Strategy Learning Report

Part 1:

In this assignment, I employ three indicators, bollinger band, momentum, and exponential moving average. Correspondingly, the manual strategy and strategy learning methods both implement simulations based on above three indicators. The equations are shown as follows,

- Bollinger band

$$\text{bollinger bands}(t) = (\text{price}(t) - \text{SMA}(t))/(2 * \text{std}(t)),$$

where price[t] is the current price, SMA(t) is called simple moving average that is defined as SMA(t) = price[t-N:t].mean, std(t) is the standard deviation of moving average.

- Momentum

$$\text{Momentum}(t) = \text{price}(t)/\text{price}(t-N) - 1$$

- The exponential moving average (EMA)

$$\text{EMA}(\text{today}) = \text{EMA}(\text{yesterday}) + \alpha * (\text{price}(\text{today}) - \text{EMA}(\text{yesterday})),$$

where $\alpha = 2/(N+1)$.

The indicator of EMA is calculated as EMA_index = price/EMA-1.

This project is about the application of random tree learner and bag learner (regression learning). The bag number is 20, the window size of calculating indicators is 15, the leaf size is 5. My strategy code has already passed all the tests.

Experiment 1:

As mentioned in the part 1, three indicator indexes are used in the manual and strategy learner methods.

In the manual strategy, the sell and buy signals are the combination of three indicator indexes, as follows.

Sell signal: Momentum(t) < -0.07 or bolliner_bands(t) >1 or EMA_index > 0.1

Buy signal: Momentum(t)> 0.0014 or bolliner_bands(t) <-1 or EMA_index < -0.1

The comparison of manual and strategy learner methods is as the following picture.

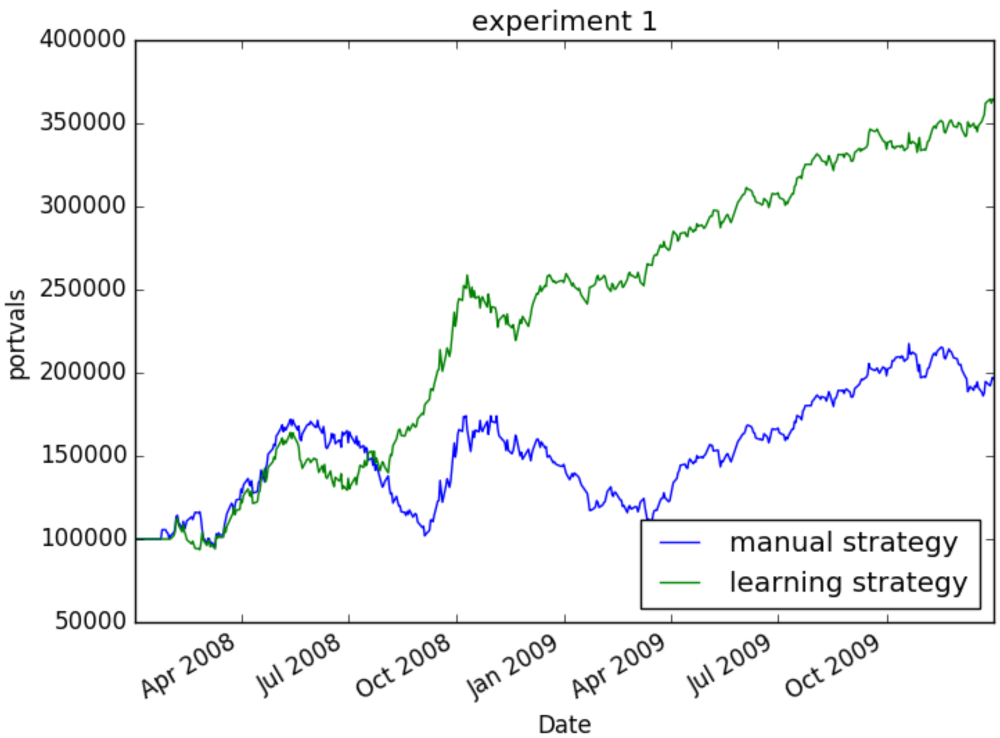

Fig. 1 Difference of manual and learning strategy

Based on the in-sample date of "AAPL", it is shown that the learning strategy performs much better than the manual strategy. The final portval value of learning strategy is almost 2 times than that of the manual strategy. I expect this relative result every time with in-sample data. Because the random tree is trained and built using the same data set. The performance of random tree learning is almost great in terms of in-sample data.

Experiment 2:

In this experiment, I study the relationship of impact and trade times, the relationship of impact and normed portvals return(e.g. normed_portvals[-1]/normed_portvals[0]).

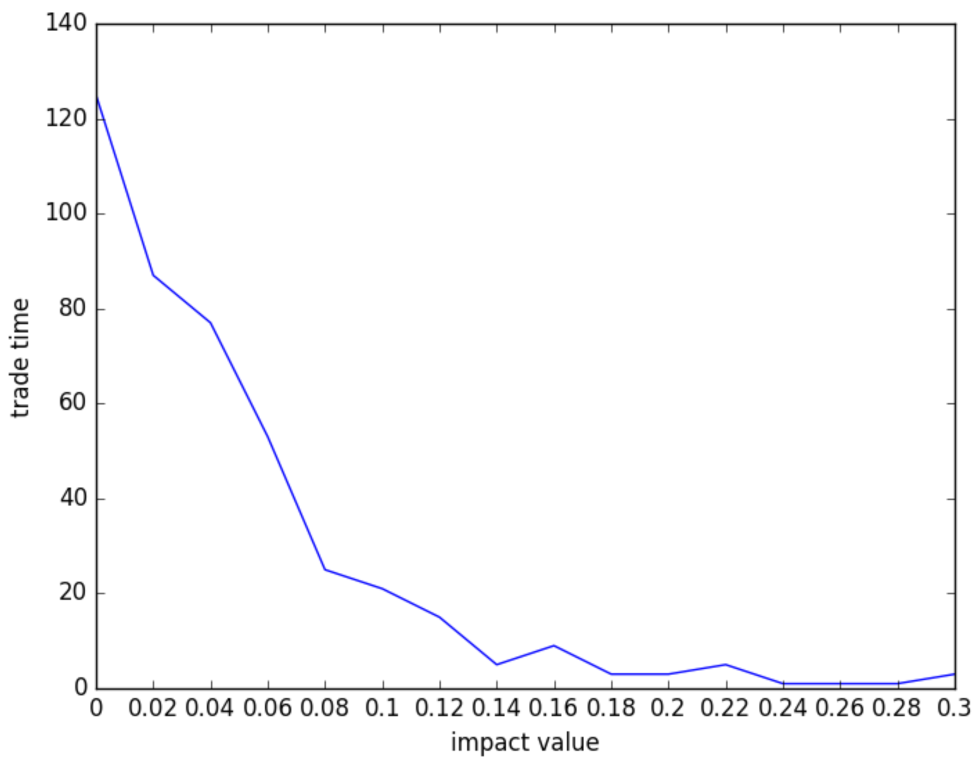

Fig. 2. Relationship of impact value and trade time

From Fig. 2, it is obvious that the trade time decrease significantly with the market impact, meaning the trade is at a high cost when the impact is considered. When the number is less than 0.02, the trader number is still very high. However, as the number increases to 0.08, the trader is 20, decreasing by 83%. From Fig. 3, when the impact is considered, the cumulative return of normed port_value decline fast, from 2.5 to 0. If the impact is more than 0.04, the cumulative return increases slightly. However, the cumulative return of normed port_value still has a poor performance.

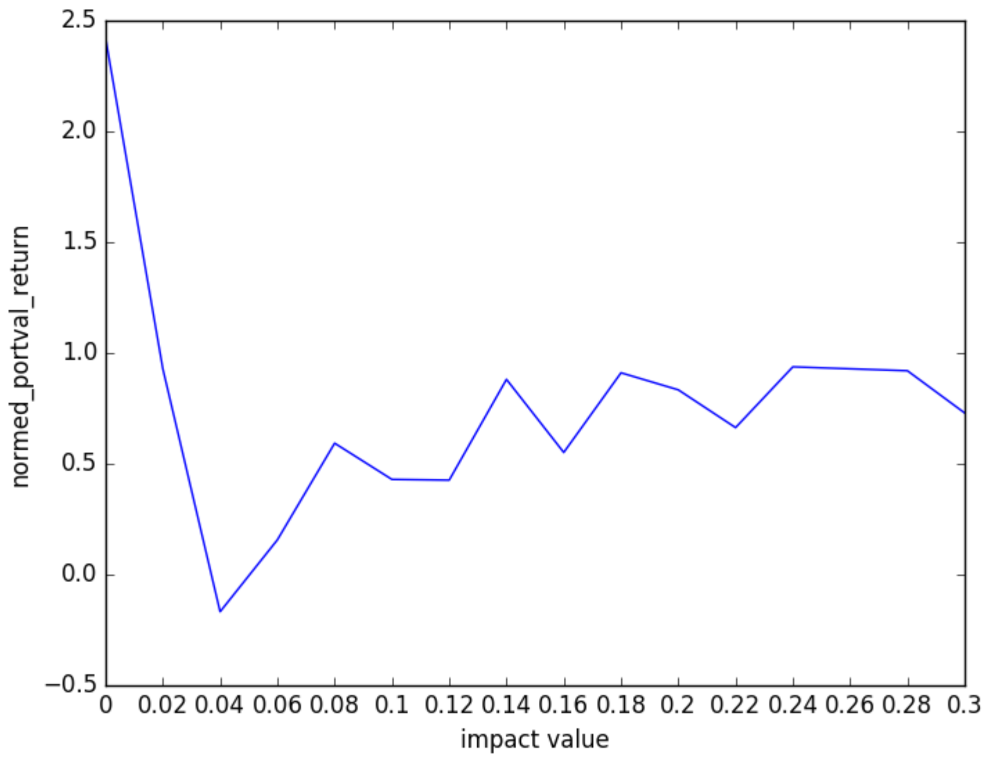

Fig 3. The relationship of cumulative return of normed port_value and impact value