# Multi-Agent Reinforcement Learning with Partial Knowledge over Networks

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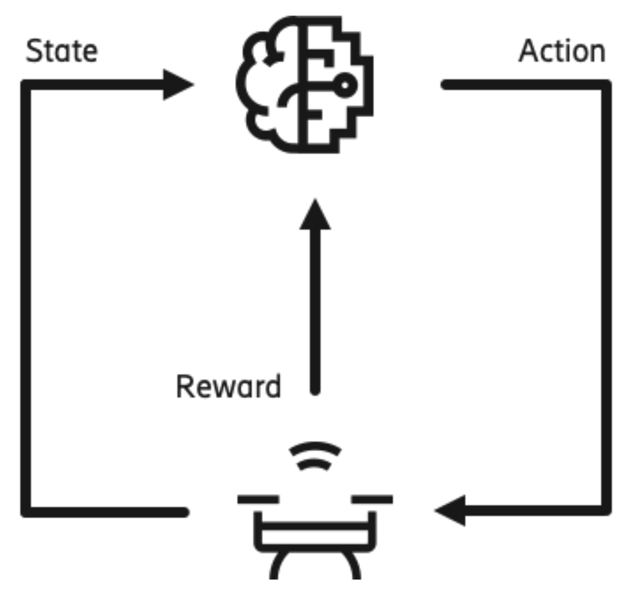
*Part of the course* EP3260: Fundamentals of Machine Learning Over Networks

### Reinforcement learning

Reinforcement learning is an area of machine learning inspired by behaviorist psychology, concerned with how software *agents* learn to take *actions* in an *environment* by interacting with it to maximize some notion of cumulative *reward*.




### SARL optimization reformulation

- **Goal: A single agent** determines the policy to maximize the long-term reward, which can be solved by the **Bellman optimality equation**

$$V^\pi = R^\pi + \gamma P^\pi V^\pi.$$

- This can formulated into the equivalent regularized saddle-point optimization

$$\min_\theta \max_w \frac{1}{n}\sum_{t=1}^n \mathcal{L}_t(w,\theta),$$

where

$$\mathcal{L}_t(w,\theta) = \frac{1}{2}w^T(A_t\theta - b_t) - \frac{1}{2}\|w\|^2_{C_t} + \rho\|\theta\|^2$$

$$A_t = \phi_t(\phi_t - \gamma\phi_t')^T$$

$$b_t = \phi_t r_t$$

$$C_t = \phi_t\phi_t^T$$

$\phi_t$ is current feature vector, and

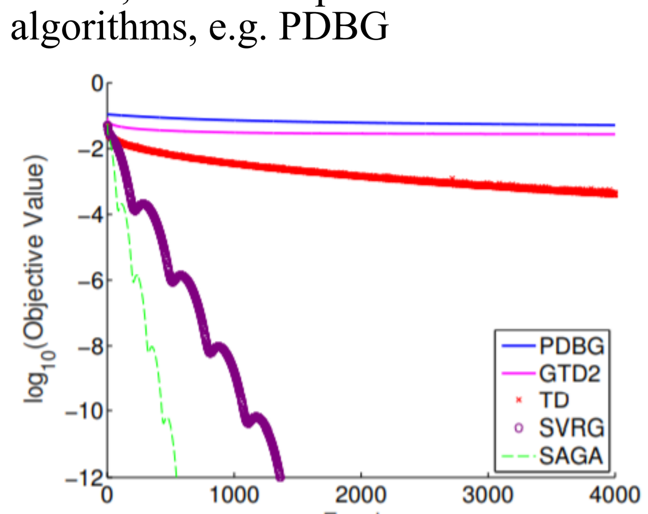
$r_t$ is current reward.

- The saddle-point problem can be solved by classical algorithms, e.g. **gradient descent**, **SVRG**, **SAGA** etc.

$$\theta \leftarrow \theta - \gamma_\theta \frac{1}{n}\sum_{t=1}^n \nabla_\theta \mathcal{L}_t(w,\theta)$$
$$w \leftarrow w + \gamma_w \frac{1}{n}\sum_{t=1}^n \nabla_w \mathcal{L}_t(w,\theta)$$

### MDP simulations

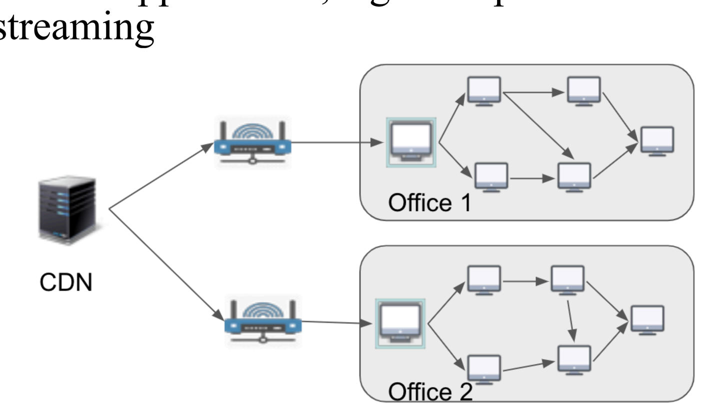
- Generate 400 tasks and 10 actions.
- SVRG, SAGA outperforms traditional algorithms, e.g. PDBG




(a) $\rho = 0$

### Extension to MARL optimization

- MARL applications, e.g. enterprise video streaming




- **Goal: multiple agents** collaboratively determine the policy the maximize long-term reward.
- **Assumptions:** States and actions are broadcasted among agents, while reward is private.
- We can derive multi-agent optimization

$$\min_\theta \max_{w_i, i=1,2,\ldots,N} \frac{1}{n}\frac{1}{N}\sum_{t=1}^n\sum_{i=1}^N \mathcal{L}_t(w_i,\theta),$$

where

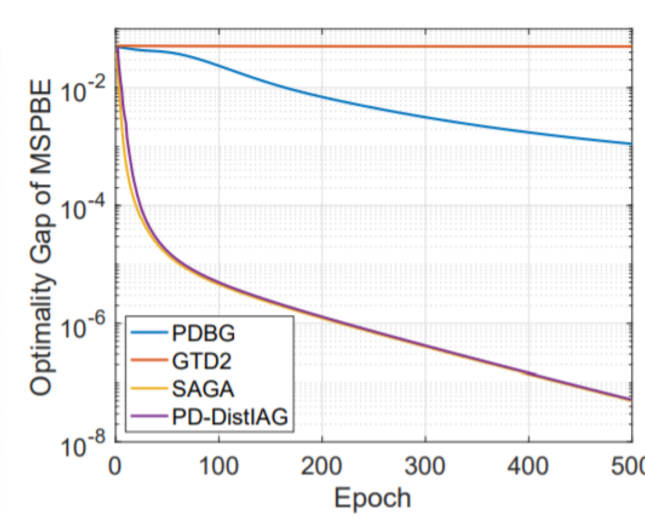
$$\mathcal{L}_t(w_i,\theta) = \frac{1}{2}w_i^T(A_t\theta - b_{t,i}) - \frac{1}{2}\|w_i\|^2_{C_t} + \rho\|\theta\|^2.$$

$$b_{t,i} = \phi_t r_t^i$$

$r_t^i$ is the local reward of agent $i$

- This multi-agent problem can be easily solved by SAGA and consensus-based averaging, `PD-DistIAG` (Wai et.al, 2018).

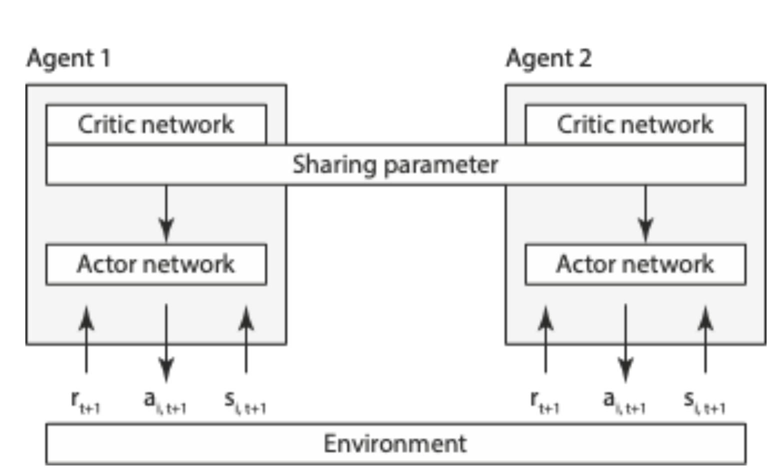
### MDP Simulations on Mountain Car




- `PD-DistIAG` is **comparable** to centralized algorithms (even faster).

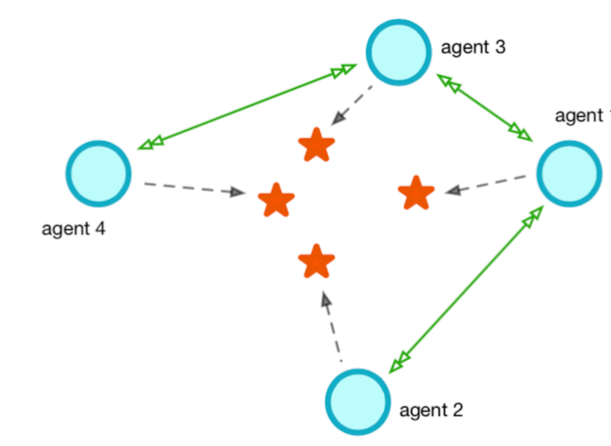
### Actor-critic MARL algorithms

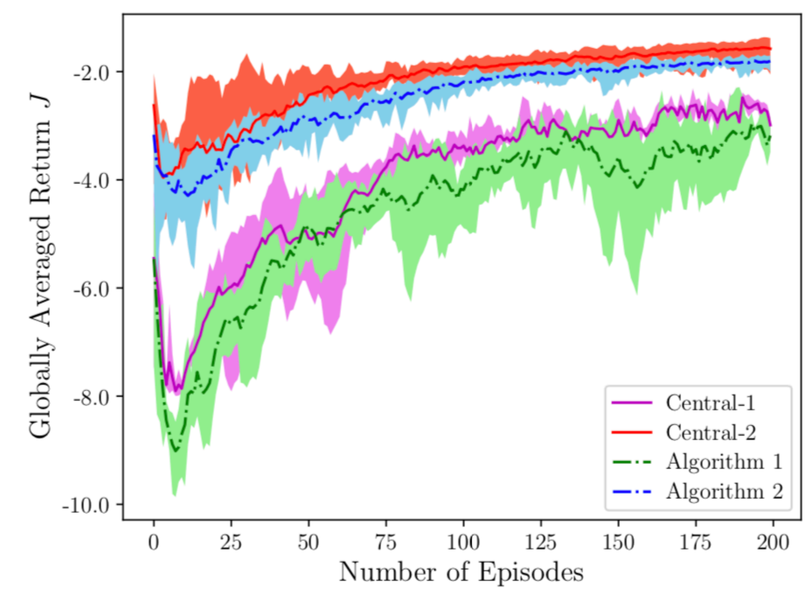
- Actor-critic algorithms can reduce variance but guarantee fast convergence.
- Extended for MARL (Zhang et.al, 2018).




### Safe cooperative navigation simulations

- Each agent's local reward represents a distance to its targeted landmark and a penalty depending on distance to other agents.




- Distributed actor-critic algorithms are **comparable** to centralized counterparts.

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