
Hierarchical Deep Q-Network from Imperfect Demonstrations in Minecraft

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Abstract

We present hierarchical Deep Q-Network (HDQfD) that took first place in MineRL competition. HDQfD works on imperfect demonstrations utilize hierarchical structure of expert trajectories extracting effective sequence of meta-actions and subgoals. We introduce structured task dependent replay buffer and adaptive prioritizing technique that allow the HDQfD agent to gradually erase poor-quality expert data from the buffer. In this paper we present the details of the HDQfD algorithm and give the experimental results in Minecraft domain.

1 Introduction

Deep reinforcement learning (RL) has achieved compelling success on many complex sequential decision-making problems especially in simple domains. In such example as AlphaStar [7], AlphaZero [6], OpenAI Five human or super-human level of performance was attained. However, RL algorithms usually require a huge amount of environment-samples required for training to reach good performance [5]. Learning from demonstration is a well-known alternative, but until now, this approach has not achieved serious success in complex non-single-task environments. This was largely due to the fact that obtaining high-quality expert demonstrations in sufficient quantity in sample-limited, real-world domains is a separate non-trivial problem.

Minecraft as a compelling domain for the development of reinforcement and imitation learning based methods was recently introduced [3]. It presents unique challenges because Minecraft is a 3D, first-person, open-world game where the agent should gather resources and create of structures and items to achieve any goal. Due to its popularity as a video game it turned out to be possible to collect a large number of expert trajectories in which individual subtasks are solved. This allowed the appealing MineRL competition to run. Organizers have released the largest-ever dataset of human demonstrations on a Minecraft domain. The primary goal of the competition is to foster the

development of algorithms that can efficiently leverage human priors to drastically reduce the number of samples needed to solve complex, hierarchical, and sparse environments.

The main difficulty in solving the MineRL problem was the imperfection of demonstrations and the presence of hierarchical relationships of subtasks. In this paper we present hierarchical Deep Q-Network from Demonstrations (HDQfD) that allowed us to take the first place in MineRL competition [2]. HDQfD works on imperfect demonstrations and utilize hierarchical structure of expert trajectories extracting effective sequence of meta-actions and subgoals. Each subtask is solved by its own simple strategy, which extends DQfD approach [1] and relies on a structured buffer and gradually decrease ratio of poor-quality expert data. In this paper we present the details of our algorithm and give the results that allow the HDQfD agent to play Minecraft at the human level.

2 Background

One way to explore the domain with the use of expert data is to do behavioral cloning (BC). Pure supervised learning methods based on BC suffer from distribution shift: because the agent greedily imitates demonstrated actions, it can drift away from demonstrated states due to error accumulation. The other way to use expert data in search of exploration policy is to use conventional RL methods like PPO, DDDQN, etc. and guide exploration through enforcing occupancy measure matching between the learned policy and current demonstrations. Main approach is to use demonstration trajectories sampled from an expert policy to guide the learning procedure, by either putting the demonstrations into a replay buffer or using them to pretrain the policy in a supervised manner.

Organizers of MineRL competition provided us a few baselines. Standard DQfD [4] get the max score of 64 after 1000 episodes, PPO get max of 55 after 800 episode, rainbow also get max of 55 after 800 episodes of training.

Our best solution exploits the method of injecting expert data into agent replay buffer. The DQfD, which our method is based on, is an advanced approach to reinforcement learning with additional expert demonstrations. The main idea of DQfD is to use an algorithm called Deep Q-Network (DQN) and combine loss function $J(Q)$, with the main component $J_E(Q)$:

$$J(Q) = J_{DQ}(Q) + \lambda_1 J_n(Q) + \lambda_2 J_E(Q) + \lambda_3 J_{L2}(Q). \quad (1)$$

The loss function $J_{DQ}(Q)$ is a standard TD-error:

$$J_{DQ}(Q) = (R(s, a) + \gamma Q(s_{t+1}, a_{t+1}^{\max}; \theta') - Q(s, a; \theta))^2. \quad (2)$$

The loss function $J_n(Q)$ is the so-called N-step return, that allows the agent to extend the utility of trajectories to several steps, which leads to a better strategy:

$$J_n(Q) = r_t + \gamma r_{t+1} + \dots + \gamma^{n-1} r_{t+n-1} + \max_a \gamma^n Q(s_{t+n}, a). \quad (3)$$

The main part $J_E(Q)$ is a margin loss function. It is responsible for copying expert behavior and gives penalty to the agent for performing actions other than experts:

$$J_E(Q) = \max_{a \in A} [Q(s, a) + l(a_E, a)] - Q(s, a_E). \quad (4)$$

Finally $J_{L2}(Q)$ is L2 regularization is added to prevent overfitting.

3 Hierarchical Deep Q-Network from Demonstrations

Action and state space

To make the demonstration data convenient for RL agent we used action discretization, and some techniques for state space preparation: framestack and frameskip. In MineRL simulator the agent could choose between 10 actions (see table 1). The expert action is mapped to the agent's action in the order shown in table 1. For example, "turn the camera right 10 degrees, turn the camera up 5 degrees, run forward" will be mapped with the first action - turn the camera right 5 degrees and attack. All "move"-actions (back, forward, left, right) were allowed because experts used mostly them to point the camera at tree block.

Table 1: Discretization of actions used for all subtasks with frameskip 4. The expert action is mapped to the agent’s action in the order shown in this table. The rotation angle is determined using the sum of 4 frames. For other actions, the most frequent was selected.

actions	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
pitch +5	+									
pitch -5		+								
yaw +5			+							
yaw -5				+						
forward					+	+				
left							+			
right								+		
back									+	
jump						+				+
attack	+	+	+	+	+	+	+	+	+	+

Adaptive ration of expert data

Despite this action space discretization allowed to make good behaviour cloning, there are some noise in demonstrations due to which the agent could not improve his strategy above a certain threshold. We solved this problem by adding the ability to change the ratio of expert data. Demonstrations and agents’ trajectories were stored separately in Aggregating Buffer, which controls the proportion of demonstrations in mini-batches. Proportion decreases linearly depending on the number of episodes (see picture 1a).

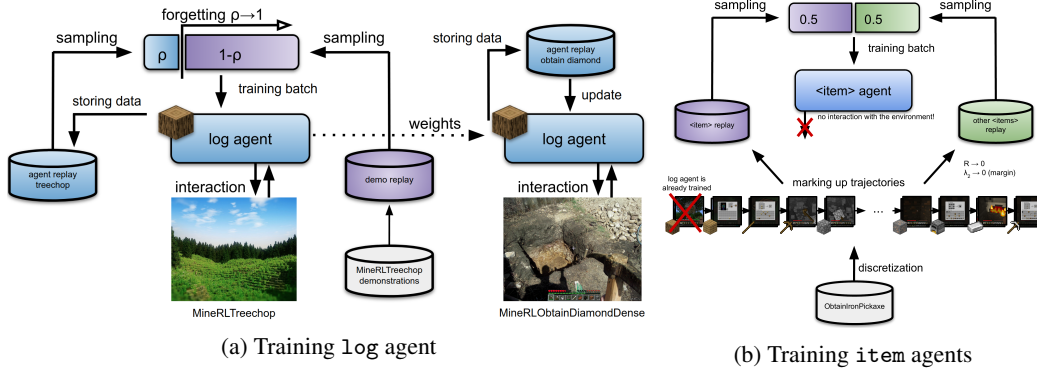


Figure 1: (a) Aggregated buffer is used to store expert and agent trajectories. The amount of data in the mini-batch sampled from the demo replay buffer is gradually decreasing. (b) For `item` agents each trajectory is divided into expert and non-expert segments. The item agent learns to solve one subtask using data from other subtasks, which it considers as non-expert.

Extracting hierarchical subtask structure

We separately examined each expert’s trajectory and considered the time of appearance of items in the inventory in chronological order. An example of a possible order of obtaining items is shown in the figure 2. In addition, this sequence can be considered as a semantic network with two types of nodes: certain agent’s actions and subtasks defined on agent’s inventory. We consider each subtask node in this network as a mandatory sub-goal which the agent must complete in order to move on. We train the separate strategy for the agent to achieve each sub-goal and it can be considered as a set of individual agents. The task of such agents is to obtain the necessary number of items in the inventory.

The agent that solves the subtask is divided into two agents which take actions at the same time: the agent performing basic actions in the environment (POV or `item` agent) and the agent interacting with semantic actions – sequentially performs the action denoted in the corresponding node of the

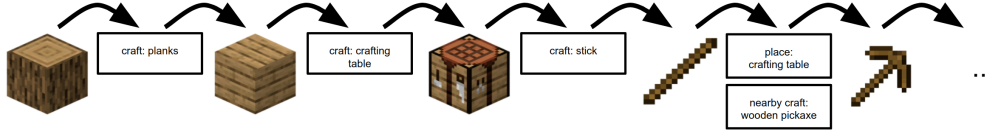


Figure 2: An example of expert’s trajectory from demonstrations.

semantic network. The training scheme for `item` agents is presented in the figure 1b. During the training process all expert data from the `ObtainIronPickaxe` environment of MineRL simulator is used.

Frames of a mini-batch that correspond to the currently trained `item` agent are considered as expert data. All other frames are considered as additional data and their rewards are nullified. This approach allows both training the agent to move from solving one subtask to another and the effective use of available data.

4 Experiments

There we will consider our successful submissions in round 2 of the MineRL competition. All agents except the `log` agent were trained on expert data gathered from `ObtainIronPickaxeDense` dataset. A summary of all submissions is presented in the table 2.

Table 2: Round 2 Submissions

Log agent: <code>Treechop</code> \Rightarrow <code>ObtainDiamondDense</code>						
	Treechop episodes	Reward	Episodes	Reward	Pre-training	Evaluation
Submit 1	-	-	-	-	10^4 steps	20.72
Submit 2	200	53.22	300	16.31	10^4 steps	55.08
Submit 3	200	53.83	300	19.19	5×10^4 steps	61.61

	Discretization	Embeddings	Episodes	Reward
SAC			300	5
GAIL	+	+	150	30
RnD	+	+	1000	35
PPO	+	+	1000	35
Pretrained PPO	+	+	150	50
Modified DQfD	+		200	60

In first submit, the HDQfD agent was trained using only expert data. Each of the `item` agents was pre-trained using 10^4 steps. Log agent learned on `Treechop` environment data. The final result was **20.72**.

In 2nd and 3rd submissions we used interaction with the environment to train the `log` agent. The `log` Agent trained 200 episodes on `Treechop` environment data, and then on 300 episodes of `ObtainDiamondDense` environment data (see dynamics in the figure 3). The difference was in the number of pre-training steps. The final results were **55.08** and **61.61**, respectively.

5 Conclusion

In this paper we introduce novel approach to learn from imperfect demonstrations. This hierarchical Deep Q-Network from Demonstrations took the first place in MineRL competition and got **61.61** score. In future work we are planning to learn all `item` agents for full hierarchical end-to-end architecture and add for these agents the access to all demonstrations from all subtask with respect to agent’s inventory for additional performance.

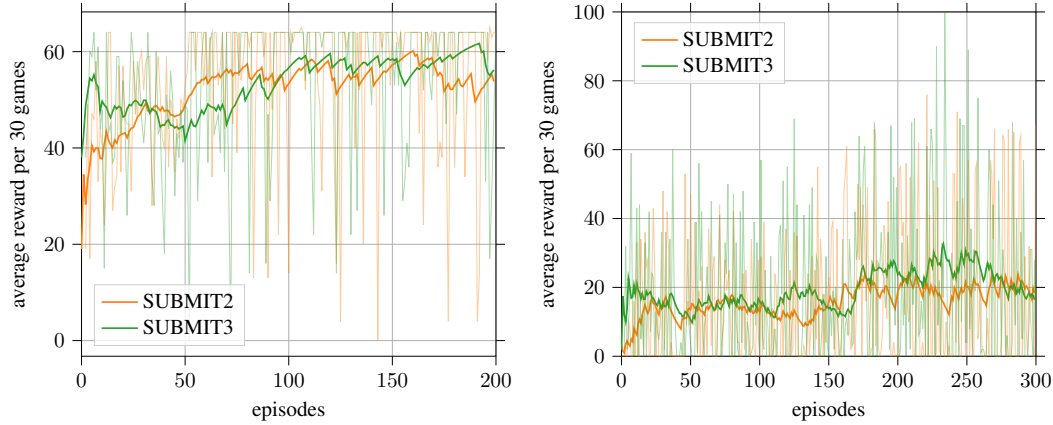


Figure 3: Log agent results for `Treechop` (left) and `ObtainDiamondDense` environment (right).

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References

- [1] Yang Gao, Ji Lin, Fisher Yu, Sergey Levine, Trevor Darrell, et al. Reinforcement learning from imperfect demonstrations. *arXiv preprint arXiv:1802.05313*, 2018.
- [2] William H Guss, Cayden Codel, Katja Hofmann, Brandon Houghton, Noboru Kuno, Stephanie Milani, Sharada Mohanty, Diego Perez Liebana, Ruslan Salakhutdinov, Nicholay Topin, et al. The minerl competition on sample efficient reinforcement learning using human priors. *arXiv preprint arXiv:1904.10079*, 2019.
- [3] William H Guss, Brandon Houghton, Nicholay Topin, Phillip Wang, Cayden Codel, Manuela Veloso, and Ruslan Salakhutdinov. Minerl: a large-scale dataset of minecraft demonstrations. *arXiv preprint arXiv:1907.13440*, 2019.
- [4] Todd Hester, Matej Vecerik, Olivier Pietquin, Marc Lanctot, Tom Schaul, Bilal Piot, Dan Horgan, John Quan, Andrew Sendonaris, Ian Osband, et al. Deep q-learning from demonstrations. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.
- [5] Sham Machandranath Kakade et al. *On the sample complexity of reinforcement learning*. PhD thesis, University of London London, England, 2003.
- [6] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, et al. Mastering the game of go without human knowledge. *Nature*, 550(7676):354, 2017.
- [7] Oriol Vinyals, Igor Babuschkin, Junyoung Chung, Michael Mathieu, Max Jaderberg, Wojciech M Czarnecki, Andrew Dudzik, Aja Huang, Petko Georgiev, Richard Powell, et al. Alphastar: Mastering the real-time strategy game starcraft ii. *DeepMind Blog*, 2019.