**Ph.D. Dissertation Defense**

**Candidate:** Zhiyuan Yao

**Degree:** Doctor of Philosophy

**School/Department.:** School of Business / Financial Engineering

**Date:** Tuesday, October 1, 2024

**Time:** 10:00 am – 11:30 am

**Location:**  Babbio 601

**Title:** Application of Reinforcement Learning in Financial Trading and Execution

**Chairperson:** Dr. Ionut Florescu, Financial Engineering, School of Business

Dr. Chihoon Lee, Financial Engineering, School of Business

**Committee Members:** Dr. Rong Liu, Information System & Analytics, School of Business

Dr. Zachary Feinstein, Financial Engineering, School of Business

Dr. Jia Xu, Computer Science, Charles V. Schaefer, Jr. School of Engineering and Science

# **Abstract**

We investigate the applicability of Reinforcement Learning (RL) to portfolio optimization problems. Training RL agents for financial problems is challenging due to two primary issues 1) communication latency between traders and trading systems, which degrades performance, and 2) the need for a realistic market simulator for effective agent learning and interaction. Our three studies tackle these challenges. We further propose a hierarchical trading framework where two RL agents reinforce each other’s decisions through dynamically improving their respective utility functions.

First, we propose an RL method to mitigate performance degradation when environments have delayed feedback. The issue is more evident in environments with higher levels of stochastic transition such as a stock market. We focus on deterministic delays and propose a model-based RL method to counteract the effects of latency. Our approach recovers the optimal policy in environments with deterministic transitions. We demonstrate its effectiveness through comparisons with previous methods and apply it to various Atari games to further analyze performance.

Second, we aim to build an agent-based market simulator driven by RL agents. Market simulators are designed to better understand the dynamics and properties of the market, and to quickly generate enormous amount of data to train models. To simulate a realistic market, the system should have different types of agents with their specific utilities. We design a simulation framework that not only captures the stylized facts but also mirrors real-world market behaviors. Additionally, we examine how RL agents respond to external shocks like flash crashes, demonstrating their adaptability to market events.

Third, we introduce a hierarchical trading framework consisting of two RL agents who work together to optimize the overall utility. Traditional asset management involves asset selection and portfolio optimization, but the success of an actively traded portfolio depends on order execution. Our framework integrates these two RL-based agents, reinforcing each other’s decisions to maximize investment returns. We showcase its effectiveness by training and testing it on the U.S. equity market and exploring optimal training methods for this dual-agent system.