Reinforcement Learning for Limit Order Book Dynamics

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1 Problem Overview

Figure 1: Visualization of a Limit Order Book (LOB) for cyptocurrency traders

In this course project, our objective is to understand the crucial role of information and speed for market makers operating within highly volatile cryptocurrency environments. We aim to address these key questions through a setup inspired by the work of [1]. Initially, a simulator will be developed based on the estimation of the limited order book or mid-price dynamics. Subsequently, a reinforcement learning (RL) agent will be trained using simulated market data generated from these estimates. The performance of the agent will be evaluated using various metrics such as the Sharpe ratio. We are particularly interested in investigating the impact of delays on algorithmic performance and the effectiveness of the training procedure to enhance the agent's efficiency. This project offers an opportunity to delve into advanced concepts in market-making strategies and RL algorithms, with potential implications for improving algorithmic trading strategies.

1.1 Project Questions

The following list provides a more detailed set of questions we are interested in. However, you are also welcome to suggest other questions.

1. How do we model the market-making dynamics typically represented as limited order books? What is a suitable state space, action space, and reward function? (This will be done jointly; most models focus on the traditional model by [2]).
2. How do we train reinforcement learning (RL) agents based on simulated data? Agents have to perform in varying market regimes. How are these changes represented within the state space? What is the impact of distributional shifts of market regimes? (cf. adversarial training [3])
3. In general, whenever an action is taken, a certain delay is experienced until the order is placed on an exchange. How do these latencies lead to suboptimal policies, and how does latency impact the optimal reward?
4. The notion of Markovianity that underlies most reinforcement learning algorithms is typically not present in financial markets. Hence, how could the model formulation or other components of the framework be adapted to provide superior performance when backtesting the model on actual data? (For instance, consider POMDP or semi-Markov decision processes.)
5. Market makers are typically focused on minimizing risk exposure. How does penalizing inventory risk affect performance? There exist several common reward functions; we are interested in how our agent is impacted by changes within the reward function.

That's a lot of questions! We know, and we are interested in candidates willing to address at least a subset of the questions in technical depth and provide novel insights that are highly relevant to practitioners or on a theoretical basis extending RL frameworks within finance. Students are also welcome to further work on the project after the course-end, for instance, as part of a semester project.

1.2 What We Provide

We offer a comprehensive support package to kick-start your project:

- A customizable simulator environment tailored for exploring Limit Order Book (LOB) dynamics, featuring various LOB models.
- Model parameters estimated from cryptocurrency limit order books across diverse market regimes.
- Curated references from literature in the field of finance.

1.3 Background Knowledge

We anticipate candidates to possess, or be driven to acquire, expertise in the following areas (with optional supplemental resources available upon request):

- Fundamental understanding of financial markets.
- Proficiency in comprehending order book mechanics in finance, particularly Limit Order Books (refer to [4] for further insights).
- Familiarity with stochastic processes, including but not limited to Brownian Motion, Poisson processes, and Hawkes Processes.
- Eagerness to implement a novel or modified RL algorithm based on GitHub resources, extending beyond the basic stable-baselines3 framework.

2 Sample Report Outline

Two papers related to market-making were previously presented at NeurIPS: [5, 6]. We would be excited to submit the results of the project to an appropriate conference. However, this depends significantly on the findings realized within the project. In the following, we provide a potential report outline that is adjustable to the conducted experiments and findings.

- **Introduction:**
  - Discuss the drivers for applying reinforcement learning in finance, highlighting key motivations and potential challenges.
  - Introduce market-making in cryptocurrency markets and its application of reinforcement learning techniques.
- **Literature Review:**
  - **Market-Making Overview:** Offer an in-depth exploration of market-making dynamics and prevalent strategies. Market makers commonly leverage mid-price or limit order book dynamics as the foundation for their models, crafting algorithms that are intricately linked to these dynamics.
  - **Market Dynamics of Cryptocurrencies:** Discuss unique dynamics and challenges in cryptocurrency markets compared to traditional markets (e.g. stocks, commodities, forex).
  - **Reinforcement Learning for Market Making:** Review literature on using reinforcement learning in market making and identify suitable algorithms.
- **Modeling Framework:**
  - Explain the proposed modeling framework for market-making using reinforcement learning, including state space, action space, reward function, and specific algorithms.
  - Address simplified assumptions and their impact on real-time applications.
- **Backtesting:**
  - **Data:** Describe the data used for backtesting purposes.
  - **Evaluation Metrics:** Define metrics for assessing market-making performance.
  - **Numerical Results:** Present and analyze numerical results from backtesting, highlighting performance variations across market conditions.
- **Conclusion:**
  - Summarize key findings and contributions.
  - Discuss implications of reinforcement learning in financial market making and suggest future research directions.

References

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[6] J. Abernethy and S. Kale. Adaptive market making via online learning. *Advances in Neural Information Processing Systems*, 26, 2013.