CORE
Control + Optimization Research Lab

Advantage Actor-Critic (A2C)

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Jul 16, 2019

Outline

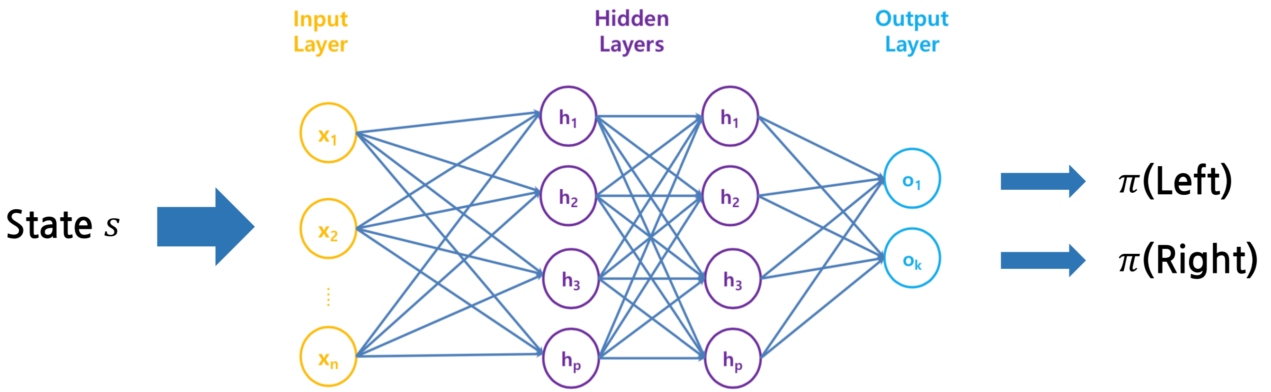
- Advantage Actor-Critic (A2C)
  - Learning process
  - Hyperparameter
  - Main loop
  - Train model
  - Train & TensorboardX
  - Learning curve & Test
- Comparison of algorithms for discrete action - Learning curve

Advantage Actor-Critic (A2C)

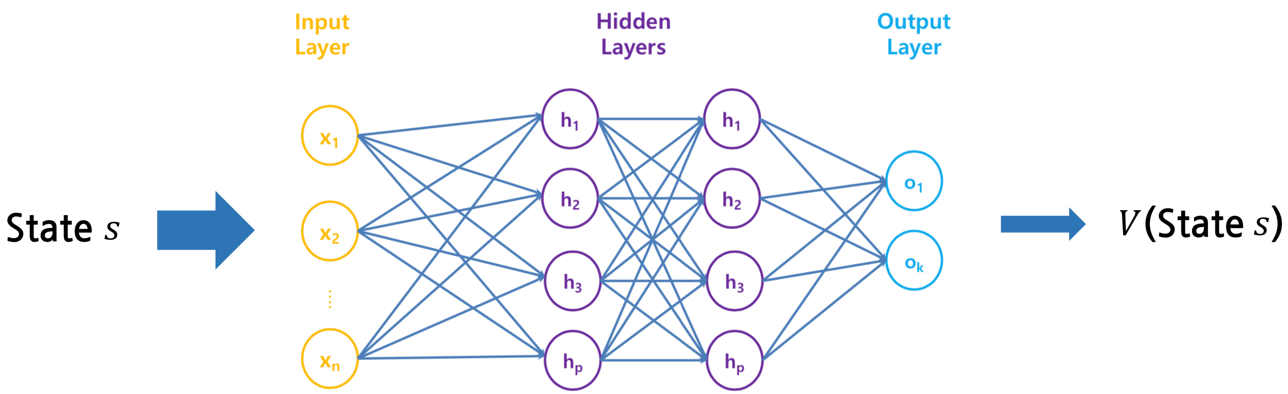
- Learning process
  1. 상태에 따른 행동 선택
  2. 환경에서 선택한 행동으로 한 time step을 진행한 후, 다음 상태와 보상을 받음
  3. Sample (s, a, r, s')로 Actor & Critic network 업데이트

Advantage Actor-Critic (A2C)

- Actor network



- Critic network



Advantage Actor-Critic (A2C)

- Actor network

```python
class Actor(nn.Module):
    def __init__(self, state_size, action_size, args):
        super(Actor, self).__init__()
        self.fc1 = nn.Linear(state_size, args.hidden_size)
        self.fc2 = nn.Linear(args.hidden_size, args.hidden_size)
        self.fc3 = nn.Linear(args.hidden_size, action_size)

    def forward(self, x):
        x = torch.tanh(self.fc1(x))
        x = torch.tanh(self.fc2(x))
        policies = torch.softmax(self.fc3(x), dim=1)

        return policies
```

Advantage Actor-Critic (A2C)

- Critic network

```python
class Critic(nn.Module):
    def __init__(self, state_size, args):
        super(Critic, self).__init__()
        self.fc1 = nn.Linear(state_size, args.hidden_size)
        self.fc2 = nn.Linear(args.hidden_size, args.hidden_size)
        self.fc3 = nn.Linear(args.hidden_size, 1)

    def forward(self, x):
        x = torch.tanh(self.fc1(x))
        x = torch.tanh(self.fc2(x))
        value = self.fc3(x)

        return value
```

Learning process

1. 상태에 따른 행동 선택

```
            policies = actor(torch.Tensor(state))
            action = get_action(policies)
```

```
def get_action(policies):
    categorical = Categorical(policies)
    action = categorical.sample()
    action = action.data.numpy()[0]

    return action
```

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

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

Learning process

3. Sample (s, a, s', r)로 Actor & Critic network 업데이트
   - Critic Loss

$$J_V(\theta) = (\underbrace{r + \gamma V_\theta(s')}_{\text{Target}} - \underbrace{V_\theta(s)}_{\text{Prediction}})^2$$

```
    # update critic
    criterion = torch.nn.MSELoss()

    value = critic(torch.Tensor(state)).squeeze(1)

    next_value = critic(torch.Tensor(next_state)).squeeze(1)
    target = reward + mask * args.gamma * next_value

    critic_loss = criterion(value, target.detach())
    critic_optimizer.zero_grad()
    critic_loss.backward()
    critic_optimizer.step()
```

Learning process

3. Sample (s, a, s', r)로 Actor & Critic network 업데이트
   - Actor Loss

$$J_\pi(\phi) = -\log \pi_\phi(a|s) \underbrace{\left(r + \gamma V_\theta(s') - V_\theta(s)\right)}_{\text{Advantage Function}} + \overbrace{\boxed{\alpha \underbrace{\left(-\sum_i \pi_{\phi_i} \log \pi_{\phi_i}\right)}_{\text{entropy}}}}^{\text{regularization term}}$$

     - Entropy is used to improve exploration by limiting the premature convergence to suboptimal policy.

Learning process

3. Sample (s, a, s', r)로 Actor & Critic network 업데이트
    - Actor Loss

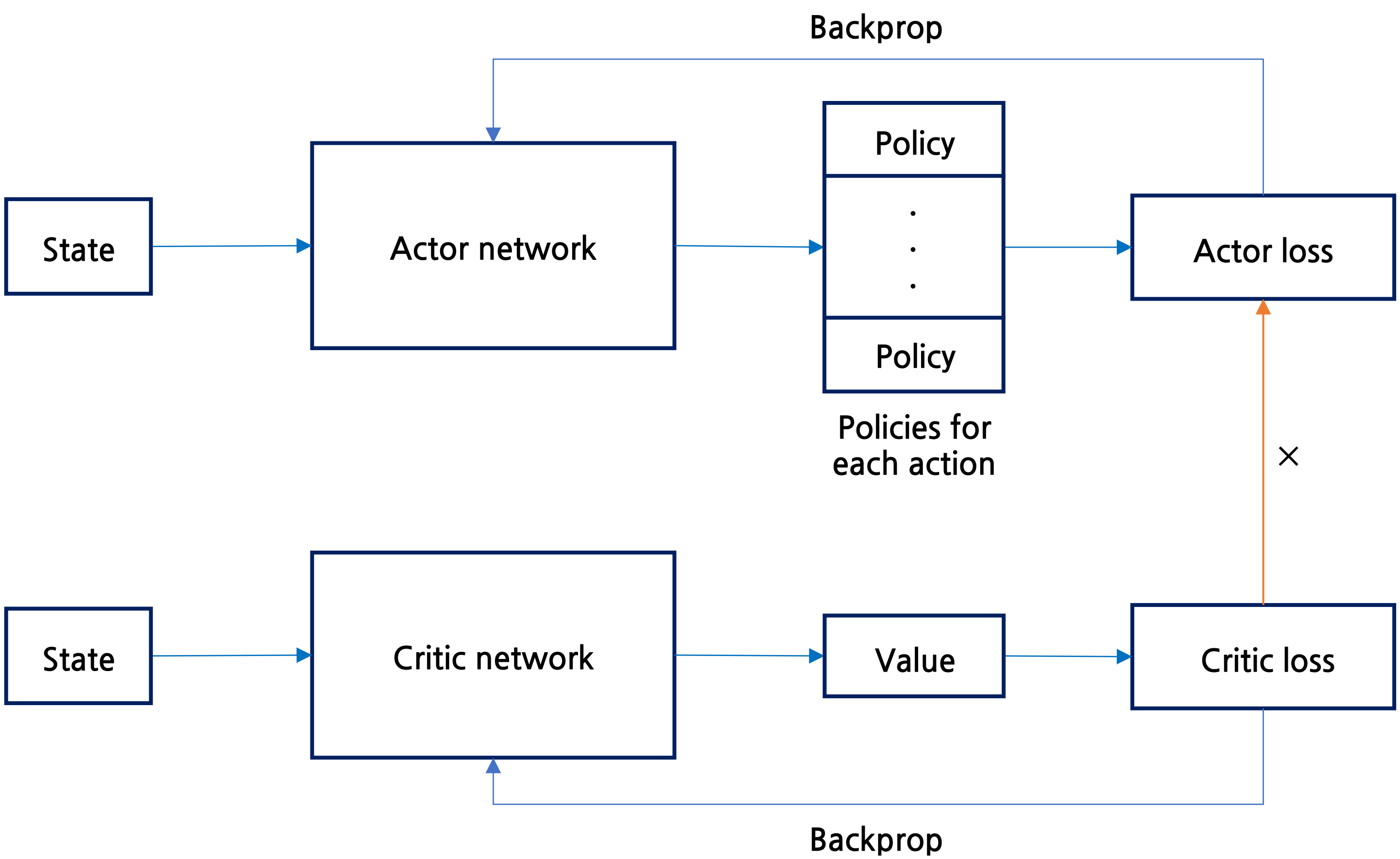
$$J_\pi(\phi) = -\underline{\log \pi_\phi(a|s)}\, \underline{\left(r + \gamma V_\theta(s') - V_\theta(s)\right)} + \alpha \underline{\left(-\sum\nolimits_i \pi_{\phi_i} \log \pi_{\phi_i}\right)}$$

```
    # update actor
    categorical = Categorical(policies)
    log_policy = categorical.log_prob(torch.Tensor([action]))
    entropy = categorical.entropy()

    advantage = target - value

    actor_loss = -log_policy * advantage.item() + args.ent_coef * entropy
    actor_optimizer.zero_grad()
    actor_loss.backward()
    actor_optimizer.step()
```

Learning process



Hyperparameter

```python
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('--actor_lr', type=float, default=1e-4)
parser.add_argument('--critic_lr', type=float, default=1e-3)
parser.add_argument('--ent_coef', type=float, default=0.1)
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
  - Actor & Critic network
  - Actor & Critic optimizer
  - TensorboardX

```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)

    actor = Actor(state_size, action_size, args)
    critic = Critic(state_size, args)

    actor_optimizer = optim.Adam(actor.parameters(), lr=args.actor_lr)
    critic_optimizer = optim.Adam(critic.parameters(), lr=args.critic_lr)

    writer = SummaryWriter(args.logdir)

    running_score = 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
  - Transition list에 저장
  - Train model
  - Running score 설정

```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()

        policies = actor(torch.Tensor(state))
        action = get_action(policies)

        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

        transition = [state, action, reward, next_state, mask]

        actor.train(), critic.train()
        train_model(actor, critic, actor_optimizer, critic_optimizer,
                    transition, policies)

        state = next_state
        score += reward

    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

```python
        if episode % args.log_interval == 0:
            print('{} episode | running_score: {:.2f}'.format(episode, running_score))
            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.tar'
            torch.save(actor.state_dict(), ckpt_path)
            print('Running score exceeds 400. So end')
            break
```

Train model

- Transition List → state, action, next_state, reward, mask 각각 나누기

```
def train_model(actor, critic, actor_optimizer, critic_optimizer, transition, policies):
    state, action, reward, next_state, mask = transition
```

- state - (1, 4)
- action
- reward
- next_state - (1, 4)
- mask

```
state [[-0.09066657 -1.56210361 -0.02062117  1.61977871]]
action 0
reward 1.0
next_state [[-0.12190864 -1.75697662  0.01177441  1.90596389]]
mask 1

state [[-0.12190864 -1.75697662  0.01177441  1.90596389]]
action 0
reward 1.0
next_state [[-0.15704817 -1.95222371  0.04989369  2.20227582]]
mask 1

state [[-0.15704817 -1.95222371  0.04989369  2.20227582]]
action 1
reward 1.0
next_state [[-0.19609265 -1.75761556  0.0939392   1.92538951]]
mask 1
```

Train model

- Update critic - MSE Loss
  - $J_V(\theta) = (\underbrace{r + \gamma V_\theta(s')}_{\text{Target}} - \underbrace{V_\theta(s)}_{\text{Prediction}})^2$

```python
    # update critic
    criterion = torch.nn.MSELoss()

    value = critic(torch.Tensor(state)).squeeze(1)

    next_value = critic(torch.Tensor(next_state)).squeeze(1)
    target = reward + mask * args.gamma * next_value

    critic_loss = criterion(value, target.detach())
    critic_optimizer.zero_grad()
    critic_loss.backward()
    critic_optimizer.step()
```

Train model

- Update actor
  - $J_\pi(\phi) = -\log\pi_\phi(a|s)\left(r+\gamma V_\theta(s') - V_\theta(s)\right) + \alpha\left(-\sum_i \pi_{\phi_i}\log\pi_{\phi_i}\right)$

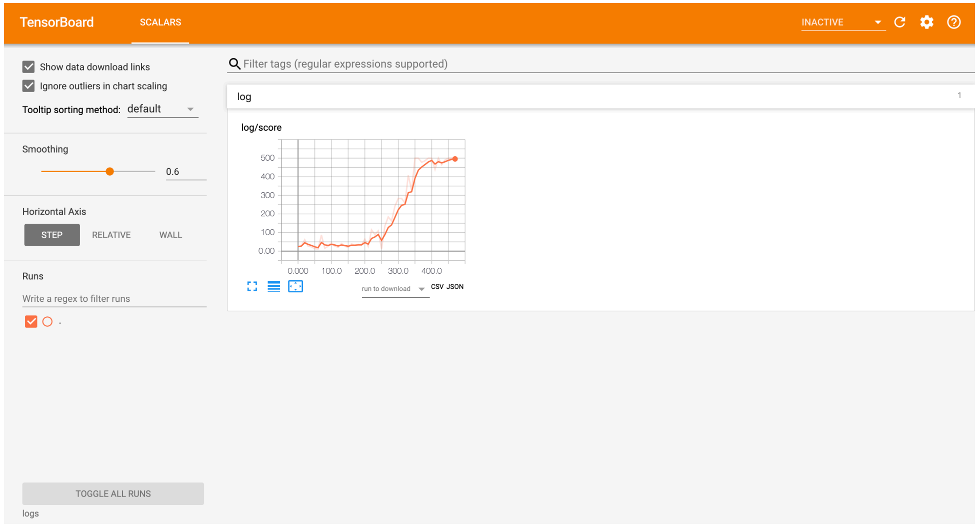
Entropy coefficient : 0.1

```python
        # update actor
        categorical = Categorical(policies)
        log_policy = categorical.log_prob(torch.Tensor([action]))
        entropy = categorical.entropy()

        advantage = target - value

        actor_loss = -log_policy * advantage.item() + args.ent_coef * entropy
        actor_optimizer.zero_grad()
        actor_loss.backward()
        actor_optimizer.step()
```

Train & TensorboardX

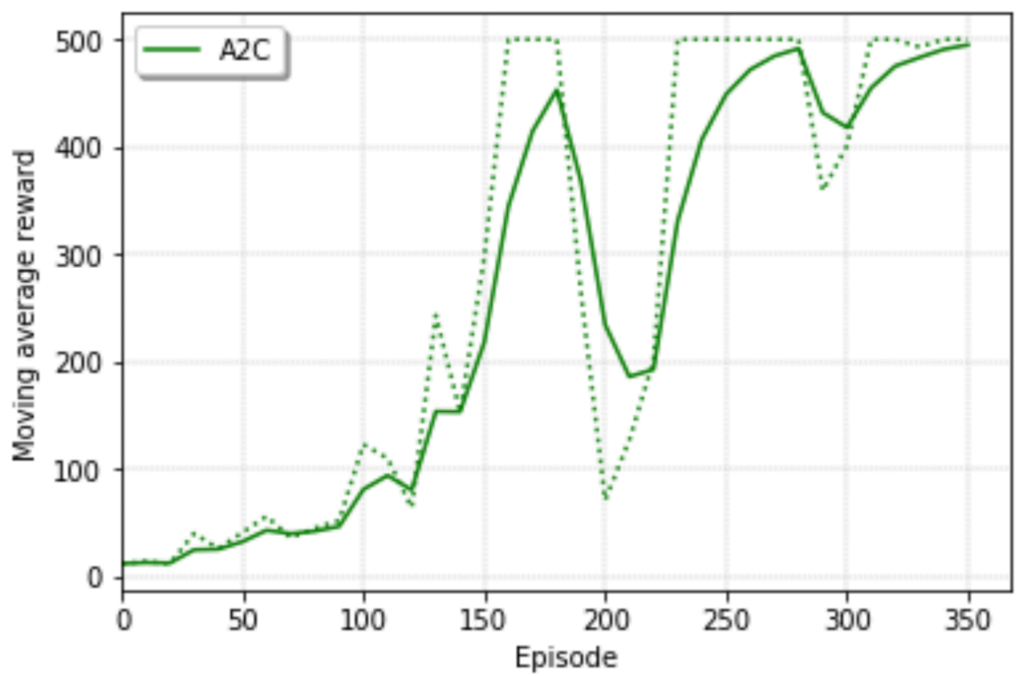
- Terminal A - train 실행
  - conda activate env_name
  - python train.py

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



Learning curve & Test

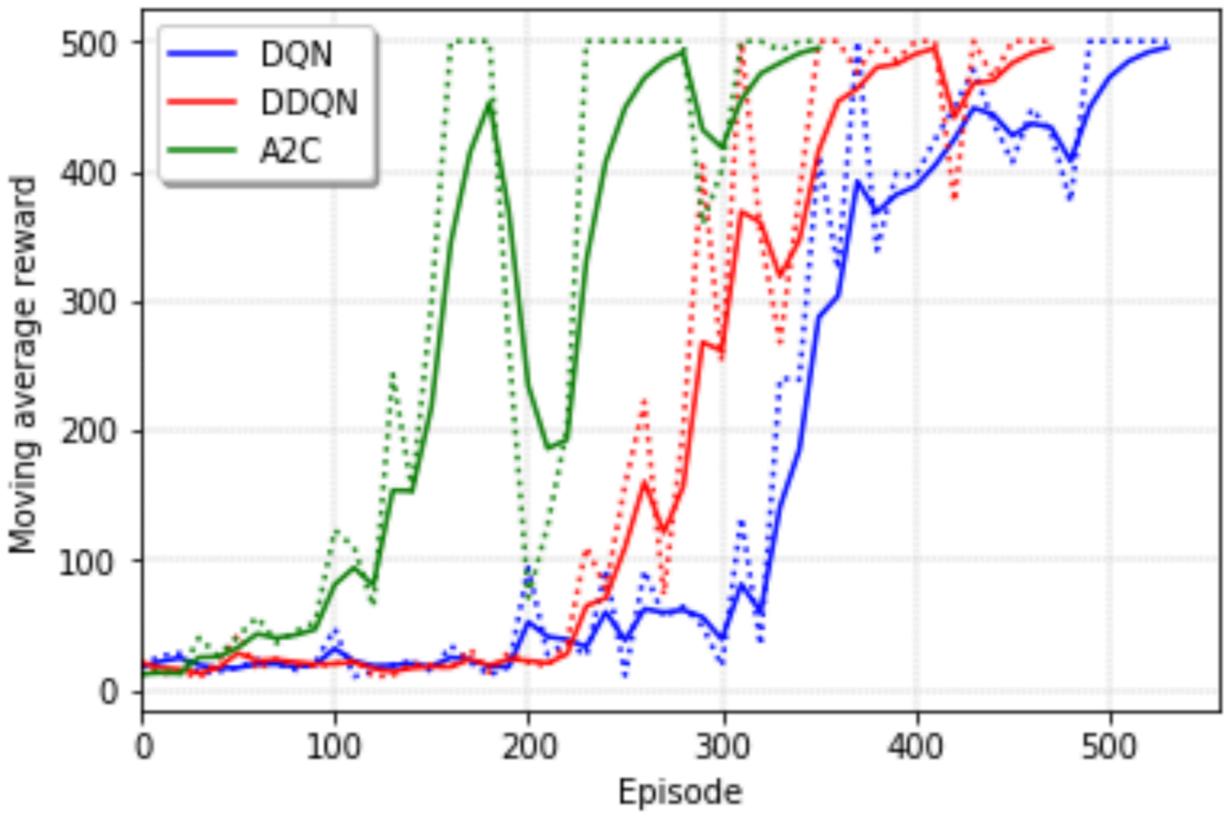
- Learning curve



- Test
  - python test.py

Comparison of algorithms for discrete action

- Learning curve



Comparison of algorithms for discrete action

Discrete action일 때는 어떤 알고리즘이 제일 좋을까요? → A2C
그리고 그 알고리즘이 왜 좋을까요?

Comparison of algorithms for discrete action

Discrete action일 때는 어떤 알고리즘이 제일 좋을까요?
그리고 그 알고리즘이 왜 좋을까요?

- DQN, DDQN (Off-policy algorithms)
  - Replay buffer의 크기 → 컴퓨터의 메모리를 많이 차지하며 **느린 학습 속도**의 원인
  - Replay buffer를 통해 학습을 진행
    → 지금 policy가 아닌 **이전 policies**를 통해 모은 sample로 학습
  - ϵ**-greedy policy**를 통한 action 선택

- A2C (On-policy algorithm)
  - Replay buffer가 **필요하지 않음**
  - **현재 policy**를 통해 학습
  - Actor에서 나오는 **policy 자체가 action에 대한 확률**이므로 따로 action에 대한 exploration을 정해주지 않아도 됨
  - Actor와 Critic **나눠서 업데이트**

Thank you