Stock market-tweets-sentiment-analysis on basis of nlp

December 24, 2022

1 STOCK MARKET SENTIMENT ANALYSIS

2 Problem Statement

Euro Investment Bank has been around for several decades. Following the recent change in leadership, there has been significant efforts to rebrand the company and bring it up to speed with recent technological advancements in the the investment banking industry. The Managing Director of Euro Investment recently read an article purplished on Lehner Investment website, which talks about how Lehner Investment Company Limited uses Natural Language Processing to inform its decisions that led to to significant profit in recent years.

While stock prices are driven by valuations in the long run, it is sentiment that drives the prices in the short run and this creates attractive opportunities for long term investors to enter the market and for active traders to eit or enter the market. The use of Natural Language Processing complements the use of fundamental and technical analysis in guaging the market sentiment (Lehner Investments(2022).

The Managing Director of Euro Investments has never heard of NaturalLanguage Processing before so he calld the Lead Data Scientist to explain the concept to him and after the explanation, instructed that he wants to see a demonstration of it. The lead Data Scientist came back from the meeting and provided me with tweets data related to the market and instructed me to prepare an NLP Pipeline for Stock Market Tweets Sentiment Analysis.

I was provided with an unlabelle dataset comrprising of tweets so this is an unsupervised learning problem. Some of the packages I intend to use include seaborn, matplotlib and word cloud for visualiation, while I will be using nltk.sentiment for the sentiment anaylsis.

3 Loading Libraries & Preparation of Data

In this section, all the packages used in this pipeline are imported and the data for the pipeline will also be imported. We will also examine the data and familiarise ourself with the nature of the data.

3.1 Import Libraries

[1]:
```
import pandas as pd
import numpy as np
import matplotlib
import seaborn as sns
```

```python
import matplotlib.pyplot as plt
%matplotlib inline
from wordcloud import WordCloud, STOPWORDS
from nltk.sentiment import SentimentIntensityAnalyzer
from textblob import TextBlob
import warnings
warnings.simplefilter("ignore")
```

3.2 Import Data

[2]:
```python
# Download data from https://www.kaggle.com/datasets/tejasurya/
↪huge-stock-market-crash-2022

stkmkt_data = pd.read_csv("E:/adnan new/archive.zip")
```

3.3 Initial Data Exploration

[3]:
```python
# In this cell, we are viewing the first few cells in the dataset
stkmkt_data.head()
```

[3]:
```
                    id                                              text  \
0  1538666561615015938      When will the #NYSE #stockmarketcrash happen?
1  1538665013799489536  Aaj ka gyan:\n\nIf a company isn't a quality c…
2  1538660868027830274  The stock market needs to crash hard to make i…
3  1538657239849836544  Those who are "Buying on DIP" will very soon b…
4  1538654339044196358  @rdrhwke I wish our so-called President were t…

  text_sentiment         username  \
0        Neutral        tradexlnc
1       Negative      niftymonday
2       Negative       kyle132313
3        Neutral  ChintanRajput16
4       Positive      DrPCJustice

                                            hashtags  \
0                      ['NYSE', 'stockmarketcrash']
1  ['stockmarkets', 'stockmarketcrash', 'trading'…
2     ['stockmarketcrash', 'economy', 'rich', 'Fed']
3  ['stockmarketcrash', 'StocksToBuy', 'stockstow…
4  ['Bidenomics', 'inflation', 'recession', 'stoc…

                  created_at  user followers count  replycount  retweetcount  \
0  2022-06-19 23:34:29+00:00                 10669           0             0
1  2022-06-19 23:28:20+00:00                   100           0             1
2  2022-06-19 23:11:52+00:00                     0           0             0
3  2022-06-19 22:57:27+00:00                    54           0             2
```

```
4  2022-06-19 22:45:55+00:00                    28           0            0

   likecount  quotecount language  media  retweetedTweet  quotedtweet  \
0          1           0       en    NaN             NaN          NaN
1          8           0       en    NaN             NaN          NaN
2          0           0       en    NaN             NaN          NaN
3          2           0       en    NaN             NaN          NaN
4          0           0       en    NaN             NaN          NaN

   inReplyToTweetId                inReplyToUser  \
0               NaN                          NaN
1               NaN                          NaN
2               NaN                          NaN
3               NaN                          NaN
4      1.538653e+18  https://twitter.com/rdrhwke

                                       mentionedUsers
0                                                 NaN
1                                                 NaN
2                                                 NaN
3                                                 NaN
4  [User(username='rdrhwke', id=43753976, display…
```

[4]:
```
# In this cell, we want to explore the metadata such as column names,␣
↪datatypes, data counts, etc
stkmkt_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33946 entries, 0 to 33945
Data columns (total 18 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    33946 non-null  int64
 1   text                  33946 non-null  object
 2   text_sentiment        33946 non-null  object
 3   username              33946 non-null  object
 4   hashtags              33945 non-null  object
 5   created_at            33946 non-null  object
 6   user followers count  33946 non-null  int64
 7   replycount            33946 non-null  int64
 8   retweetcount          33946 non-null  int64
 9   likecount             33946 non-null  int64
 10  quotecount            33946 non-null  int64
 11  language              33946 non-null  object
 12  media                 0 non-null      float64
 13  retweetedTweet        0 non-null      float64
 14  quotedtweet           0 non-null      float64
```

```
 15  inReplyToTweetId      4948 non-null   float64
 16  inReplyToUser         4948 non-null   object
 17  mentionedUsers        5533 non-null   object
dtypes: float64(4), int64(6), object(8)
memory usage: 4.7+ MB
```

[5]:
```python
# Here, a function is defined to tell us what percentage of data is missing in␣
↪each column.
def percentage_missing_data(tweets):
    total = tweets.isnull().sum()
    percent = (tweets.isnull().sum()/tweets.isnull().count()*100)
    table = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
    types = []
    for col in tweets.columns:
        dtype = str(tweets[col].dtype)
        types.append(dtype)
    table['Types'] = types
    return(np.transpose(table))
```

[6]:
```python
# Here we implement the function to see what percentage of data is missing in␣
↪each column
percentage_missing_data(stkmkt_data)
```

[6]:
```
            id    text text_sentiment username  hashtags created_at  \
Total        0       0              0        0         1          0
Percent    0.0     0.0            0.0      0.0  0.002946        0.0
Types    int64  object         object   object    object     object

        user followers count replycount retweetcount likecount quotecount  \
Total                      0          0            0         0          0
Percent                  0.0        0.0          0.0       0.0        0.0
Types                  int64      int64        int64     int64      int64

        language    media retweetedTweet quotedtweet inReplyToTweetId  \
Total          0    33946          33946       33946            28998
Percent      0.0    100.0          100.0       100.0        85.423909
Types     object  float64        float64     float64          float64

        inReplyToUser mentionedUsers
Total           28998          28413
Percent     85.423909      83.700583
Types          object         object
```

From the foregoing, we can see that the data has 33946 entries and an index range of 0 to 33945. There are 18 columns but we will not using all the columns in the sentiment analysis.

We can also see from the missing data exploration that there are no media in the tweet data provided, neither are there any retweeted tweets or quoted tweets. Other columns with high percentage of missing data are 'inReplyToTweetId', 'inReplyToUser' and 'mentionedUsers'. The good for us is that we can go ahead with our sentiment analysis, without the columns with high number of missing data.

3.4 Data visualization

As part of our data exploration, it is also a good idea to visualise the data so that we better understand what we are dealing with. To achieve this, we will be using the wordcloud library. After that, we will create a function to visualise the most prominent words in the data set.

[7]:
```
# By using wordcloud,define a function to display the most prominent words in␣
↪our dataset.
def most_prominent_words(tweets, title=""):
    text = " ".join(t for t in tweets.dropna())
    stopwords = set(STOPWORDS)

    # In addition to the stopwords, I have decided to update
    # the stopwords list to include some words associated with the stock market
    stopwords.update(["stock", "market", "buy","sell", "trade", "money","nyse",
                    "stockmarket","crypto","BTC","stockmarketcrash","buying",
                     "selling", "bearmarket"])

    # Instantiating the Word Cloud package.
    wordcloud = WordCloud(stopwords=stopwords, scale=5, max_font_size=60,␣
↪max_words=400,background_color="black").generate(text)

    # Code for plotting the world cloud
    fig = plt.figure(1, figsize=(15,15))
    plt.axis('off')
    fig.suptitle(title, fontsize=18)
    fig.subplots_adjust(top=2.3)
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.show()
```

[8]:
```
# Display the word cloud
most_prominent_words(stkmkt_data['text'], title = 'Prominent words in Stock␣
↪Market Tweets')
```

Prominent words in Stock Market Tweets

4 Sentiment analysis

Using nltk SentimentIntensityAnalyzer, we will be carrying out sentiment analysis of the stock market data in this section.

[9]:
```
# I have made reference to code from https://www.kaggle.com/pashupatigupta/
↪sentiments-transformer-vader-embedding-bert
# for this cell

# Creating an instance of the nltk sentiment analyser
sia = SentimentIntensityAnalyzer()

# Creating a function to harness the nltk sentiment analyser
def detect_tweet_sentiment(tweets):
    if sia.polarity_scores(tweets)["compound"] > 0:
        return "Positive_Tweets"
    elif sia.polarity_scores(tweets)["compound"] < 0:
        return "Negative Tweets"
    else:
        return "Neutral Tweets"
```

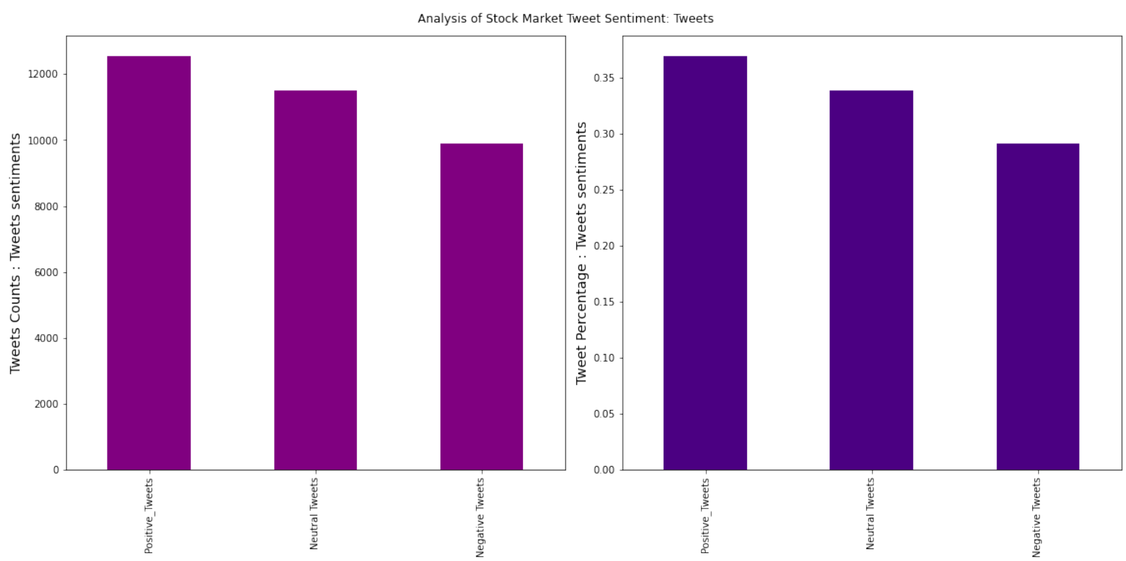
[10]:
```
# After finding the sentiments of the tweets, the next step is to visualise
# the sentiments of the tweets. To achieve this the following function is␣
↪created
```

```
def plot_tweet_sentiments(tweets, feature, title):
    counts = tweets[feature].value_counts()
    percent = counts/sum(counts)

    fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(16, 8))

    counts.plot(kind='bar', ax=ax1, color='purple')
    percent.plot(kind='bar', ax=ax2, color='indigo')
    ax1.set_ylabel(f'Tweets Counts : {title} sentiments', size=14)
    ax2.set_ylabel(f'Tweet Percentage : {title} sentiments', size=14)
    plt.suptitle(f"Analysis of Stock Market Tweet Sentiment: {title}")
    plt.tight_layout()
    plt.show()
```

[11]:
```
# In this cell, I employ both 'find_tweet_sentiment' and␣
↪'plot_tweet_sentiments' functions
# We have decided to plot both the counts and percentage for the tweets.
stkmkt_data['tweet_sentiment'] = stkmkt_data['text'].apply(lambda x:␣
↪detect_tweet_sentiment(x))
plot_tweet_sentiments(stkmkt_data, 'tweet_sentiment', 'Tweets')
```

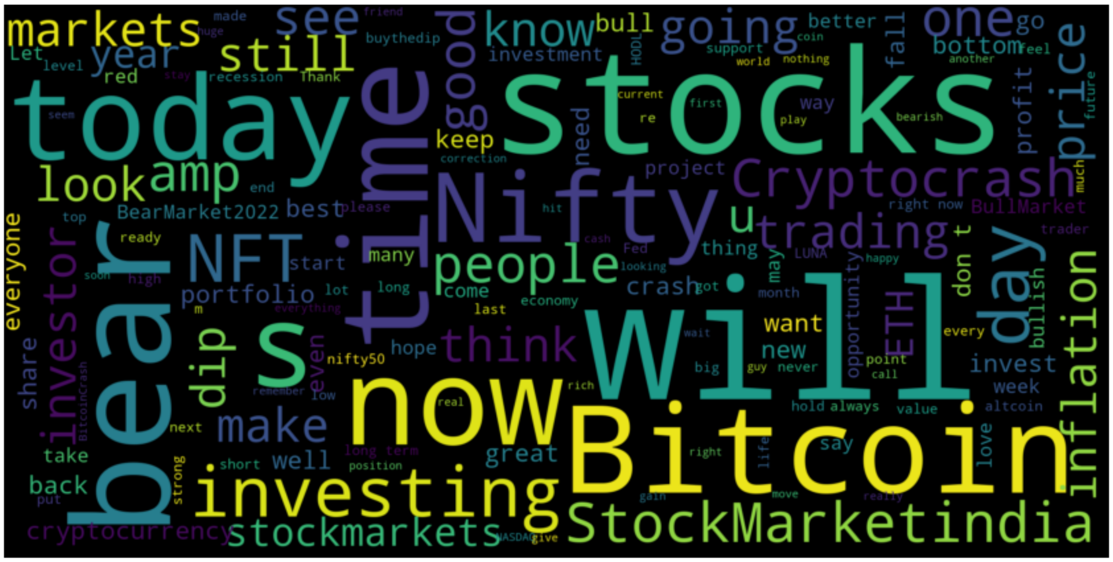


From the above plots, we can see that by count and percentage there are more positive tweets than there are neutral tweets and there are more neutral tweets than there are negative tweets. This tells us that the market sentiment is generally positive.However, lets dive a little deeper to explore what constitutes the positive, neutral and negative tweets.

4.1 Exploring Positive Tweets

In this section, we explore the prominent words associated with positive tweets using the wordcloud package.

[12]:
```
most_prominent_words(stkmkt_data.loc[stkmkt_data['text_sentiment']=='Positive', 'text'], title = 'Prominent words in texts (Positive sentiment)')
```



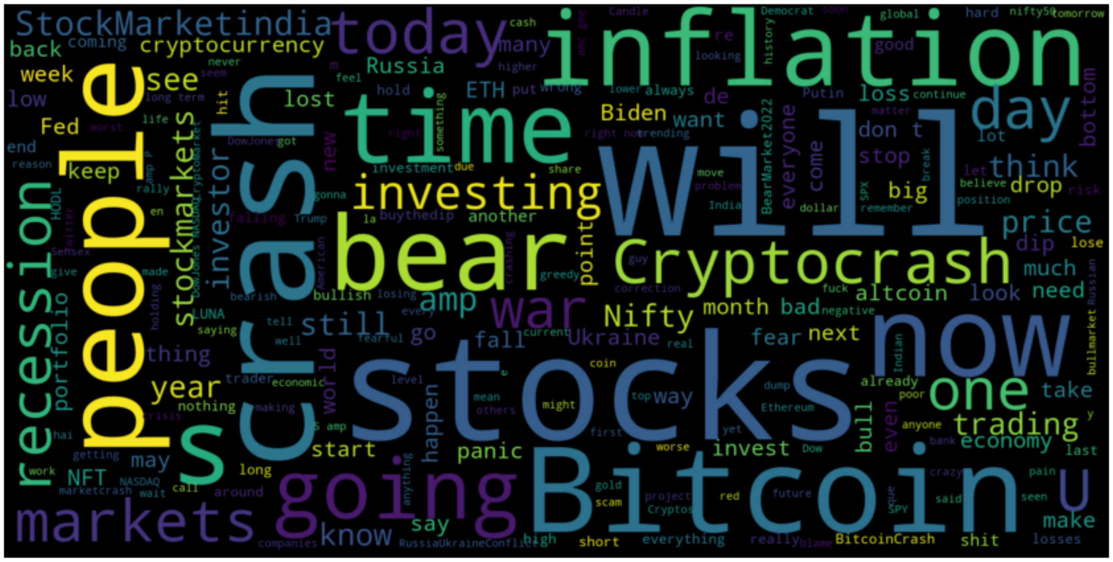
Prominent words in texts (Positive sentiment)

From the above word cloud we can see that the prominent words associated with positive tweets include “time”, “today”, “NFT”, “Bitcoin”, “bear”, “Will” amongst others.

4.2 Exploring Negative Tweets

In this section, we explore the prominent words associated with negative tweets using the wordcloud package.

[13]:
```
most_prominent_words(stkmkt_data.loc[stkmkt_data['text_sentiment']=='Negative', 'text'], title = 'Prominent words in texts (Negative sentiment)')
```



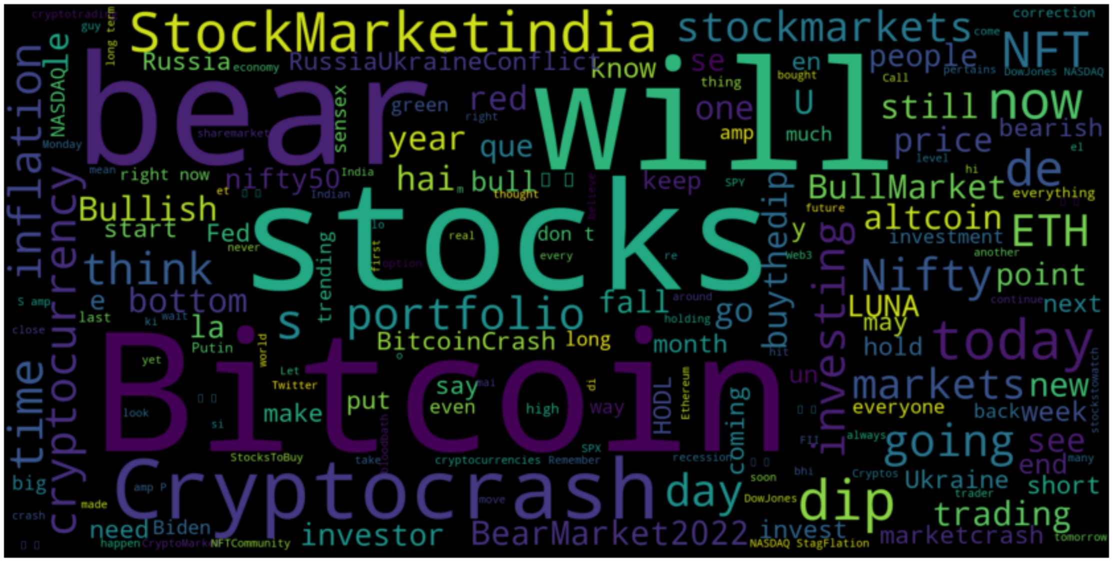
Prominent words in texts (Negative sentiment)

From the above word cloud, we can see that the priminent words associated with negative tweets include "inflation", "Will", "crash", "cryptocrash", "people" amongst other words

4.3 Exploring Neutral Tweets

In this section, we explore the prominent words associated with neutral tweets using the wordcloud package.

[14]:
```
most_prominent_words(stkmkt_data.loc[stkmkt_data['text_sentiment']=='Neutral',
 ↪'text'], title = 'Prominent words in texts (Neutral sentiment)')
```



Prominent words in texts (Neutral sentiment)

From the above word cloud, we can see that the prominent words associated with neutral tweets include “Bullish”, “Cryptocrash”, “Bitcoin”, “bear”, “NFT” amongts others.

5 Test for Polarity and Subjectivity

In addition to the sentiments of the stock martket tweets, we can also get more insights from our dataset. In this case, we will be using TextBlob package to test the sentiments for polarity and subjectivity. Typically, the polarity score is a float that falls within the range of -1.0 to 1.0 while the subjectivity test score is also a float that falls within the range 0.0 to 1.0, where 0.0 is very objective and 1.0 is very subjective (Dipanjan, 2018).

[15]:
```
# Creating a function for polarity test using TextBlob
def tweet_sentiment_polarity_test(tweet):
    blob = TextBlob(tweet)
    polarity = 0
    for sentence in blob.sentences:
        polarity += sentence.sentiment.polarity
    return polarity

# Creating a function for subjectivity test using TextBlob
def tweet_sentiment_subjectivity_test(tweet):
    blob = TextBlob(tweet)
    subjectivity = 0
    for sentence in blob.sentences:
        subjectivity += sentence.sentiment.subjectivity
    return subjectivity
```

[16]:
```
# Performing the polarity and subjectivity tests
stkmkt_data['text_sentiment_polarity'] = stkmkt_data['text'].apply(lambda x:␣
↪tweet_sentiment_polarity_test(x))
stkmkt_data['text_sentiment_subjectivity'] = stkmkt_data['text'].apply(lambda x:
↪ tweet_sentiment_subjectivity_test(x))
```

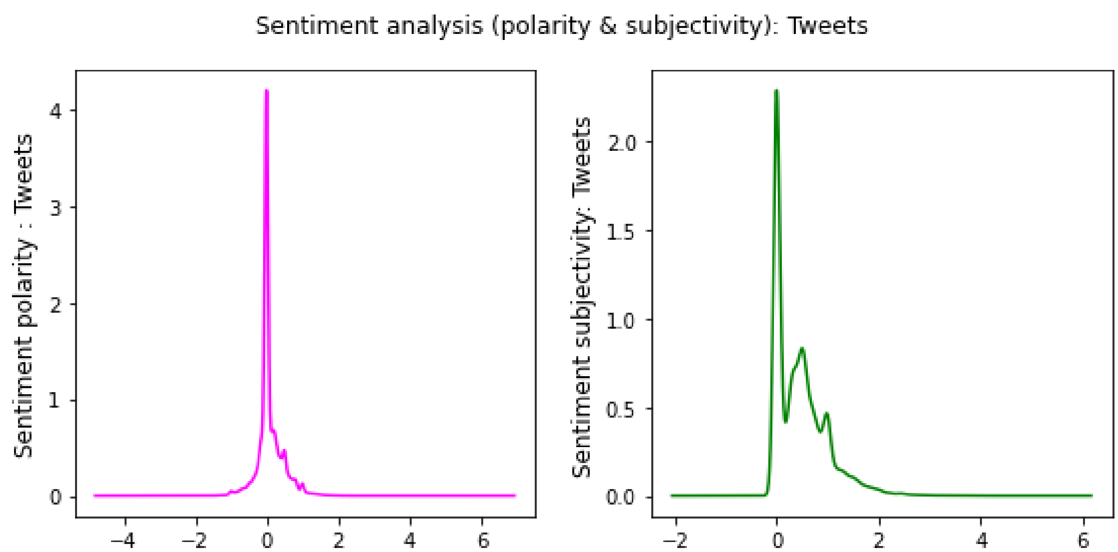
[17]:
```
# Creating function to visualise the results of the polarity and subjectivity␣
↪tests.

def plot_sentiment_polarity_subjectivity(tweets, feature, title):
    polarity = tweets[feature+'_sentiment_polarity']
    subjectivity = tweets[feature+'_sentiment_subjectivity']

    fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(8,4))

    polarity.plot(kind='kde', ax=ax1, color='magenta')
    subjectivity.plot(kind='kde', ax=ax2, color='green')
    ax1.set_ylabel(f'Sentiment polarity : {title}', size=12)
    ax2.set_ylabel(f'Sentiment subjectivity: {title}', size=12)
    plt.suptitle(f"Sentiment analysis (polarity & subjectivity): {title}")
    plt.tight_layout()
    plt.show()
```

[18]:
```
plot_sentiment_polarity_subjectivity(stkmkt_data, "text", 'Tweets')
```



From the plots above, we can see that the polarity plot appears to be balanced and close to zero. This means that the sentiments are not polarised. We can also see that from the subjectivity plot above, the tweet sentiments are more concentrated around the zero value, which means that the sentiments are very objective.

6 Conclusion

We can see that using nltk library, we are able to analyse the stock market sentiment using tweets. From the output of cell 11, we can see that there are more positive tweets than there are neutral tweets and there are more neutral tweets than there are negative tweets. This implies that the sentiment of the market is predominantly positive and this is associated with a rise in prices of stocks and the likelyhood of a bull market. In conclusion, there is no doubt that Natural Langguage Processing can be used to gauge the sentiment of the stock market.

7 References

1. Lehner Investments (2022) Sentiment Analysis – What is market sentiment and how does it affect the stock market?. Available at: https://www.lehnerinvestments.com/en/sentiment-analysis-stock-market-sentiment/ (Accessed: 11 September 2022).

2. Pashupati.G(2020) Sentiments[Transformer & VADER] + Embedding [BERT] Available at: https://www.kaggle.com/pashupatigupta/sentiments-transformer-vader-embedding-bert (Accessed: 11 September 2022).

3. Dipanjan, S.(2018) Emotion and Sentiment Analysis: A Practitioner's Guide to NLP Available at: https://www.kdnuggets.com/2018/08/emotion-sentiment-analysis-practitioners-guide-nlp-5.html (Accessed: 11 September 2022).