



# From Tweets to Token Sales: Assessing ICO Success Through Social Media Sentiments

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# Introduction

- **Blockchain and Cryptocurrencies:** These technologies have revolutionized fundraising methods like Initial Coin Offerings (ICOs) and Initial Exchange Offerings (IEOs).
- **ICOs and IEOs:** ICOs offer cost-effective fundraising by issuing new coins on blockchain platforms, while IEOs are managed by cryptocurrency exchanges acting as intermediaries between projects and investors.
- **Significant Funding:** In 2018, 3,782 ICOs raised nearly \$11.4 billion; in 2021, despite fluctuations, 113 ICOs were hosted on Coincodex.
- **Social Media Impact:** Social media platforms, especially Twitter, play a critical role in promoting ICOs and IEOs, significantly influencing their success through broad dissemination and promotion of project information.
- **Airdrop Initiatives:** These are used by businesses to increase awareness about ICOs or IEOs, rewarding participants with tokens for engaging in marketing activities like joining groups and following social media accounts.
- **Security and Efficiency:** The blockchain's efficiency in creating digital tokens through smart contracts adds security and reliability to the fundraising process.

# Related Work and Motivations

- **Limitations of Previous Studies**

- Previous studies have identified predictors of ICO success, but lack depth in exploring social media's influence
- Some studies overlook the impact of social media on investor behavior
- Limited time scope and lack of consideration for negative sentiment are notable limitations

- **Importance of Social Media Analysis**

- Twitter sentiment analysis is essential for evaluating ICO effectiveness
- Analyzing social media metrics and sentiment guides effective investor targeting and platform selection
- Understanding social media's influence aids startups in refining marketing strategies and engaging with investors

- **Study Objectives**

- Comprehensively explore the impact of global social media strategies on ICO success
- Contrast with regional studies to provide a holistic understanding
- Offer invaluable insights for ICO fundraising efforts

# Hypotheses

**Hypothesis 1:** Positive sentiment in ICO-related tweets correlates with ICO success.

**Hypothesis 2:** Higher social media engagement metrics positively correlate with ICO success.

**Table 1.** Example of data used for sentiment analysis.

	<b>Tweet Content</b>	<b>Sentiment</b>
Original Tweet	Just bought more \$SOL, feeling great about this investment!!	Positive
Reply	I'm not convinced, I think \$SOL is overvalued	Negative
Reply	Quite bullish on it too, the fundamentals are really strong	Positive
Reply	Waiting to see how the market develops, but currently looking for better options in the market	Negative

**Table 2.** Example of data used for engagement metrics.

<b>Metric</b>	<b>Data collected for \$MATIC</b>
Number of mentions	799,849
Number of retweets	1,471,118
Number of likes	1,280,414
Number of project followers	34,755,686



# Data Collection

## • ICOs Data Collection

- Data collected from ICObench and CryptoRank using manual download and automatic scraping
- Recorded ICO-related data for each cryptocurrency project

## • Twitter Data Collection

- Data collected using Twitter API and Scrapy, an open-source Python framework
- Collected tweets that:
  - ✓ Mentioned a cryptocurrency project's keyword (e.g. "\$SOL" or "\$MATIC")
  - ✓ Were posted by the project's official Twitter handle
- Recorded data for tweets featuring the token keyword
- Excluded tweets from the project's own account, as they were deemed not directly relevant to the research hypotheses
- Categorized tweets into direct mentions (explicitly containing the token keyword) and indirect mentions (responding to another tweet featuring the token keyword or the project's official Twitter handle)
- Only considered tweets published prior to the ICO date to avoid look-ahead bias

**Table 3.** ICO data collected.

Data description	Data type	Hypothesis
Project name	String	1, 2
Project token	String	1, 2
Soft cap	Integer	1, 2
Total raised	Integer	1, 2
ICO Date	Date	1, 2

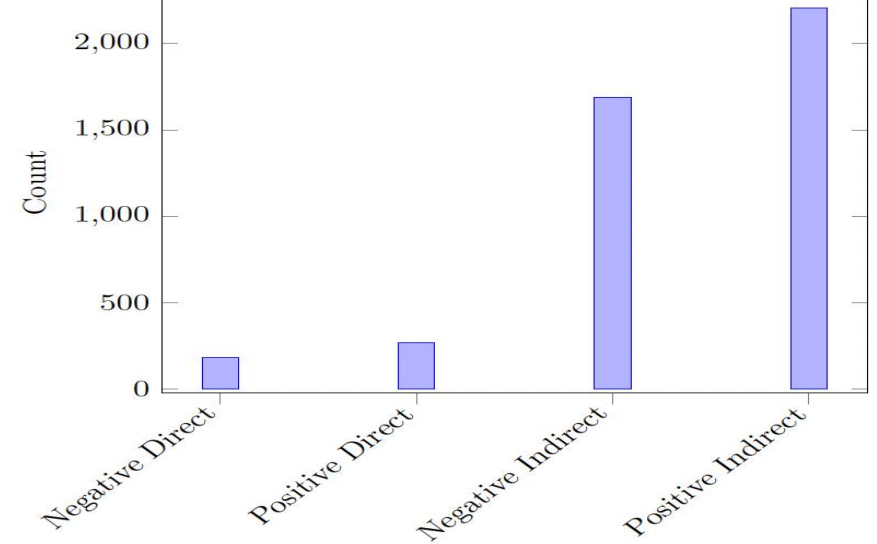
**Table 4.** Twitter data collected.

Data description	Data type	Hypothesis
Content of tweets - direct mentions	List of String	1
Content of tweets - indirect mentions	List of String	1
Total number of direct mentions	Integer	2
Total number of indirect mentions	Integer	2
Total number of likes	Integer	2
Total number of retweets	Integer	2
Number of official account followers	Integer	2
Total number of followers of users mentioning project	Integer	2



# Data Processing

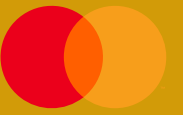
- **Sentiment Analysis**
  - Used NRC Word-Emotion Association Lexicon to assign sentiments (positive or negative) to words
  - Utilized TextBlob, a Python library, to quantify sentiment polarity of each tweet
- **ICO Success Determination**
  - Compared total capital raised to soft cap defined by project
  - Classified 582 ICOs as successful (surpassed soft cap) and 234 as unsuccessful (did not meet soft cap)
  - Structured dataset into 12 columns, each representing a discrete attribute of an ICO
- **Resulted in a test dataset** consisting of 3 CSV files at [https://github.com/inflaton/Success-Indicators-of-Initial-Coin-Offerings/blob/main/data\\_training/](https://github.com/inflaton/Success-Indicators-of-Initial-Coin-Offerings/blob/main/data_training/)
  1. [cleaned\\_combined\\_data.csv](#)
  2. [cleaned\\_engagement\\_data.csv](#)
  3. [cleaned\\_sentiment\\_data.csv](#)



**Fig. 1.** Sentiment scores for DUO Network (DUO) tweets.

**Table 8.** Feature labels and description.

Index	Column	Data type	Description
1	total_direct_mentions	Integer	Total number of direct mentions
2	total_positive_direct_mentions	Integer	Total number of direct mentions with positive sentiment
3	total_negative_direct_mentions	Integer	Total number of direct mentions with negative sentiment
4	total_indirect_mentions	Integer	Total number of indirect mentions
5	total_positive_indirect_mentions	Integer	Total number of indirect mentions with positive sentiment
6	total_negative_indirect_mentions	Integer	Total number of indirect mentions with negative sentiment
7	total_retweets	Integer	Total retweets of tweets with token keyword and official account tweets
8	total_likes	Integer	Total likes of tweets with token keyword and official account tweets
9	total_project_followers	Integer	Total followers of official account
10	total_indirect_followers	Integer	Total followers of users mentioning the project
11	soft_cap	Integer	Project soft cap
12	ico_success	Integer	Boolean (0 or 1) to indicate success of ICO



# Machine Learning Methods

- **Objective**

- Predict the likelihood of success for ICOs by classifying them into categories based on their potential to succeed.

- **Methodology**

- Divided the data into two subsets:
  - ❖ Training dataset, comprising 80% of the total data.
  - ❖ Testing dataset, comprising the remaining 20%.
- Implemented six different classification algorithms to analyze the data:
  - ❖ Support Vector Machines (SVMs)
  - ❖ Logistic Regression
  - ❖ Random Forest
  - ❖ Naïve Bayes
  - ❖ Categorical Boosting (CatBoost)
  - ❖ Neural Network
- Performed parameter optimization using grid search techniques to enhance accuracy.
- All relevant codes and checkpoints are accessible on GitHub at the following URL:
  - ❖ [https://github.com/inflaton/Success-Indicators-of-Initial-Coin-Offerings/blob/main/data\\_training/](https://github.com/inflaton/Success-Indicators-of-Initial-Coin-Offerings/blob/main/data_training/)



# Experimental Results

## Individual Hypothesis Testing

### • Hypothesis 1 Results (Table 5)

- Models showed moderate performance scores
- Highest accuracy achieved by Neural Network model at 74.4%
- F1 Scores ranged from 70.9% to 81.9%, indicating moderate predictive power
- Results suggest Hypothesis 1 has some merit in predicting ICO success based on positive sentiment in tweets

### • Hypothesis 2 Results (Table 6)

- Models performed better overall
- Highest accuracy achieved by Random Forest model at 76.8%
- Precision and Recall scores were relatively high, ranging from 65.2% to 82.9% and 58.9% to 100.0%, respectively
- F1 Scores ranged from 68.9% to 83.5%, indicating slightly higher predictive power than Hypothesis 1

Results suggest that social media engagement (Hypothesis 2) might be a better predictor of ICO success than sentiment (Hypothesis 1)

Table 5. Hypothesis 1 predictive results

Model	Accuracy	Precision	Recall	F1 Score
Naïve Bayes	65.9%	66.0%	98.1%	78.9%
SVM	65.2%	65.2%	<b>100.0%</b>	79.0%
Logistic Regression	66.5%	<b>81.7%</b>	62.6%	70.9%
Random Forest	73.8%	75.4%	88.8%	81.5%
CatBoost	73.8%	75.4%	88.8%	81.5%
Neural Network	<b>74.4%</b>	76.0%	88.8%	<b>81.9%</b>

Table 6. Hypothesis 2 predictive results

Model	Accuracy	Precision	Recall	F1
Naïve Bayes	64.6%	65.4%	97.2%	78.2%
SVM	65.2%	65.2%	<b>100.0%</b>	79.0%
Logistic Regression	65.2%	<b>82.9%</b>	58.9%	68.9%
Random Forest	<b>76.8%</b>	78.0%	89.7%	<b>83.5%</b>
CatBoost	76.2%	76.6%	91.6%	83.4%
Neural Network	73.8%	76.2%	86.9%	81.2%





# Experimental Results

## Combined Hypothesis Testing

- Combining feature sets from both hypotheses improved overall performance
- CatBoost model showed significant improvement
- Top-performing models in terms of accuracy were CatBoost and Random Forest

This suggests that using a combination of features from both hypotheses can lead to better predictive power, and that CatBoost and Random Forest are the most effective models in this case.

**Table 7.** Combined predictive results

Model	Accuracy	Precision	Recall	F1
Naïve Bayes	64.0%	65.2%	96.3%	77.7%
SVM	65.2%	65.2%	<b>100.0%</b>	79.0%
Logistic Regression	64.6%	85.5%	55.1%	67.0%
Random Forest	<b>78.0%</b>	<b>79.3%</b>	89.7%	84.2%
CatBoost	<b>78.0%</b>	77.1%	94.4%	<b>84.9%</b>
Neural Network	67.1%	66.5%	<b>100%</b>	79.9%



## Further Discussion

- **Comprehensive Engagement Measures:** Social media engagement metrics (mentions, retweets, likes, followers) provide a more comprehensive measure of interest and support for a project than positive sentiments in tweets, which might not capture all forms of engagement and can be influenced by bots and fake accounts.
- **Limitations of Sentiment Analysis:** Sentiment expressed in tweets may not always reflect the true feelings and opinions of the community. It can be affected by external factors like competition, influencers, and events, which can skew the sentiment positively or negatively irrespective of the project's actual quality.
- **Unintended Effects of Negative Sentiment:** Negative sentiments on social media can sometimes have positive effects by generating more attention and discussion, leading to increased visibility and exposure for a project. This phenomenon suggests that both positive and negative sentiments should be considered when evaluating a project's potential success.
- **Reliability of Engagement Metrics:** Engagement metrics are less likely to be influenced by external factors compared to sentiment analysis, making them more robust and reliable indicators of genuine interest and support.
- **Strategic Focus on Engagement:** The findings suggest that ICO projects should focus strategically on enhancing their social media engagement to attract and sustain interest. Effective strategies might include creating engaging content, managing vibrant communities, and collaborating with influencers to increase visibility.



# Conclusion

- **Summary of Findings:**
  - **Impact of Twitter Sentiment:** Positive sentiment on Twitter is linked to greater ICO fundraising achievements, highlighting Twitter's crucial role in ICO promotion and as an information source for investors.
  - **Correlation with Success:** ICOs with more positive commentary and higher engagement on Twitter generally secure larger funding amounts. A strong relationship was observed between fundraising success and both Twitter sentiment and follower volume.
  - **Predictive Analysis:** Six classifiers were used to assess predictive accuracy—Support Vector Machines, Logistic Regression, Random Forest, Naïve Bayes, Categorical Boosting, and Neural Network. Random Forest and Categorical Boosting were the most effective.
- **Future Research Directions:**
  - **Pump and Dump Schemes:** Investigate ICO projects where social media engagement may be artificially inflated by bots and paid accounts. Understanding these tactics is crucial to detect and prevent fraud.
  - **Influence of Key Figures:** Study how influential figures on social media can affect cryptocurrency prices and ICO success, which could lead to insights on mitigating risks associated with their influence.
  - **Marketing Expenses:** Explore the relationship between social media marketing expenditures and ICO financial performance.
  - **Governance Signals:** Examine how governance-related signals from ICOs influence their fundraising success, providing insights into effective ICO management strategies.



# Questions?

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