SIGMA CLERMONT
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AI Memo 002 July 20, 2020

Yet Another Collaborative and competitive Agent Implementation

by

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Abstract: This project implements the method Deep Deterministic Policy Gradient DDPG (an end-to-end method) for resolve the problem of generate a control policy of a competitive problem. The results show that this implementation using the hyper-parameters summarized in this report obtain an average score of at least 0.5 points after training during 2063 episodes. Finally, it is done a brief discussion about which improvement and future directions can be taken to improve this repo. The use of the associated code is well explained in the README file.

Keywords: Deep Reinforcement Learning; DDPG; Robot Control

Special thanks to Udacity community for helping with this implementation.

1 Method

Model architecture. This repo presents the implementation of a Deep Deterministic Policy Gradient DDPG algorithm to teach an agent to follow a continuous moving target. Concretely, here is implemented an Actor-Critic method, thus two different networks are used. Both, actor and critic, networks are composed with 2 fully connected layers with 128 units. But, actor network has an output fully connected layer with 4 unit and the critic network has attached an output fully connected layer of 1 unit representing action value function (Q-function). While after each hidden layer is used a rectified linear function in both networks for clipping negative values. Actor network output layer triggers an hyperbolic tangent function to clip output values in the range of $[-1,\ 1]$. To prevent overfitting is used dropout (proba. equal to 0.4) after each hidden layer in both networks and batch normalization.

While the error function used with the critic function approximation is the mean squared, the actor deep networks used the negative mean. Here, ADAMS method is used for optimize the network parameters, with different DN learning rates. To prevent that oscillations during training and ensure its convergence, I decided to use a clipping strategy after each backward propagation.

Double DQN. As it was discussed in [2] works, use a double network strategy, where one is updated each step and the outher is used as a target, is mandatory for achieving stability during RL when is used a function approximation. Double DQN [3] keeps update this two equal deep q-networks DQN (for critic as well as

Table 1: Hyper-parameter configuration

Hyper-parameter	**Value**	**Comments**
buffer size	100000	Replay buffer size.
batch size	512	Minibatch size.
γ	0.99	Discount rate.
τ	0.001	Proportional increment used for soft updating target parameter.
actor learning rate	0.0005	Learning rate used in actor ADAM optimization.
critic learning rate	0.0005	Learning rate used in critic ADAM optimization.
C	1	Every 1 step is updated local parameters.
Clipping	1	Gradient clipping.

actor network), a local and a target one, with different weights and at different rates. But, here instead to update target DQN each C steps, I decided to use a soft update strategy after each step, merging τ-times the new parameter values. Note that τ is bounded between 0 and 1. The parameter parameters are softly update according with,

$$\theta_{target} = \alpha * \theta_{local} + (1 - \alpha) * \theta_{target}$$

Experience Replay. Mnih et al. in [2] postulate the needed of using experience replay for improving learning stability. Here, it is used an uniform sampling strategy for selecting experience sample from replay buffer.

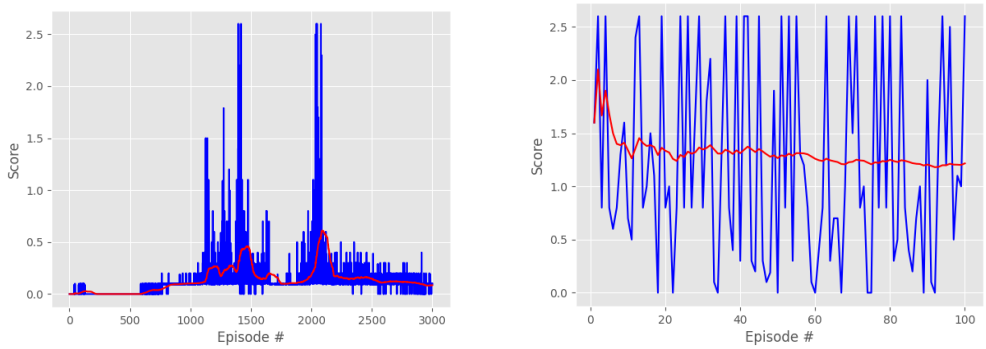
Exploration strategy. As a difference with respect to discrete action space problem, use ε-greedy policies in continuous action space problems is not possible. Instead, to solve here the problem of exploration, it is used Ornstein-Unlenbeck process to generate noise over the predicted action values.

2 Experiments

Training Details Here, it is used a competitive environment set up with 2 agent facing each other. Each instance has its own random seed to enhance the domain problem exploration (noise generation) during the training process. Instead of using an strategy of early stop when score reach a desired level (0.5 points over last 100 episodes – of the best agent –), I decided to fix a constant number of episodes (5000 episodes). This strategy let us observe if the learning achieve better performance after reaching the desired level which really often happened. Moreover, to increase the number of good samples each episode has a fixed top number of steps (in my implementation 2000). The rest of hyper-parameters are summarize in table 1.

Evaluation Details. The agent is executed during 100 episodes without noise in action prediction. The cumulative discounted reward is averaged over the last 100 episodes, reaching an average of 1.22, a maximum score of 2.6. In addition, say that instead of fixing the number of step per episode, during evaluation an episode finish when any of the instances is done. But the episode finishes after 2000 steps if there is not a winner.

Figure 1: Training and evaluation results. This figure presents training plot (left) and evaluation results (right). While the blue curve is current score, red line is the average score during last 100 episodes. Training reach 0.6 points (averaged during last 100 epi.) in the 2092 episode.



3 Discussions and Conclusions

Results show that this method reach an average of cumulative reward of at least 0.5 (up to 0.6) points. Also an interesting behaviour observed during the training is that the convergence of this method is as faster as satisfactory examples is experimented during the exploration. This leads to think that a clever solution is to fix the big number of steps for episode, because this increase the chances of reach desired actions. Figure 1 shows that the training values keep constant (over 0.1) during all time but temporary reach peaks of performance (in this report 2 times reach values close to 0.5).

Some interesting improves that can be contemplated for this task are the implementation of prioritised experience replay as well as the dueling DQN for the critic network. Also, the implementation of Rainbow [1] which extend Actor critic strategies is another interesting improvement. Add LSTM layer to the network architecture is also considered for future improvements. Because, I have shown here that this problem is resolve using sequential input data, LSTM exploit time sequential input data.

References

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