Project: Wrangling and Analyze Data

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Introduction

The dataset I'll be wrangling is from the tweet archive of this Twitter user @dog_rates, also known as WeRateDogs. WeRateDogs is a Twitter account that rates people's dogs with humorous comment about the dogs.

The wrangling process will involve:

1. Gathering data
2. Assessing data
3. Cleaning data
4. Storing data

Data Gathering

Data will be gathered from three (3) sources for this project:

> The first file is a Twitter archive data (csv file), which I'll directly download, upload and read into a pandas dataframe
>
> For the second file, I'll use the Requests library to programmatically download the tweet image prediction (image_predictions.tsv) from a neural network hosted on Udacity's servers
>
> Finally, for the last file, I'll use the Tweepy library to query additional data through the Twitter API for each tweet's JSON data and store each tweet's entire set of JSON data in a file called tweet_json.txt file.

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

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

In [2]:
```
twitter_archive_df = pd.read_csv('twitter-archive-enhanced.csv')

twitter_archive_df.head()
```

Out[2]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	source

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

Data inspection

In [3]:
```
twitter_archive_df.info()
```

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

In [4]:
```
twitter_archive_df['rating_numerator'].unique()
```

Out[4]:
```
array([  13,   12,   14,    5,   17,   11,   10,  420,  666,    6,   15,
        182,  960,    0,   75,    7,   84,    9,   24,    8,    1,   27,
          3,    4,  165, 1776,  204,   50,   99,   80,   45,   60,   44,
        143,  121,   20,   26,    2,  144,   88], dtype=int64)
```

In [5]:
```
twitter_archive_df['rating_denominator'].unique()
```

Out[5]:
```
array([ 10,   0,  15,  70,   7,  11, 150, 170,  20,  50,  90,  80,  40,
       130, 110,  16, 120,   2], dtype=int64)
```

In [14]:
```
# row with invalid denominator rating of zero (0)

twitter_archive_df[twitter_archive_df['rating_denominator']==0]
```

Out[14]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	sourc
313	835246439529840640	8.352460e+17	26259576.0	2017-02-24 21:54:03 +0000	< href="http://twitter.com/download/iphone r

In [18]:
```
# Some invalid data are seen as names

twitter_archive_df['name'].sample(5)
```

Out[18]:
```
1936     one
807     None
1198    Link
1106    None
497     None
Name: name, dtype: object
```

In [19]:
```
# Some texts are retweets and not original tweets, an example can be seen in entry 818

twitter_archive_df['text'].sample(5)
```

Out[19]:
```
206     This is Aspen. She's never tasted a stick so s...
2185    This is Ruby. She's a Bimmington Fettuccini. O...
1282    This is Coco. She gets to stay on the Bachelor...
1126    Say hello to Ollie. He conducts this train. He...
818     RT @dog_rates: Here's a doggo blowing bubbles....
Name: text, dtype: object
```

In [6]:
```
# Displaying rows that contain retweet in their texts

twitter_archive_df.loc[twitter_archive_df['text'].str.contains('RT')].head()
```

Out[6]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	source
19	888202515573088257	NaN	NaN	2017-07-21 01:02:36 +0000	<a href="http://twitter.com/download/iphone" r..
32	886054160059072513	NaN	NaN	2017-07-15 02:45:48 +0000	<a href="http://twitter.com/download/iphone" r..
36	885311592912609280	NaN	NaN	2017-07-13 01:35:06 +0000	<a href="http://twitter.com/download/iphone" r..

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	source
68	879130579576475649	NaN	NaN	2017-06-26 00:13:58 +0000	<a href="http://twitter.com/download/iphone" r..
73	878404777348136964	NaN	NaN	2017-06-24 00:09:53 +0000	<a href="http://twitter.com/download/iphone" r..

In [7]:
```
# No duplicated data is seen in the dataset

twitter_archive_df.duplicated().sum()
```

Out[7]:
```
0
```

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

In [3]:
```
response = requests.get('https://d17h27t6h515a5.cloudfront.net/topher/2017/August/599fd2ac

with open('image_predictions.tsv', 'w') as f:
    f.write(response.text)
image_prediction_df = pd.read_csv('image_predictions.tsv', sep = '\t')

image_prediction_df1 = image_prediction_df.copy()
image_prediction_df.head()
```

Out[3]:

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

Data inspection

In [9]:
```
image_prediction_df.info()
```

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

```
 10  p3_conf    2075 non-null   float64
 11  p3_dog     2075 non-null   bool
dtypes: bool(3), float64(3), int64(2), object(4)
memory usage: 152.1+ KB
```

In [10]:
```
image_prediction_df.duplicated().sum()
```

Out[10]:
```
0
```

In [11]:
```
image_prediction_df['p1_dog'].unique()
```

Out[11]:
```
array([ True, False])
```

In [12]:
```
image_prediction_df['p1_conf'].unique()
```

Out[12]:
```
array([0.465074 , 0.506826 , 0.596461 , ..., 0.716012 , 0.323581 ,
       0.0970486])
```

