Portfolio Optimisation Case Study

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

```
C:\Users\Ajay Dhariwal\Anaconda3\lib\site-packages\pandas\compat\_optional.py:138: UserWarning: Pandas requir
es version '2.7.0' or newer of 'numexpr' (version '2.6.8' currently installed).
  warnings.warn(msg, UserWarning)
```

In [2]:
```
# The yfinance module is used to get the data from yahoo finance
startdate='2017-01-01'
enddate='2020-12-31'
df_msft=yf.download('MSFT',start=startdate,end=enddate)
df_apple=yf.download('AAPL',start=startdate,end=enddate)
df_orcl=yf.download('ORCL',start=startdate,end=enddate)
df_amd=yf.download('AMD',start=startdate,end=enddate)
```

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

In [3]:
```
df_msft.head(2)
```

Out[3]:

	Open	High	Low	Close	Adj Close	Volume
Date						
2017-01-03	62.790001	62.84	62.130001	62.580002	58.291965	20694100
2017-01-04	62.480000	62.75	62.119999	62.299999	58.031158	21340000

With the yfinance imported as yf, the yf.download('company_name',startdat,enddate), we get the data from the yahoo finance as a dataframe directly into the python.

Creating a Portfolio of selected stocks

In [4]:
```
# First, we want to normalise the stock prices. In this case, we want to convert the dollar value into daily returns
# The Goal is to make changes observabe easier
```

In [5]:
```
df_orcl.head(2)
```

Out[5]:

Date	Open	High	Low	Close	Adj Close	Volume
2017-01-03	38.450001	38.689999	38.299999	38.549999	35.671886	11051300
2017-01-04	38.549999	38.919998	38.549999	38.740002	35.847702	9545500

In [6]:
```
portfolio=[df_msft,df_orcl,df_apple,df_amd]
for stock in portfolio:
    stock['Normalising return']=stock['Adj Close']/stock.iloc[0]['Adj Close']
```

In [7]:
```
# We have created a new colum Normalising return where in we have included the returns
df_apple.head(2)
```

Out[7]:

Date	Open	High	Low	Close	Adj Close	Volume	Normalising return
2017-01-03	28.950001	29.082500	28.690001	29.037500	27.372364	115127600	1.000000
2017-01-04	28.962500	29.127501	28.937500	29.004999	27.341724	84472400	0.998881

In [8]:
```
# First, we assign the weights to the stocks in the portflio
weights=[0.25,0.25,0.25,0.25]
portfolio_with_weight=zip(portfolio,weights)
for stock,weight in portfolio_with_weight:
    stock['Allocation']=stock['Normalising return']*weight
```

In [9]:
```
# now, we have allocated equal amount of money in all the stocks in the portfolio
df_apple.head(2)
```

Out[9]:

Date	Open	High	Low	Close	Adj Close	Volume	Normalising return	Allocation
2017-01-03	28.950001	29.082500	28.690001	29.037500	27.372364	115127600	1.000000	0.25000
2017-01-04	28.962500	29.127501	28.937500	29.004999	27.341724	84472400	0.998881	0.24972

In [10]:
```
# now, let's invest 20,000 $ in the portfolio
for stock in portfolio:
    stock['Initial_position']=stock['Allocation']*20000
```

In [11]:
```
df_apple.head(1)
```

Out[11]:

Date	Open	High	Low	Close	Adj Close	Volume	Normalising return	Allocation	Initial_position
2017-01-03	28.950001	29.0825	28.690001	29.0375	27.372364	115127600	1.0	0.25	5000.0

In [12]:
```
# Now let's create a dataframe for the initial position of all the stocks and visualise it
```

In [13]:
```
df_stocks_initial_position=pd.DataFrame({'Apple':df_apple['Initial_position'],'Microsoft':df_msft['Initial_po
sition'],
                                         'Oracle':df_orcl['Initial_position'],'AMD':df_amd['Initial_position'
]
                                        })
```

In [14]:
```
df_stocks_initial_position['Total']=df_stocks_initial_position.sum(axis=1)
```

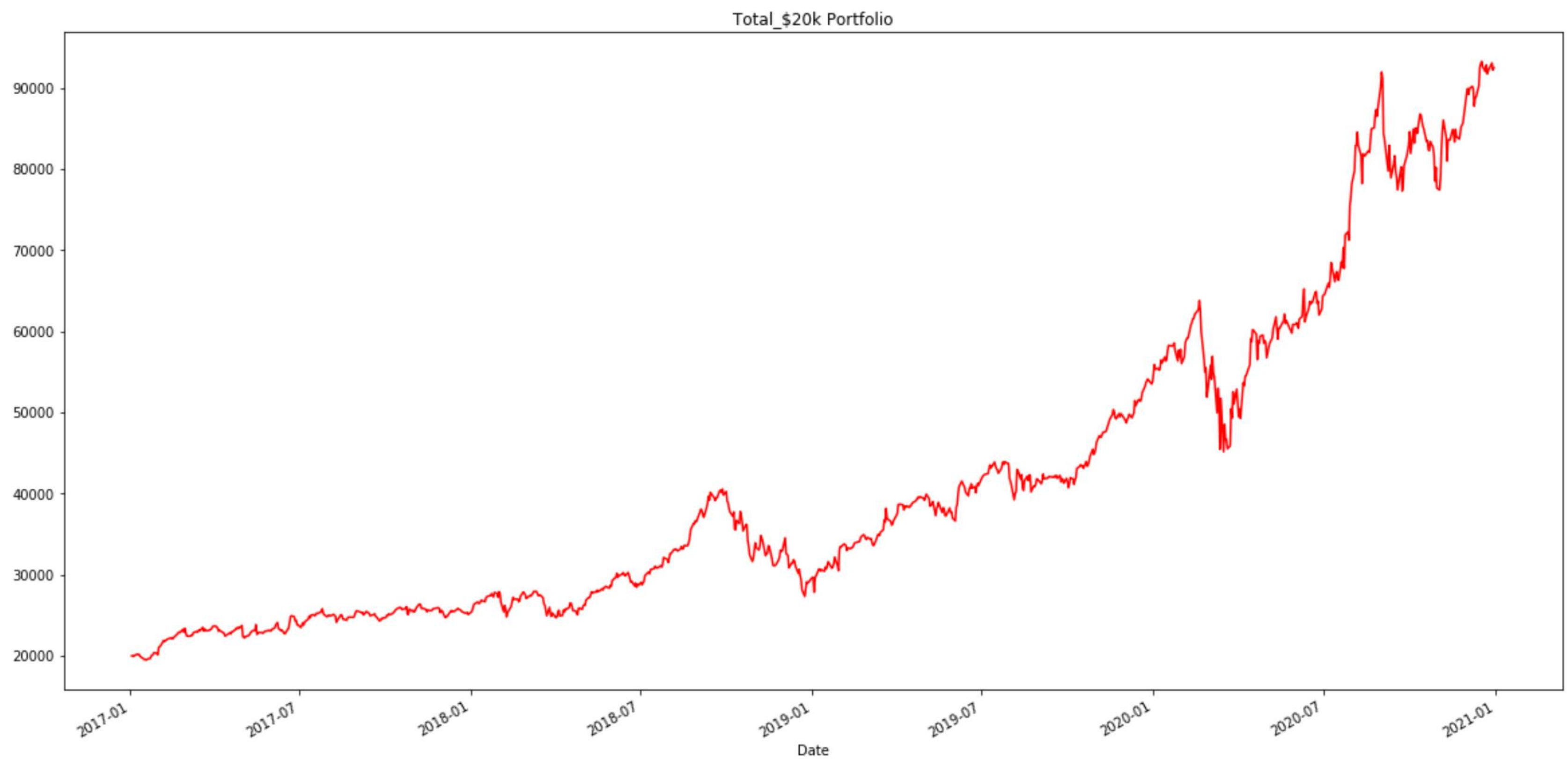
In [15]:
```
df_stocks_initial_position.head(2)
```

Out[15]:

	Apple	Microsoft	Oracle	AMD	Total
Date					
2017-01-03	5000.000000	5000.000000	5000.000000	5000.0	20000.000000
2017-01-04	4994.403178	4977.629247	5024.643438	5000.0	19996.675863

In [34]:
```
df_stocks_initial_position['Total'].plot(kind='line',figsize=(20,10),title='Total_$20k Portfolio',color='red'
)
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x145b64123c8>



In [17]:
```
name=['Apple','Microsoft','Oracle','AMD','Total']
```

In [18]:
```
fig,ax1=plt.subplots(nrows=2,ncols=3,figsize=(20,10),constrained_layout=True)
ax1=ax1.flatten()
for i,j in enumerate(name):
    df_stocks_initial_position[j].plot(kind='line',ax=ax1[i],title=j)

df_stocks_initial_position.drop('Total',axis=1).plot(kind='line',ax=ax1[5],title='Combined_graph')
```

Out[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x145b88da978>
```

In [37]:
```
# cumulative portfolio return in percentage terms
cumulative=((df_stocks_initial_position['Total'][-1]/df_stocks_initial_position['Total'][0])-1)
print('The cumulative return from the portfolio of the stocks over the given time period is {} %'.format(cumu
lative))
```

```
The cumulative return from the portfolio of the stocks over the given time period is 3.6232248727343483 %
```

