www.ijbar.org
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

Machine Learning Meets Economic Theory: A Framework for Asset Pricing and Portfolio Optimization

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Abstract: Financial market analysis has changed as a result of the combination of economic theory with machine learning (ML), especially in the areas of asset pricing and portfolio optimization. This study uses bibliometric techniques and a VOS reader to conduct a Systematic Literature Review (SLR) of 401 pertinent articles in order to synthesize existing research, identify gaps, and clarify the impact of machine learning (ML) on improving economic models and strategies. The findings indicate a rising trend in publications, with China and the United States at the top and key roles played by organizations like the Massachusetts Institute of Technology and Shanghai University of Finance and Economics. Five major topics emerge from cluster analysis: algorithmic trading, data-driven portfolio management and optimization, asset pricing and predictive analysis, financial market projections for cryptocurrencies, and reinforcement learning and adaptive tactics. The suggested conceptual framework, which emphasizes the possible overlap between machine learning and economic theory, includes data collection and management, preprocessing and feature engineering, model selection and training, constraint formulation, theory-driven validation, and real-time adaptation and monitoring. This work offers a structured method for improving asset pricing models and portfolio optimization strategies by shedding light on the convergence of machine learning and economic theory. Subsequent investigations ought to enhance this integration, emphasizing pragmatic implementation and flexibility in response to novel financial instruments and market circumstances.
Keywords: Economic theory, asset pricing, machine learning, and portfolio optimization

Introduction

The banking industry has seen a revolution thanks to machine learning (ML), which makes it possible to process vast amounts of varied data and identify intricate non-linear relationships. The application of machine learning (ML) technology in conjunction with conventional economic theory is causing a major shift in the fields of asset pricing and portfolio optimization. The constraints of traditional approaches, which are becoming more and more incapable of managing the enormous volumes of data and intricate relationships seen in today's financial markets, are the reason behind this paradigm change (Hannsgen, 2012). The superiority of machine learning techniques over conventional tactics has been emphasized by studies by Rundo et al. (2019); Carta et al. (2021), which show improved success in statistical arbitrage trading strategies through improved risk and return management. The blend of economic theory with cutting-edge machine learning algorithms, such as Long Short-Term Memory (LSTM), has opened new avenues for predicting stock returns and optimizing portfolios (Choudhary and Arora, 2024). To achieve superior market performance, even in volatile conditions, this strategy makes use of hyperparameter tuning kernels, modified asset selection models, and sophisticated portfolio optimization frameworks such as the Markowitz mean-variance model, both in its classic and modified forms (Ferguson-Cradler, 2023).

There are currently very few articles that successfully integrate relevant economic theory with machine learning. In order to improve financial modeling and analysis, this work intends to close the gap in the literature by combining machine learning (ML) with conventional economic theories.

Specifically, this study seeks to evaluate the research landscape, identify influential works, authors and institutions and uncover trends in applying

ML to economic and financial issues through bibliometric data analysis. This analysis includes citation counts, co-citation networks, keyword frequencies and the proposal of a conceptual framework to integrate machine learning and economic theory. This study addresses the following research questions:

- RQ1: How can bibliometric analysis reveal trends and patterns in integrating machine learning with traditional economic theories in asset pricing and portfolio optimization
- RQ2: How can the proposed conceptual framework for integrating machine learning with economic theory enhance financial modeling and analysis

The analysis highlights the most impactful contributions, reveals key methodologies, datasets and evaluation metrics employed, sheds light on collaborative networks among researchers and institutions and identifies limitations and challenges in this research area, such as data scarcity, computational complexity and the interpretability of ML models in economic contexts. The conceptual framework proposed in this study is central to understanding how ML can be effectively integrated with economic theories.

Methods

Because of its extensive coverage and large range of diverse publications, Scopus serves as the primary database for this study and is a trustworthy source of in-depth information in a variety of sectors worldwide. Compared to other databases, Scopus offers better indexing quality, giving researchers a solid dataset to work with. For precise bibliometric research, it guarantees high-quality metadata (Mongeon and Paul-Hus, 2016). Document categories like articles, proceedings, book chapters, books, and other pertinent document types and themes that fit the research emphasis are used to examine the literature search in Scopus. Because to its excellent indexing quality and wide range of multidisciplinary coverage, Scopus was chosen above other databases like Web of Science or Google Scholar. Fig. 1 illustrates the selection process for research literature.

The ability of the bibliometric methodology to methodically assess and analyze the academic literature landscape led to its selection. Bibliometric analysis works especially well when studying the nexus between domains like finance and machine learning. It assists in locating important articles, trends, and well-known writers in the field (Zapata and Mukhopadhyay, 2022). 401 pertinent documents were found using this research methodology, demonstrating the substantial interest and contributions in this specialized field. The study period was limited to 2015–2024 in order to account for current trends and advancements.

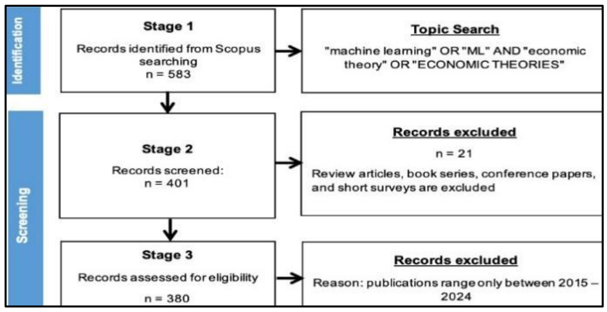

Fig. 1: Flow chart of the literature selection

This study uses VOS viewer as a sophisticated tool for bibliometric analysis by utilizing bibliometric indicators such temporal trends, the influence of highly cited texts, and the prolificacy of nations and institutions. Key contributors and influential works in particular study topics, such the use of machine learning in finance, can be found through bibliometric studies conducted with VOS viewer (Sánchez García and Cruz Rambaud, 2022). A node's size indicates the importance of the object it represents, and the link's thickness between two nodes shows how strongly they are related, allowing for a more in-depth analysis of influence and collaboration trends in this area.

This study admits a number of limitations that could affect the validity and generalizability of the results, even with the strong approach. By leaving out pertinent studies that are indexed in other databases, such as Web of Science or Google Scholar, and maybe leaving out material from lesser-known sources or non-English publications, depending just on Scopus could result in selection bias. According to Singh et al. (2021), a comparative analysis revealed notable differences in journal coverage between Web of Science and Scopus, which affects how thorough bibliometric evaluations are based on the database employed. Bibliometrics analysis relies on citation data, which might be biased in perceived impact and influence due to self-citations, the delay between publication and citation, and different disciplinary citation processes.

Results

General Trends

The use of Machine Learning (ML) in asset valuation and portfolio optimization has received attention from researchers with the number of publications increasing from 2015 to 2023 (Fig. 2). To keep up with the development of related writings, this article categorizes the discussion of results in five main periods; specifically "the foundational a long time" (2015-2016), "extension and application" (2017-2018), "profound learning and enormous information analytics" (2019-2020), “integration and interdisciplinary approaches” (2021-2022), “towards autonomous finance” (2023-2024).

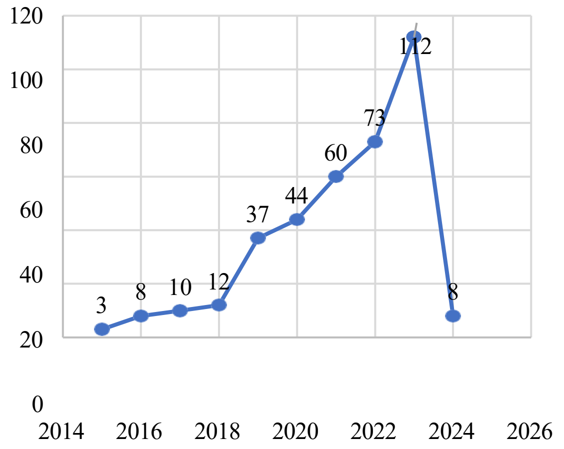

Fig. 2: Number of publications

2015-2016: The Foundational Years

Thanks to the groundbreaking work of academics like Bertsimas and Takeda (2015), Ghoddusi et al. (2019), and Bonissone (2015), the introduction of Machine Learning (ML) into the financial industry in the first half of 2015–2016 was a turning point in the development of financial technologies. These early efforts established a strong basis for using machine learning (ML) to improve conventional financial models and streamline portfolio management. By demonstrating how machine learning (ML) might handle complicated datasets to optimize asset allocation and risk management techniques, Bertsimas and Takeda (2015) illustrated the transformational potential of robust mixed-integer optimization approaches in financial decision-making. Simultaneously, Ghoddusi et al. (2019) investigated the addition of different data sources to the Black-Litterman model, demonstrating machine learning's capacity to integrate a broader range of data, including social media insights and market data, to improve investment strategies with better market forecasts.

Building on this framework, Deplano et al. (2016)'s work further highlighted the useful uses of machine learning in financial markets, specifically in the area of budget-constrained portfolio optimization. Their study demonstrated ML's ability to handle financial difficulties with previously unheard-of accuracy, providing solutions that optimize profits while respecting budgetary constraints. Furthermore, Bonissone (2015) highlighted the value of model fusion and ensemble approaches in developing more robust and accurate financial analysis tools that can adjust to market fluctuations. Collectively, these early investigations into the application of machine learning (ML) in finance not only confirmed the theoretical advantages but also cleared the path for subsequent developments, setting a standard for the application of computational and data-driven methods to transform asset pricing, risk assessment, and portfolio management tactics.

Implications: These foundational efforts set the stage for future advancements by validating the theoretical benefits of ML and demonstrating its practical applications in finance. They highlight the importance of integrating diverse data sources and advanced optimization techniques to improve financial decision-making.

2017-2018: Expansion and Application

During the years 2017-2018, the finance sector witnessed an expansion in the application of Machine Learning (ML) techniques, heralding a new era of analytical capabilities in market analysis, risk management and asset allocation. This period was characterized by a significant shift towards leveraging alternative data sources to enhance asset pricing models, illustrating the growing recognition of ML's versatility and effectiveness in capturing complex market signals beyond traditional financial indicators. Studies like those by Houlihan and Creamer (2017) emphasized the potential of sentiment analysis from social media and options volume as predictive tools for future asset returns, showcasing the innovative ways in which ML could integrate diverse data types to improve investment strategies and model performance.

Furthermore, the exploration of intraday online investor sentiment by Renault (2017) and the development of portfolio optimization models by Ha *et al.* (2017) exemplified the practical applications of ML in real-time market conditions and portfolio management. These advancements underscored the ability of ML to not only analyze vast datasets but also to derive actionable insights that could anticipate market movements and optimize investment portfolios with a degree of precision and efficiency previously unattainable. The integration of quantitative data analysis techniques, as discussed by Shi *et al.* (2017), along with the innovative application of ML algorithms for multi-objective loan portfolio optimization by Srinivas and Rajendran (2017), further highlighted the transformative impact of ML on financial decision-making processes. This period marked a crucial phase in the evolution of finance, setting the stage for more sophisticated and data-driven approaches to investment management and financial analysis.

Implications: The expansion during this period underscores the importance of utilizing alternative data sources and advanced ML techniques to gain deeper insights into market dynamics. It suggests that integrating sentiment analysis and other non-traditional data can significantly enhance the predictive power of financial models.

2019-2020: Deep Learning and Big Data Analytics

The years 2019 and 2020 marked a transformative period in the financial sector, distinguished by groundbreaking strides in the application of deep learning and big data analytics. This era ushered in novel methodologies that profoundly reshaped traditional asset pricing and portfolio management frameworks. Aldridge's (2019) seminal work shed light on the untapped potential of big data in enhancing portfolio allocation strategies. By challenging the conventional wisdom of mean-variance portfolio theory, Aldridge demonstrated that optimizing the inverse of the correlation matrix rather than the matrix itself could significantly amplify the efficacy of portfolio selection strategies. This innovative approach was shown to deliver substantial outperformance over traditional strategies, including a remarkable 400% improvement over equally weighted allocations in a 20-year S&P 500 portfolio analysis. Concurrently, the research by Cong *et al*. (2021) delved into the realm of deep sequence modeling for asset pricing, showcasing the capability of deep learning to decipher complex datasets and extract pivotal insights for financial modeling.

These advancements signified a pivotal shift toward data-centric finance, where machine learning algorithms became instrumental in refining asset pricing models and optimizing investment strategies. The exploration into residential asset pricing prediction by Luo (2019) and the neural network-based framework for financial model calibration by Liu *et al*. (2019) exemplified the burgeoning role of machine learning in enhancing the precision of financial predictions. These methodologies leveraged diverse and intricate data sets, ranging from micro-level property features to broad market indicators, demonstrating an unparalleled ability to forecast asset prices with high accuracy. Furthermore, the integration of machine learning into portfolio optimization processes not only improved the strategic allocation of investments but also fostered a more dynamic and responsive investment management approach. This period of innovation laid the groundwork for a new era in finance, characterized by an emphasis on data-driven decision-making and the adoption of sophisticated analytical models. As these technologies continue to evolve, their potential to revolutionize financial analysis and investment strategies is boundless, promising ever-more refined and efficient solutions in the complex landscape of modern finance.

Implications: The advancements in deep learning and big data analytics highlight the transformative potential of these technologies in finance. They suggest that deep learning models can significantly improve the accuracy and efficiency of financial predictions and portfolio optimization, paving the way for more sophisticated data-driven approaches.

2021-2022: Integration and Interdisciplinary Approach

The years 2021-2022 further solidified the integration of Machine Learning (ML) into the financial sector, focusing on developing holistic and interdisciplinary frameworks that blend economic theory with advanced computational techniques. This period underscored the significance of leveraging the strengths of both fields to enhance the accuracy and efficiency of financial models. Notably, sustainability and ethical considerations began to play a crucial role in portfolio management, with ML models incorporating these factors to create more responsible investment strategies. For instance, William *et al*. (2021) highlighted the advantages of deep sequence modeling in asset pricing, demonstrating how ML can capture complex historical dependencies that traditional time-series models might overlook, thereby offering a more nuanced approach to predicting asset returns and measuring risk premiums.

In 2022, the field witnessed innovative explorations into the realms of smart beta and factor investing through the lens of Hsu *et al*. (2022) critiqued the performance of smart beta products, advocating for a diversified approach across a broader set of global factors. Their research underscored the effectiveness of ML models, such as linear ridge and gradient boosting, in generating significant excess returns by fitting expected returns to a comprehensive set of factors. This period also saw the application of ML in identifying companies with lasting competitive advantages (Jiménez-Preciado *et al*., 2022), demonstrating ML's potential to enhance stock portfolio optimization by identifying key financial ratios indicative of a company's moat. These advancements exemplify the increasing sophistication of ML applications in finance, highlighting a trend towards more dynamic, informed and ethically conscious investment strategies that leverage the predictive power and analytical depth of ML algorithms.

Implications: This integration period emphasizes the importance of interdisciplinary approaches that combine economic theories with ML techniques. It highlights the growing trend towards incorporating sustainability and ethical considerations into financial models, reflecting a broader shift towards responsible and informed investment strategies.

