TTIC 31230, Fundamentals of Deep Learning

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Deep Reinforcement Learning

Q-Learning

The Q Function

For discounted reward:

$$Q^\pi(s,a) \;=\; E_\pi \;\sum_t \;\gamma^t r_t \;\;|\; \pi,\;\; s_0 = s,\;\; a_0 = a$$

$$Q^*(s,a) \;=\; \sup_\pi \;Q^\pi(s,a)$$

$$\pi^*(a|s) \;=\; \operatorname*{argmax}_a \;Q^*(s,a)$$

$$Q^*(s,a) \;=\; R(s,a) + \gamma E_{s' \sim P_T(\cdot|s,a)} \;\max_{a'} \;Q^*(s',a')$$

Q Function Iteration

It is possible to define Q-iteration by analogy with value iteration, but this is generally not discussed.

Value iteration is typically done for finite state spaces. Let S be the number of states and A be the number of actions.

One update of a Q table takes $O(S^2A^2)$ time while one update of value iteration is $O(S^2A)$.

Q-Learning

When learning by updating the Q function we typically assume a parameterized Q function $Q_\Phi(s,a)$.

Bellman Error:

$$\mathrm{Bell}_\Phi(s,a) \doteq \left(Q_\Phi(s,a) - \left(R(s,a) + \gamma \; E_{s' \sim P_T(s'|s,a)} \; \max_{a'} \; Q_\Phi(s',a')\right)\right)^2$$

Theorem: If $\mathrm{Bell}_\Phi(s,a) = 0$ for all (s,a) then the induced policy is optimal.

Algorithm: Generate pairs (s,a) from the policy $\mathrm{argmax}_a \; Q_\Phi(s_t,a)$ and repeat

$$\Phi \mathrel{-}= \eta \nabla_\Phi \; \mathrm{Bell}_\Phi(s,a)$$

Issues with Q-Learning

Problem 1: Nearby states in the same run are highly correlated. This increases the variance of the cumulative gradient updates.

Problem 2: SGD on Bellman error tends to be unstable. Failure of Q_Φ to model unused actions leads to policy change (exploration). But this causes Q_Φ to stop modeling the previous actions which causes the policy to change back ...

To address these problems we can use a **replay buffer**.

Using a Replay Buffer

We use a replay buffer of tuples (s_t, a_t, r_t, s_{t+1}).

Repeat:

1. Run the policy $\mathrm{argmax}_a\, Q_\Phi(s,a)$ to add tuples to the replay buffer. Remove oldest tuples to maintain a maximum buffer size.
2. $\Psi = \Phi$
3. for N times select a random element of the replay buffer and do

$$\Phi \mathrel{-}= \eta \nabla_\Phi \left(Q_\Phi(s_t, a_t) - (r_t + \gamma \max_a Q_\Psi(s_{t+1}, a)\right)^2$$

Replay is Off-Policy

Note that the replay buffer is from a **mixture of policies** and is **off-policy** for $\mathrm{argmax}_a\ Q_\Phi(s,a)$. This seems to be important for stability.

This seems related to the issue of stochastic vs. deterministic policies. More on this later.

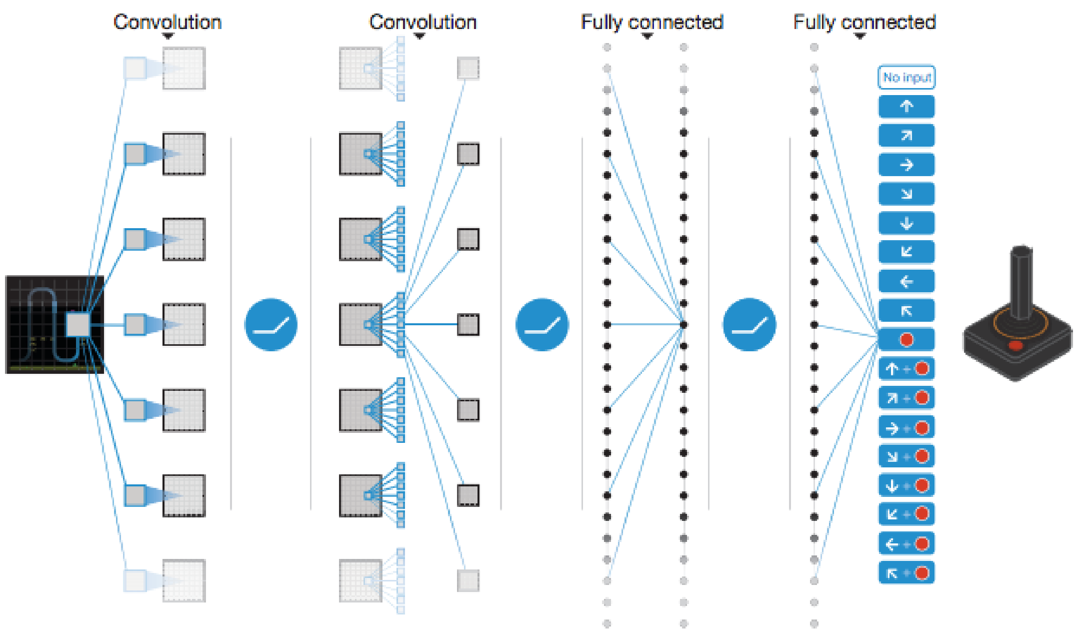
Multi-Step Q-learning

$$\Phi \mathrel{-}= \sum_t \nabla_\Phi \left(Q_\Phi(s_t, a_t) - \sum_{\delta=0}^{D} \gamma^\delta r_{(t+\delta)} \right)^2$$

Human-level control through deep RL (DQN)

Mnih et al., Nature, 2015. (Deep Mind)

We consider a CNN $Q_\Phi(s, a)$.



Watch The Video

https://www.youtube.com/watch?v=V1eYniJ0Rnk

Asynchronous Q-Learning (Simplified)

No replay buffer. Many asynchronous threads each repeating:

$\tilde{\Phi} = \Phi$ (retrieve Φ)

using policy $\mathrm{argmax}_a \, Q_{\tilde{\Phi}}(s, a)$ compute

$$s_t, a_t, r_t, \ldots, s_{t+K}, a_{t+K}, r_{t+K}$$

Φ -= $\eta \sum_{i=t}^{t+K-D} \nabla_{\tilde{\Phi}} \left(Q_{\tilde{\Phi}}(s_i, a_i) - \sum_{\delta=0}^{D} \gamma^\delta r_{i+\delta} \right)^2$ (update Φ)

END