NOISE, OVERESTIMATION AND EXPLORATION IN DEEP REINFORCEMENT LEARNING

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Abstract. We will discuss some statistical noise related phenomena, that were investigated by different authors in the framework of Deep Reinforcement Learning algorithms. The following algorithms are touched: DQN, Double DQN, DDPG, TD3, Hill-Climbing. Firstly, we consider overestimation, that is the harmful property resulting from noise. Then we deal with noise used for exploration, this is the useful noise. We discuss setting the noise parameter in TD3 for typical PyBullet environments associated with articulate bodies such as HopperBulletEnv and Walker2DBulletEnv. In the appendix, in relation with the Hill-Climbing algorithm, we will look at one more example of noise: adaptive noise.

1. Introduction

In 1993, Thrun and Schwartz in [TS93] gave an example in which the overestimation (caused by noise) asymptotically lead to suboptimal policies. In the other hand, adding noise to the action space helps algorithms in more efficient exploration, which is not correlated to something unique, see [OpenAI]. We will look at Deep Reinforcement Learning algorithms in terms of issues related to noise. In this article, we will touch the following algorithms: DQN, Double DQN, DDPG, TD3, Hill-Climbing.

In Section 2, we will see how researchers tried to overcome overestimation in models. First step is decoupling of the action selection from action evaluation. It was realized in Double DQN model. The second step relates to the Actor-Critic architecture: here we decouple the value neural network (critic) from the policy neural network (actor). In essence, this is a generalization of what was done in Double DQN, on the continuous action spaces case. DDPG and TD3 algorithms use this architecture. [Lil15, Fu18]. A very significant advantage of the TD3 in overcoming overestimation is the use of Auto-Critic with two critics architecture.

In Section 3 we consider how exploration is implemented in DQN, Double DQN, DDPG and TD3. Exploration is a major challenge of learning. The main issue of Section 3 is exploration noise. Neural network models using some noise parameters have more capabilities for exploration and are more successful in Deep Reinforcement Learning (Deep RL) algorithms. There is a certain problem to find the true noise parameter for exploration. We discuss setting of this parameter in TD3 for PyBullet environments associated with articulate bodies such as HopperBulletEnv and Walker2DBulletEnv.

In the Appendix, we consider the Hill-Climbing, the simple gradient-free algorithm. This algorithm adds adaptive noise directly to input variables, namely to the weight matrix determining the neural network.
2. In efforts to overcome overestimation

Deep Q-Network (DQN) and Double Deep Q-Network (Double DQN) algorithms turned out to be very successful in the case of discrete action spaces. However, it is known that these algorithms suffer from overestimation. This harmful property is much worse than underestimation, because underestimation does not accumulate. Let us see how researchers tried to overcome overestimation.

2.1. Overestimation in DQN. Let us consider the operator used for the calculation of the target value $G_t$ in the key $Q$-learning equation (a.k.a Sarsamx equation). This operator is called maximization operator:

$$G_t = R_{t+1} + \gamma \max_a Q(S_{t+1}, a)$$

Suppose, the evaluation value for $Q(S_{t+1}, a)$ is already overestimated. Then, the agent observes that error also accumulates for $Q(S_t, a)$:

$$Q(S_t, a) \leftarrow Q(S_t, a) + \alpha (R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, a_t))$$

or

$$Q(S_t, a) \leftarrow Q(S_t, a) + \alpha (G_t - Q(S_t, a_t)).$$

Here, $R_t$ is the reward at time $t$, $G_t$ is the cumulative reward also known as TD-target; $Q(s, a)$ is the $Q$-value table of the shape $[\text{space } \times \text{ action}]$, [St20a].

In 1993, Thrun and Schwartz observed that using function approximators (i.e, neural networks) instead of just lookup tables (this is the basic technique of Q-learning) causes some noise on the output predictions. They gave an example in which the overestimation asymptotically lead to suboptimal policies, [TS93].

2.2. Decoupling in Double DQN. In 2015, Hasselt et. al. shown that estimation errors can drive the estimates up and away from the true optimal values. They supposed the solution that reduces the overestimation in the discrete case: Double DQN, [Has15]. The important thing that has been done in Double DQN is decoupling of the action selection from action evaluation. Let us make this clear.

$$G_t^{\text{DQN}} = R_{t+1} + \gamma Q(S_{t+1}, \argmax_a Q(S_{t+1}, a; \theta_t); \theta_t)$$

Evaluation of the $Q$-value by taking that action at that state

$$G_t^{\text{DoubleDQN}} = R_{t+1} + \gamma Q(S_{t+1}, \argmax_a Q(S_{t+1}, a; \theta_t'); \theta_t')$$
• $G^DQN_t$ ($G_t$ for $DQN$): the $Q$-value $Q(S_{t+1}, a)$ used for the action selection (red underline) and the $Q$-value $Q(S_{t+1}, a)$ used for the action evaluation (blue underline) are determined by the same neural network with the weight vector $\theta_t$.

• $G^{DoubleDQN}_t$ ($G_t$ for Double $DQN$): the $Q$-value used for the action selection and the $Q$-value used for the action evaluation are determined by two different neural networks with weight vectors $\theta_t$ and $\theta'_t$. These networks are called current and target.

However, due to the slowly changing policy, estimates of the value of the current and target neural networks are still too similar, and this still causes a consistent overestimation, [Fu18].

2.3. Actor-Critic architecture in DDPG. DDPG is one of the first algorithms that tried to use the $Q$-learning technique of $DQN$ models for continuous action spaces. DDPG stands for Deep Deterministic Policy Gradient, [Spi]. In this case, we cannot use the maximization operator of $Q$-values over all actions. However, we can use the function approximator, a neural network representing $Q$-values. We presume that there exists a certain function $Q(s, a)$ which is differentiable with respect to the action $a$. However, finding

$$\arg\max_{a} (Q(S_t, a))$$

on all actions $a$ for the given state $S_t$ means that we must solve the optimization problem at every time step. This is a very expensive task. To overcome this obstacle, a group of researchers from DeepMind used the Actor-Critic architecture, [Lil15]. They used two neural networks: one, as before, in $DQN$: $Q$-network representing $Q$-values; another one is the actor function $\pi(s)$ supplying the action which gives the maximum of the value function $Q(s, a)$. For the current state $s = s_t$ we have

$$\pi(s_t) = a^*, \text{ where } a^* = \arg\max_{a} Q(s_t, a)$$

For any state $s$,

$$\max_{a} Q(s, a) \approx Q(s, \pi(s))$$

2.4. A pair of independently trained critics in TD3. The actor-critic Double $DQN$ as well as $DDPG$ suffer from overestimation. In [Fu18] p.5, it was suggested that a failure can occur due to the interplay between the actor and critic updates. Overestimation occurs when the policy is poor, “and the policy will become poor if the value estimate itself is inaccurate”. In [Fu18], authors suggested using a pair of critics ($Q_{\theta_1}$, $Q_{\theta_2}$), and taking the minimum value between them to limit overestimation. It was originally supposed that there would also be 2 actors ($\pi_1$, $\pi_2$) with cross updating: $Q_{\theta_1}$ with $\pi_2$, , $Q_{\theta_2}$ with $\pi_1$ (where $\pi_i$ is optimized with respect $Q_{\theta_i}$).
y_1 = r + \gamma Q_{\theta_2}(s', \pi_1(s'))
\quad y_2 = r + \gamma Q_{\theta_1}(s', \pi_1(s'))

By [Fu18], due to the computational costs, the single actor can be used. This reduction in the number of actors does not cause an additional bias. The method of two critics outperforms many other algorithms including DDPG.

3. Exploration as a major challenge of learning

3.1. Why explore? In addition to overestimation, there is another problem in Deep RL, no less difficult. This is exploration. We cannot unconditionally believe in maximum values of the Q-table or in action function \(\pi(s)\) supplying the best actions. Why not? Firstly, at the beginning of training, the corresponding neural network is still “young and stupid”, and its maximum values or best actions are far from reality. Secondly, perhaps not the maximum values and not the best actions will lead us to the optimal strategy after hard training.

In life, we often have to solve the following problem:

to follow the beaten path – there is little risk and little reward; or to take a new unknown path with great risk – but, with some probability, a big win is possible there. Maybe it will be just super, you dont know.

3.2. Exploration vs. exploitation. Exploitation means, that the agent uses the accumulated knowledge to select the following action. In our case, this means that for the given state, the agent finds the following action that maximizes the Q-value. The exploration means that the following action will be selected randomly. There is no rule that determines which strategy is better: exploration or exploitation. The real goal is to find a true balance between these two strategies. As we can see, the balance strategy changes in the learning process.

