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
- Comparison of algorithms for continuous action

Soft Actor-Critic (SAC)

- SAC Algorithm

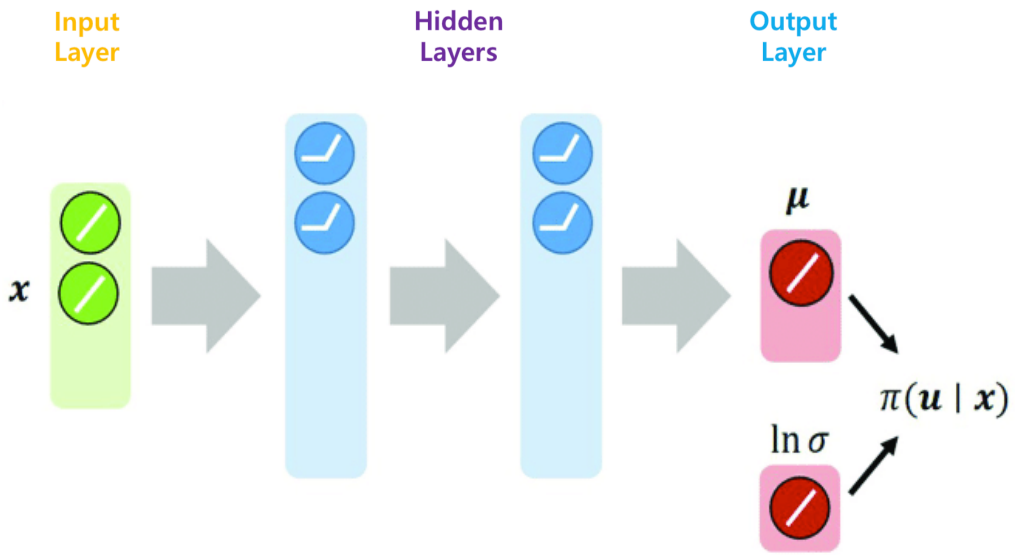
Algorithm 1 Soft Actor-Critic

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)

- Actor network



source : Link

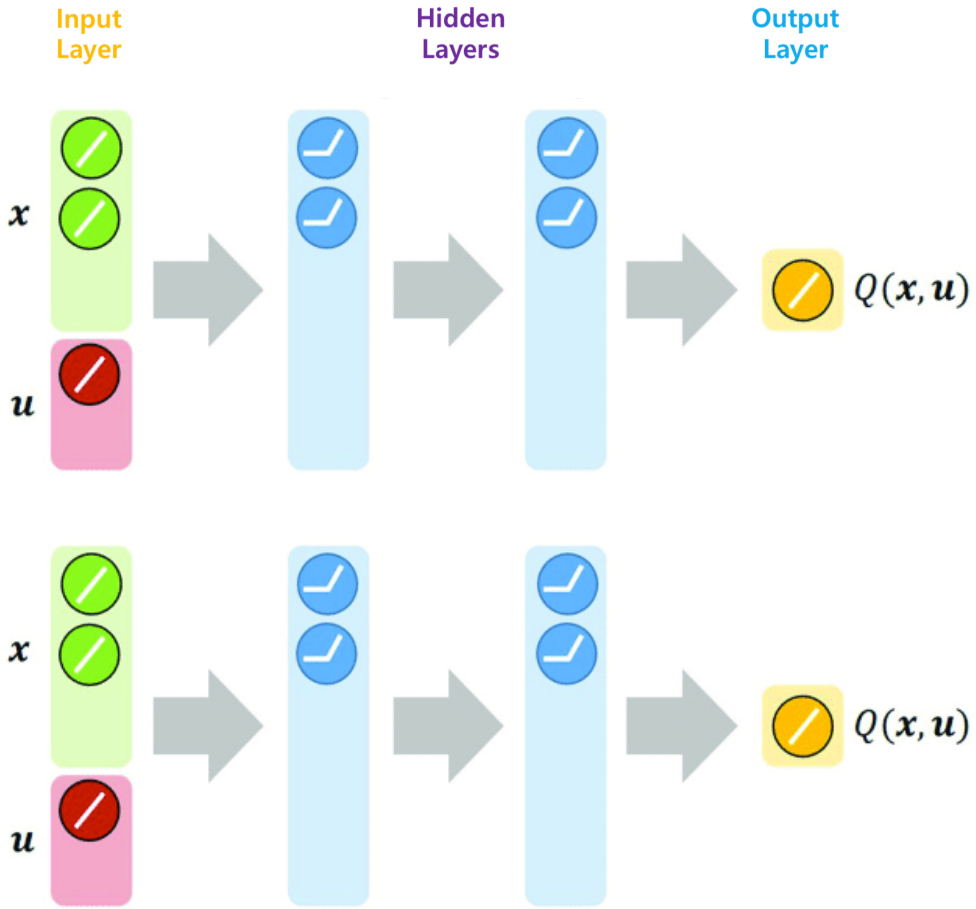
Soft Actor-Critic (SAC)

