CBD 3335 6 [B123]

Data Mining and Analysis

Assignment-1

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Collecting tweets related to the stock market

*Note: Sub-titles are not captured in Xplore and should not be used

line 1: 1st Given Name Surname line 2: dept. name of organization (of Affiliation) line 3: name of organization (of Affiliation) line 4: City, Country

line 5: email address or ORCID

line 1: 2nd Given Name Surname line 2: dept. name of organization (of Affiliation) line 3: name of organization (of

Affiliation) line 4: City, Country

line 5: email address or ORCID

line 1: 3rd Given Name Surname line 2: dept. name of organization (of Affiliation)

line 3: name of organization (of Affiliation)

line 4: City, Country

line 5: email address or ORCID

line 1: 4th Given Name Surname line 2: dept. name of organization (of Affiliation) line 3: name of organization (of

Affiliation) line 4: City, Country

line 5: email address or ORCID

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line 5: email address or ORCID

Abstract—This assignment is based on Twitter data analysis. We are downloading tweets of some specific keywords.

- 1. Collecting data: In this assignment, we are collecting data related to the stock market from Twitter for one week. On Twitter, ticker symbols are used for stocks and companies. We are using keywords Altcoin, Bitcoin, Coindesk, Cryptocurrency, Gold, APPL, GOOG YHOO
- 2. Saving data: You need to save the requested data into csv format of 8 files where data related to each keyword is saved. Each file consist of four columns: tweet id, time of tweet, user id, and text.
- 3. Cleaning data: remove duplication, remove punctuations, remove numbers in tweets, and remove words with lengths less than 2.
- 4. Visualizing data: You need to present the daily number of tweets for each keyword as well as the daily number of users. Use Clustering of similar tweets if feasible and applicable

I. INTRODUCTION

Python is our preferred programming language, which we use for various purposes (API connections, Modelling, Data engineering). We are creating a Twitter API call in Python to download stock market keywords as a hashtag. We downloaded data and cleaned it with Python (library functions). In addition, we have included a basic visualization of the cleaned data. For twitter analysis, Information is collected by either the user, the access point, what's in the post, and how users view or use your post. Using this information, we can understand demographics, total view on your profile or how many people have seen a person's Tweet.

II. FETCHING DATA FROM TWITTER

A. Importing libraries

```
import datetime
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from nltk.sentiment.vader import SentimentIntensitvAnalyze
import nltk
import tweepy
import configparser
```

Fig. 1. Importing libraries

Tweepy: Tweepy is an open-source, user-friendly Python library for interacting with the Twitter API.

Time: This module offers a variety of time-related functions.

Pandas: Pandas is an open-source data analysis and manipulation tool that is fast, powerful, flexible, and straightforward. It is built on top of the Python programming language.

Textblob: Textblob is a text processing library. It provides a straightforward API for delving into standard natural language processing (NLP) tasks like part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more.

Wordcloud: a data visualization technique for representing text data in which the size of each word indicates the frequency or importance of that word.

Numpy: Numpy is a Python programming language opensource library. It is used in scientific computing and array manipulation.

Re: The re module provides a set of powerful regular expression facilities that allow you to quickly check whether a given string matches or contains a given pattern (via the match function) (using the search function).

B. Using key essentials

Using Keys from the Twitter developer account,we can download tweets related to our keywords.

```
api_key = "APEDNnbf8c064u182UB6YXuEx"

api_key_secret = "MXX318xd0aaQspDDhfNSXdYQoBZoqnHgsCKT6yyNFlxgV6xTUW"

access_token = "1526337285337282689-aMQw7o5LYmx8lo1szlJ9w0U2JHsV9q"

access_token_secret = "lkxwrDw8K928c8H6rJSponlHAmwhirELXyp8Nbuprq9L"

# authentication
auth = theepy.0AuthHandler(api_key, api_key_secret)
auth.set_access_token(access_token, access_token_secret)

api = tweepy.API(auth, wait_on_rate_limit=True,wait_on_rate_limit_notify=True)
```

Fig. 2. Using keys for fetching tweets

We are creating the access token and access token secret and making the API object while passing in the auth information.

C.Fetch market data

We are mining stock market data here by creating a function fetch_data (). We obtain tweets for all eight tickers by storing them in a list and iterating over it. We get the tweets' creation date, username, tweet and location, and keywords, i.e., Tickers.

```
In [7]: def fetch_data():

# Tichers on what we saroch the tweets
tickers = ("Britcoin," sepide", "allocain", "#Condeak", "#Cryptocurrency", "aAPPL", "800005", "BRIDO"]
# Present the Limit is set to 10 to sove the computational time
limit-10

# Creating a distifferm in which the tweets extracted one stored
df = ptd.DetaTrame(columns = ["Created &t", "User", "Tweet", "Location", "Tickers"])
data = []
# Specifying the distriction of time span in which the tweets are extracted
data. [int-[282-87-81], "282-87-89", "2822-87-89", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "282-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "282-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "2822-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85", "282-87-85",
```

Fig. 3. Fetching tweets for specific keywords

III. DATA CLEANING

Data is cleaned by removing duplicates, punctuation marks, and words of length less than 2.

```
# Create a function to clean the tweets

def cleanTxt(text):
    text - re.sub("A[-Ze-20-9]*," text) # Removing Wenetions
    text - re.sub("A[-Ze-20-9]*,", text) # Removing '*' hash tag
    text - re.sub("A[-Ze-2]*,", text) # Removing wordts less than Length of 2
    text - re.sub("A[-Ze-2]*,", text) # Removing wordts less than Length of 2
    text - re.sub("A[-Ze-2]*,", text) # Removing hyperlish
    return text

df3["Tweet"] = df3["Tweet"].apply(cleanTxt)

df3

tickers = ['#bitcoin', '#gold', '#Altcoin', '#Coindesk', '#Cryptocurrency', '#APPL', '#GOOG', '#YMOO']

df3['Created At'] = pd.to_datetime(df3['Created At'])

start_date='2022-07-09'

tweets_in_past_day = []

for ticker in tickers:

mast_* (df3['Created At'] > start_date) & (df3['Created At'] <= end_date> & (df3['Tickers'] == ticker)
    num_tweets_len(df3.loc_mast)
    tweets_in_past_day_append(num_tweets)

C:\Ulbers'thskuppdestallocalineps/inylenenl_Sf6/2577241891.py:2: SettingbithCopyblarning:
    A value is trying to be set on a copy of a slike from a DateFrame.

Try using .loc[row_indexer_oc_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
    df3['Created At'] = pd.to_datetime(df3['Created At'])
```

Fig. 4. Data cleaning

IV. DATA VISUALIZATION

A. The number of tweets in the past day

```
tweets_in_past_day
[60, 120, 180, 240, 295, 325, 381, 381]
visualization_df = pd.DataFrame({'Tickers':tickers, 'Number of'tweets':tweets_in_past_day})
ax = visualization_df.plot.bar(x='Tickers', y='Number of tweets', rot=90)
```

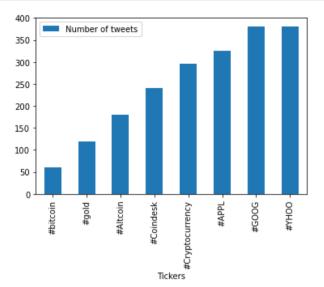


Fig. 5. Number of tweets in the past days

B.Number of users tweeting in a day/hour for ticker symbol

```
start_date='2022-07-01'
end_date='2022-07-01'

distinct_users_in_past_day = []

for ticker in tickers:
    mask = (df3['Created At'] > start_date) & (df3['Created At'] <= end_date) & (df3['Tickers'] == ticker)
    num_users = df3.loc[mask]
    n = len(f0.unique(num_users['User']))
    distinct_users_in_past_day.append(n)</pre>
```

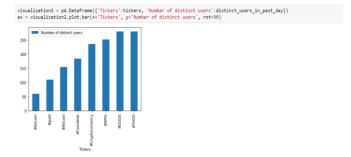


Fig. 6. Number of users tweeting a day

V. DOWNLOADING INDIVIDUAL DATA FRAME

Now, we are going to download individual dataset files for each and every keyword by converting it into CSV files.

A. Individual Bitcoin Dataset



Fig. 7. Bitcoin dataset

B.Individual dataset for Gold

	Created At	User	Tweet	Location	Tickers	Created_Date
0	2022-06-30 23:59:59+00:00	EngleFord	RT @IncomeSharks: From July 1st to November 1s		#gold	2022-06-30
1	2022-06-30 23:59:59+00:00	DeepStar22	RT @OfficialTravlad: What tf is this #Bitcoin	New Delhi, India	#gold	2022-06-30
2	2022-06-30 23:59:57+00:00	nerivansouza01	RT @milkshake_io: MicroStrategy chief executiv		#gold	2022-06-30
3	2022-06-30 23:59:56+00:00	EngleFord	RT @CedYoungelman: Your home is not worth more		#gold	2022-06-3
4	2022-06-30 23:59:56+00:00	AndersTintin	RT @OfficialTravlad: What tf is this #Bitcoin	New Norway, Alberta	#gold	2022-06-3
			216			
135	2022-07-06 23:55:56+00:00	wojtekcrypto08	#Gold: Barrick Gold Corp (GOLD) closed today a		#gold	2022-07-0
136	2022-07-06 23:55:44+00:00	muzzleloaderman	RT @roxiewin7: Excited to share this item from	Oregon, USA	#gold	2022-07-0
137	2022-07-06 23:55:03+00:00	TalkMarkets	Rare #Gold-#Silver Crystal Sighting GLD SLV		#gold	2022-07-0
138	2022-07-06 23:54:05+00:00	BHC_Valentine	#Hopping into some #hydroneer #earlyaccess #Ga		#gold	2022-07-0
139	2022-07-06 23:53:01+00:00	SalvadorMaurice	\$STK \n\nMULTIPLE NEW #GOLD ZONES AND HIGH-GRA	Bali Indonesia	#gold	2022-07-0

Fig. 8. Gold dataset

C.Altcoin



Fig. 9. Altcoin dataset

D.Coindesk

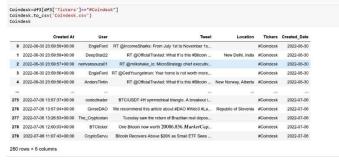


Fig. 10. Coindesk dataset

D.APPL

	Created At	User	Tweet	Location	Tickers	Created_Date
0	2022-06-30 23:59:59+00:00	EngleFord	RT @IncomeSharks: From July 1st to November 1s		#APPL	2022-06-30
1	2022-06-30 23:59:59+00:00	DeepStar22	RT @OfficialTravlad: What tf is this #Bitcoin	New Delhi, India	#APPL	2022-06-30
2	2022-06-30 23:59:57+00:00	nerivansouza01	RT @milkshake_io: MicroStrategy chief executiv		#APPL	2022-06-30
3	2022-06-30 23:59:56+00:00	EngleFord	RT @CedYoungelman: Your home is not worth more		#APPL	2022-06-30
4	2022-06-30 23:59:56+00:00	AndersTintin	RT @OfficialTravlad: What tf is this #Bitcoin	New Norway, Alberta	#APPL	2022-06-30
***				***	141	***
409	2022-07-06 06:07:27+00:00	im_ba1tazar	@gandalfcryptto Love 💗 #AITX #ai #APPL #MSFT		#APPL	2022-07-06
410	2022-07-06 05:06:15+00:00	PyScaleLLC	RT @im_ba1tazar: @BabyCatCoin @cz_binance Love	Miami, FL	#APPL	2022-07-06
411	2022-07-06 05:06:14+00:00	PyScaleLLC	RT @im_ba1tazar: Love 💗 #AITX #ai #APPL #MSFT	Miami, FL	WAPPL	2022-07-06
412	2022-07-06 05:08:00+00:00	PyScaleLLC	RT @im_ba1tazar: @jesmotril @Cheemslnu Same! L	Miami, FL	#APPL	2022-07-06
413	2022-07-06 05:01:38+00:00	lm_ba1tazar	@jesmotril @CheemsInu Same! Love * #AITX #ai		#APPL	2022-07-06

Fig. 11. APPL dataset

E.Cryptocurrency



Fig. 12. Cryptocurrency dataset

F.GOOG



Fig. 13. GOOG dataset

G.YAHOO

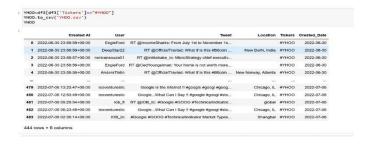


Fig. 14. YAHOO dataset

References

- [1] https://dev.twitter.com/overview/documentation
- [2] https://www.python.org/doc/