
	S8	CALL			CALL	RAISE

Match B1	2	1	0

Discriminator Logic



Poker Game Trajectory

State	Player 1	Player 2	Player 3	Brain 1	Brain 2
S1	RAISE			RAISE	RAISE
S2		FOLD		FOLD	CALL
S3			CALL	FOLD	CALL
S4	CHECK			CHECK	CHECK
S5			CHECK	CHECK	CHECK
S6	CHECK			CHECK	RAISE
S7			RAISE	CALL	RAISE
S8	CALL			CALL	RAISE

Match B1	2	1	0
Match B2	0	0	2

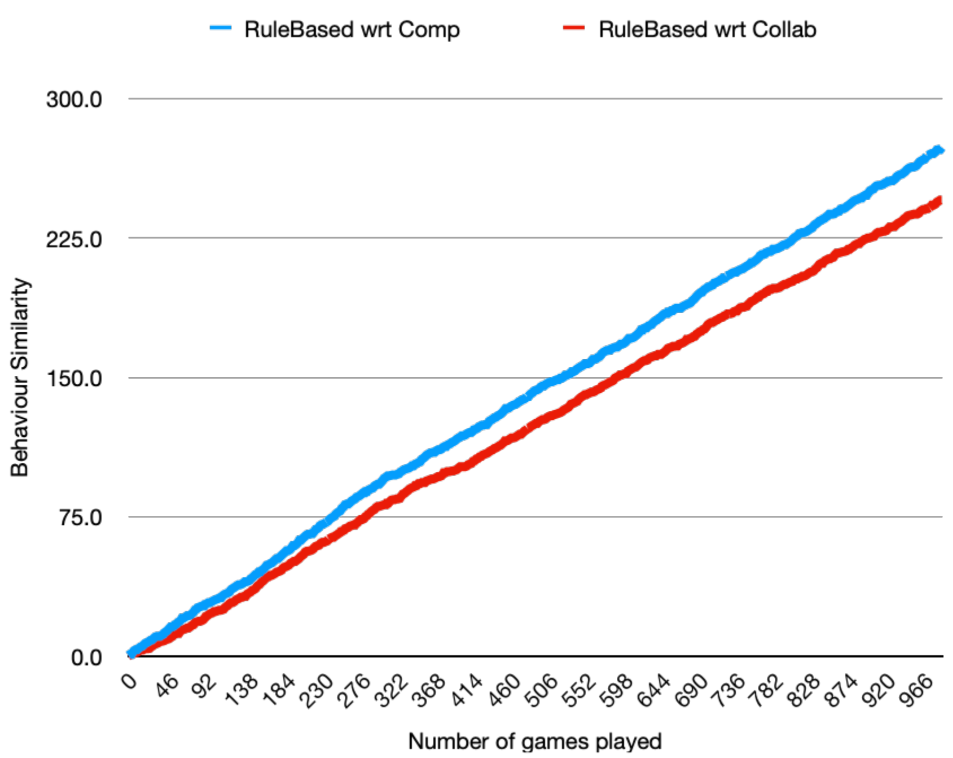
Discriminator Evaluation

Discriminator Evaluation

- GT Fair: RuleBased Agent
- GT Cheater1: Surrogate Cheater
- GT Cheater2: Surrogate Cheater

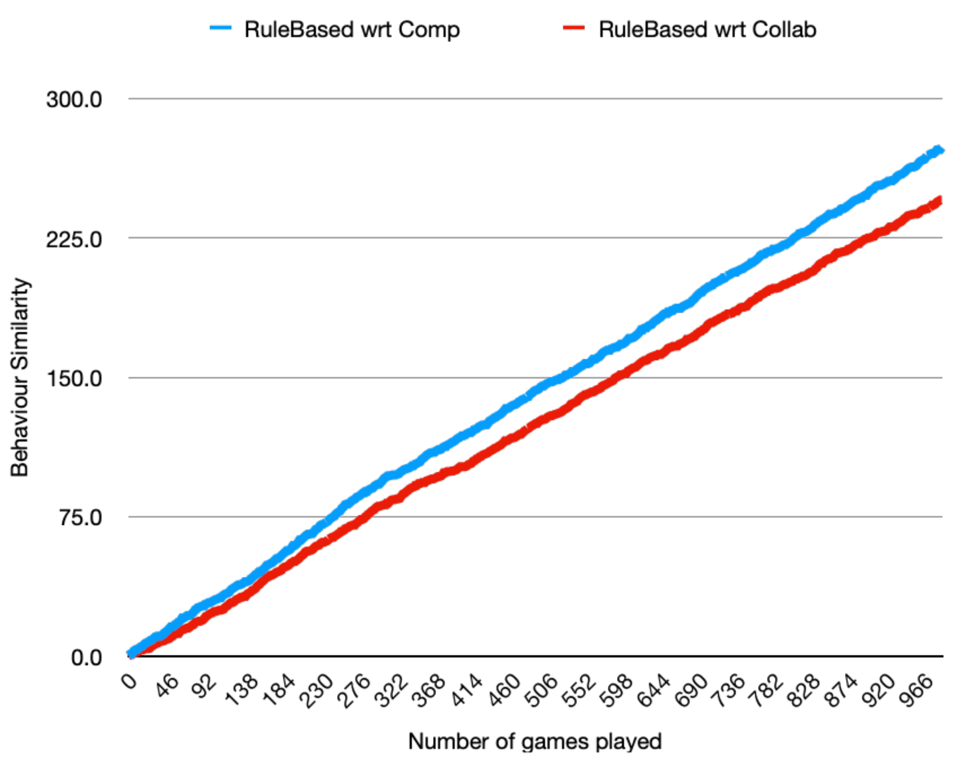
Discriminator Evaluation

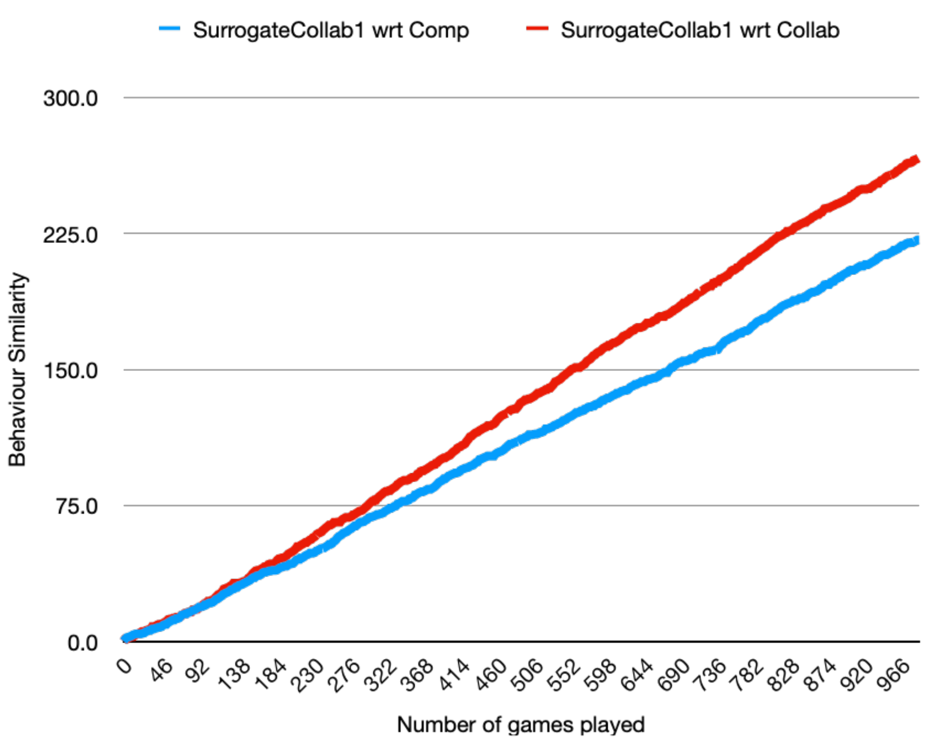
- GT Fair: RuleBased Agent
- GT Cheater1: Surrogate Cheater
- GT Cheater2: Surrogate Cheater