2023-2024: Towards Autonomous Finance

The financial industry saw significant change in 2019 and 2020, characterized by ground-breaking advancements in the use of big data analytics and deep learning. This period saw the introduction of innovative techniques that significantly altered

conventional models for portfolio management and asset pricing. Aldridge's groundbreaking research from 2019 illuminated the unrealized potential of big data to improve portfolio allocation techniques. Aldridge showed that optimizing the inverse of the correlation matrix instead of the matrix itself could greatly increase the effectiveness of portfolio selection strategies, defying the accepted wisdom of mean-variance portfolio theory. A 20-year S&P 500 portfolio analysis revealed that this novel approach significantly outperformed conventional strategies, including an astounding 400% improvement over evenly weighted allocations. At the same time, Cong et al.'s study from 2021 explored deep sequence modeling for asset pricing, demonstrating how deep learning can interpret complicated datasets and extract crucial information for financial modeling.

These developments signaled a significant turn toward data-centric finance, where machine learning algorithms played a key role in improving investment strategies and asset pricing models. Luo's (2019) investigation into residential asset pricing prediction and Liu et al.'s (2019) neural network-based framework for financial model calibration demonstrated the growing significance of machine learning in improving the accuracy of financial forecasts. These approaches showed an unmatched capacity to predict asset prices with a high degree of accuracy by utilizing a variety of complex and varied data sets, from broad market indicators to micro-level property attributes. Additionally, using machine learning into portfolio optimization procedures promoted a more dynamic and responsive approach to investment management in addition to bettering the strategic allocation of investments. A new age in finance, marked by a focus on data-driven decision-making and the use of advanced analytical models, was made possible by this innovative period. These technologies have the potential to completely transform financial research and investing strategies as they develop further, offering ever-more-sophisticated and effective answers in the intricate world of contemporary finance.

Repercussions: Big data analytics and deep learning developments demonstrate how these technologies have the ability to revolutionize the financial industry. They contend that deep learning models have the potential to greatly increase the precision and effectiveness of financial forecasts and portfolio optimization, opening the door for increasingly complex data-driven strategies.

2021–2022: Multidisciplinary Approach and Integration

The financial industry's adoption of Machine Learning (ML) was further cemented in 2021–2022, with an emphasis on creating comprehensive, multidisciplinary frameworks that combine cutting-edge computational methods with economic theory. This time period demonstrated how important it is to use both disciplines' capabilities to improve the

financial model efficiency and accuracy. Notably, ethical and sustainable issues started to become important in portfolio management, and ML models started to take these things into account to develop more conscientious investment plans. William et al. (2021), for example, emphasized the benefits of deep sequence modeling in asset pricing by showing how machine learning (ML) can capture intricate historical dependencies that conventional time-series models might miss, providing a more sophisticated method of estimating risk premiums and forecasting asset returns.

Through the perspective of Hsu et al. (2022), the field saw creative investigations into the domains of smart beta and factor investing in 2022. They criticized the performance of smart beta products and argued for a diversified strategy across a wider range of global factors. Their study demonstrated how well machine learning models, such linear ridge and gradient boosting, can fit predicted returns to a wide range of parameters and produce sizable excess returns. During this time, machine learning (ML) was also used to find businesses that had long-lasting competitive advantages (Jiménez-Preciado et al., 2022). This showed how ML may improve stock portfolio optimization by identifying important financial parameters that indicate a company's moat. These developments demonstrate the growing sophistication of machine learning (ML) applications in the financial industry and point to a trend toward more dynamic, knowledgeable, and morally responsible investment strategies that make use of the analytical depth and predictive capacity of ML algorithms.

Implications: The significance of multidisciplinary approaches that blend economic theory with machine learning techniques is highlighted by this integration period. As part of a larger movement toward ethical and responsible investing practices, it draws attention to the expanding trend of integrating environmental and ethical issues into financial models. 2023–2024: Towards Autonomous Finance

In the years 2023–2024, the financial sector has started a paradigm shift toward autonomous finance, in which machine learning (ML) and artificial intelligence (AI) technology handle financial strategy development and decision-making. Significant developments in AI-driven portfolio management systems and reinforcement learning are major factors driving this change. These technologies hold the potential to completely transform asset pricing and portfolio optimization by providing previously unheard-of levels of accuracy and efficiency. In addition to increasing the speed and flexibility of financial operations, the implementation of fully automated trading methods and decision-making procedures offers a new degree of customization based on the preferences of specific investors and market conditions. This shift to autonomous finance marks a break from conventional, manual financial market activity and points the way toward a time when computers and artificial intelligence

More efficiently than ever before, systems can adapt dynamically to changes in the market in real time, maximize investment returns, and reduce risks.

The financial industry's transition to autonomy in 2023–2024 is a turning point in its history and is indicative of a larger trend of digital transformation in international marketplaces. It is anticipated that these AI-driven systems will be able to manage progressively more intricate financial activities as they develop, ranging from risk management and asset allocation to asset pricing prediction analytics. In addition to bringing in a new era of financial technology, this development presents investors, asset managers, and regulatory agencies with both new opportunities and challenges. Beyond just improving operational efficiency, autonomous finance holds promise for a future in which financial markets function with increased transparency, decreased human error, and improved resistance to market volatility. Autonomous finance will be a key component of the next-generation financial services sector as AI and ML are integrated into the financial sector, which promises to reinvent asset management and investment strategy concepts.

Repercussions: The development of financial technology has advanced significantly with autonomous finance. It implies that AI-driven systems are better than conventional techniques at minimizing risks, optimizing investment returns, and dynamically adapting to real-time market fluctuations. Investors, asset managers, and regulatory agencies face both new opportunities and challenges as a result of this evolution, which portends a time when financial markets will function with more openness and less human error.

Furthermore, a notable worldwide trend toward the use of computational methods for financial market analysis is demonstrated by the combination of economic theories and machine learning in asset pricing and portfolio optimization. With a noteworthy engagement value of 98, the United States is at the forefront of this cutting-edge industry and has demonstrated a strong commitment to furthering financial technology research and application (Fig. 3). With a rating of 81, China comes in second, indicating its significant investments in financial sector machine learning applications. Significant contributions are also shown by the UK (28), and India (35), highlighting the broad interest in this field in both developed and developing nations.

Countries with a wide range of economic backgrounds are participating in this study field, continuing the trend. For example, Germany (21), Italy (14) and France (13) make significant contributions, demonstrating the desire in Europe to combine conventional economic theory with contemporary computer methods. Likewise, South Korea's engagement score of 10 is consistent with its well-known propensity for technical innovation, especially when it comes to implementing machine learning in financial markets. Other nations that actively participate include Brazil and Canada (each with a value of 10), demonstrating the widespread appeal and application of these cutting-edge strategies for comprehending and managing the intricacies of international financial markets.

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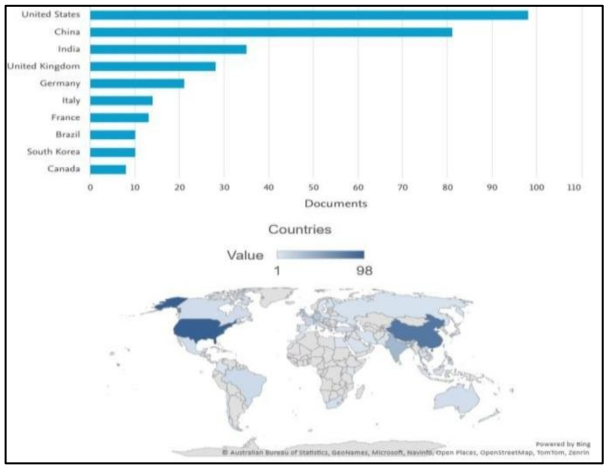

Fig. 3: Publications by countries

This broad spectrum of engagement from the United States and China to countries like South Korea and beyond emphasizes a global shift towards data-driven financial decision-making. It reflects a collective recognition of the potential that machine learning and artificial intelligence hold for enhancing the accuracy of asset pricing models and the efficiency of portfolio optimization strategies. This paradigm shift is not confined to the financial sectors of highly developed economies but is also evident in emerging markets, suggesting a future where technology and economics are increasingly intertwined to address the challenges and opportunities presented by global financial systems.

