Retrospective Analysis of the 2019 MineRL Competition on Sample Efficient Reinforcement Learning

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Editors: Hugo Jair Escalante and Raia Hadsell

Abstract

To facilitate research in the direction of sample-efficient reinforcement learning, we held the MineRL Competition on Sample-Efficient Reinforcement Learning Using Human Priors at the Thirty-fourth Conference on Neural Information Processing Systems (NeurIPS 2019). The primary goal of this competition was to promote the development of algorithms that use human demonstrations alongside reinforcement learning to reduce the number of samples needed to solve complex, hierarchical, and sparse environments. We describe the competition and provide an overview of the top solutions, each of which use deep reinforcement learning and/or imitation learning. We also discuss the impact of our organizational decisions on the competition as well as future directions for improvement.

Keywords: reinforcement learning competition, reinforcement learning, imitation learning

1. Introduction

Many of the recent, celebrated successes of artificial intelligence (AI), such as AlphaStar (Vinyals et al., 2019), AlphaZero (Silver et al., 2018), and OpenAI Five[1] achieve human or super-human performance using deep reinforcement learning (DRL). Improvements to the state-of-the-art have, thus far, used exponentially increasing computational power[2]. In part, this increase is due to the computation required per environment sample; however, it is primarily due to the increasing number of environment samples required for training. These growing computational requirements mean that a shrinking portion of the AI community can reproduce these results, let alone improve upon these systems. One well-known way to

1. `https://openai.com/five/`
2. `https://blog.openai.com/ai-and-compute/`

reduce environment-sample complexity is to leverage human demonstrations and priors of desired behavior (Dubey et al., 2018).

To facilitate the development of methods which address this problem, we held the first-ever MineRL Competition on Sample-Efficient Reinforcement Learning Using Human Priors[3] at NeurIPS 2019 (Guss et al., 2019). Teams developed procedures for training an agent to obtain a diamond in Minecraft. To limit computational requirements, the procedures were evaluated by retraining from random weights under a strict computational and environment-sample budget. Our challenge attracted over 1000 registrated participants with a total of 662 submissions[4].

In this work, we describe the competition paradigm and procedure, and provide a summary of the top 9 solutions. We identify common high-level approaches, such as leveraging human demonstrations and using hierarchical reinforcement learning, used in the top solutions. We also discuss the outcomes of our choices as organizers of the competition, including how we evaluated the submissions and specified the rules.

2. Background

Minecraft Minecraft is a 3D, first-person, open-world game revolving around gathering resources and creating structures and items. Because it is a sandbox environment, designers can devise a variety of goals and challenges for intelligent agents. Additionally, because it is an embodied domain and the agent's surroundings are varied and dynamic, it presents many of the same challenges as in real-world robotics. As a result, it is a promising and popular testbed for both single- and multi-agent reinforcement learning (RL) and planning algorithms (Abel et al., 2015, 2016; Oh et al., 2016; Tessler et al., 2017; Shu et al., 2018; Frazier and Riedl, 2019; Master et al., 2019; Arumugam et al., 2019; Trott et al., 2019).

Reinforcement Learning Competitions To our knowledge, no previous competitions explicitly focused on using imitation learning (and, more generally, learning from demonstrations) alongside RL. Most previous RL competitions (Kidziski et al., 2018; Nichol et al., 2018; Perez-Liebana et al., 2019; Juliani et al., 2019) focused on performing well on a given domain, and not on developing robust algorithms that can perform well on a broad set of domains. Consequently, winning submissions often required hand-engineered features and stemmed from using large amounts of computational resources for training and development.

