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 [58]:
```
# 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
import time
import datetime

# 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 [59]:
```
# 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 20:53:27 2019
MD5 hash of file: 216176fb098cd5d6b40b373b98bd3e6d
Located at data/realdonaldtrump_recent_tweets.json
```

In [60]:
```
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 tweet."""

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

In [61]:
```
trump_tweets = load_tweets(dest_path)
```

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

In [62]:
```
assert 2000 <= len(trump_tweets) <= 4000
print(True)
```

```
True
```

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 [63]:
```
# Enter the number of the month of the oldest tweet (e.g. 1 for January)
### BEGIN SOLUTION

last_tweet = trump_tweets[len(trump_tweets)-1]
time_set = time.strptime(last_tweet['created_at'], "%a %b %d %X %z %Y")
oldest_month = time_set[1]

#last_tweet.pipe(
# .pipe: oldest_month = time_set[1])


#TODO
### END SOLUTION
```

In [64]:
```
### BEGIN HIDDEN TESTS
assert oldest_month > 9
assert oldest_month < 12
print(True)
### END HIDDEN TESTS
```

```
True
```

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 [65]:
```
# 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 20:53:27 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 [66]:
```
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 [67]:
```
pprint(old_trump_tweets[0])
```

```
Pretty printing has been turned ON
```

As a dictionary we can also list the keys:

In [68]:
```
old_trump_tweets[0].keys()
```

Out[68]:
```
dict_keys(['created_at', 'id', 'id_str', 'text', 'truncated', 'entities', 'extended_entities', 'source', 'in_
reply_to_status_id', 'in_reply_to_status_id_str', 'in_reply_to_user_id', 'in_reply_to_user_id_str', 'in_reply
_to_screen_name', 'user', 'geo', 'coordinates', 'place', 'contributors', 'is_quote_status', 'retweet_count',
'favorite_count', 'favorited', '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 [69]:
```
### BEGIN SOLUTION
old_tweets_ids_set = set()     #Both need to be sets in order to check unique ids, since sets keep original v
alues, no repetitions
trump_tweets_ids_set = set()
for old_tweet_text in old_trump_tweets:
    old_tweets_ids_set.add(old_tweet_text['id'])
for Trump_tweet_text in trump_tweets:
    trump_tweets_ids_set.add(Trump_tweet_text['id'])

old_tweets_with_unique_ids = old_tweets_ids_set - trump_tweets_ids_set #filter out the duplicate tweets
# filter(lambda tweet: tweet not in trump_tweets_ids_set, old_tweets_ids_set)


filtered_old_tweets = list()
for tweet_text in old_trump_tweets:
    if tweet_text['id'] in old_tweets_with_unique_ids:#Checks unique ids
        filtered_old_tweets.extend([tweet_text])

all_tweets = filtered_old_tweets + trump_tweets  #Combine the filtered_old_tweets with the trump_tweets
#TODO
### END SOLUTION
```

In [70]:
```
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])
print(True)
### END HIDDEN TESTS
```

```
True
```

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 [71]:
```
### BEGIN SOLUTION

for tweet_text in all_tweets:
    if 'full_text' in tweet_text.keys():  #You check the keys()
        popped_text = tweet_text.pop('full_text') #you remove the 'full' and put the info in 'text'
        tweet_text['text'] = popped_text

trump = pd.DataFrame(all_tweets).set_index(['id']).sort_index()  #Creates dataframe, sex index to 'id', sorte
d by index.
trump['created_at'] = pd.to_datetime(trump['created_at'])    #Create column for when the tweet is created. En
code the timestamp.
trump = trump[['created_at', 'source', 'text', 'retweet_count']].rename(columns = {'created_at': 'time'}) #re
name columns "time"

#TODO
### END SOLUTION
```

In [72]:
```
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', 'retweet_count'])
# If you fail these tests, you probably tried to use __dict__ or _json to 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.DatetimeTZDtype)
assert trump['text'].dtype == np.dtype('O')
assert trump['retweet_count'].dtype == np.dtype('int64')
print(True)
```

```
True
```

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 [73]:
```
trump['source'].unique()
```

Out[73]:
```
array(['<a href="http://twitter.com/download/android" rel="nofollow">Twitter for Android</a>',
       '<a href="http://twitter.com/download/iphone" rel="nofollow">Twitter for iPhone</a>',
       '<a href="http://twitter.com" rel="nofollow">Twitter Web Client</a>',
       '<a href="https://mobile.twitter.com" rel="nofollow">Mobile Web (M5)</a>',
       '<a href="http://instagram.com" rel="nofollow">Instagram</a>',
       '<a href="http://twitter.com/#!/download/ipad" rel="nofollow">Twitter for iPad</a>',
       '<a href="https://studio.twitter.com" rel="nofollow">Media Studio</a>',
       '<a href="https://periscope.tv" rel="nofollow">Periscope</a>',
       '<a href="https://ads.twitter.com" rel="nofollow">Twitter Ads</a>'],
      dtype=object)
```

Question 4a

Remove the HTML tags from the source field.

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

In [74]:
```
### BEGIN SOLUTION
trump['source'] = trump['source'].str.replace('<[^<]+?>', '')
#TOD<
### END SOLUTION
```

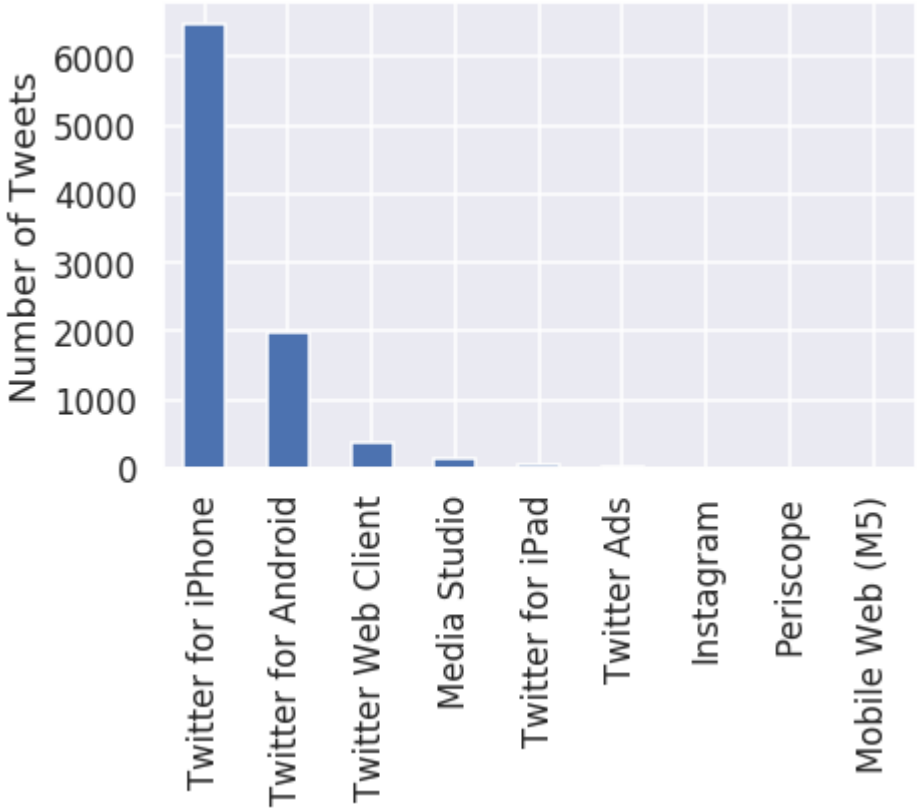
In [75]:
```
from datetime import datetime, timezone
ELEC_DATE = datetime(2016, 11, 8, tzinfo=timezone.utc)
INAUG_DATE = datetime(2017, 1, 20, tzinfo=timezone.utc)
assert set(trump[(trump['time'] > ELEC_DATE) & (trump['time'] < INAUG_DATE) ]['source'].unique()) == set(['Tw
itter Ads',
'Twitter Web Client', 'Twitter for Android', 'Twitter for iPhone'])
print(True)
```

```
True
```

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

In [76]:
```
trump['source'].value_counts().plot(kind="bar")
plt.ylabel("Number of Tweets")
```

Out[76]: 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 [77]:
```
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 [78]:
```
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[78]:

id	time	source	text	retweet_count	est_time
690171032150237184	2016-01-21 13:56:11+00:00	Twitter for Android	"@bigop1: @realDonaldTrump @SarahPalinUSA https://t.co/3kYQGqeVyD"	1059	2016-01-21 08:56:11-05:00
690171403388104704	2016-01-21 13:57:39+00:00	Twitter for Android	"@AmericanAsPie: @glennbeck @SarahPalinUSA Remember when Glenn gave out gifts to ILLEGAL ALIENS at crossing the border? Me too!"	1339	2016-01-21 08:57:39-05:00
690173226341691392	2016-01-21 14:04:54+00:00	Twitter for Android	So sad that @CNN and many others refused to show the massive crowd at the arena yesterday in Oklahoma. Dishonest reporting!	2006	2016-01-21 09:04:54-05:00
690176882055114758	2016-01-21 14:19:26+00:00	Twitter for Android	Sad sack @JebBush has just done another ad on me, with special interest money, saying I won't beat Hillary - I WILL. But he can't beat me.	2266	2016-01-21 09:19:26-05:00
690180284189310976	2016-01-21 14:32:57+00:00	Twitter for Android	Low energy candidate @JebBush has wasted $80 million on his failed presidential campaign. Millions spent on me. He should go home and relax!	2886	2016-01-21 09:32:57-05:00

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 [79]:
```
### BEGIN SOLUTION
time_splicing = [re.findall('(\d+)-(\d+)-(\d+) (\d+):(\d+):(\d+)', str(entry)) for entry in trump['est_time'
]]
trump['hour'] = [(float(entry[0][3]) + (float(entry[0][4])/60) + (float(entry[0][5])/(60**2))) for entry in t
ime_splicing]
#Slice the given estimated time entry, then calculate the hour of the day as a floating point number

#TODO
### END SOLUTION
```

In [80]:
```
assert np.isclose(trump.loc[690171032150237184]['hour'], 8.93639)
print(True)
```

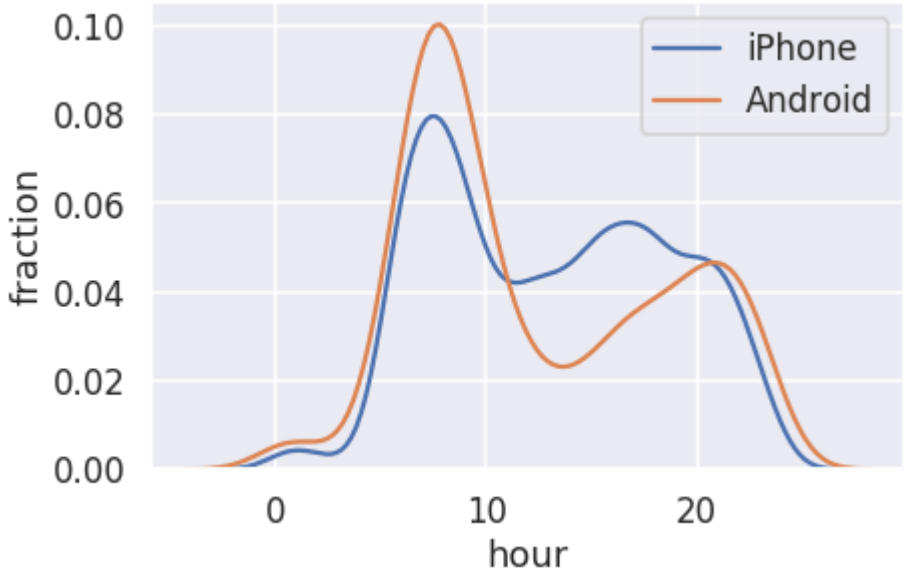
```
True
```

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 [81]:
```
### make your plot here
### BEGIN SOLUTION

vals_of_plt = trump[['hour', 'source']].set_index('source').loc[['Twitter for iPhone', 'Twitter for Android'
]]
#Set index to source. Locate the Twitter for IPhone, then the Android Twitter.
Android_entries = vals_of_plt.loc[vals_of_plt.index == 'Twitter for Android']
iPhone_entries = vals_of_plt.loc[vals_of_plt.index == 'Twitter for iPhone']


#Create the Distplot exactly the way it was written in the problem.
sns.distplot(iPhone_entries['hour'], label = 'iPhone', hist = False)
#Make sure the graph is not shown as a histogram.
sns.distplot(Android_entries['hour'], label = 'Android', hist = False)
plt.ylabel('fraction')

#TODO
### END SOLUTION
```

Out[81]: Text(0, 0.5, 'fraction')



Question 4d

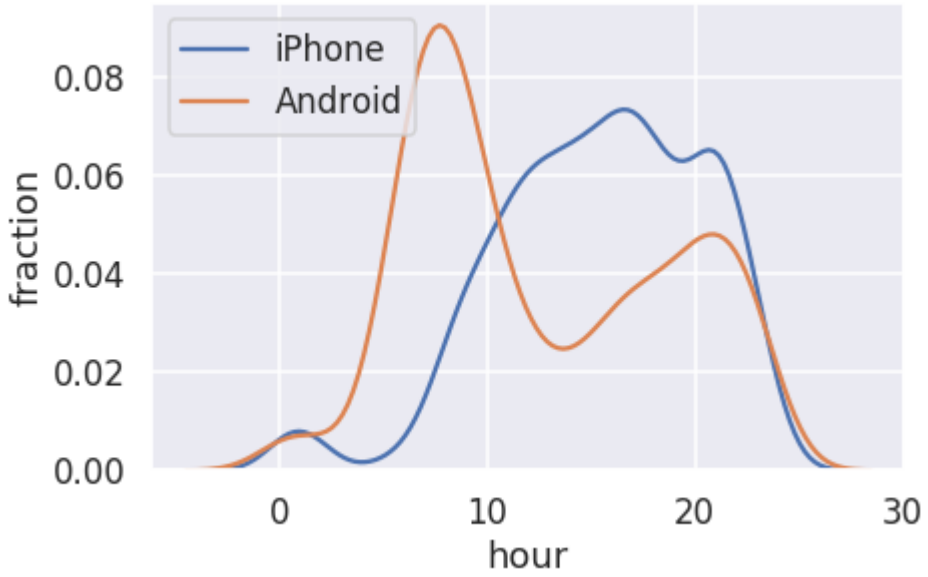
According to this Verge article (https://www.theverge.com/2017/3/29/15103504/donald-trump-iphone-using-switched-android), Donald Trump switched from an Android to an iPhone sometime in March 2017.

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 [82]:
```
### make your plot here
vals_of_plt = trump[['hour', 'source']].set_index('source').loc[['Twitter for iPhone', 'Twitter for Android'
]]
start_2016 = datetime(2016, 1, 1, tzinfo=timezone.utc)
end_2016 = datetime(2017,1,1, tzinfo=timezone.utc)
Android_entries = pd.Series(trump[(trump['source'] == 'Twitter for Android') &
                                  ((trump['est_time'] >= start_2016) & (trump['est_time'] <= end_2016))]['hou
r'],name="Android")
iPhone_entries = pd.Series(trump[(trump['source'] == 'Twitter for iPhone') &
                                 ((trump['est_time'] >= start_2016) & (trump['est_time'] <= end_2016))]['hou
r'], name="iPhone")

# Android_entries = vals_of_plt.loc[vals_of_plt.index == 'Twitter for Android']
# iPhone_entries = vals_of_plt.loc[vals_of_plt.index == 'Twitter for iPhone']
sns.distplot(iPhone_entries, label = 'iPhone', hist = False)
sns.distplot(Android_entries, label = 'Android', hist = False)
plt.ylabel('fraction')
plt.xlabel('hour')

answer4d = '''Given that during the campaign, it was theorized that Donald Trumps tweets from Android were wr
itten by
      him personally, and the tweets from iPhone were from his staff. Just based on the amount of tweets by a
ndroid and the
      tweets by iPhone, it is very difficult to tell since the frequency differs, since when the Android twee
ts decreased,
      the iPhone tweet amount significantly increased. But after reading the Verge article, this figure provi
des support to
      this theory since our figure shows that the Android tweets were typically very late at night when Donal
d Trump is known
      to tweet, and when paid staff are unlikely to be posting. '''

print(answer4d)

### BEGIN SOLUTION
#TODO
### END SOLUTION
```

```
Given that during the campaign, it was theorized that Donald Trumps tweets from Android were written by
      him personally, and the tweets from iPhone were from his staff. Just based on the amount of tweets by a
ndroid and the
      tweets by iPhone, it is very difficult to tell since the frequency differs, since when the Android twee
ts decreased,
      the iPhone tweet amount significantly increased. But after reading the Verge article, this figure provi
des support to
      this theory since our figure shows that the Android tweets were typically very late at night when Donal
d Trump is known
      to tweet, and when paid staff are unlikely to be posting.
```



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.

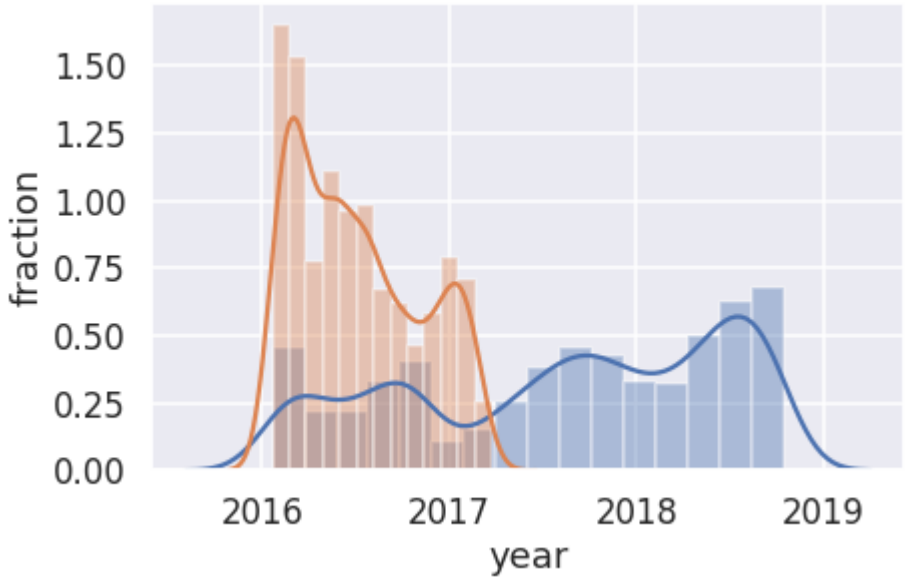
(Code borrowed from https://stackoverflow.com/questions/6451655/python-how-to-convert-datetime-dates-to-decimal-years (https://stackoverflow.com/questions/6451655/python-how-to-convert-datetime-dates-to-decimal-years))

In [83]:
```
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 [84]:
```
### BEGIN SOLUTION

vals_of_plt = trump[['year', 'source']].set_index('source').loc[['Twitter for iPhone', 'Twitter for Android'
]]
#Set index to source. Locate the Twitter for IPhone, then the Android Twitter.
Android_entries = vals_of_plt.loc[vals_of_plt.index == 'Twitter for Android']
iPhone_entries = vals_of_plt.loc[vals_of_plt.index == 'Twitter for iPhone']


#Create the Distplot exactly the way it was written in the problem.
sns.distplot(iPhone_entries['year'], label = 'iPhone', hist = True)
#Make sure the graph is not shown as a histogram.
sns.distplot(Android_entries['year'], label = 'Android', hist = True)
plt.ylabel('fraction')




#TODO
### END SOLUTION
```

Out[84]: Text(0, 0.5, 'fraction')



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) 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 [85]:
```
print(''.join(open("vader_lexicon.txt").readlines()[:10]))
```

```
$:      -1.5    0.80623 [-1, -1, -1, -1, -3, -1, -3, -1, -2, -1]
%)      -0.4    1.0198  [-1, 0, -1, 0, 0, -2, -1, 2, -1, 0]
%-)     -1.5    1.43178 [-2, 0, -2, -2, -1, 2, -2, -3, -2, -3]
&-:     -0.4    1.42829 [-3, -1, 0, 0, -1, -1, -1, 2, -1, 2]
&:      -0.7    0.64031 [0, -1, -1, -1, 1, -1, -1, -1, -1, -1]
( '}{' )        1.6     0.66332 [1, 2, 2, 1, 1, 2, 2, 1, 3, 1]
(%      -0.9    0.9434  [0, 0, 1, -1, -1, -1, -2, -2, -1, -2]
('-:    2.2     1.16619 [4, 1, 4, 3, 1, 2, 3, 1, 2, 1]
(':     2.3     0.9     [1, 3, 3, 2, 2, 4, 2, 3, 1, 2]
((-:    2.1     0.53852 [2, 2, 2, 1, 2, 3, 2, 2, 3, 2]
```

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 [86]:
```
### BEGIN SOLUTION
with open('vader_lexicon.txt') as lexicon_doc:
    lexicon_collection = lexicon_doc.readlines()

tokens = lexicon_collection[0]
#You want to find the first element in the emoji_collection
token_series = [tokens.split('\t') for tokens in lexicon_collection]
#Split the tabulated values
sent = pd.DataFrame(token_series).rename(columns={0: 'tokens', 1: 'polarity'})
sent = sent.set_index('tokens')[['polarity']]
#Set index to tokens and polarity.
sent['polarity'] = pd.to_numeric(sent['polarity'])
#Made sure that sent['polarity'] was numeric

#TODO
### END SOLUTION
```

In [87]:
```
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])
print(True)
```

```
True
```

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 [88]:
```
### BEGIN SOLUTION
trump['text'] = [tweet_text.lower() for tweet_text in trump['text']]
#TODO
### END SOLUTION
```

In [89]:
```
assert trump['text'].loc[884740553040175104] == 'working hard to get the olympics for the united states (l.
a.). stay tuned!'
print(True)
```

```
True
```

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 [90]:
```
# Save your regex in punct_re
### BEGIN SOLUTION
#TODO
punct_re = r'[^(\w\s)]'
#punctuation includes string literals of two punctuation characters, and any word character
trump['no_punc'] = trump['text'].str.replace(punct_re, ' ')
### END SOLUTION
```

In [91]:
```
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  biased 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!'
print(True)
```

```
True
```

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) 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 [92]:
```
### BEGIN SOLUTION
no_spaces_format = pd.DataFrame(trump['no_punc'].str.replace('\s+', ' ').str.split(expand=True).stack())
#Uses the stack data structure to handle the rest of the space_removing
no_spaces_format.reset_index(inplace=True)
#Make sure the index is reset and it is done in place
tidy_format = no_spaces_format.set_index('id').rename(columns={'level_1': 'num', 0: 'word'})
#Index based on id, then rename the columns to what they represent


#TODO
### END SOLUTION
```

In [93]:
```
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 where he lied about his service so he can at least say he was there'
print(True)
```

```
True
```

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 [94]:
```
### BEGIN SOLUTION
word_polarity = (tidy_format.merge(sent, how = "inner", left_on = "word", right_index = True))
word_polarity_sum = word_polarity.groupby('id').sum()
trump['polarity'] = word_polarity_sum[['polarity']]
trump = trump.fillna(value=0)


#TODO
### END SOLUTION
```

In [95]:
```
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)
print(True)
```

```
True
```

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 [96]:
```
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 pouring into the u.s. postal system from c
hina. 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 corrupt and illegal activity. all credibility is gone from this terrible hoax, an
d much more will be lost as it proceeds. no collusion!

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

   there is no collusion! the robert mueller rigged witch hunt, headed now by 17 (increased from 13, includin
g an obama white house lawyer) angry democrats, was started by a fraudulent dossier, paid for by crooked hill
ary 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 crooked hillary and the democrats. phony dossier, fisa disgrace and so many lying
and dishonest people already fired. 17 angry dems? stay tuned!
```

In [97]:
```
print('Most positive tweets:')
for t in trump.sort_values('polarity', ascending=False).head()['text']:
    print('\n  ', t)
```

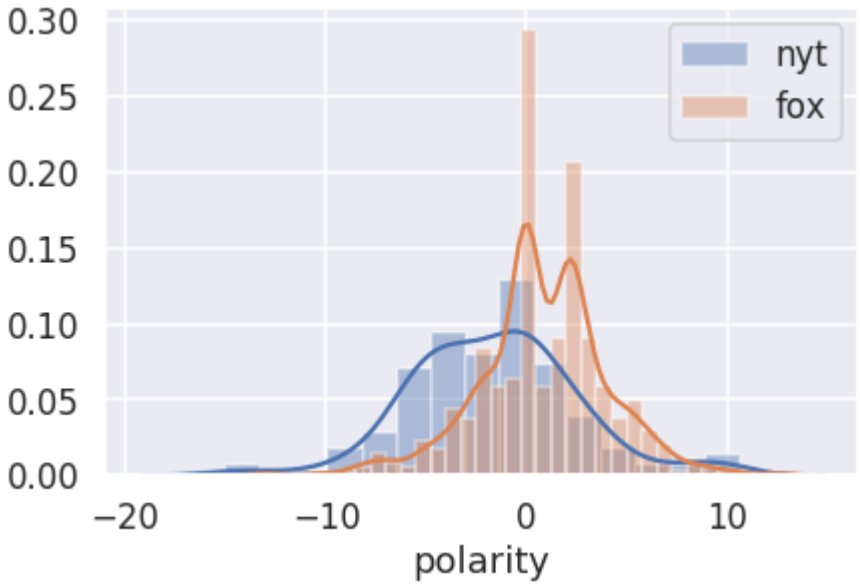
```
Most positive tweets:

   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 champion!

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

   thank you to all of my great supporters, really big progress being made. other countries wanting to fix cr
azy trade deals. economy is roaring. supreme court pick getting great reviews. new poll says trump, at over 9
0%, is the most popular republican in history of the party. wow!

   thank you, @wvgovernor jim justice, for that warm introduction. tonight, it was my great honor to attend t
he “greenbrier classic – salute to service dinner” in west virginia! god bless our veterans. god bless americ
a - 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 tho
se who have a great chance of winning in november. the economy is sooo strong, and with nancy pelosi wanting
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 [98]:
```
### BEGIN SOLUTION

nyt_related_tweets = trump[trump['no_punc'].str.contains('nyt')]['polarity']
sns.distplot(nyt_related_tweets, label = 'nyt')
fox_related_tweets = trump[trump['no_punc'].str.contains('fox')]['polarity']
sns.distplot(fox_related_tweets, label = 'fox')


plt.legend()



#TODO
### END SOLUTION
```

Out[98]: <matplotlib.legend.Legend at 0x2af3a5acf5f8>



Comment on what you observe:

We notice that the president appears to say more positive things about Fox than the New York Times. We also notice that the polarity is very high for the fox news data, while the polarity is mostly negative for the NYT data.

In [99]:
```
tidy_format
```

Out[99]:

id	num	word
690171032150237184	0	bigop1
690171032150237184	1	realdonaldtrump
690171032150237184	2	sarahpalinusa
690171032150237184	3	https
690171032150237184	4	t
690171032150237184	5	co
690171032150237184	6	3kyqgqevyd
690171403388104704	0	americanaspie
690171403388104704	1	glennbeck
690171403388104704	2	sarahpalinusa
690171403388104704	3	remember
690171403388104704	4	when
690171403388104704	5	glenn
690171403388104704	6	gave
690171403388104704	7	out
690171403388104704	8	gifts
690171403388104704	9	to
690171403388104704	10	illegal
690171403388104704	11	aliens
690171403388104704	12	at
690171403388104704	13	crossing
690171403388104704	14	the
690171403388104704	15	border
690171403388104704	16	me
690171403388104704	17	too

id	num	word
690173226341691392	0	so
690173226341691392	1	sad
690173226341691392	2	that
690173226341691392	3	cnn
690173226341691392	4	and
...	...	...
1052219253384994816	37	is
1052219253384994816	38	still
1052219253384994816	39	working
1052219253384994816	40	for
1052219253384994816	41	the
1052219253384994816	42	department
1052219253384994816	43	of
1052219253384994816	44	justice
1052219253384994816	45	can
1052219253384994816	46	this
1052219253384994816	47	really
1052219253384994816	48	be
1052219253384994816	49	so
1052232230972678145	0	rt
1052232230972678145	1	whitehouse
1052232230972678145	2	https
1052232230972678145	3	t
1052232230972678145	4	co
1052232230972678145	5	rnqlpots3o
1052233253040640001	0	register

id	num	word
1052233253040640001	1	to
1052233253040640001	2	https
1052233253040640001	3	t
1052233253040640001	4	co
1052233253040640001	5	0pwiwchgbh
1052233253040640001	6	maga
1052233253040640001	7	https
1052233253040640001	8	t
1052233253040640001	9	co
1052233253040640001	10	actme53tzu

217077 rows × 2 columns

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.

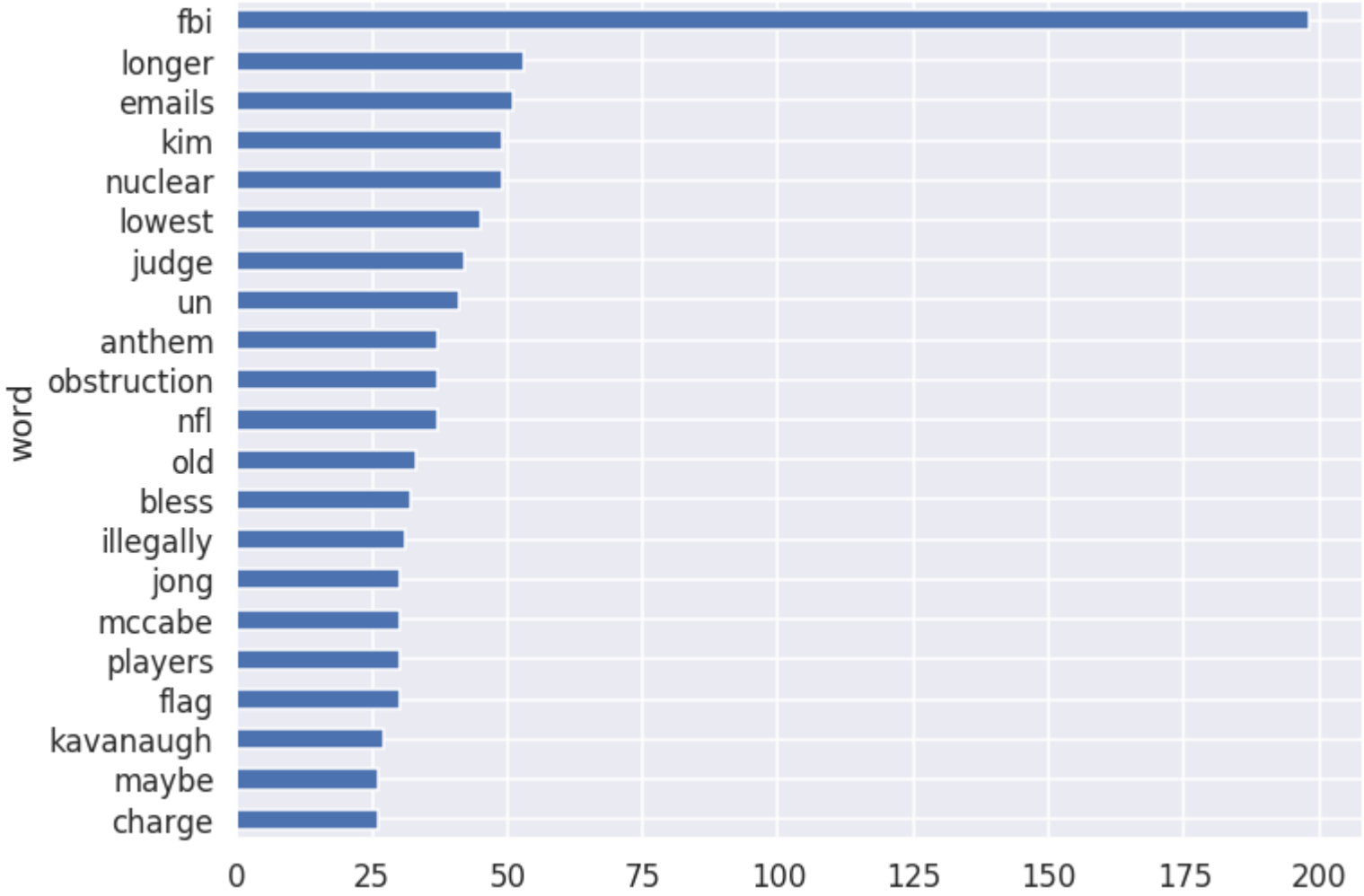
In [100]:
```
### BEGIN SOLUTION

tidy_form = (tidy_format.merge(trump, how = 'inner', left_index = True, right_index = True))
retweet_count = tidy_form[['word', 'retweet_count']].groupby('word').count()
tweets_at_least_25_retweets = retweet_count[retweet_count['retweet_count'] >= 25]
merged_table = (tidy_form.merge(tweets_at_least_25_retweets, how='inner', left_on='word', right_index=True))
retweet_sum = merged_table[['word','retweet_count_x']].groupby(['word']).sum()
merged_sum = retweet_sum.merge(tweets_at_least_25_retweets, how='inner', left_index=True, right_index=True)
merged_sum['average'] = merged_sum['retweet_count_x']/merged_sum['retweet_count']
top_20 = merged_sum.sort_values('average', ascending=False).iloc[0:21]

#TODO
### END SOLUTION
```

In [101]:
```
# Although it can't be guaranteed, it's very likely that some of these words 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
print(True)
```

```
True
```

Here's a bar chart of your results:

In [102]:
```
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". Plus, if there were more non-noun words, then it is a possibility that that tweet would have more retweets.
2. False. We removed hashtags in our text when we removed punctuation. This means that any whitespace Unicode character character is not only put in a column called no_punc, but is removed, so to remove duplicate words.
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?

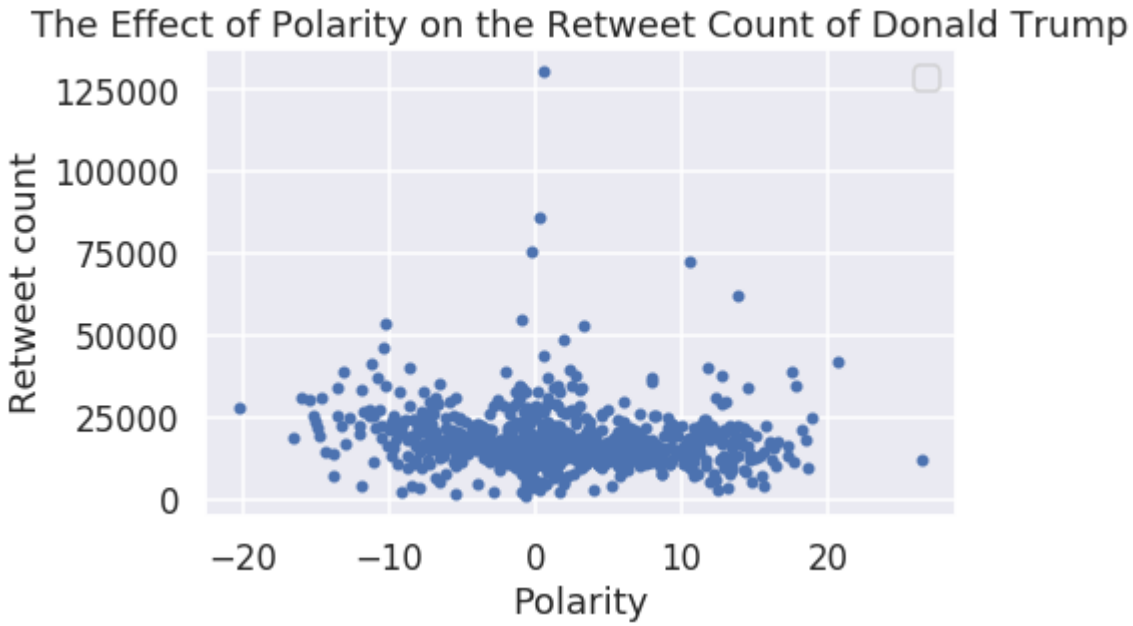
You can look at other data sources and even tweets.

Plot:

In [103]:
```
retweet_count = trump[['polarity', 'retweet_count']]
avg = retweet_count.groupby('polarity').mean()
avg['polarity']=avg.index
avg.plot(x='polarity', y='retweet_count', kind="scatter", use_index=True)
plt.title('The Effect of Polarity on the Retweet Count of Donald Trump')
plt.xlabel('Polarity')
plt.ylabel('Retweet count')
plt.legend()
```

```
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will
have precedence in case its length matches with 'x' & 'y'.  Please use a 2-D array with a single row if you r
eally want to specify the same RGB or RGBA value for all points.
No handles with labels found to put in legend.
```

Out[103]: <matplotlib.legend.Legend at 0x2af3a3984518>



Discussion of Your Plot:

2.Does sentiment affect retweet count? Answer: Given the graph, it indicates the average polarity with respect to the overall retweet count. There seems to be an overall stagnant correlation, since the higher or lower the polarity, the retweet amount is fairly similar.

Based on the trends, for the tweets with a polarity of -15 to 20, the average average retweet count is from 0-75,000 retweets. However, a selective few tweet, that seem to fluctuate around -10 to 12 polarity have more than 75,000 retweets meaning that the data becomes more variable, or fluctuated, meaning a majority of the data is spread towards the bottom side of the graph, not following a logarithmic curve or a linear trend. This is probably due to Trump tweets that many supporters, or non-supporters may not react with several retweets (or be slighly negatively polarizing and slightly positively polarizing), giving his tweets a sense of controversy.

In essense, the sentiment towards Donald Trump's tweets does change variably change with the polarity of the tweets with regards to the average retweet amount. It's perhaps based on certain words he may use within the tweet, or a combination of many that causes the sentiment to be highly negative or highly positive, therefore resulting in a high amount of retweets.

Submission

Congrats, you just finished Project 1!