act_report

July 5, 2018

1 Analysis and Insights

1.0.1 by Saravanan Natarajan

1.0.2 Import libraries

```
In [93]: import matplotlib
         import matplotlib.pyplot as plt
         import pandas as pd
         import datetime as dt
         import seaborn as sns
         import numpy as np
         import sqlalchemy

         %matplotlib inline
```

```
In [94]: matplotlib.style.use('ggplot')
```

Read the master data from SQL, we can also read it from CSV

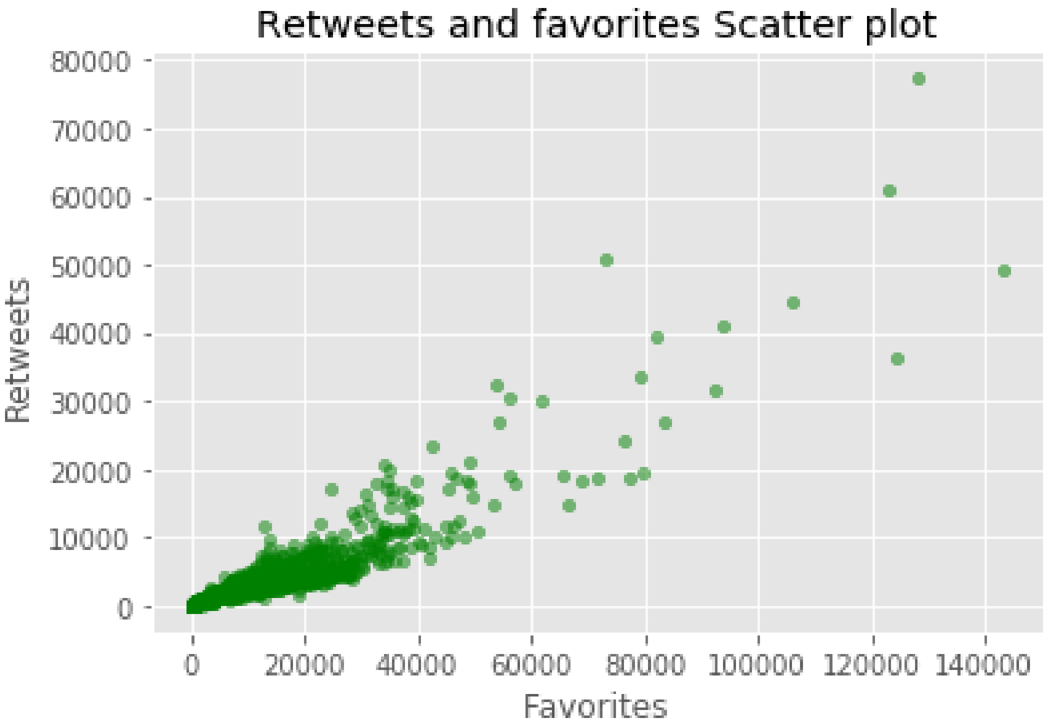
```
In [96]: #df_master = pd.read_csv('twitter_archive_master.csv')
         engine = sqlalchemy.create_engine('sqlite:///twitter_archive_master.db')
         df_master = pd.read_sql('SELECT * FROM master', engine)
         df_master.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1994 entries, 0 to 1993
Data columns (total 17 columns):
tweet_id              1994 non-null int64
timestamp             1994 non-null object
source                1994 non-null object
text                  1994 non-null object
expanded_urls         1994 non-null object
rating_numerator      1994 non-null float64
rating_denominator    1994 non-null float64
name                  1994 non-null object
jpg_url               1994 non-null object
img_num               1994 non-null float64
```

```
favorites             1994 non-null int64
retweets              1994 non-null int64
dog_breed             1994 non-null object
confidence            1994 non-null float64
dog_type              1994 non-null object
dog_name              1369 non-null object
dog_gender            862 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 264.9+ KB
```

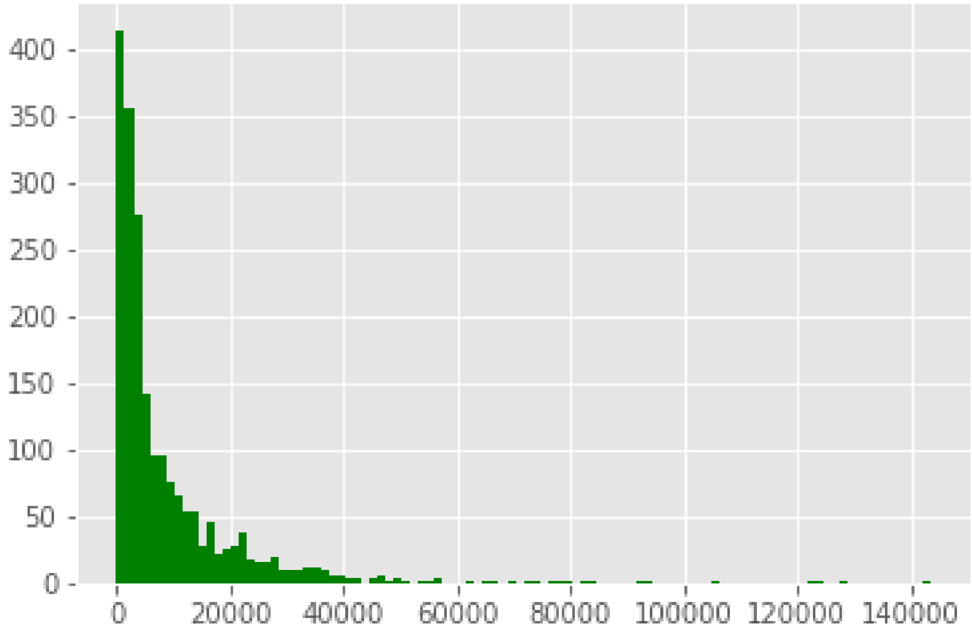
1.0.3 Favourites and retweets

```
In [154]: df_master.plot(kind = 'scatter', x = 'favorites', y = 'retweets', alpha = 0.5, color =
          plt.xlabel('Favorites')
          plt.ylabel('Retweets')
          plt.title('Retweets and favorites Scatter plot')
          plt.figure(1, figsize = (11, 8.5))
          plt.show()
```

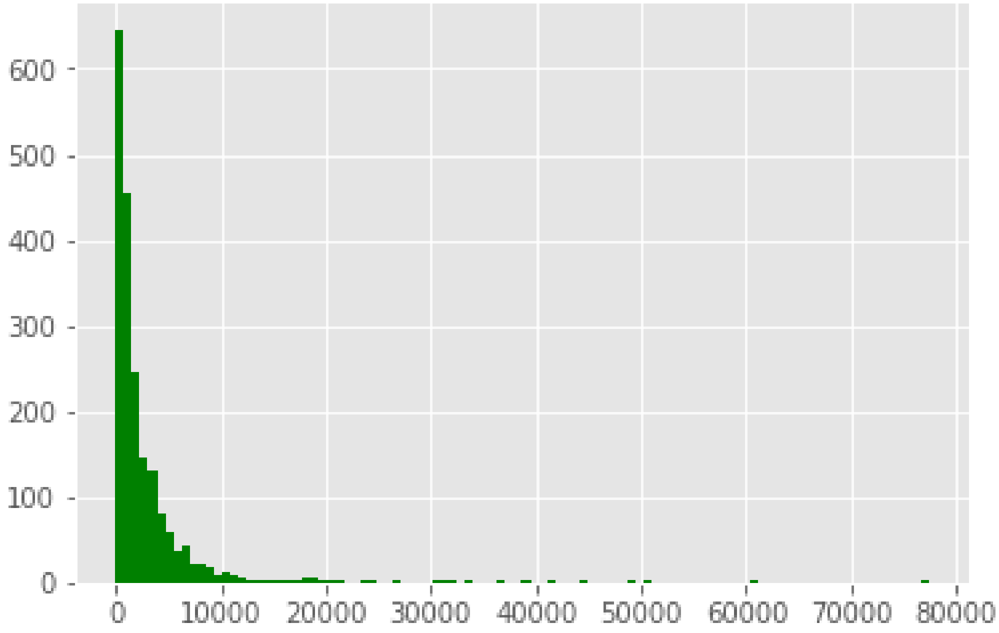


`Favorites` count and `Retweets` count are correlated pretty strongly. Let's analyse further the data.

```
In [113]: plt.hist(x = df_master.favorites, bins = 100, color = 'green')
          plt.show()
```



```
In [114]: plt.hist(x = df_master.retweets, bins = 100, color = 'green')
          plt.show()
```

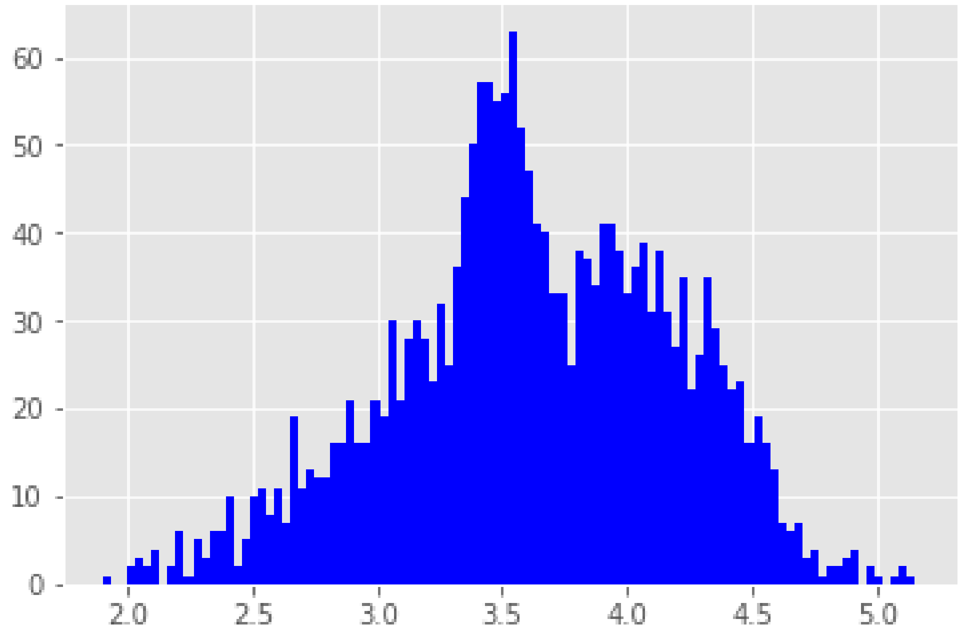


The distribution of `Retweets` count and `Favorites` count look similar. We will further analyse using log values.

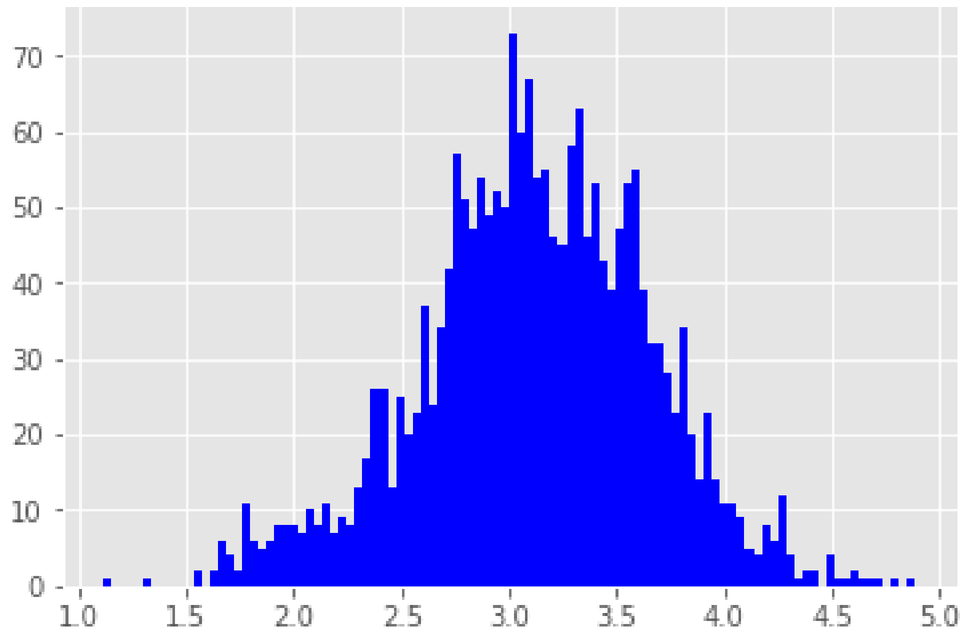
1.0.4 Log value of favorites and retweets

```
In [115]: to_log = ['favorites', 'retweets']
          df_logged = df_master[to_log].applymap(lambda x: np.log10(x))
```

```
In [116]: plt.hist(x = df_logged.favorites, bins = 100, color = 'blue')
          plt.show()
```



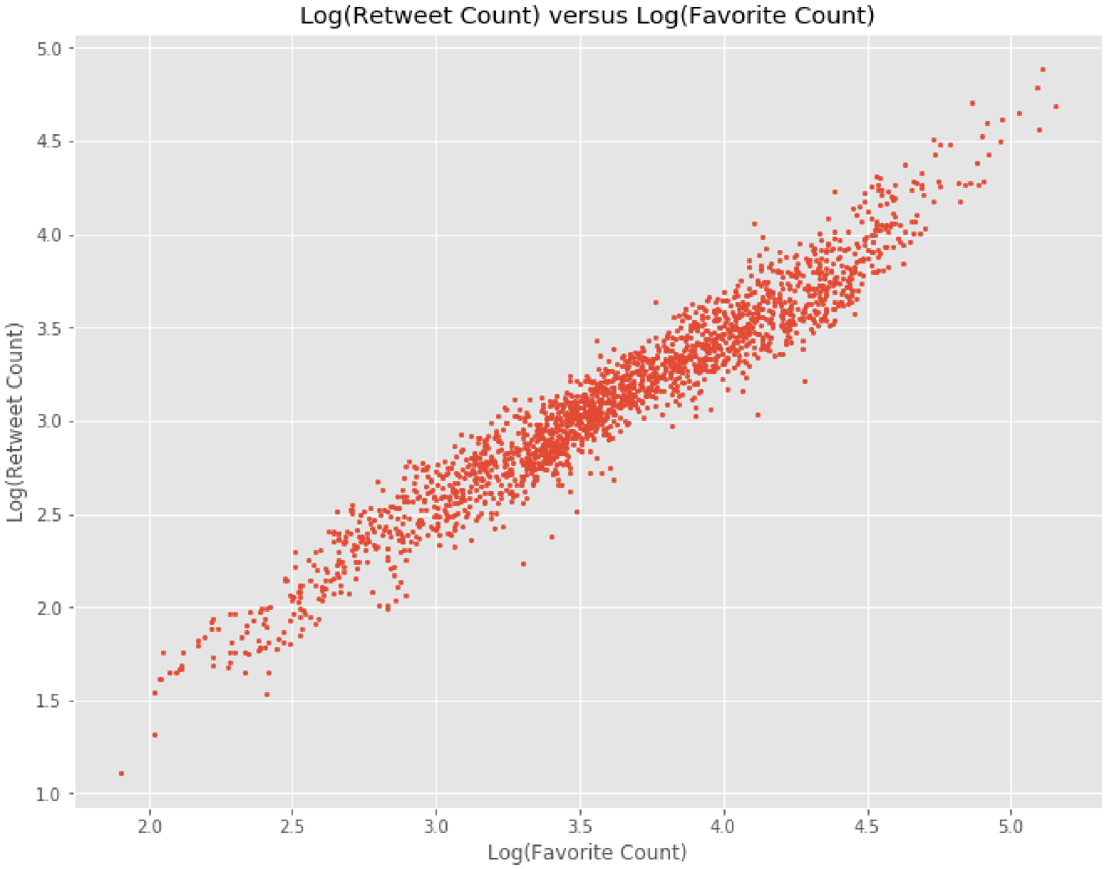
```
In [117]: plt.hist(x = df_logged.retweets, bins = 100, color = 'blue')
          plt.show()
```



The log transformation of `Retweets` count and `Favorites` count makes them appear more normal.

1.0.5 Corelation coefficient

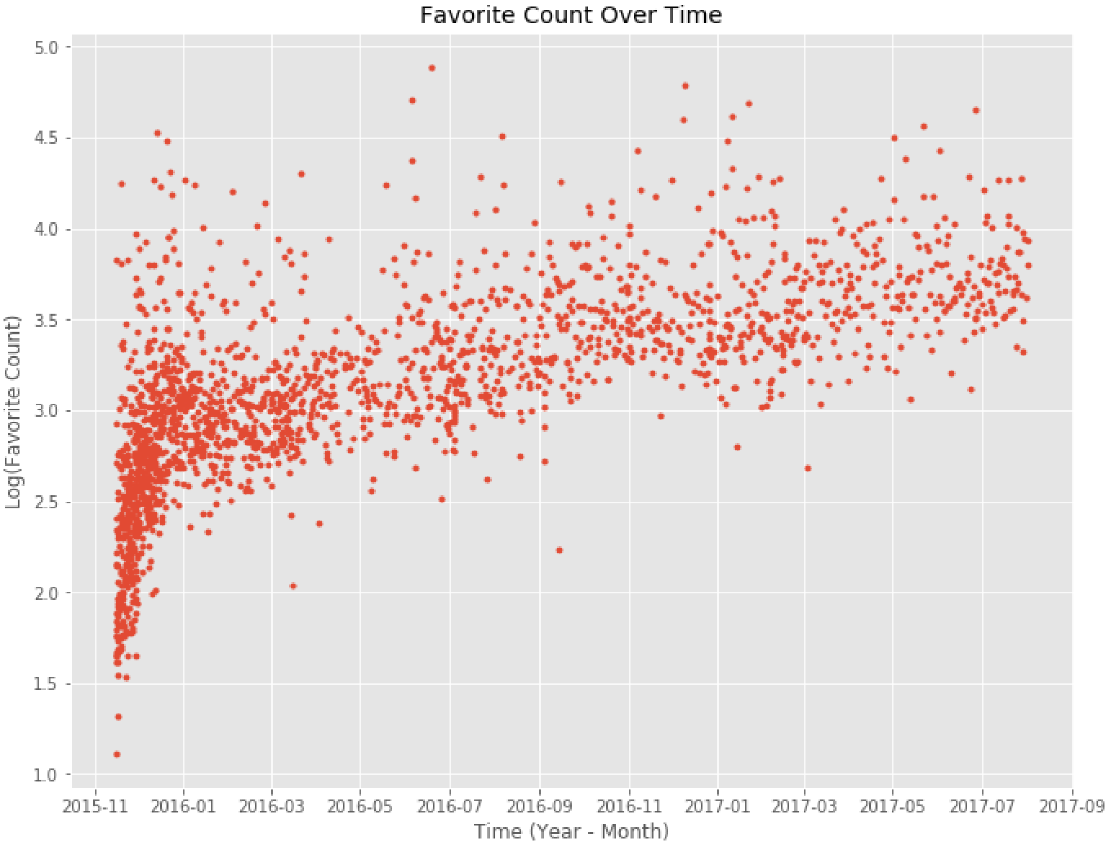
```
In [118]: plt.figure(1, figsize = (11, 8.5))
          plt.plot(df_logged.favorites, df_logged.retweets, marker='o', linestyle='', ms=2 )
          plt.title('Log(Retweet Count) versus Log(Favorite Count)')
          plt.xlabel('Log(Favorite Count)')
          plt.ylabel('Log(Retweet Count)')
          plt.show()
          np.corrcoef(df_logged.retweets, df_logged.favorites)[0][1]
```



```
Out[118]: 0.96796386832658809
```

`Favorites` and `Retweets` have a pretty strong direct relationship.
Make sure the timestamp is data time format.

```
In [119]: df_master.timestamp = pd.to_datetime(df_master.timestamp)
          plt.figure(1, figsize = (11, 8.5))
          plt.plot(df_master.timestamp ,df_logged.retweets, marker = 'o', linestyle = '', ms = 3
          plt.title('Favorite Count Over Time')
          plt.xlabel('Time (Year - Month)')
          plt.ylabel('Log(Favorite Count)')
          plt.show()
```

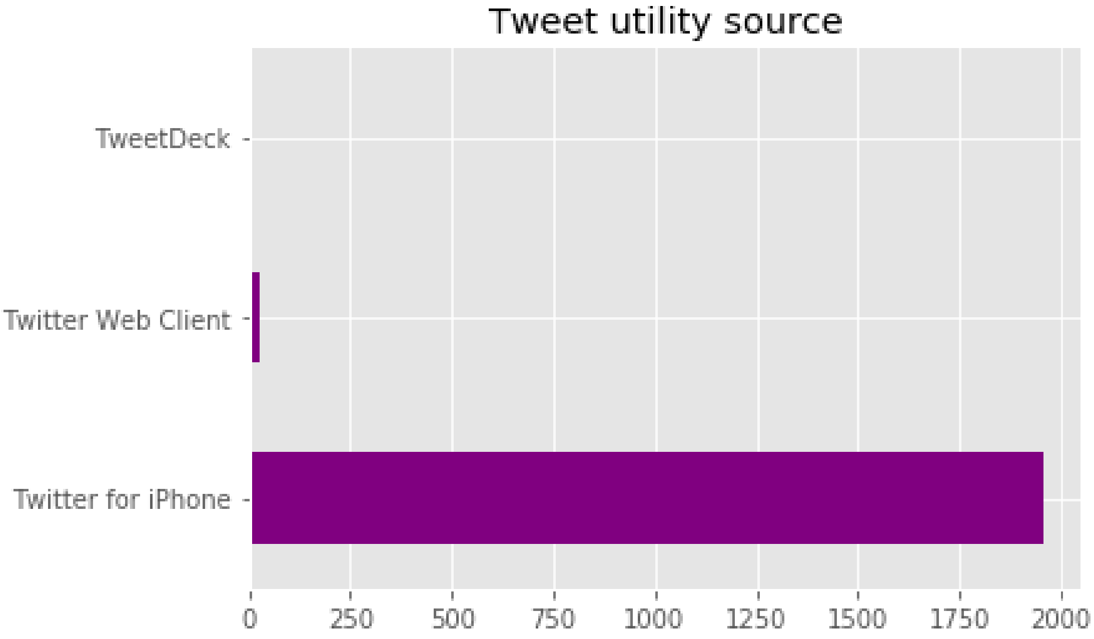


The popularity of `WeRateDogs` were peak during the year 2015. With steady amount of growth during the successive years. It also started slow down once the hype cooled down.

1.0.6 Source of tweet

```
In [120]: df_master.source.value_counts().plot(kind = 'barh', color = 'purple')
          plt.title('Tweet utility source')
```

```
Out[120]: Text(0.5,1,'Tweet utility source')
```



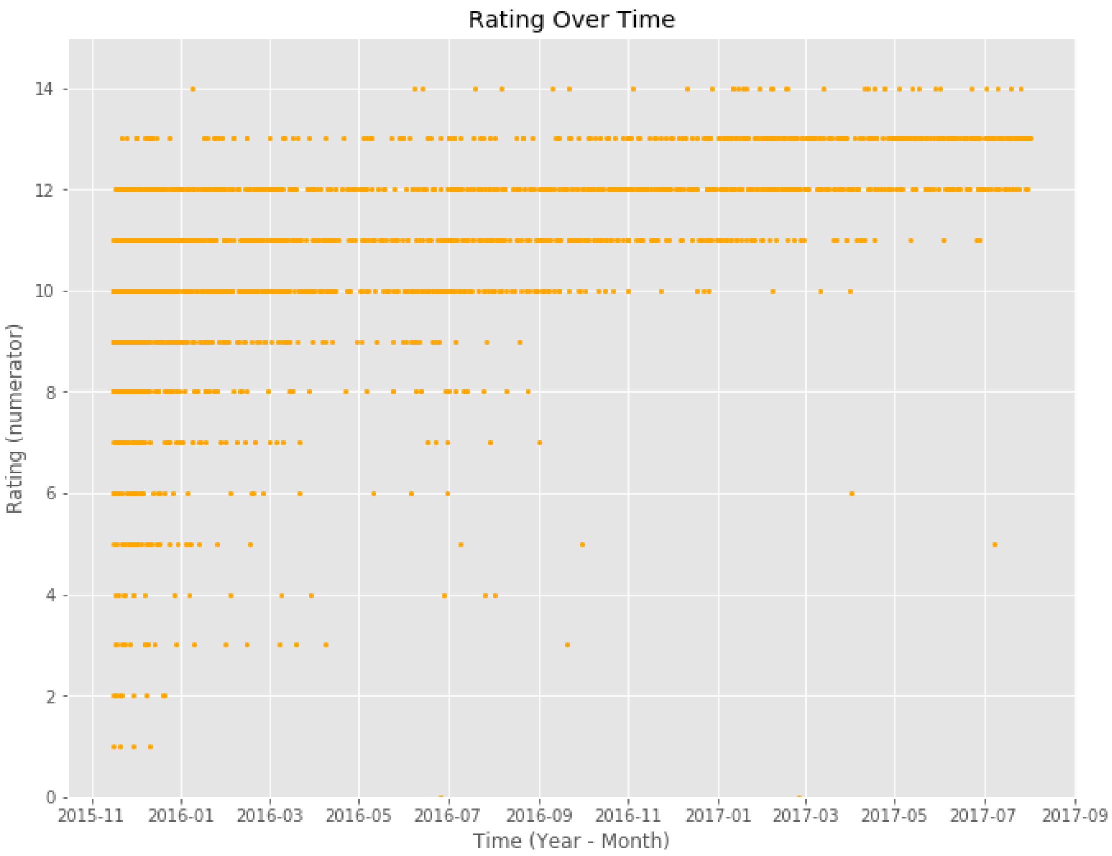
```
In [128]: df_master.source.describe()
```

```
Out[128]: count                     1994
          unique                       3
          top       Twitter for iPhone
          freq                      1955
          Name: source, dtype: object
```

Most people used `iPhone` as the source for tweet, since it has camera and internet, it's easy to tweet.

1.0.7 Rating System

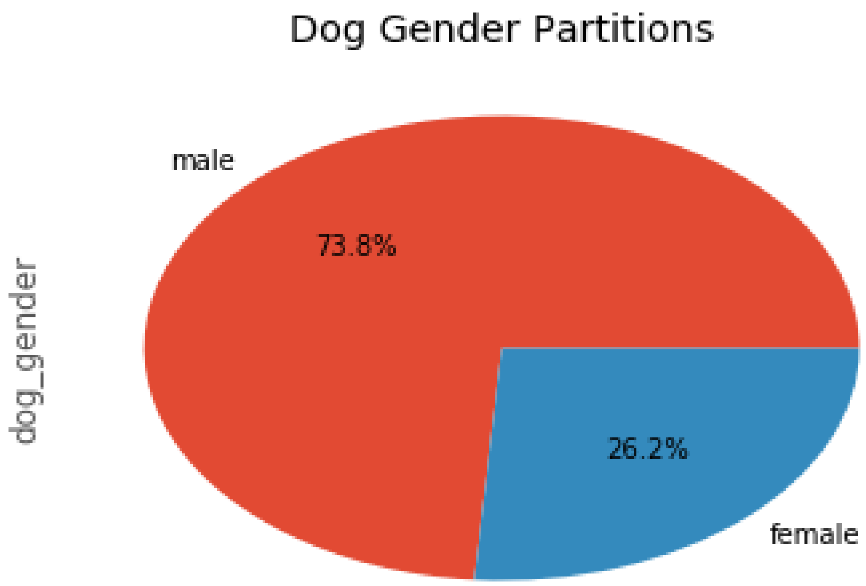
```
In [124]: plt.figure(1, figsize = (11, 8.5))
          plt.plot(df_master.timestamp, df_master.rating_numerator, marker='o', linestyle='', ms
          plt.ylim(0,15)
          plt.title('Rating Over Time')
          plt.ylabel('Rating (numerator)')
          plt.xlabel('Time (Year - Month)')
          plt.show()
```



- More than 75% of the data has more than 12/10 as rating
- The They're good dogs Brent meme/tweet was tweeted on September 12th 2016. The rating system shifted to exclusively ratings that are a 10 or higher around 2016-09.

1.0.8 Famous dog gender

```
In [143]: df_master[df_master['dog_gender'].notnull()]['dog_gender'].value_counts().plot(kind =
          plt.figure(1, figsize = (11, 8.5))
          plt.title('Dog Gender Partitions')
          plt.show()
```



```
In [129]: df_master[['dog_gender', 'rating_numerator']][df_master.dog_gender.notnull()].groupby(
```

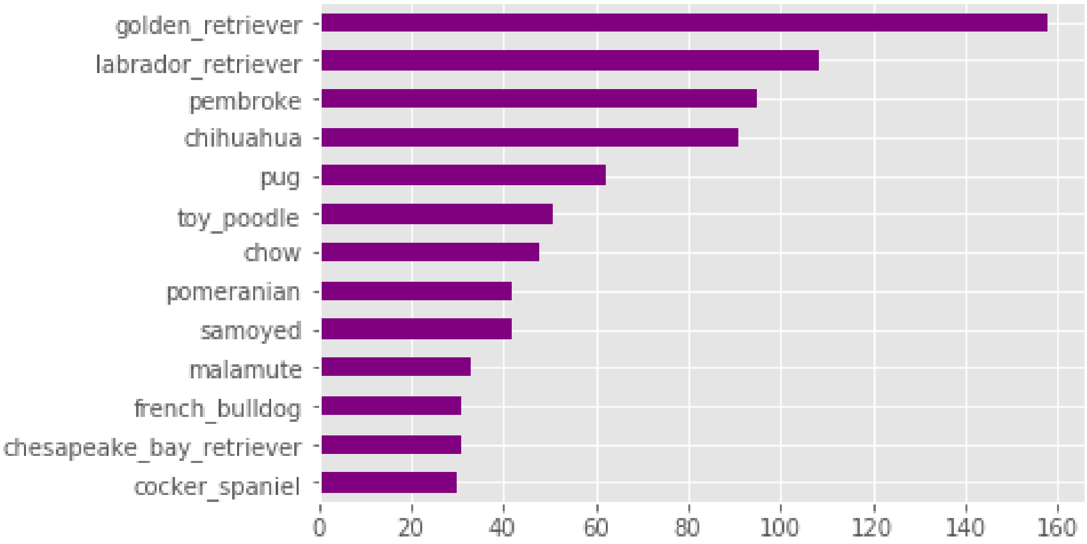
```
Out[129]:             rating_numerator
          dog_gender
          female             11.858407
          male               10.825472
```

- It's clear that male dogs were more famous among the tweets, the same can be used as prediction model for further analysis.
- female rating mean is more than the male rating mean.

1.0.9 Famous dog breed

```
In [157]: only_dogs = df_master['dog_breed'] != 'Unidentifiable'
          df_master[only_dogs].dog_breed.value_counts()[12::-1].plot(kind='barh', color = 'purpl
```

```
Out[157]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1aaf9cc0>
```



```
In [163]: df_by_breed.groupby('dog_breed')['confidence'].describe()
```

```
Out[163]:                            count      mean       std       min       25%  \
          dog_breed
          Unidentifiable             308.0  0.000000  0.000000  0.000000  0.000000
          beagle                      20.0  0.488758  0.321281  0.000216  0.309089
          cardigan                    21.0  0.486599  0.280289  0.043627  0.229944
          chesapeake_bay_retriever    31.0  0.429673  0.290641  0.003523  0.177652
          chihuahua                   91.0  0.523031  0.295237  0.001252  0.289647
          chow                        48.0  0.537033  0.325614  0.002307  0.264277
          cocker_spaniel              30.0  0.485912  0.279093  0.002713  0.311455
          eskimo_dog                  22.0  0.379626  0.210454  0.027494  0.209661
          french_bulldog              31.0  0.662573  0.327298  0.018759  0.404999
          german_shepherd             21.0  0.694426  0.221308  0.194044  0.515933
          golden_retriever           158.0  0.646680  0.294107  0.000087  0.470158
          labrador_retriever         108.0  0.590595  0.290134  0.000010  0.371536
          malamute                    33.0  0.541271  0.267540  0.040696  0.370152
          miniature_pinscher          25.0  0.456652  0.289800  0.072885  0.214200
          pembroke                    95.0  0.675733  0.264244  0.070567  0.478514
          pomeranian                  42.0  0.686306  0.300430  0.064627  0.467678
          pug                         62.0  0.667843  0.335615  0.000077  0.408610
          samoyed                     42.0  0.717440  0.297224  0.047601  0.471308
          shih-tzu                    20.0  0.510067  0.316287  0.105416  0.208954
          siberian_husky              20.0  0.492967  0.231578  0.120849  0.290908
          staffordshire_bullterrier   21.0  0.446155  0.220753  0.059344  0.284492
          toy_poodle                  51.0  0.470862  0.310234  0.005887  0.191539

                                          50%       75%       max
```