Daily Returns

In [20]:
```
# calculating the Daily returns
df_stocks_initial_position.head(2)
```

Out[20]:

Date	Apple	Microsoft	Oracle	AMD	Total
2017-01-03	5000.000000	5000.000000	5000.000000	5000.0	20000.000000
2017-01-04	4994.403178	4977.629247	5024.643438	5000.0	19996.675863

In [21]:
```
df_stocks_initial_position['Daily_Return_%_change']=(df_stocks_initial_position['Total'].pct_change())*100
df_stocks_initial_position.head()
```

Out[21]:

Date	Apple	Microsoft	Oracle	AMD	Total	Daily_Return_%_change
2017-01-03	5000.000000	5000.000000	5000.000000	5000.000000	20000.000000	NaN
2017-01-04	4994.403178	4977.629247	5024.643438	5000.000000	19996.675863	-0.016621
2017-01-05	5019.801056	4977.629247	5011.671800	4916.885158	19925.987261	-0.353502
2017-01-06	5075.763699	5020.773333	4987.030501	4951.880749	20035.448283	0.549338
2017-01-09	5122.254878	5004.793896	5062.256374	5026.246485	20215.551634	0.898923

In [38]:
```
# Sharpe Ratio: The return per unit amount of risk in addition to the risk free rate is termed as the sharpe
 ratio.
# Here, for ease of calculation purposes, we assume the risk free rate to be 0
sharpe_ratio=df_stocks_initial_position['Daily_Return_%_change'].mean()/df_stocks_initial_position['Daily_Ret
urn_%_change'].std()
sharpe_ratio
```

Out[38]: 0.0869489367846341

Annualised Sharpe ratio

Since we have the daily volatility, to convert it into annual volatility, we multiply the daily volatility with sqrt of 252

In [39]:
```
sharpe_ratio_annualised=sharpe_ratio*(np.sqrt(252))
sharpe_ratio_annualised
```

Out[39]: 1.3802715809617072

Now, we will use the Sharpe ratio to connstruct a portfolio with Optimal performance. Based on Modern Portfolio Thoery, We want to make Portfolios that give us the most amount of return with a least amount of risk. We try to reach the GLobal Minimum variance portfolio

Set up for Portfolio Optimisation

We want to optimise our portfolio to reach the highest sharpe ratio

In [40]:
```
# concatenating the Adjusted close prices for all the stocks
df_new=pd.concat([df_msft['Adj Close'],df_apple['Adj Close'],df_orcl['Adj Close'],df_amd['Adj Close']],axis=1
)
df_new.columns=['Microsoft','Apple','Oracle','AMD']
df_new.head()
```

Out[40]:

	Microsoft	Apple	Oracle	AMD
Date				
2017-01-03	58.291965	27.372364	35.671886	11.43
2017-01-04	58.031158	27.341724	35.847702	11.43
2017-01-05	58.031158	27.480764	35.755157	11.24
2017-01-06	58.534149	27.787130	35.579357	11.32
2017-01-09	58.347855	28.041645	36.116047	11.49

In [41]:
```
# This will show the daily returns of the stocks in the portfolio over the time period chosen
stocks_return=df_new.pct_change(1)
stocks_return.head()
```

Out[41]:

Date	Microsoft	Apple	Oracle	AMD
2017-01-03	NaN	NaN	NaN	NaN
2017-01-04	-0.004474	-0.001119	0.004929	0.000000
2017-01-05	0.000000	0.005085	-0.002582	-0.016623
2017-01-06	0.008668	0.011148	-0.004917	0.007117
2017-01-09	-0.003183	0.009159	0.015084	0.015018

Preparing Variables for the Portfolio Optimisation Technique

In [26]:
```
# We will find 20,000 different portfolio weight combinations and we will select the portfolio with the maxim
um sharpe ratio
number_portfolio_combinations=20000
all_weights=np.zeros((number_portfolio_combinations,len(df_new.columns)))
```

In [27]:
```
all_weights.shape
```

Out[27]: (20000, 4)

In [28]:
```
# Prelocating space for Protfolio calculations
returns_array=np.zeros(number_portfolio_combinations)
volatility_array=np.zeros(number_portfolio_combinations)
sharpe_array=np.zeros(number_portfolio_combinations)
```

Calculate Portfolio Combinations

In [29]:
```
stocks=df_stocks_initial_position[['Apple','Microsoft','Oracle','AMD','Total']]
stocks.head()
```

Out[29]:

Date	Apple	Microsoft	Oracle	AMD	Total
2017-01-03	5000.000000	5000.000000	5000.000000	5000.000000	20000.000000
2017-01-04	4994.403178	4977.629247	5024.643438	5000.000000	19996.675863
2017-01-05	5019.801056	4977.629247	5011.671800	4916.885158	19925.987261
2017-01-06	5075.763699	5020.773333	4987.030501	4951.880749	20035.448283
2017-01-09	5122.254878	5004.793896	5062.256374	5026.246485	20215.551634

In [94]:
```
import random
random.seed(3)
# we want to do 20,000 portfolio combinations to get the the portfolio with the Maximum return per unit amoun
t of risk
for i in range(number_portfolio_combinations):
    # Generate random weights
    numbers=np.array(np.random.random(4))

    # here,4 random numbers are generated in every iteration
    weights=numbers/np.sum(numbers)

    # 4 weights are generated with the above code.
    # every row is assigned the weights which are the weights of the stocks in the portfolio.
    all_weights[i,:]=weights

    # Expected Return
    returns_array[i]=np.sum(stocks_return.mean()*252*weights)

    #Expected Volatility
    volatility_array[i]=np.sqrt(np.dot(weights.T,np.dot(stocks_return.cov()*252,weights)))

    #Sharpe Ratio
    sharpe_array[i]=returns_array[i]/volatility_array[i]
```

In [95]:
```
sharpe_array
```

Out[95]:
```
array([1.36778882, 1.21472223, 1.42277805, ..., 1.361104  , 1.43499746,
       1.28844508])
```

In [96]:
```
print('All weights',all_weights)
print('First combinaiton',all_weights[0])
```

```
All weights [[0.07350126 0.23291167 0.26403763 0.42954944]
 [0.19573019 0.18859026 0.52930361 0.08637594]
 [0.26247179 0.19219816 0.1884837  0.35684635]
 ...
 [0.42582155 0.13056453 0.31035431 0.13325961]
 [0.40451889 0.12335634 0.0949991  0.37712566]
 [0.20093195 0.02418382 0.38173389 0.39315034]]
First combinaiton [0.07350126 0.23291167 0.26403763 0.42954944]
```

Finding the highest sharpe ratio

In [97]:
```
sharpe_array.max()
```

Out[97]:
```
1.5452020275627916
```

Finding the index of the higest sharpe ratio portfolio

In [101]:
```
sharpe_array_max_index=sharpe_array.argmax()
sharpe_array_max_index
```

Out[101]:
```
5361
```

Getting the portfolio weights for the highest shape ratio portfolio

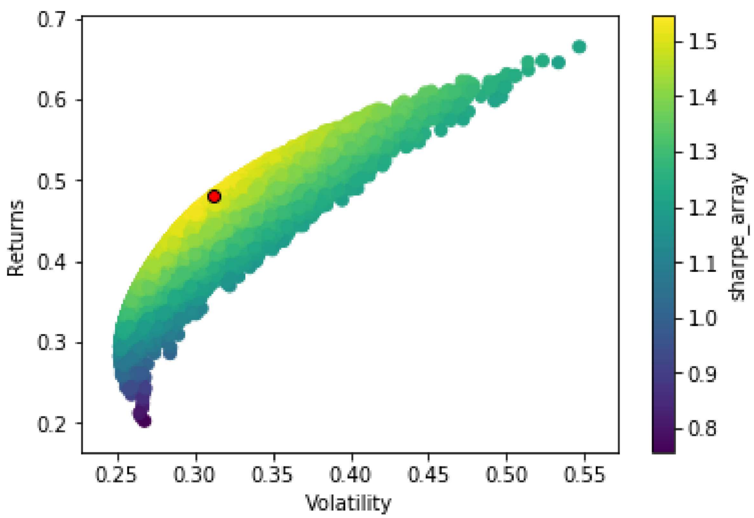
In [105]:
```
print(all_weights[5361])
print(stocks.columns)
```

```
[0.23790736 0.55176976 0.0033548  0.20696808]
Index(['Apple', 'Microsoft', 'Oracle', 'AMD', 'Total'], dtype='object')
```

Plot the Efficient Frontier

In [115]:
```
plt.scatter(volatility_array,returns_array,c=sharpe_array)
plt.xlabel('Volatility')
plt.ylabel('Returns')
plt.colorbar(label='sharpe_array')
# Plotting the portfolio with the highest sharpe ratio
plt.scatter(volatility_array[sharpe_array_max_index],returns_array[sharpe_array_max_index],color='red',edgeco
lors='black')
```

Out[115]:
```
<matplotlib.collections.PathCollection at 0x145ba821438>
```



We have found the optimal weights for the portfolio from 20,000 random weights.

We plotted the efficient frontier and found the minimum variance portfolio that maximises the sharpe Ratio(Return for the investor)