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DIPLOMA THESIS

Advancing Market Integrity: A Reinforcement Learning Approach to Detect Spoofing and Layering in Algorithmic Trading

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ABSTRACT

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Foundations of Algorithmic Trading and Market Integrity

The objective of this chapter is to present the terminology required for a better understanding of the main topic of the thesis, specifically providing a brief theoretical insight on algorithmic trading. Furthermore, we explore how *spoofing* and *layering* are performed, and how such manipulative tactics can deeply impact financial markets.

2.1 Introduction to Algorithmic Trading

Undoubtedly, the landscape of modern financial markets has undergone major transformations in recent decades due to the widespread adoption of algorithmic strategies. In general, *algorithmic trading* (or widely referred to as *automated trading* or *black-box trading*) represents the execution of trades at precise moments by leveraging the use of computer programming. Put another way, algorithmic trading improves the *liquidity* of markets by ruling out the involvement of human emotions and execution delays specific to *traditional market-making*. In their seminal work, Hendershott & Riordan (2013) provide a comprehensive examination of algorithmic trading and its implications for market liquidity, by studying the impact of algorithmic trading strategies on market dynamics [HR13].

In the context of market manipulation, we aim to focus specifically on *high-frequency trading* (HFT), which is characterised by speedy execution, when it comes to buying or selling securities. HFT is applied not only in stock markets, but in exchanging stock options and futures as well [Dur10].

Thanks to recent advancements in hardware development and the impact of *Field Programmable Gate Arrays* (FPGAs) on ultra-low latency, even a couple of *nanoseconds* could make the difference between *profit* and *loss*.

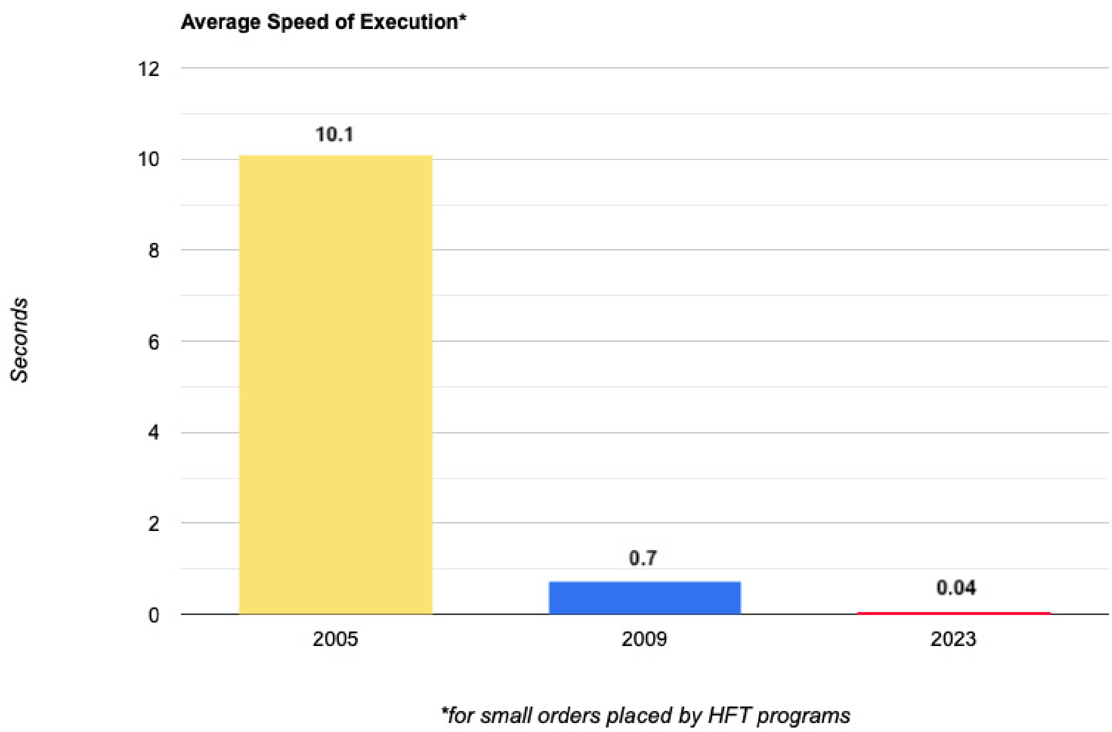

Figure 2.1: The average speed of execution for small orders in HFT has come to the realm of nanoseconds thanks to the development of ultra-low latency systems.

