CORE
Control + Optimization Research Lab

Soft Actor-Critic (SAC)

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Outline

- Soft Actor-Critic (SAC)
  - Learning process
  - Hyperparameter
  - Main loop
  - Train model
  - Train & TensorboardX
  - Learning curve & Test
- DDPG vs. SAC - Learning curve

Soft Actor-Critic (SAC)

- SAC Algorithm

Algorithm 1 Soft Actor-Critic

Input: θ_1, θ_2, ϕ ▷ Initial parameters
$\bar{\theta}_1 \leftarrow \theta_1, \bar{\theta}_2 \leftarrow \theta_2$ ▷ Initialize target network weights
$\mathcal{D} \leftarrow \emptyset$ ▷ Initialize an empty replay pool
for each iteration **do**
  for each environment step **do**
    $\mathbf{a}_t \sim \pi_\phi(\mathbf{a}_t|\mathbf{s}_t)$ ▷ Sample action from the policy
    $\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$ ▷ Sample transition from the environment
    $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{s}_t, \mathbf{a}_t, r(\mathbf{s}_t, \mathbf{a}_t), \mathbf{s}_{t+1})\}$ ▷ Store the transition in the replay pool
  end for
  for each gradient step **do**
    $\theta_i \leftarrow \theta_i - \lambda_Q \hat{\nabla}_{\theta_i} J_Q(\theta_i)$ for $i \in \{1, 2\}$ ▷ Update the Q-function parameters
    $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi)$ ▷ Update policy weights
    $\alpha \leftarrow \alpha - \lambda \hat{\nabla}_\alpha J(\alpha)$ ▷ Adjust temperature
    $\bar{\theta}_i \leftarrow \tau\theta_i + (1-\tau)\bar{\theta}_i$ for $i \in \{1, 2\}$ ▷ Update target network weights
  end for
end for
Output: θ_1, θ_2, ϕ ▷ Optimized parameters

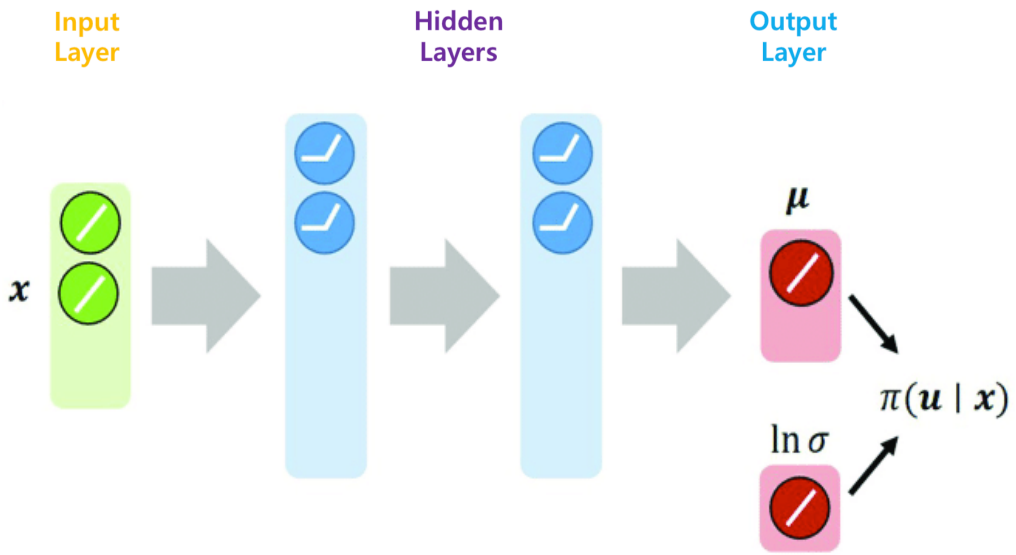
source : https://arxiv.org/pdf/1812.05905.pdf

Soft Actor-Critic (SAC)

- 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 Actor & Critic network 업데이트
  6. Temperature parameter alpha 업데이트
  7. Critic에 대해 soft target 업데이트

Soft Actor-Critic (SAC)

- Actor network



source : Link

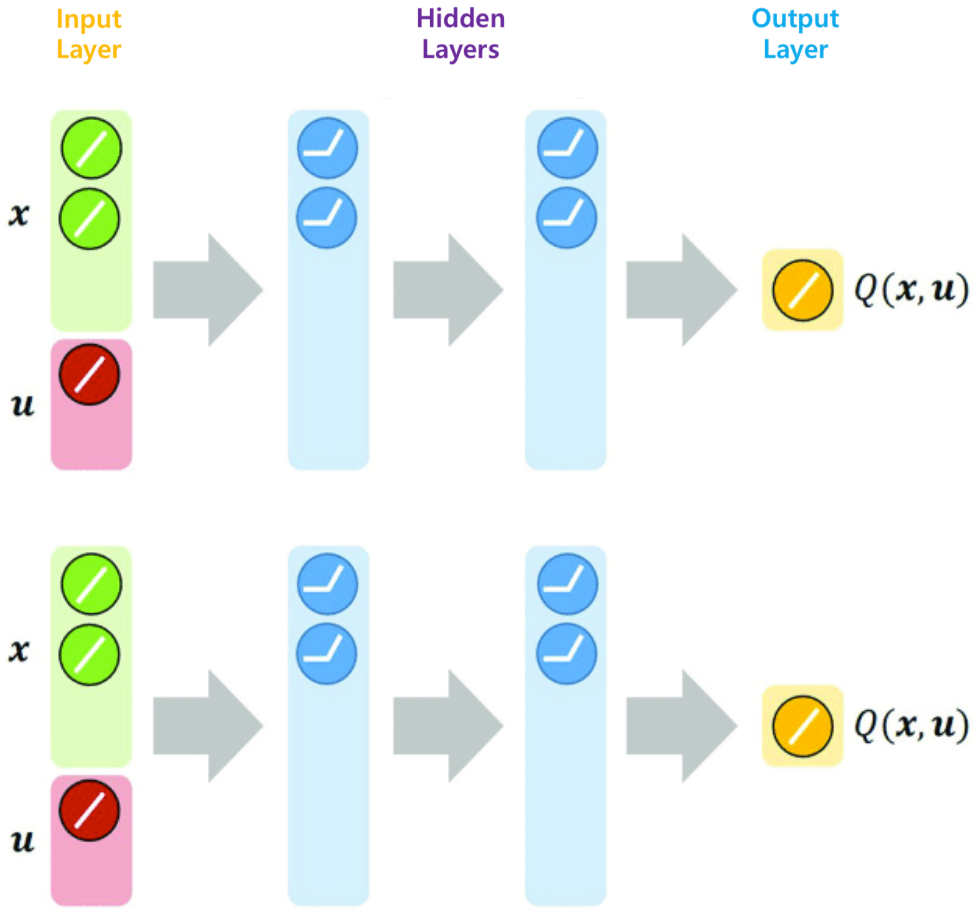
Soft Actor-Critic (SAC)

- Actor network

```python
class Actor(nn.Module):
    def __init__(self, state_size, action_size, args, log_std_min=-20, log_std_max=2):
        super(Actor, self).__init__()
        self.log_std_min = log_std_min
        self.log_std_max = log_std_max

        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)
        self.fc4 = nn.Linear(args.hidden_size, action_size)

    def forward(self, x):
        x = torch.relu(self.fc1(x))
        x = torch.relu(self.fc2(x))

        mu = self.fc3(x)
        log_std = self.fc4(x)

        log_std = torch.clamp(log_std, min=self.log_std_min, max=self.log_std_max)
        std = torch.exp(log_std)

        return mu, std
```

Soft Actor-Critic (SAC)

- Critic network



source : Link

Soft Actor-Critic (SAC)

- Critic network

```python
class Critic(nn.Module):
    def __init__(self, state_size, action_size, args):
        super(Critic, self).__init__()

        # Q1 architecture
        self.fc1 = nn.Linear(state_size + action_size, args.hidden_size)
        self.fc2 = nn.Linear(args.hidden_size, args.hidden_size)
        self.fc3 = nn.Linear(args.hidden_size, 1)

        # Q2 architecture
        self.fc4 = nn.Linear(state_size + action_size, args.hidden_size)
        self.fc5 = nn.Linear(args.hidden_size, args.hidden_size)
        self.fc6 = nn.Linear(args.hidden_size, 1)

    def forward(self, states, actions):
        x = torch.cat([states, actions], dim=1)

        x1 = torch.relu(self.fc1(x))
        x1 = torch.relu(self.fc2(x1))
        q_value1 = self.fc3(x1)

        x2 = torch.relu(self.fc4(x))
        x2 = torch.relu(self.fc5(x2))
        q_value2 = self.fc6(x2)

        return q_value1, q_value2
```

Learning process

1. 상태에 따른 행동 선택

```
mu, std = actor(torch.Tensor(state))
action = get_action(mu, std)
```

```
def get_action(mu, std):
    normal = Normal(mu, std)
    z = normal.rsample() # reparameterization trick (mean + std * N(0,1))
    action = torch.tanh(z)

    return action.data.numpy()
```

- Normal(mu, std) - Normal(Gaussian) distribution에서 sampling을 할 경우, 분산을 일정하게 유지하면서 지속적인 exploration이 가능

- normal.rsample()

```
[docs]    def rsample(self, sample_shape=torch.Size()):
        shape = self._extended_shape(sample_shape)
        eps = _standard_normal(shape, dtype=self.loc.dtype, device=self.loc.device)
        return self.loc + eps * self.scale
```

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 : 64)

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

Learning process

5. 추출한 sample로 Actor & Critic network 업데이트
   - Critic Loss

$$J_Q(\theta) = \left(\underbrace{Q_\theta(s,a)}_{\text{Prediction}} - \underbrace{\left(r + \gamma\left(Q_{\theta^-}(s',a') - \alpha \log \pi_\phi(a'|s') \right) \right)}_{\text{Target}} \right)^2$$

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

# get Q-values using two Q-functions to mitigate overestimation bias
q_value1, q_value2 = critic(torch.Tensor(states), actions)

# get target
mu, std = actor(torch.Tensor(next_states))
next_policy, next_log_policy = eval_action(mu, std)
target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)

min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
target = rewards + masks * args.gamma * min_target_next_q_value

critic_loss1 = criterion(q_value1.squeeze(1), target.detach()) # Equation 5
critic_optimizer.zero_grad()
critic_loss1.backward()
critic_optimizer.step()

critic_loss2 = criterion(q_value2.squeeze(1), target.detach()) # Equation 5
critic_optimizer.zero_grad()
critic_loss2.backward()
critic_optimizer.step()
```

Learning process

5. 추출한 sample로 Actor & Critic network 업데이트
   - Actor Loss

$$J_\pi(\phi) = \frac{1}{N}\sum \alpha \log \pi_\phi(f_\phi(\epsilon; s)|s) - Q_\theta(s, f_\phi(\epsilon; s))$$

```
# update actor
mu, std = actor(torch.Tensor(states))
policy, log_policy = eval_action(mu, std)

q_value1, q_value2 = critic(torch.Tensor(states), policy)
min_q_value = torch.min(q_value1, q_value2)

actor_loss = ((alpha * log_policy) - min_q_value).mean() # Equation 9
actor_optimizer.zero_grad()
actor_loss.backward()
actor_optimizer.step()
```

Learning process

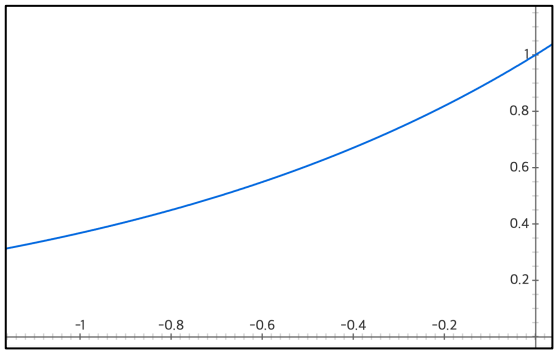
6. Temperature parameter alpha 업데이트
   - Alpha Loss

$$J(\alpha) = -\frac{1}{N}\sum \alpha(\log \pi_\phi(f_\phi(\epsilon; s)|s) + \bar{\mathcal{H}})$$

```
# update alpha
alpha_loss = -(log_alpha * (log_policy + target_entropy).detach()).mean() # Equation 18
alpha_optimizer.zero_grad()
alpha_loss.backward()
alpha_optimizer.step()

alpha = torch.exp(log_alpha)

return alpha
```

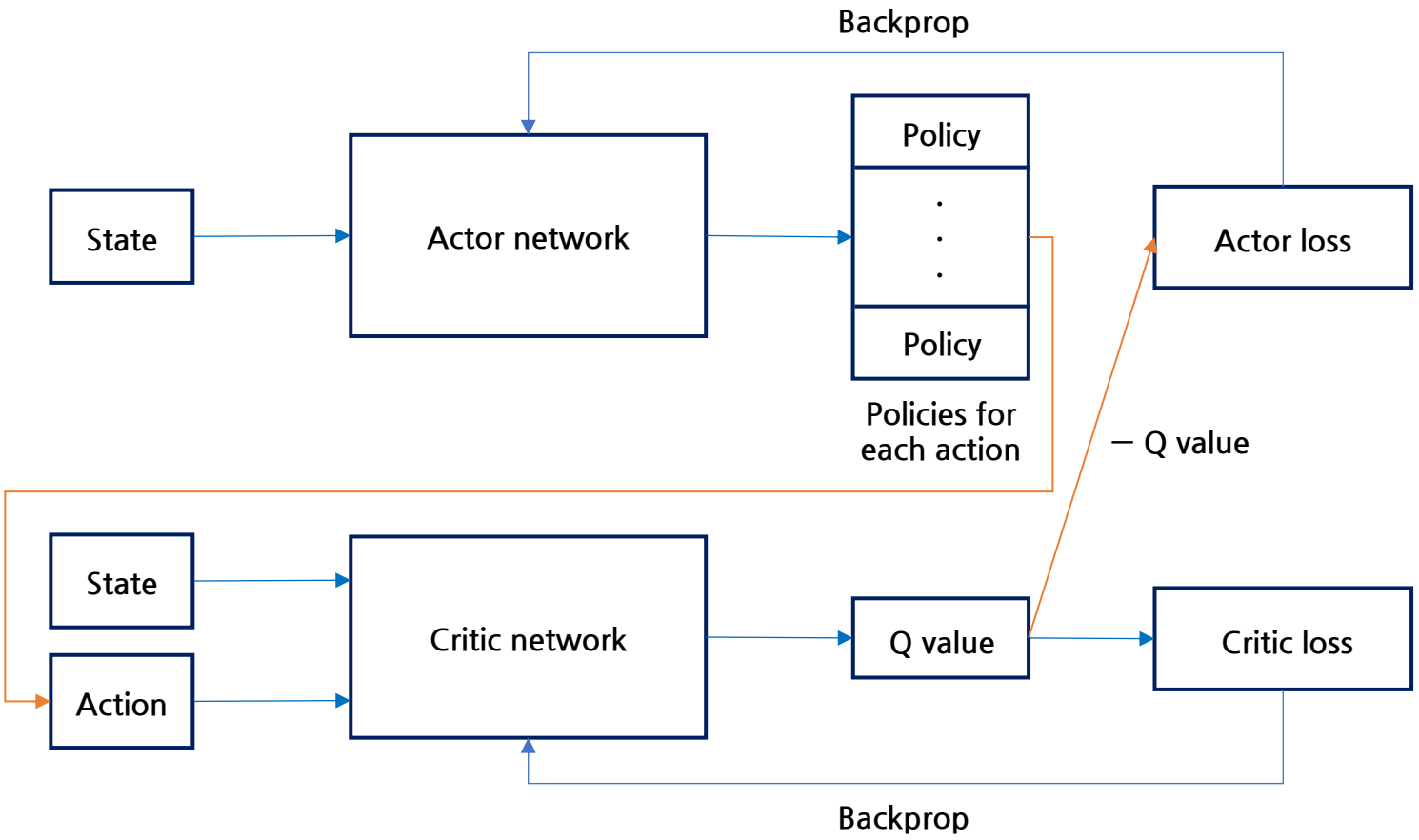
   - log_alpha : alpha를 $(0,1]$ 사이의 값으로 만들어주기 위해 사용

```
log_alpha tensor([0.], requires_grad=True)
alpha tensor([1.], grad_fn=<ExpBackward>)

log_alpha tensor([-0.0001], requires_grad=True)
alpha tensor([0.9999], grad_fn=<ExpBackward>)

log_alpha tensor([-0.0002], requires_grad=True)
alpha tensor([0.9998], grad_fn=<ExpBackward>)

log_alpha tensor([-0.0003], requires_grad=True)
alpha tensor([0.9997], grad_fn=<ExpBackward>)

log_alpha tensor([-0.0004], requires_grad=True)
alpha tensor([0.9996], grad_fn=<ExpBackward>)
```



y = exp(x)

Learning process



Learning process

7. Critic에 대해 soft target 업데이트
   - Initialize target model

```
hard_target_update(critic, target_critic)
```

```
def hard_target_update(net, target_net):
    target_net.load_state_dict(net.state_dict())
```

   - Soft target update (τ : 0.005)

$$\theta^{Q'} \leftarrow \tau\theta^{Q} + (1-\tau)\theta^{Q'}$$

$$\phi^{\pi'} \leftarrow \tau\phi^{\pi} + (1-\tau)\phi^{\pi'}$$

```
soft_target_update(critic, target_critic, args.tau)
```

```
def soft_target_update(net, target_net, tau):
    for param, target_param in zip(net.parameters(), target_net.parameters()):
        target_param.data.copy_(tau * param.data + (1.0 - tau) * target_param.data)
```

Hyperparameter

```
parser = argparse.ArgumentParser()
parser.add_argument('--env_name', type=str, default="Pendulum-v0")
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=64)
parser.add_argument('--actor_lr', type=float, default=1e-3)
parser.add_argument('--critic_lr', type=float, default=1e-3)
parser.add_argument('--alpha_lr', type=float, default=1e-4)
parser.add_argument('--tau', type=float, default=0.005)
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=-300)
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
  - Target critic network
  - Actor & Critic optimizer
  - Hard target update
  - Automatic entropy tuning
    - Target entropy
    - Log alpha, alpha
    - Alpha optimizer
  - TensorboardX
  - Replay buffer
  - Recent rewards

```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.shape[0]
    print('state size:', state_size)
    print('action size:', action_size)

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

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

    hard_target_update(critic, target_critic)

    # initialize automatic entropy tuning
    target_entropy = -torch.prod(torch.Tensor(action_size)).item()
    log_alpha = torch.zeros(1, requires_grad=True)
    alpha = torch.exp(log_alpha)
    alpha_optimizer = optim.Adam([log_alpha], lr=args.alpha_lr)

    writer = SummaryWriter(args.logdir)

    replay_buffer = deque(maxlen=10000)
    recent_rewards = deque(maxlen=100)
    steps = 0
```

Main loop

- Episode 진행
  - 상태에 따른 행동 선택
  - 다음 상태와 보상을 받음
  - Replay buffer에 저장

```
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

        mu, std = actor(torch.Tensor(state))
        action = get_action(mu, std)

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

        next_state = np.reshape(next_state, [1, state_size])
        mask = 0 if done else 1

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

        state = next_state
        score += reward
```

Main loop

- Episode 진행
  - Replay buffer에서 랜덤으로 64개의 sample을 추출 → Mini batch
  - Train model
  - Critic에 대해 Soft target update

```
        if steps > args.batch_size:
            mini_batch = random.sample(replay_buffer, args.batch_size)

            actor.train(), critic.train(), target_critic.train()
            alpha = train_model(actor, critic, target_critic, mini_batch,
                                actor_optimizer, critic_optimizer, alpha_optimizer,
                                target_entropy, log_alpha, alpha)

            soft_target_update(critic, target_critic, args.tau)

        if done:
            recent_rewards.append(score)
```

Main loop

- Print & Visualize log
- Termination : 최근 100개의 episode의 평균 score가 -300보다 크다면
  - Save model
  - 학습 종료

```
        if episode % args.log_interval == 0:
            print('{} episode | score_avg: {:.2f}'.format(episode, np.mean(recent_rewards)))
            writer.add_scalar('log/score', float(score), episode)

        if np.mean(recent_rewards) > 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(actor.state_dict(), ckpt_path)
            print('Recent rewards exceed -300. So end')
            break
```

Train model

- Mini batch → Numpy array
- Mini batch에 있는 64개의 sample들을 각각 나눔
  - state - (64, 3)
  - action - (64, 1)
  - reward - (64)
  - next_state - (64, 3)
  - mask - (64)

```
def train_model(actor, critic, target_critic, mini_batch,
                actor_optimizer, critic_optimizer, alpha_optimizer,
                target_entropy, log_alpha, alpha):
    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.Tensor(actions).squeeze(1)
    rewards = torch.Tensor(rewards).squeeze(1)
    masks = torch.Tensor(masks)
```

Train model

- Prediction
- Target

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

# get Q-values using two Q-functions to mitigate overestimation bias
q_value1, q_value2 = critic(torch.Tensor(states), actions)

# get target
mu, std = actor(torch.Tensor(next_states))
next_policy, next_log_policy = eval_action(mu, std)
target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)

min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
target = rewards + masks * args.gamma * min_target_next_q_value
```

Train model

- Prediction
  - q_value1, 2 - (64, 1)
- Target

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

# get Q-values using two Q-functions to mitigate overestimation bias
q_value1, q_value2 = critic(torch.Tensor(states), actions)
```

Train model

- Prediction
  - **q_value1, 2** - (64, 1)
- Target
  - **mu, std** - (64, 1)

```
# get target
mu, std = actor(torch.Tensor(next_states))
next_policy, next_log_policy = eval_action(mu, std)
target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)

min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
target = rewards + masks * args.gamma * min_target_next_q_value
```

Train model

```python
def eval_action(mu, std, epsilon=1e-6):
    normal = Normal(mu, std)
    z = normal.rsample() # reparameterization trick (mean + std * N(0,1))
    action = torch.tanh(z)
    log_prob = normal.log_prob(z)

    # Enforcing Action Bounds
    log_prob -= torch.log(1 - action.pow(2) + epsilon)
    log_policy = log_prob.sum(1, keepdim=True)

    return action, log_policy
```

- The probability density of the normal distribution

$$\pi_\phi(a|s) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(a-\mu_\phi(s))^2}{2\sigma^2}\right)$$

- Multiply the log on both sides

$$\log \pi_\phi(a|s) = -\log\sigma - \log\sqrt{2\pi} - \frac{\left(a-\mu_\phi(s)\right)^2}{2\sigma^2}$$

Train model

```python
def eval_action(mu, std, epsilon=1e-6):
    normal = Normal(mu, std)
    z = normal.rsample() # reparameterization trick (mean + std * N(0,1))
    action = torch.tanh(z)
    log_prob = normal.log_prob(z)

    # Enforcing Action Bounds
    log_prob -= torch.log(1 - action.pow(2) + epsilon)
    log_policy = log_prob.sum(1, keepdim=True)

    return action, log_policy
```

$$\log \pi_\phi(a|s) = -\frac{\left(a - \mu_\phi(s)\right)^2}{2\sigma^2} - \log \sigma - \log \sqrt{2\pi}$$

```
[docs]    def log_prob(self, value):
        if self._validate_args:
            self._validate_sample(value)
        # compute the variance
        var = (self.scale ** 2)
        log_scale = math.log(self.scale) if isinstance(self.scale, Number) else
self.scale.log()
        return -((value - self.loc) ** 2) / (2 * var) - log_scale - math.log(math.sqrt(2 *
math.pi))
```

Train model

- Prediction
  - q_value1, 2 - (64, 1)
- Target
  - mu, std - (64, 1)

C Enforcing Action Bounds

We use an unbounded Gaussian as the action distribution. However, in practice, the actions needs to be bounded to a finite interval. To that end, we apply an invertible squashing function (tanh) to the Gaussian samples, and employ the change of variables formula to compute the likelihoods of the bounded actions. In the other words, let $\mathbf{u} \in \mathbb{R}^D$ be a random variable and $\mu(\mathbf{u}|\mathbf{s})$ the corresponding density with infinite support. Then $\mathbf{a} = \tanh(\mathbf{u})$, where tanh is applied elementwise, is a random variable with support in $(-1, 1)$ with a density given by

$$\pi(\mathbf{a}|\mathbf{s}) = \mu(\mathbf{u}|\mathbf{s}) \left| \det \left(\frac{\mathrm{d}\mathbf{a}}{\mathrm{d}\mathbf{u}} \right) \right|^{-1}. \tag{25}$$

Since the Jacobian $\mathrm{d}\mathbf{a}/\mathrm{d}\mathbf{u} = \mathrm{diag}(1 - \tanh^2(\mathbf{u}))$ is diagonal, the log-likelihood has a simple form

$$\log \pi(\mathbf{a}|\mathbf{s}) = \log \mu(\mathbf{u}|\mathbf{s}) - \sum_{i=1}^{D} \log \left(1 - \tanh^2(u_i)\right), \tag{26}$$

where u_i is the i^{th} element of $\mathbf{u}$.

Train model

- Prediction
  - q_value1, 2 - (64, 1)
- Target
  - mu, std - (64, 1)

```python
def eval_action(mu, std, epsilon=1e-6):
    normal = Normal(mu, std)
    z = normal.rsample() # reparameterization trick (mean + std * N(0,1))
    action = torch.tanh(z)
    log_prob = normal.log_prob(z)

    # Enforcing Action Bounds
    log_prob -= torch.log(1 - action.pow(2) + epsilon)
    log_policy = log_prob.sum(1, keepdim=True)

    return action, log_policy
```

$$\log \pi(\mathbf{a}|\mathbf{s}) = \log \mu(\mathbf{u}|\mathbf{s}) - \sum_{i=1}^{D} \log \left(1 - \tanh^2(u_i)\right)$$

Train model

- Prediction
  - **q_value1, 2** - (64, 1)
- Target
  - **mu, std** - (64, 1)
  - **next_policy, next_log_policy** - (64, 1)
  - **target_next_q_value1, 2** - (64, 1)
  - **min_target_next_q_value** - (64)
  - **target** - (64)

```
# get target
mu, std = actor(torch.Tensor(next_states))
next_policy, next_log_policy = eval_action(mu, std)
target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)

min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
target = rewards + masks * args.gamma * min_target_next_q_value
```

Train model

- Update critic - MSE Loss
  - $J_Q(\theta) = (\underbrace{Q_\theta(s,a)}_{\text{Prediction}} - \underbrace{\left(r + \gamma \left(Q_{\theta^-}(s',a') - \alpha \log \pi_\phi(a'|s') \right) \right)}_{\text{Target}})^2$

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

# get Q-values using two Q-functions to mitigate overestimation bias
q_value1, q_value2 = critic(torch.Tensor(states), actions)

# get target
mu, std = actor(torch.Tensor(next_states))
next_policy, next_log_policy = eval_action(mu, std)
target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)

min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
target = rewards + masks * args.gamma * min_target_next_q_value

critic_loss1 = criterion(q_value1.squeeze(1), target.detach()) # Equation 5
critic_optimizer.zero_grad()
critic_loss1.backward()
critic_optimizer.step()

critic_loss2 = criterion(q_value2.squeeze(1), target.detach()) # Equation 5
critic_optimizer.zero_grad()
critic_loss2.backward()
critic_optimizer.step()
```

Train model

- Update actor
  - **mu, std** - (64, 1)
  - **policy, log_policy** - (64, 1)
  - **q_value1, 2** - (64, 1)
  - **min_q_value** - (64, 1)
  - **alpha** - (1)
  - $J_\pi(\phi) = \frac{1}{N}\sum \alpha \log \pi_\phi(f_\phi(\epsilon; s)|s) - Q_\theta(s, f_\phi(\epsilon; s))$

```
# update actor
mu, std = actor(torch.Tensor(states))
policy, log_policy = eval_action(mu, std)

q_value1, q_value2 = critic(torch.Tensor(states), policy)
min_q_value = torch.min(q_value1, q_value2)

actor_loss = ((alpha * log_policy) - min_q_value).mean() # Equation 9
actor_optimizer.zero_grad()
actor_loss.backward()
actor_optimizer.step()
```

Train model

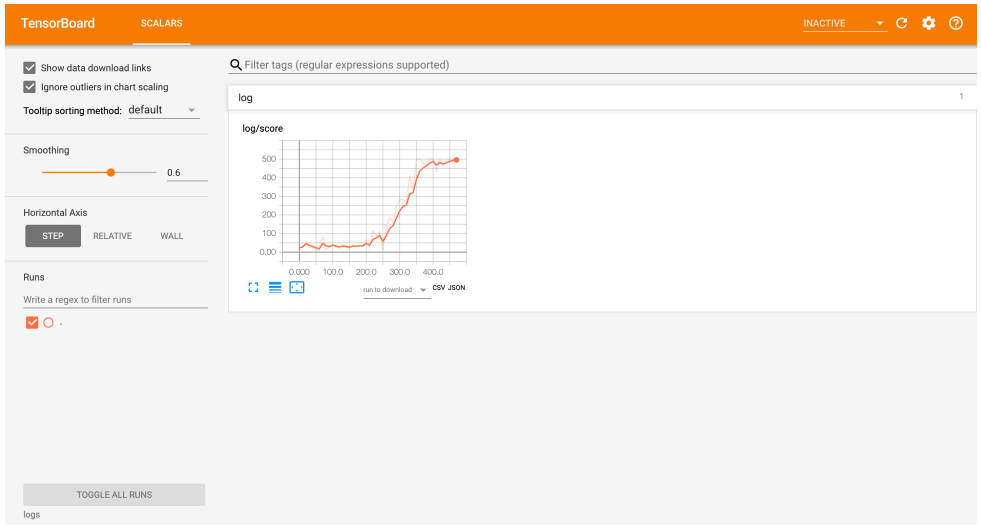
- Update alpha
  - log_alpha - (1)
  - log_policy - (64, 1)
  - target_entropy → -0.0
  - $J(\alpha) = -\frac{1}{N}\sum \alpha(\log \pi_\phi(f_\phi(\epsilon; s)|s) + \bar{\mathcal{H}})$
  - alpha - (1)

```
# update alpha
alpha_loss = -(log_alpha * (log_policy + target_entropy).detach()).mean()
alpha_optimizer.zero_grad()
alpha_loss.backward()
alpha_optimizer.step()

alpha = torch.exp(log_alpha)

return alpha
```

Train & TensorboardX

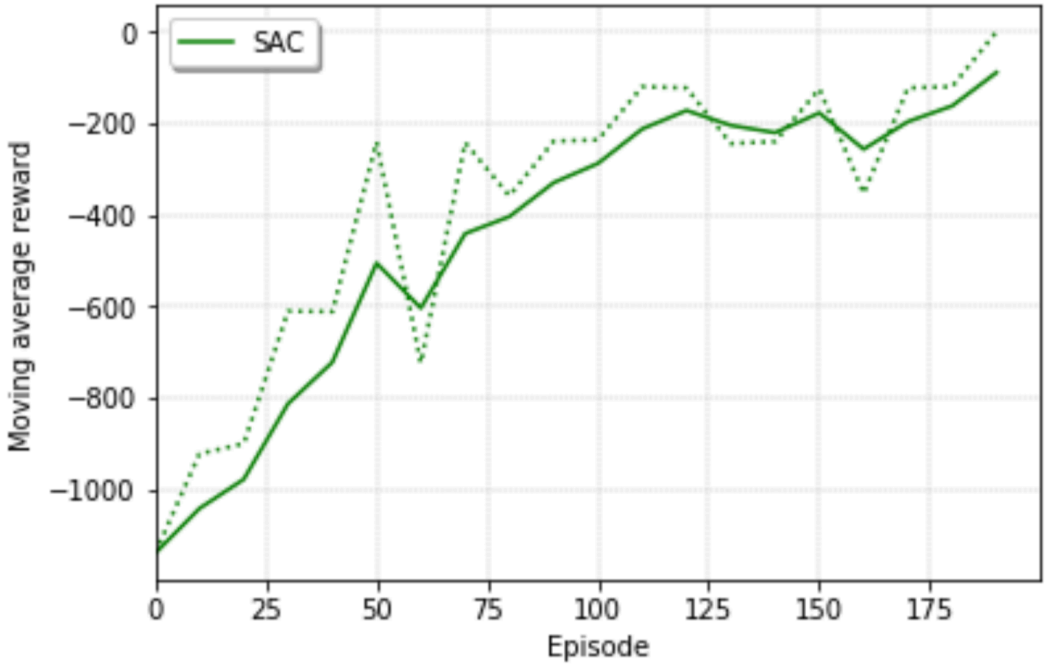
- Terminal A - train 실행
  - conda activate env_name
  - python train.py

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



Learning curve & Test

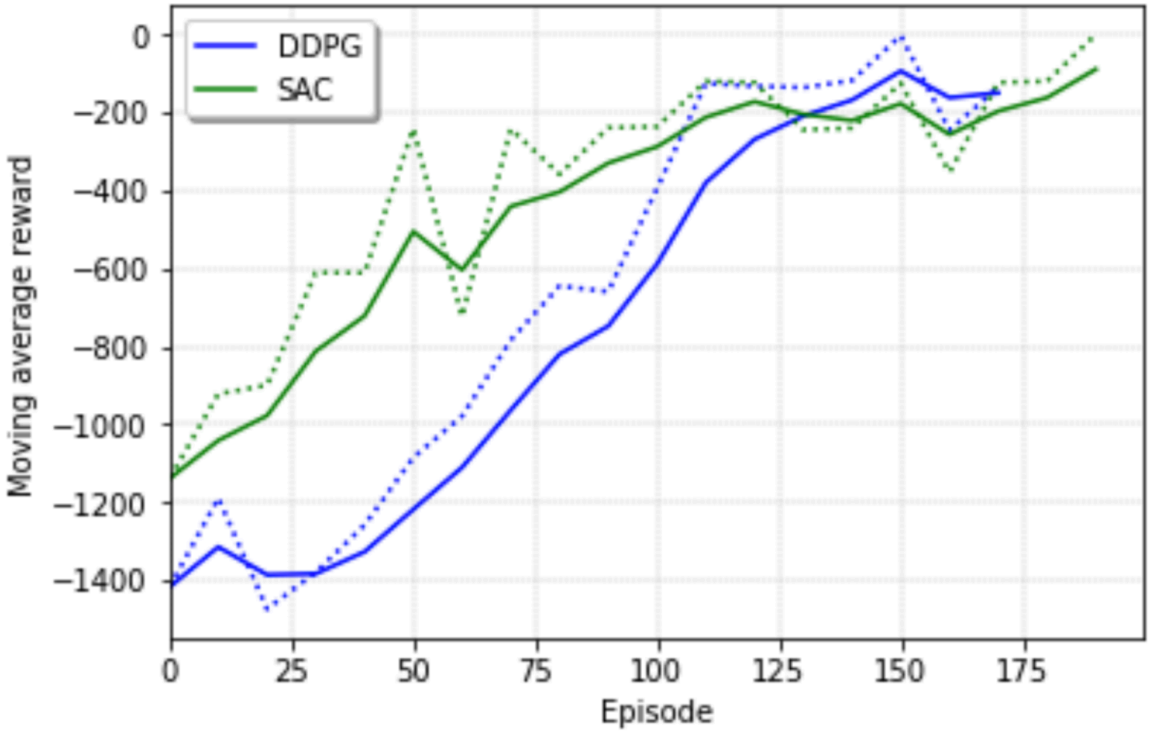
- Learning curve



- Test
  - ➢ python test.py

DDPG vs. SAC

- Learning curve



Thank you