A Blackjack-Inspired Approach to Portfolio Optimization

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Abstract

This project explores a novel portfolio optimization model that uses a simple scoring system inspired by the card game blackjack. Just as card counters keep a running score to make betting decisions, this model aims to assign scores to stocks to adjust how much capital is allocated to each stock in the portfolio. While this project will focus only on stocks, the idea can be applied to various financial instruments.

1 Introduction

Investment strategies have evolved significantly over the decades. What started as simple buy-and-hold approaches has become an arms race to develop more sophisticated models that seek to optimize returns relative to risk of a volatile financial market. This project proposes a novel approach to capital allocation through the development of an integer score-based model, inspired by blackjack card counting. By assigning each stock in the portfolio with a score based on various financial and technical indicators, this model aims to dynamically adjust portfolio compositions in response to changing market conditions and potentially able to maximise risk-adjusted returns. Such a method is intuitive to a blackjack card counter while also being grounded in the context of the financial market.

The inspiration from blackjack strategies, specifically Hi-Lo [15] card counting, comes from an analogy for financial decision-making. Just as the card counter adjusts their bets based on a running score, an investor will adjust their bets (capital allocation) based on a variety of factors in the market. An integer score for these market factors draws an even closer parallel between the live markets and the blackjack analogy.

For example, in the game of blackjack, if the dealer is showing a 10 and the player has a hand of King and 3, the score is $-1 - 1 + 1 = -1$ meaning the player should place a lower bet next time because there are less high cards in the deck, meaning a lower probability of winning. If a stock has a score of -1 then the investor would "lower their bet", probably to 0 so they can invest in stocks with higher scores.

The primary objectives of this project are twofold. First, to develop the score-based model for real-time dynamic portfolio management. Second, to evaluate and compare it's effectiveness against both live and simulated market conditions. This project is structured to first lay the theoretical foundation for the score-based model, followed by a detailed description of the methodological approach, including data collection, model development, and testing scenarios. Finally, the project will conclude with a comprehensive analysis of the model's performance compared to traditional methods of portfolio optimization.

2 Background and Literature Review

Portfolio optimization has been a core aspect of financial theory for decades, evolving significantly since the early 20th century. With the development of computers came the advent of quantitative methods which has shifted the focus from qualitative assessments to mathematical models that aim to systematically enhance the risk-adjusted returns of investment portfolios. Risk-adjusted returns means an investor would prefer an asset with moderate returns and low volatility over an asset with high returns and high volatility. This way, the investor chooses stocks with an upside potential that's worth the possibility of a loss.

Developed by Harry Markowitz in 1952 and later awarded a Nobel Prize, Modern Portfolio Theory [4] introduced the concept of the 'efficient frontier', a graphical representation of asset combinations that investors can choose the optimal portfolio to maximize returns for a given level of risk. This theory has been used in shaping risk management strategies in investment portfolios by demonstrating the importance for diversification to reduce risk.

Despite its widespread adoption, MPT has some fundamental issues for example its heavy reliance on historical data, which may not always be a reliable predictor of future performance. Another problem comes from the assumption of market efficiency and normal distribution of returns, foundational to MPT, which often does not hold in the live market conditions. This has led to the exploration of alternative models that incorporate more adaptive and forward-looking measures.

An example of an alternative to MPT is the The Black-Litterman model [14]. BL integrates investors' subjective views with the equilibrium market returns to generate more personalized and potentially more accurate portfolio allocations, for example "Stock A will outperform stock B by 10%". This model reflects a shift towards incorporating investor subjective intuition and expectations, allowing for more control from the investor. However, the issue with this model is the subjective views are not explicitly defined and there's no specific guidelines so one investors model will be different to another investors model resulting in different outputs.

Recent advancements have also explored the integration of machine learning techniques such as reinforcement learning and deep neutral networks into portfolio optimizations[6]. These advanced techniques allow models to develop dynamic trading strategies that can adapt to new market information. These approaches offer an edge as they are capable of incorporating hidden and abstract patterns hidden in the data that a human made model won't capture.

Furthermore, the rapid rise of big data analytics means modern day models will be processing vast amounts of unstructured data for automatically analysing market sentiment, which can then be used in the decision-making process. By analyzing publicly posted news articles, social media trends and financial reports, investors can get a comprehensive view of market dynamics outside the quantitative market data [1].

Building on these ideas, this project introduces a novel, blackjack-inspired scoring system for portfolio optimization. By dynamically assigning scores to stocks, e.g. once a quarter, based on a variety of financial and technical indicators, the model seeks to overcome some of MPT's limitations by adapting to real-time market changes.

3 Methodology

3.1 Overview

This project is designed to develop and evaluate a novel portfolio optimization model that incorporates a blackjack-inspired integer scoring system. This approach aims to address the limitations of traditional portfolio management strategies, such as those described in Modern Portfolio Theory (MPT), by introducing a dynamic and adaptive scoring mechanism that reacts to real-time market changes without relying only on the historical performance.

The methodological framework consists of several components: data collection from recognized financial databases such as Yahoo and Bloomberg, development of a scoring model based on selected financial and technical indicators, application of this scoring to a portfolio optimization model, and rigorous testing through real-time performance and simulations. This comprehensive approach ensures that the portfolio's performance can be evaluated under various market conditions, providing a robust test of the model's effectiveness.

The choice of a blackjack-inspired scoring system is justified by its potential to integrate quantitative data with strategic decision-making processes, akin to how blackjack players adjust their bets based on the changing odds of the game. This analogy supports the development of a model that not only relies on statistical and financial indicators but also incorporates elements of adaptive strategy.

By implementing and testing this model, I expect to demonstrate its capability to outperform traditional models in terms of risk-adjusted returns, especially in markets characterized by high volatility and unpredictability. The findings are anticipated to contribute valuable insights into the practical applications of combining financial analysis with strategic gaming theories, potentially offering a new toolkit for investors and financial analysts.

3.2 Scoring System Development

The core of the methodology is the scoring system, which evaluates assets within the portfolio based on a combination of financial performance indicators, industry comparisons, intrinsic value assessments, and market sentiment analyses. This multifaceted scoring mechanism is intended to provide a robust basis for investment decisions. The final score will consist of the following factors.

3.2.1 Financial Performance Ratios

Traditional investor's decision making will be influenced by these key financial ratios that are critical to assessing the financial health and potential of a company:

- **Price to Earnings (P/E)**: A lower P/E ratio is preferred, indicating that the stock is potentially undervalued compared to its earnings. [13]
- **Return on Equity (ROE)**: A higher ROE suggests that the company is efficiently generating profits from its equity. [5]
- **Debt to Equity (D/E)**: A lower D/E ratio is favored as it indicates that the company is not excessively reliant on debt to finance its operations. [12]

These three performance metrics will be combined into just a single "Ratio Score" to reduce model complexity.

3.2.2 Relative Industry Performance

The performance of assets within the same industry is compared by examining the mean log returns. For example a positive score if an individual tech stock has abnormally high returns compared to other tech stocks.

3.2.3 Discounted Cash Flow (DCF) Value

The DCF model [8] is employed to estimate the intrinsic value of assets based on the discounted sum of future dividends. Stocks with market prices below their DCF value are considered undervalued and thus scored higher. Conversely, overvalued stocks receive lower scores. Stocks that do not pay dividends are assigned a neutral score as DCF modelling doesn't apply to these stocks. This could cause issues as the model may overlook high potential growth stocks that don't pay dividends.

3.2.4 Analyst Sentiment

Professional analysts publicly post their sentiment for individual stocks they have looked at. Their ratings are in the form: "strong buy","buy","hold","sell","strong sell". A positive score is assigned for "strong buy" and "buy", a zero score for "hold" and a negative score for "sell" and "strong sell".

3.2.5 Technical Performance

Originally planned to be the objective function, the Performance of a stock is a combination of the Sharpe and Sortino ratios that measure risk-adjusted returns. However, in the final version, the objective function was simplified and Performance became a score factor.

3.3 Data Collection

Data required for calculating the scores and testing the model are sourced from two main platforms:

3.3.1 Bloomberg

DCF values are extracted from Bloomberg XLTP function. The DCF Excel template gives two calculations for the stocks current DCF.

3.3.2 Yahoo Finance

Other than DCF, the rest of the data comes from Yahoo Finance, accessed automatically by the python library yfinance [16].

3.4 Portfolio Optimization Model

3.4.1 The original model

In the preliminary report the model's objective was to maximise a weighted sum of performance ratios scaled by the stocks weight called Performance.

$$\text{Sharpe ratio}_i = \frac{\mu_i - R_f}{\sigma_i} \tag{1}$$

μ_i is the expected return of the stock, σ_i is the standard deviation of these returns and R_f is the risk free rate, often given by the yield of Gilts.

The Sortino ratio is similar to Sharpe but with they key difference that it considers risk as the standard deviation of downside return rather than of returns. This way the Sortino ratio is particularly useful for investors who are more risk averse.

$$\text{Sortino Ratio}_i = \frac{\mu_i - R_f}{\sigma_{d,i}} \tag{2}$$

where $\sigma_{d,i}$ is the downside deviation of stock i.

A combination of these ratios would allow for investors to prioritise excess returns or minimised downside by choosing some $0 \leq k \leq 1$.

$$\text{Performance}_i = k \cdot w_i \cdot f(s_i) \cdot \text{Sharpe}_i + (1-k) \cdot w_i \cdot f(s_i) \cdot \text{Sortino}_i \tag{3}$$

Where $f(s_i)$ is a function of the integer score for a stock with weight w_i. However after implementation, I found that the integer scores had little affect on the optimal weights compared to the performance ratios themselves. To fix this, the new objective is to maximise score and Performance was added to the list of factors.

3.4.2 Linear Optimization Model

The initial phase of the portfolio optimization utilizes a linear model, where the objective function aims to maximize the total score calculated from the scoring system. This model serves as a foundation for understanding basic asset allocation without complex risk considerations.

The objective function is expressed as:

$$\min_{\mathbf{w}} \quad -\mathbf{w}^T \mathbf{s}$$

where s_i represents the score of the i-th asset, and w_i is the capital allocation weight of the i-th asset in the portfolio. In the financial context, the investor want to maximise the sum of chosen asset scores, but standard notation is written as a minimization problem. This model fits with the blackjack analoge as a card counter will place a higher bet on games with higher scores so stocks with higher scores should be given a higher weight.

This is a simple problem that can be solved using the simplex method. [9]

3.4.3 Quadratic Optimization Model

To accommodate risk considerations through diversification, the portfolio optimization is extended to a quadratic model. This model explicitly incorporates the covariance matrix $\mathbf{Q}$ of the stock returns, which enables the minimization of correlated risks across the portfolio. The objective function is formulated as:

$$\min_{\mathbf{w}} \quad \mathbf{w}^T\mathbf{Q}\mathbf{w} - \mathbf{w}^T\mathbf{s}$$

where $\mathbf{Q}$ represents the covariance matrix and $\mathbf{s}$ is the vector of normalized scores for each asset. By minimizing $\mathbf{w}^T\mathbf{Q}\mathbf{w}$, the model aims to reduce overall portfolio risk by limiting exposure to highly correlated assets, thereby enhancing the robustness of the investment strategy against market volatility's and systematic risk. The quadratic problem is solved using the interior-point method.

3.4.4 Constraints

The optimization models are subject to several constraints to ensure practicality and compliance with typical portfolio management standards:

- Full investment constraint: $\sum_{i=1}^{n} w_i = 1$, ensuring all available capital is deployed.
- No short selling: $w_i \geq 0$ for all i, prohibiting the assumption of negative positions.
- Maximum allocation per asset: $w_i \leq M$ for all i, to prevent over-concentration in any single asset and promote diversification. Default value is $M = \frac{1}{4}$.

These constraints are critical for maintaining a balanced and regulatory-compliant portfolio structure.

4 Implementation

4.1 Data Preparation

For this project, data was sourced from reputable financial platforms Bloomberg and Yahoo Finance, ensuring a broad and reliable data set. Python scripts automated data retrieval and preprocessing, allowing an any investor to reproduce these results from just a list of tickers.

Logarithmic returns were calculated to normalize price data and better capture relative changes over time, which are crucial for accurate trend analysis and forecasting. The formula used is:

$$r_t = \log(\frac{P_t}{P_{t-1}})$$

where r_t is the log return at time t, P_t is the price at time t, and P_{t-1} is the price at time $t-1$. Logarithmic returns are particularly useful in financial modeling as they are time additive – a property important for the analysis of portfolios over time and across different assets.

4.2 Model Execution

The portfolio optimization models were implemented using Python. The models' construction and solving were facilitated by widely-used libraries tailored for optimization problems:

- Cvxopt: The cvxopt library, known for handling convex optimization problems, was utilized to address the linear and quadratic portfolio optimization model, which included handling the covariance matrix of returns. [2]
- Pyportfolioopt: The pyportfolioopt library a simple framework for solving classical mean-variance optimization techniques including MPT. [10]

4.3 Simulated Testing

To validate the effectiveness of the model under varying market conditions, simulated testing was conducted under the assumptions of Geometric Brownian Motion [7]:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dW \tag{4}$$

$$S_t = S_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma W_t} \tag{5}$$

Modelling each stock as GBM allows for the simulation of stock price paths under assumed market dynamics such as returns being log normally distributed. This is better than simply looking at true market performance as it enables the assessment of portfolio performance across a continuum of market possibilities, providing analysis of potential outcomes rather than relying solely on past performance.

4.4 Challenges

Implementing the proposed models presented several challenges that required strategic decisions and adaptations:

4.4.1 Data Availability and Completeness

Despite initial plans to analyze all 100 stocks in the FTSE100, complete and reliable data were only available for 69 stocks. This limitation was primarily due to the absence of consistent historical data and sufficient analyst coverage so a decision was made to exclude stocks with incomplete data sets to prevent potential biases and inaccuracies in model outcomes.

4.4.2 Encouraging Diversification

One of the key objectives was to ensure diversified portfolio allocations to minimize risk. An intuitive solution is to force a maximum weight $M = 0.25$ for example to require a minimum of 4 stocks in the portfolio. Without this constraint, the linear model would allocate all capital to a single stock and the quadratic model would allocate all capital to only two stocks, which goes against the key principle of diversification.

5 Results and Discussion

5.1 Overview

This section presents the empirical results from the application of a novel portfolio optimization model inspired by a blackjack integer scoring system. The primary goal of this analysis is to test the effectiveness of the scoring system in predicting stock returns. The results will be compared the traditional MPT strategy.

5.2 True Results

Since all the data was collected ending Q4 2023, the portfolios can be tested in the live markets by comparing their performance by the end of Q1 2024.

5.2.1 Linear Model

Table 1 shows 4 equally distributed stocks as a result of the $M = \frac{1}{4}$ constraint. The best performing stock chosen by the linear model is "EZJ.L" with the highest Total Return of 12.0% in Q1 2024.

Table 1: Summary of Linear Model Returns

Ticker	Total Return	Mean Daily Return	Std. Daily Return	Weight
AAL.L	0.011808	0.000187	0.021775	0.25
CNA.L	-0.096982	-0.001539	0.017775	0.25
EZJ.L	0.120749	0.001917	0.017483	0.25
TW.L	-0.035677	-0.000566	0.015824	0.25

5.2.2 Quadratic Model

Table 2: Summary of Quadratic Model Returns

Ticker	Total Return	Mean Daily Return	Std. Daily Return	Weight
AZN.L	0.022895	0.000363	0.014916	0.050078
CNA.L	-0.096982	-0.001539	0.017775	0.250000
EZJ.L	0.120749	0.001917	0.017483	0.250000
NG.L	0.007533	0.000120	0.009099	0.082285
REL.L	0.096187	0.001527	0.009582	0.116103
TW.L	-0.035677	-0.000566	0.015824	0.250000

Table 2 provides a summary of true returns and portfolio weights chosen by the quadratic optimization model that considers the covariance of stocks in the portfolio as well as the scores. While some stocks like "CNA.L" and "EZJ.L" has the same allocation as the linear model, the quadratic model also introduces some new stocks meaning 6 stocks were selected despite the $M = \frac{1}{4}$ constraint. For example, REL.L has a Total Return of 9.62% in Q1 2024 with a capital allocation weight of 11.6% in the quadratic model but this stock isn't chosen in the linear model.

5.2.3 MPT

Table 3: Summary of MPT Model Returns

Ticker	Total Return	Mean Daily Return	Std. Daily Return	Weight
BA.L	0.194924	0.003094	0.009322	0.10480
CNA.L	-0.096982	-0.001539	0.017775	0.17211
LSEG.L	0.023024	0.000365	0.007335	0.19775
MKS.L	-0.027164	-0.000431	0.017034	0.27745
REL.L	0.096187	0.001527	0.009582	0.04156
SGE.L	0.087396	0.001387	0.010731	0.18349
TW.L	-0.035677	-0.000566	0.015824	0.02284

The MPT portfolio is the traditional method of portfolio allocation and has a much more varied distribution of weights. Since diversification is a key aspect of modern portfolio theory, it's not a surprise that it chose the most stocks compared to the other models.

5.3 Simulated Results

Each of the three portfolios ran 10,000 simulations to analyse the stochastic nature of portfolio value. By simulating the random paths of each stock in the portfolio, then performing a weighted sum of the returns of these price paths, the continuum of possible portfolio values

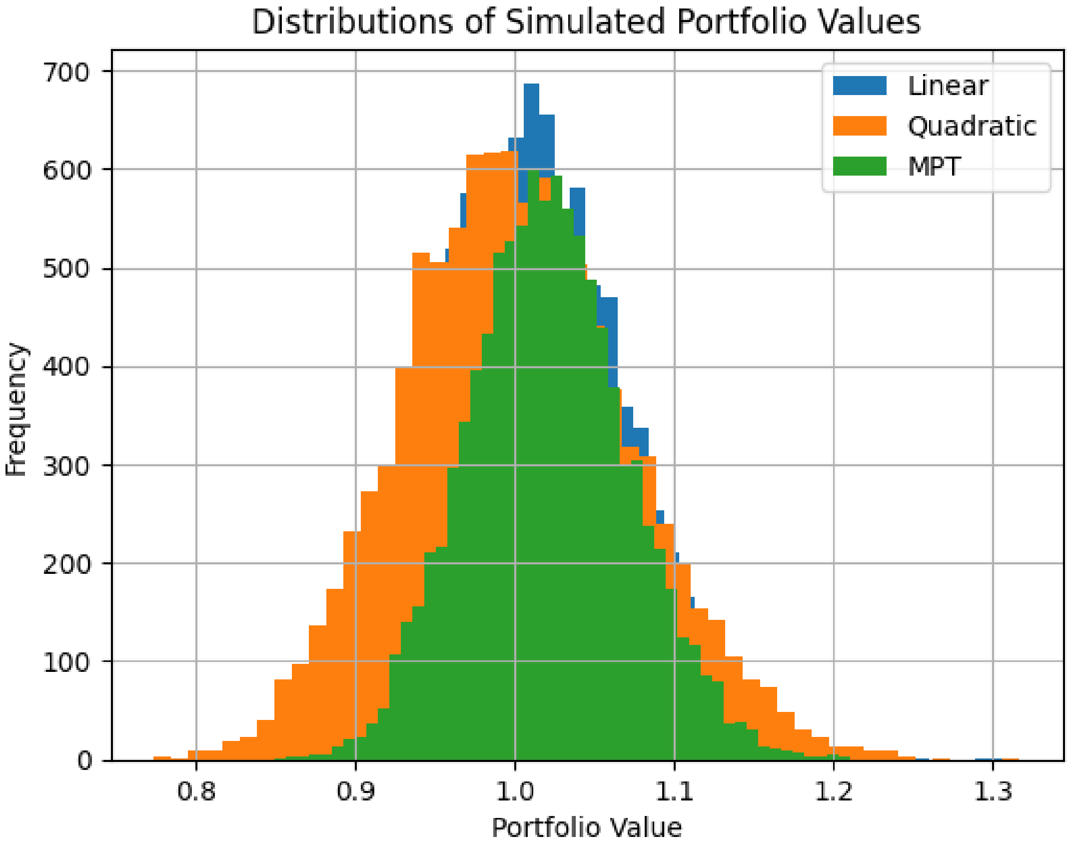

Figure 1: Comparing the distribution of portfolio values at the end of Q1.

can be discussed rather than just the state of the market in the real world. Analysing the true performance of a portfolio without looking at the distribution of possible values would be like analysing the behaviour of an electron by measuring it's state but without considering it's wave function.

Due to the GBM assumption that log returns are normally distributed, these portfolio value pdfs have a normal looking shape but are not identical.

Figure 1 shows the distribution of portfolio values for the three models. A negative skew with low spread is desired as that would suggest a high mean value with small volatility. Table 4 shows the best performing strategy is the traditional MPT as over all the simulations it has the highest mean and lowest standard deviation. It also appears that the Linear model beats the Quadratic model which was unexpected.

Table 4: Portfolio Value Distribution Statistics

Strategy	Mean Portfolio Value	Std. Dev. of Portfolio Value
Linear	1.009	0.060
Quadratic	1.001	0.072
MPT	1.020	0.051

5.4 Testing scores

The performance of the blackjack-inspired scoring system relies on its ability to capture the complexity of the market through assigned scores. An investor would hope to chose scores where there is a high correlation between scores and stock returns.

5.4.1 Statistical Correlation

Calculating the Pearson correlation coefficient is a simple way to quantify the linear relationship between stock scores and their returns [11]. The heat map in Figure 2 shows the correlation of each score with asset returns, alongside their respective p-values to test the significance of the correlation. These results suggest the chosen scores in this project might not be capturing the forces behind the market dynamics as they're all weakly correlated with a low statistical significance. The lack of statistical correlation between the integer score factors and market returns explains why this model was unable to beat the market. Incorporating additional factors that are significantly correlated with increasing returns would likely allow a blackjack-inspired portfolio optimization model to beat market returns.

5.5 Discussion

This project introduced a novel portfolio optimization model that integrated blackjack-inspired scoring system with the primary goal of investigating whether such a scoring system could improve an investors chances at beating the market, especially in terms of risk-adjusted returns. However, the results from both the live and simulated testing suggests that the model, while innovative, did not significantly outperform traditional Modern Portfolio Theory.

5.5.1 Interpretation of Results

The empirical evidence indicates that the traditional MPT model provided higher mean portfolio values with lower risk, measured by standard deviation of portfolio value, compared to both the linear and quadratic models based on the blackjack scoring system. MPT is deeply rooted in the principle of diversification and is specifically designed to minimize unsystematic risk which is why it offers as a good benchmark.

The blackjack-inspired models did not show an advantage over the traditional model. One possible explanation could be the insufficient predictive power of the factors used in the scoring system shown by the statistical analysis of the correlation between counted scores and live returns. It's likely the performance of the model would improve if better score factors are chosen with statistically significant correlation with returns.

These results held for all tested values of the diversification constraint $0 \leq M \leq 1$. Ideally, a model will be able to diversify

5.5.2 Challenges

This project had several challenges along the way. First, the model only used three simple factors that may have been too simplistic. Also, the integer-based scoring may not capture the continuous nature of market data and investor sentiment effectively. It may be beneficial to investigate scaling the influence of each factor so that some scores are more valuable than others. Additionally, dropping the 31 stocks with missing data likely had an affect on the outcome as it's possible the true optimal portfolio contains some of these missing stocks.

5.6 Future Research and Conclusion

Furute research should focus on refining the feature selection of the scoring system. This could involve integrating more sophisticated and diverse data analytics, using machine learning to identify more abstract predictive factors or even incorporate forward looking options-implied market data to reduce the dependence on historical data [3]. Additionally, exploring different

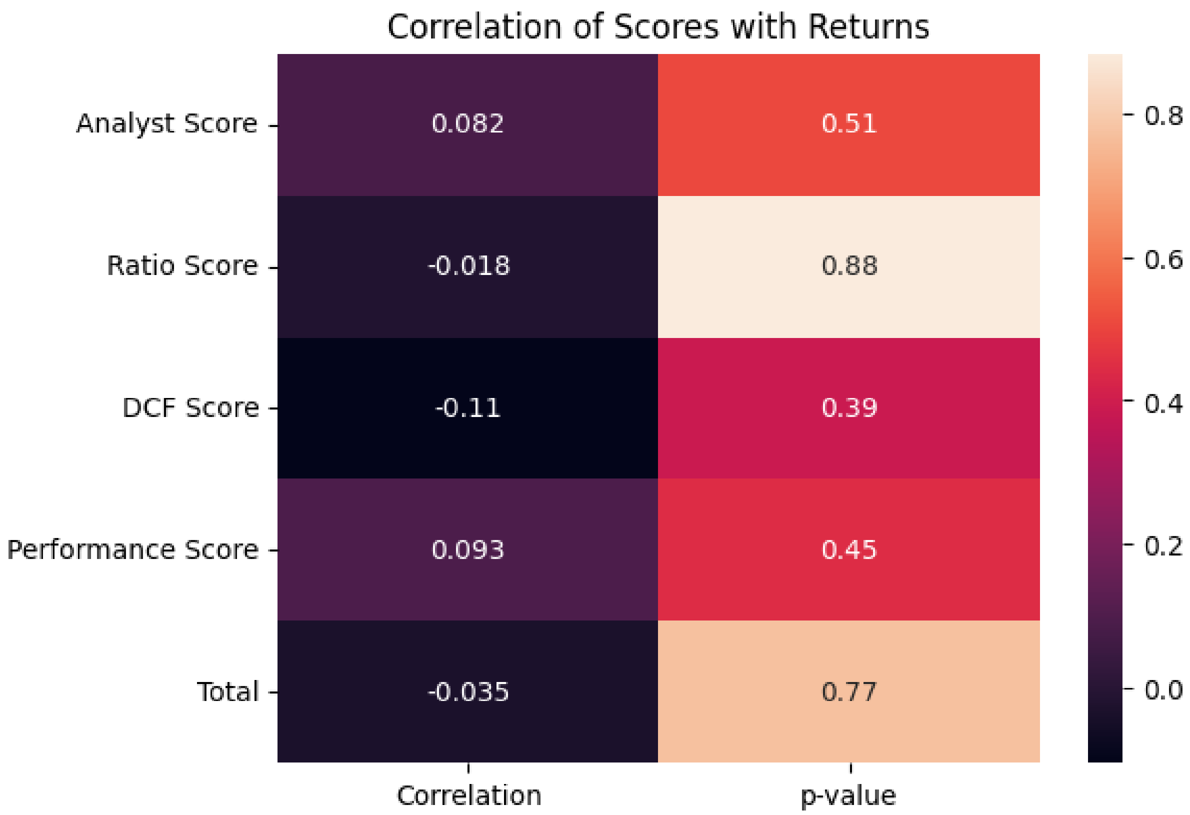

Figure 2: A low correlation and high p-value for every score shows the model can't significantly predict future returns

scoring algorithms for assigning scores to each stocks that are able to adapt to changing market conditions may be able to enhance the model's responsiveness and predictive accuracy.

While the blackjack-inspired scoring system presents an innovative approach to portfolio optimization, this project ultimately demonstrates the challenges of beating the existing MPT model.

References

[1] Johan Bollen, Huina Mao, and Xiaojun Zeng. "Twitter mood predicts the stock market". In: *Journal of computational science* (2011).

[2] *CVXOPT: Python Software for Convex Optimization.* `https://cvxopt.org`.

[3] Victor DeMiguel et al. "Improving portfolio selection using option-implied volatility and skewness". In: *Journal of Financial and Quantitative Analysis* 48.6 (2013), pp. 1813–1845.

[4] Edwin J Elton et al. *Modern Portfolio Theory and Investment Analysis.* 9th ed. Wiley, 2014. ISBN: 978-1118469941.

[5] Mohd Heikal, Muammar Khaddafi, and Ainatul Ummah. "Influence analysis of return on assets (ROA), return on equity (ROE), net profit margin (NPM), debt to equity ratio (DER), and current ratio (CR), against corporate profit growth in automotive in Indonesia Stock Exchange". In: *International Journal of Academic Research in Business and Social Sciences* 4.12 (2014), p. 101.

[6] Jian Huang, Junyi Chai, and Stella Cho. "Deep learning in finance and banking: A literature review and classification". In: *Frontiers of Business Research in China* (2020).

[7] John C Hull and Sankarshan Basu. *Options, futures, and other derivatives.* Pearson Education India, 2016.

[8] Lutz Kruschwitz and Andreas Löffler. *Discounted cash flow: a theory of the valuation of firms.* John Wiley & Sons, 2006.

[9] John A Nelder and Roger Mead. "A simplex method for function minimization". In: *The computer journal* (1965).

[10] *pyportfolioopt: Python Software for MPT Optimization.* `https://cvxopt.org`.

[11] Philip Sedgwick. "Pearson's correlation coefficient". In: *Bmj* 345 (2012).

[12] Widya Shabrina and Niki Hadian. "The influence of current ratio, debt to equity ratio, and return on assets on dividend payout ratio". In: *International Journal of Financial, Accounting, and Management* 3.3 (2021), pp. 193–204.

[13] Peter Shen. "The P/E ratio and stock market performance". In: *Economic review-Federal reserve bank of Kansas city* 85.4 (2000), pp. 23–36.

[14] CFA Walters et al. "The Black-Litterman model in detail". In: *Available at SSRN 1314585* (2014).

[15] Wizard of Odds. *Introduction to the High-Low Card Counting Strategy.* `https://wizardofodds.com/games/blackjack/card-counting/high-low/`. 2023.

[16] *yfinance: Yahoo Finance Market Data Downloader.* `https://pypi.org/project/yfinance/`.