DEPARTMENT OF COMPUTER SCIENCE, GEORGIA INSTITUTE OF TECHNOLOGY

Trading Strategies Using Technical Analysis

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1 INTRODUCTION

This paper is segmented into 6 sections, analyzing the AAPL stock performance by applying technical indicators, rules, and ML algorithms. We use a 14- day window length for computing the indicators, and 21-day holding period to compute our entry positions taken on both rule and ML-based portfolios. We consider standard scores (z scores) defined as follows:

$$z = \frac{x - \mu}{\sigma}$$

where x is the daily adjusted closing price, and μ is the mean and σ is the standard deviation across the entire adjusted closing prices [1]. This scoring metrics is applied to all indicators. Adjusted closing prices are normalized in the analysis.

DATA Analysis is conducted over an in-sample/training period of January 1, 2008 to December 31, 2009, and out of sample/testing period, January 1, 2010 to December 31, 2011. The starting cash is \$100,000. Fig.1.1 depicts AAPL's adjusted pricing over the in-sample period. The 14-day window length necessitates knowing the pricing data from December 11, 2007 onward.

2 TECHNICAL INDICATORS

We identify and implement 4 technical indicators: Bollinger Bands (BB), Relative Strength Index (RSI), Williams % R (WILLR), and Keltner's Channels (KELT).

2.1 BOLLINGER BANDS (BB)

BB is a measure of stock volatility consisting of its simple moving average (SMA) over the last n trading days. The upper band tracks the stock movement at K times the n-day standard deviation (σ) above the moving average ($SMA + K\sigma$), whereas the lower band tracks the movement at K times the n-day standard deviation at below the average ($SMA - K\sigma$). Fig. 2.1 depicts the Adjusted Closing vs Bollinger Bands with $n = 14$ and $K = 2$, over the AAPL adjusted closing in red line. Note AAPL is standardized to meet the same Z scoring metric for the indicator. The BB Indicator is standardized over one σ as seen in Fig. 2.2:

$$\text{BB Indicator} = \frac{x - SMA}{K - \sigma}$$

where x is the daily adjusted closing price of AAPL. BB Indicator > 1 means prices have broken through the upper band, whereas BB Indicator < -1 means prices have dipped below the lower band.

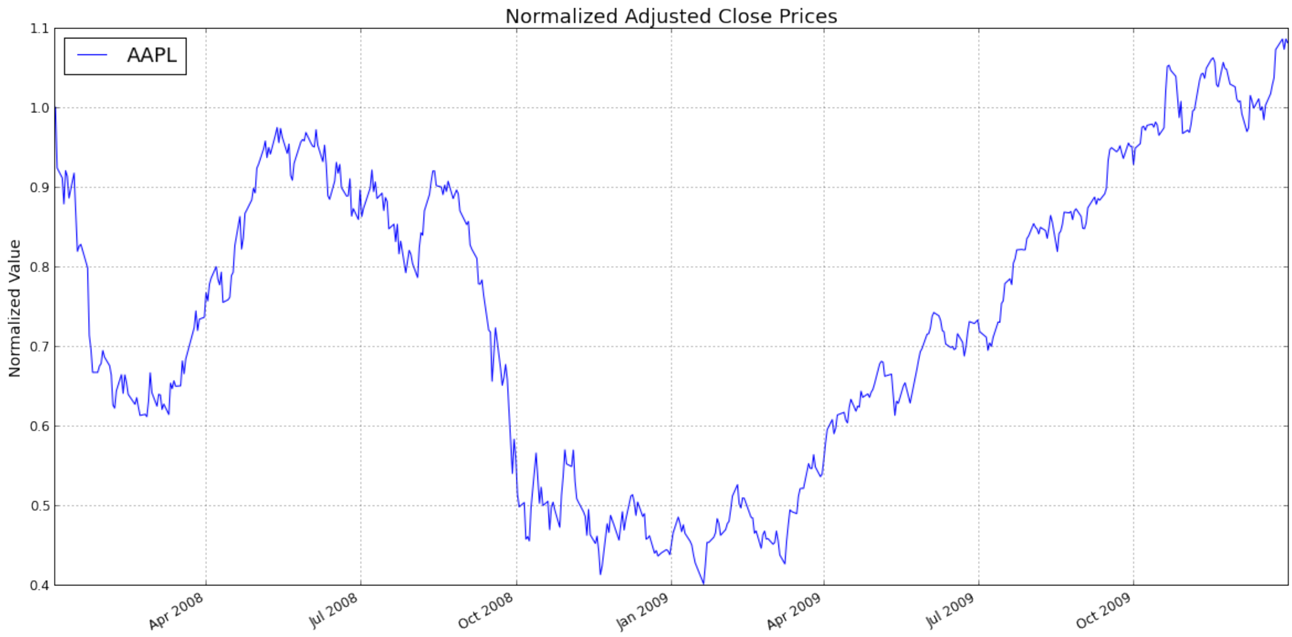

Figure 1.1: Normalized Adjusted Close over the In-Sample Period

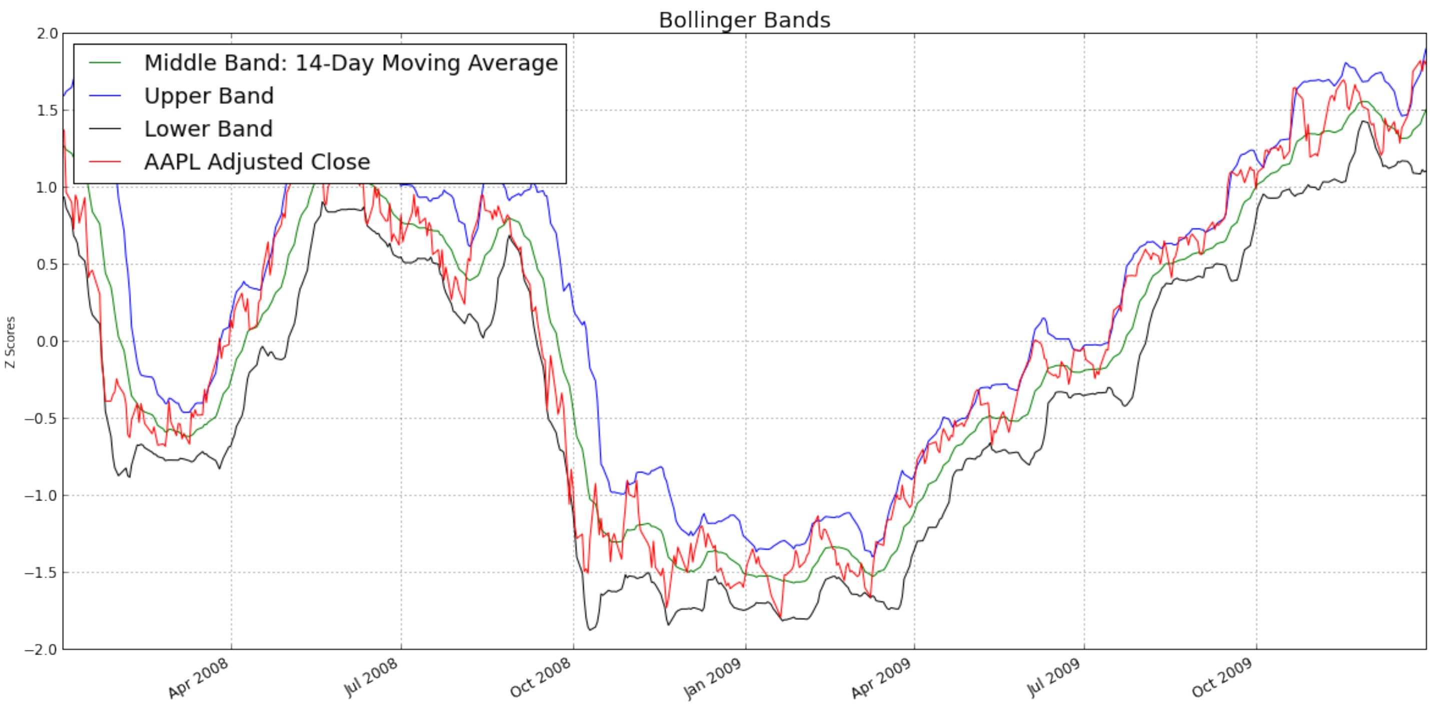

Figure 2.1: Bollinger Bands over AAPL's Adjusted Closing.

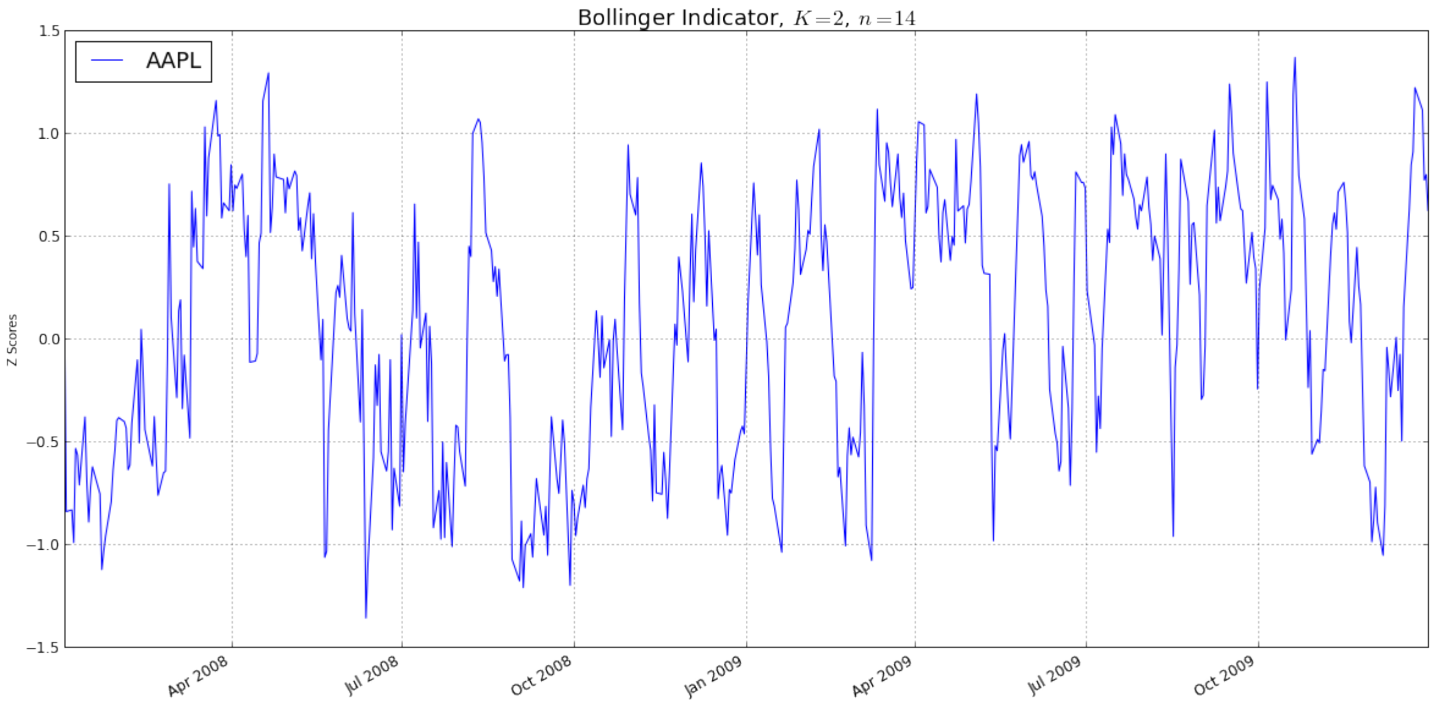

Figure 2.2: Bollinger Bands on AAPL's Adjusted Closing at $n = 14$.

2.2 Relative Strength Index (RSI)

We define RSI using a simple moving average (SMA). RSI measures the speed and change of a stock [3]. One computes the daily upward (up) and downward ($down$) changes by the following means:

$$up = \max(0, \delta) \qquad down = \max(0, |\delta|)\,,$$

where δ is the difference in adjusted closing price of each pair of consecutive trading days. We compute the simple moving averages of both up and $down$ movements of the target stock, arriving at its relative strength ratio, $RS = \text{SMA}(up)$ / SMA($down$), which oscillates normally between 0 and 100. Finally, the RSI index is defined as

$$RSI = 100 - \frac{100}{1 + RS}$$

RSI is considered overbought when it is > 70, and undersold when it is < 30. Fig. 2.3 depicts its standardized values.

2.3 Williams % R (WILLR)

WILLR, or %R, is a momentum indicator that normalizes pricing as a percentage between 0 and -100. WILLR is used to locate both entry and exit points over n days [2]. The formula is given by

$$\%R = \frac{H_n - x}{H_n - L_n} \times -100$$

where x is the current market closing price, H_n and L_n are the highest and lowest market closing prices, respectively, in the past n days. We use adjusted closing prices and find the highest and lowest among them. The result is a moving $\%R$. When $-20 < \%R < 0$, we have overbought market conditions, whereas when $-100 < \%R < -80$, we have oversold market conditions [2]. Fig. 2.4 depicts its scores from 0 to -100.

2.4 Keltner Channels (KELT)

KELT consists of 3 lines, a simple moving average (Middle) with its upper (Upper) and lower (Lower) bands similar to Bolliger bands. The standard KELT implementation involves the use of Average True Range (ATR) instead of standard deviation over a range of n period exponential moving averages (EMA). ATR represents the largest price difference between prices. In this paper, we employ a simpler implementation without ATR and EMA:

$$Middle = (High + Low + x)/3 \qquad Upper = (4 * High - 2 * Low + x)/3 \qquad Lower = (-2 * High + 4 * Low + x)/3,$$

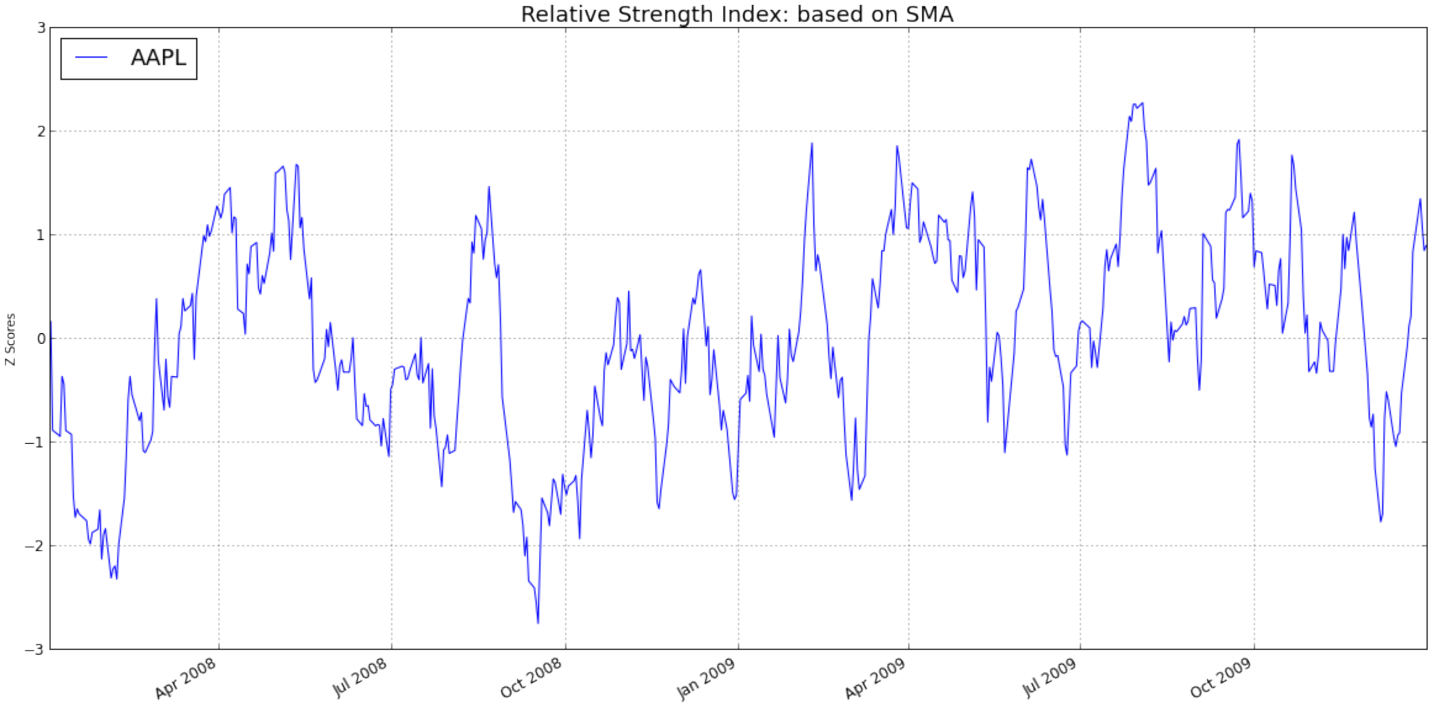

Figure 2.3: RSI over $n = 14$.

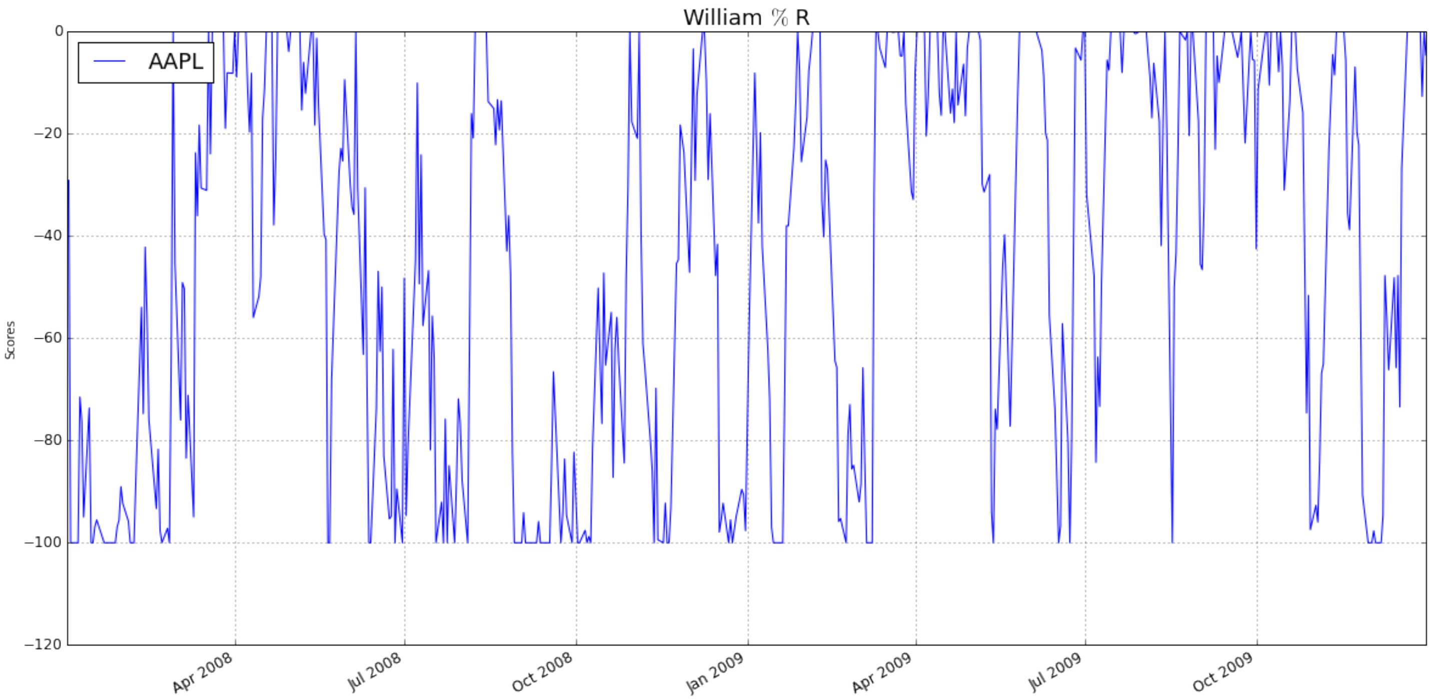

Figure 2.4: William % R.

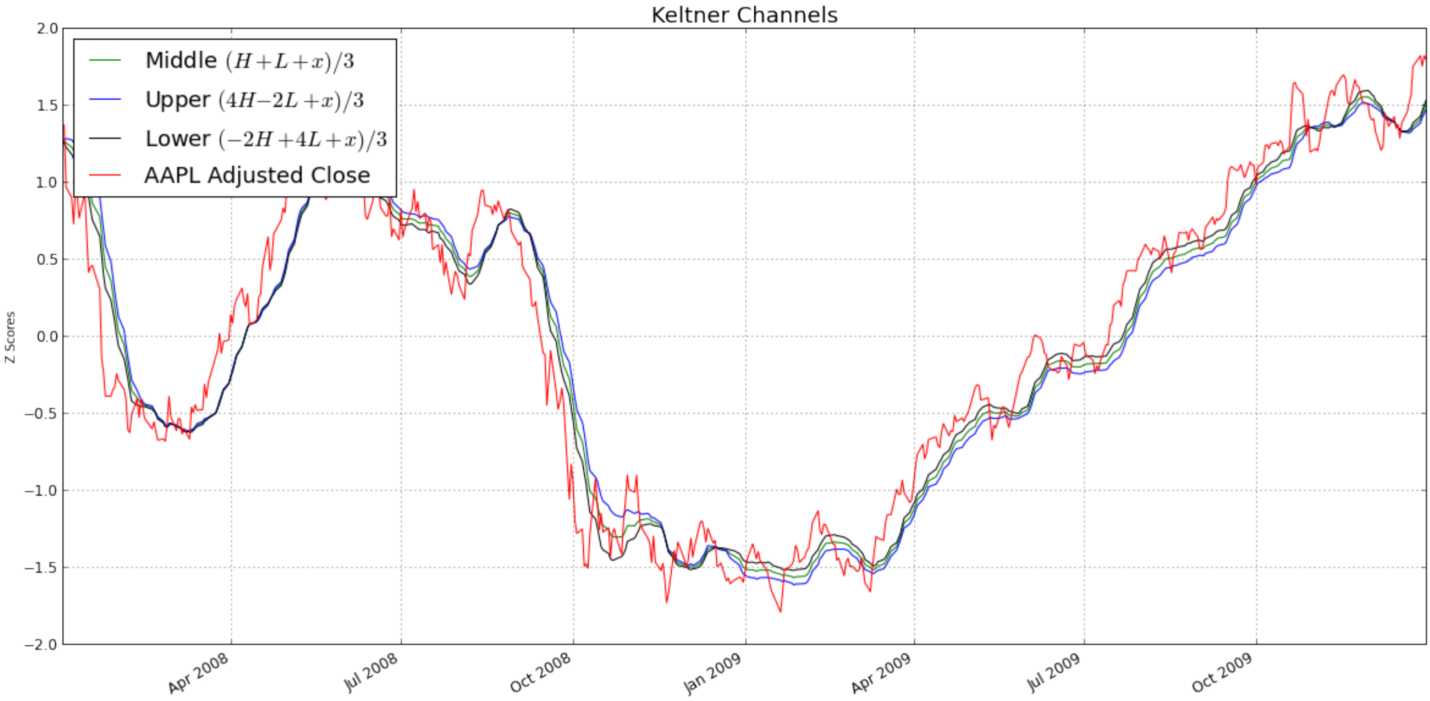

Figure 2.5: Keltner Channels over AAPL's Adjusted Closing at $n = 14$

Table 3.1: Benchmark vs Best Possible Strategy Profiles

	Benchmark	Best Possible Portfolio
Cumulative Return	0.03164	2.94948
Standard Deviation	0.00874	0.00322
Mean Daily Return	0.00010	0.00273
Final Portfolio Value	$103,164	$394,948

where x is the adjusted closing price, $Middle$ is the middle moving average line, and $High$ and Low are the highest and lowest prices over n days, respectively. KELT is used to monitor and trend stock moves; a surge above the Upper channel signifies the beginning of a strong wave whereas a move that dips below the Lower channel insinuates the end of a trend. Fig. 2.5 depicts the 3 Keltner's channels with respect to AAPL's adjusted closing in red.

3 Best Possible Strategy

We obtain the best possible portfolio for AAPL over the in-sample period. We compare the best portfolio with the performance of a benchmark, starting with $100,000, investing in 200 shares of AAPL at the beginning of the period and holding that position until its end. The 21-day holding requirement does not apply to this analysis. The order limit is either 200 shares long, 200 shares short, or 0 share on each day. We close on our positions daily using the stock's adjusted closing prices. Fig. 3.1 depicts the equity curves with respect to the benchmark (in black) and the best possible strategy (in blue), normalized over to 1.0 at the start line. Table 3.1 reports the cumulative returns, standard deviation of daily returns, and mean daily returns of both approaches.

4 Manual Rule-Based Trader

We devise 7 indicator triggers/rules, using the indicators defined in Part 1, to trigger either a LONG (1) or SHORT (-1) entry with a 21-trading day hold. The conditions for LONG and SHORT entries are mutually exclusive. The entry value is 0 on days when there are no trades. Once an entry is entered, we remain in the position for 21 consecutive trading days. The indicators for this section are Relative Strength Indicator (rsi), Bollinger Bands (bb), William %R (willr), and the upper band of Keltner's Channels. To aid our selection of indicator values, we plot the entry value of the rule-based output (-1, 0, 1) against the AAPL stock price, arriving at the following rules:

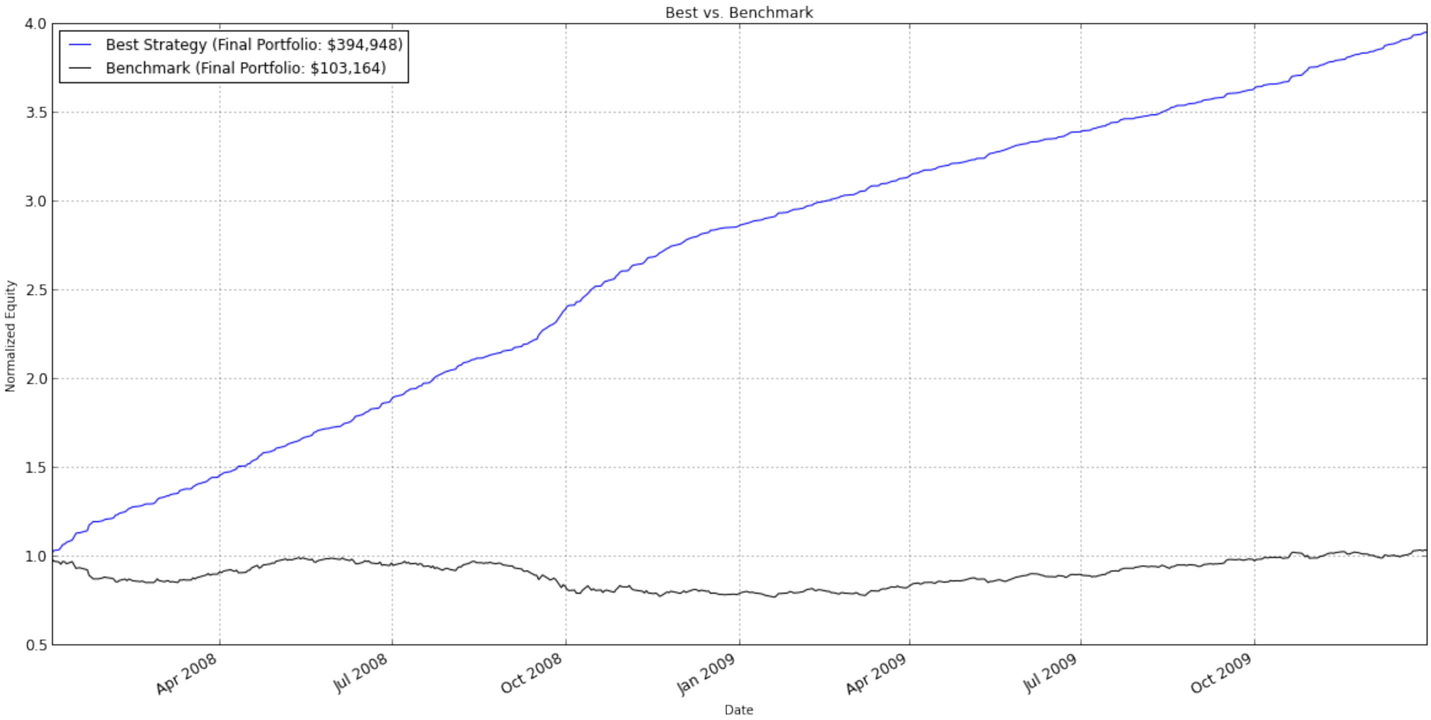

Figure 3.1: Benchmark vs Best Possible Portfolio for AAPL

For LONG:

- rsi > 0.0 (standardized)
- bb < -0.5 (standardized)
- willr < -80.0 AND willr > -100.0
- kelt upper < adjust close (standardized)

For SHORT:

- rsi < -0.09 (standardized)
- bb > 2.0 (standardized)
- willr < 0.0 AND willr > -20.0

Computation for indicator values requires 14 days of historic data (starting with December 11, 2007) prior to the in-sample starting date (January 1, 2008). We use Adjusted Closing, High, and Low data points from AAPL. We standardize our indicators with the exception of William % R. We felt it is easier to reference the established oversold and overbought thresholds in William %R in designing our rule based system.

Fig. 4.1 depicts the rule-based performance over the benchmark as defined earlier. The rule based portfolio outperforms the benchmark over the in-sample period. The historic benchmark is based on the aforementioned buy and hold strategy; its value is normalized to 1.0 in black, whereas the rule-based portfolio is normalized to 1.0 in blue. The vertical green lines indicate LONG entry points, whereas the vertical red lines indicate SHORT entry points. Each red or green entry points are at least 21 days from each other.

4.1 Manual Rule-Based: Discussion

The rule-based strategy as illustrated is limited by its domain knowledge, a set of rules in an infinitude of problem space. This is similar to an expert knowledge system governed by a myriad of decision rules in a finite space lacking its ability to synthesize and create information in a changing environment. However, the rule-based strategy provides consistent answers to repetitive decisions and processes, while maintaining significant amount of information that may be useful to trades.

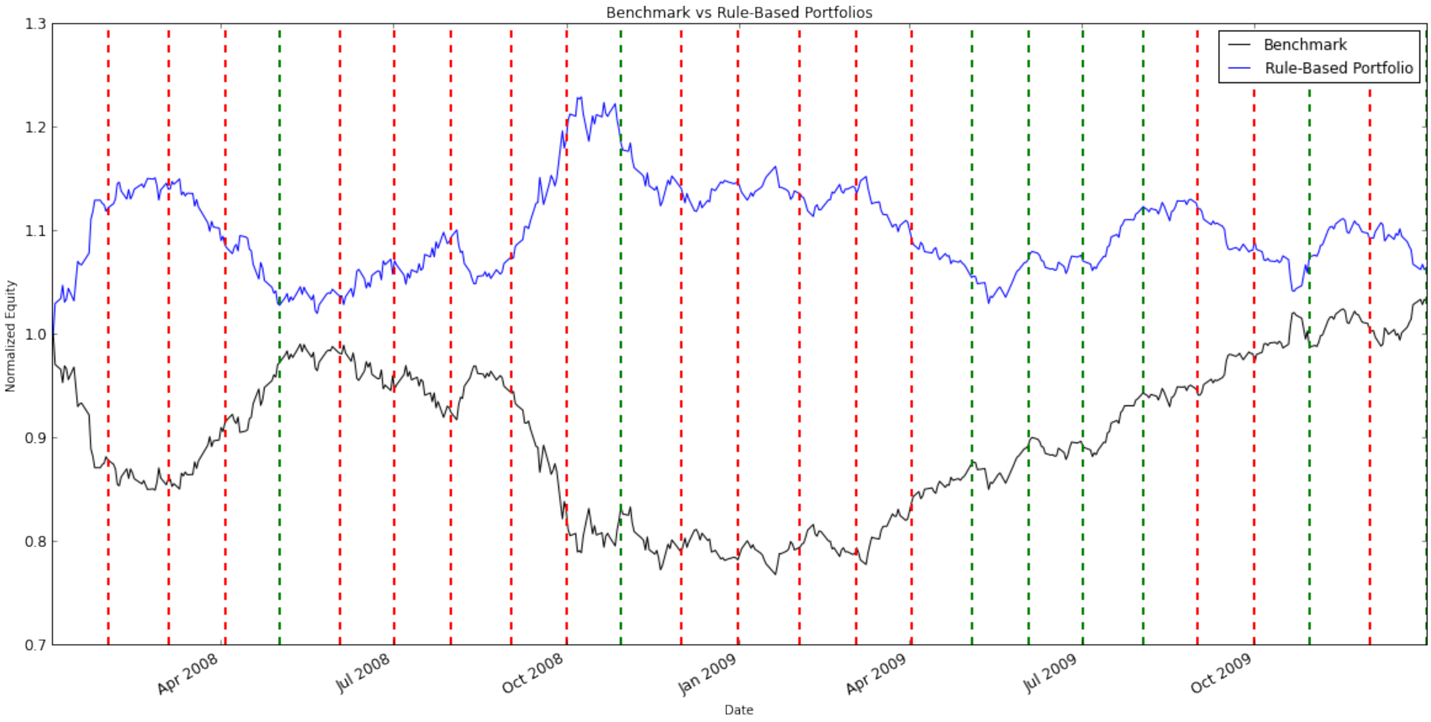

Figure 4.1: Rule-Based Portfolio vs Benchmark for AAPL

5 ML TRADER

ML STRATEGY DESCRIPTION & PARAMETER TUNING The ML learner employs random trees with bootstrap aggregating (bagging). We convert our decision tree learner (RTLearner.py) into a classification learner, and modify bagging (BagLearner.py) to accommodate RTLearner and to improve its stability and accuracy. The conversion involves passing in the classification indicators, YBUY and YSELL (see below), into the BagLearner and RTLearner, respectively, to output either 1 (LONG), -1 (SHORT), or 0 (NO TRADE).

We set the learner's leaf size to 5 to mitigate the risk of arriving at a degenerate overfit solution. We adjust the number of bags from [1, 5, 10, 15, 20] and notice an increasing bias at higher number of bags. Bags = 10 is selected to balance variance and bias in predicting our dataset; increasing bags yield very little improvement. Model training requires evidence: X_{train} and Y_{train}.

X_{train} is obtained each day by computing indicator values from Part I, over the current dataset. Three key technical indicators are selected for our learner: RSI, Bollinger, and Will %R. We require 14 days of historic data (starting with December 11, 2007) prior to the in-sample starting date (January 1, 2008) to train the indicators. We use Adjusted Closing, High, and Low data points from AAPL. These data points are transformed, flattened, and reshaped into the correct dimensionality as the learner's input. We standardize our indicator values resulting in a uniform spread in X.

Y is our classification data. Y_{train} is based on 21 day return, using data from the future. Prior to training, we grid search a combination of YBUY and YSELL, arriving at YBUY = 0.0 and YSELL=-0.019 which gives us the optimal classification result. In our experiment, $Y_{train} = 1$ (LONG) if the 21 day return exceeds YBUY; $Y_{train} = -1$ (SHORT) if the 21 day return falls below YSELL. $Y_{train} = 0$ (NO TRADE) otherwise. The conditions for LONG, SHORT, and NO TRADE are mutually exclusive. Note we require a future lookup of 21 days to build Y_{train}; the first 21 days of the out-of-sample period is still in-sample.

Querying/testing is conducted over the in-sample period. When either a classification node, LONG or SHORT, is encountered, we enter the corresponding position with 200 shares of AAPL. The 21-day hold is placed on all positions. This yields approximately 20-23 LONG/SHORT positions over the in-sample period under this hold requirement.

ML RESULTS The ML strategy outperforms all others. Table 7.1 lists the in-sample cumulative return of 72.50% for the ML trader, with respect to both benchmark (3.16%) and the rule-based strategy (6.40%) in the same period. That is it, ML outperforms benchmark by 23 folds in the in-sample period. Fig. 5.1 depicts the result of 3 portfolios: benchmark, rule-based, and ML-based spanning January 1, 2008 to December 31, 2009. The historic benchmark is based on the aforementioned buy and hold strategy; its value is normalized to 1.0 in black. The rule-based portfolio is normalized to

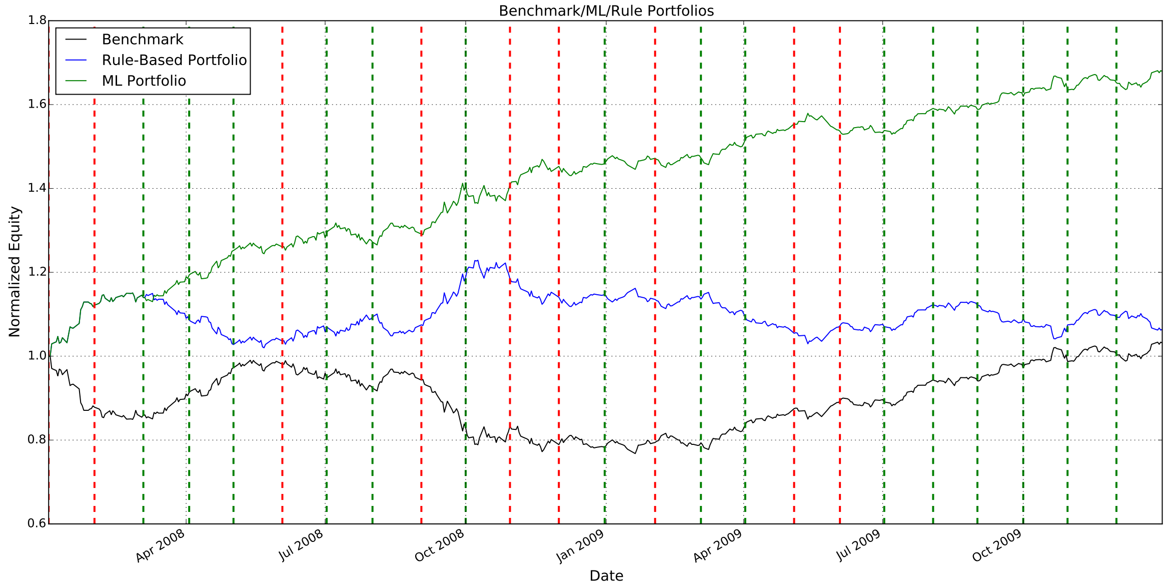

Figure 5.1: Benchmark vs Rule-Based vs. ML-Based Portfolios for AAPL

1.0 in blue, whereas the ML portfolio is normalized to 1.0 in green. The vertical green lines indicate LONG entry points, whereas the vertical red lines indicate SHORT entry points.

5.1 ML Trader: Discussion

A ML-based strategy builds its domain knowledge and generalization of data through inter and extrapolation. The more data we have, the more information we equip an ML classifier with. Combined with the effect of bagging, we reduce variance and increase our model's bias to increase its predicability and accuracy, as evident in our ML analysis.

6 Visualization of Data

Two technical indicators are selected: RSI and Bollinger Bands, which are standardized over the in-sample period for AAPL. Three scatter plots with respect to the indicators and the following are generated:

- Rule-based strategy (Fig. 6.1).
- The training data for the ML strategy (Fig. 6.2).
- Response of the learner when queried with the same data, after training (Fig. 6.3).

X data are consistently the same across the plots. Y data vary with different sets of LONG (1), SHORT (-1) or NO-TRADE (0). Both LONG and SHORT dots are slightly enlarged over the NO-TRADE dots in the charts for better visualization.

7 Comparative Analysis

We evaluate the performance of both the rule-based and ML-based strategies over the out-of-sample/testing period (January 1, 2010 to December 31, 2011). Training is performed over the in-sample period. For both strategies, we employ the same settings (parameters, indicator rules, classification learner, etc.) from the earlier sections of this report. Fig. 7.1 depicts the normalized equity curves for the benchmark (black), rule-based (blue), and ML-based (green) strategies, over the out-of-sample period.

Table 7.1 summarizes the performance of the benchmark, the manual strategy and the ML strategy for both in sample and out of sample periods.

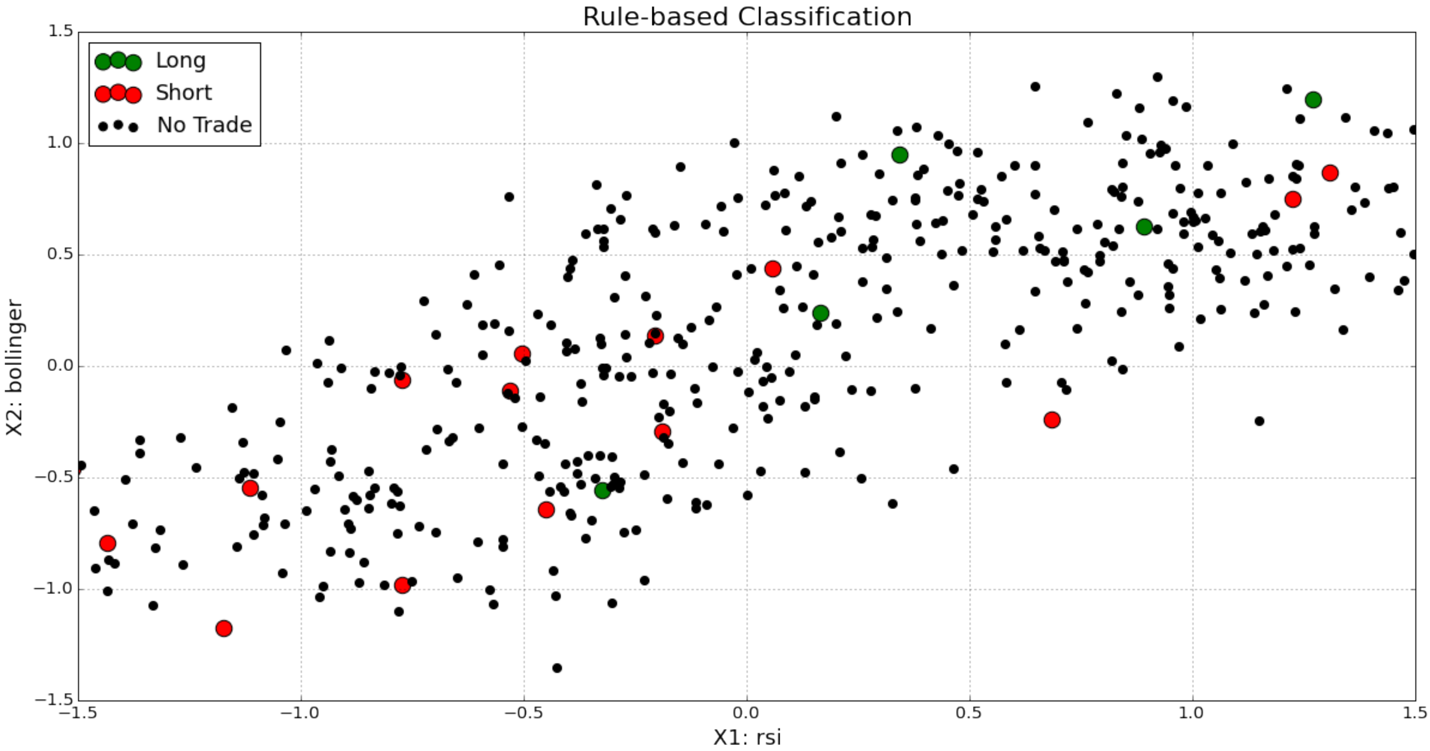

Figure 6.1: Indicator Plot: Rule-based Strategy

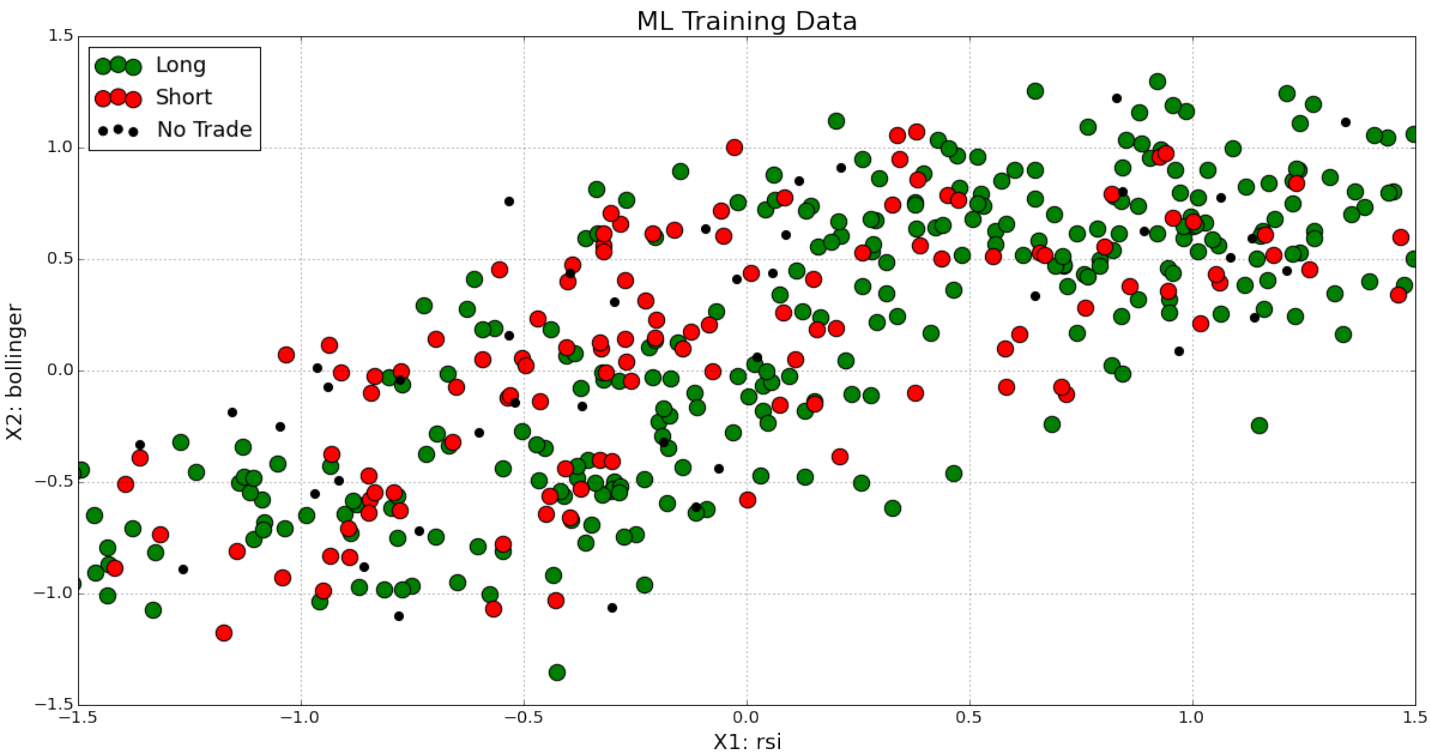

Figure 6.2: Indicator Plot: ML-based Training Data

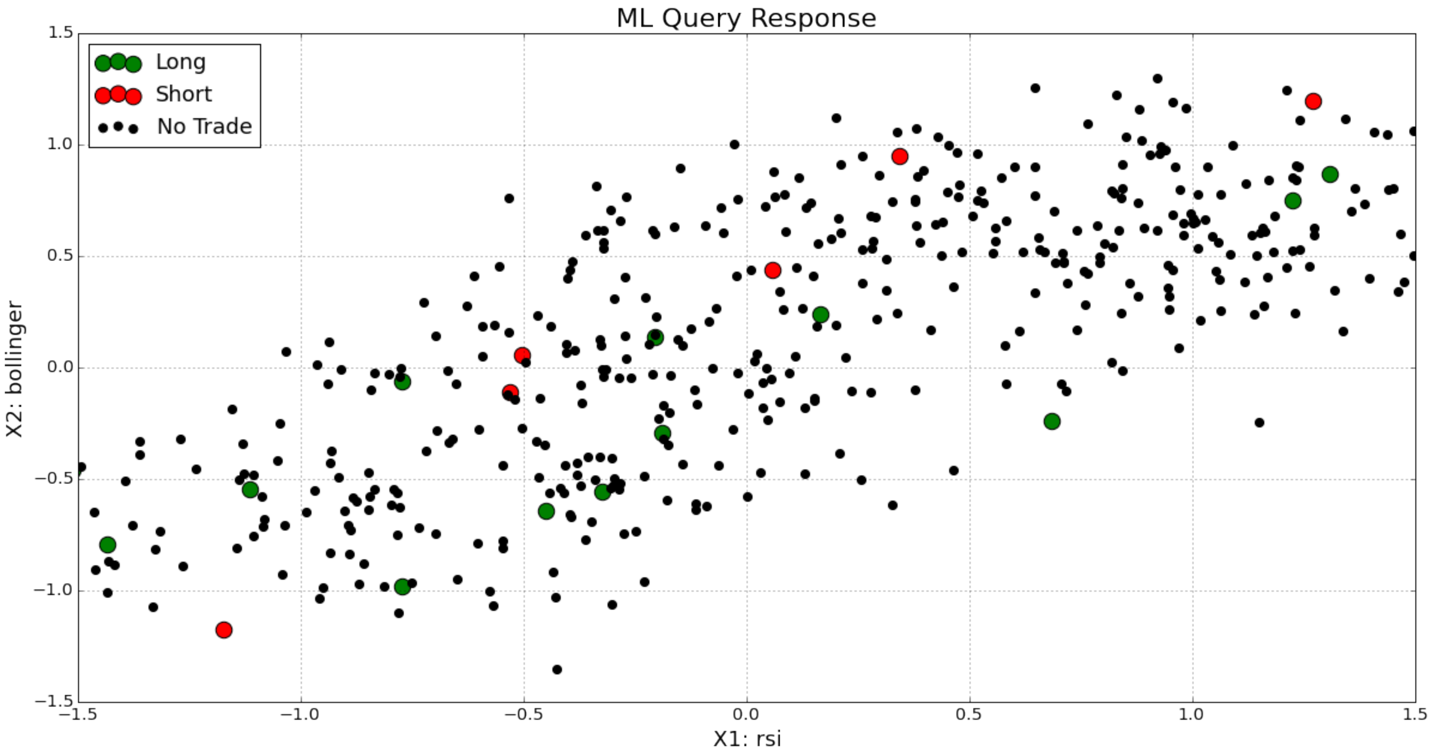

Figure 6.3: Indicator Plot: ML-based Query Response

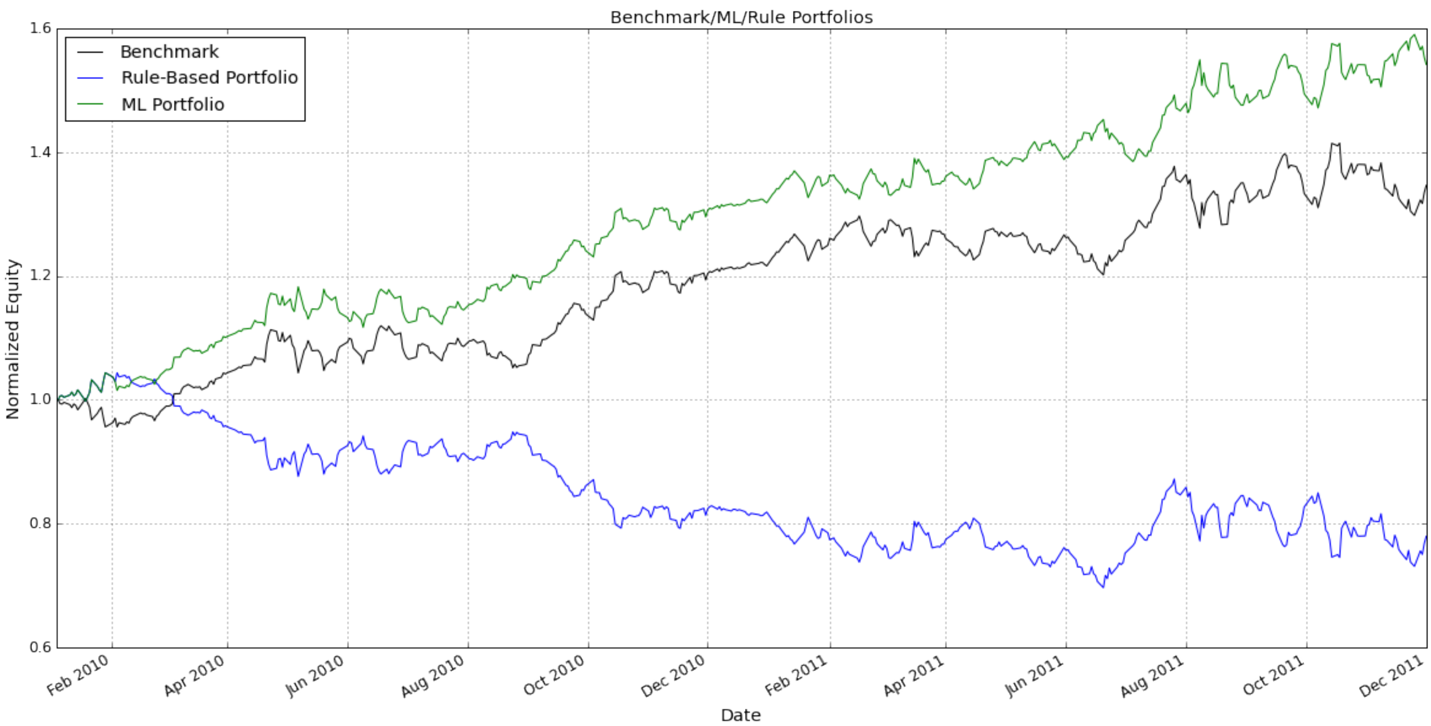

Figure 7.1: Out of Sample: Benchmark vs Rule-Based vs. ML-Based Portfolios

Table 7.1: Testing Performance Comparison: Benchmark, Rule-Based, and ML Strategies

Strategy	In-Sample	Out-of-Sample
Benchmark Return (%)	3.16	38.03
Rule-Based Return (%)	6.40	-22.03
ML-Based Return (%)	72.50	50.65
Benchmark STD	0.00874	0.00855
Rule-Based STD	0.00705	0.01286
ML-Based STD	0.00573	0.00794
Benchmark Mean Daily Return (%)	0.00010	0.00068
Rule-Based Mean Daily Return (%)	0.00015	-0.00043
ML-Based Mean Daily Return (%)	0.00110	0.00088

Out of Sample ML trader performs slightly worse than its in-sample counterpart. At a return of 50.65%, the out of sample ML strategy still outperforms any in-sample and out of sample rule and benchmark traders. This speaks for the ML classifier's ability to generalize beyond the information given. Rule-based strategy, on the contrary, performs poorly on out-of-sample with a negative return of 22%; this is expected as our indicator rules are not adaptive and expressive enough for the changing environment. As seen in Fig. 7.1, overfitting for the rule-based strategy occurs around late February to March 2010, when both ML and benchmark equities cross the rule based portfolio for the better.

8 Conclusion

In this paper, we compare and contrast both manual rule-based and ML-based strategies in terms of their performance on AAPL. Several technical indicators including RSI, BB, Williams % R and Keltner's Channels are used to train and query the ML learner. In testing our data, overfitting becomes apparent on the rule based strategy, insinuating its lack of expressiveness and robustness. This is in contrast to the ML strategy, which performs well on the unseen test set, insinuating its ability to encapsulate good information, especially at a leaf size = 10 and bags = 5. Furthermore, the ML strategy outperforms the benchmark (buy and hold) on out of sample data. For future experiments, one can parameter-tune the model further to reduce its variance and study the performance with respect to both the problem space and iterations, in a convergence analysis, to help with the learning process.

References

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[3] Relative Strength Indicator (RSI) *https://www.fidelity.com/learning-center/trading-investing/technical-analysis/technical-indicator-guide/RSI*. April 3, 2017.