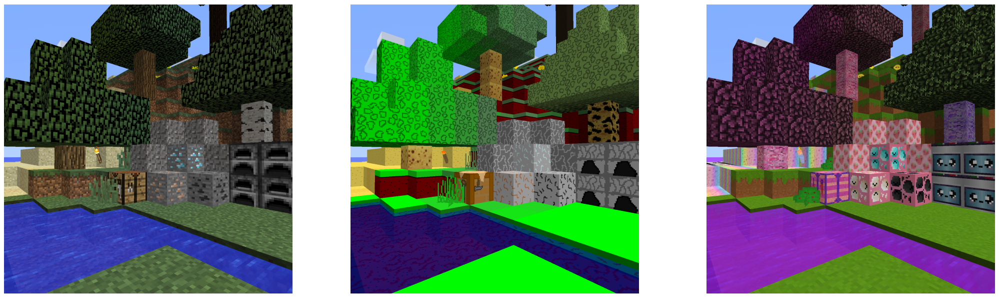
3. Competition Overview

We provide an overview of our competition. We describe the primary task and environment in Section 3.1. In Section 3.2, we describe the structure of our competition. We conclude by listing the resources that we provided participants in Section 3.3.

3.1. Task

Competitors were tasked with solving the ObtainDiamond environment. The task consists of controlling an embodied agent to obtain a diamond by navigating the complex item

3. http://minerl.io/
4. https://www.aicrowd.com/challenges/neurips-2019-minerl-competition



(*a*) Original texture (*b*) Validation texture (*c*) Test texture

Figure 1: An example game state rendered with three different textures.

hierarchy of Minecraft. In solving this task, a learning algorithm has direct access to a 64x64 pixel point-of-view observation from the perspective of the embodied Minecraft agent, and a set of discrete observations of the agents inventory for each item required for obtaining a diamond. The action space is the Cartesian product of continuous view adjustment (turning and pitching), binary movement commands (left/right, forward/backward), and discrete actions for placing blocks, crafting items, smelting items, and mining/hitting enemies.

An agent receives reward for completing the full task of obtaining a diamond, and for the first time it reaches each milestone in a sequence of milestones of increasing difficulty, which together form a set of prerequisites for the full task. For each item obtained in the sequence of prerequisite milestone items, an agent receives twice the reward as received for the previous item (starting from a reward of 1) — except for the diamond, which is worth 4 times as much as the previous item.

3.2. Competition Design

The competition was split into two rounds. In Round 1, participants trained their agents and submitted trained models for evaluation to determine their leaderboard ranks. We limited participants to 25 total submissions. At the end of Round 1, participants submitted their source code, and the top teams were reviewed by the rules committee to verify that the approaches comply with the rules. A submission's score is the average reward over 100 episodes. The 13 top-scoring teams advanced to Round 2. We invited these teams to present their work at the NeurIPS 2019 competition workshop. With the support of Microsoft Research, we gave each team a $1200 USD travel grant to attend the conference.

In Round 2, each team could submit up to 5 learning procedures to be trained from random weights on a held-out test environment, which is illustrated in Figure 3.1. Each submission was independently trained for 6 days using Azure NC6 and NC12 instances with a strict environment step budget of 8 million samples. To encourage generalizability and compliance with rules, we retrained the solutions submitted in the final round using: 1) a perturbed action space, and 2) an entirely new, previously-unseen texture pack[5]. To enable teams to test whether their approaches could generalize to previously-unseen environments, we provided them with a validation texture pack to use during training[6]. The final ranking was determined based on each team's highest-scoring submission.

5. The test texture pack we used can be found here.
6. We used a modified version of this texture pack as our validation texture pack.

Given the unique paradigm of training learning procedures, we set strict rules to encourage sample efficiency and generalizability, and prevent participants from loading pretrained models. Sample efficiency was achieved by setting a strict environment sample limit of 8 million frames or roughly 110 hours of in-game interactions, as well as limiting computation to 144 hours of wall clock time. We permitted frame skipping, but each frame skipped counted against the sample budget. Participants were also free to shape the observations of the agent, but they could not directly encode them in the policy. A detailed discussion of the competition paradigm can be found in previous work (Houghton et al., 2019).

Participants submitted their code as standalone repositories which are compatible with AIcrowd-repo2docker[7]. These repositories included the code, trained models, and runtime specifications, which enabled us to build consistent Docker images out of the submissions. These images were orchestrated on a custom Kubernetes cluster while respecting the round specific policies. All the submissions were evaluated in complete network isolation to avoid any leak of information due to malicious code submitted by participants. In Round 2, any files (in the submitted code repository) greater than 4MB were programmatically deleted to avoid participants including pre-trained models in their submissions.

3.3. Resources

In addition to the Obtain Diamond task, we created a number of auxiliary tasks. These tasks were provided to participants as Gym environments (Brockman et al., 2016). Additionally, we provided the participants with a starter pack[8], consisting of extensive documentation, starter code, a description of the submission procedure, a Microsoft Azure quick-start template, and the Docker images that we used to validate the training procedures during retraining. We gave the participants a large dataset of human demonstrations (Guss* et al., 2019) to leverage for training their agents. Preferred Networks[9] provided extensive baselines[10], including behavioral cloning, deep Q-learning from demonstrations (DQfD) (Hester et al., 2018), Rainbow (Hessel et al., 2018), generative adversarial inverse RL (GAIL) (Ho and Ermon, 2016), and proximal policy optimization (PPO) (Schulman et al., 2017).

AIcrowd[11] provided a unified interface for participants to sign-up, ask questions, and monitor progress. We also created a public Discord server for more informal communication with participants.

Through our generous sponsor, Microsoft Azure, we provided compute grants of $500USD each in Micrsoft Azure[12] credits for 50 individuals that self identified as lacking access to the necessary compute power to participate in the competition. Also thanks to Microsoft Azure, we provided each of the top teams from Round 1 with up to $1500USD of Azure credits for their experiments in Round 2.

7. https://github.com/AIcrowd/repo2docker
8. https://github.com/minerllabs/competition_submission_starter_template
9. https://preferred.jp/en/
10. https://github.com/minerllabs/baselines
11. https://www.aicrowd.com/
12. https://azure.microsoft.com/en-us/

Team Name	Round 1 Score
MeatMountain	48.42
xt	46.75
shadowyzy	37.82
CraftRL	33.15
CDS	29.62
mc_rl	27.43
I4DS	23.96
UEFDRL	21.70
TD240	17.12

Team Name	Round 2 Score
CDS	61.61
mc_rl	42.41
i4DS	40.80
CraftRL	23.81
UEFDRL	17.90
TD240	15.19
LAIR	14.73
Elytra	8.25
karolisram	7.87

Table 1: Scores of best-performing submissions of top teams in Round 1 and Round 2.

4. Outcomes for Participants

In Section 4.1, we provide quantitative information about the submissions to our competition. In Section 4.2, we summarize the approaches used by the top 9 teams in the final round. In Section 4.3, we describe the special awards awarded as part of the competition.

4.1. Submission Performance Overview

In Round 1, there were over 540 submissions, and 25 teams drastically outperformed the provided baselines. Table 1 shows that the top 3 teams from Round 2 on average outperformed the top 3 teams from Round 1 (means: 48.27 and 44.33, respectively), despite the Round 2 agents being trained on a hold-out test environment. Perhaps unsurprisingly, the Round 1 scores had a higher mean (31.77) and lower standard deviation (10.22) than the Round 2 scores (25.84 and 17.37, respectively). Additionally, the Round 1 scores had a smaller range (31.30) than the Round 2 scores (53.74). Figure 4.1 shows the maximum item score over the evaluation episodes of Round 2. Although no team obtained a diamond, the top team obtained the penultimate prerequisite item to obtaining a diamond.

