Trader Influencers Stream

Pool dataset into jupyter notebook from Google SQL, credential file is named macrox.json.

All seven streams are included in the tables list, this file will focus on Trader Influencers dataset only

In [1]:
```
#pip install gcsfs
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import sys

import re,string #deal with special characteristics in hashtag and text

import datetime
from timeit import default_timer as timer

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
os.environ['GOOGLE_APPLICATION_CREDENTIALS'] = 'macrox.json'

tables = ['twitter_stream_macro_institutions',
 'twitter_stream_econ_news',
 'twitter_stream_investment_communities',
 'twitter_stream_us_politicians',
 'twitter_stream_federal_reserve',
 'twitter_stream_india_covid',
 'twitter_stream_trader_influencers']
```

In [3]:
```
df = pd.read_csv('gs://capstone_twitter/capstone/' + tables[6] + '.csv', index_col= 0)
```

1. Simple EDAs

1.1 General Information

In [4]:
```
df.head()
```

Out[4]:

	status_id	created_at	user_screen_name	user_id	followers	location	coordinates	is_retweet	retweet_count

	status_id	created_at	user_screen_name	user_id	followers	location	coordinates	is_retweet	retweet_count
0	1417364080533274625	2021-07-20 06:01:44	sogrand46866232	1415620489339277313	0	None	None	False	0
1	1417364878285807617	2021-07-20 06:04:55	wtfanother	1409182719863668745	7	None	None	False	0
2	1417367179029188614	2021-07-20 06:14:03	EvWaugh91	1410864411594526720	6	New York	None	False	0
3	1418689535324610563	2021-07-23 21:48:37	TwitTomTwit	38369111	0	None	None	False	0
4	1417367949325729796	2021-07-20 06:17:07	RahulSi02050001	1140158377789575168	66	None	None	False	0

In [5]:

```
df.text[4]
```

Out[5]:

```
'@charliebilello Now wait and see how majority of them grow. In that order..'
```

In [6]:

```
df.user_mentions[4]
```

Out[6]:

```
'[{"screen_name": "charliebilello", "name": "Charlie Bilello", "id": 1413027896, "id_str": "1413027896", "indices": [0, 1
5]}]'
```

In [7]:

```
## total number of tweets in this dataset\
print("There are totally " + str(len(df)) + " Tweets in this dataset")
```

```
There are totally 88828 Tweets in this dataset
```

See when twitter are sent in this dataset

In [8]:
```
def time_frame(df_name):
    df_name_copy = df_name
    df_name_copy['created_at'] = df_name_copy['created_at'].astype('datetime64[ns]')

    print("\nLatest date of dataset:")
    print(df_name_copy.created_at.max())

    print("\nEarliest date of dataset:")
    print(df_name_copy.created_at.min())

    print("\nNumber of days between Latest and Earliest date of dataset:")
    print((df_name_copy.created_at.max() - df_name_copy.created_at.min()).days)
```

In [9]:
```
# time of when those tweets are being created
time_frame(df)
```

```
Latest date of dataset:
2021-10-01 16:00:23

Earliest date of dataset:
2021-06-19 16:30:50

Number of days between Latest and Earliest date of dataset:
103
```

1.2 Accounts Information

In [10]:
```
print("There are totally " + str(len(list(df['user_id'].unique()))) + " accounts in this dataset")
```

```
There are totally 51188 accounts in this dataset
```

In [11]:
```
df['tweets_Count'] = [1]* len(df)
```

In [12]:
```
df_f1 = df.groupby(['user_screen_name']).mean()
```

In [13]:

```
df_f2 = df.groupby(['user_screen_name']).sum()
df_f2 = df_f2.reset_index()
```

In [14]:

```
del df_f2['followers']
```

In [15]:

```
df_f2 = pd.merge(df_f2, df_f1['followers'], on = ['user_screen_name'])
```

In [150…

```
def Account_info(df_f2, feature):
    df_f2.set_index(feature, inplace=True)
    df_f2.sort_index(inplace=True, ascending=False)
    df_f2.reset_index(feature, inplace=True)
    return df_f2[['user_screen_name','followers', 'retweet_count', 'tweets_Count']][:10]
```

Top 10 accounts that have the most followers

In [151…

```
Account_info(df_f2, 'followers')
```

Out[151…

	user_screen_name	followers	retweet_count	tweets_Count
0	elonmusk	5.926437e+07	907.0	1.0
1	mcuban	8.508500e+06	0.0	1.0
2	paulkrugman	4.614354e+06	43772.0	416.0
3	cz_binance	3.051051e+06	0.0	1.0
4	kathygriffin	2.094973e+06	0.0	1.0
5	gtconway3d	1.803369e+06	0.0	1.0
6	BoredElonMusk	1.753451e+06	0.0	2.0
7	PreetBharara	1.732738e+06	1.0	4.0
8	jimcramer	1.731165e+06	4.0	1.0
9	sacca	1.652744e+06	1.0	3.0

Top 10 accounts that have the most Retweets

In [152…

```
Account_info(df_f2, 'retweet_count')
```

Out[152…

	user_screen_name	followers	retweet_count	tweets_Count
0	paulkrugman	4.614354e+06	43772.0	416.0
1	charliebilello	2.954569e+05	16250.0	501.0
2	profgalloway	4.085344e+05	10316.0	999.0
3	LizAnnSonders	1.969388e+05	9225.0	1118.0
4	RayDalio	7.160335e+05	6746.0	346.0
5	morganhousel	2.915241e+05	6715.0	368.0
6	CathieDWood	1.064271e+06	5019.0	40.0
7	elerianm	4.031230e+05	4656.0	564.0
8	eWhispers	2.741054e+05	1813.0	120.0
9	chamath	1.533016e+06	1607.0	46.0

10 Accounts that tweets the most

In [153…

```
Account_info(df_f2, 'tweets_Count')
```

Out[153…

	user_screen_name	followers	retweet_count	tweets_Count
0	LizAnnSonders	1.969388e+05	9225.0	1118.0
1	profgalloway	4.085344e+05	10316.0	999.0
2	MKucala	1.368561e+03	0.0	804.0
3	elerianm	4.031230e+05	4656.0	564.0
4	charliebilello	2.954569e+05	16250.0	501.0
5	paulkrugman	4.614354e+06	43772.0	416.0
6	morganhousel	2.915241e+05	6715.0	368.0
7	RayDalio	7.160335e+05	6746.0	346.0
8	JordanJamesEtem	1.459674e+04	15.0	276.0

	user_screen_name	followers	retweet_count	tweets_Count
9	emmetlsavage	1.439512e+04	20.0	148.0

1.3 Time series of Tweet/Retweet

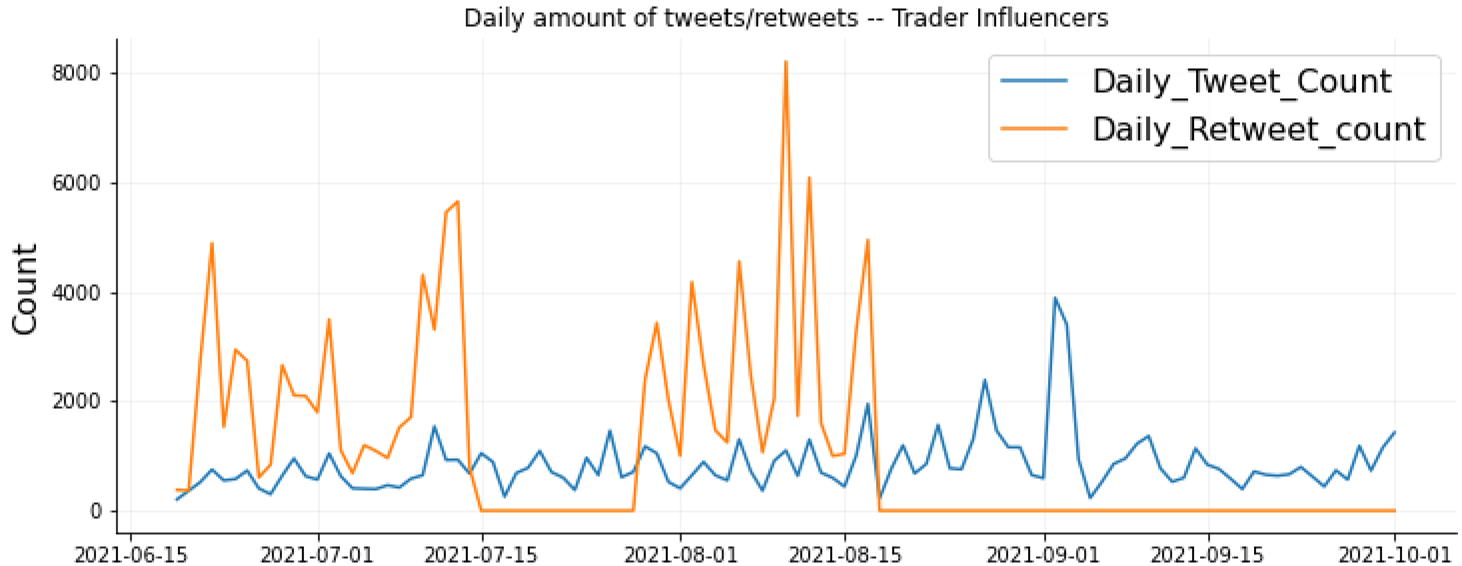
In [19]:
```
df['created_at'] = pd.to_datetime(df['created_at'])
```

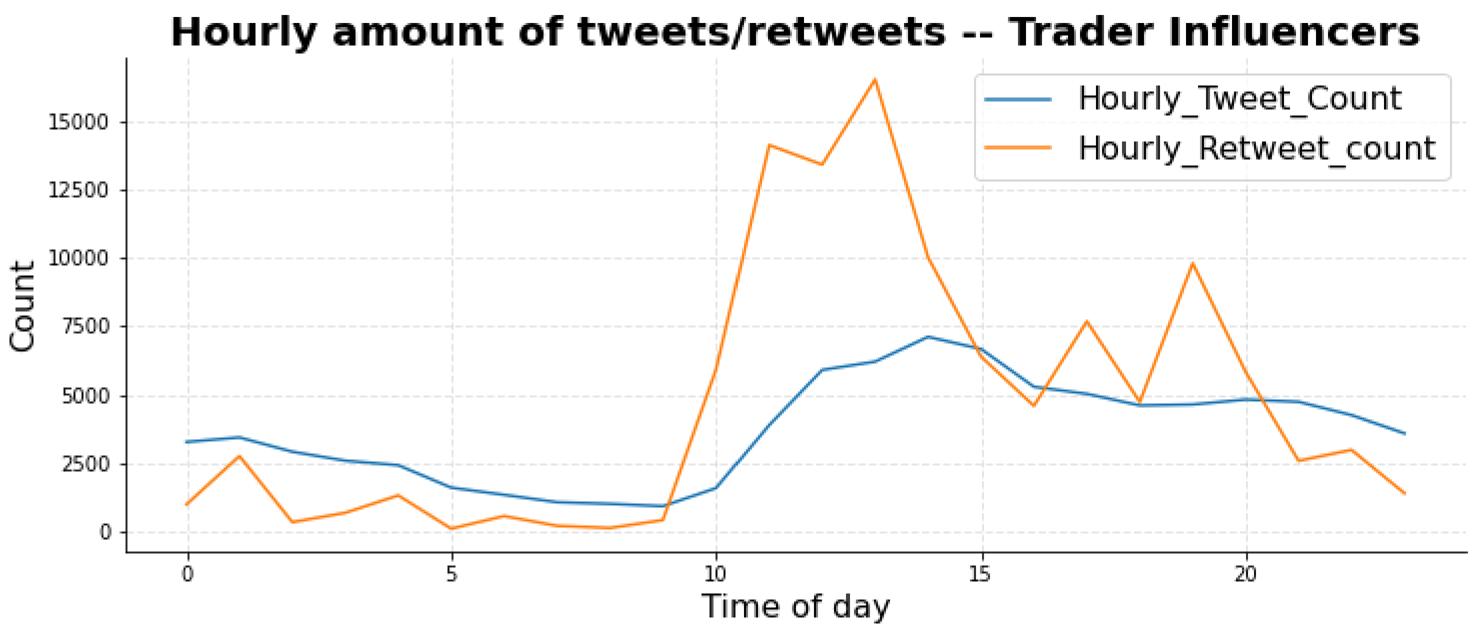
In [20]:
```
df["Date"] = df['created_at'].dt.date
df_time_series = df.groupby(['Date']).sum()
df_time_series = df_time_series.reset_index()
```

In [21]:
```
df["Hour"] = df['created_at'].dt.hour
df_time_series2 = df.groupby(['Hour']).sum()
df_time_series2 = df_time_series2.reset_index()
```

In [22]:
```
fig, ax = plt.subplots(2,1,figsize = (12,10))

ax[0].plot(df_time_series['Date'], df_time_series['tweets_Count'],'-',markersize=2, label='Daily_Tweet_Count')
ax[0].plot(df_time_series['Date'], df_time_series['retweet_count'],'-',markersize=2, label='Daily_Retweet_count')
ax[0].grid(color = 'grey', alpha =0.1)
ax[0].set_title(('Daily amount of tweets/retweets -- Trader Influencers'))
ax[0].spines['top'].set_color('none')
ax[0].spines['right'].set_color('none')
ax[0].set_ylabel("Count", fontsize= 16)
ax[0].legend(prop={'size': 16})

ax[1].plot(df_time_series2['Hour'], df_time_series2['tweets_Count'],'-',markersize=2, label='Hourly_Tweet_Count')
ax[1].plot(df_time_series2['Hour'], df_time_series2['retweet_count'],'-',markersize=2, label='Hourly_Retweet_count')
ax[1].grid(color = 'grey', alpha =0.1)
ax[1].set_title(('Hourly amount of tweets/retweets -- Trader Influencers'),fontweight="bold", fontsize=20)
ax[1].grid(linestyle='--', linewidth='1', color = 'grey', alpha =0.2)
ax[1].spines['top'].set_color('none')
ax[1].spines['right'].set_color('none')
ax[1].set_xlabel("Time of day", fontsize=16)
ax[1].set_ylabel("Count", fontsize= 16)
ax[1].legend(prop={'size': 16})
```

```
# fig.savefig("Tweets_Time_Series", bbox_inches="tight")
plt.show()
```





2. Preprocessing the dataset

2.1 Consisting Data types and None types

A problem caused by inconsistence of missing data types, some of the missing data has empty values with string 'None' and others are missing values (nan), replace all None values with nan

In [23]:
```
df.replace(to_replace=['None'], value=np.nan, inplace=True)
```

In [24]:
```
## check Nulls
df.isnull().sum(axis=0)
```

Out[24]:
```
status_id              0
created_at             0
user_screen_name       0
user_id                0
followers              0
location           39761
coordinates        88822
is_retweet             0
retweet_count          0
text                   0
topic                  0
hashtags           85511
symbols            85914
user_mentions       9703
urls               60178
tweets_Count           0
Date                   0
Hour                   0
dtype: int64
```

2.2 Drop Unnecessary columns

In [25]:
```
df = df.drop(columns = ['location'])
```

Only 7 unique values in coordiantes, column does not contain much information, thus drop it

In [26]:
```
len(df['coordinates'].unique())
```

Out[26]: 7

In [27]:
```
df = df.drop(columns = ['coordinates'])
```

The data indicates all is_retweet is false, therefore drop the column.
if is_retweet column is needed, url can bring this column back. Most of twitters do not contain any symbols, so symbols feature is dropped as well

In [28]:
```
df.groupby('is_retweet').count().reset_index()
```

Out[28]:

	is_retweet	status_id	created_at	user_screen_name	user_id	followers	retweet_count	text	topic	hashtags	symbols	user_mentions	
0	False	88828	88828	88828	88828	88828	88828	88828	88828	3317	2914	79125	28

In [29]:
```
df = df.drop(columns = ['is_retweet'])
```

In [30]:
```
df = df.drop_duplicates()
```

2.3 Extract all hashtags, symbols and user_mentions

In [31]:
```
#pip install tqdm
from tqdm import tqdm # progress bar for loop
import json
```

In [47]:
```
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
```

In [162…
```
text_list = df.text.to_list()
```

In [167…
```
text_all = ' '.join(text_list).split()
```

In [81]:

```
def extact_info(text_all, starting_symbol):
    Info_list = [j for j in text_all if j.startswith(starting_symbol)] #eg. capture all hashtags starting with '#'
    info = ' '.join(Info_list)
    info = re.sub(r"[^a-zA-Z0-9]"," ", info).lower() # Removing punct and emojis
    info = lemmatizer.lemmatize(info)

    return info
```

In [206…

```
lemmatizer.lemmatize('buy, buying')
```

Out[206…

```
'buy, buying'
```

hashtag

In [82]:

```
hashtag = extact_info(text_all, '#')
```

Symbol

In [84]:

```
symbol = extact_info(text_all, "$")
```

user_mentions

In [85]:

```
mention = extact_info(text_all, "@")
```

2.4 Clean text for LDA (Tokenize)

In [265…

```
from nltk.tokenize import TweetTokenizer
tknzr = TweetTokenizer()

#Add the directory that contains the preprocessing.py module to the system path for import
base_dir = os.getcwd() #get the current working directory
sys.path.insert(0,base_dir)

import preprocessing
```

```
from preprocessing import stop_words, nlp
import string
```

Define several helper function to do the preprocessing:

1.strip_links: input text, output text, remove links.

2.strip_all*entities: input text, output text, remove all mentions as well as mention user screen names, it is designed espically to deal with situations where there is* '' in user screen name: e.g.: @unusual_whales

In [97]:

```
def strip_links(text):
    link_regex = re.compile('((https?):((//)|(\\\\))+([\w\d:#@%/;$()~_?\+-=\\\.&](#!)?)*)', re.DOTALL)
    links = re.findall(link_regex, text)
    for link in links:
        text = text.replace(link[0], '')
    return text

def strip_all_entities(text):
    entity_prefixes = ['@','_']
    for separator in string.punctuation:
        if separator not in entity_prefixes :
            text = text.replace(separator,' ')
    words = []
    for word in text.split():
        word = word.strip()
        if word:
            if word[0] not in entity_prefixes:
                words.append(word)
    return ' '.join(words)

def remove_number(text):
    return re.sub("\S*\d\S*", "", text).strip()

def remove_stops_words(text):
    text = [w for w in text if not w in list(stop_words)] #remove stopwords
    return text

def remove_punc(text):
    return text.translate(str.maketrans('', '', string.punctuation))
```

In [98]:

```
def clean_text2(text):
    text = strip_links(text)
    text = strip_all_entities(text)
```

```
    text = remove_number(text)
    return text
```

pre_process() takes 5 parameters:

- **df - the dataframe of tweets with a 'text' column**
- **keywords - List of any keywords to remove**
- **rm_emojis - Boolean flag for whether to remove emojis from text**
- **filter_pos - Boolean flag for whether to remove stop words and filter part of speach to just the target parts of speech (i.e. ADJ, NOUN, ADV, SYMBOLS, and INTERJECTIONS)**
- **lemm - Boolean flag for whether to lemmatize the text**

****

In [99]:

```
def pre_process(df):
    df['clean_text'] = df['text'].apply(clean_text2)
    df['clean_text'] = df['clean_text'].str.lower()
    df['clean_text'] = df.clean_text.str.replace('’',"\'")
    df['clean_text'] = df.clean_text.str.replace('#',"").str.replace('$',"").str.replace('%',"").str.replace("-"," ").str
#    df['clean_text'] = df.clean_text.str.replace('u.s.',"usa").str.replace('u.s.a.',"usa")
    df['clean_text'] = df.clean_text.apply(preprocessing.remove_whitespace)
    df['clean_text'] = df.clean_text.apply(lambda x: preprocessing.find_urls(x,rm=True))
    df['clean_text'] = df.clean_text.apply(lambda x: preprocessing.find_emojis(x,rm=True))
    df['clean_text'] = df.clean_text.apply(preprocessing.expand_contractions) #this expands possessie contractions to '..
    df['clean_text'] = df.clean_text.apply(preprocessing.remove_apostrophe) #remove any lingering appostrophes in accents
    df['clean_text'] = df.clean_text.apply(preprocessing.remove_handles)
    df['clean_text'] = df.clean_text.apply(remove_punc)
    df['clean_text'] = df.clean_text.apply(tknzr.tokenize)
    df['clean_text'] = df.clean_text.apply(remove_stops_words)
```

In [260…

```
%%time
pre_process(df)
```

```
Wall time: 39.6 s
```

In [261…

```
df.clean_text
```

Out[261…

```
0        [recommend, great, solar, lights, seller, amaz...
1                                                 [remind]
```

```
2               [political, liberating, monocular, mindset]
3               [print, trillion, money, voila, unexpected]
4                              [wait, majority, grow, order]
                                        ...
88823                      [understand, usd, compared, euro]
88824    [fantasy, cathie, reason, invested, heavily, r...
88825    [perfect, sense, purposely, shrink, debt, gdp,...
88826                          [wood, cei, investment, plan]
88827    [shakalaka, start, teeing, change, decade, foc...
Name: clean_text, Length: 88828, dtype: object
```

3. Wordcloud

In [46]:

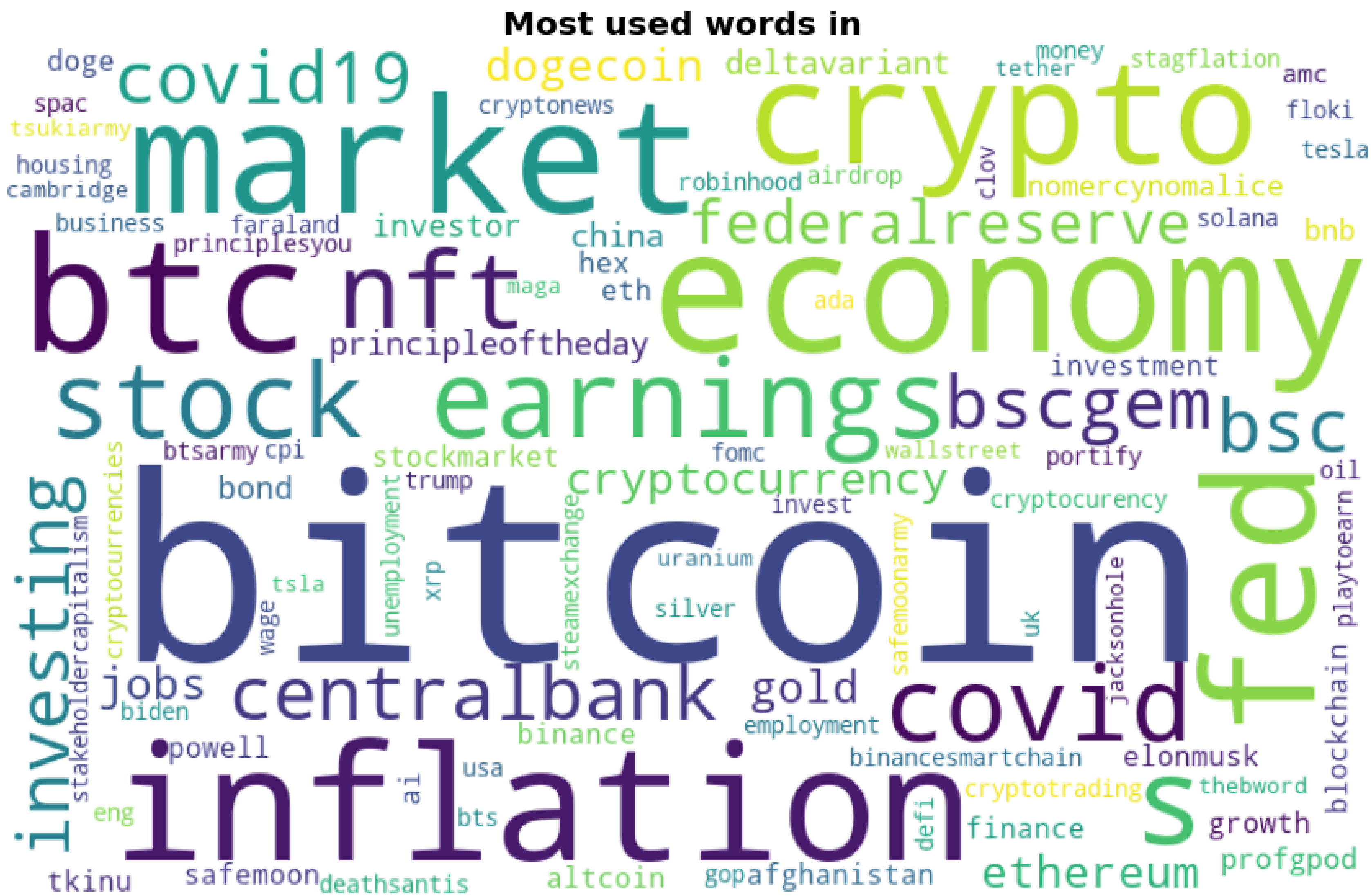
```
from wordcloud import WordCloud
from PIL import Image
base_dir = os.getcwd() #get the current working directory
from os import path
```

In [74]:

```
def wordcloud_func(words, Stop_Words = [], Twitter_Icon = False, feature_name = '', if_save = False):

    #set wordcloud style
    if Twitter_Icon:
        mask = np.array(Image.open(path.join(base_dir, "Twitter.png")))
        data_wordcloud = WordCloud(stopwords = Stop_Words, background_color = "white", collocations = False,
                                   max_words = 100, contour_width=1,width=800, height=500, mask=mask)
    else:
         data_wordcloud = WordCloud(stopwords = Stop_Words, background_color = "white", collocations = False,
                                   max_words = 100, contour_width=1,width=800, height=500)
    #produce wordcloud
    data_wordcloud.generate(words)
    #     wordcloud_image = data_wordcloud.to_image()
    plt.subplots(figsize=(15,12))
    plt.imshow(data_wordcloud, interpolation='bilinear')
    plt.title('Most used words in %s'%feature_name,fontweight ='bold', fontsize = 20)
    plt.axis("off")

    if if_save:
         plt.savefig('Most used words in %s'%feature_name, bbox_inches="tight")

    plt.show()
```

3.1 hashtag

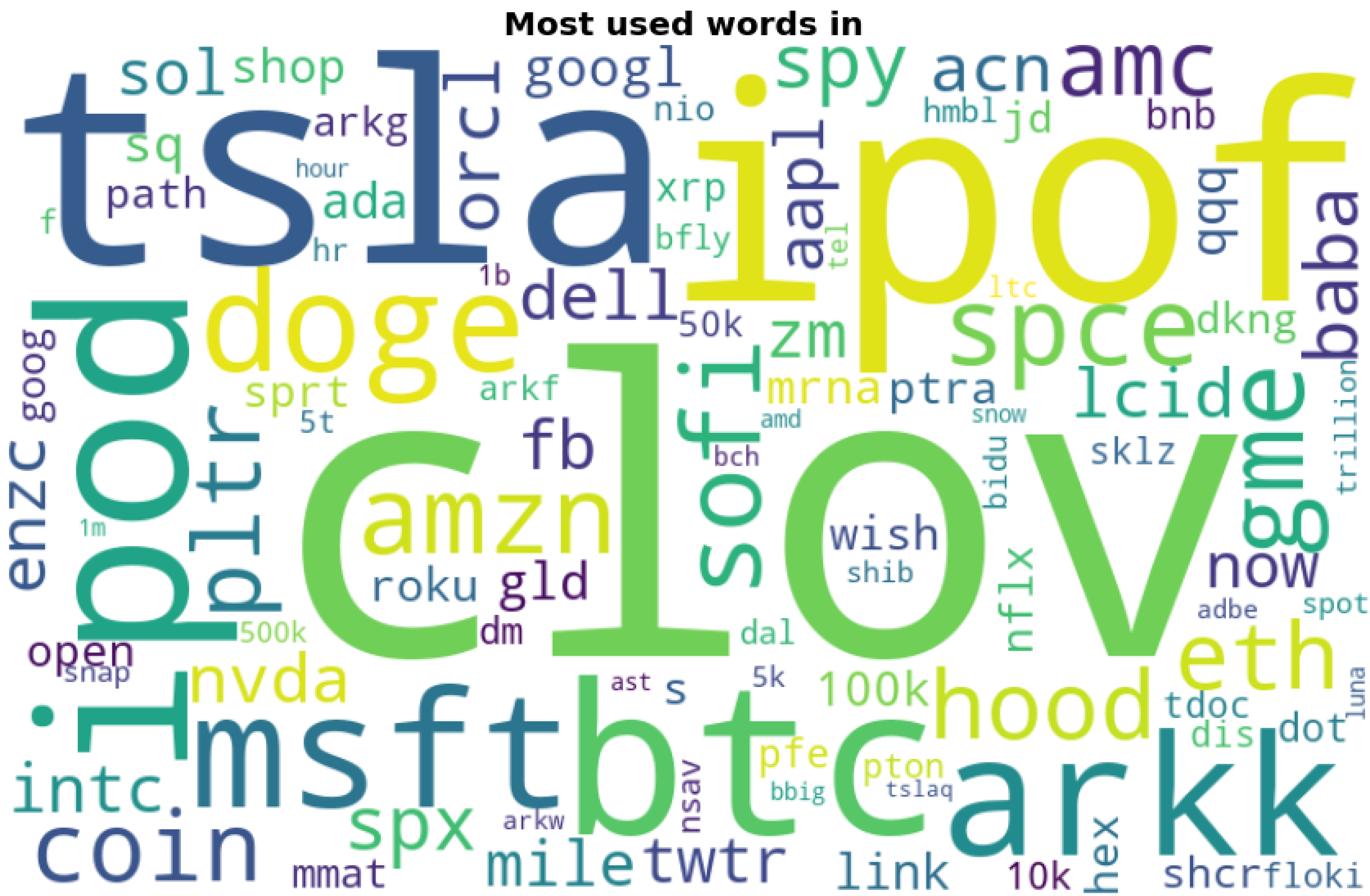
In [83]:
```
wordcloud_func(hashtag, Stop_Words = [''], Twitter_Icon = False, feature_name = '', if_save = False)
```



In [78]:
```
# wordcloud_func(hashtag, Stop_Words = [''], Twitter_Icon = True, feature_name = 'Hashtag', if_save = True)
```

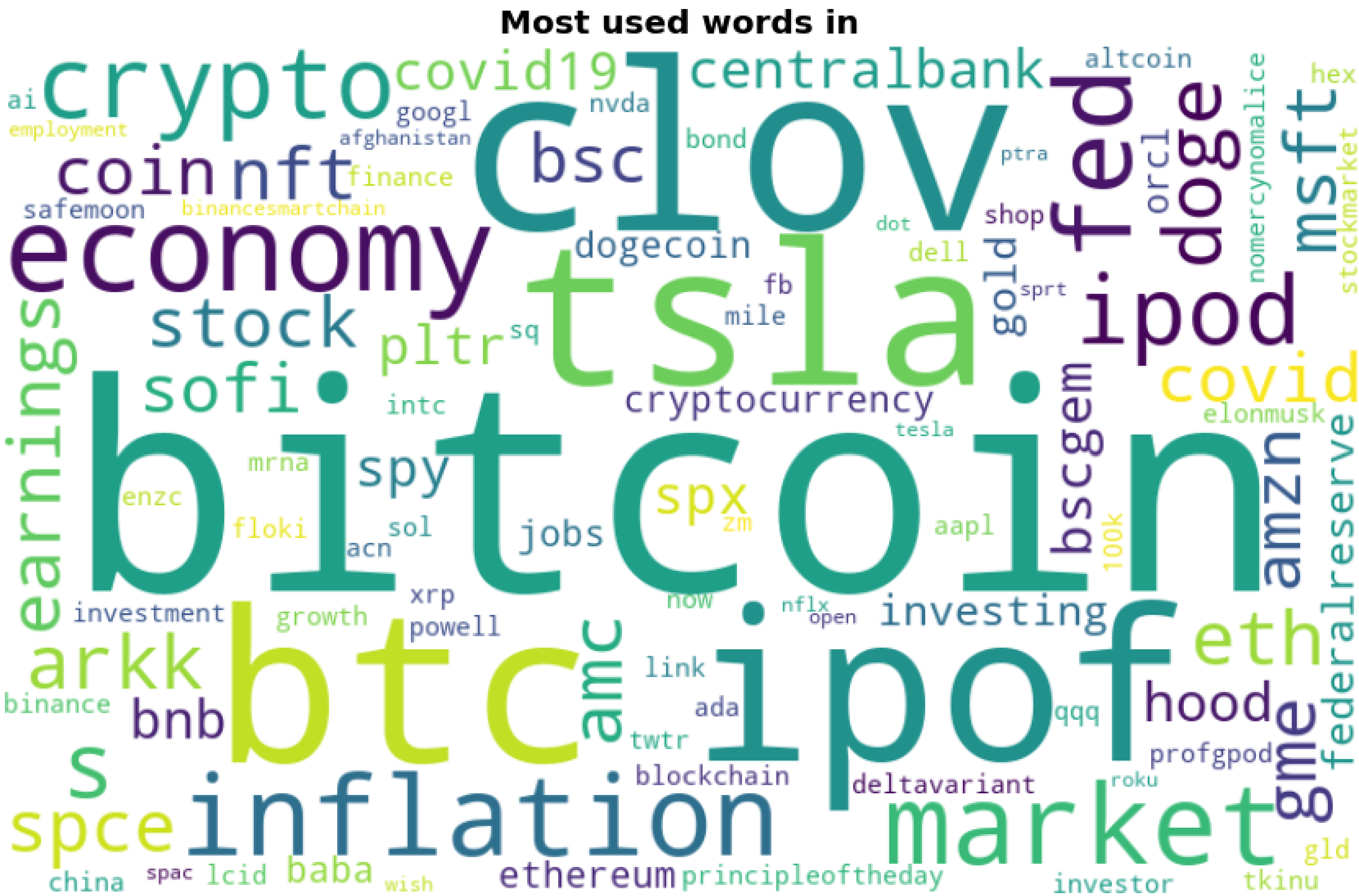
3.2 symbol

In [79]:
```
wordcloud_func(symbol, Stop_Words = [''], Twitter_Icon = False, feature_name = '', if_save = False)
```



3.3 Hashtag and Symbol

In [80]:
```python
hash_sym = hashtag + ' ' + symbol
wordcloud_func(hash_sym, Stop_Words = [''], Twitter_Icon = False, feature_name = '', if_save = False)
```



3.4 Clean Text

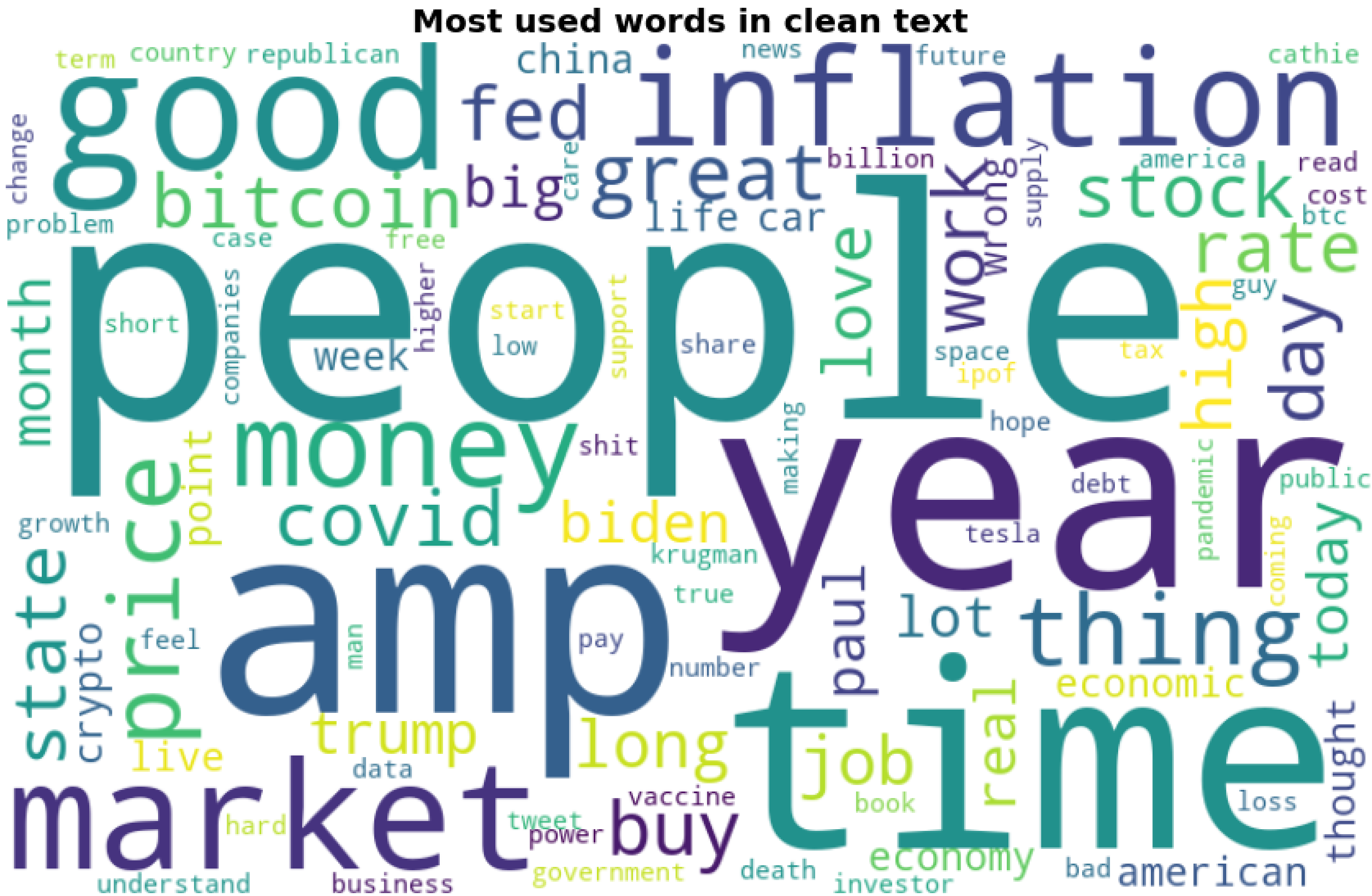
In [321…
```python
clean_text_all = [x for j in df.clean_text for x in j]
```

In [322…

```
clean_text_string = ' '.join(clean_text_all)
```

In [323…

```
wordcloud_func(clean_text_string, Stop_Words = ['year', 'time', 'good', 'people', 'amp', 'thing', 'bad', 'lot', 'day',
                                               'today', 'understand', 'number', 'great', 'real', 'coming', 'true', 'love'
                                               'live', 'shit', 'ago', 'big','making','human', 'man', 'hope', 'week',
                                               'things', 'happened', 'point', 'wrong', 'work', 'feel', 'month','guy',
                                               'care', 'fact', 'nice', 'life', 'guys', 'reason','start','post', 'thought'
                                               'talk', 'months','happen', 'buying', 'higher', 'friend', 'years', 'person'
                                               ],
               Twitter_Icon = False, feature_name = 'clean text', if_save = False)
```




```
In [223…
# # delete some words that frequently shows but useless according from wordcloud
# Useless_Words_wc = ['year', 'time', 'good', 'people', 'amp', 'thing', 'bad', 'lot', 'day',
#                     'today', 'understand', 'number', 'great', 'real', 'coming', 'true', 'love',
#                     'live', 'shit', 'ago', 'big','making','human', 'man', 'hope', 'week',
#                     'things', 'happened', 'point', 'wrong', 'work', 'feel', 'month','guy',
#                     'care', 'fact', 'nice', 'life', 'guys', 'reason','start','post', 'thought',
#                     'talk', 'months','happen', 'buying', 'higher', 'friend', 'years', 'person',
#                                               ]
```

In [ ]:
```
# def remove_useless_words(text):
#     text = [w for w in text if not w in list(Useless_Words_wc)] #remove stopwords
#     return text

# df['clean_text2'] = df.clean_text.apply(remove_useless_words)
```

4. Sentiment analysis

4.1 Vader

NLTK's Vader sentiment analysis tool uses a bag of words approach (a lookup table of positive and negative words) with some simple heuristics (e.g. increasing the intensity of the sentiment if some words like "really", "so" or "a bit" are present).

The advantage of this approach is that sentences containing negated positive words (e.g. "not happy", "not good") will still receive a negative sentence sentiment (thanks to the heuristics to flip the sentiment of the word following a negation).

The disadvantage of this approach is that Out of Vocab (OOV) words that the sentiment analysis tool has not seen before will not be classified as positive/negative (e.g. typos).

In [120…
```
import nltk
# nltk.download('vader_lexicon')
from nltk.sentiment.vader import SentimentIntensityAnalyzer
sid = SentimentIntensityAnalyzer()
```

In [121…
```
def hand_annoate_vader(df, row_begin, row_end, column):
    for i in range(row_begin,row_end+1):
        text = df.loc[i,column]
        scores = sid.polarity_scores(text)
        print(text)
        print(scores)
        print("-"*110)
```

In [122…
```
hand_annoate_vader(df, 6, 10,'text')
```

```
@charliebilello Kinda gross that $UNI is down less from ATH than $LINK

Even after the heist which exposed how vulnerable Uniswap is.

Unicorns ngmi
{'neg': 0.222, 'neu': 0.778, 'pos': 0.0, 'compound': -0.6133}
----------------------------------------------------------------------------------------------------------------
@charliebilello Not a store of value, not a currency, not much remains standing in the crypto bubble.
{'neg': 0.127, 'neu': 0.873, 'pos': 0.0, 'compound': -0.2584}
----------------------------------------------------------------------------------------------------------------
@charliebilello Put up Sciacoin $SC
{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
----------------------------------------------------------------------------------------------------------------
@charliebilello @RemindMe_OfThis 1 month
{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
----------------------------------------------------------------------------------------------------------------
@charliebilello @Deals4We Hello Guys, we have built a specialised job board for the Crypto and Blockchain Industry, if yo
u are looking for a new career or looking to hire top talent take a look https://t.co/JsqatnH55j
{'neg': 0.0, 'neu': 0.867, 'pos': 0.133, 'compound': 0.5574}
----------------------------------------------------------------------------------------------------------------
```

In [123…
```
def time_vader(df, rows, column):
    from timeit import default_timer as timer
    start = timer()
    for i in range(rows):
        text = df.loc[i, column]
        scores = sid.polarity_scores(text)
    end = timer()
    time = end - start
    print("For model vader, it takes " + str(time) +"s to process " + str(rows) + " rows")
```

In [124…
```
time_vader(df, 10000, 'text')
```

```
For model vader, it takes 2.4785053999999036s to process 10000 rows
```

4.2 Textblob

In [125…
```
#pip install textblob
```

In [126…

```
from textblob import Blobber
from textblob.sentiments import NaiveBayesAnalyzer
from textblob import TextBlob
```

In [127…

```
def hand_annoate_textblob(df, row_begin, row_end, column):
    for i in range(row_begin,row_end+1):
        text = df.loc[i,column]
        scores = TextBlob(text).sentiment
        print(text)
        print(scores)
        print("-"*110)
```

In [128…

```
hand_annoate_textblob(df, 6, 10,'text')
```

```
@charliebilello Kinda gross that $UNI is down less from ATH than $LINK

Even after the heist which exposed how vulnerable Uniswap is.

Unicorns ngmi
Sentiment(polarity=-0.20555555555555555, subjectivity=0.2138888888888889)
--------------------------------------------------------------------------------------------------------------
@charliebilello Not a store of value, not a currency, not much remains standing in the crypto bubble.
Sentiment(polarity=-0.1, subjectivity=0.2)
--------------------------------------------------------------------------------------------------------------
@charliebilello Put up Sciacoin $SC
Sentiment(polarity=0.0, subjectivity=0.0)
--------------------------------------------------------------------------------------------------------------
@charliebilello @RemindMe_OfThis 1 month
Sentiment(polarity=0.0, subjectivity=0.0)
--------------------------------------------------------------------------------------------------------------
@charliebilello @Deals4We Hello Guys, we have built a specialised job board for the Crypto and Blockchain Industry, if yo
u are looking for a new career or looking to hire top talent take a look https://t.co/JsqatnH55j
Sentiment(polarity=0.3181818181818182, subjectivity=0.4772727272727273)
--------------------------------------------------------------------------------------------------------------
```

In [129…

```
def time_textblob(df, rows, column):
    from timeit import default_timer as timer
    start = timer()
    for i in range(rows):
        text = df.loc[i, column]
        scores = TextBlob(text).sentiment
    end = timer()
```

```
    time = end - start
    print("For model textblob, it takes " + str(time) +"s to process " + str(rows) + " rows")
```

In [130…

```
time_textblob(df, 10000,'text')
```

```
For model textblob, it takes 2.6331913000003624s to process 10000 rows
```

4.3 Flair

In [131…

```
#pip install flair
```

In [132…

```
from flair.models import TextClassifier
from flair.data import Sentence
import flair
classifier = TextClassifier.load('en-sentiment')
```

```
2021-10-24 21:54:53,453 loading file C:\Users\Jingwen\.flair\models\sentiment-en-mix-distillbert_4.pt
```

In [133…

```
def hand_annoate_flair(df, row_begin, row_end, column):
    for i in range(row_begin,row_end+1):
        text = df.loc[i,column]
        flair_text = flair.data.Sentence(text)
        classifier.predict(flair_text)
        # make score in negative sentiment less than, match up with previous sentiment rules
        if flair_text.labels[0].value == "NEGATIVE":
            flair_score = -1 * flair_text.labels[0].score
        else:
            flair_score = flair_text.labels[0].score
        print(text)
        print(flair_score)
        print("-"*110)
```

In [134…

```
hand_annoate_flair(df, 6, 10,'text')
```

```
@charliebilello Kinda gross that $UNI is down less from ATH than $LINK

Even after the heist which exposed how vulnerable Uniswap is.
```

```
Unicorns ngmi
-0.9995381832122803
--------------------------------------------------------------------------------------------------------------
@charliebilello Not a store of value, not a currency, not much remains standing in the crypto bubble.
-0.9998775720596313
--------------------------------------------------------------------------------------------------------------
@charliebilello Put up Sciacoin $SC
-0.900278627872467
--------------------------------------------------------------------------------------------------------------
@charliebilello @RemindMe_OfThis 1 month
-0.9844755530357361
--------------------------------------------------------------------------------------------------------------
@charliebilello @Deals4We Hello Guys, we have built a specialised job board for the Crypto and Blockchain Industry, if yo
u are looking for a new career or looking to hire top talent take a look https://t.co/JsqatnH55j
0.9800581932067871
--------------------------------------------------------------------------------------------------------------
```

4.4 Sentiment packages comparison, correlation, and distribution

In [135…

```
def sentiment_comp(df, row_begin, row_end, column):
    for i in range(row_begin,row_end+1):
        text = df.loc[i,column]
        print(text)

        ############### VADER ###############
        vader_scores = sid.polarity_scores(text).get('compound') #vader returns a dict, we only need the compound scores
        vader_scores = round(vader_scores,3)
        print("\nVader score is " + str(vader_scores) + "\n")

        ############### TEXTBLOB ###############
        textblob_score = TextBlob(text).sentiment
        textblob_polarity = round(textblob_score.polarity,3) # round to 3 decimals
        textblob_subjectivity = round(textblob_score.subjectivity,3)
        print("TextBlob polarity is " + str(textblob_polarity) + ", subjectivity is " + str(textblob_subjectivity) + "\n"

        ################ FLAIR ################
        flair_text = flair.data.Sentence(text)
        classifier.predict(flair_text)

        # make score in negative sentiment less than, match up with previous sentiment rules
        if flair_text.labels[0].value == "NEGATIVE":
            flair_score = round(-1 * flair_text.labels[0].score,3)
        else:
            flair_score = round(flair_text.labels[0].score,3)
```

```
        print("Flair score is " + str(flair_score) + "\n")
        print("-"*110)
```

In [136…

```
sentiment_comp(df, 111, 123,'text')
```

```
@charliebilello But only @GameXOfficial1 all I see is green candles #GMX $GMX

Vader score is 0.0

TextBlob polarity is -0.1, subjectivity is 0.65

Flair score is -0.996

--------------------------------------------------------------------------------------------------------------
@charliebilello 💎JOIN THE RISING STAR OF NFT GAME IN THE SPACE💎 AIRDROPS OF 38 NFT from the developers of the new cryp
to games. @CrazyCyberBunny

Website:https://t.co/cCb057ElyL
Telegram:https://t.co/YNpJYpIvWl
Discord: https://t.co/k65nYQ5hQD
Crazy CybΞr Bunny (@CrazyCyberBunny)

Vader score is -0.625

TextBlob polarity is -0.288, subjectivity is 0.585

Flair score is 0.997

--------------------------------------------------------------------------------------------------------------
@charliebilello Thanks for reminding me

Vader score is 0.44

TextBlob polarity is 0.2, subjectivity is 0.2

Flair score is 0.813

--------------------------------------------------------------------------------------------------------------
@charliebilello Oversold IMO. Not much has changed. China crackdown is the catalyst but once hash rate returns and a “pos
itive” catalyst like lower interest rates or large stimulus we will back back on a steep up curve.

Vader score is 0.665
```

TextBlob polarity is 0.068, subjectivity is 0.235

Flair score is -1.0

@charliebilello You can sleep well... be quiet. https://t.co/xnmv41wKec

Vader score is 0.0

TextBlob polarity is 0.0, subjectivity is 0.333

Flair score is -0.762

@charliebilello Lol.. #XRP didn't made the new ath but yet dumped more than 70% 😂
Diamond 💎hands of #XRPCommunity 😂😂

Vader score is -0.014

TextBlob polarity is 0.479, subjectivity is 0.552

Flair score is -0.999

@elerianm @Tesla @Lexus Good that you don't own one, they SUCK! If you really really want an electric vehicle you should go for a Taycan.

Vader score is 0.11

TextBlob polarity is 0.55, subjectivity is 0.6

Flair score is -1.0

@profgalloway Never got the glorification of the mob in movies or pictures.

Vader score is -0.357

TextBlob polarity is 0.0, subjectivity is 0.0

Flair score is -1.0

@RayDalio Thank You
@elonmusk

```
Vader score is 0.361

TextBlob polarity is 0.0, subjectivity is 0.0

Flair score is 0.897

--------------------------------------------------------------------------------------------------------------
@charliebilello @RemindMe_OfThis in 2 months

Vader score is 0.0

TextBlob polarity is 0.0, subjectivity is 0.0

Flair score is 0.559

--------------------------------------------------------------------------------------------------------------
@charliebilello Sentinel Hub has over 20k #IBC transfers within the #Cosmos ecosystem, this number will soon increase exp
onentially as we are now connected to @cosmos Hub

We are ready and eagerly anticipate the launch of @emerisHQ #GravityDeX

#DeFi #dVPN #dWeb https://t.co/8PFjHCUaUm

Vader score is 0.777

TextBlob polarity is 0.2, subjectivity is 0.5

Flair score is 0.992

--------------------------------------------------------------------------------------------------------------
@charliebilello Million token is +86%

Vader score is 0.0

TextBlob polarity is 0.0, subjectivity is 0.0

Flair score is 0.993

--------------------------------------------------------------------------------------------------------------
@charliebilello Buy the fucking dip?

Vader score is 0.0

TextBlob polarity is -0.6, subjectivity is 0.8

Flair score is -0.971
```

Sentiment analysis works better with orignal text. The cleaning process for sentiment analysis is abandoned

Get sentiment for each text

In [141…
```
from time import time
```

In [142…
```
start = time()
df['TextBlob_Sentiment'] = df.text.apply(lambda x:TextBlob(x).sentiment.polarity)
end = time()
result = end - start
print('%.3f seconds' % result) # Report execution time
```

```
25.973 seconds
```

In [144…
```
start = time()
df['Vader_Sentiment'] = df.text.apply(lambda x:sid.polarity_scores(x)['compound'])
end = time()
result = end - start
print('%.3f seconds' % result) # Report execution time
```

```
25.403 seconds
```

In [145…
```
def flair_sa(text):
    flair_text = Sentence(text)
    classifier.predict(flair_text)
    # make score in negative sentiment less than, match up with previous sentiment rules
    if flair_text.labels[0].value == "NEGATIVE":
        return -1 * flair_text.labels[0].score
    else:
        return flair_text.labels[0].score
```

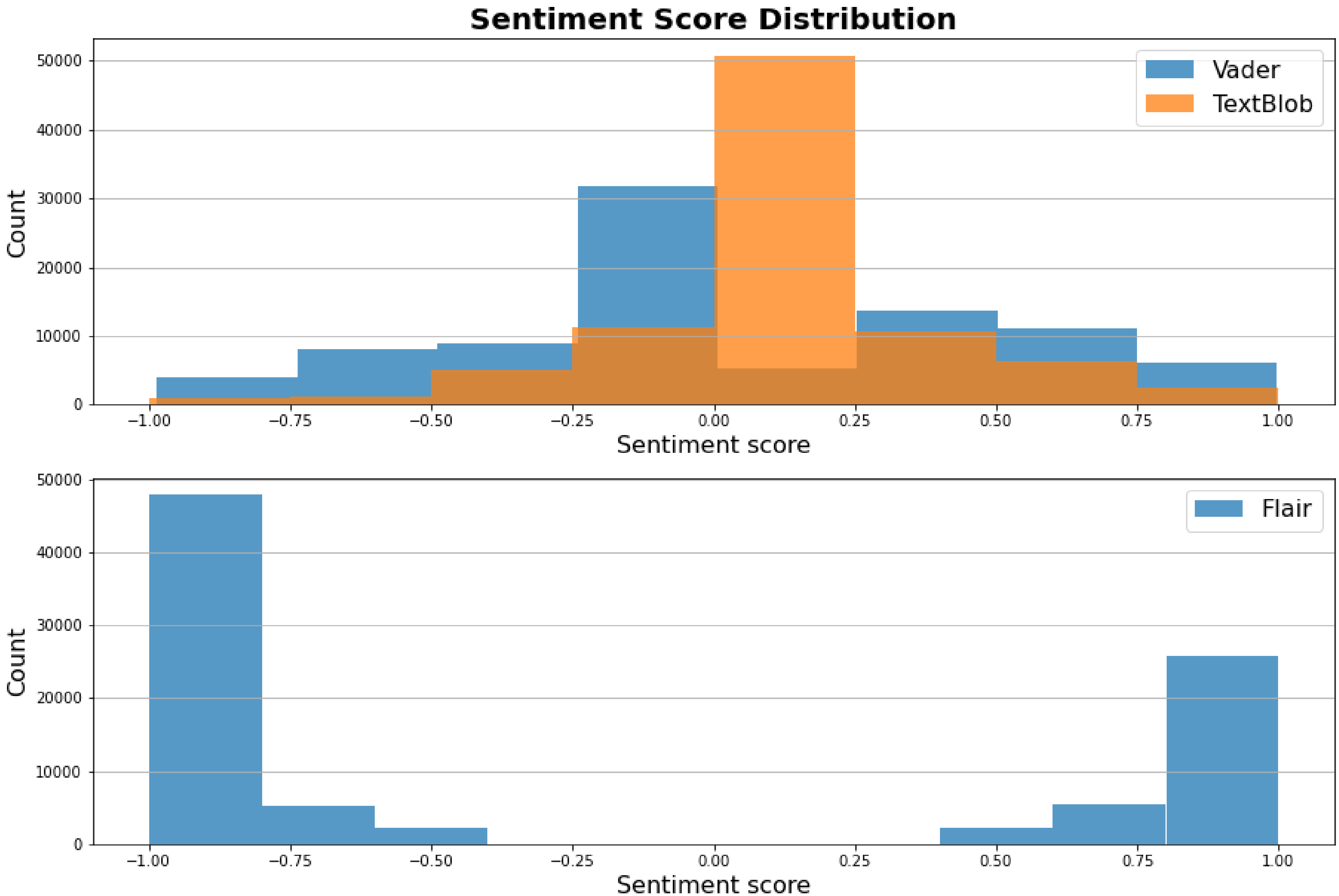
In [146…
```
start = time()
df['Flair_Sentiment'] = df.text.apply(lambda x:flair_sa(x))
end = time()
result = end - start
print('%.3f seconds' % result) # Report execution time
```

```
1170.104 seconds
```

Distribution

In [160…

```
fig, ax = plt.subplots(2,1,figsize = (15,10))

ax[0].hist(df['Vader_Sentiment'], bins= 8, alpha=0.75, label = 'Vader')
ax[0].hist(df['TextBlob_Sentiment'], bins= 8, alpha=0.75, label = 'TextBlob')
ax[0].set_title('Sentiment Score Distribution',fontsize = 20, fontweight ='bold')
ax[0].grid(axis='y')
ax[0].set_xlabel("Sentiment score", fontsize = 16)
ax[0].set_ylabel("Count",fontsize = 16)
ax[0].legend(prop={'size': 16})

ax[1].hist(df['Flair_Sentiment'], bins= 10, rwidth=0.99, alpha=0.75, label = 'Flair')
ax[1].grid(axis='y')
ax[1].set_xlabel("Sentiment score", fontsize = 16)
ax[1].set_ylabel("Count",fontsize = 16)
ax[1].legend(prop={'size': 16})

# fig.savefig("Sentiment_distribution", bbox_inches="tight")
plt.show()
```



Get daily average sentiment

In [154…

```
df_sa = df.groupby(['Date']).mean()
df_sa = df_sa.reset_index()
```

In [156…

```
Sentiment_corr = pd.concat([df_sa['Vader_Sentiment'],df_sa['TextBlob_Sentiment'], df_sa['Flair_Sentiment'],df_time_series
```

Correlation (of above daily average data)

In [157…

```
correlation_mat = Sentiment_corr.corr()
correlation_mat
```

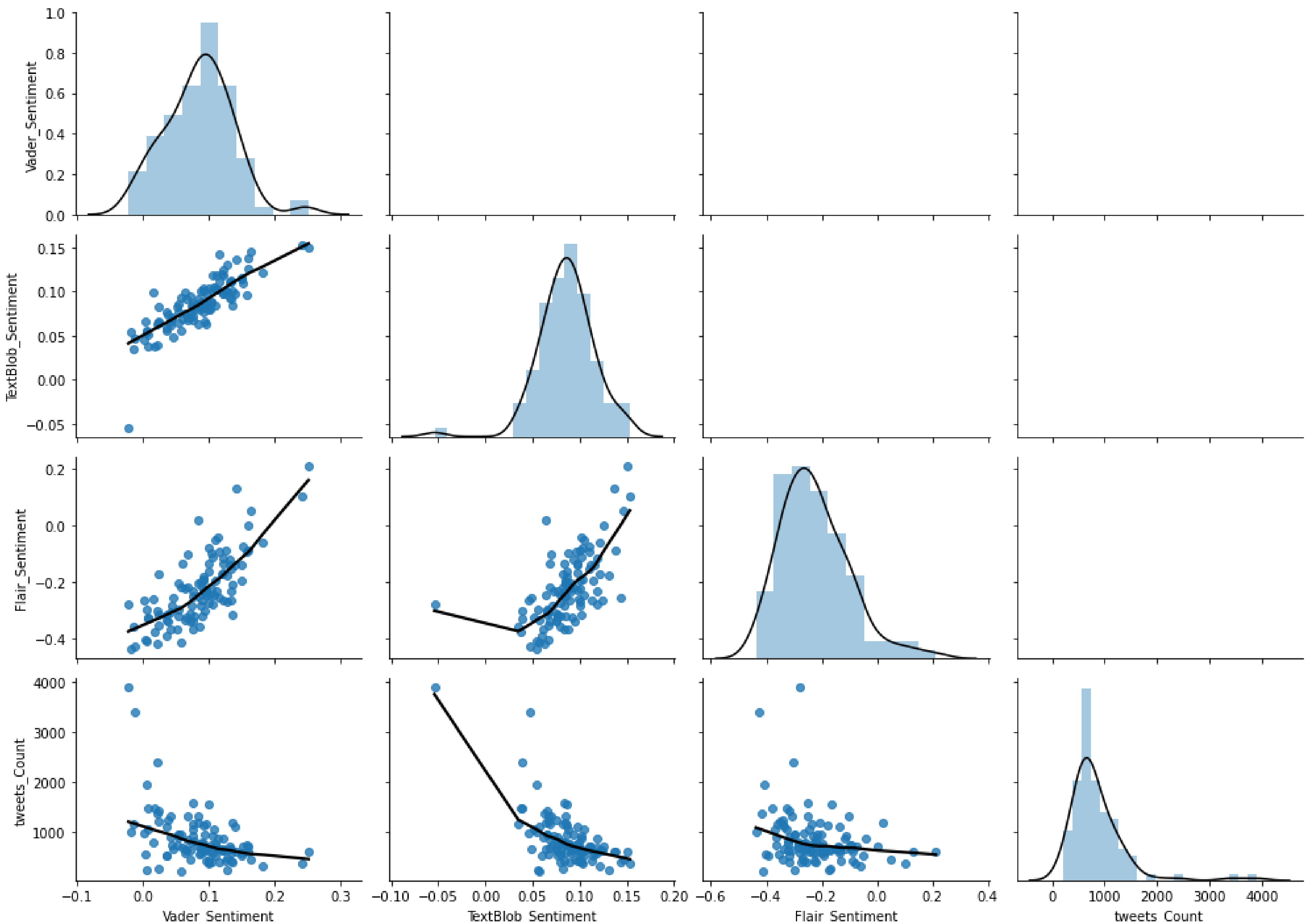
Out[157…

	Vader_Sentiment	TextBlob_Sentiment	Flair_Sentiment	tweets_Count
Vader_Sentiment	1.000000	0.825131	0.754487	-0.486764
TextBlob_Sentiment	0.825131	1.000000	0.621677	-0.634808
Flair_Sentiment	0.754487	0.621677	1.000000	-0.286399
tweets_Count	-0.486764	-0.634808	-0.286399	1.000000

In [158…

```
import seaborn as sns
g = sns.PairGrid(Sentiment_corr, aspect=1.4, diag_sharey=False)
g.map_lower(sns.regplot, lowess=True, ci=False, line_kws={'color': 'black'}) #lower triangle
g.map_diag(sns.distplot, kde_kws={'color': 'black'}) #diagonal

#title:
g.fig.suptitle('Sentiments Scatter Plots', y=1.08)

plt.show()
plt.cla()
plt.clf()
```

Sentiments Scatter Plots

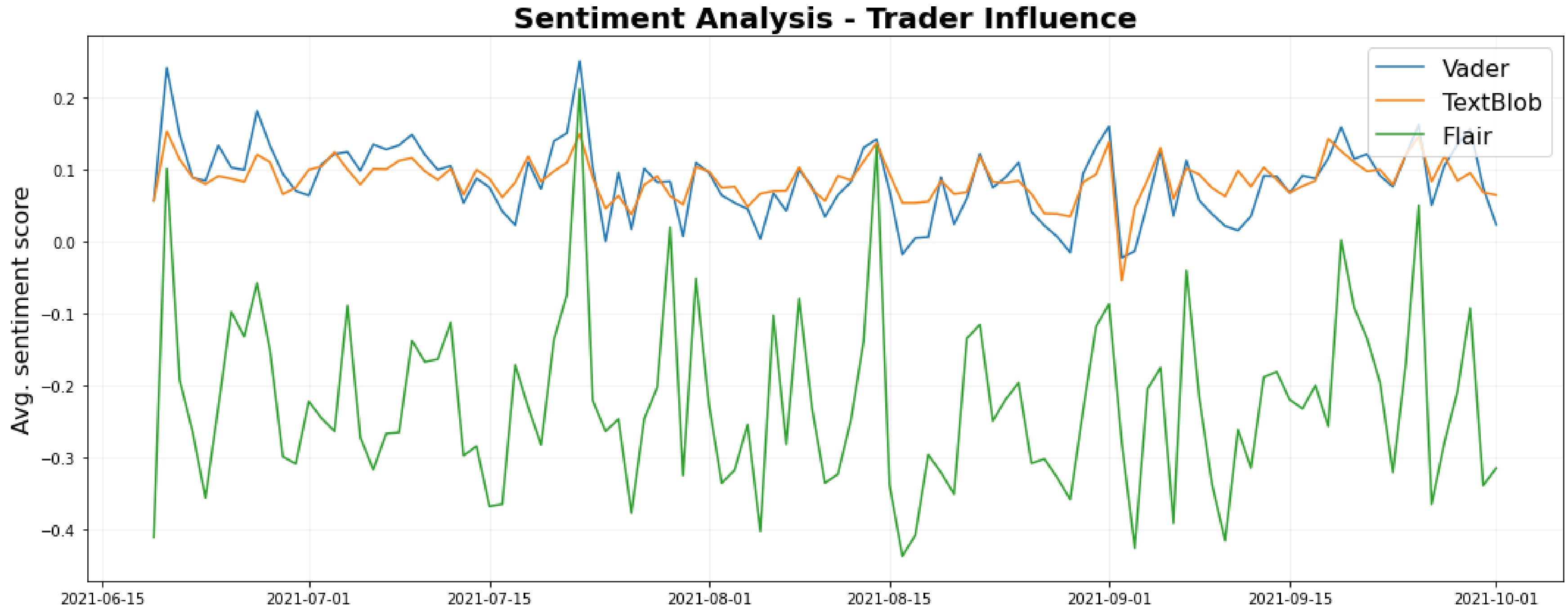


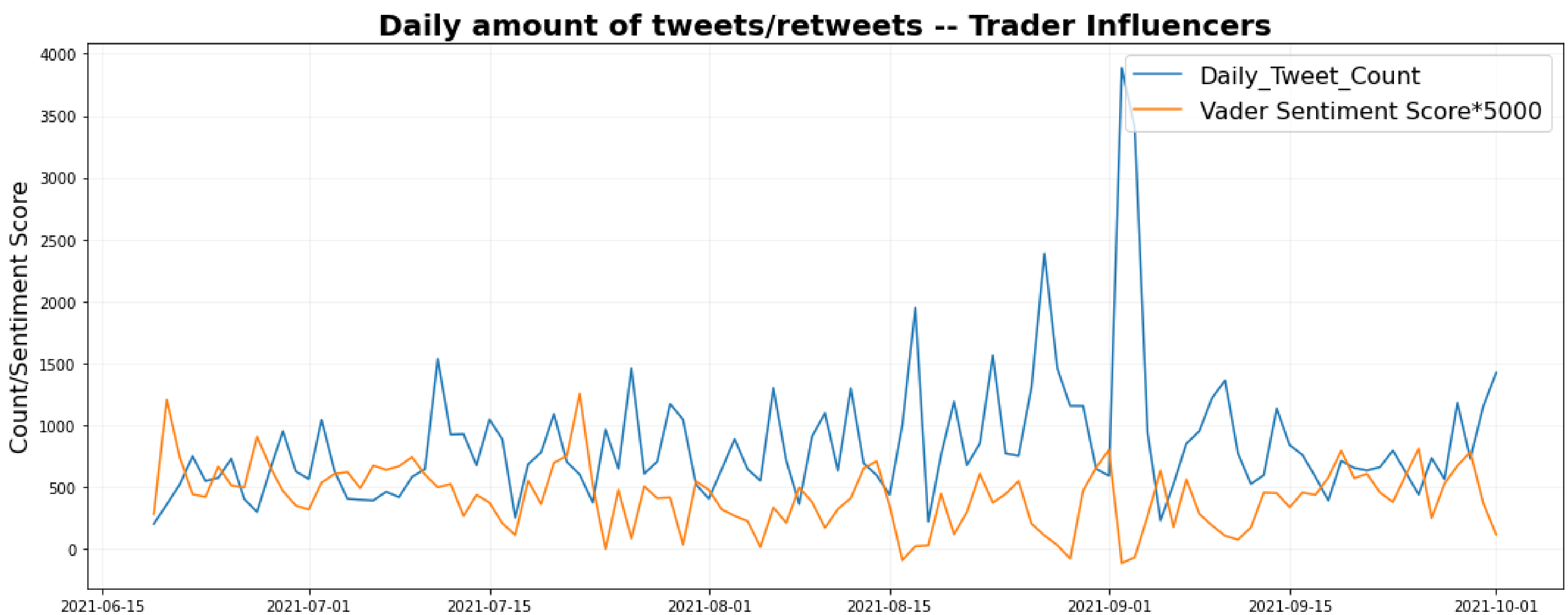

```
<Figure size 432x288 with 0 Axes>
```

4.6 Time series of sentiment analysis

In [169…

```
fig, ax = plt.subplots(2,1,figsize = (18,15))

ax[0].plot(df_sa['Date'], df_sa['Vader_Sentiment'],'-',markersize=2, label='Vader')
ax[0].plot(df_sa['Date'], df_sa['TextBlob_Sentiment'],'-',markersize=2, label='TextBlob')
ax[0].plot(df_sa['Date'], df_sa['Flair_Sentiment'],'-',markersize=2, label='Flair')
ax[0].grid(color = 'grey', alpha =0.1)
ax[0].set_title(('Sentiment Analysis - Trader Influence'),fontweight ='bold', fontsize = 20)
ax[0].set_ylabel(('Avg. sentiment score'), fontsize = 16)
ax[0].legend(prop={'size': 16},loc='upper right')

ax[1].plot(df_time_series['Date'], df_time_series['tweets_Count'],'-',markersize=2, label='Daily_Tweet_Count')
ax[1].plot(df_sa['Date'], df_sa['Vader_Sentiment']*5000,'-',markersize=2, label='Vader Sentiment Score*5000')
# ax[1].plot(df['Date'], df_time_series['retweet_count'],'-',markersize=2, label='Daily_Retweet_count')
ax[1].grid(color = 'grey', alpha =0.1)
ax[1].set_title(('Daily amount of tweets/retweets -- Trader Influencers'),fontweight ='bold', fontsize = 20)
ax[1].set_ylabel(('Count/Sentiment Score'), fontsize = 16)
ax[1].legend(prop={'size': 16}, loc='upper right')

fig.savefig("Sentiment_Time_Series", bbox_inches="tight")
plt.show()
```


Sentiment Analysis - Trader Influence
Vader
TextBlob
Flair
Avg. sentiment score
0.2
0.1
0.0
−0.1
−0.2
−0.3
−0.4
2021-06-15
2021-07-01
2021-07-15
2021-08-01
2021-08-15
2021-09-01
2021-09-15
2021-10-01


Daily amount of tweets/retweets -- Trader Influencers
Daily_Tweet_Count
Vader Sentiment Score*5000
Count/Sentiment Score
4000
3500
3000
2500
2000
1500
1000
500
0
2021-06-15
2021-07-01
2021-07-15
2021-08-01
2021-08-15
2021-09-01
2021-09-15
2021-10-01

5. LDA

will filter dataframe for 7 days

In [242…

```
max_days_ago = 7

#filter dates
latest_date= max(df.Date)

earliest_date = latest_date - datetime.timedelta(days=max_days_ago)

earliest_date
```

Out[242…

```
datetime.date(2021, 9, 24)
```

In [244…

```
#filter for 7 days
df_lda = df[df['Date'] >= earliest_date]
len(df_lda)
```

Out[244…

```
6856
```

5.1 Lemmatization

In [292…

```
import spacy, gensim, nltk
```

In [293…

```
# Initialize spacy 'en' model, keeping only tagger component (for efficiency)
# Run in terminal: python3 -m spacy download en
nlp = spacy.load('en_core_web_sm', disable=['parser', 'ner'])
```

In [294…

```
def lemmatization(texts, allowed_postags=['NOUN', 'ADJ', 'VERB', 'ADV']):
    """https://spacy.io/api/annotation"""
    texts_out = []
    for sent in texts:
        doc = nlp(" ".join(sent))
```

```
        texts_out.append(" ".join([token.lemma_ for token in doc if token.pos_ in allowed_postags]))
    return texts_out
```

In [299…

```
# Do lemmatization keeping only Noun
data_lemmatized = lemmatization(df_lda.clean_text.to_list(), allowed_postags=['NOUN', 'ADJ', 'VERB', 'ADV'])

print(data_lemmatized[:2])
```

```
['long', '']
```

In [316…

```
def process_text(data: list, ngrams: str) -> list:
    '''
    Input:
        data: list of strings
    Output:
        perform text transformation and return list of processed strings
    '''

    # split text strings into tokens
    data = [doc.split() for doc in data]

    # form n-grams
    if ngrams == "freq":
        bigram_mod = preprocessing.build_bigram_models(data)  # using corpus with no retweets.
        data_words_ngrams = preprocessing.make_freq_bigrams(data, bigram_mod)
    elif ngrams == "bi":
        data_words_ngrams = list(map(all_bigrams, data))
    elif ngrams == "tri":
        data_words_ngrams = list(map(all_trigrams, data))
    else:
        data_words_ngrams = data

    return [' '.join(doc) for doc in data_words_ngrams]  # join tokens in each doc to make a list of strings
```

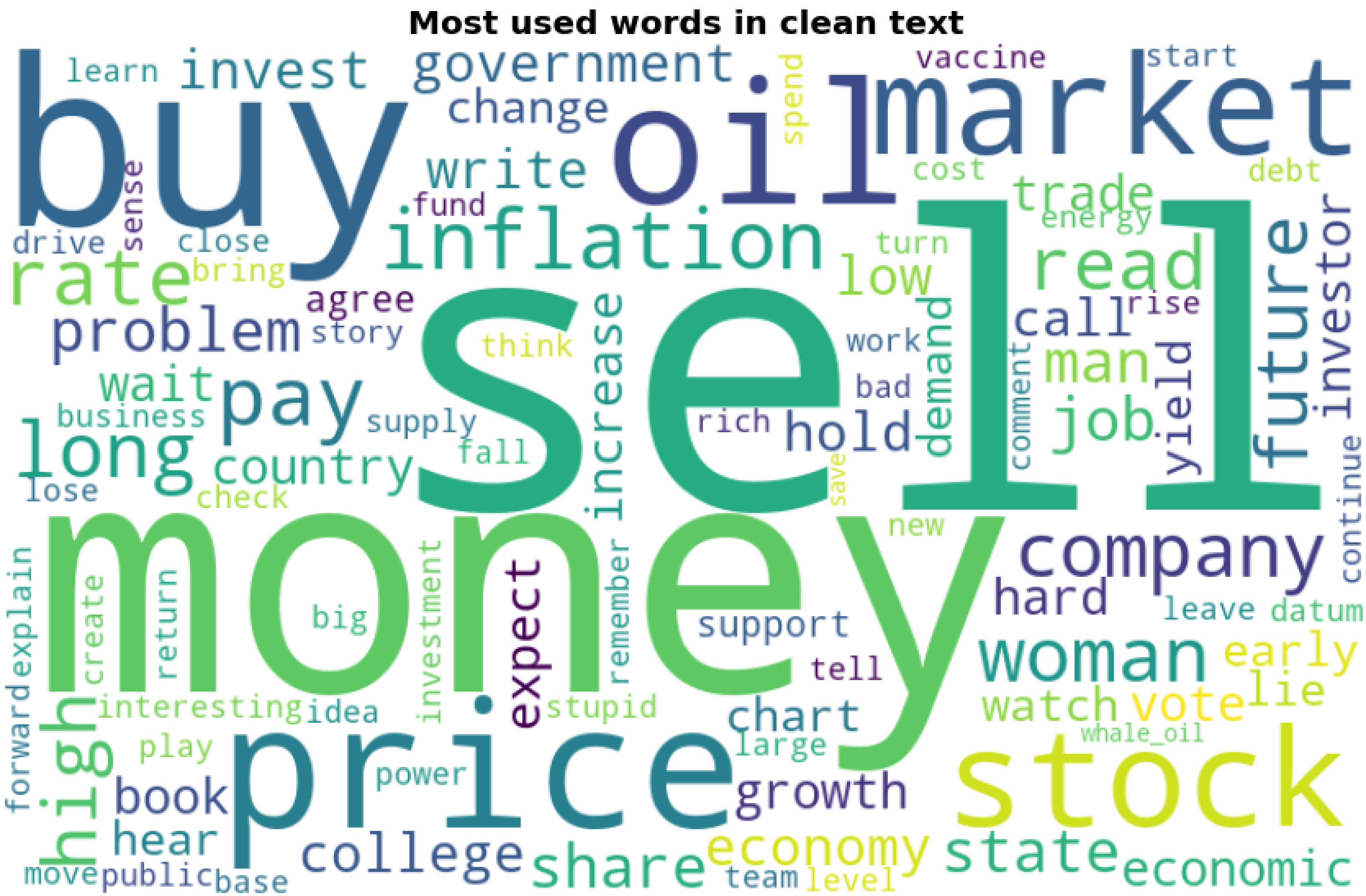
In [317…

```
bbb= process_text(data_lemmatized, 'freq')
```

