Project: Wrangle and Analyze Twitter Data

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Introduction

The Twitter data from 'WeRateDogs' account has been analyzed in this project. First, I gathered the data from various sources, then I inspected the properties of the data and performed necessary data cleaning. With the cleaned data, I am able to analyze and visualize some interesting features and details from this Twitter account.

First of all, I will import in the cell below all the libraries and modules needed for this project.

In [10]:

```
# import all the packages needed for the project
# data analysis and plotting
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import requests # download data
import re # text processing
import tweepy # using Twitter api
import json # json data processing

# display image from HTML
from IPython.display import HTML, display

import time

import warnings
warnings.filterwarnings('ignore')
```

Data Wrangling

Gathering Data

(1) WeRateDogs Twitter archive

First I downloaded a data file named 'twitter-archive-enhanced.csv' from Udacity, which contains the WeRateDogs Twitter archive (tweet ID, timestamp, text, etc.) for all 5000+ of their tweets as they stood on August 1, 2017. I loaded it into a pandas dataframe called df_twitter_archive.

In [11]:

```
# load twitter-archive-enhanced csv
df_twitter_archive = pd.read_csv('twitter-archive-enhanced.csv')
df_twitter_archive.head()
```

Out[11]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	source	
0	892420643555336193	NaN	NaN	2017-08-01 16:23:56 +0000	<a href="http://twitter.com/download/iphone" r...	Ph m boy
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	<a href="http://twitter.com/download/iphone" r...	This i She ch I
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	<a href="http://twitter.com/download/iphone" r...	Arcl is Norv Pou
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	<a href="http://twitter.com/download/iphone" r...	Darl comm a s mid
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	<a href="http://twitter.com/download/iphone" r...	Frank wou you t

In [12]:

```
# basic info of df_twitter_archive
df_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                    2356 non-null int64
in_reply_to_status_id       78 non-null float64
in_reply_to_user_id         78 non-null float64
timestamp                   2356 non-null object
source                      2356 non-null object
text                        2356 non-null object
retweeted_status_id         181 non-null float64
retweeted_status_user_id    181 non-null float64
retweeted_status_timestamp  181 non-null object
expanded_urls               2297 non-null object
rating_numerator            2356 non-null int64
rating_denominator          2356 non-null int64
name                        2356 non-null object
doggo                       2356 non-null object
floofer                     2356 non-null object
pupper                      2356 non-null object
puppo                       2356 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 313.0+ KB
```

(2) Tweet image predictions

The tweet image predictions, i.e., what breed of dog (or other object, animal, etc.) is present in each tweet according to a neural network. This file (image_predictions.tsv) is hosted on Udacity's servers and should be

according to a neural network. This file (image_predictions.tsv) is hosted on Udacity's servers and should be downloaded programmatically using the Requests library and the following URL. The detail of obtaining the data is shown as follows:

In [13]:

```
# use url request to access data
url = "https://d17h27t6h515a5.cloudfront.net/topher/2017/August/599fd2ad_image-predictions/image-predictions.tsv"
response = requests.get(url)
```

In [14]:

```
# save the data to image_predictions.tsv
with open("image_predictions.tsv", mode = "wb") as file:
    file.write(response.content)
```

In [15]:

```
# load the tsv file as df_image_prediction dataframe
df_image_prediction = pd.read_csv('image_predictions.tsv', sep='\t' )
df_image_prediction.head()
```

Out[15]:

	tweet_id	jpg_url	img_num	p1	p1_conf	p1_
0	666020888022790149	https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg	1	Welsh_springer_spaniel	0.465074	T
1	666029285002620928	https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg	1	redbone	0.506826	T
2	666033412701032449	https://pbs.twimg.com/media/CT4521TWwAEvMyu.jpg	1	German_shepherd	0.596461	T
3	666044226329800704	https://pbs.twimg.com/media/CT5Dr8HUEAA-lEu.jpg	1	Rhodesian_ridgeback	0.408143	T
4	666049248165822465	https://pbs.twimg.com/media/CT5IQmsXIAAKY4A.jpg	1	miniature_pinscher	0.560311	T

The dataframe lists the basic infomation of the tweet image and three predictions of the object in the image with confidence level.

(3) Additional Twitter Data

There are extra twitter features from WeRateDogs that I will utilize in the analysis, e.g. each tweet's retweet count and favorite ("like") count. Next I used the Twitter api to fetch Twitter data from WeRateDogs (the alternative way is to download the tweet_json file directly from Udacity). In the below cell I only showed the basic method, there are more details on how to use Twitter API to get data via this link:
https://stackoverflow.com/questions/28384588/twitter-api-get-tweets-with-specific-id

In [8]:

```
# use the key and token from your API account to access the data
consumer_key = ''
consumer_secret = ''
access_token = ''
access_secret = ''

auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_token, access_secret)

api = tweepy.API(auth)
```

In [9]:

```
# use df_list to save additional twitter data
df_list = []
error_list = []

start_time = time.time()
```

```
# iterate through tweet id and save each tweet as a json file
for tweet_id in df_twitter_archive['tweet_id']:
    try:
        tweet = api.get_status(tweet_id, wait_on_rate_limit=True, wait_on_rate_limit_noti
fy=True)
        # appending the tweets as json objects
        df_list.append(tweet._json)
        tweet = ""
    except:
        print("Tweet id: " + str(tweet_id) + " failed.")

with open ('tweet_json.txt', 'w') as outfile:
    json.dump(df_list, outfile)

print("Tweet information stored successfully!")

end_time = time.time()
print (end_time - start_time)
```

```
Tweet id: 888202515573088257 failed.
Tweet id: 873697596434513921 failed.
Tweet id: 872668790621863937 failed.
Tweet id: 872261713294495745 failed.
Tweet id: 869988702071779329 failed.
Tweet id: 866816280283807744 failed.
Tweet id: 861769973181624320 failed.
Tweet id: 856602993587888130 failed.
Tweet id: 851953902622658560 failed.
Tweet id: 845459076796616705 failed.
Tweet id: 844704788403113984 failed.
Tweet id: 842892208864923648 failed.
Tweet id: 837366284874571778 failed.
Tweet id: 837012587749474308 failed.
Tweet id: 829374341691346946 failed.
Tweet id: 827228250799742977 failed.
Tweet id: 812747805718642688 failed.
Tweet id: 802247111496568832 failed.
Tweet id: 779123168116150273 failed.
Tweet id: 775096608509886464 failed.
Tweet id: 771004394259247104 failed.
Tweet id: 770743923962707968 failed.
Tweet id: 759566828574212096 failed.
```

```
Rate limit reached. Sleeping for: 669
```

```
Tweet id: 754011816964026368 failed.
Tweet id: 680055455951884288 failed.
```

```
Rate limit reached. Sleeping for: 665
```

```
Tweet information stored successfully!
1955.787596464157
```

The gathering process takes ~30 min, the try-except block helps us identify some twitter ids that we were not able to fetch the data. Now I have the additional twitter data saved as tweet_json.txt, I wrote it into a pandas dataframe called df_tweet_json.

In [16]:

```
# use a list to store the info extracted from tweet_json.txt
twitter_api = []

with open("tweet_json.txt", "r") as file:
    for line in file:
        try:
            tweet = json.loads(line)
            twitter_api.append({"tweet_id": tweet["id"],
                                "favorite_count": tweet["favorite_count"],
                                "retweet_count": tweet["retweet_count"],
                                "retweeted": tweet["retweeted"]})
```

```
        except:
            print("reading line error")

# load twitter_api into a pandas dataframe
df_tweet_json = pd.DataFrame(twitter_api, columns = ["tweet_id", "favorite_count", "retw
eet_count", "retweeted"])
df_tweet_json.head()
```

Out[16]:

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

Assessing Data

The quality and tidiness of each dataframe are examined in detail, first I performed a quick visual assessment, by browsing twitter_archive_enhanced.csv and image_prediction.tsv in Excel and tweet_json.txt in text editor to get a general idea of the data, then I systematically assessed each of them using different Python commands shown in this section. A summary of data assessing is given at the end of this section.

df_twitter_archive

In [17]:

```
# check using info method
df_twitter_archive.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                    2356 non-null int64
in_reply_to_status_id       78 non-null float64
in_reply_to_user_id         78 non-null float64
timestamp                   2356 non-null object
source                      2356 non-null object
text                        2356 non-null object
retweeted_status_id         181 non-null float64
retweeted_status_user_id    181 non-null float64
retweeted_status_timestamp  181 non-null object
expanded_urls               2297 non-null object
rating_numerator            2356 non-null int64
rating_denominator          2356 non-null int64
name                        2356 non-null object
doggo                       2356 non-null object
floofer                     2356 non-null object
pupper                      2356 non-null object
puppo                       2356 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 313.0+ KB
```

We can see that there are many missing values, mainly in the columns related to reply and retweet. Since we are only interested in the original tweets, I will drop them later in the data cleaning section.

Another observation is that we also need to change the data type of the timestamp column to datetime.

In [18]:

```
# pick 5 sample rows
df_twitter_archive.sample(5)
```

Out[18]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	source	
1057	742150209887731712	NaN	NaN	2016-06-13 00:22:53 +0000	<a href="http://twitter.com/download/iphone" r...	Ed s
116	870308999962521604	NaN	NaN	2017-06-01 16:00:09 +0000	<a href="http://twitter.com/download/iphone" r...	R b re
339	832273440279240704	NaN	NaN	2017-02-16 17:00:25 +0000	<a href="http://twitter.com/download/iphone" r...	Sa S tl
635	793601777308463104	NaN	NaN	2016-11-01 23:53:02 +0000	<a href="http://twitter.com/download/iphone" r...	D l
2143	669970042633789440	NaN	NaN	2015-11-26 20:04:40 +0000	<a href="http://twitter.com/download/iphone" r...	Ju w o

We can see from the above 5 sample tweets that (1) not all the dogs in the posts have names; (2) WeRateDogs classifies dogs as doggo/floofer/pupper/puppo, but not all the dogs necessarily have a category.

In [19]:

```
# check whether duplicates exist
df_twitter_archive['tweet_id'].duplicated().sum()
```

Out[19]:

```
0
```

Luckily we don't have duplicate entries. Now let's focus on the rating numerator (later on rating denominator), these dog ratings almost always have a denominator of 10. The numerators are almost always greater than 10. 11/10, 12/10, 13/10, etc. Why? Because "they're good dogs Brent."

In [20]:

```
# count the rating numerator
df_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
```

There are various numerators, including 0 and some extraodinary large numbers, such as 1776, 960, etc. I would like to access the text of these tweets to see the details.

In [21]:

```
# access tweet text for specific numerators
pd.set_option('display.max_colwidth', -1)
print(df_twitter_archive.query("rating_numerator == '1776'").text)
print(df_twitter_archive.query("rating_numerator == '27'").text)
print(df_twitter_archive.query("rating_numerator == '1'").text)
print(df_twitter_archive.query("rating_numerator == '0'").text)
```

```
979    This is Atticus. He's quite simply America af. 1776/10 https://t.co/GRXwMxLBkh
Name: text, dtype: object
763    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
Name: text, dtype: object
605     RT @dog_rates: Not familiar with this breed. No tail (weird). Only 2 legs. Doesn't bark. Surprisingly quick. Shits eggs. 1/10 https://t.co/…
1446    After reading the comments I may have overestimated this pup. Downgraded to a 1/10. Please forgive me
1869    What kind of person sends in a picture without a dog in it? 1/10 just because that's a nice table https://t.co/RDXCfk8hK0
1940    The millennials have spoken and we've decided to immediately demote to a 1/10. Thank you
2038    After 22 minutes of careful deliberation this dog is being demoted to a 1/10. The longer you look at him the more terrifying he becomes
2091    Flamboyant pup here. Probably poisonous. Won't eat kibble. Doesn't bark. Slow af. Petting doesn't look fun. 1/10 https://t.co/jxukeh2BeO
2261    Never seen dog like this. Breathes heavy. Tilts head in a pattern. No bark. Shitty at fetch. Not even cordless. 1/10 https://t.co/i9iSGNn3fx
2335    This is an Albanian 3 1/2 legged  Episcopalian. Loves well-polished hardwood flooring. Penis on the collar. 9/10 https://t.co/d9NcXFKwLv
2338    Not familiar with this breed. No tail (weird). Only 2 legs. Doesn't bark. Surprisingly quick. Shits eggs. 1/10 https://t.co/Asgdc6kuLX
Name: text, dtype: object
315     When you're so blinded by your systematic plagiarism that you forget what day it
```

```
is. 0/10 https://t.co/YbEJPkg4Ag
1016    PUPDATE: can't see any. Even if I could, I couldn't reach them to pet. 0/10 much
disappointment https://t.co/c7WXaB2nqX
Name: text, dtype: object
```

From the text and corresponding links, 1776 is a valid numerator (the dog is in a US national flag to celebrate the country's establishment in year 1776). There are numerators, such as 0 or 1, because the pictures don't have dogs inside at all. Besides, there seems to be fractional numerators (maybe in denominator as well), such as 11.27/10, let's check.

In [22]:

```
# define pattern1, which represents fractional numbers that have decimals in the numerato
r
pattern1 = "(\d+\.\d*\/\d+)"
# search through the text for ratings with decimal numerators
with pd.option_context('max_colwidth', 200):
    display(df_twitter_archive[df_twitter_archive['text'].str.contains(pattern1)]
            [['tweet_id', 'text', 'rating_numerator', 'rating_denominator']])
```

	tweet_id	text	rating_numerator	rating_denominator
45	883482846933004288	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	10
340	832215909146226688	RT @dog_rates: 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/yBO5wu...	75	10
695	786709082849828864	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	10
763	778027034220126208	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	10
1689	681340665377193984	I've been told there's a slight possibility he's checking his mirror. We'll bump to 9.5/10. Still a menace	5	10
1712	680494726643068929	Here we have uncovered an entire battalion of holiday puppers. Average of 11.26/10 https://t.co/eNm2S6p9BD	26	10

There are 6 tweets and their ratings from the text have decimal numbers in the numerator. For example, there are 13.5/10, 9.75/10, etc. I also found some errors in the rating_numerator cloumn, it falsely takes the number after the decimal point as the rating numerator instead of using the whole float number (e.g. should be 9.75, but is 75 actually), we need to clean this as well.

Now I will check the rating_denominator similarly.

In [23]:

```
# count the rating_denominator
df_twitter_archive.rating_denominator.value_counts()
```

Out[23]:

```
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
```

Almost all the denominators are 10 except a few ones with different values, let's check the original text for some of them.

In [24]:

```
# access tweet text for specific denominators
pd.set_option('display.max_colwidth', -1)
print(df_twitter_archive.query("rating_denominator == '170'").text)
print(df_twitter_archive.query("rating_denominator == '0'").text)
```

```
1120    Say hello to this unbelievably well behaved squad of doggos. 204/170 would try to pet all at once https://t.co/yGQI3He3xv
Name: text, dtype: object
313    @jonnysun @Lin_Manuel ok jomny I know you're excited but 960/00 isn't a valid rating, 13/10 is tho
Name: text, dtype: object
```

170 is a valid denominator as in 240/170 from the first text line above. There is also a 0 in the denominator, the text of which actually has two ratings. Based on the text, 13/10 seems to be the more appropriate rating. But it brings to us that we need to deal with tweets with more than one ratings properly in the clean section.

Similarly, I'd like to check for decimal denominators.

In [25]:

```
# pattern for decimal denominator
pattern2 = "(\d+\/\d+\.\d+)"
# search through the text for decimal denominator
with pd.option_context('max_colwidth', 200):
    display(df_twitter_archive[df_twitter_archive['text'].str.contains(pattern2)]
            [['tweet_id', 'text', 'rating_numerator', 'rating_denominator']])
```

	tweet_id	text	rating_numerator	rating_denominator

It's good news that we don't have decimal denominators in our tweet archive. As I mentioned before, there are multiple occurences of ratings in one tweet. Let's check.

In [26]:

```
# count for occurance of ratings in one text
pattern = "(\d+(\.\d+)?\/\d+(\.\d+)?)"
df_twitter_archive["rating_count"] = df_twitter_archive.text.str.count(pattern)
df_twitter_archive["rating_count"].value_counts()
```

Out[26]:

```
1    2323
2    32
3    1
Name: rating_count, dtype: int64
```

We need to deal with 32 tweets with 2 ratings in the text and 1 tweet with 3 ratings in the text. One of the reasons for this is there might be more than one dogs in a picture.

In [27]:

```
# go through the texts of tweets with multiple ratings
df_twitter_archive[["text", "rating_count"]].query("rating_count != 1")
```

Out[27]:

	text	rating_count
55	@roushfenway These are good dogs but 17/10 is an emotional impulse rating. More like 13/10s	2
313	@jonnysun @Lin_Manuel ok jomny I know you're excited but 960/00 isn't a valid rating, 13/10 is tho	2
561	RT @dog_rates: "Yep... just as I suspected. You're not flossing." 12/10 and 11/10 for the pup not flossing https://t.co/SuXcI9B7pQ	2
766	"Yep... just as I suspected. You're not flossing." 12/10 and 11/10 for the pup not flossing https://t.co/SuXcI9B7pQ	2
784	RT @dog_rates: After so many requests, this is Bretagne. She was the last surviving 9/11 search dog, and our second ever 14/10. RIP https:/…	2
860	RT @dog_rates: Meet Eve. She's a raging alcoholic 8/10 (would b 11/10 but pupper alcoholism is a tragic issue that I can't condone) https:/…	2
1007	This is Bookstore and Seaweed. Bookstore is tired and Seaweed is an asshole. 10/10 and 7/10 respectively https://t.co/eUGjGjjFVJ	2
1068	After so many requests, this is Bretagne. She was the last surviving 9/11 search dog, and our second ever 14/10. RIP https://t.co/XAVDNDaVgQ	2
1165	Happy 4/20 from the squad! 13/10 for all https://t.co/eV1diwds8a	2
1202	This is Bluebert. He just saw that both #FinalFur match ups are split 50/50. Amazed af. 11/10 https://t.co/Kky1DPG4iq	2
1222	Meet Travis and Flurp. Travis is pretty chill but Flurp can't lie down properly. 10/10 & 8/10\nget it together Flurp https://t.co/AkzI5ynMmE	2
1359	This is Socks. That water pup w the super legs just splashed him. Socks did not appreciate that. 9/10 and 2/10 https://t.co/8rc5I22bBf	2
1459	This may be the greatest video I've ever been sent. 4/10 for Charles the puppy, 13/10 overall. (Vid by @stevenxx_) https://t.co/uaJmNgXR2P	2
1465	Meet Oliviér. He takes killer selfies. Has a dog of his own. It leaps at random & can't bark for shit. 10/10 & 5/10 https://t.co/6NgsQJuSBJ	2
1508	When bae says they can't go out but you see them with someone else that same night. 5/10 & 10/10 for heartbroken pup https://t.co/aenk0KpoWM	2
1525	This is Eriq. His friend just reminded him of last year's super bowl. Not cool friend\n10/10 for Eriq\n6/10 for friend https://t.co/PlEXTofdpf	2
1538	Meet Fynn & Taco. Fynn is an all-powerful leaf lord and Taco is in the wrong place at the wrong time. 11/10 & 10/10 https://t.co/MuqHPvtL8c	2
1662	This is Darrel. He just robbed a 7/11 and is in a high speed police chase. Was just spotted by the helicopter 10/10 https://t.co/7EsP8LmSp5	2
1795	Meet Tassy & Bee. Tassy is pretty chill, but Bee is convinced the Ruffles are haunted. 10/10 & 11/10 respectively https://t.co/fgORpmTN9C	2
1832	These two pups just met and have instantly bonded. Spectacular scene. Mesmerizing af. 10/10 and 7/10 for blue dog https://t.co/gwryaJO4tC	2
1897	Meet Rufio. He is unaware of the pink legless pupper wrapped around him. Might want to get that checked 10/10 & 4/10 https://t.co/KNfLnYPmYh	2
1901	Two gorgeous dogs here. Little waddling dog is a rebel. Refuses to look at camera. Must be a preteen. 5/10 & 8/10 https://t.co/YPfw7oahbD	2
1970	Meet Eve. She's a raging alcoholic 8/10 (would b 11/10 but pupper alcoholism is a tragic issue that I can't condone) https://t.co/U36HYQlijg	2
2010	10/10 for dog. 7/10 for cat. 12/10 for human. Much skill. Would pet all https://t.co/uhx5gfpx5k	3
2064	Meet Holly. She's trying to teach small human-like pup about blocks but he's not paying attention smh. 11/10 & 8/10 https://t.co/RcksaUrGNu	2
2113	Meet Hank and Sully. Hank is very proud of the pumpkin they found and Sully doesn't give a shit. 11/10 and 8/10 https://t.co/cwoP1ftbrj	2
2177	Here we have Pancho and Peaches. Pancho is a Condoleezza Gryffindor, and Peaches is just an asshole. 10/10 & 7/10 https://t.co/Lh1BsJrWPp	2
2216	This is Spark. He's nervous. Other dog hasn't moved in a while. Won't come when called. Doesn't fetch well 8/10&1/10 https://t.co/stEodX9Aba	2
2263	This is Kial. Kial is either wearing a cape, which would be rad, or flashing us, which would be rude. 10/10 or	2

	text	rating_count
	4/10 https://t.co/8zcwIoIuqR	
2272	Two dogs in this one. Both are rare Jujitsu Pythagoreans. One slightly whiter than other. Long legs. 7/10 and 8/10 https://t.co/ITxxcc4v9y	2
2298	After much debate this dog is being upgraded to 10/10. I repeat 10/10	2
2306	These are Peruvian Feldspars. Their names are Cupit and Prencer. Both resemble Rand Paul. Sick outfits 10/10 & 10/10 https://t.co/ZnEMHBsAs1	2
2335	This is an Albanian 3 1/2 legged Episcopalian. Loves well-polished hardwood flooring. Penis on the collar. 9/10 https://t.co/d9NcXFKwLv	2

Aside from having multiple dogs, some other objects in the pictures get rated as well (cats, human, etc.), resulting in more than 1 ratings.

Now I want to inspect the `name` column.

In [28]:

```
# count the names
df_twitter_archive.name.value_counts()
```

Out[28]:

```
None            745
a                55
Charlie          12
Cooper           11
Oliver           11
Lucy             11
Lola             10
Tucker           10
Penny            10
Winston           9
Bo                9
the               8
Sadie             8
Daisy             7
Toby              7
Buddy             7
an                7
Bailey            7
Koda              6
Milo              6
Dave              6
Jack              6
Jax               6
Stanley           6
Scout             6
Oscar             6
Leo               6
Rusty             6
Bella             6
Gus               5
                ..
Damon             1
Flurpson          1
Filup             1
unacceptable      1
Gilbert           1
Lipton            1
Bodie             1
Jaycob            1
Huxley            1
Millie            1
Bruno             1
Baron             1
Hall              1
Shikha            1
Josep             1
Rhino             1
Stella            1
```

```
Jeremy          1
Tino            1
Dewey           1
Mack            1
Harnold         1
Alf             1
Leonard         1
Noah            1
Aqua            1
Kaiya           1
Mary            1
Jarod           1
Sid             1
Name: name, Length: 957, dtype: int64
```

There is an issue associated with the name column, it contains wrong names like "a", "the", "an".

Next I will inspect the dog_type infomation (doggo/floofer/pupper/puppo) and see how often they appear in the twitter archive.

In [29]:

```
# count each of the dog_type
df_twitter_archive["doggo"].value_counts()
```

Out[29]:

```
None     2259
doggo    97
Name: doggo, dtype: int64
```

In [30]:

```
df_twitter_archive["floofer"].value_counts()
```

Out[30]:

```
None       2346
floofer    10
Name: floofer, dtype: int64
```

In [31]:

```
df_twitter_archive["pupper"].value_counts()
```

Out[31]:

```
None      2099
pupper    257
Name: pupper, dtype: int64
```

In [32]:

```
df_twitter_archive["puppo"].value_counts()
```

Out[32]:

```
None     2326
puppo    30
Name: puppo, dtype: int64
```

In [33]:

```
# fractions of classified dog_type over all the tweets
print (97/2356, 10/2356, 257/2356, 30/2356)
```

```
0.041171477079796265 0.004244482173174873 0.10908319185059423 0.012733446519524618
```

Only a small fraction of the dogs (from 0.4% to 10.9%) got corresponding dog types in these column, I think we should combine dog type columns into one for simplicity.

df_image_prediction

In [34]:

```
# info of the df_image_prediction dataframe
df_image_prediction.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2075 entries, 0 to 2074
Data columns (total 12 columns):
tweet_id    2075 non-null int64
jpg_url     2075 non-null object
img_num     2075 non-null int64
p1          2075 non-null object
p1_conf     2075 non-null float64
p1_dog      2075 non-null bool
p2          2075 non-null object
p2_conf     2075 non-null float64
p2_dog      2075 non-null bool
p3          2075 non-null object
p3_conf     2075 non-null float64
p3_dog      2075 non-null bool
dtypes: bool(3), float64(3), int64(2), object(4)
memory usage: 152.1+ KB
```

In terms of missing values, the df_image_prediction looks fine.

In [35]:

```
# pick 10 samples
df_image_prediction.sample(10)
```

Out[35]:

	tweet_id	jpg_url	img_num	p1	p1_conf	p
1985	872261713294495745	https://pbs.twimg.com/media/DBrlZk2UQAAfAkd.jpg	2	Labrador_retriever	0.972019	
1638	806629075125202948	https://pbs.twimg.com/media/CzG425nWgAAnP7P.jpg	2	Arabian_camel	0.366248	
575	678643457146150913	https://pbs.twimg.com/media/CWsGnyMVEAAM1Y1.jpg	1	Labrador_retriever	0.338757	
1633	805932879469572096	https://pbs.twimg.com/media/Cy8_qt0UUAAHuuN.jpg	1	Norwegian_elkhound	0.657967	
1917	854732716440526848	https://pbs.twimg.com/media/C9ye3b3WAAAlTo0.jpg	1	Pembroke	0.695548	
118	668154635664932864	https://pbs.twimg.com/media/CUXDGR2WcAAUQKz.jpg	1	Arctic_fox	0.473584	
1166	735635087207878657	https://pbs.twimg.com/media/CjWANBlVAAAaN-a.jpg	1	pug	0.891871	
1934	859851578198683649	https://pbs.twimg.com/media/C-7OcfyXsAAsqzU.jpg	4	Labrador_retriever	0.899086	
225	670338931251150849	https://pbs.twimg.com/media/CU2FsRnVAAA3TEg.jpg	1	cairn	0.245033	
1381	765371061932261376	https://pbs.twimg.com/media/Cp8k6oRWcAUL78U.jpg	2	golden_retriever	0.829456	

The predictions (p1, p2, p3) are sometimes in lower case, sometimes in upper case (connected by underscores), we should edit these strings to make them consistent. Besides, not all the predictions are dogs , they can be other objects (vacuum, sea_lion) that we need to deal with.

To find whether there are duplicates in the image_prediction, we can look at the jpg_url column.

In [36]:

```
# duplicates in the dataframe by image url
df_image_prediction.jpg_url.duplicated().sum()
```

Out[36]:

```
66
```

In [37]:

```
# duplicates in the dataframe by tweet id
df_image_prediction.tweet_id.duplicated().sum()
```

Out[37]:

```
0
```

In [38]:

```
# appearance of identical image in df_image_prediction
df_image_prediction.jpg_url.value_counts().head()
```

Out[38]:

```
https://pbs.twimg.com/media/CtzKC7zXEAALfSo.jpg
2
https://pbs.twimg.com/media/C4KHj-nWQAA3poV.jpg
2
https://pbs.twimg.com/media/CvoBPWRWgAA4het.jpg
2
https://pbs.twimg.com/media/CYLDikFWEAAIy1y.jpg
2
https://pbs.twimg.com/ext_tw_video_thumb/815965888126062592/pu/img/JleSw4wRhgKDWQj5.jpg
2
Name: jpg_url, dtype: int64
```

In [39]:

```
# one duplicate example from the first link in the above cell outcome
df_image_prediction[df_image_prediction.jpg_url == "https://pbs.twimg.com/media/Ct2qO5PXEAE6eB0.jpg"]
```

Out[39]:

	tweet_id	jpg_url	img_num	p1	p1_conf	p1_dog	
1492	782969140009107456	https://pbs.twimg.com/media/Ct2qO5PXEAE6eB0.jpg	1	seat_belt	0.474292	False	golder
1640	807059379405148160	https://pbs.twimg.com/media/Ct2qO5PXEAE6eB0.jpg	1	seat_belt	0.474292	False	golder

In df_image_prediction, we need to deal with 66 duplicate entries. However, we are lucky since these duplicate predictions are actually coming from retweet/reply, given there are no duplicates based on tweet id but only on url.

Let's count rows which predictions are not dogs at all.

In [40]:

```
# rows that all three predictions are not dogs
df_image_prediction.query("p1_dog == False and p2_dog == False and p3_dog == False").count()
```

Out[40]:

```
tweet_id    324
jpg_url     324
img_num     324
p1          324
p1_conf     324
p1_dog      324
p2          324
p2_conf     324
p2_dog      324
p3          324
p3_conf     324
p3_dog      324
dtype: int64
```

There are 324 rows, the predictions of which don't have any dog at all.

In [41]:

```
# for each prediction, whether it's predicting dog or not
print(df_image_prediction.p1_dog.value_counts())
print(df_image_prediction.p2_dog.value_counts())
print(df_image_prediction.p3_dog.value_counts())
```

```
True     1532
False    543
Name: p1_dog, dtype: int64
True     1553
False    522
Name: p2_dog, dtype: int64
True     1499
False    576
Name: p3_dog, dtype: int64
```

There are rows that don't predict the object in the image as a dog . The reasons are (1) the dogs are sometimes in the background; (2) the pictures don't have any dogs at all. Because we only want tweets with dogs, so we might drop non-dog rows in the cleaning section later.

df_tweet_json

In [42]:

```
# tweet_json info
df_tweet_json.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2354 entries, 0 to 2353
Data columns (total 4 columns):
tweet_id          2354 non-null int64
favorite_count    2354 non-null int64
retweet_count     2354 non-null int64
retweeted         2354 non-null bool
dtypes: bool(1), int64(3)
memory usage: 57.5 KB
```

In [43]:

```
# count duplicates
df_tweet_json.tweet_id.duplicated().sum()
```

Out[43]:

```
0
```

For df_tweet_json, we don't have any missing values or duplicates .

In [44]:

```
# 5 samples from tweet_json
df_tweet_json.sample(5)
```

Out[44]:

	tweet_id	favorite_count	retweet_count	retweeted
1608	685532292383666176	3336	1298	False
1208	715680795826982913	4719	1813	False
89	874680097055178752	28439	4875	False
217	850333567704068097	3647	367	False
1781	677673981332312066	3603	1677	False

In [45]:

```
df_tweet_json.retweeted.value_counts()
```

Out[45]:

```
False    2354
Name: retweeted, dtype: int64
```

For the tweets in df_tweet_json, they are all not from retweet. Overall, tweet_json data looks fine.

Assessing Summary (11 quality issues and 2 tidiness issues)

quality (completeness, validity, accuracy, consistency):

df_twitter_archive:

- **there are missing values in the dataframe to deal with.**
- **there are retweets and replies in the dataframe that we're not interested in.**
- **the data type of timestamp should be change to datetime.**
- **some ratings are not correctly extracted from the text, especially when the rating numerator is a float number.**
- **sometimes there are more than one ratings for single tweet.**
- **some of the dog names are wrong (with names like 'a', 'the', 'an').**
- **many of the dogs don't have a dog type (doggo/floofer/pupper/puppo).**

df_image_prediction:

- **there are duplicate predictions from retweets that we're not interested in.**
- **some pictures got predicted even though they don't show dogs.**
- **the prediction results are inconsistent in using lower/upper case letters.**
- **we should condense the 3 predictions into one based on the confidence level, it's redundent to analyze prediction with low confidence.**

df_tweet_json: this dataframe looks fine overall.

Tidiness summary:

df_twitter_archive:

- **the four columns (doggo/floofer/pupper/puppo) should be combined into one because there are lots of 'None' values, it also makes the analysis easier.**

df_image_prediction: this dataframe looks fine overall.

df_tweet_json:: this dataframe looks fine overall.

others:

- **we should merge the three tables since they share tweet_id, it helps with analysis as well, e.g. we can easily compare tweet likes and dog ratings.**

Cleaning Data

Based on the quality and tidiness of the three dataframes (df_twitter_archive, df_image_prediction, df_tweet_json), I figured out the following data cleaning steps:

- **first, merge the three dataframes by tweet_id, which makes data cleaning easier to perform. e.g. if I'm to remove retweets from df_twitter_archive, I will have to do it for df_image_prediction as well. However, for the merged dataframe I only need to do this cleaning step once.**
- **drop rows with missing values if they are not important for analysis.**
- **change the data type of timestamp to datetime.**
- **drop all the data related to reply or retweet.**

- **drop columns we don't need for analysis.**
- **correct the rating numerators, drop the row if there are multiple ratings.**
- **fix the name if it's "the, a, an, etc.",**
- **combine the dog type columns (doggo/floofer/pupper/puppo) into one column.**
- **drop rows without image or image without dogs, extract the best dog prediction and confidence for each tweet.**

I will use the define-code-test procedure to process each cleaning step.

Define

- **Merge three dataframes**

Code

In [46]:

```
# make backup copies of three dataframes
df_twitter_archive_copy = df_twitter_archive.copy()
df_image_prediction_copy = df_image_prediction.copy()
df_tweet_json_copy = df_tweet_json.copy()
```

In [47]:

```
# merge three dataframes into df_all
df_all = pd.merge(df_twitter_archive_copy, df_image_prediction_copy, on = "tweet_id", ho
w = "outer")
df_all = pd.merge(df_all, df_tweet_json_copy, on = "tweet_id", how = "outer")
```

Test

In [48]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2356 entries, 0 to 2355
Data columns (total 32 columns):
tweet_id                      2356 non-null int64
in_reply_to_status_id         78 non-null float64
in_reply_to_user_id           78 non-null float64
timestamp                     2356 non-null object
source                        2356 non-null object
text                          2356 non-null object
retweeted_status_id           181 non-null float64
retweeted_status_user_id      181 non-null float64
retweeted_status_timestamp    181 non-null object
expanded_urls                 2297 non-null object
rating_numerator              2356 non-null int64
rating_denominator            2356 non-null int64
name                          2356 non-null object
doggo                         2356 non-null object
floofer                       2356 non-null object
pupper                        2356 non-null object
puppo                         2356 non-null object
rating_count                  2356 non-null int64
jpg_url                       2075 non-null object
img_num                       2075 non-null float64
p1                            2075 non-null object
p1_conf                       2075 non-null float64
p1_dog                        2075 non-null object
p2                            2075 non-null object
p2_conf                       2075 non-null float64
p2_dog                        2075 non-null object
p3                            2075 non-null object
p3_conf                       2075 non-null float64
p3_dog                        2075 non-null object
```

```
favorite_count                2354 non-null float64
retweet_count                 2354 non-null float64
retweeted                     2354 non-null object
dtypes: float64(10), int64(4), object(18)
memory usage: 607.4+ KB
```

Define

- **Remove retweets**

Code

In [49]:

```
# choose all the tweets without retweeted_status_id
df_all = df_all[df_all["retweeted_status_id"].isnull()]
```

Test

In [50]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2175 entries, 0 to 2355
Data columns (total 32 columns):
tweet_id                      2175 non-null int64
in_reply_to_status_id         78 non-null float64
in_reply_to_user_id           78 non-null float64
timestamp                     2175 non-null object
source                        2175 non-null object
text                          2175 non-null object
retweeted_status_id           0 non-null float64
retweeted_status_user_id      0 non-null float64
retweeted_status_timestamp    0 non-null object
expanded_urls                 2117 non-null object
rating_numerator              2175 non-null int64
rating_denominator            2175 non-null int64
name                          2175 non-null object
doggo                         2175 non-null object
floofer                       2175 non-null object
pupper                        2175 non-null object
puppo                         2175 non-null object
rating_count                  2175 non-null int64
jpg_url                       1994 non-null object
img_num                       1994 non-null float64
p1                            1994 non-null object
p1_conf                       1994 non-null float64
p1_dog                        1994 non-null object
p2                            1994 non-null object
p2_conf                       1994 non-null float64
p2_dog                        1994 non-null object
p3                            1994 non-null object
p3_conf                       1994 non-null float64
p3_dog                        1994 non-null object
favorite_count                2175 non-null float64
retweet_count                 2175 non-null float64
retweeted                     2175 non-null object
dtypes: float64(10), int64(4), object(18)
memory usage: 560.7+ KB
```

In [51]:

```
# check retweeted column to see if they are all false
df_all['retweeted'].value_counts()
```

Out[51]:

```
False    2175
```

```
Name: retweeted, dtype: int64
```

Define

- **Remove replies**

Code

In [52]:

```
# similarly we only want tweets without reply status
df_all = df_all[df_all["in_reply_to_status_id"].isnull()]
```

Test

In [53]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2097 entries, 0 to 2355
Data columns (total 32 columns):
tweet_id                      2097 non-null int64
in_reply_to_status_id         0 non-null float64
in_reply_to_user_id           0 non-null float64
timestamp                     2097 non-null object
source                        2097 non-null object
text                          2097 non-null object
retweeted_status_id           0 non-null float64
retweeted_status_user_id      0 non-null float64
retweeted_status_timestamp    0 non-null object
expanded_urls                 2094 non-null object
rating_numerator              2097 non-null int64
rating_denominator            2097 non-null int64
name                          2097 non-null object
doggo                         2097 non-null object
floofer                       2097 non-null object
pupper                        2097 non-null object
puppo                         2097 non-null object
rating_count                  2097 non-null int64
jpg_url                       1971 non-null object
img_num                       1971 non-null float64
p1                            1971 non-null object
p1_conf                       1971 non-null float64
p1_dog                        1971 non-null object
p2                            1971 non-null object
p2_conf                       1971 non-null float64
p2_dog                        1971 non-null object
p3                            1971 non-null object
p3_conf                       1971 non-null float64
p3_dog                        1971 non-null object
favorite_count                2097 non-null float64
retweet_count                 2097 non-null float64
retweeted                     2097 non-null object
dtypes: float64(10), int64(4), object(18)
memory usage: 540.6+ KB
```

In [54]:

```
# double check we don't have tweets from reply
df_all.in_reply_to_status_id.value_counts()
```

Out[54]:

```
Series([], Name: in_reply_to_status_id, dtype: int64)
```

Define

- **Drop unnecessary columns**

Code

In [55]:

```
# drop columns we don't need
df_all.drop(["in_reply_to_status_id", "in_reply_to_user_id", "retweeted_status_id",
             "retweeted_status_user_id", "retweeted_status_timestamp", "retweeted"],
            axis = 1, inplace = True)
```

Test

In [56]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2097 entries, 0 to 2355
Data columns (total 26 columns):
tweet_id              2097 non-null int64
timestamp             2097 non-null object
source                2097 non-null object
text                  2097 non-null object
expanded_urls         2094 non-null object
rating_numerator      2097 non-null int64
rating_denominator    2097 non-null int64
name                  2097 non-null object
doggo                 2097 non-null object
floofer               2097 non-null object
pupper                2097 non-null object
puppo                 2097 non-null object
rating_count          2097 non-null int64
jpg_url               1971 non-null object
img_num               1971 non-null float64
p1                    1971 non-null object
p1_conf               1971 non-null float64
p1_dog                1971 non-null object
p2                    1971 non-null object
p2_conf               1971 non-null float64
p2_dog                1971 non-null object
p3                    1971 non-null object
p3_conf               1971 non-null float64
p3_dog                1971 non-null object
favorite_count        2097 non-null float64
retweet_count         2097 non-null float64
dtypes: float64(6), int64(4), object(16)
memory usage: 442.3+ KB
```

Define

- **Drop rows without image**

Code

In [57]:

```
# get rid of rows without image
df_all.dropna(subset = ["jpg_url"], inplace = True)
```

Test

In [58]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 0 to 2355
Data columns (total 26 columns):
```

```
Data columns (total 26 columns):
tweet_id               1971 non-null int64
timestamp              1971 non-null object
source                 1971 non-null object
text                   1971 non-null object
expanded_urls          1971 non-null object
rating_numerator       1971 non-null int64
rating_denominator     1971 non-null int64
name                   1971 non-null object
doggo                  1971 non-null object
floofer                1971 non-null object
pupper                 1971 non-null object
puppo                  1971 non-null object
rating_count           1971 non-null int64
jpg_url                1971 non-null object
img_num                1971 non-null float64
p1                     1971 non-null object
p1_conf                1971 non-null float64
p1_dog                 1971 non-null object
p2                     1971 non-null object
p2_conf                1971 non-null float64
p2_dog                 1971 non-null object
p3                     1971 non-null object
p3_conf                1971 non-null float64
p3_dog                 1971 non-null object
favorite_count         1971 non-null float64
retweet_count          1971 non-null float64
dtypes: float64(6), int64(4), object(16)
memory usage: 415.8+ KB
```

After finishing the previous steps, I found the dataframe now has no missing values, which is a good news.

Define

- **Drop tweets that don't predict dogs in any of the 3 predictions**

Code

In [59]:

```
df_all.drop(df_all.query("p1_dog == False and p2_dog == False and p3_dog == False").index
, inplace = True)
```

Test

In [60]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1666 entries, 1 to 2355
Data columns (total 26 columns):
tweet_id               1666 non-null int64
timestamp              1666 non-null object
source                 1666 non-null object
text                   1666 non-null object
expanded_urls          1666 non-null object
rating_numerator       1666 non-null int64
rating_denominator     1666 non-null int64
name                   1666 non-null object
doggo                  1666 non-null object
floofer                1666 non-null object
pupper                 1666 non-null object
puppo                  1666 non-null object
rating_count           1666 non-null int64
jpg_url                1666 non-null object
img_num                1666 non-null float64
p1                     1666 non-null object
p1_conf                1666 non-null float64
```

```
p1_dog                1666 non-null object
p2                    1666 non-null object
p2_conf               1666 non-null float64
p2_dog                1666 non-null object
p3                    1666 non-null object
p3_conf               1666 non-null float64
p3_dog                1666 non-null object
favorite_count        1666 non-null float64
retweet_count         1666 non-null float64
dtypes: float64(6), int64(4), object(16)
memory usage: 351.4+ KB
```

Define

- **Fix duplicate images in image prediction**

Code/Test

In [61]:

```
df_all.jpg_url.duplicated().sum()
```

Out[61]:

```
0
```

Since the duplicate images are from retweets and replies, it should already been removed after we dropped the retweets and replies, and it's true from the outcome above, we no longer have duplicate image predictions.

Define

- **Fix wrong numerators**

Code

In [62]:

```
# how many wrong numerators left in df_all now (4)
pattern1 = "(\d+\.\d*\/\d+)"
with pd.option_context('max_colwidth', 200):
    display(df_all[df_all['text'].str.contains(pattern1)]
            [['tweet_id', 'text', 'rating_numerator', 'rating_denominator']])
```

	tweet_id	text	rating_numerator	rating_denominator
45	883482846933004288	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	10
695	786709082849828864	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	10
763	778027034220126208	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	10
1712	680494726643068929	Here we have uncovered an entire battalion of holiday puppers. Average of 11.26/10 https://t.co/eNm2S6p9BD	26	10

I will first extract the correct ratings from the original text of these 4 tweets.

In [63]:

```
# extract the ratings from the original text
df_all["text"].str.extract(pattern1, expand = True)[0].dropna()
```

Out[63]:

```
45      13.5/10
695      9.75/10
763     11.27/10
1712    11.26/10
Name: 0, dtype: object
```

The correct rating numerators for these tweets at float numbers. To solve this issue, I changed the column type for rating numerator and denominator to 'float'.

In [64]:

```
df_all.rating_numerator = df_all.rating_numerator.astype("float64")
df_all.rating_denominator = df_all.rating_denominator.astype("float64")
```

In [65]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1666 entries, 1 to 2355
Data columns (total 26 columns):
tweet_id              1666 non-null int64
timestamp             1666 non-null object
source                1666 non-null object
text                  1666 non-null object
expanded_urls         1666 non-null object
rating_numerator      1666 non-null float64
rating_denominator    1666 non-null float64
name                  1666 non-null object
doggo                 1666 non-null object
floofer               1666 non-null object
pupper                1666 non-null object
puppo                 1666 non-null object
rating_count          1666 non-null int64
jpg_url               1666 non-null object
img_num               1666 non-null float64
p1                    1666 non-null object
p1_conf               1666 non-null float64
p1_dog                1666 non-null object
p2                    1666 non-null object
p2_conf               1666 non-null float64
p2_dog                1666 non-null object
p3                    1666 non-null object
p3_conf               1666 non-null float64
p3_dog                1666 non-null object
favorite_count        1666 non-null float64
retweet_count         1666 non-null float64
dtypes: float64(8), int64(2), object(16)
memory usage: 351.4+ KB
```

I decided to manually fix them since we only have 4 wrong entries.

In [66]:

```
# correct the rating numerators manually by tweet_id from previous cells
df_all.loc[(df_all.tweet_id == 883482846933004288), 'rating_numerator'] = 13.5
df_all.loc[(df_all.tweet_id == 786709082849828864), 'rating_numerator'] = 9.75
df_all.loc[(df_all.tweet_id == 778027034220126208), 'rating_numerator'] = 11.27
df_all.loc[(df_all.tweet_id == 680494726643068929), 'rating_numerator'] = 11.26
```

Test

In [67]:

```
# check to make sure the rating numerators are right now
with pd.option_context('max_colwidth', 200):
    display(df_all[df_all['text'].str.contains(pattern1)]
            [['tweet_id', 'text', 'rating_numerator', 'rating_denominator']])
```

	tweet_id	text	rating_numerator	rating_denominator
45	883482846933004288	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	13.50	10.0
695	786709082849828864	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	9.75	10.0
763	778027034220126208	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	11.27	10.0
1712	680494726643068929	Here we have uncovered an entire battalion of holiday puppers. Average of 11.26/10 https://t.co/eNm2S6p9BD	11.26	10.0

The issue of rating numerators is solved, the other issue remains is that there are tweets with multiple ratings (on multiple dogs, or other object). I will simply drop them out.

Define

- **Drop tweets with multiple ratings**

Code

In [68]:

```
# query tweets with two or more ratings
df_all[["text", "rating_count"]].query("rating_count != 1")
```

Out[68]:

	text	rating_count
766	"Yep... just as I suspected. You're not flossing." 12/10 and 11/10 for the pup not flossing https://t.co/SuXcI9B7pQ	2
1007	This is Bookstore and Seaweed. Bookstore is tired and Seaweed is an asshole. 10/10 and 7/10 respectively https://t.co/eUGjGjjFVJ	2
1068	After so many requests, this is Bretagne. She was the last surviving 9/11 search dog, and our second ever 14/10. RIP https://t.co/XAVDNDaVgQ	2
1165	Happy 4/20 from the squad! 13/10 for all https://t.co/eV1diwds8a	2
1202	This is Bluebert. He just saw that both #FinalFur match ups are split 50/50. Amazed af. 11/10 https://t.co/Kky1DPG4iq	2
1222	Meet Travis and Flurp. Travis is pretty chill but Flurp can't lie down properly. 10/10 & 8/10\nget it together Flurp https://t.co/AkzI5ynMmE	2
1359	This is Socks. That water pup w the super legs just splashed him. Socks did not appreciate that. 9/10 and 2/10 https://t.co/8rc5I22bBf	2
1465	Meet Oliviér. He takes killer selfies. Has a dog of his own. It leaps at random & can't bark for shit. 10/10 & 5/10 https://t.co/6NgsQJuSBJ	2
1508	When bae says they can't go out but you see them with someone else that same night. 5/10 & 10/10 for heartbroken pup https://t.co/aenk0KpoWM	2
1525	This is Eriq. His friend just reminded him of last year's super bowl. Not cool friend\n10/10 for Eriq\n6/10 for friend https://t.co/PlEXTofdpf	2
1538	Meet Fynn & Taco. Fynn is an all-powerful leaf lord and Taco is in the wrong place at the wrong time. 11/10 & 10/10 https://t.co/MuqHPvtL8c	2
1662	This is Darrel. He just robbed a 7/11 and is in a high speed police chase. Was just spotted by the helicopter 10/10 https://t.co/7EsP8LmSp5	2
1795	Meet Tassy & Bee. Tassy is pretty chill, but Bee is convinced the Ruffles are haunted. 10/10 & 11/10 respectively https://t.co/fgORpmTN9C	2
1832	These two pups just met and have instantly bonded. Spectacular scene. Mesmerizing af. 10/10 and 7/10 for blue dog https://t.co/gwryaJO4tC	2

	text	rating_count
1897	Meet Rufio. He is unaware of the pink legless pupper wrapped around him. Might want to get that checked 10/10 & 4/10 https://t.co/KNfLnYPmYh	2
1901	Two gorgeous dogs here. Little waddling dog is a rebel. Refuses to look at camera. Must be a preteen. 5/10 & 8/10 https://t.co/YPfw7oahbD	2
1970	Meet Eve. She's a raging alcoholic 8/10 (would b 11/10 but pupper alcoholism is a tragic issue that I can't condone) https://t.co/U36HYQlijg	2
2010	10/10 for dog. 7/10 for cat. 12/10 for human. Much skill. Would pet all https://t.co/uhx5gfpx5k	3
2064	Meet Holly. She's trying to teach small human-like pup about blocks but he's not paying attention smh. 11/10 & 8/10 https://t.co/RcksaUrGNu	2
2113	Meet Hank and Sully. Hank is very proud of the pumpkin they found and Sully doesn't give a shit. 11/10 and 8/10 https://t.co/cwoP1ftbrj	2
2177	Here we have Pancho and Peaches. Pancho is a Condoleezza Gryffindor, and Peaches is just an asshole. 10/10 & 7/10 https://t.co/Lh1BsJrWPp	2
2216	This is Spark. He's nervous. Other dog hasn't moved in a while. Won't come when called. Doesn't fetch well 8/10&1/10 https://t.co/stEodX9Aba	2
2263	This is Kial. Kial is either wearing a cape, which would be rad, or flashing us, which would be rude. 10/10 or 4/10 https://t.co/8zcwIoiuqR	2
2272	Two dogs in this one. Both are rare Jujitsu Pythagoreans. One slightly whiter than other. Long legs. 7/10 and 8/10 https://t.co/ITxxcc4v9y	2
2306	These are Peruvian Feldspars. Their names are Cupit and Prencer. Both resemble Rand Paul. Sick outfits 10/10 & 10/10 https://t.co/ZnEMHBsAs1	2
2335	This is an Albanian 3 1/2 legged Episcopalian. Loves well-polished hardwood flooring. Penis on the collar. 9/10 https://t.co/d9NcXFKwLv	2

In [69]:

```
# drop tweets with multiple ratings
df_all.drop(df_all.query("rating_count != 1").index, inplace = True)
```

Test

In [70]:

```
# double check they are dropped
df_all[["text", "rating_count"]].query("rating_count != 1")
```

Out[70]:

	text	rating_count

In [71]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1640 entries, 1 to 2355
Data columns (total 26 columns):
tweet_id              1640 non-null int64
timestamp             1640 non-null object
source                1640 non-null object
text                  1640 non-null object
expanded_urls         1640 non-null object
rating_numerator      1640 non-null float64
rating_denominator    1640 non-null float64
name                  1640 non-null object
doggo                 1640 non-null object
floofer               1640 non-null object
pupper                1640 non-null object
puppo                 1640 non-null object
rating_count          1640 non-null int64
jpg_url               1640 non-null object
img_num               1640 non-null float64
p1                    1640 non-null object
p1_conf               1640 non-null float64
```

```
p1_dog                1640 non-null object
p2                    1640 non-null object
p2_conf               1640 non-null float64
p2_dog                1640 non-null object
p3                    1640 non-null object
p3_conf               1640 non-null float64
p3_dog                1640 non-null object
favorite_count        1640 non-null float64
retweet_count         1640 non-null float64
dtypes: float64(8), int64(2), object(16)
memory usage: 345.9+ KB
```

Define

- **Combine dog stage columns into one column named 'dog_stage'**

Code

In [72]:

```
# find how many dogs are classfied in each of the dog stage
print (df_all[df_all['text'].str.contains('doggo')].shape[0])
print (df_all[df_all['text'].str.contains('floofer')].shape[0])
print (df_all[df_all['text'].str.contains('pupper')].shape[0])
print (df_all[df_all['text'].str.contains('puppo')].shape[0])
```

```
64
3
182
27
```

I will replace all the 'None' as '', then concatenate four columns using string addition, store the final string into a column called dog_stage.

In [73]:

```
for _ in ["doggo", "floofer", "pupper", "puppo"]:
    df_all[_].replace("None", "", inplace = True)

df_all['dog_stage'] = df_all['doggo'].map(str) + df_all['floofer'].map(str) + df_all['pu
pper'].map(str) + df_all['puppo'].map(str)
df_all["dog_stage"].replace("", 'None', inplace = True)
```

In [74]:

```
df_all['dog_stage'].value_counts()
```

Out[74]:

```
None            1385
pupper          164
doggo           54
puppo           21
doggopupper     7
floofer         7
doggopuppo      1
doggofloofer    1
Name: dog_stage, dtype: int64
```

It's interesting that there are dogs in more than one categories, because we have dog_stage like doggopupper, let's check the details of these 9 rows.

In [75]:

```
# 9 rows has multiple stages
df_all[['text', 'dog_stage']].query("dog_stage == 'doggopupper' or dog_stage == 'doggoflo
ofer' or dog_stage == 'doggopuppo'")
```

Out[75]:

	text	dog_stage
191	Here's a puppo participating in the #ScienceMarch. Cleverly disguising her own doggo agenda. 13/10 would keep the planet habitable for https://t.co/cMhq16isel	doggopuppo
200	At first I thought this was a shy doggo, but it's actually a Rare Canadian Floofer Owl. Amateurs would confuse the two. 11/10 only send dogs https://t.co/TXdT3tmuYk	doggofloofer
460	This is Dido. She's playing the lead role in "Pupper Stops to Catch Snow Before Resuming Shadow Box with Dried Apple." 13/10 (IG: didodoggo) https://t.co/m7isZrOBX7	doggopupper
531	Here we have Burke (pupper) and Dexter (doggo). Pupper wants to be exactly like doggo. Both 12/10 would pet at same time https://t.co/ANBpEYHaho	doggopupper
575	This is Bones. He's being haunted by another doggo of roughly the same size. 12/10 deep breaths pupper everything's fine https://t.co/55Dqe0SJNj	doggopupper
889	Meet Maggie & Lila. Maggie is the doggo, Lila is the pupper. They are sisters. Both 12/10 would pet at the same time https://t.co/MYwR4DQKll	doggopupper
956	Please stop sending it pictures that don't even have a doggo or pupper in them. Churlish af. 5/10 neat couch tho https://t.co/u2c9c7qSg8	doggopupper
1063	This is just downright precious af. 12/10 for both pupper and doggo https://t.co/o5J479bZUC	doggopupper
1113	Like father (doggo), like son (pupper). Both 12/10 https://t.co/pG2inLaOda	doggopupper

I read through the text and extracted the correct dog_stage based on the pictures, the results are as follows.

In [77]:

```
# handle multiple stages
df_all.loc[df_all.dog_stage == 'doggopupper', 'dog_stage'] = 'doggo, pupper'
df_all.loc[df_all.dog_stage == 'doggopuppo', 'dog_stage'] = 'doggo, puppo'
df_all.loc[df_all.dog_stage == 'doggofloofer', 'dog_stage'] = 'doggo, floofer'

# handle missing values
df_all.loc[df_all.dog_stage == '', 'dog_stage'] = 'None'
```

In [78]:

```
# recheck the dog_stage, now they are all correct
df_all['dog_stage'].value_counts()
```

Out[78]:

```
None              1385
pupper             164
doggo               54
puppo               21
doggo, pupper        7
floofer              7
doggo, puppo         1
doggo, floofer       1
Name: dog_stage, dtype: int64
```

In [79]:

```
# drop the 'doggo','floofer','pupper','puppo' columns
df_all = df_all.drop(['doggo','floofer','pupper','puppo'], axis=1)
df_all['dog_stage'].fillna('None', inplace=True)
```

Test

In [80]:

```
df_all.head()
```

Out[80]:

	tweet_id	timestamp	source	text
				This is Tilly. She's just

	tweet_id	timestamp	source	text	
1	892177421306343426	2017-08-01 00:17:27 +0000	Twitter for iPhone	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. 13/10 https://t.co/0Xxu71qeIV	
2	891815181378084864	2017-07-31 00:18:03 +0000	Twitter for iPhone	This is Archie. He is a rare Norwegian Pouncing Corgo. Lives in the tall grass. You never know when one may strike. 12/10 https://t.co/wUnZnhtVJB	
3	891689557279858688	2017-07-30 15:58:51 +0000	Twitter for iPhone	This is Darla. She commenced a snooze mid meal. 13/10 happens to the best of us https://t.co/tD36da7qLQ	
4	891327558926688256	2017-07-29 16:00:24 +0000	Twitter for iPhone	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	https://twitter.com/do
5	891087950875897856	2017-07-29 00:08:17 +0000	Twitter for iPhone	Here we have a majestic great white breaching off South Africa's coast. Absolutely h*ckin breathtaking. 13/10 (IG: tucker_marlo) #BarkWeek https://t.co/kQ04fDDRmh	

5 rows × 23 columns

Define

- **Fix wrong names (replace with None)**

Code

I read through all the dog names and the wrong names all start in lower cases, which are easy to pick out, I made them into a list called wrong_name_list as follows.

In [81]:

```
# remove wrong names
wrong_name_list = ['a', 'the', 'an', 'very', 'quite', 'just', 'one', 'getting', 'actuall
y', 'no', 'mad', 'old', 'by',
                   'his', 'such', 'infuriating', 'light', 'all', 'space', 'my', 'unaccept
able', 'life', 'this', 'officially']
# replace wrong names with None
for _ in wrong_name_list:
    df_all['name'].replace(_, 'None', inplace = True)
```

Test

In [82]:

```
# double check the names
df_all['name'].value_counts()
```

Out[82]:

```
None         467
Cooper        10
```

```
Cooper      10
Lucy        10
Charlie     10
Oliver       9
Tucker       9
Penny        8
Winston      7
Sadie        7
Daisy        7
Jax          6
Toby         6
Lola         6
Koda         6
Rusty        5
Stanley      5
Oscar        5
Bo           5
Leo          5
Bella        5
Jack         4
Bear         4
Duke         4
Oakley       4
Louis        4
Maggie       4
Finn         4
Winnie       4
Milo         4
Sophie       4
            ..
Kaiya        1
Meyer        1
Mary         1
Jarod        1
Dewey        1
Bodie        1
Lipton       1
Hall         1
Baron        1
Tyrone       1
Pete         1
Clybe        1
Dutch        1
Butter       1
Levi         1
Coopson      1
Sweet        1
Vinscent     1
Bell         1
Joshwa       1
Bruno        1
Timison      1
Ron          1
Gordon       1
Bloo         1
Tyrus        1
Logan        1
Ralphus      1
Millie       1
Shooter      1
Name: name, Length: 822, dtype: int64
```

In [83]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1640 entries, 1 to 2355
Data columns (total 23 columns):
tweet_id              1640 non-null int64
timestamp             1640 non-null object
source                1640 non-null object
text                  1640 non-null object
```

```
text                  1640 non-null object
expanded_urls         1640 non-null object
rating_numerator      1640 non-null float64
rating_denominator    1640 non-null float64
name                  1640 non-null object
rating_count          1640 non-null int64
jpg_url               1640 non-null object
img_num               1640 non-null float64
p1                    1640 non-null object
p1_conf               1640 non-null float64
p1_dog                1640 non-null object
p2                    1640 non-null object
p2_conf               1640 non-null float64
p2_dog                1640 non-null object
p3                    1640 non-null object
p3_conf               1640 non-null float64
p3_dog                1640 non-null object
favorite_count        1640 non-null float64
retweet_count         1640 non-null float64
dog_stage             1640 non-null object
dtypes: float64(8), int64(2), object(13)
memory usage: 307.5+ KB
```

Define

- **Use the best predictions and remove others**

Code

In [84]:

```
# check p1 has the highest value (first prediction is the most accurate)
df_all.query("(p2_conf > p1_conf) or (p3_conf > p1_conf)")
```

Out[84]:

tweet_id	timestamp	source	text	expanded_urls	rating_numerator	rating_denominator	name	rating_count	jpg_url	...	p1

0 rows × 23 columns

In [85]:

```
# I will use the most confident breed and condidence instead of 3 predictions
# define a function that returns the most confident prediction that is dog
attributes1 = ["p1_dog", "p1", "p2_dog", "p2", "p3_dog", "p3"]
attributes2 = ["p1_dog", "p1_conf", "p2_dog", "p2_conf", "p3_dog", "p3_conf"]
def dog_breed(list):
    if list[0] == True:
        return list[1]
    elif list[2] == True:
        return list[3]
    else:
        return list[5]

# add two columns called breed and confidence to store predictions
df_all["breed"] = df_all[attributes1].apply(dog_breed, axis = 1)
df_all["confidence"] = df_all[attributes2].apply(dog_breed, axis = 1)
```

In [86]:

```
# drop original prediction columns
attributes = ["p1", "p1_dog", "p1_conf", "p2", "p2_dog", "p2_conf", "p3", "p3_dog", "p3_c
onf"]
df_all.drop(attributes, inplace = True, axis = 1)
df_all.head()
```

Out[86]:

	tweet_id	timestamp	source	text	
1	892177421306343426	2017-08-01 00:17:27 +0000	Twitter for iPhone	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. 13/10 https://t.co/0Xxu71qeIV	
2	891815181378084864	2017-07-31 00:18:03 +0000	Twitter for iPhone	This is Archie. He is a rare Norwegian Pouncing Corgo. Lives in the tall grass. You never know when one may strike. 12/10 https://t.co/wUnZnhtVJB	
3	891689557279858688	2017-07-30 15:58:51 +0000	Twitter for iPhone	This is Darla. She commenced a snooze mid meal. 13/10 happens to the best of us https://t.co/tD36da7qLQ	
4	891327558926688256	2017-07-29 16:00:24 +0000	Twitter for iPhone	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	https://twitter.com/do
5	891087950875897856	2017-07-29 00:08:17 +0000	Twitter for iPhone	Here we have a majestic great white breaching off South Africa's coast. Absolutely h*ckin breathtaking. 13/10 (IG: tucker_marlo) #BarkWeek https://t.co/kQ04fDDRmh	

Test

In [87]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1640 entries, 1 to 2355
Data columns (total 16 columns):
tweet_id              1640 non-null int64
timestamp             1640 non-null object
source                1640 non-null object
text                  1640 non-null object
expanded_urls         1640 non-null object
rating_numerator      1640 non-null float64
rating_denominator    1640 non-null float64
name                  1640 non-null object
rating_count          1640 non-null int64
jpg_url               1640 non-null object
img_num               1640 non-null float64
favorite_count        1640 non-null float64
retweet_count         1640 non-null float64
dog_stage             1640 non-null object
breed                 1640 non-null object
confidence            1640 non-null float64
dtypes: float64(6), int64(2), object(8)
memory usage: 217.8+ KB
```

Define

- **Make the format in breed column consistent**

Code

In [88]:

```
# for all the entries, use lower case letters and replace '_' with ' '
df_all['breed'] = df_all['breed'].str.lower()
df_all['breed'] = df_all['breed'].str.replace("_", " ")
```

Test

In [89]:

```
# count the breed
df_all['breed'].value_counts()
```

Out[89]:

```
golden retriever                  154
labrador retriever                105
pembroke                           93
chihuahua                          87
pug                                62
toy poodle                         50
chow                               48
samoyed                            42
pomeranian                         39
malamute                           33
french bulldog                     31
chesapeake bay retriever           29
cocker spaniel                     29
miniature pinscher                 24
eskimo dog                         22
cardigan                           21
german shepherd                    21
staffordshire bullterrier          20
beagle                             20
shih-tzu                           20
siberian husky                     19
rottweiler                         18
maltese dog                        18
shetland sheepdog                  18
italian greyhound                  17
basset                             17
kuvasz                             17
lakeland terrier                   16
west highland white terrier        16
american staffordshire terrier     16
                                   ..
weimaraner                          4
tibetan terrier                     4
irish setter                        4
scottish deerhound                  4
tibetan mastiff                     4
cairn                               3
toy terrier                         3
irish water spaniel                 3
curly-coated retriever              3
brabancon griffon                   3
greater swiss mountain dog          3
komondor                            3
giant schnauzer                     3
briard                              3
leonberg                            3
afghan hound                        3
sussex spaniel                      2
groenendael                         2
black-and-tan coonhound             2
appenzeller                         2
wire-haired fox terrier             2
standard schnauzer                  1
clumber                             1
```

```
crumber                          1
silky terrier                    1
entlebucher                      1
japanese spaniel                 1
australian terrier               1
bouvier des flandres             1
irish wolfhound                  1
scotch terrier                   1
Name: breed, Length: 113, dtype: int64
```

Define

- **Correct the timestamp data type to datetime**

Code

In [90]:

```
# change timestamp data type
df_all["timestamp"] = pd.to_datetime(df_all.timestamp)

for _ in ["retweet_count", "favorite_count", "img_num"]:
    df_all[_] = df_all[_].astype("int64")
```

In [91]:

```
# reset the index
df_all.reset_index(drop = True, inplace = True)
```

Test

In [92]:

```
df_all.head()
```

Out[92]:

	tweet_id	timestamp	source	text	
0	892177421306343426	2017-08-01 00:17:27+00:00	Twitter for iPhone	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. 13/10 https://t.co/0Xxu71qeIV	
1	891815181378084864	2017-07-31 00:18:03+00:00	Twitter for iPhone	This is Archie. He is a rare Norwegian Pouncing Corgo. Lives in the tall grass. You never know when one may strike. 12/10 https://t.co/wUnZnhtVJB	
2	891689557279858688	2017-07-30 15:58:51+00:00	Twitter for iPhone	This is Darla. She commenced a snooze mid meal. 13/10 happens to the best of us https://t.co/tD36da7qLQ	
3	891327558926688256	2017-07-29 16:00:24+00:00	Twitter for iPhone	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	https://twitter.com
		2017-07-29	<a	Here we have a majestic great white breaching off South Africa's coast. Absolutely h*ckin	

	tweet_id	timestamp	source	text
4	891087950875897856	2017-07-29 00:08:17+0000	href="http://twitter.com/download/iphone" rel="nofollow">Twitter for iPhone	Absolutely ri ckin breathtaking. 13/10 (@ tucker_marlo) #BarkWeek https://t.co/kQ04fDDRmh

In [93]:

```
df_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1640 entries, 0 to 1639
Data columns (total 16 columns):
tweet_id              1640 non-null int64
timestamp             1640 non-null datetime64[ns, UTC]
source                1640 non-null object
text                  1640 non-null object
expanded_urls         1640 non-null object
rating_numerator      1640 non-null float64
rating_denominator    1640 non-null float64
name                  1640 non-null object
rating_count          1640 non-null int64
jpg_url               1640 non-null object
img_num               1640 non-null int64
favorite_count        1640 non-null int64
retweet_count         1640 non-null int64
dog_stage             1640 non-null object
breed                 1640 non-null object
confidence            1640 non-null float64
dtypes: datetime64[ns, UTC](1), float64(3), int64(5), object(7)
memory usage: 205.1+ KB
```

The data has been cleaned, I will save it as a csv file named 'twitter_archive_master.csv'

In [94]:

```
df_all.to_csv('twitter_archive_master.csv', index = False)
```

Data Analysis and Visualization

In this section, I will provide some insights and visualizations on the WeRateDogs twitter dataframe, based on the following questions I came up with:

- **what are the dog breeds with the most tweets?**
- **what are the dog breeds with the highest average ratings?**
- **what are the dog breeds with the most numbers of favorites or retweets?**
- **what are the distributions of the rating, favorite_count and retweet_count?**
- **what is the relation between the average rating and favorite/retweet counts for different dog breeds.**
- **what is the most liked/retweeted single tweet?**
- **what is the average favorite/retweet count on different dog_stage?**
- **what is the WeRateDogs account activity by year, month, day of the week, hour of the day?**
- **what is the distribution of favorite counts by month in each year?**

In [95]:

```
# copy the df_all dataframe in case
df_all_copy = df_all.copy()
```

1. what are the dog breeds with the most tweets?

In [96]:

```
# groupby breed and count number of tweets respectively
# save the top 20 most tweeted breeds in df_breed
df_breed = df_all_copy.groupby('breed')['tweet_id'].count().sort_values(ascending=False)
```

```
[0:20]
sorted_index = df_breed.index
df_breed
```

Out[96]:

```
breed
golden retriever             154
labrador retriever           105
pembroke                      93
chihuahua                     87
pug                           62
toy poodle                    50
chow                          48
samoyed                       42
pomeranian                    39
malamute                      33
french bulldog                31
chesapeake bay retriever      29
cocker spaniel                29
miniature pinscher            24
eskimo dog                    22
german shepherd               21
cardigan                      21
shih-tzu                      20
beagle                        20
staffordshire bullterrier     20
Name: tweet_id, dtype: int64
```

In [97]:

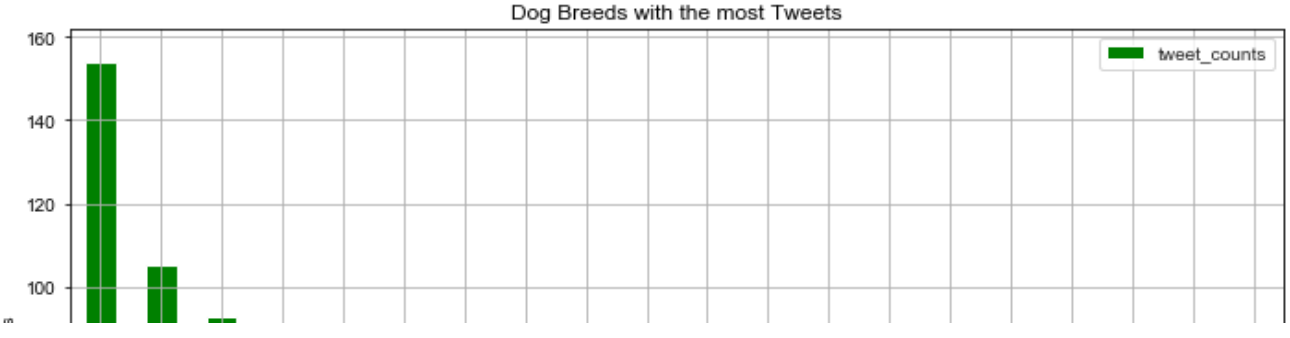
```
# convert df_breed pandas series to dataframe
df_breed = pd.DataFrame(df_breed)
df_breed = df_breed.reset_index()
df_breed.columns = ['dog_breed', 'tweet_counts']
df_breed.head()
```

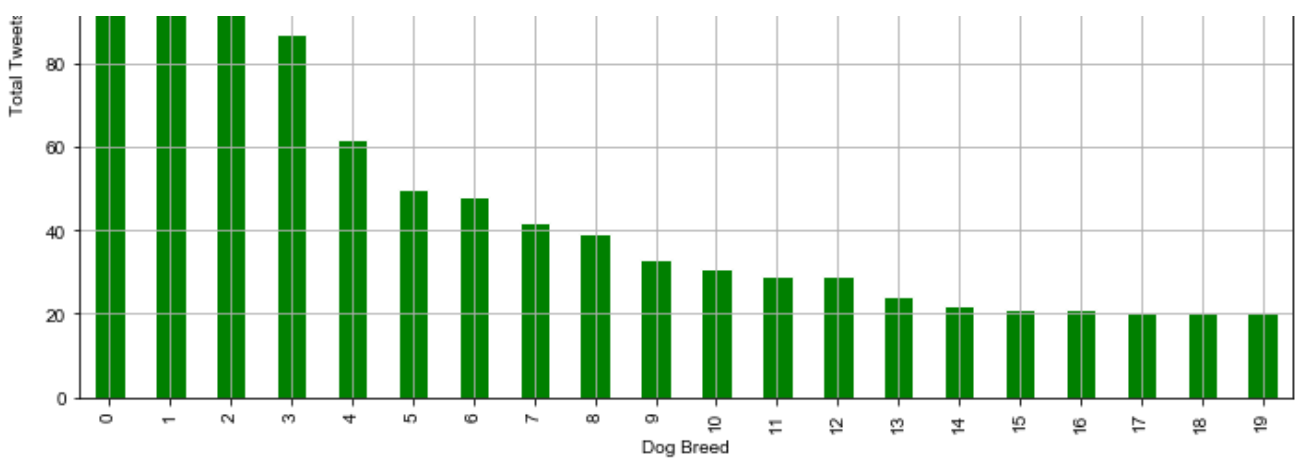
Out[97]:

	dog_breed	tweet_counts
0	golden retriever	154
1	labrador retriever	105
2	pembroke	93
3	chihuahua	87
4	pug	62

In [98]:

```
# visualize the top 20 most tweeted breeds
fig, ax = plt.subplots(figsize=(10, 6))
sns.set_style("whitegrid")
# create a new bar char
ax = df_breed.plot.bar(ax=ax, color = 'g')
ax.set_title('Dog Breeds with the most Tweets')
ax.set_xlabel("Dog Breed")
ax.set_ylabel('Total Tweets')
plt.tight_layout()
```





The above plot shows the 20 breeds with the most tweets, the top 3 of them are golden retriever (tweeted 154 times), labrador retriever (105) and pembroke (93).

2. what are the dog breeds with the highest average ratings?

In [99]:

```
# add a column 'decimal rating', which is rating numerator divided by denominator
df_all_copy['decimal_rating'] = df_all_copy['rating_numerator'] / df_all_copy['rating_denominator']
df_all_copy.head()
```

Out[99]:

	tweet_id	timestamp	source	text	
0	892177421306343426	2017-08-01 00:17:27+00:00	Twitter for iPhone	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. 13/10 https://t.co/0Xxu71qeIV	
1	891815181378084864	2017-07-31 00:18:03+00:00	Twitter for iPhone	This is Archie. He is a rare Norwegian Pouncing Corgo. Lives in the tall grass. You never know when one may strike. 12/10 https://t.co/wUnZnhtVJB	
2	891689557279858688	2017-07-30 15:58:51+00:00	Twitter for iPhone	This is Darla. She commenced a snooze mid meal. 13/10 happens to the best of us https://t.co/tD36da7qLQ	
3	891327558926688256	2017-07-29 16:00:24+00:00	Twitter for iPhone	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	https://twitter.com
4	891087950875897856	2017-07-29 00:08:17+00:00	Twitter for iPhone	Here we have a majestic great white breaching off South Africa's coast. Absolutely h*ckin breathtaking. 13/10 (IG: tucker_marlo) #BarkWeek https://t.co/kQ04fDDRmh	

In [100]:

```
# function to find average rating given dog breed
def average_rating (dog_breed):
    breed_rating = df_all_copy.query('breed == @dog_breed')['decimal_rating'].mean()
    return breed_rating
```

In [101]:

```
# add to df_breed an average rating column
df_breed['average_rating'] = df_breed['dog_breed'].apply(lambda p : average_rating(p))
df_breed.sort_values('average_rating', ascending=False, inplace=True)
df_breed.head()
```

Out[101]:

	dog_breed	tweet_counts	average_rating
0	**golden retriever**	**154**	**1.177783**
7	**samoyed**	**42**	**1.169048**
2	**pembroke**	**93**	**1.144086**
6	**chow**	**48**	**1.141667**
14	**eskimo dog**	**22**	**1.140909**

In [102]:

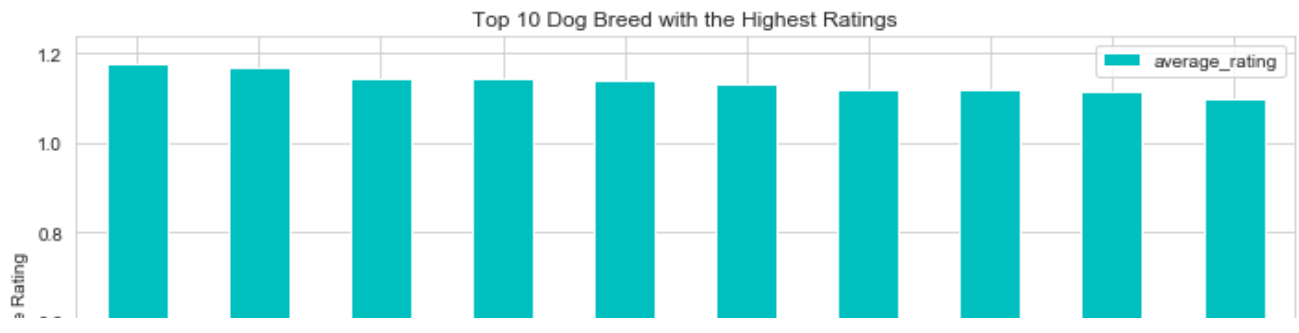
```
# 10 dogs with the highest avg rating
df_rating_top_10 = df_breed.sort_values('average_rating', ascending=False)[:10]
df_rating_top_10
```

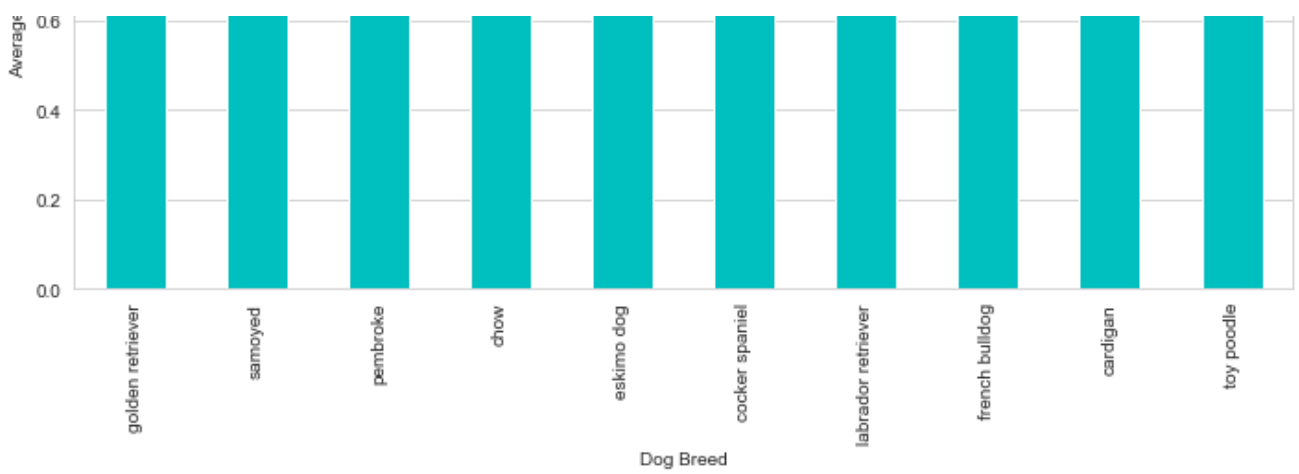
Out[102]:

	dog_breed	tweet_counts	average_rating
0	**golden retriever**	**154**	**1.177783**
7	**samoyed**	**42**	**1.169048**
2	**pembroke**	**93**	**1.144086**
6	**chow**	**48**	**1.141667**
14	**eskimo dog**	**22**	**1.140909**
12	**cocker spaniel**	**29**	**1.131034**
1	**labrador retriever**	**105**	**1.120000**
10	**french bulldog**	**31**	**1.119355**
16	**cardigan**	**21**	**1.114286**
5	**toy poodle**	**50**	**1.100000**

In [103]:

```
# visualze breeds with the highest average ratings
ax = df_rating_top_10.plot.bar(x='dog_breed', y='average_rating', color = 'c', figsize=(
10,6))
ax.set_title('Top 10 Dog Breed with the Highest Ratings')
plt.ylabel("Average Rating")
ax.set_xlabel('Dog Breed')
plt.tight_layout()
```





The plot above gives ten dog breeds with the highest average ratings, the top 3 breeds and ratings are: golden retriever (1.178), samoyed (1.169) and pembroke (1.144).

3. what are the dog breeds with the most numbers of favorites or retweets?

In [104]:

```
# functions to sum over favorites and retweets given breed
def favorite_count (dog_breed):
    fav_count = df_all_copy.query('breed == @dog_breed')['favorite_count'].sum()
    return fav_count
def retweet_count (dog_breed):
    ret_count = df_all_copy.query('breed == @dog_breed')['retweet_count'].sum()
    return ret_count
```

In [105]:

```
# add favorite counts to each breed in df_breed
df_breed['favorite_counts'] = df_breed['dog_breed'].apply(lambda p : favorite_count(p))
df_breed.sort_values('favorite_counts', ascending=False, inplace=True)
df_breed.head()
```

Out[105]:

	dog_breed	tweet_counts	average_rating	favorite_counts
0	golden retriever	154	1.177783	1915088
1	labrador retriever	105	1.120000	1264586
2	pembroke	93	1.144086	1036756
3	chihuahua	87	1.055172	714274
7	samoyed	42	1.169048	583906

In [106]:

```
# add retweet counts to each breed in df_breed
df_breed['retweet_counts'] = df_breed['dog_breed'].apply(lambda p : retweet_count(p))
df_breed.sort_values('retweet_counts', ascending=False, inplace=True)
df_breed.head()
```

Out[106]:

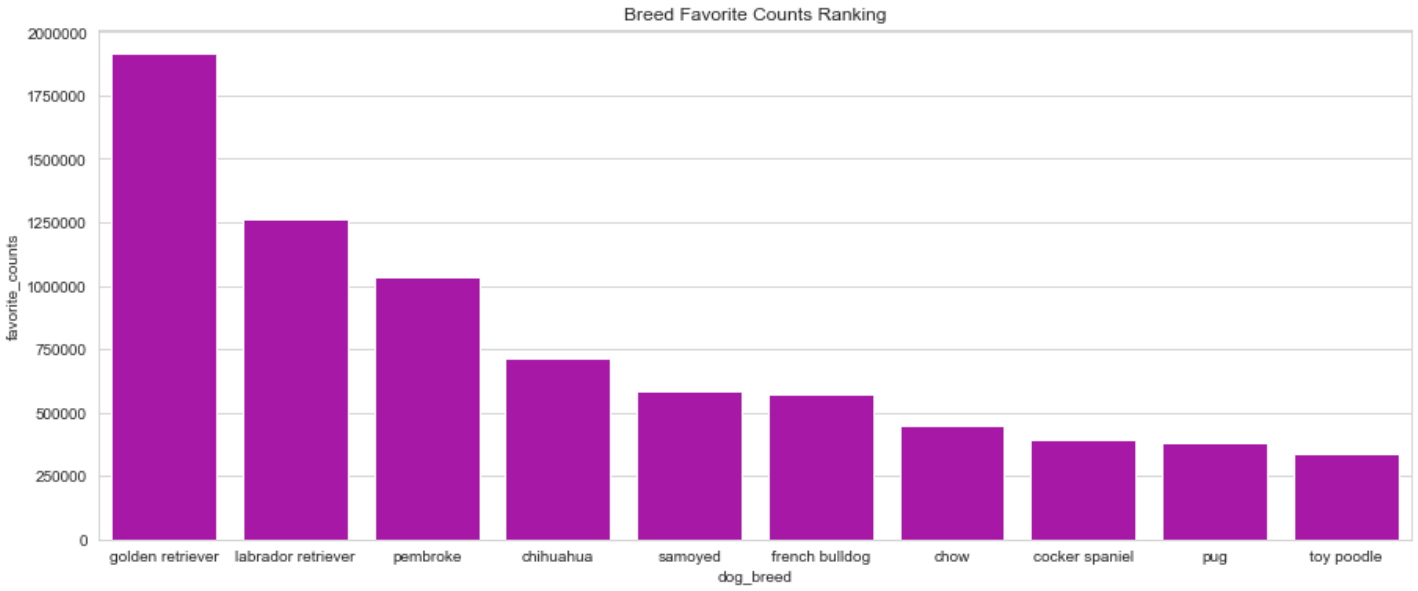
	dog_breed	tweet_counts	average_rating	favorite_counts	retweet_counts
0	golden retriever	154	1.177783	1915088	573953
1	labrador retriever	105	1.120000	1264586	405163
2	pembroke	93	1.144086	1036756	291262
3	chihuahua	87	1.055172	714274	234198
7	samoyed	42	1.169048	583906	203446

In [107]:

```
# visualize favorite counts
fig, ax = plt.subplots(figsize = (15,6))
ax = sns.barplot(x = "dog_breed", y = "favorite_counts", data = df_breed.sort_values("fa
vorite_counts", ascending=False).iloc[:10], color = 'm')
ax.set_title("Breed Favorite Counts Ranking")
```

Out[107]:

```
Text(0.5, 1.0, 'Breed Favorite Counts Ranking')
```

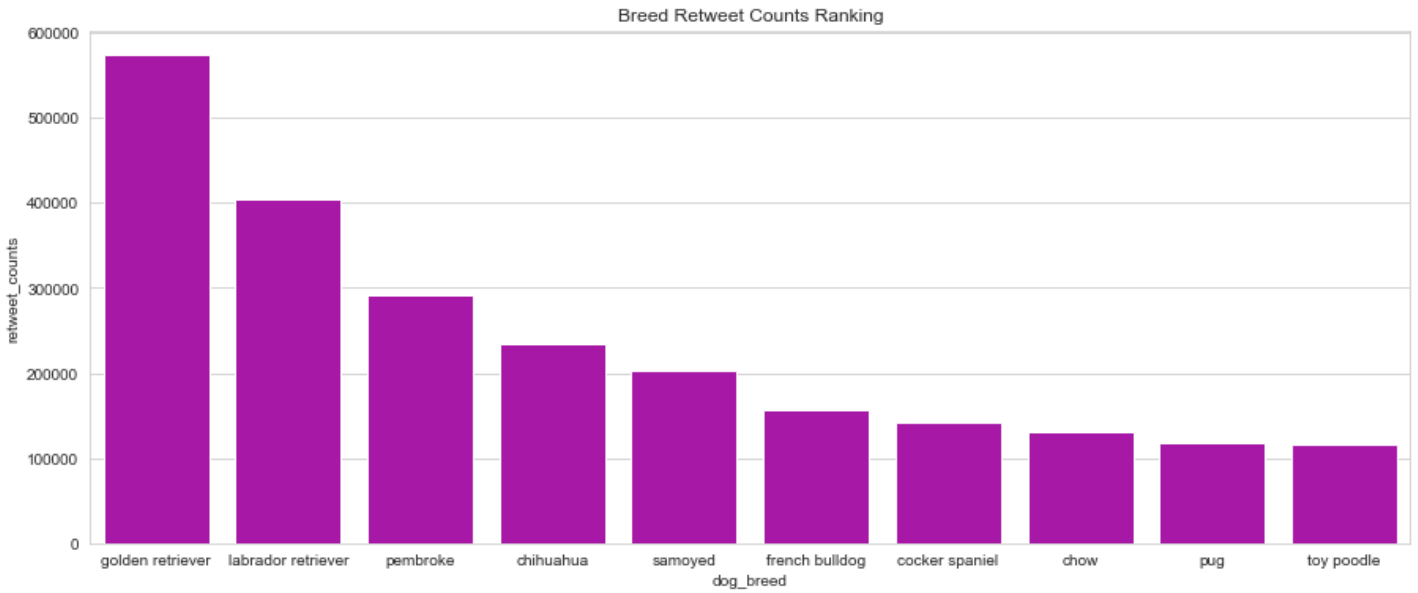


In [108]:

```
# visualize retweet counts
fig, ax = plt.subplots(figsize = (15,6))
ax = sns.barplot(x = "dog_breed", y = "retweet_counts", data = df_breed.sort_values("ret
weet_counts", ascending=False).iloc[:10], color = 'm')
ax.set_title("Breed Retweet Counts Ranking")
```

Out[108]:

```
Text(0.5, 1.0, 'Breed Retweet Counts Ranking')
```



Golden retriever (1915008 favorites, 573953 retweets), labrador retriever (1264586 favorites, 405163 retweets), pembroke (1036756 favorites, 291262 retweets) are top 3 on both favorite and retweet lists.

4. what are the distributions of the rating, favorite_count and retweet_count?

In [109]:

```
# statistics on rating, favorite and retweet
df_all_copy[['decimal_rating', 'favorite_count', 'retweet_count']].describe()
```

Out[109]:

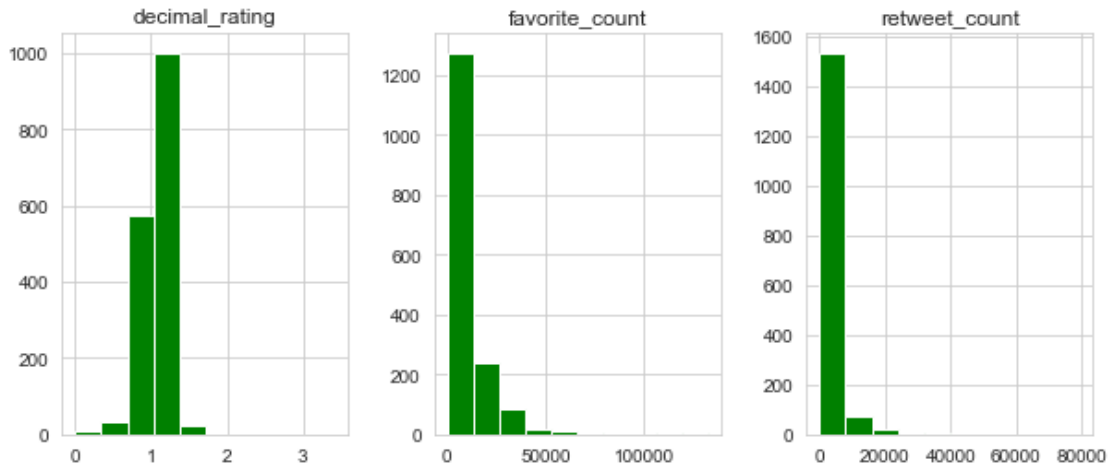
	decimal_rating	favorite_count	retweet_count
count	1640.000000	1640.000000	1640.000000
mean	1.085858	9371.344512	2853.065854
std	0.185706	12699.965595	4850.693086
min	0.000000	81.000000	16.000000
25%	1.000000	2243.000000	664.750000
50%	1.100000	4534.000000	1460.500000
75%	1.200000	11851.500000	3270.750000
max	3.428571	132810.000000	79515.000000

In [110]:

```
# plot 3 histograms
df_all_copy[['decimal_rating', 'favorite_count', 'retweet_count']].hist(figsize = (10, 4
), layout = (1, 3), color = 'g')
```

Out[110]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x0000020353E11DD8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000020353E3F780>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x0000020353E64FD0>]],
      dtype=object)
```



The average rating on dogs is 1.09, with a min rating of 0.00 and a max rating of 3.43. The interquatile range is 1.00 to 1.20.

The average favorite count of all tweets is 9371, with a min count of 81 and a max count of 132810. The interquatile range is 2243 to 11852.

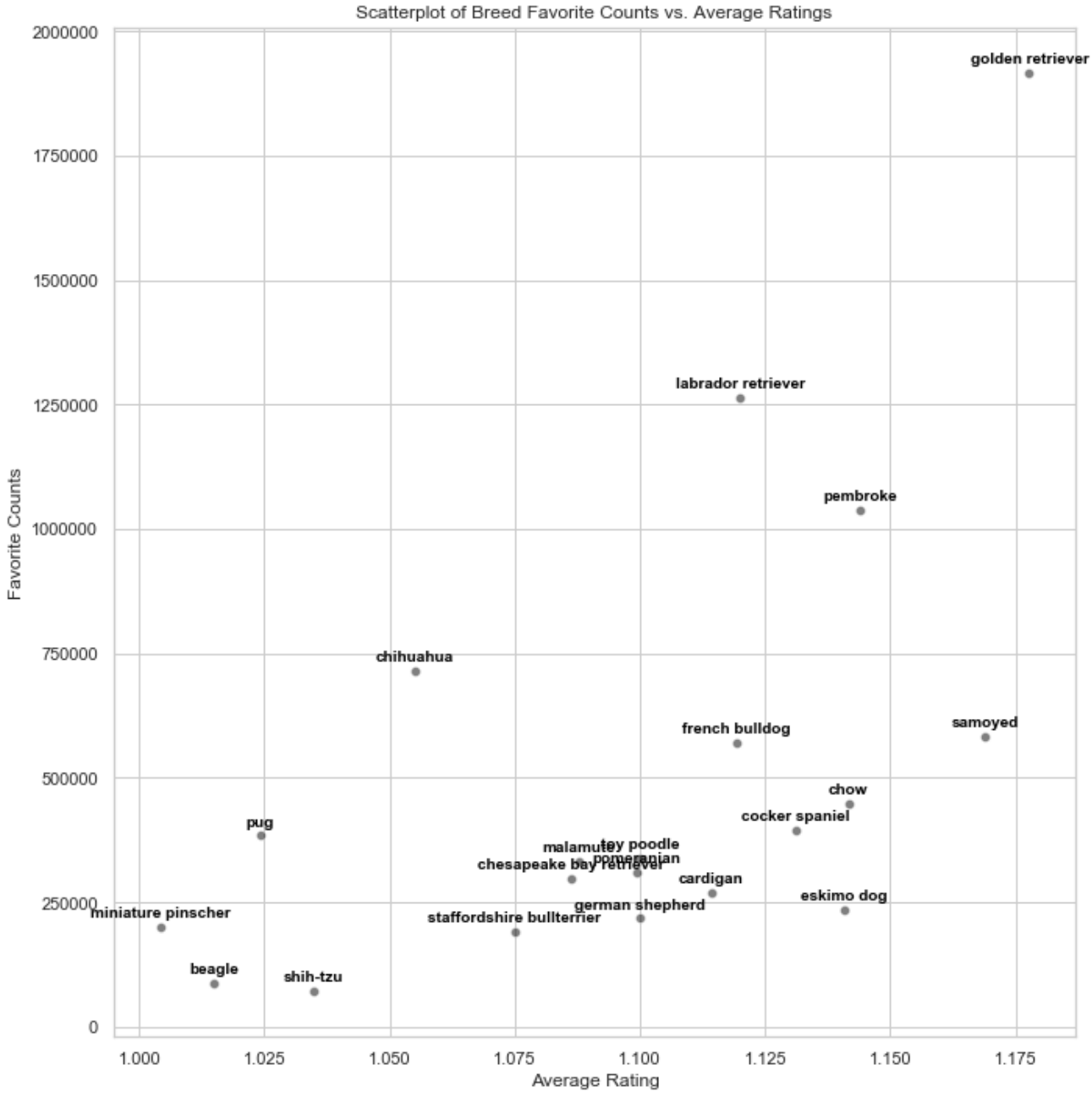
The average retweet count of all tweets is 2853, with a min count of 16 and a max count of 79515. The interquatile range is 665 to 3271.

5. what is the relation between the average rating and favorite/retweet counts for different dog breeds.

In [111]:

```
# scatter plot of favorite count on average rating for breeds

with sns.plotting_context("notebook"):
    # create a matplotlib figure
    fig, ax = plt.subplots(figsize = (10,10))
```

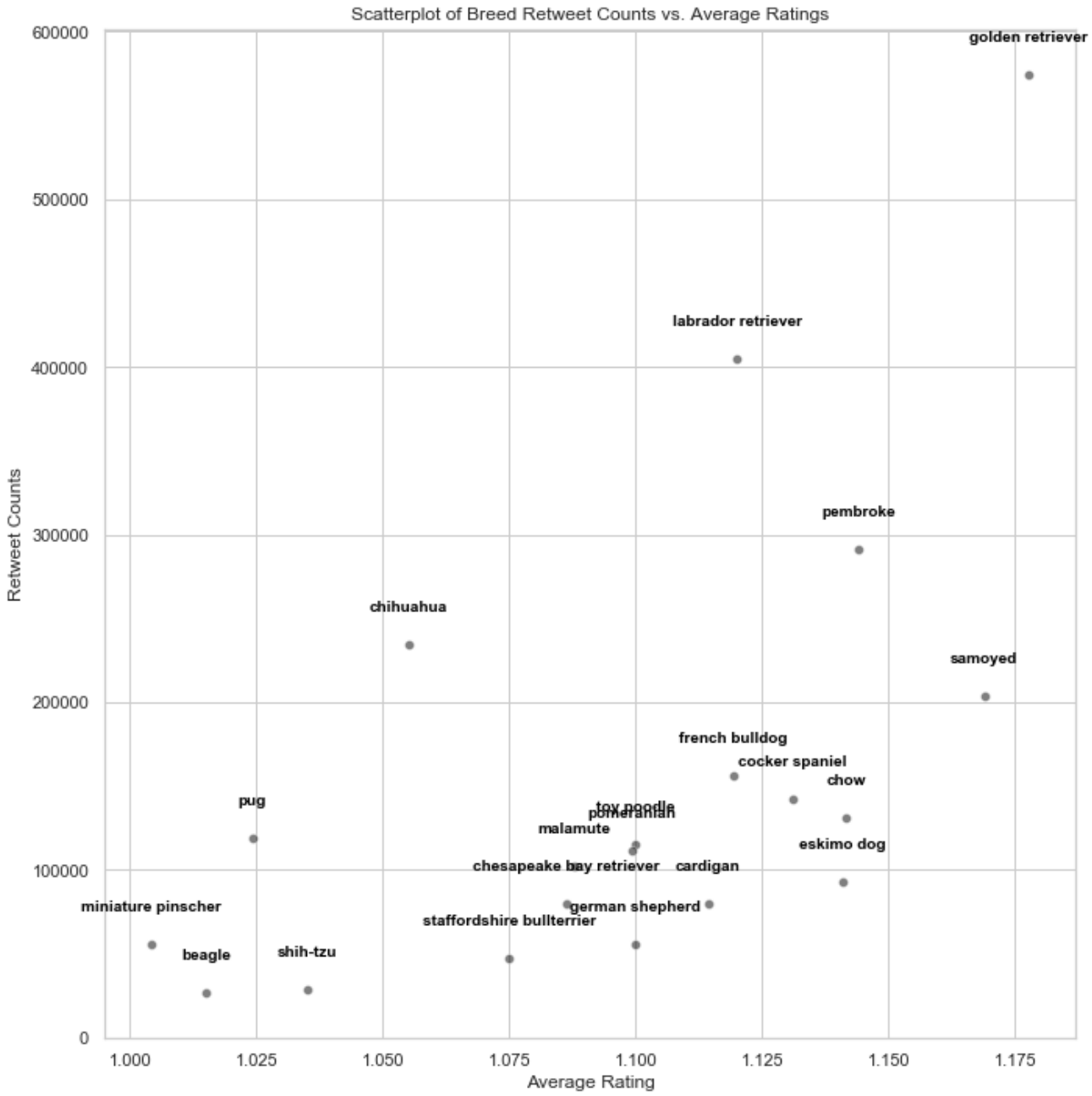
```
    # plot the scatterplot of dog average_rating and favorite_counts
    p1 = sns.scatterplot(x='average_rating', y='favorite_counts', data = df_breed, alpha
= 0.5, color = "k", lw = 2)

    for line in range(0,df_breed.shape[0]):
        p1.text(df_breed.average_rating[line], df_breed.favorite_counts[line]+20000,
        df_breed.dog_breed[line], horizontalalignment='center', size='small', color='bla
ck', weight='semibold')

    # set the title, legend, x & y labels

    plt.xlabel('Average Rating')
    plt.ylabel('Favorite Counts')
    plt.title('Scatterplot of Breed Favorite Counts vs. Average Ratings')

    plt.tight_layout()
```



In [112]:

```
# scatter plot of retweet count on average rating for breeds

with sns.plotting_context("notebook"):
    # create a matplotlib figure
    fig, ax = plt.subplots(figsize = (10,10))

    # plot the scatterplot of dog average_rating and retweet_counts
    p1 = sns.scatterplot(x='average_rating', y='retweet_counts', data = df_breed, alpha
= 0.5, color = "k", lw = 2)
```

```
    for line in range(0,df_breed.shape[0]):
        p1.text(df_breed.average_rating[line], df_breed.retweet_counts[line]+20000,
        df_breed.dog_breed[line], horizontalalignment='center', size='small', color='bla
ck', weight='semibold')

    # set the title, legend, x & y labels

    plt.xlabel('Average Rating')
    plt.ylabel('Retweet Counts')
    plt.title('Scatterplot of Breed Retweet Counts vs. Average Ratings')

    plt.tight_layout()
```



We can see from the two scatterplots above, the favorite/retweet count is roughly proportional to the average rating of the breed. the higher the rating, the more likely the post will get more likes and retweets. Among all the breeds, golden retriever is the most popular breed and gets far more favorites/retweets then expected .

6. what is the most liked/retweeted single tweet?

In [113]:

```
# find max on favorite count
df_all.iloc[df_all['favorite_count'].idxmax()]
```

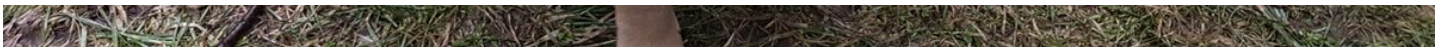
Out[113]:

```
tweet_id                822872901745569793
```

```
tweet_id                8226729017455697 93

timestamp               2017-01-21 18:26:02+00:00

source                  <a href="http://twitter.com/download/iphone" rel="nofollow">Twitter
for iPhone</a>
text                    Here's a super supportive puppo participating in the Toronto  #Wome
nsMarch today. 13/10 https://t.co/nTz3FtorBc
expanded_urls           https://twitter.com/dog_rates/status/822872901745569793/photo/1

rating_numerator        13

rating_denominator      10

name                    None

rating_count            1

jpg_url                 https://pbs.twimg.com/media/C2tugXLXgAArJO4.jpg

img_num                 1

favorite_count          132810

retweet_count           48265

dog_stage               puppo

breed                   lakeland terrier

confidence              0.196015

Name: 275, dtype: object
```

In [114]:

```
# display the dog picture
display(HTML('<img src="https://pbs.twimg.com/media/C2tugXLXgAArJO4.jpg"/>'))
```



The most favorite picture is a a super supportive puppo participating in the Toronto #WomensMarch, and received 132810 favorites.

In [115]:

```
# find max on retweet count
df_all.iloc[df_all['retweet_count'].idxmax()]
```

Out[115]:

```
tweet_id                744234799360020481

timestamp               2016-06-18 18:26:18+00:00

source                  <a href="http://twitter.com/download/iphone" rel="nofollow">Twitter
for iPhone</a>
text                    Here's a doggo realizing you can stand in a pool. 13/10 enlightene
d af (vid by Tina Conrad) https://t.co/7wE9LTEXC4
expanded_urls           https://twitter.com/dog_rates/status/744234799360020481/video/1

rating_numerator        13

rating_denominator      10

name                    None

rating_count            1

jpg_url                 https://pbs.twimg.com/ext_tw_video_thumb/744234667679821824/pu/img/
1GaWmtJtdqzZV7jy.jpg
img_num                 1

favorite_count          131075

retweet_count           79515

dog_stage               doggo

breed                   labrador retriever

confidence              0.825333

Name: 684, dtype: object
```

In [116]:

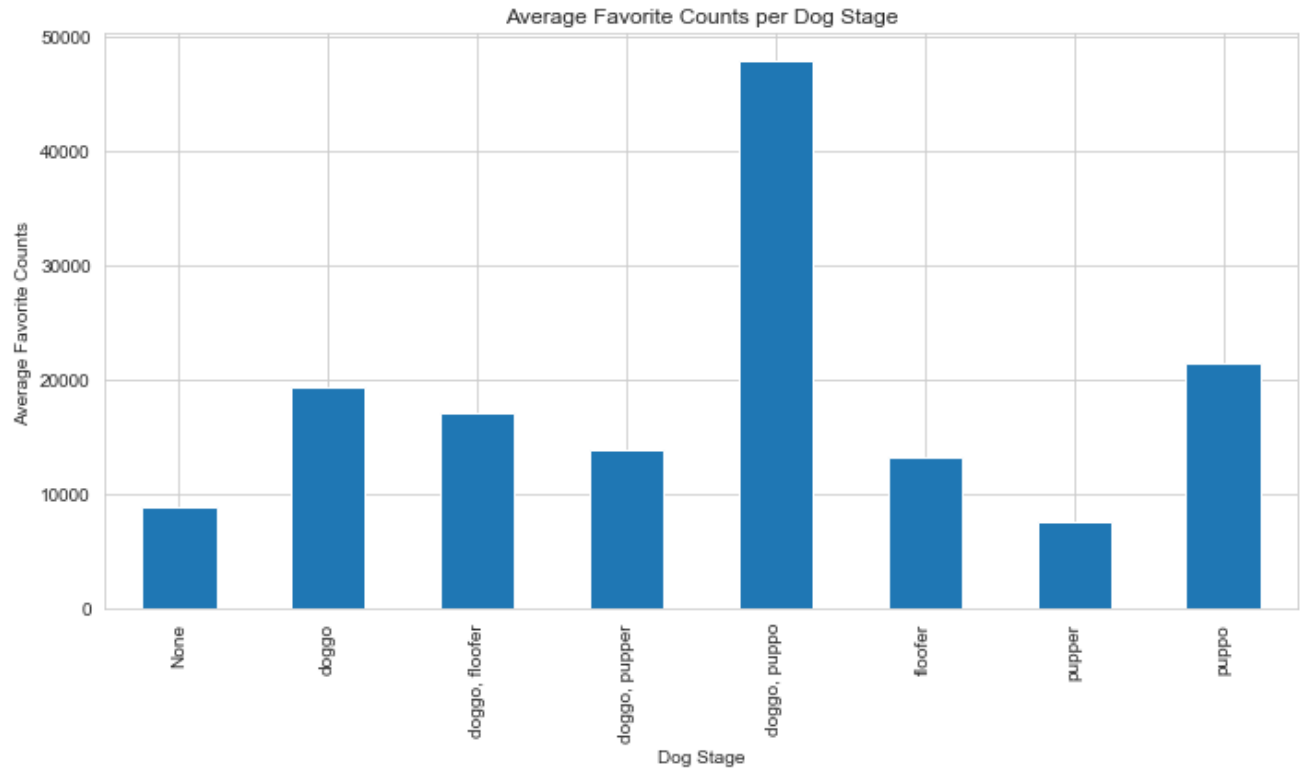
```
# display the dog picture
display(HTML('<img src="https://pbs.twimg.com/ext_tw_video_thumb/744234667679821824/pu/im
g/1GaWmtJtdqzZV7jy.jpg"/>'))
```

The most retweeted picture is a doggo that realizes it can stand in a pool (swimming actually), and it received 79515 retweets.

7. what is the average favorite/retweet count on different dog_stage?

In [118]:

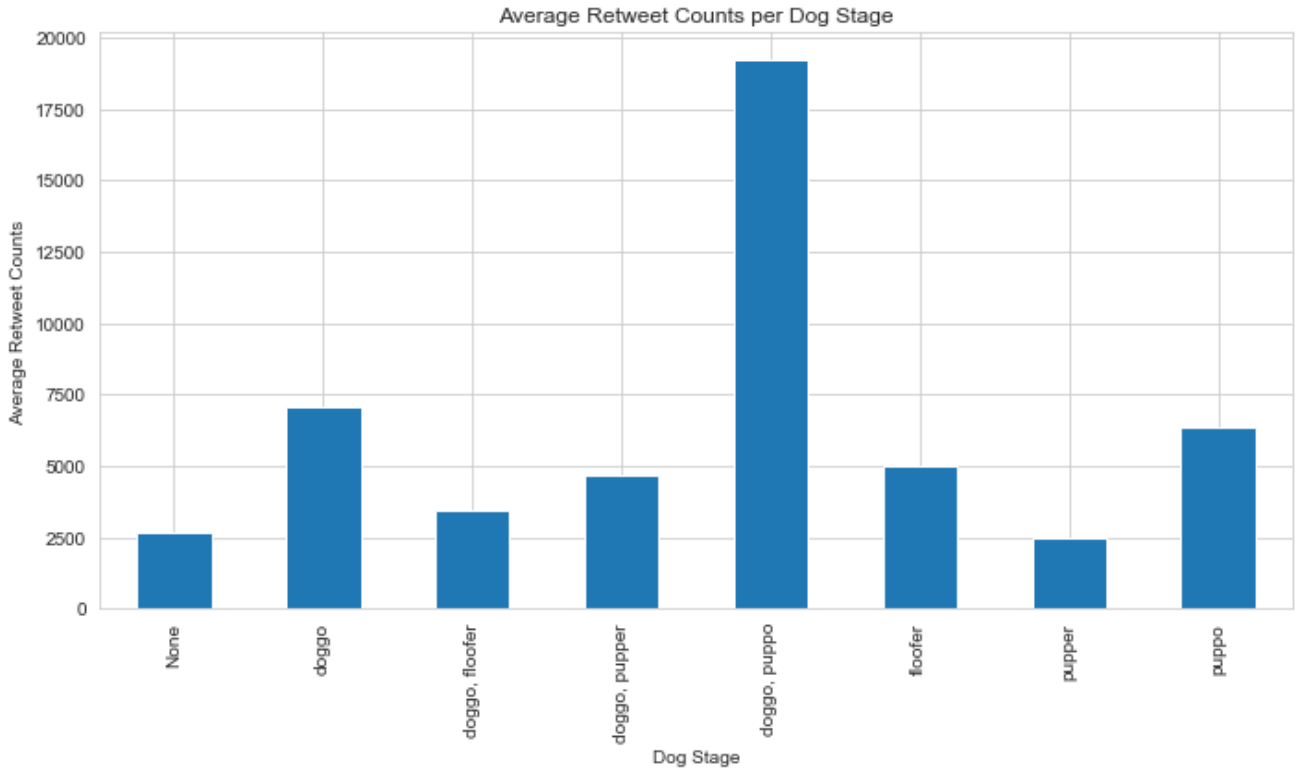
```
# groupby dog_stage and calculate the mean favorite count
df_stage = df_all_copy.groupby('dog_stage')['favorite_count'].mean()
# visualization
df_stage.plot.bar(figsize = (10, 6))
plt.title('Average Favorite Counts per Dog Stage')
plt.xlabel('Dog Stage')
plt.ylabel('Average Favorite Counts')
plt.tight_layout()
```



In [119]:

```
# groupby dog_stage and calculate the mean retweet count
```

```
df_stage_2 = df_all_copy.groupby('dog_stage')['retweet_count'].mean()
# visualization
df_stage_2.plot.bar(figsize = (10, 6))
plt.title('Average Retweet Counts per Dog Stage')
plt.xlabel('Dog Stage')
plt.ylabel('Average Retweet Counts')
plt.tight_layout()
```



If we consider there are in total only 9 tweets where the dogs have multipe stages, and we exclude them in comparison because these posts might not contain general results, overall, puppo on average gets the most favorite count, doggo on average gets the most retweet count (slightly leading puppo).

8. what is the WeRateDogs account activity by year, month, day of the week, hour of the day?

In [120]:

```
# use timestamp data, add year, month, day, hour, day_of_week columns
df_all_copy['year'] = df_all_copy["timestamp"].apply(lambda x: x.year)
df_all_copy['month'] = df_all_copy["timestamp"].apply(lambda x: x.month)
df_all_copy['day'] = df_all_copy["timestamp"].apply(lambda x: x.day)
df_all_copy['hour'] = df_all_copy["timestamp"].apply(lambda x: x.hour)
df_all_copy["day_of_week"] = df_all_copy["timestamp"].apply(lambda x: x.dayofweek)
```

In [121]:

```
df_all_copy.timestamp.describe()
```

Out[121]:

```
count                 1640
unique                1640
top       2015-12-08 16:21:41+00:00
freq                     1
first     2015-11-15 22:32:08+00:00
last      2017-08-01 00:17:27+00:00
Name: timestamp, dtype: object
```

We can see all the tweets are from 2015/11/15 to 2017/08/01.

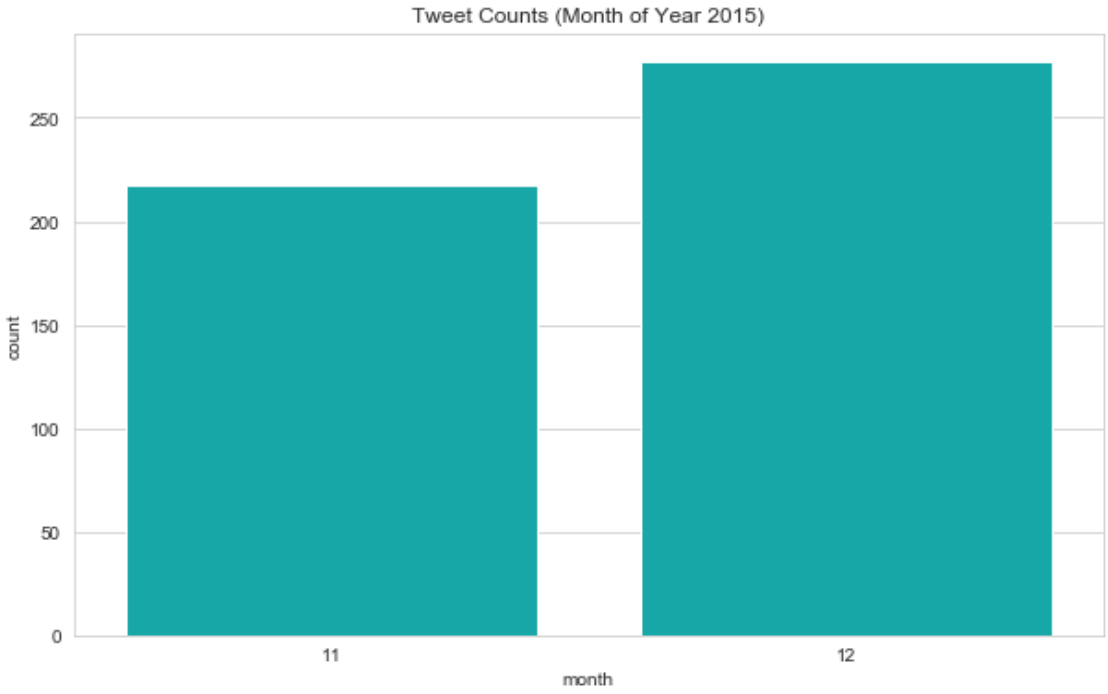
In [122]:

```
# twitter counts by month in 2015
fig, ax = plt.subplots(figsize = (10,6))
```

```
ax = sns.countplot(x = "month", data = df_all_copy.query("year == 2015"), color = 'c')
ax.set_title('Tweet Counts (Month of Year 2015)')
```

Out[122]:

```
Text(0.5, 1.0, 'Tweet Counts (Month of Year 2015)')
```

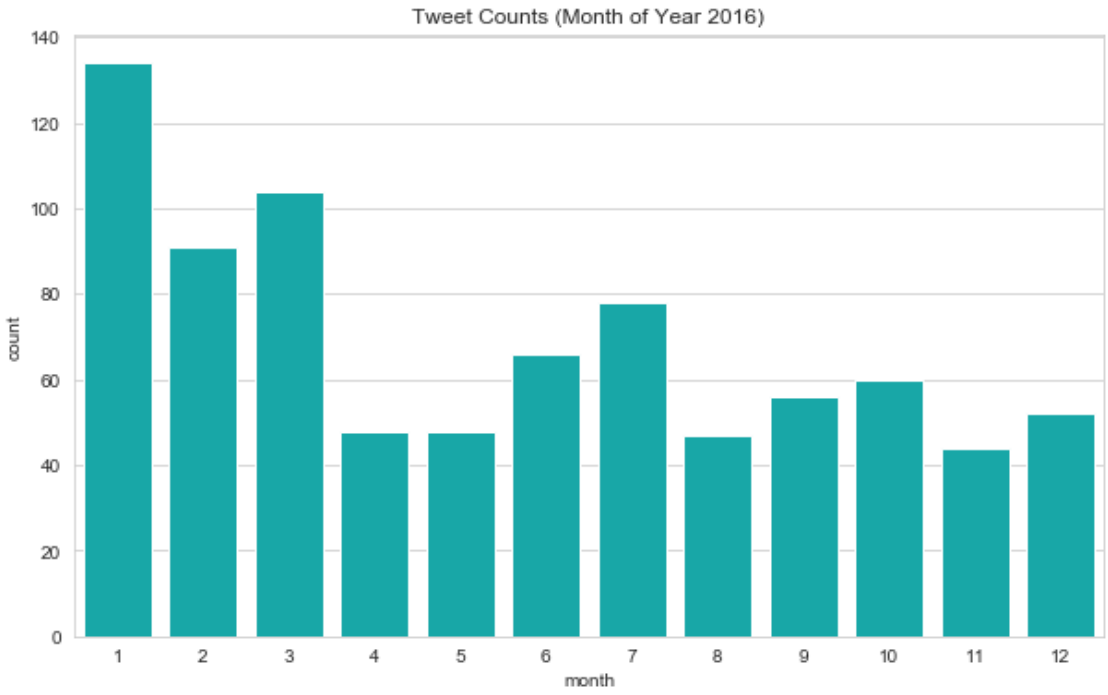


In [123]:

```
# twitter counts by month in 2016
fig, ax = plt.subplots(figsize = (10,6))
ax = sns.countplot(x = "month", data = df_all_copy.query("year == 2016"), color = 'c')
ax.set_title('Tweet Counts (Month of Year 2016)')
```

Out[123]:

```
Text(0.5, 1.0, 'Tweet Counts (Month of Year 2016)')
```

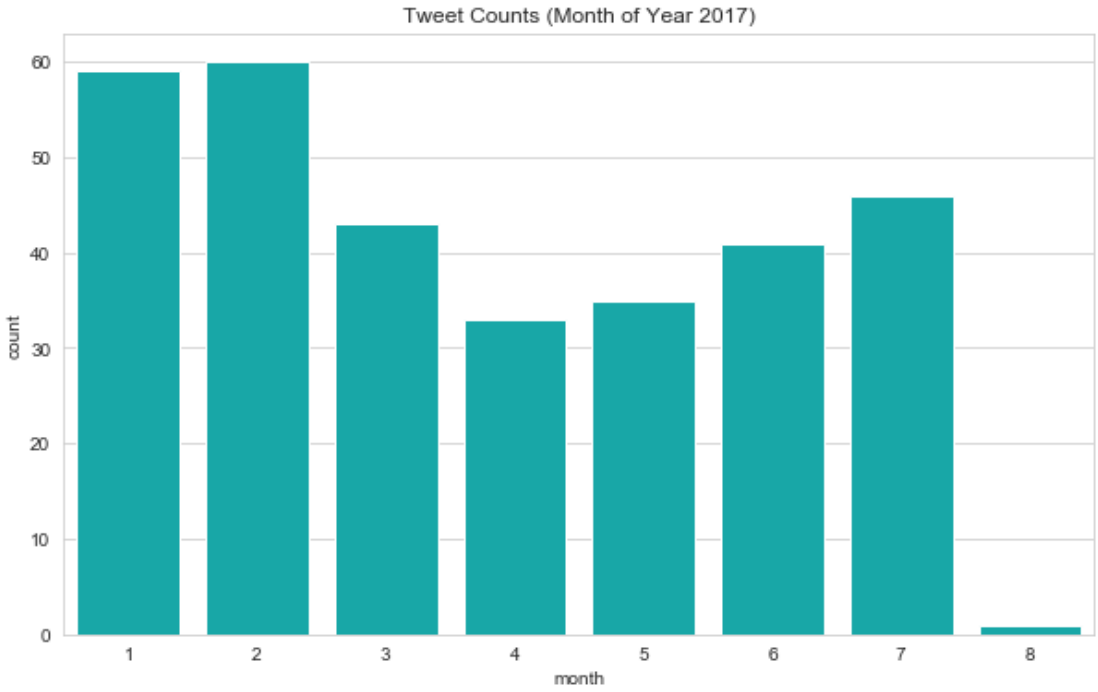


In [124]:

```
# twitter counts by month in 2017
fig, ax = plt.subplots(figsize = (10,6))
ax = sns.countplot(x = "month", data = df_all_copy.query("year == 2017"), color = 'c')
ax.set_title('Tweet Counts (Month of Year 2017)')
```

Out[124]:

```
Text(0.5, 1.0, 'Tweet Counts (Month of Year 2017)')
```



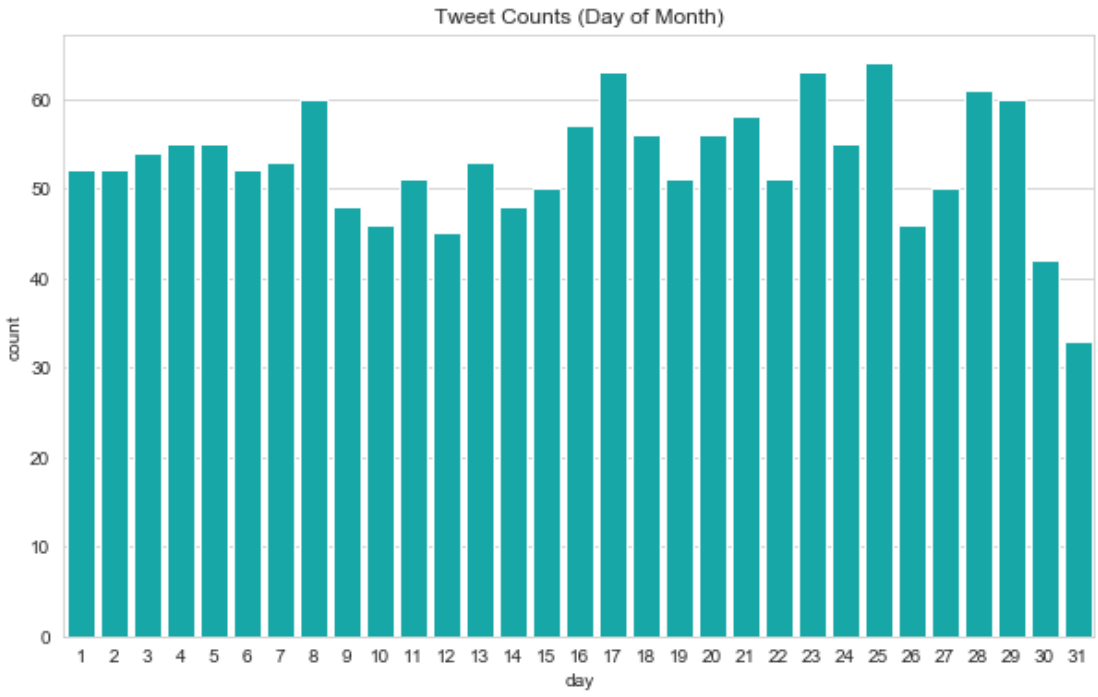
WeRateDogs on average posts more than 200 tweets during November and December in 2015, this number drops for the next 3 months (Jan, Feb, Mar of 2016) with ~100 tweets/month, then drops again and stablizes from April 2016 until July 2017 (averages 40 to 50 tweets a month).

In [125]:

```
# tweets by day of month
fig, ax = plt.subplots(figsize = (10,6))
ax = sns.countplot(x = "day", data = df_all_copy, color = 'c')
ax.set_title('Tweet Counts (Day of Month)')
```

Out[125]:

```
Text(0.5, 1.0, 'Tweet Counts (Day of Month)')
```



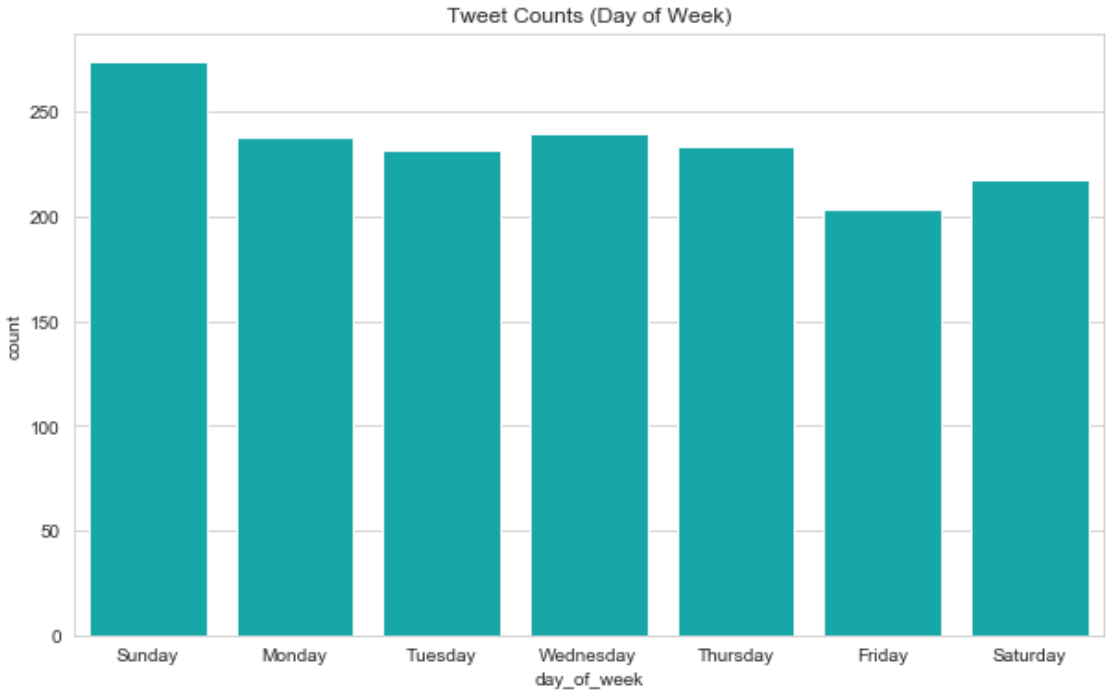
The total tweet counts in each day of the month are pretty stable (fewer tweets on 30 or 31 is because some months don't have the 30th or 31st day).

In [126]:

```
# tweet counts on day of week
fig, ax = plt.subplots(figsize = (10,6))
ax = sns.countplot(x = "day_of_week", data = df_all_copy, color = 'c')
ax.set_xticklabels(['Sunday', 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Sa
turday'])
ax.set_title('Tweet Counts (Day of Week)')
```

Out[126]:

```
Text(0.5, 1.0, 'Tweet Counts (Day of Week)')
```



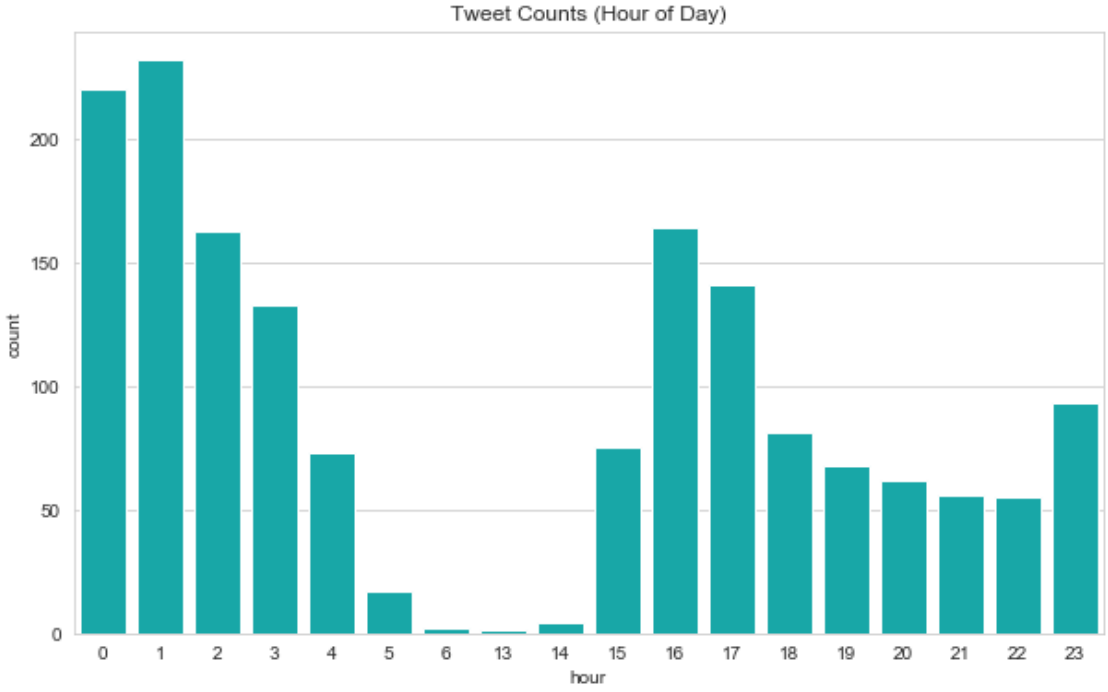
From the day of week total posts, WeRateDogs seems to post more tweets on Sunday (with a total post number of ~270) then any other day of the week.

In [127]:

```
# hour of day post number
fig, ax = plt.subplots(figsize = (10,6))
ax = sns.countplot(x = "hour", data = df_all_copy, color = 'c')
ax.set_title('Tweet Counts (Hour of Day)')
```

Out[127]:

```
Text(0.5, 1.0, 'Tweet Counts (Hour of Day)')
```



More tweets actually come from hours of 0-3 and 16-17, There is no single post for the hours of 7-12 (maybe it's the sleep time for the people who run the account).

9. what is the distribution of favorite counts by month in each year?

In [128]:

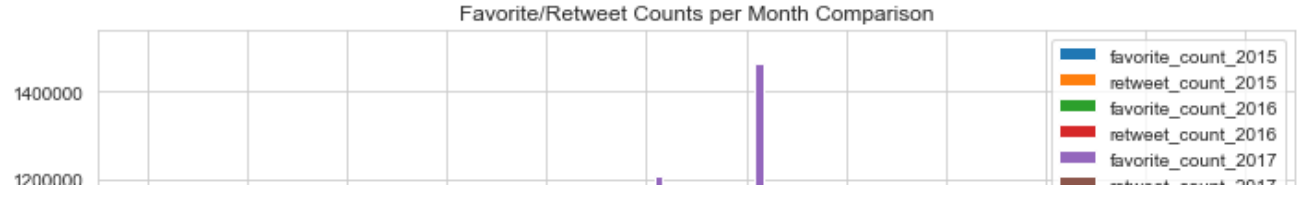
```
# query data from each year and find favorite/retweet counts of each month in these years
df_all_2015 = df_all_copy.query("year == 2015").groupby("month", as_index = False).sum()
df_all_2015 = df_all_2015[['month', 'favorite_count', 'retweet_count']]
df_all_2015.rename(columns={'favorite_count': 'favorite_count_2015', 'retweet_count': 'r
etweet_count_2015'}, inplace=True)

df_all_2016 = df_all_copy.query("year == 2016").groupby("month", as_index = False).sum()
df_all_2016 = df_all_2016[['month', 'favorite_count', 'retweet_count']]
df_all_2016.rename(columns={'favorite_count': 'favorite_count_2016', 'retweet_count': 'r
etweet_count_2016'}, inplace=True)

df_all_2017 = df_all_copy.query("year == 2017").groupby("month", as_index = False).sum()
df_all_2017 = df_all_2017[['month', 'favorite_count', 'retweet_count']]
df_all_2017.rename(columns={'favorite_count': 'favorite_count_2017', 'retweet_count': 'r
etweet_count_2017'}, inplace=True)

# create a monthly count dataframe that stores favorite/retweet counts from each month
df_monthly_count = pd.merge(df_all_2015, df_all_2016, on='month', how='outer')
df_monthly_count = pd.merge(df_monthly_count, df_all_2017, on='month', how='outer')

df_monthly_count.sort_values('month', ascending=True, inplace=True)
df_monthly_count.reset_index(drop = True, inplace = True)
df_monthly_count
```

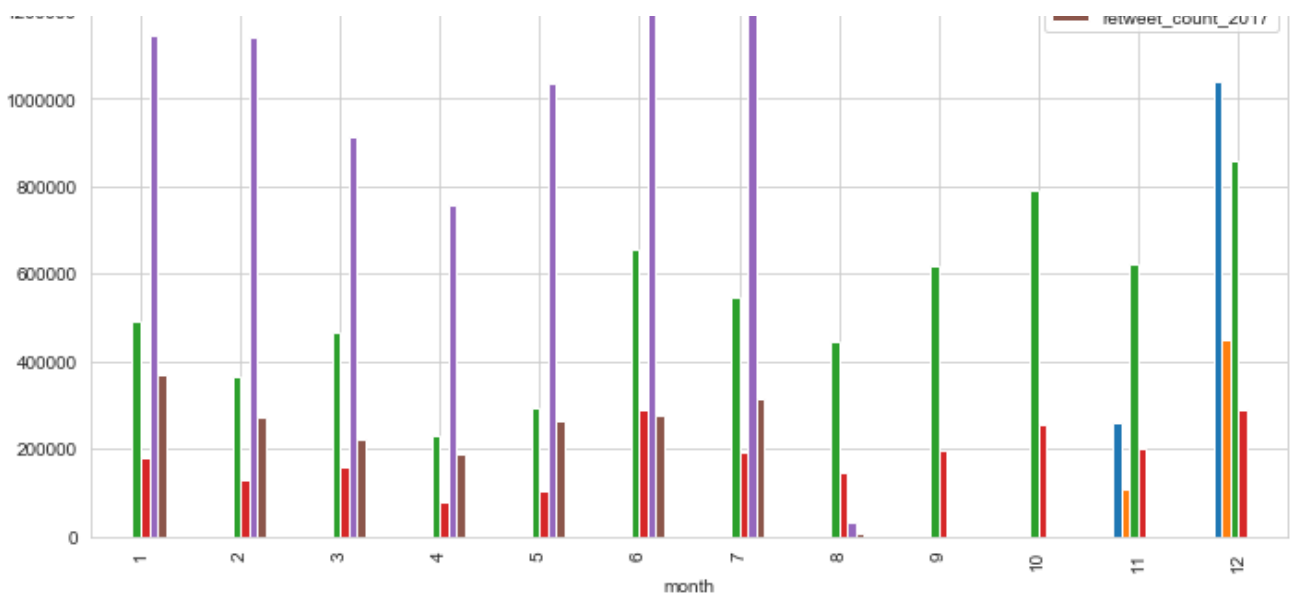
Out[128]:

	month	favorite_count_2015	retweet_count_2015	favorite_count_2016	retweet_count_2016	favorite_count_2017	retweet_co
0	1	NaN	NaN	491338.0	178155.0	1143224.0	
1	2	NaN	NaN	362751.0	129548.0	1139249.0	
2	3	NaN	NaN	464598.0	160181.0	913580.0	
3	4	NaN	NaN	230346.0	79402.0	754984.0	
4	5	NaN	NaN	292435.0	101909.0	1033073.0	
5	6	NaN	NaN	656763.0	289640.0	1207392.0	
6	7	NaN	NaN	544135.0	193387.0	1465000.0	
7	8	NaN	NaN	445238.0	144553.0	33819.0	
8	9	NaN	NaN	618661.0	197830.0	NaN	
9	10	NaN	NaN	791553.0	253481.0	NaN	
10	11	261130.0	105995.0	620546.0	199158.0	NaN	
11	12	1040206.0	448178.0	858984.0	287266.0	NaN	

In [129]:

```
# show monthly favorite/retweet counts and conpare between years
fig, ax = plt.subplots(figsize = (10,6))
ax = df_monthly_count.plot.bar(x='month', ax=ax)
ax.set_title("Favorite/Retweet Counts per Month Comparison")
plt.tight_layout()
```





Overall, the account is gaining popularity in receiving favorites and retweets over the years (we can see increases in height from the green bar to the purple bar showing trend in favorites, red bar to the brown bar showing trend in retweets). The decrease from blue bar to green bar is actually due to different numbers of tweets in the respective months (Dec), we have many more tweets in Dec 2015 than Dec 2016).

Summary and Conclusion

In this project, I investigated the **twitter data from WeRateDogs**. This project goes through the process of **data gathering, assessing, cleaning and analysis (visualization)**. During the analysis section, I provided and answered 9 interesting questions.

In [ ]: