Exploring Unknown States with Action Balance

Yan Song*  Yingfeng Chen*  Yujing Hu*  Changjie Fan*
*NetEase Fuxi Lab
{songyan, chenyingfeng1, huyujing, fanchangjie}@corp.netease.com

ABSTRACT

Exploration is a key problem in reinforcement learning. Recently bonus-based methods have achieved considerable successes in environments where exploration is difficult such as Montezuma’s Revenge, which assign additional bonus (e.g., intrinsic reward) to guide the agent to rarely visited states. Since the bonus is calculated according to the novelty of the next state after performing an action, we call such methods the next-state bonus methods. However, the next-state bonus methods bring extra issues. It may lead agent to be trapped in states that fewer being visited and ignore to explore unknown states. Moreover, the behavior policy of the agent is also influenced by the bonus added to the state (or state-action) values indirectly. In contrast to the bonus-based methods which explore in known states, in this paper, we focus on the other part of exploration: exploration for finding unknown states. We propose the action balance exploration method to overcome the defects of the next-state bonus methods, which balances the chosen time of each action in each state and can be treated as an extension of upper confidence bound (UCB) to deep reinforcement learning. To take both the advantages of the next-state bonus method and our action balance exploration method, we propose the action balance RND method, which takes both parts of exploration into consideration. The experiments on grid world and Atari games demonstrate action balance exploration has a better capability in finding unknown states and can improve the real performance of RND in some hard exploration environments respectively.

KEYWORDS

deep reinforcement learning; exploration bonus; action balance, UCB

1 INTRODUCTION

Reinforcement learning methods are aimed at learning policies that maximize the cumulative reward. The state-of-the-art RL algorithms such as DQN [15], PPO [21] work well when facing with dense-reward environment, but tend to fail when the environment has sparse rewards, e.g. Montezuma’s Revenge. This is because with the immediate rewards of most state-action pairs being zero, there is little useful information for updating policy. Reward shaping [16] is one solution that introduces human expertise and converts the original sparse problem to a dense one. However, this method is not universal and transforming human knowledge into numeric rewards is usually complicated in real tasks.

Recently bonus based exploration methods have achieved great success in video games [5, 19]. The main idea of these methods is to quantify the novelty of experienced states and encourage agent to visit novel states more often. Specifically, exploration bonuses are added to environment rewards according to the novelty of next states after an action is performed, we call them next-state bonus methods. Although this is in accord with human intuition that novel states have more potential to be explored, two defects may limit the exploration ability of these methods: “trapped in known states” and indirect guidance on exploration.

“Trapped” in known states. The next-state bonus methods firstly collect samples by random policy and then exploit the novelty of the experienced states. It should be noted that the additional bonus is assigned to the states that have already been visited. Thus, these methods cannot help to encourage the agent to enter into unseen states since unseen states could only be considered after being visited. What’s more, the next-state bonus may “trap” the agent in known states for redundant exploration, which has negative effects on discovering unknown states. An illustration is shown in Figure 1. Two areas connected by a narrow corridor and a treasure is placed in the right area. An agent is born in the middle of the corridor and decides which area to explore at the beginning of each episode (Figure 1a). Assuming the agent adopts the next-state bonus method and chooses to go left by chance at the first step. Since the left area is entirely novel for the agent, bonuses will be assigned to the states in there. The agent will then continuously reenter the left area and ignore the right area because it has been “trapped” (Figure 1b). In fact, the agent has no opportunity to enter the right area until the bonuses of the left area are exhausted since the bonus in the left is higher than the right (Figure 1c). Eventually, the agent will start exploring the right area and find the treasure after many tries (Figure 1d).

Figure 1: An example of “trapped agent” with next-state bonus method. The circle represents agent and the star represents treasure. Green area indicates visited area, the more time visited, the darker colored. a) Agent stands in the middle of the corridor at the start of each episode. b) Agent steps left by chance and “trapped” in the left area (shallow green). c) the left area has been explored exhaustedly (deep green). d) Agent decides to go right by chance and finally find the treasure.
When making a decision, the next-state bonus methods focus on how to exploit the samples already collected, but do not directly consider how to generate valuable new samples, which is one key point of exploration. Furthermore, the concentration on known states that the next-state bonus methods encourage can have a negative influence on final performance.

Indirect guidance on exploration. The next-state bonus methods encourage the agent to explore the relatively unfamiliar states that have been visited with additional rewards. The additional rewards are accumulated in state (or state-action) values and then gradually affect the policy with gradient-based methods [5, 19, 20, 24]. The guidance on exploration is sluggish because it is not directly applied on the occasion of action selection. It might be better to consider exploring directly on action selection since essentially exploration is choosing actions that have higher potential value when making a decision.

In this paper, we divide exploration into two different parts:

- **Exploration for unknown states**, which aims to find totally unknown states and makes agent see a more wide world.
- **Exploration in known states**, which does deep exploration in known states for better cognition of them.

Although these two parts have different duties in exploration, they can influence each other in some way and a good combination can result in better exploration performance (described in 3.1). As we described above, the next-state bonus methods belong to the second part (exploration in known states).

In order to fix the defects of the next-state bonus methods, we propose a new exploration method, called action balance exploration, that concentrates on finding unknown states (i.e., exploration for unknown states). The main idea is to balance the frequency of selecting each action and it can be treated as an extension of upper confidence bound (UCB) to deep network. Specifically, we record the frequency of selecting each action in a given state and raise the probabilities of actions that are not often taken. For agent that uses the next-state bonus methods, the action balance exploration can avoid it from paying excessive attention to individual actions and improve the ability to find unknown states. Besides, the action balance exploration has a direct influence on action selection, which makes it work faster than the next-state bonus methods.

By making combination of our action balance exploration method and the random network distillation exploration (RND exploration or RND [5]) method, we propose a novel exploration method, action balance RND, which can find unknown states more efficiently and simultaneously guide agents to visit unfamiliar states more frequently. We first test the action balance RND in a grid world that complete absence of rewards. The result shows that the action balance RND outperforms RND all through and overcomes the random baseline with about 2.5 times faster, which means the action balance exploration improves the capability in finding unknown states of RND. Also, the action balance RND covers about 15 more grids, which is about 3% higher in percentage increase than RND at last. Second, in the reaching goals environment the action balance RND obtains the lowest trajectory length, which is about 1.23 times smaller in average than RND. Finally, we demonstrate that the action balance exploration can improve the real performance of RND in some hard exploration Atari games.

## 2 RELATED WORK

Count-based methods [4, 10] have a long research line, which use the novelty of states as intrinsic bonus to guide exploration. Count-based methods are easy to implement and efficient in tabular environments, but they are not applicable to large scale problems once the state space is not enumerable. In order to solve this problem, many improvement schemes are proposed. TRPO-AE-hash [23] use SimHash [6] to hash the state space. Although it can decrease the state space to some extent, it relies on the design of the hash algorithm. DDQN-PC [3], A3C+ [3], DQN-PixelCNN [18] and ϕ-EB [12] adopt density models [17] to measure the visited time of states. ICM [19] and RND [5] use the prediction error of supervised learning to measure state novelty. The more time a sample is trained by a neural network, the low prediction error will be outputted for the sample. Therefore, novel states will have higher prediction errors than states that have been visited frequently. The use of neural network makes them easy to implement and have high generalization in high dimensional state space. [20] solves ‘noisy-TV’ problem of ICM by introducing into a memory buffer.

Although many different methods for calculating intrinsic bonus [1, 24] exist, they usually consider only the next state and regard the bonus as an additional reward. This makes it must work in the same way as the extrinsic reward does. Also, the exploration only occurs in known states because unknown states have no bonus.

As for exploration methods without the next state bonus, UCB1 [2] records the frequency of selecting each action and gives high priorities to the actions that are not often selected, which is widely used in tree-based search [11, 22], but not suitable for innumerable state.

Entropy-based exploration methods use a different way to maintain a diversity policy. [14] calculates the entropy of policy and adds it to the loss function as a regularization. This is easy to implement but only has a limit effect. Because it uses no extra information. [8] provided a way to find a policy that has maximum entropy in state space. The method works well in tabular setting environments, but hard to scale up in large state space. [13] provided a policy optimization strategy (Exploratory Conservative Policy Optimization, ECPO) that conducts maximum entropy exploration by changing the gradient estimator at each updating. The changed gradient makes it not only maximize the expected reward but also try to search for policy with large entropy nearby. However, the computation relies on collected samples.

DQN-UCB [9] proves the validity of using UCB to perform exploration in Q-learning. However, DQN-UCB was not widely tested in more environments. Go-Explore [7] used a search-based algorithm to solve hard exploration problems.

## 3 METHOD

Consider an agent interacting with an environment. At each time step $t$, the agent obtained an observation $o_t \in O$ from the environment and samples an action with a policy $\pi(o_t)$. After taking that action in the environment, the agent receives a scalar reward $r_t$, the new observation $o_{t+1}$ and a terminal signal. The goal of
Exploring Unknown States with Action Balance

Figure 2: The overall approach of action balance RND.

Figure 3: Relationship between the two parts of exploration. Exploration in known states makes agent revisit novel states. Revisit novel states makes the exploration for unknown states start in these novel states, which is easier to find more unknown states. Newly generated unknown states can be used in the exploration in known states for better cognition of environment.

The agent is to maximize the expected discounted sum of rewards $R = \sum_{t} \gamma^t r_t$. An environment that is hard to explore usually means the rewards are sparse (most of $r_t$ are zeros) in each episode, which makes the agent have little information for updating policy.

In this work we primarily focus on improving the performance of the next-state bonus methods, which may limit the exploration ability in hard exploration environments. We propose action balance exploration, which committed to improve the performance of the exploration in known states, to accomplish this goal. Moreover, it is convenient to combine the action balance exploration with the next-state bonus methods. An illustration of the overall combination is shown in Figure 2. Here we refer RND exploration as the method of the exploration in known states, so we call the combined method as action balance RND. Specifically, we first use the action bonus module to generate the bonus vector $r_s^{ab}$ of current state. Then, we combine the bonus vector and the old policy $\pi_0(a|s)$, which is generated by the policy net, by an element-wise add. This will give us a new policy $\pi(a|s)$ that takes the frequency of selecting each action into consideration. After generating action by $a \sim \beta_\theta(a|s)$, we use this action to interact with the environment and turn into the RND exploration process. Finally, all parameters are updated with the modified samples.

In the following sections, we first introduce the relationship between the exploration for unknown states and exploration in known states in Section 3.1, which also explain why it is possible to make a combination of the action balance exploration and RND exploration. Then in Section 3.2 to 3.4, the details of action balance exploration are introduced step by step.

3.1 Relationship between the two parts of exploration

As mentioned above, exploration can be divided into two parts: exploration for unknown states and exploration in known states. The first part aims to find complete unknown states and extend known space. The second part is for doing deep exploration between known states in order to get better cognition of them. Although they have different duties in exploration, they may influence each other in some way.

Intuitively, on the one hand, a better way of finding unknown states will expand the influence regions of the second part. Because the inputs of the second part are based on the outputs of the first part. A powerful unknown states finder will generate useful inputs for the second part continually and retard the second part from losing effect. On the other hand, during the process of exploring known novel states, it will also have a higher probability to find totally unknown states. Since states that near novel states are likely to be novel too.

For example (Figure 3), if using the next-state bonus methods (e.g. ICM, RND exploration) to do deep exploration in known states (i.e., exploration in known states), the agent will revisit novel states more frequently. This makes the exploration of finding totally unknown states (i.e., exploration for unknown states) most start at these novel states. As states nearby novel states may be novel too, the performance of finding unknown states will be enhanced and more unknown states will be generated. Moreover, more unknown states makes the agent have more wide regions to do deep exploration. As this circulation going on, the agent can gradually get a better understanding of the environment.

These connections make the two parts of exploration influence each other and a better combination can result in better exploration performance.

3.2 Random network distillation module

In the following sections, we will introduce our action balance exploration step by step. First, we introduce a module used in our action balance exploration method, which is called random network distillation module. This module is proposed in RND exploration [5] and is used to measure the occurrence frequency of input which is continuous or not enumerable.

Random network distillation module transforms the counting process into a supervised learning task by using two neural networks: target network and predictor network, which have same architecture. The target network is fixed and randomly initialized, it generates target value by mapping the input to an embedding representation $f : \mathcal{O} \rightarrow \mathbb{R}^k$. The predictor network $\hat{f} : \mathcal{O} \rightarrow \mathbb{R}^k$ tries to predict the target value and is trained to minimize the MSE:

$$r_t^i = \|f(s; \theta) - f(s)\|$$  (1)
Algorithm 1: Action balance RND

Input: Initial state \(s\), policy network \(\pi_\theta(a|s)\).

repeat
   for \(i=1,...,k\) do
      Get embedded representation \(a_E\) of action \(a_i\) by eq. (3) (opt)
      Calculate action bonus \(b_{a_i}\) by:
      \[ b_{a_i} = \hat{r}^{ab}(s, a_i) = \|\hat{g}(s, a_E; \theta') - g(s, a_E)\| \]
   end
   Get action bonus vector \(r_s^{ab}\) of state \(s\) by concatenating the action bonuses:
   \[ r_s^{ab} = (b_{a_1}, b_{a_2}, ..., b_{a_k}) \]
   Modify the original policy by:
   \[ \beta_\theta(a|s) = \pi_\theta(a|s) + \text{Normalize}(r_s^{ab}) \]
   Interact with the environment to get next state \(s_{t+1}\) and \(r\).
   Use RND-exploration with \((s_{t+1}, r)\) and get new reward \(r'\).
   Collect samples \((s, a, r', s_{t+1})\).
   Update \(\theta'\) by gradient descent on:
   \[ \nabla_\theta r^{ab}(s, a) = \nabla_\theta \|\hat{g}(s, a_E; \theta') - g(s, a_E)\| \]
   Update the parameters of random network distillation module in RND exploration with \(s_{t+1}\).
   Update policy network parameter \(\theta\) with \((s, a, r', s_{t+1})\).
   \(s \leftarrow s_{t+1}\).
until Max iteration or time reached.

Where \(\hat{f}\) is parameterized by \(\theta\).

Based on the fact that the loss of specific input will decrease as training times increase, the prediction errors of novel inputs are expected to be higher. This makes the intrinsic reward \(r_s^{ab}\) establish a relationship with the occurrence frequency of input and has the ability to quantify the novelty of it.

3.3 Action bonus module

The goal of the action balance exploration is to balance the frequency of selecting each action in each state. Thus, we need to record the occurrence frequency of state-action pair \((s, a)\), instead of only state \(s\). To accomplish this goal in a more general way, we use the random network distillation module to count the frequency of selecting each action. The bonus of an action \(a\) at state \(s\) is given by:

\[
\hat{r}^{ab}(s, a) = \|\hat{g}(s, a_E; \theta') - g(s, a_E)\| \tag{2}
\]

Where \(g\) and \(\hat{g}\) map the input to an embedding vector of \(\mathbb{R}^k\) and have the same role as \(f\) and \(\hat{f}\) do respectively, \(a_E\) is the fixed embedded representation of action \(a\) (e.g., one-hot embedding). This bonus can be used to guide the exploration in future learning.

Another thing needs to be declared is how we process the input of state-action pair. Since \(g\) is a neural network, the most common way is using the combination of \(s\) and \(a_E\) as one input and obtaining the output in one computation. However, the proportion each part takes in the combination will directly influence the output. For example, when \(a\) takes very low proportion in the combination of \((s, a)\), the action bonus \(r^{ab}(s, a)\) will be decided by \(s\) and have little to do with \(a\), vice versa. In an ideal condition, \(s\) and \(a\) have an equal proportion in the input combination, we will get the perfect output as we expect.

Although the common used one-hot encoding is more recognizable than just use the index of action, it may not sufficient when the dimension of the state is much higher than action. Based on this situation, we propose an encoding method that maps 1-d action to 2-d array, which is suitable for 2-d states. An illustration is shown in Figure 4. Specifically, given a default \(m \times n\) zero matrix \(M \in \mathbb{R}^{m \times n}\), the action is represented by:

\[
M_{i,c} = c, \forall i \in \{a \times \lfloor \frac{m}{k}\rfloor, a \times \lfloor \frac{m}{k}\rfloor + 1, ..., (a + 1) \times \lfloor \frac{m}{k}\rfloor - 1\} \tag{3}
\]

Where \(a\) is the index of action, \(k\) is the dimension of action and \(c\) is the padding value. Since this 2-d array can be regarded as another input channel for convolution neural network, we call it action channel.

3.4 Applying action bonus on exploration

Given a state \(s\), we can get the frequency of selecting each action by using \(r^{ab}(s, a)\). Then, we concatenate the bonus of each action to get the bonus vector of state \(s\):

\[
r_s^{ab} = (b_{a_1}, b_{a_2}, ..., b_{a_k}) = (r^{ab}(s, a_1), r^{ab}(s, a_2), ..., r^{ab}(s, a_k)) \tag{4}
\]

where \(k\) is the number of actions.

Before using the bonus vector \(r_s^{ab}\) to influence exploration, a normalization of \(r_s^{ab}\) is performed. On the one hand, normalization raises the difference between each element in \(r_s^{ab}\), which means more straightforward encourage or restrain on each action. On the other hand, this modification is harmless since it does not either change the relative relation of elements in \(r_s^{ab}\) nor disturb the outputs of other inputs. Then, this modified bonus vector will...
directly add to the original policy \( \pi_0(a|s) \):

\[
\beta_0(a|s) = \pi_0(a|s) + \text{Normalize}(r_{\pi}^{ab})
\]  

(5)

At this point, we get a new policy \( \beta_0(a|s) \) which considers the frequency of selecting each action and the behavior action will be sampled from policy \( a \sim \beta_0(a|s) \).

The parameter \( \theta' \) of \( \hat{\theta} \) is updated by minimizing the MSE \( r_{\pi}^{ab}(s,a) \) with samples collected by agent. The pseudocode of the action balance RND is presented in Algorithm 1. Note that, the bonus vector \( r_{\pi}^{ab} \) is calculated before actually take one action. So we can use all actions as input to calculate the bonus vector \( r_{\pi}^{ab} \). In addition, the behavior policy \( \beta_0(a|s) \) is slightly different from the target policy \( \pi_0(a|s) \). Theoretically, it makes the action balance RND become an off-policy method and need correction. We find the method works well without any correction in our experiments.

4 EXPERIMENTS

The primary purpose of our experiments is to demonstrate that the action balance exploration has a better performance in finding new states and can speed up the exploration process of RND exploration in some environments. Thus, we primary compare three exploration methods: random, RND exploration and action balance RND. We first compare the ability of finding unknown states in a grid world that complete absence of rewards. Second, we compare the exploratory behaviors of different methods including the action balance exploration. Third, in order to explain how much the differences in finding unknown states will influence actual tasks, we construct another reaching goals experiment in grid world. Finally, we test our method on six hard exploration video games of Atari. The code is published here.

4.1 Comparison of finding unknown states

In this experiment, we use a simple grid world with four actions: up, down, left, right. Especially, it is complete absence of rewards in any of the grids and also no goals. What the agent could do is just walk around and explore the environment until reaching its max episode length. These settings make the grid world similar to a hard exploration environment and eliminate all the factors that may influence the exploration strategy. Based on these conditions, we can compare the differences in behaviors between exploration methods on it. Moreover, we use state coverage rate \( R_x = N_{visited}/N_{all} \) to quantify the performance of exploration, where \( N_{visited} \) is the number of unique states that have been visited and \( N_{all} \) is the number of total unique states. A better strategy is expected to have a higher state coverage rate during the exploration process.

Specifically, the size of the gridworld is set to \( 40 \times 40 \) and we use the coordinates \([x, y]\) of the agent as state representation. The start point is fixed at \( P_0(0, 0) \) and the max episode length is \( 200 \). In order to trace the exploration process in the long term, we run 100 episodes for each method and record the state visited rates every 10 steps during this process. The result is shown in Figure 5, which are averaged by 100 runs.

**Comparison on state coverage rate.** Figure 5a shows the state coverage rate along with step number. The action balance RND covers about 15 more grids than RND at last. In order to make the relations more clearly, we calculate the percentage increase with respect to random (shown in Figure 5b). Specifically, it is calculated by \((x - \text{random})/\text{random}\), where \( x \) is RND (i.e., state visited rate of RND) or action balance RND. As shown in Figure 5b, the action balance RND overcomes random baseline with about 2.5 times faster and outperforms RND all through, which is about 3 percentage higher in the end. The result demonstrate that the action balance RND has a better ability in finding unknown states than RND, which owe to the usage of action balance exploration.

**Analyses of exploratory behaviors.** Another result worth to say is random performs better than RND and action balance RND in the initial phase (Figure 5b). This is because the difficulty of reaching a grid increase when the random agent tries to get far from the start point. In the beginning, since most of the grids near the start point are not ever being visited, the state coverage rate rise rapidly even when using random selection. As time goes by, it gets harder and harder for a random agent to find unknown states since most of the grids near the start point have already been visited and it is difficult to get further for the random agent.

In contrast to RND, instead of finding unknown states, the agent tends to do deep exploration in known states, which leads to a lower coverage rate in the initial phase. However, RND makes it possible for the agent to directly go to states far from the start point and begin exploration there. Since it is much wider away from the start point, the agent has more opportunity to see unknown states in there, which results in a higher visited rate in the latter phase. After introducing the action balance exploration into RND (i.e., action balance RND), the speed of finding unknown states has been accelerated a lot and the final visited rate is increased too.

Figure 6 shows the heat maps of one run in this experiment. It shows that a random agent tends to hover around start point and generate disorder trajectories. The action balance exploration appears more serried around the start point since the agent tends to choose low-frequency actions. As for RND, although the agent succeeds in exploring a more wider range, but due to the lack of strategy on finding unknown states, the agent unremittingly explores individual regions and earns nearly the same performance.

![Figure 5: Comparison of finding unknown states in no-ends grid world.](https://github.com/gomiss/action-balance-exploration)
4.2 Influence in reaching goals task.

This is another toy experiment that aims to show how much the differences in finding new states will influence actual tasks. We follow the fundamental settings described in section 4.1, except there is an goal in the environment. As we only care about the exploration efficiency, we make the game finish as soon as the agent first reach the endpoint and record the length of this trajectory for comparison. The trajectory length is expected to be smaller for a better exploration method.

In this experiment, we randomly select 5 endpoints to test on and run 100 times for each endpoint. As shown in Figure 7, random gets the highest median and third quartile number of trajectory length, RND is slightly lower than random and action balance RND obtains the lowest number. Detail results are shown in Table 1. The result shows that the action balance RND is about 1.23 times smaller in the lowest number. Detail results are shown in Table 1. The result shows that the action balance RND is about 1.23 times smaller in the lowest number. As shown in the figure, the entropy of the raw number appears almost as random selection. As for action balance RND, the agent not only explores wider (via RND) but also more even in each direction (via the action balance exploration) than the others.

Table 1: Trajectory lengths when first reach the endpoint.

| end (x, y) | random | RND  | action balance RND |
|-----------|--------|------|--------------------|
| (0, 20)   | 10583.86 | 10304.23 | **8118.19**         |
| (20, 0)   | 11142.43 | 11062.97 | **8360.99**         |
| (10, 20)  | 12772.29 | 13434.67 | **9248.96**         |
| (16, 16)  | 18755.5 | 12339.32 | **11364.08**        |
| (20, 10)  | 13464.31 | 11197.49 | **10384.51**        |
| average   | 13343.678 | 11667.736 | **9495.346**        |

4.3 Atari

In this section, we test our method on six hard exploration video games of Atari: Gravitar, Montezuma’s Revenge, Pitfall!, Private Eye, Solaris, and Venture. First, we compare different processing methods on the action bonus vector, which tries to make the elements in bonus vector more distinguishable. After that is a comparison of different action embedding methods, which aims to find an appropriate representation of action. These two experiments are trying to increase the performance of action balance exploration in different ways. Finally, we contrast the reward curves of the learning process. All the results are averaged by 5 runs.

**Normalize action bonus vector.** In this experiment, we compare the effect of L2 normalization on raising the difference of elements in the action bonus vector. Figure 8 shows the entropy of the action bonus vector as a function of parameter updates on Montezuma’s Revenge. Lower number of entropy means larger differences in each element of bonus vector, and also more straightforward encourage or restrain on each action. The raw curve (legends shown in Figure 9) means just uses the original output as bonus. In contrast, we apply an L2 normalization on the raw number. As shown in the figure, the entropy of the raw number appears almost
the same value, which means the difference of each element in the bonus vector is very small. After applying L2 normalization on it, the changing becomes more obvious in each update, which is advantageous to the action balance exploration.

Adding action channel. This experiment compares different action embedding methods and tries to find an appropriate representation for Atari games. Specifically, unless particularly stated, we use one-hot embedding as the default method to embed actions. Since the input state of Atari games is a 2-dimensional array, one-hot action can not directly combine to the input when calculating the action bonus. One solution is using convolution networks to process the input and generate a 1-dimensional feature, which will be concatenated to the one-hot action. We adopt this method in relevant experiments. However, the feature generated by convolution networks usually has an overlarge dimension than the one-hot action in Atari games (thousands to tens in our case), which results in too large proportion in the combination of state-action and may cover up the effect of action when calculating the action bonus of given state.

In order to increase the proportion of action when calculating action bonus, we add another action channel to the input state (described in Section 3.3). We use 0.01 as the padding value of the channel ($c = 0.01$ in eq. (3)).

As the result of Montezuma’s Revenge shown in Figure 8, using an action channel makes the entropy lower than others, which means the effect of action in calculating action bonus being enhanced. However, this enhancement may influence the effect of state. Figure 9 shows the value of action bonus as a function of parameter updates. As we can see, the action bonus of only using one-hot action ($L2$ normalize) is more volatile than using an additional action channel ($Channel + L2$). This is because the space of action channel is much smaller than the state channel and the convolution calculation on the channels reduces the influence of changing states. Although this is not the ideal situation, the action balance exploration with action channel should also work as wish since the action bonus still varies a lot as input change. A better action embedding method that makes state and action have equal proportion should improve the performance of action balance exploration. Since this is not the main problem this paper concerned about, we leave it as future work.

Reward curves during training. Figure 10 shows the mean episodic return of different games. Since the curves of Pitfall! and Private Eye quickly converged, it’s not obvious to do comparisons on them. We focus on the first few updates of the two games and show it in Figure 11. Based on the results shown in Figure 10 and Figure 11, we can see action balance RND speed up the promotion of mean episodic return in Montezuma’s Revenge, Gravitar and Pitfall!, but not change much in Private Eye, Solaris and Venture. Besides, using additional action channel makes the results even better than only using one-hot action in most of the games.

As shown in Section 4.1, the action balance exploration makes agent exploring the environment in a more uniform way. The rewards of Montezuma’s Revenge, Gravitar, and Pitfall! are relatively uniform and dense in state space than the other three and this is beneficial for the action balance exploration. Specifically, the agent can obtain rewards by touch something in most rooms of Montezuma’s Revenge. In Pitfall! it is dodge something. Although one needs to fire and destroy enemies in Gravitar in order to obtain rewards, the enemy is quite more in each room and it’s meaningful to travel around. In contrast, positive rewards appear only in very low-frequency situations in Private Eye. Solaris is a little complex to obtain rewards than others. Venture has similar settings as Gravitar, but it is more dangerous and only one reward in most rooms. These game settings make only a few actions (or strategies) related to the reward, which is not conducive for the action balance exploration to take an effect.

5 CONCLUSION

In this work we propose an exploration method, we call action balance exploration, which focuses on the other part of exploration: exploration for finding unknown states, contrasts to the next-state bonus methods which focus on exploration in known states. We also propose a novel exploration method, action balance RND, which combines our action balance exploration method and RND exploration method. The experiments on grid world and Atari games
Figure 10: Mean episodic return as a function of parameter updates.

Figure 11: First 300 updates. Legends are shown in Figure 10.

demonstrate the action balance exploration has a better capability in finding unknown states and can improve the real performance of RND in some hard exploration environments. In the future, we first, we want to find a more elegant way to embed the action since the action channel may hurt the precision of the state channel. Second, we want to try more complicated methods to combine the action balance exploration and RND exploration, like adaptation coefficient, hierarchical exploration.

REFERENCES

[1] Arthur Aubret, Lã­Aэтïtita Matignon, and Salima Hassas. 2019. A survey on intrinsic motivation in reinforcement learning. CoRR abs/1908.06976 (2019). http://arxiv.org/abs/1908.06976

[2] Peter Auer, Nicolò Cesa-Bianchi, and Paul Fischer. 2002. Finite-time analysis of the multilayer bandit problem. Machine learning 47, 2-3 (2002), 235–256.

[3] Marc G. Bellemare, Sriram Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, and Rã­mã­ni Munos. 2016. Unifying Count-Based Exploration and Intrinsic Motivation. In Advances in Neural Information Processing Systems 29. Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain. 1471–1479. http://papers.nips.cc/paper/6385-unifying-count-based-exploration-and-intrinsic-motivation

[4] Ronen I. Brafman and Moshe Tennenholtz. 2001. R-MAX - A General Polynomial Time Algorithm for Near-Optimal Reinforcement Learning. In Proceedings of the Seventeenth International Joint Conference on Artificial Intelligence, IJCAI 2001, Seattle, Washington, USA, August 4-10, 2001. 953–958.

[5] Yuri Burda, Harrison Edwards, Amos J. Storkey, and Oleg Klimov. 2019. Exploration by random network distillation. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. https://openreview.net/forum?id=H1JhRE5ym

[6] Moses Charikar. 2002. Similarity estimation techniques from rounding algorithms. In Proceedings on 34th Annual ACM Symposium on Theory of Computing, May 19-21, 2002, Montréal, Québec, Canada. 380–388. https://doi.org/10.1145/509907.509965

[7] Adrien Ecoffet, Joost Huizinga, Joel Lehman, Kenneth O. Stanley, and Jeff Clune. 2019. Go-Explore: a New Approach for Hard-Exploration Problems. CoRR abs/1901.10995 (2019). http://arxiv.org/abs/1901.10995

[8] Eldad Hazan, Sham M. Kakade, Karan Singh, and Abhy Va Soest. 2019. Provably Efficient Maximum Entropy Exploration. In Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA. 2681–2691. http://proceedings.mlr.press/v97/hazan19a.html

[9] Chi Jin, Zeyuan Allen-Zhu, SÃ­leÃ¨bautien Bubeck, and Michael I. Jordan. 2018. Is Q-Learning Provably Efficient? In Advances in Neural Information Processing Systems 31: Annual Conference on Neural Information Processing Systems 2018, NeurIPS 2018, 3-8 December 2018, Montréal, Canada. 4868–4878. http://papers.nips.cc/paper/7735-is-q-learning-provably-efficient

[10] Michael J. Kearns and Satinder P. Singh. 2002. Near-Optimal Reinforcement Learning in Polynomial Time. Machine Learning 49, 2-3 (2002), 209–232. https://doi.org/10.1023/A:1017984413808

[11] Levente Kocsis and Csaba Szepesvári. 2006. Bandit-Based Monte-Carlo Planning. In Machine Learning: ECML 2006, 17th European Conference on Machine Learning, Berlin, Germany, September 18-22, 2006, Proceedings. 282–293. https://doi.org/10.1007/11871842_29

[12] Jarryd Martin, Suraj Narayanan Sashikumar, Tom Everitt, and Marcus Hutter. 2017. Count-Based Exploration in Feature Space for Reinforcement Learning. In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI 2017, Melbourne, Australia, August 19-25, 2017. 2471–2478. https://doi.org/10.24963/ijcai.2017/344

[13] Jincheng Mei, Chenjun Xiao, Ruoting Huang, Dale Schuurmans, and Martin MÃ¡jiller. 2019. On Principled Entropy Exploration in Policy Optimization. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI 2019, Macao, China, August 10-16, 2019. 3130–3136. https://doi.org/10.24963/ijcai.2019/434

[14] Volodymyr Mnih, AdriÃ­Á—young M. Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. 2016. Asynchronous Methods for Deep Reinforcement Learning. In Proceedings of the 33rd International Conference on Machine Learning, ICML 2016, New York, NY, USA, June 19-24, 2016. 1928–1937. http://proceedings.mlr.press/v48/mnih16.html

[15] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, Martin A. Riedmiller, Andreas Fidjeland, Georg Ostrovski, Stig Petersen, Charles Beattie, Amir Sadik, Ioannis Antonoglou, Helen King, Dharnesh Kuraman, Daan Wierstra, Shane Legg, and Demis Hassabis. 2015. Human-level control through deep reinforcement learning. Nature 518, 7540
Exploring Unknown States with Action Balance

(2015), 529–533. https://doi.org/10.1038/nature14236

[16] Andrew Y. Ng, Daishi Harada, and Stuart J. Russell. 1999. Policy Invariance Under Reward Transformations: Theory and Application to Reward Shaping. In Proceedings of the Sixteenth International Conference on Machine Learning (ICML 1999), Bled, Slovenia, June 27 - 30, 1999: 278–287.

[17] AÃďron van den Oord, Nal Kalchbrenner, Lasse Espeholt, Koray Kavukcuoglu, Oriol Vinyals, and Alex Graves. 2016. Conditional Image Generation with PixelCNN Decoders. In Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain. 4790–4798. http://papers.nips.cc/paper/6527-conditional-image-generation-with-pixelcnn-decoders

[18] Georg Ostrovski, Marc G. Bellemare, AÃďron van den Oord, and RÃľmi Munos. 2017. Count-Based Exploration with Neural Density Models. In Proceedings of the 34th International Conference on Machine Learning, ICML 2017, Sydney, NSW, Australia, 6-11 August 2017. 2721–2730. http://proceedings.mlr.press/v70/ostrovski17a.html

[19] Deepak Pathak, Pulkit Agrawal, Alexei A. Efros, and Trevor Darrell. 2017. Curiosity-driven Exploration by Self-supervised Prediction. In Proceedings of the 34th International Conference on Machine Learning, ICML 2017, Sydney, NSW, Australia, 6-11 August 2017. 2778–2787. http://proceedings.mlr.press/v70/pathak17a.html

[20] Nikolay Savinov, Anton Raichuk, Damien Vincent, RaphaÃńl Marinier, Marc Pollefeys, Timothy P. Lillicrap, and Sylvain Gelly. 2019. Episodic Curiosity through Reachability. In 7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019. https://openreview.net/forum?id=SkeK3s0qKQ

[21] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. 2017. Proximal Policy Optimization Algorithms. CoRR abs/1707.06347 (2017). http://arxiv.org/abs/1707.06347

[22] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, and others. 2017. Mastering the game of go without human knowledge. Nature 550, 7676 (2017), 354.

[23] Haoran Tang, Rein Houthooft, Davis Foote, Adam Stooke, Xi Chen, Yan Duan, John Schulman, Filip De Turck, and Pieter Abbeel. 2017. #Exploration: A Study of Count-Based Exploration for Deep Reinforcement Learning. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA. 2753–2762. http://papers.nips.cc/paper/6888-exploration-a-study-of-count-based-exploration-for-deep-reinforcement-learning

[24] Adrien Ali TaÃЃrga, William Fedus, Marlos C. Machado, Aaron C. Courville, and Marc G. Bellemare. 2019. Benchmarking Bonus-Based Exploration Methods on the Arcade Learning Environment. CoRR abs/1908.02388 (2019). http://arxiv.org/abs/1908.02388