3.3. Exploration in DQN and Double DQN. One way to ensure adequate exploration in DQN and Double DQN is to use the annealing-greedy mechanism. [St20b]. For the first episodes, exploitation is selected with a small probability, for example, 0.02 (i.e., the action will be chosen very randomly) and the exploration is selected with a probability 0.98. Starting from a certain number of episode \(M_e\), the exploration will be performed with a minimal probability \(\varepsilon_m\). For example, if \(\varepsilon_m = 0.01\), the exploitation is chosen with probability 0.99. The probability formula of exploration \(\varepsilon\) can be realized as follows:

\[\varepsilon = \max(\frac{\varepsilon_m - 1}{M_e}i + 1, \varepsilon_m),\]

where \(i\) is the episode number. Let \(M_e = 100, \varepsilon_m = 0.01\). Then, the probability \(\varepsilon\) of exploration looks as follows:
3.4. Exploration in DDPG. In RL models with continuous action spaces, instead of \( \varepsilon \)-greedy mechanism \textbf{undirected exploration} is applied. This method is used in \textit{DDPG}, \textit{PPO} and other continuous control algorithms. Authors of \textit{DDPG} algorithm, \cite{Lil15}, constructed undirected exploration policy \( \pi \) by adding noise sampled from a noise process \( N \) to the actor policy \( \pi(s) \):

\[
\pi'(s_t) = \pi(s_t|\theta_t) + N,
\]

where \( N \) is the noise given by Ornstein-Uhlenbeck, correlated noise process, \cite{OU}. In the \textit{TD3} paper, \cite{Fu18}, authors proposed to use the classic Gaussian noise, this is the quote:

\[
\ldots \text{we use an off-policy exploration strategy, adding Gaussian noise } N(0; 0.1) \text{ to each action. Unlike the original implementation of DDPG, we used uncorrelated noise for exploration as we found noise drawn from the Ornstein-Uhlenbeck (Uhlenbeck \\& Ornstein, 1930) process offered no performance benefits.}
\]

The usual failure mode for \textit{DDPG} is that the learned \( Q \)-function begins to overestimate \( Q \)-values, then the policy (actor function) leads to significant errors.

3.5. Exploration in TD3. The name \textit{TD3} stands for Twin Delayed Deep Deterministic. \textit{TD3} algorithm retains the Actor-Critic architecture used in \textit{DDPG}, and adds 3 new properties that greatly help to overcome overestimation:

- \textit{TD3} maintains a \textbf{pair of critics} \( Q_1 \) and \( Q_2 \) (hence the name twin) along with a single actor. For each time step, \textit{TD3} uses the smaller of the two \( Q \)-values.

- \textit{TD3} updates the policy (and target networks) less frequently than the \( Q \)-function updates (one policy update (actor) for every two \( Q \)-function (critic) updates).

- \textit{TD3} adds \textbf{exploration noise} to the target action. \textit{TD3} uses Gaussian noise, not Ornstein–Uhlenbeck noise as in \textit{DDPG}.

3.6. \textbf{PyBullet trained agents: Hopper and Walker2D}. \textit{PyBullet} is a Python module for robotics and \textit{Deep RL} using \textit{PyBullet} environments is based on the \textit{Bullet Physics SDK}, \cite{Pyb20, Pyb}. Let us look at the trained agents for HopperBulletEnv and Walker2DBulletEnv, typical \textit{PyBullet} environments associated with articulated bodies:
3.7. **Exploration noise in trials with PyBullet Hopper.** The HopperBulletEnv environment is considered solved if the achieved score exceeds 2500. In TD3 experiments with the HopperBulletEnv environment, I got, among others, the following training curves for $std = 0.1$ and $std = 0.3$:

Here, $std$ is the standard deviation of exploration noise in TD3. In both trials, threshold 2500 was not reached. However, I noticed the following features:

- In the experiment with $std = 0.3$, there are a lot of values near 2500 (but less than 2500) and at the same time, the average score decreases all the time. This is explained as follows: the number of small score values prevails over the number of large score values, and the difference between these numbers increases.

- In the experiment with $std = 0.1$, the average score values reach large values but in general, the average scores decrease. The reason of this, as above, is that the number of small score values prevails over the number of large score values.

- It seemed to me that the prevalence of very small values is associated with too big noise standard deviation. Then, I decide to reduce $std$ to 0.02, it was enough to solve the environment.
Hopper and Walker2D are solved with TD3, see [TD3a, TD3b]

APPENDIX A. Hill-Climbing algorithm with adaptive noise

A.1. Forerunner of tensors. We illustrate the properties of the Hill-Climbing algorithm applied to the Cartpole environment, [St20a]. Here, the neural network model is so simple that does not use tensors (no PyTorch, no Tensorflow). Only the simplest matrix of shape $[4 \times 2]$ is used here, that is the forerunner of tensors. The Hill-Climbing algorithm seeks to maximize a target function $G_0$, which in our particular case is the cumulative discounted reward:

$$G_0 = R_1 + \gamma R_2 + \gamma^2 R_3 + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{k+1}$$

where $\gamma$ is the discount factor, $0 < \gamma < 1$, and $R_k$ is the reward obtained at the time step $k$ of the episode. The target function $G_0$ looks in Python as follows:

```python
discounts = [gamma** i for i in range(len(rewards) + 1)]
Gt = sum([a*b for a,b in zip(discounts, rewards)])
```

A.2. Two Cartpole environments. What is Cartpole? A pole is attached by an joint to a cart, which moves along a track. The system is controlled by applying a force of +1 or -1 to the cart. The pendulum starts upright, and the goal is to prevent it from falling over. A reward of +1 is provided for every timestep that the pole remains upright. The episode ends when the pole $> 15$ degrees from vertical, or the cart moves $> 2.4$ units from the center, [St20b]. The differences between Cartpole-v0 (resp. Cartpole-v1) are in two parameters: threshold $= 195$ (resp. 475) and max episode steps $= 200$ (resp 500). Solving the environment Cartpole-v0 (resp. Cartpole-v1) require an average total reward that exceeds threshold for 100 consecutive episodes.

For github projects that solve both Cartpole-v0 and Cartpole-v1 environments with DQN and Double DQN, see [Cp20a] and [Cp20b].

A.3. Weight matrix in Hill-Climbing model. Hill-Climbing is a simple gradient-free algorithm. We try to climb to the top of the curve by only changing the arguments of the target function $G_0$ using a certain adaptive noise. The argument of $G_0$ is the weight matrix determining the neural network that underlies in our model.
A.4. **Adaptive noise scale.** The adaptive noise scaling for our model is realized as follows. If the current value of the target function is better than the best value obtained for the target function, we divide the noise scale by 2, and the corresponding noise is added to the weight matrix. If the current value of the target function is worse than the best obtained value, we multiply the noise scale by 2, and the corresponding noise is added to the best obtained value of the weight matrix. In both cases, a noise scale is added with some random factor different for any element of the matrix.

```python
if Gt > best_Gt: # found better weights
    if Gt > best_R: # decrease the noise: noise = noise/2 (till 0.001)
        best_Gt = Gt
        best_w = policy.w
        noise_scale = max(1e-3, noise_scale / 2)
        policy.w += noise_scale * np.random.rand(*policy.w.shape)
    else: # did not find better weights
        if Gt > best_R: # increase the noise: noise = 2*noise (till 2)
            noise_scale = min(2, noise_scale * 2)
            policy.w = best_w + noise_scale * np.random.rand(*policy.w.shape)

The Cartpole-v0 environment is solved in 113 episodes, Cartpole-v1 is solved in 112 episodes. For more information on Cartpole-v0/Cartpole-v1 with adaptive noise scaling, see jupyter notebooks [Cp20a, Cp20b].

A.5. **A more generic formula for the noise scale.** As we saw above, the noise scale adaptively increases or decreases depending on whether the target function is lower or higher than the best obtained value. The noise scale in this algorithm is 2. In [Pl17], authors consider more generic formula:

\[
\sigma_{k+1} = \begin{cases} 
\alpha \sigma_k & \text{if} \quad d(\pi, \tilde{\pi}) < \delta, \\
\frac{1}{\alpha} \sigma_k & \text{otherwise},
\end{cases}
\]

where \(\alpha\) is a noise scale, \(d\) is a certain distance measure between perturbed and non-perturbed policy, and \(\delta\) is a threshold value. In [Pl17 App. C], authors consider the possible forms of the distance function \(d\) for algorithms DQN, DDPG and TPRO.
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