

CAREER: A Skill-Driven Cooperative Learning Framework for Cyber-Physical Autonomy

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Goal: The *goal* of this project is to advance foundational knowledge and scientific methodologies of reinforcement learning for generalization and scalability in cyber-physical systems (CPS).

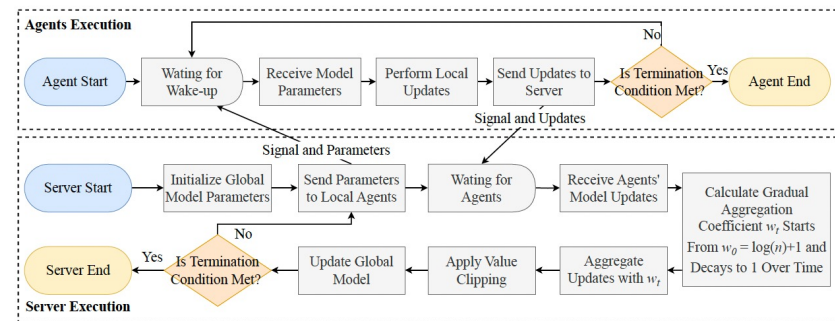
Challenge:

- The nature of many CPS is heterogeneous and high-dimensional, making the hand-coded functions and task-specific information hard to design.
- Large amount of training data is often required for achieving the desired performance which limits the generalization to other tasks.

Scientific Impact: This project advances the scientific foundations and methodologies of intelligent control design for CPS in high-dimensional and heterogeneous environment. The developed algorithms and associated architectures have provided critical insights and guidelines to foster autonomous learning and generalization in CPS.

Solution:

Design Federated Reinforcement Learning (FRL) methods for CPS



Flowchart of the developed FRL-QGradual algorithm: to increase the learning efficiency while preserving the agent privacy.

Design RL-based methods for hierarchical multiplayer systems

Facilitates the development of more sophisticated and adaptive control approaches and enables AI players to efficiently navigate hierarchical multiplayer environments.

Broader impact

- Provide critical insights and guidelines to foster autonomous learning and generalization in CPS.
- Integrate research and education plan to enrich the participation of students with different backgrounds.

Phased weight-adjustment mechanism

$$w_t = \begin{cases} w_0 - \frac{t(w_0 - 1)}{\delta}, & \text{if } 0 < t < t_\delta, \\ 1, & \text{if } t \geq t_\delta, \end{cases}$$

Value clipping strategy to prevent overflow

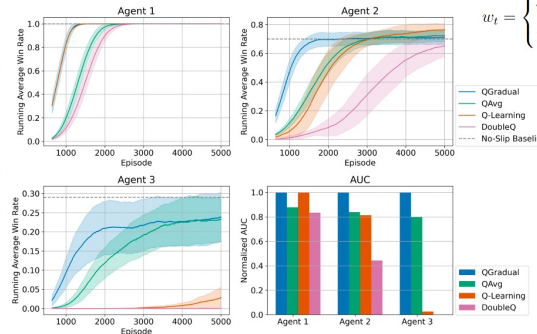
$$\Delta \bar{Q}_t(s, a) = \begin{cases} V_{min}, & \Delta \bar{Q}_t(s, a) < V_{min}, \\ \Delta \bar{Q}_t(s, a), & V_{min} \leq \Delta \bar{Q}_t(s, a) \leq V_{max}, \\ V_{max}, & \Delta \bar{Q}_t(s, a) > V_{max}, \end{cases}$$

Aggregation updates

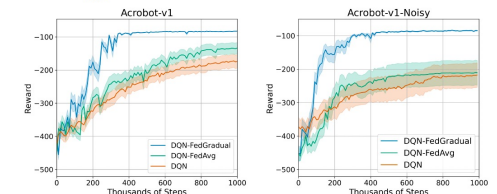
$$\Delta \bar{Q}_t(s, a) = \frac{w_t}{n} \sum_{k \in \mathcal{K}} \Delta Q_t^k(s, a), \forall s, a.$$

Model updates

$$\bar{Q}_{t+1}(s, a) \leftarrow \bar{Q}_t(s, a) + \Delta \bar{Q}_t(s, a), \forall s, a.$$



Running average win rates for 3 agents in a heterogeneous stochastic Frozen Lake with varying starting points over 5000 episodes.



Performance of deep FRL in the heterogeneous Acrobot-v1 and Acrobot-Noisy environments.

Design Computationally Efficient IRL Approach

A new featurization network to accommodate trajectories and output aligned feature vectors automatically without human intervention.