Strategy Learner

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(1171 words, 5 pages, and 4 figures)

1. Technical Indicators

Summary: In previous project, I am using the following three indicators to perform future technical analysis and determine whether we will buy or sell stock in future. They are:

- Support & resistance: **Pivot point;**
  - A pivot point is a price level that is used by traders as a possible indicator of market movement. A pivot point is calculated as an average of significant prices (high, low, close) from the performance of a market in the prior trading period. [1]

$$Pivot\ Point = (Highest\ Price + Lowest\ Price + Closed\ Price)/3$$

- Trend: Simple moving average (**SMA**)/price;
  - SMA is a calculation to analyze data points by creating a series of averages of different subsets of the full data set.[2]

$$SMA = \frac{1}{N}\sum_{i=1}^{n} Price_i$$

- Volatility: Bollinger Bands (**BB**). -> Choose this as indicator for manual strategy.
  - Bollinger Bands are a type of indicator characterizing the prices and volatility over time of a financial stock, using a formulaic method propounded by John Bollinger in the 1980s.[3]

$$Upper\ band = SMA + 2 * \sigma\ (prices)$$

$$Lower\ band = SMA - 2 * \sigma(prices)$$

The detailed descriptions were included in project 6 report. Please check the details from that report.

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[1] https://en.wikipedia.org/wiki/Pivot_point_(technical_analysis)
[2] https://en.wikipedia.org/wiki/Moving_average
[3] https://en.wikipedia.org/wiki/Bollinger_Bands

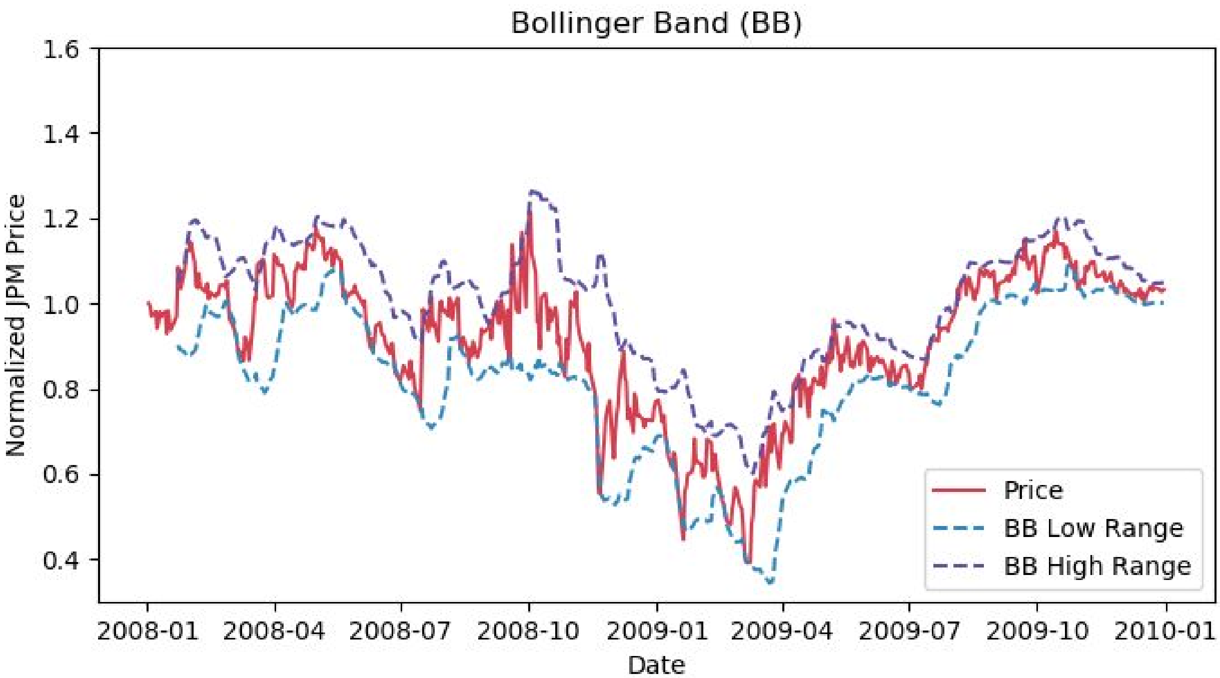

Figure 1 Demonstration of JPM stock on price, BB lower range and high range

2. Design of the strategy learner

The trading action based on stock price can be converted to a classification problem, where the relevant price indicators are input (X), and the actions are output (Y). In order to train the model, I applied the model with Bag Learner (learner: Random Forest). For the training dataset, the input were concrecated by three technical indicators and the output were decided by the future price (n = 5). If the future price is higher than current, then the action is BUY (+1). Otherwise, the action is SELL (-1). Nothing happen if the prices are the same.

- Train X: three technical indicators;
- Train Y: action decided by comparison with current price and price 5 days later;
- Test X: three technical indicators, same with Train X;
- Test Y: actions predicted by bagger learner.

3. Experiment 1

Summary and Assumption:

We trained a classification model based on technical indicators and real future price, then we applied this model for the prediction of real price. The hypothesis is learning strategy should have a better performance than manual strategy, since our previous model is based on BB bands. Current bag learner with random forest should have a better classification performance than previous merely BB-bands.

Parameter and Steps:

Stock parameters: JPM from 2008-01-01 to 2009-12-31, with only -1000, 1000, and 0 stocks.

Staring cash: $100,000

Commission: $0.00 Impact: 0.00

Leaning Indicator: BB, SMA, and PP;

Leaning parameters: Leaf-size: 5 Bag-size: 20

Steps:

- Train the model with bag learner (random forest), train X are combined value of three indicators, and train Y are decided by comparing current price and future price (5 days later);
- Then input the test X only, and predict the test Y. The trading action was decided by test Y value;
- The trading action were decided by comparing the difference of stock holding between today and previous transaction day;
- The total value were calculated by cash in hand and stock value in hand, after the deduction of commission fee and the price adjustment with impact factor.
- Run python3 experiment1.py

Outcome and Result:

The outputs are portfolio value of each transaction day. Here I summarized the cumulative return, mean value and standard deviation for each strategy. The Learning strategy have a better performance than manual and benchmark. The cumulative return for learning strategy is 216 fold of that of benchmark, 8-fold of that of manual strategy. Meanwhile, the mean value of cumulative return per day is also higher in learning strategy. From the standard deviation, manual strategy seems to have a stable return than that of learning strategy.

Table 1: Performance of benchmark, Manual Strategy and Learning Strategy
(2008-2009, impact = 0, commision = 0)

JPM stock performance	Benchmark	Manual Strategy	Learning Strategy
Cumulative Return	0.0123	0.336	2.664 (higher)
Mean Value	0.000168	0.000591	0.00261 (higher)
Standard Deviation	0.0170	0.00562 (stable)	0.00767

If we check the distribution of each day, the learning strategy had a better performance from the beginning. A quick accumulation was observed during 2008-10, which might be the reason why it had a higher standard deviation.

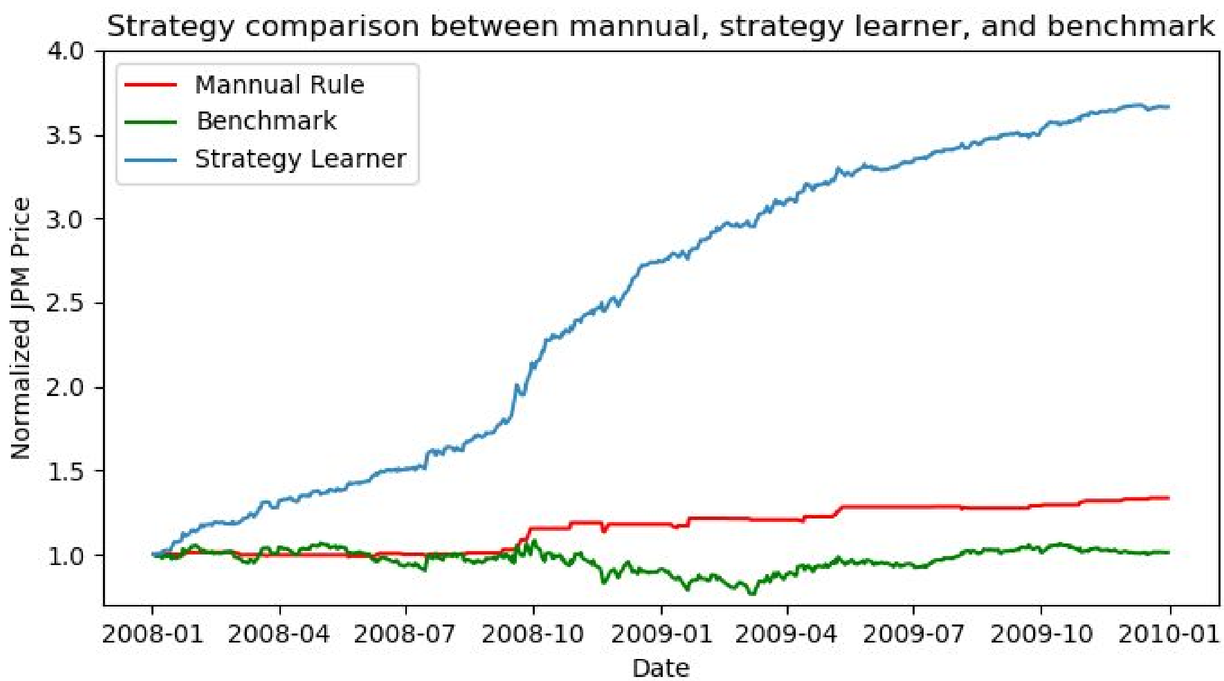

Figure 2 Comparison of three trading strategy (impact = 0)

Conclusion and Discussion:

Learning Strategy has a better performance than the other two trading strategy. The result is expected because we are building the model in-sample. I have tried the models for several times, the cumulative return varies from 2 to 3, but always be higher than manual strategy.

4. Experiment 2

Summary and Assumption:

The impact factor will affect the trading actions by changing the price. If the price varied frequently and the impact factor is large, then the decision of trading may be wrong. Therefore, we are testing whether the impact factor affect trading actions and set the impact as 0.005 and 0.05. The hypothesis is: the higher impact factor, the lower cumulative return.

Parameter and Steps:

Stock parameters: JPM from 2008-01-01 to 2009-12-31, with only -1000, 1000, and 0 stocks.

Staring cash: $100,000

Commission: $0.00 Impact: **0.005**

Leaning Indicator: BB, SMA, and PP;

Leaning parameters: Leaf-size: 5 Bag-size: 20

Steps:

- Run python3 experiment2.py

Outcome and Result:

As described from the table, the benchmark didn't change so much because the trading number is only two. However, for both manual and learning strategy, the cumulative return did dropped. The cumulative return of Manual strategy dropped to ~64%, while learning strategy dropped to ~71%. The higher decreased for manual strategy maybe caused by frequent trading in high variable time. For learning strategy, the decision is predicted by future price, therefore have a lower chance to be affected by high variable price.

Most importantly, when we increased the impact factor, the cumulative return is negative for both strategies. In other words, the more trading, the more loss, which actually means no trading may be better. From Fig 3 and Fig 4, we have the same observations for each day.

Conclusion and discussion:

As we assumed, the higher the impact factor, the lower the cumulative return. Therefore, in a higher variable market, the return are hard to be predicted because the price is highly variable. It's better to keep current holding and do nothing.

Table 2: Performance of benchmark, Manual Strategy and Learning Strategy
(2008-2009, impact = 0.005/0.05, commision = 0)

JPM stock performance	Manual Strategy (0.005)	Manual Strategy (0.05)	Learning Strategy (0.005)	Learning Strategy (0.05)
Cumulative Return	0.213	-0.895	1.898 (higher)	-1.800
Mean Value	0.000387	-0.004	0.00215 (higher)	0.228
Standard Deviation	0.00573 (stable)	0.0179	0.00838	3.154

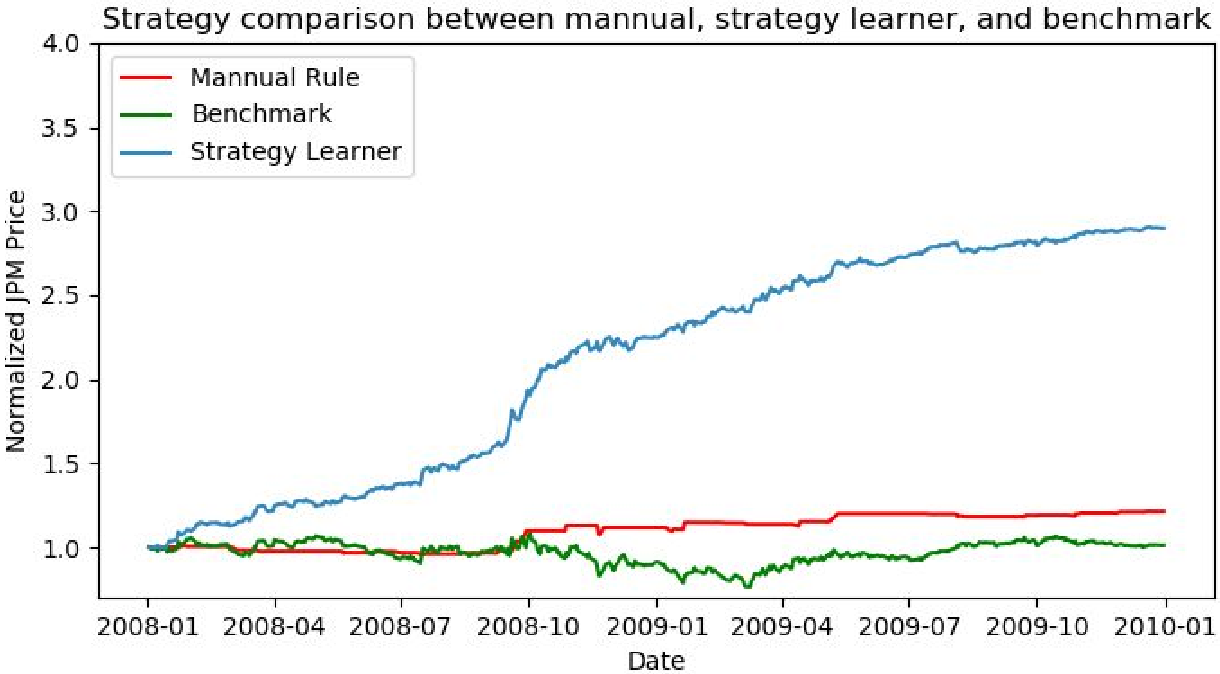

Figure 3 Comparison of three trading strategy (impact = 0.005)

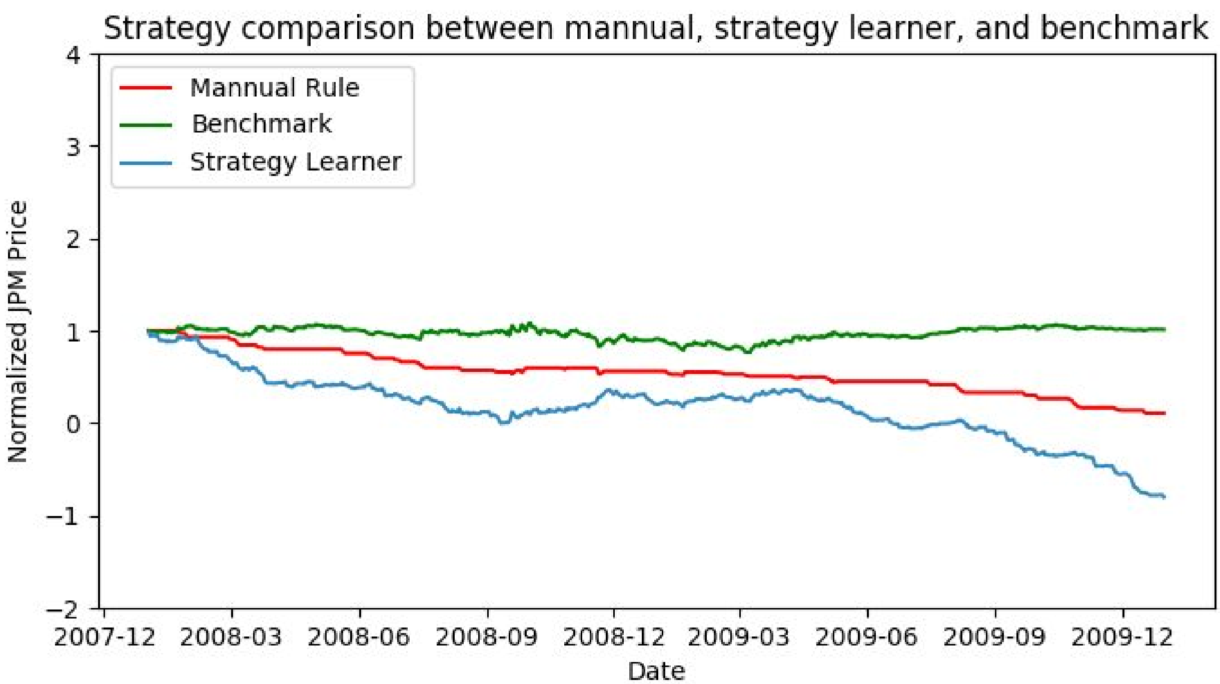

Figure 4 Comparison of three trading strategy (impact = 0.05)