CSE/ECO 578 – Computational Investment – Fall 2022

Portfolio Optimization

- Team name: Unbiased Strategists
- Team Members:
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Motivation:

We chose to implement a portfolio optimization project, which involves finding the best allocation of investments out of a given pool. Allocation is used not only as a risk management tool but as a way of maximizing returns and is the foundation of modern investing; this is the reason for our interest in the topic. Could sophisticated allocation methods give better returns than naive allocation? We understood that financial economists had studied the naïve distribution, and some have produced results superior to more advanced methods. If the optimization strategies we evaluate, including mean variance optimization and hierarchical risk parity, produce superior results compared to the easy-to-implement naïve distribution, this knowledge would be of prime importance to portfolio managers and inexperienced investors.

Data Selection:

1. Stocks: We took the opportunity to use skewness as the method of choosing the member stocks of the portfolio. We took stratified random samples of five stocks from each sector of the member stocks of the Russell 3000 and from these chose two of the five with the highest positive skewness. This represents the portfolio of a risk-loving investor.
2. ETFs (U.S./Germany): Represented the tastes of a more risk-averse investor who would prefer a higher level of diversification. One was made up of a selection of ETFs from each sector of the U.S. market, and the other was the FSE Euro and American “blended” portfolio, kindly provided by Kaspars’ team.

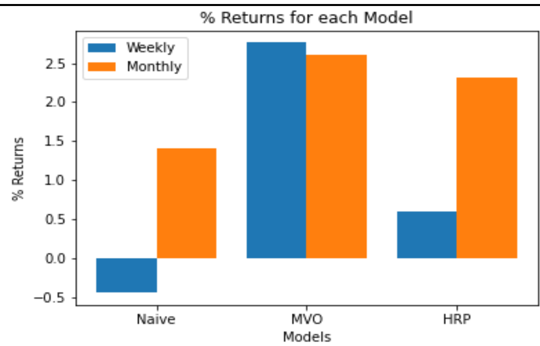
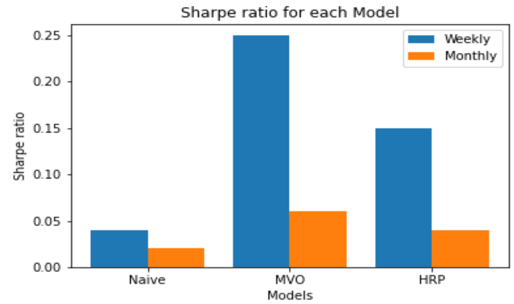
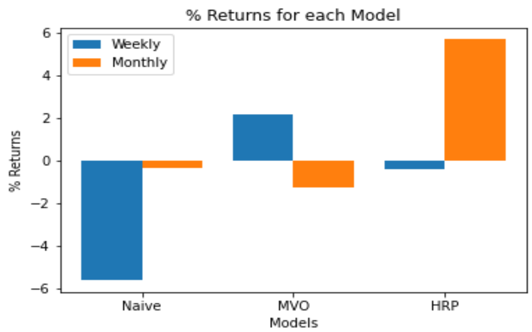
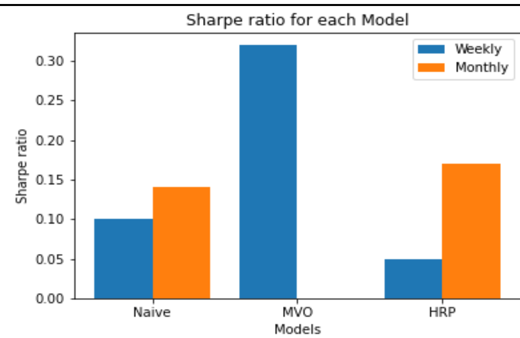
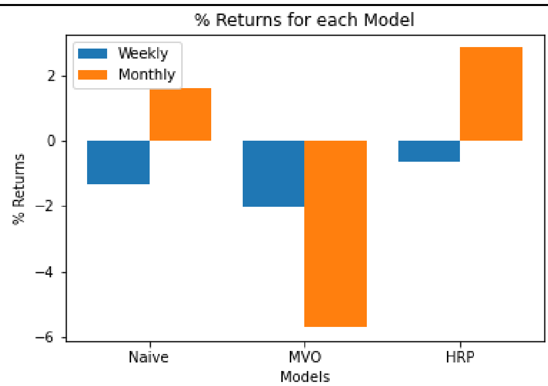
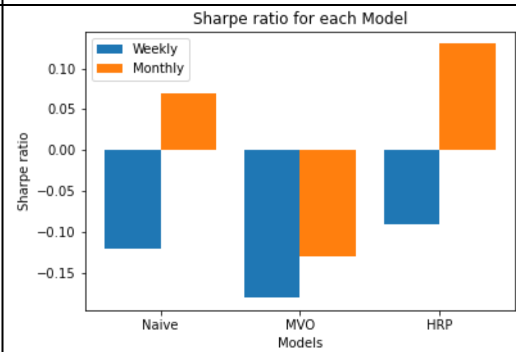
Methodology:

1. Data extraction and pre-processing: The Yahoo Finance API was used to fetch the data. The data frequency was 'daily.'
2. The three portfolios explained above were considered regarding three different optimization techniques including "naive" allocation, mean variance optimization, and hierarchical risk parity optimization.
3. Models were trained with data from 01/01/2022 to 10/31/2022 and tested on 2 periods – a one week period (11/01/2022 to 11/08/2022) and one month period (11/01/2022 to 12/01/2022). Based on feedback received in class, additional training was done using data from 01/03/2021 to 12/31/2021 and tested on one year's data from 01/03/2022 to 12/01/2022, to infer a better conclusion from results.
4. The data was processed and fed to the three algorithms to calculate the weights using the library PyPortfolioOpt.
5. These weights were then used to allocate funds.
6. The performance was evaluated for the allocation provided by these models based on 3 parameters:
    a. Percentage returns
    b. Sharpe ratio
    c. Cumulative returns over a given time
7. The results are combined for all 3 methods on all 3 portfolios using pickle file and matlplotlib library (python). Finally, the results are analyzed to observe and draw conclusions on the trends and patterns.

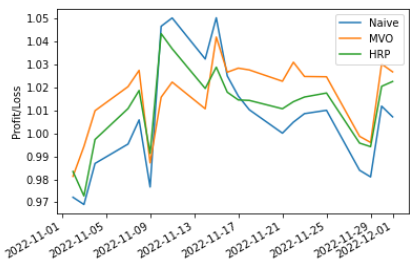
Algorithms:

1. Naïve distribution: All stocks/ETFs in consideration are given equal weightage by the total amount allocated.
2. Mean-Variance Optimization: MVO strategy works by giving a balance of the returns to risk of the portfolio. It tries to maximize the returns for each level of risk of the portfolio.
3. Hierarchical Risk Parity: HRP algorithm is a combination of graph theory and unsupervised machine learning that tries to allocate the risk instead of allocation capital.

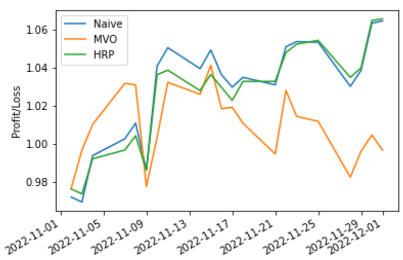
Results:

	% Returns	Sharpe ratio
Stocks		
ETF US		
ETF DE		

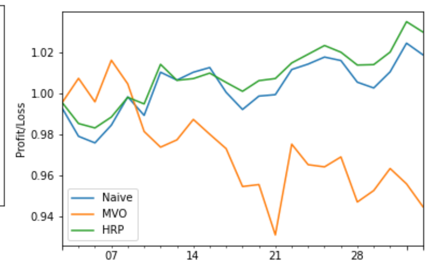
Cumulative returns (monthly):



Stock Portfolio



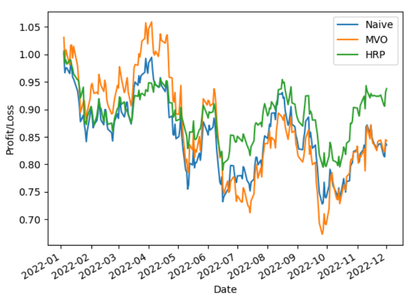
ETF USA Portfolio



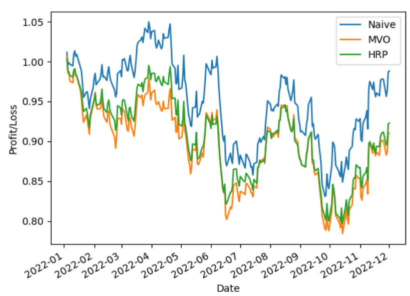
ETF DE Portfolio

For the more recent training period of January 2022 through October 2022, our results are as follows. For the stock portfolio, mean variance optimization outperformed the other optimization techniques except for a brief period between November 9th and November 17th. The naive portfolio performed best for the U.S. ETF portfolio, albeit similarly to HRP for the latter half of the month. For the blended portfolio, HRP slightly outperformed the naive portfolio for most of the month, and MVO performed poorly. The performance of MVO is highly variable; it is either the best or worst performer of the three by a significant margin, and after a large loss in returns, it performs particularly badly.