wordcloud for lemmatized text

In [320…

```
bbb = ' '.join(bbb)
wordcloud_func(bbb, Stop_Words = [''],
               Twitter_Icon = False, feature_name = 'clean text', if_save = False)
```



5.2 LDA

In [ ]:
```
import gensim
import gensim.corpora as corpora
from gensim.models import CoherenceModel
from gensim.models.ldamodel import LdaModel
```

In [ ]:
```
import pyLDAvis
import pyLDAvis.gensim #note, in newer versions of pyLDAvis, this is pyLDAvis.gensim_models
```

In [ ]:
```

```

In [ ]:
```

```

In [ ]:
```

```

6. Affect Analysis (extra)

In [379…
```
from empath import Empath #this is a free alternative to LIWC

#for filtering on datetimes
from datetime import datetime, timedelta
import pytz #for managing time zones in datetime objects
utc=pytz.UTC
```

In [380…
```
lexicon = Empath() #initialize object
```

In [381…
```
liwc_categories = ['positive_emotion','negative_emotion' ,'sadness','anger','achievement','religion','work','home','money
```

In [382…
```
def get_all_empath_categories():
    return list(lexicon.analyze("sample text").keys())
```

In [383…
```
all_categories = get_all_empath_categories()
print(len(all_categories))
```

194

In [423…
```
lexicon.analyze("I love red color", categories=["colors"], tokenizer="default", normalize=False)
```

Out[423…
```
{'colors': 0.0}
```

In [395…
```
lexicon.analyze("too expensive", categories=["money"], tokenizer="default", normalize=False)
```

Out[395…
```
{'money': 1.0}
```

In [433…
```
def filter_date(df, date_col='created_at', end_time='',duration=''):

    ## filter dataframe for the specified time frame
    if not end_time: #if no date is specified, start from the latest collected tweet
        end_time = df[date_col].max()

    if not duration:
        duration = end_time - df[date_col].min() #from the first collected tweet to the end of collection

    #set start time by duration
    start_time = end_time - duration

    #filter dataframe for time frame
    df_time_window = df[(df[date_col] >= start_time) & (df[date_col] <= end_time)].copy()

    return df_time_window

def liwc(text, categories=liwc_categories):
    #apply lexicon to each tweet text

    if isinstance(text,str): #if this tweet has any clean_text
        #get emotions counts
        res = lexicon.analyze(text, categories=categories, tokenizer="default", normalize=False)
        #total word count in this tweet:
        res['word_count'] = len(text.split())
    else:
        res = dict.fromkeys(categories, 0) #dictionary of 0s using all the column names from previous tweet
        res['word_count'] = 0

    return res
```

In [434…
```
#with liwc categories
def get_df_liwc(df, text_col='clean_text', date_col='created_at', end_time='',duration='', categories=liwc_categories):
```

```
    #filter dates
    df_filtered = filter_date(df, date_col=date_col, end_time=end_time, duration=duration)

    #apply liwc dictionary to tweets
    ser_of_dicts = df_filtered[text_col].apply(lambda x: liwc(x,categories=categories)) #returns a series of dictionaries
    #convert the result to dataframe
    df_liwc = ser_of_dicts.apply(pd.Series) #makes output into a dataframe

    #add datetime as index to new liwc dataframe
    df_liwc = df_filtered[[date_col]].join(df_liwc) #left join on index
    df_liwc.set_index(date_col, inplace=True) #make the creation datetime the index
    df_liwc.sort_index(inplace=True) #sort tweets in ascending date order

    return df_liwc
```

In [435…

```
%%time
df_liwc = get_df_liwc(df,categories=all_categories)
```

```
Wall time: 10min 50s
```

In [436…

```
df_liwc.sum(axis=0).sort_values(ascending=False)
```

Out[436…

```
word_count      655470.0
economics        32154.0
money            26174.0
business         23835.0
valuable         18932.0
                  ...
irritability       444.0
exotic             443.0
exasperation       432.0
superhero          420.0
anonymity          190.0
Length: 195, dtype: float64
```

In [527…

```
pd.DataFrame(df_liwc.sum(axis=0).sort_values(ascending=False), columns = ['Count'])[:10]
```

Out[527…

	Count
word_count	655470.0
economics	32154.0

	Count
money	26174.0
business	23835.0
valuable	18932.0
negative_emotion	18864.0
payment	18141.0
banking	18048.0
communication	16014.0
shopping	15824.0

In [468…

```
def plot_timeseries(df, freq_str='6H', ncol=3, ignore=[], normalize=False):
    #df is dataframe of word/emotion counts
    #if normalize is True, the plot is the rolling average of % of each tweet. If False, the plot is a rolling sum of emo

    ## Bin dataframe by frequency
    #resampling string id's:
    # Month, Week, Day, Hour, Minute, Seconds: [#]M, [#]W, [#]D,[#]H,[#]T,[#]S
    ts = df.resample(freq_str).sum().copy()

    ## Normalize each emotional count by the total word_count
    if normalize:
        ts = ts.div(ts.word_count, axis=0) #element-wise divide each column by the total word_count

    ## Remove irrelevant columns
    #remove word_count from dataframe
    if 'word_count' not in ignore:
        ignore.append('word_count')
    #remove all irrlevant columns by name
    for colname in ignore:
        if colname in ts.columns:
            del ts[colname]

    ## Rolling
    if normalize: #if values are normalized by word_count, then plot needs to be rolling average
        ts = ts.rolling(1).apply(np.mean)
    else:
        ts = ts.rolling(1).apply(sum)  #rolling() aggregates by ## of records
```

```
    ## Plot
    ts.plot(figsize=(10,6), alpha =0.9,markersize=1 ) #options: steps, steps-post,  steps-mid, steps-pre
    plt.legend(bbox_to_anchor=(1.0, 1.0), ncol=ncol)
    plt.ylabel('% of word count') if normalize else plt.ylabel('word count')
    plt.show()
```

In [464…

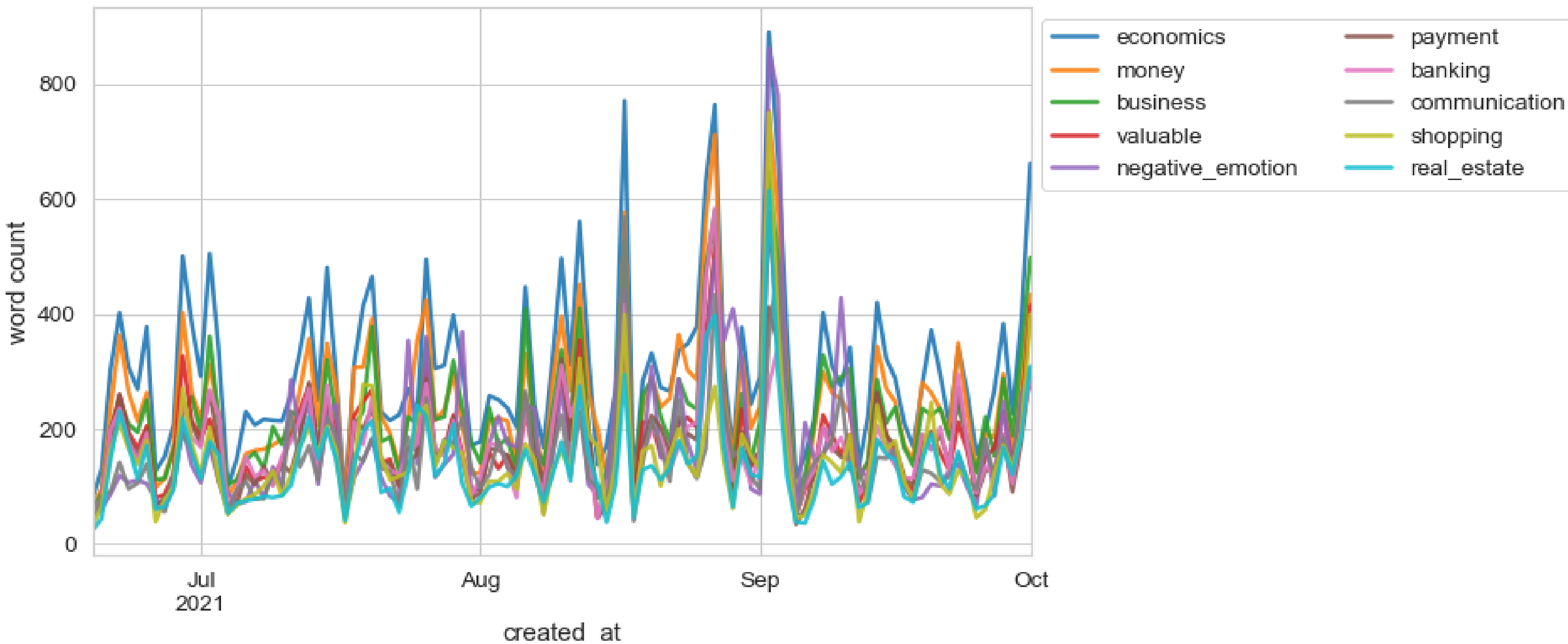
```
#choose the size of the bin. freq_str = Month, Week, Day, Hour, Minute, Seconds: [#]M, [#]W, [#]D,[#]H,[#]T,[#]S
```

In [465…

```
cat_list = df_liwc.sum(axis=0).sort_values(ascending=False).index[:11].to_list()
```

In [469…

```
plot_timeseries(df_liwc[cat_list], freq_str='D', ncol=2, ignore=[], normalize=False)
```



In [ ]: