Deep Reinforcement Learning: Theory and Application

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Introduction	Results	Conclusions
How can we create something that learns how	400 - 300 - 200 - 200 -	Initial tests showed that less neurons would lead to better

to act in its environment?

Here, we apply the Proximal Policy Optimization (PPO 2017) Reinforcement Learning algorithm to solve a simple environment, and demonstrate multiagent convergence in a zero sum task.



Testing Average	15.75	31.8
Reward		

Tests with OpenAl PPO1 template algorithm were unsuccessful, but better performance was achieved with less neurons.

Tests with PyTorch barebones PPO implementation proved convergence.



performance – probably due to increased capability for generalization.

PyTorch PPO implementation proved to show convergence after around 1000 games played.

Constant negative reward

was necessary to teach snake to take efficient pathing.

Methods

- Map Environmental State
 to data representation,
 including reward signal
 for changes between
 states.
- 2) Neural Network with 256 Neurons maps states to actions and determines state value.
- 3) PPO is used to train the network in batches of 20 step action/state chains.
- 4) For multiagent learning, an evolutionary algorithm

Algorithm was able to learn and consistently solve single agent game, after only 10k training games; around 10 minutes on i7 laptop.



Multiagent learning in zero sum, competitive environment proved to achieve convergence and avoidance strategies.



Multiagent training was successful and particularly effective in the start of the process, as the snake must learn to avoid body more

is used to select the superior model and force it to train against itself.

quickly.

Literature Cited

Schulman, J. 2017. Proximal Policy Optimization Algorithms. arXiv:1707.06347.

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Further Information

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