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The Application and Prospects of Deep Learning in the Field of Quantitative Investment

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Abstract: This literature review provides a comprehensive overview of key developments in quantitative trading theory, machine learning-based financial time series forecasting, deep learning-based financial time series forecasting, and modern quantitative investment strategies. It highlights seminal contributions from renowned scholars and researchers in the field. This review first explores the Efficient Market Hypothesis (EMH) proposed by Eugene Fama in 1970 and its empirical validation, which lays the foundation for understanding stock market dynamics. It then focuses on the application of machine learning to financial time series forecasting, including Hull's Delta strategy, Hujll J's multifactor model regression series, and Junhua Chen's seminal work in 2009, which emphasizes the role of machine learning in solving the challenges of financial time series data. Finally, an overview of the development of deep learning in financial time series forecasting is presented, including the comprehensive model of Bowie et al., the success of Junhua Chen's Deep Belief Network (DBN), and the sequence data processing capabilities of the Multi-stage Attention Network (MAN) model. In terms of modern quantitative investment strategies, it covers research areas such as EBIT/EV-based stock ranking studies, higher-order moment analysis, frequent trading strategies, and investor sentiment indicators. In summary, this literature review showcases the evolution of quantitative trading theory, the emergence of machine learning and deep learning in financial time series forecasting, and the development of modern quantitative investment strategies, offering valuable insights and tools for investors, researchers, and practitioners in financial markets.

Keywords: quantitative trading theory, machine learning, modern quantitative investment strategies

1. Introduction

The literature review explores key developments in quantitative trading theory, machine learning-based financial time series forecasting, deep learning-based financial time series forecasting, and modern quantitative investment strategies. It discusses the contributions of various scholars and researchers in these domains and their impact on our understanding of financial markets.

2. Methods

2.1. Factors that Can Influence Stock Prices

Numerous economists and scholars have conducted extensive research on the factors that can influence stock prices. Among these, Eugene Fama [1] proposed the Efficient Market Hypothesis (EMH), which posits that past information about an asset can to some extent determine its current price. Fama conducted empirical research on this hypothesis and adjusted for three subsets of relevant information about security prices. The results indicated that, except for a few exceptions, the Efficient Market Model holds theoretical ground.

Nineteen years later, Fama and French [2] analyzed the expected returns on common stocks. They concluded that expected returns are lower during strong economic conditions and higher during weak economic conditions. This finding aligns with the relationship between market expectations of returns and economic conditions. Four years after that, Fama and French [3] further investigated the factors influencing stock returns and introduced the Three-Factor Model, which identifies three common risk factors: the overall market, company size, and book-to-market ratio. They believed that these three factors can explain average stock returns. This model has been widely applied in stock investment strategies and risk management, offering crucial guidance to investors.

These studies provide important theoretical and empirical support for understanding the factors influencing stock prices. They help us better predict and navigate the dynamics of the stock market, enhancing investment effectiveness and risk management capabilities.

Carhart [4] did the Three-Factor Model by adding a momentum factor. This momentum factor primarily considers the trend in stock price changes and attempts to explain stock price movements through market expectations and emotions. The introduction of this factor model enriched our understanding of the factors influencing stock prices. Burton G. Malkiel introduced the Random Walk Theory, a concept that posits that today's stock prices are entirely independent and devoid of any relationship with yesterday's prices. This theory, in its essence, challenges the long-standing and widely accepted Efficient Market Hypothesis. Malkiel's [5] proposition ignited a profound reevaluation of market efficiency and prompted a closer examination of the dynamics governing stock price movements. The notion that stock prices move in a random, unpredictable manner triggered a significant shift in how market participants perceive and analyze financial markets.

However, this paradigm shift didn't go unchallenged. In 2004, a pivotal study conducted by Titman [6] and colleagues raised questions about the validity of existing factor models in predicting stock market trends. Their research argued that neither Eugene Fama's nor Carhart's factor models accurately anticipated the future direction of the stock market. A key revelation from their work was the observation that certain substantial investments made by companies did not translate into corresponding stock price growth. Instead, these investments led to negative returns. This revelation was a groundbreaking discovery, as it cast doubt on the efficacy of conventional factors, particularly company size and book-to-market ratio, in explaining stock returns. In essence, it challenged the conventional wisdom regarding the impact of these factors on stock prices.

To address this newfound complexity, Eugene Fama and Kenneth French [7] took a proactive approach in 2006 by introducing a novel model. This model departed from the traditional factors and incorporated expected investment and book-to-market value ratio as predictive elements of stock returns. They employed a dividend discount model, a sophisticated valuation technique, to more accurately anticipate a firm's profitability and, by extension, forecast its future stock returns. This innovative model ushered in a new era for investors by providing them with a richer, more precise framework for crafting their stock investment strategies. It represented a significant leap forward in our understanding of the multifaceted factors influencing stock returns and marked a pivotal moment in the ongoing evolution of financial theory and practice.

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2.2. Machine Learning-Based Financial Time Series Forecasting

Quantitative trading strategies have been the subject of extensive research, with a diverse array of approaches and methodologies.

Hull J [8] a significant contribution to the world of quantitative trading by introducing the Delta strategy, which has since become a timeless classic in the field. This strategy revolves around the fundamental concept of purchasing securities when their prices are in an upward trajectory and selling them when their values are on a downward trend. And he also embarked on a deep exploration of the quantitative trading landscape. his research was marked by a meticulous examination of nine potential factors that held the power to sway portfolio returns and influence risk levels. Through a rigorous analytical process, they skillfully isolated and identified eight of these factors as being particularly influential. Building on this foundation of insights, Hujll J and their team proceeded to construct a multifactor model regression sequence. This pioneering research effort not only contributed to the quantitative trading arena but also laid the groundwork for a more nuanced and sophisticated comprehension of the intricate relationships among these factors. The multifactor model regression sequence emerged as a valuable tool in deciphering how these factors interplay in shaping trading strategies, further enhancing the quantitative trading landscape.

The year 2009 marked a significant turning point in the realm of financial time series data analysis, thanks to the pioneering work of Chan [9]. In their research, Chan prominently highlighted the formidable challenges associated with this type of data, emphasizing its notorious traits of nonlinearity, non-stationarity, and the pervasive presence of substantial noise. Financial time series data, once considered manageable, had evolved into a highly complex and dynamic landscape that traditional time series analysis tools struggled to address effectively. These traditional tools, which were previously reliable, were now deemed inadequate in the face of such data intricacies.

However, Chan's research didn't merely shed light on the challenges—it also pointed the way forward. With the rapid advancement of data science techniques, a transformative solution emerged: machine learning. This powerful paradigm shift in analytical approaches offered a robust toolkit for tackling the complexities of financial time series data. Machine learning, with its adaptability to nonlinearity, capacity to handle non-stationarity, and ability to extract meaningful signals from noisy data, has found extensive applications in the field of financial time series analysis. It represents a revolutionary leap in the ability to model and understand the intricate dynamics of financial markets, providing researchers and practitioners with a powerful set of tools to navigate the evolving landscape of finance. Chan's research, therefore, not only highlighted the challenges but also ushered in a new era of data-driven analysis in finance.

2.3. Deep Learning-Based Financial Time Series Forecasting

Machine learning faces significant limitations when dealing with ultra-high dimensional datasets, and is prone to problems such as dimensionality catastrophe and ineffective feature representation. However, deep learning models, due to their unique algorithmic principles, perform well in coping with ultra-high dimensional financial time series datasets. Thus the application of deep learning algorithms in the financial time series domain has become a high-profile research direction in recent years.

Wei Bao et al. [10] proposed an innovative deep learning framework that skillfully integrates three models, namely, wavelet transform (WT), stacked auto-encoders (SAEs), and long- short-term memory networks (LSTMs), with each other for the task of predicting stock price trends. The results of this study show that this integrated model exhibits significant advantages in several key aspects.

First, by introducing the wavelet transform into the model, the researchers were able to better capture and process the different frequency components of the financial time series data, thereby

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improving the representation of the data. This helps to capture the cyclicality and volatility of stock prices more accurately. Then, the use of stacked self-encoders (SAEs) allowed the model to learn and extract key features and representations automatically, eliminating the need for manual feature engineering. This means that the model can better adapt to the complexity and variability of the data, resulting in improved prediction accuracy. Most importantly, the Long Short-Term Memory Network (LSTM), as part of the model, has the ability to process sequential data to capture temporal correlations and dependencies, which is crucial for stock price prediction. The introduction of the LSTM helps the model to better understand and predict future price trends.

Overall, the deep learning framework proposed by Wei Bao et al. has achieved significant success in stock price trend prediction by fusing these three key models and fully utilizing their respective strengths. This research provides an innovative example of deep learning applications in finance, offering powerful tools and methods to improve forecasting accuracy and profitability performance. In 2012, Jun-Hua Chen and his team conducted research on predicting crude oil futures prices using the Deep Belief Network (DBN) model [11]. Their experimental results unveiled the remarkable performance of deep learning models, particularly the Deep Belief Network (DBN), in the domain of financial time series modeling. This provided robust support for forecasting crude oil futures prices.

First and foremost, the DBN model introduced in the study possesses the capability of multi-level feature extraction and representation learning. This implies that the model can automatically learn and extract highly abstract features from raw crude oil futures price data without the need for extensive manual feature engineering. This automated feature learning contributes to better capturing crucial patterns and trends inherent in the data. What's more, the deep structure of the DBN model enables it to handle long-term dependencies and nonlinear relationships within time series data effectively. This is particularly significant in financial time series data, where price movements are often influenced by various factors and intricate temporal correlations. The DBN model excels at capturing these complex associations, consequently enhancing the accuracy of crude oil futures price predictions.

Most importantly, the study's empirical evidence unequivocally demonstrated the outstanding performance of deep learning models, especially the DBN model, establishing it as a potent tool for analyzing and forecasting financial time series data. This discovery paves the way for new methodologies and techniques in predicting crude oil futures prices, offering improved market insights and wiser decision-making for investors and stakeholders. The research by Jun-Hua Chen and colleagues serves as a catalyst for the widespread adoption of deep learning in the realm of finance, providing valuable tools for participants in financial markets.

The Multistage Attention Network (MAN) prediction model is a deep learning framework that utilizes attention mechanisms. This model employs an LSTM encoder-decoder structure and integrates both local and global attention mechanisms into the encoder. Additionally, it incorporates a time attention mechanism and an external influence factor fusion module in the decoder. Based on this architecture, the MAN model demonstrates excellent predictive performance in empirical studies.

At first, the MAN model adopts the LSTM encoder-decoder structure, enabling effective handling of sequential data. The encoder is responsible for encoding the input sequence into meaningful representations, while the decoder generates the target sequence. This structure allows the MAN model to capture essential information and patterns within sequences. After that, the model introduces both local and global attention mechanisms to focus on different positions of the sequence. The local attention mechanism allows the model to concentrate on specific parts of the sequence, while the global attention mechanism considers information from the entire sequence. The combined use of different levels of attention enhances the model's predictive capabilities. Also, the MAN model utilizes a time attention mechanism and an external influence factor fusion module to

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comprehensively consider the impact of time and external factors on predictions. This comprehensive modeling enables the MAN model to make more accurate predictions of the target sequence.

In this case, the Multistage Attention Network (MAN) model is a deep learning framework with outstanding predictive performance. It combines various attention mechanisms and factors, such as time and external influences to provide a powerful tool for sequence data prediction. The successful application of the MAN model in empirical research opens up new breakthroughs and opportunities in the field of sequence data analysis and prediction. In summary, scholars have demonstrated that deep learning algorithms, such as RNN, LSTM, DBN, and other models, can well predict financial time series.

3. Results

The research in quantitative trading theory, including Fama's EMH and the Three-Factor Model, has provided valuable insights into stock price dynamics. Carhart's inclusion of a momentum factor challenged traditional models, and Titman's study raised questions about their validity. Fama and French responded with an innovative model that incorporated expected investment and book-to-market value ratio, advancing our understanding of stock returns. In machine learning-based financial time series forecasting, Hull's Delta strategy, Hujll J's multifactor model, and Chan's work highlighted the role of machine learning in addressing data challenges. This shift in approach marked a significant development in financial analysis.

Deep learning-based financial time series forecasting, as demonstrated by Wei Bao et al.'s integrated model and Jun-Hua Chen's use of DBN, showed promise in capturing complex patterns in financial data. These models offered improved predictive accuracy and represented a new era in data-driven financial analysis.

4. Conclusion

Modern quantitative investment has a history of over thirty years in foreign countries, with its roots tracing back to the 1980s when American scholars started leveraging computer technology in various areas of finance, including portfolio management and quantitative factors.

Sareewiwatthana Paiboon and colleagues [12] conducted an in-depth investigation into the quantitative investment strategies employed by renowned investors in the Thailand Stock Exchange over the period spanning from 2002 to 2016. The outcomes of their research unveiled a particularly interesting finding: when stocks were ranked based on enterprise value (EBIT/EV), this approach yielded the highest risk-adjusted return among the 30 carefully selected stocks under scrutiny.

Additionally, in a separate study conducted by Lu Wanbo [13] and his team in 2016, a cutting-edge technique known as time-varying moment component analysis was employed to extract high-order moment absorption rates from financial data. Building upon this analysis, they enhanced the existing threshold-based method for determining the number of high-order moment factors. Moreover, they introduced a novel concept: a joint moment component analysis based on element values. This pioneering approach paved the way for the formulation of a quantitative investment strategy that capitalized on the high-order moment correlation structure inherent in the stock market. Remarkably, the research results stemming from this strategy indicated its effectiveness in predicting movements in stock prices.

These two distinct research endeavors underscore the significance of quantitative analysis in the realm of finance. They exemplify how quantitative methodologies can be applied to identify valuable insights in investment strategies. Sareewiwatthana Paiboon, et al.'s work, emphasized the practical application of EBIT/EV-based stock ranking for superior risk-adjusted returns. Similarly, Lu Wanbo et al.'s research highlighted the potential of advanced moment component analysis to enhance the predictive power of quantitative investment strategies, ultimately contributing to more informed investment decisions and portfolio optimization.

The development of modern quantitative investment has significantly impacted financial markets worldwide, with continuous advancements in computational techniques and data analytics playing a crucial role. Scholars and practitioners have been actively exploring various quantitative strategies to optimize portfolio performance and enhance risk-adjusted returns. These studies in Thailand and abroad contribute to the growing body of knowledge in the field of quantitative finance and underscore the importance of quantitative methods in investment decision-making.

Zihe Tang [14] and their research team, in their comprehensive study published in 2017, delved deeply into the realm of frequent trading strategies, with a particular focus on rational investors who adopt a long-term conservative approach within this domain. Their extensive research efforts led to significant revelations regarding the critical influence of stock price trends on quantitative investment strategies.

Through a rigorous analysis of empirical data and the extraction of practical insights, their work yielded invaluable investment recommendations aimed at assisting investors in harnessing the potential of market volatility to their advantage. This research effectively served as a guiding beacon for investors, offering concrete strategies on how to navigate the complex terrain of market fluctuations, especially in the context of frequent trading.

The findings and recommendations stemming from their study underscored the importance of a well-informed and strategic approach to frequent trading, equipping investors with the knowledge and tools needed to make informed decisions in dynamic market conditions. Zihe Tang and their colleagues' research contributed significantly to the understanding of rational investment strategies and their application in the ever-changing landscape of financial markets.

Moreover, Wang Chenglong and his team [15] adopted a quantitative investment framework with a specific emphasis on investor sentiment. They selected various metrics such as trading volume, turnover rate, price-to-earnings ratio (PE), and price-to-book ratio (PB) as proxy variables for investor sentiment. By employing statistical methodologies, they derived representative indicators, which were subsequently utilized to construct a sentiment index. This index served as a foundation for constructing regression models. Their empirical findings demonstrated the efficacy of this strategy in accurately predicting the upward or downward movements of stock portfolios.

The literature contributions primarily revolved around innovations in quantitative factors and portfolio selection. By pioneering novel quantitative trading strategies, these studies achieved higher returns and provided investors with valuable tools to navigate the complex landscape of financial markets. The research insights offered practical guidance for investors seeking to optimize their investment strategies and navigate the ever-changing dynamics of the financial world.

Future research in quantitative trading theory can continue to explore innovative factor models and their application to stock pricing. Machine learning and deep learning-based approaches should be further developed to address evolving data challenges in financial time series analysis. Additionally, exploring integrating sentiment analysis and other alternative data sources in quantitative investment strategies holds promise for future advancements in the field.

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