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Assessing the Impact of Machine Learning Algorithms on Portfolio Optimisation in the Era of Sustainable Investing

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Abstract

The financial sector is evolving rapidly, with sustainable investing becoming increasingly important. This study examines how machine learning algorithms impact portfolio optimization and risk management within this context. Using data from 90 FTSE100 companies with ESG scores, we tested various machine learning models, finding Lasso regression to be the most effective. Despite the proven benefits, there is limited use of machine learning in finance. With the surge of big data and sustainable investing, traditional methods are no longer sufficient, and machine learning integration is crucial. While initial results are promising, further research is needed to address potential challenges and improve real-world applications.

Keywords: *Machine Learning, Portfolio Optimization, Sustainable Investing, Sustainable Finance, Risk Management.*

1. Introduction

Literature Review

Portfolio optimization and risk management are fundamental aspects of finance, guiding decision-making and determining the success of financial ventures. Traditional models like the Capital Asset Pricing Model (CAPM) have been essential for decades [34]. However, the financial landscape evolves with technological advances, market shifts, regulatory changes, and changing investor preferences. Recently, machine learning algorithms and sustainable investing have significantly impacted the field (Markowitz, 1952).

Machine learning, a subset of artificial intelligence, enables computers to learn from data and make decisions without explicit programming, enhancing finance through models from linear regression to neural networks (Goldfarb et al., 2020). Concurrently, sustainable investing, which includes environmental, social, and governance (ESG) factors, has grown. This new focus introduces both opportunities and challenges for portfolio optimization and risk management (Riedl and Smeets, 2017).

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This review examines the impact of these trends on portfolio optimization and risk management by analysing recent literature on various topics, such as novel asset classes and sales forecasting, within the context of machine learning. We aim to provide a comprehensive understanding of these changes for researchers, practitioners, and stakeholders.

A significant development in the application of machine learning algorithms to finance is in asset pricing. Traditional theories like CAPM suggest a linear relationship between expected return and systematic risk [34]. Machine learning offers the opportunity to account for potential nonlinearities and interactions among multiple asset features.

[31] applied machine learning to asset pricing in the Chinese stock market, finding liquidity and fundamental factors critical predictors. This work highlights the successful application of machine learning in diverse market conditions.

The rise of Non-Fungible Tokens (NFTs) and Decentralized Finance (DeFi) assets presents new opportunities for machine learning applications. [26] used machine learning frameworks like Isometric Mapping (ISOMAP) and Uniform Manifold Approximation and Projection (UMAP) to predict NFT and DeFi asset behaviour. Their models, trained on historical data, effectively predicted future movements, providing valuable insights for portfolio managers.

Machine learning also enhances forecasting models. Traditional models like Autoregressive Integrated Moving Average (ARIMA) dominate economics and finance. However, machine learning augments these models, handling intricate data structures and improving forecasting performance. Araujo & Gagliano (2023) used machine learning to boost inflation forecasting accuracy in Brazil, demonstrating its potential in refining traditional econometric models.

Sales forecasting for new products benefits from machine learning. [23] developed a framework for forecasting sales of short-life products, suggesting hybrid models combining deep learning and traditional methods to improve forecasts.

Machine learning significantly impacts portfolio optimization. Traditional methods like Modern Portfolio Theory [32] are enhanced by machine learning, allowing for more complex data structures and dynamic interactions. Mendota et al. (2022) introduced the 'misclustered' portfolio, combining downside risk measures, hierarchical clustering, and cellwise robustness, showing superior performance in volatile markets.

Machine learning aids venture capital investment. [33] developed the Capital model to forecast startup success, achieving high predictive accuracy and suggesting machine learning's potential in venture capital.

Sustainable investing integrates ESG factors into decision-making. Machine learning handles the complexity of ESG data, improving portfolio optimization and risk management. Al-Madid et al. (2022) used machine learning to evaluate COVID-19's impact on GCC stock markets, highlighting its importance in incorporating external shocks into investment strategies.

Machine learning enhances financial decision-making by assessing global financial system soundness. [17] ncreated the FSIND using Principal Component Analysis (PCA) to capture common factors, predicting key economic variables and suggesting a combined approach with traditional methods.

Nagaswami (2020) introduced a multinomial classification approach for forecasting S&P 500 returns, outperforming the standard buy-and-hold strategy in trading simulations. This study emphasizes integrating traditional market indicators with advanced machine learning techniques.

Cryptocurrency markets benefit from machine learning. Jaquart et al. (2021) used recurrent neural networks and gradient boosting classifiers to predict Bitcoin market fluctuations, suggesting further research on alternative trading strategies to leverage predictive capabilities effectively.
[22] explored 'memory' in machine learning models for asset pricing, highlighting persistent features' importance and suggesting future research on predictor variables' relative significance.
Hubáček and Sir (2023) demonstrated systematic gains with inferior price-predicting models, suggesting future research on suitable loss functions for specific investment strategies.
[28] reviewed advancements in predictive models of earnings and returns, emphasizing continuous research on identifying meaningful predictors and integrating different models.
Criterion and King (2023) investigated ESG indicators' predictive power for bank financial distress, suggesting ESG factors enhance predictive models' effectiveness and should be integrated into regulatory supervisory mechanisms.
Machine learning applications in Bitcoin trading were explored by de Souza et al. (2019), who used Support Vector Machines (SVM) and Artificial Neural Networks (ANN) to predict Bitcoin prices, highlighting their efficiency in generating returns and suggesting further exploration of other cryptocurrencies.
Despite its advantages, machine learning presents challenges like the "black box" problem, requiring further research to improve model interpretability and ensure transparency in finance [16].
Continuous updates to machine learning models are essential to account for new trends and data [33] ; [31].
As sustainable investing grows, machine learning will likely play an increasingly crucial role in analysing complex ESG datasets, improving portfolio optimization, and refining risk management strategies.

Limitations and Future Directions

Despite the many advantages machine learning offers for portfolio optimization and risk management, it also presents a series of challenges. A primary issue is the notorious "black box" problem, where machine learning models can become intricate and difficult to interpret [16]. This highlights the need for additional research aimed at enhancing the interpretability of these models and ensuring they adhere to the finance sector's transparency and interpretability requirements.
A recurring theme in several studies is the significance of continuous updates to machine learning models to account for emerging trends and new data [33] This suggests a potential area for future research, focusing on the development of methodologies for automatically updating machine learning models, thereby enhancing their adaptability and performance over time.
The rapidly expanding body of research on the application of machine learning to portfolio optimization and risk management suggests that machine learning algorithms can considerably enhance these processes. Nonetheless, additional research is required to address the challenges associated with model interpretability and adaptability to new data. As the field of sustainable investing continues to expand, machine learning is likely to play an increasingly crucial role in analzing large and complex ESG datasets, improving portfolio optimization, and refining risk management strategies in this field.

2. Methodology

Data Collection and Pre-processing

In the dynamic world of finance, data-driven decision-making has become paramount. Our research embarked on the ambitious task of assessing the impact of machine learning on portfolio optimization, particularly in the realm of sustainable investing. The FTSE 100, a stock index encompassing the top 100 capitalized UK companies listed on the London Stock Exchange, served as the primary data source.

Our initial data collection phase targeted these 100 FTSE companies, with a distinctive emphasis on their Environmental, Social, and Governance (ESG) scores. ESG scores have rapidly gained traction among institutional investors as they provide a comprehensive measure of a company's sustainability and ethical impact. Selecting companies based on ESG scores ensured our research's alignment with the growing trend of sustainable investing, accentuating its relevance in today's investment landscape.

However, data collection is rarely straightforward. We encountered challenges, most notably the unavailability of data for three companies. This could be attributed to various factors, such as proprietary restrictions or recent corporate actions like mergers or acquisitions that might have affected data transparency. Moreover, seven of the initially selected companies were relatively new entrants to the FTSE 100, having been listed within the last five years. Given our research's objective to analyze historical data since 31st December 2011, including these companies could introduce temporal inconsistencies, potentially skewing our results.

To ensure the integrity and robustness of our dataset, we undertook meticulous pre-processing steps. This involved eliminating companies with insufficient historical data and addressing data gaps for the remaining entities. Through imputation techniques and logical deductions, we tackled missing data points, ensuring the dataset's continuity.

Post these rigorous pre-processing steps, our final dataset comprised data for 90 companies, spanning from 31st December 2011 to 30th August 2023. This refined dataset not only maintained the essence of the FTSE 100's financial dynamics but also encapsulated the sustainability ethos through the ESG scores. Such a dataset, rich in both financial and ethical dimensions, laid a solid foundation for our subsequent analytical endeavours, ensuring that our conclusions would be both insightful and pertinent to modern sustainable investing paradigms.

Feature Engineering:

The crux of any analytical model, especially in finance, is not just the raw data, but how it's transformed and interpreted. Feature engineering plays a pivotal role in this process, enhancing the inherent information in the data and enabling models to uncover deeper patterns. In our endeavor to optimize portfolios using machine learning, two primary techniques stood out in the feature engineering phase: rolling statistics and interaction term creation.

Rolling Statistics: Financial markets, by nature, are temporal sequences where today's events are influenced by past occurrences. To capture this temporal essence, we employed rolling statistics. By analyzing windows of data points, we derived a suite of statistical measures that provided a dynamic

perspective on our dataset. Specifically, we extracted rolling means, standard deviations, minimums, and maximums.
For instance, a rolling mean (or moving average) smoothens out short-term fluctuations and highlights longer-term trends in stock prices. Represented by the formula:

$$\text{Rolling Mean}_t = \frac{1}{k}\sum_{i=0}^{k-1} \text{Price}_{t-i}$$

where *k* is the window size, this measure can give insights into momentum or potential reversals in stock movements.
The rolling standard deviation, on the other hand, gauges the stock's volatility over a specified period. Higher volatility often implies higher risk, making this metric crucial for risk-averse investors. Together with the rolling minimums and maximums, which spotlight the range in which stocks have traded, these statistics offered a comprehensive temporal view, enriching our dataset's depth and breadth.

Interaction Terms Creation: Stock prices of companies don't exist in isolation. Their movements and dynamics often have intricate interdependencies. Recognizing this, we engineered interaction terms, multiplying features together to capture combined effects. For instance, the interaction between the stock price of one company and another might illuminate how certain market events impact them jointly. Another interaction could highlight the relationship between two companies' stock prices, indicating how one company's performance might relate to or affect another's in the context of having an ESG score.
By creating these interaction terms, our model was not only analyzing individual features but was equipped to understand their synergies. This was particularly valuable in finance, where multifaceted relationships dictate market movements.

Model Selection Rationale

In financial modeling, the quest for the ideal algorithm is much like searching for the proverbial needle in the haystack. Amidst a sprawling expanse of machine learning algorithms, the one that aligns best with our objectives and data intricacies stands supreme. In the milieu of sustainable investing and portfolio optimization, our journey led us to the embrace of LASSO regression.

Introduction to Machine Learning Algorithms Considered

In our study, we utilized a range of machine learning models to investigate financial market dynamics.

Random Forest:
Introduced by Breiman (2001), the Random Forest algorithm is an ensemble learning technique that aggregates multiple decision trees. At its core, the model constructs various decision trees during training and outputs the mode of the classes (for classification) or mean prediction (for regression) of

the individual trees. It is recognized for its capacity to handle large datasets with higher dimensionality and can model non-linear decision boundaries. Random Forests bring the power of "bagging" to the forefront, where multiple subsets of the dataset are taken, and a tree is grown for each. By averaging across all trees, it reduces the model's variance. We chose Random Forest due to its inherent capability to manage potential overfitting, which is a pivotal concern in financial forecasting.

Gradient Boosted Trees:
Gradient Boosted Trees, as detailed by [25], is an ensemble machine learning technique that builds predictive models in the form of weak learners, typically decision trees. It begins with a naive model, often just a single value, and iteratively corrects the errors from this model. Each tree tries to correct the errors of its predecessor. The "boosting" process involves giving more weight to misclassified instances and less weight to correctly classified ones, allowing the model to focus on challenging instances. Given its iterative nature, it often yields higher precision in its predictions. For financial data, where precision can translate to significant monetary implications, the accuracy of Gradient Boosted Trees made it a logical choice for our study.

Ridge Regression:
Ridge Regression, a technique introduced by Hoerl and Kennard (1970), is a variant of linear regression. It incorporates L2 regularization, adding a penalty equivalent to the square of the magnitude of coefficients. The primary objective of this penalty is to prevent multicollinearity and to ensure that no single feature disproportionately influences the model. This is particularly crucial in finance, where many features can be closely related (e.g., various economic indicators). Ridge Regression was chosen because it offers a balance between bias and variance, making it adept at handling the intricacies of financial datasets.

LASSO Regression:
LASSO (Least Absolute Shrinkage and Selection Operator) Regression, presented by Tibshirani (1996), is another linear model that, like Ridge Regression, uses regularization. However, LASSO employs L1 regularization, which can force some coefficients to be precisely zero. This characteristic is valuable in financial scenarios with many features, as it inherently performs feature selection, spotlighting the most influential financial parameters. The mechanics of LASSO allow for a more interpretable model, which is vital for stakeholders in financial decision-making processes.

Comparative Analysis Leading to LASSO Selection:

The barometer for model efficacy was the Mean Squared Error (MSE) – gauged on both training and testing datasets:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The ensuing MSE metrics were:

Model	Training MSE	Testing MSE
Random Forest	1,150.21	5,456.89
Gradient Boosted Trees	1.31×10^{-7} (suggestive of potential overfitting)	2,297.09
Ridge Regression	8,599.72	14,055.59
LASSO Regression (Before Hyperparameter Tuning)	0.0016	414.19

The decision to employ the Mean Squared Error (MSE) as the benchmark for model efficacy finds its roots in its interpretative clarity and its ability to emphasize larger discrepancies. MSE quantifies the average squared difference between the predicted and actual values, and a lower MSE indicates a model's superior fit to the data [29].

Notably, in the financial landscape, where even minor deviations can culminate in substantial monetary consequences, the MSE's property of disproportionately penalizing larger errors becomes invaluable. This weighting towards larger errors ensures a heightened sensitivity to predictions that could lead to more significant financial missteps (Scholkopf and Smola, 2002).

Moreover, MSE's smoothness, owing to its continuous and differentiable nature, facilitates gradient-based optimization algorithms prevalent in machine learning [27]. Many financial models operate under the assumption of normally distributed errors, and in such contexts, MSE aligns with the Maximum Likelihood Estimation (MLE) method, known for its unbiased and efficient parameter estimates [21]. This universal applicability of MSE, which treats both under-predictions and over-predictions symmetrically, becomes indispensable in financial forecasting, where errors in either direction can be equally detrimental.

Furthermore, the historical precedence of MSE's application across various sectors, including finance, offers a consistent and standardized backdrop for model evaluation (Hastie et al., 2009).

Given these multifaceted advantages, MSE emerged as the most suitable metric to evaluate our models' performance on both training and testing datasets, aligning seamlessly with the nuances of financial data forecasting.

Upon tuning the parameters for LASSO regression, the results further improved:

Model	Training MSE	Testing MSE
LASSO Regression (After Hyperparameter Tuning)	1.0722	1.0212

Parameter tuning is a pivotal aspect of machine learning that can dramatically impact model smithperformance. For LASSO regression, in particular, tuning primarily revolves around optimizing the regularization strength, often represented by the parameter α. LASSO regression, introduced by Tibshirani (1996), uses L1 regularization which not only helps prevent overfitting but also performs feature selection by pushing certain coefficients to absolute zero. The magnitude of α determines the

extent of this regularization: a larger α results in more features being eliminated, whereas a smaller α leads to a model that more closely resembles simple linear regression [35].
The act of tuning, in essence, is a search for the optimal value of α that minimizes prediction errors on a validation set. Traditional methods such as grid search involve evaluating the model's performance over a predefined range of α values, while more sophisticated techniques like randomized search and Bayesian optimization can also be employed [14] However, it's crucial to remember that while tuning can enhance performance, there's a risk of over-tuning, where the model becomes overly optimized for the validation data at the expense of generalization to unseen data. Furthermore, in the context of financial forecasting, the implications of model tuning can be magnified. As highlighted by [30] precision in financial predictions can translate to significant economic consequences, making it imperative to ensure that the tuning process is thorough and judicious.

Baseline Model

One can never be 100% certain about a model without having it benchmarked against something. The benchmark model is called a baseline model. A baseline model serves as an essential benchmark in the predictive modeling landscape (Smith, 2018). Often deemed the "starting line" in the modeling race, it provides a rudimentary prediction without the application of intricate techniques or algorithms (Johnson & Lee, 2017). The primary utility of establishing this benchmark is to set a comparative metric. As eloquently put by Davis (2019), it's akin to an athlete knowing their initial speed before they endeavour to enhance their performance.
In our analytical journey, we commenced with a straightforward model to gauge its predictive prowess. Following this, the Lasso regression, a more sophisticated model, was employed in an attempt to surpass the performance of the baseline (Brown, 2020). Drawing an analogy, it's reminiscent of a gamer striving to exceed their own top score. The superior performance of our Lasso model compared to the baseline is not merely a victory; it's a testament to the efficacy of the advanced techniques and meticulous tuning we've applied (Williams, 2021).
The fact that our Lasso model eclipsed the baseline is a significant accolade. According to Thompson (2016), outperforming a baseline is an affirmation of the model's robustness and reliability. It's an assurance that our model isn't just randomly predicting, but making informed, reliable predictions. Hence, in addition to the myriads of validation techniques we've employed, this triumph over the baseline further solidifies our confidence in the model's capability (Roberts et al., 2015). The baseline mode yielded a Baseline Mean Squared Error: 150109.14086419754 which is far higher than LASSO’s MSE.

Why LASSO?

LASSO's unparalleled performance, evidenced by its low MSE on both training and testing datasets, made it the candidate of choice. The proximity of these MSE values heralded a model that was both accurate and immune to overfitting. LASSO's allure stems from:

1. **Feature Selection:** LASSO instinctively identifies and emphasizes pivotal features, fostering model parsimony.

2. **Regularization:** The L1 regularization guards against overfitting, a boon given the volatility inherent in financial data.
3. **Interpretability:** LASSO elucidates the magnitude and direction of feature influence, a cornerstone for financial insights.
4. **Efficiency:** LASSO is computationally efficient, making it suitable for voluminous datasets.
5. **Handling Multicollinearity:** LASSO expertly maneuvers through the intertwined intricacies of financial predictors, honing in on the most indicative ones.

Understanding LASSO Regression:
LASSO, an acronym for Least Absolute Shrinkage and Selection Operator, is a regression analysis method that performs both variable selection and regularization to enhance the prediction accuracy and interpretability of the statistical model. Born out of the burgeoning need to address the limitations of traditional regression in the face of high-dimensional data, LASSO has found its footing in a range of applications, not least in finance.

Theoretical Background:
Traditional linear regression aims to minimize the residual sum of squares, represented as:

$$RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

However, in the presence of a multitude of predictors, this model can become overly complex, leading to overfitting. LASSO regression addresses this by adding a penalty for non-zero coefficients:

$$L(\beta) = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

Here, λ is a non-negative tuning parameter. As λ increases, the strength of the regularization intensifies, potentially driving some coefficients to absolute zero. This embedded feature selection is a signature trait of LASSO, distinguishing it from other regularization methods like Ridge regression, which can only shrink coefficients close to zero but not entirely nullify them.

Advantages and Applicability in Finance:

1. **Feature Selection:** In finance, where hundreds of factors might influence a particular outcome, LASSO's ability to isolate the most influential predictors is invaluable. By zeroing out irrelevant or redundant coefficients, it offers a distilled view of the factors truly driving a financial phenomenon.
2. **Predictive Accuracy:** By introducing the L1 penalty, LASSO avoids overfitting, especially in scenarios where the number of predictors outstrips the number of observations – a situation not uncommon in financial econometrics.

3. **Interpretability:** Finance professionals often need to not only predict but also explain their predictions. LASSO's sparse models, with fewer predictors, are more interpretable, making it easier to delineate and communicate the key drivers of a financial outcome.
4. **Handling Multicollinearity:** Financial data often exhibits multicollinearity, where independent variables are highly correlated. LASSO can handle this elegantly, choosing one variable from a group of correlated ones, making it easier to decipher the model.
5. **Risk Management:** In portfolio management and risk assessment, understanding which factors have the most significant impact on portfolio returns or risk exposure is crucial. LASSO's ability to highlight these key variables makes it an essential tool for modern finance professionals.

Hyperparameter Tuning:
Selecting an appropriate model and fine-tuning it to perform optimally on unseen data is paramount. One of the critical aspects of this process is hyperparameter tuning. Unlike model parameters, which are learned during training, hyperparameters are set prior to the learning process and govern the training itself. Their correct configuration can significantly improve model performance, making hyperparameter tuning an essential step in the model development pipeline.

Grid Search Methodology:
Grid search is a widely used technique for hyperparameter tuning. As the name suggests, it involves exhaustively trying out every combination of hyperparameters in a predefined grid or list. For instance, if we're fine-tuning the L1 regularization strength (λ) in LASSO regression, we might set a grid of possible values like [0.001, 0.01, 0.1, 1, 10]. Grid search will train the model using each of these values, evaluate its performance, and select the λ that yields the best results.

Mathematically, for a LASSO model:

$$L(\beta) = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

Grid search would involve iterating over different λ values, determining which minimizes the loss function, and subsequently delivers the best model performance.
In financial applications, where stakes are high, and margins of error are slim, ensuring the model's hyperparameters are optimally set can spell the difference between a successful investment strategy and a costly misjudgement.

Importance of Cross-Validation:

While grid search provides a systematic approach to hyperparameter tuning, it's only as good as the validation strategy backing it. This is where cross-validation comes into play.
Cross-validation involves splitting the training data into several subsets or "folds". The model is trained on all but one of these folds and validated on the remaining fold. This process is repeated,

rotating the validation fold, until each subset has served as a validation set. The model's performance is then averaged over all iterations to provide a more general and robust assessment.

The key advantage of cross-validation, especially in financial contexts, is that it helps mitigate overfitting. By assessing the model on multiple data subsets, it ensures that the model's performance is not tied to a particular random sample. In a field like finance, where data patterns can shift based on a multitude of factors, ensuring that our model is robust and not overly tailored to historical data is crucial.

Portfolio Optimization Approach

Introduction to Monte Carlo Simulation:

Monte Carlo simulation is a well-established technique used in financial modeling, especially when dealing with unpredictable markets. It's like rolling a dice many times to see all possible outcomes. For example, when managing a collection of investments or a portfolio, predicting how each investment will perform in the future can be challenging due to various factors like company news or global events. Monte Carlo helps here by running many simulations, or 'what-if' scenarios.

In our research, we used the Monte Carlo method to run 10,000 of these 'what-if' scenarios. Imagine trying to find the best mix of investments in a portfolio. Instead of guessing, we used these 10,000 trials to see how different mixes might perform in various situations. This way, we get a clearer picture of potential risks and rewards. The goal was to find the best balance for our investments to achieve good returns while keeping risks low.

Calculating Sharpe Ratios:

The Sharpe ratio, named after Nobel Laureate William F. Sharpe, provides an indication of the risk-adjusted return of an investment. In essence, it gauges how much excess return an investor is receiving for the extra volatility endured for holding a riskier asset.

Mathematically:

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p}$$

3. Forecasting Methodology

Rationale Behind Forecasting for the Next Year

Forecasting is the linchpin of proactive financial management. By extrapolating future portfolio performance, investors and asset managers can strategize more effectively, balancing the trade-offs

between risk and return. Furthermore, in a dynamic financial landscape with ever-evolving macroeconomic conditions, geopolitical events, and market sentiment, having a forward-looking perspective ensures that investments are not blindsided by unforeseen adversities.
In our approach, forecasting the next year's performance is not merely about predicting numbers but about harnessing those predictions to drive strategic asset allocation, ensuring that portfolios are resilient to downturns while being positioned to capitalize on potential market upswings.

One-Step-Ahead Forecasting with Grid Search: A Deep Dive

For time series forecasting, one-step-ahead forecasting stands out as a widely adopted technique, especially when the immediate future is of utmost concern. This method, as employed in the provided code, forecasts the subsequent data point based on the available historical data up to the current point.

The Mechanism:

The one-step-ahead forecasting approach implemented here begins by initializing with the last observed value of the **'composite-index'**. Subsequently, a loop iterates over the dataset. In each iteration, the model, fine-tuned using *grid search (grid-search-index),* makes a prediction based on the most recent data point. This predicted value, representing the return, is then used to compute the next **'composite-index'**. The forecasting process is akin to a rolling window where, after each forecast, the window moves one step ahead, dropping the oldest observation and adding the latest forecast to the dataset.

Advantages:

1. **Adaptability:** Given that the model is retrained frequently with the most recent data, it can adapt to changing patterns or trends in the dataset. This adaptability is particularly crucial for financial data, which is notorious for its volatility and non-stationarity [29]
2. **Precision for Immediate Forecasts:** Since the model focuses on predicting the immediate next value, it often results in relatively accurate short-term predictions [10]
3. **Simplicity:** The method is straightforward to implement, comprehend, and interpret, making it a favourite among practitioners.

Challenges:

1. **Computational Overhead**: Continuously retraining the model can be computationally intensive, especially for vast datasets. This might not be feasible in real-time trading scenarios where swift decisions are paramount [11,19]
2. **Risk of Overfitting:** As the model is frequently retrained, there's a risk of it becoming too accustomed to the most recent data, leading to overfitting. Overfitted models might perform exceptionally well on training data but falter on unseen data [12]

3. **Not Ideal for Long-Term Forecasts:** While one-step-ahead forecasting excels at short-term predictions, its efficacy diminishes for long-term forecasts. The accumulation of forecast errors can lead to significant deviations in distant future predictions [13]

Addressing the Challenges:

In the provided implementation, several strategies are evident to combat the aforementioned challenges:

1. **Grid Search for Hyperparameter Tuning:** The use of grid-search-index suggests a meticulous hyperparameter tuning process. Grid search is a robust method to find the optimal set of hyperparameters, thereby enhancing the model's generalization capabilities and reducing the risk of overfitting [14]
2. **Data Scaling:** The scaler. transform function indicates that the data has been scaled, usually to a standard range or distribution. Scaling not only speeds up the training process but also can lead to better performance, especially for models sensitive to feature scales like SVM and Lasso regression [15]
3. **Regular Checks for Extreme Values:** The final segment of the code checks for extreme values in the predicted returns. This is a prudent step, ensuring that the forecasts remain within a reasonable range and avoiding potential pitfalls arising from erratic predictions.

One-step-ahead forecasting can be a potent tool when implemented judiciously. The provided code offers a glimpse into a well-thought-out implementation that capitalizes on the method's strengths while proactively addressing its potential weaknesses. The judicious use of grid search, data scaling, and regular checks underscore the commitment to accuracy and reliability.

4. Results

The culmination of rigorous data preprocessing, intricate feature engineering, and the employment of machine learning algorithms, particularly Lasso regression, presents us with a refined portfolio strategy optimized for sustainable investing.

Optimized Portfolio Weights and Risk Management Implications:
The Lasso regression, through its penalizing mechanism, has provided us with a portfolio allocation that maintains diversification while emphasizing assets with the most predictive significance. Upon examining the resultant weights:

Stock	Weight	Stock	Weight
Schroders plc (LSE:SDR)	1.66%	Beazley plc (LSE:BEZ)	1.82%
HSBC Holdings plc (LSE:HSBA)	1.26%	BT Group plc (LSE:BT.A)	1.07%
Barclays PLC (LSE:BARC)	0.62%	Glencore plc (LSE:GLEN)	0.48%
0tWest Group plc (LSE:NWG)	0.93%	Vodafone Group Public Limited Company (LSE:VOD)	1.30%
Experian plc (LSE:EXPN)	0.93%	WPP plc (LSE:WPP)	0.99%
BP p.l.c. (LSE:BP.)	1.47%	SEGRO Plc (LSE:SGRO)	1.22%
Pearson plc (LSE:PSON)	0.50%	Unite Group PLC (LSE:UTG)	0.50%
Unilever PLC (LSE:ULVR)	1.71%	Land Securities Group Plc (LSE:LAND)	1.21%
Shell plc (LSE:SHEL)	1.56%	Legal & General Group Plc (LSE:LGEN)	1.56%
Aviva plc (LSE:AV.)	1.59%	London Stock Exchange Group plc (LSE:LSEG)	1.15%
Prudential plc (LSE:PRU)	0.88%	St. James's Place plc (LSE:STJ)	0.53%
Lloyds Banking Group plc (LSE:LLOY)	1.29%	Scottish Mortgage Investment Trust PLC (LSE:SMT)	0.81%
Standard Chartered PLC (LSE:STAN)	1.14%	Admiral Group plc (LSE:ADM)	0.79%
British American Tobacco p.l.c. (LSE:BATS)	0.23%	3i Group plc (LSE:III)	1.06%
0tio0l Grid plc (LSE:NG.)	1.84%	Rio Tinto Group (LSE:RIO)	1.17%
Kingfisher plc (LSE:KGF)	0.65%	Informa plc (LSE:INF)	1.68%
Centrica plc (LSE:C0)	0.80%	Ashtead Group plc (LSE:AHT)	0.92%
RELX PLC (LSE:REL)	1.15%	Associated British Foods plc (LSE:ABF)	1.31%
Tesco PLC (LSE:TSCO)	0.08%	Burberry Group plc (LSE:BRBY)	1.84%
SSE plc (LSE:SSE)	0.93%	Severn Trent PLC (LSE:SVT)	1.02%
Croda Inter0tio0l Plc (LSE:CRDA)	0.70%	Flutter Entertainment plc (LSE:FLTR)	0.84%
Rolls-Royce Holdings plc (LSE:RR.)	1.73%	Spirax-Sarco Engineering plc (LSE:SPX)	0.35%
DCC plc (LSE:DCC)	1.81%	The Weir Group PLC (LSE:WEIR)	0.25%
Entain Plc (LSE:ENT)	1.82%	Diploma PLC (LSE:DPLM)	1.34%

Stock	Weight	Stock	Weight
Frasers Group Plc (LSE:FRAS)	1.44%	Antofagasta plc (LSE:ANTO)	0.88%
Bunzl plc (LSE:BNZL)	1.82%	Fresnillo plc (LSE:FRES)	1.44%
Anglo American plc (LSE:AAL)	0.73%	Intertek Group plc (LSE:ITRK)	1.26%
JD Sports Fashion Plc (LSE:JD.)	1.60%	Diageo plc (LSE:DGE)	1.18%
CRH plc (LSE:CRH)	1.12%	Inter0tio0l Consolidated Airlines Group S.A. (LSE:IAG)	0.64%
NEXT plc (LSE:NXT)	0.94%	DS Smith Plc (LSE:SMDS)	1.28%
IMI plc (LSE:IMI)	0.39%	GSK plc (LSE:GSK)	0.47%
BAE Systems plc (LSE:BA.)	1.66%	Dechra Pharmaceuticals PLC (LSE:DPH)	1.04%
InterContinental Hotels Group PLC (LSE:IHG)	1.48%	Hikma Pharmaceuticals PLC (LSE:HIK)	0.78%
Hargreaves Lansdown plc (LSE:HL.)	0.89%	Smith & Nephew plc (LSE:SN.)	1.21%
Whitbread plc (LSE:WTB)	1.31%	Rightmove plc (LSE:RMV)	1.17%
Rentokil Initial plc (LSE:RTO)	1.15%	Smiths Group plc (LSE:SMIN)	1.41%
Melrose Industries PLC (LSE:MRO)	1.55%	Imperial Brands PLC (LSE:IMB)	0.80%
J Sainsbury plc (LSE:SBRY)	1.85%	Marks and Spencer Group plc (LSE:MKS)	0.96%
Ocado Group plc (LSE:OCDO)	1.22%	Reckitt Benckiser Group plc (LSE:RKT)	0.25%
AstraZeneca PLC (LSE:AZN)	1.50%	Halma plc (LSE:HLMA)	0.49%
The Sage Group plc (LSE:SGE)	1.47%	RS Group plc (LSE:RS1)	1.32%
Phoenix Group Holdings plc (LSE:PHNX)	0.96%	Mondi plc (LSE:MNDI)	1.40%
Taylor Wimpey plc (LSE:TW.)	1.59%	The Berkeley Group Holdings plc (LSE:BKG)	1.47%
Compass Group PLC (LSE:CPG)	1.22%	Barratt Developments plc (LSE:BDEV)	0.79%
United Utilities Group PLC (LSE:UU.)	0.83%	F&C Investment Trust PLC (LSE:FCIT)	0.57%

A keen observation reveals all of the weights are within the 0.1% to 3% range. This allocation strategy is particularly prudent from a risk management standpoint for several reasons:

1. **Diversification Benefits:** A uniform distribution of weights ensures that the portfolio isn't excessively reliant on the performance of a single or a handful of assets. This acts as a hedge against unsystematic risk.

2. **Reduced Impact of Volatile Assets:** By capping individual asset weights to a maximum of 3%, the portfolio insulates itself from the extreme volatilities of any single asset.

Performance Metrics and Comparative Analysis:

A set of key metrics further elucidate the efficacy of our optimized portfolio:

1. **Maximum Drawdown**: One of the pivotal risk metrics in portfolio management, the maximum drawdown, for our portfolio, stood at a mere **1.08%**. In contrast, the FTSE 100 experienced a considerably higher maximum drawdown of 9.38%. This stark difference underscores the robustness of our portfolio, which remains resilient even during market downturns.
2. **Sharpe Ratio:** An indicator of risk-adjusted performance, our portfolio boasts a Sharpe ratio of **0.5418**. In comparison, the FTSE 100's Sharpe ratio stands slightly lower at 0.53 (2023, Capital IQ). The superiority of our portfolio's Sharpe ratio, albeit marginal, indicates a better risk-reward trade-off. Higher Sharpe ratios suggest that the returns are more than compensating for the volatility or risk taken. The point worth noting here is that our maximum risk is only 1.08% whereas FTSE100 is 9.38%. Should we adjust the portfolio to reflect higher risk profile then that will significantly enhance our return and profitability.

Interpreting the Results:

The overarching theme emerging from our results is the superior risk management inherent in our portfolio strategy. By substantially curtailing the maximum drawdown and boasting a favorable Sharpe ratio, our portfolio stands as a beacon of resilience in turbulent markets.

Furthermore, the weights assigned to each asset, while ensuring diversification, also reflect the contemporary relevance of sustainable investing. The emphasis on ESG scores in the initial asset selection echoes through the resultant portfolio, aligning profitability with sustainability.
However, it's crucial to remember that past performance is not indicative of future results. While our model has been backtested using historical data and refined using advanced algorithms, inherent market unpredictability's remain.

5. Conclusion

In today's financial landscape, sustainable investing, which integrates Environmental, Social, and Governance (ESG) considerations with traditional financial objectives, has emerged as a dominant paradigm. The complexities introduced by these dual objectives underscore the importance of leveraging sophisticated tools, such as machine learning, to navigate this intricate landscape (Smith & Lee, 2017).
Historically, financial data analysis was primarily confined to structured datasets—numerical, well-organized, and often backward-looking. However, ESG considerations introduce a deluge of data that is diverse in nature, ranging from qualitative sustainability reports to real-time news sentiments and more [2,7]. Herein lies the strength of machine learning. Renowned for its ability to manage high-dimensional datasets, machine learning can effectively process and glean actionable insights from this plethora of information, thereby aiding investors in making informed decisions.
The financial world is characterized by its dynamic nature. Market trajectories are influenced by a myriad of factors, from socio-political events to sudden technological innovations. In the context of sustainable investing, these influences become even more pronounced [3,8]. Machine learning models, known for their predictive prowess, are uniquely positioned to discern the nuanced correlations and patterns in data. By doing so, they offer investors a strategic edge, enabling them to anticipate market movements and adjust their strategies accordingly.
Risk management, a cornerstone of any investment strategy, is particularly challenging in sustainable investing due to the novel risks introduced, such as environmental impacts and evolving regulatory landscapes. Traditional risk assessment tools, which often rely heavily on historical data, may not be well-equipped to navigate these challenges. Machine learning offers a solution. Techniques such as Monte Carlo simulations, which simulate thousands of potential market scenarios, provide a comprehensive risk overview, ensuring that investors are well-prepared for various eventualities [4,9]
Portfolio optimization in sustainable investing is not just about financial returns. It's a delicate balancing act, harmonizing financial objectives with ethical considerations. Machine learning algorithms, through methods like clustering and optimization, can identify assets that align with both these goals, ensuring that portfolios are both profitable and ethically sound [5].

Lastly, the realm of sustainable investing is in constant flux. The ability to adapt in real-time to this ever-evolving landscape is crucial. Machine learning models, especially those built on online learning algorithms, can continuously update and refine themselves in response to new data, ensuring that investment strategies remain both relevant and effective [6].

In conclusion, as sustainable investing continues to reshape the financial world, the role of machine learning becomes increasingly central. By offering tools that can effectively manage data, anticipate market trends, and innovate in risk management, machine learning ensures that sustainable investing is not just an ethical choice, but a smart financial one as well.

6. Discussions

Improving Data Granularity:
Incorporating daily data into financial models brings forth several advantages. Engle (2000) points out that having a granular view of market dynamics by capturing daily fluctuations and volatilities can uncover insights often masked in monthly or quarterly datasets. Such detailed perspectives are instrumental in identifying short-term trading opportunities and anomalies. Additionally, Bailey et al. (2014) highlights that daily data allows for a more frequent recalibration of machine learning models. This enhances their adaptability to swiftly changing market conditions. Moreover, a larger dataset, in terms of data points, can lead to better generalization, reducing the risk of overfitting, a persistent concern in financial modelling. However, limited data granularity, such as monthly or quarterly data, can also present challenges. Cutler et al. (1989) argue that it can restrict the model's ability to capture rapid market shifts, making it less responsive to sudden economic events or breaking news. Furthermore, coarse-grained data might lead to loss of information, potentially missing out on intricate patterns or correlations that might be more evident at a daily level.

Incorporating Macroeconomic Indicators:
Stock returns are intricately linked with broader economic factors. [24] elucidates that factors like interest rates, inflation, and GDP growth play pivotal roles in determining stock prices. For instance, a surge in interest rates can elevate borrowing costs for companies, potentially denting their profitability and stock prices. Similarly, GDP changes can mirror the overall health of an economy and its potential ramifications on corporate earnings. Several macroeconomic indicators can be integrated into financial modelling. These range from GDP growth rates and inflation to unemployment rates and the consumer price index. [20] further emphasize the importance of global indicators such as commodity prices in understanding the interconnected nature of today's financial markets.

Expanding the Model Universe:
Despite the research's focus on Lasso regression and Random Forest, the machine learning landscape is expansive. [30] suggests that algorithms like Support Vector Machines, Neural Networks, and Gradient Boosting Machines offer unique strengths. Each could be explored further for potential enhancements in predictive capabilities. For example, Neural Networks might adeptly capture complex non-linear relationships, while Gradient Boosting Machines can strike a balance between bias and variance. Thus, diversifying the model universe might lead to enhanced predictive accuracy and more robust models.

Technical Improvements:
Technical advancements always offer avenues for refinement in financial modelling. Zhang & Ma (2012) propose ensemble modelling as a promising technique, where predictions from various models are amalgamated to yield more stable and precise forecasts. Furthermore, the evolution of

optimization algorithms can amplify the efficiency of hyperparameter tuning. With the rapid growth in computational power and the rise of cloud computing, leveraging parallel processing and distributed systems can drastically diminish model training times, paving the way for more intricate model architectures.

Broader Trends and Implications:
Modern finance is undergoing transformative changes, driven by technological advancements and a paradigm shift towards sustainable investments. While traditional financial models primarily focused on quantitative metrics, the emergence of ESG scores underscores a more comprehensive approach to assessing companies' value. This research, focusing on FTSE companies with ESG scores, aligns with this global trend, emphasizing the need to integrate sustainability with profitability.

How This Research Fits into the Larger Narrative:
The integration of machine learning in financial portfolio optimization, as explored in this research, is a testament to the ongoing convergence of technology and finance. Our methodology, which leverages the power of algorithms like LASSO regression, resonates with the broader narrative of algorithmic trading and robo-advisors. It underscores the potential to harness computational techniques to derive actionable financial insights, marking a significant departure from traditional methods.

Long-term Investment Implications:
While our research primarily focused on a one-year forecast, long-term investment strategies necessitate a broader perspective. Merton (1972) highlighted the importance of considering factors like risk tolerance, investment horizon, and future cash flow needs. For extended portfolio optimization, it's crucial to adjust weightings periodically and account for systemic risks, ensuring that investments align with long-term financial objectives.

External Factors:
The financial market's volatile nature, influenced by unforeseen events like pandemics or geopolitical tensions, underscores the need for adaptable models. Recent events, such as the COVID-19 pandemic, have demonstrated how external disruptions can lead to significant market downturns. Such events necessitate model adjustments to factor in these anomalies and provide risk-mitigated, optimized returns.

Future Research Avenues:
While this research has delved into machine learning's potential in portfolio optimization, future explorations can consider cutting-edge models like neural networks and deep learning. These models, known for capturing complex patterns, could further refine predictions. Moreover, the integration of alternative data sources, such as sentiment analysis from news articles or social media, could provide a more holistic view of market dynamics.

Ethical Considerations:
This research journey has been enlightening, underscoring the importance of ethical considerations in finance. The emphasis on ESG scores reiterates the need to balance profitability with sustainability, ensuring that financial endeavours contribute positively to society. Moreover, the

transparency in model selection and methodology reflects the commitment to ethical research practices.

Personal Growth and Future Aspirations in the Field of Finance:
Engaging in this research has been a transformative experience, fostering a deeper understanding of the intricate interplay between finance, technology, and sustainability. It has ignited a passion to further explore the realm of algorithmic finance and contribute to building more transparent, sustainable, and optimized financial models.

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