In [1]:
```
# importing the required packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
# ?disabling the warnings
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
# Json packages
import tweepy
from tweepy import OAuthHandler
import json
from timeit import default_timer as timer
```

Data Gathering

1: comma separated values (csv) data source loading

In [4]:
```
# Data loading and processing
data = pd.read_csv("twitter-archive-enhanced-2.csv")
# creating a local data copy
df = data.copy()
```

2 : tab separated values file (tsv)

In [5]:
```
image = pd.read_csv("image-predictions-3.tsv",sep = "\t")
image.head()
```

Out[5]:

	tweet_id	jpg_url	img_num	p1	
0	666020888022790149	https://pbs.twimg.com/media/CT4udn0WwAA0aMy.jpg	1	Welsh_springer_spaniel	0
1	666029285002620928	https://pbs.twimg.com/media/CT42GRgUYAA5iDo.jpg	1	redbone	0
2	666033412701032449	https://pbs.twimg.com/media/CT4521TWwAEvMyu.jpg	1	German_shepherd	0
3	666044226329800704	https://pbs.twimg.com/media/CT5Dr8HUEAA-lEu.jpg	1	Rhodesian_ridgeback	0
4	666049248165822465	https://pbs.twimg.com/media/CT5IQmsXIAAKY4A.jpg	1	miniature_pinscher	0

In [6]:
```
# understanding the image summary statistics
image.describe(include='all')
```

Out[6]:

	tweet_id	jpg_url	img_num	p1	p1_conf	p1_dog
count	2.075000e+03	2075	2075.000000	2075	2075.000000	2075
unique	NaN	2009	NaN	378	NaN	2
top	NaN	https://pbs.twimg.com/media/CZhn-QAWwAASQan.jpg	NaN	golden_retriever	NaN	True
freq	NaN	2	NaN	150	NaN	1532
mean	7.384514e+17	NaN	1.203855	NaN	0.594548	NaN
std	6.785203e+16	NaN	0.561875	NaN	0.271174	NaN
min	6.660209e+17	NaN	1.000000	NaN	0.044333	NaN
25%	6.764835e+17	NaN	1.000000	NaN	0.364412	NaN
50%	7.119988e+17	NaN	1.000000	NaN	0.588230	NaN
75%	7.932034e+17	NaN	1.000000	NaN	0.843855	NaN
max	8.924206e+17	NaN	4.000000	NaN	1.000000	NaN

In [7]:
```
# processing the image data
link = []
img_name = []
img_media = []
extension=[]
for x in range(0,len(image)):
    extension = image['jpg_url'][x].split(".")
#     link = image['jpg_url'][x].split(".")[-1]
#     img_media = image['jpg_url'][x].split(".")[-1]
    link.append(extension)
tsv_data = pd.DataFrame(link,columns =['link',"image_name","image_media","image_format"]
print(tsv_data.head())
print('#####################################################################')
print('The shape of data is as shown below')
print(tsv_data.shape)
```

```
          link image_name                image_media image_format
0  https://pbs (https://pbs)      twimg  com/media/CT4udn0WwAA0aMy          jpg
1  https://pbs (https://pbs)      twimg  com/media/CT42GRgUYAA5iDo          jpg
2  https://pbs (https://pbs)      twimg  com/media/CT4521TWwAEvMyu          jpg
3  https://pbs (https://pbs)      twimg  com/media/CT5Dr8HUEAA-lEu          jpg
4  https://pbs (https://pbs)      twimg  com/media/CT5IQmsXIAAKY4A          jpg
#####################################################################
The shape of data is as shown below
(2075, 4)
```

JSON- api data loading

In [8]:
```
json_list = []
testlist = []
with open('tweet_json.txt') as file:
    for line in file:
        tweets = json.loads(line)
        tweet_id = tweets['id']
        retweet_count = tweets['retweet_count']
        favorite_count = tweets['favorite_count']
        entities = tweets['entities']
        full_text = tweets['full_text']
        created_at = tweets['created_at']
        display_text_range = tweets['display_text_range']
        user = tweets['user']
        testlist.append(tweets)
#         print(testlist)
        json_list.append({'tweet_id':tweet_id,
                          'retweet_count':retweet_count,
                          'favorite_count':favorite_count,
                           'full_text': full_text,
                           'entities' : entities,
                           'created_at': created_at,
                           'display_text_range':display_text_range,
                           'user':user
                          })
json_data = pd.DataFrame(json_list,columns=['created_at','tweet_id','user','retweet_cou
json_data.head()
print(f"the shape of the data is :{json_data.shape} ")
print("-------------------------------------------------")
print(json_data.describe())


print("-------------------------------------------------")
json_data.info()
```

```
the shape of the data is :(2354, 8)
-------------------------------------------------
           tweet_id  retweet_count  favorite_count
count  2.354000e+03    2354.000000     2354.000000
mean   7.426978e+17    3164.797366     8080.968564
std    6.852812e+16    5284.770364    11814.771334
min    6.660209e+17       0.000000        0.000000
25%    6.783975e+17     624.500000     1415.000000
50%    7.194596e+17    1473.500000     3603.500000
75%    7.993058e+17    3652.000000    10122.250000
max    8.924206e+17   79515.000000   132810.000000
-------------------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2354 entries, 0 to 2353
Data columns (total 8 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   created_at          2354 non-null   object
 1   tweet_id            2354 non-null   int64 
 2   user                2354 non-null   object
 3   retweet_count       2354 non-null   int64 
 4   display_text_range  2354 non-null   object
 5   favorite_count      2354 non-null   int64 
 6   full_text           2354 non-null   object
 7   entities            2354 non-null   object
dtypes: int64(3), object(5)
memory usage: 147.2+ KB
```

Data Assessment

1: Visual Assessment

In [9]:
```
# printing the head of the data
data.head()
```

Out[9]:

	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/download/i
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com/download/i
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com/download/i
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com/download/i
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com/download/i

In [10]:
```
# printing the tail of the data
data.tail()
```

Out[10]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
2351	666049248165822465	NaN	NaN	2015-11-16 00:24:50 +0000	href="http://twitter.com/downlo
2352	666044226329800704	NaN	NaN	2015-11-16 00:04:52 +0000	href="http://twitter.com/downlo
2353	666033412701032449	NaN	NaN	2015-11-15 23:21:54 +0000	href="http://twitter.com/downlo
2354	666029285002620928	NaN	NaN	2015-11-15 23:05:30 +0000	href="http://twitter.com/downlo
2355	666020888022790149	NaN	NaN	2015-11-15 22:32:08 +0000	href="http://twitter.com/downlo

In [11]:
```
# getting the sample data values
data.sample(5)
```

Out[11]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
1997	672591271085670400	NaN	NaN	2015-12-04 01:40:29 +0000	href="http://twitter.com/downlo
303	836397794269200385	NaN	NaN	2017-02-28 02:09:08 +0000	href="http://twitter.com/downlo
249	845306882940190720	NaN	NaN	2017-03-24 16:10:40 +0000	href="http://twitter.com/downlo
1968	673320132811366400	NaN	NaN	2015-12-06 01:56:44 +0000	href="http://twitter.com/downlo
501	813096984823349248	NaN	NaN	2016-12-25 19:00:02 +0000	href="http://twitter.com/downlo

In [12]:
```
# understanding the data summary statistics
data.describe().T
```

Out[12]:

	count	mean	std	min	25%	50%	
tweet_id	2356.0	7.427716e+17	6.856705e+16	6.660209e+17	6.783989e+17	7.196279e+17	7
in_reply_to_status_id	78.0	7.455079e+17	7.582492e+16	6.658147e+17	6.757419e+17	7.038708e+17	8
in_reply_to_user_id	78.0	2.014171e+16	1.252797e+17	1.185634e+07	3.086374e+08	4.196984e+09	4
retweeted_status_id	181.0	7.720400e+17	6.236928e+16	6.661041e+17	7.186315e+17	7.804657e+17	8
retweeted_status_user_id	181.0	1.241698e+16	9.599254e+16	7.832140e+05	4.196984e+09	4.196984e+09	4
rating_numerator	2356.0	1.312649e+01	4.587665e+01	0.000000e+00	1.000000e+01	1.100000e+01	1
rating_denominator	2356.0	1.045543e+01	6.745237e+00	0.000000e+00	1.000000e+01	1.000000e+01	1

In [13]:
```
# getting the data types and information
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2356 entries, 0 to 2355
Data columns (total 17 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   tweet_id                    2356 non-null   int64  
 1   in_reply_to_status_id       78 non-null     float64
 2   in_reply_to_user_id         78 non-null     float64
 3   timestamp                   2356 non-null   object 
 4   source                      2356 non-null   object 
 5   text                        2356 non-null   object 
 6   retweeted_status_id         181 non-null    float64
 7   retweeted_status_user_id    181 non-null    float64
 8   retweeted_status_timestamp  181 non-null    object 
 9   expanded_urls               2297 non-null   object 
 10  rating_numerator            2356 non-null   int64  
 11  rating_denominator          2356 non-null   int64  
 12  name                        2356 non-null   object 
 13  doggo                       2356 non-null   object 
 14  floofer                     2356 non-null   object 
 15  pupper                      2356 non-null   object 
 16  puppo                       2356 non-null   object 
dtypes: float64(4), int64(3), object(10)
memory usage: 313.0+ KB
```

2 : Programmatic Assessment

In [14]:
```
data.T.shape
```

Out[14]:
```
(17, 2356)
```

In [15]:
```
data[(data.doggo!="None") & (data.floofer!="None") ]
```

Out[15]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
200	854010172552949760	NaN	NaN	2017-04-17 16:34:26 +0000	href="http://twitter.com/downloa

In [16]:
```
data[(data.pupper !="None") & (data.floofer!="None") ]
```

Out[16]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	source	text	retweeted_status_id	retweete

In [17]:
```
data.doggo.value_counts()
```

Out[17]:
```
None     2259
doggo      97
Name: doggo, dtype: int64
```

""" tweet_id is the last part of the tweet URL after "status/" → https://twitter.com/dog_rates/status/889531135344209921 (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."""

visual assessment and observations made

Data Tidyness:

A) data stacture is not tidy as observed. very variable does not form a column in the dataset, there are columns in the likes of entities with more variables in them. this thus disagrees with the rules of tidy data. Every column being a variable.
B) it can be observed tha not every cell is not a single value. there are cell observed to contain multiples elements in them. a good example as observed was the cell of belonging to the column users. it had the details of the user within the same cell. This bridge the rule of having a single element in a single single.
C) The data semantic is also observed to have been compromised, for instance. the columns doggo, floofer, pupper and puppo are the dogs breeds and needed to have been stored in a single.

In [18]:
```
# Data Understanding
# we need to tidy the columns doggo,floofer, pupper and puppo to make a single column of
breeds = data[['doggo', 'floofer', 'pupper', 'puppo']]
breeds.columns.to_list()
```

Out[18]:
```
['doggo', 'floofer', 'pupper', 'puppo']
```

In [19]:
```
# data.columns.to_list()
```

In [20]:
```
# perfoming a melt on the data
data_with_breeds=pd.melt(data,
        id_vars=['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',],
       value_vars=breeds.columns.to_list(),
       value_name='Breed',)
data.shape,data.shape
```

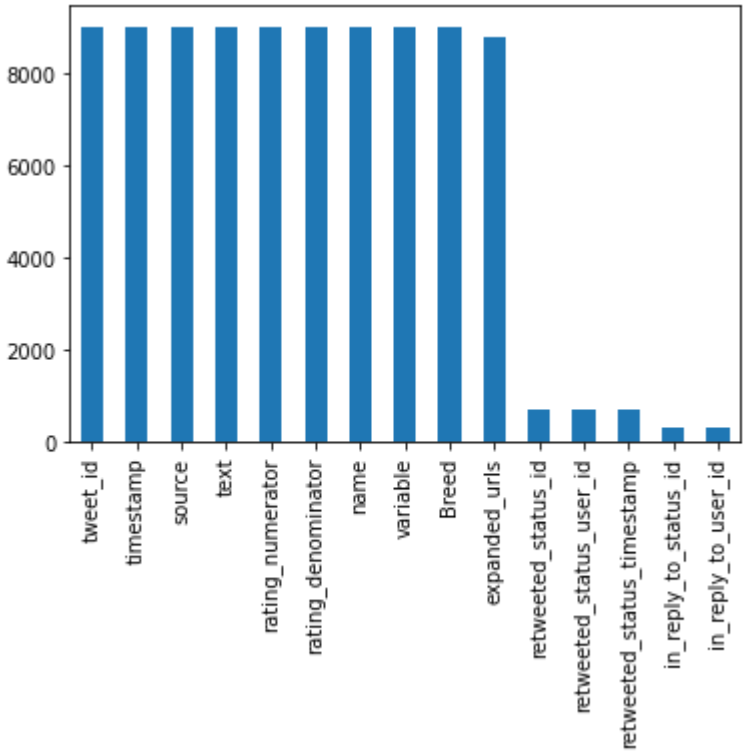
Out[20]:
```
((2356, 17), (2356, 17))
```

In [21]:
```
data_with_breeds.shape
```

Out[21]:
```
(9424, 15)
```

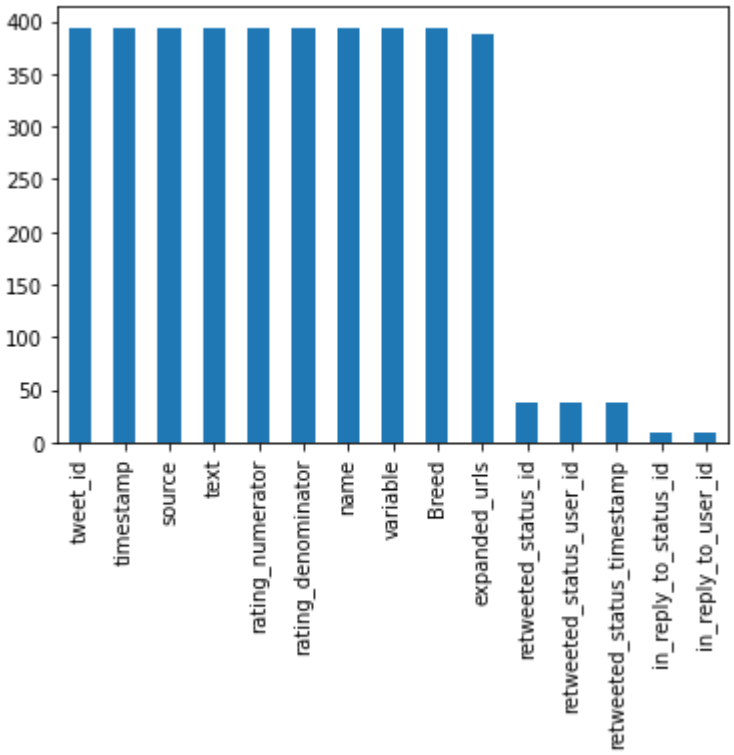
In [22]:
```
# checking for the distributioin of None values in the dataset
data_with_breeds[data_with_breeds.Breed=="None"].count().sort_values(ascending=False).pl
# it appears the columns that are not much affected by the None probles are only the thr
# quite insightfull. most tweets were actually replied and that is what we are noticing.
```

Out[22]: <AxesSubplot:>



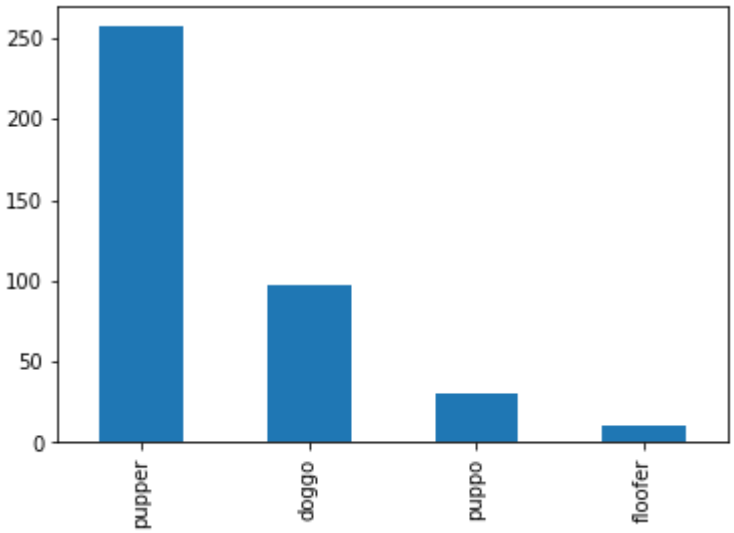
In [23]:
```
data_with_breeds[data_with_breeds.Breed!="None"].count().sort_values(ascending=False).pl
```

Out[23]: <AxesSubplot:>



In [24]:
```
data_with_breeds[data_with_breeds.Breed!="None"].Breed.value_counts().plot(kind='bar',)
```

Out[24]: <AxesSubplot:>



In [25]:
```
print(data.shape,data_with_breeds[data_with_breeds.Breed!="None"].shape)
```

```
(2356, 17) (394, 15)
```

In [26]:
```
data_with_breeds[(data_with_breeds.Breed!="None") & (data_with_breeds.name!='None')].sha
```

Out[26]: (226, 15)

In [27]:
```
data = data_with_breeds[(data_with_breeds.Breed!="None") & (data_with_breeds.name!='None
data.shape
```

Out[27]: (226, 15)

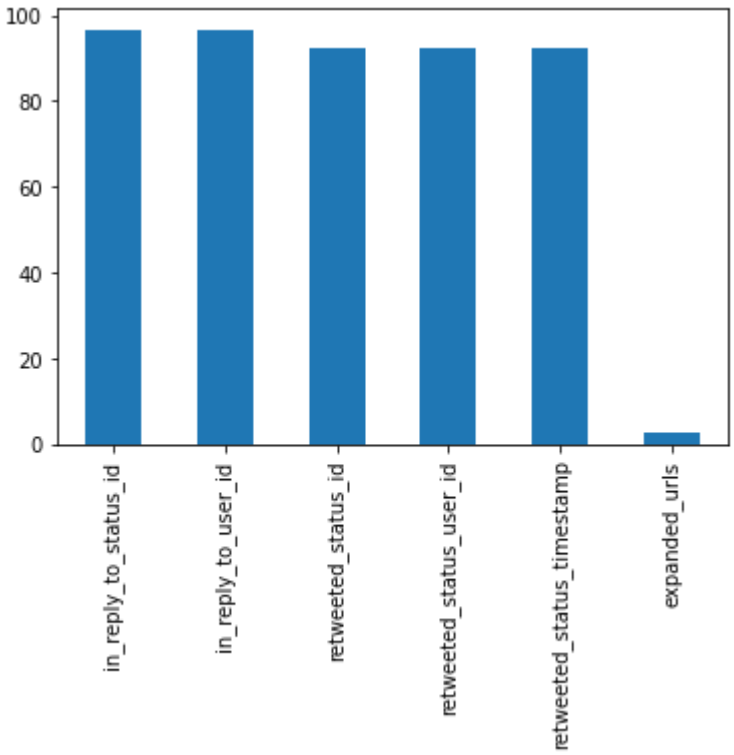
In [28]:
```
df.head()
```

Out[28]:

	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/download/i
1	892177421306343426	NaN	NaN	2017-08-01 00:17:27 +0000	href="http://twitter.com/download/i
2	891815181378084864	NaN	NaN	2017-07-31 00:18:03 +0000	href="http://twitter.com/download/i
3	891689557279858688	NaN	NaN	2017-07-30 15:58:51 +0000	href="http://twitter.com/download/i
4	891327558926688256	NaN	NaN	2017-07-29 16:00:24 +0000	href="http://twitter.com/download/i

In [29]:
```
missing_ration = (df.isna().sum()/df.shape[0])*100
missing_percentage = missing_ration[missing_ration.values > 0.0].sort_values(ascending=F
missing_percentage.plot(kind='bar')
# all this columns are missing data, we cant drop them as it would not be prudent. best
# this is becouse, tweet as a coplumn for instance must not neccessarity have a retweet.
```

Out[29]: <AxesSubplot:>



2: Data Quality Issues

a) the data has numerous missing values, this can be seen from the nan values in the cells
b) there is data inconsistency being observed, specifically the records.
c) a significant percentage of data had none data items. this means the data cant be operated upon as none cant be statistically operated upon.
d)

In [30]:
```
data.sample()
```

Out[30]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
447	819015331746349057	NaN	NaN	2017-01-11 02:57:26 +0000	href="http://twitter.com/downloa

In [31]:
```
expanded_urls=pd.DataFrame(data['expanded_urls'])
```

In [32]:
```
def split_expanded_urls(col):
    for x in range(len(col)):
        temp =col.iloc[x]
    return temp
```

In [33]:
```
data['expanded_urls'].isna().sum()
data['expanded_urls'] = data['expanded_urls'].fillna("")
```

In [34]:
```
df.expanded_urls.str.split('/').sample(5).iloc[1][3:]
# df.expanded_urls
```

Out[34]:
```
['dog_rates', 'status', '668636665813057536', 'photo', '1']
```

In [35]:
```
df.expanded_urls=df.expanded_urls.fillna("")
```

In [36]:
```
df.expanded_urls.isna().sum()
```

Out[36]:
```
0
```

In [37]:
```
data.head()
```

Out[37]:

	tweet_id	in_reply_to_status_id	in_reply_to_user_id	timestamp	
9	890240255349198849	NaN	NaN	2017-07-26 15:59:51 +0000	href="http://twitter.com/downloa
43	884162670584377345	NaN	NaN	2017-07-09 21:29:42 +0000	href="http://twitter.com/downloa
108	871515927908634625	NaN	NaN	2017-06-04 23:56:03 +0000	href="http://twitter.com/downloa
121	869596645499047938	NaN	NaN	2017-05-30 16:49:31 +0000	href="http://twitter.com/downloa
211	851953902622658560	NaN	NaN	2017-04-12 00:23:33 +0000	href="http://twitter.com/downloa

