DeepTraderX: Challenging Conventional Trading Strategies with Deep Learning in Multi-Threaded Market Simulations

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Abstract: In this paper, we introduce *DeepTraderX* (DTX), a simple Deep Learning-based trader, and present results that demonstrate its performance in a multi-threaded market simulation. In a total of about 500 simulated market days, DTX has learned solely by watching the prices that other strategies produce. By doing this, it has successfully created a mapping from market data to quotes, either bid or ask orders, to place for an asset. Trained on historical Level-2 market data, i.e., the *Limit Order Book* (LOB) for specific tradable assets, DTX processes the market state S at each timestep T to determine a price P for market orders. The market data used in both training and testing was generated from unique market schedules based on real historic stock market data. DTX was tested extensively against the best strategies in the literature, with its results validated by statistical analysis. Our findings underscore DTX's capability to rival, and in many instances, surpass, the performance of public-domain traders, including those that outclass human traders, emphasising the efficiency of simple models, as this is required to succeed in intricate multi-threaded simulations. This highlights the potential of leveraging "*black-box*" Deep Learning systems to create more efficient financial markets.

1 INTRODUCTION

Recent advancements in computing have catalysed profound transformations in Artificial Intelligence (AI), which now permeates many facets of our daily lives.

One area impacted by this transformation is the financial sector, or more specifically, financial markets. They are made up of traders, whether human or machine, with the core objective of being as profitable as possible. We call "algorithmic traders" the software-driven entities that have replaced human traders, performing based on pre-defined, complex algorithms derived from complex financial engineering. As markets and technology evolve together, the need for adaptability to fluctuating conditions is of foremost importance. Enter the age of AI traders: more efficient, enabled to make decisions based on instantaneous data analysis, and navigating markets better than their predecessors.

However, the true paradigm shift is heralded by the rise of Deep Learning. Its changing potential is evident across sectors, from chatbots to advanced medical diagnostics. Deep Learning Neural Networks (DLNNs), modelled after human neural pathways (Shetty et al., 2020), are at the forefront of this AI revolution. Their applications span diverse domains such as speech recognition, natural language processing, and even cancer detection (Abed, 2022). Recent studies underscore the effectiveness of DLNN-based traders, which have demonstrated capabilities rivalling, if not exceeding, traditional algorithmic traders (Calvez and Cliff, 2018). Moreover, the rapid democratisation of computational power has led to increasingly sophisticated market simulations, enabling a vast number of research prospects — especially for the AI community.

Algorithmic traders execute the most of daily trades in a market, processing millions of transactions at sub-second rates. While much of the existing literature evaluates trading strategies in simplified market simulations, the intricate and asynchronous nature of real-world financial markets often remains unaddressed. The purpose of this work is to bridge this research gap in the literature with these core contributions:

- Train an intelligent trader based on a proven DLNN architecture on historical simulated data.
- Integrate our trader in an asynchronous market simulator to enable a solid experiment base.

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- Evaluate our trader against other traders in the literature based on profits obtained.
- Validate the results through statistical analysis and reflect on the model's strengths and weaknesses.

The core contribution is creating a system that could outperform existing strategies in a multi-threaded market simulator. A positive result could have an impact in the real world, with the only barrier represented by the access to some of the LOB data the model requires. Customer limit prices are not public when trading, so owning such historical data would prove to be great leverage. In the case of a negative result, this research would prove useful underlying causes and ascertain the vulnerabilities that a DLNN trader has when deployed in a realistic setting, albeit with the caveat of accessing certain proprietary LOB data. Our exploration is both an homage and an extension of the efforts of two previous pieces of research, DeepTrader (Wray et al., 2020) and the Threaded Bristol Stock Exchange (TBSE) (Rollins and Cliff, 2020), seeking to chart new horizons in the confluence of AI and financial trading.

1.0.1 Context on Financial Markets and Algorithmic Traders

Over the course of this paper, there are a number of specialised terms and concepts relevant to our work, especially regarding the LOB, which are going to be expanded on in the following sub-section.

At the core of most financial markets lies the Continuous Double Auction (CDA) mechanism (Smith, 1962). Unlike the traditional auction setup, where items are sold one at a time with bidders actively competing until the highest price is reached, the CDA operates continuously, allowing buyers and sellers to place orders at any time. The "double" in CDA signifies that it facilitates both buying and selling, dynamically matching buy orders with corresponding sell orders based on price preferences.

