



USING ARTIFICIAL INTELLIGENCE (AI) AND DEEP LEARNING TECHNIQUES IN FINANCIAL RISK MANAGEMENT

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Abstract

In this study, we explore the current applications of advanced technologies in financial risk management, specifically focusing on various approaches to managing financial risks. We conducted a comprehensive review of existing literature and identified areas where these technologies have been extensively researched, as well as topics that require further investigation. Well-researched fields include credit rating, fraud detection, bankruptcy prediction, and volatility forecasting. In these areas, advanced models, including deep learning, have been widely employed to improve accuracy and predictive power. However, certain sectors such as claims modeling, loss reserving, and mortality forecasting have not been given the same level of attention. Our analysis highlights the extensive use of sophisticated statistical models in financial risk management. While some progress has been made, more challenges need to be addressed, especially in traditional statistical models. Recent advancements in machine learning, particularly deep learning, offer significant potential for improving the efficiency and effectiveness of risk management systems. These advancements provide more accurate models for dealing with complex data, making them highly valuable for the financial performance management (FPM) field. One notable area of recent development is the incorporation of uncertainty estimation techniques in machine learning models, which allow for more precise risk assessment in unpredictable financial environments. Moreover, federated learning systems present a promising solution for ensuring privacy and security when dealing with sensitive financial data. This approach allows for collaborative learning without compromising the confidentiality of data, an essential factor in financial risk management. Despite these advances, there is still much work to be done regarding the explainability and fairness of machine learning models used in financial risk management. Ensuring that these models are transparent and unbiased is crucial for their broader adoption in the financial

industry. Future research must prioritize developing models that can provide clear explanations of their decision-making processes, as well as ensuring that they do not disproportionately affect certain groups. In conclusion, our review of current applications in financial risk management highlights both well-explored areas and emerging opportunities for future research. While deep learning models have significantly improved predictive capabilities in some fields, other areas, such as claims modeling and loss reserving, require more focused research. The financial industry stands to benefit greatly from recent advancements in machine learning, but challenges around model transparency, fairness, and data security must be addressed to realize their full potential.

Keywords: *AI, deep learning techniques, risk management, finance.*

1. Introduction

The concept of portfolio management as a means of reducing investment risk has given people access to the best investment plans that fit their spending limits and income levels. Portfolio management has shown itself to be an excellent tool in the financial industry for the management of different investments in the forms of cash, bonds, or liquidity assets, to reduce risk. The management of portfolio remains an instrumental to help investors safeguard their investments to ensure that they receive the highest possible returns over time. Portfolio management raises the likelihood of a profit while reducing the risks associated with investing. Historically, economic theories and quantitative models have been the cornerstones of portfolio management. These models are intended to facilitate the appropriate management and monitoring of investment portfolios. These traditional approaches include methods like the Capital Asset Pricing Model (CAPM), which helps with asset pricing and portfolio construction by describing the relationship between systematic risk and expected return of assets; the Efficient Market Hypothesis (EMH), which postulates that asset prices fully reflect all available information and implies that stock picking and market timing cannot consistently outperform the market; and the Black-Litterman Model, which overcomes the drawbacks of using only historical data by including investor views into the mean-variance optimization framework. Li and Hoi (2014), furthermore. The four portfolio management strategies were identified and subsequently classified as follow-the-winner, follow-the-lose, pattern-Matching, and meta-matching. The first two categories rely on financial models that have already been created, while they might also include some machine learning methods to help with parameter calculations (Li et al., 2012; Cover, 1996). The validity of the models in various marketplaces affects how well these strategies perform. Pattern-Matching algorithms directly optimise the

portfolio based on the sampled distribution and forecast the upcoming market distribution using a sample of past data (Györfi et al., 2006).

The last class, Meta-Learning method combine multiple strategies of other categories to attain more consistent performance (Vovk and Watkins, 1998; Das and Banerjee, 2011). Furthermore, static risk and regularly distributed returns are assumed by Modern Portfolio Theory (MPT) and CAPM, which frequently falter in times of market turbulence and crisis. Because markets aren't always fully efficient, the Efficient Market Hypothesis (EMH) ignores behavioural biases. Because investor psychology is subjective, behavioural finance is not very predictive. Fama-French factor models, for example, may be overfit to past data and fail to adapt to changing market conditions. Lastly, in unpredictable contexts, quantitative models like VaR and Monte Carlo Simulation can be less accurate due to their tendency to underestimate extreme risks (tail occurrences) and their heavy reliance on assumptions about prior data. It is still challenging for economists and financial specialists to implement the best strategies to reduce investment risk in spite of all the aforementioned ideas and models.

Numerous studies have been carried out using machine learning models to forecast risks and returns to solve all of the restrictions (Henrique et al., 2021). The application of machine learning models has been shown to be more advantageous and suitable in some recent studies, given the challenges associated with determining which models are most appropriate for forecasting risk and returns in portfolio management. With return estimates of 26% and 18% gains in Sharpe ratios with neural networks and Random Forest, respectively, compared to those of the buy-hold, (Gu et al., 2020) discover that employing machine learning for market timing is beneficial.

Excellent results have been obtained by integrating sophisticated machine learning algorithms into video games (Mnih et al., 2015). Another is a board game (Silver et al., 2016). the application Cutting-edge machine learning algorithms have demonstrated remarkable outcomes in board games and computer games (Mnih et al., 2015; Silver et al., 2016). Financial traders have taken a particular interest in reinforcement learning since the computer program AlphaGo beat Lee Sedol, the greatest human player of the modern Go board game, in 2016 (Khushi and Terry Lingze, 2019). Although portfolio development can be accomplished by machine learning techniques, reinforcement learning is thought to be more important in this field (Bartram et al., 2021). (Li et al., 2020) point out that reinforcement learning can be useful in wealth management.

Recent research by Wen et al. (2021) demonstrated that the reinforcement learning model might outperform the traditional buy-and-hold approach in terms of returns. Zhang et al. (2020), focussing on futures contracts, demonstrated that, despite high transaction costs, the devised trading strategies utilising reinforcement learning beat the time series momentum techniques, producing positive returns. Furthermore, reinforcement learning can be used to train a machine learning system to hedge options in real-world scenarios (Kolm and Ritter, 2019). The minimal variance hedge is selected via reinforcement learning depending on the provided transaction cost function.

In this study, we aimed to compare the performance of traditional models and methods stated above with different machine learning and reinforce models. An outline of the paper follows. Section 2 reviews the literature. Section 3 describes the portfolio allocation methodology, including the utility-maximization problem and models. Section 4 demonstrates the results of using the machine learning portfolio allocation strategy, and Section 5 concludes.

2. Related Literature

The best forecasting and timing of financial risks and managements have been made possible in large part by the developments of artificial intelligence (AI) and machine learning (ML) in the fields of social science, finance, and banking. For these reasons, economists are increasingly turning to ML's toolset to perform creative empirical investigations. With ML, economists can now access databases that were previously unreachable through conventional methods, such as multidimensional databases, images, and texts. Also, ML has made it possible to investigate novel issues that are significant to the field, particularly those in which the primary research question is the prediction of an event. Because of this conceptual advancement in the field, ML can be viewed as an advanced methodology when compared to previous models. ML thus broadens the economist's toolkit by adding not only

Since the stock market is the most popular target for ML-based sentiment metrics, sentiment aggregated to markets such as that is of primary importance to us in finance. Measures of sentiment towards stocks are used in most relevant studies to examine their impact on future market performance. Numerous studies create a gauge of investor sentiment from social media. For example, Antweiler and Frank (2004) classify user posts on the Yahoo Finance forum as positive or negative using naïve Bayes and SVM methods, then aggregate their classifications to create a gauge of sentiment towards the stock market. Apart from examining texts, Obaid & Pukthuanthong (2022) find that machine learning can take the place of text-based metrics when

applied to news images to generate a sentiment measure for stocks. Analyst reports and annual reports are used in other research to gauge sentiment. Weiwei Jianghas (2020) examined around 66 research papers published in 2021 to determine the effect of machine learning on the stock market. In his review, he examined a range of stock market indices, diverse data kinds, a range of input feature types, and a range of artificial intelligence approaches, such as deep learning, reinforcement learning, and machine learning. The trading process is covered, along with how it fits within the RL framework (Alameer et al., 2022). He then discusses RL foundational concepts, such as elements of the Markov Decision Process and the fundamental methods for determining optimal policies within the RL framework. Additionally, he functions approximation RL. Lastly, he talks about why RL implementation in QT applications a hot topic for research is still. It is possible to reduce the risk significantly with the development of computationally complex methods. As stated by Kumar et al. (2021). The application of computationally sophisticated techniques to stock market forecasting is the focus. Artificial neural networks, fuzzy logic, genetic algorithms, and other evolutionary techniques are a few instances of these techniques. We provide a current overview of the research conducted in stock market forecasting utilising computational intelligence-based methodologies.

2.1. Sentiment Analysis

Trading signals can be produced by sentiment analysis. Sentiment is just one element in a complicated market; correlations may exist, but depending solely on it might be dangerous. Combining it with other technical and fundamental assessments is crucial. Sentiment data reflects personal goals and opinions and might be noisy and biased. Prior to making any conclusions, thoroughly consider the sources and any potential biases. Due to market inefficiencies and competition, gains would not be guaranteed even if market sentiment could accurately forecast market moves. Sentiment analysis-based market manipulation presents moral questions. Make sure rules are followed and information is used responsibly.

Algorithms can forecast possible future performance measurements, such as employee turnover, customer satisfaction, or even financial results, by assessing historical data and executive traits. Personalized development plans can be recommended by ML models based on the unique traits of managers and their influence on the organization, emphasizing areas with the most room for progress. When trained on a variety of datasets and subjected to fairness checks, machine learning algorithms have the potential to detect and reduce measurement biases.

The quality of machine learning models is contingent upon the quality of the training data. Inaccurate and biased outcomes can be produced by biased or inadequate data, which reinforces already-existing disparities. Make sure the datasets used are representative and diversified. It might be challenging to comprehend how machine learning models arrive at their findings because many of them are opaque and sophisticated. This can be troublesome, particularly when assessing people. Select models that are comprehensible and provide as much justification for them as you can. Data security and confidentiality are essential, particularly when handling sensitive data like leadership evaluations. Put strong security measures in place and make sure everyone gives their informed consent. Human supervision and responsibility: human judgement should not be completely replaced by machine learning. Make decisions with the help of machine learning, not by fully automating them.

Research creates metrics for business attributes with Measures of a company's financial attributes and risk exposures serve as the foundation for most machine learning techniques. Using ML on annual reports, Buehlmaier & Whited (2018) create a gauge of budgetary restrictions. The approaches employed in the literature to forecast failure in small and medium-sized businesses are reviewed by Cheraghali & Molnár (2023). Thus, ML can support business culture research as well. Conference call transcripts are used by Li et al. (2021) to extract company culture elements. In fact, they research how it affects metrics of corporate performance including value and operational effectiveness. Lastly, the development of new business connectivity measures is made possible by the capabilities of machine learning.

2.2. Measures of Credit Risk

One common issue with economic forecasting is credit risk (Mestiri & Hamdi 2012). Finding out which prospective borrowers will ultimately default is its aim. Based on borrower data, Tantri (2021) uses strengthened regression trees to predict consumer credit default. Credit card transaction data is used by Mestiri (2024) to forecast repayment trends. Another area where ML can offer better credit risk forecasts is corporate credit risk. firm bankruptcy is directly predicted by Tian et al. (2015) and Hamdi & Mestiri (2014) using market data and firm financial filings.

In the discipline of corporate finance, studying the factors that influence firm-specific outcomes is a crucial area of research that can be the focus of machine learning-based forecasting. Two research forecast distinct financial outcomes using machine learning. In their analysis of corporate capital structure as a common issue in corporate finance, Amini et al. (2021) forecast

corporate leverage using common capital structure drivers. Using random forests, Mestiri (2024) forecasted business profitability based on accounting information. Corporate malfeasance is an additional issue with predicting. We will examine accounting fraud, a type of business malfeasance identified by Bao et al. (2020). Rahman & Zhu (2024) create financial distress prediction (FDP) models for businesses using machine learning techniques. They then assess how well these models classify data in comparison to traditional Z-Score models. Their findings demonstrate the potential of these cutting-edge methods in improving predictive accuracy and reliability by confirming that machine learning classifiers may successfully forecast financial distress. Tron et al. (2023) used both the Logit and Random Forest models because prior research has identified these models as among the most effective in predicting corporate defaults. They also compared the predictive performance of corporate governance variables in predicting financial distress status. apply ML-based textual analysis to predict start-up acquisitions based on company data. Non-parametric models (Mestiri & Farhat, 2021) have been investigated in the literature.

The risk of insuring a novice motorist is evaluated by an insurance provider. They used to rely on things like geography, driving history, and age. To generate a more complex risk profile and ultimately produce more accurate and equitable insurance rates, machine learning (ML) algorithms are now able to assess additional data, including vehicle telematics (gathered via smartphone apps), social networking activities, and even meteorological circumstances. Many banks employ machine learning to evaluate creditworthiness in addition to traditional credit ratings, enabling underprivileged communities to access financial services.

3. Methodology

K-Nearest Neighbors

K-Nearest Neighbors (KNN) classification was developed from the need to perform discriminant analysis when reliable parametric estimates of probability densities are unknown or difficult to determine. In an unpublished US Air Force School of Aviation Medicine report in 1951, Fix and Hodges introduced a non-parametric method for pattern classification that has since become known the k-nearest neighbor rule. They introduced a novel approach to nonparametric classification by relying on the 'distance' between points or distributions.

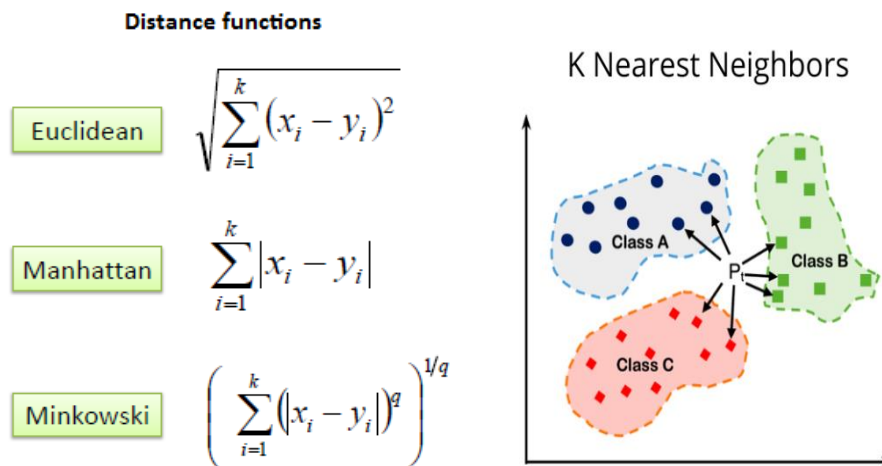
The K-Nearest Neighbor (KNN) algorithm is a good classification method with close proximity to data mining based on an object and its terms.(Liantoni, 2016) K-Nearest Neighbor can be a good classification method.(Kurniawan & Barokah, 2020) This method is carried

out by testing and comparing data, between training data and testing data.(Liantoni, 2016) Using the K-Nearest Neighbor method can help us solve a problem and have high accuracy.(Farhad Khorshid & Mohsin Abdulazeez, 2021) KNN is a non-parametric, instance-based learning algorithm. For a given data point, it assigns the label of the majority class among its nearest neighbors. The formula for predicting the class y of a new data point x is based on the distance metric (commonly Euclidean distance):

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^n (X_{ik} - \bar{X}_{jk})^2}$$

$$\bar{Y} = \arg \max_c \sum_{i \in N(x)} I(y_i = c)$$

x_i and x_j are feature vectors of two data points, and n is the number of features.

