Wrangle_act

July 13, 2020

```
In [1]: #Importing all the libraries needed in this project
        import pandas as pd
        import numpy as np
        import os, fnmatch
        import json
        import glob
        import requests
        import matplotlib.pyplot as plt
        %matplotlib inline
        import seaborn as sns
        sns.set(style="darkgrid")
```

1 Gather (DS1)

```
In [2]: #Import the first data package we do have
        df_archive = pd.read_csv('twitter-archive-enhanced.csv')
```

2 Assess (DS1)

```
In [4]: df_archive.head(1)
```

```
Out[4]:             tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
        0  892420643555336193                    NaN                  NaN

                           timestamp  \
        0  2017-08-01 16:23:56 +0000

                                                      source  \
        0  <a href="http://twitter.com/download/iphone" r...

                                                        text  retweeted_status_id  \
        0  This is Phineas. He's a mystical boy. Only eve...                  NaN

          retweeted_status_user_id retweeted_status_timestamp  \
        0                      NaN                        NaN
```

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

   rating_denominator     name doggo floofer pupper puppo
0                  10  Phineas  None    None   None  None
```

In [5]: df_archive.shape

Out[5]: (2356, 17)

In [6]: df_archive.describe()

```
Out[6]:            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 [7]: df_archive.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                      2356 non-null int64
in_reply_to_status_id         78 non-null float64
```

```
in_reply_to_user_id           78 non-null float64
timestamp                     2356 non-null object
source                        2356 non-null object
text                          2356 non-null object
retweeted_status_id           181 non-null float64
retweeted_status_user_id      181 non-null float64
retweeted_status_timestamp    181 non-null object
expanded_urls                 2297 non-null object
rating_numerator              2356 non-null int64
rating_denominator            2356 non-null int64
name                          2356 non-null object
doggo                         2356 non-null object
floofer                       2356 non-null object
pupper                        2356 non-null object
puppo                         2356 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 313.0+ KB
```

```
In [8]: df_archive.query('rating_numerator > 20' or df_archive.query('rating_numerator < 10' or
                                                                             df_archive.query('rat
```

```
Out[8]:                 tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
        188   855862651834028034           8.558616e+17         1.943518e+08
        189   855860136149123072           8.558585e+17         1.361572e+07
        290   838150277551247360           8.381455e+17         2.195506e+07
        313   835246439529840640           8.352460e+17         2.625958e+07
        340   832215909146226688                    NaN                  NaN
        433   820690176645140481                    NaN                  NaN
        516   810984652412424192                    NaN                  NaN
        695   786709082849828864                    NaN                  NaN
        763   778027034220126208                    NaN                  NaN
        902   758467244762497024                    NaN                  NaN
        979   749981277374128128                    NaN                  NaN
        1120  731156023742988288                    NaN                  NaN
        1202  716439118184652801                    NaN                  NaN
        1228  713900603437621249                    NaN                  NaN
        1254  710658690886586372                    NaN                  NaN
        1274  709198395643068416                    NaN                  NaN
        1351  704054845121142784                    NaN                  NaN
        1433  697463031882764288                    NaN                  NaN
        1634  684225744407494656           6.842229e+17         4.196984e+09
        1635  684222868335505415                    NaN                  NaN
        1712  680494726643068929                    NaN                  NaN
        1779  677716515794329600                    NaN                  NaN
        1843  675853064436391936                    NaN                  NaN
        2074  670842764863651840                    NaN                  NaN
```

```
                       timestamp  \
188   2017-04-22 19:15:32 +0000
189   2017-04-22 19:05:32 +0000
290   2017-03-04 22:12:52 +0000
313   2017-02-24 21:54:03 +0000
340   2017-02-16 13:11:49 +0000
433   2017-01-15 17:52:40 +0000
516   2016-12-19 23:06:23 +0000
695   2016-10-13 23:23:56 +0000
763   2016-09-20 00:24:34 +0000
902   2016-07-28 01:00:57 +0000
979   2016-07-04 15:00:45 +0000
1120  2016-05-13 16:15:54 +0000
1202  2016-04-03 01:36:11 +0000
1228  2016-03-27 01:29:02 +0000
1254  2016-03-18 02:46:49 +0000
1274  2016-03-14 02:04:08 +0000
1351  2016-02-28 21:25:30 +0000
1433  2016-02-10 16:51:59 +0000
1634  2016-01-05 04:11:44 +0000
1635  2016-01-05 04:00:18 +0000
1712  2015-12-25 21:06:00 +0000
1779  2015-12-18 05:06:23 +0000
1843  2015-12-13 01:41:41 +0000
2074  2015-11-29 05:52:33 +0000

                                                 source  \
188   <a href="http://twitter.com/download/iphone" r...
189   <a href="http://twitter.com/download/iphone" r...
290   <a href="http://twitter.com/download/iphone" r...
313   <a href="http://twitter.com/download/iphone" r...
340   <a href="http://twitter.com/download/iphone" r...
433   <a href="http://twitter.com/download/iphone" r...
516   <a href="http://twitter.com/download/iphone" r...
695   <a href="http://twitter.com/download/iphone" r...
763   <a href="http://twitter.com/download/iphone" r...
902   <a href="http://twitter.com/download/iphone" r...
979   <a href="https://about.twitter.com/products/tw...
1120  <a href="http://twitter.com/download/iphone" r...
1202  <a href="http://twitter.com/download/iphone" r...
1228  <a href="http://twitter.com/download/iphone" r...
1254  <a href="http://twitter.com/download/iphone" r...
1274  <a href="http://twitter.com/download/iphone" r...
1351  <a href="http://twitter.com/download/iphone" r...
1433  <a href="http://twitter.com/download/iphone" r...
1634  <a href="http://twitter.com/download/iphone" r...
1635  <a href="http://twitter.com/download/iphone" r...
1712  <a href="http://twitter.com/download/iphone" r...
```

```
1779  <a href="http://twitter.com/download/iphone" r...
1843  <a href="http://twitter.com/download/iphone" r...
2074  <a href="http://twitter.com/download/iphone" r...

                                                   text  retweeted_status_id  \
188   @dhmontgomery We also gave snoop dogg a 420/10...                  NaN
189   @s8n You tried very hard to portray this good ...                  NaN
290                                 @markhoppus 182/10                  NaN
313   @jonnysun @Lin_Manuel ok jomny I know you're e...                  NaN
340   RT @dog_rates: This is Logan, the Chow who liv...         7.867091e+17
433   The floofs have been released I repeat the flo...                  NaN
516   Meet Sam. She smiles 24/7 &amp; secretly aspir...                  NaN
695   This is Logan, the Chow who lived. He solemnly...                  NaN
763   This is Sophie. She's a Jubilant Bush Pupper. ...                  NaN
902   Why does this never happen at my front door...                  NaN
979   This is Atticus. He's quite simply America af...                  NaN
1120  Say hello to this unbelievably well behaved sq...                  NaN
1202  This is Bluebert. He just saw that both #Final...                  NaN
1228  Happy Saturday here's 9 puppers on a bench. 99...                  NaN
1254  Here's a brigade of puppers. All look very pre...                  NaN
1274  From left to right:\nCletus, Jerome, Alejandro...                  NaN
1351  Here is a whole flock of puppers.  60/50 I'll ...                  NaN
1433  Happy Wednesday here's a bucket of pups. 44/40...                  NaN
1634  Two sneaky puppers were not initially seen, mo...                  NaN
1635  Someone help the girl is being mugged. Several...                  NaN
1712  Here we have uncovered an entire battalion of ...                  NaN
1779  IT'S PUPPERGEDDON. Total of 144/120 ...I think...                  NaN
1843  Here we have an entire platoon of puppers. Tot...                  NaN
2074  After so many requests... here you go.\n\nGood...                  NaN

      retweeted_status_user_id retweeted_status_timestamp  \
188                        NaN                        NaN
189                        NaN                        NaN
290                        NaN                        NaN
313                        NaN                        NaN
340               4.196984e+09  2016-10-13 23:23:56 +0000
433                        NaN                        NaN
516                        NaN                        NaN
695                        NaN                        NaN
763                        NaN                        NaN
902                        NaN                        NaN
979                        NaN                        NaN
1120                       NaN                        NaN
1202                       NaN                        NaN
1228                       NaN                        NaN
1254                       NaN                        NaN
1274                       NaN                        NaN
1351                       NaN                        NaN
```

```
1433                      NaN                         NaN
1634                      NaN                         NaN
1635                      NaN                         NaN
1712                      NaN                         NaN
1779                      NaN                         NaN
1843                      NaN                         NaN
2074                      NaN                         NaN

                                        expanded_urls  rating_numerator  \
188                                               NaN               420
189                                               NaN               666
290                                               NaN               182
313                                               NaN               960
340   https://twitter.com/dog_rates/status/786709082...                75
433   https://twitter.com/dog_rates/status/820690176...                84
516   https://www.gofundme.com/sams-smile,https://tw...                24
695   https://twitter.com/dog_rates/status/786709082...                75
763   https://twitter.com/dog_rates/status/778027034...                27
902   https://twitter.com/dog_rates/status/758467244...               165
979   https://twitter.com/dog_rates/status/749981277...              1776
1120  https://twitter.com/dog_rates/status/731156023...               204
1202  https://twitter.com/dog_rates/status/716439118...                50
1228  https://twitter.com/dog_rates/status/713900603...                99
1254  https://twitter.com/dog_rates/status/710658690...                80
1274  https://twitter.com/dog_rates/status/709198395...                45
1351  https://twitter.com/dog_rates/status/704054845...                60
1433  https://twitter.com/dog_rates/status/697463031...                44
1634  https://twitter.com/dog_rates/status/684225744...               143
1635  https://twitter.com/dog_rates/status/684222868...               121
1712  https://twitter.com/dog_rates/status/680494726...                26
1779  https://twitter.com/dog_rates/status/677716515...               144
1843  https://twitter.com/dog_rates/status/675853064...                88
2074  https://twitter.com/dog_rates/status/670842764...               420

      rating_denominator      name doggo floofer  pupper puppo
188                   10      None  None    None    None  None
189                   10      None  None    None    None  None
290                   10      None  None    None    None  None
313                    0      None  None    None    None  None
340                   10     Logan  None    None    None  None
433                   70      None  None    None    None  None
516                    7       Sam  None    None    None  None
695                   10     Logan  None    None    None  None
763                   10    Sophie  None    None  pupper  None
902                  150      None  None    None    None  None
979                   10   Atticus  None    None    None  None
1120                 170      this  None    None    None  None
1202                  50  Bluebert  None    None    None  None
```

```
1228                  90      None  None     None     None  None
1254                  80      None  None     None     None  None
1274                  50      None  None     None     None  None
1351                  50         a  None     None     None  None
1433                  40      None  None     None     None  None
1634                 130      None  None     None     None  None
1635                 110      None  None     None     None  None
1712                  10      None  None     None     None  None
1779                 120      None  None     None     None  None
1843                  80      None  None     None     None  None
2074                  10      None  None     None     None  None
```

In [9]:
```
lowercase_names= df_archive.name.str.contains('^[a-z]', regex=True)
df_archive[lowercase_names].name.unique()
```

Out[9]:
```
array(['such', 'a', 'quite', 'not', 'one', 'incredibly', 'mad', 'an',
       'very', 'just', 'my', 'his', 'actually', 'getting', 'this',
       'unacceptable', 'all', 'old', 'infuriating', 'the', 'by',
       'officially', 'life', 'light', 'space'], dtype=object)
```

In [10]:
```
df_archive['name'].value_counts()
```

Out[10]:
```
None           745
a               55
Charlie         12
Oliver          11
Lucy            11
Cooper          11
Penny           10
Lola            10
Tucker          10
Bo               9
Winston          9
Sadie            8
the              8
Daisy            7
an               7
Buddy            7
Toby             7
Bailey           7
Rusty            6
Scout            6
Koda             6
Oscar            6
Bella            6
Jax              6
Milo             6
Stanley          6
Leo              6
```

```
Dave                 6
Jack                 6
George               5
                  ...
Einstein             1
his                  1
Harrison             1
Teddy                1
Cermet               1
Zuzu                 1
Crimson              1
Strudel              1
Kulet                1
Chase                1
Spencer              1
Chesney              1
Sweets               1
Divine               1
Jo                   1
Sonny                1
River                1
Rooney               1
Juckson              1
Brockly              1
Cleopatricia         1
Coopson              1
Ralphson             1
Stormy               1
Clybe                1
Arlen                1
Joey                 1
Michelangelope       1
Scruffers            1
Blue                 1
Name: name, Length: 957, dtype: int64
```

3 Gather (DS2)

```
In [11]: 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_archive.tweet_id.values
len(tweet_ids)
file_name = 'tweet_json.txt'
# 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
if not os.path.isfile(file_name):
    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)
```

```
0.00025107900000875816
{}
```

```
In [12]: df_list = []
         with open ('tweet_json.txt', 'r') as file:
             for line in file:
```

```
            response = json.loads(line)
            tweet_id = response["id"]
            retweet_count = response["retweet_count"]
            favorite_count = response["favorite_count"]
            df_list.append({"tweet_id":tweet_id, "retweet_count": retweet_count,
                            "favorite_count":favorite_count})

    df_api= pd.DataFrame(df_list, columns = ["tweet_id", "retweet_count", "favorite_count"]
```

4 Assess (DS2)

In [13]: `df_api.head()`

Out[13]:

	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

In [14]: `df_api.shape`

Out[14]: (2354, 3)

In [15]: `df_api.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2354 entries, 0 to 2353
Data columns (total 3 columns):
tweet_id          2354 non-null int64
retweet_count     2354 non-null int64
favorite_count    2354 non-null int64
dtypes: int64(3)
memory usage: 55.2 KB
```

In [16]: `df_api['favorite_count'].isnull().sum()`

Out[16]: 0

In [17]: `df_api.describe()`

Out[17]:

	tweet_id	retweet_count	favorite_count
count	2.354000e+03	2354.000000	2354.000000
mean	7.426978e+17	3164.797366	8080.968564
std	6.852812e+16	5284.770364	11814.771334
min	6.660209e+17	0.000000	0.000000
25%	6.783975e+17	624.500000	1415.000000
50%	7.194596e+17	1473.500000	3603.500000
75%	7.993058e+17	3652.000000	10122.250000
max	8.924206e+17	79515.000000	132810.000000

In [18]: df_api['tweet_id'].isnull().sum()

Out[18]: 0

5 Gather (DS3)

In [19]:
```
#Import Image predictions Data "third data package we do have"
url ='https://d17h27t6h515a5.cloudfront.net/topher/2017/August/599fd2ad_image-predictio
file_name = url.split('/')[-1]
response = requests.get(url)
if not os.path.isfile(file_name):
    with open (os.path.join(url.split('/')[-1]), mode='wb') as file:
        file.write(response.content)
```

In [20]: fnmatch.filter(os.listdir('.'), '*.tsv')

Out[20]: ['image-predictions.tsv']

In [21]: df_prediction = pd.read_csv('image-predictions.tsv', '\t')

6 Asesss (DS3)

In [22]: df_prediction.tail(10)

Out[22]:
```
                tweet_id                                          jpg_url  \
2065  890240255349198849  https://pbs.twimg.com/media/DFrEyVuW0AAO3t9.jpg
2066  890609185150312448  https://pbs.twimg.com/media/DFwUU__XcAEpyXI.jpg
2067  890729181411237888  https://pbs.twimg.com/media/DFyBahAVwAAhUTd.jpg
2068  890971913173991426  https://pbs.twimg.com/media/DF1eOmZXUAALUcq.jpg
2069  891087950875897856  https://pbs.twimg.com/media/DF3HwyEWsAABqE6.jpg
2070  891327558926688256  https://pbs.twimg.com/media/DF6hr6BUMAAzZgT.jpg
2071  891689557279858688  https://pbs.twimg.com/media/DF_q7IAWsAEuuN8.jpg
2072  891815181378084864  https://pbs.twimg.com/media/DGBdLU1WsAANxJ9.jpg
2073  892177421306343426  https://pbs.twimg.com/media/DGGmoV4XsAAUL6n.jpg
2074  892420643555336193  https://pbs.twimg.com/media/DGKD1-bXoAAIAUK.jpg

      img_num                        p1   p1_conf  p1_dog                  p2  \
2065        1                  Pembroke  0.511319    True            Cardigan
2066        1             Irish_terrier  0.487574    True        Irish_setter
2067        2                Pomeranian  0.566142    True          Eskimo_dog
2068        1               Appenzeller  0.341703    True       Border_collie
2069        1  Chesapeake_Bay_retriever  0.425595    True       Irish_terrier
2070        2                    basset  0.555712    True    English_springer
2071        1               paper_towel  0.170278   False  Labrador_retriever
2072        1                 Chihuahua  0.716012    True            malamute
2073        1                 Chihuahua  0.323581    True            Pekinese
2074        1                    orange  0.097049   False               bagel
```

```
        p2_conf  p2_dog                        p3   p3_conf  p3_dog
2065  0.451038    True                 Chihuahua  0.029248    True
2066  0.193054    True   Chesapeake_Bay_retriever  0.118184    True
2067  0.178406    True                  Pembroke  0.076507    True
2068  0.199287    True                 ice_lolly  0.193548   False
2069  0.116317    True            Indian_elephant  0.076902   False
2070  0.225770    True German_short-haired_pointer  0.175219    True
2071  0.168086    True                   spatula  0.040836   False
2072  0.078253    True                    kelpie  0.031379    True
2073  0.090647    True                  papillon  0.068957    True
2074  0.085851   False                    banana  0.076110   False
```

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

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

In [24]:
```
df_prediction.info()
```

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

In [25]:
```
df_prediction.describe().style.format('{0:,.5f}')
```

Out[25]:
```
<pandas.io.formats.style.Styler at 0x7f63bfb32710>
```

In [26]:
```
df_prediction['p1'].value_counts()
```

Out[26]:
```
golden_retriever             150
Labrador_retriever           100
Pembroke                      89
Chihuahua                     83
pug                           57
chow                          44
```

Samoyed	43
toy_poodle	39
Pomeranian	38
cocker_spaniel	30
malamute	30
French_bulldog	26
Chesapeake_Bay_retriever	23
miniature_pinscher	23
seat_belt	22
Staffordshire_bullterrier	20
Siberian_husky	20
German_shepherd	20
web_site	19
Cardigan	19
Maltese_dog	18
beagle	18
Eskimo_dog	18
Shetland_sheepdog	18
teddy	18
Lakeland_terrier	17
Rottweiler	17
Shih-Tzu	17
kuvasz	16
Italian_greyhound	16
	...
fountain	1
Japanese_spaniel	1
traffic_light	1
slug	1
mailbox	1
bow	1
pool_table	1
coffee_mug	1
timber_wolf	1
rotisserie	1
lynx	1
groenendael	1
clog	1
handkerchief	1
cheeseburger	1
cowboy_boot	1
orange	1
quilt	1
four-poster	1
leaf_beetle	1
radio_telescope	1
shield	1
tricycle	1

```
pedestal                         1
Scotch_terrier                   1
piggy_bank                       1
otter                            1
ice_lolly                        1
maze                             1
zebra                            1
Name: p1, Length: 378, dtype: int64
```

In [27]:
```
df_prediction['p2'].value_counts()
```

Out[27]:
```
Labrador_retriever                  104
golden_retriever                     92
Cardigan                             73
Chihuahua                            44
Pomeranian                           42
French_bulldog                       41
Chesapeake_Bay_retriever             41
toy_poodle                           37
cocker_spaniel                       34
Siberian_husky                       33
miniature_poodle                     33
beagle                               28
Eskimo_dog                           27
Pembroke                             27
collie                               27
kuvasz                               26
Italian_greyhound                    22
American_Staffordshire_terrier       21
Pekinese                             21
miniature_pinscher                   20
toy_terrier                          20
Samoyed                              20
malinois                             20
chow                                 20
Norwegian_elkhound                   19
Boston_bull                          19
Staffordshire_bullterrier            18
pug                                  17
Irish_terrier                        17
kelpie                               16
                                   ...
hair_slide                            1
mosquito_net                          1
hay                                   1
EntleBucher                           1
wood_rabbit                           1
snorkel                               1
```

```
neck_brace                      1
purse                           1
sweatshirt                      1
crate                           1
toucan                          1
nail                            1
medicine_chest                  1
sombrero                        1
sandal                          1
printer                         1
tiger                           1
pickup                          1
lesser_panda                    1
computer_keyboard               1
peacock                         1
hatchet                         1
lifeboat                        1
polecat                         1
wombat                          1
rifle                           1
Bernese_mountain_dog            1
cliff                           1
Japanese_spaniel                1
komondor                        1
Name: p2, Length: 405, dtype: int64
```

In [28]:
```
df_prediction['p3'].value_counts()
```

Out[28]:
```
Labrador_retriever                79
Chihuahua                         58
golden_retriever                  48
Eskimo_dog                        38
kelpie                            35
kuvasz                            34
Staffordshire_bullterrier         32
chow                              32
cocker_spaniel                    31
beagle                            31
toy_poodle                        29
Pomeranian                        29
Pekinese                          29
Chesapeake_Bay_retriever          27
Great_Pyrenees                    27
Pembroke                          27
malamute                          26
French_bulldog                    26
American_Staffordshire_terrier    24
Cardigan                          23
```

```
pug                              23
basenji                          21
toy_terrier                      20
bull_mastiff                     20
Siberian_husky                   19
Shetland_sheepdog                17
Boston_bull                      17
Lakeland_terrier                 16
boxer                            16
doormat                          16
                                 ..
swimming_trunks                   1
cliff                             1
notebook                          1
shovel                            1
bib                               1
conch                             1
screen                            1
pier                              1
mosquito_net                      1
window_screen                     1
croquet_ball                      1
eel                               1
goldfish                          1
bell_cote                         1
grocery_store                     1
hatchet                           1
prairie_chicken                   1
pickup                            1
barber_chair                      1
coffeepot                         1
jeep                              1
go-kart                           1
oxcart                            1
mongoose                          1
kimono                            1
rapeseed                          1
wombat                            1
rifle                             1
green_lizard                      1
cardoon                           1
Name: p3, Length: 408, dtype: int64
```

In [29]:
```
(df_prediction['tweet_id'].value_counts()).unique()
```

Out[29]:
```
array([1])
```

In [30]:
```
all_columns = pd.Series(list(df_archive) + list(df_prediction))
all_columns[all_columns.duplicated()]
```

```
Out[30]: 17    tweet_id
         dtype: object
```

Quality

`Archive` **table**

- Unwanted retweets.
- Unwanted replies.
- Erroneous datatypes (timestamp and tweet id columns)
- Inaccurate records of rating numerator.
- Invalid records of rating numerator and denminator.
- Unwanted empty expanded url cell.
- Nulls represented as (None) in dog stage columns.
- "None" entries in name column.
- Invalid names in name column.

`API` **table**

- Erroneous datatypes (tweet_id)

`Prediction` **table**

- Erroneous datatypes (image num and tweet_id)
- Lowercase dog_breed with no ("_").

Tidiness

- Unwanted Columns of replies "Archive table"
- Unwanted Columns of retweets "Archive table"
- Four dog stages columns to be merged in one "Archive table"
- Cleaned archive and api tables to be merged "API tabe".
- Wide format of nine columns predictions-related to be long of onlu three columns "prediction table".
- Max prediction value per each tweet in a new dataframe to be merged with archive dataset "prediction table".
- Rating denominator not needed and name of numerator rating "Archive table".
- Columns to be ordered where the numerical ones to be in the front "Archive table".

7 Clean

```
In [31]: archive_clean = df_archive.copy()
         api_clean = df_api.copy()
         prediction_clean = df_prediction.copy()
```

7.1 Archive Table

7.1.1 Q1:

Define Drop all of the rows of retweets that don't match the criteria which is (only original tweets)

Code

```
In [32]: #Filter oringinal tweets only with no retweets
         archive_clean = archive_clean[~(archive_clean.retweeted_status_id.notnull())]
```

Test

```
In [33]: #Data decreased to 2175 rows where 181 rows of tweets had been dropped
         archive_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2175 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                      2175 non-null int64
in_reply_to_status_id         78 non-null float64
in_reply_to_user_id           78 non-null float64
timestamp                     2175 non-null object
source                        2175 non-null object
text                          2175 non-null object
retweeted_status_id           0 non-null float64
retweeted_status_user_id      0 non-null float64
retweeted_status_timestamp    0 non-null object
expanded_urls                 2117 non-null object
rating_numerator              2175 non-null int64
rating_denominator            2175 non-null int64
name                          2175 non-null object
doggo                         2175 non-null object
floofer                       2175 non-null object
pupper                        2175 non-null object
puppo                         2175 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 305.9+ KB
```

7.1.2 Q2:

Define Drop all of the rows of replies that don't match the criteria which is (only original tweets)

Code

```
In [34]: #Filter oringinal tweets only with no retweets
         archive_clean = archive_clean[~(archive_clean.in_reply_to_status_id.notnull())]
```

Test

```
In [35]: #Data decreased to 2097 rows where 78 rows of tweets had been dropped
         archive_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2097 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                      2097 non-null int64
in_reply_to_status_id         0 non-null float64
in_reply_to_user_id           0 non-null float64
timestamp                     2097 non-null object
source                        2097 non-null object
text                          2097 non-null object
retweeted_status_id           0 non-null float64
retweeted_status_user_id      0 non-null float64
retweeted_status_timestamp    0 non-null object
expanded_urls                 2094 non-null object
rating_numerator              2097 non-null int64
rating_denominator            2097 non-null int64
name                          2097 non-null object
doggo                         2097 non-null object
floofer                       2097 non-null object
pupper                        2097 non-null object
puppo                         2097 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 294.9+ KB
```

7.1.3 Tidiness 1&2:

Define Drop all empty columns related to retweets.

Code

```
In [36]: #Filter oringinal tweets only with no retweets
         archive_clean.drop(['retweeted_status_id', 'retweeted_status_user_id','retweeted_status
```

Test

```
In [37]: list(archive_clean)

Out[37]: ['tweet_id',
          'in_reply_to_status_id',
          'in_reply_to_user_id',
          'timestamp',
          'source',
          'text',
          'expanded_urls',
```

```
 'rating_numerator',
 'rating_denominator',
 'name',
 'doggo',
 'floofer',
 'pupper',
 'puppo']
```

Define Drop all empty columns related to replies.

Code

```
In [38]: #Filter oringinal tweets only with no retweets
         archive_clean.drop(['in_reply_to_status_id', 'in_reply_to_user_id'],axis=1, inplace=Tru
```

Test

```
In [39]: list(archive_clean)

Out[39]: ['tweet_id',
          'timestamp',
          'source',
          'text',
          'expanded_urls',
          'rating_numerator',
          'rating_denominator',
          'name',
          'doggo',
          'floofer',
          'pupper',
          'puppo']
```

7.1.4 Q3:

Define Erroneous datatypes (timestamp and tweet id) Convert timestamp to datetime and tweet id to a string

Code

```
In [40]: #Convert timestamp column to date time
         archive_clean ['timestamp'] = pd.to_datetime(archive_clean['timestamp'])

         #Convert tweet id column to date time
         archive_clean ['tweet_id'] = archive_clean['tweet_id'].astype(str)
```

Test

```
In [41]: archive_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2097 entries, 0 to 2355
Data columns (total 12 columns):
tweet_id              2097 non-null object
timestamp             2097 non-null datetime64[ns]
source                2097 non-null object
text                  2097 non-null object
expanded_urls         2094 non-null object
rating_numerator      2097 non-null int64
rating_denominator    2097 non-null int64
name                  2097 non-null object
doggo                 2097 non-null object
floofer               2097 non-null object
pupper                2097 non-null object
puppo                 2097 non-null object
dtypes: datetime64[ns](1), int64(2), object(9)
memory usage: 213.0+ KB
```

7.1.5 Q4:

Define Fix the inaccurate records of rating numerator besides the innvalid records of rating numerator and denminator.

Code

```
In [42]: #Manual fix for these indexes where their rating are already existing
         archive_clean.at[1662, 'rating_numerator'] = 10
         archive_clean.at[1202, 'rating_numerator'] = 11
         archive_clean.at[1165, 'rating_numerator'] = 13
         archive_clean.at[1068, 'rating_numerator'] = 14
         archive_clean.at[695, 'rating_numerator'] = 9.75
         archive_clean.at[763, 'rating_numerator'] = 11.27
         archive_clean.at[2335, 'rating_numerator'] = 9

         archive_clean.at[1662, 'rating_denominator'] = 10
         archive_clean.at[1202, 'rating_denominator'] = 10
         archive_clean.at[1165, 'rating_denominator'] = 10
         archive_clean.at[1068, 'rating_denominator'] = 10
         archive_clean.at[695, 'rating_denominator'] = 10
         archive_clean.at[763, 'rating_denominator'] = 10
         archive_clean.at[2335, 'rating_denominator'] = 10
```

```
In [43]: #Drop the rest which have no ratings in the text besides having ratings far from the un
         archive_clean =archive_clean[archive_clean['rating_denominator'] == 10]
```

```
#Drop the numerators which are greater than 20 as they don't make any sense
archive_clean =archive_clean[archive_clean['rating_numerator'] < 20]
```

Test

```
In [44]: archive_clean.query('rating_numerator > 20' or archive_clean.query('rating_numerator <
                                                                              archive_clean.query(
```

```
Out[44]: Empty DataFrame
         Columns: [tweet_id, timestamp, source, text, expanded_urls, rating_numerator, rating_de
         Index: []
```

7.1.6 Q5:

Define Drop the empty expanded urls cells.

Code

```
In [45]: archive_clean = archive_clean[~(archive_clean.expanded_urls.isnull())]
```

Test

```
In [46]: archive_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2079 entries, 0 to 2355
Data columns (total 12 columns):
tweet_id              2079 non-null object
timestamp             2079 non-null datetime64[ns]
source                2079 non-null object
text                  2079 non-null object
expanded_urls         2079 non-null object
rating_numerator      2079 non-null int64
rating_denominator    2079 non-null int64
name                  2079 non-null object
doggo                 2079 non-null object
floofer               2079 non-null object
pupper                2079 non-null object
puppo                 2079 non-null object
dtypes: datetime64[ns](1), int64(2), object(9)
memory usage: 211.1+ KB
```

7.1.7 Q6 & Tidiness 3:

Replace the "None" value with null and melt all of the four columns of dog stages into one column

Define Replace all the None with np.nan values, then merge all of the four columns (melt concept)

Code

```
In [47]: #Replace all of the None entries in the mentioned four columns with nothing:
         dog_stage_list = ['doggo', 'floofer', 'pupper', 'puppo']

         for c in dog_stage_list:
             archive_clean[c] = archive_clean[c].apply(lambda x: x.replace("None", ""))

In [48]: #Augment the four column together for creating one columns (melt method concept)
         archive_clean['dog_stage'] = archive_clean['doggo'] + archive_clean['floofer'] +archive
         archive_clean.drop(['doggo', 'floofer', 'pupper', 'puppo'], axis=1, inplace= True)

In [49]: #Replace and clean the entries to be easily read
         archive_clean['dog_stage'] = archive_clean['dog_stage'].replace(to_replace=["", "doggop
                                                                        value=[np.nan,"doggo-puppo",
```

Test

```
In [50]: archive_clean.sample(20)

Out[50]:                  tweet_id           timestamp  \
         1586  686760001961103360 2016-01-12 04:01:58
         757   778624900596654080 2016-09-21 16:00:17
         1572  687664829264453632 2016-01-14 15:57:26
         1515  690989312272396288 2016-01-23 20:07:44
         1968  673320132811366400 2015-12-06 01:56:44
         347   831911600680497154 2017-02-15 17:02:36
         131   867051520902168576 2017-05-23 16:16:06
         368   828708714936930305 2017-02-06 20:55:28
         2301  667044094246576128 2015-11-18 18:17:59
         2048  671511350426865664 2015-12-01 02:09:16
         1995  672594978741354496 2015-12-04 01:55:13
         1814  676617503762681856 2015-12-15 04:19:18
         1363  702932127499816960 2016-02-25 19:04:13
         2178  669015743032369152 2015-11-24 04:52:37
         174   858107933456039936 2017-04-28 23:57:28
         1804  676946864479084545 2015-12-16 02:08:04
         271   841077006473256960 2017-03-13 00:02:39
         1503  692017291282812928 2016-01-26 16:12:33
         2248  667866724293877760 2015-11-21 00:46:50
         725   782722598790725632 2016-10-02 23:23:04

                                                          source  \
         1586  <a href="http://vine.co" rel="nofollow">Vine -...
         757   <a href="http://twitter.com/download/iphone" r...
         1572  <a href="http://twitter.com/download/iphone" r...
```

```
1515  <a href="http://vine.co" rel="nofollow">Vine -...
1968  <a href="http://twitter.com/download/iphone" r...
347   <a href="http://twitter.com/download/iphone" r...
131   <a href="http://twitter.com/download/iphone" r...
368   <a href="http://twitter.com/download/iphone" r...
2301  <a href="http://twitter.com/download/iphone" r...
2048  <a href="http://twitter.com/download/iphone" r...
1995  <a href="http://twitter.com/download/iphone" r...
1814  <a href="http://twitter.com/download/iphone" r...
1363  <a href="http://twitter.com/download/iphone" r...
2178  <a href="http://twitter.com/download/iphone" r...
174   <a href="http://twitter.com/download/iphone" r...
1804  <a href="http://twitter.com/download/iphone" r...
271   <a href="http://twitter.com/download/iphone" r...
1503  <a href="http://twitter.com/download/iphone" r...
2248  <a href="http://twitter.com/download/iphone" r...
725   <a href="http://twitter.com/download/iphone" r...

                                                   text  \
1586  This pupper forgot how to walk. 12/10 happens ...
757   This is Penny. She's a sailor pup. 11/10 would...
1572  Meet Opal. He's a Belgian Dijon Poofster. Upse...
1515  We've got a doggy down. Requesting backup. 12/...
1968  This is Frankie. He's wearing blush. 11/10 rea...
347   Meet Kuyu. He was trapped in a well for 10 day...
131   Oh my this spooked me up. We only rate dogs, n...
368   This is Fiona. She's an exotic dog. Seems rath...
2301            12/10 gimme now https://t.co/QZAnwgnOMB
2048  Say hello to Hammond. He's just a wee lil pup...
1995  Meet Scott. Just trying to catch his train to ...
1814  I promise this wasn't meant to be a cuteness o...
1363  This is Chip. He's an Upper West Nile Pantaloo...
2178  Super rare dog right here guys. Doesn't bark. ...
174   This is Wyatt. He had an interview earlier tod...
1804  This pups goal was to get all four feet as clo...
271   This is Dawn. She's just checking pup on you. ...
1503  This is Kingsley Wellensworth III. He owns 7 r...
2248  This is Shaggy. He knows exactly how to solve ...
725   This is Penny. She fought a bee and the bee wo...

                                          expanded_urls  rating_numerator  \
1586                       https://vine.co/v/iMvubwT260D                12
757   https://twitter.com/dog_rates/status/778624900...                11
1572  https://twitter.com/dog_rates/status/687664829...                11
1515                       https://vine.co/v/iOZKZEU2nHq                12
1968  https://twitter.com/dog_rates/status/673320132...                11
347   https://twitter.com/dog_rates/status/831911600...                14
131   https://twitter.com/dog_rates/status/867051520...                13
```

```
368   https://twitter.com/dog_rates/status/828708714...                 10
2301  https://twitter.com/dog_rates/status/667044094...                 12
2048  https://twitter.com/dog_rates/status/671511350...                  8
1995  https://twitter.com/dog_rates/status/672594978...                  9
1814  https://twitter.com/dog_rates/status/676617503...                 13
1363  https://twitter.com/dog_rates/status/702932127...                  6
2178  https://twitter.com/dog_rates/status/669015743...                 10
174   https://twitter.com/dog_rates/status/858107933...                 12
1804  https://twitter.com/dog_rates/status/676946864...                 12
271   https://twitter.com/dog_rates/status/841077006...                 12
1503  https://twitter.com/dog_rates/status/692017291...                  9
2248  https://twitter.com/dog_rates/status/667866724...                 10
725   https://twitter.com/dog_rates/status/782722598...                 10

      rating_denominator      name dog_stage
1586                  10      None    pupper
757                   10     Penny       NaN
1572                  10      Opal       NaN
1515                  10      None       NaN
1968                  10   Frankie       NaN
347                   10      Kuyu       NaN
131                   10      None       NaN
368                   10     Fiona       NaN
2301                  10      None       NaN
2048                  10   Hammond       NaN
1995                  10     Scott    pupper
1814                  10      None    pupper
1363                  10      Chip       NaN
2178                  10      None       NaN
174                   10     Wyatt       NaN
1804                  10      None       NaN
271                   10      Dawn       NaN
1503                  10  Kingsley       NaN
2248                  10    Shaggy       NaN
725                   10     Penny       NaN
```

