Haoyang Hong

Oregon State University

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Interests

I work on theory and algorithms in reinforcement learning and causal inference. I welcome collaborations on intelligent decision-making systems, recommendation systems, and online advertising.

Education

Oregon State University — Ph.D. in Artificial Intelligence (in progress)   Sep 2024 – Jul 2029
Focus: Reinforcement Learning Theory

University of Science and Technology of China (School of the Gifted Young) — B.S. in Statistics   Sep 2020 – Jul 2024

Research Summary

My research studies how to design learning algorithms that remain robust in uncertain, interference-rich environments. I focus on the exploration–exploitation trade-off in RL, causal structure modeling, and inference accuracy in online learning.

Projects

Dueling Bandit Trade-off: Achieving Optimal Regret–Inference Balance   May 2024 – Present
Manuscript in preparation; first-author project
We design a new dueling bandit algorithm that attains low online regret while enabling precise treatment-effect estimation. The method incorporates a forced-exploration mechanism and achieves a Pareto-optimal trade-off between learning efficiency and statistical inference, supported by theory.
Applications: A/B testing with minimal user-experience degradation while improving effect estimation, e.g., recommendation platforms and survey/intervention assignment.

Design-Based Bandits under Network Interference: A Theoretical Trade-off between Regret and Inference   Feb 2024 – Present
NeurIPS 2025 — Accepted
Led experiment design and evaluation. Built a multi-agent network bandit simulator and empirically verified the Pareto frontier between regret and inference accuracy under network interference. Evaluated the proposed algorithm EXP3-N-CS.
Authors: Zichen Wang, Haoyang Hong, Zhiheng Zhang, Chuanhao Li, Haoxuan Li, Zhiheng Zhang, Huazheng Wang (co-first authors)
Applications: Ad allocation and medical trial design on social networks where interference (peer effects) is present, enabling robust effect estimation.

When Can You Poison Rewards? A Tight Characterization of Attack-ability in Linear MDPs   Feb 2024 – Present

Ongoing project
Contributed to theory and modeling. We characterize necessary and sufficient conditions for the attack-ability of linear MDPs under reward-poisoning attacks, establishing the vulnerability/robustness boundary. Validated the framework via linear approximations in deep RL environments.
Applications: Financial risk control and autonomous driving—diagnosing algorithmic structures that remain stable under adversarial perturbations.