

1 Introduction

Multi-agent reinforcement learning (MARL) problems are about finding a set of agents that define an optimal set of policies for some environment. Optimality is usually interpreted in terms of exploitability, meaning if we swapped out one of our agents with a new agent, they could not achieve a higher level of performance than the agent before them. Most people associate these sorts of equilibrium with the nash equilibrium[?], but the MARL framework is typically more general.

Most multi-agent reinforcement learning algorithms involve reasoning over empirical games. These games are abstractions over a possibly complex environment that allow us to reason about things like the nash equilibrium by framing it as a normal-form game. The most common formulation of these meta-games is to define the actions to be the set of currently existing agents, $\{\pi_1, \pi_2, \dots \pi_n\}$ and the payoff to be the expected payoff of playing the agents against each other. If we can find an equilibrium solution to this game using some kind of meta-solver, we can then find a new agent that is a best response to this equilibrium by training it against this distribution using standard reinforcement learning techniques. We can then add this agent to our population of agents and repeat. This general framework is known as Policy Space Repeating Oracle (PSRO) [3]. Eventually, this iterative process will coverage to the solution for our actual game.

One commonly used and powerful meta-solver is α -rank. [5] [4] This computes a ranking over the agents by analyzing the payoff matrix, M . For the two player symmetric case, this matrix stores the expected payoff, or ν of using agent i , π_i , versus agent j , π_j , such that $M_{i,j} = \nu(\pi_i, \pi_j)$. Importantly, in the most common setting for α -rank, the only thing that matters is whether or not $\nu(\pi_i, \pi_j) > \nu(\pi_j, \pi_i)$. Meaning, that we can replace our dense payoff matrix, M , with an equivalent binary one

Most analyses for α -rank, including its introduction, assume you have a perfect estimate of M . However, this is not realistic in most cases. When we are interested in stochastic agents and environments, our M becomes a random variable, \hat{M} , that we need to estimate via simulation. Often times, these simulations are expensive to run. Not only that, but our payoff matrix grows exponentially as we add new players and strategies.

This then becomes an interesting multi-armed bandit problem: how do we allocate those samples to each agent configuration to have the lowest probability of making an error with our meta-solver? [8] introduced this formulation and provide some algorithms and bounds for doing so, including the sample complexity required to have a $1 - \delta$ error guarantee for our meta-solution. Both this approach [7] and α -rank itself [?], have had improvements suggested in performance. We would like to see if we can use this problem framing to not just improve the performance of each part separately, but the process as a whole. At the very least, we would like to perform an empirical analysis of the different convergence properties of these types of algorithms.

2 Motivation

For a few decades, the large majority of research being done in reinforcement learning only considered the single-agent or independent learning case. Here, the environment is static. Anything being simulated as part of the environment will never learn how to adapt to the agent. For example, the common set of Atari baselines [2] include games that simulate other agents, i.e. the other paddle in pong, but these agents will never adapt in response to the agent. Multi-agent reinforcement learning (MARL) is any type of environment in which an agent has to learn an optimal behavior in the presence of other agents who are trying to optimize their own behaviors.

MARL has received large amounts of interest recently, as many people have identified it as a major gap for the practical use of reinforcement learning. Real world environment often involve dealing with

other agents who are non-static. These approaches broadly have application areas including war gaming, advertising, trading, and policy simulation.

3 Plan

Our plan is to follow in a framework similar to [1]. We will first:

1. **Exploration:** Implement and analyze baselines in simple normal-form games. This gives a quick iterative feedback loop that we can use to compare our approximate algorithm to the ground truth solution.
2. **Design:** Through the lens of multi-armed bandit problems, attempt to design a scalable algorithm for computing the approximate equilibria.
3. **Application:** Modify this algorithm to work with deep reinforcement learning agents and demonstrate its application on a more complex environment.

Since this is a research project, we want to make sure that we have a good number of off-ramps when things do not go as planned. Once we have implemented our baselines, if we cannot develop an improved algorithm, we can pivot to an application setup where we apply some of the multi-agent algorithms to an interesting problem. The only step that is mandatory is the completion of our exploratory setup.

In terms of environments, we want to find something that is scalable. Meaning, we want a problem that can both work as a normal-form game (or similar) and by updating the parameters it can scale to something that will require deep reinforcement learning. By having a parameter or set of parameters that allow us to smoothly scale complexity, we can treat this as another dimension in our analysis. Meaning instead of having a sliding scale of separate environments that represent different levels of complexity, we can plot complexity as a function of a specific parameter. One possible environment that we currently have in mind are Erdos-Selridge-Spencer(ESS)[6] games. These not only fit the previous description, they also have an analytical optimal solution that can always be computed as a linear function of the state. In other words, we can compute the exploitability of an agent analytically without relying on an estimate. However, the main types of ESS games seem to have action spaces that would be complicated to simulate as a simple normal-form game and they are lacking open source implementations.

4 Related Works

We have cited a few related works throughout this document, but the most important ones are: the original α -rank paper [5], the paper about connecting α -rank with PSRO [4], and the paper about interpreting the payoff matrix estimation as a multi-armed bandit problem [8]. By simply optimizing the payoff table collection, they were able to establish a PAC bound on sample complexity. However, this bound relies on unrealistic information, i.e. knowing some information about the gaps between the agents beforehand.

References

- [1] Thomas Anthony, Tom Eccles, Andrea Tacchetti, János Kramár, Ian Gemp, Thomas C. Hudson, Nicolas Porcel, Marc Lanctot, Julien Pérolat, Richard Everett, Roman Werpachowski, Satinder Singh, Thore Graepel, and Yoram Bachrach. Learning to play no-pressure diplomacy with best response policy iteration, 2020.
- [2] Marc G. Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *CoRR*, abs/1207.4708, 2012.
- [3] Marc Lanctot, Vinicius Zambaldi, Audrunas Gruslys, Angeliki Lazaridou, Karl Tuyls, Julien Perolat, David Silver, and Thore Graepel. A unified game-theoretic approach to multiagent reinforcement learning, 2017.

- [4] Paul Muller, Shayegan Omidshafiei, Mark Rowland, Karl Tuyls, Julien Pérolat, Siqui Liu, Daniel Hennes, Luke Marris, Marc Lanctot, Edward Hughes, Zhe Wang, Guy Lever, Nicolas Heess, Thore Graepel, and Rémi Munos. A generalized training approach for multiagent learning. *CoRR*, abs/1909.12823, 2019.
- [5] Shayegan Omidshafiei, Christos Papadimitriou, Georgios Piliouras, Karl Tuyls, Mark Rowland, Jean-Baptiste Lespiau, Wojciech M. Czarnecki, Marc Lanctot, Julien Perolat, and Remi Munos. alpha-rank: Multi-agent evaluation by evolution, 2019.
- [6] Maithra Raghu, Alex Irpan, Jacob Andreas, Robert Kleinberg, Quoc V. Le, and Jon Kleinberg. Can deep reinforcement learning solve erdos-selfridge-spencer games?, 2018.
- [7] Tabish Rashid, Cheng Zhang, and Kamil Ciosek. Estimating α -rank by maximizing information gain. *CoRR*, abs/2101.09178, 2021.
- [8] Mark Rowland, Shayegan Omidshafiei, Karl Tuyls, Julien Pérolat, Michal Valko, Georgios Piliouras, and Rémi Munos. Multiagent evaluation under incomplete information. *CoRR*, abs/1909.09849, 2019.