Quantitative Asset Allocation: Moving from Mean-Variance to AI Clustering

Spark Hu
London, United Kingdom

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Executive Summary

The goal of this project was to compare two different ways of building an investment portfolio. I started by using the standard approach, **Mean-Variance Optimization (MVO)**, which uses historical data to optimize the balance between risk and return.

However, because standard models often fail when markets get volatile, I built a second model using **Hierarchical Risk Parity (HRP)**. This approach uses machine learning clustering to group assets based on how they behave. I tested both models using data from 2021 to 2025. The results showed that while the standard model is good for theory, the machine learning model has a more stable way to manage risk in real scenarios.

1 Phase I: The Standard Model (MVO)

1.1 Running the Simulation

To understand how different assets work together, I wrote a Python script to run a Monte Carlo simulation. 10,000 different possible portfolios were simulated to see which one performs best. I looked at a mix of Tech stocks, Banks, Bonds, Gold, and Energy.

The goal was to maximize the **Sharpe Ratio**, which measures the return you get for every unit of risk you take.

$$S_p = \frac{\text{Return} - \text{Risk Free Rate}}{\text{Volatility}} \tag{1}$$

1.2 What the Model Found

The simulation produced an "Efficient Frontier"—a curve showing the best possible returns for any risk level (Figure 1). Interestingly, the model suggested avoiding Tech stocks completely because they were too volatile in 2022. Instead, it allocated heavy weights to **Banks (JPM)** and **Gold**, creating a "defensive" portfolio.

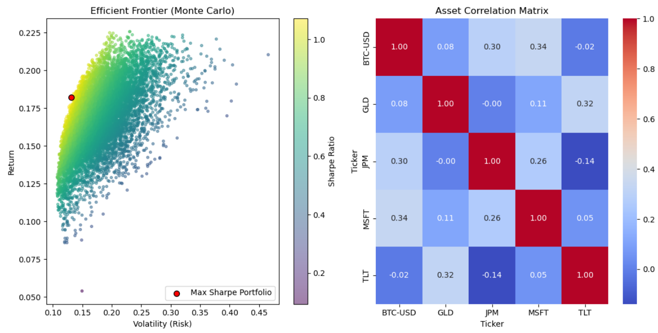

Figure 1: The Efficient Frontier. Each dot represents one of the 10,000 simulated portfolios.

2 Phase II: The Advanced Model (HRP)

2.1 Why Standard Models Fail

The problem with the first model is relying too much on correlation, i.e., the idea if Stock A goes up, Stock B goes down. In a market crash, these relationships often break, and everything goes down together. This makes the standard model inaccurate.

2.2 The Machine Learning Solution

To fix this, I implemented **Hierarchical Risk Parity (HRP)**. Instead of using complex matrix math that can be unstable, HRP uses a method called "clustering."

- **Step 1:** The algorithm looks at how assets move and categorizes similar ones together (e.g., putting all Tech stocks in one group and Bonds in another).
- **Step 2:** It allocates capital to the groups based on their risks.

This prevents the model from allocating all assets in one type of stock just because the historical data looks good.

3 Real-World Testing

3.1 Walk-Forward Backtest

To prove the model works, I can't just look at the past. I ran a "Walk-Forward" backtest. This simulates real life: By setting the model to rebalance the portfolio every month, and using only the data available at that time. This ensures I wasn't having a look-ahead bias.

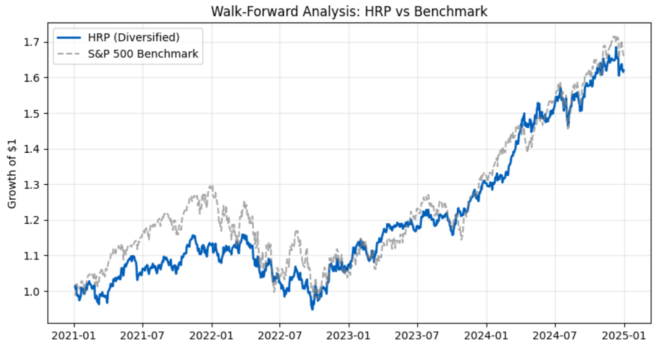

Figure 2: The Test Results. The Blue line (HRP model) kept up with the Grey line (S&P 500) while holding more diverse assets.

3.2 Performance Analysis

The results in Figure 2 show that the HRP model (Blue) performed very well. Even though it held "safe" assets like Gold and Energy, it still matched the growth of the S&P 500 (Grey).

Usually, safer portfolios lag behind during bull markets. However, because this algorithm included Energy stocks (XLE), it was able to benefit from growth when Tech stocks were struggling. This confirms that using clustering to manage risk allows for a more stable performance without sacrificing too much profit.

4 Conclusion

This project taught me that complex math isn't always better. The standard Mean-Variance model suggested a portfolio that looked good on paper but relied on past data which can be unstable. By switching to the machine learning approach (HRP), I built this system that organizes assets logically. The backtest proved that this method has steadier results, and able to match the market's performance while maintaining a smarter and more diversified allocation.