CORE
Control + Optimization Research Lab

Double DQN (DDQN)

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Jul 16, 2019

Outline

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

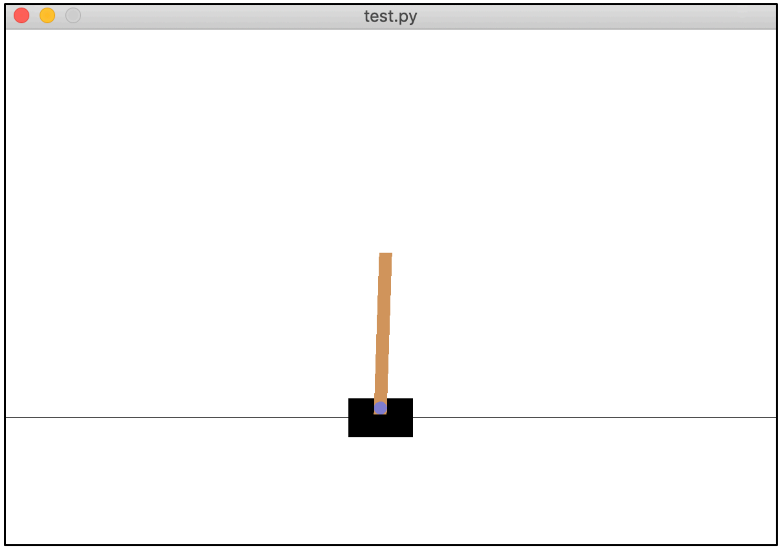
CartPole

- 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

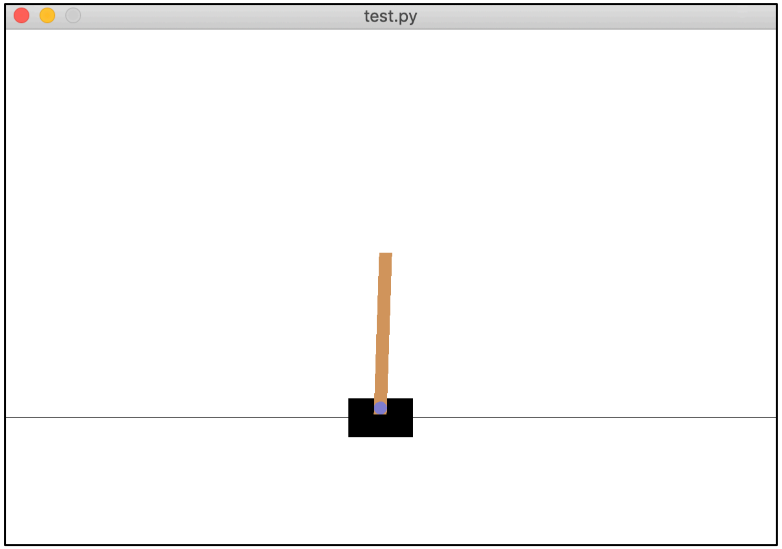
- Actions : Discrete action spaces

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 ± 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 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**
    With probability ε select a random action a_t
    otherwise select $a_t = \mathrm{argmax}_a Q(\phi(s_t), a; \theta)$
    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 $(y_j - Q(\phi_j, a_j; \theta))^2$ with respect to the network parameters θ
    Every C steps reset $\hat{Q} = Q$
  End For
End For