7.1.8 Q7:

Define Replace all the invalid names and the "None" entries with null values.

Code

In [51]:
```
#Names seem to start with capital letter, so such small letter entries aren't names
invalid_names= archive_clean.name.str.contains('^[a-z]', regex=True)
archive_clean[invalid_names].name.unique()
```

Out[51]:
```
array(['such', 'a', 'quite', 'not', 'one', 'incredibly', 'very', 'my',
       'his', 'an', 'actually', 'just', 'getting', 'mad', 'unacceptable',
```

```
         'all', 'old', 'infuriating', 'the', 'by', 'officially', 'life',
         'light', 'space'], dtype=object)
```

In [52]:
```
archive_clean.loc[invalid_names, 'name'] = np.nan
archive_clean['name'] = archive_clean['name'].replace(to_replace=["None"],
                                                      value=[np.nan])
```

Test

In [53]:
```
archive_clean['name'].value_counts()
```

Out[53]:
```
Lucy           11
Charlie        11
Cooper         10
Oliver         10
Tucker          9
Penny           9
Lola            8
Sadie           8
Winston         8
Toby            7
Daisy           7
Stanley         6
Oscar           6
Koda            6
Bella           6
Bo              6
Jax             6
Bailey          6
Milo            5
Chester         5
Dave            5
Bentley         5
Leo             5
Scout           5
Louis           5
Buddy           5
Rusty           5
Duke            4
Sammy           4
Alfie           4
               ..
Tebow           1
Ivar            1
Vinscent        1
Mo              1
Ralphson        1
Cleopatricia    1
```

```
Tassy              1
Juckson            1
Canela             1
Bodie              1
Grizzwald          1
Gunner             1
Bloop              1
Tyrone             1
Kara               1
Rascal             1
Mairi              1
Ralphie            1
Chase              1
Spencer            1
Chesney            1
Bode               1
Sweets             1
Divine             1
Jo                 1
Sonny              1
River              1
Rooney             1
Kulet              1
Blue               1
Name: name, Length: 929, dtype: int64
```

7.2 API Table

7.2.1 Q1:

Define Erroneous datatypes (timestamp and tweet id) Convert tweet id to a string

Code

```
In [54]: #Convert tweet id column to date time
         api_clean['tweet_id'] = api_clean['tweet_id'].astype(str)
```

Test

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2354 entries, 0 to 2353
Data columns (total 3 columns):
tweet_id          2354 non-null object
retweet_count     2354 non-null int64
favorite_count    2354 non-null int64
dtypes: int64(2), object(1)
memory usage: 55.2+ KB
```

7.2.2 Tidiness 1:

Define Merge Archive_clean and API_clean tables into one dataset where all of the data complement each other.

Code

```
In [56]: archive_clean = pd.merge(archive_clean, api_clean, on= "tweet_id", how= 'left')
```

Test

```
In [57]: archive_clean.sample(1)

Out[57]:                tweet_id           timestamp  \
         964  718454725339934721 2016-04-08 15:05:29

                                                            source  \
         964  <a href="http://twitter.com/download/iphone" r...

                                                              text  \
         964  This pic is old but I hadn't seen it until tod...

                                                     expanded_urls  rating_numerator  \
         964  https://twitter.com/dog_rates/status/718454725...                13

              rating_denominator name dog_stage  retweet_count  favorite_count
         964                  10  NaN       NaN           1685            5320
```

7.3 Prediction Table

7.3.1 Tidiness1:

Reshaping image prediction dataset from wide to long (less columns)

Define Merge the nine columns into three columns by gathering the p columns together and similarly for p_conf and p_dog columns

Code

```
In [58]: p_list = ["p1", "p2", "p3" ]
         p_conf_list = ["p1_conf", "p2_conf", "p3_conf"]
         p_dog_list = ["p1_dog", "p2_dog", "p3_dog"]

         prediction_clean = prediction_clean.melt(id_vars=["tweet_id","jpg_url", "img_num", "p1_
                                                 "p3_conf", "p3_dog"],
                                          value_vars= p_list, var_name = "prediction", value_nam

         prediction_clean = prediction_clean.melt(id_vars=["tweet_id","jpg_url", "img_num", "pre
                                                 , "p3_dog"],
```

```
                                value_vars= p_conf_list, var_name = "Var2" ,value_name

prediction_clean = prediction_clean.melt(id_vars=["tweet_id","jpg_url", "img_num", "pre
                                value_vars= p_dog_list, var_name = "Var3" ,value_name=

#Removing all of unneeded rows and columns
prediction_clean = prediction_clean[(prediction_clean['prediction']== prediction_clean[
             & (prediction_clean['prediction']== prediction_clean['Var3'].str[:2])]

prediction_clean.drop(['Var2', 'Var3'], axis =1, inplace=True)

#Resetting index to the normal way
prediction_clean = prediction_clean.reset_index(drop=True)
```

Test

```
In [59]: prediction_clean.head(2)
```

```
Out[59]:              tweet_id                                          jpg_url  \
         0  666020888022790149  https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg
         1  666029285002620928  https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg

           img_num prediction                  dog_breed  prediction_confidence  validity
         0       1         p1  Welsh_springer_spaniel               0.465074      True
         1       1         p1                 redbone               0.506826      True
```

7.3.2 Q1:

Define Erroneous datatypes (image_num and tweet id) Convert tweet id to a string and image num to category

Code

```
In [60]: #Converting image_num colum to category dtype besides tweet_id to string
         prediction_clean['img_num'] = prediction_clean['img_num'].astype('category')

         #Converting tweet_id to string
         prediction_clean['tweet_id'] = prediction_clean['tweet_id'].astype('str')
```

Test

```
In [61]: prediction_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6225 entries, 0 to 6224
Data columns (total 7 columns):
tweet_id                 6225 non-null object
jpg_url                  6225 non-null object
img_num                  6225 non-null category
```

```
prediction                 6225 non-null object
dog_breed                  6225 non-null object
prediction_confidence      6225 non-null float64
validity                   6225 non-null bool
dtypes: bool(1), category(1), float64(1), object(4)
memory usage: 255.6+ KB
```

7.3.3 Q2:

Define Decapitalize all of the names and replace "_" with whitespace (dog breed column to be edited regarding their way of display)

Code

```
In [62]: #Unifying the p columns to be of the same consistency
         prediction_clean['dog_breed'] = prediction_clean['dog_breed'].apply(lambda x: x.replace
```

Test

```
In [63]: prediction_clean['dog_breed'].head(5)

Out[63]: 0    welsh springer spaniel
         1                   redbone
         2           german shepherd
         3        rhodesian ridgeback
         4         miniature pinscher
         Name: dog_breed, dtype: object
```

7.3.4 Tidiness2:

Define Group by the max confidence level per each tweet and put into a dataframe in order to get its corresponding breed and merge it with the archive clean table

Code

```
In [64]: bestofbest= prediction_clean.groupby(['tweet_id'])['prediction_confidence'].max()

         df_bestofbest = pd.DataFrame(bestofbest, columns = ["dog_breed", "prediction_confidence

         df_bestofbest = pd.merge(df_bestofbest, prediction_clean, on = ['tweet_id', 'prediction
                                  how = 'inner')

         df_bestofbest.drop(["dog_breed_x", "jpg_url", "img_num","prediction", "validity"], axis

         df_bestofbest = df_bestofbest.rename(columns={"dog_breed_y":"dog_breed"})

In [65]: df_bestofbest.head()
```

```
Out[65]:               tweet_id  prediction_confidence                dog_breed
         0  666020888022790149               0.465074  welsh springer spaniel
         1  666029285002620928               0.506826                 redbone
         2  666033412701032449               0.596461         german shepherd
         3  666044226329800704               0.408143     rhodesian ridgeback
         4  666049248165822465               0.560311      miniature pinscher
```

```
In [66]: archive_clean = pd.merge(archive_clean, df_bestofbest, on= "tweet_id", how= 'inner')
```

Test

```
In [67]: archive_clean.head(1)
```

```
Out[67]:               tweet_id           timestamp  \
         0  892420643555336193 2017-08-01 16:23:56

                                                       source  \
         0  <a href="http://twitter.com/download/iphone" r...

                                                         text  \
         0  This is Phineas. He's a mystical boy. Only eve...

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

            rating_denominator     name dog_stage  retweet_count  favorite_count  \
         0                  10  Phineas       NaN           8853           39467

            prediction_confidence dog_breed
         0               0.097049    orange
```

7.4 Archive Table "Final Version"

7.4.1 Tidiness4:

Define Drop the rating_denominator and rename the column rating_numerator to rating:

Code

```
In [68]: #As it is all of 10 and not needed for the analysis
         archive_clean['rating_denominator'].unique()
```

```
Out[68]: array([10])
```

```
In [69]: archive_clean.drop(['rating_denominator'], axis=1, inplace=True)
         archive_clean.rename(columns= {"rating_numerator":"rating"}, inplace=True)
```

Test

```
In [70]: list(archive_clean)
```

```
Out[70]: ['tweet_id',
          'timestamp',
          'source',
          'text',
          'expanded_urls',
          'rating',
          'name',
          'dog_stage',
          'retweet_count',
          'favorite_count',
          'prediction_confidence',
          'dog_breed']
```

7.4.2 Tidiness5:

Define Rorder the columns where the numrical ones to be alongside each other and in the front

Code

```
In [71]: col_list = list(archive_clean.columns)
```

```
In [72]: col_list = ['tweet_id', 'timestamp', 'rating', 'retweet_count', 'favorite_count',
                     'dog_breed', 'prediction_confidence', 'name', 'dog_stage', 'source', 'text'

         archive_clean = archive_clean[col_list]
```

Test

```
In [73]: archive_clean.head(1)
```

```
Out[73]:              tweet_id            timestamp  rating  retweet_count  \
         0  892420643555336193 2017-08-01 16:23:56      13           8853

            favorite_count dog_breed  prediction_confidence     name dog_stage  \
         0           39467    orange               0.097049  Phineas       NaN

                                                        source  \
         0  <a href="http://twitter.com/download/iphone" r...

                                                          text
         0  This is Phineas. He's a mystical boy. Only eve...
```

8 Store

Store the final dataset after cleaning the three datasets and merge the extracted columns of interest into one dataset which is "Archive_clean"

Code

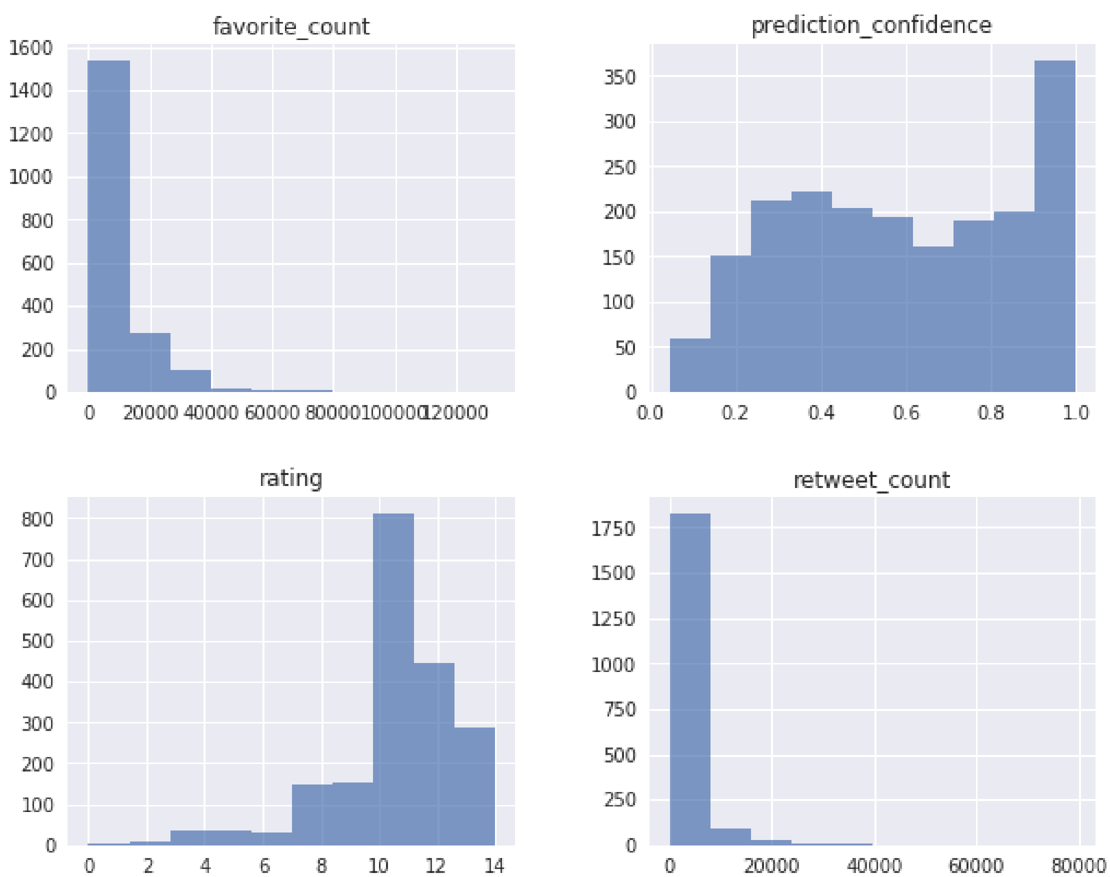
```
In [75]: archive_clean.to_csv('twitter_archive_master.csv', index=False)
```

Test

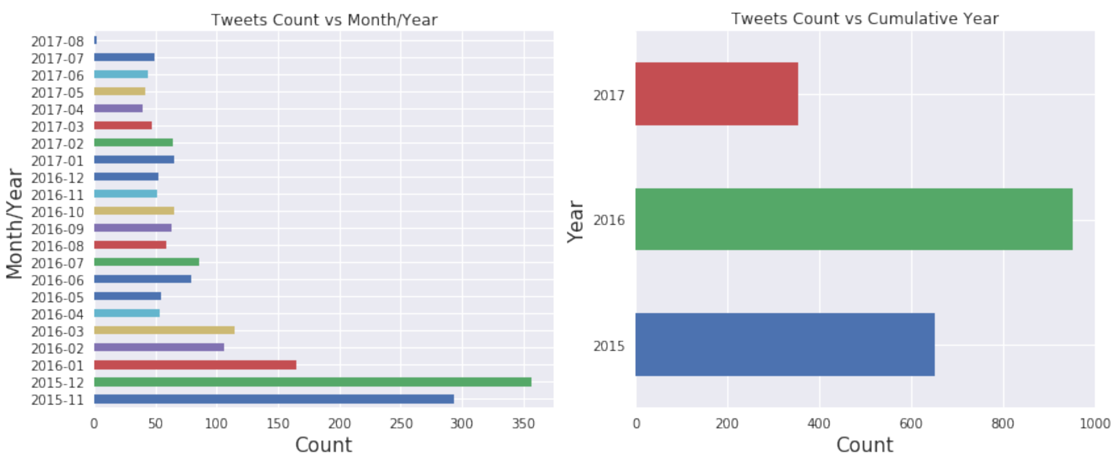
```
In [76]: fnmatch.filter(os.listdir('.'), '*.csv')

