

# **Sample-efficient deep reinforcement learning from single agent to multiple agents**

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under the supervision of Dr. Jing Jiang, A/Prof. Guodong Long, and Prof. Chengqi Zhang

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# CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Han Zheng declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution. This research is supported by the Australian Government Research Training Program.

September,2021 Han Zheng

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## ABSTRACT

Deep reinforcement learning (DRL) has recently become a very popular topic in the academic field. However, it usually suffers the sample inefficiency problem due to the lack of effective exploration, instability, or temporal credit assignment issue. High sample complexity leads to a huge computation cost and adversely affects the employment of DRL techniques in practice. Despite many methods proposed to address this challenge, further improvements are still needed. This thesis contributes to developing sample-efficient DRL methods for continuous control from two perspectives: single agent and multiple agents. Specifically, the key contribution includes an uncertainty regularized policy learning method for single agent and two ensemble learning frameworks for multiple agents. Importantly, this thesis highlights that the multiple agents' methods can be seen as bridging gaps among on-policy, off-policy RL, and evolutionary algorithms. Moreover, our approach achieves consistent improvements over the baseline methods and gives novel insight into effectively taking advantage of different methods to get the best of them.

Dissertation directed by Dr. Jing Jiang, A/Prof. Guodong Long, Prof. Chengqi Zhang

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## List of Works

- C-1. **Han Zheng**, Jing Jiang, Pengfei Wei, Guodong Long and Chengqi Zhang, "Competitive and Cooperative Heterogeneous Reinforcement Learning". *Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020)* (CORE Rank A\* Conference, 8 pages)
- C-2. **Han Zheng**, Pengfei Wei, Jing Jiang, Guodong Long, Qinghua Lu and Chengqi Zhang. "Cooperative Heterogeneous Deep Reinforcement Learning". *34th Conference on Neural Information Processing Systems (NeurIPS 2020)* (CORE Rank A\* Conference, 9 pages)
- C-3. **Han Zheng**, Jing Jiang, Pengfei Wei, Guodong Long, Xuan Song and Chengqi Zhang. "Uncertainty Regularized Policy Learning for Offline Reinforcement Learning". *Draft to be submitted to ICLR 2022*
- C-4. **Han Zheng**, Xufang Luo, Pengfei Wei, Xuan Song, Dongsheng Li and Jing Jiang. "Adaptive conservative Q-ensemble learning for offline-online interleaving learning". *Draft to be submitted to ICLR 2022*

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