Curating Alphas on BTC and ETH Cryptocurrency Market

Zelta Automations

untrade

INTER IIT TECH MEET 13.0

Team 67

Background & Problem Description

- Includes gathering and preprocessing high-quality, reliable historical data, designing strategies using statistical models such as trend-following, and conducting backtesting to evaluate performance under realistic market conditions.

- The approach leverages the significant correlation and interdependence between Bitcoin and Ethereum price movements, alongside reinforcement learning techniques, to maximize returns while maintaining controlled risk levels.

Market Dynamics

- The markets for **Bitcoin (BTC) and Ethereum (ETH)** are among the most active and liquid in the cryptocurrency business, and they often exhibit a **high level of interconnection.**
- Bitcoin frequently influences shifts in the value of other assets, like Ethereum, by acting as an indicator for the market. This relationship is demonstrated by their **positive correlation.**
- Bitcoin is primarily regarded as a store of value, but Ethereum serves as a framework for smart contracts and decentralized applications. Bitcoin and Ethereum are key to understanding and controlling cryptocurrency market dynamics due to their **unique uses, high trade volumes, volatility, and sensitivity to global events.**

Our strategy on

Ethereum (ETH)

- Hypothesis
- Core Idea
- Features
- Risk Management
- Results

Correlation

Our Hypothesis

Hourly price movements of BTC exhibit a strong positive correlation with those of ETH, indicating a significant co-movement between the two cryptocurrencies.

BTC exerts a notable influence on the subsequent price movements of ETH, highlighting its dominant role in shaping the market dynamics.

Hypothesis Testing

- Null Hypothesis (H_0): BTC and ETH hourly data have a weak correlation ($r \leq 0.5$).
- Alternative Hypothesis (H_1): BTC and ETH hourly data have a significant correlation ($r > 0.5$).

Methodology and Results

Cross Correlation Analysis

- Analyzed log returns of BTC and ETH.
- BTC lag-1 vs. ETH log returns: Correlation = 0.0551.
- 5% significance is at level $(1/\sqrt{T}) = 0.0378$.

Pearson Correlation

- $r = 0.7851$, indicating strong positive correlation.
- p-value < 0.001, well below the 5% threshold.

Conclusion

Based on the extremely low p-value, we reject the null hypothesis.

There is strong evidence that BTC and ETH are significantly correlated, with past BTC movements impacting ETH prices.


Core Idea
Trend Identification
Correlation Analysis
Volatility Mapping
CUSUM and Filtering
Entry/Exit Signals
BUY
BUY
BUY
SELL
SELL

Unique Approaches

Hurst Exponent

A statistical measure that quantifies the long-term memory of a time series, helping to determine its trend behavior.

Interpretations:

$H < 0.5$: Mean-reverting behavior.

$H = 0.5$: Random walk with no significant trend.

$H > 0.5$: Persistent trending behavior.

Application in Strategy:

Focused on trending regions ($H > 0.5$) to align with momentum-based strategies.

Trending markets were prioritized, as they are more likely to yield profitable trades.

Correlation Analysis

Rolling correlation analysis was performed on BTC and ETH closing prices using a 7-hour window to capture real-time relationships.

Interpretation of Signals:

High Correlation (> 0.6): BTC and ETH prices are moving together, aligning trades with the broader market trend.

Low or Diverging Correlation: Indicates potential uncertainty in ETH price movement relative to BTC, signalling caution.

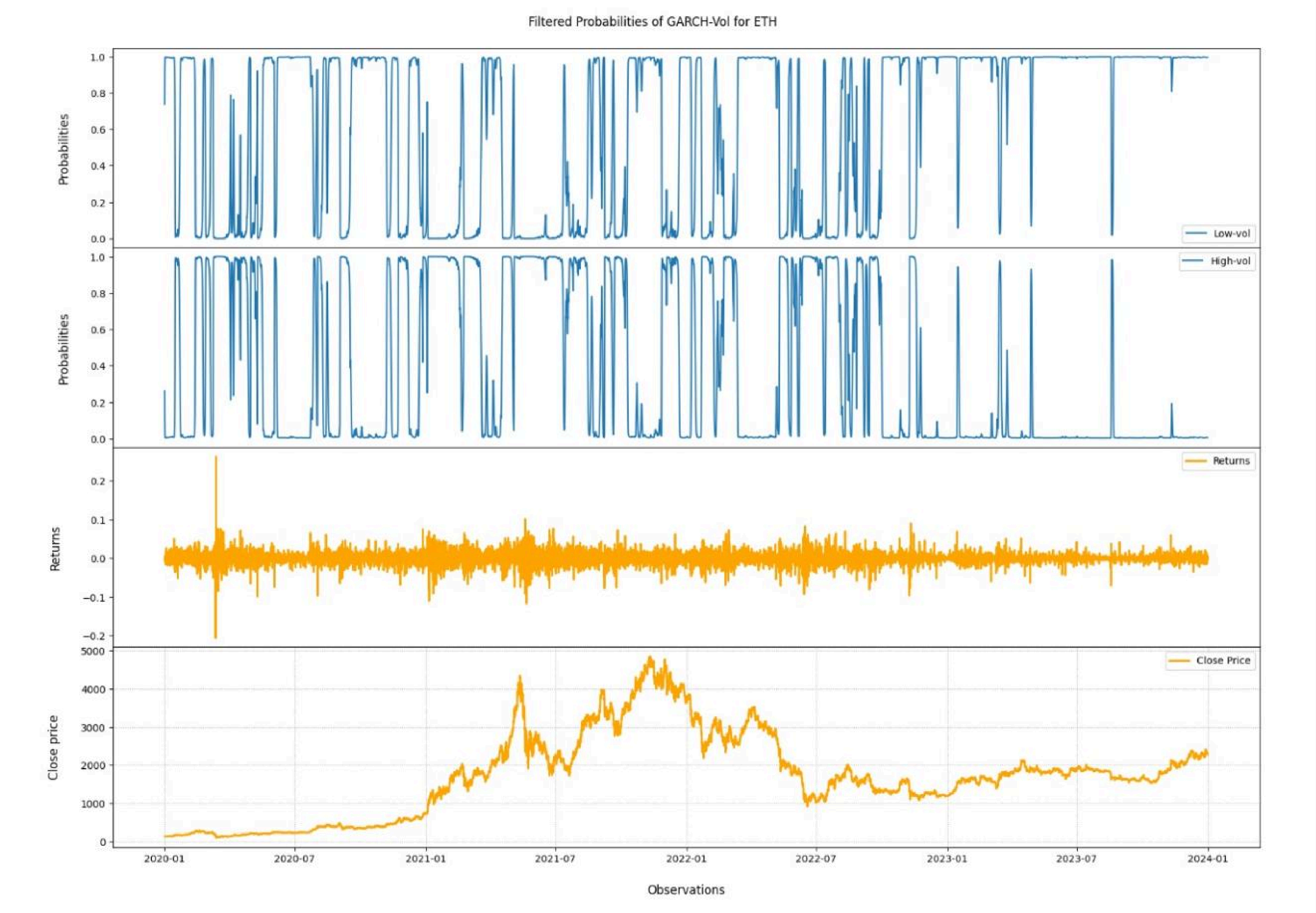
Experimented Approaches for Volatility

Volatility Clustering using PCA and K-Means

Used PCA and K-means clustering to generate different volatility clusters, in order to reduce dimensionality and group similar trading periods.

Markov Regime Switching Models

Combined the GARCH framework for modelling volatility with the Markov regime-switching mechanism, enabling it to capture regime- dependent volatility dynamics more flexibly and realistically.

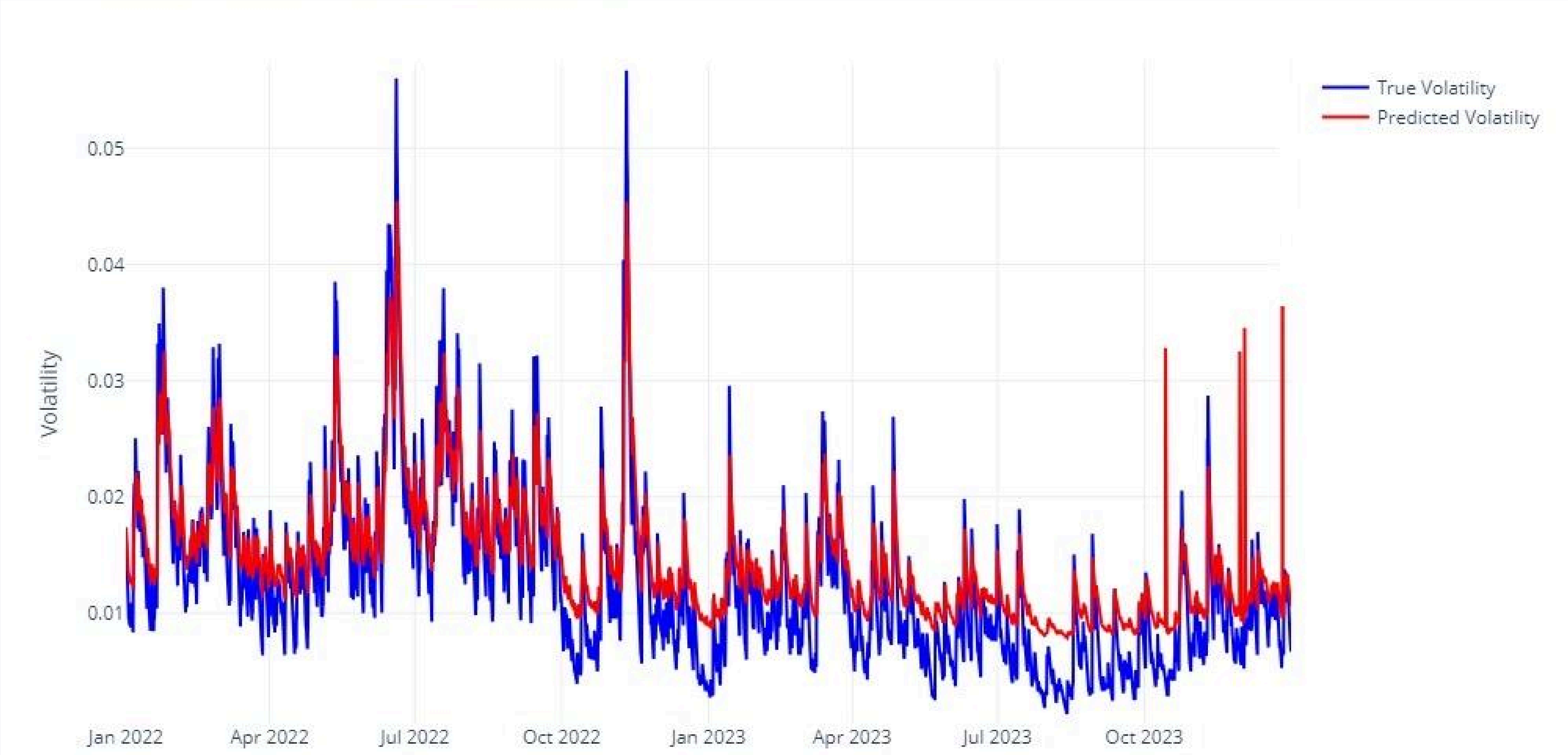


Experimented Approaches for Volatility

GARCH based volatility forecasting

Employed the GARCH(1,1) model to forecast future volatility by capturing time-varying patterns in market data.

Blue line represents the observed (true) volatility, while the red line shows the model's predicted volatility.



ATR Based Volatility Clustering

What is ATR?

The Average True Range (ATR) measures market volatility and focuses on low-volatility conditions to improve predictability and trend sustainability.

True Range (TR):

$$TR_t = \max(\text{High}_t - \text{Low}_t, |\text{High}_t - \text{Close}_{t-1}|, |\text{Low}_t - \text{Close}_{t-1}|)$$

$$ATR_n = \frac{1}{n}\sum_{i=1}^{n} TR_i$$

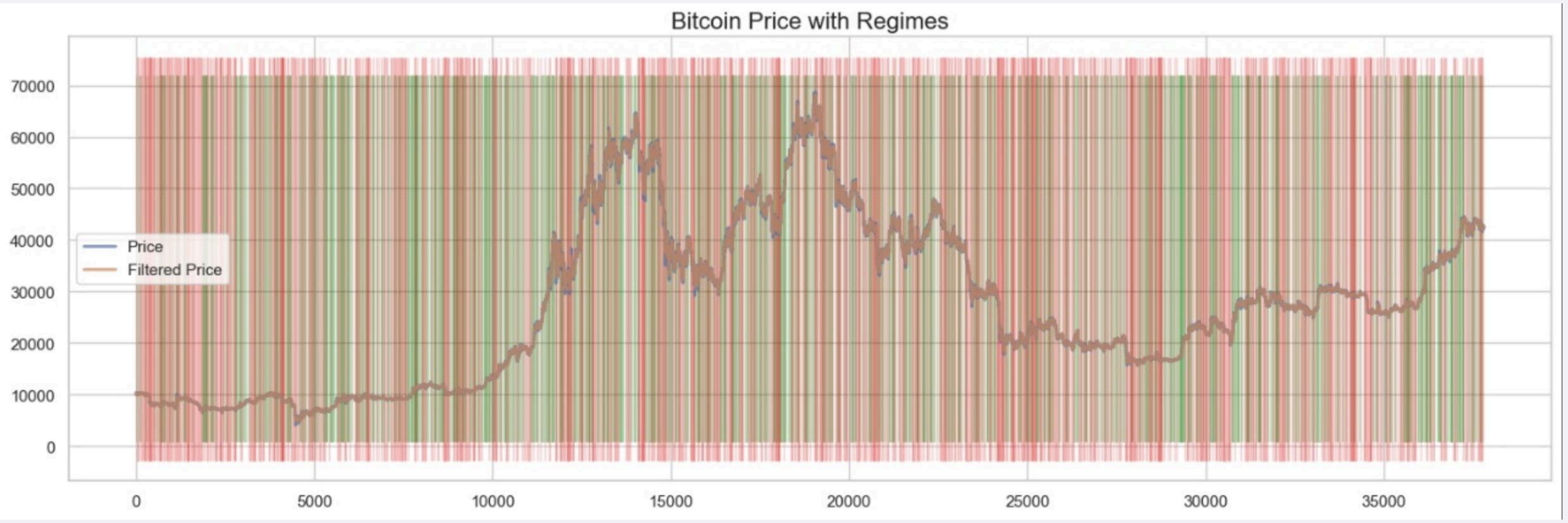
Why ATR?

We selected the ATR-based approach due to its simplicity and effectiveness in identifying low-volatility conditions, which exhibit smaller, predictable price movements, making trades more reliable by avoiding erratic behavior seen during high-volatility regimes.

By setting an ATR threshold (less than 1% of the BTC opening price), we ensured a focus on sustained trends conducive to profitability.

CUSUM

CUSUM (Cumulative Sum) is a statistical method used to detect shifts in the mean of a process over time. It identifies consistent deviations from a reference value (μ_0) to signal potential market changes.



Key Calculations

Deviation: The difference between the observed value xi (e.g., price) and the reference value:

$$d_i = x_i - \mu_0$$

Cumulative Sum: Tracks the cumulative deviations over time:

$$S_m = \sum_{i=1}^{m} (x_i - \mu_0)$$

V-Mask & Dynamic Volatility Threshold

V-Mask:

V-shaped overlay on the CUSUM chart; values within the V-mask indicate market stability, while those outside signal regime shifts.

Dynamic Volatility Threshold

The threshold k adjusts dynamically to market volatility using $k=\delta\times\sigma$, where δ is a sensitivity factor and σ is the rolling standard deviation.

Filtering Techniques for Reference Value (μ_0)

Kalman Filter | Gaussian Filter | Heikin Ashi

Outcome

Kalman Filter was the most effective, improving the reliability of CUSUM in identifying market shifts and deviations.

Indicators to trade on ETH

Indicators on ETH

Hurst Exponent:

- Trending Market (H>0.5): Trades align with momentum.
- Mean-Reverting Market (H≤0.5): Trades avoided or exited early.

Supertrend Direction:

Combines price and volatility using ATR and a moving average.

Strategy Use:

- Bullish (Supertrend > 0): Uptrend, ideal for long trades.
- Bearish (Supertrend < 0): Downtrend, suitable for shorts.

Indicators on BTC

Average True Range (ATR)

Tracks cumulative deviations from a reference price to detect persistent trends.

Strategy Use:

- Identifying Bullish , Bearish & Neutral regimes for ETH data.

CUSUM

Tracks cumulative deviations from a reference price to detect persistent trends.

Strategy Use:

- Identifying Bullish & Bearish regimes for BTC data.

Relative Strength Index (RSI):

Momentum oscillator (0-100) identifying overbought (RSI>70) or oversold (RSI<30) conditions.

Strategy Use:

- Bullish Trend following RSI > 70 & Bearish Trend following RSI < 30.

Bollinger Bands (BB):

A volatility indicator with a moving average and upper/lower bands based on standard deviations.

Strategy Use:

- Confirms bearish trends in down trending markets.

Entry & Exit Conditions

Common Trading Conditions

- BTC ATR < 1% BTC Close Price
- BTC-ETH Correlation > 0.6
- ETH Hurst Exponent > 0.5

Long Trades

Entry Conditions

- BTC RSI > 70
- BTC Close Price > BTC Middle Bollinger Band
- BTC Regime = BULLISH (CUSUM)
- ETH Supertrend Direction = 1

Exit Conditions

- BTC RSI < 30
- BTC Close Price < BTC Lower Bollinger Band
- BTC Regime = BEARISH (CUSUM)
- ETH RSI (t) < ETH RSI (t-1)
- ETH Supertrend Direction = -1

Short Trades

Entry Conditions

- BTC RSI < 30
- BTC Close Price < BTC Lower Bollinger Band
- BTC Regime = BEARISH (CUSUM)
- ETH Supertrend Direction = -1

Exit Conditions

- BTC RSI > 70
- BTC Close Price > BTC Middle Bollinger Band
- BTC Regime = BULLISH (CUSUM)
- ETH RSI (t) > ETH RSI (t-1)
- ETH Supertrend Direction = 1

Risk Management Strategies

Trailing Stop-Loss Mechanism

Long Position:

The final stop price is the 24-hour low or the average of the trailing stop (10%) and 24-hour low.

Short Position:

The stop-loss trails 10% above the lowest price reached since entry.

Volatility-Based Exit

If Bitcoin's Average True Range (ATR) exceeds 2.5% of its opening price, the position is closed immediately.

Time-Based Exit

All trades, both long and short, are held for a maximum of 4 weeks (28 days).

Cooldown Period

After a stop-loss is triggered, a 24-hr cool-down period is enforced before initiating a new trade.

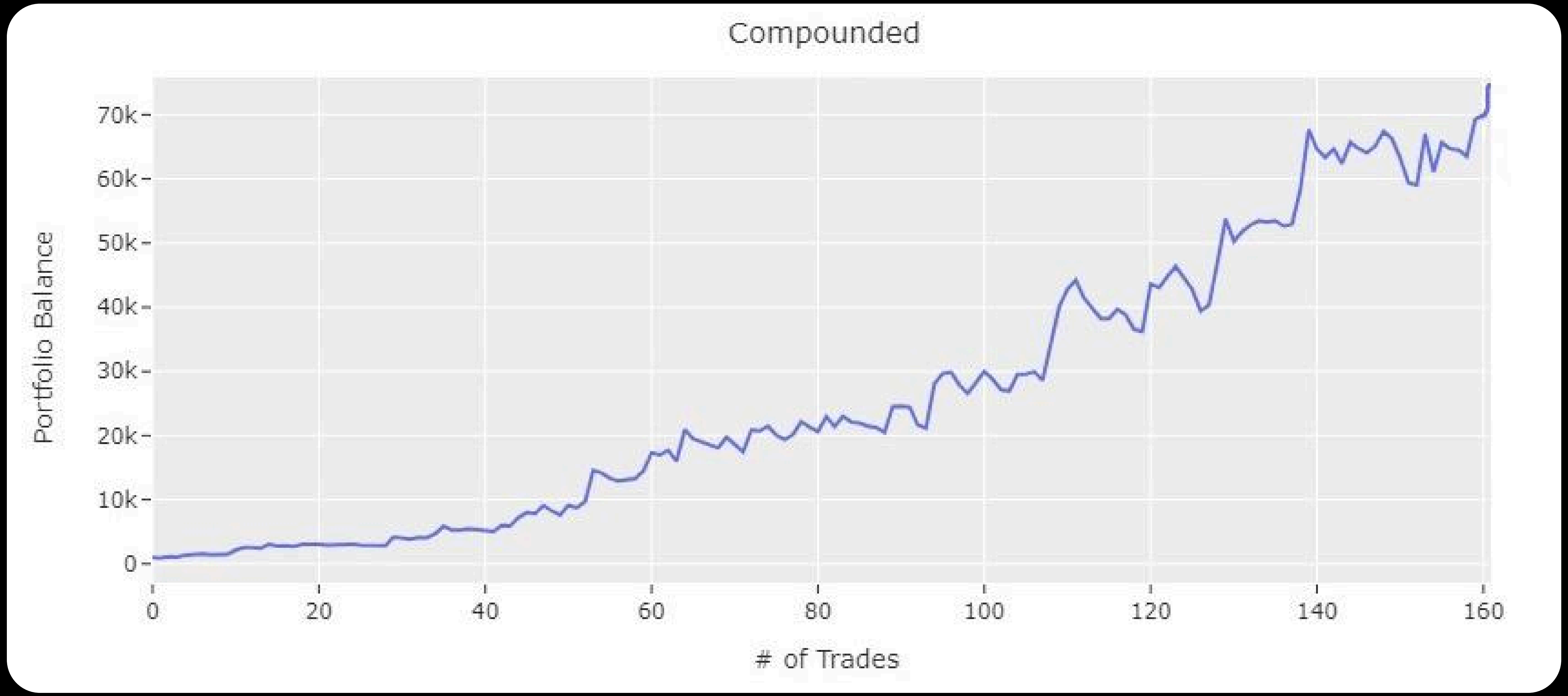
Results & Key Metrics

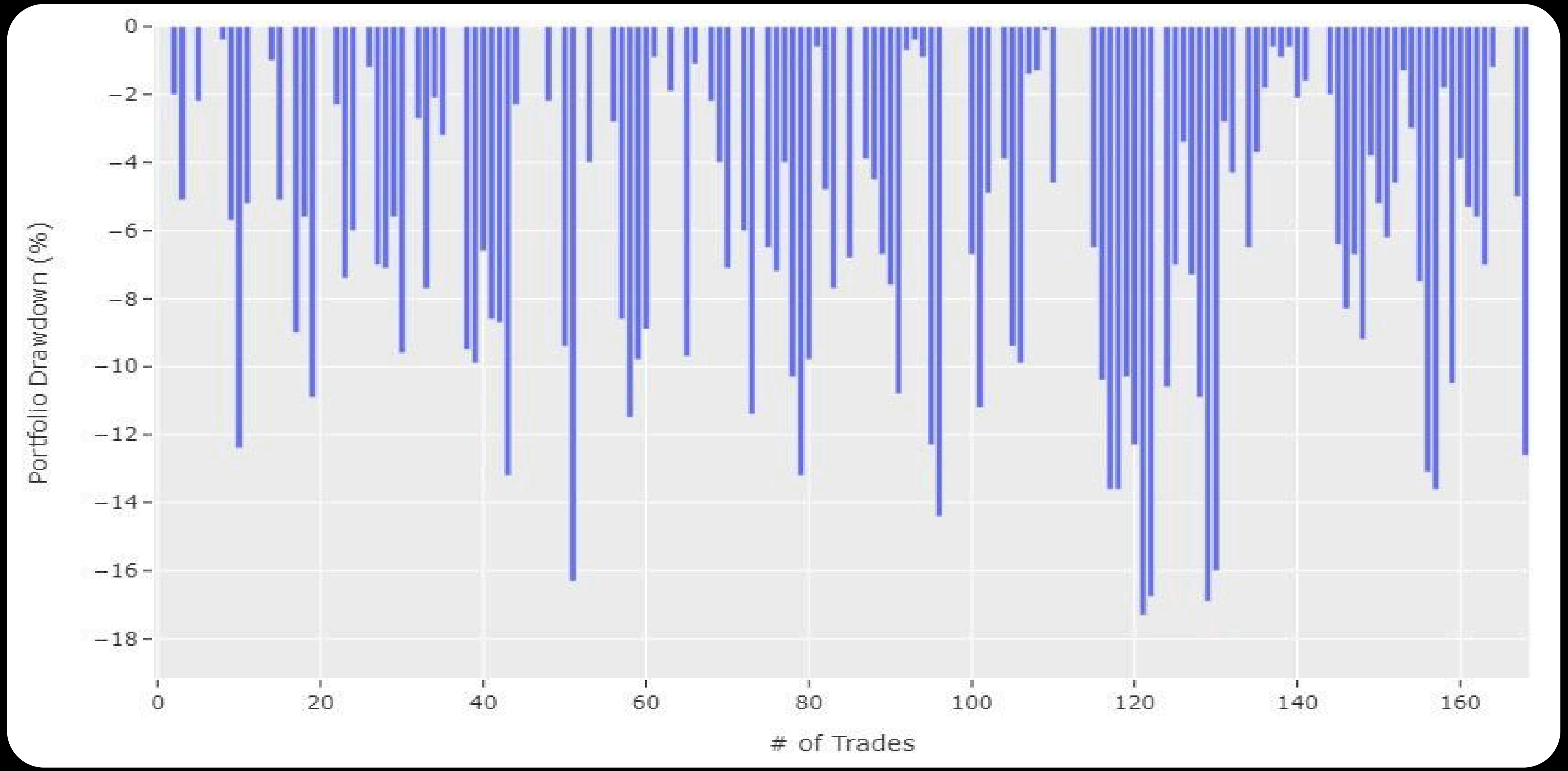
Key Metrics

Net returns - 7684.52%
Benchmark returns - 1687.59%
Max Drawdown - 17.14%

Max TTR - 44 Days
Sharpe Ratio - 5.966
Sortino Ratio - 19.67

Risk : Reward - 1 : 2.87
MAE - 14.67%
Average Adverse Excursion - 3.70





Quarterly Results

01/20 - 03/20 Profit - 116.2% Benchmark - 2.9%	01/21 - 03/21 Profit - -7.8% Benchmark - 161.8%	01/22 - 03/22 Profit - 34% Benchmark - -11.8%	01/23 - 03/23 Profit - 22.4% Benchmark - 52.5%
04/20 - 06/20 Profit - 49.9% Benchmark - 70.9%	04/21 - 06/21 Profit - 92.6% Benchmark - 17.6%	04/22 - 06/22 Profit - -4.6% Benchmark - -67.5%	04/23 - 06/23 Profit - 27.1% Benchmark - 6.1%
07/20 - 09/20 Profit - 74.6% Benchmark - 59.8%	07/21 - 09/21 Profit - 11.3% Benchmark - 33.6%	07/22 - 09/22 Profit - 38.8% Benchmark - 21.2%	07/23 - 09/23 Profit - 10% Benchmark - -13.6%
10/20 - 12/20 Profit - 56.6% Benchmark - 105.2%	10/21 - 12/21 Profit - 10.6% Benchmark - 21.8%	10/22 - 12/22 Profit - 33.9% Benchmark - -9.8%	10/23 - 12/23 Profit - -1.4% Benchmark - 45.5%

Our strategy on

Bitcoin (BTC)

- Sequential Decision-Making
- Bellman Equation
- Reward Function
- Q - Learning
- Exploration-Exploitation

Our Approach: Reinforcement Learning

Why RL?

01 Sequential Decision-Making

02 Handling Uncertainty and Complexity

03 Balancing Long-Term Goals

04 Customizable Reward Functions

05 Adaptability to Changing Markets

06 Incorporation of Multiple Inputs

Key Features of Q-Learning

Model-Free Learning

Q-Learning does not require knowledge of transition probabilities (P(s′ | s,a)

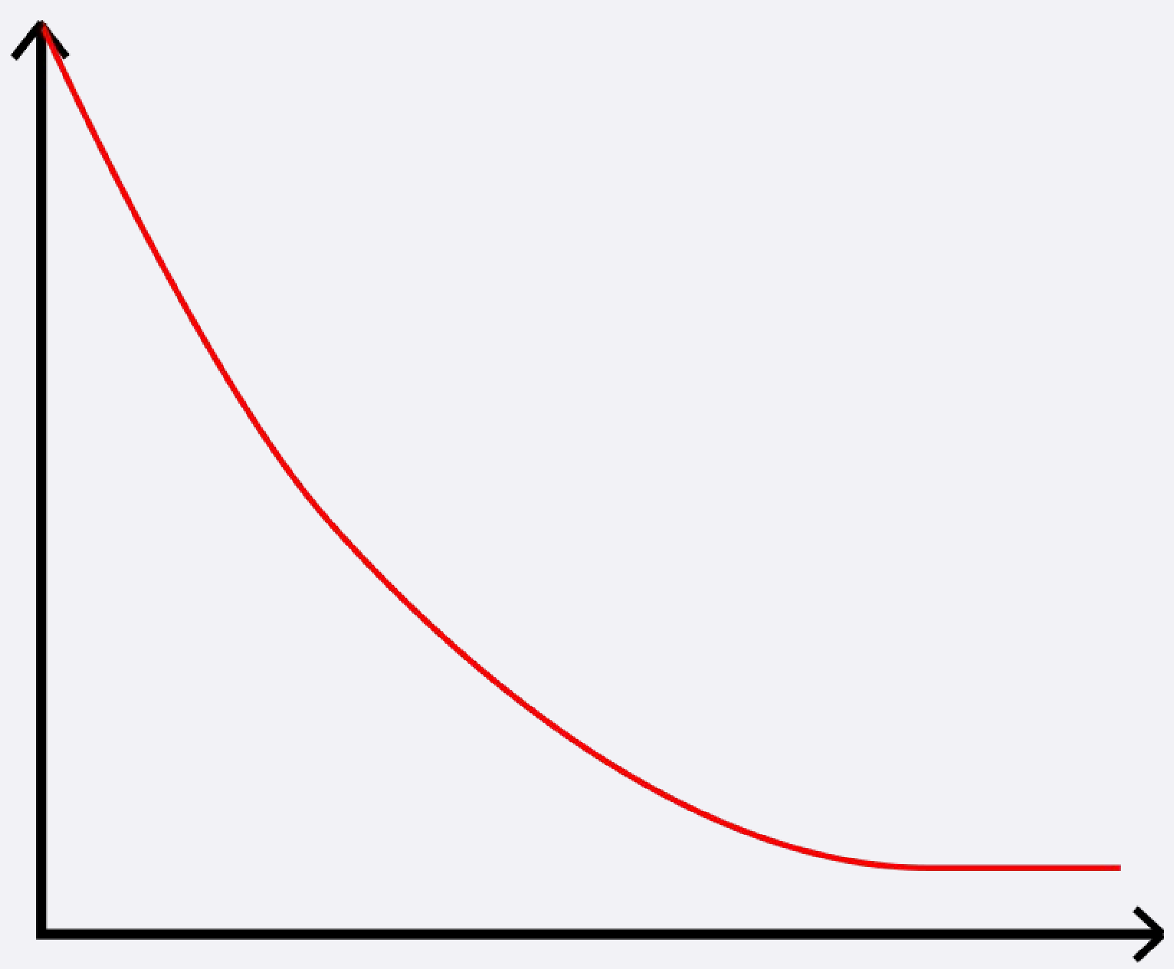
Optimal Policy

The agent learns the optimal policy while exploring.

Guaranteed Convergence

With sufficient exploration, decaying epsilon and a proper discount factor, Q-Learning converges to the optimal Q-function

Q - Learning



Q-Learning Algorithm

Step 1: The Q-table, Q(s,a), is initialised to zero for all state-action pairs:

Q(s,a)=0 ∀ s∈S , a∈A(s)

Step 2: Choose an action using the epsilon-greedy strategy

- With probability $1-\epsilon$: Choose the action that maximizes the Q-value for the current state s:

$$a = \arg\max_a Q(s,a)$$

- With probability ϵ: Choose a random action $a \in A(s)$.

Step 3: Perform action At, get reward Rt+1, and next state St+1.

Step 4: Update Q(St,At)

The Q-value is updated using the Temporal Difference (TD) update formula:

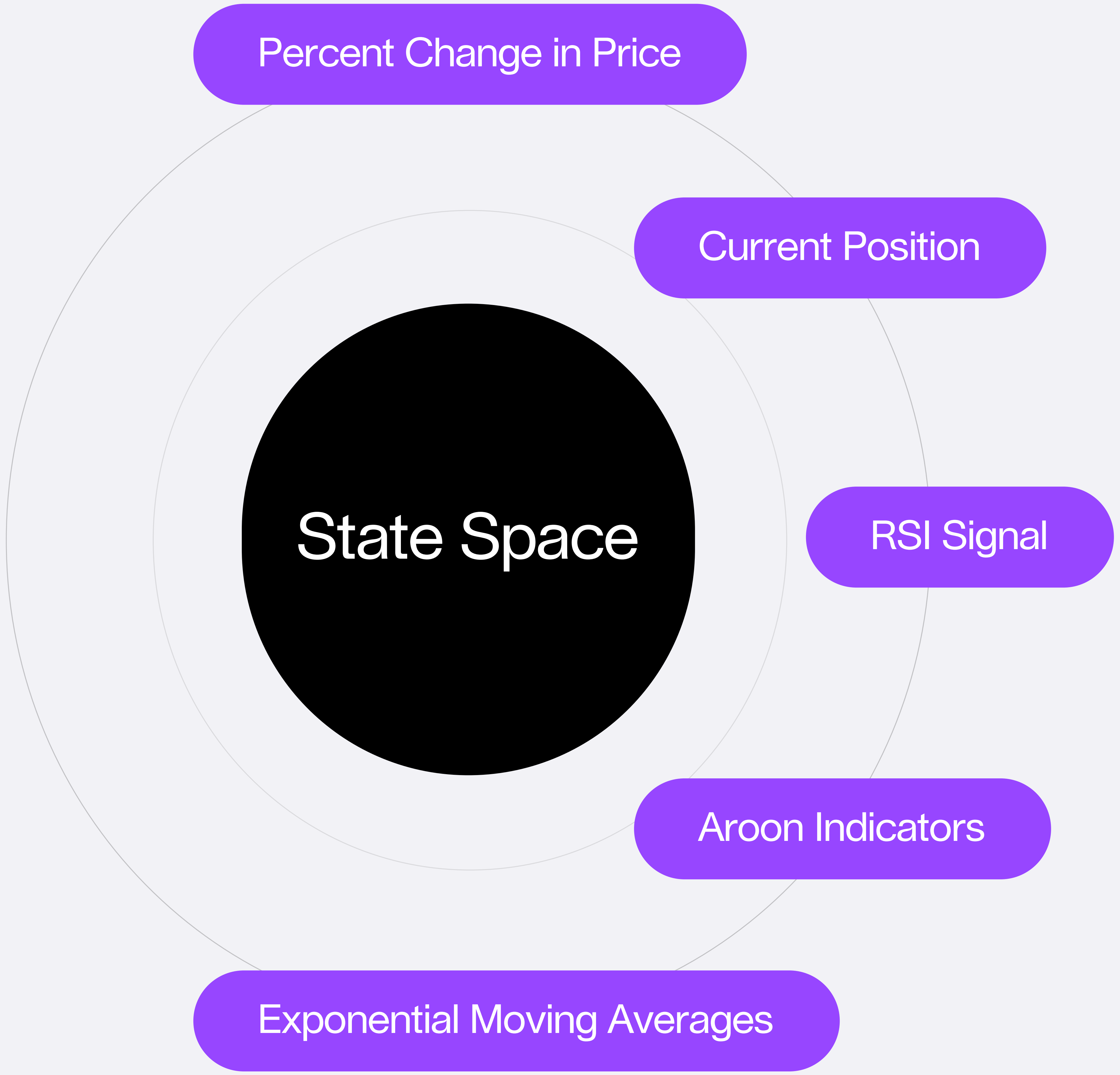
$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t) \right]$$

Where:

- α: Learning rate ($0 < \alpha \leq 1$).
- R_{t+1}: Reward observed after action A_t.
- γ: Discount factor ($0 \leq \gamma \leq 1$).
- $\max_a Q(S_{t+1}, a)$: Maximum Q-value for the next state S_{t+1} over all possible actions.

The BTC returns time series data is confirmed to be stationary by ADF test.

A stationary time series is proven to work better with RL.



Percentage Change in Price - 20 bins

The percentage change in price is divided into 20 distinct bins from -5 to 5 percent, while clipping the outliers in the outermost bin.

Position (s)

0 : No Position 1 : Long Position -1 : Short Position

RSI Signal

The RSI is calculated based on the previous 14 candles. The RSI signals are classified as:

1: If RSI > 75 -1: If RSI < 35 0: Otherwise

Aroon Indicators

It helps to assess the strength and direction of a trend, providing insights into potential reversals or continuation of market movement. It is calculated as:

1: Bullish signal -1: Bearish signal

Exponential Moving Averages

Three Exponential Moving Averages (EMAs) calculated over different periods: EMA(7), EMA(14), and EMA(28). These EMAs indicate short-term, medium-term, and long-term trends. The relationship between the EMAs as follows:

1 : If EMA(7) > EMA(14) > EMA(28) (bullish trend)

-1 : If EMA(7) < EMA(14) < EMA(28) (bearish trend)

0 : Otherwise

Actions

1

Enter Long

- A commission is subtracted as a penalty upon entering a long position.
- If switching from a short position, the reward includes the realized profit or loss from closing the short position minus the associated commission.

2

Exit Long

- Reward includes the realized profit or loss from closing the long position minus the associated commission.

0

Hold

- Reward includes change in net worth.

3

Exit Short

- Reward includes the realized profit or loss from closing the short position minus the associated commission.

4

Enter Short

- A commission is subtracted as a penalty upon entering a short position.
- If switching from a long position, the reward includes the realized profit or loss from closing the long position minus the associated commission.

Rewards

Risk Management

Stoploss & Position Sizing

A 5% Stop Loss is implemented to limit potential losses by exiting the position when the price drops 5% from the entry level.

While training, the agent takes a short position using only 75% of the available wealth to mitigate risk and manage potential losses in case the price moves upward.

Heavy Penalisation

During training phase if net worth goes below a certain threshold, the agent get a heavy negative reward so it doesn't follow that path again.

Results & Key Metrics

(BTC 2023-24)

Key Metrics

Net returns - 224.90%
Benchmark returns - 157.08%
Max Drawdown - 13.50%

TTR - 47 Days
Sharpe Ratio - 9.153
Sortino Ratio - 26.95

Win Rate - 64.51%
MAE - 8.73
Average Adverse Excursion - 3.68

Trade Metrics vs Training

Learning Phase

Episodes - 1000

Net returns - 225.59%

Max Drawdown - 12.20%

TTR : 200.16 Days

MAE : 7.42

Max Holding : 198 Days

Initial Training

Episodes : 100

Net returns : -2.65%

Max Drawdown : 46.36%

TTR : N/A

MAE : 14.58

Max Holding : 65 Days

Final Metrics

Episodes - 1400

Net returns - 224.90%

Max Drawdown - 13.50%

TTR : 53.12

MAE : 8.73

Max Holding: 47 Days

Quarterly Results

01/23 - 03/23
Profit: 88.9 %
Benchmark: 72.1 %
Win Rate :72.7 %

07/23 - 09/23
Profit: 13.7 %
Benchmark: -11.5 %
Win Rate :60.0 %

04/23 - 06/23
Profit: -5 %
Benchmark: 7.1 %
Win Rate : 42.9 %

10/23 - 12/23
Profit: 64.2 %
Benchmark: 56.9 %
Win Rate : 85.7 %

Unseen Data Generalisation

ETH/USDT 2023-24

Net Returns: 79.235 %

Max Drawdown :30.106

Benchmark Return :92.33%

Max Holding Time: 31 Days

TTR : 58.29 Days

MAE : 10.206

SOL/USDT 2023-24

Net Returns: 408.987 %

Max Drawdown : 45.0757

Benchmark Return : 938.268%

Max Holding Time: 22 Days

TTR : 52.041 Days

MAE : 16.581

*RL Agent has been trained on BTC 2020-23

Thank you.