CORE
Control + Optimization Research Lab

# Double DQN (DDQN)


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Jul 16, 2019

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# Outline

- Environment : CartPole
- Points to note when implementing RL algorithms
- Double DQN (DDQN)
- DQN vs. DDQN - Learning curve

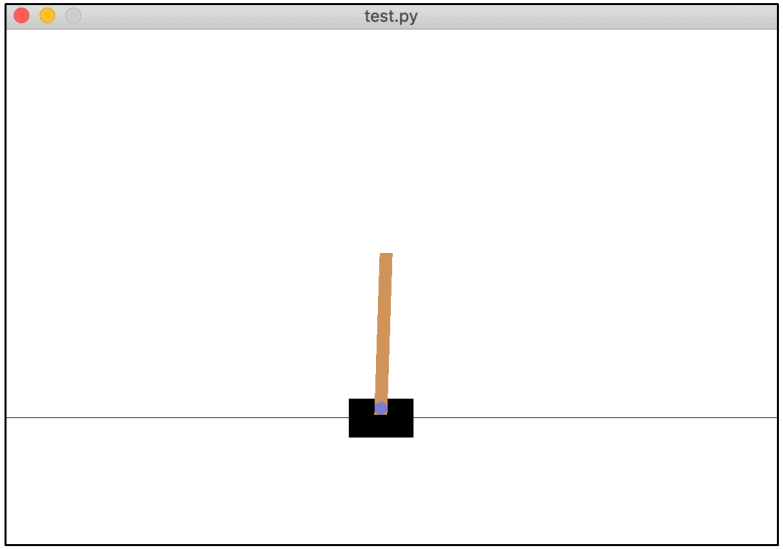
# CartPole

- Env name : CartPole-v1
- States : Continuous observation spaces

| Num | Observation | Min | Max |
|---|---|---|---|
| 0 | Cart Position | -2.4 | 2.4 |
| 1 | Cart Velocity | -Inf | Inf |
| 2 | Pole Angle | ~ -41.8° | ~ 41.8° |
| 3 | Pole Velocity At Tip | -Inf | Inf |

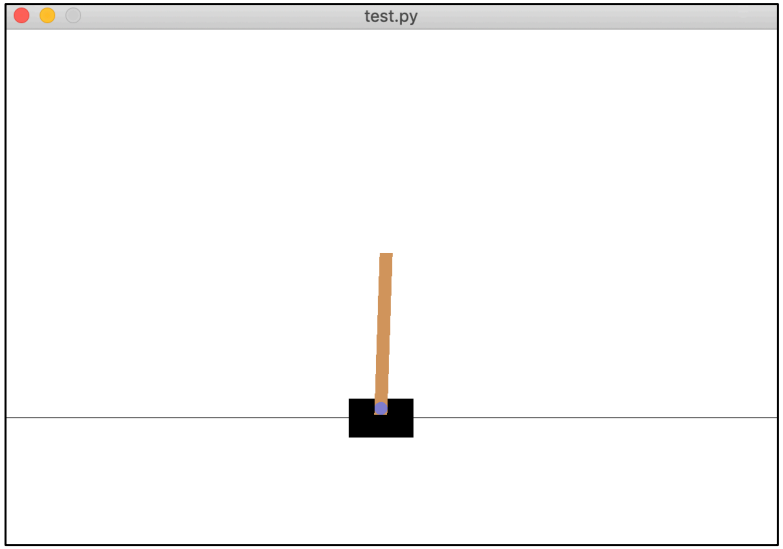
- Actions : Discrete action spaces

| Num | Action |
|---|---|
| 0 | Push cart to the left |
| 1 | Push cart to the right |



# CartPole

- Reward
  - Reward is 1 for every step taken, including the termination step
- Episode Termination
  - Pole Angle is more than $\pm 12^{\circ}$
  - Cart Position is more than $\pm 2.4$
  - Episode length is greater than 500



# CartPole

- Test code

```python
import gym

env = gym.make('CartPole-v1')

for episode in range(10000):
    done = False
    state = env.reset()

    while not done:
        env.render()

        action = env.action_space.sample()
        next_state, reward, done, _ = env.step(action)

        print('state: {} | action: {} | next_state: {} | reward: {} | done: {}'.format(
                state, action, next_state, reward, done))

        state = next_state

        if done:
            break
```

Episode

Step

```
state: [ 0.02882383  0.53942364 -0.06136833 -0.95704334] | action: 1 |
next_state: [ 0.0396123   0.73531478 -0.0805092  -1.26835788] | reward:
 1.0 | done: False
state: [ 0.0396123   0.73531478 -0.0805092  -1.26835788] | action: 1 |
next_state: [ 0.0543186   0.93136736 -0.10587636 -1.58512834] | reward:
 1.0 | done: False
state: [ 0.0543186   0.93136736 -0.10587636 -1.58512834] | action: 0 |
next_state: [ 0.07294594  0.73765175 -0.13757892 -1.32725157] | reward:
 1.0 | done: False
```

# Points to note when implementing RL algorithms

- 우선적으로 **환경**이 잘 동작하는지 random agent를 통해 확인해야 한다.
  - State, action, reward, next state, done 출력해보기
  - 각 action이 어떠한 action인지, 어떤 값인지를 확인하기

- Tensor의 **shape**을 항상 주의 깊게 봐야한다. (**제일 중요!**)

- Tensor의 **자료형**이 현재 일반 list인지, numpy의 array인지, torch의 tensor인지를 잘 확인해야한다.

# Double DQN (DDQN)

- DQN (Final version) + DDQN

**Algorithm 1: deep Q-learning with experience replay.**

Initialize replay memory $D$ to capacity $N$

Initialize action-value function $Q$ with random weights $\theta$

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**

    With probability $\varepsilon$ 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 $(\phi_j, a_j, r_j, \phi_{j+1})$ from $D$

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

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

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

  **End For**

**End For**

$$L^{DoubleQ} = (r + \gamma Q_{\theta^{-}}(s', \underset{a'}{\text{argmax}}\, Q_\theta(s', a')) - Q_\theta(s, a))^2$$

$$L^{Q} = (r + \gamma \max_{a'} Q_{\theta^{-}}(s', a') - Q_\theta(s, a))^2$$

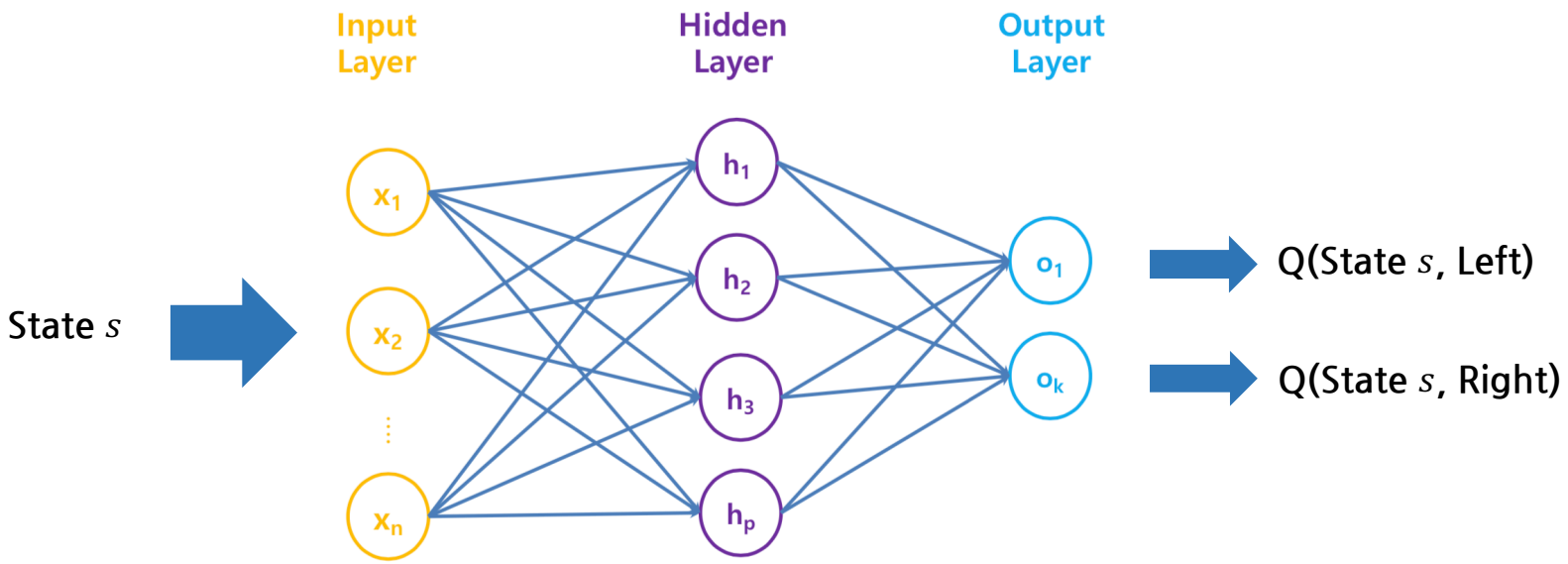
source : https://storage.googleapis.com/deepmind-media/dqn/DQNNaturePaper.pdf

