**HFT using DRL For Limit Order Book Data**

Amr Mohamed Abd Albadee 201500358

Abdelmoez Elsaadany 201500438

**Zewail City of Science and Technology**

**Table of Contents**

1. [**Information About the Internship:**](#_o4rjgix53wn7) **3**
2. [**Detailed Internship Description:**](#_3rg1er4uyhkn) **5**

**2.1** [**Abstract:**](#_wrqboaxpubtt) **5**

[**2.2 Introduction:**](#_3eg0ot9qe3k9) **5**

[**2.3 Literature Review:**](#_rci5h980ivhc) **6**

1. [**Our Contribution:**](#_ijxhixsbhpd) **7**

[**3.1. Challenges Faced:**](#_23xk26cnlbha) **8**

1. [**References:**](#_58ga7b7nvqo8) **9**

# **Information About the Internship:**

**Research topic:** Applying DRL on LOB Data.

**Company**: Zewail City for Science and Technology.

**Supervisor**: Dr. Mohamed Elshenawy.

**Department:**

Our training was associated with and under the supervision of Dr. Mohamed El Shenawy, Professor in Communication and Information (CIE) major at Zewail City University. The CIE major has a concentration in Artificial Intelligence and Big Data Analytics which facilitated the Deep Learning training we performed as the department had 2 very highly equipped machines that we had access to during the internship duration.

**Internship description :**

We aimed to develop a multi-stock trading Agent by employing DRL on Limit order Book Data. The Training Data was sample data from <https://lobsterdata.com>, It contains one-day limit order book data of five stocks from 9:30 to 16:00. The five stocks are Apple, Google, Amazon, Intel, and Microsoft.

**Related Courses from the CIE Program:**

1. *Introduction to Computer Science.*
2. *Fundamentals of Programming.*
3. *Data Structures, Algorithms, and Algorithmic Analysis.*
4. *Introduction to Machine Learning***:** Was a key tool in this internship as it taught us to:
   1. Understand the basic principles underlying machine learning algorithms and their applications in data processing and analysis.
   2. Evaluate different learning algorithms and understand their weaknesses and strengths.
   3. Distinguish between supervised and unsupervised learning methods and understand their limitations.
   4. Develop machine learning models and use them to make classifications, clustering, and predictions.
5. *Neural Networks and Deep Learning:*This was a key tool in this internship as it taught us to:
   1. Understand the fundamentals of neural networks and how they are used to solve machine-learning problems.
   2. Identify key deep learning models and their applications in areas such as computer vision, speech recognition, robotics, and natural language processing.
   3. Describe common optimization strategies in training deep architectures.
   4. Design from scratch and train deep convolutional and recurrent neural networks models.
   5. Understand selected deep unsupervised learning techniques and outline some of their applications.
   6. Discuss some of the ongoing deep learning research efforts and recognize some of the open problems.

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# **2. Detailed Internship Description:**

# **2.1 Abstract:**

Managing metric predictions in high-frequency financial markets is a complex problem. One efficient method to detect the information edge is to watch the dynamics of a limit order book. Deep learning, in particular, has been frequently employed in the financial arena to forecast price changes from the limit order book. This study constructs a consistently profitable trading system that takes market actions. Using reinforcement learning algorithms with suitable environment design, the agent might learn from limited order dynamics and take advantage of good periods to boost profitability.

# **2.2 Introduction:**

Financial markets have been a hotbed of very high-frequency data during the last decade. Prediction of such data is complex, and all market players desire a competitive advantage to maximize their profits. Market actions are documented in the Limit Order Book (LOB) [1, 2, 3,]. Limit orders placed by an experienced investor or a computer algorithm influence the trading activity. The benefit of a computer algorithm is that it is quick and can work indefinitely. Meanwhile, the financial market is constantly changing and influenced by various events, including politics, weather, scandals, and advertising. In order to capitalize on such opportunities, the algorithm must monitor the market and determine how to execute appropriate transactions to maximize profits while minimizing risk. As a result, the algorithm must be both quick and intelligent, which is why artificial intelligence is used.

The Limit Order Book is a collection of data that might describe the situation of the market and how it evolves. Many complex systems may be constructed to serve many purposes, such as market-making, trading, and detecting spoofing [4]. The limit order book data includes ask price, ask volume, bid price, and bid volume at various depths. The fluctuations in prices and volumes at various depths can indicate the traders' thinking. Ntakaris and Magris [4] created the first publicly available LOB-ITCH dataset for machine learning research on mid-price prediction. Due to its chaotic character, HFT is primarily a scalping strategy [5]. Artificial intelligence may create a complicated trading algorithm for HFT to capture vital information that humans cannot discover [6]. Artificial intelligence will likely surpass human traders [7, 8].

