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THE IMPACT OF AI ON ALGORITHMIC TRADING: HOW AI ALGORITHMS ARE CHANGING THE LANDSCAPE OF STOCK TRADING, INCLUDING THE ETHICAL IMPLICATIONS

Teja Reddy Gatla

Associate Director at DTCC, AI Specialist Operations, Department of Information Technology

ABSTRACT—The objective of this research is to analyze the impact of artificial intelligence on algorithmic trading. Given the complexity of modern markets, it is near impossible to isolate the impact of individual market participants due to the countless interactions/trades that occur throughout the market's lifespan. The scope of this paper is to address the new emerging as well as existing techniques of AI in algorithmic trading. This paper tries to understand the impact of AI on algorithmic trading using observations and results from the research conducted. This paper broadly covers the types of trading and advantages of algorithmic trading. It also explains how AI has been implemented in algorithmic trading techniques to enhance the profit making model. In the due course, various AI techniques have been explained which has provided an insight to AI readers about how complex and simple AI techniques have been helpful to predict the financial markets. Quantitative momentum investment strategies were first brought to the forefront in 1994 by Jegadeesh and Titman, who showed the efficacy of relative strength in the United States. A few years later, in 1997, Hsu, Myers, and Baesel conducted a study to test whether a simple moving average strategy would result in abnormal returns after transaction costs [1]. The results of the study, as expected, strongly suggested that the performance of these investment strategies was dependent on the frequency at which the portfolios are rebalanced. Given that moving average rules are trend-following in nature and are best suited for trending markets. These strategies differ greatly from the more traditional ones used by pension funds, in that they typically seek to produce returns that are uncorrelated with the major asset classes, with moderate to high levels of risk[1,2]. With the success of these strategies, a framework for evaluating and comparing quantitative investment strategies is imperative to provide the basis for selecting between them.

Keywords— Algorithmic trading, stock trading, cryptocurrencies, artificial intelligence, ethics, automation, trading innovation.

I. INTRODUCTION

With the analysis overly complex and time-consuming and the steps in decision-making too ambiguous, there is growing interest to create machine agents that imitate human intelligence aimed at automating any aspect of the algorithm to a point where it achieves adaptive behavior. This has resulted in a wide range of AI development [2]. From an academic viewpoint, it is often used as an experimentation in learning or predictive methods with the use of a simple agent. Development by industry centers around the goal to automate a trade generation method with intelligence that extends the simple rule of a predetermined method. The agent can even be set to a goal of buying intelligence itself as a leftover from its interaction with said market event[3]. Any automation effort aims to shift human decision and action by an algorithm, with the improvement often being measured against a human benchmark. Algorithmic trading has been done to date mainly on the sell side. However, any advance in AI has the potential to be a huge blow to the job market for active traders in changing the nature of which studies are conducted on market events.

The development of algorithmic trading has sparked huge interest in the intelligence that drives the trade. Generation of a prediction and analysis of a market event to guide a trade requires a high level of intelligence. Traditionally, this was always applied by human interaction. However, with the advancement of statistical methods and technology, AI has become a key player in the way events are predicted and conclusions are drawn[3]. Building a system to analyze market events and make decisions on whether to buy or sell requires a decision-making procedure usually best exhibited by a logical structure. For any prediction, there are many methods from neural networks and expert systems to time series analysis. With the objective to maximize profitability, risk management, and execution quality, it is often the case that analysis will lead to a decision to trade on a short-term prediction with the goal to buy and sell the same event. Simulation and testing on past data is also a large job for algorithmic traders[4,5]. Test results must be compared with different strategies, usually with the intent of moving to futures with the optimal strategy. This has great appeal. The simulation is literally a game that is played against the version of the market that is being analyzed, with the result being a direct comparison of wealth relative to the same event in the real world.

