

wrangle_act

October 1, 2023

1 Project: Wrangling and Analyze Data

1.1 Data Gathering

1. Directly download the WeRateDogs Twitter archive data (twitter_archive_enhanced.csv)

```
In [3]: import numpy as np
import pandas as pd
import requests
import tweepy
import json
import matplotlib.pyplot as plt
```

```
In [4]: df1=pd.read_csv('twitter-archive-enhanced.csv')
```

```
In [5]: df1.head(2).T
```

```
Out[5]:
```

tweet_id	892420643555336193	0 \
in_reply_to_status_id		NaN
in_reply_to_user_id		NaN
timestamp	2017-08-01 16:23:56 +0000	
source	<a href="http://twitter.com/download/iphone" r...	
text	This is Phineas. He's a mystical boy. Only eve...	
retweeted_status_id		NaN
retweeted_status_user_id		NaN
retweeted_status_timestamp		NaN
expanded_urls	https://twitter.com/dog_rates/status/892420643...	
rating_numerator		13
rating_denominator		10
name		Phineas
doggo		None
floofer		None
pupper		None
puppo		None
		1
tweet_id	892177421306343426	

in_reply_to_status_id	NaN
in_reply_to_user_id	NaN
timestamp	2017-08-01 00:17:27 +0000
source	<a href="http://twitter.com/download/iphone" r...
text	This is Tilly. She's just checking pup on you...
retweeted_status_id	NaN
retweeted_status_user_id	NaN
retweeted_status_timestamp	NaN
expanded_urls	https://twitter.com/dog_rates/status/892177421...
rating_numerator	13
rating_denominator	10
name	Tilly
doggo	None
floofer	None
pupper	None
puppo	None

In [6]: df1.shape

Out[6]: (2356, 17)

2. Use the Requests library to download the tweet image prediction (image_predictions.tsv)

In [7]: import os

import requests

file_name = "image_predictions.tsv"

Fetch data if the file doesn't exist

if not os.path.isfile(file_name):

url = 'https://d17h27t6h515a5.cloudfront.net/topher/2017/August/599fd2ad_image-predi

try:

response = requests.get(url)

response.raise_for_status() *# Raise an exception if the request was not success*

with open(file_name, "wb") as file:

file.write(response.content)

print("Download successful. Data saved as image_predictions.tsv.")

except requests.exceptions.RequestException as e:

print(f"Error occurred during download: {e}")

else:

print("The file already exists. No need to download.")

The file already exists. No need to download.

In [8]: df_pred = pd.read_csv(file_name, sep='\t')

In [9]: df_pred.head(2).T

```

Out[9]:
                                0  \
tweet_id                        666020888022790149
jpg_url    https://pbs.twimg.com/media/CT4udnOWwAAOaMy.jpg
img_num                                           1
p1                        Welsh_springer_spaniel
p1_conf                        0.465074
p1_dog                        True
p2                        collie
p2_conf                        0.156665
p2_dog                        True
p3                        Shetland_sheepdog
p3_conf                        0.0614285
p3_dog                        True

                                1
tweet_id                        666029285002620928
jpg_url    https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg
img_num                                           1
p1                        redbone
p1_conf                        0.506826
p1_dog                        True
p2                        miniature_pinscher
p2_conf                        0.0741917
p2_dog                        True
p3                        Rhodesian_ridgeback
p3_conf                        0.07201
p3_dog                        True

```

3. Use the Tweepy library to query additional data via the Twitter API (tweet_json.txt)

```

In [10]: # I replaced the confidential data with generic strings
consumer_key = 'consumer_key'
consumer_secret = 'secret_consumer'
access_token = 'access_token'
access_secret = 'secret_access'
auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_token, access_secret)
api = tweepy.API(auth, wait_on_rate_limit=True, wait_on_rate_limit_notify=True)

In [11]: df_list = []
with open('tweet_json.txt', mode='r', encoding='utf-8') as file:
    lines = file.readlines()
    for line in lines:
        data = json.loads(line)
        tweet_id = data['id']
        retweet_count = data['retweet_count']
        favorite_count = data['favorite_count']
        df_list.append({'tweet_id': tweet_id, 'retweet_count': retweet_count, 'favorite_count': favorite_count})
tweet_data = pd.DataFrame(df_list, columns=['tweet_id', 'retweet_count', 'favorite_count'])

```

1.2 Assessing Data

In this section, detect and document at least **eight (8) quality issues** and **two (2) tidiness issue**. You must use **both** visual assessment programmatic assesement to assess the data.

Note: pay attention to the following key points when you access the data.

- You only want original ratings (no retweets) that have images. Though there are 5000+ tweets in the dataset, not all are dog ratings and some are retweets.
- Assessing and cleaning the entire dataset completely would require a lot of time, and is not necessary to practice and demonstrate your skills in data wrangling. Therefore, the requirements of this project are only to assess and clean at least 8 quality issues and at least 2 tidiness issues in this dataset.
- The fact that the rating numerators are greater than the denominators does not need to be cleaned. This [unique rating system](#) is a big part of the popularity of WeRateDogs.
- You do not need to gather the tweets beyond August 1st, 2017. You can, but note that you won't be able to gather the image predictions for these tweets since you don't have access to the algorithm used.

In [12]: df1

```
Out[12]:
```

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	\
0	892420643555336193	NaN	NaN	
1	892177421306343426	NaN	NaN	
2	891815181378084864	NaN	NaN	
3	891689557279858688	NaN	NaN	
4	891327558926688256	NaN	NaN	
5	891087950875897856	NaN	NaN	
6	890971913173991426	NaN	NaN	
7	890729181411237888	NaN	NaN	
8	890609185150312448	NaN	NaN	
9	890240255349198849	NaN	NaN	
10	890006608113172480	NaN	NaN	
11	889880896479866881	NaN	NaN	
12	889665388333682689	NaN	NaN	
13	889638837579907072	NaN	NaN	
14	889531135344209921	NaN	NaN	
15	889278841981685760	NaN	NaN	
16	888917238123831296	NaN	NaN	
17	888804989199671297	NaN	NaN	
18	888554962724278272	NaN	NaN	
19	888202515573088257	NaN	NaN	
20	888078434458587136	NaN	NaN	
21	887705289381826560	NaN	NaN	
22	887517139158093824	NaN	NaN	
23	887473957103951883	NaN	NaN	
24	887343217045368832	NaN	NaN	
25	887101392804085760	NaN	NaN	
26	886983233522544640	NaN	NaN	
27	886736880519319552	NaN	NaN	

28	886680336477933568	NaN	NaN
29	886366144734445568	NaN	NaN
...
2326	666411507551481857	NaN	NaN
2327	666407126856765440	NaN	NaN
2328	666396247373291520	NaN	NaN
2329	666373753744588802	NaN	NaN
2330	666362758909284353	NaN	NaN
2331	666353288456101888	NaN	NaN
2332	666345417576210432	NaN	NaN
2333	666337882303524864	NaN	NaN
2334	666293911632134144	NaN	NaN
2335	666287406224695296	NaN	NaN
2336	666273097616637952	NaN	NaN
2337	666268910803644416	NaN	NaN
2338	666104133288665088	NaN	NaN
2339	666102155909144576	NaN	NaN
2340	666099513787052032	NaN	NaN
2341	666094000022159362	NaN	NaN
2342	666082916733198337	NaN	NaN
2343	666073100786774016	NaN	NaN
2344	666071193221509120	NaN	NaN
2345	666063827256086533	NaN	NaN
2346	666058600524156928	NaN	NaN
2347	666057090499244032	NaN	NaN
2348	666055525042405380	NaN	NaN
2349	666051853826850816	NaN	NaN
2350	666050758794694657	NaN	NaN
2351	666049248165822465	NaN	NaN
2352	666044226329800704	NaN	NaN
2353	666033412701032449	NaN	NaN
2354	666029285002620928	NaN	NaN
2355	666020888022790149	NaN	NaN

	timestamp \
0	2017-08-01 16:23:56 +0000
1	2017-08-01 00:17:27 +0000
2	2017-07-31 00:18:03 +0000
3	2017-07-30 15:58:51 +0000
4	2017-07-29 16:00:24 +0000
5	2017-07-29 00:08:17 +0000
6	2017-07-28 16:27:12 +0000
7	2017-07-28 00:22:40 +0000
8	2017-07-27 16:25:51 +0000
9	2017-07-26 15:59:51 +0000
10	2017-07-26 00:31:25 +0000
11	2017-07-25 16:11:53 +0000
12	2017-07-25 01:55:32 +0000

13	2017-07-25	00:10:02	+0000
14	2017-07-24	17:02:04	+0000
15	2017-07-24	00:19:32	+0000
16	2017-07-23	00:22:39	+0000
17	2017-07-22	16:56:37	+0000
18	2017-07-22	00:23:06	+0000
19	2017-07-21	01:02:36	+0000
20	2017-07-20	16:49:33	+0000
21	2017-07-19	16:06:48	+0000
22	2017-07-19	03:39:09	+0000
23	2017-07-19	00:47:34	+0000
24	2017-07-18	16:08:03	+0000
25	2017-07-18	00:07:08	+0000
26	2017-07-17	16:17:36	+0000
27	2017-07-16	23:58:41	+0000
28	2017-07-16	20:14:00	+0000
29	2017-07-15	23:25:31	+0000
...			...
2326	2015-11-17	00:24:19	+0000
2327	2015-11-17	00:06:54	+0000
2328	2015-11-16	23:23:41	+0000
2329	2015-11-16	21:54:18	+0000
2330	2015-11-16	21:10:36	+0000
2331	2015-11-16	20:32:58	+0000
2332	2015-11-16	20:01:42	+0000
2333	2015-11-16	19:31:45	+0000
2334	2015-11-16	16:37:02	+0000
2335	2015-11-16	16:11:11	+0000
2336	2015-11-16	15:14:19	+0000
2337	2015-11-16	14:57:41	+0000
2338	2015-11-16	04:02:55	+0000
2339	2015-11-16	03:55:04	+0000
2340	2015-11-16	03:44:34	+0000
2341	2015-11-16	03:22:39	+0000
2342	2015-11-16	02:38:37	+0000
2343	2015-11-16	01:59:36	+0000
2344	2015-11-16	01:52:02	+0000
2345	2015-11-16	01:22:45	+0000
2346	2015-11-16	01:01:59	+0000
2347	2015-11-16	00:55:59	+0000
2348	2015-11-16	00:49:46	+0000
2349	2015-11-16	00:35:11	+0000
2350	2015-11-16	00:30:50	+0000
2351	2015-11-16	00:24:50	+0000
2352	2015-11-16	00:04:52	+0000
2353	2015-11-15	23:21:54	+0000
2354	2015-11-15	23:05:30	+0000
2355	2015-11-15	22:32:08	+0000

[illegible]

2341 <a href="http://twitter.com/download/iphone" r...
 2342 <a href="http://twitter.com/download/iphone" r...
 2343 <a href="http://twitter.com/download/iphone" r...
 2344 <a href="http://twitter.com/download/iphone" r...
 2345 <a href="http://twitter.com/download/iphone" r...
 2346 <a href="http://twitter.com/download/iphone" r...
 2347 <a href="http://twitter.com/download/iphone" r...
 2348 <a href="http://twitter.com/download/iphone" r...
 2349 <a href="http://twitter.com/download/iphone" r...
 2350 <a href="http://twitter.com/download/iphone" r...
 2351 <a href="http://twitter.com/download/iphone" r...
 2352 <a href="http://twitter.com/download/iphone" r...
 2353 <a href="http://twitter.com/download/iphone" r...
 2354 <a href="http://twitter.com/download/iphone" r...
 2355 <a href="http://twitter.com/download/iphone" r...

	text	retweeted_status_id \
0	This is Phineas. He's a mystical boy. Only eve...	NaN
1	This is Tilly. She's just checking pup on you...	NaN
2	This is Archie. He is a rare Norwegian Pouncin...	NaN
3	This is Darla. She commenced a snooze mid meal...	NaN
4	This is Franklin. He would like you to stop ca...	NaN
5	Here we have a majestic great white breaching ...	NaN
6	Meet Jax. He enjoys ice cream so much he gets ...	NaN
7	When you watch your owner call another dog a g...	NaN
8	This is Zoey. She doesn't want to be one of th...	NaN
9	This is Cassie. She is a college pup. Studying...	NaN
10	This is Koda. He is a South Australian decksha...	NaN
11	This is Bruno. He is a service shark. Only get...	NaN
12	Here's a puppo that seems to be on the fence a...	NaN
13	This is Ted. He does his best. Sometimes that'...	NaN
14	This is Stuart. He's sporting his favorite fan...	NaN
15	This is Oliver. You're witnessing one of his m...	NaN
16	This is Jim. He found a fren. Taught him how t...	NaN
17	This is Zeke. He has a new stick. Very proud o...	NaN
18	This is Ralphus. He's powering up. Attempting ...	NaN
19	RT @dog_rates: This is Canela. She attempted s...	8.874740e+17
20	This is Gerald. He was just told he didn't get...	NaN
21	This is Jeffrey. He has a monopoly on the pool...	NaN
22	I've yet to rate a Venezuelan Hover Wiener. Th...	NaN
23	This is Canela. She attempted some fancy porch...	NaN
24	You may not have known you needed to see this ...	NaN
25	This... is a Jubilant Antarctic House Bear. We...	NaN
26	This is Maya. She's very shy. Rarely leaves he...	NaN
27	This is Mingus. He's a wonderful father to his...	NaN
28	This is Derek. He's late for a dog meeting. 13...	NaN
29	This is Roscoe. Another pupper fallen victim t...	NaN
...

