Portfolio Optimization Using Financial Models and Machine Learning

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Introduction

Portfolio optimization stands as a cornerstone in investment management, with the overarching goal of maximizing returns while mitigating risks. Nevertheless, the landscape of financial markets is constantly evolving, rendering traditional optimization methods inadequate in responding to dynamic shifts. This project seeks to bridge this gap by harnessing the power of advanced financial models and machine learning techniques, offering investors adaptive strategies tailored to navigate the complexities of modern financial environments effectively.

In the initial phase of our project, we embarked on integrating established financial models such as Markowitz and Black-Litterman with cutting-edge machine learning methodologies to achieve optimal portfolio allocation. Through meticulous analysis, we identified several areas ripe for improvement: Inefficiency in existing portfolio optimization strategies, suboptimal investment outcomes attributable to traditional methods, and challenges in accommodating the diverse risk preferences of investors. These findings underscore the pressing need for innovative solutions that can not only address these shortcomings but also pave the way for more robust and adaptable portfolio management practices.

Dataset

The foundation of our analysis rests upon historical financial data procured from Yahoo Finance, capturing a diverse array of assets including renowned stocks like AAPL, MSFT, and AMZN. This dataset spans at least a year timeframe based on user input and encompasses adjusted close prices, forming the bedrock for computing log returns crucial in assessing asset performance over time. Additionally, integration of risk-free rates from the Federal Reserve Economic Data (FRED) API enhances the analytical depth by incorporating the time value of money, ensuring a comprehensive approach to portfolio optimization.

Methods

Low-Risk Goal

We prioritized the development of a user-friendly interface to streamline portfolio management. This interface seamlessly integrated the Markowitz model, Black-Litterman model, and the Prophet model, catering to investors seeking lower-risk investment strategies. Leveraging the Markowitz model's mean-variance optimization principles, employing the Sequential Least Squares Quadratic Programming (SLSQP) method, the interface provided personalized portfolio suggestions by considering historical returns, volatility, and covariance matrices of assets. Investors could effortlessly interact with this model through the interface, receiving tailored recommendations aligned with their risk preferences.

Complementing the Markowitz model, the interface also incorporated the Black-Litterman model, enhancing portfolio optimization with qualitative investor sentiment analysis. By blending quantitative market data with subjective investor views, the model adjusted portfolio allocations to reflect updated beliefs on asset returns and correlations. Additionally, the Prophet model's time series forecasting capabilities were integrated, offering insights into future asset price movements. Together, these models within the user-friendly interface empowered investors to make informed decisions, navigate financial markets with confidence, and construct portfolios optimized for lower risk profiles.

Medium-Risk Goal

In addressing our medium-risk objective, our focal point was to refine the performance of the Black-Litterman model, a pivotal component in portfolio optimization. One of the primary issues identified during Phase 1 was the need to enhance the model's return generation capability. To achieve this, we embarked on a series of refinements and enhancements aimed at augmenting the overall effectiveness of the Black-Litterman model, particularly in generating more favorable returns for medium-risk investment strategies. The key strategy employed to enhance the Black-Litterman model's return generation involved a comprehensive review and adjustment of the model's underlying parameters and assumptions. By reassessing and fine-tuning factors such as market data inputs, investor views, and covariance matrices, we aimed to improve the model's ability to accurately reflect market dynamics and investor sentiment. Through iterative testing and refinement, we sought to achieve a more robust and effective Black-Litterman model that could deliver enhanced returns and performance for medium-risk investment portfolios.

$$\mu_{BL} = (\tau\Sigma)^{-1}(\tau\Sigma)^{-1}(\Pi + \Omega\tau)^{-1}\Pi + (\tau\Sigma)^{-1}$$

- μ_{BL}: Expected returns vector based on the Black-Litterman model.
- τ: Scaling factor reflecting the confidence in the equilibrium returns.
- Σ: Covariance matrix of asset returns.
- Π: Equilibrium excess returns vector.
- Ω: Diagonal matrix of the uncertainty in the investor's views.

