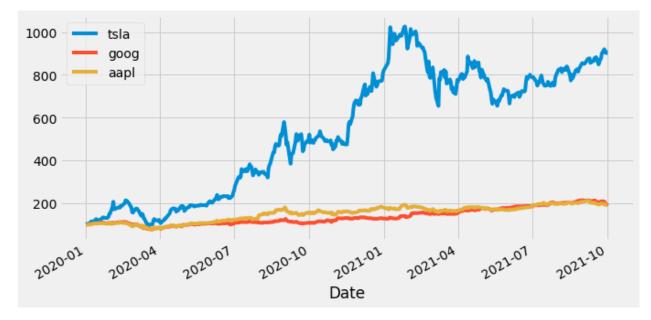
```
In [1]: import numpy as np
import pandas as pd
import yfinance as yf
from datetime import datetime
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
from pypfopt.efficient_frontier import EfficientFrontier as ef
from pypfopt import risk_models
from pypfopt import expected_returns
from pypfopt import EfficientFrontier
from pypfopt import risk_models
from pypfopt import expected_returns
```

```
In [2]: #1 get data
ticker = ['tsla', 'goog', 'aapl']
df = pd.DataFrame()
for t in ticker:
    df[t] = yf.download(t, start="2020-01-01", end="2021-10-02")['Adj
```

```
In [3]: (df / df.iloc[0] * 100).plot(figsize=(10,5))
```

Out[3]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7fd9f8842220>



```
In [4]: logreturns = np.log(df / df.shift(1))
```

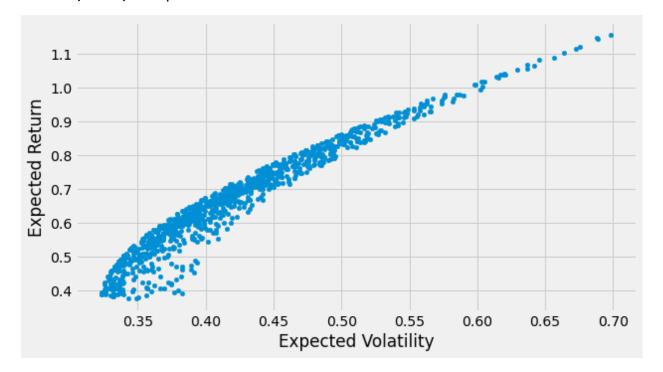
```
In [5]: logmean = logreturns.mean()
logmeanyr = logreturns.mean() * 250
```

```
In [6]: logreturns.cov() * 250
Out [6]:
                   tsla
                          goog
                                   aapl
           tsla 0.573044 0.109173 0.145100
          goog 0.109173 0.107732 0.091722
          aapl 0.145100 0.091722 0.151105
In [7]:
         logreturns.corr()
Out[7]:
                   tsla
                          goog
                                  aapl
           tsla 1.000000 0.439387 0.49310
          goog 0.439387 1.000000 0.71889
          aapl 0.493100 0.718890 1.00000
In [8]: # generate weights
         arr = np.random.random(10)
         num_ticker = len(ticker)
         w = np.random.random(num_ticker)
         w \neq np_sum(w)
         W
Out[8]: array([0.28445229, 0.27294889, 0.44259882])
In [9]: #portfolio mean returns
         mu = np.sum(w * logreturns.mean()) * 250
         #portfolio volatility
         std = np.dot(w.T, np.dot(logreturns.cov() * 250, w)) ** 0.5
```

```
In [10]: |#monte carlo
                    pfolio returns = []
                    pfolio_volatilities = []
                    sharpe_ratio = []
                    for x in range (1000):
                            w = np.random.random(num ticker)
                            w /= np.sum(w)
                            pfolio_returns.append(np.sum(w *logreturns.mean()) * 250)
                            pfolio_volatilities.append(np.sqrt(np.dot(w.T, np.dot(logreturns.d
                    pfolio returns = np.array(pfolio returns)
                    pfolio volatilities = np.array(pfolio volatilities)
                    pfolio_returns,
                    pfolio_volatilities
                    portfolio = pd.DataFrame ({'Return': pfolio_returns, 'Volatility': pfd
                    sharpe ratio = pfolio returns / pfolio volatilities
                    sharpe ratio
                                    1./0/), 1.000, 1.000, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.00, 1.0
                                   1.52569879, 1.43373728, 1.58014702, 1.4210092 , 1.68258427,
                                   1.72186389, 1.70426931, 1.65754323, 1.63285165, 1.69995421,
                                   1.56053842, 1.68899949, 1.7191024 , 1.52728591, 1.51550962,
                                   1.69406222, 1.59814169, 1.42634473, 1.61499463, 1.38032187,
                                   1.64035118, 1.5139743 , 1.54817861, 1.67657378, 1.53341693,
                                   1.71722603, 1.35177919, 1.63530832, 1.72422543, 1.70811566,
                                   1.63771315, 1.42238972, 1.57009574, 1.44663864, 1.64379241,
                                   1.65330309, 1.61296017, 1.60873669, 1.64893417, 1.30166594,
                                   1.64205652, 1.46593943, 1.68496783, 1.25017561, 1.30206194,
                                   1.67071389, 1.41058513, 1.61302881, 1.11430477, 1.59950519,
                                   1.4174194 , 1.08684031, 1.6856177 , 1.70159898, 1.42208223,
                                   1.69583241, 1.66619008, 1.23562859, 1.57629426, 1.47340861,
                                   1.70763239, 1.59338937, 1.66932897, 1.67336025, 1.65709343,
                                   1.66169356, 1.62011465, 1.68845422, 1.61633301, 1.55888766,
                                   1.57076409, 1.62301514, 1.68998601, 1.64099753, 1.35428933,
                                   1.5942375 , 1.70602795, 1.41178134, 1.6157278 , 1.36394291,
                                   1.4995121 , 1.65641859, 1.61642529, 1.63720623, 1.4087025 ,
                                   1.45171642, 1.42121459, 1.58953989, 1.64294568, 1.52132555,
                                   1.26875152, 1.47474423, 1.5933191 , 1.6979904 , 1.65931326,
```

```
In [11]: portfolio.plot(x='Volatility', y='Return', kind='scatter', figsize=(9, plt.xlabel('Expected Volatility') plt.ylabel('Expected Return')
```

## Out[11]: Text(0, 0.5, 'Expected Return')



```
In [12]: mu = expected_returns.mean_historical_return(df)
S = risk_models.sample_cov(df)
```

```
In [13]: # Optimize for maximal Sharpe ratio
    ef = EfficientFrontier(mu, S)
    raw_weights = ef.max_sharpe()
    cleaned_weights = ef.clean_weights()
    ef.save_weights_to_file("weights.csv") # saves to file
    ef.portfolio_performance(verbose=True)
    print(cleaned_weights)
```

```
Expected annual return: 247.6%
Annual volatility: 75.1%
Sharpe Ratio: 3.27
OrderedDict([('tsla', 0.98235), ('goog', 0.01765), ('aapl', 0.0)])
```