Google Developer Group
Incheon National University

Playing Atari with Deep Reinforcement Learning

GDGoC INU AI Part Paper Seminar
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1. Introduction

1. Introduction

- 목표: 다양한 Atari game을 잘하는 강화학습 모델 제작
- Atari game 예시:

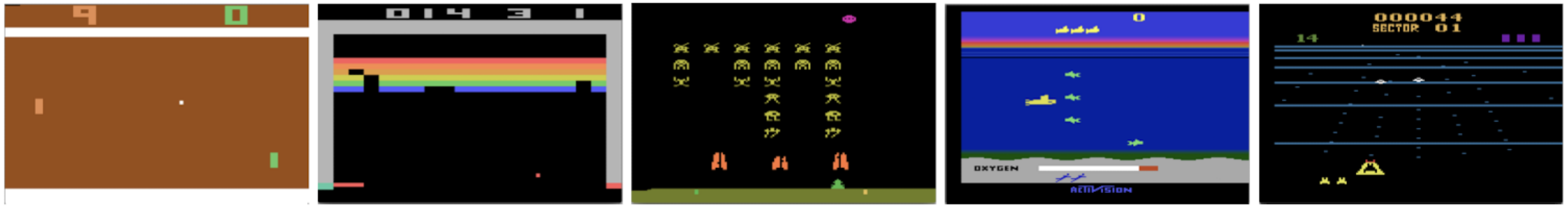

Figure 1. Atari games

https://youtu.be/V1eYniJ0Rnk?feature=shared&t=24

2. Background

2. Background

Reinforcement Learning Architecture

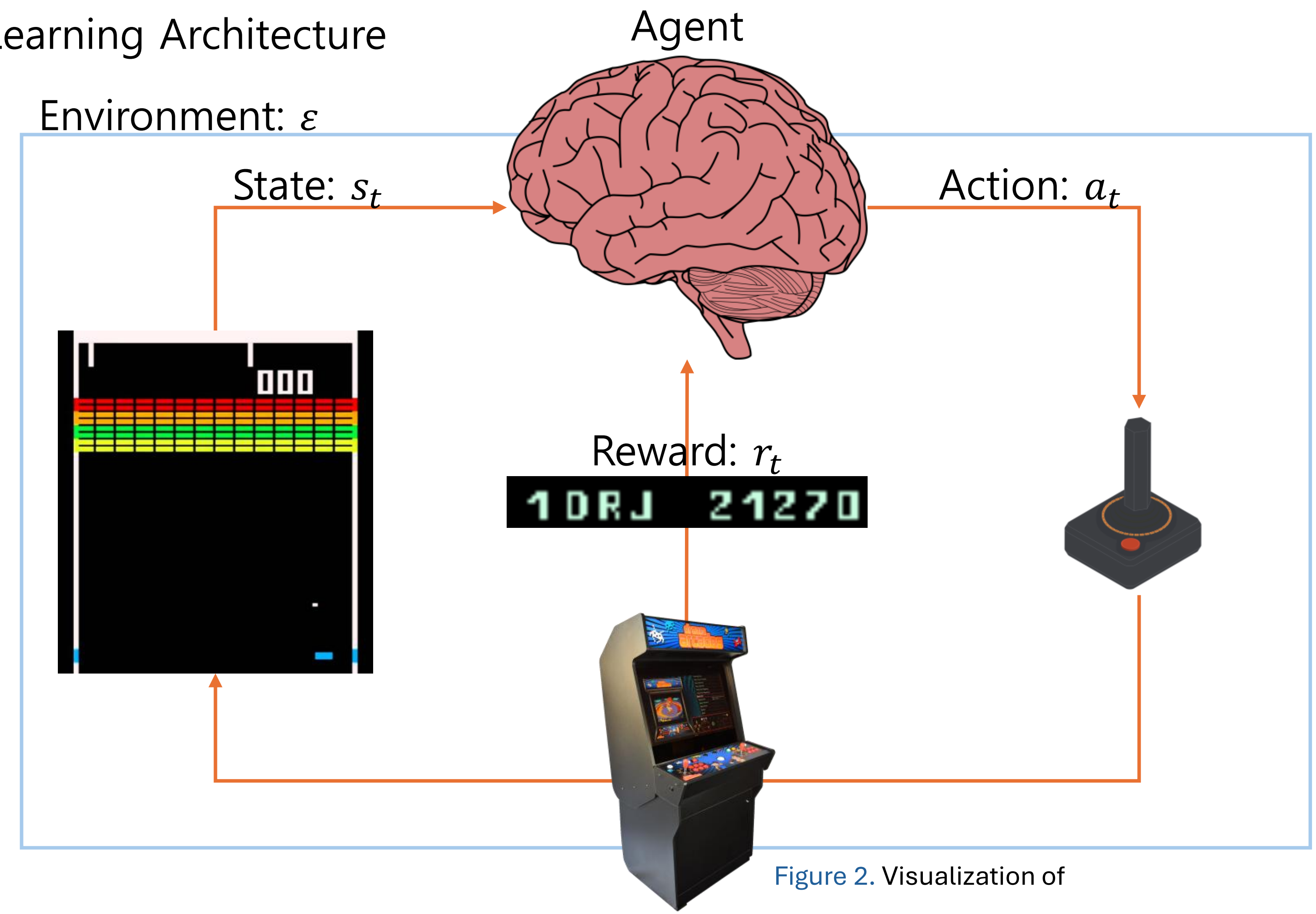

Figure 2. Visualization of

Image: $x_t \in \mathbb{R}^d$, a vector of raw pixel values representing the current screen

State: $s_t = x_1, a_1, x_2, \cdots, a_{t-1}, x_t$

2. Background

목표: return을 최대화하는 action하기

Return:

$$R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$$

T: game terminates

γ: time-step, $\gamma \in [0, 1]$ $\longrightarrow$ 1. 발산 방지 2. 빠르게 reward 받는 것을 선호

$\longrightarrow$ return 값은 미래 보상에 의존

$\longrightarrow$ return 값을 예측하는 optimal action-value function인 Q^* 사용(학습): Q-learning

Optimal action-value function(Q function):

$$Q^*(s, a) = \mathbb{E}_{s' \sim \varepsilon}[r + \gamma Q^*(s', a') \mid s, a]$$

$r + \gamma Q^*(s', a')$: R_t의 점화식 표현

변환된 목표: Q function 값을 최대화하는 action하기

2. Background

Q-learning: 총 {‘state 수’ × ‘action 수’}개의 Q 함수 필요

	→	←	↑	↓
Start	0	0	0	0
Idle	0	0	0	0
Hole	0	0	0	0
End	0	0	0	0

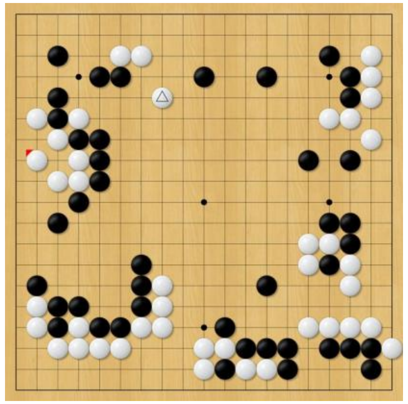

Figure 3. Q 함수 행렬 및 바둑

⟶ Q-Network

⟶ Network를 통해 Q 함수를 학습

$Q(s,a;\theta) \approx Q^*(s,a)$: Weights θ as a Q-Networks

⟶ $L_i(\theta_i) = \mathbb{E}_{(s,a,r,s')\sim\rho(\cdot)}[(y_i - Q(s,a;\theta_i))^2]$, each iteration i : 오차가 정규분포에 따라 모델링 가능하다고 가정

⟶ $\rho(s,a)$: behaviour distribution ⟶ 일반적으로 uniform distribution 사용

2. Background

ϵ-greedy Algorithm: 가끔 랜덤한 시도를 진행

$$a = \begin{cases} \max_a Q(s, a; \theta), & p \leq \epsilon \\ random\ action, & otherwise \end{cases}, \qquad random\ value\ p \in [0, 1]$$

3. Deep Reinforcement Learning

3. Deep Reinforcement Learning

Experience Replay: 메모리를 사용하여 성능 향상

Experience: $e_t = (s_t, a_t, r_t, s_{t+1})$

Replay Buffer: Data-set $\mathcal{D} = e_1, \cdots, e_N$: 이전 경험들을 저장

Deep Q-learning

State Representation: $\phi(s_t) = stacked[x_{t-3}, x_{t-2}, x_{t-1}, x_t]$

$\longrightarrow$ DQN의 입력 값으로 전처리 되었음 $\longrightarrow$ 최근 4개 상황의 프레임을 저장

$\phi(s_t) \longrightarrow$

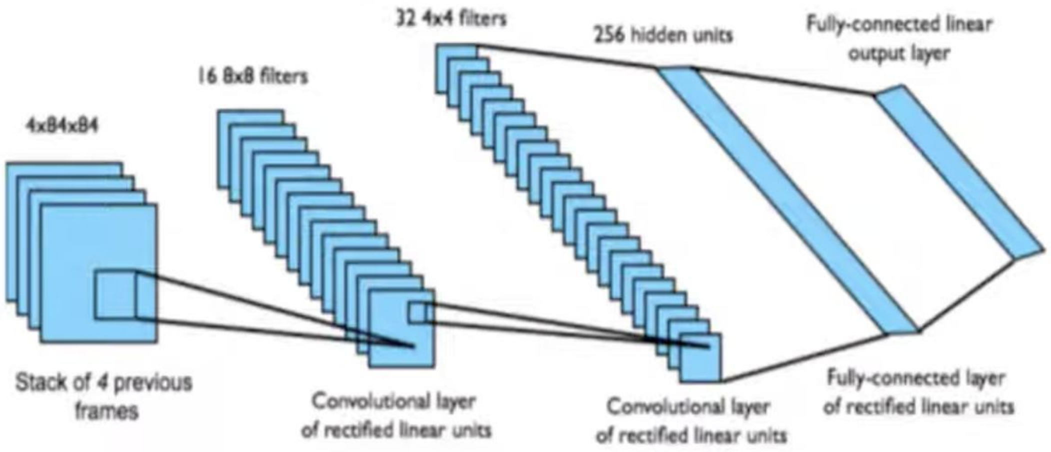

Figure 4. Network architecture

3. Deep Reinforcement Learning

Deep Q-learning

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do** How many times the agent plays the game
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$ $= stacked[x_1, x_1, x_1, x_1]$
  for $t = 1, T$ **do** Game start
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$ ϵ –greedy algorithm: select action
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
1) Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
2) Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  Learning
  end for Equation 3: $\nabla_{\theta_i} L_i(\theta_i)$
end for

1. State: $s_t = x_1, a_1, x_2, \cdots, a_{t-1}, x_t$
2. Transition $(\phi_t, a_t, r_t, \phi_{t+1})$: $e_t: (s_t, a_t, r_t, s_{t+1}) \rightarrow (\phi_t, a_t, r_t, \phi_{t+1})$, state representation

3. Deep Reinforcement Learning

DQN vs Q-learning

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$ → 데이터 재활용하여 효율적 학습 가능
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    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 $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$ → 랜덤으로 minibatch를 불러와서 근방의 큰 상관관계를 낮춤: 유사한 상황에서 반복된 action이 일어나는 것을 방지
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation $\boxed{3}$
  end for
end for

4.1. Preprocessing

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210 x 160 pixels

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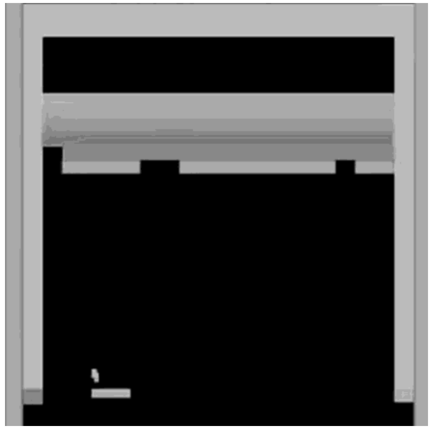
210 x 160 pixels
Gray Scale

