

Deep Reinforcement Learning with Double Q-learning

Double DQN

Q-learning

$Q - value$: 상태(s_t)에서 행동(a_t)을 했을 때의 평균 *Return* $G_t = R_{t+1} + \gamma R_{t+2} + \dots + R_{t+\infty}$

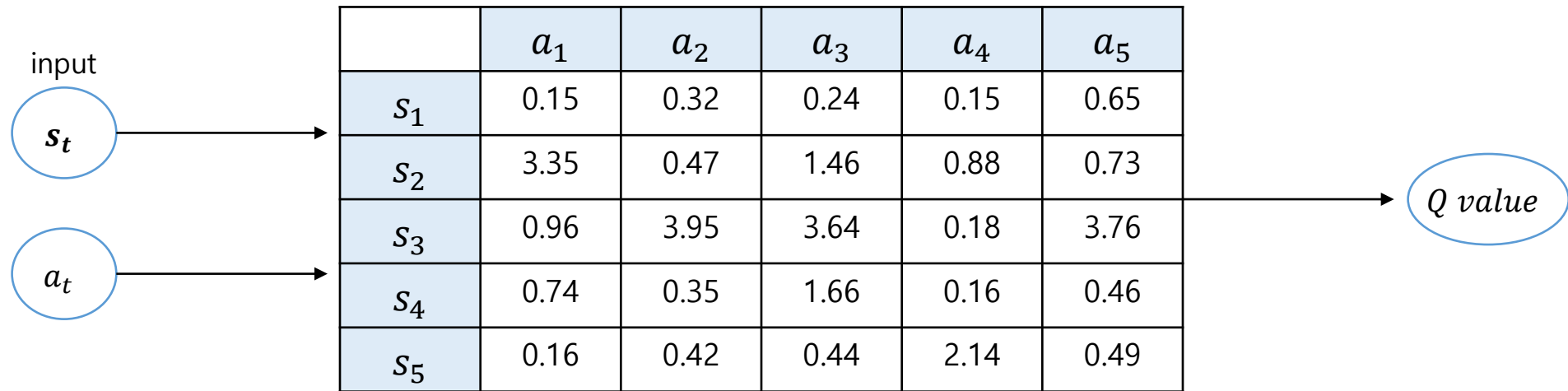
각각의 $Q - value$ 를 최대화하는 방향으로 학습하여 최종적인 optimal Q 를 학습

Q-learning의 update

$$Q(s_t, a_t) \leftarrow (1 - \alpha)Q(s_t, a_t) + \alpha(R_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}))$$

Q-learning

Example)



단점 : $n(s)$ 또는 $n(a)$ 가 많아질수록 많은 양의 공간을 필요로 한다.

