DEVIEW 2016

딥러닝과 강화 학습으로 나보다 잘하는 쿠키런 AI 구현하기

김태훈
DEVSISTERS

저는

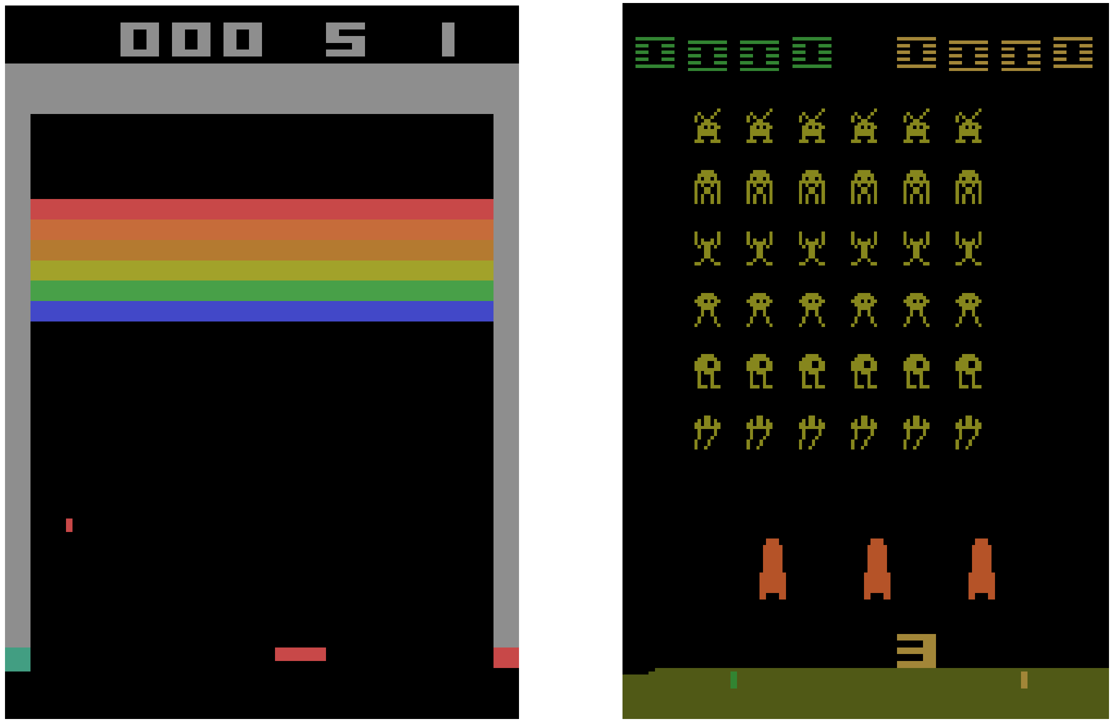
UNIST 졸업

DEVSISTERS 병특

EMNLP, DataCom, IJBDI 논문 게재

http://carpedm20.github.io

딥러닝 + 강화 학습



Playing Atari with Deep Reinforcement Learning (2013)

https://deepmind.com/research/dqn/

Mastering the game of Go with deep neural networks and tree search (2016)

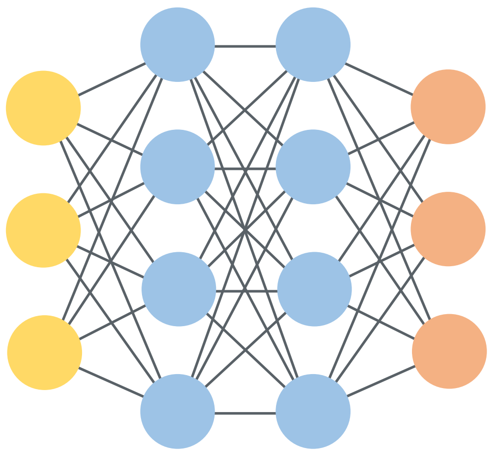
https://deepmind.com/research/alphago/

VIZDOOM (2016)

http://vizdoom.cs.put.edu.pl/

딥러닝 + 강화 학습

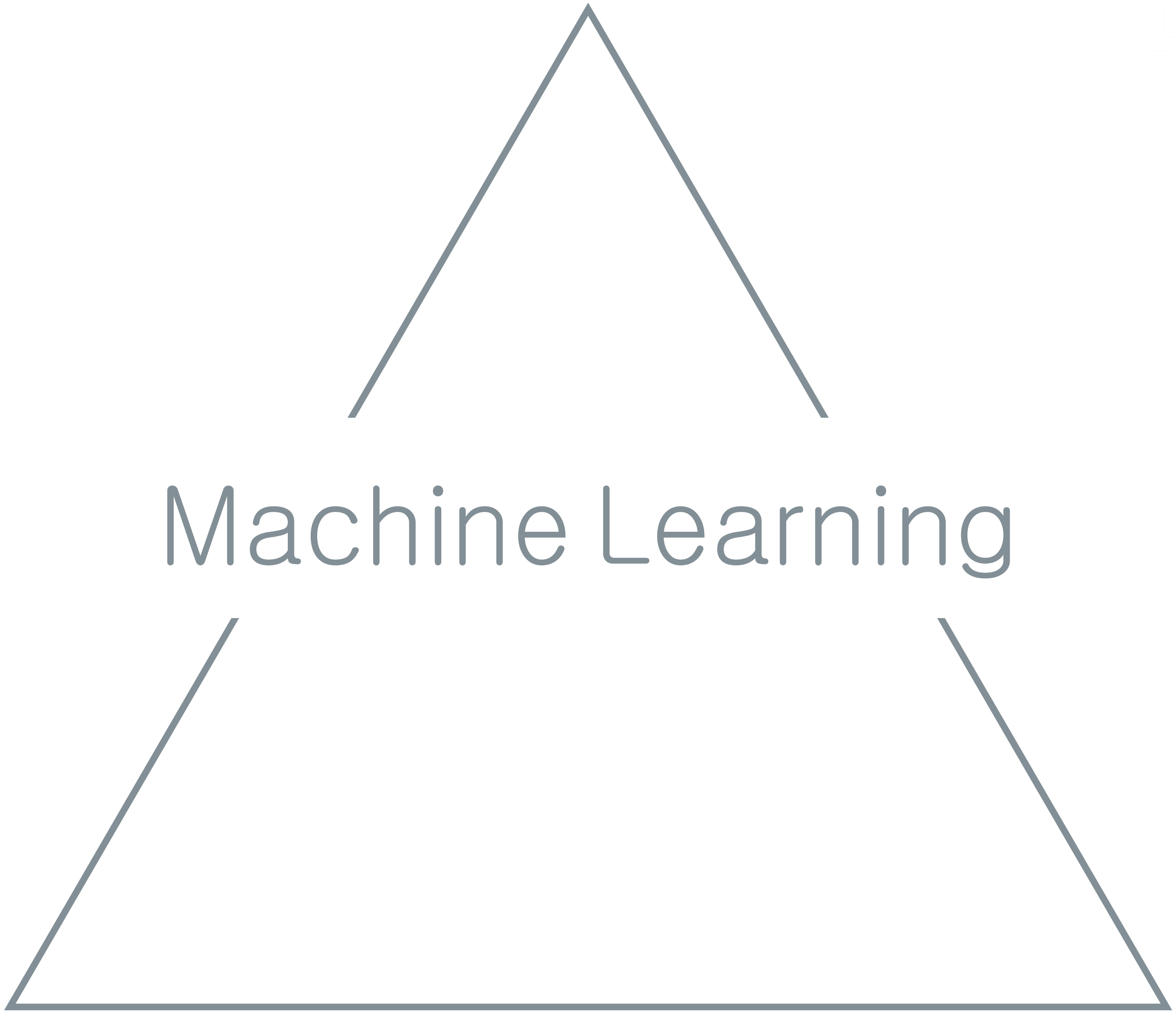
딥러닝 + 강화 학습

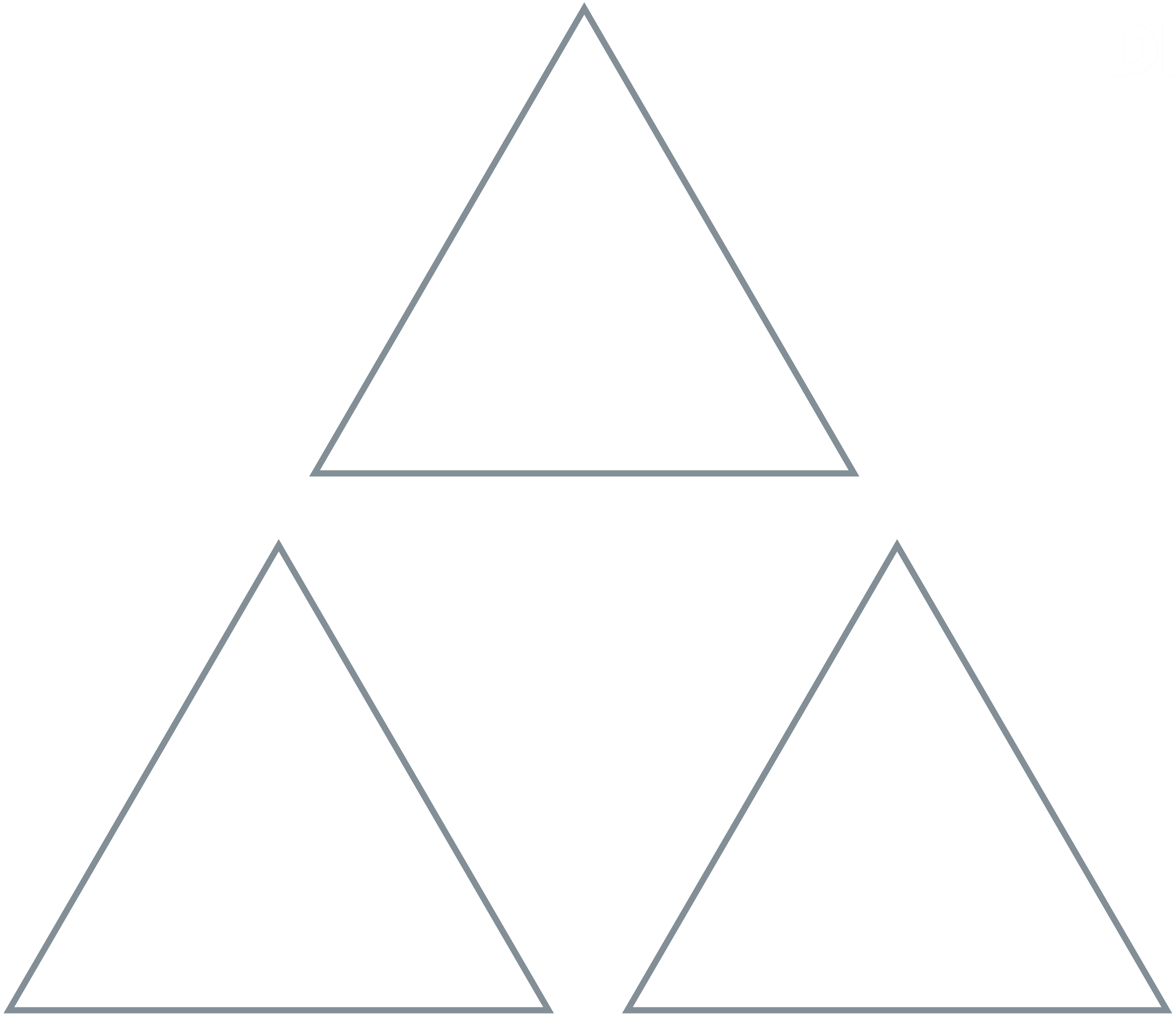


"뉴럴뉴럴"한 뉴럴 네트워크

딥러닝 + 강화 학습?

Reinforcement Learning


Machine Learning




지도 학습

지도 학습

비지도 학습

지도 학습

비지도 학습

강화 학습

지도 학습

비지도 학습

강화 학습

지도 학습

동전

음식

동

전

음

식

지도 학습

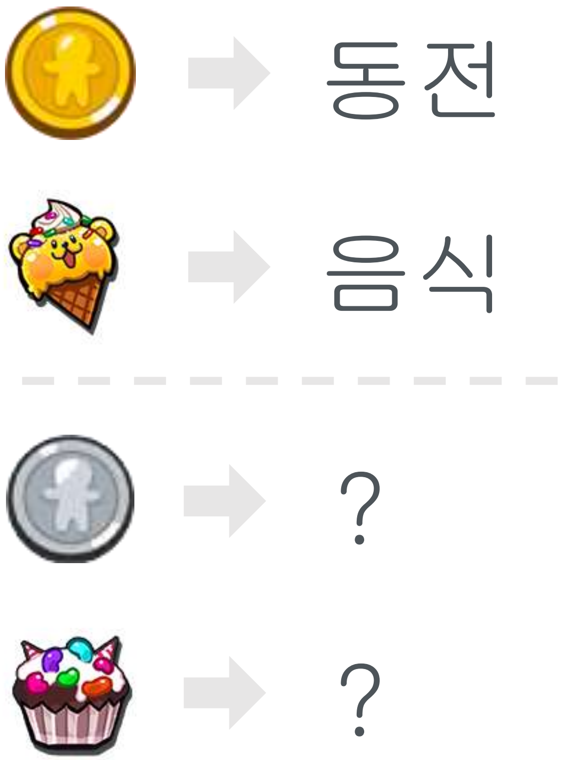
 → 동전

 → 음식

 → ?

 → ?

지도 학습



분류

Classification


지도 학습
비지도 학습
강화 학습

비지도 학습

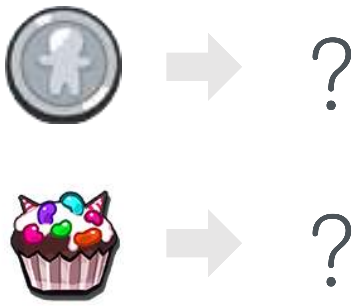
비지도 학습

비지도 학습

군집화

Clustering


지도 학습
비지도 학습
강화 학습



분류도 아니고 군집화도 아닌것?

로봇를 걷게 하려면?

처음에는 학습할 데이터가 없다

조금씩 관절을 움직여 보면서

(처음에는 아무것도 모르니 랜덤으로)

시행 착오로부터 배운다

(정답이 없기 때문에 학습 결과는 다양함)

쿠키런 오븐브레이크

강화 학습

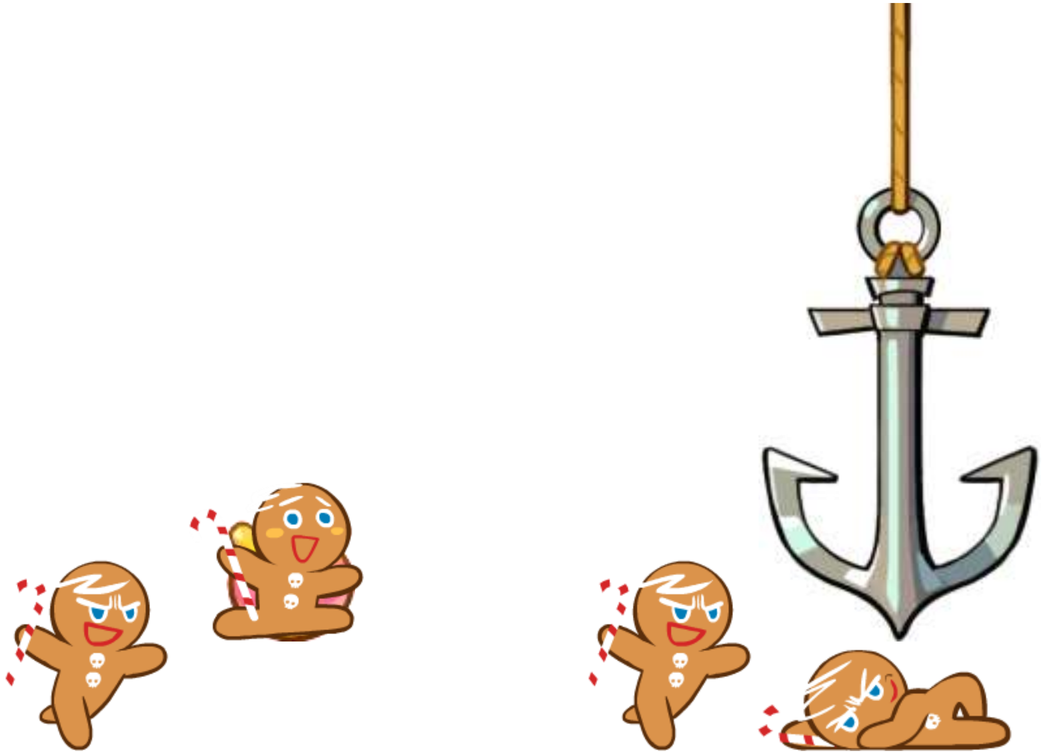
(Reinforcement Learning)

목표

목표

목표

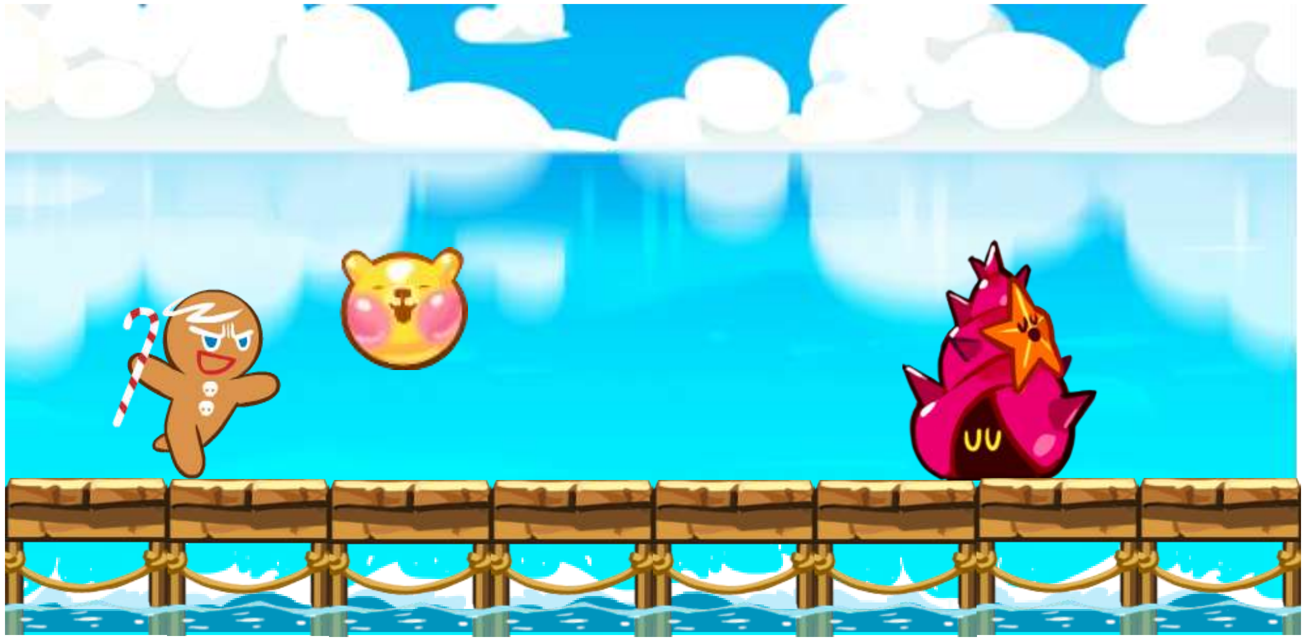
목표



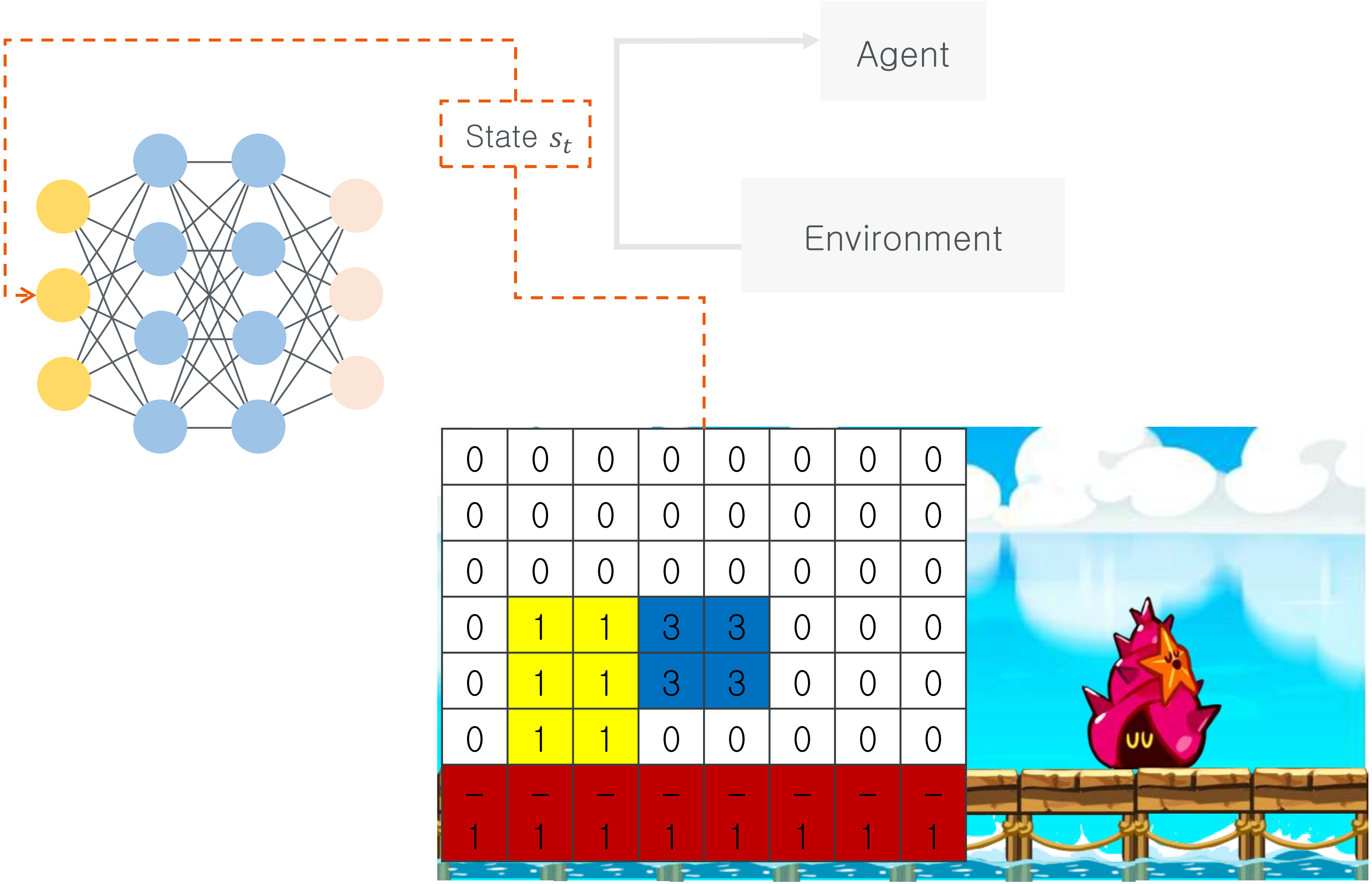
Agent

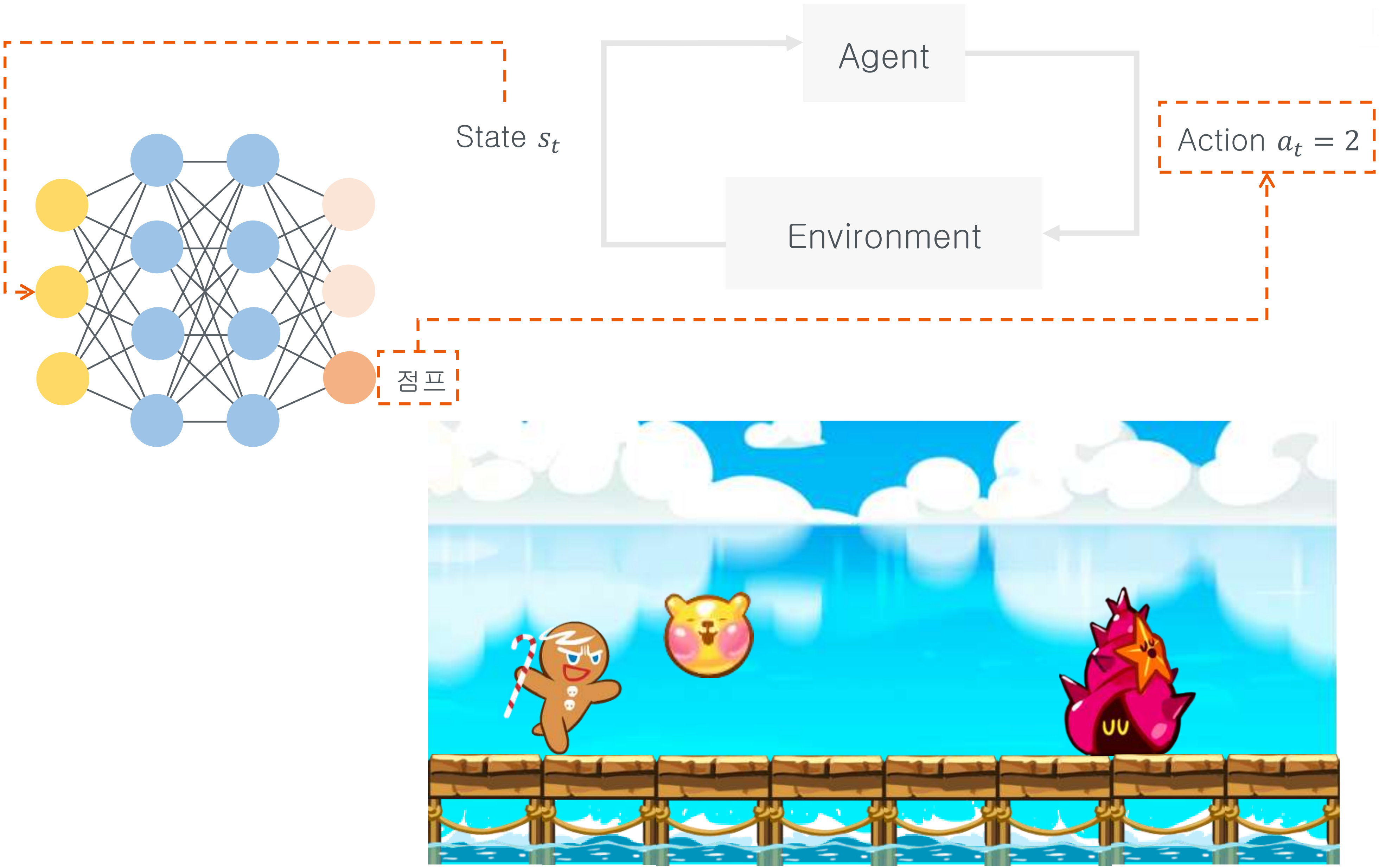
Agent

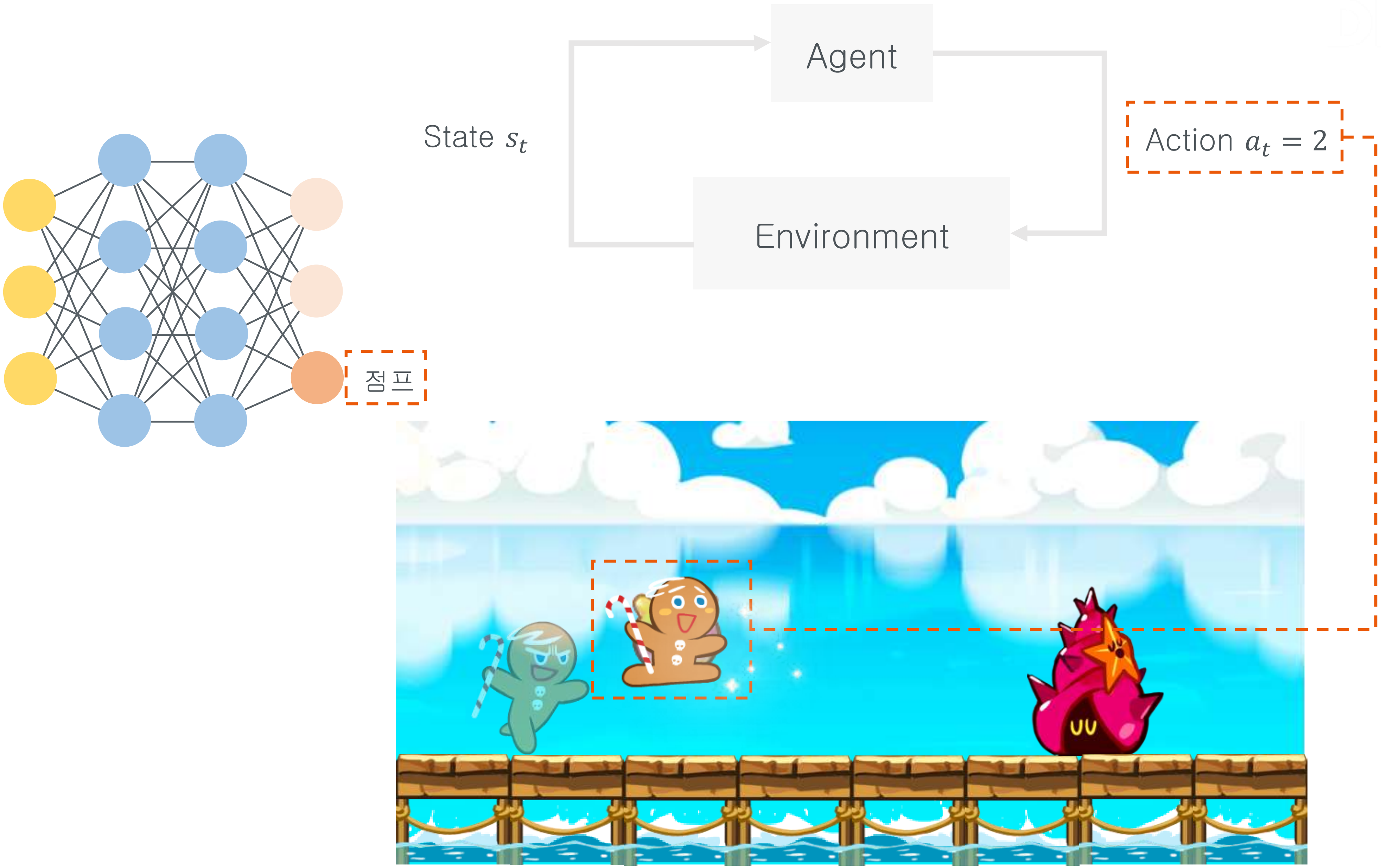
Environment

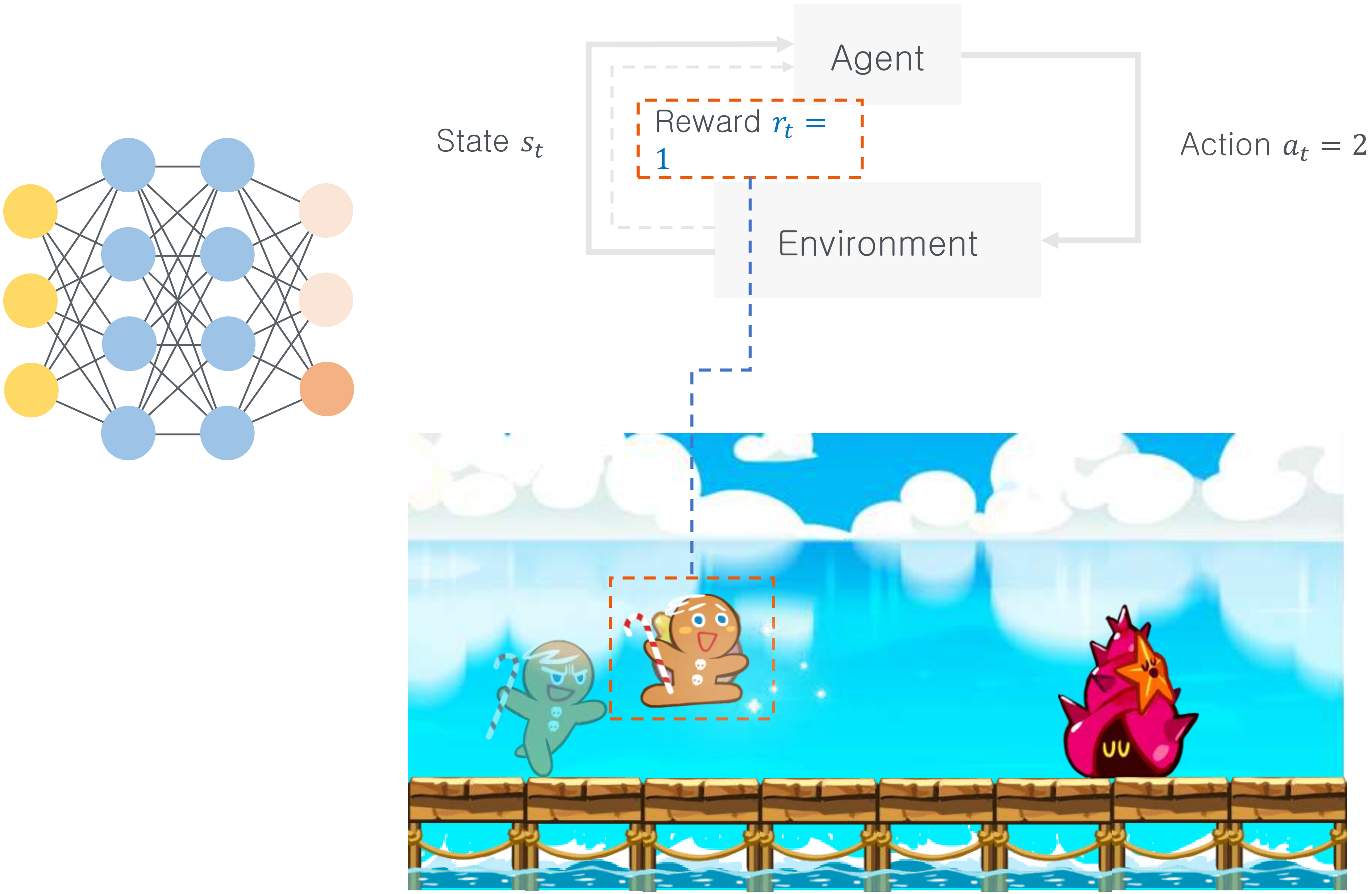


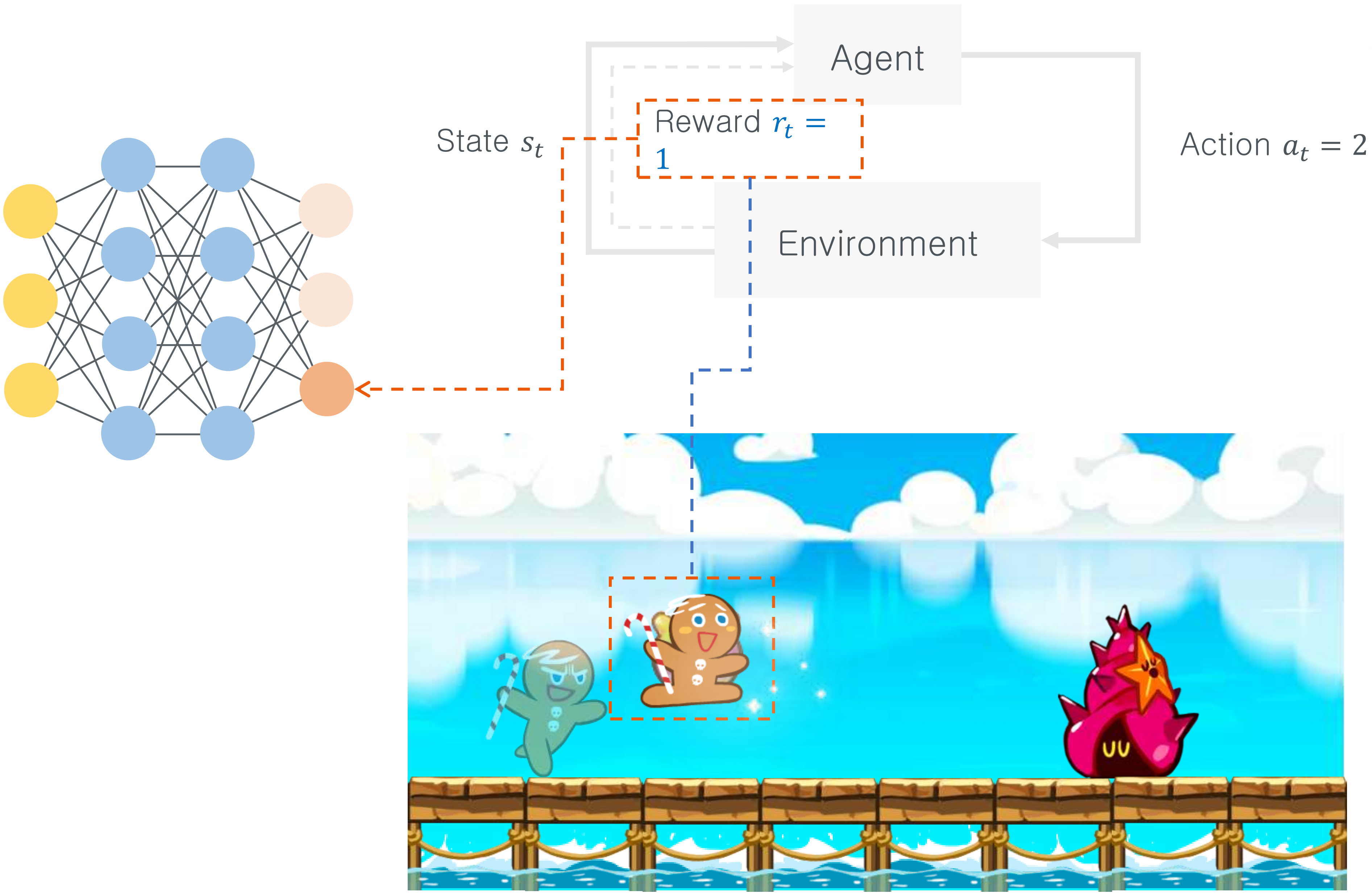

Agent
State s_t
Environment


Agent
Environment
State s_t
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 1 1 3 3 0 0 0
0 1 1 3 3 0 0 0
0 1 1 0 0 0 0 0
-1 -1 -1 -1 -1 -1 -1 -1