Figure 1: Black-Litterman model equation

High-Risk Goal

We introduced a sophisticated optimization technique leveraging Reinforcement Learning (RL) principles. Specifically, we employed the Advantage Actor Critic (A2C) model, an innovative approach that utilizes neural networks to estimate the quality of different investment actions. This method combines aspects of both value-based methods (like Q-learning) and policy-based methods (like policy gradients). In actor-critic models, the actor is responsible for selecting actions based on the current policy, while the critic evaluates the actions taken by the actor by estimating the value function.

The iterative training process of RL based methods refines their decision-making capabilities, gradually improving their ability to maximize returns while minimizing risk based on available market information. By continuously learning from past experiences and market feedback, this method converges to optimal portfolio allocations, offering investors a powerful tool for navigating high-risk investment environments. Through the integration of RL techniques, particularly the A2C model, our aim was to provide investors with a sophisticated and adaptive approach to portfolio optimization, capable of capitalizing on market opportunities while mitigating risks associated with high-risk investment strategies.

Results

Low Risk Outcome

The implementation of a user-friendly interface facilitated seamless exploration of stock price history and forecasting capabilities using Prophet. Additionally, portfolio construction utilizing the Markowitz model yielded promising outcomes, with a commendable return of 79.38% and a portfolio volatility of 28% with Sharpe ratio of 2.64. This approach enabled the creation of portfolios characterized by stable returns, effectively mitigating risk exposure for investors targeting low-risk profiles. (see Figure 2)

Medium Risk Outcome

Refinement of the Black-Litterman model resulted in significant performance improvements, achieving a high return of 82% while maintaining a volatility of 23% and a Sharpe ratio of 3.46. These outcomes underscore the effectiveness of the enhanced model in generating favorable returns while effectively managing risk, providing investors with a robust framework for medium-risk portfolio optimization. (see Figure 3, Figure 4)

High Risk Outcome

In this initiative, we aimed to implement an Advantage Actor Critic (A2C) model for learning to trade stocks under dynamic market conditions. We designed and trained an A2C model to predict Buy/Sell/Hold calls in a trading environment. Although the A2C did not perform as well as we expected, likely due to the complexity of training a reinforcement learning model in financial markets and the inherent uncertainties in real-world data, it still allowed us to learn about the domain and get some good insights. The best result the RL system achieved was a 1561% return on initial investment over a period of 10 years. But RL methods often have high variance and when the results were averaged over 10 runs, we got an average return of around 622%. The successful implementation of the A2C model represents a significant advancement in algorithmic trading and investment management, with potential applications in real-world portfolio optimization. (see Figure 5)

Conclusion

In conclusion, the integration of the Streamlit interface has provided investors with a user-friendly platform for exploring stock price histories and forecasting capabilities, as well as constructing personalized portfolios. Through this interface, investors can seamlessly navigate portfolio management complexities and make informed decisions aligned with their risk preferences and financial goals. Additionally, while the A2C model for aggressive portfolio optimization did not perform as well as our expectations, its implementation represents a significant advancement in algorithmic trading and investment management. Moreover, enhancements to the Black-Litterman model have significantly improved portfolio performance, generating favorable returns while effectively managing risk. By incorporating qualitative investor sentiment and refining portfolio allocations, the enhanced model offers tailored solutions that balance risk and return, providing investors with a robust framework for portfolio optimization in dynamic market environments. The synergy between user-friendly interface design, sophisticated model enhancements, and innovative approaches such as the A2C model empowers investors to construct portfolios optimized for their specific needs, thereby enhancing their ability to achieve financial objectives effectively and navigate market uncertainties with confidence.

