STRATEGY EVALUATION

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1 INTRODUCTION

Stock price prediction and strategy formulation for stock trading, have been a popular issue, and machine learning, as a common prediction and classification tool at present, can be applied to stock trading. This project uses manual strategies and Qlearner-based strategies for stock trading decisions through the selection of indicators, discretization of indicators, and hyperparameter tuning.

The basic assumptions of this project are:

(1) The date range of in-sample data is from 2008-1-1 to 2009-12-31.

(2) The date range of out of sample data is from 2010-1-1 to 20011-12-31.

(3) The start cash is 100000, the impact is 0.005 and commission is 9.95

2 INDICATOR OVERVIEW

In this project, I use three indicators to train strategies, they are SMA, momentum and bollinger band value.

SMA, which is known as simple moving average, it is one kind of moving average. The formula is shown below.

$$SMA = \frac{p_1 + p_2 + \ldots + p_n}{n}$$

Where p_n is the price of an asset at period n, and n is the number of total periods.

The formula of momentum is as below.

$$M = \frac{p}{p_n} - 1$$

Where p_n is the stock price n days ago.

In order to calculate Bollinger bands value, we need to first calculate upper Bollinger band and lower bollinger band, the formulas are

$$BOLU = SMA(p, n) + m * \sigma$$

$$BOLD = SMA(p, n) - m * \sigma$$

Where $SMA(p, n)$ is simple moving average of price p over n periods, m is number of standard deviations, in this project, it is set to be 2. σ is standard deviation over last n periods, which means it is the standard deviation of SMA. And the final Bollinger band value is

$$BB = \frac{p - SMA(p, n)}{m * \sigma}$$

The formula of CCI is shown below

$$CCI = \frac{p - MA(p, n)}{0.015 * \sigma(p)}$$

Where $\sigma(p)$ is the standard deviation of price.

The formula of fast stochastic indicator is as below

$$\%K = \frac{p - BOLD}{BOLU - BOLD}$$

The lookback period of fast stochastic indicator is usually 5 days or 14 days

3 MANUAL STRATEGY

3.1 DESCRIPTION

In this section, I select three indicators, which are Bollinger band value, fast stochastic and CCI, to help build trades table, and the look back day is 20 in manual strategy. The specific strategies can be divided into three states, when the account holds +1000 shares, when the account holds -1000 shares and when the account holds 0 shares. The manual strategy includes "BUY" signal and "SELL" signal, and the strategy is

(1) When account holds 0 shares, if bollinger<-1 or fast<0.2 or CCI<-50, then buy 1000 shares

(2) When account holds 0 shares, if bollinger>1 or fast>0.8 or CCI>50, then sell 1000 shares

(3) When account holds 1000 shares, if bollinger>1 or fast>0.8 or CCI>50, then sell 2000 shares

(4) When account holds 1000 shares, if bollinger>1 or fast>0.8 or 50>CCI>30, then sell 1000 shares

(5) When account holds -1000 shares, if bollinger<-1 or fast<0.2 or CCI<-50, then buy 2000 shares

(6) When account holds -1000 shares, if bollinger<-1 or fast<0.2 or -50<CCI<-30, then buy 1000 shares

As the definition of bollinger bands said "when prices move closer to the upper band, it indicates that the market may be overbought. Conversely, the market may be oversold when prices end up moving closer to the lower or bottom band", In manual strategy, I choose 1 and -1 as threshold to indicate the sell signal and buy signal.

Fast stochastic indicator is usually used as an indicator of buy signals. A stock is considered overbought if the fast stochastic indicator is above 80 and oversold if fast stochastic indicator is below 20. In the code, the original value is divided by 100, hence, if fast>0.8, the strategy will give a sell signal, and if fast<0.2, it will give a buy signal.

CCI is the indicator to identify if the stock price is out of the normal distribution range. When the CCI moves from negative or near-zero territory to above 100, that may indicate the price is starting a new uptrend. When the indicator goes from positive or near-zero readings to below -100, then it may indicator a downtrend. In this project, I use a more aggressive strategy, which use -50, -30, 30 and 50 as threshold.

3.2 COMPARISON

Figure 1—The benchmark and manual strategy of in-sample data

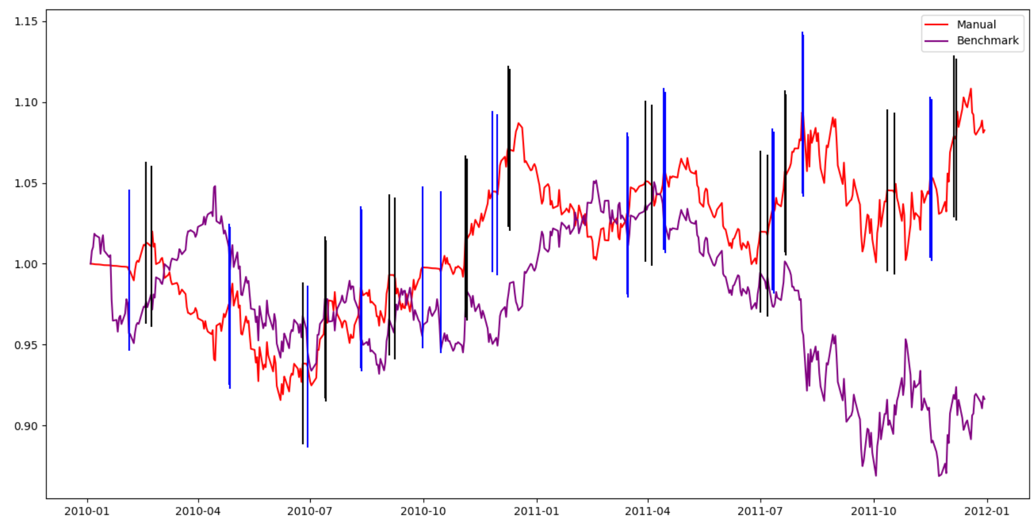

Figure 2—The benchmark and manual strategy of out of sample

3.3 EVALUATION

The daily return of benchmark and manual strategy of in sample and out of sample are shown in figure 1 and figure 2, it can be noticed that, in in-sample data, the total return is over 1.35, but in out of sample data, the total return is around 1.1, which is lower than the total return in in-sample, this is caused by overfitting. Due to the different structure of the in-sample and out of sample datasets, overfitting of the manual model on the in-sample dataset leads to reduced performance on the out of sample dataset. We can also find that these two data sets have similar frequency of transactions.

4 STRATEGY LEARNER

In strategy learner, we assume the number of actions is 3, the description of each action is in table 1. I choose momentum, bollinger band value and SMA. After discretizing the data, these three indicators are cut into 5 classes, which means the number of states is 5*5*5=125.

Table 1—The description of actions

Action	Description
0	Buy 2000 shares
1	Sell 2000 shares
2	Hold

Qlearner is applied in this section and I also use dyna to improve the performance of the model. After tuning, the hyperparameters are

Table 2—The values of hyperparameters

Hyperparameters	value
num_states	125
num_actions	3
alpha	0.5

gamma	0.6
radr	0.9
rar	0.99
dyna	200
epochs	15

The reward function is shown below.

$$reward = holding * (prices - last\_day\_price) - abs(impact * holding) - commission$$

Where holding is "shares" in the account.

4.1 COMPARISON

Figure 3—The benchmark and Qlearner of in-sample dataset

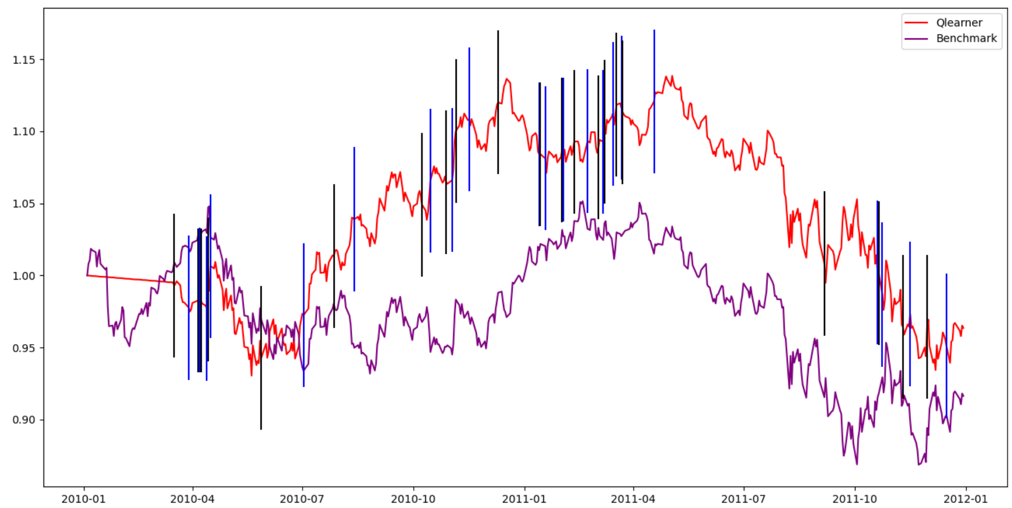

Figure 4—The benchmark and Qlearner of out of sample dataset

4.2 EVALUATION

Same with manual strategy, the performance of in-sample dataset is much better than out of sample dataset. The total return of in-sample dataset is around 3.5, but for out of sample dataset, the total return is only around 0.98.

This is because overfitting. Qlearner is a machine learning model. For machine learning models, when training set is small, or if there is heterogeneity between the training and test sets, overfitting will occour.

5 EXPERIMENT 1

In experiment 1, I compare the performance of benchmark, manual strategy and strategy learner. The assumption of manual strategy is the same with section 3. The hyperparameters of Qlearner in experiment 1 is shown in table 3.

Table 3—The values of hyperparameters

Hyperparameters	value
num_states	125
num_actions	3

alpha	0.5
gamma	0.6
radr	0.99
rar	0.99
dyna	200
epochs	15

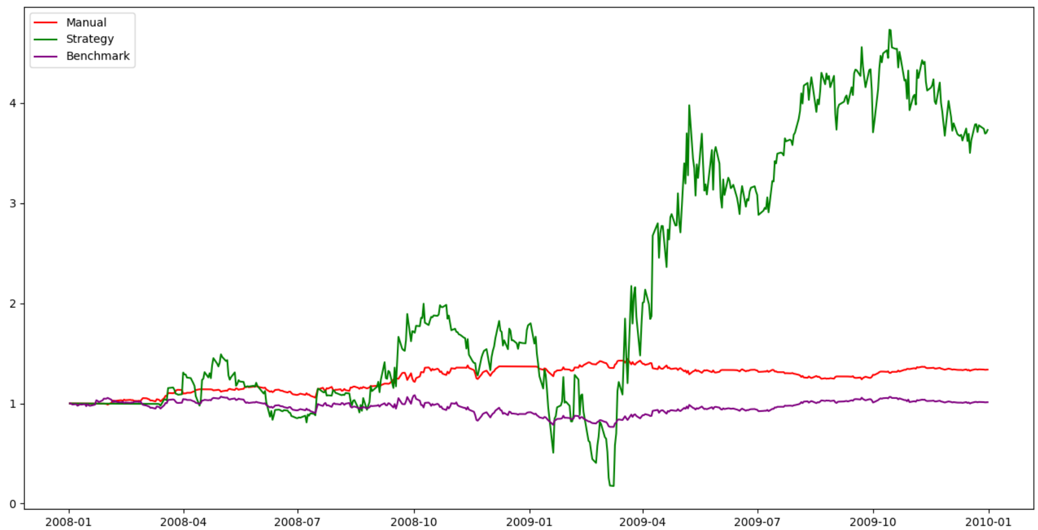

Figure 5—The benchmark, manual and Qlearner of in- sample dataset

Figure 5 apply three strategies to in-sample dataset, and we can notice that strategy learner has the best performance, manual strategy is the next and benchmark has the worst performance.

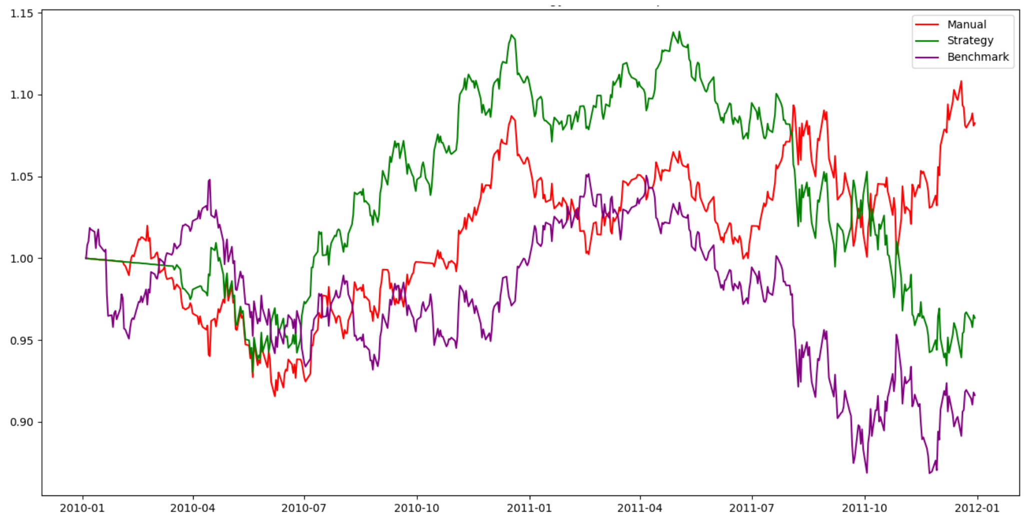

Figure 6—The benchmark, manual and Qlearner of out of sample dataset

Different with in-sample dataset, manual strategy in out of sample has a better performance than strategy learner, and strategy learner is better than benchmark.

Because Qlearner has a serious overfitting problem, the performance of Qlearner in in-sample dataset and out of sample dataset differs greatly. Manual strategy selects "SELL" and "BUY" signal by using knowledge in real stock market; hence, the overfitting problem is much better than Qlearner. This is why the two strategies perform very differently in the in-sample dataset and out of sample dataset.

6 EXPERIMENT 2

The hyperparameters of experiment 2 are shown in table 4. I select 6 different impact values, which are 0.005, 0.015, 0.025, 0.035, 0.045, 0.055, to show how impact affects in-sample trading behavior and results.

7 *Table 4—The values of hyperparameters*

Hyperparameters	value
num_states	125
num_actions	3

alpha	0.5
gamma	0.6
radr	0.9
rar	0.99
dyna	200
epochs	15

Figure 7 shows the in-sample trading results under different impact.

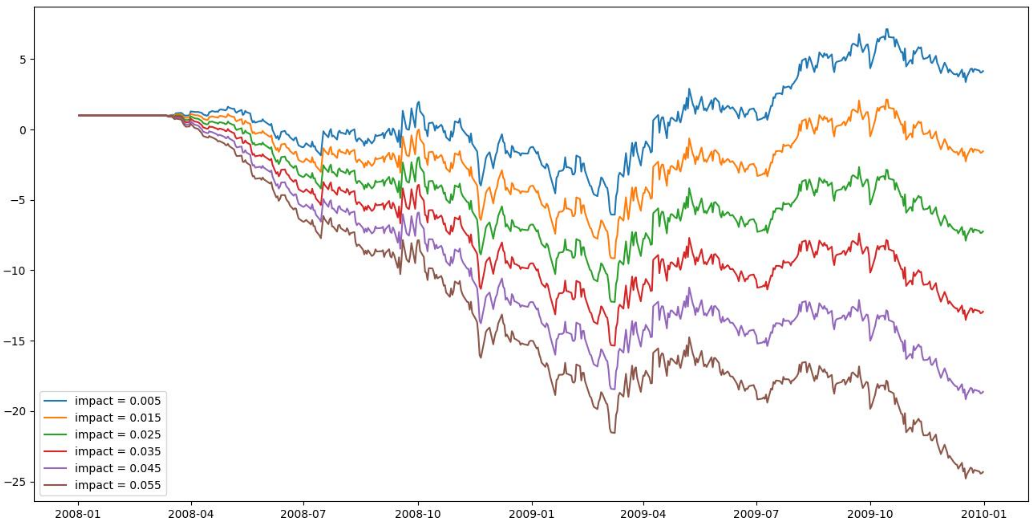

Figure 7—In-sample trading results under different impact

I use cumulative return and average daily return to show performance of in-sample trading results with different impact values. The results are in table 5.

Table 8*—cumulative return and average daily return under different impact*

Impact	cumulative return	average daily return
0.005	3.1606515	-0.051989996
0.015	-2.5371425	-0.174456119821752
0.025	-8.2349364999999	0.009609858768
0.035	-13.9327304999	-0.0245650015589
0.045	-19.630524500	-0.0121186093817
0.055	-25.32831849999993	0.006243922695394331

We can find that when impact value increases, cumulative return will decrease, and the trend of average daily return not depends on impact value.