1. Introduction

Curating alphas for the Bitcoin and Ethereum market was challenging due to its **highly volatile and unpredictable nature.** This renders stand-alone traditional indicators ineffective in identifying the underlying market microstructure and providing reliable signals.
We created only one strategy which works for both markets where only one parameter changes showing the robustness of our alphas. The flow of our alpha creation dealt with **denoising data** so that we could correctly **identify the regimes of the market**, followed by **segregation based on the bullish and the bearish trends**, giving us insight into what our strategies must indicate and giving us genuine signals.

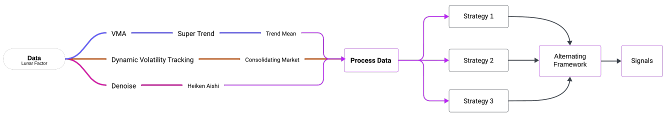

Figure 1. ALTERNATING FRAMEWORK

2. Reasoning

2.1. Denoising

We utilised two approaches for data denoising: Heiken Ashi and Variable Moving Average (VMA).

Heiken Ashi

- Heiken Ashi smoothens raw price movements by **averaging open, close, high, and low prices** into new candles.
- It reduces market noise and emotional spikes, revealing the market's underlying rhythm.
- We have used it for minimal noise reduction, not deviating from the original trends.

Variable Moving Average (VMA)

VMA adjusts to market activity dynamically, reducing the lag issues associated with the **traditional rolling averages**.

- It denoises the data with little delay, even in active markets.
- We have used this for trend segmentation to decrease noise and produce a more accurate price series for further analysis.

2.2. Trend Identification

Indicators can generate **erroneous signals** during modest dips in moving markets, such as indicating **short trades during positive pullbacks**. This results in **lower returns and worse drawdowns**. We used a trend confirmation indicator to match positions with market trends to overcome this.

Supertrend Indicator

We used the Supertrend indicator to identify trends effectively, even in Sideways or Ranging Markets:

- **ATR is factored** in to be used as an indicator for the volatility of the markets.
- Replaced traditional OHLCV data with **denoised OHLCV (using Variable Moving Average)** for improved sensitivity and reduced lag.

Integration

The trend confirmation output was averaged and integrated into the signal generation process as a filter to enhance reliability.

2.3. Market Regime Identification

Strategies rarely work well across all market regimes, often leading to overfitting. To address this, we implemented a **rolling clustering algorithm using ATR** to dynamically track market regimes.

Volatility Clusters

Market regimes are identified using ATR to capture volatility. Volatility clusters are defined as:

$$\textbf{clusters} = \begin{bmatrix} \text{volatility}_{\text{min}} + \text{vol\_range} * \text{high\_vol}, \\ \text{volatility}_{\text{min}} + \text{vol\_range} * \text{mid\_vol}, \\ \text{volatility}_{\text{min}} + \text{vol\_range} * \text{low\_vol} \end{bmatrix}$$

where volatility range = max(volatility) − min(volatility).

Clustering and Regime Allocation

ATR values are assigned to the nearest cluster, with centers updated as the mean of the assigned ATR values.

- **High and medium volatility** clusters correspond to **trendy regimes**.
- **Low volatility** clusters correspond to **sideways regimes**.

A smoothening process ensures clear regime division for better application in strategy execution.

2.4. Signal Generation

2.4.1. Strategy 1

We needed a generic indicator that could generate **returns in both sideways and trendy markets**, for which we used **Keltner bounds with Lunar Modification**. This is a volatility-based indicator with a central EMA line for trend identification and the upper and lower bound, based on ATR, for capturing volatility.

Calculation

- **Middle Line:** $\text{EMA}(n, \text{Close})$
- **True Range (TR):** $\max(\text{High} - \text{Low}, |\text{High} - \text{Close}_{\text{prev}}|, |\text{Low} - \text{Close}_{\text{prev}}|)$
- **Average True Range (ATR):** $\text{EMA}(n, \text{TR})$
- **Upper Bound:** Middle Line $+ k \cdot \text{ATR}(n)$
- **Lower Bound:** Middle Line $- k \cdot \text{ATR}(n)$

Here, $k = 2.25$ and $n = 20$.

Trading Signals

- **Buy:** Enter a long trade when the close price crosses above the upper Keltner band, confirmed by a 75-window SMA of the Supertrend.
  Crossing above the upper band indicates bullish momentum, and the SMA confirmation ensures the trend is not a false breakout.
- **Sell:** Enter a short trade when the close price crosses below the lower Keltner band, confirmed by a 75-window SMA of the Supertrend.
  Crossing below the lower band indicates bearish momentum, and the SMA confirmation ensures the trend is not a false breakout.

To enhance the signals from Keltner Channels, we optimize them using Lunar Cycles. As **Keltner Channels are lagging indicators**, they provide signals after a trend has started. **Lunar Cycles help identify short-term trend reversal** earlier by analyzing market momentum before the Full and New Moon phases. The conditions are as follows:

- **Buy (Lunar):** If the closing price, defined number of hours before the Full Moon, is lower than the Full Moon day, take long positions.
- **Sell (Lunar):** If the closing price, a defined number of hours before the New Moon, is higher than the New Moon day, then we take short positions.

This approach integrates market sentiment, influenced by Lunar Cycles along with astrological beliefs and geomagnetic field changes, to predict short-term trends and catch them early to maximize our profits.

2.4.2. Strategy 2

The Hawkes process is an advanced statistical model that **captures self-exciting events**, making it perfect for volatile markets like cryptocurrency. Unlike lagged indicators like MACD, it leverages current market action to determine the possibility of major price moves, allowing for **quick trend spotting.**
ATR-based Normalized Range
To normalize price fluctuations and account for asset volatility, the Average True Range (ATR) is computed as:

$$\text{ATR}_t = \text{Average}_n\big(\ln(\text{High}_t) - \ln(\text{Low}_t)\big)$$

The normalized range is:

$$\text{Normalized Range}_t = \frac{\ln(\text{High}_t) - \ln(\text{Low}_t)}{\text{ATR}_t}$$

Normalization adjusts price changes to **reflect recent volatility**, ensuring consistency.

Hawkes Process

We use **exponential decay** to model how current volatility affects future movements. The **decay parameter κ controls the influence of historical volatility** ($\alpha = e^{-\kappa}$). The process is:

$$v_{\text{hawk}}[t] = \kappa\big(\alpha \cdot v_{\text{hawk}}[t-1] + \text{Normalized Range}_t\big)$$

An Important Note

Since the data that is fed into the Hawkes' algorithm iteratively starts from the first index of given data, **left slicing of data** is bound to generate slightly different signals as **the origin of the data has shifted**. Also note that the lookback period used in the calculation of Normalized Range has a maximum limit of the length of data, thus altering signals on left slicing. This **does not imply forward bias**, it simply means the process recursively and dynamically improves itself using the historical array of signals.

Volatility Signals

Trading signals are generated by comparing v_{hawk} with **rolling quantile thresholds**:

- **Signal Reset:** $v_{\text{hawk}}[t] < q_x\%[t]$ resets the signal to neutral (0).
- **Signal Activation:** $v_{\text{hawk}}[t]$ crossing above $q_y\%[t]$ triggers a signal.
- **Trade Direction:**
  - **Buy (+1):** Positive price change since last reset.
  - **Sell (-1):** Negative price change since last reset.

The parameters for hawkes were discovered by **GPSO methodology**, an extended concept of **particle swarm optimization** used on multiple datasets to ensure robustness.

2.4.3. Strategy 3

Fibonacci retracement is an orthodox support and resistance method that has **worked great in sideways and reverting markets**. It suits our requirements best in the sideways and reverting market when the other strategies perform mediocre. The levels of the Fibonacci bounds are derived from the Fibonacci series and are mathematically related.