References

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Appendix

Figure 2: Optimization using Markowitz model

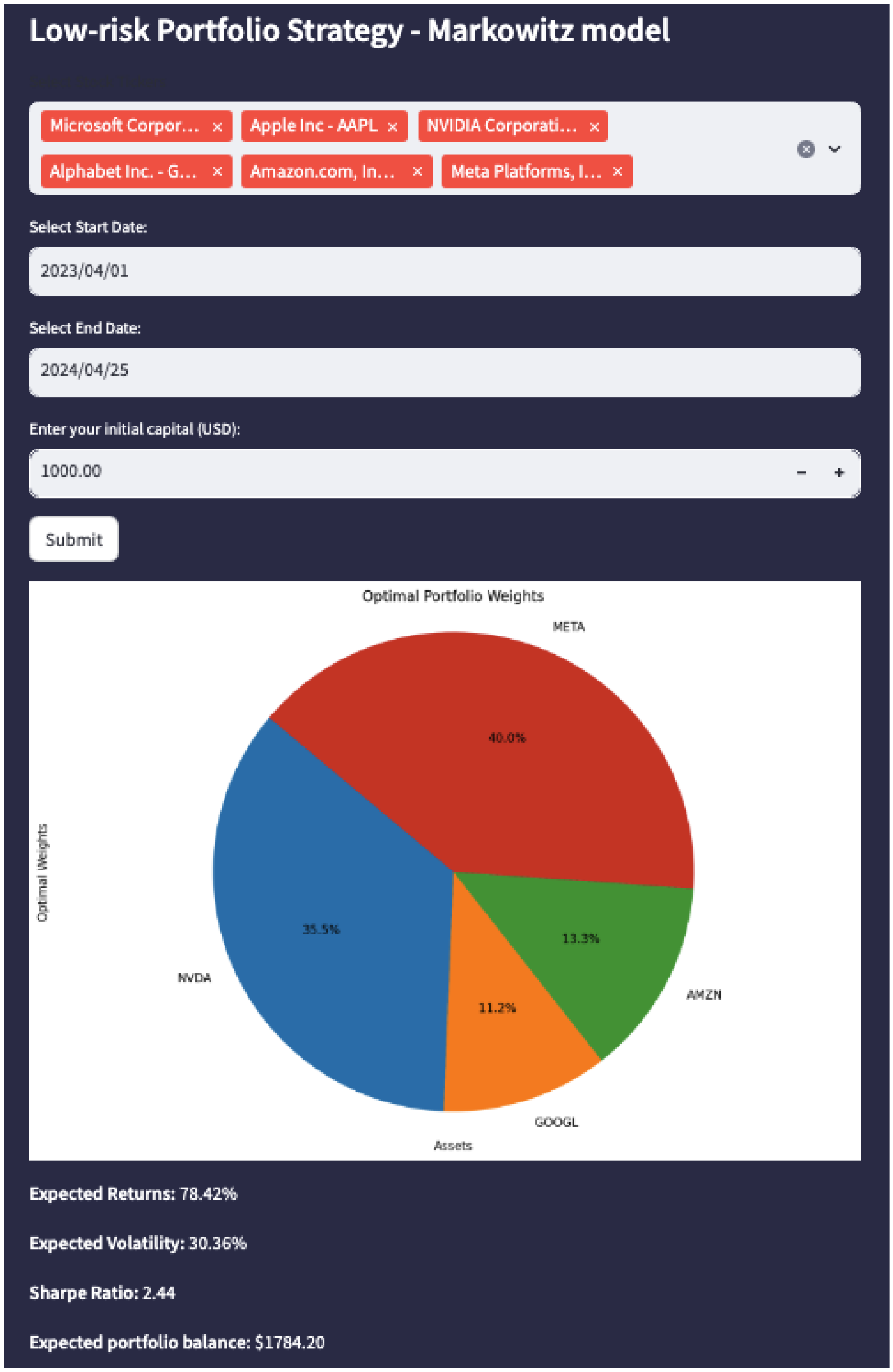

Figure 3: Optimization using Black-Litterman model

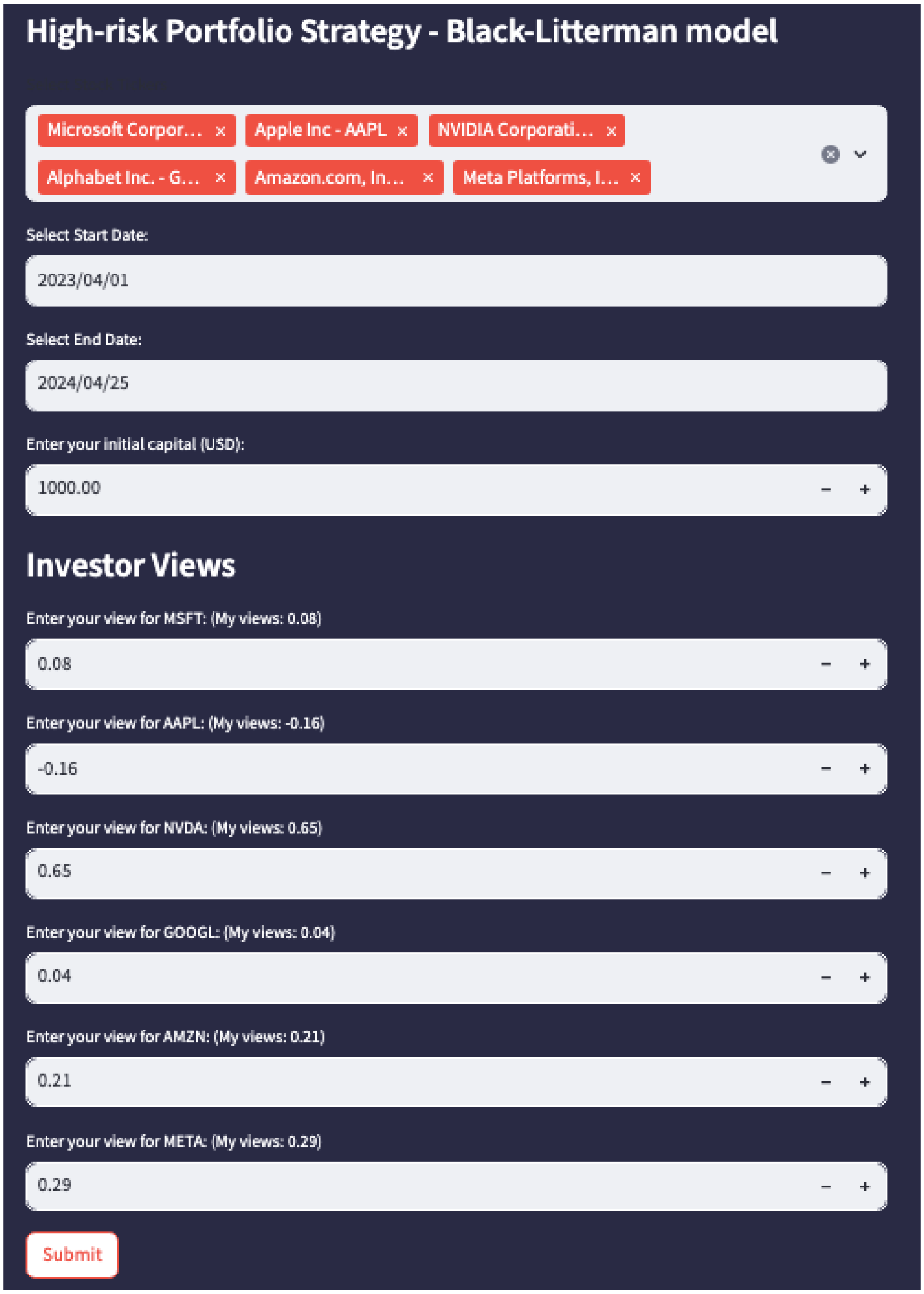

Figure 4: Optimal portfolio weights using Black-Litterman model

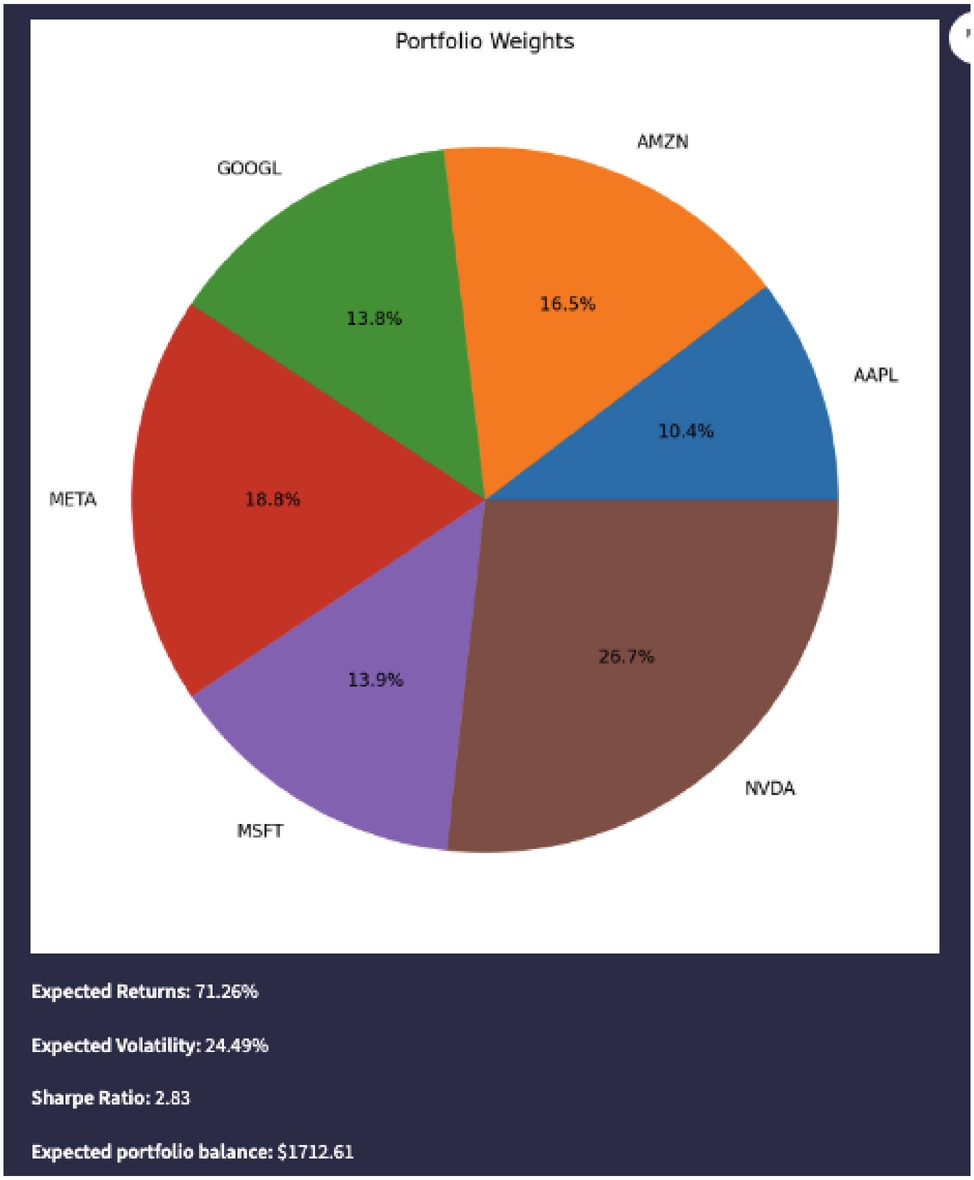

Figure 5: Results of trading the MSFT stock for a duration of 10 years using the A2C model

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Failed goes: 2 / 100, Avg Rewards per successful game: 32616.369140625
Avg % profit per game: 622.7236328125
Avg % profit per finished game: 635.4322509765625
highest profit tensor(1561.0123, device='cuda:0')
highest loss tensor(-100., device='cuda:0')
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