IDS 705 Final Report

Bitcoin Returns with Sentiment Analysis

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Abstract

In this study, we carefully explored the relationship between cryptocurrency returns and human sentiment [1]. Our approach involved integrating established market indicators with sentiment data from various sources, including Bitcoin price data from Yahoo Finance, news data from the TIINGO News API, Twitter sentiment from Bloomberg, and Google Trends information, following a detailed review of relevant literature. We focused on enhancing the prediction of Bitcoin's 15-day moving average daily return, a metric chosen for its potential to moderate the market's inherent volatility. Our methodology included the use of four distinct feature sets, each designed to provide different insights into market behaviors. We employed both a foundational linear regression model and a more detailed Random Forest model, rigorously testing each for consistency and stability across diverse data sets. To demonstrate the practical application of our findings, we also conducted a sample trading strategy. This strategy helped confirm the feasibility of using our models in real-world trading scenarios, supporting the credibility of our research while carefully managing claims about its potential impact.

Introduction

Our project is focused on understanding the relationship between cryptocurrency returns and human sentiment [2] by refining a machine learning model. This model incorporates fundamental and technical indicators along with sentiment analysis from diverse data sources, such as news feeds, Twitter, and Google Trends. We aim to improve on the baseline performance levels found in existing literature by methodically applying and assessing our approach. By utilizing a mix of Linear Regression and Random Forest models, each tested with four distinct sets of features, we seek to ensure the model's stability and practical applicability. Our objective is to provide a reliable predictive model that enhances our comprehension of market dynamics influenced by sentiment, offering informed insights without overstating its impact.

Background

The inherent volatility of cryptocurrencies [3] presents a substantial risk for investors, emphasizing the need for precise forecasting tools to guide investment decisions effectively. Our review of the literature reveals a variety of approaches that have been explored to enhance the accuracy of cryptocurrency predictions. For instance, the 2022 study by Duygu Ider and Stefan Lessmann [4] demonstrates the efficacy of using BERT (Bidirectional Encoder Representations from Transformers) [5] classifiers in sentiment analysis to predict cryptocurrency returns. This method leverages advanced natural language processing to interpret market sentiments, which has shown promising results in capturing nuances that influence market movements.

Further, research by Arratia and López-Barrantes in 2021 [6], along with the 2019 study by Nasir, Huynh, Nguyen, et al. [7], has highlighted how data from search engines, specifically Google Trends, can predict fluctuations in Bitcoin prices. This underscores the value of integrating publicly available search data as a predictor, reflecting broader public interest and its potential impact on the market.

Additionally, studies by Critien, Gatt, and Ellul in 2022 [8], and earlier work by Peter Gabrovsek et al. in 2017 [9], illustrate the significant influence of Twitter sentiment on Bitcoin prices. Jing-Zhi Huang, William Huang, and Jun Ni's 2019 [10] study advocates for the inclusion of high-dimensional technical indicators in Bitcoin return predictions, enhancing our model's diversity. N. N. Y. Vo and G. Xu's 2017 [11] research provides insights into Bitcoin's volatility and its relationship with the broader financial markets. These studies validate the use of social media sentiment as a crucial factor in our predictive models, providing real-time reflections of public mood and expectations that correlate with market trends.

From these studies, we learned that integrating diverse data sources like social media, search trends, and sentiment analysis can provide a more rounded and dynamic approach to understanding and predicting cryptocurrency price movements. Each of these methodologies has contributed to the field by offering new insights into the factors that drive cryptocurrency markets. Typically, most research leveraging these models and methodologies reports achieving around a 60% accuracy rate in predicting the direction of Bitcoin price movements, underscoring their potential utility yet also highlighting the room for further enhancement in predictive accuracy.

Data

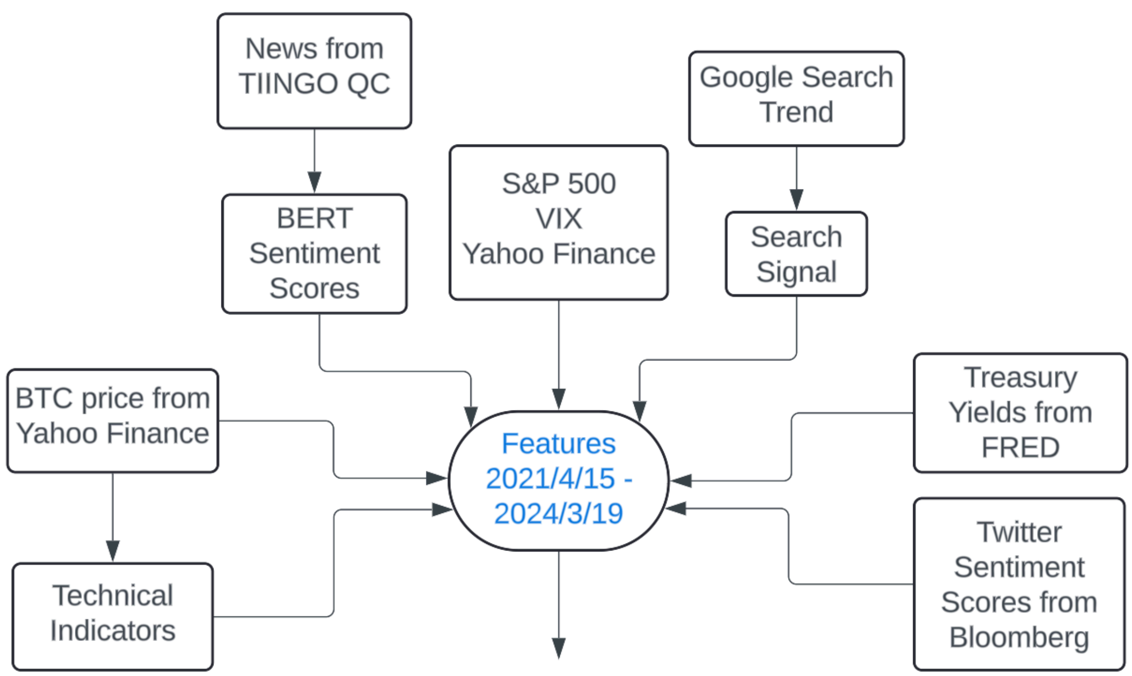

Figure 1: Data Source and Preprocessing Pipeline

We sourced our data from reputable platforms to ensure accuracy and reliability in our analysis: Yahoo Finance for comprehensive Bitcoin price data, FRED for detailed treasury yield information, Bloomberg for real-time Twitter sentiment scores, and Google Trends for search trend data. News articles were obtained from QuantConnect's TIINGO platform, and we employed BERT models to assign sentiment scores to these articles, enhancing the depth and accuracy of our sentiment analysis. Each source was chosen for its specific strengths and reliability, providing a solid foundation for our predictive models.

Bitcoin price data are sourced from Yahoo Finance, a reputable platform for tracking asset prices. Yahoo Finance aggregates Bitcoin prices from various exchanges, averaging them to provide a comprehensive reflection of the market across all trading platforms. The calculation of returns utilizes the daily closing price, focusing on log returns to measure the rate of price change more accurately. Furthermore, according to the following figure we can observe that bitcoin returns resemble a normal distribution with long tails (indicating some days of extreme returns).

