Experiment 2

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Aim: Implementation of Modern Portfolio Theory (Efficient frontier) on a given dataset.

Objective:

- Understand the basic principles of Modern Portfolio Theory (MPT).
- Calculate the expected return and risk of a portfolio of assets.
- Construct an efficient frontier of portfolios.
- Analyze the implications of MPT for portfolio selection.

Theory:

Modern Portfolio Theory (MPT) is a mathematical framework for constructing portfolios that maximize expected return for a given level of risk. The theory was developed by Harry Markowitz in the 1950s, and it has become a cornerstone of modern investment theory.

The key idea of MPT is diversification. By investing in a diversified portfolio of assets, investors can reduce the overall risk of their portfolio without sacrificing too much expected return. This is because the risk of a portfolio is not simply the sum of the risks of the individual assets in the portfolio. Instead, the risk of a portfolio is determined by the correlation between the assets in the portfolio.

The efficient frontier is a graph that shows all the portfolios that offer the highest possible expected return for a given level of risk. The efficient frontier is a theoretical construct, but it can be approximated using real-world data.

MPT is based on the following assumptions:

- Investors are risk-averse. This means that they prefer portfolios with higher expected returns to portfolios with lower expected returns, all else being equal.
- Investors can only estimate expected returns and risk. This means that they do not know for certain what the future returns of their investments will be.
- Investors can choose any combination of assets they want. This means that there are no restrictions on the types of assets that investors can include in their portfolios.

MPT uses the following formula to calculate the expected return of a portfolio:

$$gE(R) = w1*E(R1) + w2*E(R2) + ... + wn*E(Rn)$$

where:

- E(R) is the expected return of the portfolio
- w1, w2, ..., wn are the weights of the assets in the portfolio
- E(R1), E(R2), ..., E(Rn) are the expected returns of the individual assets

MPT uses the following formula to calculate the risk of a portfolio:

$$\sigma(R) = \sqrt{(w1^2*\sigma1^2 + w2^2*\sigma2^2 + ... + wn^2*\sigma n^2 + 2*w1*w2*\rho12*\sigma1*\sigma2)}$$

where:

- σ(R) is the risk of the portfolio
- σ1, σ2, ..., σn are the standard deviations of the individual assets
- ρ12 is the correlation coefficient between assets 1 and 2

The efficient frontier is a graph that shows all the portfolios that offer the highest possible expected return for a given level of risk. The efficient frontier is a theoretical construct, but it can be approximated using real-world data.

The efficient frontier is a powerful tool for portfolio selection. It can be used to identify the portfolios that offer the best combination of expected return and risk.

Here are some additional insights about MPT:

- The efficient frontier is not a straight line. This is because the risk of a portfolio is not simply the sum of the risks of the individual assets in the portfolio. Instead, the risk of a portfolio is determined by the correlation between the assets in the portfolio.
- The efficient frontier is upward-sloping. This means that portfolios with higher expected returns also have higher risks.
- The efficient frontier is not unique. There are many different efficient frontiers, each of which is associated with a different level of risk aversion.

<u>Lab Experiment to be done by students:</u>

1. Download a dataset of historical stock prices.
2. Calculate the expected return and risk of each stock in the dataset.
3. Construct an efficient frontier of portfolios using the stocks in the dataset.
4. Analyze the implications of MPT for portfolio selection

[1]
```
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

[2]
```
tickers = ['AAPL', 'MSFT', 'GOOGL', 'AMZN', 'TSLA']
```

```
data = yf.download(tickers, start="2019-01-01", end="2024-01-01")['Adj Close']
```

```
[*********************100%***********************]  5 of 5 completed
```

[4]
```
returns = data.pct_change().dropna()
```

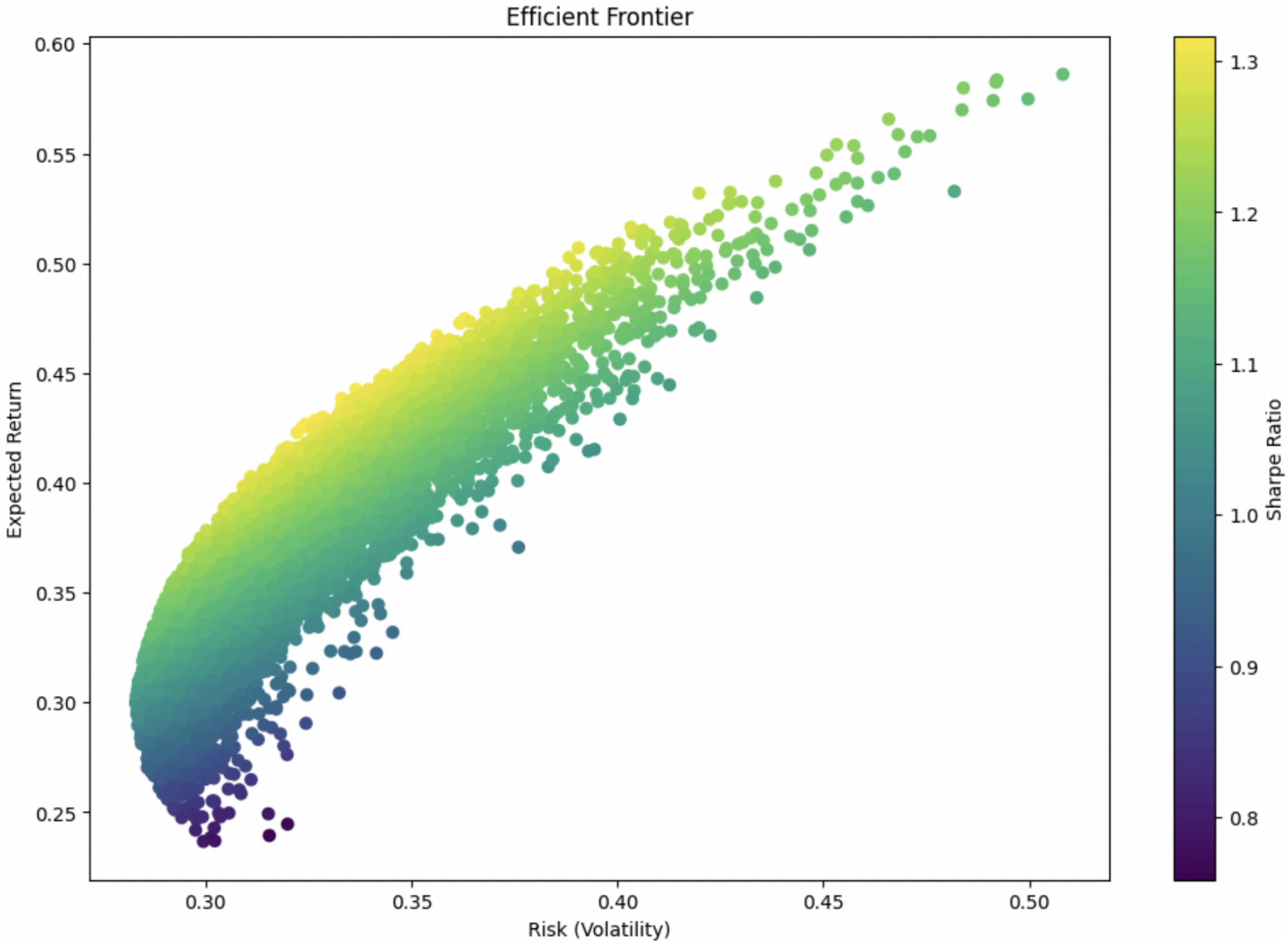
[5]
```
expected_returns = returns.mean() * 252
risk = returns.std() * np.sqrt(252)
```

[6]
```
risk_return_df = pd.DataFrame({
    'Expected Return': expected_returns,
    'Risk (Volatility)': risk
})
```

[7]
```
num_portfolios = 10000
all_weights = np.zeros((num_portfolios, len(tickers)))
ret_arr = np.zeros(num_portfolios)
vol_arr = np.zeros(num_portfolios)
sharpe_arr = np.zeros(num_portfolios)
```

[8]
```
for i in range(num_portfolios):
    weights = np.random.random(len(tickers))
    weights /= np.sum(weights)
    all_weights[i,:] = weights
    ret_arr[i] = np.sum(weights * expected_returns)
    vol_arr[i] = np.sqrt(np.dot(weights.T, np.dot(returns.cov() * 252, weights)))
    sharpe_arr[i] = ret_arr[i] / vol_arr[i]
```

```
plt.figure(figsize=(12, 8))
plt.scatter(vol_arr, ret_arr, c=sharpe_arr, cmap='viridis')
plt.colorbar(label='Sharpe Ratio')
plt.xlabel('Risk (Volatility)')
plt.ylabel('Expected Return')
plt.title('Efficient Frontier')
plt.show()
```



[10]
```
print("Risk-Return Characteristics:")
print(risk_return_df)
```

```
Risk-Return Characteristics:
        Expected Return  Risk (Volatility)
Ticker
AAPL           0.378031           0.322345
AMZN           0.198360           0.352214
GOOGL          0.245988           0.318100
MSFT           0.320295           0.304908
TSLA           0.708129           0.647000
```

[11]
```
max_sharpe_idx = sharpe_arr.argmax()
max_sharpe_allocation = all_weights[max_sharpe_idx,:]
```

[12]
```
min_vol_idx = vol_arr.argmin()
min_vol_allocation = all_weights[min_vol_idx,:]
```

[13]
```
print("\nPortfolio with Maximum Sharpe Ratio:")
print(f"Return: {ret_arr[max_sharpe_idx]}")
print(f"Volatility: {vol_arr[max_sharpe_idx]}")
print(f"Weights: {dict(zip(tickers, max_sharpe_allocation))}")
```

```
Portfolio with Maximum Sharpe Ratio:
Return: 0.43846836623557417
Volatility: 0.3330590808256404
Weights: {'AAPL': 0.3847387262516757, 'MSFT': 0.0018804944145134799, 'GOOGL': 0.030786032616074127, 'AMZN': 0.32867936611072757, 'TSLA': 0.2539153806070093}
```

```
print("\nPortfolio with Minimum Volatility:")
print(f"Return: {ret_arr[min_vol_idx]}")
print(f"Volatility: {vol_arr[min_vol_idx]}")
print(f"Weights: {dict(zip(tickers, min_vol_allocation))}")
```

```
Portfolio with Minimum Volatility:
Return: 0.30023734360734705
Volatility: 0.2830637854455445
Weights: {'AAPL': 0.2939438396707601, 'MSFT': 0.14288650797729338, 'GOOGL': 0.2650240959593815, 'AMZN': 0.2979202219817659, 'TSLA': 0.00022533441079924048}
```

Conclusion:

- **Efficient Frontier**: Helps in visualizing the best possible return for each level of risk.
- **MPT Implications**:Investors should choose portfolios on the efficient frontier to maximize returns for a given level of risk. The portfolio with the highest Sharpe Ratio offers the best risk-adjusted returns.The minimum volatility portfolio is ideal for risk-averse investors.