Accessing the Stock Price Data

In [1]:

```
!pip install pandas-datareader
```

...

In [34]:

```
!pip install yfinance
```

...

In [197]:

```
from pandas_datareader import data as pdr
import yfinance as yf
import datetime
import pandas as pd
```

In [198]:

```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

In [199]:

```
start = datetime.datetime(2019,1,1)
end = datetime.datetime(2022,12,31)
```

In [200]:

```
# fucntion that gets the stock data
def get_stock(ticker):
    yf.pdr_override()
    data = pdr.get_data_yahoo(f"{ticker}",start,end)
    data[f'{ticker}'] = data["Close"]
    data = data[[f'{ticker}']]
    data.reset_index(inplace=True)
    data.index = data.index.astype(int)
    return data
```

In [201]:

```
# pfizer = get_stock("PFE")
# jnj = get_stock("JNJ")
```

Stocks to be pulled are:

Healthcare : Moderna (MRNA), Pfizer (PFE), Johnson & Johnson (JNJ)

Tech : Google (GOOGL), Facebook/META (META), Apple (AAPL)

Retail : Costco (COST), Walmart (WMT), Kroger Co (KR)

Finance : JPMorgan Chase & Co (JPM), Bank of America (BAC), HSBC Holding (HSBC)

In [202]:

```
from functools import reduce

def combine_stocks(tickers):
    data_frames = []
    for i in tickers:
        data_frames.append(get_stock(i))
    df_merged = reduce(lambda  left,right: pd.merge(left,right,on=['Date'], how='outer'), data_frames)
    print(df_merged.head())
    return df_merged
```

In [203]:

```
stocks = ["MRNA", "PFE", "JNJ", "GOOGL",
          "META", "AAPL", "COST", "WMT", "KR", "JPM",
          "BAC", "HSBC"]
portfolio = combine_stocks(stocks)
```

```
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[*********************100%***********************]  1 of 1 completed
[*********************100%***********************]  1 of 1 completed
        Date       MRNA        PFE         JNJ      GOOGL        META  \
0 2019-01-02  15.330000  41.034157  127.750000  52.734001  135.679993
1 2019-01-03  15.500000  39.886147  125.720001  51.273499  131.740005
2 2019-01-04  16.959999  40.796963  127.830002  53.903500  137.949997
3 2019-01-07  16.270000  41.015179  127.010002  53.796001  138.050003
4 2019-01-08  16.950001  41.204933  129.960007  54.268501  142.529999

        AAPL        COST        WMT         KR         JPM        BAC  \
0  39.480000  204.759995  93.339996  27.299999   99.309998  24.959999
1  35.547501  200.419998  92.860001  27.350000   97.110001  24.559999
2  37.064999  206.240005  93.440002  27.660000  100.690002  25.580000
3  36.982498  207.000000  94.540001  27.920000  100.760002  25.559999
4  37.687500  208.550003  95.199997  28.459999  100.570000  25.510000

        HSBC
0  40.880001
1  40.430000
2  41.610001
3  41.049999
4  41.160000
```

In [204]:

```
portfolio.to_csv("portfolio.csv", index=False)
```

In [205]:

```
portfolio = pd.read_csv("portfolio.csv", parse_dates=['Date'])
```

Mean Variance Optimization

In [63]:

```
!pip install PyPortfolioOpt
```

...

In [206]:

```
from pypfopt.expected_returns import mean_historical_return
from pypfopt.risk_models import CovarianceShrinkage
```

In [207]:

```
from pypfopt import plotting
```

In [208]:

```
# portfolio[['MRNA', 'PFE', 'JNJ', 'GOOGL', 'META', 'APPL', 'COST', 'WMT', 'KR', 'JPM', 'BAC', 'HSBC']] = portfolio[['MRNA', 'PFE', 'JNJ',
```

In [209]:

```
mu = mean_historical_return(portfolio[['MRNA', 'PFE', 'JNJ', 'GOOGL', 'META', 'AAPL', 'COST', 'WMT', 'KR', 'JPM', 'BAC', 'HSBC']])
S = CovarianceShrinkage(portfolio[['MRNA', 'PFE', 'JNJ', 'GOOGL', 'META', 'AAPL', 'COST', 'WMT', 'KR', 'JPM', 'BAC', 'HSBC']]).ledoit_wol
```

In [210]:

```
from pypfopt.efficient_frontier import EfficientFrontier

ef = EfficientFrontier(mu,S)
weights = ef.max_sharpe()

cleaned_weights = ef.clean_weights()
print(dict(cleaned_weights))
print("----------------------------------")
ef.portfolio_performance(verbose=True)
```

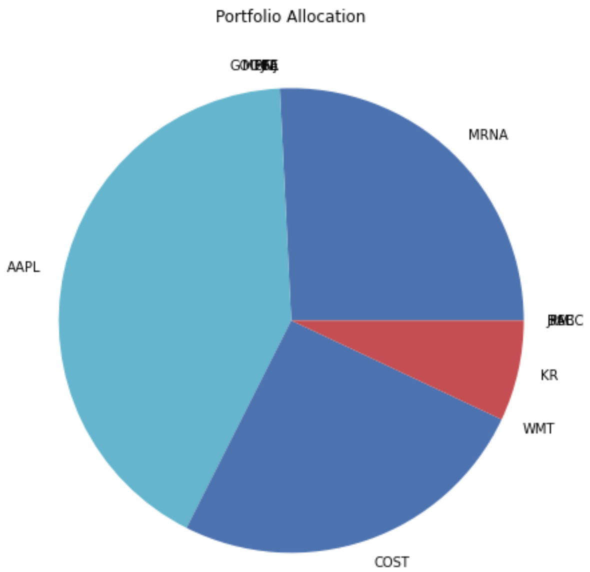
```
{'MRNA': 0.25786, 'PFE': 0.0, 'JNJ': 0.0, 'GOOGL': 0.0, 'META': 0.0, 'AAPL': 0.41782, 'COST': 0.25427, 'WMT': 0.0, 'KR': 0.
07006, 'JPM': 0.0, 'BAC': 0.0, 'HSBC': 0.0}
----------------------------------
Expected annual return: 43.0%
Annual volatility: 30.7%
Sharpe Ratio: 1.34
```

Out[210]:

```
(0.4302485476813618, 0.30677106892250045, 1.3373117260448144)
```

In [211]:

```
# plotting.plot_weights(weights, title="Portfolio Allocation")

weights_dict = dict(cleaned_weights)

# Create a figure and axis for the pie chart
fig, ax = plt.subplots(figsize=(8, 8))

# Create the pie chart
ax.pie(weights_dict.values(), labels=weights_dict.keys())

# Set the title of the chart
ax.set_title('Portfolio Allocation')

# Display the chart
plt.show()
```



Considering the investment amount as $100,000

In [212]:

```
from pypfopt.discrete_allocation import DiscreteAllocation, get_latest_prices

latest_prices = get_latest_prices(portfolio).dropna()
latest_prices = pd.to_numeric(latest_prices, errors='coerce')
latest_prices = latest_prices.iloc[1:]  # drop the first row
# print(latest_prices)
amount = 100000
da = DiscreteAllocation(weights, latest_prices, total_portfolio_value=amount)

allocation, leftover = da.greedy_portfolio()
print("Discrete allocation:", allocation)
print("Funds remaining: ${:.2f}".format(leftover))
```

```
Discrete allocation: {'AAPL': 321, 'MRNA': 143, 'COST': 56, 'KR': 157}
Funds remaining: $43.75
```

Conclusion For Mean Variance Optimization

We see that our portfolio performs with an expected annual return of 43 percent. The Sharpe ratio value of 1.34 indicates that the portfolio optimization algorithm performs well with our current data. Of course, this return is inflated and is not likely to hold up in the future.

Mean variance optimization doesn't perform very well since it makes many simplifying assumptions, such as returns being normally distributed and the need for an invertible covariance matrix. Fortunately, methods like HRP and mCVAR address these limitations.

Hierarchical Risk Parity (HRP)

In [213]:

```
from pypfopt import HRPOpt
```

In [214]:

```
returns = portfolio[['MRNA', 'PFE', 'JNJ', 'GOOGL', 'META', 'APPL', 'COST', 'WMT', 'KR', 'JPM', 'BAC', 'HSBC']] = portfolio[['MRNA', 'PFE
```

In [216]:

```
hrp = HRPOpt(returns)
hrp_weights = hrp.optimize()
```

In [217]:

```
print(dict(hrp_weights))
print("-----------------------------------")
hrp.portfolio_performance(verbose=True)
```

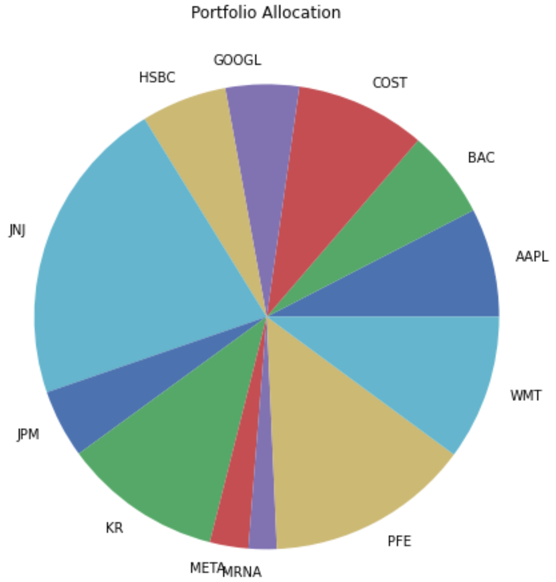
```
{'AAPL': 0.07578508276058257, 'BAC': 0.061285362879451764, 'COST': 0.09043492065023764, 'GOOGL': 0.051059553492855965, 'HSB
C': 0.059511423787638025, 'JNJ': 0.2146142053950624, 'JPM': 0.04755542704459071, 'KR': 0.11038355390831939, 'META': 0.02676
4887036446836, 'MRNA': 0.019619010874009676, 'PFE': 0.1420019409662181, 'WMT': 0.1009846312045869}
-----------------------------------
Expected annual return: 15.9%
Annual volatility: 18.5%
Sharpe Ratio: 0.75
```

Out[217]:

```
(0.15888304757454455, 0.1846398191886778, 0.7521836198974188)
```

In [218]:

```
# plotting.plot_weights(hrp_weights, title="Portfolio Allocation")

weights_dict = dict(hrp_weights)

# Create a figure and axis for the pie chart
fig, ax = plt.subplots(figsize=(8, 8))

# Create the pie chart
ax.pie(weights_dict.values(), labels=weights_dict.keys())

# Set the title of the chart
ax.set_title('Portfolio Allocation')

# Display the chart
plt.show()
```



In [219]:

```
da_hrp = DiscreteAllocation(hrp_weights, latest_prices, total_portfolio_value=100000)

allocation, leftover = da_hrp.greedy_portfolio()
print("Discrete allocation (HRP):", allocation)
print("Funds remaining (HRP): ${:.2f}".format(leftover))
```

```
Discrete allocation (HRP): {'JNJ': 121, 'PFE': 277, 'KR': 247, 'WMT': 71, 'COST': 20, 'AAPL': 58, 'BAC': 185, 'HSBC': 191,
'GOOGL': 58, 'JPM': 36, 'META': 22, 'MRNA': 11}
Funds remaining (HRP): $40.58
```

Conclusion Hierarchical Risk Parity (HRP)

We see that we have an expected annual return of 15.9 percent, which is significantly less than the inflated 43.0 percent we achieved with mean variance optimization. We also see a diminished Sharpe ratio of 0.75. This result is much more reasonable and more likely to hold up in the future since HRP is not as sensitive to outliers as mean variance optimization is.

We see that our algorithm suggests we invest heavily into Kroger (KR), HSBC, Johnson & Johnson (JNJ) and Pfizer (PFE) and not, as the previous model did, so much into Moderna (MRNA) and Apple (AAPL). Further, while the performance decreased, we can be more confident that this model will perform just as well when we refresh our data. This is because HRP is more robust to the anomalous increase in Moderna and Apple stock prices.

Mean Conditional Value at Risk (mCVAR)

In [220]:

```
from pypfopt.efficient_frontier import EfficientCVaR
```

In [221]:

```
S = portfolio[['MRNA', 'PFE', 'JNJ', 'GOOGL', 'META', 'APPL', 'COST', 'WMT', 'KR', 'JPM', 'BAC', 'HSBC']].cov()
ef_cvar = EfficientCVaR(mu, S)
cvar_weights = ef_cvar.min_cvar()

cleaned_weights = ef_cvar.clean_weights()
print(dict(cvar_weights))
print("-----------------------------------")
ef_cvar.portfolio_performance(verbose=True)
```

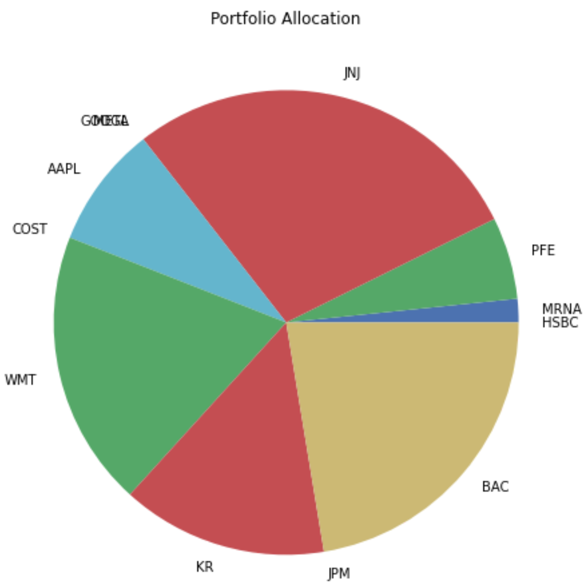
```
{'MRNA': 0.0164112362579626, 'PFE': 0.0570599244725613, 'JNJ': 0.2818814967502368, 'GOOGL': 2.30506716e-08, 'META': 2.22640
728e-08, 'AAPL': 0.0851246432923121, 'COST': 3.86006137e-08, 'WMT': 0.1922373482936009, 'KR': 0.14329097529392622, 'JPM': 4.
07974923e-08, 'BAC': 0.2239942403932198, 'HSBC': 1.05333297e-08}
-----------------------------------
Expected annual return: 12.7%
Conditional Value at Risk: -0.01%
```

Out[221]:

```
(0.12695234386727605, -0.00012160499953229924)
```

In [222]:

```
# plotting.plot_weights(cleaned_weights, title="Portfolio Allocation")

weights_dict = dict(cleaned_weights)

# Create a figure and axis for the pie chart
fig, ax = plt.subplots(figsize=(8, 8))

# Create the pie chart
ax.pie(weights_dict.values(), labels=weights_dict.keys())

# Set the title of the chart
ax.set_title('Portfolio Allocation')

# Display the chart
plt.show()
```



In [224]:

```
da_cvar = DiscreteAllocation(cvar_weights, latest_prices, total_portfolio_value=100000)

allocation, leftover = da_cvar.greedy_portfolio()
print("Discrete allocation (CVAR):", allocation)
print("Funds remaining (CVAR): ${:.2f}".format(leftover))
```

```
Discrete allocation (CVAR): {'JNJ': 160, 'BAC': 676, 'WMT': 135, 'KR': 321, 'AAPL': 66, 'PFE': 111, 'MRNA': 9}
Funds remaining (CVAR): $15.45
```

Conclusion Mean Conditional Value at Risk (mCVAR)

We see that this algorithm suggests we invest heavily into Johnson & Johnson (JNJ) and Bank of America (BAC). Also it suggests to buy a single share of HSBC. Also we see that the expected return is 12.7 percent.As with HRP, this result is much more reasonable than the inflated 43 percent returns given by mean variance optimization since it is not as sensitive to the anomalous behaviour of the Moderna stock price.