Report On Portfolio Optimization Model Using Monte Carlo Simulation:

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Introduction:

Portfolio optimization is a critical task for investors aiming to maximize returns while managing risks. Traditional methods often use historical data and statistical techniques to construct optimal portfolios. Modern Portfolio Theory (MPT), a hypothesis put forth by Harry Markowitz in his paper "Portfolio Selection," (published in 1952 by the Journal of Finance) is an investment theory based on the idea that risk-averse investors can construct portfolios to optimize or maximize expected return based on a given level of market risk, emphasizing that risk is an inherent part of higher reward. It is one of the most important and influential economic theories dealing with finance and investment. Monte Carlo Simulation (MCS) has emerged as a powerful tool for portfolio optimization. MCS helps in simulating various market scenarios, allowing investors to make informed decisions. This report explores the application of Monte Carlo Simulation in portfolio optimization, analysing its benefits and limitations.

Monte Carlo Simulation (MCS):

Monte Carlo simulation is a computational technique used to model and analyze complex systems and processes through random sampling. It is named after the famous casino city, Monte Carlo, because of the element of chance and randomness involved in the method.

Key concepts of MCS are:

1. Simulation Technique:

Monte Carlo simulation involves using random sampling methods to obtain numerical results for problems that might be deterministic in principle. By using random numbers, it simulates the behavior of a system over time.

2. Random Sampling:

Random numbers are generated to represent uncertain or variable inputs in a mathematical model. These inputs can be anything from market prices and project timelines to physical constants and other quantitative factors.

3. Probability Distributions: The simulation incorporates probability distributions to represent the uncertainty associated with input variables. Common distributions include normal, uniform, and triangular distributions, depending on the nature of the uncertainty.

4. Modeling Complex Systems:

Monte Carlo simulation is particularly useful for modeling complex systems where many variables interact. It is widely used in finance, engineering, physics, and other fields to analyze and optimize processes and predict outcomes.

5. Numerical Estimations:

Through repeated random sampling, Monte Carlo simulation provides numerical estimations of system behavior. This could be the average output, the probability of an event occurring, or the range of possible outcomes.

6. Applications:

- Finance: Assessing investment risks, options pricing, and portfolio optimization.
- Engineering: Analyzing structural integrity, fluid dynamics, and reliability of systems.
- Statistics: Estimating population parameters and conducting hypothesis testing.
- Project Management: Evaluating project timelines, costs, and risks.
- Science: Modeling physical processes, predicting outcomes of experiments, and analyzing complex biological systems.

7. Advantages:

- Provides insights into complex systems without the need for analytical solutions.
- Captures uncertainty and variability in input parameters.
- Flexible and applicable to a wide range of problems.

8. Limitations:

- Requires a large number of random samples for accurate results.
- Can be computationally intensive for complex models.
- Results are as good as the quality of the input data and assumptions made in the model.

In summary, Monte Carlo simulation is a powerful tool for decision-making and risk analysis in various fields. It helps in understanding the probable outcomes of complex systems by incorporating randomness and uncertainty, making it an indispensable method for professionals dealing with intricate, unpredictable scenarios.

Monte Carlo Simulation for Optimization Search:

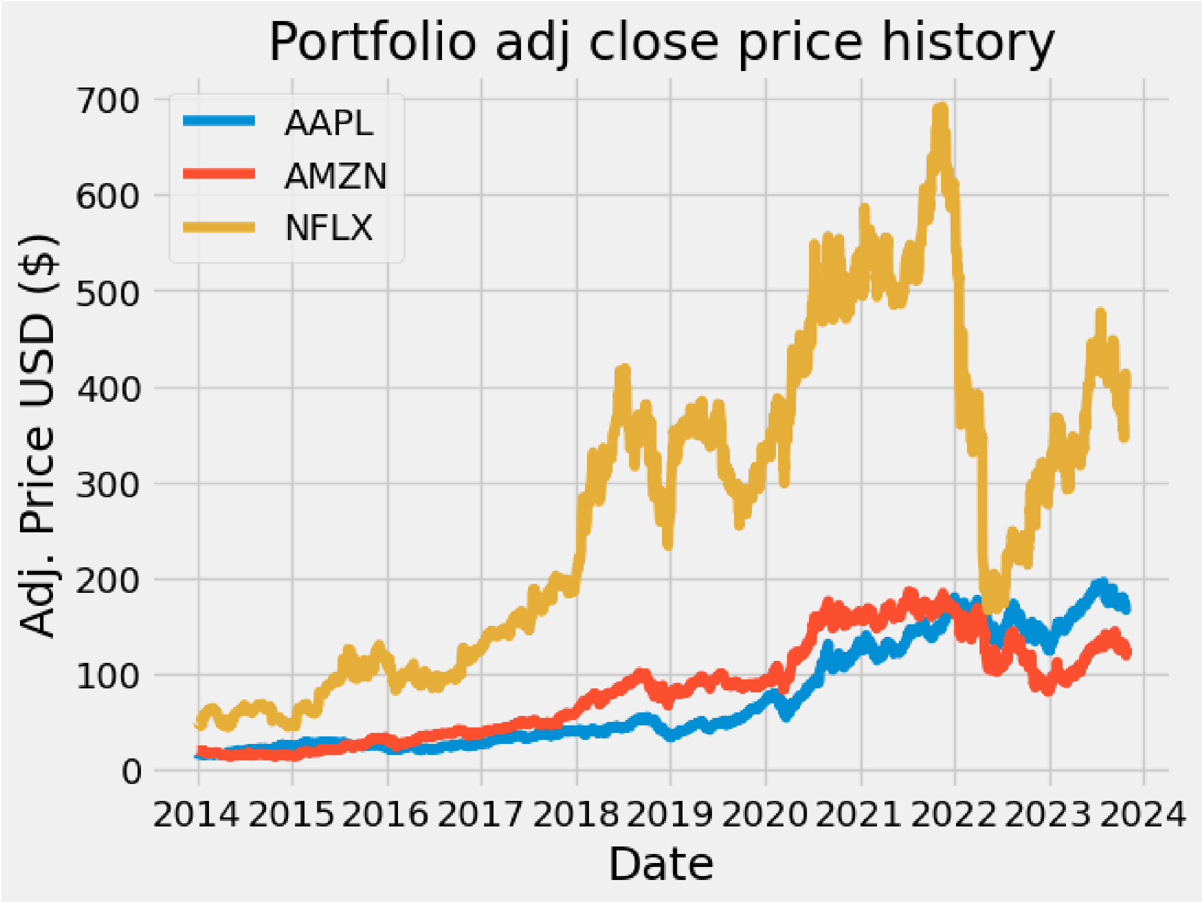
We could randomly try to find the optimal portfolio balance using Monte Carlo simulation.

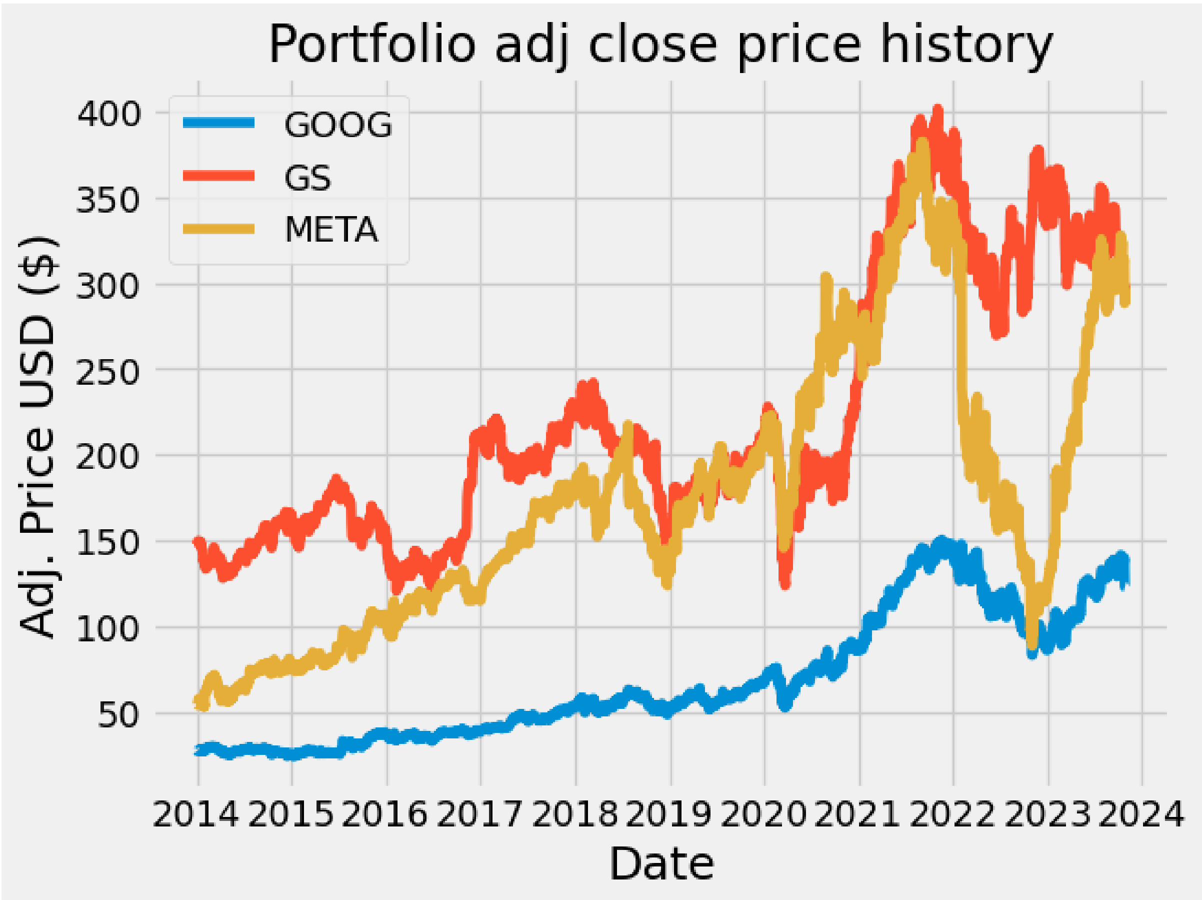
Procedure:

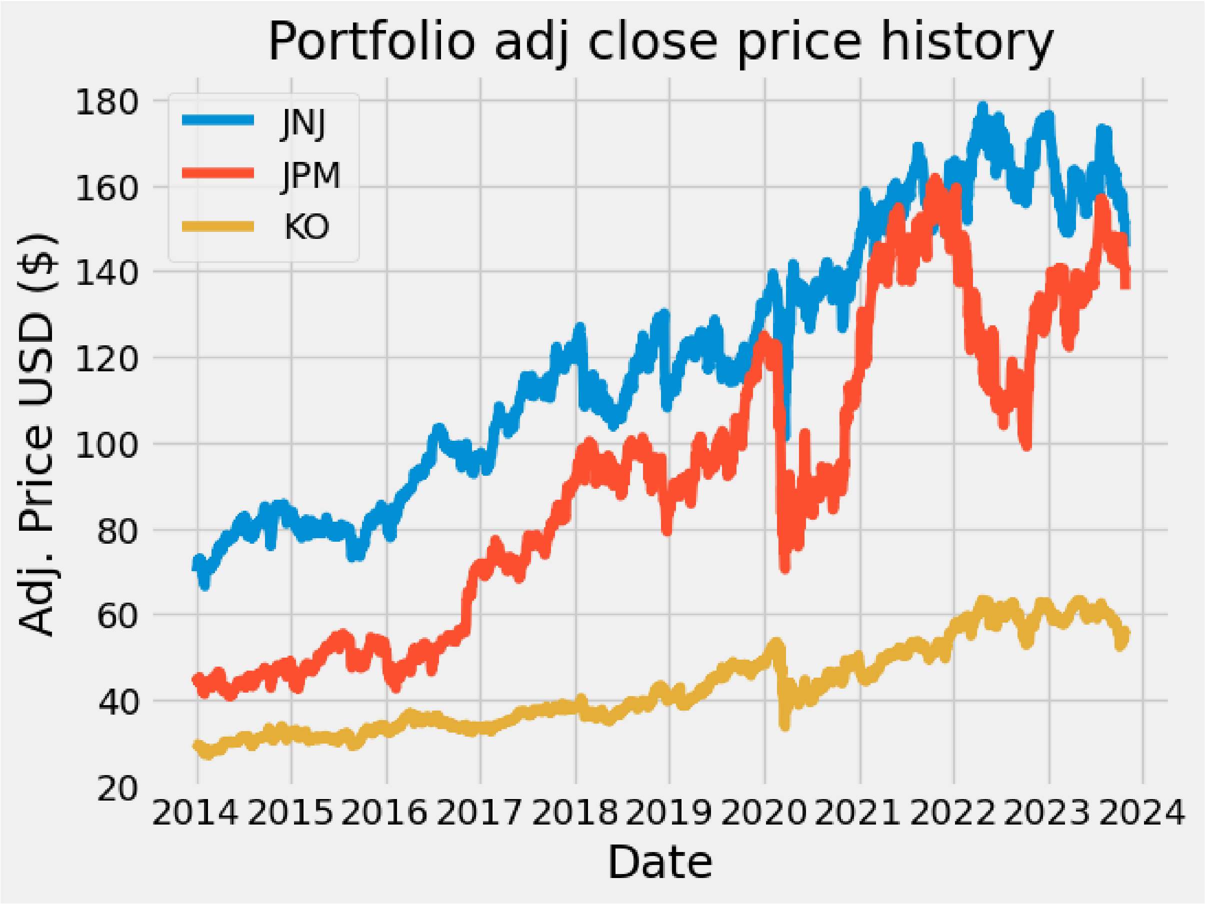
1. Made four different portfolios with three stocks each and got their daily returns data from web.
   Portfolios made are:
      1. Amazon , Apple , Netflix
      2. Google , Meta , Goldman Sachs
      3. JP Morgan , Johnson & Johnson , Coco Cola
      4. Microsoft , Accenture , Meta

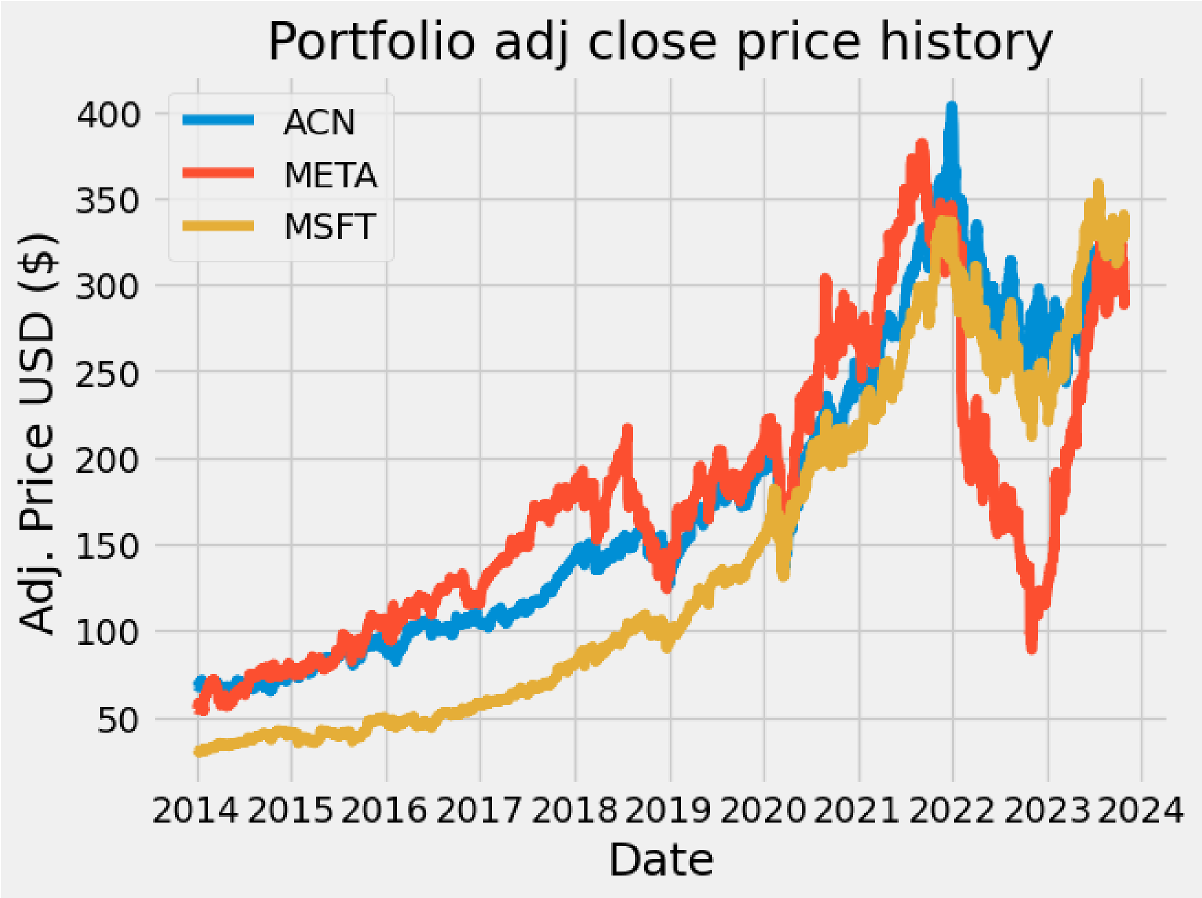
2. Calculated mean daily returns, percent change in stocks and correlation between them for each portfolio.
   Mean daily returns:
      1. AAPL 0.001081 AMZN 0.000972 NFLX 0.001231
      2. GOOG 0.000760 GS 0.000430 META 0.000969
      3. JNJ 0.000362 JPM 0.000598 KO 0.000314
      4. ACN 0.000703 META 0.000969 MSFT 0.001099
3. Simulated thousands of possible allocations.

4. Plotted graphs for Portfolio Adj. Close Price History.


Portfolio adj close price history
AAPL
AMZN
NFLX
Adj. Price USD ($)
0
100
200
300
400
500
600
700
2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024
Date

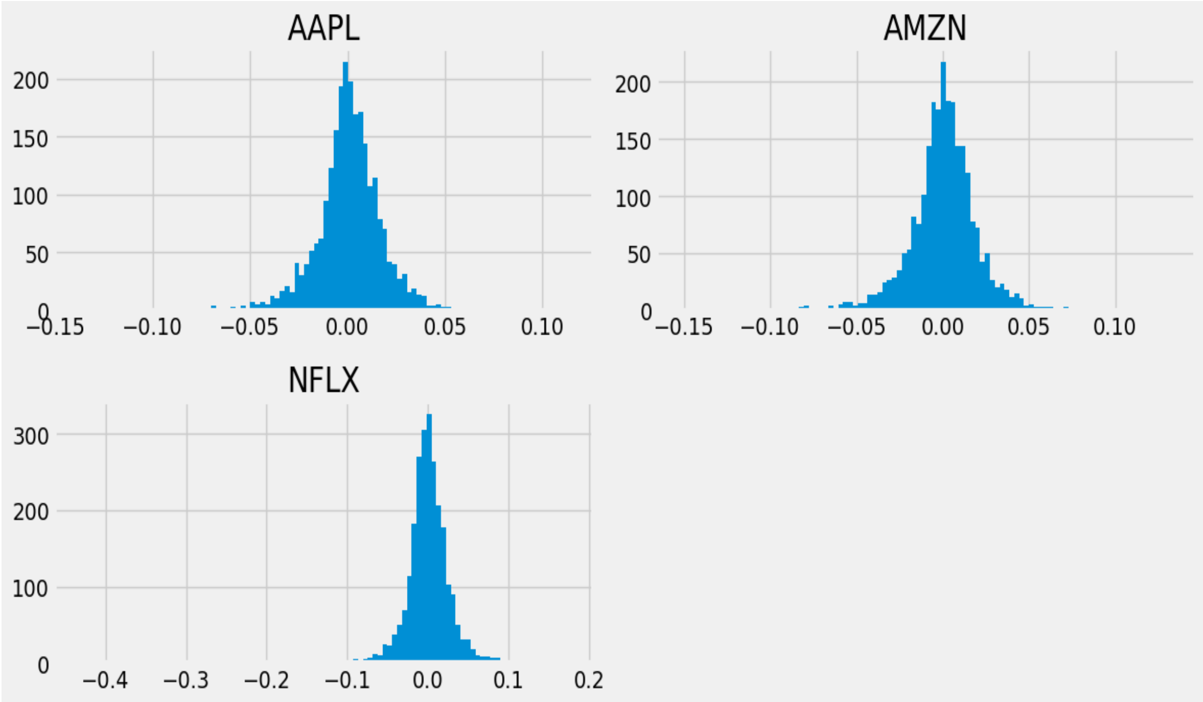

Portfolio adj close price history
GOOG
GS
META
Adj. Price USD ($)
50
100
150
200
250
300
350
400
2014 2015 2016 2017 2018 2019 2020 2021 2022 2023 2024
Date

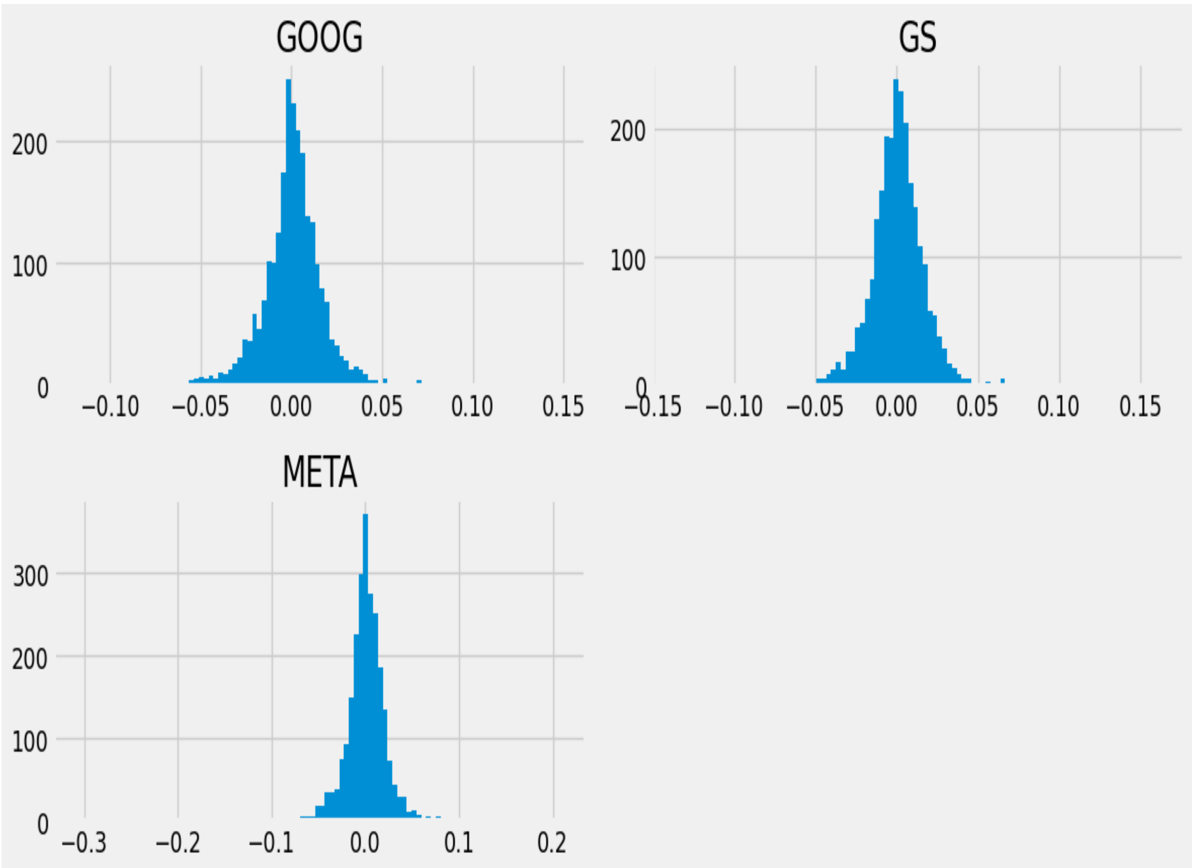

Portfolio adj close price history
JNJ
JPM
KO
Adj. Price USD ($)
180
160
140
120
100
80
60
40
20
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
Date

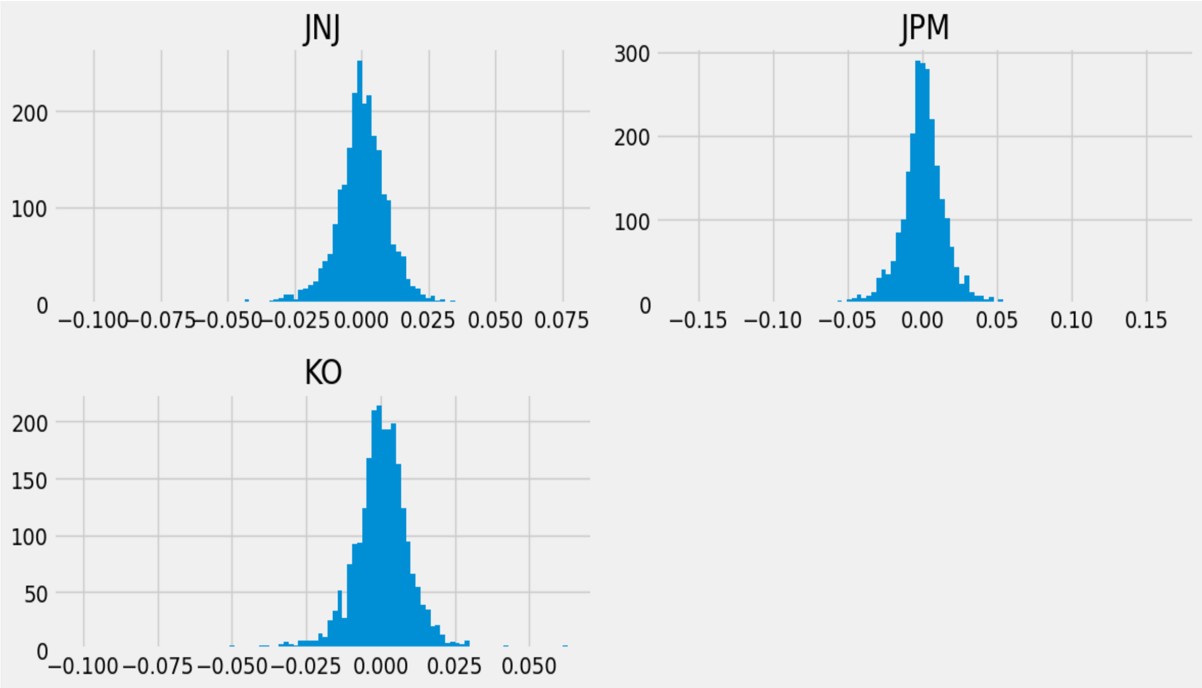


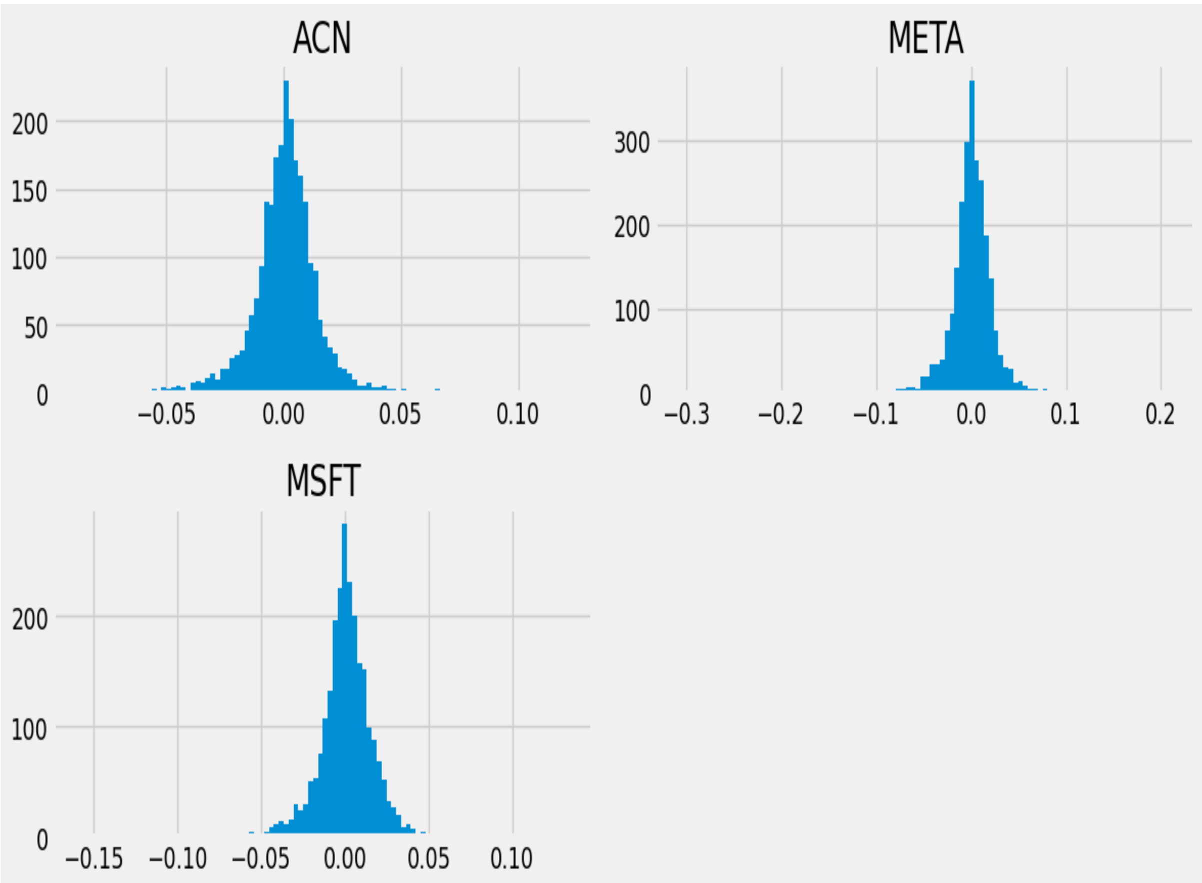
<u>We will now switch over to using log returns instead of arithmetic returns. Most technical analyses require detrending/normalizing the time series and using log returns is a nice way to do that.</u>

5. Computed log returns, its mean, pairwise covariance of columns and multiplied it by number of days (i.e. 252)


AAPL
AMZN
NFLX
0
50
100
150
200
300
−0.15
−0.10
−0.05
0.00
0.05
0.10
−0.4
−0.3
−0.2
−0.1
0.0
0.1
0.2


GOOG
GS
META
0
100
200
300
−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15
−0.3
−0.2
−0.1
0.0
0.1
0.2


JNJ
JPM
KO
0
100
200
300
−0.100
−0.075
−0.050
−0.025
0.000
0.025
0.050
0.075
−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15
50
150


ACN
META
MSFT
0
50
100
150
200
300
−0.05
0.00
0.05
0.10
−0.3
−0.2
−0.1
0.0
0.1
0.2
−0.15
−0.10

Mean log returns:

1. AAPL ; 0.231629 AMZN : 0.189546 NFLX : 0.207770
2. GOOG : 0.152212 GS : 0.68556 META : 0.172361
3. JNJ : 0.074813 JPM : 0.114069 KO : 0.062789
4. ACN : 0.147677 META : 0.172361 MSFT : 0.239886

6. We then ran it for some random allocation and then again did it many times.

7. Created random weights, rebalanced and saved them.

8. Calculated expected return, expected volatility and Sharpe ratio.

Expected Portfolio return:

1. 0.209491650398994170
2. 0.10993143233757413
3. 0.09458764070741771
4. 0.1626577032673327

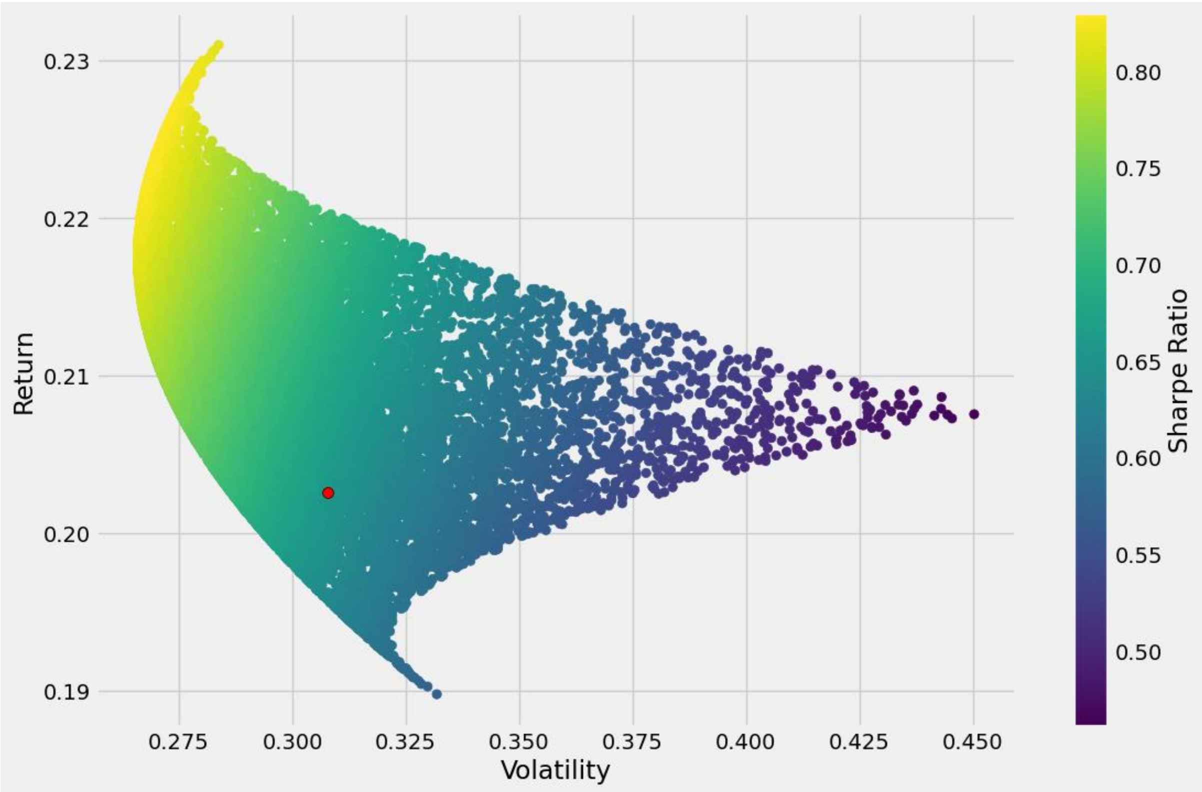
Expected Volatility

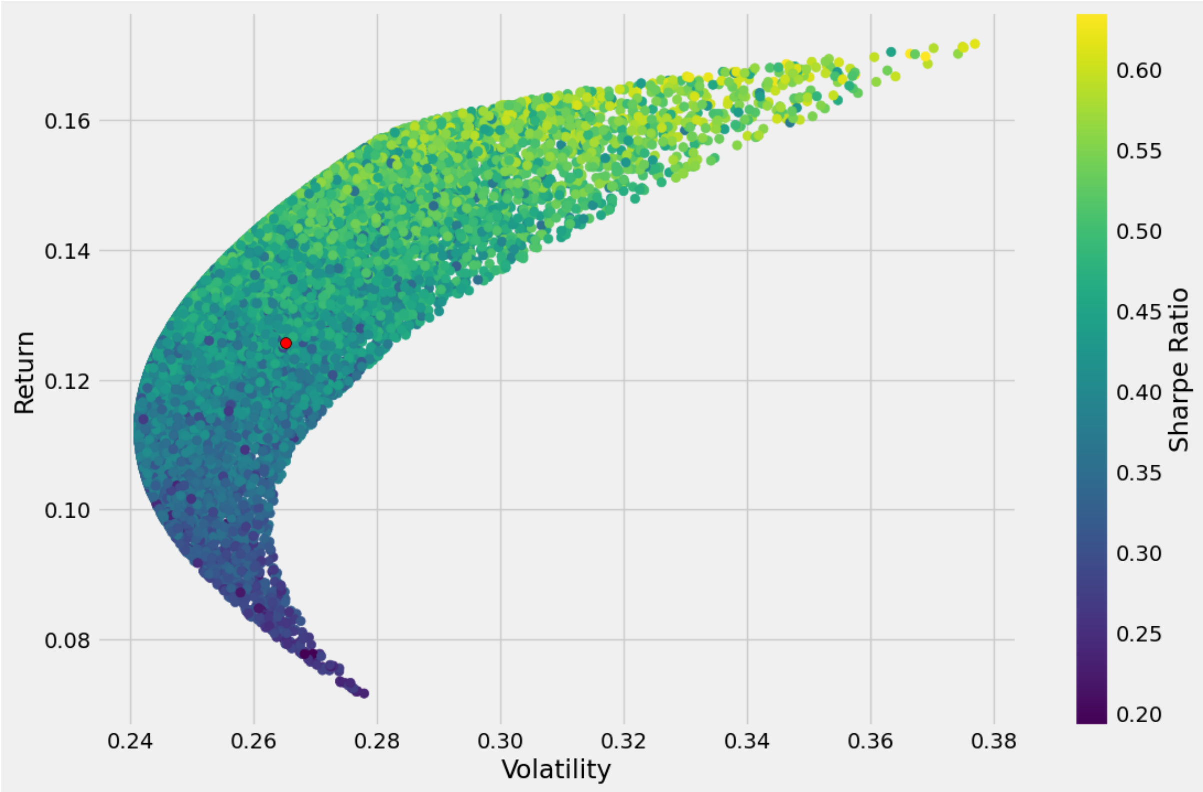
1. 0.2725684960762145
2. 0.24145310264261208
3. 0.19187411176677283
4. 0.2723362768863687

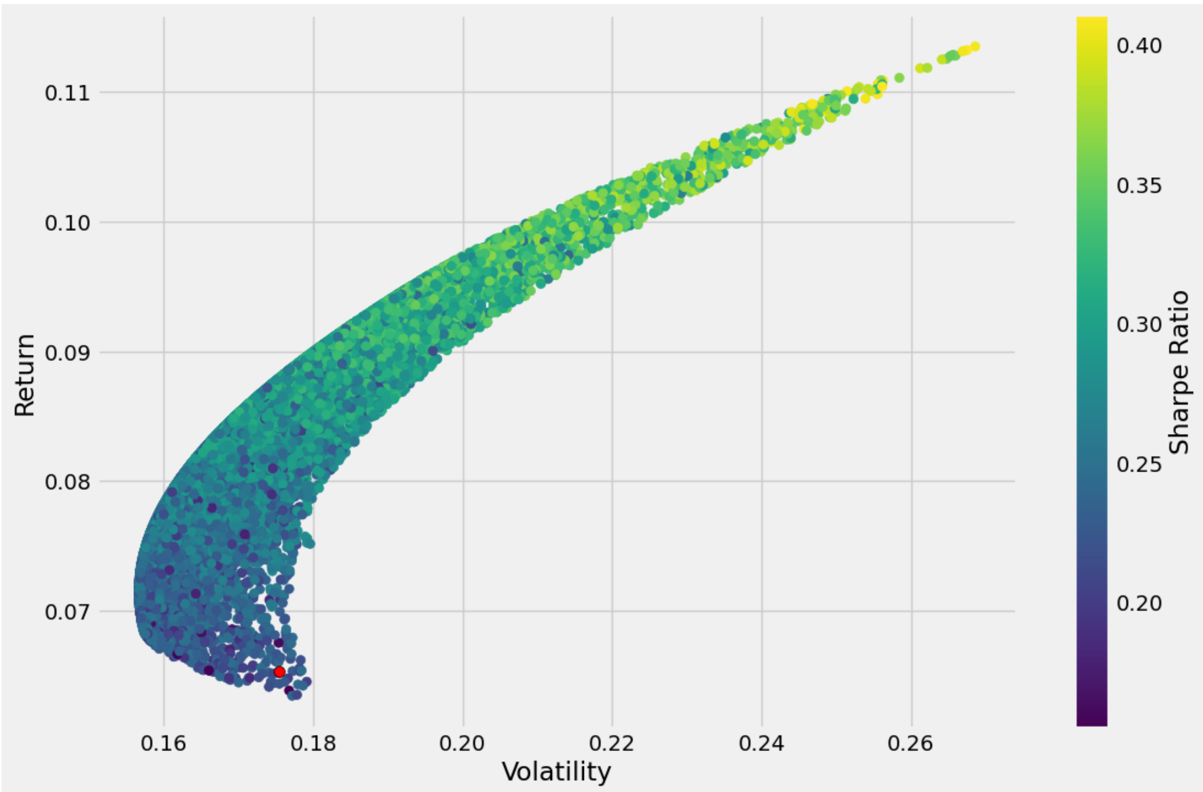
Sharpe ratio:

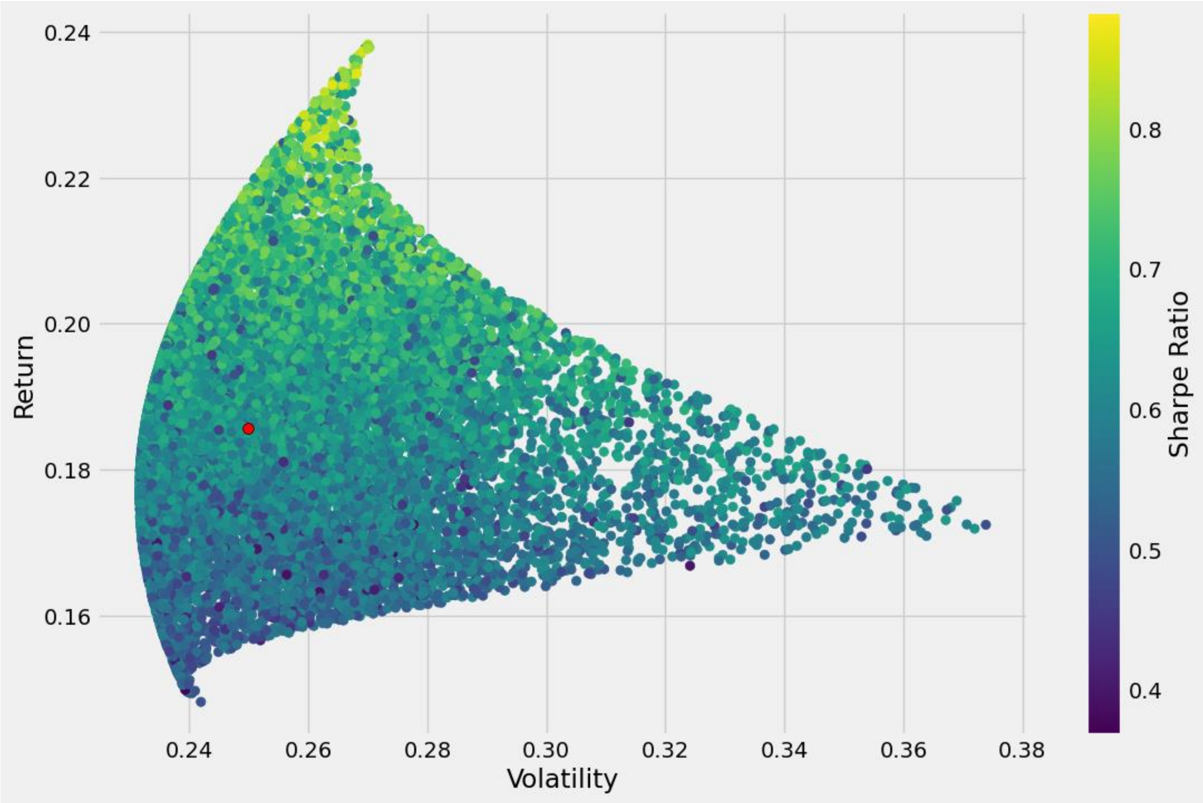
1. 0.768583506218624
2. 0.4552910322311726
3. 0.49296718476743256
4. 0.597267852549813

1. Plotted the graph between returns and volatility.




Return
Volatility
Sharpe Ratio
0.16
0.14
0.12
0.10
0.08
0.24
0.26
0.28
0.30
0.32
0.34
0.36
0.38
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20


Return
Volatility
Sharpe Ratio
0.11
0.10
0.09
0.08
0.07
0.16
0.18
0.20
0.22
0.24
0.26
0.40
0.35
0.30
0.25
0.20

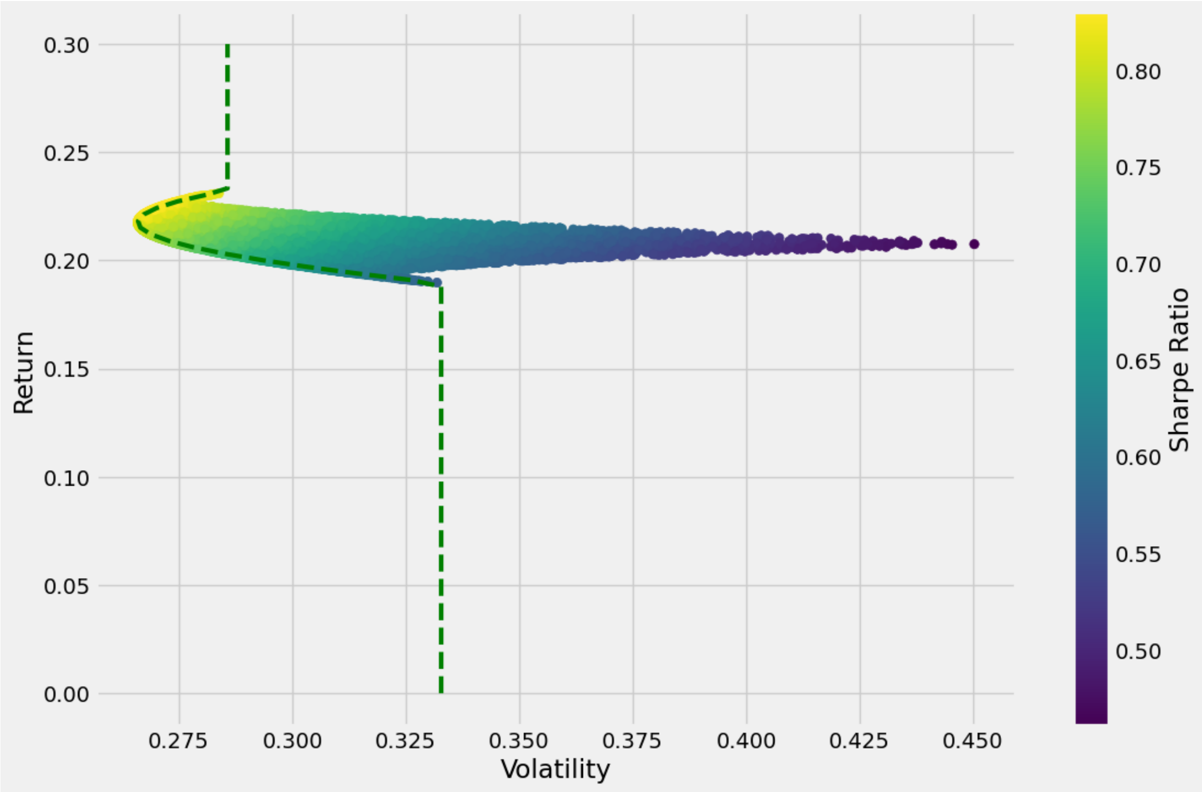


There are much better ways to find good allocation weights than just guess and check! We can use optimization functions to find the ideal weights mathematically!
Optimization works as a minimization function, since we actually want to maximize the Sharpe Ratio, we will need to turn it negative so we can minimize the negative Sharpe (same as maximizing the positive Sharpe)

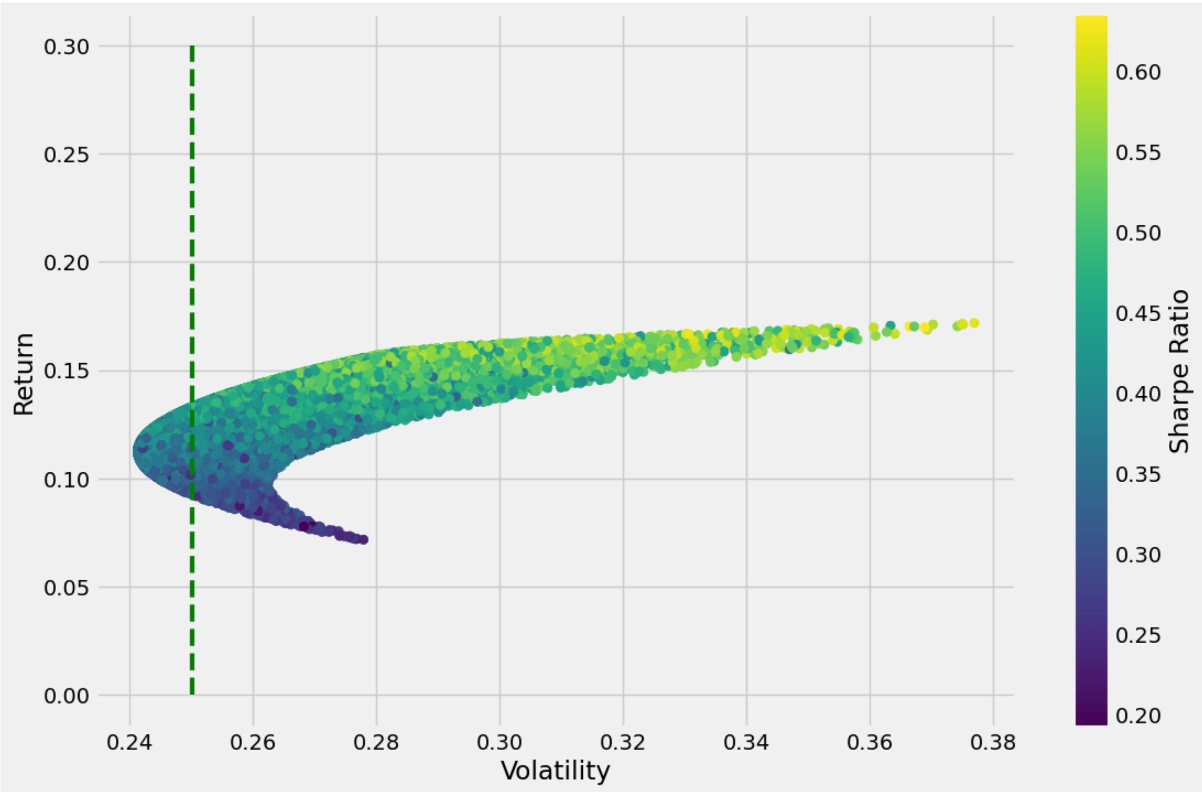
2. Calculated the optimal results using SLSQP method of minimize function.

3. Made all optimal portfolios (Efficient Frontier) and plotted the graph between return and volatility.

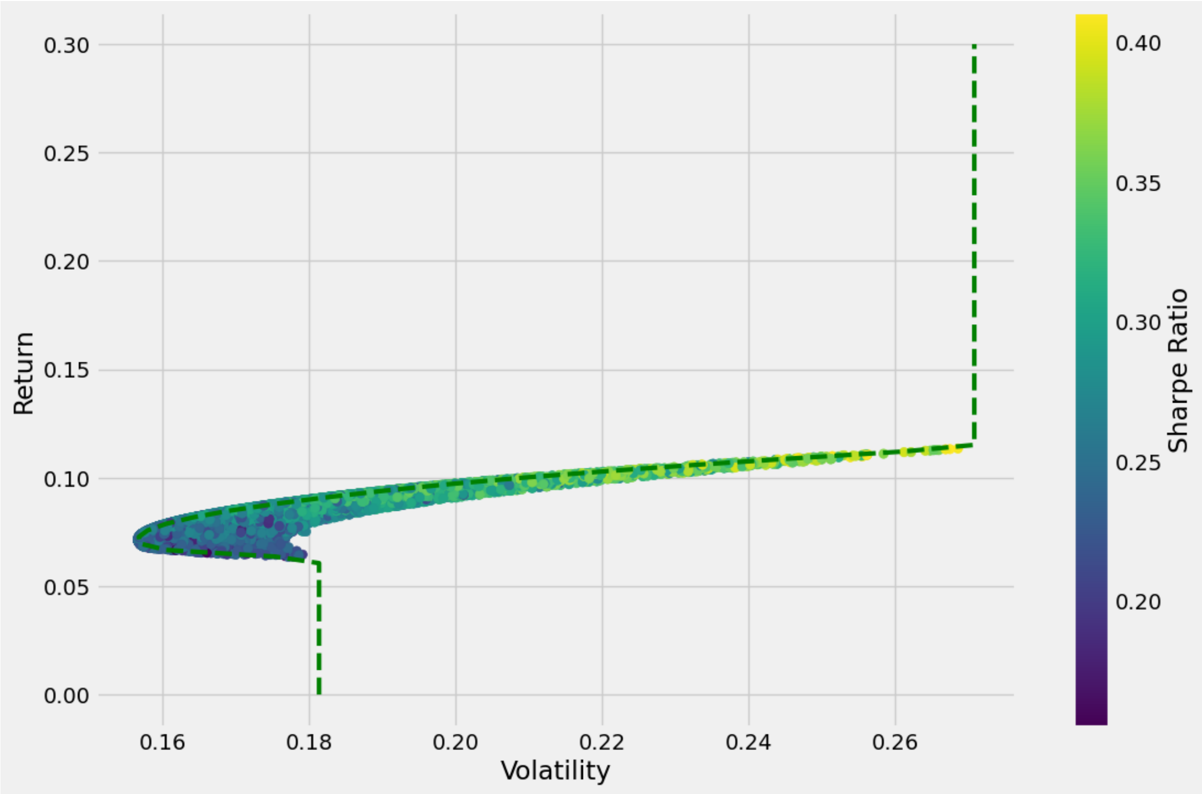
The efficient frontier is the set of optimal portfolios that offers the highest expected return for a defined level of risk or the lowest risk for a given level of expected return. Portfolios that lie below the efficient frontier are sub-optimal, because they do not provide enough return for the level of risk. Portfolios that cluster to the right of the efficient frontier are also sub-optimal, because they have a higher level of risk for the defined rate of return.

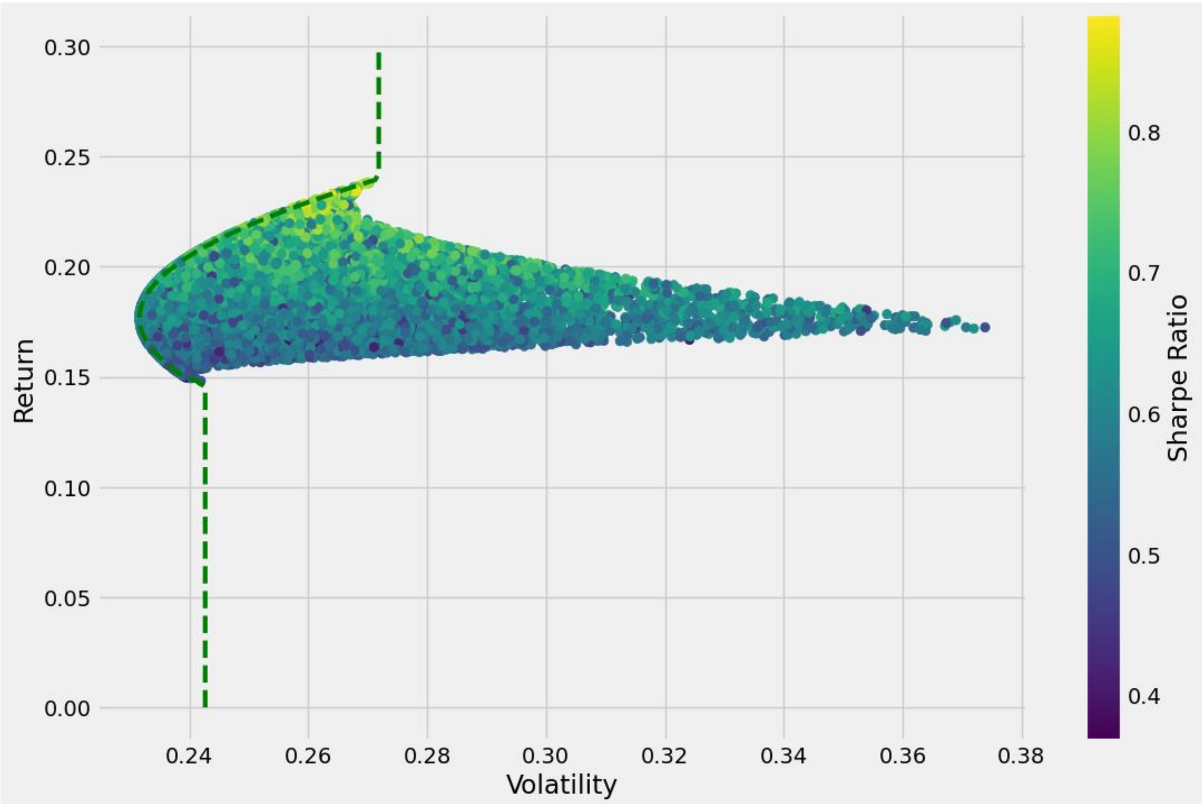


0.30
0.25
0.20
0.15
0.10
0.05
0.00
Return
0.275
0.300
0.325
0.350
0.375
0.400
0.425
0.450
Volatility
0.80
0.75
0.70
0.65
0.60
0.55
0.50
Sharpe Ratio



0.30
0.25
0.20
0.15
0.10
0.05
0.00
Return
0.24
0.26
0.28
0.30
0.32
0.34
0.36
0.38
Volatility
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
Sharpe Ratio


0.30
0.25
0.20
0.15
0.10
0.05
0.00
Return
0.16
0.18
0.20
0.22
0.24
0.26
Volatility
0.40
0.35
0.30
0.25
0.20
Sharpe Ratio


0.30
0.25
0.20
0.15
0.10
0.05
0.00
Return
0.24
0.26
0.28
0.30
0.32
0.34
0.36
0.38
Volatility
0.8
0.7
0.6
0.5
0.4
Sharpe Ratio

Conclusion:

Monte Carlo Simulation provides a powerful framework for portfolio optimization, enabling investors to make more informed decisions in the face of uncertainty. By simulating a wide range of market scenarios, investors can gain insights into the potential risks and rewards associated with different investment strategies. However, it is crucial to recognize the limitations and challenges associated with MCS and to use it in conjunction with other analytical tools and qualitative judgment for robust portfolio construction. As financial markets continue to evolve, the application of Monte Carlo Simulation is expected to play an increasingly important role in the field of portfolio management.