Central to the operation of the CDA is the LOB. The LOB is a dynamic, electronic record of all the outstanding buy and sell orders in the market for a particular asset. These orders are organised by price level, with the "bid" price representing the maximum amount a buyer is willing to pay and the "ask" price indicating the minimum amount a seller is willing to accept. The difference between the highest bid and the lowest ask is known as the "spread". A key feature of the LOB is that orders are processed based on price-time priority. This means that orders at the best price are always executed first, and among orders at the same price, the one placed earlier gets priority. In a typical market scenario, traders—either humans or algorithms—submit orders. These orders can be of two main types:

- *Limit Orders*: A trader is given a price and quantity. For buyers, this price is the maximum they're willing to pay, and for sellers, it's the minimum they're willing to accept. These orders are added to the LOB, waiting for a matching order to arrive.
- *Market Orders*: A trader specifies only the quantity, aiming to buy or sell immediately at the best available price. These orders are not added to the LOB; instead, they are matched with the best available opposite order from the LOB.

The market's primary objective is to facilitate trading by matching buy and sell orders. The continuous updating and matching in the LOB ensure liquidity and dynamic price discovery, reflecting the current consensus value of an asset.

The data we require from the LOB is referred to as "Level-2" data, meaning that we get all the current active orders. For context, "Level-1" market data contains only the prices and quantities of the best bid and ask in the market.

The TBSE is an advanced, asynchronous version of the open-source Bristol Stock Exchange (BSE) (Cliff, 2022), a faithful, detailed simulation of a financial exchange where a variety of public-domain automated trading algorithms interact via a CDA. It is asynchronous in the way traders interact with the market, with each trying to buy or sell an asset by placing *Limit Orders* concomitantly. Abiding by Smith's guidelines (Smith, 1962), traders solely aim for profit, ensuring no trades occur at a loss. Unlike its predecessor, where traders were sequentially polled for orders, TBSE grants each trader its own thread. Throughout a market session, traders continuously receive market updates and decide on placing orders. This structure privileges faster algorithms, as orders are queued on a "first in, first out" (FIFO) basis, emulating real-world market dynamics more closely.

The following terms will be relevant when defining our model's features. The LOB midprice is the average of the highest bid and the lowest ask prices in the LOB. The microprice refines this midprice by factoring in the order imbalance and the depth of the order book. Imbalance represents the proportionate difference between buy and sell orders, highlighting directional pressure. Total quotes on the LOB refer to the aggregate of all buy and sell orders present. The estimate $P*$ of the competitive equilibrium price predicts where supply meets demand, ensuring market clearance. Lastly, Smith's *"alpha"* α metric gauges how closely the market price approaches this equilibrium, serving as a measure of market efficiency.

Now having cleared the domain-specific context, we transition to showing how experimental economics evolved from Smith's inaugural work to AI algorithmic traders, understanding how our work builds on existing knowledge in Section 2. The rest of this paper, based on (Cismaru, 2023), will detail how the model that DTX uses was trained and the experimental setup in Section 3. The results showing how DTX outperforms existing traders are shown in Section 4. Section 5 will further analyse these findings, with Section 6 providing a view on limitations and future work, concluding with Section 7. (OpenAI, 2023)

2 BACKGROUND

2.0.1 Beginnings of Experimental Economics and Agent Based Modelling

The groundwork for experimental economics was laid by Vernon Smith in 1962 by publishing "An Experimental Study of Competitive Market Behaviour" in The Journal of Political Economy (JPE) (Smith, 1962). Smith has implemented a series of experiments based on the CDA system, where buyers and sellers are announcing bids and others in real-time, with the possibility of a trade being executed any time the prices match.

The experiments were performed with small groups of human traders. They were instructed to trade an arbitrary commodity on an open-pit trading floor with the intention of maximising profitability, namely the difference between the limit price and the trade price. Each trader was given a pre-defined limit price: for sellers, the minimum they are allowed to sell their units at, and for buyers, the maximum price they can pay for a unit of the traded asset, thus preventing loss-making trades. The simulations were carried out as "trading days", namely time intervals of 5 to 10 minutes. The quotes that were shouted by the traders resembled the LOBs of modern markets. Once a trader agreed on a trade with its counterparty, both would leave the market as they only had a single unit to trade. The results showed rapid convergence to the theoretical equilibrium price, measured by Smith's α metric. It measures how well and efficiently the market is converging to the equilibrium price. The experiments capture the asynchronous nature of financial markets, one of the issues that this work is aiming to explore. Vernon Smith received the Nobel Prize in 2002 for his pioneering work in experimental economics, with his experiment styles being the basis of most research carried out in this field and the methodology used in this paper.

Three decades later, in 1993, Gode and Sunder introduced the Zero Intelligence traders (Gode and Sunder, 1993). Their focus is on studying how automated traders perform in markets dominated by human traders. They introduced two trading strategies: Zero Intelligence Unconstrained (ZIU) and Zero Intelligence Constrained (ZIC). ZIU is generating purely random quotes, while ZIC is limited, constrained to a price interval. Their experiments, carried out in the style of Vernon Smith, showed ZIC to outperform human traders. A few years later, in 1997, Cliff published a paper proposing Zero Intelligence Plus (ZIP) traders, which, by using a simple form of Machine Learning (ML), can be adaptive and converge in any market condition (Cliff, 1997). ZIP is based on a limit price and an adaptive profit margin. The margin is influenced by a learning rule and the conditions of the market.

In 1998, Gjerstad & Dickhaut described an adaptive agent, GD (Gjerstad and Dickhaut, 1998), with Tesauro & Bredin publishing a paper in 2002 describing the GD eXtended (GDX) trading algorithm (Tesauro and Bredin, 2002). In 2006, Vytelingum's thesis introduced what is called the Aggressive-Adaptive (AA) strategy (Vytelingum, 2006), which was thought to be the best-performing agent until recently. In 2019, Cliff and Snashall performed comprehensive experiments comparing AA and GDX, simulating over a million markets. The results show that AA is routinely outperformed by GDX, arguing that advancements in cloud computing and compute power open new possibilities for strategy evaluation that were not possible before (Snashall and Cliff, 2019).

2.0.2 Rise of Intelligence in Market Modelling and Price Prediction

The advent of AI has attracted the attention of the finance and trading fields. Increasing numbers of papers detail how advanced Deep Learning methods became powerful tools in the world of agent-based trading, market making, and price forecasting. In their report, Axtell and Farmer argue that the advance in computing has enabled agent-based trading (ABM), impacting how trading is performed today (Axtell and Farmer, 2018). In finance, ABM helped us understand markets, volatility, and risk better. Their report is comprehensive and can be considered a higher-level point of reference on how agents are applied in different branches of finance and economics. Njegovanović published a paper in 2018 that discusses the implications of AI in finance, with a focus on how the human brain and its behaviour have inspired the architecture of automatic decision models (Njegovanović, 2018).

In the past decade, a number of studies have explored the potential of Deep Learning in finance. In 2013, Stotter, Cartlidge, and Cliff introduced a new method for assignment adaptation in ZIP, performing balanced group tests against the well-known ZIP and AA strategies (Stotter et al., 2013). Their results show that assignment-adaptive (ASAD) traders equilibrate more quickly after market shocks than base strategies.

In 2020, Silva, Li, and Pamplona use LSTM-based trading agents to predict future trends in stock index prices. Their proposed method, named LSTM-RMODV, demonstrates the best performance out of all studied methods, and it is shown to work in both bear and bull markets (Silva et al., 2020). In 2019, Sirignano and Cont proposed a Deep Learning model applied to historic US equity markets. The information extracted from the LOBs uncovers a relationship between past orders and the direction of future prices. They conclude that this is better than specialised predictions for specific assets. Their results illustrate the applicability and power of Deep Learning methods in modelling market behaviour and generalisation (Sirignano and Cont, 2019).

2.0.3 Need for Intelligence and Realistic Modelling

The work in this paper continues what Calvez and Cliff started in 2018 (Calvez and Cliff, 2018), when they introduced a DLNN system trained to replicate adaptive traders in a simulated market. Purely based on the observation of the best bid and ask prices, the DLNN has managed to perform better than the trader observed. In 2020, Wray, Meades, and Cliff will take this further by introducing the first version of DeepTrader, a high-performing algorithmic trader (Wray et al., 2020) trained to perform in a sequential market. Based on a LSTM, it automatically replicates a successful trader by training on 14 features derived from Level-2 market data. The first version of DeepTrader matches or outperforms existing trading algorithms in the public-domain literature. Most studies are performed on sequential simulations, in which the speed at which the traders react to changes in the market does not matter. Axtell and Farmer argue in their above-mentioned report, that the real social and economic worlds are parallel and asynchronous, but we try to replicate it with single-threaded code (Axtell and Farmer, 2018). Rollins and Cliff try to mitigate this in a paper they published in 2020 (Rollins and Cliff, 2020). They propose TBSE, as we introduced in Section 1.0.1, on which they perform pair-wise experiments between well-known trading strategies. The results reported intriguing insights, with a new dominance hierarchy of trading algorithms emerging.

Our work aims to integrate an optimised version of DeepTrader in TBSE and test it againts existing strategies. We will dive into the details of this in the next section, asking the question: Can we train this model to learn from a variety of traders and conditions and study its behaviour in a parallel simulation? We hope that the results of our study can provide more insight into its potential real-world performance.

3 METHODS

The core of our work relies on TBSE, as introduced in Section 1.0.1. It was used to generate the large amounts of data required for training DTX when running against the other public-domain trading strategies. The code of our project is available online at GitHub at github.com/armandcismaru/DeepTraderX for easy reproducibility.

The market is defined by the the limit orders given to traders, based on supply and demand schedules. TBSE was designed to use stochastically-altered real-world historical data to create variable, more realistic schedules. For our training and experiment sessions, we used IBM stock data from the August 31, 2017 NYSE trading day, namely the best/worst bids/asks at 1 minute intervals.

