act_report

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1 Analysis and Insights

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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

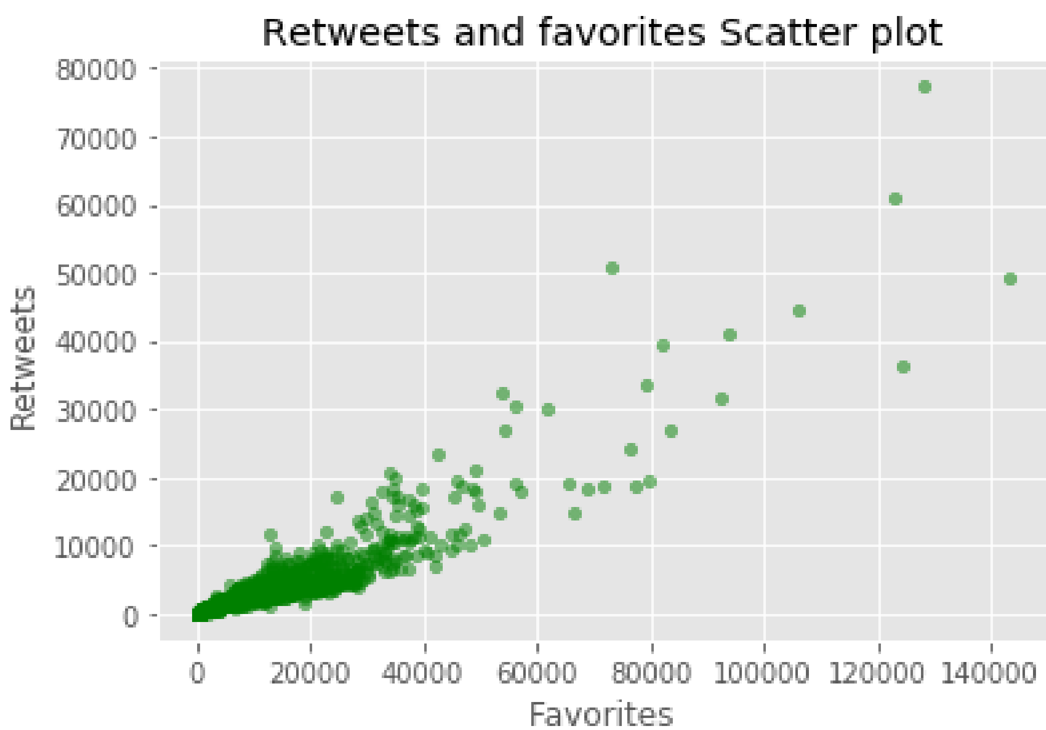
```
In [96]: #df_master = pd.read_csv('twitter_archive_master.csv')
         engine = sqlalchemy.create_engine('sqlite:///twitter_archive_master.db')
         df_master = pd.read_sql('SELECT * FROM master', engine)
         df_master.info()
```

```
<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
```

