Dueling Network Architectures for Deep Reinforcement Learning (ICML 2016)

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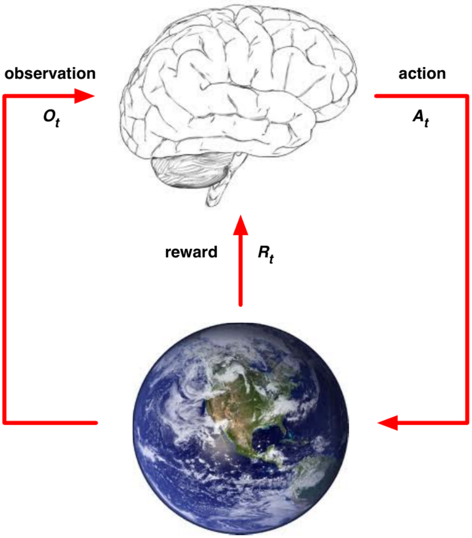
Outline

Outline

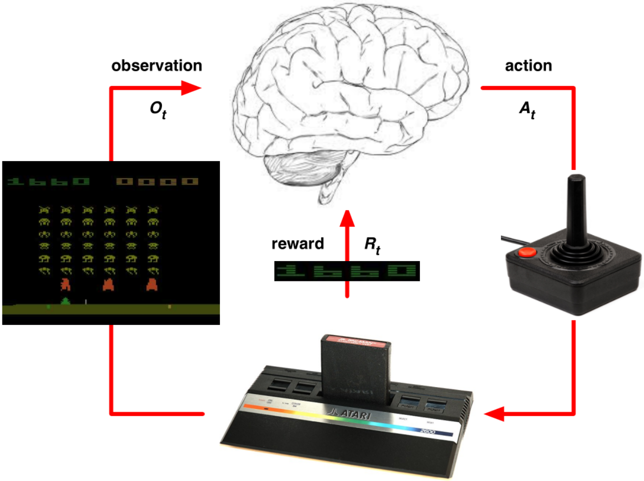
Definition of RL

general setting of RL



Definition of RL

atari setting



POSTECH

Outline

Reinforcement Learning

Definition of RL

Mathematical formulations

Algorithms

Neural Fitted Q Iteration

Deep Q Network

Double Deep Q Network

Prioritized Experience Replay

Dueling Network

Mathematical formulations

objective of RL

Definition

Return G_t is the cumulative discounted reward from time t

$$G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots$$

Mathematical formulations

objective of RL

Definition

Return G_t is the cumulative discounted reward from time t

$$G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \dots$$

Definition

A policy π is a function that selects actions given states

$$\pi(s) = a$$

- The goal of RL is to find π that maximizes G_0

Mathematical formulations

Q-Value

$$G_t = \sum_{i=0}^{\infty} \gamma^k r_{t+i+1}$$

Definition

The action-value (Q-value) function $Q_\pi(s, a)$ is the expectation of G_t under taking action a, and then following policy π afterwards

$$Q_\pi(s, a) = \mathbb{E}_\pi[G_t | S_t = s, A_t = a, A_{t+i} = \pi(S_{t+i}) \forall i \in \mathbb{N}]$$

- "How good is action a in state s?"

Mathematical formulations

Optimal Q-value

Definition

The optimal Q-value function $Q_*(s, a)$ is the maximum Q-value over all policies

$$Q_*(s, a) = \max_{\pi} Q_{\pi}(s, a)$$

Mathematical formulations

Optimal Q-value

Definition

The optimal Q-value function $Q_*(s, a)$ is the maximum Q-value over all policies

$$Q_*(s, a) = \max_{\pi} Q_\pi(s, a)$$

Theorem

There exists a policy π_* such that $Q_{\pi_*}(s, a) = Q_*(s, a)$ for all s, a

- Thus, it suffices to find Q_*

Mathematical formulations

Q-Learning

Bellman Optimality Equation

$Q_*(s, a)$ satisfies the following equation:

$$Q_*(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) \max_{a'} Q_*(s', a')$$

Bellman Optimality Equation

$Q_*(s, a)$ satisfies the following equation:

$$Q_*(s, a) = R(s, a) + \gamma \sum_{s'} P(s'|s, a) \max_{a'} Q_*(s', a')$$

Q-Learning

Let a be ϵ-greedy w.r.t. Q, and a' be optimal w.r.t. Q. Q converges to Q_* if we iteratively apply the following update:

$$Q(s, a) \leftarrow \alpha(R(s, a) + \gamma Q(s', a')) + (1 - \alpha)Q(s, a)$$

Mathematical formulations

Other approcahes to RL

Value-Based RL

- Estimate $Q_*(s, a)$
- Deep Q Network

Policy-Based RL

- Search directly for optimal policy π_*
- DDPG, TRPO...