# Double DQN (DDQN)

- Learning process
  1. 상태에 따른 행동 선택
  2. 환경에서 선택한 행동으로 한 time step을 진행한 후, 다음 상태와 보상을 받음
  3. Sample $(s, a, r, s')$을 replay buffer에 저장
  4. Replay buffer에서 랜덤으로 sample을 추출
  5. 추출한 sample로 학습
  6. 일정한 step마다 target model 업데이트

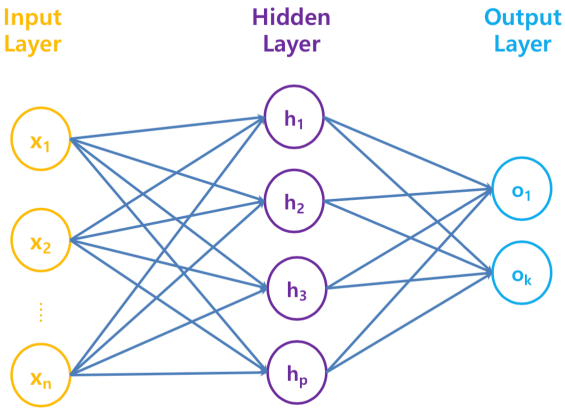
# Double DQN (DDQN)

- Q-Network (Function approximator)



# Double DQN (DDQN)

- Q-Network (Function approximator)




```python
import torch
import torch.nn as nn

class QNet(nn.Module):
    def __init__(self, state_size, action_size, args):
        super(QNet, self).__init__()
        self.fc1 = nn.Linear(state_size, args.hidden_size)
        self.fc2 = nn.Linear(args.hidden_size, action_size)

    def forward(self, x):
        x = torch.tanh(self.fc1(x))
        q_values = self.fc2(x)
        return q_values
```

# Learning process

1. 상태에 따른 행동 선택

```
110             q_values = q_net(torch.Tensor(state))
111             action = get_action(q_values, action_size, args.epsilon)
```

- $\epsilon$-greedy policy (Exploitation vs. Exploration)

$$\pi(s) = \begin{cases} \underset{a}{\text{argmax}}\, Q(s,a), & 1-\epsilon \\ a\ random\ action, & \epsilon \end{cases}$$

```
64  def get_action(q_values, action_size, epsilon):
65      if np.random.rand() <= epsilon:
66          return random.randrange(action_size)
67      else:
68          _, action = torch.max(q_values, 1)
69          return action.numpy()[0]
```

- $\epsilon$ decay $= 0.00005$ (Initial value $\epsilon = 1$, Initial exploration $= 1000$)

```
124             if steps > args.initial_exploration:
125                 args.epsilon -= args.epsilon_decay
126                 args.epsilon = max(args.epsilon, 0.1)
```

# Learning process

2. 환경에서 선택한 행동으로 한 time step을 진행한 후, 다음 상태와 보상을 받음

```
113                 next_state, reward, done, _ = env.step(action)
```

3. Sample $(s, a, r, s')$을 replay buffer에 저장

```
93      replay_buffer = deque(maxlen=10000)
```

```
117                 mask = 0 if done else 1
118
119                 replay_buffer.append((state, action, reward, next_state, mask))
```

4. Replay buffer에서 랜덤으로 sample을 추출 (Batch size : 32)

```
128                     mini_batch = random.sample(replay_buffer, args.batch_size)
```

# Learning process

5. 추출한 sample로 학습

- MSE Loss

$$L^{DoubleQ} = \left( \underbrace{r + \gamma Q_{\theta^-}\left(s', \underset{a'}{\operatorname{argmax}}\, Q_\theta(s', a')\right)}_{\text{Target}} - \underbrace{Q_\theta(s, a)}_{\text{Prediction}} \right)^2$$

```
45      criterion = torch.nn.MSELoss()
46
47      # get Q-value
48      q_values = q_net(torch.Tensor(states))
49      q_value = q_values.gather(1, actions.unsqueeze(1)).view(-1)
```

  - Gather - gather(dim, index)

```
tensor = torch.Tensor([[1,3], [3,2], [5,4], [1,4], [4,2]])
index = torch.LongTensor([[0], [1], [0], [0], [1]])

tensor = tensor.gather(1, index)
print(tensor)
'''
tensor([[1.],
        [2.],
        [5.],
        [1.],
        [2.]])
'''
```

# Learning process

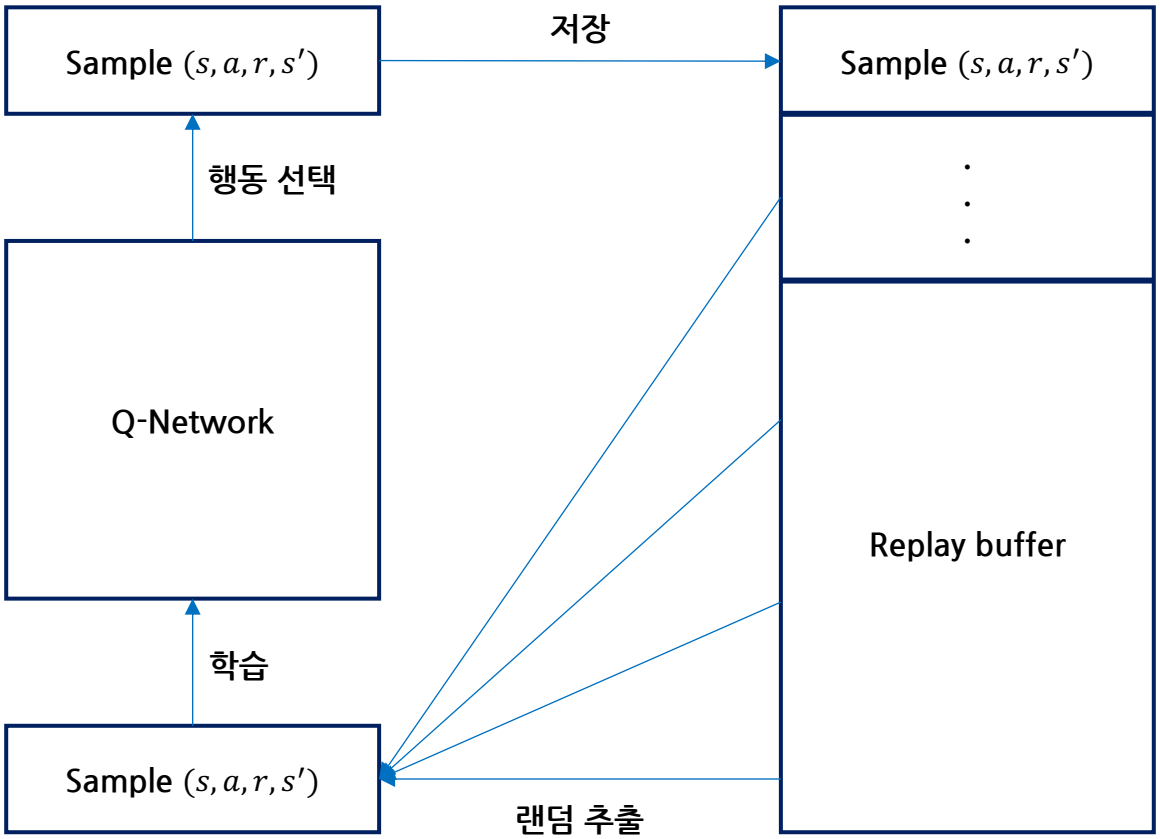
5. 추출한 sample로 학습

- MSE Loss

$$L^{DoubleQ} = \left( \underbrace{r + \gamma Q_{\theta^-}\left(s', \underset{a'}{\operatorname{argmax}}\, Q_\theta(s', a')\right)}_{\text{Target}} - \underbrace{Q_\theta(s, a)}_{\text{Prediction}} \right)^2$$

```
45      criterion = torch.nn.MSELoss()
46
47      # get Q-value
48      q_values = q_net(torch.Tensor(states))
49      q_value = q_values.gather(1, actions.unsqueeze(1)).view(-1)
50
51      # get target
52      next_q_values = q_net(torch.Tensor(next_states))
53      next_q_value_index = next_q_values.max(1)[1]
54
55      target_next_q_values = target_q_net(torch.Tensor(next_states))
56      target_next_q_value = target_next_q_values.gather(1, next_q_value_index.unsqueeze(1)).view(-1)
57      target = rewards + masks * args.gamma * target_next_q_value
58
59      loss = criterion(q_value, target.detach())
60      optimizer.zero_grad()
61      loss.backward()
62      optimizer.step()
```

# Learning process



# Learning process

6. 일정한 step마다 target model 업데이트
   - Initialize target model

```
89      update_target_model(q_net, target_q_net)
```

```
71  def update_target_model(net, target_q_net):
72      target_q_net.load_state_dict(net.state_dict())
```

   - Target model 업데이트 (Update target : 100 step)

```
133                 if steps % args.update_target:
134                     update_target_model(q_net, target_q_net)
```

# Hyperparameter

```
14    parser = argparse.ArgumentParser()
15    parser.add_argument('--env_name', type=str, default="CartPole-v1")
16    parser.add_argument('--load_model', type=str, default=None)
17    parser.add_argument('--save_path', default='./save_model/', help='')
18    parser.add_argument('--render', action="store_true", default=False)
19    parser.add_argument('--gamma', type=float, default=0.99)
20    parser.add_argument('--hidden_size', type=int, default=64)
21    parser.add_argument('--batch_size', type=int, default=32)
22    parser.add_argument('--initial_exploration', type=int, default=1000)
23    parser.add_argument('--epsilon', type=float, default=1.0)
24    parser.add_argument('--epsilon_decay', type=float, default=0.00005)
25    parser.add_argument('--update_target', type=int, default=100)
26    parser.add_argument('--max_iter_num', type=int, default=1000)
27    parser.add_argument('--log_interval', type=int, default=10)
28    parser.add_argument('--goal_score', type=int, default=400)
29    parser.add_argument('--logdir', type=str, default='./logs',
30                        help='tensorboardx logs directory')
31    args = parser.parse_args()
```

# Main loop

- Initialization
  - Seed - random number 고정
  - Q-Network
  - Target Q-Network
  - Optimizer
  - Target model
  - TensorboardX
  - Replay buffer

```
75  def main():
76      env = gym.make(args.env_name)
77      env.seed(500)
78      torch.manual_seed(500)
79
80      state_size = env.observation_space.shape[0]
81      action_size = env.action_space.n
82      print('state size:', state_size)
83      print('action size:', action_size)
84
85      q_net = QNet(state_size, action_size, args)
86      target_q_net = QNet(state_size, action_size, args)
87      optimizer = optim.Adam(q_net.parameters(), lr=0.001)
88
89      update_target_model(q_net, target_q_net)
90
91      writer = SummaryWriter(args.logdir)
92
93      replay_buffer = deque(maxlen=10000)
94      running_score = 0
95      steps = 0
```

# Main loop

- Episode 진행
  - Reshape state vector (4) → (1,4)
  - 상태에 따른 행동 선택
  - 다음 상태와 보상을 받음
  - Reshape next state vector
  - Reward, mask 설정
  - Replay buffer에 저장

```
97      for episode in range(args.max_iter_num):
98          done = False
99          score = 0
100
101         state = env.reset()
102         state = np.reshape(state, [1, state_size])
103
104         while not done:
105             if args.render:
106                 env.render()
107
108             steps += 1
109
110             q_values = q_net(torch.Tensor(state))
111             action = get_action(q_values, action_size, args.epsilon)
112
113             next_state, reward, done, _ = env.step(action)
114
115             next_state = np.reshape(next_state, [1, state_size])
116             reward = reward if not done or score == 499 else -1
117             mask = 0 if done else 1
118
119             replay_buffer.append((state, action, reward, next_state, mask))
120
121             state = next_state
122             score += reward
```

# Main loop

- Episode 진행
  - Step 수가 1000보다 작으면 계속 random action을 선택
  - Step 수가 1000보다 크면
    - $\epsilon$ decay (Initial value $\epsilon = 1$)
    - Replay buffer에서 랜덤으로 32개의 sample을 추출 → Mini batch
    - Train model
    - 100 step마다 target model 업데이트
  - Running score 설정

```
124             if steps > args.initial_exploration:
125                 args.epsilon -= args.epsilon_decay
126                 args.epsilon = max(args.epsilon, 0.1)
127
128                 mini_batch = random.sample(replay_buffer, args.batch_size)
129
130                 q_net.train(), target_q_net.train()
131                 train_model(q_net, target_q_net, optimizer, mini_batch)
132
133                 if steps % args.update_target:
134                     update_target_model(q_net, target_q_net)
135
136         score = score if score == 500.0 else score + 1
137         running_score = 0.99 * running_score + 0.01 * score
```

# Main loop

- Print & Visualize log
- Running score > 400
  - Save model
  - 학습 종료

```
0 episode | running_score: 0.31 | epsilon: 1.00
10 episode | running_score: 2.37 | epsilon: 1.00
20 episode | running_score: 4.44 | epsilon: 1.00
30 episode | running_score: 6.04 | epsilon: 1.00
40 episode | running_score: 7.83 | epsilon: 1.00
50 episode | running_score: 9.19 | epsilon: 0.99
60 episode | running_score: 10.81 | epsilon: 0.98
70 episode | running_score: 11.89 | epsilon: 0.96
80 episode | running_score: 12.68 | epsilon: 0.95
90 episode | running_score: 13.73 | epsilon: 0.94
100 episode | running_score: 14.36 | epsilon: 0.93
```

```
139         if episode % args.log_interval == 0:
140             print('{} episode | running_score: {:.2f} | epsilon: {:.2f}'.format(
141                 episode, running_score, args.epsilon))
142             writer.add_scalar('log/score', float(score), episode)
143 
144         if running_score > args.goal_score:
145             if not os.path.isdir(args.save_path):
146                 os.makedirs(args.save_path)
147 
148             ckpt_path = args.save_path + 'model.pth'
149             torch.save(q_net.state_dict(), ckpt_path)
150             print('Running score exceeds 400. So end')
151             break
```

# Train model

- Mini batch → Numpy array
  - mini_batch - (32, 5)

```
33  def train_model(q_net, target_q_net, optimizer, mini_batch):
34      mini_batch = np.array(mini_batch)
```

```
[array([[ 0.06638455,  0.44188166, -0.05941764, -0.71998114]]) 0 1.0
 array([[ 0.07522218,  0.24762993, -0.07381726, -0.44657625]]) 1]

[array([[ 0.03859636,  0.54112043, -0.05626789, -0.85790688]]) 0 1.0
 array([[ 0.04941877,  0.34680833, -0.07342603, -0.58343404]]) 1]

[array([[ 0.11499082,  0.93411447, -0.1403067 , -1.50586197]]) 1 1.0
 array([[ 0.13367311,  1.13063172, -0.17042394, -1.83885608]]) 1]

[array([[ 0.03836089, -0.0380637 , -0.03338654, -0.04749324]]) 0 1.0
 array([[ 0.03759962, -0.2326914 , -0.03433641,  0.2344718 ]]) 1]

[array([[-0.11449923,  0.0169064 ,  0.15822003,  0.29739237]]) 1 1.0
 array([[-0.1141611 ,  0.20946075,  0.16416787,  0.05849141]]) 1]
```

# Train model

- Mini batch → Numpy array
  - mini_batch - (32, 5)

- Mini batch에 있는 32개의 sample들을 각각 나눔
  - states - (32, 4)
  - next_states - (32, 4)

- List → Torch tensor
  - actions - (32)
  - rewards - (32)
  - masks - (32)

```
33  def train_model(q_net, target_q_net, optimizer, mini_batch):
34      mini_batch = np.array(mini_batch)
35      states = np.vstack(mini_batch[:, 0])
36      actions = list(mini_batch[:, 1])
37      rewards = list(mini_batch[:, 2])
38      next_states = np.vstack(mini_batch[:, 3])
39      masks = list(mini_batch[:, 4])
40
41      actions = torch.LongTensor(actions)
42      rewards = torch.Tensor(rewards)
43      masks = torch.Tensor(masks)
```

# Train model

- MSE Loss
  - $L^{DoubleQ} = ( \underbrace{r + \gamma Q_{\theta^-}\left(s', \underset{a'}{\operatorname{argmax}}\, Q_\theta(s', a')\right)}_{\text{Target}} - \underbrace{Q_\theta(s, a)}_{\text{Prediction}} )^2$
    - cf) $L^Q = ( r + \gamma \max_{a'} Q_{\theta^-}(s', a') - Q_\theta(s, a) )^2$

```
45      criterion = torch.nn.MSELoss()
46
47      # get Q-value
48      q_values = q_net(torch.Tensor(states))
49      q_value = q_values.gather(1, actions.unsqueeze(1)).view(-1)
50
51      # get target
52      next_q_values = q_net(torch.Tensor(next_states))
53      next_q_value_index = next_q_values.max(1)[1]
54
55      target_next_q_values = target_q_net(torch.Tensor(next_states))
56      target_next_q_value = target_next_q_values.gather(1, next_q_value_index.unsqueeze(1)).view(-1)
57      target = rewards + masks * args.gamma * target_next_q_value
58
59      loss = criterion(q_value, target.detach())
60      optimizer.zero_grad()
61      loss.backward()
62      optimizer.step()
```

# Train model

- Prediction
  - **q_values** - (32, 2)
  - **action.unsqueeze(1)** - (32, 1)
  - **q_value** - (32)
- Target
  - **next_q_values** - (32, 2)
  - **next_q_values.max(1)[1]** - (32)
  - **target_next_q_values** - (32, 2)
  - **next_q_values_index.unsqueeze(1)** - (32, 1)
  - **target** - (32)

```
45      criterion = torch.nn.MSELoss()
46
47      # get Q-value
48      q_values = q_net(torch.Tensor(states))
49      q_value = q_values.gather(1, actions.unsqueeze(1)).view(-1)
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56      target_next_q_value = target_next_q_values.gather(1, next_q_value_index.unsqueeze(1)).view(-1)
57      target = rewards + masks * args.gamma * target_next_q_value
58
59      loss = criterion(q_value, target.detach())
60      optimizer.zero_grad()
61      loss.backward()
62      optimizer.step()
```
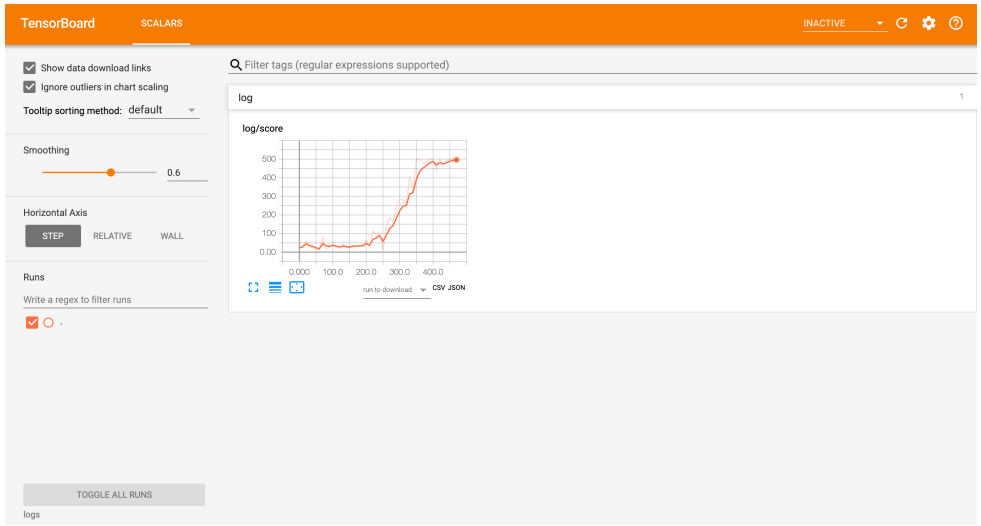

# Train & TensorboardX

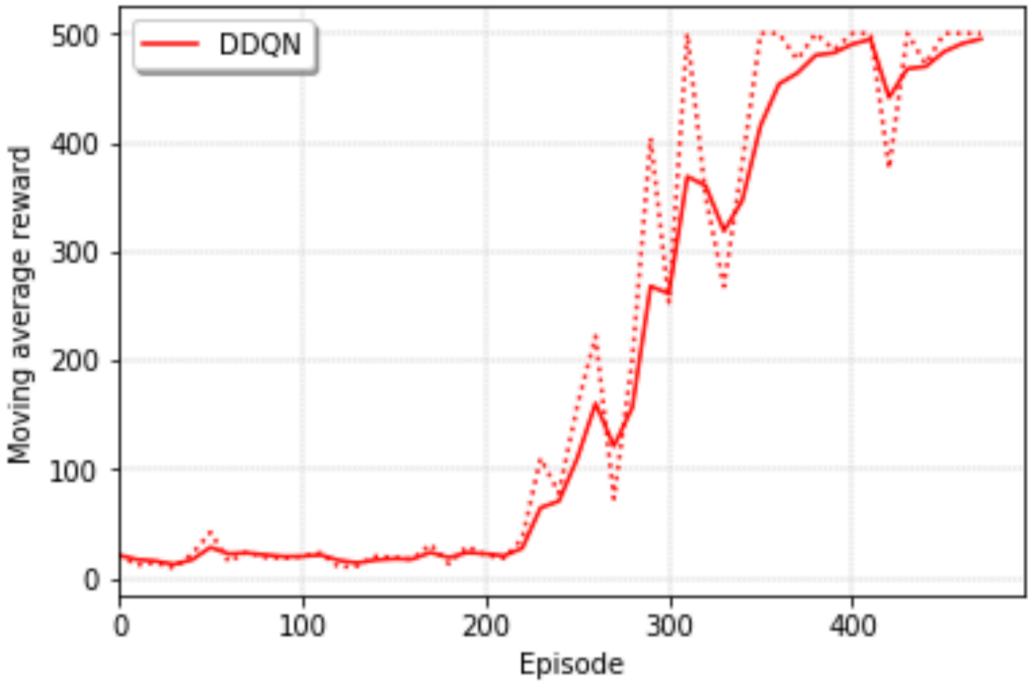
- Terminal A - train 실행
  - conda activate env_name
  - python train.py

- Terminal B - tensorboardX 실행
  - conda activate env_name
  - tensorboard --logdir logs
  - (웹에서) localhost:6006



# Learning curve & Test

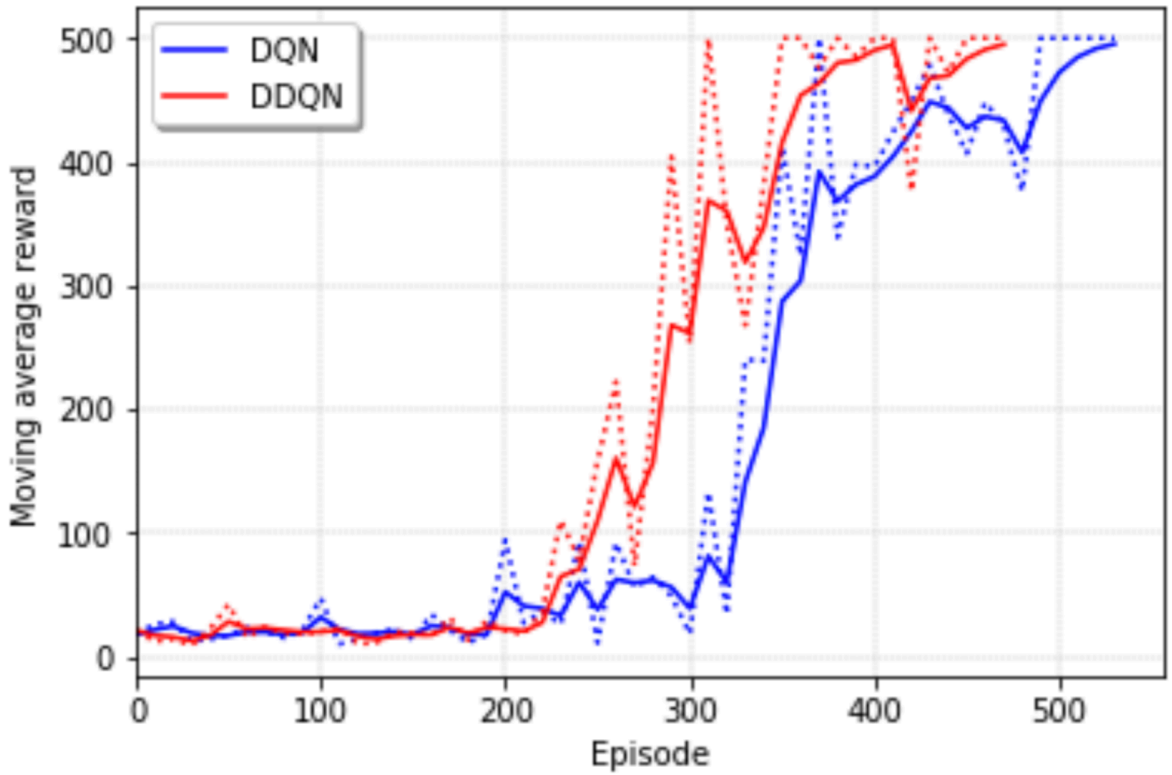
- Learning curve




- Test
  - python test.py

# DQN vs. DDQN

- Learning curve



Thank you