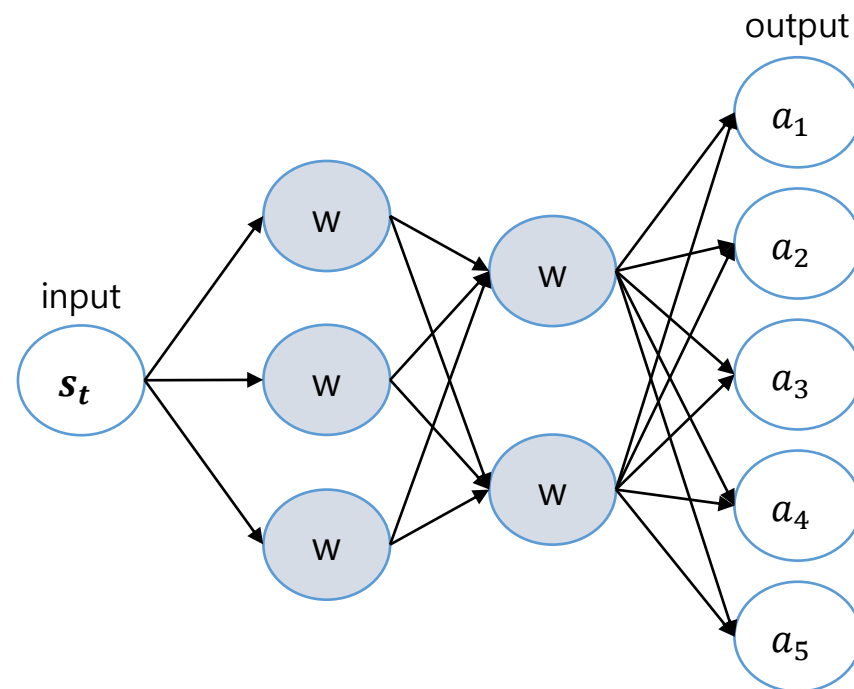
DQN

상태(s_t)에서의 모든 행동(a_t)에 대한 Q 값을 예측

Example)

input			a_1	a_2	a_3	a_4	a_5	
s_t	s_1	0.15	0.32	0.24	0.15	0.65	$Q\ value$	
	s_2	3.35	0.47	1.46	0.88	0.73		
	s_3	0.96	3.95	3.64	0.18	3.76		
s_4	0.74	0.35	1.66	0.16	0.46			
s_5	0.16	0.42	0.44	2.14	0.49			

Q-learning



Deep Neural Network + Q-learning

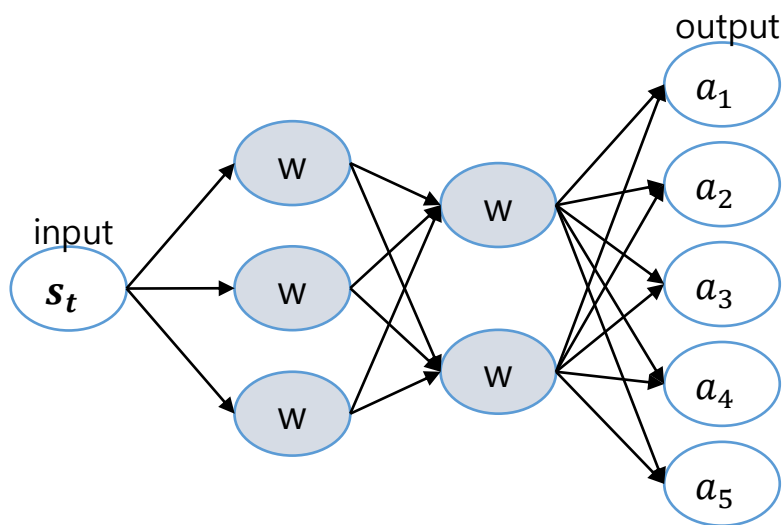
DQN

$$Q(s_t, a_t) \leftarrow (1 - \alpha)Q(s_t, a_t) + \alpha(R_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}))$$

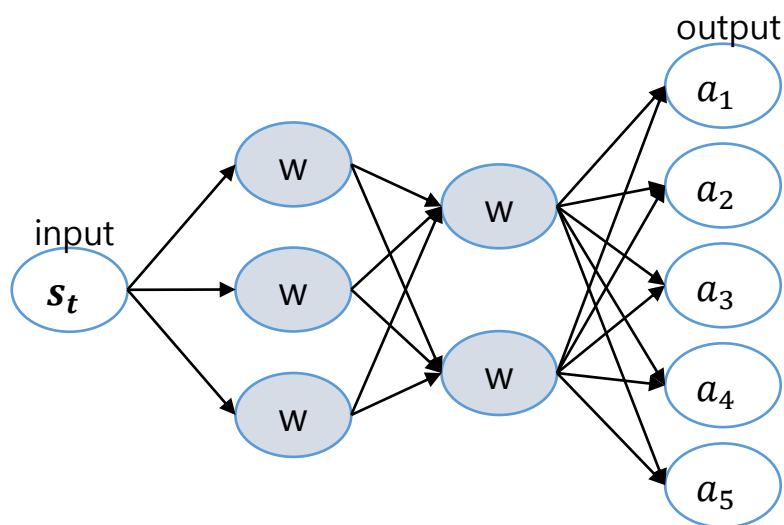


Fixed Q_{target}

$$Q(s_t, a_t; w_{main}) \leftarrow (1 - \alpha)Q(s_t, a_t; w_{main}) + \alpha(R_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; w_{target}))$$



main

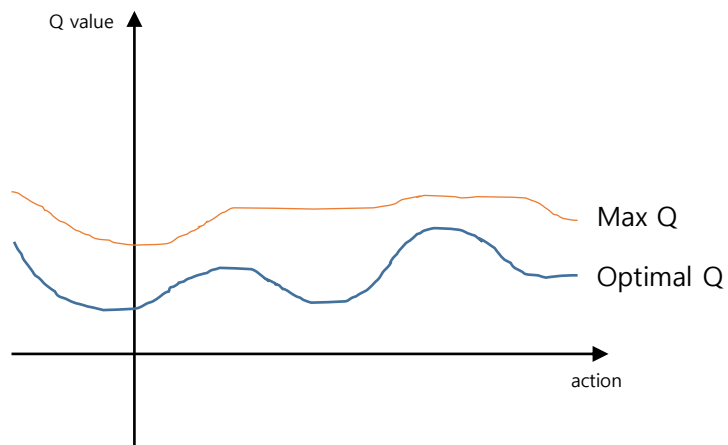


target

DQN

$$Q(s_t, a_t; w_{main}) \leftarrow (1 - \alpha)Q(s_t, a_t; w_{main}) + \alpha(R_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; w_{target}))$$

단점 : Q-learning의 overestimate action values



$$Max\ Q - Optimal\ Q \geq \sqrt{\frac{C}{m-1}} \quad (C > 0, m: action\ 의\ 총\ 개수)$$

Let $\varepsilon_a = Q(s_t, a_t) - Q^*(s_t, a_t)$

Goal

$$\text{Max } Q - \text{Optimal } Q \geq \sqrt{\frac{C}{m-1}} \quad (C > 0, m: n(\text{action}))$$

Condition

1. s_t 가 주어졌을 때 모든 action에 대해 $Q^*(s_t, a_t)$ 의 값이 같다.
2. $\sum_a \varepsilon_a = 0$
3. $\frac{1}{m} \sum_a \varepsilon_a^2 = C$ $(C > 0, m: \text{action의 총 개수})$

Condition

$$2. \sum_a \varepsilon_a = 0$$

$$3. \frac{1}{m} \sum_a \varepsilon_a^2 = C \quad (C > 0, m: \text{action의 총 개수})$$

Let $n: \varepsilon_a^+ (\varepsilon_a > 0)$ 의 *action*의 개수, $m - n: \varepsilon_a^- (\varepsilon_a \leq 0)$ 의 *action*의 개수

Case 1) 모든 $\varepsilon_a = 0$ 이면 Condition 2는 성립하지만 Condition 3 불만족이라 성립이 되지 않는다.

Case 2) $m - n \geq 1, n \geq 1$ 이면 Condition 2가 성립하며 Condition 3가 성립할 수 있다.

Case 2) $m - n \geq 1, n \geq 1$

$$\therefore \sum_a \varepsilon_a^+ \leq n \times \max \varepsilon_a^+$$

Assume : $\max \varepsilon_a < \sqrt{\frac{c}{m-1}}$

논리적 오류를 통한 증명

Assume : $\max \varepsilon_a < \sqrt{\frac{c}{m-1}}$

이 모순임을 보여,

Proof : $\max \varepsilon_a \geq \sqrt{\frac{c}{m-1}}$

을 증명

Case 2) $m - n \geq 1, n \geq 1$

$$\therefore \sum_a \varepsilon_a^+ \leq n \times \max \varepsilon_a^+$$

Assume : $\max \varepsilon_a < \sqrt{\frac{c}{m-1}}$

$$1. \sum_a |\varepsilon_a^-| \leq n \times \max |\varepsilon_a^-| < n \times \sqrt{\frac{c}{m-1}}$$

