1. MADDPG

MADDPG stands for "Multi-Agents Deep Deterministic Policy Gradient", originally proposed by Lowe et al., 2017

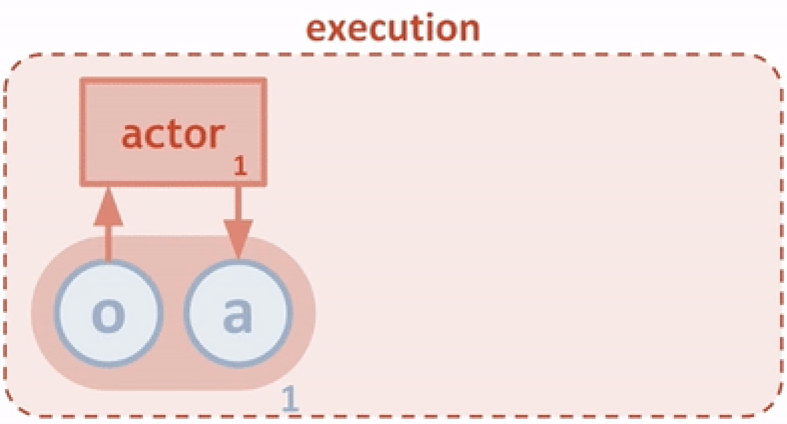
1.1 Introduction

- When a game involves multiple agents, sometimes we need the agents to learn a policy w.r.t. global advantages by compete or collaborate with each other to win the game.
- Due to the interactions between multiple agents, the state of game could be not stationary, and hard (impossible) to learn.
- The solution is using Actor-Critic, more specifically "centralized critic" + "decentralized actors"
- Using "centralized critic" to evaluate the global advantages, to find the path to win the game
- Using "decentralized actors" to form a policy for each agent based on the guides from "centralized critic"
- Questions, which not solved in this project yet.
    - I implement a general MADDPG with centralized critic in this project, however how and what the actors should communicate or sense with each other was not discussed in this project yet.
- A short review of single agent DDPG from my last project.

1.2 Notation and Model

- There are N agents
- with a set of state S in total
- each agent has a set of possible action $\mathcal{A}_1, \dots, \mathcal{A}_N$
- each agent has a set of observation $\mathcal{O}_1, \dots, \mathcal{O}_N$
- each agent has own a stochastic policy $\pi_{\theta_i} : \mathcal{O}_i \times \mathcal{A}_i \mapsto [0, 1]$
    - or a deterministic policy $\mu_{\theta_i} : \mathcal{O}_i \mapsto \mathcal{A}_i$
- let $\vec{o} = o_1, o_2, \dots, o_N$ as observation of all agents

- let $\vec{\mu} = \mu_1, \mu_2, \ldots, \mu_N$, which are parameterized by $\vec{\theta} = \theta_1, \theta_2, \ldots, \theta_N$, where μ_{θ_i} abbreviated as μ_i.
- the critic in MADDPG learns **a centralized action-value function** $Q_i^{\vec{\mu}}(\vec{x}, a_1, a_2, \ldots, a_N)$ for the i-th agent, where $a_1 \in \mathcal{A}_1 \ldots a_N \in \mathcal{A}_N$
    - For the simplest case, we concatenate states of all agents together as $\vec{x} = \vec{o} = (o_1, o_2, \ldots, o_N)$
    - or we can add more reward structure for competitive setting or others.
- each $Q_i^{\vec{\mu}}$ is learned **separately**.
    - separately means each agent has own critic network
    - the critic of each agent learns from training data of all agents
    - a better illustration can be found in below fig.



Critic Updates

$$\mathcal{L}(\theta_i) = \mathbb{E}[(Q_i^{\vec{\mu}}(\vec{o}, a_1, a_2, \ldots, a_N) - y)^2]$$
$$\text{where } y = r_i + \gamma Q_i^{\vec{\mu}'}(\vec{o}', a_1', a_2', \ldots, a_N')|_{a_j' = \vec{\mu}_j'(o_j)}$$

- prime notion means target network, e.g. $Q_i^{\vec{\mu}'}$ is target critic network, delayed updating. $\vec{\mu}'$ is **target actor network**.
- $|_{a_j' = \vec{\mu}_j'(o_j)}$ means using action a_j' of the j-th agent from j-th **target actor network**, which suppose to max Q

psudo codes

```
# use this experience
# states  -> rank=3, shape=[batch_size, agent_id, state_size]
# actions -> rank=3, shape=[batch_size, agent_id, action_size]
# rewards -> rank = 2, shape = [batch_size, agent_id]
# next_states -> rank = 3, shape = [batch_size, agent_id, state_size]
# dones   -> rank=2, shape=[batch_size, agent_id]
states, actions, rewards, next_states, dones = experiences

# to update this agent
agent = self.agent_pool[agent_id]
```

```
# -----------------------------------------
# update centralized critic
# -----------------------------------------
# -- recall update critic for normal DDPG
# best_actions = self.actor_target(next_states)
# Q_next_max = self.critic_target(next_states, best_actions)
# Q_target = rewards + gamma * Q_next_max * (1 - dones)
# Q_local = self.critic_local(states, actions)
# critic_loss = F.mse_loss(Q_local, Q_target.detach())
# self.critic_optimizer.zero_grad()
# critic_loss.backward()
# self.critic_optimizer.step()

target_actions = self.eval_target_act(next_states)
# out list of tensor, tensor rank=2, shape=[batch_size, out_actor]

target_actions = torch.cat(target_actions, dim=1)
# out tensor, rank=2, shape=[batch_size, n_agent*action_size]

# in tensor, rank=2, shape=[batch_size, n_agent*state_size]
# in tensor, rank=2, shape=[batch_size, n_agent*action_size]
target_critic_input = torch.cat((next_states.view(self.batch_size, -1),
                                 target_actions),
                                dim=1).to(device)
# out tensor, rank=2, shape=[batch_size, n_agent*(state_size+action_size)]

with torch.no_grad():
    q_next = agent.target_critic(target_critic_input)
    # out tensor, rank=2, shape=[batch_size, 1]

agent_rewards = rewards[:, agent_id]
# out tensor, rank = 1, shape = [batch_size]

agent_dones = dones[:, agent_id]
# out tensor, rank = 1, shape = [batch_size]

q_target = agent_rewards.view(-1, 1) + gamma * q_next * (1 -
agent_dones.view(-1, 1))
# out tensor, rank=2, shape=[batch_size, 1]

# out tensor, rank=2, shape=[batch_size, n_agent*state_size]
# out tensor, rank=2, shape=[batch_size, n_agent*action_size]
local_critic_input = torch.cat((states.view(self.batch_size, -1),
                                actions.view(self.batch_size, -1)),
                                dim=1).to(device)
q_local = agent.local_critic(local_critic_input)

critic_loss = F.mse_loss(q_local, q_target.detach())

agent.critic_optimizer.zero_grad()
critic_loss.backward()
agent.critic_optimizer.step()
```

Actor Update

$$\nabla_{\theta_j} J(\mu_j) = \mathbb{E}_{\vec{o},a\in\mathcal{D}}[\nabla_{\theta_j}\mu_i(a_i|o_i)\nabla_{a_i} Q_i^{\vec{\mu}}(\vec{o},a_1,\ldots,a_N)|_{a_i=\mu_i(o_i)}]$$