# **2.3 Literature Review:**

Many intriguing deep learning algorithms for forecasting mid-price movement using limit order book data have been introduced [9, 10]. Some researchers are particularly interested in developing deep learning through feature engineering. To categorize the mid-price movement direction, a fully connected deep neural network with a kernel provided was developed [11]. The same researchers [12] also provided a convolution neural network with a kernel function. Some researchers favor no feature engineering. Raw limit order book with a convolutional neural network [13], a long short-term memory neural network [14], and CNN and LSTM together [15] are thoroughly explored.

The experiments described above use the same limit order book dataset, which was provided as a benchmark dataset in a publication [16]. The benchmark dataset comprises various normalized handmade characteristics [17] derived from the limit order book data of five equities traded on the London Stock Exchange. Kesko Oyj, Outokumpu Oyj, Sampo Oyj, Rautaruukki Oyj, and Wartsila Oyj are the five companies. There are ten days of limit order book data for the five stocks, with each day ranging from 10:00 to 18:25. While those researchers are focused on developing clever new features and complex new models, they disregard the issues arising from raw data.

## **3. Our Contribution:**

We used the sample data from <https://lobsterdata.com> and prepared the data to match the preprocessing used by Yan [18]. Originally, the data had inconsistent time steps which we changed to be evenly spaced with 0.25 seconds of spacing. We used the FinRL library as our Deep Reinforcement Learning (DRL) framework and used one of their example codes for the basic environment for our agent. We made a lot of changes to the environment to match our specifications which includes using Limit Order Book data, being able to do long and short trading, implementing portfolio allocation, and letting users limit the number of shares owned, the maximum time of every position; these specifications will be explained. Long trading is the concept of buying shares from certain stocks and selling them in the future to gain profits. Short trading is another concept in which we sell shares planning to buy them later for the buyer. Portfolio allocation means the ability to do the above tasks with different stocks at the same time. The agent can choose an action for each stock independently which is either to start a long or short position, end these positions, or hold them and the number of shares to apply these actions on. Finally, the model used for training is known as the actor-critic model, and it updates both the actor scheme — the policy — and the critical scheme — the Q-function — at the same time. The critic is used to estimate the Q-function, while the actor updates the policy probability distribution, and they iterate in a feedback process to update the policy and the Q-function. This method enables the actor to learn to do better acts while also assisting the critic in criticizing those behaviors [19]. We tried the model with different combinations of limiters; their results are shown below:

1. The results when we applied a shares limit of 1000 and the maximum holding position of 250 secs are:

==============A2C Strategy Stats===========

Cumulative returns -2.721930

Annual volatility 45.626816

Sharpe ratio -0.048493

Max drawdown -3.295523

Omega ratio 0.855219

Sortino ratio -0.050743

Tail ratio 1.070354

Daily value at risk -5.757219

1. The results when no limits were applied are:

==============A2C Strategy Stats===========

Cumulative returns -3.076447

Annual volatility 50.664869

Sharpe ratio 0.121508

Max drawdown -3.436573

Omega ratio 1.588832

Sortino ratio 0.245898

Tail ratio 1.093646

Daily value at risk -6.358744

## **3.1. Challenges Faced:**

## We faced a lot of challenges in this project. First of all, the FinRL framework does not support Limit Order Book data as an input so we had to change how the input is represented in our environment. We wanted the agent to choose 2 independent actions for each stock given to the model, so we had to define the actions to be an array with the length of 2 times the number of stocks and the actions for each stock is 2 values of this array, one represents the type of action and the other for the number of shares. Finally, the agent used to keep on adding shares to the same position with no limits which may make it hold an unrealistic number of shares in each position indefinitely, so we had to add limits to the maximum number of shares and the maximum time allowed for each position.

**3.2. Limitations:**

The data we are working on is for just one day and this affected our results badly.

The library did not do a good job parallelizing the code so it takes a lot of time running even on a powerful GPU.

**3.3. Future Work:**

We will work on collecting more data and to a more variety of stocks as the stocks used are stable and didn’t have any significant changes. We will also work on adding historical data to the observation of the agent and adding a variable to limit the Tomax number of entries from the history as this will affect the RAM of the device. We will also work on parallelizing the code to take better advantage of the system resources.

## 

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