$$2. \sum_a \varepsilon_a^+ \leq n \times \max \varepsilon_a^+ < n \times \sqrt{\frac{c}{m-1}}$$

$$1. \sum_a |\varepsilon_a^-| \leq n \times \max |\varepsilon_a^-| < n \times \sqrt{\frac{C}{m-1}}$$

$$\Rightarrow \sum_a |\varepsilon_a^-| \times \sum_a |\varepsilon_a^-| \leq \sum_a |\varepsilon_a^-| \times \max |\varepsilon_a^-| < \left(n \times \max |\varepsilon_a^-| \right)^2 < \left(n \times \sqrt{\frac{C}{m-1}} \right)^2$$

$$\Rightarrow \sum_a |\varepsilon_a^-|^2 \leq \sum_a |\varepsilon_a^-| \times \max |\varepsilon_a^-| < \frac{n^2 \times C}{m-1}$$

$$\Rightarrow \sum_a |\varepsilon_a^-|^2 \leq \sum_a |\varepsilon_a^-| \times \max |\varepsilon_a^-| < \frac{n^2 \times C}{m-1} < (m-1) \times C \quad \because m-n \geq 1 \rightarrow m-1 \geq n$$

$$2. \sum_a \varepsilon_a^+ \leq n \times \max \varepsilon_a^+ < n \times \sqrt{\frac{C}{m-1}}$$

$$\Rightarrow \sum_a \varepsilon_a^+ \times \sum_a \varepsilon_a^+ \leq \sum_a \varepsilon_a^+ \times \max \varepsilon_a^+ < n \times (\max \varepsilon_a^+)^2 < n \times \left(\sqrt{\frac{C}{m-1}} \right)^2$$

$$\Rightarrow \sum_a (\varepsilon_a^+)^2 \leq n \times \frac{C}{m-1}$$

$$1. \sum_a |\varepsilon_a^-|^2 \leq \sum_a |\varepsilon_a^-| \times \max |\varepsilon_a^-| < \frac{n^2 \times C}{m-1} < (m-1) \times C$$

$$2. \sum_a (\varepsilon_a^+)^2 \leq n \times \frac{C}{m-1}$$

$$\Rightarrow \sum_a |\varepsilon_a^-|^2 + \sum_a (\varepsilon_a^+)^2 \leq \sum_a |\varepsilon_a^-| \times \max |\varepsilon_a^-| + \sum_a (\varepsilon_a^+)^2 < \frac{n^2 \times C}{m-1} + \frac{n \times C}{m-1}$$

$$\Rightarrow \sum_a (\varepsilon_a)^2 \leq \sum_a |\varepsilon_a^-| \times \max |\varepsilon_a^-| + \sum_a (\varepsilon_a^+)^2 < \frac{n^2 \times C}{m-1} + \frac{n \times C}{m-1} < (m-1) \times C + C \quad \because m-1 \geq n$$

