FIN 320: Portfolio Management

Research Paper:

Enhancing portfolio management using artificial intelligence

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Summary:

1- Introduction:

Portfolio management is a continuous process of creating portfolios based on an investor's preferred level of risk and reward and then adjusting it over time to maximize returns. This process includes three subsequent layers, namely planning, execution, and feedback.

The first layer of the process is **the planning layer**. The asset owner mandates an asset manager to manage a specific portfolio according to an investment policy (the client's needs, circumstances, and constraints to achieve a particular reward goal at a given risk level)

Strategic asset allocation (SAA) is part of this investment policy. Typically, the SAA is defined as upper and lower boundaries for the asset class allocation.

The second layer of the portfolio management process is **the execution layer**. The execution starts with determining the overall macroeconomic conditions across countries and asset classes, exploring the risk and-return characteristics of asset classes. This analysis determines the capital allocation across countries and asset classes ("tactical asset allocation").

Finally, after the portfolio experienced the market dynamics of an investment period, **the feedback layer** evaluates past performance, updates the market conditions, checks if the investment policy still holds or needs to be adjusted, and finally rebalances the portfolio.

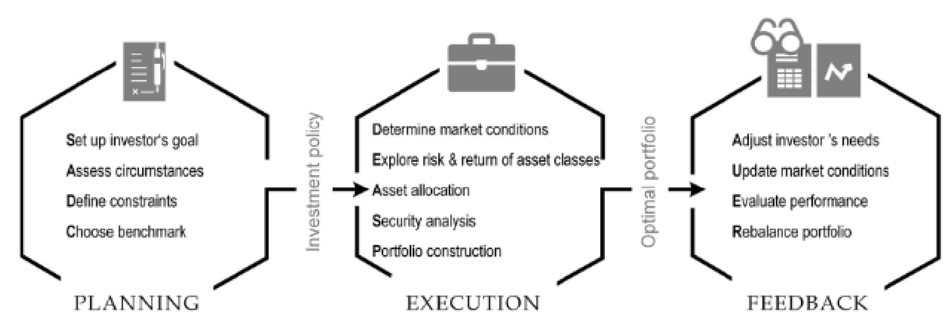

FIGURE 1
Portfolio management process.

In recent years, artificial intelligence (AI) has disrupted most industries, including the financial sector. AI techniques can contribute to portfolio management in many ways, improving the shortcomings of classical portfolio construction techniques and extending the opportunities to generate additional alpha.

For instance, machine learning (ML) can create systems that learn from experience and be used for asset price prediction.

Reinforcement learning (RL) is one of the most promising tools for developing a sequential and dynamic portfolio optimization theory.

Text mining and sentiment analysis can enhance portfolio management with fresh news from the market.

AI can produce better asset return and risk estimates and solve portfolio optimization problems under complex constraints, resulting in better out-of-sample AI-based portfolio performance than traditional approaches. From a technical point of view, the key players in the financial sector are embracing AI as a tool for automating and enhancing operational efficiency, processing vast amounts of data, improving risk management, and suggesting solutions that better suit investors' needs and accommodate risk.

2- Investment portfolio management in a nutshell:

Markowitz marks the birth of modern portfolio theory (MPT) by introducing the mean-variance efficient frontier framework. As the name suggests, the mean and variance have been employed to measure a portfolio's expected return and risk.

Inspired by Markowitz's work, Treynor, Sharpe, and Lintner independently introduced a factor model, named Capital Asset Pricing Model (CAPM), which describes the relationship between systematic risk and expected returns. Technically, CAPM decomposes an asset's return into factors common to all assets and factors specific to a particular asset.

However, one factor is not enough to quantify risk and returns adequately. This resulted in so-called multi-factor models generalized by Ross; Roll and Ross (1980), known as Arbitrage Pricing Theory (APT).

The primary difference between CAPM and APT is how a systematic investment risk is defined. CAPM includes a single, market-wide risk factor, while APT advocates several factors that capture market-wide risks.

Artificial intelligence approaches for signal generation AI techniques can be considered decision tools with a straightforward application to the different stages of portfolio execution. The ability to describe underlying market structures, process vast amounts of structural and nonstructural information, or capture the non-linearity between different variables makes AI a key role in handling market complexity. AI tools guide the portfolio manager through the entire process, from visualizing the market to identifying assets, constructing the portfolio, executing trades, and interpreting results. This contributes toward achieving trust in AI-driven portfolio management systems. This section introduces AI techniques beneficial for various subtasks in portfolio management, contributing to trust in AI-driven systems.

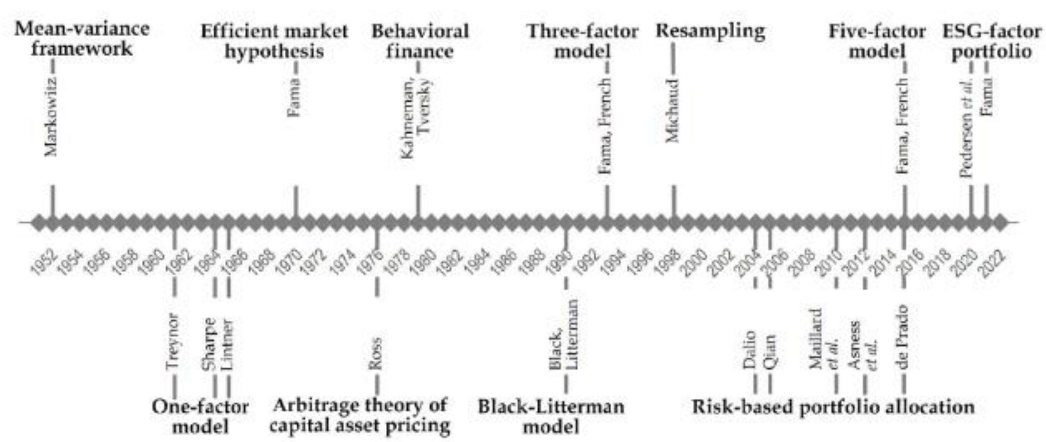

FIGURE 2
Advancements in investment portfolio management

3- Artificial intelligence approaches for signal generation:

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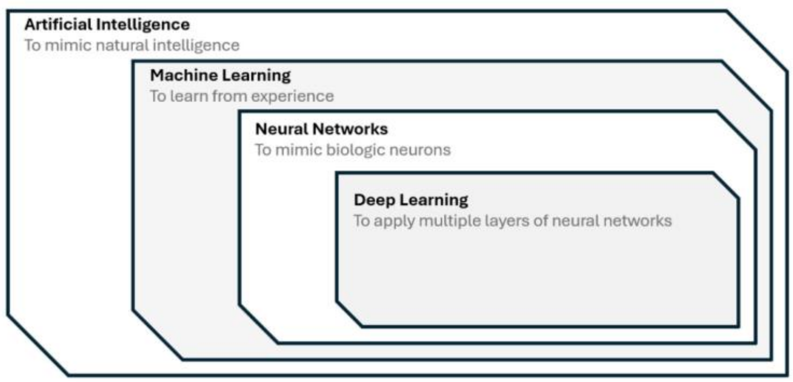

FIGURE 3
AI, ML, NN, and DL relationship diagram.

3.1- High-dimensional forecasting and predictors selection based on linear models:

Two conventional dimensionality reduction techniques that help the portfolio manager tackle the market complexity are Principal Component Regression (PCR) and Partial Least Square (PLS), regression-based procedures designed to forecast time series parsimoniously.

The first is a two-step procedure that involves constructing the principal components using Principal Components Analysis (PCA) and then using these components as the predictors explaining most of the variance in a linear regression model. The first principal component can be taken as a proxy of the market factor. The link between portfolio optimization models and PCA is straightforward, as explained in Meucci, Partovi and Caputo. The more natural choice of uncorrelated risk for a portfolio is by a PCA decomposition of the return covariance:

$$E' \Sigma E \equiv \Lambda,$$

where the diagonal matrix $\Lambda \equiv diag(\lambda_1, ..., \lambda_N)$ contains the eigenvalues of Σ, sorted in decreasing order. In this way, the complexity of portfolio selection is reduced if there are no correlations among the assets. Comparatively, PLS regression reduces dimensionality by incorporating the forecasting objective or response.

Linear combinations maximize the covariance between the target variable and each standard component obtained from the predictors. Kelly and Pruitt are one of the first attempts to apply PLS regression to finance. In Kelly and Pruitt, the three-pass regression filter (3PRF) was proposed, which has been proven to be consistent for the infeasible best forecast when both the time dimension and cross-section dimension become large. Unlike PLS, the 3PRF enables the selection of additional disciplining variables based on economic theory. PCR and PLS are techniques that merge the set of predictors from dimension D to a much smaller number of L linear combinations. Comparatively, Ridge, LASSO and Elastic net methods focus more on shrinkage, moving the model coefficients to zero. Ridge penalizes the square sum of coefficients called l2, reducing the variance compared with Ordinary Least Square (OLS). LASSO regularization penalizes the absolute sum of coefficients called l1 shrunk toward zero, achieving a selection of the predictors, which outperforms OLS as well. Elastic net includes a regularization that combines l1 and l2, handling the weight of each by a hyper-parameter. Specifically, LASSO, a form of regularized regression, combines variable selection and regularization to improve prediction accuracy. It automatically selects the most predictive input factors from a set enabling the exploration of lead-lag relationships between asset groups. This approach is crucial in determining influential predictors, such as industry or market output, preventing overfitting, and controlling model complexity in machine learning methods. Table 1 gives good examples of selecting significant predictors.

TABLE 1 Forecasting with a high number of potential predictors.

Application purpose	Method	Description	References
Combined index	Dynamic factor model	Development of new indexes to represent leading and coincident economic indicators	Stock and Watson, 1989, 1998
Feature selection	Double-selection estimation procedure	Framework for systematically evaluating the contribution of individual factors relative to existing factors	Feng et al., 2020
Feature selection	Adaptive Group LASSO	Non-parametric method to determine variables that provide incremental information for the cross-section of expected returns	Freyberger et al., 2020
Volatility forecasting	PCA, PLS	Forecasting models for achieving information integration improving the accuracy of volatility predictions	Poncela et al., 2011; Asgharian et al., 2013; Cepni et al., 2019; Li X. et al., 2022
Volatility forecasting	MIDAS-RV-PLS, MIDAS-RV-PCA	Forecast combination methods for information integration methods	Yan et al., 2022
Volatility forecasting	MIDAS-LASSO	Forecasting stock market volatility	Marsilli, 2014; Lu et al., 2020; Li R. et al., 2022
Path algorithm	Generalized LASSO	They investigate the generalized penalty problems using lasso penalties focused on computational aspects	Tibshirani and Taylor, 2011; Arnold and Tibshirani, 2016

3.2- Time series forecasting:

While traditional market representation often relies on the risk-return relation for different asset classes, data-mining techniques, including complex information filtering, clustering, and graph theory supported by various machine learning methods, offer new approaches for diversification.

3.3- Correlations, clustering, and network analysis

In the classical Mean-Variance approach to portfolio allocation, the optimal portfolio seeks to minimize the variance (σp) while maintaining a specified portfolio return.

Random Matrix Theory (RMT) is a mathematical tool that allows us to analyze the dispersion of correlation matrix when applied to the financial market. The objective is to mitigate bias in future risk estimates by simplifying the large correlation matrices. This is achieved by extracting the systematic part of a signal hidden in the correlation data.

Cluster analysis, a well-established unsupervised classification method, has proven valuable across various fields, including finance. It aids in visually positioning assets by revealing underlying similarities. From a different perspective, clustering simplifies markets by reducing dimensionality and complexity, facilitating portfolio optimization. Two main clustering algorithms are hierarchical and partitional, with hierarchical identifying nested clusters and partitional finding clusters simultaneously. However, a common challenge lies in the need for cluster validation and the lack of cluster stability. The grouping methods used in the partitional clustering process are the classical K-means and the PAM (Partitioning Around Medoids) algorithm, which picks one stock from each cluster with the highest Sharpe ratio.

Duarte and De Castro segment the assets into clusters of correlated assets, allocate resources for each cluster and then within each cluster by different partitional clustering algorithms (K-medoids PAM and Fuzzy clustering). Khedmati and Azin include K-means and K-medoids but also spectral and hierarchical clustering considering transaction costs for different data sets. Soleymani and Vasighi addresses a large portfolio dataset to find the most and least risky K-means clusters of stocks based on VaR and CVaR measures and working only on financial returns.

In unsupervised learning, specifically within partitional clustering and using diverse time-series representations, a significant research direction involves applying fuzzy clustering to economic time series. For instance, D'Urso and D'Urso utilized a model-based approach with various fuzzy cluster variations and different distance metrics in financial markets. As an alternative to ultra metric spaces clustering methods, the Self-Organized Map (SOM) method was employed to cluster DJIA and NASDAQ100 portfolios, focusing on non-linear correlations between stocks. The authors concluded that the SOM method is more relevant and promising for clustering large, ill-structured databases requiring nonlinear processing. The correlation matrix of financial time series can be used to arise hierarchical tree structures, taking the correlations ρij as similarity measurement. The correlation-based clustering represented by network graphs allows for easy market visualization. On the standard methodology to build trees, for each pair i, j of assets, the distance d:

$$d_{i,j} = \sqrt{2(1 - \rho_{ij})}$$

d is computed, where ρij describes the correlation between log-return time-series. Having di,j , we can compute MST or, equivalently, the Single Linkage Clustering Algorithms (SLCA) by using, for instance, Kruskal's algorithm. Such clustering analysis for portfolio optimization was explored by Tola. Marti provides an in-depth overview of the state-of-the-art hierarchical clustering of financial time series. The hierarchical tree structure corresponds to diversification aspects in portfolio optimization models, where assets in the classic Markowitz portfolio are consistently located on the outer leaves of the tree.

Network representation of complex financial markets offers a profound understanding of the underlying processes in the economic system, enhancing the information available to decision makers. Analyzing stock market dynamics through network analysis can yield valuable insights and sound indicators for portfolio management.

During market crises, two network properties, normalized tree length and mean occupation layer from a central node (highest degree), decreased, indicating increased centralization. Additionally, stocks in optimal portfolios with minimal risks, as per the Markowitz model, tended to be in the network periphery, suggesting using network peripherality as an optimality indicator.

3.4- Exploring the risk-and-return characteristics of asset classes:

Asset allocation strategy involves forecasting risk-and-return characteristics for different asset classes or risk premiums. It includes determining the allocation percentages for each asset class in the portfolio.

ML techniques offer a more efficient means for portfolio managers to handle expected values based on various forecasting models for risk and returns, considering for each case different risk measurements that distinguish downside from upside risk. The predictive models should be adapted depending on the target group of assets, considering traditional stocks, bonds or alternative investments.

ML methods, with their high-dimensional nature, encompass diverse techniques, from traditional statistical learning methods like Gradient-Boosted Trees and Random Forest (RF) to the latest and popular algorithms such as Deep Learning (DL) or Deep Neural Networks (DNN). These methods use learning algorithms to identify the best-performing assets based on profitability and risk for a specific period. The goal of all of these methods is to approximate best the conditional expectation E(ri, t+1|Ft), where ri,t+1 is an asset's return over the risk-free, and Ft is the actual and observable information set of market participants.

Portfolio efficiency, gauged in profitability, is enhanced when assets are preselected based on return predictability, with the prominent application of ML. The most promising ML applications focus on finding predictive signals among the noise and capturing the alpha. So, the goal is to achieve good indicators proven to detect successful companies in terms of stock level signals combining different scores. In this way, the high amount of potentially good factors as signal makes ML effective for various reasons:

• ML is specially designed for forecasting purposes

• It can cope with a large number of predictors and overcome the high dimensionality of the problem by combining many weak sources of information

• Detection of nonlinear and complex relations and specially designed to mitigate overfitting

• High sensitivity to low signal-to-noise ratios on the data

• Avoiding crowded trades for highly correlated signals on different investors.

TABLE 2 Applications of correlations, clustering, and network analysis.

Application purpose	Method	Description	References
Robust covariance matrix estimation	RMT	Analysis of the statistical structure of the empirical correlations and signal-noise separation based on the density of eigenvalues	Laloux et al., 2000; Frahm and Jaekel, 2005
Clustering-based stock selection	K-means, SOM, Fuzzy C-means	The clustering approach categorizes stocks listed in the Bombay Stock Exchange on specific investment criteria. The selected stocks from the clusters are used to construct a portfolio, aiming to minimize portfolio risk	Nanda et al., 2010
Clustering-based stock selection	K-means, PAM	A technique of portfolio construction based on establishing several portfolio positions are proposed, as well as choosing cluster representatives for the Warsaw Stock Exchange	Korzeniewski, 2018
Identifying market structures	Fuzzy PAM clustering, DTW distance	The proposed clustering method exploits dynamic time warping (DTW) distance to identify common time patterns for stocks composing the FTSE MIB index	D'Urso et al., 2021
Stock clustering	Cepstral-based fuzzy PAM clustering	Cepstral representation considers dynamic features in the clustering process. The approach efficiently clusters stocks based on the Sharpe ratio for each security	D'Urso et al., 2020
Industrial networks	Symbolic time series, hierarchical clustering, MST,	Symbolic representation reduce market dimensionality, and a hierarchical organization of DJIA companies is derived. The resulting clusters can be utilized to explore sector relationships and construct financial portfolios.	Brida and Risso, 2009
Stock network	Hierarchical clustering, MST	MST was established to represent the stock market by cross-correlations as a network	Mantegna R, 1999
Dependency modeling	Hierarchical clustering, MST	MST were constructed with links calculated using Pearson correlation for linear dependencies and mutual information for nonlinear dependencies. Utilizing the distance matrix and network measures from Onnela et al. (2002), the study revealed significant nonlinear correlations emerging during financial crises	Haluszczynski et al., 2017
Correlation regimes	Hierarchical clustering, MST	In a multi-asset futures portfolio, the framework establishes a macro-to-micro connection, classifying regimes at the macro level and characterizing individual markets based on their location within a network or cluster at the micro level	Papenbrock and Schwendner, 2015
Portfolio optimization	Networks, centrality measures,	Networks were created from the full cross-correlation and global-motion matrix. The study found that portfolios with more peripheral assets outperformed those with central assets. The beneficial role of eigenvalue decomposition of the system into market modes was demonstrated	Li Y. et al., 2019

Deep Learning or deep neural networks algorithms refer to models represented in Figure 4 that consist of L layers or stages of nonlinear information. Each hidden layer takes the output from the previous layers and transforms it into an output as follows using the standard terminology stated in Lee et al. (2017); Hayou et al. (2019) for a fully connected random neural network of depth L, widths (Nl)1≤l≤L, weights Wl ij iid ~ N (0, σ 2 b). For some input a ∈ R d, the propagation of this input through the network is given for an activation function φ : R → R:

$$y_i^1(a) = \sum_{j=1}^{d} W_{ij}^1 a_j + B_i^1,$$

$$y_i^l(a) = \sum_{j=1}^{N_{l-1}} W_{ij}^l \phi(y_j^{l-1}(a)) + B_i^l, \quad for\ l \geq 2.$$

Indeed, an activation function ϕ decides whether a neuron should be activated and whether the input is important. Typically, ϕ takes the rectified linear form

ϕ (x) = ReLU(xk) = max(xk , 0). The more common activation functions besides ReLU are the following:

$$
\begin{aligned}
ReLU: \phi(x) &= max(0, x), \\
Sigmoid: \phi(x) &= \frac{1}{1+e^{-x}}, \\
Tanh: \phi(x) &= \frac{1-e^{-2x}}{1+e^{-2x}}, \\
LeakyReLU: \phi(x) &= \begin{cases} x & if \quad x > 0 \\ 0.01x & otherwise \end{cases},
\end{aligned}
$$

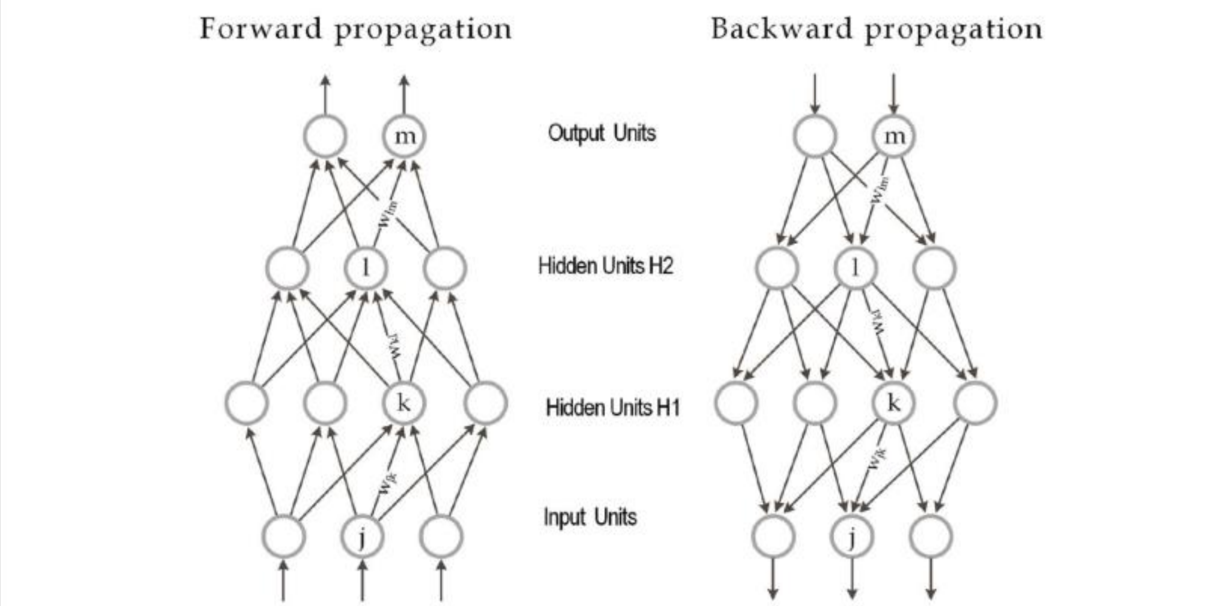

FIGURE 4
Multilayer neural network with forward and backpropagation and two hidden layers. Source: LeCun et al. (2015).

and they have shown their utility in complex non-linear associations and, more generally, in selection problems. These algorithms have demonstrated the potential to improve the implementation of different portfolio management strategies mapping data into the value of returns outperforming very different benchmark index, we can see an excellent example in Huang applying which is called Multitask Learning (MTL) for value extraction of hundreds of accounting terms in financial statements.

The family of DL algorithms applied for portfolio construction is broad, and they are used in different stages of portfolio management. We anticipate that Deep Learning, Reinforcement Learning, and Deep Reinforcement Learning applications in portfolio optimization will be algorithms applied for portfolio construction is broad, and they are used in different stages of portfolio management. We anticipate that Deep Learning, Reinforcement Learning, and Deep Reinforcement Learning applications in portfolio optimization will be specifically treated when we explain optimal portfolio construction techniques.

Random Forest (RF) is an ensemble ML algorithm introduced by Breiman, employing a majority vote across individual decision tree learners. These non-metric models make no assumptions about data distribution and have fewer parameters to optimize compared to many other ML models. RF effectively handles complex signals like excess returns or risk premia, providing a good variance-bias trade-off and being reported as highly accurate learning algorithms.

Additionally, RF models mitigate the impact of noise and changing relationships in past data between predictors and target variables, such as excess returns. Another popular approach is Gradient Boosting Trees (GBT), which builds trees sequentially, with each new tree aiming to correct the errors of the combined ensemble of the previous trees. GBT is typically applied to construct portfolios by leveraging their ability to predict asset returns and optimizing the portfolio based on those predictions. More examples of ML used for portfolio construction are displayed in Table 3.

TABLE 3 Picking attractive securities.