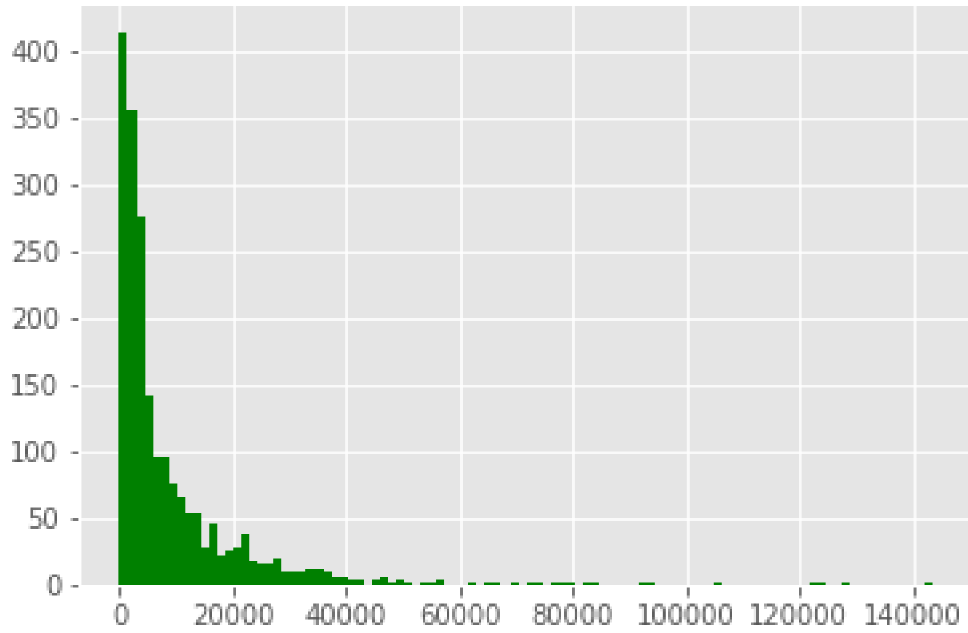
1.0.3 Favourites and retweets

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()
```

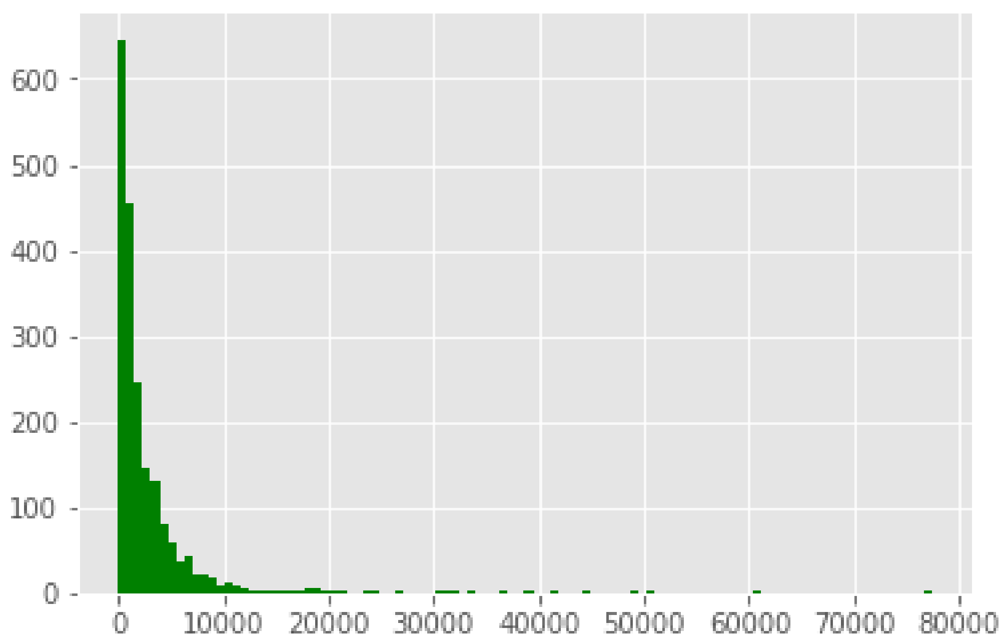


Favorites count and Retweets count are correlated pretty strongly. Let's analyse further the data.

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()
```

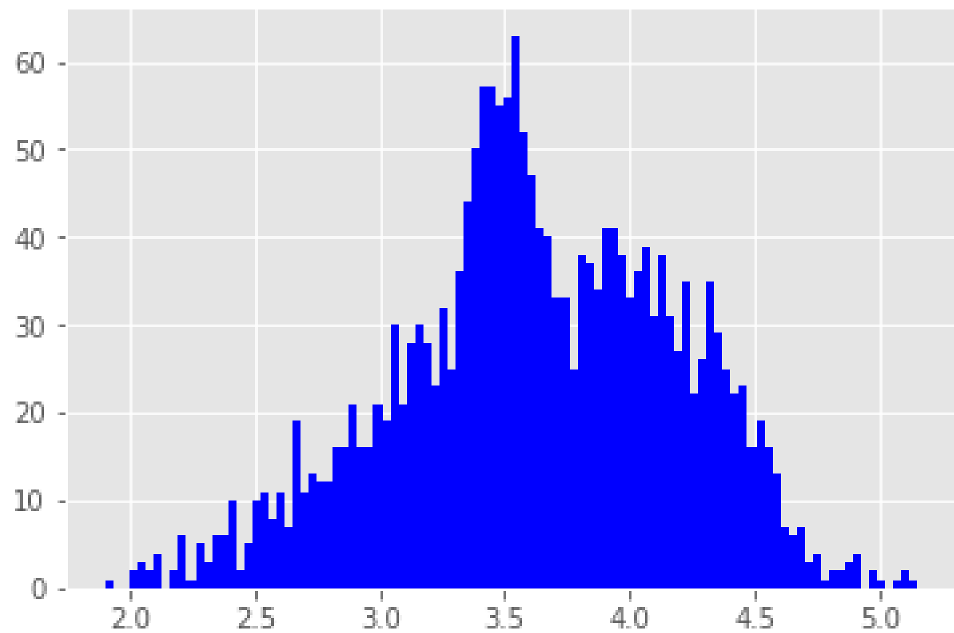


The distribution of `Retweets` count and `Favorites` count look similar. We will further analyse using log values.

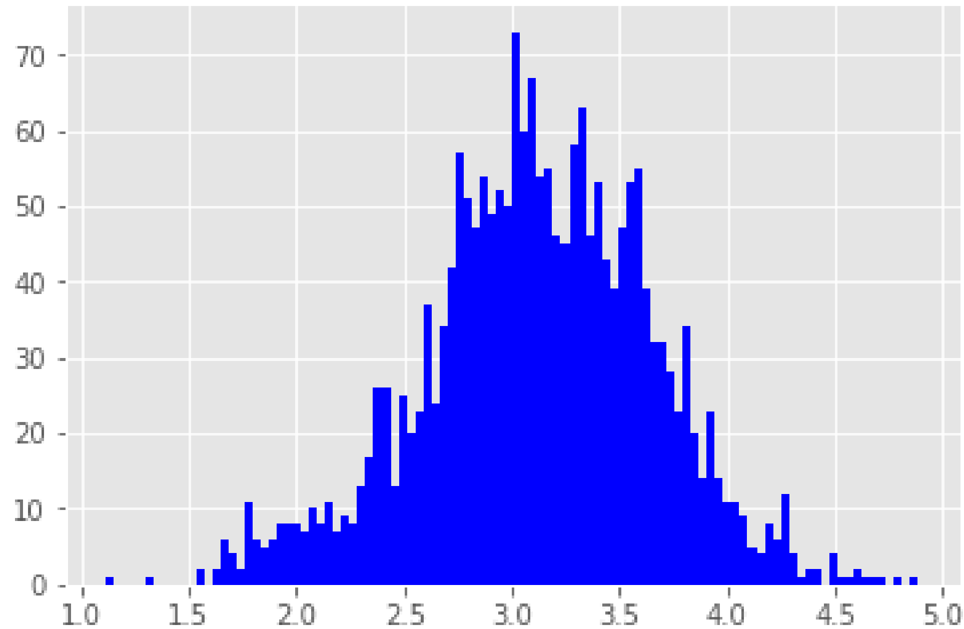
1.0.4 Log value of favorites and retweets

```
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()
```



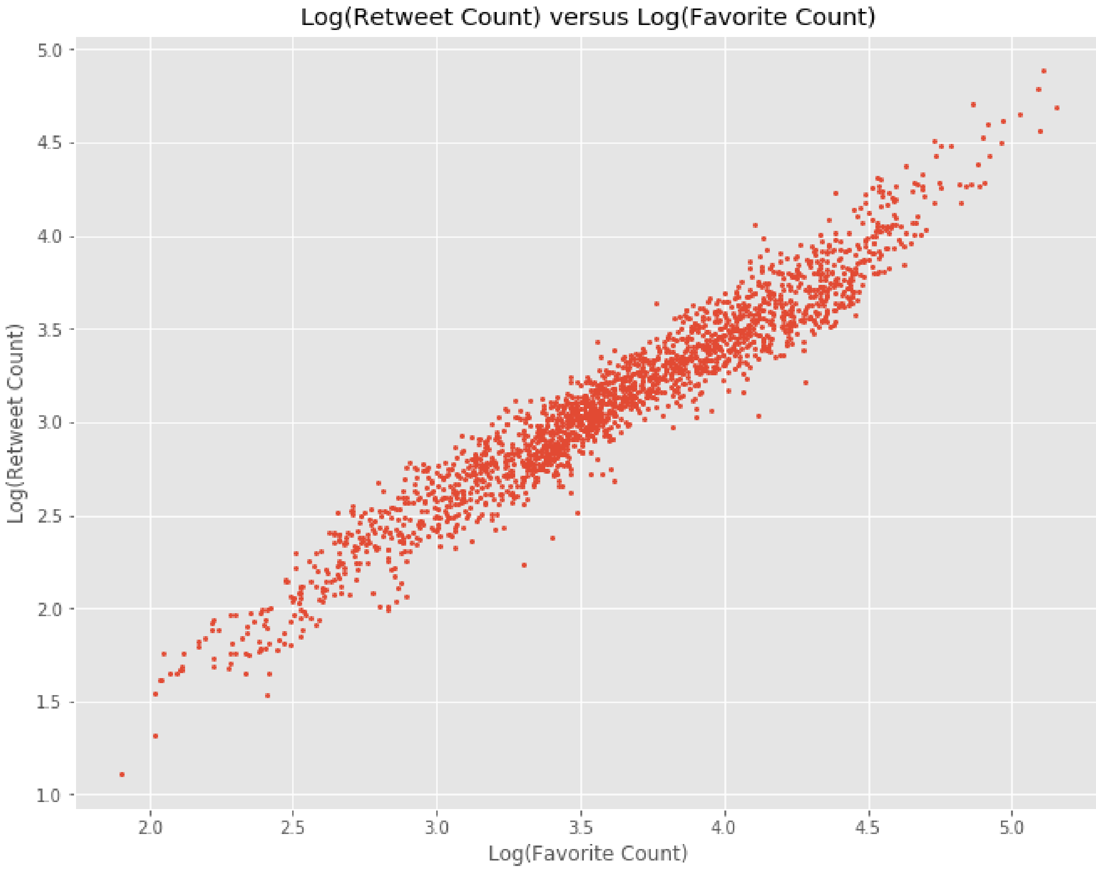

```
In [117]: plt.hist(x = df_logged.retweets, bins = 100, color = 'blue')
          plt.show()
```



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

1.0.5 Corelation coefficient

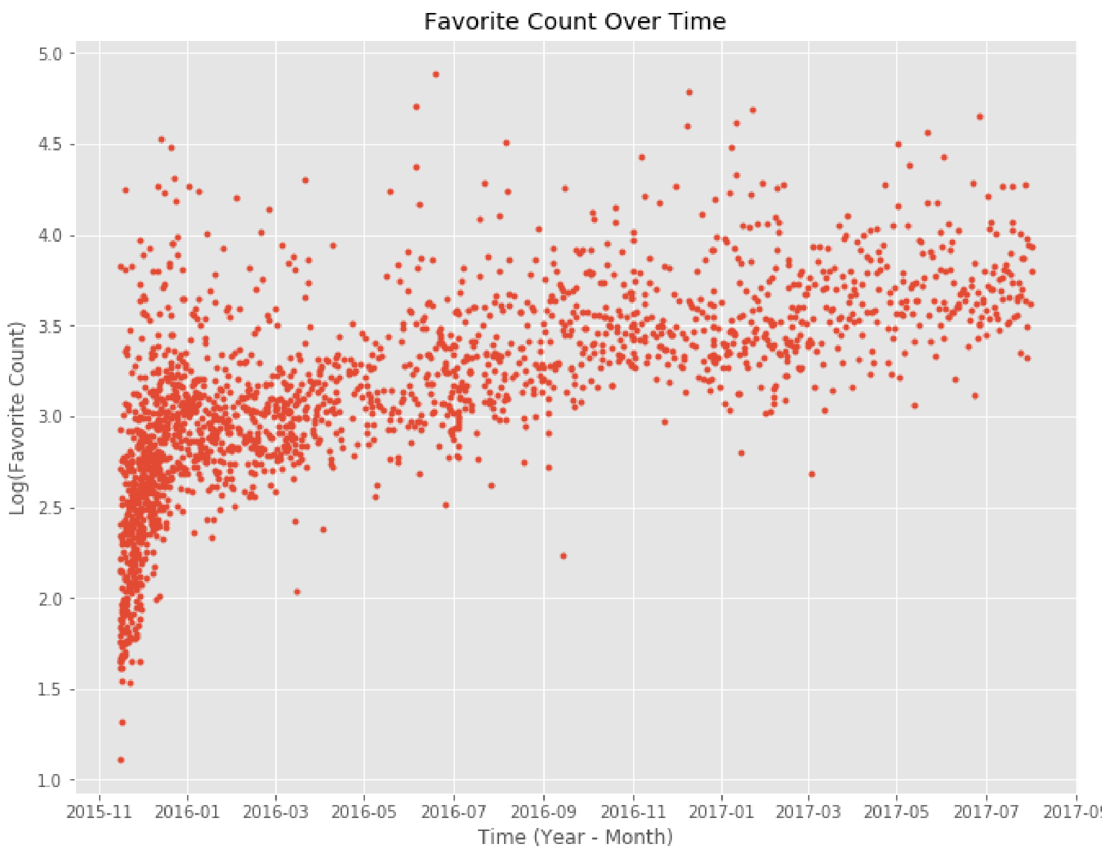
```
In [118]: plt.figure(1, figsize = (11, 8.5))
          plt.plot(df_logged.favorites, df_logged.retweets, marker='o', linestyle='', ms=2 )
          plt.title('Log(Retweet Count) versus Log(Favorite Count)')
          plt.xlabel('Log(Favorite Count)')
          plt.ylabel('Log(Retweet Count)')
  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

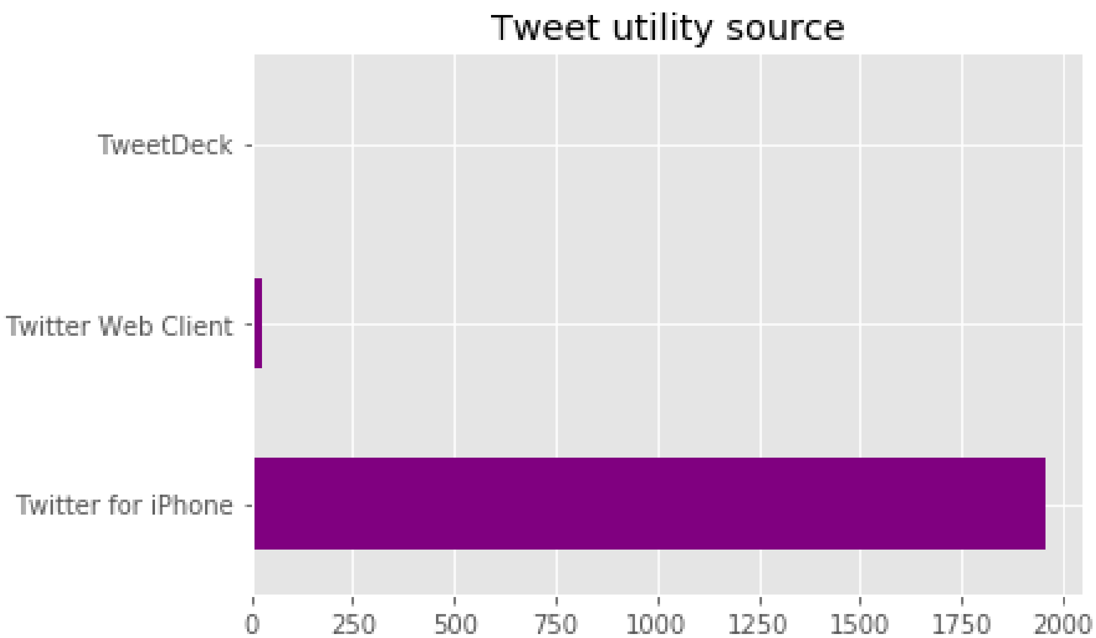


The popularity of `WeRateDogs` were peak during the year 2015. With steady amount of growth during the successive years. It also started slow down once the hype cooled down.

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')
```



