Quantum Finance: Final Report

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December 7, 2016

1 Introduction: Motivation

Currently, mitigating financial risk and stock discovery are specialties that quantitative developers perform for hedge funds and asset management firms using sophisticated and expensive software. Without backgrounds in related fields, average investors are hardly capable of performing such a task. Uncertainty in future optimized returns, poor user interface, computational expense, and complexity plague current risk tools.

2 Problem Definition

Over 156 million Americans are invested in the stock market, over half of them being the average investor. Hence, there exists market demand for financial tools that cater towards this target audience. By leveraging complex algorithms through simple interactive visualizations presented in a clean and easy to understand user interface, we aim to provide portfolio recommendations that makes sense for the user. Without a quantitative background, investors will be able to remove unnecessary risk from their portfolio and maximize return through either shifting their current portfolio weights or investing in new recommended equities.

3 Survey

Data Manipulation:
We have chosen pandas for data handling as it has low computational expense due to being wrapped in C. Although pandas does not have physical storage like the SQL database, it reads whole tables, retrieves the data, and executes analytic queries must faster [9].

Equity Portfolio Risk Management:
Portfolio diversification is important to investors. However, U.S. investors are under-diversified. This gives us motivation to build a tool that will help U.S. investors diversify their portfolio and give us insights on the ideal degree of diversification [5, 13].

Sharpe Ratio computes the return we get per unit of risk taken by subtracting the risk free rate from the returns matrix and dividing by the volatility in product with the time frame constant. Sharpe Ratios incur a variance in their estimation based on time frame, which is a potential shortcoming. However, we can choose a daily evaluation period and make this a useful metric for our optimization function. Value-at-risk compares standard deviation to efficient frontiers. This is a good metric but does not directly relate portfolio strength and instead focuses on high risk. This will not be as strong of a choice as Sharpe Ratio for our purposes as we want a metric that details portfolio strength and not purely risk [1, 3, 15, 18, 19].

There are three determinants of portfolio return which are investment policy, market timing, and security selection. The team sees these determinants as potential valuable metrics for our investment portfolio analysis [4].

Machine Learning & Optimization Algorithms:

With regards to optimization by maximizing Sharpe Ratio there are two highly recommended choices: Mean-Variance Optimization (MVO) and Mean-Absolute Deviation (MAD). Both methods are essentially the same except MAD assumes returns are normally distributed and allows stock shorting, which are shortcomings of MVO. MAD is computationally inexpensive for large portfolios but incurs more complexity in algorithm implementation. Our portfolios should not consist of over 100 stocks, so MVO should be a good choice for our objective function. With our optimization method we can consider a multi-criterion technique that will improve optimization, but will increase computational complexity. For our purposes this methodology will add unnecessary expense to our program so we will not pursue it [6, 7,16,17].

Stochastic programming is an alternative algorithm to the mean-variance optimization. Due to its complexity, the team will only see it as a backup plan. We also have a possibility of generalizing a one-time portfolio optimization to a multi-period and lifetime portfolio selection [8,12].

Forward selection allows us to bypass searching through all possible subsets and instead allows us to search through a path. We use this algorithm to sequentially add more stocks that optimize our sharpe ratio model [14]. Opposingly, neural networks can reduce the effect of a nonlinear stock market model. However, neural networks require a long training phase which will work against the team's tight schedule. Hence, the team decided to apply the forward selection algorithm [2].

Visualization:

For visualization, we will implement the motion chart, as we want to present an interactive approach to explore patterns in multidimensional data over a specific period of time [10,11]. By detailing information on individual data points, the user will be engaged in an informative process and will thus facilitate more deliberate decisions [10, 20]. Time requirement is high with a motion chart and large data set, but this chart blends well with the bootstrap framework.

4 Proposed Method

4.1 Intuition: Why should it be better than the state of the art?

Quantum Finance truly believes that understanding and action arise from simplicity. Current portfolio management tools target sophisticated audiences with relative quantitative backgrounds, hence forgetting the average investor. A portfolio manager can easily look at a screen of binary numbers and discern a pattern or signal, however their clients among the average investor are not fully capable of this. Having easy to understand visualizations and interactions tunneled underneath with the complex machine learning and optimization will allow the user to understand where their portfolio needs improvement and what actions to take to achieve this improvement. Our method of simplicity and understanding will make our platform better than the state of the art as we perform similar low-level computations but present them in a beautiful and interactive way that makes sense to all audiences, not only the financial rocket scientist.

