ZeltaLab Crypto Challenge Final Report

Team 96

Abstract
This report presents a comprehensive analysis and development of algorithmic trading strategies for the BTC/USDT pair. Focusing on addressing the challenges and opportunities in cryptocurrency markets, it involves extensive data analysis, strategy design using various technical indicators, and rigorous backtesting. The strategies incorporate aspects like MACD, MFI, linear regression, reversion, and trend following, alongside risk management techniques. The aim is to achieve superior performance over standard benchmarks while adhering to strict risk protocols.

Contents

1. Problem Statement

To develop and evaluate effective algorithmic trading strategies outperforming on 14 standard metrics for the BTC/USDT crytocurrency pair. Our methodology encompasses several key phases:

1. **Data Acquisition and Analysis:** Historical data, including price and trading volume of BTC/USDT from January 1, 2018, to December 31, 2022, was provided for tick size 3m, 5m, 15m, 30, 1h. It went through a extensive fundamental and technical analysis as a part of building intelligent and robust alphas

2. **Strategy Development:** The core of our work involves crafting algorithmic trading strategies. These are based on a blend of statistical models, enhanced with machine learning techniques, to exploit market trends and anomalies.

3. **Backtesting and Evaluation:** We conduct thorough backtesting of our strategies against historical data, considering transaction costs and slippage, set at a rate of 0.10%. This process is crucial to assess the viability and performance of our approaches.

4. **Risk Management:** Integral to our strategy development is the implementation of stringent risk management rules, aimed at safeguarding capital and minimizing losses in volatile market conditions.

5. **Optimization:** The final phase involves refining and optimizing our strategies to balance return and risk effectively, guided by insights gained from backtesting.

This work enumerated the Zelta Tech Algorithmic Trading Strategy Development Problem Statement as a part of Inter IIT Tech 12.0, with an emphasis on developing robust trading strategies for the volatile cryptocurrency market. Our aim is to outperform standard benchmarks while adhering to a strict risk management protocol.

2. Data Analysis

We have looked at various aspects to understand more the data we have and nature of Cryptocurrency by conducting a lot test which include

2.1 Statistical Analysis

Descriptive statistics will provide a summary of the central tendency, dispersion, and shape of the dataset's distribution, excluding NaN values. The measures include standard deviation, variance, kurtosis, and skewness. These metrics can help identify the typical values, the spread, and the asymmetry of the distribution in the Bitcoin prices and trading volumes. In this situation of BTC/USDT, analyzing the daily return vs date on different statistical variables

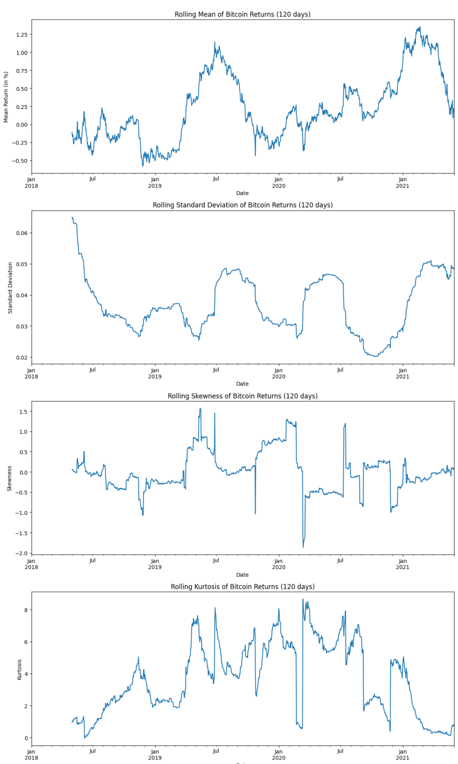

Figure 1. Statistics

Here using the rolling mean of returns over a period of 120 days shows that returns were confined in a small range till 2019 but after that the variation increased significantly. This fact further strengthened from the plot of standard deviation which represents the risk associated with the asset which showed variation in its values after 2019-2020. Furthermore, we looked at the skewness and kurtosis: The skewness values are slightly negative, indicating a small inclination towards more frequent extreme negative returns while the kurtosis values are slightly above 1, suggesting that the distribution of returns has heavier tails than a normal distribution. This implies a higher risk of extreme returns, both positive and negative, though not excessively so.

2.2 Macroeconomic Events

Here we worked on identifying if there any impact of macroeconomic events such as FOMC Meetings on bitcoin prices or volume.
The Federal Open Market Committee (FOMC) meeting is a regular session held by the members of the Federal Open Market Committee, a branch of the Federal Reserve that decides on the monetary policy of the United States
FOMC Meetings have a direct impact on US Stock Market and other markets, we wished to know whether they have any impact on crypto market. We looked at candlestick pattern around the dates of these events from 2018-2021. Through analyzing at them visually we concluded that no major anomaly or change is happening in terms of volume or prices in 10 day interval around the meeting date.

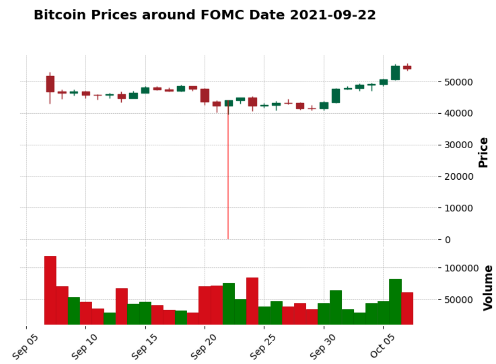

Figure 2. FOMC dates on candlesticks

2.3 Time Series Analysis

Understanding the behavior of Bitcoin price as a time series involves examining its stationarity and seasonality—two fundamental properties that can greatly influence the modeling and forecasting accuracy.

2.3.1 Stationarity

A time series is said to be stationary if its statistical properties do not change over time. This means that the mean, variance, and autocorrelation (the linear dependency of the current data point with its previous values) remain constant over time. A stationary series is much easier to predict since its future values depend on a consistent relationship from its past values.

To determine stationarity, **autocorrelation** is a commonly used tool. If the autocorrelation of a dataset degrades quickly, the data can be considered stationary. This degradation means that the values of the series are less correlated with their past values, indicating stability over time. If the autocorrelation does not degrade, indicating that present values are significantly correlated with their past values far back in time, the series is likely non-stationary.

From the Raw Bitcoin Price Autocorrelation Plot (Figure 3), we can infer that there are consistently high autocorrelation at regular intervals indicates strong, persistent cycles in

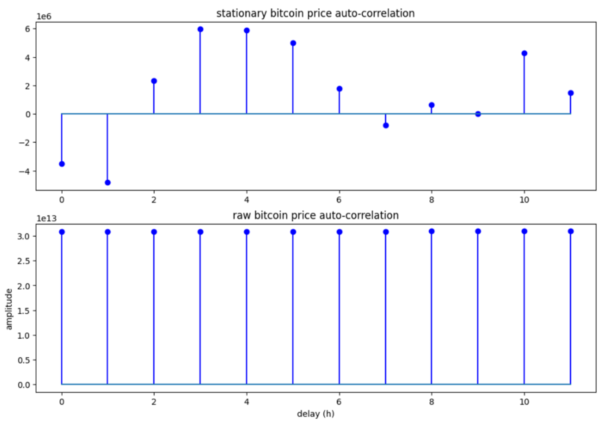

Figure 3. Autocorrelation of Bitcoin prices at different lags

the raw data, likely reflecting non-stationary elements like trends or seasonal effects and the presence of these regular peaks may point to underlying market mechanisms or periodic events influencing Bitcoin prices.

Non-stationarity in data can often be mitigated by differenc-

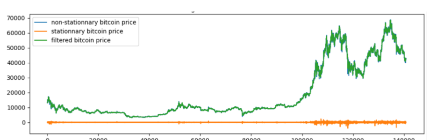

Figure 4. Stationary and Non stationary part of data

ing the data, which involves computing the change between consecutive data points, effectively focusing on the speed of change rather than the absolute values. Additionally, applying a filter such as a Gaussian kernel can smooth out short-term fluctuations and highlight underlying trends. By subtracting the smoothed data from the original data, one may remove non-stationary components, making the time series stationary.

2.3.2 Seasonality

Seasonality refers to regular and predictable patterns that repeat over a specific period. For Bitcoin, such patterns might not follow traditional seasonal patterns seen in other domains but could reflect periodic behaviors tied to market cycles, investor behaviors, or macroeconomic events.

Fourier analysis is a powerful method for identifying seasonality within time series data. It transforms the time series into the frequency domain, revealing the cyclical components. The magnitude of the Fast Fourier Transform (FFT) output indicates the importance of each frequency component to the overall data behavior. The phase tells us when these cycles begin. If the magnitude or phase of the FFT resembles white noise, it suggests that the series does not have a dominant frequency component and may not exhibit strong seasonality.

Peaks in the magnitude spectrum indicate dominant frequencies present in the signal. The highest peak represents the fundamental frequency of the signal, which corresponds to the dominant cycle in the data. From the given data, the

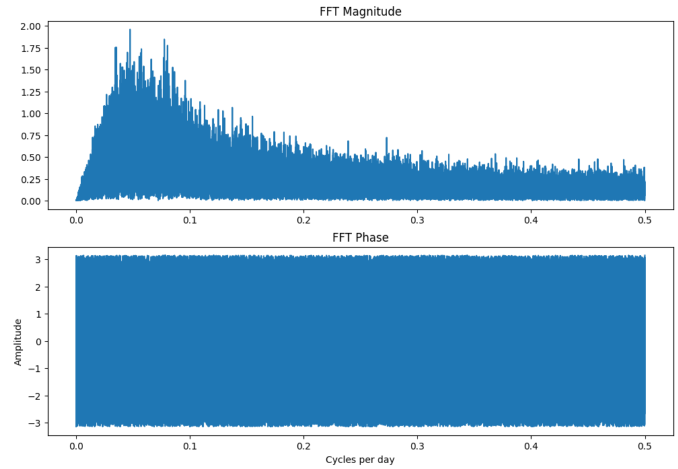

Figure 5. Fast Fourier Transforms

dominant frequency is approximately 0.0037 per hour which when converted into dominant period, which is the inverse of the dominant frequency, is about 269.75 hours. This value indicates the length of time it takes for the most significant cyclic pattern in your data to complete one full cycle. In simpler terms, it's the time duration between the repeating patterns or trends in your 'close' price data.

When converted into days, the dominant period is around 11.24 days. This conversion makes the interpretation more intuitive in the context of daily or weekly cycles. It suggests that the most prominent cycle or pattern in your data repeats roughly every 11 days.

The stationarity analysis helps in identifying a suitable prediction window. By evaluating the rate at which the distribution of raw prices changes over time, one can ascertain the temporal range within which predictions are reliable. If the price distributions of neighboring time points are similar (high correlation), predictions are more dependable since less change is expected in the short term.

2.4 Volatility Analysis

Volatility is defined as how much variance is there in values of a particular quantity.

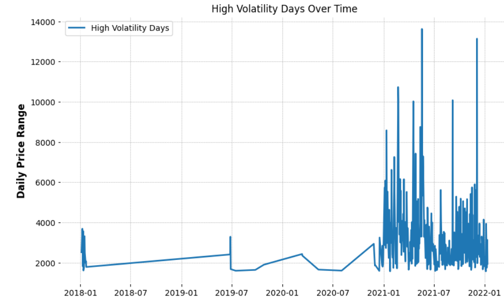

Figure 6. Daily volatility from 2018 - 2021

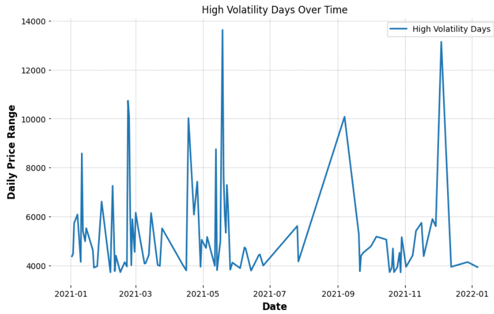

Figure 7. Volatility from 2019-2021

Top Indicators for Tick size = 1h

	return	return_abs	return_2	return_2_abs
MINUS_DM	1.5474	34.5269	1.9159	32.9895
ROC	-2.3049	-7.7108	-2.4782	-6.846
ROCP	-2.3049	-7.7108	-2.4782	-6.846
ROCR	-2.3049	-7.7108	-2.4782	-6.846
ROCR100	-2.3049	-7.7108	-2.4782	-6.846
BOP	-2.4281	-1.5495	-2.8628	-1.2608
MOM	-2.7575	-9.247	-3.1265	-8.2203

Pearson

	return	return_abs	return_2	return_2_abs
MINUS_DM	1.5474	34.5269	1.9159	32.9895
STOCHF_K	-1.6388	-2.6835	-2.0428	-2.4441
PPO	-1.6025	-8.3786	-2.232	-7.9192
MACDFIX	-1.8015	-11.2059	-2.3188	-10.4411
MACD	-1.8103	-11.2232	-2.3294	-10.4558
ROC	-2.3049	-7.7108	-2.4782	-6.846
ROCP	-2.3049	-7.7108	-2.4782	-6.846
ROCR	-2.3049	-7.7108	-2.4782	-6.846
ROCR100	-2.3049	-7.7108	-2.4782	-6.846
BOP	-2.4281	-1.5495	-2.8628	-1.2608
MOM	-2.7575	-9.247	-3.1265	-8.2203

Figure 8. Results from top indicators

2.5 Correlation Analysis

Correlation Analysis is statistical method that is used to discover if there is a relationship between two variables, and how strong that relationship may be. We did extensive correlation analysis on 30+ technical indicators (momentum, volatility, volume,etc.) to identify presence of any relationship between the values given by indicators at current timestamp (t) with return $(\frac{close(t+1)}{close(t} - 1)$ and $return_2 = (\frac{close(t+2)}{close(t)} - 1)$

2.6 Trade Visualization Tool

The Trade Visualization Tool is a comprehensive software designed for the dynamic visualization and analysis of financial trades. It enables users to effectively plot trading data and apply a variety of technical indicators for in-depth market analysis.

An example output of the trade visualizer output is shown in Figure 9

Figure 9. Example output of our trade visualizer shows the candlestick chart over a certain duration before, after, and during a trade. The trade entry and exit are denoted by vertical lines, and the volume is indicated at the bottom of the graph

Core Functionalities

- **Dynamic Data Plotting:** Facilitates the plotting of trade data over various timeframes, allowing for a granular and macroscopic view of market trends.
- **Zoom and Detail Exploration:** Users can zoom in to examine specific data points closely or zoom out for a broader market view.
- **Interactive Data Points:** Hover-over effects reveal detailed information for each data point, including price, volume, and indicator values.

3. Strategy Design

3.1 MACD

3.1.1 Motivation

The Moving Average Convergence Divergence (MACD) is a popular technical indicator used for analysing financial markets. It is a combination of 3 indicators and is defined as follows

$$\text{MACD, Signal, Histogram} = \text{MACD(Prices, Fast Period, Slow Period, Signal Period)}$$

where:

$$\text{MACD = Fast Period EMA - Slow Period EMA}$$

$$\text{Signal = Signal Period MACD}$$

$$\text{Histogram = MACD - Signal}$$

The MACD is a handy indicator since it can be used to identify trends, measure momentum, and can be used for divergence analysis.

Table 1. Technical Indicators

Volume Indicators	
AD	Chaikin A/D Line
ADOSC	Chaikin A/D Oscillator
OBV	On Balance Volume
Momentum Indicators	
ADX	Average Directional Movement Index
ADXR	Average Directional Movement Index Rating
APO	Absolute Price Oscillator
AROON	Aroon
AROONOSC	Aroon Oscillator
BOP	Balance Of Power
CCI	Commodity Channel Index
CMO	Chande Momentum Oscillator
DX	Directional Movement Index
MACD	Moving Average Convergence/Divergence
MACDEXT	MACD with controllable MA type
MACDFIX	Moving Average Convergence/Divergence Fix 12/26
MFI	Money Flow Index
MINUS_DI	Minus Directional Indicator
MINUS_DM	Minus Directional Movement
MOM	Momentum
PLUS_DI	Plus Directional Indicator
PLUS_DM	Plus Directional Movement
PPO	Percentage Price Oscillator
ROC	Rate of change: ((price/prevPrice)-1)*100
ROCP	Rate of change Percentage: (price-prevPrice)/prevPrice
ROCR	Rate of change ratio: (price/prevPrice)
ROCR100	Rate of change ratio 100 scale: (price/prevPrice)*100
RSI	Relative Strength Index
STOCH	Stochastic
STOCHF	Stochastic Fast
STOCHRSI	Stochastic Relative Strength Index
TRIX	1-day Rate-Of-Change (ROC) of a Triple Smooth EMA
ULTOSC	Ultimate Oscillator
WILLR	Williams' %R

3.1.2 Usage

The MACD strategy can be used in multiple ways, some of the common uses are trend following, moving average crossover, momentum trading, etc. Since cryptocurrency markets are usually driven by public sentiments, they open up to a lot of potential momentum-based trading strategies. We will look at a basic MACD momentum-based strategy:

$$\text{Buy if Signal(t)} > \text{ Signal(t-1)}$$

$$\text{Sell if Signal(t)} < \text{ Signal(t-1)}$$

3.1.3 Experiment and Analysis

We will only look at the Signal indicator to develop a profitable strategy to trade Bitcoin. This is because the MACD output is extremely noisy owing to the highly volatile nature of bitcoin. Since the Signal indicator is a smoothened-out version of MACD, it will help us in generating true signals. In Figure 10, we can see the behavior of the Signal indicator with the open price of bitcoin for a few timestamps.

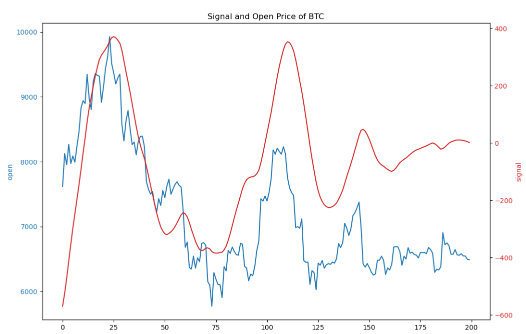

Figure 10. Open prices of Bitcoin and the calculated Bitcoin indicator

Coming up with a Basic Strategy We will trade on daily data. This is generated by sampling a particular timestamp (for example 21:30 hours everyday) on the 1hr data provided. Since we are only using open prices, we need to worry about changing High, Low, Close, and volume. The choice to use daily data is to minimize trades - to save up on transaction costs. We also tried to incorporate our strategy on smaller timescales, but due to higher number of trades (and thus a higher transaction cost), and a smaller return per trade, we could not come up with anything profitable.

As seen from the graph, we will come up with a basic stategy: we will generate a buy signal if $Signal(t) > Signal(t-1)$, otherwise we will generate a sell signal. This will be stored in the flag column

Hyperparameter-Tuning After dividing the dataset into train, validation, and test dataset, our goal is now to obtain a set of optimal hyperparameters, that will generate the maximum PNL on the train set. We also added a naive form of stop-loss, which will track the loss encountered by the current open trade, and if the loss exceeds a threshold, will exit the trade.

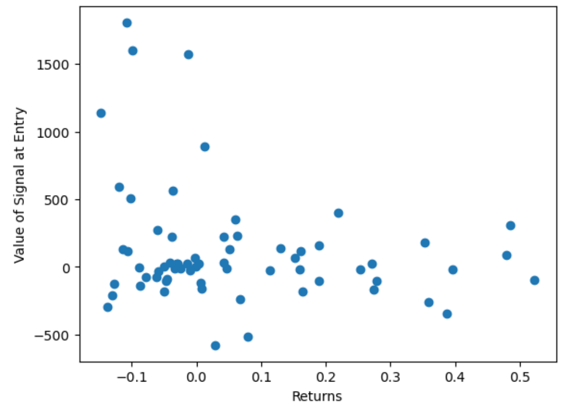

Figure 11. Value of Signal when trade opened, vs returns

For this, we will performed a grid search on the possible set of hyperparameters, and obtain the following parameters as optimal:

Time = 21:30:30

Fast Period = 14

Slow Period = 20

Signal Period = 14

Stoploss Threshold = 10%

Results: PNL 2810 on train and 1000 on validation

Analysing Trades and Improving Strategy We will now proceed with the best parameters obtained until now, and analyze the trades we performed, and try to remove some of the bad trades

As can be seen from Figure 11, if the absolute value of the signal at entry is very high, this leads to mostly negative returns, hence we will set a threshold of generating flags while entering. Similar to before, we will perform hyperparameter tuning on the train set, to obtain an optimal parameter for this threshold, and an optimal parameter comes out to be:

Signal Threshold = 500

Note that our strategy is:

$$\text{Buy if Signal(t)} < \text{ Signal(t-1) and abs(Signal(t))} < 500$$

$$\text{Sell if Signal(t)} < \text{ Signal(t-1) and abs(Signal(t))} < 500$$

Results: 2600 PNL on train and 1600 on validation

Towards a better risk management system We now want to improve our stop-loss architecture. Currently, we are employing a very crude form of stoploss which checks the stoploss once a day. To improve upon this, the first idea is to use a finer stop-loss - such as on the 1-hour dataset This means that while we will only enter the daily sampled timeframe, to check for stop-loss we will use the 1-hour data, and we can exit on the 1 hour timeframe

Why will this help? If we set our stoploss to 10%, and lets say we bought bitcoin on Day 1 21:30:00, and we observe that the price of bitcoin on Day 2 has fallen by 15%. Our stoploss system will tell us to exit the trade now, but even though our stoploss was 10%, we made a loss of 15%. If we had used a finer dataset to check prices, it would have been much more likelier that we would have exited the trade at a 10% loss.

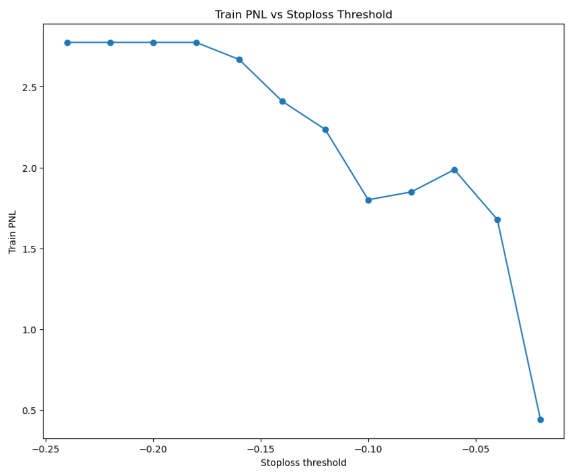

Figure 12. Train PNL vs Stoploss Threshold

We see from Figure 12 that the highest PNL is when there is an 18-24% stop-loss. This effectively means, there is no stop-loss at this range, and all trades are exited based on the true signal. Even though this gives a better PNL, this is not the right value to be chosen, since we can get worse points in the validation and test dataset.

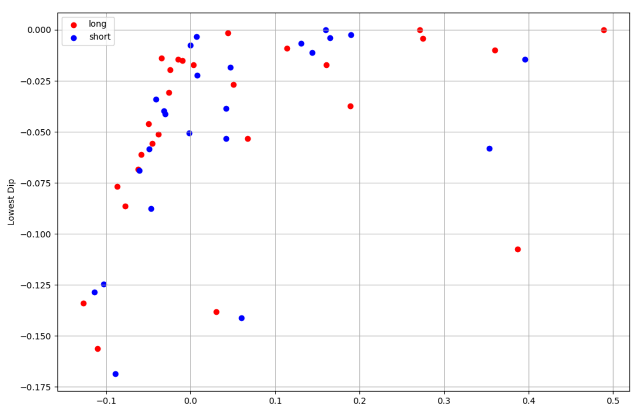

Figure 13. Lowest Returns vs Final Returns

To analyse why this is the case, let us plot the lowest returns against the final returns of the trades performed by our strategy. In the Figure 13 we can observe the following: Lets say if we keep a 15% stop loss. Only the bottom 2 points will be affected. They will be capped to give a 15% loss, but without stop-loss they only gave a 10% loss (approx). Hence it is not always necessary that a stop-loss will indeed help our PNL, and this analysis can easily help us to verify if having a simple stop-loss would be helpful or not.

Dynamic Stoploss based on ATR We will now try to improve our risk management system by incorporating a dynamic stoploss mechanism. The idea behind this is quite simple - to allow for a larger stoploss when the market is volatile, and a smaller stoploss when the market is not so volatile. We will use the ATR indicator to measure volatility and tune the hyperparameters

$$\text{True Range (TR)} = \max\begin{pmatrix} \text{High} - \text{Low}, \\ |\text{High} - \text{Previous Close}|, \\ |\text{Low} - \text{Previous Close}| \end{pmatrix}$$

$$\text{Average True Range (ATR)} = \text{MA}(\text{TR}, n)$$

where n is the lookback period. We will now update our stoploss function which sets the stoploss threshold as a multiplier of the calculated ATR:

$$\text{Stoploss Threshold = (ATR Multiplier)(ATR)/Open Price}$$

We will now perform hyperparameter tuning by performing a grid search. The optimal hyperparameters obtained are:

$$n(\text{ ATR Lookback}) = 15$$

$$\text{ATR Multiplier} = 9$$

Results: We see that we have been able to improve the train performace (2750 over 2600) without much loss on the validation dataset. Also note that, the average value of the stoploss is 8% which is lower than the optimal stoploss we had derived in the static case (around 15%). Hence we have reduced our overall risk exposure whilst improving the PNL

Improving Holding Period : Since we are almost trading once every day, our holding time is going to be very high. The downside to this is that we have inherent long-term exposure to the volatility of the cryptocurrency market. To overcome this, we wish to cap the maximum holding time to a certain threshold.

First we calculate the maximum holding time and the average holding time of our current trades. We observe the following results:

$$\text{Maximum Hold Time} = 52 \text{ Days}$$

$$\text{Average Hold Time} = 15.33 \text{ Days}$$

From Figure 14, we observe that if reduce our maximum holding time, the train PNL reduces. This also makes sense we are effectively increasing the number of trades, and thus increasing our transaction cost - without any change in the total PNL. There is some variance since we exit out and then open the next trade within 1 hour, but we expect lower PNL as we reduce the maximum hold time, We can see that if we have a maximum hold time of 19 days, our average holding time is 10 days (down from 15 days) We can also reduce the

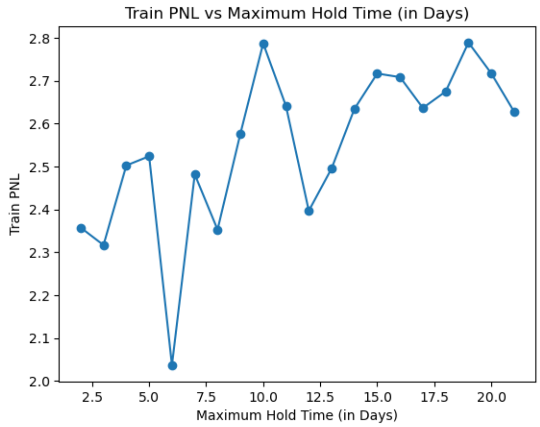

Figure 14. Train PNL vs Maximum Hold Time

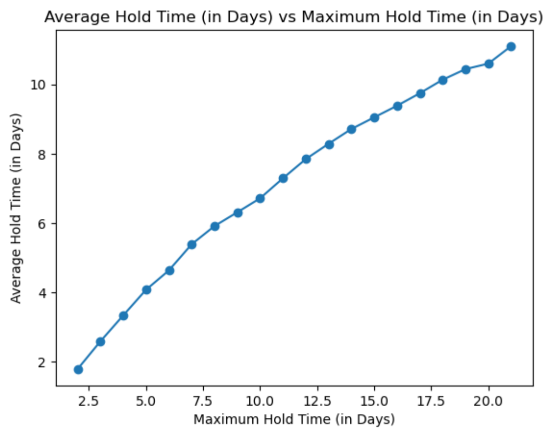

Figure 15. Average Hold Time vs Maximum Hold Time

maximum hold time to 9 days, and our average hold time becomes 6 days, but we have to lose around 40% returns over train + validation.

We choose the optimal parameters to be:

$$\text{Maximum Hold Time} = 19 \text{ Days}$$

$$\text{Average Hold Time} = 10 \text{ Days}$$

Results

Maximum Hold Time of 19 days: Train PNL = 2790 and Validation PNL = 1520

3.1.4 Results

Final Parameters

$$\text{Time} = 21{:}30{:}30$$

$$\text{Fast Period} = 14$$

$$\text{Slow Period} = 20$$

$$\text{Signal Period} = 14$$

$$\text{Signal Threshold} = 500$$

$$n(\text{ ATR Lookback}) = 15$$

$$\text{ATR Multiplier} = 9$$

$$\text{Maximum Hold Time} = 19 \text{ Days}$$

The graph for PNL over time on train, validation and test sets are shown in Figures 16 and 17

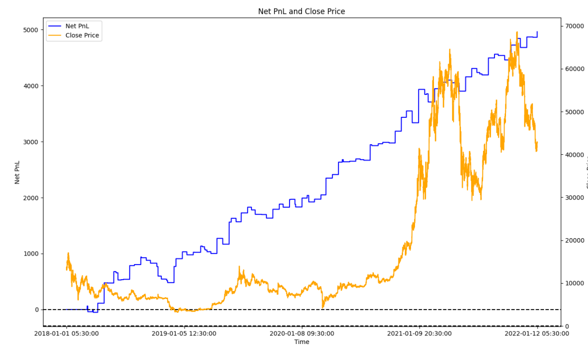

Figure 16. Static PNL over time for the train + validation + test dataset

Table 2. Results for Static Method

Metric	Value
Net PnL	4879.51
Buy and Hold PnL	2154.33
Total Trades Closed	103
Gross Profit	7544.78
Gross Loss	-2665.27
Largest Winning Trade	577.51
Largest Losing Trade	-230.44
Min Net PnL	-138.50
Sharpe Ratio	0.36
Average Winning Trade	145.09
Average Losing Trade	-52.26
Number of Winning Trades	52
Number of Losing Trades	51
Total Transaction Cost	154.5
Max Drawdown	22.23
Maximum Trade Holding Duration	19 days 10:00:00
Average Trade Holding Duration	13 days 04:45:26

3.2 MFI

3.2.1 Motivation

The Money Flow Index (MFI) serves as a valuable technical indicator in the realm of financial analysis, aiding traders and investors in gauging the strength and momentum of a financial instrument's price movement. Unlike some indicators that solely rely on price data, the MFI incorporates both price and volume information, providing a more comprehensive perspective on market dynamics.

Table 3. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	101.36%	22.24%
2019	81.49%	10.64%
2020	143.96%	10.42%
2021	151.07%	13.48%
2022	10.07%	0.00%

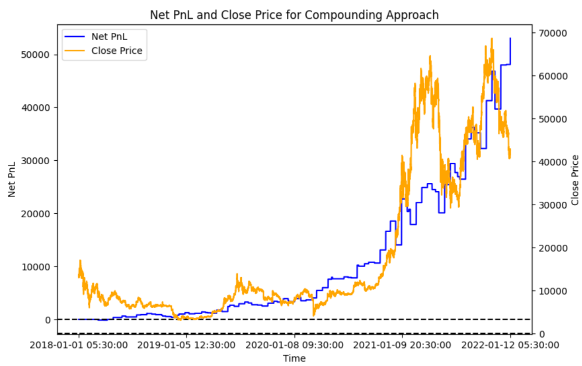

Figure 17. Compounding PNL over time for the train + validation + test

3.2.2 Formula

The Money Flow Index is calculated using the following formula:

$$\text{MFI} = 100 - \frac{100}{1 + \text{Money Flow Ratio}} \quad (1)$$

where the Money Flow Ratio (MFR) is determined by the following steps:

$$\text{TP} = \frac{\text{High} + \text{Low} + \text{Close}}{3} \quad (2)$$

$$\text{RMF} = \text{Typical Price} \times \text{Volume} \quad (3)$$

$$\text{MFR} = \frac{\text{Positive Money Flow}}{\text{Negative Money Flow}} \quad (4)$$

$$\text{PMF} = \sum_{\text{days}} \text{if}(\text{TP}_{\text{today}} > \text{TP}_{\text{yesterday}}, \text{RMF}_{\text{today}}, 0) \quad (5)$$

$$\text{NMF} = \sum_{\text{days}} \text{if}(\text{TP}_{\text{today}} < \text{TP}_{\text{yesterday}}, \text{RMF}_{\text{today}}, 0) \quad (6)$$

Explanation

Price Movement Analysis

At its core, the MFI assesses the dynamics between buyers and sellers within a given market. By considering not only the price changes but also the accompanying trading volume, it aims to unveil the underlying forces driving the market sentiment.

Identifying Buying and Selling Pressure

Table 4. Results for Compounding Method

Metric	**Value**
Net PnL	53029.95
Buy and Hold PnL	2154.33
Total Trades Closed	103
Gross Profit	87296.79
Gross Loss	-34266.84
Largest Winning Trade	9028.24
Largest Losing Trade	-7141.14
Min Net PnL	-137.83
Sharpe Ratio	0.01
Average Winning Trade	1678.78
Average Losing Trade	-671.90
Number of Winning Trades	52
Number of Losing Trades	51
Total Transaction Cost	1655.24
Max Drawdown	-35.36
Maximum Trade Holding Duration	19 days 10:00:00
Average Trade Holding Duration	13 days 04:45:26

Table 5. Annual Returns and Drawdowns

Year	**Annual Returns**	**Annual Maximum Drawdowns**
2018	125.69%	35.36%
2019	92.69%	17.59%
2020	245.95%	23.04%
2021	226.29%	20.65%
2022	10.07%	0.00%

One of the key aspects the MFI focuses on is the buying or selling pressure in the market. In periods of strong buying interest, the MFI tends to register higher values, reflecting the increased demand for the asset. Conversely, during times of intense selling activity, the MFI may dip lower, signaling a surge in selling pressure.

Trend Reversals and Market Extremes

Traders frequently turn to the MFI for its ability to identify potential trend reversals and extremes in market conditions. An MFI value above 80 is often interpreted as an indication of overbought conditions, suggesting a potential reversal or correction in the price. On the other hand, an MFI below 20 is seen as oversold, potentially signaling a buying opportunity.

Overall Market Sentiment

By amalgamating price and volume data, the Money Flow Index provides a more holistic view of market sentiment. It helps market participants to make informed decisions by revealing the balance of power between buyers and sellers, contributing to a more nuanced understanding of market trends.

In summary, the Money Flow Index stands as a versatile tool, combining price and volume analysis to give traders insights into the dynamics of market sentiment, facilitating the identification of trend reversals, and aiding in decision-making processes.

3.2.3 Experiment and Analysis

To analyse whether any of our indicator is any good, we looked at how the value of the indicator was related with the future return values.

- RET1 : This shows the percentage return after one time-stamp has passed.
- RET5 : This shows the percentage return after five time-stamp has passed.
- RET10 : This shows the percentage return after ten time-stamp has passed.
- RET30 : This shows the percentage return after thirty time-stamp has passed.

MFI	ret_1	ret_10	ret_30	ret_5
(-0.01, 28.09]	-2.27	-47.48	-45.56	-23.74
(28.09, 35.37]	-3.00	-30.77	-47.77	-13.96
(35.37, 40.86]	2.24	0.84	19.67	2.11
(40.86, 45.58]	1.05	12.29	15.49	3.98
(45.58, 50.08]	-1.99	12.97	9.05	7.34
(50.08, 54.53]	0.57	1.04	-5.32	-0.98
(54.53, 59.41]	1.78	7.14	-1.10	8.50
(59.41, 64.99]	-1.06	2.86	16.90	0.87
(64.99, 72.07]	1.99	25.11	31.03	10.89
(72.07, 100.0]	3.09	34.74	25.86	18.90

Table 6. MFI: Analysis on the train dataset

ret_5	**ret_1**	**ret_10**	**ret_30**
5.45	1.27	8.41	3.56

Table 7. Correlations(in percent) of MFI with returns

If our indicator has positive correlation with the future returns it essentially means that it is a good prediction of price movement. For our analysis we looked at how the indicator varied with price, and how correlated it was with the future. From this we were able to deduce that the indicator beyond a certain threshold is a good predictor of the future. However the movement might change later on if we don't lock out our profits, hence once a buy sell signal was encountered, we decided to square it off after 10 timestamps, this number as to when to close out a trade was derived from our analysis

3.2.4 Usage

Use upper and lower thresholds to decide when to enter a long and short position respectively.

$$\text{Upper Threshold} = 77$$

$$\text{Lower Threshold} = 13$$

Square the position off after 10 timstamps

3.2.5 Results

Final Parameters

$$\text{Upper Threshold} = 77$$

$$\text{Lower Threshold} = 13$$

$$\text{Period} = 10$$

$$\text{Exit} = 13$$

$$n(\text{ ATR Lookback}) = 15$$

$$\text{ATR Multiplier} = 9$$

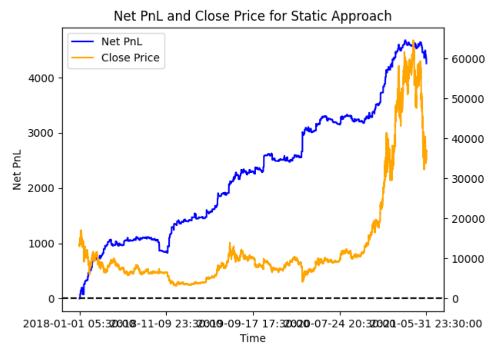

Figure 18. MFI PNL over time for the train dataset – static

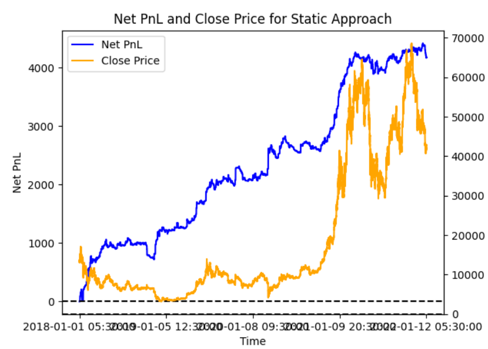

Figure 19. MFI PNL over time for the total dataset – static

3.3 Median Reversion

3.3.1 Motivation

Our initial trading strategies, designed to capitalize on 1-hour and 1-day data, yielded satisfactory results. However, a significant gap was observed when dealing with the granularity of 3-minute data. This discrepancy highlighted the need for a more adaptable and refined trading strategy that could effectively navigate the nuances of short-term market fluctuations.

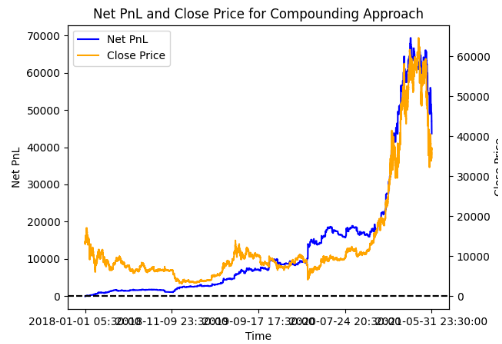

Figure 20. MFI PNL over time for the train dataset – compounding

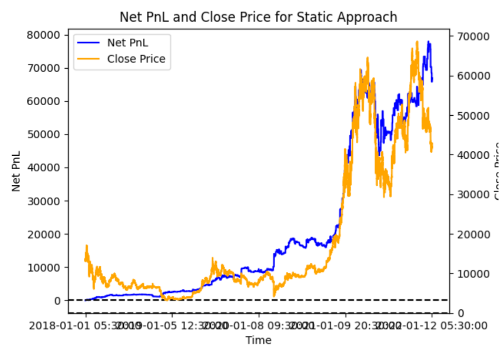

Figure 21. MFI PNL over time for the total dataset – compounding

Table 8. Results for Static Method

Metric	Value
Net PnL	4749.97
Buy and Hold PnL	2154.33
Total Trades Closed	758
Gross Profit	11731.05
Gross Loss	-6981.08
Largest Winning Trade	351.34
Largest Losing Trade	-100.72
Min Net PnL	0
Sharpe Ratio	0.16
Average Winning Trade	31.03
Average Losing Trade	-18.37
Number of Winning Trades	378
Number of Losing Trades	380
Total Transaction Cost	1137.0
Max Drawdown	13.61
Maximum Trade Holding Duration	3 days 02:00:00
Average Trade Holding Duration	0 days 19:19:28

Table 9. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	135.48%	13.61%
2019	115.56%	8.44%
2020	137.42%	10.17%
2021	99.77%	23.44%
2022	-13.23%	15.31%

3.3.2 Experiment and Analysis

The quest for a more robust trading approach led us to a detailed analysis of the market behavior, particularly focusing on the volume activity and price movements within these short intervals. A critical observation was made: the market exhibited **sideways movements** in 3m regions.

Coming up with a Basic Strategy

We implemented a simple mean reversion strategy, which executed trades based on the following logic:

- **Sell** when:

$$\text{Price} > \mu + \text{REVERSION\_THRESH} \times \sigma$$

- **Buy** when:

$$\text{Price} < \mu - \text{REVERSION\_THRESH} \times \sigma$$

The Shift from Mean to Median: Unfortunately, these attempts resulted in suboptimal outcomes, primarily because mean reversion strategies were significantly impacted by **sudden and sharp** price spikes. Mean, as a measure of central tendency, was highly sensitive to outliers and extreme values, thereby capturing the 'noise' rather than the 'signal' in the market data. In contrast, the median, by its very nature, provided a more stable and reliable measure, unaffected by such aberrations. This stability is particularly crucial in the high-frequency environment of 3-minute trades, where sudden price movements are not uncommon.

Separating Entry and Exit Logic

Until now, our trading strategy employed the same logic for both entry and exit, leading to a notable issue: an increased average holding time. This was particularly evident when analyzing individual trades. A significant number of loss-making trades were characterized by timely and strategic entries, but the exits were suboptimal. This issue often manifested as the price failing to reach the lower band set for exit, resulting in trades not closing at the anticipated levels and thereby impacting the overall profitability of the strategy.

Hence, we shifted our focus and redesigned the exit logic. The new strategy was based on a combination of a stop-loss and a profit cap. This adjustment aimed to optimize the exit timing, reduce the duration of trades, and enhance overall trade performance by ensuring exits at more strategic points.

Making Trend our Friend

Further analysis of our loss-making trades revealed that median reversion strategies were less effective in trending markets. To mitigate this, we incorporated a trend indicator known as the Directional Movement Indicator (DDI), which

Table 10. Results for Compounding Method

Metric	Value
Net PnL	66722.41
Buy and Hold PnL	2154.33
Total Trades Closed	758
Gross Profit	261575.86
Gross Loss	-194853.45
Largest Winning Trade	6590.44
Largest Losing Trade	-6151.24
Min Net PnL	0
Sharpe Ratio	0.01
Average Winning Trade	691.99
Average Losing Trade	-512.77
Number of Winning Trades	378
Number of Losing Trades	380
Total Transaction Cost	26183.54
Max Drawdown	-36.49
Maximum Trade Holding Duration	3 days 02:00:00
Average Trade Holding Duration	0 days 19:19:28

Table 11. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	241.30%	25.86%
2019	184.76%	13.86%
2020	241.23%	14.82%
2021	134.06%	36.49%
2022	-12.75%	14.63%

is essentially the difference between the positive (+DI) and negative (-DI) directional indicators. This integration allowed us to refine our approach based on market trends.These conditions aimed to align our trading decisions more closely with the prevailing market trends, thereby enhancing the effectiveness of our median reversion strategy during different market phases.

Towards dynamic Stoploss and Profitcap

During our analysis and application of the trading strategy, we observed certain drawbacks that necessitated further refinement:

- **Hitting the Profit Cap:** We frequently observed that trades were hitting the profit cap. This indicated that there might still have been potential for additional profit, which our current strategy was not capturing.
- **Inadequate Stop Loss:** In some instances, the stop loss level was not sufficient, leading to larger losses than anticipated. This highlighted the need for a more adaptive approach to setting the stop loss threshold.

This observation led us to the concept of a dynamic stoploss and profit cap.

The core idea behind this approach is to adjust these thresholds based on the behavior observed in the last n trades. We keep track of how often our trades hit the profit cap. If the profit cap is consistently being reached, it suggests that our trades are capable of yielding more profit than we initially anticipated. In response, we incrementally increase the profit cap.

Conversely, if stoplosses are triggered more frequently than expected, it indicates that our initial risk assessment might be too optimistic. To mitigate this, we adjust our strategy by reducing the stoploss threshold. This dynamic approach allows us to fine-tune our trading strategy in real-time, adapting to market conditions and optimizing our trade performance.

To address these issues and further mitigate the risk of faulty trades, we introduced a dynamic risk management strategy. This new approach involves continuously monitoring and adjusting the stop loss and profit cap based on the performance and patterns observed in recent trades. By doing so, we aim to enhance the overall efficacy of our trading strategy, making it more responsive to changing market conditions and trade outcomes.

3.3.3 Reducing Holding Time and Dynamic Adjustment of Parameters

In our continuous effort to optimize the trading strategy, we introduced an additional refinement: setting a maximum holding period for each trade. This decision was driven by the need to reduce the average holding time, thereby minimizing exposure to market volatility and enhancing trade turnover.

Reducing Holding Time A key aspect of refining our trading strategy was the introduction of measures to reduce the holding time of trades. We implemented the following strategies:

- **Maximum Holding Period:** To avoid prolonged market exposure and the associated risks, we set a maximum duration for each trade. This ensures that positions are not held longer than necessary, especially in situations where the desired profit cap or stoploss levels are not quickly met. This measure helps in maintaining a disciplined approach and mitigating potential risks due to changing market conditions.
- **Dynamic Adjustment of Stoploss and Profit Cap:** Recognizing the importance of time in trade management, we introduced a dynamic system for adjusting the stoploss and profit cap as the trade progresses. As time increases, the stoploss threshold is incrementally raised to safeguard against adverse market shifts, while the profit cap is lowered to secure profits before potential reversals. This time-dependent strategy ensures that our trades adapt to ongoing market dynamics, optimizing for both profitability and risk management.

3.3.4 Usage

Entry Logic

Our entry logic is bifurcated based on the Directional Movement Indicator (DDI) readings:

Reversion Strategy: Applied when $|\text{DDI}| < \text{DDI\_REV\_THRESH}$.

- Sell Signal: Triggered when price $> \mu + \sigma \times$ REVERSION_THRESH.
- Buy Signal: Triggered when price $< \mu - \sigma \times$ REVERSION_THRESH.

Trend Strategy: Applied when $|\text{DDI}| > \text{DDI\_TREND\_THRESH}$.

- Buy Signal: Triggered when price $> \mu + \sigma \times$ TREND_THRESH.
- Sell Signal: Triggered when price $< \mu - \sigma \times$ TREND_THRESH.

Exit Logic

The exit strategy employs dynamic parameters based on the recent trade performance:

- **Dynamic Parameters:**
  - Profit Ratio (profit_ratio): Proportion of profitable exits in the last n trades.
  - Stoploss Ratio (stoploss_ratio): Proportion of exits due to stoploss in the last n trades.
  - Time Ratio (time_ratio): Elapsed time as a fraction of the maximum holding period.
- **Threshold Adjustments:**
  - $\text{Profit Cap} = \max(\text{MIN\_PROFIT\_CAP}, \text{profit\_ratio} \times \text{PROFIT\_CAP\_MULTIPLIER} \times (1 - \text{time\_ratio}))$.
  - $\text{Stoploss} = \text{STOPLOSS\_MULTIPLIER} \times \text{stoploss\_ratio} \times \text{time\_ratio}$.
- **Trade Exit Conditions:** A trade is exited if any of the following conditions are met:
  - The time ratio reaches 1 (maximum holding period is reached).
  - The profit cap or stoploss threshold is reached.

3.3.5 Results

Final Parameters after parameter tuning

$$\text{MEDIAN\_WINDOW} = 40$$

$$\text{REVERSION\_THRESH} = 2$$

$$\text{TREND\_THRESH} = 3$$

$$\text{STOPLOSS} = 0.09$$

$$\text{PROFIT\_CAP} = 0.02$$

$$\text{MIN\_PROFIT\_CAP} = 0.004$$

$$\text{MAX\_TRADE\_HOLD} = 1800$$

$$\text{PROFIT\_CAP\_MULTIPLIER} = 0.05$$

$$\text{STOPLOSS\_MULTIPLIER} = 0.11$$

$$\text{DI\_WINDOW} = 15$$

$$\text{DDI\_REV\_THRESH} = 10$$

$$\text{DDI\_TREND\_THRESH} = 50$$

$$\text{PROFIT\_LOSS\_WINDOW} = 25$$

Table 12. Results for Static Method

Metric	**Value**
Net PnL	3869.97
Buy and Hold PnL	2129.68
Total Trades Closed	1071
Gross Profit	19890.75
Gross Loss	-16020.78
Largest Winning Trade	91.71
Largest Losing Trade	-101.18
Min Net PnL	0
Sharpe Ratio	0.04
Average Winning Trade	27.06
Average Losing Trade	-47.68
Number of Winning Trades	735
Number of Losing Trades	336
Total Transaction Cost	1606.5
Max Drawdown	14.05
Maximum Trade Holding Duration	3 days 15:57:00
Average Trade Holding Duration	1 days 02:22:55

Table 13. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	275.41%	13.92%
2019	-8.81%	48.66%
2020	1.29%	39.94%
2021	127.60%	25.74%
2022	-8.50%	8.77%

3.4 Linear Regression

3.4.1 Motivation

Our fundamental goal as a trader is to be able to predict the future returns accurately. We thus try a Linear Regression model to predict the returns cleverly using the available data. Main motivation to use a Linear Regression model was its simplicity. It is easy to train and its robustness towards noisy financial data, avoids overfitting in general. Major task was to find the features that capture the relevant information to predict the future.

Table 14. Results for Compounding Method

Metric	Value
Net PnL	21047.96
Buy and Hold PnL	2129.68
Total Trades Closed	1071
Gross Profit	167913.74
Gross Loss	-146865.77
Largest Winning Trade	1281.28
Largest Losing Trade	-1361.10
Min Net PnL	0
Sharpe Ratio	0.01
Average Winning Trade	228.14
Average Losing Trade	-438.41
Number of Winning Trades	736
Number of Losing Trades	335
Total Transaction Cost	14170.52
Max Drawdown	-51.10
Maximum Trade Holding Duration	3 days 15:57:00
Average Trade Holding Duration	1 days 02:22:58

Table 15. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	1155.05%	20.48%
2019	-21.38%	44.79%
2020	-12.88%	46.94%
2021	179.27%	30.93%
2022	-8.16%	9.64%

3.4.2 Experiment and Analysis

We need a choice of indicators and target variable to fit our linear model. We began by chosing our target, i.e. future returns. We analysed, for a 100% accurate prediction of next k ticks return. and found that $k = 2$ generated the maximum profit. Now, to figure out good indicators, we began our search with a pool of available indicators, by finding our correlation values of the indicator with Next 2h returns. Along with those, we also built our own indicator **expRSI**.

expRSI : RSI, a popular momentum oscillator measures the speed and change of price movements. It measures how overbought or oversold the market is currently. High RSI values indicate the market is currently in an overbought state and prices will decline, while a low RSI indicates the opposite. However RSI in itself did not give good correlation with the returns. We then decided to strengthen the RSI signal. So, an RSI value between 90-100 is a much stronger signal than the RSI value around 50 (which adds noise to the data). However such a property cannot be captured by a Linear Model. To cater to this issue, we exponentiated our RSI values in a clever manner in the following way:

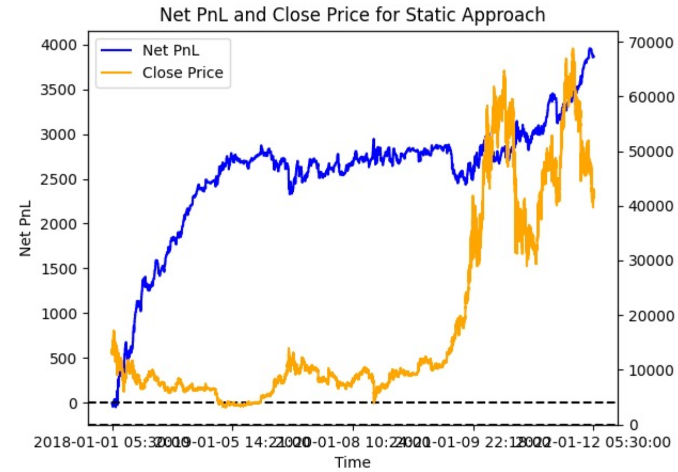

Figure 22. Median:PNL over time using Static Approach

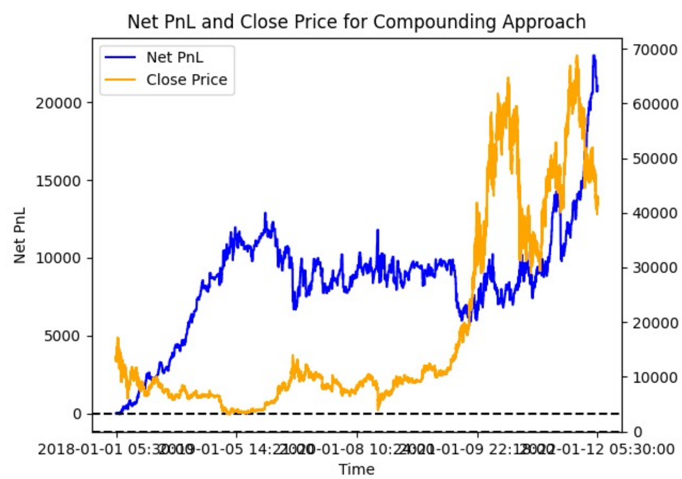

Figure 23. Median:PNL over time using Compounding Approch

```
rsi = talib.RSI(df['close'],
    timeperiod=period)
rsi -= 50
rsi = rsi.apply(lambda x: x if x >
    20 or x < -20 else 0)
rsi = rsi.apply(lambda x: x - 20 if
    x >= 20 else x)
rsi = rsi.apply(lambda x: x + 20 if
    x <= -20 else x)
```

In short, we shift the RSI values by 50, clip the values from -20 to 20 to 0. Then shift the remaining values by 20 toward 0. Now, our RSI varies from -30 to 30. With all the noise zeroed down. Now, the signal gets strengthened in the ends, by exponentiating the absolute value of the modified RSI.

```
df['exp_RSI'] = np.exp(np.abs(df['
```

```
    ↪ RSI']))
df['exp_RSI'] = np.where(df['RSI'] >
    ↪ 0, -df['exp_RSI'], df['
    ↪ exp_RSI'])
```

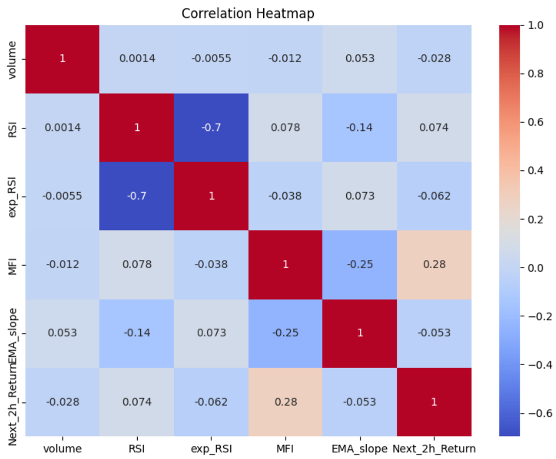

Figure 24. Correlation matrix of all the features and the target

Finally we chose to use 'volume', 'Daily_Return', 'RSI', 'exp_RSI', 'MFI', 'EMA_Slope', 'MFI' as our features and 'Next_2h_Return' as our target.

Data Split : We first, split our data in three portions train, val, test. After doing all the analysis and training on the train data, we tested the model on val and test dataset. Although the model performed well on both the datasets, we saw a slight dip in performance on the newer data. This can easily be overcome by training the weights again on the latest data.

Trading Logic : When evaluating the model on any dataset, we get the predicted returns as the model output. Now the question arises how to trade using these returns. A naive approach is to put a buy signal is the predicted return is ¿ 1.5, and a sell signal if it is ¡ 1.5 However we adopt a different approach finally, we some top and bottom quantile values, and but a buy trade is our predicted return lies beyond that quantile value, and similarly for a sell signal.

3.4.3 Usage

Train the weights for the Linear Regression model on the the train data (60%) and then execute the trades on the validation/test dataset.
Following were the final hyperparameters used :

- OPTIMAL_PERIOD_FOR_RSI = 80
- OPTIMAL_PERIOD_FOR_EMA = 2
- TIME_FRAME = "1h"
- OPTIMAL_PERIOD_FOR_MFI = 14
- STOPLOSS_THRESHOLD = 0.2
- OPTIMAL_POSITIVE_QUANTILE = 92.45
- OPTIMAL_NEGATIVE_QUANTILE = 92.45

3.4.4 Results

We used our backtesting engine to generate the results for the training dataset, and the val + train dataset. It can be clearly seen that model's performance decreases in more recent data. To overcome this, we can retrain the model on new data.

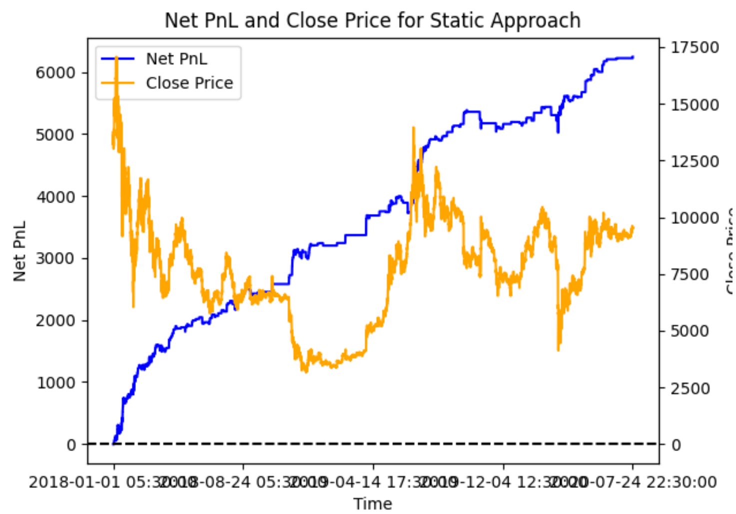

Figure 25. LR Static Results on val + train data

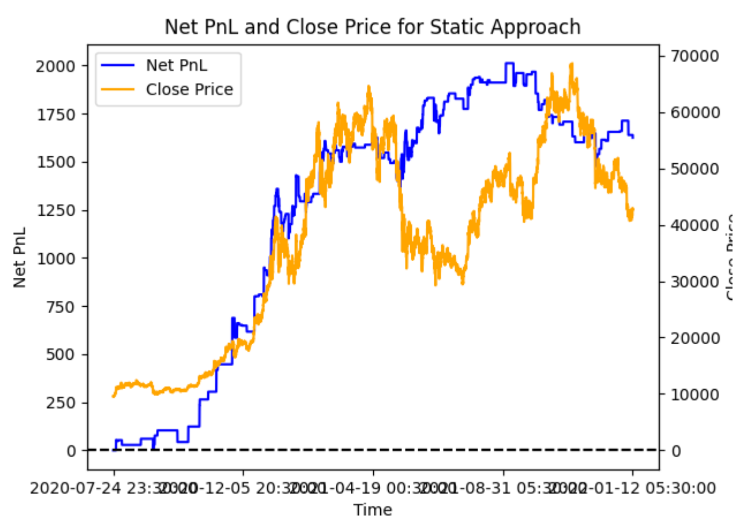

Figure 26. LR Static Results on val + train data

3.5 Rolling Regression

3.5.1 Motivation

Inspired by the insights obtained during our analysis and in depth study of linear regression, we develop this variant.

Table 16. Results for Static Method

Metric	Value
Net PnL	1624.94
Total Trades Closed	261
Gross Profit	5459.13
Gross Loss	-3834.19
Largest Winning Trade	240.97
Largest Losing Trade	-169.14
Min Net PnL	0
Sharpe Ratio	0.13
Average Winning Trade	34.33
Average Losing Trade	-37.59
Number of Winning Trades	159
Number of Losing Trades	102
Total Transaction Cost	391.5
Max Drawdown	17.72
Maximum Trade Holding Duration	20 days 09:00:00
Average Trade Holding Duration	1 day 11:58:09

Table 17. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2020	91.01%	6.06%
2021	74.90%	25.39%
2022	-3.42%	8.40%

The basic idea is to keep updating the weights of the linear regression model as we see new data. To do so, we define a look_back window and a prediction window. We train on prediction window, and predict on the prediction window, then again update the weights again by sliding the window.

3.5.2 Experiment and Analysis

We used the features : 'exp_RSI', 'EMA_Slope', 'ADOSC', 'macd_signal for this implementation. These were chosed based on the look back windows which gave maximum correlation with the future 2h returns.

expRSI and EMA_slope were defined earlier in Linear Regression. macd_signal is calculated as:

```
    macd, signal, hist = talib.MACD(df["
        ↪ close"], fastperiod=
        ↪ MACD_FAST_PERIOD, slowperiod=
        ↪ MACD_SLOW_PERIOD, signalperiod
        ↪ =MACD_SIGNAL_PERIOD)
df['macd_signal'] = df['signal'].diff(1)
```

ADOSC is a volume indicator. It is computed as the difference between the 3-day exponential moving average and the 10-day exponential moving average of the Accumulation/Distribution Line. The Accumulation/Distribution Line is a running total of each period's Money Flow Volume. It is calculated as follows:

- The Money Flow Multiplier (MFI) is the relationship of the close to the high-low range
- The MFI is multiplied by the period's volume to come up with a Money Flow Volume (MFV).
- A running total of the Money Flow Volume forms the Accumulation Distribution Line

We also observed how the weights of the model vary along with the correlations of the corresponding features and future returns.

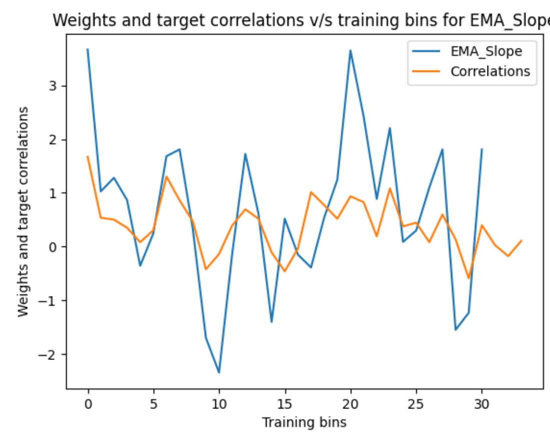

Figure 27. Weights of EMA_Slope and Correlation of EMA_slope with returns

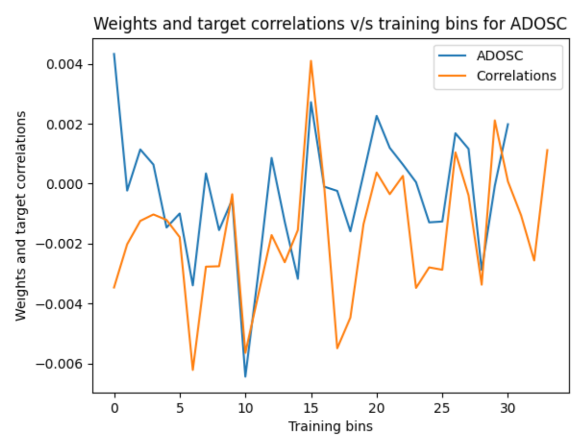

Figure 28. Weights of ADOSC and Correlation of ADOSC with returns

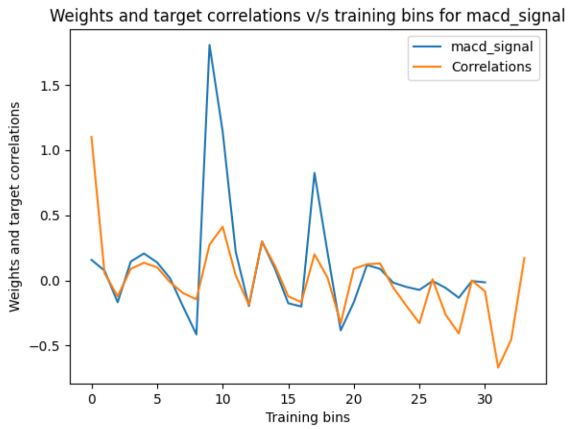

Figure 29. Weights of macd_signal and Correlation of macd_signal with returns

The major hyperparameters used are

- Lookback window : Number of datapoints for training
- Prediction window : Number of datapoints for predictions
- Cut : The cutoff predictions, i.e. generate a buy/sell signal only if the absolute predicted return is greater than Cut

The threshold to execute the trade (cut), first of all prevents a lot of useless trades, and trades only when we predict a strong change in market, i.e. stronger than to cover the transaction cost(1.5)

We also tried some more variations of this model. One of them was to use a moving average of the model weights as we slide through the data. The Motivation being that it would capture the previous market history with decreasing weights. We tried different ratios of importance for the moving average but it only gave marginal improvements and is really sensitive.

We built a **multithreaded** script to do the hyperparameter tuning on the training data.

3.5.3 Usage

Our rolling_lr strategy can be used with the following hyperparameters to generate the documented results.

- Lookback window : 1248
- Prediction window : 1056
- Cut : 2.5

In our final implementation, we train on lookback window, and trade on the prediction window, once we generate predictions, we slide our window to retrain and continue making money.

3.5.4 Results

Here are the results obtained using the above parameters for both static and compounding approaches

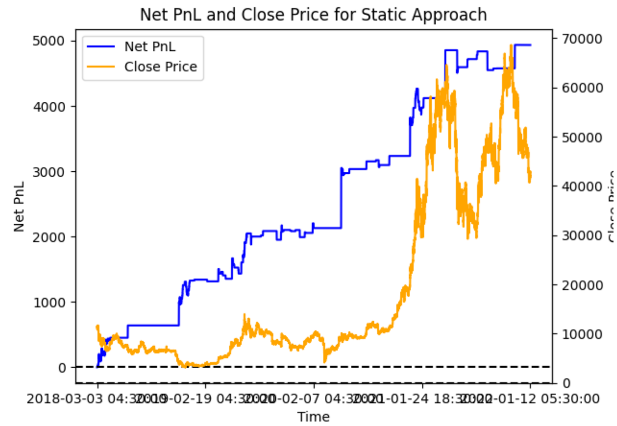

Figure 30. Rolling LR static results

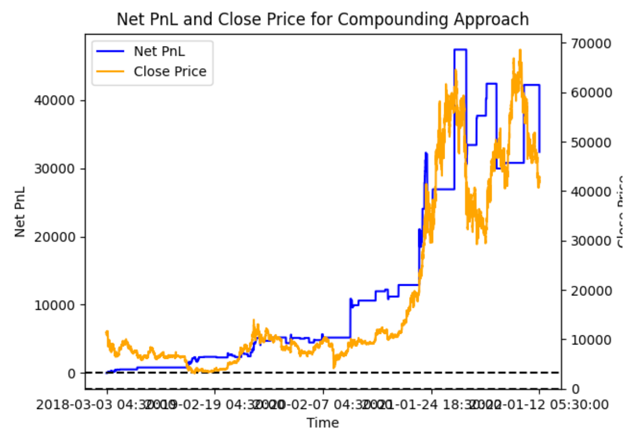

Figure 31. Rolling LR compounding results

3.6 Trend Follower

3.6.1 Motivation

We had discussed exploring momentum-based strategies based on the volatile and sentiment-driven nature of the Bitcoin market. Specifically, we discussed using the MACD indicator to capture the momentum in the market and developed a profitable trading strategy using it. Nevertheless, the market cannot forever exhibit momentum, and it has to revert at some time. Hence, it is extremely crucial to identify and differentiate between mean-reverting and trend-following regions, to successfully deploy our momentum strategy. In this section, we will look at a few ways of differentiating between mean-reverting and trend-following regions, and come up with a profitable strategy

The inception of the Trend Follower strategy was primarily motivated by the recognition of the BTC/USDT market's inherent volatility. In the dynamic world of cryptocurrency trading, where market conditions can change rapidly, our analysis highlighted the need for a strategy that not only adapts to but also capitalizes on these frequent and significant market

Table 18. Results for Static Method

Metric	Value
Net PnL	4933.09
Buy and Hold PnL	2865.84
Total Trades Closed	213
Gross Profit	8604.20
Gross Loss	-3671.12
Largest Winning Trade	919.22
Largest Losing Trade	-347.49
Min Net PnL	0
Sharpe Ratio	0.20
Average Winning Trade	63.27
Average Losing Trade	-47.68
Number of Winning Trades	136
Number of Losing Trades	77
Total Transaction Cost	319.5
Max Drawdown	9.49
Maximum Trade Holding Duration	153 days 05:00:00
Average Trade Holding Duration	5 days 09:44:47

Table 19. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	132.60%	9.49%
2019	66.56%	17.41%
2020	197.92%	6.00%
2021	96.24%	30.73%

Table 20. Results for Compounding Method

Metric	Value
Net PnL	32385.09
Buy and Hold PnL	2865.84
Total Trades Closed	213
Gross Profit	99774.87
Gross Loss	-67389.78
Largest Winning Trade	20465.70
Largest Losing Trade	-16807.89
Min Net PnL	0
Sharpe Ratio	0.0049
Average Winning Trade	733.64
Average Losing Trade	-875.19
Number of Winning Trades	136
Number of Losing Trades	77
Total Transaction Cost	2764.92
Max Drawdown	-36.01
Maximum Trade Holding Duration	153 days 05:00:00
Average Trade Holding Duration	5 days 15:00:16

Table 21. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	231.77%	19.89%
2019	64.81%	21.31%
2020	358.22%	11.65%
2021	72.38%	36.01%
2022	-22.71%	22.71%

movements. This led to the development of a specialized approach, combining traditional volatility indicators with innovative techniques to accurately identify and follow market trends. Our aim was to create a robust trading strategy that offers a high degree of confidence in decision-making, even in the face of the market's unpredictable nature, thus providing traders with a reliable tool to navigate and profit from the volatility of the BTC/USDT market.

3.6.2 Experiment and Analysis

The first hypothesis we tested was to use **traded volume** to differentiate between identifying momentum and mean reverting regions. Our hypothesis hinged on the fact that if the traded volume increases in a particular region, we expect momentum in the bitcoin market, and if the traded volume reduces in a particular region, we expect reversion.

To test this hypothesis, we used the **15min tick-size** data available to us and divided the data into blocks of **50** time stamps. Next, we defined a block to be of increasing volume if:

$$\sum_{i=1}^{50} \text{Sign (Volume (i)} > \text{Volume (i-1))} > 0$$

The problem with this hypothesis is that even with using data of varying tick sizes and block sizes, we were not getting enough blocks which have increasing volume. On average, only 10% of the blocks had an increasing volume. Since we want to focus on momentum-based strategies, using this approach would just not generate enough trades. Next, we looked at using a statistical approach in defining momentum and mean reversion regions. Let R be a region defined as follows:

$$R \in \text{ (MA(Lookback) - Multiplier*(Standard Deviation)} \\ \text{MA(Lookback) + Multiplier*(Standard Deviation))}$$

If the price of the bitcoin is in R, we hypothesize that the price will revert, or else it will continue to follow the trend. (It has broken out of the band, and we use this as an indicator). Strategy can be defined as follow (SD is Standard deviation):

$$\text{Buy if Price} > \text{MA(Lookback) - Multiplier*(SD)}$$

$$\text{Sell if Price } < \text{ MA(Lookback) - Multiplier*(SD)}$$

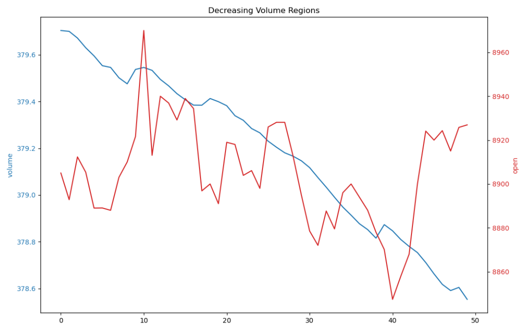

Figure 32. An example block that has decreasing volume. We can see reversion

Figure 33. An example block that has increasing volume. We can see momentum in the price

The hyperparameters to tune were the lookback period of the SMA, the multiplier for the standard deviation, and the stop-loss threshold. The optimal values of

$$\text{SMA (Lookback)} = 70$$

$$\text{Multiplier} = 2.6$$

$$\text{Stoploss Threshold } = 7\%$$

3.6.3 Results

We can also look at the backtesting results, and the PNL over time for the static and the compounding approach in Figures 34 and 35

4. Backtesting

We have developed our own backtesting engine to get detailed analysis of the performance of the strategies developed. The engine gives detailed metrics, and plots summarising the strategy.

Data Input

The engine takes in a csv file with the following necessary columns:

- `datetime`: Timestamp of the data point.
- `open`: Opening price of BTC/USDT.
- `close`: Closing price of BTC/USDT.

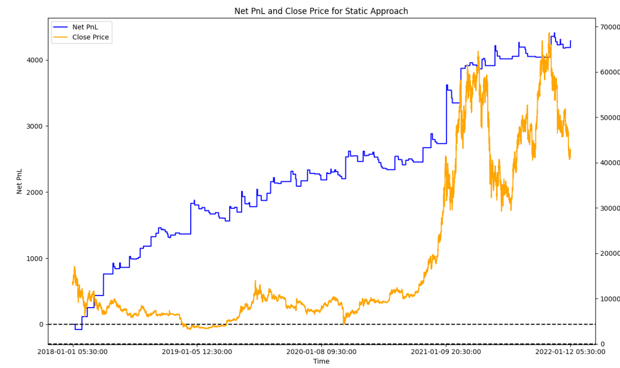

Figure 34. Trend Follower: PNL over time using Static Approach

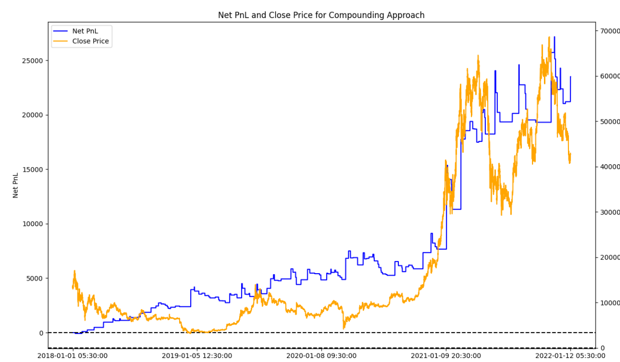

Figure 35. Trend Follower: PNL over time using Compounding Approach

- `signals`: Trading signals, taking values 1 (buy), -1 (sell), and 0 (hold).

The `signals` column follows the constraint that only one trade can be open at a time.

Engine Modes

The backtesting engine can be run in two modes:

- **Static Mode**: Invests 1000$ in each trade.
- **Compounding Mode**: Starts with 1000$, and profits/losses are reinvested.

The engine can be executed using the following command:

```
python3 run_engine.py --logs "location
↪ of logs file" --method "static/
↪ compounding/both"
```

To trade on the opening price instead of the closing price, modify the `main_engine.py` file, changing `price = close` to `price = open` in both the `Static` and `Compounding` engine classes.

Table 22. Results for Static Method

Metric	Value
Net PnL	4291.06
Buy and Hold PnL	2154.33
Total Trades Closed	154
Gross Profit	8292.74
Gross Loss	-4001.68
Largest Winning Trade	887.94
Largest Losing Trade	-108.38
Min Net PnL	-78.98
Sharpe Ratio	0.21
Average Winning Trade	125.65
Average Losing Trade	-45.47
Number of Winning Trades	66
Number of Losing Trades	88
Total Transaction Cost	231.00
Max Drawdown	10.95
Maximum Trade Holding Duration	45 days 13:00:00
Average Trade Holding Duration	8 days 12:14:02

Table 23. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	180.48%	6.05%
2019	47.02%	21.14%
2020	45.91%	20.89%
2021	145.31%	14.44%
2022	10.38%	0.00%

Table 24. Results for Compounding Method

Metric	Value
Net PnL	23502.38
Buy and Hold PnL	2154.33
Total Trades Closed	154
Gross Profit	65851.35
Gross Loss	-42348.96
Largest Winning Trade	7692.75
Largest Losing Trade	-2032.82
Min Net PnL	-78.98
Sharpe Ratio	0.0074
Average Winning Trade	997.75
Average Losing Trade	-481.24
Number of Winning Trades	66
Number of Losing Trades	88
Total Transaction Cost	2063.23
Max Drawdown	-27.73
Maximum Trade Holding Duration	45 days 13:00:00
Average Trade Holding Duration	8 days 12:14:02

Table 25. Annual Returns and Drawdowns

Year	Annual Returns	Annual Maximum Drawdowns
2018	381.09%	14.06%
2019	33.24%	22.00%
2020	35.16%	26.38%
2021	156.22%	24.69%
2022	10.38%	0.00%

Backtesting Metrics

The backtesting engine provides various metrics to evaluate the performance of the trading strategy. The following metrics are available for both static and compounding modes:

- **Net PnL**
- **Buy and Hold PnL**
- **Total Trades Closed**
- **Gross Profit**
- **Gross Loss**
- **Largest Winning Trade**
- **Largest Losing Trade**
- **Min Net PnL**
- **Sharpe Ratio**
- **Average Winning Trade**
- **Average Losing Trade**
- **Number of Winning Trades**
- **Number of Losing Trades**
- **Total Transaction Cost**
- **Max Drawdown**
- **Maximum Trade Holding Duration**
- **Average Trade Holding Duration**
- **Annual Returns**
- **Annual Maximum Drawdowns**

These metrics collectively provide a comprehensive evaluation of the trading strategy's performance under different conditions and can be used to assess its robustness and effectiveness.

All the plots above visualising the PnL were generated by this engine only.

Additional Details

Transaction Cost and Slippage : We assume a 0.15% of the amount invested in each trade as transaction cost and slippage. So, for the static approach, for each trade, we shell out 1.5$ and similarly for compounding, if be place a buy/sell order to open a trade at a price p, we shell out $\$1.5 * p$.
Sanity Check for Valid Signals The engine generates a warning whenever the signal does not follow the constraint of single open trade

Finer Details of each Trade One can easily see the PnL generated by each trade, total assets bought, Net PnL till that point, and the exact time stamp each trade was executed for finer analysis of the strategy. This can easily be done by uncommenting the 2 lines following the comment "Uncomment to see each trade".

5. Risk Management

5.1 Naive Static Stoploss

A very simple form of stop-loss is adding a maximum threshold for loss beyond which you exit the trade. Note that if your strategy is profitable, adding a stoploss on expectation will reduce PNL. In other words:

$$\mathbb{E}\,(\text{PNL with Stoploss}) < \mathbb{E}\,(\text{PNL without Stoploss})$$

This is because you are exiting a positive expectancy trade before they are completely realised. Nonetheless, the obvious upside to this is you limit your risk appetite, and your downsides are capped

As an example, we can look at Figure 40, where the PNL over different values of threshold has been plotted. As can be inferred, The PNL is the highest for a very high value of stop-loss threshold, where effectively no trades are exited prematurely. As we make the threshold tighter, we are exiting out of trades earlier and as a result, we are realising lower PNL from each trade (on expectation)

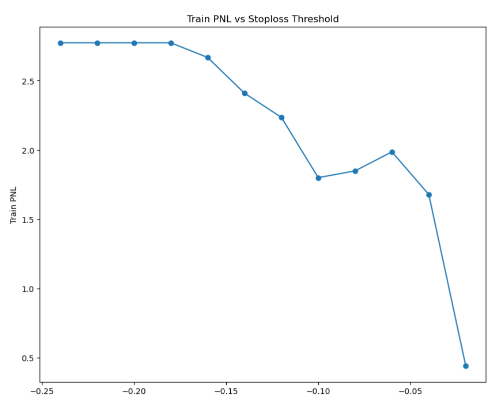

Figure 36. PNL vs Stoploss Threshold

To visualise the upside of adding stoploss, in Figure 37, where we can see the variation of the loss made on the worst trade (y-axis) against the stoploss threshold. The overall trend we observe is that as we can make the stoploss threshold tighter, we see that the PNL we make on the worst trade also increases, which is the entire idea of adding a stoploss.

5.2 Stoploss Plot

To better help visualise trades and the need for stoploss, we have also developed a `stoploss_plot()` function. This function takes in input as the logs of the trades (exactly similar

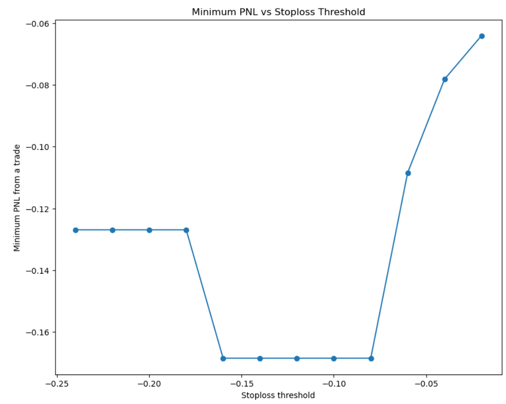

Figure 37. Min PNL vs Stoploss Threshold

to what the backtesting engine does) and plots the lowest return against the true returns of all the trades. Lowest returns can be mathematically defined as follows:

$$\text{Lowest Returns} = \min_{t \in (\text{Entry, Exit})} \frac{(\text{Open(t) - Open(Entry)}) \times \text{Sign}}{\text{Open(Entry)}}$$

where Sign is 1, if it is a long trade, and -1 otherwise.

An example plot is shown in Figure 38, where we have plotted the trades for the MACD strategy. We experienced that applying stoploss reduces the overall PNL of our trades. This is because lets say if we keep a 15% stop loss. Only the bottom 2 points will be affected. They will be capped to give a 15% loss, but without stop-loss, they only gave a 10% loss (approx). Hence it is not always necessary that a stop-loss will indeed help our PNL, and this analysis can easily help us to verify if having a simple stop-loss would be helpful or not.

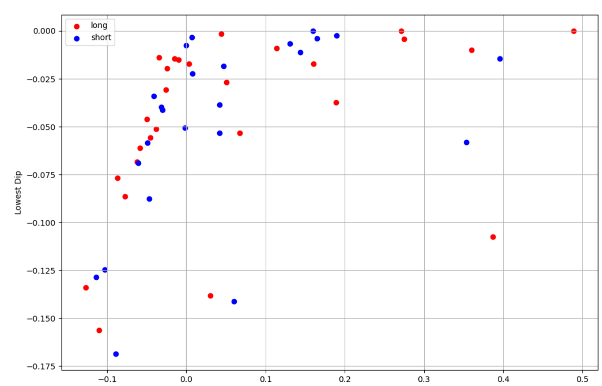

Figure 38. Lowest returns vs Final returns of example trades on the bitcoin market

5.3 ATR based Dynamic Stoploss

Another area where we can improve our risk management system is incorporating a dynamic stop-loss mechanism. The idea behind this is quite simple - to allow for a larger stop-loss when the market is volatile, and a smaller stop-loss when the market is not so volatile. We will use the ATR (Average True Range) indicator to measure volatility, and is defined as follows:

$$\text{True Range (TR)} = \max\left(\begin{array}{c}\text{High} - \text{Low},\\ |\text{High} - \text{Previous Close}|,\\ |\text{Low} - \text{Previous Close}|\end{array}\right)$$

$$\text{Average True Range (ATR)} = \text{MA}(\text{TR}, n)$$

where n is the lookback period. We will now update our stop-loss function which sets the stop-loss threshold as a multiplier of the calculated ATR:

$$\text{Stoploss Threshold} = (\text{ATR Multiplier})(\text{ATR})/\text{Open Price}$$

Using such a type of dynamic stop-loss, allows us to adjust for the risk depending on the volatility in the market instead of using a static fixed stop-loss.

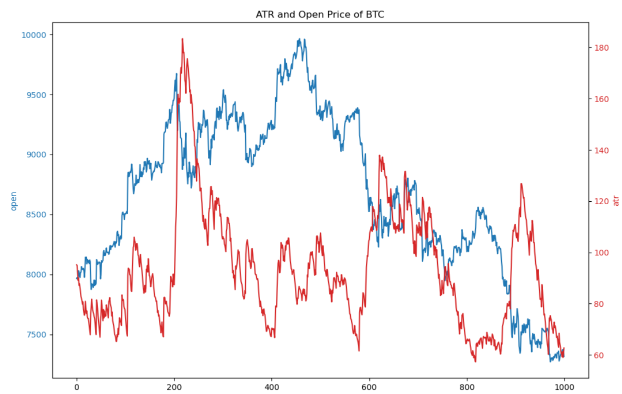

Figure 39. ATR vs Open Price of Bitcoin

In Figure 39, we can observe that when the open price of bitcoin is very volatile, the value of ATR is high and vice versa.

5.4 Fixed - period exit

MFI	ret_1	ret_10	ret_30	ret_5
(-0.01, 28.09]	-2.27	-47.48	-45.56	-23.74
(28.09, 35.37]	-3.00	-30.77	-47.77	-13.96
(35.37, 40.86]	2.24	0.84	19.67	2.11
(40.86, 45.58]	1.05	12.29	15.49	3.98
(45.58, 50.08]	-1.99	12.97	9.05	7.34
(50.08, 54.53]	0.57	1.04	-5.32	-0.98
(54.53, 59.41]	1.78	7.14	-1.10	8.50
(59.41, 64.99]	-1.06	2.86	16.90	0.87
(64.99, 72.07]	1.99	25.11	31.03	10.89
(72.07, 100.0]	3.09	34.74	25.86	18.90

Table 26. Analysis on the values of returns with indicator value

Reducing Exposure Time

By observing that the correlation between MFI and returns decreases over time, we identified that the predictive power of MFI diminishes with an increase in the time horizon. Therefore, we decided to square off the position after a certain amount of time. This reduces the exposure to the market and limits the impact of unforeseen events that might occur over longer timeframes.

ret_5	ret_1	ret_10	ret_30
5.45	1.27	8.41	3.56

Table 27. Correlations(in percent) of MFI with returns

Integration with Other Indicators

Implementing a time-based exit strategy makes your trading approach more adaptable and integrable with other indicators. Combining multiple indicators can provide a more comprehensive view of market conditions. If one indicator's effectiveness diminishes over time, others may still provide valuable insights.

Dynamic Risk Adjustment

The strategy allows for dynamic adjustments to risk. If the correlation between MFI and returns weakens over time, you're effectively acknowledging this change in market behavior and adjusting your strategy accordingly. This adaptability helps in avoiding prolonged exposure to a strategy that may be less effective in current market conditions.

5.5 Adaptive Profit Cap

During our analysis of the trading strategy, we observed certain drawbacks:

- **Hitting the Profit Cap:** We frequently observed that trades were hitting the profit cap. This indicated that there might still have been potential for additional profit, which our current strategy was not capturing.

- **Inadequate Stop Loss:** In some instances, the stop loss level was not sufficient, leading to larger losses than anticipated. This highlighted the need for a more adaptive approach to setting the stop loss threshold.

The core idea behind this approach is to adjust these thresholds based on the behavior observed in the last n trades. We keep track of how often our trades hit the profit cap. If the profit cap is consistently being reached, it suggests that our trades are capable of yielding more profit. In response, we incrementally increase the profit cap.

Conversely, if stoplosses are triggered more frequently than expected, it indicates that our initial risk assessment might be too optimistic. To mitigate this, we adjust our strategy by reducing the stoploss threshold.

5.5.1 Reducing Holding Time and Dynamic Adjustment of Parameters

In our continuous effort to optimize the trading strategy, we introduced an additional refinement: setting a maximum holding period for each trade. This decision was driven by the need to reduce the average holding time, thereby minimizing exposure to market volatility and enhancing trade turnover.

A key aspect of refining our trading strategy was the introduction of measures to reduce the holding time of trades. We implemented the following strategies:

- **Maximum Holding Period:** To avoid prolonged market exposure and the associated risks, we set a maximum duration for each trade. This ensures that positions are not held longer than necessary, especially in situations where the desired profit cap or stoploss levels are not quickly met. This measure helps in maintaining a disciplined approach and mitigating potential risks due to changing market conditions.
- **Dynamic Adjustment of Stoploss and Profit Cap:** Recognizing the importance of time in trade management, we introduced a dynamic system for adjusting the stoploss and profit cap as the trade progresses. As time increases, the stoploss threshold is incrementally raised to safeguard against adverse market shifts, while the profit cap is lowered to secure profits before potential reversals. This time-dependent strategy ensures that our trades adapt to ongoing market dynamics, optimizing for both profitability and risk management.

Figure 40. Dynamic Adaptive Profit Cap and StopLoss

5.6 Dynamic Drawdown Stop (DDS)

The two paramount metrics for evaluating algorithmic trading strategies are the total profit and loss (PnL) and the maximum drawdown. Upon scrutinizing the feedback received on the alphas, it was discerned that the current risk management approaches necessitated more robust methodologies to achieve an optimal balance between total PnL and maximum drawdown. In this context, dynamic drawdown is implemented by utilizing the PnL generated in a trade and the aggregate PnL accrued up to time t. This implementation mandates the optimization of two critical parameters: the downward threshold and the upward threshold. These parameters are optimized through a dual approach, encompassing technical analysis (plotting PnL against time) and a grid search methodology (analyzing Total PnL and Maximum Drawdown). The Dynamic Drawdown Stop can be implemented with any algo trading strategy. Down strategy is kept more strict as compared to up strategy balance the trade off in total PnL and drawdown.

Mathematical Formulation Let $\text{totalPnL}(t)$ be the total profit and loss at time t, and maxTotalPnL the maximum total PnL observed until time t. The drawdown and trading control mechanism is defined as follows:

- **Updating maxTotalPnL**:

$$\text{maxTotalPnL} = \begin{cases} \text{totalPnL}(t) & \text{if totalPnL}(t) > \text{maxTotalPnL} \\ \text{maxTotalPnL} & \text{otherwise} \end{cases} \tag{7}$$

- **Calculating Drawdown**:

$$\text{Drawdown}(t) = \frac{\text{maxTotalPnL} - \text{totalPnL}(t)}{\text{maxTotalPnL}} \tag{8}$$

- **Trading Control**:
  - If $\text{Drawdown}(t) > \text{downThreshold}$, and upflag is false suspend trading post time t. Store
  - If Drawdown(t-1) $>$ Drawdown(t) set upflag true
  - If uplflag is true and $\text{Drawdown}(t) > \text{upThreshold}$ and $\text{totalPnL}(t)$ is increasing, continue suspending trade
  - if upflag is true and $\text{Drawdown}(t) < \text{upThreshold}$ and $\text{totalPnL}(t)$ is increasing, resume trading activity and set upflag to false

- **Trade Execution Decision**:

$$\text{Execute Trade} = \begin{cases} \text{True} & \text{if Drawdown}(t) < \text{upThreshold} \\ \text{False} & \text{otherwise} \end{cases} \tag{9}$$

6. Conclusion

The strategies developed in this report demonstrate the effective utilization of various analytical techniques and indicators for trading in the volatile BTC/USDT market. Through extensive testing and optimization, these strategies have shown the potential in outperforming standard benchmarks. The integration of dynamic risk management and the careful selection of indicators and parameters have been crucial. The findings contribute significantly to the realm of algorithmic trading in cryptocurrencies, offering insights and tools for traders to navigate and profit in this challenging market.