Why do it yourself?:
Project 8: Strategy Evaluation

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1 INTRODUCTION

This paper to the culmination of all the previous exercises, using technical indicators as the features for a machine learning approach to trading, a manual approach to trading, and finally comparing both approaches to a simple benchmarking scenario. The purpose of it is to use all that was learned within the this class. The exercise will focus on the JPM prices between Jan 1, 2008 to Dec 31, 2009 as the In Sample period, and an Out of Sample period between Jan 1, 2010 to Dec 31, 2011.
The benchmark scenario for both in sample and out of sample is purchasing 1000 shares of JPM and holding till the end of the period.

2 INDICATOR OVERVIEW

The three indicators used for this exercise are Bollinger Bands % (BB%), Moving Average Convergence Divergence (MACD), Stochastic Oscillator.

2.1 Bollinger Band %

BB% is a variation of Bollinger Band that follows the equation:
$BB = prices \pm (2xmoving\_std(prices, 20))$
$BB\% = \frac{BB_{upper} - prices}{BB_{upper} - BB_{lower}}$
(Shihab, 2024)
The 20 in the first equation is the lookback window value which is normally set to 20.
The values of BB% determine the position of the prices in comparison with the Bollinger Bands. A value of 0 means that the price is equal to value of the lower band, while a value of 1 means that the price is equal to the value of the upper band. Values between 0 & 1 mean the price is between the bands, and values outside of 0 & 1 mean they are out of the envelope.

The parameter for BB% used in the learners is the windowing used for the moving standard deviation, which determines the length of the lookback period.

2.2 Moving Average Convergence Divergence

MACD is a three part indicator where part one (also called MACD) takes two Exponential Moving Average (normally 12-day and 26-day windows), converting them into a momentum oscillator.

- Calculate the price EMA for 12-day (fast) and 26-day (slow) window
- MACD = EMA(Price,12) - EMA(Price,26).
  MACD is considered as the slow line.
- Signal = EMA(MACD,9).
  Signal is considered the fast line
- Histogram = MACD - Signal

Part two is the signal line, which is the exponential moving average of the MACD. Part three, the histogram, is the difference between MACD and Signal, and is used to represent current selling pressures in the marketplace.(Shihab, 2024)

The parameters used for MACD fast window & slow window to determine the MACD, and signal window to determine the Signal line. Histogram won't be used within this exercise (although this is a point of improvement). Finally a MACD decision threshold was added for the Manual Learner in order to determine at what value the MACD should exceed in order to initiate a buy/sell signal.

2.3 Stochastic Oscillator

The Stochastic Oscillators is a momentum indicator with four main components. The first is the K component, which compares the closing price to the range of the prices over a window. D averages K out over a slower window. Both K and D are compared against each other and two thresholds marked as the oversold/overbought lines.

```
SO_K = (Close - Min(Lows,k_window))/(Max(Highs,k_window) - Min(Lows,k_window))
SO_D = MovingAverage(SO_K,D_window)
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Using these four lines, the algorithm for using Stochastic Oscillators is:

```
if K and D above overbought line and K < D and previous K > previous D: sell
else if K and slow D oversold line and K > D and previous K < previous D: buy
else: do nothing
```

(Shihab, 2024)

The four parameters for Stochastic Oscillators are the K & D window values, and the Overbought/Oversold thresholds.

3 MANUAL STRATEGY

The manual strategy is just as it sounds, use the indicators as is to create buy/sell signals purely with the logic stated in the previous section. Here is the logic for combining the indicators:

1. Get the indicator values based on the parameters as described above
2. If the majority of indicators vote match, take that action
3. If there is a tie between conflicting indicators, hold.
4. Otherwise hold

This list of signals was then inputted into the market simulator to calculate the portfolio values and metrics needed to compare.

It is the belief of the author that this is an effective strategy as it takes into consideration solid and proven metrics used by many traders to make informed decisions on buying/selling. Due to the nature of the assignment, the metrics may not been used to their fullest potential, and this is a point of future improvement.

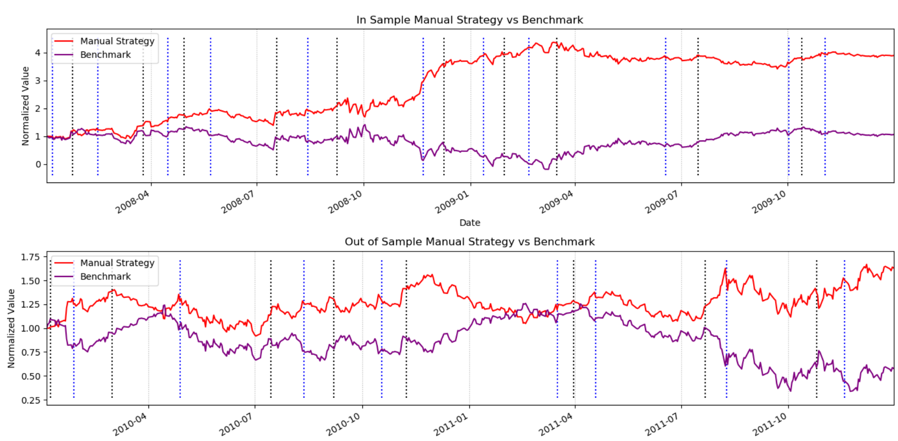

Figure 1—Manual Strategy vs Benchmark

As shown in the chart above and table below, the metrics have out performed the benchmark, meaning that the strategy has some merit. One point of note is that since all three metrics used were lagging indicators, they seemed to do a little worse when prices were on the rise, as seen in the Out of Sample when the Benchmark and Manual Strategy lines would converge. Still, the strategy seemed to hold its own, doing 95.63% better in the in sample period and 74.57% better in the out of sample period with regards to Sharpe Ratio (given a 0% risk free rate).

Another difference *(and point to take into consideration)* is that the manual strategy was *(trying)* being reactive to the market in the hopes of profiting from the ups and downs of the market using the indicators, while the benchmark is left to the whims of the market, going up and down.

	Benchmark		Manual	
	In Sample	Out Of Sample	In Sample	Out Of Sample
CumRet	0.062128	-0.421517	2.893935	0.632408
AvgDR	-0.013033	0.000712	0.003440	0.001497
StdDR	0.629293	0.060582	0.038950	0.032473
SR	-0.328781	0.186566	1.401999	0.731623

Table 1—Manual vs. Benchmark: In-Sample and Out-of-Sample Metrics

4 STRATEGY LEARNER

Unlike the manual strategy, the learner needed to be trained on the data. The X data for the learner is the raw metric values (non-discretized). This would give the Random Trees way more range to split on. The y values were effectively using the N-day forward looking returns converted into buy/sell signals using buy/sell thresholds (y_buy, y_sell). Now, since there are infinitely many values for the parameters, scipy.optimize.minimize[1] was used to find the values of the parameters to minimize the negative sharpe ratio. The bounds given to each are:

- N: (5, 20)
- y_sell[2]: (0.8,0.99)
- y_buy: (1.01, 1.2)

1 Due to the long runtime of the code, this part wasn't submitted so it doesn't timeout.

2 The author when coding returns, didn't realize they forgot to subtract 1 from the $\frac{prices_(t+N)}{prices_t}$ equation, and as such, the values of y_sell and y_buy are centered around 1 rather than 0

The values that the optimizer landed on were approx. 5, 0.98, and 1.02 respectively. With the y_buy and y_sell thresholds, converting the returns from continuous to discrete values was as easy as checking if the returns were greater than (y_buy+impact) or less than (y_sell-impact) and assigning a 1 (buy) or -1 (sell) respectively. If none of the conditions were met, assigned 0 (hold) For the Bagged

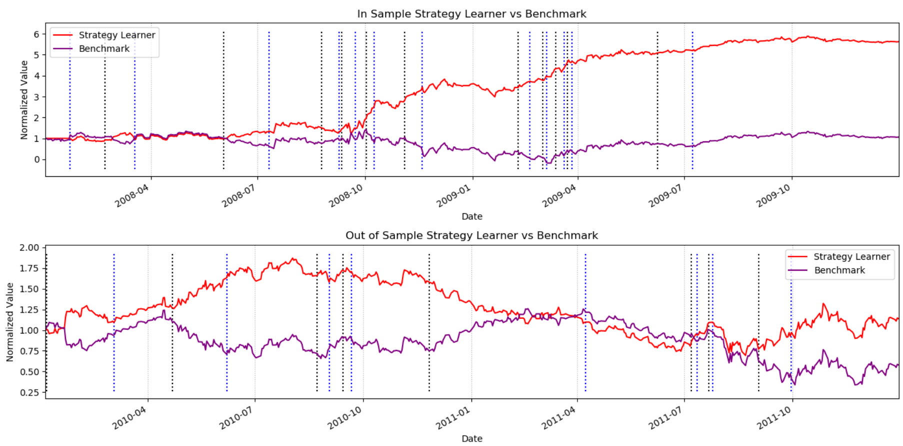

Figure 2—Strategy Learner

Random Trees, the hyperparameters used were the number of bags and leaf_size. To optimize these parameter, another scipy.optimize.minimize[3] was used with bag search values between 10 to 20 and leaf_size search values between 5 to 20. The values that the optimizer landed on were 20 and 5 respectively.

	In Sample	Out Of Sample
CumRet	4.624748	0.138677
AvgDR	0.004297	0.000933
StdDR	0.041930	0.036815
SR	1.626666	0.402239

Table 2—Strategy Learner: In-Sample and Out-of-Sample Metrics

Similarly to Manual Strategy, the Strategy Learner beat the benchmark in both the In Sample and Out of Sample periods.

3 Due to the long runtime of the code, this part wasn't submitted so it doesn't timeout.

5 EXPERIMENT 1: MANUAL STRATEGY / STRATEGY LEARNER

Experiment 1 was comparing the results of all three scenarios and understanding the pros/cons of each. For each indicator, the lookback periods and other parameters were kept the same. The hypothesis that the strategy learner would not perform as well as the manual strategy in the long term, but may perform very well in the in sample portion. The reason for this hypothesis is that in normal timeseries models, the approach would be to continually train the model as new data would come in and keep the prediction period short.

In our example, the prediction period would be *(for example)* 5 days forward *(which was the N of our Strategy Learner)*. Given the start date of Jan 1, 2008, the model would be trained on data till today, and predict the return of the next 5 days. Tomorrow, the new data would be added to the training model and repeat. Since this project required no batch learning, the hypothesis was that in the in sample period, the model would out perform, but in the long term, would begin to falter. Also, the bagging is causing the model to cheat a little with some data leakage. Timeseries data should be looked at in order, not bootstrapped with random samples of time in each bag. There are different models that are more equipped to handle timeseires such as ARIMA, GARCH, and Holt-Winters are a few that this author remembers from the OMSCS class Introduction to Analytical Modelling *(ISYE-6501)*.

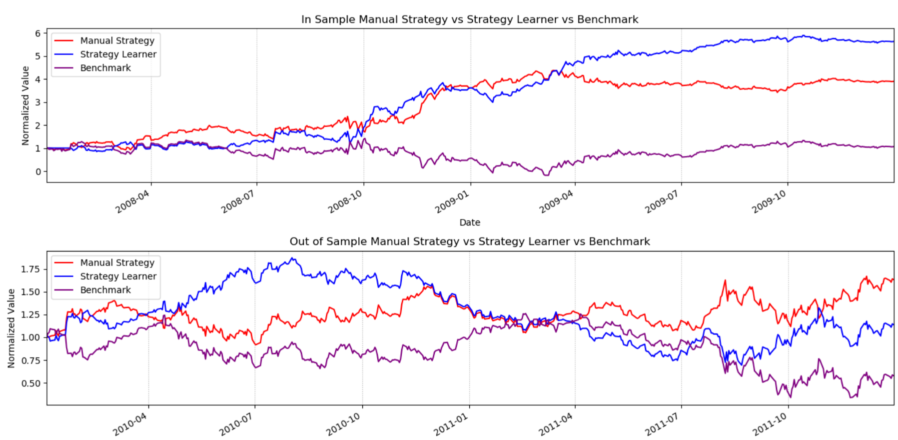

***Figure* 3**—Experiment 1

As seen in the chart above, the strategy learner moves along with the manual strategy until it starts to over take it around April 2009, where the manual

strategy stops its growth and levels out. This is possibly due to the learners interpretation of the indicators and how they work with the discretized return values. Manual Strategy was based on the indicators and their interaction with one another, which may or may not synergize well. It is worth mentioning that the model was trained on the in sample portion, so it is effectively a "master" at all the data for this ticker in this period. It's memorized the effects and trends of this time. It is the expectation of the author that this relative result would be expected everytime with in sample data.
However, in the Out of Sample, the models switch and the manual strategy takes the lead at around March 2011. The models trees may not have enough understanding of the new situation of the new years, and as such, it begins to struggle a little. Manual Strategy on the other hand is a set of rules, and isn't bound to the same constraints as the strategy learner.
A point of improvement would be to implement some sort of batch learning to see if the strategy learner can keep up with the manual strategy.

6 EXPERIMENT 2: STRATEGY LEARNER

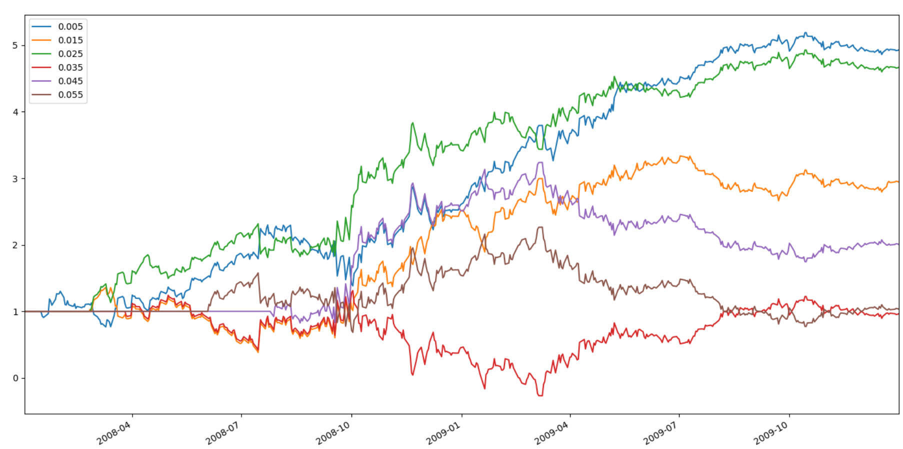

Figure 4—Experiment 2

This experiment was designed to look at the effect of impact on the Strategy Learner since y_buy and y_sell are affected by it. The expectation is as impact gets larger, the returns get smaller since less buys and sells will take place by raising the required threshold to become a signal.
The experiment will look at this effect by comparing the cumulative return, average daily return, standard deviation of daily return, and sharpe ratio of the trades outputted by the strategy learner with 6 different impact levels, each

separated by 0.01 difference between each level.

As shown in the chart above and table below, the higher the impact, the harder it is for the model to predict any trades since when impact is higher, the amount of buy and sell signals converted from the returns goes down.

	0.005	0.015	0.025	0.035	0.045	0.055
CumRet	3.928167	1.947110	3.666512	-0.038425	1.007880	0.034270
AvgDR	0.004032	0.004481	0.003551	0.050671	0.002393	0.001934
StdDR	0.042237	0.070655	0.031491	0.817527	0.045382	0.061772
SR	1.515293	1.006767	1.790220	0.983912	0.837217	0.496960

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7 REFERENCES

[1] Shihab, Mahmoud (Mar. 2024). *Give me a sign. Project 6: Indicators/TOS*. English.