Algorithmic Trading in Python

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Advanced Algorithmic Trading Strategies in the Automotive Industry

Introduction

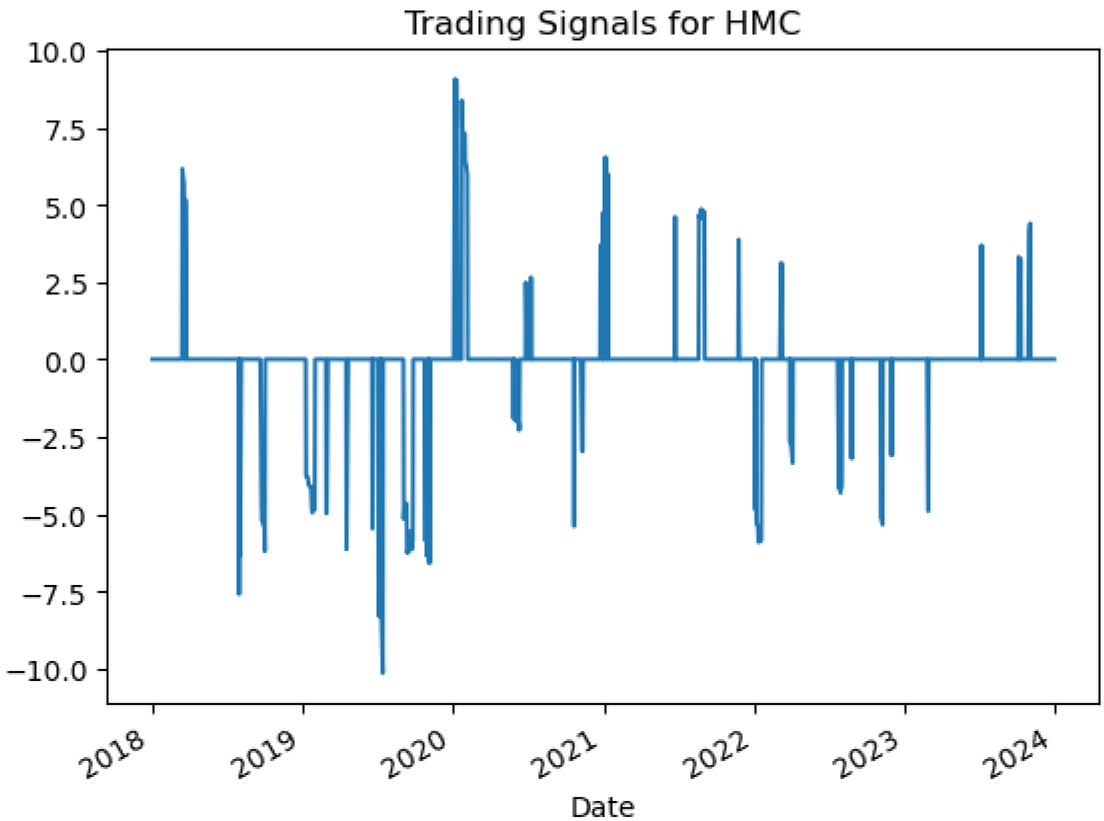
Algorithmic trading leverages advanced statistical and machine learning techniques to develop trading strategies that can outperform traditional buy-and-hold strategies. This paper explores the development, optimization, and backtesting of algorithmic trading strategies for two automotive industry stocks: Honda (HMC) and Toyota (TM). I employ Bayesian optimization to fine-tune technical indicators and use machine learning to predict both the direction and magnitude of stock price movements, combining these predictions into a trading strategy.

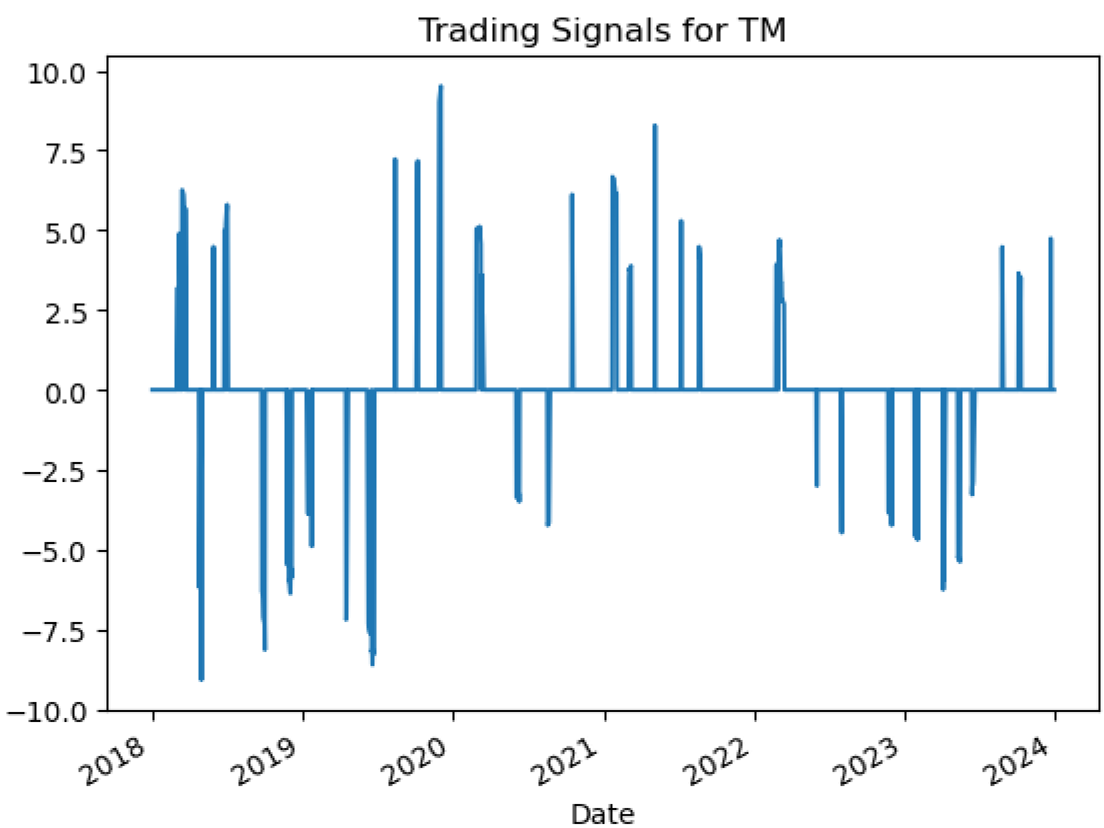
Data Collection

Historical stock price data was collected for Honda and Toyota from January 1, 2018, to January 1, 2024. Additionally, S&P 500 index data was fetched to serve as a benchmark.

Description of Strategy

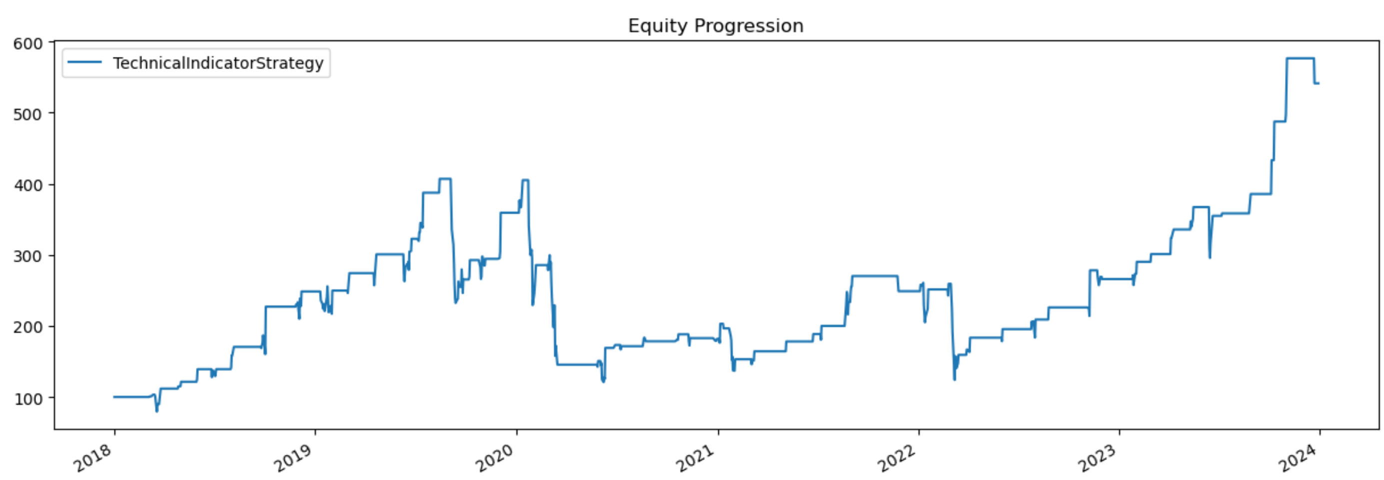
The Technical Indicator Strategy uses Bayesian Optimization to fine-tune Exponential Moving Averages (EMA) and Relative Strength Index (RSI) parameters for trading Honda (HMC) and Toyota (TM). Buy signals are generated when the short-term EMA crosses above the long-term EMA with RSI below 70, while sell signals occur when the short-term EMA crosses below the long-term EMA with RSI above 30. Position sizes are dynamically adjusted based on stock volatility, and trades are executed daily, ensuring alignment with the signals. This strategy aims to maximize returns by capturing short-term trends while managing risk through optimized indicators.

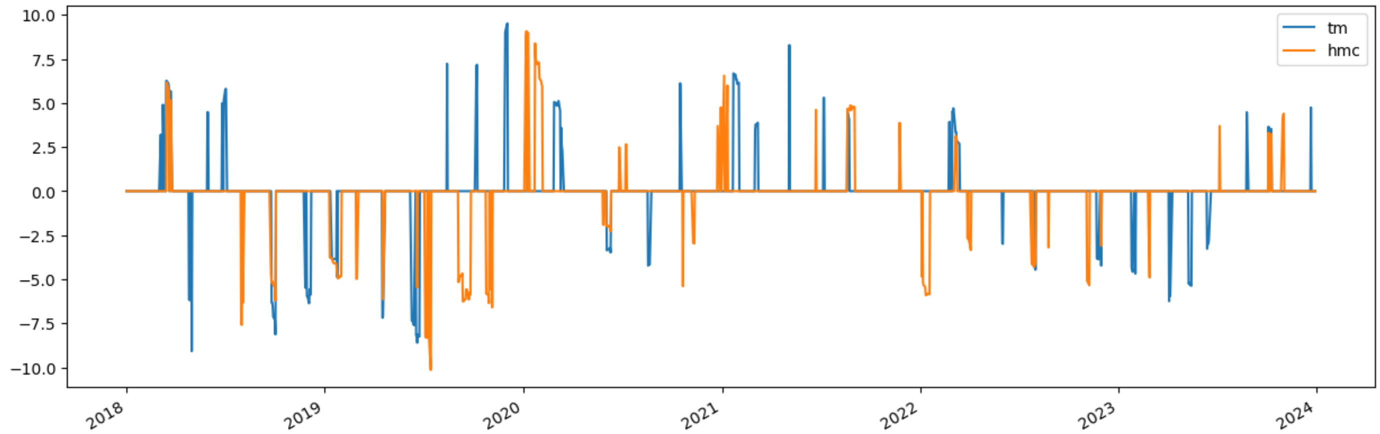





```
Backtest Results:
Stat                 TechnicalIndicatorStrategy
-------------------  ----------------------------
Start                2018-01-01
End                  2023-12-29
Risk-free rate       0.00%

Total Return         441.06%
Daily Sharpe         0.78
Daily Sortino        1.28
CAGR                 32.56%
Max Drawdown         -70.30%
```

```
Calmar Ratio          0.46

MTD                   -6.11%
3m                    40.38%
6m                    52.52%
YTD                   103.55%
1Y                    103.55%
3Y (ann.)             44.63%
5Y (ann.)             16.87%
10Y (ann.)            -
Since Incep. (ann.)   32.56%

Daily Sharpe          0.78
Daily Sortino         1.28
Daily Mean (ann.)     43.97%
Daily Vol (ann.)      56.71%
Daily Skew            1.70
Daily Kurt            36.31
Best Day              41.65%
Worst Day             -31.03%

Monthly Sharpe        0.89
Monthly Sortino       1.27
Monthly Mean (ann.)   41.69%
Monthly Vol (ann.)    47.03%
Monthly Skew          -1.61
Monthly Kurt          4.12
Best Month            28.98%
Worst Month           -47.74%

Yearly Sharpe         0.51
Yearly Sortino        1.29
Yearly Mean           28.49%
Yearly Vol            55.90%
Yearly Skew           -0.13
Yearly Kurt           0.81
Best Year             103.55%
Worst Year            -49.40%

Avg. Drawdown         -13.23%
Avg. Drawdown Days    113.43
Avg. Up Month         10.27%
Avg. Down Month       -8.29%
Win Year %            80.00%
Win 12m %             70.49%
```





Metrics Explanation

Metric	Explanation
Total Return	The strategy generated a total return of 441.06% over the backtesting period, indicating significant portfolio growth.
Daily Sharpe	A value of 0.78 indicates that the strategy achieved a daily risk-adjusted return of 0.78 times the risk-free rate per unit of risk (volatility). A higher Sharpe ratio indicates better risk-adjusted performance.
CAGR	The compound annual growth rate of 32.56% shows the mean annual growth rate of the portfolio over the specified period, representing substantial yearly growth.
Max Drawdown	The maximum drawdown of -70.30% shows the largest peak-to-trough decline during the period, indicating the worst potential loss.

Equity Progression Explanation

The equity progression graph displays the portfolio's value from January 1, 2018, to January 1, 2024, for the Technical Indicator Strategy.

Key Observations:

- **Significant Growth:** Achieved a total return of 441.06%, indicating high profitability.
- **Volatility:** Exhibits sharp fluctuations, notably around 2020 and early 2022.
- **Drawdowns:** Experienced deep drawdowns, especially in 2020, with subsequent recoveries.
- **Resilience:** Shows strong recovery phases, particularly in late 2023.

Security Weights Explanation

The security weights graph shows the allocation to Honda and Toyota stocks over the same period.

Key Observations:

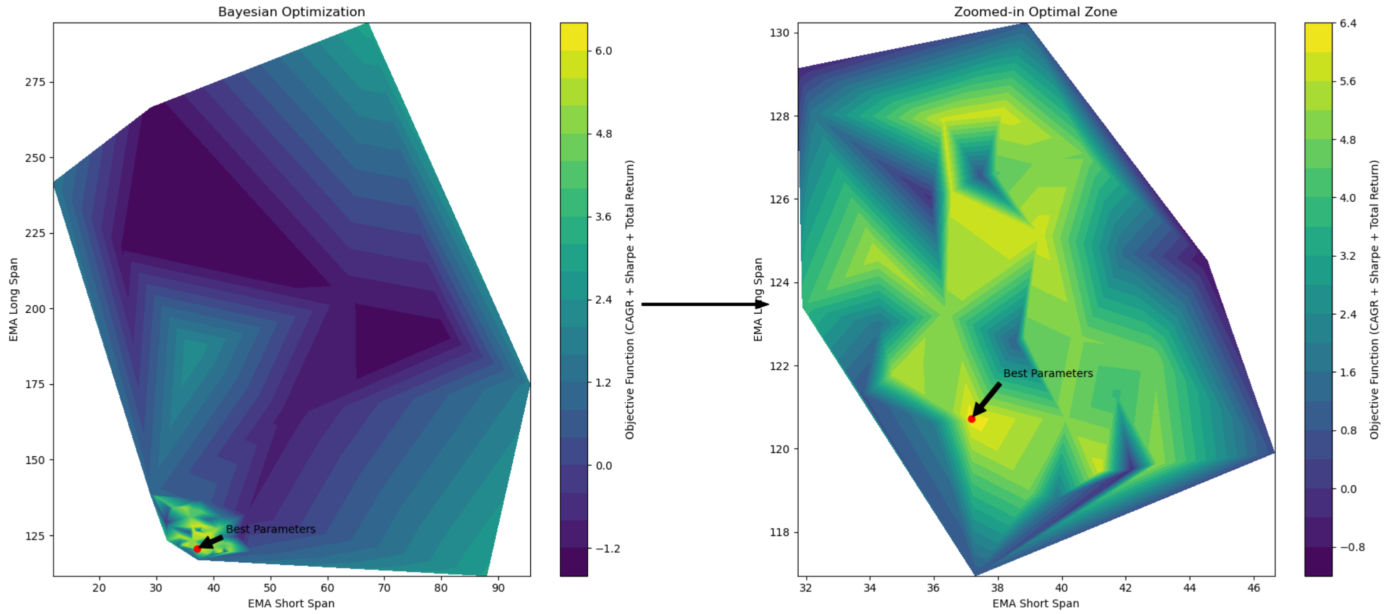
- **Dynamic Adjustments:** Frequent changes in allocation based on market conditions.
- **Significant Rebalancing:** Notable around market downturns and recoveries.
- **Weight Stability:** Periods of stable allocation, especially in the latter half.
- **Performance Contribution:** Differing weight adjustments indicate individual stock contributions to overall performance.

Optimization Bayesian Optimization: Optimizes the EMA short

span, EMA long span, and RSI window to maximize CAGR, Sharpe and Total Return.

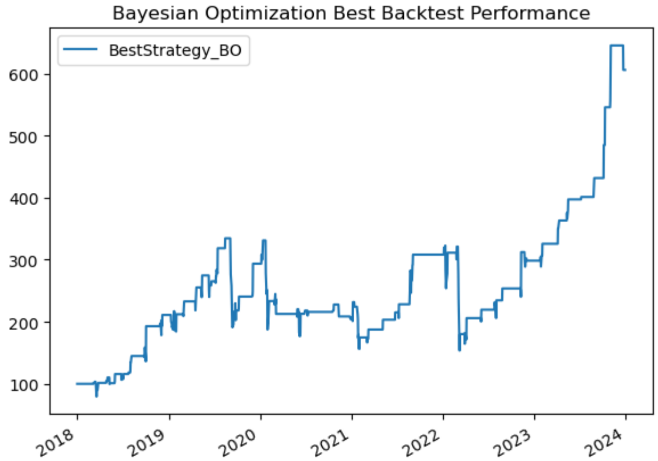
iter	target	ema_lo...	ema_sh...	rsi_wi...
1	1.713	174.9	95.56	23.3
2	-1.275	219.7	24.04	8.9
3	2.866	111.6	87.96	20.03
4	1.537	241.6	11.85	29.25
5	-1.487	266.5	29.11	9.546
6	0.2275	136.7	37.38	18.12
7	2.368	186.4	36.21	20.3
8	5.729	127.9	36.29	14.16
9	-1.425	191.2	80.67	9.992
10	-1.178	202.8	63.32	6.161
11	2.997	294.3	66.92	29.65
12	-0.801	132.2	45.91	7.163
13	-1.029	165.0	53.12	8.57
14	2.921	294.5	67.13	28.67
15	5.507	124.7	34.26	14.3
16	-0.4543	129.1	31.73	10.81
17	0.6293	126.6	37.46	18.23
18	-0.1624	126.0	35.9	10.72
19	3.885	123.4	31.89	14.31
20	5.729	126.2	36.56	14.55
21	5.404	121.8	34.73	14.36
22	1.726	123.0	34.32	16.76
23	0.6967	121.3	33.74	12.15
24	5.854	128.1	38.14	14.92
25	5.066	123.2	36.39	13.26
26	5.854	125.2	39.3	14.49
27	4.746	127.1	40.73	14.59
28	6.253	120.7	37.17	14.57
29	4.676	122.2	42.91	14.95
30	4.855	120.7	40.12	13.05
31	1.825	118.8	39.84	16.69
32	-0.8683	124.5	44.55	11.51
33	4.37	132.8	37.87	13.97
34	4.55	122.7	38.85	15.71
35	0.5217	119.9	46.66	17.02
36	1.516	131.0	41.31	16.53
37	0.8433	116.9	37.3	12.07
38	1.774	128.1	32.21	16.36
39	0.9913	130.2	38.9	12.6
40	5.131	134.2	34.97	14.37
41	4.328	131.1	35.94	15.25
42	1.387	124.7	42.02	16.58
43	0.7246	136.8	37.76	12.63
44	5.059	119.6	43.02	13.25
45	4.033	134.2	32.94	15.52
46	3.776	137.7	29.94	13.43
47	-0.2687	119.5	42.2	10.05
48	0.9315	138.5	29.0	17.9
49	0.8869	134.3	32.29	12.4
50	2.038	120.6	36.01	16.16
51	4.855	122.7	40.62	13.73
52	4.855	126.9	39.27	13.91
53	5.03	120.9	36.52	13.2
54	1.149	122.6	38.55	12.72
55	4.328	126.6	37.94	15.14
56	3.975	133.9	36.32	15.33
57	4.947	122.4	36.82	15.24
58	4.749	119.0	39.03	13.95
59	5.854	119.5	41.22	14.68

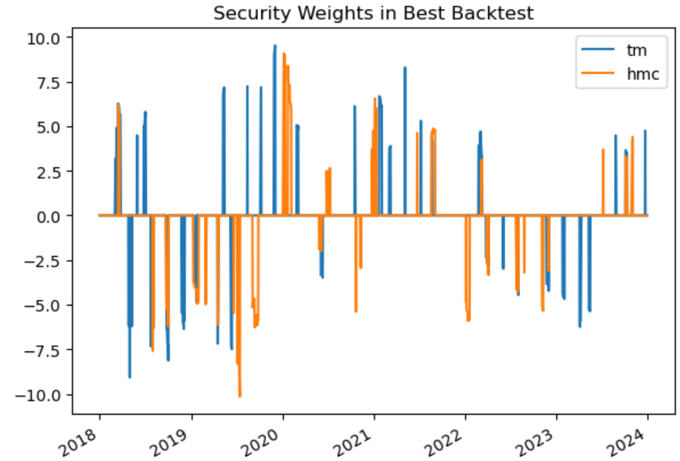
```
| 60          | 3.902       | 121.3       | 41.72       | 15.19       |
==============================================================================
```




```
Best Backtest Results from Bayesian Optimization:
Stat                   BestStrategy_BO
-------------------    -----------------
Start                  2018-01-01
End                    2023-12-29
Risk-free rate         0.00%

Total Return           505.81%
Daily Sharpe           0.84
Daily Sortino          1.42
CAGR                   35.08%
Max Drawdown           -54.08%
Calmar Ratio           0.65

MTD                    -6.11%
3m                     40.38%
6m                     52.52%
YTD                    103.01%
1Y                     103.01%
3Y (ann.)              43.71%
5Y (ann.)              23.52%
10Y (ann.)             -
Since Incep. (ann.)    35.08%

Daily Sharpe           0.84
Daily Sortino          1.42
Daily Mean (ann.)      42.38%
Daily Vol (ann.)       50.22%
Daily Skew             2.01
Daily Kurt             39.31
Best Day               41.65%
Worst Day              -27.17%

Monthly Sharpe         0.96
Monthly Sortino        1.43
Monthly Mean (ann.)    41.29%
Monthly Vol (ann.)     43.19%
Monthly Skew           -1.41
Monthly Kurt           4.30
Best Month             28.98%
Worst Month            -43.71%

Yearly Sharpe          0.62
Yearly Sortino         2.46
```

```
Yearly Mean          31.65%
Yearly Vol           50.92%
Yearly Skew          0.31
Yearly Kurt          -0.31
Best Year            103.01%
Worst Year           -29.36%

Avg. Drawdown        -11.62%
Avg. Drawdown Days   92.88
Avg. Up Month        10.12%
Avg. Down Month      -6.23%
Win Year %           60.00%
Win 12m %            55.74%
```





Key Metrics Explanation After Bayesian Optimization

Key Metrics:

Metric	Explanation
Total Return	The strategy achieved a total return of 505.81% over the backtesting period, indicating substantial growth.
Daily Sharpe	A Sharpe ratio of 0.84 suggests that the strategy achieved a daily risk-adjusted return of 0.84 times the risk-free rate per unit of risk (volatility).
CAGR	The compound annual growth rate of 35.08% indicates the mean annual growth rate of the portfolio over the specified period.
Max Drawdown	A maximum drawdown of -54.08% indicates the largest peak-to-trough decline during the period, reflecting the worst potential loss.