- $|_{a_i=\mu_i(o_i)}$ means using action from **local actor network**.
- $\mathcal{D}$ contains the SARS tuples (o,a,r,o') for **all agents**.
- $Q_i^{\vec{\mu}}$ is centralized action-value function.
- $Q_i^{\vec{\mu}}(\vec{o},a_1,\ldots,a_N)$ is the TD view of $R(\tau)=r_1+r_2+\cdots+r_H+r_{H+1}$, recall

$$\nabla_\theta J(\theta) \approx \hat{g} := \frac{1}{m}\sum_i^m \sum_{t=0}^H \nabla_\theta \log \pi_\theta(a_t^{(i)}|s_t^{(i)})R(\tau^{(i)})$$

psudo codes

```
# ------------------------------------------
# update actor
# ------------------------------------------
# -- recall update actor for normal DDPG
# actions_pred = self.actor_local(states)
# Q_baseline = self.critic_local(states, actions_pred)
# actor_loss = -Q_baseline.mean()  # I think this is a good trick to make loss
to scalar
# # note, gradients from both actor_local and critic_local will be calculated
# # however we only update actor_local
# self.actor_optimizer.zero_grad()
# actor_loss.backward()
# self.actor_optimizer.step()

pred_actions = self.eval_local_act(states)
# list of tensor, tensor rank=2, shape=[batch_size, out_actor]

pred_actions = torch.cat(pred_actions, dim=1)
# tensor, rank=2, shape=[batch_size, n_agent*action_size]

# tensor, rank=2, shape=[batch_size, n_agent*state_size]
# tensor, rank=2, shape=[batch_size, n_agent*action_size]
local_critic_input2 = torch.cat((states.view(self.batch_size, -1),
                                 pred_actions),
                                dim=1).to(device)

q_baseline = agent.local_critic(local_critic_input2)

# get the policy gradient
actor_loss = -q_baseline.mean()  # scalar trick for gradients
agent.actor_optimizer.zero_grad()
actor_loss.backward()
agent.actor_optimizer.step()
```

1.3 Inferring Policies of Other Agents (Communication)

- How ? based on task, key implementation for real project

1.4 Agents with Policy Ensembles

- each agent has K different sub-policies
  - equivalents to K actor networks
- At each episode, we randomly select one particular sub-policy for each agent to execute.

1.5 Reward Design for Collaborate and Competitive

- How? based on task, Key implementation for real project

Reference

- a good state of the art blog
- the original paper (Lowe et al., 2017).
- The original paper and this explanation blog have very clean and beautiful math notation.
- a good blog from openai

2. Implementation Details

2.1 Setups

```
agents = MADDPG(state_size=24,
                action_size=2,
                n_agents=2,
                gamma=0.99,
                tau=1e-3,
                lr_actor=1e-4,
                lr_critic=5e-4,
                learn_n_times_per_step=3,
                update_target_every=10,
                memory_size=int(1e5),
                batch_size=256)
```

- who often update target network from local network is a **KEY** parameter for convergence and consistence training result.
- add proper noise to action is a **KEY** step to explore efficiently.
    - e.g. dx from Ornstein-Uhlenbeck Process can not be too small. in this project, I used sigma=0.5
- learning rate of critic network is important

Actor Network

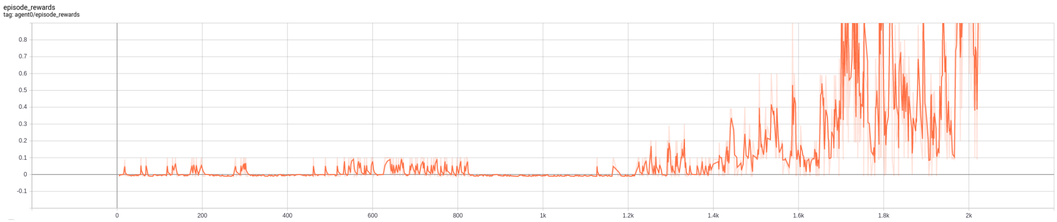
```
# input layer
# fully connected layer 1, 24x400
# batch normalization
# Relu
# fully connected layer 2, 400x300
# Relu
# fully connected layer 3, 300x2
# tanh
```

Critic Network

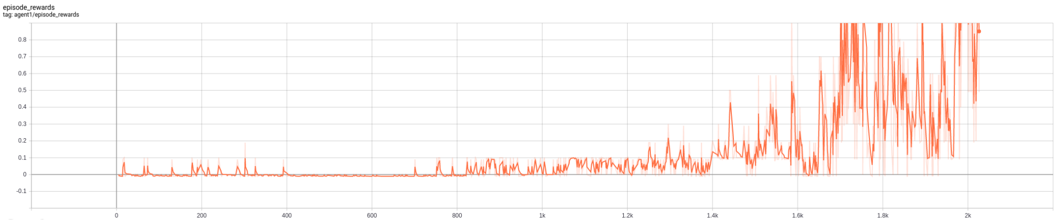
```
# input layer
# fully connected layer 1, 52x400
# batch normalization
# Relu
# fully connected layer 2, 400x300
# Relu
# fully connected layer 3, 300x1
```

2.2 Results and Discussion

- episodic rewards of two agents
  - agent0



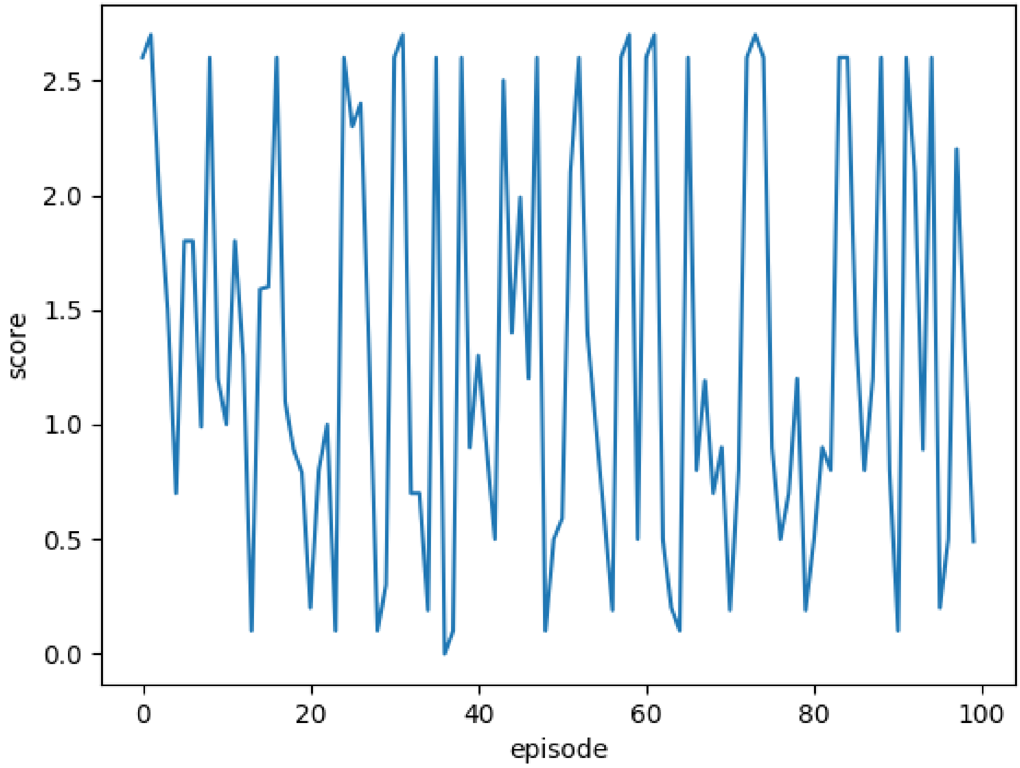
  - agent1



Here are some interesting guess. I observed episodic rewards of the two agents. From episode 0-400, it seems both agents were doing exploration. For episode 400-1200, it seems two agent have **complementary** performance, like adversary, one became great, the other turns to weak, very interesting.

However in this project I didn't add communication between agents for actor input and explicit extra rewards for collaboration. It is **NOT** very clear, in my opinion, whether the agent has just finally improved own skills or it really learned to play with considering collaboration.

- evaluation
  - average score of 100 episodes is 1.33 (> 0.5 -> solved)



2.3 Future Works

test and implement crawler environments with competition rewards and limited communication between agents.