Project 1: Trump, Twitter, and Text

In this project, we will work with the Twitter API in order to analyze Donald Trump's tweets.

The project is due 11:59pm Sunday, October 20

If you find yourself getting frustrated or stuck on one problem for too long, we suggest coming into office hours and working with friends in the class.

In [1]:
```
# Run this cell to set up your notebook
import csv
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import zipfile
import json

# Ensure that Pandas shows at least 280 characters in columns, so we can see full tweets
pd.set_option('max_colwidth', 280)

%matplotlib inline
plt.style.use('fivethirtyeight')
import seaborn as sns
sns.set()
sns.set_context("talk")
import re
```

Getting the data

The starting point and a key aspect of any data science project is getting the data. To get Twitter data, Twitter conveniently provides a developer API using which we can scrape data. More on that will follow in the coming discussions!

For now, we've made life easier for you by providing the data.

Start by running the following cells, which will download and then load Donald Trump's most recent tweets.

In [2]:
```
# Download the dataset
from utils import fetch_and_cache
data_url = 'https://cims.nyu.edu/~policast/recent_tweets.json'
file_name = 'realdonaldtrump_recent_tweets.json'

dest_path = fetch_and_cache(data_url=data_url, file=file_name)
print(f'Located at {dest_path}')
```

```
Using version already downloaded: Mon Oct  7 20:53:03 2019
MD5 hash of file: 216176fb098cd5d6b40b373b98bd3e6d
Located at data/realdonaldtrump_recent_tweets.json
```

In [3]:
```
def load_tweets(path):
    """Loads tweets that have previously been saved.

    Calling load_tweets(path) after save_tweets(tweets, path)
    will produce the same list of tweets.

    Args:
        path (str): The place where the tweets were be saved.

    Returns:
        list: A list of Dictionary objects, each representing one twee
t."""

    with open(path, "rb") as f:
        import json
        return json.load(f)
```

In [4]:
```
trump_tweets = load_tweets(dest_path)
```

If everything is working correctly correctly this should load roughly the last 3000 tweets by `realdonaldtrump`.

In [5]:
```
assert 2000 <= len(trump_tweets) <= 4000
```

If the assert statement above works, then continue on to question 2b.

Question 1

We are limited to how many tweets we can download. In what month is the oldest tweet from Trump?

In [6]:
```
# Enter the number of the month of the oldest tweet (e.g. 1 for January)
### BEGIN SOLUTION
oldest_month = 10
### END SOLUTION
```

In [7]:
```
old_trump_tweets[0]['created_at']
```

```
--------------------------------------------------------------------------
----
NameError                                 Traceback (most recent call l
ast)
<ipython-input-7-2622d756a450> in <module>
----> 1 old_trump_tweets[0]['created_at']

NameError: name 'old_trump_tweets' is not defined
```

In [8]:
```
### BEGIN HIDDEN TESTS
assert oldest_month > 9
assert oldest_month < 12
### END HIDDEN TESTS
```

IMPORTANT! PLEASE READ

What if we want to access Donald Trump's old tweets?
Unfortunately, you cannot download old tweets using the public Twitter APIs. Fortunately, we have a snapshot of earlier tweets of Donald Trump that we can combine with the newer data that you downloaded

We will again use the `fetch_and_cache` utility to download the dataset.

In [9]:
```
# Download the dataset
from utils import fetch_and_cache
data_url = 'https://cims.nyu.edu/~policast/old_trump_tweets.json.zip'
file_name = 'old_trump_tweets.json.zip'

dest_path = fetch_and_cache(data_url=data_url, file=file_name)
print(f'Located at {dest_path}')
```

```
Using version already downloaded: Mon Oct  7 20:53:03 2019
MD5 hash of file: b6e33874de91d1a40207cdf9f9b51a09
Located at data/old_trump_tweets.json.zip
```

Finally, we we will load the tweets directly from the compressed file without decompressing it first.

In [10]:
```
my_zip = zipfile.ZipFile(dest_path, 'r')
with my_zip.open("old_trump_tweets.json", "r") as f:
    old_trump_tweets = json.load(f)
```

This data is formatted identically to the recent tweets we just downloaded:

In [11]:
```
print(old_trump_tweets[0])
```

{'created_at': 'Wed Oct 12 14:00:48 +0000 2016', 'id': 7862049786291855
36, 'id_str': '786204978629185536', 'text': 'PAY TO PLAY POLITICS. \n#C
rookedHillary https://t.co/wjsl8ITVvk', 'truncated': False, 'entities':
{'hashtags': [{'text': 'CrookedHillary', 'indices': [23, 38]}], 'symbol
s': [], 'user_mentions': [], 'urls': [], 'media': [{'id': 7862048853185
61792, 'id_str': '786204885318561792', 'indices': [39, 62], 'media_ur
l': 'http://pbs.twimg.com/ext_tw_video_thumb/786204885318561792/pu/img/
XqMoixLm83FzkAbn.jpg', 'media_url_https': 'https://pbs.twimg.com/ext_tw
_video_thumb/786204885318561792/pu/img/XqMoixLm83FzkAbn.jpg', 'url': 'h
ttps://t.co/wjsl8ITVvk', 'display_url': 'pic.twitter.com/wjsl8ITVvk',
'expanded_url': 'https://twitter.com/realDonaldTrump/status/78620497862
9185536/video/1', 'type': 'photo', 'sizes': {'thumb': {'w': 150, 'h': 1
50, 'resize': 'crop'}, 'medium': {'w': 600, 'h': 338, 'resize': 'fit'},
'small': {'w': 340, 'h': 191, 'resize': 'fit'}, 'large': {'w': 1024,
'h': 576, 'resize': 'fit'}}}]}, 'extended_entities': {'media': [{'id':
786204885318561792, 'id_str': '786204885318561792', 'indices': [39, 6
2], 'media_url': 'http://pbs.twimg.com/ext_tw_video_thumb/7862048853185
61792/pu/img/XqMoixLm83FzkAbn.jpg', 'media_url_https': 'https://pbs.twi
mg.com/ext_tw_video_thumb/786204885318561792/pu/img/XqMoixLm83FzkAbn.jp
g', 'url': 'https://t.co/wjsl8ITVvk', 'display_url': 'pic.twitter.com/w
jsl8ITVvk', 'expanded_url': 'https://twitter.com/realDonaldTrump/statu
s/786204978629185536/video/1', 'type': 'video', 'sizes': {'thumb':
{'w': 150, 'h': 150, 'resize': 'crop'}, 'medium': {'w': 600, 'h': 338,
'resize': 'fit'}, 'small': {'w': 340, 'h': 191, 'resize': 'fit'}, 'larg
e': {'w': 1024, 'h': 576, 'resize': 'fit'}}, 'video_info': {'aspect_rat
io': [16, 9], 'duration_millis': 30106, 'variants': [{'bitrate': 83200
0, 'content_type': 'video/mp4', 'url': 'https://video.twimg.com/ext_tw_
video/786204885318561792/pu/vid/640x360/6vt24D3ZQSvYuDqe.mp4'}, {'bitra
te': 2176000, 'content_type': 'video/mp4', 'url': 'https://video.twimg.
com/ext_tw_video/786204885318561792/pu/vid/1280x720/rSbgQdvR9TPIlRWr.mp
4'}, {'bitrate': 320000, 'content_type': 'video/mp4', 'url': 'https://v
ideo.twimg.com/ext_tw_video/786204885318561792/pu/vid/320x180/JuNJDqr1K
HqoP83N.mp4'}, {'content_type': 'application/x-mpegURL', 'url': 'http
s://video.twimg.com/ext_tw_video/786204885318561792/pu/pl/IugUNii3a7lmj
ApS.m3u8'}]}, 'additional_media_info': {'monetizable': False}}]}, 'sour
ce': 'Twitt
er for iPhone', 'in_reply_to_status_id': None, 'in_reply_to_status_
id_str': None, 'in_reply_to_user_id': None, 'in_reply_to_user_id_str':
None, 'in_reply_to_screen_name': None, 'user': {'id': 25073877, 'id_st
r': '25073877', 'name': 'Donald J. Trump', 'screen_name': 'realDonaldTr
ump', 'location': 'Washington, DC', 'description': '45th President of t
he United States of America🇺🇸 ', 'url': None, 'entities': {'descriptio
n': {'urls': []}}, 'protected': False, 'followers_count': 35307313, 'fr
iends_count': 45, 'listed_count': 74225, 'created_at': 'Wed Mar 18 13:4
6:38 +0000 2009', 'favourites_count': 12, 'utc_offset': -14400, 'time_z
one': 'Eastern Time (US & Canada)', 'geo_enabled': True, 'verified': Tr
ue, 'statuses_count': 35480, 'lang': 'en', 'contributors_enabled': Fals
e, 'is_translator': False, 'is_translation_enabled': True, 'profile_bac
kground_color': '6D5C18', 'profile_background_image_url': 'http://pbs.t
wimg.com/profile_background_images/530021613/trump_scotland__43_of_70_c
c.jpg', 'profile_background_image_url_https': 'https://pbs.twimg.com/pr
ofile_background_images/530021613/trump_scotland__43_of_70_cc.jpg', 'pr
ofile_background_tile': True, 'profile_image_url': 'http://pbs.twimg.co
m/profile_images/874276197357596672/kUuht00m_normal.jpg', 'profile_imag
e_url_https': 'https://pbs.twimg.com/profile_images/874276197357596672/
kUuht00m_normal.jpg', 'profile_banner_url': 'https://pbs.twimg.com/prof
ile_banners/25073877/1501916634', 'profile_link_color': '1B95E0', 'prof

```
ile_sidebar_border_color': 'BDDCAD', 'profile_sidebar_fill_color': 'C5C
EC0', 'profile_text_color': '333333', 'profile_use_background_image': T
rue, 'has_extended_profile': False, 'default_profile': False, 'default_
profile_image': False, 'following': False, 'follow_request_sent': Fals
e, 'notifications': False, 'translator_type': 'regular'}, 'geo': None,
'coordinates': None, 'place': {'id': '4ec01c9dbc693497', 'url': 'http
s://api.twitter.com/1.1/geo/id/4ec01c9dbc693497.json', 'place_type': 'a
dmin', 'name': 'Florida', 'full_name': 'Florida, USA', 'country_code':
'US', 'country': 'United States', 'contained_within': [], 'bounding_bo
x': {'type': 'Polygon', 'coordinates': [[[-87.634643, 24.396308], [-79.
974307, 24.396308], [-79.974307, 31.001056], [-87.634643, 31.00105
6]]]}, 'attributes': {}}, 'contributors': None, 'is_quote_status': Fals
e, 'retweet_count': 24915, 'favorite_count': 42242, 'favorited': False,
'retweeted': False, 'possibly_sensitive': False, 'lang': 'en'}
```


