Prompt

Assessing Data for this Project

After gathering each of the above pieces of data, assess them visually and programmatically for quality and tidiness issues. Detect and document at least eight (8) quality issues and two (2) tidiness issues in your wrangle_act.ipynb Jupyter Notebook. To meet specifications, the issues that satisfy the Project Motivation (see the Key Points header on the previous page) must be assessed.

Cleaning Data for this Project

Clean each of the issues you documented while assessing. Perform this cleaning in wrangle_act.ipynb as well. The result should be a high quality and tidy master pandas DataFrame (or DataFrames, if appropriate). Again, the issues that satisfy the Project Motivation must be cleaned.

Storing, Analyzing, and Visualizing Data for this Project

Store the clean DataFrame(s) in a CSV file with the main one named twitter_archive_master.csv. If additional files exist because multiple tables are required for tidiness, name these files appropriately. Additionally, you may store the cleaned data in a SQLite database (which is to be submitted as well if you do).

Analyze and visualize the wrangled data with at least three (3) insights and one (1) visualization.

Introduction

I will explore four different questions:

- Which dog stages receive the highest rating
- Breed and rating relationship
- What are the most popular dog names
- What dog stages have the highest favorite count

To answer these questions, the data cleaning and data restructure will aim to clean the best of relevant columns. The rest of the dataset will be omiited/ ignored as they do not contribute to give insights for the questions above (e.g: timestamp of the tweets)

In [ ]:

```
import numpy as np
import os
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import requests
import tweepy
import json
from timeit import default_timer as timer
from tweepy import OAuthHandler
```

In [ ]:

```
#Read archived dataset
df = pd.read_csv('twitter-archive-enhanced.csv')
```

In [3]:

```
#Read prediction dataset
r = requests.get('https://d17h27t6h515a5.cloudfront.net/topher/2017/August/5
with open('image-predictions.tsv', mode='wb') as file:
    file.write(r.content)

img_df = pd.read_csv('image-predictions.tsv', sep='\t')
```

Twitter data collection process

Data collected from Udacity online platform

In [ ]:

```
# Query Twitter API for each tweet in the Twitter archive and save JSON in a
# These are hidden to comply with Twitter's API terms and conditions
consumer_key = 'HIDDEN'
consumer_secret = 'HIDDEN'
access_token = 'HIDDEN'
access_secret = 'HIDDEN'

auth = OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_token, access_secret)

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

# NOTE TO STUDENT WITH MOBILE VERIFICATION ISSUES:
# df_1 is a DataFrame with the twitter_archive_enhanced.csv file. You may ha
# change line 17 to match the name of your DataFrame with twitter_archive_en
# NOTE TO REVIEWER: this student had mobile verification issues so the follo
# Twitter API code was sent to this student from a Udacity instructor
# Tweet IDs for which to gather additional data via Twitter's API
tweet_ids = df_1.tweet_id.values
len(tweet_ids)

# Query Twitter's API for JSON data for each tweet ID in the Twitter archive
count = 0
fails_dict = {}
start = timer()
# Save each tweet's returned JSON as a new line in a .txt file
with open('tweet_json.txt', 'w') as outfile:
    # This loop will likely take 20-30 minutes to run because of Twitter's r
    for tweet_id in tweet_ids:
        count += 1
        print(str(count) + ": " + str(tweet_id))
        try:
            tweet = api.get_status(tweet_id, tweet_mode='extended')
            print("Success")
            json.dump(tweet._json, outfile)
            outfile.write('\n')
        except tweepy.TweepError as e:
            print("Fail")
            fails_dict[tweet_id] = e
            pass
end = timer()
print(end - start)
print(fails_dict)
```

In [4]:
```
#Read json dataset
df_json = pd.DataFrame(columns=['tweet_id', 'retweet_count', 'favorite_count
with open('tweet-json.txt') as data_file:
    for line in data_file:
        tweet = json.loads(line)
        tweet_id = tweet['id_str']
        retweet_count = tweet['retweet_count']
        favorite_count = tweet['favorite_count']
        df_json = df_json.append(pd.DataFrame([[tweet_id, retweet_count, fav
        columns=['tweet_id', 'retweet_count', 'favorite_count']))
        df_json = df_json.reset_index(drop=True)
```

Access data

Access dataframe

In [5]:
```
df.head()
```

Out[5]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
0	892420643555336193	NaN	NaN	2017-08-01 16:23:56 +0000	href="http://twitter.com/d
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com/d
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com/d
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com/d
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com/d

In [6]:
```
#The "expanded_url" column provides every link that the website can find wit
df.expanded_urls[6]
```

Out[6]:
```
'https://gofundme.com/ydvmve-surgery-for-jax,https://twitter.com/dog_rates/stat
us/890971913173991426/photo/1'
```

In [7]:

```
#The doggo, floofer, pupper and poppo columns seem weird, I will randomly ch
df.sample(20)[['doggo','floofer','pupper','puppo']]
```

Out[7]:

	doggo	floofer	pupper	puppo
864	None	None	None	None
11	None	None	None	None
1175	None	None	None	None
687	None	None	None	None
1268	None	None	None	None
825	None	None	None	None
2166	None	None	None	None
343	None	None	None	None
62	None	None	None	None
642	None	None	None	None
184	None	None	None	None
1162	None	None	None	None
96	None	None	None	None
1479	None	None	None	None
2090	None	None	None	None
348	None	None	None	None
1850	None	None	pupper	None
1050	None	None	None	None
2081	None	None	None	None
2295	None	None	None	None

In [8]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                      2356 non-null int64
in_reply_to_status_id         78 non-null float64
in_reply_to_user_id           78 non-null float64
timestamp                     2356 non-null object
source                        2356 non-null object
text                          2356 non-null object
retweeted_status_id           181 non-null float64
retweeted_status_user_id      181 non-null float64
retweeted_status_timestamp    181 non-null object
expanded_urls                 2297 non-null object
rating_numerator              2356 non-null int64
rating_denominator            2356 non-null int64
name                          2356 non-null object
doggo                         2356 non-null object
floofer                       2356 non-null object
pupper                        2356 non-null object
puppo                         2356 non-null object
dtypes: float64(4), int64(3), object(10)
memory usage: 313.0+ KB
```

In [9]:
```
1 # No duplicated rows
2 df[df.duplicated()].shape
```

Out[9]:
```
(0, 17)
```

In [10]:
```
#Check bad name
df[df.name.str.islower()].name.value_counts()
```

Out[10]:
```
a               55
the              8
an               7
very             5
one              4
just             4
quite            4
getting          2
actually         2
not              2
mad              2
officially       1
life             1
infuriating      1
unacceptable     1
space            1
old              1
his              1
incredibly       1
such             1
by               1
light            1
all              1
my               1
this             1
Name: name, dtype: int64
```

Comment:

- There are a total of 2356 rows
- Retweeted and in_reply columns (in_reply_to_status_id, in_reply_to_user_id, retweeted_status_id, etweeted_status_user_id,) have a high number of null values (but we will not be using that). The "expanded_urls" column has a few missing data.
- Timestamp and retweeted_status_timestamp is an object, which will be converted into a timestamp.
- We will not be using retweets data, and this dataset includes the retweets category. Thus, we have to filter out the retweet rows.
- Dog stages columns have very bad structure (which implies that it has gone through one-hot encoding, but instead of Nan values, they are 'None' values). I will have to reorganize them.
- Dog names column is not clean. Some observations are not even names

Access image prediction

In [11]:
```
1 img_df.head()
```

Out[11]:

	tweet_id	jpg_url	img_num	
0	666020888022790149	https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg	1	Welsh_springer_s
1	666029285002620928	https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg	1	re
2	666033412701032449	https://pbs.twimg.com/media/CT4521TWwAEvMyu.jpg	1	German_she
3	666044226329800704	https://pbs.twimg.com/media/CT5Dr8HUEAA-lEu.jpg	1	Rhodesian_ridg
4	666049248165822465	https://pbs.twimg.com/media/CT5IQmsXIAAKY4A.jpg	1	miniature_pi

In [12]:
```
1 img_df.sample(20)
```

Out[12]:

	tweet_id	jpg_url	img_num	
1838	837471256429613056	https://pbs.twimg.com/media/C59LpELWUAEUmYh.jpg	1	Norwegian_
1021	710269109699739648	https://pbs.twimg.com/media/Cdth_KyWEAEXH3u.jpg	1	
1329	757596066325864448	https://pbs.twimg.com/media/CoOFmk3WEAAG6ql.jpg	1	
829	693622659251335168	https://pbs.twimg.com/media/CaA-IR9VIAAqg5l.jpg	1	r
1486	781955203444699136	https://pbs.twimg.com/media/CtoQGu4XgAQgv5m.jpg	1	p
1763	826240494070030336	https://pbs.twimg.com/media/C3dlVMbXAAUd-Gh.jpg	1	French
808	692142790915014657	https://pbs.twimg.com/media/CZr8LvyXEAABJ9k.jpg	3	to
192	669567591774625800	https://pbs.twimg.com/media/CUrlK1DWoAAhECq.jpg	1	Cl
1732	821149554670182400	https://pbs.twimg.com/ext_tw_video_thumb/82114...	1	German_s
1503	784826020293709826	https://pbs.twimg.com/media/CuRDF-XWcAIZSer.jpg	1	
1812	833124694597443584	https://pbs.twimg.com/media/C4_ad1IUoAEspsk.jpg	3	
650	681981167097122816	https://pbs.twimg.com/media/CXbiQHmWcAAt6Lm.jpg	1	Labrador_
1998	875144289856114688	https://pbs.twimg.com/ext_tw_video_thumb/87514...	1	Siberia
1235	746507379341139972	https://pbs.twimg.com/media/Clwgf4bWgAAB15c.jpg	1	to
1032	711652651650457602	https://pbs.twimg.com/media/CeBMT6-WIAA7Qqf.jpg	1	
1904	852189679701164033	https://pbs.twimg.com/media/C9OV99SXsAEmj1U.jpg	1	
740	687312378585812992	https://pbs.twimg.com/media/CYnS9VWW8AAeR8m.jpg	1	
644	681579835668455424	https://pbs.twimg.com/media/CXV1Ot_W8AEpkQO.jpg	1	F
1778	828408677031882754	https://pbs.twimg.com/media/C38ZSzlWIAEpQzs.jpg	1	We
1450	776218204058357768	https://pbs.twimg.com/media/CsWuVEdWcAAqbe9.jpg	1	S

In [13]:
```
1 img_df.shape
```

Out[13]:
```
(2075, 12)
```

In [14]:
```
1 #Describe the dataset
2 img_df.describe()
```

Out[14]:

	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 [15]:
```
1 img_df.info()
```

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

In [16]:
```
1 print ('Number of duplicated links:', img_df[img_df.jpg_url.duplicated()].sh
```

```
Number of duplicated links: 66
```

In [17]:
```
1 img_df.img_num.value_counts()
```

Out[17]:
```
1    1780
2     198
3      66
4      31
Name: img_num, dtype: int64
```

Comment:

- No null values, but there are some duplicated rows.

Access df_json

In [18]:
```
1 df_json.sample(20)
```

Out[18]:

	tweet_id	retweet_count	favorite_count
1440	696754882863349760	396	1615
658	791406955684368384	4797	14670
707	785264754247995392	1911	8128
1729	679844490799091713	887	2593
634	793601777308463104	1908	8926
1482	693231807727280129	841	3133
401	824325613288833024	11848	12999
2067	671134062904504320	212	796
2305	666826780179869698	105	266
1289	708119489313951744	1102	2937
2182	668988183816871936	516	961
635	793500921481273345	2786	11953
1744	679132435750195208	1314	3253
1974	672995267319328768	328	1001
213	851464819735769094	7855	25944
1129	728986383096946689	917	3460
1565	687826841265172480	1292	2989
824	769335591808995329	8830	0
1045	743510151680958465	4185	8671
2158	669567591774625800	61	248

In [19]:
```
1 df_json.shape
```

Out[19]:
```
(2354, 3)
```

In [20]:
```
1 df_json.describe()
```

Out[20]:

	tweet_id	retweet_count	favorite_count
count	2354	2354	2354
unique	2354	1724	2007
top	669324657376567296	3652	0
freq	1	5	179

In [21]:
```
1 #No null values
2 df_json.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2354 entries, 0 to 2353
Data columns (total 3 columns):
tweet_id          2354 non-null object
retweet_count     2354 non-null object
favorite_count    2354 non-null object
dtypes: object(3)
memory usage: 55.3+ KB
```

In [22]:
```
1 #No duplicated values
2 df_json[df_json.duplicated()].shape[0]
```

Out[22]: 0

Messiness Issues

df:

(1) Missing data in columns: in_reply_to_status_id, in_reply_to_user_id, retweeted_status_id, retweeted_status_user_id, retweeted_status_timestamp, expanded_urls

(2) This dataset includes retweets, but I will not use retweet dataset. Thus, I have to filter out those rows that are retweets

(3) Timestamp and retweeted_status_timestamp is an object. Need to be fixed into timestamp format

(4) The expanded_url includes all possible links within that url. If one wants to use this link, they will have to filter out one link only

(5) Some dog names are suspiciously not names. I will have to delete them out of the dataset.

(6) The fact that the rating numerators are greater than the denominators does not need to be cleaned. This unique rating system is a big part of the popularity of WeRateDogs. I will process this to calculate the true rating

img_df:

(1) dog breeds are funnily not consistent in all p1,p2,p3 in at least 20 first data. I created a subset of random 20 rows, same thing happen. Thus, dog breeds

column is unreliable data.

df_tweet_json: tweet_id format (currently object)

Tidiness Issues
df: 'doggo','floofer','pupper','puppo' columns should be binary (Yes, No/ 0,1) rather than repeating the whole column name/ Nan
img_df and df_json: Need to merge with the df dataset
img_df: There are three prediction algorithm. I will have to create a new algorithm to choose the best prediction out of all possible values.

DATA CLEANING

THINGS TO DO

```
1)All timestamps to be changed into datetime format.

2)One column for dog stages: doggo, floofer, pupper, puppo

3)Dog breed: Depending on the algorithm function. If 1st algorithm perfo
rms too bad, move to the next one. Threshold: 30% for each. If none reac
hes 30%, it's empty

4)Change the prediction dog breed to all lower case

5)Delete retweets

6)Dog ratings get standardized.

7)Merge the copied df_clean, img_df_clean, and _json_clean dataframes

8)Remove columns no longer needed: in_reply_to_status_id, in_reply_to_us
er_id, retweeted_status_id, retweeted_status_user_id, and retweeted_stat
us_timestamp

9)Tweet_id format for merging

10)Remove rows with non-dog names
```

In [40]:
```
df_clean = df.copy()
img_df_clean = img_df.copy()
df_json_clean = df_json.copy()
```

In [41]:

```
# (1) Timestamp to datetime format
df_clean['timestamp'] = pd.to_datetime(df_clean['timestamp'], format='%Y-%m-

#Test
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 17 columns):
tweet_id                      2356 non-null int64
in_reply_to_status_id         78 non-null float64
in_reply_to_user_id           78 non-null float64
timestamp                     2356 non-null datetime64[ns, UTC]
source                        2356 non-null object
text                          2356 non-null object
retweeted_status_id           181 non-null float64
retweeted_status_user_id      181 non-null float64
retweeted_status_timestamp    181 non-null object
expanded_urls                 2297 non-null object
rating_numerator              2356 non-null int64
rating_denominator            2356 non-null int64
name                          2356 non-null object
doggo                         2356 non-null object
floofer                       2356 non-null object
pupper                        2356 non-null object
puppo                         2356 non-null object
dtypes: datetime64[ns, UTC](1), float64(4), int64(3), object(9)
memory usage: 313.0+ KB
```

In [42]:

```
# (2) Dog stages to one column

#Change the name before merging into one column
df_clean.doggo.replace([np.NaN, 'None'], '', inplace=True)
df_clean.floofer.replace([np.NaN, 'None'], '', inplace=True)
df_clean.pupper.replace([np.NaN, 'None'], '', inplace=True)
df_clean.puppo.replace([np.NaN, 'None'], '', inplace=True)

#Some dogs have 2 stages, we need to merge them together
df_clean['stage'] = df_clean.doggo + df_clean.floofer + df_clean.pupper + df

# Drop unnecessary columns
df_clean.drop(['doggo', 'floofer', 'pupper', 'puppo'], axis=1, inplace=True)
df_clean.stage.replace('', np.nan, inplace=True)

#Test
df_clean.stage[0:10]
```

Out[42]:

```
0      NaN
1      NaN
2      NaN
3      NaN
4      NaN
5      NaN
6      NaN
7      NaN
8      NaN
9    doggo
Name: stage, dtype: object
```

In [43]:
```
#(3) Dog breed: Choose among three image prediction algorithm
breed = []
for i in range (len(img_df_clean)):
    if (img_df_clean.p1_dog[i] == True) & (img_df_clean.p1_conf[i] > 0.3) :
        breed.append(img_df_clean.p1[i])
    elif (img_df_clean.p2_conf[i] > 0.3) & img_df_clean.p2_dog[i] == True:
        breed.append(img_df_clean.p2[i])
    elif (img_df_clean.p3_conf[i] > 0.3) & img_df_clean.p3_dog[i] == True:
        breed.append(img_df_clean.p3[i])
    else:
        breed.append('Unidentified')

# (4)Change the prediction dog breed to all lower case
breed = [element.lower() for element in breed]
img_df_clean['breed'] = breed

img_df_clean['breed'][0:10]
```

Out[43]:
```
0    welsh_springer_spaniel
1                   redbone
2            german_shepherd
3       rhodesian_ridgeback
4        miniature_pinscher
5      bernese_mountain_dog
6                unidentified
7                       chow
8                unidentified
9                unidentified
Name: breed, dtype: object
```

In [44]:
```
# (5) Delete retweets
df_clean = df_clean.drop(df_clean[(df_clean['in_reply_to_status_id'].isnull(

#Test => ZERO values
sum ((df_clean['in_reply_to_status_id'].isnull() == False) | (df_clean['retw
```

Out[44]:
```
0
```

In [45]:
```
# (6) Calculate dog rating
df_clean['rate'] = df_clean.rating_numerator/ df_clean.rating_denominator

#Test
df_clean['rate'][0:5]
```

Out[45]:
```
0    1.3
1    1.3
2    1.2
3    1.3
4    1.2
Name: rate, dtype: float64
```

In [46]:

```
# (7) Merge (8) Change tweet_id format for merging function
df_clean.tweet_id = df_clean.tweet_id.astype(np.int64)
img_df_clean.tweet_id = img_df_clean.tweet_id.astype(np.int64)
df_json_clean.tweet_id = df_json_clean.tweet_id.astype(np.int64)
data = pd.merge (df_clean, img_df_clean, on = ['tweet_id'], how = 'inner')
data = pd.merge (data, df_json_clean, on = ['tweet_id'], how = 'left')

#Test
data.head()
```

Out[46]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
0	892420643555336193	NaN	NaN	2017-08-01 16:23:56+00:00	href="http://twitter.c
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27+00:00	href="http://twitter.c
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03+00:00	href="http://twitter.c
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51+00:00	href="http://twitter.c
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24+00:00	href="http://twitter.c

5 rows × 29 columns

In [47]:

```
## (9) Remove unnecessary columns
data.columns
```

Out[47]:

```
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', 'stage', 'rate', 'jpg_url', 'img_num',
       'p1', 'p1_conf', 'p1_dog', 'p2', 'p2_conf', 'p2_dog', 'p3', 'p3_conf',
       'p3_dog', 'breed', 'retweet_count', 'favorite_count'],
      dtype='object')
```

In [48]:
```
data.drop(['in_reply_to_status_id', 'in_reply_to_user_id',
       'source', 'text', 'retweeted_status_id', 'retweeted_status_user_id',
       'retweeted_status_timestamp', 'expanded_urls', 'p1', 'p1_conf', 'p1_d
        'p2_conf', 'p2_dog', 'p3', 'p3_conf',
       'p3_dog'], axis=1, inplace=True)

#Test
data.columns
```

Out[48]:
```
Index(['tweet_id', 'timestamp', 'rating_numerator', 'rating_denominator',
       'name', 'stage', 'rate', 'jpg_url', 'img_num', 'breed', 'retweet_count',
       'favorite_count'],
      dtype='object')
```

In [49]:
```
# (10) Clean dog names
failed_name = data[data.name.str.islower()].name.unique()
data['name'] = data['name'].replace(failed_name, np.nan)
data['name'] = data['name'].replace('None', np.nan)
data.name.dropna(inplace = True)
```

In [52]:
```
#Test => ZERO values of nonsense names
sum(data.name.str.islower())
```

Out[52]:
```
0
```

In [50]:
```
#There are still missing data, but I will accept these missing data. This da
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1971 entries, 0 to 1970
Data columns (total 12 columns):
tweet_id              1971 non-null int64
timestamp             1971 non-null datetime64[ns, UTC]
rating_numerator      1971 non-null int64
rating_denominator    1971 non-null int64
name                  1349 non-null object
stage                 303 non-null object
rate                  1971 non-null float64
jpg_url               1971 non-null object
img_num               1971 non-null int64
breed                 1971 non-null object
retweet_count         1971 non-null object
favorite_count        1971 non-null object
dtypes: datetime64[ns, UTC](1), float64(1), int64(4), object(6)
memory usage: 195.3+ KB
```

STORE DATA VALUES

In [53]:
```
data.to_csv('data.csv', encoding='utf-8', index=False)
```

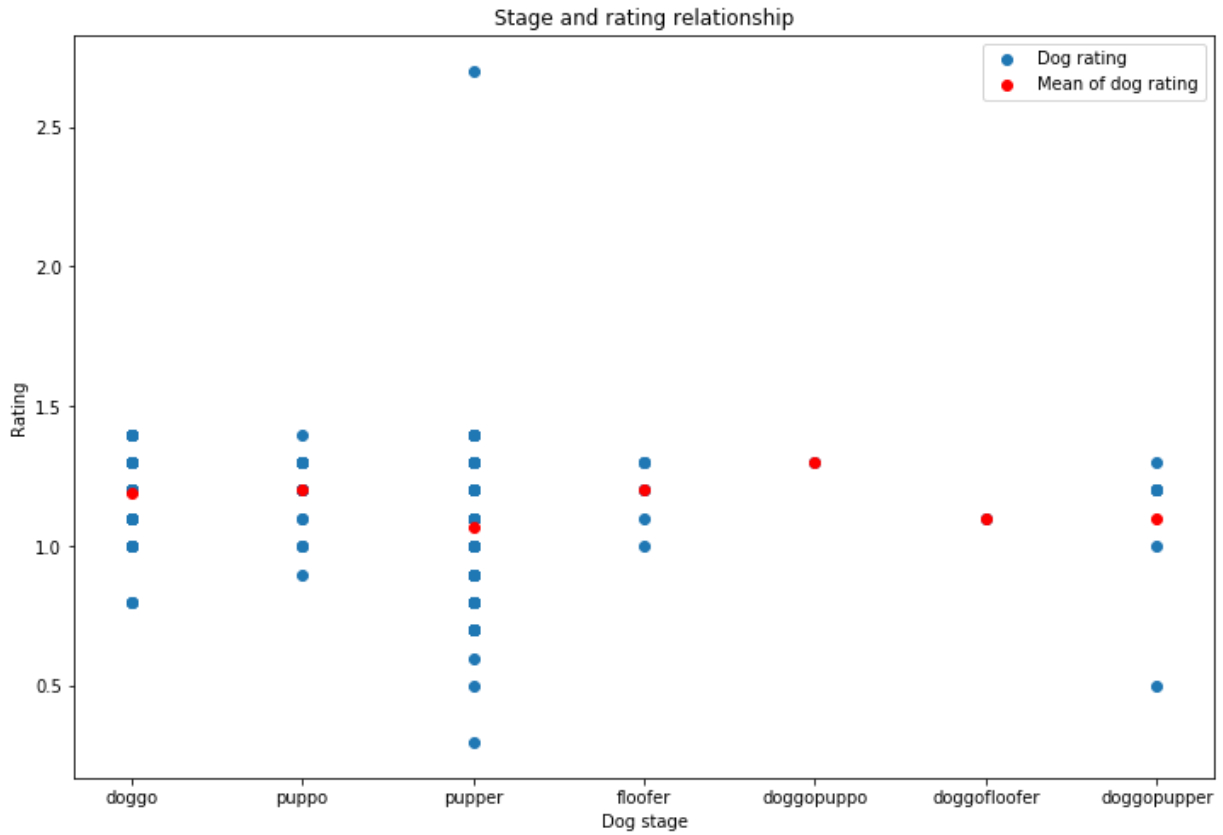
In [54]:
```
1 data = pd.read_csv('data.csv')
```

In [55]:
```
1 data.stage.unique()
```

Out[55]:
```
array([nan, 'doggo', 'puppo', 'pupper', 'floofer', 'doggopuppo',
       'doggofloofer', 'doggopupper'], dtype=object)
```

Analysis question 1: Which dog stages receive the highest rating

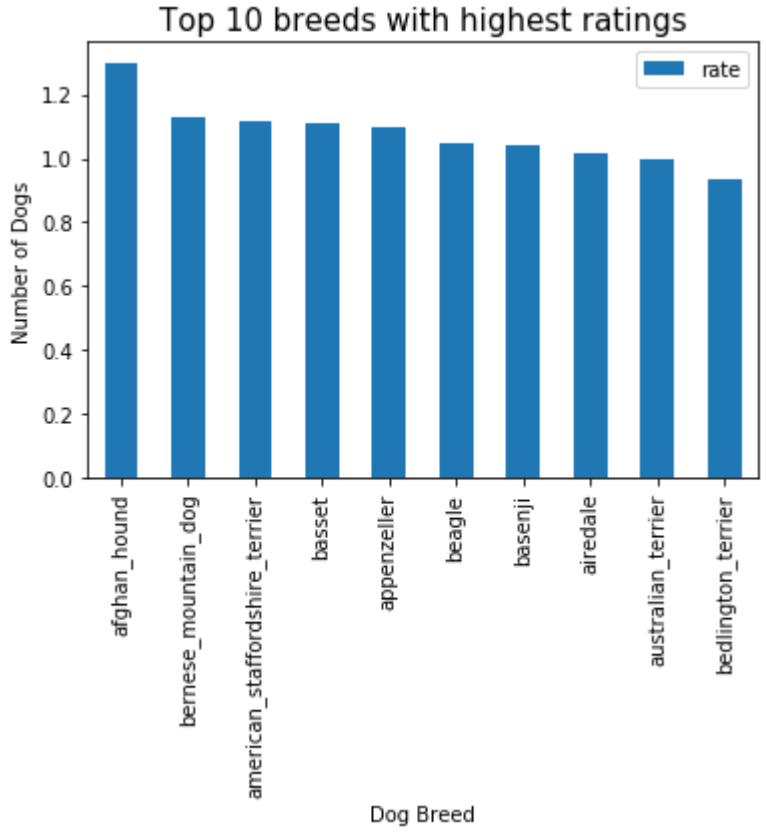
In [56]:
```
1  unique_stage = data.stage.unique()
2  plt.figure (figsize = (12,8))
3  plt.scatter (data['stage'][data['stage'].isnull()==False], data['rate'][data
4  for i in range (len(unique_stage)):
5      if i == 0:
6          plt.scatter(unique_stage[i],np.mean(data['rate'][data['stage']==uniq
7      else:
8          plt.scatter(unique_stage[i],np.mean(data['rate'][data['stage']==uniq
9  plt.title('Stage and rating relationship')
10 plt.xlabel ('Dog stage')
11 plt.ylabel ('Rating')
12 plt.legend()
13 plt.show()
```



Analysis question 2: Breed and rating relationship

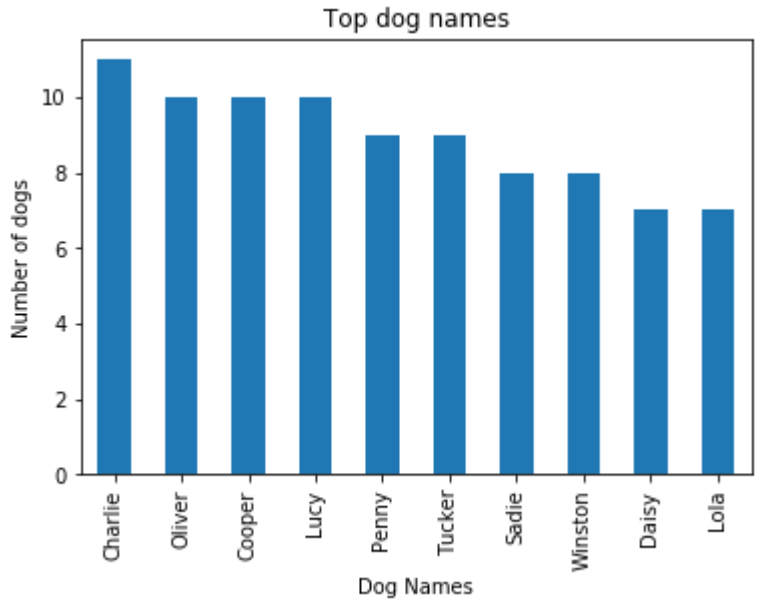
In [57]:

```
data.groupby('breed')[['rate']].mean()[0:10].sort_values(ascending=False, by
plt.ylabel('Number of Dogs')
plt.title('Top 10 breeds with highest ratings', size=15)
plt.xlabel('Dog Breed')
plt.show()
```



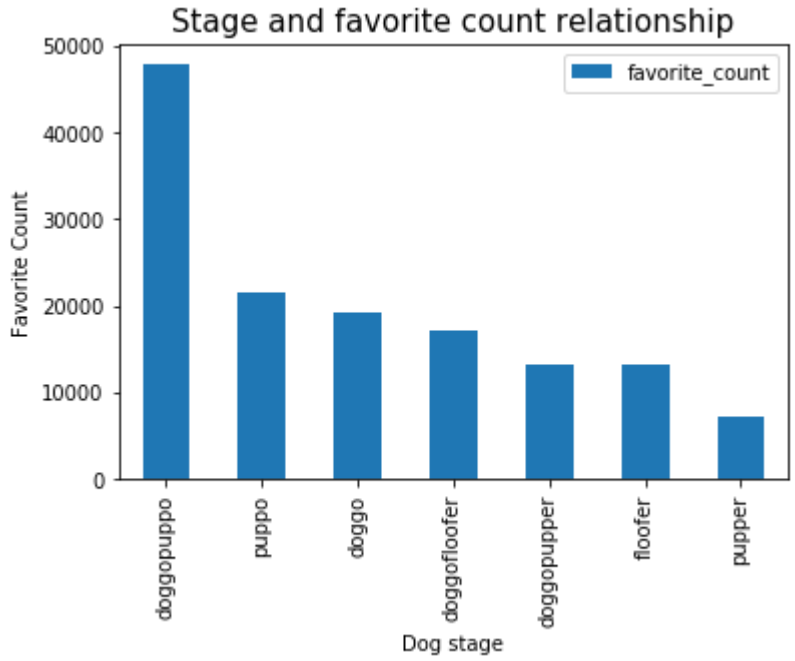
Analysis question 3: What are the most popular dog names

In [58]:
```
data['name'].value_counts()[0:10].sort_values(ascending=False).plot(kind = '
plt.ylabel('Number of dogs')
plt.title('Top dog names')
plt.xlabel('Dog Names')
plt.plot();
```



Analysis question 4: What dog stages have the highest favorite count

In [59]:
```
data.groupby('stage')[['favorite_count']].mean().sort_values(ascending=False
plt.ylabel('Favorite Count')
plt.title('Stage and favorite count relationship', size=15)
plt.xlabel('Dog stage')
plt.show()
```



Summary

1. I define the question to analyse before performing the data cleaning process. Thus, I save time by not cleaning the unnecessary columns that I will delete anyway (e.g: source).
2. The rating and dog breeds require some of my intuition in defining the final value of the dataset. This value is negotiable if the people in charge have a better ideas on how to define these columns.
3. I decided to keep Nan rows at the final dataset, because if I remove all rows with Nan, I will have a small dataset that is not enough for further analysis.
4. Doggopuppo receives a few ratings, but end up staying at the highest rate. Surprisingly, it also has the highest favorite count in the dataset. I thought the highest ratings appear due to the small sample size, but the favorite count says that it is not coincidence.