# Portfolio Optimization

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## Introduction

This report details a portfolio optimization project aimed at identifying optimal stock weightings to maximize risk-adjusted returns, specifically using the Sharpe Ratio and a Monte Carlo Simulation. The project analyses historical stock data of high market cap stocks from various sectors to provide insights on the weightings of a portfolio that should be invested into each sector.

## Methodology

The core of this project involves several key steps:

1. **Data Acquisition**: Historical adjusted closing prices for a selection of stocks across different sectors are downloaded using the yfinance library.
2. **Data Preprocessing**: Daily logarithmic returns are calculated from the adjusted closing prices. This transformation is crucial for financial analysis as it normalizes returns and makes them additive over time.
3. **Descriptive Statistics and Visualization**: Various plots are generated to visualize the raw stock data, daily returns, annual mean returns, and daily standard deviations. A correlation matrix is also computed and visualized to understand the relationships between stock returns.
4. **Monte Carlo Simulation for Portfolio Generation**: A large number of random portfolios (10,000 in this case) are generated. For each portfolio, random weights are assigned to the selected stocks, and then normalized so their sum equals 1. The expected annual return, expected volatility (standard deviation), and Sharpe Ratio are calculated for each simulated portfolio
5. **Optimization**: The project employs scipy.minimize to find the portfolio that yields the maximum Sharpe Ratio. Constraints are applied to ensure that individual stock weights are within a specified range (0.02 to 0.25 in this case), preventing over concentration in any single asset.
6. **Results Visualization**: The simulated portfolios and the optimized portfolio are plotted on an Efficient Frontier graph, which visually represents the trade-off between risk and return. Finally, a bar chart illustrates the optimized sector allocation.

## Code Overview

Key libraries used include

* yfinance for data
* Matplotlib and seaborn for visualization
* Pandas for data
* Numpy for numerical operations
* Fredapi for the risk-free rate
* mpf
* Scipy for the portfolio optimization

## Stock Selection

The stocks selected were chosen based on their large market cap in the following sectors : Tech, healthcare, finance, energy and consumer discretionary.

## Daily Close

Daily Close Price allows us to see the growth of the company over time, volatility through price fluctuations and how the general market sentiment changes over time.

A graph of stock prices

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## Correlation Heatmap

A screenshot of a graph

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This heatmap visualizes the pairwise correlation between daily log returns of the selected stocks. A lower correlation between assets means their prices do not move in tandem, which enhances diversification. Diversified portfolios tend to have lower total volatility, as negative movements in one asset can be offset by gains in another. This reduction in overall risk is one of the core principles of modern portfolio theory.

## Mean Return and Volatility Bar plots

A graph of stock market data

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A graph of blue bars

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The comparison of annual mean log returns with daily standard deviation provides insight into the risk-return trade-off across sectors. NVIDIA (NVDA) delivered the highest return, but it also had the greatest volatility. Meta (META) and JPMorgan (JPM) offered strong returns with relatively moderate volatility, suggesting efficient risk-adjusted performance. In contrast, Nike (NKE) and Pfizer (PFE) not only underperformed in returns but also had elevated volatility levels, making them less attractive from a return-to-risk perspective. Johnson & Johnson (JNJ) and Chevron (CVX) had the lowest volatility, but this stability came with minimal return, highlighting their role as potential defensive holdings rather than growth drivers.

## Monte Carlo Simulation and Optimization:

A diagram of a red blue and white dotted diagram

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This efficient frontier plot visualizes the trade-off between annual return and risk (standard deviation) for the thousands of randomly weighted portfolios. The colour gradient represents the Sharpe Ratio portfolios in deep red offer superior risk-adjusted returns.

* **Maximum Sharpe Ratio Portfolio (Blue Star)**: This point represents the portfolio with the highest Sharpe Ratio, indicating the best risk-adjusted return. It is often considered the optimal portfolio for investors seeking to maximize return per unit of risk.
* **Minimum Volatility Portfolio (Green Star)**: This point represents the portfolio with the lowest overall risk (volatility). While it minimizes risk, it does not offer strong returns.
* **Optimized Portfolio (Orange Star)**: This point shows the result of the optimization process, which aims to find the portfolio with the highest Sharpe Ratio given the defined constraints (Maximum stock weighting of 25%)

## Recommended Sector Weighting

A graph of a bar chart

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It is important to note that a weighting constraint of 25% maximum allocation and 0% minimum allocation (to stop shorting) was applied to the stocks.

The portfolio optimizer allocated 50% of the weight to the Tech sector, which reflects the strong performance of stocks like NVIDIA and Meta. These stocks had some of the highest annual log returns in my analysis. Although they also exhibited higher standard deviations, the optimizer clearly valued their strong return-to-risk profile, which contributed to a higher Sharpe ratio.

Finance received a 30% allocation, likely due to stocks like JPMorgan offering a balance of respectable returns and lower volatility. In the standard deviation graph, finance stocks were among the most stable, supporting their selection as a lower-risk anchor in the portfolio.

The optimizer assigned 20% to Healthcare, likely recognizing the low volatility of stocks like JNJ and PFE. Even though their returns were modest, they likely added diversification and helped reduce overall portfolio risk.

Energy and Consumer stocks were given 0% weight. This is likely because, based on the earlier return and standard deviation plots, they either underperformed or were too volatile relative to their return, thus contributing little to the Sharpe ratio