4.1. Preprocessing

110 x 84 pixels

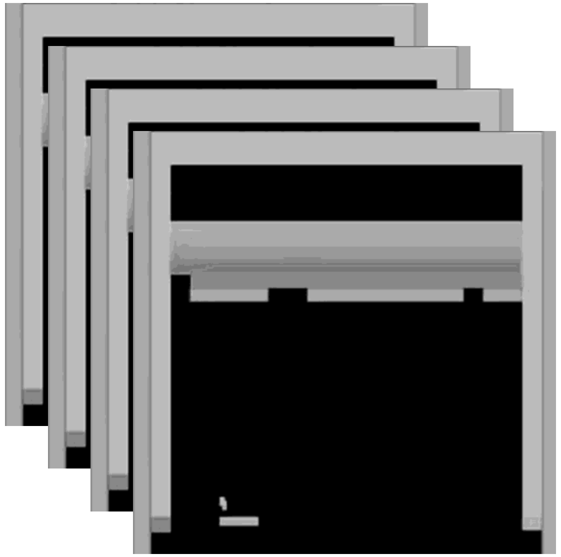
4.1. Preprocessing

84 x 84 pixels



4.1. Preprocessing

84 x 84 x 4



4.2. Model Architecture

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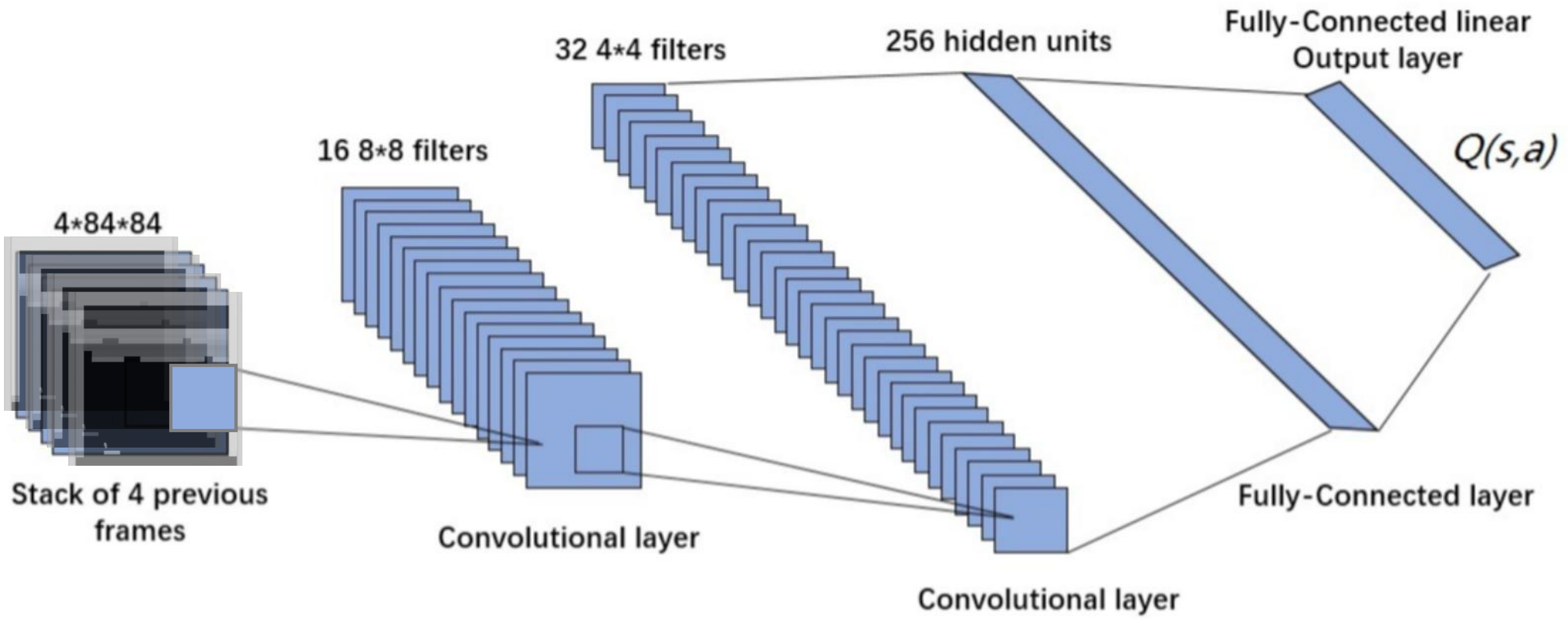
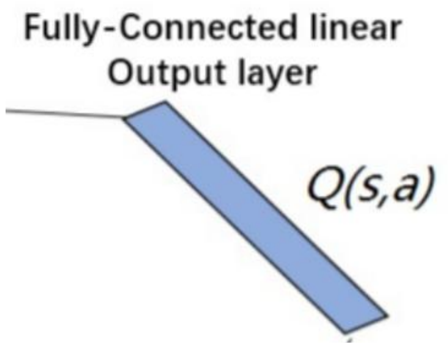


Figure 2.1: DQN structure

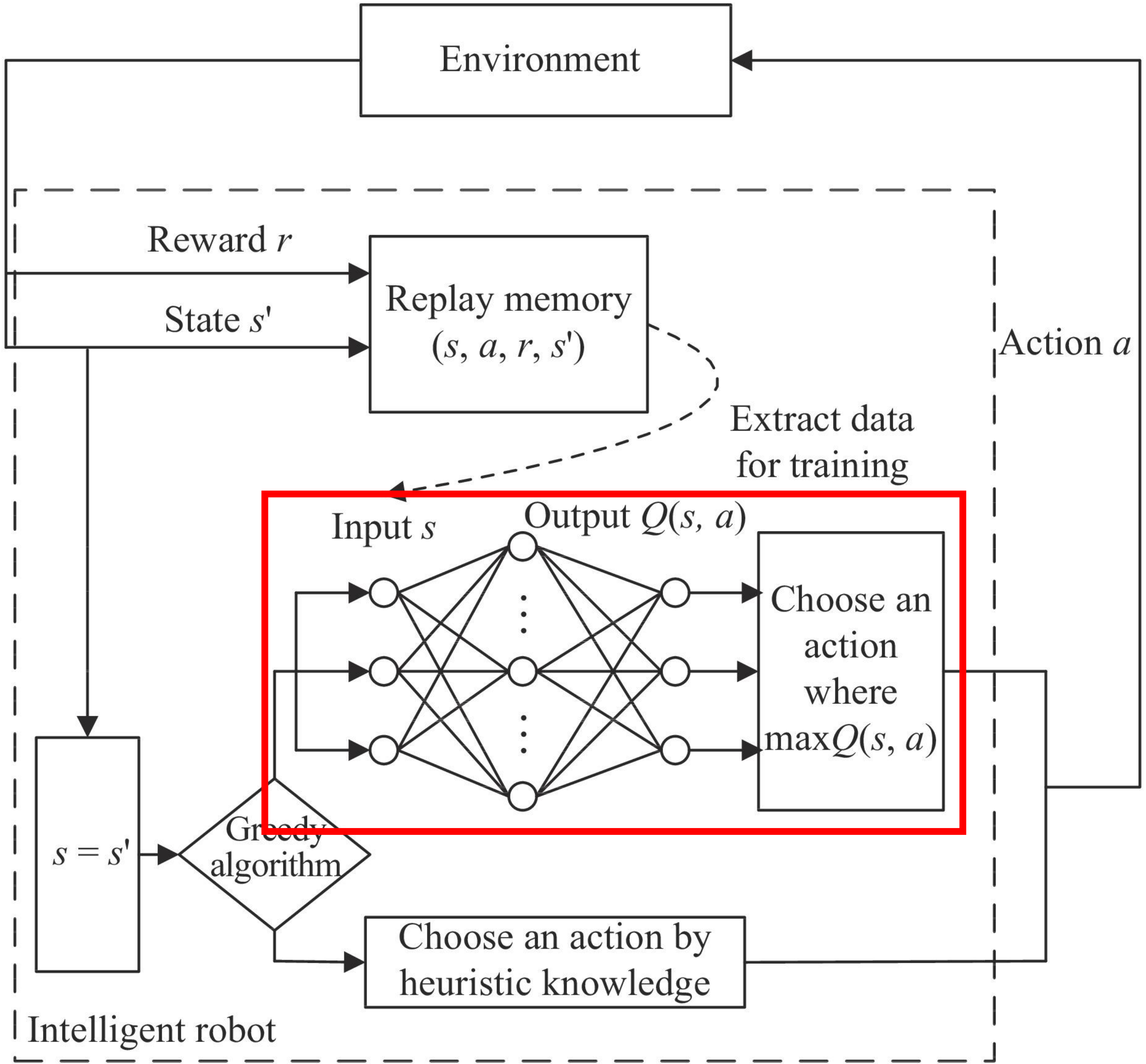
4.2. Model Architecture



e.g.

- a_1 : $move\ left$ — $Q(s, a_1) = 2.5$
- a_2 : $move\ right$ — $Q(s, a_2) = 3.8$
- a_3 : $fire$ — $Q(s, a_3) = 1.0$
- a_4 : $nothing$ — $Q(s, a_4) = 0.2$

4.2. Model Architecture

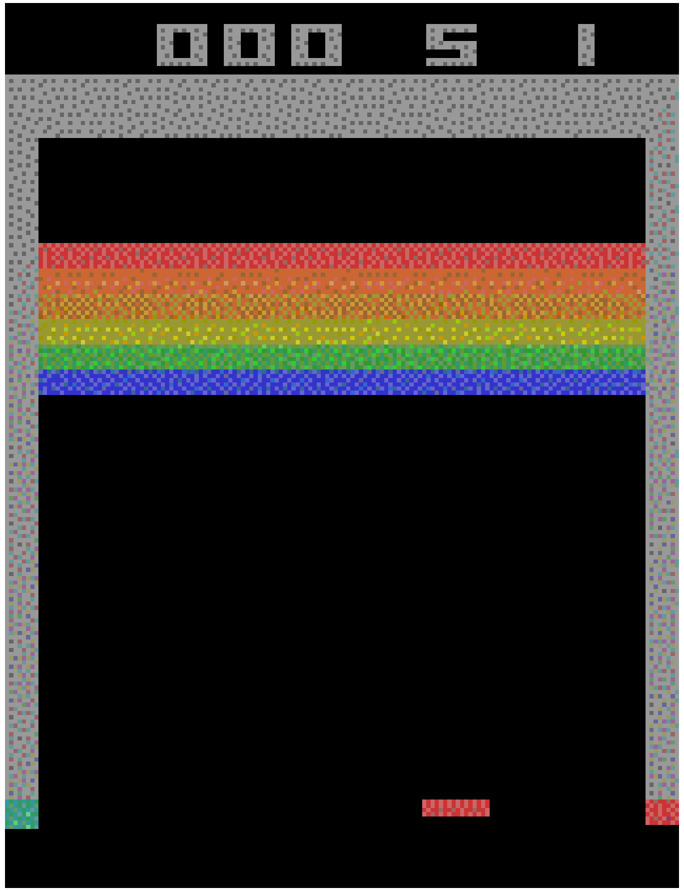


5. Experiments

평가 지표

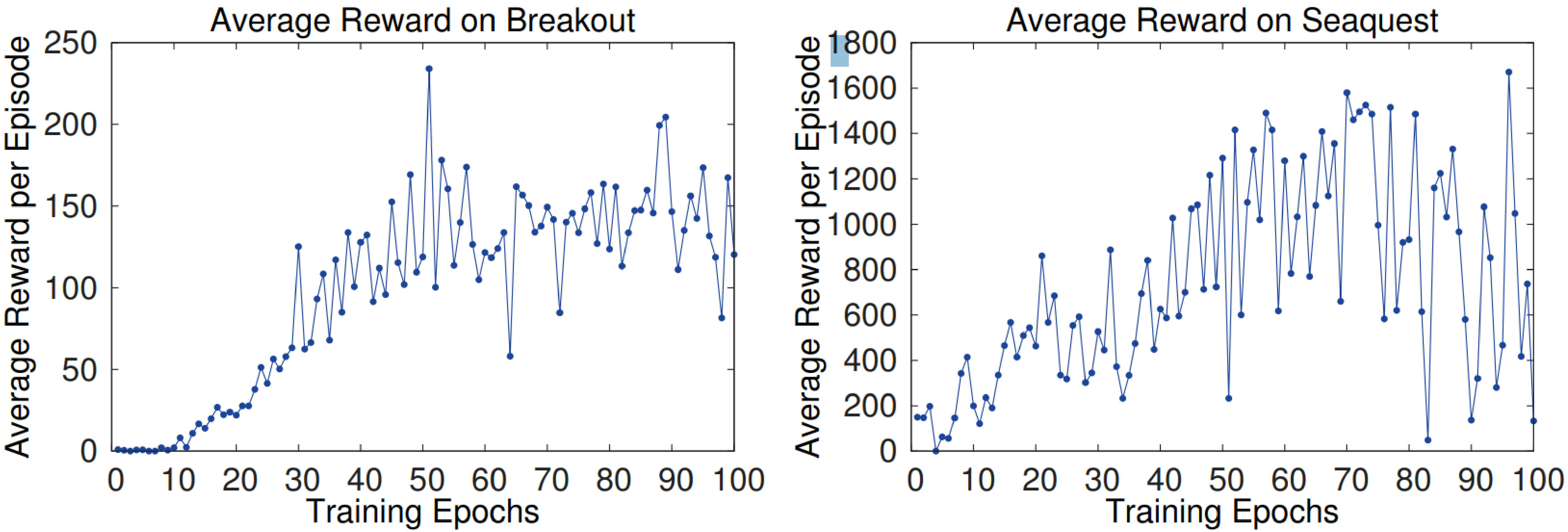
5. Experiments

Seaquest



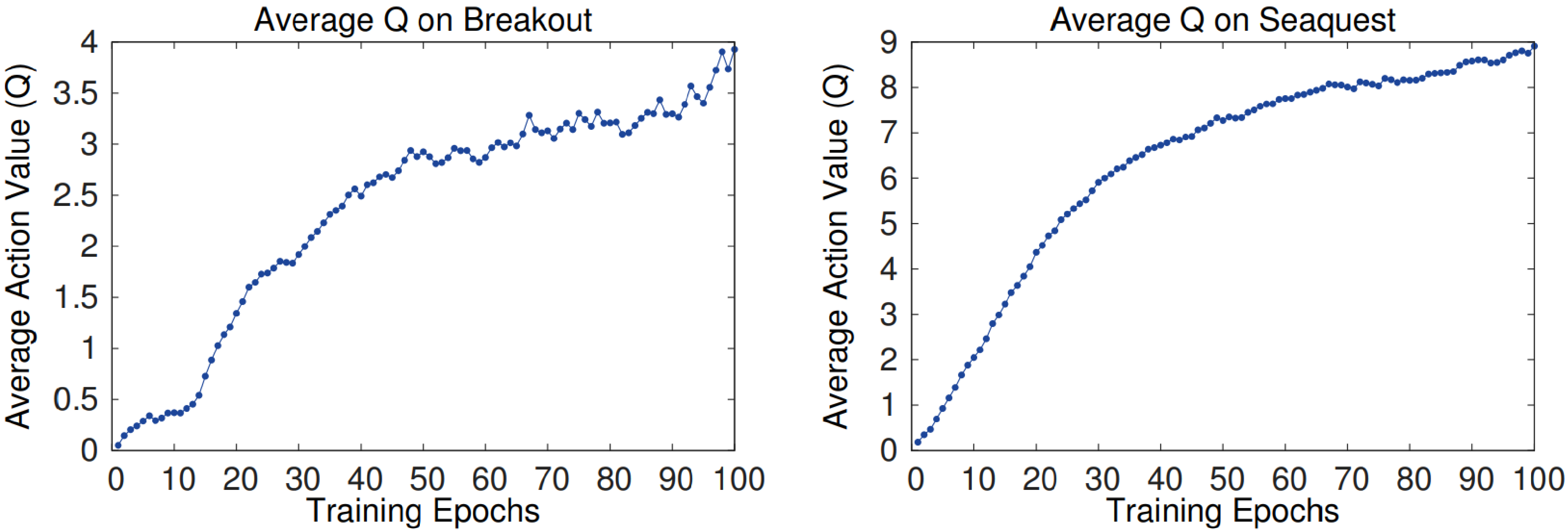
Breakout

5. Experiments



평균 보상 값

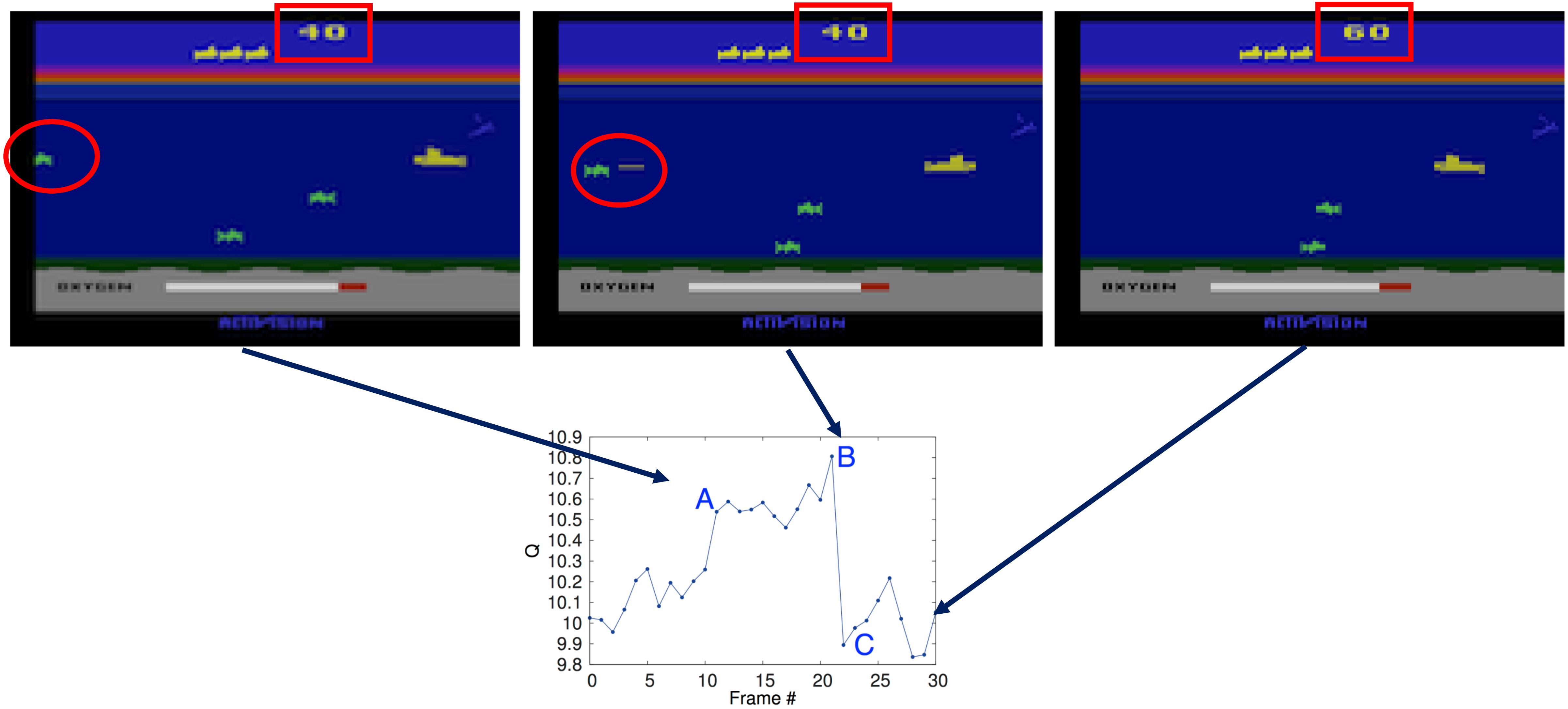
5. Experiments



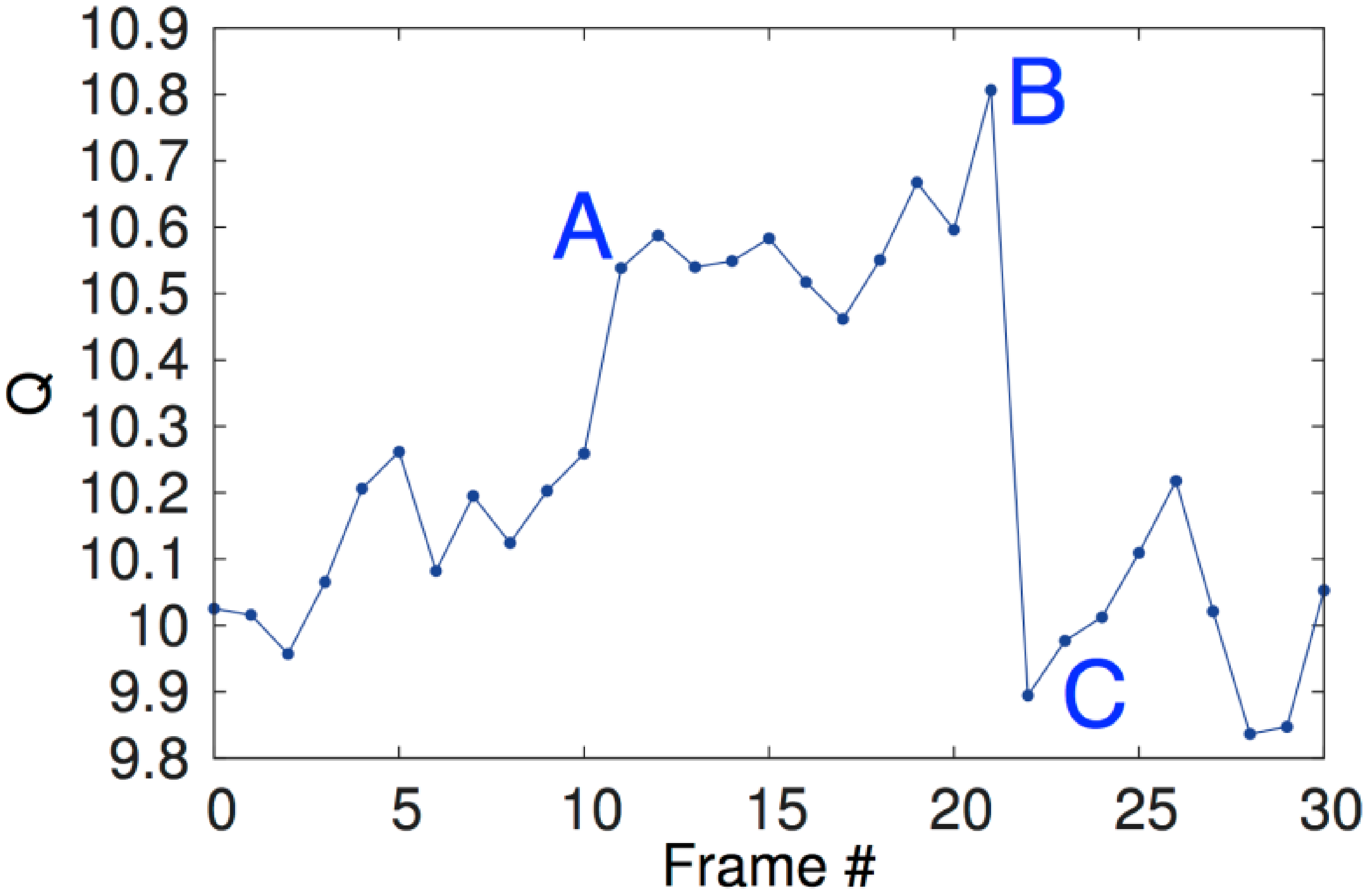
평균 maxQ 값

Q값의 시각화

5. Experiments



5. Experiments



5.1. Main Evaluation

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	B. Rider	Breakout	Enduro	Pong	Q*bert	Seaquest	S. Invaders
Random	354	1.2	0	−20.4	157	110	179
Sarsa [3]	996	5.2	129	−19	614	665	271
Contingency [4]	1743	6	159	−17	960	723	268
DQN	**4092**	**168**	**470**	**20**	**1952**	**1705**	**581**
Human	7456	31	368	−3	18900	28010	3690
HNeat Best [8]	3616	52	106	19	1800	920	**1720**
HNeat Pixel [8]	1332	4	91	−16	1325	800	1145
DQN Best	**5184**	**225**	**661**	**21**	**4500**	**1740**	1075

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6. Conclusion

- “강화학습을 위한 새로운 딥러닝 모델”
- RAW 픽셀만을 입력으로 사용하여 end-to-end 강화학습을 성공시킴.
- 별도의 하이퍼파라미터 조정없이 7개 게임 중 6개에서 기존 대비 최고성능을 기록
- Q-learning의 변형 알고리즘 제안

Q & A