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

In [ ]:
```
import tweepy
from tweepy import OAuthHandler
import json
from timeit import default_timer as timer

# Query Twitter API for each tweet in the Twitter archive and save JSON in a text file
# These are hidden to comply with Twitter's API terms and conditions
consumer_key = 'HIDDEN'
consumer_secret = 'HIDDEN'
access_token = 'HIDDEN'
access_secret = 'HIDDEN'

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

api = tweepy.API(auth, wait_on_rate_limit=True)

# NOTE TO STUDENT WITH MOBILE VERIFICATION ISSUES:
# df_1 is a DataFrame with the twitter_archive_enhanced.csv file. You may have to
# change line 17 to match the name of your DataFrame with twitter_archive_enhanced.csv
# NOTE TO REVIEWER: this student had mobile verification issues so the following
# Twitter API code was sent to this student from a Udacity instructor
# Tweet IDs for which to gather additional data via Twitter's API
tweet_ids = df.tweet_id.values
len(tweet_ids)

# Query Twitter's API for JSON data for each tweet ID in the Twitter archive
count = 0
fails_dict = {}
start = timer()
# Save each tweet's returned JSON as a new line in a .txt file
with open('tweet_json.txt', 'w') as outfile:
    # This loop will likely take 20-30 minutes to run because of Twitter's rate limit
    for tweet_id in tweet_ids:
        count += 1
        print(str(count) + ": " + str(tweet_id))
        try:
            tweet = api.get_status(tweet_id, tweet_mode='extended')
            print("Success")
```

```
            json.dump(tweet._json, outfile)
            outfile.write('\n')
        except tweepy.TweepError as e:
            print("Fail")
            fails_dict[tweet_id] = e
            pass
end = timer()
print(end - start)
print(fails_dict)
```

In [5]:

```
with open ('tweet_json.txt', encoding = "utf-8") as f:
    tweet_json_df = pd.DataFrame(pd.json_normalize([json.loads(line) for line in f.readlin

tweet_json_df1 = tweet_json_df.copy()
tweet_json_df.head()
```

Out[5]:

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

Data inspection

In [16]:

```
tweet_json_df.info()
```

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

Assessing Data

In this section, I detected and documented at least **eight (8) quality issues and two (2) tidiness issue**, using **both** visual assessment and programmatic assessement to assess the data.

Quality issues

1. Presence of 'None' for missing records, instead of pandas 'NaN'
2. From Twitter archive data: invalid data in the 'name' column like 'an', 'a', 'such', 'quite', and so on
3. Inconsistent data types in the 'retweeted_status_timestamp' column
4. 'tweet_id' column contains integer data type which might distort analysis

5. The 'text' column contains both original tweets and retweets, while we were required to work with just original tweets

6. Row contains invalid denominator rating of zero (0)

7. Most of the column headers especially in the 'image_prediction' data set are not quite descriptive like 'p1_conf', 'p1_dog', 'p2', and the rest of them

8. Presence of retweet columns that won't be needed

Tidiness issues

1. Combining the three(3) dataframes: Difference in column header names containing same data ('twitter_id' and 'id'), which will be an issue in merging the data sets

2. Separate columns for the dog stages

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).

Make copies of original pieces of data

In [17]:
```
twitter_archive_df1 = twitter_archive_df.copy()
image_prediction_df1 = image_prediction_df.copy()
tweet_json_df1 = tweet_json_df.copy()
```

Issue #1:

Define: Combining the three(3) dataframes: Difference in column header names containing same data ('tweet_id' and 'id'), which will be an issue in merging the data sets

Code :

> ### Renaming the "id" column in the tweet_json dataframe to "tweet_id" for uniformity

In [18]:
```
tweet_json_df1.rename(columns={'id':'tweet_id'}, inplace=True)
tweet_json_df1.head()
```

Out[18]:

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

Merging the 3 dataframes

In [19]:
```
twitter_archive_master = pd.merge(twitter_archive_df1, image_prediction_df1, on='tweet_id'
twitter_archive_master = pd.merge(twitter_archive_master, tweet_json_df1, on='tweet_id')
twitter_archive_master.head()
```

Out[19]:

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

5 rows × 30 columns

Test

In [20]:
```
twitter_archive_master.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2073 entries, 0 to 2072
Data columns (total 30 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   tweet_id                    2073 non-null   int64  
 1   in_reply_to_status_id       23 non-null     float64
 2   in_reply_to_user_id         23 non-null     float64
 3   timestamp                   2073 non-null   object 
 4   source                      2073 non-null   object 
 5   text                        2073 non-null   object 
 6   retweeted_status_id         79 non-null     float64
 7   retweeted_status_user_id    79 non-null     float64
 8   retweeted_status_timestamp  79 non-null     object 
 9   expanded_urls               2073 non-null   object 
 10  rating_numerator            2073 non-null   int64  
 11  rating_denominator          2073 non-null   int64  
 12  name                        2073 non-null   object 
```

```
 13  doggo                       2073 non-null   object
 14  floofer                     2073 non-null   object
 15  pupper                      2073 non-null   object
 16  puppo                       2073 non-null   object
 17  jpg_url                     2073 non-null   object
 18  img_num                     2073 non-null   int64
 19  p1                          2073 non-null   object
 20  p1_conf                     2073 non-null   float64
 21  p1_dog                      2073 non-null   bool
 22  p2                          2073 non-null   object
 23  p2_conf                     2073 non-null   float64
 24  p2_dog                      2073 non-null   bool
 25  p3                          2073 non-null   object
 26  p3_conf                     2073 non-null   float64
 27  p3_dog                      2073 non-null   bool
 28  favorite_count              2073 non-null   int64
 29  retweet_count               2073 non-null   int64
dtypes: bool(3), float64(7), int64(6), object(14)
memory usage: 459.5+ KB
```

Issue #2:

Define: Presence of 'None' for missing records, instead of pandas 'NaN'

Code :

> #### Replacing 'None' with pandas 'NaN'

In [21]:
```
twitter_archive_master.replace(to_replace="None", value=np.nan, inplace=True)
```

Test

In [22]:
```
twitter_archive_master.sample(3)
```

Out[22]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	sou
1576	675781562965868544	NaN	NaN	2015-12-12 20:57:34 +0000	href="http://twitter.com/download/iphor
1005	715733265223708672	NaN	NaN	2016-04-01 02:51:22 +0000	href="http://twitter.com/download/iphor
1577	675740360753160193	NaN	NaN	2015-12-12 18:13:51 +0000	href="http://twitter.com/download/iphor

3 rows × 30 columns

Issue #3:

Define: Separate columns for the dog stages

Code :

> Summing the different dog stages column into one

In [23]:
```
twitter_archive_master['dog_stages']= twitter_archive_master['floofer'].fillna('') + twitt

twitter_archive_master['dog_stages'].replace(to_replace='', value=np.nan, inplace=True)

twitter_archive_master.drop(['floofer', 'doggo','pupper', 'puppo'], axis=1, inplace=True )
```

Test

In [24]:
```
twitter_archive_master['dog_stages'].unique()
```

Out[24]:
```
array([nan, 'doggo', 'puppo', 'pupper', 'floofer', 'doggopuppo',
       'flooferdoggo', 'doggopupper'], dtype=object)
```

Issue #4:

Define: Invalid data in the 'name' column like 'an', 'a', 'such', 'quite', and so on

Code :

> Using regular expressions to correctly extract the dog names from the 'text' column and store them in a new column

In [25]:
```
twitter_archive_master['this_is'] = twitter_archive_master['text'].str.extract(r'(?<=This

twitter_archive_master['meet'] = twitter_archive_master['text'].str.extract(r'(?<=Meet )(

twitter_archive_master['here_is'] = twitter_archive_master['text'].str.extract(r'(?<=Here

twitter_archive_master['name_is'] = twitter_archive_master['text'].str.extract(r'(?<=Name

twitter_archive_master['that_is'] = twitter_archive_master['text'].str.extract(r'(?<=That

twitter_archive_master['say_hello_to'] = twitter_archive_master['text'].str.extract(r'(?<=

twitter_archive_master['new_names'] = twitter_archive_master['meet'].fillna('') + twitter_

twitter_archive_master['new_names'].replace(to_replace='', value=np.nan, inplace=True)

twitter_archive_master.drop(['this_is', 'meet','here_is', 'name_is', 'that_is', 'say_hello
```

Test

In [26]:
```
twitter_archive_master['new_names'].unique()
```

Out[26]:
```
array(['Phineas', 'Tilly', 'Archie', 'Darla', 'Franklin', nan, 'Jax',
       'Zoey', 'Cassie', 'Koda', 'Bruno', 'Ted', 'Stuart', 'Oliver',
       'Jim', 'Zeke', 'Ralphus', 'Gerald', 'Jeffrey', 'Canela', 'Maya',
       'Mingus', 'Derek', 'Roscoe', 'Waffles', 'Jimbo', 'Maisey', 'Lilly',
       'Earl', 'Lola', 'Kevin', 'Yogi', 'Noah', 'Bella', 'Grizzwald',
       'Rusty', 'Gus', 'Stanley', 'Alfy', 'Koko', 'Rey', 'Gary', 'Elliot',
       'Louis', 'Jesse', 'Romeo', 'Bailey', 'Duddles', 'Jack', 'Steven',
       'BeauBeau', 'Snoopy', 'Shadow', 'Emmy', 'Aja', 'Penny', 'Dante',
       'Nelly', 'Ginger', 'Benedict', 'Venti', 'Goose', 'Nugget', 'Cash',
       'Jed', 'Sebastian', 'Walter', 'Sierra', 'Monkey', 'Harry', 'Kody',
       'Lassie', 'Rover', 'Napolean', 'Boomer', 'Cody', 'Rumble',
```

'Clifford', 'Dewey', 'Scout', 'Gizmo', 'Cooper', 'Harold',
'Shikha', 'Lili', 'Jamesy', 'Coco', 'Sammy', 'Meatball', 'Paisley',
'Albus', 'Neptune', 'Belle', 'Quinn', 'Zooey', 'Dave', 'Jersey',
'Hobbes', 'Burt', 'Lorenzo', 'Carl', 'Jordy', 'Milky', 'Trooper',
'Sophie', 'Wyatt', 'Rosie', 'Thor', 'Oscar', 'Callie', 'Cermet',
'Marlee', 'Arya', 'Einstein', 'Alice', 'Rumpole', 'Benny', 'Aspen',
'Jarod', 'Wiggles', 'General', 'Sailor', 'Astrid', 'Iggy', 'Snoop',
'Kyle', 'Leo', 'Riley', 'Noosh', 'Odin', 'Jerry', 'Georgie',
'Rontu', 'Cannon', 'Furzey', 'Daisy', 'Tuck', 'Barney', 'Vixen',
'Jarvis', 'Mimosa', 'Pickles', 'Brady', 'Luna', 'Charlie', 'Margo',
'Sadie', 'Hank', 'Tycho', 'Stephan', 'Indie', 'Winnie', 'George',
'Bentley', 'Ken', 'Max', 'Dawn', 'Maddie', 'Monty', 'Sojourner',
'Winston', 'Odie', 'Arlo', 'Vincent', 'Lucy', 'Clark', 'Mookie',
'Meera', 'Ava', 'Eli', 'Ash', 'Tucker', 'Tobi', 'Chester',
'Wilson', 'Sunshine', 'Lipton', 'Bronte', 'Poppy', 'Gidget',
'Rhino', 'Willow', 'Orion', 'Eevee', 'Smiley', 'Moreton', 'Klein',
'Miguel', 'Emanuel', 'Kuyu', 'Dutch', 'Pete', 'Scooter', 'Reggie',
'Samson', 'Loki', 'Mia', 'Malcolm', 'Dexter', 'Alfie', 'Fiona',
'Mutt', 'Bear', 'Doobert', 'Beebop', 'Alexander', 'Sailer',
'Brutus', 'Kona', 'Boots', 'Ralphie', 'Cupid', 'Pawnd', 'Pilot',
'Ike', 'Mo', 'Toby', 'Sweet', 'Pablo', 'Nala', 'Crawford', 'Gabe',
'Jimison', 'Hercules', 'Duchess', 'Harlso', 'Sundance', 'Luca',
'Flash', 'Sunny', 'Peaches', 'Howie', 'Jazzy', 'Anna', 'Finn',
'Bo', 'Wafer', 'Chelsea', 'Tom', 'Florence', 'Autumn', 'Buddy',
'Dido', 'Eugene', 'Strudel', 'Tebow', 'Chloe', 'Betty', 'Timber',
'Binky', 'Moose', 'Dudley', 'Comet', 'Larry', 'Akumi', 'Titan',
'Olivia', 'Alf', 'Oshie', 'Bruce', 'Chubbs', 'Sky', 'Atlas',
'Eleanor', 'Layla', 'Rocky', 'Baron', 'Tyr', 'Bauer', 'Swagger',
'Brandi', 'Mary', 'Moe', 'Halo', 'Augie', 'Craig', 'Sam', 'Hunter',
'Pavlov', 'Phil', 'Maximus', 'Kyro', 'Wallace', 'Ito', 'Milo',
'Ollie', 'Cali', 'Lennon', 'Major', 'Duke', 'Sansa', 'Shooter',
'Django', 'Diogi', 'Sonny', 'Marley', 'Severus', 'Ronnie', 'Bones',
'Mauve', 'Chef', 'Sampson', 'Doc', 'Sobe', 'Longfellow', 'Mister',
'Iroh', 'Stubert', 'Paull', 'Davey', 'Pancake', 'Snicku', 'Ruby',
'Brody', 'Rizzy', 'Mack', 'Butter', 'Nimbus', 'Laika', 'Dobby',
'Juno', 'Maude', 'Lily', 'Newt', 'Benji', 'Nida', 'Robin',
'Monster', 'BeBe', 'Remus', 'Levi', 'Mabel', 'Misty', 'Happy',
'Mosby', 'Maggie', 'Brownie', 'Stella', 'Frank', 'Tonks',
'Lincoln', 'Rory', 'Logan', 'Dale', 'Rizzo', 'Mattie', 'Pinot',
'Dallas', 'Hero', 'Frankie', 'Stormy', 'Mairi', 'Loomis', 'Godi',
'Kenny', 'Deacon', 'Timmy', 'Harper', 'Chipson', 'Oakley', 'Dash',
'Bell', 'Jay', 'Mya', 'Strider', 'Wesley', 'Arnie', 'Solomon',
'Huck', 'O', 'Blue', 'Anakin', 'Finley', 'Sprinkles', 'Heinrich',
'Shakespeare', 'Bungalo', 'Chip', 'Grey', 'Roosevelt', 'Gromit',
'Willem', 'Dakota', 'Fizz', 'Dixie', 'Al', 'Jackson', 'Carbon',
'DonDon', 'Kirby', 'Lou', 'Chevy', 'Tito', 'Philbert', 'Louie',
'Rupert', 'Rufus', 'Brudge', 'Shadoe', 'Colby', 'Angel', 'Brat',
'Tove', 'Aubie', 'Kota', 'Leela', 'Glenn', 'Shelby', 'Sephie',
'Bonaparte', 'Albert', 'Wishes', 'Rose', 'Theo', 'Rocco', 'Fido',
'Emma', 'Spencer', 'Lilli', 'Boston', 'Brandonald', 'Corey',
'Leonard', 'Chompsky', 'Beckham', 'Devón', 'Gert', 'Watson',
'Rubio', 'Keith', 'Dex', 'Ace', 'Tayzie', 'Grizzie', 'Gilbert',
'Meyer', 'Zoe', 'Stewie', 'Calvin', 'Lilah', 'Spanky', 'Jameson',
'Beau', 'Piper', 'Atticus', 'Blu', 'Dietrich', 'Divine', 'Tripp',
'Quizno', 'Cora', 'Huxley', 'Bookstore', 'Abby', 'Shiloh',
'Gustav', 'Arlen', 'Percy', 'Lenox', 'Sugar', 'Harvey', 'Blanket',
'Geno', 'Stark', 'Beya', 'Kilo', 'Kayla', 'Maxaroni', 'Doug',
'Edmund', 'Aqua', 'Theodore', 'Baloo', 'Chase', 'Nollie', 'Rorie',
'Simba', 'Charles', 'Bayley', 'Axel', 'Storkson', 'Remy',
'Chadrick', 'Kellogg', 'Buckley', 'Livvie', 'Terry', 'Hermione',
'Ralpher', 'Aldrick', 'Rooney', 'Crystal', 'Ziva', 'Stefan',
'Pupcasso', 'Puff', 'Flurpson', 'Coleman', 'Enchilada', 'Raymond',
'Rueben', 'Cilantro', 'Karll', 'Sprout', 'Blitz', 'Bloop',
'Lillie', 'Fred', 'Ashleigh', 'Kreggory', 'Sarge', 'Luther',
'Reginald', 'Ivar', 'Jangle', 'Schnitzel', 'Panda', 'Berkeley',
'Ralphé', 'Charleson', 'Clyde', 'Harnold', 'Sid', 'Pippa', 'Otis',

```
'Carper', 'Bowie', 'Alexanderson', 'Suki', 'Barclay', 'Ebby',
'Flávio', 'Smokey', 'Link', 'Jennifur', 'Bluebert', 'Stephanus',
'Bubbles', 'Zeus', 'Bertson', 'Nico', 'Michelangelope', 'Siba',
'Calbert', 'Curtis', 'Travis', 'Thumas', 'Kanu', 'Lance', 'Opie',
'Kane', 'Olive', 'Chuckles', 'Staniel', 'Sora', 'Beemo', 'Gunner',
'Lacy', 'Tater', 'Olaf', 'Cecil', 'Vince', 'Karma', 'Billy',
'Walker', 'Rodney', 'Klevin', 'Malikai', 'Bobble', 'River',
'Jebberson', 'Remington', 'Farfle', 'Jiminus', 'Keurig', 'Clarkus',
'Finnegus', 'Cupcake', 'Kathmandu', 'Ellie', 'Katie', 'Kara',
'Adele', 'Zara', 'Ambrose', 'Jimothy', 'Bode', 'Terrenth', 'Reese',
'Chesterson', 'Lucia', 'Bisquick', 'Ralphson', 'Socks', 'Rambo',
'Fiji', 'Rilo', 'Bilbo', 'Coopson', 'Yoda', 'Millie', 'Chet',
'Crouton', 'Daniel', 'Kaia', 'Murphy', 'Dotsy', 'Eazy', 'Coops',
'Fillup', 'Miley', 'Charl', 'Reagan', 'CeCe', 'Cuddles', 'Claude',
'Jessiga', 'Carter', 'Ole', 'Blipson', 'Reptar', 'Trevith', 'Berb',
'Bob', 'Colin', 'Brian', 'Oliviér', 'Grady', 'Kobe', 'Freddery',
'Bodie', 'Dunkin', 'Wally', 'Tupawc', 'Amber', 'Herschel', 'Edgar',
'Kingsley', 'Brockly', 'Richie', 'Molly', 'Vinscent', 'Cedrick',
'Hazel', 'Lolo', 'Eriq', 'Phred', 'Maxwell', 'Geoff', 'Covach',
'Durg', 'Fynn', 'Ricky', 'Herald', 'Lucky', 'Trip', 'Clarence',
'Hamrick', 'Brad', 'Pubert', 'Frönq', 'Derby', 'Lizzie', 'Blakely',
'Opal', 'Marq', 'Kramer', 'Tyrone', 'Gordon', 'Baxter', 'Mona',
'Horace', 'Crimson', 'Birf', 'Hammond', 'Lorelei', 'Marty',
'Brooks', 'Petrick', 'Hubertson', 'Gerbald', 'Oreo', 'Bruiser',
'Perry', 'Bobby', 'Jeph', 'Obi', 'Tino', 'Kulet', 'Lupe', 'Tiger',
'Jiminy', 'Griffin', 'Banjo', 'Brandy', 'Lulu', 'Darrel', 'Taco',
'Joey', 'Patrick', 'Kreg', 'Todo', 'Tess', 'Ulysses', 'Toffee',
'Apollo', 'Carly', 'Asher', 'Glacier', 'Chuck', 'Champ', 'Ozzie',
'Griswold', 'Cheesy', 'Moofasa', 'Hector', 'Goliath', 'Kawhi',
'Ozzy', 'Emmie', 'Penelope', 'Willie', 'Rinna', 'Mike', 'William',
'Dwight', 'Evy', 'Hurley', 'Linda', 'Tug', 'Tango', 'Grizz',
'Jerome', 'Crumpet', 'Jessifer', 'Ralph', 'Sandy', 'Humphrey',
'Tassy', 'Juckson', 'Chuq', 'Tyrus', 'Karl', 'Godzilla', 'Vinnie',
'Kenneth', 'Herm', 'Bert', 'Striker', 'Donny', 'Pepper', 'Bernie',
'Buddah', 'Lenny', 'Arnold', 'Zuzu', 'Mollie', 'Laela', 'Tedders',
'Superpup', 'Rufio', 'Jeb', 'Rodman', 'Jonah', 'Chesney', 'Henry',
'Bobbay', 'Mitch', 'Kaiya', 'Acro', 'Aiden', 'Obie', 'Dot',
'Shnuggles', 'Kendall', 'Jeffri', 'Steve', 'Eve', 'Mac',
'Fletcher', 'Kenzie', 'Pumpkin', 'Schnozz', 'Gustaf', 'Cheryl',
'Ed', 'Leonidas', 'Norman', 'Caryl', 'Scott', 'Taz', 'Darby',
'Jackie', 'Jazz', 'Franq', 'Pippin', 'Rolf', 'Snickers', 'Ridley',
'Cal', 'Bradley', 'Bubba', 'Tuco', 'Patch', 'Mojo', 'Batdog',
'Dylan', 'Mark', 'JD', 'Alejandro', 'Scruffers', 'Pip', 'Julius',
'Tanner', 'Sparky', 'Anthony', 'Holly', 'Jett', 'Amy', 'Sage',
'Andy', 'Mason', 'Trigger', 'Antony', 'Creg', 'Traviss', 'Gin',
'Jeffrie', 'Danny', 'Ester', 'Pluto', 'Bloo', 'Edd', 'Willy',
'Herb', 'Damon', 'Peanut', 'Nigel', 'Butters', 'Sandra', 'Fabio',
'Randall', 'Liam', 'Tommy', 'Ben', 'Raphael', 'Julio', 'Andru',
'Kloey', 'Shawwn', 'Skye', 'Kollin', 'Ronduh', 'Billl', 'Saydee',
'Dug', 'Tessa', 'Sully', 'Kirk', 'Ralf', 'Clarq', 'Jaspers',
'Samsom', 'Terrance', 'Harrison', 'Chaz', 'Jeremy', 'Jaycob',
'Lambeau', 'Ruffles', 'Amélie', 'Bobb', 'Banditt', 'Kevon',
'Winifred', 'Hanz', 'Churlie', 'Zeek', 'Timofy', 'Maks',
'Jomathan', 'Kallie', 'Marvin', 'Spark', 'Gòrdón', 'Jo', 'DayZ',
'Jareld', 'Torque', 'Ron', 'Skittles', 'Cleopatricia', 'Erik',
'Stu', 'Tedrick', 'Shaggy', 'Filup', 'Kial', 'Naphaniel', 'Dook',
'Hall', 'Philippe', 'Biden', 'Fwed', 'Genevieve', 'Joshwa',
'Timison', 'Bradlay', 'Pipsy', 'Clybe', 'Keet', 'Carll', 'Jockson',
'Josep', 'Lugan', 'Christoper'], dtype=object)
```

In [27]:

```
twitter_archive_master.sample(5)
```

Out[27]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	sou

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	sou
1510	677918531514703872	NaN	NaN	2015-12-18 18:29:07 +0000	href="http://twitter.com/download/iphor
1502	678396796259975168	NaN	NaN	2015-12-20 02:09:34 +0000	href="http://twitter.com/download/iphor
1660	673919437611909120	NaN	NaN	2015-12-07 17:38:09 +0000	href="http://twitter.com/download/iphor
1665	673709992831262724	NaN	NaN	2015-12-07 03:45:53 +0000	href="http://twitter.com/download/iphor
1138	703382836347330562	NaN	NaN	2016-02-27 00:55:11 +0000	href="http://twitter.com/download/iphor

5 rows × 28 columns

Issue #5:

Define: Inconsistent data types in the 'retweeted_status_timestamp' column

Code :

> ### Converting the data type to datetime

In [28]:
```
twitter_archive_master['retweeted_status_timestamp']=pd.to_datetime(twitter_archive_master
```

Test

In [29]:
```
twitter_archive_master['retweeted_status_timestamp'].dtypes
```

Out[29]:
```
datetime64[ns, UTC]
```

Issue #6:

Define: row with invalid denominator rating of zero (0)

Code :

> ### Dropping off row with invalid denominator rating of zero (0)

In [21]:
```
inalid_denominator = twitter_archive_master.loc[twitter_archive_master['rating_denominator
inalid_denominator
twitter_archive_master.drop(twitter_archive_master.index[inalid_denominator], inplace=True
```

Test

In [22]:
```
twitter_archive_df1[twitter_archive_df1['rating_denominator']==0]
```

Out[22]:

tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	source	text	retweeted_status_id	retweeted_status_u

Issue #7:

Define: The 'text' column contains both original tweets and retweets, while we were required to work with just original tweets

Code :

> The retweets usually contain 'RT', and this will be used to drop all rows containing 'retweet' in the 'text' colunm

In [32]:
```
retweets = twitter_archive_master.loc[twitter_archive_master['text'].str.contains('RT')].i
retweets
twitter_archive_master.drop(twitter_archive_master.index[retweets], inplace=True)
```

Test

In [33]:
```
twitter_archive_master.loc[twitter_archive_master['text'].str.contains('RT')]
```

Out[33]:

tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	source	text	retweeted_status_id	retweeted_status_u

0 rows × 28 columns

Issue #8:

Define: 'time_stamp' column contains object data type

Code :

> Converting the data type to datetime

In [34]:
```
twitter_archive_master['timestamp']=pd.to_datetime(twitter_archive_master['timestamp'])
```

Test

In [35]:
```
twitter_archive_master['timestamp'].dtypes
```

Out[35]:
```
datetime64[ns, UTC]
```

Issue #9:

Define: Most of the column headers especially in the 'image_prediction' data set are not quite descriptive like 'p1_conf', 'p1_dog', 'p2', and the rest of them

Code :

Renaming headers to something more descriptive

In [36]:
```
twitter_archive_master=twitter_archive_master.rename(columns={'p1':'prediction1', 'p1_conf
```

Test

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1986 entries, 0 to 2072
Data columns (total 28 columns):
 #   Column                      Non-Null Count  Dtype              
---  ------                      --------------  -----              
 0   tweet_id                    1986 non-null   object             
 1   in_reply_to_status_id       23 non-null     float64            
 2   in_reply_to_user_id         23 non-null     float64            
 3   timestamp                   1986 non-null   datetime64[ns, UTC]
 4   source                      1986 non-null   object             
 5   text                        1986 non-null   object             
 6   retweeted_status_id         0 non-null      float64            
 7   retweeted_status_user_id    0 non-null      float64            
 8   retweeted_status_timestamp  0 non-null      datetime64[ns, UTC]
 9   expanded_urls               1986 non-null   object             
 10  rating_numerator            1986 non-null   int64              
 11  rating_denominator          1986 non-null   int64              
 12  name                        1444 non-null   object             
 13  jpg_url                     1986 non-null   object             
 14  img_num                     1986 non-null   int64              
 15  prediction1                 1986 non-null   object             
 16  prediction1_confidence      1986 non-null   float64            
 17  prediction1_dog             1986 non-null   bool               
 18  prediction2                 1986 non-null   object             
 19  prediction2_confidence      1986 non-null   float64            
 20  prediction2_dog             1986 non-null   bool               
 21  prediction3                 1986 non-null   object             
 22  prediction3_confidence      1986 non-null   float64            
 23  prediction3_dog             1986 non-null   bool               
 24  favorite_count              1986 non-null   int64              
 25  retweet_count               1986 non-null   int64              
 26  dog_stages                  305 non-null    object             
 27  new_names                   1347 non-null   object             
dtypes: bool(3), datetime64[ns, UTC](2), float64(7), int64(5), object(11)
memory usage: 409.2+ KB
```

Issue #10:

Define: Presence of retweet columns that won't be needed

Code :

Dropping off retweet columns

In [38]:
```
twitter_archive_master.drop(['retweeted_status_user_id','retweeted_status_id','retweeted_s
```

Test

In [39]:
```
twitter_archive_master.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1986 entries, 0 to 2072
Data columns (total 22 columns):
```

```
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   tweet_id                1986 non-null   object
 1   timestamp               1986 non-null   datetime64[ns, UTC]
 2   source                  1986 non-null   object
 3   text                    1986 non-null   object
 4   expanded_urls           1986 non-null   object
 5   rating_numerator        1986 non-null   int64
 6   rating_denominator      1986 non-null   int64
 7   jpg_url                 1986 non-null   object
 8   img_num                 1986 non-null   int64
 9   prediction1             1986 non-null   object
 10  prediction1_confidence  1986 non-null   float64
 11  prediction1_dog         1986 non-null   bool
 12  prediction2             1986 non-null   object
 13  prediction2_confidence  1986 non-null   float64
 14  prediction2_dog         1986 non-null   bool
 15  prediction3             1986 non-null   object
 16  prediction3_confidence  1986 non-null   float64
 17  prediction3_dog         1986 non-null   bool
 18  favorite_count          1986 non-null   int64
 19  retweet_count           1986 non-null   int64
 20  dog_stages              305 non-null    object
 21  new_names               1347 non-null   object
dtypes: bool(3), datetime64[ns, UTC](1), float64(3), int64(5), object(10)
memory usage: 316.1+ KB
```

Storing Data

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

In [40]:
```
twitter_archive_master.to_csv('twitter_archive_master.csv', index=False)
```

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.**

In [41]:
```
pd.options.display.max_columns = 999

twitter_archive_master.sample(5)
```

Out[41]:

	tweet_id	timestamp	source	text	
1792	671115716440031232	2015-11-29 23:57:10+00:00	<a href="http://twitter.com/download/iphone" r...	Meet Phred. He isn't steering, looking at the ...	https://twitter.com/do
2005	667177989038297088	2015-11-19 03:10:02+00:00	<a href="http://twitter.com/download/iphone" r...	This is a Dasani Kingfisher from Maine. His na...	https://twitter.com/do

	tweet_id	timestamp	source	text	
1383	684188786104872960	2016-01-05 01:44:52+00:00	<a href="http://twitter.com/download/iphone" r...	"Yo Boomer I'm taking a selfie, grab your stic...	https://twitter.com/do
566	785639753186217984	2016-10-11 00:34:48+00:00	<a href="http://twitter.com/download/iphone" r...	This is Pinot. He's a sophisticated doggo. You...	https://twitter.com/do
1191	698703483621523456	2016-02-14 03:01:06+00:00	<a href="http://twitter.com/download/iphone" r...	This is Rusty. He has no respect for POULTRY p...	https://twitter.com/do

Obtaining dog stage value count :

In [44]:
```
twitter_archive_master['dog_stages'].value_counts()
```

Out[44]:
```
pupper          202
doggo            63
puppo            22
doggopupper       9
floofer           7
doggopuppo        1
flooferdoggo      1
Name: dog_stages, dtype: int64
```

Obtaining average likes of each dog stage category :

In [45]:
```
twitter_archive_master.groupby('dog_stages')['favorite_count'].mean().sort_values(ascendir
```

Out[45]:
```
dog_stages
doggopuppo      47844.000000
puppo           21582.090909
doggo           19356.380952
flooferdoggo    17169.000000
floofer         13206.000000
doggopupper     12533.111111
pupper           7226.554455
Name: favorite_count, dtype: float64
```

Obtaining dog stage category with the most favorite count :

In [46]:
```
twitter_archive_master[twitter_archive_master['favorite_count']==twitter_archive_master['f
```

Out[46]:

	tweet_id	timestamp	source	text	
329	822872901745569793	2017-01-21 18:26:02+00:00	<a href="http://twitter.com/download/iphone" r...	Here's a super supportive puppo participating ...	https://twitter.com/dog_

Insights:

1. By obtaining the “value count” for each of the dog stages (using the “.value_counts()” method), The most popular dog stage as regarding this particular dataset was found to be the 'pupper' category, with 202 appearances/counts, followed by “doggo” having 63 counts, and “puppo” having 22 counts.

2. By using the “.groupby()” method and applying the “mean” on the “favorite count” for each dog stage category , The dog stage that had the least average likes was found to be the 'pupper' category, having an average of 7227 likes. The “puppo” category had a much higher average “favorite count” of about 21582 likes.

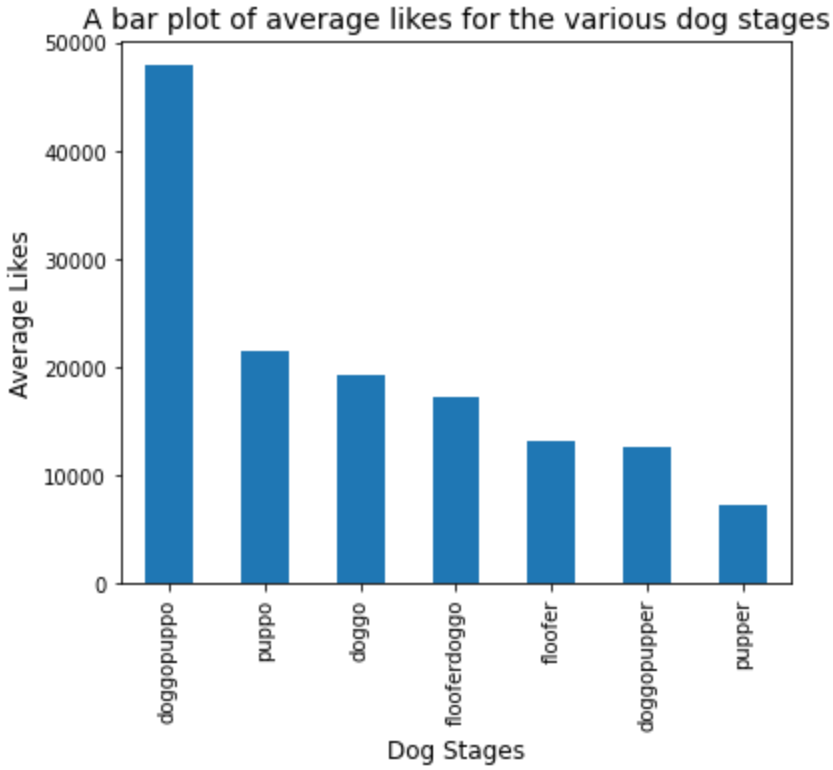
3. The third and final insight which was gotten by using the “.max()” method was that, the dog that had the most favorite count (likes) of 132,810 was from the 'puppo' category.

Visualization

A bar plot of average likes for the various dog stages

In [47]:
```
import matplotlib.pyplot as plt

plt.figure (figsize=(6,5))
twitter_archive_master.groupby('dog_stages')['favorite_count'].mean().sort_values(ascendir
plt.xlabel ('Dog Stages', fontsize=12)
plt.ylabel ('Average Likes', fontsize=12)
plt.title('A bar plot of average likes for the various dog stages', fontsize=14)
plt.show()
```



This was a visualization of the second observed insight from my analysis. The graph above graphically shows the various dog stages and their average likes. From the chart it can be seen that the dog stage that had the least average likes was found to be the 'pupper' category, having an average of 7227 likes. The “puppo” category had a much higher average “favorite count” of about 21582 likes.

This concludes my analysis on this project.