BITCOIN

Intraday Trading with Sentiment Signals

PRESENTED BY Justin

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01 RESEARCH OBJECTIVE

Analyze the impact of market sentiment on Bitcoin price

Combined with technical analysis

Aims to maximise returns in a medium trading environment (execute trades every hour)

02 LITERATURE REVIEW

Arslan (2024)

Twitter Sentiment Data → Empirical Mode Decomposition → Signal → Long-Short Term Memory → Predictions

Ider & Lessmann (2023), Vlahavas & Vakali (2024)

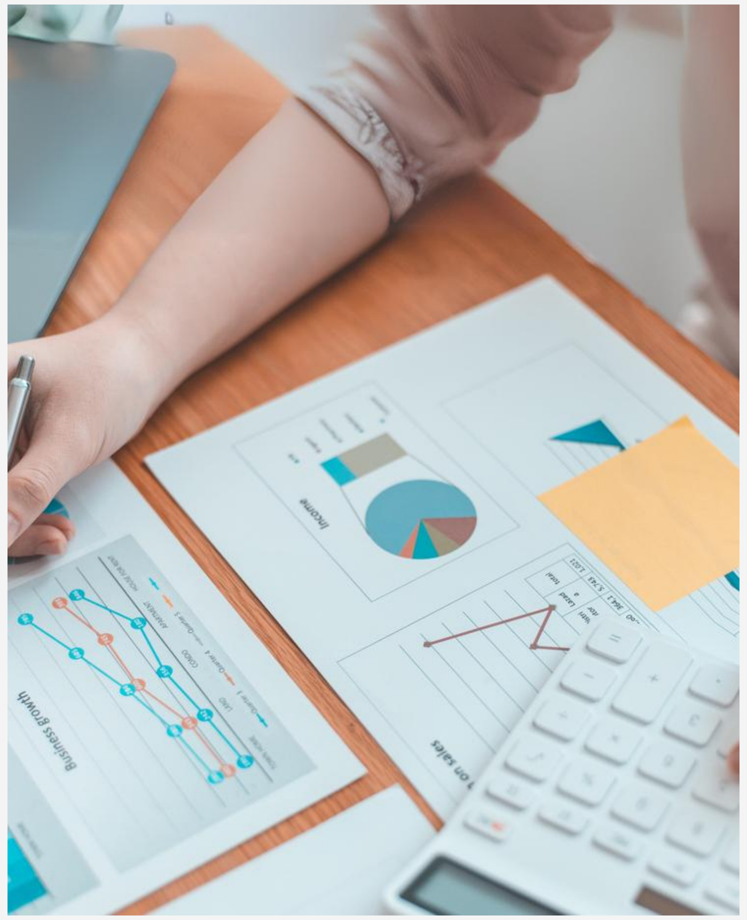
More Data Sources = More Accurate

Han et al. (2025)

XGBoost outperforms in short-term forecasting

Goyal & Welch (2008)

Equity Returns assessment over multiple horizons



02 LITERATURE REVIEW

Our Approach

We propose a comprehensive composite sentiment index generalisable to different sources in crypto space.

1. Reddit
2. Telegram
3. News

Complimented with a Multi-horizon Ensemble-style Decision Strategy

Sentiment + Technical Indicators → XGBoost → Multi-horizon Ensemble-style Strategy → Strategy Decision

Our Contributions

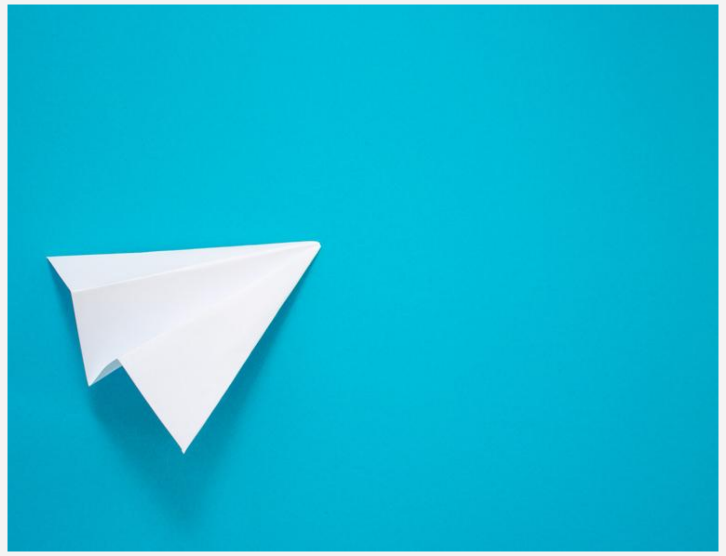
- Novel sentiment indicator - Rigorously designed & Tuned
- A simple yet comprehensive Multi-horizon Ensemble-style Trading Strategy
- Example of Sentiment Indicator Performance with Strategy

03

DATASET

Post data sparse
Ollama to extract text sentiment
Volume of activity represents public engagement

Popular Telegram Signal Channels
Casual Traders looking for guidance



01

Popular Reddit Signal Subreddits
Official Reddit API

02

All news relating to Bitcoin
Global Knowledge Graph- indexes all online news

03

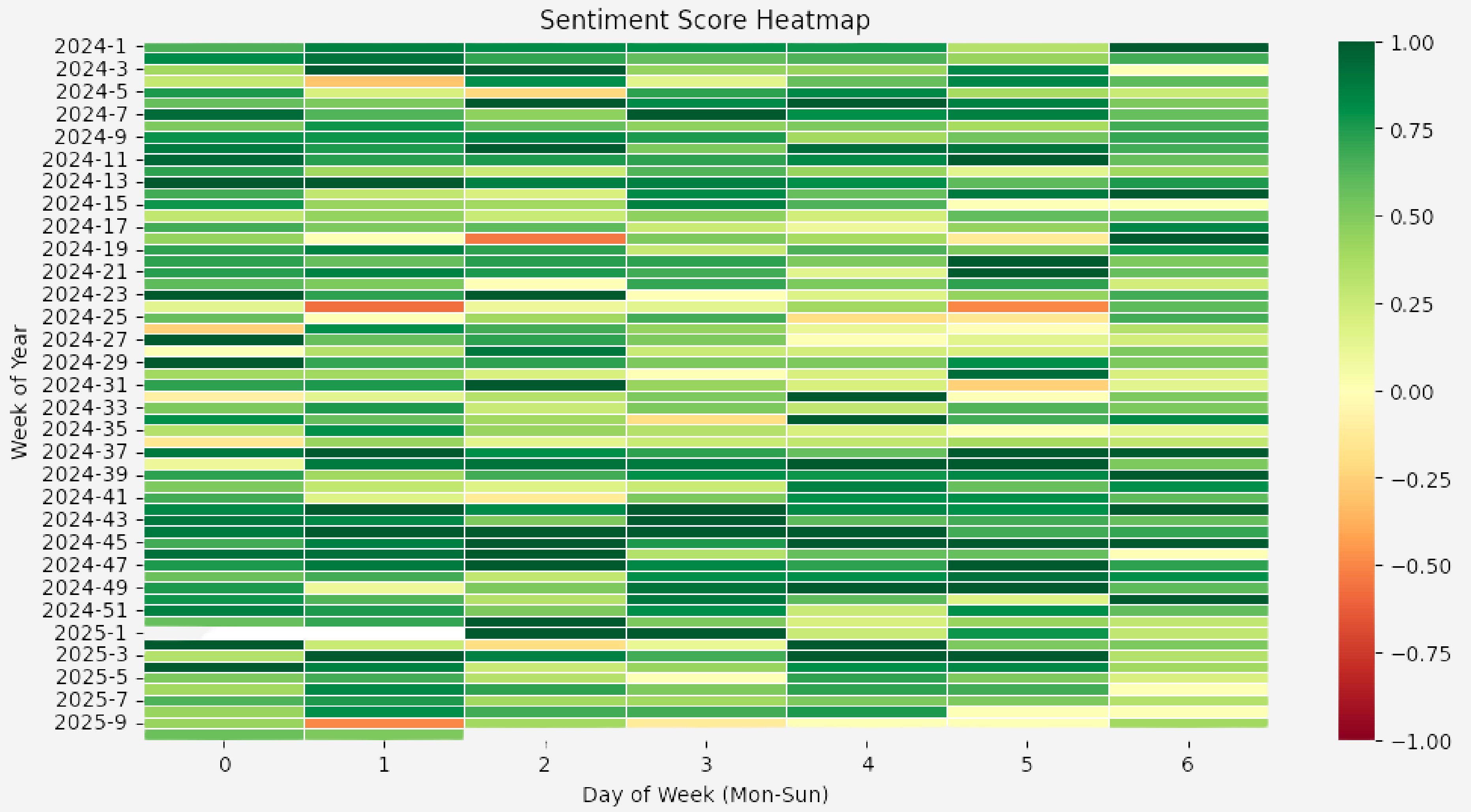
Fundamentals
Coindesk API
Feature Engineering

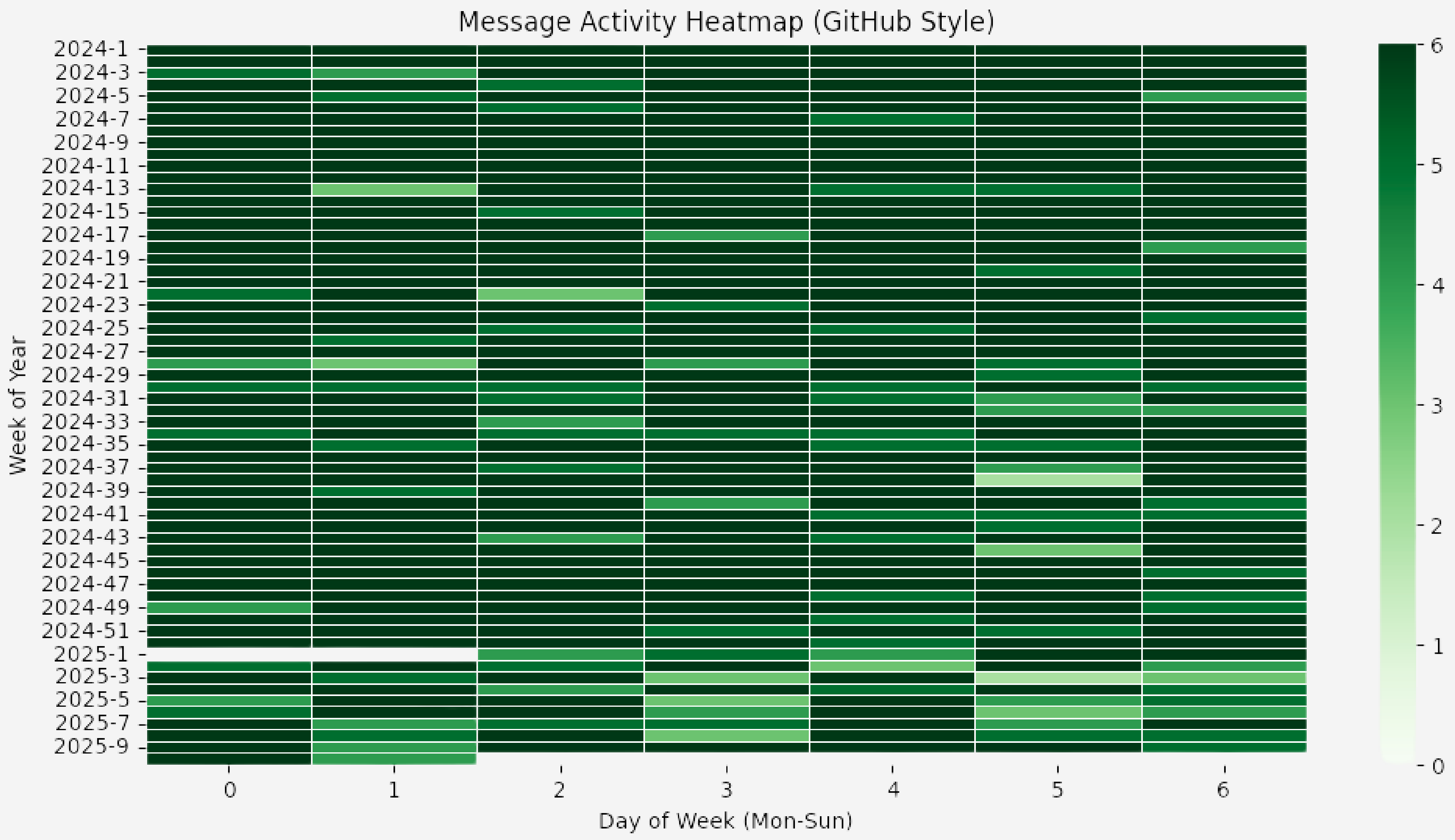
04

03

Exploratory Data Analysis

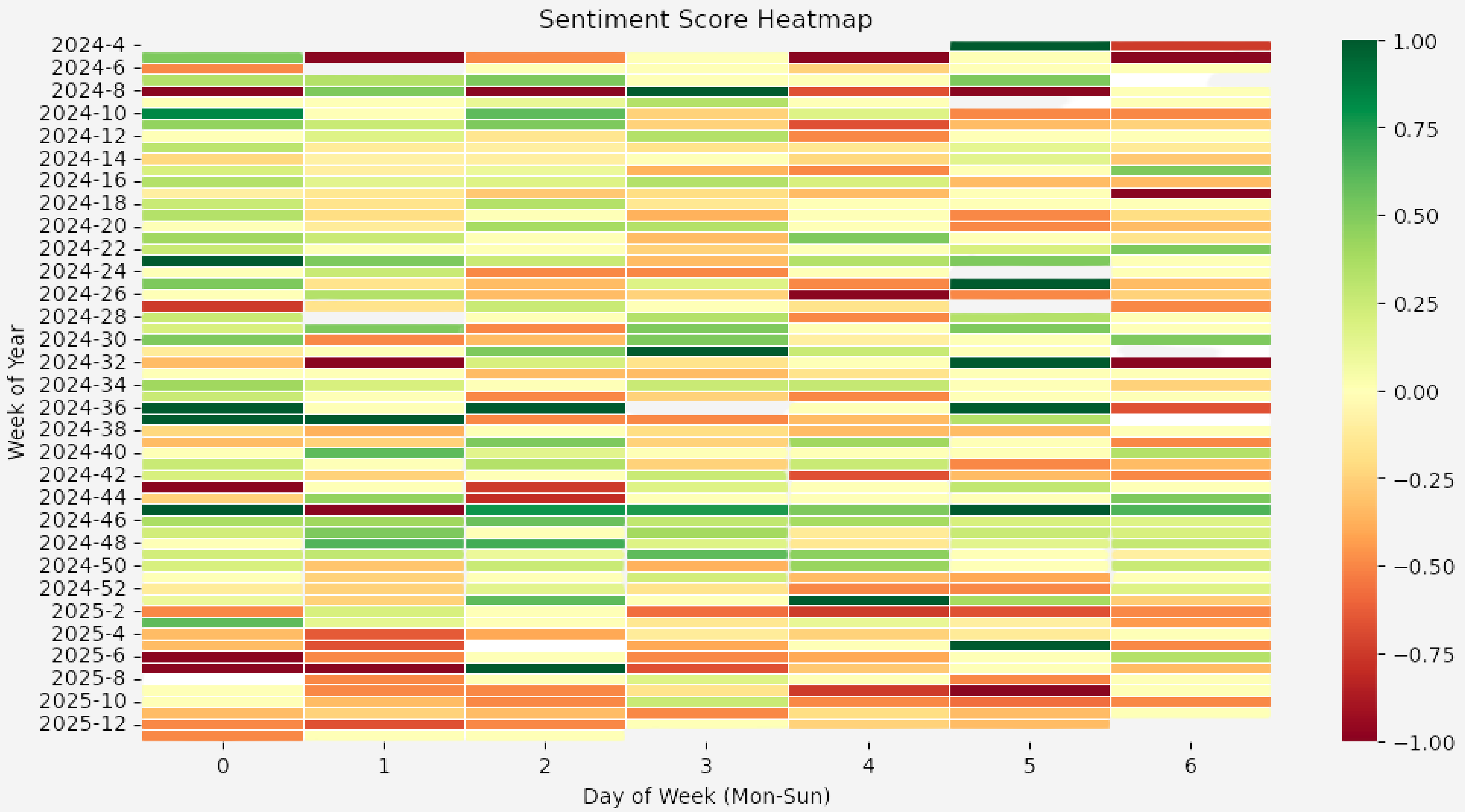
Telegram

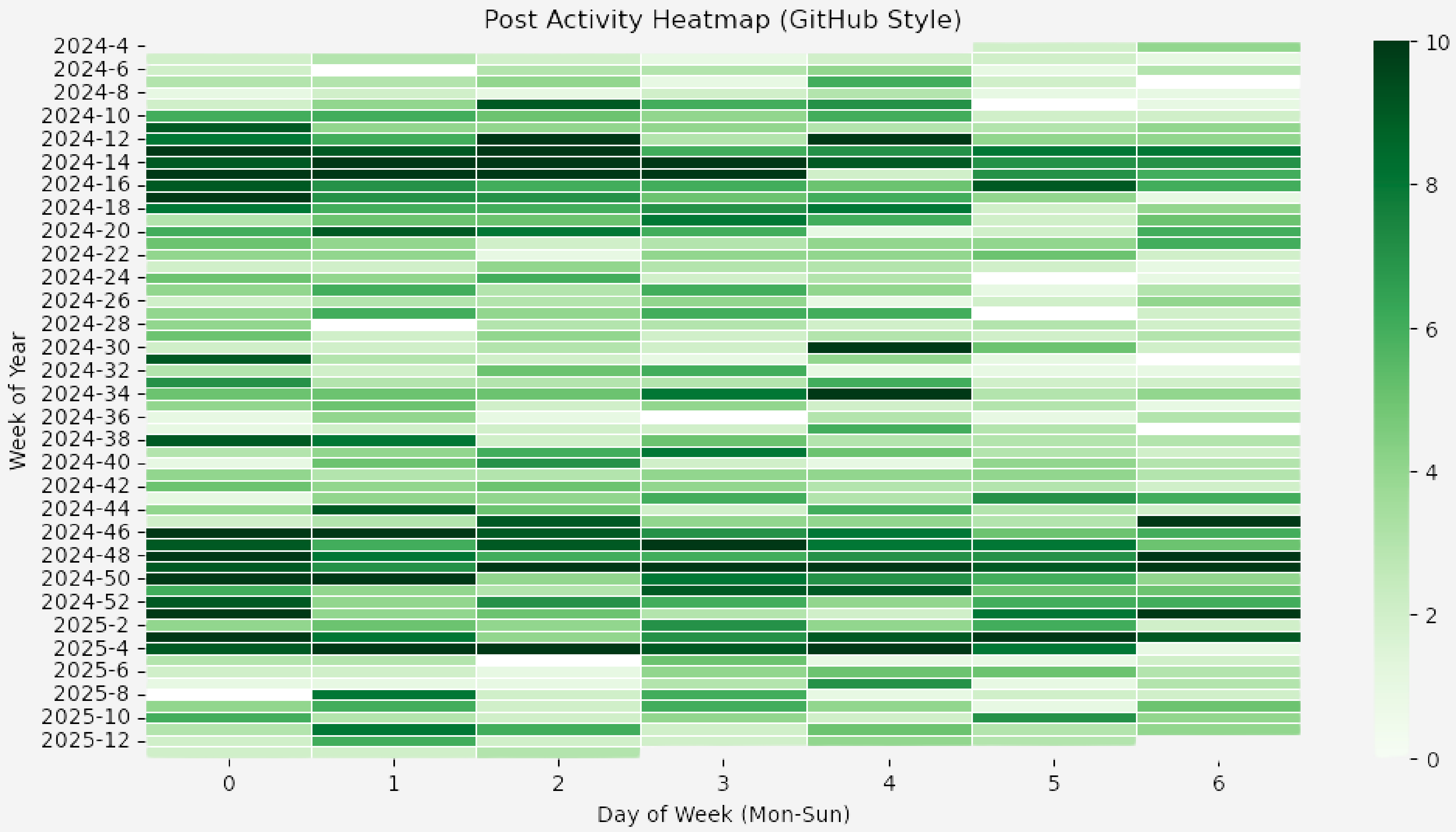




Overwhelmingly positive sentiment

03 Exploratory Data Analysis
Reddit

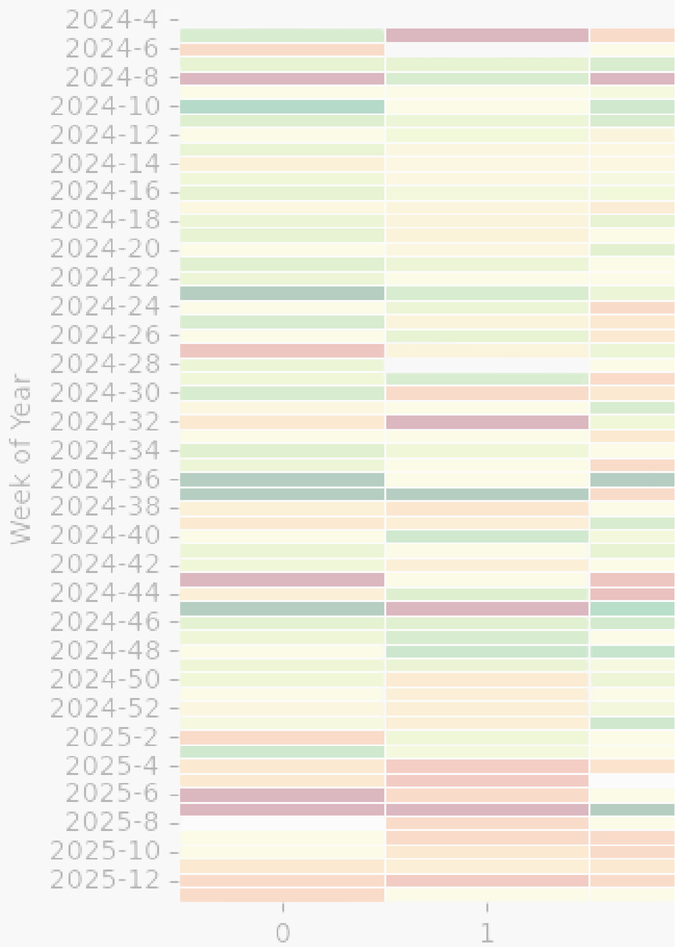


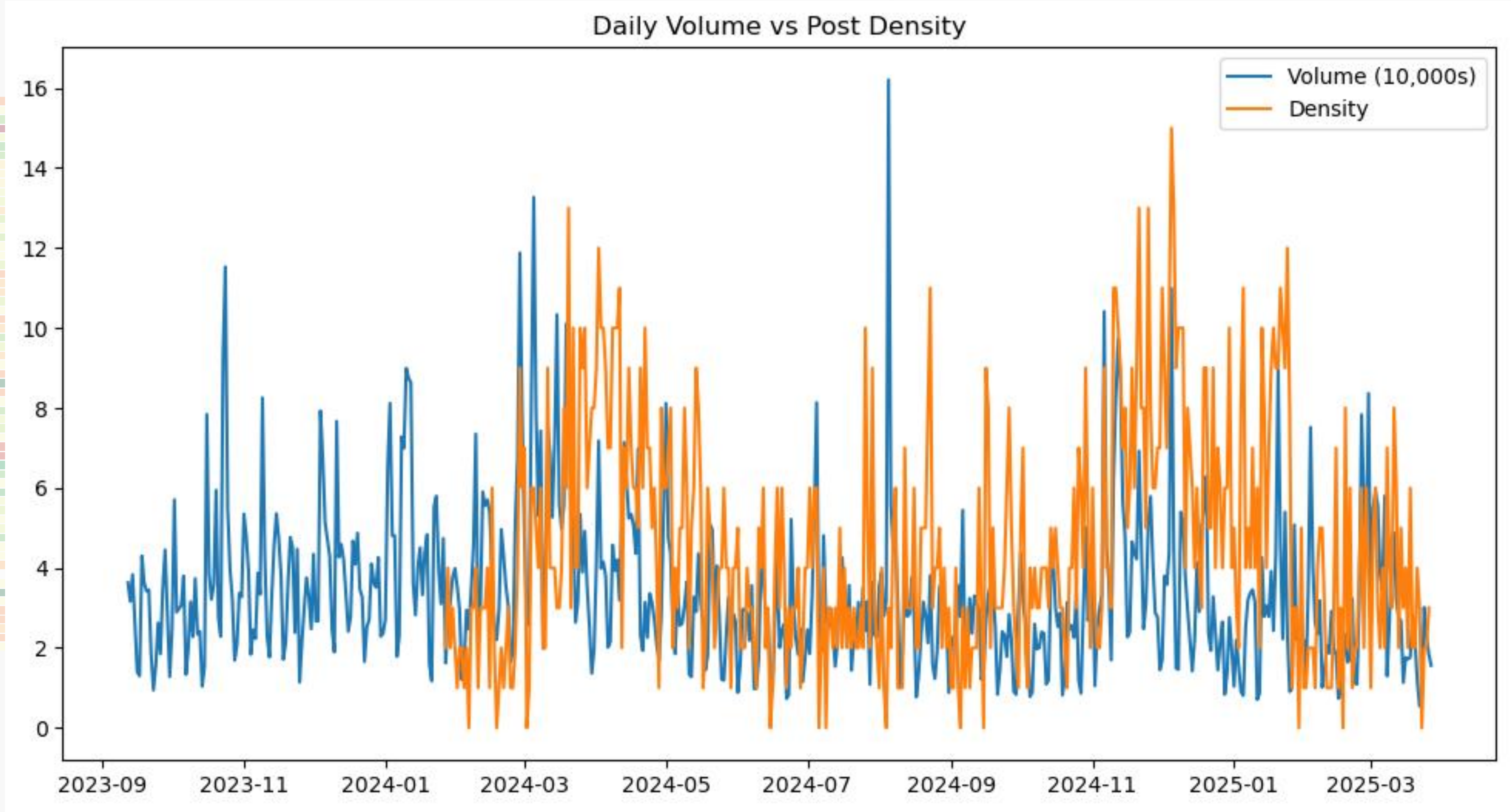


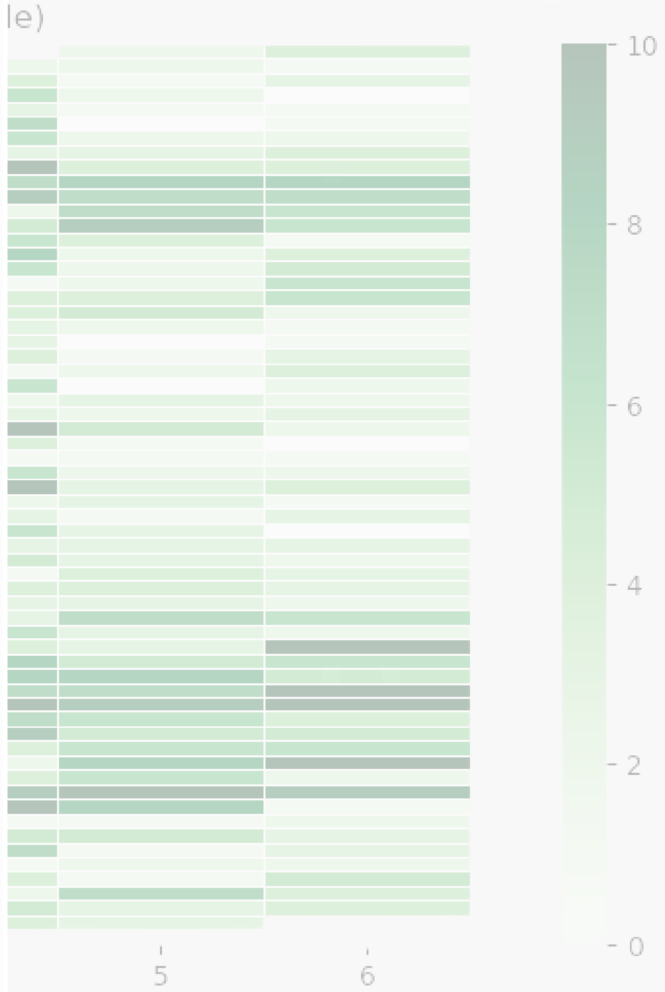
Post density highly correlated with volume
Modest polarity in sentiments

03

Exploratory Data Analysis





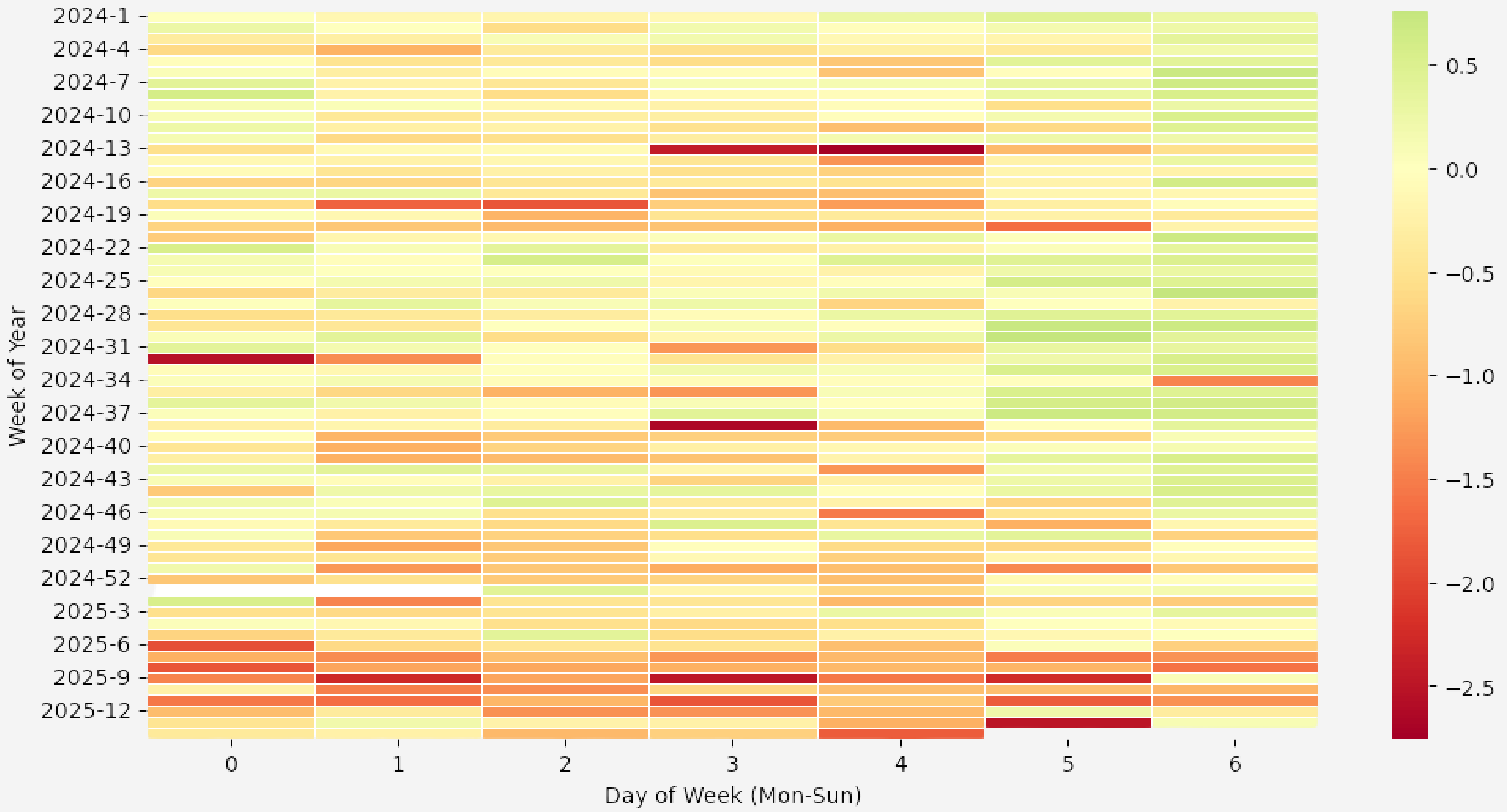


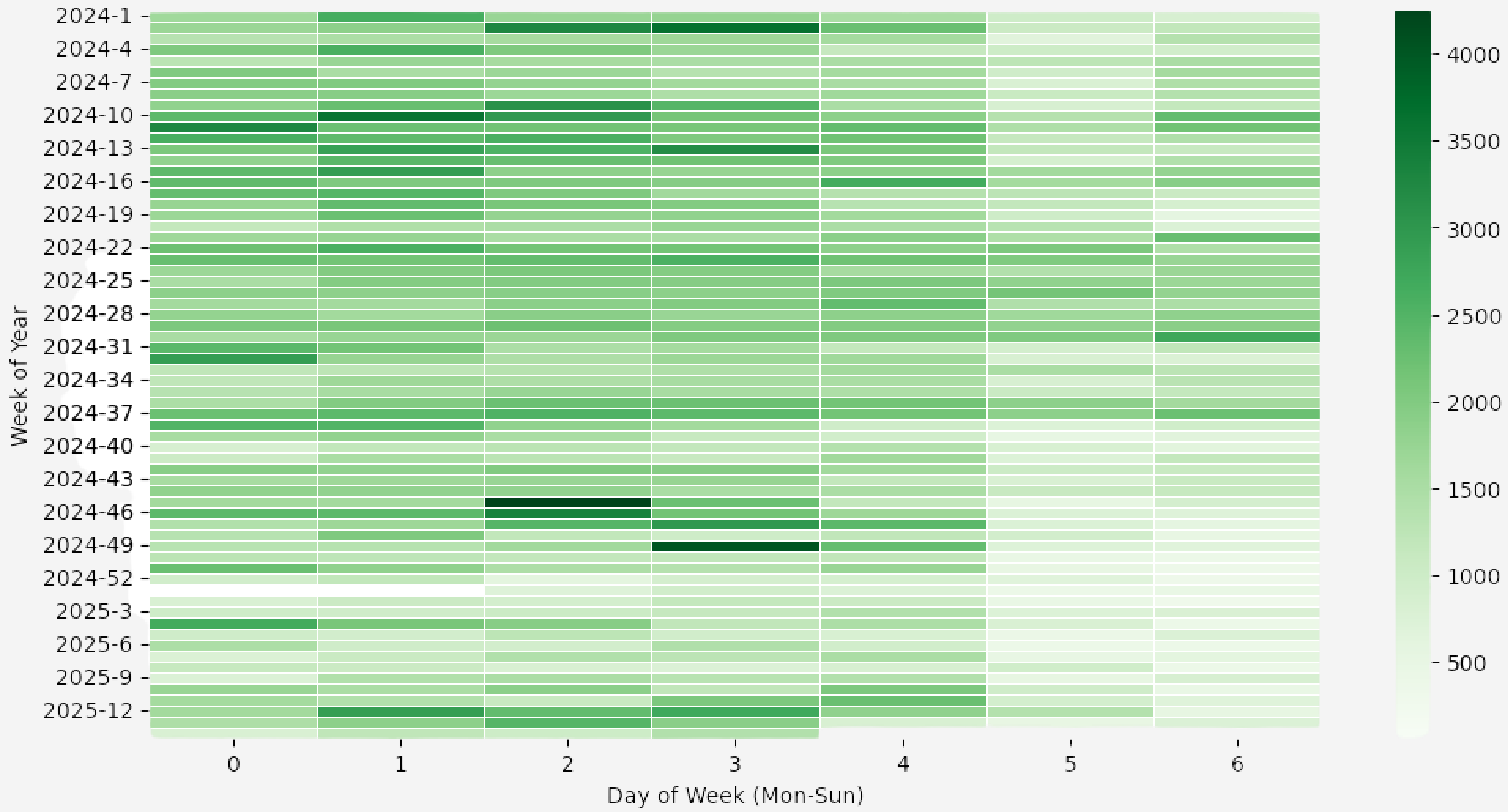
Post Density highly correlated with Volume

03

Exploratory Data Analysis

News

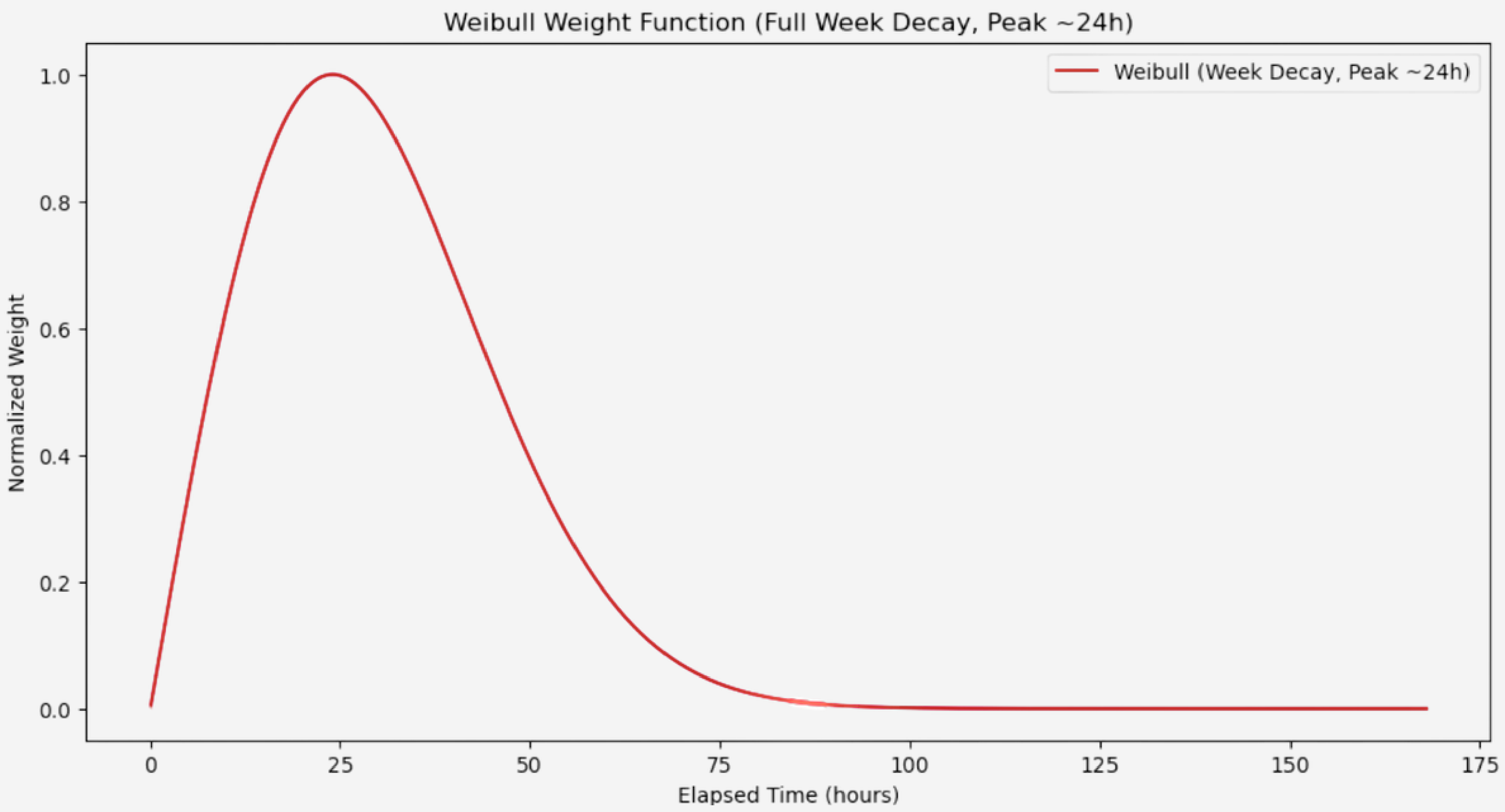




Mostly neutral with some very negative sentiments
Negative sentiments correlates with volume

03 SENTIMENT INDICATOR

Weibull
DECAY



1. Sentiment Scores assigned
Positive = 1
Negative = -1
Neutral = 0

2. Each Post/Comment/News has effects that decays in a week

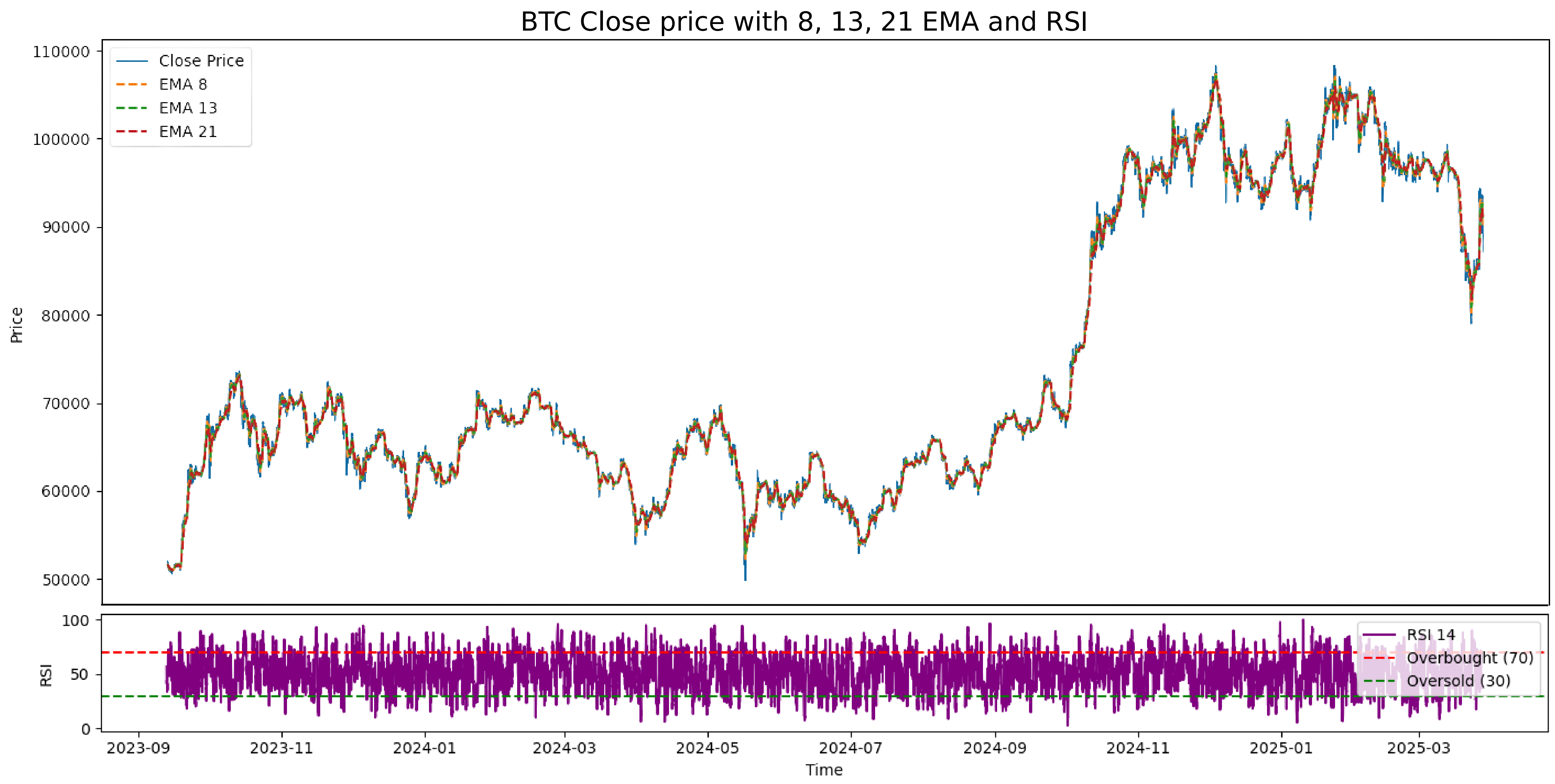
3. Highest effects (peak) at 24 hours

4. Effects summed across pieces of data

03

Exploratory Data Analysis

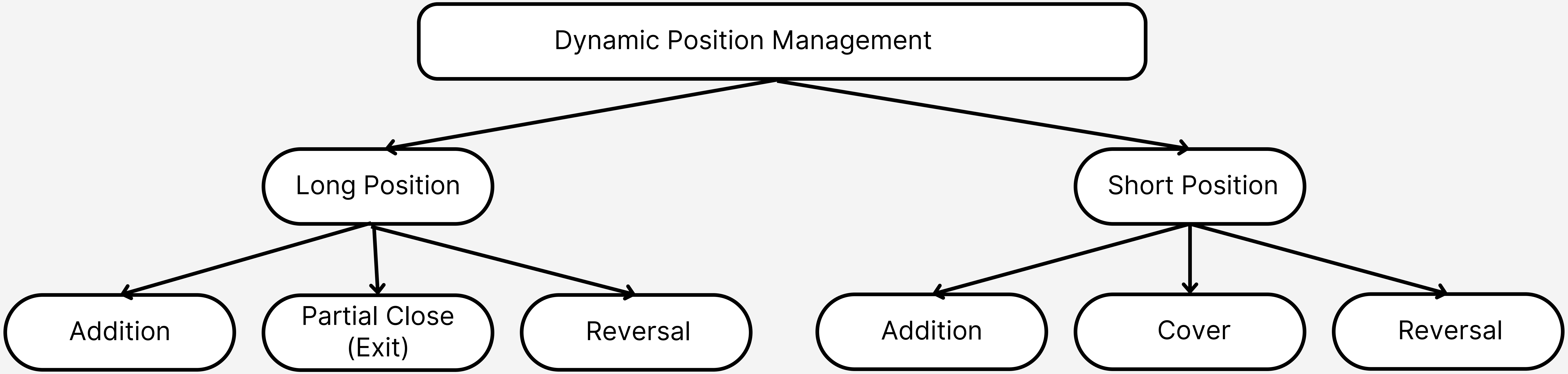
BTC Technicals



Engineered 27 common technical indicators - EMA, MACD, RSI, OBV, etc...

04 Trading Conditions

- We simulate margin trading with a maximum leverage cap of 2x the initial capital
- Orders are placed at the end of each hourly bar and executed at the next open
- One order is made on each bar given the model signal
- We experiment with transaction fees from 0.1% to 1%
- Risk free rate set at 4.3%(Roughly the % of the US 3-month treasury bills in Apr)



04 Forecasting Model: XGBoost

	Past Close	Past High	...	Target
Yt-6				[]
Yt-5				[]
...				
Yt				[]

A (7,37) DataFrame

0	...	251

A (1,252) numpy.ndarray of inputs

close_y_t+1	close_y_t+2	close_y_t+4	close_y_t+8

A (1,4) numpy.ndarray of targets

y_hat_t+1	y_hat_t+2	y_hat_t+4	y_hat_t+8

A (1,4) numpy.ndarray of outputs

04 Input Features

Trend Indicators

- EMA
- SMA
- Golden Cross

Volatility Indicators

- Bolinger Bands
- Average True Range

Momentum Indicators

- MACD
- RSI
- %K%D Oscillation

Volume-based Indicators

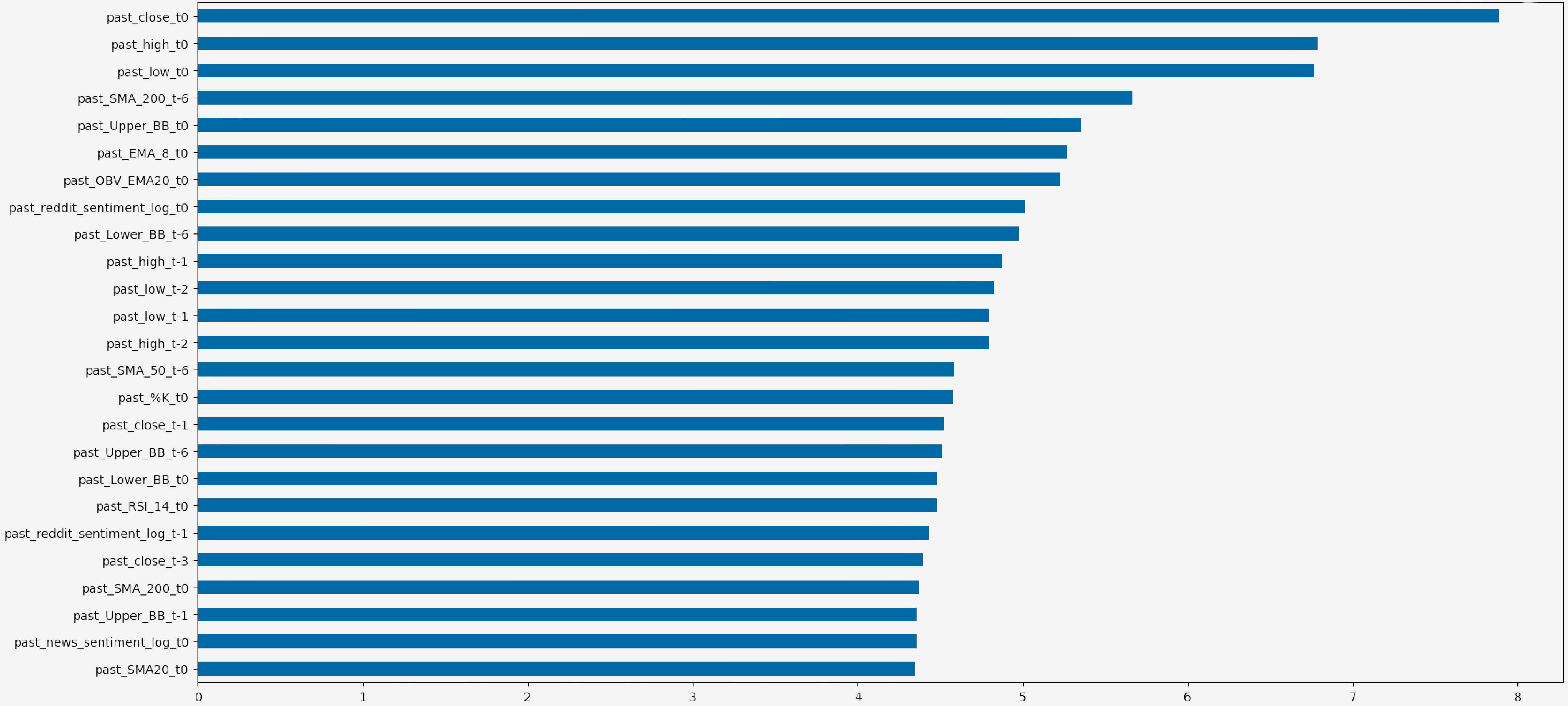
- OBV
- VWAP

Sentiment Indicators

- Reddit Sentiment
- Telegram Sentiment
- News Sentiment

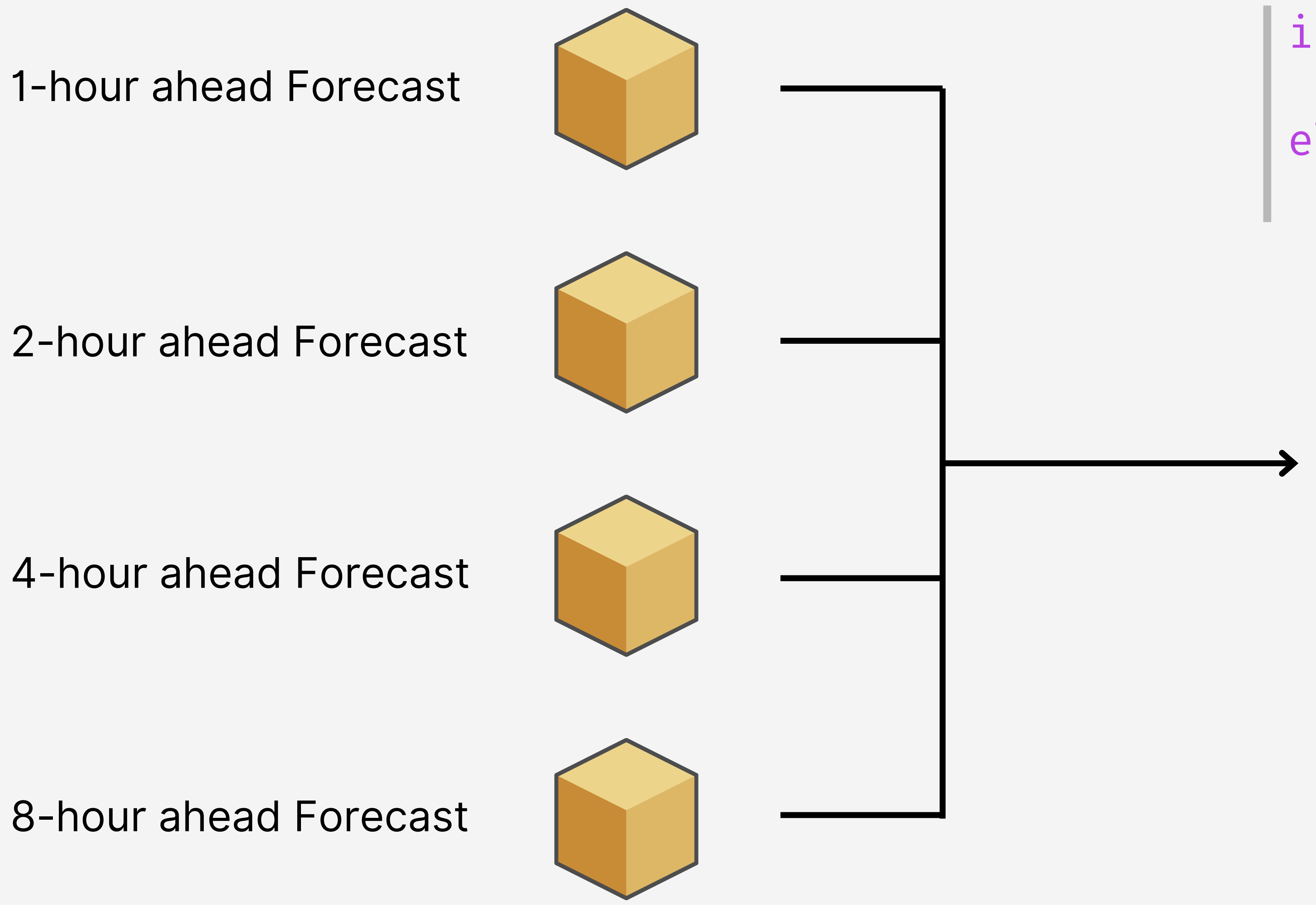
```
base_price_data = ['datetime','Close','Open','High','Low','VOLUME']

technical_indicators = [
    # Trend Indicators
    'EMA_8', 'EMA_13', 'EMA_21', 'EMA_Signal', 'EMA_short', 'EMA_long',
    'SMA20', 'SMA_50', 'SMA_200', 'GoldenCross_Signal',

    # Momentum Indicators
    'MACD', 'Signal_Line', 'MACD_Signal', 'MACD_Hist',
    'RSI_14', 'BB_RSI_Signal', 'RSI_Signal',
    '%K', '%D', 'Stochastic_Signal',

    # Volatility Indicators
    'STD20', 'Upper_BB', 'Lower_BB', 'ATR', 'TR',

    # Volume-Based Indicators
    'OBV', 'OBV_EMA20', 'OBV_Signal', 'VWAP_Signal'
]
```

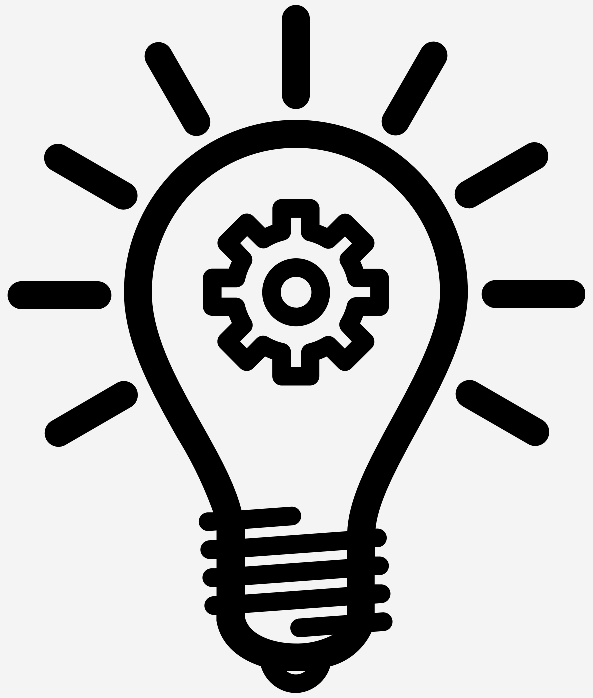
04 Feature Importance



04 Multi-forecast Ensemble-style Decision

```
def trading_strategy:
    if at least ¾ forecasts > current close:
        execute buy
    else if at least ¾ forecasts < current close:
        execute sell
```





04 Strategy

```python
class XGBoostStrategy(Strategy):
    def __init__(self,model,bet_size = 0.1,initial_data=None):
        super().__init__()
        self.model = model
        self.initial_data = initial_data
        self.bet_size = bet_size  # 10% of cash

    def on_bar(self):

        temp_df = pd.concat([self.initial_data, self.data])

        features = self.sequencing_data(temp_df, window_size=6)

        predictions = self.model.predict(features)
        signal = self.determine_signal(predictions)
        if signal == 1:
            self.buy(
                "btc",
               size = round(self.bet_size * (self.cash) / self.close(), 8)
            )
        elif signal == -1:
            self.sell(
                "btc",
                size = round( self.bet_size * (self.cash) / self.close(), 8)
            )
        else:
            pass
```

04 # Bet size Optimization

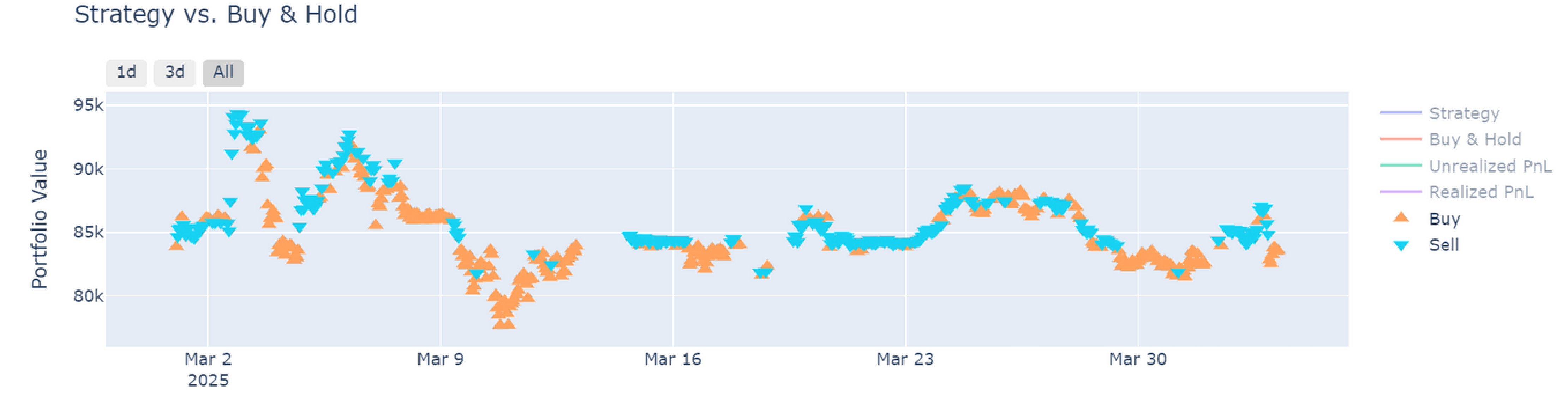
OPTUNA

- Used Optuna, an automatic hyperparameter optimization software framework for automated optimization of trade size.
- Conducted 100 trials to maximize the Sharpe Ratio
- Trials were done over the validation period from 1st Jan 2025 to 28th Feb 2025
- Optimized bet size resulted in 1% of available capital per trade (0.010036924986373125).

04 ASSESSMENT METRICS

Metric	Definition
Total Return (%)	The overall percentage gain or loss over the full time period
CAGR (%)	The smoothed annual return if the performance grew steadily each year
Volatility (%)	How much the returns fluctuate over time
Sharpe Ratio	Return earned per unit of risk taken
Max Drawdown (%)	The biggest drop from a peak to a low — shows the worst historical loss
Average Exposure (%)	The percentage of time the strategy was actively trading or invested
Number of Trades	Total count of buy and sell trades executed
Number of Buys	Number of times the strategy entered a long (buy) position
Number of Sells	Number of times the strategy exited or opened a short (sell) position
Win Rate (%)	Percentage of closed trades (exits and covers) that were profitable
Avg Profit per Trade	Average amount of profit earned per closed trade.
Final Unrealized PnL	Profit or loss on open positions not yet closed.
Final Realized PnL	Profit or loss from trades that have been completed.

04 Back testing Strategy



Metric	Value
Total Return (%)	3.47
Buy-and-Hold Total Return (%)	-1.39
Average Exposure to Asset (%)	50.78
Strategy CAGR (%)	45.77
Buy & Hold CAGR (%)	-6.58
Strategy Volatility (%)	6.37
Buy & Hold Volatility (%)	12.80
Strategy Sharpe Ratio	7.18
Buy & Hold Sharpe Ratio	-0.52
Strategy Max Drawdown (%)	-5.21
Buy & Hold Max Drawdown (%)	-17.68
Number of Trades	668.00
Number of Buys	373.00
Number of Sells	295.00
Win Rate (%)	80.68
Avg Profit per Trade	14.29
Final Unrealized PnL	-682.46
Final Realized PnL	4215.03
Avg Holding Time (Closed Trades) (days)	10.96
Avg Holding Time (Open Positions) (days)	11.01

Final Portfolio Value	$103465.72
Position Size	0.99429
Position Value	$82867.84

05 OUTCOMES

Buy-and-hold (Benchmark)

Metric	Sharpe Ratio	Total Return	CAGR	Volatility	Max Drawdown	Number of Buys	Number of Sells
Outcomes	-0.52	-1.39%	-6.58	12.80	-17.68	1	0

Our Strategy

Metric	Sharpe Ratio	Total Return	CAGR	Volatility	Max Drawdown	Number of Buys	Number of Sells
Outcomes	1.86	3.47%	45.77	6.37	-5.21	373	295

Our Novelties

- Novel sentiment indicator - Rigorously designed & Tuned
- A simple yet comprehensive Multi-horizon Ensemble-style Trading Strategy
- Example of Sentiment Indicator Performance with Strategy

THANK YOU

Github

4211-Group-BTC-Day-Trading

NAME OF PROJECT

Low to Medium Frequency Trading with Sentiment

Project was done with my mates, Ethan, Yu Cai and ustin. Contact for more information.

06

REFERENCES

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