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до кваліфікаційної роботи бакалавра

на тему «Компаративний аналіз підходів на основі GPT та класичних методів вибору інвестиційного портфеля»

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Міністерство освіти і науки України
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Навчально-науковий інститут комп’ютерних наук та штучного інтелекту
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З А В Д А Н Н Я
НА КВАЛІФІКАЦІЙНУ РОБОТУ

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1. Тема роботи ”Компаративний аналіз підходів на основі GPT та класичних методів вибору інвестиційного портфеля”

керівник роботи Бабенко Віталіна Олексіївна, д.е.н., к.т.н., професор кафедри математичного моделювання та аналізу даних,
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2. Строк подання студентом роботи 5 червня 2025 року

3. Перелік питань, які потрібно розробити
Аналіз класичних моделей оптимізації портфеля, застосування великих мовних моделей (GPT) для обробки фінансових даних, розробка гібридного підходу до формування інвестиційного портфеля, побудова промтів, обробка відповідей LLM, формування ваг активів, порівняльне тестування підходів, побудова графіків, обчислення фінансових метрик

4. План роботи

№ з/п	Назви етапів роботи
1	Аналіз класичних моделей оптимізації портфеля
2	Вивчення можливостей GPT у фінансовому аналізі
3	Побудова програмної системи для інтеграції GPT
4	Реалізація класичних та AI-методів у Python
5	Проведення обчислювального експерименту
6	Аналіз результатів, побудова графіків, висновки
7	Оформлення роботи, підготовка до захисту

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ANNOTATION

This bachelor thesis consists of 71 pages, 21 figures, 3 tables, 2 appendices, and 38 references.

The thesis explores and compares two approaches to investment portfolio construction: classical models (such as Markowitz optimization and Fama-French multifactor models) and a novel method based on large language models (LLMs), specifically GPT-3.5. The work applies machine learning techniques, natural language processing (NLP), and mathematical modeling for data-driven financial decision making.

The proposed solution includes the design and implementation of a GPT-powered chatbot for portfolio advisory, with integration of FastAPI, AWS, and React technologies. The work evaluates the effectiveness of GPT-based recommendations versus traditional quantitative models using historical stock market data. Results indicate that LLM-based systems can provide competitive and interpretable investment suggestions.

Keywords: GPT, Portfolio, Classical Approaches, Machine Learning, Artificial Intelligence.

CONTENTS

LIST OF FIGURES

LIST OF ABBREVIATIONS

LLM	Large Language Models
GPT	Generative Pre-trained Transformer
MPT	Modern Portfolio Theory
CAPM	Capital Asset Pricing Model
FF3	Fama-French Three-Factor Model
FF5	Fama-French Five-Factor Model
APCA	Asymptotic Principal Component Analysis
SMB	Small Minus Big
HML	High Minus Low
RMW	Robust Minus Weak
CMA	Conservative Minus Aggressive
AI	Artificial Intelligence
ML	Machine Learning
MKT	Market Risk Factor
HTTP	Hypertext Transfer Protocol
HTTPS	Hypertext Transfer Protocol Secure
GDPR	General Data Protection Regulation
PCI DSS	Payment Card Industry Data Security Standard
API	Application Programming Interface
CI/CD	Continuous Integration/Continuous Deployment
AWS	Amazon Web Services
GCP	Google Cloud Platform

LIST OF SYMBOLS

m	number of observations
n	number of features
X	matrix of training data
y	matrix of target values
β	matrix of fitted linear variables
α	matrix of error terms
W	diagonal matrix of weights
R_i	excess return of asset i over the risk-free rate
MKT	market risk factor
SMB	size premium factor
HML	value premium factor
ϵ_i	idiosyncratic error term
R_f	risk-free rate
$E(R_p)$	expected return on the portfolio
RMW	profitability premium factor
CMA	investment premium factor
Σ	covariance matrix of asset returns
σ_{ij}	covariance between returns of assets i and j
B	matrix representing factor sensitivities of assets
F	matrix representing expected factor returns
Q_f	factor covariance matrix
D	vector representing asset-specific idiosyncratic risk (variance)

INTRODUCTION

Investing in today's global economy goes beyond just a simple financial activity; it serves as a crucial tool for generating wealth and ensuring economic stability. The democratization of financial markets, facilitated by technological improvements and legislative changes, has substantially reduced the obstacles to investment. This advancement has facilitated the inclusion of a wider range of individuals from society in financial markets, extending beyond experienced professionals or those who are monetarily privileged.

1 THE EVOLUTION OF FINANCIAL MARKETS

The advent of the digital revolution has radically transformed the process of making and managing investments. Online platforms and mobile applications have streamlined the procedure of purchasing stocks, bonds, and other financial instruments, hence increasing the accessibility of these markets to the general people. This kind of accessibility is essential in a society where conventional means of saving money are no longer adequate for ensuring financial stability. Given the historically low interest rates in many industrialized economies, investing in financial markets is a practical way to protect and increase wealth in the long run.

1.1 The Significance of Financial Literacy

The increase in accessibility necessitates an improvement in financial literacy. Individual investors now consider it essential to comprehend market dynamics, evaluate risks, and diversify their portfolios. Analyzing economic trends, geopolitical happenings, and company-specific news is crucial for making well-informed investing decisions. This understanding enables investors to efficiently navigate the volatility and intricacies of contemporary financial markets.

1.1.1 The Importance of Information and Technology

The widespread availability of financial information, sophisticated analytical tools, and real-time data has fundamentally changed the way investment plans are developed and implemented. Investors currently have unparalleled access to market insights, financial reports, and predictive analytics. When utilized effectively, this abundance of information can greatly improve investing results. Nevertheless, it also poses difficulties in terms of an excessive amount of information and the necessity for distinguishing valuable data from irrelevant information through critical evaluation skills.

1.1.2 Investing for Long-term Growth

In addition to personal financial objectives, investing plays a vital role in stimulating economic expansion. Investments stimulate economic growth, employment generation, and technological progress by directing resources towards enterprises, infrastructure, and innovation. Developing a carefully thought-out investing strategy can help individual investors achieve financial independence and stability, enabling them to carry out personal objectives like buying a home, pursuing school, and planning for retirement.

Amidst this ever-changing scenario, the tools and processes used in investing are constantly adapting. One of the most important developments is the use of artificial intelligence and machine learning technologies, such as Large Language Models (LLMs), which have the potential to completely transform investment analysis and portfolio management. As mentioned earlier, it is essential to recognize the fundamental purpose and significance of investing. This knowledge becomes more important when we explore how traditional and modern approaches, such as the introduction of LLMs, are influencing the strategies used by investors to achieve financial development and stability.

1.2 Traditional and Modern Approaches to Investment Portfolio Selection

The techniques used in investment portfolio selection have undergone substantial changes, reflecting the overall shifts in financial markets and the underlying technologies supporting them[10][14]. This transformation signifies a transition from conventional analytical frameworks to more agile, data-centric methodologies facilitated by the emergence of artificial intelligence (AI) and machine learning (ML), which includes the deployment of Large Language Models (LLMs) such as GPT.

1.2.1 Traditional Financial Models

The core of traditional portfolio selection is based on the groundbreaking research of Harry Markowitz on Modern Portfolio Theory (MPT), which introduced the idea of diversification to minimize risk and maximize returns. The Capital Asset Pricing Model (CAPM) [13] and the Fama-French three-factor model further enhanced these ideas by incorporating market, size, and value factors into the process of making investment decisions. These models have established a strong quantitative foundation for portfolio selection, using historical market data and statistical analysis to guide investing choices[12]. Their approach to analyzing risk and return is systematic, with a focus on achieving optimal portfolio performance through balance and diversification.

1.2.2 The Advent of AI and ML in Finance

The introduction of AI and ML into finance brings a dynamic and predictive element to portfolio management, contrasting with the static and historical data-centric approach of traditional models. LLMs[2], specifically, present a substantial advancement by providing the capability to process and analyze vast amounts of unstructured data — from financial news and reports to social media sentiment. This capability allows for a more sophisticated understanding of market trends, investor sentiment, and the macroeconomic factors influencing asset prices[8]. By incorporating these models into the investment analysis process, portfolio managers can utilize predictive insights to make more informed, forward-looking investment decisions.

1.2.3 Complementarity and Challenges

The use of LLMs and other AI-powered technologies into conventional portfolio selection procedures offers both prospects and obstacles. LLMs can enhance standard models by offering more profound insights into issues that can be hard to quantify but have substantial consequences for [7]investment results, such as geopolitical risk or regulatory changes. However, successfully incorporating these technologies necessitates skillful management of obstacles pertaining to the accuracy of data, the ability to understand and explain models, and the risk of biased algorithms.

1.2.4 The Hybrid Approach

The future of portfolio selection is expected to be a hybrid strategy that combines the quantitative precision of traditional financial models with the qualitative, data-intensive insights provided by modern AI and ML technologies. This method will not only improve analytic abilities for investors but also create a more flexible and responsive framework for managing portfolios in a market that is becoming more turbulent and complex.

To summarize, the transition from conventional portfolio selection techniques to contemporary methodologies supplemented with artificial intelligence represents a notable progression in financial research. Examining the strengths, limitations, and potential synergies between these techniques is essential in order to create investment strategies that are resilient and flexible in response to the evolving financial market environment.

1.3 The Role of Large Language Models in Long-Term Investing

The emergence of Large Language Models (LLMs) like GPT has introduced a new era in the domain of financial analysis and portfolio management, namely in the realm of long-term investing[15]. These advanced AI technologies have the exceptional ability to analyze, comprehend, and produce text that resembles human writing. They can extract valuable information from large volumes of unorganized data, which conventional financial models struggle to effectively employ. This section examines the revolutionary capacity of LLMs in long-term investing, highlighting their ability to enhance conventional investment methods with profound, data-based insights[11].

1.3.1 Unstructured Data and Market Insights

LLMs have a significant edge in their capacity to analyze unstructured data sources, including financial news, analyst reports, and social media discussion, which provides valuable market insights. This talent is extremely beneficial in long-term investing, as it can have a substantial impact on investment decisions to understand wider market patterns, company-specific storylines, and the macroeconomic climate. LLMs have the ability to analyze this data in order to detect patterns in sentiment, identify emerging market themes, and uncover potential investing risks or opportunities that may not be apparent through quantitative research alone.

1.3.2 Enhancing Traditional Analysis

While conventional financial models prioritize quantitative measurements and historical data, LLMs introduce a qualitative aspect to investment analysis. LLMs can enhance standard models by presenting a comprehensive perspective on potential investment opportunities through their ability to analyze market sentiment and thematic tendencies. For example, an LLM could examine earnings call recordings to evaluate executive sentiment or evaluate the probable consequences of regulatory changes on a particular industry. This analysis would offer significant background for making informed long-term investing plans.

1.3.3 Overcoming Difficulties

Although LLMs have great promise, there are problems in integrating them into the investing process. The opaqueness of these models, where the justification for their outputs may not be completely obvious, presents a difficulty for investors attempting to comprehend the foundation of insights given by LLMs. Moreover, the reliability and validity of the analyses performed by LLMs might be influenced by the quality and bias of the training data utilized in their development. To overcome these obstacles, a meticulous strategy to selecting, training, and validating models is necessary. This ensures that LLMs are utilized in a manner that improves, rather than hinders, the investment decision-making process.

1.3.4 Operationalizing LLM Insights

To effectively utilize LLMs in long-term investing, it is crucial to include their observations in the overall investment strategy. This involves creating systems for converting LLM-generated data into practical investment choices, as well as building procedures for consistently reviewing and revising these insights based on fresh information. The objective is to develop a flexible investment strategy that can adjust to evolving market conditions, guided by both conventional financial analysis and the valuable qualitative insights offered by LLMs.

LLMs play a crucial role in long-term investing by providing a notable improvement in financial analysis. They have the potential to enhance traditional investment techniques by supplying comprehensive insights based on data analysis. As discussed in this section, harnessing this potential necessitates thoughtful examination of the obstacles linked to LLM integration, while also presenting opportunities to improve long-term investment results in a progressively intricate and data-abundant market setting.

1.4 Objective and Prospects of the Study

This thesis aims to dissect the intersection at which traditional financial analysis methods connect with the growing field of artificial intelligence, exemplified by the rise of Large Language Models (LLMs) such as GPT. The main goal is to thoroughly investigate the capacity of LLMs to transform long-term investment strategies, specifically in the context of portfolio selection and management. This study aims to conduct a comparative analysis of LLMs (Liquidity-based Asset Pricing Models) and traditional financial models, such as Markowitz's model, the Capital Asset Pricing Model (CAPM), and the Fama-French multi-factor models. The objective is to determine whether the inclusion of LLMs can provide added value to investors who seek long-term profitability.

1.4.1 Progressing Beyond Conventional Models

For many years, traditional portfolio selection models have been used to develop investment strategies. These models give a systematic way to manage risk and maximize returns. Nevertheless, the ever-changing nature of worldwide financial markets and the intricate architecture of contemporary economic systems require a more sophisticated and data-driven approach. This study examines the potential of LLMs to enhance existing models by using their capacity to handle and analyze large volumes of textual data. It aims to gain deeper insights into market trends, investor sentiment, and the macroeconomic factors that impact asset performance.

1.4.2 Assessing the Effectiveness of LLMs in Financial Analysis

The use of LLMs into financial analysis presents distinct problems and prospects. This study will thoroughly analyze the effectiveness of LLMs in improving portfolio selection procedures, evaluating their ability to accurately forecast outcomes, adapt to different situations, and be practically applied in real-world investing scenarios. At the core of this assessment is the examination of LLMs' opaque nature, the comprehensibility of their results, and the inherent biases in their training data, which may impact investment choices.

1.4.3 Contributions to Financial Modeling and Investment Strategy

The study will investigate the possibilities of creating hybrid investing strategies that combine the quantitative precision of standard financial models with the qualitative, insight-driven analysis provided by LLMs. The project seeks to establish a framework for portfolio management that can successfully incorporate many analytical techniques, enabling it to navigate the intricacies of current financial markets in a flexible and responsive manner.

This thesis aims to provide a valuable contribution to the ongoing discussion on the use of artificial intelligence (AI) in finance. It provides empirical proof of the benefits that Language Model Models (LLMs) can bring to the formulation of investment strategies and the management of portfolios. The objective is to reduce the disparity between the theoretical capabilities of LLMs and their actual implementation in finance. This aims to offer valuable insights that can guide future advancements in financial modeling, investment analysis, and portfolio management methods. The study seeks to achieve these objectives by not only shedding light on the possible synergies between conventional financial models and LLMs, but also by emphasizing the routes and obstacles involved in utilizing AI to stimulate innovation in investing practices for the purpose of long-term value generation.

2 RELATED WORK

2.1 Financial Portfolio Optimization

The pursuit of effective portfolio optimization has been a central focus of financial modeling, aiming to balance the twin goals of maximizing returns and limiting risk[6]. The thorough overview of this undertaking may be found in the fundamental textbook *Optimization Methods in Finance* (Second Edition) by Cornuejols, G., Pena, J., & Tütüncü, R.[3] The authors thoroughly examine the mathematical foundations that govern portfolio optimization, offering a comprehensive account of its historical development and acting as a useful resource for modern financial engineering.

The text explores the fundamental ideas of modern portfolio theory (MPT) by revisiting the conventional mean-variance portfolio optimization models developed by Harry Markowitz in the 1950s. These models promote the strategy of diversifying assets in order to attain an ideal equilibrium between anticipated returns and risk, which is assessed in terms of variance. However, Cornuejols and his colleagues go beyond historical analysis. They explore deeper into the domain of financial innovation by examining more recent advancements, such as models specifically created for achieving the best possible trade execution. These models tackle the practical difficulties of processing huge orders without causing considerable impact on market prices.

Furthermore, the book explores dynamic portfolio allocation strategies that take into account transaction costs and taxes, which accurately represent the complexities that investors encounter in the real world. The relevance of this subject is particularly obvious in today's dynamic financial markets, where the underlying assumptions of classical models frequently require reassessment and modification.

The text combines theoretical rigor with practical relevance, providing readers with valuable insights into effective solution strategies for the primary categories of optimization issues faced in finance.

Within the scope of this thesis, the work of Cornuejols et al. is utilized as a crucial benchmark, offering a fundamental comprehension of conventional financial models that can be used to evaluate the capabilities and advancements of Large Language Models. As we investigate the capabilities of LLMs in finance, the ideas and methodology described in this article will serve as the standard for assessing the effectiveness and efficiency of these new technologies in portfolio optimization.