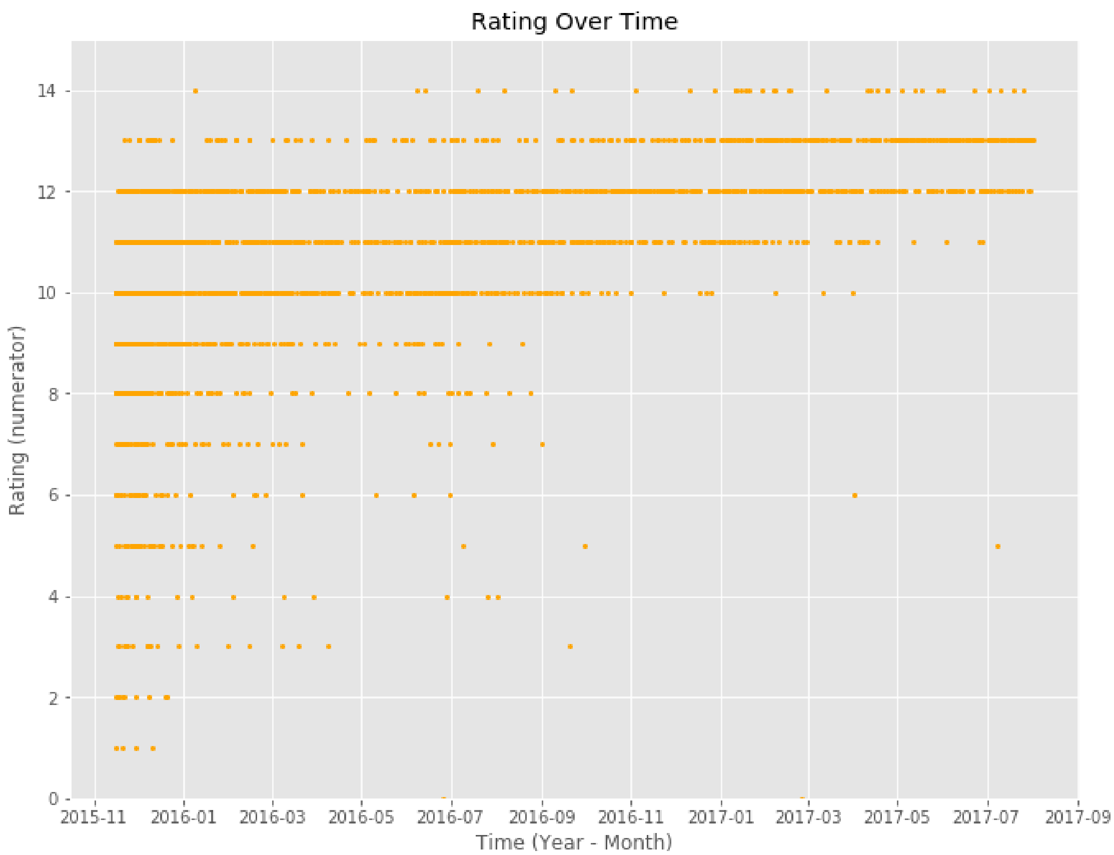

```
In [128]: df_master.source.describe()

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

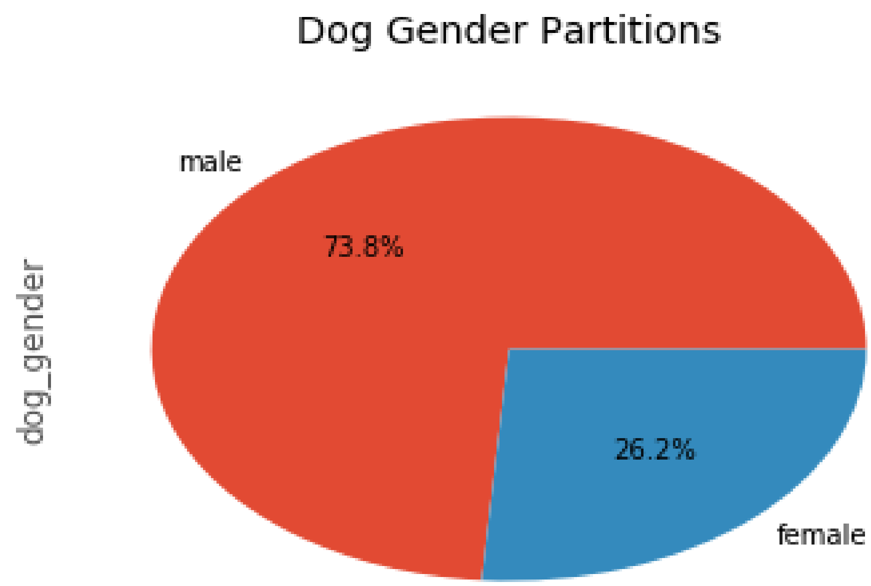
```
In [124]: plt.figure(1, figsize = (11, 8.5))
          plt.plot(df_master.timestamp, df_master.rating_numerator, marker='o', linestyle='', ms
          plt.ylim(0,15)
          plt.title('Rating Over Time')
          plt.ylabel('Rating (numerator)')
          plt.xlabel('Time (Year - Month)')
  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

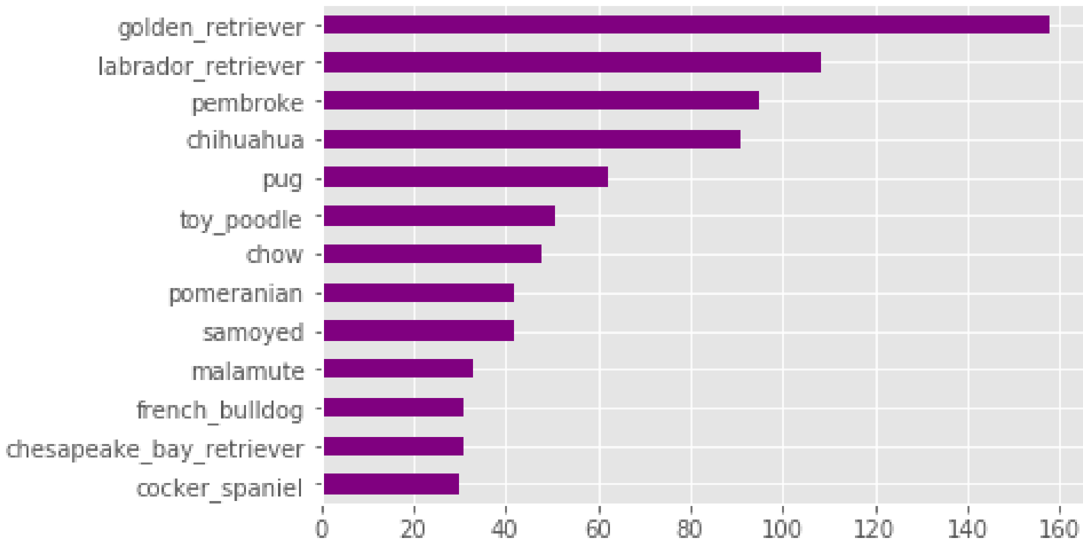
```
Out[129]:             rating_numerator
          dog_gender
          female             11.858407
          male               10.825472
```

- 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]:

dog_breed	count	mean	std	min	25%
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

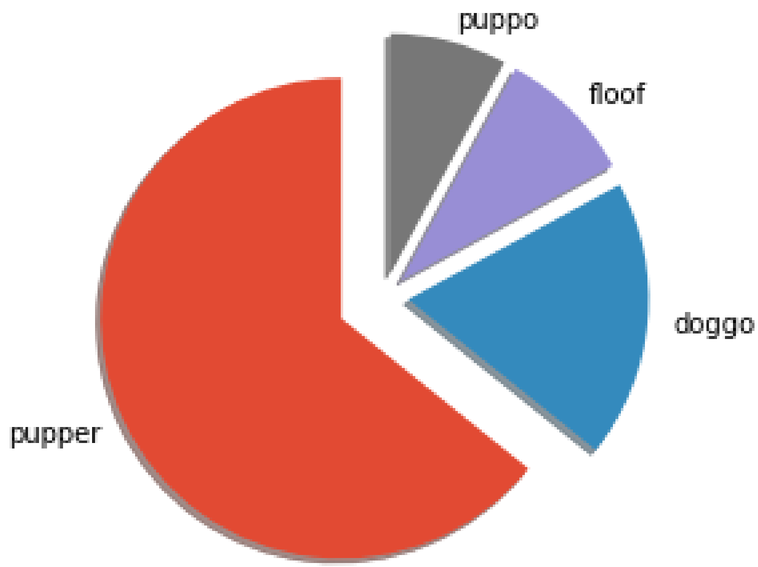
```
dog_breed
Unidentifiable              0.000000  0.000000  0.000000
beagle                      0.432760  0.723097  0.993333
cardigan                    0.566911  0.700182  0.984725
chesapeake_bay_retriever    0.382220  0.698747  0.878822
chihuahua                   0.505370  0.765064  0.993661
chow                        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. Exploring various data such as source of tweet, famous dog gender, famous dog breeds and famous dog type gave lots of insight about data wrangle and analysis.

The same dataset have lots of potential to analyse further, by exploring the various images in prediction data and JSON data in twitter API :)