- 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



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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
```

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

Learning process

1. 상태에 따른 행동 선택

```
140                 mu, std = actor(torch.Tensor(state))
141                 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.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

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

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

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

```
146                 mask = 0 if done else 1
147
148                 replay_buffer.append((state, action, reward, next_state, mask))
```

4. Replay buffer에서 랜덤으로 sample을 추출 (Batch size : 64)

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

Learning process

5. 추출한 sample로 Actor & Critic network 업데이트

- Critic Loss

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

Prediction

Target

```
48      # update critic
49      criterion = torch.nn.MSELoss()
50
51      # get Q-values using two Q-functions to mitigate overestimation bias
52      q_value1, q_value2 = critic(torch.Tensor(states), actions)
53
54      # get target
55      mu, std = actor(torch.Tensor(next_states))
56      next_policy, next_log_policy = eval_action(mu, std)
57      target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)
58
59      min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
60      min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
61      target = rewards + masks * args.gamma * min_target_next_q_value
62
63      critic_loss1 = criterion(q_value1.squeeze(1), target.detach()) # Equation 5
64      critic_optimizer.zero_grad()
65      critic_loss1.backward()
66      critic_optimizer.step()
67
68      critic_loss2 = criterion(q_value2.squeeze(1), target.detach()) # Equation 5
69      critic_optimizer.zero_grad()
70      critic_loss2.backward()
71      critic_optimizer.step()
```

Learning process

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

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

```
73      # update actor
74      mu, std = actor(torch.Tensor(states))
75      policy, log_policy = eval_action(mu, std)
76
77      q_value1, q_value2 = critic(torch.Tensor(states), policy)
78      min_q_value = torch.min(q_value1, q_value2)
79
80      actor_loss = ((alpha * log_policy) - min_q_value).mean() # Equation 9
81      actor_optimizer.zero_grad()
82      actor_loss.backward()
83      actor_optimizer.step()
```

Learning process

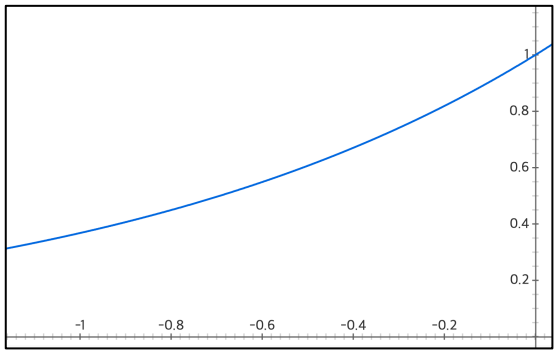
6. Temperature parameter alpha 업데이트
   - Alpha Loss

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

```
85      # update alpha
86      alpha_loss = -(log_alpha * (log_policy + target_entropy).detach()).mean() # Equation 18
87      alpha_optimizer.zero_grad()
88      alpha_loss.backward()
89      alpha_optimizer.step()
90
91      alpha = torch.exp(log_alpha)
92
93      return alpha
```

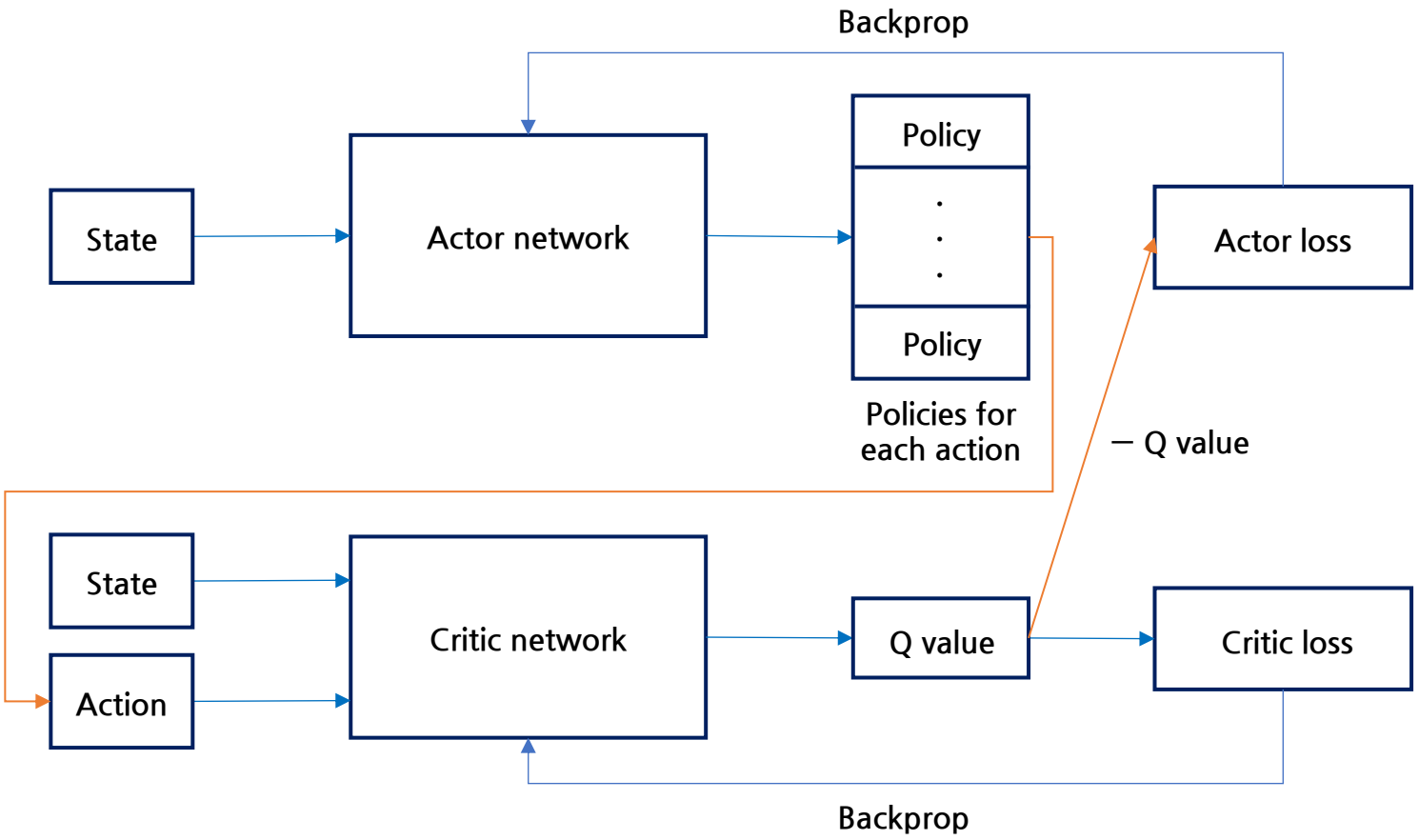
   - log_alpha : alpha를 $(0,1]$ 사이의 값으로 만들어주기 위해 사용

```
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

```
113        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)

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

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

```
161                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

```
15    parser = argparse.ArgumentParser()
16    parser.add_argument('--env_name', type=str, default="Pendulum-v0")
17    parser.add_argument('--load_model', type=str, default=None)
18    parser.add_argument('--save_path', default='./save_model/', help='')
19    parser.add_argument('--render', action="store_true", default=False)
20    parser.add_argument('--gamma', type=float, default=0.99)
21    parser.add_argument('--hidden_size', type=int, default=64)
22    parser.add_argument('--batch_size', type=int, default=64)
23    parser.add_argument('--actor_lr', type=float, default=1e-3)
24    parser.add_argument('--critic_lr', type=float, default=1e-3)
25    parser.add_argument('--alpha_lr', type=float, default=1e-4)
26    parser.add_argument('--tau', type=float, default=0.005)
27    parser.add_argument('--max_iter_num', type=int, default=1000)
28    parser.add_argument('--log_interval', type=int, default=10)
29    parser.add_argument('--goal_score', type=int, default=-300)
30    parser.add_argument('--logdir', type=str, default='./logs',
31                        help='tensorboardx logs directory')
32    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

```
96  def main():
97      env = gym.make(args.env_name)
98      env.seed(500)
99      torch.manual_seed(500)
100
101     state_size = env.observation_space.shape[0]
102     action_size = env.action_space.shape[0]
103     print('state size:', state_size)
104     print('action size:', action_size)
105
106     actor = Actor(state_size, action_size, args)
107     critic = Critic(state_size, action_size, args)
108     target_critic = Critic(state_size, action_size, args)
109
110     actor_optimizer = optim.Adam(actor.parameters(), lr=args.actor_lr)
111     critic_optimizer = optim.Adam(critic.parameters(), lr=args.critic_lr)
112
113     hard_target_update(critic, target_critic)
114
115     # initialize automatic entropy tuning
116     target_entropy = -torch.prod(torch.Tensor(action_size)).item()
117     log_alpha = torch.zeros(1, requires_grad=True)
118     alpha = torch.exp(log_alpha)
119     alpha_optimizer = optim.Adam([log_alpha], lr=args.alpha_lr)
120
121     writer = SummaryWriter(args.logdir)
122
123     replay_buffer = deque(maxlen=10000)
124     recent_rewards = deque(maxlen=100)
125     steps = 0
```

Main loop

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

```
127     for episode in range(args.max_iter_num):
128         done = False
129         score = 0
130 
131         state = env.reset()
132         state = np.reshape(state, [1, state_size])
133 
134         while not done:
135             if args.render:
136                 env.render()
137 
138             steps += 1
139 
140             mu, std = actor(torch.Tensor(state))
141             action = get_action(mu, std)
142 
143             next_state, reward, done, _ = env.step(action)
144 
145             next_state = np.reshape(next_state, [1, state_size])
146             mask = 0 if done else 1
147 
148             replay_buffer.append((state, action, reward, next_state, mask))
149 
150             state = next_state
151             score += reward
```

Main loop

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

```
153             if steps > args.batch_size:
154                 mini_batch = random.sample(replay_buffer, args.batch_size)
155 
156                 actor.train(), critic.train(), target_critic.train()
157                 alpha = train_model(actor, critic, target_critic, mini_batch,
158                                     actor_optimizer, critic_optimizer, alpha_optimizer,
159                                     target_entropy, log_alpha, alpha)
160 
161                 soft_target_update(critic, target_critic, args.tau)
162 
163             if done:
164                 recent_rewards.append(score)
```

Main loop

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

```
166         if episode % args.log_interval == 0:
167             print('{} episode | score_avg: {:.2f}'.format(episode, np.mean(recent_rewards)))
168             writer.add_scalar('log/score', float(score), episode)
169 
170         if np.mean(recent_rewards) > args.goal_score:
171             if not os.path.isdir(args.save_path):
172                 os.makedirs(args.save_path)
173 
174             ckpt_path = args.save_path + 'model.pth'
175             torch.save(actor.state_dict(), ckpt_path)
176             print('Recent rewards exceed -300. So end')
177             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)

```
34  def train_model(actor, critic, target_critic, mini_batch,
35                  actor_optimizer, critic_optimizer, alpha_optimizer,
36                  target_entropy, log_alpha, alpha):
37      mini_batch = np.array(mini_batch)
38      states = np.vstack(mini_batch[:, 0])
39      actions = list(mini_batch[:, 1])
40      rewards = list(mini_batch[:, 2])
41      next_states = np.vstack(mini_batch[:, 3])
42      masks = list(mini_batch[:, 4])
43
44      actions = torch.Tensor(actions).squeeze(1)
45      rewards = torch.Tensor(rewards).squeeze(1)
46      masks = torch.Tensor(masks)
```

Train model

- Prediction
- Target

```
48      # update critic
49      criterion = torch.nn.MSELoss()
50
51      # get Q-values using two Q-functions to mitigate overestimation bias
52      q_value1, q_value2 = critic(torch.Tensor(states), actions)
53
54      # get target
55      mu, std = actor(torch.Tensor(next_states))
56      next_policy, next_log_policy = eval_action(mu, std)
57      target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)
58
59      min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
60      min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
61      target = rewards + masks * args.gamma * min_target_next_q_value
```

Train model

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

```
48      # update critic
49      criterion = torch.nn.MSELoss()
50
51      # get Q-values using two Q-functions to mitigate overestimation bias
52      q_value1, q_value2 = critic(torch.Tensor(states), actions)
```

Train model

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

```
54      # get target
55      mu, std = actor(torch.Tensor(next_states))
56      next_policy, next_log_policy = eval_action(mu, std)
57      target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)
58
59      min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
60      min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
61      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
```

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

```
[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)

```
54      # get target
55      mu, std = actor(torch.Tensor(next_states))
56      next_policy, next_log_policy = eval_action(mu, std)
57      target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)
58
59      min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
60      min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
61      target = rewards + masks * args.gamma * min_target_next_q_value
```

Train model

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

Prediction

Target

```
48      # update critic
49      criterion = torch.nn.MSELoss()
50
51      # get Q-values using two Q-functions to mitigate overestimation bias
52      q_value1, q_value2 = critic(torch.Tensor(states), actions)
53
54      # get target
55      mu, std = actor(torch.Tensor(next_states))
56      next_policy, next_log_policy = eval_action(mu, std)
57      target_next_q_value1, target_next_q_value2 = target_critic(torch.Tensor(next_states), next_policy)
58
59      min_target_next_q_value = torch.min(target_next_q_value1, target_next_q_value2)
60      min_target_next_q_value = min_target_next_q_value.squeeze(1) - alpha * next_log_policy.squeeze(1)
61      target = rewards + masks * args.gamma * min_target_next_q_value
62
63      critic_loss1 = criterion(q_value1.squeeze(1), target.detach()) # Equation 5
64      critic_optimizer.zero_grad()
65      critic_loss1.backward()
66      critic_optimizer.step()
67
68      critic_loss2 = criterion(q_value2.squeeze(1), target.detach()) # Equation 5
69      critic_optimizer.zero_grad()
70      critic_loss2.backward()
71      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)
  - $J_\pi(\phi) = \frac{1}{N}\sum \alpha \log \pi_\phi(f_\phi(\epsilon; s)|s) - Q_\theta(s, f_\phi(\epsilon; s))$

```
73      # update actor
74      mu, std = actor(torch.Tensor(states))
75      policy, log_policy = eval_action(mu, std)
76
77      q_value1, q_value2 = critic(torch.Tensor(states), policy)
78      min_q_value = torch.min(q_value1, q_value2)
79
80      actor_loss = ((alpha * log_policy) - min_q_value).mean() # Equation 9
81      actor_optimizer.zero_grad()
82      actor_loss.backward()
83      actor_optimizer.step()
```

Train model

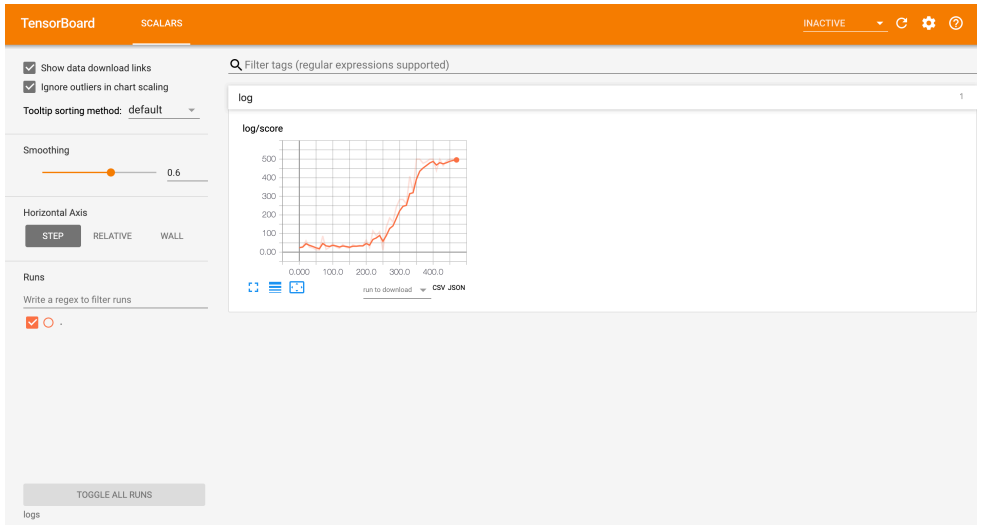
- Update alpha
  - log_alpha - (1)
  - log_policy - (64, 1)
  - target_entropy → -0.0
  - $J(\alpha) = -\frac{1}{N}\sum \alpha(\log \pi_\phi(f_\phi(\epsilon; s)|s) + \bar{\mathcal{H}})$
  - alpha - (1)

```
85      # update alpha
86      alpha_loss = -(log_alpha * (log_policy + target_entropy).detach()).mean() # Equation 18
87      alpha_optimizer.zero_grad()
88      alpha_loss.backward()
89      alpha_optimizer.step()
90
91      alpha = torch.exp(log_alpha)
92
93      return alpha
```

Train & TensorboardX

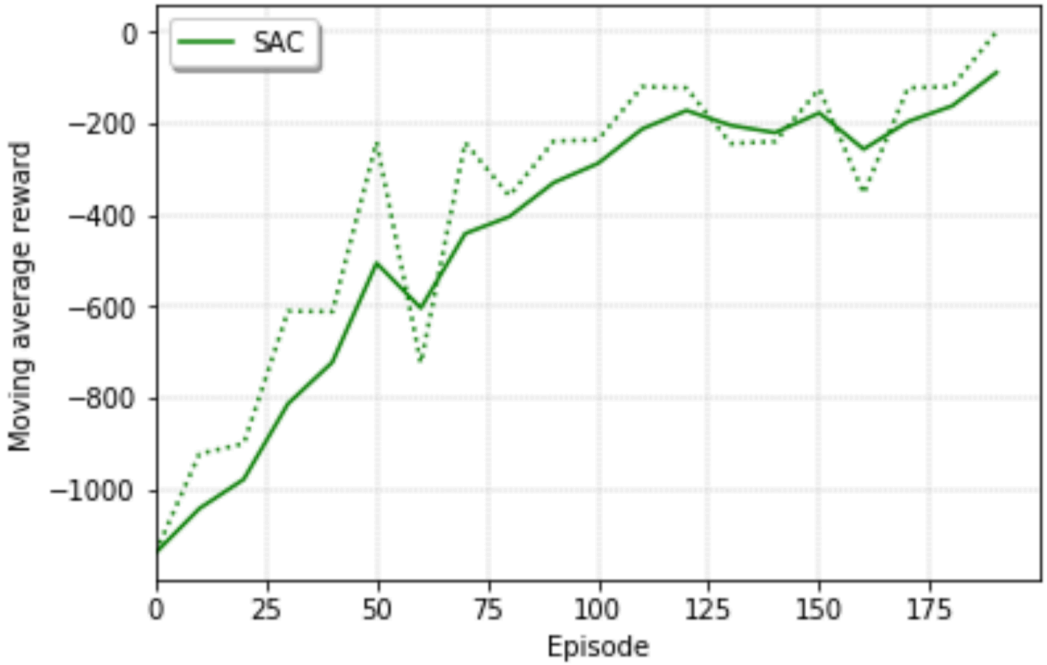
- Terminal A - train 실행
  - conda activate env_name
  - python train.py

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



Learning curve & Test

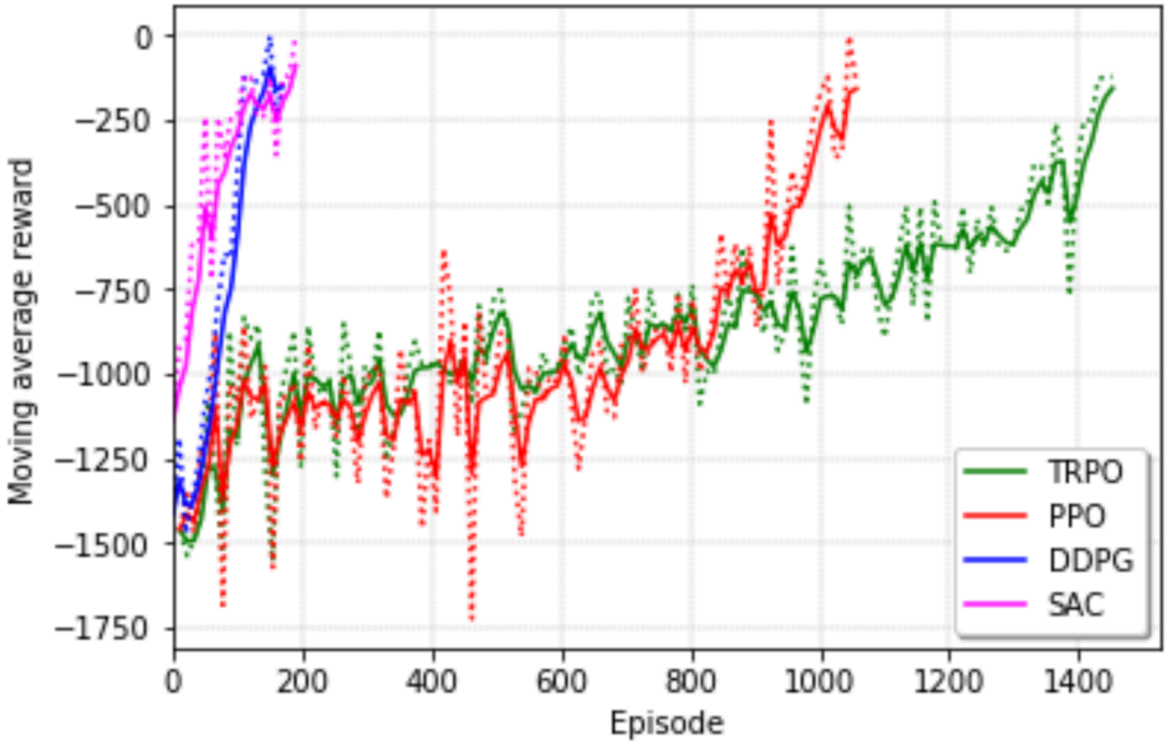
- Learning curve



- Test
  - ➢ python test.py

Comparison of algorithms for continuous action

- Learning curve



Comparison of algorithms for continuous action

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

- TRPO, PPO (On-policy algorithms)
  - **Poor sample efficiency** → 업데이트를 하기 위해서는 새로운 sample들을 수집해야 함
  - The number of gradient step and samples per step that are **extravagantly expensive**
- DDPG (Off-policy algorithm)
  - The interplay between the **deterministic actor** and the Q-function typically makes DDPG extreme **difficult to stabilize and brittle to hyperparameter settings**
  - Exploration noise can cause **sudden failures in unstable environments**
- SAC (Off-policy algorithm)
  - The **stochastic actor** aims to maximize expected reward while also **maximizing entropy**
  - **Automatic** gradient-based **temperature hyperparameter tuning** method

Thank you