软Q网络

当DQN在2013年由DeepMind公布时，全世界都惊讶于它的简单性和有希望的结果，但由于低效率和稳定性，很难解决许多问题。在所有这些年来，人们提出了越来越多复杂的想法来改进，其中许多人使用分布式Deep-RL，需要大量的核心来运行模拟器。然而，所有这些技术背后的基本思想有时只是修改后的DQN。所以我们提出了一个简单的问题，是否有更优雅的方法来改进DQN模型？而不是在上面添加越来越多的小补丁，我们重新设计了在流行的经验熵正则化框架下的问题设置，这带来了更好的性能和理论保证。最后，我们提出了SQN，一个具有更好性能和稳定性的新off-policy算法。

关键词：RL · 熵 · DQN · 效率

1 引言

近年来，在复杂序列决策问题中扩展强化学习（RL）的成功被Deep-Q-Networks算法（Mnih等，2015）所启动。它将Q-learning与卷积神经网络和经验回放缓冲区相结合，使它能够从原始像素中学习，从而在人类水平上玩许多阿塔里游戏。从那时起，许多扩展已经被提议，以提高其速度或稳定性。Double DQN（Van Hasselt等，2016）通过解耦选择和评估防止过估计，Prioritized experience replay（Schaul等，2015）通过选择更多可以学习的过渡来提高数据效率，Dueling network架构（Wang等，2015）通过分别表示状态值和动作优势来帮助一般化，A3C（Mnih等，2016）通过从多个步骤的Bootstrap目标学习来转移偏差-方差权衡，Distributional Q-learning（Bellemare等，2017）学习对数正态分布的折扣回报，Noisy（Fortunato等，2017）使用随机网络层来探索。

然而，大多数当前的方法很容易受到局部最优位置的影响，它们找到的解决方案在短期内看起来很好，但往往牺牲了长期性能，例如，也许代理学会了待在原地以避免死亡，这并不是我们想要的。其次，模型自由的方法有一个坏名字，因为它的低样本效率，即使一些简单的任务需要数百万次的环境与环境交互，当它面对复杂决策问题时，总间隔步数可能会很容易达到\(10^{10}\)（Kapturowski等，2018），对于大多数域来说是不可访问的。

许多方法都极其脆弱地依赖于其超参数，并且它们通常有太多的超参数需要调整。这意味着我们需要小心地调整参数，其中最重要的是，它们往往被困在局部最优。在很多情况下，它们会无法找到奖励信号，即使奖励信号相对密集，它们仍然无法找到最优解，一些研究人员设计这样一个复杂的奖励函数，为每个环境他们想要解决的目标给予奖励。
In this paper, we propose a different approach to deal with complex tasks with deep reinforcement learning and investigate an entropy regularization approach to learning a good policy under the SQN framework. Extensive experiments on Atari tasks demonstrate the effectiveness and advantages of the proposed approach, which performs the best among a set of previous state-of-the-art methods.

2 BACKGROUND

Reinforcement learning addresses the problem of an agent learning to act in an environment to maximize a scalar reward signal. No direct supervision is provided to the agent. We first introduce notation and summarize the standard Soft Actor-Critic framework.

2.1 MDP

Our problem is searching an optimal policy which maximize our accumulate future reward in Markov Decision Process (MDP) defined by the tuple \((S, A, P, R)\) [Hafner et al., 2018].

- \(S\) represent a set of states
- \(A\) represent a set of actions,
- \(P : S \times A \rightarrow \mathcal{P}(S)\) stand for the transition function which maps state-actions to probability distributions over next states \(P(s'|s, a)\)
- \(R : S \times A \times S \rightarrow \mathbb{R}\) correspond to the reward function, with \(r_t = R(s_t, a_t, s_{t+1})\)

Within this framework, the agent acting in the environment according to \(a \in A\), the environment changes to a new state following \(s' \sim P(.|s, a)\). Next, an state \(s \in S\) and reward \(r \sim R(s, a)\) are received by the agent. Although there are many approaches suitable for the MDP process, we focus on using the policy gradient method with an entropy bonus. The Deep Q-Network agent (DQN) [Mnih et al., 2015] learns to play games from the Atari-57 benchmark by using frame-stacking of 4 consecutive frames as observations, and training a convolutional network to represent a value function with Q-learning, from data continuously collected in a replay buffer. Other algorithms like the A3C, use an LSTM and are trained directly on the online stream of experience without using a replay buffer. In paper [Song et al., 2018] combined DDPG with an LSTM by storing sequences in the replay and initializing the recurrent state to zero during training.

2.2 Soft Actor Critic

Some of the most successful RL algorithms in recent years such as Trust Region Policy Optimization [Schulman et al., 2015], Proximal Policy Optimization [Schulman et al., 2017], and Asynchronous Actor-Critic Agents [Mnih et al., 2016] suffer from sample inefficiency. This is because they learn in an “on-policy” manner. In contrast, Q-learning based “off-policy” methods such as Deep Deterministic Policy Gradient [Lillicrap et al., 2015] and Twin Delayed Deep Deterministic Policy Gradient [Fujimoto et al., 2018] can learn efficiently from past samples using experience replay buffers. However, the problem with these methods is that they are very sensitive to hyper-parameters and require a lot of tuning to get them to converge. Soft Actor-Critic follows in the tradition of the latter type of algorithms and adds methods to combat the convergence brittleness.

2.2.1 The Theory Of SAC

SAC is defined as RL tasks involving continuous actions. The biggest feature of SAC is that it uses a modified RL objective function. Instead of only seeking to maximize lifetime rewards, SAC seeks to also maximize the entropy of the policy. Entropy is a quantity which, roughly speaking, says how random a random variable is. If a coin is weighted so that it almost always comes up heads, it has low entropy; if it’s evenly weighted and has a half chance of either outcome, it has high entropy.

Let \(x\) be a random variable with probability mass or density function \(P\). The entropy \(H\) of \(x\) is computed from its distribution \(P\) according to:

\[
H(P) = \mathbb{E}_{x \sim P}[-\log P(x)]
\]
The standard reinforcement learning object is finding a policy which can maximize expected future return which we can purpose as in Equation 3:

\[
P(\tau|\pi) = \rho_0(s_0) \prod_{t=0}^{T-1} P(s_{t+1}|s_t, a_t)\pi(a_t|s_t)
\]

\[
J(\pi) = \int_{\tau} P(\tau|\pi)R(\tau) = \mathbb{E}_{\tau \sim \pi}[R(\tau)]
\]

In addition to encouraging policy to converge toward a set of probabilities over actions that lead to a high long-term reward, we although add an “entropy bonus” to the loss function. This bonus encourages the agent to take action more unpredictably. Entropy bonuses are used because without them an agent can too quickly converge on a policy that is locally optimal, but not necessarily globally optimal. Anyone who has worked on RL problems empirically can attest to how often an agent may get stuck learning a policy that only runs into walls, or only turns in a single direction, or any number of clearly sub-optimal, but low-entropy behaviors. In the case where the globally optimal behavior is difficult to learn due to sparse rewards or other factors, an agent can be forgiven for settling on something simpler, but less optimal. The entropy bonus is used to attempt to counteract this tendency by adding an entropy increasing term to the loss function, and it works well in most cases. This changes the RL problem to:

\[
\pi^* = \arg \max_{\pi} \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t \left( R(s_t, a_t, s_{t+1}) + \alpha H(\pi(\cdot|s_t)) \right) \right]
\]

Rather than optimizing for the reward at every timestep, agents are trained to optimize for the long-term sum of future rewards. We can apply this same principle to the entropy of the agent’s policy, and optimize for the long-term sum of entropy. So value functions in this setting should include entropy bonuses at each timestep which leads to a different definition than before. Now \(V^\pi\) which include the entropy bonuses is:

\[
V^\pi(s) = \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t \left( R(s_t, a_t, s_{t+1}) + \alpha H(\pi(\cdot|s_t)) \right) \right]_{s_0 = s}
\]

The temperature parameter \(\alpha\) making trade-off between the importance of the entropy term against the environment’s reward. When \(\alpha\) is large, the entropy bonuses play an important role in reward, so the policy will tend to have larger entropy, which means the policy will be more stochastic, on the contrary, if \(\alpha\) become smaller, the policy will become more deterministic. And \(Q^\pi\) has to be modified to contain the entropy bonuses as well:

\[
Q^\pi(s, a) = \mathbb{E}_{\tau \sim \pi} \left[ \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t, s_{t+1}) + \alpha \sum_{t=1}^{\infty} \gamma^t H(\pi(\cdot|s_t)) \right]_{s_0 = s, a_0 = a}
\]

The original Bellman operator is augmented with an entropy regularize term, with equation(5)(6) the connection between \(V^\pi\) and \(Q^\pi\) can be easily derived as:

\[
V^\pi(s) = \mathbb{E}_{a \sim \pi} [Q^\pi(s, a)] + \alpha H(\pi(\cdot|s))
\]

Given these equations above, the Bellman equation for \(Q^\pi\) is changing to:

\[
Q^\pi(s, a) = \mathbb{E}_{s', a' \sim P} [R(s, a, s') + \gamma (Q^\pi(s', a') + \alpha H(\pi(\cdot|s')))]
\]

\[
= \mathbb{E}_{s' \sim P} [R(s, a, s') + \gamma V^\pi(s')]
\]
3 METHOD

In particular, SAC makes use of two soft Q-functions to mitigate positive bias in the policy improvement step that is known to degrade the performance of value-based methods. Function approximators are used for both the soft Q-function and the policy. Instead of running evaluation and improvement to convergence, we alternate between optimizing both networks with stochastic gradient descent. We will consider two parameterized soft Q-function $Q_{\phi_1}, Q_{\phi_2}$ and a tractable policy $\pi_\theta$. The parameters of these networks are $\phi$ and $\theta$.

**LEARNING Q-FUNCTIONS:** The Q-functions are learned by MSBE minimization, using a target value network to form the Bellman backups. They both use the same target, like in TD3, and have loss functions:

$$L(\phi_i, D) = E_{(s,a,r,s',d) \sim D} \left[ (Q_{\phi_i}(s,a) - (r + \gamma(1-d)V_{\phi_{targ}}(s'))^2 \right]$$

(10)

As for target value network, we can obtain it by polyak averaging the value network parameters over the course of training. It not hard to rewrite the connection equation between value function and Q-function as follows:

$$V^\pi(s) = E_{a \sim \pi} [Q^\pi(s,a) + \alpha H(\pi(\cdot|s))]$$

(11)

$$= E_{a \sim \pi} [Q^\pi(s,a) - \alpha \log \pi(a|s)]$$

(12)

The value function is implicitly parameterized through the soft Q-function parameters via Equation[12] We use clipped double-Q like TD3[Monteiro et al., 2018] and SAC[Haarnoja et al., 2018a] for express the TD target, and takes the minimum Q-value between the two approximators, So the loss for Q-function parameters are:

$$L(\phi_i, D) = E_{(s,a,r,s',d) \sim D} \left[ (Q_{\phi_i}(s,a) - (r + (1-d)(\min_{i=1,2}Q_{\phi_i}(s,\tilde{a}) - \alpha \log \pi_\theta(\tilde{a}|s)))^2 \right]$$

(13)
The update makes use of a target soft Q-function, that is obtained as an exponentially moving average of the soft Q-function weights, which has been shown to stabilize training. Importantly, we do not use actions from the replay buffer here: these actions are sampled fresh from the current version of the policy.

**LEARNING THE POLICY:** The policy should, in each state, act to maximize the expected future return plus expected future entropy. That is, it should maximize $V^\pi(s)$, which we expand out (as before) into

$$E_{a \sim \pi}[Q^\pi(s, a) - \alpha \log \pi(a|s)]$$

The target density is the Q-function, which is represented by a neural network an can be differentiated, and it is thus convenient to apply the reparameterization trick instead, resulting in a lower variance estimate, in which a sample from $\pi_{\theta}(\cdot|s)$ is drawn by computing a the deterministic function of the state, policy parameters, and independent noise. following the authors of the SAC paper[Haarnoja et al., 2018b], we use a squashed Gaussian policy, which means that samples are obtained according to

$$\tilde{a}_{\theta}(s, \xi) = \tanh(\mu_{\theta}(s) + \sigma_{\theta}(s) \odot \xi), \quad \xi \sim \mathcal{N}(0, I)$$

The reparameterization trick allows us to rewrite the expectation over actions (which contains a pain point: the distribution depends on the policy parameters) into an expectation over noise (which removes the pain point: the distribution now has no dependence on parameters):

$$E_{a \sim \pi_{\theta}}[Q^\pi_{\theta}(s, a_{\theta}(s, \xi)) - \alpha \log \pi_{\theta}(a_{\theta}(s, \xi)|s)]$$

To get the policy loss, the final step is that we need to substitute $Q^\pi_{\theta}$ with one of our function approximators. The same as in TD3, we use $Q_{\phi_1}$. The policy is thus optimized according to

$$L(\theta) = E_{\xi \sim \mathcal{N}}[Q_{\phi_1}(s, \tilde{a}_{\theta}(s, \xi)) - \alpha \log \pi_{\theta}(\tilde{a}_{\theta}(s, \xi)|s)]$$

**LEARNING $\alpha$:** As it proposed in[Haarnoja et al., 2018b], for the purpose of improving performance, we leaning the temporal parameter $\alpha$ by minimizing the dual objective as well:

$$\alpha_+^t = \underset{\alpha_t}{\text{argmin}} E_{a_{t} \sim \pi_{t}^*}[-\alpha_t \log(\pi_{T}^*(a_T|s_T; \alpha_T)) - \alpha_T H]$$

Prior give us tools to achieve this, as shown in [Boyd and Vandenberghe, 2004], approximating dual gradient descent is a way to achieve that. Because we use a function approximator and it is impractical to optimizing with respect to the primal variables fully, we compute gradients for $\alpha$ with the following objective:

$$L(\alpha) = E_{a \sim \pi_{t}}[-\alpha \log \pi_{t}(a_t|s_t) - \alpha H]$$

Inspired by SAC we derived our SQN method, SAC is aimed for discrete space so the policy network is necessary however here DQN gives great example of how to sample an action directly from Q function, combine this two idea means sample an action with entropy bonus, it comes to:

$$\pi(a_n | s) = \text{StopGradient} \left( \text{Softmax} \left( \frac{1}{\alpha} Q_{\phi_1} (s, a_n) \right) \right)$$

$$Q_{\phi_1} (s, a_n) = Q_{\phi_1} (s) \cdot \text{Onehot}(a_n)$$
Algorithm 1: SQN

Input : Q-function parameters $\phi_1, \phi_2$
- Temperature $\alpha$
- Empty replay buffer $D$

1. Set target parameters equal to main parameters $\bar{\phi}_1 \leftarrow \phi_1, \bar{\phi}_2 \leftarrow \phi_2$

2. while not converge do
   3. for each environment step do
      4. $a_t \sim \pi_\theta(s_t)$ // Sample action from the policy
      5. $s_{t+1} \sim p(s_{t+1}|s_t, a_t)$ // Sample transition from the environment
      6. $D \leftarrow \cup \{(s_t, a_t, r_t, s_{t+1})\}$ // Store the transition in the replay buffer
   7. end
   8. for each update step do
      9. $\{\{(s, a, r, s', d)\}_{B=1} \sim D$ // Randomly sample a batch of transitions
      10. Compute targets for Q functions:
          11. $y_v(s') = \min_{i=1, 2} Q_{\bar{\phi}_i}(s', a_n) - \alpha \sum_{a_n} \pi(a_n | s') \log \pi(a_n | s')$
          12. $y_q(r, s', d) = r + \gamma (1 - d) y_v(s')$ // Calculate the TD target
      13. Update Q-functions by gradient descent using:
          14. $\phi_i \leftarrow \phi_i + \lambda \phi_i \frac{1}{|B|} \sum_{(s, a, r, s', d) \in B} (Q_{\bar{\phi}_i}(s, a) - y_q(r, s', d))^2$, for $i = 1, 2.$
          15. Update the temperature by one step of gradient descent using ($H$ is the target entropy):
              16. $\alpha \leftarrow \alpha + \lambda \alpha \frac{1}{|B|} \sum_{s \in B} -\alpha (H + \log \pi(a_n | s))$ // Update temperature parameter
      17. Update target networks with:
          18. $\bar{\phi}_i \leftarrow \rho \bar{\phi}_i + (1 - \rho) \phi_i$, for $i = 1, 2.$ // Update target network weights
   19. end
20. end

It clearly shows that policy parameter update step won’t exist at all. The overall architecture of our algorithm is shown in Algorithm 1. As for value function update, it is same to SAC which described in section 3. The final algorithm is listed in Algorithm 1. The method alternates between collecting experience from the environment with the current policy and updating the function approximators using the stochastic gradients from batches sampled from a replay pool. Using off-policy data from a replay pool is feasible because both value estimators and the policy can be trained entirely on off-policy data. The algorithm is agnostic to the parameterization of the policy, as long as it can be evaluated for any arbitrary state-action tuple.

4 EXPERIMENT

In order to test our agent, We designed our experiments to answer the following questions:

1. Can SQN be used to solve challenging Atari problems? How does our agent compare with other methods when applied to these problems, concerning the final performance, computation time, and sample complexity?
2. what is the impact of different reward scale, and how different hyper-parameter influence the stability of our agent
3. We add entropy bonus on our agent, does this parts give us a more powerful agent

To answer (1) we compare the performance of our agent with other methods in session 4.1. With regard to (2)(3), we addressed the ablation study on our algorithm in session 4.2 testing how does different settings and network design influence the performance.
Figure 2: (a) Pong, (b) Breakout, (c) Qbert, (d) Different update scheme

Figure 2: 2a to 2d are the training curves on Atari benchmarks, SQN agent performs consistently across all tasks and outperforming both on-policy and off-policy methods in the most challenging tasks. 2d shows the training curve of different $\alpha$ and update method.

The results show overall our agent outperforms baseline with a large margin, both in terms of learning speed and the final performance. The quantitative results attained by our agent is our experiments also compare very favorably to results reported by other methods in prior work, indicating that both the sample efficiency and the final performance of our agent on these benchmark tasks exceeds the state of art.

4.1 Atari

The Atari Learning Environment (ALE) has been the testing ground of most recent deep reinforcement agents. It posed challenging reinforcement learning problems including exploration, planning, reactive play, and complex visual input. Most games feature very different visuals and game mechanics which makes this domain particularly challenging. The goal of this experimental evaluation is to understand how the sample complexity and stability of our method compare with prior deep reinforcement learning algorithms. We compare our method to prior techniques on a range of challenging Atari tasks from the OpenAI gym benchmark suite. Although the easier tasks can be solved by a wide range of different algorithms, the more complex benchmarks are exceptionally difficult to solve with off-policy algorithms. The stability of the algorithm also plays a large role in performance: easier tasks make it more practical to tune hyper-parameters to achieve good results, while the already narrow basins of effective hyper-parameters become prohibitively small for the more sensitive algorithms on the hardest benchmarks, leading to poor performance [Gu et al., 2016].

To allow for a reproducible and fair comparison, we evaluate all the algorithm with a similar network structure, for the off-policy algorithm, we use a two-layer feed-forward neural network of 400 and 300 hidden nodes respectively, with rectified linear units (ReLU) between each layer for both the actor and critic, we use the parameters with is shown superior in prior work [Henderson et al., 2018] as the comparison of our agent. Both network parameters are updated using Adam [Kingma and Ba, 2014] with a the learning rate of $10^{-4}$, with no modifications to the environment or reward.

Figure 2 compares three individual runs with both variants, initialized with different random seeds. SQN performs much better, shows that our agent significantly outperforms the baseline, indicating substantially better stability and stability. As evident from the figure, with jointly training and internal reward, we can achieve stable training. This becomes especially important with harder tasks, where tuning hyperparameters is challenging.
It shows our agent outperforms other baseline methods with a large marginal, indicate both the efficiency and stability of the method is superior

4.2 ABLATION STUDY

We have at most three different kinds of update scheme. Figure 2 shows how learning performance changes when the update schemes are changed. For large $\alpha$, the policy becomes nearly random, and consequently fails to exploit the reward signal, resulting in substantial degradation of performance. For small temporary coefficient, the value function is enhanced with exploring so the model learns quickly at first, but the policy then becomes nearly deterministic, leading to poor local minimal due to the lack of adequate exploration and worse state representation, as for $\alpha$ which scale is right, due to the reward become larger at the end of training, entropy bonus becomes nearly nothing to the algorithm, still it can not achieve awesome performance. With learned $\alpha$, the model balance exploration and exploitation, model head make sure, our agent can take advantage of joint optimization, and achieve stable training.

5 CONCLUSION

Empirically results show that SQN outperforms DQN by a large marginal, notice this is the "plain" version of SQN, so it could become an important cornerstone for many modern algorithms like IMPALA [Espeholt et al., 2018], APEX [Horgan et al., 2018], R2D2 [Kapturowski et al., 2018] and so on. We illustrate SQN have the potential to combine with all kinds of improvement made on DQN and improving the performance and efficiency from the starting point. More experiments need to be done to test if SQN could replacing DQN and become a standard algorithm to use. But as we purposed, promising results already illustrate SQN is simple but powerful enough to solve many interesting problems DQN can’t solve. In the future, we will focus on some challenging tasks (like the new google football environment) examining the limit of our algorithm.

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