

## 04 Wrangle And Analyze Data Part 2

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## **Contents**

## 0.1 Wrangle Act Part 2: Data Analysis

After cleaning and storing the data into two CSV-sources I will try now to draw several conclusions from the datasets. Before doing so I will import the necessary python modules and read the data sources into DataFrames. ### Environment Preperation

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib
from output_wrapper import ow
%matplotlib inline
```

```
tam_df = pd.read_csv('twitter_archive_master.csv',sep=',')
tip_df = pd.read_csv('twitter_image_prediction.csv',sep=',')
```

```
tip_df.head(1)
```

| L |   | tweet_id           | jpg_url   | <b>p1</b>              | p1_conf  | p1_dog |
|---|---|--------------------|---|------------------------|----------|--------|
| C | ) | 666020888022790149 | https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg | Welsh_springer_spaniel | 0.465074 | Γrue   |

```
tam_df.head(1)
```

|    |   | tweet_id           | timestamp |                         | text | name    | dogtype | rating | retweet_count | favorite_count |
|----|---|--------------------|-----------|-------------------------|------|---------|---------|--------|---------------|----------------|
| Γ  |   | 892420643555336193 |           | This is                 |      | Phineas | none    | 1.3    | 8281          | 37925          |
| I. |   |                    |           | Phineas. I              | _    |         |         |        |               |                |
| ľ  | , |                    |           | a mystical<br>bov. Onlv | _    |         |         |        |               |                |
| ı  |   |                    |           |                         |      |         |         |        |               |                |
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## 0.1.1 First Insight: Correlation of dog rating and Retweet Count/Favourite Count

## **Assumption**

My first insight will examine the correlation between the **Rating** and the **retweet\_count** and **favourite\_count**. My obvious assumption is that dogs with higher ratings will have higher amounts of retweets and favorite markings. I will utilize the pandas **corr** function to correlate every column with each other:

#### Code

tam\_df.corr()

|                | tweet_id | rating   | retweet_count | favorite_count |
|----------------|----------|----------|---------------|----------------|
| tweet_id       | 1.000000 | 0.047361 | 0.379280      | 0.508291       |
| rating         | 0.047361 | 1.000000 | 0.013992      | 0.014403       |
| retweet_count  | 0.379280 | 0.013992 | 1.000000      | 0.798627       |
| favorite_count | 0.508291 | 0.014403 | 0.798627      | 1.000000       |

#### **Evaluation**

The only strong correlation with a practical relevance can be observated between the **retweet\_count** and the **favorite\_count**. That means a dog tweet that will be often retweeted will also be often favorised. I guess this correlation is reasonable. Unfortunately there is a almost non-existent correlation between **retweet\_count** and the rating.

## 0.1.2 Second Insight: High Confidence in Image Classification for "Dogtionary" labeled dogs

## Assumption

Now I will try to verify my assumption, that dogs that got a label from "WeRateDogs" like "doggo" should have a very high level of mean confidence compared to the entries without a label. I have this assumption, because I believe that a dog that can be labeled according to the "WeRateDogs Dogtionary", should have a very typical dog appearance and thus can be classified by a estimator with a high confidence.

#### Code

Mean over all confidence levels of estimated dog pictures:

 $\verb"ow(tip_df.pl_conf.mean())"$ 

Output:

0.594548263614

```
ow(1*tip_df.p1_dog.sum())
```

```
Output:
```

1532

Mean over confidence level with a label from "WeRateDogs":

```
dogs_with_label = list(tam_df[tam_df.dogtype != 'none'].tweet_id)
ow(tip_df[tip_df['tweet_id'].isin(dogs_with_label)]['pl_conf'].mean())
```

#### Output:

0.610198121068

#### **Evaluation**

There is only a slightly increase of the mean confidence for the dogs that got a label according to the "WeRateDogs Dogtionary". For me this isn't a evidence for a better estimation confidence for dogs with a classification label.

# 0.1.3 Third Insight and Visualisation: Increase of Social Media Activity and Classification Confidence over time

## **Assumption**

As many social media trends become more successful respectively get more user interaction simply by their level of awareness over the user base it's an interesting assumption for me, that the interaction with "WeRateDog" postings will increase at all independently from the objective quality of a posting.

## **Code for Visualisation**

It seems that the timestamp data type "datetime" doesn't remain over writing into a csv and reading it again. Therefore we have to convert it again and reindex for having chronologically order from earliest to most current post:

```
tam_df_rev = tam_df.reindex(index=tam_df.index[::-1])
dates = matplotlib.dates.date2num(pd.to_datetime(tam_df_rev['timestamp']))
```

```
fig = plt.figure(figsize=(15,10))

plt.plot_date(dates,tam_df_rev['retweet_count'])
plt.plot_date(dates,tam_df_rev['favorite_count'],alpha=0.7)
plt.xlabel('Time in Months')
plt.ylabel('Counts')
plt.gca().legend(('Retweet Count','Favourite Count'))
plt.gca().set_ylim([0,100000])
plt.grid(b=None, which='major', axis='both')
```

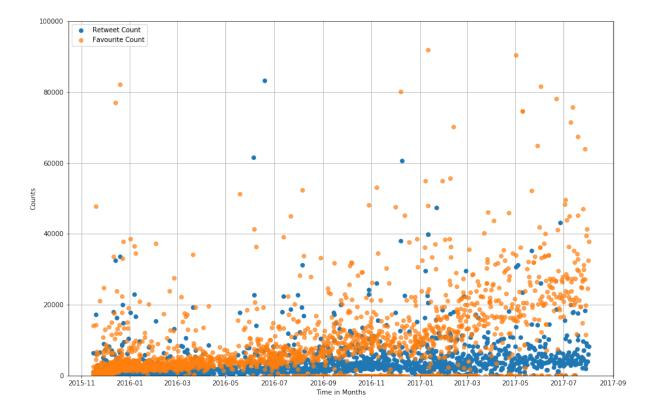


Figure 1: png

It seems, that the Favourite Count will increase at all with the time. To proof this observation I will calculate the **Linear Regression** for both, the Favourite Count and the Retweet Count over the time to verify it.

## **Code for Linear Regression and updated Visualisation**

```
from scipy import stats

fav_slope, fav_intercept, r_value, p_value, std_err = stats.linregress(dates, tam_df_rev['favorite_count'])
ret_slope, ret_intercept, r_value, p_value, std_err = stats.linregress(dates, tam_df_rev['retweet_count'])
```

```
fig = plt.figure(figsize=(15,10))

plt.plot_date(dates,tam_df_rev['retweet_count'])
plt.plot_date(dates,tam_df_rev['favorite_count'],alpha=0.7)
plt.plot_date(dates,dates*fav_slope*fav_intercept,'r-')
plt.plot_date(dates,dates*ret_slope*ret_intercept,'c-')
plt.xlabel('Time in Months')
plt.ylabel('Counts')
plt.gca().legend(('Retweet Count','Favourite Count','Linear Regression for Favorite Count','Linear Regression for Retweet Count'))
plt.gca().set_ylim([0,100000])
plt.grid(b=None, which='major', axis='both')
```

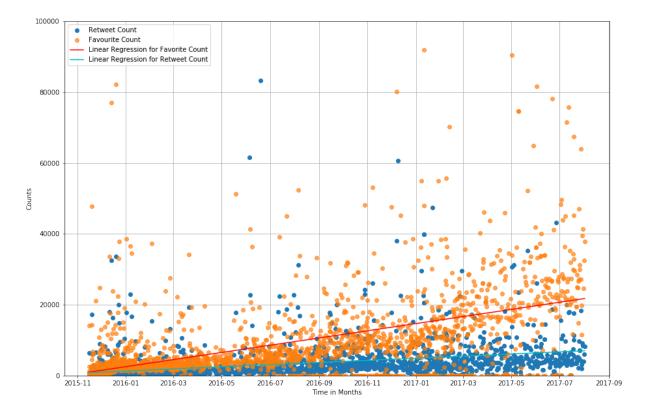


Figure 2: png

Actually, there is an obvious increase for the Favourite account over time. It seems, that a quadratic polynomial regression would match the course of the dots in a slightly more accurate way but I think it's good enough to verify the first observation.

## **Evaluation**

To explain the difference in increase we can ask for our own behaviour on social media like Twitter. The effort of will to like or favourise a post is much smaller than retweeting it and reveal a stronger commitment, i.e. a stronger opinion to the content of the post.

**Important:** Overall we have to take into consideration a specific factor to correct the rating of "WeRateDogs" posts based on Retweet Counts and Favourite Counts if observing the whole timeline.