



Experiment 1

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Batch: D11

Aim: Analysis of returns and risk adjusted returns on a given dataset

Objective:

- Understand the concept of risk-adjusted returns.
- Calculate risk-adjusted returns using different methods.
- Analyze the returns and risk-adjusted returns of a given dataset.

Theory:

- Risk is the uncertainty of future returns. It is often measured by the standard deviation of returns.
- Return is the income or profit that an investment generates. It is often measured by the average return over a period of time.
- Risk-adjusted returns are a measure of how well an investment has performed relative to its risk. They consider both the return and the risk of an investment.

There are a number of different methods for calculating risk-adjusted returns, but some of the most common include:

1. Sharpe ratio: The Sharpe ratio is the most common ratio for comparing reward (return on investment) to risk (standard deviation). This allows us to adjust the returns on an investment by the amount of risk that was taken in order to achieve it. The Sharpe ratio also provides a useful metric to compare investments. The calculations are as follows:

$$\text{Sharpe ratio} = \frac{\bar{R} - R_f}{\sigma}$$

\bar{R} : annual expected return of the asset in question.

R_f : annual risk-free rate. Think of this like a deposit in the bank earning x% per annum.

σ : annualized standard deviation of returns

Since our data frequency is daily, we need to annualize the expected return and standard deviation. This can be achieved by multiplying the daily average return by 255. And multiplying the daily standard deviation by $\sqrt{255}$. For simplicity we will assume that the risk-free rate $R_f = 1\%$ throughout the 7-year period.



2. Sortino Ratio: The Sortino ratio is very similar to the Sharpe ratio, the only difference being that where the Sharpe ratio uses all the observations for calculating the standard deviation the Sortino ratio only considers the harmful variance. So in the plot below, we are only considering the deviations colored red. The rationale for this is that we aren't too worried about positive deviations, however, the negative deviations are of great concern, since they represent loss of our money.

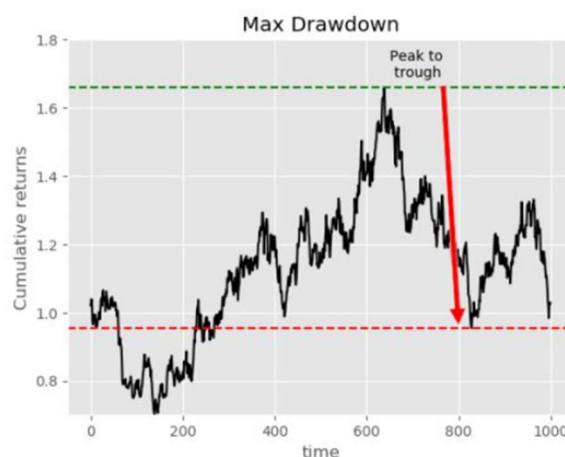
$$\text{Sortino ratio} = \frac{\bar{R} - R_f}{\sigma^-}$$

Everything in the ratio above is the same as the Sharpe ratio except σ^- represents the annualized downside standard deviation.

3. Max Drawdown Ratio: Max drawdown quantifies the steepest decline from peak to trough observed for an investment. This is useful for a number of reasons, mainly the fact that it doesn't rely on the underlying returns being normally distributed. It also gives us an indication of conditionality amongst the returns increments. Whereas in the previous ratios, we only considered the overall reward relative to risk, however, it may be that consecutive returns are not independent leading to unacceptably high losses of a given period of time. To calculate max drawdown first we need to calculate a series of drawdowns as follows:

$$\text{drawdowns} = \frac{\text{peak} - \text{trough}}{\text{peak}}$$

We then take the minimum of this value throughout the period of analysis.





4. Calmar Ratio: The final risk/reward ratio we will consider is the Calmar ratio. This is similar to the other ratios, with the key difference being that the Calmar ratio uses max drawdown in the denominator as opposed to standard deviation.

$$\text{Calmar ratio} = \frac{\bar{R}}{\text{max drawdown}}$$

Lab Experiment to be done by students:

1. Download a dataset of historical stock returns.
2. Calculate the risk-adjusted returns of the stocks in the dataset using Sharpe ratio, Sortino ratio, Max Drawdown Ratio, and Calmer Ratio.
3. Plot the risk-adjusted returns of the stocks on a chart.
4. Analyze the returns and risk-adjusted returns of the stocks in the dataset.

