PERFORMANCE ANALYSIS OF MOMENTUM ALGORITHM IN CRYPTOCURRENCY TRADING

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Abstract

This paper provides insights into the performance of my custom-modified algorithmic trading script that is publicly available at the website momentumalgorithm.com. The script is based on the assumption that the strong positive price movements of the most prominent cryptocurrencies will be followed by consecutive price growth. Therefore, when the momentum is spotted, the algorithm takes a long position and takes advantage of the subsequent price growth. Given that all the momentum parameters such as percentage price advance and trade time-frequency are configurable, the paper further tests the performance of the algorithm on 5-minute, 15-minute, and 30-minute charts. In addition to the core functionality, the algorithm is able to receive and act on external signals. It uses data from Tradingview, and these returns buy signals according to the most relevant indicators. The research results are also tested with different combinations of stop-loss and take-profit parameters for each of the examined charts. The main findings outline that the momentum-based strategy does not provide consistently positive results and that the initial price advance might not be followed by the further advance. This experimental project has taken several common strategies for algorithmic trading and tested them on the cryptocurrency market, collecting data from those such as moving average crossover, mean reversion, and pairs trading. While focusing on automated cryptocurrency trading with the help of institutional-grade algorithmic trading technology.

Acknowledgments

I wish to extend my special thanks to MSc Finance Igor J. for providing me with an extensive introduction to automated cryptocurrency trading and suggestions to improve the research.
Introduction

In traditional stock markets, momentum behavior is defined as a herd behavior where the market participants expect further stock price growth or decline, based on the initial price inertion. The momentum-based strategies that are exploiting this behavior are focused on identifying the signal to enter the trade as well as on scalping the profit of the expected price movement.

Jegadeesh and Titman (1993) show that momentum strategies can lead to consistent positive results in the mid-term. The authors showed that buying 10% of the stocks exhibiting the highest returns and selling 10% of the poorest performers in the last 6 months generates monthly gains of 1%. Thomas J. George and Chuan-Yang Hwang (2004) also outline that stocks enjoying positive news momentum trade closest to their 52-week maximum.

With the emergence of cryptocurrencies in 2009, the growing public interest is set to explain whether the momentum strategies can be utilized successfully in crypto markets. Given the extremely volatile data of cryptocurrencies (Jong-Min Kim et al. 2021), the existence of momentum can be used to generate profitable trading strategies in short term (Panagiotis Tzouvanasa et al. 2019).

Borgards Oliver (2021) finds strong support for the existence of momentum in the most prominent cryptocurrencies for both intra-day and inter-day trades. Moreover, the crypto market enjoys stronger momentum due to the inability to accurately determine the intrinsic value of the assets. As such, the crypto market significantly outperforms the equity asset class.

Along similar lines, Victoria Dobrynskaya (2021) concludes that the short-term momentum exists in the cryptocurrency market and that it is most prominent in the horizon of 2 to 4 weeks. Moreover, the generated returns are statistically significant and cannot be explained by the risk factors that are present in these markets.

Similar to the momentum strategies, pairs trading strategies are frequently used as the core component of algorithmic trading strategies leveraged by the majority of hedge funds in the 1990s (Nicholas, 2004). The strategies are based on a high positive correlation between two financial instruments.
Based on the historical correlation of the pair, the long or short position is taken once this relation deviates from the historical. Profits are taken when investors sell short the outperforming and buy underperforming because their correlation tends to return to the historical levels. When that occurs, the long trade will profit from the further price increase while the short trade exploits the downward price movement. This is graphically presented in Graph 1.

Graph 1 – Pairs trading strategy

This graph shows the movement of the two instrument’s prices over time. On the 28th of January, the two instruments have identical prices. This relation diverges further which leaves room for the trades to long the underperformer and short the overperformer to exploit further the price growth and decline, respectively.

Huafeng Chen et al. (2012) show that the pair trading strategy generates abnormal and significant returns and that the generated returns are not merely due to the short-term return reversals.

In more recent research, Miroslav Fil (2020) tests the pair trading performance on the US equities data from 1990 to 2020 including the Covid-19 crisis. The author finds that the strategy still generates excessive returns but that the returns have diminished in recent periods. Moreover, the pairs trading strategies outperform the market benchmark in the bear market but fail to beat it during the bull market.
Given that the previous literature provides evidence that the momentum strategies can outperform the market, this paper tests further long strategy that is based on the momentum and the hypothesis that the initial price gain leads to further price advances. Benchmark for the trades is a long position that holds the asset for the same duration.

The next section explains the methodology that my custom-modified algorithm uses to execute the trades, introduces the dataset, and provides insights into the configuration that the algorithm is instructed with.

Methodology

The core algorithm of this article uses Binance.Com crypto exchange for the live data and trade execution, by leveraging the paper-trading option of Binance.Com. In this context, paper trading means that the algorithm uses no real funds but still executes on the real-time data to simulate the real trades.

USDT (United States dollar tether) is taken to be the base currency of the trades and all the gains or losses are expressed in USDT. Since the USDT/USD pair has a correlation of approximately 1, the interpretation of the results is similar as if it was traded in USD. The USDT/USD relation is given in Graph 2.

Graph 2 – USDT/USD
The USDT/USD pair value from December 2017 through March 2022. The relationship is mostly stable in recent years and it is fixed at 1. The small oscillations are in decimals and can be neglected for the purpose of this study.

The algorithm focuses on the 105 most prominent crypto tokens of the Binance.Com stock exchange and executes the trades if the conditions are met. The extensive list of these cryptocurrencies is given in Table 1. Also, it is worth noting that the terms such as crypto tokens and cryptocurrencies are used interchangeably in this paper.

Table 1 – Crypto tokens the algorithm trades

<table>
<thead>
<tr>
<th>1-11</th>
<th>12-22</th>
<th>23-33</th>
<th>34-44</th>
<th>45-55</th>
<th>56-66</th>
<th>67-77</th>
<th>78-88</th>
<th>89-99</th>
<th>100-105</th>
</tr>
</thead>
<tbody>
<tr>
<td>1INC</td>
<td>H</td>
<td>BCD</td>
<td>CCXX</td>
<td>DOT</td>
<td>HNT</td>
<td>LSK</td>
<td>NEO</td>
<td>RAY</td>
<td>UMA</td>
</tr>
<tr>
<td>AAVE</td>
<td>BCH</td>
<td>CEL</td>
<td>EGLD</td>
<td>HT</td>
<td>LTC</td>
<td>NEXO</td>
<td>RENBTC</td>
<td>UNI</td>
<td></td>
</tr>
<tr>
<td>ADA</td>
<td>BCHA</td>
<td>CELO</td>
<td>ENJ</td>
<td>ICP</td>
<td>LUNA</td>
<td>OCEAN</td>
<td>RLC</td>
<td>UST</td>
<td></td>
</tr>
<tr>
<td>ALGO</td>
<td>BNB</td>
<td>CHSB</td>
<td>EOS</td>
<td>ICX</td>
<td>LUSD</td>
<td>OKB</td>
<td>RUNE</td>
<td>VGX</td>
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<tr>
<td>ALPHA</td>
<td>BNT</td>
<td>COMP</td>
<td>ETC</td>
<td>KCS</td>
<td>MANA</td>
<td>OMG</td>
<td>SNX</td>
<td>WAVES</td>
<td></td>
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<tr>
<td>AR</td>
<td>BSV</td>
<td>CRV</td>
<td>ETH</td>
<td>KLAY</td>
<td>MDX</td>
<td>ONT</td>
<td>SOL</td>
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<td>CTC</td>
<td>FIL</td>
<td>KNC</td>
<td>MIOTA</td>
<td>ORC</td>
<td>STORJ</td>
<td>WBTC</td>
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<tr>
<td>ATOM</td>
<td>BTCB</td>
<td>DAI</td>
<td>FLOW</td>
<td>KSM</td>
<td>MIR</td>
<td>PROM</td>
<td>STX</td>
<td>WRX</td>
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</tr>
<tr>
<td>AVAX</td>
<td>BTCS</td>
<td>DASH</td>
<td>FTT</td>
<td>LEO</td>
<td>MKR</td>
<td>PUNDIX</td>
<td>SUSHI</td>
<td>XMR</td>
<td></td>
</tr>
<tr>
<td>BAKE</td>
<td>BTG</td>
<td>DCR</td>
<td>GRT</td>
<td>LINK</td>
<td>NANO</td>
<td>QNT</td>
<td>THETA</td>
<td>XRP</td>
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</tr>
<tr>
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<td>NEAR</td>
<td>QTUM</td>
<td>TTT</td>
<td>XTZ</td>
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</tbody>
</table>
The table gives 105 symbols that the algorithm trades. The symbol names are taken from the Binance.Com exchange. The column names reflect the numbering of the symbols under that column e.g. 1-11 means that the symbol one through the symbol eleven is given in this column.

The introduced algorithm monitors all the symbols from Table 1 by examining the price difference of each symbol compared to the previous 5, 15, and 30-minute price levels. If the price difference is found to be greater than 2%, 3%, or 5%, the algorithm labels the crypto token as bullish and takes a long position by investing USDT 120 in the given cryptocurrency. Take profit and stop-loss are set to 3% and 2%, respectively.

Once the long position is taken, the code continuously checks the active trades against the take profit and stop-loss limit. This checking is configurable and it is set to happen 10 times for each analyzed time frequency. For instance, in the 5 minute-based trades, the recheck will happen 10 times within every 5 minutes from the moment the long position is entered.

Table 2 – Tested algorithm configurations

<table>
<thead>
<tr>
<th>5-minute</th>
<th>15-minute 30-minute</th>
</tr>
</thead>
<tbody>
<tr>
<td>2%</td>
<td>2% 2%</td>
</tr>
<tr>
<td>3%</td>
<td>3% 3%</td>
</tr>
<tr>
<td>5%</td>
<td>5% 5%</td>
</tr>
</tbody>
</table>

The column names suggest the time-frequency for the price difference that is taken as a signal to take a long position. The row values are percentages of the price gains within that time frequency that must be met in order for the algorithm to long the crypto token.

If the market does not reflect an intense level of activity in terms of the price positive volatility, the program is paused and waits for 1 minute before the next check. The trigger for waiting is the condition of 50% plus 1 exponential moving average (EMAs) indicating the price downtrend. The exact configuration for the program to pause is when at least 8 of 15 moving averages of a crypto token indicate the price downtrend.

All the scenarios from Table 2 are tested during the 24h period on working days in a week. The following section summarises the results.
Results

Momentum cryptocurrency trading algorithms are proving to be very effective, however, it is crucial to know that cryptocurrency is extremely volatile and all algorithms operate very differently in different market situations. Interestingly the testing was taken place during a crab environment, which is one of the toughest scenarios for our algorithmic trading script. A crab environment is defined as a market pattern where price fluctuates but eventually return to some level of stability.

Over the span of Feb 16th to March 17th, the bot has conducted 129 trades, averaging about 4.3 trades a day. With a 73% profit hit rate, ranging from ~2% to ~5% profit on each. The results are very pleasing considering how choppy the market is. Note that momentum algorithms work best in a confirmed BULL or BEAR market. Previously we have seen it perform at >80% accuracy when the market is in trend, and naturally, they are the most profitable times.

This project so far has gathered significant attention from the Github dev community. This algorithmic trading script is still in development and will be further refined and polished, in addition, a user-friendly web app is on course for this project.
Conclusion

Cryptocurrencies have taken the financial industry by storm, leaving tremendous amounts of opportunities for retail and institutional traders and investors to trade alongside the volatility. As the industry matures, volatility does expect to reduce. Although, this shouldn’t deter traders from starting now.

The cryptocurrency market can experience some of the most substantial price action outside of typical market hours. This limits some to the overall ability to produce a significant profit by the end of the day. Luckily, there is a way for traders to reduce the profits lost from inactivity.

Automated Trading

Monitoring the performance of the entire market throughout the whole day can be an exhausting task for many traders. This is why automated trading has become so common in the industry. Using this strategy, algorithms can be trained to recognize opportunities by extracting minute-to-minute data about charts and other indicators.

Depending on the trader, indicators will vary to match the goal of the strategy at hand. Exponential moving average (EMA) and simple moving average (SMA) can be used to measure the weighted average price of an asset over time. Simply put, this indicator plots averages across any selected chart.

Momentum Algorithms

As an extension to automated trading, this technique is based on various momentum-based indicators that traders can utilize to build advanced strategies to widen the possibility of steady profits. Indicators such as the relative strength index (RSI) and moving average convergence divergence (MACD) are great starting points to building a momentum algorithm for trading cryptocurrencies.

As mentioned previously, cryptocurrency assets are often unpredictable. Though, these indicators make it substantially easier to detect trading opportunities. Combined with other indicators and backtesting to fine-tune the algorithm, it can increase the capabilities of many traders. Using these indicators alongside consistent trading parameters can contribute significant value to a trader’s strategy over time. More importantly, these indicators can be used individually or collectively to enhance the strategy further.
BIBLIOGRAPHY

1. Borgards Oliver (2021)
5. Jong-Min Kim and Chulhee Jun and Junyoup Lee (2021)
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