portfolio-project

August 3, 2024

Importing Libraries

[59]:
```
import pandas as pd
import numpy as np
import yfinance as yf
import matplotlib.pyplot as plt
from datetime import date,timedelta
from tqdm import tqdm
import warnings
warnings.filterwarnings('ignore')
import seaborn as sns
```

Data Collection

[60]:
```
stockTickers = list(pd.read_csv('https://archives.nseindia.com/content/indices/
  ↪top10nifty50_030724.csv')['SYMBOL']+'.NS')
stockTickers
```

[60]:
```
['HDFCBANK.NS',
 'RELIANCE.NS',
 'ICICIBANK.NS',
 'INFY.NS',
 'LT.NS',
 'TCS.NS',
 'ITC.NS',
 'BHARTIARTL.NS',
 'AXISBANK.NS',
 'SBIN.NS']
```

[61]:
```
startDate, endDate = date(2021,1,1), date(2022,12,31)
tradingDays = 252
rfRate = 0.06
investmentFund = 100000000 # 10 Million
```

Import Data

[62]:
```
spotData = yf.download(tickers = stockTickers,start = startDate, end =␣
  ↪endDate)['Adj Close'].fillna(method = 'bfill')
```

```
indexData = yf.download(tickers = '^NSEI', start = startDate,end =␣
 ↪endDate)['Adj Close'].fillna(method = 'bfill')
```

```
[*********************100%%**********************]  10 of 10 completed
[*********************100%%**********************]  1 of 1 completed
```

Equity Returns

[63]:
```
class Returns:
    def __init__(self,data):
       self.data = data

    def AbsoluteReturns(self):
        return self.data.diff().iloc[1:]

    def DiscretePropotionalReturns(self):
        return self.data.pct_change().iloc[1:]

    def ContinousPropotionalReturns(self):
        return np.log(1+ self.data.pct_change()).iloc[1:]
```

[64]:
```
spotData
```

[64]:
```
Ticker      AXISBANK.NS  BHARTIARTL.NS  HDFCBANK.NS  ICICIBANK.NS  \
Date
2021-01-01   621.093811     501.116852  1368.017456    514.302124
2021-01-04   621.989929     503.013763  1359.329712    518.397095
2021-01-05   661.567505     499.998199  1369.601318    523.808228
2021-01-06   651.411743     510.990356  1363.697632    533.021790
2021-01-07   668.188599     530.396912  1359.569580    527.561829
…                 …              …            …             …
2022-12-26   926.078674     807.291748  1589.273315    878.643677
2022-12-27   929.568726     811.074341  1590.882568    885.972229
2022-12-28   922.089966     800.124634  1589.614746    884.299988
2022-12-29   931.912109     816.997131  1600.831177    893.251648
2022-12-30   931.114380     802.414124  1588.005371    876.331909

Ticker          INFY.NS      ITC.NS        LT.NS  RELIANCE.NS     SBIN.NS  \
Date
2021-01-01  1171.958374  183.908066  1242.344116  1815.729614  262.983643
2021-01-04  1197.806519  183.521072  1259.202637  1818.790161  264.536713
2021-01-05  1202.967041  181.844116  1251.252441  1796.179077  265.195618
2021-01-06  1192.088257  176.641205  1258.627930  1748.810181  268.301697
2021-01-07  1173.539062  174.405212  1282.526367  1745.978027  270.796021
…                 …           …            …            …           …
2022-12-26  1455.328857  317.026215  2051.543945  2321.496582  576.057739
2022-12-27  1467.388672  315.652374  2083.969482  2340.489746  580.688599
2022-12-28  1462.835938  316.836761  2081.026123  2340.259766  579.868530
```

```
2022-12-29  1470.004150  317.736847  2071.018799  2339.201904  590.239685
2022-12-30  1460.946899  314.136383  2046.393188  2342.788818  592.072754

Ticker           TCS.NS
Date
2021-01-01  2726.469727
2021-01-04  2830.007324
2021-01-05  2879.866455
2021-01-06  2841.226562
2021-01-07  2823.814941
…                   …
2022-12-26  3104.079102
2022-12-27  3110.377441
2022-12-28  3108.087158
2022-12-29  3119.203857
2022-12-30  3107.705322

[496 rows x 10 columns]
```

[65]:
```
spotReturns = Returns(data = spotData).DiscretePropotionalReturns()
indexReturns = Returns(data = indexData).DiscretePropotionalReturns()
```

Portfolio Construction Risk Return Profile

[66]:
```
# Individual Securities

riskReturnProfile = pd.DataFrame({
    'Mean': spotReturns.mean() * tradingDays,
    'Standard Deviation': spotReturns.std() * np.sqrt(tradingDays)
}, index = spotReturns.columns)

riskReturnProfile['Sharpe Ratio'] = (riskReturnProfile['Mean'] - rfRate) /␣
 ↪riskReturnProfile['Standard Deviation']
riskReturnProfile
```

[66]:

Ticker	Mean	Standard Deviation	Sharpe Ratio
AXISBANK.NS	0.249929	0.296252	0.641107
BHARTIARTL.NS	0.272985	0.258401	0.824243
HDFCBANK.NS	0.106511	0.248339	0.187289
ICICIBANK.NS	0.308474	0.273995	0.906858
INFY.NS	0.142413	0.245672	0.335460
ITC.NS	0.299873	0.233614	1.026793
LT.NS	0.285861	0.252477	0.894579
RELIANCE.NS	0.164121	0.262449	0.396728
SBIN.NS	0.458607	0.301968	1.320032
TCS.NS	0.091308	0.221945	0.141060

[67]:
```
riskReturnProfile[riskReturnProfile['Sharpe Ratio'] ==
 ↪riskReturnProfile['Sharpe Ratio'].max()]
```

[67]:

	Mean	Standard Deviation	Sharpe Ratio
Ticker			
SBIN.NS	0.458607	0.301968	1.320032

The stock with the maximum Sharpe ratio is considered the best return-giving stock in a portfolio. The Sharpe ratio measures risk-adjusted return, making it a crucial metric. A higher Sharpe ratio indicates better performance relative to risk. Thus, selecting stocks with high Sharpe ratios can optimize portfolio returns.

Index

[68]:
```
riskReturnProfile_i =  pd.DataFrame({
    'Mean': indexReturns.mean() * tradingDays,
    'Standard Deviation': indexReturns.std() * np.sqrt(tradingDays)
},index =['NIFTY50'])

riskReturnProfile_i['Sharpe Ratio'] = (riskReturnProfile_i['Mean'] - rfRate) /
 ↪riskReturnProfile_i['Standard Deviation']
riskReturnProfile_i
```

[68]:

	Mean	Standard Deviation	Sharpe Ratio
NIFTY50	0.143913	0.165201	0.507945

Asset Allocation 01 : Equally Weighted Portfolio

[69]:
```
equalWeights = np.array([1/len(stockTickers)] * len(stockTickers))
print(round(sum(equalWeights)),equalWeights)
```

```
1 [0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1]
```

[70]:
```
portfolioReturns = spotReturns.dot(equalWeights)

riskReturnProfile = pd.DataFrame ({
        'Mean': portfolioReturns.mean() *  tradingDays,
        'Standard Deviation': portfolioReturns.std() * np.sqrt(tradingDays),
        'Sharpe Ratio' : (riskReturnProfile['Mean'].mean() -rfRate ) /
 ↪riskReturnProfile['Standard Deviation']
    },index = ['Equally Weighted Portfolio'])

riskReturnProfile
```

[70]:

	Mean	Standard Deviation	Sharpe Ratio
Equally Weighted Portfolio	0.238008	0.17211	NaN

02 : Random - Weighted Portfolio

```
[71]: # Generating Random Weights for Assest Allocation
randomNum = np.random.random(len(stockTickers))
randomWeights = np.array(randomNum / sum(randomNum))
print(round(sum(randomWeights)),randomWeights)
```

```
1 [0.05360182 0.05694115 0.07112576 0.23968806 0.01439134 0.19943061
 0.14509579 0.10842431 0.02408671 0.08721446]
```

```
[72]: portfolioReturns = spotReturns.dot(randomWeights)

riskReturnProfile = pd.DataFrame({
    'Mean': portfolioReturns.mean() * tradingDays,
    'Standard Deviation': portfolioReturns.std() * np.sqrt(tradingDays)
}, index = ['Random Weighted Portfolio'])

riskReturnProfile['Sharpe Ratio'] = (riskReturnProfile['Mean'] - rfRate) /
 ↪riskReturnProfile['Standard Deviation']
riskReturnProfile
```

[72]:

	Mean	Standard Deviation	Sharpe Ratio
Random Weighted Portfolio	0.250589	0.175681	1.084858

The Sharpe ratio of the randomly weighted portfolio outperforms the equal-weighted portfolio. Where (EWP)Equally Weighted Portfolio is 1.104602 and (RWP) Random Weighted Portfolio is 1.245832

Simulating Random Weights Simulating random weights in a portfolio involves assigning random proportions to assets, rather than equal or fixed weights. This method explores a wide range of potential portfolios, identifying those with optimal risk-return profiles. Advantages include discovering non-intuitive asset combinations and enhancing diversification.

```
[76]: simulations = 10000  # number of simulated portfolios
simulatedPortfolios = []

for i in tqdm(range(simulations)):
    # Generate random weights
    randomNum = np.random.random(len(stockTickers))
    randomWeights = randomNum / sum(randomNum)

    # Construct random-weighted portfolio
    portfolioReturns = spotReturns.dot(randomWeights)
    riskReturnProfile = pd.DataFrame({
        'Mean': [portfolioReturns.mean() * tradingDays],
        'Standard Deviation': [portfolioReturns.std() * np.sqrt(tradingDays)],
        'Weights': [randomWeights]
    })
```

```
    riskReturnProfile['Sharpe Ratio'] = (riskReturnProfile['Mean'] - rfRate) /␣
↪riskReturnProfile['Standard Deviation']

    # Consolidate portfolios
    simulatedPortfolios.append(riskReturnProfile)

# Concatenate all dataframes
simulatedPortfolios = pd.concat(simulatedPortfolios, ignore_index=True)

simulatedPortfolios
```

```
100%|     | 10000/10000 [00:26<00:00, 374.64it/s]
```

[76]:

```
          Mean  Standard Deviation  \
0     0.259785            0.171157
1     0.262482            0.175384
2     0.234285            0.170582
3     0.277039            0.186534
4     0.194906            0.176237
…          …                 …
9995  0.204918            0.172571
9996  0.233128            0.175523
9997  0.251313            0.177258
9998  0.228357            0.174865
9999  0.273187            0.174694

                                                Weights  Sharpe Ratio
0     [0.026274523071248473, 0.20456860327352158, 0…      1.167262
1     [0.04858474225695794, 0.13022447212301613, 0.0…      1.154505
2     [0.04047171880849317, 0.06559499196717326, 0.0…      1.021707
3     [0.11405685661658577, 0.13601087067291, 0.0914…      1.163534
4     [0.10909751999672296, 0.03633031048962468, 0.0…      0.765485
…                                                   …           …
9995  [0.16617239261166764, 0.1616436395648485, 0.13…      0.839756
9996  [0.17124383434879228, 0.11845191323929531, 0.1…      0.986357
9997  [0.05915126455631367, 0.008348985030495687, 0…      1.079295
9998  [0.038152984215463974, 0.11222577269538103, 0…      0.962785
9999  [0.10143238129380812, 0.19447682926653403, 0.0…      1.220345

[10000 rows x 4 columns]
```

[77]:

```
# finding the optimal Portfolio
optimalPortfolio = simulatedPortfolios[simulatedPortfolios['Sharpe Ratio']==␣
↪simulatedPortfolios['Sharpe Ratio'].max()]
optimalPortfolio
```

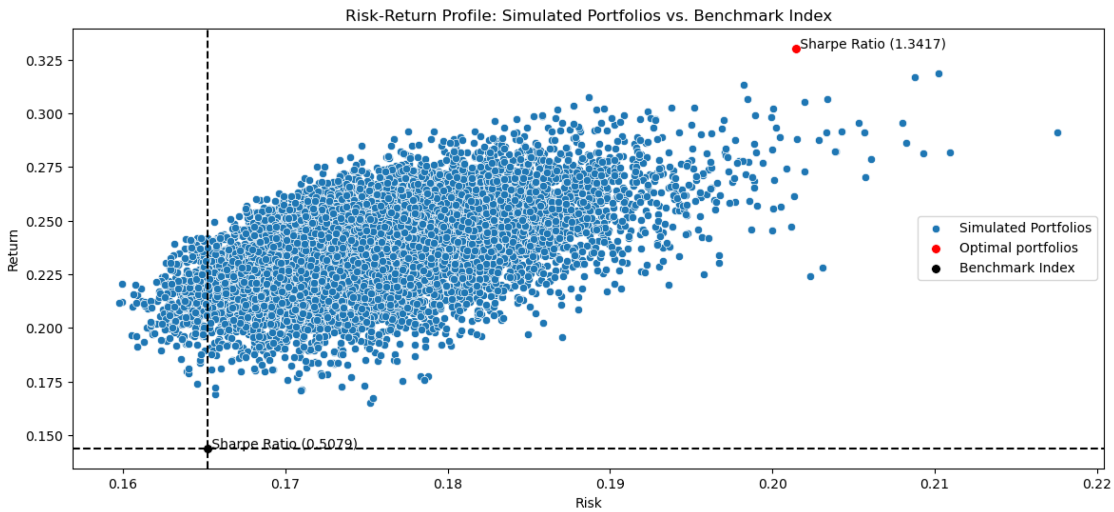
[77]:

```
            Mean  Standard Deviation  \
4527  0.330263            0.201427


                                                Weights  Sharpe Ratio
4527  [0.09832074524522255, 0.14826075123809396, 0.0…      1.341742
```

Data Visualization

[78]:

```
plt.figure(figsize=(14,6))

#simulated portfolios
sns.scatterplot(x=simulatedPortfolios['Standard Deviation'],␣
↪y=simulatedPortfolios['Mean'], label='Simulated Portfolios')

#optimal portfolio
sns.scatterplot(x=optimalPortfolio['Standard Deviation'],␣
↪y=optimalPortfolio['Mean'], color='r', s=50, label='Optimal portfolios')
plt.annotate(f" Sharpe Ratio ({optimalPortfolio['Sharpe Ratio'].values[0].
↪round(4)})", (optimalPortfolio['Standard Deviation'],␣
↪optimalPortfolio['Mean']))

#benchmark index
sns.scatterplot(x=riskReturnProfile_i['Standard Deviation'],␣
↪y=riskReturnProfile_i['Mean'], color='k', s=50, label='Benchmark Index')
plt.annotate(f" Sharpe Ratio ({riskReturnProfile_i['Sharpe Ratio'].values[0].
↪round(4)})", (riskReturnProfile_i['Standard Deviation'],␣
↪riskReturnProfile_i['Mean']))
plt.axvline(riskReturnProfile_i['Standard Deviation'].values[0], color='k',␣
↪linestyle='--')
plt.axhline(riskReturnProfile_i['Mean'].values[0], color='k', linestyle='--')

plt.title('Risk-Return Profile: Simulated Portfolios vs. Benchmark Index')
plt.xlabel('Risk')
plt.ylabel('Return')
plt.legend()
plt.show()
```



[ ]: Creating a Passive Investment Fund using the optimalWeights

[83]:
```
#Collecting the Data
startDate , endDate = date(2023,1,1), date(2023,12,31)
spotData = yf.download(tickers = stockTickers,start = startDate, end =␣
  ↪endDate)['Adj Close'].fillna(method = 'bfill')
indexData = yf.download(tickers = '^NSEI', start = startDate,end =␣
  ↪endDate)['Adj Close'].fillna(method = 'bfill')
```

```
[*********************100%%**********************]  10 of 10 completed
[*********************100%%**********************]  1 of 1 completed
```

[116]:
```
spotReturns_p = Returns(data = spotData).DiscretePropotionalReturns()
spotReturns_p
```

[116]:

Ticker	AXISBANK.NS	BHARTIARTL.NS	HDFCBANK.NS	ICICIBANK.NS	INFY.NS	\
Date						
2023-01-03	0.021984	0.005040	0.006539	-0.001219	-0.000952	
2023-01-04	-0.005040	-0.007094	-0.017873	-0.002496	-0.018226	
2023-01-05	-0.008251	-0.005790	-0.006428	-0.022189	-0.013112	
2023-01-06	-0.010163	-0.013753	-0.003313	-0.010294	-0.018099	
2023-01-09	0.020055	0.029397	0.001944	0.003735	0.024819	
…	…	…	…	…	…	
2023-12-22	-0.006482	0.011913	-0.009397	-0.010056	0.017513	
2023-12-26	0.005467	0.010409	0.006943	0.000805	-0.012125	
2023-12-27	0.011058	0.021353	0.012393	0.007185	0.014994	
2023-12-28	0.001356	0.015178	0.001145	0.003642	-0.002840	
2023-12-29	-0.005010	-0.004341	0.002346	-0.009246	-0.012639	

Ticker ITC.NS LT.NS RELIANCE.NS SBIN.NS TCS.NS

```
Date
2023-01-03 -0.005258 -0.000239    -0.007318  0.000327  0.015300
2023-01-04 -0.012383 -0.008808    -0.015056 -0.011757  0.000996
2023-01-05  0.019725  0.008114    -0.001787 -0.000165 -0.001071
2023-01-06  0.004798 -0.000383     0.009089 -0.007354 -0.030066
2023-01-09  0.008954  0.016846     0.023611  0.011737  0.033753
…               …         …          …         …         …
2023-12-22  0.008307  0.015712     0.000976 -0.010874  0.009637
2023-12-26  0.002746  0.003479     0.005068  0.002042 -0.007440
2023-12-27  0.001424  0.015458     0.003413  0.016456  0.004123
2023-12-28  0.015314 -0.007322     0.007229  0.004394 -0.002965
2023-12-29 -0.004309  0.002260    -0.007906 -0.014354 -0.001711

[244 rows x 10 columns]
```

01:Investment Funds : Passive (Tactical Allocation) | Investment strategy: Buy and Hold

[97]:
```python
## Allocating the Funds by refering to the Simulated optimal Weights
assetAllocation = pd.DataFrame()
assetAllocation['Purchase Price'] = spotData.head(1).transpose() # Day one Current Market price of of All Stock in Data
assetAllocation['Allocation'] = optimalPortfolio['Weights'].values[0]   # Assigning the Optial Weights to the fund
assetAllocation['Intial Investment'] = investmentFund * assetAllocation['Allocation'] #Allocating the Funds to each stock  based on Optimal Weights genrated by Simulations
assetAllocation['Purchase Quantity'] = round(assetAllocation['Intial Investment'] / assetAllocation['Purchase Price']) # Calculating the no .of shares can buy with allocated funds
assetAllocation['Intial Investment'] = round(assetAllocation['Purchase Quantity'] * assetAllocation['Purchase Price'],2) #Arriving at Total Invested corpus of funds
assetAllocation['Sale Price'] = spotData.tail(1).transpose() # CMP of Last day in the Timeperiod
assetAllocation['Profit ($)'] =  round((assetAllocation['Sale Price'] - assetAllocation['Purchase Price']) * assetAllocation['Purchase Quantity'],2) # Calculating the profit for each stock
assetAllocation['Profit (%)'] = (assetAllocation['Profit ($)'] / assetAllocation['Intial Investment']) * 100 # converting Absolute profit it into percentage
assetAllocation
```

[97]:
```
               Purchase Price  Allocation  Intial Investment  \
Ticker
AXISBANK.NS        938.942200    0.098321         9831663.77
BHARTIARTL.NS      809.780334    0.148261        14826268.14
```

```
HDFCBANK.NS       1588.541626    0.019910          1990442.66
ICICIBANK.NS       887.742920    0.040266          4026801.88
INFY.NS           1476.252075    0.017109          1710976.16
ITC.NS             315.368134    0.130096         13009566.24
LT.NS             2049.974121    0.084851          8484842.89
RELIANCE.NS       2369.185791    0.019993          1999592.81
SBIN.NS            590.625610    0.384985         38498749.16
TCS.NS            3112.238037    0.056208          5620701.90

               Purchase Quantity   Sale Price  Profit ($)  Profit (%)
Ticker
AXISBANK.NS              10471.0  1101.449951  1701618.67   17.307535
BHARTIARTL.NS            18309.0  1032.199951  4072280.76   27.466661
HDFCBANK.NS               1253.0  1686.223877   122395.86    6.149178
ICICIBANK.NS              4536.0   996.599976   493775.60   12.262227
INFY.NS                   1159.0  1534.253052    67223.13    3.928934
ITC.NS                   41252.0   447.474670  5449658.86   41.889628
LT.NS                     4139.0  3498.498779  5995443.56   70.660631
RELIANCE.NS                844.0  2584.949951   182104.95    9.107102
SBIN.NS                  65183.0   631.460632  2661749.24    6.913859
TCS.NS                    1806.0  3739.971436  1133686.52   20.169839
```

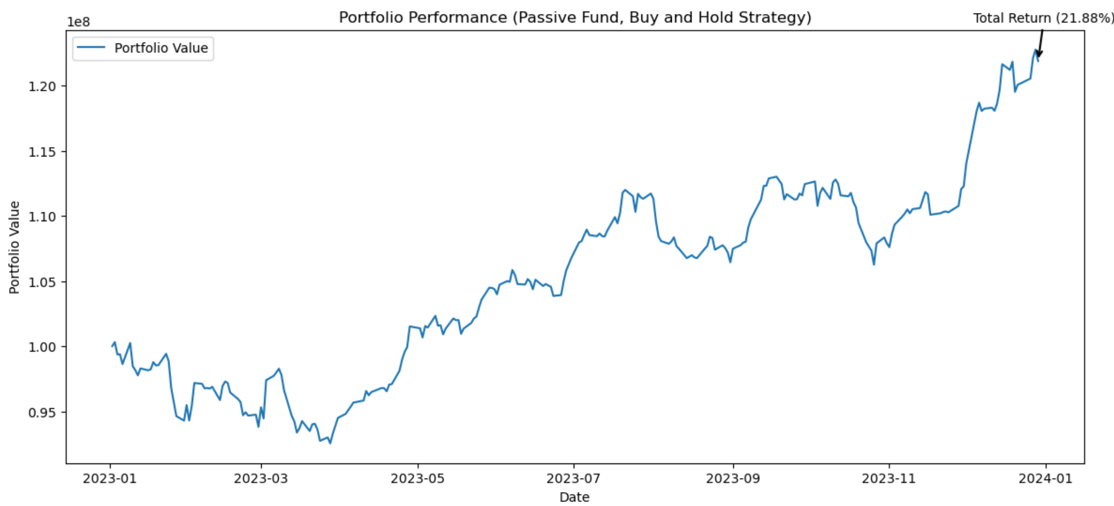
Remaining Funds

[88]:
```
cashLeftover = investmentFund- assetAllocation['Intial Investment'].sum()
print('CashLeftOver', cashLeftover)
```

```
CashLeftOver 394.391357421875
```

[98]:
```
# Calculate total returns
total_return = (spotData.tail(1).values * assetAllocation['Purchase Quantity'].
 ↪values).sum()
total_return_percentage = ((total_return - assetAllocation['Intial Investment'].
 ↪sum()) / assetAllocation['Intial Investment'].sum()) * 100



# Plot portfolio performance
plt.figure(figsize=[14, 6])
portfolio_values = (spotData * assetAllocation['Purchase Quantity']).sum(axis=1)
plt.plot(spotData.index, portfolio_values, label='Portfolio Value')
plt.title('Portfolio Performance (Passive Fund, Buy and Hold Strategy)')
plt.xlabel('Date')
plt.ylabel('Portfolio Value')

# Annotate the plot
last_date = spotData.tail(1).index[0]
last_value = portfolio_values[-1]
```

```python
plt.annotate(f"Total Return ({round(total_return_percentage, 2)}%)",
             xy=(last_date, last_value),
             xytext=(-50, 30),
             textcoords='offset points',
             arrowprops=dict(arrowstyle='->', lw=1.5))

plt.legend()
plt.show()
```



Calculation of VaR using Historical Simulation Method

VaR (Value at Risk) `Value at Risk (VaR) measures the potential risk of an investment or portfolio over a specified time horizon with a given confidence interval under normal market conditions. It estimates the maximum potential loss that may occur with a certain level of confidence, providing a quantifiable metric for risk management.`

Advantages of Historical Simulation `Simplicity:` Easy to understand and implement without requiring complex mathematical models.

`Non-parametric:` Does not assume a normal distribution of returns, making it flexible for different types of data.

`Captures Actual Market Conditions:` Reflects real historical market movements and conditions.

Disadvantages of Historical Simulation `Historical Dependence:` Assumes that past market behavior will repeat in the future, which may not always be true.

`Data Intensive:` Requires a substantial amount of historical data for accurate results.

`Ignores New Risks:` Does not account for new risks or structural changes in the market that have not occurred in the historical data.

Why VaR ? `1. Risk Quantification:` VaR provides a quantifiable measure of potential losses in a portfolio over a specified time period and confidence level. This helps in understanding and communicating the risk involved in an investment.

`2. Regulatory Compliance:` Financial institutions are often required by regulators to measure and report VaR to ensure they maintain adequate capital reserves against potential losses. This helps in maintaining the stability of the financial system.

`3. Risk Management:` VaR is a critical tool for risk managers to identify and mitigate potential risks. By knowing the potential maximum loss, they can make informed decisions about hedging, diversifying, or adjusting the portfolio to manage risk better.

`4. Performance Assessment:` VaR allows investors to compare the risk-adjusted performance of different portfolios or investment strategies. A portfolio with a high return but also high VaR might be less attractive than one with a slightly lower return but significantly lower VaR.

`5. Strategic Decision Making:` Investors and portfolio managers use VaR to make strategic decisions about asset allocation and risk exposure. It helps in determining the amount of risk that is acceptable for achieving investment goals.

`6. Stress Testing:` VaR can be used in stress testing scenarios to evaluate how a portfolio might perform under extreme market conditions. This helps in preparing for adverse market movements and planning for worst-case scenarios.

`7. Risk-Adjusted Return:` VaR is often used in conjunction with other metrics like the Sharpe Ratio to assess the risk-adjusted return of an investment. This helps in identifying investments that offer the best return for a given level of risk.formed decision-making and regulatory compliance.

[150]:
```
assetAllocation
```

[150]:
```
               Purchase Price  Allocation  Intial Investment  \
Ticker
AXISBANK.NS        938.942200    0.098321         9831663.77
BHARTIARTL.NS      809.780334    0.148261        14826268.14
HDFCBANK.NS       1588.541626    0.019910         1990442.66
ICICIBANK.NS       887.742920    0.040266         4026801.88
INFY.NS           1476.252075    0.017109         1710976.16
ITC.NS             315.368134    0.130096        13009566.24
LT.NS             2049.974121    0.084851         8484842.89
RELIANCE.NS       2369.185791    0.019993         1999592.81
SBIN.NS            590.625610    0.384985        38498749.16
TCS.NS            3112.238037    0.056208         5620701.90

               Purchase Quantity   Sale Price  Profit ($)  Profit (%)
Ticker
AXISBANK.NS              10471.0  1101.449951  1701618.67   17.307535
BHARTIARTL.NS            18309.0  1032.199951  4072280.76   27.466661
```

```
HDFCBANK.NS              1253.0  1686.223877   122395.86   6.149178
ICICIBANK.NS             4536.0   996.599976   493775.60  12.262227
INFY.NS                  1159.0  1534.253052    67223.13   3.928934
ITC.NS                  41252.0   447.474670  5449658.86  41.889628
LT.NS                    4139.0  3498.498779  5995443.56  70.660631
RELIANCE.NS               844.0  2584.949951   182104.95   9.107102
SBIN.NS                 65183.0   631.460632  2661749.24   6.913859
TCS.NS                   1806.0  3739.971436  1133686.52  20.169839
```

[133]:

```
#Collecting the Data
startDate , endDate = date(2023,1,1), date(2023,12,31)
spotData = yf.download(tickers = stockTickers,start = startDate, end =␣
 ↪endDate)['Adj Close'].fillna(method = 'bfill')
indexData = yf.download(tickers = '^NSEI', start = startDate,end =␣
 ↪endDate)['Adj Close'].fillna(method = 'bfill')
```

```
[*********************100%%**********************]  10 of 10 completed
[*********************100%%**********************]  1 of 1 completed
```

[134]:

```
spotReturns_p = Returns(data = spotData).DiscretePropotionalReturns()
spotReturns_p
```

[134]:

```
Ticker      AXISBANK.NS  BHARTIARTL.NS  HDFCBANK.NS  ICICIBANK.NS   INFY.NS  \
Date
2023-01-03     0.021984       0.005040     0.006539     -0.001219 -0.000952
2023-01-04    -0.005040      -0.007094    -0.017873     -0.002496 -0.018226
2023-01-05    -0.008251      -0.005790    -0.006428     -0.022189 -0.013112
2023-01-06    -0.010163      -0.013753    -0.003313     -0.010294 -0.018099
2023-01-09     0.020055       0.029397     0.001944      0.003735  0.024819
…                  …             …            …             …         …
2023-12-22    -0.006482       0.011913    -0.009397     -0.010056  0.017513
2023-12-26     0.005467       0.010409     0.006943      0.000805 -0.012125
2023-12-27     0.011058       0.021353     0.012393      0.007185  0.014994
2023-12-28     0.001356       0.015178     0.001145      0.003642 -0.002840
2023-12-29    -0.005010      -0.004341     0.002346     -0.009246 -0.012639

Ticker        ITC.NS     LT.NS  RELIANCE.NS   SBIN.NS    TCS.NS
Date
2023-01-03 -0.005258 -0.000239    -0.007318  0.000327  0.015300
2023-01-04 -0.012383 -0.008808    -0.015056 -0.011757  0.000996
2023-01-05  0.019725  0.008114    -0.001787 -0.000165 -0.001071
2023-01-06  0.004798 -0.000383     0.009089 -0.007354 -0.030066
2023-01-09  0.008954  0.016846     0.023611  0.011737  0.033753
…              …         …            …         …         …
2023-12-22  0.008307  0.015712     0.000976 -0.010874  0.009637
2023-12-26  0.002746  0.003479     0.005068  0.002042 -0.007440
2023-12-27  0.001424  0.015458     0.003413  0.016456  0.004123
```

```
2023-12-28  0.015314 -0.007322     0.007229  0.004394 -0.002965
2023-12-29 -0.004309  0.002260    -0.007906 -0.014354 -0.001711

[244 rows x 10 columns]
```

[135]:

```
Weights = optimalPortfolio['Weights'].values[0]
portfolio_returns = spotReturns_p.dot(Weights)
portfolio_returns
```

[135]:

```
Date
2023-01-03    0.003109
2023-01-04   -0.009445
2023-01-05    0.000180
2023-01-06   -0.007576
2023-01-09    0.016426
                ...
2023-12-22   -0.000375
2023-12-26    0.003165
2023-12-27    0.013178
2023-12-28    0.005545
2023-12-29   -0.007827
Length: 244, dtype: float64
```

[149]:

```
confidence_level= 0.99
relativeVaR = np.percentile(portfolio_returns,1 - confidence_level) * 100
absoluteVaR = total_return * relativeVaR
print(f" relative VaR at {confidence_level*100}% confidence level: ↪{relativeVaR}",
      f" Absolute VaR at {confidence_level*100}% confidence level: ↪{absoluteVaR}")
```

```
 relative VaR at 99.0% confidence level: -2.2982655992263012  Absolute VaR at
99.0% confidence level: -280111560.37069345
```

[ ]:

```

```