Data Wrangling Project

June 19, 2019

1 Project: Data Wrangling WeRateDogs

1.1 Table of Contents

Introduction

This project Real-world data rarely comes clean. Using Python and its libraries, I will gather data from a variety of sources and in a variety of formats, assess its quality and tidiness, then clean it. This is called data wrangling. This task is intended for Udacity Nanodegree Data Wrangling Project.

The dataset that I will be wrangling (and analyzing and visualizing) is the tweet archive of Twitter user @dog_rates, also known as WeRateDogs. The data separated in 3 part, 1 from local file which provided by Udacity, second data from Udacity server, and the last one from twitter API.

The goal: wrangle WeRateDogs Twitter data to create interesting and trustworthy analyses and visualizations. The Twitter archive is great, but it only contains very basic tweet information. Additional gathering, then assessing and cleaning is required for "Wow!"-worthy analyses and visualizations.

Gathering The Data

I parse my library needed in each task so it will easier to know what kind library needed from that task.

1. Get Data Twitter Archive

Todo: 1. Import library needed 2. Read twitter_archive_enhanced.csv from the same folder 3. Make sure that data has been read correctly - print head

```
In [1]: import pandas as pd
```

In [2]:
```
twitter_archive_df = pd.read_csv('data_udacity/twitter-archive-enhanced.csv')
twitter_archive_df = twitter_archive_df.sort_values('timestamp')
twitter_archive_df.head(2)
```

Out[2]:
```
                 tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
2355  666020888022790149                    NaN                  NaN
2354  666029285002620928                    NaN                  NaN

                      timestamp  \
2355  2015-11-15 22:32:08 +0000
2354  2015-11-15 23:05:30 +0000

                                                 source  \
2355  <a href="http://twitter.com/download/iphone" r...
2354  <a href="http://twitter.com/download/iphone" r...

                                                   text  retweeted_status_id  \
2355  Here we have a Japanese Irish Setter. Lost eye...                  NaN
2354  This is a western brown Mitsubishi terrier. Up...                  NaN

      retweeted_status_user_id retweeted_status_timestamp  \
2355                       NaN                        NaN
2354                       NaN                        NaN

                                          expanded_urls  rating_numerator  \
2355  https://twitter.com/dog_rates/status/666020888...                 8
2354  https://twitter.com/dog_rates/status/666029285...                 7

      rating_denominator  name doggo floofer pupper puppo
2355                  10  None  None    None   None  None
2354                  10     a  None    None   None  None
```

2. Get Data Tweet Image Prediction

Todo: 1. Import library needed 2. Read image-predictions.tsv from Udacity's server that can be access from https://d17h27t6h515a5.cloudfront.net/topher/2017/August/599fd2ad_image-predictions/image-predictions.tsv 3. Make sure that data has been read correctly - print head - describe domain knowledge about the data

In [3]:
```
import requests
```

In [4]:
```
url = "https://d17h27t6h515a5.cloudfront.net/topher/2017/August/599fd2ad_image-predictio
response = requests.get(url)

with open('data_udacity/image-predictions.tsv', mode ='wb') as file:
    file.write(response.content)
```

In [5]:
```
#Read TSV file
image_prediction_df = pd.read_csv('data_udacity/image-predictions.tsv', sep='\t' )
image_prediction_df.head(2)
```

```
Out[5]:              tweet_id                                          jpg_url  \
        0  666020888022790149  https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg
        1  666029285002620928  https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg

           img_num                      p1   p1_conf  p1_dog                  p2  \
        0        1  Welsh_springer_spaniel  0.465074    True              collie
        1        1                 redbone  0.506826    True  miniature_pinscher

            p2_conf  p2_dog                   p3   p3_conf  p3_dog
        0  0.156665    True    Shetland_sheepdog  0.061428    True
        1  0.074192    True  Rhodesian_ridgeback  0.072010    True
```

The description:

- tweet_id is the last part of the tweet URL after "status/" → https://twitter.com/dog_rates/status/889531135344209921
- p1 is the algorithm's #1 prediction for the image in the tweet → golden retriever
- p1_conf is how confident the algorithm is in its #1 prediction → 95%
- p1_dog is whether or not the #1 prediction is a breed of dog → TRUE
- p2 is the algorithm's second most likely prediction → Labrador retriever
- p2_conf is how confident the algorithm is in its #2 prediction → 1%
- p2_dog is whether or not the #2 prediction is a breed of dog → TRUE
- etc.

3. Configure Twitter Account
Todo: 1. Import library needed 2. Declare twitter configuration with consumer_key, consumer_secret, access_token, and access_secret 3. Make configuration

```
In [6]: import tweepy
```

```
In [7]: # for security reasons, I save my configuration in csv
        twitter_configuration = pd.read_csv("twitter_configuration.csv")
```

```
In [8]: try:
            auth = tweepy.OAuthHandler(twitter_configuration.consumer_key[0], twitter_configurat
            auth.set_access_token(twitter_configuration.access_token[0], twitter_configuration.a
        except tweepy.TweepError as t:
            print(t.message)

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

4. Get Data Twitter with API & JSON
Todo: 1. Import library needed (if not exist before) 2. Get twitter data in JSON by id from file point 1 - add data JSON from a list - add ids data that we can't find that with API - calculate the number id we wan to looking for - calculate number succes and fail data we looking for - save data tweets in txt file so we can accsess that many time 3. Read and save tweets data in dataframe so we can access in our notebook 4. Make sure that data has been read correctly - print head

```
In [9]: import json
        from timeit import default_timer as timer
```

```
In [10]: tweets = []
         ids_not_found_tweet = []
         ids_fail_get_tweet = []
         num_tweet_id = len(twitter_archive_df.tweet_id)
         num_succes_get_data = 0
         num_fail_get_data = 0

         start = timer()
         for tweet_id in twitter_archive_df.tweet_id:
             try:
                 temp = api.get_status(tweet_id)._json
                 tweets.append({'tweet_id':temp['id'],
                                'favorite_count':temp['favorite_count'],
                                'favorited':temp['favorited'],
                                'retweet_count':temp['retweet_count'],
                                'retweeted':temp['retweeted']})
                 num_succes_get_data += 1
                 print('{} : done, {}/{}'.format(tweet_id, num_succes_get_data, num_tweet_id))
             except tweepy.TweepError as t:
                 num_fail_get_data += 1
                 if (t.args[0][0]['message'] == 'No status found with that ID.'):
                     ids_not_found_tweet.append(tweet_id)
                 else:
                     ids_fail_get_tweet.append(tweet_id)
                 print('{} : {}, total fail= {}'.format(tweet_id, t, num_fail_get_data))

         end = timer()
         print("The time we need to get JSON file: {} second".format(end - start))
```

```
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796080075804475393 : done, 1730/2356
796116448414461957 : done, 1731/2356
796125600683540480 : done, 1732/2356
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796387464403357696 : done, 1735/2356
796484825502875648 : done, 1736/2356
796563435802726400 : done, 1737/2356
796759840936919040 : done, 1738/2356
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796865951799083009 : done, 1739/2356
796904159865868288 : done, 1740/2356
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797236660651966464 : done, 1742/2356
797545162159308800 : done, 1743/2356
797971864723324932 : done, 1744/2356
798209839306514432 : done, 1745/2356
798340744599797760 : done, 1746/2356
798576900688019456 : done, 1747/2356
798585098161549313 : done, 1748/2356
798628517273620480 : done, 1749/2356
798644042770751489 : done, 1750/2356
798665375516884993 : done, 1751/2356
798673117451325440 : done, 1752/2356
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798694562394996736 : done, 1755/2356
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800751577355128832 : done, 1774/2356
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802952499103731712 : done, 1791/2356
803276597545603072 : done, 1792/2356
803321560782307329 : done, 1793/2356
803380650405482500 : done, 1794/2356
803638050916102144 : done, 1795/2356


Rate limit reached. Sleeping for: 613


803692223237865472 : done, 1796/2356
803773340896923648 : done, 1797/2356
804026241225523202 : done, 1798/2356
804413760345620481 : done, 1799/2356
804475857670639616 : done, 1800/2356
804738756058218496 : done, 1801/2356
805207613751304193 : done, 1802/2356
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806576416489959424 : done, 1812/2356
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806629075125202948 : done, 1814/2356
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809448704142938112 : done, 1828/2356
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810284430598270976 : done, 1832/2356
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813812741911748608 : done, 1860/2356
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815390420867969024 : done, 1868/2356
815639385530101762 : done, 1869/2356
815736392542261248 : done, 1870/2356
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819711362133872643 : done, 1909/2356
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820837357901512704 : done, 1919/2356
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826240494070030336 : done, 1960/2356
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826598365270007810 : done, 1962/2356
826598799820865537 : done, 1963/2356
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828408677031882754 : done, 1978/2356
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858843525470990336 : done, 2170/2356
858860390427611136 : done, 2171/2356
859074603037188101 : done, 2172/2356
859196978902773760 : done, 2173/2356
859607811541651456 : done, 2174/2356
859851578198683649 : done, 2175/2356
859924526012018688 : done, 2176/2356
860177593139703809 : done, 2177/2356
860184849394610176 : done, 2178/2356
860276583193509888 : done, 2179/2356
860524505164394496 : done, 2180/2356
860563773140209665 : done, 2181/2356
860924035999428608 : done, 2182/2356
860981674716409858 : done, 2183/2356
861005113778896900 : done, 2184/2356
861288531465048066 : done, 2185/2356
861383897657036800 : done, 2186/2356
861769973181624320 : [{'code': 144, 'message': 'No status found with that ID.'}], total fail= 15
862096992088072192 : done, 2187/2356
862457590147678208 : done, 2188/2356
862722525377298433 : done, 2189/2356
862831371563274240 : done, 2190/2356
863062471531167744 : done, 2191/2356
863079547188785154 : done, 2192/2356
863427515083354112 : done, 2193/2356
863432100342583297 : done, 2194/2356
863471782782697472 : done, 2195/2356
863553081350529029 : done, 2196/2356
863907417377173506 : done, 2197/2356
864197398364647424 : done, 2198/2356
864279568663928832 : done, 2199/2356
864873206498414592 : done, 2200/2356
865006731092295680 : done, 2201/2356
865359393868664832 : done, 2202/2356
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865718153858494464 : done, 2203/2356
866094527597207552 : done, 2204/2356
866334964761202691 : done, 2205/2356
866450705531457537 : done, 2206/2356
866686824827068416 : done, 2207/2356
866720684873056260 : done, 2208/2356
866816280283807744 : [{'code': 144, 'message': 'No status found with that ID.'}], total fail= 16
867051520902168576 : done, 2209/2356
867072653475098625 : done, 2210/2356
867421006826221569 : done, 2211/2356
867774946302451713 : done, 2212/2356
867900495410671616 : done, 2213/2356
868552278524837888 : done, 2214/2356
868622495443632128 : done, 2215/2356
868639477480148993 : done, 2216/2356
868880397819494401 : done, 2217/2356
869227993411051520 : done, 2218/2356
869596645499047938 : done, 2219/2356
869702957897576449 : done, 2220/2356
869772420881756160 : done, 2221/2356
869988702071779329 : [{'code': 144, 'message': 'No status found with that ID.'}], total fail= 17
870063196459192321 : done, 2222/2356
870308999962521604 : done, 2223/2356
870374049280663552 : done, 2224/2356
870656317836468226 : done, 2225/2356
870726314365509632 : done, 2226/2356
870804317367881728 : done, 2227/2356
871032628920680449 : done, 2228/2356
871102520638267392 : done, 2229/2356
871166179821445120 : done, 2230/2356
871515927908634625 : done, 2231/2356
871762521631449091 : done, 2232/2356
871879754684805121 : done, 2233/2356
872122724285648897 : done, 2234/2356
872261713294495745 : [{'code': 144, 'message': 'No status found with that ID.'}], total fail= 18
872486979161796608 : done, 2235/2356
872620804844003328 : done, 2236/2356
872668790621863937 : [{'code': 144, 'message': 'No status found with that ID.'}], total fail= 19
872820683541237760 : done, 2237/2356
872967104147763200 : done, 2238/2356
873213775632977920 : done, 2239/2356
873337748698140672 : done, 2240/2356
873580283840344065 : done, 2241/2356
873697596434513921 : [{'code': 144, 'message': 'No status found with that ID.'}], total fail= 20
874012996292530176 : done, 2242/2356
874057562936811520 : done, 2243/2356
874296783580663808 : done, 2244/2356
874434818259525634 : done, 2245/2356
```

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874680097055178752 : done, 2246/2356
875021211251597312 : done, 2247/2356
875097192612077568 : done, 2248/2356
875144289856114688 : done, 2249/2356
875747767867523072 : done, 2250/2356
876120275196170240 : done, 2251/2356
876484053909872640 : done, 2252/2356
876537666061221889 : done, 2253/2356
876838120628539392 : done, 2254/2356
877201837425926144 : done, 2255/2356
877316821321428993 : done, 2256/2356
877556246731214848 : done, 2257/2356
877611172832227328 : done, 2258/2356
877736472329191424 : done, 2259/2356
878057613040115712 : done, 2260/2356
878281511006478336 : done, 2261/2356
878316110768087041 : done, 2262/2356
878404777348136964 : done, 2263/2356
878604707211726852 : done, 2264/2356
878776093423087618 : done, 2265/2356
879008229531029506 : done, 2266/2356
879050749262655488 : done, 2267/2356
879130579576475649 : done, 2268/2356
879376492567855104 : done, 2269/2356
879415818425184262 : done, 2270/2356
879492040517615616 : done, 2271/2356
879674319642796034 : done, 2272/2356
879862464715927552 : done, 2273/2356
880095782870896641 : done, 2274/2356
880221127280381952 : done, 2275/2356
880465832366813184 : done, 2276/2356
880872448815771648 : done, 2277/2356
880935762899988482 : done, 2278/2356
881268444196462592 : done, 2279/2356
881536004380872706 : done, 2280/2356
881633300179243008 : done, 2281/2356
881666595344535552 : done, 2282/2356
881906580714921986 : done, 2283/2356
882045870035918850 : done, 2284/2356
882268110199369728 : done, 2285/2356
882627270321602560 : done, 2286/2356
882762694511734784 : done, 2287/2356
882992080364220416 : done, 2288/2356
883117836046086144 : done, 2289/2356
883360690899218434 : done, 2290/2356
883482846933004288 : done, 2291/2356
883838122936631299 : done, 2292/2356
884162670584377345 : done, 2293/2356
```

