CORE
Control + Optimization Research Lab

# Generalized Advantage Estimator (GAE)


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# Outline

- Generalized Advantage Estimator (GAE)
  - Learning process
  - Hyperparameter
  - Main loop
  - Train model
  - Train & TensorboardX
  - Learning curve & Test
- TRPO vs. TRPO + GAE - Learning curve

# Generalized Advantage Estimator (GAE)

- Learning process (TRPO + GAE)
  1. 상태에 따른 행동 선택
  2. 환경에서 선택한 행동으로 한 time step을 진행한 후, 다음 상태와 보상을 받음
  3. Sample $(s, a, r)$을 trajectories set에 저장
  4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
     - Step 1 : Return과 GAE 구하기
     - Step 2 : Critic network 업데이트
     - Step 3 : Surrogate loss를 통해 actor loss의 gradient 구하기
     - Step 4 : Conjugate gradient method를 통해 search direction 구하기
     - Step 5 : Step size와 maximal step 구하기
     - Step 6 : Backtracking line search를 통해 trust region안에서 actor network 업데이트

# Generalized Advantage Estimator (GAE)

- Actor network

```
4   class Actor(nn.Module):
5       def __init__(self, state_size, action_size, args):
6           super(Actor, self).__init__()
7           self.fc1 = nn.Linear(state_size, args.hidden_size)
8           self.fc2 = nn.Linear(args.hidden_size, args.hidden_size)
9           self.fc3 = nn.Linear(args.hidden_size, action_size)
10
11      def forward(self, x):
12          x = torch.tanh(self.fc1(x))
13          x = torch.tanh(self.fc2(x))
14
15          mu = self.fc3(x)
16          log_std = torch.zeros_like(mu)
17          std = torch.exp(log_std)
18
19          return mu, std
```

# Generalized Advantage Estimator (GAE)

- Critic network

```
21  class Critic(nn.Module):
22      def __init__(self, state_size, args):
23          super(Critic, self).__init__()
24          self.fc1 = nn.Linear(state_size, args.hidden_size)
25          self.fc2 = nn.Linear(args.hidden_size, args.hidden_size)
26          self.fc3 = nn.Linear(args.hidden_size, 1)
27
28      def forward(self, x):
29          x = torch.tanh(self.fc1(x))
30          x = torch.tanh(self.fc2(x))
31          value = self.fc3(x)
32
33          return value
```

# Learning process

1. 상태에 따른 행동 선택

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

train.py

```
5    def get_action(mu, std):
6        normal = Normal(mu, std)
7        action = normal.sample()
8
9        return action.data.numpy()
```

utils.py

- Normal(mu, std)
  - Normal(Gaussian) distribution에서 sampling을 할 경우, 분산을 일정하게 유지하면서 지속적인 exploration이 가능
  - std를 1로 고정함으로써 일정한 폭을 가지는 normal distribution에서 sampling

# Learning process

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

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

3. Sample $(s, a, r)$을 trajectories set에 저장

```
124             trajectories = deque()
```

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

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 1 : Return과 GAE 구하기
     - time step 6까지 진행하고 episode가 끝났을 경우를 가정

$$G_1 = R_2 + \gamma R_3 + \gamma^2 R_4 + \gamma^3 R_5 + \gamma^4 R_6$$
$$G_2 = R_3 + \gamma R_4 + \gamma^2 R_5 + \gamma^3 R_6$$
$$G_3 = R_4 + \gamma R_5 + \gamma^2 R_6$$
$$G_4 = R_5 + \gamma R_6$$
$$G_5 = R_6$$

     - 거꾸로 계산하며 계산해놓은 return값을 이용

$$G_5 = R_6$$
$$G_4 = R_5 + \gamma G_5$$
$$G_3 = R_4 + \gamma G_4$$
$$G_2 = R_3 + \gamma G_3$$
$$G_1 = R_2 + \gamma G_2$$

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 1 : Return과 GAE 구하기
     - Generalized advantage estimator (GAE)

$$\hat{A}_t^{\mathrm{GAE}(\gamma,\lambda)} = \sum_{\ell=0}^{\infty} (\gamma\lambda)^{\ell} \delta_{t+\ell}^{V}$$

$$\delta_t^V = r_t + \gamma V^{\pi}(s_{t+1}) - V^{\pi}(s_t) = \hat{A}_t^{\pi}$$

     - time step 5까지 진행하고 episode가 끝났을 경우를 가정

$$\hat{A}_1^{(1)} = \delta_1^V$$

$$\hat{A}_1^{(2)} = \delta_1^V + \gamma\lambda\delta_2^V$$

$$\hat{A}_1^{(3)} = \delta_1^V + \gamma\lambda\delta_2^V + \gamma^2\lambda^2\delta_3^V$$

$$\hat{A}_1^{(4)} = \delta_1^V + \gamma\lambda\delta_2^V + \gamma^2\lambda^2\delta_3^V + \gamma^3\lambda^3\delta_4^V$$

$$\hat{A}_1^{(5)} = \delta_1^V + \gamma\lambda\delta_2^V + \gamma^2\lambda^2\delta_3^V + \gamma^3\lambda^3\delta_4^V + \gamma^4\lambda^4\delta_5^V$$

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 1 : Return과 GAE 구하기
     - 최종적으로 구하고 싶은 GAE

$$\hat{A}_1^{(5)} = \delta_1^V + \gamma\lambda\delta_2^V + \gamma^2\lambda^2\delta_3^V + \gamma^3\lambda^3\delta_4^V + \gamma^4\lambda^4\delta_5^V$$

     - 거꾸로 계산하며 계산해놓은 delta값을 이용

| | |
|---|---|
| $\delta_5^V = r_5 - V^\pi(s_5)$ | $\delta_5^V$ |
| $\delta_4^V = r_4 + \gamma V^\pi(s_5) - V^\pi(s_4)$ | $\delta_4^V + \gamma\lambda\delta_5^V$ |
| $\delta_3^V = r_3 + \gamma V^\pi(s_4) - V^\pi(s_3)$ | $\delta_3^V + \gamma\lambda\delta_4^V + \gamma^2\lambda^2\delta_5^V$ |
| $\delta_2^V = r_2 + \gamma V^\pi(s_3) - V^\pi(s_2)$ | $\delta_2^V + \gamma\lambda\delta_3^V + \gamma^2\lambda^2\delta_4^V + \gamma^3\lambda^3\delta_5^V$ |
| $\delta_1^V = r_1 + \gamma V^\pi(s_2) - V^\pi(s_1)$ | $\delta_1^V + \gamma\lambda\delta_2^V + \gamma^2\lambda^2\delta_3^V + \gamma^3\lambda^3\delta_4^V + \gamma^4\lambda^4\delta_5^V$ |

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 1 : Return과 GAE 구하기

utils.py

```python
def get_gae(rewards, masks, values, args):
    returns = torch.zeros_like(rewards)
    advantages = torch.zeros_like(rewards)

    running_returns = 0
    previous_value = 0
    running_advants = 0

    for t in reversed(range(0, len(rewards))):
        # return
        running_returns = rewards[t] + masks[t] * args.gamma * running_returns
        returns[t] = running_returns

        # advantage
        running_deltas = rewards[t] + masks[t] * args.gamma * previous_value - values.data[t]
        running_advants = running_deltas + masks[t] * args.gamma * args.lamda * running_advants

        previous_value = values.data[t]
        advantages[t] = running_advants

    advantages = (advantages - advantages.mean()) / advantages.std()

    return returns, advantages
```

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 2 : Critic network 업데이트
     - Critic Loss
       - $J_V(\phi) = (V_\phi(s) - R)^2$

         Prediction Target
       - n = 2200
       - Batch size = 64

```
args.batch_size * i 0
args.batch_size * (i + 1) 64

args.batch_size * i 64
args.batch_size * (i + 1) 128

args.batch_size * i 128
args.batch_size * (i + 1) 192

            .
            .
            .

args.batch_size * i 1984
args.batch_size * (i + 1) 2048

args.batch_size * i 2048
args.batch_size * (i + 1) 2112

args.batch_size * i 2112
args.batch_size * (i + 1) 2176
```

train.py

```
49      # ----------------------------
50      # step 2: update critic
51      criterion = torch.nn.MSELoss()
52
53      n = len(states)
54      arr = np.arange(n)
55
56      for _ in range(5):
57          np.random.shuffle(arr)
58
59          for i in range(n // args.batch_size):
60              mini_batch_index = arr[args.batch_size * i : args.batch_size * (i + 1)]
61              mini_batch_index = torch.LongTensor(mini_batch_index)
62
63              states_samples = torch.Tensor(states)[mini_batch_index]
64              values_samples = critic(states_samples)
65
66              target_samples = returns.unsqueeze(1)[mini_batch_index]
67
68              critic_loss = criterion(values_samples, target_samples)
69              critic_optimizer.zero_grad()
70              critic_loss.backward()
71              critic_optimizer.step()
```

# Learning process

❖ 정리

1) Get surrogate objective function

$$\mathbb{E}_{s,a\sim\pi_{\theta_{old}}}\left[\frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)}A_{\pi_{\theta_{old}}}(s,a)\right]$$

2) Find search direction, step size and maximal step through CGM and Hessian of KL

- Search direction : $H^{-1}g$
- Step size : $\sqrt{\frac{2\delta}{g^TH^{-1}g}}$
- Maximal step : $\sqrt{\frac{2\delta}{g^TH^{-1}g}}H^{-1}g$

3) Do line search on that direction inside trust region through Backtracking line search

$$\theta_{k+1}=\theta_k+\alpha^j\sqrt{\frac{2\delta}{g^TH^{-1}g}}H^{-1}g$$

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 3 : Surrogate loss를 통해 actor loss의 gradient 구하기

train.py

```
73      # -----------------------------
74      # step 3: get gradient of actor loss through surrogate loss
75      mu, std = actor(torch.Tensor(states))
76      old_policy = get_log_prob(actions, mu, std)
```

utils.py

```
35  def get_log_prob(actions, mu, std):
36      normal = Normal(mu, std)
37      log_prob = normal.log_prob(actions)
38
39      return log_prob
```

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

- Multiply the log on both sides

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

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 3 : Surrogate loss를 통해 actor loss의 gradient 구하기

train.py

```
73      # ----------------------------
74      # step 3: get gradient of actor loss through surrogate loss
75      mu, std = actor(torch.Tensor(states))
76      old_policy = get_log_prob(actions, mu, std)
77      actor_loss = surrogate_loss(actor, advantages, states, old_policy.detach(), actions)
```

utils.py

```
41  def surrogate_loss(actor, advantages, states, old_policy, actions):
42      mu, std = actor(torch.Tensor(states))
43      new_policy = get_log_prob(actions, mu, std)
44
45      advantages = advantages.unsqueeze(1)
46
47      surrogate_loss = torch.exp(new_policy - old_policy) * advantages
48      surrogate_loss = surrogate_loss.mean()
49
50      return surrogate_loss
```

   - surrogate_loss

$$\mathcal{L}_{\theta_{old}}(\theta) = \mathbb{E}_{s,a\sim\pi_{\theta_{old}}}\left[\frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)} A_{\pi_{\theta_{old}}}(s,a)\right]$$

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 3 : Surrogate loss를 통해 actor loss의 gradient 구하기

train.py

```
73      # ----------------------------
74      # step 3: get gradient of actor loss through surrogate loss
75      mu, std = actor(torch.Tensor(states))
76      old_policy = get_log_prob(actions, mu, std)
77      actor_loss = surrogate_loss(actor, advantages, states, old_policy.detach(), actions)
78
79      actor_loss_grad = torch.autograd.grad(actor_loss, actor.parameters())
80      actor_loss_grad = flat_grad(actor_loss_grad)
```

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 4 : Conjugate gradient method를 통해 search direction 구하기

train.py

```
82      # -----------------------------
83      # step 4: get search direction through conjugate gradient method
84      search_dir = conjugate_gradient(actor, states, actor_loss_grad.data, nsteps=10)
```

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 5 : Step size와 maximal step 구하기

train.py

```
86      # ----------------------------
87      # step 5: get step size and maximal step
88      gHg = (hessian_vector_product(actor, states, search_dir) * search_dir).sum(0, keepdim=True)
89      step_size = torch.sqrt(2 * args.max_kl / gHg)[0]
90      maximal_step = step_size * search_dir
```

   - Step size : $\sqrt{\frac{2\delta}{g^T H^{-1} g}}$ $(Hx = g)$, (max_kl $\delta$ : 0.01)
   - Maximal step : $\sqrt{\frac{2\delta}{g^T H^{-1} g}} H^{-1} g$

# Learning process

4. 일정 sample들이 모이면 trajectories set으로 Actor & Critic network 업데이트
   - Step 6 : Backtracking line search를 통해 trust region안에서 actor network 업데이트

train.py

```
92      # ----------------------------
93      # step 6: perform backtracking line search and update actor in trust region
94      params = flat_params(actor)
95
96      old_actor = Actor(state_size, action_size, args)
97      update_model(old_actor, params)
98
99      backtracking_line_search(old_actor, actor, actor_loss, actor_loss_grad,
100                               old_policy, params, maximal_step, args.max_kl,
101                               advantages, states, actions)
```

# Hyperparameter

```
14    parser = argparse.ArgumentParser()
15    parser.add_argument('--env_name', type=str, default="Pendulum-v0")
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('--lamda', type=float, default=0.98)
21    parser.add_argument('--hidden_size', type=int, default=64)
22    parser.add_argument('--batch_size', type=int, default=64)
23    parser.add_argument('--critic_lr', type=float, default=1e-3)
24    parser.add_argument('--max_kl', type=float, default=1e-2)
25    parser.add_argument('--max_iter_num', type=int, default=500)
26    parser.add_argument('--total_sample_size', type=int, default=2048)
27    parser.add_argument('--log_interval', type=int, default=5)
28    parser.add_argument('--goal_score', type=int, default=-300)
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
  - Actor & Critic network
  - Critic optimizer
  - TensorboardX
  - Recent rewards

```
104  def main():
105      env = gym.make(args.env_name)
106      env.seed(500)
107      torch.manual_seed(500)
108
109      state_size = env.observation_space.shape[0]
110      action_size = env.action_space.shape[0]
111      print('state size:', state_size)
112      print('action size:', action_size)
113
114      actor = Actor(state_size, action_size, args)
115      critic = Critic(state_size, args)
116      critic_optimizer = optim.Adam(critic.parameters(), lr=args.critic_lr)
117
118      writer = SummaryWriter(args.logdir)
119
120      recent_rewards = deque(maxlen=100)
121      episodes = 0
```

# Main loop

- Episode 진행
  - Initialize trajectories set
  - 상태에 따른 행동 선택
  - 다음 상태와 보상을 받음
  - Trajectories set에 저장

```
123     for iter in range(args.max_iter_num):
124         trajectories = deque()
125         steps = 0
126 
127         while steps < args.total_sample_size:
128             done = False
129             score = 0
130             episodes += 1
131 
132             state = env.reset()
133             state = np.reshape(state, [1, state_size])
134 
135             while not done:
136                 if args.render:
137                     env.render()
138 
139                 steps += 1
140 
141                 mu, std = actor(torch.Tensor(state))
142                 action = get_action(mu, std)
143 
144                 next_state, reward, done, _ = env.step(action)
145 
146                 mask = 0 if done else 1
147 
148                 trajectories.append((state, action, reward, mask))
149 
150                 next_state = np.reshape(next_state, [1, state_size])
151                 state = next_state
152                 score += reward
153 
154                 if done:
155                     recent_rewards.append(score)
```

# Main loop

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

```
157         actor.train(), critic.train()
158         train_model(actor, critic, critic_optimizer, trajectories, state_size, action_size)
159
160         writer.add_scalar('log/score', float(score), episodes)
161
162         if iter % args.log_interval == 0:
163             print('{} iter | {} episode | score_avg: {:.2f}'.format(iter, episodes, np.mean(recent_rewards)))
164
165         if np.mean(recent_rewards) > args.goal_score:
166             if not os.path.isdir(args.save_path):
167                 os.makedirs(args.save_path)
168
169             ckpt_path = args.save_path + 'model.pth.tar'
170             torch.save(actor.state_dict(), ckpt_path)
171             print('Recent rewards exceed -300. So end')
172             break
```

# Train model

- Trajectories → Numpy array
- Trajectories에 있는 2200개의 sample들을 각각 나눔
  - state - (2200, 3)
  - action - (2200, 1)
  - reward - (2200)
  - mask - (2200)

```
33  def train_model(actor, critic, critic_optimizer, trajectories, state_size, action_size):
34      trajectories = np.array(trajectories)
35      states = np.vstack(trajectories[:, 0])
36      actions = list(trajectories[:, 1])
37      rewards = list(trajectories[:, 2])
38      masks = list(trajectories[:, 3])
39
40      actions = torch.Tensor(actions).squeeze(1)
41      rewards = torch.Tensor(rewards).squeeze(1)
42      masks = torch.Tensor(masks)
```

# Train model

- **values** - (2200, 1)
- **returns** - (2200)
- **advantages** - (2200)
- **n** - 2200
- **batch_size** - 64

```
44      # -----------------------------
45      # step 1: get returns and GAEs
46      values = critic(torch.Tensor(states))
47      returns, advantages = get_gae(rewards, masks, values, args)
48
49      # -----------------------------
50      # step 2: update critic
51      criterion = torch.nn.MSELoss()
52
53      n = len(states)
54      arr = np.arange(n)
55
56      for _ in range(5):
57          np.random.shuffle(arr)
58
59          for i in range(n // args.batch_size):
60              mini_batch_index = arr[args.batch_size * i : args.batch_size * (i + 1)]
61              mini_batch_index = torch.LongTensor(mini_batch_index)
62
63              states_samples = torch.Tensor(states)[mini_batch_index]
64              values_samples = critic(states_samples)
65
66              target_samples = returns.unsqueeze(1)[mini_batch_index]
67
68              critic_loss = criterion(values_samples, target_samples)
69              critic_optimizer.zero_grad()
70              critic_loss.backward()
71              critic_optimizer.step()
```

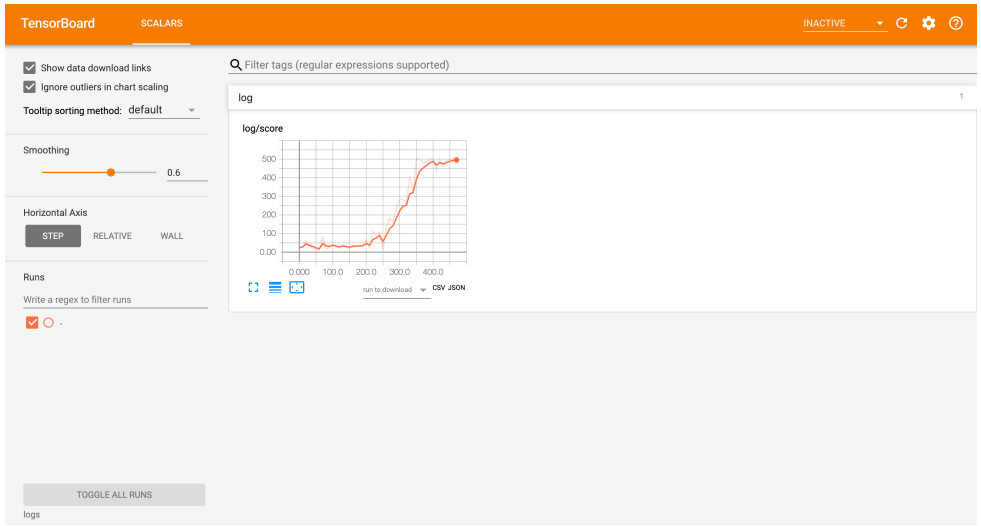
# Train model

```
73      # ----------------------------
74      # step 3: get gradient of actor loss through surrogate loss
75      mu, std = actor(torch.Tensor(states))
76      old_policy = get_log_prob(actions, mu, std)
77      actor_loss = surrogate_loss(actor, advantages, states, old_policy.detach(), actions)
78
79      actor_loss_grad = torch.autograd.grad(actor_loss, actor.parameters())
80      actor_loss_grad = flat_grad(actor_loss_grad)
81
82      # ----------------------------
83      # step 4: get search direction through conjugate gradient method
84      search_dir = conjugate_gradient(actor, states, actor_loss_grad.data, nsteps=10)
85
86      # ----------------------------
87      # step 5: get step size and maximal step
88      gHg = (hessian_vector_product(actor, states, search_dir) * search_dir).sum(0, keepdim=True)
89      step_size = torch.sqrt(2 * args.max_kl / gHg)[0]
90      maximal_step = step_size * search_dir
91
92      # ----------------------------
93      # step 6: perform backtracking line search and update actor in trust region
94      params = flat_params(actor)
95
96      old_actor = Actor(state_size, action_size, args)
97      update_model(old_actor, params)
98
99      backtracking_line_search(old_actor, actor, actor_loss, actor_loss_grad,
100                               old_policy, params, maximal_step, args.max_kl,
101                               advantages, states, actions)
```

# Train & TensorboardX

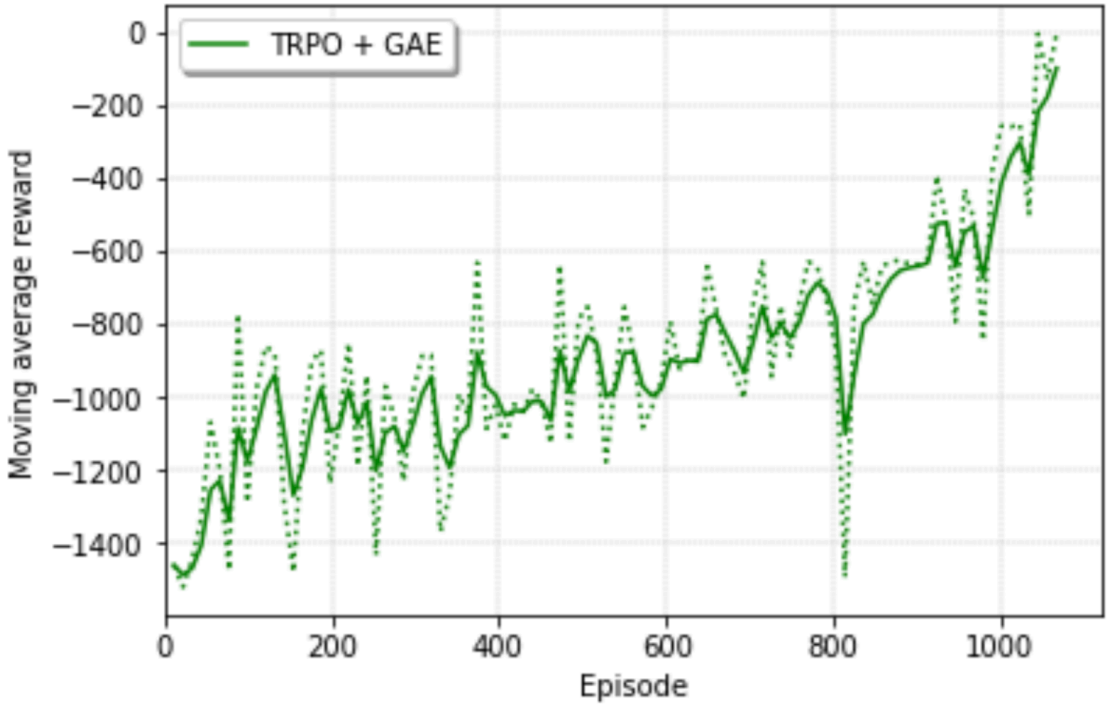
- Terminal A - train 실행
  - conda activate env_name
  - python train.py

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



# Learning curve & Test

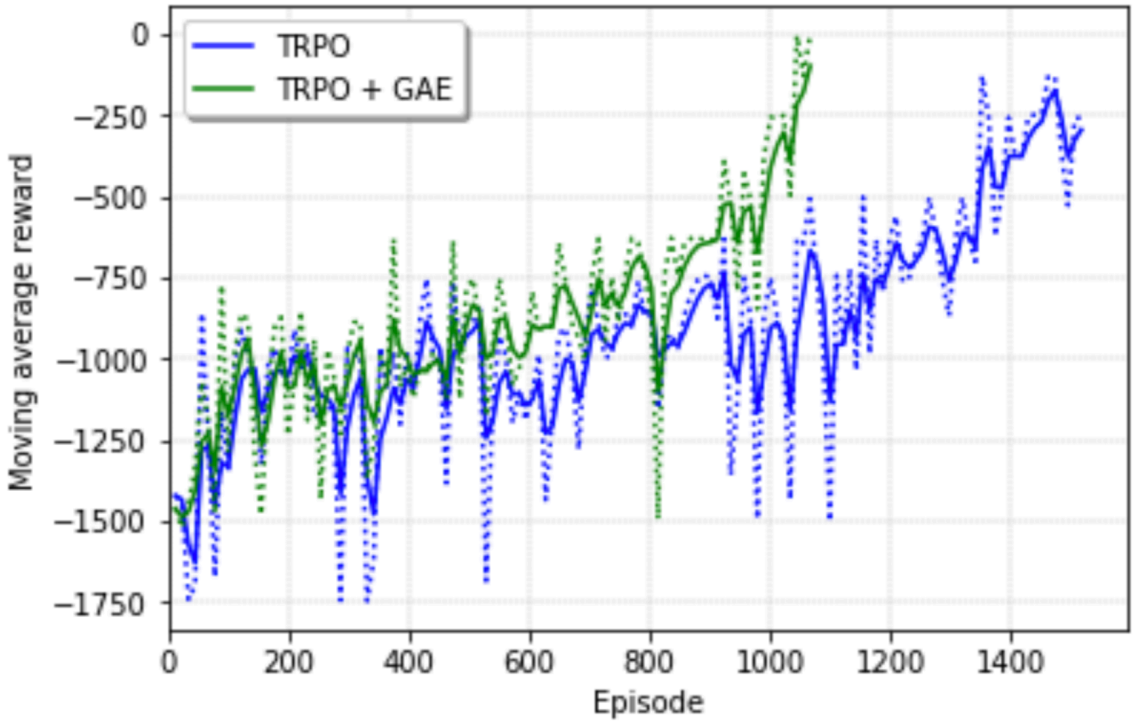
- Learning curve




- Test
  - ➢ python test.py

# TRPO vs. TRPO + GAE

- Learning curve



Thank you