4.2 Description of approaches: back-end and front-end

Our back-end consists of data collection, data handling, financial metric calculation, portfolio optimization, forward step-wise regression, and helper functions that allow us to format data and pass it to the user interface. For data collection, we dynamically scraped yahoo finance through the following libraries: pandas, requests, and urllib2. Pandas was used to pull our adjusted close prices through the pandas web data-reader. Here, we would scrape a list of tickers and return a bundle of equity data in a dataframe. However, we needed to filter out data such as open, high, low, and close prices; which are not relevant for our algorithms. Requests and urllib2 were used to scrape company descriptions, tickers, and other fundamental metrics. Every time information was entered and the submit button was clicked our scrapers would fire and dynamically pull this data. This was great as we did not have to physically store our data after or before the user querys were run. We constructed a portfolio class with parameters tickers, shares, start,end, and initial cash, that are specified by the user. We took an object oriented approach as it is easy to read code in the backend. It is important to have readable code as Adam and Binglun had to work together to understand and work on each others' code. We have a method that performs mean variance optimization and forward step-wise regression. The mean variance optimization algorithm was build using scipy as it is very quick and the forward step-wise regression algorithm was coded from scratch with help from the Elements of Statistical Learning by Jerome H. Friedman, Robert Tibshirani, and Trevor Hastie. The Mean Variance Optimization is great for a user who does not which to invest in alternate stocks, and simply shift around their current portfolio holdings. This is great for a user who wishes to seek higher returns. The forward step-wise regression is great for a user who is looking to venture into new stocks. This is great for a user who seeks to diversify their portfolio and minimize risk.

Our front-end was created with the Semantic UI and Bootstrap framework. Bootstrap was used primarily for our log-in and create account page while Semantic UI components were used for the main page showcasing the main functionality of our web application. Both bootstrap and Semantic UI are great web frameworks with a supportive community and were great for helping setup our front-end. We are using D3 for our charts as we found them to be very clean, interactive, and fit well with our CSS. Interactive line charts will allow the user to see how each stock in the portfolio has performed, scrolling bar charts will let the user see their monthly profit and loss, force diagrams will let the user see the correlation between stocks in their portfolio and the major stock indexes, a radar graph will show portfolio diversification between the recommended portfolio and the original portfolio, and a motion chart will show how the original portfolio has performed on a rolling basis compared to our recommended portfolio. Our user interface has four distinct tabs: original, optimized, discovery, and comparison. The original and optimized tabs detail the line chart, profit and loss chart, and the force diagram. They also show the portfolio tickers, weights, and individual stock return. The discovery tab shows a radar chart detailing portfolio diversification between the recommended portfolio and the original portfolio. Below the radar chart, there are stock cards detailing information about each stock in the portfolio as well as information about the recommended stocks from the forward step-wise regression. The comparison tab shows the motion chart and provides a table of comparative metrics between the original and optimized portfolios.

Our bridge between the back-end and front-end is handled by the flask microframework and jinja2. Here, we dump python data into a JSON and send it to the HTML so that it renders for the user on the page.

5 Experiments/Evaluation

Previously, to test our mean variance optimization algorithm we optimized a portfolio consisting of CMG, AAPL, KO, and MSFT from 11/1/2016 to 11/7/2016 and then test forward using the new weights until 11/12/2016. Our original allocation was [0.25,0.25,0.25,0.25] (500 shares for each stock) and our optimizer gave us an allocation of [1.0,0,0,0] telling us to put all the money into CMG (all 2000 shares). Looking forward the original portfolio made $16,545 while the optimized portfolio made $76,120. The optimized portfolio then netted us $59,575 over the original portfolio. Since then, we have made $35,080 with our recommended optimized portfolio while only $6880 with our original portfolio. Thus, we have net $28,200 more with our optimized portfolio. Additionally, we tested other smaller and larger portfolios and have made a positive return on each recommended portfolio and have lowered volatility. Looking at our forward step-wise regression we noticed that it always recommends stocks that create a more diverse portfolio. For instance, whenever we passed in a full technology portfolio we were recommended equities in the consumer goods sector or the utilities sector. Whenever we had a utilities heavy portfolio we were recommended more health care and technology equities. This showed us that if the portfolio was too risky, we would be recommended a safer portfolio. If the portfolio was too safe we would be recommended a slightly riskier portfolio. If we looked at the spread of diversification on our radar chart we always were given a recommended portfolio that had greater variance around the sectors. This is great because it ensures that the portfolio will remain safe in case of a bubble. A diverse portfolio is a great asset for the average investor as it ensures that their portfolio value will be safe.

6 Final Product

Below are some images from our finished web application:

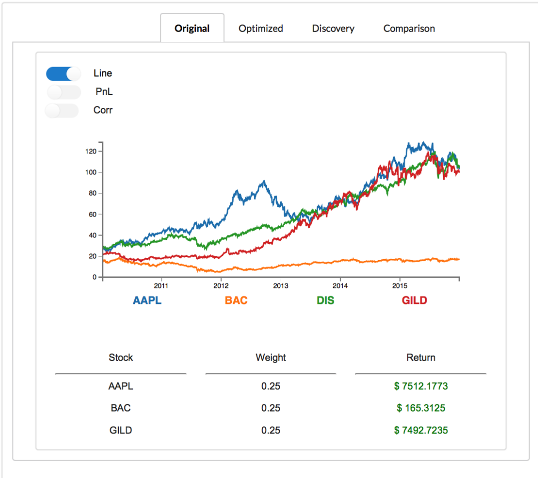

Figure 1: Line chart from an original portfolio.

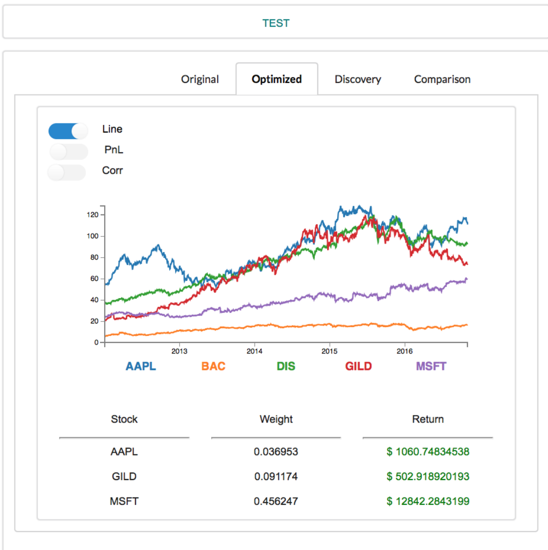

Figure 2: Line chart from an optimized portfolio.

Figure 3: Profit and Loss Chart.

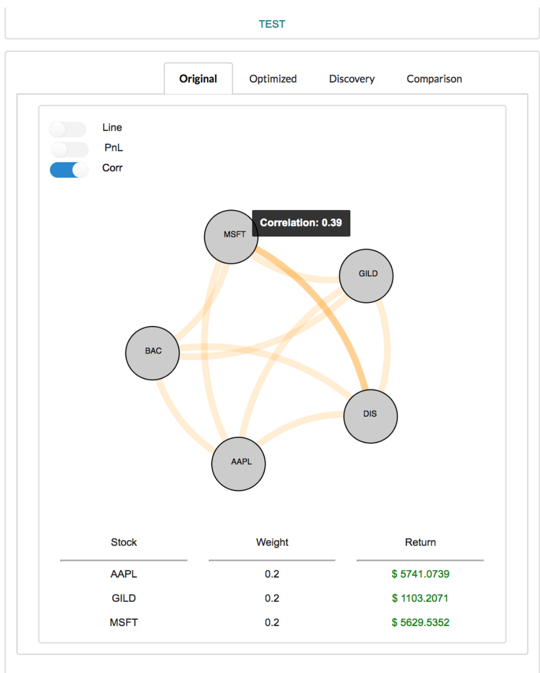

Figure 4: Portfolio Correlation with major stock indexes Chart

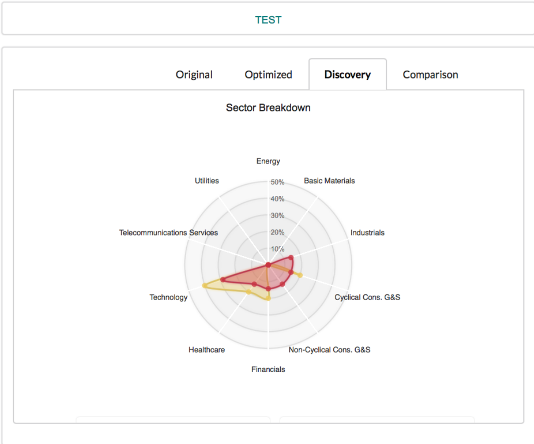

Figure 5: Radar chart showing original and optimized portfolio diversification

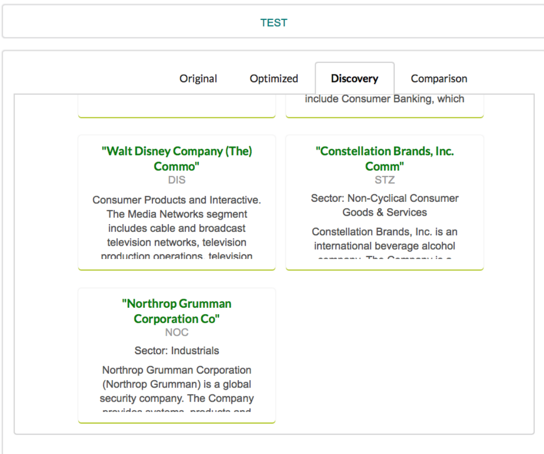

Figure 6: Stock cards showing information about forward step-wise regression discovery stocks

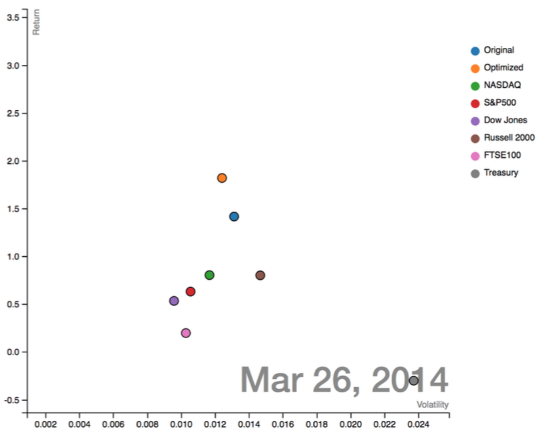

Figure 7: Motion chart displaying original and optimized portfolio compared to major stock indexes

7 Conclusion & Discussion

In conclusion, Quantum Finance aims to make portfolio management comprehensive for the average investor. Through experiments, the team has illustrated that Quantum Finance has the potential to improve portfolio return drastically for its users. However, the tool has its limitations. Quantum Finance is less helpful for investors with a quantitative background. Also, having Sharpe Ratio as the main objective function might neglect some potential opportunities associated with volatility. With that being said, the team can allow this trade-off as less experienced investors should try to worry less about arbitrage on positive volatility swings. From our experiments, our suggested portfolios have higher returns, lower volatility, and are more diverse than the original user portfolio.

8 Team Effort Distribution

Adam Lieberman and Binglun Li handled the core back-end functionality including the web scrapers, portfolio construction class, mean variance optimizer, and forward step-wise regression algorithm. Adam build the UI/UX and bridged the back end to the front end and provided the data for the D3 charts. Binglun built the interactive line charts and helped Adam build the profit and loss chart and radar chart. Wai Man Si and Jason Kolbush built the Motion Chart and force diagram as well as styled styled them and helped debug the front end. Ai He and Anzhi Mou helped with research and planning. All group members participated equally with the poster and papers.

9 References

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