Non-linear Value Function Approximation: Double Deep Q-Networks

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*Slides are based on Deep Reinforcement Learning: Q-Learning by Garima Lalwani, Karan Ganju, Unnat Jain. Illinois

Overview

1. Recap: DQN
2. Double Deep Q Network

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Recap: Deep Q-Networks (DQN)

- Represent value function by deep Q-network with weights w

$$Q(s, a, w) \approx Q^{\pi}(s, a)$$

- Define objective function

$$\mathcal{L}(w) = \mathbb{E}\left[\left(\underbrace{r + \gamma \max_{a'} Q(s', a', w)}_{\text{target}} - Q(s, a, w)\right)^2\right]$$

- Leading to the following Q-leaning gradient

$$\frac{\partial \mathcal{L}(w)}{\partial w} = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q(s', a', w) - Q(s, a, w)\right) \frac{\partial Q(s, a, w)}{\partial w}\right]$$

- Optimize objective end-to-end by SGD, using $\frac{\partial L(w)}{\partial w}$

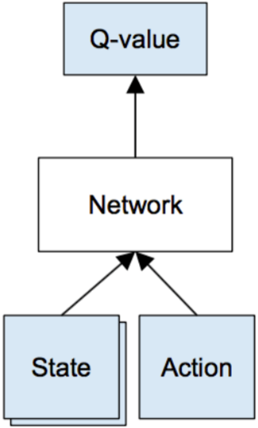
Deep Q-Networks

DQN provides a stable solution to deep value-based RL

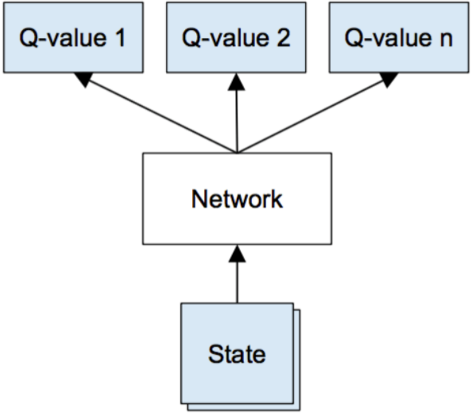
1. Use experience replay
2. Freeze target Q-network
3. Clip rewards or normalize network adaptive to sensible range

Deep Q-Network (DQN) Architecture

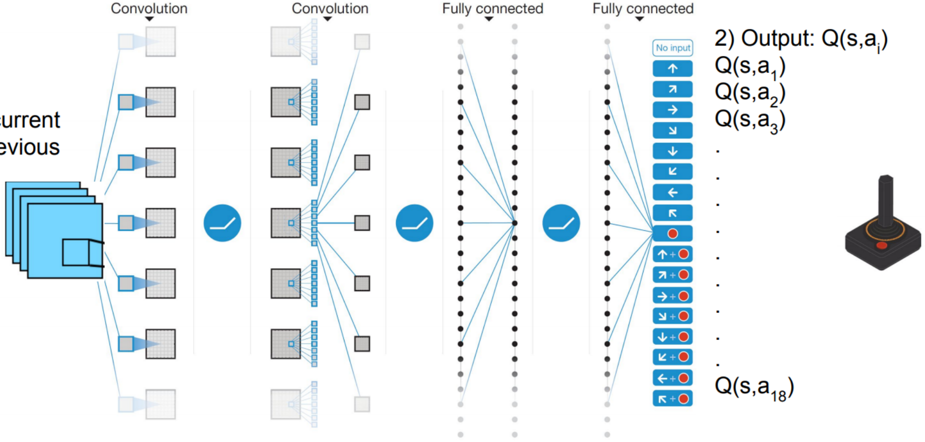
Naive DQN



Optimized DQN used by DeepMind



DQN in Atari



1) Input:
4 images = current frame + 3 previous

2) Output: $Q(s,a_i)$
$Q(s,a_1)$
$Q(s,a_2)$
$Q(s,a_3)$
.
.
.
.
.
.
.
.
$Q(s,a_{18})$

DQN Algorithm

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function $\boxed{Q}$ with random weights θ

Initialize target action-value function $\boxed{\hat{Q}}$ with weights $\theta^{-} = \theta$

For episode $= 1, M$ **do**

Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

For $t = 1$,T **do**

With probability ε select a random action a_t

otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$

Execute action a_t in emulator and observe reward r_t and image x_{t+1}

Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D

Sample random minibatch of transitions $\left(\phi_j, a_j, r_j, \phi_{j+1}\right)$ from D

$$\text{Set } y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ \boxed{r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^{-}\right)} & \text{otherwise} \end{cases}$$

Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ

Every C steps reset $\hat{Q} = Q$

End For

End For

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One (Estimator) Isn't Good Enough?

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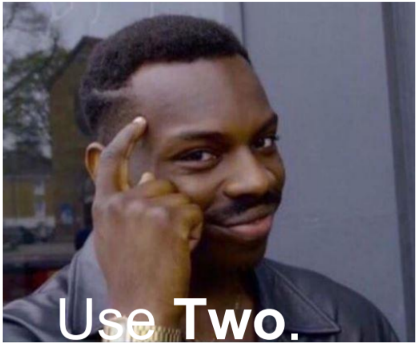

https://pbs.twimg.com/media/C5ymV2tVMAYtAev.jpg

Double Q-learning

Two estimators:

- Estimator Q_1: Obtain best actions
- Estimator Q_2: Evaluate Q for the above action

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What is the main motivation?

Double Q-learning

Two estimators:

- Estimator Q_1: Obtain best actions
- Estimator Q_2: Evaluate Q for the above action

Chances of both estimators overestimating at same action is lesser

Double Q-learning

Two estimators:

- Estimator Q_1: Obtain best actions
- Estimator Q_2: Evaluate Q for the above action

$$Q_1(s, a) \leftarrow Q_1(s, a) + \alpha(\text{Target} - Q_1(s, a))$$

Q Target: $r(s, a) + \gamma \max_{a'} Q_1(s', a')$

Double Q-learning

Two estimators:

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Q Target: $r(s,a) + \gamma \max_{a'} Q_1(s',a')$

Double Q Target: $r(s,a) + \gamma Q_2(s', \arg\max_{a'}(Q_1(s',a')))$

Double Q-learning

Algorithm 1 Double Q-learning

Initialize Q^A,Q^B,s
repeat
  Choose a, based on $Q^A(s,\cdot)$ and $Q^B(s,\cdot)$, observe r, s'
  Choose (e.g. random) either UPDATE(A) or UPDATE(B)
  if UPDATE(A) **then**
    Define $\underline{a^* = \arg\max_a Q^A(s',a)}$
    $Q^A(s,a) \leftarrow Q^A(s,a) + \alpha(s,a)\left(\boxed{r + \gamma Q^B(s',a^*)} - Q^A(s,a)\right)$
  else if UPDATE(B) **then**
    Define $\underline{b^* = \arg\max_a Q^B(s',a)}$
    $Q^B(s,a) \leftarrow Q^B(s,a) + \alpha(s,a)(\boxed{r + \gamma Q^A(s',b^*)} - Q^B(s,a))$
  end if
  $s \leftarrow s'$
until end

Double Deep Q Network

Two estimators:

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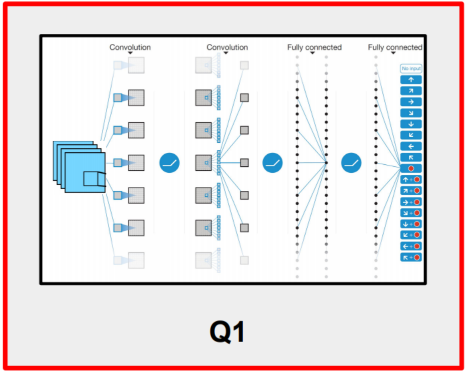

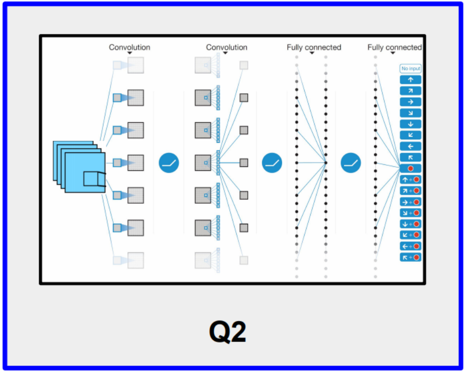

Double Deep Q Network

Algorithm 1 : Double Q-learning (Hasselt et al., 2015)

Initialize primary network Q_θ, target network $Q_{\theta'}$, replay buffer $\mathcal{D}$, $\tau << 1$
for each iteration **do**
    for each environment step **do**
        Observe state s_t and select $a_t \sim \pi(a_t, s_t)$
        Execute a_t and observe next state s_{t+1} and reward $r_t = R(s_t, a_t)$
        Store (s_t, a_t, r_t, s_{t+1}) in replay buffer $\mathcal{D}$
    for each update step **do**
        sample $e_t = (s_t, a_t, r_t, s_{t+1}) \sim \mathcal{D}$
        Compute target Q value:
            $Q^*(s_t, a_t) \approx r_t + \gamma\, Q_\theta(s_{t+1}, argmax_{a'} Q_{\theta'}(s_{t+1}, a'))$
        Perform gradient descent step on $(Q^*(s_t, a_t) - Q_\theta(s_t, a_t))^2$
        Update target network parameters:
            $\theta' \leftarrow \tau * \theta + (1 - \tau) * \theta'$

Are the Q-values accurate?