Algorithmic Trading Based on Trading Signals

Group 3

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Part 2: Tradings Based on Individual Technical Indicators

Part 3: Model Performance

Part 4: Current Findings and Future Plan

Assumptions:

- 1. Algorithmic Trading Based on Technical Analysis is practicable.
- 2. Algorithmic Trading Model will perform better on large cap stocks.
- 3. Algorithmic Trading Model will perform the worst on Cryptocurrencies and some meme stocks.
- 4. The more Trading Signals we use in our model, the more accurate or better performance our model will be/get.

Data Collection and Time Frame

Historical Stock and Cryptocurrency Data:

Yahoo Finance Library

Historical Stock and Cryptocurrency Technical Indicators Data:

Stockstats Library

Training Time Frame:

01/01/2016 - 12/31/2019

Testing Time Frame:

01/01/2020 - 04/30/2021

Machine Learning Libraries/Models

Scikit Learn - Random Forest Classifier

Scikit Learn - Naive Bayes Gaussian NB Classifier

Other Models we tried but didn't put in this presentation:

Gradient Boosting Classifier

CatBoost Classifier

CatBoost Regressor

Trading based on Individual Signals

\$ETH-USA -- Ethereum, Market Cap: \$446.33B, Cryptocurrency

\$MRO -- Marathon Oil, Market Cap: \$9.18B, Mid Cap

\$EXPR -- Express, Inc., Market Cap: \$198.11M, Small Cap

\$TSLA -- Tesla, Inc., Market Cap: \$605.97B, Large Cap

Technical Indicators and Trading Strategy

Relative Strength Index (RSI)

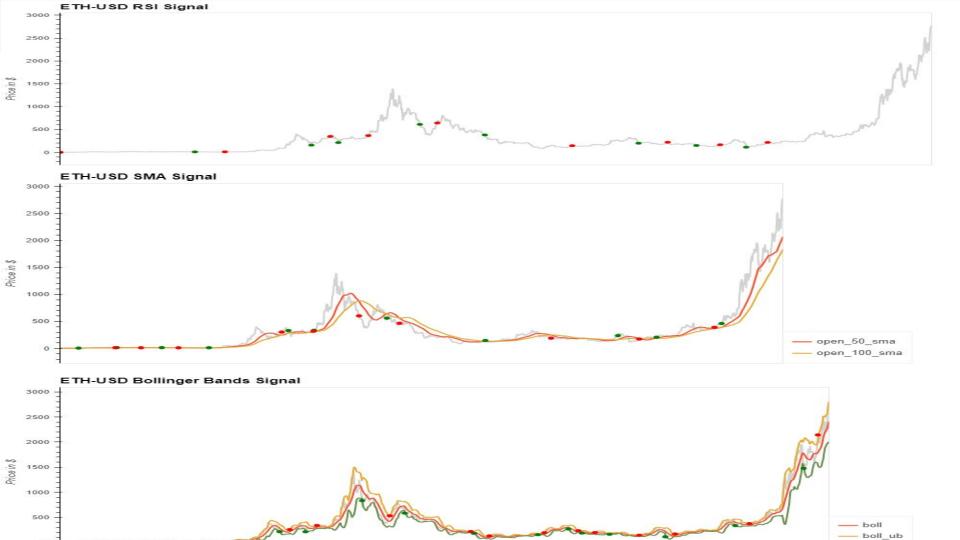
Buy when RSI < 30, Sell when RSI > 70.

Simple Moving Average(SMA)

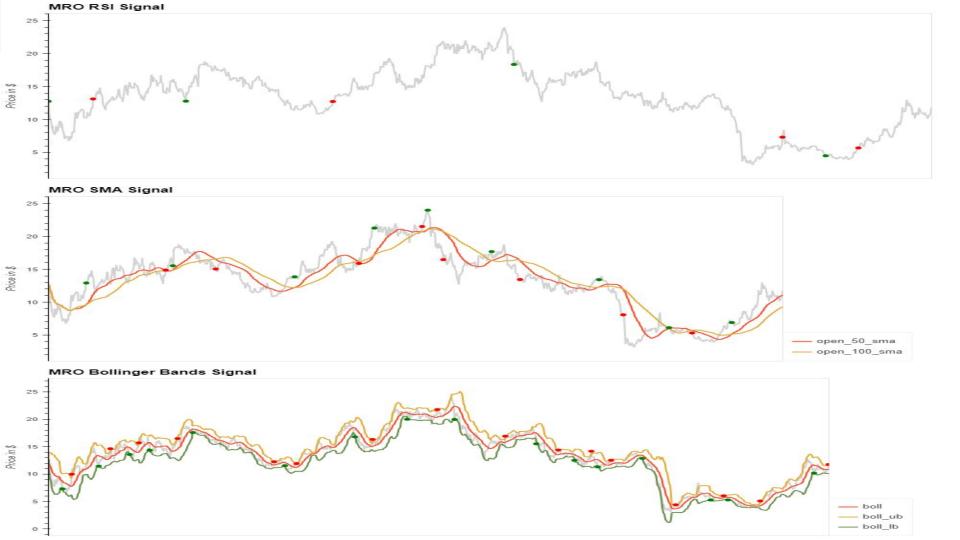
Buy when SMA50 Cross SMA100 from below, Sell when Cross from above.

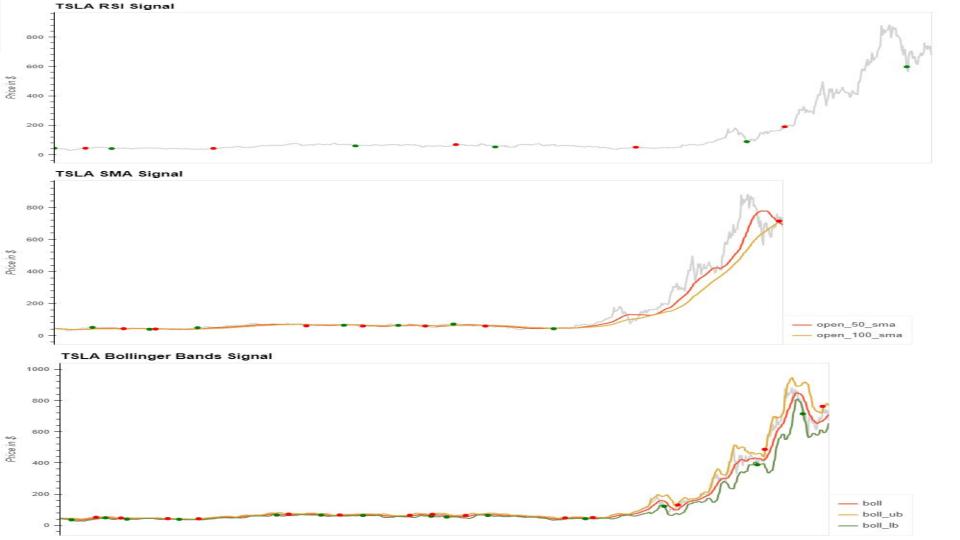
Bollinger Bands(BOLL)

Buy when Close < Bollinger Lower Band, Sell when Close > Bollinger Upper Band.









Training and Testing Data

```
# Add predicted results to DataFrame
ETH_nb_results = pd.DataFrame()

ETH_nb_results[ETH_x_var_list] = ETH_X_test[ETH_x_var_list]

ETH_nb_results['actual_value'] = ETH_results['actual_value']

ETH_nb_results['prediction'] = ETH_nb_model.predict(ETH_nb_test_X)

ETH_nb_results['daily_return'] = ETH_signals[['daily_return']]

ETH_nb_results.head()
```

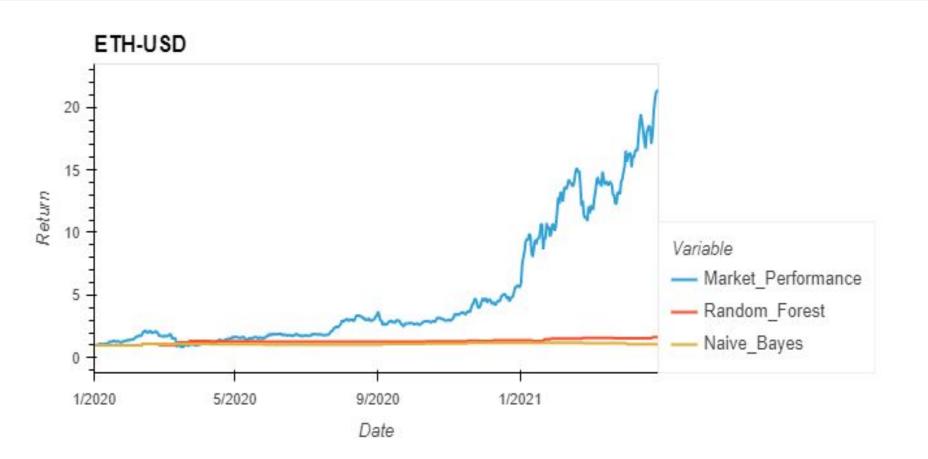
Date	vwap_signal	rsi_signal	sma_Entry/Exit	bollinger_signal	actual_value	prediction	daily_return
	e						
2020-01-0	2 0.0	0.0	0.0	0.0	1.0	0.0	0.028518
2020-01-0	3 0.0	0.0	0.0	0.0	1.0	0.0	0.029633
2020-01-0	6 0.0	0.0	0.0	0.0	1.0	0.0	0.019255
2020-01-0	7 0.0	0.0	0.0	0.0	1.0	0.0	0.038801
2020-01-0	8 0.0	0.0	0.0	0.0	1.0	0.0	0.049205

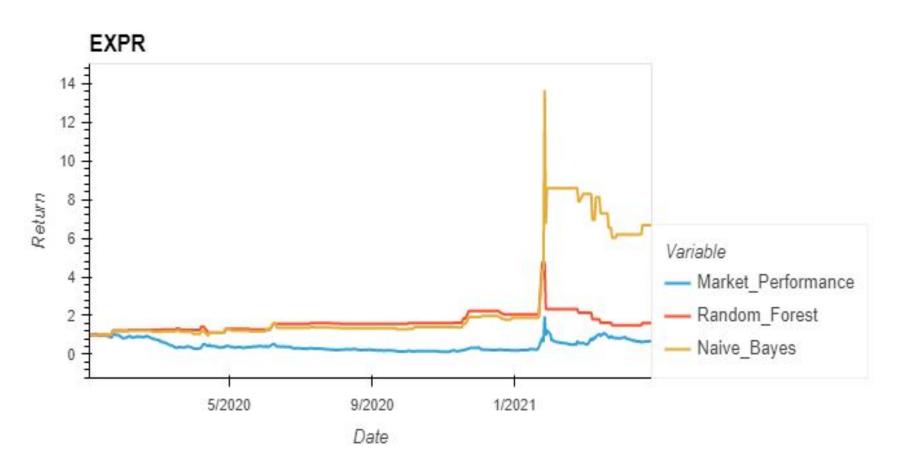
Model Performance vs Market Performance

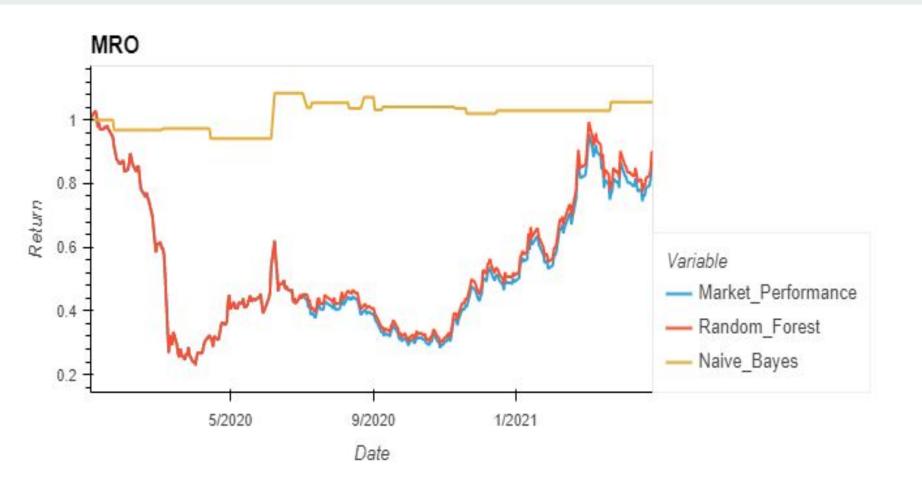
Market Performance

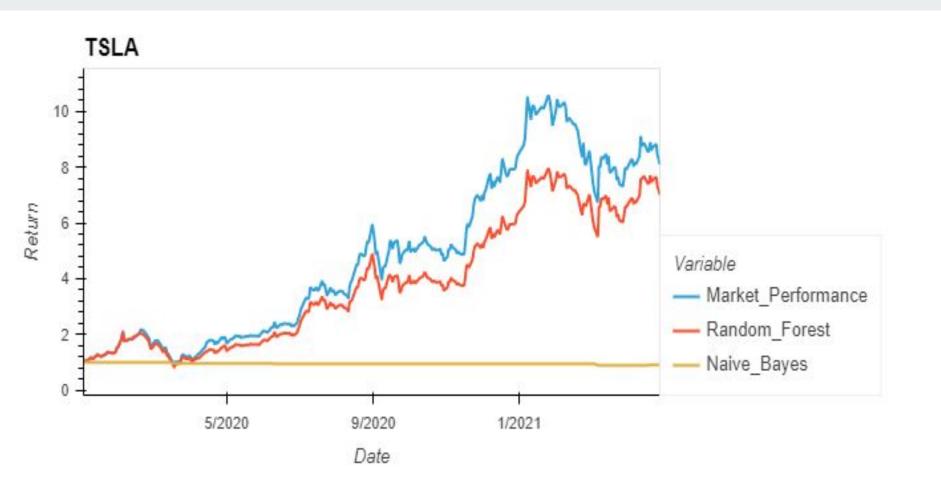
Random Forest Classifier Model Performance

Naive Bayes Classifier Model Performance









Current Findings

- 1. Accuracy Scores for both models are low, the reason could be because we used too few technical trading indicators and the trading indicators don't trigger buy/sell signals very often. It caused our performance to be very similar to market performance or 'HODL'. On the other hand, we added one more trading signal(VWAP volume weighted average price, window = 3) into our model after we produced the charts in this presentation. But we did not see a significant increase in our model accuracy or performance.
- 2. The larger cap the Ticker is, the more like market performance we will get.
- 3. Overall, Naive Bayes worked better in a flat or a downtrend market, for a uptrend market, we'd be better off if we just HODL.

Next Steps

- 1. Perfect our model by adding/removing/adjusting Technical Indicators, adjusting our triggers of the signals, balancing our training data and so forth.
- 2. Create a Ticker pool from different market sections (Industries, Market Caps, Index).
- 3. Add Fundamental Indicators to screen out overvalued(TBD) Tickers.
- 4. Build a trading bot to execute our trading strategy.
- 5. Hopefully it doesn't yolo at the peak of some meme stocks or cryptocurrencies.

Questions?