Cooperation in an Adversarial Multi-Agent Game

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ABSTRACT

Our ambition with this project was to explore how independent agents can learn to cooperate and work as a team to achieve a common goal. A multi-agent game with two teams competing against each other through the use of reinforcement learning provides us an environment where we are able to test and analyse the strategies and cooperation methods developed by each team. Multiple games could fulfil this purpose, but the game we ended up choosing was a simplified version of "hide and seek" in a 2D squared board in which two teams (one hiding and one seeking) compete against each other. Moreover though the use of a dynamic board and team size with this project we plan to study the scalability in cooperative behaviour and in learning. Finally, by implementing obstacles in the board we want to analyse how agents deal with a variable environment and their ability to deal and cooperate through adversity. David will create the virtual environment. João will create the rules for the environment and the agents, and Rafael will apply learning algorithms to the agents.

KEYWORDS

Multi-Agent; Reinforcement Learning; Cooperation; Hide and Seek

1 INTRODUCTION

In the last couple years the field of Artificial Intelligence has become more prevalent than ever. One of the areas of most interest is not only how an AI agent can make decisions alone but also how many autonomous agents can make decisions in order to cooperate in solving a task. The real world applications for cooperative AI systems are endless, from fully-autonomous driving to exploration of hazardous environments. This field of study shows true potential and we believe that in the near future some of the major contributions to humanity will come from it.

For these reasons, in this project we chose to explore a cooperative multi-agent system. The first problem we faced was choosing from multiple options an environment and a problem to implement the system. What we found was that a game provides us the perfect competitive environment with perfectly defined objectives and task for the agents to perform. The strict rules of a simulated game also help eliminate the inconsistencies of a real world's setting and can help reduce exponentially the complexity of the implementation. For this reason our system will operate in a computer simulation. The next step was to find a game that suited our needs. For this we took inspiration from the Self and Other Modelling in Cooperative Resource Gathering with Multi-agent Reinforcement Learning paper [1] where researchers applied Open AI to a Hide and Seek Game and obtained truly amazing results. Therefore, we chose to implement a simplified version of the Hide and Seek game in a 2D board where agents can only move to their adjacent board cells. The described environment shall host two teams of autonomous self-learning agents that will compete against each other in the hide and seek game (one team hiding and the other one seeking).

We believe this environment will provide the appropriate setting to study and develop self-learning models to foment cooperation among teams to achieve a set result. In terms of AI techniques we plan on using reinforcement learning to produce the model. In a single agent reinforcement learning setting there is a cap in performance after some time. The model is bound by the games rules and once the agent learns how to perform the task it reaches its peak performance. By adding two teams competing against each other we sort of create an adversarial setting in which there's competition and they adjust to each others behaviour. This is a much more dynamic and interesting environment to study.

Our game will be comprised of two teams of dynamic size competing in a game of hide and seek on a 2D board of dynamic size as well. The rules are simple, the game is turn based and each turn and agent picks a neighbour board cell to move to. If one of the agents from the hiding team is on an adjacent cell to one of the seeking agents then it is eliminated from the game. Because we will not limit the amount of turns in a board we will measure the performance by the number of turns the seeking team took to find the hiding team. We will supervise the model while it trains and observe patterns and strategies developed by each team.

2 APPROACH

As a base for the project we will start with a simple board NxM with a limited amount of agents. Each agent will be assigned a team (either the seeking or hiding team) and they are able to see all agents from the same team, however they can only see agents from the other team if they're in a certain range from each-other. The hiding team will have a bigger sight radius than the seeking team. All agents start at random locations. The game is turn based, so every turn the agent will have to output an action, possibly moving to a surrounding board cell. If a hiding agent ends up in a neighbour cell of a seeking agent then the hiding agent will be eliminated from the game. The game will only end when all hiding agents are eliminated.

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The agents will take as input information about the cells around itself (empty or if it has an enemy), the positions of the teammates, and output a decision. The action of the agent can be up, down, left or right. The agents can not move diagonally but we will consider a diagonal cell as a neighbouring cell.

In this project we wanted to dive deeper into Neural Models. After learning more about how OpenAI is revolutionizing the world of self-learning and reading the papers applying Reinforcement Learning to games we choose to also dive deeper into Q-Learning and Reinforcement Learning. Therefore, each model will have an independent neural network that will be trained through the use of the previously mentioned techniques. The output of the neural network shall be the moving action of the agent and the inputs shall be the neighbouring cell information and the positions of the teammates.

Using reinforcement learning for this environment seems fitting since the more complex version of it (the 3D Hide and Seek [1]) showed success by using it. Of course, making a simpler version of the game might render that same learning method useless. We will have enough time to see if it works and make changes accordingly.

Because the rules are extremely simple some loopholes may be discovered by the agents leading to poor results. If this is the case then we will adjust the rules to prevent these behaviours.

3 EMPIRICAL EVALUATION

Because the game is turn based we will measure the performance of each team by the number of turns until all members from the hiding team are caught. As a baseline for measuring if the performance is increasing we will compare it against the first runs of the model which will basically be a random movement of agents.

By closely supervising the model while it's running we will also analyse the strategies that each team will come up with. This can give us a better insight of how the neural network is handling the inputs and of how its generating decisions.

The objectives and metrics of success of this project we defined as being able to see clear cooperative behaviour among team members. Cooperative behaviour can be classified as an interaction of two or more people or organizations directed toward a common goal which is mutually beneficial. If we notice a pattern in which agents are taking action not individually but in a team setting we will consider it a success.

REFERENCES

[1] Liusko T. Panov Davydov, V. 2021. Self and Other Modelling in Cooperative Resource Gathering with Multi-agent Reinforcement Learning. Advances in Intelligent Systems and Computing. (2021). https://doi.org/10.1007/978-3-030-65596-9_9