Assignment 1 - CBD3334 - Data Mining and Analysis

Team Members:

- 1. Aanal Patel - C0910376
- 2. Bimal Shresta - C0919385
- 3. Danilo Diaz - C0889539
- 4. Ernie Sumoso - C0881591
- 5. Jayachandhran Saravanan - C0910392

1 & 2. Collecting, Saving Data, and basic Exploratory Data Analysis (EDA)

Let's start by **collecting the data from the given CSV files**.

For starters, we will **save the file names into a list** so that we can later loop through them.

For that we will need to **import some functions from the os library**.

In [ ]:
```
!wget --no-cache -O init.py -q https://raw.githubusercontent.com/NILodio/data-mining/master/init.py
import init; init.init(force_download=False);
```

```
replicating local resources
```

In [ ]:
```
from os import listdir
from os.path import isfile, join

# get the list of file names from the data path
data_path = 'local'
files = [file for file in listdir(data_path) if isfile(join(data_path, file))]
files
```

Out[ ]:
```
['APPL.csv',
 'altcoin.csv',
 'GOOG.csv',
 'bitcoin.csv',
 'Cryptocurrency.csv',
 'Gold.csv',
 'YHOO.csv',
 'coindesk.csv']
```

Now that we have the file names, let's **read these CSV files and save them as Pandas Dataframes**.

We will also **display a sample row from each dataframe**, just to have some initial visualization of our available data.

We will **save all dataframes inside one list.**

In [ ]:
```
import pandas as pd

# function to read multiple csv files from a path into a list of dataframes
def read_csvs_from_path(data_path : str):
    # get list of file names
    files = [file for file in listdir(data_path) if isfile(join(data_path, file))]
    dfs = []

    # loop through files, read the csv file and save the dataframe
    for i, file in enumerate(files):
        df = pd.read_csv(data_path + "/" + file)

        #label the data to make exploration after concatenation easier
        df['tag'] = str(file)[:-4]

        print(str(i+1) + ". Sample data extracted from: '" + file + "'")
        display(df.tail(1))
        dfs.append(df)

    # return the list of dataframes
    return dfs

dfs = read_csvs_from_path(data_path)
```

1. Sample data extracted from: 'APPL.csv'

	Datetime	Tweet Id	Text	URL	User	tag
3180	2023-03-05 00:03:31+00:00	1632169937350303744	Apple’s Approval Process Delays Uniswap’s Mobi...	https://twitter.com/ZhotCrypto/status/16321699...	https://twitter.com/ZhotCrypto	APPL

2. Sample data extracted from: 'altcoin.csv'

	Datetime	Tweet Id	Text	URL	User	tag
5000	2023-03-09 19:03:33+00:00	1633906384160034817	🔔 Public Company Accounting Oversight Board (P...	https://twitter.com/Altcoin_Alerts/status/1633...	https://twitter.com/Altcoin_Alerts	altcoin

3. Sample data extracted from: 'GOOG.csv'

	Datetime	Tweet Id	Text	URL	User	tag
5000	2023-03-05 12:01:20+00:00	1632350581569490946	Get instant updates and free trials join here ...	https://twitter.com/Smith28301/status/16323505...	https://twitter.com/Smith28301	GOOG

4. Sample data extracted from: 'bitcoin.csv'

	Datetime	Tweet Id	Text	URL	User	tag
5000	2023-03-10 22:03:06+00:00	1634313959904886786	@JulesXavier9 Obama didn’t take office until 2...	https://twitter.com/btc_liberates/status/16343...	https://twitter.com/btc_liberates	bitcoin

5. Sample data extracted from: 'Cryptocurrency.csv'

	Datetime	Tweet Id	Text	URL	User	tag
5000	2023-03-10 14:44:37+00:00	1634203611403022336	Silvergate and Cryptocurrency 😖😖	https://twitter.com/tamoinam/status/1634203611...	https://twitter.com/tamoinam	Cryptocurrency

6. Sample data extracted from: 'Gold.csv'

	Datetime	Tweet Id	Text	URL	User	tag
5000	2023-03-10 22:37:01+00:00	1634322493056905217	Check out Vintage Bracelet Gold Tone Pink Ston...	https://twitter.com/ShopThar/status/1634322493...	https://twitter.com/ShopThar	Gold

7. Sample data extracted from: 'YHOO.csv'

	Datetime	Tweet Id	Text	URL	User	tag
3643	2023-03-05 00:00:48+00:00	1632169253079072768	@NguboAyimbathwa @ChristoThurston @ThuliMadons...	https://twitter.com/Bright_Afrika/status/16321...	https://twitter.com/Bright_Afrika	YHOO

8. Sample data extracted from: 'coindesk.csv'

	Datetime	Tweet Id	Text	URL	User	tag
5000	2023-03-06 04:06:30+00:00	1632593471042142213	@milkyway16eth source coindesk - Arca’s Hotz ...	https://twitter.com/hashtronaut207/status/1632...	https://twitter.com/hashtronaut207	coindesk

As we can see all of **our data has the same columns and around 3k - 5k rows.**

Let's **implement a class to perform an Exploratory Data Analysis** on these datasets.

This class will be in charge of **displaying the shape (number of rows and columns) and column names of the datasets.**

But first, we will need a couple of functions to verify our method parameters and to print lines.

In [ ]:
```python
# function to verify a parameter type
def verify_parameter(param, param_name, type_):
    if not isinstance(param, type_):
        raise ValueError("Parameter '" + param_name + "' must be a " + str(type_))
```

In [ ]:
```python
# function to print a simple line of chars
def print_lines(line:str = '-', n:int = 40):
    # verify parameters type
    verify_parameter(line, 'line', str)
    verify_parameter(n, 'n', int)

    # print the line
    print(line * n)
```

In [ ]:
```python
class EDA:
    def display_shape_and_colnames_df(self, df:pd.DataFrame, return_shape:bool = True):
        # verify parameters type
        verify_parameter(df, 'df', pd.DataFrame)
        verify_parameter(return_shape, 'return_shape', bool)

        # display dataframe shape and column names
        print("Dataframe Rows:", df.shape[0])
        print("Dataframe Columns:", df.shape[1])
        print("Column names:", df.columns.to_list())

        # return the shape if needed
        if return_shape: return df.shape

    def display_shape_and_colnames_dfs(self, dfs:list, names:list):
        # verify parameters type
        verify_parameter(dfs, 'dfs', list)
        verify_parameter(names, 'names', list)
        assert len(names) == len(dfs), "'dfs' and 'names' must have same length"

        # display
        total_rows = 0
        for i, df in enumerate(dfs):
            print_lines()
            print("Dataframe from file:", names[i])
            df_shape = self.display_shape_and_colnames_df(df)
```

```
            total_rows += df_shape[0]
        print_lines(line='=')
        print("TOTAL ROWS:", total_rows)

eda = EDA()
eda.display_shape_and_colnames_dfs(dfs, files)
```

```
---------------------------------------
Dataframe from file: APPL.csv
Dataframe Rows: 3181
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
---------------------------------------
Dataframe from file: altcoin.csv
Dataframe Rows: 5001
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
---------------------------------------
Dataframe from file: GOOG.csv
Dataframe Rows: 5001
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
---------------------------------------
Dataframe from file: bitcoin.csv
Dataframe Rows: 5001
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
---------------------------------------
Dataframe from file: Cryptocurrency.csv
Dataframe Rows: 5001
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
---------------------------------------
Dataframe from file: Gold.csv
Dataframe Rows: 5001
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
---------------------------------------
Dataframe from file: YHOO.csv
Dataframe Rows: 3644
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
---------------------------------------
Dataframe from file: coindesk.csv
Dataframe Rows: 5001
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
```

```
======================================
TOTAL ROWS: 36831
```

Once again we find that our datasets have the same columns, and around 3k to 5k rows.

Let's **describe these columns**:

- **Datetime**: date and time of the posted tweet
- **Tweet ID**: unique identifier of the posted tweet
- **Text**: raw text data from the tweet (needs further cleaning)
- **URL**: link from the internet to the posted tweet
- **User**: username owner of the tweet

Also, in **total (from all datasets) we have around 36.8k rows.**

As our datasets are very similar we can **perform a concatenate as the next step.**

In [ ]:
```
# applying a vertical concat on all our datasets
df = pd.concat(dfs, axis=0).reset_index(drop=True)
df.tail()
```

Out[ ]:

	Datetime	Tweet Id	Text	URL	User	
36826	2023-03-06 04:17:24+00:00	1632596213588455425	RT @missmayad: Excited for Consensus. Always i...	https://twitter.com/varggasllosa/status/163259...	https://twitter.com/varggasllosa	c
36827	2023-03-06 04:16:06+00:00	1632595887057932289	@AndrewDARMACAP @BillHughesDC Yes - but @CoinD...	https://twitter.com/MattCorva/status/163259588...	https://twitter.com/MattCorva	c
36828	2023-03-06 04:12:35+00:00	1632595004299386882	由CoinDesk策划，是加密货币和Web3领域最大的年度活动之一Consensus大会，似...	https://twitter.com/xl941228/status/1632595004...	https://twitter.com/xl941228	c
36829	2023-03-06 04:11:47+00:00	1632594802242977792	@ahmad_alfalasi @CoinDesk do u think binance c...	https://twitter.com/buridangripto1/status/1632...	https://twitter.com/buridangripto1	c
36830	2023-03-06 04:06:30+00:00	1632593471042142213	@milkyway16eth source coindesk - Arca's Hotz ...	https://twitter.com/hashtronaut207/status/1632...	https://twitter.com/hashtronaut207	c

Now we have one **single dataset that contains all data from our 8 different file sources**.

Let's display its shape and column names.

Let's also **implement a second class in class of further exploratory data analysis** with tasks like:

- **checking missing values**
- **checking duplicated rows**
- **checking unique values per column**

In [ ]:
```
eda.display_shape_and_colnames_df(df, return_shape=False)
```

```
Dataframe Rows: 36831
Dataframe Columns: 6
Column names: ['Datetime', 'Tweet Id', 'Text', 'URL', 'User', 'tag']
```

In [ ]:
```python
class EDA2():
    def check_missing_values_df(self, df : pd.DataFrame):
        # verify parameters type
        verify_parameter(df, 'df', pd.DataFrame)

        # display missing values per column
        print_lines(n=30, line='=')
        print("# Missing values per column:")
        display(df.isna().sum())
        print_lines(n=30)
        print("% Missing values per column:")
        display(df.isna().mean() * 100)
        print_lines(n=30, line='=')

    def check_duplicated_rows_df(self, df : pd.DataFrame):
        # verify parameters type
        verify_parameter(df, 'df', pd.DataFrame)

        # display duplicates from the dataset
        print_lines(n=30, line='=')
        print("# Duplicated rows:", df.duplicated().sum())
        print_lines(n=30)
        print("% Duplicated rows:", round(df.duplicated().mean() * 100, 2))
        print_lines(n=30, line='=')

    def check_unique_values_df(self,df : pd.DataFrame):
        # verify parameters type
        verify_parameter(df, 'df', pd.DataFrame)

        # display unique values per column
        print_lines(n=30, line='=')
        print("# Unique values per column:")
        display(df.nunique())
        print_lines(n=30)
        print("% Unique values per column (relative to total rows):")
        display(round(df.nunique()*100 / df.shape[0], 2))
        print_lines(n=30, line='=')

eda = EDA2()
eda.check_missing_values_df(df)
```

```
eda.check_duplicated_rows_df(df)
eda.check_unique_values_df(df)
```

```
==============================
# Missing values per column:
Datetime    0
Tweet Id    0
Text        0
URL         0
User        0
tag         0
dtype: int64
------------------------------
% Missing values per column:
Datetime    0.0
Tweet Id    0.0
Text        0.0
URL         0.0
User        0.0
tag         0.0
dtype: float64
==============================
==============================
# Duplicated rows: 0
------------------------------
% Duplicated rows: 0.0
==============================
==============================
# Unique values per column:
Datetime    29029
Tweet Id    36371
Text        35661
URL         36371
User        18564
tag             8
dtype: int64
------------------------------
% Unique values per column (relative to total rows):
```

```
Datetime    78.82
Tweet Id    98.75
Text        96.82
URL         98.75
User        50.40
tag          0.02
dtype: float64
==============================
```

As we explore our final dataset we **gained the following insights**:

- Fortunately there are **no missing values within any of the columns**.
- The dataset contains **460 duplicated rows, which represents 1.25%** of the entire data.
- We have a very **elevated number of unique values per column**, which is expected as we are dealing with different tweets from users on various dates.

Let's proceed with the data cleaning step.

3. Cleaning Data

On this step we will **focus on cleaning the 'Text' column**, as it contains the **most valuable textual data from our dataset**.

Let's start by **implementing a class** in charge of **removing duplicates**.

These **duplicated rows only represented 1.25% of the total rows**; deleting them will benefit our analysis as we are **eliminating redundant data** probably wrongly measured from the real world.

Our class will be also in charge of the following tasks:

- **removing duplicated rows**
- **removing punctuations from the text**
- **removing numbers from the text**

In [ ]:
```
import string
import re
```

```python
class CleanData():

    def remove_duplicates_df(self, df : pd.DataFrame, reset_index : bool = True):
        # verify parameters type
        verify_parameter(df, 'df', pd.DataFrame)
        verify_parameter(reset_index, 'reset_index', bool)

        # perform the duplicate removal on a copy of the dataframe
        df_copy = df.copy()

        # check duplicates before and after removal
        eda = EDA2()
        print("Before Removal:")
        eda.check_duplicated_rows_df(df_copy)

        # actually remove the duplicates and reset index if specified
        df_copy.drop_duplicates(inplace=True)
        if reset_index: df_copy.reset_index(drop=True, inplace=True)

        # check duplicates before and after removal
        print("After Removal:")
        eda.check_duplicated_rows_df(df_copy)

        return df_copy


    def remove_punctuation_string(self, text : str):
        # verify parameters type
        verify_parameter(text, 'text', str)

        # return the string value but without punctuation
        return text.translate(str.maketrans('', '', string.punctuation))

    def remove_numbers_string(self, text : str):
        # verify parameters type
        verify_parameter(text, 'text', str)

        # return the string value but without numbers
        return re.sub(r'\d+', '', text)

cd = CleanData()
```

In [ ]:
```
# remove duplicates
df = cd.remove_duplicates_df(df)
# remove punctuation in Text column
df['Text'] = df['Text'].apply(cd.remove_punctuation_string)
# remove numbers in Text column
df['Text'] = df['Text'].apply(cd.remove_numbers_string)
```

```
Before Removal:
==============================
# Duplicated rows: 0
------------------------------
% Duplicated rows: 0.0
==============================
After Removal:
==============================
# Duplicated rows: 0
------------------------------
% Duplicated rows: 0.0
==============================
```

In [ ]:
```
df.tail()
```

Out[ ]:

	Datetime	Tweet Id	Text	URL	User	
36826	2023-03-06 04:17:24+00:00	1632596213588455425	RT missmayad Excited for Consensus Always impr...	https://twitter.com/varggasllosa/status/163259...	https://twitter.com/varggasllosa	coir
36827	2023-03-06 04:16:06+00:00	1632595887057932289	AndrewDARMACAP BillHughesDC Yes but CoinDesk ...	https://twitter.com/MattCorva/status/163259588...	https://twitter.com/MattCorva	coir
36828	2023-03-06 04:12:35+00:00	1632595004299386882	由CoinDesk策划，是加密货币和Web领域最大的年度活动之一Consensus大会，似乎...	https://twitter.com/xl941228/status/1632595004...	https://twitter.com/xl941228	coir
36829	2023-03-06 04:11:47+00:00	1632594802242977792	ahmadalfalasi CoinDesk do u think binance can ...	https://twitter.com/buridangripto1/status/1632...	https://twitter.com/buridangripto1	coir
36830	2023-03-06 04:06:30+00:00	1632593471042142213	milkywayeth source coindesk Arca's Hotz said...	https://twitter.com/hashtronaut207/status/1632...	https://twitter.com/hashtronaut207	coir

After performing the previously described cleaning steps we notice that our text column does not contain punctuation or numbers now, and we have also removed duplicated rows.

Now the number of **remaining rows on our dataset is around 36.3k.**

However, we **still have some non-relevant words and characters within our text column.**

For example: words of length 1 like emojis or other single character strings.

Let's **implement a second cleaning class** that will be in charge of:

- **identifying words of length "n"** (number defined as parameter) within the column 'Text'

- **removing these n-length words from the column 'Text'**
- **removing non alphabetic characters from the column 'Text'**

In [ ]:
```
import nltk
nltk.download('punkt')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

Out[ ]: True

In [ ]:
```
from nltk import word_tokenize

class CleanData2():

    def get_words_len_n(self, df : pd.DataFrame, col : str, n : int, display : bool = False, return_list : bool = True):
        # verify parameters type
        verify_parameter(df, 'df', pd.DataFrame)
        verify_parameter(col, 'col', str)
        verify_parameter(n, 'n', int)
        verify_parameter(display, 'display', bool)
        verify_parameter(return_list, 'return_list', bool)

        # initialize list of words of len n
        words = []

        # loop through unique values of the specified column
        for unique in df[col].unique():

            # get unique words len n from tokens of unique
            words += [word for word in word_tokenize(unique) if len(word) == n]

        # sort and delete repeated values in the list
        words = sorted(list(set(words)))

        if display:
            print("Words of length", n, "from column '" + col + "'")
            print(words)
        if return_list: return words
```

```
    def remove_words_df_col(self, df : pd.DataFrame, col : str, words : list):
        # verify parameters type
        verify_parameter(df, 'df', pd.DataFrame)
        verify_parameter(col, 'col', str)
        verify_parameter(words, 'words', list)

        # perform removal on a copy of the dataframe
        df_copy = df.copy()

        # loop through unique values of the column
        for unique in df[col].unique():
            # tokenize the unique value from the column
            tokens = word_tokenize(unique)

            # remove the words from the tokens
            tokens = [token for token in tokens if token not in words]

            # replace the new value in the df column
            df_copy[col].replace(unique, ' '.join(tokens), inplace=True)

        return df_copy

    def remove_chars_df_col(self, df : pd.DataFrame, col : str, chars : list):
        # verify parameters type
        verify_parameter(df, 'df', pd.DataFrame)
        verify_parameter(col, 'col', str)
        verify_parameter(chars, 'chars', list)

        # perform removal on a copy of the dataframe
        df_copy = df.copy()

        # remove all chars from the column values
        for char in chars:
            df_copy[col] = df_copy[col].str.replace(char, '', regex=False)

        return df_copy

cd2 = CleanData2()
```

In [ ]:
```
# save and display words of length 1 from column Text
```

```
words = cd2.get_words_len_n(df, 'Text', 1, display=True)
```

```
Words of length 1 from column 'Text'
['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L', 'M', 'N', 'O', 'P', 'Q', 'R', 'S', 'T', 'U', 'V', 'W', 'X', 'Y', 'Z', 'a',
'b', 'c', 'd', 'e', 'f', 'g', 'h', 'i', 'j', 'k', 'l', 'm', 'n', 'o', 'p', 'q', 'r', 's', 't', 'u', 'v', 'w', 'x', 'y', 'z', '¡', '£',
'¥', '«', '¯', '°', '±', '´', '·', '»', '¿', 'À', 'È', 'É', 'Ö', 'à', 'á', 'å', 'è', 'é', 'ñ', 'ó', 'ü', 'ý', 'ı', '̀', '̳', '̂', 'Ξ', 'ή',
'η', 'ω', 'А', 'В', 'И', 'С', 'У', 'Я', 'а', 'в', 'з', 'и', 'о', 'п', 'с', 'у', 'я', 'і', '،', 'ي', 'و', 'م', 'ف', 'ع', 'د', 'ب', '؟',
'٪', 'ँ', 'ॅ', 'आ', 'न', 'ට', 'ඣ', 'ඉ', 'ด', 'อ', '่', '฿', '׳', 'ạ', 'ở', '\u200b', '‐', '–', '‘', '’', '“', '”', '„', '•', '‣', '…', '․',
'›', '‿', '\u2060', '₦', '€', '₱', '₹', '₺', '₿', '⃣', '↑', '→', '↓', '∂', '−', '√', '∠', '⊂', '⊃', '⋆', '⏎', '⏏', '⏪', '⏫', '⏬',
'⏰', '⏳', '─', '│', '┐', '║', '╥', '▬', '■', '▪', '▰', '▶', '▸', '►', '◆', '●', '◔', '◼', '★', '☆', '♗', '♡', '♥', '♦', '♪',
'♫', '♾', '⚒', '⚔', '⚠', '⚡', '⚦', '⚽', '⛏', '⛓', '⛔', '⛵', '✅', '✊', '✌', '✍', '✔', '✨', '❌', '❓', '❜', '❤',
'➕', '➖', '➡', '➤', '⟶', '　', '⦁', '⦿', '⧫', '⭐', '。', '【', '】', 'あ', 'え', 'っ', 'と', 'の', 'み', '・', 'ー', 'ㅋ', ' ',
'与', '个', '億', '円', '和', '哎', '在', '夜', '将', '据', '日', '月', '来', '様', '歩', '猫', '町', '的', '腸', '話', '谈', '金', '鍵',
'革', '黒', 'ꝋ', '간', '갈', '걍', '거', '건', '것', '곳', '그', '꼭', '나', '날', '내', '넌', '년', '눈', '늘', '다', '더', '돈', '돼',
'된', '등', '또', '막', '말', '몸', '뭐', '뭘', '미', '및', '배', '비', '수', '시', '싹', '썰', '아', '안', '앗', '약', '에', '온', '왜',
'원', '으', '의', '이', '인', '일', '자', '잘', '저', '전', '제', '좀', '줄', '중', '짱', '참', '첩', '캐', '코', '쿳', '키', '트', '폰',
'한', '할', '해', '헉', '화', '후', '훗', '﴾', '﴿', 'ﷺ', '︿', '！', '＋', '，', '／', '：', '＼', '～', '｡', '￼', '𝐈', '𝐼', '𝑰', '🆒',
'🆓', '🆕', '🆘', '🌃', '🌄', '🌆', '🌈', '🌊', '🌍', '🌎', '🌏', '🌐', '🌕', '🌙', '🌚', '🌛', '🌝', '🌞', '🌟', '🌠', '🌮',
'🌱', '🌴', '🌷', '🌸', '🌹', '🌺', '🌽', '🍀', '🍄', '🍅', '🍌', '🍎', '🍑', '🍒', '🍓', '🍕', '🍜', '🍝', '🍡', '🍪', '🍫',
'🍱', '🍴', '🍵', '🍹', '🍺', '🍻', '🍿', '🎁', '🎂', '🎉', '🎍', '🎏', '🎓', '🎙', '🎢', '🎣', '🎤', '🎥', '🎧', '🎨', '🎩',
'🎫', '🎬', '🎮', '🎯', '🎰', '🎱', '🎲', '🎵', '🎶', '🎸', '🎼', '🎾', '🏀', '🏅', '🏆', '🏇', '🏏', '🏑', '🏗', '🏚', '🏢',
'🏥', '🏛', '🏧', '🏫', '🏹', '🐀', '🐂', '🐇', '🐉', '🐋', '🐍', '🐎', '🐕', '🐈', '🐖', '🐝', '🐞', '🐟', '🐣', '🐦', '🐨',
'🐬', '🐮', '🐯', '🐰', '🐱', '🐲', '🐳', '🐶', '🐸', '🐺', '🐻', '🐾', '👀', '👁', '👂', '👃', '👇', '👈', '👉', '👊', '👋',
'👌', '👍', '👎', '👏', '👑', '👛', '👟', '👠', '👥', '👧', '👴', '👹', '👻', '👼', '👽', '👾', '💀', '💂', '💉', '💊', '💋',
'💍', '💎', '💐', '💓', '💔', '💕', '💖', '💗', '💙', '💚', '💛', '💜', '💞', '💠', '💡', '💣', '💥', '💧', '💩', '💪', '💫',
'💬', '💭', '💯', '💰', '💱', '💲', '💳', '💵', '💶', '💸', '💹', '💻', '💼', '💿', '📀', '📃', '📅', '📈', '📉', '📊', '📋',
'📌', '📍', '📎', '📏', '📑', '📒', '📓', '📕', '📖', '📚', '📝', '📞', '📢', '📣', '📦', '📩', '📰', '📱', '📲', '📷', '📽',
'📺', '📻', '🔁', '🔆', '🔉', '🔋', '🔌', '🔍', '🔎', '🔐', '🔑', '🔔', '🔖', '🔗', '🔜', '🔝', '🔞', '🔟', '🔥', '🔧', '🔫',
'🔭', '🔮', '🔱', '🔲', '🔴', '🔵', '🔶', '🔷', '🔸', '🔹', '🔺', '🔻', '🔼', '🔽', '🕑', '🕒', '🕯', '🖇', '🖐', '🖕', '🖤',
'🗒', '🖼', '🗑', '🗓', '🗞', '🗺', '🗼', '🗿', '😀', '😁', '😂', '😃', '😄', '😅', '😆', '😇', '😈', '😉', '😊', '😋', '😌',
'😍', '😎', '😏', '😐', '😑', '😒', '😓', '😔', '😕', '😖', '😘', '😙', '😛', '😜', '😝', '😞', '😟', '😠', '😡', '😢', '😣',
'😤', '😥', '😦', '😨', '😩', '😪', '😫', '😬', '😭', '😮', '😰', '😱', '😲', '😳', '😴', '😶', '😹', '😺', '😻', '😼', '🙁',
'🙂', '🙃', '🙄', '🙅', '🙈', '🙉', '🙊', '🙋', '🙌', '🙏', '🚀', '🚂', '🚗', '🚨', '🚩', '🚫', '🚹', '🚿', '🛐', '🛒', '\U000
1f6df', '🛠', '🛸', '🛻', '🟠', '🟡', '🟢', '🟣', '🟥', '🟦', '🟩', '🤌', '🤍', '🤎', '🤑', '🤒', '🤓', '🤔', '🤕', '🤖',
'🤗', '🤘', '🤙', '🤝', '🤞', '🤟', '🤠', '🤡', '🤢', '🤣', '🤤', '🤦', '🤧', '🤨', '🤩', '🤪', '🤫', '🤬', '🤭', '🤮', '🤯',
'🤲', '🤳', '🤴', '🤷', '🥀', '🥁', '🥂', '🥇', '🥈', '🥉', '🥊', '🥐', '🥑', '🥘', '🥞', '🥡', '🥣', '🥤', '🥰', '🥱', '🥲',
'🥳', '🥴', '🥵', '🥶', '🥷', '🥸', '\U0001f979', '🥺', '🥽', '🦄', '🦅', '🦇', '🦈', '🦉', '🦊', '🦍', '🦗', '🦘', '🦾',
'🧀', '🧃', '🧊', '🧐', '🧙', '🧠', '🧡', '🧢', '🧧', '🧩', '🧪', '🧬', '🧱', '🧲', '🧵', '🧸', '🧹', '🧼', '🧿', '\U0001fa7
7', '🩸', '🪂', '🪄', '🪙', '🪜', '🪞', '🪦', '\U0001faa9', '\U0001fab7', '🪻', '🫐', '\U0001fae0', '\U0001fae1', '\U0001fae2', '\U
0001fae3', '\U0001fae5', '\U0001faf0', '\U0001faf4', '\U0001faf5', '\U0001faf6']
```

We have defined n as 1, and we rapidly notice **very unusual 1-length words like emojis, and other language characters.**

Let's proceed by **removing them from our 'Text' column.**

In [ ]:
```
# remove words of length 1 from column Text
df = cd2.remove_words_df_col(df, 'Text', words)
```

In [ ]:
```
df.tail()
```

Out[ ]:

	Datetime	Tweet Id	Text	URL	User	
36826	2023-03-06 04:17:24+00:00	1632596213588455425	RT missmayad Excited for Consensus Always impr...	https://twitter.com/varggasllosa/status/163259...	https://twitter.com/varggasllosa	coir
36827	2023-03-06 04:16:06+00:00	1632595887057932289	AndrewDARMACAP BillHughesDC Yes but CoinDesk n...	https://twitter.com/MattCorva/status/163259588...	https://twitter.com/MattCorva	coir
36828	2023-03-06 04:12:35+00:00	1632595004299386882	由CoinDesk策划，是加密货币和Web领域最大的年度活动之一Consensus大会，似乎...	https://twitter.com/xl941228/status/1632595004...	https://twitter.com/xl941228	coir
36829	2023-03-06 04:11:47+00:00	1632594802242977792	ahmadalfalasi CoinDesk do think binance can be...	https://twitter.com/buridangripto1/status/1632...	https://twitter.com/buridangripto1	coir
36830	2023-03-06 04:06:30+00:00	1632593471042142213	milkywayeth source coindesk Arca Hotz said the...	https://twitter.com/hashtronaut207/status/1632...	https://twitter.com/hashtronaut207	coir

Event though we removed 1-length words, we still have some emojis due to these being considered words for being attached between blank spaces.

Let's actually **check the non-alphabetic characters** now and **remove these unusual characters from our text.**

In [ ]:
```
# get non-alphabetic characters
unique_chars = list(set(df['Text'].apply(list).sum()))
non_alphabetic_chars = [char for char in unique_chars if not char.isalpha()]
if ' ' in non_alphabetic_chars: non_alphabetic_chars.remove(' ')

# remove non-alphabetic characters from column Text
df = cd2.remove_chars_df_col(df, 'Text', non_alphabetic_chars)
```

In [ ]:
```
df.tail()
```

Out[ ]:

	Datetime	Tweet Id	Text	URL	User	
36826	2023-03-06 04:17:24+00:00	1632596213588455425	RT missmayad Excited for Consensus Always impr...	https://twitter.com/varggasllosa/status/163259...	https://twitter.com/varggasllosa	coir
36827	2023-03-06 04:16:06+00:00	1632595887057932289	AndrewDARMACAP BillHughesDC Yes but CoinDesk n...	https://twitter.com/MattCorva/status/163259588...	https://twitter.com/MattCorva	coir
36828	2023-03-06 04:12:35+00:00	1632595004299386882	由CoinDesk策划是加密货币和Web领域最大的年度活动之一Consensus大会似乎活动...	https://twitter.com/xl941228/status/1632595004...	https://twitter.com/xl941228	coir
36829	2023-03-06 04:11:47+00:00	1632594802242977792	ahmadalfalasi CoinDesk do think binance can be...	https://twitter.com/buridangripto1/status/1632...	https://twitter.com/buridangripto1	coir
36830	2023-03-06 04:06:30+00:00	1632593471042142213	milkywayeth source coindesk Arca Hotz said the...	https://twitter.com/hashtronaut207/status/1632...	https://twitter.com/hashtronaut207	coir

Now we have a **more clean dataset** and the goal of this section has been achieved.

Let's proceed to the data visualization.

4. Visualizing Data

In [ ]:
```
# library to plot wordclouds
from wordcloud import WordCloud
```

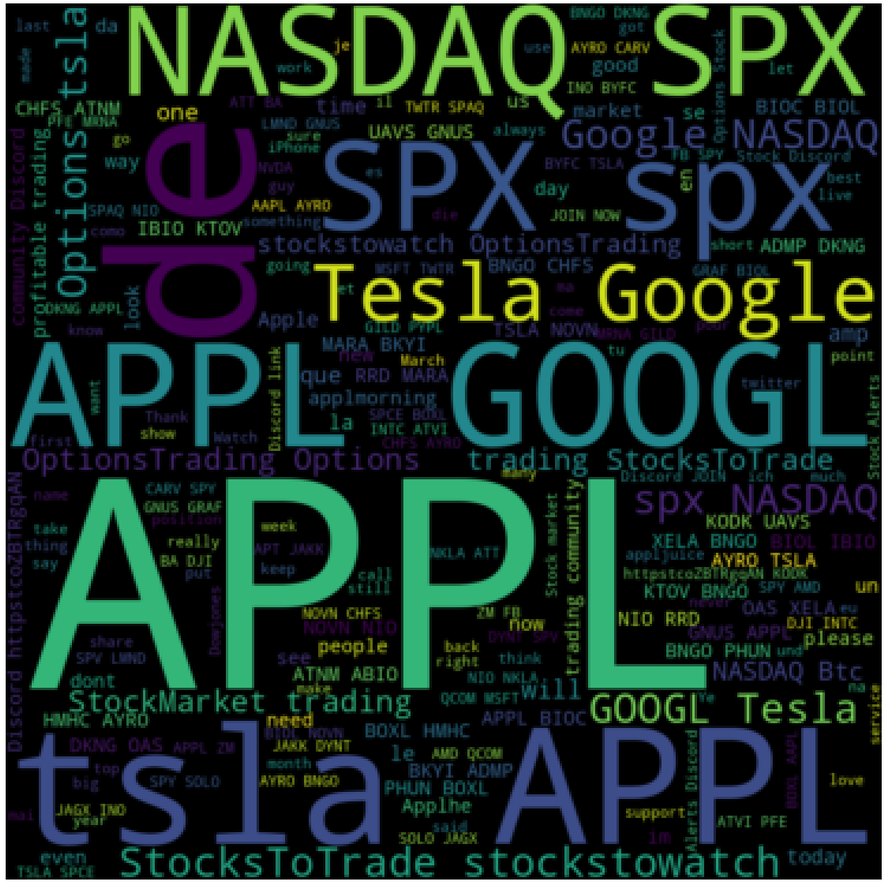
Let's plot the word clouds for every stock market tweets group.

We will **loop through the tags and plot 1 wordcloud for every unique tag (8 in total)**

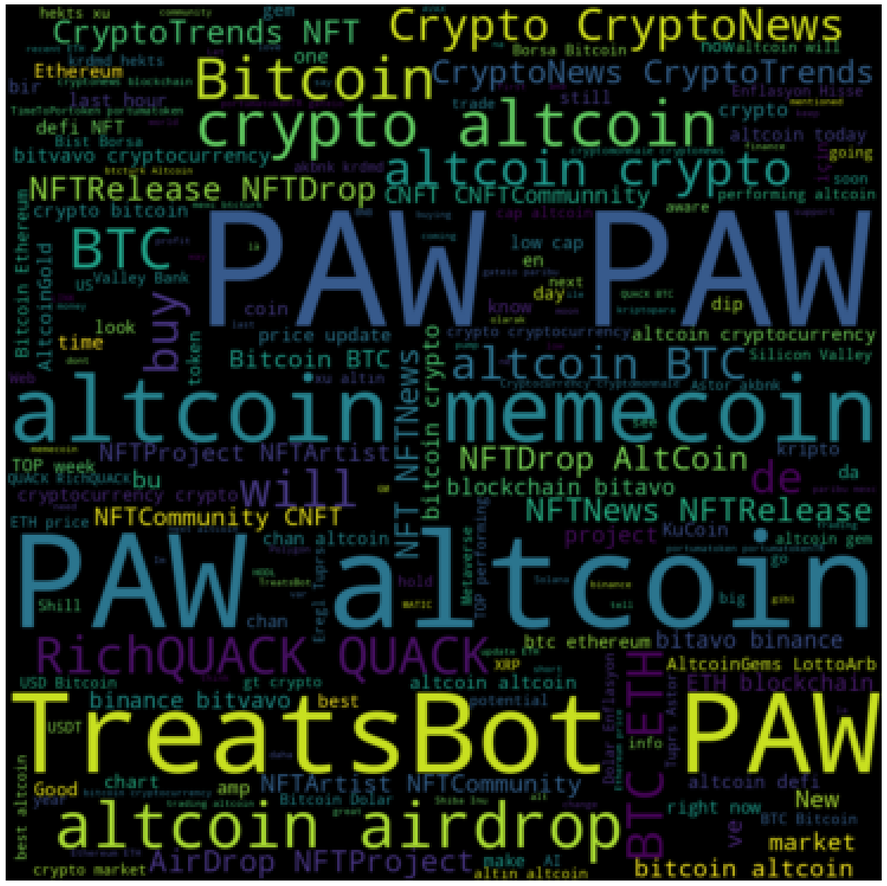
These wordclouds show us the **most common words within the tweets for each of the stock market tags.**

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns
for tag in df['tag'].unique():
  data = df[df['tag']==tag]
  text = ' '.join(data['Text'])

  wordcloud = WordCloud(width=900, height=900, background_color='black').generate(text)
  # Display the generated image:
  plt.imshow(wordcloud, interpolation='bilinear')
  plt.title(f'Wordcloud for {tag} tweets')
  plt.axis("off")
  plt.show()
```

Wordcloud for APPL tweets



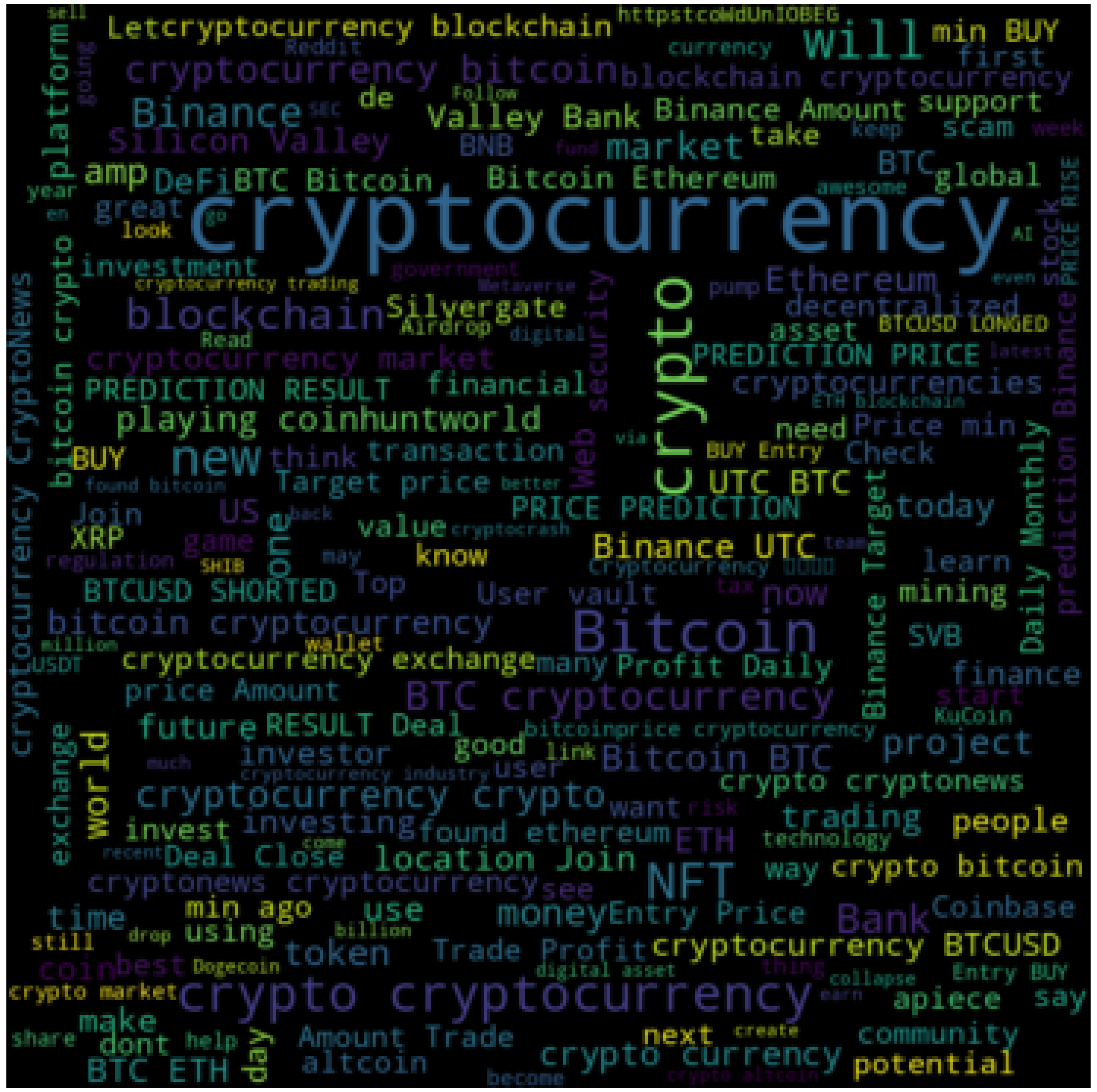
Wordcloud for altcoin tweets



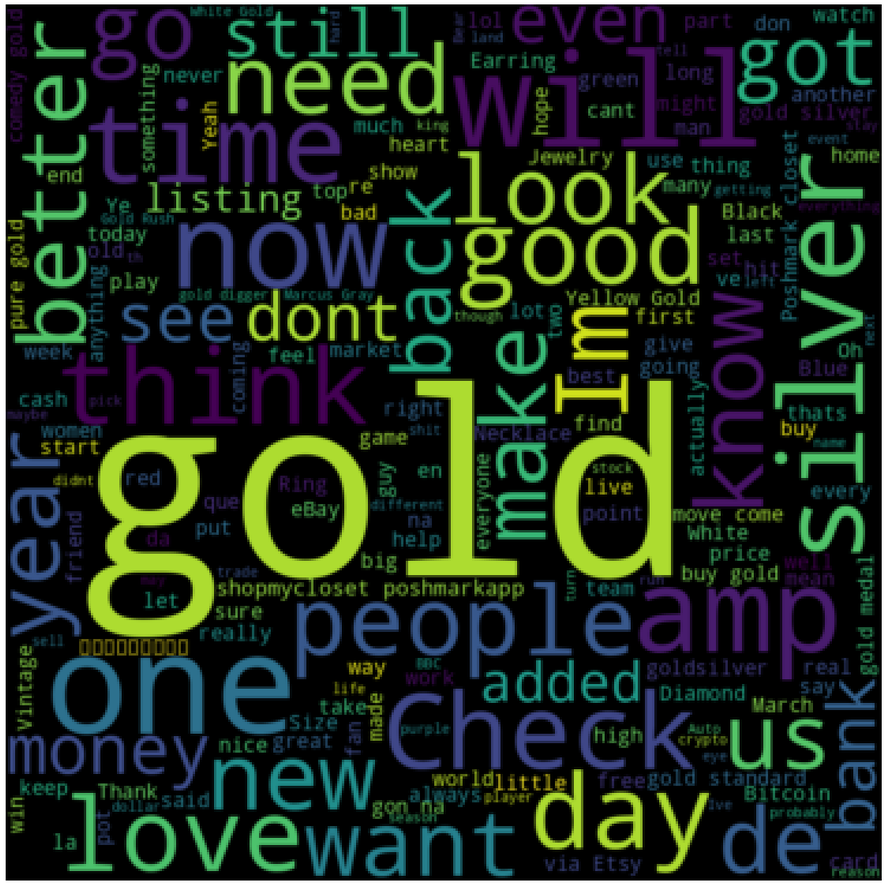
Wordcloud for GOOG tweets

Wordcloud for bitcoin tweets

Wordcloud for Cryptocurrency tweets



Wordcloud for Gold tweets



Wordcloud for YHOO tweets

Now that we identified the most common words within the tweets.

Let's actually **plot the daily number of tweets per keywords and per user.**

First, we will need to **convert our datetime column into datetime type.**

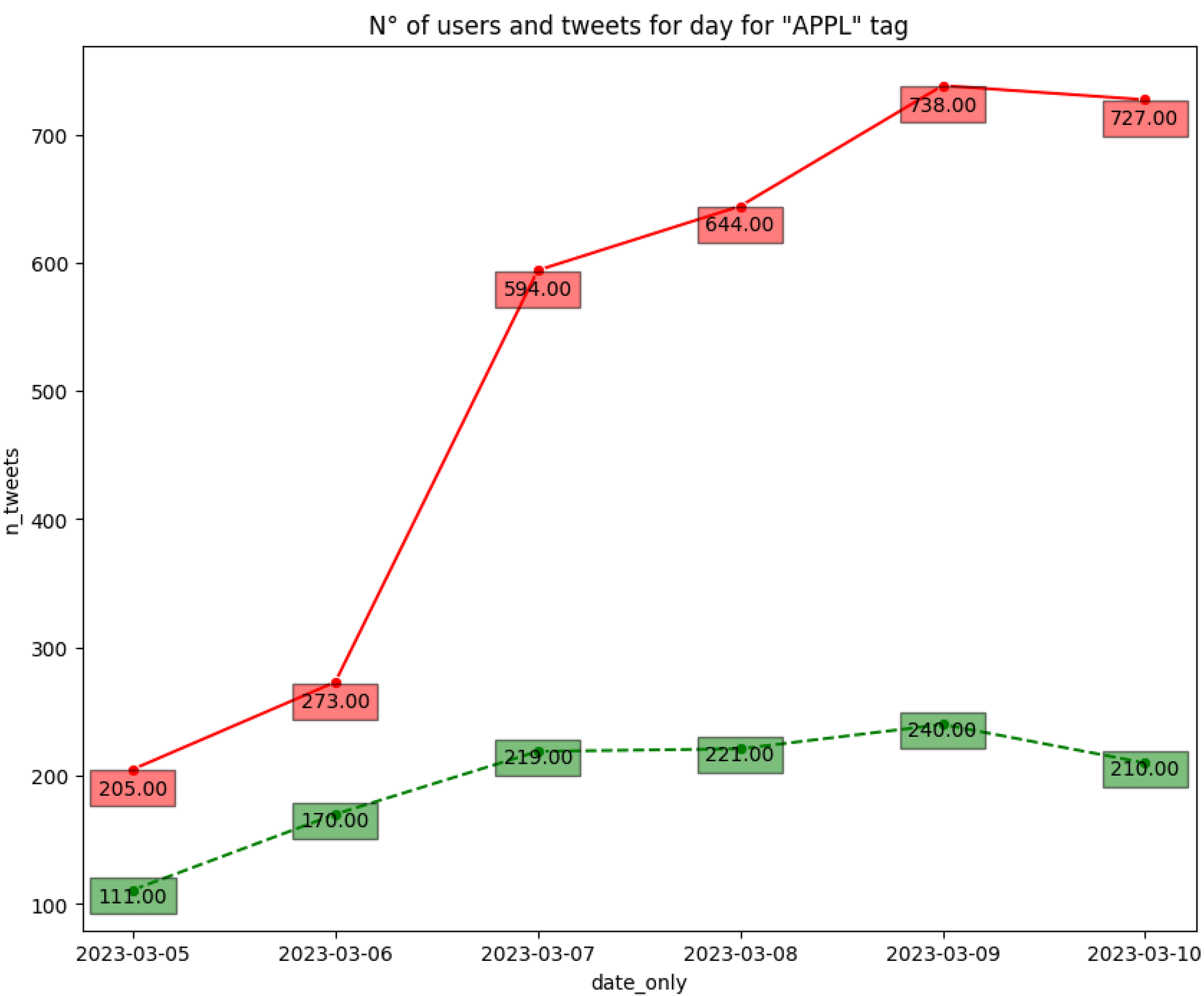
Then we will **loop through the tags and plot the number of tweets and users over time using a line plot.**

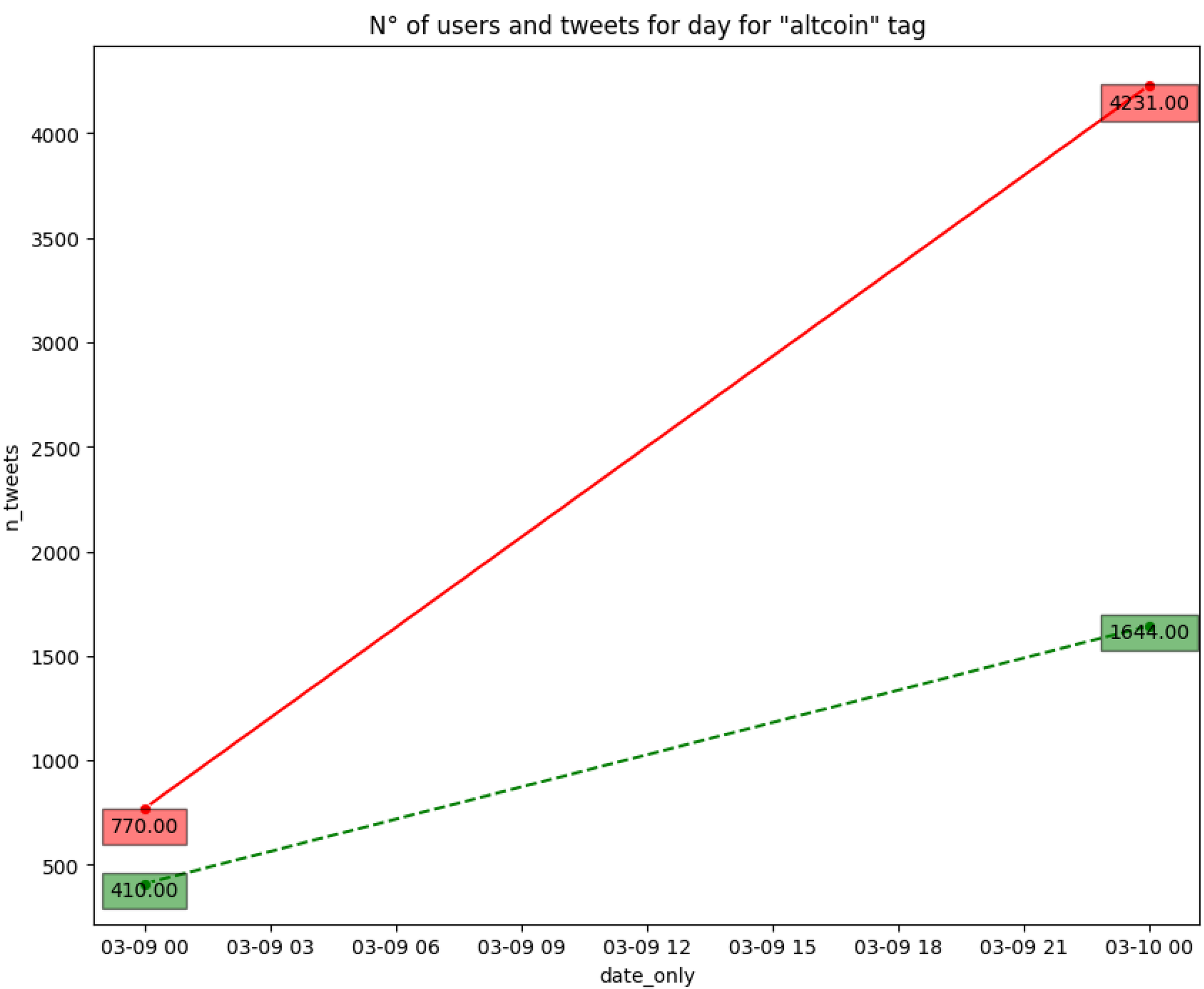
Remember:

- **red line represents number of tweets**
- **green line represents number of users.**

In [ ]:
```
# convert date column into datetime type
df['Datetime'] = df['Datetime'].apply(pd.to_datetime)
```

In [ ]:
```
#create a date column just for the date so we can group per day
df['date_only'] = df['Datetime'].dt.date

# group for each tags
for tag in df['tag'].unique():
  #subset the data
  temp = df[df['tag']==tag]
  #number of uniques in tweets and users for a date
  temp_grouped = temp.groupby('date_only').agg( n_tweets = ('Tweet Id','nunique'), n_users = ('User','nunique'))

  #creating a plot
  plt.figure(figsize= (10,8))
  #lineplot for no of tweets
  sns.lineplot(temp_grouped, x = 'date_only', y = 'n_tweets', color = 'r', marker = 'o')
  #margin for the annotation
  margin = 0.02 * max(temp_grouped['n_tweets'])
  #setting up annotation
for x, y in zip(temp_grouped.index,temp_grouped['n_tweets']):
        plt.text(x,y-margin ,f'{y:.2f}',horizontalalignment='center',
    verticalalignment='center',bbox=dict(facecolor='red', alpha = 0.5)) #some decorations

sns.lineplot(temp_grouped, x = 'date_only', y = 'n_users', color = 'g',marker = 'o',  linestyle = '--' )

margin = 0.02 * max(temp_grouped['n_users'])
for x, y in zip(temp_grouped.index,temp_grouped['n_users']):
        plt.text(x,y-margin,f'{y:.2f}', horizontalalignment='center',
    verticalalignment='center',bbox=dict(facecolor='green', alpha = 0.5))

plt.title(f'N° of users and tweets for day for "{tag}" tag')
```


N° of users and tweets for day for "APPL" tag
n_tweets
700
600
500
400
300
200
100
738.00
727.00
644.00
594.00
273.00
205.00
219.00
221.00
240.00
210.00
170.00
111.00
2023-03-05
2023-03-06
2023-03-07
2023-03-08
2023-03-09
2023-03-10
date_only


N° of users and tweets for day for "altcoin" tag
n_tweets
4000
3500
3000
2500
2000
1500
1000
500
4231.00
1644.00
770.00
410.00
03-09 00
03-09 03
03-09 06
03-09 09
03-09 12
03-09 15
03-09 18
03-09 21
03-10 00
date_only

N° of users and tweets for day for "GOOG" tag

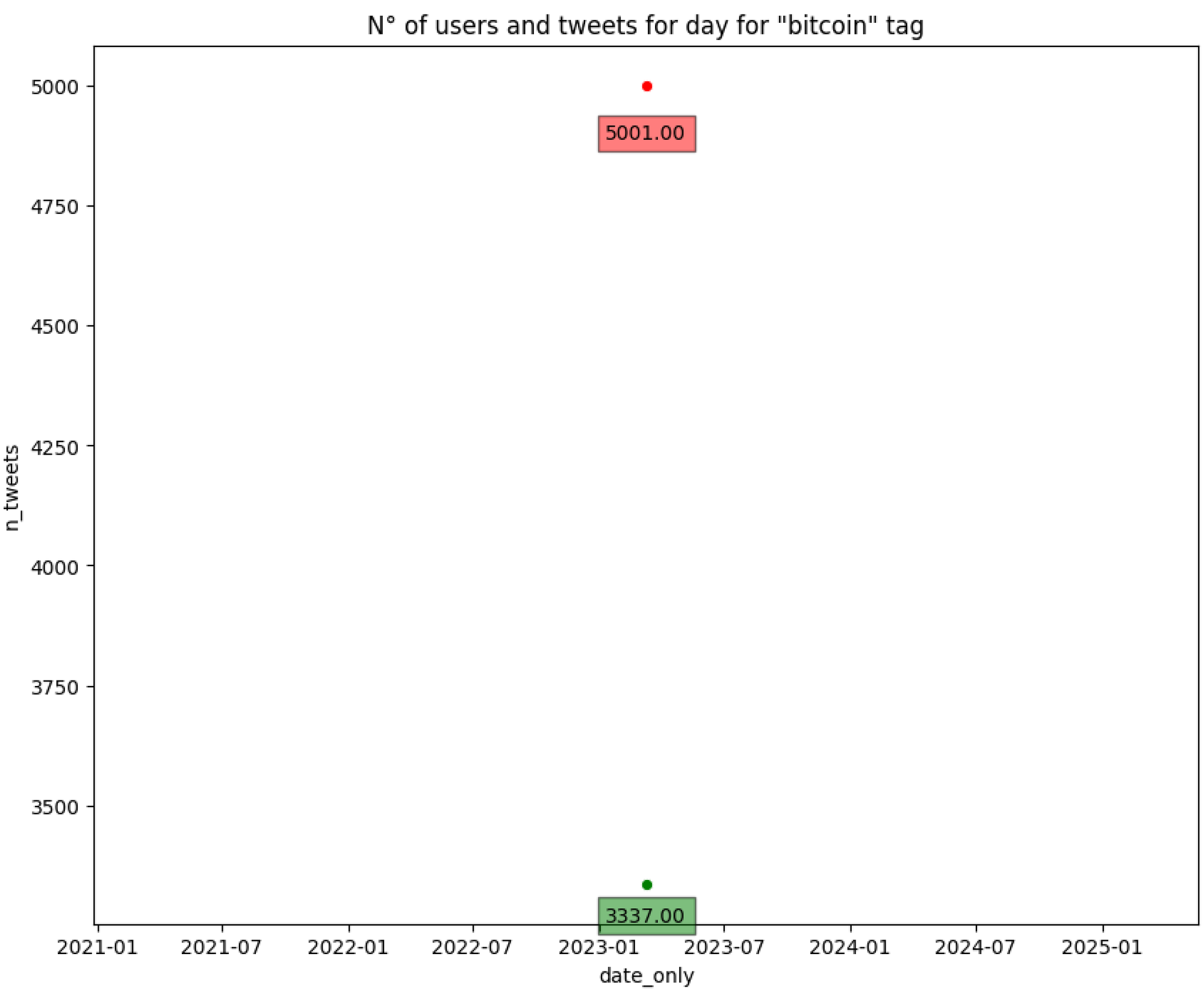
n_tweets

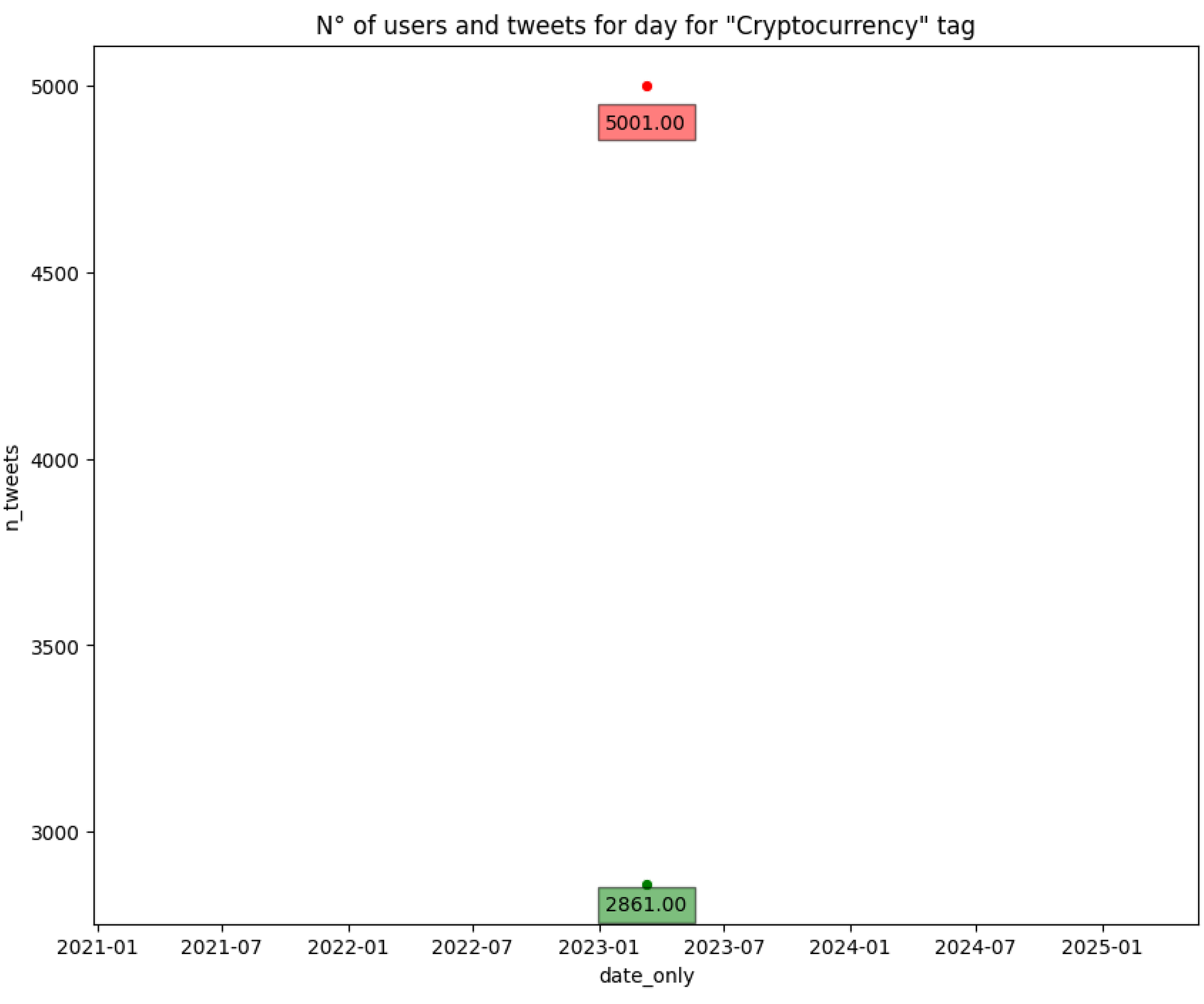
1000
900
800
700
600
500
400
300

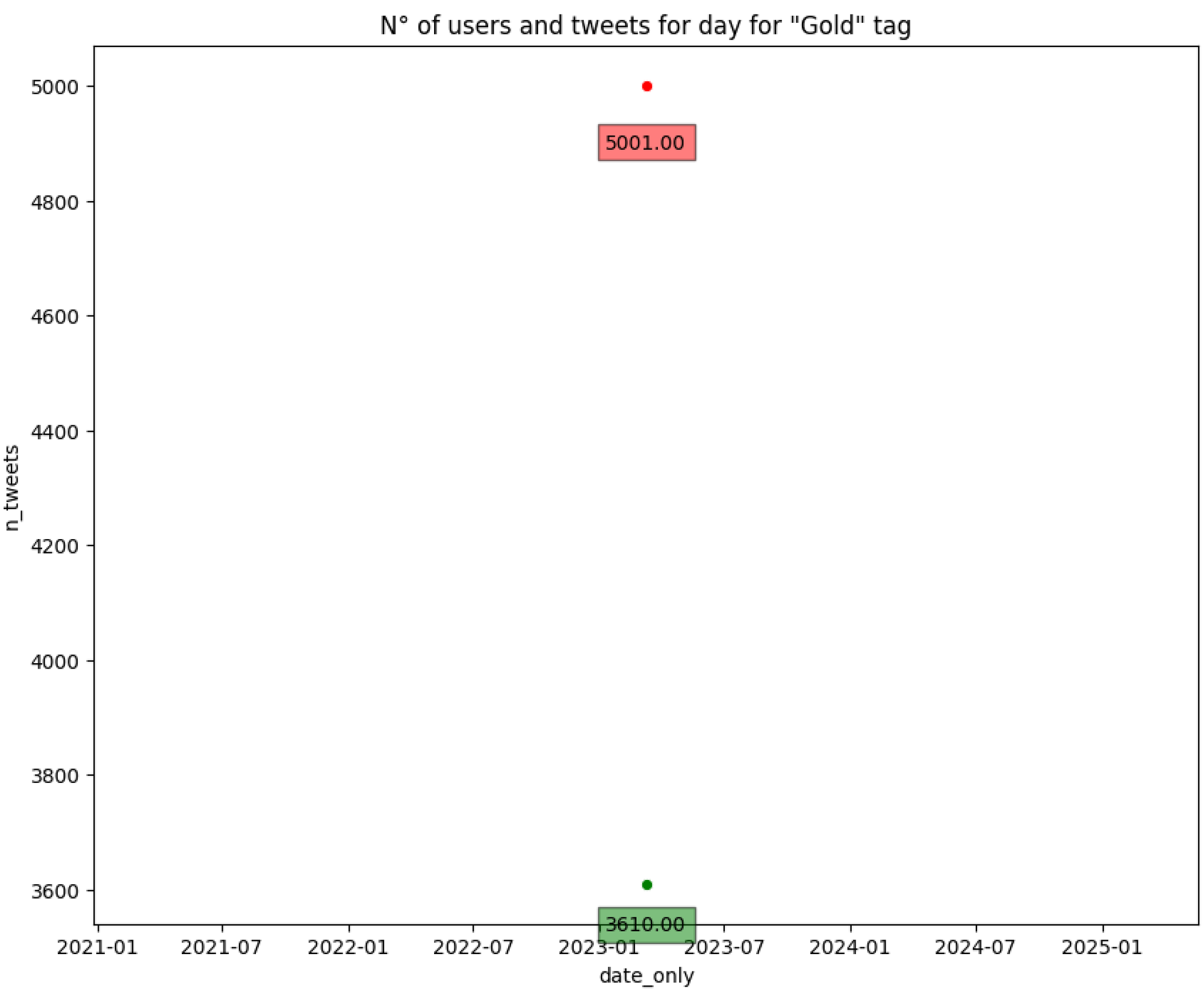
827.00
855.00
963.00
1006.00
917.00
433.00
529.00
499.00
543.00
530.00
484.00
250.00

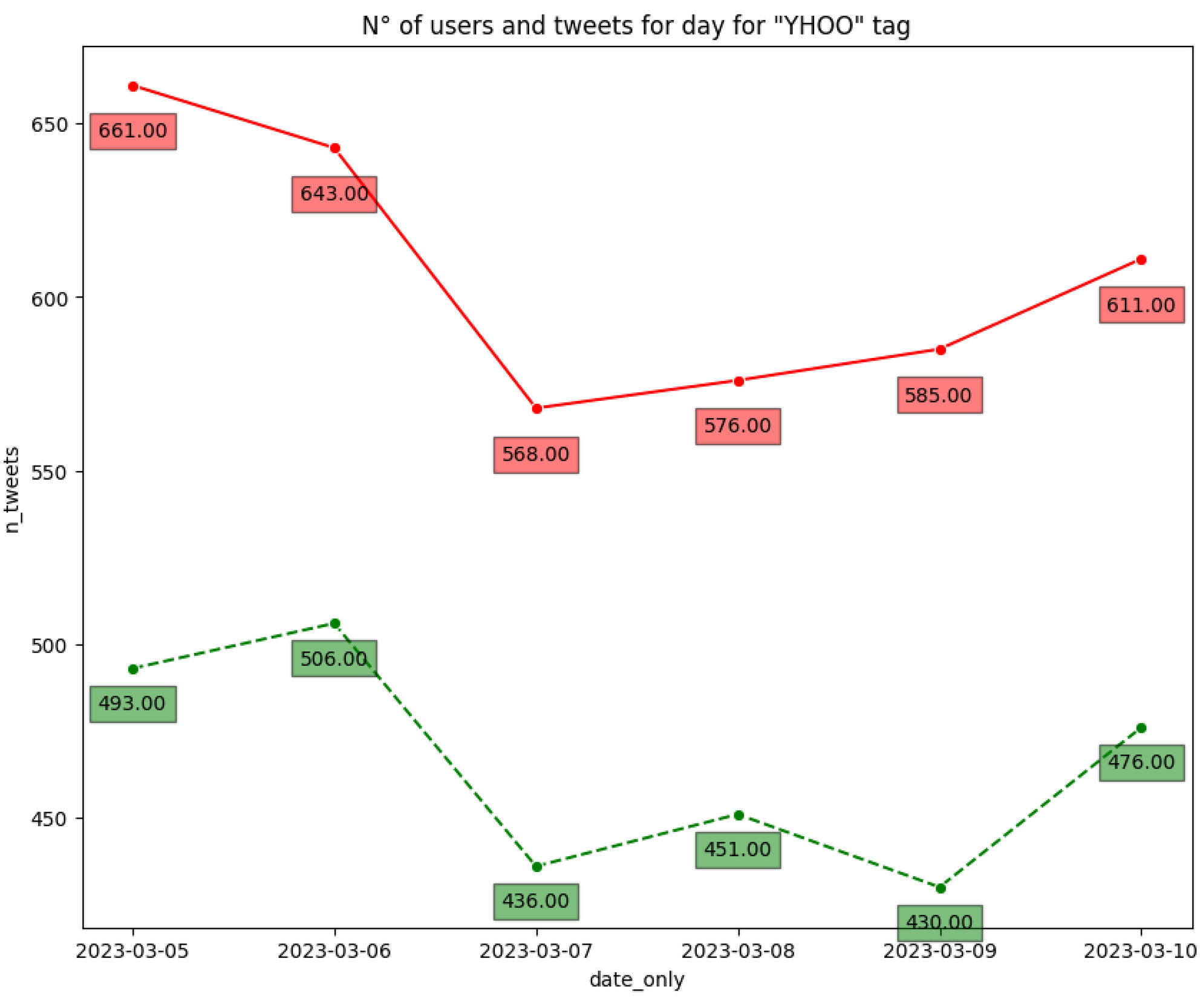
2023-03-05
2023-03-06
2023-03-07
2023-03-08
2023-03-09
2023-03-10

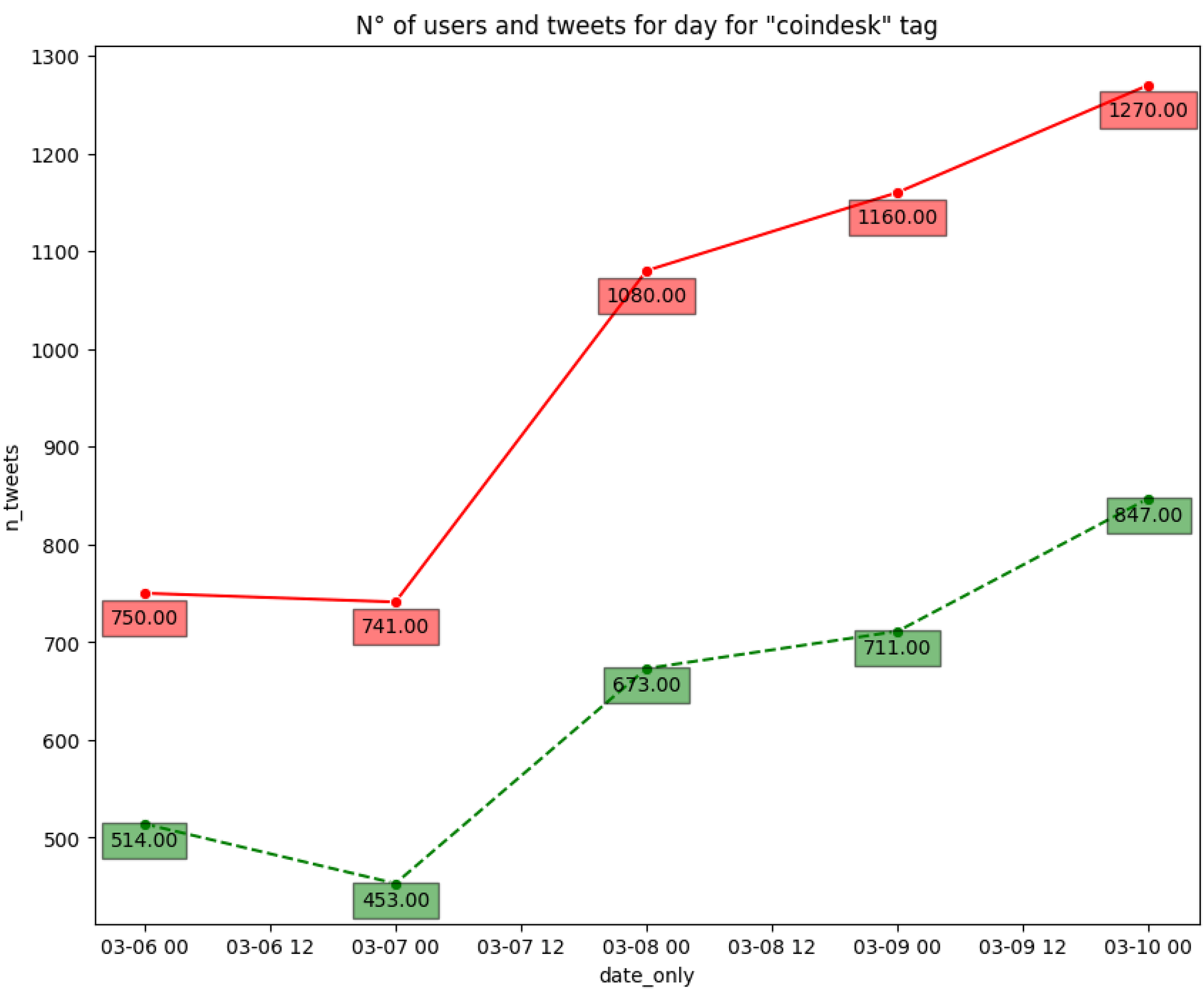
date_only


N° of users and tweets for day for "bitcoin" tag
5001.00
3337.00
5000
4750
4500
4250
4000
3750
3500
n_tweets
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01
date_only


N° of users and tweets for day for "Cryptocurrency" tag
5001.00
2861.00
5000
4500
4000
3500
3000
n_tweets
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01
date_only


N° of users and tweets for day for "Gold" tag
5001.00
3610.00
5000
4800
4600
4400
4200
4000
3800
3600
n_tweets
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01
date_only


N° of users and tweets for day for "YHOO" tag
n_tweets
650
600
550
500
450
661.00
643.00
568.00
576.00
585.00
611.00
493.00
506.00
436.00
451.00
430.00
476.00
2023-03-05
2023-03-06
2023-03-07
2023-03-08
2023-03-09
2023-03-10
date_only


N° of users and tweets for day for "coindesk" tag
n_tweets
date_only
1300
1200
1100
1000
900
800
700
600
500
03-06 00
03-06 12
03-07 00
03-07 12
03-08 00
03-08 12
03-09 00
03-09 12
03-10 00
1270.00
1160.00
1080.00
750.00
741.00
847.00
711.00
673.00
514.00
453.00

We notice that for most of the stock market groups, the **number of tweets and users keep growing over time**, **except for the YAHOO tag**, which started **decreasing around May 202__3 and then slowly __came back until October 2023**.

Another thing to notice is that for **some tags like bitcoin, crpytocurrency, and Gold**; there are single points data, meaning that **most of these data comes from a single day.**

Let's proceed with a **unified view of the # of users over time per each category/tag.**

In [ ]:
```
# Group by 'date' and 'tag', and count the unique number of users
data_counts = df.groupby(['date_only', 'tag'])['User'].nunique().unstack()

plt.figure(figsize = (10,8))
sns.lineplot(data_counts, marker = 'o',palette = 'coolwarm')

#labels and title
plt.title('Number of Users for Each Tags Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Users')
plt.legend(title='Tags')

plt.show()
```

Number of Users for Each Tags Over Time

Tags
APPL
Cryptocurrency
GOOG
Gold
YHOO
altcoin
bitcoin
coindesk

Number of Users
3500
3000
2500
2000
1500
1000
500
0

2023-03-05
2023-03-06
2023-03-07
2023-03-08
2023-03-09
2023-03-10

Date

As we can visualize, most of the categories follow a similar behaviour on the number of users.

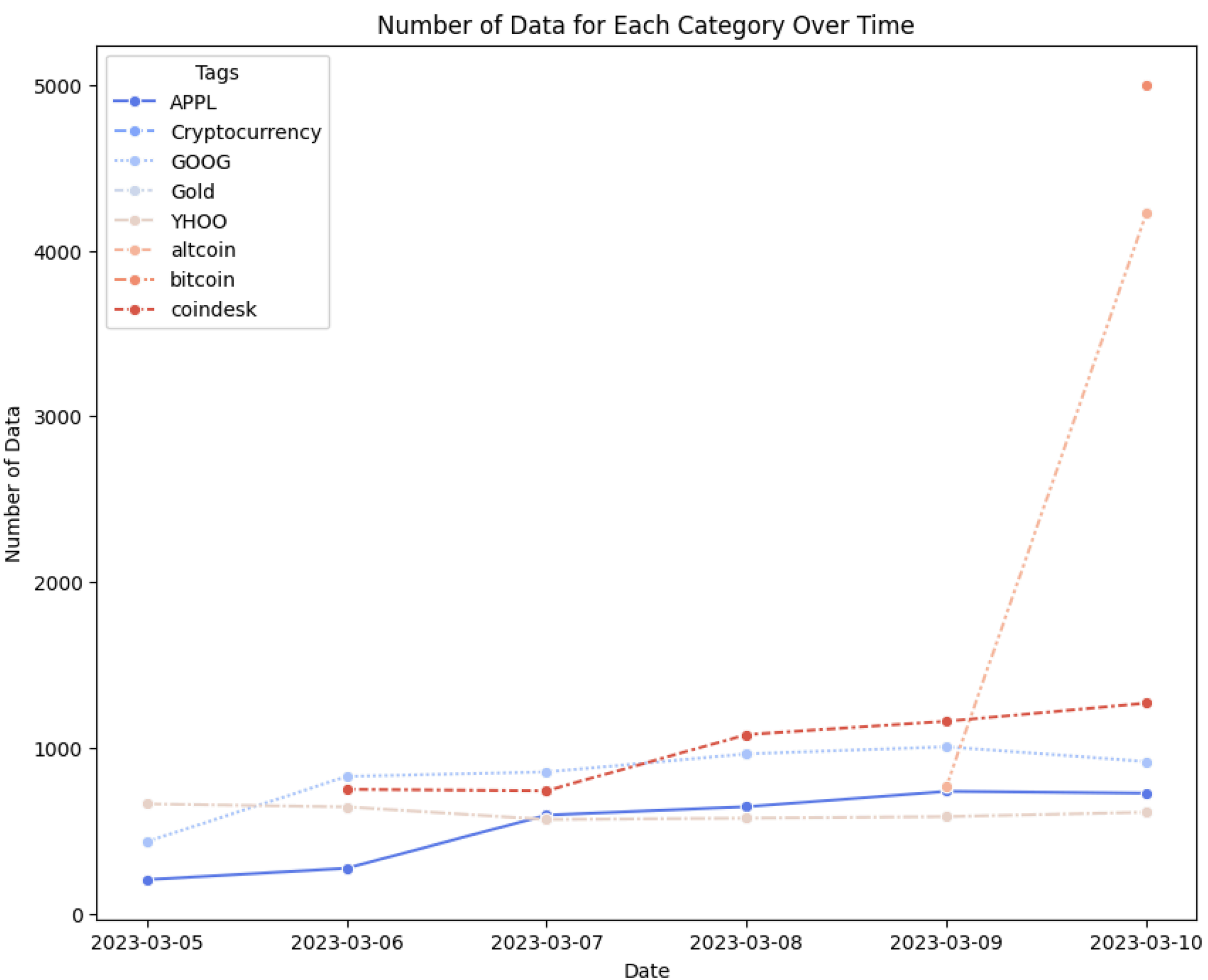
However, **'altcoin' presents an unusual spike** just at the right end of the timeline **(September - October 2023).**

Once again we notice that overall, **all categories have slowly increased their number of users over time.**

Let's finalize our visualization by **plotting a timeline of unique number of tweets per category.**

For this plot we will use the column 'Tweet Id' as it's the unique identifier of the posted tweet.

In [ ]:
```
# Group by 'date' and 'tag', and count the unique number of tweets
data_counts = df.groupby(['date_only', 'tag'])['Tweet Id'].nunique().unstack()

plt.figure(figsize = (10,8))
sns.lineplot(data_counts, marker = 'o', palette = 'coolwarm')

# labels and title
plt.title('Number of Data for Each Category Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Data')
plt.legend(title='Tags')

plt.show()
```


Number of Data for Each Category Over Time
Tags
APPL
Cryptocurrency
GOOG
Gold
YHOO
altcoin
bitcoin
coindesk
Number of Data
5000
4000
3000
2000
1000
0
2023-03-05
2023-03-06
2023-03-07
2023-03-08
2023-03-09
2023-03-10
Date

Final insights:

- **Unique tweets over time also displays a slowly growth over time for the year 2023.**
- **'altcoin'** presents an **unsual spike** of over **4 thousand** unique tweets from September - October 2023.
- **'YAHOO'** category has instead **decreased** the number of unique tweets over time.
- **Overall, we uncovered a hidden pattern within the tweets, demystifying the growth of tweets and users for the 2023 year for each category and identifying unique outlier behaviours (altcoin and Yahoo).**