In Europe, countries like Germany, Italy and France are merging traditional economic principles with modern computational techniques, further highlighted by Germany's engagement in integrating solvency capital requirements with machine learning for portfolio optimization. Similarly, South Korea's investment in machine learning for the financial sector reflects its penchant for technological innovation, particularly in financial markets. This collective movement towards leveraging artificial intelligence across the financial sector suggests a future where technology and economics are increasingly interwoven to navigate global market complexities. In the United States, deep learning innovations and the identification of novel factors influencing asset prices are forefront, as evidenced by research from Chen *et al*. (2024), which showcases the use of neural networks for dynamic asset pricing models. This is complemented by Maasoumi *et al*. (2024), who apply debiased machine learning for high-dimensional risk factor identification and (Peng and Linetsky, 2022), proposing new portfolio optimization frameworks that incorporate economic theories with machine learning. In contrast, Chinese research delves into market dynamics and investor behavior, employing data fusion techniques to enhance asset pricing and portfolio strategies, as seen in the works by Jin and Sui (2022); Henrique *et al*. (2019)

who explore the predictive capabilities of machine learning models under varying market conditions. Similarly, in Korea, innovative approaches like those of Kim *et al*. (2023) leverage conditional autoencoders to improve the explanatory power of asset pricing models, indicative of a broader trend in the Korean financial research community towards adopting advanced computational techniques for financial modeling. This global engagement in machine learning applications for financial analysis underscores a collective recognition of its potential to revolutionize asset pricing accuracy and portfolio optimization efficiency, marking a significant paradigm shift in the financial sectors of both developed and emerging markets worldwide.

The analysis of institutions (Fig. 4) appearing in the list provides an overview of the academic entities playing a crucial role in integrating economic theory and machine learning in the context of asset pricing and portfolio optimization. Shanghai University of Finance and Economics, with the highest frequency of 7, stands out as one of the leaders in this field. This institution likely maintains a specific focus on financial economics research and the application of machine learning in asset and portfolio analysis. Additionally, tecnológico de Monterrey, Massachusetts Institute of technology, Stevens Institute of technology, the University of Chicago and The University of Chicago booth school of business, each with a frequency of 6, also play significant roles in developing methods that combine economic theory with cutting-edge technology in asset and portfolio management. Furthermore, institutions like the University of Johannesburg, Southwestern University of Finance and economics and the University of California, Berkeley, each with a frequency of 5, have a substantial presence in the thinking and research related to the topic. These institutions provide an ideal environment for interdisciplinary collaboration between economics and computer science, enabling the development of innovative solutions in asset analysis and portfolio management. Through this frequency distribution, it is evident that these institutions play crucial roles in advancing the integration of economic theory and machine learning for the purpose of asset valuation and portfolio optimization.

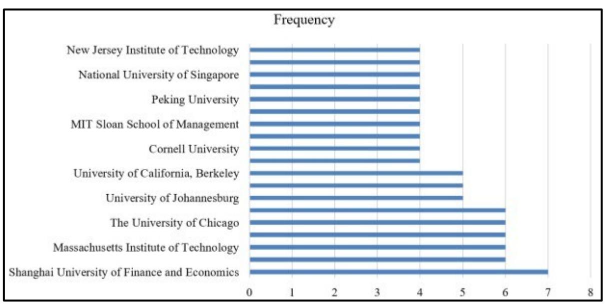

Fig. 4: Number of publications by institutions

Table 1: Number of publications by journal

Journal	Number of citations
Lecture notes in computer science	16
Expert systems with applications	14
Quantitative Finance	8
Lecture notes in Networks and Systems	7
Journal of Financial Data Science	7
Annals of Operations Research	5
ACM international conference proceeding series	5
Mathematics	4
Journal of risk and financial management	4
Journal of finance and data science	4

The academic landscape in various fields is often characterized by the prominence of journals that serve as important platforms for disseminating research findings (Table 1). In the realm of computer science and related disciplines, the "lecture notes in computer science" journal stands out with a notable citation count of 16, indicating its significant impact on the field. Similarly, "expert systems with applications" garners attention with 14 citations, underscoring its influence in the realm of applied artificial intelligence. In the realm of finance, "quantitative finance" is recognized with 8 citations, reflecting its importance in advancing quantitative methodologies for financial analysis and decision-making. Additionally, "lecture notes in networks and systems" and the "journal of financial data science" both receive 7 citations, highlighting their contributions to the understanding of network systems and financial data analysis, respectively. Furthermore, journals such as the "annals of operations research" and the "ACM international conference proceeding series" each receive 5 citations, signifying their roles in disseminating research on operational and computational aspects of various disciplines. Lastly, "mathematics," "journal of risk and financial management," and "journal of finance and data science" all receive 4 citations, demonstrating their relevance in publishing research at the intersection of mathematics, risk management and financial analytics. Collectively, these journals play vital roles in shaping scholarly discourse and advancing knowledge within their respective domains.

Furthermore, Table 2 summarizes ten articles that explore the integration of machine learning techniques in various aspects of finance. The first article by Gu *et al.* (2020) demonstrates substantial economic gains for investors through machine learning forecasts, identifying tree and neural network methods as particularly effective. Heaton *et al.* (2017) investigate the application of deep learning hierarchical models for financial prediction, showing improvements over traditional methods. Renault (2017) derives investor sentiment from social media and its impact on intraday stock returns, outperforming conventional sentiment analysis approaches. Zhang *et al*. (2019) propose a Generative Adversarial Network (GAN) for stock market prediction, yielding promising results in predicting closing prices. Beck and Jentzen (2019) introduce a method for solving high-dimensional fully nonlinear PDEs, demonstrating its efficiency in financial modeling. Elmachtoub and Grigas (2022) present a framework called Smart "Predict, then Optimize" (SPO), which leverages optimization problem structures to design better prediction models. Adapt machine learning methods for portfolio optimization, showing superiority over traditional benchmarks. Lamperti *et al*. (2018) combine machine learning and iterative sampling for efficient calibration of agent-based models, resulting in accurate model approximations. Buehler *et al*. (2019) introduce deep hedging, a framework for portfolio hedging using reinforcement learning methods, which shows promising results across different scenarios.

Last *et al*. (2020) propose a decision-making model for day trading investments using machine learning and portfolio selection, achieving significant performance improvements. These articles collectively contribute to advancing the use of machine learning in finance, offering insights and methodologies for various financial applications.

Based on Fig. 5, each cluster seems to represent a thematic focus area within the broader context of finance, economics and machine learning. Here are the proposed themes for each cluster.

Table 2: Most-cited articles related to the economic aspects of MSW management systems

Reference	Journal	Number of citations	Main result
Gu *et al*. (2020)	Review of financial studies	551	Demonstrated economic gains to investors using machine learning forecasts, identifying best-performing methods (trees and neural networks)
Heaton *et al*. (2017)	Applied Stochastic models in business	280	Explored deep learning hierarchical models for financial prediction, showing improved results over standard methods in finance and industry
Renault (2017)	Journal of Banking and finance	194	Derived investor sentiment from social media and its relation to intraday stock returns, outperforming standard methods in sentiment analysis
Zhang *et al*. (2019)	Procedia Computer science	163	Proposed a Generative Adversarial Network (GAN) for stock market prediction, showing promising performance in closing price prediction
Beck and Jentzen (2019)	Journal of Nonlinear science	155	Proposed a method for solving high-dimensional fully nonlinear PDEs, demonstrating their efficiency in financial models
Elmachtoub and Grigas (2022)	Management Science	147	Introduced a framework, Smart "Predict, then Optimize" (SPO), for designing better prediction models by leveraging optimization problem structure
Ban *et al*. (2018)	Management Science	142	Adapted machine learning methods, regularization and cross-validation, for portfolio optimization, showing dominance over benchmark methods
Lamperti *et al*. (2018)	Journal of Economic dynamics and control	140	Combined machine-learning and iterative sampling for efficient calibration of agent-based models, showing accurate model approximations
Buehler *et al*. (2019)	Quantitative Finance	138	Presented a framework, deep hedging, for portfolio hedging using reinforcement learning methods, showing promising results in various scenarios
Paiva *et al*. (2019)	Expert systems with applications	128	Proposed a decision-making model for day trading investments using machine learning and portfolio selection, showing significant results

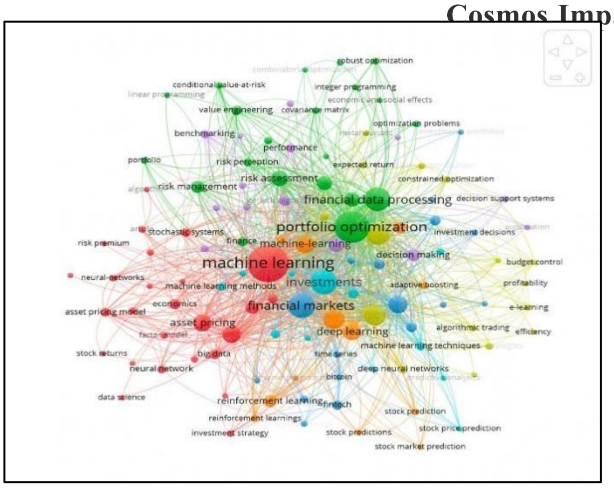

Fig. 5: Segmentation clustering

Cluster 1: Asset Pricing and Predictive Analysis

This cluster provides a thorough understanding of how ML approaches are incorporated into asset pricing. It explores how well different machine learning models predict asset prices, contrasts them with more conventional asset pricing techniques, and critically assesses empirical research in the area. It examines how well different machine learning models predict asset prices, contrasting them with more conventional asset pricing techniques and providing a critical analysis of the empirical data in the field. Notably, it has been demonstrated that ML predictions can greatly improve performance over conventional regression-based techniques; models such as trees and neural networks are particularly effective in this regard (Gu et al., 2020). Additionally, in the context of asset pricing, Fang and Taylor (2021) highlight the superiority of machine learning techniques—such as regularized linear, support vector machines, neural networks, and tree-based—over simple ordinary least squares linear regression. When combined with realized skewness, the LSTM model significantly improves asset pricing performance, outperforming other ML techniques and conventional approaches on a number of criteria (Choudhary and Arora, 2024). Furthermore, compared to leading factor models, autoencoder neural networks have shown the capacity to generate out-of-sample pricing errors that are far smaller and typically insignificant (Gu et al., 2021).

When predicting stock prices, bond yields, or real estate values, the choice of machine learning model is critical and differs based on the asset pricing job at hand. This suggests a preference for distinct ML approaches. Neural network classifiers have demonstrated remarkable performance, and machine learning algorithms have regularly outperformed established benchmark models like ARIMA and random walk-in predicting prices of Bitcoin futures (Akyildirim et al., 2021).

accurate in foreseeing significant stock price changes (Kamalov, 2020). ML techniques also enhance linear asset pricing models by facilitating multiple hypothesis testing, thereby reducing false positives and improving hedge fund evaluation performance (Giglio *et al*., 2018). These findings affirm ML models as transformative in asset pricing, offering unparalleled predictive accuracy and performance across different asset classes and market scenarios relative to traditional models.

In practical settings, employing ML in asset pricing necessitates thoughtful consideration of data sources, preprocessing techniques and model selection. ML effectively integrates economic indicators, media content and momentum spillovers from related firms to improve asset pricing performance (Huang *et al*., 2022). However, the quality of financial data plays a pivotal role in the success of ML models, addressing challenges like missing Non-stationarity, noise, and data are typical in financial datasets. Normalization, feature engineering, and dimensionality reduction are examples of data preprocessing techniques that are crucial for getting data ready for efficient machine learning analysis. Furthermore, because they determine the significance of particular features to the comprehension of the diversity in returns across various securities, sorting techniques are a fundamental tool in asset pricing. These methods, which are usually built around particular company characteristics like market size or value-to-market ratio, can also include predictive evaluations to measure forecast accuracy (Coqueret, 2020). According to Blitz et al. (2023), classic machine learning (ML) studies in asset pricing often emphasize factors with good short-term predictive potential and attempt to forecast stock returns one month in advance. This method has difficulties since it requires a large amount of training data to obtain a comparable number of independent observations, even if it is not intrinsically inappropriate for long-term return projections. A decade's worth of training data, for example, produces 120 independent monthly observations but only 10 yearly ones, making it more difficult to estimate long-term returns because of the short data history. Coqueret (2020) documents the importance of memory in ML-based models that use firm characteristics for asset pricing, and the shift from short-term to long-term return predictions highlights the significance of characteristics in ML predictions. The study finds that predictive algorithms perform best when trained on large samples with long-term returns as dependent variables.

An organized summary of the different machine learning models and the authors that have contributed to the subject of asset pricing is given in Table 3. A variety of computational techniques used in financial analysis are represented by the models provided, including support vector machines, random forests, and neural networks.

Table 3: Machine learning for asset pricing

Best-performing model	Authors
Neural network	Ceffer *et al*. (2019); Drobetz and Otto (2021); Fang *et al*. (2023); Gu *et al*. 2020; Kamalov (2020)
Random Forest	Alanis (2022); Escribano and Wang (2021); Götze *et al*. (2020); Yu *et al*. (2010)
Support Vector Machine	Aggarwal *et al*. (2020); Başoğlu Kabran and Ünlü (2021); Sedighi *et al*. (2019)
Recurrent Neural Network (RNN)	Koudjonou and Rout (2020); Lamothe-Fernández *et al*. (2020); Liu (2019)
Convolutional Neural Network (CNN)	Korade and Zuber (2023); Lee and Ko (2019); Liu and Wu (2023); Li *et al*. (2022)
Long Short-Term Memory (LSTM)	Fischer and Krauss (2018); Gao *et al*. (2021); Liu and Zhang (2023);
Bayesian Neural Network	Cocco *et al*. (2021); Jang and Lee (2019)
K-Nearest Neighbors	Gu *et al*. (2022); Tang *et al*. (2020a-b)
XGBoost	Akyildirim *et al*. (2023a-b); Ben Jabeur *et al*. (2021); Jiang *et al*. (2020)

Source: own work (2023)

Theoretical Foundation and Framework Integration

The theoretical foundation of this first cluster includes the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT), which are foundational models in asset pricing that describe the relationship between systematic risk and expected return for assets, particularly stocks. This theoretical framework aids in understanding the transformative impact of ML on asset pricing models, data preprocessing techniques and the overall financial decision-making process.

CAPM is a foundational model in finance that describes the relationship between systematic risk and expected return for assets, particularly stocks (Sharpe, 1964). The limitation of CAPM is the assumption of a linear relationship and it often fails to account for complex market dynamics and nonlinearities.

CAPM Formula:

$$E(R_i) = R_f + \beta_i(ER_m - R_f)$$

Arbitrage Pricing Theories (APT) is an extension of CAPM that considers multiple factors in determining asset prices (Ross, 1976), allowing for a more nuanced understanding of risk and return. APT has a limitation in identifying the correct factors and their influence on asset prices and APT also still assumes linear relationships.

APT Formula:

$$E(r_p) = r_f + \beta_1\lambda_1 + \beta_2\lambda_2 + \cdots + \beta_k\lambda_k$$

APT extends CAPM by incorporating multiple factors, providing a more nuanced understanding of asset prices. However, identifying the correct factors and their influence can be challenging and APT still assumes linear relationships.

Machine Learning (ML) techniques offer a transformative approach to asset pricing by addressing the limitations of CAPM and APT. Unlike traditional models, ML algorithms can capture complex, nonlinear relationships and interactions within financial data. For instance, neural networks, Support Vector Machines (SVM) and random forests can process large volumes of data and identify patterns that traditional models might miss. Empirical studies have demonstrated the superior performance of ML models over traditional methods in predicting asset prices, highlighting their ability to enhance predictive accuracy and uncover insights from diverse data sources.

The connection of this cluster with the technical aspects of machine learning can be seen in Chapter 4.

Cluster 2: Algorithmic Trading

The groundbreaking work of Bogousslavsky et al. (2024), who presented a novel method for measuring informed trading, has revolutionized algorithmic trading. Their study represents a major breakthrough in the industry by creating an educated Trading Intensity (ITI) metric and using machine learning techniques to a data set full of educated trades. This metric is especially useful for forecasting return reversals and their effects on asset pricing during major market events including news releases, mergers and acquisitions, and earnings announcements. ITI's power resides in its capacity to provide a detailed knowledge of the mechanics of informed trading by capturing intricate nonlinear correlations and interactions between trade volume, market volatility, and informed trading. Such an approach is an important tool for studying market efficiency since it not only clarifies the dynamics of informed trading but also investigates aspects such as impatient trading habits, commonality in informed trading across various assets, and theoretical models of informed trading.

A Context-Aware Hierarchical Attention Mechanism (CHARM), developed by Tan et al. (2024), is a complement to this and is intended to encode unstructured textual media content. This cutting-edge program skillfully tracks the concrete effects of news on media-influenced stock movements. CHARM enables the investigation and display of their combined influence on stock market movements by utilizing tensor-based learning to integrate encoded media information with other structured market data. Additionally, a technique for anticipating trading clue turning point locations is used, which increases the effectiveness of every investment opportunity. In comparison to other models such as AZFinText, TeSIA, eLSTM, CMT, MAC, and SA-DLSTM, it not only improves the clarity of investment strategies but also dramatically increases investment returns and predicted accuracy.

Zhao et al. (2016) add to the discussion by concentrating on return reversal predicting using a two-tiered method. First, from a wide range of economic factors, a Dynamical Bayesian Factor Graph (DBFG) is used to isolate important elements that are strongly linked to return reversals. These important variables are then used to anticipate return reversals by feeding them into a variety of predictive models, including the Hidden Markov Model (HMM), Support Vector Machine (SVM), and Artificial Neural Network (ANN). Although the critical variables for return reversals change every year, their examination of the U.S. stock market shows that components related to the liquidity impact theory are always important. Notably, the DBFG-ANN model achieves prediction accuracies above 60, outperforming its competitors.

The field of algorithmic trading has significantly advanced as a result of these investigations. These studies provide new ways to analyze market movements, increase the efficacy of investment strategies, and improve the predicted accuracy of market analysis through the use of cutting-edge measurements, complex data processing tools, and sophisticated prediction models.

Theoretical Background and Framework Integration

The theoretical foundation of this cluster is rooted in the Efficient Market Hypothesis (EMH). The Efficient Market Hypothesis (EMH) defines that asset prices fully reflect all available information, meaning that it is impossible to consistently achieve returns higher than the overall market average (Malkiel and Fama, 1970). The formal expression of EMH can be summarized as follows.

EMH formula:

$$P^e_{t+1} = P^e_{t-1} \rightarrow R^e = R^{of} \rightarrow R^{of} = R^*$$

A limitation of EMH is that it assumes all market participants have access to all available information and interpret it in the same way, which often does not hold true in reality. Markets can be influenced by irrational behavior, information asymmetry and other anomalies that EMH does not account for.

By combining the concepts from EMH with Machine Learning (ML) techniques, algorithmic trading can enhance market efficiency and liquidity while reducing transaction costs. The use of ML models can help quantify informed trading and predict market movements more accurately, thereby aligning trading strategies with the theoretical underpinnings of EMH.

The connection of this cluster with the technical aspects of machine learning can be seen in chapter 4.

Cluster 3: Data-Driven Portfolio Management and Optimization

Machine learning techniques have demonstrated significant effectiveness in portfolio optimization for financial assets. These techniques range from clustering analysis, genetic algorithms and neural networks, to adaptive Bayesian optimization, each offering unique advantages in portfolio management. For instance, the application of Long Short-Term Memory (LSTM) networks for forecasting financial time series, in tandem with mean-variance models, significantly optimizes portfolio formation and asset preselection (Gu *et al*., 2022). Integrating unsupervised machine learning methods, like clustering analysis, into mean-variance portfolio optimization models enhances the selection of assets in a portfolio (Tolun Tayalı, 2020). Novel frameworks like the DSRG Network have demonstrated superior performance in terms of returns compared to traditional strategies (Qin *et al*., 2022). Additionally, the application of clustering analysis and in-band optimization in dynamic portfolio optimization presents a competitive advantage over classical approaches in financial mathematics (Mahdavi-Damghani *et al*., 2021). Genetic algorithms in machine learning can optimally combine funds to create diversified portfolios that outperform market benchmarks. This method is particularly effective in combining various funds to achieve optimal portfolio diversification (Onek, 2019). Neural networks can enhance portfolio performance by incorporating macroeconomic conditions. They have shown superior results in terms of annualized return, volatility, Sharpe ratio and 99% Conditional Value at Risk (CVaR), compared to alternative methods (Chang and Yu, 2014; Yuan *et al*., 2020). Adaptive Bayesian optimization in machine learning can manage risks effectively while achieving positive investment outcomes. This is achieved by adaptively tuning parameters to optimize the portfolio (Nyikosa *et al*., 2019). Furthermore, portfolios constructed using k-means clustering have yielded returns exceeding those of leading indices and mutual funds, affirming its strength in portfolio construction (Kedia *et al*., 2018). The integration of machine learning in portfolio theory offers advanced analytical tools for optimizing investment strategies and enhancing traditional models with data-driven insights and predictive capabilities.

Furthermore, Heaton *et al*. (2017) showcased the application of deep learning in constructing portfolios through a four-step algorithm that emphasizes model development and validation. This process consisting of auto-encoding, calibration, validation and verification presents a novel, model-independent approach to predictive analytics. This methodology aims to outline a comprehensive process for achieving specific investment goals, such as outperforming a benchmark, with success heavily reliant on the market framework defined by historical data. Here, portfolio optimization and inefficiency identification emerge as predominantly data-driven tasks, offering a fresh perspective divergent from classical portfolio theories.

The integration of ML is transforming decision-making processes through data-driven insights and optimization. Research in data-driven portfolio management, such as the works of Bogousslavsky *et al*. (2024); Cui *et al*. (2024), highlight ML's capability to not only dissect the micro-level intricacies of market dynamics like informed trading intensity but also to navigate the macro-level complexities of multi-period portfolio optimization through Deep Reinforcement Learning (DRL). These studies illustrate ML's broad applicability, from predicting market movements based on informed trades to optimizing investment strategies over time with significant efficiency gains.

In practical settings, ML techniques have evolved beyond theoretical constructs to become essential elements of real-world financial strategy formulation. These approaches harness data-driven insights and predictive analytics to redefine investment strategy landscapes. A key feature of these methodologies is their adaptability, offering the capacity for real-time updates and adjustments in response to evolving investor risk profiles.

Table 4 shows a range of machine learning applications in portfolio optimization. These studies employ various techniques that contribute to the evolving landscape of asset management. The listed methodologies reflect a trend toward leveraging complex algorithms for enhanced financial decision-making, signifying a paradigm shift in how data analytics can drive investment strategies.

Theoretical Foundation and Framework Integration

The most prominent theoretical basis of this cluster is Modern Portfolio Theory (MPT), Key concepts of MPT include diversification, the trade-off between risk and return, the efficient frontier, expected return and portfolio variance, all aimed at creating an optimal investment strategy. This foundational theory in finance was introduced by Harry Markowitz in his seminal paper "portfolio selection" (Markowitz, 1952).

MPT portfolio return:

$$R_p = \sum_{t=1}^{n} x_1 R_1$$

MPT portfolio risk:

$$\sigma_p = \sqrt{X_1^2\sigma_1^2 + X_2^2\sigma_2^2 + 2X_1X_1(r_{12}\sigma_1\sigma_2)}$$

The limitation of MPT is that asset returns are normally distributed, this assumption often does not hold true in real markets, where returns can exhibit skewness and kurtosis. This misalignment can lead to inaccurate risk assessments (Leahy, 2001). Furthermore, MPT involves a static optimization process, assuming that the statistical properties of returns, such as mean and variance, remain constant over time. This static nature fails to accommodate the dynamic and evolving conditions of financial markets. MPT also assumes homogeneous expectations among investors, which is unrealistic as investors often have varying information, risk preferences and investment horizons.

Table 4: Machine learning for portfolio optimization

No.	Author	Year	Machine learning algorithm
1	Pun and Wang (2021)	2019	Range-based risk using SVR
2	Naveed *et al*. (2023)	2019	Artificial Neural Network (ANN)
3	Kim *et al*. (2019)	2019	GA-rough set theory
4	Guo *et al*. (2020)	2020	Deep matching algorithm and deep stock profiling method
5	Kim and Kim (2020)	2020	Deep latent representation learning
6	Chen *et al*. (2020)	2020	Sparse-group lasso regularization
7	Ta *et al*. (2020)	2020	Long-short term memory network
8	Zhang *et al*. (2022)	2021	Listwise learn-to-rank algorithm
9	Zhang and Chen (2021)	2021	Double-screening Socially Responsible Investment (DSSRI)
10	Liu *et al*. (2021a-b)	2021	MGC algorithm and MGC-EM
11	Padhi *et al*. (2022)	2022	Intelligent fusion model
12	Chaweewanchon and Chaysiri (2022)	2022	Hybrid machine learning model

Source: own work (2023)

Machine Learning (ML) techniques, particularly clustering analysis, offer significant enhancements to MPT by addressing these limitations. Clustering algorithms, such as k-means clustering, can group assets based on their return characteristics and risk profiles, improving the asset selection process and enhancing portfolio diversification. This method goes beyond the simplistic linear relationships assumed by MPT, capturing more complex interactions and dependencies among assets.

The connection of this cluster with the technical aspects of machine learning can be seen in chapter 4.

Cluster 4: Reinforcement Learning and Adaptive Strategies in Financial Markets

The burgeoning field of financial technology has witnessed significant advancements through the application of Reinforcement Learning (RL), offering dynamic and adaptable solutions for portfolio optimization and strategic decision-making in the volatile realms of financial markets. Sarkar *et al*. (2024) pioneered the use of RL to enhance portfolio allocation strategies, showcasing its superiority over traditional methods by adeptly adapting to market fluctuations to maximize returns and minimize risks. This approach, validated through rigorous testing against historical data, marks a departure from static investment strategies, demonstrating RL's potential to achieve superior risk-adjusted returns in turbulent markets. Complementing this, Cui *et al*. (2024) introduced a Deep Reinforcement Learning (DRL) hyper-heuristic framework aimed at multi-period portfolio optimization, addressing scalability challenges and leveraging domain knowledge to outperform existing models. Furthermore, Khemlichi *et al*. (2020) expanded the horizon by integrating Multi-Agent Reinforcement Learning (MARL) with Proximal Policy Optimization (PPO) to foster a more realistic simulation of market conditions, thereby enhancing the robustness of investment strategies. Collectively, these studies underscore the transformative impact of RL and DRL in navigating the complexities of financial markets, offering innovative, data-driven approaches that promise to redefine the landscape of investment strategies and portfolio management with unprecedented adaptability and strategic depth.

Theoretical Background and Framework Integration

This cluster, like the previous ones, is anchored in the same foundational financial theories such as Modern Portfolio Theory (MPT). However, the primary distinction lies in the application and enhancement of these theories through Reinforcement Learning (RL) and its advanced variants.

MPT portfolio return:

$$R_p = \sum_{t=1}^{n} x_1 R_1$$

MPT portfolio risk:

$$\sigma_p = \sqrt{X_1^2\sigma_1^2 + X_2^2\sigma_2^2 + 2X_1X_1(r_{12}\sigma_1\sigma_2)}$$

Reinforcement Learning (RL) builds on the concepts of MPT by not only considering the trade-off between risk and return but also incorporating the ability to adapt and optimize portfolios continuously. MPT provides a framework for constructing portfolios that maximize expected return for a given level of risk through static optimization, typically assuming that the statistical properties of returns remain constant over time.

The connection of this cluster with the technical aspects of machine learning can be seen in chapter 4.

Cluster 5: Cryptocurrency Markets Predictions

Because of their volatility and abundance of data, cryptocurrency markets are leading the way in the use of machine learning forecasts. Using a prototype-based clustering algorithm designed especially for the cryptocurrency space, Lorenzo and Arroyo (2023) offer a novel risk-based portfolio allocation technique. This method tackles how mean-variance portfolio optimization models are sensitive to risk-return estimate uncertainties, which frequently lead to poor performance. The research provides a strategic edge in managing investments in the volatile cryptocurrency market by utilizing machine learning models like Random Forest and concentrating on a chosen cluster of crypto assets that match an investor's risk aversion.

Simultaneously, Erfanian et al. (2022) investigate the prediction of Bitcoin values using an economic theory framework, utilizing machine learning techniques such as support vector regression to identify the impact of technical, blockchain, macroeconomic, and microeconomic factors. Notably, their study validates the applicability of technical analysis by identifying specific technical indicators as crucial for short-term Bitcoin price forecasts. They discovered that blockchain and macroeconomic data are important long-term predictors, indicating that supply, demand, and cost-based pricing theories are the essential foundation for Bitcoin price forecasts. Their results highlight the superiority of machine learning over conventional statistical analysis in price forecasting, which has a major impact on asset pricing and investment choices.

In their investigation of Bitcoin and Ethereum, Saad et al. (2020) look into network characteristics that are related to price fluctuations. They make links to economic theories by analyzing data on user and network activity and how it significantly affects cryptocurrency pricing. By examining correlations between factors like hash rate, user count, and transaction rate, the study finds important network characteristics.

and the overall number of bitcoins, providing insight into the dynamics of supply and demand in the

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ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

cryptocurrency market. By utilizing machine learning techniques such as regression, LSTM networks, and the conjugate gradient algorithm, they create models that can accurately forecast cryptocurrency prices. The effectiveness of their algorithms has been validated on two large datasets, showing up to 99% accuracy in predicting the prices of Ethereum and Bitcoin.

Together, these studies show how machine learning may be used to understand the intricate dynamics of cryptocurrency markets and provide useful techniques for improving investment strategies, managing portfolios, and predicting prices. These contributions open the door for more advanced and successful methods of negotiating the complexities of cryptocurrency investing by utilizing machine learning and economic theory.

Integration of the Framework and Theoretical Background

Similar to the preceding clusters, this one is based on the Efficient Market Hypothesis (EMH). According to the EMH, trading techniques based on accessible information cannot consistently produce returns higher than the market average since asset prices fully represent all available information.

EMH formula:

$$P^e_{t+1} = P^e_{t+1} \rightarrow R^e = R^{of} \rightarrow R^{of} = R^*$$

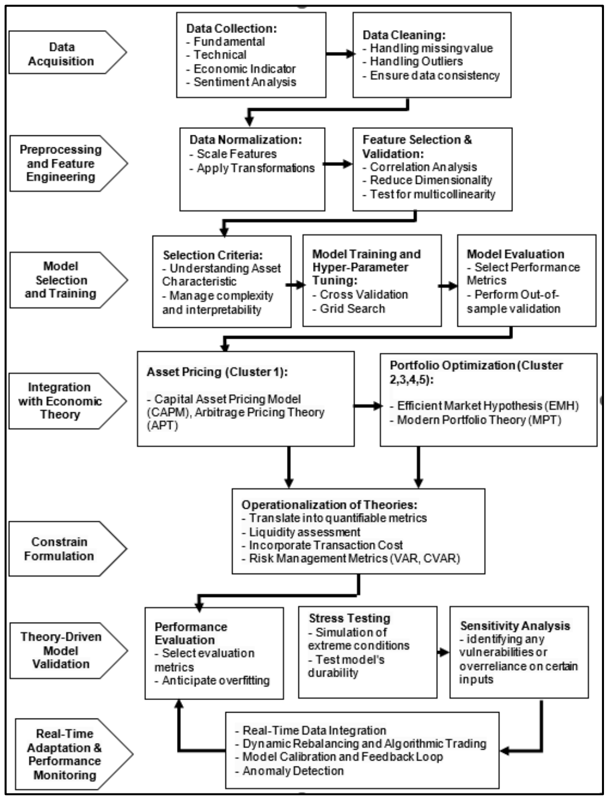
The application of EMH to cryptocurrency markets presents unique challenges. Cryptocurrency markets are newer, less regulated and more susceptible to price manipulation, information asymmetry and extreme volatility. These factors can lead to deviations from the ideal market efficiency postulated by EMH.

Machine Learning (ML) techniques significantly enhance the ability to navigate the challenges of cryptocurrency markets, as evidenced by the studies in this cluster. By employing methods such as prototype-based clustering, random forest, Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) networks, ML models can effectively manage the high volatility and unpredictability of these markets.

The connection of this cluster with the technical aspects of machine learning can be seen in chapter 4.

Conceptual Framework

The comprehensive conceptual framework presented in the image aligns with the key findings and themes discussed in the provided document content. The conceptual framework in Fig. 6 presents a comprehensive approach for integrating Machine Learning (ML) with economic theory in the domain of asset pricing and portfolio optimization.



Source: own work (2024)

Fig. 6: Conceptual framework for machine learning and economic theory integration

The framework begins with data acquisition, which involves collecting fundamental, technical, economic and sentiment analysis data. The collected data then undergoes preprocessing and feature engineering, including data cleaning, handling missing values, dealing with outliers and ensuring data consistency. The preprocessed data is normalized and relevant features are selected and validated using techniques such as correlation analysis, reduced dimensionality and testing for multicollinearity.

The next stage is model selection and training, where appropriate ML models are chosen based on the asset characteristic, complexity and interpretability. The selected models are trained using cross-validation, grid search and hyper-parameter tuning techniques and then evaluated using performance metrics such as out-of-sample validation and perform validation. This stage involves choosing appropriate ML models based on asset characteristics, complexity and interpretability, resonating with the document's findings on the importance of model selection, with various ML models showing superior performance in asset pricing and portfolio optimization tasks.

The integration with the economic theory stage incorporates well-established financial theories such as the Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), the Efficient Market Hypothesis (EMH) and Modern Portfolio Theory (MPT), anchoring the ML models in sound economic principles. The CAPM, introduced by Sharpe (1964), describes the relationship between systematic risk and expected return for assets, particularly stocks. By taking into account a variety of factors when establishing asset values, Ross's (1976) APT expands on the CAPM and provides a more sophisticated understanding of risk and return. According to the EMH, which was created by Malkiel and Fama in 1970, asset prices accurately reflect all available information, making it impossible to regularly generate returns that are higher than the average for the market. According to MPT, which was first proposed by Markowitz in 1952, investors can use diversity to create an ideal portfolio that maximizes expected return for a specific degree of risk. This step highlights the document's constant emphasis on the connection between economic theory and machine learning.

Through sensitivity analysis to find weaknesses or an over-reliance on specific inputs, stress testing under harsh conditions, and durability testing, theory-driven model validation makes sure the models' outputs are in line with economic theory. This is consistent with the document's focus on machine learning models that follow the economic justification and the need of model validation methods. Through the integration of real-time data, the use of dynamic rebalancing and algorithmic trading, the calibration of models through a feedback loop, and the detection of anomalies, real-time adaptation and performance monitoring ensure that the models stay current and relevant while continuously improving performance. This is in line with the paper's analysis of the shift to autonomous finance and the significance of flexibility in response to shifting investor preferences and market conditions.

The document's five primary phases, which are well-represented in the framework's interrelated stages, demonstrate the gradual integration of machine learning and economic theory in asset pricing and portfolio optimization. The document's cluster analysis indicates 5 primary themes: The components of the framework include asset pricing and predictive analysis, algorithmic trading, data-driven portfolio management and optimization, reinforcement learning and adaptive tactics in financial markets, and predictions for the cryptocurrency market. To sum up, the conceptual framework provides an organized method for integrating machine learning and economic theory in asset pricing and portfolio optimization by thoroughly encapsulating the major discoveries, patterns, and topics covered in the supplied document material.

Conclusion

This paper shows how combining economic theory and machine learning (ML) can revolutionize financial market analysis, especially in the areas of asset pricing and portfolio optimization. The suggested conceptual framework, which is backed by thorough bibliometric analysis, captures the complementary possibilities of economic theory and machine learning and offers an organized way to improve conventional models and methods. In order to guarantee that the final models are reliable, flexible, and sensitive to the intricacies of contemporary financial markets, the framework includes data collection and management, preprocessing and feature engineering, model selection and training, constraint formulation, theory-driven validation, and real-time adaptation and monitoring.

The suggested framework incorporates cutting-edge machine learning techniques that enable more dynamic and data-driven approaches to asset pricing and portfolio management when compared to other frameworks like the conventional Capital Asset Pricing Model (CAPM), Arbitrage Pricing Theory (APT), Efficient Market Hypothesis (EMH), and Modern Portfolio Theory (MPT). The intricacies of financial markets may be difficult for traditional models to fully capture because they frequently depend on linear relationships and static assumptions. Our approach, on the other hand, makes use of machine learning's predictive capabilities to adjust to shifting market conditions, improving the precision and resilience of financial models.

This connection gives practitioners access to more advanced, data-driven financial techniques that improve risk management and decision-making while also possibly increasing returns. Policymakers can exploit these findings to develop regulations that preserve market stability and safeguard investors, considering ethical considerations, data privacy issues and potential biases in algorithmic trading.

The study identifies five key themes, including asset pricing and predictive analysis, algorithmic trading, data-driven portfolio management and optimization, reinforcement learning and adaptive strategies in financial markets, and cryptocurrency market predictions. It also shows the increasing interest and contributions in this interdisciplinary field, with the United States and China emerging as leaders. This work opens the door for developments that combine the depth of economic knowledge with machine learning agility, resulting in more intelligent, successful, and efficient asset pricing and portfolio management strategies as the financial landscape grows more complicated.

Subsequent studies ought to concentrate on improving this integration and modifying the framework to accommodate new financial products and market circumstances. This entails creating increasingly complex models that can manage the intricacies of novel financial products, like cryptocurrencies, as well as tackling the moral and legal issues brought on by the growing application of machine learning in the financial industry. By carrying on with

By investigating and improving the relationship between machine learning and economic theory, scholars can help create a more effective and flexible method of financial modeling and analysis.

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