2.2 Large Language Models in Financial Portfolio Selection

The emergence of Large Language Models (LLMs) like GPT in the domain of financial portfolio selection signifies a noteworthy transformation in the application of artificial intelligence in finance. These models are highly proficient at handling and examining large amounts of written data, allowing for unique insights in financial analysis that go beyond the limitations of conventional numerical data. This transition is especially important for understanding the qualitative elements that impact asset prices, such as market mood, geopolitical events, and regulatory changes. These factors have historically been difficult to measure and incorporate into portfolio selection methods. The ability of LLMs to analyze financial reports, news stories, and real-time market feeds enables a more profound comprehension of market dynamics. LLMs offer a detailed perspective on a company's future prospects and market trends by analyzing patterns in financial news that have historically preceded market moves, as well as by examining earnings call transcripts and management remarks. This nuanced view goes beyond what can be inferred from financial measures alone. The incorporation of LLMs into finance facilitates better investment choices by allowing investors to make educated judgments based on valuable insights obtained from an analysis that considers the intricate interactions of several elements that impact the market.

Nevertheless, the integration of LLMs into financial portfolio selection is not without difficulties. The lack of transparency in these models, frequently referred to as a ”black box,” gives rise to questions over the interpretability and dependability of their results. The lack of transparency in this matter requires investors and financial analysts to be cautious. It emphasizes the need to not entirely depend on LLM advice without a thorough grasp of their analytical foundation. Furthermore, the effectiveness and inherent prejudices of LLMs are greatly impacted by the variety and extent of the data they are trained on. It is crucial to train these models using comprehensive and diverse datasets to prevent biased analyses. This emphasizes the importance of continuously improving LLMs as new data becomes available and market conditions evolve. Although there are difficulties, the growing research on LLM applications for portfolio selection shows promise. It indicates that when used alongside standard investment strategies, LLMs could provide a stronger foundation for portfolio management. This research project seeks to showcase the potential effectiveness of LLMs in improving portfolio selection. Additionally, it aims to investigate techniques for integrating LLMs with traditional models to maximize investment results in the changing field of financial technology.

2.3 Existing Papers on Standard Model Usage in Financial Portfolio Selection

2.3.1 Portfolio Optimization with a Mean-Entropy-Mutual Information Model

The article titled ”Portfolio Optimization with a Mean-Entropy-Mutual Information Model” by Novais, Wanke, Antunes, and Tan presents an innovative portfolio optimization model that replaces the conventional metrics of variance and covariance with entropy and mutual information. Their investigation demonstrates that although mean-entropy (ME) models have benefits in enhancing portfolio variety, they do not consistently surpass mean-variance (MV) and robust optimization strategies in terms of overall performance. The paper highlights the significance of having a diverse and stable portfolio, especially when facing different limitations on returns. It proposes that ME models may be more appropriate for specific market conditions or investment strategies, thereby making a nuanced contribution to the field of financial optimization.

2.3.2 Markowitz Mean-Variance Portfolio Optimization with Predictive Stock Selection Using Machine Learning

The research article titled ”Markowitz Mean-Variance Portfolio Optimization with Predictive Stock Selection Using Machine Learning” by Chaweewanchon and Chaysiri integrates machine learning techniques with the Markowitz model to optimize portfolio selection. Their methodology employs a combination of CNN and BiLSTM model for forecasting stock prices. The objective is to enhance portfolio selection by guaranteeing the inclusion of superior stock inputs. Through a comparison with conventional models using historical data from the Stock Exchange of Thailand, the researchers show that their method outperforms in terms of the Sharpe ratio, mean return, and risk. This emphasizes the potential of combining predictive stock selection with standard portfolio optimization models.

2.3.3 A Network View of Portfolio Optimization Using Fundamental Information

This article authored by Xiangzhen Yan, Hanchao Yang, Zhongyuan Yu, and Shuguang Zhang introduces a new method for portfolio optimization called ”Fundamental Networks” (FN). FN is a highly efficient and resilient network-based method that incorporates fundamental factors. It can be used as a substitute for traditional mean-variance framework models. A fundamental network is a collection of stocks that are interconnected based on their similarity in fundamental information. These links serve as a measure of similarity and directly influence asset allocation. This paper presents two empirical models that serve as applications of Fundamental Networks. Our analysis reveals that, in terms of out-of-sample performance, FN's efficient portfolios tend to be more mean-variance efficient compared to Markowitz's efficient portfolios. Portfolios designed with the aim of achieving profitability targets provide additional returns in a market that typically trends upwards. On the other hand, portfolios focused on operational fitness perform better in a market that is currently trending downwards and can be seen as a defensive strategy during a crisis.

3 THEORETICAL BACKGROUND

3.1 Mathematical Models for Portfolio Optimization

Portfolio optimization is an investment approach that seeks to choose a combination of assets that will maximize the anticipated return while considering a specific amount of risk. This chapter presents a comprehensive overview of the fundamental mathematical models that serve as the foundation for portfolio optimization.

3.1.1 Markowitz Portfolio Optimization

Harry Markowitz's Modern Portfolio Theory (MPT), which was first presented in 1952, transformed investing methods by utilizing a mathematical framework to achieve a balance between a portfolio's anticipated return and its level of risk[11]. The main breakthrough of MPT is the introduction of the efficient frontier, which denotes a collection of optimal portfolios that provide the greatest anticipated return for a specific level of risk or the lowest risk for a specific level of return.

3.1.2 Efficient Frontier Formulation

The efficient frontier is derived by calculating the returns and variances of all possible combinations of assets in a given set. For a portfolio of n risky assets, the expected return $E(R_p)$ is a weighted sum of the individual expected returns $E(R_i)$:

$$E(R_p) = \sum_{i=1}^{n} w_i E(R_i) \tag{3.1}$$

where w_i is the weight of the ith asset in the portfolio.

The risk of the portfolio, measured as the standard deviation of the portfolio's return σ_p, is found by:

$$\sigma_p = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}} \tag{3.2}$$

where σ_{ij} is the covariance between the returns of assets i and j. **Portfolio Selection** Investors select portfolios positioned on the efficient frontier based on their level of risk tolerance. A portfolio positioned below the efficient frontier is considered poor as it fails to generate sufficient returns relative to its level of risk.

3.1.3 Critical Analysis

Although MPT is of great significance, it operates under the assumption that investors behave rationally and markets function efficiently. Nevertheless, the distribution of asset returns is not consistently following a normal distribution, and the correlation between assets might vary over time, resulting in a possible miscalculation of risk.

The framework developed by Markowitz establishes the foundation for investigating in this thesis whether a Large Language Model may proficiently choose portfolios that have historically been situated on or close to the efficient frontier. In the following sections, we will examine further mathematical models and assess their ability to optimize portfolios in comparison to techniques based on LLM. Having a solid grasp of Markowitz's model is essential for comprehending the unique methods examined in this research.

3.1.4 Fama-French Three-Factor Model

The Fama-French Three-Factor Model expands on the Modern Portfolio Theory by including three significant risk factors that are believed to account for the increased expected returns of portfolios over a period of time[1]. Eugene Fama and Kenneth French developed this model in the early 1990s, and it has since become a fundamental aspect of financial economics.

Three Risk Factors:

- Market Risk (MKTRF): This factor is similar to the single risk factor in the CAPM and reflects the excess return of the market over the risk-free rate.
- Size of Firms (SMB - Small Minus Big): This factor captures the additional return investors can expect from investing in smaller companies with lower market capitalizations over larger companies.
- Value of Firms (HML - High Minus Low): This factor represents the excess return of value stocks (with high book-to-market ratios) over growth stocks (with low book-to-market ratios).

The expected return of a portfolio according to the Fama-French model is formulated as:

$$E(R_p) = R_f + \beta_{\text{MKTRF}}(E(R_m) - R_f) + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} \tag{3.3}$$

where:

- $E(R_p)$ is the expected return on the portfolio,

- R_f is the risk-free rate,
- β_{MKTRF}, β_{SMB}, and β_{HML} are the sensitivities of the portfolio to the market, size, and value factors, respectively,
- SMB is the size premium,
- HML is the value premium.

The Fama-French model is extremely helpful when evaluating the performance of diversified portfolios due to its ability to go beyond market risk and consider elements that encompass many aspects of business structure and market behavior. It is also used to evaluate the success of mutual funds and other investment portfolios, attributing variations in returns to the investment style of fund managers rather than their ability to time the market or select securities.

In this study, the Fama-French model is utilized to examine risk and return from several perspectives. It serves as a benchmark against which the performance of portfolios guided by Large Language Models can be assessed. The research will specifically investigate whether LLMs can accurately recognize and take advantage of the size and value aspects in a way that matches or surpasses the expected historical performance according to the Fama-French model.

To put it concisely, the Fama-French Three-Factor Model improves upon conventional market theory by enabling investors to use a more comprehensive range of elements in the construction and assessment of portfolios. The inclusion of this concept in the thesis offers a detailed understanding of the relationships between risk and return, which is crucial for evaluating the unique LLM-based method for optimizing portfolios.

3.1.5 Fama-French Five-Factor Model

The Fama-French Five-Factor Model is an extension of their three-factor model, incorporating two additional elements to enhance the explanation of asset returns. Eugene Fama and Kenneth French developed this model to address anomalies that were not accounted for by the three-factor model[5].

3.1.6 Additional Risk Factors

- Profitability (RMW - Robust Minus Weak): This factor posits that companies with higher operating profitability yield higher returns than those with lower profitability.
- Investment Patterns (CMA - Conservative Minus Aggressive): This factor suggests that companies with more conservative investment practices have higher returns compared to firms with more aggressive investments.

The five-factor model can be mathematically represented as:

$$\begin{aligned} E(R_p) = R_f + \beta_{\text{MKTRF}}(E(R_m) - R_f) + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} \\ + \beta_{\text{RMW}}\text{RMW} + \beta_{\text{CMA}}\text{CMA} \end{aligned} \tag{3.4}$$

where:

- $E(R_p)$ is the expected return on the portfolio,
- R_f is the risk-free rate,
- β_{MKTRF}, β_{SMB}, β_{HML}, β_{RMW}, and β_{CMA} are the sensitivities of the portfolio to the market, size, value, profitability, and investment factors, respectively,

- SMB is the size premium,
- HML is the value premium,
- RMW is the profitability premium,
- CMA is the investment premium.

3.1.7 Implementing the Five-Factor Model

Practically, the Fama-French five-factor model necessitates investors to calculate the five beta coefficients for their portfolio. These coefficients can be derived by doing regression analysis on historical asset returns. It presupposes that these factors are enduring and widespread influences on asset returns.

Empirical studies provide evidence that the inclusion of RMW and CMA enhances the explanatory power of the five-factor model in explaining the cross-section of returns across different portfolios, especially those that are ordered based on these specific characteristics.

In this thesis, the five-factor model is used as a comprehensive standard for constructing portfolios. The performance of the portfolio will be compared to portfolios created using knowledge obtained from Large Language Models (LLMs), specifically examining whether LLMs can accurately identify and utilize profitable investment patterns to improve portfolio returns.

This research seeks to determine whether there is a notable benefit to utilizing LLMs in portfolio optimization compared to portfolios constructed using the Fama-French five-factor model. The study specifically focuses on the additional factors of profitability and investment patterns that the Fama-French model emphasizes. This will enhance comprehension of the capabilities and constraints of employing sophisticated AI methods in financial decision-making.

3.1.8 Alternative Principal Component Analysis (APCA)

Alternative Principal Component Analysis (APCA) is a complex statistical method used to decrease the number of variables in financial datasets while retaining as much of the data's variability as possible. This approach is especially valuable in the field of portfolio optimization, where the goal is to condense the fundamental aspects of market fluctuations and relationships between asset prices into a smaller and more manageable collection of components.

3.1.9 Principles of APCA

APCA transforms original variables (e.g., asset returns) into a new set of uncorrelated variables known as principal components. These components are ordered so that the first few retain most of the variation present in all of the original variables. Mathematically, APCA involves the eigendecomposition of the covariance matrix of the asset returns or, alternatively, the singular value decomposition of the data matrix itself.

The covariance matrix Σ of asset returns is decomposed to find its eigenvalues and eigenvectors. The eigenvectors correspond to the principal components, and the eigenvalues represent the variance explained by each component. The first principal component is the direction in which the data varies the most, the second component is the direction of the next highest variation orthogonal to the first, and so on.

APCA is a useful tool in portfolio management for identifying the fundamental factors that influence the returns of assets. Investors can enhance their decision-making about asset selection for their portfolio by prioritizing the primary components that account for a substantial proportion of the return variability. This strategy aids in mitigating portfolio risk by enabling the detection and separation of investment opportunities that are not connected with each other.

Decreases complexity and computational expense by narrowing focus to a small number of primary components instead of a big number of assets. Assists in discovering hidden patterns in the returns of assets that may not be immediately apparent, potentially providing insights into the dynamics of the market and elements that pose risks.

Understanding the principle components can be difficult because they are formed by combining the original variables in a linear manner and may not have a clear economic interpretation. This method assumes linearity and heavily depends on previous data, which may not invariably encompass future market conditions or the ramifications of unforeseen events.

APCA's purpose in this study is to offer a methodological alternative to the conventional and factor-based models that were previously described. The research aims to evaluate the feasibility and efficacy of dimensionality reduction techniques in portfolio optimization by comparing the performance of portfolios derived from APCA with those constructed using Markowitz optimization, the Fama-French three and five-factor models, and insights from LLMs. This analysis will determine whether transforming financial data into primary components has any benefits in forecasting portfolio performance and mitigating risk, particularly when compared to the more intricate and data-driven approach facilitated by LLMs.

In summary, APCA is an essential tool for analyzing financial data. It provides a distinct viewpoint on portfolio optimization that complements conventional models. The research conducted in this thesis highlights the complex and diverse character of financial analysis in the age of big data and artificial intelligence.

3.2 Large Language Models (LLMs) in Financial Analysis

Large Language Models (LLMs) like OpenAI's GPT series are a significant advancement in natural language processing within the field of artificial intelligence. The capacity of these models to comprehend, produce, and analyze text has created fresh opportunities in diverse domains, such as financial analysis. This section provides a comprehensive overview of the mechanics of LLMs, their relevance to financial analysis, and the underlying ideas that establish them as effective instruments for portfolio optimization.

3.2.1 Understanding LLMs

- LLMs work based on the premise of forecasting the subsequent word in a sequence, after being trained on huge datasets consisting of varied text sources. This instruction empowers individuals to grasp the intricacies of language, encompassing grammar, context, and sentiment.

- The architecture of models such as GPT-3 incorporates transformer networks that employ self-attention processes to analyze words in connection to all other words in a phrase or sequence. This enhances their ability to accurately forecast and understand the context.

Relevance to Financial Analysis

- Financial markets are impacted by numerous factors, a significant portion of which are subjective and can be found in unstructured textual data such as news stories, financial reports, and social media comments. The ability of LLMs to evaluate large amounts of data and generate relevant insights makes them extremely beneficial for financial analysis.

- LLMs let financial analysts incorporate a wider range of information into investment decision-making processes by converting qualitative data into measurable insights, going beyond the conventional quantitative measurements.

Mathematical Foundations and Comparisons

- LLMs take a different approach to financial analysis compared to traditional models. Instead of using historical numerical data, LLMs use probabilistic language interpretation.

- LLMs supplement established financial models by providing a different perspective on risk assessment and market prediction.

- Assessing the efficacy of LLMs in financial tasks requires the use of metrics that gauge the models' comprehension and forecasting abilities, which differ from the statistical measurements commonly used in traditional financial analysis.

3.2.2 Applications in Portfolio Management

- LLMs provide the capability to comprehend and analyze financial narratives, offering a new and valuable tool for portfolio managers. This has the potential to enhance investment strategies by providing detailed and sophisticated market insights.

- This includes the automated examination of market patterns, analysis of investor forums to determine mood, and the provision of prognostic information regarding economic indicators.

- By combining LLM-derived insights with standard portfolio optimization techniques, it is possible to develop a more adaptable and responsive investing strategy that effectively balances quantitative data analysis with qualitative market insights.

Challenges and Considerations

- Implementing LLMs in financial analysis presents certain difficulties. Relevant difficulties include data bias, the lack of transparency in model predictions (the ”black box” issue), and the computational requirements for training and running large models.

- The utilization of LLMs in finance also involves navigating ethical and regulatory environments, where the clarity and justification of AI-generated suggestions must be evident and defensible.

LLMs are positioned at the convergence of artificial intelligence and financial analysis, signaling a possible transformation in the interpretation of market data and the process of making investment decisions. LLMs have the potential to enhance portfolio optimization by incorporating insights from unstructured text data into established analytical frameworks, resulting in a more informed and comprehensive approach.

3.3 Best Practices of Chatbot Creation for Financial Advisory Services

The development of a chatbot for financial advising services requires a meticulous approach that combines technical accuracy with a focus on user experience. This method guarantees that the chatbot is not just functional but also user-friendly, safe, and in accordance with financial requirements. Based on the specified architecture outlined for the financial chatbot, below is a comprehensive analysis specifically designed for this project.

3.3.1 Designing for User Engagement and Clarity

- The chatbot's user interface is constructed using React or Next.js, selected for their resilience and adaptability in crafting dynamic online apps. These frameworks facilitate the creation of a smooth user experience, where financial data is shown in a user-friendly and comprehensible style.

- An essential aspect of design is prioritizing the needs and preferences of the user, with a particular emphasis on creating a user-friendly experience through intuitive navigation and the effective communication of information in a brief and unambiguous manner. This encompasses the deliberate arrangement of interactive components and the integration of feedback mechanisms to consistently enhance user engagements.

3.3.2 Backend Development with FastAPI

- FastAPI is chosen for backend development because of its high performance and ability to handle asynchronous operations, which are crucial for managing real-time data processing and sophisticated computations needed for financial advice services.

- The backend is accountable for the algorithmic processing of user inputs, including financial inquiries and data requests, and executing the requisite procedures to retrieve or compute the pertinent financial information. This entails the integration of financial databases, utilization of APIs for real-time market data, and implementation of algorithms for financial analysis.

3.3.3 Integrating Frontend and Backend

- The seamless connectivity between the frontend and backend components is important to the optimal functioning of the chatbot. This is accomplished through a well-defined API that enables efficient communication and exchange of data.

- The frontend transmits user queries to the backend, where FastAPI handles these requests and provides the corresponding responses. The security of this communication is strengthened by employing HTTPS protocols and ensuring that the exchange of data adheres to legislation governing the handling of financial information.

3.3.4 Ensuring Robust Security Measures

- Due to the delicate nature of financial information, it is imperative to install sophisticated security measures. This encompasses the use of data encryption, robust user authentication techniques, and stringent access restrictions to safeguard against illegal access and data breaches.

- The chatbot undergoes regular security audits and compliance tests to ensure it complies with industry standards and regulations, such as GDPR and PCI DSS. This helps protect user data and preserve confidence.

User Data Privacy and Compliance

- The chatbot design adheres to rigorous data privacy norms, guaranteeing that user data is gathered, retained, and handled in accordance with applicable privacy legislation and regulations.

- The chatbot's operation is designed to prioritize transparency with users on data usage and to provide them with control over their personal information. These practices serve to strengthen user trust and ensure compliance with regulations.

By following these best practices, the development of a financial advisory chatbot can strike a harmonious equilibrium between advanced functionality and user-friendly design. This methodology guarantees that the chatbot functions as an efficient instrument for providing financial advice, with the ability to handle intricate inquiries while upholding rigorous standards of security and compliance.

3.4 Cloud Selection and Deployment for the Financial Chatbot

Deploying the financial chatbot necessitates a methodical approach to choosing and managing cloud services in order to guarantee that the application can handle increased demand, maintain a high level of security, and operate efficiently even during times of fluctuating usage. This deployment strategy is crucial for effectively managing the processing of real-time financial data and ensuring a dependable service for users.

3.4.1 Cloud Platform Evaluation and Selection

- Selecting a cloud service provider is of utmost importance for the chatbot's infrastructure. Considerations include the platform's worldwide network, scalability choices, adherence to financial regulations, and distinctive features such as managed databases, machine learning services, and analytics capabilities.

- Amazon Web Services (AWS), Google Cloud Platform (GCP), and Microsoft Azure are considered the top choices since they offer a wide range of services specifically designed for complicated applications. The ultimate decision depends on the provider that offers the most comprehensive support for the technologies and frameworks utilized in the chatbot, specifically FastAPI for the backend and React or Next.js for the frontend.

3.4.2 Ensuring Compliance and Security

- Financial applications necessitate rigorous compliance with regulatory standards and implementation of best practices in data security. The selected cloud platform should include tools and services that simplify adherence to rules such as GDPR, PCI DSS, and other legislation pertaining to financial data.

- The deployment plan includes the implementation of end-to-end encryption for data in transit and at rest, secure access management, and regular security assessments to protect sensitive user data.

3.4.3 Scalability for Peak Performance

- The cloud infrastructure is specifically engineered for elasticity, enabling the chatbot to dynamically adjust its resource allocation in response to real-time demand. This guarantees that the program maintains its responsiveness even during periods of market volatility when there may be a surge in user requests.

- Services such as auto-scaling groups, load balancers, and elastic compute instances are set up to efficiently manage sudden increases in website traffic without sacrificing performance or incurring excessive expenses during periods of low activity.

3.4.4 Deployment Strategy

- A containerized methodology utilizing Docker streamlines the deployment procedure and guarantees uniformity between development, testing, and production environments. Kubernetes is utilized for the orchestration, efficient management, deployment, and scalability of containerized applications.

- A Continuous Integration and Continuous Deployment (CI/CD) pipeline is created by utilizing tools like Jenkins or GitHub Actions. This pipeline streamlines the process of testing and deploying, enabling quick and repeated cycles of development and ensuring that code modifications undergo rigorous evaluation before being implemented.

3.4.5 Monitoring and Continuous Improvement

- It is crucial to continuously monitor the performance, usage trends, and any security threats of the program after it has been deployed. Cloud providers offer monitoring and analytics solutions that offer valuable information about the performance and usage of applications.

- The chatbot undergoes continuous enhancements driven by feedback loops and analytics. The application's updates are informed by performance statistics and customer feedback, ensuring that it effectively adapts to suit the changing needs of users and the market.

By deploying the financial chatbot on a cloud platform that meets its technological and operational needs, it guarantees that the application is not only efficient and adaptable, but also meets the necessary security measures and complies with financial standards. The meticulous development and implementation of the deployment strategy are crucial for the chatbot's success, allowing it to provide dependable financial advise services to users.

4 PROPOSED SOLUTION

In addressing the challenge of portfolio selection and optimization, this chapter outlines a novel approach that integrates Large Language Models (LLMs) into the financial analysis framework. Leveraging the advancements in natural language processing and AI, the proposed solution aims to enhance traditional financial models with the deep, contextual insights that LLMs can provide. This chapter is divided into three main sections, detailing the process of prompt engineering for effective LLM utilization, the methodology for comparing the performance of classical models with LLMs, and the development of an LLM-powered chatbot designed to offer financial advisory services.

This chapter presents a new method that combines Large Language Models (LLMs) with the financial analysis framework to tackle the problem of portfolio selection and optimization. By utilizing the progress made in natural language processing and artificial intelligence, the suggested approach seeks to improve conventional financial models by including the profound and contextual insights offered by large language models (LLMs). This chapter is divided into three primary sections, which include a comprehensive explanation of prompt engineering for optimal usage of LLMs, the methodology for comparing the performance of traditional models with LLMs, and the creation of a chatbot powered by LLMs that is specifically built to give financial advisory services.

4.1 Prompt Engineering for LLM

Prompt engineering is crucial for leveraging the capabilities of Large Language Models (LLMs) such as GPT for advanced financial analysis. The objective is to create prompts that will guide the model to produce insights that are pertinent to financial situations and practical for investment strategies.

4.1.1 Constructing Financially Informed Prompts

The process of creating prompts begins with the combination of financial theory and market expertise. By utilizing well-established financial measurements and models, such as the projected returns calculated using the Capital Asset Pricing Model (CAPM) or the risk characteristics outlined in the Fama-French models, prompts can direct the LLM towards a focused analysis of investment prospects and potential risks.

For example, a prompt may require the LLM to evaluate the influence of present macroeconomic trends on the anticipated returns of the technology sector, taking into account both market volatility and sector-specific risk variables.

4.1.2 Refining Prompts through Iterative Feedback

The precision and applicability of the LLM's responses are evaluated in relation to real-world financial problems. The LLM continuously improves its prompts based on feedback to ensure that the information it provides is relevant and actionable.

This may involve an iterative procedure in which an initial prompt regarding portfolio diversification techniques is refined to encompass specific asset classes or to assess the robustness of diversified portfolios in the face of historical market downturns[4].

4.1.3 Ensuring Prompt Clarity and Directiveness

Prompt engineering emphasizes the importance of clear and unambiguous instructions, which guide the LLM to provide focused responses. Prompts must be unambiguous and carefully designed to extract precise information regarding investment topics.

An example may be a prompt requesting a comparison of the performance of the technology and healthcare industries during phases of economic recovery, using quantitative data and analysis of market sentiment.

4.1.4 Utilizing Prompts for Scenario Analysis

Prompts are utilized to direct LLMs to conduct scenario studies, which involve simulating different market scenarios to assess their potential impact on investment portfolios.

This may involve providing instructions to the LLM to use past market data and current events in order to predict the impact of political instability on emerging market bonds.

4.1.5 Monitoring and Adapting to Market Responses

The effectiveness of prompt engineering in real-world scenarios is monitored by studying market reactions and making appropriate adjustments to the prompts. This flexible methodology enables the model to adjust to changes in the market and emerging patterns.

For instance, a prompt can be modified continuously to emphasize the influence of recent fiscal policies on the investment landscape, reflecting the changing priorities and concerns of the financial market.

4.2 Comparative Performance Analysis: Classical Models vs. LLM

In order to incorporate LLMs into financial portfolio management, it is necessary to do a thorough comparative analysis against classical financial models. This section will discuss the process of assessing the effectiveness of LLM recommendations compared to traditional models using a systematic comparison methodology.

4.2.1 Benchmarking and Evaluation Metrics

To assess the efficiency of LLMs for portfolio optimization, it is necessary to establish a series of benchmarks and metrics. These metrics include risk-adjusted returns, such as the Sharpe and Sortino ratios, maximum drawdowns, and alpha generation. The evaluation also takes into account the robustness of portfolios during market downturns, as well as their ability to adjust to new information. An LLM may be required to create a portfolio based on current market conditions, which is then evaluated against these benchmarks to measure its performance compared to a traditionally derived portfolio.

4.2.2 Methodology for Backtesting

Backtesting provides a historical perspective on the performance of investment strategies suggested by LLMs. By doing simulations to assess the performance of an LLM's suggestions in previous market events, we may determine the reliability of its insights. A prompt may require the LLM to construct a portfolio using information from a previous economic crisis. The LLM will then analyze their own approach and compare it to how a Markowitz-optimized portfolio would have performed during the same period.

4.2.3 Model Robustness and Error Analysis

LLMs function as a ”black box”, and understanding their decision-making process is difficult. Hence, a crucial aspect of the comparative performance study entails dissecting model outputs and analyzing any errors or anomalies in the predictions. This not only serves as a means of verifying the model’s resilience but also aids in improving the design of prompts to generate more precise responses. For example, if there are discrepancies between the recommendations made by the LLM and the expected results based on established financial theory, it may be necessary to modify the prompts in order to better match the model’s outputs with the theoretical expectations.

4.2.4 Integration with Investment Decision-Making

Integrating LLM insights into the investment decision-making process necessitates developing a framework for integrating and balancing these insights with conventional financial models. This guarantees that investment strategies will take advantage of the predictive capabilities of LLMs while still being firmly based on established financial theories. The implementation of this method may involve using conventional models for primary strategy creation, together with LLM insights to take advantage of immediate opportunities or protect against upcoming risks detected through natural language processing.

4.3 LLM Chatbot Creation

The culmination of integrating Large Language Models (LLMs) with financial analytics is embodied in the development of a sophisticated LLM-powered chatbot. This chatbot seeks to help make financial advising services accessible to a wider audience by utilizing the advanced learning capabilities of LLMs to offer individualized investment advice and market analysis. This section provides an overview of the development process, with a specific emphasis on the selection of the model, the development of the backend and frontend, and the strategies used for integration.

4.3.1 Model Selection and Training

The foundation of the chatbot's intelligence is based on a cutting-edge LLM. Due to the complex nature of financial terminology and ideas, GPT-3, a model famous for its comprehensive training on a wide range of datasets, including financial literature, market reports, and investor forums, is selected. In order to customize the LLM's responses for financial advise situations, a process of fine-tuning is carried out using a carefully selected dataset consisting of financial queries and high-quality responses. This dataset focuses on market analysis, providing portfolio suggestions, and offering risk management strategies.

4.3.2 Backend Development with FastAPI

The backend framework FastAPI is chosen for its ability to handle asynchronous operations and scalability, which are crucial for managing the dynamic nature of financial queries. The backend is responsible for handling user inputs, interacting with the LLM, and producing coherent and contextually appropriate financial advice. The implementation of security features is done with great attention to detail, ensuring the safety of user data and financial information communicated during transactions. This includes the use of data encryption and secure API endpoints.

4.3.3 Frontend User Interface

The user interface of the chatbot is created using React, which was selected for its component-driven architecture and responsive design capabilities. This allows for a smooth and engaging user experience, with real-time updates and interactive components that improve the accessibility of financial advice. The design considerations prioritize simplicity and user-friendliness, emphasizing straightforward navigation, intuitive input methods for queries, and the presentation of LLM-generated advice in an understandable format.

4.3.4 Integration and Deployment

The link between the frontend and the backend involves the utilization of RESTful APIs, which allow for efficient communication and exchange of data. This setup guarantees that user requests are correctly transferred to the backend, where the LLM analyzes the input and provides responses. The deployment utilizes cloud services to achieve scalability and reliability. Utilizing containerization through Docker and orchestration via Kubernetes streamlines the process of deploying and managing applications across various development, testing, and production environments. A CI/CD pipeline simplifies the development, test, and deployment procedures, guaranteeing that the chatbot is relevant with the most recent financial data and LLM improvements.

4.3.5 Version Control and Continuous Improvement

The chatbot undergoes continuous monitoring and improvement, utilizing version control tools to handle revisions to the codebase and LLM model. User feedback and interaction analytics are essential for finding areas of improvement in several aspects of the chatbot, such as its user interface and experience, the accuracy and relevancy of financial advice, and the speed of backend processing.

4.3.6 Challenges and Future Directions

The LLM-powered chatbot is a significant advance in financial advising services. However, it has issues in maintaining model interpretability, ensuring the timeliness of financial data, and complying with regulations. Future advancements will prioritize overcoming these challenges, improving the chatbot's functionalities, and exploring new applications of LLM technology in the field of finance.

5 EXPERIMENTS AND RESULTS

5.1 Mathematical Models for Portfolio Creation

In our research the problem which we are solving is the Portfolio Optimization[9], In which it contains models which has mathematical frameworks used to construct investment portfolios with the aim of achieving specific objectives, such as maximizing returns, minimizing risk, or achieving a balance between the two. There are many publicly available models for doing this task but for our research we are focused on using Markowitz Optimization model.

To compare reward and risk measures across the two trading universes, as well as the Fama-French 3 and Fama-French 5 portfolios, we computed optimal portfolios on the efficient frontier using the Markowitz mean-variance portfolio selection model with additional constraints. Before delving into the details of our computations, we will discuss the data used for running our optimization problems and estimating expected returns and covariances. To ensure alignment with the training data period of GPT-3.5, we utilized historical financial data up until September 2021 for our optimization formulations, followed by evaluating portfolio performance using out-of-sample data from August 2021 to July 2023.

In summary, the data utilized consisted of the following:

- Weekly data spanning five years prior to August 2018, which was employed for computing expected returns and covariance matrices (in-sample data for optimization). Given that the GPT-3.5 model was trained on data preceding September 2018, we opted to utilize historical data predating September 2018 for deriving parameters for the mean-variance portfolio selection model and its extensions.

- Out-of-sample data utilized for testing and comparing portfolios encompassed three distinct periods:

  1. Out-of-sample period 1: spanning from August 2018 to July 2023, representing the total post-training data period of GPT-3.5.
  2. Out-of-sample period 2: ranging from April 4, 2023, to July 28, 2023.

These delineated periods were selected to provide a comprehensive evaluation of portfolio performance across different market conditions, facilitating robust comparisons and analyses.

5.2 Asymptotic PCA (APCA)

The Asymptotic PCA (APCA) model is a factor analysis technique used for extracting latent factors from a dataset. In this section, we describe the formulation used for fitting the APCA model to the data.

5.2.1 Formulation

The APCA model is formulated as follows:

Let X be the matrix of training data with dimension (m, n), where m is the number of observations and n is the number of features. The APCA model aims to find a low-dimensional representation of X using a reduced set of components.

$$y = X\beta + \alpha \tag{5.1}$$

where:

- y is a matrix of target values with dimension (m, k).

- β is a matrix of fitted linear variables with dimension (n, k).

- α is a matrix of error terms with dimension (m, k).

The APCA model fits the coefficients β and α by minimizing the weighted least squares objective function.

$$\min_{\beta,\alpha} \|W^{1/2}(X - X\beta - \alpha)\|_F^2 \tag{5.2}$$

where W is a diagonal matrix of weights. The coefficients β and α are estimated using closed-form solutions.

5.2.2 Implementation

The APCA model is implemented using the ‘APCA‘ class, which provides methods for fitting the model to the data and extracting factor exposures, factor returns, and residual returns.

5.3 Fama-French 3 (FF3)

The Fama-French 3 (FF3) model is a factor model commonly used in asset pricing and portfolio management. In this section, we describe the formulation used for estimating the FF3 model parameters.

5.3.1 Formulation

The FF3 model is formulated as follows:

$$\begin{aligned} E(R_p) = R_f + \beta_{\text{MKTRF}}(E(R_m) - R_f) + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} \\ + \beta_{\text{RMW}}\text{RMW} + \beta_{\text{CMA}}\text{CMA} \end{aligned} \tag{5.3}$$

where:

- R_i is the excess return of asset i over the risk-free rate.
- MKT, SMB, and HML are the Fama-French factors.
- α_i is the intercept term.
- $\beta_{i,MKT}$, $\beta_{i,SMB}$, and $\beta_{i,HML}$ are the factor loadings of asset i on MKT, SMB, and HML, respectively.
- ϵ_i is the idiosyncratic error term.

The FF3 model estimates the factor loadings and intercept terms using linear regression.

5.3.2 Implementation

The FF3 model is implemented using the 'FamaFrench3' class, which provides methods for estimating the model parameters and performing portfolio analysis.

5.4 Fama-French 5 (FF5)

The Fama-French 5 (FF5) model extends the FF3 model by adding two additional factors: RMW (Profitability) and CMA (Investment). In this section, we describe the formulation used for estimating the FF5 model parameters.

5.4.1 Formulation

The FF5 model is formulated similarly to the FF3 model, but with additional factors:

$$R_i = \alpha_i + \beta_{i,\text{MKT}} \times \text{MKT} + \beta_{i,\text{SMB}} \times \text{SMB} + \beta_{i,\text{HML}} \times \text{HML} \\ + \beta_{i,\text{RMW}} \times \text{RMW} + \beta_{i,\text{CMA}} \times \text{CMA} + \epsilon_i \tag{5.4}$$

where:

- RMW and CMA are the additional Fama-French factors.
- $\beta_{i,RMW}$ and $\beta_{i,CMA}$ are the factor loadings of asset i on RMW and CMA, respectively.

The FF5 model estimates the factor loadings, intercept terms, and residual variance using linear regression.

5.4.2 Implementation

The FF5 model is implemented using the ‘FamaFrench5‘ class, which extends the functionality of the FF3 model to accommodate the additional factors.

5.5 Portfolio Optimization using Markowitz Mean-Variance Model

The `frontiers` function is designed to construct efficient portfolios using the principles of the Markowitz mean-variance optimization model. This model aims to maximize expected return while minimizing portfolio variance, thereby achieving an optimal trade-off between risk and return.

The function takes several inputs:

- `B`: A matrix representing the factor sensitivities of assets in the portfolio.
- `F`: A matrix representing the expected factor returns.

- `alpha`: A vector representing the asset-specific expected excess returns.
- `Q_f`: A matrix representing the factor covariance matrix.
- `D`: A vector representing the asset-specific idiosyncratic risk (variance).
- `asset_list`: A list of asset names or identifiers.
- `num_portf`: The number of portfolios to generate (default value: 200).
- `lb`: Lower bound for asset weights in the portfolio (default value: 0.03).
- `ub`: Upper bound for asset weights in the portfolio (default value: 0.13).
- `rf`: Risk-free rate of return (default value: 0.01).

The function begins by initializing the parameters and defining the optimization problem for each portfolio. It iterates over a range of target returns and solves the optimization problem for each target return using the CVXPY optimization library.

For each target return ϵ, the function solves the following optimization problem:

$$\begin{aligned}
\underset{w}{\text{minimize}} \quad & w^T Q_f w + w^T D \\
\text{subject to} \quad & (\alpha + (B^T F))^T w \geq \epsilon \\
& Bw = x \\
& \sum_{i=1}^{n} w_i = 1 \\
& w_i \geq \text{lb} \\
& w_i \leq \text{ub}
\end{aligned} \tag{5.5}$$

where:

$$
\begin{aligned}
w &: \text{Portfolio weights} \\
Q_f &: \text{Factor covariance matrix} \\
D &: \text{Asset-specific idiosyncratic risk (variance)} \\
\alpha &: \text{Asset-specific expected excess returns} \\
B &: \text{Factor sensitivities of assets} \\
F &: \text{Expected factor returns} \\
x &: \text{Auxiliary variable} \\
\epsilon &: \text{Target return} \\
\text{lb} &: \text{Lower bound for asset weights} \\
\text{ub} &: \text{Upper bound for asset weights}
\end{aligned}
$$

The function computes various portfolios, including the minimum variance portfolio, portfolios with maximum Sharpe ratio, and portfolios with minimum expected shortfall. These portfolios represent different points on the efficient frontier, which is the set of portfolios that offer the highest expected return for a given level of risk or the lowest risk for a given level of return.

The output of the function is a dictionary containing information about each portfolio, including portfolio weights, expected return, and portfolio variance.

5.5.1 Top 10 Asset Frequencies in Portfolios

Explanation: This plot illustrates the frequency with which each asset appears in the top 10 by weights in portfolios generated using different optimization techniques.

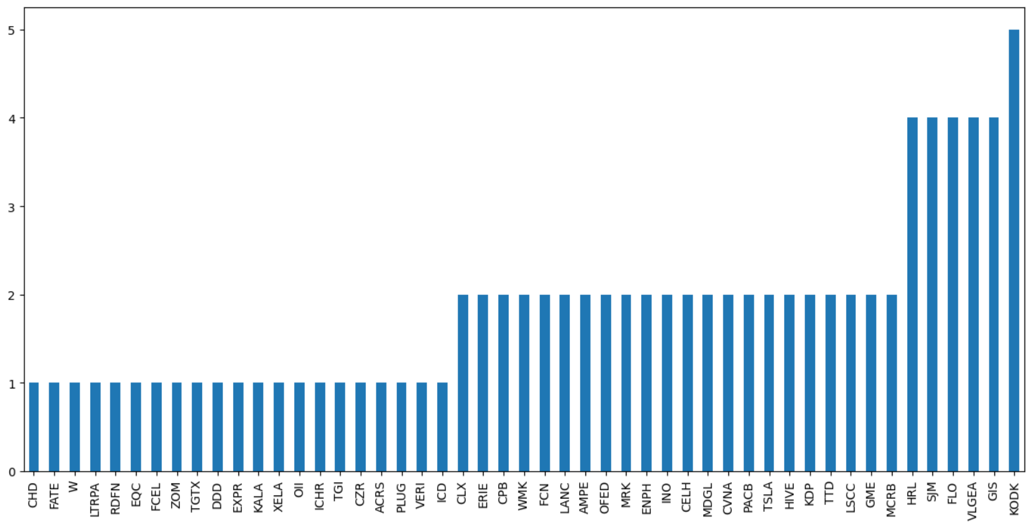

Figure 5.1: Top 10 asset frequencies in portfolios

5.5.2 Cumulative Portfolio Returns over Time

Explanation: This plot shows the cumulative returns over time for each portfolio constructed using various optimization results and asset weights.

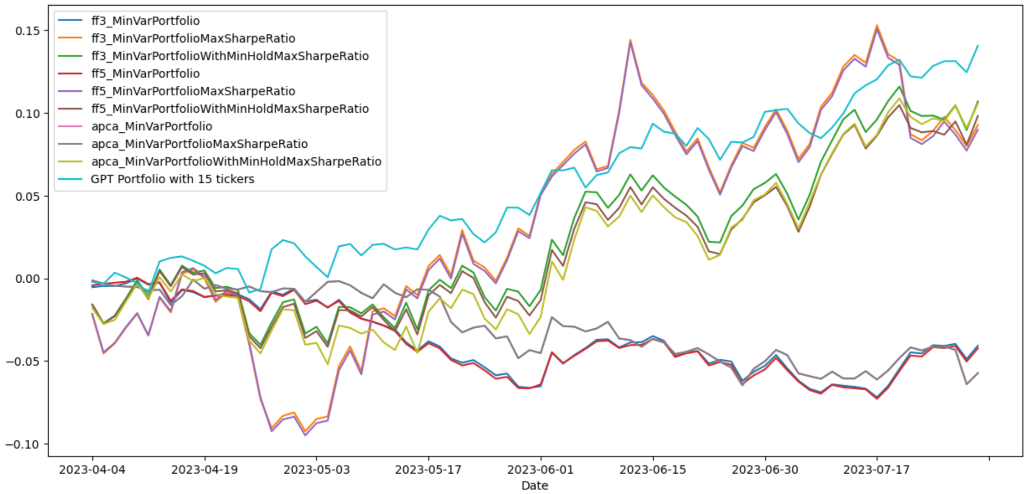

Figure 5.2: Cumulative portfolio returns over time

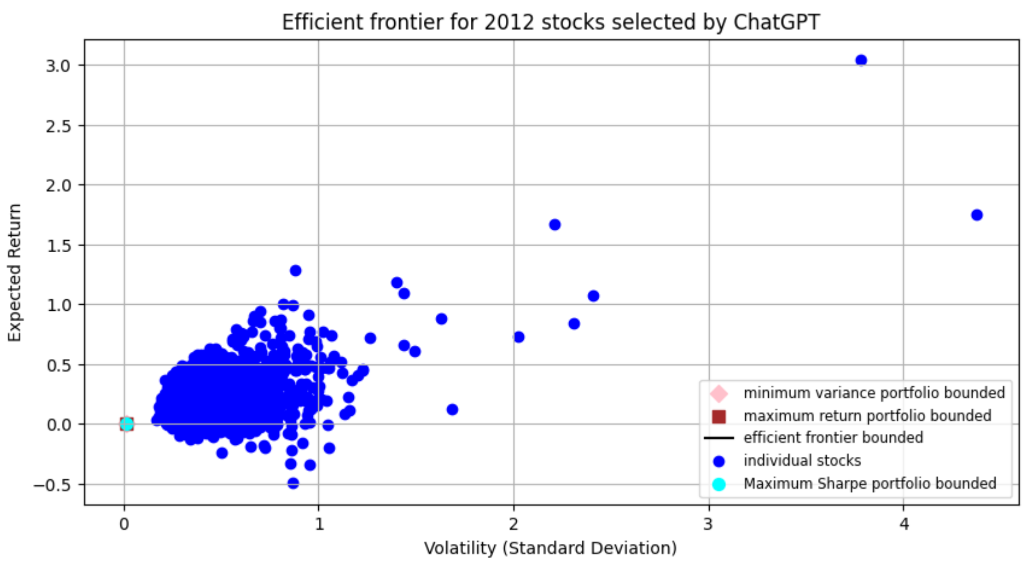

Figure 5.3: Efficient frontier plot

5.5.3 Efficient Frontier Plot

Explanation: This plot illustrates the efficient frontier, which represents the set of optimal portfolios that offer the highest expected return for a given level of risk or the lowest risk for a given level of return. Each point on the efficient frontier corresponds to a portfolio with a different allocation of assets, optimized using various optimization techniques and asset weights.

5.6 LLM Chatbot MVP Results

A Minimum Viable Product (MVP) for an LLM-powered chat-bot has been successfully developed to enhance the accessibility of financial advisory services to a broader range of users, yielding encouraging outcomes. The chatbot demonstrates its capacity to provide tailored investment guidance and market analysis to a wider range of people by leveraging cutting-edge technology and robust development frameworks. Here is an in-depth examination of the primary findings and outcomes:

5.6.1 Model Selection and Training

GPT-3.5 comprises the core of the chatbot's intelligence, demonstrating its expertise in comprehending complex financial concepts. The LLM demonstrates its ability to offer tailored solutions that are suitable for financial advisory settings by carefully adjusting and leveraging a curated dataset.

5.6.2 Backend Development with FastAPI

The utilization of FastAPI as the underlying framework demonstrates its crucial role in managing asynchronous processes and guaranteeing scalability. User data and financial information are safeguarded by employing robust security methods, such as data encryption and secure API endpoints.

The choice of Python as the primary programming language was based on its

Figure 5.4: Chatbot User Interface

versatility and effectiveness in developing artificial intelligence models. The extensive range of tools and resources available in Python's ecosystem, such as the Matplotlib library, were utilized to effectively utilize images and charts, guaranteeing the delivery of accurate and visually appealing information. By implementing this strategic decision, the chatbot is capable of readily generating informative visualizations, hence enhancing the comprehension and lucidity of the financial guidance provided to users.

5.6.3 Frontend User Interface

The user interface, constructed with React and powered by Next.js, offers a seamless and captivating experience, distinguished by real-time updates and intuitive navigation. The design considerations prioritize simplicity and user-friendliness, enhancing the accessibility of financial guidance for a diverse variety of users. Next.js enhances website optimization and search engine optimization (SEO), which is crucial for efficient marketing.

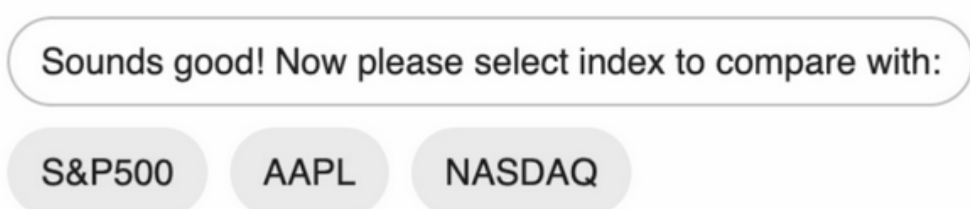

Figure 5.5: Example of interaction

To ensure prompt and precise responses, the chatbot employs asynchronous communication with the backend through Axios requests. This enables immediate processing of user inputs and retrieval of customized predictions and market evaluations.

Figure 5.6: LLM Chatbot MVP Results

While consumers are waiting for responses, they are informed with an interactive ”thinking” signal, indicating that the chatbot is actively generating personalized material for their query. This integration enhances user engagement and satisfaction by providing a seamless and engaging experience that is both dynamic and informative.

5.7 Integration and Deployment

The use of RESTful APIs enables efficient data delivery for LLM processing and response generation, facilitating efficient data interaction between the frontend and backend. Utilizing AWS and Vercel services, including Nginx, Docker, and Vercel’s platform, for hosting infrastructure ensures scalability, reliability, and optimal performance for both frontend and backend components.

5.8 Version Control and Continuous Improvement

Version control technologies are utilized to consistently monitor and enhance the chatbot. These tools facilitate the efficient management of codebase revisions and updates to the LLM model. User input and interaction analytics are crucial in finding areas for development and ensuring that the chatbot remains at the forefront of financial advisory technology by adapting to meet user expectations.

5.9 Hosting Infrastructure

The chatbot is hosted on a combination of AWS and Vercel services, which provide a strong hosting environment with scalable infrastructure and efficient containerization. AWS's services, including Nginx, Docker, and Kubernetes, are compatible with Vercel's platform, enabling seamless deployment and hosting of React-based frontend applications. This partnership guarantees exceptional performance, scalability, and dependability for both the user interface and server-side components of the chatbot.

6 CONCLUSION

6.1 Summary of Results

This thesis has conducted a thorough analysis of the use of Large Language Models (LLMs), particularly GPT models, in the field of financial portfolio selection. The performance of LLMs was compared to standard financial models such as Markowitz's Modern Portfolio Theory and Fama-French multi-factor models. The study examined the novel method of employing LLMs to read and evaluate huge amounts of unorganized data in order to make well-informed decisions on portfolios. LLMs have the ability to outperform standard approaches by detecting subtle market signals that are frequently ignored by conventional models, although facing significant operational difficulties.

6.2 Contributions

This study adds to the expanding domain of financial technology by showcasing the successful use of LLMs to increase portfolio management procedures. This study proposes the construction of a hybrid model that combines LLM insights with traditional financial analytics. The goal is to enhance asset allocation and decision-making transparency, thereby facilitating compliance with regulatory norms.

6.3 Limitations

Although LLMs hold significant potential, their effective implementation is impeded by the inherent opacity of their decision-making processes, which may present difficulties in ensuring regulatory compliance and managing risks. Furthermore, the reliance on data of superior quality and the necessity for ongoing model training to adjust to emerging market conditions are substantial obstacles that require attention.

6.4 Future Work

6.4.1 Theoretical and Empirical Enhancements

Subsequent investigations should prioritize enhancing the comprehensibility of LLM outputs, rendering these models more clear and intelligible to users. Conducting empirical investigations using actual financial data and real-time trading scenarios would help to further confirm the effectiveness of portfolio strategies based on LLM.

6.4.2 Technical Improvements

Technological advancements should aim at developing more robust LLMs that can dynamically adapt to new market information and learn from non-textual data to provide a more holistic view of the financial landscape.

6.4.3 Expansion into New Areas

Exploring the application of LLMs in other areas of finance such as risk management, regulatory compliance, and automated trading systems could also provide fruitful avenues for further research.

6.5 Final Thoughts

To summarize, this thesis not only emphasizes the potential of LLMs in revolutionizing financial portfolio management but also paves the way for future advancements in the incorporation of AI and financial services. The statement emphasizes the necessity of adopting a well-rounded approach that combines conventional financial theories with contemporary AI technology in order to transform investment strategies and financial analysis.

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