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884247878851493888 : done, 2294/2356
884441805382717440 : done, 2295/2356
884562892145688576 : done, 2296/2356
884876753390489601 : done, 2297/2356
884925521741709313 : done, 2298/2356
885167619883638784 : done, 2299/2356
885311592912609280 : done, 2300/2356
885518971528720385 : done, 2301/2356
885528943205470208 : done, 2302/2356
885984800019947520 : done, 2303/2356
886054160059072513 : done, 2304/2356
886258384151887873 : done, 2305/2356
886267009285017600 : done, 2306/2356
886366144734445568 : done, 2307/2356
886680336477933568 : done, 2308/2356
886736880519319552 : done, 2309/2356
886983233522544640 : done, 2310/2356
887101392804085760 : done, 2311/2356
887343217045368832 : done, 2312/2356
887473957103951883 : done, 2313/2356
887517139158093824 : done, 2314/2356
887705289381826560 : done, 2315/2356
888078434458587136 : done, 2316/2356
888202515573088257 : [{'code': 144, 'message': 'No status found with that ID.'}], total fail= 21
888554962724278272 : done, 2317/2356
888804989199671297 : done, 2318/2356
888917238123831296 : done, 2319/2356
889278841981685760 : done, 2320/2356
889531135344209921 : done, 2321/2356
889638837579907072 : done, 2322/2356
889665388333682689 : done, 2323/2356
889880896479866881 : done, 2324/2356
890006608113172480 : done, 2325/2356
890240255349198849 : done, 2326/2356
890609185150312448 : done, 2327/2356
890729181411237888 : done, 2328/2356
890971913173991426 : done, 2329/2356
891087950875897856 : done, 2330/2356
891327558926688256 : done, 2331/2356
891689557279858688 : done, 2332/2356
891815181378084864 : done, 2333/2356
892177421306343426 : done, 2334/2356
892420643555336193 : done, 2335/2356
The time we need to get JSON file: 1989.8182586169999 second
```

```
In [11]: print("Success to get {} data, and fail to get {} data (no_tweet: {}, just fail: {}), f
               .format(num_succes_get_data, num_fail_get_data,\
```

```
                    len(ids_not_found_tweet), len(ids_fail_get_tweet),\
                    num_tweet_id))
```

```
Success to get 2335 data, and fail to get 21 data (no_tweet: 21, just fail: 0), from total 2356
```

```
In [12]: json.dump(tweets,open('data_generated/tweets.txt', 'w', encoding="utf8"), ensure_ascii=
         print('Success save the json file')
```

```
Success save the json file
```

```
In [13]: # read json file into dataframe
         with open('data_generated/tweets.txt','r') as f:
             data = json.load(f)

         scrapped_tweet_df = pd.DataFrame(data)
         scrapped_tweet_df.head(2)
```

Out[13]:

	favorite_count	favorited	retweet_count	retweeted	tweet_id
0	2498	False	493	False	666020888022790149
1	124	False	46	False	666029285002620928

Conclusion: - We get the third data - 21 data from tweet_id are failed to get from tweet API because the id is not found, the twitter must be deleted - We get first data from file that we save in same folder, second data from Udacity's server, and third data from Twitter API - After see tweet_json.txt from Udacity, I decide to get some column (not all column) because another column has been save in first data, and some cols not need yet (like column user) - Because twitter have range limit time, so we need extra time (because of sleep) to get all data. In this project we need 1989.8 second

Accessing The Data

For now, we have 3 data: twitter_archive_df, image_prediction_df, and scrapped_tweet_df . Todo in accessing data:

Check length of data
Check the type of data
Check the value of data
Check missing value of data
Check stat describe data
Founded Issues

```
In [14]: import matplotlib.pyplot as plt
         import seaborn as sns
         import numpy as np

         %matplotlib inline
```

1. Check length of data

```
In [15]: def print_length(name, data_frame):
             print("The length of {} is {}".format(name, len(data_frame)))
```

```
In [16]: print_length('twitter_archive_df', twitter_archive_df)
         print_length('image_prediction_df', image_prediction_df)
         print_length('scrapped_tweet_df', scrapped_tweet_df)
```

```
The length of twitter_archive_df is 2356
The length of image_prediction_df is 2075
The length of scrapped_tweet_df is 2335
```

From that data we get info that twitter_archive_df has different length with scrapped_tweet_df because we failed to get 22 data from twitter. We can delete some row in data so we will have the same length in each table.

2. Check the type of data

```
In [17]: twitter_archive_df.dtypes
```

```
Out[17]: tweet_id                        int64
         in_reply_to_status_id         float64
         in_reply_to_user_id           float64
         timestamp                      object
         source                         object
         text                           object
         retweeted_status_id           float64
         retweeted_status_user_id      float64
         retweeted_status_timestamp     object
         expanded_urls                  object
         rating_numerator                int64
         rating_denominator              int64
         name                           object
         doggo                          object
         floofer                        object
         pupper                         object
         puppo                          object
         dtype: object
```

```
In [18]: image_prediction_df.dtypes
```

```
Out[18]: tweet_id      int64
         jpg_url      object
         img_num       int64
         p1           object
         p1_conf     float64
         p1_dog         bool
         p2           object
         p2_conf     float64
         p2_dog         bool
         p3           object
         p3_conf     float64
         p3_dog         bool
         dtype: object
```

In [19]: scrapped_tweet_df.dtypes

```
Out[19]: favorite_count    int64
         favorited          bool
         retweet_count     int64
         retweeted          bool
         tweet_id          int64
         dtype: object
```

Object in the data type mean string, we not have some problem in there except timestamp. It must be date

3. Check the value of data

In [20]: twitter_archive_df.name.value_counts().head()

```
Out[20]: None       745
         a           55
         Charlie     12
         Oliver      11
         Cooper      11
         Name: name, dtype: int64
```

There is 5 sorted dog name with the biggest total value. We find that "None" is typically missing data, and I assumed that "a" also a missing data, so we must find and uniformly all missing data value in each label.

In [21]: twitter_archive_df.retweeted_status_id.value_counts().head()

```
Out[21]: 7.757333e+17    1
         8.001414e+17    1
         8.174239e+17    1
         6.742918e+17    1
         6.833919e+17    1
         Name: retweeted_status_id, dtype: int64
```

We only need original tweet (not retweeted by another tweet), so we must drop row that retweeted_status_id doesn't missing

In [22]: scrapped_tweet_df.retweeted.value_counts()

```
Out[22]: False    2335
         Name: retweeted, dtype: int64
```

Retweeted indicates whether this Tweet has been Retweeted by the authenticating user, because all value are false so this column be not informatif anymore.

In [23]: twitter_archive_df.duplicated(['tweet_id']).sum()

```
Out[23]: 0
```

```
In [24]: twitter_archive_df.duplicated(['expanded_urls']).sum()

Out[24]: 137

In [25]: twitter_archive_df[twitter_archive_df.duplicated(['expanded_urls'])].head(3)

Out[25]:                 tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
         2189  668967877119254528           6.689207e+17         2.143566e+07
         2149  669684865554620416           6.693544e+17         4.196984e+09
         2038  671550332464455680           6.715449e+17         4.196984e+09

                               timestamp  \
         2189  2015-11-24 01:42:25 +0000
         2149  2015-11-26 01:11:28 +0000
         2038  2015-12-01 04:44:10 +0000

                                                           source  \
         2189  <a href="http://twitter.com/download/iphone" r...
         2149  <a href="http://twitter.com/download/iphone" r...
         2038  <a href="http://twitter.com/download/iphone" r...

                                                             text  retweeted_status_id  \
         2189                      12/10 good shit Bubka\n@wane15                  NaN
         2149  After countless hours of research and hundreds...                  NaN
         2038  After 22 minutes of careful deliberation this ...                  NaN

               retweeted_status_user_id retweeted_status_timestamp expanded_urls  \
         2189                      NaN                        NaN           NaN
         2149                      NaN                        NaN           NaN
         2038                      NaN                        NaN           NaN

               rating_numerator  rating_denominator  name doggo floofer pupper puppo
         2189                12                  10  None  None    None   None  None
         2149                11                  10  None  None    None   None  None
         2038                 1                  10  None  None    None   None  None

In [26]: twitter_archive_df[twitter_archive_df.duplicated(['expanded_urls'])].expanded_urls.valu

Out[26]: https://twitter.com/dog_rates/status/739238157791694849/video/1
         https://twitter.com/dog_rates/status/820749716845686786/photo/1,https://twitter.com/dog
         https://twitter.com/dog_rates/status/750719632563142656/photo/1
         Name: expanded_urls, dtype: int64

In [27]: twitter_archive_df.query("expanded_urls == 'https://twitter.com/dog_rates/status/767754

Out[27]:                tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
         837  767754930266464257                    NaN                  NaN
         558  803321560782307329                    NaN                  NaN
```

```
                     timestamp  \
837  2016-08-22 16:06:54 +0000
558  2016-11-28 19:35:59 +0000

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

                                                  text  retweeted_status_id  \
837  This is Philbert. His toilet broke and he does...                  NaN
558  RT @dog_rates: This is Philbert. His toilet br...         7.677549e+17

     retweeted_status_user_id retweeted_status_timestamp  \
837                       NaN                        NaN
558              4.196984e+09  2016-08-22 16:06:54 +0000

                                         expanded_urls  rating_numerator  \
837  https://twitter.com/dog_rates/status/767754930...                11
558  https://twitter.com/dog_rates/status/767754930...                11

     rating_denominator      name doggo floofer pupper puppo
837                  10  Philbert  None    None   None  None
558                  10  Philbert  None    None   None  None
```

There are some images that duplicated, we must re-check are they are have same value in each cols (except the id, because we don't have any duplicate tweet id)

```
In [28]: scrapped_tweet_df.favorited.value_counts()
```

```
Out[28]: False    2335
         Name: favorited, dtype: int64
```

retweeted and favorited data only have 1 value, so it is not important anymore, we must to drop it.

```
In [29]: twitter_archive_df.source.value_counts()
```

```
Out[29]: <a href="http://twitter.com/download/iphone" rel="nofollow">Twitter for iPhone</a>
         <a href="http://vine.co" rel="nofollow">Vine - Make a Scene</a>
         <a href="http://twitter.com" rel="nofollow">Twitter Web Client</a>
         <a href="https://about.twitter.com/products/tweetdeck" rel="nofollow">TweetDeck</a>
         Name: source, dtype: int64
```

To make the data more clear, we need to change source cols value
4. Check missing value of data
list function name: get_missing_value_percentage

```
In [30]: def get_missing_value_percentage(data_frame):
             data_missing = data_frame.isna()
```

```
        num_data_missing = data_missing.sum()
        num_data = len(data_frame)
        return (num_data_missing * 100)/num_data
```

```
In [31]: get_missing_value_percentage(twitter_archive_df)
```

```
Out[31]: tweet_id                       0.000000
         in_reply_to_status_id         96.689304
         in_reply_to_user_id           96.689304
         timestamp                      0.000000
         source                         0.000000
         text                           0.000000
         retweeted_status_id           92.317487
         retweeted_status_user_id      92.317487
         retweeted_status_timestamp    92.317487
         expanded_urls                  2.504244
         rating_numerator               0.000000
         rating_denominator             0.000000
         name                           0.000000
         doggo                          0.000000
         floofer                        0.000000
         pupper                         0.000000
         puppo                          0.000000
         dtype: float64
```

```
In [32]: get_missing_value_percentage(image_prediction_df)
```

```
Out[32]: tweet_id    0.0
         jpg_url     0.0
         img_num     0.0
         p1          0.0
         p1_conf     0.0
         p1_dog      0.0
         p2          0.0
         p2_conf     0.0
         p2_dog      0.0
         p3          0.0
         p3_conf     0.0
         p3_dog      0.0
         dtype: float64
```

```
In [33]: get_missing_value_percentage(scrapped_tweet_df)
```

```
Out[33]: favorite_count    0.0
         favorited         0.0
         retweet_count     0.0
         retweeted         0.0
         tweet_id          0.0
         dtype: float64
```

Data twitter_archive_df have some missing value in variable in_reply_to_status_id (96.69%), in_reply_to_user_id (96.69%), retweeted_status_id (92.32%), retweeted_status_user_id (92.32%), retweeted_status_timestamp (92.32%), and expanded_urls (2.50%). Because of the large missing value (>90%), 5 cols in twitter_archive_df must be deleted. For expanded_urls, must be check after join with other table. Data image_prediction_df didn't have any missing value, the scrapped_tweet_df also didn't have missing value.

5. Check stat describe data

In [34]:
```
twitter_archive_df.describe()
```

Out[34]:
```
           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 [35]:
```
image_prediction_df.describe()
```

Out[35]:
```
           tweet_id      img_num      p1_conf       p2_conf       p3_conf
count  2.075000e+03  2075.000000  2075.000000  2.075000e+03  2.075000e+03
mean   7.384514e+17     1.203855     0.594548  1.345886e-01  6.032417e-02
std    6.785203e+16     0.561875     0.271174  1.006657e-01  5.090593e-02
min    6.660209e+17     1.000000     0.044333  1.011300e-08  1.740170e-10
25%    6.764835e+17     1.000000     0.364412  5.388625e-02  1.622240e-02
50%    7.119988e+17     1.000000     0.588230  1.181810e-01  4.944380e-02
```

```
75%    7.932034e+17     1.000000     0.843855  1.955655e-01  9.180755e-02
max    8.924206e+17     4.000000     1.000000  4.880140e-01  2.734190e-01
```

In [36]:
```
scrapped_tweet_df.describe()
```

Out[36]:

	favorite_count	retweet_count	tweet_id
count	2335.000000	2335.000000	2.335000e+03
mean	7810.989293	2859.129336	7.419847e+17
std	12111.582433	4837.919767	6.820978e+16
min	0.000000	1.000000	6.660209e+17
25%	1359.500000	575.500000	6.783065e+17
50%	3402.000000	1338.000000	7.184600e+17
75%	9578.000000	3337.000000	7.986692e+17
max	161719.000000	82136.000000	8.924206e+17

tweed_id musn't describe as numeric variable that we can conclude the statistic description, it is more suitable as a string

Founded Issues:

quality issues: 1. Axist not original tweet 2. tweet_id format in third data doesn't like first data so maybe it can make some problem if we join the two table 3. tweet_id position in third table not same like the other table, so we can't easily see the id 4. timestamp in first table not in datetime format 5. Missing value was not uniformly, sometime NaN but some other None 6. There are exist columns that have >90% missing value, also exist dog name that just have 1 character ('a') 7. Cols retwitted and favorited have same value in all row 8. Cols source have html format 9. Cols expanded_urls and jpg_urls have duplicated value

tidiness issues: 1. Stage of dog must be 1 cols instead of 4 cols 2. Join all data is needed to make easier for analysis

Cleaning and Tidying The Data

In cleaning and tydinf data, we want to make sure that issues we founded before will not exist. Todo in cleaning data:

Cleaning: Delete not original tweet
Cleaning: Change Tweet id format in each table
Cleaning: Change tweet_id position into first col
Cleaning: Change timestamp format
Cleaning: Uniformly missing value
Tidying: Make dog stages into 1 column
Cleaning: Delete duplicated row from expanded and jpg urls
Cleaning: Delete col with missing value >90% from total rows
Cleaning: Delete cols with same value
Cleaning: Get source col without HTML format
Tidying: Join all table

1. Delete not original tweet

In [37]:
```
twitter_archive_df = twitter_archive_df[pd.isna(twitter_archive_df.retweeted_status_id)
pd.notna(twitter_archive_df['retweeted_status_id']).sum()
```

Out[37]: 0

In [38]:
```
pd.notna(twitter_archive_df.retweeted_status_timestamp).sum()
```

Out[38]: 0

In [39]:
```
pd.notna(twitter_archive_df.retweeted_status_user_id).sum()
```

Out[39]: 0

Now we only have the original tweet
2. Change Tweet id format in each table
list function name: convert_to_str

In [40]:
```
def convert_to_str(cols):
    return cols.astype(str).infer_objects()
```

In [41]:
```
twitter_archive_df.tweet_id = convert_to_str(twitter_archive_df.tweet_id)
twitter_archive_df.head(1)
```

Out[41]:
```
                tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
2355  666020888022790149                    NaN                  NaN   

                      timestamp  \
2355  2015-11-15 22:32:08 +0000   

                                                 source  \
2355  <a href="http://twitter.com/download/iphone" r...   

                                                   text  retweeted_status_id  \
2355  Here we have a Japanese Irish Setter. Lost eye...                  NaN   

      retweeted_status_user_id retweeted_status_timestamp  \
2355                       NaN                        NaN   

                                          expanded_urls  rating_numerator  \
2355  https://twitter.com/dog_rates/status/666020888...                 8   

      rating_denominator  name doggo floofer pupper puppo  
2355                  10  None  None    None   None  None  
```

In [42]:
```
image_prediction_df.tweet_id = convert_to_str(image_prediction_df.tweet_id)
image_prediction_df.head(1)
```

Out[42]:
```
             tweet_id                                          jpg_url  \
0  666020888022790149  https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg   

   img_num                      p1   p1_conf  p1_dog      p2   p2_conf  \
0        1  Welsh_springer_spaniel  0.465074    True  collie  0.156665   

   p2_dog                 p3   p3_conf  p3_dog  
0    True  Shetland_sheepdog  0.061428    True  
```

In [43]:
```
scrapped_tweet_df.tweet_id = convert_to_str(scrapped_tweet_df.tweet_id)
scrapped_tweet_df.head(1)
```

Out[43]:

	favorite_count	favorited	retweet_count	retweeted	tweet_id
0	2498	False	493	False	666020888022790149

3. Change tweet_id position into first col

In [44]:
```
scrapped_tweet_df = scrapped_tweet_df.reindex(\
                    ['tweet_id','favorite_count','favorited','retweet_count','retwe
                    axis=1)
scrapped_tweet_df.head(1)
```

Out[44]:

	tweet_id	favorite_count	favorited	retweet_count	retweeted
0	666020888022790149	2498	False	493	False

4. Change timestamp format

In [45]:
```
twitter_archive_df.timestamp = pd.to_datetime(twitter_archive_df.timestamp)
twitter_archive_df.timestamp.head(1)
```

Out[45]:
```
2355   2015-11-15 22:32:08+00:00
Name: timestamp, dtype: datetime64[ns, UTC]
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2175 entries, 2355 to 0
Data columns (total 17 columns):
tweet_id                      2175 non-null object
in_reply_to_status_id         78 non-null float64
in_reply_to_user_id           78 non-null float64
timestamp                     2175 non-null datetime64[ns, UTC]
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: datetime64[ns, UTC](1), float64(4), int64(2), object(10)
memory usage: 305.9+ KB
```

5. Uniformly missing value
list function name: uniformly_missing_value

```
In [47]: def uniformly_missing_value(data_frame):
             missing_value_names = ['NaN','None', 'N/A', 'NA', 'Unknown']
             for column in data_frame.columns:
                 for phrase in missing_value_names:
                     data_frame[column].replace(to_replace=missing_value_names, value=np.nan, in
             return data_frame
```

I assume that Dog Name 'a' is null value, so I will make it as NULL

```
In [48]: twitter_archive_df.loc[twitter_archive_df.query("name == 'a'").index,'name'] = np.nan
         twitter_archive_df.name.value_counts().head(5)
```

```
Out[48]: None       680
         Lucy        11
         Charlie     11
         Cooper      10
         Oliver      10
         Name: name, dtype: int64
```

To other variables, I uniformly that missing value with function uniformly_missing_value() that was declare before.

```
In [49]: twitter_archive_df = uniformly_missing_value(twitter_archive_df)
         twitter_archive_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2175 entries, 2355 to 0
Data columns (total 17 columns):
tweet_id                      2175 non-null object
in_reply_to_status_id         78 non-null float64
in_reply_to_user_id           78 non-null float64
timestamp                     2175 non-null datetime64[ns, UTC]
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 float64
expanded_urls                 2117 non-null object
rating_numerator              2175 non-null int64
rating_denominator            2175 non-null int64
name                          1440 non-null object
doggo                         87 non-null object
floofer                       10 non-null object
pupper                        234 non-null object
puppo                         25 non-null object
dtypes: datetime64[ns, UTC](1), float64(5), int64(2), object(9)
memory usage: 385.9+ KB
```

from information above, we find that cols doggo, flooger, ... , puppo have a lot of missing value, but that data is untidy, it must be 1 column.

```
In [50]: image_prediction_df = uniformly_missing_value(image_prediction_df)
         image_prediction_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2075 entries, 0 to 2074
Data columns (total 12 columns):
tweet_id    2075 non-null object
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(1), object(5)
memory usage: 152.1+ KB
```

```
In [51]: scrapped_tweet_df = uniformly_missing_value(scrapped_tweet_df)
         scrapped_tweet_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2335 entries, 0 to 2334
Data columns (total 5 columns):
tweet_id          2335 non-null object
favorite_count    2335 non-null int64
favorited         2335 non-null bool
retweet_count     2335 non-null int64
retweeted         2335 non-null bool
dtypes: bool(2), int64(2), object(1)
memory usage: 59.4+ KB
```

6. Make dog stages into 1 column
Todo:
Validation check there is 1 single value for 1 row
Add new cols to save dog stages
Change value into dog stages
Remove cols not needed
1. Validation there is 1 single value for 1 row
list function name: is_not_nan

```
In [52]: def is_not_nan(data_frame, index:int, col:str):
             cell = data_frame.iloc[index,data_frame.columns.get_loc(col)]
             return pd.notna(cell)
```

```
In [53]: twitter_archive_df['validation'] = 0
         num_rows = len(twitter_archive_df)

         for i in range(num_rows):
             validation_value = twitter_archive_df.iloc[i,twitter_archive_df.columns.get_loc('va

             twitter_archive_df.iloc[i,twitter_archive_df.columns.get_loc('validation')] = \
                 validation_value + \
                 is_not_nan(twitter_archive_df, i, 'doggo') + \
                 is_not_nan(twitter_archive_df, i, 'floofer') + \
                 is_not_nan(twitter_archive_df, i, 'pupper') + \
                 is_not_nan(twitter_archive_df, i, 'puppo')

         twitter_archive_df['validation'].value_counts()
```

```
Out[53]: 0    1831
         1     332
         2      12
         Name: validation, dtype: int64
```

from the value_counts above we find they are 12 row not vallid because they have 2 type of dog. Let's see the data

```
In [54]: twitter_archive_df.query("validation > 1 ").head(2)
```

```
Out[54]:                tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
         1113  733109485275860992                    NaN                  NaN
         1063  741067306818797568                    NaN                  NaN

                              timestamp  \
         1113 2016-05-19 01:38:16+00:00
         1063 2016-06-10 00:39:48+00:00


                                                          source  \
         1113  <a href="http://twitter.com/download/iphone" r...
         1063  <a href="http://twitter.com/download/iphone" r...


                                                            text  retweeted_status_id  \
         1113  Like father (doggo), like son (pupper). Both 1...                  NaN
         1063  This is just downright precious af. 12/10 for ...                  NaN

               retweeted_status_user_id  retweeted_status_timestamp  \
         1113                       NaN                         NaN
         1063                       NaN                         NaN
```

```
                                        expanded_urls  rating_numerator  \
1113  https://twitter.com/dog_rates/status/733109485...                12
1063  https://twitter.com/dog_rates/status/741067306...                12

      rating_denominator  name  doggo floofer  pupper puppo  validation
1113                  10   NaN  doggo     NaN  pupper   NaN           2
1063                  10  just  doggo     NaN  pupper   NaN           2
```

I don't know what the right stage,and the duplicate count just 14 row (0.5% from total row) so I decide to delete unvalid stage

```
In [55]: twitter_archive_df = twitter_archive_df[twitter_archive_df.validation <= 1]
         twitter_archive_df['validation'].value_counts()
```

```
Out[55]: 0    1831
         1     332
         Name: validation, dtype: int64
```

2. Add new colomn to save dog stage

```
In [56]: twitter_archive_df['dog_stage'] = np.nan
         twitter_archive_df.head(2)
```

```
Out[56]:                 tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
         2355  666020888022790149                    NaN                  NaN
         2354  666029285002620928                    NaN                  NaN

                              timestamp  \
         2355 2015-11-15 22:32:08+00:00
         2354 2015-11-15 23:05:30+00:00

                                                          source  \
         2355  &lt;a href="http://twitter.com/download/iphone" r...
         2354  &lt;a href="http://twitter.com/download/iphone" r...

                                                            text  retweeted_status_id  \
         2355  Here we have a Japanese Irish Setter. Lost eye...                  NaN
         2354  This is a western brown Mitsubishi terrier. Up...                  NaN

               retweeted_status_user_id  retweeted_status_timestamp  \
         2355                       NaN                        NaN
         2354                       NaN                        NaN

                                               expanded_urls  rating_numerator  \
         2355  https://twitter.com/dog_rates/status/666020888...                 8
         2354  https://twitter.com/dog_rates/status/666029285...                 7

               rating_denominator name doggo floofer pupper puppo  validation  \
         2355                  10  NaN   NaN     NaN    NaN   NaN           0
```

```
2354                  10  NaN   NaN     NaN    NaN   NaN           0

      dog_stage
2355        NaN
2354        NaN
```

3. Change value column dog_stage
list used function: is_not_nan

In [57]:
```
num_rows = len(twitter_archive_df)

for i in range(num_rows):
    result = twitter_archive_df.iloc[i,twitter_archive_df.columns.get_loc('dog_stage')]

    if(is_not_nan(twitter_archive_df, i, 'doggo')):
        result = twitter_archive_df.iloc[i,twitter_archive_df.columns.get_loc('doggo')]
    elif(is_not_nan(twitter_archive_df, i, 'floofer')):
        result = twitter_archive_df.iloc[i,twitter_archive_df.columns.get_loc('floofer'
    elif(is_not_nan(twitter_archive_df, i, 'pupper')):
        result = twitter_archive_df.iloc[i,twitter_archive_df.columns.get_loc('pupper')
    elif(is_not_nan(twitter_archive_df, i, 'puppo')):
        result = twitter_archive_df.iloc[i,twitter_archive_df.columns.get_loc('puppo')]

    twitter_archive_df.iloc[i,twitter_archive_df.columns.get_loc('dog_stage')] = result

twitter_archive_df.dog_stage.value_counts()
```

Out[57]:
```
pupper     224
doggo       75
puppo       24
floofer      9
Name: dog_stage, dtype: int64
```

4. Remove cols not needed

In [58]:
```
twitter_archive_df.columns
```

Out[58]:
```
Index(['tweet_id', 'in_reply_to_status_id', 'in_reply_to_user_id', 'timestamp',
       'source', 'text', 'retweeted_status_id', 'retweeted_status_user_id',
       'retweeted_status_timestamp', 'expanded_urls', 'rating_numerator',
       'rating_denominator', 'name', 'doggo', 'floofer', 'pupper', 'puppo',
       'validation', 'dog_stage'],
      dtype='object')
```

Because we add column dog_stage so we don't need columns: 'doggo', 'floofer', 'pupper', 'puppo', and we also don't need column validation.

In [59]:
```
twitter_archive_df.drop(['doggo', 'floofer', 'pupper', 'puppo','validation'], axis=1, i
twitter_archive_df.columns
```

```
Out[59]: Index(['tweet_id', 'in_reply_to_status_id', 'in_reply_to_user_id', 'timestamp',
               'source', 'text', 'retweeted_status_id', 'retweeted_status_user_id',
               'retweeted_status_timestamp', 'expanded_urls', 'rating_numerator',
               'rating_denominator', 'name', 'dog_stage'],
              dtype='object')
```

```
In [60]: get_missing_value_percentage(twitter_archive_df)
```

```
Out[60]: tweet_id                        0.000000
         in_reply_to_status_id          96.440129
         in_reply_to_user_id            96.440129
         timestamp                       0.000000
         source                          0.000000
         text                            0.000000
         retweeted_status_id           100.000000
         retweeted_status_user_id      100.000000
         retweeted_status_timestamp    100.000000
         expanded_urls                   2.681461
         rating_numerator                0.000000
         rating_denominator              0.000000
         name                           33.656958
         dog_stage                      84.650948
         dtype: float64
```

The missing value from dog_stage quietly high, but I think this variable save such as good information. So I decide to not delete it.
7. Ensure unique twitter by expanded_urls and jpg_urls

1. Expanded URLS

```
In [61]: twitter_archive_df.duplicated(['expanded_urls']).value_counts()
```

```
Out[61]: False    2105
         True       58
         dtype: int64
```

```
In [62]: twitter_archive_df[twitter_archive_df.duplicated(['expanded_urls'])].expanded_urls.valu
```

```
Out[62]: https://vine.co/v/ea0OwvPTx9l    1
         Name: expanded_urls, dtype: int64
```

```
In [63]: twitter_archive_df.query('expanded_urls == "https://vine.co/v/ea0OwvPTx9l"')
```

```
Out[63]:                 tweet_id  in_reply_to_status_id  in_reply_to_user_id  \
         2212  668587383441514497                    NaN                  NaN
         657   791774931465953280                    NaN                  NaN

                               timestamp  \
         2212 2015-11-23 00:30:28+00:00
```

```
657   2016-10-27 22:53:48+00:00

                                                    source  \
2212  <a href="http://vine.co" rel="nofollow">Vine -...
657   <a href="http://vine.co" rel="nofollow">Vine -...

                                                      text  retweeted_status_id  \
2212  Never forget this vine. You will not stop watc...                  NaN
657   Vine will be deeply missed. This was by far my...                  NaN

      retweeted_status_user_id  retweeted_status_timestamp  \
2212                       NaN                         NaN
657                        NaN                         NaN

                     expanded_urls  rating_numerator  rating_denominator  \
2212  https://vine.co/v/ea0OwvPTx9l                13                  10
657   https://vine.co/v/ea0OwvPTx9l                14                  10

     name dog_stage
2212  the       NaN
657   NaN       NaN
```

I don't know what the real value from that photo, and because of that value just appear in small row (2) so I decide to delete it. And for other duplicate row I also delete it because the expanded_urls value is missing value.

```
In [64]: twitter_archive_df.dropna(subset=['expanded_urls'], how='all', inplace = True)
         twitter_archive_df.duplicated(['expanded_urls']).value_counts()
```

```
Out[64]: False    2104
         True        1
         dtype: int64
```

```
In [65]: twitter_archive_df.drop_duplicates(subset=['expanded_urls'], keep=False, inplace = True
         twitter_archive_df.duplicated(['expanded_urls']).value_counts()
```

```
Out[65]: False    2103
         dtype: int64
```

2. JPG URLS

```
In [66]: image_prediction_df.duplicated(['jpg_url']).value_counts()
```

```
Out[66]: False    2009
         True       66
         dtype: int64
```

```
In [67]: image_prediction_df[image_prediction_df.duplicated(['jpg_url'])].jpg_url.head(5)
```

```
Out[67]: 1297    https://pbs.twimg.com/ext_tw_video_thumb/67535...
         1315      https://pbs.twimg.com/media/CWza7kpWcAAdYLc.jpg
         1333      https://pbs.twimg.com/media/CWyD2HGUYAQ1Xa7.jpg
         1345      https://pbs.twimg.com/media/CU1zsMSUAAAS0qW.jpg
         1349      https://pbs.twimg.com/media/CkNjahBXAAQ2kWo.jpg
         Name: jpg_url, dtype: object
```

```
In [68]: image_prediction_df.query("jpg_url == 'https://pbs.twimg.com/media/CU1zsMSUAAAS0qW.jpg'
```

```
Out[68]:                tweet_id                                          jpg_url  \
         224   670319130621435904  https://pbs.twimg.com/media/CU1zsMSUAAAS0qW.jpg
         1345  759159934323924993  https://pbs.twimg.com/media/CU1zsMSUAAAS0qW.jpg

               img_num             p1   p1_conf  p1_dog      p2   p2_conf  p2_dog  \
         224         1  Irish_terrier  0.254856    True  briard  0.227716    True
         1345        1  Irish_terrier  0.254856    True  briard  0.227716    True

                                        p3   p3_conf  p3_dog
         224   soft-coated_wheaten_terrier  0.223263    True
         1345  soft-coated_wheaten_terrier  0.223263    True
```

```
In [69]: twitter_archive_df.query("tweet_id == '670319130621435904'").expanded_urls
```

```
Out[69]: 2127    https://twitter.com/dog_rates/status/670319130...
         Name: expanded_urls, dtype: object
```

```
In [70]: twitter_archive_df.query("tweet_id == '759159934323924993'").expanded_urls
```

```
Out[70]: Series([], Name: expanded_urls, dtype: object)
```

From observasion above, I find that one of twitter id from duplicated jpg url, doesn't axist in first table. So I will elimited twitter_id that doesn't exist in first table.

```
In [71]: jpg_url_duplicated = image_prediction_df[image_prediction_df.duplicated(['jpg_url'])]['
```

```
In [72]: need_to_drop = image_prediction_df[image_prediction_df.jpg_url.isin(jpg_url_duplicated)
         need_to_drop.head(2)
```

```
Out[72]:               tweet_id                                          jpg_url  \
         85   667509364010450944  https://pbs.twimg.com/media/CUN4Or5UAAAa5K4.jpg
         224  670319130621435904  https://pbs.twimg.com/media/CU1zsMSUAAAS0qW.jpg

              img_num             p1   p1_conf  p1_dog                  p2   p2_conf  \
         85         1         beagle  0.636169    True  Labrador_retriever  0.119256
         224        1  Irish_terrier  0.254856    True              briard  0.227716

              p2_dog                           p3   p3_conf  p3_dog
         85     True             golden_retriever  0.082549    True
         224    True  soft-coated_wheaten_terrier  0.223263    True
```

In [73]:
```
# count row we must to keep
need_to_drop['tweet_id'].isin(twitter_archive_df.tweet_id).sum()
```

Out[73]: 64

In [74]:
```
# drop row need_to_drop if the id exist in first table
need_to_drop = need_to_drop[~need_to_drop['tweet_id'].isin(twitter_archive_df.tweet_id)
need_to_drop['tweet_id'].isin(twitter_archive_df.tweet_id).sum()
```

Out[74]: 0

In [75]:
```
# drop row not exist in first table
image_prediction_df = image_prediction_df[~image_prediction_df.tweet_id.isin(need_to_dr
image_prediction_df.duplicated(['jpg_url']).value_counts()
```

Out[75]:
```
False    2007
dtype: int64
```

8. Delete col with missing value >90% from total rows
list function name: drop_missing_value
list used function: drop_missing_value

In [76]:
```
def drop_missing_value(data_frame, treshold:int = 0.9):
    data = get_missing_value_percentage(data_frame)
    cols_will_drop = []

    for col,percentage_missing_value in data.items():
        if percentage_missing_value > 90:
            cols_will_drop.append(col)

    return data_frame.drop(cols_will_drop, axis = 1)
```

In [77]:
```
twitter_archive_df = drop_missing_value(twitter_archive_df)
get_missing_value_percentage(twitter_archive_df)
```

Out[77]:
```
tweet_id               0.000000
timestamp              0.000000
source                 0.000000
text                   0.000000
expanded_urls          0.000000
rating_numerator       0.000000
rating_denominator     0.000000
name                  31.811698
dog_stage             84.498336
dtype: float64
```

In [78]:
```
drop_missing_value(image_prediction_df)
get_missing_value_percentage(image_prediction_df)
```

Out[78]:
```
tweet_id    0.0
jpg_url     0.0
img_num     0.0
p1          0.0
p1_conf     0.0
p1_dog      0.0
p2          0.0
p2_conf     0.0
p2_dog      0.0
p3          0.0
p3_conf     0.0
p3_dog      0.0
dtype: float64
```

In [79]:
```
drop_missing_value(scrapped_tweet_df)
get_missing_value_percentage(scrapped_tweet_df)
```

Out[79]:
```
tweet_id          0.0
favorite_count    0.0
favorited         0.0
retweet_count     0.0
retweeted         0.0
dtype: float64
```

9. Delete cols with same value
list function name: drop_uniform_value

In [80]:
```
def drop_uniform_value(data_frame):
    cols = data_frame.columns
    cols_will_drop = []

    for col in cols:
        num_value = len(data_frame[col].unique().tolist())
        if(num_value <= 1):
            cols_will_drop.append(col)
    return data_frame.drop(cols_will_drop, axis = 1)
```

In [81]:
```
# first data before
twitter_archive_df.nunique()
```

Out[81]:
```
tweet_id              2103
timestamp             2103
source                   4
text                  2103
expanded_urls         2103
rating_numerator        34
rating_denominator      15
name                   951
dog_stage                4
dtype: int64
```

In [82]:
```
# second data before
image_prediction_df.nunique()
```

Out[82]:
```
tweet_id    2007
jpg_url     2007
img_num        4
p1           378
p1_conf     2004
p1_dog         2
p2           405
p2_conf     2002
p2_dog         2
p3           408
p3_conf     2004
p3_dog         2
dtype: int64
```

In [83]:
```
# third data before
scrapped_tweet_df.nunique()
```

Out[83]:
```
tweet_id          2335
favorite_count    1975
favorited            1
retweet_count     1698
retweeted            1
dtype: int64
```

Because the the only table exist 1 unique value is third data so we change only third data.

In [84]:
```
# third data after
scrapped_tweet_df = drop_uniform_value(scrapped_tweet_df)
scrapped_tweet_df.nunique()
```

Out[84]:
```
tweet_id          2335
favorite_count    1975
retweet_count     1698
dtype: int64
```

In [85]:
```
twitter_archive_df.rating_denominator.value_counts()
```

Out[85]:
```
10     2085
50        3
11        2
80        2
7         1
170       1
150       1
130       1
120       1
```

```
110        1
90         1
70         1
40         1
20         1
2          1
Name: rating_denominator, dtype: int64
```

For rating denominator I expect constanta value (10) but because I get information from Udacity that there is unique rating system is a big part of the popularity of WeRateDogs, so I decide to keep them.

10. Get source col without HTML format

```
In [86]: import re
```

list function name: get_name_in_source

```
In [87]: def get_name_in_source(col_source):
             return str(re.findall("<a.*?>(.+?)</a>", col_source)[0])
```

```
In [88]: for index in range(len(twitter_archive_df)):
             value = twitter_archive_df.iloc[index,twitter_archive_df.columns.get_loc('source')]
             twitter_archive_df.iloc[index,twitter_archive_df.columns.get_loc('source')] = get_n

         twitter_archive_df.source.value_counts()

Out[88]: Twitter for iPhone     1974
         Vine - Make a Scene      88
         Twitter Web Client       30
         TweetDeck                11
         Name: source, dtype: int64
```

11. Join all table

```
In [89]: # join first and second table
         twitter_df = pd.merge(twitter_archive_df, scrapped_tweet_df, how = 'inner', on = ['twee

         # join second and third table
         twitter_df = pd.merge(twitter_df, image_prediction_df, how = 'inner', on = ['tweet_id']

         # check the result
         twitter_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1978 entries, 0 to 1977
Data columns (total 22 columns):
tweet_id              1978 non-null object
timestamp             1978 non-null datetime64[ns, UTC]
source                1978 non-null object
```

```
text                   1978 non-null object
expanded_urls          1978 non-null object
rating_numerator       1978 non-null int64
rating_denominator     1978 non-null int64
name                   1383 non-null object
dog_stage              294 non-null object
favorite_count         1978 non-null int64
retweet_count          1978 non-null int64
jpg_url                1978 non-null object
img_num                1978 non-null int64
p1                     1978 non-null object
p1_conf                1978 non-null float64
p1_dog                 1978 non-null bool
p2                     1978 non-null object
p2_conf                1978 non-null float64
p2_dog                 1978 non-null bool
p3                     1978 non-null object
p3_conf                1978 non-null float64
p3_dog                 1978 non-null bool
dtypes: bool(3), datetime64[ns, UTC](1), float64(3), int64(5), object(10)
memory usage: 314.9+ KB
```

list used function: drop_missing_value

In [90]:
```
# cek the percentage of missing value
get_missing_value_percentage(twitter_df)
```

Out[90]:
```
tweet_id                 0.000000
timestamp                0.000000
source                   0.000000
text                     0.000000
expanded_urls            0.000000
rating_numerator         0.000000
rating_denominator       0.000000
name                    30.080890
dog_stage               85.136502
favorite_count           0.000000
retweet_count            0.000000
jpg_url                  0.000000
img_num                  0.000000
p1                       0.000000
p1_conf                  0.000000
p1_dog                   0.000000
p2                       0.000000
p2_conf                  0.000000
p2_dog                   0.000000
p3                       0.000000
```

```
p3_conf                0.000000
p3_dog                 0.000000
dtype: float64
```

In [91]:
```python
twitter_df.head(2)
```

Out[91]:
```
             tweet_id                  timestamp              source  \
0  666020888022790149 2015-11-15 22:32:08+00:00  Twitter for iPhone
1  666029285002620928 2015-11-15 23:05:30+00:00  Twitter for iPhone

                                            text  \
0  Here we have a Japanese Irish Setter. Lost eye...
1  This is a western brown Mitsubishi terrier. Up...

                                   expanded_urls  rating_numerator  \
0  https://twitter.com/dog_rates/status/666020888...                 8
1  https://twitter.com/dog_rates/status/666029285...                 7

   rating_denominator name dog_stage  favorite_count  ...  img_num  \
0                  10  NaN       NaN            2498  ...        1
1                  10  NaN       NaN             124  ...        1

                       p1   p1_conf p1_dog                  p2   p2_conf  \
0  Welsh_springer_spaniel  0.465074   True              collie  0.156665
1                 redbone  0.506826   True  miniature_pinscher  0.074192

  p2_dog                   p3   p3_conf p3_dog
0   True     Shetland_sheepdog  0.061428   True
1   True   Rhodesian_ridgeback  0.072010   True

[2 rows x 22 columns]
```

In [92]:
```python
# save csv
twitter_df.to_csv("data_generated/twitter_archive_master.csv", index=False)
```

In [93]:
```python
# save each of data
twitter_archive_df.to_csv("data_generated/first_data_twitter_archive.csv", index=False)
image_prediction_df.to_csv("data_generated/second_data_image_prediction.csv", index=Fal
scrapped_tweet_df.to_csv("data_generated/third_data_scrapped_tweet.csv", index=False)
```

Analyzing and Visualizing Data
Question:
Are there any outlier in the data?
How about correlation between variables?
Does the retweet count and favorite count increase with time?
Does the rating increase with time?
Are the rating affect with the number of favorite and retweet count?
How much each algorithm predict the picture is dog?
What are the most popular dog names?

What are the most popular dog predict?
What are the most popular dog predict when all algorithm predict the same dog?
This plot for answer number 1:

In [94]:
```
# to analyzing, I add new column "rating" that can be calculate by numerator/denominato
twitter_df['rating'] = pd.to_numeric((twitter_df.rating_numerator*1.0)/(twitter_df.rati
twitter_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1978 entries, 0 to 1977
Data columns (total 23 columns):
tweet_id              1978 non-null object
timestamp             1978 non-null datetime64[ns, UTC]
source                1978 non-null object
text                  1978 non-null object
expanded_urls         1978 non-null object
rating_numerator      1978 non-null int64
rating_denominator    1978 non-null int64
name                  1383 non-null object
dog_stage             294 non-null object
favorite_count        1978 non-null int64
retweet_count         1978 non-null int64
jpg_url               1978 non-null object
img_num               1978 non-null int64
p1                    1978 non-null object
p1_conf               1978 non-null float64
p1_dog                1978 non-null bool
p2                    1978 non-null object
p2_conf               1978 non-null float64
p2_dog                1978 non-null bool
p3                    1978 non-null object
p3_conf               1978 non-null float64
p3_dog                1978 non-null bool
rating                1978 non-null float64
dtypes: bool(3), datetime64[ns, UTC](1), float64(4), int64(5), object(10)
memory usage: 330.3+ KB
```

In [95]:
```
# statistic description
twitter_df.describe()
```

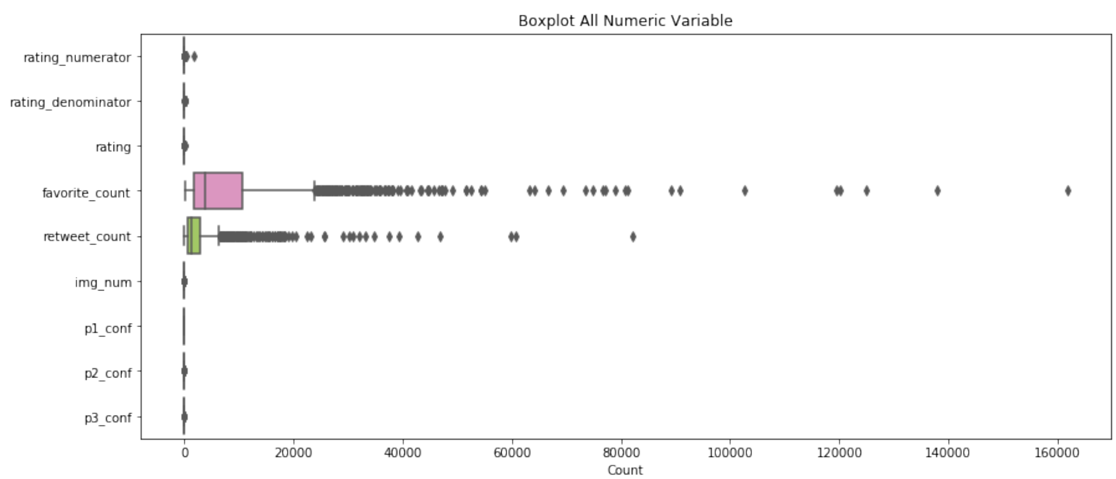
Out[95]:

	rating_numerator	rating_denominator	favorite_count	retweet_count	\
count	1978.000000	1978.000000	1978.000000	1978.000000	
mean	12.287159	10.536400	8511.986855	2576.833670	
std	41.664877	7.350117	12539.485491	4622.355184	
min	0.000000	2.000000	76.000000	11.000000	
25%	10.000000	10.000000	1832.750000	577.250000	
50%	11.000000	10.000000	3811.000000	1241.000000	
75%	12.000000	10.000000	10645.500000	2934.000000	

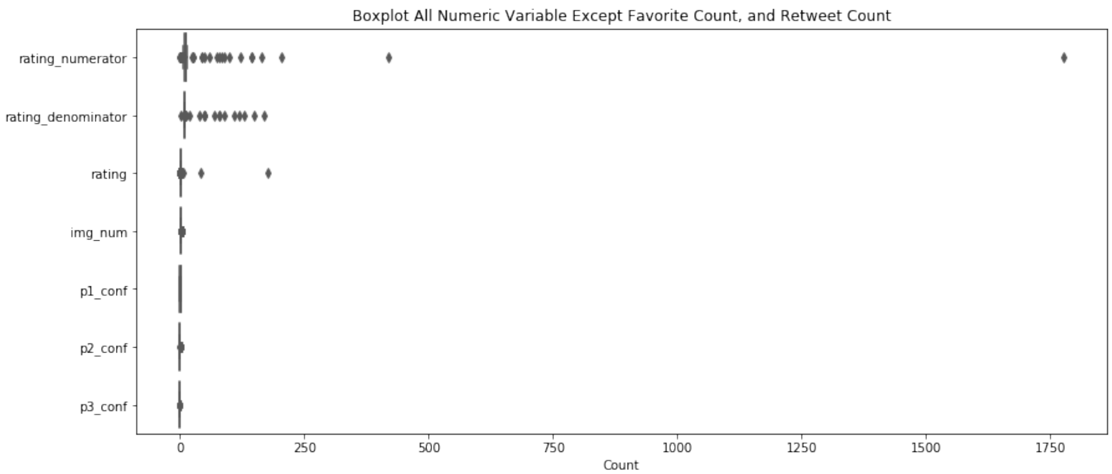
```
max        1776.000000          170.000000   161719.000000   82136.000000

           img_num      p1_conf       p2_conf       p3_conf        rating
count  1978.000000  1978.000000  1.978000e+03  1.978000e+03  1978.000000
mean      1.203741     0.592434  1.347591e-01  6.043538e-02     1.169405
std       0.562211     0.271780  1.006778e-01  5.090927e-02     4.083458
min       1.000000     0.044333  1.011300e-08  1.740170e-10     0.000000
25%       1.000000     0.360998  5.432547e-02  1.638385e-02     1.000000
50%       1.000000     0.586944  1.178485e-01  4.975535e-02     1.100000
75%       1.000000     0.841932  1.953582e-01  9.166433e-02     1.200000
max       4.000000     1.000000  4.880140e-01  2.734190e-01   177.600000
```

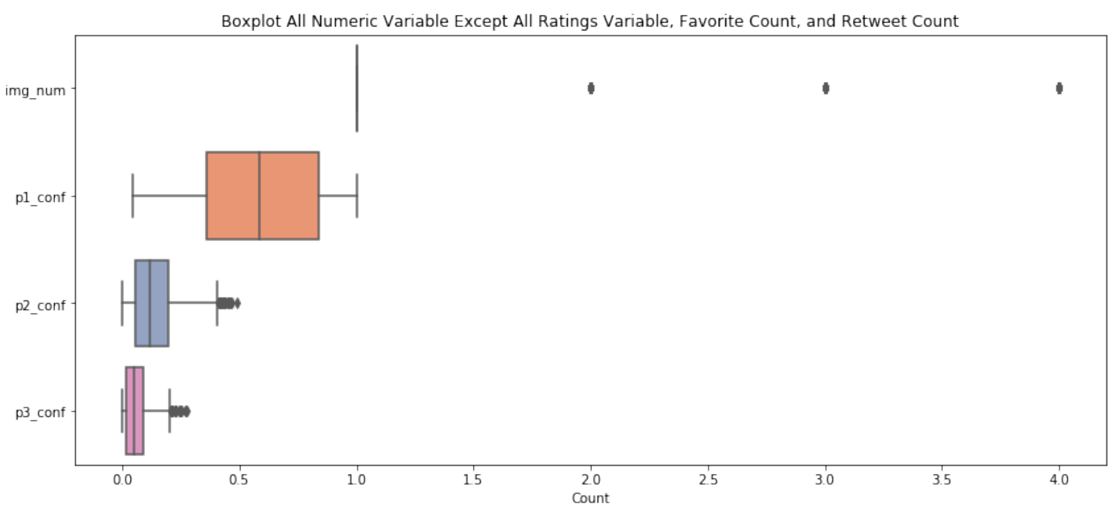
In [96]:
```
# visualitation
fig, ax = plt.subplots()
fig.set_size_inches(14, 6)
sns.boxplot(data=twitter_df[['rating_numerator','rating_denominator','rating','favorite
                                  'retweet_count','img_num','p1_conf','p2_conf','p3_con
                 orient="h", palette="Set2", ax=ax);
plt.title('Boxplot All Numeric Variable');
plt.xlabel('Count');
plt.savefig('plot/1_Boxplot All Numeric Variable.png')
```



In [97]:
```
fig, ax = plt.subplots()
fig.set_size_inches(14, 6)
sns.boxplot(data=twitter_df[['rating_numerator','rating_denominator','rating',\
                                  'img_num','p1_conf','p2_conf','p3_conf']],\
                 orient="h", palette="Set2", ax=ax);
plt.title('Boxplot All Numeric Variable Except Favorite Count, and Retweet Count');
plt.xlabel('Count');
plt.savefig('plot/2_Boxplot All Numeric Variable Except Favorite Count, and Retweet Cou
```

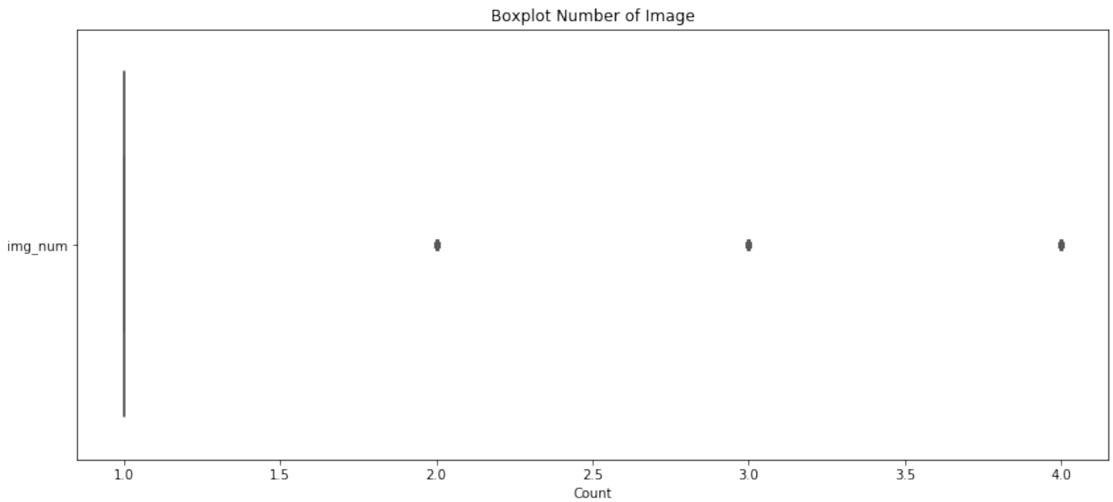



```
In [98]: fig, ax = plt.subplots()
         fig.set_size_inches(14, 6)
         sns.boxplot(data=twitter_df[['img_num','p1_conf','p2_conf','p3_conf']],\
                           orient="h", palette="Set2", ax=ax);
         plt.title('Boxplot All Numeric Variable Except All Ratings Variable, Favorite Count, an
         plt.xlabel('Count');
         plt.savefig('plot/3_Boxplot All Numeric Variable Except All Ratings Variable, Favorite
```




```
In [99]: fig, ax = plt.subplots()
         fig.set_size_inches(14, 6)
         sns.boxplot(data=twitter_df[['img_num']],\
                           orient="h", palette="Set2", ax=ax);
         plt.title('Boxplot Number of Image');
```

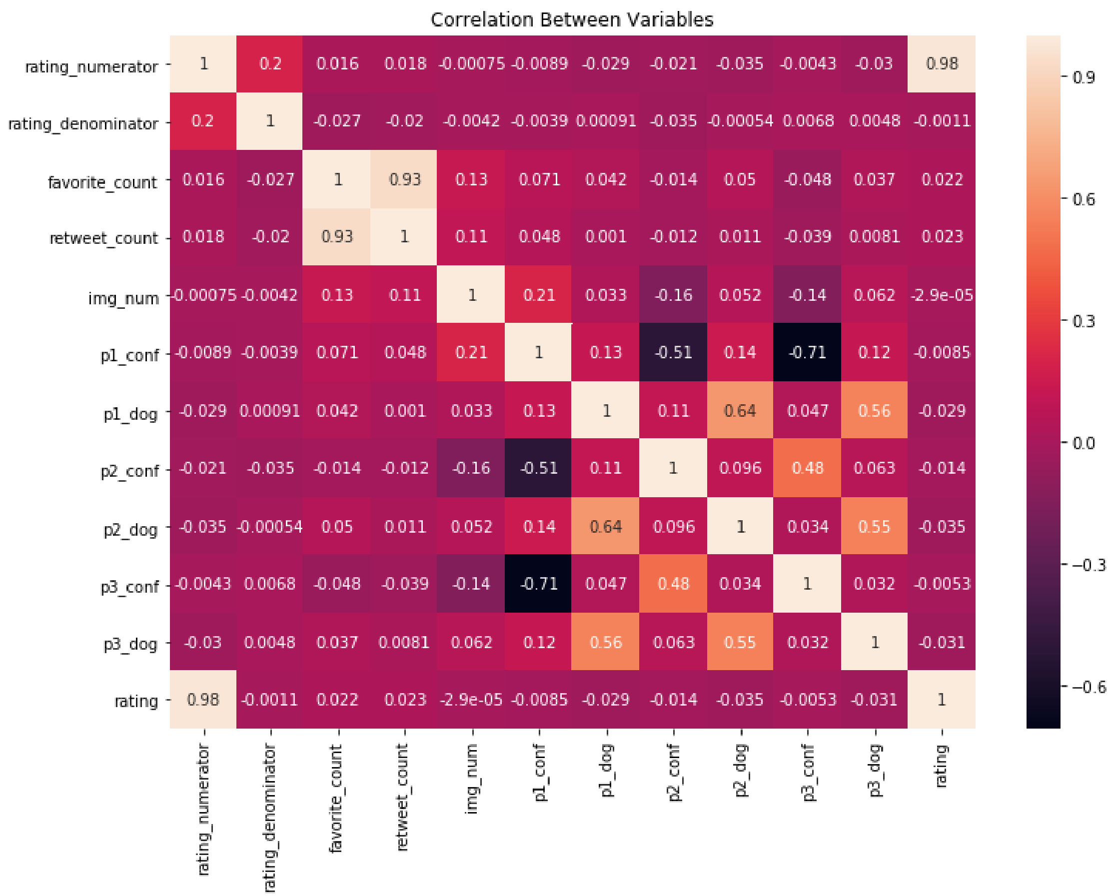
```
plt.xlabel('Count');
plt.savefig('plot/4_Boxplot Number of Image.png')
```



1. Are there any outlier in the data? Answer: - In numeric data, all cols have outlier except p1_conf and rating_denominator. Just like the information from udacity, some they use unique rating so the result maybe not between 0 until 1. - From statistic description, we found that distance min max from variables rating_numerator, rating_denominator, favorite_count, retweet_count, and ratings are high. But for all rating variable, we can find that Q3 is not too far from another Q, so the max value from that variables definitely outlier. - In img_num just like the stat desc, the min until Q3 the result are 1, so the other value except 1 was missing value

This plot for question number 2:

```
In [100]: # correlation
          fig, ax = plt.subplots()
          fig.set_size_inches(11.7, 8.27)
          sns.heatmap(twitter_df.corr(), annot=True, ax=ax);
          plt.title('Correlation Between Variables');
          plt.savefig('plot/5_Correlation Between Variables.png')
```

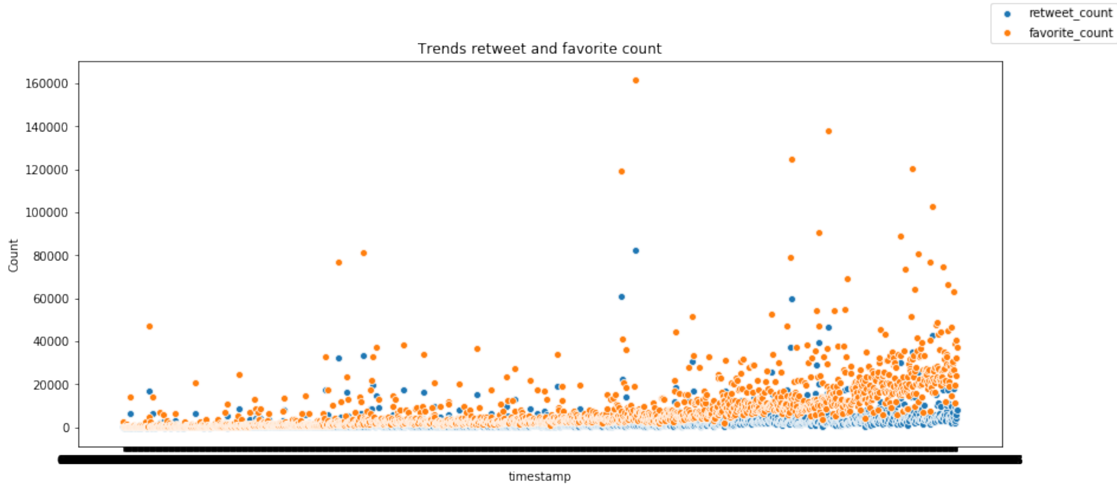


2. How about correlation between variables? Answer: Note: The correlation value between -1 until 1, negative just to make we know the correlation direction, the closer to the value 0, the smaller the correlation. It use pearson correlation so they just see the linear relationship between each variables. - To this plot please ignore correlation between rating and rating_numerator or rating_denominator because the result should be strong because rating is a calculation from both of them. But surprisingly the correlation between rating and rating_denominator is small. The answer can be found from stat desc that show if value rating_numerator is more varied than rating_denominator (std rating_denominator more hight than rating_numerator but their quantiles just similar each other) - We can see hight positive correlation between favorite_count and retweet_count. Its mean the more favorited the more retweeted - The correlation between all confidence variables also quite high. Somehow when p1_conf hight the confidence in p2 and p3 will decreese, but when confidence p3 increase the confidence in p2 will lightly increese.

This plot for question number 3:

```
In [101]: fig, ax = plt.subplots()
          fig.set_size_inches(14, 6)
          sns.scatterplot(x="timestamp", y="retweet_count", data=twitter_df,ax=ax);
          sns.scatterplot(x="timestamp", y="favorite_count", data=twitter_df,ax=ax);
          fig.legend(labels=['retweet_count','favorite_count']);
          plt.title('Trends retweet and favorite count');
```

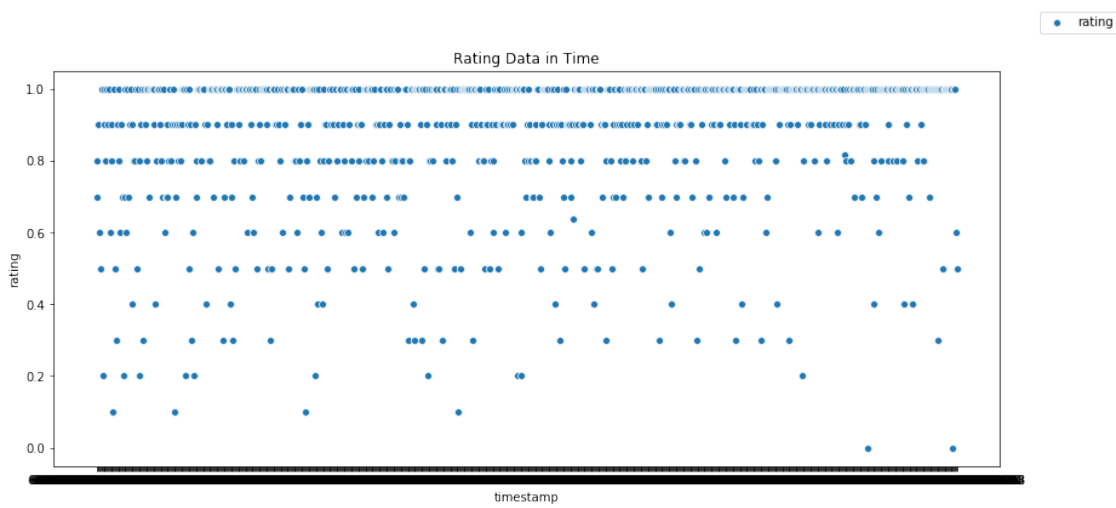
```python
plt.ylabel('Count');
plt.savefig('plot/6_Trends retweet and favorite count.png')
```



3. Does the retweet count and favorite count increase with time? Answer: From that visualization, favorite count and retweet count always increase with time. The trends are increasing for both variables. But favorite count growing larger than retweet count

This plot for question number 4:

```python
In [103]: fig, ax = plt.subplots()
          fig.set_size_inches(14, 6)
          sns.scatterplot(x="timestamp", y="rating", data=twitter_df.query('rating<=1'),ax=ax);
          fig.legend(labels=['rating']);
          plt.title('Rating Data in Time');
          plt.savefig('plot/7_Rating Data in Time.png');
```



4. Does the rating increase with time? Answer: Rating are sparated from min to max value in anytime, but from that plot from same date the rating are missing because the data was missing. Just like the correlation that rating didn't correlate with any variables.

This plot for question number 5:

In [105]:
```
# frist let make rating level
# this function will help to make level from quantile and return categories column
def get_class(df, column:str):
    # find quantile to decide that class
    min_value = df[column].min()
    quantile_1 = df[column].describe()[4]
    quantile_2 = df[column].describe()[5]
    quantile_3 = df[column].describe()[6]
    max_value = df[column].max()

    # bin edges that will be used to "cut" the data into groups
    bin_level = [ min_value, quantile_1, quantile_2, quantile_3, max_value]
    # labels for the four budget level groups
    bin_name = [ 'Low', 'Medium', 'High', 'Very High']
    # creates budget_levels column
    name = '{}_levels'.format(column)
    df[name] = pd.cut(df[column], bin_level, labels=bin_name, include_lowest = True)
    return df
```

In [106]:
```
rank_level_df = get_class(twitter_df, "rating")
rank_level_df = rank_level_df[['favorite_count','retweet_count','rating_levels']]
rank_level_df.head(3)
```

Out[106]:

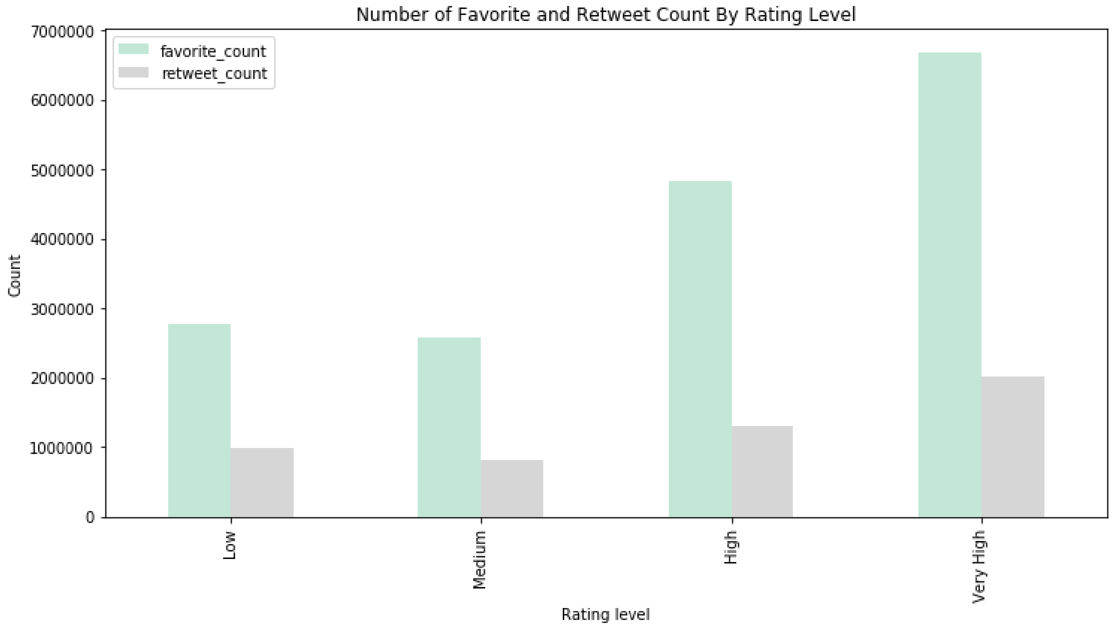
	favorite_count	retweet_count	rating_levels
0	2498	493	Low
1	124	46	Low
2	120	43	Low

In [107]:
```
rank_level_df = rank_level_df.groupby(['rating_levels']).sum()
rank_level_df
```

Out[107]:

rating_levels	favorite_count	retweet_count
Low	2757832	982252
Medium	2576693	810931
High	4822163	1296971
Very High	6680022	2006823

In [108]:
```
rank_level_df.plot(kind='bar',figsize=(12, 6),colormap='Pastel2',alpha=0.8).legend(loc
plt.xlabel('Rating level');
plt.ylabel('Count');
plt.title('Number of Favorite and Retweet Count By Rating Level');
plt.savefig('plot/8_Number of Favorite and Retweet Count By Rating Level.png')
```



5. Are the rating affect with the number of favorite and retweet count? Answer: From all data, we found that the higher the rating the higher the count (favorite and retweet). From that plot we also know that count in favorite alway higher than retweet.

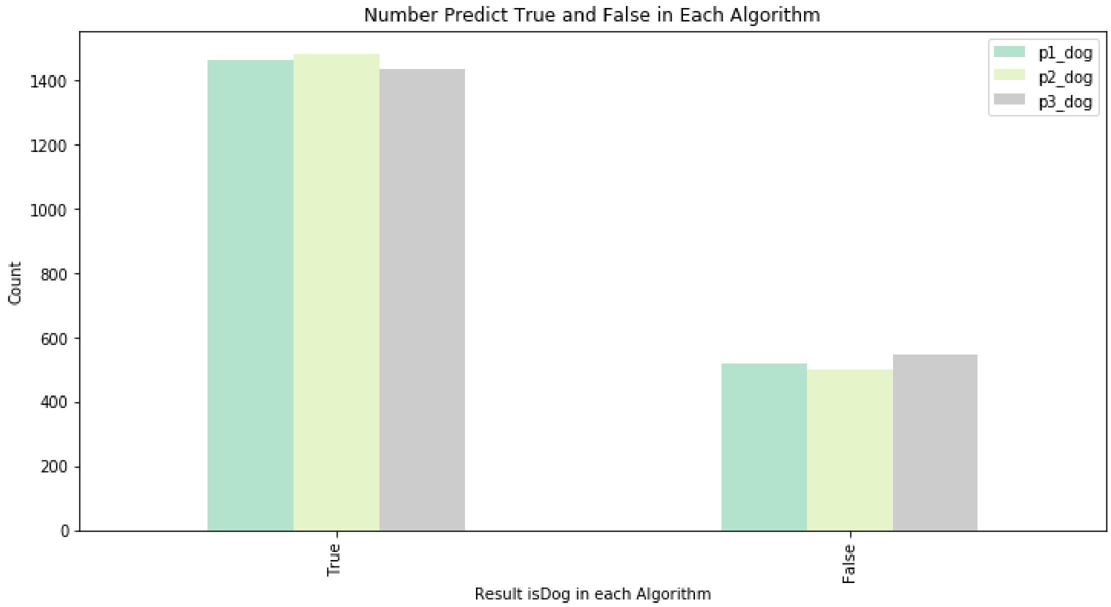
This plot for question number 6:

In [109]:
```
count = pd.DataFrame()
count['p1_dog'] = twitter_df.p1_dog.value_counts()
count['p2_dog'] = twitter_df.p2_dog.value_counts()
count['p3_dog'] = twitter_df.p3_dog.value_counts()
count
```

Out[109]:

	p1_dog	p2_dog	p3_dog
True	1462	1481	1433
False	516	497	545

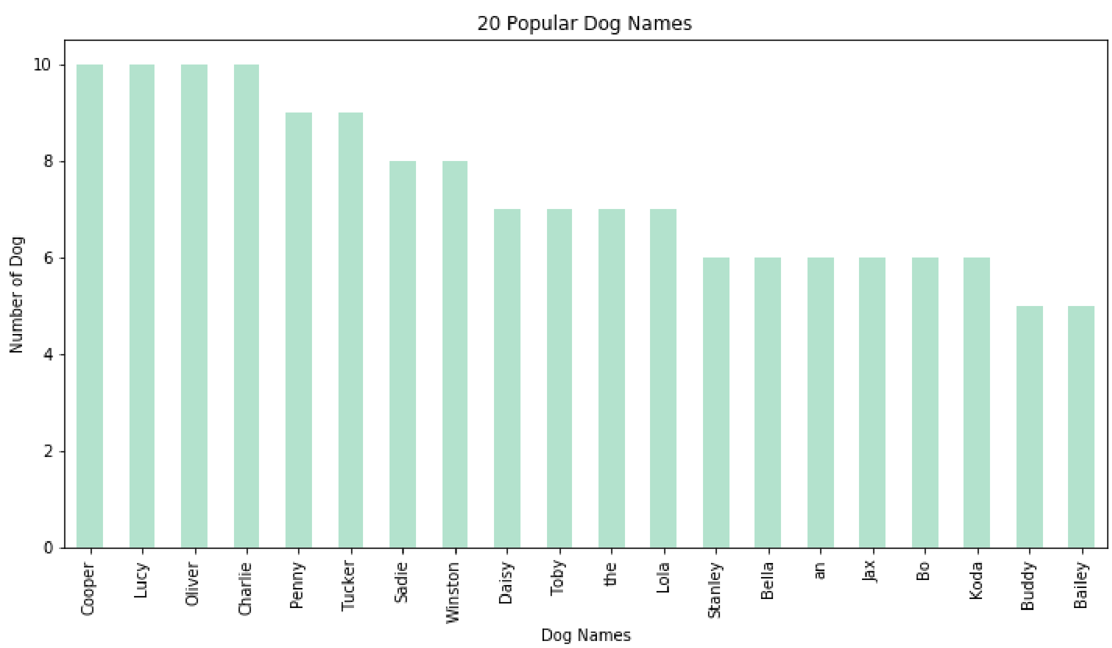
In [110]:
```
count.plot.bar(colormap='Pastel2',figsize=(12, 6));
plt.xlabel('Result isDog in each Algorithm');
plt.ylabel('Count');
plt.title('Number Predict True and False in Each Algorithm');
plt.savefig('plot/9_Number Predict True and False in Each Algorithm.png')
```



6. How much each algorithm predict the picture is dog? Answer: P2 predict picture dog large than p1 and p3. The smallest predicted is dog come from p3.

This plot for question number 7:

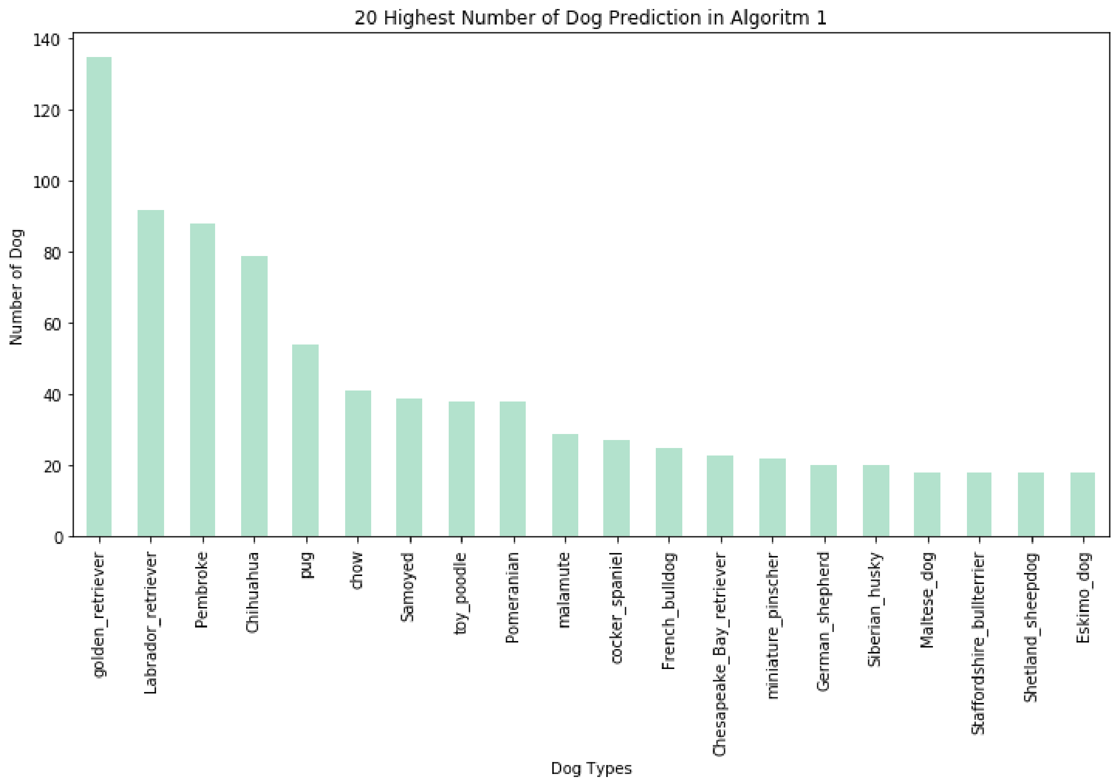
```
In [111]: twitter_df.name.value_counts()[0:20].plot.bar(colormap='Pastel2',figsize=(12, 6));
          plt.xlabel('Dog Names');
          plt.ylabel('Number of Dog');
          plt.title('20 Popular Dog Names');
          plt.savefig('plot/10_20 Popular Dog Names.png')
```



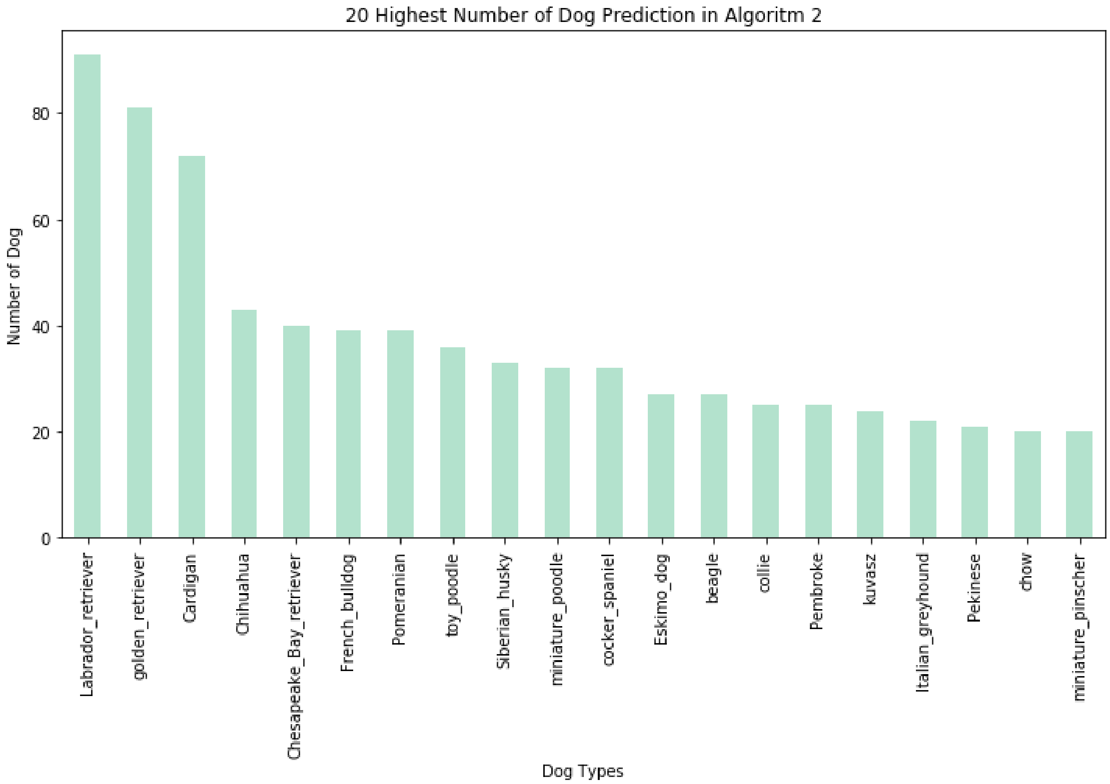
7. What are the most popular dog names? Answer: “Oliver”, “Lucy”, “Charlie”, and “Cooper” is the commond dog names in that table.

This plot for question number 8:

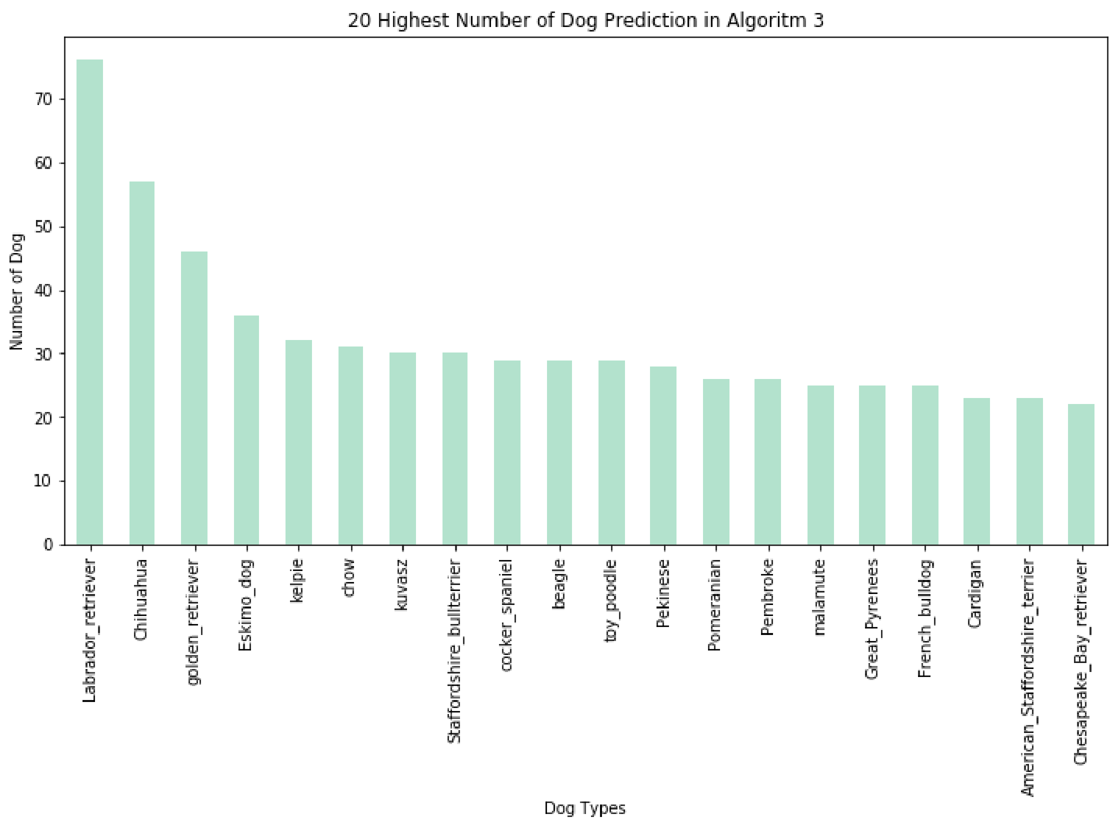
```
In [112]: twitter_df[twitter_df.p1_dog == True].p1.value_counts()[0:20].plot.bar(colormap='Paste
          plt.xlabel('Dog Types');
          plt.ylabel('Number of Dog');
          plt.title('20 Highest Number of Dog Prediction in Algoritm 1');
          plt.savefig('plot/11_20 Highest Number of Dog Prediction in Algoritm 1.png')
```




```
In [113]: twitter_df[twitter_df.p2_dog == True].p2.value_counts()[0:20].plot.bar(colormap='Paste
          plt.xlabel('Dog Types');
          plt.ylabel('Number of Dog');
          plt.title('20 Highest Number of Dog Prediction in Algoritm 2');
          plt.savefig('plot/12_20 Highest Number of Dog Prediction in Algoritm 2.png')
```



In [114]:
```
twitter_df[twitter_df.p3_dog == True].p3.value_counts()[0:20].plot.bar(colormap='Paste
plt.xlabel('Dog Types');
plt.ylabel('Number of Dog');
plt.title('20 Highest Number of Dog Prediction in Algoritm 3');
plt.savefig('plot/12_20 Highest Number of Dog Prediction in Algoritm 3.png')
```



8. What are the most popular dog predict? Answer: In Algorithm 1, golden retriever are the most popular dog, but in Algorithm 2 and 3, labrator retriever is the most popular dog.

This code for answer question number 9:

```
In [115]: top_dog = twitter_df.query('(p1 == p2) | (p2 == p3) | (p1 == p3)')
          top_dog
```

```
Out[115]:                tweet_id           timestamp              source  \
          1390  770414278348247044  770414278348247044  Twitter for iPhone

                                                           text  \
          1390  Meet Al Cabone. He's a gangsta puppa. Rather h...

                                                  expanded_urls  rating_numerator  \
          1390  https://twitter.com/dog_rates/status/770414278...                11

                rating_denominator name dog_stage  favorite_count  ...   p1_conf p1_dog  \
          1390                  10   Al       NaN            6587  ...  0.580528  False

                     p2   p2_conf  p2_dog                p3  p3_conf  p3_dog  rating  \
          1390  maillot  0.081449   False  golden_retriever  0.05357    True     1.1
```

```
      rating_levels
1390        Medium

[1 rows x 24 columns]
```

9. What are the most popular dog predict when all algorithm predict the same dog? Answer: When I select data with same answer in at least 2 Algorithm, there are just 1 data, that predict mailot and exist in algorithm 1 and 2.

Predict dog_stage

Because dog_stage have many missing value, so I try to predict them with simple decision tree model. Todo:

Make sure the type of our table

Define X and Y as predictor and label

Encode categorical predictor

Split train, and test data

Make prediction

Show Metrics from prediction

The predictions

1.Make sure the type of our table

In [116]:
```
# because rating_levels from analyzing data have categorical datatype,
# so we must parse it to object (just like another columns)
twitter_df.rating_levels = twitter_df.rating_levels.astype("object")
twitter_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1978 entries, 0 to 1977
Data columns (total 24 columns):
tweet_id              1978 non-null object
timestamp             1978 non-null object
source                1978 non-null object
text                  1978 non-null object
expanded_urls         1978 non-null object
rating_numerator      1978 non-null int64
rating_denominator    1978 non-null int64
name                  1383 non-null object
dog_stage             294 non-null object
favorite_count        1978 non-null int64
retweet_count         1978 non-null int64
jpg_url               1978 non-null object
img_num               1978 non-null int64
p1                    1978 non-null object
p1_conf               1978 non-null float64
p1_dog                1978 non-null bool
p2                    1978 non-null object
p2_conf               1978 non-null float64
p2_dog                1978 non-null bool
p3                    1978 non-null object
```

```
p3_conf               1978 non-null float64
p3_dog                1978 non-null bool
rating                1978 non-null float64
rating_levels         1978 non-null object
dtypes: bool(3), float64(4), int64(5), object(12)
memory usage: 345.8+ KB
```

2. Define X and Y as predictor and label

```
In [117]: # I use data with not na in dog stage tobe my dataset in my models
          dataset = twitter_df[pd.notna(twitter_df.dog_stage)]
          dataset.dog_stage.value_counts()

Out[117]: pupper     203
          doggo       62
          puppo       22
          floofer      7
          Name: dog_stage, dtype: int64
```

Because of imbalance data, I decide to upsampling the other label into 203 data just like 'puupper'

```
In [118]: def rand_sampling_dog_stage(query, n:int, dataFrame):
              col_df = dataFrame.query(query)
              return col_df.sample(n = n, replace=True, random_state=9835)

In [119]: new_dataset = pd.DataFrame()
          new_dataset = pd.concat([dataset.query('dog_stage == "pupper"'),\
                                   rand_sampling_dog_stage('dog_stage == "doggo"', 203,dataset),\
                                   rand_sampling_dog_stage('dog_stage == "puppo"', 203,dataset),\
                                   rand_sampling_dog_stage('dog_stage == "floofer"', 203,dataset)]
          new_dataset.dog_stage.value_counts()

Out[119]: puppo      203
          pupper     203
          doggo      203
          floofer    203
          Name: dog_stage, dtype: int64

In [120]: # define predictor and label

          Y = new_dataset.dog_stage
          X = new_dataset.drop(['dog_stage','timestamp','tweet_id','expanded_urls','jpg_url'], a
```

3. Encode categorical predictor

```
In [121]: # Make mask for categorical dtypes only
          categorical_feature_mask = X.dtypes==object
          # filter categorical columns using mask and turn it into a list
          categorical_cols = X.columns[categorical_feature_mask].tolist()
```

In [122]:
```python
from sklearn.preprocessing import LabelEncoder

# instantiate labelencoder object to help us encode each variable
le = LabelEncoder()
```

In [123]:
```python
# Our categorical variable
categorical_cols
```

Out[123]:
```
['source', 'text', 'name', 'p1', 'p2', 'p3', 'rating_levels']
```

In [124]:
```python
# apply our le to categorical feature columns

X[categorical_cols] = X[categorical_cols].apply(lambda col: le.fit_transform(col.astyp
X[categorical_cols].head(10)
```

Out[124]:

	source	text	name	p1	p2	p3	rating_levels
331	2	140	21	107	14	28	1
333	2	214	107	62	63	121	1
339	2	228	124	107	14	33	2
346	2	111	70	6	61	44	0
353	2	93	135	20	26	0	1
356	2	208	102	117	73	127	1
357	2	264	164	76	20	77	0
363	2	143	26	97	51	110	2
367	2	144	27	89	111	81	1
368	2	147	29	107	7	20	1

4. Split train, and test data

In [125]:
```python
from sklearn.model_selection import train_test_split

# split sratify so all lebel is balance, use 30% data to be our data test
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.3, stratify =
```

In [126]:
```python
# label in data train
y_train.value_counts()
```

Out[126]:
```
pupper     142
puppo      142
doggo      142
floofer    142
Name: dog_stage, dtype: int64
```

In [127]:
```python
# label in data test
y_test.value_counts()
```

Out[127]:
```
puppo      61
pupper     61
doggo      61
floofer    61
Name: dog_stage, dtype: int64
```

5. Make prediction

```
In [128]: from sklearn.tree import DecisionTreeClassifier

          # Make classifier object, in there I use gini
          clf_gini = DecisionTreeClassifier(criterion = "gini", random_state = 9835)

          # Train the model
          clf_gini.fit(X_train, y_train)

          # Predict with test sample
          y_pred = clf_gini.predict(X_test)
```

6. Show Metrics from prediction

```
In [130]: from sklearn.metrics import confusion_matrix, accuracy_score, classification_report, f

          print("Confusion Matrix:\n",
          confusion_matrix(y_test, y_pred))

          print ("Accuracy:\n",
          accuracy_score(y_test,y_pred)*100)

          print("Report:\n",
          classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[59  0  1  1]
 [ 0 61  0  0]
 [14  0 42  5]
 [ 0  0  0 61]]
Accuracy:
 91.39344262295081
Report:
               precision    recall  f1-score   support

       doggo       0.81      0.97      0.88        61
     floofer       1.00      1.00      1.00        61
      pupper       0.98      0.69      0.81        61
       puppo       0.91      1.00      0.95        61

   micro avg       0.91      0.91      0.91       244
   macro avg       0.92      0.91      0.91       244
weighted avg       0.92      0.91      0.91       244
```

Because the metrics are good enough, so let's predict another row

In [131]: # get the data

```
data_predict = twitter_df.copy()
data_predict.head(2)
```

Out[131]:

```
              tweet_id           timestamp              source  \
0  666020888022790149  666020888022790149  Twitter for iPhone
1  666029285002620928  666029285002620928  Twitter for iPhone

                                                text  \
0  Here we have a Japanese Irish Setter. Lost eye...
1  This is a western brown Mitsubishi terrier. Up...

                                       expanded_urls  rating_numerator  \
0  https://twitter.com/dog_rates/status/666020888...                 8
1  https://twitter.com/dog_rates/status/666029285...                 7

   rating_denominator name dog_stage  favorite_count  ...   p1_conf p1_dog  \
0                  10  NaN       NaN            2498  ...  0.465074   True
1                  10  NaN       NaN             124  ...  0.506826   True

                  p2   p2_conf  p2_dog                  p3   p3_conf  \
0             collie  0.156665    True    Shetland_sheepdog  0.061428
1  miniature_pinscher  0.074192    True  Rhodesian_ridgeback  0.072010

   p3_dog  rating rating_levels
0    True     0.8           Low
1    True     0.7           Low

[2 rows x 24 columns]
```

In [132]: # encode the data

```
data_predict[categorical_cols] = data_predict[categorical_cols].apply(lambda col: le.f
data_predict[categorical_cols].head(10)
```

Out[132]:

```
   source  text  name   p1   p2   p3  rating_levels
0       2   174   919   77  149   73              1
1       2  1801   919  287  253   66              1
2       2   164   919   32  246  120              1
3       2  1792   919   60  304  257              1
4       2   171   919  243   63   25              1
5       2  1799   919   13   27   41              1
6       2  1810   910  119  263  365              1
7       2   158   919  137   75  194              1
8       2   530   919  304  319  200              1
9       2   166   926  244  230  345              1
```

In [133]: # make prediction

```
data_predict.loc[:,'dog_stage'] = clf_gini.predict(data_predict.drop(['dog_stage','tim
data_predict.head()
```

```
Out[133]:              tweet_id           timestamp  source  text  \
          0  666020888022790149  666020888022790149       2   174
          1  666029285002620928  666029285002620928       2  1801
          2  666033412701032449  666033412701032449       2   164
          3  666044226329800704  666044226329800704       2  1792
          4  666049248165822465  666049248165822465       2   171

                                                 expanded_urls  rating_numerator  \
          0  https://twitter.com/dog_rates/status/666020888...                 8
          1  https://twitter.com/dog_rates/status/666029285...                 7
          2  https://twitter.com/dog_rates/status/666033412...                 9
          3  https://twitter.com/dog_rates/status/666044226...                 6
          4  https://twitter.com/dog_rates/status/666049248...                 5

             rating_denominator  name dog_stage  favorite_count  ...   p1_conf p1_dog  \
          0                  10   919    pupper            2498  ...  0.465074   True
          1                  10   919    pupper             124  ...  0.506826   True
          2                  10   919    pupper             120  ...  0.596461   True
          3                  10   919    pupper             288  ...  0.408143   True
          4                  10   919    pupper             104  ...  0.560311   True

              p2   p2_conf  p2_dog   p3   p3_conf  p3_dog  rating  rating_levels
          0  149  0.156665    True   73  0.061428    True     0.8              1
          1  253  0.074192    True   66  0.072010    True     0.7              1
          2  246  0.138584    True  120  0.116197    True     0.9              1
          3  304  0.360687    True  257  0.222752    True     0.6              1
          4   63  0.243682    True   25  0.154629    True     0.5              1

          [5 rows x 24 columns]
```

```
In [134]: # let's make their into 1 table

          # change col name so it will not be duplicated
          data_predict = data_predict[['tweet_id','dog_stage']]
          data_predict.columns =["tweet_id", "predict_dog_stage"]
          data_predict.head()
```

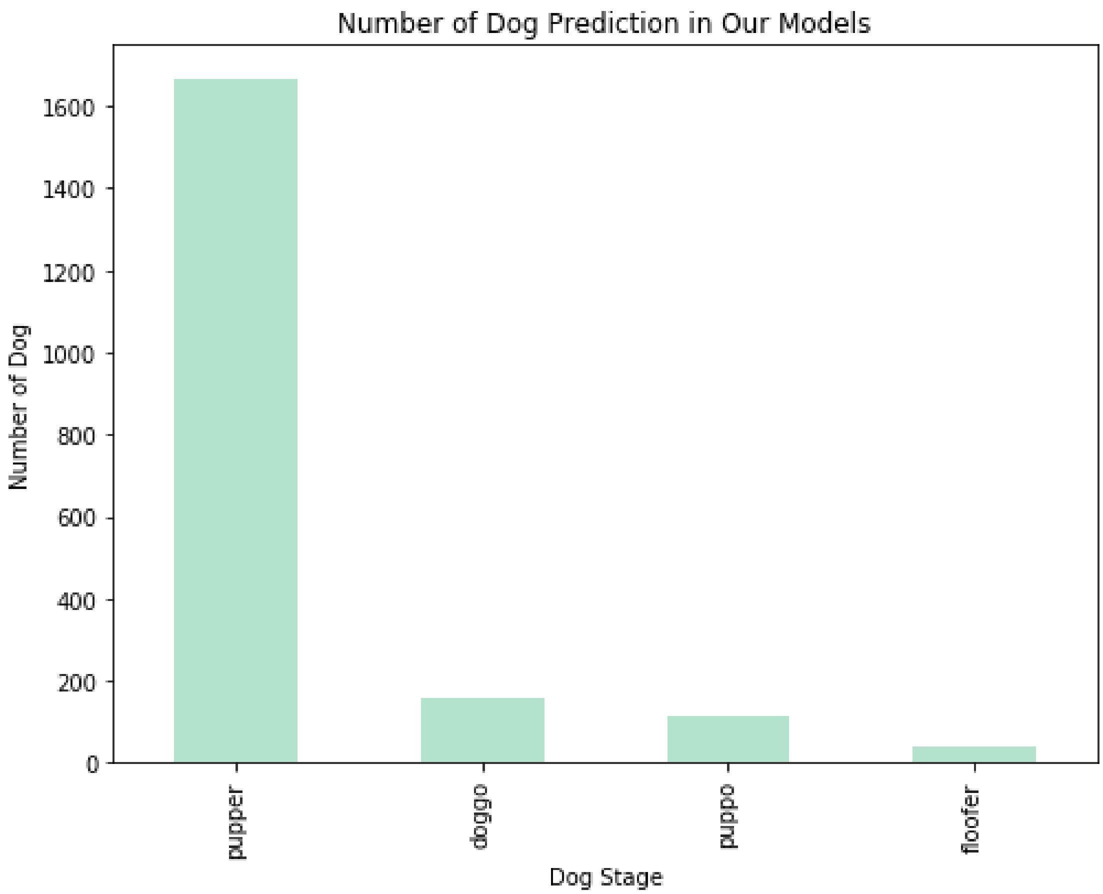
```
Out[134]:              tweet_id predict_dog_stage
          0  666020888022790149            pupper
          1  666029285002620928            pupper
          2  666033412701032449            pupper
          3  666044226329800704            pupper
          4  666049248165822465            pupper
```

```
In [135]: # join table
          twitter_predict_df = pd.merge(twitter_df, data_predict, how = 'inner', on = ['tweet_id
          twitter_predict_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1978 entries, 0 to 1977
```

```
Data columns (total 25 columns):
tweet_id              1978 non-null object
timestamp             1978 non-null object
source                1978 non-null object
text                  1978 non-null object
expanded_urls         1978 non-null object
rating_numerator      1978 non-null int64
rating_denominator    1978 non-null int64
name                  1383 non-null object
dog_stage             294 non-null object
favorite_count        1978 non-null int64
retweet_count         1978 non-null int64
jpg_url               1978 non-null object
img_num               1978 non-null int64
p1                    1978 non-null object
p1_conf               1978 non-null float64
p1_dog                1978 non-null bool
p2                    1978 non-null object
p2_conf               1978 non-null float64
p2_dog                1978 non-null bool
p3                    1978 non-null object
p3_conf               1978 non-null float64
p3_dog                1978 non-null bool
rating                1978 non-null float64
rating_levels         1978 non-null object
predict_dog_stage     1978 non-null object
dtypes: bool(3), float64(4), int64(5), object(13)
memory usage: 361.2+ KB
```

```
In [136]: twitter_predict_df.predict_dog_stage.value_counts()[0:20].plot.bar(colormap='Pastel2',
          plt.xlabel('Dog Stage');
          plt.ylabel('Number of Dog');
          plt.title('Number of Dog Prediction in Our Models');
          plt.savefig('plot/13_Number of Dog Prediction in Our Models');
```



Just like the value before uppersampling, the popular dog_stage is pupper.

In [137]:
```
# save the prediction dataframe
twitter_predict_df.to_csv('data_generated/twitter_predict_df.csv',index=False)
```