Algorithmic trading is the use of any electronic information for trade to execute transactions. Trade is initiated, managed, and executed based on a set of encoded instructions, such as those that are common in algorithmic trader agent technology[5]. This is both in terms of venues where the instructions are initiated and executed, as well as the type of instructions to be carried out. It is a tool being used by investors ranging from institutional orders to the individual investor. In general, algorithmic order types that are used in terms of their specific instructions can be categorized into the following: market data, intermediation, conditional, placement, and logic types. The term algorithmic trading primarily refers to the trade itself; however, analysis is specific to the type of algorithm that generates the trade. This analysis, viewed in the modern context, is one of predictive statistical nature.

II. RESEARCH PROBLEM

The main research problem is to assess the impact of AI on algorithmic trading. Given that there are literally hundreds of forms and iterations of algorithmic trading strategies, a comprehensive classification of trading tactics and their effects is an enormous task. The current incarnation of AI innovation over the past decade has rapidly thrust itself into the realm of possibility for industry application, from machine learning and data mining algorithms to more complex AI agents such as autonomous software and decision-making systems. AI companies see the finance industry as a prime market, and it is quite clear that they will seek to develop and test AI systems with an aim to replace and improve upon current algorithmic methods. However, the AI innovation timeline holds potential negative consequences for the finance industry, and the ultimate impact is as yet unknown. This is our research problem.The finance industry is an industry that relies heavily on timing and accuracy in decision making[6]. Any low-risk investment strategies that can improve investor wealth will be in high demand and develop a competitive advantage if they are applied to successful investment decisions. Take, for example, the massive growth of the hedge fund industry over the last decade.The shift towards automation has given birth to algorithmic trading[7]. Largely, algorithmic trading involves trying to optimize given investment objectives by making decisions at micro-levels and translates to increased use of mathematics and decision science in the investment process. Many investment strategies employed today by investment managers are, in fact, algorithmic in nature and can be readily expressed using a finite set of instructions to complete the task. This leads us to the current innovation era and its potential impact on the finance industry. Artificial intelligence has long been used as a buzzword and an idealistic endpoint for simulation and automation in complex systems[7]. The timeline of technological innovation in any industry is crucial to that industry's success and competitiveness in the long term.

III. LITERATURE REVIEW

A. AI IN TRADING

Understanding the past and contemporary commercial methods is a significant way to forecast the future prospects of financial markets and to identify the future trading strategies. This can be one reason why there is a large body of literature on the studies of the past trading methods. Based on the method used to enter orders, algorithmic traders are of different types[8]. These can be model-driven traders who use models to find advantageous trading outcomes, statistical traders (or "quants") whose trading decision-making process consists of a series of statistical steps, and the Direct Market Access (DMA) traders who use algorithmic trading systems to split up large orders into smaller orders so the market impact is less. Modeling types can be further broken down into a suite of specific strategies. These strategies can be categorized in many different ways. Mimicking the decision-making processes of human traders at a higher speed and frequency, an automated system will stick to a set of rules and criteria to determine every aspect of a trade [8]. This is identifiable with AI, thus algorithmic trading is a form of AI applied to an investment strategy. With the alarming rate of change in the economics of financial markets, a plethora of complex automated methods have been created to implement algorithms. It is these early applications of AI to economics that have been successful and have led to a recent expansion in research and development of AI in trading.

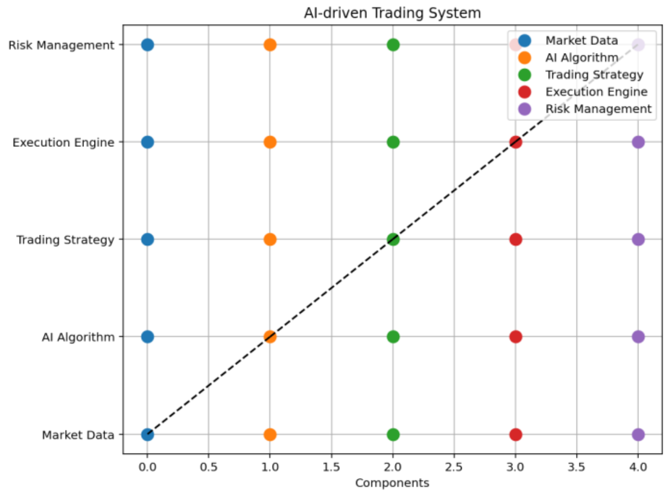

Fig. 1 AI-driven Trading System

B. OVERVIEW OF ALGORITHMIC TRADING

Terms related to algorithmic trading include statistical arbitrage, automated trading, black-box trading, and algo trading. These encompass a wide range of strategies used to trade any security. Methods can involve high frequency trading, market making, and trading on information. These algorithms are used to find hidden trading opportunities and can be automatically executed with little human intervention[8,9]. AT can be divided into the buy-side and sell-side. Buy-side traders (traders at mutual funds, hedge funds, pension funds etc.) use algorithmic trading strategies to buy a security while the sell-side traders (typically market makers and prop-traders) use AT to provide liquidity to the market. Statistical arbitrage found popularity with the sell-side market making community. It involves exploiting a mispricing between two related securities, and typically involves a mean reversion strategy. Step one of the strategy is to determine the "correct" relative value of the two securities[9]. Step two is to monitor the gap between the current and correct relative value. If the two values diverge, the algorithm would buy the underpriced security and sell the overpriced security, with the intention of holding both securities until the prices revert back to the mean. Step three involves exiting the trade when the securities have converged back to their correct relative value.

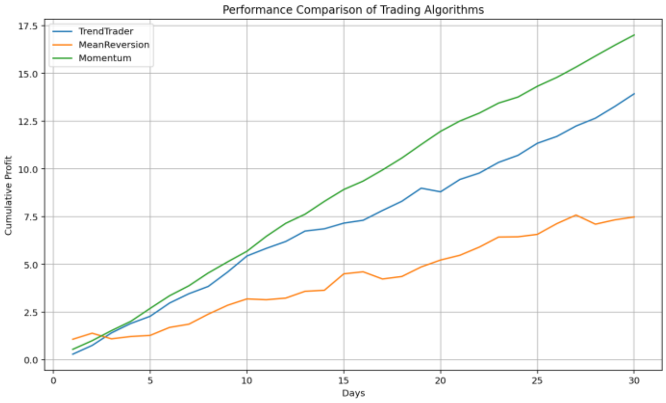

Fig. 2 Performance Comparison of Trading Algorithms

C. Role of AI in Algorithmic Trading

The many AI algorithm packages currently being developed are no different: given the same human traders are now a worthy market adversary, the key objective is to mimic and replace what they do. It may be too late for cQuant with their down-scaling of resources and SVD based forecasts, but the aim to challenge human parity is a clear and present danger for most algorithmic trading firms. In 5 to 10 years time, AI algorithms will be directly competing with each other in a winner take all fight, the modern electronic market[1]. To the victor goes whatever the latest proxy for alpha is…it matters not for by that time, there will be nothing left for human traders but to join them.

