ZELTA AUTOMATIONS UNTRADE

CURATING ALPHAS ON THE BTC AND USDT CRYPTO MARKET

TEAM-67

Trading Strategy Development for BTC & ETH

Progress Update

As a first step in developing the strategy, we verified the completeness of the BTC and ETH datasets and looked for any missing information. After that, we applied a number of denoising strategies to improve the price data's signal clarity. This procedure included applying the wavelet transform to break down price data and identify important movements, as well as employing the Kalman filter to efficiently separate signals from noise, producing clearer trends for examination. In order to provide a more lucid view of the underlying trends, Heikin Ashi candles were employed to further smooth price swings. Renko candles were also taken into consideration, but they were eventually disqualified because of brick sizing issues that led to irregularities and made it impossible to precisely record significant market moves.

The investigation then turned to the concepts of **reinforcement learning**, with a particular emphasis on the Bellman Equation, which helps guide dynamic decision-making in erratic markets. One of the clear benefits of reinforcement learning was its capacity to manage the extremely volatile BTC and ETH markets. Through a reward system that takes cumulative risk and reward over time into account, the model's self-learning capabilities enable it to adjust and optimize depending on real-time data in search of favorable returns. Furthermore, the transparent nature of reinforcement learning, which eliminates the need for external libraries, and its resilience in handling noisy data help it avoid the drawbacks of black-box methods and provide a straightforward and understandable method for trading decisions.

We also found that there was a **strong positive correlation** between BTC and ETH, and that ETH was more volatile than BTC. Based on this, we created a **correlation-based strategy** for ETH that included both entry and confirmation signals. By using a set of technical indicators applied to both BTC and ETH, we were able to confirm the entry signals, which were based on the correlation patterns between BTC and ETH and indicated alignment or divergence in their price movements. This created a dual-confirmation mechanism that minimizes false positives and makes sure that entries are in line with general market trends.

Moving forward, the goal is to refine and enhance this strategy further. We will focus on optimizing reinforcement learning states and reward function, improving noise-filtering methods, and fine-tuning entry and exit conditions to strengthen the strategy's robustness and adaptability to real-time market conditions.

1 Unique Aspects of the BTC/USDT Strategy and Difference from Traditional Methods

This strategy leverages a distinct blend of technical indicators, stochastic modeling, and reinforcement learning, creating a robust framework that adapts to the unique volatility and structure of cryptocurrency markets.

1.1 Geometric Fractional Brownian Motion (fGBM)

Unlike typical models such as Geometric Brownian Motion (GBM), which assumes price changes are random and memoryless, fGBM captures **long-term dependencies** by introducing memory into price changes. This memory effect helps model markets with mean-reverting tendencies or persistent trends, making it well-suited for speculative assets like BTC, which often exhibit high, clustered volatility.

1.2 Consolidation Signal and Transitional Periods

By identifying **consolidation periods**—phases of low volatility where prices remain stable within a defined range—the strategy can anticipate breakouts or breakdowns. The consolidation signal actively penalizes the model for inaction when prices move beyond these ranges, incentivizing responsiveness to likely breakout opportunities. This helps the model take advantage of inefficiencies during transitional periods, moments when markets shift from low volatility (consolidation) to sudden price changes, often triggered by new information or shifts in trading sentiment.

1.3 Reinforcement Learning (RL)

Reinforcement learning allows the strategy to learn optimal actions (such as holding, buying, or shorting) through trial and error during training. This continuous learning is valuable in dynamic markets, as the strategy can adapt to changing conditions, rewarding actions that lead to gains and penalizing losses. Unlike static systems, RL models can adjust their approach based on historical performance, making them more resilient to the unpredictable nature of cryptocurrency markets.

2 Data Preparation and Indicator Calculation

2.1 Technical Indicators Calculation

Several technical indicators are calculated to capture different aspects of market behavior:

2.1.1 Exponential Moving Averages (EMA)

- **EMA_Signal:** Signals bullish (+1) when EMA7 > EMA14 > EMA28, bearish (−1) when EMA7 < EMA14 < EMA28, else neutral (0).

2.1.2 Relative Strength Index (RSI)

- **RSI_Signal:** Signals overbought (+1) when RSI_14 > 75, oversold (−1) when RSI_14 < 35, else neutral (0).

2.1.3 Aroon Indicator

- **Aroon_Signal:** Signals bullish (+1) when Aroon_Up > Aroon_Down, else bearish (0).

2.1.4 Percentage Change

- **pct_change:** The percentage change in the closing price from the previous period.

2.1.5 Consolidation Signal

Function: `add_consolidation_signal()`

Purpose: Identifies periods of price consolidation (low volatility) based on the range between the highest high and lowest low within a rolling window.

Logic: If the price stays within a certain threshold range, it's considered consolidation.

3 Reinforcement Learning Agent with Q-Learning

3.1 Overview

Uses **Q-learning**, a model-free RL algorithm, to learn the optimal policy for trading. The agent updates a Q-table that maps states to actions based on expected future rewards.

3.2 State Space Definition

Components:

- **Aroon_Signal:** Discretized into 2 bins (0 or 1).
- **RSI_Signal:** Discretized into 3 bins (−1, 0, +1).
- **EMA_Signal:** Discretized into 3 bins (−1, 0, +1).
- **Holdings State:** Represents the agent's current position (−1 for short, 0 for neutral, +1 for long).

- **fgbm_signal:** Discretized into 3 bins (-1, 0, $+1$).
- **pct_change_signal:** Discretized into 50 bins based on the percentage change in price.

3.3 Action Space

Actions: `[Hold, Buy, Sell, Short, Cover Short]` corresponding to `[0, 1, 2, 3, 4]`.

3.4 Reward Function

- **Positive Rewards:** Profit gained from successful trades.
- **Negative Rewards:**
  - Trading commissions (penalty for making a trade).
  - Losses from trades.
  - Penalties for holding positions during non-consolidation periods.
- **Special Conditions:**
  - **Stop-Loss Triggered:** Large negative reward to discourage the agent from entering positions that could lead to significant losses.
  - **Consolidation Reward:** Additional reward when holding during consolidation periods.

3.5 Training Process

- **Episodes:** The agent is trained over multiple episodes (e.g., 5000).
- **Epsilon-Greedy Policy:** Balances exploration and exploitation.
  - **Epsilon Decay:** Reduces exploration over time to focus on exploiting learned policies.
- **Q-Table Update:** Uses the Bellman equation to update the Q-values:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left(r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right) \tag{1}$$

  Where:[α , γ, r, (s, s') , (a, a')] corresponding to [learning rate, discount factor, immediate reward, current and next states, current and next actions].

4 Risk Management

- **Stop-Loss Mechanism:**
  - Automatically exits positions if the price moves adversely beyond the stop-loss threshold set at **2.5%**.
- **Position Sizing:**
  - Limits the size of short positions to **75%** of available balance to manage leverage and risk.

Key Metrics

Category	Metric	Value
Static Statistics	From	2023-01-01 14:00:00
	To	2024-01-01 00:00:00
	Total Trades	30
	Leverage Applied	2.0
	Winning Trades	14
	Losing Trades	16
	No. of Long Trades	30
	No. of Short Trades	0
	Benchmark Return (%)	157.08
	Benchmark Return (on $1000)	1570.81
Performance Metrics	Win Rate	46.67%
	Winning Streak	4
	Losing Streak	6
	Gross Profit	2256.06
	Net Profit	2166.06
	Average Profit	72.20
	Maximum Drawdown (%)	22.34%
Drawdown and Loss Metrics	Average Drawdown (%)	3.41%
	Largest Win	594.6
	Average Win	220.24
	Largest Loss	-80.61
	Average Loss	-57.33
	Maximum Holding Time	75 days 22:59:59
	Average Holding Time	12 days 0:25:59
Adverse Excursion	Maximum Adverse Excursion	5.26
	Average Adverse Excursion	2.63
Ratios	Sharpe Ratio	7.80
	Sortino Ratio	34.86

Category	Metric	Value
Compound Statistics	Flag	Trades Executed: 30
	Initial Balance	1000.0
	Leverage Applied	2.0
	Number of Trades	30
	Profit Percentage	448.06%
	Maximum Drawdown	33.72%
	Average Drawdown	6.28%
	Time to Recovery (TTR)	76 days
TTR Metrics	Average TTR	25.61 days
	Maximum PNL	1479.68
	Minimum PNL	-353.56
	Max Portfolio Balance	5958.35
	Minimum Portfolio Balance	1000.0
	Final Balance	5480.60
	Total Fee	251.59

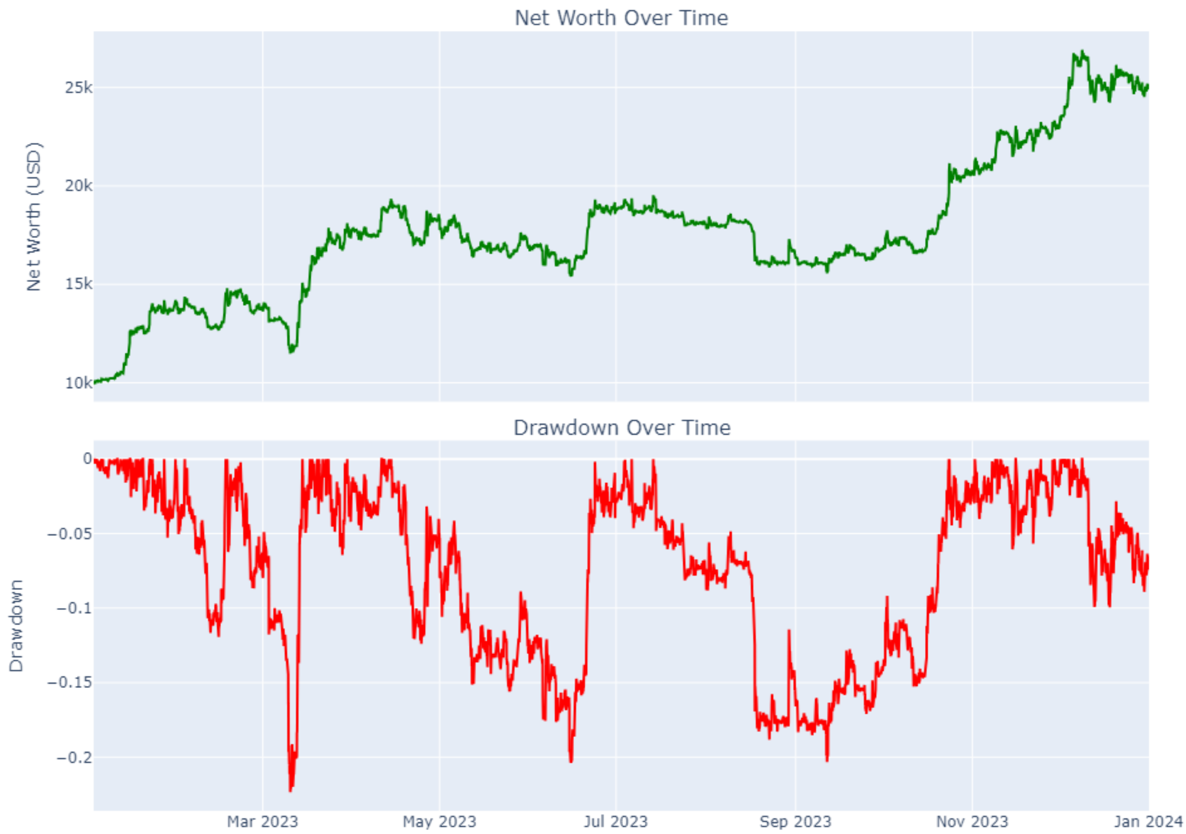


Figure 1: Net Worth and Drawdown

5 Unique Aspects of the ETH/USDT Strategy and Difference from Traditional Methods

Overview

In financial analysis, the correlation between two assets, such as BTC and ETH, measures the degree to which their prices move in relation to each other. This strategy leverages the correlation to identify trading opportunities by exploiting relative strength or weakness between BTC and ETH, targeting profitable trades based on observed divergences.

Core Concept and Objectives

The strategy seeks to utilize BTC-ETH correlation as a primary signal for entering or exiting ETH trades, with additional technical indicators for refined entry and exit points. By identifying periods of divergence, the strategy aims to capitalize on potential mispricings, focusing on ETH relative to BTC.

Key Features and Indicators

Correlation Analysis

The primary indicator is the rolling correlation of BTC and ETH closing prices, calculated over a 7-hour window. This correlation measure helps indicate whether BTC and ETH are likely to move in tandem, providing a reliable signal basis for trades.

Indicators on BTC for ETH Trades

- **Moving Average Convergence Divergence (MACD):** BTC's MACD indicates momentum. A bullish MACD crossover signals an upward trend, while a bearish crossover suggests a downward trend.
- **Average True Range (ATR):** The ATR for BTC assesses market volatility. Positions are entered only when ATR is below a dynamic threshold (1% of BTC's opening price) to ensure low volatility and reduced risk of sharp price swings.

Indicators on ETH for ETH Trades

- **Relative Strength Index (RSI):** ETH's RSI is used to gauge momentum, identifying overbought (RSI above 70) or oversold (RSI below 30) market conditions.
- **Aroon Indicator:** ETH's Aroon Up and Down indicators help identify trend strength and potential reversals. A high Aroon Up compared to Aroon Down indicates a strong upward trend, while the reverse suggests a downward trend.

Entry and Exit Conditions

Long Trades

- **Entry Condition:** A long position is entered if the ETH RSI is above 60, the BTC-ETH correlation exceeds 0.6, BTC's MACD line is above the signal line, and ETH's Aroon Up is greater than Aroon Down.
- **Exit Condition:** The position is closed if the price falls 10% below its highest value since entry, or if it is held for more than 20 days. Additional exit triggers include an ETH RSI below 30 or a weakened correlation.

Short Trades

- **Entry Condition:** A short position is entered when the ETH RSI is below 30, the BTC-ETH correlation is greater than 0.6, BTC's MACD line is above the signal line, and ETH's Aroon Up is greater than Aroon Down.
- **Exit Condition:** The short position is closed if the price rises 10% above its lowest value since entry, or if it is held for more than 20 days. The position is also exited if ETH's RSI rises above 60 or if correlation diminishes.

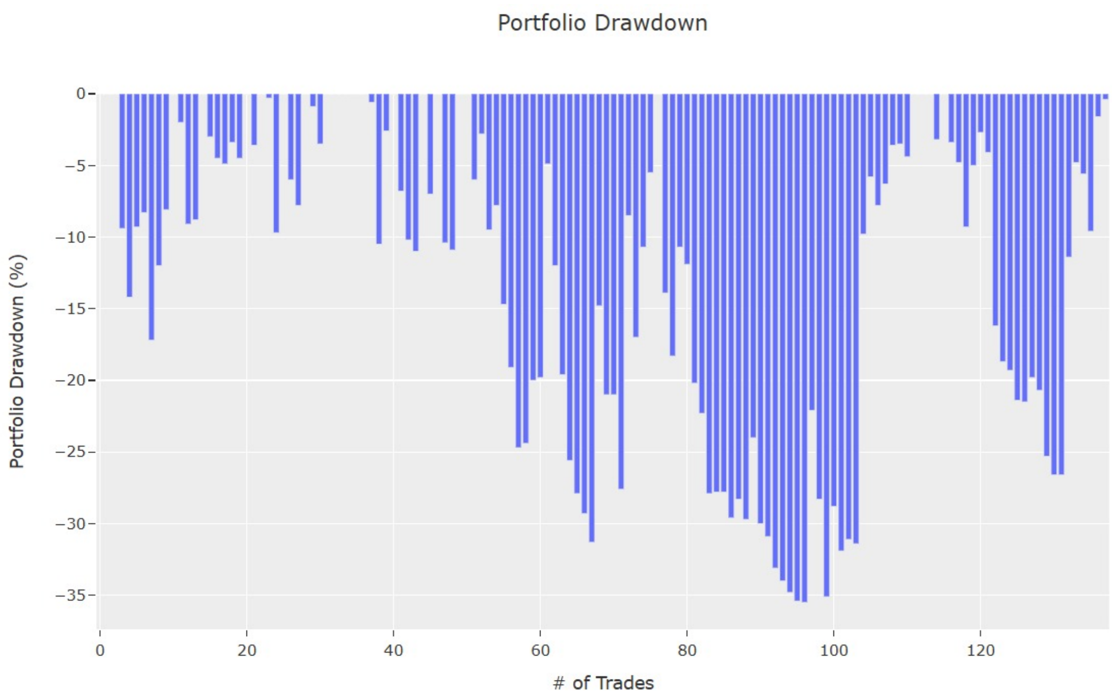
Future Prospects and Improvements

- **Enhanced Signal Generation:** Future iterations will integrate advanced spread/divergence indicators to strengthen signals for both long and short trades.
- **High-Volatility Market Expansion:** The strategy will be extended to high-volatility conditions to take advantage of larger price movements, in addition to the current low-volatility focus.

Conclusion

This BTC-ETH correlation strategy uses a combination of technical indicators, including MACD, ATR, RSI, and Aroon indicators, tailored specifically for ETH trades. By leveraging the correlation between BTC and ETH, the strategy aims to provide more precise entry and exit points. The strategy's future improvements focus on refining signal generation and expanding into high-volatility environments, which may enhance its robustness and applicability across diverse market conditions.


Equity Curves
Static Position
Static PnL
Compounded Portfolio
Net Profit/Loss
0
10k
20k
30k
40k
0
20
40
60
80
100
120
# of Trades
Compounded
Portfolio Balance
0
100k
200k
300k
0
20
40
60
80
100
120
# of Trades


Portfolio Drawdown
Portfolio Drawdown (%)
0
−5
−10
−15
−20
−25
−30
−35
0
20
40
60
80
100
120
# of Trades

Key Metrics (Untrade's Backtester)

Category	**Metric**	**Value**
Static Statistics	From	2020-01-01 00:00:00
	To	2023-12-31 00:00:00
	Total Trades	137
	Leverage Applied	1.0
	Winning Trades	64
	Losing Trades	73
	No. of Long Trades	106
	No. of Short Trades	31
Benchmark Return (%)	Benchmark Return (%)	1687.58
	Benchmark Return (on $1000)	$16,875.87
Trade Metrics	Win Rate	46.71%
	Winning Streak	6
	Losing Streak	6
	Gross Profit	4982.87
	Net Profit	4777.37
	Average Profit	34.87
	Maximum Drawdown (%)	8.72%
Loss Metrics	Average Drawdown (%)	2.45%
	Largest Win	770.69
	Average Win	123.88
	Largest Loss	-137.33
	Average Loss	-43.16
Holding Time	Maximum Holding Time	20 days
	Average Holding Time	7 days 8:46:51
Adverse Excursion	Maximum Adverse Excursion	19.14
	Average Adverse Excursion	4.29
Performance Ratios	Sharpe Ratio	5.09
	Sortino Ratio	17.70
Compound Statistics	Flag	Trades Executed: 137
	Initial Balance	1,000
	Leverage Applied	1.0
	Number of Trades	137
	Profit Percentage	3909.76%
Drawdown Metrics	Maximum Drawdown	33.51%
	Average Drawdown	11.27%
	Time to Recovery (TTR)	132.27 days
	Average TTR	38.84 days
PNL and Portfolio Balance	Maximum PNL	8,508.90
	Minimum PNL	-4680.08.65
	Max Portfolio Balance	40,097.65
	Minimum Portfolio Balance	1,000.00
	Final Balance	40,097.65
	Total Fee	3,747.66

6 Unique Approaches and Innovations

6.1 Fractional Brownian Motion

The prices of financial assets are often assumed to follow Brownian motion. In standard Geometric Brownian Motion (GBM), the increments over non-overlapping time intervals are independent and follow a random walk. However, real markets frequently exhibit trends or momentum, where price changes are not independent; instead, prices often tend to follow previous movements. This dependency, driven by factors such as investor sentiment, macroeconomic influences, and behavioral biases, challenges the assumption of independent increments in standard GBM. When prices are influenced by prior movements, GBM may fail to capture these dependencies effectively.

To address this challenge, **Fractional Brownian Motion (fBM)** was introduced. Fractional Brownian Motion incorporates a parameter called the **Hurst Component**, which measures the degree of autocorrelation in a time series, revealing whether a system is trending, mean-reverting, or random (independent). The covariance function of fBM is given by:

$$E[B_H(t)B_H(s)] = \frac{1}{2}\left(|t|^{2H} + |s|^{2H} - |t-s|^{2H}\right) \tag{2}$$

where H is the **Hurst exponent**.

6.1.1 Interpretation of the Hurst Exponent

- When the Hurst exponent $H > 0.5$, it indicates a **persistence** or **trending behavior**, meaning that price movements are more likely to continue in the same direction.
- A Hurst exponent $H < 0.5$ reflects **mean-reverting** behavior, where prices are more likely to reverse direction.
- When $H = 0.5$, the process reduces to standard Brownian motion with independent increments, implying no correlation between movements.

Since the rolling Hurst exponent is greater than 0.5 most of the time, we can leverage momentum in the short term for trading strategies.

6.1.2 Mathematical Models for Asset Prices

The asset prices follow these equations when modeled through Brownian Motion:

- **Geometric Brownian Motion (GBM):**

$$S_t = S_0 \exp\left(\sigma B(t) + \left(\mu - \frac{\sigma^2}{2}\right)t\right) \tag{3}$$

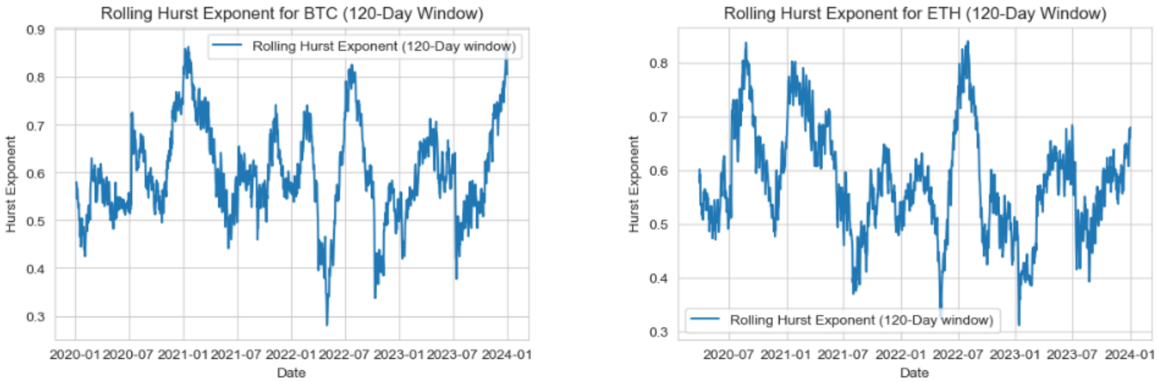


Figure 2: Hurst Exponent on rolling window of 120 hours

- **Fractional Geometric Brownian Motion (fGBM):**

$$S(t) = S_0 \exp\left(\sigma B_H(t) + \mu t - \frac{1}{2}\sigma^2 t^{2H}\right) \tag{4}$$

Here, the parameters μ (drift) and σ (volatility) are typically estimated from historical data. When modeling with Brownian motion, it is often beneficial to estimate these parameters over shorter periods to capture recent trends more accurately.

6.1.3 Limitations and Hybrid Approach

One limitation of using Fractional Geometric Brownian Motion (fGBM) alone is its reliance on the long memory of asset prices. This reliance may be disrupted by sudden events or shifts in market sentiment, leading to inaccurate forecasts. To address this limitation, we can employ a hybrid model that combines insights from both GBM and fGBM, enhancing the model's adaptability to recent changes in the market.

Markov Regime Switching Models

The Markov Regime-Switching Model is a statistical model that captures time series data with different "regimes" or states, where each state follows its own distinct behavior (e.g., bull and bear market regimes in finance). The model assumes that transitions between these regimes are governed by a Markov process, where the probability of switching from one state to another depends only on the current state, not on previous states.

The Markov Regime-Switching (MRS) Model is well-suited for analyzing cryptocurrencies like Bitcoin and Ethereum due to its ability to:

- Identify Volatility Zones: Separates high and low volatility regimes, clarifying market trends and adapting to rapid shifts between phases like bullish and bearish. Making it ideal for the crypto market with rapid shifts .

- Adaptation: Responds to real-time regime changes, supporting agile trading decisions
- Enhanced Risk Management: Optimizes portfolio exposure by limiting leverage in volatile markets and increasing it in stable periods.

Mathematical Description of model

The time series is modeled with a first-order autoregression:

$$y_t = c_1 + \phi y_{t-1} + \epsilon_t \tag{5}$$

However, the value of c1 changes with time in order to get back the model to fit in forecasts, Hence, larger model encompassing them both:

$$y_t = c_s t + \phi y_{t-1} + \epsilon_t \tag{6}$$

In this model, we estimate the transition probability for each switching possibility. For example, in a 2-regime model, the transition probabilities for $1 \to 1$, $1 \to 2$, $2 \to 1$, and $2 \to 2$ are calculated. The transition probability is given by:

$$\Pr(s_t = j \mid s_{t-1} = i, s_{t-2} = k, \ldots, y_{t-1}, y_{t-2}, \ldots) = \Pr(s_t = j \mid s_{t-1} = i) = p_{ij} \tag{7}$$

7 MSGARCH

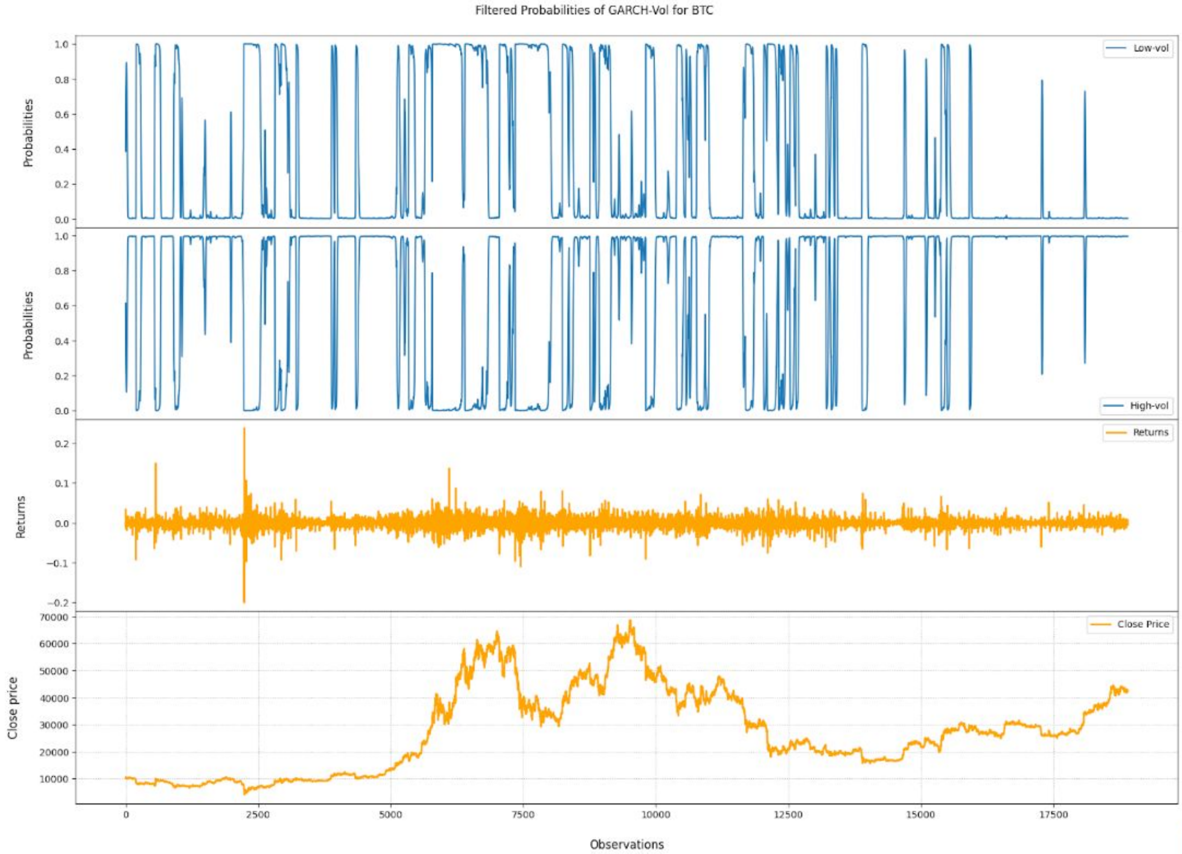
Markov-Switching Generalized Autoregressive Conditional Heteroskedasticity () The Markov-Switching Generalized Autoregressive Conditional Heteroskedasticity (MSGARCH) model is a statistical approach used to analyze and model financial time series with changing volatility regimes. It combines the GARCH framework for modeling volatility with the Markov regime-switching mechanism, enabling it to capture regime-dependent volatility dynamics in a more flexible and realistic way.

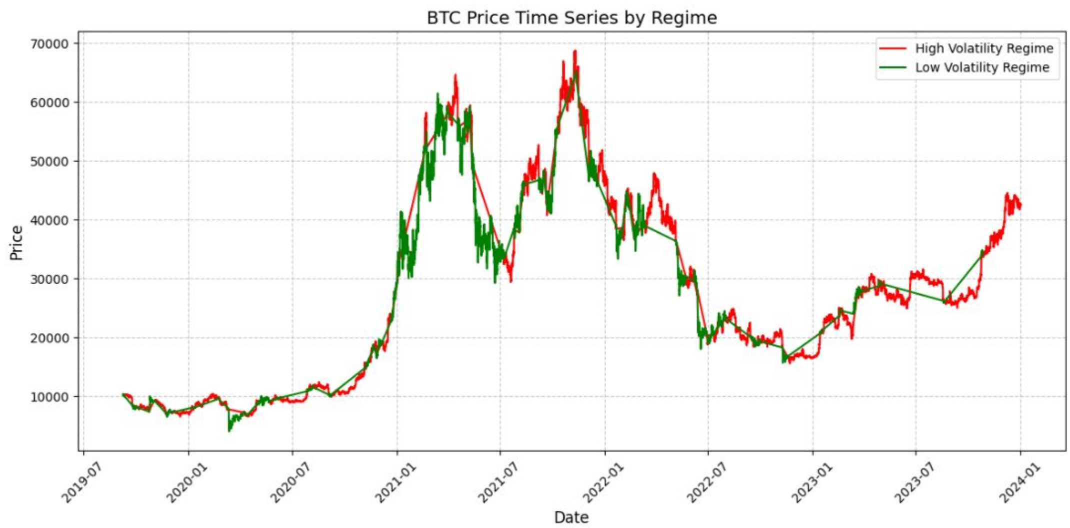
GARCH Model Mathematical Description: Consider here a GARCH(1,1) model in which the coefficients are subject to changes regime,

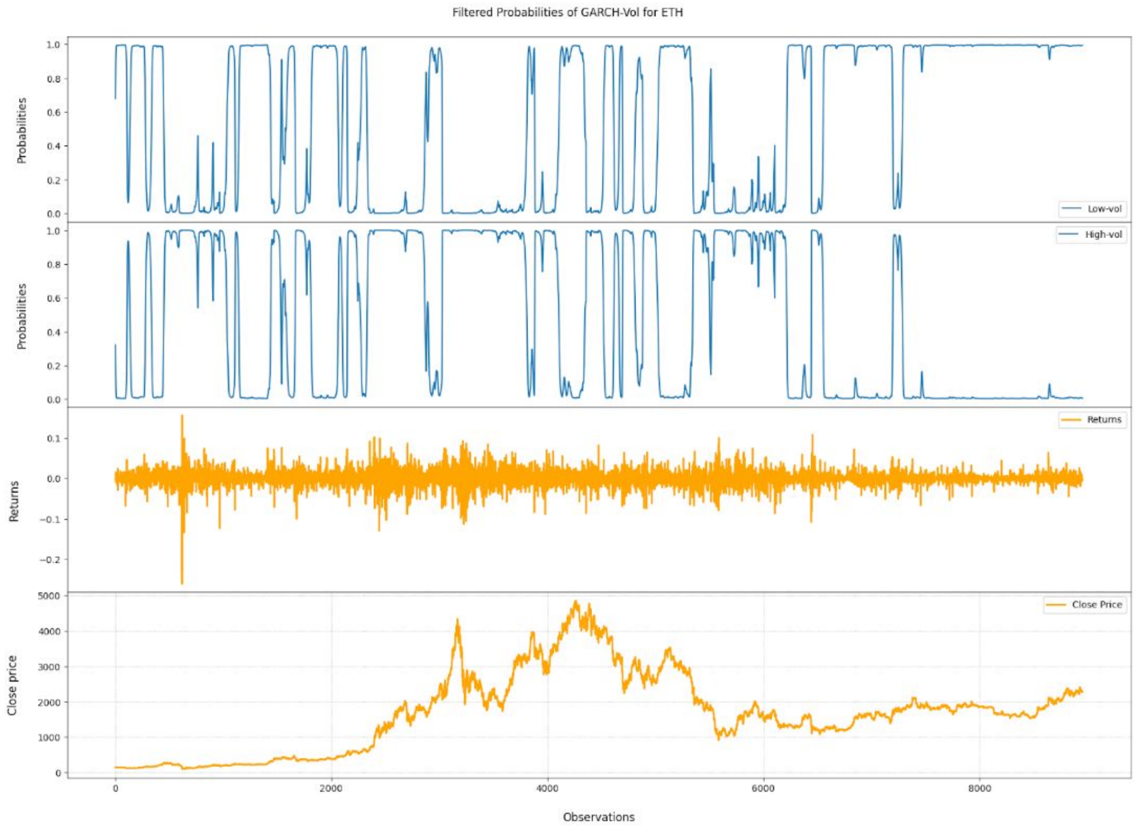
$$y_t = h_t v_t, \quad \text{where} \quad v_t \sim N(0,1)$$

Garch model is typically modeling the conditional variance .

$$h_t^2 = \gamma_{s_t} + \alpha_{s_t} y_{t-1}^2 + \beta_{s_t} h_{t-1}^2$$


Filtered Probabilities of GARCH-Vol for BTC
Low-vol
High-vol
Returns
Close Price
Probabilities
Probabilities
Returns
Close price
Observations


BTC Price Time Series by Regime
High Volatility Regime
Low Volatility Regime
Price
Date



Fractal Theory in Financial Markets

In financial markets, fractal theory suggests that repeating patterns, or fractals, often indicate psychological points of reversal, where price trends may shift. Market movements are shaped by traders' reactions, rooted in human nature and collective memory, which create predictable cycles. These patterns, influenced by historical price action and sentiment, can help anticipate future market changes. Fractal Geometry Introduction and Basic Fractals Fractal theory in financial markets suggests that repeating patterns can signal psychological reversal points where trends may change. Market movements, driven by collective memory and human nature, create cycles that can help predict future price shifts. The fractal structure consists of five bars labeled as p_1, p_2, p_3, p_4, p_5. The middle bar p_3 must have the peak within the pattern.

Bullish Fractal Structure

The middle bar p_3 must have lowest low with the pattern.

Low(p_3)$<$Low(p_2)$<$Low(p_4).

Low(p_2)$>$Low(p_1) and Low(p_4) $>$Low(p_4).

Bearish Fractal Structure

The middle bar p_3 must have highest high, with the pattern.

High(p_3)$>$High(p_2)$>$High(p_4).

High(p_2)$<$High(p_1) and High(p_4) $<$High(p_4).