A Comparative Analysis of Deep Learning and Traditional Portfolio Optimization Models in Developed Financial Markets

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Divyanshu
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CANDIDATES DECLARATION

I hereby certify that the work, which is being presented in the report, entitled **A Comparative Analysis of Deep Learning and Traditional Portfolio Optimization Models in Developed Financial Markets** , in partial fulfilment of the requirement for the award of the Degree of **Masters of Business Administration** and submitted to the institution is an authentic record of my own work carried out during the period *June 2023* to *October 2023* under the supervision of **Dr. Vishal Vyas**. I have also cited the references about the text(s)/figure(s)/table(s) from where they have been taken.

Date: Signatures of the Candidates

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Date: Signatures of the Research Supervisor

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Abstract

Advancements in machine learning have opened up a wide range of new possibilities for using advanced computer algorithms, such as deep learning in portfolio risk management. However, very little evidence has been provided on the superior performance of deep learning models over traditional optimization models following the mean-variance framework in different financial market settings. This study uses two experiments with data from the Indian and U.S. securities markets to justify whether advanced machine learning models could outperform traditional portfolios' cumulative returns while optimizing the Sharpe ratio.

Keywords- Deep Learning, Optimization, Securities Market,

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CHAPTER 1

Introduction

In section 1.1 of this chapter, an overview of the background for the Portfolio Optimisation project is provided. The study work flow is then introduced step by step in section 1.2 as a result of the motives that have been provided. The motivation is discussed in section 1.3. The Research Workflow are then described in section 1.4.

1.1 Context

Portfolio optimization is a crucial element of asset management, aiming to maximize returns at a given risk level by selecting the optimal asset distribution within a portfolio. This concept was first pioneered by (Markowitz, 1952) leading to the development of Modern Portfolio Theory (MPT).

The primary advantage of constructing a diversified portfolio is the ability to reduce risk and create a smoother equity curve. Diversification allows for a higher return per unit of risk compared to investing solely in individual assets. This principle holds true as long as the assets in the portfolio are not highly correlated.

Indeed, while the benefits of diversification in portfolio allocation are indisputable, the process of selecting the "optimal" asset allocations is far from straightforward. This complexity arises from the dynamic nature of financial markets, which undergo significant changes over time. Assets that have exhibited strong negative correlations in the past may become positively correlated in the future, introducing an additional layer of risk and potentially compromising the portfolio's future performance.

Furthermore, the sheer breadth of available assets for portfolio construction poses a formidable challenge. For instance, in the context of the U.S. stock markets alone, there are more than 5000 individual stocks to consider. Additionally, a well-structured portfolio often extends beyond equities and may include bonds and commodities, significantly expanding the array of options available for allocation.

1.2 Objectives

To overcome the limitations associated with traditional mean-variance methods based on quadratic optimization, researchers have explored novel approaches in the field of portfolio optimization. These alternatives encompass both statistical and machine learning methods, offering promising avenues for improving portfolio management strategies.

Statistical approaches have been a focus of attention in this study. These methods include Autoregressive Conditional Heteroscedasticity (ARCH) introduced by (Engle and Granger, 1987) Autoregressive Integrated Moving Average (ARIMA), and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) proposed by (Bollerslev, 1986). These statistical techniques have traditionally been employed to model financial time series data and capture volatility dynamics.

In recent times, machine learning methods have gained significant traction for portfolio optimization, particularly in the context of forecasting. Approaches such as Neural Networks (NNs) (Bisoi et al., 2019) Support Vector Regression (SVR) (Chen et al., 2015) and ensemble learning (Zhou et al., 2019) have become popular choices. According to several comparative studies, machine learning exhibits greater capability in handling non-linear and non-stationary situations compared to statistical methods (Wang et al., 2020).

In addition to using machine learning models for return prediction in portfolio construction, this study introduces advanced methods that leverage Deep learning to directly optimize portfolios. This approach deviates from traditional techniques (McNeil et al., 2015) which typically involve forecasting projected returns, often using econometric models. Notably, these prediction stages do not guarantee optimal portfolio performance (Moody et al., 1998) as they seek to minimize a prediction loss that does not necessarily align with maximizing the portfolio's total gains.

In contrast, the proposed method focuses on optimizing the Sharpe ratio, which represents the return on investment per unit of risk. By directly optimizing this metric, it aims to enhance portfolio performance, offering a different and potentially more effective approach to portfolio optimization compared to traditional methods.

This innovative approach underscores the evolving landscape of portfolio optimization, as researchers increasingly explore machine learning and Deep learning techniques to address the challenges and complexities of modern financial markets.

1.3 Motivation

In recent years, there has been a growing utilization of machine learning techniques within the realm of finance, potentially influencing how hedge fund managers perceive the risk-reward ratio in financial markets (Wu et al., 2021). Notably, advanced machine learning algorithms have demonstrated remarkable achievements in various domains, including video games (Mnih et al., 2015) and board games (Silver et al., 2016).

Following the historic victory of the computer program AlphaGo over Lee Sedol, one of the most formidable human players in the game of Go, in 2016, professionals in the financial trading sector have developed a keen interest in deep learning methods, particularly Deep reinforcement learning (Meng and Khushi, 2019).

Machine learning techniques offer substantial potential in portfolio construction, with deep learning assuming an increasingly pivotal role within the industry (Bartram et al., 2021). This shift underscores the importance of leveraging advanced computational approaches to enhance decision-making processes and manage investment portfolios effectively.

Furthermore, in the context of wealth management, (Li et al., 2020) have highlighted the effective application of deep learning techniques, in optimizing asset allocation strategies. This indicates that machine learning, and deep learning in particular, have become integral tools for financial professionals seeking to navigate the complexities of modern wealth management and investment strategies.

1.4 Project work flow

The primary objective of this study is to conduct a comprehensive performance comparison of ten distinct portfolio construction methodologies, encompassing a wide array of approaches mentioned in the finance literature. These methodologies include mean-variance techniques (such as equally weighted portfolios, portfolios maximizing the Sharpe ratio, minimum variance portfolios, and portfolios aiming to maximize decorrelation), statistical approaches (comprising hierarchical risk parity, principal component analysis, and Holt's smoothing process), as well as deep learning models implemented through deep neural networks.

Financial asset prices exhibit a strong connection to their volatility patterns over time. Naturally, the predictability of stable stocks tends to surpass that of stocks with relatively higher levels of price noise. Therefore, to provide a more comprehensive assessment of the performance of various portfolio construction methods, the study incorporates multiple timeframes and asset types in its experimental design. This multifaceted approach allows for a more holistic understanding of how these methods perform under varying conditions.

The research employs two distinct experimental designs, each representing different timeframes and asset types. This approach enables a nuanced evaluation of the portfolio construction methods' effectiveness across diverse contexts, taking into account the varying characteristics of assets over different time horizons.

Additionally, to enhance the comparability of the methods under investigation, the study adopts a standardized input framework. Specifically, historical closing prices of financial assets serve as the sole input for all models. This standardized input approach ensures a level playing field, allowing for a fair comparison of the ability of these methods to process and leverage non-linear relationships. Notably, deep learning, as well as reinforcement learning, have demonstrated the capability to harness such non-linear relationships, potentially leading to superior results when compared to more linear methods commonly employed in portfolio construction.

In summary, this study adopts a rigorous and systematic approach to evaluate the performance of various portfolio construction methods, encompassing mean-variance, statistical, and deep learning techniques. By considering different timeframes, asset types, and utilizing a consistent input framework, the research aims to provide valuable insights into the effectiveness of these methods in optimizing portfolio construction within the realm of finance.

CHAPTER 2

Literature Review

Naïve diversification, also known as equal-weighted portfolio construction, is a simple approach for reducing a portfolio's idiosyncratic risk without sacrificing the expected rate of return. It involves allocating equal weights to assets in the portfolio. In contrast, portfolio optimization, pioneered by Harry Markowitz, aims to find the optimal allocation of weights that achieves an acceptable expected return with minimal volatility.

Modern Portfolio Theory (MPT), by (Markowitz, 1952), maximizes returns for a given risk level via mean-variance portfolio construction. The theory centers on the efficient frontier, guiding investors in optimizing expected returns for a chosen risk level.

Markowitz's efficient frontier is a core MPT concept. It's the part of the minimum-variance curve extending above and to the right of the global minimum variance portfolio. Rational, risk-averse investors prefer portfolios on this frontier for their superior risk-return trade-off. As risk escalates, the efficient frontier curve flattens, underscoring a key MPT principle: continually pursuing higher returns entails disproportionately more risk. Thus, effective diversification is crucial to balancing risk and return. In essence, MPT encourages investors to construct portfolios along the efficient frontier to maximize expected returns while recognizing the diminishing returns associated with escalating risk.

Market capitalization-weighted portfolios have garnered criticism for their inefficiency and long-term underperformance compared to equally weighted portfolios. This observation is supported by studies such as those by (Bolognesi et al., 2013) and (Malladi and Fabozzi, 2017). Additionally, research by (DeMiguel et al., 2009) not only reaffirmed the superior efficiency of equal-weighted portfolios over capitalization-weighted ones but also demonstrated that equal-weighting outperforms mean-variance-based portfolio strategies in out-of-sample testing.

Recent research, such as the study by (Taljaard and Maré, 2021) has highlighted a shift in the performance dynamics of equal-weighted portfolios. Specifically, it has been observed that an equal-weighted portfolio of stocks in the S&P 500 now significantly underperforms the market capitalization-weighted portfolio, especially in the short term. This contrasts with earlier findings.

Moreover, (Kritzman et al., 2010) argued that optimized portfolios, which are constructed through sophisticated optimization techniques, demonstrate superior out-of-sample performance when compared to equal-weighted portfolios. This suggests that optimization methods can provide better results than the traditional equal-weighting approach.

Given these evolving dynamics, it is prudent to consider a comprehensive comparison of various portfolio construction approaches, including both baseline methods like equal-weighting and more advanced optimization techniques. Such an assessment can provide a more nuanced understanding of the changing landscape of portfolio performance and help investors make informed decisions based on their specific objectives and investment horizons.

The foundation of the Markowitz efficient frontier is constructed upon certain assumptions that have faced scrutiny when applied to real-world contexts (Ma et al., 2021). Specifically, it presupposes that all investors exhibit rational behavior and are uniformly risk-averse. Furthermore, the model assumes that every investor enjoys equal access to borrowing funds at a risk-free interest rate, despite this not aligning with the actual circumstances. Additionally, the traditional concept of the efficient frontier operates on the premise that asset returns conform to a normal distribution, whereas, in practice, asset returns frequently deviate significantly, often extending as far as three standard deviations from the mean.

Machine learning offers significant potential for the development of effective trading strategies, particularly in the realm of high-frequency trading, a feasibility that was previously limited (Arnott et al., 2019). The benefits of employing algorithmic machine learning in trading are extensive (Zhang et al., 2020), with a primary focus on enhancing alpha, or excess returns ((Sirignano and Cont, 2019) and (Zhang, Zohren and Roberts, 2019)). Much of the research concentrates on regression and classification pipelines, which involve forecasting excess returns or market movements over specific, predefined time horizons.

The utilization of machine learning techniques in finance has been on the rise, potentially influencing the way hedge fund managers assess risk-reward ratios within the financial market. Hedge funds, known for their adaptability, have been garnering increasing interest from investors (Wu et al., 2021). In a comprehensive research endeavor, (Wu et al., 2021) employed machine learning for hedge fund return prediction and selection, demonstrating that machine learning-based forecasting methods consistently outperformed the respective Hedge Fund Research indices across various scenarios. Among the four machine learning methods examined by (Wu et al., 2021), neural networks emerged as particularly noteworthy.

Concerning risk management, (Arroyo et al., 2019) have demonstrated the utility of machine learning in aiding venture capital investors in their decision-making processes. This technology assists in identifying investment prospects and evaluating associated risks. Additionally, (Jurczenko, 2020) has found that machine learning algorithms play a valuable role in enhancing stock risk forecasts, particularly when it comes to out-of-sample predictions of equity beta.

In a comprehensive research conducted by (Gu et al., 2020) it was found that machine learning tools surpass linear methods in terms of their predictive capabilities. The effectiveness of portfolios constructed using machine learning algorithms has been established, particularly for portfolios that have not undergone optimization, as highlighted by (Kaczmarek and Perez, 2021). Despite its widespread acceptance, the modern portfolio theory has faced criticism for its practical limitations ((Kolm et al., 2014) and (DeMiguel et al., 2009)). Consequently, a growing body of literature is dedicated to enhancing portfolio optimization techniques. This includes exploring alternatives such as replacing the statistical moments of asset returns with more reliable predictions (DeMiguel et al., 2009) or applying machine learning methods in place of traditional quadratic optimization, as proposed by (De Prado, 2016).

In the context of optimized strategies, (Kaczmarek and Perez, 2021) have demonstrated that when machine learning methods are employed for the preselection of stocks within portfolios, conventional portfolio optimization methods such as mean-variance and hierarchical risk parity exhibit an enhancement in the risk-adjusted returns of these portfolios. This improvement results in the outperformance of equal-weighted portfolios in out-of-sample analyses.

Recently, there has been a growing interest in applying Deep learning techniques to portfolio allocation tasks within the field of finance. This surge in interest began following the seminal work of (Zhang, Zhong, Dong, Wang and Wang, 2019), leading to the emergence of a new branch of finance focused on the utilization of Deep learning methods in portfolio construction. Initially, these methods were applied to various financial domains, including cryptocurrencies, and as well as other asset classes.

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