Imported Packages

In [ ]:
```
import numpy as np
import pandas as pd
from pandas_datareader import data
import matplotlib.pyplot as plt
%matplotlib inline
```

Reading Data

In [ ]:
```
test = data.DataReader(['TSLA', 'FB'], 'yahoo', start='2018/01/01', end='2019/12/31')

#Obtaining the closing price [Always use adjusted closing price]
test = test['Adj Close']
test.head()
```

Out[ ]:

Symbols	TSLA	FB
Date		
2018-01-02	64.106003	181.419998
2018-01-03	63.450001	184.669998
2018-01-04	62.924000	184.330002
2018-01-05	63.316002	186.850006
2018-01-08	67.281998	188.279999

Tesla

In [ ]:
```
tesla = test['TSLA'].pct_change().apply(lambda x: np.log(1+x)) #Percentage change (pct_change) is only the arthimetic returns. To obtain the log returns we use the fu
tesla.head()
```

Out[ ]:
```
Date
2018-01-02         NaN
2018-01-03   -0.010286
2018-01-04   -0.008325
2018-01-05    0.006210
2018-01-08    0.060755
Name: TSLA, dtype: float64
```

Variance

In [ ]:
```
var_tesla = tesla.var()
var_tesla
```

Out[ ]:
```
0.0011483734269334606
```

Facebook

In [ ]:
```
fb = test['FB'].pct_change().apply(lambda x: np.log(1+x))
fb.head()
```

Out[ ]:
```
Date
2018-01-02         NaN
2018-01-03    0.017756
2018-01-04   -0.001843
2018-01-05    0.013579
2018-01-08    0.007624
Name: FB, dtype: float64
```

Variance

In [ ]:
```
var_fb = fb.var()
var_fb
```

Out[ ]:
```
0.0004569725841702254
```

Volatility

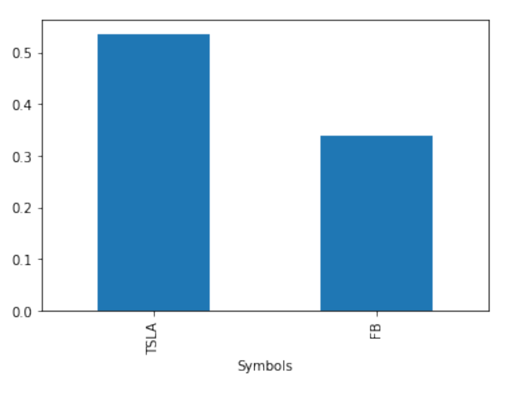
We multiply the SD by 250 because of a standard of 250 trading days. This then makes the SD interms of annual rather than daily

In [ ]:
```
# Volatility
tesla_vol = np.sqrt(var_tesla * 250)
fb_vol = np.sqrt(var_fb * 250)
tesla_vol, fb_vol
```

Out[ ]:
```
(0.5358109337568292, 0.33799873674698305)
```

In [ ]:
```
test.pct_change().apply(lambda x: np.log(1+x)).std().apply(lambda x: x*np.sqrt(250)).plot(kind='bar')
```

Out[ ]:
```
<AxesSubplot:xlabel='Symbols'>
```



Testing Covaraince

In [ ]:
```
test1 = test.pct_change().apply(lambda x: np.log(1+x))
test1.head()
```

Out[ ]:

Symbols	TSLA	FB
Date		
2018-01-02	NaN	NaN
2018-01-03	-0.010286	0.017756
2018-01-04	-0.008325	-0.001843
2018-01-05	0.006210	0.013579
2018-01-08	0.060755	0.007624

In [ ]:
```
test1['TSLA'].cov(test1['FB'])
```

Out[ ]:
```
0.0001826162315603096
```

Testing Correlation

In [ ]:
```
test1['TSLA'].corr(test1['FB'])
```

Out[ ]:
```
0.2520883272466129
```

Optimized Risky Portfolio

In [ ]:
```
df = data.DataReader(['AAPL', 'NKE', 'GOOGL', 'AMZN'], 'yahoo', start='2015/01/01', end='2019/12/31')
df = df['Adj Close']
df.head()
```

Out[ ]:

Symbols	AAPL	NKE	GOOGL	AMZN
Date				
2014-12-31	24.915258	44.524044	530.659973	310.350006
2015-01-02	24.678257	44.005405	529.549988	308.519989
2015-01-05	23.983025	43.296913	519.460022	302.190002
2015-01-06	23.985281	43.042233	506.640015	295.290009
2015-01-07	24.321604	43.931309	505.149994	298.420013

Using a Covariance and Correlation matrix

In [ ]:
```
cov_matrix = df.pct_change().apply(lambda x: np.log(1+x)).cov()
cov_matrix
```

Out[ ]:

Symbols	AAPL	NKE	GOOGL	AMZN
Symbols				
AAPL	0.000245	0.000084	0.000122	0.000142
NKE	0.000084	0.000219	0.000085	0.000092
GOOGL	0.000122	0.000085	0.000221	0.000176
AMZN	0.000142	0.000092	0.000176	0.000333

In [ ]:
```
corr_matrix = df.pct_change().apply(lambda x: np.log(1+x)).corr()
corr_matrix
```

Out[ ]:

Symbols	AAPL	NKE	GOOGL	AMZN
Symbols				
AAPL	1.000000	0.361188	0.524818	0.496704
NKE	0.361188	1.000000	0.387448	0.341680
GOOGL	0.524818	0.387448	1.000000	0.647952
AMZN	0.496704	0.341680	0.647952	1.000000

Applying resampling to the data to make them in yearly data

In [ ]:
```
ind_er = df.resample('Y').last().pct_change().mean()
ind_er
```

Out[ ]:
```
Symbols
AAPL     0.282997
NKE      0.192698
GOOGL    0.217545
AMZN     0.472289
dtype: float64
```

In [ ]:
```
ann_sd = df.pct_change().apply(lambda x: np.log(1+x)).std().apply(lambda x: x*np.sqrt(250))
ann_sd
```

Out[ ]:
```
Symbols
AAPL     0.247734
NKE      0.233803
GOOGL    0.235191
AMZN     0.288559
dtype: float64
```

In [ ]:
```
assets = pd.concat([ind_er, ann_sd], axis=1) # Creating a table for visualising returns and volatility of assets
assets.columns = ['Returns', 'Volatility']
assets
```

Out[ ]:

	Returns	Volatility
Symbols		
AAPL	0.282997	0.247734
NKE	0.192698	0.233803
GOOGL	0.217545	0.235191
AMZN	0.472289	0.288559

Creating a lopop of random values to create multiple instances of weights

In [ ]:
```
p_ret = [] # Define an empty array for portfolio returns
p_vol = [] # Define an empty array for portfolio volatility
p_weights = [] # Define an empty array for asset weights
```

In [ ]:
```
num_assets = len(df.columns)
num_portfolios = 10000
```

In [ ]:
```
for portfolio in range(num_portfolios):
    weights = np.random.random(num_assets)
    weights = weights/np.sum(weights)
    p_weights.append(weights)
    returns = np.dot(weights, ind_er) # Returns are the product of individual expected returns of asset and its
                                      # weights
    p_ret.append(returns)
    var = cov_matrix.mul(weights, axis=0).mul(weights, axis=1).sum().sum()# Portfolio Variance
    sd = np.sqrt(var) # Daily standard deviation
    ann_sd = sd*np.sqrt(250) # Annual standard deviation = volatility
    p_vol.append(ann_sd)
```

Compiling the data

In [ ]:
```
data = {'Returns':p_ret, 'Volatility':p_vol}

for counter, symbol in enumerate(df.columns.tolist()):
    data[symbol+' weight'] = [w[counter] for w in p_weights]
```

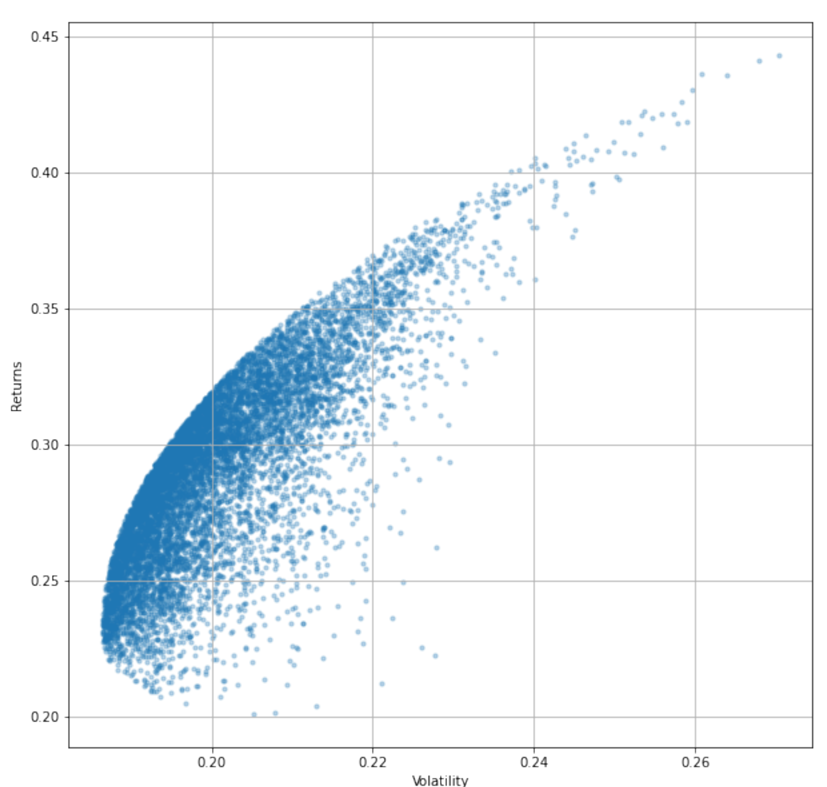
In [ ]:
```
portfolios  = pd.DataFrame(data)
portfolios.head() # Dataframe of the 10000 portfolios created
```

Out[ ]:

	Returns	Volatility	AAPL weight	NKE weight	GOOGL weight	AMZN weight
0	0.259541	0.191119	0.266113	0.510940	0.076628	0.146319
1	0.263758	0.188340	0.232161	0.398215	0.209024	0.160599
2	0.287587	0.198641	0.056220	0.314607	0.337979	0.291194
3	0.242238	0.191440	0.198836	0.259903	0.470064	0.071198
4	0.315785	0.207953	0.059465	0.227134	0.320882	0.392518

In [ ]:
```
portfolios.plot.scatter(x='Volatility', y='Returns', marker='o', s=10, alpha=0.3, grid=True, figsize=[10,10])
```

Out[ ]:
```
<AxesSubplot:xlabel='Volatility', ylabel='Returns'>
```



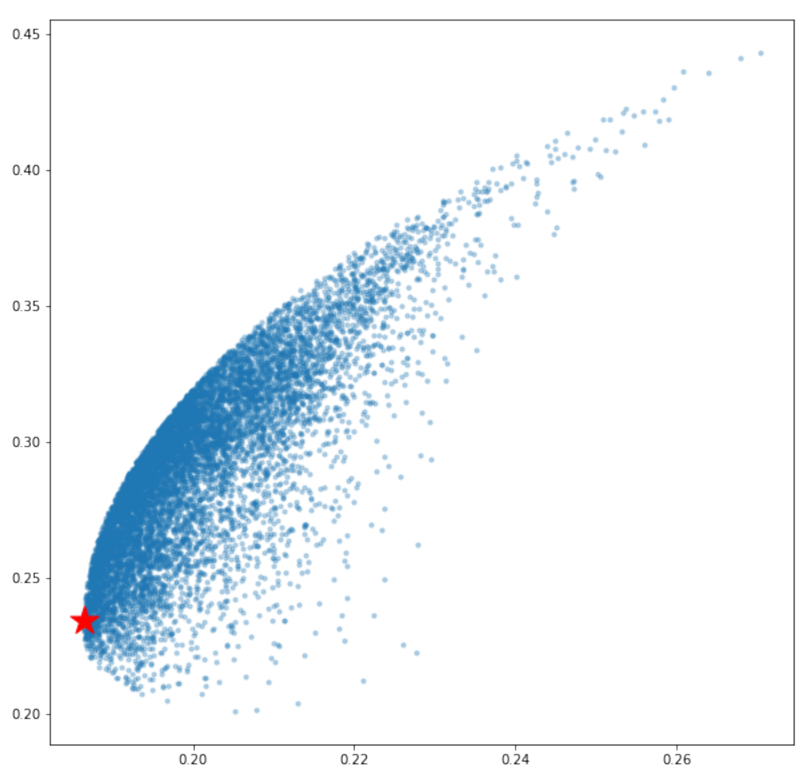
Minimum risk portfolio

In [ ]:
```
min_vol_port = portfolios.iloc[portfolios['Volatility'].idxmin()]
# idxmin() gives us the minimum value in the column specified.
min_vol_port
#Return index of first occurrence of minimum over requested axis. NA/null values are excluded.
```

Out[ ]:
```
Returns         0.233995
Volatility      0.186478
AAPL weight     0.256271
NKE weight      0.410757
GOOGL weight    0.294179
AMZN weight     0.038793
Name: 2001, dtype: float64
```

In [ ]:
```
plt.subplots(figsize=[10,10])
plt.scatter(portfolios['Volatility'], portfolios['Returns'],marker='o', s=10, alpha=0.3)
plt.scatter(min_vol_port[1], min_vol_port[0], color='r', marker='*', s=500)
```

Out[ ]:
```
<matplotlib.collections.PathCollection at 0x121f02a10>
```



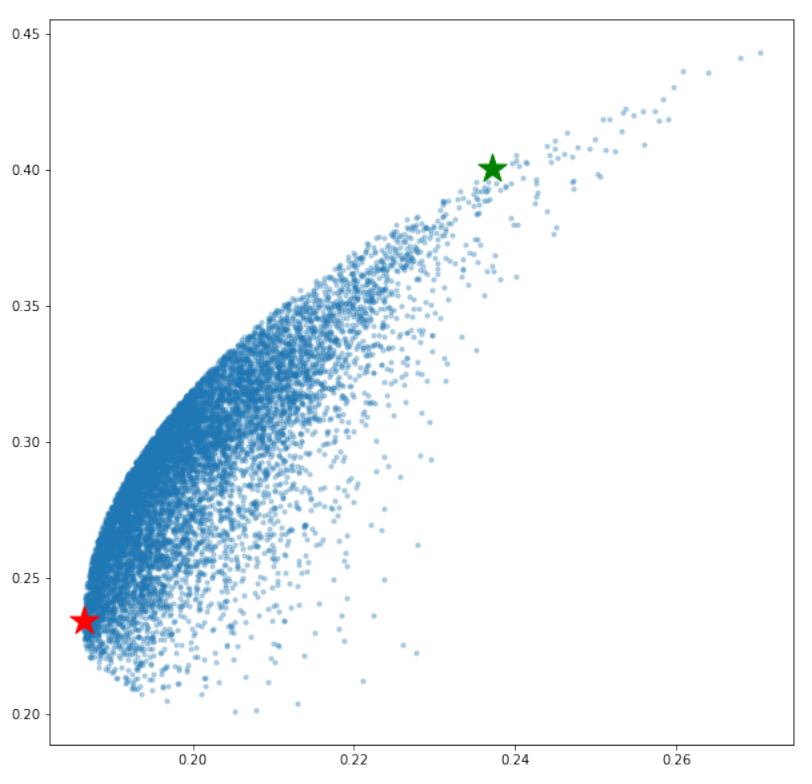
Optimal Risky Portfolio

In [ ]:
```
rf = 0.01 # risk factor #Risk free rate
optimal_risky_port = portfolios.iloc[((portfolios['Returns']-rf)/portfolios['Volatility']).idxmax()]
optimal_risky_port
```

Out[ ]:
```
Returns         0.400621
Volatility      0.237216
AAPL weight     0.237868
NKE weight      0.088985
GOOGL weight    0.006918
AMZN weight     0.666229
Name: 3567, dtype: float64
```

In [ ]:
```
plt.subplots(figsize=(10, 10))
plt.scatter(portfolios['Volatility'], portfolios['Returns'],marker='o', s=10, alpha=0.3)
plt.scatter(min_vol_port[1], min_vol_port[0], color='r', marker='*', s=500)
plt.scatter(optimal_risky_port[1], optimal_risky_port[0], color='g', marker='*', s=500)
```

Out[ ]:
```
<matplotlib.collections.PathCollection at 0x11e828e20>
```



In [ ]: