AIS – a Metric for assessing the Impact of an Influencer's Twitter Activity on the Price of a Cryptocurrency

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Abstract. Individual users on social media platforms like Twitter can significantly influence highly volatile assets, including cryptocurrencies. However, current research has overlooked this aspect, focusing on sentiment analysis that includes all posts from all users. Making it challenging to detect trends caused by individuals. To address this gap, we introduce the Asset Influence Score (AIS), a percentage-based metric that assesses the likelihood of a newly issued tweet aligning with periods of heightened trading activity. By analyzing price data and tweets concurrently, we identify correlations that enable to predict the likelihood of specific users' tweets co-occurring with increased trading activity. Evaluating the AIS using a publicly available prototype and Twitter data from 2020 to 2023, we find that using the AIS as a buy signal outperforms buy-and-hold and technical trading strategies while maintaining high liquidity. Demonstrating the applicability of AIS in improving trading decisions and identifying key individuals on social media platforms.

Keywords: Twitter · Cryptocurrency · Prediction · Social Media Analysis · Trading Indicator

1 Introduction

Cryptocurrencies have ushered in a new era of financial assets. The novelty and opportunity of this asset class do not come without their fair share of price volatility. [13] Assets like the cryptocurrency "Dogecoin" saw its price rise by over 15000% during early 2021, despite it being abandoned by its founders and being created as a joke. This can mostly be attributed to Elon Musk, who made his fondness of the asset public on his personal Twitter account. Now that Musk mostly stopped tweeting about Dogecoin, the asset has lost roughly 90% of its value at the time of writing compared to its peak. [2] [1]

The psychological phenomenon of investors following others rather than conducting their independent research is described as herd investing [17] [6]. Herd behavior can lead to extremely overvalued assets and in turn panic selling, akin to a bubble forming and bursting, resulting in huge losses for investors that made risky investment decisions due to herd mentality [6]. This effect is further amplified when spearheaded by a publicly well-known entity like Elon Musk, combined with cryptocurrency like Dogecoin which's objective fair value is difficult to determine. [11]

Existing crypto-focused trading approaches are unable to identify, quantify and exploit this phenomena. Most work focuses on technical factors [7] [16], tweet volume and Google search trends [3] [12] or broader social media analysis, neglecting individual users behavior [8] [19]. In turn the approaches that incorporate specific user behaviour are overly focused on single handpicked users, such as Elon Musk [15] or Donald Trump [9] [14], lacking the general applicability to identify herd behaviour and key individuals in today's dynamic social networks.

When looking at existing work, a gap in identifying and transparently quantifying the influence of opinion leaders (fittingly described as "tastemakers" by [10]) becomes apparent. Doing so can serve as a tool for investor protection, providing insight as to who might be able to induce herd behavior in investors. Knowing who can cause market moves can also be used to create a trading advantage by making price moves caused by social influencers less unexpected.

To achieve this, we propose the Asset Influence Score (AIS), a metric that approximates the certainty (in percent) of a user's newly issued tweet coinciding with a period of abnormal (elevated trading activity - see following paragraph) price action. We combine the most relevant tweets about a cryptocurrency for each hour with the price data in OHCLV-candles (Open, High, Close, Low, Volume) for the respective hour over a long timeframe (in our case roughly 3 years) to identify users which's tweets tend to appear in a period of abnormal price action, indicating possible causation for such price moves.

To quantify price moves we propose a metric we call *Velocity* (V), which represents each candlestick's range (High to Low) amplified by the trading volume. To identify a period of abnormal price action we employ a sliding window approach [5] that computes the average V over a given timeframe. For each following candle we can compare its V to that of the sliding window average. To normalize and quantify the relation of the current candle's V to the window average, we propose the term *Magnitude* (M), which represents the factor with which the candle compares to the window average. E.g., if a candle's V is twice that of the current window, its M is 2. If a candle's M exceeds a certain threshold (we propose the term *Breakout Threshold Factor – BTF* ($\in \mathbb{Q}_{>1}$)), this candle is deemed as abnormal, indicating relevance to our model. To repeat, the AIS approximates the certainty of which a user's tweet will coincide with a candle whose magnitude exceeds the BTF (= abnormal candles).

To perform the necessary calculations, we have created a fully open-source Java-based client application[1] that performs the necessary data fetching and preparation as well as the AIS calculation for easy replicability. The user can specify parameters like the cryptocurrency, timeframe, *sliding window size* (WS) as well as the BTF, making this application universally applicable to all assets and configurations.

[1] `https://git01lab.cs.univie.ac.at/university_research/masterarbeiten/ais`

The AIS will be evaluated by applying it to Dogecoin, a cryptocurrency which's price action has been notoriously tied to the tweets of Elon Musk. We will also evaluate the AIS on Bitcoin, which is the most established cryptocurrency to date. We will use the AIS as a trading indicator, entering positions based on tweets by users with a high AIS. We compare our results to both a buy-and-hold investor, as well as a strategy based on a technical analysis and show that the AIS, a model that can be run on commodity off-the-shelf hardware, is capable of generating above-market returns by minimizing losses attributable to the constant market exposure of the buy-and-hold investor.

This paper is organized as follows: Prerequisites and the proposed approach are introduced in Section 2. Details on the exact process of the AIS calculation are given in Section 2 and 3. The evaluation and comparison of the AIS-based trading algorithm with the buy-and-hold as well as the technical trading algorithm is covered in Section 4. In Section 5 we highlight comparable approaches and related work. Finally, results are discussed and concluded in Section 6, where future work is also outlined.

2 Prerequisites and General Approach

The AIS is calculated using a combination of price and Twitter data. We start by fetching hourly price data and the most popular tweets for each hour for the user-specified timeframe. For fetching price data, we use Cryptocompare[2], a free API that returns price data in OHLCV form. To quantify price moves, we propose the term *Velocity (V)*. $V \in \mathbb{Q}^+$ and captures the size of the price move (high point vs. low point) combined with the base 10 logarithm of the trading volume in US-dollars. The exact definition of the fields used in this formula can be found in subsection 2.2.

$$V_P = (P_h - P_l) \times \log_{10} P_v$$

We use a logarithmic approach for trading volume because it allows us incorporate it without outweighing price moves if significant trading volume occurs. Without the logarithm, a significant general increase in volume starts to dilute the weight of price moves. V plays an integral role in the AIS calculation process, as it represents how the market reacts to tweets in our AIS model. Our approach combines the $Velocity$ with historic data from Twitter to identify possible correlations between twitter behavior and price activity.

For fetching tweets we use the Twitter API v2[3]. We have been granted academic access to the API, which allows us to fetch tweets from the past. We then extract relevant information like user details, text, the timestamp and the tweet's engagement metrics into dataframes. Dataframes are a data structure we propose that contains an hour of price action and the tweets that were issued within the respective hour, intended to represent an hour of market activity.

[2] `https://min-api.cryptocompare.com/`

[3] `https://developer.twitter.com/en/docs/twitter-api`

Figure 1 shows an overview of the AIS calculation process. In step ① the user specifies values like the name and ticker-symbol of the asset that should be analyzed, the timeframe over which the AIS should be calculated as well as parameters like the BTF, WS *(Window Size)* and the PCC to Bitcoin. These values and their effect on the AIS will be explained in greater detail in chapter 3 and 4 respectively, but in essence, these values specify the sensitivity of the AIS to price changes.

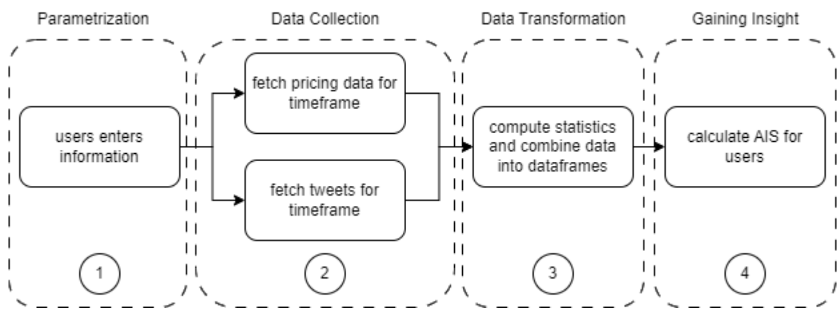

Fig. 1: An overview of the AIS calculation process

In step ② the client application fetches tweets and pricing data from the aformentioned API's. In step ③ the data is transformed into dataframes. Finally in step ④ we use the dataframes to calculate the AIS for each twitter user, which will be covered in chapter 3. We will now go over the data and the dataframe creation from steps ② and ③ in more detail.

2.1 Tweets

Definition 1 (Tweets). *Let $T_i := \langle t_1, \cdots, t_n \rangle$, T_i being a finite bag of n* `tweets` *and $i \in \mathbb{N}$, representing the starting millisecond of a trading hour as a UNIX-timestamp.*

Let further $t_n := \{t_c, t_u, t_t, t_l, t_r\}$. $t_c \in String$ represents the `content` *of the tweet; $t_u \in String$ represents the* `username` *of the user who issued the tweet; $t_t \in \mathbb{N}$ represents the exact UNIX-timestamp when t was issued; $t_l \in \mathbb{N}$ and $t_r \in \mathbb{N}$ represent the* `likes` *and* `retweets` *of t respectively.*

Tweets were searched for both the ticker-symbol and the full name of the cryptocurrency. For Dogecoin, the query would be "Dogecoin or DOGE", which also covers the hashtags "#Dogecoin" and "#DOGE". In addition to the tweet's content we gather information about the issuing user, the exact time the tweet was issued as well as the social metrics of the tweet (likes and retweets). Only tweets written in English were considered.

Our approach uses these social metrics to calculate the ES (*Engagement Share* - essentially the percentage of likes and retweets a tweet garners within its time segment - covered in the subsequent chapter), which is what we use to weigh the impact of a tweet and attribute it to the $Velocity$ of the price.

We fetch the first page (containing between 80 - 120 tweets) of the API response for every hour, sorted by Twitter's built-in relevancy algorithm. The AIS is based around the hypothesis that tastemakers generate high engagement on Twitter, therefore limiting the tweet data to roughly 120 tweets per hour does not pose an issue in terms of thoroughness and prediction accuracy for the most influential users.

By utilizing this approach, it is impossible to overlook significant tweets that could likely identify tastemakers, while ensuring adequate performance and reasonable size of the underlying data set by omitting users and tweets that don't generate any significant engagement. We experimented with fetching multiple pages (up to 1000 tweets per hour), but found that there was no impact on the top 100 users ranked by AIS. It only increased the memory requirement and data fetching time, thus degrading performance significantly.

We leverage Twitter's built in sorting algorithm, as the API sorts the tweets based on social metrics, the user's follower count and overall impressions in descending order (most engaged tweet comes first), which is exactly the approach we would employ when sorting tweets.

2.2 Price Data

Definition 2 (Price Data). *Let P_i be a set of* `fields` $p_i := \{p_o, p_h, p_l, p_c, p_v\} \in \mathbb{Q}$ *and* $i \in \mathbb{N}$, *representing the starting millisecond of the trading hour as a UNIX-timestamp.* P_i *represents one hour of price activity.*

p_o *represents the* `open price`*,* p_h *represents the* `high price`*;* p_l *represents the* `low price`*,* p_c *represents the* `close price` *and* p_v *represents the* `trading volume` *of* p_i *respectively.*

In addition to tweets, we also fetch the price data in hourly OHLCV-form (Open, High, Low, Close, Volume) for the specified timeframe, both for the user-specified cryptocurrency as well as Bitcoin. The data is utilized to calculate V as well as subsequent price metrics, which will be explained in great detail in the following chapter (chapter 3). It is an integral part of the AIS, as we use it to derive how the market values and interprets Twitter activity, thus allowing for the calculation of the AIS. The price data is fetched from Binance[4], as it is the largest and most popular exchange by trading volume.

We fetch Bitcoin's corresponding price action because most crypto assets are significantly correlated to Bitcoin, as shown in [22]. As the correlation of cryptocurrency assets changes with time, we fetch the most up to date correlation coefficient from Cryptowatch[5], a free service that provides this information. By taking that into account, we can more accurately determine whether only a specific asset experienced volatility or whether the market experienced a general

[4] `https://www.binance.com/en`
[5] `https://cryptowat.ch/correlations`

price move. The *Asset Influence Scores* can also be computed for Bitcoin. In this case, the outlined price normalization approach is skipped.

2.3 Dataframes

Definition 3 (Dataframe). *Let D_i be a Dataframe. $i \in \mathbb{N}$ represents the starting UNIX-timestamp of exactly 1 hour of market activity; D_i consists of the fields P_i (2), T_i (1) and S_i, therefore $D_i = \{P_i, T_i, S_i\}$.*

Let further $S_i = \{WS, \mu V\}$. Hereby, $WS \in \mathbb{N}$ represents the `size of the sliding window`*, and $\mu V \in \mathbb{Q}^+$ represents the average $Velocity$ (V) for the past WS P_i.*

Dataframes are the data structure we propose to represent an hour of market activity. In addition to the aforementioned price and Twitter data, a dataframe also contains price action statistics based on $Velocity$ (V), which are computed based on a sliding window. We interpret and derive V's meaning by comparing to other V in its vicinity. By utilizing a sliding window approach we can ensure that we derive outbreaks based on recent trading activity rather than overall historical trading activity.

After Musk first mentioned Dogecoin for example, the asset's baseline trading activity (and thus its hourly V) rose significantly, even without any mentions by Musk. Without a sliding window, every hour after Musk's mention would be identified as an outlier when compared with the time period before Musk's mention, whereas an appropriately sized sliding window allows us to quickly adapt to the new norm and compare V among only more recent price candles. This approach was heavily inspired by [5].

The sliding window is used to compute the mean $Velocity$ μV for the past WS *(Window Size)* amount of price candles.

$$\mu V = \sum_{i=0}^{WS} \frac{V_{P_i}}{WS}$$

If a proceeding candle exceeds μV by the user-specified *Breakout Threshold Factor* (BTF), we deem this candle to be abnormal. To repeat, the AIS approximates the certainty with which a user's tweet occurs such an abnormal time segment. Each dataframe contains μV of the previous WS amount of candles. These dataframes form the necessary basis for the AIS calculation. How they are used and how the AIS is calculated will be discussed now.

3 Gaining Insight

To extract value and knowledge from the dataframes and calculate the *Asset Influence Score*, we must first define the proposed terms used in calculating the AIS. We will follow up by explaining the algorithm in detail and providing a concrete calculation example for the AIS.

3.1 Definitions

We have touched on the importance of *Velocity* (V), as it represents the measurement of the market's price activity for any given hour. As stated, we need a way to relate $Velocities$ to one another. *Magnitude(M)* ($\in \mathbb{Q}^+$) allows us to relate the Vs to each other, as is represents the **factor** by which V changes compared to the average of the sliding window.

$$M_{P_i} = \frac{V_{P_i}}{\mu V}$$

To recall, the *Breakout Threshold Factor (BTF)* defines the $Magnitude$ threshold for a candle to be considered $abnormal$. The AIS then approximates the certainty with which a users tweet will occur within the same timeframe as a candle of which M exceeds the BTF (= *abnormal* candles).

We now have a way of discerning between standard and abnormal price movements, but we can not yet attribute these movements to any particular user. In our model, we assume that price moves can be directly related to Twitter users activities. To differentiate between users, we propose a metric called the *Engagement Share (ES)* ($\in \mathbb{Q}$). The ES is the percentage of the sum of all engagement gathered by tweets about an asset within a specific hour. We define *Engagement (E)* ($\in \mathbb{N}$) as:

$$E_t = t_l + 2t_r$$

Or in other words: *Likes* $+ 2 \times$ *Retweets*. Retweets are multiplied by two because retweeting something shows up on the retweeting user's timeline as well, generating even more reach and indicating more "commitment" to the content, if a user is willing to have it displayed on their own timeline.

We can now attribute a percentage of each hourly segment's *Engagement* E_{T_i} to each tweet. The *user*'s ES is simply the $\sum ES$ of their tweets (where $t_u = user_u$) within that hourly segment. The portion of the price move attributed to a user is proportional to their ES.

$$ES_t = \frac{E_t}{\sum E_{T_i}}$$

We now have almost all necessary building blocks to move on the defining and calculating the AIS. We can compute each time segment's *Magnitude (M)*, as well as corresponding engagement metrics. Before moving on to calculating the AIS for a specific user, there is one important factor that must be incorporated - the crypto market's high correlation to Bitcoin. We cannot properly judge the price action of a cryptocurrency without looking at Bitcoin's price performance during the same period, as the top cryptocurrencies have an average Pearson Correlation Coefficient to BTC of over 0.77[6] (at the time of writing). To incorporate this aspect we propose a separate metric which expands on M - the *Magnitude attributable to External Factors (MEF)* ($\in \mathbb{Q}$). The MEF reduces a

[6] `https://cryptowat.ch/correlations`

time segment's M by Bitcoin's M from that segment (weighted by correlation), resulting in a metric for weighing moves unrelated to Bitcoin's price action. We define the MEF as:

$$MEF_{P_i} = M_{P_i} - (M_{bitcoin_i} \times PCC)$$

We have now defined all general metrics for extracting insight from the dataframes. We use these metrics for creating *TweetMaps*, a custom structure we propose and employ for calculating the AIS for a user.

3.2 Structuring Information

During the mapping process, we iterate over each dataframe D_i (one hour at a time). We look at T_i within D_i and either create (if it's the user's first tweet) or add to an existing *TweetMap*. A TweetMap contains the Twitter user and a list of their respective tweets, that were issued during the entire timeframe which matched the search criteria specified in section 2.1. We also embed the *MEF* of the respective hourly segment within every tweet and calculate its ES. This results in a dictionary where we can look up a specific user and find all their tweets issued on the asset (during the timeframe), the ES every tweet received during its hour of issuance, as well as the corresponding market activity during that same hour (represented by the MEF). This information is used to calculate the AIS.

3.3 Calculating the AIS

After the mapping process is finished and the TweetMaps have been created, we utilize them to start the AIS calculation on a per-user basis. All the steps described are universally applicable to all TweetMaps and therefore to all Twitter users.

In Table 1 you can see a representation of Musk's TweetMap spanning over the timeframe of January 1, 2020 until May 31, 2023. The size of the sliding window was set to 36 candles (the MEF varies depending on the WS). The tweets were sorted according to their respective MEF.

We then utilize the TweetMap to compute the average *Average Attributable Magnitude (AMM)* ($\in \mathbb{Q}$) for a user. The AAM represents the average M which we attribute to each user based on their average received ES. This metric allows us to differentiate between users that just happen to tweet during times of elevated M, and users that might have actually caused significant trading activity with their tweets. All the variables (ES_u as well as the number of tweets $|T_u|$) are user-specific.

$$AAM_u = \frac{\frac{\sum ES_u}{100}}{|T_u|} \times \frac{\sum MEF}{|T_u|}$$

If we apply this formula to Musk's TweetMap, we get an AAM for Elon Musk of 5.6971.

Table 1: Elon Musk's TweetMap from of Jan 1, 2020 until May 31, 2023

Rank	Text	ES	MEF
1	SpaceX is going to put a literal Dogecoin on the literal moo ...	98.46	28.14
2	Tesla will make some merch buyable with Doge & see how i ...	88.12	20.09
3	One word: Doge	99.70	13.93
4	Do you want Tesla to accept Doge?	92.50	10.31
5	Tesla merch can be bought with Doge, soon SpaceX merch too	92.63	9.85
6	High time I confessed I let the Doge out ...	96.98	7.10
7	No highs, no lows, only Doge	55.59	6.11
8	Dogecoin is the people's crypto	42.34	6.11
9	Tesla merch buyable with Dogecoin	92.61	5.91
10	Doge day afternoon	85.30	5.51
11	I will eat a happy meal on tv if @McDonalds accepts Dogecoin	95.28	5.17
12	Release the Doge!	95.63	4.37
13	I will keep supporting Dogecoin	92.77	4.34
14	If major Dogecoin holders sell most of their coins, it will ...	98.14	3.78
15	Bought some Dogecoin for lil X, so he can be a toddler hodle ...	95.15	3.36
16	Doge meme shield (legendary item)	97.48	3.32
17	Working with Doge devs to improve system transaction efficie ...	93.54	2.86
18	Who let the Doge out	93.72	2.52
19	Baby Doge, doo, doo, doo, doo, doo, Baby Doge, doo, doo, doo ...	97.72	2.25
20	If you'd like to help develop Doge, please submit ideas on G ...	91.24	1.42
21	How much is that Doge in the window?	92.83	1.39
22	Doge Barking at the Moon	96.84	1.16
23	Doge spelled backwards is Egod	99.03	1.00
24	SpaceX launching satellite Doge-1 to the moon next year ...	93.28	0.74

$$AAM_{elonmusk} = 0.907025 \times 6.2811 = 5.6971$$

The AAM is the final metric we employ to calculate the AIS. As mentioned, it represents the average MEF in relation to each user according to their ES. To recall, the MEF *(Magnitude attributable to External Factors)* is the total M adjusted for Bitcoin's M in relation to their *Pearson Correlation Coefficient*. This means that - on average - we assume that a tweet of User u will occur in a period whose MEF is equal to their AAM, or in our case, we can expect a tweet from Musk to co-occur within a period whose MEF is 5.6971. We can now move on to calculating the AIS.

AIS - Baseline: The AIS approximates the certainty with which a user's tweet will co-occur within a period whose MEF exceeds the BTF *(Breakout Threshold Factor)*. This is done by dividing the AAM of user by the BTF. To address the potential for a skewed AAM and in turn a skewed AIS due to outliers, we also incorporate an *Anomaly Ratio*, which represents the ratio of tweets whose MEF exceed the BTF (`= Anomaly`), compared to the total number of tweets issued by user $|T_u|$. The maximum value a user can achieve here is 100, or 100% certainty.

AIS - Penalty: From this we then deduct a *penalty*, the average difference between a tweet's MEF and the BTF (complementary values), for all tweets whose MEF did not exceed the BTF. This ensures that a user can only achieve an AIS of 100 if every single one of their tweet's MEF exceeds the BTF. Furthermore, this "punishes" users that have very low consistency in their associated MEF's, adequately adjusting the AIS if skewed to the upside by outliers. We amplify the penalty by the complementary value of the average ES to 100%, punishing users with lower ES's for failing to generate adequate engagement.

We can therefore define the AIS **(**$\in \mathbb{Q},\ 0 \leq x \leq 100$**) as follows**:

$$
\begin{aligned}
AIS_u = \min(\frac{AAM_u \times \frac{|Anomaly_u|}{|T_u|} \times 100}{BTF}, 100) \ \textbf{(Baseline)} \\
-(\frac{\sum_{i \in !Anomaly} BTF - MEF_i}{|!Anomaly_u|} * (1 - \frac{\frac{\sum ES}{100}}{|T_u|}) \ \textbf{(Penalty)}
\end{aligned}
$$

Now we can apply the AIS calculation to our running example of Elon Musk. In our example we use a BTF of 1 and a WS of 36. Musk has issued a total of 24 tweets about Dogecoin within the timeframe between Jan 5, 2020 and May 31, 2023, 22 of which occurred within a period with a MEF above 1, 2 of which did not. This results in an *Anomaly Ratio* of 91,67% (22/24). We are left with the following calculation:

$$
\begin{aligned}
AIS_{musk} = \min(\frac{5,6971 \times \frac{22}{24} \times 100}{1}, 100) \ \textbf{(Baseline)} \\
-(\frac{(1 - 1 + 1 - 0,74)}{2} * (1 - 0,907025) \ \textbf{(Penalty)} \\
= \mathbf{99,976}
\end{aligned}
$$

In other words, our model predicts a newly issued tweet of Elon Musk which matches the search term "Dogecoin OR DOGE" will co-occur within an hourly period whose V exceeds the previous 36 hour's average (by a factor of 1 - which is the average; if we had set the BTF to 2 we would predict double the trading activity compared to the average) with a certainty of 99,976 %.

The AIS is naturally heavily dependent on the chosen BTF. A higher BTF requires a more substantial change in trading activity, thus raising the bar for a user to receive a high AIS. In Table 2 we demonstrate how different BTF's affect users AIS's for Dogecoin.

It becomes apparent that Musk is by far the highest ranking user for Dogecoin according to our model. When raising the BTF, other users quickly fall to single digit influence, while Musk's AIS stays pretty much unphazed. At a BTF of 10 (not shown in the table), only Musk is able to achieve an $AIS > 0$ of just 8.93, leading us to determine that Musk is the most influential Twitter user when it comes to the suggested influence over the trading activity of Dogecoin.

To evaluate the AIS's usefulness, we will employ it as a trading indicator. Trade entries will be timed based on tweets issued by the top users ranked by the AIS and position size will be determined by their AIS.

Table 2: the AIS's for different users and different BTF's (1, 1.5, 2, 3) on May 31, 2023

BTF: 1	BTF: 1.5	BTF: 2	BTF: 3
elonmusk (99.98)	elonmusk (99.96)	elonmusk (99.92)	elonmusk (99.87)
lilyachty (60.00)	lilyachty (33.83)	frankiemuniz (15.46)	frankiemuniz (9.19)
frankiemuniz (54.22)	frankiemuniz (28.45)	KEEMSTAR (13.19)	lilyachty (4.46)
CorinnaKopf (39.99)	CorinnaKopf (21.93)	lilyachty (12.19)	KEEMSTAR (4.38)
KEEMSTAR (33.18)	KEEMSTAR (20.72)	cz_binance (7.901)	CorinnaKopf (3.52)
cz_binance (23.97)	Dexerto (13.00)	IamKrisLondon (6.71)	IamKrisLondon (3.10)
IamKrisLondon (20.60)	IamKrisLondon (12.98)	Troydan (6.63)	cz_binance (2.24)

4 Evaluation

In this section we discuss and evaluate the AIS in a trading environment. Our aim is to find the best performing configuration and compare it to simple buy-and-hold strategy as well as a trading strategy that incorporates the previous day's return and volume, price momentum and volatility. The AIS-based trading strategy was executed using our own publicly available prototypical implementation, which can be found on Github[7].

Buy-and-Hold Strategy: We compare it to a buy-and-hold strategy (also referred to as "investor"), as it a very common, hands-off investment strategy practiced by many individuals and institutions and was also used by Gjerstad et. al. [14] in a very similar evaluation setting in the context of Donald Trump and the S&P500. It relies on achieving historic market returns instead of actively managing positions. All tests will be performed on Dogecoin, as it is an asset whose price action was arguably closely tied to Twitter activity, especially that of Elon Musk. We will also showcase the AIS when applied to Bitcoin and will demonstrate, that the AIS's impact is heavily dependent on how susceptible the asset is to social media activity.

Technical Trading Strategy: The other comparison will be against the baseline strategy described by Xiao and Chen [25], who used a combination of the previous day's return and volume, price momentum and volatility as a baseline and then expanded upon said baseline to evaluate whether it could be improved by incorporating Twitter sentiment when applied to stock trading. This was the only concrete trading baseline we could find in a comparable environment. Unfortunately the authors did not describe the exact parameters they used, which is why we estimated and optimized them to the best of our ability.

We enter long or short positions when the previous day's return is positive or negative and volume as well as volatility exceed or go below their 72 hour moving averages (our optimal WS) respectively. We enter every trade with 33% of the available portfolio balance (a rough estimate of the average AIS), which is also

[7] `https://git01lab.cs.univie.ac.at/university_research/masterarbeiten/ais`

$10,000 to begin with. The exact trading script is available on Github[8] folder. It was written in Pinescript v5 and executed and backtested on Tradingview [24].

AIS-based Trading Strategy: To evaluate the AIS as a trading indicator, we iterate over the dataframes during the specified trading timeframe hour by hour, updating the TweetMaps and subsequently the AIS's for all current users, keeping a record of the top 8 users ranked by AIS. If one of the users issues a tweet, we enter a long-position (we buy Dogecoin) proportionate to that user's AIS. This means, if a user with e.g. an AIS of 15 issues a tweet, we buy Dogecoin with 15% of our available portfolio balance. If multiple users tweet during that day, we fill the positions on a first-come-first-serve basis. At the end of each day (00:00 AM), all positions, no matter the trading result, are converted back to US-dollars. If no top-user tweets, the capital sits in US-dollars, waiting to be deployed again. This comes with the added benefit of available capital for the trader - liquidity that could be used otherwise.

At any given hour, the strategy can only capture 80% of the price move. This is to emulate price moves that occurred within the hour as well as incorporate the likelihood of existing bots also utilizing tweets as buy signals.

Timeframe: We believe it is realistic to assume that an average, decently crypto-savvy investor could've started investing in Dogecoin after its first strong appearance in mainstream media at the beginning of 2021, just after it had reached 1 cent, which was on January 6, 2021. Before this date, we believe the likelihood of a rational investor with a standard risk tolerance and no insider information investing in Dogecoin to be negligible. This marks the start of our trading period. We end our evaluation on May 31, 2023, as this marks the last full month of data available at the time of performing the evaluation.

4.1 Optimizing Parameters

The AIS is heavily influenced by the user chosen parameters, those being the size of the sliding window (WS), the minimum number of issued tweets to be eligible for AIS calculation and most importantly the BTF. The parameter optimization was done semi-automatically. We used the historic data available to us to execute the trading algorithm with various parameter configurations, comparing trading performance and end-balances among the different iterations to find the best configuration.

Breakout Threshold Factor (BTF): How the BTF influences the AIS has already been shown in Table 2. A higher BTF significantly reduces certainty of a tweet's co-occurence with the elevated $Magnitude$, therefore reducing the frequency of trades taken. The most successful BTF in terms of trading results was a BTF of 1, meaning any M above the current window's average was considered as an anomaly or elevated trading activity.

Window Size (WS): WS impacted the trading results in a bell-curve-like manner, where both very small and very large windows performed significantly

[8] `https://git01lab.cs.univie.ac.at/university_research/masterarbeiten/ais/-/blob/main/eval/Doge_PDR_Vol_Momentum_Vol.pine`

worse compared to medium sized windows. We tested configurations with a WS of 6, 12, 24, 30, 36, 48, 60, 72 and 96, with the best performing WS being 72 for both Dogecoin and Bitcoin. We attribute the poor performance of smaller windows to the inability to identify proper breakouts. The smaller windows too quickly averaged out during hours of high activity, causing the algorithm to miss trades during periods of high Twitter activity. If the window is too large, it likely incorporates other high-activity periods, causing recent ones to be drowned out by previous activity. A WS of 72 seems to be a sweet spot in our evaluation scenario.

Minimum Tweets: The results for the minimum number of tweets similarly followed a bell-curve-like distribution, where both comparatively low and high numbers yielded the worst results. We tested a minimum number of 1, 2, 3, 4, 5, 6, 7 and 10 tweets. We attribute the poor performance of the low number to poor trades induced by individuals that could not be described as tastemakers, but rather lucky individuals that just happened to tweet with fortunate timing. The increase of the minimum comes at the tradeoff of the algorithm taking longer to incorporate actual tastemakers (like Musk), which explains its poor performance. The best performance was achieved with a minimum of 4 tweets.

Optimal Configuration: The best trading performance was achieved with a BTF of 1, a WS of 72 and a minimum number of tweets issued by a user of 4, for both BTC and DOGE. The full result set for all combinations can be found in CSV format on Github[9].

4.2 The AIS as a Trading Indicator

We can now backtest and plot the results of our AIS-based trading algorithm and compare them to the results of the buy-and-hold-investor as well as our technical trading strategy. As mentioned, the trading algorithm entered a long position whenever one of the top 8 AIS users issued a tweet, at 80% of that hourly candle's total price move (open - close). All positions were liquidated at the end of each day and the algorithm would be wait until further tweets occurred. The trading timeframe starts on January 6, 2021 (the date we argue a rational investor could've started investing) and ends on May 31, 2023. Both the investor and trading algorithms start with a balance of $10,000.

The AIS as well as the trading algorithm were executed and tested on two separate machines with the same results.

Windows Machine: Ryzen 5 1600 (6-core CPU) and 16GB DDR4 Memory.

MacOS Machine: M1 Macbook Air (2021) with 16GB of Memory.

As shown in Fig. 2, the AIS algorithm was able to significantly outperform the buy-and-hold investor, while only deploying capital on 182 out of a total of 873 trading days.

In its first trading year, a period with extremely bullish price action and heavy twitter activity, it achieved a gain of 2,534% on its balance. While the

[9] `https://git01lab.cs.univie.ac.at/university_research/masterarbeiten/ais/-/tree/main/eval`

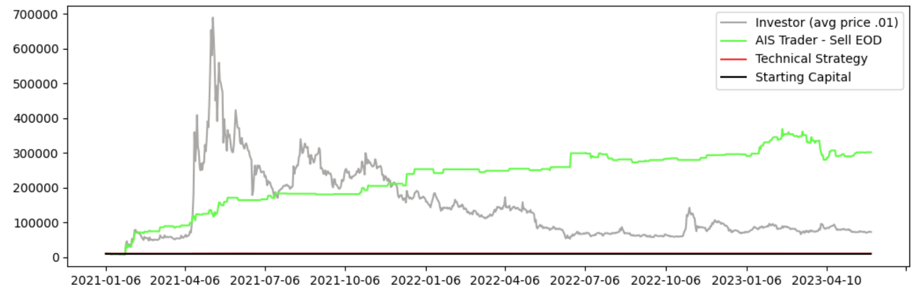

Fig. 2: Dogecoin - Comparison of *AIS* Trading Algorithm and Investor - Jan 6 2021 until May 31 2023

buy-and-hold investor did temporarily outperform the trading algorithm, the balance after the first year amounted to $171,100, or a gain of 1,711%.

In its second trading year, a bearish period over which Dogecoin lost 60% of its value, the *AIS* algorithm managed to increase its balance by a further 16,7% to $296,030, suggesting the *AIS*'s effectiveness for Twitter-correlated assets like Dogecoin. This increase was also achieved using only long positions and no short-selling, a method that trading strategies generally employ, especially during bearish periods. The buy-and-hold investor lost 60% of their portfolio, ending the year 2022 with a balance of $68,400.

The *AIS* algorithm ended with a final balance of $301,965.93, a gain of 3,019% compared to the start, while the investor's balance stands at $72,310, a gain of 723%, on May 31, 2023. This means that the algorithm outperformed the trader by 417,6% while maintaining full liquidity 79.15% of the time. The *AIS*-based trading algorithm also displays a very strong upward trajectory, almost steadily increasing its balance during the entire trading period.

The trading strategy inspired by Xiao et. al. [25] generated a profit of 2.38% over the same period, while taking 1,798 trades. The strategy peaked at a maximum profit of 7.83% early on, but slowly lost capital afterwards. The technical strategy's performance gets dwarfed by the AIS in Fig 2, therefore we provide a more detailed view of its performance in Fig. 3.

The absence of exposure and only entering trades on Twitter impulses can also prove beneficial for less Twitter-correlated assets like Bitcoin. Bitcoin is arguably much less susceptible to Twitter activity due to its comparatively large market capitalization and higher trading volume as well as broader public adoption as an investment vehicle, but its price can still be susceptible to news or opinions published on Twitter. As can be seen in Fig. 4, the *AIS* trading algorithm was not able to capture initial highs, but still managed to nearly steadily increase its balance over the trading period by 20% to $12,021.66 while maintaining a similar 78,4% liquidity rate, while the investor lost 12,2% over the same period with no excess liquidity.

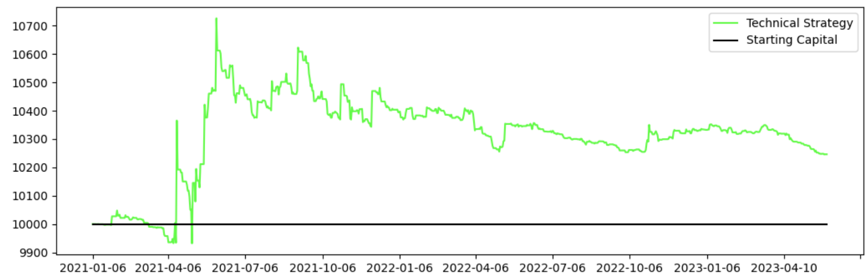

Fig. 3: Dogecoin - Technical Trading Strategy Performance - Jan 6 2021 until May 31 2023

The technical trading strategy did not execute a single trade when tested on Bitcoin, which is why it was omitted from the graph.

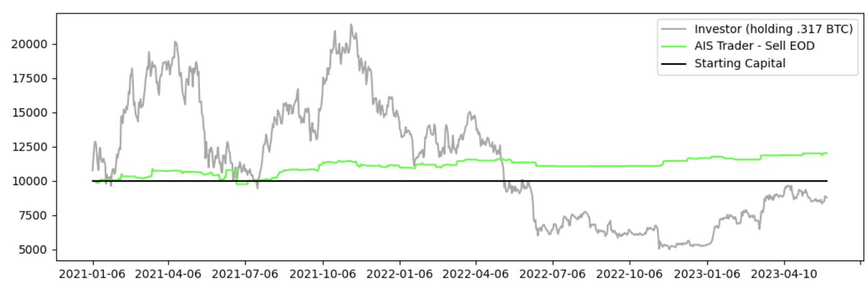

Fig. 4: Bitcoin - Comparison of *AIS* Trading Algorithm and Investor - Jan 6 2021 until May 31 2023

5 Related Work

Existing work fails to focus on the influence of a single user, but rather utilizes Twitter to source broad sentiment [8] [21] [23] or twitter volume [18]. Xiao et. al. [25] incorporate sentiment analysis in addition to technical indicators (as described in our evaluation approach) to predict price direction and actually provide backtests that supplement their predictions, something that hardly any authors do.

Gjerstad et. al. [14] employ a similar approach to ours by utilizing a baseline of buy-and-hold on the S&P500 and entering a temporary short position when Trump tweeted in the context of "Trade War", but their approach failed to outperform the buy-and-hold strategy. The strategy also differs from ours, as both their baseline and their trading strategy rely on holding shares of S&P500.

Oliveira et. al. [20] focus on forecasting stock market variables for the S&P500, but don't evaluate subsequent trading performance nor do they focus on individual users either.

Bollen et al. [8] used sentiment analysis on large-scale Twitter feeds and mapped the determined sentiment to the Dow Jones Industrial Average (DJIA) by using a self- organized fuzzy neural network. They were able to make a price direction with 87.6% accuracy. They did however not focus on the influence of an individual user, but rather a broad and homogenous user group. Abraham et al. [4] focused their research on tweet volume and Google trends, rather than sentiment alone. They did find significant correlation between both Google trends data as well as tweet volume and the price of Bitcoin but determined sentiment analysis to be a non-reliable indicator.

Given these limitations in existing work we saw a necessity in developing a user-agnostic, universally applicable metric to assess the suggested influence of a Twitter user over the trading activity of a cryptocurrency. Abraham et. al.'s findings of sentiment analysis not being a useful indicator in their evaluation led us to omitting this aspect for our prototypical implementation.

6 Discussion and Outlook

This paper focused on developing and testing the AIS, a novel, fully transparent metric for assessing the suggested influence twitter users have over an asset's trading activity, which was successfully evaluated against both a buy-and-hold investing, as well as a technical trading strategy.

Our challenge was to provide complete transparency in the development, calculation and testing of our metric, making it easily replicable for anybody that might want to expand on our research. We have achieved this by documenting and open-sourcing every necessary step to replicate the exact results achieved by us. We conclude that our proposed approach was successful by proving that it would've been able to outperform both a buy-and-hold investor as well as similar technical trading strategies, solely employing the AIS as a trading indicator.

We attribute the success of the AIS trading algorithm to reduced exposure during times of market downturns, effectively capturing market upside caused by Twitter activity while maintaining significant liquidity during low social media activity.

For future work we plan on incorporating the aspect of network science, specifically how users influence each other among themselves and determining the degree of influence one user has over the actions of other users. This could lead us to more efficiently discover influential users compared to our current approach.

Another aspect we plan on incorporating in future iterations is sentiment analysis. While some authors like Abraham et. al. [4] found sentiment analysis to be a non-reliable indicator, others like Bollen et. al. [8] did achieve success with it, therefore we believe this is an aspect worth exploring.

We will also explore the application of the AIS to other cryptocurrency assets and even other asset classes like stocks. Furthermore, we plan on experimenting with aspects like dynamic holding periods (the algorithm always sold at the end of the trading day), the option of short-selling during bearish market periods (the *AIS* algorithm could only enter long-positions) as well as the option to trade multiple assets simultaneously.

Finally, we only incorporated solely Twitter as a data source. For future iterations we will explore data streams from other social media networks, e.g. Facebook and LinkedIn, as well as other microblogging platforms like Mastodon or Meta's newly released Threads.

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