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Soft-HGRNs: soft hierarchical graph recurrent networks for multi-agent partially observable environments

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Key words: Deep reinforcement learning; Graph-based communication; Maximum-entropy learning; Partial observability; Heterogeneous settings

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Motivation

1. Human society could be regarded as a large-scale partially observable environment, where everyone has the functions of communicating with neighbors and remembering his/her own experience. Similarly, a large-scale multi-agent system can be modeled as a graph to solve cooperation problems.
2. Deterministic multi-agent deep reinforcement learning (MADRL) strategies in large-scale multi-agent systems suffer from the insufficient exploration and poor robustness. Therefore, we consider designing a stochastic strategy to enhance the exploration capability.
3. Collaboration of heterogeneous agents often has a wider range of application scenarios. We seek to aggregate information from heterogeneous agents effectively.

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Main ideas

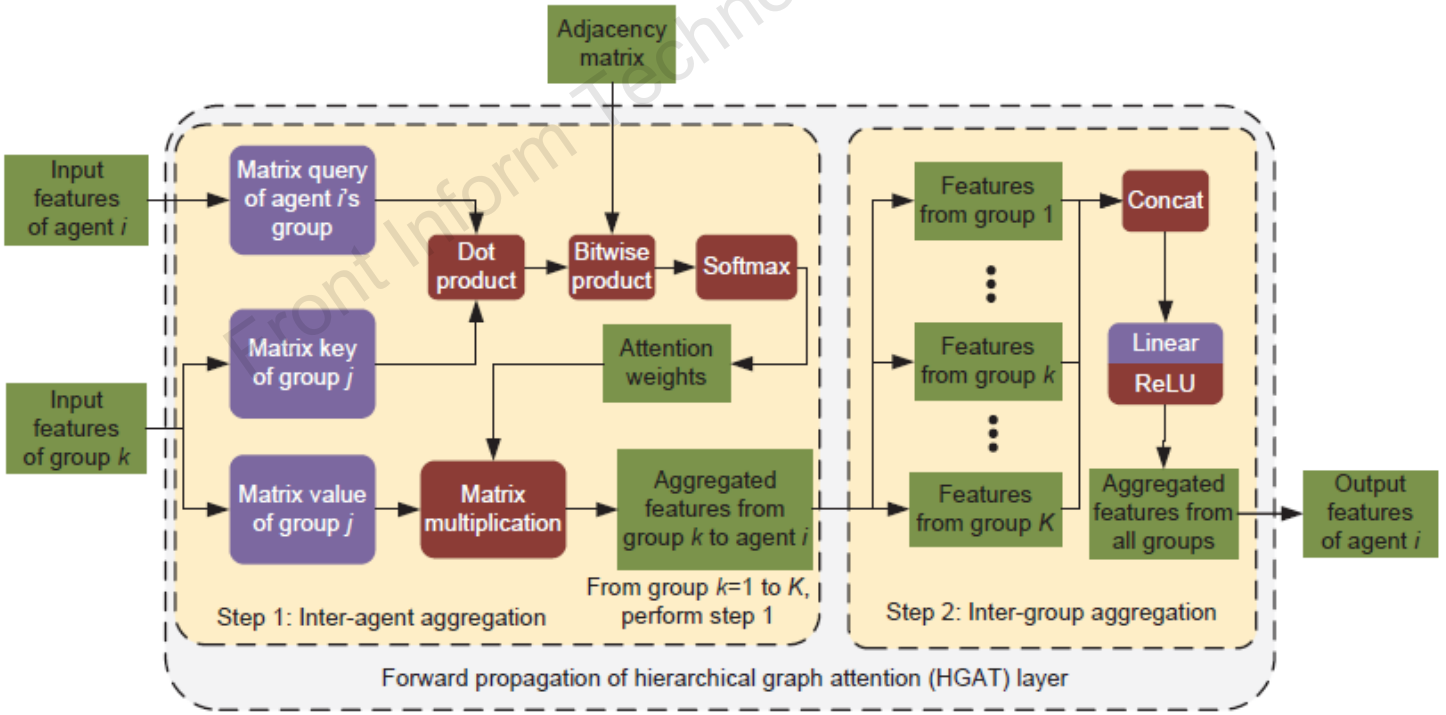
1. Inspired by the observation of human society, we propose a network structure called the hierarchical graph recurrent network (HGRN). HGRN combines the advantages of a graph convolutional network and a recurrent unit in MADRL. It uses spatio-temporal information to handle heterogeneous partially observable environments.
2. We propose two maximum-entropy MADRL algorithms (Soft-HGRN and SAC-HGRN) that introduce a learnable temperature parameter to learn our HGRN-structured policy with a configurable target action entropy.
3. Experiments show that our approach outperforms four MADRL baselines in several homogeneous and heterogeneous environments.

