

Bitcoin Signal Report

From Twitter API

Date Generated: 2021-08-13

0-day moving average used on signals

Purpose and Method

Overview:

Cryptocurrency prices are highly dependent on sentiment. This report explores whether signals from the source API can capture sentiment accurately enough to predict price.

Price of the specified coin is paired with metrics scraped from that time to see if there is correlation. A lag function is also applied to see if the metric is correlated to prices in the future, testing to see if signals can predict future prices.

Findings regarding each signal tested can be found below, including a simple backtest to see if a trading strategy reliant on the signal could be profitable.

Definitions and assumptions:

Predictive power is defined as correlation > 0.6 and p-value < 0.05 .

Hit rate measures how often the signal and price move in the same direction.

Strong signals have predictive power and hit rates above 0.5 for at least 50% of lag days tested.

Report Highlights

Signal 1: Retweet_count

- Not strong signal
- No days of lag have predictive power
- 0.586 is the highest hit rate at 9 days of lag

Signal 2: Favorite_count

- Not strong signal
- No days of lag have predictive power
- 0.564 is the highest hit rate at 3 days of lag

Signal 3: Account_followers

- Not strong signal
 - No days of lag have predictive power
 - 0.519 is the highest hit rate at 7 days of lag
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Retweet_count

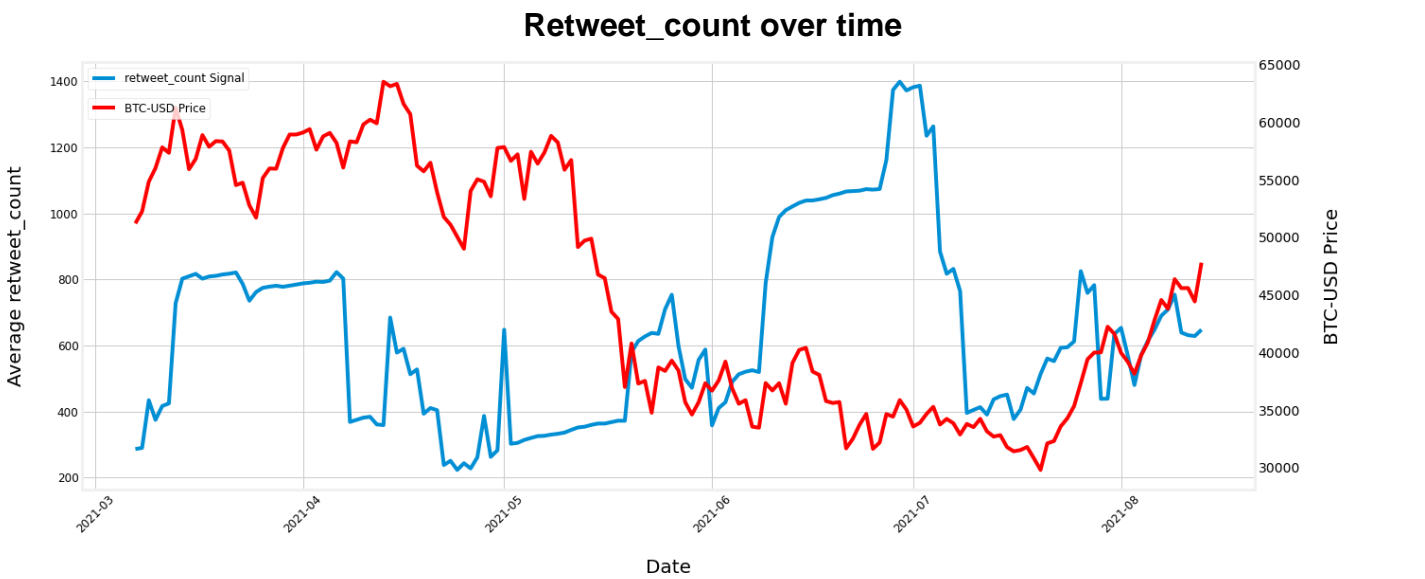


Figure 1; this figure plots signal against price over time.

Correlations With Retweet_count

Lag_Days	Hit_Rate	Pearson	Pearson_p-value	Pearson_Log	Spearman	Spearman_p-value	Spearman_Log
3 days	0.558	-0.312	0.0	-0.319	-0.265	0.001	-0.265
4 days	0.535	-0.314	0.0	-0.323	-0.276	0.001	-0.276
1 days	0.513	-0.319	0.0	-0.325	-0.264	0.001	-0.264
0 days	0.497	-0.319	0.0	-0.325	-0.258	0.001	-0.258
2 days	0.478	-0.319	0.0	-0.324	-0.27	0.001	-0.27

Figure 2; this figure shows the top five lag days with highest hit rates and corresponding correlations.

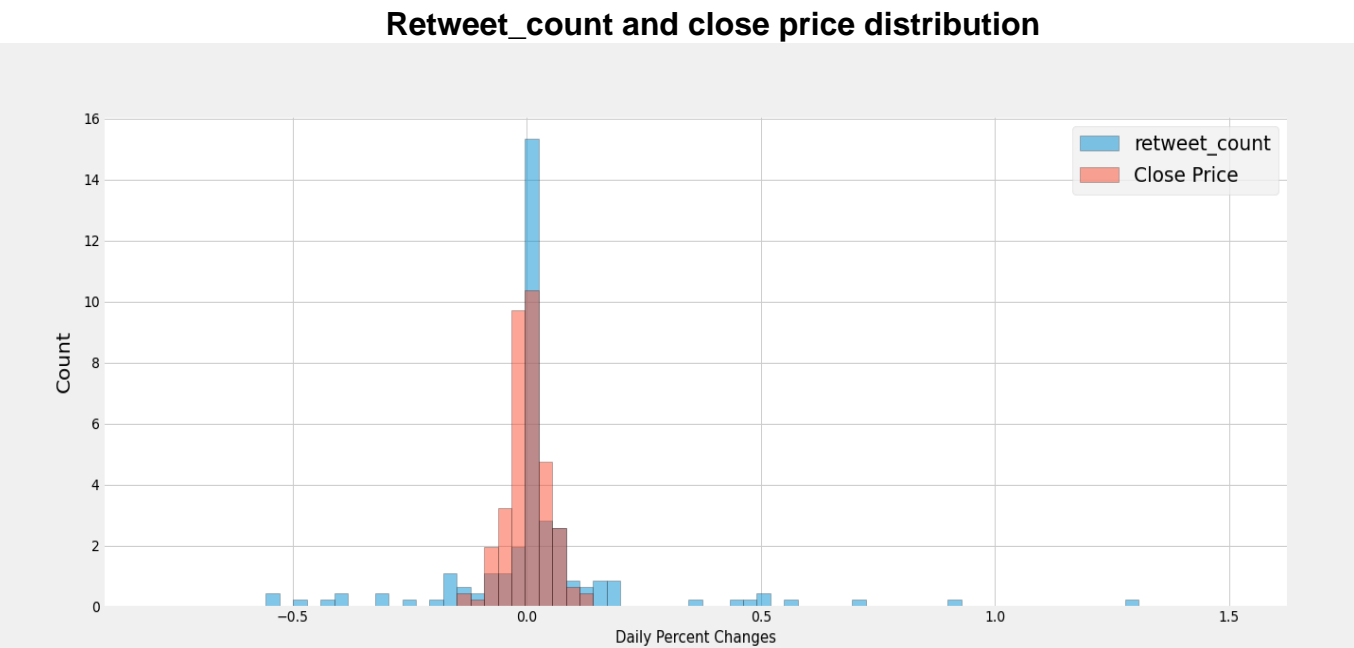


Figure 3; this figure shows the distribution of daily changes for price and signal.

