ALPHAPORTFOLIO: DISCOVERY OF PORTFOLIO OPTIMIZATION AND ALLOCATION METHODS USING LLMS

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ABSTRACT

Traditional long-only portfolio allocation strategies, including equal-weighted, risk-parity, and equal-risk contribution approaches; often struggle with rigid assumptions, excessive concentration in low-volatility assets, and sensitivity to changing market conditions. These methods frequently fail to balance risk and return optimally in dynamic financial environments. This paper introduces **AlphaPortfolio**, a novel framework that leverages Large Language Models (LLMs) to iteratively generate, refine, and validate portfolio optimization methods. By integrating inverse covariance risk-adjusted returns, entropy-based diversification, and volatility normalization, AlphaPortfolio significantly outperforms classical allocation techniques in both risk-adjusted performance and drawdown resilience. Our experimental findings, cross-validated across 15 years of historical financial data from 3,246 US stocks and ETFs, demonstrate that AlphaPortfolio achieves a **71.04%** increase in the Sharpe Ratio, a **73.54%** improvement in the Sortino Ratio, and a **116.31%** boost in the Calmar Ratio. Additionally, AlphaPortfolio reduces maximum drawdowns by **53.77%**, ensuring greater stability in turbulent market conditions. These results highlight the transformative potential of LLM-driven discovery in redefining portfolio optimization methodologies, providing institutional investors and portfolio managers with more resilient allocation strategies.

1 INTRODUCTION

Portfolio construction is a cornerstone of financial decision-making, determining how capital is allocated across assets to optimize returns while mitigating risk. Traditional approaches, such as mean-variance optimization (MVO) proposed by Markowitz (1952), and risk-based strategies such as Risk Parity (Qian, 2005) and Minimum Variance Portfolios (DeMiguel et al., 2009), offer valuable but imperfect solutions. These strategies exhibit several well-documented limitations:

- **Sensitivity to Market Conditions**: Portfolio weights derived from the past can become unreliable when market conditions shift significantly, leading to suboptimal allocations.
- **Over-Reliance on Historical Correlations**: Assumptions that asset correlations remain stable often fail in market stress, reducing diversification effectiveness (Meucci, 2009).
- **Extreme Concentration in Low-Volatility Assets**: Risk-based approaches tend to allocate excessively to low-volatility assets, which may limit return potential.
- **Limited Generalization**: Many classical portfolio strategies follow predefined allocation rules that may not generalize effectively across different asset classes or economic regimes.

To address these challenges, we propose AlphaPortfolio, an innovative LLM-driven portfolio optimization framework that leverages AI-generated heuristics to evolve robust, adaptive allocation strategies. AlphaPortfolio builds on foundational financial principles but introduces LLM-driven evolutionary refinement, allowing for the discovery of novel asset allocation methodologies that balance return optimization with dynamic risk management. This paper presents the first application of LLMs in discovering entirely new portfolio optimization strategies through iterative generation, mutation, and scoring, enhancing traditional approaches' adaptability and interpretability. The discovered AlphaPortfolio achieves superior risk-adjusted performance, reduced downside exposure, and enhanced stability compared to established allocation methods.

KEY FINDINGS

- **Adaptive Optimization**: AlphaPortfolio autonomously discovers novel allocation strategies, addressing the limitations of traditional portfolio methods.
- **Superior Risk Management**: The framework discovered a new strategy that significantly reduces Maximum Drawdown (MDD) by **-53.77%** and enhances stability through entropy-based diversification, ensuring improved portfolio resilience.
- **Empirical Outperformance**: The discovered strategy achieves a **71.04%** increase in Sharpe Ratio (Sharpe, 1966), a **73.54%**improvement in Sortino Ratio (Sortino & Price, 1994), and a **116.31%** boost in Calmar Ratio (Young, 1991) over traditional approaches.

2 RELATED WORK

2.1 TRADITIONAL PORTFOLIO OPTIMIZATION STRATEGIES

Classic portfolio construction methodologies have been widely studied and applied in finance. Some of the most commonly used strategies include:

- **Equal-Weighted Portfolio (EW)**: Assigns an equal allocation to all assets, ensuring high diversification but ignoring asset return forecasts and risk-adjusted performance.
- **Mean-Variance Optimization (MVO)**: Introduced by Markowitz (1952), MVO seeks to maximize expected return for a given level of risk but suffers from high sensitivity to estimation errors in expected returns and covariances.
- **Risk Parity (RP)**: Balances risk contribution across assets, often leading to over-allocation to low-volatility assets, limiting upside potential (Qian, 2005).
- **Minimum Variance Portfolio (MVP)**: Minimizes overall portfolio variance but disregards return expectations, leading to overly conservative allocations (DeMiguel et al., 2009).
- **Equal Risk Contribution (ERC)**: Similar to Risk Parity, ERC distributes risk equally but does not necessarily maximize portfolio efficiency (Maillard et al., 2010).

While these strategies offer valuable asset allocation frameworks, they rely on static assumptions that may not hold in dynamic market conditions. Moreover, they cannot learn and evolve, which is crucial in responding to changing economic environments.

2.2 MACHINE LEARNING IN PORTFOLIO CONSTRUCTION

Recent advances in machine learning (ML) have led to new data-driven approaches for portfolio optimization, including reinforcement learning-based asset allocation (Silver et al., 2017) and deep neural networks predicting optimal portfolio weights (Fort et al., 2019). Yet, they have drawbacks:

- **Black-Box Nature**: Many ML models, such as deep reinforcement learning, generate highly non-transparent allocation decisions, making them difficult to interpret and trust in high-stakes financial applications.
- **Overfitting Risk**: Recent advances include reinforcement learning-based asset allocation (Bailey & López de Prado, 2014).
- **Computational Complexity**: Some ML techniques require extensive training and fine-tuning, making them impractical for real-time allocation.

2.3 LARGE LANGUAGE MODELS IN SCIENTIFIC DISCOVERY

LLMs have recently demonstrated remarkable capabilities in generating novel algorithms, equations, and optimization heuristics across multiple domains, including mathematics and software engineering. Recent advancements in reinforcement learning, particularly through AlphaTensor and AlphaCode, provide a blueprint for iterative optimization and creative problem-solving. AlphaTensor, introduced by Fawzi et al. (2022), uses multi-agent reinforcement learning to optimize algorithms iteratively, discovering efficient methods for matrix multiplication. Its iterative optimization framework inspired the proposed approach for evolving financial metrics. Similarly, AlphaPortfolio employs LLMs to propose, score, and refine financial metrics through an iterative workflow, ensuring continuous improvement. AlphaCode, demonstrated by Li et al. (2022), highlights the potential of large-scale models in generating high-quality code for competitive programming tasks. Its ability to learn from examples and refine outputs through iterative feedback strongly parallels the generation of financial metrics optimized for out-of-sample robustness. Others such as Romera-Paredes et al. (2024), also demonstrated how LLMs can contribute to mathematical discovery by automating the search for novel programs and equations, and Lu et al. (2024), who proposed a framework for fully automated, open-ended scientific discovery using LLMs. These works further highlighted the growing potential of AI to drive innovation in scientific and technical domains, reinforcing the potential of LLM-driven iterative workflows like AlphaPortfolio to redefine financial metric design. In this study, we explore their potential for discovering new portfolio optimization methodologies that improve upon traditional finance heuristics while maintaining interpretability and robustness. By leveraging LLM-driven generation and mutation, our framework enables the autonomous evolution of portfolio allocation methods outperforming human-engineered strategies in financial markets.

3 METHODOLOGY

LLMs, such as OpenAI's GPT, Meta's LLama, have demonstrated exceptional capabilities in generating codes for creative and robust algorithms across several domains. In this work, LLMs are used to revolutionize portfolio optimization method discovery by:

- **Automated Code Generation:** Similar to AlphaCode, LLMs can autonomously generate high-quality implementations for portfolio optimization methods or allocation strategies.
- **Critical Thinking and Synthesis:** By analyzing the academic literature, LLMs can integrate theoretical insights into the portfolio allocation method, ensuring novelty and rigor.
- **Cross-Domain Inspiration:** Drawing on extensive training data across domains, LLMs can introduce concepts from other disciplines to innovate portfolio allocation methods.
- **Iterative Optimization:** Utilizing evolutionary strategies and feedback loops to iteratively refine generated metrics for better robustness and predictive power.
- **Few-Shot Generation:** Leveraging few-shot examples to generate creative variations of existing and discovered metrics, combining domain expertise with data-driven insights.
- **Mutational Refinement:** Inspired by evolutionary algorithms, LLMs can suggest mutations to existing portfolio allocation strategies, optimizing robustness and generalization.

The AlphaPortfolio is a novel method designed to iteratively optimize portfolio optimization methods, for out-of-sample robustness by leveraging large language models (LLMs) for creativity and critical thinking. The framework employs an evolutionary approach that blends the implicit domain expertise of LLMs and evolutionary strategies to design metrics that exhibit superior robustness and generalization capabilities. LLMs, such as GPT-based models, generate novel metrics by drawing inspiration from academic literature and best practices in financial analysis. Few-shot learning and prompt engineering guide LLMs in producing relevant and innovative metrics. The framework employs a structured, four-step iterative process to discover and refine portfolio optimization strategies:

1. **Portfolio Strategy Generation**: LLMs generate candidate portfolio optimization functions by integrating financial literature, optimization principles, and risk-return heuristics.
2. **Cross-over, Mutation, and Refinement**: The generated strategies undergo evolutionary refinement through cross-over and targeted mutation, incorporating adjustments for risk scaling, diversification, entropy-based regularization, and regime-specific adjustments.
3. **Scoring & Evaluation**: Generated strategies are cross-validated across historical market data, scored and ranked based on their Sharpe, Calmar, and Sortino ratios over cross-validation folds; reflecting risk-adjusted return stability, and drawdown characteristics.
4. **Iteration & Convergence**: The best-performing strategies w.r.t. combined ranks are continuously refined through successive iterations, improving robustness and adaptability.

Portfolio allocation strategies are ranked based on quality and diversity; only top candidates are retained for cross-over in further iterations. Cross-over combines these top-ranked methods from the scoring phase to create hybrids blending their computational elements. This process leverages the strengths of individual strategies while mitigating their weaknesses. Strategies that rank poorly are discarded, ensuring only a diverse set of high-quality ones are bred (Cully & Demiris, 2017).

4 EXPERIMENTS

Time-series cross-validation was employed to validate and rank metrics as they evolve. The dataset, comprising 15 years of historical data from 3,246 US stocks and ETFs, was split into overlapping folds after separating 20% of the data for the out-of-sample test (3 years). Portfolio allocation strategies are evolved based on their obtained risk-return ratios within the cross-validation folds, ensuring robust evaluation across different periods. This is critical to guide the evolution towards the most robust allocation strategies having consistent performance across time. The evolved allocation methods were finally blind-tested during recent periods of extreme market stress, including the 2020 COVID-19 market crash, highlighting their robustness and stability under high-volatility conditions (Lipton & Lopez de Prado, 2020). The discovered strategy, AlphaPortfolio 1, is open-sourced.

Algorithm 1 AlphaPortfolio Allocation

Require: $\mathbf{R}_{excess} \in \mathbb{R}^{n \times t}$ ▷ Excess log returns as an $n \times t$ tensor
Ensure: $\mathbf{w} \in \mathbb{R}^{n}$ ▷ Optimized portfolio weights

1: Compute positive risk-adjusted returns through the inverted covariance matrix

$$\mathbf{r}_{adj} = \max(0, (\mathrm{Cov}(\mathbf{R_{excess}}) + \epsilon\mathbf{I})^{\mathbf{-1}} \cdot \mathrm{mean}(\mathbf{R_{excess}}, \mathrm{dim} = \mathbf{1}))$$

2: Enhance returns using stability factor and compute softmax-normalized weights:

$$\mathbf{w} = \mathrm{softmax}(\frac{\mathbf{r}_{adj} \cdot (1 + \mathrm{std}(\mathbf{r}_{adj}))}{\sqrt{\mathrm{diag}(\mathbf{\Sigma}) + \epsilon} + \delta})$$

3: Apply entropy-based regularization, and return the normalized portfolio weights:

$$\mathbf{w} = \mathrm{l1normalize}(\mathbf{w} \cdot \exp(\mathrm{mean}(\mathbf{w}) \cdot \log(\mathbf{w} + \delta)))$$

4.1 DISCOVERED ALPHAPORTFOLIO

Traditional portfolio allocation techniques like the Risk Parity Portfolio and Equal Risk Contribution Portfolio often struggle with stability, extreme return sensitivity, and risk-adjusted return maximization inefficiencies Qian (2005); Maillard et al. (2010). The LLM-driven discovery of portfolio allocation methods has led to developing a novel approach—**AlphaPortfolio** 1. This newly discovered method significantly enhances portfolio performance by integrating inverse covariance risk-adjusted returns, stability-adjusted weighting, entropy regularization, and volatility normalization. The comparison in Table 1 demonstrates that it achieves the highest Sharpe Ratio and Calmar Ratio, outperforming traditional portfolio optimization techniques by a significant margin.

The newly discovered AlphaPortfolio optimization method follows a structured approach, where it allocates a long-only portfolio by adjusting weights for stability, volatility, and diversification while preserving an optimal adjusted risk-return profile. The optimal allocation weights of the AlphaPortfolio are computed with the following optimization target using a closed-form analytical solution:

$$w^* = \arg\max \left(\tilde{R} - \lambda S - \gamma D\right) \tag{1}$$

- $\tilde{R}$: Stability-adjusted risk-return measure incorporating an inverse asset covariance scaling.
- S: Risk contribution entropy-based penalty, ensuring balanced diversification of the risks.
- D: Inverse covariance-adjusted return vector to enhance risk-adjusted return maximization.

Portfolio Strategy	Δ_{Sharpe} (%)	Δ_{Sortino} (%)	Δ_{Calmar} (%)	Δ_{MDD} (%)
Equal Weighted	0.00%	0.00%	0.00%	0.00%
Risk Parity	+38.32%	+37.46%	+10.36%	-9.39%
Equal Risk Cont.	+38.55%	+37.62%	+10.44%	-9.46%
AlphaPortfolio	**+71.04%**	**+73.54%**	**+116.31%**	**-53.77%**

Table 1: Performance surplus of risk-aware long-only allocation strategies w.r.t. Equal Weighted.

As demonstrated in the provided algorithm, AlphaPortfolio 1 first computes the inverse covariance-adjusted return vector through the inverted covariance matrix. Then, it introduces a **stability factor** by incorporating the standard deviation of the inverse covariance-adjusted risk-return vector, apply **volatility normalization** and **softmax normalization** to derive initial asset allocations. Lastly, it also introduces **entropy regularization** to ensure diversification penalizing dominant assets, ensuring risk-balanced allocation while preventing excessive concentration. By integrating volatility normalization and entropy-based diversification, AlphaPortfolio achieves higher return efficiency, reduced drawdowns, and improved stability compared to conventional portfolio allocation methods.

The results in Table 1 highlight the superiority of **AlphaPortfolio** over conventional portfolio allocation strategies across key financial metrics. Compared to the **Equal Weighted Portfolio** (DeMiguel et al., 2009), AlphaPortfolio exhibits substantial improvements in **risk-adjusted returns, downside protection, and drawdown resilience**. These findings underscore the effectiveness of **LLM-driven portfolio optimization**, which leverages adaptive, entropy-regularized, and stability-enhanced allocation strategies. The key takeaways from the quantitative experimental results are as follows:

- **Highest Sharpe Ratio Improvement**: AlphaPortfolio achieves a remarkable **+71.04%** increase, significantly enhancing baseline risk-adjusted returns.
- **Superior Sortino Ratio**: **+73.54%** improvement demonstrates superior downside risk management and reduced exposure to extreme losses.
- **Unmatched Calmar Ratio**: A **+116.31%** boost indicates enhanced return efficiency relative to MDD, marking the strategy as stronger in turbulent markets.
- **Largest Reduction in MDD**: A substantial **-53.77%** reduction in drawdowns underscores its ability to mitigate extreme losses with high resilience.
- **Risk-Aware Stability**: The approach prevents excessive concentration in high-volatility assets, ensuring a well-diversified and balanced allocation.
- **Entropy-Based Diversification**: Encouraging **balanced risk contributions across assets**, it reduces dependency on single volatile securities, reinforcing long-term stability.

These results reaffirm LLM-driven discovery of portfolio optimization methods can evolve superior strategies like AlphaPortfolio that **outperform traditional risk-aware allocation methods** by integrating **robust optimization techniques** enhancing **return efficiency and downside protection**.

5 CONCLUSION

This paper introduced AlphaPortfolio, an innovative LLM-driven portfolio optimization framework that iteratively discovers, refines, and validates asset allocation methodologies. By leveraging inverse covariance risk-adjusted returns, entropy-based diversification, and volatility normalization, AlphaPortfolio mitigates key limitations of traditional portfolio methods, including sensitivity to estimation errors, excessive concentration in low-volatility assets, and limited adaptability to market shifts. Experimental results confirm that LLMs can autonomously generate and refine financial heuristics, demonstrating their potential in AI-driven quantitative finance. By integrating evolutionary strategies and adaptive learning, AlphaPortfolio enables automated discovery of robust, interpretable, and high-performance portfolio optimization techniques. AlphaPortfolio represents a paradigm shift in quantitative investing, offering a scalable, interpretable, and adaptive approach to portfolio construction. This research paves the way for the next generation of intelligent asset allocation strategies by bridging AI-driven discovery with financial theory.

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