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```
In [ ]: import pandas_datareader.data as web
import datetime as dt
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.style.use('ggplot')
```

```
In [ ]: import datetime as dt
import yfinance as yf

start = dt.datetime(2013, 1, 1)
end = dt.datetime(2022, 10, 1)

tickers = ['AAPL', 'AMZN', 'MSFT', 'GOOGL', 'NVDA']

# Download data from Yahoo Finance
stocks = yf.download(tickers, start=start, end=end)['Adj Close']

# Display the first few rows of the DataFrame
print(stocks.head())
```

```
[*****100%*****] 5 of 5 completed
```

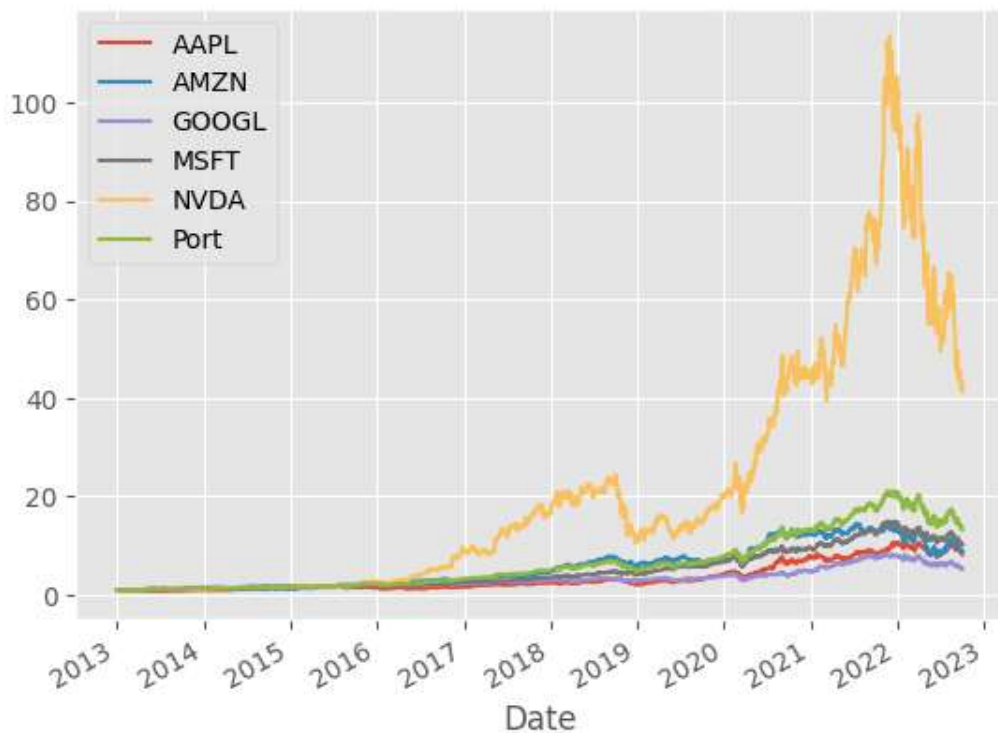
	AAPL	AMZN	GOOGL	MSFT	NVDA
Date					
2013-01-02	16.813856	12.8655	18.099348	22.668222	2.936478
2013-01-03	16.601625	12.9240	18.109859	22.364567	2.938786
2013-01-04	16.139202	12.9575	18.467718	21.945997	3.035745
2013-01-07	16.044262	13.4230	18.387136	21.904961	2.948021
2013-01-08	16.087439	13.3190	18.350851	21.790060	2.883382

```
In [ ]: df = stocks.pct_change().dropna()
df['Port'] = df.mean(axis=1) # 20% apple, ... , 20% facebook
(df+1).cumprod().plot()

(df+1).cumprod()[-1:]
```

Out[]:

	AAPL	AMZN	GOOGL	MSFT	NVDA	Port
Date						
2022-09-30	8.181971	8.78318	5.284721	10.197531	41.31677	13.225672



The plot shows the growth of \$1 invested on 1st Jan 2013 until 10th Oct 2022. For every \$1 you invested in Apple in 2013 you would now have approximately \$8 and so-forth.

SHARPE RATIO

The Sharpe ratio is the most common ratio for comparing reward (return on investment) to risk (standard deviation). This allows us to adjust the returns on an investment by the amount of risk that was taken in order to achieve it. The Sharpe ratio also provides a useful metric to compare investments. The calculations are as follows:

Sharpe ratio

$$(R - R_f) / \sigma$$

R : annual expected return of the asset.

R_f : annual risk-free rate. Think of this like a deposit in the bank earning x% per annum.

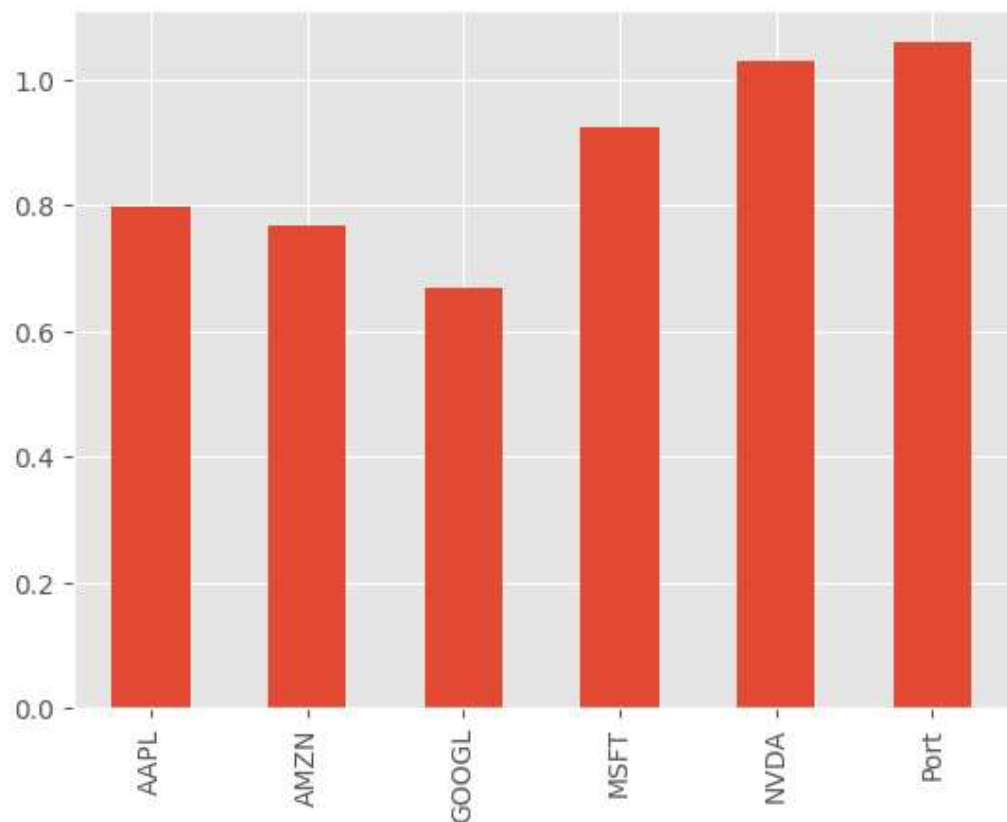
σ : annualized standard deviation of returns.

```
In [ ]: def sharpe_ratio(return_series, N, rf):
        mean = return_series.mean() * N - rf
        sigma = return_series.std() * np.sqrt(N)
        return mean / sigma

N = 255 #255 trading days in a year
rf = 0.03 #3% risk free rate
sharpes = df.apply(sharpe_ratio, args=(N,rf,),axis=0)

sharpes.plot.bar()
```

Out[]: <Axes: >



SORTINO RATIO

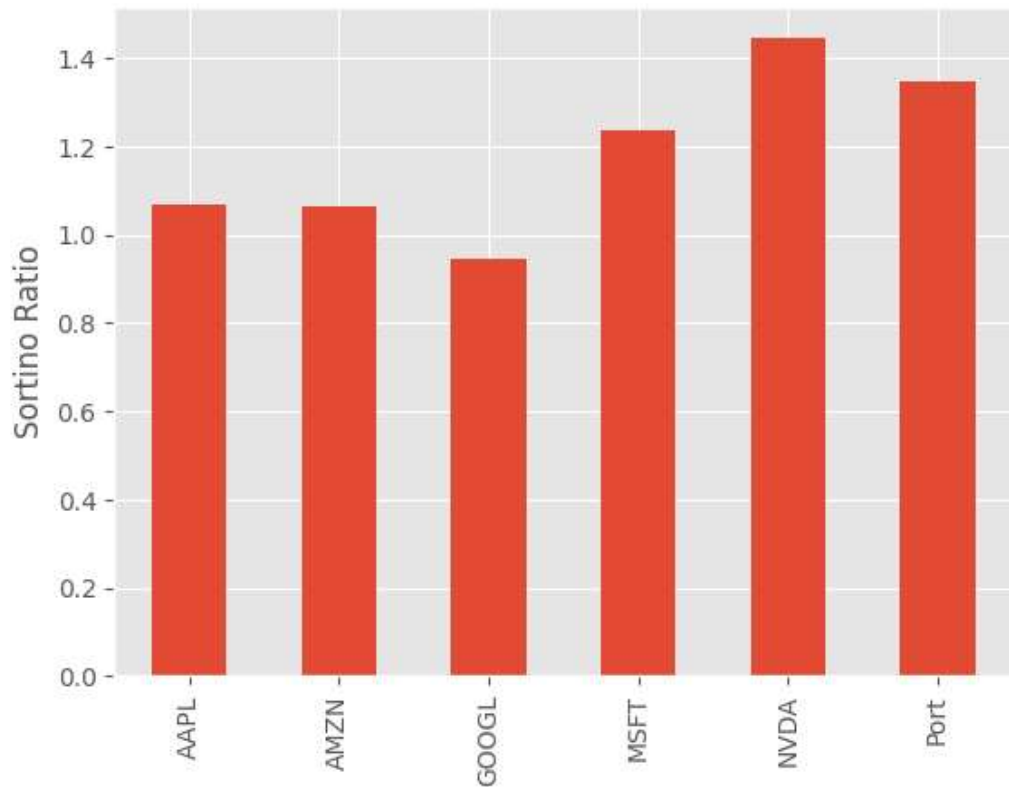
Sortino ratio = $(R - R_f) / \sigma_-$

Everything in the ratio above is the same as the Sharpe ratio except σ_- represents the annualized down-side standard deviation.

```
In [ ]: def sortino_ratio(series, N, rf):
        mean = series.mean() * N - rf
        std_neg = series[series<0].std()*np.sqrt(N)
        return mean/std_neg

        sortinos = df.apply(sortino_ratio, args=(N, rf, ), axis=0 )
        sortinos.plot.bar()
        plt.ylabel('Sortino Ratio')
```

```
Out[ ]: Text(0, 0.5, 'Sortino Ratio')
```



Max Drawdown

To calculate max drawdown first we need to calculate a series of drawdowns as follows:

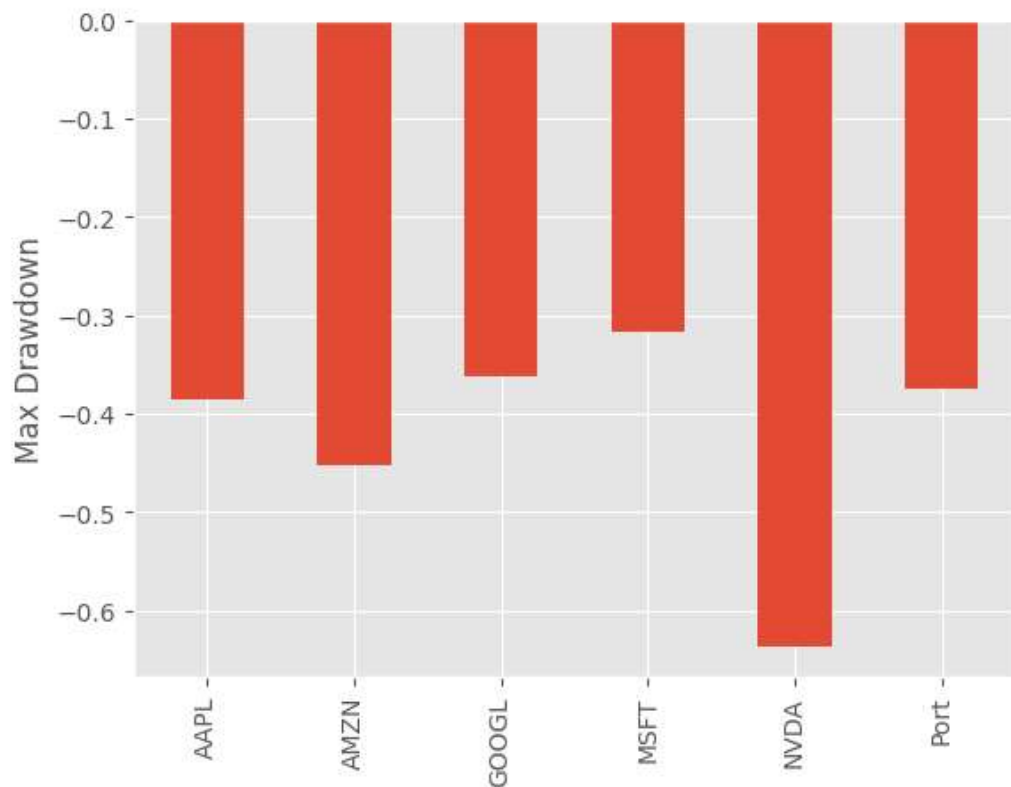
drawdowns

peak-trough/ peak

```
In [ ]: def max_drawdown(return_series):
        comp_ret = (return_series+1).cumprod()
        peak = comp_ret.expanding(min_periods=1).max()
        dd = (comp_ret/peak)-1
        return dd.min()

max_drawdowns = df.apply(max_drawdown,axis=0)
max_drawdowns.plot.bar()
plt.ylabel('Max Drawdown')
```

```
Out[ ]: Text(0, 0.5, 'Max Drawdown')
```



Calmer Ratio

The final risk/reward ratio we will consider is the Calmar ratio. This is similar to the other ratios, with the key difference being that the Calmar ratio uses max drawdown in the denominator as opposed to standard deviation.

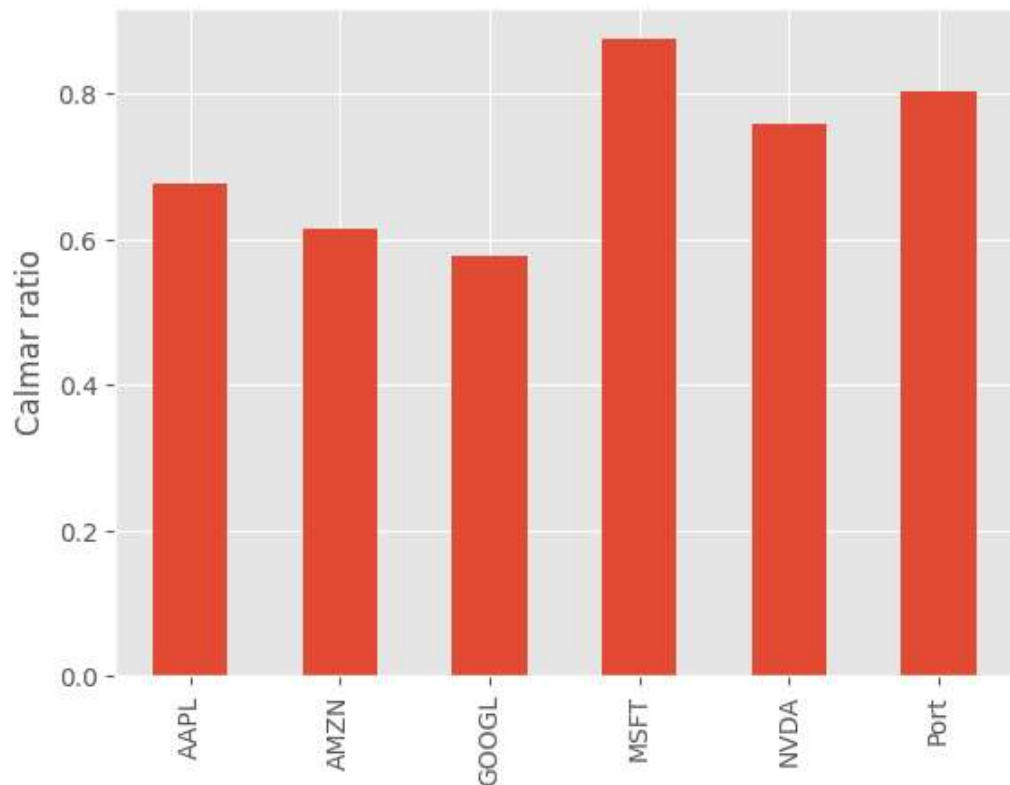
Calmar ratio

$R / \text{max drawdown}$


```
In [ ]: calmars = df.mean()*255/abs(max_drawdowns)

calmars.plot.bar()
plt.ylabel('Calmar ratio')
```

```
Out[ ]: Text(0, 0.5, 'Calmar ratio')
```



Combining All Ratio's

```
In [ ]: btstats = pd.DataFrame()
btstats['sortino'] = sortinos
btstats['sharpe'] = sharpes
btstats['maxdd'] = max_drawdowns
btstats['calmar'] = calmars

btstats
```

```
Out[ ]:
```

	sortino	sharpe	maxdd	calmar
AAPL	1.068419	0.797304	-0.385159	0.675952
AMZN	1.061729	0.768339	-0.451628	0.614954
GOOGL	0.943511	0.667806	-0.361646	0.576838
MSFT	1.236827	0.924025	-0.316774	0.875126
NVDA	1.444132	1.029911	-0.636004	0.759611
Port	1.347444	1.058855	-0.374970	0.803810