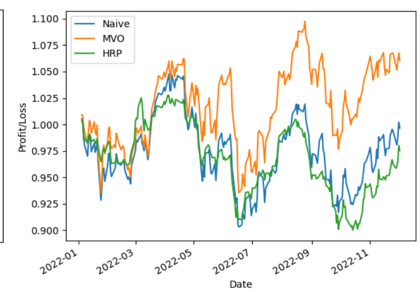
Cumulative returns (yearly):



Stock Portfolio



ETF USA Portfolio



ETF DE Portfolio

For the 2021 training period in which we tested the optimization techniques on each month of 2022, we can see that mean variance optimization performs best in the first half of the year and worst in the second half of the year. Curiously, for the U.S. ETF portfolio, the naive portfolio performed best consistently for the entirety of 2022, and mean variance optimization performed best for most of the year for the blended ETF portfolio. This result is critical in proving that a straightforward allocation can sometimes consistently outperform algorithmic optimization methods. We can see again in the stock and U.S. ETF portfolios that after a steep decline in returns, the MVO portfolio doesn't exceed the other two methods; however, for the blended ETF portfolio, this does not hold. It is also unusual that MVO works well for the stock portfolio in which we chose risky stocks, as one of the assumptions for MVO is that an investor is risk averse. The MVO is also sensitive to the change in training period data. In much of our data, the naive and HRP allocations perform similarly.

Conclusion:

With our comparisons from monthly and yearly data, we notice naïve and HRP perform similar, with HRP performing better in most cases. For MVO, we could see a significant difference when the training and/or testing period is changed: It performed exceptionally well for yearly data, whereas it performed the least for monthly data analysis for ETF DE. Overall, the optimization strategy performed better. The returns were higher, except for one of the six scenarios. The only scenario where it didn't work well was the yearly test on the ETF USA portfolio. Sometimes, the naïve portfolio outperforms the algorithmic optimization.

Although data-driven decisions are important in the optimization process, human analysis, such as portfolio and stock selection, and data for training & testing are essential for optimal performance. Compared to older data, the data closer to our testing period is more relevant. Particular models are suitable for specific trends/patterns in the market. Also, the time period for training is essential and can impact the results.

References:

1. Reed, E. (2019). How Mean-Variance Optimization Works in Investing. https://smartasset.com/financial-advisor/mean-variance-optimization
2. https://pyportfolioopt.readthedocs.io/en/latest/
3. De Prado, M.L., 2016. Building diversified portfolios that outperform out of sample. *The Journal of Portfolio Management*, *42*(4), pp.59-69. (https://jpm.pm-research.com/content/42/4/59.short)

4. Vyas, A. D. A. Portfolio Optimisation with PortfolioLab: Hierarchical Risk Parity. Hudson and Thames. https://hudsonthames.org/portfolio-optimisation-with-portfoliolab-hierarchical-risk-parity/

Appendix:

1. Optimization Strategies:
    a. Naïve Allocation: Every asset in the portfolio receives an equal allocation. Each asset in the portfolio obtains a weight equal to 1/(number of assets).
    b. MVO Allocation: Mean-Variance Optimization (MVO) is a strategy (part of the Modern Portfolio Theory [MPT]) to allocate weights to assets in a portfolio by striking a balance between the returns and risk of each asset in the portfolio. It considers each asset's expected returns and the risk (variance) to maximize the overall returns or to reduce the overall risk post-allocation. There are various internal optimization techniques, such as maximizing the returns without regarding risk, minimizing the risk by sacrificing returns, and maximizing the Sharpe Ratio (Returns to Risk Ratio). We aimed to maximize the Sharpe Ratio to optimize the portfolio. It implies that the optimization algorithm will allocate weights such that the expected returns to the risk ratio (Sharpe Ratio) are maximum for the portfolio. In this strategy, some assets could get zero allocation, reducing the total number of assets.
    c. Efficient Frontier
    d. HRP Allocation: Hierarchical Risk Parity (HRP) is a strategy that uses graph theory and machine learning (clustering) internally to construct a hierarchical structure of the portfolio. The assets are clustered based on their returns and covariance data. This algorithm has three significant steps: hierarchical tree clustering, covariance matrix reorganization, and recursive bisection. The first step involves clustering similar assets into groups based on the returns data. The second step (quasi-diagonalization), places similar assets closer together in the group and dissimilar assets further apart. The final step involves weight assignment to each asset in the cluster. The HRP strategy is more

robust than MVO in weight assignment, such that it tries to assign a weight to every asset rather than giving some of them an allocation weight of zero.

2. Packages:
    a. Language: Python
    b. Pandas
    c. matplotlib
    d. PyPortfolioOpt
    e. pandas_datareader
    f. numpy