Out[76]: ['twitter-archive-enhanced.csv', 'twitter_archive_master.csv']
```

9 Analyze

```
In [77]: #Import the cleaned data to for analysis and visualisation:
         archive_analyze = pd.read_csv('twitter_archive_master.csv',dtype={"tweet_id":"str"})
         archive_analyze ['timestamp'] = pd.to_datetime(archive_analyze['timestamp'])

In [78]: #Summary Statistics for all the numerical data:
         archive_analyze[['rating', 'retweet_count', 'favorite_count', 'prediction_confidence']]

Out[78]: <pandas.io.formats.style.Styler at 0x7f63bf0b9ac8>

In [79]: #A glimpse how the data distribution seem:
         archive_analyze.hist(figsize = (10,8), alpha=0.7);
```

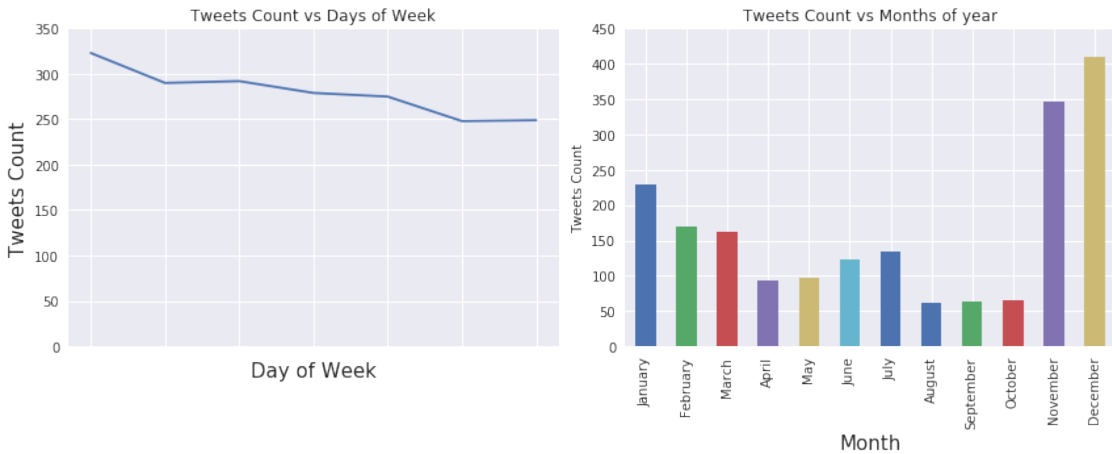


In [80]:
```
#Interactions with WeRateDogs through tweets over months of specified years in the data
z= archive_analyze['timestamp'].dt.year
h= archive_analyze['timestamp'].dt.to_period('M')

fig, (ax1,ax2) = plt.subplots(1,2, figsize=(12,5))
archive_analyze.groupby(h)['tweet_id'].count().plot(kind='barh', ax=ax1, title='Tweets
ax1.set_xlabel('Count', size=15)
ax1.set_ylabel('Month/Year', size=15)

archive_analyze.groupby(z)['tweet_id'].count().plot(kind='barh', ax=ax2, title='Tweets
ax2.set_xlabel('Count', size=15)
ax2.set_ylabel('Year', size=15)

plt.tight_layout()
```

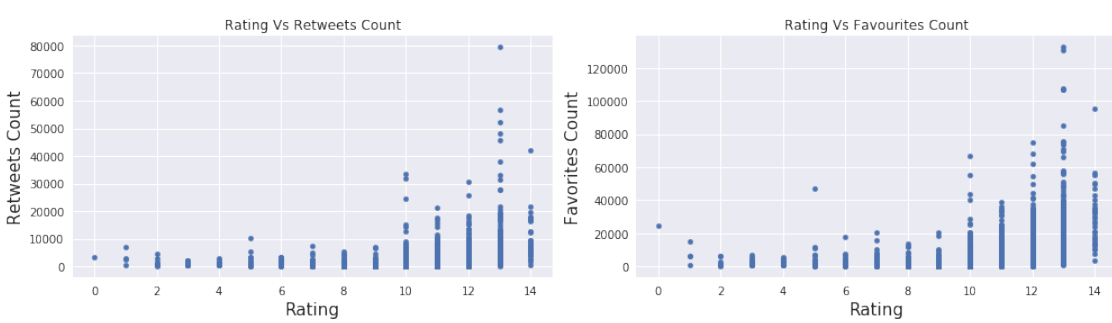


In [81]:
```
#Interactions with WeRateDogs through tweets over the days of week and months across th

weekdays = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday
months = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'Se

x= archive_analyze['timestamp'].dt.day_name()
y= archive_analyze['timestamp'].dt.month_name()

fig, (ax1,ax2) = plt.subplots(1,2, figsize=(12,5))
archive_analyze.groupby(x)['tweet_id'].count().reindex(weekdays).plot(kind='line',ylim=
ax1.set_xlabel('Day of Week', size=15)
ax1.set_ylabel('Tweets Count', size=15)
```

```
archive_analyze.groupby(y)['tweet_id'].count().reindex(months).plot(kind='bar',ylim=(0,
ax2.set_xlabel('Month', size=15)
ax2.set_ylabel('Tweets Count', size=10)

ax1.tick_params(axis ='x', rotation = 90)
ax2.tick_params(axis ='x', rotation = 90, which='both')
plt.tight_layout()
```



In [82]:
```
#Rating Vs. Retweet count and favourite count

fig, (ax1,ax2) = plt.subplots(1,2, figsize=(14,4))
archive_analyze.plot(x='rating',y='retweet_count', kind='scatter', ax=ax1, title= 'Rati
ax1.set_xlabel('Rating', size=15)
ax1.set_ylabel('Retweets Count', size=15)

archive_analyze.plot(x='rating',y='favorite_count', kind='scatter', ax=ax2, title="Rati
ax2.set_xlabel('Rating', size=15)
ax2.set_ylabel('Favorites Count', size=15)

plt.tight_layout()
```

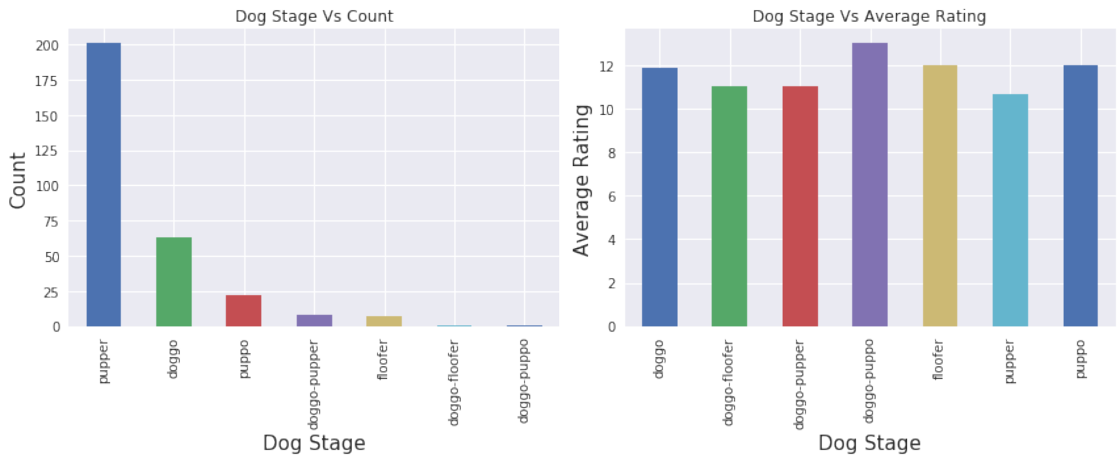


```
In [83]: #Summary Statistics of Dog Stages
         archive_analyze.groupby('dog_stage')['rating'].describe()
```

Out[83]:

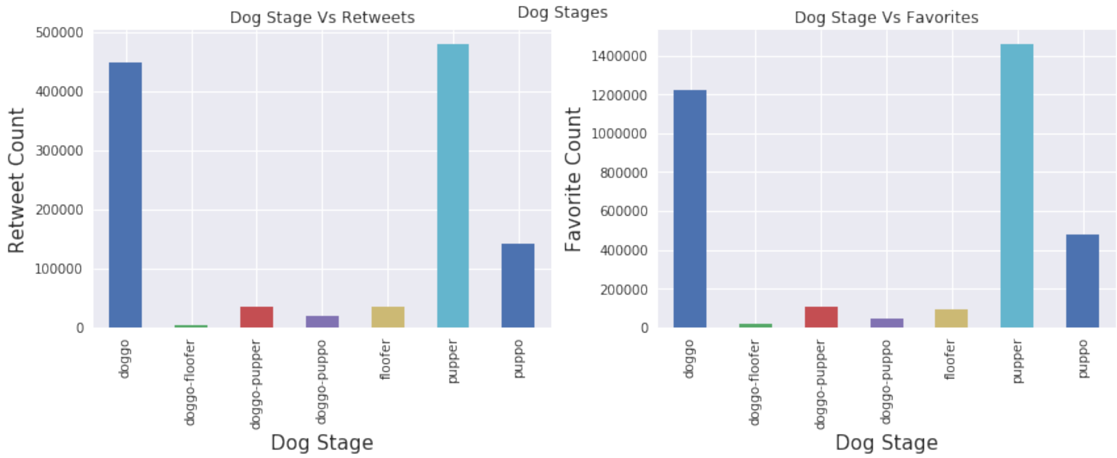
dog_stage	count	mean	std	min	25%	50%	75%	max
doggo	63.0	11.888889	1.471351	8.0	11.00	12.0	13.0	14.0
doggo-floofer	1.0	11.000000	NaN	11.0	11.00	11.0	11.0	11.0
doggo-pupper	8.0	11.000000	2.563480	5.0	11.50	12.0	12.0	13.0
doggo-puppo	1.0	13.000000	NaN	13.0	13.00	13.0	13.0	13.0
floofer	7.0	12.000000	1.154701	10.0	11.50	12.0	13.0	13.0
pupper	201.0	10.636816	1.735638	3.0	10.00	11.0	12.0	14.0
puppo	22.0	12.000000	1.309307	9.0	11.25	12.0	13.0	14.0

```
In [84]: #Dog Stages Count available in the dataset besides the average rating per each stage
         fig, (ax1,ax2) = plt.subplots(1,2, figsize=(12,5))

         archive_analyze['dog_stage'].value_counts().plot(kind='bar', ax=ax1, title="Dog Stage V
         ax1.set_xlabel('Dog Stage', size=15)
         ax1.set_ylabel('Count', size=15)

         archive_analyze.groupby('dog_stage')['rating'].mean().plot(kind='bar', title="Dog Stage
         ax2.set_xlabel('Dog Stage', size=15)
         ax2.set_ylabel('Average Rating', size=15)

         plt.tight_layout()
```

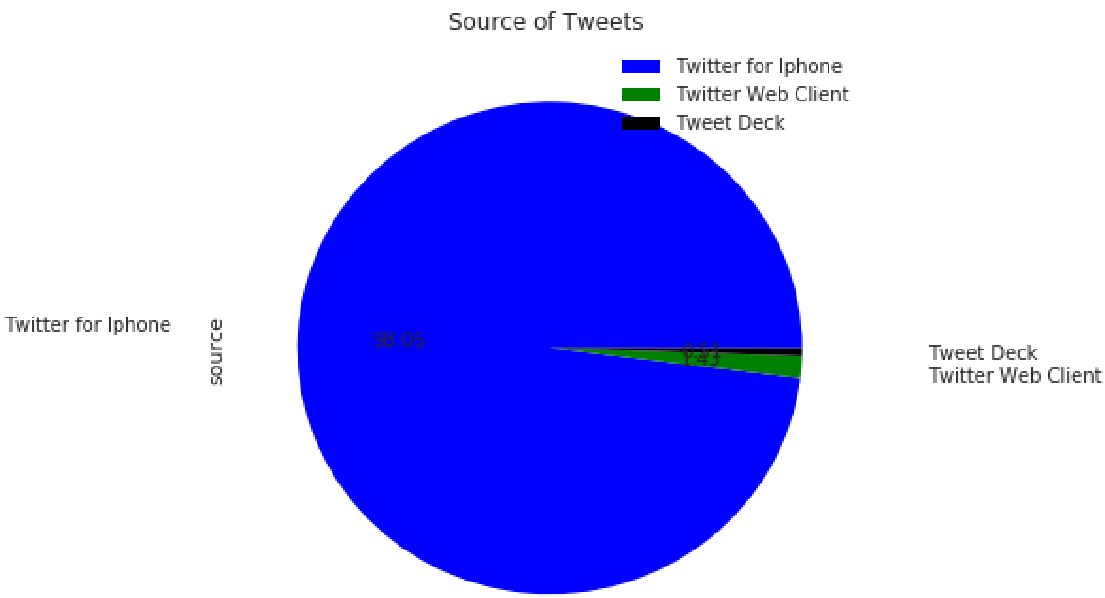



```
In [85]: #Total Retweets and Favorites per each dog stage
         fig, (ax1,ax2) = plt.subplots(1,2, figsize=(12,5))

         archive_analyze.groupby('dog_stage')['retweet_count'].sum().plot(kind='bar', ax=ax1, ti
         ax1.set_xlabel('Dog Stage', size=15)
         ax1.set_ylabel('Retweet Count', size=15)
```

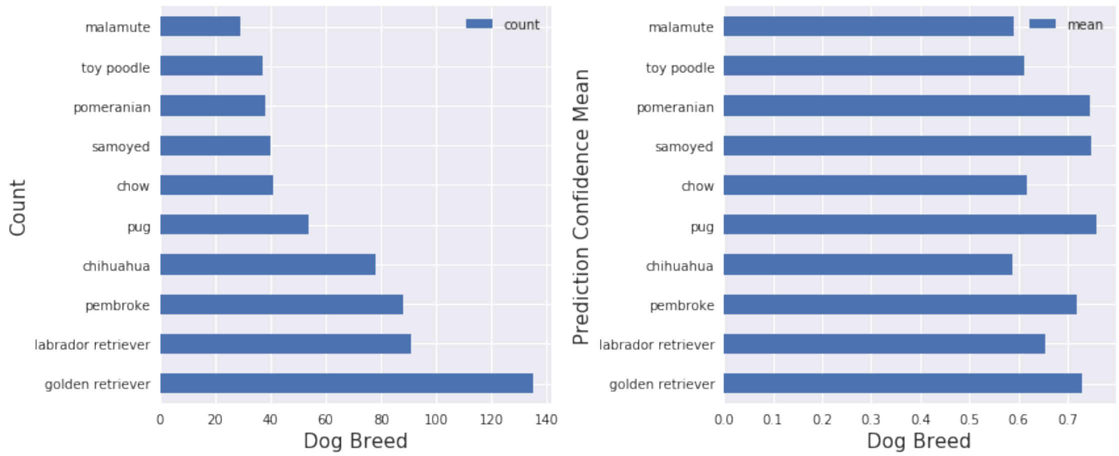
```
archive_analyze.groupby('dog_stage')['favorite_count'].sum().plot(kind='bar', ax=ax2, t
ax2.set_xlabel('Dog Stage', size=15)
ax2.set_ylabel('Favorite Count', size=15)

plt.suptitle('Dog Stages')
plt.tight_layout()
```




```
In [91]: #How the tweets were posted
         archive_analyze['source'].value_counts().plot.pie(labels=['Twitter for Iphone', 'Twitte
                                                  colors=['blue', 'g', 'black'], autopct='%.2f', fonts
                                                           title="Source of Tweets ",labeldistanc
```



In [92]:
```
#Top 10 predicted dog breeds and their corresponding prediction confidence mean
fig, (ax1,ax2) = plt.subplots(1,2, figsize=(12,5))

archive_analyze.groupby('dog_breed')['prediction_confidence'].describe().sort_values(as
ax1.set_xlabel('Dog Breed', size=15)
ax1.set_ylabel('Count', size=15)

archive_analyze.groupby('dog_breed')['prediction_confidence'].describe().sort_values(as
ax2.set_xlabel('Dog Breed', size=15)
ax2.set_ylabel('Prediction Confidence Mean', size=15)

plt.tight_layout()
```



In [93]:
```
#Top 10 prediction confidence mean of dog breeds and their corressponding count
archive_analyze.groupby('dog_breed')['prediction_confidence'].describe().sort_values(as
```

Out[93]:

dog_breed	count	mean
ping-pong ball	1.0	0.999945
peacock	1.0	0.999924
school bus	1.0	0.999833
bib	1.0	0.998814
slug	1.0	0.998075
zebra	1.0	0.997673
fountain	1.0	0.997509
china cabinet	1.0	0.996031
flamingo	1.0	0.992710
fiddler crab	1.0	0.992069