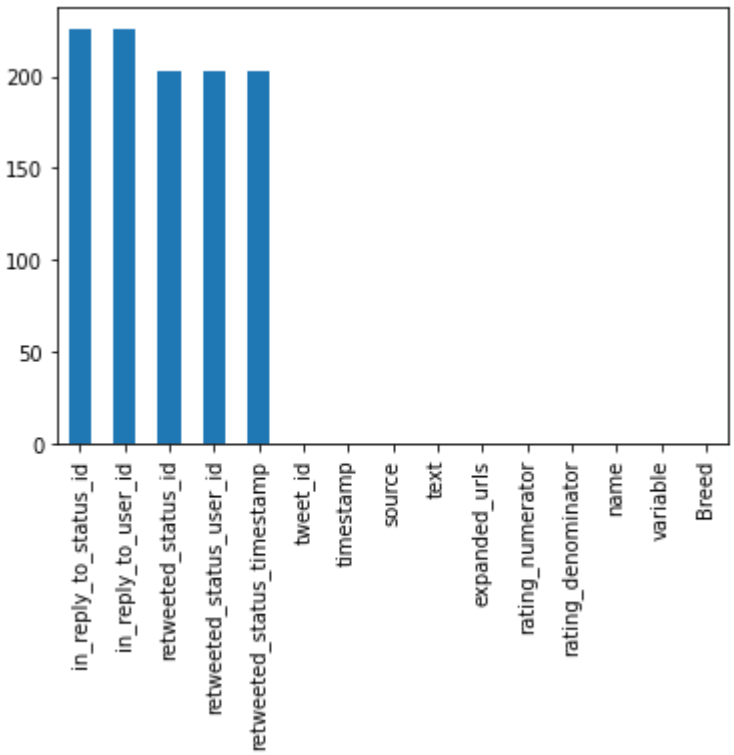
In [38]:
```
data.source
```

Out[38]:
```
9       <a href="http://twitter.com/download/iphone" r...
43      <a href="http://twitter.com/download/iphone" r...
108     <a href="http://twitter.com/download/iphone" r...
121     <a href="http://twitter.com/download/iphone" r...
211     <a href="http://twitter.com/download/iphone" r...
                              ...
7781    <a href="http://vine.co" rel="nofollow">Vine -...
8029    <a href="http://twitter.com/download/iphone" r...
8103    <a href="http://twitter.com/download/iphone" r...
8116    <a href="http://twitter.com/download/iphone" r...
8151    <a href="http://twitter.com/download/iphone" r...
Name: source, Length: 226, dtype: object
```

Removing the duplicated values for the tweet id column

In [39]:
```
# investigating the data
data.isna().sum().sort_values(ascending=False).plot(kind='bar')
data.tweet_id.duplicated().count()
```

Out[39]: 226



In [40]:
```
data.isna().sum().sort_values(ascending=False)
```

Out[40]:
```
in_reply_to_status_id          226
in_reply_to_user_id            226
retweeted_status_id            203
retweeted_status_user_id       203
retweeted_status_timestamp     203
tweet_id                         0
timestamp                        0
source                           0
text                             0
expanded_urls                    0
rating_numerator                 0
rating_denominator               0
name                             0
variable                         0
Breed                            0
dtype: int64
```

Removing the non important columns

In [41]:
```
# identifying the columns to remove
cols_to_remove = ['retweeted_status_timestamp','retweeted_status_user_id','retweeted_sta
# droping the columns
data.drop(axis=1,columns = cols_to_remove,inplace=True)
# rechecking the data for any possible missing values
data.isna().sum().sort_values(ascending=False)
```

Out[41]:
```
tweet_id              0
timestamp             0
source                0
text                  0
expanded_urls         0
rating_numerator      0
rating_denominator    0
name                  0
variable              0
Breed                 0
dtype: int64
```

In [42]:
```
# droping the raws with missing links
data.drop(axis=0,columns=['expanded_urls'],inplace=True)
# rechecking the data fro missing values
data.isna().sum().sort_values(ascending=False)
```

Out[42]:
```
tweet_id              0
timestamp             0
source                0
text                  0
rating_numerator      0
rating_denominator    0
name                  0
variable              0
Breed                 0
dtype: int64
```

In [43]:
```
# Removing the duplicated values
data  = data.drop_duplicates(subset=['tweet_id'],keep = False)
# data.tweet_id.value_counts()
```

Cleaning the date format

In [44]:
```
data.timestamp = pd.to_datetime(data.timestamp).dt.date
data.timestamp
```

Out[44]:
```
9       2017-07-26
43      2017-07-09
108     2017-06-04
121     2017-05-30
211     2017-04-12
           ...
7781    2016-10-07
8029    2016-07-07
8103    2016-06-20
8116    2016-06-16
8151    2016-06-03
Name: timestamp, Length: 214, dtype: object
```

In [45]:
```
# setting the time stamp as the data index for the dataframe
data.set_index('timestamp',inplace=True)
data.head()
```

Out[45]:

timestamp	tweet_id	source	text	rating_numerator	rating_
2017-07-26	890240255349198849	<a href="http://twitter.com/download/iphone" r...	This is Cassie. She is a college pup. Studying...	14	
2017-07-09	884162670584377345	<a href="http://twitter.com/download/iphone" r...	Meet Yogi. He doesn't have any important dog m...	12	
2017-06-04	871515927908634625	<a href="http://twitter.com/download/iphone" r...	This is Napolean. He's a Raggedy East Nicaragu...	12	
2017-05-30	869596645499047938	<a href="http://twitter.com/download/iphone" r...	This is Scout. He just graduated. Officially a...	12	
2017-04-12	851953902622658560	<a href="http://twitter.com/download/iphone" r...	RT @dog_rates: This is Astrid. She's a guide d...	13	

In [46]:
```
data.source[0].split('/')
```

Out[46]:
```
['<a href="http:',
 '',
 'twitter.com',
 'download',
 'iphone" rel="nofollow">Twitter for iPhone<',
 'a>']
```

In [47]:
```
# splitting the source column and creating a new dataframe from it
source_data = data.source.str.split('/',expand=True)
# creating a dataframe from split
source_data = pd.DataFrame(source_data)
# filtering the required columns from the data
source_data['domain'] = source_data[2]
source_data['source_']  = source_data[3]
# getting the columns of interest
source_data = source_data[['domain','source_']]
# source_data.apply(np.where(source_data.source_ == 'a>',source_data.drop(axis=1),source
# removing unwanted part of data
source_data.head()
```

Out[47]:

timestamp	domain	source_
2017-07-26	twitter.com	download
2017-07-09	twitter.com	download
2017-06-04	twitter.com	download
2017-05-30	twitter.com	download
2017-04-12	twitter.com	download

In [48]:
```
# dropping the source column as it is not that useful now
data.drop('source',axis = 1, inplace=True)
```

In [49]:
```
# checking a sample of the dataset
data.sample(5)
```

Out[49]:

timestamp	tweet_id	text	rating_numerator	rating_denominator	name	variable	Bre
2017-05-24	867421006826221569	This is Shikha. She just watched you drop a sk...	12	10	Shikha	puppo	pup
2015-12-05	672988786805112832	This is Schnozz. He's had a blurred tail since...	10	10	Schnozz	pupper	pupp
2017-05-30	869596645499047938	This is Scout. He just graduated. Officially a...	12	10	Scout	doggo	dog
2017-01-06	817502432452313088	RT @dog_rates: Meet Herschel. He's slightly bi...	7	10	Herschel	pupper	pupp
2016-01-18	689143371370250240	Meet Trip. He likes wearing costumes that aren...	10	10	Trip	pupper	pupp

In [50]:
```
# concatenating the two dataframes
dts = [data,source_data]
# combining the dataframes
merged = pd.concat(dts,axis=1)
merged.head()
```

Out[50]:

timestamp	tweet_id	text	rating_numerator	rating_denominator	name	variable	Bre
2017-07-26	890240255349198849	This is Cassie. She is a college pup. Studying...	14	10	Cassie	doggo	dog
2017-07-09	884162670584377345	Meet Yogi. He doesn't have any important dog m...	12	10	Yogi	doggo	dog
2017-06-04	871515927908634625	This is Napolean. He's a Raggedy East Nicaragu...	12	10	Napolean	doggo	dog
2017-05-30	869596645499047938	This is Scout. He just graduated. Officially a...	12	10	Scout	doggo	dog
2017-04-12	851953902622658560	RT @dog_rates: This is Astrid. She's a guide d...	13	10	Astrid	doggo	dog

In [51]:
```
merged = merged[merged['source_'] != 'a>']
merged.drop(['variable','tweet_id'],axis=1,inplace=True)
merged.shape
```

Out[51]: (206, 7)

In [52]:
```
source_data.shape
```

Out[52]: (214, 2)

In [53]:
```
data[data.name =='None'].shape
```

Out[53]: (0, 7)

Done With Data Cleaning

In [54]:
```
# saving the clean dataset into a csv file
merged.to_csv('cleaned_tweets.csv',index = False)
```

Data Analysis

In [55]:
```
merged.head()
```

Out[55]:

timestamp	text	rating_numerator	rating_denominator	name	Breed	domain	source_
2017-07-26	This is Cassie. She is a college pup. Studying...	14	10	Cassie	doggo	twitter.com	download
2017-07-09	Meet Yogi. He doesn't have any important dog m...	12	10	Yogi	doggo	twitter.com	download
2017-06-04	This is Napolean. He's a Raggedy East Nicaragu...	12	10	Napolean	doggo	twitter.com	download
2017-05-30	This is Scout. He just graduated. Officially a...	12	10	Scout	doggo	twitter.com	download
2017-04-12	RT @dog_rates: This is Astrid. She's a guide d...	13	10	Astrid	doggo	twitter.com	download

In [56]:
```
# sns.pairplot(merged)
```

In [57]:
```
merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 206 entries, 2017-07-26 to 2016-06-03
Data columns (total 7 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   text                206 non-null    object
 1   rating_numerator    206 non-null    int64 
 2   rating_denominator  206 non-null    int64 
 3   name                206 non-null    object
 4   Breed               206 non-null    object
 5   domain              206 non-null    object
 6   source_             206 non-null    object
dtypes: int64(2), object(5)
memory usage: 12.9+ KB
```

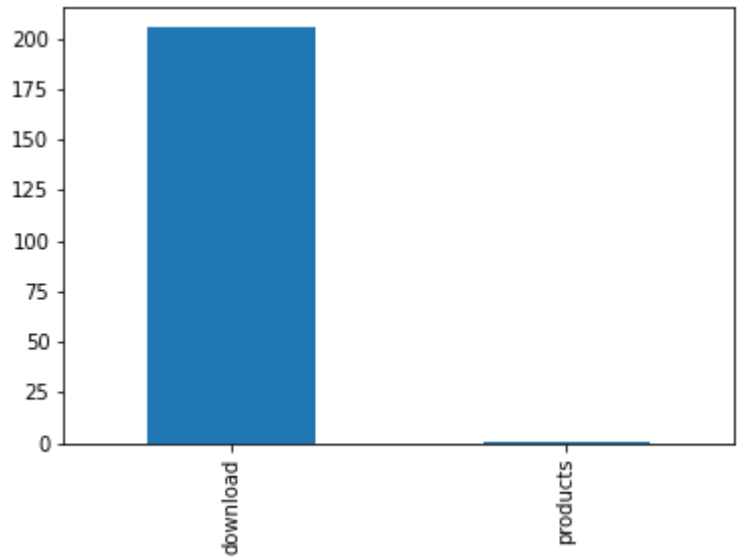
In [58]:
```
merged.describe()
```

Out[58]:

	rating_numerator	rating_denominator
count	206.000000	206.0
mean	10.995146	10.0
std	2.119589	0.0
min	3.000000	10.0
25%	10.000000	10.0
50%	11.000000	10.0
75%	12.000000	10.0
max	27.000000	10.0

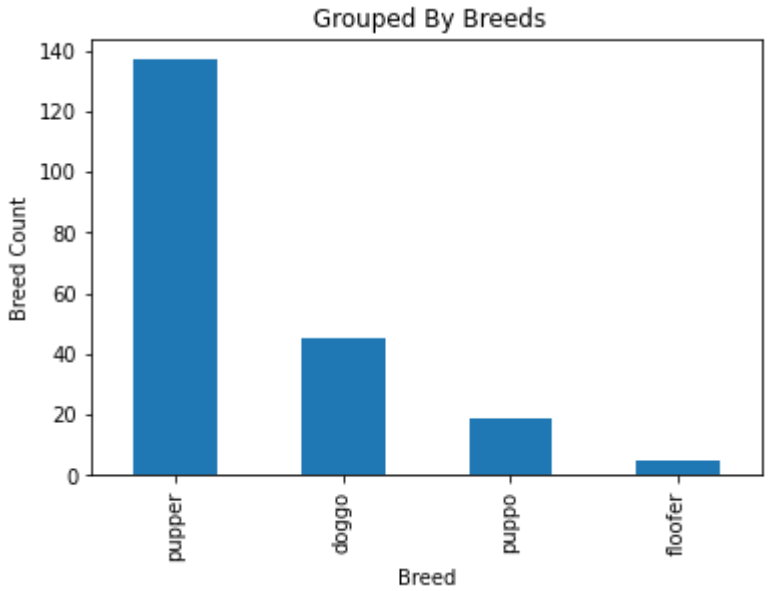
In [59]:
```
# ploting the unique data values fro product category
merged.source_.value_counts().plot(kind='bar')
```

Out[59]: <AxesSubplot:>



In [60]:
```
merged.Breed.value_counts().plot(kind='bar')
plt.title(" Grouped By Breeds")
plt.xlabel('Breed')
plt.ylabel('Breed Count')
```

Out[60]: Text(0, 0.5, 'Breed Count')



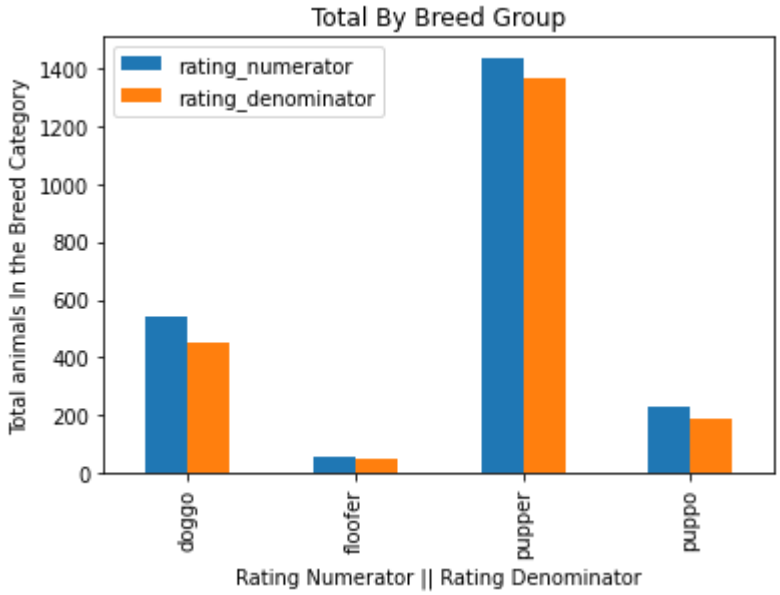
In [61]:
```
data.head()
```

Out[61]:

timestamp	tweet_id	text	rating_numerator	rating_denominator	name	variable	Bre
2017-07-26	890240255349198849	This is Cassie. She is a college pup. Studying...	14	10	Cassie	doggo	dog
2017-07-09	884162670584377345	Meet Yogi. He doesn't have any important dog m...	12	10	Yogi	doggo	dog
2017-06-04	871515927908634625	This is Napolean. He's a Raggedy East Nicaragu...	12	10	Napolean	doggo	dog
2017-05-30	869596645499047938	This is Scout. He just graduated. Officially a...	12	10	Scout	doggo	dog
2017-04-12	851953902622658560	RT @dog_rates: This is Astrid. She's a guide d...	13	10	Astrid	doggo	dog

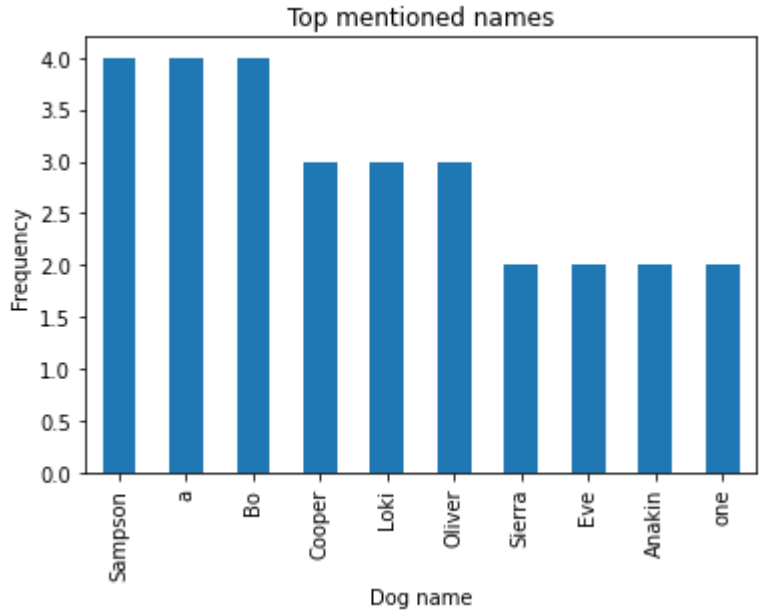
In [62]:
```
tempdf=merged.reset_index()
grouped_breed=tempdf.groupby(tempdf['Breed'])['rating_numerator', 'rating_denominator']
# grouped_breed = grouped_breed.sort_values(by=[],ascending=False)
grouped_breed.plot.bar()
plt.title("Total By Breed Group")
plt.xlabel('Rating Numerator || Rating Denominator')
plt.ylabel("Total animals In the Breed Category")
```

Out[62]:
```
Text(0, 0.5, 'Total animals In the Breed Category')
```



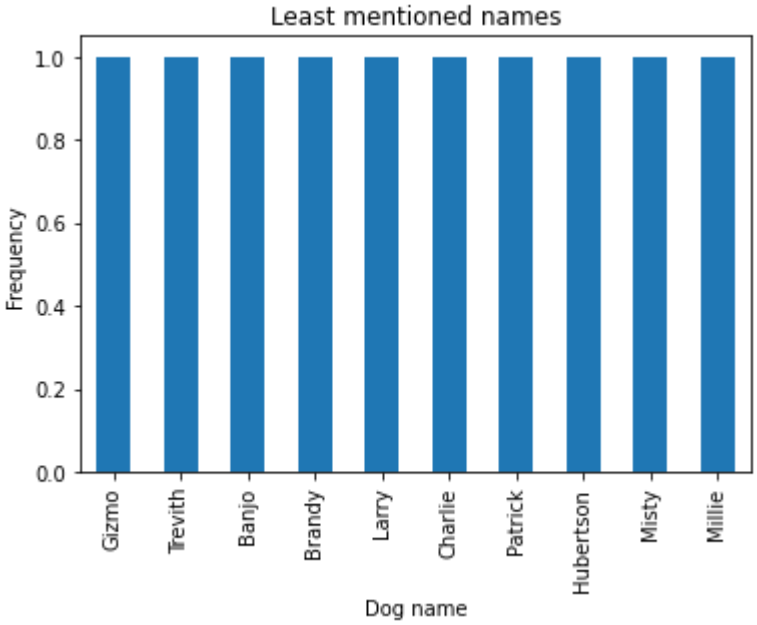
In [63]:
```
# grouped_by_name=tempdf.groupby('name')['rating_numerator', 'rating_denominator'].sum()
# grouped_by_name
# groupby does not work well with this data
# visualizing the most mentioned dog
merged.name.value_counts().nlargest(10).plot.bar(rot=90)
plt.title("Top mentioned names")
plt.xlabel("Dog name")
plt.ylabel("Frequency")
```

Out[63]:
```
Text(0, 0.5, 'Frequency')
```



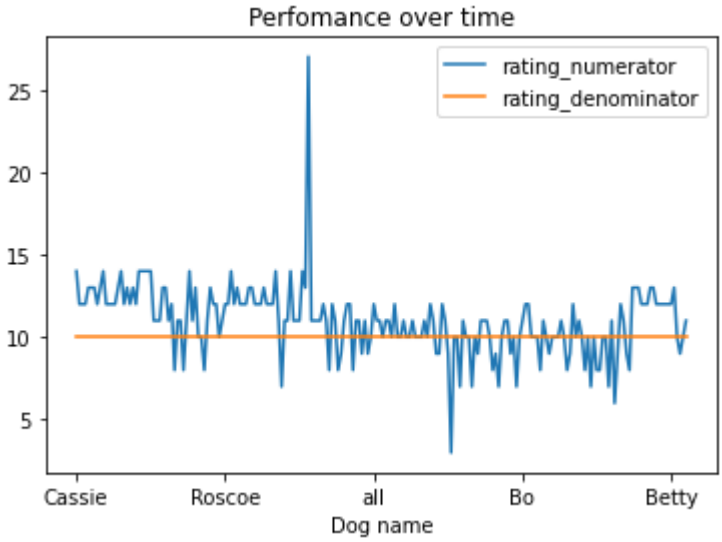
In [64]:
```
# visualizing the least mentioned dog
merged.name.value_counts().nsmallest(10).plot.bar(rot=90)
plt.title("Least mentioned names")
plt.xlabel("Dog name")
plt.ylabel("Frequency")
```

Out[64]:
```
Text(0, 0.5, 'Frequency')
```



In [65]:
```
merged.plot('name')
plt.title("Perfomance over time")
plt.xlabel("Dog name")
```

Out[65]:
```
Text(0.5, 0, 'Dog name')
```



End of Analysis

In [ ]: