Report

Learning Algorithm (using DDPG)

Initialize Actor Network with weight θ and Critic Network ω

Initialize target Actor Network and Critic Network with weights $\theta\_$ and $\omega\_$

Initial replay buffer R

For each episode do

Initialize a random process for action exploration

Initial observation state

While

Choose action a_t from s_t using policy derived from current θ also plus exploration noisy

Execute action a_t and observe new state s_{t+1}

Store transition (s_t, a_t, r_t, s_{t+1}) in R

Sample a random minibatch transitions (s_i, a_i, r_i, s_{i+1}) from R

Evaluate target value using $\omega\_$ where choose action a_{i+1} from s_{i+1} using $\theta\_$

Update critic by minimizing MSE loss function

Update actor policy using sampled policy gradient

Soft update the $\theta\_$ and $\omega\_$

Until done

End For

Hyperparameters

epsilon = 1.0

decay = 0.9999

actor_alpha = 1e-4

critic_alpha = 1e-4

tau = 1e-3

gamma = 0.99

batch_size = 64

max_memory_size = 50000

update_every=4

Model Architecture

Actor network:

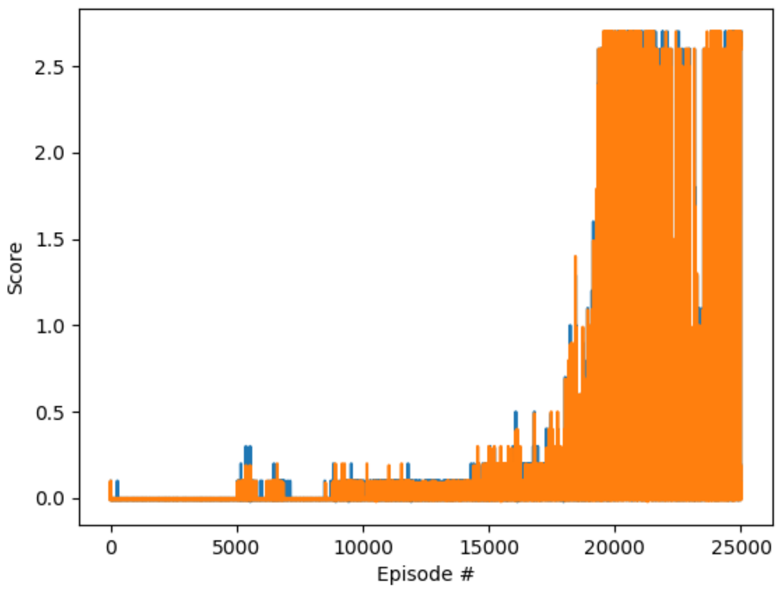
Input: state_size→fc1:64 →ReLU→fc2:128→ReLU→fc3: action_size→tanh

Critic network:

Input: state_size→fc1:64 →ReLU→fc2:128→ReLU→256→fc4: 128→ ReLU→fc5: 1

Input: action_size→fc3:128→ReLU

Plot of Rewards



```
No.100 score this episode: -0.0020,
......
No.7000 score this episode: 0.0359,
No.7100 score this episode: 0.0245,
No.7200 score this episode: 0.0165,
No.7300 score this episode: 0.0130,
No.7400 score this episode: 0.0325,
No.7500 score this episode: 0.0240,
No.7600 score this episode: 0.0240,
No.7700 score this episode: 0.0280,
No.7800 score this episode: 0.0210,
No.7900 score this episode: 0.0270,
No.8000 score this episode: 0.0325,
No.8100 score this episode: 0.0410,
No.8200 score this episode: 0.0440,
No.8300 score this episode: 0.0385,
No.8400 score this episode: 0.0360,
No.8500 score this episode: 0.0345,
No.8600 score this episode: 0.0405,
No.8700 score this episode: 0.0460,
No.8800 score this episode: 0.0355,
No.8900 score this episode: 0.0420,
No.9000 score this episode: 0.0475,
No.9100 score this episode: 0.0435,
No.9200 score this episode: 0.0380,
No.9300 score this episode: 0.0485,
No.9400 score this episode: 0.0530,
No.9500 score this episode: 0.0565,
No.9600 score this episode: 0.0610,
No.9700 score this episode: 0.0505,
No.9800 score this episode: 0.0465,
No.9900 score this episode: 0.0560,
No.10000 score this episode: 0.0490,
No.10100 score this episode: 0.0575,
No.10200 score this episode: 0.0550,
No.10300 score this episode: 0.0480,
No.10400 score this episode: 0.0565,
No.10500 score this episode: 0.0620,
No.10600 score this episode: 0.0590,
No.10700 score this episode: 0.0645,
No.10800 score this episode: 0.0870,
No.10900 score this episode: 0.0965,
No.11000 score this episode: 0.0980,
No.11100 score this episode: 0.1010,
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```
No.11200 score this episode: 0.1290,
No.11300 score this episode: 0.1270,
No.11400 score this episode: 0.0975,
No.11500 score this episode: 0.1490,
No.11600 score this episode: 0.1250,
No.11700 score this episode: 0.0985,
No.11800 score this episode: 0.1450,
No.11900 score this episode: 0.2020,
No.12000 score this episode: 0.1435,
No.12100 score this episode: 0.1630,
No.12200 score this episode: 0.1795,
No.12300 score this episode: 0.2590,
No.12400 score this episode: 0.2485,
No.12500 score this episode: 0.2015,
No.12600 score this episode: 0.2541,
No.12700 score this episode: 0.3976,
No.12800 score this episode: 1.1521,
```

References

Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., ... & Wierstra, D. (2015). Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*.