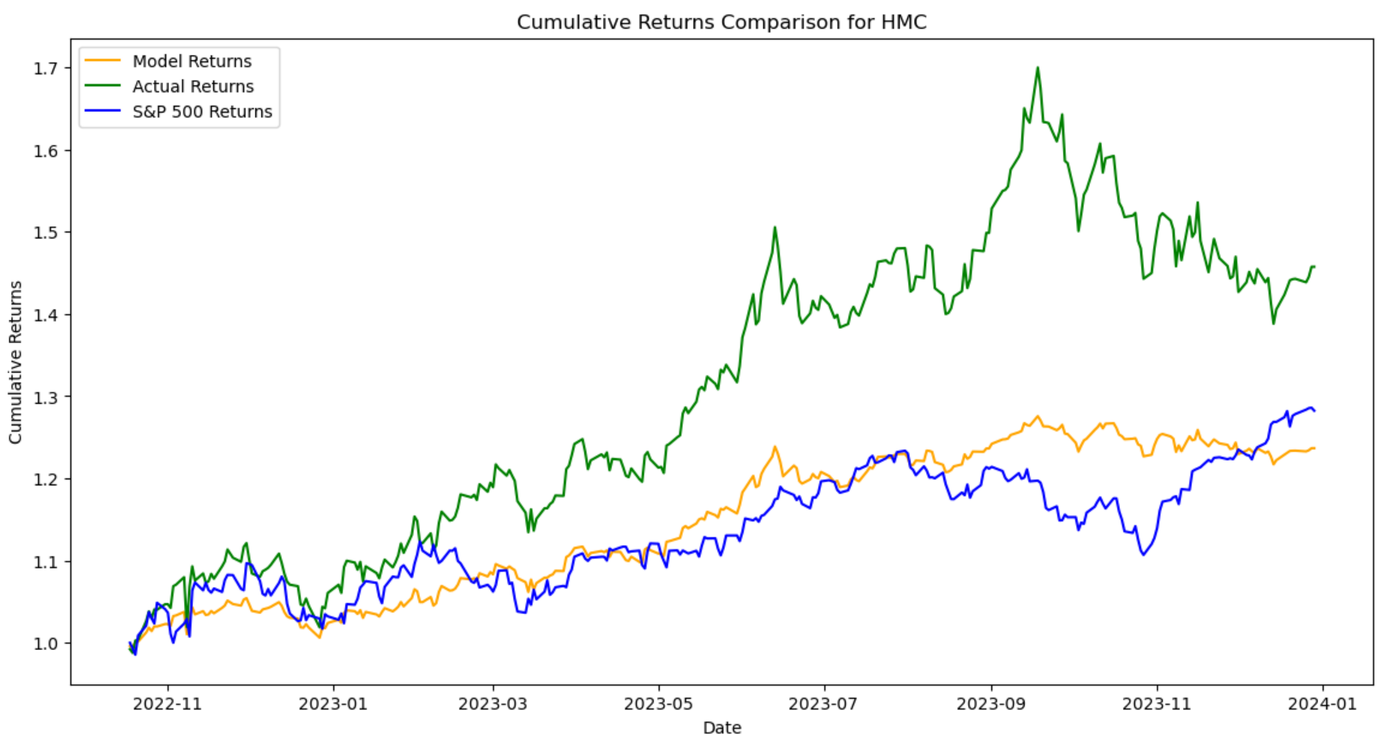
Key Observations:

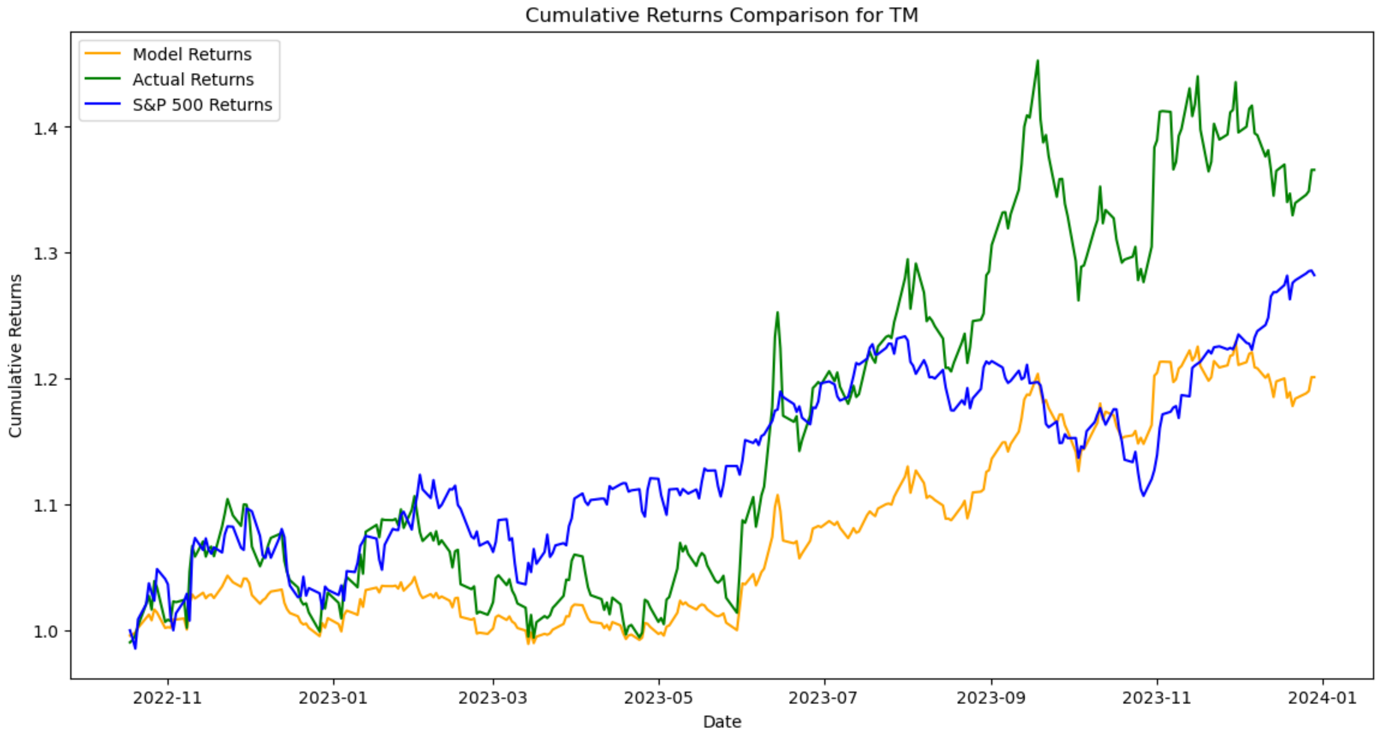
- **Total Return:** The optimized strategy demonstrated impressive growth with a total return of 505.81%.
- **Sharpe Ratio:** With a Sharpe ratio of 0.84, the strategy shows a favorable risk-adjusted return.
- **Annual Growth:** A CAGR of 35.08% highlights the strategy's ability to generate significant annual returns.
- **Drawdown:** The max drawdown of -54.08% indicates considerable risk, underscoring the importance of managing downside risk.

Machine learning

In this code, the labels include not only the direction (up or down) but also the magnitude of the price change.

```
[*********************100%%**********************]  1 of 1 completed
Accuracy for hmc: 0.48
[[101  36]
 [120  45]]
              precision    recall  f1-score   support

           0       0.46      0.74      0.56       137
           1       0.56      0.27      0.37       165

    accuracy                           0.48       302
   macro avg       0.51      0.50      0.47       302
weighted avg       0.51      0.48      0.46       302

Accuracy for tm: 0.52
[[84 50]
 [96 72]]
              precision    recall  f1-score   support

           0       0.47      0.63      0.54       134
           1       0.59      0.43      0.50       168

    accuracy                           0.52       302
   macro avg       0.53      0.53      0.52       302
weighted avg       0.54      0.52      0.51       302
```





Machine Learning Model Performance

Key Metrics

Metric	Explanation
Accuracy (HMC)	The model's accuracy for Honda (HMC) is 48%, indicating that the model correctly predicts the stock movement 48% of the time.
Confusion Matrix (HMC)	The confusion matrix for HMC shows 101 true positives, 36 false positives, 120 false negatives, and 45 true negatives.
Accuracy (TM)	The model's accuracy for Toyota (TM) is 52%, indicating that the model correctly predicts the stock movement 52% of the time.
Confusion Matrix (TM)	The confusion matrix for TM shows 84 true positives, 50 false positives, 96 false negatives, and 72 true negatives.

Observations

- **Accuracy**: The accuracy of the model for both stocks is around 50%, indicating that the model's predictions are slightly better than random guessing.
- **Precision and Recall**: For both stocks, the precision and recall metrics indicate that the model struggles more with predicting upward movements (label 1) accurately compared to downward movements (label 0).
- **Confusion Matrices**: The confusion matrices for both HMC and TM highlight the challenge in correctly predicting upward movements, with a significant number of false negatives.

Visual Analysis

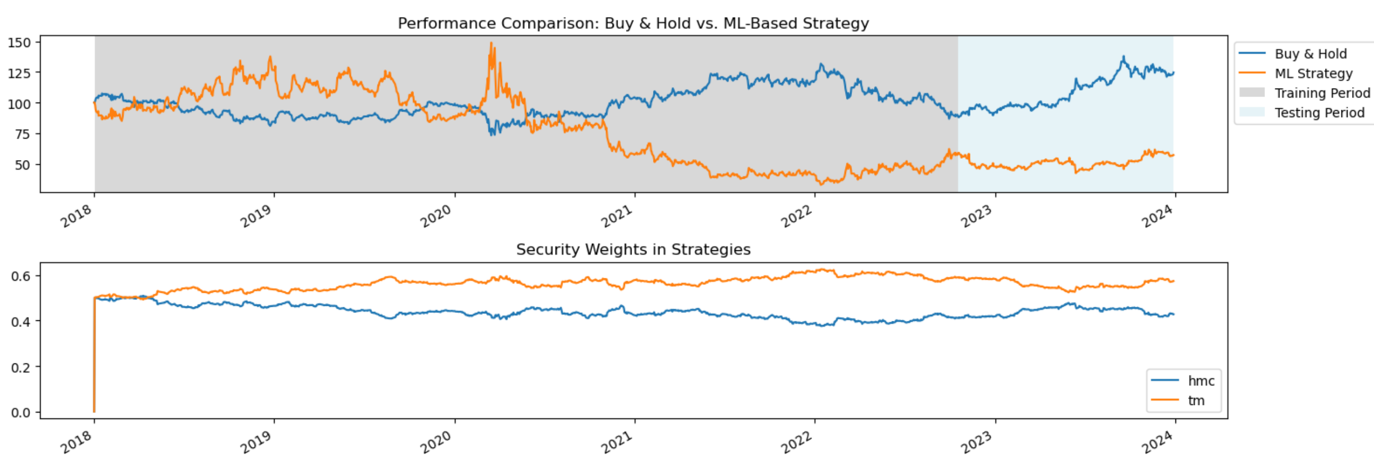
The cumulative returns comparison plots for HMC and TM provide a visual representation of the model's performance:

- **Model Returns vs. Actual Returns**: The model's returns (orange line) are compared to the actual returns (green line) and the S&P 500 returns (blue line). The model's performance is generally aligned with actual returns but tends to underperform compared to the S&P 500 benchmark.

- **Performance Trends**: The plots show periods where the model's predictions closely follow actual stock movements and other times where there are noticeable deviations, particularly during volatile market periods.

These observations suggest that while the machine learning model provides a framework for predicting stock price movements, there is room for improvement in terms of prediction accuracy and handling market volatility.

```
Accuracy for hmc: 0.48
[[101  36]
 [120  45]]
              precision    recall  f1-score   support

           0       0.46      0.74      0.56       137
           1       0.56      0.27      0.37       165

    accuracy                           0.48       302
   macro avg       0.51      0.50      0.47       302
weighted avg       0.51      0.48      0.46       302

Accuracy for tm: 0.52
[[84 50]
 [96 72]]
              precision    recall  f1-score   support

           0       0.47      0.63      0.54       134
           1       0.59      0.43      0.50       168

    accuracy                           0.52       302
   macro avg       0.53      0.53      0.52       302
weighted avg       0.54      0.52      0.51       302

Accuracy for tm: 0.52
[[84 50]
 [96 72]]
              precision    recall  f1-score   support

           0       0.47      0.63      0.54       134
           1       0.59      0.43      0.50       168

    accuracy                           0.52       302
   macro avg       0.53      0.53      0.52       302
weighted avg       0.54      0.52      0.51       302
```




```
Stat                    Buy & Hold     ML Strategy
-------------------     ------------   -------------
Start                   2018-01-01     2018-01-01
```

```
End                     2023-12-29    2023-12-29
Risk-free rate          0.00%         0.00%

Total Return            24.67%        -42.96%
Daily Sharpe            0.28          0.01
Daily Sortino           0.46          0.01
CAGR                    3.75%         -8.95%
Max Drawdown            -34.26%       -78.10%
Calmar Ratio            0.11          -0.11

MTD                     -1.63%        -4.23%
3m                      -2.57%        8.83%
6m                      9.45%         27.24%
YTD                     36.60%        19.17%
1Y                      36.01%        18.66%
3Y (ann.)               6.28%         -0.45%
5Y (ann.)               8.14%         -14.76%
10Y (ann.)              -             -
Since Incep. (ann.)     3.75%         -8.95%

Daily Sharpe            0.28          0.01
Daily Sortino           0.46          0.01
Daily Mean (ann.)       6.21%         0.29%
Daily Vol (ann.)        22.49%        43.88%
Daily Skew              0.01          -0.06
Daily Kurt              3.76          4.51
Best Day                7.66%         17.58%
Worst Day               -8.77%        -15.65%

Monthly Sharpe          0.25          -0.05
Monthly Sortino         0.46          -0.08
Monthly Mean (ann.)     4.64%         -1.61%
Monthly Vol (ann.)      18.66%        35.39%
Monthly Skew            -0.07         0.33
Monthly Kurt            -0.37         0.84
Best Month              12.66%        35.93%
Worst Month             -14.57%       -18.80%

Yearly Sharpe           0.46          -0.42
Yearly Sortino          0.98          -0.67
Yearly Mean             9.92%         -11.55%
Yearly Vol              21.34%        27.22%
Yearly Skew             -0.64         0.57
Yearly Kurt             1.74          -3.25
Best Year               36.60%        19.17%
Worst Year              -22.53%       -35.32%

Avg. Drawdown           -8.06%        -13.77%
Avg. Drawdown Days      153.07        144.13
Avg. Up Month           5.01%         7.78%
Avg. Down Month         -4.11%        -8.74%
Win Year %              80.00%        40.00%
Win 12m %               54.10%        45.90%
```

Metrics Explanation

Metric	Explanation
Total Return	The Buy & Hold strategy yielded a total return of 24.67%, while the ML Strategy resulted in a -42.96% total return. This indicates that the Buy & Hold strategy was significantly more profitable.
Daily Sharpe	The Buy & Hold strategy had a daily Sharpe ratio of 0.28, indicating a modest risk-adjusted return. The ML Strategy had a near-zero Sharpe ratio, suggesting it did not provide meaningful risk-adjusted returns.
Max Drawdown	The maximum drawdown for the Buy & Hold strategy was -34.26%, showing the largest peak-to-trough decline. The ML Strategy experienced a severe drawdown of -78.10%, indicating a high level of risk.

CAGR	The compound annual growth rate for the Buy & Hold strategy was 3.75%, reflecting steady growth. The ML Strategy, however, had a negative CAGR of -8.95%, indicating a decline in portfolio value over the period.

These metrics highlight that the Buy & Hold strategy outperformed the ML-based strategy both in terms of returns and risk-adjusted performance. The ML Strategy's higher volatility and drawdowns suggest it requires further refinement to be viable for investment purposes.

Conclusion

This paper explored the development and backtesting of an algorithmic trading strategy for automotive industry stocks, specifically Honda (HMC) and Toyota (TM). By employing Bayesian optimization and machine learning techniques, aimed to predict stock price movements and combine these predictions into a profitable trading strategy. Despite the sophisticated approach, the ML-based strategy underperformed compared to the traditional Buy & Hold strategy, yielding lower returns and higher volatility.

Future work could involve refining the machine learning model, incorporating additional features, and exploring more advanced techniques to improve predictive accuracy and overall strategy performance.

In conclusion, while algorithmic trading holds promise for achieving superior returns, this study underscores the importance of thorough backtesting, continuous optimization, and careful consideration of risk management. The insights gained from this research provide a foundation for further exploration and enhancement of algorithmic trading strategies.

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