Contents

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1 Dr. Yielding's Questions

While HARL is indeed a subfield of MARL, the distinction between the two can often be unclear or inconsistently used in the literature. In the broadest sense, 'heterogeneous' may refer to any MARL scenario where the agents are not identical. However, using this broad definition risks diluting the practical significance of the term.

To provide a more useful distinction, HARL should be invoked when the heterogeneity of the agents is fundamental, essential, or definitional rather than merely incidental. This means the differences among agents are critical to their roles and interactions within the system, not just minor variations.

Prior to my literature review, I would have considered HARL to apply specifically to cases where agents are distinct from the outset, either in their capabilities (For action-space $\mathcal{A}$, $\mathcal{A}_1 \neq \mathcal{A}_2$) or their observation spaces ($\mathcal{O}_1 \neq \mathcal{O}_2$). This intrinsic heterogeneity is evident in works like [1] (the Irish conference paper mentioned in Dr. Yielding's question) and implicitly reflected in [2] (OpenAI Five), even though they do not explicitly label their methods as HARL.

The most comprehensive source on HARL usage is Zhong et al. [3], whose work has greatly influenced my understanding. They focus on implementing algorithms that encourage the development of heterogeneous policies among agents. Their framework increases the likelihood of individual agents converging on distinct policies, which I term emergent heterogeneity.

In my prospectus, I also mention a suspicion that this approach might not entirely prevent agents from converging on policies that are functionally similar, thus lacking true diversity. However, this assertion remains an ancillary detail as it is not yet substantiated by empirical evidence.

Therefore, I propose distinguishing between intrinsic heterogeneity, where agents are fundamentally different before training, and emergent heterogeneity, where differences arise as a result of the learning process. In the cases where the heterogeneity of the agents falls below a level of functional relevance, and appears to be incidental, I argue that they should not be labeled as HARL. By maintaining these distinctions, we can more accurately categorize and understand the applications and implications of HARL and MARL.

Below, I apply these distinctions to the cases proposed:

1.1 HAA2C and HADDPG are among the numerous algorithms proposed by Zhong et al. [3]. While it seems reasonable that their algorithms could be applied to situations with intrinsic heterogeneity, their implementations and tests are applied to environments with agents that are functionally the same.

I intend to implement (at least a subset of) their algorithms to the extent that time allows. In doing so, I hope to either corroborate or contradict their results by comparing them to similar algorithms under different conditions. This exploration aims to identify any apparent advantages of these algorithms when applied to the experimental variables proposed for Contribution 1. These experimental variables represent smaller difficulties that we expect to face in Contributions 2 and 3.

1.2 (a) The scenario described in this part of the question is, perhaps unintuitively, more akin to single-agent than multi-agent reinforcement learning. This becomes clearer when considering a single agent acting as an 'overlord,' where the observation space is a combination of observations from all the individual agents. The actions taken by this overlord are combinations of actions chosen for each agent. Essentially, a single policy processes the combined observation and outputs the combined action.

(b) This example is a strong example of MARL, and because the agents utilize copies of a singular policy, this example is free from any of the types of heterogeneity described in the answer for question 1.1.

(c) The types of problems accurately described by the scenario provided in this part of the question appear to be a subset of MARL problems and a superset of HARL problems.

Many MARL algorithms allow the member policies to develop distinctly (e.g., [4]–[6]), but they are not optimized to facilitate the development of distinct policies.

Zhong et al. [3] formulate their series of HARL algorithms with optimizations intended to facilitate the development of distinct policies. One weakness of this formulation is that there is no guarantee that the multiple policies will not converge to a behaviorally indistinct set, similar to the concept of carcinization observed in evolutionary biology.

Thus, the resulting heterogeneity of the agents in these scenarios is not intrinsic but emergent. Whether the algorithm itself is labeled as MARL or HARL is distinguished by intent.

1.3 Referencing Centralized Training Decentralized Execution (CTDE) and Decentralized Training Decentralized Execution (DTDE) as employed by Li et al. in their FA2A paper [7], we see that CTDE is the most common format for Actor-Critic based MARL algorithms [4]–[8].

Li et al. [7] and Wen et al. [9] are the only papers I found that discuss the contrary implementation, DTDE. In both cases, the authors motivate DTDE with practical concerns, particularly the limitations of inter-agent communication in distributed systems. These considerations are important, but the relation to HARL remains the same as described in answer 1.2 (c).

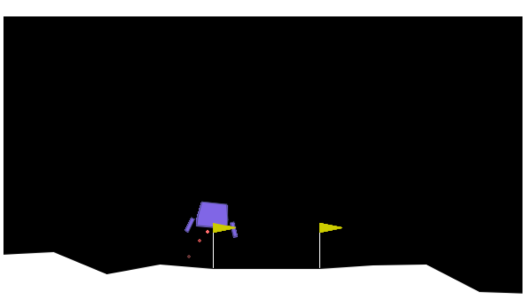
2 Dr. Robbins' Questions

In addition to being included in the appendices of this exam, all code used to run the experiments is available on my github at https://github.com/bhosley/Specialty-Exam. It is written to be run on any ANT-Center VSCode server containers, but should work in a generic virtual environment. The github readme has a short guide for setting up the virtual environment in the ANT-Center for easy replication.

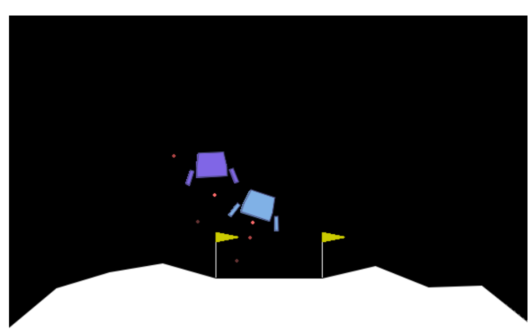
The answers for this section are drawn from the experiment running script,

2.1

Multi-Agent Lunar Lander



(a) Lunar Lander



(b) Lunar Lander

3 Dr. Cox's Questions

A Experiment Running Script