Project: Data Wrangling - We Rate Dogs

In [1]:
```
# Load the library necessary for the analysis

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt, mpld3
import matplotlib.patches as mpatches
import plotly.express as px

%matplotlib inline
```

In [2]:
```
# Loading the first dataset

twitter_archive = pd.read_csv('twitter-archive-enhanced.csv')
```

In [3]:
```
# View the first few lines of twitter archive for "WeRateDogs"

twitter_archive.head()
```

Out[3]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
0	892420643555336193	NaN	NaN	2017-08-01 16:23:56 +0000	href="http://twitter.com/down
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com/down
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com/down
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com/down
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com/down

In [4]:
```
# Loading the second part of data

import requests
import os

image_folder = 'Image_prediction'
if not os.path.exists(image_folder):
    os.makedirs(image_folder)

url = "https://d17h27t6h515a5.cloudfront.net/topher/2017/August/599fd2ad_image-predicti
image_data = requests.get(url)

with open(os.path.join(image_folder, url.split('/')[-1]), mode='wb') as f:
    f.write(image_data.content)
```

In [5]:
```
# Loading the second data as a dataframe

image_prediction = pd.read_csv(r"C:\Users\Samuel Chika\Documents\Nanodegree\Data Wrangl
```

In [6]:
```
# View the top rows of second data

image_prediction.head()
```

Out[6]:

	tweet_id	jpg_url	img_num	
0	666020888022790149	https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg	1	Welsh_springer_span
1	666029285002620928	https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg	1	redbo
2	666033412701032449	https://pbs.twimg.com/media/CT4521TWwAEvMyu.jpg	1	German_shephe
3	666044226329800704	https://pbs.twimg.com/media/CT5Dr8HUEAA-lEu.jpg	1	Rhodesian_ridgeba
4	666049248165822465	https://pbs.twimg.com/media/CT5IQmsXIAAKY4A.jpg	1	miniature_pinsch

In [7]:
```
# Getting the third data

import json

tweet_list = []
with open('tweet-json.txt') as f:
    for data in f:
        tweet = json.loads(data)
        key = tweet.keys()
        user = tweet.get('user')
        id_str = tweet.get('id_str')
        retweet_count = tweet.get('retweet_count')
        favorite_count = tweet.get('favorite_count')
        tweet_list.append({'id_str': id_str,
                           'retweet_count': retweet_count,
                           'favorite_count': favorite_count})
```

In [8]:
```
# Load third data into dataframe
```

```
tweet_data_count = pd.DataFrame(tweet_list, columns = ['id_str', 'retweet_count', 'favo
```

In [9]:
```
# Inspect the top rows of third dataframe

tweet_data_count.head()
```

Out[9]:

	id_str	retweet_count	favorite_count
0	892420643555336193	8853	39467
1	892177421306343426	6514	33819
2	891815181378084864	4328	25461
3	891689557279858688	8964	42908
4	891327558926688256	9774	41048

Now, data from all thre data sources have been read into a data frame. It is now time to start analysis of the data and performing all necessary cleaning. Hence, we begin with the data in "twitter_archive" ...

In [10]:
```
twitter_archive.head()
```

Out[10]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
0	892420643555336193	NaN	NaN	2017-08-01 16:23:56 +0000	href="http://twitter.com/down
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com/down
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com/down
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com/down
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com/down

In [11]:
```
# Assess some basic info about each column in the dataset

twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 17 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   tweet_id                    2356 non-null   int64  
 1   in_reply_to_status_id       78 non-null     float64
 2   in_reply_to_user_id         78 non-null     float64
 3   timestamp                   2356 non-null   object 
 4   source                      2356 non-null   object 
 5   text                        2356 non-null   object 
 6   retweeted_status_id         181 non-null    float64
 7   retweeted_status_user_id    181 non-null    float64
 8   retweeted_status_timestamp  181 non-null    object 
 9   expanded_urls               2297 non-null   object 
 10  rating_numerator            2356 non-null   int64  
 11  rating_denominator          2356 non-null   int64  
 12  name                        2356 non-null   object 
 13  doggo                       2356 non-null   object 
 14  floofer                     2356 non-null   object 
 15  pupper                      2356 non-null   object 
 16  puppo                       2356 non-null   object 
dtypes: float64(4), int64(3), object(10)
memory usage: 313.0+ KB
```

In [12]:
```
# View summary of the numerical variables in the data

twitter_archive.describe()
```

Out[12]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	retweeted_status_id	retweeted_status_user
count	2.356000e+03	7.800000e+01	7.800000e+01	1.810000e+02	1.810000e+
mean	7.427716e+17	7.455079e+17	2.014171e+16	7.720400e+17	1.241698e+
std	6.856705e+16	7.582492e+16	1.252797e+17	6.236928e+16	9.599254e+
min	6.660209e+17	6.658147e+17	1.185634e+07	6.661041e+17	7.832140e+
25%	6.783989e+17	6.757419e+17	3.086374e+08	7.186315e+17	4.196984e+
50%	7.196279e+17	7.038708e+17	4.196984e+09	7.804657e+17	4.196984e+
75%	7.993373e+17	8.257804e+17	4.196984e+09	8.203146e+17	4.196984e+
max	8.924206e+17	8.862664e+17	8.405479e+17	8.874740e+17	7.874618e+

Accooring to the instructions given for this project, retweets are not to be considered. Therefore, the tweets listed above are retweets, and they representa group of tweets that we will not be using in our analysis.

In [13]:
```
# View the number of rows and columns in the data
```

In [13]:
```
twitter_archive.shape
```

Out[13]:
```
(2356, 17)
```

In [14]:
```
# Insoect the first few rows of the second data

image_prediction.head()
```

Out[14]:

	tweet_id	jpg_url	img_num	
0	666020888022790149	https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg	1	Welsh_springer_span
1	666029285002620928	https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg	1	redbo
2	666033412701032449	https://pbs.twimg.com/media/CT4521TWwAEvMyu.jpg	1	German_shephe
3	666044226329800704	https://pbs.twimg.com/media/CT5Dr8HUEAA-lEu.jpg	1	Rhodesian_ridgeba
4	666049248165822465	https://pbs.twimg.com/media/CT5IQmsXIAAKY4A.jpg	1	miniature_pinsch

In [15]:
```
# Insoect first few rows of third data

tweet_data_count.head()
```

Out[15]:

	id_str	retweet_count	favorite_count
0	892420643555336193	8853	39467
1	892177421306343426	6514	33819
2	891815181378084864	4328	25461
3	891689557279858688	8964	42908
4	891327558926688256	9774	41048

In [16]:
```
# View number of rows and columns in thrird data

tweet_data_count.shape
```

Out[16]:
```
(2354, 3)
```

In [17]:
```
# View information about the columns in the third data

tweet_data_count.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2354 entries, 0 to 2353
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   id_str          2354 non-null   object
 1   retweet_count   2354 non-null   int64 
```

```
 2   favorite_count  2354 non-null   int64
dtypes: int64(2), object(1)
memory usage: 55.3+ KB
```

Instruction given for the project indicates that we are expected to highlight at least 8 data quality issues and 2 data tidiness issues.

Quality

The following observations were made from data in the Twitter Archive

- The column name "id_str" does not match with any other column in the other tables. This column name needs to be changed to "tweet_id".
- Some of the columns in the table contain missing values. Some of the affected columns are in_reply_to_status_id, in_reply_to_user_id, retweeted_status_id, retweeted_status_user_id, etc.
- The data type of the tweet_id is integer, but needs should be an object.
- The table contains both retweets and replies, but since the instruction specifically states that only original tweets are allowed, these would have to be removed.
- The datatype of the timestamp needs to be changed to "datetime".
- The dog names are not in capital letters since they are nouns.
- There are lots of columns with 'none' as the entry.

Under the image preditions data, issues observed includes

- The format of the names in columns p1, p2 and p3 are not consistent, the names starts with a mixture of both capital and small letters, which should be corrected.

Tidiness

- The data in all the tables must be combined to form just one table.
- Some of the tweets represents more than one dog.
- The column representing texts contains multiple information such as urls and even ratings.

In [18]:
```
# View how many times a name appeared in the "name" column

twitter_archive.name.value_counts()
```

Out[18]:
```
None          745
a              55
Charlie        12
Cooper         11
Lucy           11
              ...
Dex             1
Ace             1
Tayzie          1
Grizzie         1
```

```
Christoper      1
Name: name, Length: 957, dtype: int64
```

From the overview of the result above, it is observed that there are 745 cases in which the name of the dog was "none". We can also see that "a" occured 55 times. These two point to the fact that soxme of the names in that column are not accurate.

In [19]:
```
twitter_archive[twitter_archive.name.duplicated()]
```

Out[19]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
7	890729181411237888	NaN	NaN	2017-07-28 00:22:40 +0000	href="http://twitter.com/d
12	889665388333682689	NaN	NaN	2017-07-25 01:55:32 +0000	href="http://twitter.com/d
23	887473957103951883	NaN	NaN	2017-07-19 00:47:34 +0000	href="http://twitter.com/d
24	887343217045368832	NaN	NaN	2017-07-18 16:08:03 +0000	href="http://twitter.com/d
25	887101392804085760	NaN	NaN	2017-07-18 00:07:08 +0000	href="http://twitter.com/d
...	...	...	...	...	
2351	666049248165822465	NaN	NaN	2015-11-16 00:24:50 +0000	href="http://twitter.com/d
2352	666044226329800704	NaN	NaN	2015-11-16 00:04:52 +0000	href="http://twitter.com/d

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
2353	666033412701032449	NaN	NaN	2015-11-15 23:21:54 +0000	href="http://twitter.com/d
2354	666029285002620928	NaN	NaN	2015-11-15 23:05:30 +0000	href="http://twitter.com/d
2355	666020888022790149	NaN	NaN	2015-11-15 22:32:08 +0000	href="http://twitter.com/d

1399 rows × 17 columns

As suspected, we can see that "none" and 'a' are duplicated severally under the column "name".

In [20]:
```
# View frequency of each value in rating_numerator

twitter_archive.rating_numerator.value_counts()
```

Out[20]:
```
12      558
11      464
10      461
13      351
9       158
8       102
7        55
14       54
5        37
6        32
3        19
4        17
2         9
1         9
75        2
15        2
420       2
0         2
80        1
144       1
17        1
26        1
20        1
121       1
143       1
44        1
```

```
60        1
45        1
50        1
99        1
204       1
1776      1
165       1
666       1
27        1
182       1
24        1
960       1
84        1
88        1
Name: rating_numerator, dtype: int64
```

The result above shows the frequency of each value in the numerator column and it indicates that there are some outliers in that column. While majoity of values zfall between 8 and 12, we can also see that we have values like 1776, 666,420, etc in the column.

In [21]:
```
# View frequency of each value in rating_denominator

twitter_archive.rating_denominator.value_counts()
```

Out[21]:
```
10     2333
11        3
50        3
20        2
80        2
70        1
7         1
15        1
150       1
170       1
0         1
90        1
40        1
130       1
110       1
16        1
120       1
2         1
Name: rating_denominator, dtype: int64
```

Similar to the numerator, it can be seen from the result above that the denominator also has also has some outliers. While 10 is the overwhelming majortiy, we still have some large values like 120, 150 and 170.

In [22]:
```
# View last few rows in this data

image_prediction.tail()
```

Out[22]:

	tweet_id	jpg_url	img_num	p1	p
2070	891327558926688256	https://pbs.twimg.com/media/DF6hr6BUMAAzZgT.jpg	2	basset	0.5

	tweet_id	jpg_url	img_num	p1	p
2071	891689557279858688	https://pbs.twimg.com/media/DF_q7IAWsAEuuN8.jpg	1	paper_towel	0.1
2072	891815181378084864	https://pbs.twimg.com/media/DGBdLU1WsAANxJ9.jpg	1	Chihuahua	0.7
2073	892177421306343426	https://pbs.twimg.com/media/DGGmoV4XsAAUL6n.jpg	1	Chihuahua	0.3
2074	892420643555336193	https://pbs.twimg.com/media/DGKD1-bXoAAIAUK.jpg	1	orange	0.0

In [23]:
```
image_prediction.shape
```

Out[23]:
```
(2075, 12)
```

In [24]:
```
# View basic information about each column in this data

image_prediction.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2075 entries, 0 to 2074
Data columns (total 12 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   tweet_id  2075 non-null   int64  
 1   jpg_url   2075 non-null   object 
 2   img_num   2075 non-null   int64  
 3   p1        2075 non-null   object 
 4   p1_conf   2075 non-null   float64
 5   p1_dog    2075 non-null   bool   
 6   p2        2075 non-null   object 
 7   p2_conf   2075 non-null   float64
 8   p2_dog    2075 non-null   bool   
 9   p3        2075 non-null   object 
 10  p3_conf   2075 non-null   float64
 11  p3_dog    2075 non-null   bool   
dtypes: bool(3), float64(3), int64(2), object(4)
memory usage: 152.1+ KB
```

The result above hints at the fact that there are no missing values in this dataframe.

In [25]:
```
# View frequency of each value in "p1" column

image_prediction.p1.value_counts()
```

Out[25]:
```
golden_retriever      150
Labrador_retriever    100
Pembroke               89
Chihuahua              83
pug                    57
                     ...
pillow                  1
carousel                1
bald_eagle              1
lorikeet                1
orange                  1
Name: p1, Length: 378, dtype: int64
```

In [26]:
```
# View frequency of each value in "p2" column

image_prediction.p2.value_counts()
```

Out[26]:
```
Labrador_retriever    104
golden_retriever       92
Cardigan               73
Chihuahua              44
Pomeranian             42
                     ...
medicine_chest          1
quail                   1
horse_cart              1
waffle_iron             1
bagel                   1
Name: p2, Length: 405, dtype: int64
```

In [27]:
```
# View frequency of each value in "p3" column

image_prediction.p3.value_counts()
```

Out[27]:
```
Labrador_retriever    79
Chihuahua             58
golden_retriever      48
Eskimo_dog            38
kelpie                35
                      ..
ox                     1
assault_rifle          1
axolotl                1
pot                    1
banana                 1
Name: p3, Length: 408, dtype: int64
```

The results above indicate that Labrodor Retriever and Golden Retriever are two of the most popular dog breeds in our dataset.

In [28]:
```
# View last few rows in this data

tweet_data_count.tail()
```

Out[28]:

	id_str	retweet_count	favorite_count
2349	666049248165822465	41	111
2350	666044226329800704	147	311
2351	666033412701032449	47	128
2352	666029285002620928	48	132
2353	666020888022790149	532	2535

In [29]:
```
# View number of rows and columns in this data

tweet_data_count.shape
```

Out[29]:
```
(2354, 3)
```

In [30]:
```
tweet_data_count.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2354 entries, 0 to 2353
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   id_str          2354 non-null   object
 1   retweet_count   2354 non-null   int64 
 2   favorite_count  2354 non-null   int64 
dtypes: int64(2), object(1)
memory usage: 55.3+ KB
```

In [31]:
```
# View summary of numerial columns in this data

tweet_data_count.describe()
```

Out[31]:

	retweet_count	favorite_count
count	2354.000000	2354.000000
mean	3164.797366	8080.968564
std	5284.770364	11814.771334
min	0.000000	0.000000
25%	624.500000	1415.000000
50%	1473.500000	3603.500000
75%	3652.000000	10122.250000
max	79515.000000	132810.000000

DATA CLEANING

Now that we have examined the different dataset, we need to clean the data. However, we would first duplicate each dataset so that we have a backup just in case something goes wrong.

In [32]:
```
# Make a copy of each of these data

clean_twitter_archive = twitter_archive.copy()
clean_image_prediction = image_prediction.copy()
clean_tweet_data_count = tweet_data_count.copy()
```

Now that the tables are duplicated, we would start cleaning them one after another, starting with the "Clean Twitter Archive".

In [33]:
```
clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 17 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   tweet_id                    2356 non-null   int64  
 1   in_reply_to_status_id       78 non-null     float64
 2   in_reply_to_user_id         78 non-null     float64
 3   timestamp                   2356 non-null   object 
 4   source                      2356 non-null   object 
 5   text                        2356 non-null   object 
 6   retweeted_status_id         181 non-null    float64
 7   retweeted_status_user_id    181 non-null    float64
 8   retweeted_status_timestamp  181 non-null    object 
 9   expanded_urls               2297 non-null   object 
 10  rating_numerator            2356 non-null   int64  
 11  rating_denominator          2356 non-null   int64  
 12  name                        2356 non-null   object 
 13  doggo                       2356 non-null   object 
 14  floofer                     2356 non-null   object 
 15  pupper                      2356 non-null   object 
 16  puppo                       2356 non-null   object 
dtypes: float64(4), int64(3), object(10)
memory usage: 313.0+ KB
```

To start with, we are going to remove all retweets and replies so as to ensure only original tweets are left as instructed.

Define

Remove all retweets and replies leaving only original tweets in the data

Code

In [34]:
```
# Removing the retweets in the dataset

remove_retweet = clean_twitter_archive[pd.notnull(clean_twitter_archive['retweeted_stat
clean_twitter_archive.drop(index=remove_retweet, inplace=True)
```

In [35]:
```
# Removing replies from the dataset

remove_reply = clean_twitter_archive[pd.notnull(clean_twitter_archive['in_reply_to_stat
clean_twitter_archive.drop(index=remove_reply, inplace=True)
```

Test

In [36]:
```
# Checking to ensure the codes above worked as expected

clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2097 entries, 0 to 2355
Data columns (total 17 columns):
 #   Column                      Non-Null Count  Dtype  
```

```
 ---  ------                       --------------  -----
 0    tweet_id                     2097 non-null   int64
 1    in_reply_to_status_id        0 non-null      float64
 2    in_reply_to_user_id          0 non-null      float64
 3    timestamp                    2097 non-null   object
 4    source                       2097 non-null   object
 5    text                         2097 non-null   object
 6    retweeted_status_id          0 non-null      float64
 7    retweeted_status_user_id     0 non-null      float64
 8    retweeted_status_timestamp   0 non-null      object
 9    expanded_urls                2094 non-null   object
 10   rating_numerator             2097 non-null   int64
 11   rating_denominator           2097 non-null   int64
 12   name                         2097 non-null   object
 13   doggo                        2097 non-null   object
 14   floofer                      2097 non-null   object
 15   pupper                       2097 non-null   object
 16   puppo                        2097 non-null   object
dtypes: float64(4), int64(3), object(10)
memory usage: 294.9+ KB
```

From the output above, we can see some columns are now empty, hence we can drop those columns.

Define

Drop the columns we do not need from the dataset

Code

In [37]:

```
# Drop the listed columns

clean_twitter_archive = clean_twitter_archive.drop(['in_reply_to_status_id', 'in_reply_
                                                    'retweeted_status_id', 'retweeted
                                                    'retweeted_status_timestamp'], ax
```

Test

In [38]:

```
# Inspect to confirm last action

clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2097 entries, 0 to 2355
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   tweet_id            2097 non-null   int64
 1   timestamp           2097 non-null   object
 2   source              2097 non-null   object
 3   text                2097 non-null   object
 4   expanded_urls       2094 non-null   object
 5   rating_numerator    2097 non-null   int64
 6   rating_denominator  2097 non-null   int64
```

```
 7   name                2097 non-null   object
 8   doggo               2097 non-null   object
 9   floofer             2097 non-null   object
 10  pupper              2097 non-null   object
 11  puppo               2097 non-null   object
dtypes: int64(3), object(9)
memory usage: 213.0+ KB
```

In [39]:
```
# View first two rows of this data

clean_twitter_archive.head(2)
```

Out[39]:

	tweet_id	timestamp	source	text	
0	892420643555336193	2017-08-01 16:23:56 +0000	<a href="http://twitter.com/download/iphone" r...	This is Phineas. He's a mystical boy. Only eve...	https://twitter.com/
1	892177421306343426	2017-08-01 00:17:27 +0000	<a href="http://twitter.com/download/iphone" r...	This is Tilly. She's just checking pup on you....	https://twitter.com/

Define

Remove the "source" column.

