MC3P4 Report

Yuanda Zhu

For this project, I incorporate Q-learning as the core algorithm to make decision whether I shall hold or trade my stocks.

Technical Indicators

Three technical indicators are considered, including momentum, moving average (SMA) and Bollinger Bands (bbp). While setting the delay a small number of days, momentum is to measure short time price change. Moving average records the general behavior of the stock price over a longer period. Bollinger Bands indicate whether the stock is overbought or oversold. Its delay is the largest among all three indicators.

Each technical indicator is calculated throughout all trading days. Upon calculating the maximum and minimum values for each of the three indicators, I discretize each entry of the indicator data frame into integers, ranging from 0 to pre-defined states_N. That is the state index for each technical indicator.

Building Q-table

Besides above mentioned states indicators, the state_0 is referred to the position state. To prevent messing up the actions allowed under each position state, the position state itself has been used for a fourth state indicator. Thus, the final state for each trading day is calculated in this way:

*State = state_0*state_N**3+ X1* state_N**2+X2* state_N+X3*

X1, X2 and X3 correspond to the technical indicators.

The next step is to define actions in the Q-table. For the top one-third of the table, the actions are 0, +200 and +400 since the current position is -200. For the one-third portion of the table in the middle, the actions are -200, 0 and +200 since the current position is 0. For the bottom one-third of the table, the actions are -400, -200 and 0 since the current position is +200.

Plus, the reward for each state is calculated based on the two-day stock price difference multiplied by current position. In this way, I tend to sell when price goes high and buy when price drops.

Adjusting Parameters

Four parameters are adjusted to achieve better results. The same number of discretized states for all technical indicators and the different delayed days for each of them. Here, I perform two experiments to show the relationship between the benchmark and the different days delayed in two technical indicators. Both experiments are tested on dataset "UNH".

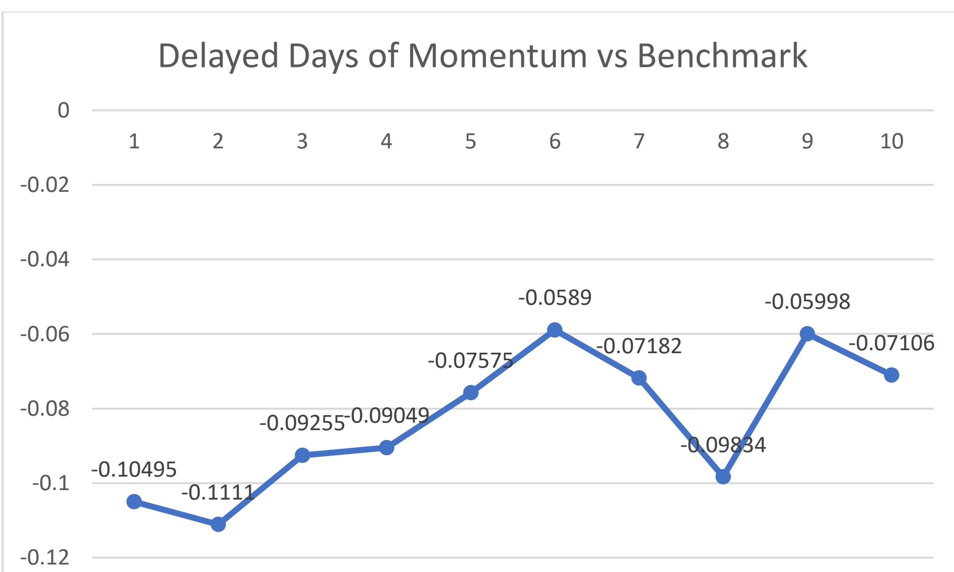

Figure 1. Benchmark vs. Number of Days Delayed in Momentum.

By fixing the number of days delayed in moving average and Bollinger Bands, as well as number of states in each technical indicator, I vary the number of days delayed in momentum to show how such variant will influence the benchmark. Benchmark changes dramatically and non-uniformly. Generally delayed days greater than five has better results than smaller delayed days.

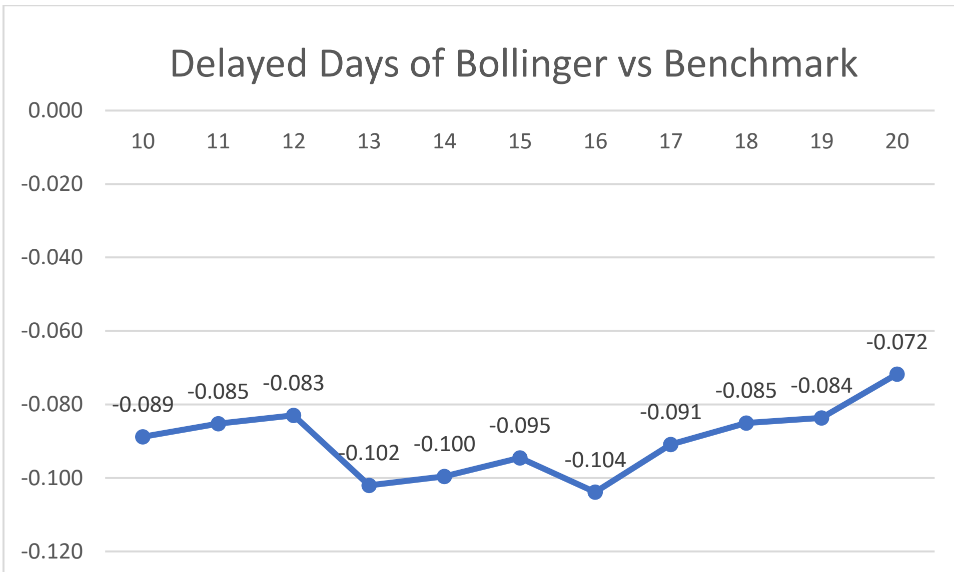

Figure 2. Benchmark vs. Number of Days Delayed in Bollinger Bands.

By fixing the number of days delayed in momentum and moving average, as well as number of states in each technical indicator, I vary the number of days delayed in Bollinger Bands. The benchmark tends to be close to each other with days delayed ranging from ten to twenty. Still, bbp on the right has slightly better results. Thus, Bollinger Bands with longer periods considered performs better.

Test Case Results

My code passes three out of four test cases. No matter how I adjust parameters, I would fail the "ML4T-220" test case. Both of my in-sample and out-of-sample benchmarks are around 0.77 which is smaller than the required 1.

"ML4T-220" is a special test case, whose stock price looks like a clean sine wave. In order to conquer this, future work (if any) could focus on improving the reward and adding other more efficient technical indicators, such as RSI.