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

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

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

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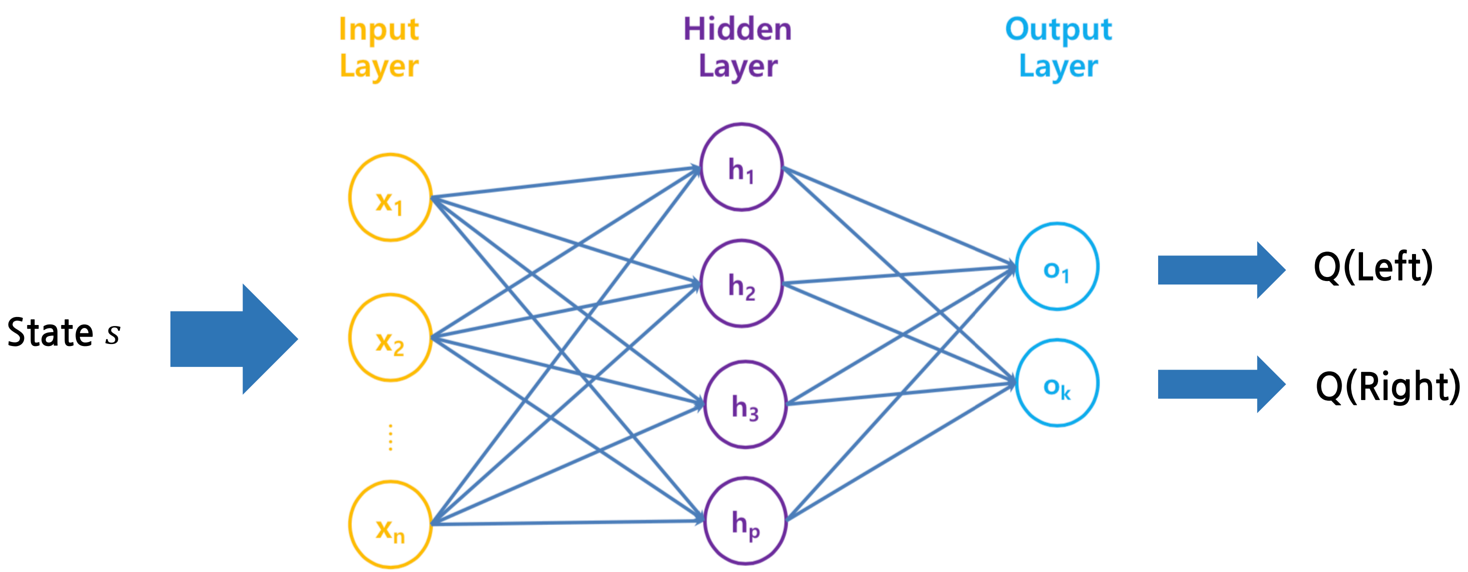
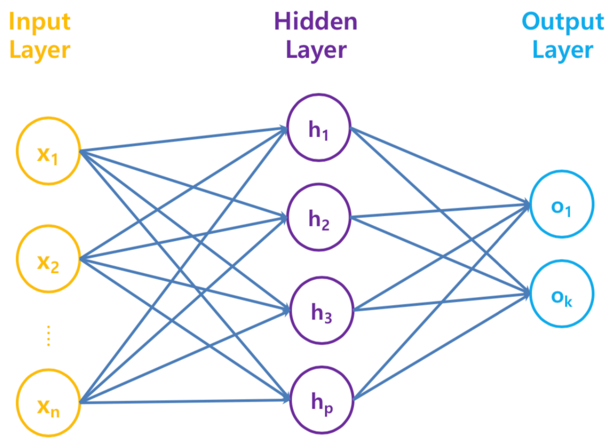
Double DQN (DDQN)

- 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
```

- Initialize Q-Network & Optimizer

```python
q_net = QNet(state_size, action_size, args)
target_q_net = QNet(state_size, action_size, args)
optimizer = optim.Adam(q_net.parameters(), lr=0.001)
```

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

Learning process

1. 상태에 따른 행동 선택

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

- ϵ-greedy policy (Exploitation vs. Exploration)

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

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

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

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

Learning process

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

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

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

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

```
mask = 0 if done else 1

replay_buffer.append((state, action, reward, next_state, mask))
```

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

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

Learning process

5. 추출한 sample로 학습
   - MSE Loss

$$L = (\underbrace{r + \gamma \max_{a'} Q_{\theta^-}(s', a')}_{\text{Target}} - \underbrace{Q_\theta(s, a)}_{\text{Prediction}})^2$$

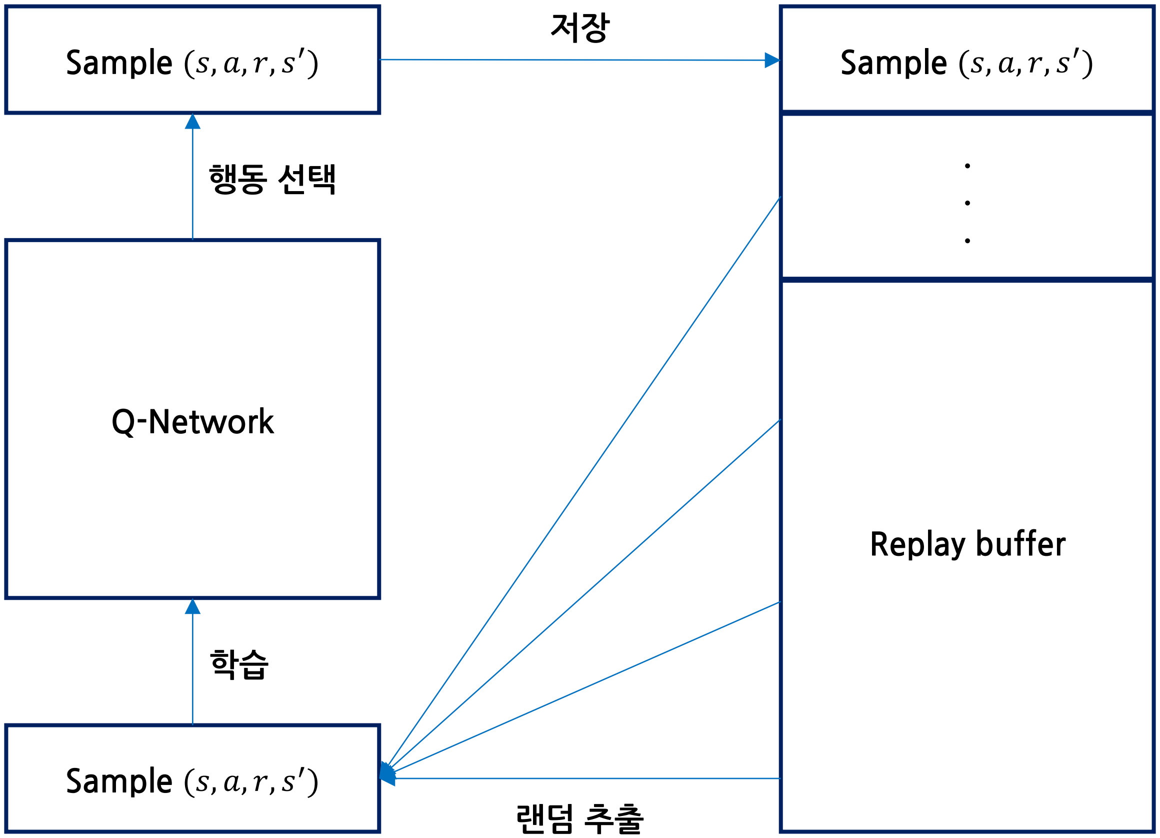
```
criterion = torch.nn.MSELoss()

# get Q-value
q_values = q_net(torch.Tensor(states))
q_value = q_values.gather(1, actions.unsqueeze(1)).view(-1)

# get target
target_next_q_values = target_q_net(torch.Tensor(next_states))
target = rewards + masks * args.gamma * target_next_q_values.max(1)[0]

loss = criterion(q_value, target.detach())
optimizer.zero_grad()
loss.backward()
optimizer.step()
```

Learning process



Learning process

6. 일정한 step마다 target model 업데이트
   - Initialize target model

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

```
def update_target_model(q_net, target_q_net):
    target_q_net.load_state_dict(q_net.state_dict())
```

   - Target model 업데이트 (Update target : 100 step)

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

Hyperparameter

```
parser = argparse.ArgumentParser()
parser.add_argument('--env_name', type=str, default="CartPole-v1")
parser.add_argument('--load_model', type=str, default=None)
parser.add_argument('--save_path', default='./save_model/', help='')
parser.add_argument('--render', action="store_true", default=False)
parser.add_argument('--gamma', type=float, default=0.99)
parser.add_argument('--hidden_size', type=int, default=64)
parser.add_argument('--batch_size', type=int, default=32)
parser.add_argument('--initial_exploration', type=int, default=1000)
parser.add_argument('--epsilon', type=float, default=1.0)
parser.add_argument('--epsilon_decay', type=float, default=0.00005)
parser.add_argument('--update_target', type=int, default=100)
parser.add_argument('--max_iter_num', type=int, default=1000)
parser.add_argument('--log_interval', type=int, default=10)
parser.add_argument('--goal_score', type=int, default=400)
parser.add_argument('--logdir', type=str, default='./logs',
                    help='tensorboardx logs directory')
args = parser.parse_args()
```

Main loop

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

```python
def main():
    env = gym.make(args.env_name)
    env.seed(500)
    torch.manual_seed(500)

    state_size = env.observation_space.shape[0]
    action_size = env.action_space.n
    print('state size:', state_size)
    print('action size:', action_size)

    q_net = QNet(state_size, action_size, args)
    target_q_net = QNet(state_size, action_size, args)
    optimizer = optim.Adam(q_net.parameters(), lr=0.001)

    update_target_model(q_net, target_q_net)

    writer = SummaryWriter(args.logdir)

    replay_buffer = deque(maxlen=10000)
    running_score = 0
    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

```python
for episode in range(args.max_iter_num):
    done = False
    score = 0

    state = env.reset()
    state = np.reshape(state, [1, state_size])

    while not done:
        if args.render:
            env.render()

        steps += 1

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

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

        next_state = np.reshape(next_state, [1, state_size])
        reward = reward if not done or score == 499 else -1
        mask = 0 if done else 1

        replay_buffer.append((state, action, reward, next_state, mask))

        state = next_state
        score += reward
```

Main loop

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

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

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

                q_net.train(), target_q_net.train()
                train_model(q_net, target_q_net, optimizer, mini_batch)

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

        score = score if score == 500.0 else score + 1
        running_score = 0.99 * running_score + 0.01 * score
```

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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
```

```python
        if episode % args.log_interval == 0:
            print('{} episode | running_score: {:.2f} | epsilon: {:.2f}'.format(
                episode, running_score, args.epsilon))
            writer.add_scalar('log/score', float(score), episode)

        if running_score > args.goal_score:
            if not os.path.isdir(args.save_path):
                os.makedirs(args.save_path)

            ckpt_path = args.save_path + 'model.pth'
            torch.save(q_net.state_dict(), ckpt_path)
            print('Running score exceeds 400. So end')
            break
```

Train model

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

```
def train_model(q_net, target_q_net, optimizer, mini_batch):
    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)

```python
def train_model(q_net, target_q_net, optimizer, mini_batch):
    mini_batch = np.array(mini_batch)
    states = np.vstack(mini_batch[:, 0])
    actions = list(mini_batch[:, 1])
    rewards = list(mini_batch[:, 2])
    next_states = np.vstack(mini_batch[:, 3])
    masks = list(mini_batch[:, 4])

    actions = torch.LongTensor(actions)
    rewards = torch.Tensor(rewards)
    masks = torch.Tensor(masks)
```

Train model

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

```
criterion = torch.nn.MSELoss()

# get Q-value
q_values = q_net(torch.Tensor(states))
q_value = q_values.gather(1, actions.unsqueeze(1)).view(-1)

# get target
next_q_values = q_net(torch.Tensor(next_states))
next_q_value_index = next_q_values.max(1)[1]

target_next_q_values = target_q_net(torch.Tensor(next_states))
target_next_q_value = target_next_q_values.gather(1, next_q_value_index.unsqueeze(1)).view(-1)
target = rewards + masks * args.gamma * target_next_q_value

loss = criterion(q_value, target.detach())
optimizer.zero_grad()
loss.backward()
optimizer.step()
```

Train model

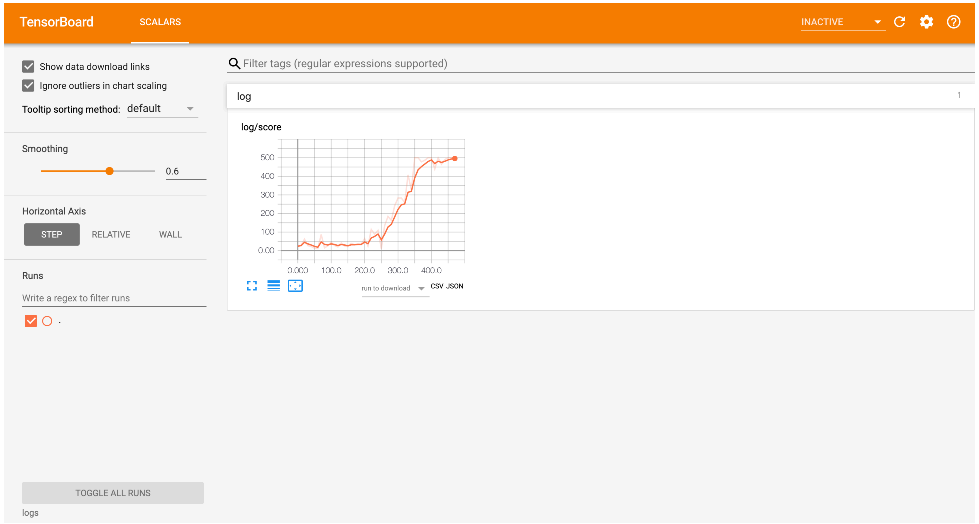
- Prediction
  - **q_values -** (32, 2)
  - **action.unsqueeze(1) -** (32, 1)
  - **q_value -** (32)
- Target
  - **next_q_values -** (32, 2)
  - **next_q_values.max(1)[1] -** (32)
  - **target_next_q_values -** (32, 2)
  - **next_q_values_index.unsqueeze(1) -** (32, 1)
  - **target -** (32)

```
criterion = torch.nn.MSELoss()

# get Q-value
q_values = q_net(torch.Tensor(states))
q_value = q_values.gather(1, actions.unsqueeze(1)).view(-1)

# get target
next_q_values = q_net(torch.Tensor(next_states))
next_q_value_index = next_q_values.max(1)[1]

target_next_q_values = target_q_net(torch.Tensor(next_states))
target_next_q_value = target_next_q_values.gather(1, next_q_value_index.unsqueeze(1)).view(-1)
target = rewards + masks * args.gamma * target_next_q_value

loss = criterion(q_value, target.detach())
optimizer.zero_grad()
loss.backward()
optimizer.step()
```

Train & TensorboardX

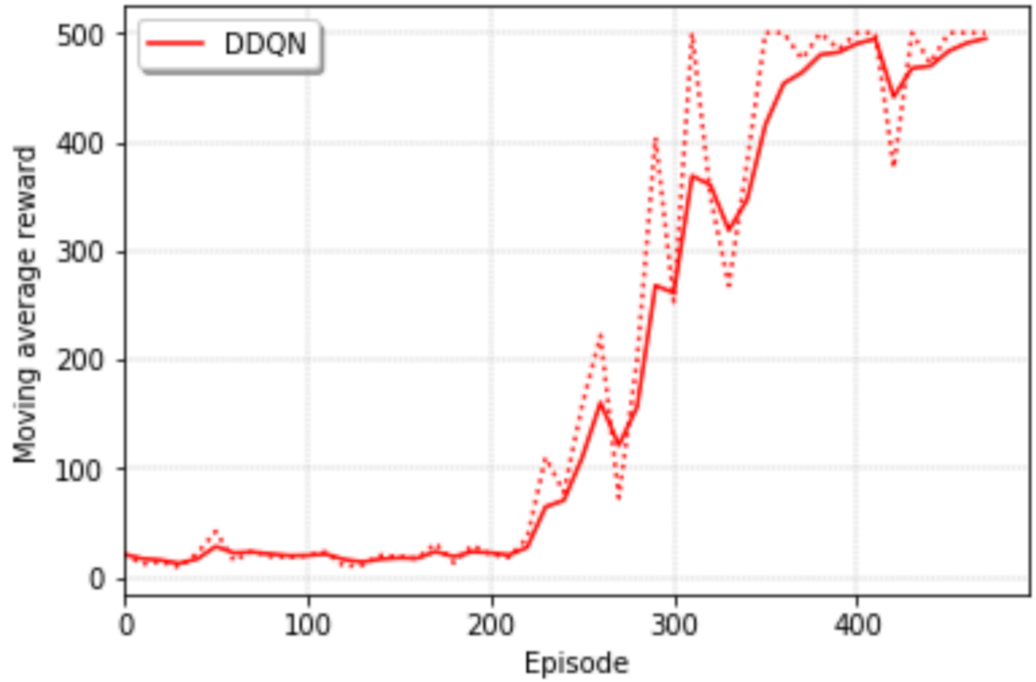
- Terminal A - train 실행
  - ➢ conda activate env_name
  - ➢ python train.py

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



Learning curve & Test

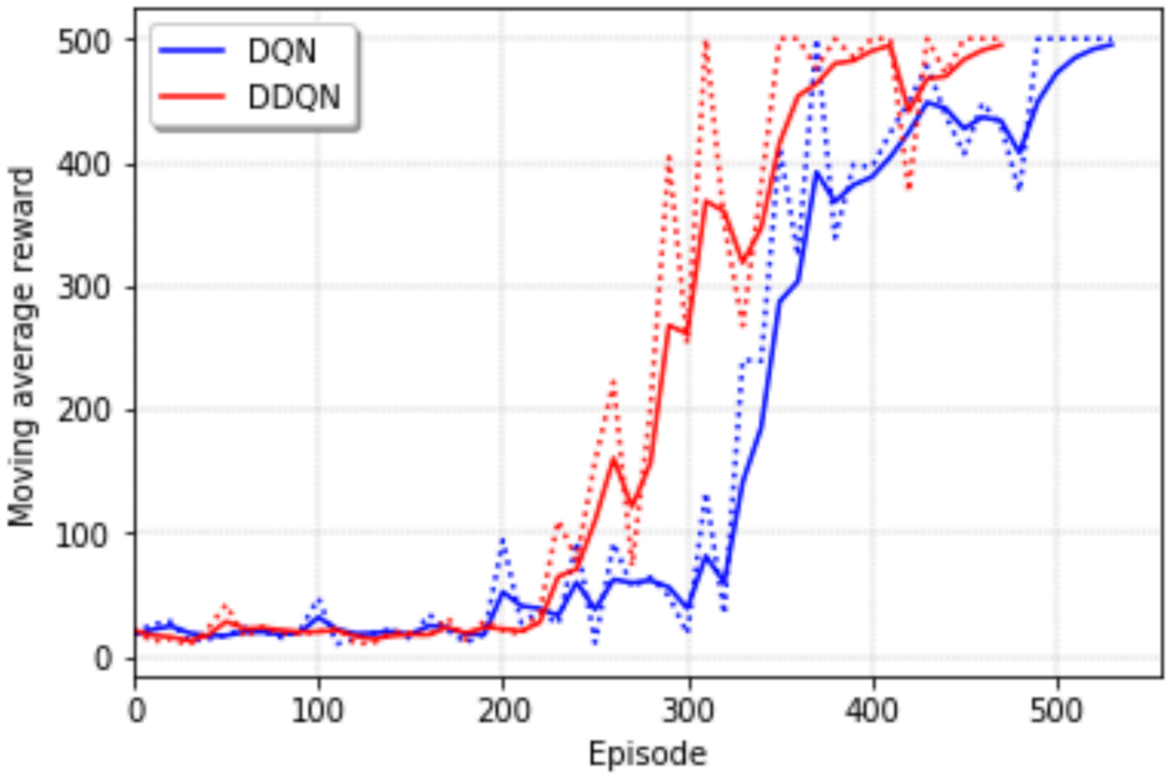
- Learning curve



- Test
  - python test.py

DQN vs. DDQN

- Learning curve



Thank you