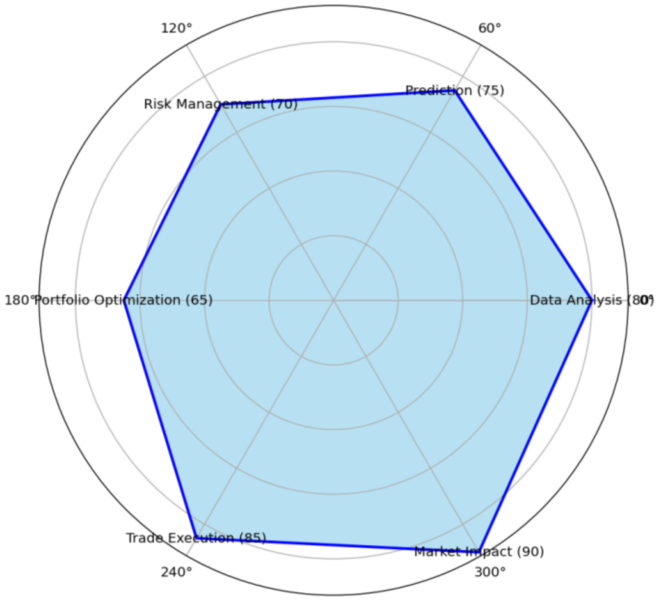

Fig. 3 Roles of AI in Algorithmic Trading

From a holistic view of algorithmic trading, it is reprehensible that AI methods will be called for at all stages of IT development and deployment. Primarily, modern trading systems will be self-learning adaptive agents, designed to profitably locate liquidity and thereby minimize implementation shortfall. Such brokers will be defined in terms of an order type and an objective function, and it is here that AI methods will become integral. AI methods will be required for the construction of efficient frontier type models that accurately map an order type to its corresponding strategy, a mapping that will be trained and executed in a simulated environment[10]. As AI methods mature, the agent will progress to directly learning the strategy it is to execute in live markets, the final and most challenging progression will involve the agent learning to dynamically switch between strategies in response to information received during the trade. This type of agent represents the holy grail of automated trading, it is a system that can independently and optimally trade an order to its completion without human intervention. At the strategy level, autonomous agents will be used by buy-side and sell-side institutions to interactively seek out and negotiate the best possible deal in complex and often convoluted electronic markets[11]. This will require the development of game theoretic models of strategic interaction and the construction of agent based simulation environments in which strategies can be both tested and trained to master a particular market. AI methods will also be used in the development and analysis of market data, for it is AI that will ultimately make sense of the ever increasing volume, variety and velocity of financial data.

D. Ethical Implications of AI in Trading

The intriguing issue of 'rogue traders' is one that is more relevant to rule based AI than to machine learning. An infamous example is that of Brian Hunter, a trader for Amaranth Advisors who single handedly caused the fund to lose $9 billion through speculation in natural gas futures. In his testimony to the US Federal Energy Regulatory Commission, Hunter attributed his large losses to a 'bias trade[11,`2]'. This was in reference to a trade that will only work if certain assumptions on market conditions are correct, so as a result the trade is biased by the trader's belief. The trade in question was based on a complex calendar spread option and it is actually an ideal candidate for an AI based event strategy[12]. Step simulation can be used to test a similar set of conditions and if the rule was deemed to be effective, a live implementation would only require slight deviations from simulated results. It is not inconceivable that in the future, a move would be made to prevent such trades from incurring further losses by use of market manipulation. This was the case of Hunter's final attempt to recover losses on the failed option with real-time trading the underlying futures. He admittedly increased the position size and changed the trade when simulation results were unfavorable.

Conversely, it is also possible for traders to spend a large amount of time on implementation, only to find that the rules no longer apply due to changing market conditions. This essentially causes a strategy to become redundant. With markets as dynamic as the one for foreign exchange, this is a big problem[1]. Capturing data attributing to the influence of a given rule on market conditions can also be an onerous task that may require extensive back testing by its very own nature. This sort of rule data is critical in the event of strategy failure, in which case it can act as a road map for future attempts. High quality rule data is an asset which can be passed on or even sold to other parties. Any automatic rules identified using pattern recognition techniques are also at risk in markets of changing behavior.[13] In a scenario where traders using artificial intelligence are competing against one another, there is also the possibility of a particular strategy becoming less effective as its rules are effectively reverse engineered by other AI algorithms.

E. Impact of AI Algorithms on Stock Trading

The use of AI in algorithmic stock trading has raised significant interest from researchers across multiple academic disciplines. Many AI methods have been applied to trading, however, specific implications and effects of such methods have not been properly addressed. AI, much like stock trading, has a high level of uncertainty and non-linearity. Traditional methods of AI learning, such as the neural network, have been used to model stock prices and do trading. These methods have been chosen for their ability to model complex, non-linear systems such as stock markets, however their ability to do this is debatable [14,15]. Neural networks are well known for their ability to model complex systems, however in the case of the stock market this feature may be a hindrance. A neural network models data by changing weights in order to minimize error, given the high level of noise in stock prices it is common for the network to model the noise in data, rather than the underlying signal. This has been termed "overfitting". The network becomes so tuned to the specific data that it is unable to generalize to new data. In the stock market this is very undesirable, an algorithm may perform remarkably well while test trading, however when it is used in a live market situation it will make huge losses [16].

This is due to the noise in the modeled data changing, the algorithm will be unable to react because it believes the data is taking a different path, when in fact the noise has pushed it off the track of the underlying signal.

IV. SIGNIFICANCE AND BENEFITS

The use of algorithmic trading has provided impressive economic benefits to the United States. The automation of the trading process has increased efficiency in the US markets, which is highly desirable in this time of slow economic growth. These higher productivity levels are likely to help the US trade deficit and will help the US financial sector to maintain growth and innovation. Conspicuously, the rise in the swiftness and accuracy of US equity markets aided by algorithmic trading causes investors to incur big savings on trading cost[17]. The Tabb Group report estimates that investors would have saved about $11.5 billion in 2006[1]. The rise in the quality of the US market credited international investors with more to invest in US equities. For instance, between 2005 and 2007 the US equity trading accounts of European based traders have fallen from 28% to only 16%; the majority of trading is now done in the United States which is more liquid and cheaper [18]. Overall, the increase in trade volume and cost savings has led to an estimated $2 trillion increase in funds allocated to US equity markets. All of these measures of success - trade volume, quality, and investment in the US equity markets - are expected to bring a significant positive impact on the long-term economic growth in the United States.

In terms of creating new job opportunities, a global simulation approach to AI impact on employment predicts that a 1% increase in new AI raises the growth rate of employment by 0.88% and the growth rate of the wage by 0.93%[19]. This simulation suggests that the productivity increases due to AI will significantly increase the demand for labor, but the effect on employment and job wage will depend on the price changes of AI relative to human wages.Firms engaging in algorithmic trading are not only competing on strategy. They are, much like the rest of the business world, competing for resources. This could be talent, such as a quant with a PhD in math specializing in a particular area of statistical arbitrage, or computing resources to test and run their strategies. As such, there is a race to get the latest and greatest methods of pricing and volatility discovery, signal generation, alpha creation and risk management into the market.

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V. ENHANCEMENTS

Machine learning techniques, for example, have proven themselves to be superior to static model strategies due to their ability to more closely model complex systems and changing environments. In the future, it is likely that machine learning will be expected as a basic requirement for any trading algorithm, just as online trading is today. This will be both a pro and con. On one hand, with machine learning being a statistically based process, it is nearly impossible to prove that the strategy behind an algorithm is not discriminatory in some way [19]. This could leave the door open to another wave of litigation if public opinion turns and there are mass complaints against "unfair" trading practices. On the other hand, with trading becoming a thoroughly machine-based process, the probability of trading errors caused by humans will decrease and the need for a human to directly supervise an algorithm will also decrease. This could lead to significant reductions in employment within the financial sector.Algorithmic trading specifically may or may not come under closer regulatory scrutiny. Algorithmic and high-frequency trading were big news in 2010, as the U.S. Securities and Exchange Commission and other regulatory agencies began to investigate any possible connection between the "flash crash" and the automated trading strategies that quickly offloaded positions as stock prices declined [20].

VI. CONCLUSION

The aim of the research is to give a deeper understanding of algorithmic trading and its relation with AI, and how AI can affect the trading itself. This research is more intended to provide formal information with complete sources for a better understanding, especially for AI developers and people who work in the trading market and want to improve their trading analysis methods.A high number of algorithmic trading firms are more likely to depend on AI, as their profit is highly time dependent. AI is not just being used for investment decisions and trading strategies, many firms are looking for different ways they can use AI to gain a competitive edge, whether that be through alpha generation, risk management and compliance, operational efficiency, and even client interaction. Classification of an algorithm making a certain decision in order to maximize some expected value as different from one making that same decision out of utility to a human is not one that the current legal system is equipped to handle. A situation where algorithm developers are held liable for actions of their algorithms offers no incentive to use algorithms in place of humans, while no differentiation from the status quo offers no reason to expect a difference in the results. Regulations do not only affect whether a given algorithm can be implemented, but also its competitiveness with the rest of the market. If constraints add costs to specific types of trading, firms will move resources away from developing strategies that are no longer cost effective.

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