
# Various Stock Market Analyses

*Active Trading Strategy, Sector Portfolio Analysis, and Improved Stock Clustering*

**Dylan Alexander**

Capstone Project for Springboard Intermediate Data Science in Python

02/10/2019

# Introduction

Traditionally, finance professionals divide the S&P 500 into 11 sectors for analysis and traders try their best to earn profits from the market by buying low and selling high. Trading styles range from highly active traders entering and exiting multiple positions everyday to earn quick 1-2% profits to long term investors who want to “set it and forget” with a portfolio they are confident will yield vast returns over the years. With the emergence of Data Science professionals implementing analyses on the vast amount of price data the stock market provides, many fine tunes strategies for both types of investors have been developed. In this project, three areas will be covered in depth. First, for the active trader we discuss and analyze a trading strategy that exploits the data produced from a powerful yet lesser known indicator called the Fisher Transform. Next, we will find portfolio allocations within each traditional sector for both risk averse investors and savvy investors who will take on a bit more risk for a justified, higher return. Finally, we will use machine learning to see whether or not these traditional sectors provide investors with the most efficient clusters in regards to stock price returns and volatility when choosing a portfolio of stocks.

# Data Wrangling

I gathered a total of 36 datasets. They are time series datasets with a start date of 04-29-2013 and an end date of 01-09-2019.

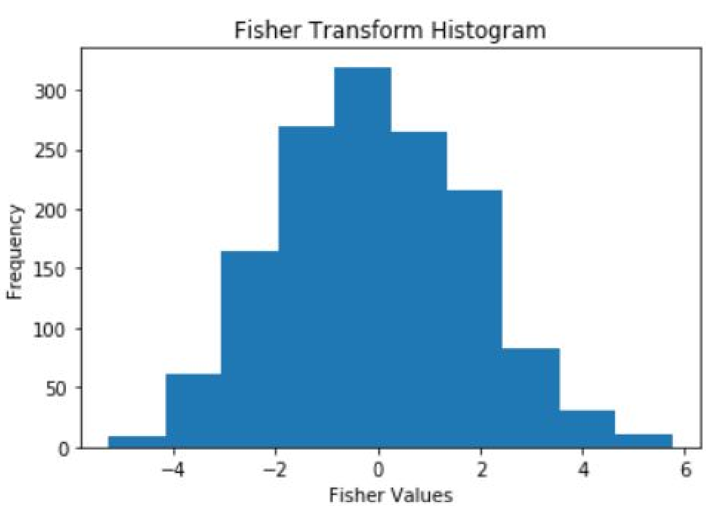
- A dataset for each sector containing the *prices* of 8 - 10 stocks from their respective sectors (11 datasets)
- A dataset containing the *prices* of all chosen stocks in all sectors (1 dataset)
- A dataset for each sector containing the *returns* of 8 - 10 stocks from their respective sectors (11 datasets)
- A dataset containing the *returns* of all chosen stocks in all sectors (1 dataset)
- A dataset for each sector containing the daily volume, open price, close price, low price, and high price for 8 -10 stocks from their respective sectors (11 datasets)
- A dataset containing the daily volume, open price, close price, low price, and high price for all chosen stocks in all sectors (1 dataset)

I selected the stocks based off volume on a random day. I filtered each sector from the S&P 500 by volume in descending order. I then chose the top 10 highest volume stocks from each sector for that day. I acquired my data through the api from Tiingo.com using pandas_datareader.data. I used the pivot, concat, and drop functions to name a few. I also used the pct_change() method to calculate returns where necessary and a for loop to quickly identify missing values.

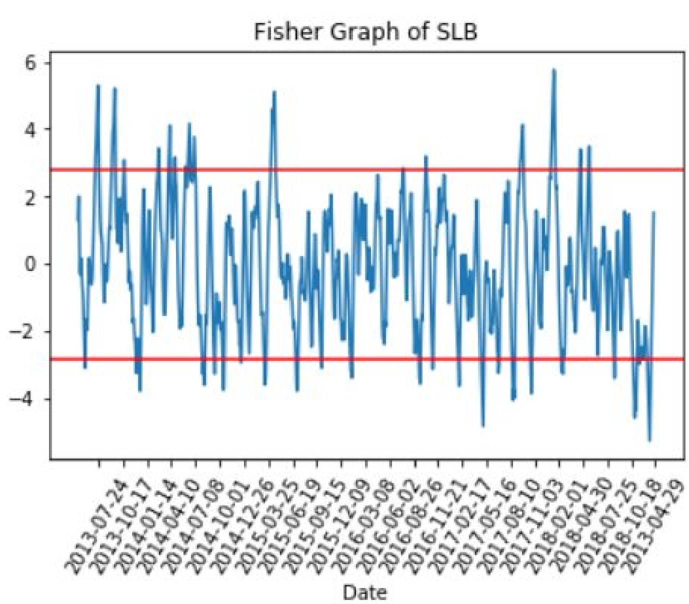
# Fisher Strategy for Active Traders

For investors who would like to actively trade, the Fisher Transform is a useful indicator for finding buy and sell signals. Created and introduced by John Ehlers in 2002, the Fisher Transform takes price as an input and "transforms" it into an approximately Gaussian distribution. Overlaying the price chart of an asset with its Fisher Transform output can lead to insights for traders. In this section, a strategy of buying when the selected asset's Fisher Transform value goes below 1.5 standard deviations and selling when the asset's Fisher Transform value goes above 1.5 standard deviations is tested. Schlumberger (SLB) is the selected asset in this study.

First, the histogram of the Fisher Transform values shows the new Gaussian representation of the SLB price:




Next, two lines, the first at 2.8146 and the second at -2.8146, are plotted over the SLB Fisher Transform values to represent the range between 1.5 standard deviations.



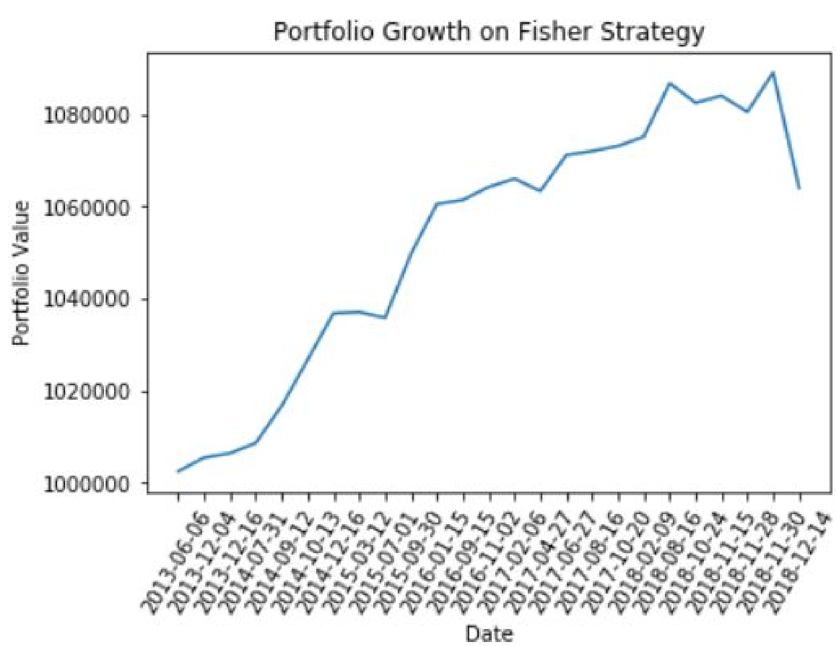
The DataFrame of all trades shows the start dates, end dates, and profits for each trade executed by the strategy.

| | Price | Profit | End Date | low |
|---|---|---|---|---|
| **date** | | | | |
| **2013-06-06** | 63.936309 | 0.549521 | 2013-06-07 | 62.627927 |
| **2013-12-04** | 76.697001 | 0.764510 | 2013-12-06 | 76.011579 |
| **2013-12-16** | 76.450952 | 0.237262 | 2013-12-20 | 74.614372 |
| **2014-07-31** | 96.036831 | 0.726545 | 2014-08-11 | 94.185028 |
| **2014-09-12** | 90.900451 | 2.436580 | 2014-09-16 | 90.571424 |
| **2014-10-13** | 80.860673 | 2.703359 | 2014-10-17 | 76.476607 |
| **2014-12-16** | 71.646199 | 2.403395 | 2014-12-17 | 70.109456 |
| **2015-03-12** | 72.737616 | 0.062906 | 2015-03-19 | 71.344692 |
| **2015-07-01** | 76.174972 | -0.307230 | 2015-07-10 | 74.295447 |
| **2015-09-30** | 62.725269 | 2.837507 | 2015-10-05 | 60.542572 |
| **2016-01-15** | 57.676290 | 2.004620 | 2016-01-22 | 54.554942 |
| **2016-09-15** | 71.711209 | 0.196085 | 2016-09-22 | 70.375961 |
| **2016-11-02** | 72.607599 | 0.653618 | 2016-11-03 | 71.823257 |
| **2017-02-06** | 76.728914 | 0.441457 | 2017-02-10 | 74.690700 |
| **2017-04-27** | 68.834471 | -0.585906 | 2017-05-08 | 66.363272 |
| **2017-06-27** | 62.215074 | 1.532532 | 2017-07-03 | 61.967584 |
| **2017-08-16** | 60.644467 | 0.161820 | 2017-08-25 | 59.549801 |
| **2017-10-20** | 60.585851 | 0.211067 | 2017-10-26 | 58.906908 |
| **2018-02-09** | 63.479536 | 0.408980 | 2018-02-20 | 61.707289 |
| **2018-08-16** | 61.294802 | 2.226583 | 2018-08-21 | 60.873026 |
| **2018-10-24** | 52.415984 | -0.682268 | 2018-11-07 | 50.151645 |
| **2018-11-15** | 47.541228 | 0.227423 | 2018-11-19 | 46.542546 |
| **2018-11-28** | 45.889942 | -0.504285 | 2018-11-29 | 44.752828 |
| **2018-11-30** | 44.594621 | 1.186553 | 2018-12-03 | 44.179328 |
| **2018-12-14** | 39.100000 | -3.020000 | 2018-12-31 | 34.990000 |

Next, the results of the backtesting of the strategy are shown. The backtest assumes a 1 million dollar portfolio size. It also assumes trade position sizes of 100 shares, that no more than 30% of the portfolio is put into one trade, and the execution of a stop loss if 20% of the portfolio will be lost.

| | Start Port. Value | End Port. Value | End Date | Shares | Share Price | Trade Value | Profit per Share | Total Profit |
|---|---|---|---|---|---|---|---|---|
| **2013-06-06** | 1.000000e+06 | 1.002528e+06 | 2013-06-07 | 4600.0 | 63.936309 | 294107.023182 | 0.549521 | 2527.795697 |
| **2013-12-04** | 1.002528e+06 | 1.005509e+06 | 2013-12-06 | 3900.0 | 76.697001 | 299118.304396 | 0.764510 | 2981.587132 |
| **2013-12-16** | 1.005509e+06 | 1.006435e+06 | 2013-12-20 | 3900.0 | 76.450952 | 298158.713135 | 0.237262 | 925.320144 |
| **2014-07-31** | 1.006435e+06 | 1.008687e+06 | 2014-08-11 | 3100.0 | 96.036831 | 297714.177547 | 0.726545 | 2252.289192 |
| **2014-09-12** | 1.008687e+06 | 1.016728e+06 | 2014-09-16 | 3300.0 | 90.900451 | 299971.488441 | 2.436580 | 8040.714912 |
| **2014-10-13** | 1.016728e+06 | 1.026730e+06 | 2014-10-17 | 3700.0 | 80.860673 | 299184.490797 | 2.703359 | 10002.428814 |
| **2014-12-16** | 1.026730e+06 | 1.036824e+06 | 2014-12-17 | 4200.0 | 71.646199 | 300914.036651 | 2.403395 | 10094.260613 |
| **2015-03-12** | 1.036824e+06 | 1.037089e+06 | 2015-03-19 | 4200.0 | 72.737616 | 305497.988241 | 0.062906 | 264.206316 |
| **2015-07-01** | 1.037089e+06 | 1.035860e+06 | 2015-07-10 | 4000.0 | 76.174972 | 304699.888107 | -0.307230 | -1228.920071 |
| **2015-09-30** | 1.035860e+06 | 1.049763e+06 | 2015-10-05 | 4900.0 | 62.725269 | 307353.818194 | 2.837507 | 13903.782989 |
| **2016-01-15** | 1.049763e+06 | 1.060588e+06 | 2016-01-22 | 5400.0 | 57.676290 | 311451.965342 | 2.004620 | 10824.945312 |
| **2016-09-15** | 1.060588e+06 | 1.061451e+06 | 2016-09-22 | 4400.0 | 71.711209 | 315529.318228 | 0.196085 | 862.775479 |
| **2016-11-02** | 1.061451e+06 | 1.064262e+06 | 2016-11-03 | 4300.0 | 72.607599 | 312212.674826 | 0.653618 | 2810.556486 |
| **2017-02-06** | 1.064262e+06 | 1.066072e+06 | 2017-02-10 | 4100.0 | 76.728914 | 314588.548885 | 0.441457 | 1809.972065 |
| **2017-04-27** | 1.066072e+06 | 1.063377e+06 | 2017-05-08 | 4600.0 | 68.834471 | 316638.567986 | -0.585906 | -2695.166284 |
| **2017-06-27** | 1.063377e+06 | 1.071192e+06 | 2017-07-03 | 5100.0 | 62.215074 | 317296.875098 | 1.532532 | 7815.911397 |
| **2017-08-16** | 1.071192e+06 | 1.072034e+06 | 2017-08-25 | 5200.0 | 60.644467 | 315351.226225 | 0.161820 | 841.464581 |
| **2017-10-20** | 1.072034e+06 | 1.073153e+06 | 2017-10-26 | 5300.0 | 60.585851 | 321105.010424 | 0.211067 | 1118.655618 |
| **2018-02-09** | 1.073153e+06 | 1.075197e+06 | 2018-02-20 | 5000.0 | 63.479536 | 317397.680400 | 0.408980 | 2044.899920 |
| **2018-08-16** | 1.075197e+06 | 1.086776e+06 | 2018-08-21 | 5200.0 | 61.294802 | 318732.969922 | 2.226583 | 11578.233985 |
| **2018-10-24** | 1.086776e+06 | 1.082546e+06 | 2018-11-07 | 6200.0 | 52.415984 | 324979.099955 | -0.682268 | -4230.061855 |
| **2018-11-15** | 1.082546e+06 | 1.084092e+06 | 2018-11-19 | 6800.0 | 47.541228 | 323280.351412 | 0.227423 | 1546.474227 |
| **2018-11-28** | 1.084092e+06 | 1.080562e+06 | 2018-11-29 | 7000.0 | 45.889942 | 321229.592111 | -0.504285 | -3529.995518 |
| **2018-11-30** | 1.080562e+06 | 1.089105e+06 | 2018-12-03 | 7200.0 | 44.594621 | 321081.272972 | 1.186553 | 8543.182429 |
| **2018-12-14** | 1.089105e+06 | 1.064039e+06 | 2018-12-31 | 8300.0 | 39.100000 | 324530.000000 | -3.020000 | -25066.000000 |

A visual of portfolio this portfolio growth:



As seen in the image above, the strategy yields roughly an 9% portfolio return over the time of interest. These aren't phenomenal returns, but still beat inflation significantly. The dip at the end of the graph is due to lack of data. If the strategy were extended to present day, the dip would turn positive and the strategy would yield even greater returns.

## Sector Portfolio Analysis

When choosing a stock portfolio for the long term, where should an investor begin his analysis? The stock market has traditionally been divided into 11 sectors: Financial, Industrials, Communications, Technology, Consumer Staples, Consumer Discretionaries, Real Estate, Energy, Utilities, Health, and Materials. Deciding which sectors an investor would like to invest in would be a good first step. But how do they differentiate between these sectors if they would like to minimize risk, maximize return, or find a balance between risk and return they are comfortable with? Once they decide which sector or sectors they would like to invest in, how should they allocate their funds into portfolios with minimal risks or a an optimal balance of risk and return? Moving forward, we will use the Communications sector in our approach to find two portfolio allocations of interest:

- 1. A portfolio made up of Communications sector stocks for minimum risk

- 2. A portfolio made up of Communications sector stocks with a maximum Sharpe Ratio

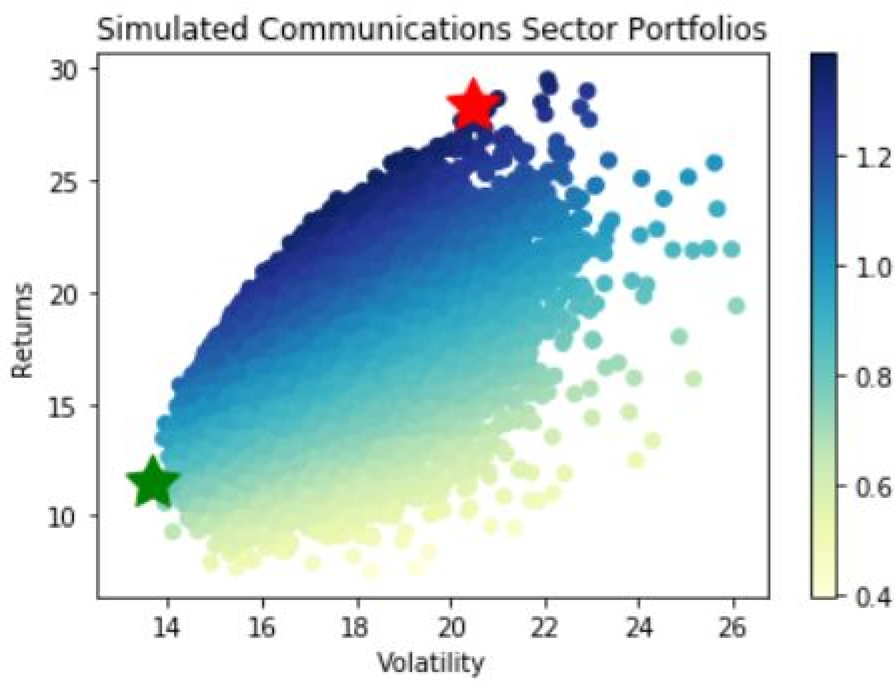
In statistical terms, risk (volatility) is calculated as the standard deviation of returns of a portfolio. Risk should always be considered when investing. One approach that finds a maximum return while still carefully factoring in risk is the calculating the Sharpe Ratio of a portfolio. The Sharpe ratio is defined by this equation:

**Sharpe Ratio(x) = (Rx - Rf) / StdDev (x)**

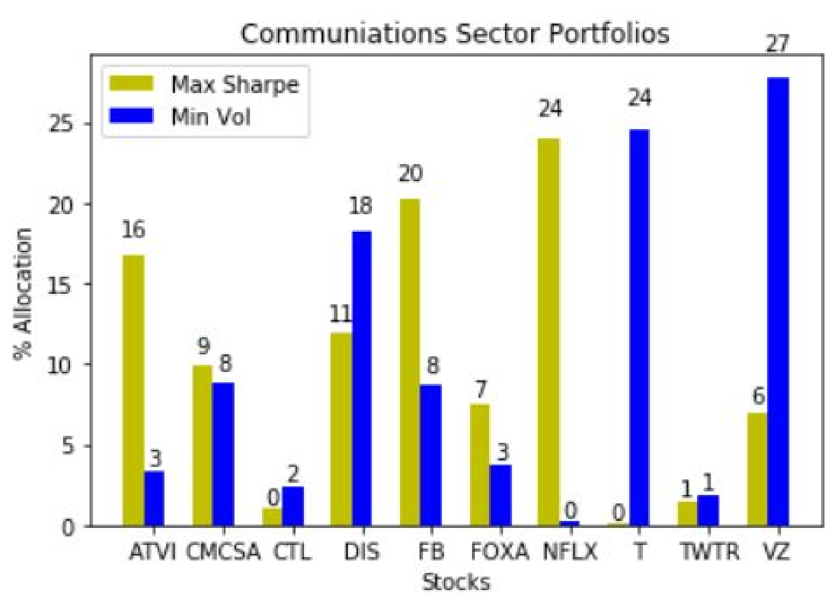
Where:
X is the investment
Rx is the average rate of return of X
Rf is the best available rate of return of a risk-free security (calculated as zero for simplicity of demonstration)
StdDev(x) is the standard deviation of Rx

For a savvy investor, finding a portfolio with the highest Sharpe Ratio is a great way to maximize returns while factoring in risk. However, some investors may want to just find a portfolio with minimal risk. Below, the process of finding both such portfolios is demonstrated for the Communications sector. Please see the Appendix for the calculations of each portfolio for all sectors.

The first step in finding our portfolios of interest is to simulate 25,000 randomly weighted portfolios consisting of the Communications sector stocks in consideration. Next, we display the portfolios in a scatter plot with volatility on the x-axis and returns on the y-axis:




This simulation provides many portfolio variations for an investor to choose from. However, we have also highlighted our portfolios of interest. The portfolio marked with the green star is the portfolio with minimum volatility (risk) for the highly risk-averse investor and the portfolio marked with the red star is the portfolio with the highest Sharpe Ratio for the savvy investor who wants to maximize return while also factoring in risk. The specific portfolio weightings for each portfolio are represented in this bar chart:



For more specific allocations, please see the data frames below.

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 11.157127 |
| stdev | 13.590495 |
| sharpe | 0.820951 |
| ATVI | 3.290000 |
| CMCSA | 8.880000 |
| CTL | 2.440000 |
| DIS | 18.200000 |
| FB | 8.740000 |
| FOXA | 3.700000 |
| NFLX | 0.260000 |
| T | 24.600000 |
| TWTR | 1.880000 |
| VZ | 27.800000 |

Maximum Sharpe Ratio Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 28.361015 |
| stdev | 20.227419 |
| sharpe | 1.402107 |
| ATVI | 16.800000 |
| CMCSA | 9.930000 |
| CTL | 0.980000 |
| DIS | 11.900000 |
| FB | 20.200000 |
| FOXA | 7.430000 |
| NFLX | 24.000000 |
| T | 0.050000 |
| TWTR | 1.490000 |
| VZ | 6.940000 |

## Stocks K-Means Clustering

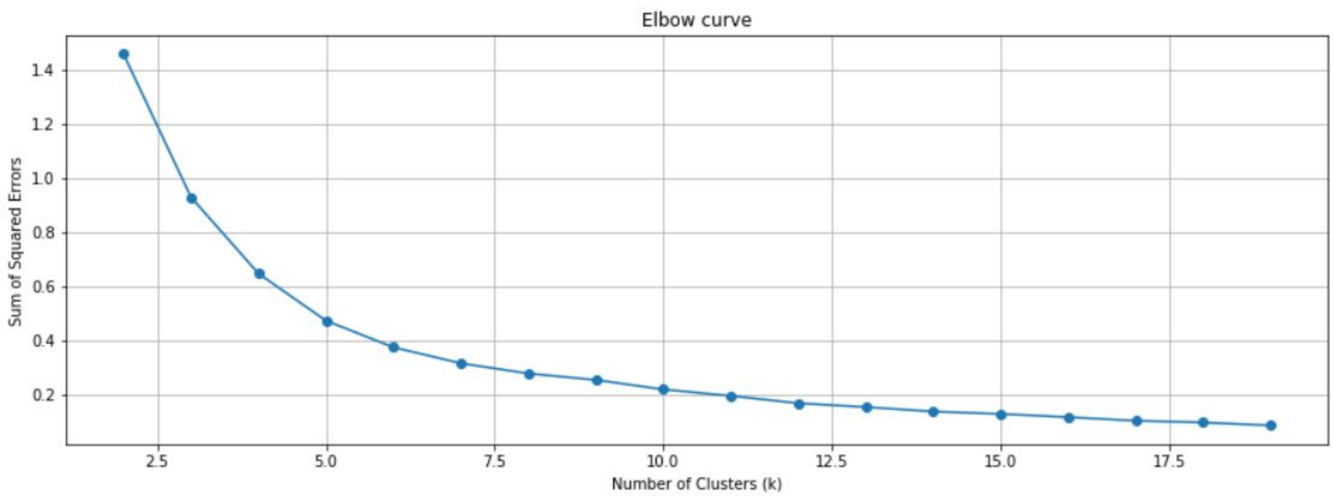
The traditional stock market division of sectors is based on the similarities companies share in their resources, products, services and operations. They can also be thought of as companies that compete for the same consumers. For instance, companies within the technology sector, such as Microsoft and Apple, provide consumers with the latest computer hardware and computer software. They have similar day to day operations, purchase similar raw materials, build similar products, and provide similar services. They compete for consumers who value technology. While this division between companies is a great way to analyze a type of business operation as a whole, do these traditional sectors provide the best clustering when it comes to stock price returns and volatility?

Using the K-Means clustering algorithm, I will find a better set of clusters of stocks in order to provide an investor with the information to build portfolios with better diversification in

regards to return and volatility.

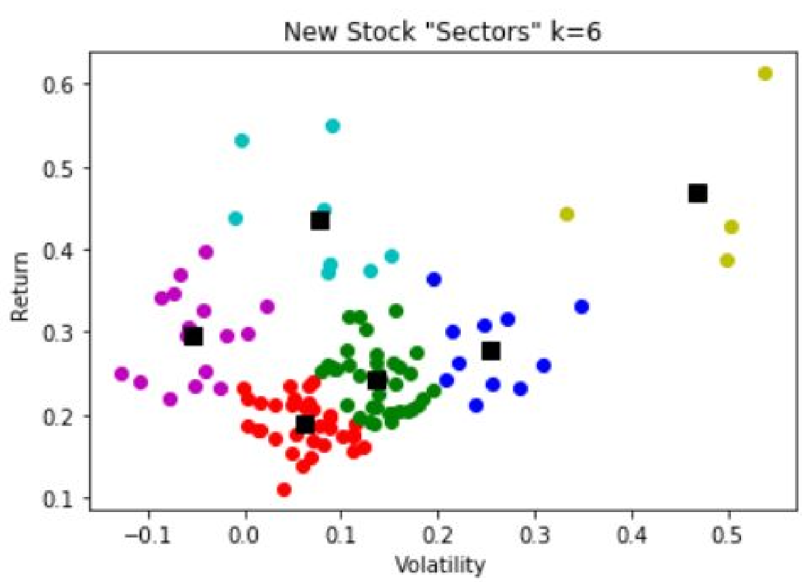
The K-Means clustering algorithm is an unsupervised learning algorithm that groups a “cluster” of data points together based off similarities in their features. In this case, the features of interest are stock price returns and stock price volatility.

First, we need to find the best number of clusters (*k*). To do this, I will use the Elbow Method. The Elbow Method provides a plot of *k* on the x-axis and the Sum of Squared Errors on the y-axis:




The best *k* based off the Elbow curve above is k=6. The best *k* is determined by where the Sum of Squared Errors is lowest and the rate of decrease of the Sum of Squared Errors slows down significantly. This happens at the “elbow” of the curve. The best *k* based off the Elbow curve above is k=6.

Next, we visualize the new clusters when k=6:



Based off the scatter plot above, we can see exactly how K-Means has divided the stocks of interest into a new set of clusters based off the similarity of their returns and volatility. Below are the new stock sectors:

| Ticker | Cluster |
|---|---|
| AAL | 0 |
| AAPL | 0 |
| AMAT | 0 |
| ATVI | 0 |
| BA | 0 |
| BSX | 0 |
| CSX | 0 |
| DAL | 0 |
| FB | 0 |
| MSFT | 0 |
| V | 0 |

| Ticker | Cluster |
|---|---|
| AMD | 1 |
| MU | 1 |
| NFLX | 1 |
| NVDA | 1 |

| Ticker | Cluster |
|---|---|
| AIV | 2 |
| C | 2 |
| CNP | 2 |
| CVS | 2 |
| CVX | 2 |
| D | 2 |
| EMR | 2 |
| EXC | 2 |
| F | 2 |
| FE | 2 |
| GIS | 2 |
| HST | 2 |
| IP | 2 |
| JCI | 2 |
| JNJ | 2 |
| KIM | 2 |
| KO | 2 |
| MO | 2 |
| PFE | 2 |
| PG | 2 |
| PM | 2 |
| PMM | 2 |
| PPL | 2 |
| SO | 2 |
| T | 2 |
| USB | 2 |
| VZ | 2 |
| WELL | 2 |
| WFC | 2 |
| WMT | 2 |
| WY | 2 |
| XEL | 2 |
| XOM | 2 |

| Ticker | Cluster |
|---|---|
| ABT | 3 |
| AES | 3 |
| AMT | 3 |
| BAC | 3 |
| BK | 3 |
| BLL | 3 |
| BMY | 3 |
| CAT | 3 |
| CELG | 3 |
| CMCSA | 3 |
| CSCO | 3 |
| DHI | 3 |
| DIS | 3 |
| EBAY | 3 |
| FDX | 3 |
| FOXA | 3 |
| GILD | 3 |
| GM | 3 |
| HBAN | 3 |
| HBI | 3 |
| INTL | 3 |
| IRM | 3 |
| JPM | 3 |
| KEY | 3 |
| KR | 3 |
| LLY | 3 |
| LYB | 3 |
| MPC | 3 |
| MRK | 3 |
| MS | 3 |
| NKE | 3 |
| NUE | 3 |
| ORCL | 3 |
| PLD | 3 |
| RF | 3 |
| SBUX | 3 |
| TJX | 3 |
| WBA | 3 |

| Ticker | Cluster |
|---|---|
| APA | 4 |
| CBRE | 4 |
| COTY | 4 |
| CTL | 4 |
| DVN | 4 |
| DWDP | 4 |
| GE | 4 |
| GPS | 4 |
| HAL | 4 |
| HCP | 4 |
| KHC | 4 |
| KMI | 4 |
| MOS | 4 |
| PCG | 4 |
| SLB | 4 |
| WRK | 4 |

| Ticker | Cluster |
|---|---|
| ARNC | 5 |
| CF | 5 |
| FCX | 5 |
| MRO | 5 |
| NEM | 5 |
| NRG | 5 |
| TWTR | 5 |
| WMB | 5 |

Also, a data frame displaying the count of stocks per cluster:

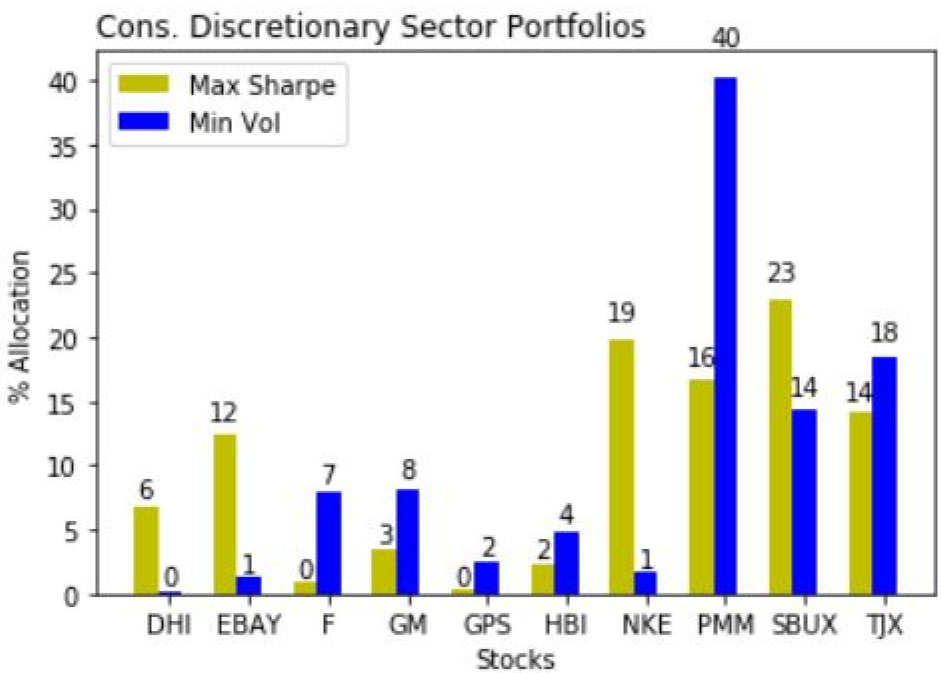
| Cluster | 0 | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| Ticker | 8 | 38 | 11 | 16 | 4 | 33 |

With these new clusters, an investor can now build more diversified portfolios by choosing stocks from “sectors” more tailored to returns and volatility. Moving forward, running the same analysis as seen in the *Sector Portfolio Analysis* section of this paper will yield different results. These results will presumably lead to better allocations for both the risk averse and savvy investors.

# Conclusion

The stock market provides a vast amount of data for analysis. In this paper, we tested a trading strategy using the Fisher Transform indicator an active trader can use to earn a great return on his or her trades. For the more common long term investor, traditional portfolio analysis was conducted to find portfolios with minimal risks and maximum Sharpe Ratios for each sector. If using historical data can provide insights to future performance, the reader now has the information to build a stock portfolio they can be confident will yield great returns. For those who want to take it a step further, machine learning has defined new clusters of stocks and even more information to make even better decisions when they approach the hyper-competitive world of the stock market.

# Appendix

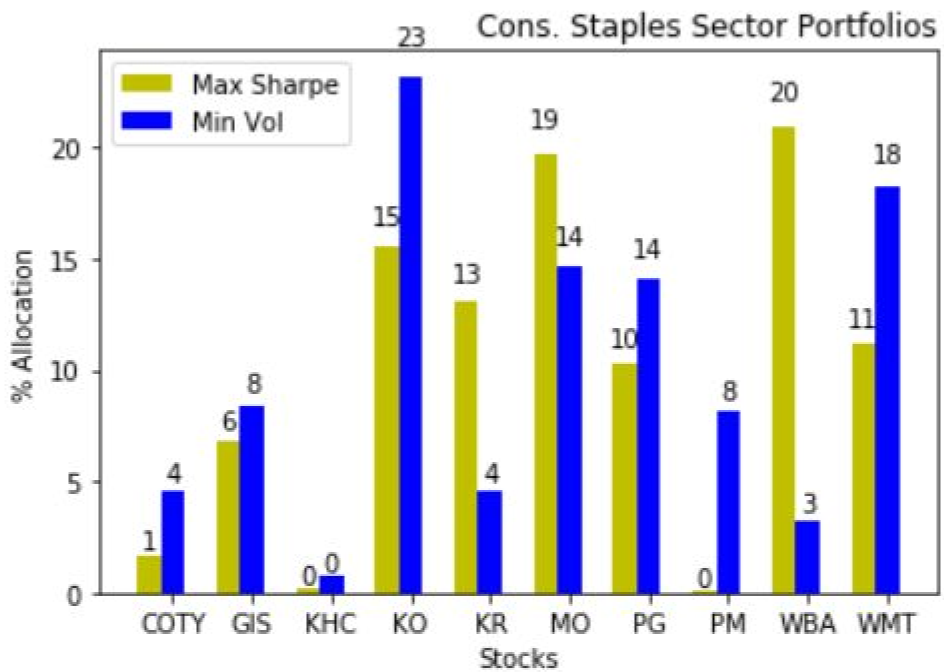



Maximum Sharpe Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 13.074932 |
| stdev | 13.114822 |
| sharpe | 0.996958 |
| DHI | 6.720000 |
| EBAY | 12.500000 |
| F | 0.890000 |
| GM | 3.390000 |
| GPS | 0.310000 |
| HBI | 2.310000 |
| NKE | 19.900000 |
| PMM | 16.600000 |
| SBUX | 23.000000 |
| TJX | 14.100000 |

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 8.650165 |
| stdev | 10.543849 |
| sharpe | 0.820399 |
| DHI | 0.240000 |
| EBAY | 1.320000 |
| F | 7.900000 |
| GM | 8.210000 |
| GPS | 2.510000 |
| HBI | 4.870000 |
| NKE | 1.630000 |
| PMM | 40.300000 |
| SBUX | 14.400000 |
| TJX | 18.400000 |

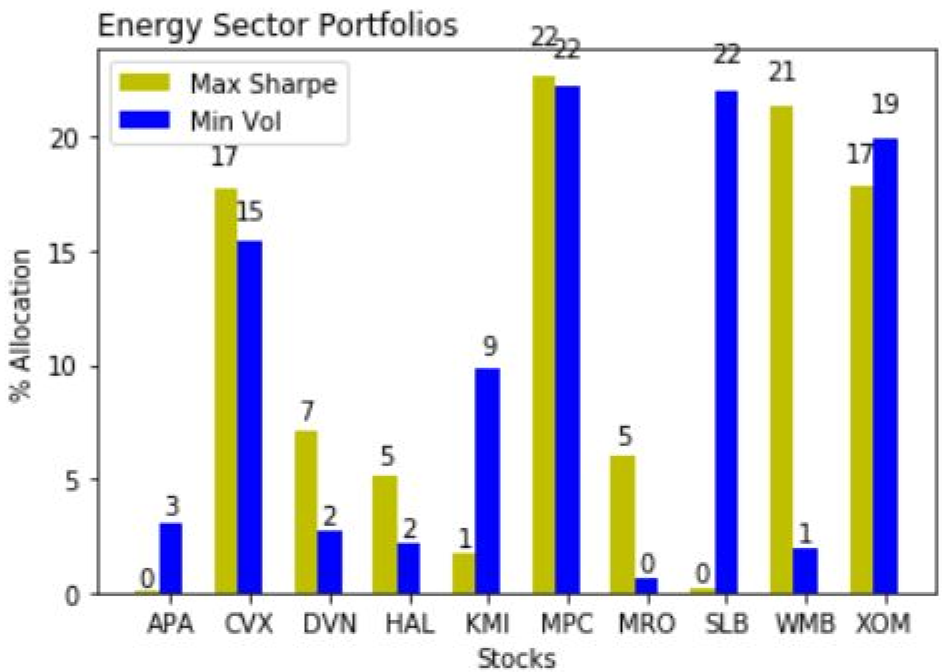



Maximum Sharpe Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 8.975357 |
| stdev | 12.963962 |
| sharpe | 0.692331 |
| COTY | 1.700000 |
| GIS | 6.820000 |
| KHC | 0.200000 |
| KO | 15.500000 |
| KR | 13.100000 |
| MO | 19.700000 |
| PG | 10.300000 |
| PM | 0.080000 |
| WBA | 20.900000 |
| WMT | 11.200000 |

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 6.188075 |
| stdev | 11.959970 |
| sharpe | 0.517399 |
| COTY | 4.530000 |
| GIS | 8.370000 |
| KHC | 0.710000 |
| KO | 23.200000 |
| KR | 4.530000 |
| MO | 14.700000 |
| PG | 14.100000 |
| PM | 8.110000 |
| WBA | 3.270000 |
| WMT | 18.200000 |

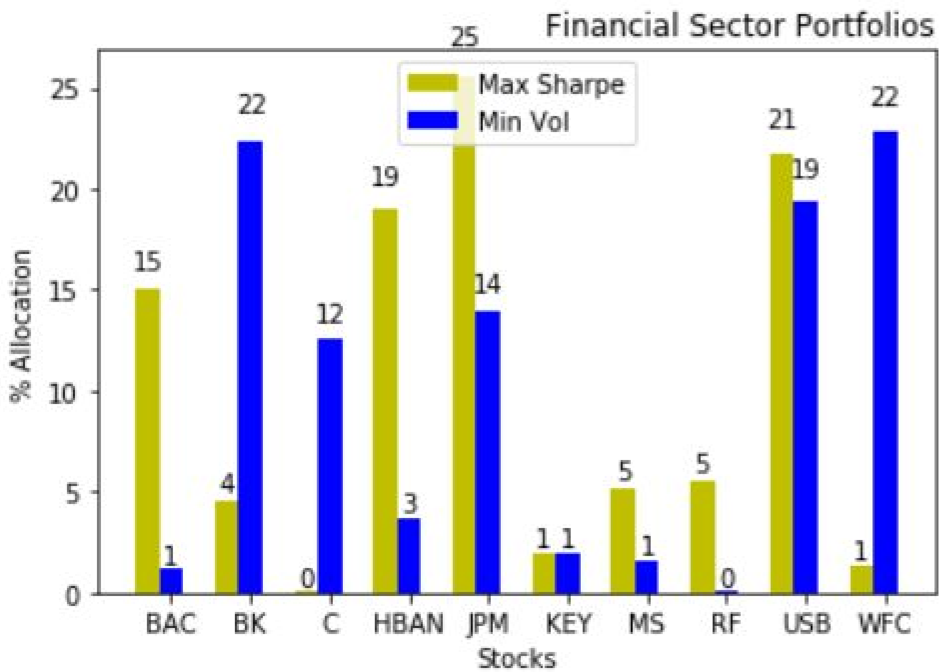



Maximum Sharpe Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 6.040179 |
| stdev | 23.905404 |
| sharpe | 0.252670 |
| APA | 0.040000 |
| CVX | 17.700000 |
| DVN | 7.060000 |
| HAL | 5.160000 |
| KMI | 1.700000 |
| MPC | 22.700000 |
| MRO | 5.980000 |
| SLB | 0.250000 |
| WMB | 21.300000 |
| XOM | 17.800000 |

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 2.716692 |
| stdev | 20.103910 |
| sharpe | 0.135133 |
| APA | 3.080000 |
| CVX | 15.400000 |
| DVN | 2.680000 |
| HAL | 2.120000 |
| KMI | 9.790000 |
| MPC | 22.200000 |
| MRO | 0.670000 |
| SLB | 22.000000 |
| WMB | 1.910000 |
| XOM | 19.900000 |

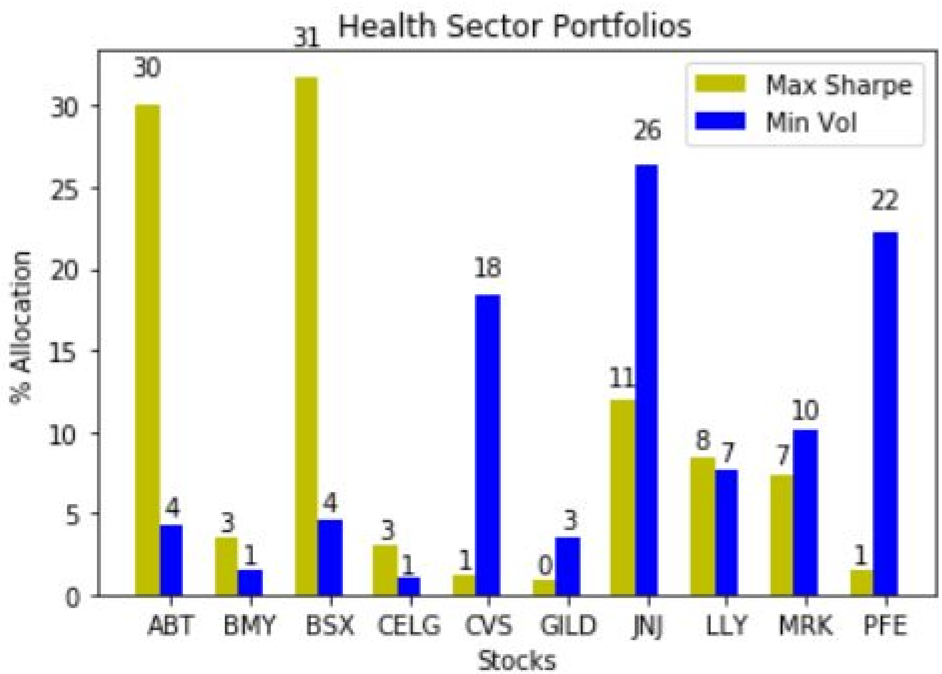



Maximum Sharpe Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 14.883989 |
| stdev | 19.842820 |
| sharpe | 0.750094 |
| BAC | 15.000000 |
| BK | 4.560000 |
| C | 0.090000 |
| HBAN | 19.000000 |
| JPM | 25.600000 |
| KEY | 1.950000 |
| MS | 5.110000 |
| RF | 5.520000 |
| USB | 21.700000 |
| WFC | 1.320000 |

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 11.649349 |
| stdev | 18.510094 |
| sharpe | 0.629351 |
| BAC | 1.190000 |
| BK | 22.400000 |
| C | 12.600000 |
| HBAN | 3.660000 |
| JPM | 14.000000 |
| KEY | 1.920000 |
| MS | 1.570000 |
| RF | 0.130000 |
| USB | 19.400000 |
| WFC | 22.800000 |

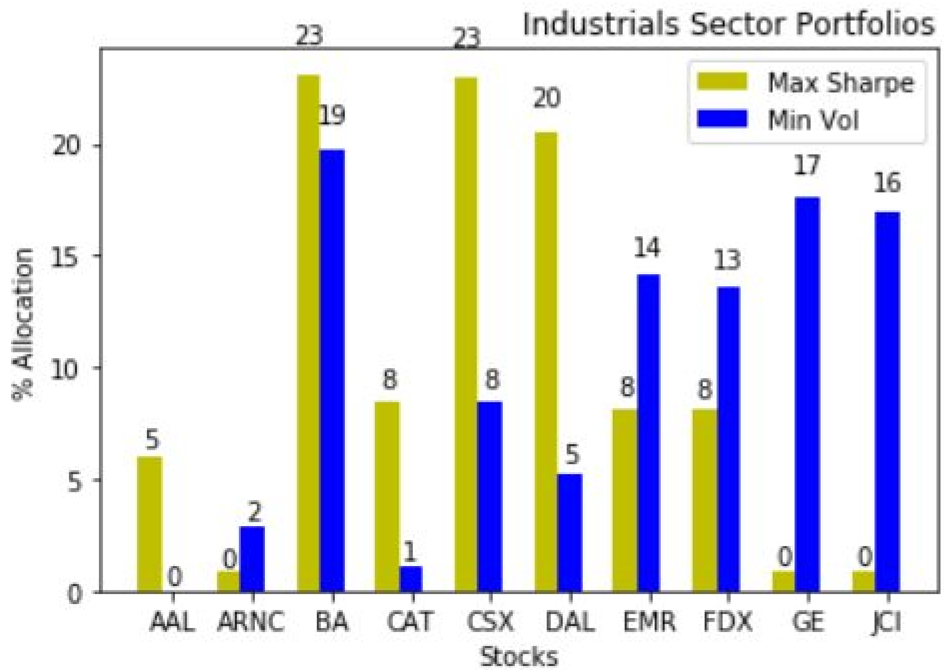



Maximum Sharpe Portfolio:

| | % Allocation |
|---|---|
| **Portfolio Characteristics** | |
| **ret** | 19.308040 |
| **stdev** | 16.584123 |
| **sharpe** | 1.164248 |
| **ABT** | 30.100000 |
| **BMY** | 3.460000 |
| **BSX** | 31.800000 |
| **CELG** | 3.030000 |
| **CVS** | 1.270000 |
| **GILD** | 0.940000 |
| **JNJ** | 11.900000 |
| **LLY** | 8.350000 |
| **MRK** | 7.380000 |
| **PFE** | 1.520000 |

Minimum Volatility Portfolio:

| | % Allocation |
|---|---|
| **Portfolio Characteristics** | |
| **ret** | 12.138708 |
| **stdev** | 13.914654 |
| **sharpe** | 0.872369 |
| **ABT** | 4.300000 |
| **BMY** | 1.560000 |
| **BSX** | 4.630000 |
| **CELG** | 1.020000 |
| **CVS** | 18.400000 |
| **GILD** | 3.570000 |
| **JNJ** | 26.400000 |
| **LLY** | 7.580000 |
| **MRK** | 10.100000 |
| **PFE** | 22.300000 |

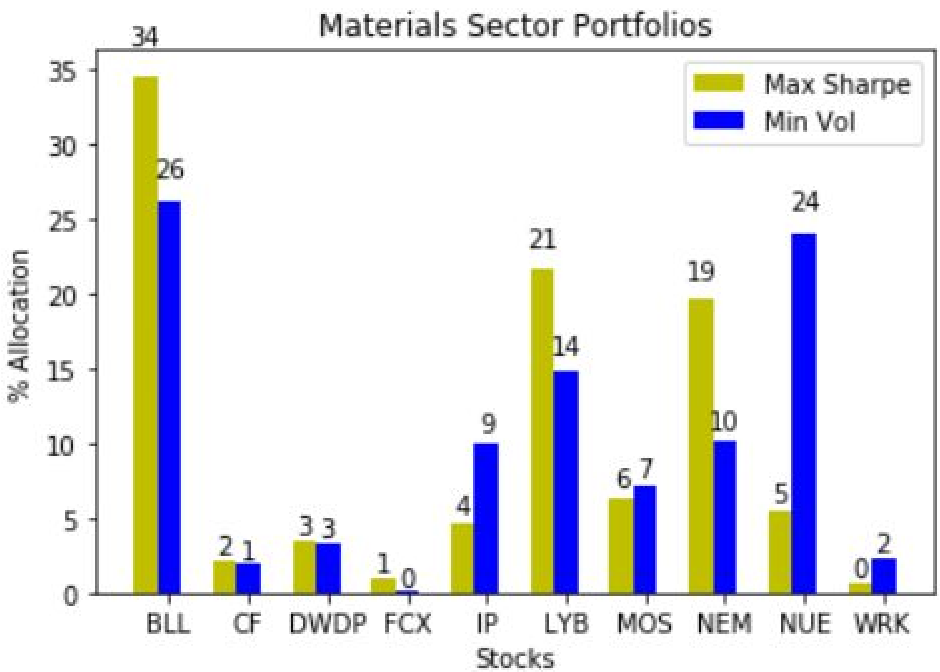



Maximum Sharpe Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| **ret** | 20.778224 |
| **stdev** | 19.072882 |
| **sharpe** | 1.089412 |
| **AAL** | 5.960000 |
| **ARNC** | 0.860000 |
| **BA** | 23.100000 |
| **CAT** | 8.480000 |
| **CSX** | 23.000000 |
| **DAL** | 20.500000 |
| **EMR** | 8.090000 |
| **FDX** | 8.080000 |
| **GE** | 0.900000 |
| **JCI** | 0.880000 |

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| **ret** | 11.031110 |
| **stdev** | 16.630362 |
| **sharpe** | 0.663311 |
| **AAL** | 0.020000 |
| **ARNC** | 2.880000 |
| **BA** | 19.700000 |
| **CAT** | 1.130000 |
| **CSX** | 8.440000 |
| **DAL** | 5.250000 |
| **EMR** | 14.100000 |
| **FDX** | 13.600000 |
| **GE** | 17.600000 |
| **JCI** | 16.900000 |

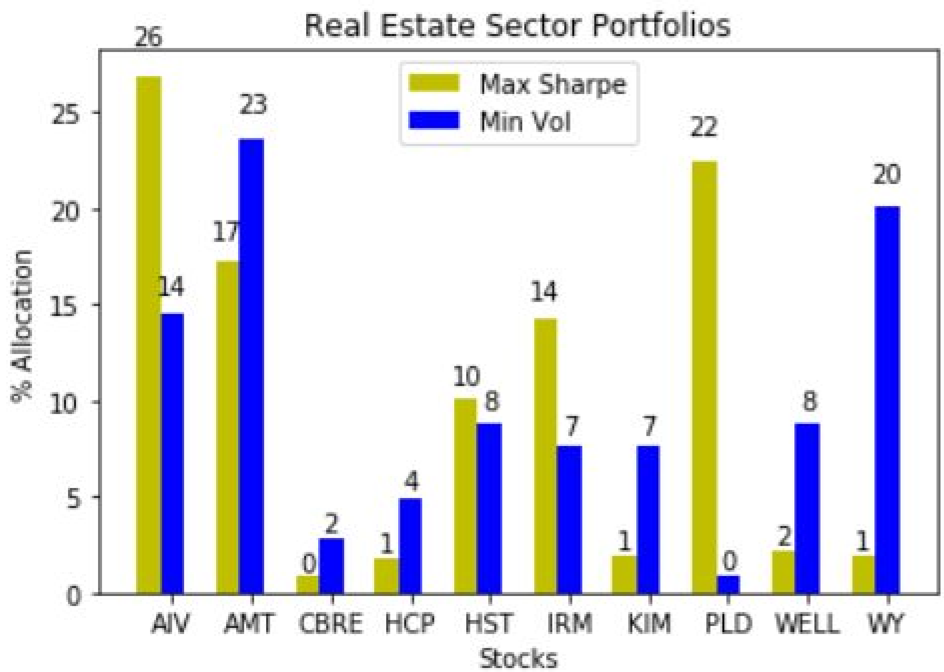



Maximum Sharpe Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| **ret** | 10.911068 |
| **stdev** | 17.825969 |
| **sharpe** | 0.612088 |
| **BLL** | 34.500000 |
| **CF** | 2.200000 |
| **DWDP** | 3.490000 |
| **FCX** | 1.030000 |
| **IP** | 4.710000 |
| **LYB** | 21.700000 |
| **MOS** | 6.370000 |
| **NEM** | 19.600000 |
| **NUE** | 5.500000 |
| **WRK** | 0.680000 |

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| **ret** | 9.901559 |
| **stdev** | 17.666680 |
| **sharpe** | 0.560465 |
| **BLL** | 26.200000 |
| **CF** | 1.920000 |
| **DWDP** | 3.290000 |
| **FCX** | 0.180000 |
| **IP** | 9.900000 |
| **LYB** | 14.800000 |
| **MOS** | 7.130000 |
| **NEM** | 10.100000 |
| **NUE** | 24.000000 |
| **WRK** | 2.300000 |

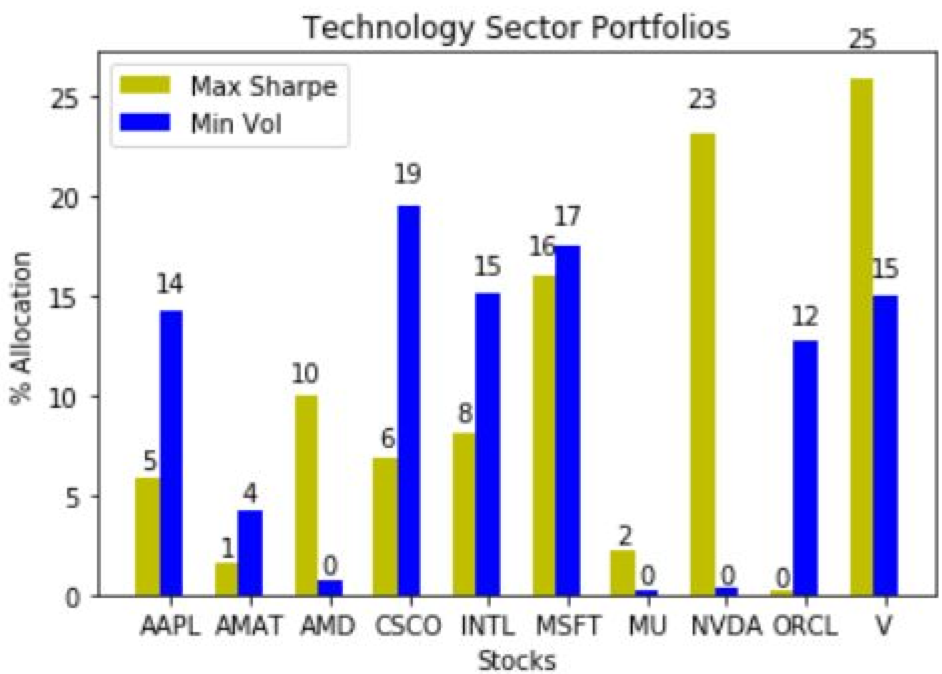



Maximum Sharpe Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 10.484709 |
| stdev | 15.990393 |
| sharpe | 0.655688 |
| AIV | 26.900000 |
| AMT | 17.300000 |
| CBRE | 0.870000 |
| HCP | 1.780000 |
| HST | 10.100000 |
| IRM | 14.300000 |
| KIM | 1.900000 |
| PLD | 22.500000 |
| WELL | 2.140000 |
| WY | 1.940000 |

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 7.092836 |
| stdev | 15.415026 |
| sharpe | 0.460125 |
| AIV | 14.500000 |
| AMT | 23.600000 |
| CBRE | 2.790000 |
| HCP | 4.890000 |
| HST | 8.870000 |
| IRM | 7.680000 |
| KIM | 7.680000 |
| PLD | 0.890000 |
| WELL | 8.850000 |
| WY | 20.100000 |

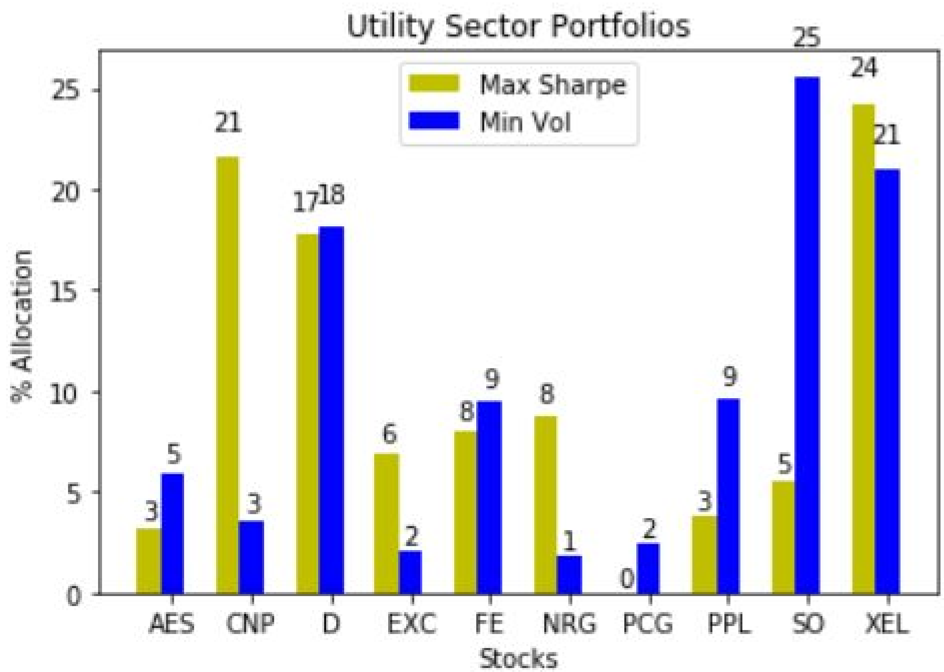



Maximum Sharpe Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 32.331541 |
| stdev | 21.460882 |
| sharpe | 1.506534 |
| AAPL | 5.830000 |
| AMAT | 1.590000 |
| AMD | 10.000000 |
| CSCO | 6.890000 |
| INTL | 8.080000 |
| MSFT | 16.000000 |
| MU | 2.170000 |
| NVDA | 23.100000 |
| ORCL | 0.170000 |
| V | 25.900000 |

Minimum Volatility Portfolio:

| Portfolio Characteristics | % Allocation |
|---|---|
| ret | 20.362403 |
| stdev | 16.660163 |
| sharpe | 1.222221 |
| AAPL | 14.200000 |
| AMAT | 4.230000 |
| AMD | 0.780000 |
| CSCO | 19.500000 |
| INTL | 15.100000 |
| MSFT | 17.500000 |
| MU | 0.280000 |
| NVDA | 0.320000 |
| ORCL | 12.700000 |
| V | 15.000000 |




Maximum Sharpe Portfolio:

| | % Allocation |
|---|---|
| **Portfolio Characteristics** | |
| **ret** | 9.331324 |
| **stdev** | 15.223198 |
| **sharpe** | 0.612967 |
| **AES** | 3.200000 |
| **CNP** | 21.600000 |
| **D** | 17.800000 |
| **EXC** | 6.900000 |
| **FE** | 8.010000 |
| **NRG** | 8.770000 |
| **PCG** | 0.020000 |
| **PPL** | 3.770000 |
| **SO** | 5.530000 |
| **XEL** | 24.200000 |

Minimum Volatility Portfolio:

| | % Allocation |
|---|---|
| **Portfolio Characteristics** | |
| **ret** | 7.237942 |
| **stdev** | 14.476308 |
| **sharpe** | 0.499985 |
| **AES** | 5.920000 |
| **CNP** | 3.590000 |
| **D** | 18.200000 |
| **EXC** | 2.110000 |
| **FE** | 9.480000 |
| **NRG** | 1.800000 |
| **PCG** | 2.480000 |
| **PPL** | 9.650000 |
| **SO** | 25.600000 |
| **XEL** | 21.000000 |

# Works Cited


- Finta library - https://github.com/peerchemist/finta
- Backtesting - https://ntguardian.wordpress.com/2018/07/17/stock-data-analysis-python-v2/
- data - https://api.tiingo.com/
- Clustering - https://www.pythonforfinance.net/2018/02/08/stock-clusters-using-k-means-algorithm-in-python/
- Sector Portfolio Analysis - https://www.pythonforfinance.net/2017/01/21/investment-portfolio-optimisation-with-python/
- Cover Image - http://www.asianage.com/business/in-other-news/290418/earnings-oil-macro-data-to-set-market-tone-in-holiday-shortened-week.html