Backtesting Correlation Based Strategy

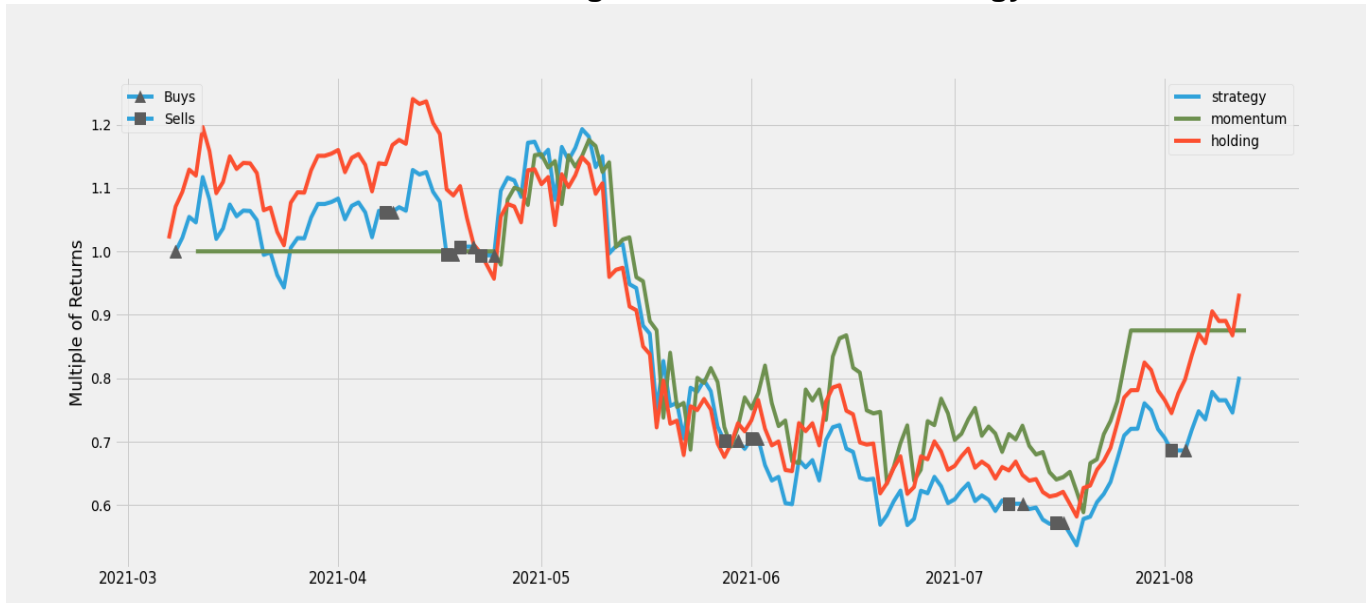


Figure 3; this figure shows the results of a strategy that uses retweet_count signal correlations

Lag: 3 days | Window: 3 days | Fees: 5.0%

- Buy triggers were executed when the signal rose 0.3517% plus -0.5 scaled standard deviations in a window of 3 days.
- Sell triggers were executed when the signal fell 0.3517% plus 0 scaled standard deviations in a window of 3 days.

Retweet_count strategy: -21.9% | Holding: -6.66% | Momentum Strategy: -12.4%

- This strategy did not beat the benchmark. Net return was -21.9%. HODLing bitcoin would net -6.66%.
- This strategy did not beat a simple momentum strategy. Net return was -21.9%. A momentum strategy would net -12.4%.
- This strategy has a Sharpe Ratio of -5.20

Note: Transaction fees vary based on exchange

Favorite_count

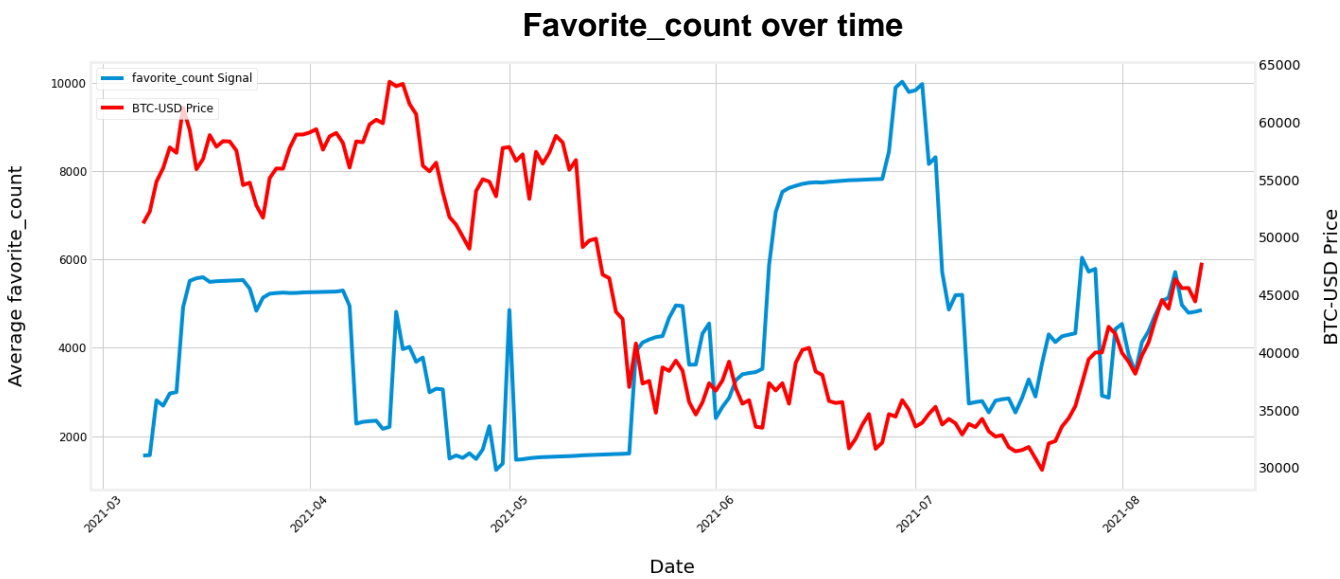


Figure 4; this figure plots signal against price over time.

Correlations With Favorite_count

Lag_Days	Hit_Rate	Pearson	Pearson_p-value	Pearson_Log	Spearman	Spearman_p-value	Spearman_Log
3 days	0.564	-0.334	0.0	-0.338	-0.247	0.002	-0.247
0 days	0.535	-0.352	0.0	-0.357	-0.25	0.002	-0.25
1 days	0.519	-0.348	0.0	-0.353	-0.253	0.001	-0.253
4 days	0.503	-0.334	0.0	-0.341	-0.254	0.001	-0.254
2 days	0.459	-0.344	0.0	-0.348	-0.256	0.001	-0.256

Figure 5; this figure shows the top five lag days with highest hit rates and corresponding correlations.

Favorite_count and close price distribution

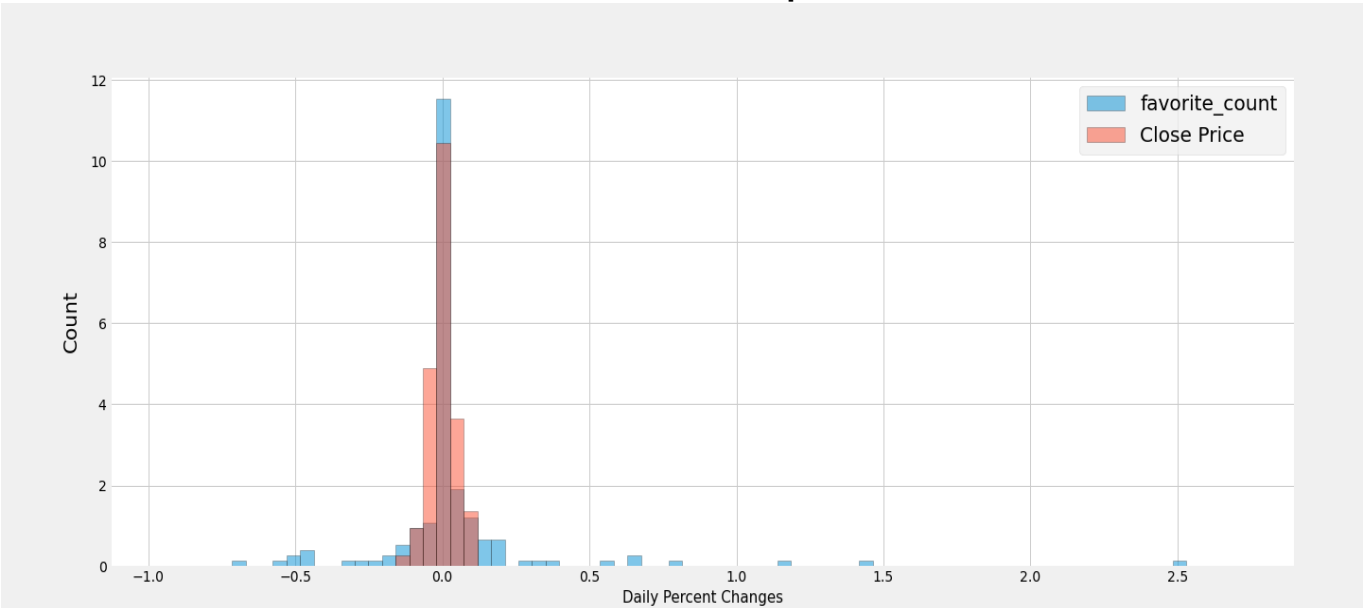


Figure 6; this figure shows the distribution of daily changes for price and signal.

Backtesting Correlation Based Strategy

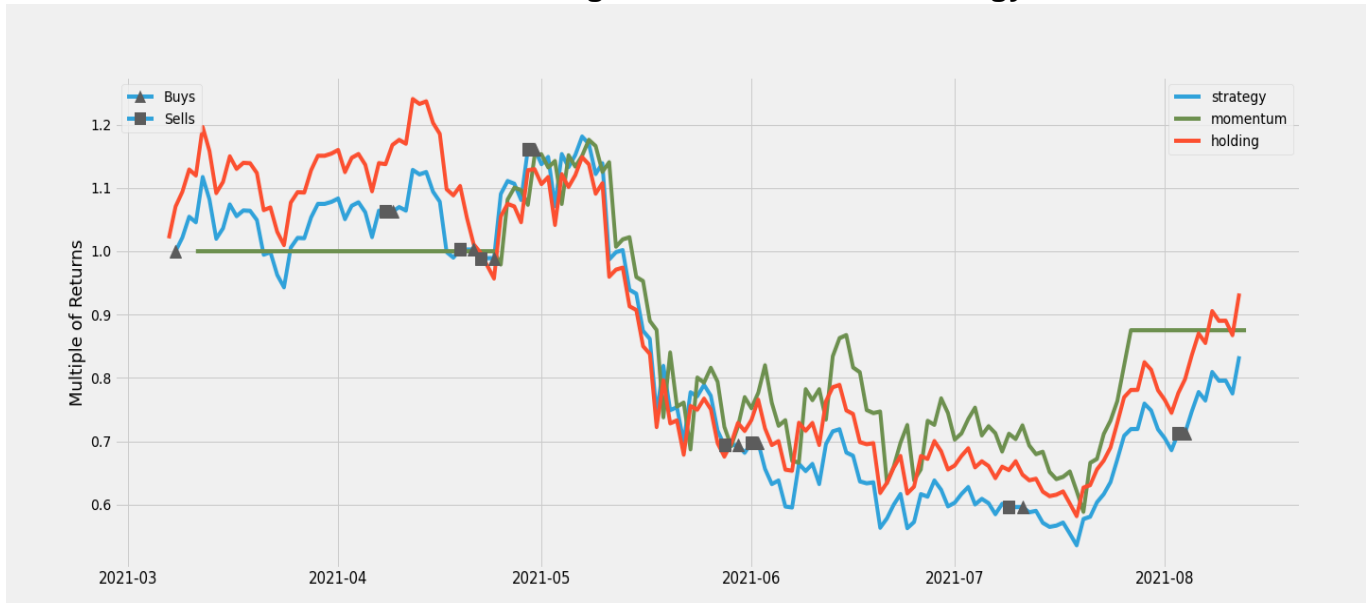


Figure 6; this figure shows the results of a strategy that uses `favorite_count` signal correlations

Lag: 3 days | Window: 3 days | Fees: 5.0%

- Buy triggers were executed when the signal rose 0.3539% plus -0.5 scaled standard deviations in a window of 3 days.
- Sell triggers were executed when the signal fell 0.3539% plus 0 scaled standard deviations in a window of 3 days.

Favorite_count strategy: -25.1% | Holding: -6.66% | Momentum Strategy: -12.4%

- This strategy did not beat the benchmark. Net return was -25.1%. HODLing bitcoin would net -6.66%.
- This strategy did not beat a simple momentum strategy. Net return was -25.1%. A momentum strategy would net -12.4%.
- This strategy has a Sharpe Ratio of -5.99

Note: Transaction fees vary based on exchange

Account_followers

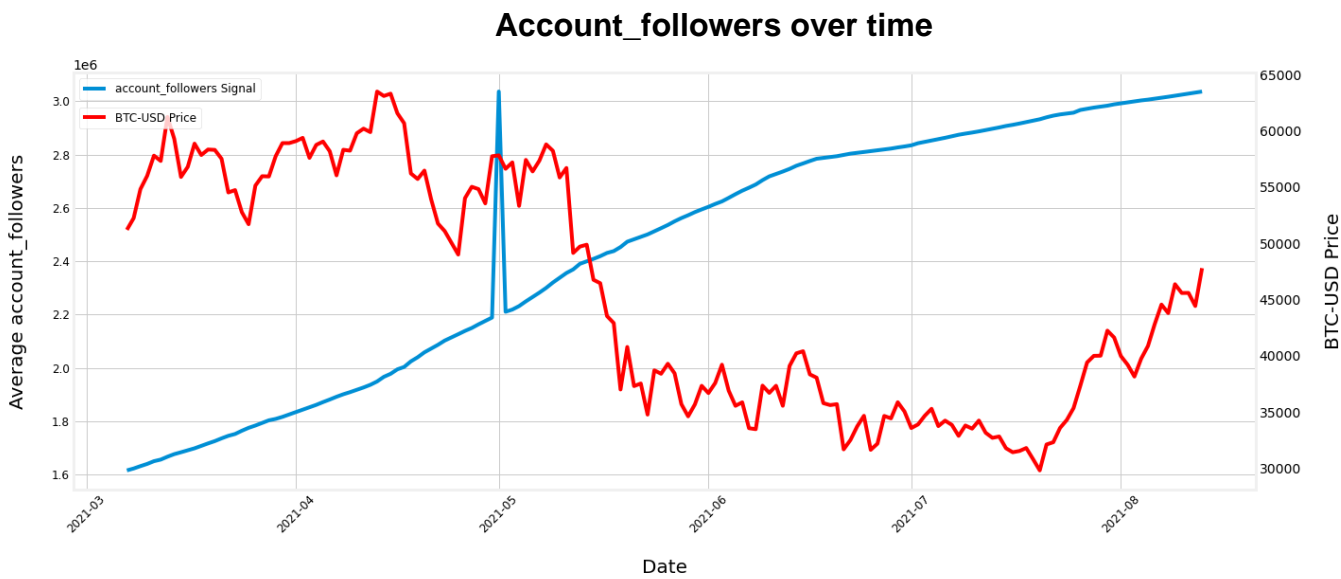


Figure 7; this figure plots signal against price over time.

Correlations With Account_followers

Lag_Days	Hit_Rate	Pearson	Pearson_p-value	Pearson_Log	Spearman	Spearman_p-value	Spearman_Log
1 days	0.519	-0.848	0.0	-0.836	-0.73	0.0	-0.73
3 days	0.513	-0.847	0.0	-0.836	-0.728	0.0	-0.728
0 days	0.509	-0.846	0.0	-0.834	-0.73	0.0	-0.73
4 days	0.503	-0.847	0.0	-0.835	-0.728	0.0	-0.728
2 days	0.503	-0.852	0.0	-0.84	-0.737	0.0	-0.737

Figure 8; this figure shows the top five lag days with highest hit rates and corresponding correlations.

Account_followers and close price distribution

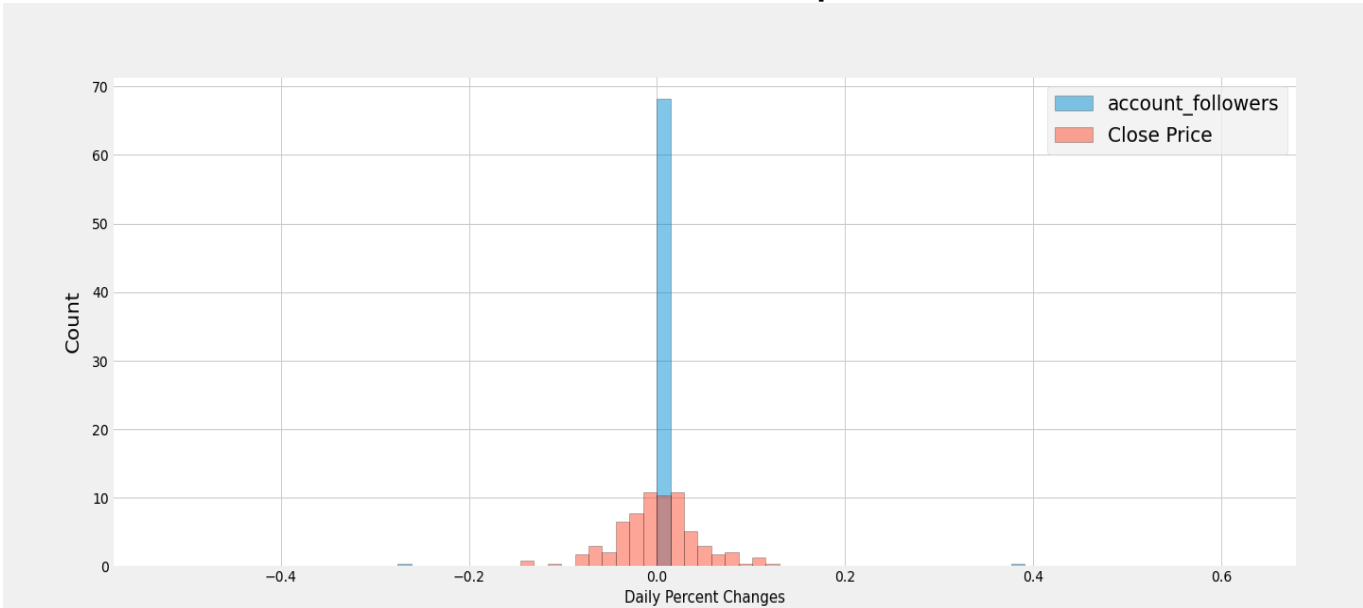


Figure 9; this figure shows the distribution of daily changes for price and signal.

Backtesting Correlation Based Strategy

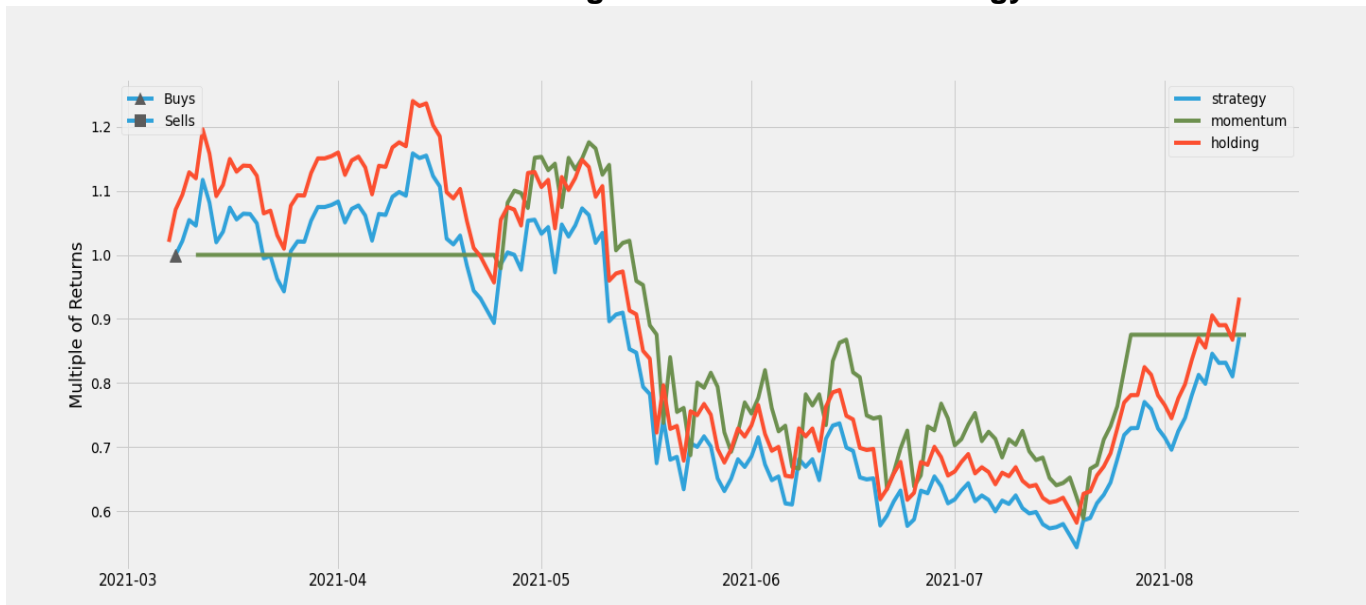


Figure 9; this figure shows the results of a strategy that uses account_followers signal correlations

Lag: 1 days | Window: 3 days | Fees: 5.0%

- Buy triggers were executed when the signal rose 0.5799% plus -0.5 scaled standard deviations in a window of 3 days.
- Sell triggers were executed when the signal fell 0.5799% plus 0 scaled standard deviations in a window of 3 days.

Account_followers strategy: -12.8% | Holding: -6.66% | Momentum Strategy: -12.4%

- This strategy did not beat the benchmark. Net return was -12.8%. HODLing bitcoin would net -6.66%.
- This strategy did not beat a simple momentum strategy. Net return was -12.8%. A momentum strategy would net -12.4%.
- This strategy has a Sharpe Ratio of -3.24

Note: Transaction fees vary based on exchange