Application purpose	Method/data	Performance criteria	References
Measuring asset price premiums	Boosted RT, RF and NN	The higher gain of ML methods compared with leading regression-based strategies for return prediction is shown	Gu et al., 2020
Risk price estimation and dimensionality reduction	Bayesian approach	Building of a robust stochastic discount factor from a large set of stock characteristics	Kozak et al., 2020
Return estimation	RT	RTs were built to determine which firm characteristics out of 30 attributes are likely to drive future returns	Coqueret and Guida, 2018
Feature extraction	Restricted Boltzmann Machine	Proposes an encoder to extract features from stock prices and pass them to a feedforward NN	Takeuchi and Lee, 2013
Prediction of stock markets	RF	Method designed to predict price trends in the stock market	Kamble, 2017; Zhang et al., 2018
Cross-section prediction of exceed return	RF	Select stocks in S&P500 and STOXX600 with the highest monthly predictions	Kaczmarek and Perez, 2021
Benchmarking of ML techniques	RF, GBT, DL	Ensembles of different ML methods in the context of statistical arbitrage for S&P500	Krauss et al., 2017
Building ML signals for long-short strategies	GBT	Boosted Trees to more than 200 features clustered in six families, building an ML signal that outperforms the benchmarks for long-short strategies	Guida and Coqueret, 2018
Distinguish "good" stocks from "bad" stocks	LR, DNN, RF	Effectiveness of the stock selection strategy is validated in the Chinese stock market in both statistical and practical aspects where stacking outperforms other models	Fu et al., 2018

3.5- Enriching feature set by natural language processing:

Natural Language Processing (NLP) coupled with Sentiment Analysis (SA) can assess the polarity of market signals in textual content from social media platforms—indicating whether sentiment is positive, negative, or neutral. Sentiment is used qualitatively and quantitatively to reflect opinions, attitudes, moods, or emotions toward securities, assets, companies, or the market.

Some studies leverage existing sentiment indicators, while others calculate sentiment indexes. Data sources for sentiment analysis include news channels and social media, and approaches range from text representation methods to artificial intelligence classifiers.

Additional sentiment analysis data sources include StockFluence sentiment data, aggregating opinions from various media channels, and Glassdoor, offering business outlook ratings from employee reviews. Twitter and Google are commonly used sentiment analysis data sources, with alternatives including sentiments extracted from Intrinio, Thompson Reuters, and Bloomberg news articles.

In general, NLP-based sentiment analysis methods could be divided into two categories. First, NLP combined with traditional machine learning like SVM, LightGBM, XGBoost and RF.Evidence supports that financial news or social media information can provide an additional advantage in predicting price or market turbulence trends. This approach often entails constructing numerous features before inputting them into the ML model.

Alternatively, some studies explore DL techniques, which can automatically extract features from news or social media. For instance, a self-regulated generative adversarial network was proposed to enhance generalization and overcome stochasticity in predicting stock movements based on financial news and historical price data.

Comparatively, a hybrid data analytics framework, integrating CNN and bidirectional LSTM, was created to predict stock trends by estimating the impact of news events and sentiment trends converging with historical financial data. Unlike other studies, LSTM was trained to automatically generate an asset allocation strategy using historical lagged data and public mood.

Financial sentiment analysis faces challenges due to specialized language and a lack of labeled data. The advent of ULMFit has facilitated effective transfer learning in NLP. For example, Feinberg (Bidirectional Encoder Representations from Transformers for financial data) is a pre-trained NLP model designed explicitly for sentiment analysis in financial text. Comparatively, Zhao proposed a RoBERTa as a pre-trained model, which exploits different fine-tuning methods for sentiment analysis and critical entity detection in online financial texts. SEntFiN 1.0 is the most recent publicly available example of a human-annotated dataset of news headlines containing multiple entities. The authors concluded that deep bidirectional pre-trained language models such as domain-specific BERT fine-tuned to SEntFiN outperform state-of-the-art learning schemes significantly.

Table 4 provides examples of papers focusing on sentiment signal generation for asset allocation

TABLE 4 The use of sentiment signals for asset allocation.

Application purpose	Method	Description	References
Stock portfolio construction	RNN, LSTM, RF, MLP, StockFluence sentiment	The study explores whether public mood collected from social media and online news is correlated or predictive of portfolio returns by constructing five portfolios from 15 NYSE stocks	Malandri et al., 2018
Stock portfolio construction	Deep RL, market sentiment	Sentiment-aware deep deterministic policy gradients approach learns from historical stock price trends and market sentiments perceived from Google News and Twitter about 30 Dow Jones companies	Koratamaddi et al., 2021
Stock portfolio construction	Sentiment extraction, ML, weblogs	Ontology-guided and rule-based web information extraction based on domain expertise and linguistic knowledge with a focus on weblogs	Klein et al., 2011
Stock portfolio construction	Hierarchical Clustering, regime-switching, ML, market sentiment,	Regime-Based asset allocation models are proposed, where investors' mood swings interpret the regime. Then, the Black-Litterman asset allocation model is used to construct a portfolio	Zhang et al., 2020
Stock portfolio construction	Spectral Clustering, stochastic NN, beliefs,	Asymmetric investors' sentiments reflect market participants' beliefs about future cash flows. These sentiments, combined with investor results and previous sentiments, inform a dynamic investor sentiment-adjusted multi-period portfolio selection model	Wei et al., 2021
Stock market prediction	Kalman Filter, ML, microblogs, survey indices	The prediction model employs sentiment and attention indicators extracted from microblogs and survey indices (AAII and II, USMC and Sentix), the use of a Kalman Filter to merge microblog and survey sources, and then several ML methods	Oliveira et al., 2017
Stock selection	LR, LightGBM, analyst reports, reviews,	The study explores the impacts of analyst attitude and crowd sentiment on stock prices, indicating that crowd wisdom is more valuable than expert wisdom in shaping investment strategies.	Wu et al., 2020
Stock beta forecasting	LASSO, RF, XGBoost, news volume, stock sentiment,	Beta are estimated using sentiment-embedded machine learning models. Market-neutral long-short portfolios are then constructed, and feature importance is determined using the Shapley value.	Jourovski et al., 2020
Stock return prediction	Employee sentiment from Glassdoor	A proposed aggregate measure of employee sentiment, derived from millions of employee online reviews, is identified as a robust predictor of market returns	Symitsi and Stamolampros, 2021
Investment recommendation	Factor model, LR, StockTwist	To predict the quality of an investment opinion, various factors derived from author information, opinion content, and the characteristics of referenced stocks are employed	Tu et al., 2018
Feature extraction	Text representation methods, NLP, ML, SemEval-2017,	The study utilizes lexicon-based feature extraction methods, word and sentence encoders, and state-of-the-art NLP transformers. A deep-learning and transfer-learning-based sentiment analysis model, coupled with machine learning models, is applied for portfolio construction	Mishev et al., 2020

3.6- Examining the interrelation between ML and market efficiency:

In classical economic theory, economists explore models with market frictions, where price competition may be dampened, leading to potential unemployment of resources. AI holds significant potential to enhance efficiency by reducing search friction. AI aids in understanding market environments, identifying patterns that enhance customer experience, and improving forecasting to promote more efficient market operations.

Indeed, determining evolving market conditions is mainly linked to capturing market inefficiencies to identify future performance. This is where the usefulness of the application of AI arises. Many studies demonstrate the superiority of AI over traditional ones. However, the question is how the massive use of information-based systems, for instance, supported by cloud services, can change the price discovery process. Unequal access to AI technology among financial actors may lead to smaller providers' limited participation, posing a concentration risk among more prominent players. AI, particularly in High-Frequency Trading (HFT), generally introduces greater complexity to conventional algorithmic trading, notably in highly automated markets such as equities and FX. AI and HFT contribute to enhanced liquidity provision and enable the execution of large orders with low market impact.

From a risk perspective, AI allows order flow management, reducing inefficiencies. HFT serves as a significant source of liquidity, so any disruption in their operation results in liquidity being pulled out, especially when AI techniques are widely deployed. At this point, we must distinguish two significant impacts of the massive application of AI on the financial markets that result in two sides of the same coin. First, AI impacts information efficiency by reducing the marginal cost of information acquisition and processing for portfolio managers. Second, the question is how AI is going to replace human decision, as the machines process much more information faster, making the markets more efficient, but at the same time with a higher risk of market manipulation by using spoofing schemes as 2010 Flash Crash being a source of nonfinancial risk.

Analyzing the interrelation between AI and market conditions and how this relation changes sophisticated investors' behavior has just begun. Regarding the first point, consider the quarterly annual reports for the Russell 3000 Index, which includes around 3000 of the largest U.S. companies, resulting in ∼12,000 documents in a fiscal year. Managing such a vast amount of information is challenging for humans. An important distinction between humans and machines is that humans tend to pay more attention to large and value firms, whereas AI accesses information more uniformly.

The studies on the interaction between information and potential impacts on market efficiency must rely on accurate metrics. For instance, the Security and Exchange Commission's (SEC) Electronic Data Gathering and Retrieval (EDGAR) website allows researchers to measure with automatic algorithms how the stock market responds at the time of earning announcements.

All internet search traffic of the EDGAR system is accessible to researchers, including the user's IP addresses and the user requesting the information. The impact of our trading decisions on the market and queries made through the SEC exchange requesting information from companies is observable. Table 5 provides the examples of paper, where the interrelation between AI and market efficiency was analyzed.

TABLE 5 Interrelation between AI and market efficiency.

Application purpose	Method	Performance criteria	References
Analysis of SEC reports and investor attention	SEC's EDGAR	The attention of sophisticated investors for the earning announcement impacting on portfolio performance is measured	Li R. et al., 2019
Analysis of endogenous information acquisition	SEC's EDGAR	A long-short portfolio based on different measures of information acquisition activity generates a monthly abnormal return of 80 basis points that is not reversed in the long-run	Li and Sun, 2022
Arbitrage trading strategy based on machine learning	LR, RF, Gradient Boosting Classifier	Volume-Weighted Average Prices (VWAP), ML models outperform the general market by far, which poses a clear challenge to the semi-strong form of market efficiency in futures markets	Waldow et al., 2021
ML algorithms to find profitable technical trading rules using past prices		Genetic algorithm, KNN, RF The out-of-sample profitability decreases through time, becoming the markets more efficient over time	Brogaard and Zareei, 2021
Analysis of cryptocurrency market efficiency	RNN applied to XBTEUR time series bitcoin market	Applying F-measures authors show that Bitcoin market is partially efficient	Hirano et al., 2018
Testing the weak-form efficient market	SVM and LR	Randomness of a sequence of rising/falling states of stock prices	Khoa and Huynh, 2021

3.7- Selection of particular assets using multiple criteria:

Modern portfolio theory initially considered mean and variance as the sole criteria for portfolio selection. However, over the past 60 years, more sophisticated methodologies and techniques have been proposed, incorporating utility/desirability functions, expectation-risk, requirements for higher moments of portfolio, stochastic dominance, etc. Furthermore, fundamental analysis and technical analysis, followed by factor analysis and attribute clustering, are sources for multi-criteria decision making (MCDM).

One notable paper on multi-criteria portfolio selection is by Zopounidis, where the author reviews decision-aid methods, their structure, and processes existing at that time. The paper also briefly explains how MCDM works in financial management. Comparatively, a significant analysis was presented by Aouni, where the author linked portfolio optimization with multiattribute portfolio selection. In his further research, the author gave more examples of how goal programming can be used in portfolio selection.

It has been emphasized that MCDM, coupled with the generalization of fuzzy sets, is gaining popularity among decision-makers and researchers. Specifically, Mohagheghi suggested how MCDM should deal with uncertainty-related issues and which optimization techniques could be useful for project portfolio construction. Moreover, they reviewed real-world applications and case studies, excluding the financial portfolio selection problem. However, Liesiö linked general project portfolios to financial portfolio selection and introduced so-called portfolio decision analysis techniques. The abovementioned methods and techniques can help solve financial portfolio selection problems as alternatives to AI black-box techniques. Furthermore, Galankash provided a list of potentially attractive criteria and reviewed related works. Moreover, they applied fuzzy ANP and showed the entire decision-making process. Such a technique could be helpful in ANN's training phase.

Optimization-based approaches traditionally use technical and fundamental indicators to determine portfolio composition. Demand and supply of stock shares and market patterns are studied using technical analysis. The basic indicators are based on information from each company's financial reports. Silva applied evolutionary algorithms using several fundamental indicators [debt ratio, ROE (return on equity) and P/E ratio] together with technical indicators to generate optimal portfolios. The repeatability of data patterns, the visual signals of indicators and oscillators, and the graphical representation of the evolution of assets are the sources for financial technical analysis. Portfolio selection based on technical analysis implies the idea that prices move up (i.e., bullish), down (i.e., bearish), and sideways (i.e., trading) in a trend and that these trends ultimately influence the movement of financial assets. Table 6 summarizes papers on MCDM and emphasizes the method, criteria used and application field. Table 7 emphasizes the purpose of the MCDM application. However, the method and criteria also are indicated. In general, MCDMs are transparent decision-making tools compared to most AI techniques. However, it is heavily dependent on the decision-makers and pre-selected criteria.

TABLE 6 MCDM techniques used for portfolio selection.

Method	Criteria used	Description	References
PROMETHEE outranking method	Outranking-based approaches	A new formulation of the PROMETHEE V method was proposed, and several alternative methods based on the concepts of marginal and c-optimal portfolios were developed. The methods provide a good approximation of the PROMETHEE ranking of all portfolios, and their application requires only a small computational effort even for significant problems	Vetschera and Almeida, 2012
MCDM, DEA, Entropy, MABAC	Risk and return parameters	The performance of the funds is analyzed using Data Envelopment Analysis (DEA) to allow an initial selection of funds. Then, the Multi-Attribute Border Approximation Area Comparisons (MABAC) is applied, where the weights are calculated using the entropy to rank the funds according to risk and return	Biswas et al., 2019
Bayesian decision problem, multivariate skewness, utility function maximization	The mean, standard deviation and cubed-root of skewness	The skew-normal distribution were employed in a method for optimal portfolio selection using a Bayesian decision theoretical framework that addresses two significant shortcomings of the traditional Markowitz approach: the ability to handle higher moments and parameter uncertainty	Harvey et al., 2010
Multi-criteria utility functions, Multiple Criterion, Stochastic Programming	Portfolio return, dividends, growth in sales, social responsibility, liquidity, etc.	It summarizes multi-criteria portfolio selection approaches, answering the question of how to incorporate additional criteria beyond risk and return into the portfolio selection process	Steuer et al., 2008
ELECTRE, MCDM	Return on assets; Return on equity; Net profit margin; turnover; Cash liquidity; etc.	The ELECTRE Tri outranking method is used to provide a multi-criteria methodology to select stocks based on financial analysis	Xidonas et al., 2009
Multiple criteria, linear programming,	Mean-risk	The multi-criteria linear programming model for the portfolio choice problem is based on risk preferences. It enables standard multi-criteria techniques to analyze the portfolio choice problem. It is also demonstrated that the classical mean-risk methods used in linear programming models are consistent with the specific solutions applied to multi-criteria model	Ogryczak, 2000
Fuzzy analytic network process (FANP)	Profitability, growth, market, and risk	A fuzzy analytical network process (FANP) and specific criteria were developed to evaluate and select the stock portfolios	Galankashi et al., 2020

TABLE 7 MCDM approaches used for particular purpose.

Purpose of application	Method/data	Criteria used	Description	References
Ranking of Stocks	MADM Methods, Financial Ratios, p-TOPSIS Method, p-VIKOR Method	Total Income (TI), Net Profit (NP), Net Worth (NW), Return on Net worth (RON), Stock Price (SP), Promoter Holding (PH), FII + DII Holding (FII), Operating Prof-it Margin (OPM), Net Profit Margin (NPM), Dividend Payout Ratio (DPR)	The model proposed in the study can provide more information on the overall performance of a particular share compared to other shares. The results obtained by the different methods clearly distinguish good companies from poorer ones, although the exact ranking varies slightly	Hwang and Yoon, 1981
Hybrid model for MCDM	TOPSIS, ANP, NGT, Multiple criteria analysis	Price/cost; On-time delivery; Product quality; Facility and technology; Responsiveness to customer needs; Professionalism of salesperson; Quality of relationship with vendor	The five-step hybrid process and the Analytical Network Process (ANP) method allow the relative weights of several assessment criteria to be determined using the Nominal Group Method (NGT)	Shyur and Shih, 2006
Decision making	Multi-Objective Programming (SMOP); Goal Programming (GP); ten stocks return rate of the Tunisian stock exchange	Return rate; the level of risk	To get the best solutions in decision-making situations a model of goal programming is formulated and a deterministic equivalent formulation of stochastic multi-objective optimization programs is considered	Aouni et al., 2008
Decision making	Analytic Hierarchy Process (AHP)	Theoretical background	Discuss why AHP is a standard methodology for a wide range of solutions and other applications and develop academic discussions regarding the effectiveness and applicability of AHP compared to competing methods by providing brief descriptions of successful applications of AHP	Forman and Gass, 2001
Asset allocation	Gray MCDM, gray-ANP, gray-DEMATEL, Shanghai Stock Exchange, China	Return, financial ratios, dividends, risk	This study uses a hybrid MCDM approach consisting of an integrated analytical network process (ANP) and a decision-making test and evaluation laboratory (DEMATEL) in a gray environment to select an optimal portfolio to provide decision-makers with both ranking and weighting information	Mills et al., 2020

4- Constructing the optimal portfolio

The most popular criteria in academic literature for constructing optimal portfolios are mean and variance of returns. However, such an approach leads to a quadratic optimization problem if constraints are no more complex than quadratic. Some authors suggested maximizing skewness together with maximizing means and minimizing variance, which resulted in the optimization problem becoming much more complex as the utility function became cubic.

Furthermore, some authors suggest using a utility function of even higher order. The other approach is related to multi-criteria utility functions. Such types of utility functions lead to linear optimization problems. However, preparations require much more decision-maker involvement as criteria weighting is time-consuming. Moreover, the result is very subjective and may be biased as every decision maker may assign different weights. It is worth mentioning that many authors recommend including historical portfolio return, various security and systematic risk measures, dividends, liquidity, turnover, P/E, P/B, ROA, ROE, workforce, etc.

Unsurprisingly, the factors mentioned above come from fundamental and technical analysis. The following subsections discuss metaheuristics and ML optimization techniques used in portfolio optimization

4.1- Metaheuristics for Portfolio Optimization:

Portfolio construction, optimization, and management challenges have been extensively tackled using various metaheuristics, offering more flexibility in problem formulation than classical optimization approaches. Unlike the mean-variance model, these models can have a richer structure, and the optimization problem may be non-convex. While heuristic methods may compromise solution optimality, they often optimize more efficiently than classical methods.

However, their effectiveness is problem-dependent, and formulating a more realistic mode with numerous constraints, such as limiting the total number of assets or specifying bounds on each asset's quantity, can be relatively complex.

An extensive survey of classical and heuristic optimization methods for portfolio optimization can be found in Mansini. Conversely, metaheuristic algorithms have a general problem-independent structure, although they may require tailoring to specific problems. Advances in parallel computing over the last decade have facilitated practical implementations of computationally intensive metaheuristic methods for large-scale complex problems.

Metaheuristic algorithms can be categorized based on various aspects, including population-based or singlesolution, naturally inspired, mimic evolution (evolutionary algorithm—EA), utilize swarm intelligence, involve global or local search, etc. These categories may overlap, and some algorithms are hybrid, incorporating techniques from multiple algorithm types. A broad introduction to various metaheuristic algorithms can be found in Talbi. We will consider many of the metaheuristic algorithms, such as genetic algorithms (GA), evolutionary strategy (ES), differential evolution (DE), particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC), simulated annealing (SA), quantum annealing (QA), and tabu search (TS).

Some models have a single objective, like minimizing the variance, while others have multiple, like minimizing variance and maximizing return, which require an application of multi-objective evolutionary algorithms (MOEAs). Table 8 summarizes some of the most critical applications of metaheuristic methods in portfolio optimization. For a comprehensive overview of MOEAs applied in portfolio management before 2012, the reader can refer to Metaxiotis and Liagkouras. A recent survey on swarm intelligence techniques in portfolio optimization is available in Ertenlice and Kalayci. Additionally, Doering offers a broad survey covering various types of metaheuristic methods for both portfolio optimization and risk management.

4.2- Deep learning, reinforcement learning, and deep reinforcement learning in portfolio optimization:

DL concept has been used lately to manage portfolios in diverse conditions based on neural networks. Thus, numerous variants of DNN may function as independent evaluators to optimize the algorithm. The cryptocurrency market is often used in this type of research to evaluate the effectiveness of the DNN-based strategy compared to traditional portfolio management strategies. Some authors add fuzzy neural networks to the market forecasting when conditions change dramatically. In other recent papers, a finite-time q-power RNN applied to solve the uncertain portfolio model is considered an improvement of classic NN.

Another solution to overcome the limitations of traditional and generic portfolio strategies considered in the recent literature is reinforcement learning (RL) using neural networks. This research direction argues for implementing RNN and conventional NN in reinforcement learning architecture to support investment decisions. The main element in this theory is the connection between agents and the environment. As a fundamental component of the ML process, in RL theory, the agents are supported by NN to memorize and predict optimal decisions based on present information for an infinite number of actions and states. The environment then estimates the rewards from these actions to help agents learn for future decisions. This process can define specific models to gradually improve overall performance based on experiences gained with several trial-and-error steps. In addition to this research direction, some authors claim that deep reinforcement learning (DRL) can be successfully used to capture the dependencies between the main features of some financial indicators, such as risk aversion, portfolio-specific characteristics and previous portfolio allocations.

At the same time, in deep consolidation learning, network composition and appropriate rewards significantly influence learning transactions in financial time series, using high-frequency data decomposed as input. A previous paper stipulated that portfolio management requires prior decisions as input to consider the effects of transaction costs, market impact or taxes, and this temporal dependence on the system's state involves reinforcement versions of standard recurrent learning algorithms. In another approach, DRL deals with low, high, and close prices through a designed depth convolution for these three characteristics. The classic methods cannot accurately estimate the critical time, so a three-dimensional warning gating network is used, giving greater importance to rising moments.

Thus, deep reinforcement learning tools obtain more substantial returns and improve profit indicators while reducing risk. In other research, recurrent consolidation learning has successfully optimized portfolios. It memorizes up-to-date market conditions and constantly rebalances the portfolio's content based on classic performance indicators. In some models, a compromise parameter is introduced to adjust the portfolio's optimism level, and learning algorithms evaluate market fluctuations and provide information to generate forecast hyperparameters. The main advantage of using these more complex methods is that the effectiveness and robustness of the portfolios obtained with their help significantly exceed the return and risk indicators obtained with the classical techniques. Other methods study the relationships between financial instruments, which are considered to vary over time. These relationships are studied with the help of CNN, in which the market operator learns and applies an investment behavior that is constantly re-evaluated. Thus, the permanent reallocation of the assets from the portfolio is ensured to optimize the yield indicators.

Recently, a new research direction has combined reinforcement learning and its applications with Python or similar programming languages coding to support understanding portfolio optimization mechanisms. These codes use dedicated open-source software as data processing media for programming. These research methods can integrate portfolio selection with portfolio optimization using multicriteria algorithms. The advanced programming languages with dynamic semantics allow every optimization step to be followed in detail, from the data entry to the extraction of the results. A significant advantage of using these methods is that free cloud-based platforms for programming effectively run the necessary programs. Thus, according to an increasing number of authors, Python or other programming languages can be used to build an efficient portfolio based on multiple optimization techniques to improve portfolio performance. Numerous results showed that the prediction models efficiently obtained high accuracy and enhanced yields. As seen from the above, regardless of the method proposed for research, most papers cited conclude that optimizing portfolios based on DL, RL, or DRL have significantly better results than traditional algorithms. The generally accepted assertion is that these modern tools are superior to even the most advanced methods based on classical instruments. Moreover, using advanced programming languages, such as Python, supported by powerful open-source software and free cloud-based platforms, leads to superior results in optimizing portfolios, increasing returns and reducing risk.