Signal Generation:

- min val = min(Close, n)
- max val = max(Close, n)
- Level 1 Long = min val+0.236×(max val−min val)
- Level 1 Short = max val − 0.236 × (max val − min val)
- Cloud Width = Level 1 Long − Level 1 Short

Trading Rules:

- **Buy (+1):** Triggered when the **cloud width is less than the threshold or the mean cloud width**, and the trend indicates an uptrend.
- **Sell (-1):** Triggered when the **cloud width is less than the threshold or the mean cloud width**, and the trend indicates a downtrend.

This strategy integrates the Fibonacci retracement concept with dynamic thresholds, making it well-suited for adaptable and precise trading decisions in varied market conditions.

3. Risk Management

3.1. Trailing Stop-loss

Trailing stop-loss is an important risk measure. We initially set a stop-loss level, and **as the prices increase, the stop-loss level also adjusts itself based on the movement of the market**(i.e. increases(in long trade) and decreases(in short trade)) to maximize the profits while minimizing our drawdowns.

3.2. Trailing Take-Profit

We initially set a take profit level for a trade, and it remains the same if the price movement goes as desired for the type of trade, whereas **if the price moves in the opposite direction, we decrease the take profit levels** to exit at a small profit instead of taking a loss.

3.3. Trailing ATR-Based Stoploss and Take Profit

We implemented an ATR-based trailing stop-loss and take-profit. It captures the gains while reducing our risk because it adjusts itself to the market conditions i.e. **broader in a high-volatile market and narrower in a low-volatile market.**

3.4. Impulse Exit Protocol

We observed that the **market reverts to fill the gap whenever there is a sudden increase in the price with Volume** in the market, according to the concept of Fair Value Gap (FVG). **We take an exit** in this type of condition to protect our portfolio. If we encounter this gap during a trade, we exit.

3.5. Holiday and Market Time Effect

Holiday Effect: We have incorporated the effect of an expected rapid **increase in volatility on holidays** to improve our strategy. We have used it to suitably **adjust ATR parameters** in regions around these dates, **relaxing stop loss and take profit**, refraining from a premature exit.

Market Time Effect: Market volatility is high during the day due to increased trading activity, primarily because most of the world's markets, like **NASDAQ and NYSE**, are open during that time. To optimize performance and manage risk, we **adjust our stop-loss settings** accordingly. During hours between **(08:00–17:00 UTC)**, we use **wider thresholds** to avoid premature exits in a volatile environment. **At night, we implement tighter limits to minimize potential losses.** This approach balances the opportunities of daytime volatility with protection against overnight risks.

4. Crucial Learning

We gained experience and knowledge of **different market regimes and microstructures**. Understanding market regimes and searching for the **perfect indicator for a particular regime** helped us learn about several popular indicators and their mathematical reasoning. **Trade-wise analysis** helped us understand problems associated with different market regimes with the traditional indicators. We also learnt the importance of **implementing different types of risk management** measures and **choosing generic parameters that may work for different regimes.**

Data analysis gave us deep insights into the market, helping us understand key **correlations between different parameters and how the market reacts to these price movements**.

We also learned that **there are various external factors which affect the microstructure of the market**. This can be explained by observation of the **Market time effect and Holiday effect**, which helped us predict the future market movement. One thing we learned from our mistakes is that it is easy to over-fit on a given data but **strategy must be robust to work in a live market for which we put a lot of effort for the robustness of our strategy.** Below are the results of our strategy on various coins without changing any parameters showing its adaptability and robustness.

Asset	Benchmark Return (%)	Profit Return (%)	Maximum Drawdown (%)
DOGE	369.54	455.09	22.79
SOL	132.87	49.44	18.81
LTC	40.64	42.63	31.78

Table 1. Performance Metrics for Cryptocurrencies