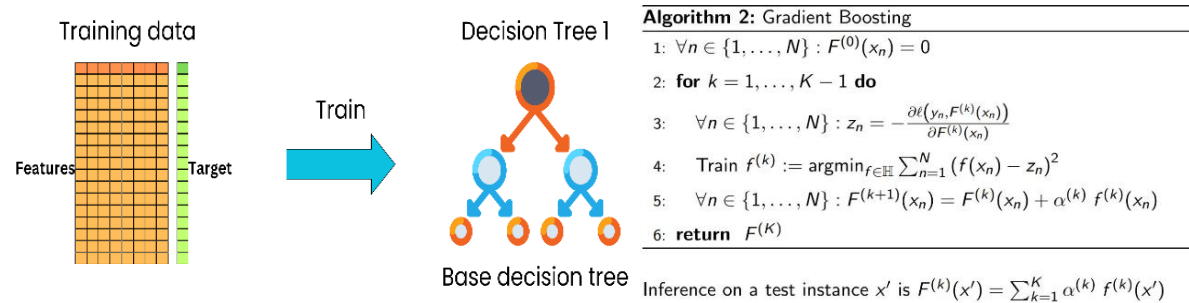


Gradient Boosting Machines

Gradient Boosting Machines (GBM) is an ensemble technique that builds models sequentially to correct the errors of prior models. The objective is to minimize a differentiable loss function. However, due to the need for resolving financial risk which in the current situation requires accurate assessments and management. With the widespread acceptance of AI and ML methods, this technology has shaped the analysis world by b expanding analysis horizons capacities to uncover unknown dynamics, find similar patterns, and predict credit risk with unmatched precision credit risk.

Recently, financial institutions such as banks and many others has been making use of AI, Machine learning to models especially (GBM) to boost their underline process when making lending decisions. This will translate to lower default rates and, in turn, better profitability. However, successful application of data science in financial risk management, however, Chang

V et al. (2020) calls not only for robust technological infrastructure but also for efficient cooperation between data professionals, risk managers, and business leaders to bring together the model outputs and business objectives, as well as regulatory compliance. Nevertheless, AI/ML still delivers the promise to credit risk management initiatives due to open data quality issues, model interpretability, and regulation, which require ongoing development and innovation to minimize the risks.



$F_m(x) = F_{m-1}(x) + v \cdot h_m(x)$ Where:

$F_m(x)$ = is the model at m-th iteration.

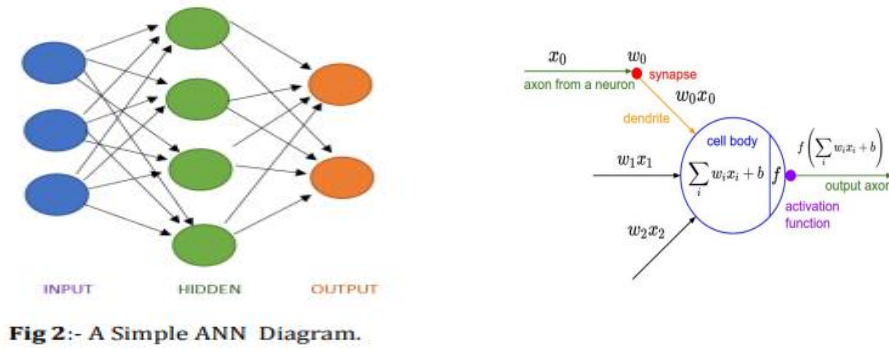
$F_{m-1}(x)$ = is the model from the previous iteration.

v is the learning rate (a shrinkage factor).

$H_m(x)$ is the new weak learner (typically a decision tree) trained to predict the negative gradient of the loss function at iteration.

Artificial Neural Networks

Artificial Neural Networks (ANNs) are artificial adaptive systems that are inspired by the functioning processes of the human brain McCulloch WS. In essence, artificial neural networks are a class of computing systems developed to analyze and process data like that of the human brain. Artificial neural networks can be tailored for a particular application and possess self-learning features that enable them to produce improved results as new data becomes available. Additionally, ANN consists of layers of neurons, where each neuron computes a weighted sum of inputs followed by a non-linear activation function σ . The output y for an input



a. Input Representation:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \dots & x_{1,M} \\ x_{2,1} & x_{2,2} & \dots & x_{2,M} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N,1} & x_{N,2} & \dots & x_{N,M} \end{bmatrix}$$

Where:

- N is the number of assets.
- M is the number of financial features (e.g., returns, volatility, momentum).
- $x_{i,j}$ is the feature j for asset i .

The output of the network is the allocation weight w for each asset in the portfolio, where, N is the number of assets, M is the number of financial features (e.g., returns, volatility, momentum), and $x_{i,j}$ is the feature j for asset i .

b. Output (Weights and Portfolio Allocation)

$$w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_N \end{bmatrix}$$

The sum of the portfolio weights is constrained to 1 (for a fully invested portfolio):

$$\sum_{i=1}^N w_i = 1$$

$$W_i = \frac{e^{z_i}}{\sum_{j=1}^N e^{z_j}}$$

Where z_i is the pre-activation output for asset iii in the final layer of the ANN.

To ensure the portfolio weights are constrained (e.g., long-only positions, non-negative weights), we can add regularization terms or enforce these constraints through the softmax output.

The Sharpe ratio SR , a common objective function in portfolio optimization, is defined as:

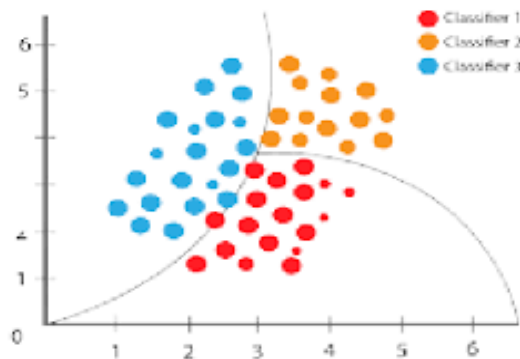
$$\sigma = \sqrt{w^T \Sigma w} \quad SR = \frac{R_p - R_f}{\sigma_p}$$

$$W_i \geq 0 \quad \forall i \text{ and } \sum_{i=1}^N w_i = 1$$

Where, R_f is the risk-free rate, R_p is the portfolio return and σ_p is the portfolio risk.

Naive Bayes (NB)

Bayes' theorem is of fundamental importance for inferential statistics and many advanced machine learning models. Bayesian reasoning is a logical approach to updating the probability of hypotheses in the light of new evidence, and it therefore rightly plays a pivotal role in science (Lippmann & R.P) 1987. Bayesian analysis allows us to answer questions for which frequentist statistical approaches were not developed. Naive Bayes (NB) is a statistical classification technique based on Bayes Theorem (Yang, 2018). It assumes that the effect of a particular feature in a class is independent of other features (Soria et al., 2011). NB is one of the simplest supervised learning algorithms. Naive Bayes reduces complexity by making a conditional independence assumption that dramatically reduces the number of parameters to be estimated when modeling $P(X|Y)$, from our original $2(2^n - 1)$ to just $2n$



Bayes Theorem: $P(c|x) = \frac{P(x|c) \cdot P(c)}{P(x)}$, classification; $\hat{C} = \arg \max(P(c) \cdot \prod_{i=1} P(x_i | c))$

$$P(x_i|c) = \frac{1}{\sqrt{2\pi\sigma^2c}} \exp\left(-\frac{(x_i - wc)^2}{2\sigma_c^2}\right)$$

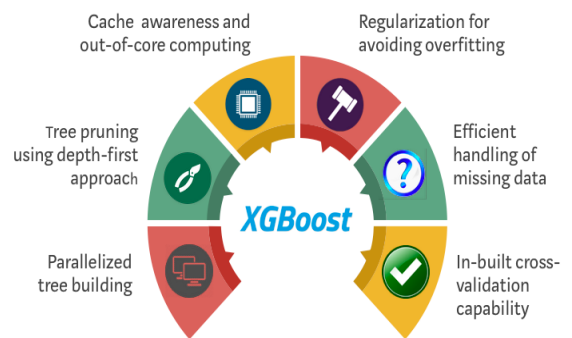
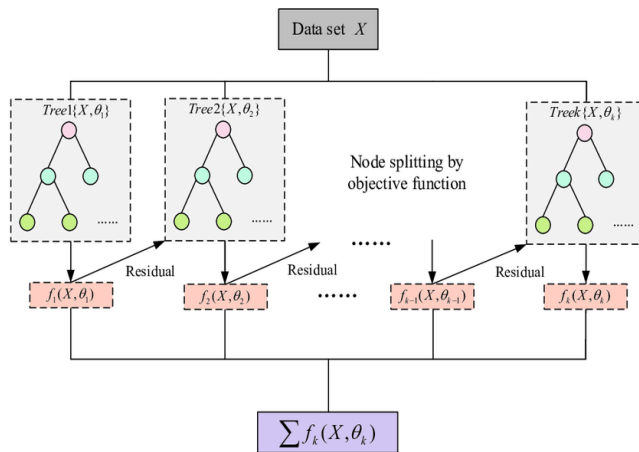
XGBoost

XGBoost (XGB) is a novel machine learning algorithm which over years has been so instrumental for carrying out complex modeling due to its exceptional ability related to high accuracy, classification versatility and interpretability of its giving observation. XGB is considered handy tools for sparse data sets using the weighted quantile sketch algorithm. This algorithm allows us to deal with non-zero entries in the feature matrix while retaining the same computational complexity as other algorithms like stochastic gradient descent.

Chen et al. (2016) their report confirmed that XGB achieves superior prediction performance and master the world of loss function reduction, utilizing its ability to identify the best strategies for reducing prediction errors. This makes it one of the suitable algorithms for mitigating loss in portfolio management. Each asset i is represented by a set of financial features X_i (e.g., historical prices, macroeconomic factors, technical indicators). The predicted return R_i is model as:

$$\hat{R}_i = \sum_{k=1}^k F_k(x_i) \quad \sigma_i^2 = \sum_{k=1}^k F_k(x_i)$$

$$\text{Max} \sum_{i=1}^n w_i \hat{R}_i \quad \text{subject to} \quad \sum_{i=1}^n w_i = 1 ; \quad (t) = \sum_{i=1}^n \left[g_i f_t(x_i) + \frac{1}{2} h_i F_t(x)^2 \right] + \Omega(F_t)$$



4. Conclusions

We have examined current financial risk management applications of machine learning. We noted both topics that need more research and areas that have been thoroughly examined. Credit rating, fraud detection, bankruptcy prediction, and volatility forecasting are among the well-

researched fields. Deep learning models and other sophisticated machine learning models have been widely employed in these tasks. However, fields like claims modelling, loss reserving, and mortality forecasting have not received as much attention. Regarding models, more high-value open problems include the more sophisticated statistical models, even if significant research challenges remain in the more conventional models. models for machine learning. Recent advances in machine learning, especially deep learning, applied to other domains have a lot to offer in the FPM field.

Among these is the recently developed uncertainty estimation machine-learning development. Federated learning systems have the potential to ensure private and more secure learning using sensitive financial data. Explainability and fairness of machine-learning models are also essential considerations for FPM that require further research. We have reviewed recent machine-learning applications in financial risk management. We identified areas that have been thoroughly examined as well as those that need more investigation. Credit rating, fraud detection, bankruptcy prediction, and volatility forecasting are among the well-researched fields. Deep learning and other advanced machine learning models have been widely used in these tasks. However, fields like claims modelling, loss reserving, and mortality forecasting have not received as much attention. In terms of models, more high-value open problems involve the more sophisticated machine-learning models, even if significant research challenges still exist in the more conventional statistical models. Recent advances in machine learning, especially deep learning, applied to other domains have a lot to offer in the FPM field. These include robust algorithms for tiny, noisy, or nonstationary data, as well as the latest techniques for estimating uncertainty in computer vision.

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