Democracy Model

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Abstract

Throughout the semester, we have learned a lot of signals and metrics. In addition to these, there are also many other statistical measurements and trends that exist to predict stock performance. Although many such measurements exist, there is no universally superior metric for predicting stock performance. We hypothesize that each metric is able to detect some aspect of the stock's performance, and if we combined the signals from multiple metrics and used them to support and smooth out each other, the resulting decision would be better and less risk-prone.

We came up with Democracy, a model that applies various techniques to generate buy/sell signals on a specific stock, then decides whether to buy or sell on a specific day by conducting a vote over all the signals from a past window of time.

When applied to a growth stock that is relatively volatile like AMD, we achieved great returns, far exceeding the returns from any single metric.

Introduction

Although many metrics and measurements of stock performance exist, there is no universally superior metric for predicting performance. For example, some metrics may only provide sparse signals over a period of time, and other metrics may sometimes provide a signal that leads to a loss if acted upon. It is difficult for one statistical metric to account for all the factors that may affect a stock (macroeconomic conditions, performance of competitors, interruption in supply chain, consumer sentiment, etc).

We hypothesize that each metric is able to detect some differing aspect of a stock's performance. Therefore, it makes sense for a model that aggregates multiple metrics and makes a final decision based on the decision of all metrics to perform better than any single metric.

Review of Existing Literature

We design Democracy out of the very simple idea of wisdom of the crowd. The majority voting idea is the same as a random forest, where each signal represents a tree and gives out a signal. Before implementing our model, we dug into the literature and discovered that trading using multiple technical indicators already exists in previous literature, some of which claiming that they have achieved returns higher than the growth of SPX over the past 10 years. What is more, using multiple signals increases the robustness of the trading algorithm. The maximum drawdown is decreased throughout time. Risks are thus lower compared to using only one technical indicator.

However, some papers also discovered that different trading signals sometimes conflict with each other, and some are intrinsically different from others. This leads not to increase profitability, but instead causes losses in trading strategy due to co-influence. Thus, trading signals need to be carefully selected to produce enhancement for the overall system. Statistical analysis might also be required to filter out repeated signals that do not generate further information. Weights of each signal should be considered to weigh the importance and quality based on prior knowledge.

Given the significant growth of computing power and stock market data, a lot of new indicators have been created over the past decade to try to capture the essence of market movement and produce buy-sell-hold signals to make money. Surprisingly, a lot of historical trading signals, such as MACD and RSI, still work well in today's market, even though their returns have somehow decreased over time. After reviewing literature comparing the strengths and weaknesses of multiple signals, we decided to go with some of the most simple and famous ones. Those signals, even though known by almost everyone in the stock market, can 1) truly measure a different aspect of the stock market at a given time; 2) is easy to understand and approachable to most traders.

Dataset

We got our data from the python yfinance library: https://pypi.org/project/yfinance/. This data is scraped from the Yahoo Finance API and allows us to directly import a dataframe with information like "Open", "Close", etc for each stock ticker at various time intervals. While working with the data, we did not encounter any significant anomalies. Overall, we think this is a very trusted and reliable source of stock information.

We did not need to process the data too much, we will describe how we modified the data in the sections below (if applicable).

Methods (modeling)

Individual Metrics

We will first detail the metrics that we used in our model. All results are computed with an initial portfolio value of $100,000 cash.

Pairs Trading

The main assumption of pairs trading is that two stocks in a similar field will be affected similarly by macroeconomic, supply chain, and market sentiment factors. For example, if farming crypto suddenly becomes lucrative and there is an increase in demand for Nvidia GPUs leading to an increase in price of NVDA, it makes sense that there would be a similar increase in demand for AMD GPUs leading to a corresponding increase in AMD. Although Pairs trading usually involves going long on one stock and short on another, we will instead only focus on one stock in the pair and use these as buy / sell signals (in order to simplify the model).

We referenced an article from Hudson And Thames titled *An Introduction to Cointegration for Pairs Trading* by Yefeng Wang. For some background, it was discovered that price, rate, and yield data matches an Integrated time series of order 1, or I(1). It follows that returns (differential of price) is of order 0: I(0). An I(0) series has the property that it is weak-sense stationary, which means the mean and variance of the time series does not change with time. This means that if the time series ever deviates from the mean, it should inevitably return later on in order to maintain the stationary property. However, we can't trade returns, only prices. This led to the creation of the term cointegration (detailed in the paper: *Cointegration and asset allocation: A new active hedge fund strategy* by Alexander et al).

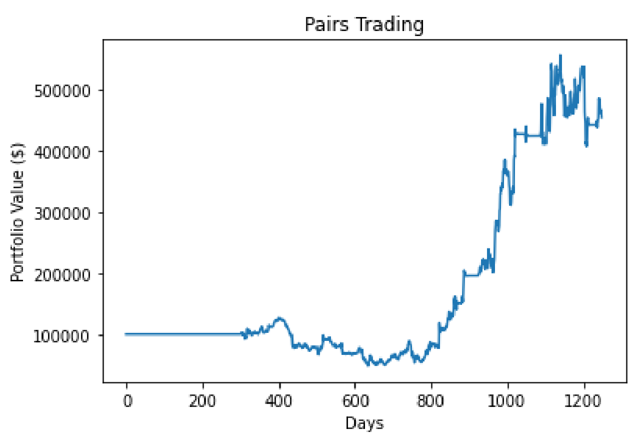
x_t and y_t are cointegrated, if x_t and y_t are $I(1)$ series and $\exists \beta$ such that $z_t = x_t - \beta y_t$ is an $I(0)$ series

Now we are able to construct a stationary time series from two price series. Pairs trading is applicable if a valid beta can be found.

The intuitive meaning of cointegration is the long-term relationship between prices. This actually has no clear relationship with correlation, which is the short-term relationship between returns.

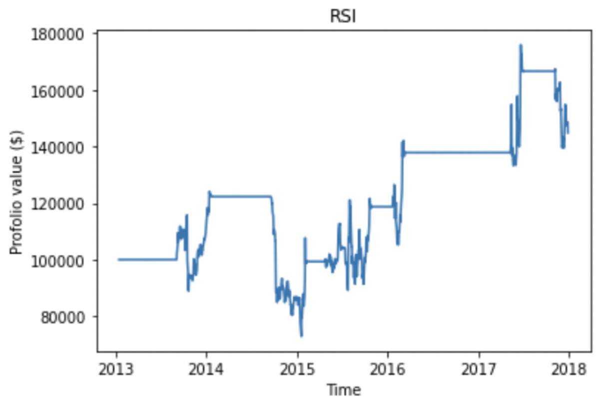
We first computed the natural log of each price because that is easier to In order to generate signals, we apply the Engle-Granger test to determine if the beta value is significant and if the price at the current time meets the threshold for determining a buy or sell signal.

Overall, pairs trading performed well as the sole signal, generating $354,105.41 in profit and outperforming the AMD stock by 115% over the same time period (2013 - 2017).



RSI

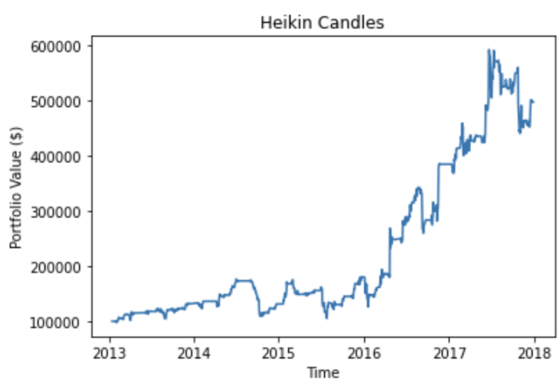
RSI (Relative Strength Index) reflects the current strength/weakness of the stock price momentum. The calculation is pretty straight forward. We use 14 days of smoothed moving average (or other moving average methods) to separately calculate the intra daily uptrend and downtrend. We denote uptrend moving average divided by downtrend moving average as the relative strength. We normalize the relative strength by 100 which becomes an index called RSI. It is commonly believed that RSI above 70 is overbought and RSI below 30 is oversold. This is the simplest way to trade on RSI. Nonetheless, there could be divergence between RSI momentum and price momentum which will not be covered in the script. The effectiveness of any divergence strategy on RSI is rather debatable.



Heikin Candles

Heikin-Ashi, the exotic name actually referring to 'Average Bar' in Japanese, is an alternative style of candlestick chart. The sophisticated rules of Heikin-Ashi are designed to filter out the noise for momentum trading. Hence, Heikin-Ashi shows more consecutive bars in contrast to the standard candlestick, which makes price momentum and reverse points more distinguishable in figures. Arguably it should outperform the standard candlestick in sideways and choppy markets.

For the strategy itself, initially we make a few transformations on four vital benchmarks - Open, Close, High, Low. The next step is to apply unique Heikin-Ashi rules on Heikin-Ashi Open, Close, High, Low to generate trading signals. The downside of Heikin-Ashi (or any momentum trading strategies) is the slow response. Thus, we should set up the stop loss position accordingly so that we don't get caught up in any flash crash.



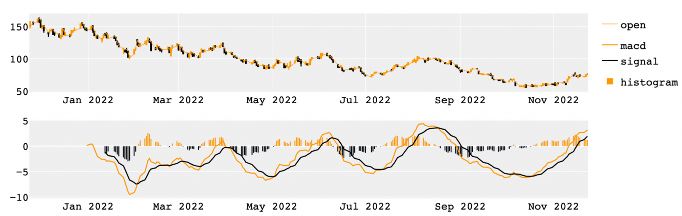
MACD

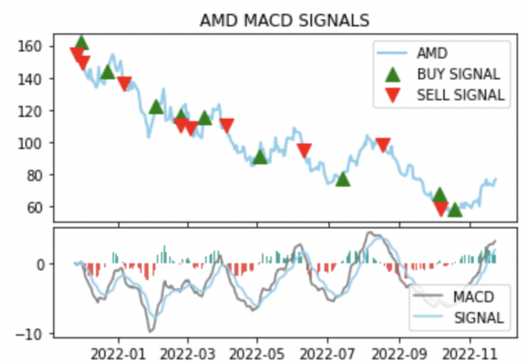
MACD, or Moving Average Convergence/Divergence, is a momentum indicator that signals shifts in market momentum. It assumes that the upward or downward momentum of a stock has a greater impact on its short term moving average than its long term moving average. If the short term moving average is greater than the long term moving average, it generates a signal to long the stock, and if the short term moving average is below the long term moving average, it generates a signal to short the stock.

How we implemented our MACD indicator:

- The MACD line is the difference between the fast length (short term) exponential moving average and the slow length (long term) exponential moving average
- The signal line is the exponential moving average of the MACD line for a given amount of time
- If the MACD line is greater than the signal line, it generates a buy signal (1)
- If the signal line is greater than the MACD line, it generates a sell signal (-1)
- If the MACD line is equal to the signal line, it generates a hold signal (0)
- The value of the position stays at 1 if we hold the stock, or if we don't own the stock, it stays at 0
- For example, if the indicator generates a sell signal (-1) and the current position is to buy (1), the next position will be updated to a hold signal (0), and it will remain at 0 until there is another buy signal or sell signal

These graphs illustrate how the MACD line and signal line have moved over time as well as the signals generated for the AMD stock:





Voting Model

The basic idea of the Democracy model relies on the concept of wisdom of the majority. By utilizing signals from different metrics which each capture different aspects of the market and situation, we can smooth out bad signals and capture good signals during a variety of market conditions. Overall, we expect our model to be less risky and make better decisions compared to just relying on one metric for buy/sell signals.

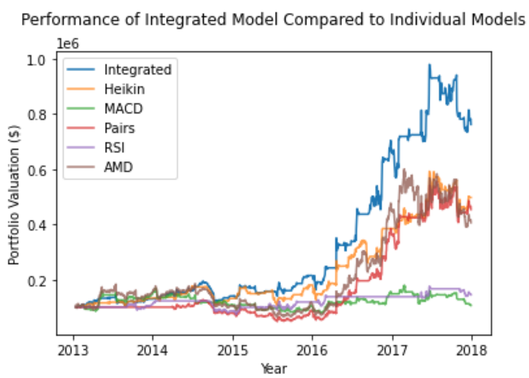
The Democracy model is implemented as follows:

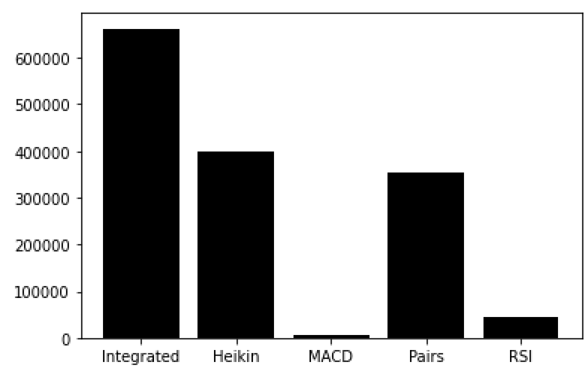
- Each metric returns a buy/sell/hold (1, -1, 0 respectively) signal for the past 10 days.
- The model conducts a vote by adding up all signals.
  - If the sum is positive, we have a buy signal.
  - If the sum is negative, we have a sell signal.
  - If the sum is zero, we have a hold signal.
- Buy and sell strategy is as follows:
  - If we end up with a buy signal, we will use 50% of our remaining funds to purchase AMD stock.
  - If we end up with a sell signal, we will sell 50% of our current holdings of AMD.
  - If we end up with a hold signal, we will do nothing.

Note that although it seems like a hold signal would be rare, our metric signals are relatively sparse so it is still pretty likely to get a hold signal overall. In addition, we chose to purchase and sell a percentage of our funds and holdings because this will ensure we are always able to act on a signal and also reduces the impact of repeated trades in one direction.

Results

We achieved significant gains using our integrated voting model, with 216.23 % more profit compared to just buy and hold AMD for 5 years from 2013 to the end of 2017. The overall return from day 2013-01-01 to 2017-12-31 was 7.62 times of our initial investment, which converts to a CAGR of 50%. By comparing our model performance with using only single signals, we discovered that our integrated model smoothes the overall cumulative return curve by avoiding certain drawdowns. The overall model return is also significantly higher than using any of the signals, proving that using the wisdom of the crowd does improve the efficiency of our trading strategy.





Conclusion

Overall, we are satisfied with the Democracy model's performance, as historically it has outperformed the AMD stock even during periods of growth. We think the overall idea of the model is solid, but there are avenues for improvement.

The obvious route of improvement would be to incorporate additional signals. These could be things like market sentiment analysis, economic calendar (such as earnings releases), macroeconomics like interest rate, and other factors.

Currently, our model also treats each signal with the same weight, so some of our metrics which give very sparse signals are likely overruled by other metrics. To resolve this, it may be worth exploring a weighted voting system, or implementing a confidence level that each metric can return to scale each signal.

Our model also has a couple hyperparameters like historical window size (10 days), initial funds ($100,000), and trade_percent (% of funds to use per trade, set to 50%). These can be tuned more to find an optimal combination.

Finally, this model should be tested in a live setting to confirm the results, as we have only backtested on historical data.

Citation

Adithyan, N. (2022, March 13). *Algorithmic trading with MACD in python*. Medium. Retrieved December 7, 2022, from https://medium.com/codex/algorithmic-trading-with-macd-in-python-1c2769a6ad1b

Alexander, C., Giblin, I. and Weddington, W., 2002. Cointegration and asset allocation: A new active hedge fund strategy. Research in International Business and Finance, 16 (5), pp.65-90.

Wang, Yefeng. “An Introduction to Cointegration for Pairs Trading.” Hudson & Thames, 6 Sept. 2021, https://hudsonthames.org/an-introduction-to-cointegration/.

West, Zack. “Calculating the MACD in Python for Algorithmic Trading.” Alpharithms, https://www.alpharithms.com/calculate-macd-python-272222/

F. X. S. D. Nugroho, T. B. Adji and S. Fauziati, "Decision support system for stock trading using multiple indicators decision tree," 2014 The 1st International Conference on Information Technology, Computer, and Electrical Engineering, 2014, pp. 291-296, doi: 10.1109/ICITACEE.2014.7065759.

Antonio C. Briza, Prospero C. Naval, Stock trading system based on the multi-objective particle swarm optimization of technical indicators on end-of-day market data, Applied Soft Computing, Volume 11, Issue 1, 2011, Pages 1191-1201, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2010.02.017.

Terence Tai-Leung Chong & Wing-Kam Ng (2008) Technical analysis and the London stock exchange: testing the MACD and RSI rules using the FT30, Applied Economics Letters, 15:14, 1111-1114, DOI: 10.1080/13504850600993598

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