TBSE provides the means to produce large quantities of ”historical” market data. The one metric we are looking to evaluate DTX on is the mean profit that each trader type achieves at the end of the session, namely profit per trader (PPT). We cannot assess these algorithmic traders the same way we would with real traders, as TBSE doesn’t simulate loss, so we are judging based on profits only.

The data to train the DLNN model is curated by taking ”snapshots” of the Level-2 LOB data, updated each time a trade occurs. During training, our DLNN-based trader is given 14 numeric inputs, deriving from these LOB snapshots, as detailed in Section 1.0.1. The 14 values are as follows:

1. The time t of the trade when it took place.
2. The type of customer order used to initiate the trade, either a ”bid” or an ”ask” order.
3. The limit price of the trader’s quote that initiated the trade.
4. The midprice of the LOB at time t.
5. The microprice of the LOB at time t.
6. The LOB imbalance at time t.
7. The spread of the LOB at time t.
8. The best (highest) bid on the LOB at time t.

9. The best (lowest) ask on the LOB at time t.
10. The difference between the current time and the time of the previous trade.
11. The quantity of all quotes on the LOB at time t.
12. An estimate P^* of the competitive equilibrium price.
13. Smith's α metric using the P^* estimate of the competitive equilibrium price at time t.
14. *The target variable*: the price of the trade.

When performing inference, our model takes in the first 13 multivariate inputs to produce the target variable, item 14, namely the price at which it is willing to trade at a specific time in the market (the quote placed by the trader).

3.0.1 Data Generation and Preprocessing

TBSE provided five working trading agents that were used to generate the training data, as included here: github.com/MichaelRol/Threaded-Bristol-Stock-Exchange. To create a large and diversified training dataset, the market simulations were run using 5 types of traders in different proportions, with a total of 40 traders per simulation. The following proportion-groups of 20 traders per side of the exchange (buyers or sellers) were used: (5, 5, 5, 5, 0), (8, 4, 4, 4, 0), (8, 8, 2, 2, 0), (10, 4, 4, 2, 0), (12, 4, 2, 2, 0), (14, 2, 2, 2, 0), (16, 2, 2, 0, 0), (16, 4, 0, 0, 0), (18, 2, 0, 0, 0), and (20, 0, 0, 0, 0). Each number in a specific position corresponds to a population of traders of a certain type for a market simulation. For example, for the specification (12, 4, 2, 2, 0), there are 12 ZIC, 4 ZIP, 2 GDX, 2 AA, and no Giveaway traders for both the buyers and sellers sides.

Using all the unique permutations of the proportions resulted in 270 trader schedules, in which the 5 traders participate equally. This ensured that the model trains to generalise from a varied and rich set of market scenarios. Each schedule was executed for 44 individual trials, amounting to $270 \times 44 = 11880$ market sessions. Each simulation represents one market hour, requiring roughly one minute of wall-clock time. If running on a single computer, generating this amount of data would require approximately 8.6 days of continuous execution, generating roughly 13 million LOB snapshots. To address this time constraint, the decision was made to use cloud computing to distribute computation across several worker nodes.

It is generally good practice to normalise the inputs of a network due to performance concerns, particularly for Deep Learning architectures like LSTMs. Normalising the inputs helps ensure that all features are contained within a similar range and prevents one feature from dominating the others. For example, we have features with different scales, such as the time, which runs from 0 to 3600, while the quote type is binary. So by normalising, we only have values in the [0,1] interval. Doing this ensures improved convergence of the optimisation algorithm and helps the model generalise better to new data. The choice was to use min-max normalisation, given that we are working with multivariate features derived from financial data.

3.0.2 Model Architecture and Training

Contrary to the usual practices for training and validating a DLNN, which consist of splitting the dataset into *training*, *validation*, and *test* subsets, we used all the dataset for training. Markets are a combination of unique factors, so our trader's profit is heavily dependent on what is happening in a specific simulation. Considering this, it is without purpose to assess its performance relative to historic data by judging the absolute values of our target variable. Rather, as the model produced a good drop in the loss level during training, the DLNN was validated by quantifying how well DTX performed in live market simulations against other traders in terms of PPT. Our dataset is large and was generated using unique simulations; thus, DTX doesn't learn to replicate specific scenarios; rather, it grows its ability to adapt and generalise in any condition.

The architecture of the Deep Learning model that DTX relies on is illustrated in Figure 1. It is comprised of three hidden layers, a LSTM with 10 units (neurons), and two consequent Dense layers with 5 and 3 units, respectively, all using the Rectified Linear Unit (ReLU) activation function. The output layers use a "linear" activation function, chosen as suitable for a continuous output variable.

When dealing with large datasets, training should be done in batches to accommodate memory limitations and speed up training. Our network accommodates this with a custom data generator based on the Sequence class, used by Keras to train a model in batches. To balance accuracy and training times, a batch size of 16384 was chosen. To to balance potential overfitting and long convergence times we chose a learning rate of $\mu = 1.5 \times 10^{-5}$. The DLNN uses the Adam optimizer for its ability to efficiently converge to a good solution, prevention of overfitting, and incorporation of momentum, speeding up learning and improving generalisation performance. The model was trained in approximately 22 hours, leveraging the GPU clusters of the *Blue Crystal 4* supercomputer.

The model was trained for 20 epochs. An epoch

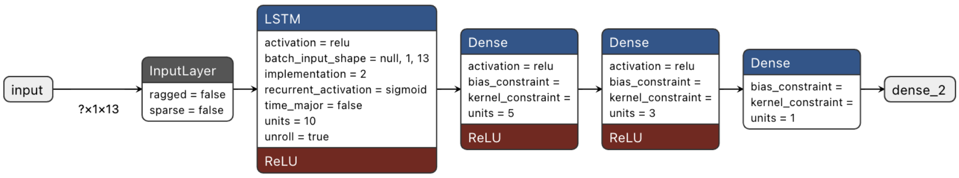


Figure 1: Architecture diagram for the DLNN model used by DTX.

refers to a single pass of the entire dataset through the neural network. So, at the end of the training session, DTX is exposed to $11880 \times 20 = 237600$ market sessions. With each experiment producing $\sim$ 1100 LOB snapshots, DTX is trained using a total of roughly 261 million snapshots. The training error (loss) was calculated using the Mean Square Error (MSE). The error decreased considerably during the first 4 epochs and approached 0 in the last epoch with a loss curve resembling an asymptote to the X axis.

3.0.3 Experiment Design and Evaluation

Our aim is to quantify how DTX performs relative to the other strategies. Finding the right methodology for doing this is as important as the strategy itself, as it is essential to isolate market conditions in repeatable experiments. Traders are dependent on the behavior of other strategies, mandating a controlled laboratory environment that allows quantitative analysis of their performance. Thus, there are two strategies used in each experiment: DTX and the others, one by one. Drawing inspiration from the work of Tesauro and Das (Tesauro and Das, 2001), we have chosen two experiment types.

For each, DTX has run in $n = 500$ independent market simulations, populated by 40 traders, 20 for each side, buyer or seller. It is worth specifying that each set of 50 trials was run on a different cloud machine, resulting in a broad distribution of profits, with each using the same seed for functions involving randomness. This is due to the well-known and researched issue in computer science, that machines cannot emulate perfect randomness (Bridle, 2022). TBSE allows full control of the experiment conditions. The time frame of the simulation, the supply and demand schedules, and the order interval can all be controlled to isolate the differences between the chosen strategies. As we use an asynchronous simulation, we are looking to evaluate DTX based on its DLNN model's efficiency and capacity to generalise on LOB data, translating into profits.

The first experiment design is the Balanced Group Tests (BGTs), in which the 20 buyers or sellers are again evenly split between the two trader types, resulting in 10 DTX traders and 10 traders of another type for each group. The choice is beneficial as it is a stochastic-controlled trial method that helps reduce bias sources and improve the internal validity of the study. We want to make sure that the traders produce different profits solely because of their inherent strategy, not noise.

The second type of experiment is the One to Many tests (OTMs), where the trading strategy that you want to observe becomes the ”invader” out of a homogenous population made up of different strategies. For clarity, this means that 2 instances of DTX will run alongside 38 traders of a given type. This is particularly useful as we are trying to see how DTX performs in a market shaped almost entirely by another trader, capturing its dynamics and producing profits. For fairness, there is one defecting strategy on both buyer and seller sides.

The research on the profitability of DTX has been conducted against four ”competitor” traders: ZIC, ZIP, GDX, and AA, adding up to eight sets of head-to-head experiments. These strategies were chosen as they are the most relevant in the literature, with AA and ZIP being ”super-human” traders, amongst the first to be proven to outperform humans.

4 RESULTS

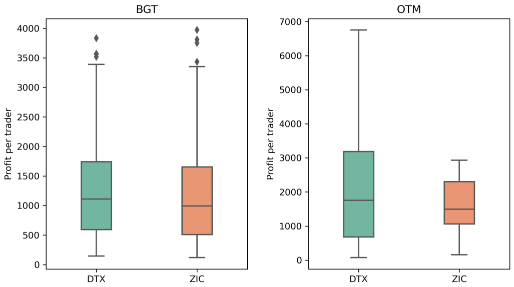
The following section presents the results of our experiments, summing 4,000 individual market simulations. The outcome largely supports our research hypothesis, with DTX dominating in 6 out of 8 experiments, with very significant differences in PPT for a number of them.

The results are presented in the form of profit distribution box plots and scatter plots of individual trial profits. An extended summary of the results and description of the statistical significance tests conducted on them can be found in Chapter 3.8 and 4 of (Cismaru, 2023). In the box plots, the vertical axis is represented by PPT across trials. The box represents the interquartile range, the range between the first quartile and the third quartile. The line inside the box represents the median of the dataset. The whiskers represent the data within 1.5 times the interquartile range, with the diamond-shaped points outside them being considered outliers from a data distribution point of view. The scatter plots show individual trials in terms of PPT obtained by both traders. The line in the scatter plot is a diagonal reference line, where the points would lie if the profits per trader for both strategies were equal. Points above the line indicate higher profits achieved by DTX, analogous for the other trader.

The figures are grouped on experiment and trader type basis. Each set of two box-plots corresponds to BGTs and OTMs between DTX and one of the 4 other traders for all experiments. Due to space constrains, the scatter plots were chosen for the more interesting experiment results, on a case by case basis. We present them in the following order: ZIC, ZIP, GDX, and AA. For each experiment, we performed a Wilcoxon-signed rank-test with a significance level of 95%. The null hypothesis is that there is no statistical difference between the means of the profits achieved by the traders. A *p-value* lower than 0.05 indicates that we can reject the hypothesis, concluding that one strategy outperforms the other in a given experiment.

4.0.1 ZIC vs. DTX

Figure 2a shows a narrow difference in means between ZIC and DTX in the BGTs. The statistical test for 95% significance level has indicated that DTX is the better strategy of this experiment. In the case of OTMs, the difference in profits is sensibly larger for DTX, as seen in the profit distribution in Figure 2b and in the cluster of profits above the diagonal in Figure 3. The statistical test has confirmed the dominance of DTX in this experiment.



(a) BGTs for ZIC vs. DTX.

(b) OTMs for ZIC vs. DTX.

Figure 2: Box-plots showing PPT for ZIC vs. DTX tests.

4.0.2 ZIP vs. DTX

The BGT experiment between ZIP and DTX is its only categorical loss. While Figure 5 doesn't indicate any immediate winner, Figure 4a shows a slight advantage for ZIP, with a higher mean PPT. The Wilcoxon signed-rank test has confirmed the result, confirming that there is a significant difference in profits in favour of ZIP.

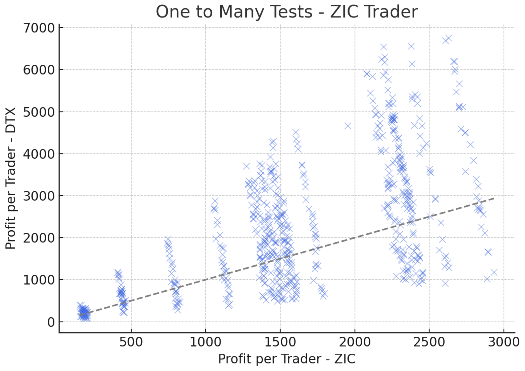
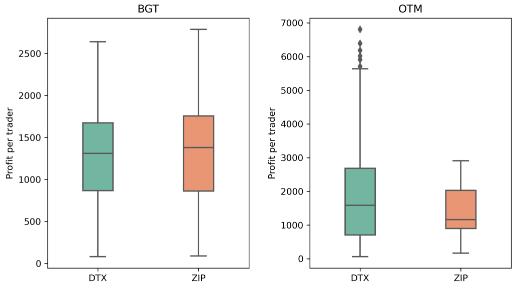


Figure 3: Scatter plot of PPT in OTMs for ZIC vs. DTX.

On the other hand, Figure 4b shows higher mean profits for DTX, although with a much bigger variance and a number of outlier values, fact backed by the result of the statistical test.



(a) BGTs for ZIP vs. DTX.

(b) OTMs for ZIP vs. DTX.

Figure 4: Box-plots showing PPT for ZIP vs. DTX tests.

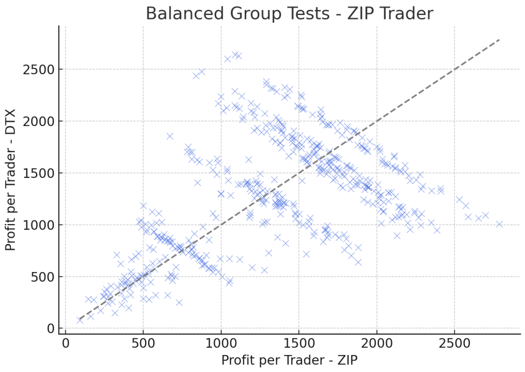
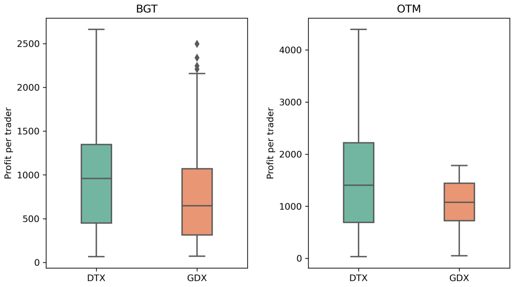


Figure 5: Scatter plot of PPT in BGTs for ZIP vs. DTX.

4.0.3 GDX vs. DTX

Figures 6a and 7 show BGT comparison of PPT scores between DTX and GDX. Upon visual inspection, the bar plot shows a significant difference between the means of DTX and its competitor, with the scatter plot placing most of its points above the diagonal, indicating the clear dominance of DTX in this experiment, with the same outcome confirmed by the outcome of our statistical test.

Figure 6b shows PPT score comparisons in the OTM experiment. The profits obtained by DTX, although they have a high variance, lay on a superior magnitude scale than those of GDX, as visible in the box-plot. The Wilcoxon signed-rank test confirms this hypothesis.



(a) BGTs for GDX vs DTX.

(b) OTMs for GDX vs. DTX.

Figure 6: Box-plots showing PPT for GDX vs. DTX tests.

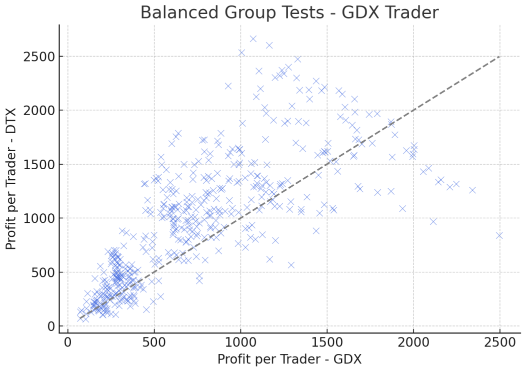
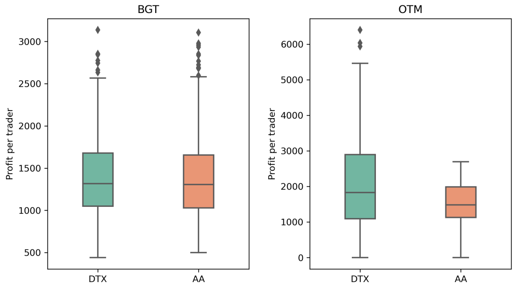


Figure 7: Scatter plot of PPT in BGTs for GDX vs. DTX.

4.0.4 AA vs. DTX

Figure 8a visually represents the profits obtained by AA and DTX in the BGTs, indicating similar results for both traders. The statistical test applied failed to prove that there is a significant difference in terms of mean profits between AA and DTX. Thus, this is our only inconclusive experiment.

On the other side, Figure 8b shows a high-profit but high-variance DTX in the OTM experiments against AA, a fact also visible by looking at the points above the diagonal in the scatter plot in Figure 9. The statistical test concludes that DTX is the higher-performing strategy in this experiment, but with increased variance.



(a) BGTs for AA vs. DTX.

(b) OTMs for AA vs. DTX.

Figure 8: Box-plots showing PPT for AA vs. DTX tests.

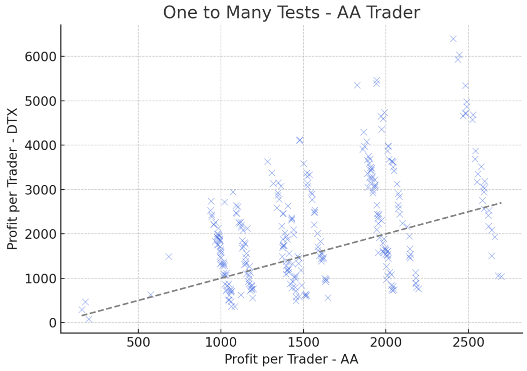


Figure 9: Scatter plot of PPT in OTMs for AA vs. DTX.

4.0.5 Summary of Results

The results presented in this section are used to objectively highlight what a trader based on a simple LSTM architecture is able to achieve. To recap, our model was exposed to prices quoted by traders at time a T and the corresponding LOB state S (as described in Section 3) during training. The scope of this is to enable the model to ”read” the market, and, alongside its own limit price, perform inference and generate a price used to place a market order. Whether that price produces profit is down to how quickly (due to the asynchronous simulation) and accurate DTX reacts to the market and the behaviour of other traders.

In summary, our empirical analyses reveal that DTX exhibits superior performance in six out of eight experiments and matches profits in one out of the eight. DTX achieves its sole purpose, which is to make profit. Notably, DTX either matches or surpasses the performance of three out of the four traders tested, including those deemed super-human. Specifically, DTX recorded two victories over GDX and exhibited a win-tie performance against AA. However, the results against Cliff’s ZIP are more nuanced;

DTX registered both a victory and a defeat in markets where both traded concurrently.

As we draw a line at the end of this section, having presented a detailed analysis of the results, it is worth noting that DTX produced very interesting results, but it is still an early development initiative. Although the performance of DTX is notable, we need to have an objective stance as we transition into the discussion, where we will delve deeper into an analysis of these results. The next section will discuss the strengths and weaknesses of DTX, relating its performance to previous results in TBSE, and exploring their broader impact on the field at the intersection of finance and artificial intelligence.

5 DISCUSSION

The biggest strength of our results is the consistent profitability of DTX across all the experimental setups. This accomplishment is particularly relevant when considering the volatility of markets, which is better captured in the multi-threaded simulation that we use. DTX's ability to outperform or match traders such as AA, GDX, or ZIC suggests that the model can be relied on to trade real money in real markets, generalising effectively across various scenarios and aggregate on-the-spot information better than humans. Our trader is not adaptive, so it reacts consistently and quickly no matter the conditions.

We treat DTX as a "*black-box*" trader, so we cannot explain its inner processes on *why* it produces a certain quote price when given its 13 input features, but we are analysing how those prices produce profits relative to other traders. The individual prices produced are almost impossible to interpret by humans, rather we judge the profits they produce, which are also a function of how and when the other traders act. DTX performed the best against ZIC and GDX. While the results againts ZIC were expected, as it is a simple, non-adaptive trader, the performance relative to GDX was impressive in both experiment types. This result might render the adaptive Dynamic Programming framework that GDX relies on as obsolete when facing modern DLNN based traders.

However, DTX has matched but not completely outperformed the "super-human" traders, AA and ZIP. In the BGTs againts these two, DTX was less effective, with a tie and a narrow loss. The simple ML rule of ZIP and the aggressive pricing system of AA are still efficient strategies, meaning that DTX is still "young", and not stable enough to dominate in larger groups. In the OTMs, DTX dominated, being able to intercept profits as an "intruder" when running againts the best traders. The high variance in these experiments suggests that DTX should not be used when seeking fast profits, but should rather be run in longer time frames to prove its efficiency.

Within the broader academic discourse on trading algorithms, our findings resonate with (Wray et al., 2020). They proposed this DLNN architecture, managing to outperform other strategies, but only trained it to copy specific traders in a sequential simulation. When they introduced TBSE (Rollins and Cliff, 2020), Rollins and Cliff proposed the idea that the traders in the literature might behave differently when tested in a concurrent simulation that better reflects real markets. Their results challenged the "status quo" of the trader dominance hierarchy, finding that they now come as follows: ZIP > AA > GDX > ZIC. By quantifying the difference in results between DTX and the four traders, we can say that the relative performance of DTX follows the same ranking.

These results have broader implications as they have proven how, among so many other applications, AI autonomous agents can generate real money. DTX is an early proof-of-concept but its ability to be consistent, resilient, and generalise suggests that such traders could be pivotal in creating fairer and more efficient markets. However, it's crucial to consider that markets populated solely by these intelligent automated systems might result in inexplicable events and our inability, as humans, to understand the new mechanisms of the financial markets we rely on.

6 LIMITATIONS & FUTURE WORK

This study, while comprehensive, is not without limitations. DTX was trained using rich data, but from only so many traders and scenarios. Also, our experimental setup was focused on only two types of traders at a time. Not to mention the considerable resource overhead involved in data collection, model training, and testing. Addressing these in future research would offer even more nuanced insights into DTX's capabilities. Moreover, an intriguing avenue for future exploration would be quantifying the correlation between the model's inference time and performance, as well as the degree of impact of each one of its 14 features.

In practical applications, a financial institution engaged in active trading could potentially deploy the DTX algorithm, provided they have access to extensive historical LOB data as well as their proprietary trading data. Given that access to limit order prices (one of the features of DTX, as described in Section

3) is typically restricted to an entity's own trading operations, DTX could be trained on this comprehensive dataset, thereby amalgamating the strengths of multiple established strategies and leveraging vast computing resources. A market populated with traders like DTX can be more efficient in allocating resources, creating a fair and predictable space. (OpenAI, 2023)

7 CONCLUSION

In the rapidly evolving domain of automated trading, our study emphasises the potential of Deep Learning trading algorithms. As markets continue to evolve, the quest for strategies that can adapt and thrive remains paramount, and DTX, as evidenced by our research, stands as a promising proof-of-concept in this landscape. In the quest for novelty and realism, we researched this in a distributed market simulation that has previously overturned the trader dominance hierarchy, with DTX being consistent with these findings.

As we stand on the cusp of this new frontier, it beckons researchers, practitioners, and policymakers alike to collaboratively shape a future where AI-augmented trading systems contribute to more efficient, stable, and equitable financial markets.

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