Inducing Cooperation through Reward Reshaping based on Peer Evaluations in Deep Multi-Agent Reinforcement Learning

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Motivation

semi-cooperative

agents may each have its own separate reward function (the joint reward scenario is a special case), but is willing to cooperate if an incentive for cooperation is appropriately provided.

social welfare

the sum of the rewards of each agent across the entire episode.

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Problem Setting

Stochastic game

a multi-agent task with each agent having its own individual reward by modeling it with a stochastic game

Semi-cooperative task

semi-cooperative tasks as the set of tasks where each agent may have a separate reward function but may benefit from cooperative strategies such as the prisoner's dilemma and the stag hunt game.

Goal: Maximizing the social welfare

the sum of the rewards of each agent across the entire episode.

$$\pi^* = \left(\pi_1^*\left(u_1 \mid o_1\right), \pi_2^*\left(u_2 \mid o_2\right), \ldots, \pi_n^*\left(u_n \mid o_n\right)\right)$$

$$\pi^* = \arg\max_{\pi} \sum_{a \in \mathcal{A}} \mathrm{E}_{s \sim \rho^{\pi}, \boldsymbol{u} \sim \pi}\left[r_a(s, \boldsymbol{u})\right]$$

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Solution

1. Change of Games via Reward Reshaping
2. Reward Update with Peer Evaluation
   1. Peer evaluation signal
   2. Reshaping reward from peer evaluation
3. Peer-evaluation based Dual DQN (PED-DQN)

Change of Games via Reward Reshaping

reward function

in the game G^t:

$$\hat{r}^t = \left(\hat{r}^t_a : a \in \mathcal{A}\right)$$

at time step $t = 0, 1, \cdots$

1. Compute the optimal π^t policy from G^t
2. Evaluate how well-coordinated G^t is by evaluating π^t
3. Update from G^t to G^{t+1} by updating from $\hat{r}^t$ to $\hat{r}^{t+1}$, using the 'evaluation feedback' from (2)
4. Increment t and go to (1)

Framework

Policy Update: $\pi^{t+1} = F\left(\pi^t, \hat{r}^t\right)$
Reward Update: $\hat{r}^{t+1} = H\left(\hat{r}^t, \pi^t\right)$

Reward Update with Peer Evaluation

Peer evaluation signal:

counterfactual evaluation signal (CES) z_k^t

for agent k:

$$z_k^t\left(o_k^t, o_k^{t+1}, u_k^t, r_k^t\right) := r_k^t + \gamma Q_k^{\pi^t}\left(o_k^{t+1}, \pi_k^t\left(o_k^{t+1}\right)\right) - Q_k^{\pi^t}\left(o_k^t, u_k^t\right)$$

Reshaping reward from peer evaluation:

agent a and agent k are peers.

For agent a:

$$Z_a^t\left[o_a^t, u_a^t\right] = \frac{1}{|K_a|}\sum_{k \in K_a} z_k^t$$

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continue

sample mangy times:

$$\hat{Z}_a^t\left[o_a^t, u_a^t\right] \approx \frac{1}{|K_a|} \sum_{k \in K_a} \times$$
$$\mathbb{E}_{(o,o',u,r)\sim\pi^t : o_a = o_a^t, u_a = u_a^t}\left[z_k\left(o_k, o_k', u_k, r_k\right)\right]$$

moving average:

$$\hat{Z}_a^{t+1}\left[o_a^t, u_a^t\right] \leftarrow (1-\alpha)\hat{Z}_a^t\left[o_a^t, u_a^t\right] + \alpha Z_a^t\left[o_a^t, u_a^t\right]$$

final the reshaped reward $\hat{r}_a^t[o_a^t, u_a^t]$:

$$\hat{r}_a^t\left[0_a^t, u_a^t\right] = r_a^t + \beta\hat{Z}_a^t\left[o_a^t, u_a^t\right]$$

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Example: Evaluation feedback exchange

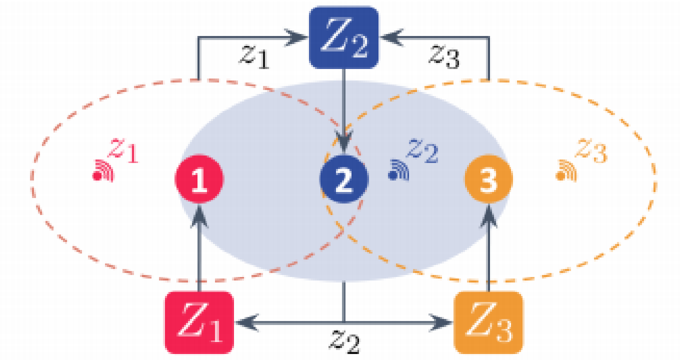

Figure: Example: Evaluation feedback exchange

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Peer-evaluation based Dual DQN (PED-DQN)

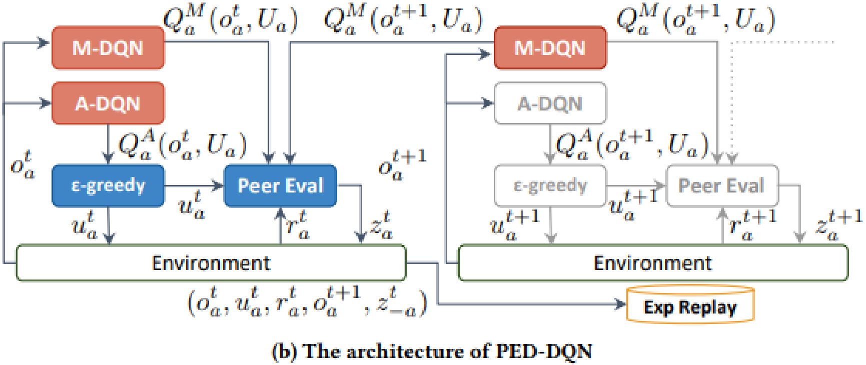

Figure: The architecture of PED-DQN

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Case study: Prisoner's dilemma

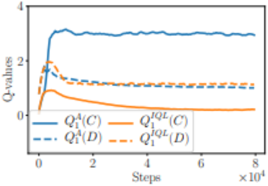
Table 1: Prisoner's dilemma

(a) original payoff

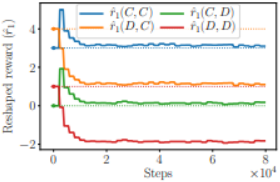
	C	D
C	3, 3	0, 4
D	4, 0	1, 1

(b) reshaped payoff

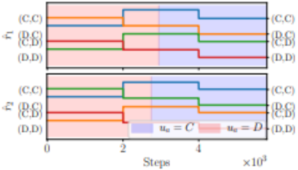
	C	D
C	3.11, 3.13	0.10, 1.13
D	1.11, 0.13	-1.90, -1.87



(a) IQL learned defection while ours learned cooperation



(b) Reshaped rewards $\hat{r}_1(D,C)$ and $\hat{r}_1(D,D)$ penalize defection



(c) Peer evaluations steered the agents'

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Experiments

Algorithms:

- QMIX
- IDQ PED-DQN
- PE:single network
- Pro DQN:directly use reward

$$z_a = r_a$$

$$\hat{r}_a = r_a + \frac{\beta}{|K_a|} \sum_{k \in K_a} r_k$$

Environments:

- Resource share
- Partially cooperative pursuit (PCP)

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Experiments

please read the paper to check the experiments details.

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Thoughts

communication & reward shaping