Seek: A Multi Agent Environment

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Introduction

Deep reinforcement learning research has grown rapidly in recent years and can be applied in a wide variety of fields such as robotics (Ibarz et al., 2021), autonomous driving (Wang et al., 2018) and games (Szita, 2012). With more particular regards to the games domain, Artificial Intelligence (AI) in games can be considered a long-standing research area. This is mainly due to the fact that various games have the potential of providing interesting and complex problems for agents to solve.

DeepMind were the first one to demonstrate that AI agents can achieve superhuman performance in a wide range of Atari video games (Mnih et al., 2013). Their proposed algorithm, so called Deep Q-Network, combined a Convolutional Neural Network for feature representation with the widespread Q-Learning methodology. The latter can be summarised at a high level as a method which seeks to find the best action for the agent given the current state (Watkins and Dayan, 1992). Its ability to perform well across games which, technically speaking, are relatively different, led us to the decision of considering it for this body of work as well, although certain adjustments were needed due to the way our game is built.

The purpose of this body of work is to study emergent competitive strategies between agents controlled by autonomous Deep Recurrent Q-Networks (DRQN). More particularly, the investigation will be carried out in a custom-built environment where two agents, a “Seeker” and a “Hider”, will play a version of the pursuit-evasion game.

With that being said, in a multi agent context like ours each agent has some effect on the environment thus leading to what is known as non-stationarity. In other words, the actions that can be performed by a particular agent can have different outcomes depending on what the other agents are doing. This is precisely why single agent techniques such as Q-Learning often struggle in multi agent environments (Lowe et al., 2017). Nevertheless, single agent reinforcement learning algorithms within multi agent domains have been thoughtfully investigated, and not without success (Hafiz and Bhat, 2020; Yu et al., 2021)

AI Techniques and approaches

As previously stated, various games provide interesting and complex problems for agents to solve, and this is exactly why creating our own custom game was the perfect choice for this research. In our scenario, agents are not provided with full information about the environment, as it was the case for DeepMind’s original work (Mnih et al., 2013). More particularly, their observation space consists only of data gained through a personal – limited in size – radar.

The fundamental difference between the aforementioned studies and our case is that we will not use a Convolutional Neural Network since we do not provide the agents with images or frames. Moreover, we will also have to investigate how the algorithm performs while two other characteristics are involved, the presence of what can be defined as a good degree of randomisation during the environment generation (i.e., walls) and the multi-agent factor, which brings in a new range of issues that should be addressed, or at least considered (Buşoniu et al., 2010).

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