Assignment 8: Strategy Evaluation
CS7646

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INTRODUCTION

In this report, we will choose multiple technical indicators for time-series stock price data and design an intuition-based strategy (MS: Manual Strategy) and machine learning-based trading strategy (SL: Strategy Learner). The same indicators will be used for both strategies to identify buying or selling potential of a particular stock. MS will be implemented by using intuition and the selected indicators. SL will be created with a choice of reinforcement-based learner (Q-learning-based strategy). We will evaluate the performance of both strategies in sample and out of sample periods and against benchmark strategy (BM) as well.

Experimentation details:

- Data: Historical stock prices
- Symbol: JPM.
- In-sample period: January 1, 2008 to December 31, 2009.
- Out-of-Sample period: January 1, 2010 to December 31, 2011.
- Starting cash: $100,000.
- Allowable positions: 1000 shares long, 1000 shares short, 0 shares.
- Only buy/sell is allowed.
- Benchmark: The performance of a portfolio starting with $100,000 cash, investing in 1000 shares of JPM and holding that position. Includes transaction costs
- There is no limit on leverage.
- Transaction costs: Commission: $9.95, Impact: 0.005.

1 INDICATOR OVERVIEW

In this project, we selected three indicators of Bollinger Bands® (% B), Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI) that includes trend, momentum, and volatility types of technical indicators.

1.1 Bollinger Bands® % (BBP): Volatility

Bollinger bands are a measurement of a stock's volatility. By leveraging the rolling standard deviation—specifically, 2 SD above and below the simple moving average —we can get a sense of the volatility based on when the current stock intersects the bands.

Optimized parameter: % B (BBP)

% B (BBP) = (Price – Lower Band)/ (Upper Band – Lower Band) *100

1.2 Moving Average Convergence Divergence (MACD): Trend/Momentum

The MACD is trend-following and momentum indicator that shows the relationship between two moving averages of a stock's price by subtracting the longer moving average from the shorter one.

Optimized parameter: MACD Histogram

MACD Histogram = MACD Line (12-day EMA - 26-day EMA) - Signal Line (9-day EMA of MACD Line)

1.3 Relative Strength Index (RSI): Momentum

RSI is an popular momentum indicator. RSI oscillates between zero and 100. RSI measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock. RSI can also be used to identify the general trend.

Optimized parameter: RSI

Avg. Gain = Sum of Gains over the past 14 periods / 14

Avg. Loss = Sum of Losses over the past 14 periods / 14

RSI = 100 – (100 / (1+ Avg. Gain / Avg. Loss RS))

2 MANUAL STRATEGY

The various combinations are run to identify a manual strategy that provides positive returns and beats the benchmark. The specific manual strategy is like follows:

Buying Strategy: *[(BBP < 0)* ***OR*** *(RSI < 30)* ***OR*** *(MACD > 1)]*

Selling Strategy: *[(BBP >100)* ***OR*** *(RSI > 70)* ***OR*** *(MACD <-1)]*

BBP Signal:

- Buying position: when the stock falls below the 2 SD band, that is a buying opportunity. % B is less than 0.
- Selling position: when the stock spikes above the 2 SD band and dips back in, that is a selling opportunity. % B is greater than 1 (100%).

RSI Signal:

- Buying position: when the RSI for the stock is below 30, it can indicate a buying opportunity (potentially market is oversold).
- Selling position: when the RSI for the stock is above 70, it can indicate a selling opportunity (potentially market is overbought).

MACD Signal:

- Buying position: The histogram is positive when the MACD line is above its signal line. When the MACD histogram is greater than 1, it can be a potential buying position.
- Selling position: The histogram is negative when the MACD line is below its signal line. When the MACD histogram is less than -1, it can be a potential selling position.

The MACD line oscillates above and below the zero line, which is also known as the centerline. Positive values mean upside momentum is increasing. Negative MACD values means downside momentum is increasing. Threshold of 1 was used for manual strategy in this project for balancing transaction frequency and to capture stronger signal from indicator.

For manual strategy, the three technical indicators are combined using logical connectors (or) to include all signals from three indicators.

Manual Strategy vs. Benchmark (In-Sample)

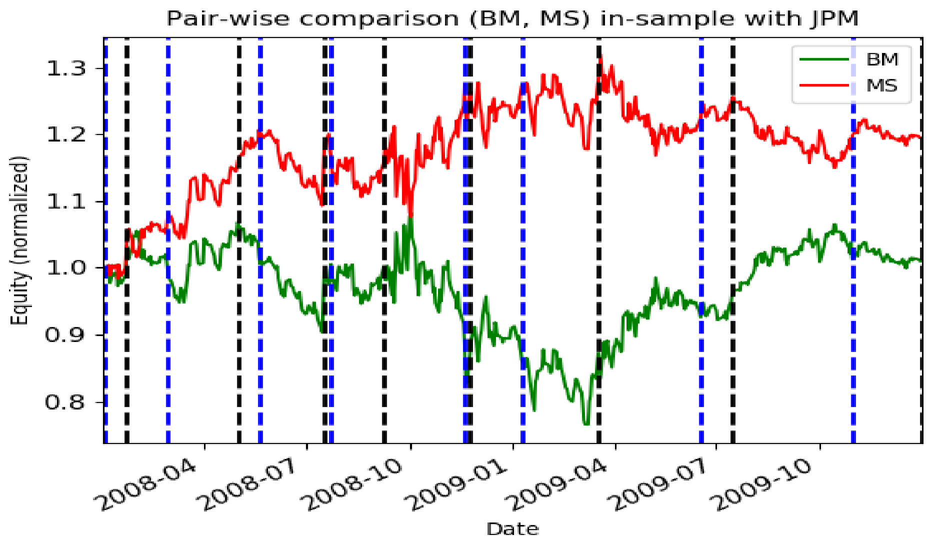

Figure 1: This figure shows performance of Manual Strategy for JPM vs. benchmark for JPM (In-sample)

Manual Strategy vs. Benchmark (Out-of-Sample)

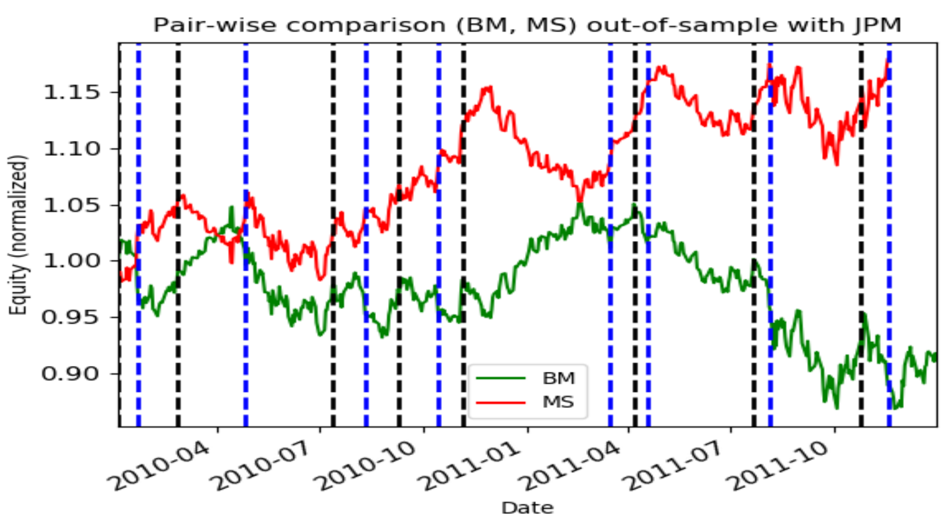

Figure 2: This figure shows performance of Manual Strategy for JPM vs. benchmark for JPM (Out- of-sample)

In above charts, we noticed that the MS provides higher returns and beats the benchmark (BM) for both in-sample and out-of-sample. During in-sample period, overall MS outperforms BM through the period and MS portfolio value is 1.2x higher than BM portfolio value at the last day of period.

In addition, based on below table, in-sample mean of daily returns is 2.8x higher for MS. The cumulative return is 19x higher for MS during in-sample period compared to BS. However standard deviation of daily return for MS is lower than BS during in-sample period. Higher cumulative return and lower standard deviation of daily return indicates that MS from three indicates are working well for JPM during this period.

MS in-sample performance is not guaranteed in out-of-sample data since MS is created using intuition and the indicators selected to beat BS. However, MS also outperforms BM during out-of-sample period and MS final portfolio value 1.3x higher than BM.

Strategy Statistics (BS vs. MS)

	In Sample		**Out of sample**	
Statistics	BS	MS	BS	MS
Cumulative Return	0.0102	0.1942	-0.0853	0.1785
Std of Daily Return	0.0170	0.0136	0.0085	0.0073
Avg. Daily Return	0.00016	0.00045	-0.00014	0.00037
Final Portfolio Value	100,819	119,184	91,273	117,601

3 STRATEGY LEARNERS

3-1 For the policy learning part:

- Initiate an instance of *QLearner* class with conventional parameters such as *num_states=3000, num_actions=3, alpha=0.2, gamma=0.9, rar=0.99, radr=0.999, dyna=0*.

- Select the same three indicators (BBP, MCSD, RSI) used in MS and compute their values for the training data.

  To fill the data at the beginning of training data, window for BBP is 20 and lookback period (delta_days) is set to 30.
- Discretize the values of three indicators: The values of three indicators were discretized with 10 bins, respectively with leveraging *pandas.qcut* and *numpy.digitize*. And each value is combined with a single 10 digit number. The indicators define most of the "state" for the learner. On the top of that, an additional component of state is used to show whether we are currently holding a position long or short or not holding. We added states (Long, Short, Cash) for each state from indicators. As a result, there are 3,000 possible states. (For example, with Short policy the range of states is between 0 to 999 and for Cash, 1000 to 1999.)
- For each day in the training data:

  - Compute the current state (including holding)

  - Compute the reward for the last action: To consider impact, reward is calculated from daily return multiplied by (1- impact) and policy.

  - Query the learner with the current state and reward to get an action except the first day.

  - Based on the action, trade shares are calculated along with current policy, accumulating trades and update a new policy (position).
- Repeat the above loop multiple times until it is converged. The condition for declaring 'converged' is either epochs are reached to 100 or cumulative return stops improving. The cumulative return change is checked with the patience parameter. If it repeats more than the value of patience (10) times, it is declared with "converged" and exit the epoch loop.

3-2 For the policy testing part:

- For each day in the testing data:

  - Compute the current state with the same discretized method and its bins which are calculated during the learning phase.

  - Query the learner with the current state to get an action

  - Based on the action, trade shares are calculated along with current policy, accumulating trades and update a new policy (position).
- Return the resulting trades in a data frame

4. EXPERIMENT 1 (MANUAL STRATEGY / STRATEGY LEARNER)

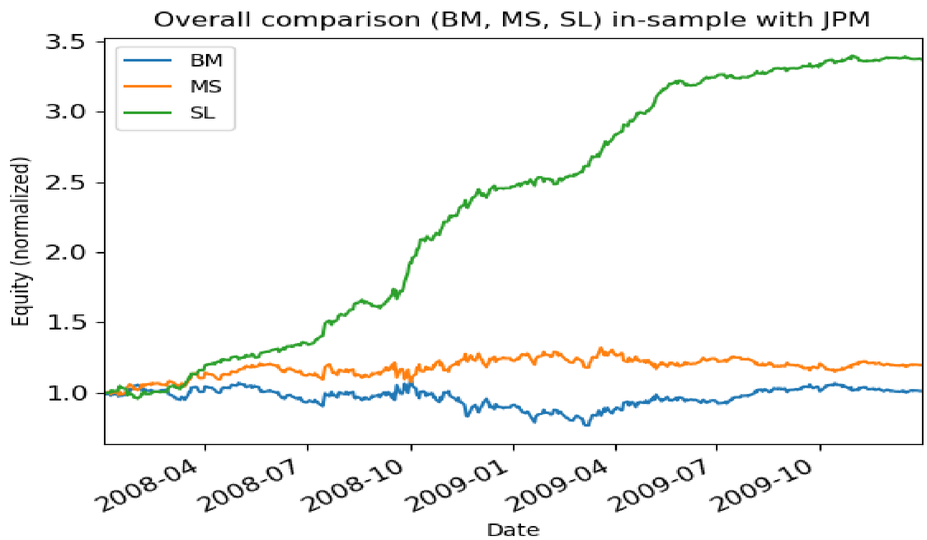

Figure 3: This figure shows performance of BM vs. MS vs. SL for JPM (In-sample)

The above chart is the comparison between benchmark, manual strategy and strategy learner with in-sample data. All experimentation details remain the same (starting cash of 100,000, allowable positions, impact = 0.005, commission = 9.95 etc.) except for test policy. Manual strategy is created by buy/sell strategies using three indicators (BBP, MSCD, RSI) based on our intuition. Strategy Learner is strategy that can learn a trading policy using *Qlearner*.

Experiment 1 shows MS outperforms BM, but SL outperforms MS and BM significantly more. For SL, we would expect this relative high performance every time with in-sample data since SL is designed to get the best performance possible during the in-sample period. However, MS would not repeat because MS is intuition-based strategy. Above chart shows MS is outperforms BM but we cannot guarantee this intuition works well again.

5. EXPERIMENT 2 (STRATEGY LEARNER)

We conducted experiment 2 with our Strategy Learner that shows how changing the value of impact should affect in-sample trading behavior. We traded JPM on the in-sample period (January 1, 2008 to December 31, 2009) with a commission of $0.00. For comparison, three matrices (Cumulative Return, Standard Deviation of Daily Return and # of Trades) are considered.

Impact Change Sensitivity (BS vs. SL)

	Impact = 0		**Impact = 0.005**		**Impact = 0.1**	
Statistics	BS	SL	BS	SL	BS	SL
Cumulative Return	0.012	3.078	0.010	2.333	-0.028	-11.287
Std of Daily Return	0.017	0.008	0.017	0.008	0.018	0.171
# of Trades	2	202	2	219	2	194

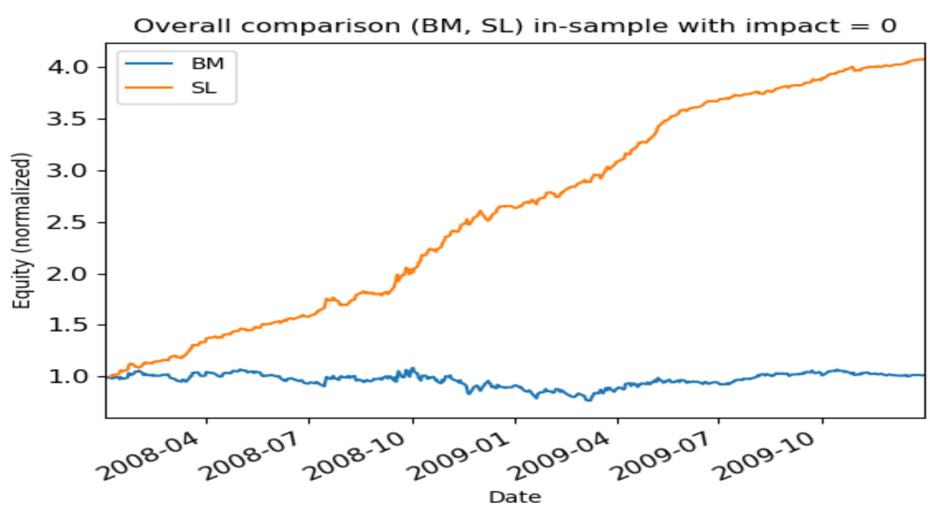

Figure 4: This figure shows performance of BM vs. SL when impact = 0 for JPM (In-sample)

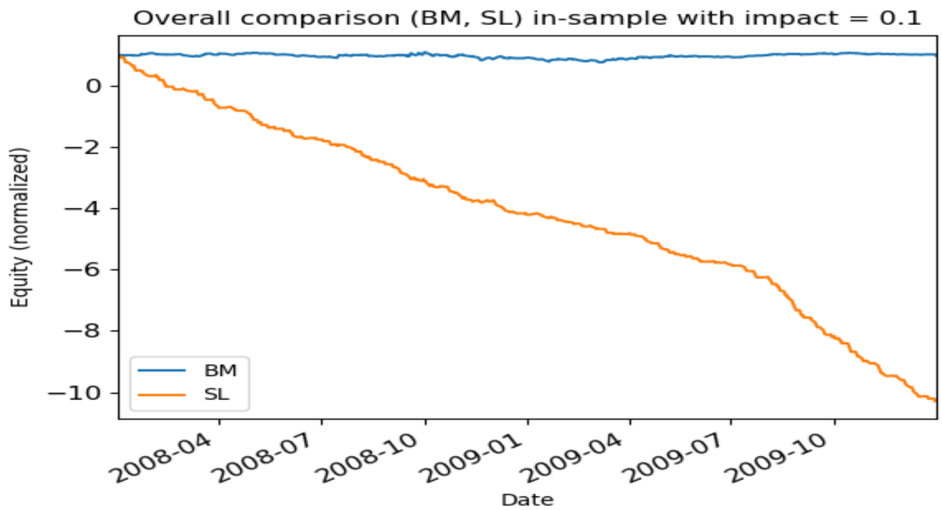

Figure 5: This figure shows performance of BM vs. SL when impact = 0.1 for JPM (In-sample)

First, cumulative return is significantly decreased from 3.078 to -11.287 when we add impact of 0.1 instead of zero. Cumulative return looks very sensitive to impact change. For standard deviation of daily return matric, there is almost no change as impact changes from zero to 0.005 but standard deviation increases from 0.017 to 0.171 when impact increases to 0.1. However, we do not see obvious changes for number of trades as the value of impact increases.