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## WRANGLING

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### STEPS

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#### 1- GATHERING THE DATA

- KNOW WHAT DATA IS NEED TO BE COLLECTED IN WHAT FORM , AND FROM WHERE TO COLLECT IT
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#### 2- Asserting

- Reading the datasets
  - EXAMINING THE DATA AND THE QULITY OR TIDNY ISSUES WITH IT
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#### 3- Cleaning

- Phase one : Data Cleaning
    - 1- Dealing with duplicate
    - 2- Removing Non-existing Data
  - Phase Two : Data Analysis in Python
  - Phase Three : Visualization and charts
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#### 4- OUTPUT AND FINAL DATA AND Visualization

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## WRANGLING

### PART 1 :: GATHERING THE DATA

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IN THIS PROJECT I HAVE TO DEAL WITH THREE DATA FROM THREE SEPARATE ORIGINS

#### \* First

BY including the provided link of the first two data and throw request in python i was able to download the two files and save both in ".csv" file format , and start to work on them.

#### \* Second

And to get the tweets from tweeter on the account of "dog\_rate" , started by creating tweeter account with more than five approvals on my request to get the approval on the "tweeter Developer account" and examine how to use the tweepy API to get tweets from certain IDs that is provided by the previously downloaded in step one and save these tweets with in ".csv" file format to start work on that file

Type *Markdown* and *LaTeX*:  $\alpha^2$

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### PART 2 :: Asserting

## Data Assessment:

## Visually and Programmatic Examining the Data

## A - Visually Assessment

## **Visual assessment:**

- By Openin the FILES [ 'api\_df.csv' , 'archive\_df.csv' , 'image\_predictions\_df.csv' ] , In Excel APP and VS CODE APP ON MY WINDOWS DESKTOP AND CHECK THE DATA

## B - Programmatic Assessment ::

- BY USING THE pandas supported function to examin the data in the data frames to see how it look like and what it contain , by looping thorw each data to see its shape columns , and what it look like thorw describe and info functions :

SOME OF THE PANDAS FUNCTIONS USED IN PROGRAMMATIC ASSESSMENT :

PP >> MEANS\_PANDAS\_DATA\_FRAME

### 1- PD head()

2- PD shape()

### 3- PD.info()

#### 4- PD.describ

## 5- PD.count()

## 6- PD.sum()

Below i provided some photos of the results of using code to visually Programmatic the data given :

```
print(df.info())
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 18 columns):
 #   Column           Non-Null Count  Dtype  
 --- 
 0   Unnamed: 0        2356 non-null   int64  
 1   tweet_id          2356 non-null   int64  
 2   in_reply_to_status_id  78 non-null   float64 
 3   in_reply_to_user_id  78 non-null   float64 
 4   timestamp          2356 non-null   object  
 5   source             2356 non-null   object  
 6   text               2356 non-null   object  
 7   retweeted_status_id 181 non-null   float64 
 8   retweeted_status_user_id 181 non-null   float64 
 9   retweeted_status_timestamp 181 non-null   object  
 10  expanded_urls      2297 non-null   object  
 11  rating_numerator  2356 non-null   int64  
 12  rating_denominator 2356 non-null   int64  
 13  name               2356 non-null   object  
 14  doggo              2356 non-null   object  
 15  floofer            2356 non-null   object  
 16  pupper              2356 non-null   object  
 17  puppo              2356 non-null   object  
dtypes: float64(4), int64(4), object(10)
memory usage: 331.4+ KB
```

[11] > ➜ ML

```
print(df.describe())
max    2355.000000  8.924206e+1/    8.8b2bb4e+1/    8.405479e+1/
      retweeted_status_id  retweeted_status_user_id  rating_numerator \
count    1.810000e+02           1.810000e+02    2356.000000
mean    7.728400e+17           1.241698e+16   13.126486
std     6.236928e+16           9.599254e+16   45.876648
min     6.661041e+17           7.832140e+05   0.000000
25%    7.186315e+17           4.196984e+09   10.000000
50%    7.804657e+17           4.196984e+09   11.000000
75%    8.203146e+17           4.196984e+09   12.000000
max     8.874740e+17           7.874618e+17  1776.000000
      rating_denominator
count    2356.000000
mean    10.455433
std     6.745237
min     0.000000
25%    10.000000
50%    10.000000
75%    10.000000
max     170.000000
*****
```

Count of actual data in each column against the total number of rows:

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```
Count of actual data in each column against the total number of rows:
      Unnamed: 0          2356
      tweet_id          2356
      in_reply_to_status_id  78
      in_reply_to_user_id  78
      timestamp          2356
      source             2356
      text               2356
      retweeted_status_id 181
      retweeted_status_user_id 181
      retweeted_status_timestamp 181
      expanded_urls      2297
      rating_numerator  2356
      rating_denominator 2356
      name               2356
      doggo              2356
      floofer            2356
      pupper              2356
      puppo              2356
      dtype: int64
*****
```

[11] > ➜ ML

Non existing data in each row:

```
      Unnamed: 0          0
      tweet_id          0
      in_reply_to_status_id  2278
      in_reply_to_user_id  2278
      timestamp          0
      source             0
      text               0
      retweeted_status_id 2175
      retweeted_status_user_id 2175
      retweeted_status_timestamp 2175
      expanded_urls      59
      rating_numerator  0
      rating_denominator 0
      name               0
      doggo              0
      floofer            0
      pupper              0
      puppo              0
      dtype: int64
*****
```

Duplicated data :

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```
*****
Shape of the data:
(2075, 13)
*****
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2075 entries, 0 to 2074
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   Unnamed: 0    2075 non-null   int64  
 1   tweet_id     2075 non-null   int64  
 2   jpg_url      2075 non-null   object  
 3   img_num      2075 non-null   int64  
 4   p1           2075 non-null   object  
 5   p1_conf      2075 non-null   float64 
 6   p1_dog       2075 non-null   bool    
 7   p2           2075 non-null   object  
 8   p2_conf      2075 non-null   float64 
 9   p2_dog       2075 non-null   bool    
 10  p3           2075 non-null   object  
 11  p3_conf      2075 non-null   float64 
 12  p3_dog       2075 non-null   bool    
dtypes: bool(3), float64(3), int64(3), object(4)
```

## C - Asserting issues with Data

### Quality and tidiness issues

#### Quality

1- Missing values :

A - Missing values in "twitter-archive-enhanced" Data set , AS AN EXAMPLE - in :

- "in\_reply\_to\_status\_id"
- "in\_reply\_to\_user\_id"
- "retweeted\_status\_id"
- "retweeted\_status\_user\_id"
- 'name'
- "source"

columns .

B - Missing values in "twitter-archive-enhanced" , AS AN EXAMPLE - in :

```
* Row # "2351" with tweet id    "666049248165822465" , have name with "None" value .
* Row # "2352" with tweet id    "666044226329800704" , have name with "a" letter value .
* Row # "2353" with tweet id    "666033412701032449" , have name with "a" letter value .
* Row # "2354" with tweet id    "666029285002620928" , have name with "a" letter value .
* Row # "2355" with tweet id    "666020888022790149" , have name with "None" value .
```

ROWS .

2- Duplicated Tweets in "twitter-archive-enhanced" Data in

```
"retweeted_status_id"      ,with count of    181
"retweeted_status_user_id" ,with count of    181
"retweeted_status_timestamp" ,with count of    181
```

columns.

#### 3- DATA TYPES

- IN "twitter-archive-enhanced", THE "retweeted\_status\_timestamp" COLUMN DATA TYPE IS 'object' NOT "TIME STAMP" OR "DATE TIME " TYPE.
- IN "twitter-archive-enhanced" , "tweet\_id" column is "int" type with no need to do analysis on it so it may convert to string .

#### 4- DATA VALUES

- Validity:

IN "twitter-archive-enhanced" there is :

```
* "rating_denominator" HAVE DATA VLUES LESS THAN 10 WICH IS THE MINMIMUM RATING FOR DOG , with count of 3 ratings
* "rating_numerator"   HAVE DATA VLUES LESS THAN 10 WICH IS THE MINMIMUM RATING FOR DOG , with count of 440 ratings
```

5 - More than one column in "image\_predictions" , for the smae vlaue and measure in AKA ( DOGS IS seperated IN 4 COLUMNS )

```
[p1, p2 ,p3]  
[ p1_dog , p2_dog , p3_dog ]  
[ p1_conf , p2_conf , p3_conf ]  
6 - In "image_predictions" , columns header are vales not variables name
```

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## Tidiness

- 1 - All the data is in relation in each other but seperated into three tables
- 2 - COLUMN with no useful , or repated data , must be droped from the final data

Type *Markdown* and *LaTeX*:  $\alpha^2$

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## PART 3 :: Cleaning

- Phase one : Data Cleaning
    - 1- Dealing with duplicate
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- 

### Data Cleaning:

- AT THE END OF THE process we need data that contain the "dog name" if available, the "dog type" AKA "dog type" if available, and "rating tweets" , that dog type get over the time .

In Cleaning either drop the repeated columns the give the same answer or merge them each category in one column

in order to do so I need a data with only "tweet id" that is not duplicated , and original tweet no retweets and also a rating with the most prediction available,

- To do so i will do the follow process :

- 1- merge the types of the dog in one column "dog type" contain the type rather than (False , True) boolean column
- 2- will drop the other two less prediction , columns , drop text name after extracting the dog type from the txt column
- 3- drop the ratings that violate the rating measures
- 4- creating a clean data and save it to new ".csv" data type .

Type *Markdown* and *LaTeX*:  $\alpha^2$

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## WRANGLING

## THE END RESULT

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### Output:

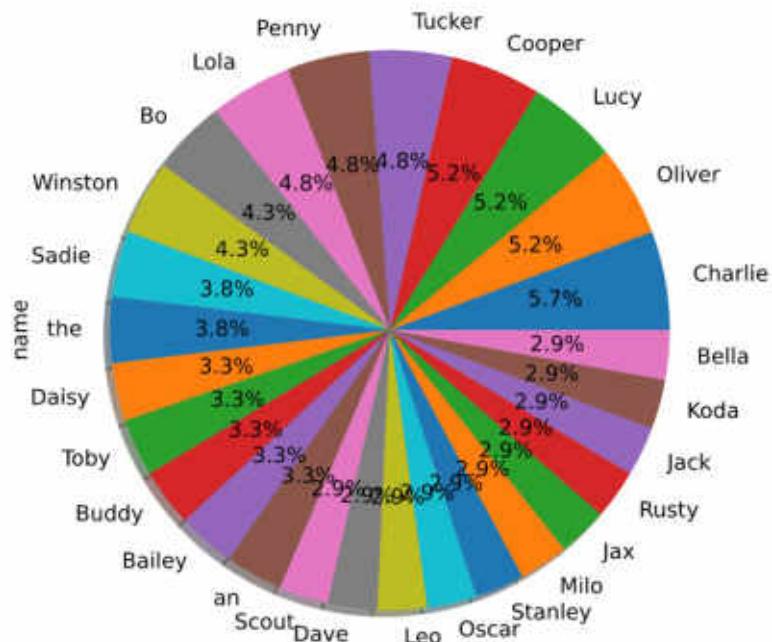
The file created as result of this process.

**THE OUTPUT FINAL FILE IS "twitter\_archive\_master.csv" DATA WHICH IS HAVE IN MY VIEW THE OPTIMAL DATA CLEANED**

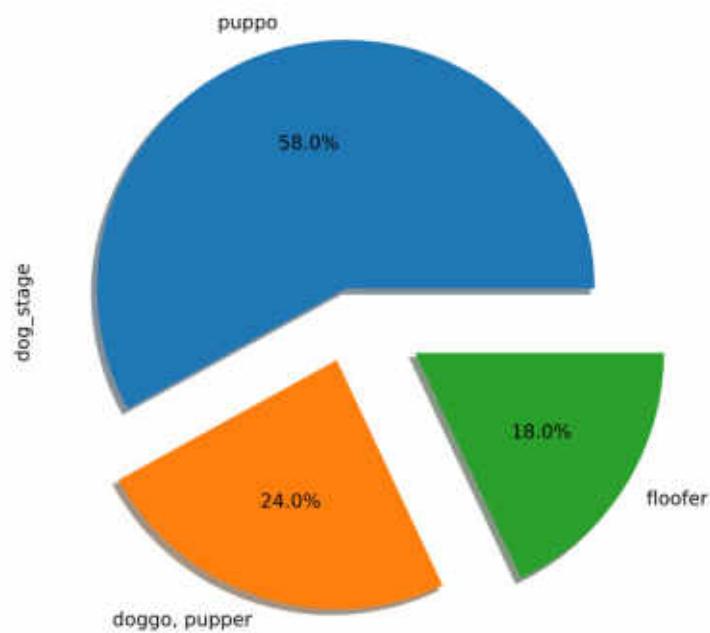
## WICH WILL BE USED IN THE NEXT PHASES :

- Phase Two : Data Analysis in Python
- Phase Three : Visualization and charts

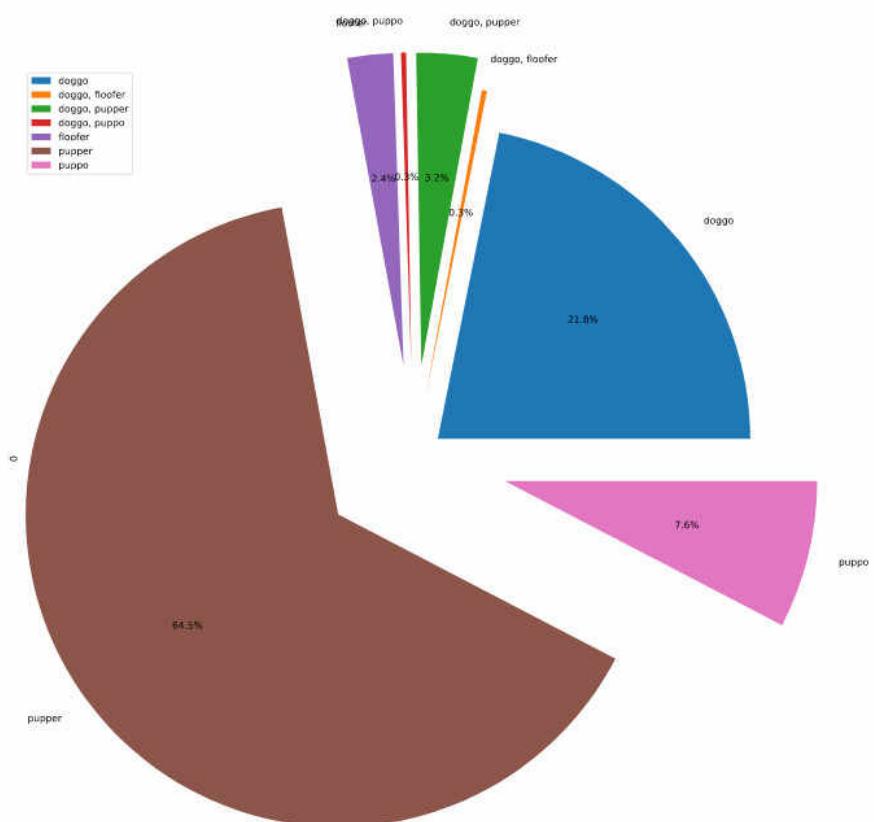
Most names , tweeted for dogs, percentage



DOG STAGE , appered int tweets for dogs, percentage



Rating numerator , apperd in tweets for dogs, percentage



In [ ]:

1