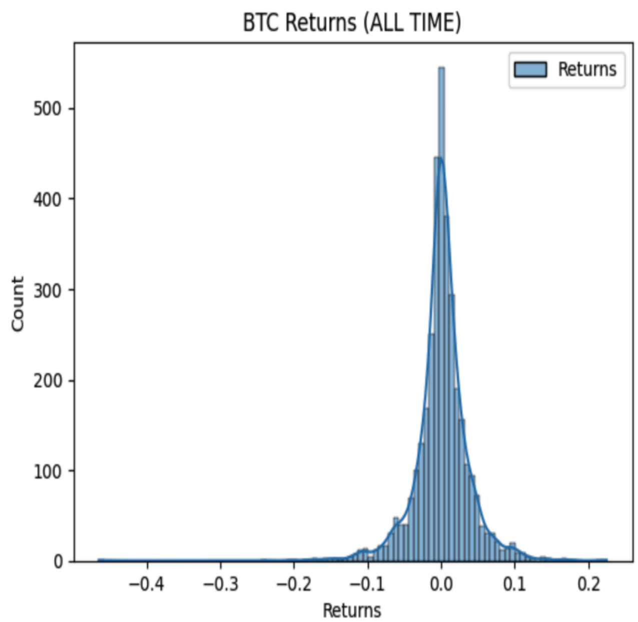

Figure 2: Distribution of all time Bitcoin returns is shown to resemble a normal distribution with long tails (which indicates some days of extreme returns)

In our study, we've opted to forecast the **15-day moving average daily price return** (**15DAR**) of Bitcoin, and project its value to price movement direction and magnitude. This approach helps mitigate the inherent volatility and noise in daily price movements, allowing us to capture more significant trends. It also enhances predictive power by smoothing out short-term fluctuations and revealing more meaningful patterns. Although using the 15-day moving average daily price return (15DAR) involves some loss of information about short-term market fluctuations, it enables us to focus on more substantial, longer-term trends. This approach reduces the impact of daily volatility and noise, enhancing the stability and reliability of our predictions, which is especially valuable for investors with medium to long-term investment horizons. The figures below visualize the reduction in noise due to this modeling consideration.

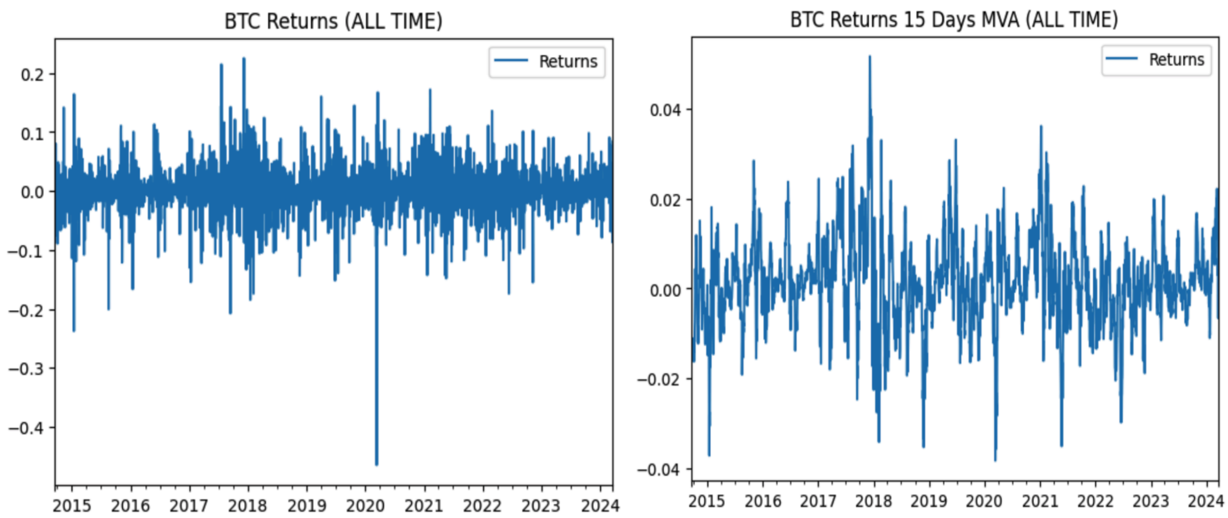

Figure 3.1 (left): Daily Bitcoin returns (bad signal to noise ratio). 3.2 (right): 15 Day Moving Average (15DAR) Bitcoin Returns (improved signal to noise ratio).

News data was sourced from TIINGO News API via the QuantConnect platform. QuantConnect is an open-source, cloud-based algorithmic trading platform for equities, FX, futures, options, derivatives and cryptocurrencies. Since TIINGO only stores news information regarding US Equities, Coinbase (the first publicly traded cryptocurrency exchange) was used to retrieve descriptions of all relevant news articles. Figure 3.1 shows the count of news articles retrieved that were relevant to Coinbase vs time. From these articles, articles that contained any reference of Bitcoin/BTC (case insensitive) were filtered to form the Bitcoin exclusive news shown in figure 3.2.

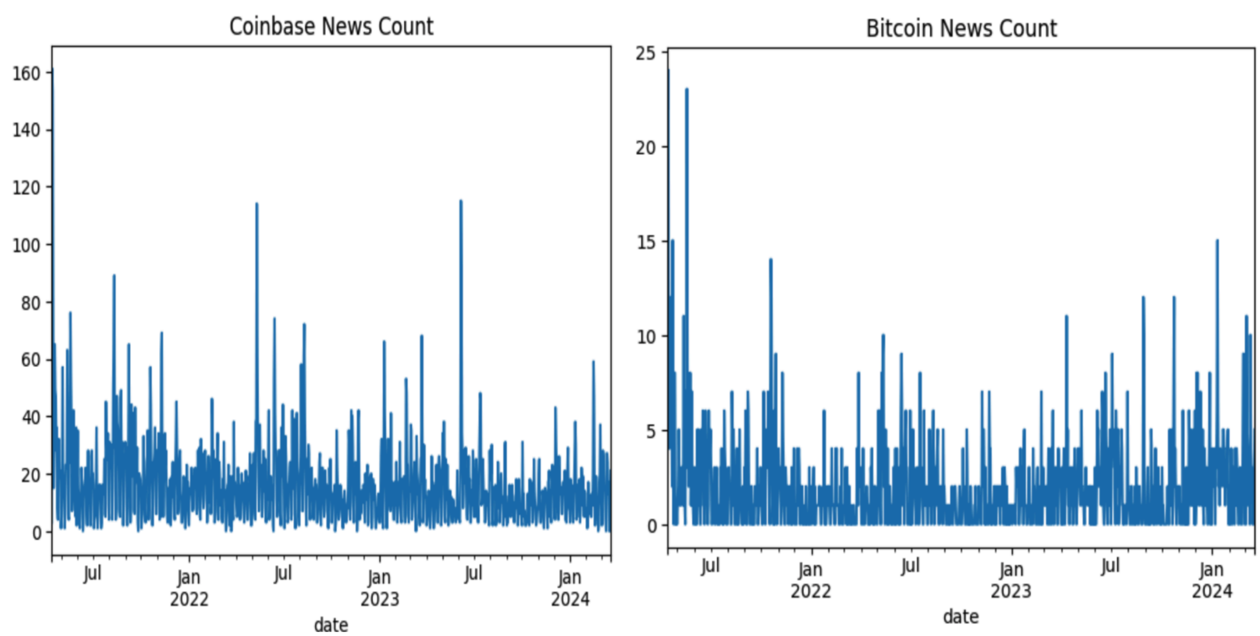

Figure 4: Count of News Articles per day from Tiingo News API.

Each news article (truncated to 512 tokens) was then passed through a fine tuned version (on financial news data) of the DistilRoberta [12] to produce our News sentiment features. Figure 5 below shows the distribution of the resulting sentiment assignments.