Given how ultra-low latency adversely affects market dynamics, we now introduce the fundamental concept in HFT: the *order*. Put succintly, a trade cannot occur without a previously placed order to initiate it.

In his article ”Limit Order Books”, Martin D. offers an ample and insightful definition for orders, as well as for fundamental terms that are frequently used in the financial literature [MDGH13]:

Definition 2.1.1 (Order) *An order $x = (p_x, \omega_x, t_x)$, submitted at time t_x, with price p_x, and size $w_x > 0$ (respectively, $w_x < 0$), is a commitment to sell (respectively, buy) up to $|\omega_x|$ units of the traded asset at a price no less than (respectively, no greater than) p_x.*

Definition 2.1.2 (Bid Price) *The bid price at time t is the highest stated price among active buy orders at time t,*

$$b(t) := \max_{x \in B(t)} p_x. \tag{2.1}$$

Definition 2.1.3 (Ask Price) *The ask price at time t is the lowest stated price among active sell orders at time t,*

$$a(t) := \min_{x \in A(t)} p_x. \tag{2.2}$$

Definition 2.1.4 (Mid Price) *The mid price at time t is*

$$m(t) := [a(t) + b(t)]/2. \tag{2.3}$$

Definition 2.1.5 (Bid-Ask Spread) *The bid-ask spread at time t is*

$$s(t) := a(t) - b(t). \tag{2.4}$$

It is important for an investor to know how to leverage the placement of two major order types in stock trading: *market orders* and *limit orders*.

A *market order* involves *buying* or *selling* a security immediately, the price of the transaction being strongly linked to the time of its execution (different from submission). This implies that the price at submission time might (at most times) deviate from the price at execution time; price remains unchanged only when the *bid/ask* price is exactly at the last traded price. Therefore, with immediate execution, market orders are more aggressive - volatility increases drastically, especially for investments with fewer shares on the market or smaller trade volumes.

Pushing the market in the opposite direction, *limit orders* (sometimes known as *pending orders*) are characterised by total price control, coming with a specific set of instructions on the execution of the trade. Investors specify the maximum *bid* price or the minimum *ask* price for their stocks. The brokerage will execute the order only if the price of the financial instrument aligns with the specified bounds; otherwise, the order will be left *unexecuted*. Interestingly, the conditions imposed in limit orders can even lead to partial orders (only a part of the shares will be traded), as the price of the investment can modify *mid-order*. In the next sub-chapter, we will delve into how the less-aggressive nature of limit orders is exploited to produce "artificial" shifts and influence the stock markets.

Since market manipulation most commonly occurs via limit orders, as previously indicated, our subsequent discussion will elaborate on basic order dynamics: how limit orders are stored, processed and amended. Most exchanges make use of *Central Limit Order Books* (CLOBs), or simply known as *Limit Order Books* (LOBs), to execute limit orders. LOBs are transparent, real-time, anonymous, and low-cost-in-execution systems that utilise *order books* and *matching engines* to map bid/ask orders of investors based on *price-time* priority. Considering a financial instrument which investors place orders for, the best market consists of mapping the highest bid offer to the lowest ask offer.

Martin D. offers the following definition for an LOB [MDGH13]:

Definition 2.1.6 (Limit Order Book) *An LOB $L(t)$ is the set of all active orders in a market at time t.*

Bid Volume	Price	Ask Volume
	71.06	1065
	71.05	733
	71.04	413
	71.03	170
	71.02	500
	71.01	167
	71.00	
125	70.99	
404	70.98	
140	70.97	
601	70.96	
523	70.95	
890	70.94	
1401	70.93	

Best Ask

Best Bid

Bid-Ask Spread
(71.01 - 70.99 = 0.02)

Figure 2.2: Graphical example of a 15-level deep LOB on a particular financial instrument. It depicts how traders judge liquidity and how they arrive at the bid-ask spread.

We continue with defining three crucial concepts for understanding CLOBs: *liquidity*, *price discovery*, and *depth of market*.

Liquidity refers to the degree to which a security can be easily traded in the market at a price reflecting its intrinsic value. Put another way, liquidity is the efficiency of converting an asset into ready cash without affecting its market price - the most liquid security is cash itself.

The most standard way of measuring liquidity is using the *current ratio* formula:

Definition 2.1.7 (Current Ratio) *The current ratio is a liquidity ratio measuring the capability of an investor of having enough resources to meet their short-term obligations:*

$$current\_ratio = \frac{current\_assets}{current\_liabilities}. \tag{2.5}$$

Price discovery denotes the (explicit or deduced) process in which buyers and sellers establish the fair price of a financial instrument in the market, at a given time. It implies conducting market research analysis, by evaluating supply and demand, environmental, geopolitical and socioeconomic factors.

Depth of Market (DOM) refers to the volume of orders pending to be transacted for a particular security at different price levels - it is the overall level (or breadth) of open orders.

A large order can significantly impact DOM and liquidity. If a large buy order enters the market, it can exhaust the available sell orders at lower prices, increasing the price as it fulfills higher-priced sell orders. Conversely, a large sell order can fulfill all the buy orders at higher prices, driving the price down as it starts matching with lower-priced buy orders. This impact on price through the supply and demand balance is a direct outcome of the market's liquidity and depth.

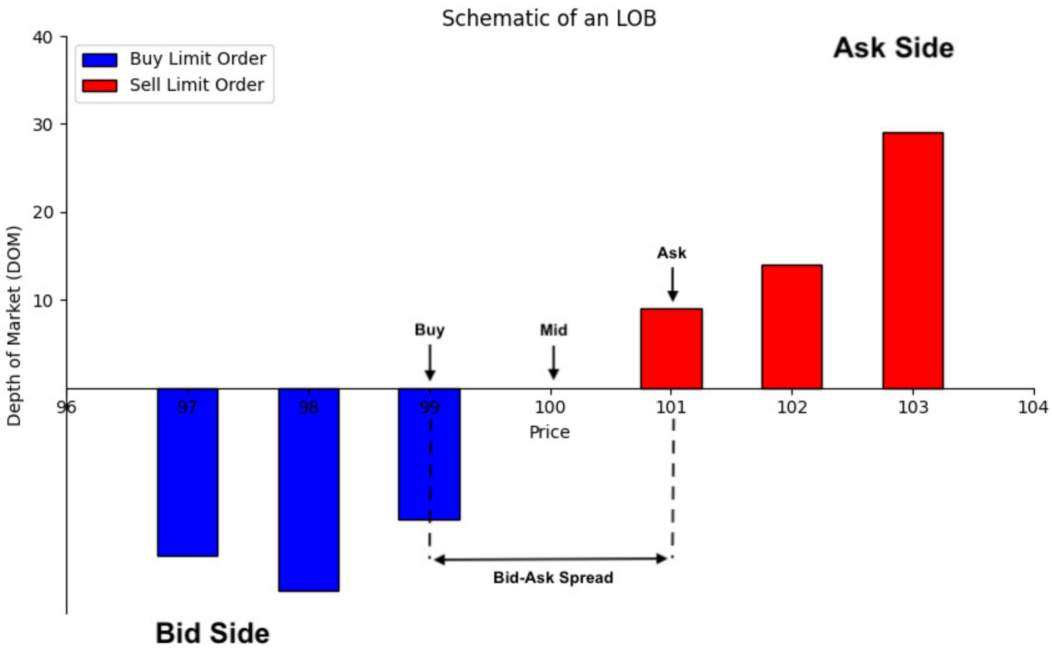

Figure 2.3: Schematic of an LOB

While we already covered the fundamentals of order placement, it is essential to acknowledge the mechanisms for order modification and cancellation in an LOB. In terms of *modification*, traders are generally allowed to update the limit price or the quantity of an existing order via the trading platform of the exchange. Modifications are generally permitted until the execution has begun, depending on the trading platform or exchange. For instance, if a buy limit order is partially filled, the quantity or price may be adjusted for the remaining unfilled portion. As a consequence, after an order has been modified, the investor should be aware about the impact of such operation on the LOB - the priority of the order in the LOB might be affected. For example, if the investor increases (respectively, decreases) the buy (respectively, ask) price of the security, the order might shift its position in the order book, as it becomes more competitive. Changing the quantity of an order could also impact both the priority in the LOB and the likelihood of execution.

Order *cancellation* in trading can occur for various strategic reasons. Cancellation for manipulative intents will be covered in a later chapter; however, traders might *legitimately* cancel limit orders because of shifting market conditions (e.g. news events affecting stock prices, market moving against their strategy). The impact of cancellations on LOBs includes the change in available liquidity, bid-ask spread and perceived market depth.

LOBs can be classified into different *levels*, based on the amount of information they provide:

1. **Level 1** - It encapsulates basic market data, such as:
   - *Bid price*;
   - *Bid size*;
   - *Ask price*;
   - *Last price*;
   - *Last size*.
2. **Level 2** - Additionally to Level 1 data, it doesn't provide just the highest bid and lowest offer, but also bids and offers at other prices:
   - *Highest bid prices*;
   - *Bid sizes*;
   - *Lowest ask prices*;
   - *Ask sizes*.
3. **Level 3** - It provides even deeper information than Level 2 data. Level 3 data refers to non-aggregated bids and asks placed by individual market makers. A Level 3 data feed would include every individual bid and ask, including *time series*.

LOB snapshots can be procured from various stock & crypto exchanges or trading platforms, via *WebSocket feeds* (for real-time data), or *REST APIs* (for historical data). The implementation proposed in this thesis will make use of *Level 3 LOB data*, to take full advantage of temporal information.

2.2 Challenges in Market Integrity: Spoofing and Layering

With the rise of algorithmic trading and the automation of financial markets, there is no doubt that the market becomes more and more exposed to major risks of fraud and exploitation. Affecting market integrity takes multiple forms, including market manipulation, insider trading, and short selling, all of them causing ample market destabilization due to their complex and ever-evolving nature. This thesis targets the challenges brought by market manipulation, particularly by two of its widely spread forms: spoofing and layering.

Market manipulation is defined as a set of ”actions intended to cause an artificial movement in the market price, so as to make a profit or avoid a loss” [AAD+16]. Therefore, it is easy to justify why such cases of misconduct erode the confidence of investors and challenge the perception of market stability.

The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 (“Dodd-Frank Act”) defines *spoofing* in the realm of algorithmic trading as ”bidding or offering with the intent to cancel the bid or offer before execution” [Dod10]. A trader places multiple large limit orders on a security with no intention of executing them. This is performed with the aim of artificially decreasing (respectively, increasing) the price of an asset, with the later intent of placing the actual buy (respectively, sell) order after cancellation, giving the false impression to other traders that the security is ”on-demand”.

Layering is a particular case of spoofing, which consists of placing multiple non-bona fide orders at *multiple price tiers*, in contrast to spoofing, where orders are entered only at the top of the order book.

0.6 s, demonstrating how quickly and effectively such manipulation behavior can affect the market and profit from the spoofed belief.

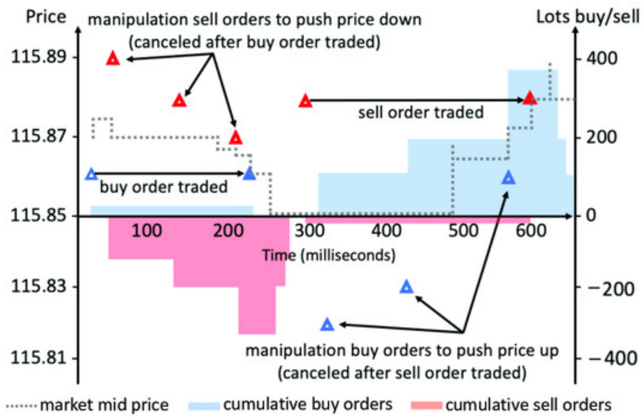

Figure 2.4: Illustrating an example of spoofing. Source: UK Financial Conduct Authority Final Notice 2013 [WHVW21].

Spoofing and layering often cause extreme volatility and rapid price movements. In such cases, they largely contribute to flash crashes. A *flash crash* is an event in electronic markets, where prices of a financial instrument *drop* dramatically, but then they immediately *rebound*. Flash crashes are *sudden* and short-lived: at the end of the day, it appears as if the crash had never happened.

While some methods are relatively straightforward (e.g. spreading *fake news*), spoofing and layering, take more subtle forms, and the methods used by malicious investors are constantly evolving. Additionally, in some cases, it is difficult to decide whether an investor has the intention of causing harm (e.g. a company buying its own shares to rise their price). This leads to the complexity of developing an efficient system that detects spoofing and layering in all of its shapes, and not misclassify peculiar cases of legal practices.

2.3 Case Studies of Notable Market Events

In his seminal work, *Spoofing, Market Manipulation, and the Limit-Order Book*, J. Montgomery highlights two notorious cases involving spoofing and layering allegations [Mon16].

One pivotal event revolves around Michael Coscia, who in November 2015 became the first person convicted of spoofing, under the *Dodd-Frank Act*. M. Coscia placed large "bait" orders for futures contracts on various commodities, through exchanges from the United States and the United Kingdom. This lead to a net profit for Mr. Coscia of *US$1.4 million* over a span of ten weeks as part of six attempts of spoofing.

In the most notable case of layering, Aleksandr Milrud lead a complex scheme for trading US securities. Mr. Milrud recruited and shared profits with online traders from China and Korea, who placed and then quickly cancelled HFT buy and sell orders at multiple price tiers, yielding net profits of as much as *US$600,000* in a day. This accumulated in net monthly profits between *US$1 million* and *US$50 millions*.

As part of our study, we aim to analyse LOB data from flash crashes, due to the high frequency of spoofing and layering attempts during such events. Specifically, we conduct our research on the flash crash of *LUNA*, from May 2022. Over a span of just three days, *Terra*, the third-largest cryptocurrency ecosystem following Bitcoin and Ethereum, experienced a dramatic collapse, erasing *US$50 billion* in market valuation [LMS23].

2.4 Ethical and Legal Considerations

The realm of financial trading is not only governed by economic principles, but also operates within a framework of ethical and legal standards. It is essential to implement and continually revise regulations to diminish the systematic losses produced by information asymmetry sourced from market manipulation.

In *"Principles of Financial Regulation"*, John Armour covers multiple aspects regarding the regulation of market manipulation, both in the European Union and the United States [AAD+16]. The integrity of financial markets hinges on the equitable treatment of all market participants. Unethical practices, such as market manipulation through spoofing and layering, undermine this fairness and can lead to significant distortions in market dynamics. Moreover, the lack of transparency in certain trading activities poses a threat to the trust essential in financial markets. This is particularly critical for retail investors, who might lack the resources to identify and navigate deceptive market practices effectively.

As mentioned in subchapter 2.2, legal frameworks, such as the *Dodd-Frank Act* (adopted in the US), play a vital role in regulating market activities and deterring unethical behavior. The legislation in both EU and US is designed to prevent market manipulation and promote a transparent trading environment. As noted in a report by Steel Eye [Steon], market manipulation in US rules under multiple laws, including *Commodity Exchange Act (CEA) (Section 4c(a)(5)(C))*, *Securities Exchange Act of 1934 10(b)*, and *FINRA Rule 2020*.

Regarding the UK and EU legislation, the *Market Abuse Regulation* (MAR) encompasses regulations related to insider trading, the illegal disclosure of privileged information, and the manipulation of markets.

Chapter 3

Reinforcement Learning in Market Surveillance

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spoof.io

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