```
Copy code
python
import yfinance as yf
import pandas as pd
import numpy as np
from scipy.optimize import minimize
# Step 1: Load the data
multi_df = pd.read_csv("PFF_IP_stock_data.csv")
# Step 2: Calculate daily returns
# Pivot the DataFrame to get a matrix of adjusted close prices
price_df = multi_df.pivot(index="Date", columns="Ticker", values="Adj Close")
# Calculate daily returns
returns_df = price_df.pct_change().dropna()
# Number of assets
num_assets = returns_df.shape[1]
# Step 3: Minimizing Volatility
# Calculate the covariance matrix of returns
cov matrix = returns df.cov()
# Objective function: minimize portfolio volatility
def portfolio_volatility(weights, cov_matrix):
    return np.sqrt(np.dot(weights.T, np.dot(cov_matrix, weights)))
# Constraints: the sum of the weights is 1
constraints = ({'type': 'eq', 'fun': lambda weights: np.sum(weights) - 1})
# Bounds: weights are between 0 and 1
bounds = tuple((0, 1) for _ in range(num_assets))
# Initial guess: equally distributed we:
initial_guess = num_assets * [1. / num_assets]
# Minimize the portfolio volatility
result_volatility = minimize(portfolio_volatility, initial_guess, args=(cov_matrix,),
                             method='SLSQP', bounds=bounds, constraints=constraints)
# Optimal weights for minimizing volatility
optimal_weights_volatility = result_volatility.x
print("Optimal Weights for Minimizing Volatility:")
print(optimal_weights_volatility)
```

Chat GPT-40 Output in response to A2 Optimisation Brief Contents



[python] Let's start by generating a list of potential portfolio optimization strategies that focus on maximizing or minimizing specific metrics using SciPy's `minimize` function. Here are a few strategies you could consider:

- Maximizing the Sharpe Ratio: Optimize the portfolio to maximize the Sharpe Ratio, which
 measures the performance of the portfolio compared to a risk-free asset, after adjusting for its
 risk.
- 2. **Minimizing Volatility**: Optimize the portfolio to minimize the overall volatility or risk, aiming for the most stable return.
- 3. **Maximizing Expected Return**: Optimize the portfolio to achieve the highest possible expected return based on historical data.
- Maximizing Return for a Given Level of Risk: Optimize the portfolio to maximize return while keeping the portfolio's risk below a specified threshold.
- 5. **Minimizing Downside Risk**: Optimize the portfolio to minimize the risk of negative returns, focusing on the lower end of the return distribution.
- 6. **Maximizing Sortino Ratio**: Optimize the portfolio to maximize the Sortino Ratio, which is similar to the Sharpe Ratio but only considers downside risk.
- 7. **Risk Parity**: Optimize the portfolio so that each asset contributes equally to the overall portfolio risk.

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# Number of assets
num_assets = returns_df.shape[1]
# Step 3: Maximizing Sortino Ratio
# Calculate portfolio return
def portfolio_return(weights, returns):
   return np.dot(returns, weights)
# Calculate the Sortino Ratio
def sortino_ratio(weights, historical_returns, risk_free_rate=0.0):
    portfolio_returns = np.dot(historical_returns, weights)
   mean_return = np.mean(portfolio_returns)
   downside_deviation = np.sqrt(np.mean(np.minimum(0, portfolio_returns - mean_return)**2
    sortino = (mean_return - risk_free_rate) / downside_deviation
    return -sortino # Negative because we want to maximize the Sortino Ratio
# Constraints: the sum of the weights is \downarrow
constraints = ({'type': 'eq', 'fun': lambda weights: np.sum(weights) - 1})
# Bounds: weights are between 0 and 1
bounds = tuple((0, 1) for _ in range(num_assets))
# Initial guess: equally distributed weights
initial_guess = num_assets * [1. / num_assets]
# Maximize the Sortino Ratio
result_sortino = minimize(sortino_ratio, initial_guess, args=(returns_df.values,),
                          method='SLSQP', bounds=bounds, constraints=constraints)
# Optimal weights for maximizing Sortino Ratio
optimal_weights_sortino = result_sortino.x
print("Optimal Weights for Maximizing Sortino Ratio:")
print(optimal_weights_sortino)
# Step 4: Calculate Portfolio Returns
# Calculate the portfolio daily returns \psi
portfolio_daily_returns_sortino = returns_df.dot(optimal_weights_sortino)
```