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Method

1. To achieve communication between heterogeneous agents, we modify the hierarchical graph attention (HGAT) to better process the graph data with heterogeneous nodes.

Forward propagation of **HGAT layer** is composed of two steps: the inter-agent and inter-group aggregation.

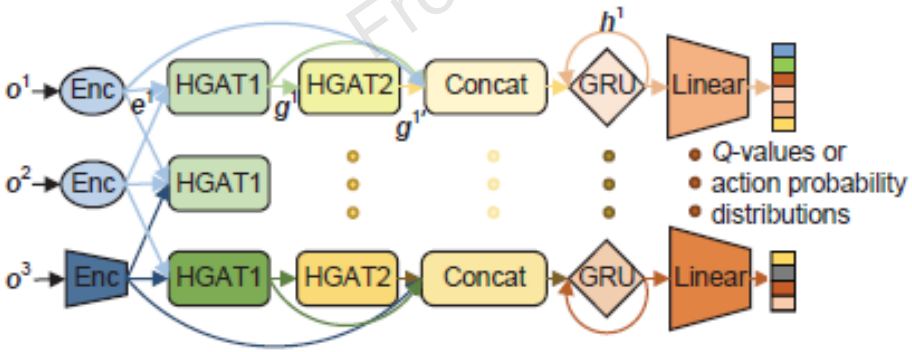


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Method (Cont'd)

2. The overall network structure of our proposed HGRN:

- We use linear **encoders** to map the raw observation of heterogeneous agents to the same dimension.
- HGRN stacks **two HGAT layers** and has a two-hop perceptive field. With the HGAT-based communication channel, each agent can aggregate information from its heterogeneous neighbors to alleviate the information loss in POMDP.
- A gated recurrent unit (**GRU**) is used to record long-term temporal information. After the GRU, a **linear transform** is applied to infer the Q-values for all actions.



Overall network structure of HGRN

For scalability and sample efficiency, agents in the same group share the same parameters

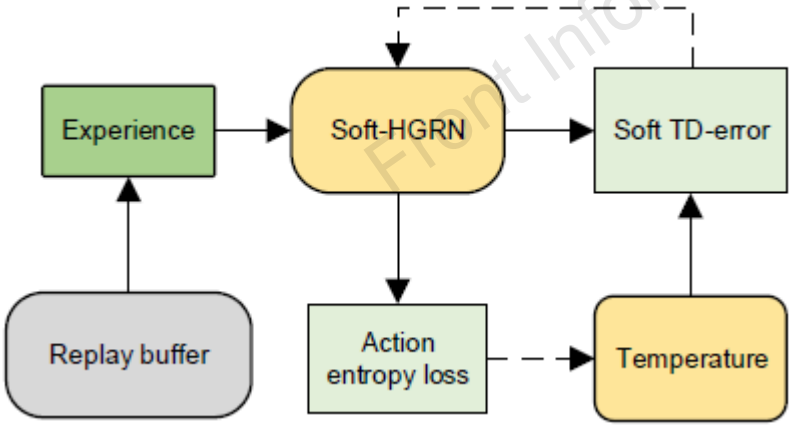
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Method (Cont'd)

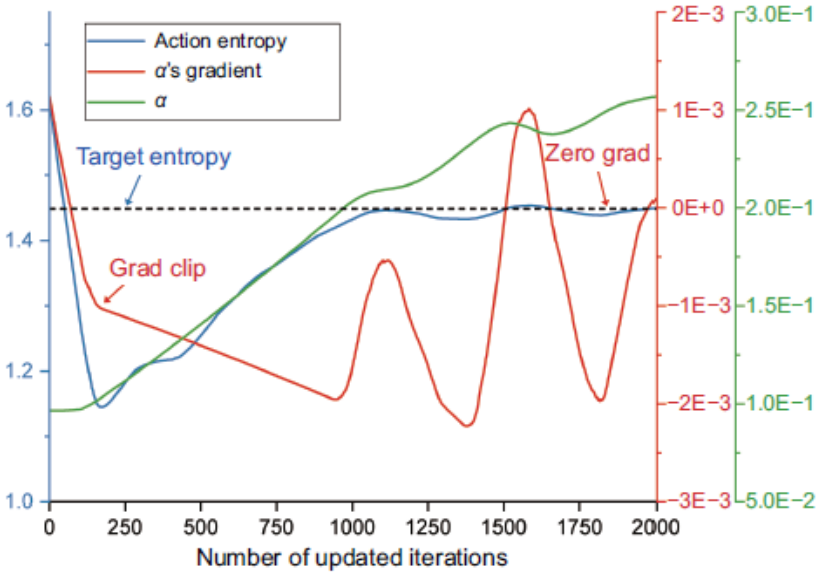
3. Deterministic policies can easily fall into a local optimum. Therefore, inspired by soft Q-learning, we adopt **maximum-entropy learning** in the multi-agent setting to train an energy-based stochastic model.

We define an action entropy to measure the degree of exploration of the policy. The action entropy is controlled by the temperature hyper-parameter α. We set a target action entropy to adaptively adjust the temperature parameter α.

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Flowchart of the Soft-HGRN learning process



Learning curves of action entropy, temperature parameter α, and its gradient

Major results

- Experiments were carried out in four partially observable simulation environments, including three homogeneous scenarios (*UAV-MBS*, *Surviving*, and *Pursuit*) and one heterogeneous scenario (*cooperative treasure collection, CTC*)
- For **homogeneous environments**, our learned model outperforms four MADRL baselines, and ablation studies showed the necessity of each component in our approach.

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Table 3 Evaluated episodic reward of different methods in three homogeneous tasks

Algorithm	Reward		
	UAV-MBS	Surviving	Pursuit
DQN	2314 ± 177	-7453 ± 74	5007 ± 150
CommNet	2377 ± 116	-7511 ± 82	5222 ± 60
MAAC	3435 ± 88	-10 ± 46	5927 ± 91
DGN	2808 ± 109	-286 ± 67	4552 ± 50
Soft-HGRN	$\underline{4051 \pm 75}$	$\underline{194 \pm 41}$	6840 ± 20
Soft-HGRN-G	3751 ± 59	-118 ± 90	$\underline{7138 \pm 96}$
Soft-HGRN-R	2935 ± 134	-26 ± 61	5649 ± 166
Soft-HGRN-S	3925 ± 46	-89 ± 35	5570 ± 30
SAC-HGRN	$\mathbf{4072 \pm 77}$	$\mathbf{325 \pm 48}$	7033 ± 55
SAC-HGRN-G	3580 ± 75	-36 ± 63	$\mathbf{7183 \pm 77}$
SAC-HGRN-R	3052 ± 22	141 ± 13	5797 ± 36
SAC-HGRN-S	3723 ± 82	-376 ± 27	-76 ± 1

"-G" means disabling HGAT-based communication among agents; "-R" means removing the GRU-based memory unit from the policy model; "-S" denotes training a deterministic policy instead of a stochastic policy. The best and second best models are indicated by bold and single underline, respectively

Major results (Cont'd)

- For the **heterogeneous environment CTC**, we focused mainly on the impact of HGAT's communication between different types of agents. It can be seen that every HGAT-based model performs better than its GAT-based variant, which demonstrates the effectiveness of the designed hierarchical communication structure.

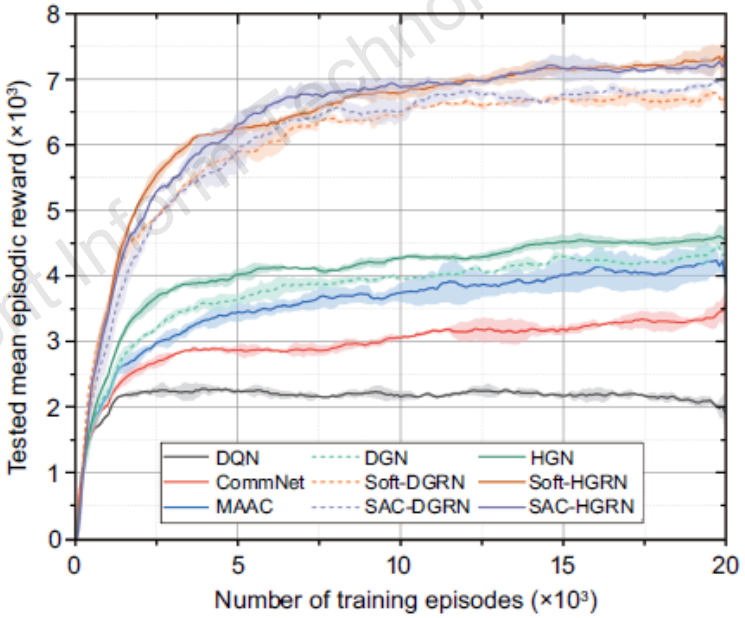


Fig. 5 Learning curves of various algorithms in cooperative treasure collection (CTC). References to color refer to the online version of this figure

Conclusions

1. We have proposed a value-based MADRL model Soft-HGRN and its actor-critic variant SAC-HGRN to address the large-scale multi-agent partially observable problem.
2. The proposed approach consists of two key components: (a) a novel network structure HGRN that could aggregate information from neighbors and history; (b) a maximum-entropy learning technique that could self-adapt the temperature parameter to learn a stochastic policy with configurable action entropy.
3. Experiments on four multi-agent environments demonstrated that the learned model outperforms four MADRL baselines. We have also analyzed the interpretability, scalability, and transferability of the learned model.

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