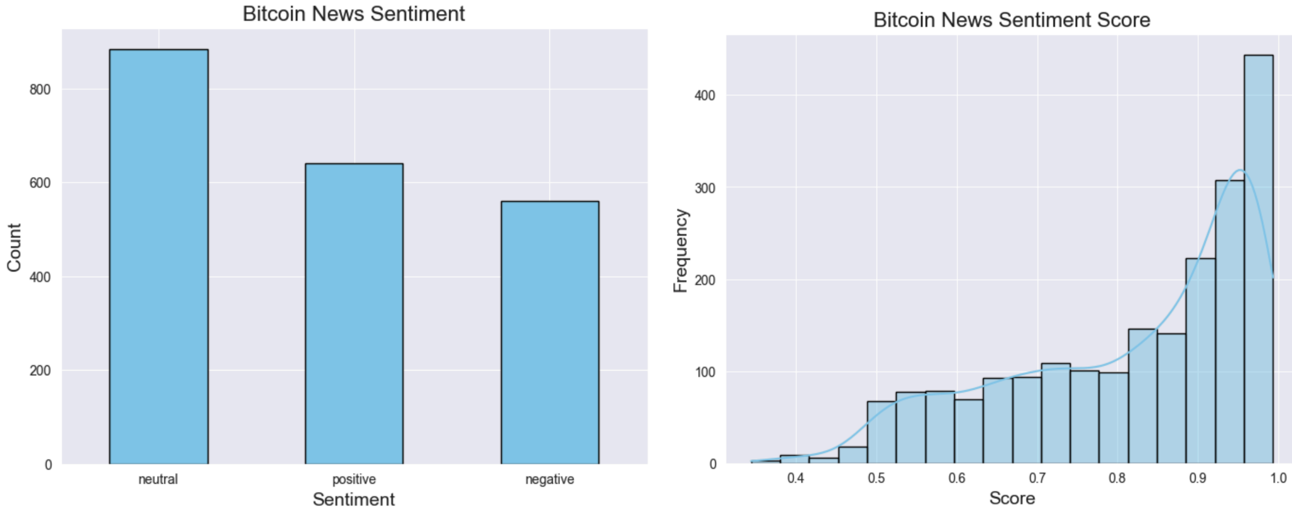

Figure 5: Distribution of generated sentiment labels and confidence scores using a financial news fine tuned version of the BERT Large Language Model [12].

The news sentiment data was then aggregated on a daily level. Some new features generated at this stage include “total news scores” and “signal (bitcoin signal)”. The total news score is calculated as a weighted sum of the average sentiment scores for positive and negative news, and is meant to be a measure of overall daily sentiment from the news. The bitcoin signal is calculated in the exact same way as the Google trends signal below. Figure 6 below shows the distribution of resulting daily features.

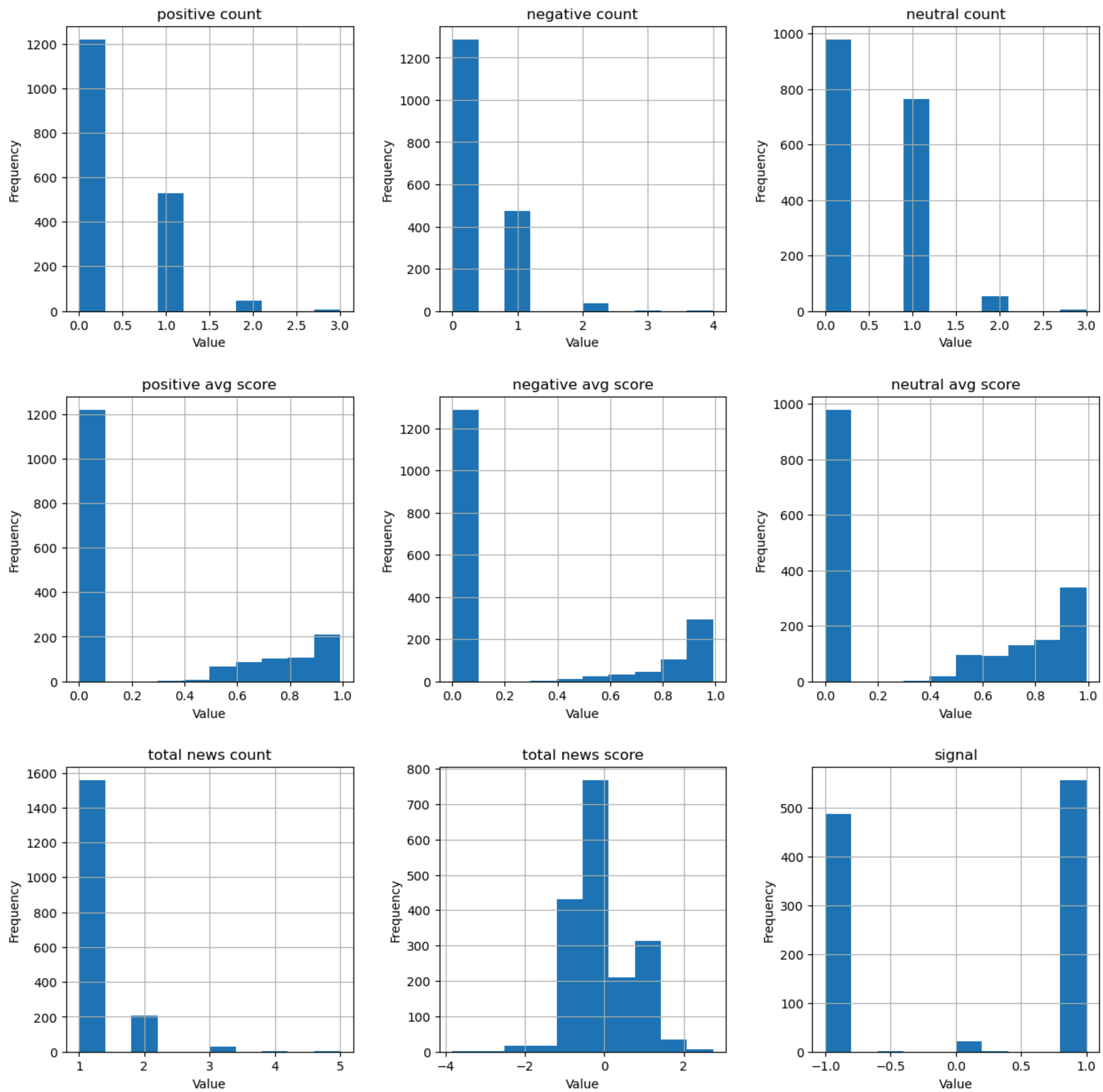

Figure 6: Distributions of all news sentiment features, generated using a financial news fine tuned version of the BERT Large Language Model [12].

Twitter Sentiment was obtained from the Bloomberg terminal, where the Bloomberg version of the total news score (News Sentiment Daily Average) is derived using a proprietary model. Despite the differences in methodology, the distribution of the Bloomberg score closely resembles the distribution of the news sentiment score obtained from Tiingo. This similarity in distribution shapes serves as validation, indicating that proper data processing techniques have been employed across both methods. Figure 7 below shows the distribution of the Twitter sentiment features. The Twitter sentiment score sourced from Bloomberg, and the TIINGO news score, derived from BERT, exhibit similar distributions in their overall sentiment scores.

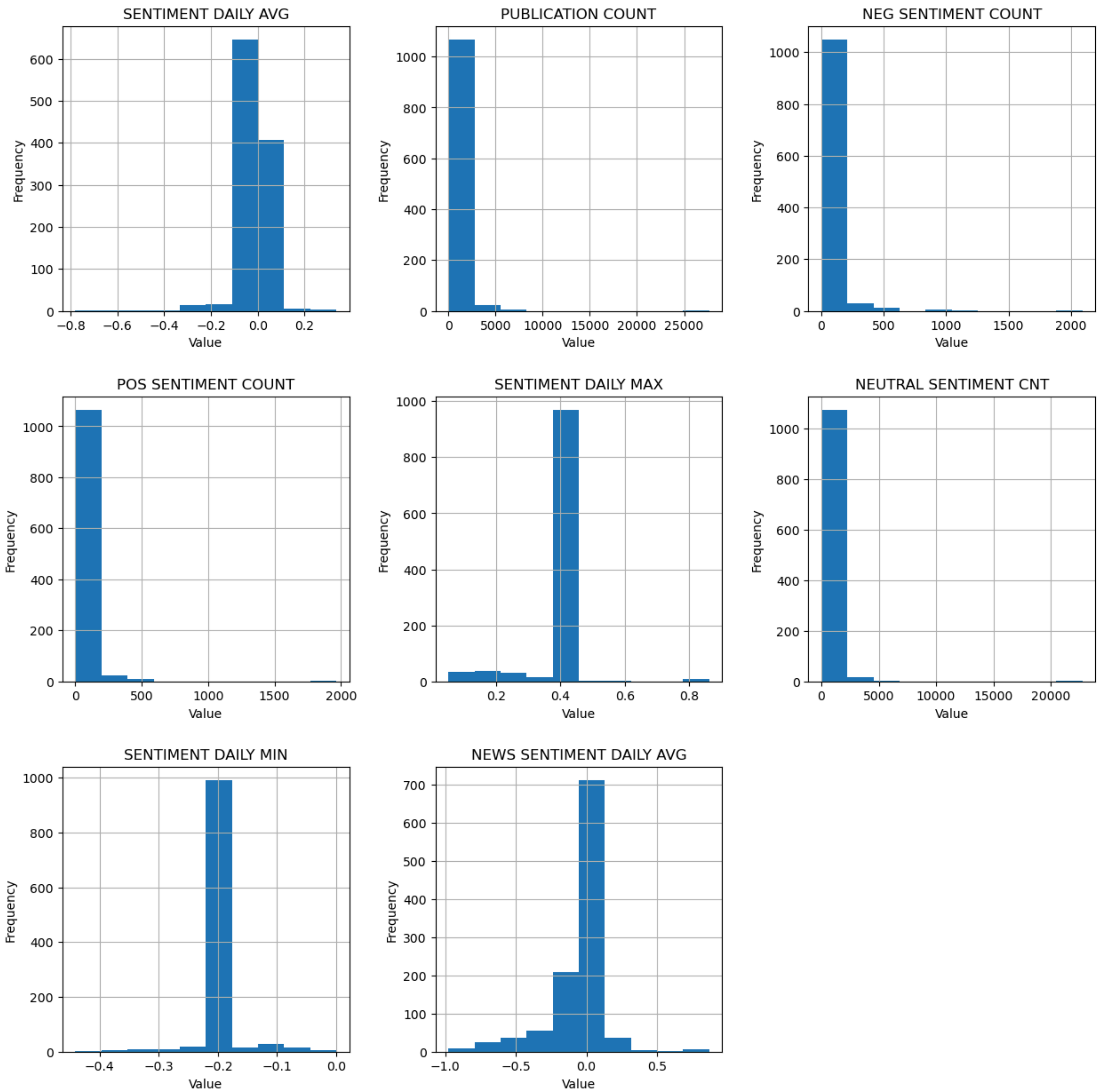

Figure 7: Distributions of all twitter sentiment features extracted from the Bloomberg Terminal.

Google Trends is a website by Google that analyzes the popularity of top search queries in Google Search across various regions and languages. To build our Google Trends signal, we query the search volume for 8 positive search keywords and 8 negative search keywords listed as Table 1. However, the raw keyword level data spreadsheets from Google Trends need some preprocessing. We download the data at weekly granularity and interpolate the data at daily level.

Table 1: Positive and Negative Search Keywords

Positive	Negative

“Bitcoin price”, “buy bitcoin”, “bitcoin”, “coin-base”, “bitcoin boom”, “make bitcoin”, “bitmex”, “long bitcoin”	“Bitcoin crash”, “bitcoin loophole”, “sell bitcoin”, “bitcoin scam”, “short bitcoin”, “bitcoin bubble”, “bitcoin illegal”, “bitcoin bear”

With the Google Trends data, in order to use each keyword search volume to the same scale, we normalize them individually:

$$\text{Volume}_{\text{keyword}}(t) \leftarrow \frac{\text{Volume}_{\text{keyword}}(t)}{\max_t(\text{Volume}_{\text{keyword}}(t))}$$

Then we define the positive and negative volumes in the following way:

$$\text{Positive Volume}(t) = \sum_{\text{keyword} \in \text{Positive keywords}} \text{Volume}_{\text{keyword}}(t)$$

$$\text{Negative Volume}(t) = \sum_{\text{keyword} \in \text{Negative keywords}} \text{Volume}_{\text{keyword}}(t)$$

Instead of directly using sentiment score, we use sentiment polarity [8] for our semantic analysis. Thus we build a normalized sentiment signal from the following formula:

$$S(t) = \frac{\text{Positive Volume}(t) - \text{Negative Volume}(t)}{\text{Positive Volume}(t) + \text{Negative Volume}(t)}$$

Non-sentiment features are integrated such as short and long-term treasury yields, the 5-year inflation forecast, and the S&P 500 and VIX indexes to offer insights into market dynamics and investor sentiment. It is complemented by technical indicators like Parkinson Volatility, Intraday Price Change, Relative Strength Index (RSI), and Stochastic Oscillator etc. Together, these metrics provide a nuanced understanding of market behavior, volatility, and Bitcoin's relative performance, enhancing the analysis of its market positioning and potential future movements.

Each data observation encompasses details up to the end of the preceding day, incorporating Bitcoin's market movements, sentiment scores of news and Twitter, and various financial indicators such as opening and closing prices, volume, moving averages, volatility measures, and economic indicators. For example, to predict January 15th returns, the model uses information up to January 14th, including sentiment scores, market trends, and economic signals, aiming for a comprehensive reflection of the factors influencing Bitcoin's price direction without using any future information. The data dictionary can be found in the appendix.

Experiments

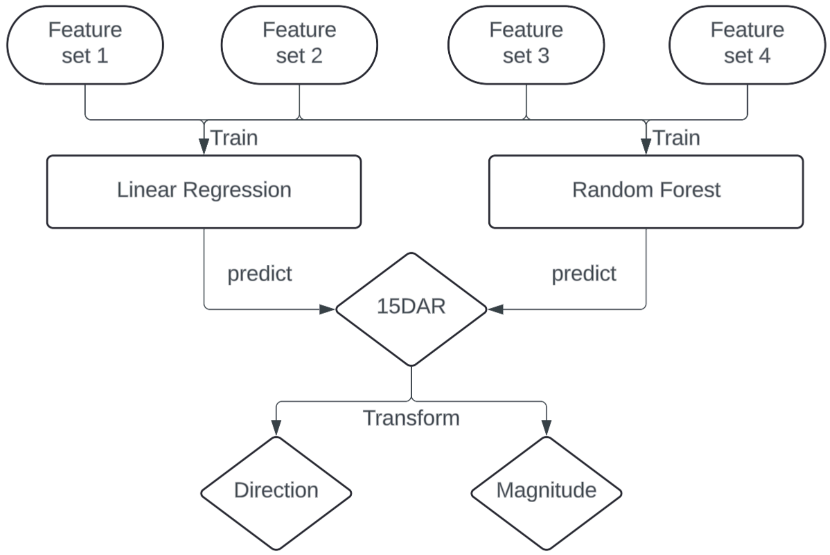

Figure 8: Experimentation flow chart

Train Test Split

Our dataset was split into two parts: training data from April 15, 2021, to March 1, 2023, and testing data from March 1, 2023, to March 19, 2024. We meticulously ensured that no future information influenced the model by lagging all features by one day, ensuring predictions for any given day were based solely on data available up to the end of the previous day. Additionally, for rolling sums and averages, we dropped initial data points to ensure each calculation was based on a complete set of information, thereby preventing any potential data leakage and maintaining the integrity of our testing process.

Experimental Features Sets

We have developed four distinct feature sets for our experiments. The first set includes a variety of features commonly regarded as effective in market predictions, alongside sentiment indicators. Examples are S&P 500 returns, counts and scores of positive and negative news, Google trends, and several technical indicators. This foundational set aligns with the objectives of our study and helps prevent initial overfitting during model training.

The second set comprises all available features, including market prices, news scores, sentiment scores derived from the BERT model, technical indicators, and Google trend data. This comprehensive set allows us to assess model performance using all possible inputs and sets the stage for subsequent feature engineering to enhance model effectiveness.

The third set expands on the previous by incorporating memory features, which include rolling sums of all features over the past 10, 20, and 30 days. One of our key contributions is the development of memory features, designed to address the limitations of lagged features [13] used in literature, which only capture historical data as isolated snapshots. Our memory features accumulate data from the past days, effectively creating a continuous 'working memory' for our predictive model.

The fourth set consists of the top 30 significant features identified after applying a random forest model.

Models

We use Linear Regression as our initial model and the Random Forest Model as a more advanced option. Each model is fitted with each set of features.

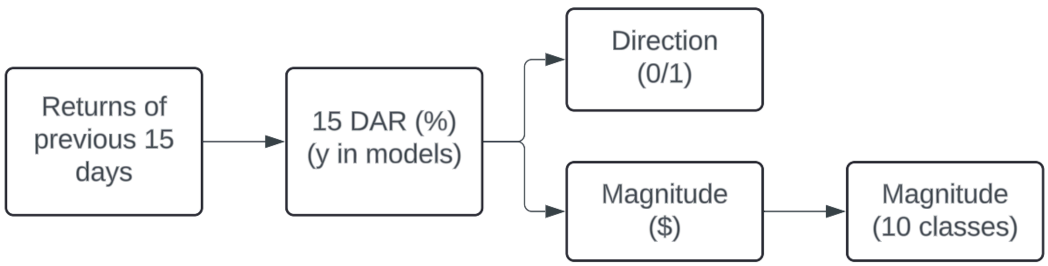

Figure 9: Target variable transformation

In order to compare the accuracy with existing research, we transform the **predicted 15DAR** into daily price change **direction** and **magnitude** movement. For direction, if the projected 15DAR is positive, we infer that the corresponding direction would also be positive (1), and conversely for negative predictions (0). For magnitude, we first multiply the predicted 15DAR to the price of the previous day, resulting in the projected value of price movement, then assign it to one of the classes below.

Table 2: Magnitude Bins for projected movement

Class	1	2	3	4	5	6	7	8	9	10
Range	Less than -$1320	-$1320 to -$990	-$990 to -$660	-$660 to -$330	-$330 to $0	$0 to $330	$330 to $660	$660 to $990	$990 to $1320	Greater than $1320

In order to assess our model, we will evaluate its performance using several key metrics: R-squared, accuracy of direction prediction, and accuracy of magnitude prediction. R-squared will help us understand how much of the variance in the dependent variable our model can explain, providing a measure of how well unseen samples are likely to be predicted by the model. The accuracy of direction prediction will assess whether our model can correctly predict the trend of the market movement—whether the price is going up or down. Finally, the accuracy of magnitude prediction will measure how well our model can estimate the size of the market changes. By analyzing these metrics, we can gain insights into both the strengths and potential limitations of our predictive approach, allowing for targeted improvements and refinement.

When configuring the Random Forest model, we select the top 30 most important features to form the fourth feature set. This approach is designed to retain the most predictive elements while excluding less relevant information, which helps prevent overfitting. This method ensures that our model remains robust and focused on the most influential variables affecting the outcome. Below is a graph illustrating the importance of features.

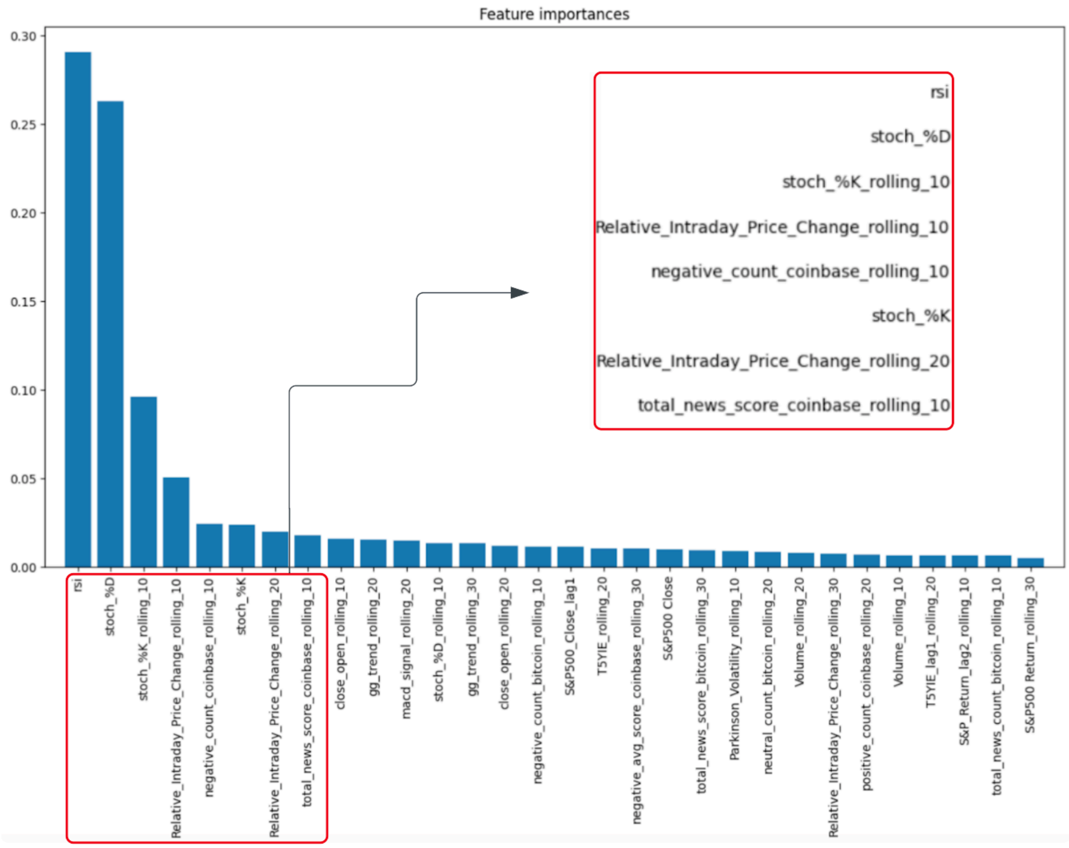

Figure 10: Feature importance of Random Forest Model

Figure 11 below provides valuable insight into a snippet of decision-making process of our Random Forest model, particularly emphasizing the straightforward nature of its decision trees. Unlike the more common black-box models such as Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) found in much of the existing literature, our approach offers investors a clearer understanding of how decisions are made. Despite Random Forests not typically being considered as interpretable models, the split rules within the trees provide a window into the logic used, offering a tangible sense of how investment decisions are derived. This clarity is advantageous as it allows investors to see why their funds are allocated in certain ways, thus boosting their confidence and facilitating more informed decision-making. In our model, the primary splits focus on technical indicators, with sentiment features becoming more influential in subsequent layers of the decision process. This methodical unveiling of decision layers helps demystify the predictive process and sets our model apart by enhancing transparency and investor engagement.

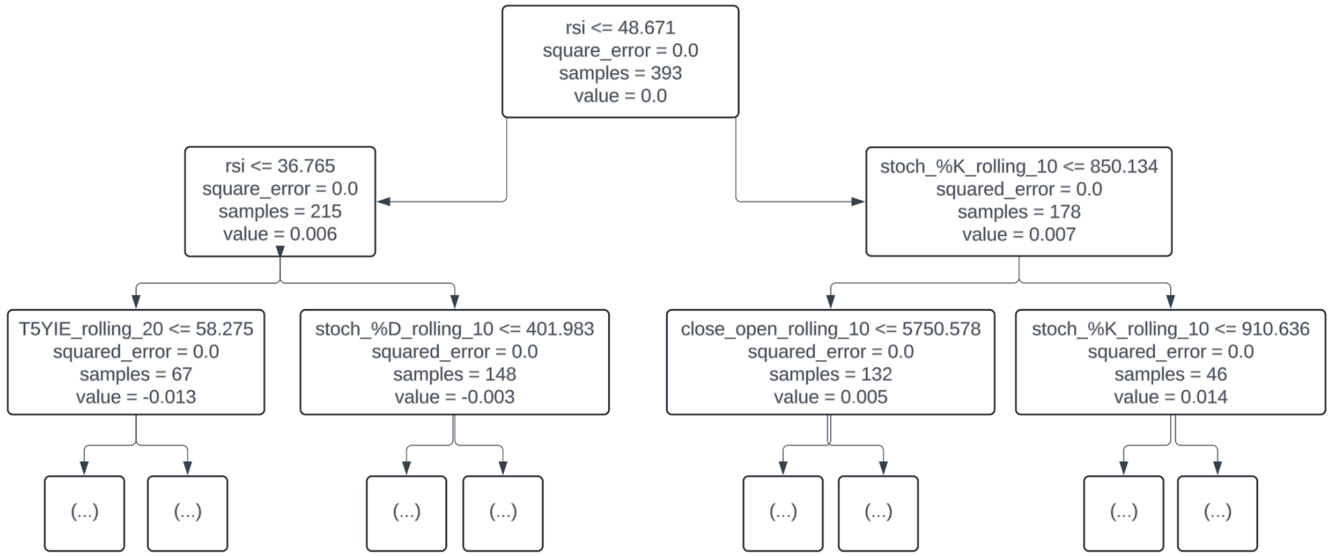

Figure 11: First two levels of a sample decision tree from Random Forest

Results

To better compare with existing literature, we project the 15DAR to the direction and magnitude of price movement. Result tables for R-squared, direction accuracy and magnitude accuracy are listed below.

Table 3: Experiment test result for 15DAR R-squared

15DAR R-squared	Feature set 1	Feature set 2	Feature set 3	Feature set 4
Linear Regression	0.57	0.63	-41.82	0.59
Random Forest	0.59	0.67	0.73	0.73

Table 4: Experiment test result for direction accuracy (random guessing: 50%)

Acc Direction	Feature set 1	Feature set 2	Feature set 3	Feature set 4
Linear Regression	0.85	0.79	0.63	0.84
Random Forest	0.86	0.87	0.87	0.88

Table 5: Experiment test result for magnitude accuracy (random guessing 10%)

Acc Magnitude	Feature set 1	Feature set 2	Feature set 3	Feature set 4
Linear Regression	0.21	0.22	0.13	0.22
Random Forest	0.22	0.22	0.21	0.22

As we can see from the result tables, with Feature set 1, which includes basic market and sentiment features, both models show decent R-squared values, suggesting a reasonable fit to the data (actual 15DAR vs predicted 15DAR). However, Random Forest slightly edges out Linear Regression, and this trend persists across all feature sets, highlighting the robustness of the Random Forest model.

The second feature set, which uses all available features, shows improved R-squared values for both models, but notably, there's a dip in the direction prediction accuracy for Linear Regression. This may indicate that the inclusion of more complex features without feature selection can introduce noise for simpler models. In contrast, the Random Forest model maintains high accuracy in direction prediction, demonstrating its capability to handle high-dimensional data without a significant loss of interpretability.

With Feature set 3, where memory features are added, there is a significant anomaly in the R-squared for Linear Regression, suggesting that the inclusion of these features could be leading to model instability or inappropriate model fit in this instance. The Random Forest, however, shows a remarkable increase in R-squared, indicating its ability to utilize these temporal features effectively without overfitting.

Feature set 4, which includes the top 30 features as selected by the Random Forest, shows a convergence in performance for both models. This suggests that when the most predictive features are used, even a simpler model like Linear Regression can achieve results comparable to a more complex model. This is particularly evident in the R-squared and magnitude prediction accuracy, although Random Forest maintains a slight advantage in direction prediction accuracy.

Table 6 below shows the performance comparison of the Random Forest with Features set 4 vs. literature review. The Random Forest exhibits superior performance over the best model identified in the literature review in predicting the direction of daily price movements, achieving an accuracy of 88% compared to 68.4%. However, when forecasting the magnitude, the Random Forest displays a slightly lower accuracy rate of 22.25% versus 51.47% for the best model from the literature review. Despite this disparity, the RFM's higher F1 score suggests a better balance between precision and recall, indicating its potential to capture nuanced price movement patterns more effectively. The methods from the literature were not implemented on our dataset; however, the comparison remains meaningful as it provides a benchmark of model performance across different market conditions and asset classes. It's comparable because it allows us to evaluate the generalizability and robustness of our models against a variety of approaches and data characteristics found in existing research. Overall, while the Random Forest may occasionally misclassify certain movements, it offers competitive performance and provides investors with valuable insights into Bitcoin price dynamics.

Table 6: Performance comparison of Random Forest with best from literature review

	Best from Literature Review [8]	**Random Forest Model**
Daily Price Direction Forecast Accuracy	68.4%	88%
Magnitude Forecast F1 Score	14.21%	16.89%
Magnitude Forecast Accuracy	51.47%	22.25%

To further prove the practicality of using the developed RFM model, a demonstrative trading strategy was implemented. The trading strategy implemented in this report relies on signals generated by the RFM to guide investment decisions in the Bitcoin market. Using the RFM's predictions of daily price movements, the strategy identifies optimal entry and exit points. When the RFM consistently predicts a positive daily direction (Bitcoin price going to go up) for 4 consecutive days, the strategy initiates a buy signal, investing available cash into buying Bitcoin. Conversely, a sell signal is triggered if the RFM predicts a negative daily direction (Bitcoin price going to go down). Furthermore, as a risk management measure,a sell signal is also generated if Bitcoin prices decline for nine consecutive days. In response to a sell signal, the strategy sells all of its Bitcoin holdings. This dynamic portfolio management approach allows the strategy to adapt to changing market conditions while aiming to capitalize on potential trends. The performance of this strategy is evaluated against a straightforward buy-and-hold approach for Bitcoin and the S&P 500 index. We chose the buy-and-hold strategies for Bitcoin and the S&P 500 index as benchmarks because they were known to be profitable for the selected period. These strategies invest all available capital on the first day of the test period and hold their positions throughout, reflecting a passive investment approach. Figure 12 below provides valuable insights into the effectiveness of our strategy relative to the passive investment approaches over the specified test period.

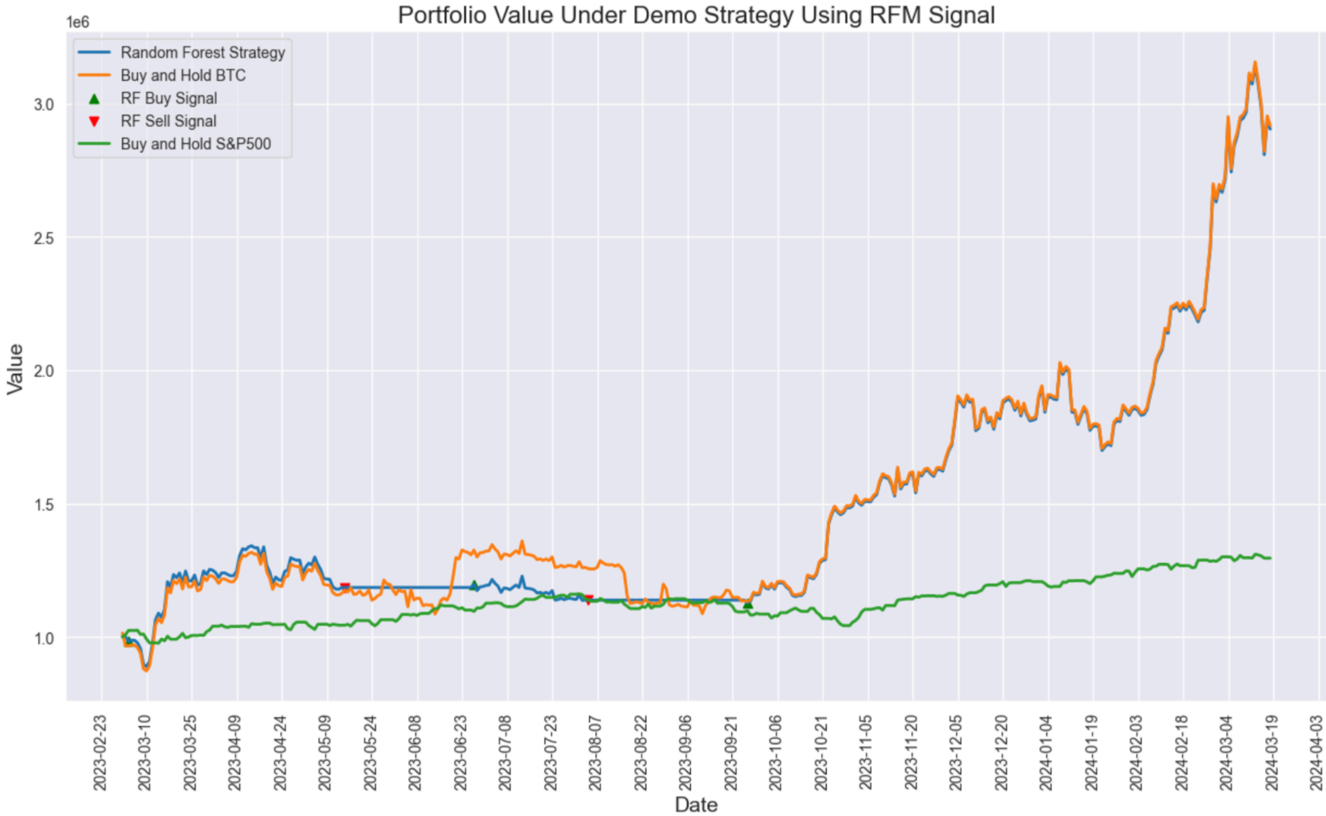

Figure 12: Performance comparison of a demo strategy using signals from the RFM against a simple buy-and-hold strategy for Bitcoin and the S&P 500 index at the beginning of the period.

Table 7 below provides a comparative analysis of the performance of the RFM derived strategy against the other known profitable strategies over the test period. The RFM Strategy demonstrates superior results, outperforming both the BTC Buy&Hold and S&P 500 Buy&Hold strategies in terms of Sharpe Ratio, with a value of 2.21 compared to 2.01 and 1.67, respectively. The Sharpe Ratio is an essential financial metric that investors use to assess the performance of an investment by adjusting for its risk. It represents the additional return per unit of risk that an investment yields over the risk-free rate, typically the return on a government bond. A higher Sharpe Ratio indicates a more favorable risk-reward profile, suggesting that the investor is receiving more return for the level of risk they are taking. Since the risk free rate affecting all three strategies are the same, they were ignored in the calculations below.

Furthermore, the RFM strategy exhibits a lower maximum drawdown of -16.71% compared to -21.48% for the BTC Buy&Hold strategy and similar maximum drawdown to the S&P 500 Buy&Hold strategy, indicating better risk management. Maximum drawdown is defined as the peak to trough decline in portfolio value over a specified period. The RFM strategy's ability to mitigate downside risk underscores its effectiveness in preserving capital and enhancing overall portfolio stability.

Lastly, the RFM Strategy boasts a respectable period return of 190.46%. This falls short of the period returns achieved by the BTC Buy&Hold Strategy (191.78%) and significantly outperforms the S&P 500 Buy&Hold (29.5%) strategy. Overall, our strategy achieves the mean risk profile of S&P 500 and Bitcoin (Low), while mirroring the return profile of Bitcoin (High).

It's worth noting that past models from literature use different data sources than our study, so we could not include them in our strategy comparison. Additionally, many past models report their results for periods before April 2021, for which our model does not have data due to constraints imposed by our data source. However, a future endeavor could involve recreating models and data from the literature for a more comprehensive comparison.

Table 7: Demo Random Forest model derived strategy performance comparison against other known profitable strategies for the time period.

	Random Forest Strategy	**BTC Buy&Hold Strategy**	**S&P 500 Buy&Hold Strategy**
Sharpe Ratio	2.21	2.01	1.67
Maximum Drawdown	-16.71%	-21.48%	-10.65%
Period Return	190.46%	191.78%	29.5%

Conclusions

Our study has developed a nuanced approach to cryptocurrency prediction, harnessing a broad spectrum of data inputs including social media trends, news sentiment, and search behaviors. While our analysis methods and feature engineering techniques differ from those commonly reported in the literature, they have allowed us to effectively capture and model the dynamic nature of cryptocurrency markets.

Particularly, the engineering and integration of memory features [14] — which provide historical context to the current data points — has shown to be beneficial, enhancing our model's ability to anticipate future market movements. Although comparing our results directly with those from existing studies is challenging due to methodological differences, our approach has demonstrated substantial promise.

The refined Random Forest model, equipped with these memory features and further enhanced by BERT classifiers for deeper sentiment analysis, over the traditional VADAR [15] model, has exhibited robust performance. This performance is carefully quantified without overstating outcomes, reflecting improvements in both predictive accuracy and interpretational clarity.

Our application of this model in a demonstrative trading strategy, which also includes comparisons to conventional market strategies like the S&P 500 buy-and-hold, has illustrated its practical value. The strategy's successful performance further validates the model's effectiveness, balancing risk and return in a manner comparable to established financial benchmarks.

Ultimately, this study contributes a carefully validated, effective model for predicting Bitcoin returns, suggesting pathways for future research in this complex field. By blending sophisticated machine learning techniques with a clear, interpretable modeling approach, we aim to enhance the strategic toolkit available to investors navigating the volatile cryptocurrency markets.

Roles

Rakeen - Chief Executive Officer (CEO) & Developer, Research Director.
Lin - Chief Financial Officer (CFO) & Developer, Finance Domain Director.
Minling - Chief Technology Officer (CTO) & Developer, Sentiment Analysis Lead.

Code and Data Repository

https://github.com/nogibjj/Flamingo-ML

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Appendix

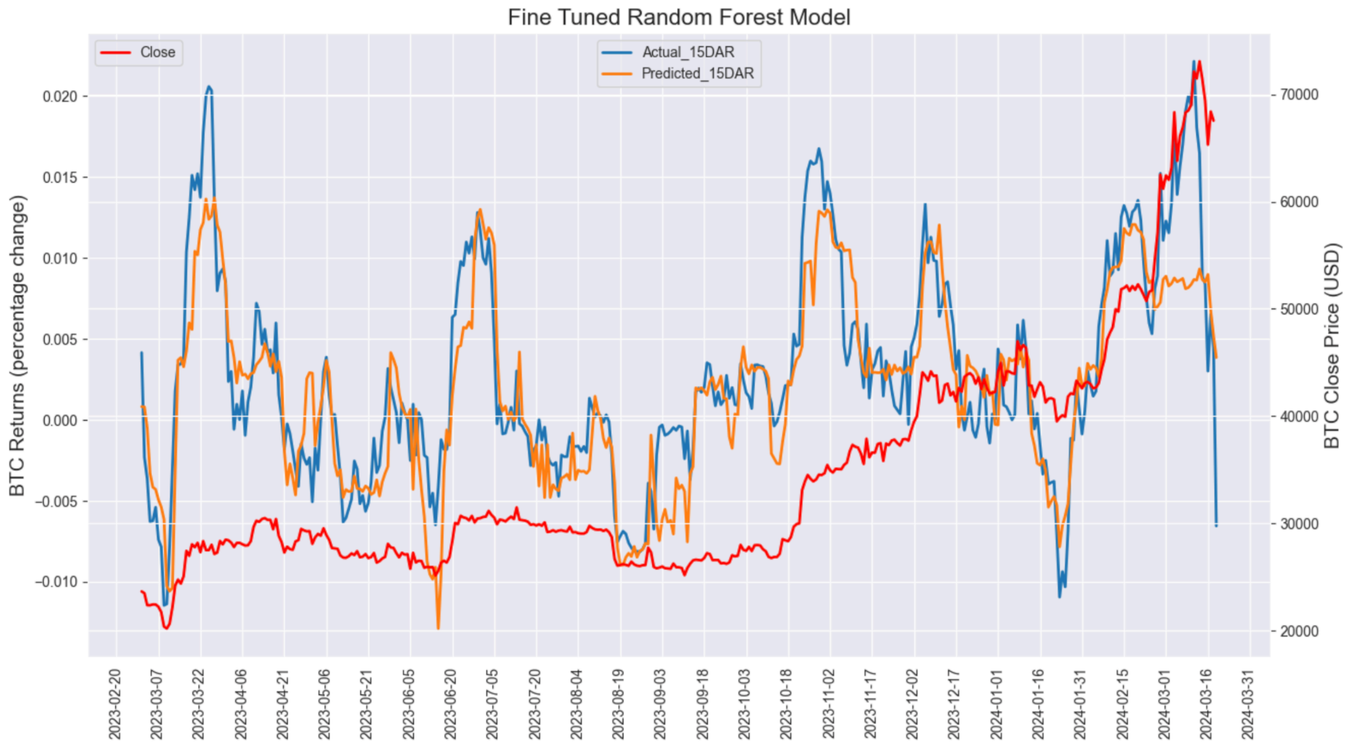
1. Data dictionary (feature table)

Column Name	Description
date dt	Date of the data entry
Direction	The direction of Bitcoin price movement (up/down)
magnitude	The magnitude of Bitcoin price movement
positive count bitcoin	Number of positive sentiments in Bitcoin-related news
negative count bitcoin	Number of negative sentiments in Bitcoin-related news
neutral count bitcoin	Number of neutral sentiments in Bitcoin-related news
positive avg score bitcoin	Average score of positive sentiments in Bitcoin-related news
negative avg score bitcoin	Average score of negative sentiments in Bitcoin-related news
neutral avg score bitcoin	Average score of neutral sentiments in Bitcoin-related news
total news count bitcoin	Total count of Bitcoin-related news
total news score bitcoin	Total score of Bitcoin-related news sentiments
signal bitcoin	Sentiment signal derived from Bitcoin-related news
TWITTER SENTIMENT DAILY AVG	Average daily Twitter sentiment score for Bitcoin
TWITTER PUBLICATION COUNT	Count of Bitcoin-related tweets
TWITTER NEG SENTIMENT COUNT	Count of negative Bitcoin-related tweets
TWITTER POS SENTIMENT COUNT	Count of positive Bitcoin-related tweets
TWITTER SENTIMENT DAILY MAX	Maximum daily Twitter sentiment score for Bitcoin
TWITTER NEUTRAL SENTIMENT CNT	Count of neutral Bitcoin-related tweets
TWITTER SENTIMENT DAILY MIN	Minimum daily Twitter sentiment score for Bitcoin
NEWS SENTIMENT DAILY AVG	Average daily news sentiment score for Bitcoin

positive count coinbase	Number of positive sentiments in Coinbase-related news
negative count coinbase	Number of negative sentiments in Coinbase-related news
neutral count coinbase	Number of neutral sentiments in Coinbase-related news
positive avg score coinbase	Average score of positive sentiments in Coinbase-related news
negative avg score coinbase	Average score of negative sentiments in Coinbase-related news
neutral avg score coinbase	Average score of neutral sentiments in Coinbase-related news
total news count coinbase	Total count of Coinbase-related news
total news score coinbase	Total score of Coinbase-related news sentiments
signal coinbase	Sentiment signal derived from Coinbase-related news
Open	Opening price of Bitcoin for the day
High	Highest price of Bitcoin for the day
Low	Lowest price of Bitcoin for the day
Close	Closing price of Bitcoin for the day
Adj Close	Adjusted closing price of Bitcoin
Volume	Trading volume of Bitcoin for the day
close open	Difference between closing and opening price of Bitcoin of a day
cumulative return	Cumulative return of Bitcoin over the entire period
30D Moving STD	30-day moving standard deviation of Bitcoin price
Parkinson Volatility	Parkinson's volatility measure for Bitcoin
Relative Intraday Price Change	Relative intraday price change of Bitcoin
Middle Band	Middle band of Bollinger Bands for Bitcoin price
Upper Band	Upper band of Bollinger Bands for Bitcoin price
Lower Band	Lower band of Bollinger Bands for Bitcoin price
rsi	Relative Strength Index for Bitcoin
stoch %K	Stochastic oscillator %K value for Bitcoin
stoch %D	Stochastic oscillator %D value for Bitcoin
macd	Moving Average Convergence Divergence value for Bitcoin
macd signal	MACD signal for Bitcoin
ATR	Average True Range for Bitcoin
DGS10	10-year Treasury Constant Maturity Rate
DTB3	3-month Treasury Bill Rate
T5YIE	5-Year Breakeven Inflation Rate

S&P500 Close	Closing value of the S&P 500 index
VIX Close	Closing value of the VIX volatility index
S&P500 Return	Return of the S&P 500 index
DGS10 lag1	Lagged value of the 10-year Treasury Rate (1-day lag)
DGS10 lag2	Lagged value of the 10-year Treasury Rate (2-day lag)
DTB3 lag1	Lagged value of the 3-month Treasury Bill Rate (1-day lag)
DTB3 lag2	Lagged value of the 3-month Treasury Bill Rate (2-day lag)
T5YIE lag1	Lagged value of the 5-Year Breakeven Inflation Rate (1-day lag)
T5YIE lag2	Lagged value of the 5-Year Breakeven Inflation Rate (2-day lag)
S&P500 Close lag1	Lagged value of the S&P 500 index closing value (1-day lag)
S&P500 Close lag2	Lagged value of the S&P 500 index closing value (2-day lag)
VIX Close lag1	Lagged value of the VIX volatility index closing value (1-day lag)
VIX Close lag2	Lagged value of the VIX volatility index closing value (2-day lag)
S&P Return lag1	Lagged value of the S&P 500 index return (1-day lag)
S&P Return lag2	Lagged value of the S&P 500 index return (2-day lag)
gg trend	Google Trends sentiment signal for Bitcoin
Daily Return	Daily Return of Bitcoin

2. Performance of the best Random Forest model in the testing period is shown in the graph below. The orange line is the predicted 15DAR, the blue line is the actual 15DAR (Left axis). The red line is the daily reported closing price of bitcoin (Right axis). The relationship between bitcoin prices and daily return is seen below.The predicted 15DAR is also shown to closely resemble the actual 15DAR.


Fine Tuned Random Forest Model
Close
Actual_15DAR
Predicted_15DAR
BTC Returns (percentage change)
BTC Close Price (USD)
0.020
0.015
0.010
0.005
0.000
-0.005
-0.010
70000
60000
50000
40000
30000
20000
2023-02-20
2023-03-07
2023-03-22
2023-04-06
2023-04-21
2023-05-06
2023-05-21
2023-06-05
2023-06-20
2023-07-05
2023-07-20
2023-08-04
2023-08-19
2023-09-03
2023-09-18
2023-10-03
2023-10-18
2023-11-02
2023-11-17
2023-12-02
2023-12-17
2024-01-01
2024-01-16
2024-01-31
2024-02-15
2024-03-01
2024-03-16
2024-03-31