Failed Goal Aware Hindsight Experience Replay

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Abstract. In multi-goal reinforcement learning for a given environment, agents learn policies to achieve multiple goals by using experiences gained from interactions with the environment. One of the key challenges in this setting is training agents using sparse binary rewards, which can be difficult due to a lack of successful experiences. To address this challenge, hindsight experience replay (HER) generates successful experiences from unsuccessful experiences. However, the process of generating successful experiences from uniformly sampled ones can be inefficient. In this paper, a novel approach called Failed goal Aware HER (FAHER) is proposed to enhance the sampling efficiency. The approach exploits the property of achieved goals in relation to failed goals that are defined as the original goals not achieved. The proposed method involves clustering episodes with different achieved goals using a cluster model and subsequently sampling experiences in the manner of HER. The cluster model is generated by applying a clustering algorithm to failed goals. The proposed method is validated by experiments with three robotic control tasks of the OpenAI gym. The results of experiments demonstrate that the proposed method is more sample efficient and achieves improved performance over baseline approaches.

Keywords: Multi-goal Reinforcement Learning, Hindsight Experience Replay, Deep Learning

1 Introduction

Reinforcement learning (RL) is a powerful framework for training an agent to make a series of actions to accomplish a specific task. In the RL framework, the agent interacts with the environment, taking actions and receiving rewards, and learns a policy that maximizes accumulated rewards. The policy function gives an action as the output, taking a state as input. The integration of deep neural networks as policy functions in RL has led to notable progress [1]. Although there are still challenges posed by certain legacy technologies, such as financial services [2], wireless communication networks [3,4], and space exploration [5,6], where the effort for the application of RL remains insufficient, RL has achieved breakthrough successes in various tasks requiring sequential decision-making by the agent, including video games [7,8], sensor networks [9,10], and robotic control [13,14,15].
In the real world, a single task can have multiple goals. For example, in the case of walking, the agent walks to various target places, and in the case of putting an object on a table, the agent can put it in various target spots on the table. The RL framework for learning these multiple goals is called multi-goal RL [16]. The main difference between the RL with a single goal and multi-goal RL is that an agent in multi-goal RL learns a goal-conditioned policy, which takes as inputs a state as well as the goal information.

In both RL frameworks, the training data consists of experiences that are obtained through exploration and stored in a replay buffer [17]. In multi-goal RL environments with sparse binary rewards, there’s a lack of successful experiences in the replay buffer, making agent training challenging. To address this, hindsight experience replay (HER), introduced in [18], generates successful experiences, named hindsight experiences, from experiences in the replay buffer. It achieves this by replacing the original goal with the achieved goal and re-computing the rewards based on the achieved goal. For training the agent to learn implicitly achievable goals, HER uses a technique that can be categorized into curriculum learning [19]. HER with off-policy RL algorithms, such as deep Q-network [1] and deep deterministic policy gradient (DDPG) [20], can learn complex tasks with sparse binary rewards. Moreover, HER can be combined with other techniques as presented in [21,22,23,24,25] for improved performance in RL.

HER generates hindsight experiences from experiences in the replay buffer that contains both unsuccessful and successful ones. However, generating hindsight experiences from successful experiences is less efficient in sampling compared to generating from failed ones. In this paper, it is found that the efficiency of HER can be increased, if experiences can be sampled in consideration of the property of achieved goals in relation to failed goals (FGs) that are defined as the original goals not achieved. From this viewpoint, Failed goal Aware HER (FAHER) is proposed to improve the sampling efficiency of HER. The proposed method introduces an additional step in the HER sampling process, involving the clustering of episodes. The clustering procedure utilizes a cluster model generated by applying a clustering algorithm to FGs. The cluster model assigns cluster indices to episodes in the replay buffer based on their last achieved goals. According to the cluster indices, the episodes are clustered into clustered buffers. The fundamental concept behind this episode clustering is to enable the agent to gain more valuable insights from unsuccessful episodes whose last achieved goals are closely related to the FGs. To verify the performance of FAHER, experiments with the DDPG algorithm are conducted in the Fetch environment of OpenAI gym [26]. The results of these experiments demonstrate that FAHER outperforms HER.

2 System Modeling

In this section, concepts related to this work, including multi-goal RL, DDPG, HER, a variant of HER, and K-means clustering, are presented.
2.1 Multi-goal Reinforcement Learning

In the multi-goal RL framework, the agent is trained to develop a policy that allows it to achieve various goals within a given task. This policy is referred to as a goal-conditioned policy, as it takes both the current state and a specified goal as inputs [27]. The reward function is defined as a function of the state, goal, and action.

At the beginning of each episode, the initial state $s_0 \in S$ of the environment and the goal $g \in G$ to be achieved are given. The state $s_t$ consists of an observation $o_t$ and an achieved goal $ag_t$, which represents the state of an object. The goal $g$ is fixed during the entire episode. In each timestep $t$, the agent observes the current state $s_t$ and the goal $g$ and takes an action $a_t \in A$ based on the policy $\pi: S \times G \rightarrow A$. The environment pertinent to the Markov decision process (MDP) is affected by the action $a_t$ and returns a reward $r_t = r(s_t, g, a_t)$ and next state $s_{t+1}$. The next state $s_{t+1}$ is observed according to the transition probability $p(s_{t+1}|s_t, a_t)$. The agent continues to interact with the environment until the terminal state corresponding to the last timestep $T$ is reached. During exploration, the experience at timestep $t$ includes, unlike in traditional RL, the goal $g$ and thus is denoted by $e_t = (s_t, g, a_t, r_t, s_{t+1})$.

2.2 Deep Deterministic Policy Gradient (DDPG)

The DDPG [20] is an off-policy and model-free RL algorithm for continuous action spaces. This algorithm uses policy optimization and Q-learning. Like the Q-learning, the optimal action $a^*(s, g)$ can be found from the optimal action-value function (Q-function) $Q^*(s, g, a)$ by solving $a^*(s, g) = \arg \max_a Q^*(s, g, a)$.

To approximate the policy $\pi(s, g)$ and the Q-function $Q(s, g, a)$, two neural networks actor network and critic network are simultaneously trained.

2.3 Hindsight Experience Replay (HER)

The main idea of HER [18] is that it is possible to learn even from unsuccessful episodes by substituting achieved goals for the original goal. For each experience $e_t = (s_t, g, a_t, r_t, s_{t+1})$ in the mini-batch, HER works as follows. Among the achieved goals in the episode containing the experiences, a hindsight goal $g^h$ is sampled, e.g., the last achieved goal $ag_T$. For the hindsight goal $g^h$, hindsight rewards for each timestep $r^h_t = r(s_t, g^h, a_t)$ are recomputed. Substitution of these two hindsight components defines a hindsight experience as $e^h_t = (s_t, g^h, a_t, r^h_t, s_{t+1})$.

2.4 Energy-Based Hindsight Experience Prioritization

In [22], energy-based prioritization (EBP) for HER is proposed, which is used in an ablation study of this paper. The basic idea of this method is similar to that of curriculum learning. The difficult but achievable experiences are prioritized. The
difficulty of the experience is evaluated by trajectory energy $E_{\text{traj}}(s_0, s_1, ..., s_T)$ defined as the sum of transition energies of the object $E_{\text{tran}}(s_{t-1}, s_t)$ which is the increase of total energy between two successive timesteps. The total energy is defined as the sum of potential, kinetic, and rotational energy.

2.5 K-means Clustering

The K-means clustering [28] is a widely used unsupervised clustering algorithm. It works by clustering input data into $k$ different clusters. The number of clusters, $k$, is a user-defined parameter. The $k$ centroids, centers of clusters, are initialized randomly. Each datum is assigned to the closest centroid. Each centroid is updated to minimize the average squared distance between data and their assigned centroid. Assigning data and updating centroids are performed iteratively until there is no more transition of centroids.

3 Proposed Method

In this section, FAHER is presented. This method leverages a cluster model to sample episodes from the replay buffer to generate a mini-batch for improved sampling efficiency.

In multi-goal environments with sparse binary rewards, HER allows agents to learn policies by generating hindsight experiences. A hindsight experience is generated by sampling a hindsight goal and recomputing a reward with the hindsight goal. The most straightforward approach to sampling hindsight goals is to use the last achieved goals from each episode. HER enables unsuccessful episodes to yield valuable positive feedback to the agent. However, generating hindsight experiences from successful episodes is less efficient in sampling compared to generating from failed ones.

The proposed method involves the incorporation of a clustering procedure into the original HER framework. The framework of HER includes three processes of uniform samplings. As shown in the upper part of Fig 1, the first process is for sampling episodes from the replay buffer, the second one is for sampling one experience from each sampled episode, and the last one is to sample experiences to be substituted by hindsight experiences among sampled experiences in the second process. The first process of HER can be designed in a way that “hard episodes” are more likely sampled instead of using uniform sampling, thereby enhancing the effectiveness of HER. The “hard episode” refers to an episode whose last achieved goal is hard to achieve by the current RL policy when the achieved goal is considered as the original goal of an episode. To realize this concept, FAHER replaces the first sampling process with two procedures: clustering of episodes using a cluster model and sampling the episodes uniformly from clustered episodes, as depicted in the lower part of Fig 1.

The clustering procedure relies on a cluster model. In order to cluster episodes while taking ”hard episodes” into account, the cluster model is generated by applying a clustering algorithm to the FGs, which are stored in the failed goal
buffer (FGB) during the exploration of the RL model. The cluster model assigns specific cluster indices to episodes in the replay buffer based on their last achieved goals. According to the cluster indices, the episodes are clustered into clustered buffers. The clustered buffers $R_i$ are a subset of the replay buffer and the number thereof is equal to the number of the clusters $k$. From each clustered buffer, $(\text{batch size}/k)$ episodes are uniformly sampled to form an episode batch containing $\text{batch size}$ episodes. With the episode batch, the second and third uniform samplings are performed in the manner of HER.

To maintain the effectiveness of the training of the RL model, the cluster model is periodically updated. This is crucial because continuing to use an outdated cluster model generated with older FGs can interfere with the training of the RL model. When the FGB is filled with entirely new FGs, the cluster model is updated. Once the cluster model is updated, the cluster model assigns the cluster index for each episode in the replay buffer. For the episodes stored after the update, the cluster index is given individually by the cluster model. The important parameters in this periodical update are the number of FGs used to update and the frequency of the update.

The important parameters in the periodical updating of the cluster model are the number of FGs used to train the cluster model and the frequency of training the cluster model. The size of the FGB representing the number of FGs to be used to update the cluster model should be carefully determined. The small-sized FGB can not properly represent the FGs of the current RL model. When the size is too large, the computational volume increases and the FGs of the past RL models are used to update the cluster model. The clustering cycle...
indicating the frequency of updating the cluster model should be determined in consideration of computational time. With a short clustering cycle, the cluster model of the sampling strategy continues to change and the RL algorithm lacks time to learn about the FGs obtained from the current RL model. With a long clustering cycle, the RL algorithm wastes time even after learning about the FGs of the current RL model. In the following section, ablation studies of these important parameters are presented.

4 Experiments

In this section, the experiment environment is described and the experimental results of the proposed method are provided.

4.1 Experiment Environment

![Illustrations of three tasks considered in experiments: Push, PickAndPlace, and Slide tasks.](image)

Fig. 2: Illustrations of three tasks considered in experiments: Push, PickAndPlace, and Slide tasks.

Experiments are conducted for tasks requiring continuous control in multi-goal environments discussed in [16]. The environment named Fetch environment is developed by the OpenAI gym [26] and the MuJoCo physics engine [29]. The performance of the proposed method is evaluated with three tasks pertinent to the Fetch environment, which are fulfilled by a 7-DOF robot arm and an object on a table as depicted in Fig 2. The three tasks are described as follows:

1. Push task(FetchPush-v1): A goal location, a small red sphere in the figure, is randomly chosen on the 0.7m × 0.5m table surface. The robot arm pushes the object (a box) to the goal location.
2. Pick and Place task(FetchPickAndPlace-v1): A goal location is randomly chosen in the 3D space above the 0.7m × 0.5m table. The robot arm grasps the object (a box) with the gripper and lifts it up to reach the goal location.
3. Slide task(FetchSlide-v1): A goal location is randomly chosen on the 0.7m × 1.2m table surface in front of the robot, but out of the reach of the robot. The robot arm slides the object (a puck) to the goal location.
In the three tasks, each episode consists of 50 timesteps. The episode is considered successful under the condition that the distance between the goal location and the object is less than a threshold value, 5cm, in the last timestep.

For DDPG, an off-policy algorithm used for the experiments, the actor and the critic networks take multi-layer perceptron architecture with rectified linear units activation functions. The ADAM optimizer is used for the backpropagation algorithm for training two networks.

4.2 Experimental Results

The experimental results of FAHER are presented in this subsection. The performance of the proposed method is evaluated in terms of the success rate. After each epoch of 200 epochs for training, the success rate is calculated with 20 test episodes. To ensure robustness and reliability, the sequence of training followed by evaluation is repeated with 5 random seeds.

In the figures of the experimental results, a solid line shows the average of five success rates for each epoch and the lower and upper boundary lines of the shaded area show the minimum and maximum success rates. The width of the shaded area represents the range of variation of the success rates with 5 random seeds. To smooth the granularity of experimental results over epochs, the moving average of the past 20 success rates is calculated and shown in the figures. The comparison criteria are determined according to the characteristics of the success rate curve for each task. Comparison criteria for Push, PickAndPlace, and Slide tasks are the number of epochs required to achieve a success rate of 97.5%, maximum success rate, and increment of the success rate from that of HER, respectively. The last criterion is measured by the average of the differences in success rates at each epoch.

For generating the cluster model in the proposed method, the K-means clustering algorithm with a predefined value of $k$ set to 8 is employed. The parameters governing the size of the FGB and the clustering cycle are both configured to be 150. When 150 new FGs are stored in the FGB, the cluster model is updated. The rate of hindsight experience in sampling is set to 0.8 for every experiment.

Comparative Evaluation of Performance In Fig 3, performances of HER and FAHER are compared for the three tasks. Fig 3(a) shows that FAHER significantly reduces the number of epochs required to achieve the success rate of 97.5% from 114 to 84 for the Push task. It is seen in Fig 3(b) for the PickAndPlace task that FAHER allows the success rate to converge at 115 epochs and achieves the maximum success rate of 97.10% which is 4.48% larger than the maximum success rate of HER. For the Slide task, FAHER marginally improves the success rate by 2.08% on average as shown in Fig 3(c).

Ablation Studies Two types of ablation studies are conducted. One is about integrating the proposed method with an existing sampling algorithm and the other is concerned with the methodology employed for the proposed method.
Fig. 3: Success rates obtained while training HER, and FAHER for all three tasks.

Fig. 4: Success rates obtained while training HER-EBP, and FAHER-EBP for all three tasks.

The first ablation study demonstrates the compatibility of the proposed method with existing sampling algorithms, yielding a modest enhancement in performance. For this ablation study, EBP is employed as the existing sampling algorithm. In EBP framework, the episodes with higher energy in the replay buffer have a higher probability of being sampled. To integrate HER and FAHER with EBP, the procedure of EBP is inserted into the "Uniform Sampling", before "Sampled Episodes" in Fig 1. From each clustered buffer, the proposed method with EBP samples the same number of episodes according to the energy-based probability. Fig 4 shows comparative results of HER with EBP (HER-EBP) and FAHER with EBP (FAHER-EBP). For the Push task, the number of epochs required to achieve the success rate of 97.5% of FAHER-EBP is smaller by 5 than that of HER-EBP. The maximum success rate of 97.62% is achieved for the PickAndPlace task by FAHER-EBP, which is 3.29% higher than that of HER-EBP. For the Slide task, the success rate is slightly improved by 1.75% on average. For all three tasks, the proposed method improves the success rates and reduces the width of the shaded area, which means the variation of the success rates for 5 random seeds.

The methodological ablation study consists of three experiments. The first experiment is about the size of the FGB, the second is about the clustering cycle, and the third is about using the FGs. Results of the methodological ablation study are listed in TABLE 1 where $N_{0.975}$, $S_{max}$, and $I_{sr}$ are the number of
Table 1: Results of methodological ablation study

| Method     | Nh    | Smax in Push | Smax in PickAndPlace | Isr in Slide |
|------------|-------|--------------|----------------------|--------------|
| HER        | 114   | 92.62%       | 0.00%                |              |
| FAHER(150) | 84    | **97.10%**   | **2.08%**            |              |
| FAHER_15   | 108   | 96.24%       | -0.32%               |              |
| FAHER_500  | 108   | 96.20%       | 0.61%                |              |
| FAHER_e    | 117   | 95.43%       | 0.82%                |              |
| FAHER_woFG | 173   | 64.95%       | -4.32%               |              |

ePOCHS required to achieve a success rate of 97.5%, maximum success rate, and increment of the success rate on average over the success rate of HER, respectively.

The size of the FGB is set to 150. To check the validity of 150 as the size of the FGB, experiments with different sizes of the FGB are conducted. FAHER with the size 150, 15, and 500 of the FGB are named FAHER_150, FAHER_15, and FAHER_500, respectively. FAHER_150 is the same as FAHER used in other experiments. As shown in Table 1, FAHER_150 outperforms FAHER_15 and FAHER_500 for all tasks. This result suggests that the FGB with the size 150 is suitable for the cluster model of the proposed method while the FGB with the size 15 is not sufficiently representative of the FGs of the RL model and the FGB with the size 500 slows the training RL model because the FGB contains the FGs of the past RL models.

The clustering cycle is set to 150 like the size of the FGB, which allows the update of the cluster model with entirely new FGs. To verify the importance of setting the clustering cycle, an extreme case of using a short clustering cycle is compared with the proposed method for the cycle of 150. The extreme case is the proposed method with the cycle of 1, which means that the updating of the cluster model and the procedure of clustering the episodes in the replay buffer are conducted in every episode (FAHER_e). For all three tasks, it can be observed in Table 1 that the result of FAHER_e is better or similar to HER and is worse than FAHER.

The cluster model is updated with FGs which are obtained from the exploration of the RL algorithm. To check the importance of using FGs, experiments of HER with the clustering procedure without FGs (FAHER_woFG) are conducted. In FAHER_woFG, the cluster model is updated with the achieved goals in the replay buffer and assigns the cluster index to each episode. For all three tasks, the result of FAHER_woFG is worse than FAHER and even worse than HER as shown in Table 1. The reason for this outcome is that when FAHER_woFG samples the same number of episodes from each cluster and one of the clusters has fewer experiences, the few experiences are repeatedly sampled unnecessarily.
5 Conclusion

This paper introduces a novel approach, referred to as the Failed Goal Aware Hindsight Experience Replay (FAHER). The proposed method samples episodes based on the procedure of clustering the episodes by a cluster model. To consider the “hard episodes”, the cluster model is generated with failed goals, the original goals of unsuccessful episodes. This approach increases the likelihood of sampling a larger number of “hard episodes” while reducing the likelihood of sampling successful episodes. Experiments on three robotic control tasks of the OpenAI gym suite show that the proposed method greatly reduces the number of epochs required for convergence by 30 and 85 in the Push and PickAndPlace tasks and marginally improves the success rates by 2.08% on average in the Slide task, as compared to HER. Additional ablation studies show the feasibility of integrating the proposed method with other existing sampling algorithms and the importance of the methodological components: the size of the failed goal buffer, clustering cycle, and failed goals.

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