Project 1:
Portfolio Forecasting

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Motivation & Summary

Hypothesis

Are dividends and earnings enough to construct an optimal portfolio of stocks?

Core Questions

1. Can we build a portfolio based on stock earnings?
2. What factors have the greatest influence on returns based on earnings?
    a. Does Initial Investment influence returns?
    b. Does number of days left in the market influence returns?
    c. To what extent does weighting influence returns?
    d. Does the number of stocks affect returns?

Summary

We initially planned to forecast at what point we should buy or sell a particular stock, and found we were limited in determining this as it would require machine learning to make effective predictions.

We discovered that we would need to build an optimal portfolio to determine returns based on the following factors: Initial Investment, number of days left in the market, weighting, and number of stocks, to begin phase two of prediction.

- We found that Initial Investment affected returns only to the extent that it heightened the difference between 95% Confidence Intervals.
- More days left in the market decreased the opportunity for high returns and created a large gap between Confidence Intervals.
- Weighting
    - Equal Weighting: The more stocks we added at equal weights increased the risk to lose entirety of initial investment.
    - Random Weighting: If choosing more than 3 stocks, varied weights are required to ensure gains.
- The more stocks included in the portfolio, the greater risk of losing the entirety of our initial investment, and conversely, the greater opportunity for reward in reaping significant gains.

Questions & Data

1. Where can we obtain data to accomplish this task?
    a. With such robust data, we wanted a way to pull the information dynamically based on the Earnings Date. We utilized DateTime and the Yahoo Earnings Calendar API to pull the information we needed.
    b. This solved our problem of pulling too much information, and minimized our need to clean the data.
2. Would weighting stocks differently result in higher returns?
    a. Weighting stocks differently presents the opportunity for higher returns.
    b. More than 10 stocks takes away risk, since it's overly diversified and the weights cancel eachother out, essentially.
    c. More stocks input = worse return.
    d. We found that the optimal number of stocks is roughly 5, which allows the weighting to optimally diversify our portfolio, providing adequate risk and in turn, adequate reward.
3. Is Monte Carlo an optimal method for forecasting our portfolio?
    a. We wanted to project when the optimal time to buy and sell would be, down to the day. By looking at the Monte Carlo simulation, we could see the simulation over 1260 days, but acknowledged the code would be extensive to determine this.
    b. We found a site on simple stock price prediction that explained machine learning would be a more precise way of predicting the market in conjunction with our portfolio.

Data Exploration & Cleanup

We utilized the Yahoo Finance Calendar and Alpaca API's to pull real time stock data. When we received the earnings calendar from yahoo, it generated a dictionary with excess data than was necessary. We wrote a for loop to generate the list based on the data we wanted. Using this for loop method, we took the stock earnings data and removed the *stock ticker* and *estimated earnings per share* for future use in its own dictionary.

When attempting to utilize a FloatSlider in the Dashboard, we were unable to connect it to the graphs to view how returns would react as we changed "Number of Days in the Market", and "Initial Investment". The result led us to utilize the Float Slider at the start of the code, which would re-run the Monte Carlo simulation and filter into the dashboard. This option is less user friendly, but functional.

Dynamically Pull Stocks Based on Earnings Date

```
today = datetime.date.today()
tomorrow = today + datetime.timedelta(days = 1)
start_time = tomorrow.strftime("%b %d %Y") + " 10:00AM"
next_day = today + datetime.timedelta(days = 2)
end_time = next_day.strftime("%b %d %Y") + " 1:00PM"

date_from = datetime.datetime.strptime(
    start_time, '%b %d %Y %I:%M%p')
date_to = datetime.datetime.strptime(
    end_time, '%b %d %Y %I:%M%p')
yec = YahooEarningsCalendar()
stock_earnings = yec.earnings_between(date_from, date_to)
```

```
stock_list = [{'ticker': ticker['ticker'], 'epsestimate': ticker['epsestimate']}
              for ticker in stock_earnings if ticker['epsestimate']]

print(stock_list)
tickers = []
for i in stock_list:
    if i["ticker"] not in tickers:
        tickers.append((i["ticker"]))

print(tickers)
```

```
[{'ticker': 'ROAD', 'epsestimate': 0.3}, {'ticker': 'ROAD', 'epsestimate': 0.3}]
['ROAD']
```

Analysis

- Are dividends and earnings enough to construct an optimal portfolio of stocks?
    - This is enough to construct a portfolio, but we found we needed to include particular variables to optimize it, such as “initial investment”, “days in the market”, “weights”, and “number of stocks”.
- Would weighting stocks differently result in higher returns?
    - After running a Monte Carlo Simulation, we found that we were likely to lose our initial investment.
    - We want to create a weighting calculator to test this theory and found… the number of stocks played more into the results than the varied weights. We found the more stocks we had, the worse the returns were.
    - Weighting does present the opportunity for higher returns.
- Is Monte Carlo an optimal method for forecasting our portfolio?
    - Machine Learning will be more efficient as Monte Carlo Simulations are static.
    - We wanted to see if there was a more efficient way of pinpointing a time in the future to buy or sell a particular stock.
- Where can we obtain data to accomplish this task?
    - Alpaca & Yahoo Finance
    - While we were able to obtain sufficient data, the data was robust, and created issues with narrowing it down and completing further cleaning.

Discussion

- Findings
  - More stocks & more days in market diluted the chance for higher returns.
  - More stocks, higher initial investment, & varied weights presented an opportunity for higher returns
- Discussion
  - Now that we have a portfolio forecaster, with variables that optimize our chances for higher returns, this should allow us to build a “predictor” that can pinpoint when we should buy and sell a particular stock.

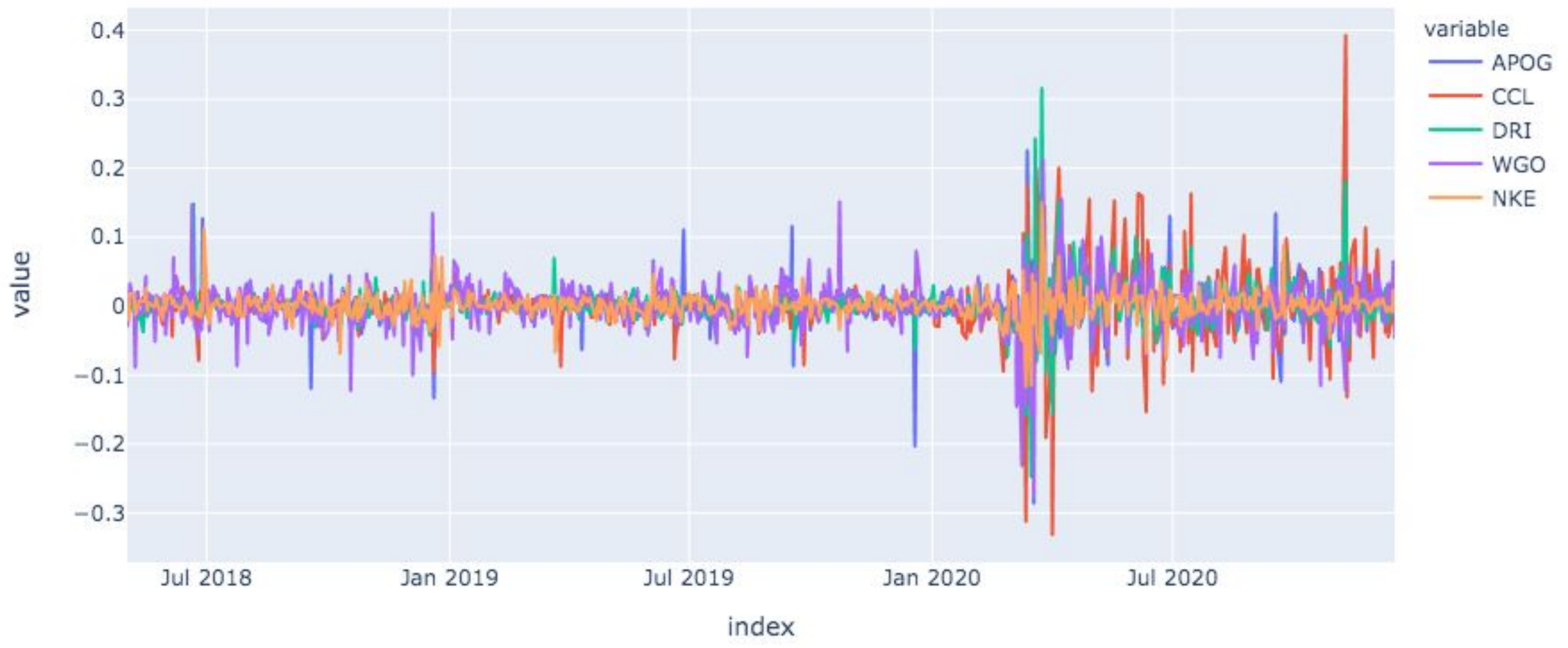
Implications

- Graphing
  - Graphs would better with dynamic sliders, to visualize how the portfolio results would change as we adjusted the number of days and initial investment amount
  - Sliders proved difficult to input at the end of the code, particularly within the dashboard. The sliders would need to be added when we finish our code, to be closer to the dashboard, and to avoid re-running the monte carlo simulation, or a “Reusable Widget”, to copy our previously used widget to the bottom of our code.
- Take it to the next step
  - Utilize machine learning to predict the optimal days to buy and sell
  - Monte carlo isn’t the optimal method to predict this type of data.

Questions?

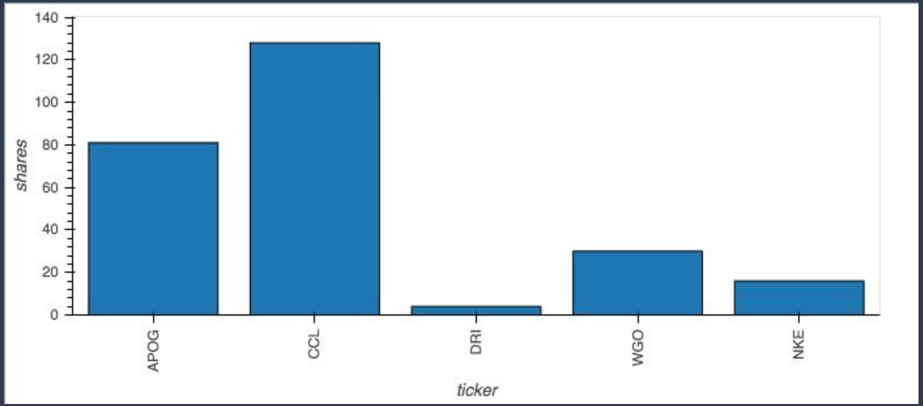
Open Floor Q&A

DAILY RETURNS

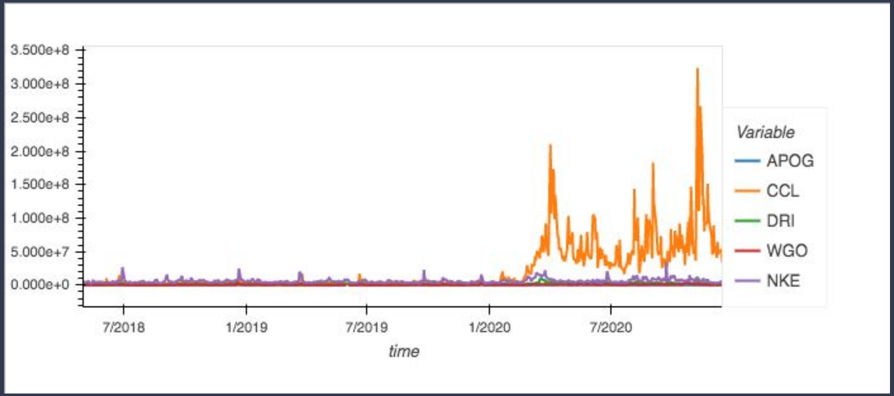


CLOSING PRICE

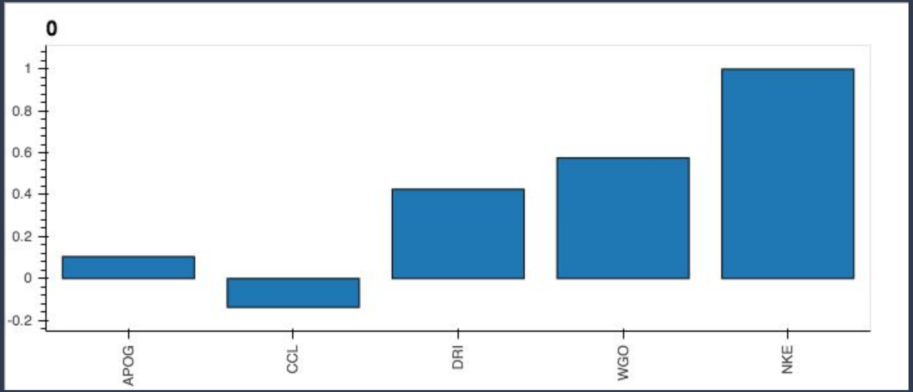
Share Purchase



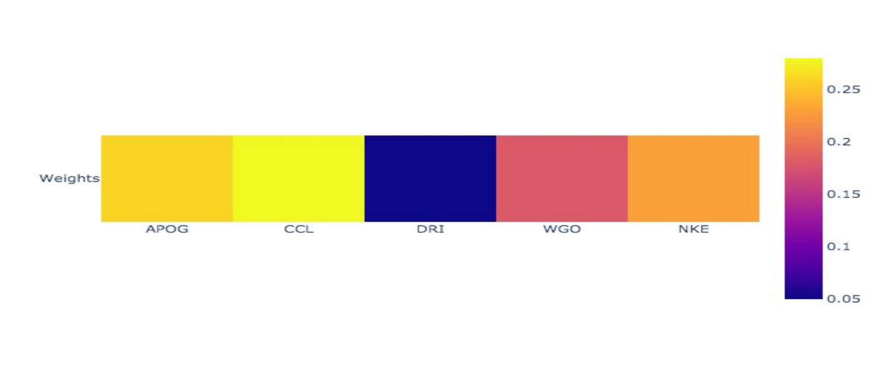
Stock Volumes



Sharpe Ratios



Stock Weights



Dashboard

Daily Returns | Sharpe Ratios | Closing Price | Stock Weights | Stock Volumes | Share Purchase

Portfolio Analysis

Summary : There is a **95%** chance that an initial investment of **$10000** in the portfolio over the next 5 years will end within in the range of **$3645.02** and **$57639.41**

	ticker	shares
0	APOG	81
1	CCL	128
2	DRI	4
3	WGO	30
4	NKE	16