

ABSTRACT

This thesis explores the application of AI and large language model (LLM)-inspired techniques to the modeling of limit order books (LOBs) in financial markets. The accurate simulation of LOBs is essential for understanding market microstructure, price formation, and liquidity, making it a crucial tool for both academic research and practical trading applications. We aimed to investigate whether the integration LLM-derived AI methodologies could enhance the realism and predictive accuracy of LOB simulations.

Our research was driven by three key questions: how to benchmark the current reference model on our dataset, which model architecture yields the best performance, and how stress testing impacts message flow simulation. Through a series of experiments, we assessed the performance of various model architectures, focusing on their ability to predict event types, timing, and mid-price movements.

The results showed that while our models could accurately predict event types and timing, and introduce some variance in returns, they struggled with mode collapse—a critical issue where the model fails to generate a diverse range of tokens, limiting its ability to replicate complex market behaviors. We developed a method for stress-testing models, which further highlighted this challenge. In response, we proposed potential solutions, including latent space encoding and customized loss functions, to address mode collapse and improve model robustness.

Our work underscores the potential of AI and LLM approaches in financial modeling, while also identifying key areas for future research. By refining these models, we can move closer to creating sophisticated simulations that accurately capture the dynamics of financial markets, offering valuable insights for both researchers and practitioners.