Team 2 Trading Competition Report

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Introduction

In this trading competition activity, we used TA Lib to implement some common technical indicators for trading on a day-to-day resolution. We began by analyzing the given data and discovered trends between the prices of stocks and the trade volume, which led us to a variety of momentum indicators. Below, we discuss some of the indicators explored, the performance of each, our final results, and ways to improve this algorithm in future works.

Indicators Explored

Throughout the process of developing our trading algorithm, we brainstormed numerous technical indicators we could use to guide our trading decisions. The first indicator we implemented was the Golden Cross. Using the TA-Lib functions, we calculated slow moving averages of the stocks with a time period of 40 and fast moving averages with a time period of 5. When the fast SMA crosses above the slow SMA, then we buy. In the opposite case, we sell. The Golden Cross test resulted in a Sharpe Ratio of 0.705.

Then, we implemented an algorithm using the Relative Strength Index (RSI) indicator. The value of this index indicates whether a stock is overbought or underbought. When the RSI is above 70, it suggests that the asset may be overbought and a price decrease could be on the horizon, and vice versa if the RSI is under 30. Using this trading logic, our RSI test generated a Sharpe Ratio of 0.7401.

Using these two technical indicators, we then wanted to combine the logics to better guide the points at which to buy and sell stocks. If the RSI indicates that an asset is overbought and a Golden Cross
If the RSI is below 30, indicating the asset is oversold, and you see a Golden Cross, this could be a strong bullish signal, or an upward trend in the future. However, the conjoined implementation of the two technical indicators resulted in a Sharpe Ratio lower than each of the individual ones.

After these, we attempted to implement the Average Directional Index (ADX) indicator, which is a trend indicator. If the ADX is above 25, then it suggests that there is a strong trend in the prices of the stock. Thus, whenever the ADX indicates such a trend, we check the direction of the trend and make decisions accordingly – buy if prices are increasing and sell if they are decreasing. However, we didn't end up getting this algorithm to work against the evaluating algorithm.

Data Analysis

When viewing the data, specifically the data sets for companies A and ZW, we were able to identify trends in data between the opening and closing prices of a stock and its following price the next day. This prompted the discussion of how these swings in opening and closing prices indicate change in volume and if we could use that to forecast potential changes in prices. Thus, we began to implement a large variety of momentum indicators in order to discover how opening and closing prices can predict prices down the line. Originally we began with a Golden Cross, however soon we realized that depending on the length of time period used for the fast and slow SMA the variance in the Golden Cross would be too great to produce accurate results. Thus we began to look at methods of analyzing the momentum that relied "relatively" less on time period, resulting in the exploration of other momentum indicators such as RSI and ADX.

Final Results
RSI has the highest Sharpe Ratio of 0.7401.

Ways to Improve
An idea we had on how to improve this algorithm would be to train a neural network to make buy/sell decisions, with several of *talib*'s indicators as inputs and +1/-1 as outputs per day. The training data could be derived from the given dataset using a two-pointer type algorithm to determine the best times to buy and sell for each ticker. Then, knowing this information, we can train the network to learn how to weight each indicator in its decision. Ideally, our strategy would combine 2 or more indicators for decision making, but the way that these are combined is quite subjective. Letting the network learn the combination numerically seems like a more logical approach to us. (It's worth noting that here, we are treating the given data as the historical dataset, and there needs to be another, separate testing dataset on which performance can be measured.

We also had hopes that the MACD indicator based trading would outperform RSI, but did not implement this in the given time. It is also possible that there are other single indicators that would outperform RSI that we did not explore. Further, we used the same indicator for *all* tickers. With some more in depth data analysis, we might have identified trends that allowed us to better tailor our indicator usage. For example, RSI might outperform ADX in some set of tickers but not others. Making this change might greatly increase overall sharpe in ways that single-indicator strategies do not, as the per-ticker strengths/weaknesses of each individual indicator are very hard to separate.

Finally, this data format makes it possible to use candlestick graphs and patterns to trade, which we mostly did not use. The TA Lib includes many pre-built candlestick pattern matchers, which is a sometimes more intuitive and graphical way to trade on this kind of data. This may be another direction to go in, and might also serve as another input into the neural model proposed above.

Conclusion
After looking through the data we decided to look at momentum indicators and how they predict future prices. We subsequently tested a series of indicators and were able to find pockets of success with our algorithm. Through our final review of the results, we've determined that our best choice is to utilize the RSI indicator/algorithm as it yields the best results in monetary terms and has the best Sharpe Ratio.