As a dictionary we can also list the keys:

In [12]:
```
old_trump_tweets[0].keys()
```

Out[12]:
```
dict_keys(['created_at', 'id', 'id_str', 'text', 'truncated', 'entitie
s', 'extended_entities', 'source', 'in_reply_to_status_id', 'in_reply_t
o_status_id_str', 'in_reply_to_user_id', 'in_reply_to_user_id_str', 'in
_reply_to_screen_name', 'user', 'geo', 'coordinates', 'place', 'contrib
utors', 'is_quote_status', 'retweet_count', 'favorite_count', 'favorite
d', 'retweeted', 'possibly_sensitive', 'lang'])
```

Since we're giving you a zipfile of old tweets, you may wonder why we didn't just give you a zipfile of ALL tweets and save you the trouble of creating a Twitter developer account. The reason is that we wanted you to see what it's like to collect data from the real world on your own. It can be a pain!

And for those of you that never got your developer accounts, you can see it can be even more of a pain that we expected. Sorry to anybody that wasted a bunch of time trying to get things working.

Question 2

Merge the `old_trump_tweets` and the `trump_tweets` we downloaded from twitter into one giant list of tweets.

Important: There may be some overlap so be sure to eliminate duplicate tweets.
Hint: the `id` of a tweet is always unique.

In [13]:
```
### BEGIN SOLUTION
def Merge(l1, l2):
    old_id=[]
    for i in list(range(len(l2))):
        old_id.append(l2[i]['id'])
    for j in list(range(len(l1))):
        if l1[j]['id'] not in old_id:
            l2.append(l1[j])
    return l2
all_tweets = Merge(trump_tweets,old_trump_tweets.copy())
### END SOLUTION
```

In [14]:
```
assert len(all_tweets) > len(trump_tweets)
assert len(all_tweets) > len(old_trump_tweets)
### BEGIN HIDDEN TESTS
assert len(set([t['id'] for t in all_tweets])) <= len([t['id'] for t in
all_tweets])
### END HIDDEN TESTS
```

Question 3

Construct a DataFrame called `trump` containing all the tweets stored in `all_tweets`. The index of the dataframe should be the ID of each tweet (looks something like `907698529606541312`). It should have these columns:

- `time`: The time the tweet was created encoded as a datetime object. (Use `pd.to_datetime` to encode the timestamp.)
- `source`: The source device of the tweet.
- `text`: The text of the tweet.
- `retweet_count`: The retweet count of the tweet.

Finally, **the resulting dataframe should be sorted by the index.**

Warning: *Some tweets will store the text in the* `text` *field and other will use the* `full_text` *field.*

In [15]:
```
### BEGIN SOLUTION
id=[]
time=[]
source=[]
text=[]
retweet_count=[]
for x in list(range(len(all_tweets))):
    id.append(all_tweets[x]['id'])
    time.append(pd.to_datetime(all_tweets[x]['created_at']))
    source.append(all_tweets[x]['source'])
    retweet_count.append(all_tweets[x]['retweet_count'])
    try:
        text.append(all_tweets[x]['text'])
    except:
        text.append(all_tweets[x]['full_text'])
trump = pd.DataFrame(data={'id': id,'time': time,'source': source,'text'
: text,'retweet_count': retweet_count},index=id)
### END SOLUTION
```

In [16]:
```
assert isinstance(trump, pd.DataFrame)
assert trump.shape[0] < 11000
assert trump.shape[1] >= 4
assert 831846101179314177 in trump.index
assert 753063644578144260 in trump.index
assert all(col in trump.columns for col in ['time', 'source', 'text', 'r
etweet_count'])
# If you fail these tests, you probably tried to use __dict__ or _json t
o read in the tweets
assert np.sometrue([('Twitter for iPhone' in s) for s in trump['source']
.unique()])
assert isinstance(trump['time'].dtype, pd.core.dtypes.dtypes.DatetimeTZD
type)
assert trump['text'].dtype == np.dtype('O')
assert trump['retweet_count'].dtype == np.dtype('int64')
```

Question 4: Tweet Source Analysis

In the following questions, we are going to find out the charateristics of Trump tweets and the devices used for the tweets.

First let's examine the source field:

In [17]:
```
trump['source'].unique()
```

Out[17]:
```
array(['<a href="http://twitter.com/download/iphone" rel="nofollow">Twi
tter for iPhone</a>',
       '<a href="http://twitter.com/download/android" rel="nofollow">Tw
itter for Android</a>',
       '<a href="http://twitter.com" rel="nofollow">Twitter Web Client
</a>',
       '<a href="https://studio.twitter.com" rel="nofollow">Media Studi
o</a>',
       '<a href="http://twitter.com/#!/download/ipad" rel="nofollow">Tw
itter for iPad</a>',
       '<a href="http://instagram.com" rel="nofollow">Instagram</a>',
       '<a href="https://mobile.twitter.com" rel="nofollow">Mobile Web
(M5)</a>',
       '<a href="https://ads.twitter.com" rel="nofollow">Twitter Ads</a
>',
       '<a href="https://periscope.tv" rel="nofollow">Periscope</a>'],
      dtype=object)
```

In [18]:
```
re.findall(r'Twitter for iPhone','<a href="http://twitter.com/download/i
phone" rel="nofollow">Twitter for iPhone</a>')
```

Out[18]:
```
['Twitter for iPhone']
```

Question 4a

Remove the HTML tags from the source field.

Hint: Use `trump['source'].str.replace` and your favorite regular expression.

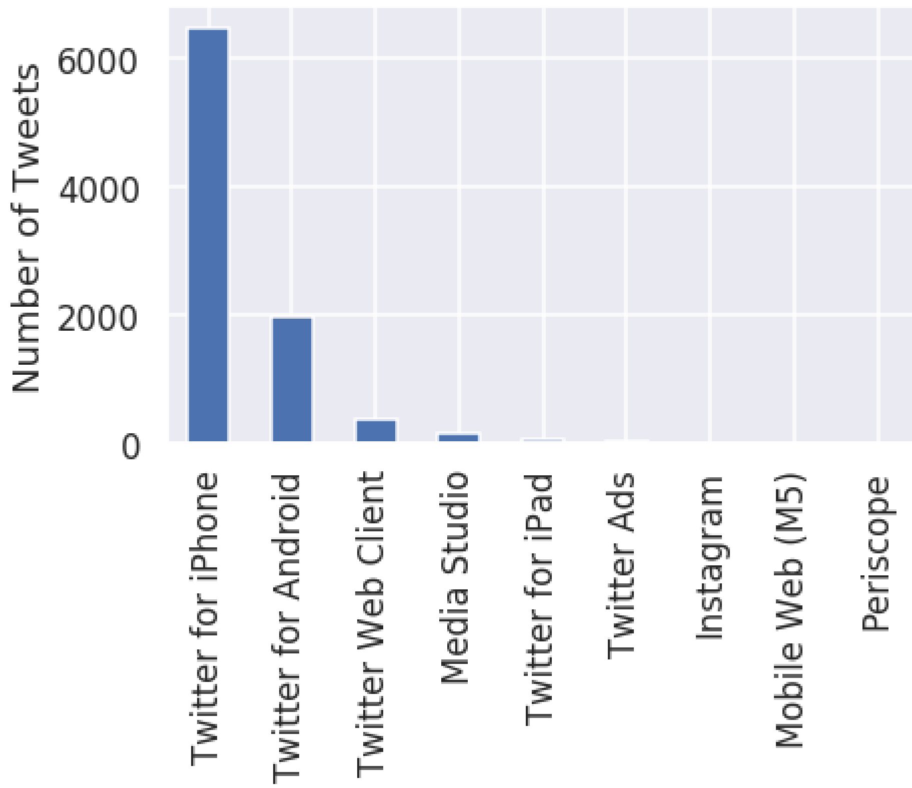
In [19]:
```
### BEGIN SOLUTION
trump['source']= trump['source'].str.replace(r'<.*?>','')
### END SOLUTION
```

In [20]:
```
from datetime import datetime, timezone
ELEC_DATE = datetime(2016, 11, 8, tzinfo=timezone.utc)
INAUG_DATE = datetime(2017, 1, 20, tzinfo=timezone.utc)
assert set(trump[(trump['time'] > ELEC_DATE) & (trump['time'] < INAUG_DA
TE) ]['source'].unique()) == set(['Twitter Ads',
 'Twitter Web Client',
 'Twitter for Android',
 'Twitter for iPhone'])
```

We can see in the following plot that there are two device types that are more commonly used

In [21]:
```
trump['source'].value_counts().plot(kind="bar")
plt.ylabel("Number of Tweets")
```

Out[21]: Text(0, 0.5, 'Number of Tweets')



Question 4b

Is there a difference between his Tweet behavior across these devices? We will attempt to answer this question in our subsequent analysis.

First, we'll take a look at whether Trump's tweets from an Android come at different times than his tweets from an iPhone. Note that Twitter gives us his tweets in the [UTC timezone (https://www.wikiwand.com/en/List_of_UTC_time_offsets)](https://www.wikiwand.com/en/List_of_UTC_time_offsets) (notice the `+0000` in the first few tweets)

In [22]:
```
for t in trump_tweets[0:3]:
    print(t['created_at'])
```

```
Tue Oct 16 16:22:11 +0000 2018
Tue Oct 16 16:18:08 +0000 2018
Tue Oct 16 15:26:33 +0000 2018
```

We'll convert the tweet times to US Eastern Time, the timezone of New York and Washington D.C., since those are the places we would expect the most tweet activity from Trump.

In [23]:
```
trump['est_time'] = (
    trump['time'].dt.tz_convert("EST") # Convert to Eastern Time
    # If your data frame is, for some reason, not timezone-aware
    # you might need the below two lines instead:
    #  trump['time'].dt.tz_localize("UTC") # Set initial timezone to UTC
    # .trump['time'].dt.tz_convert("EST") # Convert to Eastern Time
)
trump.head()
```

Out[23]:

	id	time	source	
786204978629185536	786204978629185536	2016-10-12 14:00:48+00:00	Twitter for iPhone	PAY TO PLAY POLITICS. \n#Croc https://t.co/
786201435486781440	786201435486781440	2016-10-12 13:46:43+00:00	Twitter for iPhone	Very little pick-up by the dishones incredible information p WikiLeaks. So dishonest! Rigg
786189446274248704	786189446274248704	2016-10-12 12:59:05+00:00	Twitter for Android	Crooked Hillary Clinton likes to the things she will do but she has for 30 years - why didn't she
786054986534969344	786054986534969344	2016-10-12 04:04:47+00:00	Twitter for iPhone	Thank you Florida- a MOVEMEN never been seen before and w seen again. Lets get ou https://t.co/t9
786007502639038464	786007502639038464	2016-10-12 00:56:06+00:00	Twitter for iPhone	Join me Thursday in Flo Ohio!\nWest Palm Be noon:\nhttps://t.co/jwbZnQhxg9\n OH this 7:30pm:\nhttps://t.co/5

What you need to do:

Add a column called `hour` to the `trump` table which contains the hour of the day as floating point number computed by:

$$\text{hour} + \frac{\text{minute}}{60} + \frac{\text{second}}{60^2}$$

In [24]:
```
### BEGIN SOLUTION
trump['hour'] = [trump['est_time'].iloc[x].hour + \
                 trump['est_time'].iloc[x].minute/60 +\
                 trump['est_time'].iloc[x].second/60**2 \
                 for x in list(range(len(trump['est_time'])))]
### END SOLUTION
```

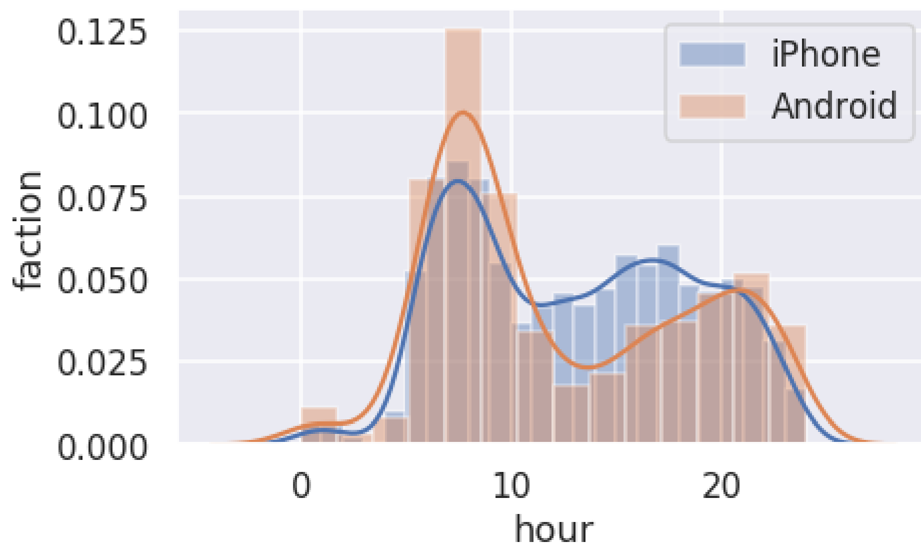
In [25]:
```
assert np.isclose(trump.loc[690171032150237184]['hour'], 8.93639)
```

Question 4c

Use this data along with the seaborn `distplot` function to examine the distribution over hours of the day in eastern time that trump tweets on each device for the 2 most commonly used devices. Your plot should look similar to the following.

```
In [26]: iPhone_frame=trump[trump['source']=='Twitter for iPhone']
         Android_frame=trump[trump['source']=='Twitter for Android']
```

```
In [27]: ### make your plot here
         ### BEGIN SOLUTION
         sns.distplot(iPhone_frame['hour'])
         sns.distplot(Android_frame['hour'])
         plt.legend(labels=['iPhone','Android'])
         plt.ylabel('faction')
         plt.show()
         ### END SOLUTION
```



Question 4d

According to [this Verge article (https://www.theverge.com/2017/3/29/15103504/donald-trump-iphone-using-switched-android)](https://www.theverge.com/2017/3/29/15103504/donald-trump-iphone-using-switched-android), Donald Trump switched from an Android to an iPhone sometime in March 2017.

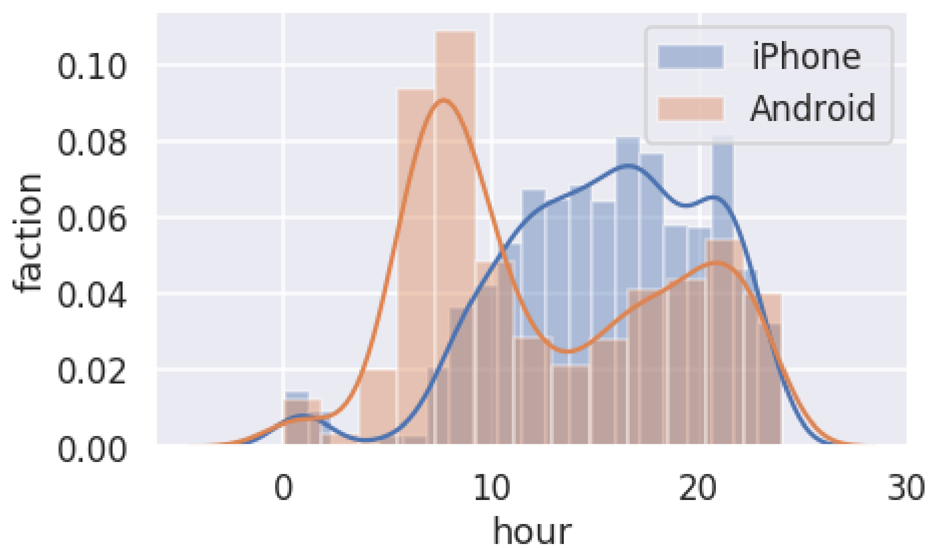
Create a figure identical to your figure from 4c, except that you should show the results only from 2016. If you get stuck consider looking at the `year_fraction` function from the next problem.

During the campaign, it was theorized that Donald Trump's tweets from Android were written by him personally, and the tweets from iPhone were from his staff. Does your figure give support to this theory?

In [28]:
```
new_iPhone_frame=trump[pd.to_datetime(trump['time']).dt.year==2016][trum
p['source']=='Twitter for iPhone']
new_Android_frame=trump[pd.to_datetime(trump['time']).dt.year==2016][tru
mp['source']=='Twitter for Android']
```

```
/share/apps/jupyterhub/2019-FA-DS-UA-112/lib/python3.7/site-packages/ip
ykernel_launcher.py:1: UserWarning: Boolean Series key will be reindexe
d to match DataFrame index.
  """Entry point for launching an IPython kernel.
/share/apps/jupyterhub/2019-FA-DS-UA-112/lib/python3.7/site-packages/ip
ykernel_launcher.py:2: UserWarning: Boolean Series key will be reindexe
d to match DataFrame index.
```

In [29]:
```
### make your plot here
### BEGIN SOLUTION
sns.distplot(new_iPhone_frame['hour'])
sns.distplot(new_Android_frame['hour'])
plt.legend(labels=['iPhone','Android'])
plt.ylabel('faction')
plt.show()
### END SOLUTION
```



In [30]:
```
q4d="""Yes this graph supports this theory as the majority of tweets
being sent by Trump himself (according to the theory) were highly
concentrated in the early hours of the day and then during the work day
the fraction of tweets being sent via iPhone (supposedly from staff) is
higher"""
print(q4d)
```

```
Yes this graph supports this theory as the majority of tweets
being sent by Trump himself (according to the theory) were highly
concentrated in the early hours of the day and then during the work day
the fraction of tweets being sent via iPhone (supposedly from staff) is
higher
```

Yes, our figure shows that the Android tweets were typically very late at night when Donald Trump is known to tweet, and when paid staff are unlikely to be posting.

Question 5

Let's now look at which device he has used over the entire time period of this dataset.

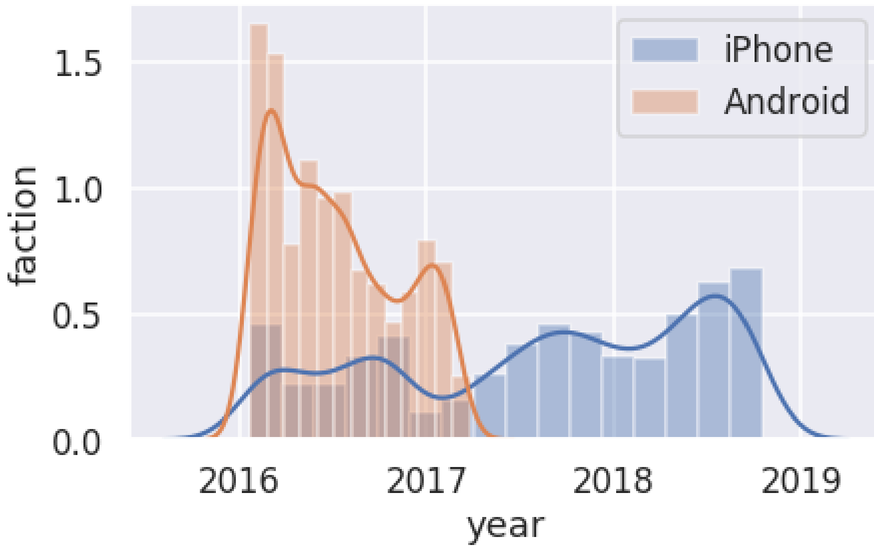
To examine the distribution of dates we will convert the date to a fractional year that can be plotted as a distribution.

(Code borrowed from https://stackoverflow.com/questions/6451655/python-how-to-convert-datetime-dates-to-decimal-years (https://stackoverflow.com/questions/6451655/python-how-to-convert-datetime-dates-to-decimal-years))

In [31]:
```
import datetime
def year_fraction(date):
    start = datetime.date(date.year, 1, 1).toordinal()
    year_length = datetime.date(date.year+1, 1, 1).toordinal() - start
    return date.year + float(date.toordinal() - start) / year_length


trump['year'] = trump['time'].apply(year_fraction)
```

Use the `sns.distplot` to overlay the distributions of the 2 most frequently used web technologies over the years. Your final plot should look like:

In [32]:
```
### BEGIN SOLUTION
iPhone_frame=trump[trump['source']=='Twitter for iPhone']
Android_frame=trump[trump['source']=='Twitter for Android']
sns.distplot(iPhone_frame['year'])
sns.distplot(Android_frame['year'])
plt.legend(labels=['iPhone','Android'])
plt.ylabel('faction')
plt.show()
### END SOLUTION
```



Question 6: Sentiment Analysis

It turns out that we can use the words in Trump's tweets to calculate a measure of the sentiment of the tweet. For example, the sentence "I love America!" has positive sentiment, whereas the sentence "I hate taxes!" has a negative sentiment. In addition, some words have stronger positive / negative sentiment than others: "I love America." is more positive than "I like America."

We will use the [VADER (Valence Aware Dictionary and sEntiment Reasoner) (https://github.com/cjhutto/vaderSentiment)](https://github.com/cjhutto/vaderSentiment) lexicon to analyze the sentiment of Trump's tweets. VADER is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media which is great for our usage.

The VADER lexicon gives the sentiment of individual words. Run the following cell to show the first few rows of the lexicon:

In [33]:
```
print(''.join(open("vader_lexicon.txt").readlines()[-100:]))
```

```
withdrawal      0.1     1.57797 [1, -1, 0, -2, -2, 2, -1, 1, 0, 3]
woe     -1.8    0.6     [-3, -2, -2, -2, -1, -1, -2, -1, -2, -2]
woebegone       -2.6    0.66332 [-3, -2, -3, -2, -2, -4, -3, -2, -2, -
3]
woebegoneness   -1.1    1.37477 [-3, 0, -1, 1, -1, -4, 0, -1, -1, -1]
woeful  -1.9    0.83066 [-1, -2, -2, -1, -3, -3, -1, -2, -1, -3]
woefully        -1.7    1.48661 [-1, -3, -2, 1, -3, -3, -2, -2, 1, -3]
woefulness      -2.1    0.7     [-3, -2, -2, -1, -2, -3, -3, -1, -2, -
2]
woes    -1.9    0.83066 [-2, -2, -2, -1, -2, -3, -3, 0, -2, -2]
woesome -1.2    1.6     [-2, -3, -2, -1, 0, 3, -2, -2, -1, -2]
won     2.7     0.9     [3, 4, 2, 2, 2, 4, 4, 2, 2, 2]
wonderful       2.7     0.78102 [2, 3, 3, 2, 4, 2, 2, 3, 4, 2]
wonderfully     2.9     0.83066 [1, 3, 3, 4, 3, 2, 3, 3, 4, 3]
wonderfulness   2.9     0.53852 [3, 2, 3, 3, 3, 3, 3, 2, 4, 3]
woo     2.1     1.37477 [4, 2, 1, 3, 2, 2, -1, 2, 2, 4]
woohoo  2.3     1.1     [3, 3, 1, 4, 4, 2, 1, 1, 2, 2]
woot    1.8     1.07703 [2, 0, 2, 2, 2, 2, 0, 4, 2, 2]
worn    -1.2    0.4     [-1, -1, -1, -1, -1, -1, -2, -1, -2, -1]
worried -1.2    0.74833 [-1, -1, -1, -1, -1, -2, -3, 0, -1, -1]
worriedly       -2.0    0.44721 [-2, -2, -3, -2, -2, -2, -2, -1, -2, -
2]
worrier -1.8    0.6     [-2, -2, -1, -2, -1, -3, -2, -2, -1, -2]
worriers        -1.7    0.45826 [-2, -1, -2, -2, -2, -2, -1, -2, -1, -
2]
worries -1.8    0.6     [-2, -2, -1, -2, -1, -2, -2, -3, -1, -2]
worriment       -1.5    0.67082 [-1, -2, -1, -1, -1, -2, -1, -3, -1, -
2]
worriments      -1.9    0.7     [-2, -1, -2, -3, -1, -2, -3, -1, -2, -
2]
worrisome       -1.7    0.64031 [-1, -1, -1, -2, -1, -2, -3, -2, -2, -
2]
worrisomely     -2.0    0.63246 [-1, -2, -1, -2, -2, -3, -2, -2, -3, -
2]
worrisomeness   -1.9    0.53852 [-2, -2, -3, -1, -2, -2, -2, -1, -2, -
2]
worrit  -2.1    0.53852 [-2, -2, -1, -2, -2, -3, -3, -2, -2, -2]
worrits -1.2    0.9798  [-1, -2, -2, -1, 0, 0, -1, -3, 0, -2]
worry   -1.9    0.7     [-2, -3, -1, -3, -1, -2, -1, -2, -2, -2]
worrying        -1.4    0.66332 [-2, -1, -2, -2, -1, 0, -1, -1, -2, -2]
worrywart       -1.8    0.9798  [-2, -2, -2, -1, -1, -1, -1, -3, -1, -
4]
worrywarts      -1.5    0.5     [-2, -1, -2, -2, -2, -1, -1, -1, -2, -
1]
worse   -2.1    0.83066 [-2, -2, -1, -3, -4, -2, -1, -2, -2, -2]
worsen  -2.3    0.78102 [-4, -3, -1, -2, -2, -2, -2, -3, -2, -2]
worsened        -1.9    1.22066 [-2, -2, -2, -1, -2, -2, -4, 1, -3, -2]
worsening       -2.0    0.44721 [-2, -3, -2, -2, -2, -2, -1, -2, -2, -
2]
worsens -2.1    0.53852 [-2, -2, -2, -2, -1, -2, -2, -3, -3, -2]
worser  -2.0    0.89443 [-2, -2, -4, -1, -2, -2, -2, -3, -1, -1]
worship 1.2     1.07703 [1, 0, 0, 1, 3, 0, 2, 3, 1, 1]
worshiped       2.4     1.0198  [1, 2, 4, 3, 4, 1, 2, 3, 2, 2]
worshiper       1.0     1.0     [0, 0, 2, 3, 0, 2, 1, 1, 1, 0]
worshipers      0.9     0.83066 [0, 0, 0, 2, 1, 1, 1, 2, 2, 0]
worshipful      0.7     1.00499 [1, -1, 3, 1, 1, 1, 0, 0, 0, 1]
worshipfully    1.1     1.3     [0, 0, 0, 1, 3, 0, 3, 3, 1, 0]
```

```
worshipfulness  1.6     0.8     [3, 1, 2, 2, 1, 1, 3, 1, 1, 1]
worshiping      1.0     1.18322 [0, 3, 0, 3, 0, 1, 1, 2, 0, 0]
worshipless     -0.6    1.0198  [0, -1, -3, -1, -1, -1, 0, 0, 0, 1]
worshipped      2.7     0.78102 [3, 2, 3, 3, 1, 4, 2, 3, 3, 3]
worshipper      0.6     0.66332 [1, 1, 0, 0, 1, 0, 0, 2, 1, 0]
worshippers     0.8     0.87178 [0, 1, 0, 0, 3, 1, 1, 1, 0, 1]
worshipping     1.6     1.28062 [1, 3, 3, 3, 0, 3, 1, 0, 2, 0]
worships        1.4     1.11355 [2, 0, 1, 3, 2, 1, 0, 3, 2, 0]
worst   -3.1    1.04403 [-4, -4, -3, -1, -3, -4, -2, -2, -4, -4]
worth   0.9     0.9434  [0, 0, 1, 1, 2, 1, 1, 3, 0, 0]
worthless       -1.9    1.13578 [-3, -1, -3, -4, -1, -3, -1, -1, -1, -
1]
worthwhile      1.4     0.4899  [1, 1, 1, 2, 1, 1, 2, 1, 2, 2]
worthy  1.9     0.53852 [2, 2, 2, 1, 1, 2, 2, 2, 3, 2]
wow     2.8     0.9798  [2, 3, 2, 4, 4, 3, 3, 2, 1, 4]
wowed   2.6     0.8     [3, 3, 4, 3, 2, 1, 3, 3, 2, 2]
wowing  2.5     0.67082 [2, 2, 3, 3, 2, 3, 4, 2, 2, 2]
wows    2.0     1.61245 [2, 3, 3, 3, 2, 1, -2, 1, 4, 3]
wowser  -1.1    2.02237 [-3, 3, 0, 2, -2, -1, -3, -2, -2, -3]
wowsers 1.0     2.14476 [0, -2, 4, 2, 3, 0, 1, 2, -3, 3]
wrathful        -2.7    0.64031 [-3, -2, -2, -3, -3, -2, -4, -2, -3, -
3]
wreck   -1.9    0.7     [-1, -2, -3, -3, -2, -2, -2, -1, -1, -2]
wrong   -2.1    1.04403 [-2, -2, -2, -2, -4, -4, -1, -1, -1, -2]
wronged -1.9    0.53852 [-2, -2, -2, -2, -2, -1, -3, -2, -2, -1]
x-d     2.6     0.91652 [2, 3, 3, 4, 1, 2, 3, 4, 2, 2]
x-p     1.7     0.45826 [2, 2, 1, 2, 2, 1, 1, 2, 2, 2]
xd      2.8     0.87178 [3, 3, 4, 2, 3, 3, 1, 2, 4, 3]
xp      1.6     0.4899  [2, 2, 2, 1, 1, 1, 2, 2, 1, 2]
yay     2.4     1.0198  [1, 3, 3, 2, 2, 1, 4, 4, 2, 2]
yeah    1.2     0.6     [1, 1, 1, 2, 1, 1, 0, 2, 1, 2]
yearning        0.5     1.0247  [0, 1, 0, 1, 0, 3, 0, 1, -1, 0]
yeees   1.7     1.00499 [1, 3, 1, 2, 1, 1, 4, 2, 1, 1]
yep     1.2     0.4     [1, 1, 1, 1, 1, 1, 2, 2, 1, 1]
yes     1.7     0.78102 [1, 2, 2, 1, 1, 1, 3, 3, 1, 2]
youthful        1.3     0.45826 [1, 2, 1, 2, 1, 1, 1, 1, 2, 1]
yucky   -1.8    0.6     [-2, -1, -1, -2, -2, -1, -2, -2, -3, -2]
yummy   2.4     1.0198  [1, 2, 4, 3, 2, 2, 3, 1, 4, 2]
zealot  -1.9    1.04403 [-2, -3, -1, -2, -1, -3, -4, -1, -1, -1]
zealots -0.8    1.83303 [-1, -2, -1, -2, -2, 1, -2, 4, -1, -2]
zealous 0.5     1.43178 [2, -1, 2, 1, 0, 0, 3, 0, -2, 0]
{:      1.8     0.9798  [1, 3, 2, 2, 1, 1, 4, 2, 1, 1]
|-0     -1.2    0.74833 [0, -2, -1, -1, -1, -1, -1, -1, -1, -3]
|-:     -0.8    0.74833 [-1, -2, 0, -1, 0, -2, -1, -1, 0, 0]
|-:>    -1.6    0.4899  [-1, -2, -2, -2, -2, -1, -1, -2, -2, -1]
|-o     -1.2    0.9798  [-1, 0, -1, -1, -1, -1, -1, -4, -1, -1]
|:      -0.5    1.68819 [2, -3, -1, 0, -1, -1, -1, -2, -1, 3]
|;-)    2.2     1.32665 [4, 1, 1, 1, 3, 2, 4, 1, 4, 1]
|=      -0.4    1.56205 [2, -2, -1, 0, -1, -1, -1, -2, -1, 3]
|^:     -1.1    0.7     [-2, 0, -1, -1, 0, -1, -1, -2, -2, -1]
|o:     -0.9    0.53852 [-1, 0, -1, -2, -1, 0, -1, -1, -1, -1]
||-:    -2.3    0.45826 [-2, -2, -2, -3, -3, -3, -2, -2, -2, -2]
}:      -2.1    0.83066 [-1, -1, -3, -2, -3, -2, -2, -1, -3, -3]
}:(     -2.0    0.63246 [-3, -1, -2, -1, -3, -2, -2, -2, -2, -2]
}:)     0.4     1.42829 [1, 1, -2, 1, 2, -2, 1, -1, 2, 1]
}:-(    -2.1    0.7     [-2, -1, -2, -2, -2, -4, -2, -2, -2, -2]
}:-)    0.3     1.61555 [1, 1, -2, 1, -1, -3, 2, 2, 1, 1]
```

Question 6a

As you can see, the lexicon contains emojis too! The first column of the lexicon is the *token*, or the word itself. The second column is the *polarity* of the word, or how positive / negative it is.

(How did they decide the polarities of these words? What are the other two columns in the lexicon? See the link above.)

Read in the lexicon into a DataFrame called `sent` . The index of the DF should be the tokens in the lexicon. `sent` should have one column: `polarity` : The polarity of each token.

In [34]:
```
### BEGIN SOLUTION
sent=pd.read_csv("vader_lexicon.txt",header=None,sep='\t')[[0,1]].set_in
dex(0)\
.rename(columns={1:'polarity'})

### END SOLUTION
```

In [35]:
```
assert isinstance(sent, pd.DataFrame)
assert sent.shape == (7517, 1)
assert list(sent.index[5000:5005]) == ['paranoids', 'pardon', 'pardoned'
, 'pardoning', 'pardons']
assert np.allclose(sent['polarity'].head(), [-1.5, -0.4, -1.5, -0.4, -0.
7])
```

Question 6b

Now, let's use this lexicon to calculate the overall sentiment for each of Trump's tweets. Here's the basic idea:

1. For each tweet, find the sentiment of each word.
2. Calculate the sentiment of each tweet by taking the sum of the sentiments of its words.

First, let's lowercase the text in the tweets since the lexicon is also lowercase. Set the `text` column of the `trump` DF to be the lowercased text of each tweet.

In [36]:
```
### BEGIN SOLUTION
trump['text']=trump['text'].str.lower()
### END SOLUTION
```

In [37]:
```
assert trump['text'].loc[884740553040175104] == 'working hard to get the
olympics for the united states (l.a.). stay tuned!'
```

Question 6c

Now, let's get rid of punctuation since it'll cause us to fail to match words. Create a new column called `no_punc` in the `trump` DF to be the lowercased text of each tweet with all punctuation replaced by a single space. We consider punctuation characters to be any character that isn't a Unicode word character or a whitespace character. You may want to consult the Python documentation on regexes for this problem.

(Why don't we simply remove punctuation instead of replacing with a space? See if you can figure this out by looking at the tweet data.)

In [57]:
```
# Save your regex in punct_re

### BEGIN SOLUTION
#TODO
punct_re=r'[,.;@:#!^/?\-]'
trump['no_punc'] = trump['text'].str.replace(punct_re,' ').str.replace(r
'[^\x00-\x7F]',' ')
### END SOLUTION
```

In [58]:
```
assert isinstance(punct_re, str)
assert re.search(punct_re, 'this') is None
assert re.search(punct_re, 'this is ok') is None
assert re.search(punct_re, 'this is\nok') is None
assert re.search(punct_re, 'this is not ok.') is not None
assert re.search(punct_re, 'this#is#ok') is not None
assert re.search(punct_re, 'this^is ok') is not None
assert trump['no_punc'].loc[800329364986626048] == 'i watched parts of
 nbcsnl saturday night live last night  it is a totally one sided  biase
d show   nothing funny at all  equal time for us '
assert trump['no_punc'].loc[894620077634592769] == 'on  purpleheartday i
thank all the brave men and women who have sacrificed in battle for this
great nation   usa   https   t co qmfdlslp6p'
# If you fail these tests, you accidentally changed the text column
assert trump['text'].loc[884740553040175104] == 'working hard to get the
olympics for the united states (l.a.). stay tuned!'
```

Question 6d:

Now, let's convert the tweets into what's called a [*tidy format* (https://cran.r-project.org/web/packages/tidyr/vignettes/tidy-data.html)](https://cran.r-project.org/web/packages/tidyr/vignettes/tidy-data.html) to make the sentiments easier to calculate. Use the `no_punc` column of `trump` to create a table called `tidy_format`. The index of the table should be the IDs of the tweets, repeated once for every word in the tweet. It has two columns:

1. `num`: The location of the word in the tweet. For example, if the tweet was "i love america", then the location of the word "i" is 0, "love" is 1, and "america" is 2.
2. `word`: The individual words of each tweet.

The first few rows of our `tidy_format` table look like:

	num	word
894661651760377856	0	i
894661651760377856	1	think
894661651760377856	2	senator
894661651760377856	3	blumenthal
894661651760377856	4	should

Note that you'll get different results depending on when you pulled in the tweets. However, you can double check that your tweet with ID `894661651760377856` has the same rows as ours. Our tests don't check whether your table looks exactly like ours.

As usual, try to avoid using any for loops. Our solution uses a chain of 5 methods on the 'trump' DF, albeit using some rather advanced Pandas hacking.

- **Hint 1:** Try looking at the `expand` argument to pandas' `str.split`.
- **Hint 2:** Try looking at the `stack()` method.
- **Hint 3:** Try looking at the `level` parameter of the `reset_index` method.

In [128]:

```
### BEGIN SOLUTION
temp = trump['no_punc'].str.split(expand=True).stack().to_frame().reset_
index()
temp.columns=['id','num','word']
tidy_format=temp.set_index('id')
### END SOLUTION
```

In [129]:

```
assert tidy_format.loc[894661651760377856].shape == (27, 2)
assert ' '.join(list(tidy_format.loc[894661651760377856]['word'])) == 'i
think senator blumenthal should take a nice long vacation in vietnam whe
re he lied about his service so he can at least say he was there'
```

Question 6e:

Now that we have this table in the tidy format, it becomes much easier to find the sentiment of each tweet: we can join the table with the lexicon table.

Add a `polarity` column to the `trump` table. The `polarity` column should contain the sum of the sentiment polarity of each word in the text of the tweet.

Hint you will need to merge the `tidy_format` and `sent` tables and group the final answer.

In [147]:
```
### BEGIN SOLUTION
temp=pd.merge(tidy_format.reset_index(),sent.reset_index(),how='inner',l
eft_on='word',right_on=0)
trump['polarity'] = temp.groupby('id')['polarity'].sum()
trump['polarity']=trump['polarity'].fillna(0)
### END SOLUTION
```

In [148]:
```
assert np.allclose(trump.loc[744701872456536064, 'polarity'], 8.4)
assert np.allclose(trump.loc[745304731346702336, 'polarity'], 2.5)
assert np.allclose(trump.loc[744519497764184064, 'polarity'], 1.7)
assert np.allclose(trump.loc[894661651760377856, 'polarity'], 0.2)
assert np.allclose(trump.loc[894620077634592769, 'polarity'], 5.4)
# If you fail this test, you dropped tweets with 0 polarity
assert np.allclose(trump.loc[744355251365511169, 'polarity'], 0.0)
```

Now we have a measure of the sentiment of each of his tweets! Note that this calculation is rather basic; you can read over the VADER readme to understand a more robust sentiment analysis.

Now, run the cells below to see the most positive and most negative tweets from Trump in your dataset:

In [149]:
```
print('Most negative tweets:')
for t in trump.sort_values('polarity').head()['text']:
    print('\n  ', t)
```

```
Most negative tweets:

   it is outrageous that poisonous synthetic heroin fentanyl comes pour
ing into the u.s. postal system from china. we can, and must, end this
now! the senate should pass the stop act – and firmly stop this poison
from killing our children and destroying our country. no more delay!

   the rigged russian witch hunt goes on and on as the “originators and
founders” of this scam continue to be fired and demoted for their corru
pt and illegal activity. all credibility is gone from this terrible hoa
x, and much more will be lost as it proceeds. no collusion!

   james comey is a proven leaker &amp; liar. virtually everyone in was
hington thought he should be fired for the terrible job he did-until he
was, in fact, fired. he leaked classified information, for which he sho
uld be prosecuted. he lied to congress under oath. he is a weak an
d.....

   there is no collusion! the robert mueller rigged witch hunt, headed
now by 17 (increased from 13, including an obama white house lawyer) an
gry democrats, was started by a fraudulent dossier, paid for by crooked
hillary and the dnc. therefore, the witch hunt is an illegal scam!

   this is an illegally brought rigged witch hunt run by people who are
totally corrupt and/or conflicted. it was started and paid for by crook
ed hillary and the democrats. phony dossier, fisa disgrace and so many
lying and dishonest people already fired. 17 angry dems? stay tuned!
```

In [150]:
```
print('Most positive tweets:')
for t in trump.sort_values('polarity', ascending=False).head()['text']:
    print('\n  ', t)
```

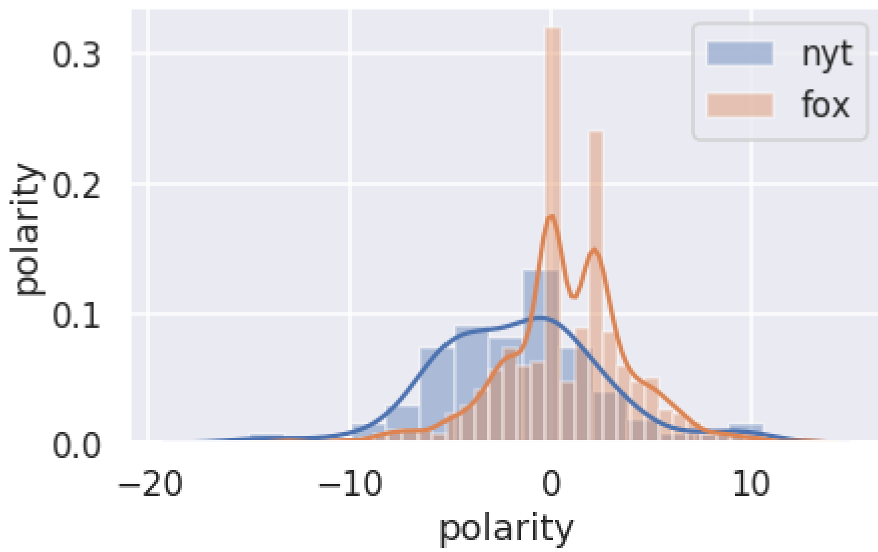
```
Most positive tweets:

   congratulations to patrick reed on his great and courageous masters
win! when patrick had his amazing win at doral 5 years ago, people saw
his great talent, and a bright future ahead. now he is the masters cham
pion!

   my supporters are the smartest, strongest, most hard working and mos
t loyal that we have seen in our countries history. it is a beautiful t
hing to watch as we win elections and gather support from all over the
country. as we get stronger, so does our country. best numbers ever!

   thank you to all of my great supporters, really big progress being m
ade. other countries wanting to fix crazy trade deals. economy is roari
ng. supreme court pick getting great reviews. new poll says trump, at o
ver 90%, is the most popular republican in history of the party. wow!

   thank you, @wvgovernor jim justice, for that warm introduction. toni
ght, it was my great honor to attend the “greenbrier classic – salute t
o service dinner” in west virginia! god bless our veterans. god bless a
merica - and happy independence day to all! https://t.co/v35qvcn8m6

   the republican party had a great night. tremendous voter energy and
excitement, and all candidates are those who have a great chance of win
ning in november. the economy is sooo strong, and with nancy pelosi wan
ting to end the big tax cuts and raise taxes, why wouldn’t we win?
```

Question 6g

Plot the distribution of tweet sentiments broken down by whether the text of the tweet contains `nyt` or `fox` . Then in the box below comment on what we observe?

In [151]:
```
nyt_df=trump[trump['text'].str.contains('nyt')]
fox_df=trump[trump['text'].str.contains('fox')]
```

In [152]:
```
### BEGIN SOLUTION
sns.distplot(nyt_df['polarity'])
sns.distplot(fox_df['polarity'])
plt.legend(labels=['nyt','fox'])
plt.ylabel('polarity')
plt.show()
### END SOLUTION
```



Comment on what you observe:

We notice that the president appears to say more positive things about Fox than the New York Times.

Question 7: Engagement

Question 7a

In this problem, we'll explore which words led to a greater average number of retweets. For example, at the time of this writing, Donald Trump has two tweets that contain the word 'oakland' (tweets 932570628451954688 and 1016609920031117312) with 36757 and 10286 retweets respectively, for an average of 23,521.5.

Find the top 20 most retweeted words. Include only words that appear in at least 25 tweets. As usual, try to do this without any for loops. You can string together ~7 pandas commands and get everything done on one line.

Your `top_20` table should have this format:

word	retweet_count
jong	40675.666667
try	33937.800000
kim	32849.595745
un	32741.731707
maybe	30473.192308

Note that the contents of the table may be different based on how many tweets you pulled and when you did so; focus on the format, not the numbers.

In [153]:
```
### BEGIN SOLUTION
top_20 = tidy_format.join(trump)[['word','retweet_count']]\
.groupby(by='word').filter(lambda x: x['word'].count()>25)\
.groupby(by='word').mean()\
.sort_values('retweet_count',ascending=False).head(20)
### END SOLUTION
```

In [154]:
```
top_20.head()
```

Out[154]:

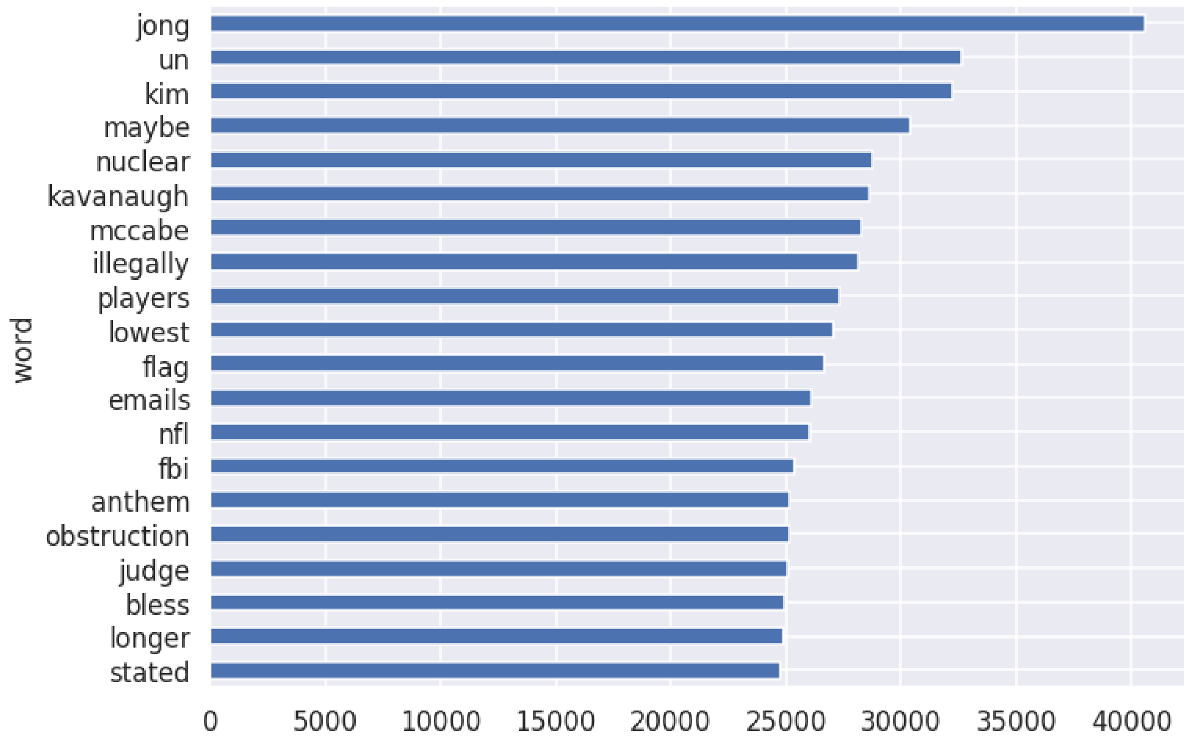
word	retweet_count
jong	40592.833333
un	32677.024390
kim	32237.306122
maybe	30413.153846
nuclear	28766.959184

In [158]:
```
# Although it can't be guaranteed, it's very likely that some of these w
ords will be in the top 20
# Although this may vary depending on when exactly you pulled your data:
assert 'un'      in top_20.index
assert 'nuclear' in top_20.index
assert 'old'     in top_20.index
assert 'nfl'     in top_20.index
```

```
------------------------------------------------------------------------
----
AssertionError                            Traceback (most recent call l
ast)
<ipython-input-158-b50cae7ecec3> in <module>
      3 assert 'un'      in top_20.index
      4 assert 'nuclear' in top_20.index
----> 5 assert 'old'     in top_20.index
      6 assert 'nfl'     in top_20.index

AssertionError:
```

Here's a bar chart of your results:

In [156]:
```
top_20['retweet_count'].sort_values().plot.barh(figsize=(10, 8));
```



Question 7b

At some point in time, "kim", "jong" and "un" were apparently really popular in Trump's tweets! It seems like we can conclude that his tweets involving jong are more popular than his other tweets. Or can we?

Consider each of the statements about possible confounding factors below. State whether each statement is true or false and explain. If the statement is true, state whether the confounding factor could have made kim jong un related tweets higher in the list than they should be.

1. We didn't restrict our word list to nouns, so we have unhelpful words like "let" and "any" in our result.
2. We didn't remove hashtags in our text, so we have duplicate words (eg. #great and great).
3. We didn't account for the fact that Trump's follower count has increased over time.

1. True. However, this will not cause "kim", "jong" and "un" to top the list of retweeted words since restricting to nouns does not affect the count of the retweets containing "kim", "jong" and "un".
2. False. We removed hashtags in our text when we removed punctuation.
3. True. This could indeed cause "kim", "jong" and "un" to appear higher on the list than it should have. If his follower count increased over time, we would expect the number of retweets over time to increase as well, regardless of what words are in the tweets. If he just started using the term "fake news" recently, it's likely that those tweets would get more retweets just because he had more followers than before.

Question 8

Using the `trump` tweets construct an interesting plot describing a property of the data and discuss what you found below.

Ideas:

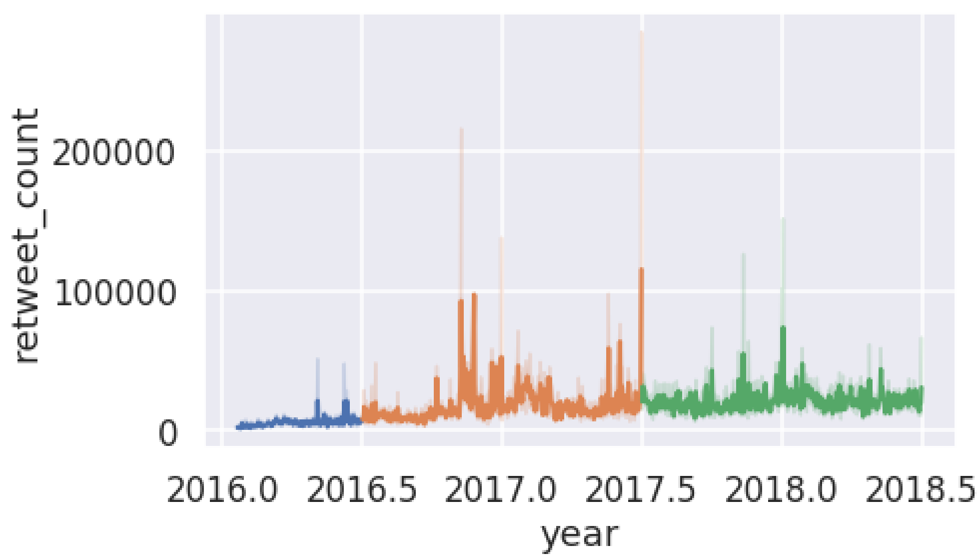
1. How has the sentiment changed with length of the tweets?
2. Does sentiment affect retweet count?
3. Are retweets more negative than regular tweets?
4. Are there any spikes in the number of retweets and do the correspond to world events?
5. *Bonus:* How many Russian twitter bots follow Trump?
6. What terms have an especially positive or negative sentiment?

You can look at other data sources and even tweets.

Plot:

In [56]:
```
sns.lineplot(x='year',y='retweet_count',data=trump[trump['year'].round()
==2016.0])
sns.lineplot(x='year',y='retweet_count',data=trump[trump['year'].round()
==2017.0])
sns.lineplot(x='year',y='retweet_count',data=trump[trump['year'].round()
==2018.0])
```

Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x2ba8ec1d1d68>



Discussion of Your Plot:

I plotted the number of retweets over the course of the year for 2016, 2017, and 2018. Leading up to the election, Trump got the least amount of retweets. After the 2016 election you see a spike of retweets on the graph, what looks like an outlier, that looks to be about the time of the election. There is another possible outlier at the 2017.5 mark. The amount of retweets he gets seems to increase the most in 2017 but stays steady for the majority of 2018 with few spikes.

Submission

Congrats, you just finished Project 1!