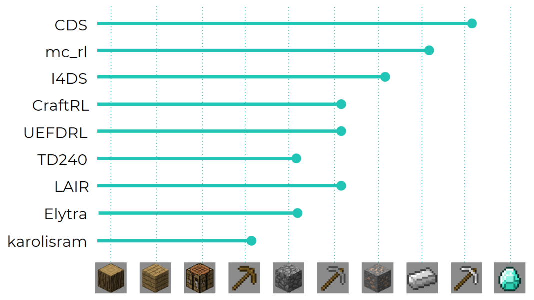


Figure 2: Maximum item score for each team over the 100 evaluation episodes in Round 2.

	Use hierarchical RL	Use human data	Use action reduction
Number of teams	6	7	9
Percent of teams	67%	78%	100%

Table 2: Overview of general approaches taken by the top 9 teams.

4.2. Summary of Top Nine Solutions

The top 4 teams used some form of hierarchical RL, taking advantage of the hierarchicality of Minecraft. All teams used some form of action reduction (e.g., removing actions that were almost never performed by human experts) to manage the complexity of the environment. Most teams leveraged the human data to improve the sample efficiency of their algorithms.

The top team, CDS, used a hierarchical deep Q-network with forgetting that uses an adaptive ratio for sampling expert demonstrations from a separate demonstration replay buffer[13] (Skrynnik et al., 2019). The second-place team, mc_rl, trained their hierarchical policies entirely from human demonstrations with *no* environment interactions[14]. The third-place team, i4DS, used demonstrations to bootstrap their hierarchical RL algorithm, effectively using the human data to pretrain the models to predict recorded human actions from observations, then using RL to refine the resulting agents.

The fourth-place team, CraftRL, aggregated grounded actions into options (Sutton et al., 1999) and then used a meta-controller to select between options. They pretrained the meta-controller on demonstration data using behavioral cloning. The fifth-place team, UEFDRL, used a single deep residual neural network trained to mimic human actions from the MineRL dataset. This team used action discretization to deal with the complexity of the environment. The sixth-place team, TD240, used a discriminator soft actor critic, which uses a discriminator based on adversarial inverse RL as a reward function.

The seventh-place team, LAIR, used meta-learning shared hierarchies (MLSH) (Frans et al., 2018), a hierarchical RL algorithm, and pretrained the master and subpolicies with human data before training MLSH with environment interactions. The eighth-place team, Elytra submitted a Rainbow baseline with modifications, including adding a small amount of stochasticity to the environment and restricting the camera movement to 1 degree of freedom. However, they explored the idea of training an ensemble of value functions and believe this approach to be promising. The ninth-place team, karolisram, used the PPO baseline with modifications, including removing frame-skip and reducing the action space.

4.3. Special Awards

In addition to evaluating teams on the performance of their learning algorithms, we awarded teams prizes for research contributions. Since this was the first year in which the competition was held, we awarded two prizes to extreme and opposite research paradigms: one based purely on imitation learning and the other one based purely on RL, with no use of human priors. We awarded the main research prize to mc_rl for their imitation-learning-based approach, and the runner-up research prize to karolisram for their purely-RL-based ap-

13. A video example of CDS's trained agent can be found here.
14. A video example of mc_rl's trained agent can be found here.

proach. We hope that these special awards will encourage future participants to maximally explore the space of solutions, even if this comes at the expense of performance.

5. Organizational Outcomes

First, we present the impact of our chosen rule set in Section 5.1. Then, in Section 5.2, we discuss the effectiveness of our distribution of competition materials. Finally, we summarize the effects of our chosen evaluation methodology in Section 5.3.

5.1. Repercussions of the Rules

Unlike many other DRL competitions, we sought to limit the use of domain knowledge through feature engineering and hard-coded policies. Though this ruleset has led to the use of more general methods, it also led to a lot of clarifying questions from participants. Since these were asked across various communication channels, there were duplicate questions and no single, comprehensive answer. In future renditions of this competition, we will have a clear place for rule clarifications and a more robust restriction on use of domain knowledge.

A secondary effect of the limitation on domain knowledge use was the difficulty in checking Round 1 submissions for this rule violation. This rule was the only one which led to complications of this type; restrictions on training time and number of samples are quantitative restrictions and therefore easy to enforce. Since competitor's submissions were not trained on a "hold out" environment, a committee spent more work hours than expected manually reviewing the code to identify manually specified policies and other violations.

5.2. Effectiveness of Competition Materials

As mentioned in Section 3.3, we provided participants with the tasks as Gym environments, the dataset, and baseline method implementations. The environments and dataset were both complete before the competition began, but the baselines were developed after the competition was announced because of delays providing the environment to our collaborators, Preferred Networks. However, Preferred Networks worked quickly to provide the baselines in time for participants to use them in Round 1, and many participants found these baselines to be crucial for developing their own algorithms. In future iterations of this competition, we will be able to provide the baselines as soon as the competition begins now that the baselines are complete.

The data was readily available and participants were generally able to successfully use it. The provided Gym environments were a wrapper around the Malmo Minecraft environment (Johnson et al., 2016). In addition to wrapping Malmo in a standardized way, we fixed bugs and added functionality which allows faster and more efficient training. These modifications have increased interest in working on Minecraft, and we have been contacted by several academic groups about further extensions to the environment.

Competitor submissions had to adhere to a specific Docker format, as outlined in Section 3.2. Use of a standard container streamlined the evaluation process during both rounds, and it saved time from our end. We provided information about how to use the provided container, but, in the future, plan to include a step-by-step demo showing how to submit an agent using the provided structure.

5.3. Impact of Evaluation Methodology

We chose to have two rounds to balance the need for an explicit computational budget with a desire to not limit participation in the competition. We did not limit the number of teams who could participate during the Round 1, but we chose a pre-specified number of teams to move to Round 2. As a result, we could commit to retraining all submissions during Round 2. This commitment was possible due to the strict limits on training time as well as the selection of a specific system on which all training and evaluation would be performed. Due to this structure, we did not use more computational resources than expected for evaluation.

However, these same strict limits on training time led to delays in obtaining final results. We delayed submission deadlines for competitors, but this reduced the time before we were scheduled to announce results. Since training had to happen for a fixed number of days on a specific system, we could not parallelize an individual competitor's submission or run it on faster hardware. Despite the delay in announcing results, we will use a similar restriction in future competitions due to the reproducibility and sample-efficiency benefits.

As mentioned in Section 3.3, we provided each team in Round 2 with a compute grant of $1500USD in Azure credits to enable training and validation of their methods. Because of the training time restrictions, participants were not incentivized to spend the remainder of their compute time on extending the training time of their final approach. We believe we allocated a sufficient amount to each team, since some teams had enough compute time remaining to continue to develop their methods even after the competition was over.

Finally, while we effectively utilized a novel visual domain randomization method to ensure generalization and rule compliance, competitors spent a great deal of effort shaping the action space using inductive bias. To yield fully generalizable competition results in future iterations of this competition, we plan to remove semantic labels of the environment's action space and apply a random bijective-mapping to the action space during evaluation.

6. Conclusion

We ran the MineRL Competition on Sample-Efficient Reinforcement Learning Using Human Priors at NeurIPS2019 in order to promote the development of algorithms that: 1) use human demonstrations alongside reinforcement learning, 2) are sample efficient, and 3) are accessible to the general AI community. We summarized the submissions and looked at the performance of competitors in different rounds. We discussed the effects of the competition rules, the provided competition materials, and the evaluation methodology. Based on the largely positive outcome of the competition, we plan to hold the competition again. Because no team obtained a diamond, we plan to focus on the same task. We also plan to keep the same paradigm promoting the development of generalizable and robust learning procedures.

Acknowledgments

We thank Microsoft Azure for providing the computational resources for the competition, NVIDIA for providing prizes, AIJ for funding the inclusion grants, and Microsoft Research for funding travel grants. We also thank AIcrowd for hosting and helping run the competition, and Preferred Networks for providing the baseline method implementations.

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