OpenBrain: Backpropagation Free RL

Guss, Zhong
Kuznetsov, Singhal, Kumar, Golmant, Johansen, Bartlett

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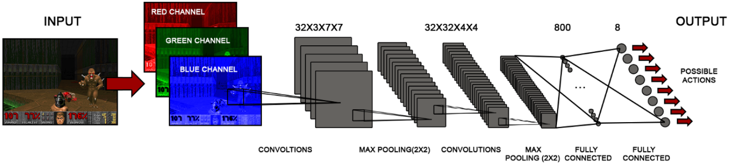
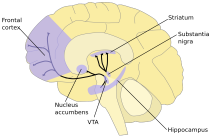
Overview

The Problem

Deep Reinforcment Learning is good, but not biologically plausible.



Reinforcement Learning is biologically plausble.



The Problem

Can we decentralize deep reinforcement learning?

The Problem

Can we decentralize deep reinforcement learning?

Yes. Here's how.

Background on Reinforcement Learning

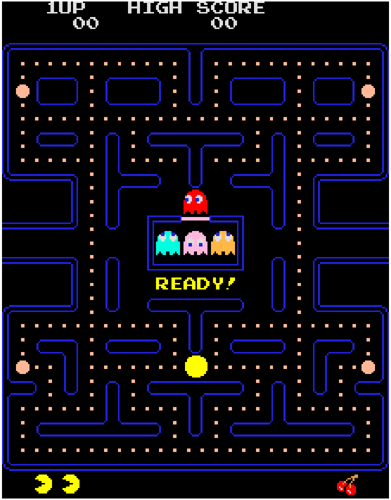
The setup.

1. Environment, $E = (\mathcal{S}, \mathcal{A}, \mathcal{R}, \rho, r)$.
   1. State space, $\mathcal{S} = \mathbb{R}^n$
   2. Action space, $\mathcal{A} = \mathbb{R}^m$
   3. Reward space, $\mathcal{R} = \mathbb{R}$
   4. Transition function, $\rho(s' \mid s, a)$. Given a previous state s and action a, environment gives s'.
   5. Reward function $r(s, a) \in \mathcal{R}$.
2. Deterministic agent $\pi : \mathcal{S} \to \mathcal{A}$ acts in E.

$$s_1 \xrightarrow{\pi} a_1 \xrightarrow{\rho, r} s_2, r_2 \xrightarrow{\pi} a_2 \xrightarrow{\rho, r} \cdots$$

Eg. Pacman sees the screen, and decides to move $\uparrow, \downarrow, \rightarrow, \leftarrow$ and then gets a reward for eating food.

Background on Reinforcement Learning



The action-value function (simplified).

1. The future expected reward of an agent π is

$$Q^\pi(s_t, a_t) = \underbrace{r(s_t, a_t)}_{\text{reward for } a_t} + \sum_{n=t+1}^{\infty} \gamma^n r(s_n, \pi(s_n))$$

2. The Bellman equation gives us

$$Q^\pi(s_t, a_t) = r_t + \gamma Q^\pi(s_{t+1}, \pi(s_{t+1}))$$

''

3. Given some state s_t, the **best** agent, π^* is one that take action

$$a_t = \arg\max_a Q(s_t, a).$$

Background on Reinforcement Learning

The action-value function (simplified).

1. The Q function for π^* is

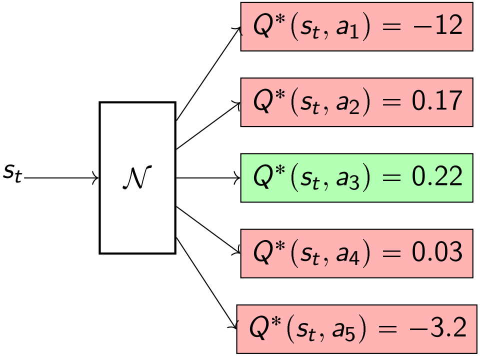
$$Q^*(s_t, a_t) = r_t + \gamma \arg\max_a Q^\pi(s_{t+1}, a).$$

2. We can *approximate* this with deep learning!
   1. Make a neural network $\mathcal{N} : \mathcal{S} \to \mathbb{R}^n$ which predicts the future reward of taking each possible action

$$\mathcal{N}(s_t) = \begin{pmatrix} Q^*(s_t, a_1) \\ Q^*(s_t, a_2) \\ \vdots \\ Q^*(s_t, a_n) \end{pmatrix}$$

Background on Reinforcement Learning

Deep Q-Learning

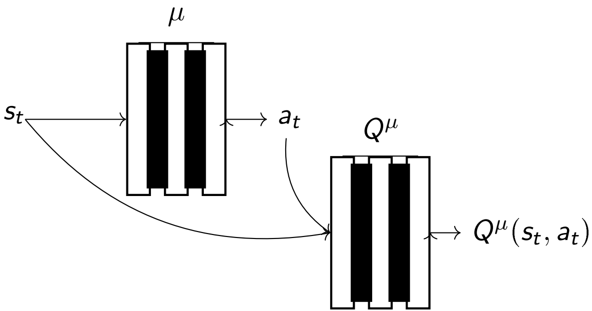


$$\pi(s_t) = \arg\max_a \mathcal{N}(s_t)$$

Can we do better?

Deep Determisitic Policy Gradient

1. Actor neural network $\mu : \mathcal{S} \to \mathcal{A}$
2. Critic network $Q^\mu : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$
3. Performance of μ is $Q^\mu(s_t, \mu(s_t))$. **Maximize performance!** $\nabla_W Q^\mu(s_t, a_t) = \nabla_a Q^\mu(s_t, a) \cdot \nabla_W \mu(s_t)$



Our Approach

ML@B

Neuromorphically Local Agents

1. Every neuron in the brain is an agent!
2. Anterior neurons are the state that μ^n sees.
3. The action of each μ^n is its output:

$$\mu^n(s_t) = \sigma\left(\sum_{i=1}^{m} W_{in} s_t^{(i)}\right) = a_t$$

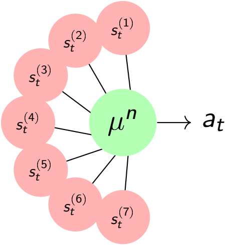


Figure: A neuron n and its environment, E^n.

Our Approach

Local Q Critics

1. Hypothesis: μ^n lives in an extremely **simple** environment.
2. Can we estimate Q^n without error backprop?
3. **Remark.** Training whole μ is equivalent to training μ^n simultaneously:

$$\nabla_{W^{(n)}} Q^n(\mu^n) = (\nabla_W Q^\mu(\mu))^{(n)}$$

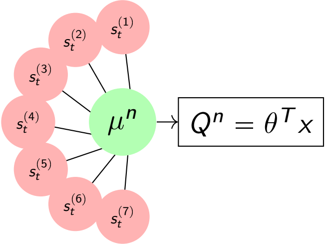


Figure: A linear critic for μ^n

Results

The Training Regime

1. We can train every neuron **simultaneously** without BP.
2. There is no "extra" Q network, just $2n$ parameters!
3. Could be biologically plausible (certainly more reasonable than BP)
4. Linear critic $\iff$ *compatability* $\iff$ no bias in Q^n

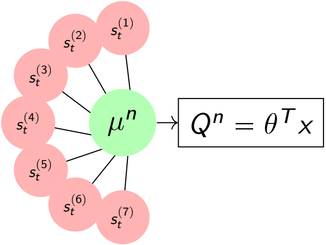


Figure: A linear critic for μ^n

Experiments

Experiment 1.

1. Test if training μ with the full $Q^n \implies$ each μ^n acting optimal to Q^n
2. Is it true in practice that $\nabla_{W^{(n)}} Q^n(\mu^n) = (\nabla_W Q^\mu(\mu))^{(n)}$?

Experiment 2.

1. Train μ^n using $Q^n \implies Q$ optimal?

Experiment 3.

1. Beat the state of the art in Atari 2600 environments!

Questions?

wguss@berkeley.edu