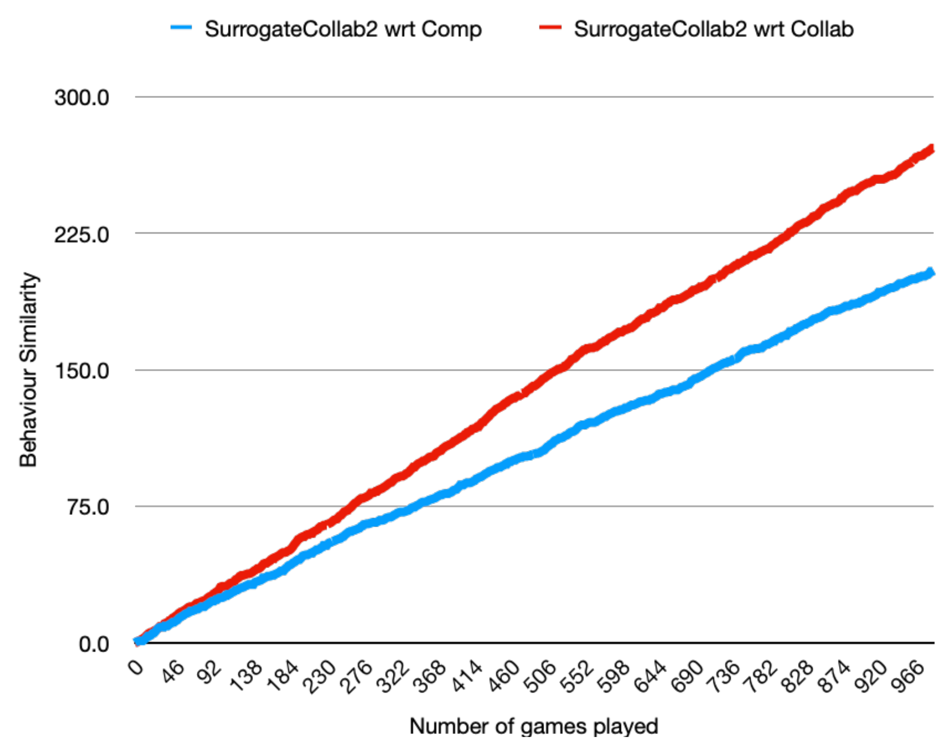


Discriminator Evaluation

- GT Fair: RuleBased Agent
- GT Cheater1: Surrogate Cheater
- GT Cheater2: Surrogate Cheater







References

1. Bowling, M., Burch, N., Johanson, M., & Tammelin, O. (2015). Heads-up limit hold'em poker is solved. *Science*, *347*(6218), 145–149. https://doi.org/10.1126/science.1259433
2. Foerster, J., Farquhar, G., Afouras, T., Nardelli, N., & Whiteson, S. (2017). *Counterfactual Multi-Agent Policy Gradients* (arXiv:1705.08926). arXiv. https://doi.org/10.48550/arXiv.1705.08926
3. Heinrich, J., Lanctot, M., & Silver, D. (2015). Fictitious self-play in extensive-form games. Proceedings of the 32nd International Conference on International Conference on Machine Learning - Volume 37, 805–813. http://proceedings.mlr.press/v37/heinrich15.pdf
4. Zhang, K., Yang, Z., & Başar, T. (2021). Multi-Agent Reinforcement Learning: A Selective Overview of Theories and Algorithms (arXiv:1911.10635). arXiv. http://arxiv.org/abs/1911.10635
5. Icons images from FlatIcon.

Takeaways

- **Pro**:
  - The agents are model-agnostic for the discriminator framework to work.
  - This can scale up to N > 3 agents since we only make use of the tractable action-space.
- **Con**:
  - Our discriminator assumes that in real life scenarios, agents who are cheating deploys strategies similar to strategies learned by our policy. However, this assumption can be broken at times.