DSE4211: Digital Currencies

Intraday Trading with Sentiment Signals

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1. Executive Summary

Research Objectives

This project develops a sentiment-driven Bitcoin trading strategy addressing three challenges: quantifying market sentiment from diverse digital sources, integrating sentiment signals with technical indicators, and designing a resilient trading framework. This research is significant as cryptocurrency markets are highly influenced by sentiment, yet existing approaches only incorporate sentiment data in simplistic ways that fail to capture complex information diffusion dynamics.

Proposed Approach

Our approach introduces two key innovations: (1) a Weibull-Distributed Sentiment Indicator that models attention dynamics with peak influence at 24 hours followed by gradual decay, and (2) a Multi-Horizon Consensus Trading Framework using XGBoost to forecast Bitcoin movements across multiple timeframes (1, 2, 4, 8 hours ahead), executing hourly trades only when there is a ¾ consensus. Apart from just the lagging News sentiments, we further incorporate Telegram and Reddit communities to capture real-time market participant sentiments.

Role of Team Members

- **Leo Qi Jie, Justin**: Subreddit scraping, Data Sequencing, Training of XGBoost Model, building backtesting framework and strategy, Simulation of results
- **Ethan Cheung**: Reddit scraping, Order book data acquisition, Feature Engineering, Creation of Weibull sentiment indicator, Back testing engine
- **Chew Yu Cai**: Telegram scraping, llama LLM sentiment extraction, Back testing framework logic debugging, Align data and outputs, Sanity checks
- **Justin Cheong**: News data scraping, Combining fragmented data, Assisting with the peripherals, Wireframing presentation slides and report

Outcomes

Our strategy significantly outperforms a buy-and-hold benchmark, achieving a Sharpe ratio of 7.18 (vs -0.52) and total return of 3.47% (vs -1.39%). The strategy projects a CAGR of 45.77% while reducing volatility to 6.37% (vs 12.80%) and minimizing maximum drawdown to -5.21% (vs -17.68%)

2. Literature Review

BTC trading has been gaining traction in academic research recently, due to the potential for higher returns, given the volatile Cryptocurrency markets. A few studies with unique contributions stand out in cutting-edge research. Arslan (2024) showed Twitter (X) conversations can effectively improve BTC price predictions. The study combines historical price data with sentiment data using Long Short-Term Memory (LSTM). The findings demonstrated that incorporating sentiment effectively aids in predicting Bitcoin prices, outperforming models without its use in accuracy metrics.

We believe that these sentiment signals are invaluable in making accurate predictions. Arslan (2024) engineers the sentiment indicator by **(1)** Extracting BTC-related tweets, **(2)** Use textblob to extract sentiments; negative and positive as [-1, 1], **(3)** Calculates the ratio of positive tweets and negative tweets as features. Our team finds such a method of combining sentiments to be too simplistic, due to the lack of temporal representation and thus, we propose a Weibull distribution modelled sentiment indicator, where each piece of information takes 24 hours to reach peak influence before tapering off, and reaching an almost-zero weight around 100 hours.

To utilize our proposed sentiment indicator, our trading strategy leverages eXtreme Gradient Boosting (XGBoost) as the foundational model to forecasting BTC prices as it has shown strong predictive capabilities across various cryptocurrencies which when tailored with asset-specific features, outperforming many other models in short-term forecasting accuracy (Han et al., 2025). Moreover, another key consideration we took into account is XGBoost's computational efficiency, a critical aspect in short-term trading, since we need to attain our results quickly before the market moves away from the predicted prices.

3. Data

3.1 Datasets

This study leverages a diverse array of datasets to construct a robust Bitcoin trading strategy. Historical Bitcoin price data was sourced from CoinDesk, providing essential insights into market dynamics and facilitating strategy development and evaluation. Sentiment data was gathered from multiple platforms, including:

- **Telegram Crypto Signal Channels:** Extracted messages from influential crypto trading groups to gauge real-time market sentiment.
- **Reddit:** Scraped text data and comments from relevant subreddits (r/bitcoin, r/btc, r/cryptocurrency, r/cryptomarkets) to capture community-driven sentiment.
- **News Sentiment:** Utilized Google's GDELT GKGv2 to gather and analyze global news sentiment, providing a macro view of market perceptions.

The diversity of these datasets aim to provide a multi-faceted view of market sentiment and to remove platform-specific biases, essential for a reliable sentiment-driven trading strategy.

We split train, validation and test datasets using a simple time series split:

Train Period	27-Jan-2024 to 31-Dec-2024	339 days; 8136 hours
Validation Period	01-Jan 2025 to 28-Feb-2025	58 days; 1392 hours
Test Period	01-Mar-2025 to 04-April-2025	34 days; 816 hours

Table 1: Train Validation Test split

3.2 Sentiment Data Preprocessing

date_created	post_id	title	body	author	upvotes	downvotes	num_comments	top_comments	is_relevant	overall_sentiment
2024-03-17	1bgvem2	What is this subs position on t...	I've just found out that this su...	fverdeja	22	0	101	[Look at who controls Bitcoin, ...	This Reddit post is indeed rele...	neutral
2024-03-17	1bh2joz	/r/CryptoCurrency is just as ce...	No text body (link post)	MemoryDealers	114	0	164	[Once you uncover the bitcoin ...	Yes. The post links to a subred...	negative
2024-03-18	1bhp7xo	"Congrats @GeneralProtocol f...	No text body (link post)	Mr-Zwets	33	0	1	[]	Yes. The post mentions Bitcoin...	neutral

*Figure 1: Reddit Data Preprocessing - **Extracted sentiments from relevant posts***

Effective preprocessing was critical in extracting accurate sentiment signals from the diverse and noisy datasets. Initially, all collected textual data underwent a rigorous relevance classification using a fine-tuned LLM (llama 3.2 1b model) hosted locally via Ollama. This step ensured that only content specifically related to Bitcoin was retained for sentiment analysis. The model demonstrated high accuracy, correctly classifying Bitcoin relevance in 19 out of 20 manually verified samples.

To enhance data richness, the comments from Reddit posts were also systematically scraped and incorporated into the analysis. Following relevance filtering, a second classification process determined sentiment polarity, assigning each text a sentiment value of -1 (negative), 0 (neutral), or 1 (positive). The same llama 3.2 1b model, guided by carefully optimized prompts, classified sentiment with an accuracy of 17 out of 20 on manually labeled samples. The data is shown in ***Figure 1***.

This structured preprocessing pipeline significantly reduced noise and improved the quality of the sentiment inputs, laying a solid foundation for subsequent feature engineering and predictive modeling.

3.3 Feature Engineering

To model how media attention evolves over time, we introduced a Weibull-weighted smoothing function to capture each post's impact.

$$f(x, k, \lambda) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}$$

$$w(x) = \frac{f(x,k,\lambda)}{max_u f(x_u,k,\lambda)}$$

where k is the smoothing and decay parameter while λ is the peak parameter. The weights,

w, is then computed by normalizing weibull weights so that they are comparable across time. We chose parameters to create a model that closely mimics real-world investor attention dynamics. Each article or post gains attention gradually, peaks around 24 hours, then decays over the course of a week, before vanishing.

These numbers were chosen to model Cryptocurrency market dynamics, where investor attention span is short, and rarely exceed a week. Attention peaks at 24 hours since information within the space tends to receive immediate discussions, while time is needed to disseminate across the world, given the always-open markets. We validated our hypothesis by testing different peak and decay parameters, concluding that our hypothesis holds against the data.

This provides us with a continuous, volume-adjusted sentiment curve, computed as the hourly cumulative score weighted by recency from the past seven days.

Technical indicators engineered included returns, volatility (12-hour rolling window), exponential moving averages (8, 13, 21 periods), MACD with a 9-period signal line, Bollinger Bands (20-period SMA and ±2 standard deviations), RSI (14-period), Golden/Death Cross (50 and 200-period SMAs), Stochastic Oscillator, On-Balance Volume (OBV) crossing its EMA, and Average True Range (ATR). These indicators provided diverse signals crucial for predictive modeling and strategic trade decisions.

4. Methodology

This section will explain the models applied and evaluate their performance.

4.1 Multi-step Price Forecasting Using XGBoost

We utilized an XGBoost model for multi-step price forecasting across multiple horizons (1, 2, 4, and 8 hours ahead). At each timestamp, a rolling lookback window of the past seven hours, including the current timestamp, were fed into the model. Predictions across these horizons offered a multi-scale perspective of expected price movements, enhancing the robustness of our trading decisions.

4.2 Trading Strategy

Our strategy involved dynamic position management under simulated realistic trading conditions, with a maximum leverage cap of 2x the initial capital though we do not enforce margin requirements. Trades were generated at hourly bar closures and executed at the next open, limited to one action per bar. At any point in time we can be in an open long or short position, with possible actions being: buy (addition/cover), sell (close, short) and reversal (buying/selling more than the current position size in either a short/long position). Transaction fee of 0.1% trade size and a risk-free rate of 4.3% mirrors short-term US treasury yield (4th April) was incorporated for realism.

Using an ensemble approach, we initiated buy or sell actions if at least three of the four forecast horizons consistently signaled a direction, otherwise holding the position. This consensus approach gives us more confidence in the direction we are entering a position into.

Optuna, a hyperparameter optimization framework, tuned the bet size parameter to optimize the Sharpe Ratio, identifying approximately 1% of the capital as optimal through extensive trials.

4.3 Backtesting Framework and Evaluation Metrics Used

Trades were simulated on historical Bitcoin data, and the strategy's performance was evaluated using metrics including Total Return, CAGR, Volatility, Sharpe Ratio, Max Drawdown, Win Rate, Average Profit per Trade, and Realized and Unrealized PnL.

5. Research Outcomes

	Metric	Sharpe Ratio	Total Return	CAGR	Volatility	Max Drawdown	Number of Buys	Number of Sells
Buy-and-hold (Benchmark)	Outcomes	-0.52	-1.39%	-6.58	12.80	-17.68	1	0
Our Strategy	Outcomes	7.18	3.47%	45.77	6.37	-5.21	373	295

*Figure 2: Key Performance Metrics - **Our strategy outperforms buy-and-hold across all metrics***

As mentioned in the executive summary our strategy clearly outperforms a buy-and-hold on purely bitcoin, as given in ***Figure 2***.

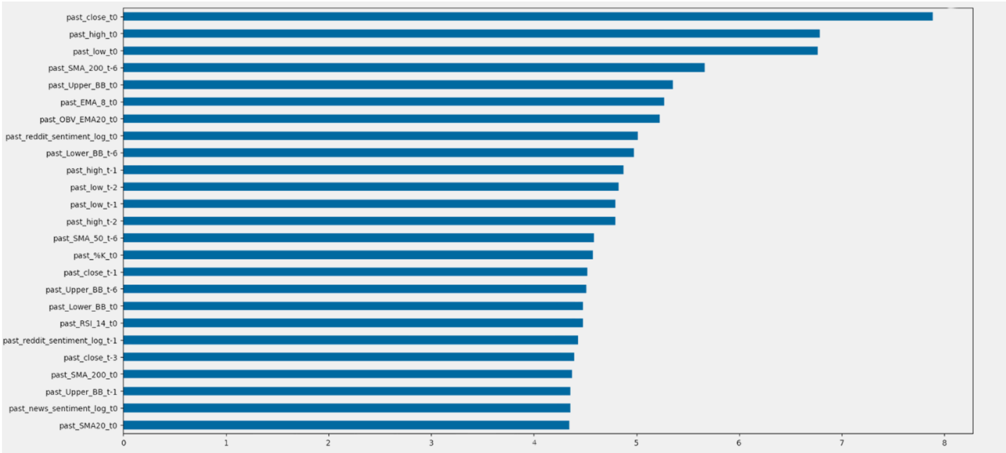

Figure 3: Feature Importance Comparison - ***Sentiment data holds considerable predictive power***

We also present our feature importance in ***Figure 3*** above, wishing to highlight the high importance attributed to reddit and news sentiment. This shows that when sentiment data is available, it does have considerable predictive power in forecasting future prices at least in our trialled context of intraday trading of bitcoin.

6. Conclusion and Recommendations

In this research, we developed a sentiment-driven Bitcoin trading strategy by synthesizing market sentiments from a diverse range of digital sources and designed a resilient trading framework. Our approach introduced two key innovations. Firstly, a temporally-aware Weibull distributed sentiment indicator and secondly, a Multi-Horizon Consensus Trading Framework which leverages on XGBoost for robust price forecasting. Our strategy outperforms the buy-and-hold benchmarks across most conventional metrics.

While this study delivers promising results, we acknowledge and suggest future work to deliver more comprehensive results, given below.

1. The Weibull-distributed Sentiment Indicator could be tested against more parameters or utilize a tuning framework, given better computational power.
2. A more diverse range of sentiment sources could be incorporated, such as Twitter (X), Discord and on-chain sentiment indicators.
3. The XGBoost model slightly underfits on the time series, capturing the overall trend well but missing out on the short spikes. An ensemble strategy of combining XGBoost with another model to model the spikes could work better.

4. XGBoost's trend predictions can be inconsistent, so using TP/SL orders or acting only when prediction confidence is high could help manage risks and improve trade decisions.

7. References

Arslan, S. (2024). Bitcoin Price Prediction Using Sentiment Analysis and Empirical Mode Decomposition. *Computational Economics*. https://doi.org/10.1007/s10614-024-10588-3

Ider, D., & Lessmann, S. (2023). *Forecasting Cryptocurrency Returns from Sentiment Signals: An Analysis of BERT Classifiers and Weak Supervision* (arXiv:2204.05781). arXiv. https://doi.org/10.48550/arXiv.2204.0578