Hierarchical Deep Q-Network with Forgetting from Imperfect Demonstrations in Minecraft

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Abstract

We present hierarchical Deep Q-Network with Forgetting (HDQF) that took first place in MineRL competition. HDQF 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 forgetting technique that allow the HDQF agent to gradually erase poor-quality expert data from the buffer. In this paper we present the details of the HDQF 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 [6], AlphaZero [2], 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 [1]. 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 [5]. 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 with Forgetting (HDQF) that allowed us to take the first place in MineRL competition [4]. HDQF 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 [7] and relies on a structured buffer and gradually forgets poor-quality expert data. In this paper we present the details of our algorithm and give the results that allow the HDQF 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, DDPQ, 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 [3] 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 $J_E(Q)$:

$$ J(Q) = J_{DQ}(Q) + \lambda_1 J_n(Q) + \lambda_2 J_E(Q) + \lambda_3 J_{L^2}(Q). \tag{1} $$

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

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

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:

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

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:

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

Finally $J_{L^2}(Q)$ is L2 regularization is added to prevent overfitting.

3 Deep Q-Network with Forgetting from Imperfect 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   | +     | +     | +     | +     | +     | +     | +     | +     | +     | +     |

Forgetting

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 forget 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 fro 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 network.
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: Treechop ⇒ ObtainDiamondDense | |
| Treechop episodes | Reward | Episodes | Reward | Pre-training | Evaluation |
| Submit 1  | - | - | - | - | - | - |
| 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 HDQF 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 submitions 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 with Forgetting 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 substask with respect to agent’s inventory for additional performance.
Figure 3: Log agent results for Treechop (left) and ObtainDiamondDense environment (right).

Acknowledgments

This work was supported by the Russian Science Foundation, project no. 18-71-00143. We would like to thank AIM Tech company for its organizational and computing support.

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