Deep Reinforcement Learning with Surrogate Agent–Environment Interface

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Abstract

In this paper we propose surrogate agent–environment interface (SAEI) in reinforcement learning. We also state that learning based on probability surrogate agent–environment interface gives optimal policy of task agent–environment interface. We introduce surrogate probability action and develope the probability surrogate action deterministic policy gradient (PSADPG) algorithm based on SAEI. This algorithm enables continuous control of discrete action. The experiments show PSADPG achieves the performance of DQN in the long run for selected tasks.

1 Introduction

Reinforcement learning is an important topic in machine learning research. Its training relies on the interaction between agent and environment. With the development of artificial neural network, deep reinforcement learning is able to handle realistic real world problem.

Agent–environment interface describes the interaction between agent and environment in reinforcement learning. The boundary between agent and environment is preset according to task. "The agent–environment boundary is determined once one has selected particular states, actions, and rewards, and thus has identified a specific decision-making task of interest" [8]. However, agent–environment interface is of little interest of algorithm development since it is related to the task definition itself more than how to solve the task.

In this paper we revisit the possibility of changing the interface in algorithm level and keep the interface intact in task level. Thus, we introduce a surrogate agent–environment interface. After introducing a surrogate probability action, we prove that the probability surrogate agent–environment interface gives the optimal policy solution to the task interface. In this framework, the learning agent interacts with surrogate agent–environment interface during the training process. It transforms the learned optimal policy of learning agent to the optimal policy of the task agent. To the best of our knowledge, it is the first time that a surrogate agent–environment interface is used to develop reinforcement learning algorithm. A search of the relevant literature yields little related articles. Some authors present surrogate action as an embedding vector in the continuous space for the original discrete actions [2]. It does not change the interface during learning process.

The contributions of this paper are as follow:

1. It is the first time that the agent–environment interface is investigated for developing reinforcement learning algorithm.
2. We prove that the surrogate probability agent–environment interface gives the optimal policy solution to the task interface.
3. We develop the probability surrogate action deterministic policy gradient (PSADPG) algorithm based on SAEI which validate the surrogate agent–environment interface framework on algorithm development.
4. PSADPG enables DQN [5] style off-policy learning algorithms (such as Double DQN [9], Dueling DQN [10], Prioritized DQN [6]) for stochastic discrete control. The experiments show PSADPG achieves the performance of DQN in the long run in selected tasks. PSADPG augments the spectrum of deep reinforcement learning algorithm with extra dimensions.

2 Surrogate agent-environment interface

The interaction between agent and environment is fundamental for reinforcement learning. In Figure 1, Agent performs action $a$ to environment. Environment dynamic then updates to next state and presents reward to agent. Markov decision process formally describes this interaction for reinforcement learning. A Markov decision process or a MDP consists of: set of states $S$, set of actions $A$, a probability function $P(s′|a, s) = P(s_{t+1} = s′|a_t = a, s_t = s)$ which gives the dynamic from state $s$ to state $s'$ under action $a$ at time $t$, a reward function $r_t = R(a, s) = R(a_t = a, s_t = s)$ which specifies the reward received at time $t$ after taking the action $a$ from state $s$. A policy for MDP is a function $a = \mu(s)$ or a probability distribution $\pi(a|s)$ determines an action $a$ in state $s$ at time $t$. The goal of reinforcement learning control is to search for policy that maximize the total reward $R = \sum_t \gamma^t r_t$ where $\gamma$ is a discount factor.

![Figure 1: Task agent-environment interface](image)

The deterministic policy directly gives a certain action. The stochastic policy, however, take additional sampling step after given a probability from distribution $\pi(a|s)$. Our idea is to extract this sampling step from agent and integrate it into environment. This presents a new interaction between agent and surrogate environment, see Figure 2.

![Figure 2: Surrogate agent-environment interface](image)

In this setting, environment takes probability parameters as action from agent. The sampling process is part of environment. We do not assume agent has information of how the environment sample the action. To prove the feasibility of this framework, we have the following definitions.

**Definition 1.** A task agent-environment interface $AEI_t$ is the agent-environment interface of the task of interest. A task Markov decision process $MDP_t$ is a MDP based on $AEI_t$.

**Definition 2.** The stochastic policy $\pi(s)$ of task agent-environment interface $AEI_t$ can be expressed as $\pi(s) = \phi \circ \tilde{\mu}_p(s)$, where $\tilde{\mu}_p(s)$ is a deterministic function mapping from state $s$ to action probability vector $p$ and $\phi$ is a sampling function mapping the probability vector $p$ to action $a$. For deterministic...
policy, $\mu(s) = \tilde{\mu}_p(s)$. The function $\tilde{\mu}_p(s)$ can be considered as a surrogate action policy from agent to environment and the sampling function $\phi$ is part of the surrogate environment. The function $\tilde{\mu}_p(s)$ is called probability surrogate action policy. The resulting interface $\hat{\text{AEI}}_p$ is called probability surrogate agent-environment interface. The probability surrogate Markov decision process $\hat{\text{MDP}}_p$ is the MDP based on $\hat{\text{AEI}}_p$.

We prove that an optimal policy learned in probability surrogate agent-environment interface is equivalent to the optimal policy in task surrogate agent-environment interface.

**Theorem 1.** If the optimal probability surrogate policy in $\hat{\text{MDP}}_p$ is $\tilde{\mu}_p$. Then $\pi_{t*} = \phi \circ \tilde{\mu}_p$ is the optimal policy $\pi_{t*}$ in MDP if the optimal policy is stochastic. If the optimal policy $\mu_{t*}$ in MDP is deterministic, $\mu_{t*} = \tilde{\mu}_p$.

**Proof.** In the case of stochastic policy, if $\pi'_t = \phi \circ \tilde{\mu}_p$ is not optimal in $\text{MDP}_t$, then there exists a state $s$ and policy $\pi$ such that $V_\pi(s) > V_{\pi'}(s)$. For $\pi(s)$ in $\text{MDP}_t$, there exists a $\tilde{\mu}_p(s)$ in $\hat{\text{MDP}}_p$ such that $\pi(s) = \phi \circ \tilde{\mu}_p(s)$. Since reward function is the same for both $\text{MDP}_t$ and $\hat{\text{MDP}}_p$, $V_\pi(s) = V_{\tilde{\mu}_p}(s)$ and $V_{\pi'}(s) = V_{\phi \circ \tilde{\mu}_p}(s)$. Thus, we have $V_{\tilde{\mu}_p}(s) > V_{\phi \circ \tilde{\mu}_p}(s)$. This contradicts the optimality of $\tilde{\mu}_p$ in $\hat{\text{MDP}}_p$. In the case of deterministic policy, $\mu_{t*} = \tilde{\mu}_p$ is trivial.

To validate the theorem, we introduce the probability surrogate action deterministic policy gradient (PSADPG) algorithm. This algorithm introduce a continuous approach on stochastic discrete action control to which off-policy policy gradient methods may apply.

### 3 Surrogate action deterministic policy gradient algorithm

The stochastic policy of discrete control not only gives a possible optimal solution but also enables a soft continuous learning process. Traditional policy gradient for discrete control utilizes likelihood ratio methods which incorporate probability distribution of action, eg. REINFORCE [11]. The idea is to weight the probability of action by the reward based on this action. The state-of-the-art actor-critic algorithm A3C [4] is more along this line.

Here we use a variant of deterministic policy gradient algorithm DPG [2] to directly capture the gradient of Q function respect to deterministic probability vector. DPG is specifically designed for continuous control. It handles the problem of instability of stochastic continuous policy gradient with the enhancement of efficiency. For high dimensional real world tasks, DDPG [3] is developed. With the probability surrogate action, we are able to transform the stochastic discrete control tasks into deterministic continuous control tasks. Algorithm 1 is a modified version of DDPG. For the purpose of comparison, we keep most of the symbols and statements intact from the original paper. Please refer to [3] for the detail of the algorithm. The difference from DDPG is that action $a$ in DDPG of learning process is replaced by probability vector $p$. Action $a$ in PSADPG sampled from $p$ is only used to interact with environment. Probability vector $p$ is the output of the softmax layer of actor network. Since the algorithm is function approximation reinforcement learning approach, the optimality may not be guaranteed by the above theorem.

### 4 Experiment

To compare with the DQN algorithm, we test the PSADPG algorithm with DQN in simple discrete control task 'Acrobot'. We choose 'Acrobot-v1' environment in OpenAI gym [1].

For the critic network, state input is first embedded through a 64 units fully connected layer with hyperbolic tangent activation. The embedding vector then is then linearly merged with probability input vector (with number of elements the same as number of actions) through 64 units fully connected layer. The critic network finally outputs the scalar Q value through another linear fully connected layer of 64 units.

The actor network takes state input through a fully connected layers with 64 units with hyperbolic tangent activation. It then linearly outputs logits through a fully connected layer with number of units the same as number of actions. A softmax layer is used to output probability surrogate action.
Algorithm 1 PSADPG Algorithm

Randomly initialize critic network $Q(s, p|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights $\theta^Q$ and $\theta^\mu$.
Initialize target network $Q'$ and $\mu'$ with weights $\theta'^Q \leftarrow \theta^Q$ and $\theta'^\mu \leftarrow \theta^\mu$.
Initialize replay buffer $R$.

For episode = 1, M do
    Receive initial observation state $s_1$
    for $t=1,T$ do
        Select probability $p_t = \mu(s_t|\theta^\mu)$ according to the current policy
        Sample action $a_t$ from probability $p_t$ with exploration
        Execute action $a_t$ and observe reward $r_t$ and observe new state $s_{t+1}$
        Store transition $(s_t, p_t, r_t, s_{t+1})$ in $R$
        Sample a random minibatch of $N$ transitions $(s_i, p_i, r_i, s_{i+1})$
        Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta'^\mu))$\[\theta'^Q\]
        Update critic by minimizing the loss: $L = \frac{1}{N} \sum_i (y_i - Q(s_i, p_i|\theta^Q))^2$
        Update the actor policy using the sampled policy gradient:
        $\nabla_{\theta^\mu} J \approx \frac{1}{N} \sum_i \nabla_p Q(s_i, p_i|\theta^Q)_{s=s_i, p=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)_{s_i}$
        Update the target networks:
        $\theta'^Q \leftarrow \tau \theta'^Q + (1 - \tau) \theta^Q$
        $\theta'^\mu \leftarrow \tau \theta'^\mu + (1 - \tau) \theta^\mu$
    end for
end for

For the target network update, we use hard update instead of soft update which stated in the Algorithm 1. The update frequency is one update per 1000 iterations.

Learning rate is set to be 0.0005. Gamma is 1. Adam optimizer is used for stochastic gradient descend. The exploration is linear reduction from 1 to 0.02 during first 100000 iterations and keep to 0.02 after that.

Figure 3 presents the learning curves of two algorithms. The episode reward is the mean value of the most recent 100 episodes. We can see two algorithms have similar learning curve performance in the long run.

5 Conclusion

The surrogate agent–environment interface enables extra ability to handle reinforcement learning tasks. In this paper, we prove that the policy optimality of probability surrogate agent–environment interface is equivalent to the task agent–environment interface. We also develop the algorithm to validate this theorem. We plan to explore more efficient algorithm based on it in future work.

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