Agent
State s_t
Action $a_t = 2$
Environment
점프


Agent
Environment
State s_t
Action $a_t = 2$
점프

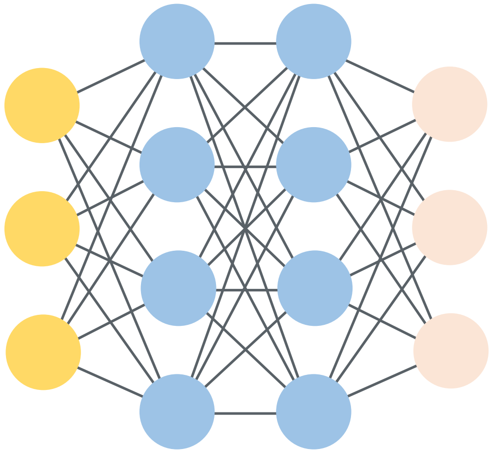

Agent
State s_t
Reward $r_t = 1$
Action $a_t = 2$
Environment

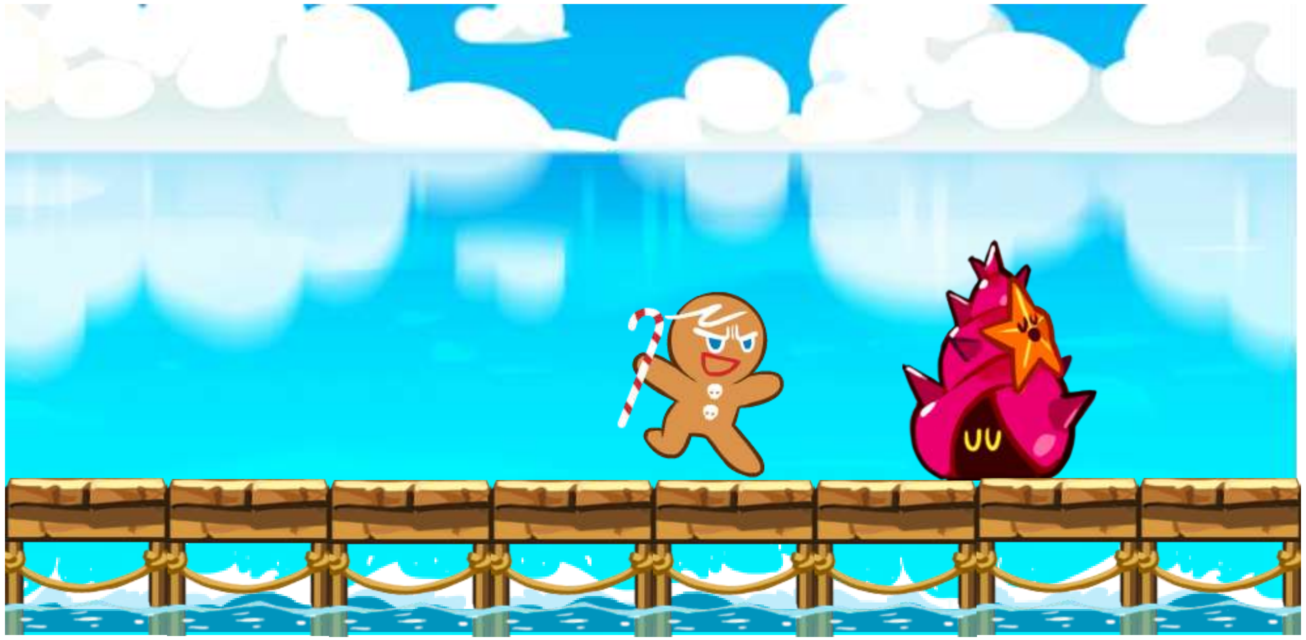

Agent
Reward $r_t = 1$
State s_t
Action $a_t = 2$
Environment

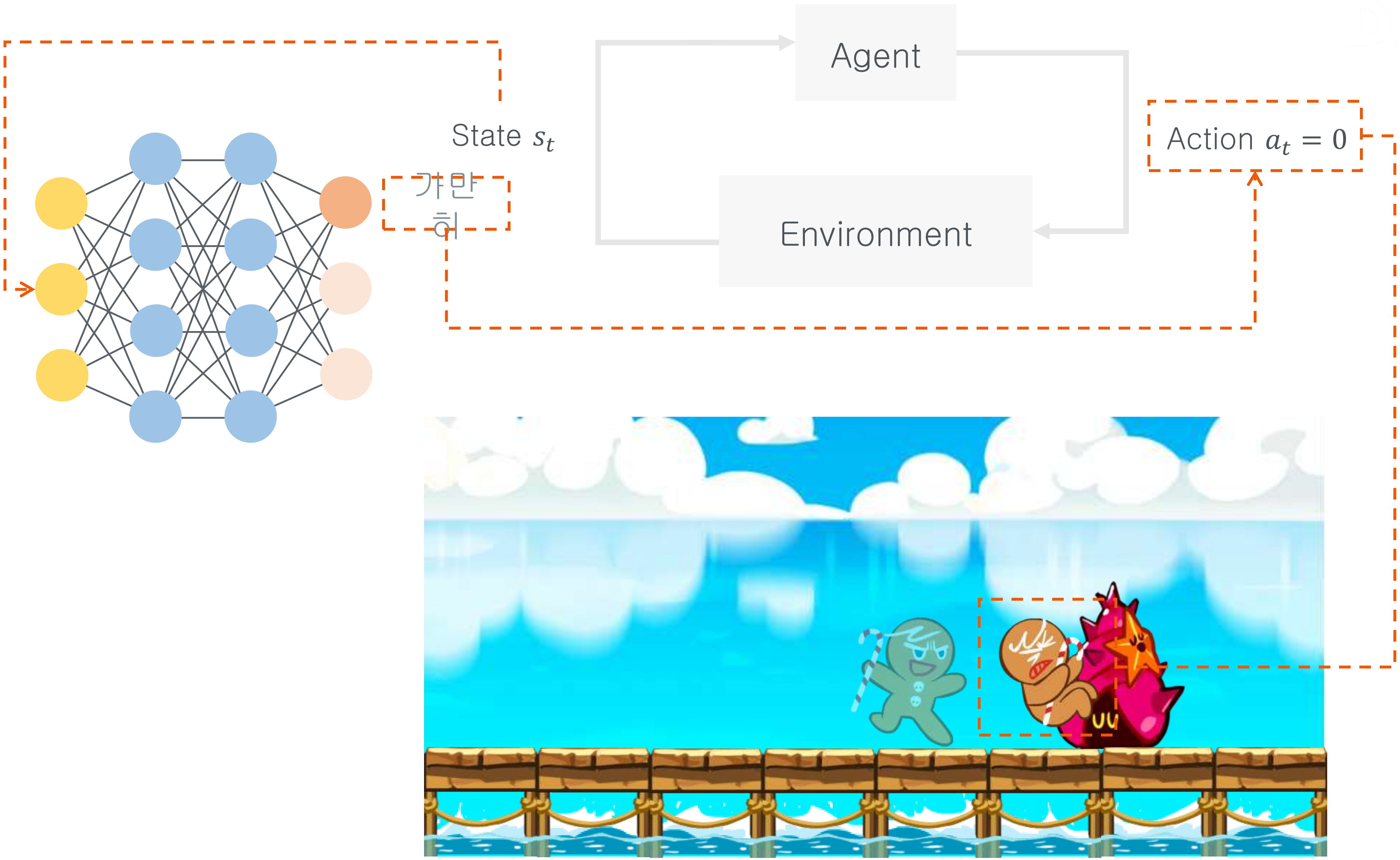
Agent

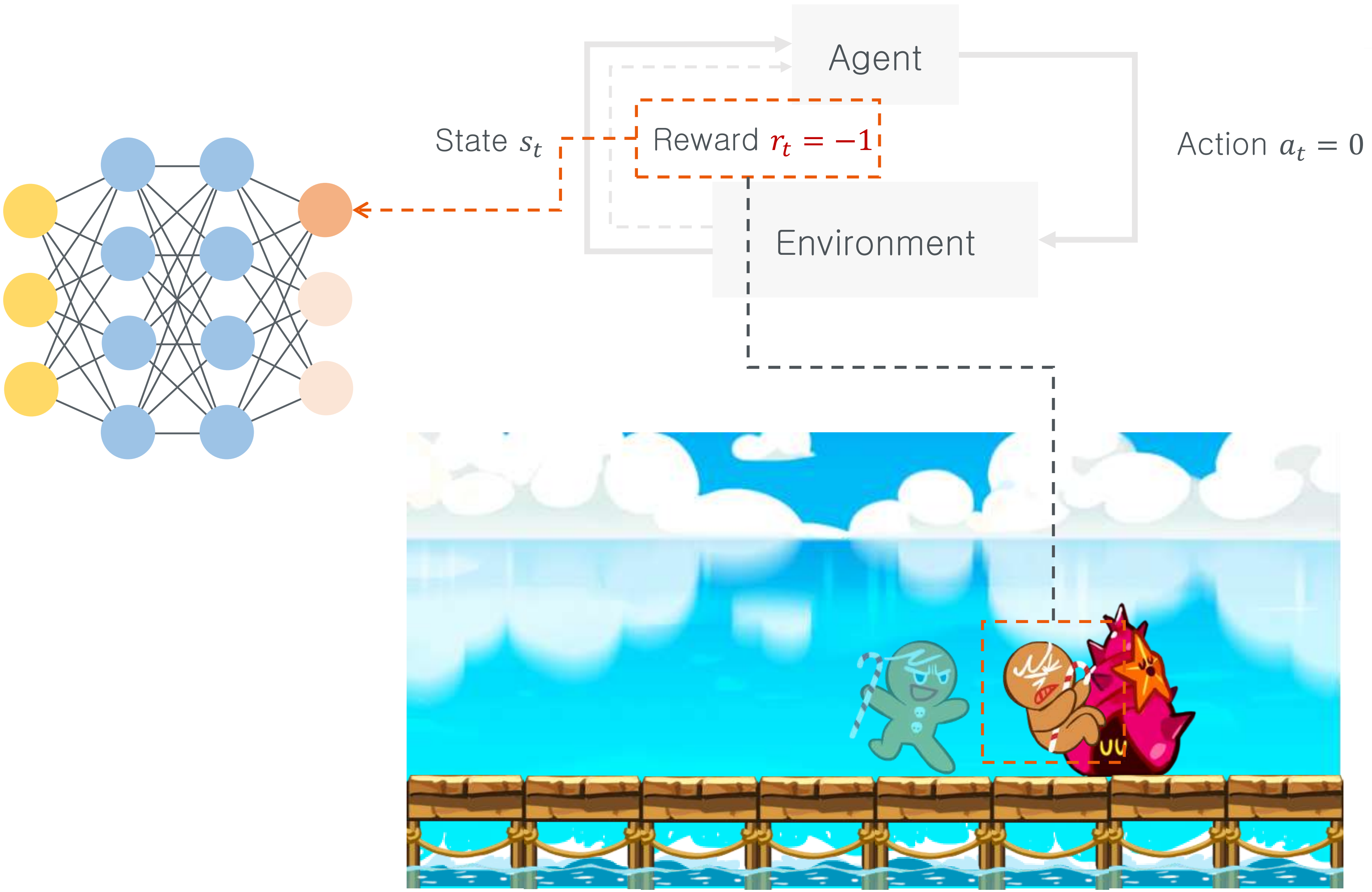
State s_t

Environment






Agent
State s_t
가만히
Environment
Action $a_t = 0$


Agent
State s_t
Reward $r_t = -1$
Action $a_t = 0$
Environment

즉, 강화 학습은

- Agent가 action을 결정하는 방법을 학습시키는 것
- 각 action은 그 다음 state에 영향을 끼친다
- 성공한 정도는 reward로 측정
- 목표 : 미래의 reward가 최대가 되도록 action을 취하는 것

Reinforcement Learning

그래서,

DL+RL 로 무엇을 했나?

AlphaRun

쿠키런
오븐브레이크

쿠키가 스스로 달릴 수 있으면?

게임 밸런싱을

자동으로 할 수 있지 않을까?

쿠키 30개 (평균 8레벨)

펫 30개

보물 9개 (2개씩 장착)

맵 7개

평균 플레이 4분

$$30 \times 8 \times 30 \times {}_9C_2 \times 7 \times 4 =$$

5,040일

평균 플레이 4초

1대 × 6개 프로세스

$$\frac{30 \times 8 \times 30 \times {}_9C_2 \times 7 \times 4}{6} =$$

14일

AlphaRun

쿠키런 A.I.를 지탱하는 기술들

DEVSISTERS

쿠키런 AI를 지탱하는 8가지 기술

1. Deep Q-Network (2013)
2. Double Q-Learning (2015)
3. Dueling Network (2015)
4. Prioritized Experience Replay (2015)
5. Model-free Episodic Control (2016)
6. Asynchronous Advantageous Actor-Critic method (2016)
7. Human Checkpoint Replay (2016)
8. Gradient Descent with Restart (2016)

DeepMind

쿠키런 AI를 지탱하는 8가지 기술

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6. Asynchronous Advantageous Actor-Critic method (2016)
7. Human Checkpoint Replay (2016)
8. Gradient Descent with Restart (2016)

DeepMind

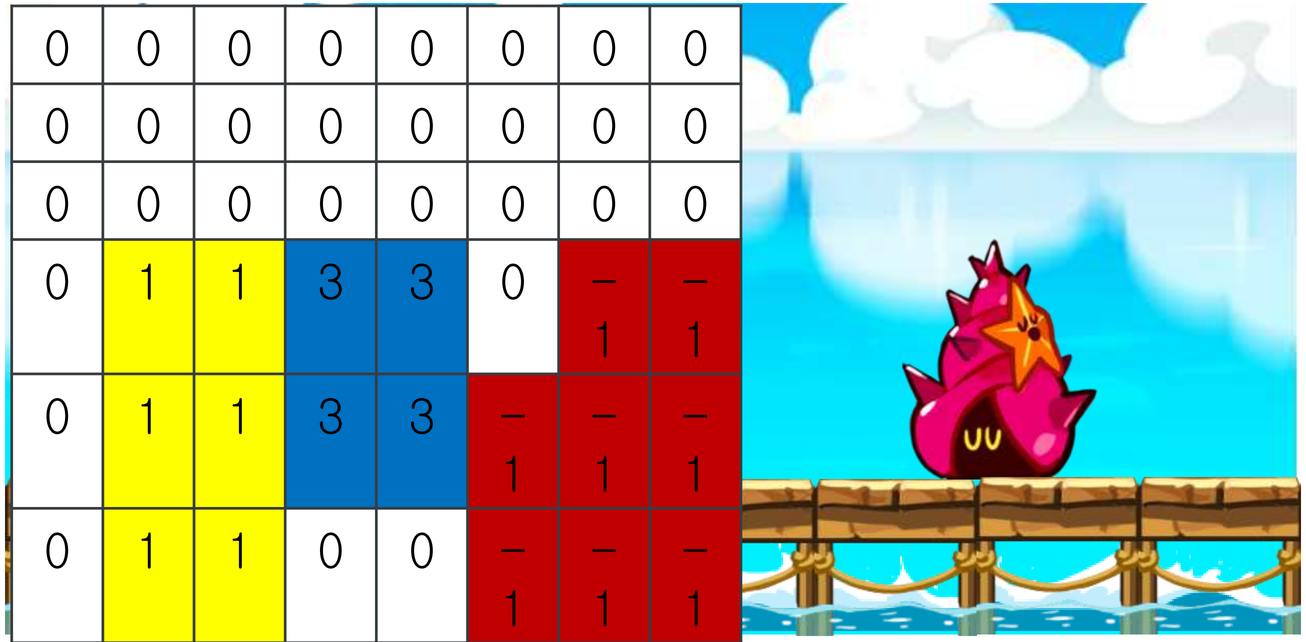
1. Deep Q-Network

State s_t

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	–1	–1
0	1	1	3	3	–1	–1	–1
0	1	1	0	0	–1	–1	–1
–1	–1	–1	–1	–1	–1	–1	–1

Action $a_t = ?$

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	−1	−1
0	1	1	3	3	−1	−1	−1
0	1	1	0	0	−1	−1	−1
−1	−1	−1	−1	−1	−1	−1	−1

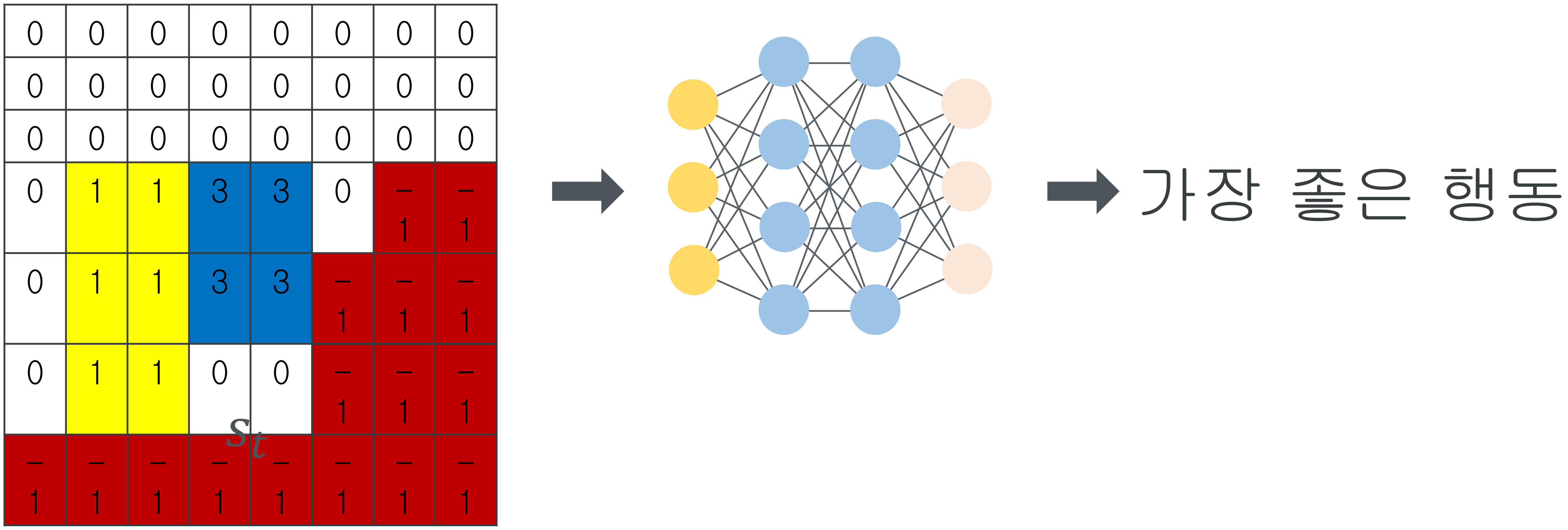


Action a_t

0　?　?　?

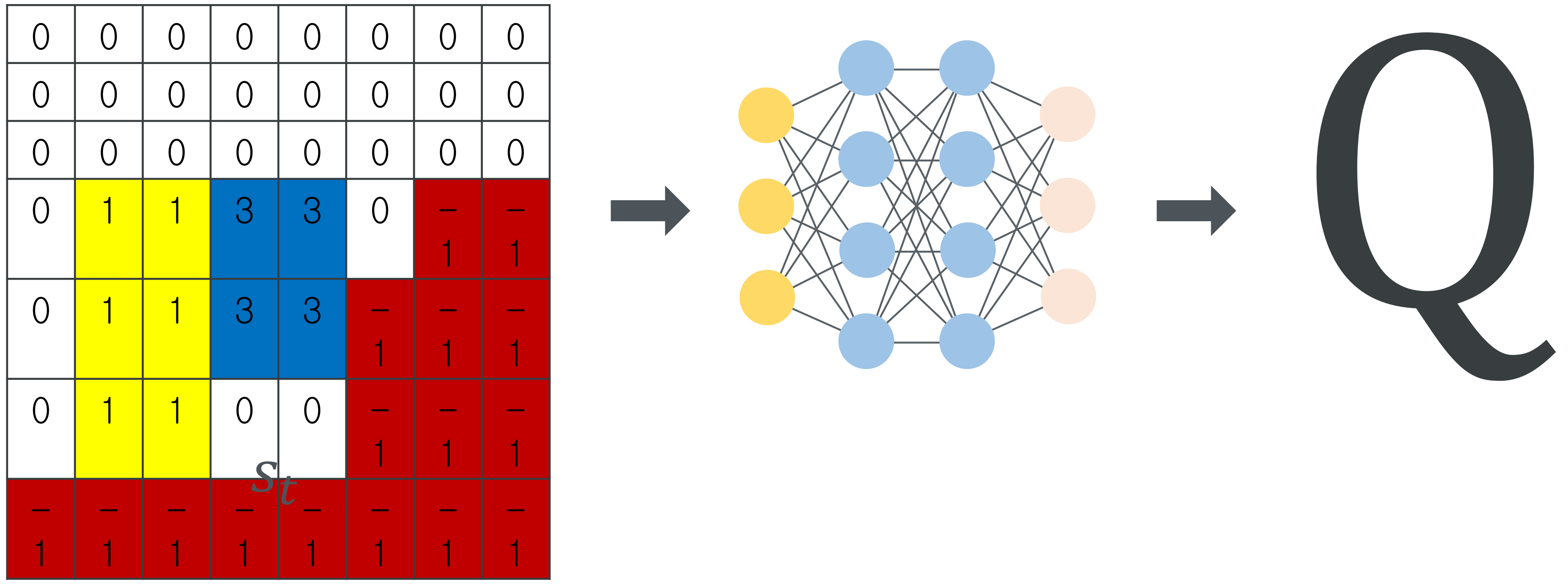
None 슬라이드 점프

Action $a_t = ?$



0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 1 1 3 3 0 –1 –1
0 1 1 3 3 –1 –1 –1
0 1 1 0 0 –1 –1 –1
–1 –1 –1 –1 –1 –1 –1 –1
s_t
가장 좋은 행동

Action $a_t = ?$

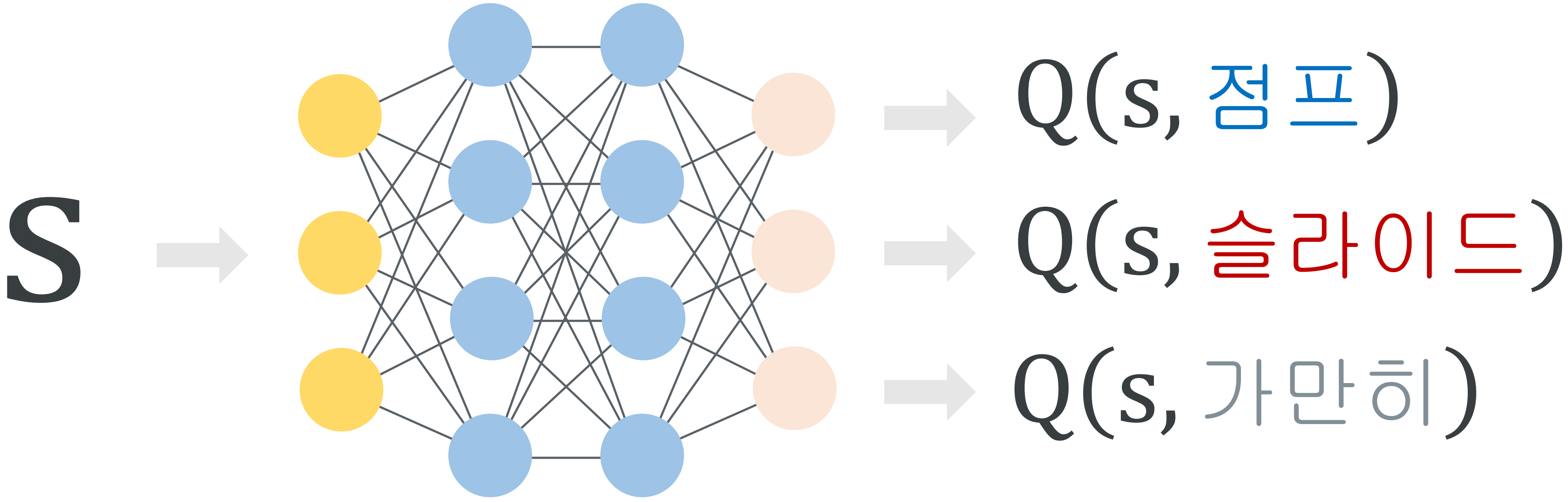

0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0
0 1 1 3 3 0 −1 −1
0 1 1 3 3 −1 −1 −1
0 1 1 0 0 −1 −1 −1
−1 −1 −1 −1 −1 −1 −1 −1
s_t
Q

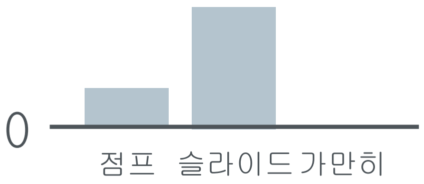
$$Q(s, a)$$

State s 에서

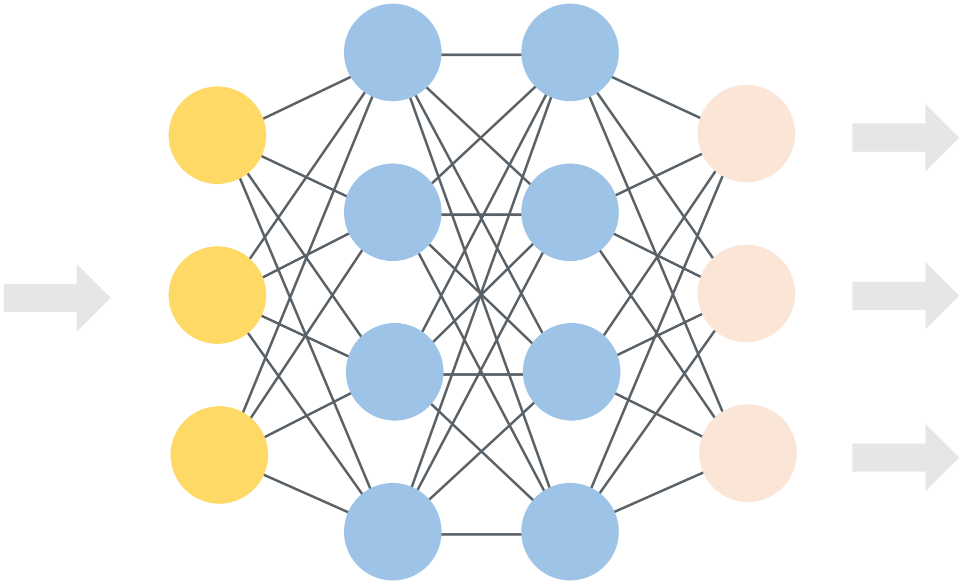
Action a 를 했을 때

기대되는 미래 가치 Q


s
Q(s, 점프)
Q(s, 슬라이드)
Q(s, 가만히)



S

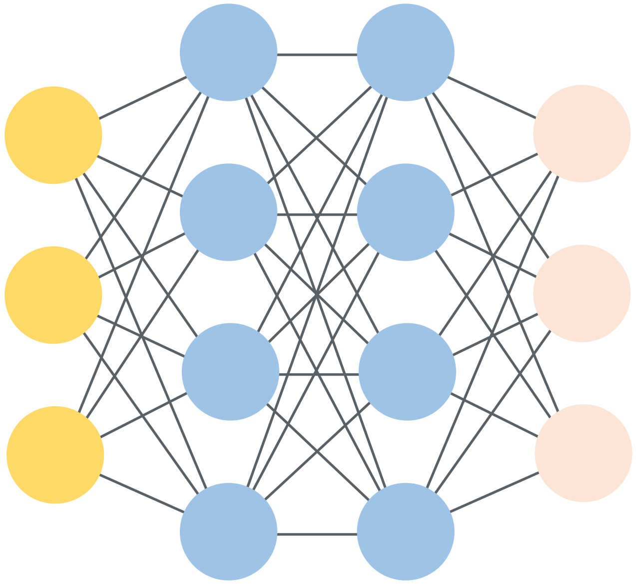


$Q(s, \text{점프}) = 1$

$Q(s, \text{슬라이드}) = 5$

$Q(s, \text{가만히}) = 0$

S



$Q(s, \text{점프}) = 1$

$Q(s, \text{슬라이드}) = 5$

$Q(s, \text{가만히}) = 0$

Q : 기대되는 미래 가치

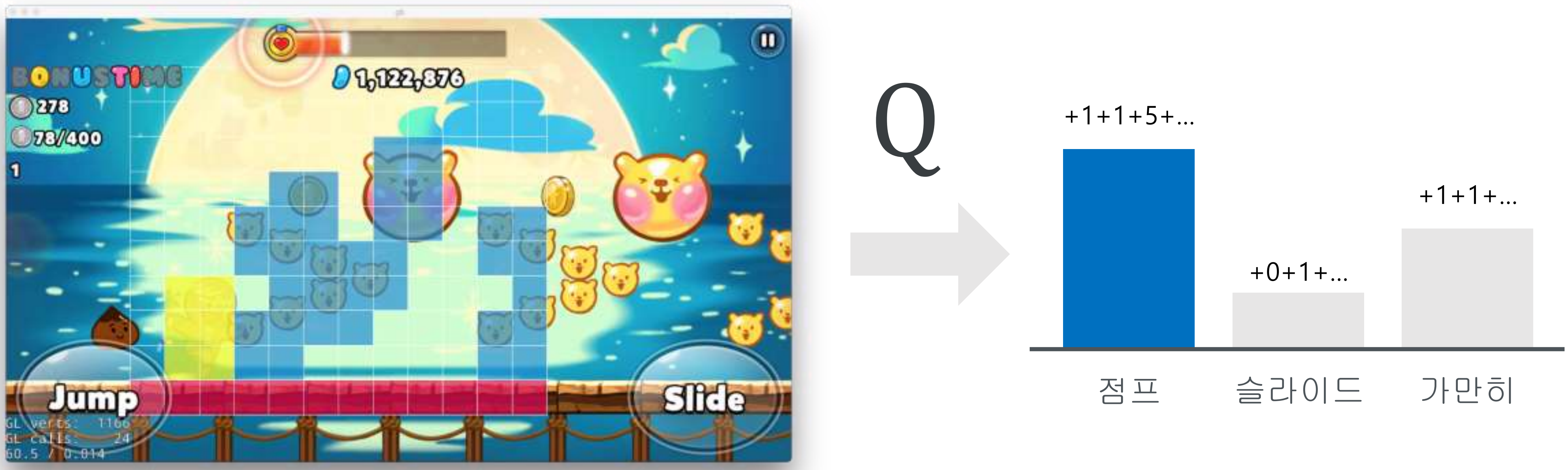
쿠키런 오븐브레이크 's 가치 =

쿠키런 오븐브레이크 's 가치 = 점수

Q

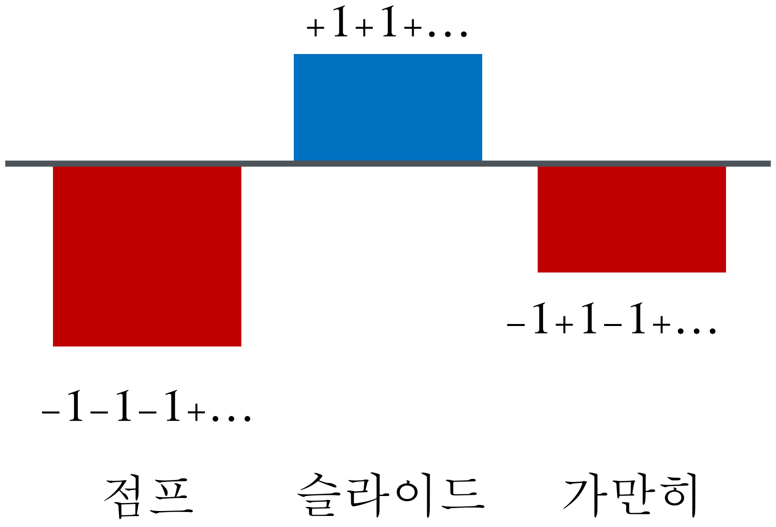
쿠키런 오븐브레이크

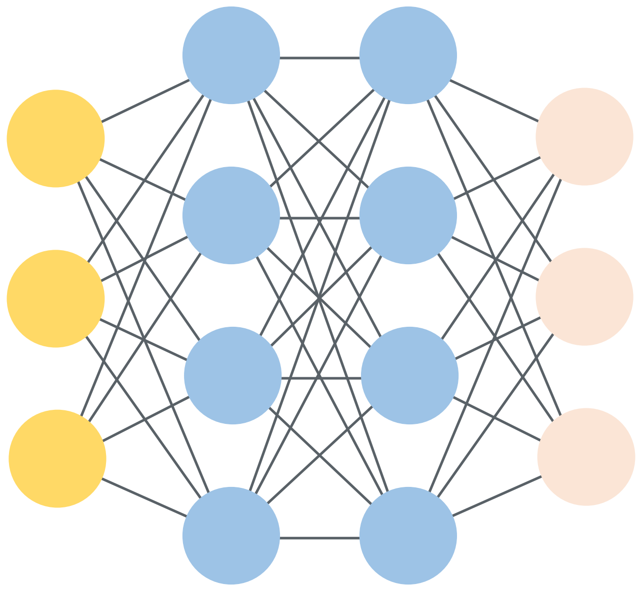
미래에 얻을 점수들의 합


BONUSTIME
278
78/400
1
1,122,876
Jump
Slide
Q
+1+1+5+...
+0+1+...
+1+1+...
점프
슬라이드
가만히


BONUSTIME
0
24,442
내 최고 점수
369,815
Jump
보물
Slide

Q


+1+1+...
-1-1-1+...
-1+1-1+...
점프
슬라이드
가만히



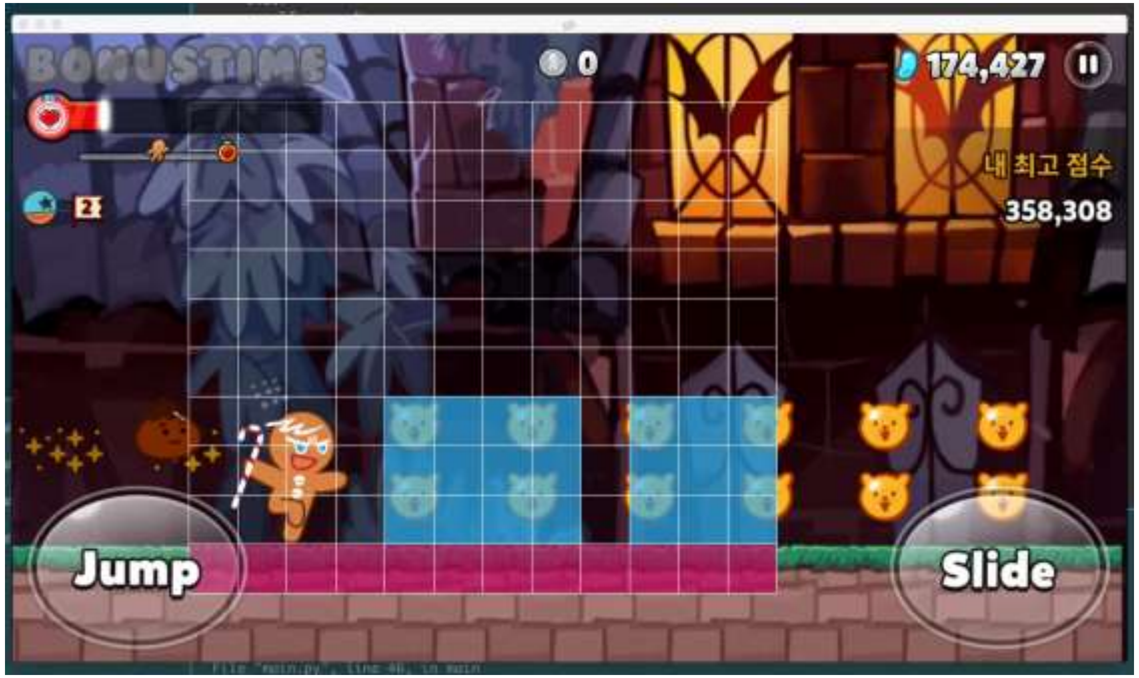
$$loss = \left(Q(s,a) - \mathrm{r} + \gamma \max_{a`} \hat{Q}(s,a`) \right)^2$$

결과는?


BONUSTIME
0
48,884
내 최고 점수
369,815
2
Jump
보물
Slide

하지만 #1...

- 왜 하나씩 놓치고, 이상한 행동을 하는 걸까



2. Double Q-Learning

핵심은,

미래의 가치를 나타내는 Q가

낙관적 예측 or 발산하는 것을 막음

$$loss = \left(Q(s,a) - \mathrm{r} + \gamma \max_{a`} \hat{Q}(s,a`) \right)^2$$

$$loss = (\text{예측} - \text{정답})^2$$

$$loss = \left(Q(s,a) - r + \gamma \max_{a`} \hat{Q}(s,a`)\right)^2$$

예측 – 정답

$$loss = \left(Q(s,a) - \mathrm{r} + \gamma \max_{a`} \hat{Q}(s,a`)\right)^2$$

0

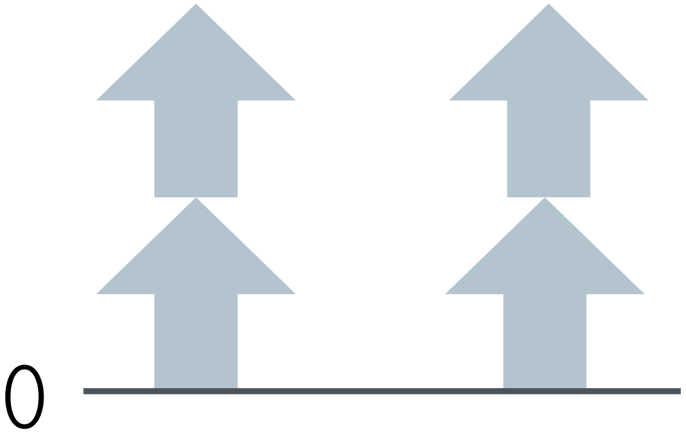
예측 − 정답

$$loss = \left(Q(s,a) - \mathrm{r} + \gamma \max_{a`} \hat{Q}(s,a`)\right)^2$$

0

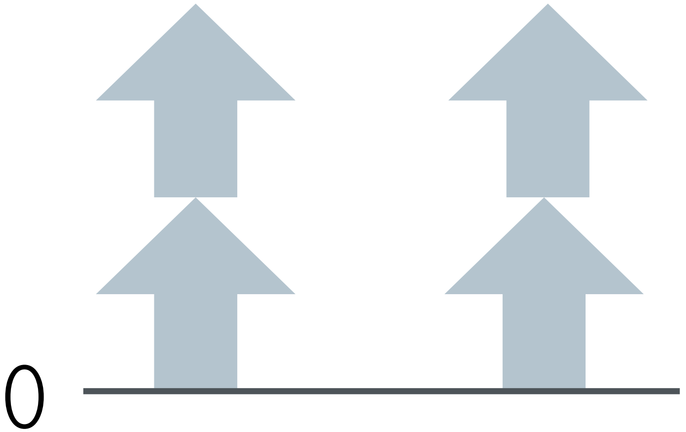
예측 – 정답

$$loss = \left(\boxed{Q}(s,a) - \mathrm{r} + \gamma \max_{a`} \boxed{\hat{Q}(s,a`)}\right)^2$$



예측 – 정답

$$loss = \left(Q(s,a) - \mathrm{r} + \gamma \max_{a`} \hat{Q}(s,a`)\right)^2$$



예측 – 정답

Q

$$loss = \left(Q(s,a) - \mathrm{r} + \gamma \max_{a`} \hat{Q}(s,a`)\right)^2$$

DQN

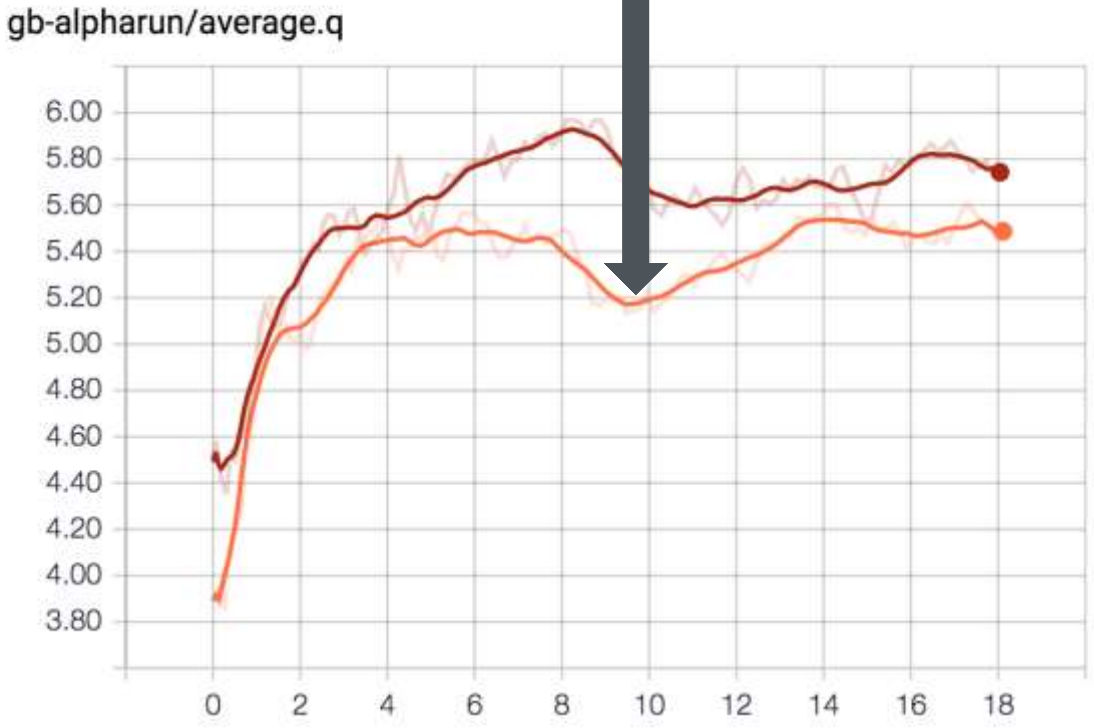
$$loss = \left(Q(s,a) - \mathrm{r} + \gamma \max_{a`} \hat{Q}(s,a`) \right)^2$$

$$= \left(Q(s,a) - \mathrm{r} + \gamma \hat{Q}\left(s, \arg\max_{a`} \hat{Q}(s,a`) \right) \right)^2$$

Double DQN

$$loss = \left(Q(s,a) - \mathrm{r} + \gamma \hat{Q}\left(s, \arg\max_{a`} Q(s,a`) \right) \right)^2$$

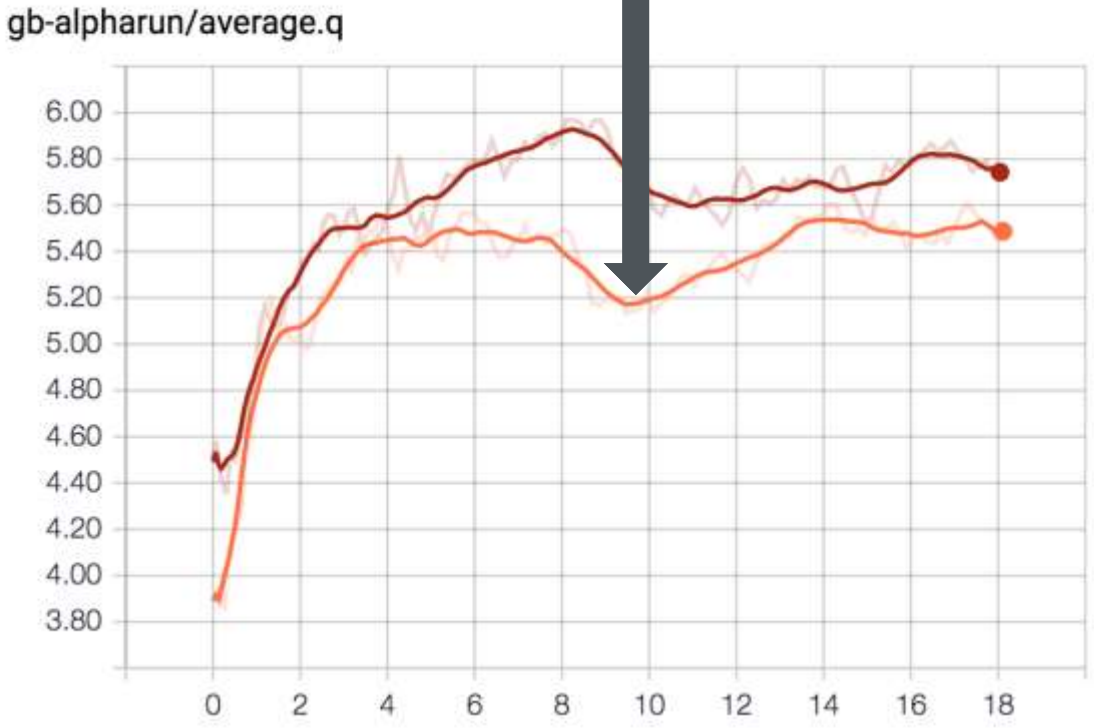
Double Q가 Q 값은 작지만

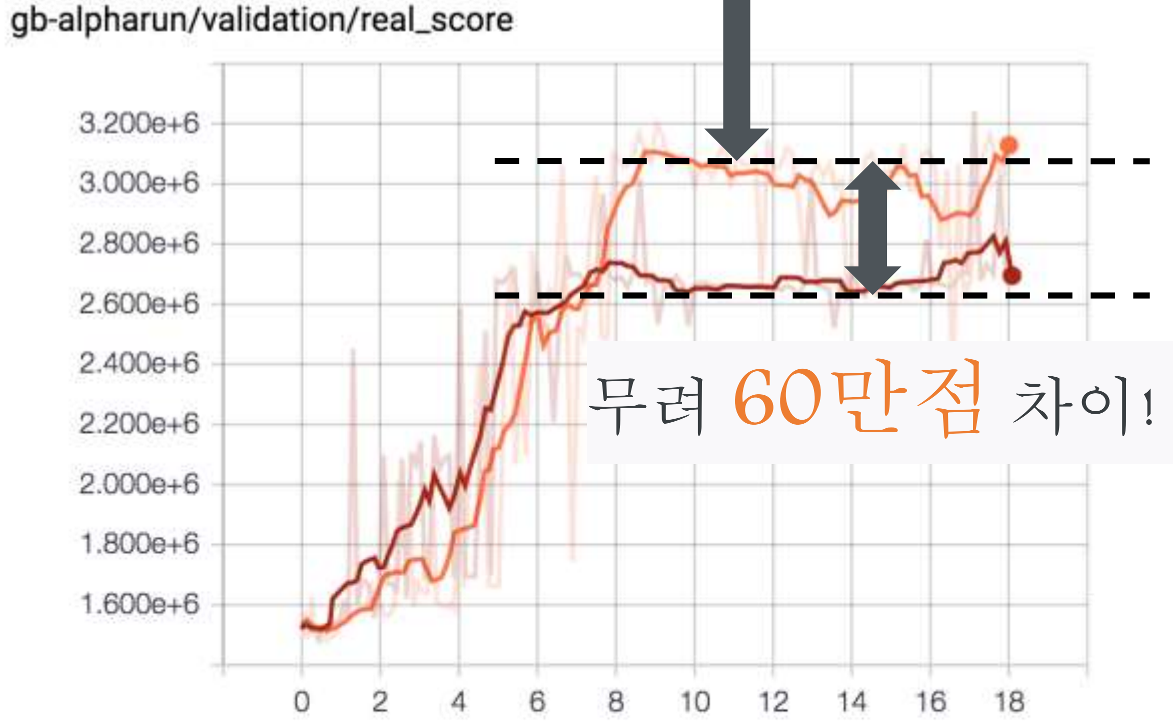


— : Deep Q-learning — : Double Q-learning

Double Q가 Q 값은 작지만

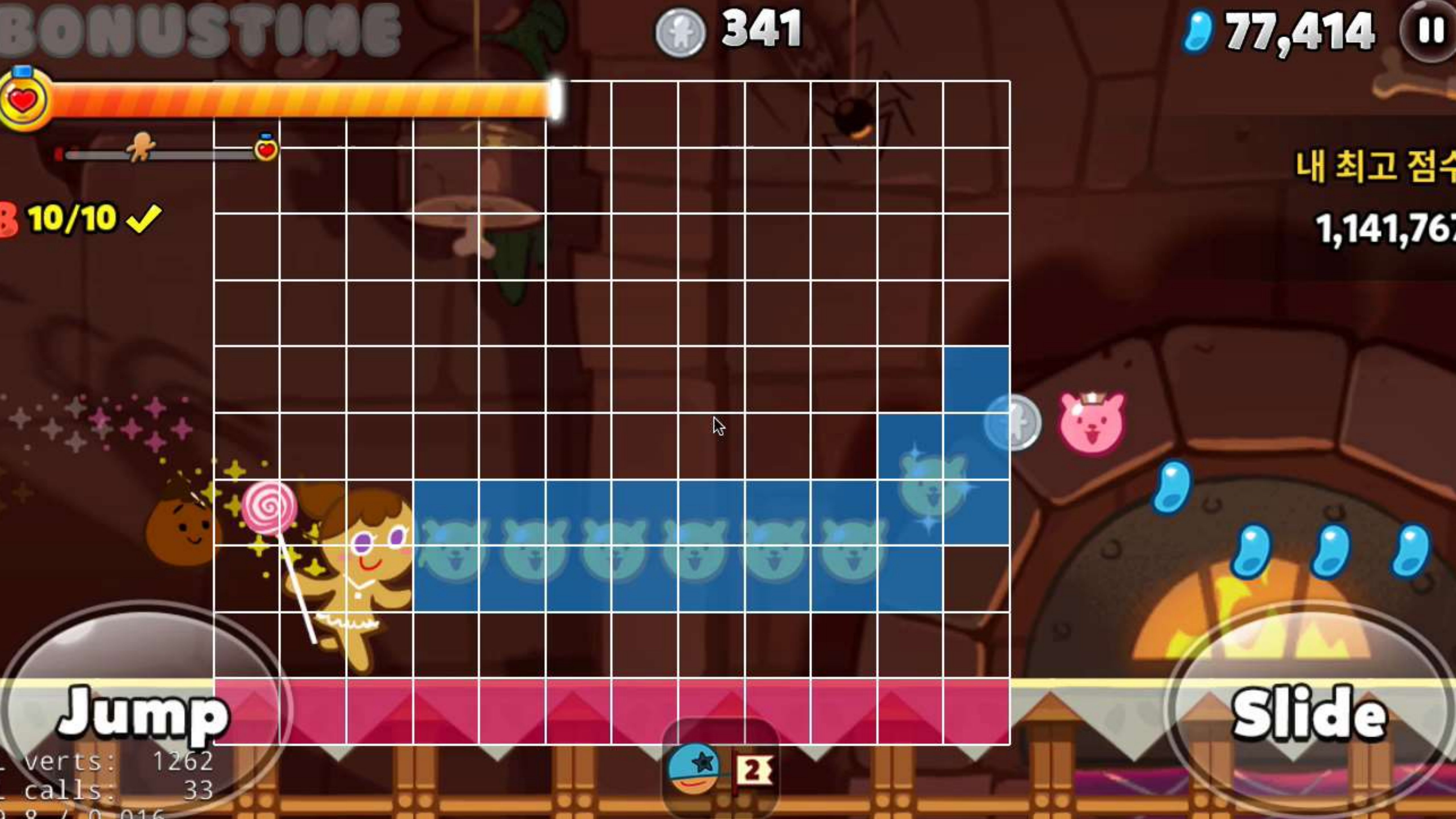
점수는 훨씬 높다!





— : Deep Q-learning — : Double Q-learning

결과는?


BONUSTIME
341
77,414
내 최고
1,141,76
10/10
Jump
Slide
verts: 1262
calls: 33
2

“아, 다했다.”

하지만 #2...

- 단조로운 land 1이 아닌 land 3를 가보니...

하지만 #2...

- 그리고 충격과 공포의 **보너스 타임**...

3. Dueling Network

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	0	0
0	1	1	3	3	0	0	0
0	1	1	0	0	0	0	0
−1	−1	−1	−1	−1	−1	−1	−1

기대되는 미래 가치

$Q(s,a)$ 의 값은?

+1+1+1…

앞에 젤리가 많은지,

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	0	0
0	1	1	3	3	0	0	0
0	1	1	0	0	0	0	0
–1	–1	–1	–1	–1	–1	–1	–1

0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
3	3	3	3	0	0
3	3	3	3	0	0
0	0	0	0	0	0
–1	–1	–1	–1	–1	–1

+1+1+1⋯ +0−1−1+⋯

앞에 젤리가 많은지, 장애물이 많은지 전혀 알 수 없음

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	0	0
0	1	1	3	3	0	0	0
0	1	1	0	0	0	0	0
−1	−1	−1	−1	−1	−1	−1	−1

0	0	0	0	0	0
0	0	0	−1	−1	0
0	0	0	−1	−1	0
−1	−1	0	−1	−1	0
−1	−1	0	−1	−1	0
−1	−1	0	−1	−1	0
−1	−1	−1	−1	−1	−1

정확한 Q 예측이 어렵다

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	0	0
0	1	1	3	3	0	0	0
0	1	1	0	0	0	0	0
−1	−1	−1	−1	−1	−1	−1	−1

?

점프 : 10? 8?

슬라이드 : −2? 1?

가만히 : 5? 12?

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	0	0
0	1	1	3	3	0	0	0
0	1	1	0	0	0	0	0
-1	-1	-1	-1	-1	-1	-1	-1

하지만!

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	0	0
0	1	1	3	3	0	0	0
0	1	1	0	0	0	0	0
−1	−1	−1	−1	−1	−1	−1	−1

Q를 정확하게 **예측**할 **필요**가 있을까?

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	1	3	3	0	0	0
0	1	1	3	3	0	0	0
0	1	1	0	0	0	0	0
−1	−1	−1	−1	−1	−1	−1	−1

슬라이드 : x (기준)

점프 : $x+1$? $x+3$?

가만히 : $x+1$? $x+2$?

10? 20?

0? 1?

14? 32?

Q

0 (기준)

+1? +3?

−1? −2?

어느 것이 **예측**하기 더 **쉬울까**?

Q

0 (기준)

+1? +3?

−1? −2?

당연히 차이를 배우는 것이 쉽다

$$Q(s,a)$$

Value

$$Q(s,a) = V(s)$$

기준점 x

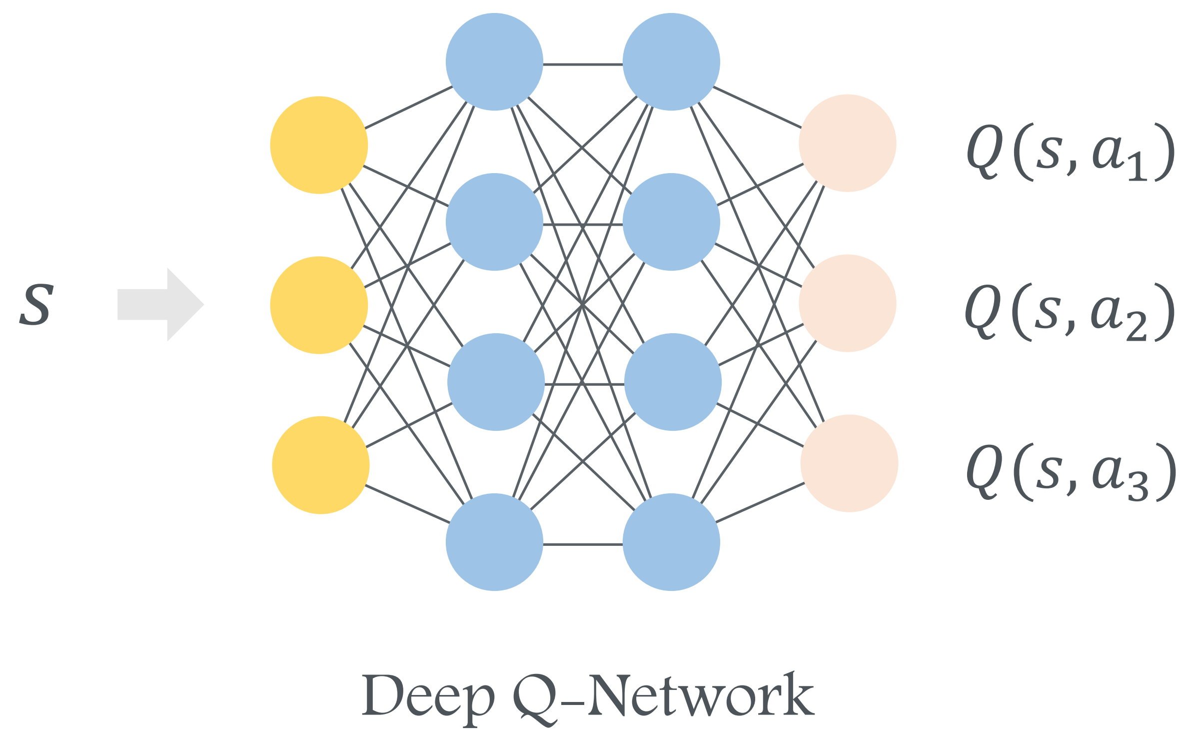
Value

Advantage

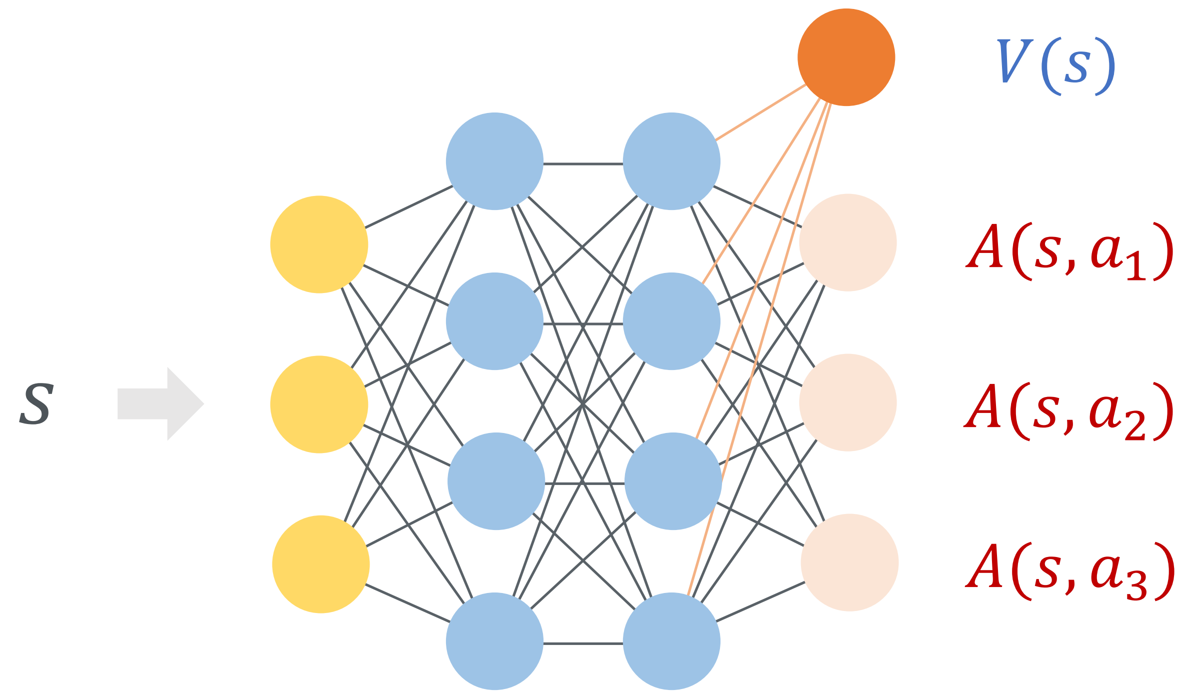
$$Q(s,a) = V(s) + A(s,a)$$

기준점 x

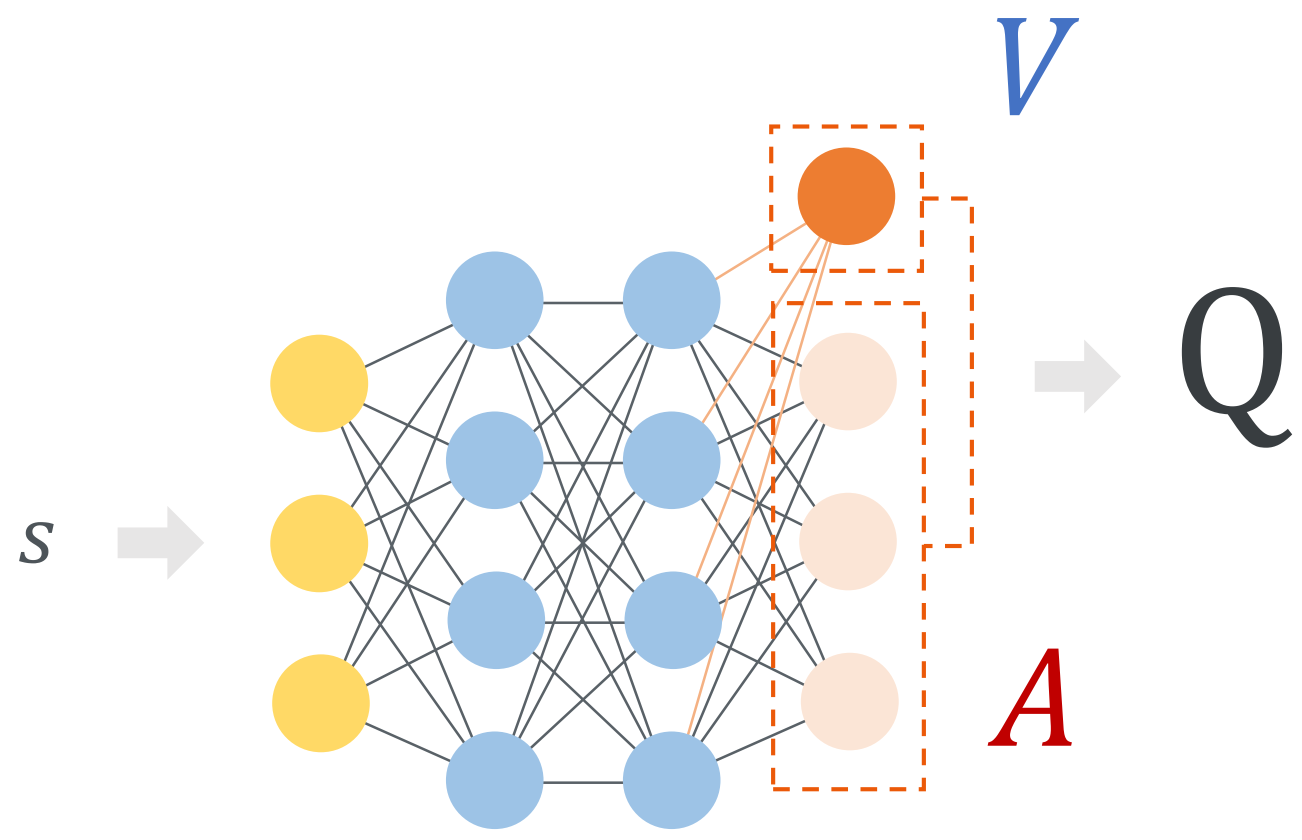
상대적인 Q값의 차이



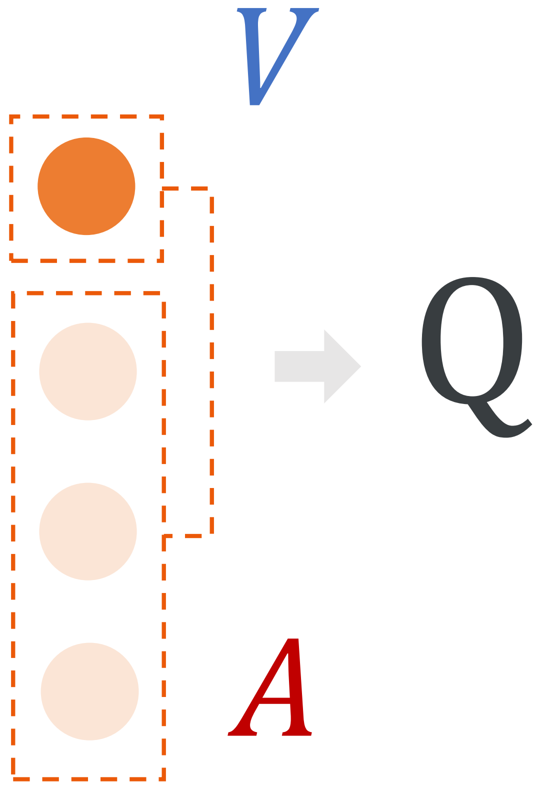
s
$Q(s, a_1)$
$Q(s, a_2)$
$Q(s, a_3)$
Deep Q-Network



Dueling Network



Dueling Network


V
Q
A

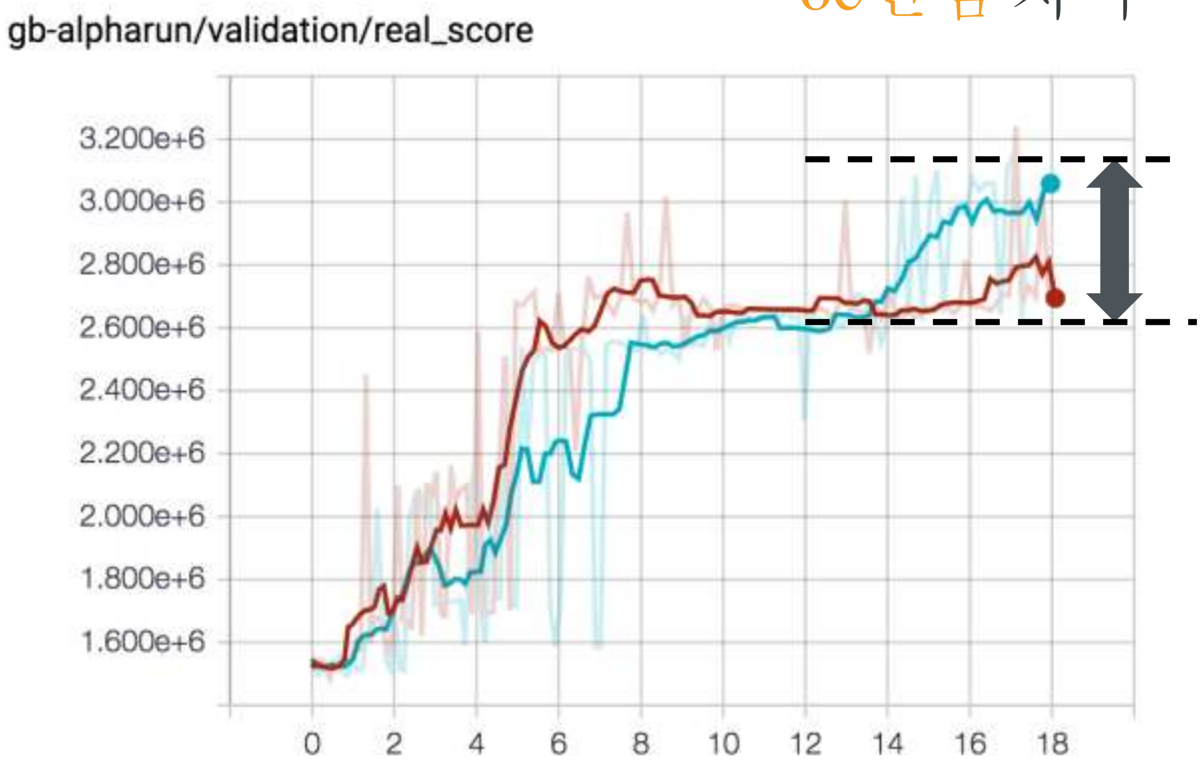
Sum : $Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) + A(s,a;\theta,\alpha)$

Max : $Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) + \left(A(s,a;\theta,\alpha) - \max_{a` \in \mathcal{A}} A(s,a`;\theta,\alpha)\right)$

Average: $Q(s,a;\theta,\alpha,\beta) = V(s;\theta,\beta) + \left(A(s,a;\theta,\alpha) - \frac{1}{|\mathcal{A}|}\sum_{a`} A(s,a`;\theta,\alpha)\right)$

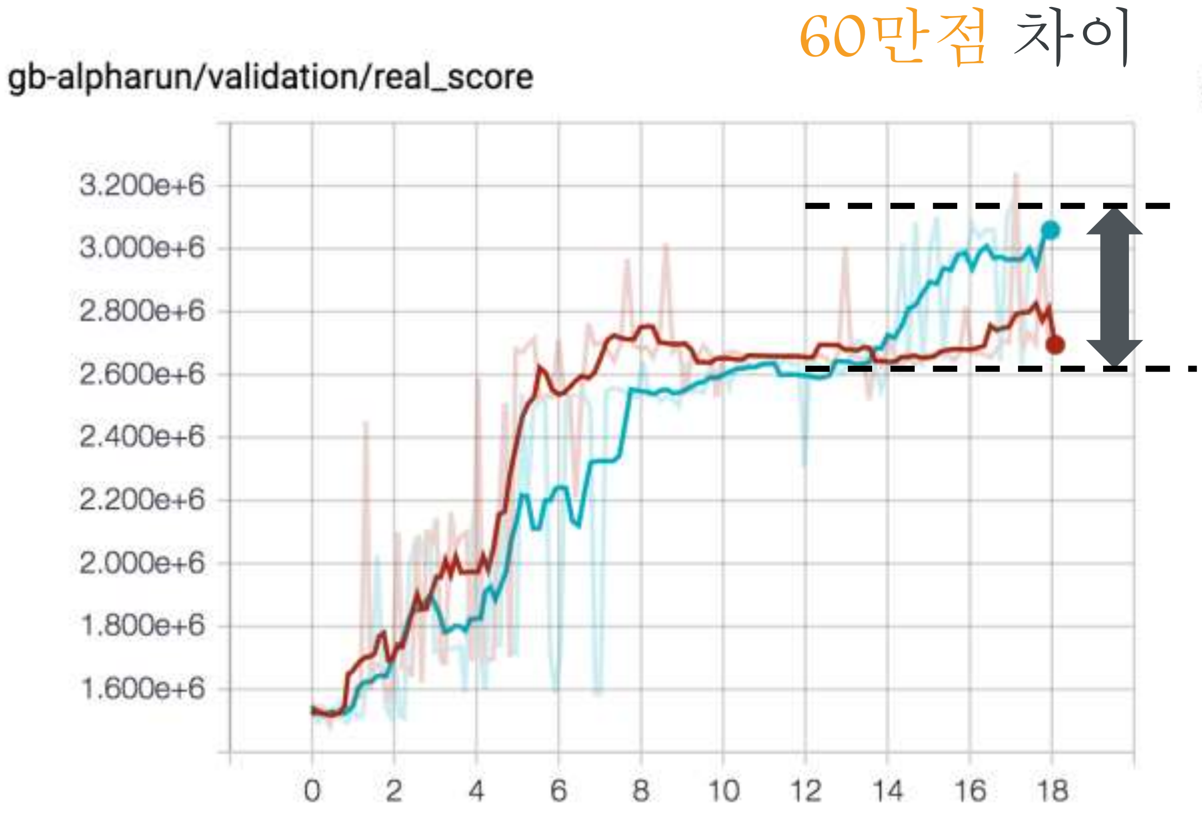
3. Dueling network

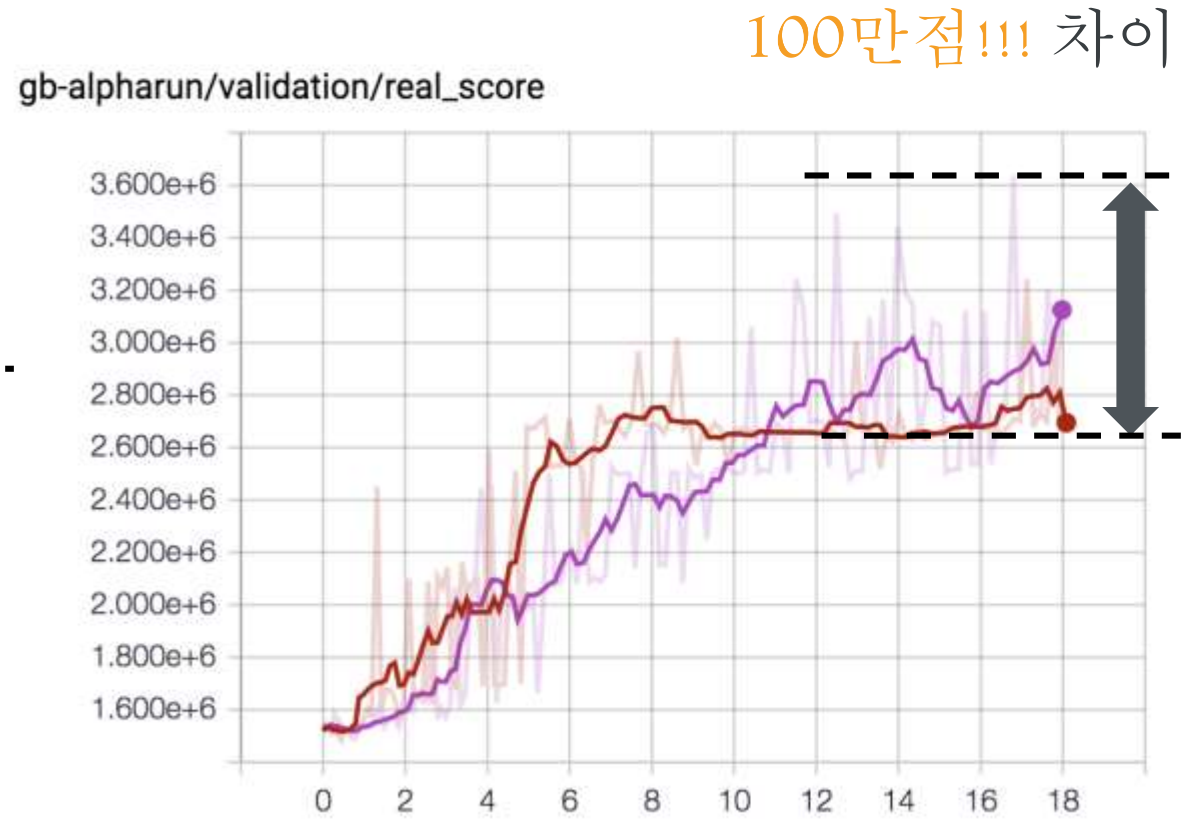
60만점 차이



— : DQN — : Sum — : Max

3. Dueling network





— : DQN — : Sum — : Max

쿠키런 AI를 지탱하는 8가지 기술

1. Deep Q-Network (2013)
2. Double Q-Learning (2015)
3. Dueling Network (2015)
4. Prioritized Experience Replay (2015)
5. Model-free Episodic Control (2016)
6. Asynchronous Advantageous Actor-Critic method (2016)
7. Human Checkpoint Replay (2016)
8. Gradient Descent with Restart (2016)

쿠키런 AI를 지탱하는 8가지 기술

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강화에 계속해서 실패한다면?

논문 8개나 갈아 넣었는데 안된다고..?

DEVSISTERS

엔지니어링 ~~이라고 쓰고 노가다라고 부른다~~

1. Hyperparameter tuning
2. Debugging
3. Pretrained model
4. Ensemble method

1. Hyperparameter tuning

네트워크 바꾸기
Optimizer 바꾸기
reward 식 바꾸기
...

총 70+개

Network

Environment

Experience memory

Training method

1. activation_fn : activation function (relu, tanh, elu, leaky)
2. initializer : weight initializer (xavier)
3. regularizer : weight regularizer (None, l1, l2)
4. apply_reg : layers where regularizer is applied
5. regularizer_scale : scale of regularizer
6. hidden_dims : dimension of network
7. kernel_size : kernel size of CNN network
8. stride_size : stride size of CNN network
9. dueling : whether to use dueling network
10. double_q : whether to use double Q-learning
11. use_batch_norm : whether to use batch normalization

1. screen_height : # of rows for a grid state
2. screen_height_to_use : actual # of rows for a state
3. screen_width : # of columns for a grid state
4. screen_width_to_us : actual # of columns for a state
5. screen_expr : actual # of row for a state
   - c : cookie
   - p : platform
   - s : score of cells
   - p : plain jelly
   - i : plain item
   - h : heal
   - m : magic
   - hi : height
   - sp : speed
   - rj : remained jump

   ex) (c+2*p)-s,i+h+m,[rj,sp], ((c+2*p)-s)/2.,i+h+m,[rj,sp,hi]
6. action_repeat : # of reapt of an action (frame skip)

1. history_length : the length of history
2. memory_size : size of experience memory
3. priority : whether to use prioritized experience memory
4. preload_memory : whether to preload a saved memory
5. preload_batch_size : batch size of preloaded memory
6. preload_prob : probability of sampling from pre-mem
7. alpha : alpha of prioritized experience memory
8. beta_start: beta of prioritized experience memory
9. beta_end_t: beta of prioritized experience memory

1. optimizer : type of optimizer (adam, adagrad, rmsprop)
2. batch_norm : whether to use batch normalization
3. max_step : maximum step to train
4. target_q_update_step : # of step to update target network
5. learn_start_step : # of step to begin a training
6. learning_rate_start : the maximum value of learning rate
7. learning_rate_end : the minimum value of learning rate
8. clip_grad : value for a max gradient
9. clip_delta : value for a max delta
10. clip_reward : value for a max reward
11. learning_rate_restart : whether to use learning rate restart

過猶不及

과유불급

성능은 올릴 수는 있지만,

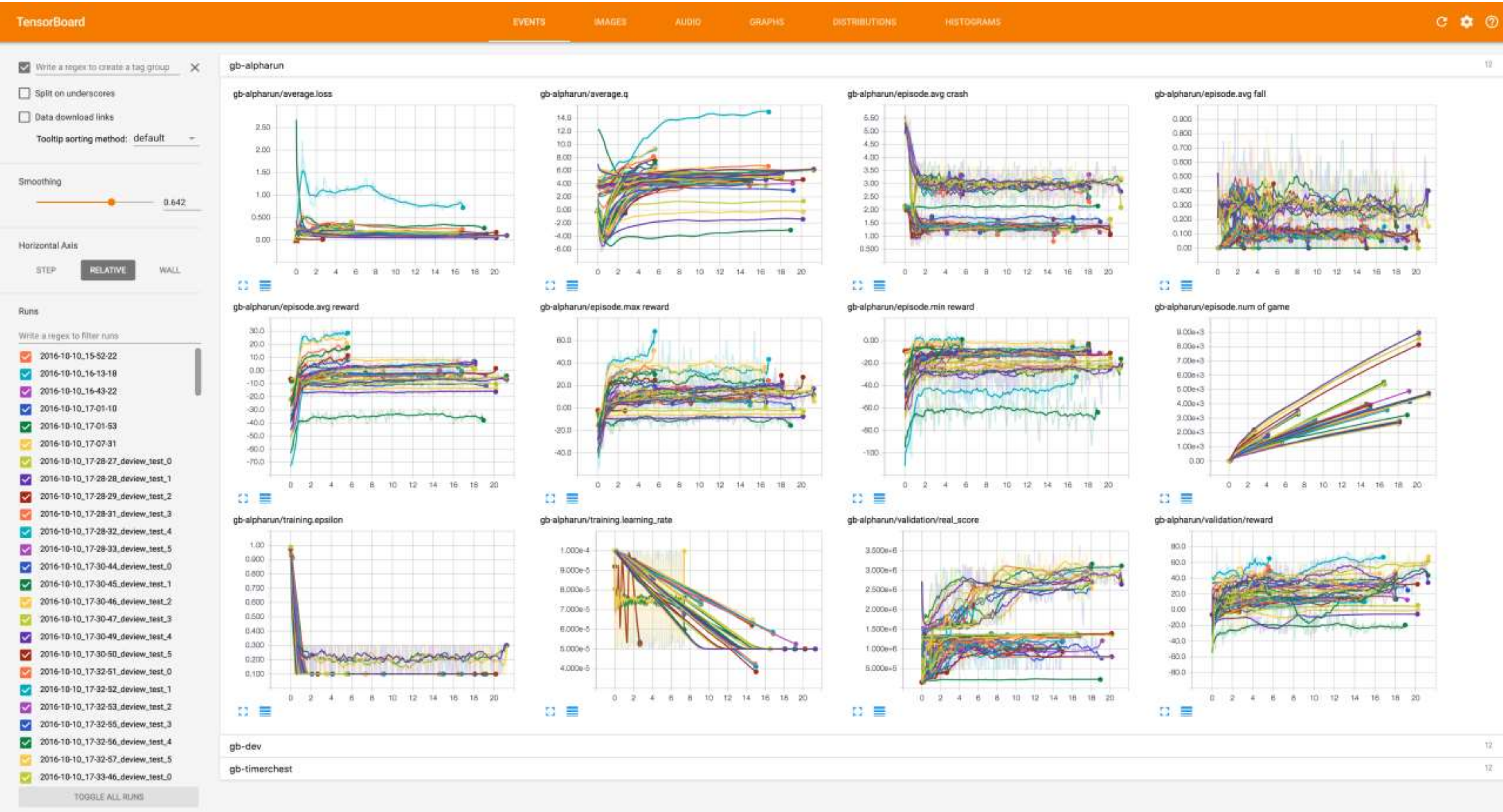
그만큼 끊임없는 실험을 해야한

다

고정시킬 변수들을 정해서

한동안 건드리지 않는다!

```
for land in range(3, 7):
  for cookie in cookies:
    options = []
    option = {
      'hidden_dims': ["[800, 400, 200]", "[1000, 800, 200]"],
      'double_q': [True, False],
      'start_land': land,
      'cookie': cookie,
    }
    options.append(option.copy())
    array_run(options, ’double_q_test')
```


TensorBoard
EVENTS
IMAGES
AUDIO
GRAPHS
DISTRIBUTIONS
HISTOGRAMS
Write a regex to create a tag group
Split on underscores
Data download links
Tooltip sorting method: default
Smoothing
0.642
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
2016-10-10_15-52-22
2016-10-10_16-13-18
2016-10-10_16-43-22
2016-10-10_17-01-10
2016-10-10_17-01-53
2016-10-10_17-07-31
2016-10-10_17-28-27_deview_test_0
2016-10-10_17-28-28_deview_test_1
2016-10-10_17-28-29_deview_test_2
2016-10-10_17-28-31_deview_test_3
2016-10-10_17-28-32_deview_test_4
2016-10-10_17-28-33_deview_test_5
2016-10-10_17-30-44_deview_test_0
2016-10-10_17-30-45_deview_test_1
2016-10-10_17-30-46_deview_test_2
2016-10-10_17-30-47_deview_test_3
2016-10-10_17-30-49_deview_test_4
2016-10-10_17-30-50_deview_test_5
2016-10-10_17-32-51_deview_test_0
2016-10-10_17-32-52_deview_test_1
2016-10-10_17-32-53_deview_test_2
2016-10-10_17-32-55_deview_test_3
2016-10-10_17-32-56_deview_test_4
2016-10-10_17-32-57_deview_test_5
2016-10-10_17-33-46_deview_test_0
TOGGLE ALL RUNS
gb-alpharun
12
gb-alpharun/average.loss
gb-alpharun/average.q
gb-alpharun/episode.avg crash
gb-alpharun/episode.avg fall
gb-alpharun/episode.avg reward
gb-alpharun/episode.max reward
gb-alpharun/episode.min reward
gb-alpharun/episode.num of game
gb-alpharun/training.epsilon
gb-alpharun/training.learning_rate
gb-alpharun/validation/real_score
gb-alpharun/validation/reward
gb-dev
12
gb-timerchest
12

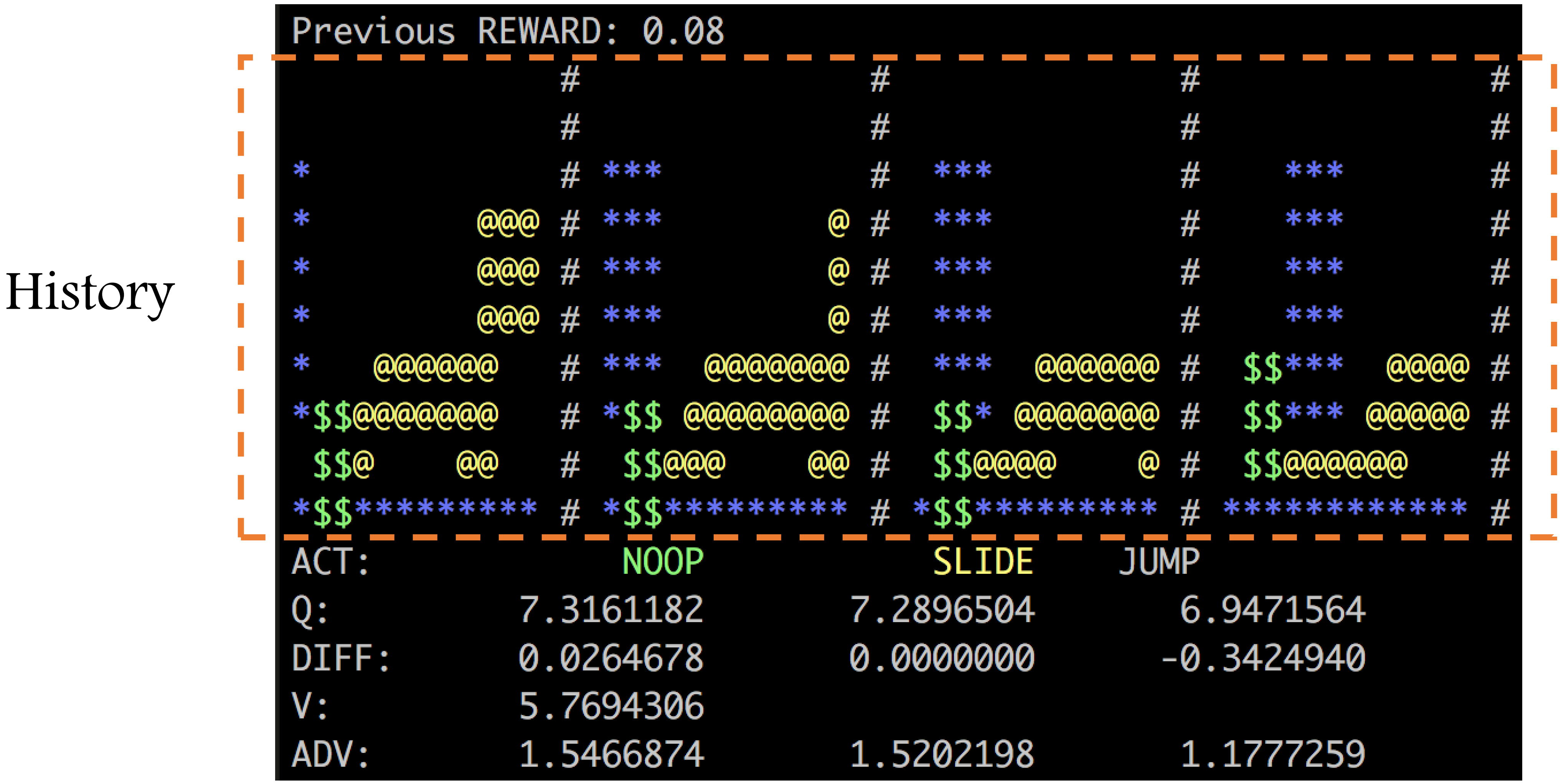
실험, 실험, 실험, 실험, 실
험, 실험, 실험, 실험, 실험,
실험, 실험, 실험, 실험, 실
험, 실험,실험, 실험, 실험,
실험, 실험, 실험, 실험, 실
험, 실험, 실험, 실험, 실험,
실험, 실험, 실험,

2. Debugging

"쿠키가 이상하게 행동하는데

이유라도 알려줬으면..."

```
Previous REWARD: 0.08
             #              #              #              #
             #              #              #              #
*            # ***          #  ***         #    ***       #
*        @@@ # ***        @ #  ***         #    ***       #
*        @@@ # ***        @ #  ***         #    ***       #
*        @@@ # ***        @ #  ***         #    ***       #
*   @@@@@@   # ***  @@@@@@@ #  ***  @@@@@@ #  $$***  @@@@ #
*$$@@@@@@@   # *$$ @@@@@@@@ #  $$* @@@@@@@ #  $$*** @@@@@ #
 $$@    @@   #  $$@@@    @@ #  $$@@@@    @ #  $$@@@@@@    #
*$$********* # *$$********* # *$$********* # ************ #
ACT:            NOOP           SLIDE    JUMP
Q:         7.3161182       7.2896504       6.9471564
DIFF:      0.0264678       0.0000000      -0.3424940
V:         5.7694306
ADV:       1.5466874       1.5202198       1.1777259
```

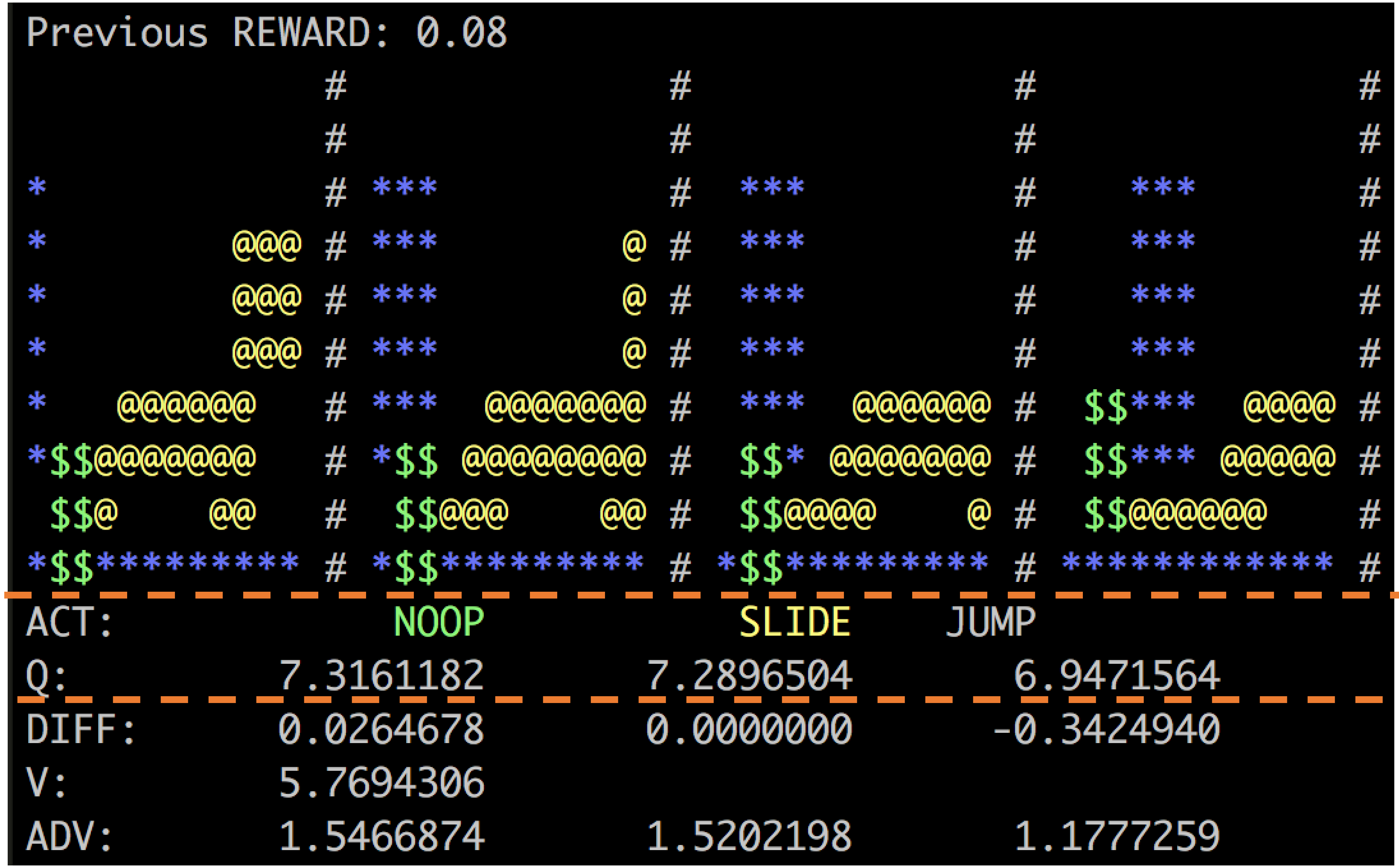

History
Previous REWARD: 0.08
ACT: NOOP SLIDE JUMP
Q: 7.3161182 7.2896504 6.9471564
DIFF: 0.0264678 0.0000000 -0.3424940
V: 5.7694306
ADV: 1.5466874 1.5202198 1.1777259


TIME
226,833
P

```
            @
            @
           @@
           @@

 $$@@     @@
*$$@@@  @@@
*$$ @@@@@@
*************
```

Q-value


Previous REWARD: 0.08
ACT: NOOP SLIDE JUMP
Q: 7.3161182 7.2896504 6.9471564
DIFF: 0.0264678 0.0000000 -0.3424940
V: 5.7694306
ADV: 1.5466874 1.5202198 1.1777259

ACT:	NOOP	SLIDE	JUMP
Q:	7.3161182	7.2896504	6.9471564
DIFF:	0.0264678	0.0000000	-0.3424940
V:	5.7694306		
ADV:	1.5466874	1.5202198	1.1777259

Dueling Network

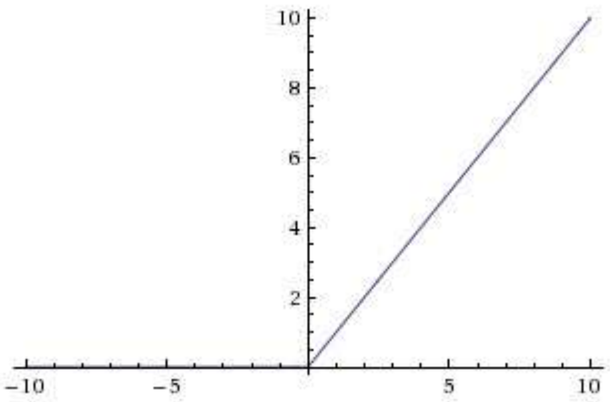
V(s)

A(s,a)

도움이 된 순간

도움이 된 순간

- 모든 action에 대해서 Q 값이 0
- State 값을 조금 바꿔서 출력해도 여전히 0
- Tensorflow의 `fully_connected` 함수에 activation function의 default값이 `nn.relu`로 설정되어 있음
- Activation function을 `None`으로 지정하니 해결!



```
-                                 scope='value_hid')
-        value = fully_connected(value_hid, 1,
-                                weights_initializer=initializer,
-                                weights_regularizer=weights_regularizer,
-                                scope='value')
-
-        advantage_hid = fully_connected(layer, hidden_dim,
-                                        activation_fn=activation_fn,
```

```
+                                 scope='value_hid')
+        self.value = fully_connected(self.value_hid, 1,
+                                     activation_fn=None,
+                                     weights_initializer=initializer,
+                                     weights_regularizer=weights_regularizer,
+                                     scope='value')
+
+        self.advantage_hid = fully_connected(layer, hidden_dim,
```

tensorflow/contrib/layers/python/layers/layers.py

```
@add_arg_scope
def fully_connected(inputs,
                    num_outputs,
                    activation_fn=nn.relu,
                    normalizer_fn=None,
                    normalizer_params=None,
```

```
  Args:
    inputs: A tensor of with at least rank 2 and value fo
      i.e. `[batch_size, depth]`, `[None, None, None, cha
    num_outputs: Integer, the number of output units in t
    activation_fn: activation function.
    normalizer_fn: normalization function to use instead
```

시도해 봤다면 좋았을 디버깅

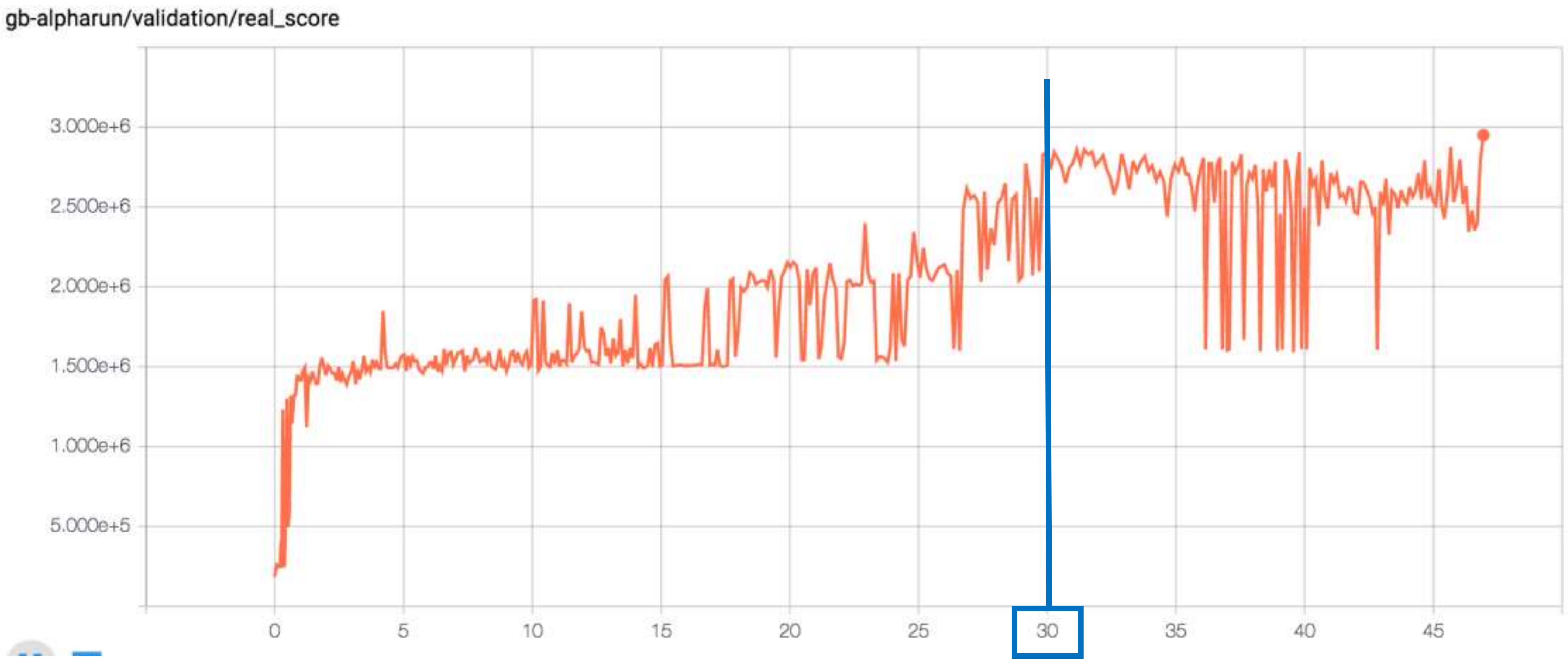
- State를 실시간으로 수정하면서 Q 변화 보기

  ex) 젤리를 쿠키 앞에 그려보면서 변화 확인

- Exploration을 어떻게 하고 있는지
  - reward는 제대로 학습 될 수 있도록 정해져 있었는지?

3. Pretrained model

하나의 모델을 처음부터 학습하기 위해선



“반복된 실험의 학습 시간

을

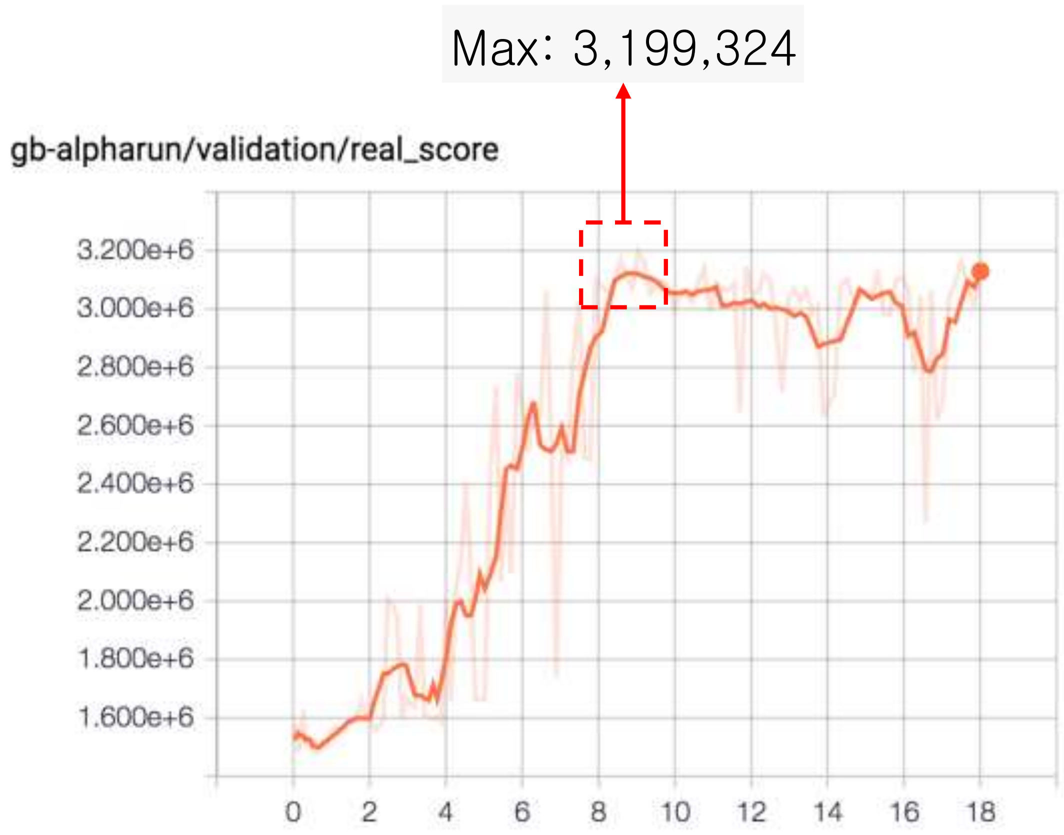
단축시켜야 한다.”

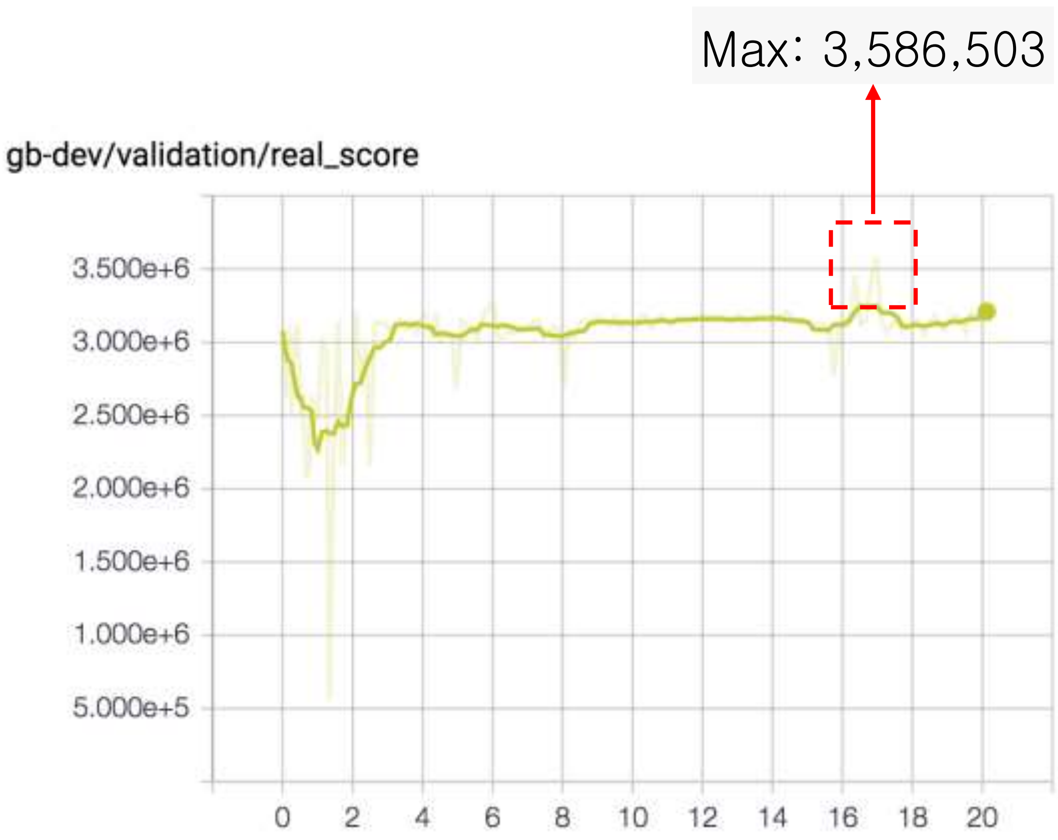
모든 네트워크의 weight를 저장하고,

새로운 실험을 할 때

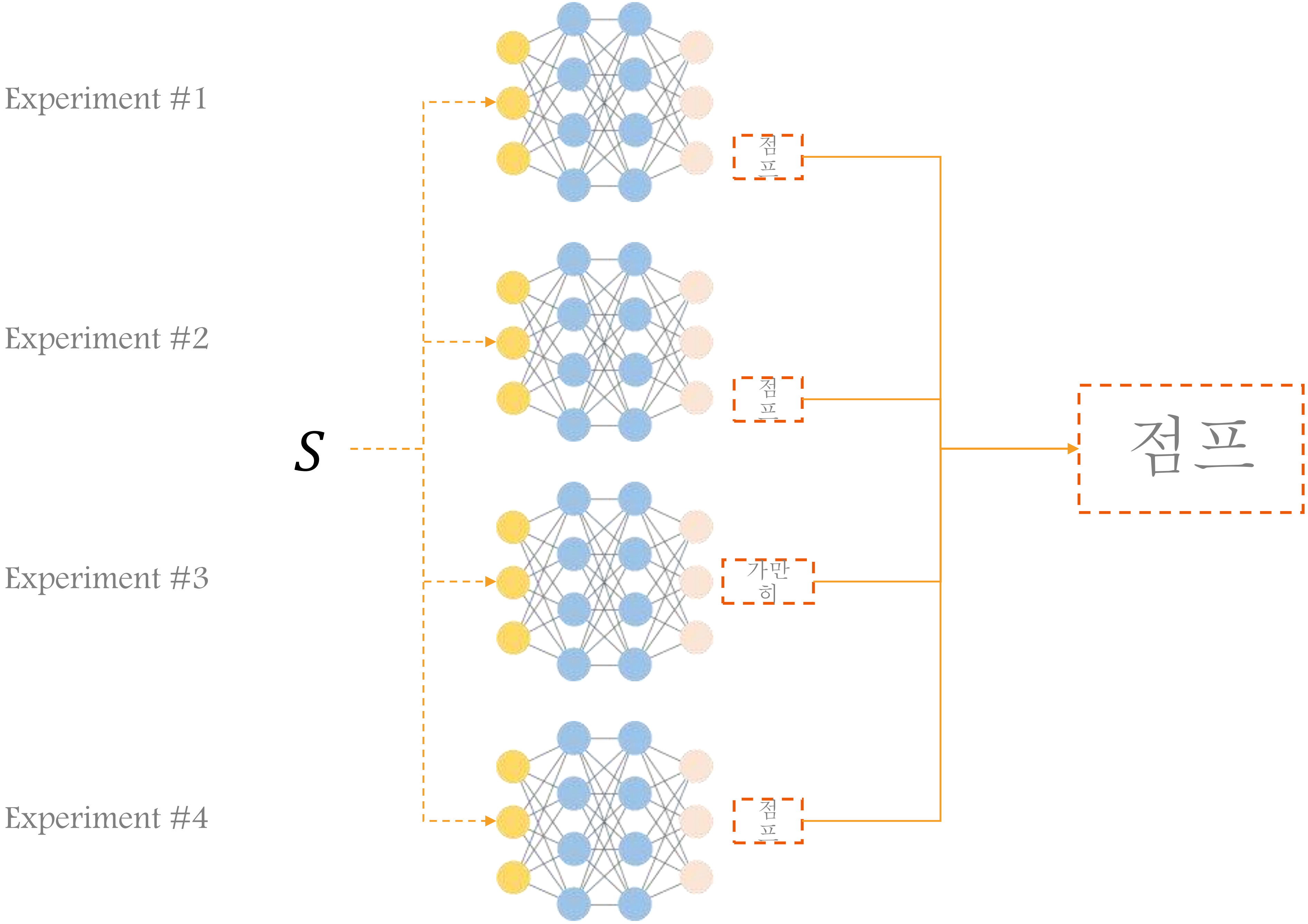
비슷한 실험의 weight를 처음부터 사용

더 높은 점수를 얻을 확률이 높다





4. Ensemble methods

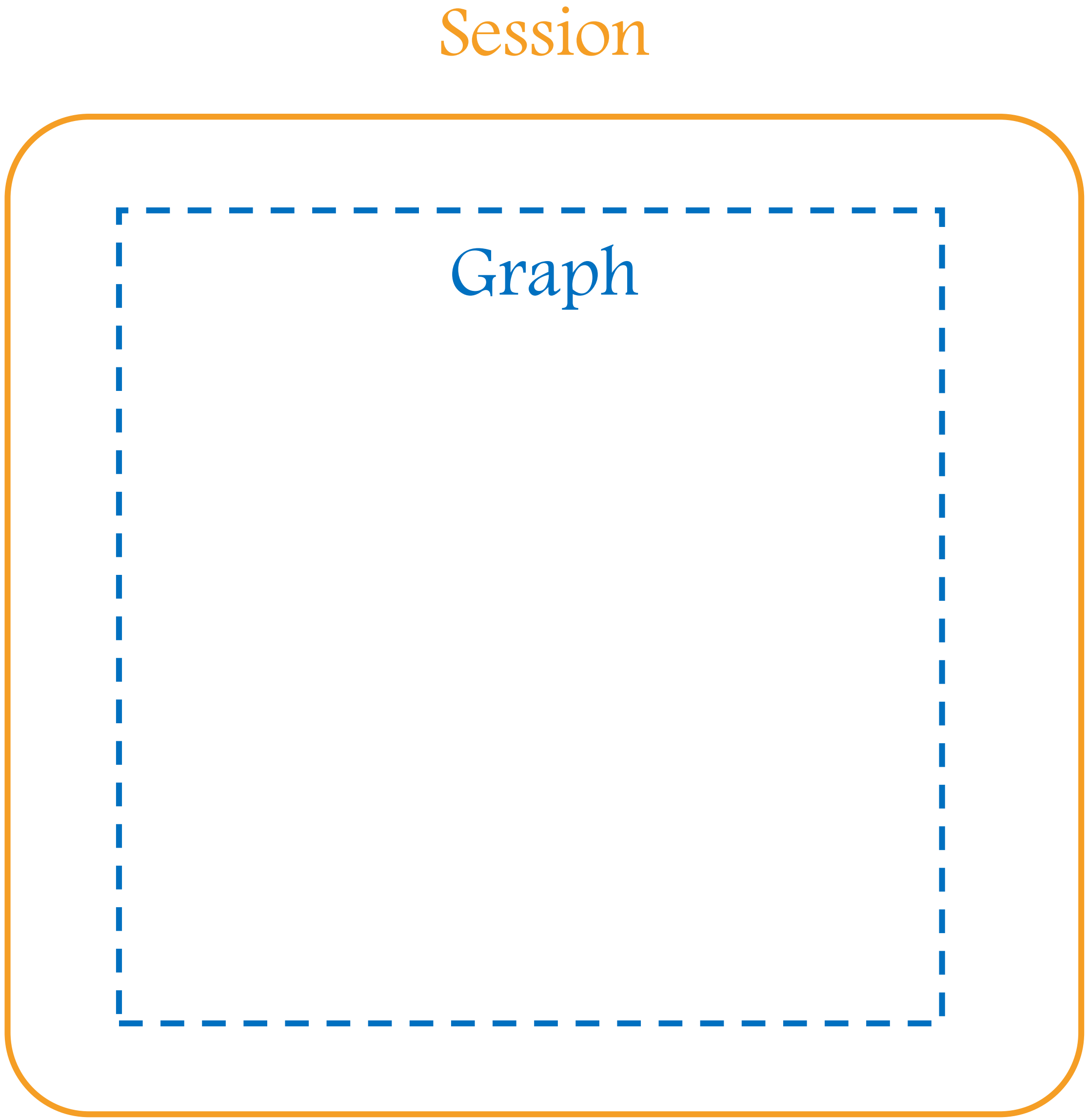

Experiment #1
Experiment #2
Experiment #3
Experiment #4
S
점프
점프
가만히
점프
점프

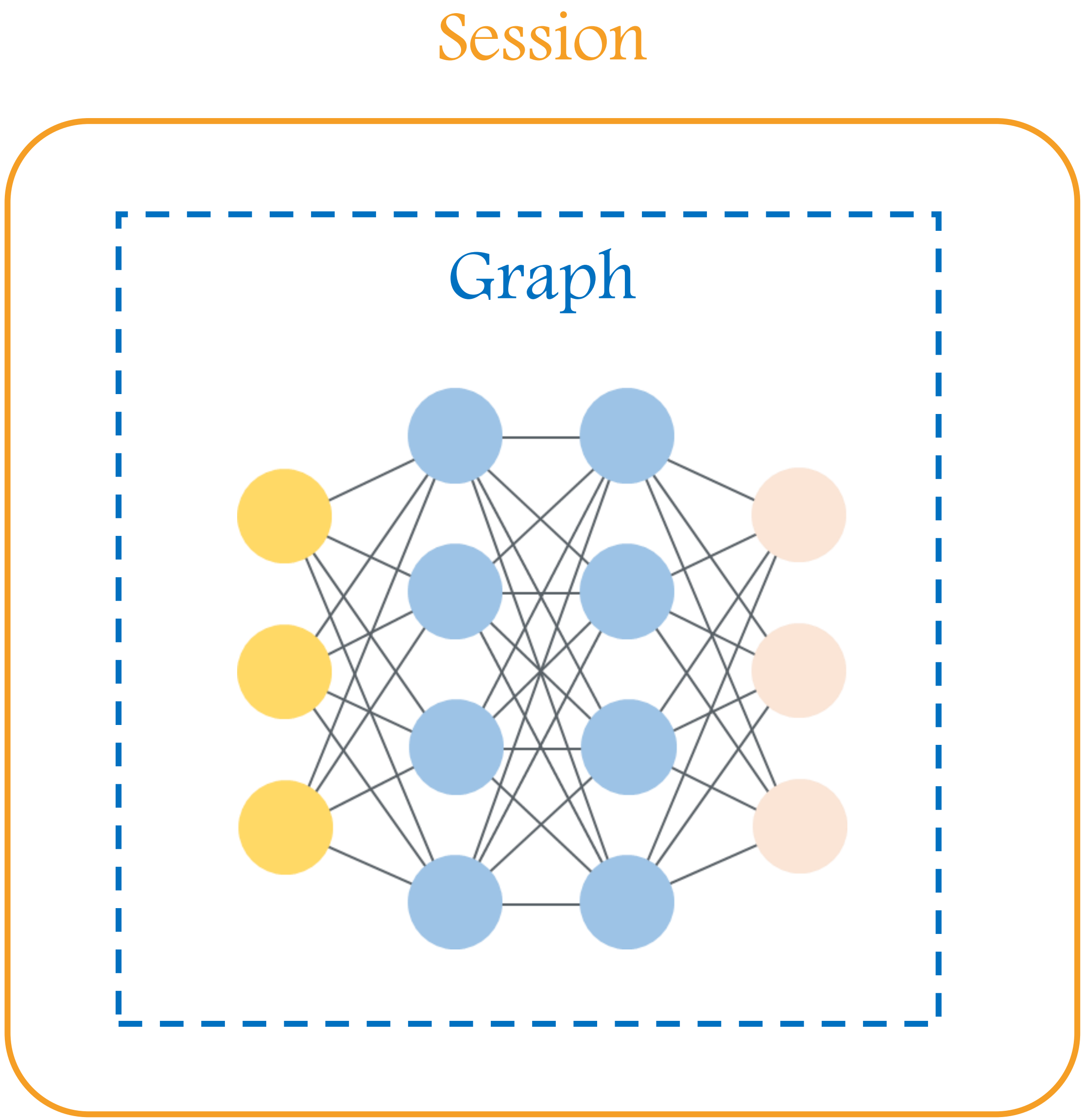
“하나의 실험에서 만들어
진
여러 weight들을
동시에 로드 하려면?”

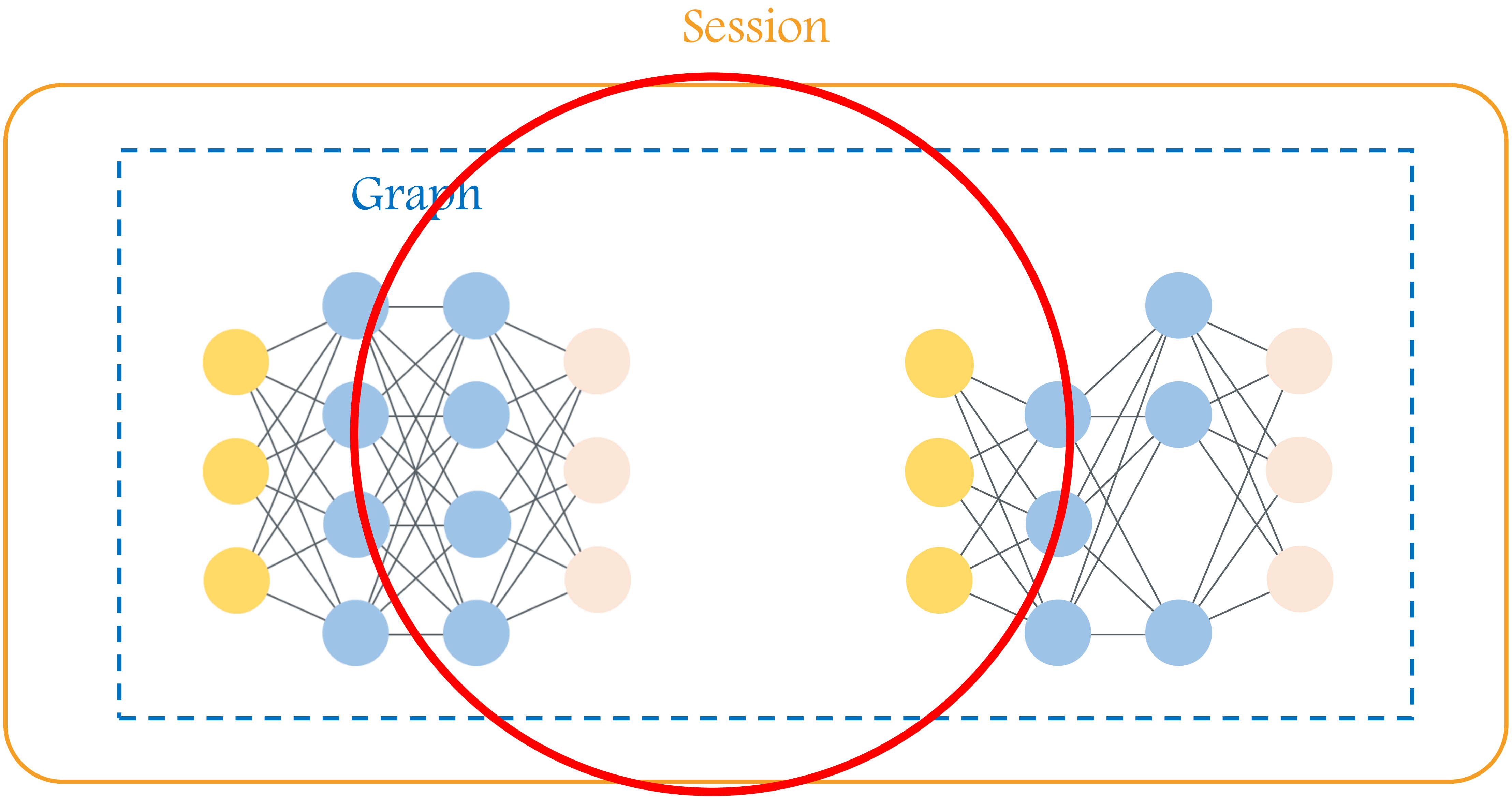
Ex) 가장 잘했던 weight는
보너스 타임은 잘하는데,
두번째로 잘하는 weight는
젤리를 잘 먹는다

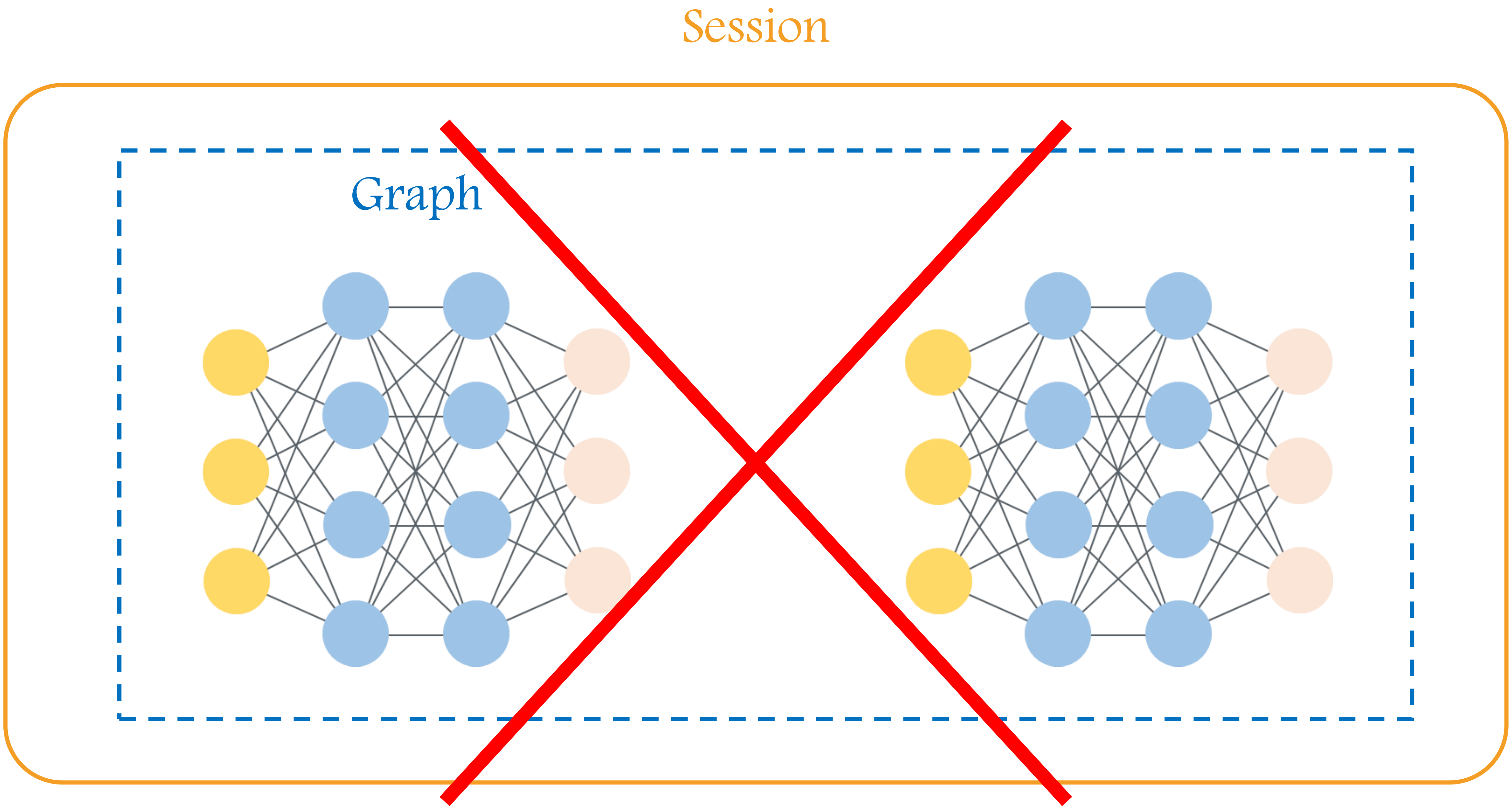
TensorFlow

Session

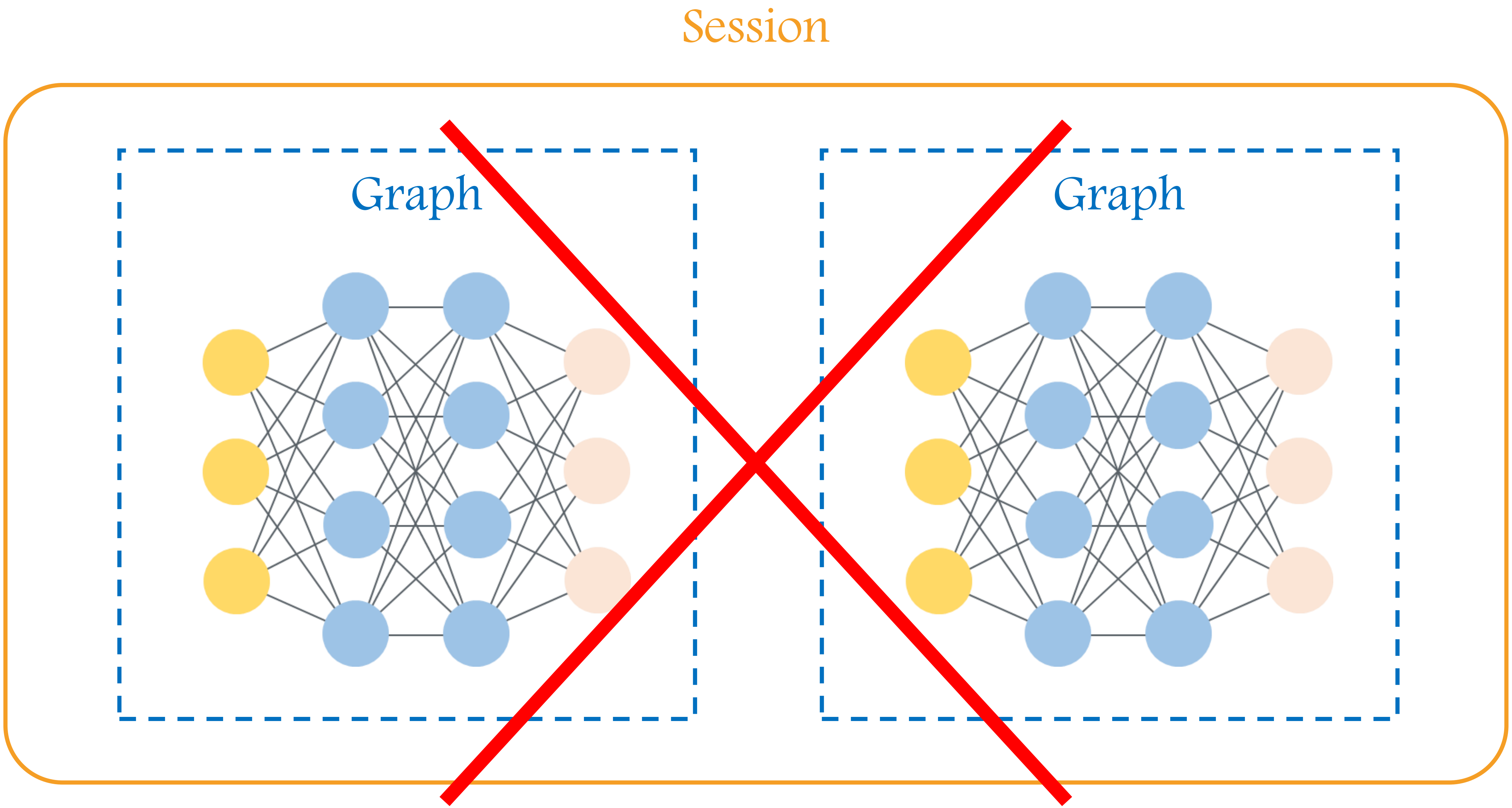

Session
Graph


Session
Graph


Session
Graph

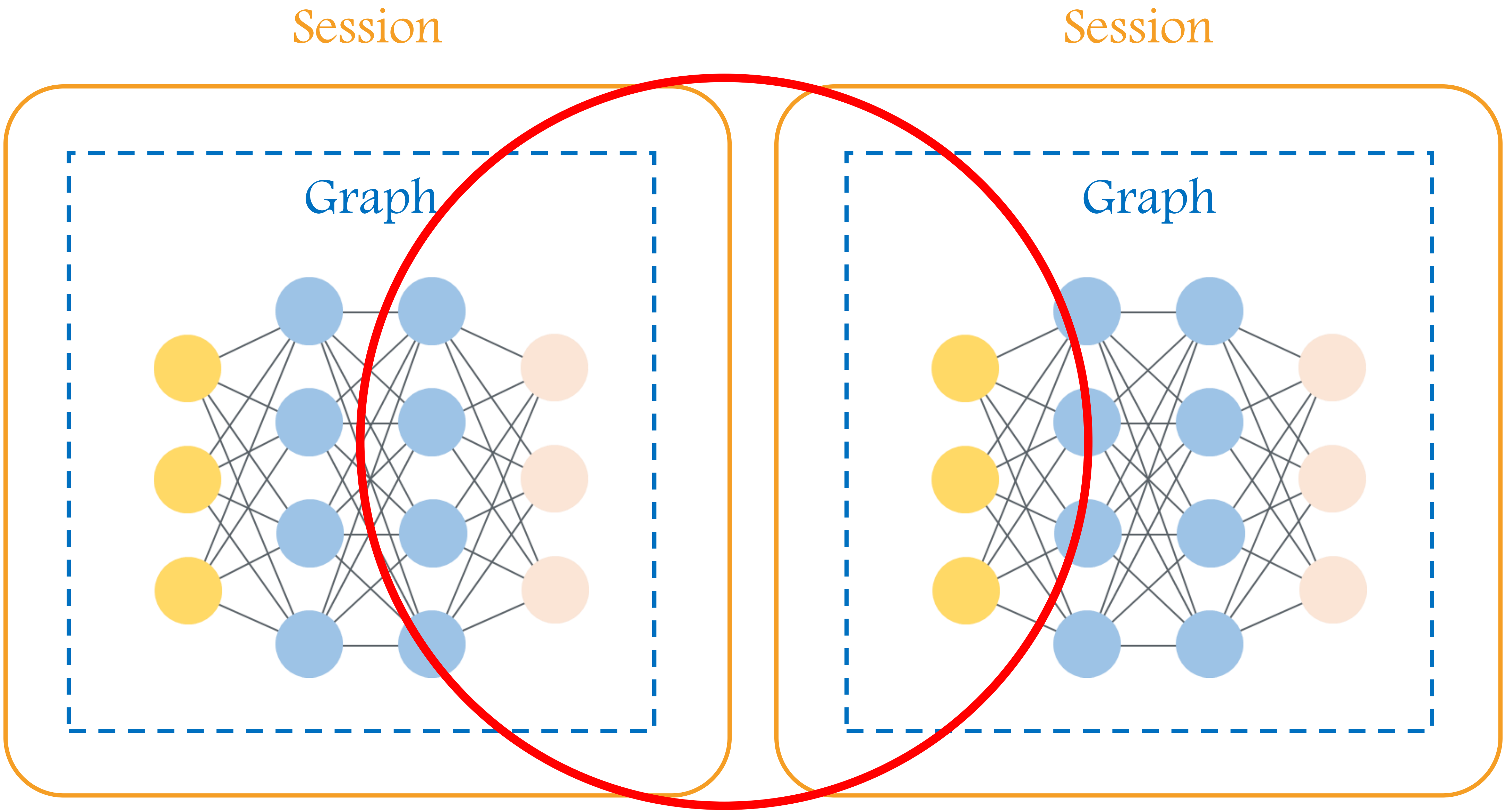

Session
Graph

같은 이름의 node는
하나의 그래프에
두개 이상 존재할 수 없다


Session
Graph
Graph

한 세션에는

하나의 그래프만 존재


Session
Graph
Session
Graph

핵심은,

평소처럼 이렇게 선언하지 마시고

```
with tf.session() as sess:
    network = Network()
    sess.run(network.output)
```

이렇게 Session을 살려서 선언하시면 됩니다

```
sessions = []
g = tf.Graph()
with g.as_default():
    network = Network()
  sess = tf.Session(graph=g)
  sessions.append(sess)

sessions[0].run(network.output)
```

같은 방식으로

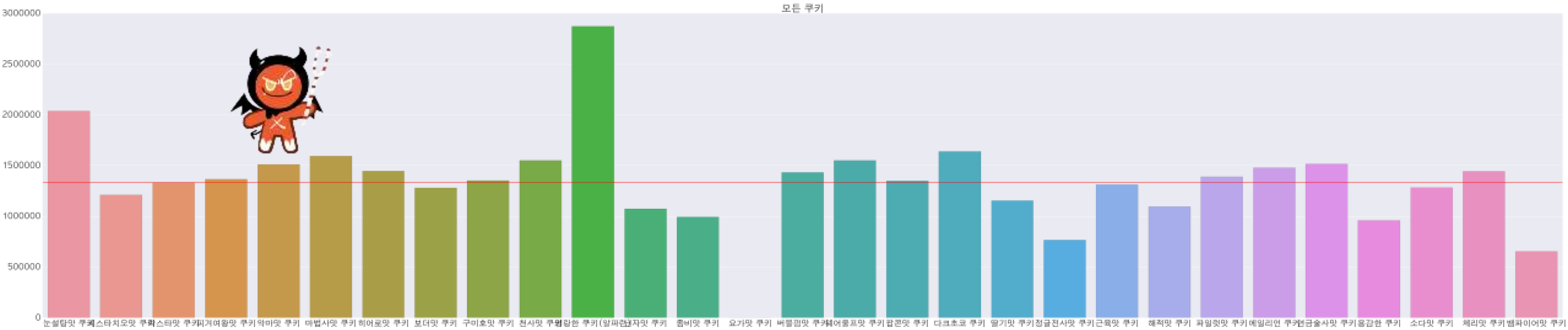
보너스 타임도 학습!


BONUSTIME
651
221/400
1
1,188,172
Giant!
Giant!
Jump
Slide
GL verts: 2436
GL calls: 26

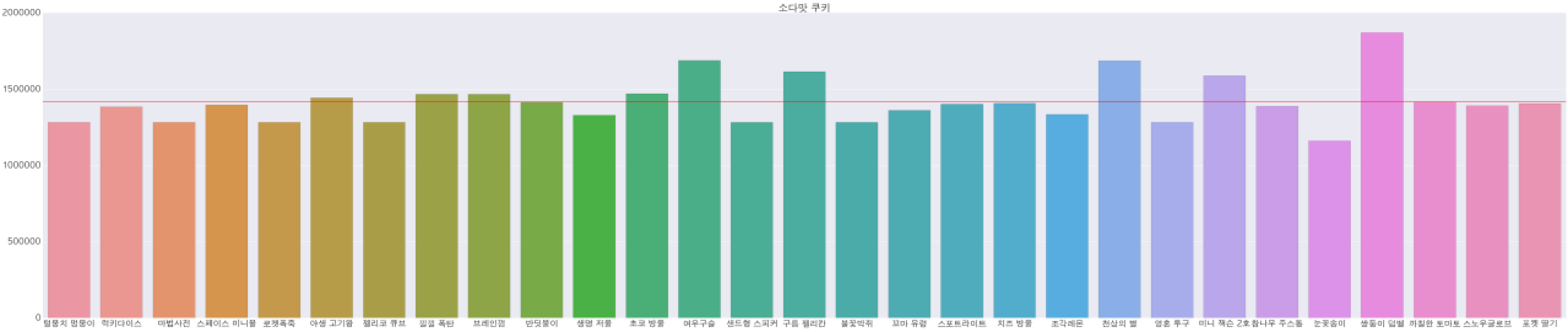
쿠키런 A.I.로 밸런싱 자동화 하기

밸런스를 360배 빠르게 해 봅시다

DEVSISTERS



학습된 A.I.로 모든 쿠키의 평균적인 점수를 계산하거나



셋을 바꿔 보면서 성능 차이를 확인하거나

네,

“알파런 잘 됩니다.”

감사합니다