$$\Rightarrow \sum_a (\varepsilon_a)^2 < m \times C$$

$$\text{Assume : } \max \varepsilon_a < \sqrt{\frac{C}{m-1}}$$

$$\text{최종 식 : } \sum_a (\varepsilon_a)^2 < m \times C$$

$$(\text{Condition 3. } \frac{1}{m} \sum_a \varepsilon_a^2 = C \text{ 에 모순})$$

Conclusion

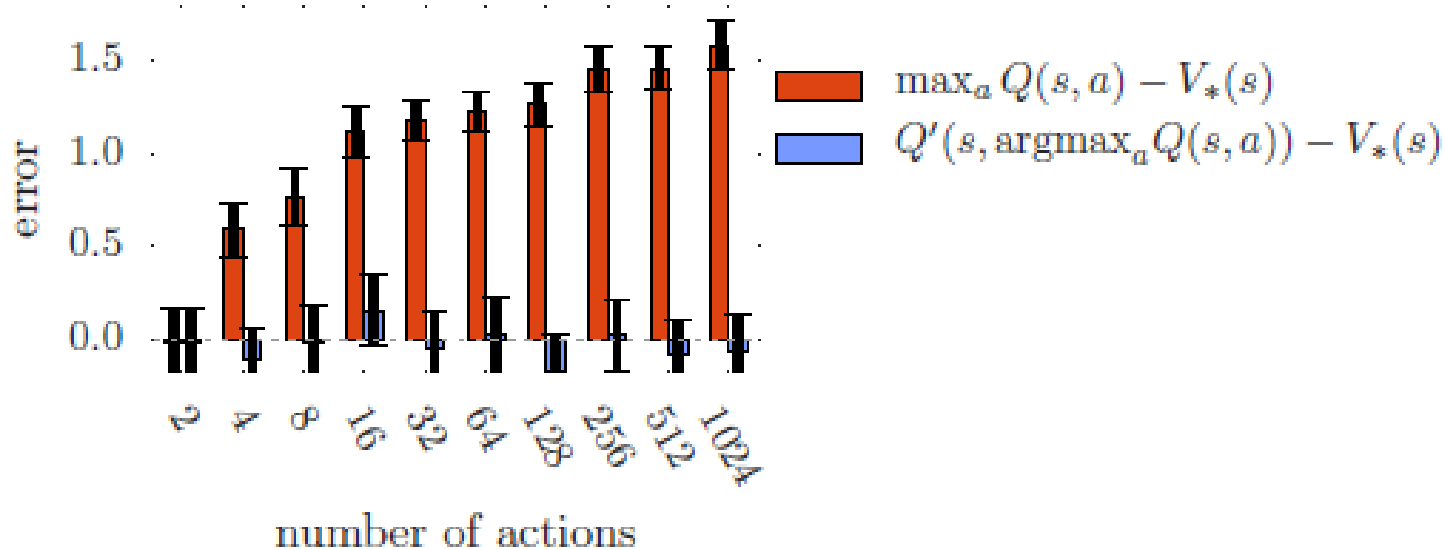
$$\text{Assume : } \max \varepsilon_a < \sqrt{\frac{C}{m-1}} \text{ 의 역인 } \text{Proof : } \max \varepsilon_a \geq \sqrt{\frac{C}{m-1}} \text{ 가 참이다.}$$

Double DQN

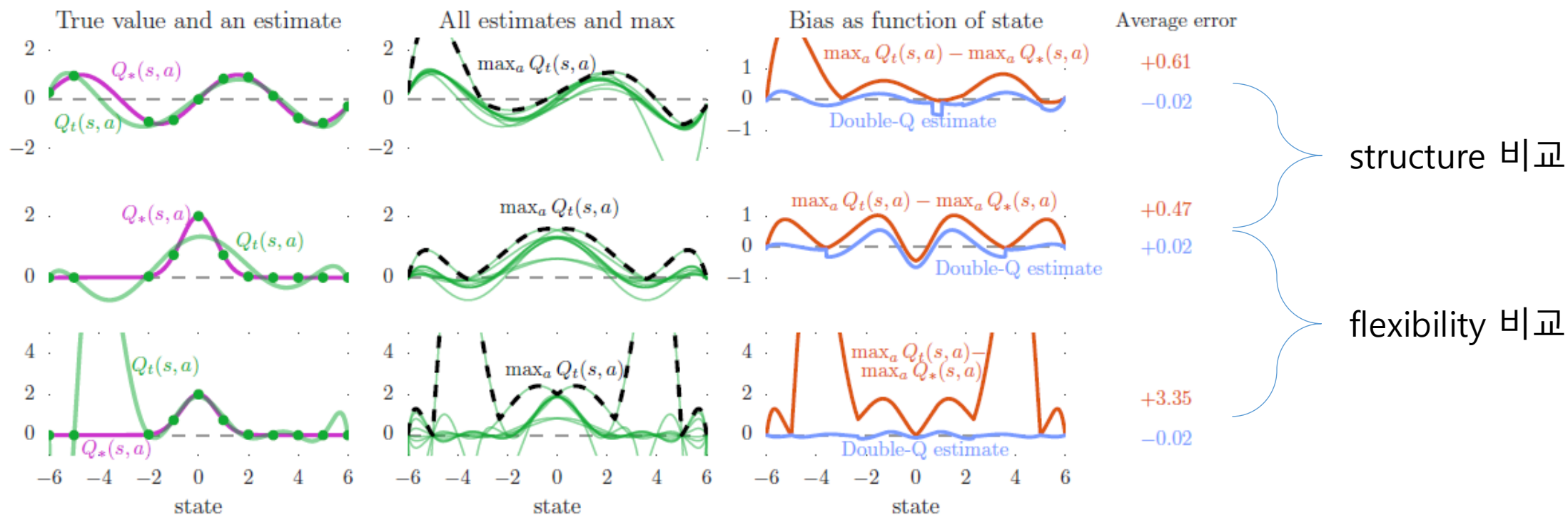
$$Q(s_t, a_t; w_{main}) \leftarrow (1 - \alpha)Q(s_t, a_t; w_{main}) + \alpha(R_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; w_{target}))$$



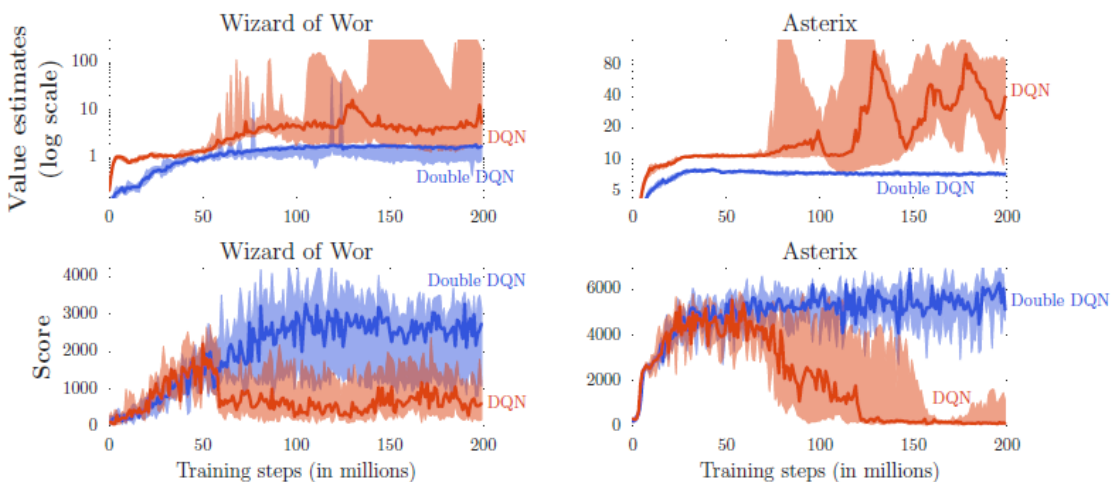
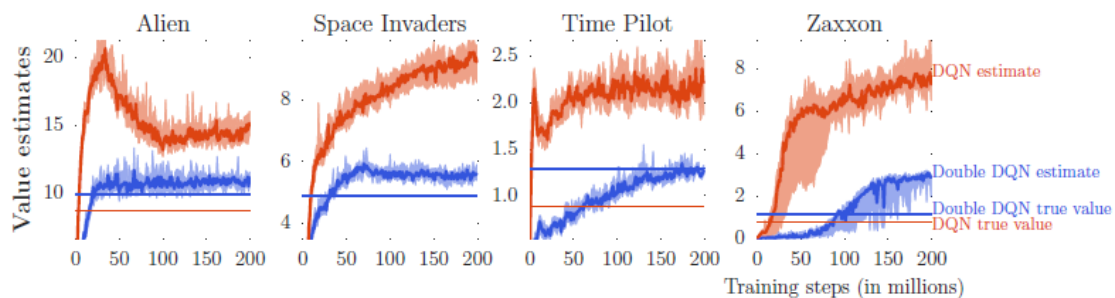
$$Q(s_t, a_t; w_{main}) \leftarrow (1 - \alpha)Q(s_t, a_t; w_{main}) + \alpha(R_{t+1} + \gamma Q(s_{t+1}, \arg\max_{a_{t+1}} Q(s_{t+1}, a_{t+1}; w_{main}); w_{target}))$$



Double DQN



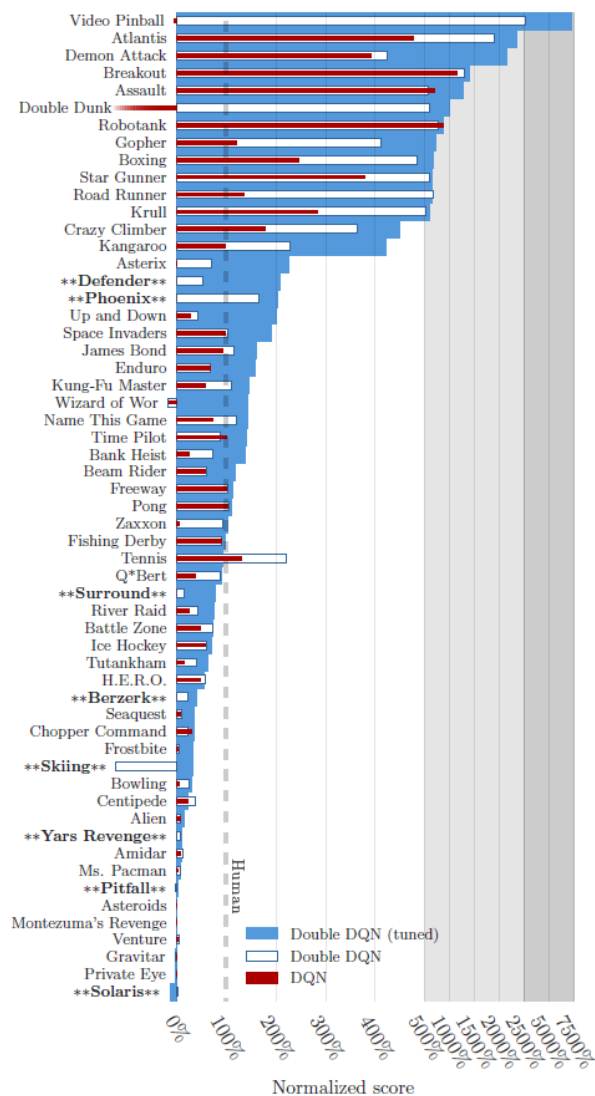
Double DQN



$$\frac{1}{T} \sum_{t=1}^T \max_a Q(s_t, a; w), \quad T = 125,000$$

Training step마다 $\max_a Q(s_t, a; w)$ 의 평균 값 비교

Double DQN



	DQN	Double DQN
Median	93.5%	114.7%
Mean	241.1%	330.3%

5분 학습 후 DQN(2015)와 성능 비교

	DQN	Double DQN	Double DQN (tuned)
Median	47.5%	88.4%	116.7%
Mean	122.0%	273.1%	475.2%

30분 학습 후 Human과 성능 비교

Double DQN

Five contributions

1. Q-learning의 내재인 추정 오류 때문에 overestimate가 될 수 있다는 것
2. Atari 2600 분석을 통해 overestimate가 실제로 더 흔하고 심각하다는 것
3. DQN에서 추가적인 네트워크나 매개 변수 없이 Double Q-learning을 적용
4. Double Q-learning을 적용함으로써 더 안정적인 학습이 가능하다는 것
5. Double DQN이 더 좋은 policy를 찾으며, Atari 2600에서 State-Of-The-Art를 보여주었다는 것

Thank you

Double DQN