Deep Multiagent Reinforcement Learning for Partially Observable Parameterized Environments

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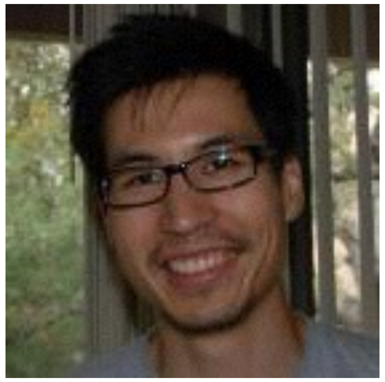
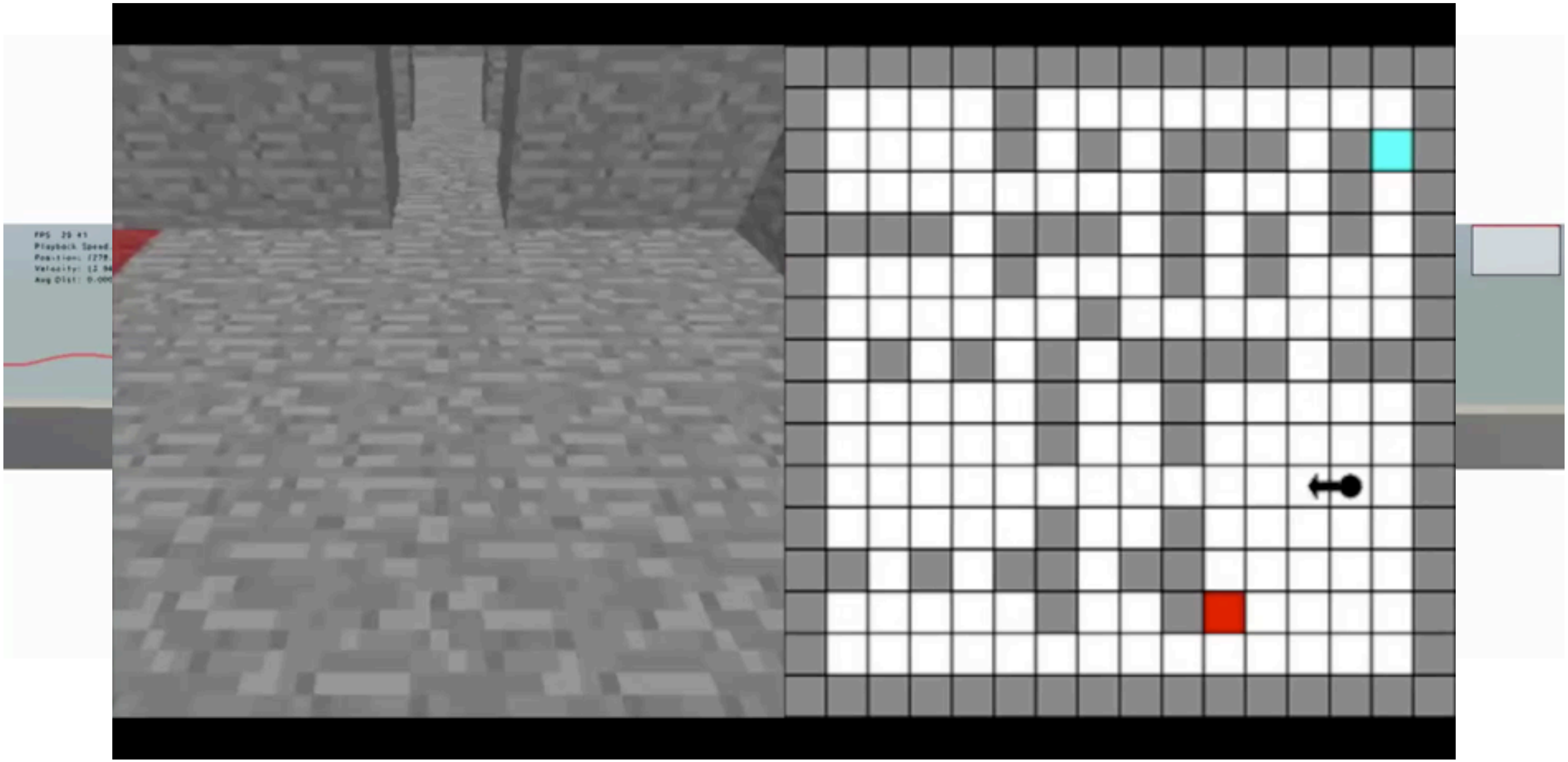
Joint work with Matthew Hausknecht



Motivation



Outline

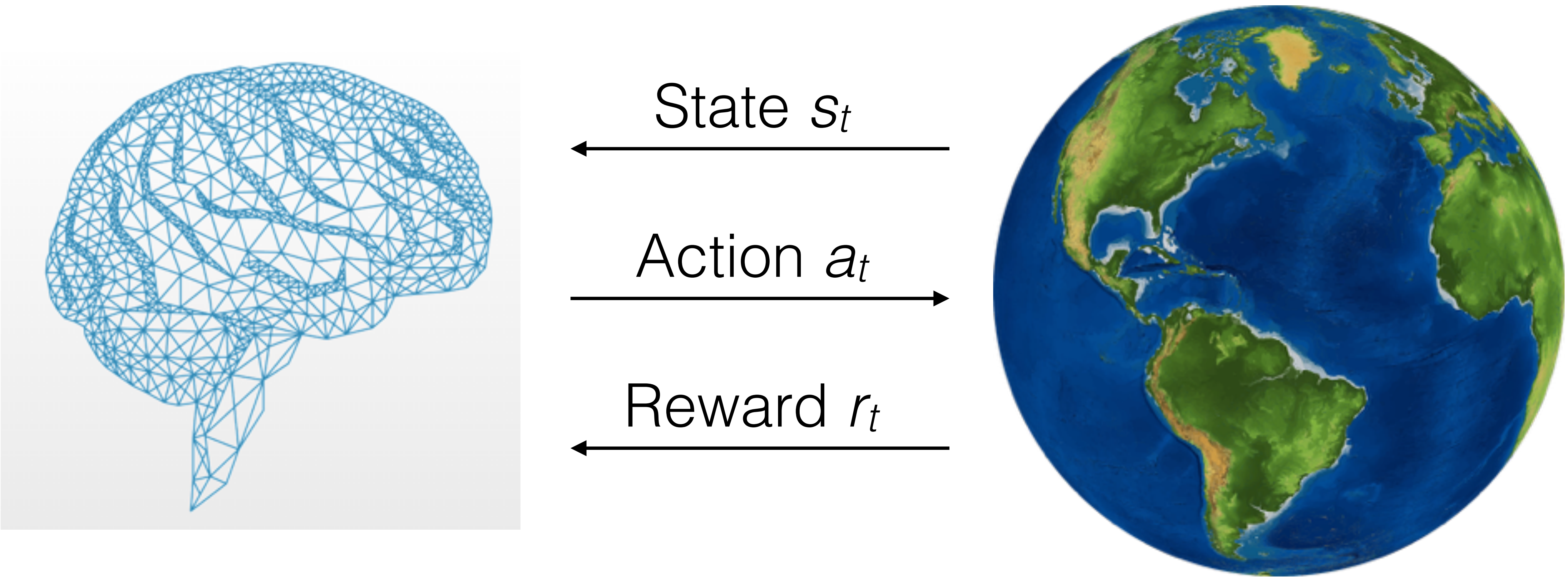
1. Background

2. Recurrent Q-Learning for partially observable MDPs

3. Deep Multiagent RL in Half-Field-Offense

4. Future Work

Markov Decision Process



Markov Property ensures s_{t+1} depends only on s_t

Learning an optimal policy π^* requires no memory

Partially Observable MDP (POMDP)

Observation o_t

Action a_t

Reward r_t

Observations provide noisy or incomplete information

Memory may help to learn a better policy

Reinforcement Learning

Reinforcement Learning provides a general framework for sequential decision making.

Objective: Learn a policy that maximizes discounted sum of future rewards.

Deterministic policy π is a mapping from states/observations to actions.

For each encountered state/observation, what is the best action to perform.

Q-Value Function

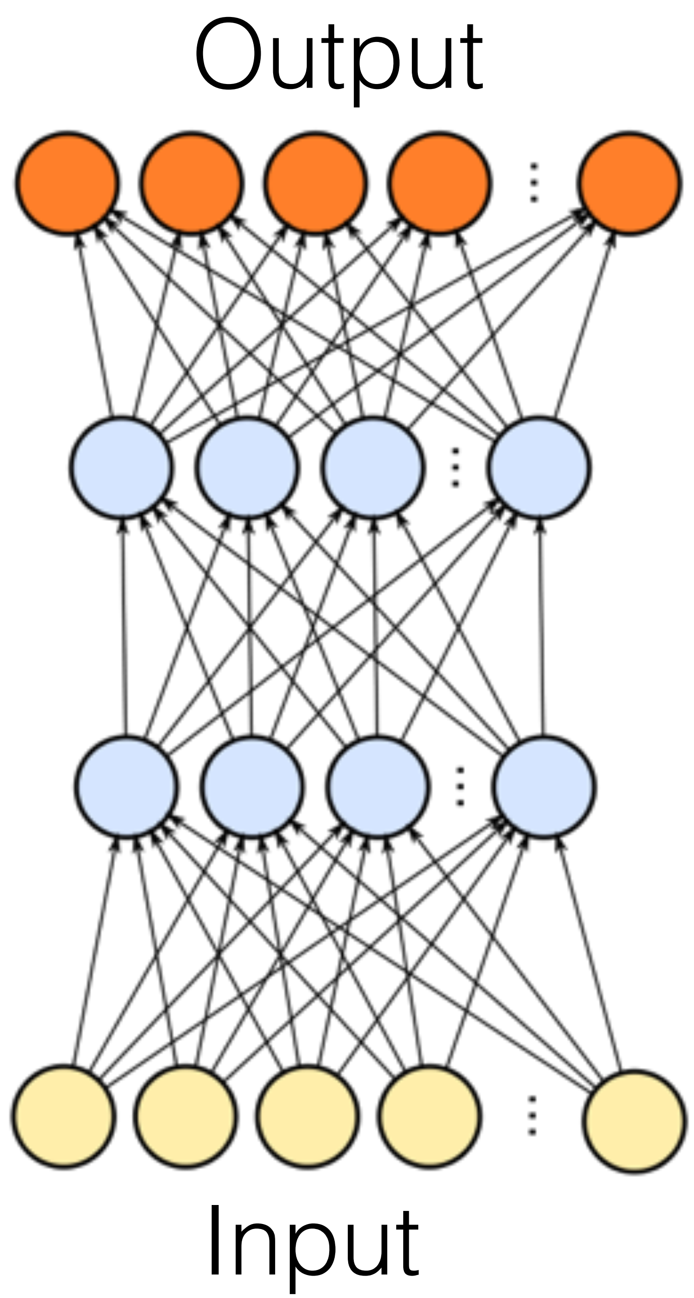
Estimates the expected return from a given state-action:

$$Q^\pi(s,a) = \mathbb{E}\left[r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots | s, a\right]$$

Answers the question: "How good is action *a* from state *s*."

Optimal Q-Value function yields an optimal policy.

Deep Neural Network



Parametric model with stacked layers of representation.

Powerful, general purpose function approximator.

Parameters θ optimized via backpropagation.

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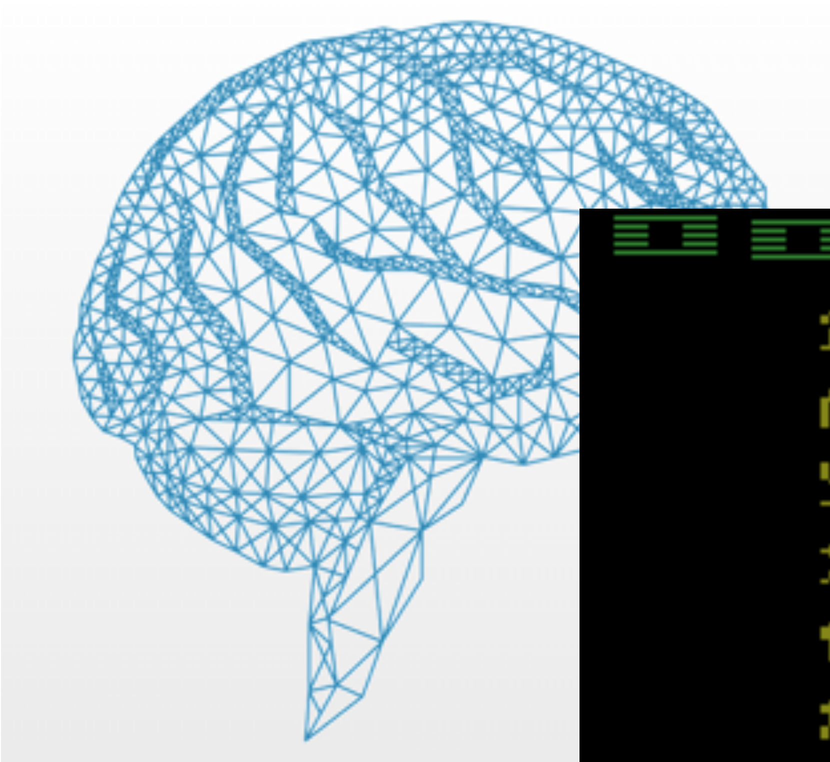
Atari Environment



Observation o_t

Reward is change in game score

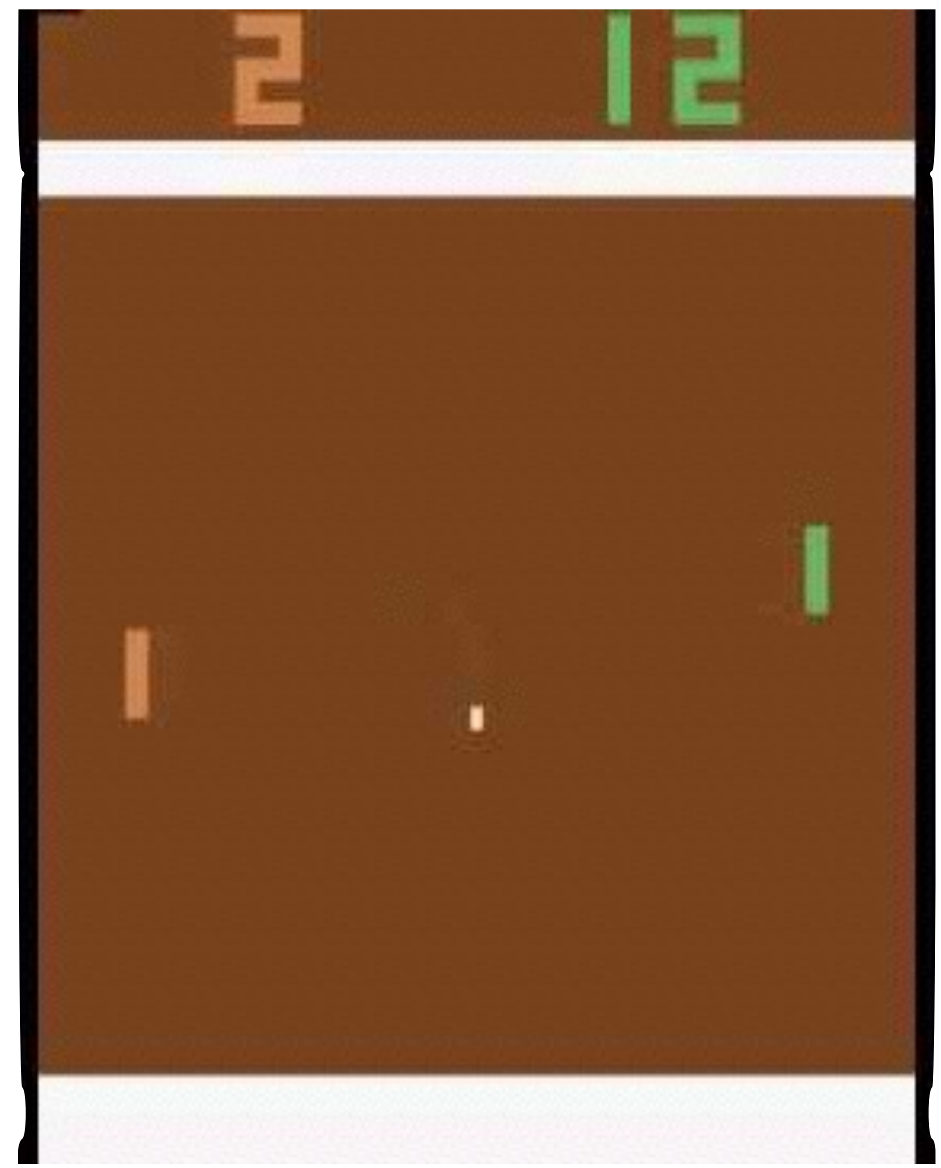
Resolution

18 discrete actions

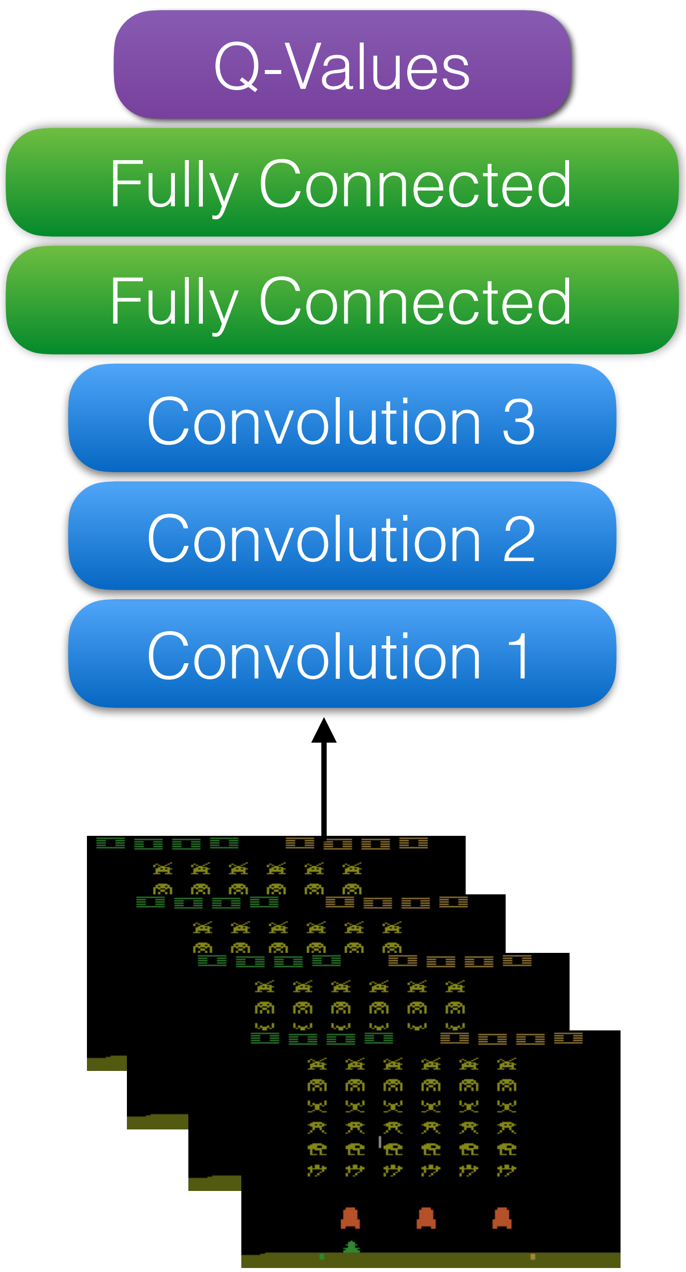
Atari: MDP or POMDP?

Depends on the number game screens used in the state representation.

Many games PO with a single frame.



Deep Q-Network (DQN)



Neural network estimates Q-Values Q(s,a) for all 18 actions:

$$Q(s|\theta) = (Q_{s,a_1} \dots Q_{s,a_n})$$

Learns via temporal difference:

$$L_i(\theta_i) = \mathbb{E}_{(s_t,a_t,r_t,s_{t+1})\sim\mathcal{D}}\left[\left(y_i - Q(s_t|\theta_i)\right)^2\right]$$

$$y_i = r_t + \gamma max(Q(s_{t+1}|\theta))$$

Accepts the last 4 screens as input.

Flickering Atari

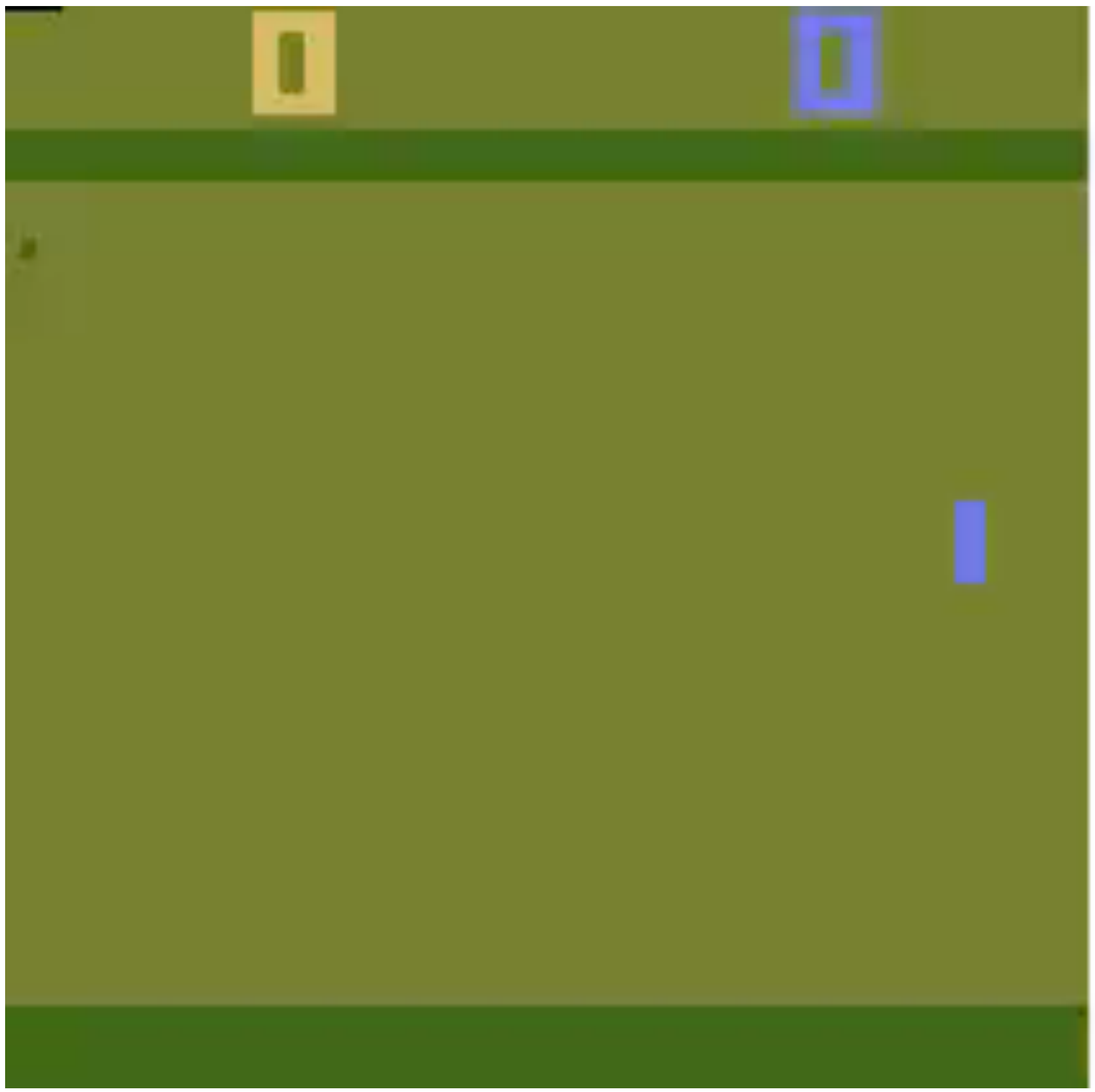
How well does DQN perform on POMDPs?

Induce partial observability by stochastically obscuring the game screen

$$o_t = \begin{cases} s_t & \text{with } p = \frac{1}{2} \\ < 0, \ldots, 0 > & \text{otherwise} \end{cases}$$

Game state must be inferred from past observations

DQN Pong



True Game Screen

Observed Game Screen

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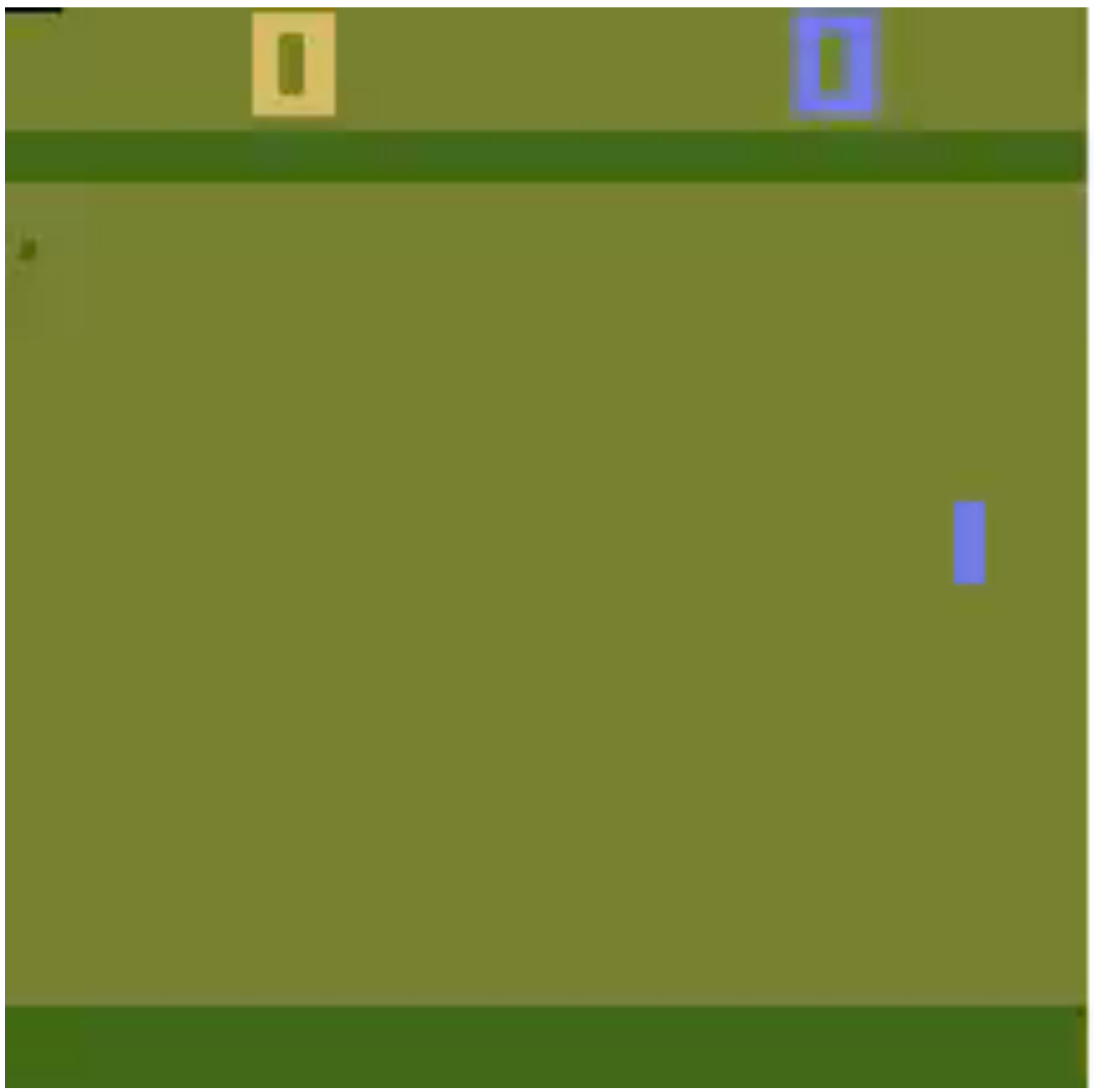
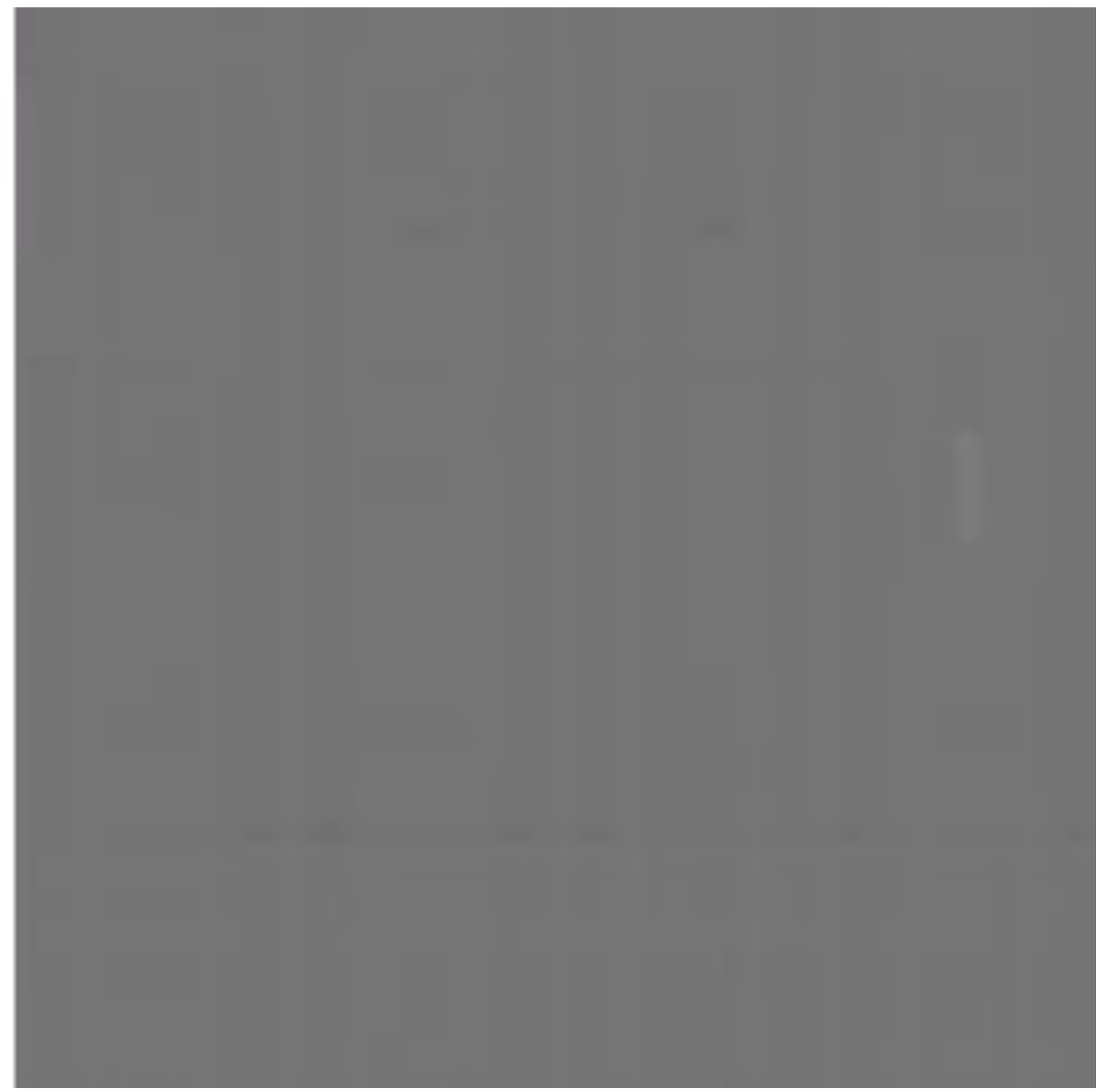
DQN Flickering Pong

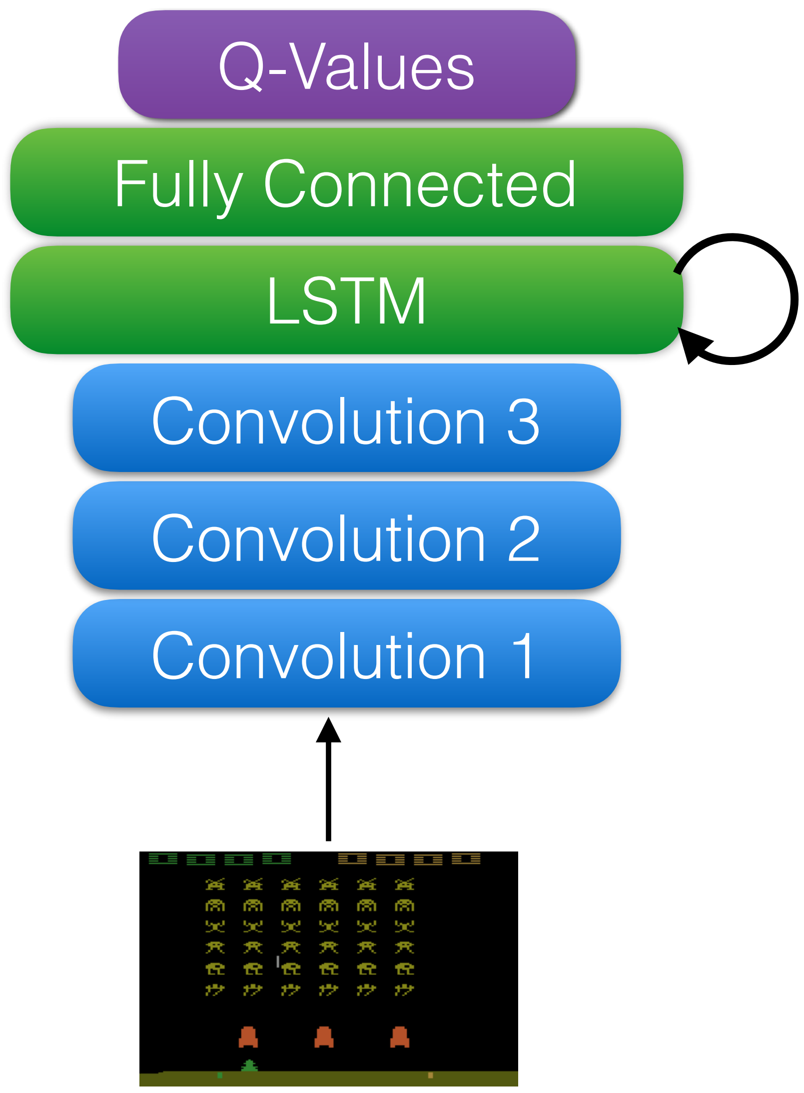


True Game Screen



Observed Game Screen

Deep Recurrent Q-Network



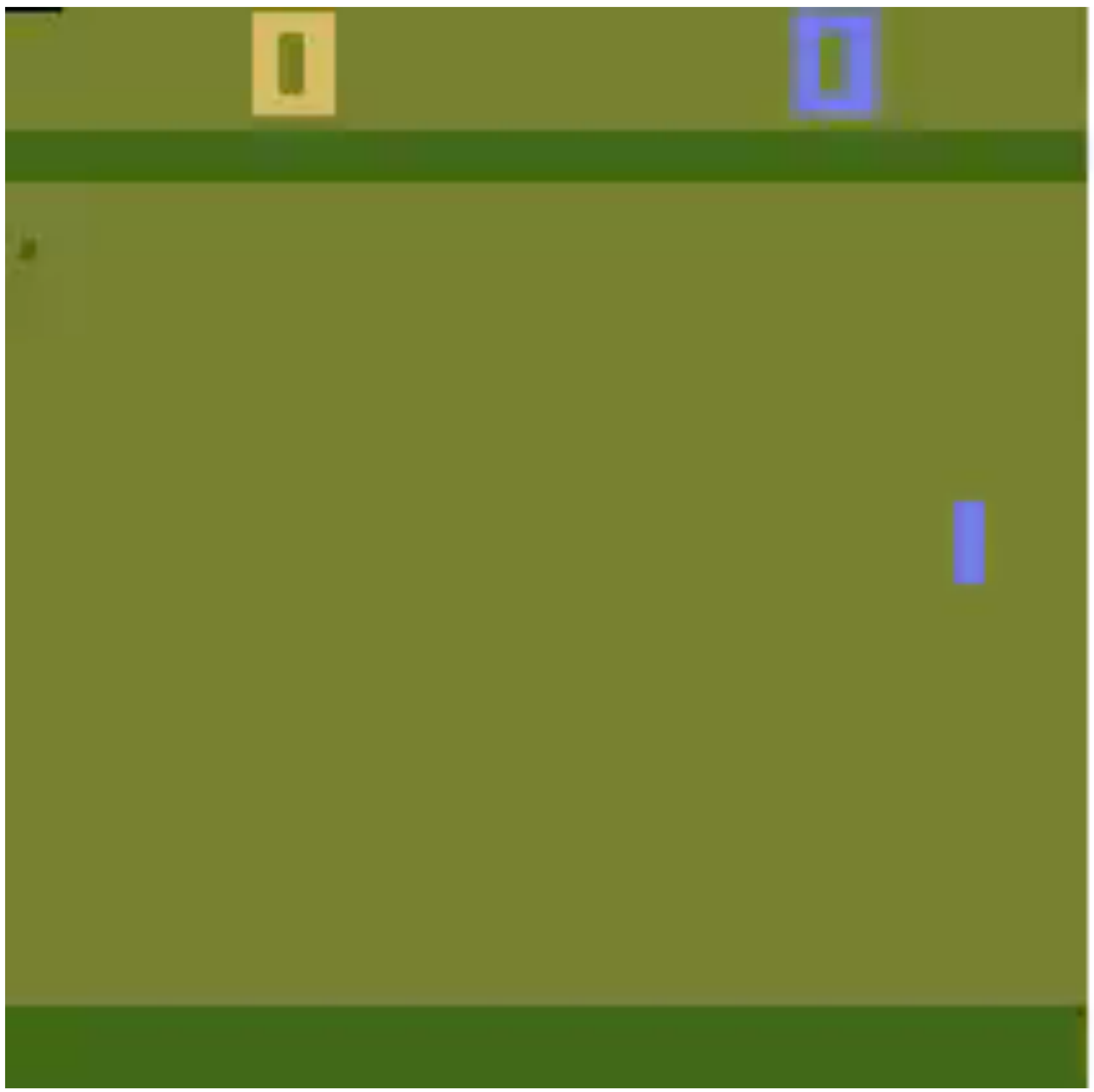
Uses a Long Short Term Memory (LSTM) to selectively remember past game screens.

Architecture identical to DQN except:

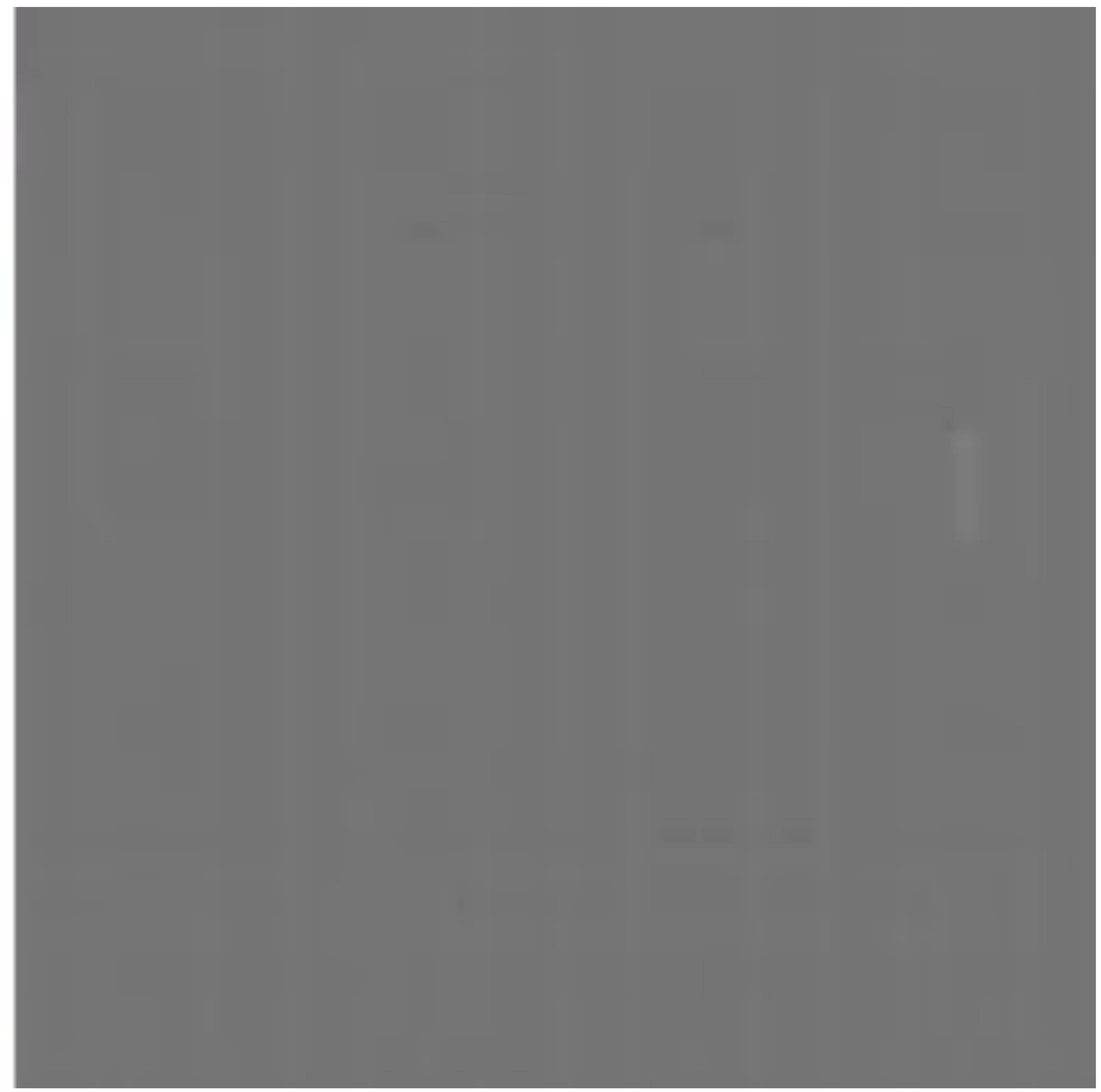
1. Replaces FC layer with LSTM
2. Single frame as input each timestep

Trained end-to-end using BPTT for last 10 timesteps.

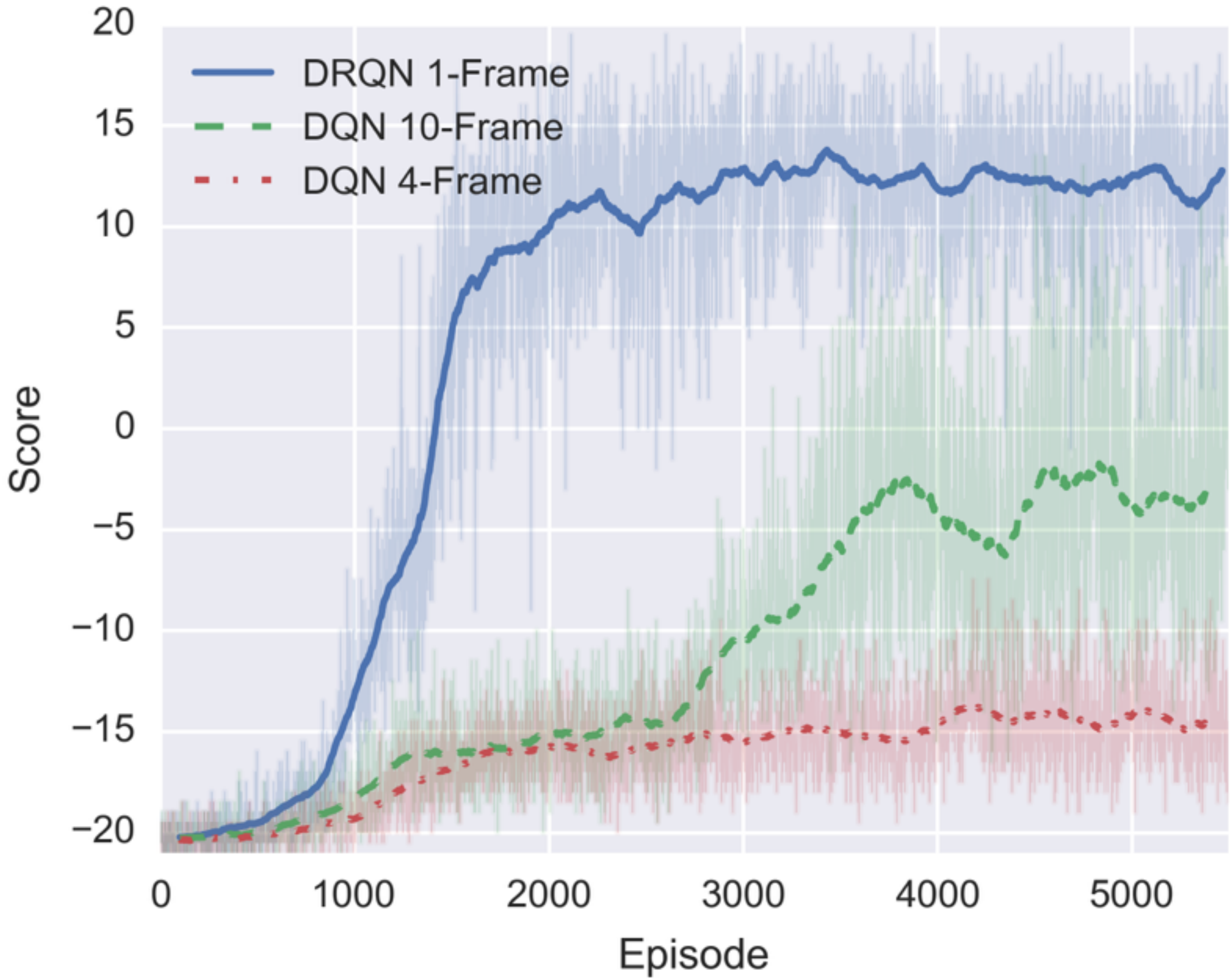
DRQN Flickering Pong



True Game Screen



Observed Game Screen



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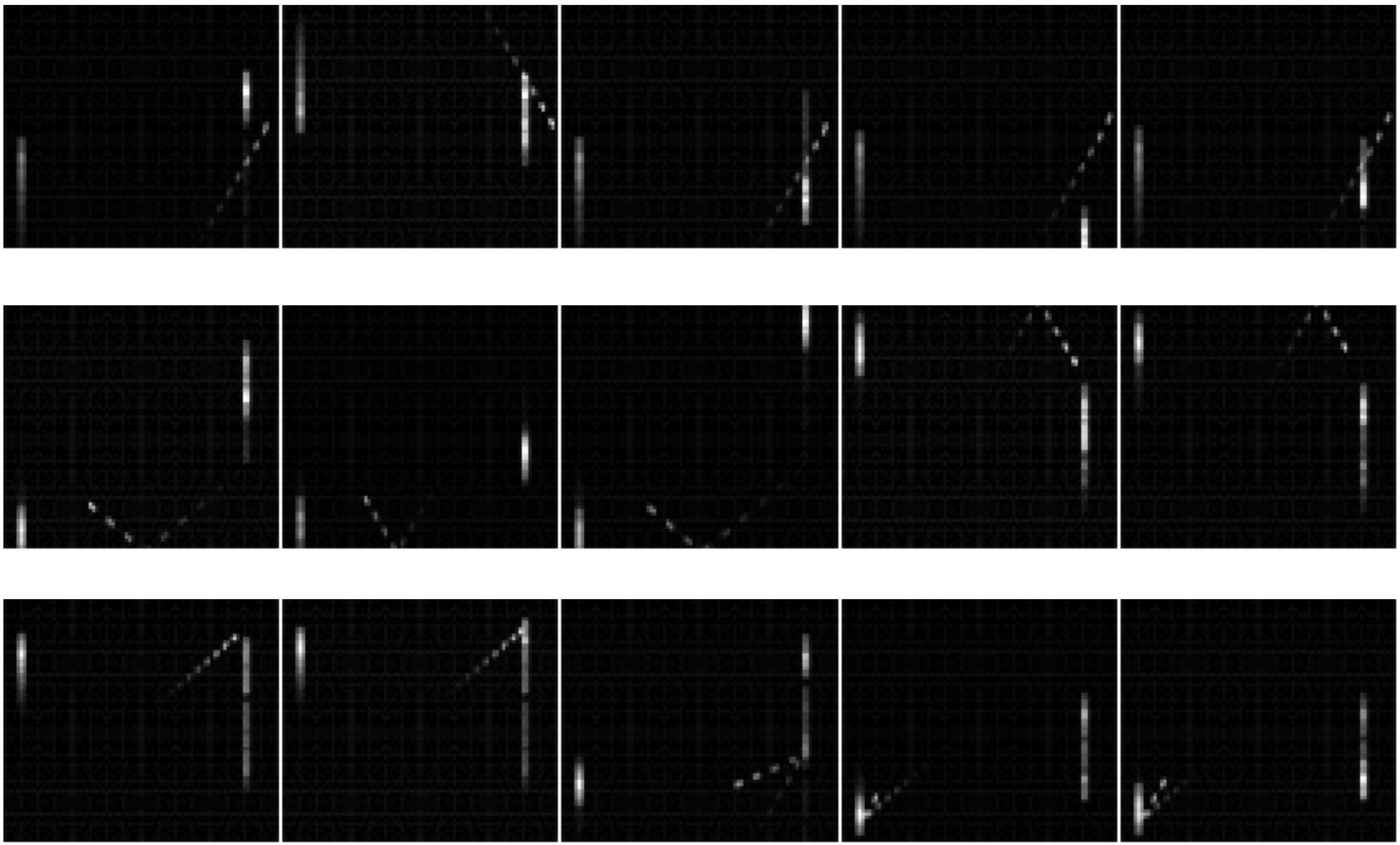
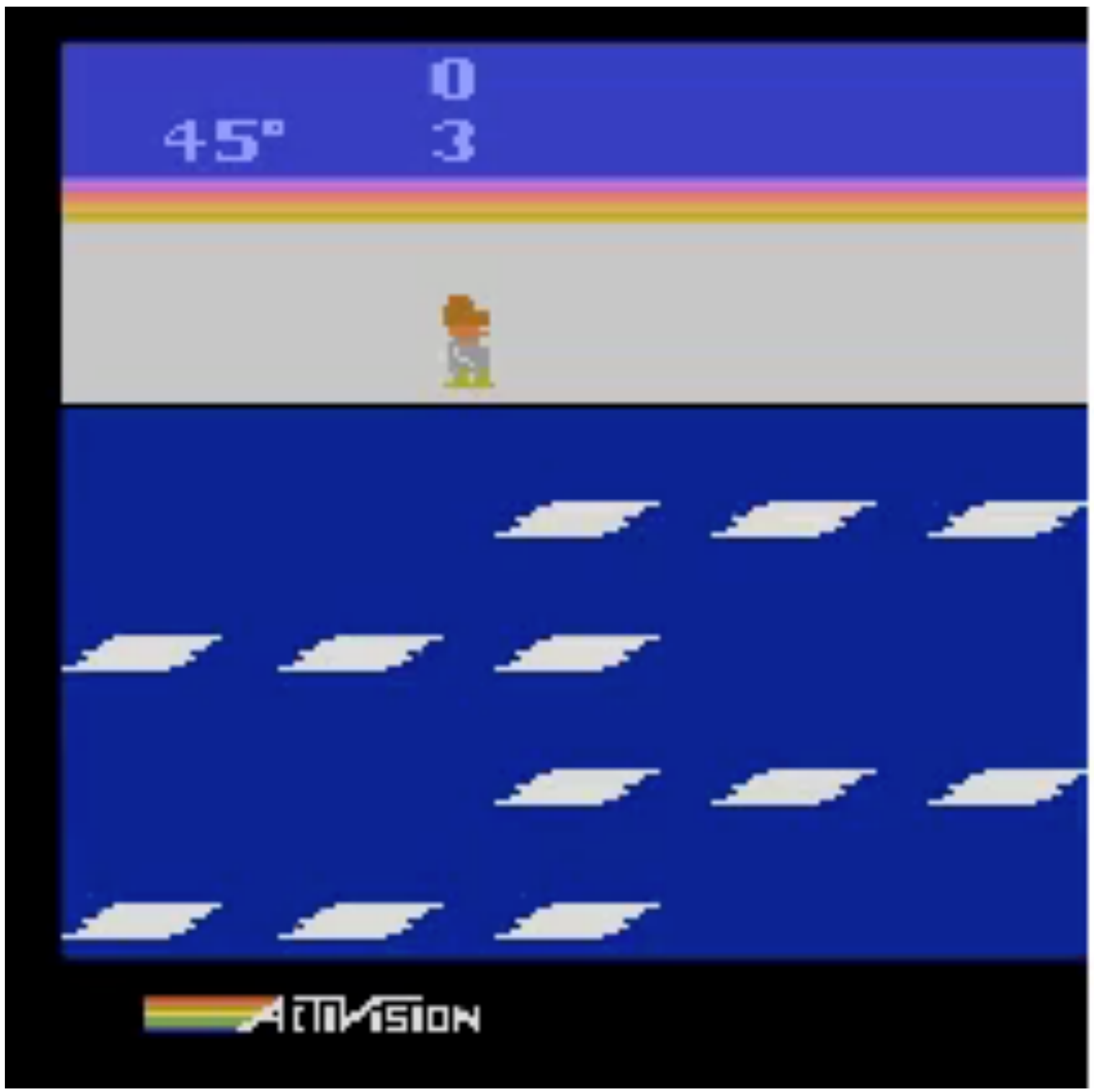
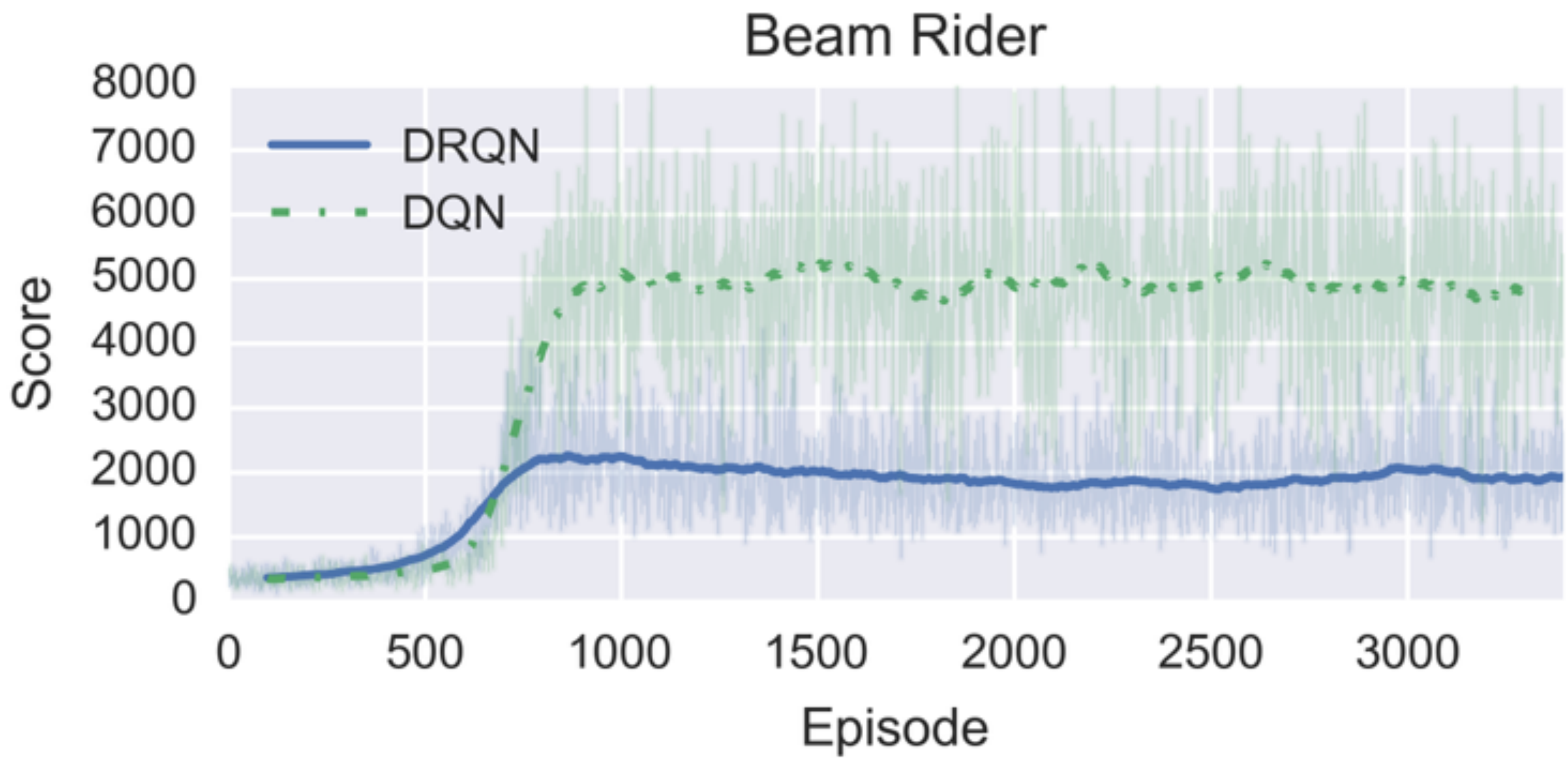
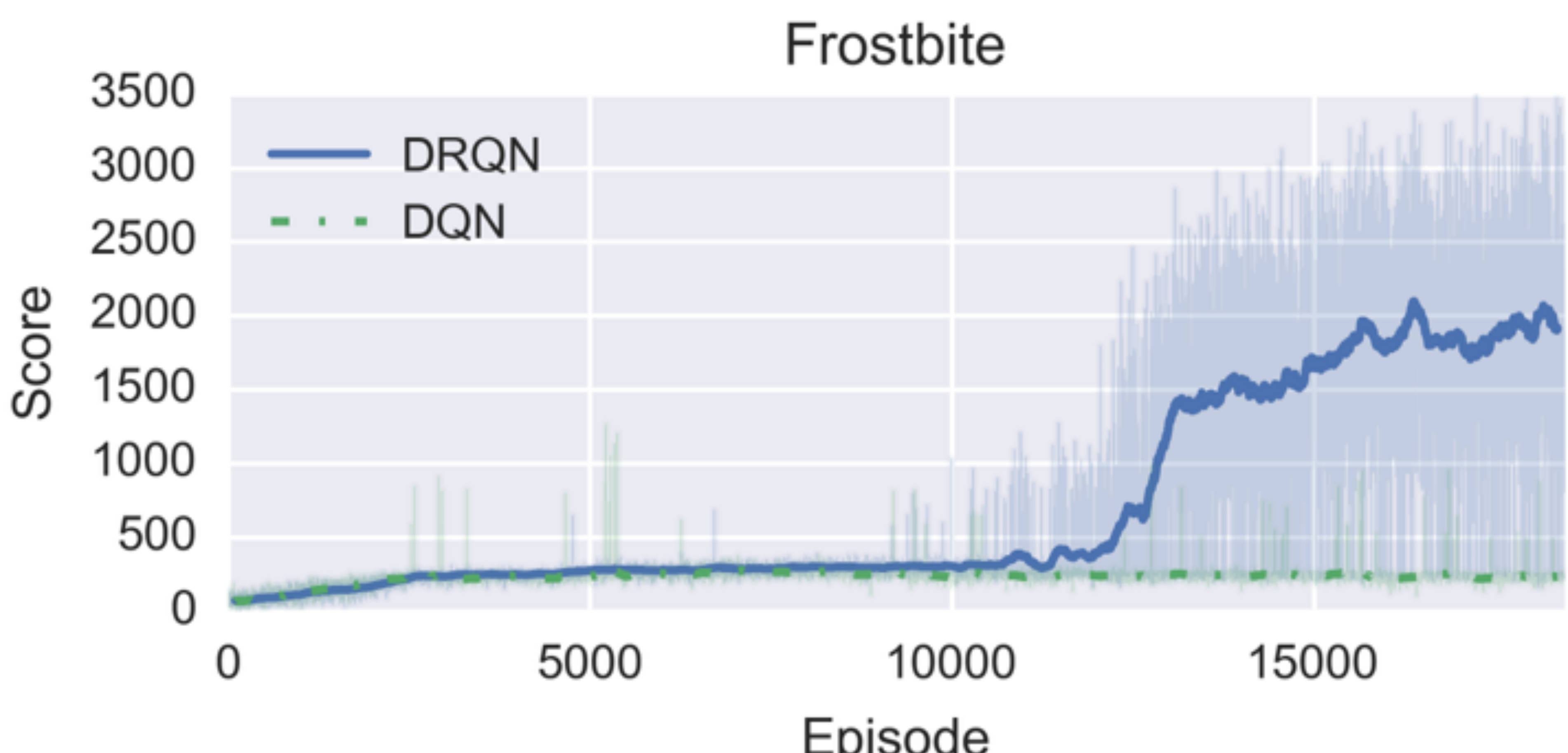
LSTM infers velocity



DRQN Frostbite




Beam Rider
DRQN
DQN
Score
8000
7000
6000
5000
4000
3000
2000
1000
0
0
500
1000
1500
2000
2500
3000
Episode


Frostbite
DRQN
DQN
Score
3500
3000
2500
2000
1500
1000
500
0
0
5000
10000
15000
Episode

Extensions

DRQN has been extended in several ways:

- Addressable Memory: *Control of Memory, Active Perception, and Action in Minecraft;* Oh et al. in ICML '16

- Continuous Action Space: *Memory Based Control with Recurrent Neural Networks;* Heess et al., 2016

[*Deep Recurrent Q-Learning for Partially Observable MDPs,* Hausknecht et al, 2015; ArXiv]

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Half Field Offense

Cooperative multiagent soccer domain built on the libraries used by the RoboCup competition

Objective: Learn a goal scoring policy for the offense agents

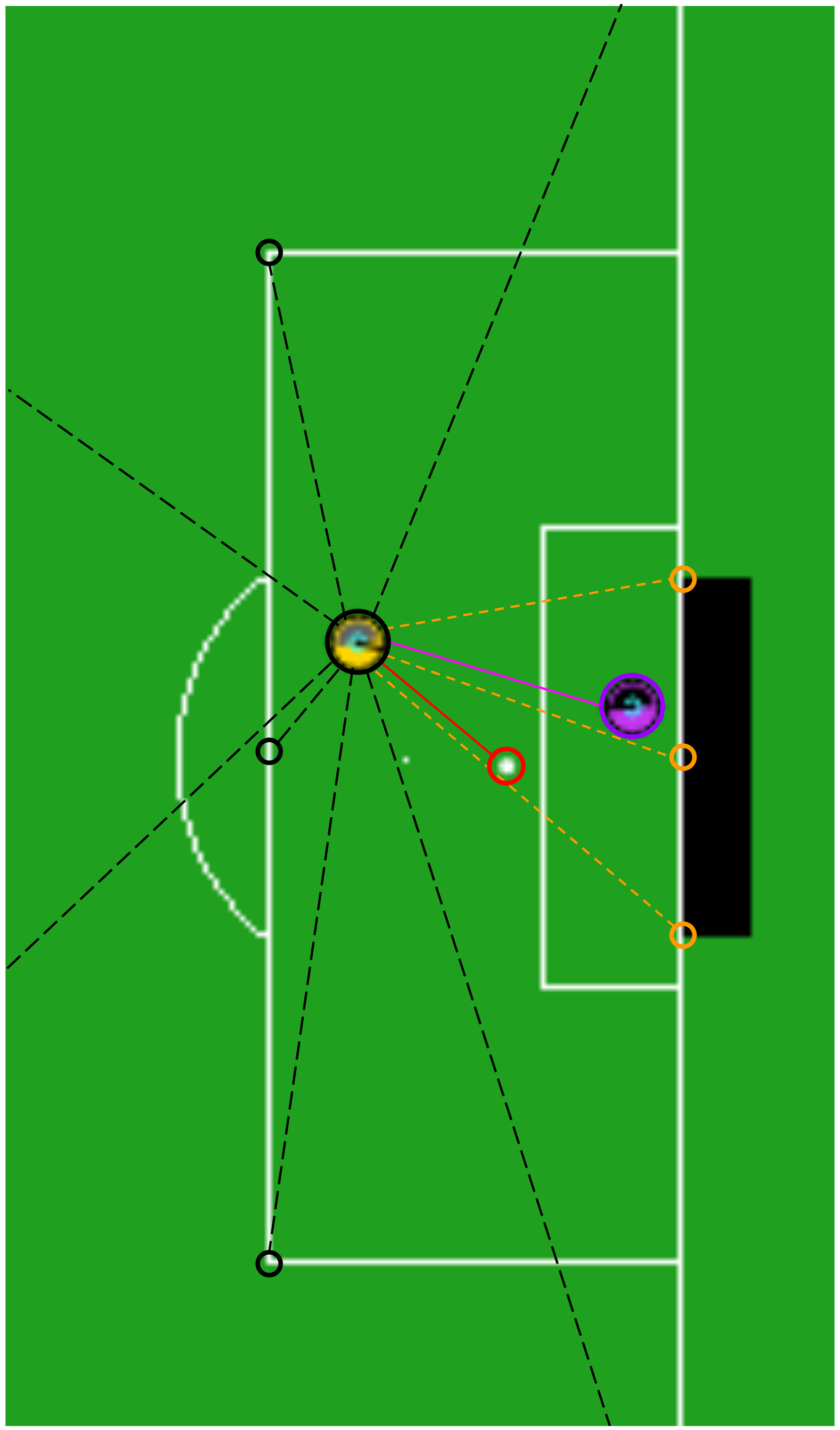
Features continuous actions, partial observability, and opportunities for multiagent coordination

State Action Spaces

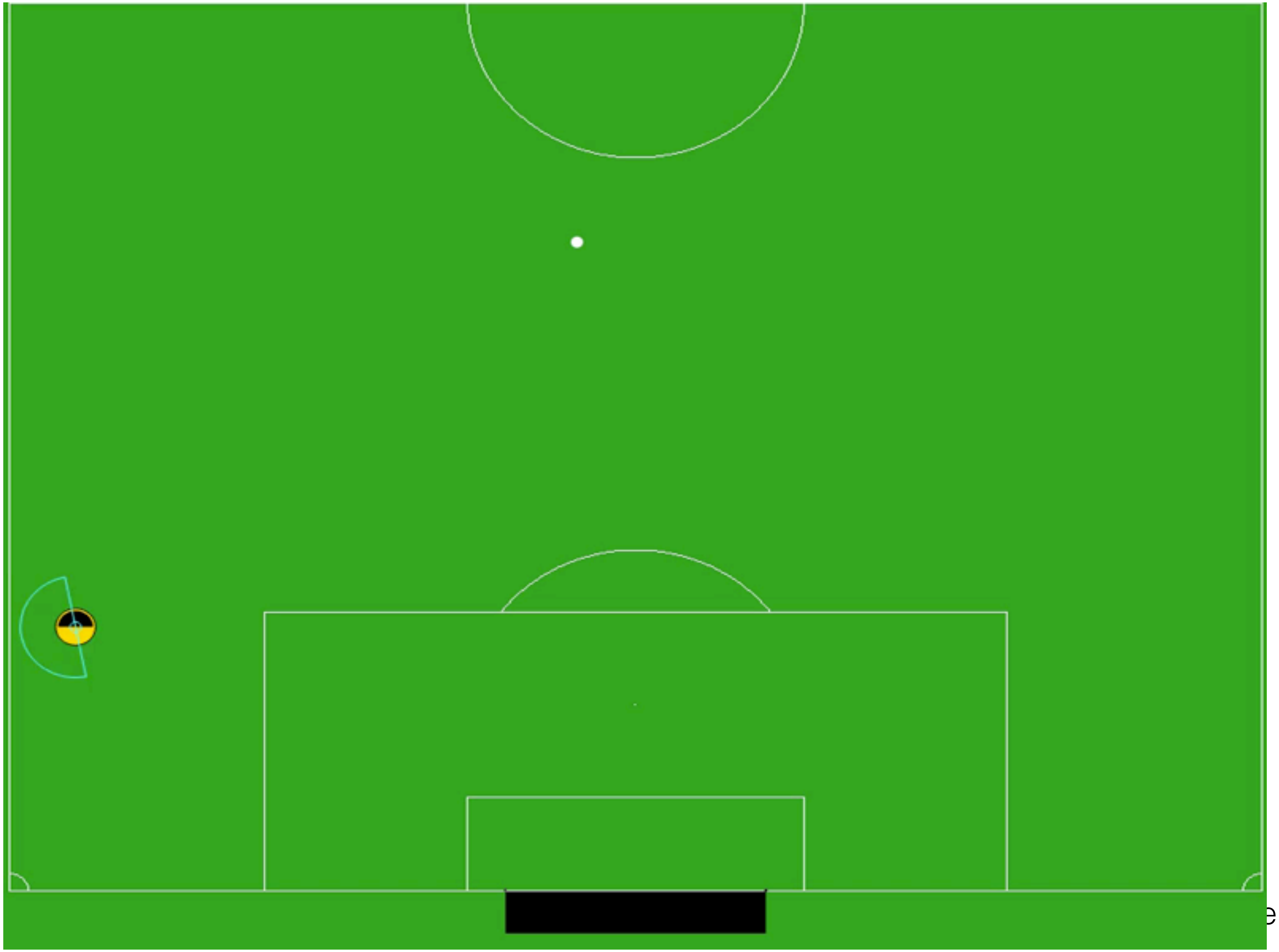
58 continuous state features encoding distances and angles to points of interest

Parameterized-Continuous Action Space:
Dash(direction, power)
Turn(direction)
Tackle(direction)
Kick(direction, power)

Choose one discrete action + parameters every timestep



Exploration is Hard



Reward Signal

$$r_t = \underbrace{-\Delta d(\text{Agent, Ball}) + I^{kick}}_{\text{Go to Ball}} + \underbrace{-3\Delta d(\text{Ball, Goal}) + 5I^{Goal}}_{\text{Kick to Goal}}$$

With only goal-scoring reward, agent never learns to approach the ball or dribble.

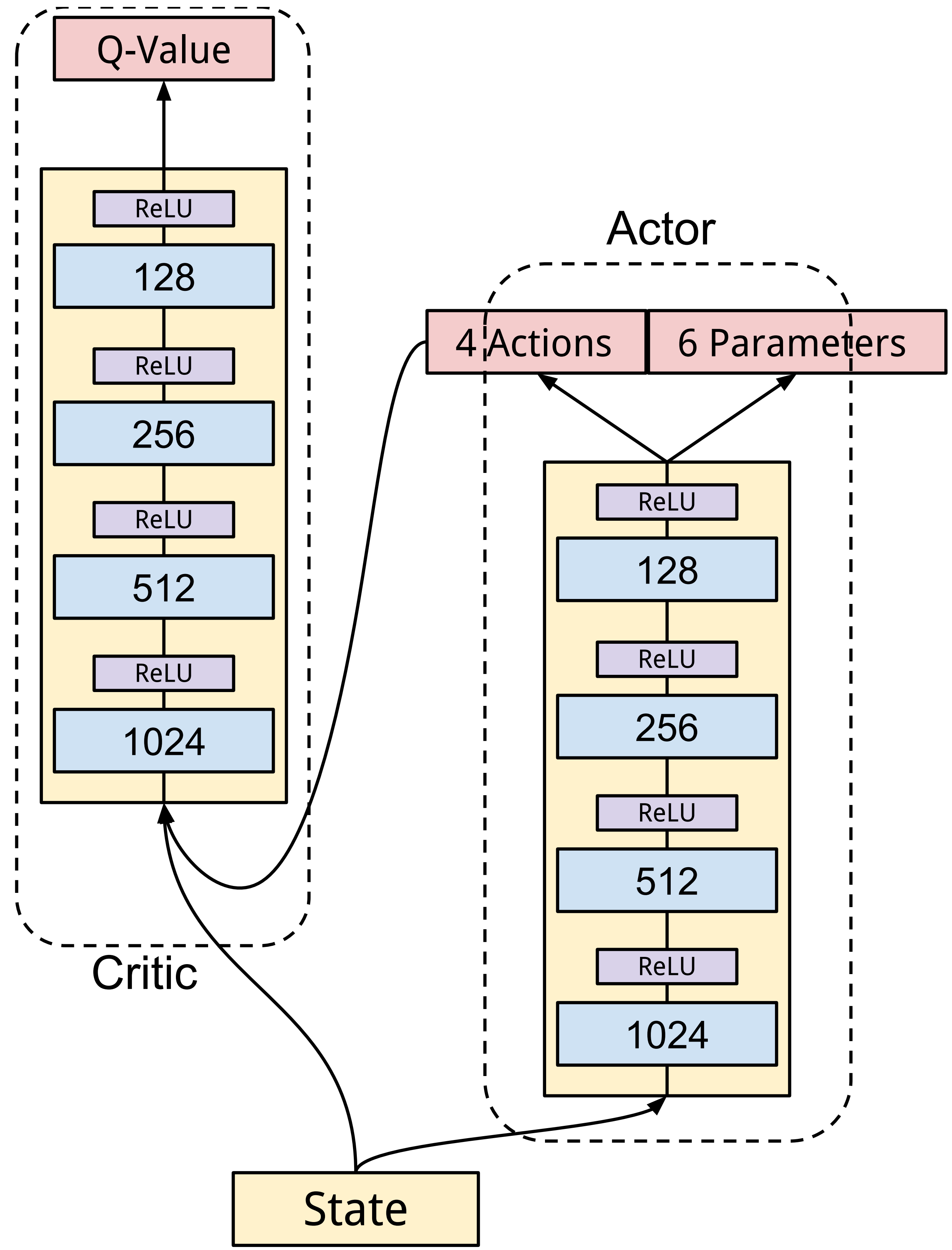
Deep Deterministic Policy Gradients

Model-free Deep Actor Critic architecture *[Lillicrap '15]*

Actor learns a policy π, Critic learns to estimate Q-values

Actor outputs all 6 possible parameters.

a_t = max(4 actions) + associated parameter(s)



Training

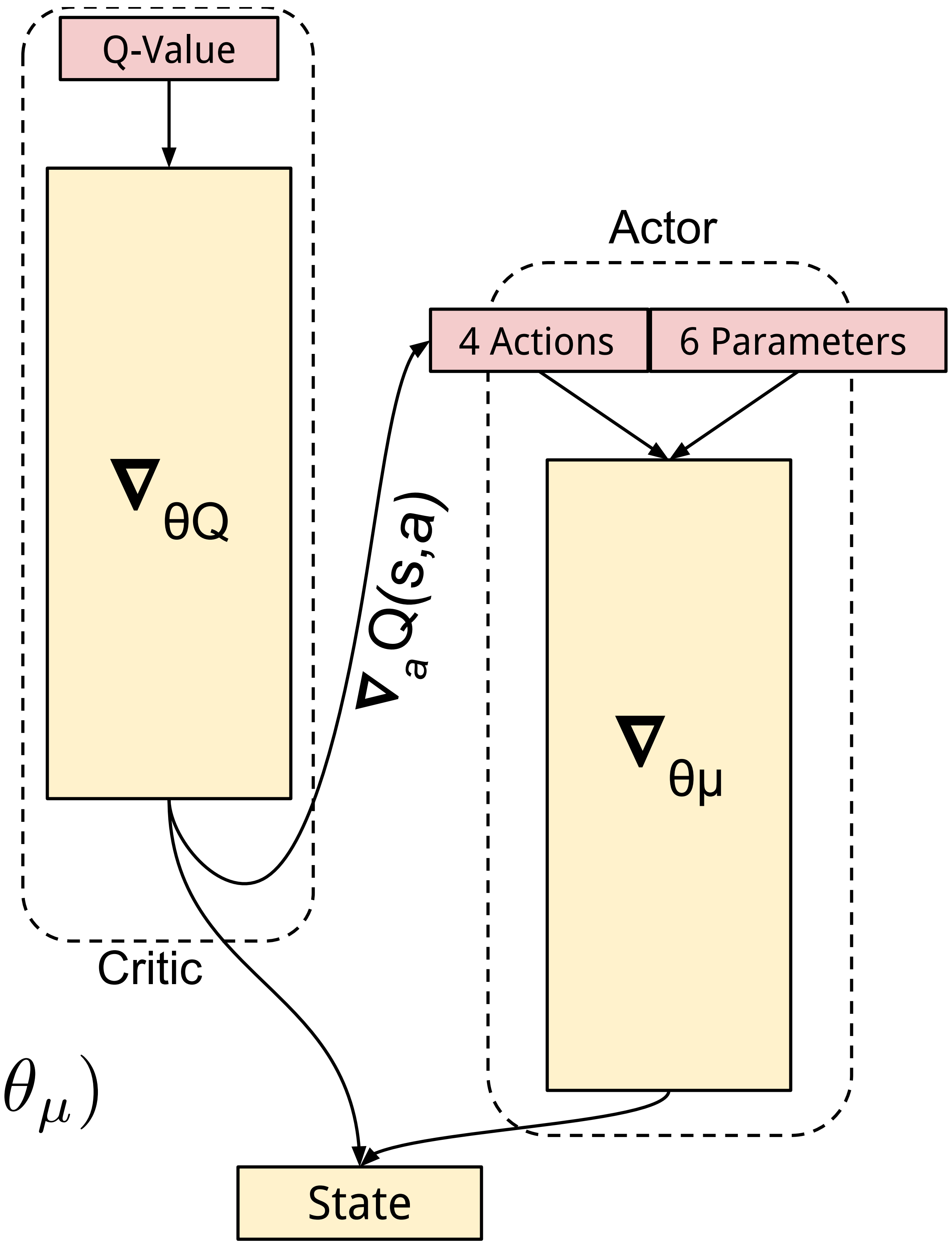
Critic trained using temporal difference:

$$L = ||Q(s_t, \mu(s_t)|\theta_Q) - y||_2^2$$

$$y = r_t + \gamma(Q(s_{t+1}, \mu(s_{t+1})|\theta_Q))$$

Actor trained via Critic gradients:

$$\nabla_{\theta_\mu}\mu(s) = \nabla_a Q(s, a|\theta_Q)\nabla_{\theta_\mu}\mu(s|\theta_\mu)$$



Bounded Action Space

HFO's continuous parameters are bounded

Dash(direction, power)
Turn(direction)
Tackle(direction)
Kick(direction, power)

Direction in [-180,180], Power in [0, 100]

Exceeding these ranges results in no action

If DDPG is unaware of the bounds, it will invariably exceed them

Bounded DDPG

We examine 3 approaches for bounding the DDPG's action space:

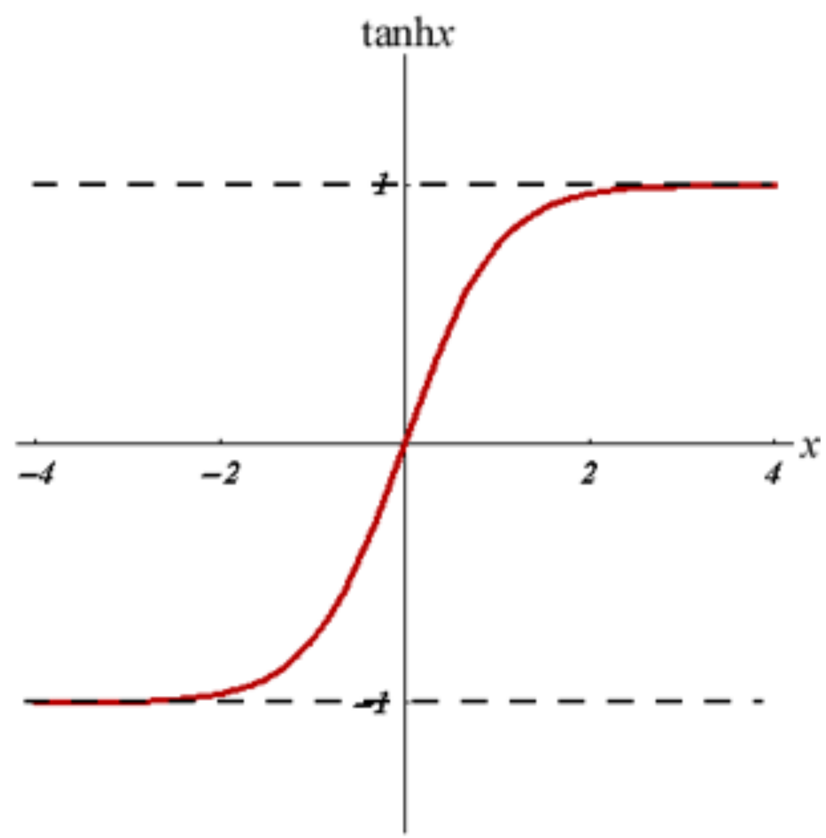
1. Squash Gradients

2. Zero Gradients

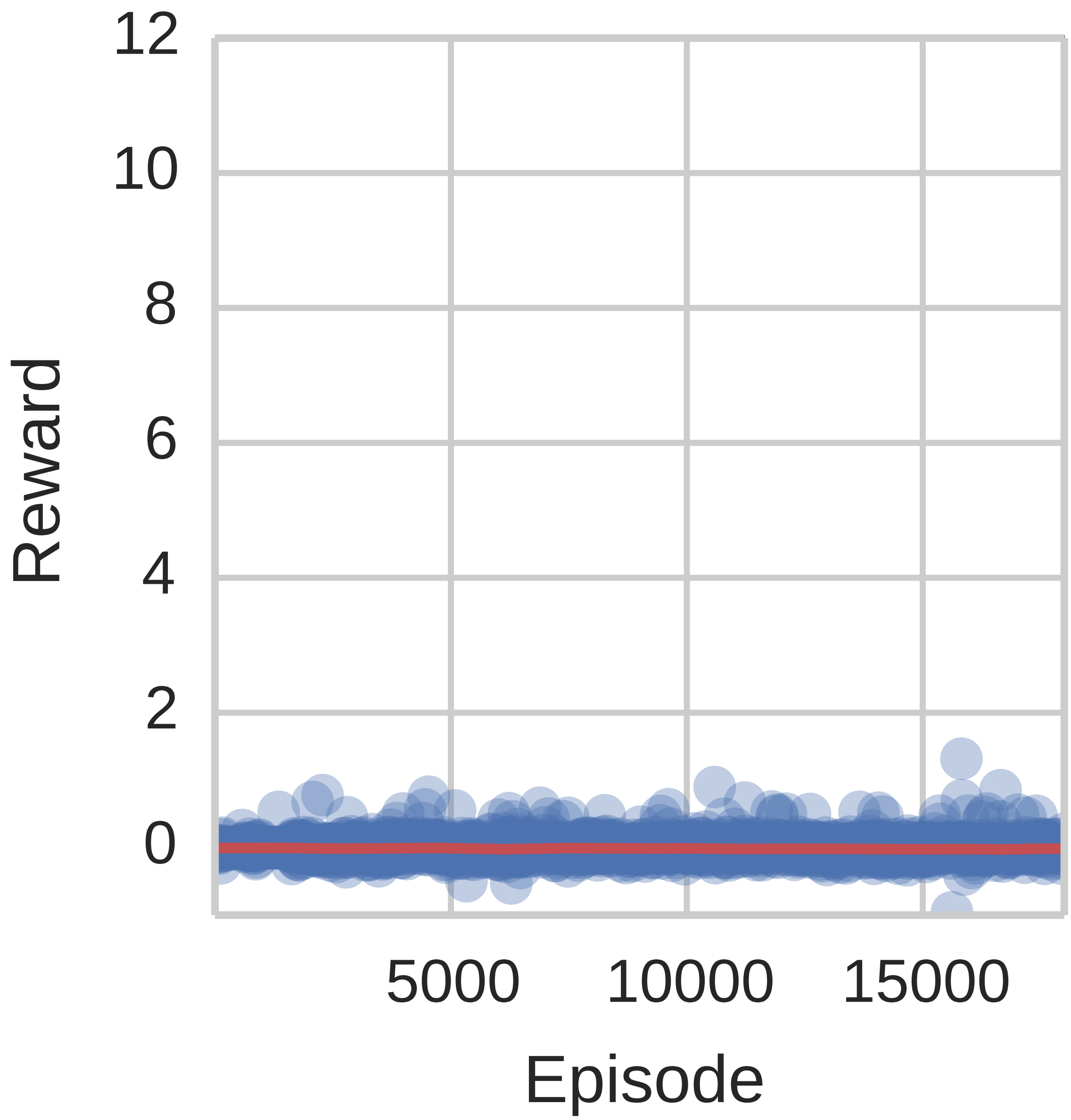
3. Invert Gradients

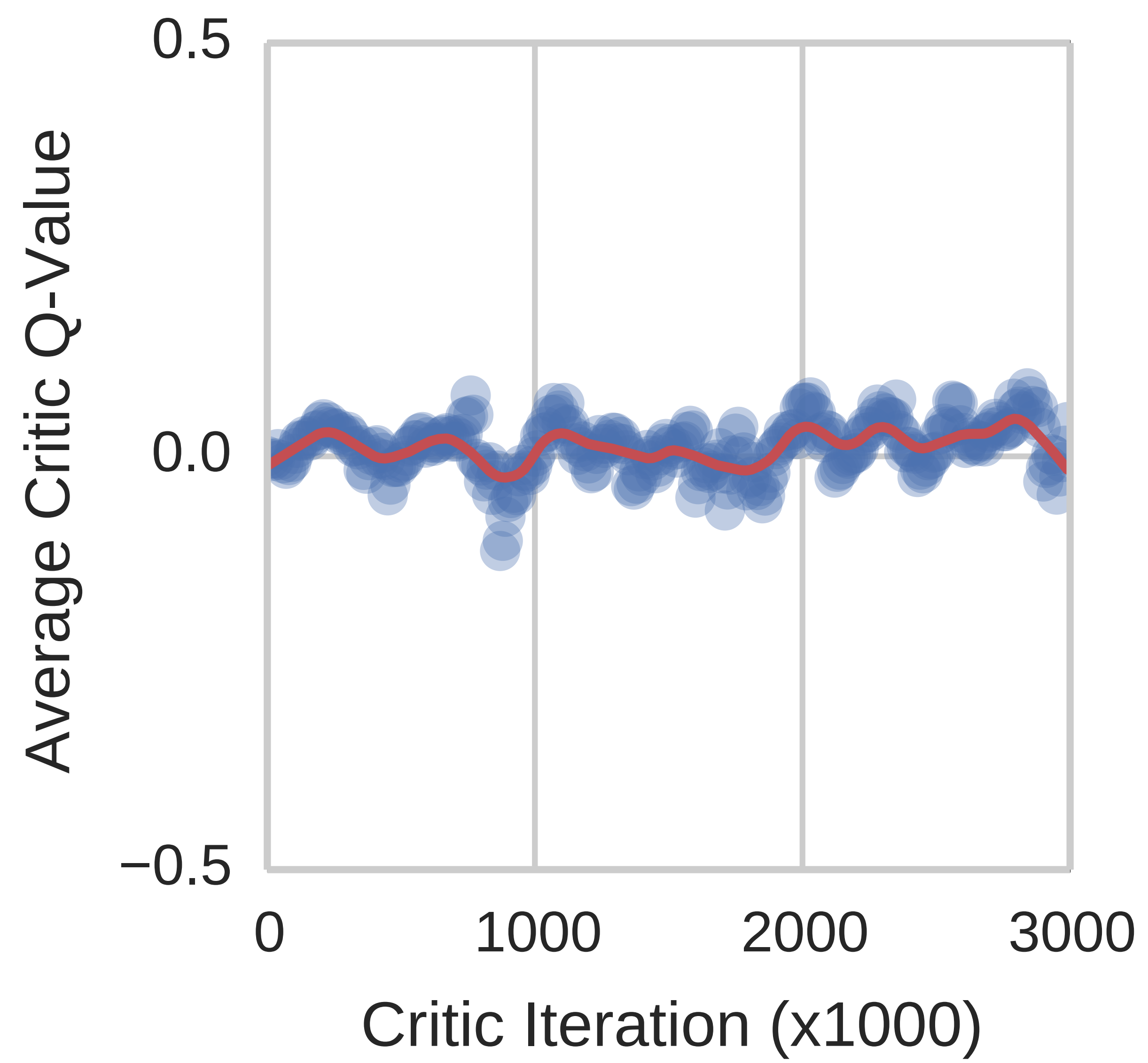
Squashing Gradients

1. Use Tanh non-linearity to bound parameter output
2. Rescale into desired range



Squashing Gradients





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Zeroing Gradients

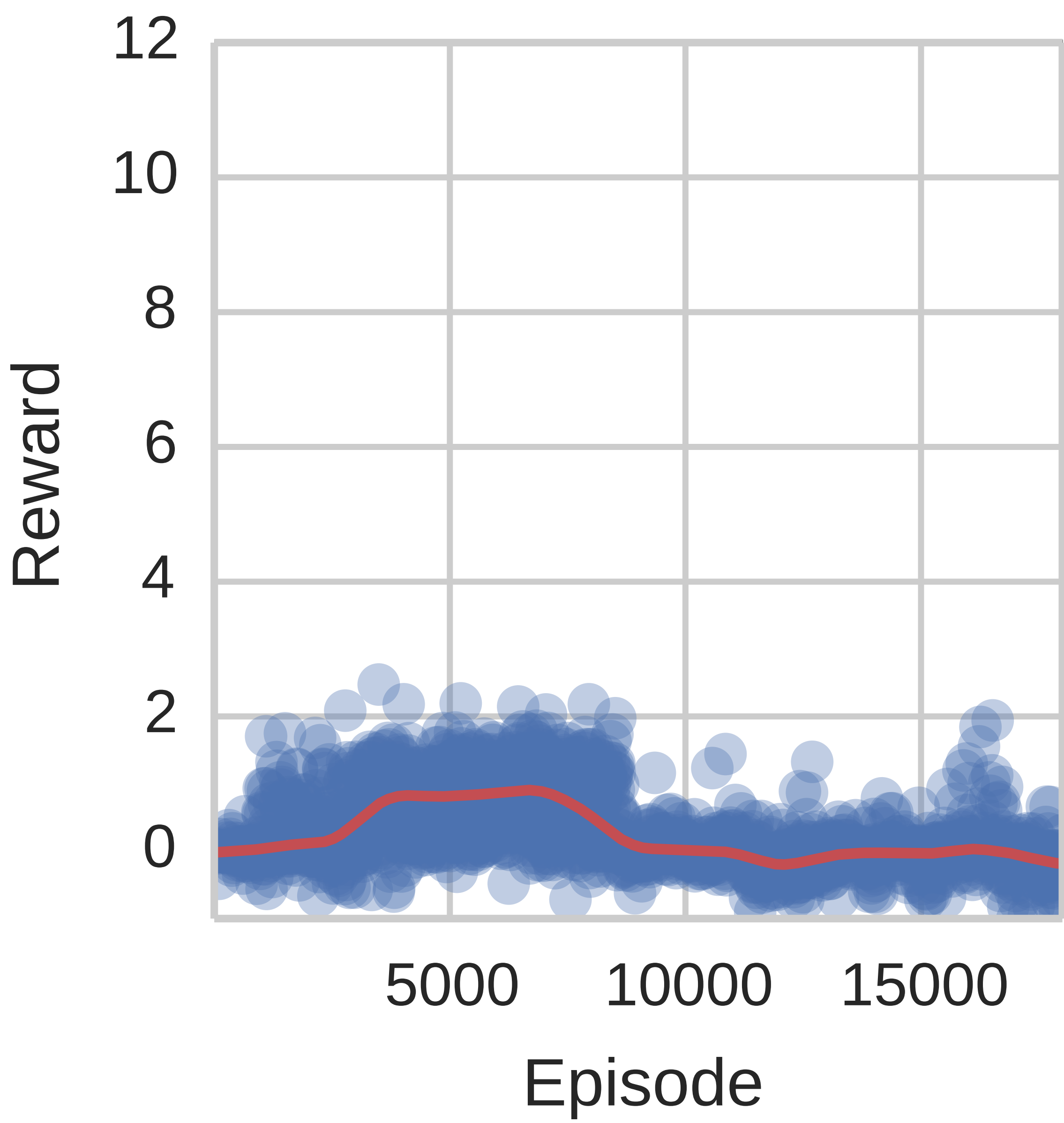
Each continuous parameter has a range: [p_{min}, p_{max}]

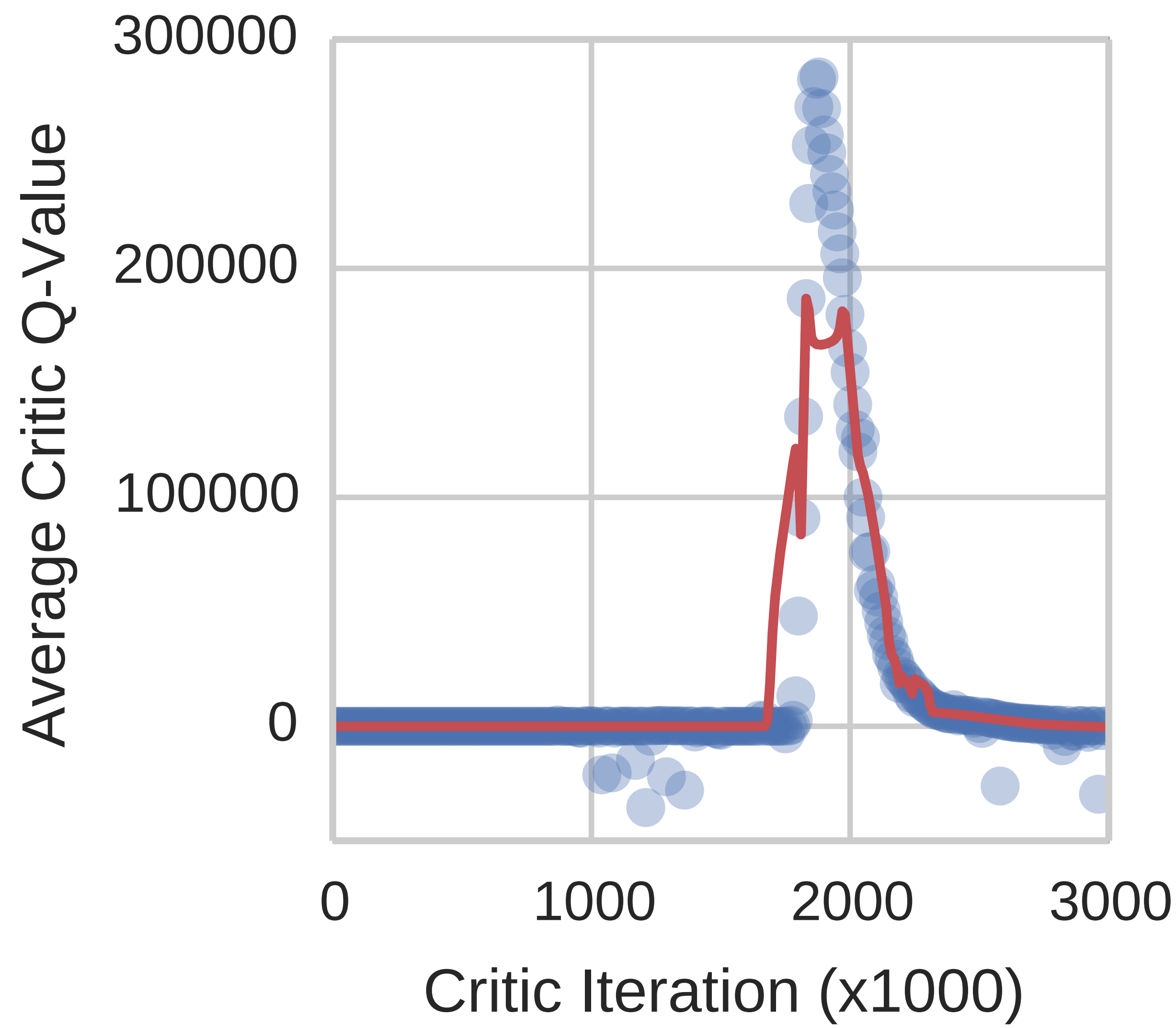
Let p denote current value of parameter, and ∇_p the suggested gradient.

Then:

$$\nabla_p = \begin{cases} \nabla_p & \text{if } p_{\min} < p < p_{\max} \\ 0 & \text{otherwise} \end{cases}$$

Zeroing Gradients





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Inverting Gradients

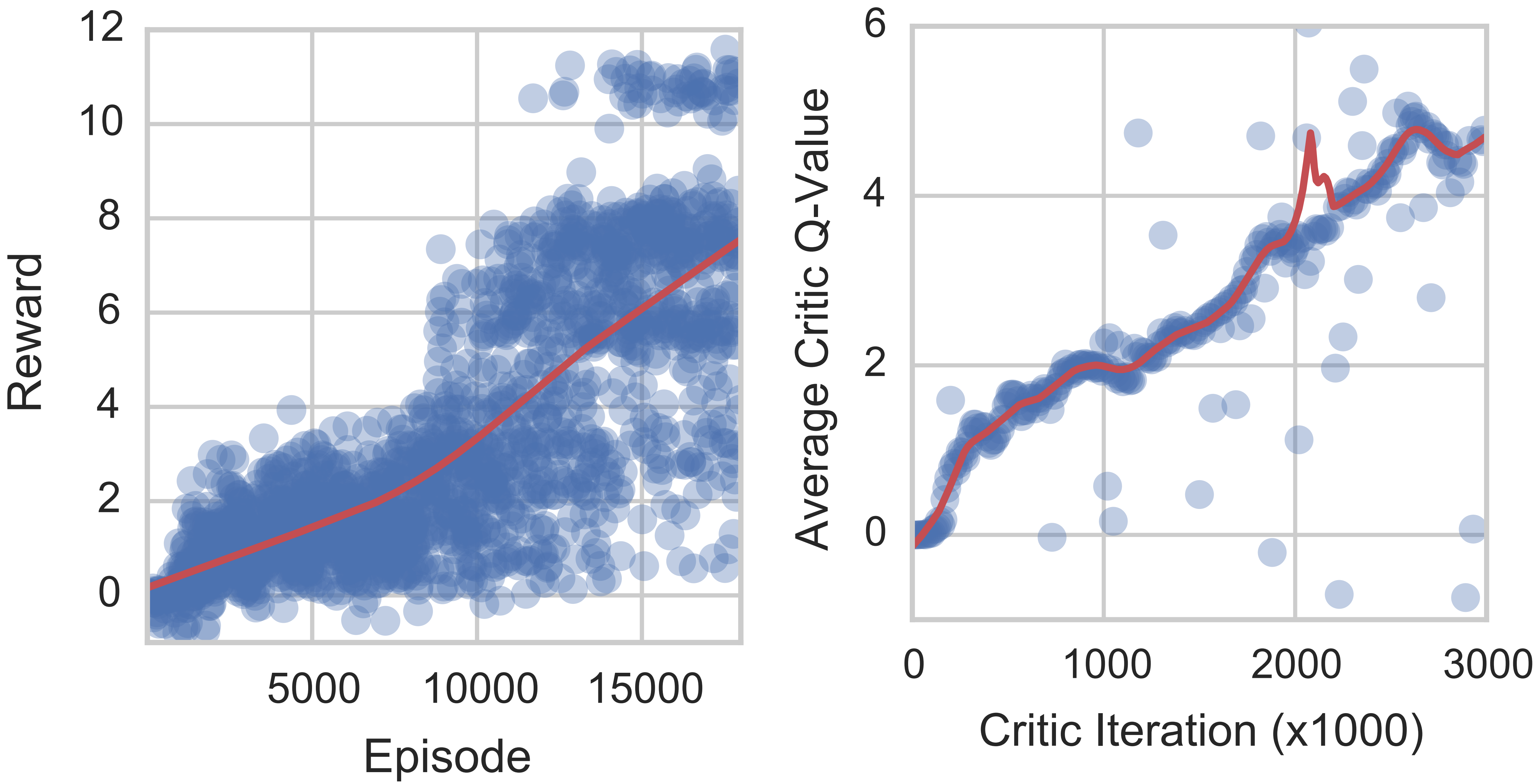
For each parameter:

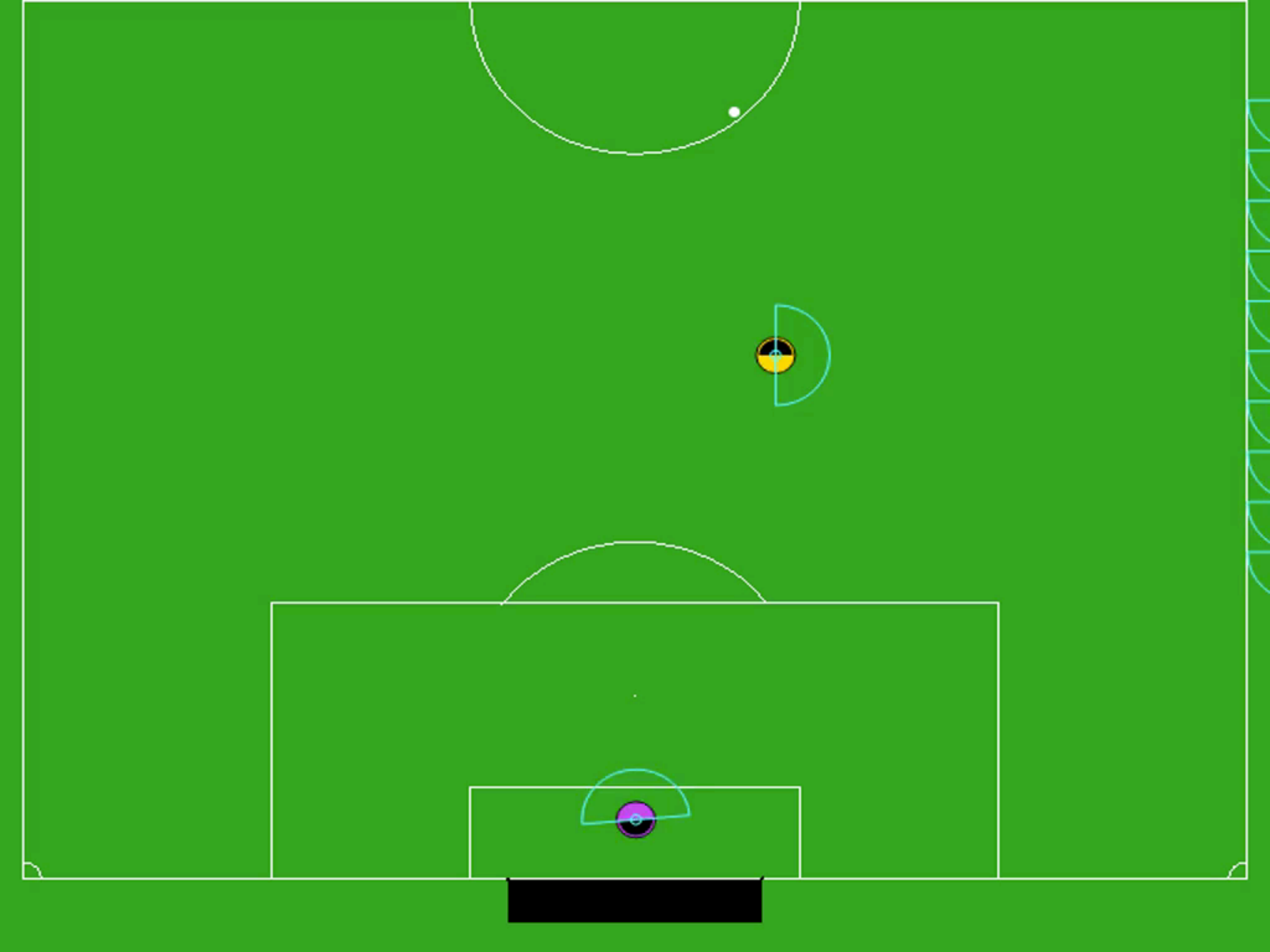
$$\nabla_p = \nabla_p \cdot \begin{cases} (p_{\text{max}} - p)/(p_{\text{max}} - p_{\text{min}}) & \text{if } \nabla_p \text{ suggests increasing } p \\ (p - p_{\text{min}})/(p_{\text{max}} - p_{\text{min}}) & \text{otherwise} \end{cases}$$

Allows parameters to approach the bounds of the ranges without exceeding them

Parameters don’t get “stuck” or saturate

Inverting Gradients





Results

	Scoring Percent	Avg. Steps to Goal
$DDPG_1$	1.0	108.0
$DDPG_2$	.99	107.1
$DDPG_3$	.98	104.8
$DDPG_4$	.96	112.3
Helios' Champion	.96	72.0
$DDPG_5$	.94	119.1
$DDPG_6$	.84	113.2
SARSA	.81	70.7
$DDPG_7$	.80	118.2

[*Deep Reinforcement Learning in Parameterized Action Space*, Hausknecht and Stone, in ICLR '16]

Deep Multiagent RL

Can multiple Deep RL agents cooperate to achieve a shared goal?

Examine several baseline architectures:

Decentralized: Independent agents

Centralized: Single controller for multiple agents

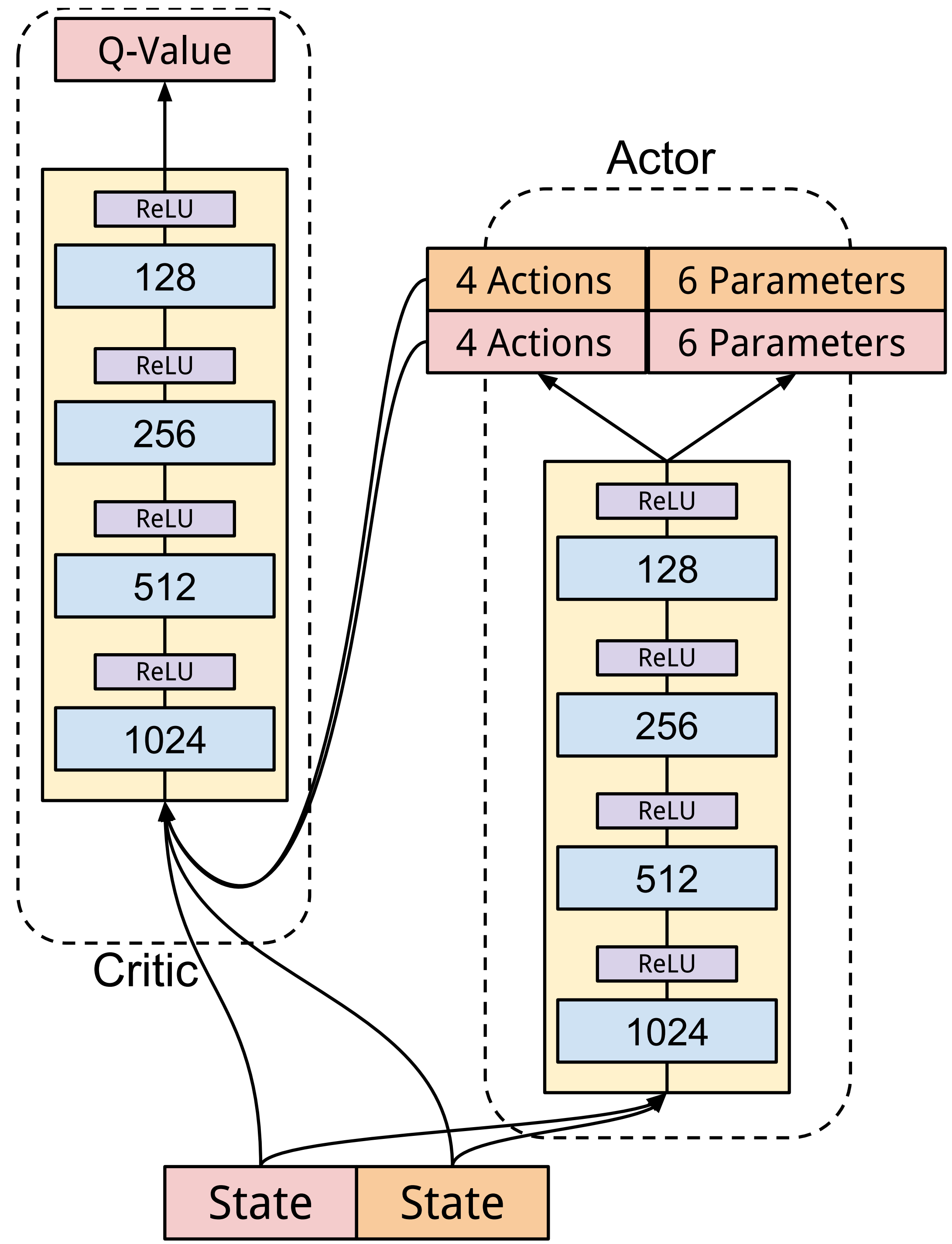
Parameter Sharing: Layers shared between agents

Centralized

Both agents are controlled by a single DDPG

State & Action spaces are concatenated

Learning is more challenging for this reason



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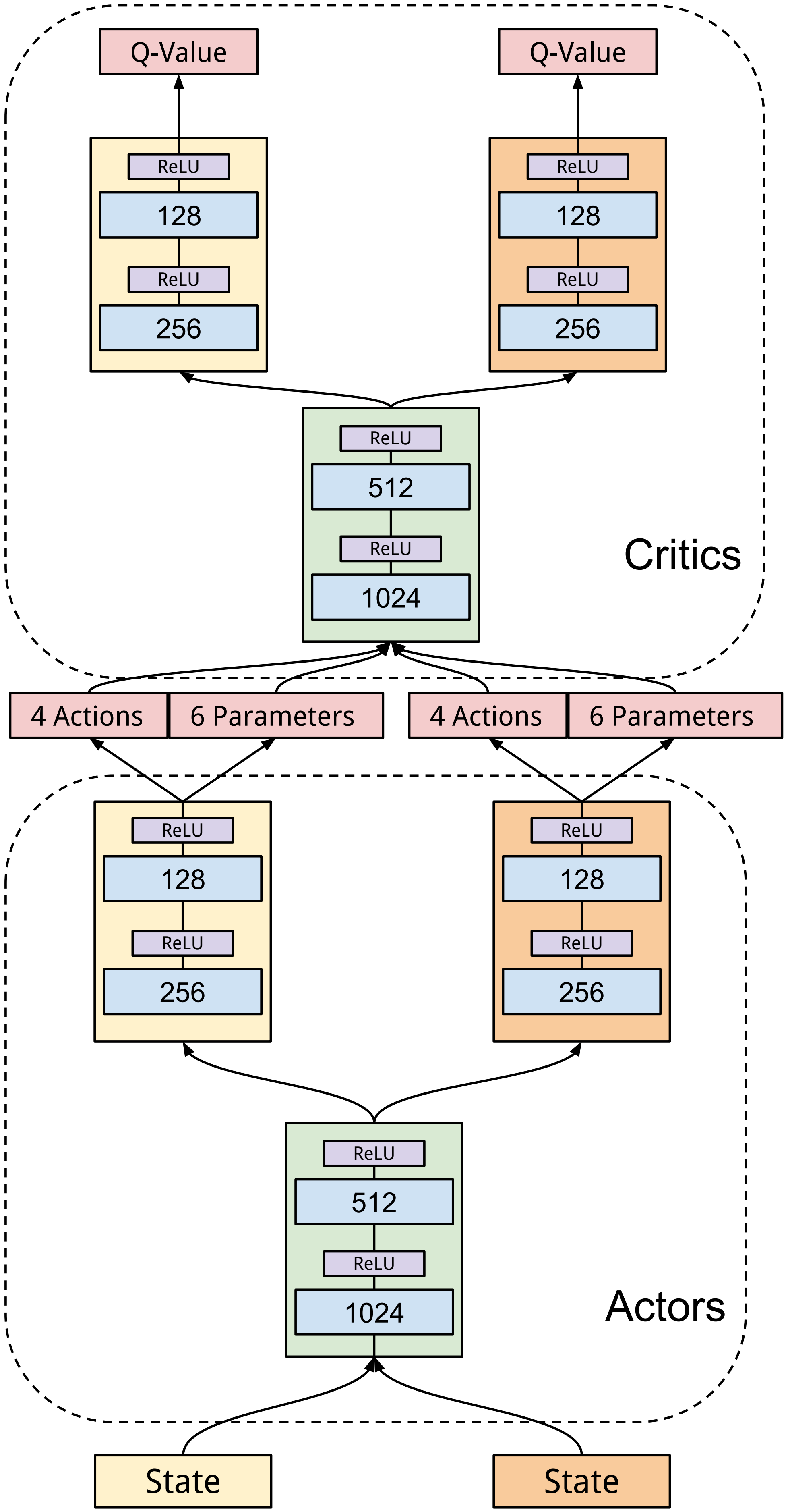
8000
7
8000
11

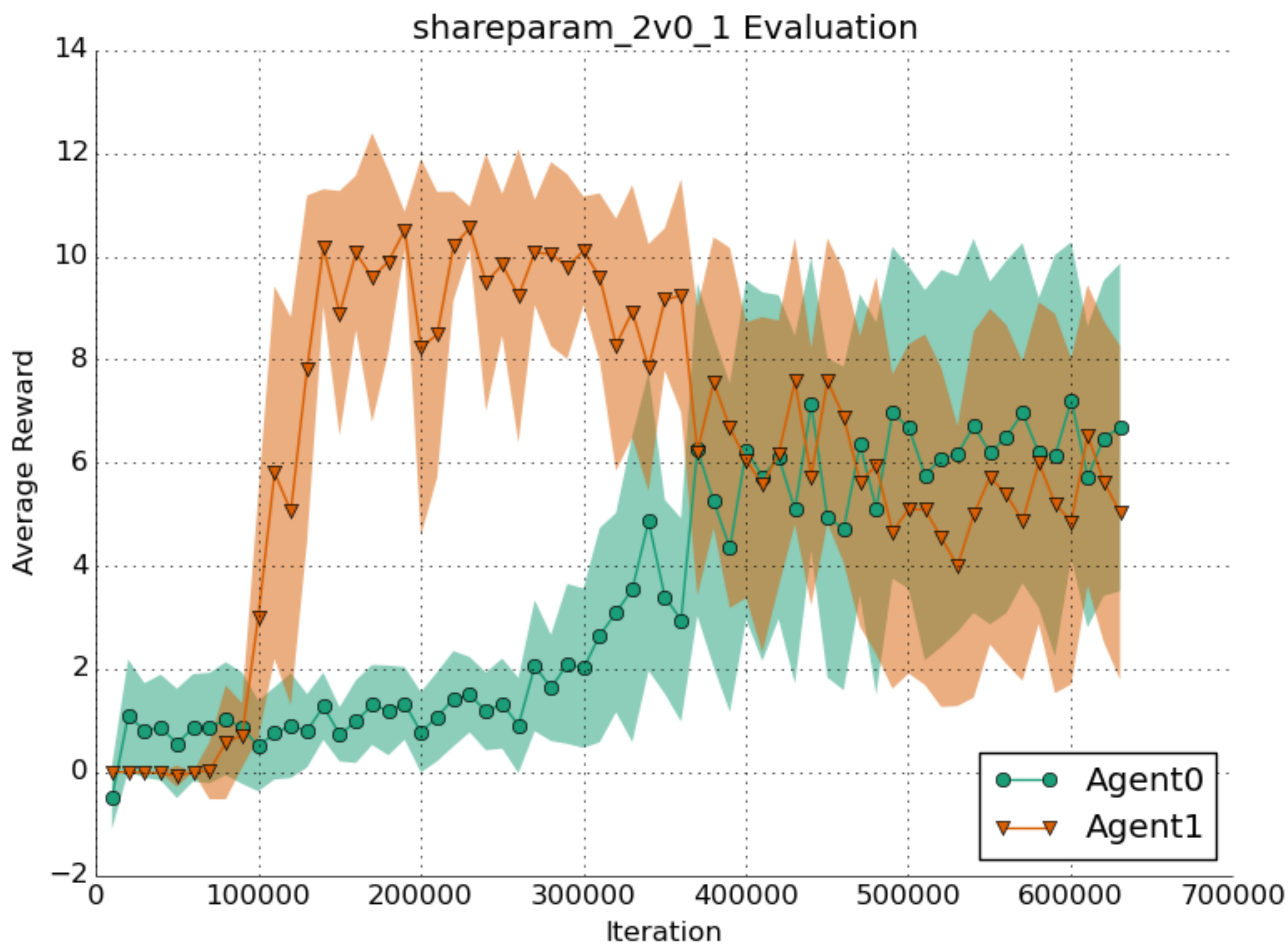
Parameter Sharing

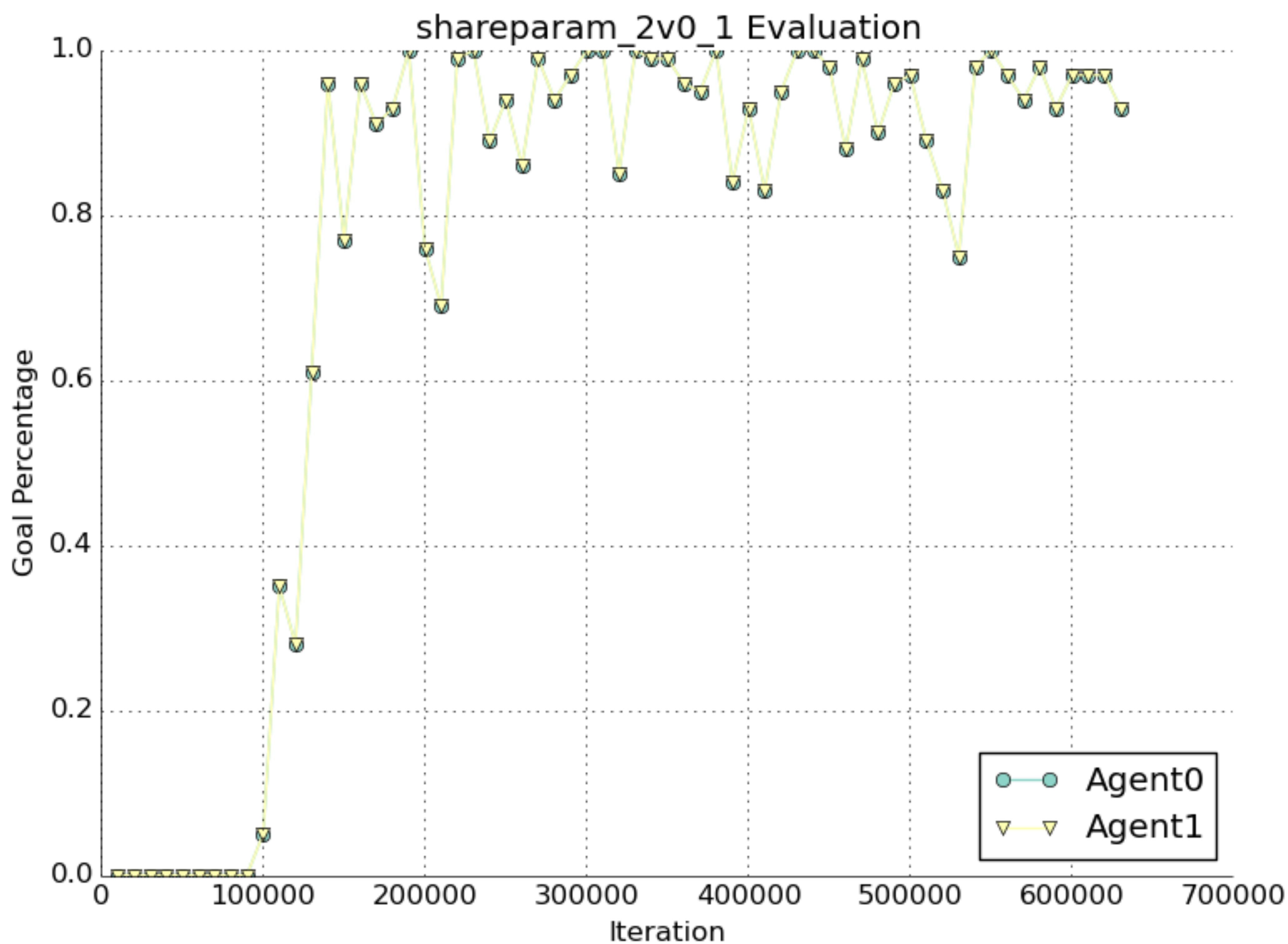
Shared weights between layers in Actor networks. Separate sharing between Critic networks.

Reduces total number of parameters!

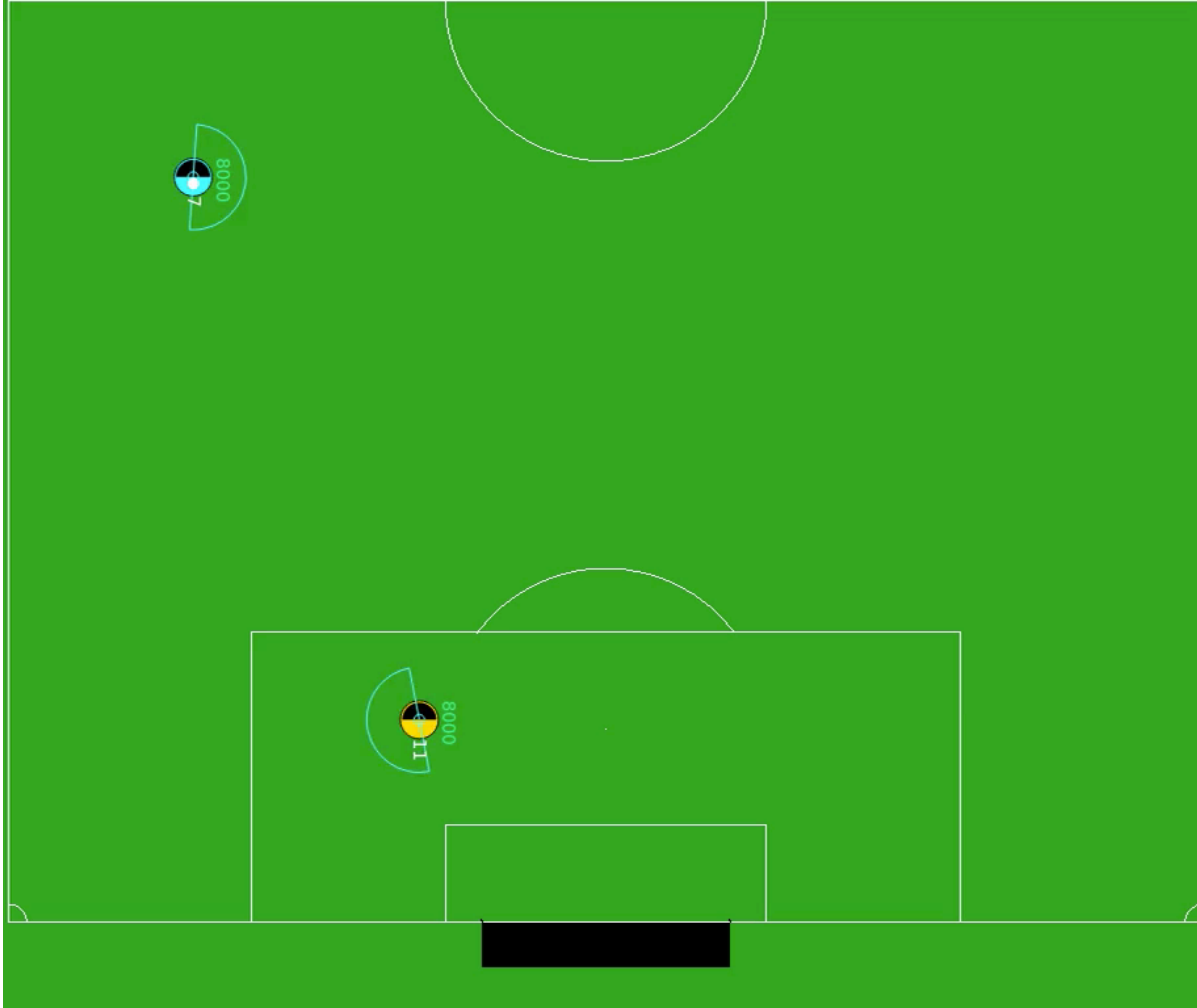
Encourages both agents to participate even though 2v0 is solvable by a single agent.




shareparam_2v0_1 Evaluation
Average Reward
Iteration
Agent0
Agent1
14
12
10
8
6
4
2
0
−2
0
100000
200000
300000
400000
500000
600000
700000



shareparam_2v0_1 Evaluation
Goal Percentage
Iteration
0.0
0.2
0.4
0.6
0.8
1.0
0
100000
200000
300000
400000
500000
600000
700000
Agent0
Agent1

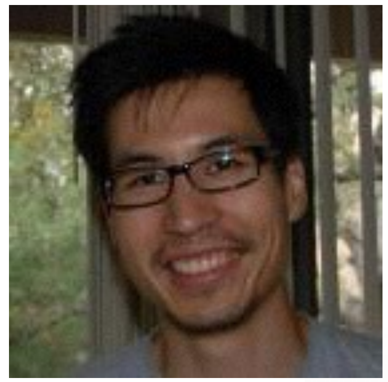

8000
7
8000
11

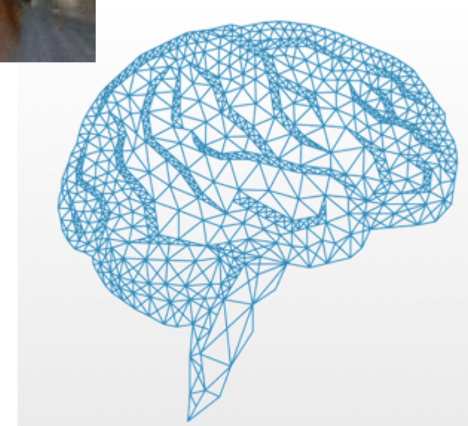
Related Work

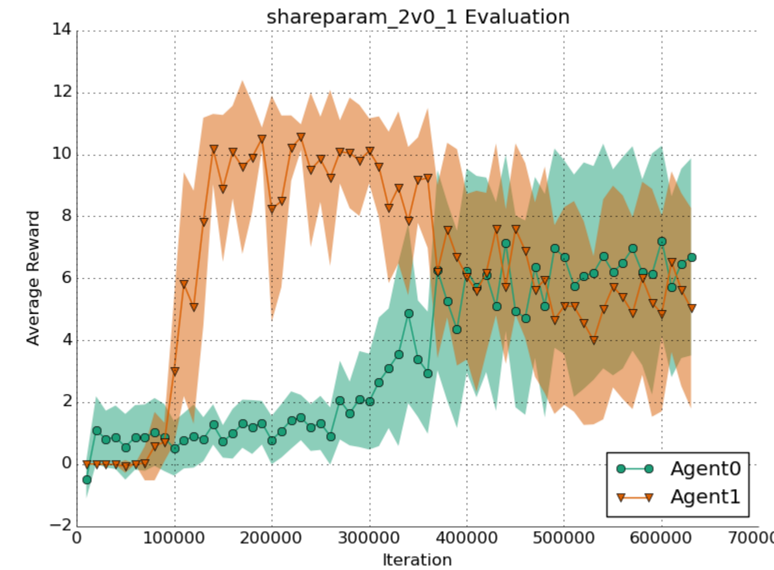
- *Multiagent Cooperation and Competition with Deep Reinforcement Learning*; Tampuu et. al, 2015
- *Learning to Communicate to Solve Riddles with Deep Distributed Recurrent Q-Networks*; Foerster et al., 2016
- *Learning to Communicate with Deep Multi-Agent Reinforcement Learning*; Foerster et al., 2016

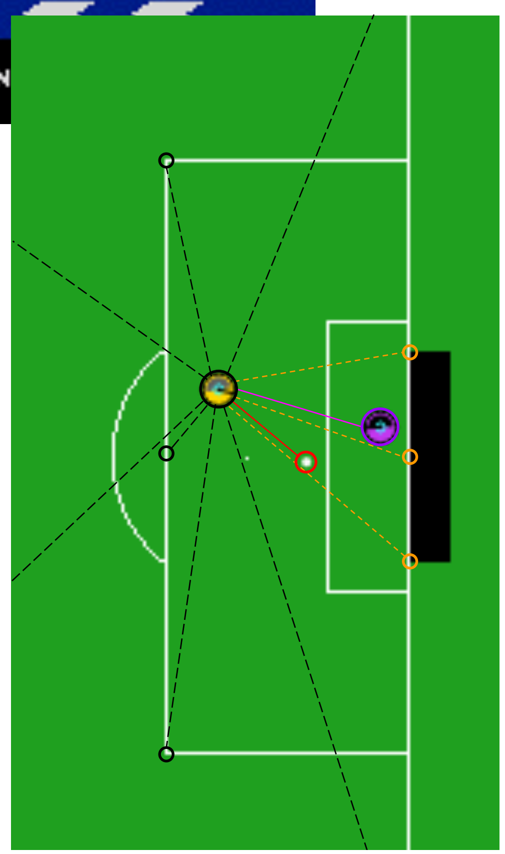
Thanks!

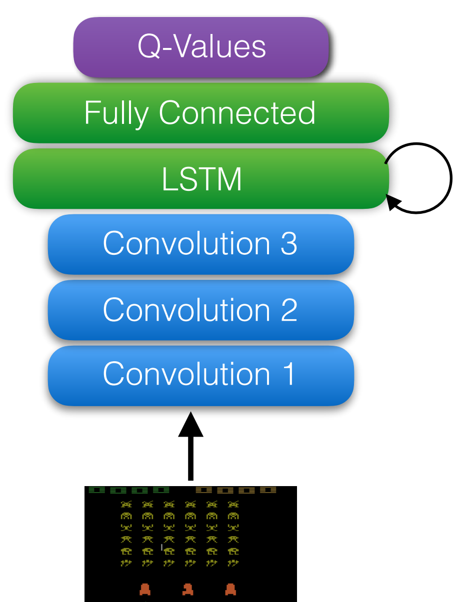

60
41° 2
ACTIVISION

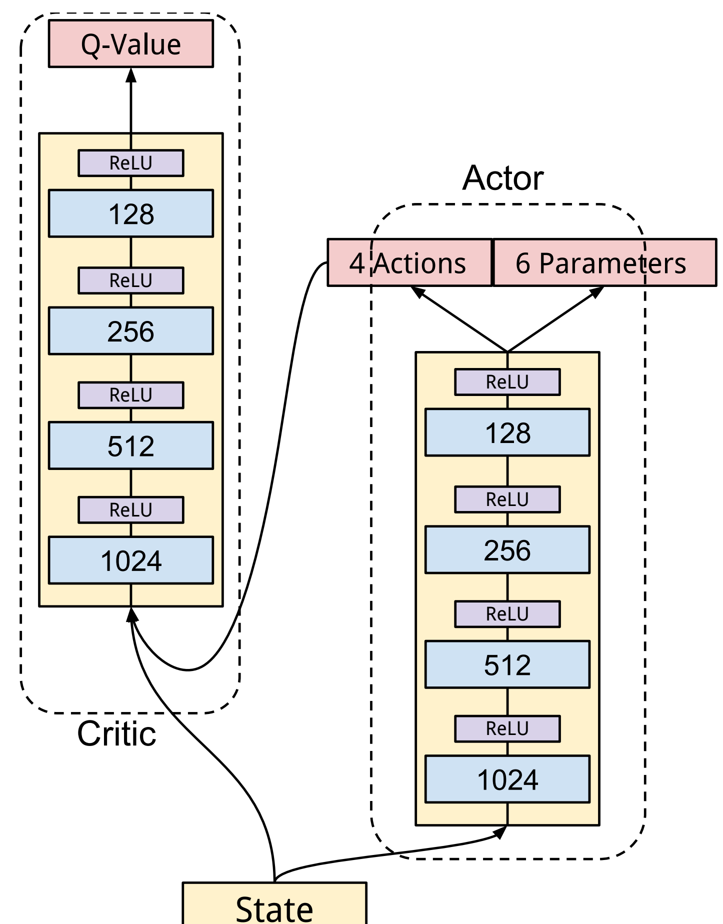





shareparam_2v0_1 Evaluation
Average Reward
Iteration
Agent0
Agent1
14
12
10
8
6
4
2
0
−2
0
100000
200000
300000
400000
500000
600000
700000




Q-Values
Fully Connected
LSTM
Convolution 3
Convolution 2
Convolution 1


Q-Value
ReLU
128
ReLU
256
ReLU
512
ReLU
1024
Critic
Actor
4 Actions
6 Parameters
ReLU
128
ReLU
256
ReLU
512
ReLU
1024
State