MGT3012: Financial Analytics

J Component – Project Report

TITLE: Portfolio Optimization

By

HARINI GOKULRAM NAIDU - 19MIA1004

SHIVANI GOKULRAM NAIDU - 19MIA1006

P SUBHASHRI - 19MIA1008

DEEKSHITHA L - 19MIA1030

HARSHINI K AIYYER - 19MIA1050

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Submitted to

Dr. JYOTIRMAYEE SATAPATHY

Assistant Professor

VITBS,

VIT, Chennai

VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

ABSTRACT

Investment and finance involve a lot of possible risks that can arise because of the same. Hence, one good solution is to diversify the investment or in other words, to optimize the portfolio. Portfolio optimization is a crucial task in finance to achieve an optimal balance between risk and return. In this project, we propose a novel approach for portfolio optimization using modern machine learning techniques. We utilize historical financial data, including stock prices, returns, and other relevant financial indicators, to construct portfolios that maximize the return while minimizing the risk. This project aims to determine the optimal portfolio using recommended techniques and methods such as Modern portfolio theory and Hierarchical Risk parity. We begin by collecting and preprocessing financial data from various sources. In MPT we use efficient frontier and in HRP hierarchical clustering is applied. We have applied both these techniques on stocks of four companies namely AWL, Hindustan Unilever, Maruti and Reliance.

INTRODUCTION

Portfolio optimization is the process of choosing the optimal portfolio among all those under consideration in a portfolio. The goal typically maximizes elements like expected return while minimizing expenses like financial risk. Optimal Portfolios are well diversified in order to do away with the unsystematic risk or non-priced risks. Diversification helps in protecting investors against the downside in case a particular asset underperforms Intangible and tangible factors are both taken into consideration, including assets, obligations, earnings, and other basics (such as selective divestment). Traditional portfolio optimization methods, such as Modern Portfolio Theory (MPT), have been widely used for decades. However, these methods may have limitations in handling complex and dynamic market conditions and may not fully capture the hierarchical structure of risks in a portfolio. In recent years, there has been growing interest in using machine learning and advanced optimization techniques to enhance portfolio optimization. One such approach is Hierarchical Risk Parity (HRP), which considers the hierarchical relationships among assets in a portfolio to achieve a more balanced risk allocation. HRP has shown promising results in improving portfolio performance compared to traditional methods. The other assets in the portfolio will protect the investor’s portfolio from crashing, and the investor stays in a comfortable zone.

In this report, we propose a portfolio optimization framework that combines MPT and HRP to create optimized portfolios. We leverage historical financial data, including stock prices, returns, and other relevant financial indicators, to construct portfolios that achieve optimal risk-return tradeoff. We utilize machine learning algorithms and advanced optimization techniques to optimize the portfolio allocation, incorporating both the principles of MPT and the hierarchical risk allocation of HRP. We will first provide a literature review on the concepts of MPT and HRP, highlighting their strengths and limitations. We will then present the methodology of our proposed portfolio optimization framework, outlining the data preprocessing, machine learning techniques, and optimization algorithms used. We will discuss the implementation of the framework on historical financial data and compare the performance of our optimized portfolios with traditional methods, such as equal-weighted portfolios and market-capitalization weighted portfolios, as well as portfolios optimized using only MPT or HRP.

Our portfolio optimization project aims to contribute to the field of finance by providing a comprehensive framework that integrates the principles of MPT and the hierarchical risk allocation of HRP to create optimized portfolios. We expect our findings to provide insights and guidance for portfolio managers in constructing well-diversified and optimized portfolios to achieve superior risk-adjusted returns.

LITERATURE SURVEY

1. A Quantum Online Portfolio Optimization Algorithm

Portfolio optimization plays a central role in finance to obtain optimal portfolio allocations that aim to achieve certain investment goals. Over the years, many works have investigated different variants of portfolio optimization. Portfolio optimization also provides a rich area to study the application of quantum computers to obtain advantages over classical computers. In this work, they have given a sampling version of an existing classical online portfolio optimization algorithm by Helmbold et al., for which they in turn develop a quantum version. The quantum advantage is achieved by using techniques such as quantum state preparation and inner product estimation. This quantum algorithm provides a quadratic speedup in the time complexity.

2. Large-scale Recommendation for Portfolio Optimization

Individual investors are now massively using online brokers to trade stocks with convenient interfaces and low fees, albeit losing the advice and personalization traditionally provided by full-service brokers. People frame the problem faced by online brokers of replicating this level of service in a low-cost and automated manner for a very large number of users. Because of the care required in recommending financial products, people focus on a risk-management approach tailored to each user's portfolio and risk profile. They show that the hybrid approach, based on Modern Portfolio Theory and Collaborative Filtering, provides a sound and effective solution. The method is applicable to stocks as well as other financial assets and can be easily combined with various financial forecasting models. They validate this proposal by comparing it with several baselines in a domain expert-based study.

3. **Robust portfolio optimization for banking foundations: a CVaR approach for asset allocation with mandatory constraints**

This paper focuses on an innovative asset allocation strategy for risk averse investors who operate on very long-time horizons, such as endowments and the Italian foundations of banking origin (FBOs). FBOs play a pivotal role in supporting economic, financial and sustainable growth in the long term. In the search for a model which optimizes FBO portfolio choices in the light of regulatory constraints on their sizeable investable portfolio, we highlight the risk-adjusted performances obtained using a robust conditional VaR (R-CVaR) approach—assuming different risk profiles—which corrects some of the Markowitz approach pitfalls and accounts for tail risk. We compare the two models using a buy and hold strategy: the R-CVaR delivers better returns than a Markowitz portfolio, even when those performances are measured with a mean–variance metric.

4. **OPTIMIZATION OF PORTFOLIO USING FUZZY SELECTION**

The problem of portfolio optimization concerns the allocation of the investor's wealth between several security alternatives so that the maximum profit can be obtained. One of the methods used is Fuzzy Portfolio Selection to understand it better. This method separates the objective function of return and the objective function of risk to determine the limit of the membership function that will be used. The goal of this study is to understand the application of the Fuzzy Portfolio Selection method over shares that have been chosen on a portfolio optimization problem, understand return and risk, and understand the budget proportion of each claim. The subject of this study is the shares of 20 companies included in Bursa Efek Indonesia from 1 January 2021 until 1 January 2022. The result of this study shows that from 20 shares, there are 10 shares that are suitable in the forming of an optimal portfolio.

5. **Efficient and Simple Heuristic Algorithm for Portfolio Optimization**

Markowitz model considers what is termed as standard portfolio optimization. The portfolio optimization problem is a problem which is based on asset allocation and diversification for maximum return with minimum risk. Thus, the standard portfolio optimization problem happens when the constraints considered are budget and no-short selling. In reality however, portfolio optimization has realistic constraints to be incorporated such as holding sizes, cardinality and transaction cost. When realistic constraints are added into a portfolio optimization problem, it becomes too complex to be solved by standard optimization methods which in this case turns out to be an extended portfolio optimization problem. Markowitz solution and the standard methods like quadratic programming become inapplicable. With such limitations, heuristic methods are usually used to deal with this extended portfolio optimization problem.

Therefore, this paper proposes a heuristic algorithm for the extended portfolio optimization problem. It is a hill climbing algorithm named Hill Climbing Simple (HC-S) which is then validated by solving the standard Markowitz model. In fact, the proposed algorithm is benchmarked with the quadratic programming (QP), which is a standard method. Also, HC-S demonstrated to be more effective and efficient than threshold accepting (TA), an established algorithm for portfolio optimization since HC-S find solutions with significant higher objective value and require less computing time as compared to standard methods.

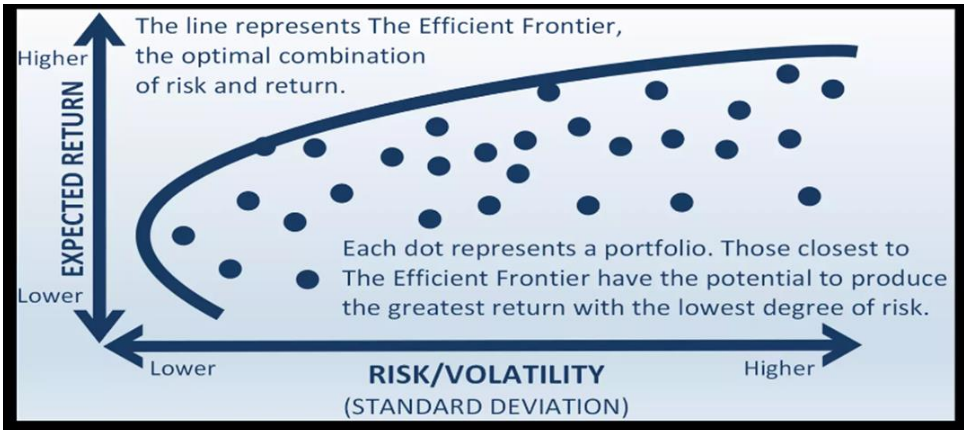
METHODOLOGY

Modern Portfolio Theory (MPT)

MPT provides a quantitative framework for portfolio construction and has been widely used in practice by investors, portfolio managers, and financial institutions. However, it also has limitations, including assumptions about the accuracy of expected returns and the validity of historical data, as well as sensitivity to model parameters and potential estimation errors. As such, MPT is often used in conjunction with other approaches and techniques, such as risk management strategies and qualitative factors, to construct well-diversified portfolios that align with an investor's specific risk tolerance, investment objectives, and market conditions.

Modern Portfolio Theory, or also known as mean-variance analysis, is a mathematical process which allows the user to maximize returns for a given risk level. MPT assumes that all investors are risk-averse, i.e, if there is a choice between low risk and high-risk portfolios with the same returns, an investor will choose one with the low risk. It is possible to reduce variance without compromising expected return by combining multiple asset types through asset allocation.

We know every asset in a portfolio has its own rate expected returns and risks. It is possible to create multiple combinations of assets that can provide high returns for a pre-defined risk level. Likewise, there can be multiple portfolios that give lowest risk for a pre-defined expected return. Efficient frontier is a graph with ‘returns’ on the Y-axis and ‘volatility’ on the X-axis. It shows the set of optimal portfolios that offer the highest expected return for a given risk level or the lowest risk for a given level of expected return. Portfolios that lie outside the efficient frontier are sub-optimal because they do not provide either enough return for the level of risk or have a higher risk for the defined rate of return.



- **Hierarchical Risk Parity (HRP)**

Various risk parity methodologies are a popular choice for the construction of better diversified and balanced portfolios. It is notoriously hard to predict the future performance of the majority of asset classes. Risk parity approach overcomes this shortcoming by building portfolios using only assets' risk characteristics and correlation matrix. Their method uses graph theory and machine learning to build a hierarchical structure of the investment universe. Such structure allows better division of assets/factors into clusters with similar characteristics without relying on classical correlation analysis.

We investigate portfolio diversification strategies based on hierarchical clustering. These hierarchical risk parity strategies use graph theory and unsupervised machine learning to build diversified portfolios by acknowledging the hierarchical structure of the investment universe. In this chapter, we consider two dissimilar measures for clustering a multi-asset multi-factor universe. While the Pearson correlation coefficient is a popular choice, we are especially interested in a measure based on the lower tail dependence coefficient. Such innovation is expected to achieve better tail risk management in the context of allocating to skewed style factor strategies. Indeed, the corresponding hierarchical risk parity strategies seem to have been navigating the associated downside risk better yet come at the cost of high turnover. A comparison based on block-bootstrapping evidence alternative risk parity strategies along economic factors to be on par in terms of downside risk with those based on statistical clusters.

IMPLEMENTATION

- We have chosen 4 Companies – Maruti, Reliance, ITC, Hindustan Unilever for the analysis.

	MARUTI.NS	RELIANCE.NS	AWL.NS	HINDUNILVR.NS
Date				
2018-01-01	9150.264648	881.918213	NaN	1240.114258
2018-01-02	9057.500000	883.275330	NaN	1234.672241
2018-01-03	8927.193359	886.813721	NaN	1245.509888
2018-01-04	8898.419922	892.145447	NaN	1247.262207
2018-01-05	8943.546875	895.005188	NaN	1251.228638
...	...	...	...	...
2023-02-27	8632.200195	2367.850098	344.450012	2468.149902
2023-02-28	8624.349609	2322.550049	361.649994	2460.649902
2023-03-01	8764.150391	2343.899902	379.700012	2466.250000
2023-03-02	8548.750000	2326.050049	398.649994	2455.350098
2023-03-03	8601.250000	2385.399902	418.549988	2471.000000

1280 rows × 4 columns

The dataset contains Stock price data from January 1st, 2018 to March 3rd 2023.

```
# Create a dataframe to store the adjusted close price of the stocks
df = pd.DataFrame()

# Store the adjusted close price of the sock into the df
for stock in assets:
  df[stock] = pdr.get_data_yahoo(stock,start=stockStartDate,end=today)['Adj Close']
```

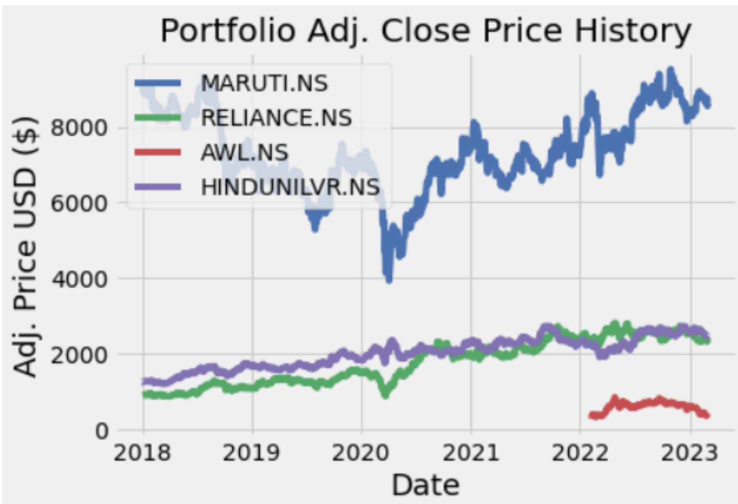
```
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
```

```
# show df
df
```

	MARUTI.NS	RELIANCE.NS	AWL.NS	HINDUNILVR.NS
Date				
2018-01-01	9150.264648	881.918213	NaN	1240.114258
2018-01-02	9057.500000	883.275330	NaN	1234.672241
2018-01-03	8927.193359	886.813721	NaN	1245.509888
2018-01-04	8898.419922	892.145447	NaN	1247.262207
2018-01-05	8943.546875	895.005188	NaN	1251.228638
...	...	...	...	...
2023-02-27	8632.200195	2367.850098	344.450012	2468.149902
2023-02-28	8624.349609	2322.550049	361.649994	2460.649902

❖ **Creating the data frame from data extraction and viewing the same**

```
title = 'Portfolio Adj. Close Price History'

# Get the stocks
my_stocks = df

# Create and plot the graph
for c in my_stocks.columns.values:
  plt.plot(my_stocks[c],label=c)

plt.title(title)
plt.xlabel('Date',fontsize=18)
plt.ylabel('Adj. Price USD ($)',fontsize=18)
plt.legend(my_stocks.columns.values,loc='upper left')
plt.show()
```



❖ From here we notice that of the 4 stocks, we have selected for designing the specific portfolio - Adani Wilmar Limited, Reliance, Maruti and Hindustan Unilever, upon plotting the graph for the adjusted closing price history, we find that Maruti has a higher margin of deviation compared to Reliance and Hindustan Unilever, that is seemingly more consistent. Adani Wilmar shows a sudden shoot up in the stocks and then a sudden drop which then becomes stagnant at the beginning of 2023.

Next, we then look at the several metrics that we use to prove our assumptions about the stocks even further.

```
# Create and show the annualized covariance matrix
cov_matrix_annual = returns.cov()*252
cov_matrix_annual
```

	MARUTI.NS	RELIANCE.NS	AWL.NS	HINDUNILVR.NS
MARUTI.NS	0.102904	0.040548	0.043245	0.028621
RELIANCE.NS	0.040548	0.098404	0.040839	0.023743
AWL.NS	0.043245	0.040839	0.379072	0.014096
HINDUNILVR.NS	0.028621	0.023743	0.014096	0.059321

```
# Calculate the portfolio variance
port_variance = np.dot(weights.T,np.dot(cov_matrix_annual,weights))
port_variance
```

```
0.06386775513666872
```

```
# Calculate the portfolio volatility aka standard deviation
port_volatility = np.sqrt(port_variance)
port_volatility
```

```
0.2527207057933099
```

```
# Calculate the annual portfolio return
portfolio_simple_annual_return = np.sum(returns.mean()*weights)*252
portfolio_simple_annual_return
```

```
0.26379913778622377
```

- **We have obtained volatility as 26% compared to the market rate.**

```
# Portfolio Optimization

# Calculate the expected returns and the annualized sample covariance matrix of asset returns
mu = expected_returns.mean_historical_return(df)
S = risk_models.sample_cov(df)

# Optimize for maximum sharpe ratio
ef = EfficientFrontier(mu,S,weight_bounds=(None,None))
ef.add_constraint(lambda w: w[0]+w[1]+w[2]+w[3] == 1)
weights = ef.max_sharpe()
cleaned_weights = ef.clean_weights()
print(cleaned_weights)
ef.portfolio_performance(verbose=True)
```

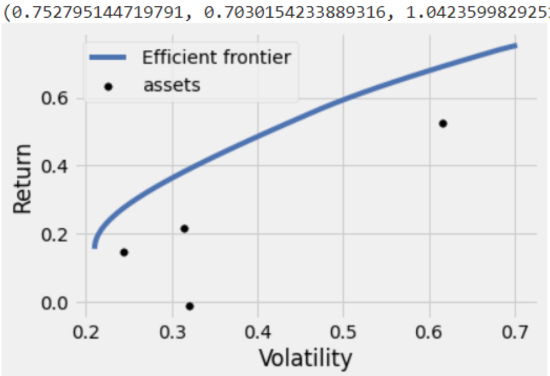
```
OrderedDict([('MARUTI.NS', -0.70412), ('RELIANCE.NS', 0.59686), ('AWL.NS', 0.42133), ('HINDUNILVR.NS', 0.68594)])
Expected annual return: 45.8%
Annual volatility: 37.7%
Sharpe Ratio: 1.16
(0.4584562823938079, 0.3768510406154081, 1.1634737207512995)
```

```
# Get the discrete allocation of each share per stock
from pypfopt.discrete_allocation import DiscreteAllocation, get_latest_prices

latest_prices = get_latest_prices(df)
weights = cleaned_weights
da = DiscreteAllocation(weights,latest_prices,total_portfolio_value = 50000)

allocation,leftover = da.lp_portfolio()
print('Discrete allocation: ',allocation)
print('Funds remaining: ${:.2f}'.format(leftover))
```

The above steps do assign weights to the portfolio, however we did calculate yet another risk ratio known as Sharpe Ratio, which we obtained as 1.16. This demonstrates an acceptable investment, for all ratios between 1 and 2 on the Sharpe scale.

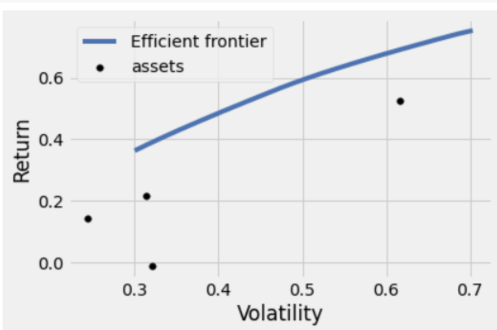
```
# Optimize for maximum sharpe ratio
ef = EfficientFrontier(mu,S,weight_bounds=(None,None))
ef.add_constraint(lambda w: w[0]+w[1]+w[2]+w[3] == 1)
plotting.plot_efficient_frontier(ef)
cleaned_weights = ef.clean_weights()
print(cleaned_weights)
ef.portfolio_performance(verbose=True)
```

```
OrderedDict([('MARUTI.NS', -1.0), ('RELIANCE.NS', 0.99867), ('AWL.NS', 1.0), ('HINDUNILVR.NS', 0.00133)])
Expected annual return: 75.3%
Annual volatility: 70.3%
Sharpe Ratio: 1.04
(0.752795144719791, 0.7030154233889316, 1.0423599829251318)
```



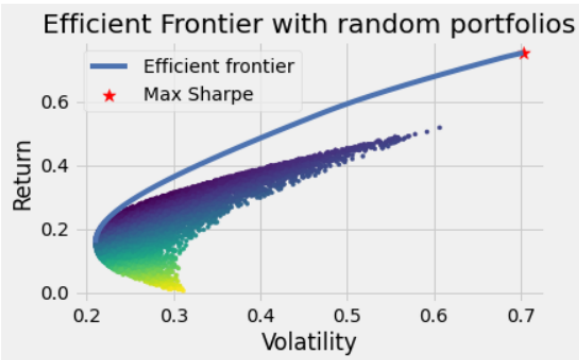
❖ The very same can be repeated for the above data. We then calculate the same for different combinations as given below.

```
# Optimize for maximum sharpe ratio
ef = EfficientFrontier(mu,S,weight_bounds=(None,None))
ef.add_constraint(lambda w: w[0]+w[1]+w[2]+w[3] == 1)
# 100 portfolios with risks between 0.10 and 0.30
risk_range = np.linspace(0.30, 0.80, 1000)
plotting.plot_efficient_frontier(ef, ef_param="risk", ef_param_range=risk_range,show_assets=True, showfig=True)

cleaned_weights = ef.clean_weights()
print(cleaned_weights)
ef.portfolio_performance(verbose=True)
```




```
OrderedDict([('MARUTI.NS', -1.0), ('RELIANCE.NS', 1.0), ('AWL.NS', 1.0), ('HINDUNILVR.NS', 0.0)])
Expected annual return: 75.3%
Annual volatility: 70.3%
Sharpe Ratio: 1.04
(0.752891681797512, 0.7031868296076523, 1.0422431862189934)
```

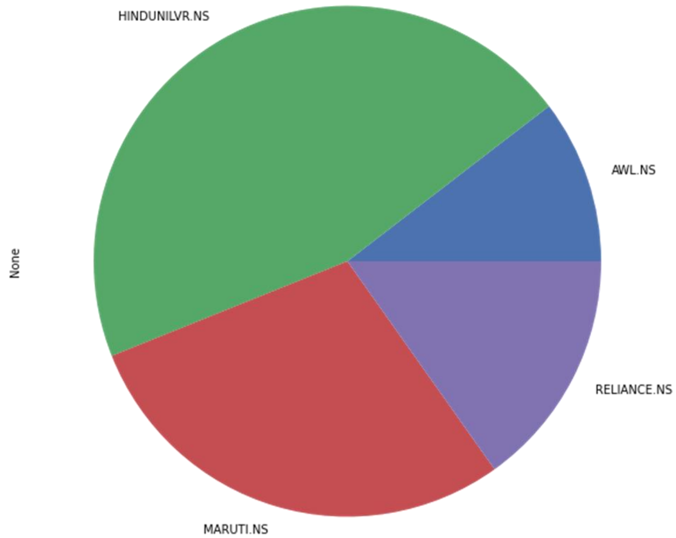
```python
ret_tangent, std_tangent, _ = ef.portfolio_performance()
ax.scatter(std_tangent, ret_tangent, marker="*", s=100, c="r", label="Max Sharpe")

# Generate random portfolios
n_samples = 10000
w = np.random.dirichlet(np.ones(len(mu)), n_samples)
rets = w.dot(mu)
stds = np.sqrt(np.diag(w @ S @ w.T))
sharpes = rets / stds
ax.scatter(stds, rets, marker=".", c=sharpes, cmap="viridis_r")

# Output
ax.set_title("Efficient Frontier with random portfolios")
ax.legend()
plt.tight_layout()
plt.savefig("ef_scatter.png", dpi=200)
plt.show()
```



- **The above diagram is a visualization for the optimal portfolio obtained using the Markowitz theory.**

```python
hrp = HRPOpt(rets)
hrp.optimize()
weights = hrp.clean_weights()
weights
```

```
OrderedDict([('AWL.NS', 0.10386),
             ('HINDUNILVR.NS', 0.45657),
             ('MARUTI.NS', 0.28806),
             ('RELIANCE.NS', 0.15151)])
```



- So here we visualize a pie chart of four companies that are AWL, Hindustan Unilever, Maruti and Reliance.
- Before this we used the optimize function.
- And based on the results from that we provide weights for each company In such a way that we get maximum profit.
- Here the highest weight is given to Hindustan Unilever after that Maruti followed by Reliance and AWL.

<u>Expected returns of the stocks of AWL, HINDUNILVR, MARUTI and RELIANCE</u>

```
from pypfopt import expected_returns

rets = expected_returns.returns_from_prices(prices)
rets.tail()
```

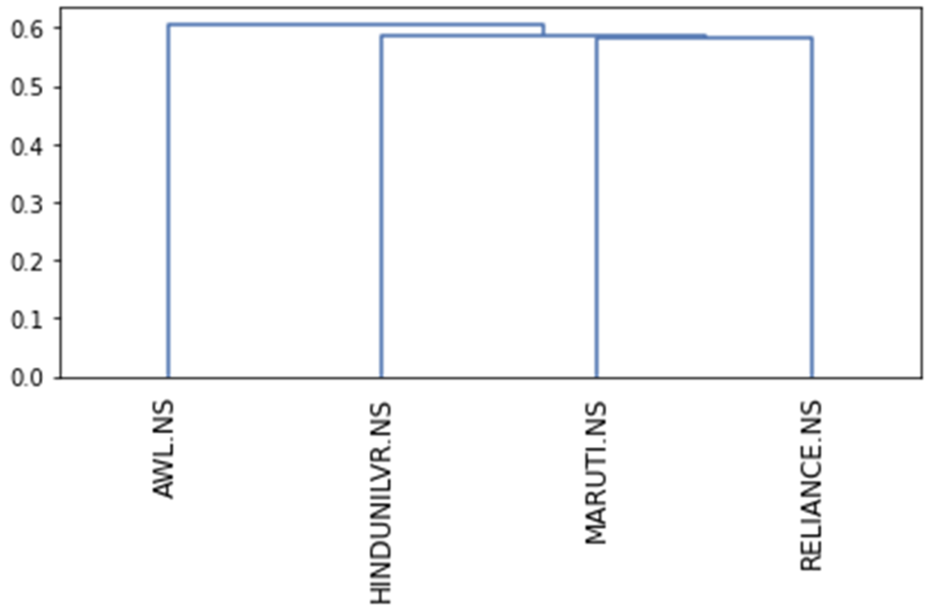
Date	AWL.NS	HINDUNILVR.NS	MARUTI.NS	RELIANCE.NS
2023-02-27	-0.049924	-0.006461	-0.003268	-0.006649
2023-02-28	0.049935	-0.003039	-0.000909	-0.019131
2023-03-01	0.049910	0.002276	0.016210	0.009192
2023-03-02	0.049908	-0.004420	-0.024577	-0.007615
2023-03-03	0.049918	0.006374	0.006141	0.025515

Here we find the expected returns of all four companies from the prices column for every record.

<u>Dendrogram based on the hierarchical structure of asset returns</u>

```
hrp.portfolio_performance(verbose=True);
```

```
Expected annual return: 27.7%
Annual volatility: 24.0%
Sharpe Ratio: 1.07
```



Here we see that Maruti and Reliance cluster together first hence showing more similarity between these two companies.

Then Hindustan Unilever clusters with these two companies and in the end AWL clusters with other companies
This is based on asset returns hence we find that Maruti and Reliance show similar asset returns. While the other two companies vary in that.

When investing in a portfolio that includes stocks of companies such as Hindustan Unilever, Maruti, Reliance, and Adani Wilmar, it is essential to consider the overall risk and reward profile. One way to achieve this is through diversification, which involves spreading the investment across multiple companies and sectors. Diversification can help minimize the risk of loss due to market fluctuations or company-specific events.

CONCLUSION

In conclusion, by using modern portfolio theory, quantitative methods, and diversification, investors can create portfolios that are tailored to their unique needs and risk tolerance. However, portfolio optimization requires ongoing monitoring and adjustment to ensure that the portfolio remains aligned with the investor's goals and market conditions. By taking a disciplined approach to portfolio optimization, investors can achieve long-term success and build wealth over time. Portfolio optimization is a crucial aspect of investment management, which involves the selection of the right combination of assets to minimize risk and maximize returns. In this context, the use of stocks of companies such as Hindustan Unilever, Maruti, Reliance, and Adani Wilmar can provide investors with a diversified portfolio that balances risk and reward.

Another important aspect of portfolio optimization is asset allocation, which involves determining the right mix of stocks, bonds, and other assets based on the investor's risk appetite and investment objectives. Investors with a high-risk tolerance may prefer to allocate a higher percentage of their portfolio to stocks, while those with a lower risk tolerance may prefer a higher allocation to bonds. In conclusion, portfolio optimization using stocks of companies such as Hindustan Unilever, Maruti, Reliance, and Adani Wilmar can provide investors with a diversified portfolio that balances risk and reward. However, it is essential to consider factors such as overall risk profile, asset allocation, and diversification when investing in such a portfolio. By taking a disciplined approach to investment management, investors can maximize their chances of achieving their long-term investment objectives.

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