Bitcoin sentiment analysis

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1 Introduction

This project asks a simple question: can the mood of the market help us make better decisions when trading cryptocurrencies? We adapted a research paper called Ghost in the Machine Bybee [1], which showed that in traditional markets, sentiment often builds up before a crash. That made us wonder if we could take similar ideas and apply them to crypto, which is even more emotional and unpredictable. The goal was to see if tracking sentiment could help us understand how prices are going to move. Often, crypto naysayers say that cryptocurrency prices rely on nothing but speculation. Therefore, trying to understand the market's "irrational" response to news can help shed light on this debate. Even though it doesn't resolve the core question of the intrinsic value of bitcoin, it can show if investors in cryptocurrency are more or less emotional than investors in "classic" assets.

We started by collecting sentiment data from places like news headlines. The idea was to measure whether the overall tone on a given day was positive, negative, or somewhere in between. For this, we used the methodology presented in the paper, which we adapted to work with Mistral AI (the Large Language Model (LLM) developed by french startup Mistral), which is cheaper and easier to scale than

GPT 3.5 (the LLM used in the paper). Feeding the headlines to the LLM helped us develop a time series of a sentiment "score" going from -1 to 1, which we can then compare to bictoin returns using a logistic regression. Then, we improve the results from this regression by using the ex-ante residuals (EAR, more information later) of the scores instead. We found that the EAR slightly improves the results from the logistic regression, although both methods beat randomness.

After that, we apply an impulse reaction function (IRF, to be defined later) to create a trading signal on Bitcoin, and compare the results with a simple long bitcoin portfolio. We find that this trading strategy gives much better results in theory. We reiterate once again that the combination or the EAR and the IRF comes entirely from the paper we decided to adapt, although it doesn't use the logistic regressions like we did.

2 Background

2.1 What is sentiment ? Why is it important in cryptocurrencies compared to traditional assets ?

In finance, market sentiment (or investor sentiment) refers to the general attitude or mood of investors towards a market or asset. It reflects crowd psychology and often manifests itself in trading behavior: optimism (bullish sentiment) can trigger frenzied buying, while fear (bearish sentiment) leads to massive selling. It is essential to note that sentiment is distinct from fundamentals: it refers to emotions and perceptions rather than intrinsic value. In equity markets, sentiment can drive prices well above or below what fundamental valuation suggests.

Bitcoin and other cryptocurrencies do not have any financial reports, cash flows or earnings needed for traditional fundamental analysis, unlike equities or bonds. Their value is largely speculative, so the emotional state of the market plays a disproportionate role. Thus, news, tweets and online discussions can move crypto prices quickly and strongly. Elon Musk's tweets, for example, have caused Bitcoin or Dogecoin to soar, illustrating how media hype or fear on social media translates into market volatility. The characteristics of the crypto market amplify these effects: it trades 24/7 and it's heavily dominated by retail investors on a global scale. This investor base, generally less experienced and more versatile than traditional investors, allows positive or negative opinions to spread like contagion in these still immature markets. The result is rapid herding behavior, with investors buying collectively in euphoria or selling in panic, thereby accentuating volatility.

Several key distinctions make sentiment dynamics unique in crypto compared to equities or other traditional assets. Firstly, traditional equities rely on fundamentals (earnings, dividends) that anchor long-term value, whereas Bitcoin's value is essentially shaped by a narrative. Crypto prices can therefore fluctuate much more wildly on sentiment alone. Equity markets certainly go through speculative phases, but extreme sentiment is partly tempered by fundamental outlook. In crypto, a meme or a rumor can spark a buying frenzy without concrete support. This is why indicators such as the Crypto Fear & Greed Index (inspired by CNN's index for stocks) are closely scrutinized: they aggregate volatility, volumes and social network sentiment to offer a unique barometer of market mood.

Secondly, unlike stock exchanges, crypto markets operate without interruption on a global scale. There's no "weekend break" to digest news, so sentiment can build continuously. A viral tweet at 3 a.m. can trigger immediate reactions all over the world. The decentralized nature of the system means that information and sentiment spread via social networks (Twitter/X, Reddit, Telegram) rather than through official channels. This democratization of the information flow makes investor sentiment both highly reactive and widely distributed, unlike conventional markets where institutional investors can moderate sudden movements.

Finally, crypto assets are often associated with online subcultures (Bitcoin on Twitter, Dogecoin on Reddit, etc.). The tone of these communities directly influences market behavior. Individual traders frequently rally to a collective sentiment, a less common phenomenon for "blue chip" stocks. Jargon and memes embody sentiment-driven investment philosophies specific to crypto. These emotional drivers are less present in traditional assets (excluding recent episodes of "meme stocks").

In short, sentiment is a key driver for Bitcoin, as its valuation relies on investor narrative and momentum. While sentiment also affects stocks and bonds, these markets have established mechanisms and fundamentals that cushion the impact. Crypto-currencies, on the other hand, move largely on sentiment-driven momentum, hence the importance of analyzing social media sentiment to understand and predict Bitcoin's price movements.

2.2 Sentiment analysis and LLMs

2.2.1 What are LLMs ? How are they useful for sentiment analysis ?

Large Language Models (LLMs) are advanced neural networks with an extremely high number of parameters (often billions) trained on huge text corpora. Modern LLMs learn the statistical patterns of language, enabling them to generate and understand text with remarkable ease. Notable examples include OpenAI's GPT series, Google's PaLM and Meta's LLaMA. These models show impressive performance on a wide range of natural language processing tasks (from translation to question answering) without task-specific training, relying on the knowledge encoded during pre-training. In concrete terms, an LLM can be given a prompt, and will then produce a human-quality text or classify the sentiment of a passage thanks to its general understanding of language.

LLMs' ability to capture context makes them powerful tools for sentiment analysis. Previous approaches often struggled with nuances such as sarcasm, idioms or domain-specific jargon. Trained on a variety of internet texts (forums, news, social media), LLMs are better equipped to interpret these subtleties. In general, LLM-based sentiment analysis does not rely on manual lists of positive/negative words but rather relies on a learned representation of language. LLMs can thus detect feelings present in complex sentences, frequent in crypto discussions. Their extensive training also gives them a vast store of contextual knowledge. These capabilities make LLMs especially suited to analyzing social media posts about Bitcoin, which often include informal language, emojis, and evolving jargon.

LLMs also offer practical advantages: being generalists, the same model can be applied to various sentiment tasks with a minimum of adaptation. For example, an LLM can be asked: "classify the sentiment of this tweet" and get a relevant answer without training a new model for weeks on an annotated dataset. In finance, specialized LLMs have even been created to increase accuracy: FinBERT, a BERT-like model refined (fine-tuned) on financial texts, is one of the best known.

In short, LLMs have become indispensable for sentiment analysis: they combine width (pre-training on huge data sets covering multiple sentiment expressions) and depth (neural architectures capable of capturing subtle linguistic patterns). They excel at understanding context, sarcasm and fine emotions, omnipresent in the sentiment conveyed on social networks about cryptocurrencies. Moreover, they can process huge volumes of data - analyzing thousands of tweets or forum comments to tease out the general trend in sentiment - making them particularly useful for tracking the mood around Bitcoin on Twitter, Reddit, etc., with a level of nuance that previous approaches couldn't achieve.

2.2.2 Limits of LLMs

While LLMs represent state-of-the-art technology, it's important to critically assess their limitations, especially in a sensitive application like financial sentiment analysis:

Firstly, unlike lexicons or logistic regression models, which offer a degree of interpretability (we can see which words are counted as positive or negative), LLMs are black boxes. When a model labels a tweet as positive or negative, it's difficult to extract a human-understandable rationale. This can be problematic in an academic or professional setting, where the analyst needs to explain why a sentiment is reported in a certain way.

Another disadvantage is that LLM responses can vary according to the wording of the task. Slight changes in wording can produce different results, undermining the consistency of an automated analysis. Reliable sentiment analysis in production therefore requires carefully designed prompts or fine-tuning, failing which the model can sometimes deviate (giving a long explanation and then, the next time, a single word, or misinterpreting a request). Imposing uniform criteria for sentiment (e.g. always returning "Positive/Neutral/Negative") requires particular care in prompt design or model tuning.

LLMs are also resource-hungry. Running GPT-4 on thousands of messages can be slow and costly compared to a lighter algorithm. In real-time trading scenarios, the latency of a large model can be too high: microsecond decisions can't wait for a model with several billion parameters to process the text.

Access to the latest LLMs also involves API costs or infrastructure that may be out of reach. At large scale (continuous analysis of every tweet on Bitcoin), the use of an LLM can therefore be expensive.

In conclusion, LLMs are powerful but not infallible tools. They need to be handled with care: watch out for biases, test for contextual pitfalls (such as sarcasm) and anticipate their resource requirements. Knowing these limitations (e.g. misinterpretation, bias, opacity, inconsistency, cost and knowledge gaps, etc) enables us to better exploit the strengths of LLMs while mitigating their weaknesses for analyzing social network sentiment around Bitcoin. Although we still use them in this project, we need to specify that this is a flawed tool and that our model has clear weaknesses.

3 Generating sentiment score

3.1 Presentation of the database

We collected a dataset from GitHub entitled Crypto News Dataset. It aggregates daily headlines from a variety of crypto news websites. Each headline is labeled with the cryptocurrencies to which it refers. They are also timestamped down to the second the news was posted on the site. We also have the number of likes, dislikes, comments and others, although these are often 0, as well as the link to the article. In this project, we will only be using the raw headlines in order to generate the scores that we need.

Here is a quick view of the pre processed dataset with our function "import_data" in the "prompts" module. This function reads the csv files from the GitHub repository linked above, then it removes unwanted columns and formats the date so that we only have the day at which it was posted. We can see that there can be multiple headlines in one day, or no headlines. This will cause issues that we will explain later on in the project.

The function also writes the prompts that we will later feed to the Large Language Model in order to properly generate the scores, which we will explain in the following section.

3.2 Generating prompts

For each headline, we generate a prompt which asks the AI its beliefs about the evolution of Bitcoin returns based on this headline. The prompt we decided to use is the exact prompt presented in Bybee [1] . The exact prompt reads :

```
Here is a piece of news:
"%s"
Do you think this news will increase or decrease BTC?
Write your answer as:
{increase/decrease/uncertain}:
{confidence (0-1)}:
{magnitude of increase/decrease (0-1)}:
{explanation (less than 25 words)}
```

Where "%s" is replaced by the headline. After editing this prompt, we notice that removing part of this prompt changes the results drastically (from "increase" to "decrease" for the same headline). Therefore, we decided to keep the prompt from the paper as is, even though we will only use the results for "increase" or "decrease" for this project. This prompt has been adapted from traditional retail investor surveys or surveys of CFOs that are used to produce a sentiment indicator. However, these are costly and slow. As presented in the paper, using AI models to replace human answers mimics the same results on a much bigger and faster scale.

More information about the construction on this prompt can be found in Bybee [1] .

Here, we use the Mistral LLM to generate prompt answers. The Mistral AI API is a service that gives us access to powerful language models, similar to ChatGPT or Claude. These models can read and interpret text, making them useful for tasks like summarizing news or detecting the tone of an article. In our project, we use the Mistral API to process financial headlines or crypto-related news and ask the model the prompt presented earlier. The model then gives us a structured answer, including its level of confidence and a short explanation.

Running sentiment scoring at a large scale using the Mistral API isn't just about sending a bunch of text to a model. It quickly becomes a technical challenge. If you're processing thousands (or even millions) of headlines, you need to manage API requests carefully. Language models are slow compared to normal scripts, and APIs often have strict rate limits. If you send too many requests too fast, you'll get throttled or even temporarily blocked. That means you need to build in delays, handle retries, and keep track of how many requests you're sending per second or minute.

To make this efficient, the code has to handle asynchronous execution and concurrency. Instead of sending requests one by one (which would make the code very inefficient and take a long time to generate answers), we wanted to send many in parallel—without breaking the API rules. That means using tools like Python's asyncio, aiohttp, or httpx, and writing logic that can pause, retry failed calls, and wait when needed. WWe however also needed to track which headlines have already been scored to handle failures cleanly. Scaling this up without crashing the system or getting banned by the API meant taking additional security measures in the code.

For a detailed overview of the steps we decided to take, please refer to the notebook "sandbox_ambroise.ipynb" on our github repository (faunebl/crypto-sentiment).

3.3 Scores methodology

After getting the scores from the LLM, we are left with categorical values for each news, while there are multiple news per day. Therefore, we decide to assign 1 if the LLM says the news will increase BTC, -1 if it says it will decrease, and if it is uncertain we will ignore the headline entirely (so as to not create noise). Then, we aggregate every headline for one day, so that we get a clean series with one sentiment score per day. To aggregate, we use the formula presented in the paper:

$$F_t^{\text{gpt}} * (X_{t+h}^k) = \frac{\sum_{i \in \mathcal{A}_t} \mathbb{I}(\text{Increase}_i^k) - \mathbb{I}(\text{Decrease}_i^k)}{\sum_{i \in \mathcal{A}_t} \mathbb{I}(\text{Increase}_i^k) + \sum_{i \in \mathcal{A}_t} \mathbb{I}(\text{Decrease}_i^k)}$$

The EAR, or Ex-Ante Residual, is meant to capture the part of sentiment that can't be predicted based on past patterns. We do this by using a simple model (like anautoregressive model i.e. AR(1)): a linear regression where the explanatory variable is simply the lagged target) to see what today's sentiment should be, based on yesterday's. Whatever's left over (i.e. the part the AR(1) model didn't expect) is the EAR. It's the surprise in the mood of the market. Here is how it is constructed mathematically:

1. We first compute an autoregressive model of sentiment (based on the score presented earlier): $\text{Sentiment}_t = \alpha + \beta \cdot \text{Sentiment}_{t-1} + \varepsilon_t$
2. Then, we compute the residuals for that model: $\text{EAR}_t = \text{Sentiment}_t - (\alpha + \beta \cdot \text{Sentiment}_{t-1})$

This surprise is important because it often reflects emotional or irrational shifts. In crypto especially, people can get overly excited or scared in ways that don't line up with the data. By focusing on these unexpected jumps in sentiment, we're trying to isolate the moments when crowd psychology might be taking over—when prices could be getting ahead of reality.

4 Comparison with BTC returns

4.1 Introduction

To extract the returns, we use the yahoo finance Yahoo Finance [2] API. The details for this can be found in the get_btc_returns function of the utils.py module in our github repository.

We use this introduction to give a little bit of background about the logistic regression. It functions as a normal linear regression, except that it applied a sigmoid function to the results in order to predict a binary outcome. Here the binary outcome is :

1. $\text{Return}_t > 0$
2. $\text{Return}_t < 0$

Which works because it is almost impossible that the logarithmic returns are exactly zero. In this context, we will only have one predictor variable (i.e. X is one-dimensional), which will alternatively be the raw scores and then the EAR. Therefore, the formula for the logistic regression is :

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}}$$

Which means that the probability that Y is 1 given the current value of X is the sigmoid (i.e., a function that yields a discrete number from a continuous value) of the result of simple linear regression. Here β_0 and β_1 are computed with the usual linear regression formula (that we don't recall here for readability purposes).

We interpret the results of a logistic regression thanks to a confusion matrix, accuracy, precision and recall.

A ***confusion matrix*** helps you understand how well your model is doing at making predictions by showing four outcomes: true positives (correctly predicted positives), true negatives (correctly predicted negatives), false positives (incorrectly predicted positives), and false negatives (positives that weren't detexted). ***Accuracy*** tells you the overall percentage of correct predictions. ***Precision*** tells you, out of all the times the model predicted "yes," how many were actually correct (useful when false alarms are costly). ***Recall*** tells you, out of all the actual "yes" cases, how many the model correctly caught (important when missing positives is risky).

4.2 Comparing with scores

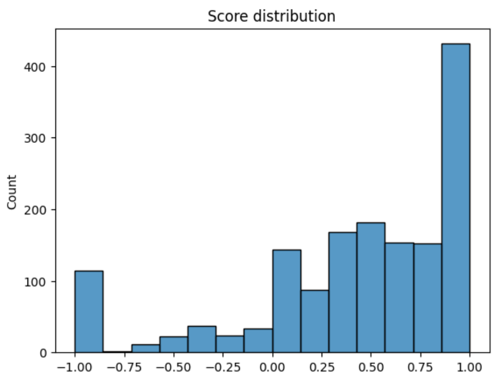
4.2.1 Results

We first show what the scores look like in time.

Figure 1: Scores vs time

We can see that, once we have a bit more data about BTC headlines, the scores start being different from just 1 or -1. Indeed, if we have only one or two headlines, it is sufficient that only one is positive to get a score of 1. This is why the model might be biased during training, although we have no way or overcoming this with the current dataset.

We also look at the distribution of the scores:



We can see a strong skew towards 1. This is particularly problematic when we compare the distribution of the returns of BTC:

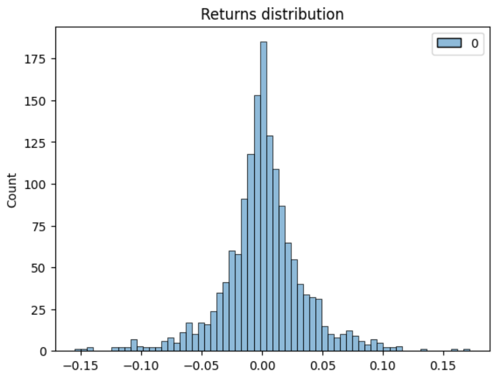


Figure 2: BTC returns distribution

We have to look at the tails of this distribution because we will binarize this and regress on if returns are positive or negative. We can plot the tails:

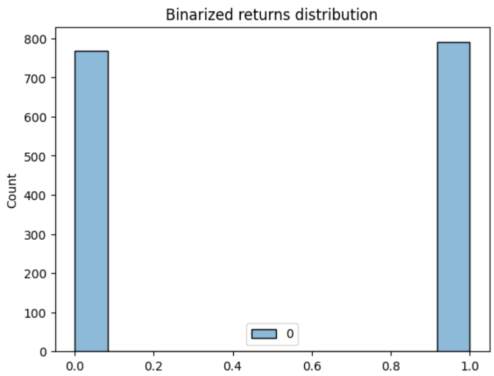


Figure 3: Binary distribution

Here, we can see that both classes are equal. This is partly why we decided to use a logistic regression instead of a simple binarizer model (which would've been, if scores > 0 then we say that returns > 0). We would have introduced a bias because of this difference in class distribution.

We then present the scores for the results:

Dataset	**Accuracy**	**Precision**	**Recall**	**F1 Score**
In Sample	0.5269	0.5270	0.5269	0.5255
Out of Sample	0.5318	0.5318	0.5318	0.4984

Table 1: Model performance metrics in and out of sample

And the confusion matrix :

4.2.2 Interpretation

These results show that the model is performing at a fairly basic level, with accuracy, precision, and recall all hovering around 53% both in-sample and out-of-sample. This means the model is just slightly better than flipping a coin when it comes to predicting the correct class. The fact that the in-sample and out-of-sample metrics are so close is actually a good sign in terms of consistency. This suggests the model isn't overfitting to the training data and generalizes in a similar way to new, unseen data.

However, the relatively low F1 score, especially out of sample (about 0.498), indicates that the balance between precision and recall is not ideal. In practical terms, this means the model is either missing some

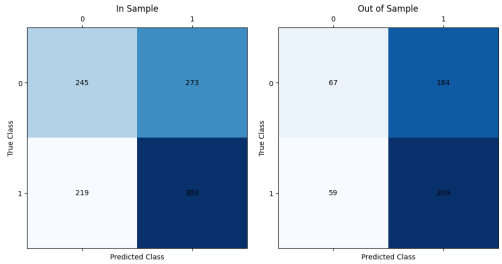


Figure 4: Scores confusion matrix

positive cases or generating more false alarms than we'd like. While it's encouraging that the model isn't falling apart on new data, these metrics also tell us there's a lot of room for improvement. We might need better features, more data, or a different model altogether to get meaningful predictive power.

The desired results for the confusion matrix would be darker diagonals, but since the classes are unbalanced it is harder to actually interpret than the scores.

4.3 Comparing with the EAR

4.3.1 Results

We once again plot the EAR compared to time:

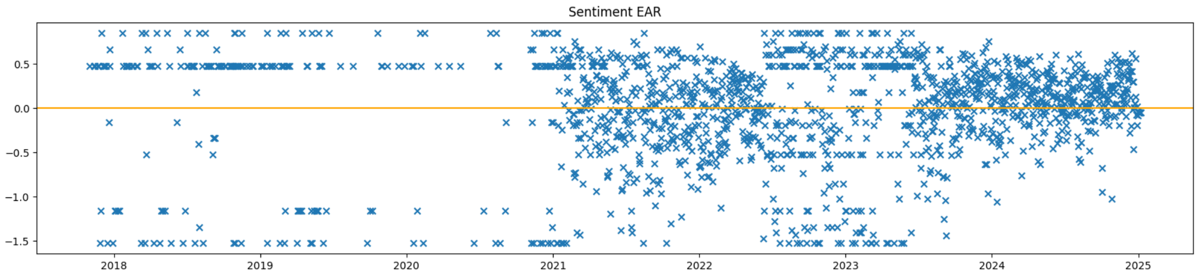
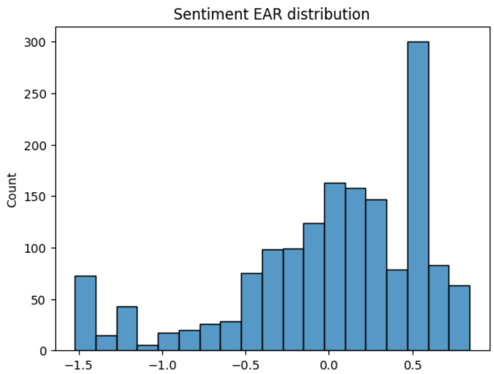


Figure 5: EAR vs Time

We notice the same pattern as per the score (less equally distributed when we have less data), only a little bit reduced. This will likely improve the results of our regression. However, we see more of a bias towards the negative which might skew our results. This might mean that the sentiment is more negative than expected. It is interesting to see that the effect is not as drastic on the positive side, implying that the AR(1) model has heteroskedasticity in the errors which are more often negative than positive. This can reflect irrational fear or panic. We will later be able to see in the trading strategy if we perform better during moments of panic or during moments of overconfidence. Given this pattern, we expect the strategy to perform better during panics, as they are more easily picked up by the model.

We plot the distribution of the EAR:



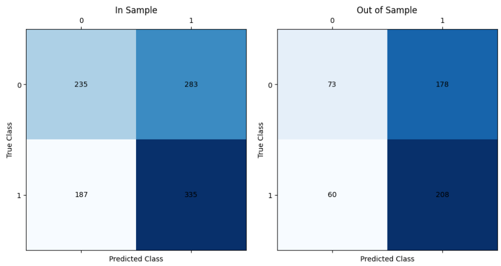
We see that although there are more moments when the EAR is positive, the negative values are more drastic than the positive values. This might indicate that the logistic regression will be only slightly better than with the scores, given the unbalanced classes, but that the trading strategy will perform well during panics.

We look at the scores

Dataset	Accuracy	Precision	Recall	F1 Score
In Sample	0.5481	0.5494	0.5481	0.5440
Out of Sample	0.5414	0.5437	0.5414	0.5123

Table 2: Model performance metrics in and out of sample

Adn the confusion matrix



4.3.2 Interpretation

We can see that the results are only slightly improved (~+2% of accuracy), but that we still have a problem with unbalanced classes.

These updated scores show a modest improvement in the model's overall performance. This suggests the model is doing a slightly better job of distinguishing between the two classes and is making more reliable predictions overall. The F1 score, which balances precision and recall, also increased (especially in-sample) indicating that the model is better at handling trade-offs between false positives and false negatives.

However, while this is a step in the right direction, the gains are still relatively small. Accuracy is still just around 54%, which means the model remains only marginally better than chance. The F1 score out of sample, while improved, is still lower than the other metrics, suggesting some imbalance or inconsistency when the model encounters new data. So, while the improvements are meaningful and suggest progress, there's still significant room for refinement if we want the model to be practically useful in a high-stakes or noisy environment like financial prediction. However, we will stick to following the methodology of the paper for this project.

4.4 Trading strategy

4.4.1 Signal with the IRF

The ***Impulse Response Function***(IRF) is a way to measure how one variable reacts over time to a sudden change in another variable. In the context of the paper, the IRF helps us understand how asset returns respond to unexpected changes in economic sentiment. So, if there's a surprise jump or drop in sentiment today, the IRF tells us what typically happens to returns in the days that follow. This is powerful because it gives us a time-based profile of the market's behavioral reaction to mood swings.

In trading, this is useful because if we know that sentiment shocks tend to cause returns to go up (or down) over the next few days or weeks, we can position accordingly: buy if returns are expected to rise, or avoid/short if they're likely to fall. The IRF, then, becomes a kind of "map" for what to expect after a mood shift, and the trading signal is built directly from that.

In the paper, the IRF is estimated using a method called local projections. For each time horizon , h the author regresses future returns on today's sentiment shock and current return as a control. The general formula looks like this:

$$\sum_{j=1}^{h} r_{t+j} = \alpha + \beta \cdot \text{EAR}_t + \gamma \cdot r_t + \varepsilon_t$$

Here, the cumulative sum of the returns is equal to the sentiment shock times how much the future returns move in response to that shock.

Once the IRF is estimated across multiple horizons, the paper builds a trading signal by multiplying today's sentiment shock by the sum of those IRF coefficients:

$$\text{PredictedReturn}_t = \text{EAR}_t \times \sum_{h=1}^{H} \beta_h$$

If this predicted return is positive, it suggests a favorable outlook, and the strategy goes long. If it's negative, the model expects a drop, and the strategy goes short or stays out. This signal is grounded in observed market behavior rather than guesswork, which is what makes the IRF such a compelling tool for strategy design.

4.4.2 Results

Here are the results for this strategy compared to a simple long bitcoin portfolio :

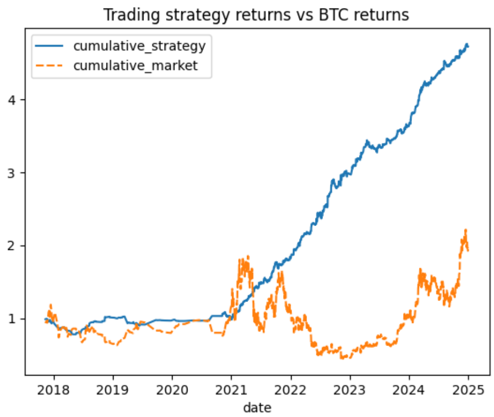


Figure 6: Strategy vs BTC

The results here are interesting: we can see that the model only slightly captures the rise during 2020 : this might be because of two factors:

1. There is less data available
2. BTC returns were less based on news about bitcoin itself and more on the current market environment (covid meant more retail investor participation who had a bias for bitcoin)

Given the small variance in our strategy but undereation to 2020, we suggest that it is a mix of both.

However, all of these results are **in-sample.**

We then look at the results with an out of sample part (30% of the dataset):

4.4.3 Interpretation

The first plot shows how the strategy performs across the full dataset, including both training and test periods. It looks very strong, consistently outperforming the market (BTC) with much less volatility. However, since this includes the data the model was trained on, the results may be overly optimistic and reflect some degree of overfitting to past patterns.

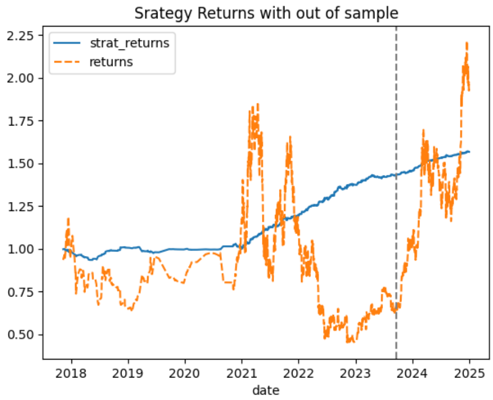


Figure 7: Out of sample returns

The second plot gives a more realistic view by separating out the out-of-sample period with a vertical line. Here, the strategy continues to perform steadily but misses the sharp gains in BTC seen after 2023. This suggests the strategy is more conservative and stable but may underperform in strong bull markets. It's still useful for limiting downside risk, but less effective for capturing big upside moves. However, we saw during the trading period and during the EAR distribution analysis that it generally performs better during panic / crashes (where irrational sentiment might play a bigger role in returns) than in bull markets. Therefore, we would need more data to really conclude on the usefulness of the strategy.

It is important to note that this might however not be possible in practice given the availability of the data in real time, the granularity of the data, transaction costs and other factors.

5 Conclusion

In this project, we explored whether sentiment, specifically expectations generated by a large language model, can help predict Bitcoin returns and guide a trading strategy. We used the Mistral API to extract directional views from crypto-related news headlines and turned those into a belief-based sentiment score. From there, we built what's called an ex-ante residual (EAR), which basically measures how surprising or unusual the sentiment is compared to its recent trend. The idea was that markets don't just move on news, they move on unexpected news.

We used these EAR values to estimate how Bitcoin tends to react to sentiment shocks over time, using impulse response functions (IRFs). These IRFs gave us a way to forecast short-term return patterns and build a trading signal. In backtests, the strategy performed consistently across both in-sample and out-of-sample periods. It didn't outperform Bitcoin during big bull runs, but it did offer more stability and avoided sharp downturns when sentiment turned negative. That makes it potentially useful in a volatile market like crypto.

We also tried a simple classification model to see if sentiment could help predict crashes. The results were modest, only slightly better than random, but they were stable across different samples, which is still a positive sign. More importantly, both the IRF-based strategy and the classifier showed that LLM-generated sentiment isn't just noise. It reflects how the market feels, and when that mood shifts unexpectedly, it often shows up in prices.

What we've built here is a simple but thoughtful approach to trading on market psychology. There's still a lot of room for improvement, whether that means using better data, more advanced models, or expanding to other assets. But the foundation is solid: by listening to how people talk about the market, we can start to get a sense of where it might go next.

5.1 Bibliography

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[2] Yahoo Finance. *Yahoo Finance - Stock Market Live, Quotes, Business and Finance News*. Accessed: 2024-05-01. 2024. URL: https://finance.yahoo.com.