Model-Based RL

- Use the (learned or given) transition model of environment
- Tree Search, DYNA ...

Outline

Neural Fitted Q Iteration

```
NFQ_main() {
input: a set of transition samples D; output: Q-value function Q_N
    k=0
    init_MLP() → Q_0;
    Do {
        generate_pattern_set P = {(input^l, target^l), l = 1, ..., #D} where:
            input^l = s^l, u^l,
            target^l = c(s^l, u^l, s'^l) + γ min_b Q_k(s'^l, b)
        Rprop_training(P) → Q_{k+1}
        k:= k+1
    } While (k < N)
```

Fig. 1. Main loop of NFQ

- Supervised learning on (s,a,r,s')

Neural Fitted Q Iteration

input

NFQ_main() {
$\boxed{\text{input: a set of transition samples } D\text{; output: Q-value function } Q_N}$

k=0

init_MLP() $\rightarrow Q_0$;

Do {

generate_pattern_set $P = \{(input^l, target^l), l = 1, \ldots, \#D\}$ where:

$input^l = s^l, u^l$,

$target^l = c(s^l, u^l, s'^l) + \gamma\, min_b Q_k(s'^l, b)$

Rprop_training$(P) \rightarrow Q_{k+1}$

k:= k+1

} While $(k < N)$

Fig. 1. Main loop of NFQ

Neural Fitted Q Iteration

target equation

NFQ_main() {
input: a set of transition samples D; output: Q-value function Q_N

k=0

init_MLP() $\rightarrow Q_0$;

Do {

generate_pattern_set $P = \{(input^l, target^l), l = 1, \ldots, \#D\}$ where:

$$\boxed{\begin{aligned} &input^l = s^l, u^l, \\ &target^l = c(s^l, u^l, s'^l) + \gamma\, min_b Q_k(s'^l, b) \end{aligned}}$$

Rprop_training(P) $\rightarrow Q_{k+1}$

k:= k+1

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Fig. 1. Main loop of NFQ

Neural Fitted Q Iteration

Shortcomings

- Exploration is independent of experience
- Exploitation does not occur at all
- Policy evaluation does not occur at all
- Even in exact(table lookup) case, not guaranteed to converge to Q_*

Outline

Deep Q Network

action policy

Algorithm 1: deep Q-learning with experience replay.
Initialize replay memory D to capacity N
Initialize action-value function Q with random weights θ
Initialize target action-value function $\hat{Q}$ 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**
    $\boxed{\text{With probability } \varepsilon \text{ select a random action } a_t}$
    $\boxed{\text{otherwise select } a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)}$
    $\boxed{\text{Execute action } a_t \text{ in emulator and observe reward } r_t \text{ and image } x_{t+1}}$
    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 $(\phi_j, a_j, r_j, \phi_{j+1})$ from D
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^-\right) & \text{otherwise} \end{cases}$
    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

- Choose an ϵ-greedy policy w.r.t. Q

Deep Q Network

network freezing

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    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
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- Get a copy of the network every C steps for stability

Deep Q Network

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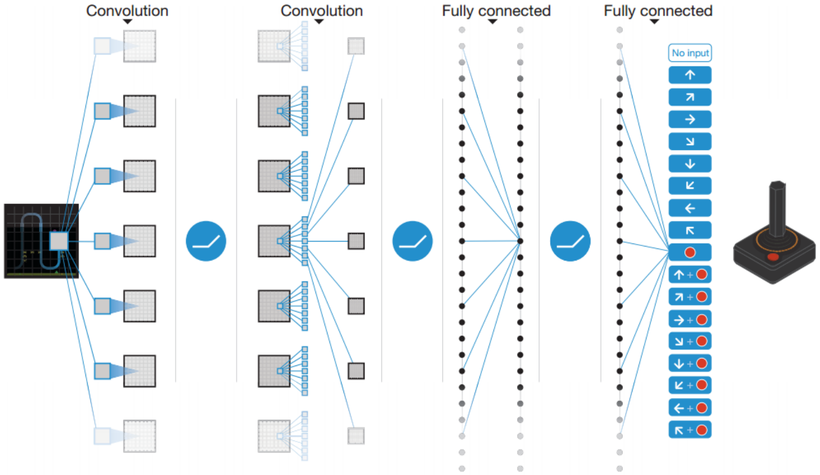
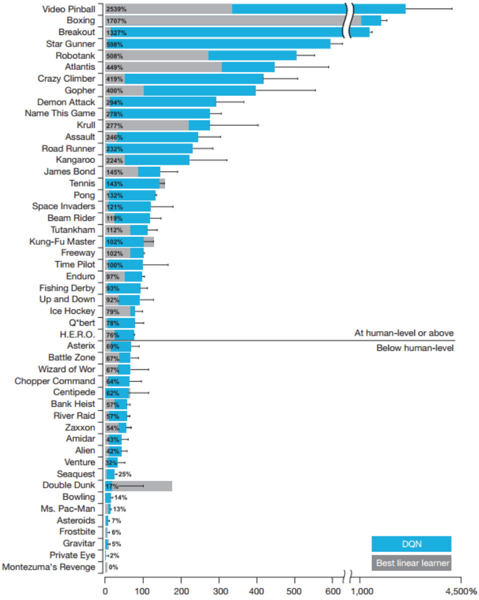
End For

Deep Q Network



Deep Q Network

performance



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Deep Q Network

overoptimism

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    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

- What happens when we overestimate Q?

Deep Q Network

Problems

- Overestimation of the Q function at any s spills over to actions that lead to $s \rightarrow$ Double DQN
- Sampling transitions uniformly from D is inefficient $\rightarrow$ Prioritized Experience Replay

Outline

Double Deep Q Network

target

We can write the DQN target as:

$$Y_t^{DQN} = R_{t+1} + \gamma Q(S_{t+1}, \underset{a}{argmax} Q(S_{t+1}, a; \theta_t^-); \theta_t^-)$$

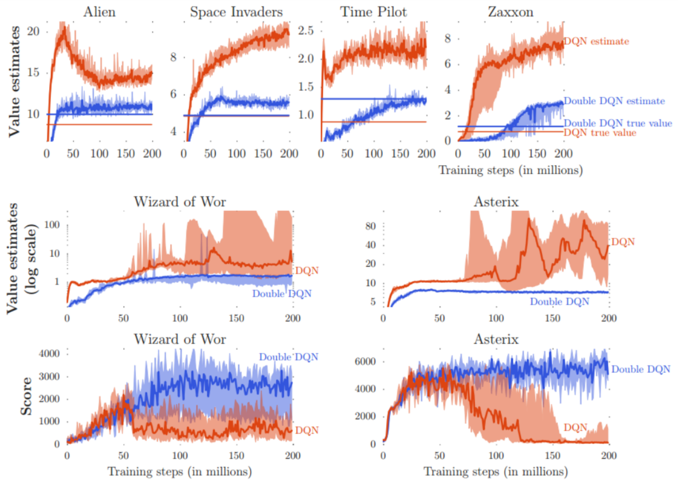
Double DQN's target is:

$$Y_t^{DDQN} = R_{t+1} + \gamma Q(S_{t+1}, \underset{a}{argmax} Q(S_{t+1}, a; \theta_t); \theta_t^-)$$

This has the effect of decoupling action selection and action evaluation

Double Deep Q Network

performance



- Much stabler with very little change in code

Outline

Prioritized Experience Replay

Algorithm 1 Double DQN with proportional prioritization

Input: minibatch k, step-size η, replay period K and size N, exponents α and β, budget T.
Initialize replay memory $\mathcal{H} = \emptyset$, $\Delta = 0$, $p_1 = 1$
Observe S_0 and choose $A_0 \sim \pi_\theta(S_0)$
for $t = 1$ **to** T **do**
  Observe S_t, R_t, γ_t
  Store transition $(S_{t-1}, A_{t-1}, R_t, \gamma_t, S_t)$ in $\mathcal{H}$ with maximal priority $p_t = \max_{i<t} p_i$
  if $t \equiv 0 \mod K$ **then**
    for $j = 1$ **to** k **do**
      Sample transition $j \sim P(j) = p_j^\alpha / \sum_i p_i^\alpha$
      Compute importance-sampling weight $w_j = (N \cdot P(j))^{-\beta} / \max_i w_i$
      Compute TD-error $\delta_j = R_j + \gamma_j Q_{\text{target}}(S_j, \arg\max_a Q(S_j, a)) - Q(S_{j-1}, A_{j-1})$
      Update transition priority $p_j \leftarrow |\delta_j|$
      Accumulate weight-change $\Delta \leftarrow \Delta + w_j \cdot \delta_j \cdot \nabla_\theta Q(S_{j-1}, A_{j-1})$
    end for
    Update weights $\theta \leftarrow \theta + \eta \cdot \Delta$, reset $\Delta = 0$
    From time to time copy weights into target network $\theta_{\text{target}} \leftarrow \theta$
  end if
  Choose action $A_t \sim \pi_\theta(S_t)$
end for

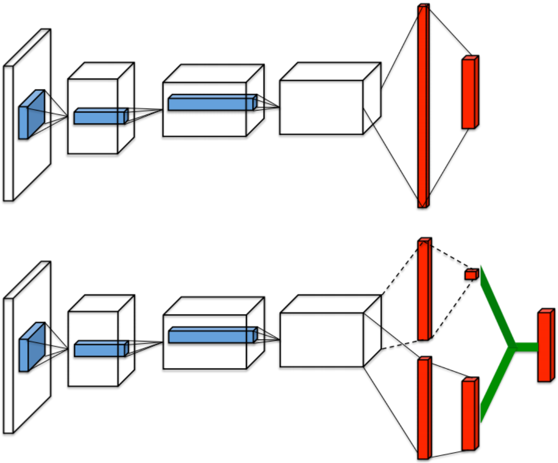
- Update 'more surprising' experiences more frequently

Outline

Reinforcement Learning
- Definition of RL
- Mathematical formulations

Algorithms
- Neural Fitted Q Iteration
- Deep Q Network
- Double Deep Q Network
- Prioritized Experience Replay
- Dueling Network

Dueling Network



- The scalar approximates V, and the vector approximates A

Dueling Network

forward pass equation

The exact forward pass equation is:

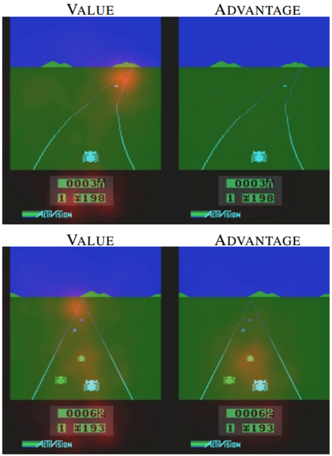
$$Q(s, a; \theta, \alpha, \beta) = V(s; \theta, \beta) + (A(s, a; \theta, \alpha) - \max_{a'} A(s, a'; \theta, \alpha))$$

The following module was found to be more stable without losing much performance:

$$Q(s, a; \theta, \alpha, \beta) = V(s; \theta, \beta) + (A(s, a; \theta, \alpha) - \frac{1}{|A|} \sum_{a'} A(s, a'; \theta, \alpha))$$

Dueling Network

attention



- Advantage network only pays attention when current action crucial

Dueling Network

performance

	30 no-ops		Human Starts	
	Mean	**Median**	**Mean**	**Median**
Prior. Duel Clip	**591.9%**	**172.1%**	**567.0%**	**115.3%**
Prior. Single	434.6%	123.7%	386.7%	112.9%
Duel Clip	**373.1%**	**151.5%**	**343.8%**	**117.1%**
Single Clip	341.2%	132.6%	302.8%	114.1%
Single	307.3%	117.8%	332.9%	110.9%
Nature DQN	227.9%	79.1%	219.6%	68.5%

- Achieves state of the art in the Atari domain among DQN algorithms

Dueling Network

Summary

- Since this is an improvement only in network architecture, methods that improve DQN(e.g. Double DQN) are all applicable here as well
- Solves problem of V and A typically being of different scale
- Updates Q values more frequently than a single-stream DQN, where only a single Q value is updated for each observation
- Implicitly splits the credit assignment problem into a recursive binary problem of "now or later"

Dueling Network

Shortcomings

- Only works for $|A| < \infty$
- Still not able to solve tasks involving long-term planning
- Better than DQN, but sample complexity is still high
- ϵ-greedy exploration is essentially random guessing