

Deep Deterministic Policy Gradients: Components and Extensions

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Abstract Actor-critic methods with deep neural networks are of growing interest in the reinforcement learning community. The *Deep Deterministic Policy Gradient* algorithm evolved as a powerful tool from the *Deep Q-Learning* algorithm combined with the *Deterministic Policy Gradient* theorem to learn a fully deterministic policy. We explain these components and how they merge together to an algorithm achieving good performance for many simulated and physical tasks. We then follow with some possible improvements for this algorithm, which could be applied to overcome its lacking data efficiency and instability issues during training.

Keywords DDPG · DQN · DPG · D4PG · Parameter Noise

1 Introduction

The field of reinforcement learning deals with solving problems that are accessible through the interaction of an agent with its environment. Such problems can be defined as *Markov Decision Processes* (Howard 1960), which consist of a tuple (S, A, R, P, γ) , where S is the state-distribution, A is the action-distribution, $R : S \times A \rightarrow \mathbb{R}$ is the reward function mapping states and actions to a scalar reward $r \in \mathbb{R}$, $P : S \times A \rightarrow S$ is the state transition function mapping states and actions to states, and γ is the discount factor used

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to make an agent more or less farsighted. The goal of an agent can then be defined by finding an optimal policy $\pi^* : S \rightarrow A$ that determines when to take which action in order to maximize the observed reward. This is equal to taking the action that maximizes the optimal action-value function $Q^* : S \times A \rightarrow \mathbb{R}$ that defines the value of state-action pairs (s, a) .

For many applications, the environment details, i.e. R and P , are not available and the agent can only observe the state s of the environment, perform an action a and observe an immediate reward $r(s, a)$ and a successor state s' . This requires the use of so-called model-free algorithms, e.g. *Q-Learning* (Watkins and Dayan 1992), which updates an internal representation of the action-value function $Q(s, a)$ by the temporal-difference error between the current and the successor state after performing an action. The internal lookup-table representation of this algorithm is not tractable for large state-action spaces. This problem is addressed by *value function methods*, e.g. the *Deep Q-Learning* (DQN) algorithm (Mnih et al. 2013), which is an adaption to Q-Learning where the action-value function is approximated with a deep neural network. Instead of approximating the value-function one could also approximate the policy $\pi(s|a)$ directly, known as *policy-gradient methods*. *Actor-critic methods* (Konda and Tsitsiklis 2000) approximate the value-function as well as the policy.

Finally, the *Deep Deterministic Policy Gradient* (DDPG) approach (Lillicrap et al. 2015) combines the above mentioned methods with the *Deterministic Policy Gradient* (DPG) (Silver et al. 2014) to an actor-critic algorithm using neural networks to approximate the policy and the action-value function while learning a deterministic policy.

We will give more detailed insights into the mentioned algorithms and how DDPG evolved from them in the next sections before we describe some possible improvements in section 5.

2 Deep Q-Learning

The general goal of a reinforcement learning algorithm is to find an optimal behavior policy $\pi^*(a|s)$ or $\pi^*(s)$ in the deterministic case, which maximizes the expected total reward an agent collects while following it during an episode. Such an optimal policy greedily chooses actions that maximize the optimal action-value function $Q^*(s, a)$, that can be defined by

$$Q^*(s, a) = \max_{\pi^*} Q^{\pi^*}(s, a) = \mathbb{E} \left[\sum_{k=0}^T \gamma^k r(s_{t+k}, a_{t+k}) | s_t = s, a_t = a, \pi^* \right]$$

where t is the current time-step and T the final time-step ending the episode. By definition, this optimal value function yields the *Bellman equation* (Sutton and Barto 2018) and can be reinterpreted as maximizing the current reward and the discounted action-value of the resulting state. The function can be

rewritten as

$$Q^*(s, a) = \mathbb{E} \left[r(s, a) + \gamma \max_{a'} Q^*(s', a') | s, a \right].$$

The *Q-Learning* approach (Watkins and Dayan 1992), one of the earliest reinforcement learning methods, uses lookup-tables to represent the policy $\pi(a|s)$ and action-value function $Q(s, a)$. The optimal action-value function is calculated by applying the *Bellman equation* using the temporal difference error between the current states and successor states. The iterative update rule is

$$Q^{(i+1)}(s, a) \leftarrow (1 - \alpha)Q^{(i)}(s, a) + \alpha \left(r + \gamma \max_{a'} Q^{(i)}(s', a') \right)$$

utilizing a hyper-parameter α as a learning rate. This update rule is proven to converge to the optimal action-value function using a lookup-table representation (Watkins and Dayan 1992; Jaakkola et al. 1994; Ribeiro and Szepesvári 1996), but becomes intractable for large state-action spaces.

The *Deep Q-Learning* approach (DQN) (Mnih et al. 2013) combines the approximation power of neural networks with traditional Q-learning to overcome this issue. The algorithm is an off-policy, model-free approach and is able to find a close to optimal action-value function for many cases (Mnih et al. 2015), and thus a close to optimal policy. For approximating the action-value function $Q(s, a|\theta) \approx Q(s, a)$ the approach uses a deep neural network with parameters θ , called the Q-Network. This network can be trained by sequentially minimizing the loss function $L_i(\theta)$ depending on the parameters θ :

$$L^{(i)}(\theta) = \mathbb{E} \left[\left(r + \gamma \max_{a'} Q(s', a'|\theta^{(i-1)}) - Q(s, a|\theta^{(i)}) \right)^2 \right]$$

This loss function is similar to the temporal-difference loss used in Q-Learning but with approximated action-value functions instead of lookup-tables. Derivating this loss w.r.t. the approximation's parameters yields the gradient

$$\nabla_{\theta^{(i)}} L^{(i)}(\theta) = \mathbb{E} \left[\left(r + \gamma \max_{a'} Q(s', a'|\theta^{(i-1)}) - Q(s, a|\theta^{(i)}) \right) \nabla_{\theta^{(i)}} Q(s, a|\theta^{(i)}) \right].$$

The expectation can be approximated by sampling from an environment and this gradient can be used to optimize the loss function by using stochastic gradient descent.

Most optimization algorithms for neural networks assume independently and identically distributed data, which does not hold for samples sequentially generated by an agent through interaction. Hence, an *experience replay buffer* has been introduced, which stores a fixed amount of samples of the environment. This allows random mini-batch sampling, which temporarily decorrelates the samples and ensures a fixed update size, unlike using whole trajectories that might defer in length. It furthermore improves the data efficiency as single episodes might potentially be used in several update steps. Sampling mini-batches also enables the efficient use of hardware optimization. This could be improved further by using empowered derivatives of stochastic gradient descent, e.g. *RPROP* as in the *neural fitted Q-Learning* approach (Riedmiller

2005) or *ADAM update* (Kingma and Ba 2014).

Using the approximated action-value function $Q(s, a|\theta)$ directly to calculate the target for the update of itself turned out to be unstable in many cases (Mnih et al. 2015). This problem can be addressed by using a *target network*, which is initialized with the same structure and parameters as the Q-network. This target network is only updated after a fixed amount of time-steps.

A pseudo-code for the DQN approach can be found in Algorithm 1. It is able to significantly outperform earlier learning methods despite incorporating almost no prior knowledge about the inputs (Mnih et al. 2013). However, it is limited by the disability to cope with continuous and high-dimensional action spaces due to the max operator in the action selection (Lillicrap et al. 2015). These limitations can be addressed by combining the approach with the *Deterministic Policy Gradient* (Silver et al. 2014), which is described in the following section.

Algorithm 1 Deep Q-Learning (DQN)

Initialize: Replay buffer D with high capacity

Initialize: Neural network for action-value function Q with random weights θ

Initialize: Neural network for target action-value function \hat{Q} with weights $\theta^- = \theta$

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for episode 1 to  $M$  do
  reset environment to state  $s_1$ 
  for  $t = 1$  to  $T$  do
    if random  $i \leq \epsilon$  then
      random action  $a_t$ 
    else
       $a_t = \operatorname{argmax}_a Q(s_t, a|\theta)$ 
    end if
    execute  $a_t \rightarrow$  reward  $r_t$  and next state  $s_{t+1}$ 
    save  $(s_t, a_t, r_t, s_{t+1})$  in  $D$ 
    sample mini-batch  $(s_i, a_i, r_i, s_{i+1})_k$  of size  $k$  from  $D$ 
     $q_i = \begin{cases} r_i & \text{if episode terminates at step } i+1 \\ r_i + \gamma \max_{a'} \hat{Q}(s_{i+1}, a'|\theta^-) & \text{else} \end{cases}$ 
    perform gradient descent on  $(q_i - Q(s_i, a_i|\theta))_\theta^2$ 
    every  $C$  steps update  $\hat{Q} = Q$ 
  end for
end for

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3 Deterministic Policy Gradient

Many model-free reinforcement learning algorithms adapt the idea *generalized policy iteration*, which consists of interleaving steps of *policy evaluation* and *policy improvement* (Sutton and Barto 2018). The most common approach to the policy improvement step for a deterministic policy is to greedily select the action maximizing the (estimated) action-value function

$$\pi(s) = \arg \max_a Q(s, a).$$

However, most problems in reinforcement learning consist of a continuous action space what makes it very difficult to greedily choose the best action given a policy because the max operator in the policy improvement step would require a global optimization at every iteration.

Rather than trying to maximize the action-value function $Q(s, a)$ globally by greedy improvements of the policy, one could move the policy in the direction of the gradient of $Q(s, a)$ w.r.t. the policy's parameters:

$$\nabla_{\theta^\pi} J(\theta^\pi) \approx \mathbb{E} [\nabla_{\theta^\pi} Q(s, a)]$$

Applying the chain rule to this equation leads to the *deterministic policy gradient (DPG) theorem*

$$\nabla_{\theta^\pi} J(\theta^\pi) \approx \mathbb{E} [\nabla_a Q(s, a)|_{a=\pi(s|\theta^\pi)} \nabla_{\theta^\pi} \pi(s|\theta^\pi)]$$

where the expectation can again be approximated by sampling from an environment.

The deterministic policy gradient is potentially more sample efficient especially for large action spaces as it only requires integrating over the state space

$$\nabla_{\theta^\pi} J(\theta^\pi) = \int_S \rho^\pi(s) \nabla_{\theta^\pi} \pi(s|\theta^\pi) \nabla_a Q(s, a)|_{a=\pi(s)} ds$$

while the stochastic policy gradient (Sutton and Barto 2018) requires integrating over the state and the action space

$$\nabla_{\theta^\pi} J(\theta^\pi) = \int_S \rho^\pi(s) \int_A \nabla_{\theta^\pi} \pi(a|s, \theta^\pi) Q(s, a) da ds$$

where $\rho^\pi(s)$ is the distribution of visited states depending on the current (parameterized) policy in both cases.

Using only deterministic action outputs makes an agent fully exploiting what its experience, so one needs to make sure there still is exploration. This is realized by using an off-policy approach, which follows a stochastic policy while learning a deterministic policy and could be implemented by simply adding some noise to the policy output. The following section describes an actor-critic architecture combining the above mentioned methods to a state-of-the-art reinforcement learning algorithm.

4 Deep Deterministic Policy Gradient

The combination of above approaches led to the *Deep Deterministic Policy Gradient (DDPG)* approach (Lillicrap et al. 2015), which is a model-free and off-policy algorithm that uses actor-critic methods, a deterministic target policy and deep Q-Learning. Both, the actor and the critic, are realized by deep neural networks. The pseudo-code for DDPG can be found in Algorithm 2.

It consists of a parameterized deterministic policy $\pi(s|\theta^\pi)$, the actor, and a parameterized action-value function $Q(s, a|\theta^Q)$, the critic. The critic is updated

using the *Bellman equation* with a TD-error similar to Q-Learning (Watkins and Dayan 1992) resulting in the loss function

$$L(\theta^Q) = \mathbb{E} [Q(s, a|\theta^Q) - (r(s, a) + \gamma Q(s', \pi(s'|\theta^\pi)|\theta^Q))^2] .$$

The actor is updated using the DPG theorem:

$$\nabla_{\theta^\pi} J(\theta^\pi) \approx \mathbb{E} [\nabla_a Q(s, a|\theta^Q)|_{a=\pi(s|\theta^\pi)} \nabla_{\theta^\pi} \pi(s|\theta^\pi)]$$

The use of neural networks to parameterize the actor and critic functions implies that convergence guarantees do not hold anymore. Therefore, the actor-critic DPG approach is combined with recent successes from DQN: To ensure independently and identically distributed data, the authors use an *experience replay buffer* and sample random mini-batches from it. This again decorrelates the samples and allows the efficient use of hardware optimization. To address instability issues from directly combining the deep neural network approximation and the DPG theorem, *target networks* are introduced, which are copies of the actor $\pi'(s|\theta^{\pi'})$ and the critic $Q'(s, a|\theta^{Q'})$. These target-networks track the learned networks and are constrained to slow changes by using soft updates: $\theta' \leftarrow \tau\theta + (1-\tau)\theta'$ with $\tau \ll 1$. This might slow down the learning process but greatly improves the stability of it, because using an older set of parameters to generate the targets adds a delay between the time we update our functions and the time these updates affect our targets. This makes divergence or oscillations during the learning process much more unlikely (Mnih et al. 2015).

Using low dimensional feature input might give very different scales for the single states, e.g. the angle of a joint, which is bounded to $[-\pi, \pi]$ and the angular velocity which is potentially unbounded. This can lead to problematic learning for the neural networks and is addressed by using *batch normalization*, which normalizes each dimension across the samples in a mini-batch.

To ensure exploration while using a deterministic policy, a *noise process* N is added to the action output of the actor network. This noise process can be chosen to suit the environment, e.g. a time-dependent Ornstein-Uhlenbeck process (Ricciardi and Sacerdote 1979) or a consistent Gaussian noise (Barth-Maron et al. 2018).

The algorithm was evaluated on more than 20 simulated physical tasks using the same algorithm, network structures and hyper-parameters including classic control problems like the cart-pole environment. Using low-dimensional feature input, the algorithm was able to find close to optimal policies for most of the tasks. Their performance is competitive with those found by a controller with full access to the environment. The algorithm was also able to find good policies using high dimensional pixel input. For simple tasks, this turned out to be as fast as using low dimensional state features.

The most challenging issues of the approach are its still poor sample efficiency and instabilities during learning. We present possible extensions to DDPG in the next chapter which might improve these issues.

Algorithm 2 Deep Deterministic Policy Gradient (DDPG)

Initialize: Replay buffer D with high capacity
Initialize: Critic network $Q(s, a|\theta^Q)$ and actor network $\pi(s|\theta^\pi)$ with random weights θ^Q and θ^π
Initialize: Initialize target networks Q' and π' with weights $\theta^{Q'} \leftarrow \theta^Q$ and $\theta^{\pi'} \leftarrow \theta^\pi$

- 1: **for** episode 1 **to** M **do**
- 2: Initialize random process N for action exploration
- 3: Reset environment to state s_1
- 4: **for** $t = 1$ **to** T **do**
- 5: Select action $a_t = \pi(s_t|\theta^\pi) + N_t$ from local actor
- 6: Execute action a_t and observe reward r_t and next state s_{t+1}
- 7: Save (s_t, a_t, r_t, s_{t+1}) in replay buffer D
- 8: Sample mini-batch $(s_i, a_i, r_i, s_{i+1})_k$ with size k from D
- 9: Set TD-target from target networks:

$$y_i = r_i + \gamma Q'(s_{i+1}, \pi'(s_{i+1}|\theta^{\pi'})|\theta^{Q'})$$
- 10: Update the critic by minimizing the loss:

$$L = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$$
- 11: Update the actor using the sampled policy gradient:

$$\nabla_{\theta^\pi} J \approx \frac{1}{N} \sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\pi(s_i)} \nabla_{\theta^\pi} \pi(s|\theta^\pi)|_{s=s_i}$$
- 12: Update the target networks:

$$\theta^{Q'} \leftarrow \tau \theta^Q + (1 - \tau) \theta^{Q'}$$

$$\theta^{\pi'} \leftarrow \tau \theta^\pi + (1 - \tau) \theta^{\pi'}$$
- 13: **end for**
- 14: **end for**

5 Improvements for DDPG

Despite its good performance on many simulated tasks, there is still some room to improve the algorithm's data efficiency and overcome its instabilities during training.

In practice, the algorithm is limited by the maximum storage size N of the replay-buffer D . Overwriting older samples by current ones when the maximum size is reached, does not differentiate between more or less important experiences because uniform random sampling does weight all experiences equally. One could use a technique similar to *prioritized sweeping* (Moore and Atkeson 1993), which uses *importance sampling* (Glynn and Iglehart 1989) to prefer transitions that are more important over others that have less value for the training process. This could be implemented by using non-uniform priorities, as in (Schaul et al. 2015; Barth-Maron et al. 2018).

Instead of adding noise to the action space to ensure exploration, it is also possible to add adaptive noise directly to the parameters of the neural network (Plappert et al. 2017). This adds some randomness into the parameters of the agent and therefore to the decisions it makes, while still fully depending on its current observation about the environment. This parameter noise makes an agent's exploration more consistent and results in a more effective exploration, increased performance and smoother behavior. It can be seen as a less extreme case of the use of *Evolutionary Strategies* to approximate the gradient of our objective function (Salimans et al. 2017). These would not require back-propagation at all and might still be competitive with state-of-the-art

reinforcement learning algorithms.

The actor and critic updates rely completely on sampling from the experience replay buffer. Therefore, this process could be parallelized using multiple independent actors, all writing to the same buffer. This achieved significant time-savings in the *Distributed Distributional Deep Deterministic Policy Gradient* (D4PG) algorithm (Barth-Maroon et al. 2018).

This algorithm furthermore adopted a distributional version of the critic update from (Bellemare et al. 2017). These distributions model the randomness due to intrinsic factors, including the underlying uncertainty from using function approximation in a continuous space. The distributional updates result in better gradients and therefore improve the performance and stability of the learning progress (Barth-Maroon et al. 2018).

Instead of using the return of the successor state, one could also use the *n-step return* when estimating the temporal difference error (Barth-Maroon et al. 2018). We hypothesize one could go even further and utilize the *TD(λ)-return* by using *eligibility traces* (Tesauro 1995).

The last point of this section addresses the use of neural networks to approximate the actor and the critic. The mentioned papers use relatively simple network architectures that leave a lot of room for improvement, especially when using convolutional neural networks for processing high-dimensional image data in pixel space. A lot of techniques have been implemented in the deep-learning community, e.g. the use of *weight sharing* (Nowlan and Hinton 1992), *pooling layers* (Zeiler and Fergus 2013) or *dropout layers* (Srivastava et al. 2014). One could experiment with much more complex network architectures, e.g. *AlexNet*, *VGGNet* or *GoogLeNet* (Szegedy et al. 2015), with *ResNet* (He et al. 2016), or even with *recurrent neural networks* (Haykin 1994) to process sequences instead of single states.

6 Conclusion

We presented a state-of-the-art reinforcement learning algorithm DDPG that evolved from the successful DQN algorithm by combining it in an actor-critic fashion with the DPG theorem. The algorithm is able to solve many simulated and real physical tasks and has several advantages over other reinforcement learning methods, e.g. the output of a fully deterministic policy and the ability to deal with the exploration-exploitation dilemma completely separated from the learning algorithm by implementing suiting action noises for exploration. Nevertheless, it still suffers from a poor sample efficiency and instabilities during the learning progress. These issues could be addressed by the presented improvements, many of which have already been successfully realized in the D4PG algorithm. Further evaluations are needed to demonstrate the effectiveness of these enhancements.

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