Graph-based Multi-agent Control

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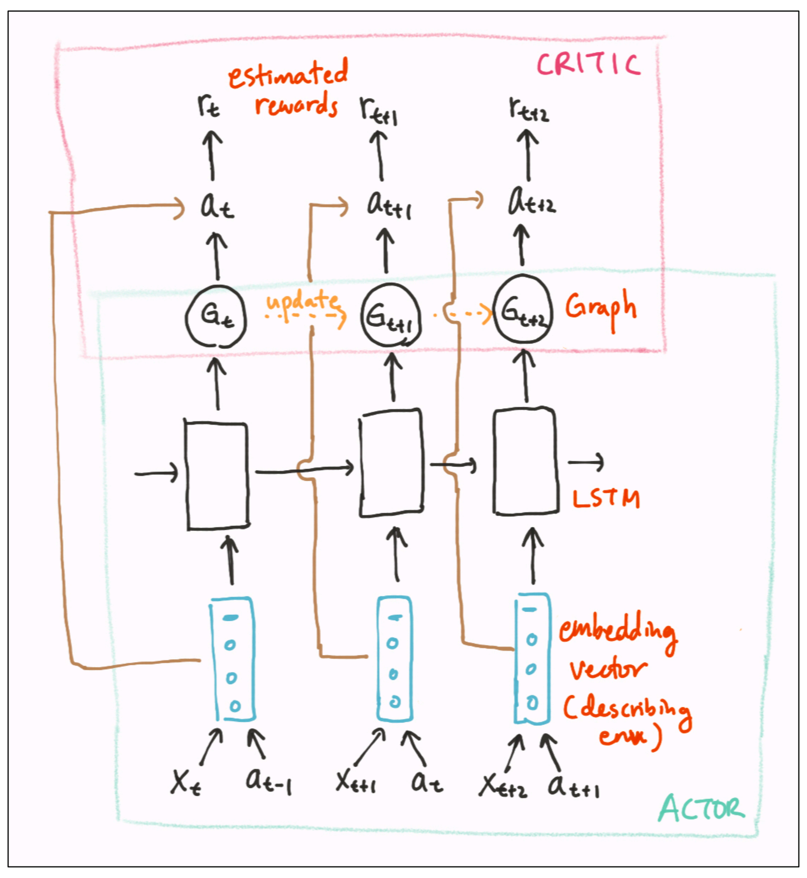
Introduction

- **Multi-agents problem:** sparse reward, lack of robustness [1]
- **Solution:** Represent all the possible information in the environment using graph neural networks
- **Our idea:** Learning to generate a graph that represents the environment status [2, 3] with self-supervised prediction [4], and edges represent to the relation between agents or items. Afterward, agents execute an action based on the trained graph.
- **Outcome:** Experiment in the Pommerman [5] and generated the graph.

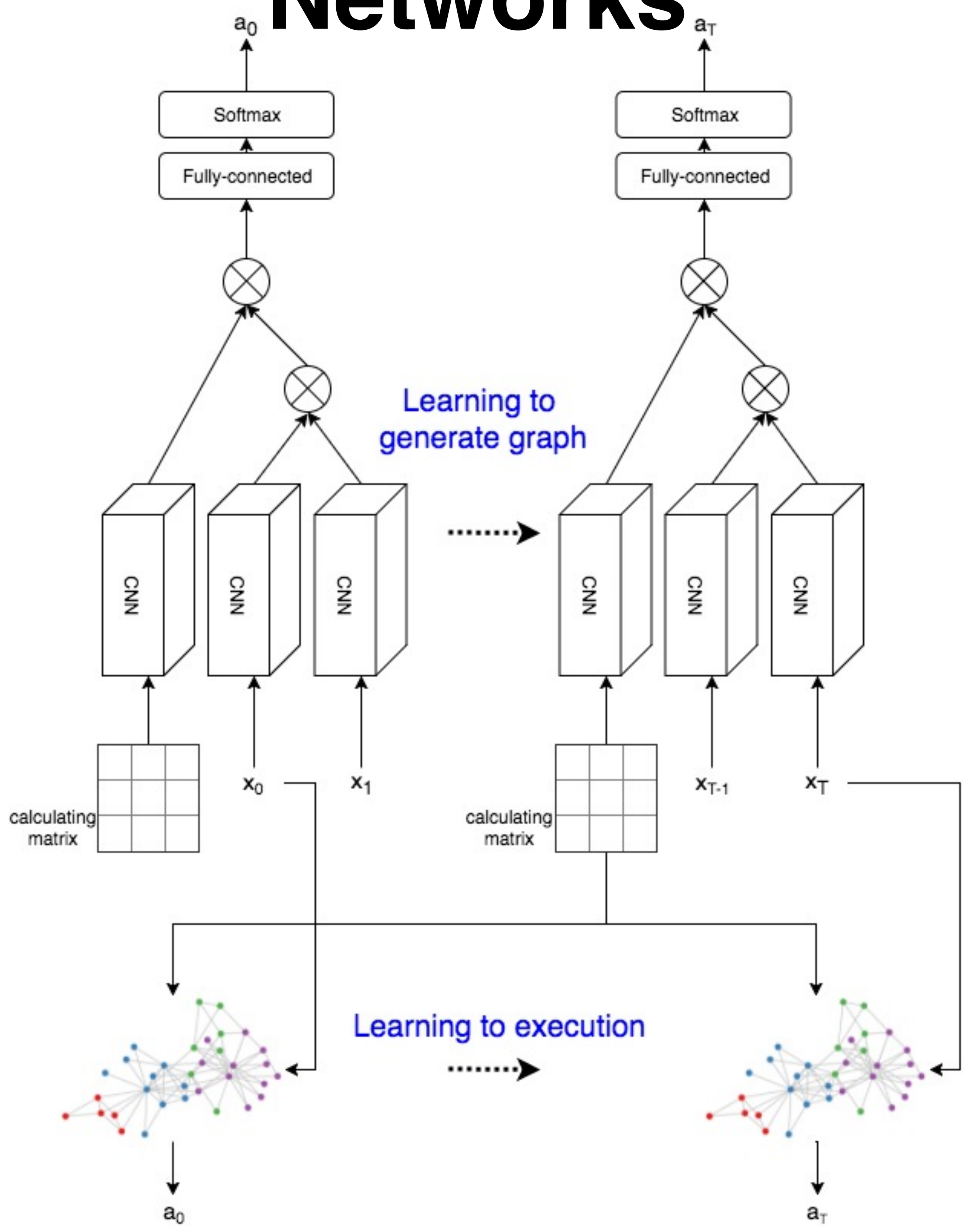
Approaches

A variant of MADDPG [1] which applies LSTM in actor and criticize actions using GNN



An embedding vector with state and action information [6] passes to LSTM to generate GNN

Networks



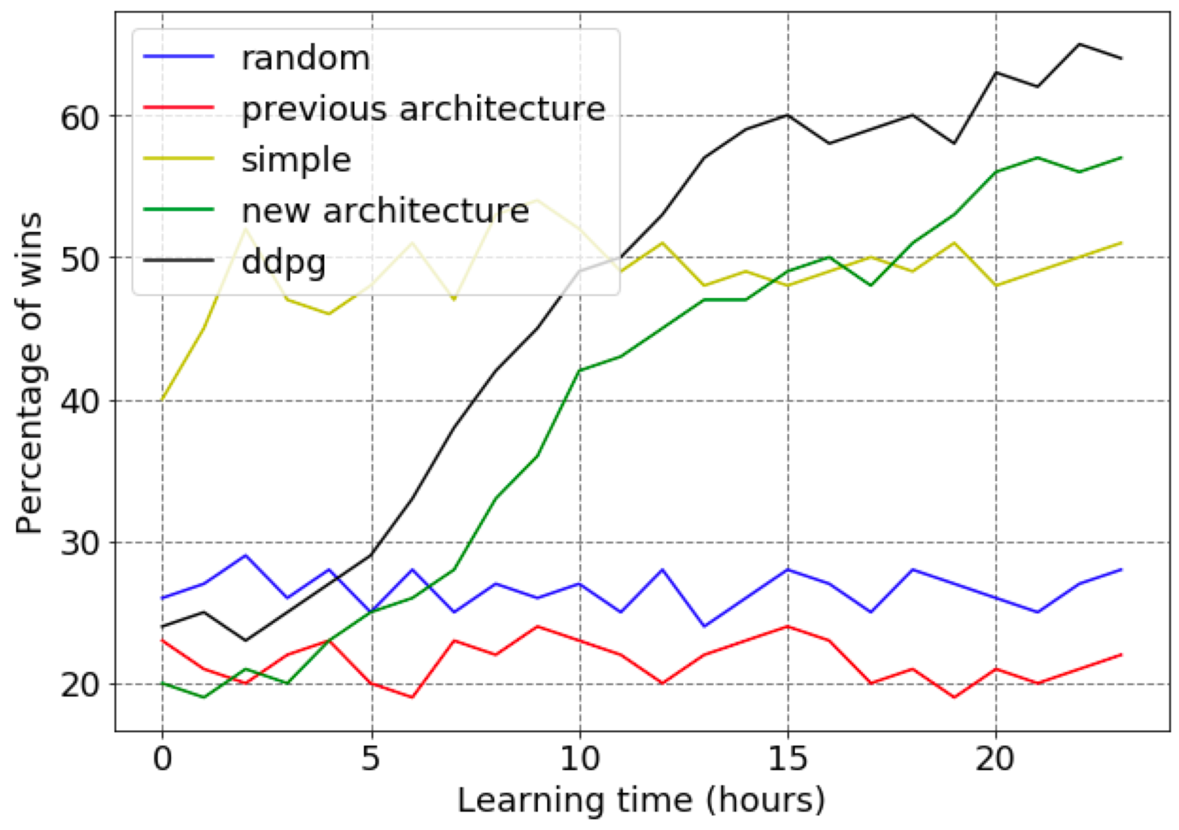
In our work, graph neural networks is generated based on previous and current states by self-supervised prediction [4] and infer previous action. Afterward, each multi-agents learn to execute optimal actions with respect to the trained graph.

Experimental Results

1. Environment:

- Pommerman: sponsored by NVIDIA, FAIR, and Google AI [5]
- For each agent
  - Observation space: 372 (board, bomb_blast strength, bomb_life, position, blast strength, can kick, teammate, ammo, enemies)
  - Action space: 6 (stop, up, down, right, left, bomb)

2. Results:



Future work

- Combine learning to generation and learning to execution stages
- Add LSTM between input states and graph generation to learn information of sequential states
- More sophisticated reward design

- ❑ [16-17] Combine Nervenet architecture [2] and graph generation
- ❑ [18-19] Combine two tasks to get end-to-end networks
- ❑ [20] Tune parameters
- ❑ [23] Compare with state-of-the-art methods
- ❑ [24-25] Prepare paper and presentation
- ❑ [26] Final presentation (Github + arXiv)

References

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[4] Pathak, D., Agrawal, P., Efros, A.A. and Darrell, T., 2017. Curiosity-driven exploration by self-supervised prediction. In *International Conference on Machine Learning (ICML).*

[5] Resnick, C., Britz, D., Ha, D., Foerster, J. and Eldridge, W. 2018. PlayGround: AI research into multi-agent learning. *https://github.com/MultiAgentLearning/playground*

[6] Oh, J., Singh, S., Lee, H. and Kohli, P., 2017. Zero-shot task generalization with multi-task deep reinforcement learning. *arXiv preprint arXiv:1706.05064.*