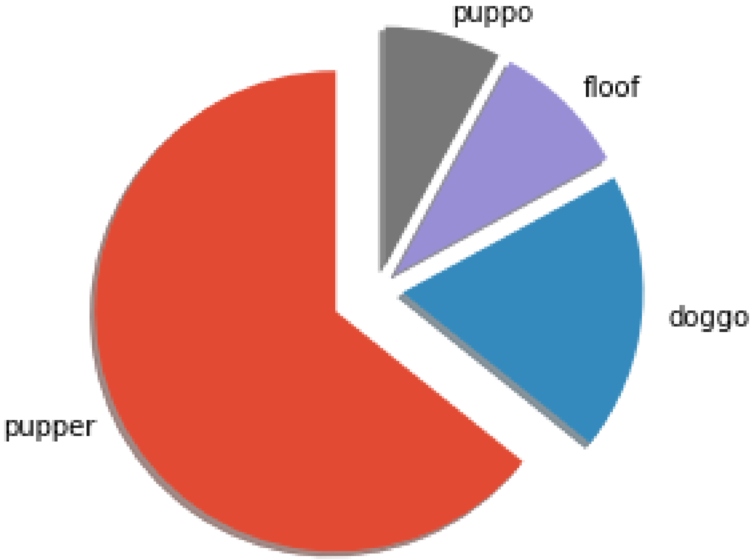
```
dog_breed
Unidentifiable              0.000000  0.000000  0.000000
beagle                      0.432760  0.723097  0.993333
cardigan                    0.566911  0.700182  0.984725
chesapeake_bay_retriever    0.382220  0.698747  0.878822
chihuahua                   0.505370  0.765064  0.993661
chow                        0.523126  0.810526  0.999953
cocker_spaniel              0.426099  0.733847  0.991011
eskimo_dog                  0.440054  0.529070  0.682082
french_bulldog              0.719559  0.943328  0.999201
german_shepherd             0.717776  0.829307  0.992339
golden_retriever            0.731101  0.888976  0.993830
labrador_retriever          0.649226  0.839552  0.999885
malamute                    0.544576  0.757764  0.985028
miniature_pinscher          0.436023  0.734744  0.956063
pembroke                    0.742320  0.924781  0.993449
pomeranian                  0.800485  0.961476  0.998275
pug                         0.798155  0.975969  0.999365
samoyed                     0.901642  0.979113  0.998201
shih-tzu                    0.554847  0.764007  0.985649
siberian_husky              0.456950  0.699611  0.951963
staffordshire_bullterrier   0.427836  0.610573  0.843359
toy_poodle                  0.478018  0.738849  0.966896
```

Based on pie chart and the confidence value the famous dog breeds were `Golden_retriver` and `Labrador_retriver`.

1.0.10 Famous dog type

```
In [149]: dog_type_count = list(df_master[df_master['dog_type'] != 'None']['dog_type'].value_cou
          dog_types = df_master[df_master['dog_type'] != 'None']['dog_type'].value_counts().inde
          explode = (0.2, 0.1, 0.1, 0.1)

          fig1, ax1 = plt.subplots()
          ax1.pie(dog_type_count, explode = explode, labels = dog_types, shadow = True, startang
          ax1.axis('equal')
          plt.figure(1, figsize = (11, 8.5))
          plt.show()
```



```
In [141]: df_master.groupby('dog_type').tweet_id.count()

Out[141]: dog_type
          None      1625
          doggo       69
          floof       34
          pupper     237
          puppo       29
          Name: tweet_id, dtype: int64
```

Based on the tweet_id we have type `None` as the highest.

1.1 Conclusion

During the start of the project the Twitter account WeRateDogs (@dog_rates) was humorous. Didn't have any confidence on learning, but wrangling data gave lots of insight about Data Analysis. Various data about favourites and retweets count gave us correlation between the data. The value 0.9679 shows strong positive relationship between favourites and retweets.

The rating system is also one of the reason for the popularity of WeRateDogs. We tried to explore various data such as source of tweet, famous dog gender, famous dog breeds and famous dog type.

We have lots of potential to have data analysis, by exploring the various images in prediction data and JSON data in twitter API :)