NROWAN-DQN: A Stable Noisy Network with Noise Reduction and Online Weight Adjustment for Exploration

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Abstract

Deep reinforcement learning has been applied more and more widely nowadays, especially in various complex control tasks. Effective exploration for noisy networks is one of the most important issues in deep reinforcement learning. Noisy networks tend to produce stable outputs for agents. However, this tendency is not always enough to find a stable policy for an agent, which decreases efficiency and stability during the learning process. Based on NoisyNets, this paper proposes an algorithm called NROWAN-DQN, i.e., Noise Reduction and Online Weight Adjustment NoisyNet-DQN. Firstly, we develop a novel noise reduction method for NoisyNet-DQN to make the agent perform stable actions. Secondly, we design an online weight adjustment strategy for noise reduction, which improves stable performance and gets higher scores for the agent. Finally, we evaluate this algorithm in four standard domains and analyze properties of hyper-parameters. Our results show that NROWAN-DQN outperforms prior algorithms in all these domains. In addition, NROWAN-DQN also shows better stability. The variance of the NROWAN-DQN score is significantly reduced, especially in some action-sensitive environments. This means that in some environments where high stability is required, NROWAN-DQN will be more

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appropriate than NoisyNets-DQN.

Keywords: Deep reinforcement learning, Exploration, Noisy networks, Noise reduction, Online weight adjustment

1. Introduction

Deep reinforcement learning has been successfully applied in various complex control tasks, such as robotic control tasks [1] [2] [29] [3], games [31] [30] [32], natural language processing [3] [9] and recommendation systems [7]. Deep Q-network (DQN) [31] is one of the most widely used deep reinforcement learning algorithms. However, there still exist a lot of problems about efficiency and stability of the original DQN, such as learning disability in sparse reward environments [20] and exponential training time in delayed reward environments [32]. A considerable part of these problems lies in immaturity of the exploration mechanism. Exploration is considered as a key challenge in reinforcement learning [34].

When it comes to guiding an agent to interact with environments, the simplest exploration method is dithering actions by random factors, such as $\varepsilon$-greedy [38]. However, when an action-state space is large, this way of exploration may be inefficient. After making some optimistic assumptions, heuristic exploration can provide theoretical guarantees for agent performance [21]. But this approach is usually limited to small action-state spaces [25]. Some efficient exploration methods have been proposed in recent years. Tang et al. extended the classical counting method in reinforcement learning to high-dimensional spaces by using counting tables, but their additional components are complex [39]; Houthooft et al. presented a practical implementation using variational inference in Bayesian neural networks, which efficiently handles continuous state space and action space [27]. However, this method dynamically modifies rewards of environment, resulting in the MDP process non-stationary to the agent. As a novel approach, object-oriented Q-map agent [33] conduct effective exploration by disturbing target instead of action so that action in the exploration process
are more consistent. Recent experiments have shown that adding noises in the parameter domain rather than the action domain can lead to better exploration \[35\]. Based on this principle, Fortunato et al. \[25\] applied noisy networks to DQN, A3C \[30\] and DuelingNet \[40\] algorithms, and developed NoisyNet-DQN, NoisyNet-A3C and NoisyNet-Dueling, which got higher scores in Atari 2600. For convenience, we use NoisyNets to generally refer to NoisyNet-DQN, NoisyNet-A3C and NoisyNet-Dueling.

The excellent performance of NoisyNets is mainly because networks with noisy parameters bring more abundant exploration. With these fully explored samples, an agent is more likely to jump out of local optimum when learning an optimal policy. However, noisy parameters also limit the efficiency of algorithms. In Fortunato’s model \[25\], the reduction of noise spontaneously occurs with a random gradient descent of TD-error, which results in a slow and insufficient reduction of noise during the learning process. Figure 1(a) shows the decision-making process of the original DQN and the change of its action noise. In a classical DQN setting, the action noise level (\(\varepsilon\) value) decreases to 1% of the initial value at 15K frames, and then the agent interacts with the environment with a relatively stable action policy. However, as shown in Figure 1(b), the noise level decreases to only 22% of the initial value at 15K frames with the parameter domain noise setting in NoisyNet-DQN. The slow and insufficient spontaneous decrease of \(\sigma\) makes it difficult to form a stable policy quickly, which affects performance of the agent.

In order to solve the problem that NoisyNets cannot form a stable policy effectively, this paper designs a differentiable online noise reduction mechanism, which can help agents form stable action policy based on parameter domain exploration. The core of this noise reduction mechanism is a deterministic factor which is differentiable to noise parameters, so this mechanism can be perfectly combined with the learning process. In the experimental part, we demonstrate that NROWAN-DQN has higher scores and better stability than the previous algorithms in both low-dimensional space and high-dimensional space. With the better stability, NROWAN-DQN is more practical than NoisyNet-DQN in some
action-sensitive environments. Finally, we further explore the relationship between the new parameter and the learning rate, and how they affect NROWAN-DQN performance.

Figure 1: Different noise methods and action noise curves

(a) Action domain noise in DQN and its action noise curve

(b) Parameter domain noise in NoisyNet-DQN and its action noise curve

The rest of this paper is organized as follows: Section 2 introduces some related work; Section 3 provides basic background; Section 4 proposes a noise reduction mechanism, an online weight adjustment strategy, and a NROWAN-DQN algorithm; Section 5 presents parameters setting and experimental evaluation of NROWAN-DQN; Section 6 concludes the paper and outlines the future work.
2. Related Work

This paper involves the exploration field of reinforcement learning. Currently, the methods to solve the exploration problems mainly include heuristic algorithm, state-space modeling, curiosity mechanism, and stochastic method.

**Heuristic algorithm.** Heuristic exploration can provide theoretical guarantees for agent performance. Thomas et al. proposed UCRL2, which achieves a (gap-dependent) regret bound that is logarithmic in learning step $T$ [8]; With some optimistic assumptions, Mohammad et al. proposed UCBVI-BF, which applies a concentration to the value as a whole and a recursive law of total variance to couple estimates across an episode. This has improved over the bound achieved by the UCRL2 algorithm [21]; Christoph et al. considered Episodic Fixed-Horizon MDPs, and proposed UCFH, which improves on previous bounds for episodic finite-horizon MDPs [9].

**State-space modeling.** State-space modeling helps an agent to efficiently find states with more information. There are two ways to model state space. One way is the count-based exploration: Strehl et al. proposed a variation of Model-based Interval Estimation called MBIE-EB [10]; Haoran et al. mapped states to hash codes, accordingly applying count-based methods in high-dimensional state spaces [39]; Marc et al. proposed an algorithm for deriving a pseudo-count from an arbitrary density model, which can generalize count-based exploration algorithms to the non-tabular case [23]. The other way is called states density modeling. These methods usually drive exploration by estimating state space density [11] [12] [13].

**Curiosity mechanism.** One kind of curiosity mechanism is generated based on the unknown information of the environment, such as Bayesian exploration in an unknown dynamic environment [14] and the theory based on the concept of maximizing intrinsic reward for active creation or discovery of new states [15]. The other kind of curiosity mechanism focuses on prediction of future state, such as forming intrinsic rewards that approximate the KL-divergence of true transition probabilities from a learned model [20] and to formulate curiosity
as the error in an agent’s ability to predict the consequence of its own actions in a visual feature space learned by a self-supervised inverse dynamics model [16].

**Stochastic method.** Adding noises to the parameter domain rather than the action domain can lead to better exploration [35]. Based on this principle, Fortunato [25] combined noisy networks with DQN, A3C [30] and DuelingNet [40]; Plappert et al. introduced parameter space noise to DQN, DDPG [29] and TRPO [36]. Both of the above approaches deliver excellent performance.

There are also some other novel methods about exploration. Houthooft et al. proposed an exploration strategy based on variational information maximization [27]; Xiong et al. and Adam et al. developed some reason-based exploration strategies, respectively [17] [18]; Target-based short trajectory exploration is also one of the novel methods [33] [19]. These methods conduct effective exploration by disturbing target instead of disturbing action.

Our method belongs to stochastic methodologies for exploration. Based on NoisyNets, this paper advocates limiting noise level of the last layer of NoisyNets, and proposes the NROWAN-DQN algorithm. More specifically, this paper designs a differentiable online noise reduction mechanism. This mechanism can help agents form stable action policies based on parameter domain exploration. In addition, because the deterministic factor for reducing noise is differentiable, this mechanism can be perfectly combined with the learning process.

3. Background

As a preparation for our method, this section introduces Markov decision process, DQN and NoisyNet-DQN.

3.1. Markov decision process in reinforcement learning

One of the main tasks in reinforcement learning is to solve the problem that how an agent learns to take actions to maximize rewards during the interaction with environments. There is no direct supervision in learning process. For
example, an agent never knows what the optimal action is \cite{26}. The interaction between agent and environment can be abstracted into Markov decision processes.

At each discrete time step \( t \) (i.e., \( t = 0, 1, 2, \cdots \)), the environment provides a state \( s_t \) to an agent, and the agent takes an action \( a_t \) as a response to this observation. Then, the environment returns a reward \( r_t \), a discount factor \( \gamma_{t+1} \), and the next state \( s_{t+1} \). The interaction process at each time step is denoted as a 5-tuple \((S, A, P, R, \gamma)\), where \( S \) is a finite set of states, \( A \) is a finite set of actions, \( P(s_{t+1}|s_t, a_t) \) is a state transition probability function, \( R \) is a reward function, \( \gamma \in [0, 1] \) is a discount factor. In the experimental part of this paper, the discount factor is set to a constant in accordance with most other experiments.

In reinforcement learning, an agent selects actions according to its policy. A policy \( \pi(a_t|s_t) \) is the conditional probability distribution of \( a_t \) at state \( s_t \). For any observation, the total reward of an agent at its current state is defined as follow:

\[
G_t = \sum_{k=0}^{\infty} \gamma^k_t R_{t+k+1}
\]

where \( \gamma^k_t R_{t+k+1} \) represents the reward obtained at the next step \( k \). The goal of the agent is to find an optimal policy by maximizing its discount total reward. In some cases, a policy can be obtained directly. However, sometimes a policy needs to be represented as a parametric equation that can be solved using a learning algorithm. In Q-value based reinforcement learning, an agent learns a Q function, which is denoted as:

\[
Q^\pi(s, a) = E^\pi(G_t|s_t = s, a_t = a)
\]

The way to iterate a new policy from a state action function is \( \varepsilon \)-greedy. In detail, at each discrete time step, an random action is taken with the probability \( \varepsilon \), or a greedy action is taken with the probability \( 1 - \varepsilon \) to maximize \( Q^\pi \).
3.2. Deep reinforcement learning and DQN

When the state or action space is large, it is very difficult for an agent to directly learn a value function or a policy. We usually use deep neural network to approximate a value function or a policy. The former is called value based deep reinforcement learning, while the latter is called policy gradient based deep reinforcement learning.

DQN \[31\] is a typical value based reinforcement learning algorithm. It uses TD-error as the loss function of a neural network, and moreover, it involves convolution, experience buffer and random experience replay. DQN successfully got human-level scores in the Atari domain. At each time step, the environment provides an agent with an observation $s_t$. First, the agent takes action according to $\epsilon$-greedy strategy, and receives the environment response $r_t$ and $s_{t+1}$. Then, a 4-tuple $(s_t, a_t, r_t, s_{t+1})$ is pushed into a experience buffer. Finally, the algorithm takes samples from the experience buffer, and uses random gradient descent to minimize the loss function.

$$L(\theta) = E[r_t + \gamma \max_{a'} Q^\pi(s_{t+1}, a'; \theta^-) - Q^\pi(s_t, a_t; \theta)]$$ (3)

where $\theta$ is the parameter of online network and $\theta^-$ is the parameter of target network. $\theta^-$ is updated to $\theta$ at every certain interval.

3.3. DQN with noisy networks

Noisy networks \[25\] refers to a neural network in which both weights and biases are disturbed by noise. We use $Q^\pi(s, a; \theta)$ to denote a parameterized $Q$ function. When using noisy networks to parameterize $Q$ functions, $\theta \overset{def}{=} \mu + \Sigma \circ \varepsilon$. We use $\zeta \overset{def}{=} (\mu, \Sigma)$ to denote a learnable parameter during learning, $\varepsilon$ denotes a zero-mean random vector with fixed statistics, and $\circ$ denotes the element-wise multiplication between vectors.

Specifically, a fully connected layer with a $p$-dimension input and a $q$-dimension output in a neural network can be written as $y = w \cdot x + b$. The corresponding
noisy layer is defined as:

\[ y = (\mu^w + \sigma^w \odot \varepsilon^w) \cdot x + (\mu^b + \sigma^b \odot \varepsilon^b) \]  \hspace{1cm} (4)

where \(\mu^w, \sigma^w \in R^{q \times p}, \mu^b, \sigma^b \in R^q\) are learnable parameters, and \(\varepsilon^w \in R^{q \times p}, \varepsilon^b \in R^q\) are noises. Figure 2 shows a classical linear layer and a noise linear layer, respectively. In the experimental part, we use Factorised Gaussian noise to generate \(p\) independent Gaussian noises \(\varepsilon_i\) and \(q\) independent Gaussian noises \(\varepsilon_j\). Then, every single weight noise \(\varepsilon_{i,j}^w\) and bias noise \(\varepsilon_j^b\) can be calculated as follows:

\[ \varepsilon_{i,j}^w = sgn(\varepsilon_i \cdot \varepsilon_j) \cdot \sqrt{|\varepsilon_i \cdot \varepsilon_j|} \]  \hspace{1cm} (5)

\[ \varepsilon_j^b = sgn(\varepsilon_j) \cdot \sqrt{|\varepsilon_j|} \]  \hspace{1cm} (6)

Since loss of a noisy network is denoted as an expectation over noise, the gradient can be obtained using \(\hat{L}(\zeta) = E[L(\theta)]\). The parameters in the original DQN are replaced with learnable parameters in noisy networks:

\[ \hat{L}(\zeta) = E[E[r_t + \gamma \max_{a'} Q^\pi(s_{t+1}, a'; \varepsilon; \zeta^-) - Q^\pi(s_t, a_t, \varepsilon; \zeta)]] \]  \hspace{1cm} (7)

4. Online noise reduction for noisy networks

This section presents two main mechanisms of NROWAN-DQN, including noise reduction and online weight adjustment.
4.1. Noise reduction

The instability of NoisyNets during the learning process is mainly affected by the noise variance $\sigma$, so the noise can be reduced by decreasing $\sigma$. However, Fortunato et al. pointed out that in some environments, $\sigma$ of Noisy Networks’ hidden layer may increase with the progress of learning, and its value maintains a large value after an agent forms a stable policy [25]. This indicates that a larger $\sigma$ in Noisy Networks’ hidden layer has a positive effect. And because the noise variance of output layer directly affects the noise of actions, we limit the overall noise level of the Q network by controlling the $\sigma$ of the output layer rather than that of all layers. The scope and effect of noise reduction mechanism are shown in Figure 3. The output probability of each neuron in the last layer is a normal distribution (blue line). At this time, the probability that this neuron output a correct action (green dotted line) is small. After sufficient learning, the mean of the distribution that the neuron output should be consistent with the correct action. That is, the neuron should be able to select the correct value with a higher probability after sufficient learning. According to the noise reduction mechanism, the distribution learned by neurons (blue dotted line) should have a smaller variance. Therefore these neurons have a greater probability of choosing the right action.

A general scheme for noise attenuation is to gradually reduce the $\sigma$ of the output layer during learning progress. However, in noisy networks, the $\sigma$ of the output layer is a parameter that is updated along the gradient direction. Therefore, reducing its value independently may cause this parameter not to be updated in gradient direction. This may result in inefficiency of learning and even prevent the agent from learning a valid policy. Therefore, we need a noise reduction mechanism that is consistent with learning process.

Our idea is to represent the noise level in a differentiable form. We use $D$ to denote the stability of NoisyNets output:

$$D = \frac{1}{(p^* + 1)N_a} (\Sigma_j^N \Sigma_i^p \sigma_{i,j}^w + \Sigma_j^N \sigma_j^b) \quad (8)$$
where $p^*$ is the input dimension of the last layer, and $N_a$ is the number of output actions. $D$ reflects the noise level of output actions of the agent. It is noticeable that $D$ is differentiable to $\sigma$. And the core idea of noise reduction is that reduce the noise level felicitously to enable the agent perform better, so we can combine the noise level with the TD error to form a new loss function.

Then, we use the sum of the original loss function and $D$ as the new loss function.

$$L^+(\zeta) = E[E[r_t + \gamma \max_{a'} Q^\pi(s_{t+1}, a', \varepsilon'; \zeta^-) - Q^\pi(s_t, a_t, \varepsilon; \zeta)] + k \cdot D] \quad (9)$$
where \( k \) is a certain proportional coefficient. \( k \) is used to control the proportion of update in the TD-error gradient direction and in the attenuation direction. We will introduce the adjustment strategy to control this proportional coefficient in the next section. According to (9), we can further obtain the update direction of parameters in our algorithm.

\[
\nabla \zeta L^+ (\zeta) = E[\nabla \zeta (E[r_t + \gamma \max_{a'} Q^\pi(s_{t+1}, a', \varepsilon'; \zeta) - Q^\pi(s_t, a_t, \varepsilon; \zeta)] + k \cdot D)] \tag{10}
\]

4.2. Online weight adjustment

There are two ways to increase the weight \( k \). The first way is to increase \( k \) monotonously with the number of training frames. As the number of training
frames increases, $k$ finally converges to a certain value.

$$k = k_{\text{final}} - k_{\text{final}} \cdot e^{-N_f/a}$$  \hspace{1cm} (11)

where $k_{\text{final}}$ denotes the final expected value of $k$, $N_f$ denotes the number of frames, and $a$ denotes a factor to control the growth rate of $k$. According to equation (11), when $N_f$ is very small, $k$ is close to 0. In this case, the agent tends to fully explore, and the update direction of $\zeta$ is the TD-error gradient direction. On the contrary, when $N_f$ is very large, $k$ is close to $k_{\text{final}}$. At this time, the agent tends to form a stabilization policy. The $\mu$ and $\Sigma$ of the inner layer are still updated along the TD-error gradient direction, and the $\Sigma$ of the last layer is updated along the sum gradient direction of the TD-error and the $D$ vector.

The second way to increase the weight $k$ is to adjust it online based on the reward:

$$k = k_{\text{final}} \cdot (r^+_t - \text{inf}(R))/(\text{sup}(R) - \text{inf}(R))$$  \hspace{1cm} (12)

where $r^+_t = \sum_{i=0}^t r_i$ denotes the current reward, $\text{sup}(R)$ denotes the maximum reward and $\text{inf}(R)$ denotes the minimum reward, respectively. In the early stage of learning, an agent cannot obtain a high reward in general. $r^+_t$ is usually close to $\text{inf}(R)$, so $k$ is close to 0. At this time, the parameters are updated in the TD-error gradient direction. When the learning reaches to a certain stage, the $\mu$ and $\Sigma$ of the inner layer are updated in the TD-error gradient direction, while the $\Sigma$ of the last layer is alternately updated in the TD-error gradient direction and the $\nabla_{\sigma}L^+$ direction. This is because at the beginning of each round of a game, $r$ is close to $\text{inf}(R)$, $k$ is close to 0, and $\Sigma$ is updated in the TD-error gradient direction. With a round of the game going on, the current reward $r^+_t$ increases, the weight $k$ gets closer and closer to $k_{\text{final}}$, and the $\Sigma$ of the last layer is updated in the $\nabla_{\sigma}L^+$ direction. After the current round ends up, the next round begins. At this point, $r^+_t$ becomes a small value again, and a new loop starts. Our experiments show that the training with this updating
Algorithm 1 NROWAN-DQN

**Input:** learning rate $\alpha$, update frequency $N_c$, min-frame to start learning $t_0$, memory capacity $N$, budget $T$, final weighting factor $k_{final}$

**Output:** $Q(s, a, \varepsilon'; \zeta^-)$

1: Initialize replay memory with capacity $N$
2: Initialize online Q-net with $\varepsilon$ and $(\mu, \Sigma)$
3: Initialize target Q-net with $\varepsilon' \leftarrow \varepsilon$ and $\zeta^- \leftarrow \zeta$
4: Observe $sup(R), inf(R) \sim Env$
5: for $t = 1$ to $T$ do
6:   Select $a_t = \text{argmax}_a Q(s_t, a, \varepsilon; \zeta)$
7:   Execute $a_t$ and observe $(r_t, s_{t+1}) \sim Env$
8:   Store experience $(s_t, a_t, r_t, s_{t+1})$ in replay buffer
9:   Calculate $D$ of online Q-net according to equation (8)
10:  $r_t^+ \leftarrow r_t^+ + r_t$ and calculate $k$ according to $r_t^+, sup(R)$ and $inf(R)$
11: if $s_{t+1}$ is a terminal state then
12:   $r_t^+ \leftarrow 0$
13: if $t > t_0$ then
14:   Sample random minibatch of experience from replay buffer
15:   $\nabla \leftarrow \nabla \zeta (r_t + \gamma \max_a Q^\pi(s_{t+1}, a'; \theta^-) - Q^\pi(s_t, a_t; \theta) + k \cdot D)$
16: $\zeta \leftarrow \zeta + \alpha \cdot \nabla$
17: if $t \mod N_c = 0$ then
18: $\zeta^- \leftarrow \zeta$

method can produce a more stable policy.

The selection of $inf(R)$ and $sup(R)$ does not need to be too strict. In some virtual environments, $inf(R)$ and $sup(R)$ can be easily obtained. When the environment rewards are not clear, $inf(R)$ can be set to a reward that a
randomly initialized policy can achieve, and \( sup(R) \) can be set to the highest reward that the current algorithm can achieve in this environment. It is worth noting that the closer \( inf(R) \) and \( sup(R) \) are, the more carefully the parameter \( k_{final} \) needs to be adjusted. In the experimental part, we will only decay the noise with online weight adjustment.

Algorithm 1 describes the training process of NROWAN-DQN. This algorithm follows the original framework of the NoisyNet-DQN algorithm [25]. In Algorithm 1, since the \( k \) is adjusted online based on the reward, additional input \( k_{final} \) is required. It is also necessary to obtain the range of environmental rewards. When calculating the current reward in line 10, the \( k \) is also calculated according to equation (12). In line 15, the updating direction of parameters is calculated. And in line 16, parameters are updated according to the updating direction and the learning rate.

5. Experiments

This section provides a description of the experimental environment, parameters setting, results of comparative experiments, and some analytical results.

5.1. Environments

Our experiments were conducted in OpenAI Gym [24], which provides a collection of environment for reinforcement learning tasks. We selected four typical environments for testing. These four environments are Cartpole, Pong, MountainCar and Acrobot. [1]

- In Cartpole, the environment provides an observation state to an agent at each frame. The observation state is a 4-tuple, which consists of the position of a cart, the speed of the cart, the angle of a pole, and the angular velocity of a pole. The agent can choose to move the cart to the left or the right. After the agent selects an action, the environment returns a “+1” reward. When the

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[1] The codes involved in this section can be found on the website https://github.com/HCodeRunner/noisy-networks-with-deterministic-factor.
total reward reaches “+200” or the pole is more than 15 degrees from vertical, the game is over.

- Pong provides an agent with an end-to-end learning environment. In each frame, the environment delivers an RGB image to the agent. The agent controls a racket to hit a ball. If the opponent misses the ball, the agent obtains a “+1” reward. If the agent misses the ball, the agent obtains a “-1” reward. When the total reward reaches “+21” or “-21”, the game is over.

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2 Descriptions of these environments can be found on website: http://gym.openai.com/envs/CartPole-v1/
3 Descriptions of these environments can be found on website: http://gym.openai.com/envs/Pong-v0/
• In MountainCar, a car is positioned between two “mountains”. The goal is to drive the car up to the mountain on the right; however, the car’s engine is not strong enough to scale the mountain in a single pass. Therefore, the only way to succeed is to drive back and forth to build up momentum.

• The Acrobot system includes two joints and two links, where the joint between the two links is actuated. Initially, the links are hanging downwards, and the goal is to swing the end of the lower link up to a given height.

Some screenshots of these games are shown in Figure 5.

5.2. Hyper-parameters

In our experiments, hyper-parameters are designed based on Hessel’s, Mnih’s, and Fortunato’s algorithms [26] [31] [25], and the network structure is exactly the same as that in Hessel’s algorithm. We have fine-tuned some of the hyper-parameters in order to fit our experimental situation better. For example, in Cartpole and Pong, it takes 30K frames and 1M frames respectively to run a round of experiments. So it is inappropriate to use a replay buffer with 1M capacity as the setting in Mnih’s algorithm [31]. When we conducted a comparative experiment, hyper-parameters of all the public parts of the algorithms are consistent in each comparison. In order to ensure the reproducibility of the experiment, we attach a detailed report in Table 1, which includes pre-processing setting, network structure setting, and public hyper-parameters setting.

In the original environment, each frame is a 3-channel color image. These pictures will be converted into single-channel grayscale images. Then these pictures will be scaled to (84, 84) and transmitted to the agent. Since the scale of the four problems is small, we don’t stack frames. During the learning process, each frame will be treated as a separate state for the agent. Correspondingly, the action will not be repeated. Since there are not involving statistics among different games, we do not clip the rewards. Since Cartpole, MountainCar and

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4 Description of this environment is cited from: http://gym.openai.com/envs/MountainCarContinuous-v0/
5 Description of this environment is cited from: http://gym.openai.com/envs/Acrobot-v1/
Table 1: Pre-processing, network structure, and public hyper-parameters setting

| Hyper-parameters | Pong | Others(Cartpole, etc.) | Description |
|------------------|------|-----------------------|-------------|
| Grey-scaling     | True | ——                    | Whether the observations are converted into single-channel images |
| Observation down-sampling | (84,84) | —— | Adjust the size of the observation |
| Frames stack     | 1    | 1                     | How many frames are stacked as one input frame |
| Action repetitions | 1    | 1                     | How many times an action is repeated |
| Reward clipping  | False| False                | Whether rewards is clipped or not |
| Q network: channels | 32,64,64 | —— | Number of filters for each layer |
| Q network: filter size | $8 \times 8$, $4 \times 4$, $3 \times 3$ | —— | Size of the filter for each layer |
| Q network: stride | 4,2,1 | —— | Step size of the filter in each layer |
| Q network: hidden layer | 512,512 | 128,128 | Number of neurons in each hidden layer |
| Q network: output layer | Numbers of actions | Numbers of actions | Number of neurons in the output layer |
| Activation function | ReLu | ReLu | Activation function in each layer except the output layer |
| Budget           | 1,000,000 | 30,000 | Number of environment frames for training |
| Batch size       | 32   | 32                   | Number of samples used for gradient descent |
| Gamma($\gamma$)  | 0.99 | 0.99                 | Reward discount factor |
| Update frequency | every 1000 | every 1000 | The frequency that the target network is updated to the current network |
| Min-frame to start learning | 10000 | 32 | Number of frames that start learning |
| Memory capacity  | 100,000 | 10,000 | Size of the replay buffer |
| Frequency of learning | every 1 step | every 1 step | Frequency of sampling and performing gradient updates |
Acrobot are not involving high-dimensional state input, the original information from these environments will be transmitted to the agent without any processing.

Our Q network structure is the same as the common Q network structure in the reinforcement learning. There are three convolution layers in our Q network. The first layer has 32 channels, the convolution kernel size is $8 \times 8$, and the step size is 4. The second layer has 64 channels, the convolution kernel size is $4 \times 4$, and the step size is 2. The third layer has 64 channels, the convolution kernel size is $3 \times 3$, and the size is 1. After convolution processing, the pixel matrix is changed into a one-dimensional vector and delivered to the fully connected layer. The fully connected layer contains a hidden layer and an output layer. The hidden layer has 512 neurons. The number of neurons in the output layer is the same with the number of environmental actions. Except the output layer, all the layers take the ReLu function as their activation function.

Since Cartpole, MountainCar and Acrobot do not need to process high-dimensional information, the state information provided by the Gym can be directly delivered to the fully connected layer. The fully connected layer has two hidden layers and an output layer. Each hidden layer has 128 neurons. The output layer has the same number of neurons as the number of environmental actions. Similarly, except the output layer, all the layers take the ReLu function as their activation function.

1M frames are required in each round of learning in Pong, and the replay buffer size is 100K. In the first 10K frames, gradient update process of Q network is not performed. The agent take actions using a random initialization network. During this process, the 4-tuple $(s_t, a_t, r_t, s_{t+1})$ is pushed into the replay buffer at each time step. After 10K frames, agent randomly samples 32 tuples from the replay buffer at each time step, and performs batch random gradient descent. Every 1K frames, the parameters of the target network are updated to the parameters of the current online network.

For Cartpole, MountainCar and Acrobot, each round of learning only takes 30K frames, and the replay buffer size is 10K. When the number of quaternions
in the replay buffer is enough for the agent to sample, the learning starts. Agent randomly samples 32 tuples from the replay buffer at each time step, and performs batch random gradient descent on the parameters in the online network. The parameters of the target network are updated to the parameters of the current online network every 1K frames.

In addition to the above setting, other hyper-parameters are involved in our algorithm. When using the online adjustment strategy, $k_{final}$ is set to 4.0. In the following experiments, $k_{final}$ will be set to a value in the range of {2.0, 2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0}.

Agents using noisy networks also have hyper-parameters setting that is not available in the original DQN. In our experiment, the initial value $\sigma_0$ is set to 0.4. The noise factor $\varepsilon_i$ and $\varepsilon_j$ are randomly generated according to a normal distribution. The shape of the normal distribution is determined by the dimension of input or output. All the agents use the Adam optimizer [28] to update the network parameters. The learning rate $\alpha$ is set to 0.0001. Table 2 shows the learning and noise parameters setting. In the following experiments, $\alpha$ will be set to a value in the range of {0.0001, 0.000075, 0.000025}.

Table 2: Learning and noise parameters setting

| Hyper-parameters | Cartpole | Pong | MountainCar | Acrobot |
|------------------|----------|------|-------------|---------|
| Learning rate    | 0.0001   | 0.0001 | 0.001       | 0.001   |
| Adam $\epsilon$ | 0        | 0     | 0           | 0       |
| Adam $\beta$    | (0.9, 0.999) | (0.9, 0.999) | (0.9, 0.999) | (0.9, 0.999) |
| Noisy linear $\sigma_0$ | 0.4   | 0.4   | 0.4         | 0.4     |
| $k_{final}$      | 4.0      | 4.0   | 4.0         | 4.0     |

5.3. Score comparison

Table 3 shows the performance of three algorithms (i.e., DQN, NoisyNet-DQN, and NROWAN-DQN) in Cartpole, Pong, MountainCar and Acrobot. With the same parameters, we trained five instances for each algorithm, and
each instance ran 64 rounds. We calculated the average score of these 64 rounds as the score of the instance. Then we calculated the average score of these five instances as the final score. The standard deviation of the scores were calculated in a similar way. NoisyNet-DQN reported in Table 3 uses online noise adjustment to decay the noise. As shown in Table 3, NROWAN-DQN scored an average of 187.04 in Cartpole, which is 16.56 higher than DQN, and 22.08 higher than NoisyNet-DQN, and the average standard deviation is nearly 3 times smaller than DQN and NoisyNet-DQN. In Pong, NROWAN-DQN has an average score of 18.80, which is 1.74 higher than DQN, 0.86 higher than NoisyNet-DQN, and the average standard deviation is 0.5 less than DQN, 0.2 less than NoisyNet-DQN. In MountainCar, NROWAN-DQN has an average score of -121.85, which is 10.05 higher than DQN, 6.52 higher than NoisyNet-DQN, and the average standard deviation is 1.21 less than DQN, 2.09 less than NoisyNet-DQN. In Acrobot, NROWAN-DQN has an average score of -84.41, which is 2.83 higher than DQN, 2.16 higher than NoisyNet-DQN, and the average standard deviation is 6.57 less than DQN, 13.74 less than NoisyNet-DQN. The results of these experiments show that NROWAN-DQN has more stable and higher performance.

In Table 3, NoisyNet-DQN performs better than DQN in Pong, which is consistent with the experimental results of Fortunato et al. [31]. However, it is unexpected that NoisyNet-DQN scores less than DQN in Cartpole. After analyzing the experimental environment, we found it is because this environment is more sensitive to noise actions. In Cartpole, for example, when the pole tilts to left, moving the cart to the left due to noise is likely to cause the game to be lost. Other environment is less sensitive to noise action. For example, in Pong, when the racket can hit the ball in the original position, it is likely that agents will still be able to receive the ball when agents move it a little bit due to noise. What’s more, the large state-action space in Pong needs to be more fully explored for the environment. With better exploration mechanism, NoisyNet-DQN outperforms DQN. Because of NROWAN-DQN exploring more fully and mitigating the effects of noise, it outperforms the other two algorithms in all environments.
Table 3: Performance comparison

| Problem   | DQN       | NoisyNet-DQN | NROWAN-DQN |
|-----------|-----------|--------------|------------|
| Cartpole  | 170.49±35.86 | 164.96±31.56 | **187.04±13.99** |
| Pong      | 17.07±3.36   | 17.95±3.08   | **18.81±2.87** |
| MountainCar | -131.90±21.09 | -128.37±21.97 | **-121.85±19.88** |
| Acrobot   | -87.24±22.33 | -86.57±29.32 | **-84.41±15.58** |

5.4. Score change in learning

Figure 6 shows the average reward trend of NoisyNet-DQN and NROWAN-DQN in Cartpole, Pong, MountainCar and Acrobot. In Pong and MountainCar, NROWAN-DQN performs better than NoisyNet-DQN during the learning process. This is because the deterministic factor makes it easier for agents to form stable policies when learning. In Cartpole, NROWAN-DQN can effectively learn in a noise sensitive environment, so its learning curve can converge to higher values. Since the Acrobot environment is simpler, both NROWAN-DQN and NoisyNet-DQN can learn quickly in this environment, and the learning curves of both can converge to approximately the same value, so it is difficult to compare NROWAN-DQN and NoisyNet-DQN in this environment. But overall, we can conclude that the learning ability of NROWAN-DQN is better than NoisyNet-DQN.

5.5. Final $k$ value and learning rate

Our algorithm introduces a new hyper-parameter $k_{\text{final}}$, which indicates the final value of $k$ in the learning process. We analyzed the relationship between $k_{\text{final}}$ and learning rate in the low-dimensional Cartpole environment, and tested the appropriate value of $k_{\text{final}}$ in the high-dimensional Pong environment.

Because $k_{\text{final}}$ and learning rate jointly control the parameter update step size in the direction of generating a stable policy, $k_{\text{final}}$ should be adjusted along with the learning rate. Figures 7 - 9 show the learning curve of the
agent in Cartpole with three different learning rates and nine different $k_{final}$ values. As we can see, too small $k_{final}$ will lead to instability, and the final results have a large variance; too large $k_{final}$ will cause output actions of the agent to be too stable, resulting in a decline in the exploration ability, thus making the agent learn slower. Figure 10 shows score results with different learning rates and different $k_{final}$ values in Cartpole. The product of $k$ and the learning rate controls the update step size of $\nabla_D D$ in equation (10) during learning. More specifically, the learning rate controls the update step size, and $k$ controls the proportion of updates in the TD-error gradient direction and in the $\nabla_D D$ direction. When $k_{final}$ and the learning rate are both small, the learning efficiency of the agent is low. When $k_{final}$ is large and the learning rate is small, the parameters of the agent is over-updated in the direction along which the stable action is generated. After repeated testing, we conclude that the large learning rate is not sensitive to the change of $k_{final}$. When $k_{final}$ is
Figure 7: Score results with different $k_{final}$ in Cartpole when learning rate is 0.0001

Figure 8: Score results with different $k_{final}$ in Cartpole when learning rate is 0.000075
Figure 9: Score results with different $k_{final}$ in Cartpole when learning rate is 0.00005

Figure 10: Score results with different learning rates and different $k_{final}$ values in Cartpole
4, the algorithm is less sensitive to the change of learning rate. Therefore, it is recommended that $k_{\text{final}}$ be set to 4.

We also tested the effect of different $k_{\text{final}}$ values on the learning outcome in a high dimensional environment. Figure 11 show that when $k_{\text{final}}$ is set to 4, the agent still has good learning ability. However, because Pong is less sensitive to noise than Cartpole, too small $k_{\text{final}}$ will not cause the agent in Pong to be unstable. On the contrary, because $k_{\text{final}}$ is small, the agent cannot form a stable policy in time, as a result, the learning speed of the agent is reduced. Too large $k_{\text{final}}$ causes the parameter to be updated too much in the direction of noise reduction, which destroys the update process of the agent along the learning direction, resulting in unstable performance of the agent. The magnitude of $k_{\text{final}}$ not only controls the balance between exploration and utilization of the agent, but also controls the proportion of parameters update in the direction of noise reduction and learning direction. So $k_{\text{final}}$ needs to be carefully set.

![Figure 11: Learning curves for different final $k$ values in Pong](image)

6. Discussion and conclusion

We have demonstrated that adding the deterministic factor to the loss function of noisy networks can enable the agent get a higher score and better stability. Moreover, we found that NROWAN-DQN outperforms NoisyNet-DQN and DQN in a noise-sensitive environment. Due to instability, DQN cannot be used in some dangerous situations which requires high action precision. In
such situations, NoisyNet-DQN is also not appropriate, since it adopts unstable behavior policy. Compared with NoisyNet-DQN, NROWAN-DQN is effective for such situations. Finally, we explore the effect of learning rate and $k_{final}$ on the learning process, and give the recommended value of $k_{final}$.

When developing NoisyNet-DQN, Fortunato et al. also applied noisy networks to DDQN, Dueling and A3C algorithms, which has better performance [25]. As a component, noisy networks can be used with other components based on Q-value, such as prioritized experience replay [37] and distributional Q-learning [22]. What’s more, noisy networks have great potential when combined with reinforcement learning algorithms of gradient descent, such as DDPG [29] and TRPO [36]. It is also very interesting to study effects and properties when combining our improved NoisyNet with the above-mentioned algorithms or components.

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