A trader strategy based on random forest algorithm

Zitao He

Abstract—A random forest-based leaner is developed to automatically make trading decisions to gain profit. The effect of impact on learner strategy is studied

1 INDICATOR OVERVIEW

1.1 Bollinger Bands Percentage (%BB)

The Bollinger Band Percentage is calculated using equations:

$$\%b = (price - sma) / (2 * std) * 100$$

Where $price$ is the stock price, *sma* is the N-days simple moving average and *std* is the N-days standard deviation of the price.

In this study, 50 is chosen as the window size (N) for the manual strategy, and 14 is chosen as the window size (N) for the learner strategy.

1.2 Momentum

Momentum shows the relative difference between the current closing price and the closing price N days ago. It is calculated as

$$Momentum = (close_{today} - close_{N\ days\ ago})/close_{N\ days\ ago} * 100$$

Where $close_{Today}$ is the closing price of today and $close_{N\ days\ ago}$ is the closing price N days ago. The unit of momentum is the percentage.

In this study, 50 is chosen as the window size (N) for the manual strategy, and 14 is chosen as the window size (N) for the learner strategy.

1.3 Moving Average Convergence Divergence (MACD)

Moving average convergence divergence (MACD) is a derivative indication of the exponential moving average(EMA).

MACD calculates the difference between the 26-days exponential moving average and the 12-days exponential moving average for stock prices:

$$MACD\ line\ =\ EMA_{12\ days}\ - EMA_{26\ days}$$

Where $EMA_{12\ days}$ and $EMA_{26\ days}$ is the 12-days and 26-days exponential moving average of stock price respectively. Then MACD signal is calculated as

$$MACD\ signal\ =\ EMA_{9\ days\ MACD}$$

Where $EMA_{9\ days\ MACD}$ is the 9-days exponential moving average of the MACD line. The indicator value is calculated:

$$Indicator\ Value\ =\ MACD\ line\ - MACD\ signal$$

The window sizes used are exactly what are mentioned above.

1.4 Relative Strength Index (RSI)

RSI shows the strength or weakness of the stock price movement. First, an upward price change U and a downward price change D is calculated:

$$U\ =\ max(price_{today} - price_{previous\ day}\ , 0), D\ =\ max(price_{previous\ day}\ - price_{today}, 0)$$

Where $price_{today}$ is today closing price. $price_{previous\ day}$ is the closing price at the previous trading day. Then, relative strength RS is calculated as

$$RS\ =\ EMA(U, n)/EMA(D, n)$$

$EMA(U, n)$ and $EMA(D, n)$ are N-days exponential moving average for U, and N-days exponential moving average for D, respectively. Lastly, the relative strength index RSI is calculated as

$$RSI\ = 100 - 100/(1 + RS)$$

In this study, 14 is chosen as the window size (N) for both the manual strategy and the learner strategy.

2 MANUAL STRATEGY

2.1 Strategy Description

A manual strategy is developed to make the trading decisions. Four indicators are combined to decide the long and short entry points.The long entry point happens when (AND is the boolean operation):

Bollinger Band Percentage < -80% AND Momentum < -3% AND Relative Strength Index < 30 AND MACD > 0.5.

The short entry point happens when:

Bollinger Band Percentage > 80% AND Momentum > 3% AND Relative Strength Index > 60 AND MACD < -0.5.

The market is highly uncertain and sometimes a single indicator may not work well as it could trigger "false positive" signals. It is more common to use multiple indicators combined to make trading decisions. Details are below.

Bollinger Band Percentage (%BB). Statistically, it is expected that most of the stock historical prices are contained in the Bollinger band. There is still a small percent of stock historical prices that move outside of the band (when %BB is higher than 100% or smaller than 100%). When this occurs, the price is likely to revert back to the moving average line. In manual strategy, the long and short entry points are set as

Long entry points: when the %BB is smaller than -80%. **Short entry points**: when the %BB is greater than 80%.

For momentum, a positive momentum indicates an uptrend since today's price is higher than the price N days ago. Similarly, a negative momentum indicates a downtrend. The absolute value of momentum indicates how strong the uptrend or downtrend is. In manual strategy, the long and short entry points are set as

Long entry points: when the momentum is smaller than -3%. **Short entry points**: when the momentum is greater than 3%.

For Relative Strength Index (RSI), it measures the ratio of buying power and selling power. RSI typically oscillates between 30 and 70. When it is below a low threshold (e.g. 20), it enters the oversold region triggering a buy signal. When it is above a high threshold(e.g. 80). The long and short entry points are set as

Long entry points: when the relative strength index is smaller than 30. **Short entry points**: when the relative strength index is greater than 60.

Note that the sum of the high threshold and the low threshold is not 100. This is because it is observed that setting a smaller high threshold has better in-sample performance. The actual meaning of a smaller high threshold is that it is less strict to enter short points.

For MACD, when 12 days EMA is greater than 26 days EMA, the stock price is on an uptrend. Otherwise, the stock price is on a downtrend. In this study, we use the difference between MACD and MACD signal lines as the indicator. The long and short entry points are set as:

Long entry points: when the MACD is greater than -0.5. **Short entry points**: when the MACD is smaller than 0.5.

Please note that this rule does not strictly follow the analysis above. This is because if we strictly follow it, the number of tradings we can make during the in-sample period will be too small as adding the additional MACD rule on top of the other three indicators makes it very strict to enter long/short points. So in this case, the rule for MACD is set to be less strict. It simply works as a protection to prevent us from entering an unwanted position when the other three indicators have "false positive" signals.

2.2 Performance Evaluation/Comparison

Manual strategy is tested against the benchmark which is to buy 1000 shares of the stock at the beginning and sell the holdings at the end. In this study, the starting cash is 100,000. The in-sample period is from January 1, 2008, to December 31, 2009. The out-sample is from January 1, 2010, to December 31, 2011. This dataset is used for the entire study.

The manual strategy was developed based on the in-sample period performance and evaluated during the out-sample period. The in-sample results and out-sample results are shown in Figure 1 and Figure 2, respectively.

Both plots show that the manual strategy beats the benchmark. There are two reasons that it performs well:

1. The manual strategy actually works to predict the short entry points and long entry points. Not all entry points successfully make profits but at least some of them are able to "buy the dip" or "sell the top". In the benchmark, the performance is really dependent on the stock price. If the stock price is on a downtrend, the benchmark will not perform well.
2. The benchmark can only make a profit for the uptrend while the manual strategy can short the stock when the price is on a downtrend and long the stock when the price is on an uptrend. This allows more possibility of making a profit.

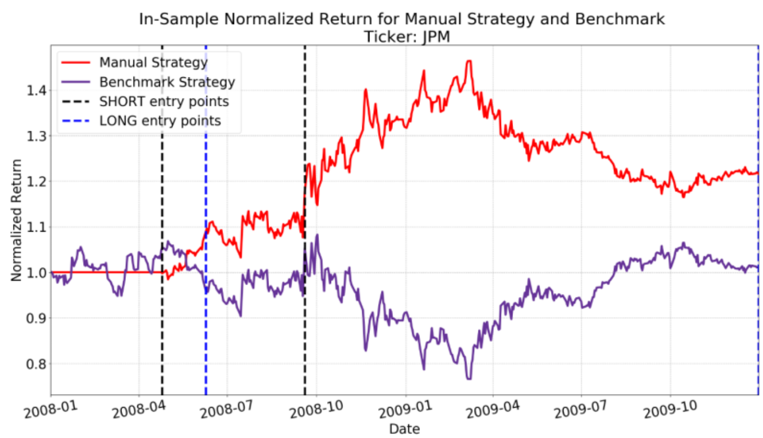

Figure 1—In-sample return for manual strategy and benchmark.

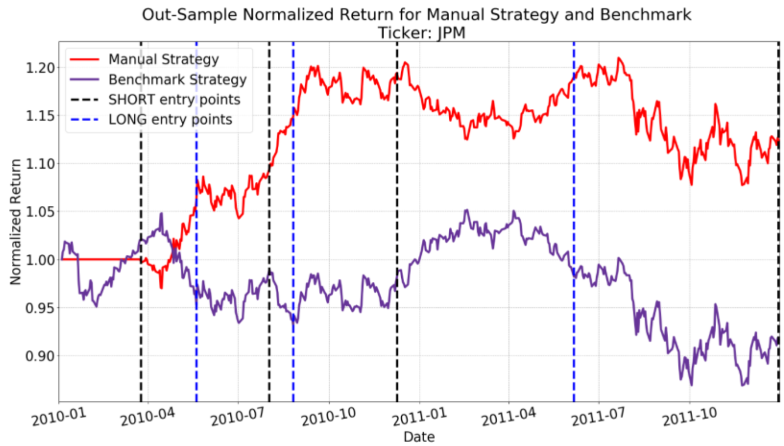

Figure 2—*Out-sample* return for manual strategy and benchmark.

It is interesting to see that the out-sample performance also works well even though the manual strategy was not developed and tuned by peeking into out-sample data. This is because the strategy makes two good decisions: the second short entry point and the second long entry point. The two points are perfect "sell the top" and "buy the dip" points.

Another interesting observation is that the manual strategy finds more long/short entry points during the out-sample period than in the in-sample period. This is because the out-sample stock price oscillates more heavily than the in-sample period, making the indicator values oscillate more. This could potentially trigger more long/short opportunities.

Table 1 shows the statistics of manual strategy and benchmark. The manual strategy beats the benchmark in terms of cumulative return, average daily return, and standard deviation of daily returns. The in-sample cumulative return/average daily return is higher than the out-sample cumulative return. This is because the stock price itself has a higher gain in the in-sample than in the out-sample.

Table 1—Statistics of manual strategy performance and benchmark

	In-Sample		Out-Sample	
	Manual Strategy	Benchmark	Manual Strategy	Benchmark
Cumulative Return	0.215295	0.012325	0.123319	-0.083579

Average Daily Returns	0.000462	0.000169	0.000255	-0.000137
Standard Deviation of Daily Returns	0.012300	0.017041	0.006883	0.008500

2.3 Strategy Learner Description

The trading has been simplified to three actions: Long, Short, and Cash. The indicators are vectorized as a value vector. Bollinger band percentage, momentum, MACD, and RSI are used. The trading problem can be now represented as: given 4 indicator values, the learner determines whether to go Long, Short, or Cash. The random forest is a good algorithm to implement this. Instead of using a regression random forest, this problem uses a classification random forest since there are only three possible outcomes: Long, Short, Cash. In the training process, we first calculate the indicator values as X, then we peek into the future by N days to calculate the return. If the return is positive and is higher than the threshold YBUY, the Y value is 999 (Long). If the return is negative and is lower than threshold YSELL, the Y value is determined as -999(Short). Otherwise, the Y value is determined as 0(Cash). Now we feed the X and Y values to the learner and train it. When query, we calculate the indicators as X and query the trained learner to get Y. Then we convert Y to trades.

The hyperparameters in this learner include

1. Leaf size of the random forest/tree. When the leaf size is too small, it may cause an overfitting problem so a relatively big value of 7 is chosen. With higher values, the in-sample performance will be worse. With smaller values, the in-sample performance can be very good but the out-sample performance could be very bad due to over-fitting.
2. Bag size of the random forest. The bagging helps to reduce the over-fitting and reduce the randomness of the model. 30 is chosen as the value in the study.
3. Number of days to peek into the future in the training process. It turns out that if this hyperparameter is too big, the learner will have a bad performance. 5 is chosen in this study.

4. Buy threshold YBUY and sell threshold YSELL. The buy threshold is set to 3% and the sell threshold is set to -3%. Bigger absolute values of the threshold mean there will be fewer potential trading actions. 3% works well for the learner.
5. The moving window for indicators. This is set to 14 for all indicators except for MACD. For MACD, the window sizes are used exactly the same as mentioned in the manual strategy.

Data is adjusted to utilize all the in-sample data for the training process. Because of the window size, the first window_size days in the in-sample period do not have any indicator values. In this study, window_size days of data before the start of the in-sample period are consulted and used to calculate the indicator values.

2.4 Experiment 1

In this experiment, the random forest learner performance is compared with the manual strategy and benchmark for JPM. The learner is trained only during the in-sample period. After the training process, the in-sample and out-sample indicator data are used to query the Y values. Then the Y values are converted to trades. Results are shown in Figure 3 and Figure 4. Before the experiment, the initial hypothesis is that the in-sample performance should beat the benchmark and manual strategy since we expect that the random tree is able to find the correlations between indicators and trading decisions better than humans. For out-sample performance, we wish the learner strategy can beat both strategies but the out-sample performance depends on many things, such as

1. Overfitting. The in-sample performance is great but the out-sample performance is poor.
2. Not sufficient training data to develop a predictable learner.
3. The stock price data of the out-sample is very different than the in-sample data such that the correlation between the indicator values and trading actions is very different. An extreme example is training during an uptrend period and testing during a downtrend period. It will be not surprising that the testing performs poorly.

All the hyperparameters used in this experiment are already in section 2.3. In Figure 3, the learner strategy beats both the benchmark and manual strategy by a significant amount. This shows the power of machine learning algorithms in trading problems! However, in Figure 4, the out-sample only beats the benchmark but does not beat the manual strategy. The reason could be any of the ones mentioned above. Another reason could be that the learner is a random forest, so randomness exists. Every time we run the training process, the constructed decision forest could be different since every non-leaf node is picked randomly. Even for a small amount of tree difference, the strategy performance could still be very different because the stock price is highly oscillating. It is also possible that further tuning the hyperparameter based on in-sample data can give a better out-sample performance.

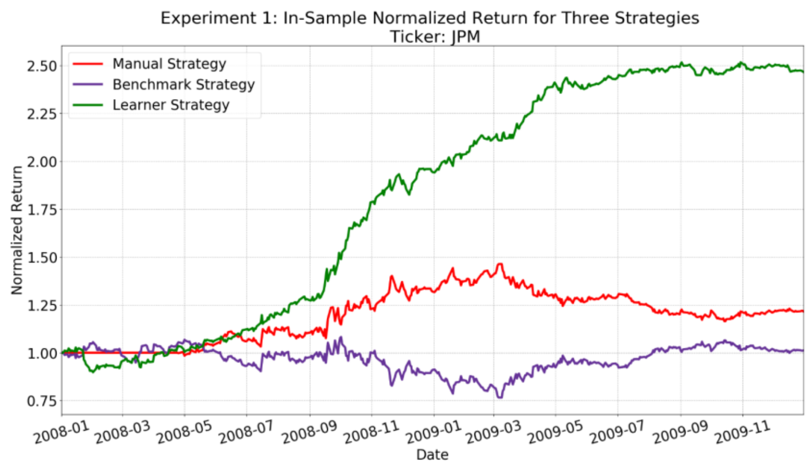

Figure 3—*In-sample* return for three strategies.

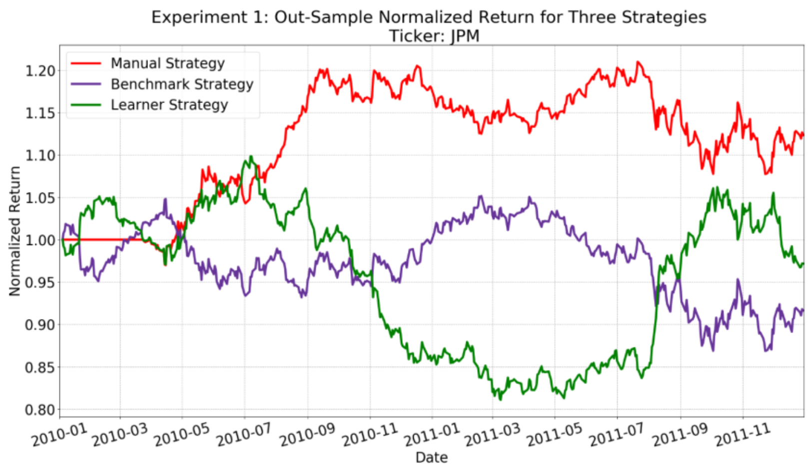

Figure 4—*Out-sample* return for three strategies.

2.5 Experiment 2

In this experiment, the effect of impact on the learner strategy has been studied. The impact is the percentage by which the stock price is increased or decreased when buying or selling the stock. High impact typically occurs when the buying/selling volume is high. There are two hypotheses:

1. High impact diminishes the potential profit because it makes the stock price higher when buying the stock and makes the stock price lower when selling the stock.
2. High impact reduces the number of trading opportunities. In the training process, we determine the trading action based on N days return. If the impact is higher, it is less likely that the N days return exceeds/goes under the buy/sell threshold. So we expect that the higher impact causes more trading actions.

To prove hypothesis 1, four cases are run with different impacts: 0.0%, 0.5%, 1%, and 1.5%. The in-sample JPM data is used for training with each of the four impacts. The results are shown n Figure 5. As you can see, a smaller impact has better returns over time. This indicates that when we do the trading, we should limit the volume of the trading orders so that the impact is as small as possible.

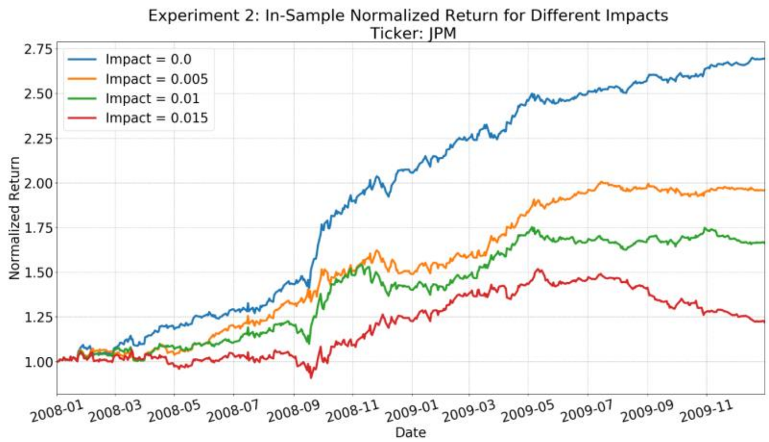

Figure 5—*In-sample* normalized return for learner strategy with different impact values.

To prove hypothesis 2, the same impact values and the same data are used. After the in-sample query, the number of buy or sell actions is counted (non-zero values in the trades vector). The results are shown in Figure 6: the overall trend shows that with higher impact, the learner tends to make fewer trading actions.

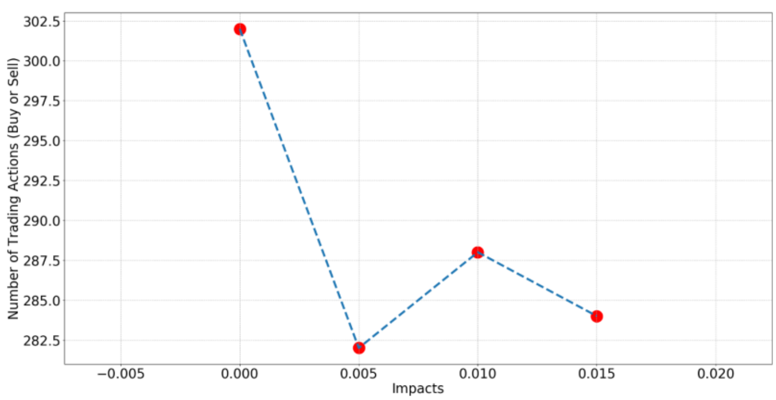

Figure 6—*In-sample* number of buy or sell actions with different impact values.