SAMPLE EFFICIENCY IN SPARSE REINFORCEMENT LEARNING: OR YOUR MONEY BACK

A PREPRINT

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August 31, 2020

ABSTRACT

Sparse rewards present a difficult problem in reinforcement learning and may be inevitable in certain domains with complex dynamics such as real-world robotics. Hindsight Experience Replay (HER) is a recent replay memory development that allows agents to learn in sparse settings by altering memories to show them as successful even though they may not be. While, empirically, HER has shown some success, it does not provide guarantees around the makeup of samples drawn from an agent’s replay memory. This may result in minibatches that contain only memories with zero-valued rewards or agents learning an undesirable policy that completes HER-adjusted goals instead of the actual goal.

In this paper, we introduce Or Your Money Back (OYMB), a replay memory sampler designed to work with HER. OYMB improves training efficiency in sparse settings by providing a direct interface to the agent’s replay memory that allows for control over minibatch makeup, as well as a preferential lookup scheme that prioritizes real-goal memories before HER-adjusted memories. We test our approach on five tasks across three unique environments. Our results show that using HER in combination with OYMB outperforms using HER alone and leads to agents that learn to complete the real goal more quickly.

Keywords reinforcement learning · replay memory · sparse rewards

1 Introduction

Reinforcement learning (RL) has shown great success in virtual environments, where generating a large number of agent-environment interactions and experimenting with various reward functions is feasible in a short amount of time. However, the application of RL to real-world systems, such as robotics, is limited by the challenges of relatively slow data collection and the difficulty in properly specifying a reward function (Kober et al., 2013). The former motivates research with the aim of improving learning efficiency in reinforcement learning agents (Yang et al., 2020; Wen and Van Roy, 2017). The latter has led to a parallel branch of research that focuses on algorithms capable of handling simple, sparse reward functions (Seo et al., 2019; Ren and Ben-Tzvi, 2020).

To overcome these issues in tandem, Andrychowicz et al. (2017) introduced Hindsight Experience Replay (HER), which is specifically designed for sparse-reward settings. HER works by artificially creating positive reward experiences. After each episode, regardless of the real goal, the agent’s memory is adjusted to show the episode’s trajectory as successful. While HER makes it possible for agents to learn in sparse-reward settings, it provides no guarantees around replay memory sampling behavior. This may lead to a large number of samples containing only non-informative experiences or to agents that learn policies to complete HER-adjusted goals instead of the actual goal.

In this paper, we introduce Or Your Money Back (OYMB), a novel sampler for the HER replay memory that allows for faster, more stable convergence of reinforcement learning agents in sparse-reward settings. Our method builds off of the success of HER by constructing an interface to the agent’s replay memory that provides guarantees around experience tuple selection during agent training. Also, it provides a preferential-lookup scheme that selects real-goal-achieving...
memories before HER-altered memories, thus discouraging the agent from learning policies that achieve the incorrect goal.

2 Background and Related Works

2.1 Reinforcement Learning

Reinforcement learning can be framed as a sequential decision-making problem represented by a finite Markov decision process. An agent interacts with an environment, $\mathcal{E}$, over a series of time steps, $t$, over the length of an episode, $T$. At each step, the agent observes a representation of the environment’s state, $s \in S$, and from that observation chooses an action, $a \in A$. Based on the merit of the agent’s action choice, a reward function produces a scalar feedback signal, $R : S \times A \to \mathbb{R}$. The agent’s purpose is to identify an action-selection policy, $\pi : S \to A$, that maximizes its discounted cumulative reward over the lifetime of a given task. From these dynamics, we arrive at the following iterative Bellman equation, that the agent updates through its interactions:

$$ Q^\pi(s, a) = \mathbb{E}[r + \gamma \arg\max_{a'} Q^\pi(s', a')] $$

where any arbitrary $Q$-function converges to optimality $Q^\pi \to Q^* \text{ as } t \to \infty$ (Sutton and Barto, 2018). The $Q$-function can be any parameterized function, either linear or nonlinear.

2.2 Deep Q-Networks

Deep Q-Networks (DQN), introduced by Mnih et al. (2015), is a model-free, deep RL algorithm designed to work in discrete action settings. Given a neural network, $\theta$, a DQN is trained by minimizing the convex loss $L_i(\theta_i) = [y_i - Q(s, a; \theta_i)]^2$. Unlike standard supervised learning models, we do not have an explicit “ground truth” to use for minimizing this loss. Instead, we use the temporal difference (TD) target, i.e., the reward and $Q$-values for the next state: $y_i = r + \gamma \arg\max_{a'} Q(s', a'; \theta_{i-N})$. Note that the authors use the network weights from a previous iteration, $\theta_{i-N}$, to help add stability to training. Together, this presents the following gradient over a sample of experiences:

$$ \nabla_{\theta_i} L_i(\theta_i) = [r + \gamma \arg\max_{a'} Q(s', a'; \theta_{i-N}) - Q(s, a; \theta_i)] \nabla_{\theta_i} Q(s, a; \theta_i) $$

2.3 Challenges of RL

In their survey work, Kober et al. (2013) outline several “curses” that create challenges in the application of RL to real-world settings such as robotics. The two that will be addressed in this work are the curse of goal specification and the curse of real-world samples.

The curse of goal specification outlines the significant role that the design of the reward function plays in determining the success of an algorithm. Oftentimes, an iterative process of defining the reward function, called reward shaping, is undertaken (Ng et al., 1999; Dong et al., 2020; Mannion et al., 2018). This method can prove to be undesirable as it requires a significant amount of time, domain expertise, and is not guaranteed to result in optimal agent behavior. Alternatively, researchers have explored methods for learning the reward function itself, called inverse reinforcement learning (Abbeel and Ng, 2004; Abbeel, 2008). In this paradigm, the agent is provided with examples of an expert performing the desired task, and it learns the implicit reward function that the expert is unknowingly maximizing. However, expert examples are not always available. Finally, the “best” reward function for a robotic agent may be complex or impossible to define due to the large number of degrees of freedom of the robot and the environment.

The curse of goal specification motivates the use of simple reward functions. The simplest reward function is a predicate, $R : S \times A \to \{0, 1\}$, which produces a sparse reward that only offers informative feedback when the desired behavior is achieved. This rarely-occurring learning presents obvious issues to the performance and convergence speed of the agent.

The curse of real-world samples deals with the collection of data. Unlike simulated environments, robotic agents require interaction with the physical world, which results in comparatively slow episode steps. Additionally, some robotic tasks may require human interaction. For example, the researcher may need to reset the robot at the beginning state or move objects with which the robot has interacted. Thus, gathering significantly large samples of experience may be infeasible. This curse motivates the need for sample-efficient algorithms.

To help encourage efficiency during training, most modern reinforcement learning algorithms use a replay memory that stores historical tuples of transitions, $(s, a, r, s')$, from which minibatches are drawn to update the Q-function. A

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1For notational brevity, current timesteps, $x$, have no special marking, and steps one into the future are marked $x'$
significant amount of research work has gone into understanding design implications of the replay memory [Liu and Zou, 2017; Cha et al., 2020; Ramicic and Bonarini, 2020; Zilli and Hasselmo, 2008].

Perhaps the most impactful aspect of replay memories is the composition of the experience tuple samples drawn from the memory. Simply sampling randomly can help break any harmful temporal correlations in the agent’s learning process [Novati and Koumoutsakos, 2019]. However, more intelligent methods can help the agent autonomously decide which memory tuples are “best”. These methods usually rely on prioritizing experiences that provide a large TD error, which suggests certain agent-environment interactions are more surprising and, therefore, informative to the agent [Schaul et al., 2016; Horgan et al., 2018]. While these methods have shown great promise, they have the clear limitation of not being applicable in sparse-reward settings where the TD error is zero an overwhelming majority of the time.

To overcome this issue, researchers have developed several methods for steering the composition of replay memory samples in sparse-reward settings. However, some methods are limited to agents that have a specific set of characteristics [Zhao and Tresp, 2018] or require a significant amount of compute overhead through the addition of an extra model [Zuo et al., 2020]. Perhaps the most prominent of these methods is Hindsight Experience Replay (HER) [Andrychowicz et al., 2017].

### 2.4 Hindsight Experience Replay

HER overcomes the issues of sparse rewards by altering the memories in the replay to present the outcomes of episodes as successful even though they may not be. At the end of each episode, the agent has the option to reproduce the episode’s trajectory using a goal other than the actual goal of the task. As outlined in the original paper, the simplest strategy is to change the goal, \( g \rightarrow g’ \), to be the final state reached in the episode, \( s_T \). Using this virtual goal, the original reward for the final step in the episode is changed, \( r_T \rightarrow r’_T \), to one regardless of whether or not the real goal is achieved. Doing so benefits the agent by filling its replay memory with experience tuples that will provide a non-zero feedback signal.

While HER provides a useful tool for dealing with sparse rewards, it has some downfalls. For one, the vanilla algorithm provides no guarantees that sampled minibatches will contain experience tuples with non-zero rewards. This means that it may be highly likely that some learning steps will only contain non-useful experience tuples, especially for tasks with large \( T \). In addition, some draws, through random chance, may contain a relatively large number of virtual-goal experience tuples as opposed to real-goal experience tuples. This may lead to the agent learning an undesirable policy that completes a virtual goal. These issues motivate a sampling strategy that grants control over minibatch makeup, as well as one that prioritizes real-goal tuples.

### 3 Or Your Money Back Sampler

To overcome the aforementioned limitations of HER, we introduce Or Your Money Back (OYMB), a novel replay memory sampler. It is designed to guarantee that minibatches contain a controllable amount of useful experience tuples by acting as a direct interface to the agent’s replay memory. OYMB provides a set of hyperparameters to control the percent of non-zero reward tuples, \( \lambda \), the decay or growth rate this percent, \( \delta_{\lambda} \), and the limit of the percentage, \( \lambda_{\min/\max} \). Together, these hyperparameters give the researcher full control over the minibatch makeup.

For example, the researcher may set a sampling schedule in the same way they might define a schedule for the learning rate hyperparameter of a neural network. Or, the researcher may set a manually-defined schedule. Observing Figure 1 below, we measured the proportion of non-zero reward samples in a minibatch over 100 episodes of agent training. Using OYMB, we dictated that the agent’s memory provides 4% until episode 25, 2.5% from episodes 25 to 50, and finally 5.5% for the remainder of training. At each episode, we drew 1000 samples from the replay memory, recording the mean, minimum, and maximum proportions. We show the means with solid lines and the spread between the minimums and maximums with shaded regions. Despite the fact that the replay memory grows as experience tuples are added, OYMB provides stable control, only showing signs of wavering from inconsistencies in floating-point precision. The proportion for vanilla HER varies wildly.
In addition to the percentage interface, OYMB also provides a preferential-lookup scheme that prioritizes sampling experience tuples from trajectories that complete the real goal before choosing experience tuples from HER-adjusted goals. This means that, as the agent begins learning to accomplish the real goal throughout training, the minibatches will contain more real-goal tuples and less virtual-goal tuples. We accomplish this by adding two vectors to the replay memory that track the in-memory location of real-goal tuples, $D_{\text{real}}$, and HER-altered tuples, $D_{\text{HER}}$. Essentially, OYMB uses HER as a temporary pathway to reaching the real goal. When the agent is able to saturate its replay memory with tuples that achieve the real goal, it will no longer draw virtual goals from the memory. In tasks with dynamic goals, the core OYMB algorithm can easily be extended to guarantee virtual-goal tuples.

The following two pseudo-code blocks outline the OYMB algorithm and then how OYMB fits within the greater training scheme.

**OYMB Sampler**

Algorithm parameters: $\lambda, \delta \lambda, \lambda_{\text{min/max}},$ batch size $B$, replay memory $D$

$\lambda \leftarrow \text{round}(B \lambda)$

$n_{\text{real}} \leftarrow \min(n, \text{length}(D_{\text{real}}))$

$n_{\text{HER}} \leftarrow n - n_{\text{real}}$

$n_{\text{random}} \leftarrow B - n$

foreach $i=1, n_{\text{real}}$ do
  sample randomly from $D_{\text{real}}$
end foreach

foreach $i=1, n_{\text{HER}}$ do
  sample randomly from $D_{\text{HER}}$
end foreach

foreach $i=1$ in $n_{\text{random}}$ do
  sample randomly from $D$
end foreach

According to schedule do

$\lambda \leftarrow \begin{cases} 
\lambda_{\text{min/max}} & \text{if } \delta \lambda \lambda \text{ outside of } \lambda_{\text{min/max}} \\
\delta \lambda \lambda & \text{otherwise}
\end{cases}$

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Figure 1: Proportion of non-zero samples in replay memory batch. HER + OYMB uses a manually-defined sampling schedule.
HER + OYMB sampler

Algorithm parameters: $M, T, \text{real goal } g, \text{batch size } B$
Initialize replay memory $D$, DQN $\theta$, target DQN $\theta_{\text{target}}$

foreach episode = 1, $M$ do
  Observe initial $s$
  foreach step = 1, $T$ do
    $a \leftarrow \pi(s||g)$ according to $\epsilon$-greedy
    Perform $a$ and observe $s'$
    Store $(s||g, a, r, s'||g)$ in $D$
    Sample $B$ transitions $(s||g, a, r, s'||g)$ from $D$ according to OYMB
    Perform optimization step on $\theta$
  endforeach
  $g' \leftarrow s_T$
  foreach $s_i, i, \text{in episode}$ do
    if $s_i = g'$ then
      $r_i \leftarrow 1$
      if $g' = g$ then
        $D_.real\_indices||i$
      else
        $D_.HER\_indices||i$
      end if
    end if
  endforeach
  $\theta_{\text{target}} \leftarrow \theta$ // Copy weights to target network
end foreach

4 Experiments

4.1 Environments

To test OYMB, we deployed it in three environments. The first is the discrete control version of the LunarLander environment\(^2\). This task is meant to simulate the simple physics problem of gently lowering a vehicle down to a landing pad. The action space is discrete and provides four choices: left thrust, right thrust, bottom thrust, or do nothing. The state space is a vector of length eight that contains information on the lander’s coordinates, velocities, angle, and indication for ground contact.

The second is the discrete control version of the MountainCar\(^3\) environment introduced by Moore (1990) in his PhD thesis. The MountainCar task is to drive a vehicle up a mountain to reach the top. However, the vehicle’s acceleration alone is not enough to power the car all the way up. The only way to solve this task is for the agent to reverse the vehicle up a hill and use the momentum from this small hill to get up the mountain. The action space is discrete and provides three options: accelerate left, do nothing, or accelerate right. The state space is continuous and contains values for the car’s position and current velocity.

The third is an environment of our own design, called Robo. It is a 10x10 gridworld configured to be a maze. The agent’s goal is to find its way to a specified square in the maze. The actions are: go forward, turn left, or turn right. The state representation is a vector of length two that gives the agent information on their distance from the goal, as well as the distance between them and a wall they might be facing, acting like a LIDAR. The distance-to-goal measurement disregards walls, as to not pass any path information to the agent. Also, artificial noise is added to the LIDAR reading by uniformly sampling from a given range of numbers dependent on the number of tiles between the agent and the wall it is facing. For more information on the noise, see Table 1, below. Altogether, this environment requires the agent to learn orientation behavior, as well as understand navigation in a noisy environment.

We evaluate our agent on three levels of difficulty in the Robo environment. The first is a “straight shot” walk (easy) in which the agent must simply learn to walk forward several tiles. The second is a “U-Turn” (medium), where the agent must learn to delay its reward by having to walk away from the goal before being able to turn around a corridor to reach

\(^2\)https://gym.openai.com/envs/LunarLander-v2/
\(^3\)https://gym.openai.com/envs/MountainCar-v0/
### Table 1: Introducing noise into LIDAR readings

| Number of squares away | LIDAR reading range |
|------------------------|---------------------|
| 1                      | [10, 30]            |
| 2                      | [31, 80]            |
| 3                      | [81, 150]           |
| ≥4                     | [151, 300]          |

Figure 2: Depiction of the Robo environment. Dark squares are walls, the green square is the beginning position of the agent, and the purple squares denote the goal positions for the hard (H), medium (M), and easy (E) tasks.

4.2 Evaluation

For all environments, we modify the reward function to return zero for all steps that do not complete the task, otherwise return one. For each task, we ran a version of the agent with vanilla HER and then a version with HER + OYMB. The LunarLander environment has an episode length of 1,000 steps, and the MountainCar environment has an episode length of 250 steps. The Robo environment has an episode length of 150, 150, and 300 for the easy, medium, and hard task, respectively.

For all tasks, our DQNs were made of two dense layers with 64 and 32 hidden units, respectively. As done by Mnih et al. (2015), we employed an $\epsilon$-greedy action-selection policy that was linearly-annealed from 1 to 0.01, dropping in value between episodes. We trained our DQNs at each episode step with a batch size of 64 using the Adam optimizer (Kingma and Ba, 2014), and updated the target network’s weights at the end of every episode. For the LunarLander task, we trained the agents for 1,000 episodes 15 times. For the MountainCar task, we trained the agents for 250 episodes 10 times. For each of the three tasks in the Robo environment, we trained the agents for 250 episodes 5 times. The metric used to evaluate every task is the cumulative number of successful real-goal completions.
5 Results

The figures presented below depict the mean performance (solid line) and one standard deviation from the mean (shaded area) across runs. See Table 2, towards the end of this section, for a full description of the OYMB hyperparameters used for each task.

Figure 3 below, shows the results of the agents trained on the LunarLander environment (left) and the MountainCar environment (right). From both plots, we see that the agents trained with a combination of HER and OYMB were able to outperform the agents that used only HER. After 1,000 training episodes in LunarLander, the HER + OYMB agents, on average, were able to complete the real goal nearly twice as often as the HER-only agents. After 250 training episodes in MountainCar, the HER + OYMB agents were able to perform at least as well as the HER-only agents.

Figure 4, below, depicts the results of the three tasks in the Robo environment. In the easy task, the HER + OYMB agents were able to complete the real goal, on average, over twice as often as the HER-only agents. In the medium task, the HER + OYMB agents performed at least as well as the HER-only agents. In the hard task, the HER + OYMB agents were able to complete the real goal, on average, over four times as often as the HER-only agents. In addition, the HER-only agents showed divergent behavior in the medium and hard tasks, as represented by the marginally-decreasing trend of their cumulative successful runs metric. We did not observe this phenomenon in the HER + OYMB agents, which instead showed a trend of marginally-increasing successful runs across all three tasks.

| Environment     | $\lambda$ | $\delta_\lambda$ | $\lambda_{\min/\max}$ |
|-----------------|-----------|------------------|------------------------|
| LunarLander     | 0.65      | 0.996            | 0.01                   |
| MountainCar     | 0.05      | 1                | 0.05                   |
| Robo (easy)     | 0.25      | 1                | 0.25                   |
| Robo (medium)   | 0.25      | 1                | 0.25                   |
| Robo (hard)     | 0.25      | 1                | 0.25                   |

Table 2: Tuned hyperparameters of OYMB for each task.
6 Conclusion

In this paper, we introduced Or Your Money Back (OYMB), a replay memory sampler designed to work with the Hindsight Experience Replay (HER) memory in sparse reinforcement learning settings. OYMB acts as a direct interface to the agent’s replay memory and guarantees stable control over the makeup of memory samples. Having this control allows for tuning of the minibatches that are used during the training process. In addition, OYMB uses a preferential-lookup scheme that prioritizes drawing real-goal tuples before drawing HER-adjusted tuples. We proved, empirically, across five tasks in three unique environments, that OYMB can be tuned to allow for more efficient training, resulting in better performance by the agent in a smaller number of training episodes.

6.1 Future Work

Currently, it is not clear how best to set the hyperparameters of the OYMB sampler. In addition, from our experiments, it appears that the best settings may vary across environments. We hypothesize that there may be some fundamental guiding principles for optimal minibatch makeup in sparse reinforcement learning settings.

Also, for tasks with dynamic or multiple goals, it is not clear how best to balance the preferential-lookup scheme within OYMB. In tasks with multiple goals, how should we split the sampling of real-goal tuples across the goals? In tasks with dynamic goals, how can we continue to encourage exploration such that the agent does not become “stuck” learning from memories that accomplish a goal that no longer applies?

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