Difference Rewards Policy Gradients

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3-4 May 2021

Multi-Agent Reinforcement Learning

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Centralized Training-Decentralized Execution (CTDE) framework:

- CT: information are shared among agents during training phase (i.e. centralized critic),
- DE: during execution, each agent has to rely only on its local information (i.e. decentralized policies).

Multi-Agent Policy Gradients

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They improve the parameters θ^i of agent i policy $\pi(s, a^i; \theta^i)$ by following the gradients:

$$\nabla_{\theta^i} J(\theta^i) = \mathbb{E}_{a^i \sim \pi_{\theta^i}(\cdot|s)} \left[\nabla_{\theta^i} \log \pi_{\theta^i}(a^i|s) G_t \right],$$

where $G_t = \sum_{l=0}^{T} \gamma^l r_{t+l}$ is the return.

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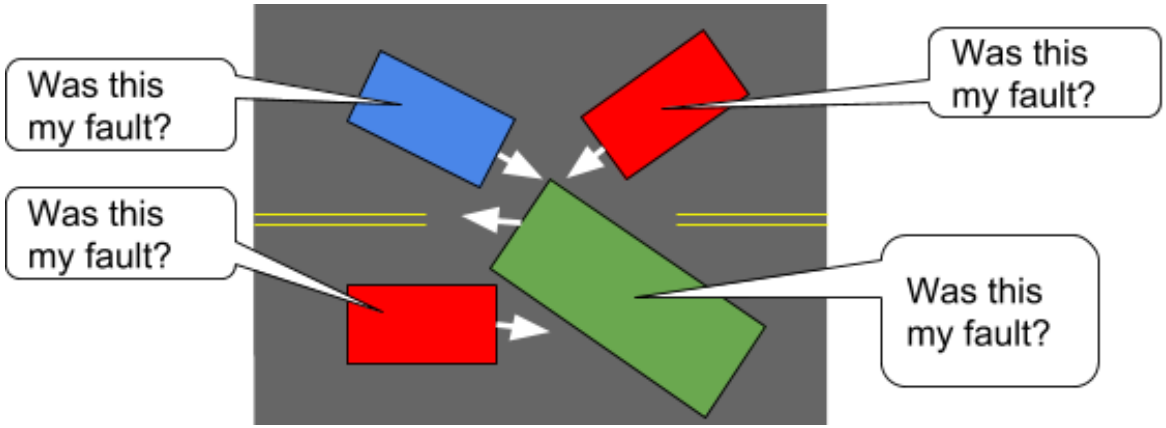
Remark: as $G_t \approx Q^{\pi_\theta}(s, a)$, one can instead learn a *centralized critic* Q_ω to approximate it.

Multi-Agent Credit Assignment



Multi-agent credit assignment: how can an agent determine how its actions are affecting the overall performance of the team?

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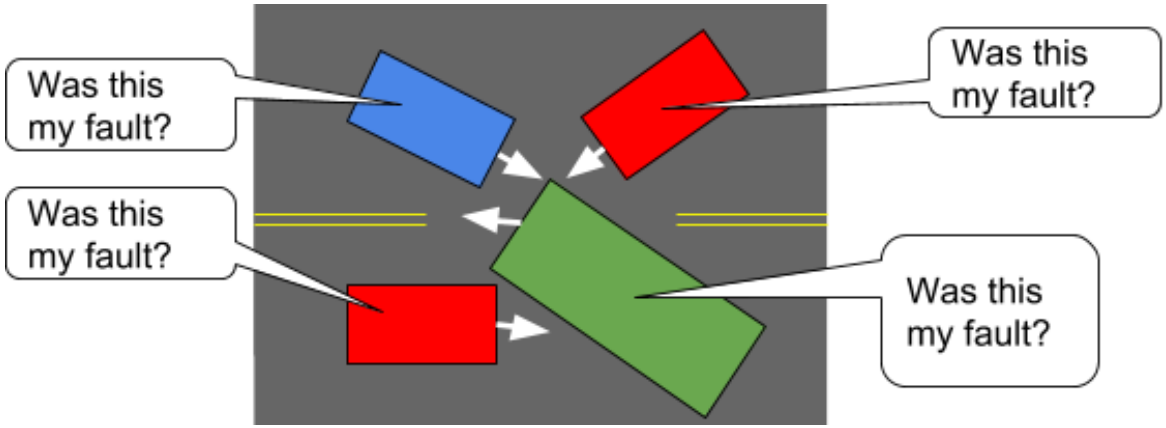

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MAPG algorithms do not usually address this key problem in MARL...

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A possible version is called *aristocrat utility*:

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Problem: usually rewards $R(s, \langle a^{-i}, b^i \rangle)$ for each local action b^i are not known...

DR: An Example

		Agent Y	
		a_1	a_2
Agent X	a_1	10	10
	a_2	5	0

$\pi^X = \pi^Y = (0.5, 0.5)$

At time step t:

- $a_t = \langle a_2, a_1 \rangle$
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$$\Delta R_t^X = r_t - \sum_{b^X \in \{a_1, a_2\}} \pi^X(b^X) R(\langle b^X, a_1 \rangle)$$

$$= 5 - (0.5 \cdot 10 + 0.5 \cdot 5) = -2.5$$

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$$\Delta R_t^Y = r_t - \sum_{b^Y \in \{a_1, a_2\}} \pi^Y(b^Y) R(\langle a_2, b^Y \rangle)$$

$$= 5 - (0.5 \cdot 5 + 0.5 \cdot 0) = 2.5$$

Counterfactual Multi-Agent Policy Gradients

COMA [Foerster et al., 2018] is combining MAPG with DR applied on the Q-function (approximated by a centralized critic $Q_\omega(s, a)$):

$$\nabla_{\theta^i} J(\theta^i) = \mathbb{E}_{a^i \sim \pi_{\theta^i}(\cdot|s)} \left[\nabla_{\theta^i} \log \pi_{\theta^i}(a^i|s) \Delta Q^i(s, a) \right],$$

where $\Delta Q^i(s, a) = Q_\omega(s, a) - \mathbb{E}_{b_i \sim \pi_{\theta_i}(\cdot|s)} [Q_\omega(s, \langle a_{-i}, b_i \rangle)]$.

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where $\Delta Q^i(s, a) = Q_\omega(s, a) - \mathbb{E}_{b_i \sim \pi_{\theta_i}(\cdot|s)} [Q_\omega(s, \langle a_{-i}, b_i \rangle)]$.

1. Learning $Q_\omega(s, a)$ is difficult because of bootstrapping and the moving target problem,
2. It depends on the (exponentially many) joint actions a,
3. Does not exploit knowledge of the reward function $R(s, a)$.

In this work...

Exploiting CTDE, we combine decentralized policy gradients with DR to learn in fully cooperative multi-agent scenarios [Castellini et al., 2021].

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1. *Dr.Reinforce*: when knowledge of the reward function is available,
2. *Dr.ReinforceR*: a *centralized reward network* $R_\psi(s, a)$ is additionally learned to compute such DR when that is not the case,
3. Learning R_ψ is a regression problem that does not involve bootstrapping or moving targets, so easier to learn than Q_ω.

Dr.Reinforce

When the reward function $R(s, a)$ is known in advance, we define the *difference return* for agent i as:

$$\Delta G^i = \sum_{t=0}^{T} \gamma^t \Delta R^i(s, a),$$

where ΔR^i is the aristocrat utility:

$$\Delta R^i(s, a) = r_t - \sum_{b^i \in A^i} \pi_{\theta^i}(b^i|s) R(s, \langle b^i, a^{-i} \rangle).$$

Dr.Reinforce (cont'd)

We then apply decentralized policy gradients using our difference return ΔG^i as:

$$\nabla_{\theta^i} J(\theta^i) = \nabla_{\theta^i} \log \pi_{\theta^i}(a^i|s) \Delta G^i.$$

This way, each agent receives a different gradient that takes into account its own contribution to the team performance.

Proof of converge in [Castellini et al., 2021].

Dr.ReinforceR

When $R(s, a)$ is unknown, we learn an additional *centralized reward network* $R_\psi(s, a)$ as:

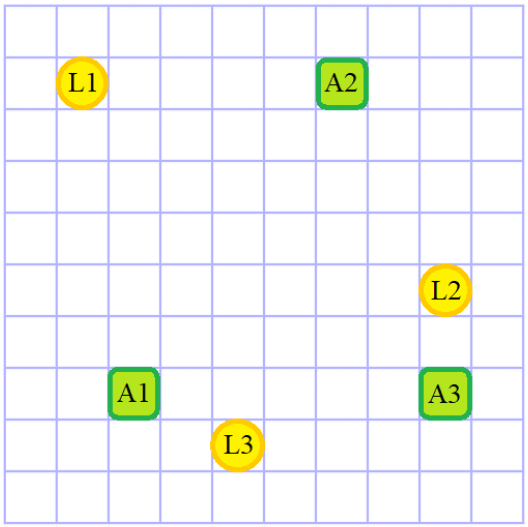
$$\mathcal{L}_t(\psi) = \frac{1}{2}\left(r_t - R_\psi(s, a)\right)^2.$$

When then compute ΔG^i in $\nabla_{\theta^i} J(\theta^i)$ by replacing the terms ΔR^i with:

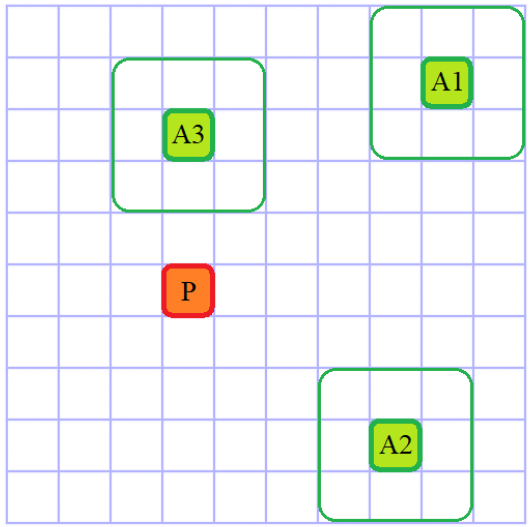
$$\Delta R^i_\psi(s, a) = r_t - \sum_{b^i \in A^i} \pi_{\theta^i}(b^i|s) R_\psi(s, \langle b^i, a^{-i} \rangle).$$

Experiments

We compared against COMA and other MAPG algorithms, as well as with a variation of the DR method in [Colby et al., 2014], on two standard cooperative benchmarks:

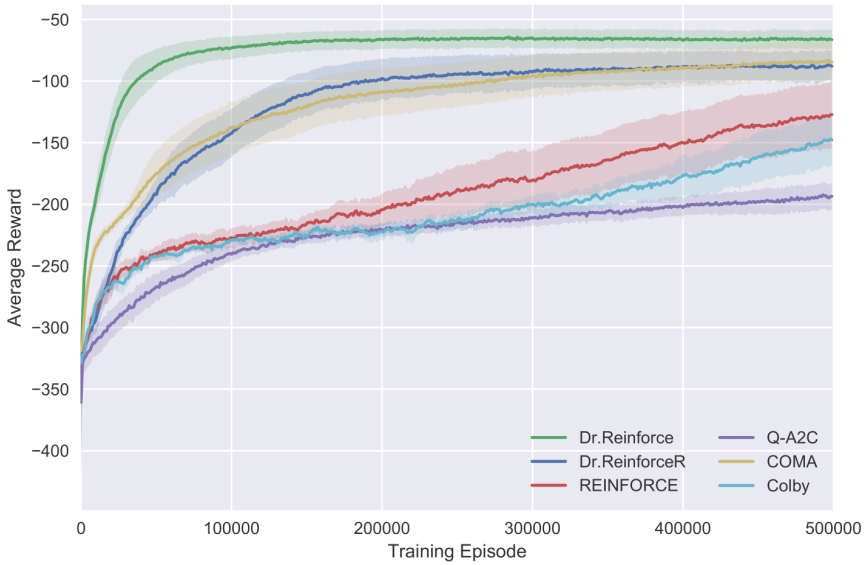


Multi-Rover

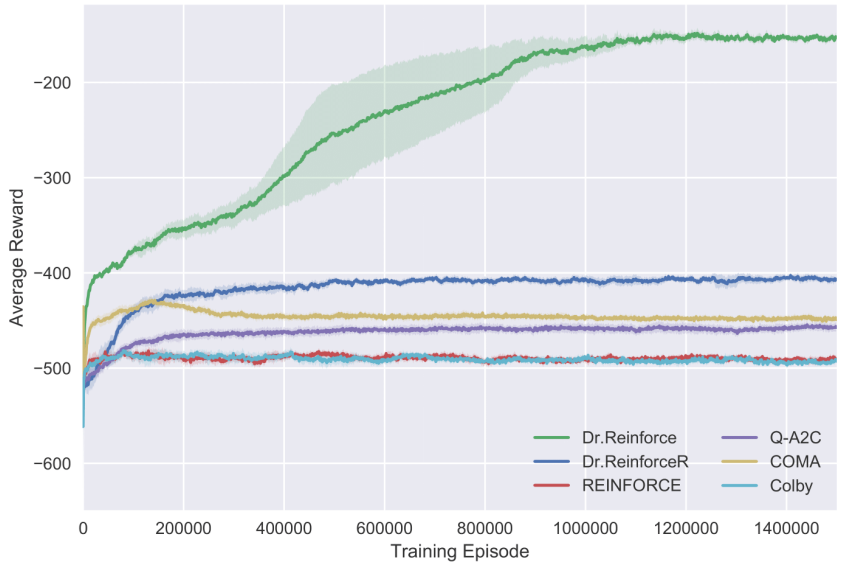


Predator-Prey

Results (Multi-Rover)



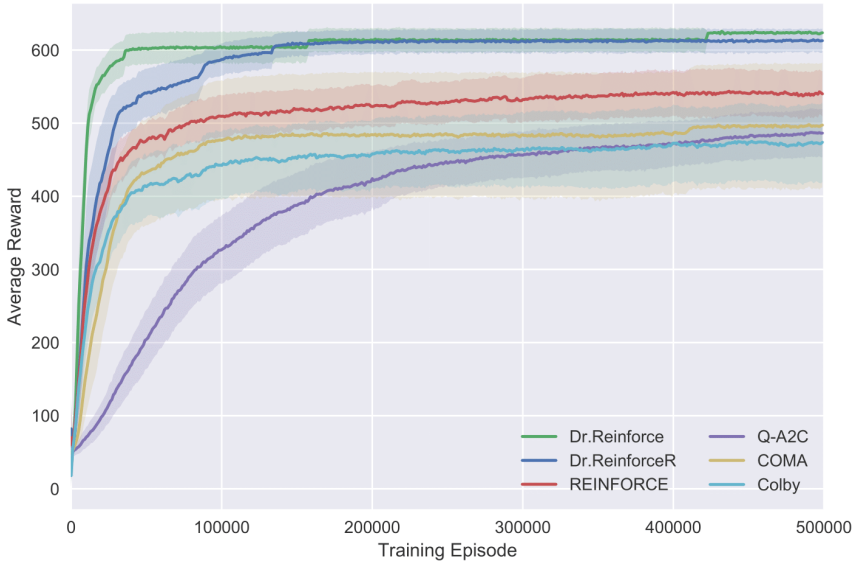
$N = 3$



$N = 8$

With few agents both are doing fine, but with more both get worse, and Dr.ReinforceR quickly stop matching Dr.Reinforce upper bound.

Results (Predator-Prey)



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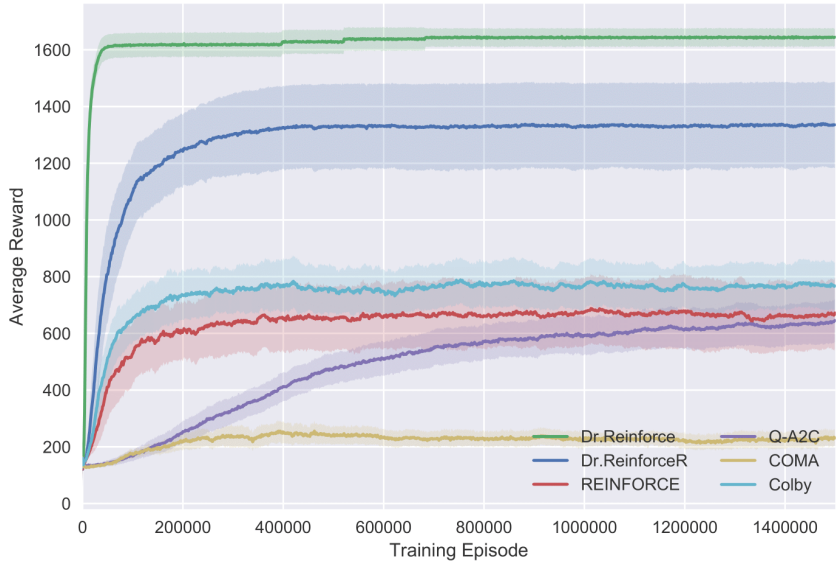

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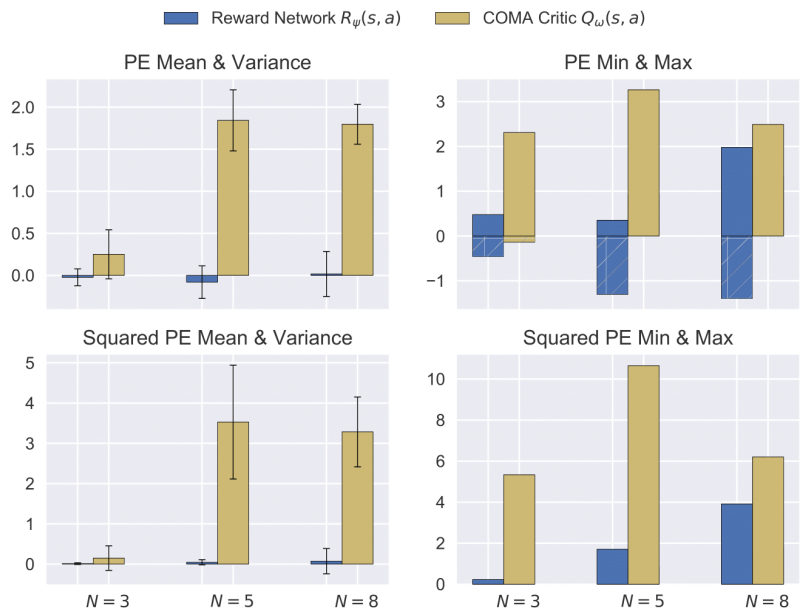
While COMA is deteriorating with more agents, Dr.ReinforceR is doing almost on-par with Dr.Reinforce!

Analysis



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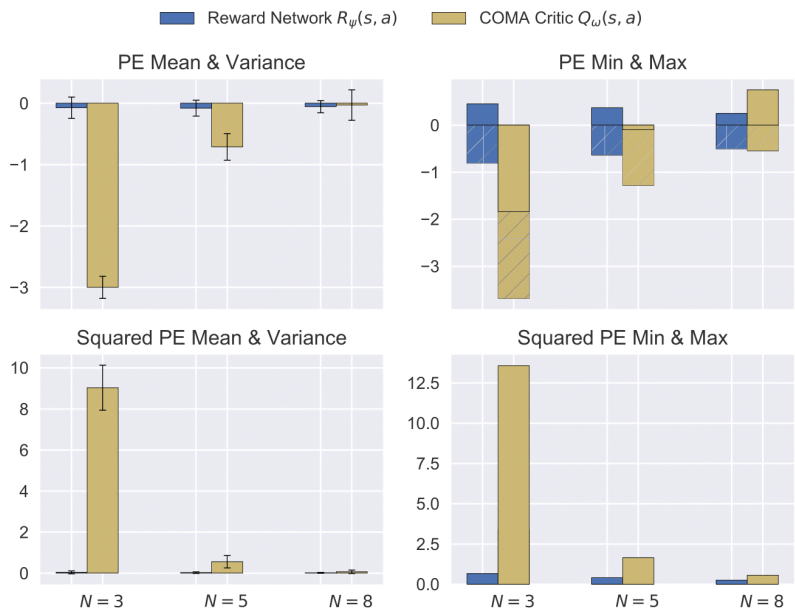

Predator-Prey

Trained R_ψ has better *prediction error* (PE) than $Q_\omega \rightarrow$ Better generalization!

Conclusions

1. *Dr.Reinforce*, combining MAPG benefits with DR, outperforms baselines and SOTA algorithms when the reward function is known,
2. *Dr.ReinforceR*, a practical methodology when that is not the case,
3. Learning R_ψ rather than Q_ω is an easier regression problem and results in lower PE and better generalization.

Download

Download the full paper from here:

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