



INTRO TO PORTFOLIO RISK MANAGEMENT IN PYTHON

Portfolio Composition

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Calculating Portfolio Returns

PORTFOLIO RETURN FORMULA:

$$R_p = R_{a_1}w_{a_1} + R_{a_2}w_{a_2} + \dots + R_{a_n}w_{a_n}$$

- R_p : Portfolio return
- R_{a_n} : Return for asset n
- w_{a_n} : Weight for asset n



Calculating Portfolio Returns in Python

Assuming `StockReturns` is a pandas `DataFrame` of stock returns, you can calculate the portfolio return for a set of portfolio weights as follows:

```
In [1]: import numpy as np
In [2]: portfolio_weights = np.array([0.25, 0.35, 0.10, 0.20, 0.10])
In [3]: port_ret = StockReturns.mul(portfolio_weights, axis=1).sum(axis=1)
In [4]: port_ret
Out [4]: Date
          2017-01-03      0.008082
          2017-01-04      0.000161
          2017-01-05      0.003448
          ...
In [5]: StockReturns["Portfolio"] = port_ret
```



Equally Weighted Portfolios in Python

Assuming `StockReturns` is a pandas `DataFrame` of stock returns, you can calculate the portfolio return for an **equally weighted** portfolio as follows:

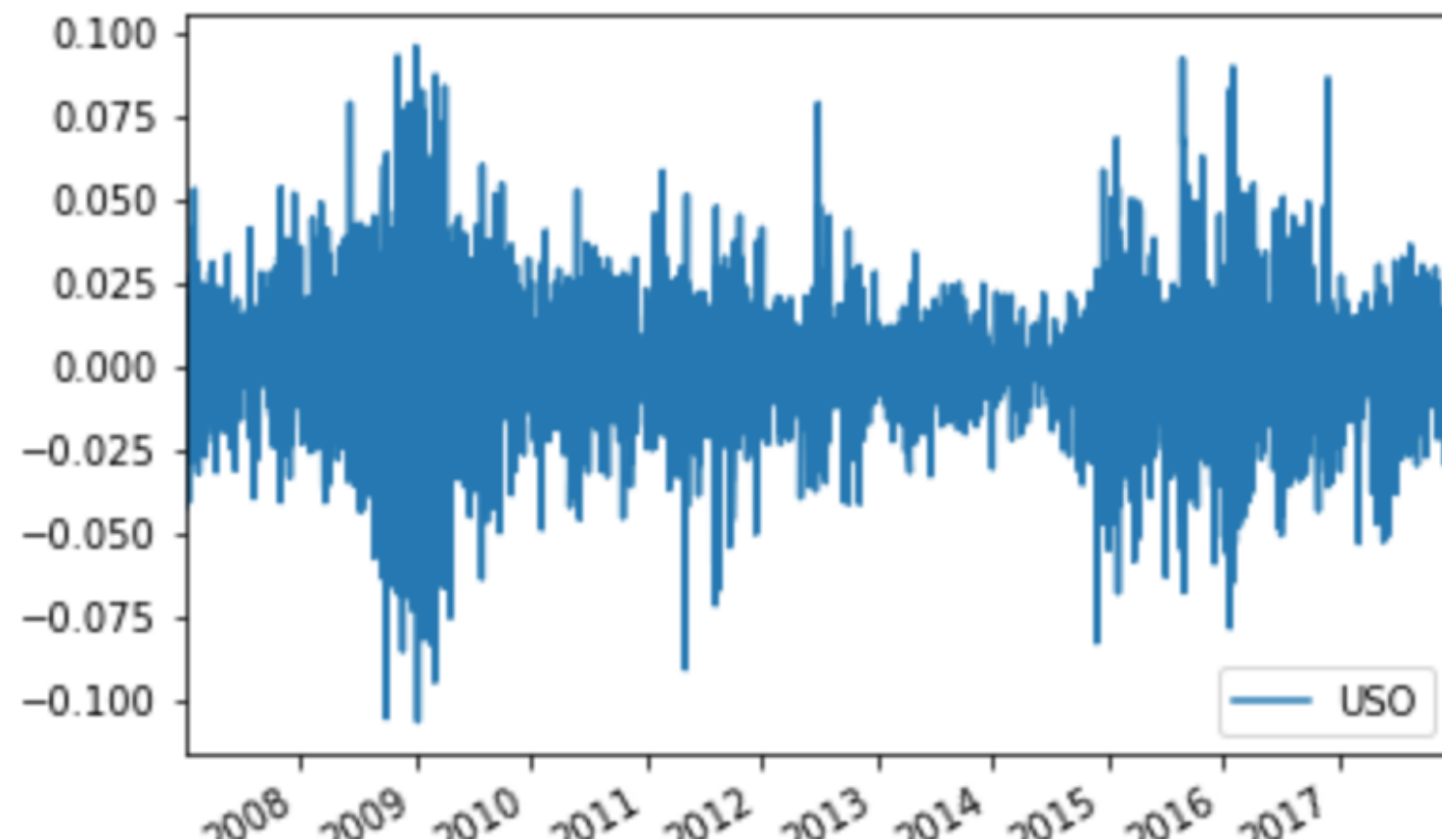
```
In [1]: import numpy as np
In [2]: numstocks = 5
In [3]: portfolio_weights_ew = np.repeat(1/numstocks, numstocks)
In [4]: StockReturns.iloc[:,0:numstocks].mul(portfolio_weights_ew, axis=1).sum(a
Out [4]: Date
          2017-01-03      0.008082
          2017-01-04      0.000161
          2017-01-05      0.003448
          ...
```



Plotting Portfolio Returns in Python

To plot the daily returns in Python:

```
In [1]: StockPrices["Returns"] = StockPrices["Adj Close"].pct_change()  
In [2]: StockReturns = StockPrices["Returns"]  
In [3]: StockReturns.plot()
```





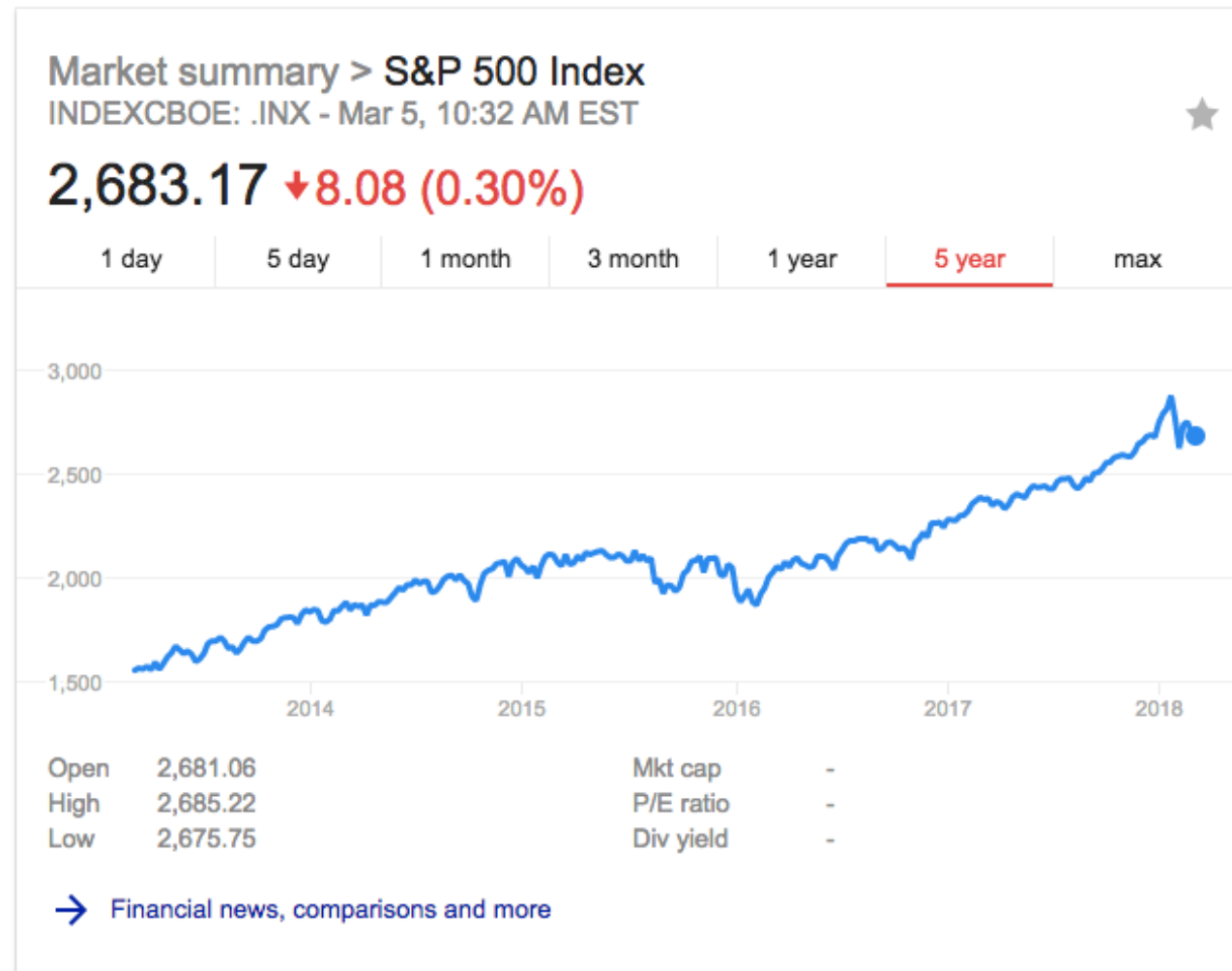
Plotting Portfolio Cumulative Returns

In order to plot the cumulative returns of multiple portfolios:

```
In [1]: import matplotlib.pyplot as plt
In [2]: CumulativeReturns = ((1+StockReturns).cumprod()-1)
In [3]: CumulativeReturns[["Portfolio", "Portfolio_EW"]].plot()
Out [3]:
```



Market Capitalization





Market Capitalization

Market Capitalization: The value of a company's publically traded shares.

Also referred to as **Market Cap**.



Market-Cap Weighted Portfolios

In order to calculate the market cap weight of a given stock n :

$$w_{mcap_n} = \frac{mcap_n}{\sum_{i=1}^n mcap_i}$$



Market-Cap Weights in Python

To calculate market cap weights in python, assuming you have data on the market caps of each company:

```
In [1]: import numpy as np
In [2]: market_capitalizations = np.array([100, 200, 100, 100])
In [3]: mcap_weights = market_capitalizations/sum(market_capitalizations)
In [4]: mcap_weights
Out [4]: array([0.2, 0.4, 0.2, 0.2])
```



INTRO TO PORTFOLIO RISK MANAGEMENT IN PYTHON

Let's practice!



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Correlation and Co-Variance

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Pearson Correlation

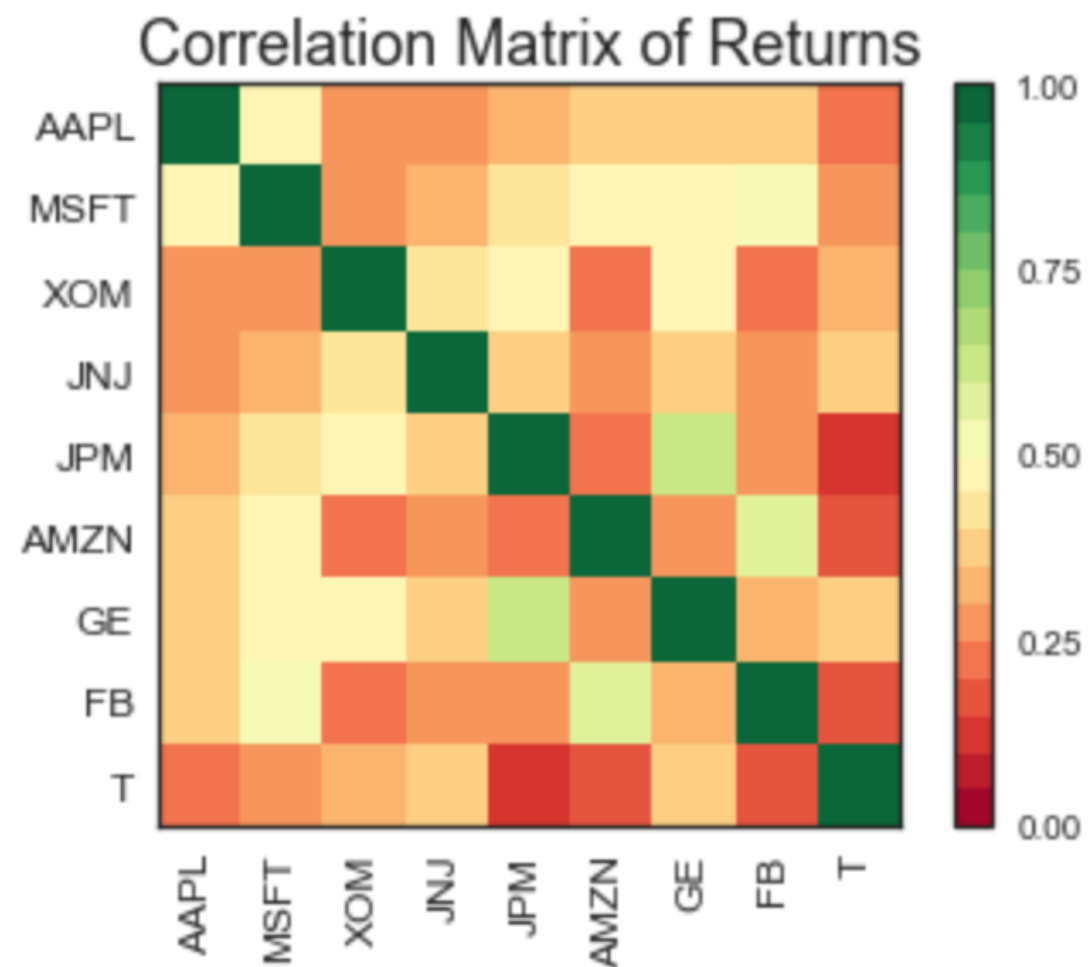
EXAMPLES OF DIFFERENT CORRELATIONS BETWEEN TWO RANDOM VARIABLES:





Pearson Correlation

A HEATMAP OF A CORRELATION MATRIX:





Correlation Matrix in Python

Assuming `StockReturns` is a pandas `DataFrame` of stock returns, you can calculate the correlation matrix as follows:

```
In [1]: correlation_matrix = StockReturns.corr()  
In [2]: print(correlation_matrix)  
Out [2]:
```



Portfolio Standard Deviation

Portfolio standard deviation for a two asset portfolio:

$$\sigma_p = \sqrt{w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1 w_2 \rho_{1,2} \sigma_1 \sigma_2}$$

- σ_p : Portfolio standard deviation
- w : Asset weight
- σ : Asset volatility
- $\rho_{1,2}$: Correlation between assets 1 and 2



The Co-Variance Matrix

To calculate the co-variance matrix (Σ) of returns X :

$$\Sigma = \begin{bmatrix} \mathbb{E}[(X_1 - \mu_1)(X_1 - \mu_1)] & \mathbb{E}[(X_1 - \mu_1)(X_2 - \mu_2)] & \cdots & \mathbb{E}[(X_1 - \mu_1)(X_n - \mu_n)] \\ \mathbb{E}[(X_2 - \mu_2)(X_1 - \mu_1)] & \mathbb{E}[(X_2 - \mu_2)(X_2 - \mu_2)] & \cdots & \mathbb{E}[(X_2 - \mu_2)(X_n - \mu_n)] \\ \vdots & \vdots & \ddots & \vdots \\ \mathbb{E}[(X_n - \mu_n)(X_1 - \mu_1)] & \mathbb{E}[(X_n - \mu_n)(X_2 - \mu_2)] & \cdots & \mathbb{E}[(X_n - \mu_n)(X_n - \mu_n)] \end{bmatrix}$$



The Co-Variance Matrix in Python

Assuming `StockReturns` is a pandas `DataFrame` of stock returns, you can calculate the covariance matrix as follows:

```
In [1]: cov_mat = StockReturns.cov()  
In [2]: cov_mat  
Out [2]:
```



Annualizing the Covariance Matrix

To annualize the covariance matrix:

```
In [2]: cov_mat_annual = cov_mat*252
```



Portfolio Standard Deviation using Covariance

The formula for portfolio volatility is:

$$\sigma_{Portfolio} = \sqrt{w_T \cdot \Sigma \cdot w}$$

- $\sigma_{Portfolio}$: Portfolio volatility
- Σ : Covariance matrix of returns
- w : Portfolio weights (w_T is transposed portfolio weights)
- \cdot The dot-multiplication operator

Matrix Transpose

Examples of **matrix transpose** operations:

$$\begin{bmatrix} 1 & 2 \end{bmatrix}^T = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}^T = \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{bmatrix}^T = \begin{bmatrix} 1 & 3 & 5 \\ 2 & 4 & 6 \end{bmatrix}$$



Dot Product

The **dot product** operation of two vectors **a** and **b**:

$$\mathbf{a} \cdot \mathbf{b} = \sum_{i=1}^n a_i b_i = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n$$



Portfolio Standard Deviation using Python

To calculate portfolio volatility assume a weights array and a covariance matrix:

```
In [1]: import numpy as np
In [2]: port_vol = np.sqrt(np.dot(weights.T, np.dot(cov_mat, weights)))
In [3]: port_vol
Out [3]: 0.035
```



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Let's practice!



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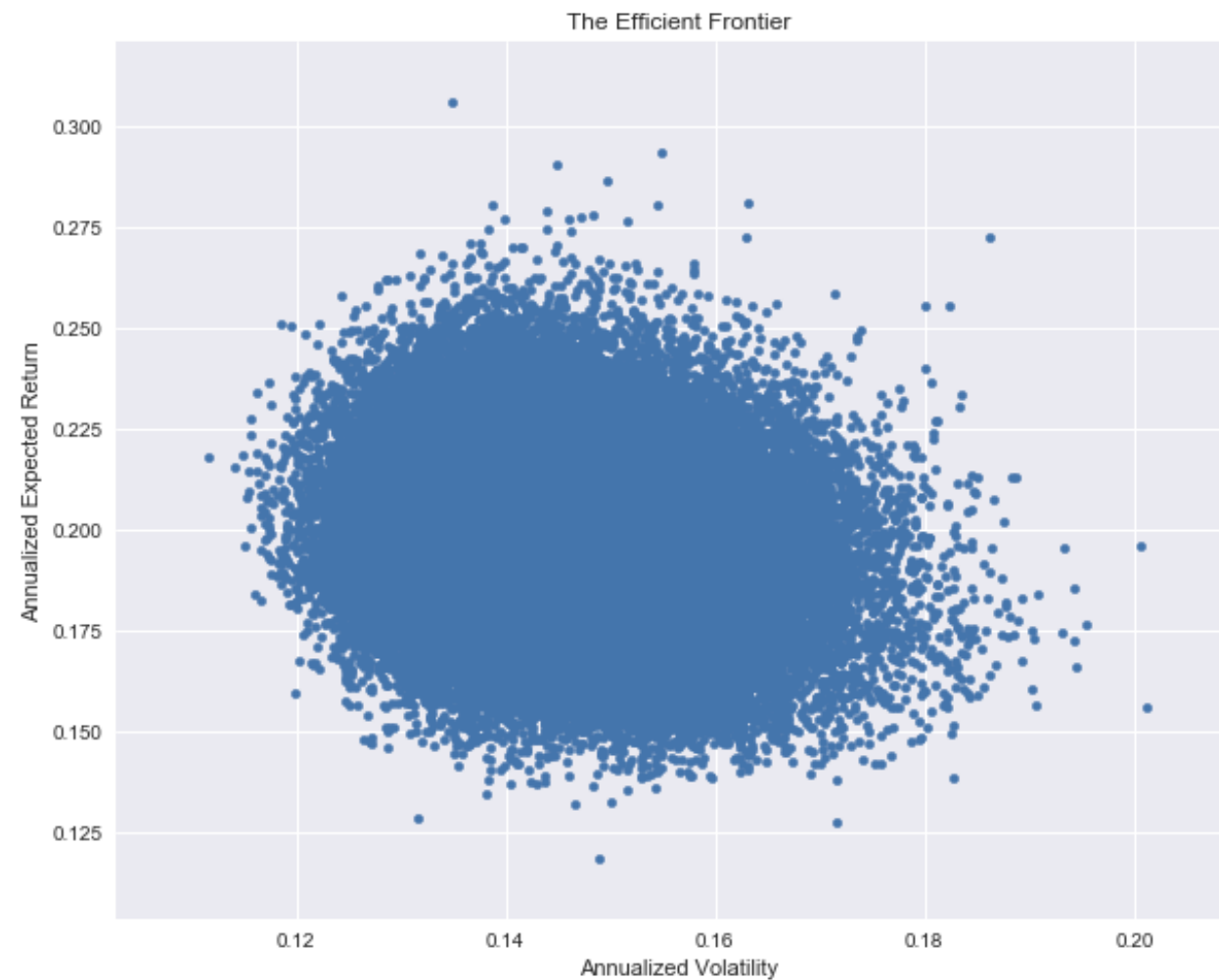
Markowitz Portfolios

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100,000 Randomly Generated Portfolios





Sharpe Ratio

The Sharpe ratio is a measure of **risk-adjusted return**.

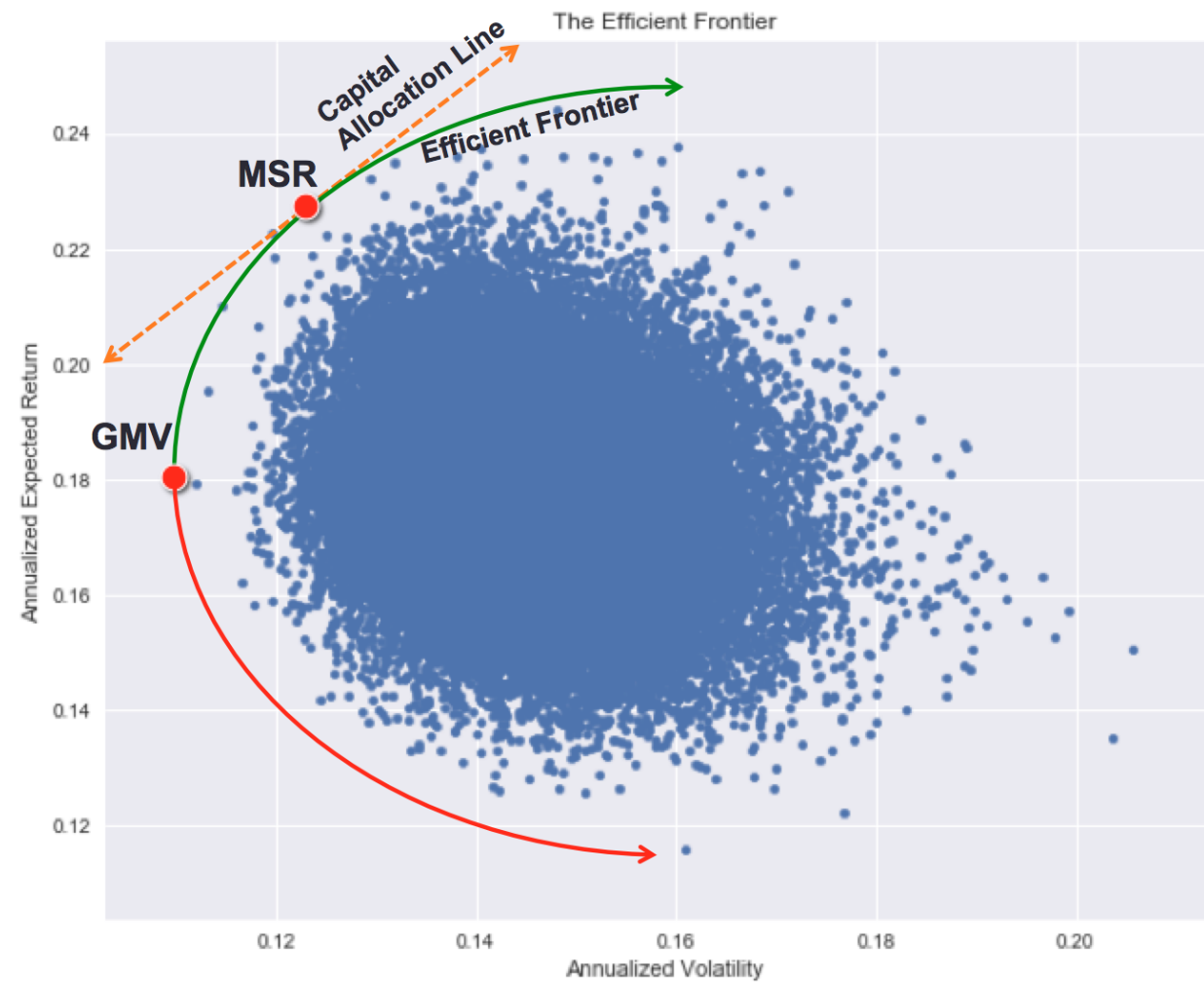
To calculate the 1966 version of the Sharpe ratio:

$$S = \frac{R_a - r_f}{\sigma_a}$$

- S : Sharpe Ratio
- R_a : Asset return
- r_f : Risk-free rate of return
- σ_a : Asset volatility



The Efficient Frontier

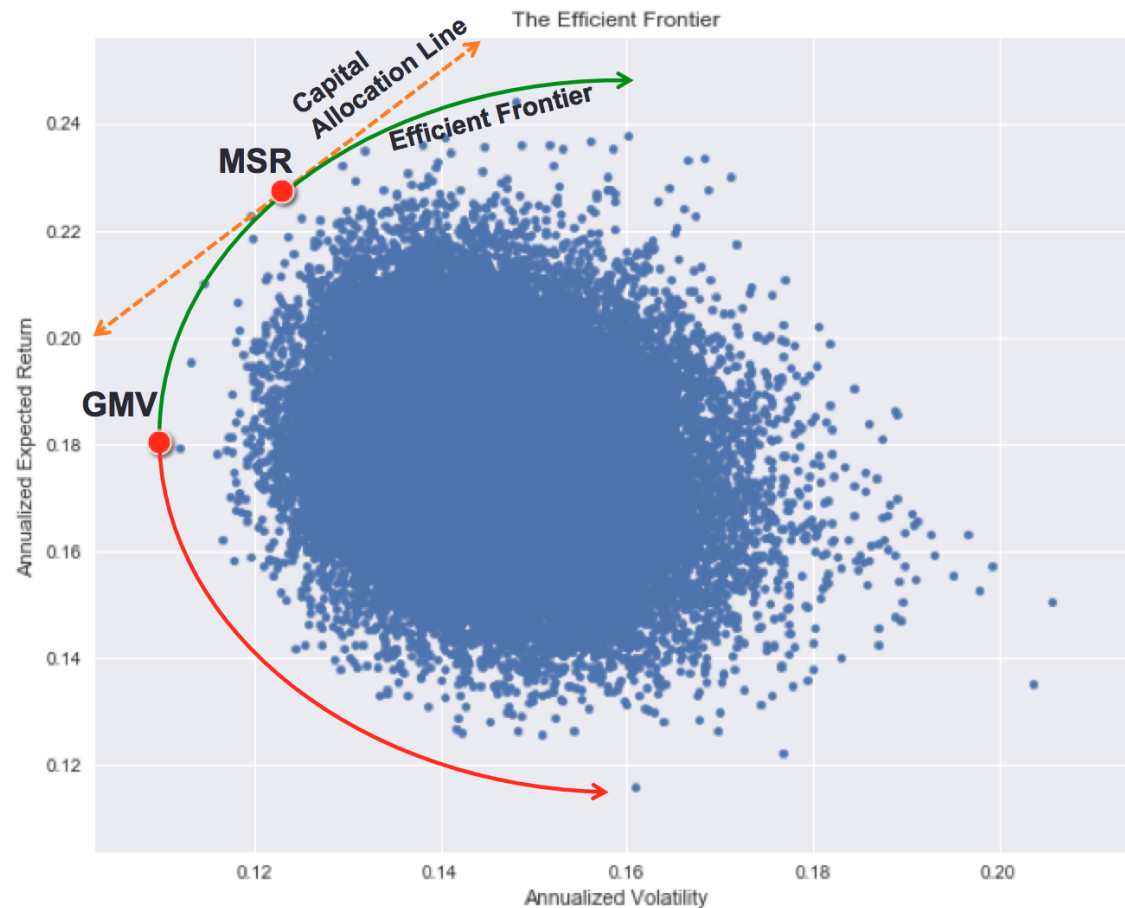


The Markowitz Portfolios

Any point on the efficient frontier is an optimum portfolio.

These two common points are called **Markowitz Portfolios**:

- **MSR**: Max **S**harpe **R**atio portfolio
- **GMV**: Global **M**inimum **V**olatility portfolio





Choosing a Portfolio

How do you choose the best Portfolio?

- Try to pick a portfolio on the bounding edge of the efficient frontier
- Higher return is available if you can stomach higher risk



Selecting the MSR in Python

Assuming a DataFrame `df` of random portfolios with `Volatility` and `Returns` columns:

```
In [1]: numstocks = 5
In [2]: risk_free = 0
In [3]: df["Sharpe"] = (df["Returns"]-risk_free)/df["Volatility"]
In [4]: MSR = df.sort_values(by=['Sharpe'], ascending=False)
In [5]: MSR_weights = MSR.iloc[0,numstocks]
In [6]: np.array(MSR_weights)
Out [6]: array([0.15, 0.35, 0.10, 0.15, 0.25])
```



Past Performance is Not a Guarantee of Future Returns

Even though a Max Sharpe Ratio portfolio might sound nice, in practice, returns are extremely difficult to predict.



Selecting the GMV in Python

Assuming a DataFrame `df` of random portfolios with `Volatility` and `Returns` columns:

```
In [1]: numstocks = 5
In [2]: GMV = df.sort_values(by=['Volatility'], ascending=True)
In [3]: GMV_weights = GMV.iloc[0,0:numstocks]
In [4]: np.array(GMV_weights)
Out [4]: array([0.25, 0.15, 0.35, 0.15, 0.10])
```



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