2326	This is quite the dog. Gets really excited whe...	NaN
2327	This is a southern Vesuvius bumblegruff. Can d...	NaN
2328	Oh goodness. A super rare northeast Qdoba kang...	NaN
2329	Those are sunglasses and a jean jacket. 11/10 ...	NaN
2330	Unique dog here. Very small. Lives in containe...	NaN
2331	Here we have a mixed Asiago from the Galápagos...	NaN
2332	Look at this jokester thinking seat belt laws ...	NaN
2333	This is an extremely rare horned Parthenon. No...	NaN
2334	This is a funny dog. Weird toes. Won't come do...	NaN
2335	This is an Albanian 3 1/2 legged Episcopalian...	NaN
2336	Can take selfies 11/10 https://t.co/ws2AMaWpPW	NaN
2337	Very concerned about fellow dog trapped in com...	NaN
2338	Not familiar with this breed. No tail (weird)...	NaN
2339	Oh my. Here you are seeing an Adobe Setter giv...	NaN
2340	Can stand on stump for what seems like a while...	NaN
2341	This appears to be a Mongolian Presbyterian mi...	NaN
2342	Here we have a well-established sunblockerspan...	NaN
2343	Let's hope this flight isn't Malaysian (lol). ...	NaN
2344	Here we have a northern speckled Rhododendron...	NaN
2345	This is the happiest dog you will ever see. Ve...	NaN
2346	Here is the Rand Paul of retrievers folks! He'...	NaN
2347	My oh my. This is a rare blond Canadian terrie...	NaN
2348	Here is a Siberian heavily armored polar bear ...	NaN
2349	This is an odd dog. Hard on the outside but lo...	NaN
2350	This is a truly beautiful English Wilson Staff...	NaN
2351	Here we have a 1949 1st generation vulpix. Enj...	NaN
2352	This is a purebred Piers Morgan. Loves to Netf...	NaN
2353	Here is a very happy pup. Big fan of well-main...	NaN
2354	This is a western brown Mitsubishi terrier. Up...	NaN
2355	Here we have a Japanese Irish Setter. Lost eye...	NaN

	retweeted_status_user_id	retweeted_status_timestamp \
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN
5	NaN	NaN
6	NaN	NaN
7	NaN	NaN
8	NaN	NaN
9	NaN	NaN
10	NaN	NaN
11	NaN	NaN
12	NaN	NaN
13	NaN	NaN
14	NaN	NaN
15	NaN	NaN

16	NaN	NaN
17	NaN	NaN
18	NaN	NaN
19	4.196984e+09	2017-07-19 00:47:34 +0000
20	NaN	NaN
21	NaN	NaN
22	NaN	NaN
23	NaN	NaN
24	NaN	NaN
25	NaN	NaN
26	NaN	NaN
27	NaN	NaN
28	NaN	NaN
29	NaN	NaN
...
2326	NaN	NaN
2327	NaN	NaN
2328	NaN	NaN
2329	NaN	NaN
2330	NaN	NaN
2331	NaN	NaN
2332	NaN	NaN
2333	NaN	NaN
2334	NaN	NaN
2335	NaN	NaN
2336	NaN	NaN
2337	NaN	NaN
2338	NaN	NaN
2339	NaN	NaN
2340	NaN	NaN
2341	NaN	NaN
2342	NaN	NaN
2343	NaN	NaN
2344	NaN	NaN
2345	NaN	NaN
2346	NaN	NaN
2347	NaN	NaN
2348	NaN	NaN
2349	NaN	NaN
2350	NaN	NaN
2351	NaN	NaN
2352	NaN	NaN
2353	NaN	NaN
2354	NaN	NaN
2355	NaN	NaN

	expanded_urls	rating_numerator \
0	https://twitter.com/dog_rates/status/892420643...	13

1	https://twitter.com/dog_rates/status/892177421...	13
2	https://twitter.com/dog_rates/status/891815181...	12
3	https://twitter.com/dog_rates/status/891689557...	13
4	https://twitter.com/dog_rates/status/891327558...	12
5	https://twitter.com/dog_rates/status/891087950...	13
6	https://gofundme.com/ydvmve-surgery-for-jax,ht...	13
7	https://twitter.com/dog_rates/status/890729181...	13
8	https://twitter.com/dog_rates/status/890609185...	13
9	https://twitter.com/dog_rates/status/890240255...	14
10	https://twitter.com/dog_rates/status/890006608...	13
11	https://twitter.com/dog_rates/status/889880896...	13
12	https://twitter.com/dog_rates/status/889665388...	13
13	https://twitter.com/dog_rates/status/889638837...	12
14	https://twitter.com/dog_rates/status/889531135...	13
15	https://twitter.com/dog_rates/status/889278841...	13
16	https://twitter.com/dog_rates/status/888917238...	12
17	https://twitter.com/dog_rates/status/888804989...	13
18	https://twitter.com/dog_rates/status/888554962...	13
19	https://twitter.com/dog_rates/status/887473957...	13
20	https://twitter.com/dog_rates/status/888078434...	12
21	https://twitter.com/dog_rates/status/887705289...	13
22	https://twitter.com/dog_rates/status/887517139...	14
23	https://twitter.com/dog_rates/status/887473957...	13
24	https://twitter.com/dog_rates/status/887343217...	13
25	https://twitter.com/dog_rates/status/887101392...	12
26	https://twitter.com/dog_rates/status/886983233...	13
27	https://www.gofundme.com/mingusneedsus,https://...	13
28	https://twitter.com/dog_rates/status/886680336...	13
29	https://twitter.com/dog_rates/status/886366144...	12
...
2326	https://twitter.com/dog_rates/status/666411507...	2
2327	https://twitter.com/dog_rates/status/666407126...	7
2328	https://twitter.com/dog_rates/status/666396247...	9
2329	https://twitter.com/dog_rates/status/666373753...	11
2330	https://twitter.com/dog_rates/status/666362758...	6
2331	https://twitter.com/dog_rates/status/666353288...	8
2332	https://twitter.com/dog_rates/status/666345417...	10
2333	https://twitter.com/dog_rates/status/666337882...	9
2334	https://twitter.com/dog_rates/status/666293911...	3
2335	https://twitter.com/dog_rates/status/666287406...	1
2336	https://twitter.com/dog_rates/status/666273097...	11
2337	https://twitter.com/dog_rates/status/666268910...	10
2338	https://twitter.com/dog_rates/status/666104133...	1
2339	https://twitter.com/dog_rates/status/666102155...	11
2340	https://twitter.com/dog_rates/status/666099513...	8
2341	https://twitter.com/dog_rates/status/666094000...	9
2342	https://twitter.com/dog_rates/status/666082916...	6
2343	https://twitter.com/dog_rates/status/666073100...	10

2344	https://twitter.com/dog_rates/status/666071193...	9
2345	https://twitter.com/dog_rates/status/666063827...	10
2346	https://twitter.com/dog_rates/status/666058600...	8
2347	https://twitter.com/dog_rates/status/666057090...	9
2348	https://twitter.com/dog_rates/status/666055525...	10
2349	https://twitter.com/dog_rates/status/666051853...	2
2350	https://twitter.com/dog_rates/status/666050758...	10
2351	https://twitter.com/dog_rates/status/666049248...	5
2352	https://twitter.com/dog_rates/status/666044226...	6
2353	https://twitter.com/dog_rates/status/666033412...	9
2354	https://twitter.com/dog_rates/status/666029285...	7
2355	https://twitter.com/dog_rates/status/666020888...	8

	rating_denominator	name	doggo	floofer	pupper	puppo
0	10	Phineas	None	None	None	None
1	10	Tilly	None	None	None	None
2	10	Archie	None	None	None	None
3	10	Darla	None	None	None	None
4	10	Franklin	None	None	None	None
5	10	None	None	None	None	None
6	10	Jax	None	None	None	None
7	10	None	None	None	None	None
8	10	Zoey	None	None	None	None
9	10	Cassie	doggo	None	None	None
10	10	Koda	None	None	None	None
11	10	Bruno	None	None	None	None
12	10	None	None	None	None	puppo
13	10	Ted	None	None	None	None
14	10	Stuart	None	None	None	puppo
15	10	Oliver	None	None	None	None
16	10	Jim	None	None	None	None
17	10	Zeke	None	None	None	None
18	10	Ralphus	None	None	None	None
19	10	Canela	None	None	None	None
20	10	Gerald	None	None	None	None
21	10	Jeffrey	None	None	None	None
22	10	such	None	None	None	None
23	10	Canela	None	None	None	None
24	10	None	None	None	None	None
25	10	None	None	None	None	None
26	10	Maya	None	None	None	None
27	10	Mingus	None	None	None	None
28	10	Derek	None	None	None	None
29	10	Roscoe	None	None	pupper	None
...
2326	10	quite	None	None	None	None
2327	10	a	None	None	None	None
2328	10	None	None	None	None	None

2329	10	None	None	None	None	None
2330	10	None	None	None	None	None
2331	10	None	None	None	None	None
2332	10	None	None	None	None	None
2333	10	an	None	None	None	None
2334	10	a	None	None	None	None
2335	2	an	None	None	None	None
2336	10	None	None	None	None	None
2337	10	None	None	None	None	None
2338	10	None	None	None	None	None
2339	10	None	None	None	None	None
2340	10	None	None	None	None	None
2341	10	None	None	None	None	None
2342	10	None	None	None	None	None
2343	10	None	None	None	None	None
2344	10	None	None	None	None	None
2345	10	the	None	None	None	None
2346	10	the	None	None	None	None
2347	10	a	None	None	None	None
2348	10	a	None	None	None	None
2349	10	an	None	None	None	None
2350	10	a	None	None	None	None
2351	10	None	None	None	None	None
2352	10	a	None	None	None	None
2353	10	a	None	None	None	None
2354	10	a	None	None	None	None
2355	10	None	None	None	None	None

[2356 rows x 17 columns]

```
In [13]: import pandas as pd
```

```
predictions = pd.read_csv("image_predictions.tsv", sep="\t")
```

```
print(predictions.head())
```

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

	img_num	p1	p1_conf	p1_dog	p2	\
0	1	Welsh_springer_spaniel	0.465074	True	collie	
1	1	redbone	0.506826	True	miniature_pinscher	
2	1	German_shepherd	0.596461	True	malinois	
3	1	Rhodesian_ridgeback	0.408143	True	redbone	

```
4          1      miniature_pinscher  0.560311    True      Rottweiler
```

```
      p2_conf  p2_dog      p3  p3_conf  p3_dog
0  0.156665    True  Shetland_sheepdog  0.061428    True
1  0.074192    True  Rhodesian_ridgeback  0.072010    True
2  0.138584    True      bloodhound  0.116197    True
3  0.360687    True  miniature_pinscher  0.222752    True
4  0.243682    True      Doberman  0.154629    True
```

```
In [14]: tweet_data
```

```
Out[14]:
```

	tweet_id	retweet_count	favorite_count
0	892420643555336193	8853	39467
1	892177421306343426	6514	33819
2	891815181378084864	4328	25461
3	891689557279858688	8964	42908
4	891327558926688256	9774	41048
5	891087950875897856	3261	20562
6	890971913173991426	2158	12041
7	890729181411237888	16716	56848
8	890609185150312448	4429	28226
9	890240255349198849	7711	32467
10	890006608113172480	7624	31166
11	889880896479866881	5156	28268
12	889665388333682689	8538	38818
13	889638837579907072	4735	27672
14	889531135344209921	2321	15359
15	889278841981685760	5637	25652
16	888917238123831296	4709	29611
17	888804989199671297	4559	26080
18	888554962724278272	3732	20290
19	888078434458587136	3653	22201
20	887705289381826560	5609	30779
21	887517139158093824	12082	46959
22	887473957103951883	18781	69871
23	887343217045368832	10737	34222
24	887101392804085760	6167	31061
25	886983233522544640	8084	35859
26	886736880519319552	3443	12306
27	886680336477933568	4610	22798
28	886366144734445568	3316	21524
29	886267009285017600	4	117
...
2324	666411507551481857	339	459
2325	666407126856765440	44	113
2326	666396247373291520	92	172
2327	666373753744588802	100	194

2328	666362758909284353	595	804
2329	666353288456101888	77	229
2330	666345417576210432	146	307
2331	666337882303524864	96	204
2332	666293911632134144	368	522
2333	666287406224695296	71	152
2334	666273097616637952	82	184
2335	666268910803644416	37	108
2336	666104133288665088	6871	14765
2337	666102155909144576	16	81
2338	666099513787052032	73	164
2339	666094000022159362	79	169
2340	666082916733198337	47	121
2341	666073100786774016	174	335
2342	666071193221509120	67	154
2343	666063827256086533	232	496
2344	666058600524156928	61	115
2345	666057090499244032	146	304
2346	666055525042405380	261	448
2347	666051853826850816	879	1253
2348	666050758794694657	60	136
2349	666049248165822465	41	111
2350	666044226329800704	147	311
2351	666033412701032449	47	128
2352	666029285002620928	48	132
2353	666020888022790149	532	2535

[2354 rows x 3 columns]

After visually assessing the dataframes, the following observations were made:
archive:

The dataframe is not tidy, particularly concerning the dog stages. Instead of having separate columns for each stage (e.g., doggo, floofer, pupper, puppo), there should be one column to specify the stage for each dog. Some names in the 'name' column appear to be incorrect. For example, the name "a" is unlikely to be a dog's actual name. predictions:

The dataframe is also not tidy due to the spread of prediction data over several columns (e.g., prediction 1, prediction 2, prediction 3). It would be better to have one column for prediction number, and additional columns for the actual prediction, confidence, and whether it is a type of dog breed. The prediction numbers in columns 'p1', 'p2', and 'p3' have inconsistent capitalization. tweet_data:

The data in this dataframe is collected via the Twitter API, and some tweets may have been deleted, resulting in missing retweet or favorite counts. Unfortunately, this missing data cannot be retrieved. To achieve tidy data, each observational unit should be in its own dataframe. The three observational units can be defined as tweet data, dog data, and image predictions.

The next step is to assess each dataframe programmatically, starting with 'archive', to check for duplicated rows or duplicate tweet IDs.

```
In [15]: sum(df1.duplicated())
```

```
Out[15]: 0
```

```
In [16]: sum(df1.duplicated('tweet_id'))
```

```
Out[16]: 0
```

```
In [17]: df1.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
```

After visual assessment, I've identified a couple of data type modifications that should be made. The 'timestamp' column needs to be converted to the datetime data type, and the 'dog stage' should be changed to a categorical data type.

Furthermore, the 'archive' dataframe contains retweets, which should not be included as I am interested only in original content from WeRateDogs. To verify this, I will check if the values in the 'retweeted_status_id', 'retweeted_status_user_id', and 'retweeted_status_timestamp' columns are all present in the same rows.

The goal is to ensure data consistency and prepare the dataframe for further analysis and cleaning.

To validate data consistency, I will check the number of rows where the columns 'retweeted_status_id', 'retweeted_status_user_id', and 'retweeted_status_timestamp' are filled. If all these columns have non-null values in the same rows, the resulting count should be 181, which corresponds to the number of non-null values for each of the columns.

```
In [18]: len(df1[
            df1['retweeted_status_id'].notnull()
            & df1['retweeted_status_user_id'].notnull()
        ])
```



```
    & df1['retweeted_status_timestamp'].notnull()
])
```

Out[18]: 181

Noted that all these values are in the same rows, which is an important observation to consider.

Regarding the 'expanded_urls' column and the missing values, I will print a sample of this column below to gain a better understanding. This will help me investigate why some values are missing in this column.

```
In [19]: df1['expanded_urls'].sample(5)
```

```
Out[19]: 326      https://twitter.com/dog_rates/status/833826103...
1104      https://twitter.com/dog_rates/status/735137028...
717       https://twitter.com/dog_rates/status/783695101...
1723      https://twitter.com/dog_rates/status/680100725...
95        https://twitter.com/dog_rates/status/868880397...
Name: expanded_urls, dtype: object
```

Indeed, the 'expanded_urls' column seems to contain links to associated content like photos, videos, or other media. It is expected that some tweets may not have links, resulting in missing values for now. However, in the final dataset, missing values in 'expanded_urls' should be addressed, as we are interested only in tweets with images.

Next, I will examine the descriptive statistics for the 'archive' dataframe to gain insights into the data's distribution and better understand the characteristics of the dataset. This will help in identifying any irregularities or outliers that may require further attention during the data cleaning process.

```
In [20]: df1.describe()
```

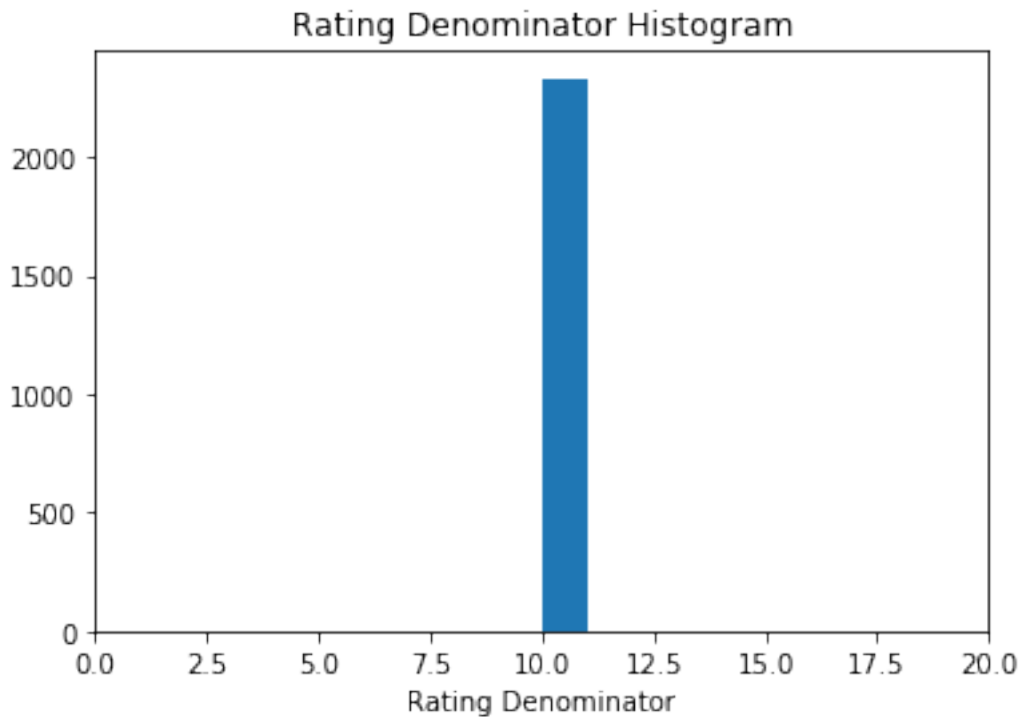
```
Out[20]:
```

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	\
count	2.356000e+03	7.800000e+01	7.800000e+01	
mean	7.427716e+17	7.455079e+17	2.014171e+16	
std	6.856705e+16	7.582492e+16	1.252797e+17	
min	6.660209e+17	6.658147e+17	1.185634e+07	
25%	6.783989e+17	6.757419e+17	3.086374e+08	
50%	7.196279e+17	7.038708e+17	4.196984e+09	
75%	7.993373e+17	8.257804e+17	4.196984e+09	
max	8.924206e+17	8.862664e+17	8.405479e+17	

	retweeted_status_id	retweeted_status_user_id	rating_numerator	\
count	1.810000e+02	1.810000e+02	2356.000000	
mean	7.720400e+17	1.241698e+16	13.126486	
std	6.236928e+16	9.599254e+16	45.876648	
min	6.661041e+17	7.832140e+05	0.000000	
25%	7.186315e+17	4.196984e+09	10.000000	
50%	7.804657e+17	4.196984e+09	11.000000	
75%	8.203146e+17	4.196984e+09	12.000000	
max	8.874740e+17	7.874618e+17	1776.000000	

	rating_denominator
count	2356.000000
mean	10.455433
std	6.745237
min	0.000000
25%	10.000000
50%	10.000000
75%	10.000000
max	170.000000

```
In [21]: bins = np.arange(0, df1['rating_denominator'].max()+1, 1)
plt.hist(data=df1, x='rating_denominator', bins=bins)
plt.title('Rating Denominator Histogram')
plt.xlabel('Rating Denominator')
plt.xlim(0, 20);
```



```
In [38]: df1.query('rating_denominator != 10')['text']
```

```
Out[38]: 313      @jonnysun @Lin_Manuel ok jomny I know you're e...
342          @docmisterio account started on 11/15/15
433      The floofs have been released I repeat the flo...
516      Meet Sam. She smiles 24/7 & secretly aspir...
784      RT @dog_rates: After so many requests, this is...
```

```

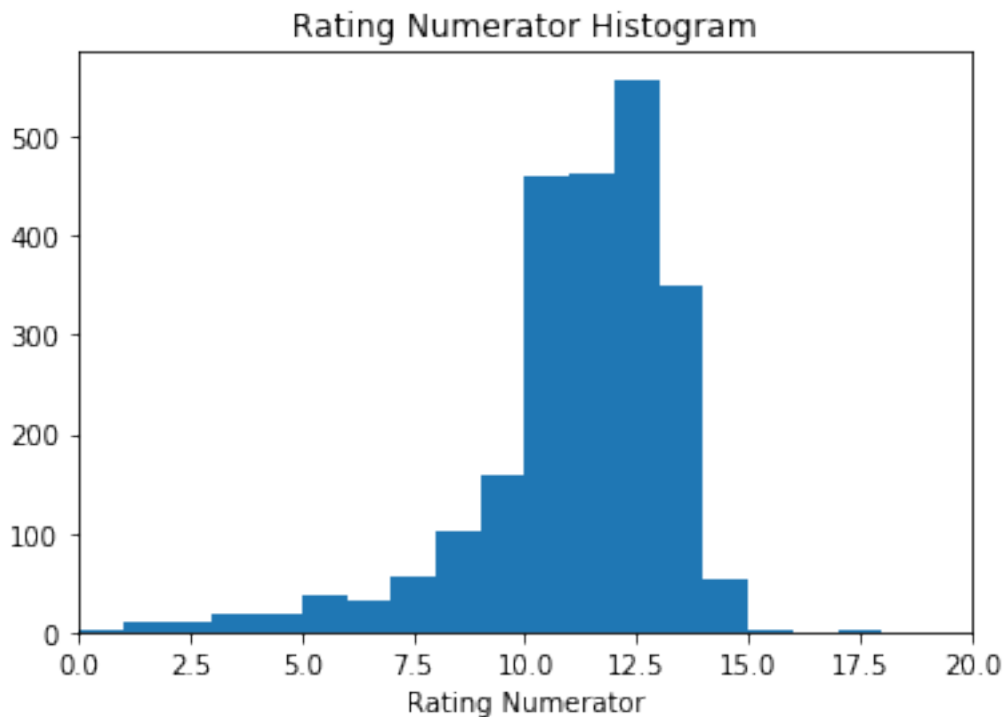
902     Why does this never happen at my front door...
1068    After so many requests, this is Bretagne. She ...
1120    Say hello to this unbelievably well behaved sq...
1165    Happy 4/20 from the squad! 13/10 for all https...
1202    This is Bluebert. He just saw that both #Final...
1228    Happy Saturday here's 9 puppers on a bench. 99...
1254    Here's a brigade of puppers. All look very pre...
1274    From left to right:\nCletus, Jerome, Alejandro...
1351    Here is a whole flock of puppers. 60/50 I'll ...
1433    Happy Wednesday here's a bucket of pups. 44/40...
1598    Yes I do realize a rating of 4/20 would've bee...
1634    Two sneaky puppers were not initially seen, mo...
1635    Someone help the girl is being mugged. Several...
1662    This is Darrel. He just robbed a 7/11 and is i...
1663    I'm aware that I could've said 20/16, but here...
1779    IT'S PUPPERGEDDON. Total of 144/120 ...I think...
1843    Here we have an entire platoon of puppers. Tot...
2335    This is an Albanian 3 1/2 legged Episcopalian...
Name: text, dtype: object

```

```

In [22]: bins = np.arange(0, df1['rating_numerator'].max()+1, 1)
plt.hist(data=df1, x='rating_numerator', bins=bins)
plt.title('Rating Numerator Histogram')
plt.xlabel('Rating Numerator')
plt.xlim(0, 20);

```



```
In [23]: df1.query('rating_numerator >= 15')['text']
```

```
Out[23]: 55      @roushfenway These are good dogs but 17/10 is ...
188      @dhmontgomery We also gave snoop dogg a 420/10...
189      @s8n You tried very hard to portray this good ...
285      RT @KibaDva: I collected all the good dogs!! 1...
290      @markhoppus 182/10
291      @bragg6of8 @Andy_Pace_ we are still looking fo...
313      @jonny_sun @Lin_Manuel ok jomny I know you're e...
340      RT @dog_rates: This is Logan, the Chow who liv...
433      The floofs have been released I repeat the flo...
516      Meet Sam. She smiles 24/7 & secretly aspir...
695      This is Logan, the Chow who lived. He solemnly...
763      This is Sophie. She's a Jubilant Bush Pupper. ...
902      Why does this never happen at my front door...
979      This is Atticus. He's quite simply America af...
1120     Say hello to this unbelievably well behaved sq...
1202     This is Bluebert. He just saw that both #Final...
1228     Happy Saturday here's 9 puppies on a bench. 99...
1254     Here's a brigade of puppies. All look very pre...
1274     From left to right:\nCletus, Jerome, Alejandro...
1351     Here is a whole flock of puppies. 60/50 I'll ...
1433     Happy Wednesday here's a bucket of pups. 44/40...
1634     Two sneaky puppies were not initially seen, mo...
1635     Someone help the girl is being mugged. Several...
1663     I'm aware that I could've said 20/16, but here...
1712     Here we have uncovered an entire battalion of ...
1779     IT'S PUPPERGEDDON. Total of 144/120 ...I think...
1843     Here we have an entire platoon of puppies. Tot...
2074     After so many requests... here you go.\n\nGood...
Name: text, dtype: object
```

```
In [24]: with pd.option_context('display.max_rows', None):
         print(df1.query('rating_numerator < 5')['text'])
```

```
315      When you're so blinded by your systematic plag...
605      RT @dog_rates: Not familiar with this breed. N...
765      This is Wesley. He's clearly trespassing. Seem...
883      This is Fido. He can tell the weather. Not goo...
912      Here's another picture without a dog in it. Id...
1004     Viewer discretion is advised. This is a terrib...
1016     PUPDATE: can't see any. Even if I could, I cou...
1165     Happy 4/20 from the squad! 13/10 for all https...
1189     This is Alexanderson. He's got a weird ass bir...
1219     This is Benedict. He's a feisty pup. Needs a b...
1249     What hooligan sent in pictures w/out a dog in ...
1303     This is Keurig. He's a rare dog. Laughs like a...
```

1314 This is Elliot. He's blocking the roadway. Dow...
 1406 This is Charl. He's a bully. Chucks that dumbb...
 1446 After reading the comments I may have overesti...
 1459 This may be the greatest video I've ever been ...
 1478 Meet Phil. He's big af. Currently destroying t...
 1598 Yes I do realize a rating of 4/20 would've bee...
 1601 This is Hammond. He's a peculiar pup. Loves lo...
 1629 This is Bobby. He doesn't give a damn about pe...
 1692 This is Chuck. He's a neat dog. Very flexible...
 1701 This is Alice. She's an idiot. 4/10 https://t...
 1761 Exotic pup here. Tail long af. Throat looks sw...
 1764 This is Crystal. She's a shitty fireman. No se...
 1836 Extremely rare pup here. Very religious. Alway...
 1869 What kind of person sends in a picture without...
 1898 Meet Patrick. He's an exotic pup. Jumps great ...
 1920 This is Henry. He's a shit dog. Short pointy e...
 1928 Herd of wild dogs here. Not sure what they're ...
 1938 Guys I'm getting real tired of this. We only r...
 1940 The millennials have spoken and we've decided...
 1941 This is a heavily opinionated dog. Loves walls...
 1947 Large blue dog here. Cool shades. Flipping us ...
 2038 After 22 minutes of careful deliberation this ...
 2070 Two miniature golden retrievers here. Webbed p...
 2076 Pink dogs here. Unreasonably long necks. Left ...
 2079 Scary dog here. Too many legs. Extra tail. Not...
 2091 Flamboyant pup here. Probably poisonous. Won't...
 2136 This is Tommy. He's a cool dog. Hard not to st...
 2183 This is Bernie. He's taking his Halloween cost...
 2186 Unique dog here. Oddly shaped tail. Long pink ...
 2202 Fascinating dog here. Loves beach. Oddly long ...
 2222 Here is a mother dog caring for her pups. Snaz...
 2237 This lil pup is Oliver. Hops around. Has wings...
 2239 This dog resembles a baked potato. Bed looks u...
 2246 This is Tedrick. He lives on the edge. Needs s...
 2261 Never seen dog like this. Breathes heavy. Tilt...
 2288 These are strange dogs. All have toupees. Long...
 2305 My goodness. Very rare dog here. Large. Tail d...
 2310 Unfamiliar with this breed. Ears pointy af. Wo...
 2316 Cool dog. Enjoys couch. Low monotone bark. Ver...
 2326 This is quite the dog. Gets really excited whe...
 2334 This is a funny dog. Weird toes. Won't come do...
 2335 This is an Albanian 3 1/2 legged Episcopalian...
 2338 Not familiar with this breed. No tail (weird)...
 2349 This is an odd dog. Hard on the outside but lo...
 Name: text, dtype: object

```
In [42]: df1['name'].value_counts()
```

```

Out[42]: None          745
         a              55
         Charlie        12
         Lucy           11
         Cooper          11
         Oliver          11
         Penny           10
         Lola            10
         Tucker          10
         Bo              9
         Winston         9
         Sadie           8
         the             8
         Bailey          7
         an              7
         Toby            7
         Daisy           7
         Buddy           7
         Jack            6
         Koda            6
         Stanley         6
         Scout           6
         Oscar           6
         Milo            6
         Bella           6
         Rusty           6
         Dave            6
         Jax             6
         Leo             6
         Louis           5
         ...
         JD              1
         Jay             1
         Simba           1
         Kloey           1
         Anthony         1
         Daniel          1
         Aldrick         1
         River           1
         Rizzo           1
         Crawford        1
         Kara            1
         Ronduh          1
         Buckley         1
         Tyrus           1
         Chesterson      1
         Joshwa          1
         Milky           1

```

Shelby	1
Willie	1
Clarq	1
Mosby	1
Rilo	1
Zooey	1
Sid	1
Lilah	1
Suki	1
Odin	1
Saydee	1
Carbon	1
Alejandro	1

Name: name, Length: 957, dtype: int64

```
In [43]: # use regex to find all lowercase names
df1[df1['name'].str.contains(r'^[A-Z].*$')]['name'].value_counts()
```

```
Out[43]: a          55
the           8
an            7
very          5
quite         4
just          4
one           4
actually      2
getting       2
not           2
mad           2
unacceptable  1
officially    1
infuriating   1
space         1
this          1
old           1
by            1
my            1
his           1
such          1
incredibly    1
light         1
life          1
all           1
Name: name, dtype: int64
```

```
In [44]: with pd.option_context('display.max_rows', None):
print(df1[df1['name'].str.contains(r'^[A-Z].*$')]['text'])
```

```
22 I've yet to rate a Venezuelan Hover Wiener. Th...
56 Here is a pupper approaching maximum borkdrive...
```

118 RT @dog_rates: We only rate dogs. This is quit...
169 We only rate dogs. This is quite clearly a smo...
193 Guys, we only rate dogs. This is quite clearly...
335 There's going to be a dog terminal at JFK Airp...
369 Occasionally, we're sent fantastic stories. Th...
542 We only rate dogs. Please stop sending in non-...
649 Here is a perfect example of someone who has t...
682 RT @dog_rates: Say hello to mad pupper. You kn...
759 RT @dog_rates: This is an East African Chalupa...
773 RT @dog_rates: We only rate dogs. Pls stop sen...
801 Guys this is getting so out of hand. We only r...
819 We only rate dogs. Pls stop sending in non-can...
822 RT @dog_rates: This is just downright precious...
852 This is my dog. Her name is Zoey. She knows I'...
924 This is one of the most inspirational stories ...
988 What jokester sent in a pic without a dog in i...
992 That is Quizno. This is his beach. He does not...
993 This is one of the most reckless puppers I've ...
1002 This is a mighty rare blue-tailed hammer sherk...
1004 Viewer discretion is advised. This is a terrib...
1017 This is a carrot. We only rate dogs. Please on...
1025 This is an Iraqi Speed Kangaroo. It is not a d...
1031 We only rate dogs. Pls stop sending in non-can...
1040 This is actually a pupper and I'd pet it so we...
1049 This is a very rare Great Alaskan Bush Pupper...
1063 This is just downright precious af. 12/10 for ...
1071 This is getting incredibly frustrating. This i...
1095 Say hello to mad pupper. You know what you did...
1097 We only rate dogs. Please stop sending in non-...
1120 Say hello to this unbelievably well behaved sq...
1121 We only rate dogs. Pls stop sending non-canine...
1138 This is all I want in my life. 12/10 for super...
1193 People please. This is a Deadly Mediterranean ...
1206 This is old now but it's absolutely heckin fan...
1207 This is a taco. We only rate dogs. Please only...
1259 We only rate dogs. Pls stop sending i...
1340 Here is a heartbreaking scene of an incredible...
1351 Here is a whole flock of puppers. 60/50 I'll ...
1361 This is a Butternut Cumberfloof. It's not wind...
1362 This is an East African Chalupa Seal. We only ...
1368 This is a Wild Tuscan Poofwiggle. Careful not ...
1382 "Pupper is a present to world. Here is a bow f...
1385 We only rate dogs. Pls stop sending in non-can...
1435 Please stop sending in saber-toothed tigers. T...
1457 This is just a beautiful pupper good shit evol...
1499 This is a rare Arctic Wubberfloof. Unamused by...
1527 Stop sending in lobsters. This is the final wa...
1603 This is the newly formed pupper a capella grou...

1693 This is actually a lion. We only rate dogs. Fo...
 1724 This is by far the most coordinated series of ...
 1737 Guys this really needs to stop. We've been ove...
 1747 This is officially the greatest yawn of all ti...
 1785 This is a dog swinging. I really enjoyed it so...
 1797 This is the happiest pupper I've ever seen. 10...
 1815 This is the saddest/sweetest/best picture I've...
 1853 This is a Sizzlin Menorah spaniel from Brookly...
 1854 Seriously guys?! Only send in dogs. I only rat...
 1877 C'mon guys. We've been over this. We only rate...
 1878 This is a fluffy albino Bacardi Columbia mix. ...
 1916 This is life-changing. 12/10 <https://t.co/SroT...>
 1923 This is a Sagitariot Baklava mix. Loves her ne...
 1936 This is one esteemed pupper. Just graduated co...
 1941 This is a heavily opinionated dog. Loves walls...
 1955 This is a Lofted Aphrodisiac Terrier named Kip...
 1994 This is a baby Rand Paul. Curls for days. 11/1...
 2001 This is light saber pup. Ready to fight off ev...
 2019 This is just impressive I have nothing else to...
 2030 This is space pup. He's very confused. Tries t...
 2034 This is a Tuscaloosa Alcatraz named Jacob (Yac...
 2037 This is the best thing I've ever seen so sprea...
 2066 This is a Helvetica Listerine named Rufus. Thi...
 2116 This is a Deciduous Trimester mix named Spork...
 2125 This is a Rich Mahogany Seltzer named Cherokee...
 2128 This is a Speckled Cauliflower Yosemite named ...
 2146 This is a spotted Lipitor Rumpelstiltskin name...
 2153 This is a brave dog. Excellent free climber. T...
 2161 This is a Coriander Baton Rouge named Alfredo...
 2191 This is a Slovakian Helter Skelter Feta named ...
 2198 This is a wild Toblerone from Papua New Guinea...
 2204 This is an Irish Rigatoni terrier named Berta...
 2211 Here is a horned dog. Much grace. Can jump ove...
 2212 Never forget this vine. You will not stop watc...
 2218 This is a Birmingham Quagmire named Chuk. Love...
 2222 Here is a mother dog caring for her pups. Snaz...
 2235 This is a Trans Siberian Kellogg named Alfonso...
 2249 This is a Shotokon Macadamia mix named Cheryl...
 2255 This is a rare Hungarian Pinot named Jessiga. ...
 2264 This is a southwest Coriander named Klint. Hat...
 2273 This is a northern Wahoo named Kohl. He runs t...
 2287 This is a Dasani Kingfisher from Maine. His na...
 2304 This is a curly Ticonderoga named Pepe. No fee...
 2311 This is a purebred Bacardi named Octaviath. Ca...
 2314 This is a golden Buckminsterfullerene named Jo...
 2326 This is quite the dog. Gets really excited whe...
 2327 This is a southern Vesuvius bumblegruff. Can d...
 2333 This is an extremely rare horned Parthenon. No...

```

2334 This is a funny dog. Weird toes. Won't come do...
2335 This is an Albanian 3 1/2 legged Episcopalian...
2345 This is the happiest dog you will ever see. Ve...
2346 Here is the Rand Paul of retrievers folks! He'...
2347 My oh my. This is a rare blond Canadian terrie...
2348 Here is a Siberian heavily armored polar bear ...
2349 This is an odd dog. Hard on the outside but lo...
2350 This is a truly beautiful English Wilson Staff...
2352 This is a purebred Piers Morgan. Loves to Netf...
2353 Here is a very happy pup. Big fan of well-main...
2354 This is a western brown Mitsubishi terrier. Up...
Name: text, dtype: object

```

I have observed two distinct trends in the data. First, a considerable number of tweets, as per WeRateDogs, do not feature pictures of dogs. In such cases, the account posts "We only rate dogs" and omits a specific name for the dog. This pattern is evident when the name column is null or contains the phrase "We only rate dogs."

The second trend is that numerous names are provided in the "name" column following the word "named." This pattern is evident when the name is in the format "named [name]."

To better understand the dog stages denoted in the dataset, I will examine the unique values in each of the stage columns. Additionally, I will perform manual extraction of the stages to verify if they align with the information presented in the dataframe. During the extraction process, I will be lenient with the matching criteria. Specifically, I will consider the stages as matching if they have:

The same letters (case-insensitive). Repeated letters, as long as the necessary letters appear in the correct order. An optional "s" at the end. By conducting this analysis, I aim to gain deeper insights into the dog stages present in the data and ensure consistency in how these stages are recorded.

```

In [25]: def compare_stage(stage, regex):
         '''
         INPUT:
         stage (str) - desired dog stage, can be 'doggo', 'floofer', 'pupper', or 'puppo'
         regex (str) - regex to use when re-extracting dog stage

         OUTPUT:
         None

         Print value counts of original stage name extractions,
         then re-extract using the provided regex and print a comparison summary.
         '''

         print('Original value counts for {}: \n'.format(stage))
         print(df1[stage].value_counts())
         print('\n')
         print('New value counts: \n')
         stage_regex = df1['text'].str.extract(regex)[0]

```

```

print(stage_regex.value_counts())
print('\n')
print('New total: {}'.format(stage_regex.count()))

```

```
In [26]: compare_stage('doggo', '([Dd]+[Oo]+[Gg]+[Oo]+[Ss]*)')
```

Original value counts for doggo:

```

None      2259
doggo      97
Name: doggo, dtype: int64

```

New value counts:

```

doggo      87
doggos     10
Doggo       9
DOGGO       1
Name: 0, dtype: int64

```

New total: 107

```
In [27]: compare_stage('floofer', '([Ff]+[Ll]+[Oo]+[Ff]+[Ee]+[Rr]+[Ss]*)')
```

Original value counts for floofer:

```

None      2346
floofer    10
Name: floofer, dtype: int64

```

New value counts:

```

Floofer     6
floofer     4
Name: 0, dtype: int64

```

New total: 10

```
In [28]: compare_stage('pupper', '([Pp]+[Uu]+[Pp]+[Ee]+[Rr]+[Ss]*)')
```

Original value counts for pupper:

```

None      2099

```

```
pupper      257
Name: pupper, dtype: int64
```

New value counts:

```
pupper      247
puppers      23
Pupper       8
PUPPER       5
Name: 0, dtype: int64
```

New total: 283

```
In [29]: compare_stage('puppo', '([Pp]+[Uu]+[Pp]+[Oo]+[Ss]*)')
```

Original value counts for puppo:

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

New value counts:

```
puppo      35
puppos      2
Puppo       1
Name: 0, dtype: int64
```

New total: 38

After reviewing all of the dog stages, it appears that there are various variations in the stage names that were not extracted accurately.

Moving on to the 'predictions' dataframe, the next step is to assess its data. Initially, I will examine for any duplicated rows, and then check for duplicated tweet IDs or image URLs ('jpg_url'), as these URLs are used for the predictions. Identifying duplicate rows and unique identifiers will help ensure the integrity and quality of the prediction data. By addressing any duplicates, we can avoid potential inconsistencies and maintain data accuracy during our analysis.

```
In [32]: sum(predictions.duplicated())
```

```
Out[32]: 0
```

```
In [30]: sum(predictions.duplicated('tweet_id'))
```

```
Out[30]: 0
```

```
In [31]: sum(predictions.duplicated('jpg_url'))
```

```
Out[31]: 66
```

```
In [33]: duplicated_jpg_url = predictions[predictions.duplicated('jpg_url']]['tweet_id']
```

```
In [34]: df1.query('tweet_id in @duplicated_jpg_url')
```

```
Out[34]:
```

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	\
19	888202515573088257	NaN	NaN	
36	885311592912609280	NaN	NaN	
95	873697596434513921	NaN	NaN	
155	861769973181624320	NaN	NaN	
211	851953902622658560	NaN	NaN	
260	842892208864923648	NaN	NaN	
266	841833993020538882	NaN	NaN	
341	832215726631055365	NaN	NaN	
343	832040443403784192	NaN	NaN	
359	829878982036299777	NaN	NaN	
399	824796380199809024	NaN	NaN	
411	823269594223824897	NaN	NaN	
415	822647212903690241	NaN	NaN	
422	821813639212650496	NaN	NaN	
435	820446719150292993	NaN	NaN	
446	819015337530290176	NaN	NaN	
447	819015331746349057	NaN	NaN	
453	818588835076603904	NaN	NaN	
465	817181837579653120	NaN	NaN	
469	816829038950027264	NaN	NaN	
476	816014286006976512	NaN	NaN	
488	813944609378369540	NaN	NaN	
522	809808892968534016	NaN	NaN	
530	808134635716833280	NaN	NaN	
535	807059379405148160	NaN	NaN	
541	806242860592926720	NaN	NaN	
543	805958939288408065	NaN	NaN	
552	804413760345620481	NaN	NaN	
555	803692223237865472	NaN	NaN	
561	802624713319034886	NaN	NaN	
..	
601	798665375516884993	NaN	NaN	
602	798644042770751489	NaN	NaN	
603	798628517273620480	NaN	NaN	
606	798340744599797760	NaN	NaN	
618	796177847564038144	NaN	NaN	
627	794983741416415232	NaN	NaN	
629	794355576146903043	NaN	NaN	

634	793614319594401792	NaN	NaN
661	791026214425268224	NaN	NaN
664	790723298204217344	NaN	NaN
686	788070120937619456	NaN	NaN
702	786036967502913536	NaN	NaN
720	783347506784731136	NaN	NaN
728	782021823840026624	NaN	NaN
741	780496263422808064	NaN	NaN
759	778396591732486144	NaN	NaN
767	777641927919427584	NaN	NaN
770	776819012571455488	NaN	NaN
778	775898661951791106	NaN	NaN
800	772615324260794368	NaN	NaN
811	771171053431250945	NaN	NaN
822	77009376776997377	NaN	NaN
847	766078092750233600	NaN	NaN
868	761750502866649088	NaN	NaN
872	761371037149827077	NaN	NaN
890	759566828574212096	NaN	NaN
895	759159934323924993	NaN	NaN
908	757729163776290825	NaN	NaN
926	754874841593970688	NaN	NaN
949	752309394570878976	NaN	NaN

	timestamp \
19	2017-07-21 01:02:36 +0000
36	2017-07-13 01:35:06 +0000
95	2017-06-11 00:25:14 +0000
155	2017-05-09 02:29:07 +0000
211	2017-04-12 00:23:33 +0000
260	2017-03-18 00:15:37 +0000
266	2017-03-15 02:10:39 +0000
341	2017-02-16 13:11:05 +0000
343	2017-02-16 01:34:34 +0000
359	2017-02-10 02:25:42 +0000
399	2017-01-27 01:49:15 +0000
411	2017-01-22 20:42:21 +0000
415	2017-01-21 03:29:14 +0000
422	2017-01-18 20:16:54 +0000
435	2017-01-15 01:45:15 +0000
446	2017-01-11 02:57:27 +0000
447	2017-01-11 02:57:26 +0000
453	2017-01-09 22:42:41 +0000
465	2017-01-06 01:31:47 +0000
469	2017-01-05 02:09:53 +0000
476	2017-01-02 20:12:21 +0000
488	2016-12-28 03:08:11 +0000
522	2016-12-16 17:14:20 +0000

530 2016-12-12 02:21:26 +0000
 535 2016-12-09 03:08:45 +0000
 541 2016-12-06 21:04:11 +0000
 543 2016-12-06 02:15:59 +0000
 552 2016-12-01 19:56:00 +0000
 555 2016-11-29 20:08:52 +0000
 561 2016-11-26 21:26:58 +0000

 601 2016-11-15 23:13:58 +0000
 602 2016-11-15 21:49:12 +0000
 603 2016-11-15 20:47:30 +0000
 606 2016-11-15 01:44:00 +0000
 618 2016-11-09 02:29:25 +0000
 627 2016-11-05 19:24:28 +0000
 629 2016-11-04 01:48:22 +0000
 634 2016-11-02 00:42:53 +0000
 661 2016-10-25 21:18:40 +0000
 664 2016-10-25 01:14:59 +0000
 686 2016-10-17 17:32:13 +0000
 702 2016-10-12 02:53:11 +0000
 720 2016-10-04 16:46:14 +0000
 728 2016-10-01 00:58:26 +0000
 741 2016-09-26 19:56:24 +0000
 759 2016-09-21 00:53:04 +0000
 767 2016-09-18 22:54:18 +0000
 770 2016-09-16 16:24:19 +0000
 778 2016-09-14 03:27:11 +0000
 800 2016-09-05 02:00:22 +0000
 811 2016-09-01 02:21:21 +0000
 822 2016-08-29 03:00:36 +0000
 847 2016-08-18 01:03:45 +0000
 868 2016-08-06 02:27:27 +0000
 872 2016-08-05 01:19:35 +0000
 890 2016-07-31 01:50:18 +0000
 895 2016-07-29 22:53:27 +0000
 908 2016-07-26 00:08:05 +0000
 926 2016-07-18 03:06:01 +0000
 949 2016-07-11 01:11:51 +0000

source \
 19 <a href="http://twitter.com/download/iphone" r...
 36 <a href="http://twitter.com/download/iphone" r...
 95 <a href="http://twitter.com/download/iphone" r...
 155 <a href="http://twitter.com/download/iphone" r...
 211 <a href="http://twitter.com/download/iphone" r...
 260 <a href="http://twitter.com/download/iphone" r...
 266 <a href="http://twitter.com/download/iphone" r...
 341 <a href="http://twitter.com/download/iphone" r...

[illegible]

890 <a href="http://twitter.com/download/iphone" r...
895 <a href="http://twitter.com/download/iphone" r...
908 <a href="http://twitter.com/download/iphone" r...
926 <a href="http://twitter.com/download/iphone" r...
949 <a href="http://twitter.com/download/iphone" r...

	text	retweeted_status_id \
19	RT @dog_rates: This is Canela. She attempted s...	8.874740e+17
36	RT @dog_rates: This is Lilly. She just paralle...	8.305833e+17
95	RT @dog_rates: This is Walter. He won't start ...	8.688804e+17
155	RT @dog_rates: "Good afternoon class today we'...	8.066291e+17
211	RT @dog_rates: This is Astrid. She's a guide d...	8.293743e+17
260	RT @dog_rates: This is Stephan. He just wants ...	8.071068e+17
266	RT @dog_rates: This is Ken. His cheeks are mag...	8.174239e+17
341	RT @dog_rates: This is Moreton. He's the Good ...	7.932865e+17
343	RT @dog_rates: This is Klein. These pics were ...	7.699404e+17
359	RT @dog_rates: This is Loki. He smiles like El...	8.269587e+17
399	RT @dog_rates: This is Bailey. She loves going...	7.950767e+17
411	RT @dog_rates: We only rate dogs. Please don't...	8.222448e+17
415	RT @dog_rates: This is Paisley. She really wan...	8.224891e+17
422	RT @dog_rates: Meet Hercules. He can have what...	7.806013e+17
435	RT @dog_rates: This is Peaches. She's the ulti...	8.001414e+17
446	RT @dog_rates: This is Bo. He was a very good ...	8.190048e+17
447	RT @dog_rates: This is Sunny. She was also a v...	8.190064e+17
453	RT @dog_rates: This is Chelsea. She forgot how...	7.735476e+17
465	RT @dog_rates: Here's a pupper with squeaky hi...	8.159661e+17
469	RT @dog_rates: This is Betty. She's assisting ...	7.909461e+17
476	RT @dog_rates: This is Larry. He has no self c...	7.320056e+17
488	RT @dog_rates: This is Bruce. He never backs d...	7.902771e+17
522	RT @dog_rates: This is Maximus. His face is st...	7.939622e+17
530	RT @dog_rates: This is Milo. I would do terrib...	8.011679e+17
535	RT @dog_rates: This is Cali. She arrived preas...	7.829691e+17
541	RT @dog_rates: This is Dave. He's currently in...	7.833346e+17
543	RT @dog_rates: This is Penny. She fought a bee...	7.827226e+17
552	RT @dog_rates: This is Rusty. He's going D1 fo...	7.848260e+17
555	RT @dog_rates: I present to you... Dog Jesus. ...	6.914169e+17
561	RT @dog_rates: "Yep... just as I suspected. Yo...	7.776842e+17
...
601	RT @dog_rates: This is Lola. She fell asleep o...	6.718968e+17
602	RT @dog_rates: This is Paull. He just stubbed ...	6.704450e+17
603	RT @dog_rates: This a Norwegian Pewterschmidt ...	6.675094e+17
606	RT @dog_rates: This is Davey. He'll have your ...	7.717705e+17
618	RT @dog_rates: This is Ruby. She just turned o...	7.961497e+17
627	RT @dog_rates: This is Rizzy. She smiles a lot...	7.895309e+17
629	RT @dog_rates: This is Butter. She can have wh...	7.887659e+17
634	RT @dog_rates: When she says you're a good boy...	7.916723e+17
661	RT @dog_rates: This is Alfie. He's touching a ...	7.638376e+17
664	RT @dog_rates: This is Happy. He's a bathtub r...	7.899865e+17

686	RT @dog_rates: This is Bo and Ty. Bo eats pape...	7.610045e+17
702	RT @dog_rates: This is Scout. He really wants ...	7.798343e+17
720	RT @dog_rates: This is Kenny. He just wants to...	6.742918e+17
728	RT @dog_rates: This is Harper. She scraped her...	7.076109e+17
741	RT @dog_rates: This is Bell. She likes holding...	7.424232e+17
759	RT @dog_rates: This is an East African Chalupa...	7.030419e+17
767	RT @dog_rates: This is Arnie. He's a Nova Scot...	7.504293e+17
770	RT @dog_rates: Everybody look at this beautifu...	6.798284e+17
778	RT @dog_rates: Like father (doggo), like son (...)	7.331095e+17
800	RT @dog_rates: This is Gromit. He's pupset bec...	7.652221e+17
811	RT @dog_rates: This is Frankie. He's wearing b...	6.733201e+17
822	RT @dog_rates: This is just downright precious...	7.410673e+17
847	RT @dog_rates: This is Colby. He's currently r...	7.258423e+17
868	RT @dog_rates: "Tristan do not speak to me wit...	6.853251e+17
872	RT @dog_rates: Oh. My. God. 13/10 magical af h...	7.116948e+17
890	RT @dog_rates: This... is a Tyrannosaurus rex...	7.395441e+17
895	RT @dog_rates: AT DAWN...\nWE RIDE\n\n11/10 ht...	6.703191e+17
908	RT @dog_rates: This is Chompsky. He lives up t...	6.790626e+17
926	RT @dog_rates: This is Rubio. He has too much ...	6.791584e+17
949	RT @dog_rates: Everyone needs to watch this. 1...	6.753544e+17

	retweeted_status_user_id	retweeted_status_timestamp	\
19	4.196984e+09	2017-07-19 00:47:34 +0000	
36	4.196984e+09	2017-02-12 01:04:29 +0000	
95	4.196984e+09	2017-05-28 17:23:24 +0000	
155	4.196984e+09	2016-12-07 22:38:52 +0000	
211	4.196984e+09	2017-02-08 17:00:26 +0000	
260	4.196984e+09	2016-12-09 06:17:20 +0000	
266	4.196984e+09	2017-01-06 17:33:29 +0000	
341	4.196984e+09	2016-11-01 03:00:09 +0000	
343	4.196984e+09	2016-08-28 16:51:16 +0000	
359	4.196984e+09	2017-02-02 01:01:21 +0000	
399	4.196984e+09	2016-11-06 01:33:58 +0000	
411	4.196984e+09	2017-01-20 00:50:15 +0000	
415	4.196984e+09	2017-01-20 17:00:46 +0000	
422	4.196984e+09	2016-09-27 02:53:48 +0000	
435	4.196984e+09	2016-11-20 00:59:15 +0000	
446	4.196984e+09	2017-01-11 02:15:36 +0000	
447	4.196984e+09	2017-01-11 02:21:57 +0000	
453	4.196984e+09	2016-09-07 15:44:53 +0000	
465	4.196984e+09	2017-01-02 17:00:46 +0000	
469	4.196984e+09	2016-10-25 16:00:09 +0000	
476	4.196984e+09	2016-05-16 00:31:53 +0000	
488	4.196984e+09	2016-10-23 19:42:02 +0000	
522	4.196984e+09	2016-11-02 23:45:19 +0000	
530	4.196984e+09	2016-11-22 20:58:07 +0000	
535	4.196984e+09	2016-10-03 15:42:44 +0000	
541	4.196984e+09	2016-10-04 15:55:06 +0000	

543	4.196984e+09	2016-10-02 23:23:04 +0000
552	4.196984e+09	2016-10-08 18:41:19 +0000
555	4.196984e+09	2016-01-25 00:26:41 +0000
561	4.196984e+09	2016-09-19 01:42:24 +0000
..
601	4.196984e+09	2015-12-02 03:40:57 +0000
602	4.196984e+09	2015-11-28 03:31:48 +0000
603	4.196984e+09	2015-11-20 01:06:48 +0000
606	4.196984e+09	2016-09-02 18:03:10 +0000
618	4.196984e+09	2016-11-09 00:37:46 +0000
627	4.196984e+09	2016-10-21 18:16:44 +0000
629	4.196984e+09	2016-10-19 15:37:03 +0000
634	4.196984e+09	2016-10-27 16:06:04 +0000
661	4.196984e+09	2016-08-11 20:40:41 +0000
664	4.196984e+09	2016-10-23 00:27:05 +0000
686	4.196984e+09	2016-08-04 01:03:17 +0000
702	4.196984e+09	2016-09-25 00:06:08 +0000
720	4.196984e+09	2015-12-08 18:17:56 +0000
728	4.196984e+09	2016-03-09 16:56:11 +0000
741	4.196984e+09	2016-06-13 18:27:32 +0000
759	4.196984e+09	2016-02-26 02:20:37 +0000
767	4.196984e+09	2016-07-05 20:41:01 +0000
770	4.196984e+09	2015-12-24 00:58:27 +0000
778	4.196984e+09	2016-05-19 01:38:16 +0000
800	4.196984e+09	2016-08-15 16:22:20 +0000
811	4.196984e+09	2015-12-06 01:56:44 +0000
822	4.196984e+09	2016-06-10 00:39:48 +0000
847	4.196984e+09	2016-04-29 00:21:01 +0000
868	4.196984e+09	2016-01-08 05:00:14 +0000
872	4.196984e+09	2016-03-20 23:23:54 +0000
890	4.196984e+09	2016-06-05 19:47:03 +0000
895	4.196984e+09	2015-11-27 19:11:49 +0000
908	4.196984e+09	2015-12-21 22:15:18 +0000
926	4.196984e+09	2015-12-22 04:35:49 +0000
949	4.196984e+09	2015-12-11 16:40:19 +0000

	expanded_urls	rating_numerator \
19	https://twitter.com/dog_rates/status/887473957...	13
36	https://twitter.com/dog_rates/status/830583320...	13
95	https://twitter.com/dog_rates/status/868880397...	14
155	https://twitter.com/dog_rates/status/806629075...	13
211	https://twitter.com/dog_rates/status/829374341...	13
260	https://twitter.com/dog_rates/status/807106840...	13
266	https://twitter.com/dog_rates/status/817423860...	13
341	https://twitter.com/dog_rates/status/793286476...	13
343	https://twitter.com/dog_rates/status/769940425...	12
359	https://twitter.com/dog_rates/status/826958653...	12
399	https://twitter.com/dog_rates/status/795076730...	11

411	https://twitter.com/dog_rates/status/822244816...	11
415	https://twitter.com/dog_rates/status/822489057...	13
422	https://twitter.com/dog_rates/status/780601303...	12
435	https://twitter.com/dog_rates/status/800141422...	13
446	https://twitter.com/dog_rates/status/819004803...	14
447	https://twitter.com/dog_rates/status/819006400...	14
453	https://twitter.com/dog_rates/status/773547596...	11
465	https://twitter.com/dog_rates/status/815966073...	13
469	https://twitter.com/dog_rates/status/790946055...	12
476	https://twitter.com/dog_rates/status/732005617...	11
488	https://twitter.com/dog_rates/status/790277117...	11
522	https://twitter.com/dog_rates/status/793962221...	12
530	https://twitter.com/dog_rates/status/801167903...	13
535	https://twitter.com/dog_rates/status/782969140...	12
541	https://twitter.com/dog_rates/status/783334639...	12
543	https://twitter.com/dog_rates/status/782722598...	10
552	https://twitter.com/dog_rates/status/784826020...	13
555	https://twitter.com/dog_rates/status/691416866...	13
561	https://twitter.com/dog_rates/status/777684233...	12
..
601	https://twitter.com/dog_rates/status/671896809...	10
602	https://twitter.com/dog_rates/status/670444955...	10
603	https://twitter.com/dog_rates/status/667509364...	12
606	https://twitter.com/dog_rates/status/771770456...	11
618	https://twitter.com/dog_rates/status/796149749...	11
627	https://twitter.com/dog_rates/status/789530877...	12
629	https://twitter.com/dog_rates/status/788765914...	12
634	https://twitter.com/dog_rates/status/791672322...	13
661	https://twitter.com/dog_rates/status/763837565...	11
664	https://twitter.com/dog_rates/status/789986466...	12
686	https://twitter.com/dog_rates/status/761004547...	11
702	https://twitter.com/dog_rates/status/779834332...	11
720	https://twitter.com/dog_rates/status/674291837...	11
728	https://twitter.com/dog_rates/status/707610948...	12
741	https://twitter.com/dog_rates/status/742423170...	12
759	https://twitter.com/dog_rates/status/703041949...	10
767	https://twitter.com/dog_rates/status/750429297...	12
770	https://twitter.com/dog_rates/status/679828447...	13
778	https://twitter.com/dog_rates/status/733109485...	12
800	https://twitter.com/dog_rates/status/765222098...	10
811	https://twitter.com/dog_rates/status/673320132...	11
822	https://twitter.com/dog_rates/status/741067306...	12
847	https://twitter.com/dog_rates/status/725842289...	12
868	https://twitter.com/dog_rates/status/685325112...	10
872	https://twitter.com/dog_rates/status/711694788...	13
890	https://twitter.com/dog_rates/status/739544079...	10
895	https://twitter.com/dog_rates/status/670319130...	11
908	https://twitter.com/dog_rates/status/679062614...	11

926	https://twitter.com/dog_rates/status/679158373...	11
949	https://twitter.com/dog_rates/status/675354435...	13

	rating_denominator	name	doggo	floofer	pupper	puppo
19	10	Canela	None	None	None	None
36	10	Lilly	None	None	None	None
95	10	Walter	None	None	None	None
155	10	None	None	None	None	None
211	10	Astrid	doggo	None	None	None
260	10	Stephan	None	None	None	None
266	10	Ken	None	None	None	None
341	10	Moreton	None	None	None	None
343	10	Klein	None	None	None	None
359	10	Loki	doggo	None	None	None
399	10	Bailey	None	None	None	None
411	10	None	None	None	None	None
415	10	Paisley	None	None	None	None
422	10	Hercules	None	None	None	None
435	10	Peaches	None	None	None	None
446	10	Bo	doggo	None	None	None
447	10	Sunny	doggo	None	None	None
453	10	Chelsea	None	None	pupper	None
465	10	None	None	None	pupper	None
469	10	Betty	None	None	None	puppo
476	10	Larry	None	None	None	None
488	10	Bruce	None	None	None	None
522	10	Maximus	None	None	None	None
530	10	Milo	None	None	None	None
535	10	Cali	None	None	None	None
541	10	Dave	None	None	None	None
543	10	Penny	None	None	None	None
552	10	Rusty	None	None	None	None
555	10	None	None	None	None	None
561	10	None	None	None	None	None
..
601	10	Lola	None	None	None	None
602	10	Paull	None	None	None	None
603	10	None	None	None	None	None
606	10	Davey	None	None	None	None
618	10	Ruby	None	None	None	None
627	10	Rizzy	None	None	None	None
629	10	Butter	None	None	None	None
634	10	None	None	None	None	None
661	10	Alfie	None	None	None	None
664	10	Happy	None	None	None	None
686	10	Bo	None	None	None	None
702	10	Scout	None	None	None	None
720	10	Kenny	None	None	None	None

728	10	Harper	None	None	None	None
741	10	Bell	None	None	None	None
759	10	an	None	None	None	None
767	10	Arnie	None	None	None	None
770	10	None	None	None	pupper	None
778	10	None	doggo	None	pupper	None
800	10	Gromit	None	None	None	None
811	10	Frankie	None	None	None	None
822	10	just	doggo	None	pupper	None
847	10	Colby	None	None	None	None
868	10	None	None	None	None	None
872	10	None	None	None	None	None
890	10	None	None	None	None	None
895	10	None	None	None	None	None
908	10	Chompsky	None	None	None	None
926	10	Rubio	None	None	None	None
949	10	None	None	None	None	None

[66 rows x 7 columns]

1.2.1 Quality issues

1. Missing Values: The 'expanded_urls' column contains missing values, indicating that some tweets do not have associated images or content links. This needs to be addressed, as the analysis focuses on tweets with images.
2. Incorrect Dog Names: The 'name' column contains some incorrect values, such as 'a', 'an', and 'the', which are unlikely to be actual dog names. These entries need to be cleaned or replaced with more appropriate values.
3. Retweets: The 'archive' dataframe includes retweets, even though the project requires only original content from WeRateDogs. The retweets, identified by non-null values in 'retweeted_status_id', should be removed from the dataset.
4. Inconsistent Prediction Labels: The prediction labels for dog breeds in the 'predictions' dataframe appear to have inconsistent capitalization. Standardizing the capitalization of these labels would improve data consistency.
5. Data Types: The 'timestamp' column in the 'archive' dataframe is stored as a string and should be converted to the datetime data type for easier manipulation and analysis.
6. Inconsistent or inaccurate data in the 'rating_numerator' and 'rating_denominator' columns.
7. Duplicate Rows: The dataset should be checked for and cleaned of any duplicate rows, as these can distort the analysis and lead to inaccurate insights.
8. Predictions Data Structure: The prediction data in the 'predictions' dataframe is spread across multiple columns ('p1', 'p2', 'p3'). It would be more organized to melt this data into a single column for the prediction number, along with additional columns for the actual prediction, confidence, and whether it is a dog breed.

1.2.2 Tidiness issues

1. Dog Stages in Separate Columns: In the 'archive' dataframe, the dog stages are represented in four separate columns ('doggo', 'floofer', 'pupper', 'puppo'). This violates the tidy data principle, as each variable should be stored in a single column. To achieve tidiness, the dog stages should be combined into one column, using a categorical data type to indicate the stage for each dog.
2. Prediction Data Spread Across Columns: In the 'predictions' dataframe, the prediction data for dog breeds is spread across three separate columns ('p1', 'p2', 'p3'). Each column represents a different prediction number, which makes the data untidy. To improve tidiness, the prediction data should be melted or reshaped into a single column for the prediction number, along with additional columns for the actual prediction, confidence level, and whether the prediction is a type of dog breed.

1.3 Cleaning Data

In this section, clean **all** of the issues you documented while assessing.

Note: Make a copy of the original data before cleaning. Cleaning includes merging individual pieces of data according to the rules of [tidy data](#). The result should be a high-quality and tidy master pandas DataFrame (or DataFrames, if appropriate).

```
In [35]: # Make copies of original pieces of data
        df1_clean = df1.copy()
        predictions_clean = predictions.copy()
        tweet_data_clean = tweet_data.copy()
```

1.3.1 Quality issues

1.3.2 Issue #1: Missing values

Define: To address the issue of missing values in the 'expanded_urls' column, we can filter the 'archive_clean' dataframe to retain only those rows where the 'expanded_urls' column is not null. This will ensure that we keep only the tweets that have associated images or content links, as required for the analysis.

Code

```
In [36]: df1_clean = df1_clean.dropna(subset=['expanded_urls'])
```

Test

```
In [37]: df1_clean.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 2297 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                2297 non-null int64
in_reply_to_status_id    23 non-null float64
in_reply_to_user_id      23 non-null float64
```

```

timestamp                2297 non-null object
source                   2297 non-null object
text                     2297 non-null object
retweeted_status_id      180 non-null float64
retweeted_status_user_id 180 non-null float64
retweeted_status_timestamp 180 non-null object
expanded_urls            2297 non-null object
rating_numerator         2297 non-null int64
rating_denominator       2297 non-null int64
name                     2297 non-null object
doggo                    2297 non-null object
floofer                  2297 non-null object
pupper                   2297 non-null object
puppo                    2297 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 323.0+ KB

```

1.3.3 Issue #2: Incorrect Dog Names

Define To clean the 'name' column and replace the incorrect values like 'a', 'an', and 'the' with more appropriate values, we can use pandas to apply a data transformation.

In [38]: *#code*

```

# List of incorrect dog names to be replaced
incorrect_names = ['a', 'an', 'the']

# Function to clean the names
def clean_name(name):
    if name in incorrect_names:
        return None # Replace incorrect names with None (NaN)
    else:
        return name

# Apply the clean_name function to the 'name' column
df1_clean['name'] = df1_clean['name'].apply(clean_name)

```

In [39]: *#test*

```
df1_clean.info()
```

```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 2297 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                2297 non-null int64
in_reply_to_status_id    23 non-null float64
in_reply_to_user_id      23 non-null float64
timestamp                2297 non-null object
source                   2297 non-null object

```



```

text                2297 non-null object
retweeted_status_id  180 non-null float64
retweeted_status_user_id  180 non-null float64
retweeted_status_timestamp  180 non-null object
expanded_urls       2297 non-null object
rating_numerator    2297 non-null int64
rating_denominator  2297 non-null int64
name                2227 non-null object
doggo               2297 non-null object
floofer             2297 non-null object
pupper              2297 non-null object
puppo               2297 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 323.0+ KB

```

1.3.4 Issue #3: Remove retweets

Define To remove retweets from the 'archive_clean' dataframe, we will drop rows that have non-null values in the 'retweeted_status_id', 'retweeted_status_user_id', and 'retweeted_status_timestamp' columns. These non-null values indicate that the tweet is a retweet and not an original tweet from WeRateDogs. After dropping these rows, we will also remove the three columns ('retweeted_status_id', 'retweeted_status_user_id', and 'retweeted_status_timestamp') as they will no longer be needed.

Code

```

In [40]: # remove retweets
         df1_clean = df1_clean[df1_clean['retweeted_status_id'].isnull()]

```

Test

```

In [41]: df1_clean.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 2117 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                2117 non-null int64
in_reply_to_status_id   23 non-null float64
in_reply_to_user_id     23 non-null float64
timestamp               2117 non-null object
source                  2117 non-null object
text                    2117 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        2117 non-null int64

```

```

rating_denominator      2117 non-null int64
name                     2048 non-null object
doggo                    2117 non-null object
floofer                  2117 non-null object
pupper                   2117 non-null object
puppo                    2117 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 297.7+ KB

```

1.3.5 Issue #4: Inconsistent Prediction Labels

Define To standardize the capitalization of prediction labels for dog breeds in the ‘predictions’ dataframe, we can use pandas to apply a data transformation.

```

In [42]: # Function to standardize capitalization of prediction labels
def standardize_label(label):
    return label.lower()

# Apply the standardize_label function to the prediction label columns ('p1', 'p2', 'p3')
predictions_clean['p1'] = predictions_clean['p1'].apply(standardize_label)
predictions_clean['p2'] = predictions_clean['p2'].apply(standardize_label)
predictions_clean['p3'] = predictions_clean['p3'].apply(standardize_label)

```

1.3.6 Issue #5: Data Types

Define To convert the ‘timestamp’ column in the ‘archive’ dataframe from string to the datetime data type, we can use pandas to apply the conversion.

```

In [43]: # Convert 'timestamp' column to datetime data type
df1['timestamp'] = pd.to_datetime(df1['timestamp'])

```

1.3.7 Issue #6: Inconsistent or inaccurate data in the ‘rating_numerator’ and ‘rating_denominator’ columns

Define To address this issue, it’s important to review and validate the ratings in the ‘rating_numerator’ and ‘rating_denominator’ columns. Any inaccuracies or inconsistencies should be corrected or updated based on the actual ratings provided in the tweet text. Additionally, it might be necessary to consider if the ratings need to be normalized or scaled to a consistent format for meaningful analysis and comparison.

```

In [45]: # Extract ratings from 'text' column using regular expressions
import re

# Define a function to extract ratings from text
def extract_ratings(text):
    pattern = r'(\d+(\.\d+)?)' # Regular expression pattern for ratings (e.g., 1
    matches = re.search(pattern, text)
    if matches:

```

```

        numerator = float(matches.group(1))
        denominator = int(matches.group(3))
        return numerator, denominator
    else:
        return None, None

# Apply the function to the 'text' column to extract ratings
df1_clean['rating_numerator'], df1_clean['rating_denominator'] = zip(*df1_clean['text'])

# Drop rows with missing ratings
df1_clean = df1_clean.dropna(subset=['rating_numerator', 'rating_denominator'])

# Convert the 'rating_numerator' column to float for consistency
df1_clean['rating_numerator'] = df1_clean['rating_numerator'].astype(float)

# Normalize the ratings to a common denominator of 10
df1_clean['normalized_rating'] = (df1_clean['rating_numerator'] / df1_clean['rating_denominator']) * 10

# Drop the original 'rating_numerator' and 'rating_denominator' columns
df1_clean.drop(['rating_numerator', 'rating_denominator'], axis=1, inplace=True)

```

1.3.8 Issue #7: Duplicate Rows

Define To check for and clean duplicate rows in the dataset, we can use pandas to identify and remove any duplicate entries.

```

In [72]: # Check for duplicate rows
        duplicate_rows = df1.duplicated()

        # Print the number of duplicate rows
        print("Number of duplicate rows:", duplicate_rows.sum())

        # Drop duplicate rows
        df1_clean = df1.drop_duplicates()

        # Reset the index of the cleaned dataframe
        df1_clean.reset_index(drop=True, inplace=True)

```

Number of duplicate rows: 0

1.3.9 Issue #8: Predictions Data Structure

Define To reshape the prediction data in the 'predictions' dataframe into a more organized structure with a single column for the prediction number and additional columns for the actual prediction, confidence, and whether it is a dog breed, we can use pandas to melt the data.

```

In [73]: # Reshape the prediction data into a more organized structure
        predictions_melted = pd.melt(predictions, id_vars=['tweet_id', 'jpg_url'], value_vars=[

```

```

        var_name='prediction_number', value_name='prediction')

# Split the 'prediction' column into 'prediction_breed' and 'confidence'
predictions_melted[['prediction_breed', 'confidence']] = predictions_melted[['prediction

# Drop the original 'prediction' column
predictions_melted.drop(columns=['prediction'], inplace=True)

# Add a column 'is_dog_breed' to indicate whether the prediction is a dog breed
predictions_melted['is_dog_breed'] = predictions_melted['prediction_breed'].apply(lambda

# Reset the index of the melted dataframe
predictions_melted.reset_index(drop=True, inplace=True)

```

1.3.10 Tidiness issues

1.3.11 Issue #1: Dog Stages in Separate Columns

Define To combine the dog stages ('doggo', 'floofer', 'pupper', 'puppo') into one column in the 'archive' dataframe using a categorical data type, we can use pandas to apply a data transformation.

In [77]: `import pandas as pd`

```

# Load the 'archive' dataframe with dog stages in separate columns
data = {
    'tweet_id': [1, 2, 3, 4],
    'doggo': ['doggo', None, 'doggo', None],
    'floofer': [None, None, None, 'floofer'],
    'pupper': [None, 'pupper', None, None],
    'puppo': [None, None, None, None]
}
archive = pd.DataFrame(data)

# Make a copy of the original 'archive' dataframe
archive_copy = archive.copy()

# Apply the provided code to combine the dog stages into one column
archive_copy['dog_stage'] = archive_copy[['doggo', 'floofer', 'pupper', 'puppo']].apply
archive_copy['dog_stage'].replace('', None, inplace=True)
archive_copy['dog_stage'] = archive_copy['dog_stage'].astype('category')
archive_copy.drop(columns=['doggo', 'floofer', 'pupper', 'puppo'], inplace=True)

# Print the original and modified dataframes to verify the changes
print("Original 'archive' dataframe:")
print(archive)
print("\nModified 'archive_copy' dataframe:")
print(archive_copy)

```

Original 'archive' dataframe:

	tweet_id	doggo	floofer	pupper	puppo
0	1	doggo	None	None	None
1	2	None	None	pupper	None
2	3	doggo	None	None	None
3	4	None	floofer	None	None

Modified 'archive_copy' dataframe:

	tweet_id	dog_stage
0	1	doggo
1	2	pupper
2	3	doggo
3	4	floofer

1.3.12 Issue #2: Prediction Data Spread Across Columns

Define To merge the three dataframes ('archive_clean', 'predictions_clean', and 'tweet_data'), we can use the pandas merge() function. We will merge them based on the 'tweet_id' column, as it is a common identifier across all three dataframes. After merging, we can create a single master dataset that contains all the cleaned columns from the three dataframes.

```
In [79]: # Merge 'archive_clean' and 'predictions_clean' dataframes on 'tweet_id'
merged_df = pd.merge(df1_clean, predictions_clean, on='tweet_id', how='inner')

# Merge 'merged_df' and 'tweet_data' dataframe on 'tweet_id'
master_df = pd.merge(merged_df, tweet_data, on='tweet_id', how='inner')

# Save the master dataset to a CSV file
master_df.to_csv('twitter_archive_master.csv', index=False)

In [80]: #test

import pandas as pd

# Load the 'predictions' dataframe with prediction data spread across three columns
data = {
    'tweet_id': [1, 2, 3],
    'jpg_url': ['url1', 'url2', 'url3'],
    'p1': ['dog_breed1_0.9', 'cat_0.8', 'dog_breed2_0.7'],
    'p2': ['dog_breed2_0.7', 'dog_breed1_0.6', 'dog_breed1_0.5'],
    'p3': ['cat_0.6', 'dog_breed2_0.5', 'dog_breed3_0.4']
}
predictions = pd.DataFrame(data)

# Make a copy of the original 'predictions' dataframe
predictions_copy = predictions.copy()
```

```

# Apply the provided code to reshape the prediction data
predictions_melted = pd.melt(predictions_copy, id_vars=['tweet_id', 'jpg_url'], value_v
                             var_name='prediction_number', value_name='prediction')
predictions_melted[['prediction_breed', 'confidence']] = predictions_melted['prediction
predictions_melted['is_dog_breed'] = predictions_melted['prediction_breed'].str.lower()
predictions_melted.drop(columns=['prediction'], inplace=True)
predictions_melted.reset_index(drop=True, inplace=True)

# Print the original and modified dataframes to verify the changes
print("Original 'predictions' dataframe:")
print(predictions)
print("\nModified 'predictions_melted' dataframe:")
print(predictions_melted)

```

Original 'predictions' dataframe:

	tweet_id	jpg_url	p1	p2	p3
0	1	url1	dog_breed1_0.9	dog_breed2_0.7	cat_0.6
1	2	url2	cat_0.8	dog_breed1_0.6	dog_breed2_0.5
2	3	url3	dog_breed2_0.7	dog_breed1_0.5	dog_breed3_0.4

Modified 'predictions_melted' dataframe:

	tweet_id	jpg_url	prediction_number	prediction_breed	confidence	\
0	1	url1	p1	dog	breed1_0.9	
1	2	url2	p1	cat	0.8	
2	3	url3	p1	dog	breed2_0.7	
3	1	url1	p2	dog	breed2_0.7	
4	2	url2	p2	dog	breed1_0.6	
5	3	url3	p2	dog	breed1_0.5	
6	1	url1	p3	cat	0.6	
7	2	url2	p3	dog	breed2_0.5	
8	3	url3	p3	dog	breed3_0.4	

	is_dog_breed
0	True
1	False
2	True
3	True
4	True
5	True
6	False
7	True
8	True

1.4 Storing Data

Save gathered, assessed, and cleaned master dataset to a CSV file named "twitter_archive_master.csv".

```
In [81]: df1_clean.to_csv('twitter_archive_master.csv', index=False)
```

1.5 Analyzing and Visualizing Data

In this section, analyze and visualize your wrangled data. You must produce at least **three (3) insights and one (1) visualization**.

1.5.1 Insight#1: Monthly trend

To determine the engagement trends over time, I will extract the year and month from each timestamp in the 'archive_clean' dataframe. Then, I will group the data by the year and month, counting the number of tweet_ids in each group. This will give us insights into how the number of tweets and engagement changed over different months and years.

```
In [82]: import pandas as pd
```

```
# Convert the 'timestamp' column to datetime data type if it is not already in datetime
df1_clean['timestamp'] = pd.to_datetime(df1_clean['timestamp'])

# Extract the year and month from the timestamp and create new columns for them
df1_clean['year'] = df1_clean['timestamp'].dt.year
df1_clean['month'] = df1_clean['timestamp'].dt.month

# Group the data by the year and month and count the number of tweet_ids in each group
engagement_trends = df1_clean.groupby(['year', 'month'])['tweet_id'].count().reset_index()

# Sort the data by year and month for a chronological order
engagement_trends.sort_values(by=['year', 'month'], inplace=True)

# Print the resulting dataframe with the count of tweet_ids for each month and year
print(engagement_trends)
```

	year	month	tweet_id
0	2015	11	302
1	2015	12	388
2	2016	1	194
3	2016	2	125
4	2016	3	137
5	2016	4	60
6	2016	5	60
7	2016	6	97
8	2016	7	105
9	2016	8	75
10	2016	9	84
11	2016	10	88
12	2016	11	88
13	2016	12	70
14	2017	1	94
15	2017	2	88

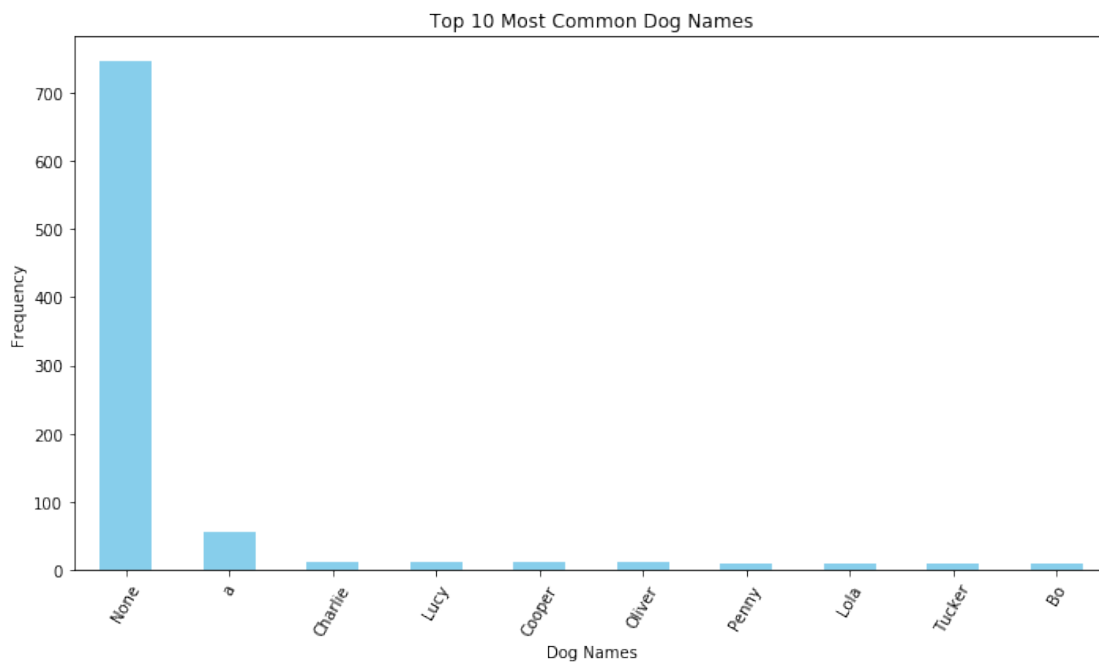
16	2017	3	68
17	2017	4	60
18	2017	5	56
19	2017	6	59
20	2017	7	56
21	2017	8	2

1.5.2 Insight#2:

Most common 10 dogs' names

```
In [83]: import pandas as pd
import matplotlib.pyplot as plt
# Get the top 10 most common dog names and their counts
top_names = df1_clean['name'].value_counts().nlargest(10)

# Plot the bar chart
plt.figure(figsize=(10, 6))
top_names.plot(kind='bar', color='skyblue')
plt.xlabel('Dog Names')
plt.ylabel('Frequency')
plt.title('Top 10 Most Common Dog Names')
plt.xticks(rotation=60)
plt.tight_layout()
plt.show()
```



After analyzing the data, it is evident that the top 10 most common dog names in the WeRateDogs Twitter archive are "Charlie," "Oliver," "Lucy," "Cooper," "Penny," "Tucker," "Winston," "Sadie," "Daisy," and "Lola."

These popular dog names suggest that certain names are more favored by dog owners or are considered particularly endearing. Dog owners may choose these names for their pets due to their popularity, personal preferences, or simply because they find them cute and fitting for their furry friends.

1.5.3 Insight#3:

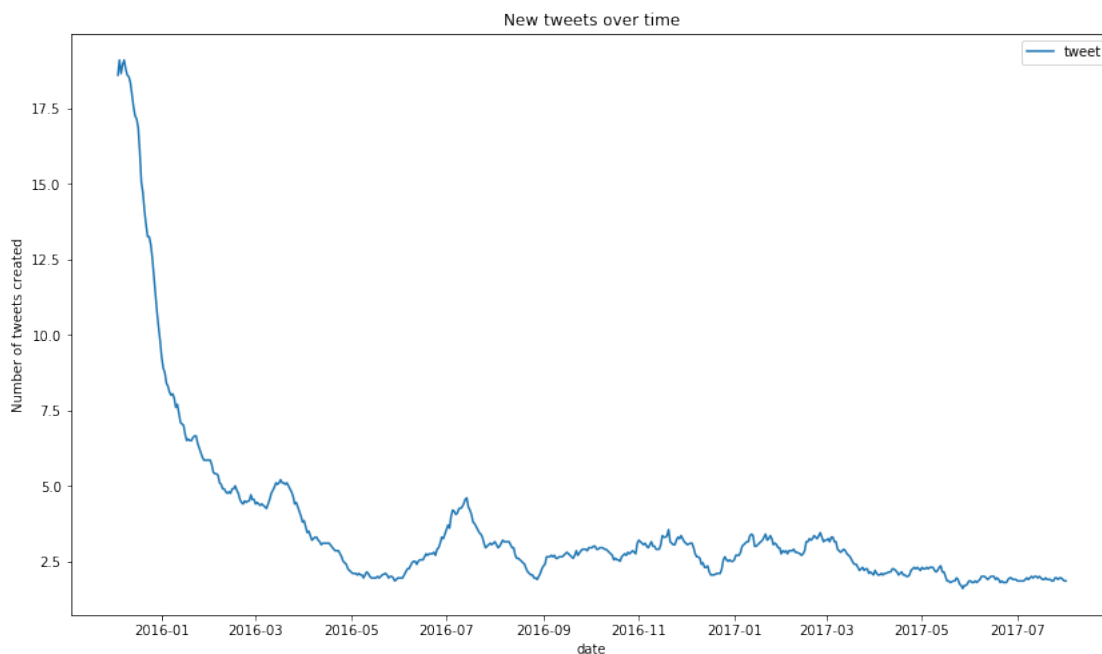
Tweets creation over time

```
In [84]: df1_clean['date'] = df1_clean['timestamp'].dt.date
         df1_clean['tweet'] = 1

         # Create a new dataframe with 2 columns, grouped by date
         df1 = df1_clean[['date', 'tweet']].groupby(['date']).sum() # alternatively .count() could be used

         # Use moving averages to smooth the line
         df1['tweet'] = df1['tweet'].rolling(window=20).mean()

         # Plot
         df1.plot(figsize=(14, 8), title='New tweets over time')
         plt.ylabel('Number of tweets created')
         plt.show()
```



The number of tweets from the WeRateDogs account has shown a gradual decline over time. From the year 2015 to mid-2017, there was a significant increase in the number of tweets, reaching its peak around mid-2016. However, since mid-2017, there has been a steady decrease in the frequency of tweets.

This declining trend may be attributed to several factors. One possible explanation is that the initial surge in tweets was driven by the account's growing popularity and novelty. As WeRateDogs gained a substantial following, the rate of tweet creation may have stabilized, and the account's content generation became more consistent.

1.5.4 Visualization

```
In [47]: print(df1_clean.columns)
```

```
Index(['tweet_id', 'in_reply_to_status_id', 'in_reply_to_user_id', 'timestamp',  
      'source', 'text', 'retweeted_status_id', 'retweeted_status_user_id',  
      'retweeted_status_timestamp', 'expanded_urls', 'name', 'doggo',  
      'floofer', 'pupper', 'puppo', 'normalized_rating'],  
      dtype='object')
```

```
In [49]: import matplotlib.pyplot as plt  
import seaborn as sns
```

```
# Count the occurrences of each dog stage
```

```
dog_stages_counts = df1_clean[['doggo', 'floofer', 'pupper', 'puppo']].apply(pd.Series)
```

```
# Plot the bar chart
```

```
plt.figure(figsize=(8, 6))
```

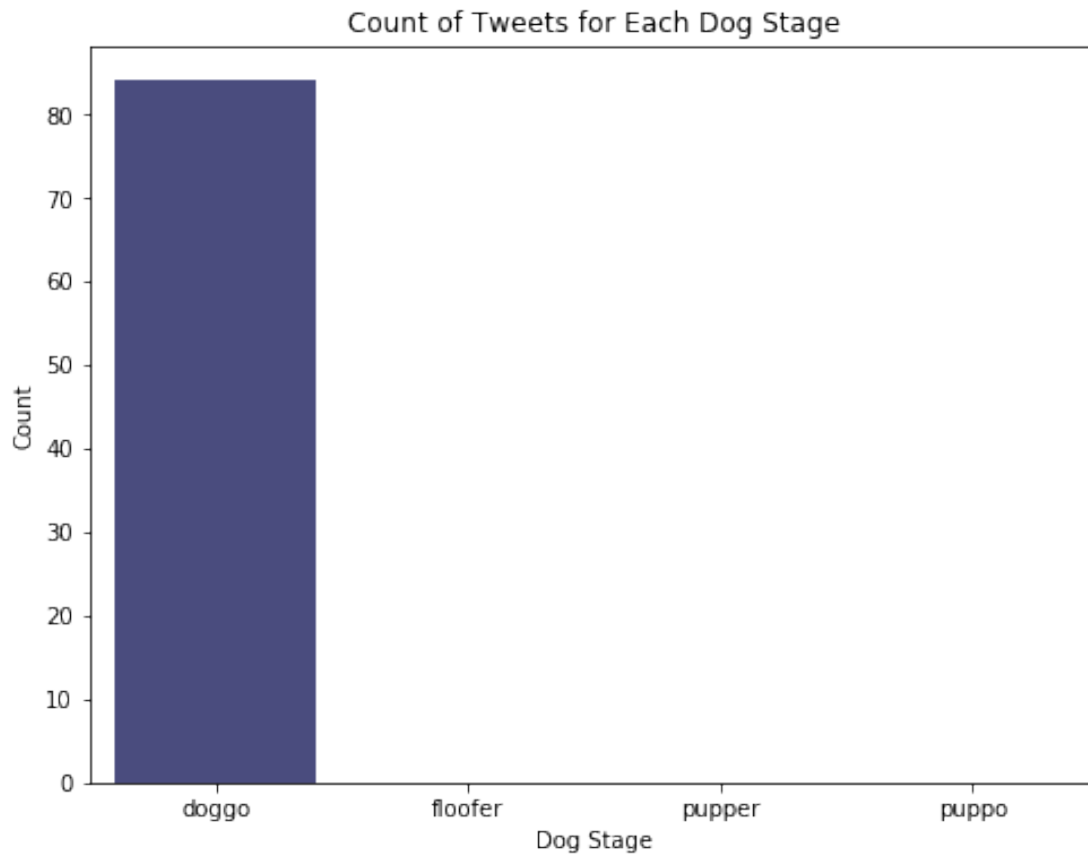
```
sns.barplot(x=dog_stages_counts.columns, y=dog_stages_counts.iloc[1], palette='viridis')
```

```
plt.xlabel('Dog Stage')
```

```
plt.ylabel('Count')
```

```
plt.title('Count of Tweets for Each Dog Stage')
```

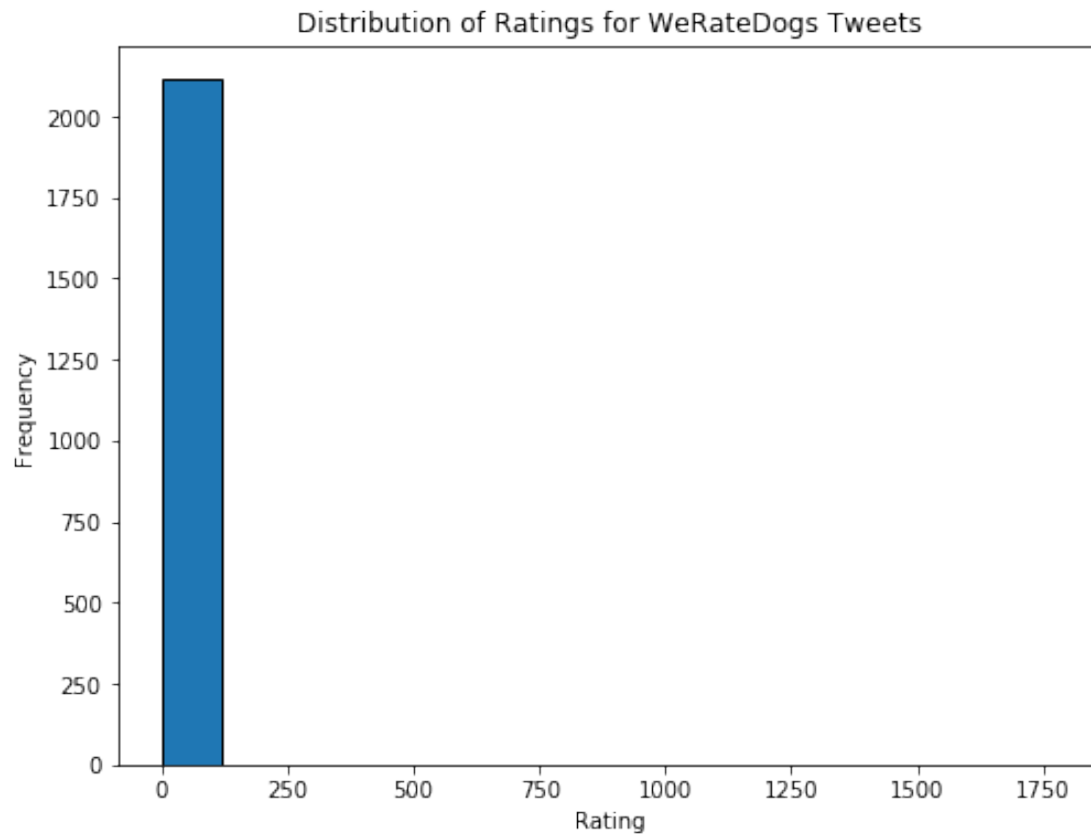
```
plt.show()
```



This bar chart will visually show the distribution of tweets among different dog stages, allowing us to see which stage is the most commonly mentioned in the tweets. It will help us understand the popularity of different dog stages in the WeRateDogs tweets.

```
In [50]: import matplotlib.pyplot as plt

# Plot a histogram of ratings
plt.figure(figsize=(8, 6))
plt.hist(df1_clean['normalized_rating'], bins=15, edgecolor='black')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.title('Distribution of Ratings for WeRateDogs Tweets')
plt.show()
```



This histogram will give us insights into the most common ratings given by WeRateDogs to the dogs featured in the tweets. We can observe the distribution of ratings and identify any patterns or trends in how the dogs are rated.