DATA WRANGLING PROJECT

WeRateDogs: Wrangling and Analyzing Twitter Archive

Flow of the Project

- Gather data
- Assess data
- Clean data

In [1]:
```
import numpy as np
import pandas as pd
import json
import requests
import tweepy
import re

import matplotlib.pyplot as plt
import warnings
%matplotlib inline
```

In [53]:
```
import seaborn as sns
sns.set(style="darkgrid")

pd.options.display.max_rows
pd.options.display.max_columns
pd.set_option('display.max_colwidth', -1)
```

```
/Users/parthpatel/opt/anaconda3/lib/python3.7/site-packages/ipykernel_l
auncher.py:6: FutureWarning: Passing a negative integer is deprecated i
n version 1.0 and will not be supported in future version. Instead, use
None to not limit the column width.
```

In [3]:
```
from IPython.display import display
```

The above imported packages have been used throughout this notebook and all the packages are imported here itself.

Let's start by gathering all the necessary data.

Gather Data

```
1) twitter_archive: It is the WeRateDogs Twitter archive provided by Udacity and I have downloaded on local machine.
2) image_predictions: It is the predictions of the tweets about what is breed of the dog using a neural network. It has been downloaded using a URL provided by Udacity using the request library.
3) tweet_1 : using the twitter API and tweet ids, we have made a JSON file storing the tweets.
```

In [4]:
```
# let's start with getting the twitter-archive data using pandas' read_csv fn()

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

twitter_archive.head()
```

Out[4]:

	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 rel="nofollow">Tw
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com rel="nofollow">Tw
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com rel="nofollow">Tw
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com rel="nofollow">Tw
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com rel="nofollow">Tw

In [5]:
```
# let us now use the URL provided by Udacity to download the .tsv file using the requests library & into a pandas DF

url = "https://d17h27t6h515a5.cloudfront.net/topher/2017/August/599fd2ad_image-predictions/image-predictions.tsv"

response = requests.get(url)

with open('image_predictions.tsv', 'wb') as file:
    file.write(response.content)

image_predictions = pd.read_csv('image_predictions.tsv', sep='\t')
```

In [6]:
```
image_predictions.head()
```

Out[6]:

	tweet_id	jpg_url	img_num	
0	666020888022790149	https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg	1	Welsh_springe
1	666029285002620928	https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg	1	
2	666033412701032449	https://pbs.twimg.com/media/CT4521TWwAEvMyu.jpg	1	German_
3	666044226329800704	https://pbs.twimg.com/media/CT5Dr8HUEAA-lEu.jpg	1	Rhodesian_r
4	666049248165822465	https://pbs.twimg.com/media/CT5IQmsXIAAKY4A.jpg	1	miniature_

In [7]:
```
# Assigning personal API keys, secrets, and token. They are missing in t
he final report due to privacy concerns.

consumer_key = ' '
consumer_secret = ' '

access_token = ' '
access_secret = ' '
```

In [8]:
```
# I have used youtube tutorials to generate this section of code.
# Use tweepy

auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_token, access_secret)
api = tweepy.API(auth, wait_on_rate_limit= True, wait_on_rate_limit_noti
fy= True)
```

In [ ]:
```
# Generate the tweet_json.txt
with open('tweet_json.txt', 'a', encoding='utf8') as f:
    for tweet_id in twitter_archive['tweet_id']:
        try:
            tweet = api.get_status(tweet_id, tweet_mode='extended')
            json.dump(tweet._json, f)
            f.write('\n')
        except:
            continue
```

```
Rate limit reached. Sleeping for: 725
```

In [9]:
```
# Putting each tweet in a list using a loop

tweet_data = []

tweet_file = open('tweet_json.txt', "r")

for line in tweet_file:
    try:
        tweet =json.loads(line)
        tweet_data.append(tweet)
    except:
        continue

tweet_file.close()
```

In [10]:
```
tweet_1 = pd.DataFrame()

# Now we will only add those columns in this DataFrame that we wont

tweet_1['id'] = list(map(lambda tweet: tweet['id'], tweet_data))
tweet_1['retweet_count'] = list(map(lambda tweet: tweet['retweet_count'
], tweet_data))
tweet_1['favorite_count'] = list(map(lambda tweet: tweet['favorite_coun
t'], tweet_data))

tweet_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3945 entries, 0 to 3944
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              3945 non-null   int64
 1   retweet_count   3945 non-null   int64
 2   favorite_count  3945 non-null   int64
dtypes: int64(3)
memory usage: 92.6 KB
```

In [11]:
```
tweet_1.head()
```

Out[11]:

	id	retweet_count	favorite_count
0	892420643555336193	7739	36368
1	892177421306343426	5730	31326
2	891815181378084864	3790	23609
3	891689557279858688	7904	39674
4	891327558926688256	8525	37877

Assess Data

Now that we have gathered all the data required, we will move to assess data. We will start using the basic head(), tail(), info() and describe() to get basic idea about the data.

Thereafter, we will focus on 2 aspects, i.e. Data Quality and Tidy Data. To go around the data quality issue, we will focus on Completeness, Validity, Accuracy, Consistency.

We will also try a more organized approach of data by data.

1) twitter_archive

In [12]:
```
twitter_archive.head()   # to view the top 5 entries
```

Out[12]:

	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 rel="nofollow">Tw
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com rel="nofollow">Tw
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com rel="nofollow">Tw
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com rel="nofollow">Tw
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com rel="nofollow">Tw

In [14]:
```
twitter_archive.tail() # to view bottom 5 entries
```

Out[14]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
2351	666049248165822465	NaN	NaN	2015-11-16 00:24:50 +0000	href="http://twitter. rel="nofollow"
2352	666044226329800704	NaN	NaN	2015-11-16 00:04:52 +0000	href="http://twitter. rel="nofollow"
2353	666033412701032449	NaN	NaN	2015-11-15 23:21:54 +0000	href="http://twitter. rel="nofollow"
2354	666029285002620928	NaN	NaN	2015-11-15 23:05:30 +0000	href="http://twitter. rel="nofollow"
2355	666020888022790149	NaN	NaN	2015-11-15 22:32:08 +0000	href="http://twitter. rel="nofollow"

In [15]:
```
twitter_archive.info()     #  to get information on the datatypes on eac
h attribute
```

```
<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 [16]:
```
# Let us try to view some text from the tweets

twitter_archive['text'].head()
```

Out[16]:
```
0    This is Phineas. He's a mystical boy. Only ever appears in the hol
e of a donut. 13/10 https://t.co/MgUWQ76dJU
1    This is Tilly. She's just checking pup on you. Hopes you're doing
ok. If not, she's available for pats, snugs, boops, the whole bit. 13/1
0 https://t.co/0Xxu71qeIV
2    This is Archie. He is a rare Norwegian Pouncing Corgo. Lives in th
e tall grass. You never know when one may strike. 12/10 https://t.co/wU
nZnhtVJB
3    This is Darla. She commenced a snooze mid meal. 13/10 happens to t
he best of us https://t.co/tD36da7qLQ
4    This is Franklin. He would like you to stop calling him "cute." He
is a very fierce shark and should be respected as such. 12/10 #BarkWeek
https://t.co/AtUZn91f7f
Name: text, dtype: object
```

In [17]:
```
# checking for null values

twitter_archive.isnull().sum()
```

Out[17]:
```
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
```

In [18]:
```
# for basic statistical idea about data

twitter_archive.describe()
```

Out[18]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	retweeted_status_id	retweeted_stat
count	2.356000e+03	7.800000e+01	7.800000e+01	1.810000e+02	1.8
mean	7.427716e+17	7.455079e+17	2.014171e+16	7.720400e+17	1.2
std	6.856705e+16	7.582492e+16	1.252797e+17	6.236928e+16	9.5
min	6.660209e+17	6.658147e+17	1.185634e+07	6.661041e+17	7.8
25%	6.783989e+17	6.757419e+17	3.086374e+08	7.186315e+17	4.1
50%	7.196279e+17	7.038708e+17	4.196984e+09	7.804657e+17	4.1
75%	7.993373e+17	8.257804e+17	4.196984e+09	8.203146e+17	4.1
max	8.924206e+17	8.862664e+17	8.405479e+17	8.874740e+17	7.8

In [19]:
```
# There are these columns like rating_denominator and rating_numerator w
here there can be a possibility of error
#  because the denominator is out of 10 and the max rating in any record
can be 10 so any numbers out of that bracket
#  of 0-10 can be considered as either human errors / outliers / machine
errors.

twitter_archive.rating_denominator.value_counts()
```

Out[19]:
```
10     2333
11     3
50     3
80     2
20     2
2      1
16     1
40     1
70     1
15     1
90     1
110    1
120    1
130    1
150    1
170    1
7      1
0      1
Name: rating_denominator, dtype: int64
```

In [20]:
```
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
1         9
2         9
420       2
0         2
15        2
75        2
80        1
20        1
24        1
26        1
44        1
50        1
60        1
165       1
84        1
88        1
144       1
182       1
143       1
666       1
960       1
1776      1
17        1
27        1
45        1
99        1
121       1
204       1
Name: rating_numerator, dtype: int64
```

In [21]:
```
# let us also have a look at the kind of sources of the tweets and its type

twitter_archive.source.value_counts()
```

Out[21]:
```
<a href="http://twitter.com/download/iphone" rel="nofollow">Twitter for iPhone</a>     2221
<a href="http://vine.co" rel="nofollow">Vine - Make a Scene</a>
91
<a href="http://twitter.com" rel="nofollow">Twitter Web Client</a>
33
<a href="https://about.twitter.com/products/tweetdeck" rel="nofollow">TweetDeck</a>    11
Name: source, dtype: int64
```

2) image_predictions

In [22]:
```
image_predictions.head()
```

Out[22]:

	tweet_id	jpg_url	img_num	
0	666020888022790149	https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg	1	Welsh_springe
1	666029285002620928	https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg	1	
2	666033412701032449	https://pbs.twimg.com/media/CT4521TWwAEvMyu.jpg	1	German_
3	666044226329800704	https://pbs.twimg.com/media/CT5Dr8HUEAA-lEu.jpg	1	Rhodesian_r
4	666049248165822465	https://pbs.twimg.com/media/CT5IQmsXIAAKY4A.jpg	1	miniature_

In [23]:
```
image_predictions.tail()
```

Out[23]:

	tweet_id	jpg_url	img_num	
2070	891327558926688256	https://pbs.twimg.com/media/DF6hr6BUMAAzZgT.jpg	2	bass
2071	891689557279858688	https://pbs.twimg.com/media/DF_q7IAWsAEuuN8.jpg	1	paper_tow
2072	891815181378084864	https://pbs.twimg.com/media/DGBdLU1WsAANxJ9.jpg	1	Chihuah
2073	892177421306343426	https://pbs.twimg.com/media/DGGmoV4XsAAUL6n.jpg	1	Chihuah
2074	892420643555336193	https://pbs.twimg.com/media/DGKD1-bXoAAIAUK.jpg	1	oran

In [24]:
```
image_predictions.info() # we see that here we have a complete data will all attributes available for all the entries
```

```
<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
```

In [25]:
```
image_predictions.describe()
```

Out[25]:

	tweet_id	img_num	p1_conf	p2_conf	p3_conf
count	2.075000e+03	2075.000000	2075.000000	2.075000e+03	2.075000e+03
mean	7.384514e+17	1.203855	0.594548	1.345886e-01	6.032417e-02
std	6.785203e+16	0.561875	0.271174	1.006657e-01	5.090593e-02
min	6.660209e+17	1.000000	0.044333	1.011300e-08	1.740170e-10
25%	6.764835e+17	1.000000	0.364412	5.388625e-02	1.622240e-02
50%	7.119988e+17	1.000000	0.588230	1.181810e-01	4.944380e-02
75%	7.932034e+17	1.000000	0.843855	1.955655e-01	9.180755e-02
max	8.924206e+17	4.000000	1.000000	4.880140e-01	2.734190e-01

In [26]:
```
# let us look into how many types of breeds are predicted by both p1 and p2 algorithms and the value_counts

image_predictions.p1.value_counts()
```

Out[26]:
```
golden_retriever      150
Labrador_retriever    100
Pembroke               89
Chihuahua              83
pug                    57
                      ..
peacock                1
orange                 1
candle                 1
nail                   1
bonnet                 1
Name: p1, Length: 378, dtype: int64
```

In [27]:
```
image_predictions.p2.value_counts()
```

Out[27]:
```
Labrador_retriever    104
golden_retriever       92
Cardigan               73
Chihuahua              44
Pomeranian             42
                     ...
snail                  1
menu                   1
confectionery          1
sarong                 1
dock                   1
Name: p2, Length: 405, dtype: int64
```

We see that both the prediction algorithms are working in a different manner.

3) tweet_1

In [28]:
```
tweet_1.head()
```

Out[28]:

	id	retweet_count	favorite_count
0	892420643555336193	7739	36368
1	892177421306343426	5730	31326
2	891815181378084864	3790	23609
3	891689557279858688	7904	39674
4	891327558926688256	8525	37877

In [29]:
```
tweet_1.tail()
```

Out[29]:

	id	retweet_count	favorite_count
3940	684225744407494656	208	1231
3941	684222868335505415	1372	3827
3942	684200372118904832	1034	2157
3943	684195085588783105	511	1914
3944	684188786104872960	1172	3494

In [30]:
```
tweet_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3945 entries, 0 to 3944
Data columns (total 3 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              3945 non-null   int64
 1   retweet_count   3945 non-null   int64
 2   favorite_count  3945 non-null   int64
dtypes: int64(3)
memory usage: 92.6 KB
```

In [31]:
```
tweet_1.describe()
```

Out[31]:

	id	retweet_count	favorite_count
count	3.945000e+03	3945.000000	3945.000000
mean	7.543871e+17	3028.682636	8534.464132
std	6.695989e+16	4820.132309	12354.663069
min	6.660209e+17	1.000000	0.000000
25%	6.920173e+17	698.000000	1879.000000
50%	7.474616e+17	1598.000000	4069.000000
75%	8.123723e+17	3472.000000	10796.000000
max	8.924206e+17	78220.000000	157001.000000

Cleaning Data

Now we will proceed to cleaning the data. I am mentioning a brief plan on how will we go about cleaning all our 3 datasets. Since we have seen above that tweet_1 data has a completed data and is something that we have formed, we will not have to explicitly clean it.

1. Tidiness Problems
    - We can also think about merging the tweet_1 with twitter_archive table to get twitter_archive_master table.
    - We then merge the twitter_archive_master with image_predictions
2. Quality Problems

    twitter_archive

    - Remove all the retweet data and replies
    - Removing tweets that don't have an image
    - Removing data without the image
    - Categories of dog are mentioned in 4 different columns, we need to melt them to form a new column which has all 4 categories in it.
    - Reducing 3 columns of confidence to only one with that of correct prediction confidence.
    - The urls are very long and not really human readable.
    - The columns 'rating_denominator' should have standard value of 10 like a 5/10 or 6/10.
    - Converting numerator rating to decimal type.
    - The column names p1 and p2 are not intuitive.
    - The predicted dog breeds have both upper and lower case for first letters.

A good practice for cleaning data is making a copy and then trying to amend that new table so that we can have a backup.

Cleaning Data

In [122]:
```
# first, let us make copies of all 3 tables.

twitter_archive_clean = twitter_archive.copy()
image_predictions_clean = image_predictions.copy()
tweet_1_clean = tweet_1.copy()
```

twitter_archive

```
Tidiness Problems
```

Problem 1: Merge all 3 datasets to form a master data set

CODE

In [123]:
```
tweet_1_clean.rename(columns={'id':'tweet_id'}, inplace= True)
```

In [124]:
```
twitter_archive_master = pd.merge(twitter_archive_clean, tweet_1_clean,
on='tweet_id', how='left')
```

In [125]:
```
twitter_archive_master.head()
```

Out[125]:

	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 rel="nofollow">Tw
1	892420643555336193	NaN	NaN	2017-08-01 16:23:56 +0000	href="http://twitter.com rel="nofollow">Tw
2	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com rel="nofollow">Tw
3	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com rel="nofollow">Tw
4	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com rel="nofollow">Tw

Problem 2: We then merge the twitter_archive_master with image_predictions

In [126]:
```
twitter_archive_master = pd.merge(twitter_archive_master, image_predicti
ons_clean, on='tweet_id', how='left')
```

TEST

In [127]:
```
pd.set_option("display.max_columns",30)
twitter_archive_master.head(10)
```

Out[127]:

	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 rel="nofollow">Tw
1	892420643555336193	NaN	NaN	2017-08-01 16:23:56 +0000	href="http://twitter.com rel="nofollow">Tw
2	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com rel="nofollow">Tw
3	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com rel="nofollow">Tw
4	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com rel="nofollow">Tw
5	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com rel="nofollow">Tw
6	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com rel="nofollow">Tw
7	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com rel="nofollow">Tw
8	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com rel="nofollow">Tw

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
9	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com rel="nofollow">Tw

In [128]:
```
display(twitter_archive.shape)
display(twitter_archive_master.shape)
```

```
(2356, 17)

(3970, 30)
```

In [129]:
```
twitter_archive_master.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3970 entries, 0 to 3969
Data columns (total 30 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   tweet_id                    3970 non-null   int64  
 1   in_reply_to_status_id       135 non-null    float64
 2   in_reply_to_user_id         135 non-null    float64
 3   timestamp                   3970 non-null   object 
 4   source                      3970 non-null   object 
 5   text                        3970 non-null   object 
 6   retweeted_status_id         342 non-null    float64
 7   retweeted_status_user_id    342 non-null    float64
 8   retweeted_status_timestamp  342 non-null    object 
 9   expanded_urls               3865 non-null   object 
 10  rating_numerator            3970 non-null   int64  
 11  rating_denominator          3970 non-null   int64  
 12  name                        3970 non-null   object 
 13  doggo                       3970 non-null   object 
 14  floofer                     3970 non-null   object 
 15  pupper                      3970 non-null   object 
 16  puppo                       3970 non-null   object 
 17  retweet_count               3945 non-null   float64
 18  favorite_count              3945 non-null   float64
 19  jpg_url                     3445 non-null   object 
 20  img_num                     3445 non-null   float64
 21  p1                          3445 non-null   object 
 22  p1_conf                     3445 non-null   float64
 23  p1_dog                      3445 non-null   object 
 24  p2                          3445 non-null   object 
 25  p2_conf                     3445 non-null   float64
 26  p2_dog                      3445 non-null   object 
 27  p3                          3445 non-null   object 
 28  p3_conf                     3445 non-null   float64
 29  p3_dog                      3445 non-null   object 
dtypes: float64(10), int64(3), object(17)
memory usage: 961.5+ KB
```

In [130]:
```
twitter_archive_master.to_csv('twitter-archive-master.csv', encoding='utf-8', index=False)

df = pd.read_csv('twitter-archive-master.csv')
```

Quality Problems

Problem 1: Remove all the retweet data and replies

CODE

In [131]:
```
df = df[df.retweeted_status_id.isnull()]
```

TEST

In [132]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3628 entries, 0 to 3969
Data columns (total 30 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   tweet_id                    3628 non-null   int64  
 1   in_reply_to_status_id       135 non-null    float64
 2   in_reply_to_user_id         135 non-null    float64
 3   timestamp                   3628 non-null   object 
 4   source                      3628 non-null   object 
 5   text                        3628 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               3525 non-null   object 
 10  rating_numerator            3628 non-null   int64  
 11  rating_denominator          3628 non-null   int64  
 12  name                        3628 non-null   object 
 13  doggo                       3628 non-null   object 
 14  floofer                     3628 non-null   object 
 15  pupper                      3628 non-null   object 
 16  puppo                       3628 non-null   object 
 17  retweet_count               3621 non-null   float64
 18  favorite_count              3621 non-null   float64
 19  jpg_url                     3294 non-null   object 
 20  img_num                     3294 non-null   float64
 21  p1                          3294 non-null   object 
 22  p1_conf                     3294 non-null   float64
 23  p1_dog                      3294 non-null   object 
 24  p2                          3294 non-null   object 
 25  p2_conf                     3294 non-null   float64
 26  p2_dog                      3294 non-null   object 
 27  p3                          3294 non-null   object 
 28  p3_conf                     3294 non-null   float64
 29  p3_dog                      3294 non-null   object 
dtypes: float64(10), int64(3), object(17)
memory usage: 878.7+ KB
```

In [133]:
```
# delete the columns related to retweets from the master dataframe.
df = df.drop(['retweeted_status_id','retweeted_status_user_id','retweeted_status_timestamp'],axis=1)
```

In [134]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3628 entries, 0 to 3969
Data columns (total 27 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   tweet_id               3628 non-null   int64  
 1   in_reply_to_status_id  135 non-null    float64
 2   in_reply_to_user_id    135 non-null    float64
 3   timestamp              3628 non-null   object 
 4   source                 3628 non-null   object 
 5   text                   3628 non-null   object 
 6   expanded_urls          3525 non-null   object 
 7   rating_numerator       3628 non-null   int64  
 8   rating_denominator     3628 non-null   int64  
 9   name                   3628 non-null   object 
 10  doggo                  3628 non-null   object 
 11  floofer                3628 non-null   object 
 12  pupper                 3628 non-null   object 
 13  puppo                  3628 non-null   object 
 14  retweet_count          3621 non-null   float64
 15  favorite_count         3621 non-null   float64
 16  jpg_url                3294 non-null   object 
 17  img_num                3294 non-null   float64
 18  p1                     3294 non-null   object 
 19  p1_conf                3294 non-null   float64
 20  p1_dog                 3294 non-null   object 
 21  p2                     3294 non-null   object 
 22  p2_conf                3294 non-null   float64
 23  p2_dog                 3294 non-null   object 
 24  p3                     3294 non-null   object 
 25  p3_conf                3294 non-null   float64
 26  p3_dog                 3294 non-null   object 
dtypes: float64(8), int64(3), object(16)
memory usage: 793.6+ KB
```

In [135]:
```
# the "in_reply_to_status_id" includes the original tweet_id if there is
a reply. There are 78 replies.
# We keep the rows that are null and remove the replies.
df = df[df.in_reply_to_status_id.isnull()]
```

In [136]:
```
df = df.drop(['in_reply_to_status_id','in_reply_to_user_id'],axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3493 entries, 0 to 3969
Data columns (total 25 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   tweet_id            3493 non-null   int64  
 1   timestamp           3493 non-null   object 
 2   source              3493 non-null   object 
 3   text                3493 non-null   object 
 4   expanded_urls       3487 non-null   object 
 5   rating_numerator    3493 non-null   int64  
 6   rating_denominator  3493 non-null   int64  
 7   name                3493 non-null   object 
 8   doggo               3493 non-null   object 
 9   floofer             3493 non-null   object 
 10  pupper              3493 non-null   object 
 11  puppo               3493 non-null   object 
 12  retweet_count       3486 non-null   float64
 13  favorite_count      3486 non-null   float64
 14  jpg_url             3256 non-null   object 
 15  img_num             3256 non-null   float64
 16  p1                  3256 non-null   object 
 17  p1_conf             3256 non-null   float64
 18  p1_dog              3256 non-null   object 
 19  p2                  3256 non-null   object 
 20  p2_conf             3256 non-null   float64
 21  p2_dog              3256 non-null   object 
 22  p3                  3256 non-null   object 
 23  p3_conf             3256 non-null   float64
 24  p3_dog              3256 non-null   object 
dtypes: float64(6), int64(3), object(16)
memory usage: 709.5+ KB
```

Problem 3: Removing tweets that don't have an image

In [137]:
```
df = df[df.jpg_url.notnull()]
```

In [138]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3256 entries, 0 to 3969
Data columns (total 25 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   tweet_id            3256 non-null   int64  
 1   timestamp           3256 non-null   object 
 2   source              3256 non-null   object 
 3   text                3256 non-null   object 
 4   expanded_urls       3256 non-null   object 
 5   rating_numerator    3256 non-null   int64  
 6   rating_denominator  3256 non-null   int64  
 7   name                3256 non-null   object 
 8   doggo               3256 non-null   object 
 9   floofer             3256 non-null   object 
 10  pupper              3256 non-null   object 
 11  puppo               3256 non-null   object 
 12  retweet_count       3249 non-null   float64
 13  favorite_count      3249 non-null   float64
 14  jpg_url             3256 non-null   object 
 15  img_num             3256 non-null   float64
 16  p1                  3256 non-null   object 
 17  p1_conf             3256 non-null   float64
 18  p1_dog              3256 non-null   object 
 19  p2                  3256 non-null   object 
 20  p2_conf             3256 non-null   float64
 21  p2_dog              3256 non-null   object 
 22  p3                  3256 non-null   object 
 23  p3_conf             3256 non-null   float64
 24  p3_dog              3256 non-null   object 
dtypes: float64(6), int64(3), object(16)
memory usage: 661.4+ KB
```

Problem 4: Categories of dog are mentioned in 4 different columns, we need to melt them to form a new column which has all 4 categories in it.

In [139]:
```
df = pd.melt(df,
        id_vars = ['tweet_id', 'timestamp', 'source', 'text', 'expanded_
urls',
       'rating_numerator', 'rating_denominator', 'name','favorite_count'
, 'retweet_count', 'jpg_url', 'img_num',
       'p1', 'p1_conf', 'p1_dog', 'p2', 'p2_conf', 'p2_dog', 'p3', 'p3_c
onf',
       'p3_dog'],
        value_vars = ['doggo', 'floofer', 'pupper', 'puppo'],
        var_name = 'types', value_name = 'dog_type')
```

In [140]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13024 entries, 0 to 13023
Data columns (total 23 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   tweet_id            13024 non-null  int64  
 1   timestamp           13024 non-null  object 
 2   source              13024 non-null  object 
 3   text                13024 non-null  object 
 4   expanded_urls       13024 non-null  object 
 5   rating_numerator    13024 non-null  int64  
 6   rating_denominator  13024 non-null  int64  
 7   name                13024 non-null  object 
 8   favorite_count      12996 non-null  float64
 9   retweet_count       12996 non-null  float64
 10  jpg_url             13024 non-null  object 
 11  img_num             13024 non-null  float64
 12  p1                  13024 non-null  object 
 13  p1_conf             13024 non-null  float64
 14  p1_dog              13024 non-null  object 
 15  p2                  13024 non-null  object 
 16  p2_conf             13024 non-null  float64
 17  p2_dog              13024 non-null  object 
 18  p3                  13024 non-null  object 
 19  p3_conf             13024 non-null  float64
 20  p3_dog              13024 non-null  object 
 21  types               13024 non-null  object 
 22  dog_type            13024 non-null  object 
dtypes: float64(6), int64(3), object(14)
memory usage: 2.3+ MB
```

In [141]:
```
df.dog_type.value_counts()
```

Out[141]:
```
None       12471
pupper       346
doggo        145
puppo         46
floofer       16
Name: dog_type, dtype: int64
```

In [142]:
```
df = df.sort_values('dog_type').drop_duplicates('tweet_id', keep = 'las
t')
df.dog_type.value_counts()
```

Out[142]:
```
None       1668
pupper      209
doggo        63
puppo        23
floofer       8
Name: dog_type, dtype: int64
```

Upon Manual check I realized that some columns are taking 2 names for dog_type i.e doggo/puppo So I have selected this rows manually and will be rectifying it.

In [143]:
```
# Change dog types identified in the tweet_ids above
df.loc[df.tweet_id == 817777686764523521, 'dog_type'] = 'doggo'
df.loc[df.tweet_id == 808106460588765185, 'dog_type'] = 'None'
df.loc[df.tweet_id == 801115127852503040, 'dog_type'] = 'doggo'
df.loc[df.tweet_id == 785639753186217984, 'dog_type'] = 'doggo'
df.loc[df.tweet_id == 759793422261743616, 'dog_type'] = 'None'
df.loc[df.tweet_id == 751583847268179968, 'dog_type'] = 'None'
df.loc[df.tweet_id == 741067306818797568, 'dog_type'] = 'None'
df.loc[df.tweet_id == 733109485275860992, 'dog_type'] = 'None'
```

In [144]:
```
df = df.drop('types', axis=1)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 3124 to 9793
Data columns (total 22 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   tweet_id            1971 non-null   int64  
 1   timestamp           1971 non-null   object 
 2   source              1971 non-null   object 
 3   text                1971 non-null   object 
 4   expanded_urls       1971 non-null   object 
 5   rating_numerator    1971 non-null   int64  
 6   rating_denominator  1971 non-null   int64  
 7   name                1971 non-null   object 
 8   favorite_count      1964 non-null   float64
 9   retweet_count       1964 non-null   float64
 10  jpg_url             1971 non-null   object 
 11  img_num             1971 non-null   float64
 12  p1                  1971 non-null   object 
 13  p1_conf             1971 non-null   float64
 14  p1_dog              1971 non-null   object 
 15  p2                  1971 non-null   object 
 16  p2_conf             1971 non-null   float64
 17  p2_dog              1971 non-null   object 
 18  p3                  1971 non-null   object 
 19  p3_conf             1971 non-null   float64
 20  p3_dog              1971 non-null   object 
 21  dog_type            1971 non-null   object 
dtypes: float64(6), int64(3), object(13)
memory usage: 354.2+ KB
```

In [145]:
```
df.dog_type.value_counts()
```

Out[145]:
```
None       1673
pupper      201
doggo        66
puppo        23
floofer       8
Name: dog_type, dtype: int64
```

Problem 5: Reducing 3 columns of confidence to only one with that of correct prediction confidence.

In [146]:
```
# create 2 empty lists to save our choice for each row in the dataset
breed = []
confidence = []

# function that iterates through prediction columns to find the best pre
diction which is a breed of dog.
def breed_confidence(row):
    if row['p1_dog'] == True:
        breed.append(row['p1'])
        confidence.append(row['p1_conf'])
    elif row['p2_dog'] == True:
        breed.append(row['p2'])
        confidence.append(row['p2_conf'])
    elif row['p3_dog'] == True:
        breed.append(row['p3'])
        confidence.append(row['p3_conf'])
    else:
        breed.append('Unknown')
        confidence.append(0)

# call function using pandas apply by columns
df.apply(breed_confidence, axis=1)

# add lists created to master dataframe
df['breed'] = breed
df['confidence'] = confidence

# check the columns have been added
df.head(2)
```

Out[146]:

	tweet_id	timestamp	source	t
3124	668480044826800133	2015-11-22 17:23:57 +0000	Twitter for iPhone	Say hello to DayZ. Sh definitely stuck on stair. Just looking someone to help 11/10 I would h https://t.co/be3zMW0
3125	668466899341221888	2015-11-22 16:31:42 +0000	Twitter for iPhone	Here is a mother caring for her pu Snazzy red moha Doesn't wag tail. P look confused. Ov 4 https://t.co/YOHe6lf0

In [ ]:
```

```

Problem 6: The urls are very long and not really human readable.

CODE

In [147]:
```
df.source.value_counts()
```

Out[147]:
```
<a href="http://twitter.com/download/iphone" rel="nofollow">Twitter for
iPhone</a>     1932
<a href="http://twitter.com" rel="nofollow">Twitter Web Client</a>
28
<a href="https://about.twitter.com/products/tweetdeck" rel="nofollow">T
weetDeck</a>    11
Name: source, dtype: int64
```

In [150]:
```
df['source'] = df['source'].replace('<a href="http://twitter.com/downloa
d/iphone" rel="nofollow">Twitter for iPhone</a>',

'Twitter for iphone')
df['source'] = df['source'].replace('<a href="http://vine.co" rel="nofol
low">Vine - Make a Scene</a>',

'Vine - Make a Scene')
df['source'] = df['source'].replace('<a href="http://twitter.com" rel="n
ofollow">Twitter Web Client</a>',

'Twitter Web Client')
df['source'] = df['source'].replace('<a href="https://about.twitter.com/
products/tweetdeck" rel="nofollow">TweetDeck</a>',

'TweetDeck')
```

In [151]:
```
df.source = df.source.astype('category')
```

TEST

In [152]:
```
df.source.value_counts()
```

Out[152]:
```
Twitter for iphone    1932
Twitter Web Client    28
TweetDeck             11
Name: source, dtype: int64
```

Problem 7: The columns 'rating_denominator' should have standard value of 10 like a 5/10 or 6/10.

CODE

In [153]:
```
df.rating_denominator = 10
```

TEST

In [154]:
```
df.rating_denominator.value_counts()
```

Out[154]:
```
10    1971
Name: rating_denominator, dtype: int64
```

In [125]:
```
twitter_archive_clean[twitter_archive_clean['rating_denominator'] !=10]
```

Out[125]:

tweet_id	timestamp	source	text	expanded_urls	rating_numerator	rating_denominator	name

Problem 8: Converting the rating_numerator into decimal type

CODE

In [156]:
```
df[df.text.str.contains(r"(\d+\.\d*\/\d+)")][['text', 'rating_numerator']]
```

Out[156]:

	text	rating_numerator
78	This is Bella. She hopes her smile made you smile. If not, she is also offering you her favorite monkey. 13.5/10 https://t.co/qjrljjt948	5
5900	Here we have uncovered an entire battalion of holiday puppers. Average of 11.26/10 https://t.co/eNm2S6p9BD	26
4251	This is Logan, the Chow who lived. He solemnly swears he's up to lots of good. H*ckin magical af 9.75/10 https://t.co/yBO5wuqaPS	75
7606	This is Sophie. She's a Jubilant Bush Pupper. Super h*ckin rare. Appears at random just to smile at the locals. 11.27/10 would smile back https://t.co/QFaUiIHxHq	27

In [ ]:
```

```

Problem 9: The column names p1 and p2 are not intuitive.

CODE

In [169]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 3124 to 9793
Data columns (total 24 columns):
 #   Column               Non-Null Count  Dtype   
---  ------               --------------  -----   
 0   tweet_id             1971 non-null   int64   
 1   timestamp            1971 non-null   object  
 2   source               1971 non-null   category
 3   text                 1971 non-null   object  
 4   expanded_urls        1971 non-null   object  
 5   rating_numerator     1971 non-null   int64   
 6   rating_denominator   1971 non-null   int64   
 7   name                 125 non-null    object  
 8   favorite_count       1964 non-null   float64 
 9   retweet_count        1964 non-null   float64 
 10  jpg_url              1971 non-null   object  
 11  img_num              1971 non-null   float64 
 12  p1                   1971 non-null   object  
 13  p1_conf              1971 non-null   float64 
 14  p1_dog               1971 non-null   object  
 15  p2                   1971 non-null   object  
 16  p2_conf              1971 non-null   float64 
 17  p2_dog               1971 non-null   object  
 18  p3                   1971 non-null   object  
 19  p3_conf              1971 non-null   float64 
 20  p3_dog               1971 non-null   object  
 21  dog_type             1971 non-null   object  
 22  breed                1971 non-null   object  
 23  confidence           1971 non-null   float64 
dtypes: category(1), float64(7), int64(3), object(13)
memory usage: 371.6+ KB
```

In [170]:
```
df.rename(columns={'p1':'Algo1_pred', 'p1_conf': 'Algo1_confidence', 'p1_dog': 'Algo1_dog',
                                    'p2': 'Algo2_pred', 'p2_conf': 'Algo2_confidence', 'p2_dog': 'Algo2_dog',
                                    'p3': 'Algo3_pred', 'p3_conf': 'Algo3_confidence', 'p3_dog': 'Algo3_dog'}, inplace = True)
```

TEST

In [171]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 3124 to 9793
Data columns (total 24 columns):
 #   Column              Non-Null Count  Dtype   
---  ------              --------------  -----   
 0   tweet_id            1971 non-null   int64   
 1   timestamp           1971 non-null   object  
 2   source              1971 non-null   category
 3   text                1971 non-null   object  
 4   expanded_urls       1971 non-null   object  
 5   rating_numerator    1971 non-null   int64   
 6   rating_denominator  1971 non-null   int64   
 7   name                125 non-null    object  
 8   favorite_count      1964 non-null   float64 
 9   retweet_count       1964 non-null   float64 
 10  jpg_url             1971 non-null   object  
 11  img_num             1971 non-null   float64 
 12  Algo1_pred          1971 non-null   object  
 13  Algo1_confidence    1971 non-null   float64 
 14  Algo1_dog           1971 non-null   object  
 15  Algo2_pred          1971 non-null   object  
 16  Algo2_confidence    1971 non-null   float64 
 17  Algo2_dog           1971 non-null   object  
 18  Algo3_pred          1971 non-null   object  
 19  Algo3_confidence    1971 non-null   float64 
 20  Algo3_dog           1971 non-null   object  
 21  dog_type            1971 non-null   object  
 22  breed               1971 non-null   object  
 23  confidence          1971 non-null   float64 
dtypes: category(1), float64(7), int64(3), object(13)
memory usage: 371.6+ KB
```

Problem 10: The predicted dog breeds have both upper and lower case for first letters.

CODE

In [172]:
```
df['Algo1_pred'] = df['Algo1_pred'].str.capitalize()
df['Algo2_pred'] = df['Algo2_pred'].str.capitalize()
df['Algo3_pred'] = df['Algo3_pred'].str.capitalize()
```

TEST

In [173]:
```
df.Algo1_pred.value_counts().head()
```

Out[173]:
```
Golden_retriever      137
Labrador_retriever    94
Pembroke              88
Chihuahua             78
Pug                   54
Name: Algo1_pred, dtype: int64
```

FINAL CHECK

In [174]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 3124 to 9793
Data columns (total 24 columns):
 #   Column              Non-Null Count  Dtype   
---  ------              --------------  -----   
 0   tweet_id            1971 non-null   int64   
 1   timestamp           1971 non-null   object  
 2   source              1971 non-null   category
 3   text                1971 non-null   object  
 4   expanded_urls       1971 non-null   object  
 5   rating_numerator    1971 non-null   int64   
 6   rating_denominator  1971 non-null   int64   
 7   name                125 non-null    object  
 8   favorite_count      1964 non-null   float64 
 9   retweet_count       1964 non-null   float64 
 10  jpg_url             1971 non-null   object  
 11  img_num             1971 non-null   float64 
 12  Algo1_pred          1971 non-null   object  
 13  Algo1_confidence    1971 non-null   float64 
 14  Algo1_dog           1971 non-null   object  
 15  Algo2_pred          1971 non-null   object  
 16  Algo2_confidence    1971 non-null   float64 
 17  Algo2_dog           1971 non-null   object  
 18  Algo3_pred          1971 non-null   object  
 19  Algo3_confidence    1971 non-null   float64 
 20  Algo3_dog           1971 non-null   object  
 21  dog_type            1971 non-null   object  
 22  breed               1971 non-null   object  
 23  confidence          1971 non-null   float64 
dtypes: category(1), float64(7), int64(3), object(13)
memory usage: 371.6+ KB
```

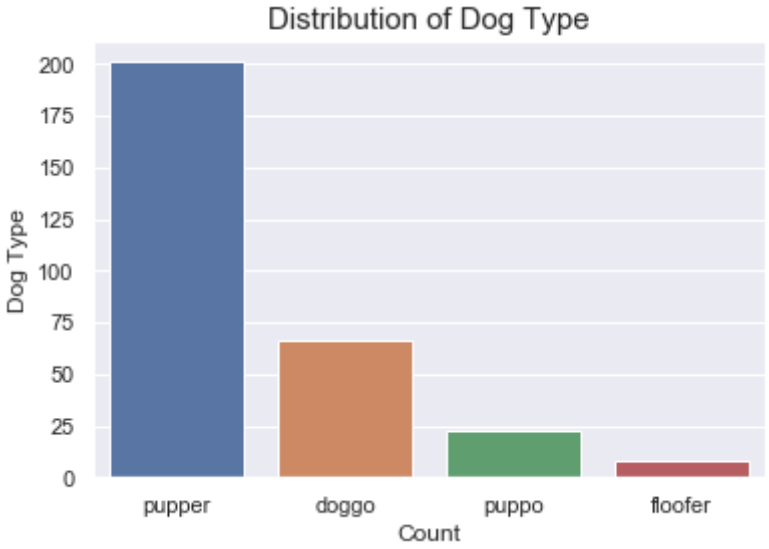
Store the final data

In [175]:
```
df.to_csv('twitter-archive-master.csv', encoding='utf-8')
```

Visualize

1) Distribution of Dog Levels

In [179]:
```
sorted_level = df.dog_type.value_counts().tail(-1).index
sns.set(style="darkgrid")
sns.countplot(data=df, x='dog_type', order=sorted_level, orient='h')
plt.xticks(rotation =360)
plt.xlabel('Count', fontsize=12)
plt.ylabel('Dog Type', fontsize=12)
plt.title('Distribution of Dog Type', fontsize=15);
```



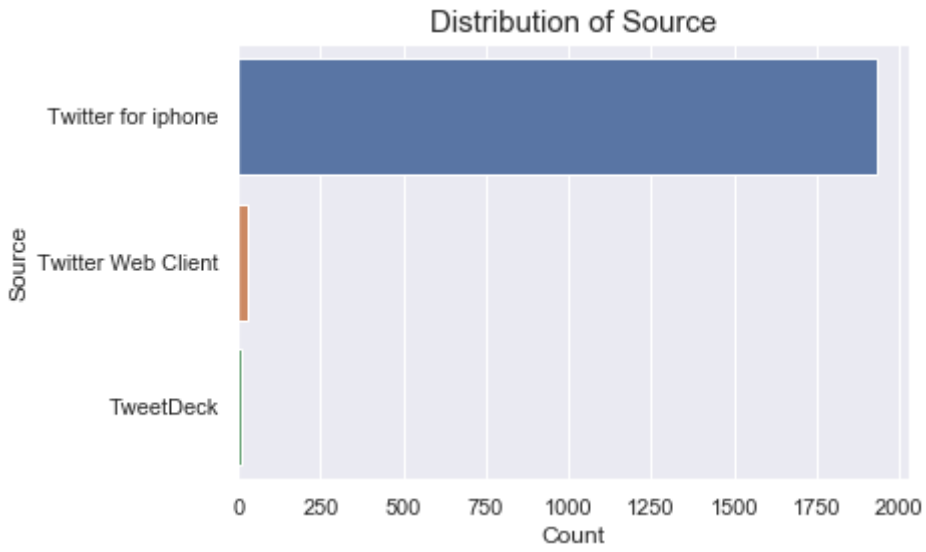
INSIGHTS: From the above graph, one can infer that the dog level called as 'pupper' (a small or young dog) is the most popular dog stage. It is followed by 'doggo' level and 'puppo' level but are significantly less. This can be attributed to the fact that people like dogs more when they are cute and really small/young. Although the visual gives us some idea about the situation, but due to lots of data missing, we cannot confirm this finding.

2) Distribution of Source

In [181]:
```
sort_source = df.source.value_counts().index
display(df.source.value_counts())

sns.set(style='darkgrid')
sns.countplot(data = df, y='source', order=sort_source)
plt.xticks(rotation =360)
plt.xlabel('Count', fontsize=12)
plt.ylabel('Source', fontsize=12)
plt.title('Distribution of Source', fontsize=15);
```

```
Twitter for iphone    1932
Twitter Web Client    28
TweetDeck             11
Name: source, dtype: int64
```



INSIGHT: From the above plot, we can tell that there is a single source among all the sources that is majority of the source which is 'Twitter for iPhone'.

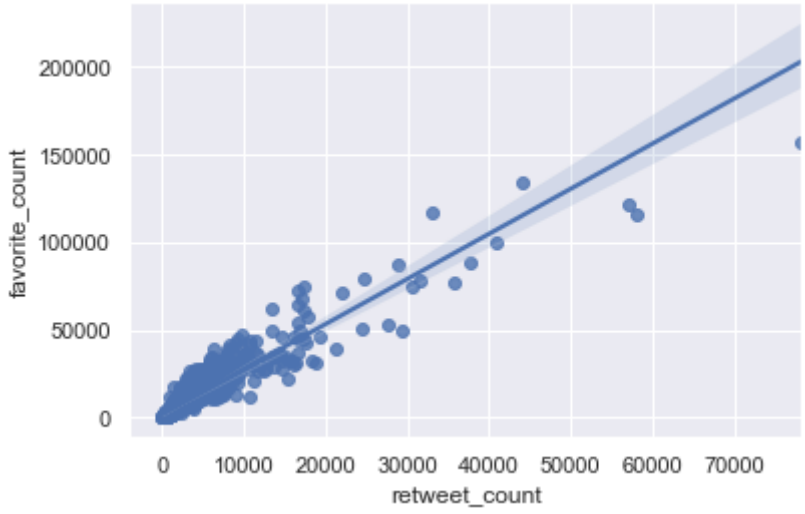
3) retweet_count and favorite_count

In [182]:
```
df.corr(method='pearson')
```

Out[182]:

	tweet_id	rating_numerator	rating_denominator	favorite_count	retweet_coun
tweet_id	1.000000	0.024917	NaN	0.610744	0.38362
rating_numerator	0.024917	1.000000	NaN	0.016764	0.01901
rating_denominator	NaN	NaN	NaN	NaN	Nal
favorite_count	0.610744	0.016764	NaN	1.000000	0.92914
retweet_count	0.383629	0.019011	NaN	0.929147	1.00000
img_num	0.215396	-0.003137	NaN	0.130802	0.10482
Algo1_confidence	0.104148	-0.006962	NaN	0.068917	0.04674
Algo2_confidence	-0.001059	-0.019657	NaN	-0.016166	-0.01424
Algo3_confidence	-0.046983	-0.004241	NaN	-0.045811	-0.03806
confidence	0.147300	-0.022331	NaN	0.071076	0.02718

In [184]:
```
sns.regplot(x='retweet_count', y='favorite_count', data=df);
```



INSIGHT: A fair insight or let's say hypothesis can be stated as 'the more popular tweet gets more retweets' and which can be deduced to be true in general. Even the coorelation coefficient is 0.8 which indicates the same.

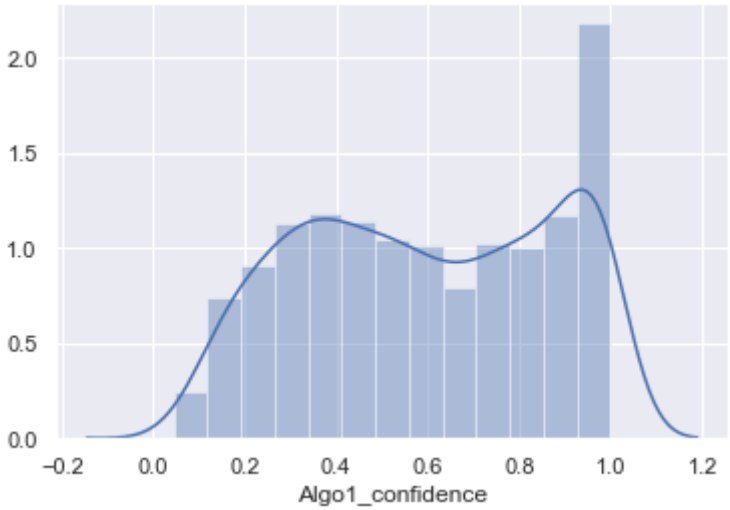
4) Dog Classification results analysis

In [185]:
```
df.Algo1_pred.value_counts().head(10)
```

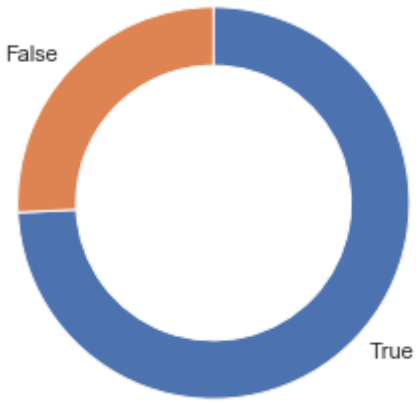
Out[185]:
```
Golden_retriever      137
Labrador_retriever     94
Pembroke               88
Chihuahua              78
Pug                    54
Chow                   41
Samoyed                40
Pomeranian             38
Toy_poodle             37
Malamute               29
Name: Algo1_pred, dtype: int64
```

Since there are lots of dog breeds, we decided to only pursue the 10 most predicted categories.

In [186]:
```
sns.set(style='darkgrid')
ax = sns.distplot(df.Algo1_confidence)
```



In [187]:
```
sort_p1 = df.Algo1_dog.value_counts()
plt.pie(sort_p1, labels=sort_p1.index, startangle=90, counterclock=False
, wedgeprops={'width': 0.3})
plt.axis('square');
```



INSIGHT: The pie chart reveals that nearly in 2 out of 3 cases, the predictions are correct. The results are low considering a deep learning model. Also the confidence level for the algorithm is considerably high.

In [ ]: