Mean Reversion Trading Algorithm

'Buy and Hold'

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Contents

1 Introduction

1.1 Mean Reversion

"Reversion to the mean is the iron rule of the financial markets" - John C. Bogle

Mean reversion is a financial theory which suggests that asset prices will tend to converge to average levels following extreme movements. One phenomenon in financial markets is that price volatility and historical returns routinely oscillate around the mean, and extreme momentum is hard to sustain for extended periods.

Our algorithmic trading strategy is developed based on this theory, which involves both the identification of the trading range and the computation of the average level using quantitative methods. In accordance with this theory, if the price falls below its computed average, we would enter into a long position with the expectation that the price will rise again and allow us to sell at a profit. Conversely, if the price rises above its average we would enter into a short position so as to repurchase it at a lower price in the future when it is expected to revert.

However, a historical mean reversion model will not fully incorporate the actual behaviour of an asset's price, which means it does not assure profitable trading. New information may emerge that has permanent impacts on the valuation of an asset. Strong directional trends are also important to consider as they can cause an assets price to continue moving away from the mean for extended periods. Due to these uncertainties, it is important to incorporate other indicators into our strategies.

2 Algorithm Selection

2.1 Overview

There are numerous algorithms and indicators that can be used to implement mean reversion trading. This project explored many of these options in order to determine which algorithm, or combination of algorithms, would produce the best results. A quantitative approach to parameter optimization was further investigated with some of these strategies. A combined analysis of these strategies over a number of different SMP500 stocks was conducted in a preliminary testing phase to reduce the scope of the project to a single strategy.

2.2 Simple Moving Average

The Simple Moving Average (SMA) indicator uses a moving average of recent price trends for a defined time period, as shown in Equation 1.

$$\text{SMA[n]} = \frac{A_1 + A_2 + ... + A_{n-1} + A_n}{n} \tag{1}$$

Where:
n is the number of samples in the selected time interval
A_n is the asset price at time n.

This indicator can be used to predict future price movements by considering the moving average and comparing this to the current trading price. For example, if in the current time period, the close price is higher than the moving average of previous periods, the asset is perceived to have risen above its typical mean. In this example the algorithm would enter a short position on the stock, under the premise the price will revert back to the original mean. The algorithm would use the inverse to decide on a time to sell, attempting to sell when the mean reverts and the stock reaches typical levels.

The potential shortcomings of this indicator are its inability to consider trade volumes and to distinguish recent prices from older prices within its calculation. These flaws are addressed in the other moving average indicators analysed within this report.

2.3 Exponential Moving Average

The Exponential Moving Average (EMA) indicator is similar to the SMA, in that it uses an average of the price over previous time periods to decide on whether to buy or sell. However with an exponential moving average, more recent data is given an exponentially higher weighting than older periods, as shown in Equation 2.

$$\mathrm{EMA}[n] = A_n \times \frac{2}{n+1} + \mathrm{EMA}[n-1] \times \left(1 - \frac{2}{n+1}\right) \tag{2}$$

Where A_n is the price at the end of interval n

We decided to omit a volume filter from the Exponential moving average as it appeared to worsen our preliminary results.

2.4 Relative Strength Indicator

The Relative Strength Index (RSI) is a very famous technical indicator used by many traders that want to perform technical analysis. It is considered to be an oscillatory type of indicator where it relies on recent price changes to detect any current and future overbought and oversold conditions in the market. The formula to calculate RSI is calculated in two steps as follows:

$$\mathrm{RS}[n] = \frac{AverageGains}{AverageLosses} \tag{3}$$

$$\mathrm{RSI}[n] = 100 - \frac{100}{1 + RS} \tag{4}$$

Where it oscillates between 0 and 100. Thus, a traditional interpretation of the indicator is that whenever it reaches 30 or lower, then it is considered to be oversold and therefore it is a good time to buy. On the other hand, if it reaches 70 and higher then it would be considered overbought and therefore selling would be a good decision.

2.5 Average Directional Index

Average Directional Index (ADX) is another technical indicator that is composed of further two indicators, positive Directional Index (+DI) and negative Directional

Index (-DI). It assists traders in determining the 'strength', and not the direction, of the overall trend. It is commonly interpreted as giving a weak signal if it is below the 25 mark, reasonably good signal if it is between 25 and 50, and a very strong signal if it is above 50. This means that if the indicator goes upward from 10 to 60, it means the current trend, whether upward or downward, is having a strong momentum, but it is expected that some time soon that trend will either converge sideways or turn in the opposite direction. The formula for ADX consists of multiple steps shown below as follows:

$$+DI = \frac{smoothed + DM}{ATR} \times 100 \tag{5}$$

$$-DI = \frac{smoothed - DM}{ATR} \times 100 \tag{6}$$

$$DX = \frac{|+DI - (-DI)|}{|+DI - (-DI)|} \times 100 \tag{7}$$

$$ADX = \frac{Prior(ADX \times 13) + CurrentADX}{14} \tag{8}$$

Where note that:

+DM (Directional Movement) = Current High - PH

PH = Previous High

-DM = Previous Low - Current Low

Smoothed $\pm DM = \sum_{t=1}^{n} DM - \frac{\sum_{t=1}^{n} DM}{n} + CDM$

CDM means Current Directional Movement

ATR means Average True Range

2.6 EMA Crossover (Selected Strategy)

Our strategy selection, and therefore algorithm, was focused on adopting a trading style that would fit a mean reversion strategy with the goal of achieving the highest possible profit. We used two Exponential Moving Averages (EMAs) omitting RSI, SMAs and ADX. We found through our optimisations that can be seen in section 3 that a short timeframe EMA and long timeframe EMA in conjunction yielded the most reliable profit. Our short timeframe EMA had a parameter of 20 days and our slow EMA had a parameter of 119 days. The premise of our strategy was to enter a long position when the short timeframe EMA crosses above the long timeframe EMA, similarly we enter a short position when the short timeframe EMA crosses below the long timeframe EMA.

We reasoned that the EMAs are most effective because they are the fastest to react to price movement which means that they were able to perform well on the bullish trends whilst also capitalising on downturns and bearish trends.

3 Algorithm Optimization

3.1 Overview

For our project we were given 1-minute interval data for any SP 500 stock we desired. This data spanned for 2 years from the current date, the data generated was in a CSV containing fields for the date, open, high, low, close and volume of the stock. The goal in optimising our algorithm was to find the best parameters for the previously discussed indicators to produce the most profitable algorithm.

3.2 Grid Searching for Optimal EMA Crossover Periods

The crossover exponential moving average strategy (EMA Crossover) has two major inputs; the lookback period of the SHORT and LONG averages. We conducted a grid search of possible parameters to optimise the output of this algorithm.

Our method was to start with a really broad grid search with large intervals and then search with higher and higher resolution in the profitable areas. Our first few grid searches were a little unsuccessful as can be seen in the initial figure 1 below. After implementing bug fixes we were able to start the process described above. Figures 2 through 4 show more localized grid search as we hone in on the most profitable areas. The final grid search concluded that 119 days and 20 days for our short term and long term EMAs are the best parameters.

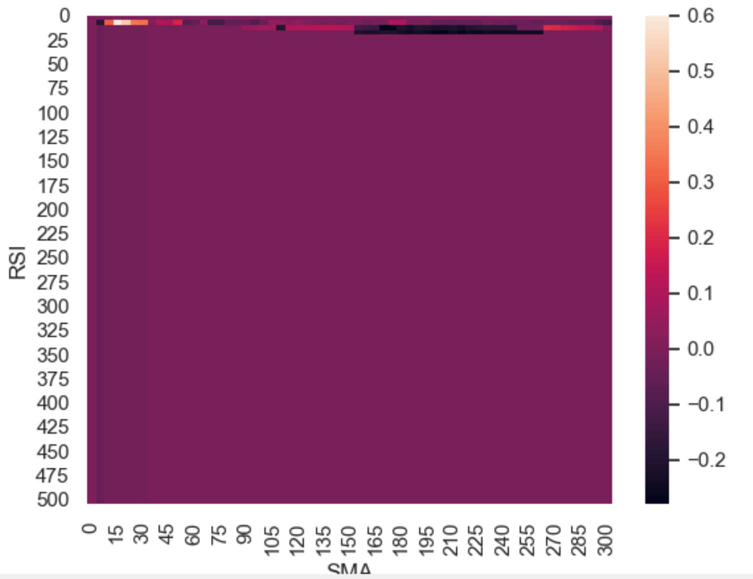

Figure 1: Grid Search Failure

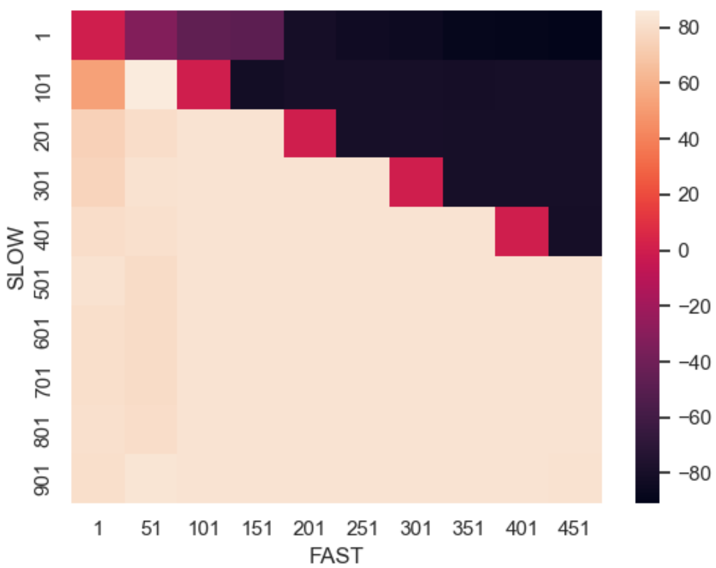

Figure 2: Broad Initial Search

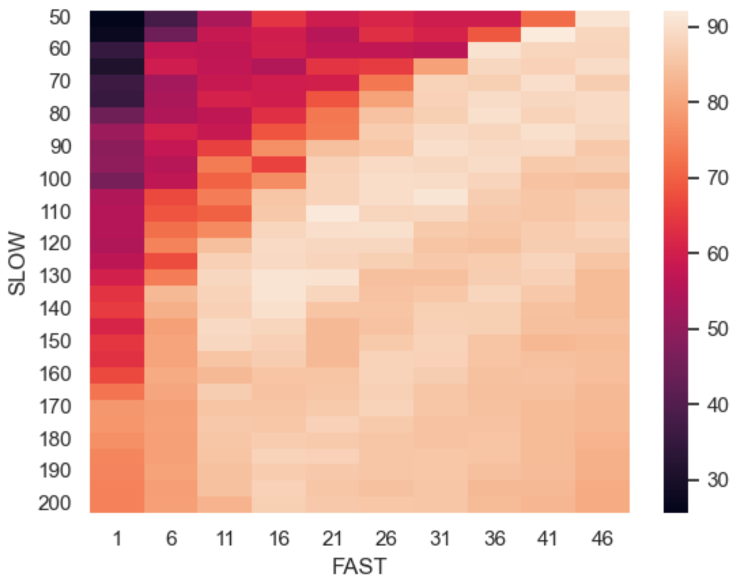

Figure 3: High Resolution Search

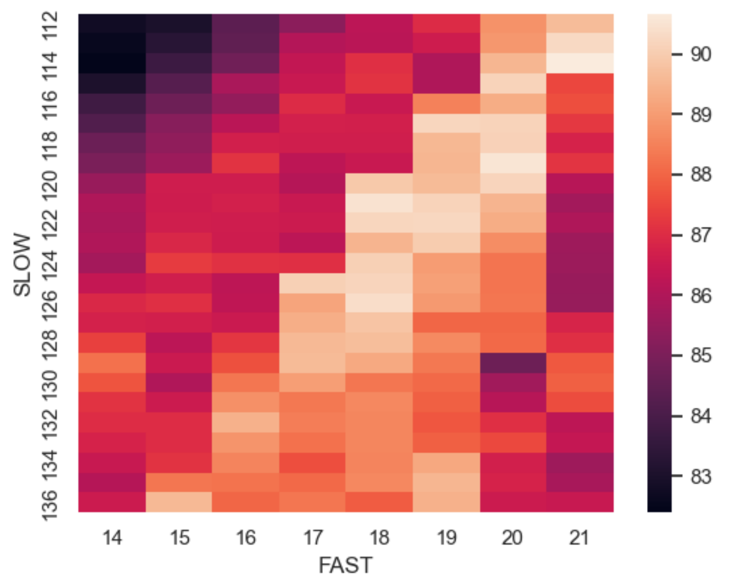

Figure 4: Highest Resolution Search in Profitable Area

3.3 Grid Searching for Optimal RSI and SMA Periods

3.4 RSI and Simple Moving Average

Similar to above, RSI and SMA both take in a lookback period that can be optimized.

The optimisation of the RSI and SMA strategy can be seen in figure 5 below where an SMA of 3 and RSI of 1 produced a little over 50 percent return. These results were not as promising as the initial grid searches of the EMA Crossover strategy, and as such, further searching was dropped.

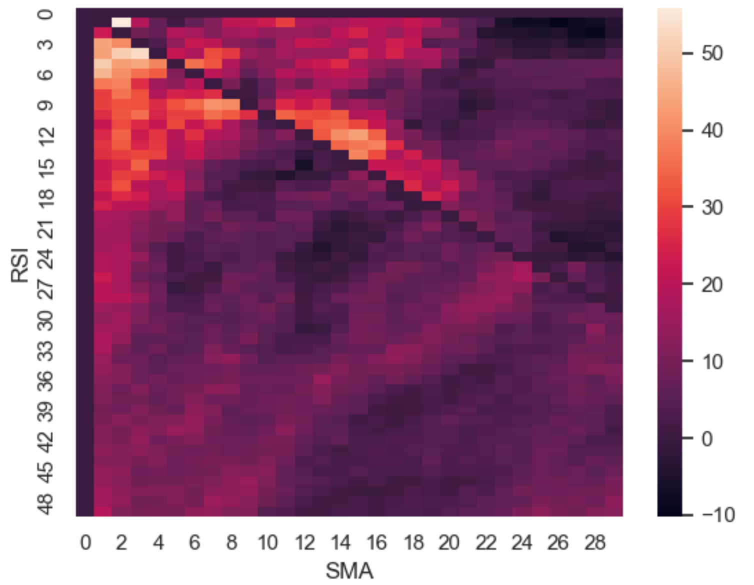

Figure 5: RSI and SMA Heatmap

4 Algorithm Performance

4.1 Heatmap Results

The EMA crossover strategy provided promising results with the broad and then higher resolution heat maps seen in figures 2 through 4. The highest preforming results from the highest resolution heatmap, as seen in figure 6, produced a little over 90 percent return on a short term EMA of 20 and a long term EMA of 119.

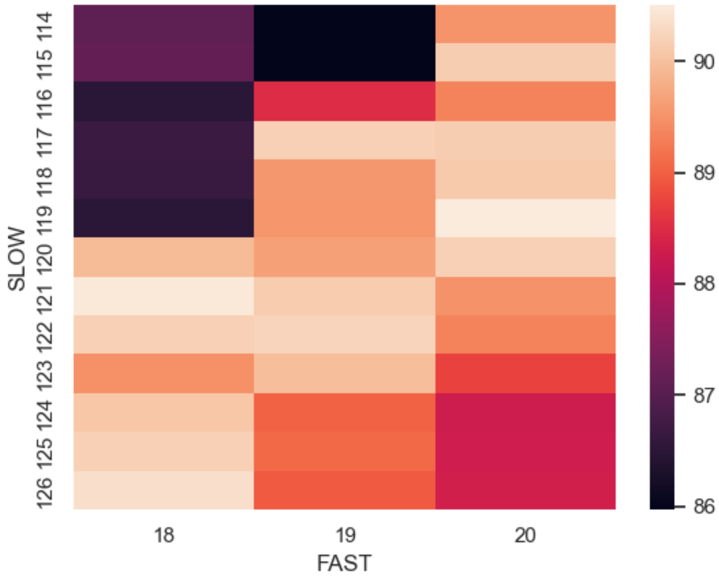

Figure 6: Optimised Parameters Heatmap

5 Summary and Findings

5.1 Discussion

Our project this semester took a very quantitative approach to mean reversion trading, not only in algorithm selection and testing but also in our result analysis. Our selected strategy that produced the most promising results was the short term and long term EMA crossover strategy. This allowed us to take advantage of long term trends producing satisfying entries for both long and shorts as can be seen in the FB chart below (figure 7) and the profit chart (figure 8). We suspect that there was some aspect of over fitting in our initial optimisation as, when taking into account all the stocks in the SP 500, our actual return drops slightly lower. Our algorithm also doesn't preform as well in long term up-trends as the two EMAs never cross and as such we just buy and hold. As the stock market generally goes up long term we suspect our algorithm and strategy would work better on more volatile or speculative markets such as futures or perhaps even cryptocurrency.

Figure 7: Resulting Trades on FB

Figure 8: Resulting Trades on FB