Code

In [40]:
```
# Drop the "source" column

clean_twitter_archive.drop(columns='source', inplace=True)
```

Test

In [41]:
```
clean_twitter_archive.head(2)
```

Out[41]:

	tweet_id	timestamp	text	expanded_urls	rating_numer

	tweet_id	timestamp	text	expanded_urls	rating_numer
0	892420643555336193	2017-08-01 16:23:56 +0000	This is Phineas. He's a mystical boy. Only eve...	https://twitter.com/dog_rates/status/892420643...	
1	892177421306343426	2017-08-01 00:17:27 +0000	This is Tilly. She's just checking pup on you....	https://twitter.com/dog_rates/status/892177421...	

Now we want to chamge the data types for some of the columns in the Twitter Archive dataset.

Define

- Chage the datatype of "tweet_id" to string
- Change datatype of "timestamp" datetime

Code

In [42]:
```
# CHange the data types for "tweet_id" and "timestamp"

clean_twitter_archive['tweet_id'] = clean_twitter_archive['tweet_id'].astype('str')
clean_twitter_archive['timestamp'] = pd.to_datetime(clean_twitter_archive['timestamp'])
```

Test

In [43]:
```
# Inspect the datatypes of "tweet_id" and "timestamp"

clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2097 entries, 0 to 2355
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype              
---  ------              --------------  -----              
 0   tweet_id            2097 non-null   object             
 1   timestamp           2097 non-null   datetime64[ns, UTC]
 2   text                2097 non-null   object             
 3   expanded_urls       2094 non-null   object             
 4   rating_numerator    2097 non-null   int64              
 5   rating_denominator  2097 non-null   int64              
 6   name                2097 non-null   object             
 7   doggo               2097 non-null   object             
 8   floofer             2097 non-null   object             
```

```
 9   pupper              2097 non-null   object
 10  puppo               2097 non-null   object
dtypes: datetime64[ns, UTC](1), int64(2), object(8)
memory usage: 196.6+ KB
```

Define

- Remove the urls currently in the body of the tweets
- Substitute all cases of "&" to "&"
- Remove the new line symbol "\n" from the text by substituting it with whitespace
- Remove all whitespaces before of after the tweet text body

Codes

In [44]:
```
# Remove the url that is in the text column

clean_twitter_archive['text'] = clean_twitter_archive.text.str.replace(r"http\S+", "");
```

```
C:\Users\SAMUEL~1\AppData\Local\Temp/ipykernel_17824/2846507828.py:3: FutureWarning: The default value of regex will change from True to False in a future version.
  clean_twitter_archive['text'] = clean_twitter_archive.text.str.replace(r"http\S+", "");
```

In [45]:
```
# Chamge "&amp;" to "&" in the text column

clean_twitter_archive['text'] = clean_twitter_archive.text.str.replace("&amp;", "&")
```

In [46]:
```
# Remove the symbol for a new line from the text column

clean_twitter_archive['text'] = clean_twitter_archive.text.str.replace("\n", " ")
```

In [47]:
```
# Now to remove any unseen spaces before and after the text

clean_twitter_archive['text'] = clean_twitter_archive.text.str.strip()
```

Test

In [48]:
```
clean_twitter_archive.head(10)
```

Out[48]:

	tweet_id	timestamp	text	expanded_urls	rating
0	892420643555336193	2017-08-01 16:23:56+00:00	This is Phineas. He's a mystical boy. Only eve...	https://twitter.com/dog_rates/status/892420643...	

	tweet_id	timestamp	text	expanded_urls	rating
1	892177421306343426	2017-08-01 00:17:27+00:00	This is Tilly. She's just checking pup on you....	https://twitter.com/dog_rates/status/892177421...	
2	891815181378084864	2017-07-31 00:18:03+00:00	This is Archie. He is a rare Norwegian Pouncin...	https://twitter.com/dog_rates/status/891815181...	
3	891689557279858688	2017-07-30 15:58:51+00:00	This is Darla. She commenced a snooze mid meal...	https://twitter.com/dog_rates/status/891689557...	
4	891327558926688256	2017-07-29 16:00:24+00:00	This is Franklin. He would like you to stop ca...	https://twitter.com/dog_rates/status/891327558...	
5	891087950875897856	2017-07-29 00:08:17+00:00	Here we have a majestic great white breaching ...	https://twitter.com/dog_rates/status/891087950...	
6	890971913173991426	2017-07-28 16:27:12+00:00	Meet Jax. He enjoys ice cream so much he gets ...	https://gofundme.com/ydvmve-surgery-for-jax,ht...	
7	890729181411237888	2017-07-28 00:22:40+00:00	When you watch your owner call another dog a g...	https://twitter.com/dog_rates/status/890729181...	
8	890609185150312448	2017-07-27 16:25:51+00:00	This is Zoey. She doesn't want to be one of th...	https://twitter.com/dog_rates/status/890609185...	
9	890240255349198849	2017-07-26 15:59:51+00:00	This is Cassie. She is a college pup. Studying...	https://twitter.com/dog_rates/status/890240255...	

Define

- Create a new column called "dog_type"
- Remove whitespaces in the newly created column

Code

In [49]:
```
# Add a new column called "dog_type"

clean_twitter_archive['dog_type'] = clean_twitter_archive.text.str.extract('(doggo | fl
```

In [50]:
```
# Eliminate any whitespace that was added to the "dog_type" column during extraction

clean_twitter_archive.dog_type = clean_twitter_archive.dog_type.str.strip()
```

Test

In [51]:
```
clean_twitter_archive.sample(2)
```

Out[51]:

	tweet_id	timestamp	text	expanded_urls	ra
1503	692017291282812928	2016-01-26 16:12:33+00:00	This is Kingsley Wellensworth III. He owns 7 r...	https://twitter.com/dog_rates/status/692017291...	
907	757741869644341248	2016-07-26 00:58:34+00:00	This is Leonard. He hides in bushes to escape ...	https://twitter.com/dog_rates/status/757741869...	

Define

Now that a column has been created for the dog type:

- Columns "doggo", "floofer", "pupper" and "puppo" can be removed from the dataset.
- Change datatype of the "dog_type" column to "category"

Codes

In [52]:
```
# Removing defined columns

clean_twitter_archive = clean_twitter_archive.drop(['doggo', 'floofer', 'pupper', 'pupp
```

In [53]:
```
# Changing the data type of "dog_type" column to category

clean_twitter_archive.dog_type = clean_twitter_archive.dog_type.astype('category')
```

Test

In [54]:
```
clean_twitter_archive.head()
```

Out[54]:

	tweet_id	timestamp	text	expanded_urls	rating
0	892420643555336193	2017-08-01 16:23:56+00:00	This is Phineas. He's a mystical boy. Only eve...	https://twitter.com/dog_rates/status/892420643...	
1	892177421306343426	2017-08-01 00:17:27+00:00	This is Tilly. She's just checking pup on you....	https://twitter.com/dog_rates/status/892177421...	
2	891815181378084864	2017-07-31 00:18:03+00:00	This is Archie. He is a rare Norwegian Pouncin...	https://twitter.com/dog_rates/status/891815181...	
3	891689557279858688	2017-07-30 15:58:51+00:00	This is Darla. She commenced a snooze mid meal...	https://twitter.com/dog_rates/status/891689557...	
4	891327558926688256	2017-07-29 16:00:24+00:00	This is Franklin. He would like you to stop ca...	https://twitter.com/dog_rates/status/891327558...	

In [55]:
```
clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2097 entries, 0 to 2355
Data columns (total 8 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   tweet_id            2097 non-null   object
 1   timestamp           2097 non-null   datetime64[ns, UTC]
 2   text                2097 non-null   object
 3   expanded_urls       2094 non-null   object
 4   rating_numerator    2097 non-null   int64
 5   rating_denominator  2097 non-null   int64
 6   name                2097 non-null   object
 7   dog_type            166 non-null    category
dtypes: category(1), datetime64[ns, UTC](1), int64(2), object(4)
memory usage: 133.3+ KB
```

Cleaning the second dataset: "clean_image_prediction"

Define

Change the datatype of "tweet_id" column

Code

In [56]:
```
# Change the data type of the tweet_id

clean_image_prediction['tweet_id'] = clean_image_prediction['tweet_id'].astype('str')
```

Test

In [57]:
```
clean_image_prediction.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2075 entries, 0 to 2074
Data columns (total 12 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   tweet_id  2075 non-null   object
 1   jpg_url   2075 non-null   object
 2   img_num   2075 non-null   int64 
 3   p1        2075 non-null   object
 4   p1_conf   2075 non-null   float64
 5   p1_dog    2075 non-null   bool  
 6   p2        2075 non-null   object
 7   p2_conf   2075 non-null   float64
 8   p2_dog    2075 non-null   bool  
 9   p3        2075 non-null   object
 10  p3_conf   2075 non-null   float64
 11  p3_dog    2075 non-null   bool  
dtypes: bool(3), float64(3), int64(1), object(5)
memory usage: 152.1+ KB
```

Define

Standardise the dog breed names, convert each column representing dog breeds to small letters

Code

In [58]:
```
# Convert the name of dog breeds to lower cases

clean_image_prediction['p1'] = clean_image_prediction['p1'].str.lower()
clean_image_prediction['p2'] = clean_image_prediction['p2'].str.lower()
clean_image_prediction['p3'] = clean_image_prediction['p3'].str.lower()
```

Test

In [59]:
```
clean_image_prediction.head()
```

Out[59]:

	tweet_id	jpg_url	img_num	p
0	666020888022790149	https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg	1	welsh_springer_spani
1	666029285002620928	https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg	1	redbor
2	666033412701032449	https://pbs.twimg.com/media/CT4521TWwAEvMyu.jpg	1	german_shephe
3	666044226329800704	https://pbs.twimg.com/media/CT5Dr8HUEAA-lEu.jpg	1	rhodesian_ridgeba
4	666049248165822465	https://pbs.twimg.com/media/CT5IQmsXIAAKY4A.jpg	1	miniature_pinsch

Cleaning the third dataset: clean_tweet_data_count

In [60]:
```
clean_tweet_data_count.head()
```

Out[60]:

	id_str	retweet_count	favorite_count
0	892420643555336193	8853	39467
1	892177421306343426	6514	33819
2	891815181378084864	4328	25461
3	891689557279858688	8964	42908
4	891327558926688256	9774	41048

Define

Change "id_str" to "tweet_id" so that column that be uniform with corresponding columns in other dataset.

Code

In [61]:
```
# Rename the specified column so that it is uniform with other two data parts

clean_tweet_data_count.rename(index=str, columns={"id_str": "tweet_id"}, inplace=True)
```

Test

In [62]:
```
clean_tweet_data_count.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2354 entries, 0 to 2353
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   tweet_id        2354 non-null   object
 1   retweet_count   2354 non-null   int64 
 2   favorite_count  2354 non-null   int64 
```

```
dtypes: int64(2), object(1)
memory usage: 73.6+ KB
```

MERGING TABLES

Now we are going to merge the datasets together, starting with "clean_twitter_archive" and "clean_image_prediction".

In [63]:
```
# Merging the "twitter_archive" table with "image_prediction" table.

clean_twitter_archive = clean_twitter_archive.merge(clean_image_prediction, on = 'tweet
```

In [64]:
```
clean_twitter_archive.head()
```

Out[64]:

	tweet_id	timestamp	text	expanded_urls	rating
0	892420643555336193	2017-08-01 16:23:56+00:00	This is Phineas. He's a mystical boy. Only eve...	https://twitter.com/dog_rates/status/892420643...	
1	892177421306343426	2017-08-01 00:17:27+00:00	This is Tilly. She's just checking pup on you....	https://twitter.com/dog_rates/status/892177421...	
2	891815181378084864	2017-07-31 00:18:03+00:00	This is Archie. He is a rare Norwegian Pouncin...	https://twitter.com/dog_rates/status/891815181...	
3	891689557279858688	2017-07-30 15:58:51+00:00	This is Darla. She commenced a snooze mid meal...	https://twitter.com/dog_rates/status/891689557...	
4	891327558926688256	2017-07-29 16:00:24+00:00	This is Franklin. He would like you to stop ca...	https://twitter.com/dog_rates/status/891327558...	

In [65]:
```
clean_twitter_archive.shape
```

Out[65]:
```
(1971, 19)
```

In [66]:
```
# Removing columns that are no longer needed
```

```
clean_twitter_archive = clean_twitter_archive.drop(['img_num', 'p2', 'p2_conf', 'p2_dog
```

In [67]:
```
clean_twitter_archive.shape
```

Out[67]:
```
(1971, 12)
```

We are now going to join the third table, "clean_tweet_data_count" to "clean_twitter_archive".

In [68]:
```
# Join tables "clean_twitter_archive" and "clean_tweet_data_count"

clean_twitter_archive = pd.merge(clean_twitter_archive, clean_tweet_data_count, on = 't
```

In [69]:
```
clean_twitter_archive.shape
```

Out[69]:
```
(1971, 14)
```

In [70]:
```
# View first 2 rows in this data

clean_twitter_archive.sample(2)
```

Out[70]:

	tweet_id	timestamp	text	expanded_urls	rating_n
909	718234618122661888	2016-04-08 00:30:51+00:00	This is Suki. She was born with a blurry tail ...	https://twitter.com/dog_rates/status/718234618...	
197	842846295480000512	2017-03-17 21:13:10+00:00	This is Charlie. He's wishing you a very fun a...	https://twitter.com/dog_rates/status/842846295...	

In [71]:
```
clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 0 to 1970
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   tweet_id            1971 non-null   object
 1   timestamp           1971 non-null   datetime64[ns, UTC]
 2   text                1971 non-null   object
 3   expanded_urls       1971 non-null   object
 4   rating_numerator    1971 non-null   int64
 5   rating_denominator  1971 non-null   int64
```

```
 6   name                1971 non-null   object
 7   dog_type            149 non-null    category
 8   jpg_url             1971 non-null   object
 9   p1                  1971 non-null   object
 10  p1_conf             1971 non-null   float64
 11  p1_dog              1971 non-null   bool
 12  retweet_count       1971 non-null   int64
 13  favorite_count      1971 non-null   int64
dtypes: bool(1), category(1), datetime64[ns, UTC](1), float64(1), int64(4), object(6)
memory usage: 204.2+ KB
```

In [72]:
```
# Convert the data type of "rating_numerator" and "rating_denominator" to floats

clean_twitter_archive.rating_numerator = clean_twitter_archive.rating_numerator.astype(
clean_twitter_archive.rating_denominator = clean_twitter_archive.rating_numerator.astyp
```

In [73]:
```
clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 0 to 1970
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   tweet_id            1971 non-null   object
 1   timestamp           1971 non-null   datetime64[ns, UTC]
 2   text                1971 non-null   object
 3   expanded_urls       1971 non-null   object
 4   rating_numerator    1971 non-null   float64
 5   rating_denominator  1971 non-null   float64
 6   name                1971 non-null   object
 7   dog_type            149 non-null    category
 8   jpg_url             1971 non-null   object
 9   p1                  1971 non-null   object
 10  p1_conf             1971 non-null   float64
 11  p1_dog              1971 non-null   bool
 12  retweet_count       1971 non-null   int64
 13  favorite_count      1971 non-null   int64
dtypes: bool(1), category(1), datetime64[ns, UTC](1), float64(3), int64(2), object(6)
memory usage: 204.2+ KB
```

In [74]:
```
# Get the date and time for the "timestamp" column

clean_twitter_archive['date'] = clean_twitter_archive['timestamp'].apply(lambda x: x.st
clean_twitter_archive['time'] = clean_twitter_archive['timestamp'].apply(lambda x: x.st
```

In [75]:
```
# Set datatype of date column to "datetime"

clean_twitter_archive.date = pd.to_datetime(clean_twitter_archive.date, dayfirst = True
```

In [76]:
```
# Now that we have "date" and "time" in our dataset, the "timestamp" column can be remo


clean_twitter_archive = clean_twitter_archive.drop('timestamp', axis = 1)
```

In [77]:
```
clean_twitter_archive.shape
```

Out[77]:
```
(1971, 15)
```

In [78]:
```
clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 0 to 1970
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   tweet_id            1971 non-null   object
 1   text                1971 non-null   object
 2   expanded_urls       1971 non-null   object
 3   rating_numerator    1971 non-null   float64
 4   rating_denominator  1971 non-null   float64
 5   name                1971 non-null   object
 6   dog_type            149 non-null    category
 7   jpg_url             1971 non-null   object
 8   p1                  1971 non-null   object
 9   p1_conf             1971 non-null   float64
 10  p1_dog              1971 non-null   bool
 11  retweet_count       1971 non-null   int64
 12  favorite_count      1971 non-null   int64
 13  date                1971 non-null   datetime64[ns]
 14  time                1971 non-null   object
dtypes: bool(1), category(1), datetime64[ns](1), float64(3), int64(2), object(7)
memory usage: 219.6+ KB
```

In [79]:
```
clean_twitter_archive.head()
```

Out[79]:

	tweet_id	text	expanded_urls	rating_numerator	rat
0	892420643555336193	This is Phineas. He's a mystical boy. Only eve...	https://twitter.com/dog_rates/status/892420643...	13.0	
1	892177421306343426	This is Tilly. She's just checking pup on you....	https://twitter.com/dog_rates/status/892177421...	13.0	
2	891815181378084864	This is Archie. He is a rare Norwegian Pouncin...	https://twitter.com/dog_rates/status/891815181...	12.0	
3	891689557279858688	This is Darla. She commenced a snooze mid meal...	https://twitter.com/dog_rates/status/891689557...	13.0	

	tweet_id	text	expanded_urls	rating_numerator	rat
4	891327558926688256	This is Franklin. He would like you to stop ca...	https://twitter.com/dog_rates/status/891327558...	12.0	

In [80]:
```
# Change some column names

clean_twitter_archive = clean_twitter_archive.rename({'jpg_url': 'tweet_image_url', 'p1
                                                      'p1_conf': 'prediction_confiden
                                                     axis = 'columns')
```

In [81]:
```
clean_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 0 to 1970
Data columns (total 15 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   tweet_id              1971 non-null   object
 1   text                  1971 non-null   object
 2   expanded_urls         1971 non-null   object
 3   rating_numerator      1971 non-null   float64
 4   rating_denominator    1971 non-null   float64
 5   name                  1971 non-null   object
 6   dog_type              149 non-null    category
 7   tweet_image_url       1971 non-null   object
 8   tweet_prediction      1971 non-null   object
 9   prediction_confidence 1971 non-null   float64
 10  dog_prediction        1971 non-null   bool
 11  retweet_count         1971 non-null   int64
 12  favorite_count        1971 non-null   int64
 13  date                  1971 non-null   datetime64[ns]
 14  time                  1971 non-null   object
dtypes: bool(1), category(1), datetime64[ns](1), float64(3), int64(2), object(7)
memory usage: 219.6+ KB
```

Because we added new columns to the dataset over the course of our analysis, we can decide to rearrange the columns in our prederred order.

In [82]:
```
# Arranging columns in preferred order

clean_twitter_archive = clean_twitter_archive[['tweet_id', 'tweet_image_url', 'date', '
                                               'retweet_count', 'text', 'name', 'dog_
                                               'tweet_prediction', 'prediction_confid
                                               'rating_numerator', 'rating_denominato
```

In [83]:
```
clean_twitter_archive.head()
```

Out[83]:

tweet_id	tweet_image_url	date	time	favorite_coun

	tweet_id	tweet_image_url	date	time	favorite_coun
0	892420643555336193	https://pbs.twimg.com/media/DGKD1-bXoAAIAUK.jpg	2017-08-01	16:23:56	3946
1	892177421306343426	https://pbs.twimg.com/media/DGGmoV4XsAAUL6n.jpg	2017-08-01	00:17:27	3381
2	891815181378084864	https://pbs.twimg.com/media/DGBdLU1WsAANxJ9.jpg	2017-07-31	00:18:03	2546
3	891689557279858688	https://pbs.twimg.com/media/DF_q7IAWsAEuuN8.jpg	2017-07-30	15:58:51	4290
4	891327558926688256	https://pbs.twimg.com/media/DF6hr6BUMAAzZgT.jpg	2017-07-29	16:00:24	4104

In [84]:
```
# NOw we can save the dataset we have as CSV files

clean_twitter_archive.to_csv('clean_twitter_archive.csv', index = False)
clean_image_prediction.to_csv('clean_image_prediciton.csv', index = False)
clean_tweet_data_count.to_csv('clean_tweet_data_count.csv', index = False)
```

In [85]:
```
# Load the CSV file containing the combine tweet information

combined_data = pd.read_csv('clean_twitter_archive.csv', encoding = 'utf-8')
combined_data.head()
```

Out[85]:

	tweet_id	tweet_image_url	date	time	favorite_coun
0	892420643555336193	https://pbs.twimg.com/media/DGKD1-bXoAAIAUK.jpg	2017-08-01	16:23:56	3946

	tweet_id	tweet_image_url	date	time	favorite_coun
1	892177421306343426	https://pbs.twimg.com/media/DGGmoV4XsAAUL6n.jpg	2017-08-01	00:17:27	3381
2	891815181378084864	https://pbs.twimg.com/media/DGBdLU1WsAANxJ9.jpg	2017-07-31	00:18:03	2546
3	891689557279858688	https://pbs.twimg.com/media/DF_q7IAWsAEuuN8.jpg	2017-07-30	15:58:51	4290
4	891327558926688256	https://pbs.twimg.com/media/DF6hr6BUMAAzZgT.jpg	2017-07-29	16:00:24	4104

In [86]:
```
# Make a copy of the combined tweet data

data_copy = combined_data.copy()
```

EXPLORATORY DATA ANALYSIS

In [87]:
```
# Assign the "time" as the index of the dataframe

data_copy = data_copy.set_index('time')
data_copy.head()
```

Out[87]:

time	tweet_id	tweet_image_url	date	favorite_count
16:23:56	892420643555336193	https://pbs.twimg.com/media/DGKD1-bXoAAIAUK.jpg	2017-08-01	39467
00:17:27	892177421306343426	https://pbs.twimg.com/media/DGGmoV4XsAAUL6n.jpg	2017-08-01	33819

time	tweet_id	tweet_image_url	date	favorite_count
00:18:03	891815181378084864	https://pbs.twimg.com/media/DGBdLU1WsAANxJ9.jpg	2017-07-31	25461
15:58:51	891689557279858688	https://pbs.twimg.com/media/DF_q7IAWsAEuuN8.jpg	2017-07-30	42908
16:00:24	891327558926688256	https://pbs.twimg.com/media/DF6hr6BUMAAzZgT.jpg	2017-07-29	41048

In [88]:
```
data_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1971 entries, 16:23:56 to 22:32:08
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   tweet_id               1971 non-null   int64  
 1   tweet_image_url        1971 non-null   object 
 2   date                   1971 non-null   object 
 3   favorite_count         1971 non-null   int64  
 4   retweet_count          1971 non-null   int64  
 5   text                   1971 non-null   object 
 6   name                   1971 non-null   object 
 7   dog_type               149 non-null    object 
 8   dog_prediction         1971 non-null   bool   
 9   tweet_prediction       1971 non-null   object 
 10  prediction_confidence  1971 non-null   float64
 11  rating_numerator       1971 non-null   float64
 12  rating_denominator     1971 non-null   float64
 13  expanded_urls          1971 non-null   object 
dtypes: bool(1), float64(3), int64(3), object(7)
memory usage: 217.5+ KB
```

We can see from the output above that "time" is no longer listed as a column, that is because it has been converted as an index of the dataframe.

In [89]:
```
# The shows the arithmetric features of the columns in the dataset

data_copy.describe()
```

Out[89]:

	tweet_id	favorite_count	retweet_count	prediction_confidence	rating_numerator	rating_den
count	1.971000e+03	1971.000000	1971.000000	1971.000000	1971.000000	19

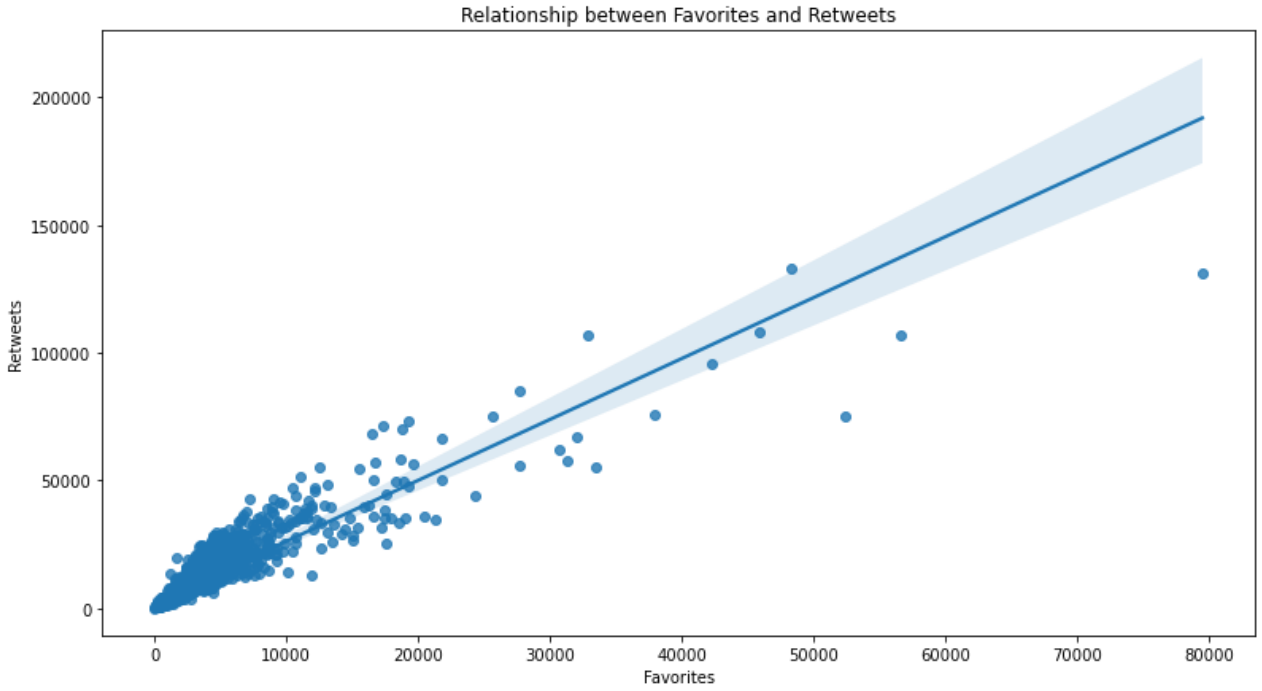
	tweet_id	favorite_count	retweet_count	prediction_confidence	rating_numerator	rating_den
mean	7.360418e+17	8949.106545	2784.449518	0.594558	12.223237	
std	6.752810e+16	12267.799790	4697.662893	0.272126	41.634034	
min	6.660209e+17	81.000000	16.000000	0.044333	0.000000	
25%	6.758656e+17	1997.000000	628.500000	0.363091	10.000000	
50%	7.088343e+17	4147.000000	1367.000000	0.587764	11.000000	
75%	7.880951e+17	11402.500000	3239.000000	0.847827	12.000000	
max	8.924206e+17	132810.000000	79515.000000	1.000000	1776.000000	17

In [90]:
```
# Let's inspect the correlation of the features

data_copy.corr()
```

Out[90]:

	tweet_id	favorite_count	retweet_count	dog_prediction	prediction_confidence	ra
tweet_id	1.000000	0.655888	0.406375	0.121573	0.104148	
favorite_count	0.655888	1.000000	0.913014	0.053040	0.078291	
retweet_count	0.406375	0.913014	1.000000	0.006693	0.053674	
dog_prediction	0.121573	0.053040	0.006693	1.000000	0.127782	
prediction_confidence	0.104148	0.078291	0.053674	0.127782	1.000000	
rating_numerator	0.024917	0.010876	0.014664	-0.030783	-0.006962	
rating_denominator	0.024917	0.010876	0.014664	-0.030783	-0.006962	

In [91]:
```
# Plot of Retweets against Favorite.

plt.figure(figsize=(13,7))
sns.regplot(x=data_copy.retweet_count, y=data_copy.favorite_count)
plt.title("Relationship between Favorites and Retweets")
plt.xlabel('Favorites')
plt.ylabel('Retweets');
```



In [92]:
```
# Find the top 5 dogs predicted

top_dogs = data_copy[data_copy.dog_prediction == True]
top_dogs.tweet_prediction.value_counts().head()
```

Out[92]:
```
golden_retriever      137
labrador_retriever     94
pembroke               88
chihuahua              78
pug                    54
Name: tweet_prediction, dtype: int64
```

In [93]:
```
# Create an array from the content of the tweet i.e the "text" column
# Create an empty list for storage
# Append each word to the empty list created

tweet_content = np.array(data_copy.text)
my_list = []
for tweet in tweet_content:
    #content_list.append(tweet_content.replace("\n",""))
    my_list.append(tweet.replace("\n",""))
```

In [94]:
```
# Load libraries needed for wordcloud and images

%pip install wordcloud

from PIL import Image
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
```

```
Requirement already satisfied: wordcloud in c:\users\samuel chika\anaconda3\lib\site-pac
kages (1.8.2.2)
Requirement already satisfied: pillow in c:\users\samuel chika\anaconda3\lib\site-packag
es (from wordcloud) (8.4.0)
Requirement already satisfied: matplotlib in c:\users\samuel chika\anaconda3\lib\site-pa
```

```
ckages (from wordcloud) (3.4.3)
Requirement already satisfied: numpy>=1.6.1 in c:\users\samuel chika\anaconda3\lib\site-
packages (from wordcloud) (1.20.3)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\samuel chika\anaconda3\lib
\site-packages (from matplotlib->wordcloud) (1.3.1)
Requirement already satisfied: cycler>=0.10 in c:\users\samuel chika\anaconda3\lib\site-
packages (from matplotlib->wordcloud) (0.10.0)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\samuel chika\anaconda3\l
ib\site-packages (from matplotlib->wordcloud) (2.8.2)
Requirement already satisfied: pyparsing>=2.2.1 in c:\users\samuel chika\anaconda3\lib\s
ite-packages (from matplotlib->wordcloud) (3.0.4)
Requirement already satisfied: six in c:\users\samuel chika\anaconda3\lib\site-packages
(from cycler>=0.10->matplotlib->wordcloud) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

In [95]:

```
# Load image that would be used as background for the wordcloud
# Save the list of words

mask = np.array(Image.open(requests.get(
    'https://clipartix.com/wp-content/uploads/2016/06/Dog-bone-pink-print-dog-paw-print
    stream=True).raw))
content = my_list
```

In [96]:

```
# Create a function that creates a word cloud given the background and list of words

def show_wcloud(content, mask):
    word_cloud = WordCloud(width = 500, height = 500, background_color='white', mask=ma
    plt.figure(figsize=(10,8),facecolor = 'white', edgecolor='green')
    plt.imshow(word_cloud)
    plt.axis('off')
    plt.tight_layout(pad=0)
    plt.show()
```

In [97]:

```
show_wcloud(content, mask)
```


thing
really
rare
fluffy
want
tongue slip
probably
pup
snug
best
pretty
day af'
need
leg
vid
take
still
even
owner
trying
dog
keep
two
help
super
good
ready
back
today
af
think
rate dogs
look
great
eye
nifty
work
face
happy
ear
many
Meet
one
time
well
quite
stuck
appear
Say hello
10'
pupper
h ckin
pet
doggo
Love
Please
damn
named
hat
got
hell
10' Meet
tho
lost
never
Thank
Will
first
h ck
now
much
know
enjoy
tongue
hug
guy
someone
see
make
Christmas
Always
give
big
send
going

In [ ]: