In [209]:

```
import re
import string
import pandas as pd
import numpy as np
from collections import Counter
import matplotlib.pyplot as plt

'''
Import below doesn't needed for basic solution
It is just for experimentations
'''
import nltk
from nltk.corpus import stopwords
# Remove below comments to add necessary libraries
# import sys
# !{sys.executable} -m pip install --user -U pandas xgboost nltk graphviz
import xgboost as xgb
from nltk.sentiment.vader import SentimentIntensityAnalyzer

nltk.download('stopwords')
nltk.download('vader_lexicon')

```

```
[nltk_data] Downloading package stopwords to /home/oak/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     /home/oak/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Out[209]:

```
True
```

In [61]:

```
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.dummy import DummyClassifier
from sklearn.neural_network import MLPClassifier
from xgboost import XGBClassifier

'''
Testing multiple classification Algorithm for a best fit
'''
classifiers = {
    'dummy' : DummyClassifier(),
    'linear_regression' : LinearRegression(),
    'gnb' : GaussianNB(),
    'random_forest' : RandomForestClassifier(n_estimators=100, max_depth=10, ma
    #'ada' : AdaBoostClassifier(),
    #'mlp' : MLPClassifier(alpha=1, max_iter=1000),
    'XGB': XGBClassifier(n_estimators=100, max_depth=7)
}



```

Helper Methods to transfor/extrac information

In [4]:

```
def get_sentiment(text):
    ''' Get sentiments from tweets '''
    sid = SentimentIntensityAnalyzer()
    return sid.polarity_scores(text)['compound']
```

In [5]:

```
def get_tags_count(text):
    '''Get POS tags from a tweet'''
    tokens = nltk.word_tokenize(text)
    tags = nltk.pos_tag(tokens)
    counts = Counter( tag for word,  tag in tags)
    return dict(counts)
```

In [6]:

```
def filter_stop_words(text):
    ''' Filter out stop words (Only for English text)'''
    filter_words = [x for x in text if x not in stopwords.words('english')]
    return filter_words
```

In [75]:

```
def unique_word_ratio(words):
    ''' Get unique words ratio'''
    word_count = len(words)
    if not word_count:
        return 0

    unique_count = len(set(words))
    return unique_count / word_count
```

In [8]:

```
def get_most_used_words(token):
    ''' Get most words used from a tokinized list'''
    return nltk.FreqDist(token)
```

In [9]:

```
def most_words_by_author(authors):
    ''' Group top words used by author '''
    top_words_by_author = dict()
    for x in authors:
        author_clean_tokens = df[df['author']== x ]['clean_tokens'].tolist()
        flat_list = [item for sublist in author_clean_tokens for item in sublis
        top_words_by_author[x] = [item[0] for item in get_most_used_words(flat_

    return top_words_by_author
```

In [10]:

```
def mark_common_word(author, tokens):
    ''' Filter out common words of a author from a tweet '''
    common_words = author_top_10_words[author]
    common_word_used = []
    for token in tokens:
        if token in common_words:
            common_word_used.append(token)

    return common_word_used
```

In [141]:

```
df = pd.read_csv('train_set.csv', sep=',')
df_test = pd.read_csv('test_set.csv', sep=',')

# Droping incosistent(Null) data
df = df.dropna()
```

In [106]:

```
df.head(5)
```

Out[106]:

	author	day	month	year	hour	minute	second	day_of_week	day_of_year	week_of
0	Neil deGrasse Tyson	3.0	2.0	2014.0	1.0	58.0	8.0	Mon	34.0	
1	Cristiano Ronaldo	22.0	12.0	2012.0	13.0	57.0	5.0	Sat	357.0	
2	Ellen DeGeneres	22.0	3.0	2019.0	18.0	58.0	24.0	Fri	81.0	
3	Sebastian Ruder	13.0	6.0	2016.0	18.0	13.0	55.0	Mon	165.0	
4	KATY PERRY	18.0	4.0	2018.0	6.0	56.0	54.0	Wed	108.0	

Target class Mapping

In [229]:

```
dict( enumerate(df['author'].astype('category').cat.categories ) )
```

Out[229]:

```
{0: 'Barack Obama',
 1: 'Cristiano Ronaldo',
 2: 'Donald J. Trump',
 3: 'Ellen DeGeneres',
 4: 'Elon Musk',
 5: 'KATY PERRY',
 6: 'Kim Kardashian West',
 7: 'Neil deGrasse Tyson',
 8: 'Sebastian Ruder',
 9: 'Snoop Dogg'}
```

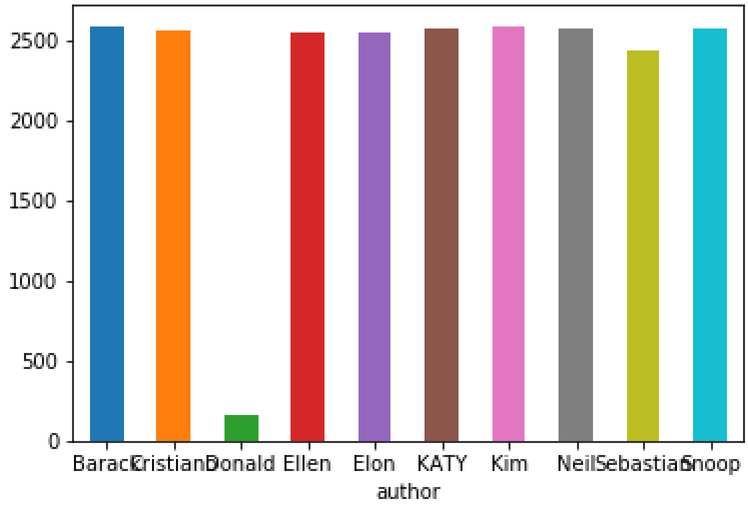
Visualizing some useful stats

In [142]:

```
df['author'] = df.apply(lambda row: row['author'].split(" ")[0], axis=1)
df.groupby('author').count()['lang'].plot.bar(x='author', y='count', rot=0)
```

Out[142]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fba203f69e8>



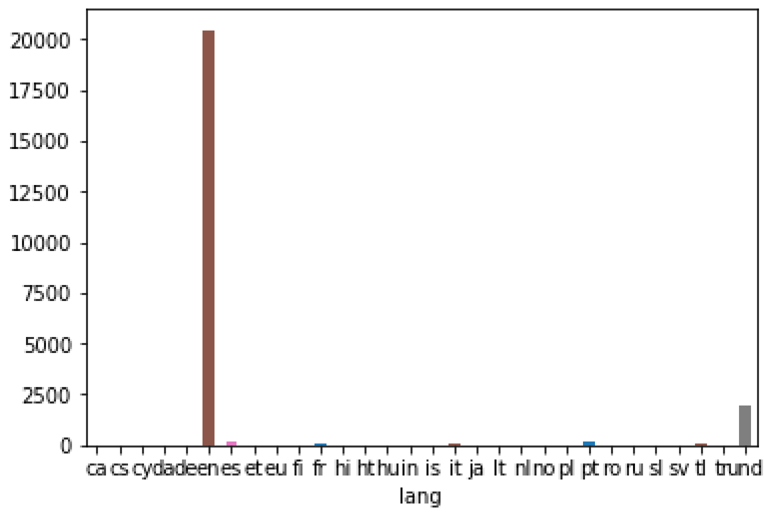
We have one imbalanced class "Donald Trump" within a dataset, it may suffer from precision if left at it is.

In [143]:

```
df.groupby('lang').count()['author'].plot.bar(x='lang', y='count', rot=0)
```

Out[143]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fba2dd05cf8>



The dataset contains a few multiple languages, but still, "en" English language is dominating. Again for simplicity we will work over the English language as a base Langugae for our solution. Although our basic solution is language independent.

In [231]:

```
df['author_numeric'] = df['author'].astype('category').cat.codes
df['lang_numeric'] = df['lang'].astype('category').cat.codes
df['day_of_week_numeric'] = df['day_of_week'].astype('category').cat.codes
df['has_mentions'] = df['has_mentions'].astype('category').cat.codes
df['is_retweet'] = df['is_retweet'].astype('category').cat.codes
df['has_hashtag'] = df['has_hashtag'].astype('category').cat.codes
df['has_url'] = df['has_url'].astype('category').cat.codes
df['has_media'] = df['has_media'].astype('category').cat.codes
corr = df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

```
/usr/lib/python3/dist-packages/matplotlib/colors.py:489: RuntimeWarnin
g: invalid value encountered in less
  np.copyto(xa, -1, where=xa < 0.0)
```

Out[231]:

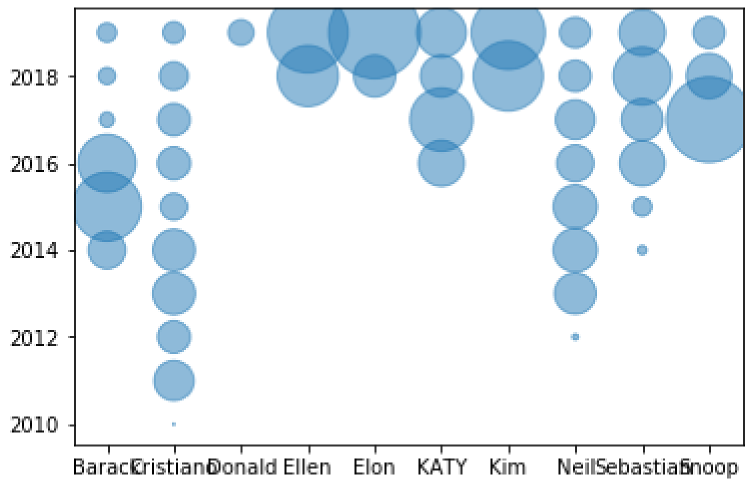
	day	month	year	hour	minute	sec
day	1	-0.00677015	-0.00122407	-0.00199287	0.00413236	-0.0076
month	-0.00677015	1	-0.114846	0.0596859	0.0146015	0.0069
year	-0.00122407	-0.114846	1	-0.092317	0.00140788	0.0277
hour	-0.00199287	0.0596859	-0.092317	1	0.00964866	-0.0121
minute	0.00413236	0.0146015	0.00140788	0.00964866	1	0.026
second	-0.0076431	0.0069516	0.0277662	-0.0121509	0.026857	
day_of_year	0.0809276	0.996123	-0.115889	0.0595529	0.0149434	0.00626
week_of_year	0.0807925	0.995685	-0.117208	0.0582205	0.0146471	0.00631
source	-6.90549e-05	-0.0557315	-0.465751	0.0448334	-0.0131161	-0.0531
is_retweet	nan	nan	nan	nan	nan	
has_hashtag	-0.00927827	-0.016578	-0.0877627	-0.00647992	-0.0182279	-0.0222
has_mentions	-0.00299876	-0.0156642	0.197416	-0.0087933	0.000905113	0.0104
has_url	0.0222063	0.0382387	0.0414157	0.0803122	-0.0129164	0.00787
has_media	0.00692653	0.0200361	0.0351509	0.0601525	-0.0027565	0.0183
tweet_length	-0.00387092	-0.0115283	-0.0842157	0.108483	-0.021287	-0.0289
punc_count	0.00500665	-0.00627069	-0.0601527	0.123514	-0.0150409	-0.0165
punc_ratio	-0.00132565	0.0114558	0.0201393	0.00366631	0.0121089	0.0238
unique_ratio	0.00496966	0.0239867	0.111988	-0.0718107	0.0169147	0.032
lang_numeric	0.0115671	0.0123931	0.0707779	-0.0571708	0.00104528	0.0149
day_of_week_numeric	-0.0176289	-0.0300092	0.000918927	0.0413936	0.00773474	0.0120
word_count	-0.00559718	-0.0235567	-0.0834921	0.0789287	-0.0223451	-0.027
author_numeric	0.0100136	-0.0154799	0.289824	-0.153019	0.0118655	-0.0321

This correlation matrix can provide us with a handy vision to select impactful parameters. As our target is author, we can see that the parameters below look promising feature set for training

- year
- source
- has_mentions
- hour
- has_hashtag
- lang_numeric

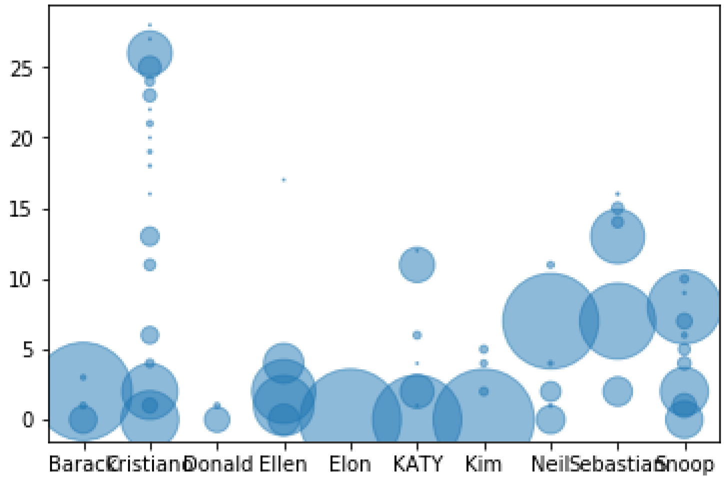
In [145]:

```
author_year_group = df.groupby(['author', 'year']).count()['day']
N = 10
colors = np.random.rand(N)

plt.scatter(author_year_group.index.get_level_values(0), author_year_group.inde
plt.show()
```



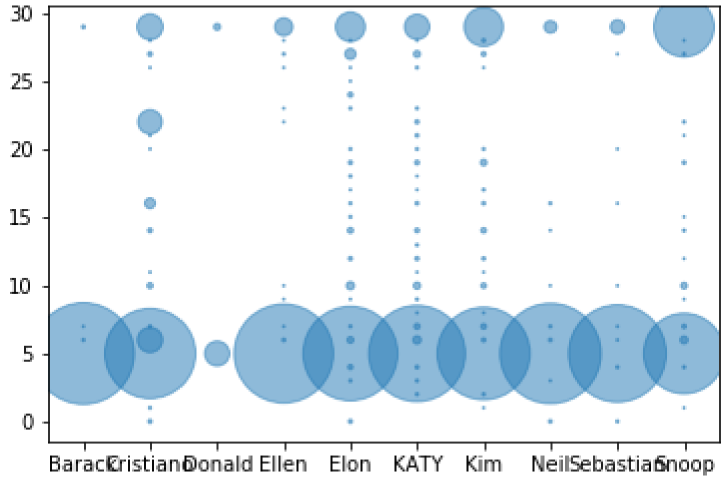
In [146]:

```
author_year_group = df.groupby(['author', 'source']).count()['day']
N = 10
colors = np.random.rand(N)

plt.scatter(author_year_group.index.get_level_values(0), author_year_group.inde
plt.show()
```



In [147]:

```
author_year_group = df.groupby(['author', 'lang_numeric']).count()['day']
N = 10
colors = np.random.rand(N)

plt.scatter(author_year_group.index.get_level_values(0), author_year_group.inde
plt.show()
```



Lets just try our luck with these handful parameters, and see what shows up.

In [122]:

```
target = df['author_numeric']
data = df[['source', 'year', 'lang_numeric', 'hour', 'has_mentions', 'has_hasht
```

In [123]:

```
for k, v in classifiers.items():
    results = cross_val_score(v, data, target, cv=5)
    print(k)
    print(results)
```

```
dummy
[0.11731723 0.10056107 0.10792143 0.11509393 0.1036941 ]
linear_regression
[0.22995842 0.2164969  0.22565512 0.21221584 0.2411846 ]
gnb
[0.5943498  0.59236081 0.58385495 0.59144893 0.58241521]
random_forest
[0.76989433 0.77665084 0.77012735 0.75534442 0.76604018]
XGB
[0.77269786 0.77772982 0.77034319 0.76700497 0.76971268]
```

It looks like we already achieved our base score by just analysing corelations between features and targets.

Now lets do reverse engineering, feeding every parameter in a model and check which one it picks to provide more information gain

In [149]:

```
target = df['author_numeric']
data = df.drop(['author', 'tweet', 'day_of_week', 'lang', 'author_numeric'], ax
```

In [150]:

```
for k, v in classifiers.items():
    results = cross_val_score(v, data, target, cv=5)
    print(k)
    print(results)
```

```
dummy
[0.10610308 0.10703496 0.0982085  0.11271864 0.1058544 ]
linear_regression
[0.26249704 0.25047481 0.25333796 0.24210176 0.27185383]
gnb
[0.63381497 0.64285714 0.62141161 0.63593176 0.63037373]
random_forest
[0.83308173 0.84333189 0.83272178 0.83049017 0.83365738]
XGB
[0.85184386 0.85347432 0.84998921 0.84193479 0.85007561]
```

Its look like we reached our goal, but which is the feature that we missed and it provided such a boost? Lets check it with feature imporatance tool of a model

In [151]:

```
clf = RandomForestClassifier(n_estimators=100, max_depth=10, max_features=6)
clf.fit(data, target)
cross_val_score(clf, data, target, cv=5)
#get_xgb_imp(clf, data.columns)
```

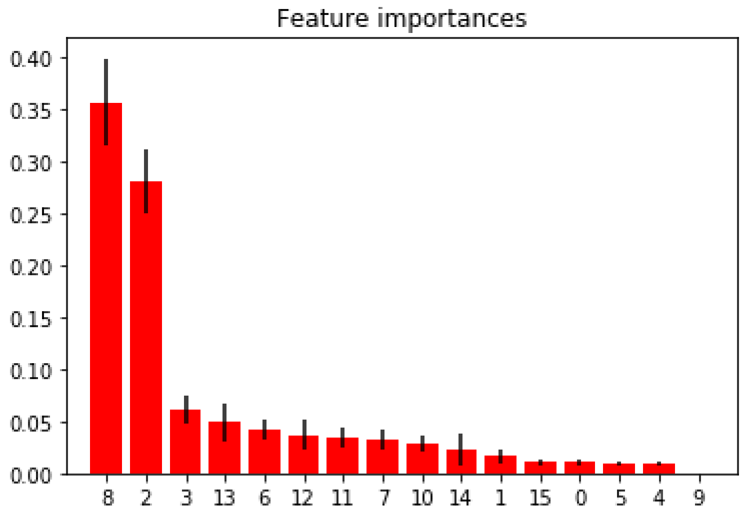
Out[151]:

```
array([0.83459133, 0.84441088, 0.83358515, 0.83156986, 0.83106502])
```

In [152]:

```
importances = clf.feature_importances_
std = np.std([tree.feature_importances_ for tree in clf.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")

for f in range(data.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indices[f]]))

# Plot the feature importances of the forest
plt.figure()
plt.title("Feature importances")
plt.bar(range(data.shape[1]), importances[indices],
       color="r", yerr=std[indices], align="center")
plt.xticks(range(data.shape[1]), indices)
plt.xlim([-1, data.shape[1]])
plt.show()
```

```
Feature ranking:
1. feature 8 (0.356490)
2. feature 2 (0.280102)
3. feature 3 (0.060904)
4. feature 13 (0.048961)
5. feature 6 (0.042167)
6. feature 12 (0.036852)
7. feature 11 (0.034603)
8. feature 7 (0.031746)
9. feature 10 (0.028550)
10. feature 14 (0.022739)
11. feature 1 (0.016175)
12. feature 15 (0.010848)
13. feature 0 (0.010789)
14. feature 5 (0.009860)
15. feature 4 (0.009214)
16. feature 9 (0.000000)
```



In [153]:

```
data.columns
```

Out[153]:

```
Index(['day', 'month', 'year', 'hour', 'minute', 'second', 'day_of_yea
r',
       'week_of_year', 'source', 'is_retweet', 'has_hashtag', 'has_men
tions',
       'has_url', 'has_media', 'lang_numeric', 'day_of_week_numeric'],
      dtype='object')
```

Gotchaaaa, so as per our Random Tree forest and XGB, we found out that "has_media" and "day_of_year" are providing much of the information which we were not able to see through corelation matrix.

Lets add these two parameters to our previous handful feature and see if it is actually true.

In [154]:

```
target = df['author_numeric']
data = df[['source', 'year', 'lang_numeric', 'hour', 'has_mentions', 'has_hashta
```

In [155]:

```
for k, v in classifiers.items():
    results = cross_val_score(v, data, target, cv=5)
    print(k)
    print(results)
```

```
dummy
[0.11257278 0.10617177 0.11051155 0.11703736 0.1073666 ]
linear_regression
[0.23399045 0.21911337 0.22596606 0.21694496 0.24468854]
gnb
[0.63295234 0.63746224 0.61838981 0.63679551 0.62367682]
random_forest
[0.83265042 0.83340527 0.83164256 0.82725113 0.82523223]
XGB
[0.841708   0.84354769 0.84221886 0.83740013 0.83624973]
```

In [194]:

```
clf = RandomForestClassifier(n_estimators=100, max_depth=10, max_features=6)
clf.fit(data, target)
cross_val_score(clf, data, target, cv=5)
#get_xgb_imp(clf, data.columns)
```

Out[194]:

```
array([0.79965495, 0.80750971, 0.80228793, 0.79140574, 0.79887665])
```

In [206]:

```
# Extract single tree
estimator = clf.estimators_[1]

from sklearn.tree import export_graphviz
# Export as dot file
export_graphviz(estimator, out_file='tree.dot',
                feature_names = data.columns,
                class_names = df['author'],
                rounded = True, proportion = False,
                precision = 2, filled = True)

# Convert to png using system command (requires Graphviz)
from subprocess import call
call(['dot', '-Tpng', 'tree.dot', '-o', 'tree.png', '-Gdpi=600'])

# Display in jupyter notebook
from IPython.display import Image
Image(filename = 'tree.png')
```

Out[206]:

Try to visualize it but its quite long

Predicting test script

In [221]:

```
meric'] = df_test['lang'].astype('category').cat.codes
_week'] = df_test['day_of_week'].astype('category').cat.codes
week_numeric'] = df_test['day_of_week'].astype('category').cat.codes
tions'] = df_test['has_mentions'].astype('category').cat.codes
eet'] = df_test['is_retweet'].astype('category').cat.codes
htag'] = df_test['has_hashtag'].astype('category').cat.codes
'] = df_test['has_url'].astype('category').cat.codes
ia'] = df_test['has_media'].astype('category').cat.codes

ata = df_test[['source', 'year', 'lang_numeric', 'hour', 'has_mentions', 'has_hashta
edict(df_test_data)
```

In [226]:

```
1
```

Out[226]:

```
[1,
 1,
 1,
 1,
 1,
 1,
 7,
 1,
 1,
 1,
 1,
 1,
 1,
 1,
 7,
 1,
 7,
 1,
```

For conclusion, the ensemble method usually provides better result as it selects best models and then aggreagates it. Randomforest particularly creates multiple trees with different parameters and then combine the results. Which is why set of features were enough to provide max accuracy and thus new feature didn't provide much of a change in the result.

Although we reached our goal, and you can ignore the below Implementations

These are just a few experiments.

Let paly with some langugae stats, and see if we can make this score much better or not

In [157]:

```
df = pd.read_csv('train_set.csv', sep=',')
df_test = pd.read_csv('test_set.csv', sep=',')

# Droping incositent(Null) data
df = df.dropna()
df['tweet'].head(10)
```

Out[157]:

```
0    A 50-yard field goal in MetLife stadium will d...
1    RT @Thiaguinhooo14: Manda um abraço em portugu...
2    Today I’m talking about a topic that affects a...
3    New blog post giving an overview of softmax ap...
4    high of the day: 0 cavities 🙏🏼\nlow: @washingt...
5    @PrintingJesus Yup. I occasionally repost afte...
6    RT @tdietterich: These rules are full of wisdo...
7    RT @kkwbeauty: BOGO! Buy one Crème Contour Sti...
8    RT @kkwbeauty: The new Body Shimmer in Gold is...
9    My 13th surprise bday party 1993 https://t.co/... (https://t.c
o/...)
Name: tweet, dtype: object
```

In [158]:

```
# Lets apply some basic NLP statistical methods

# lowering all text
df['tweet'] = df['tweet'].apply(lambda x: x.lower())

# removing retweets tags as we already know  which indecate re
df['tweet'] = df['tweet'].apply(lambda x: re.sub(r'^rt.*:', '', x))

# removing url
#df['tweet'] = df['tweet'].apply(lambda x: re.sub(r'^https?:\/\/.*[\r\n]*', '',

# tweet character length
df['tweet_length'] = df['tweet'].apply(lambda x: len(x))

# punctuation count and ratio in a tweet
df['punc_count'] = df['tweet'].apply(lambda t: len(list(filter(lambda c: c in t
df['punc_ratio'] = df['punc_count'] / df['tweet_length']

# remvoing some special characters
punc_plus_extra = '{}{}'.format(string.punctuation, '“”—')

df['tweet_no_punc'] = df['tweet'].apply(lambda x: x.translate(str.maketrans('',
df['tweet_no_punc'] = df['tweet_no_punc'].apply(lambda x: x.replace('’', ''))
df['tweet_no_punc'] = df['tweet_no_punc'].apply(lambda x: x.replace('amp', ''))

# find unique word ratio
df['unique_ratio'] = df['tweet_no_punc'].apply(lambda x: unique_word_ratio(x))

#df['sentiment'] = df['tweet'].apply(lambda x: get_sentiment(x))
```

In [159]:

```
df.head(10)
```

Out[159]:

	author	day	month	year	hour	minute	second	day_of_week	day_of_year	week_of
0	Neil deGrasse Tyson	3.0	2.0	2014.0	1.0	58.0	8.0	Mon	34.0	
1	Cristiano Ronaldo	22.0	12.0	2012.0	13.0	57.0	5.0	Sat	357.0	
2	Ellen DeGeneres	22.0	3.0	2019.0	18.0	58.0	24.0	Fri	81.0	
3	Sebastian Ruder	13.0	6.0	2016.0	18.0	13.0	55.0	Mon	165.0	
4	KATY PERRY	18.0	4.0	2018.0	6.0	56.0	54.0	Wed	108.0	
5	Neil deGrasse Tyson	7.0	12.0	2016.0	0.0	48.0	0.0	Wed	342.0	
6	Sebastian Ruder	29.0	3.0	2017.0	3.0	20.0	59.0	Wed	88.0	
7	Kim Kardashian West	6.0	4.0	2019.0	17.0	49.0	1.0	Sat	96.0	
8	Kim Kardashian West	22.0	6.0	2019.0	0.0	27.0	43.0	Sat	173.0	
9	Kim Kardashian West	29.0	3.0	2019.0	8.0	33.0	16.0	Fri	88.0	

10 rows × 23 columns

Now lets find correlation of these new parameters

In [160]:

```
corr = df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

Out[160]:

	day	month	year	hour	minute	second	day_
day	1	-0.00677015	-0.00122407	-0.00199287	0.00413236	-0.0076431	0.0
month	-0.00677015	1	-0.114846	0.0596859	0.0146015	0.0069516	0
year	-0.00122407	-0.114846	1	-0.092317	0.00140788	0.0277662	-0
hour	-0.00199287	0.0596859	-0.092317	1	0.00964866	-0.0121509	0.0
minute	0.00413236	0.0146015	0.00140788	0.00964866	1	0.026857	0.0
second	-0.0076431	0.0069516	0.0277662	-0.0121509	0.026857	1	0.00
day_of_year	0.0809276	0.996123	-0.115889	0.0595529	0.0149434	0.00626408	
week_of_year	0.0807925	0.995685	-0.117208	0.0582205	0.0146471	0.00631279	0
source	-6.90549e-05	-0.0557315	-0.465751	0.0448334	-0.0131161	-0.0531921	-0.0
tweet_length	-0.00387092	-0.0115283	-0.0842157	0.108483	-0.021287	-0.0289434	-0.0
punc_count	0.00500665	-0.00627069	-0.0601527	0.123514	-0.0150409	-0.0165529	-0.00
punc_ratio	-0.00132565	0.0114558	0.0201393	0.00366631	0.0121089	0.0238755	0.0
unique_ratio	0.00496966	0.0239867	0.111988	-0.0718107	0.0169147	0.032084	0.0

New parameters are impact directly to the author with some average correlation, which can provide an assist to model with their acummulated support

In [165]:

```
target = df['author'].astype('category').cat.codes
df['lang_numeric'] = df['lang'].astype('category').cat.codes
df['day_of_week_numeric'] = df['day_of_week'].astype('category').cat.codes
df['has_mentions'] = df['has_mentions'].astype('category').cat.codes
df['is_retweet'] = df['is_retweet'].astype('category').cat.codes
df['has_hashtag'] = df['has_hashtag'].astype('category').cat.codes
df['has_url'] = df['has_url'].astype('category').cat.codes
df['has_media'] = df['has_media'].astype('category').cat.codes
data = df[['source', 'year', 'lang_numeric', 'hour', 'has_mentions', 'has_hasht
```

In [166]:

```
for k, v in classifiers.items():
    results = cross_val_score(v, data, target, cv=5)
    print(k)
    print(results)
```

```
dummy
[0.10610308 0.10746655 0.10641053 0.1071043  0.11168719]
linear_regression
[0.23535246 0.22117424 0.22706116 0.21678906 0.24610826]
gnb
[0.6172094  0.62278809 0.60997194 0.62772619 0.61330741]
random_forest
[0.83416002 0.83664221 0.83056335 0.82811488 0.83041694]
XGB
[0.8531378  0.85627967 0.84934168 0.85143597 0.84899546]
```

These implementation failed miserably, as the model take branches w.r.t to high infomration gain, thus these new parameter always comes under previous impacted parameters.

In [ ]:

```

```

Below this I try to use NLTK, just curious if it can help

In [167]:

```
df['tokens'] = df['tweet_no_punc'].apply(lambda x: nltk.word_tokenize(x))
df.head(5)
```

Out[167]:

	author	day	month	year	hour	minute	second	day_of_week	day_of_year	week_of_year	...	has
0	Neil deGrasse Tyson	3.0	2.0	2014.0	1.0	58.0	8.0	Mon	34.0	5.0	...	
1	Cristiano Ronaldo	22.0	12.0	2012.0	13.0	57.0	5.0	Sat	357.0	51.0	...	
2	Ellen DeGeneres	22.0	3.0	2019.0	18.0	58.0	24.0	Fri	81.0	11.0	...	

In [168]:

```
df['clean_tokens'] = df['tokens'].apply(lambda x: filter_stop_words(x))
df[['tokens', 'clean_tokens']].head(5)
```

Out[168]:

	tokens	clean_tokens
0	[a, 50yard, field, goal, in, metlife, stadium,...	[50yard, field, goal, metlife, stadium, deflec...
1	[manda, um, abraço, em, português, para, seus,...	[manda, um, abraço, em, português, para, seus,...
2	[today, im, talking, about, a, topic, that, af...	[today, im, talking, topic, affects, us, mansp...
3	[new, blog, post, giving, an, overview, of, so...	[new, blog, post, giving, overview, softmax, a...
4	[high, of, the, day, 0, cavities, 🙏🏼, low, was...	[high, day, 0, cavities, 🙏🏼, low, washingtonpo...

In [169]:

```
#df['top_words'] = df['clean_tokens'].apply(lambda words: list(get_most_used_wo
author_top_10_words = most_words_by_author(pd.unique(df['author']))
df['top_words_used'] = df.apply(lambda row: mark_common_word(row['author'], row

```

In [170]:

```
1  author_top_10_words
```

Out[170]:

```
{'Neil deGrasse Tyson': ['earth',
  'moon',
  'would',
  'posted',
  'people',
  'one',
  'time',
  'day',
  'w',
  'science'],
 'Cristiano Ronaldo': ['cristiano',
  'new',
  'great',
  'game',
  'madrid',
  'thank',
  'team',
  'win',
  'im',
  'good'],
 'Ellen DeGeneres': ['happy',
  'gameofgames',
  'birthday',
  'show',
  'im',
  'love',
  'new',
  'youre',
  'time',
  'watch'],
 'Sebastian Ruder': ['learning',
  'nlp',
  'thanks',
  'new',
  'paper',
  'deeplearning',
  'great',
  'machinelearning',
  'work',
  'nlproc'],
 'KATY PERRY': ['americanidol',
  'love',
  'im',
  'get',
  'time',
  'new',
  'see',
  'one',
  'like',
  'dont'],
 'Kim Kardashian West': ['kkwbeauty',
  'new',
  'shop',
  'collection',
  'love',
```

```
  'pst',
  'available',
  'today',
  'get',
  'classic'],
 'Snoop Dogg': ['n',
  'new',
  'snoopdogg',
  'wit',
  'u',
  'get',
  'snoop',
  'jokerswild',
  'got',
  'yall'],
 'Elon Musk': ['tesla',
  'erdayastronaut',
  'spacex',
  'yes',
  'flcnhvy',
  'model',
  '3',
  'car',
  'like',
  '…'],
 'Barack Obama': ['president',
  'obama',
  'actonclimate',
  'change',
  'climate',
  'health',
  'watch',
  'time',
  'make',
  'today'],
 'Donald J. Trump': ['ed',
  'henry',
  'democrats',
  'great',
  'president',
  'news',
  'new',
  'mark',
  'levin',
  'fake']}
```

In [171]:

```
# create a new column with the count of all words
df['word_count'] = df['clean_tokens'].apply(lambda words: len(words))
df['unique_ratio'] = df['tweet_no_punc'].apply(lambda x: unique_word_ratio(x))
```

In [172]:

```
df['pos_tags'] = df['tweet_no_punc'].apply(lambda x: get_tags_count(x))
df.head(5)
```

Out[172]:

	author	day	month	year	hour	minute	second	day_of_week	day_of_year	week_of_
0	Neil deGrasse Tyson	3.0	2.0	2014.0	1.0	58.0	8.0	Mon	34.0	
1	Cristiano Ronaldo	22.0	12.0	2012.0	13.0	57.0	5.0	Sat	357.0	
2	Ellen DeGeneres	22.0	3.0	2019.0	18.0	58.0	24.0	Fri	81.0	
3	Sebastian Ruder	13.0	6.0	2016.0	18.0	13.0	55.0	Mon	165.0	
4	KATY PERRY	18.0	4.0	2018.0	6.0	56.0	54.0	Wed	108.0	

5 rows × 30 columns

In [174]:

```
#data = df.drop(['tweet', 'tokens', 'clean_tokens', 'tweet_no_punc', 'top_words
```

In [183]:

```
data['lang'] = df['lang'].astype('category').cat.codes
data['day_of_week'] = df['day_of_week'].astype('category').cat.codes
data['has_mentions'] = df['has_mentions'].astype('category').cat.codes
data['is_retweet'] = df['is_retweet'].astype('category').cat.codes
data['has_hashtag'] = df['has_hashtag'].astype('category').cat.codes
data['has_url'] = df['has_url'].astype('category').cat.codes
data['has_media'] = df['has_media'].astype('category').cat.codes
data['top_words_used'] = df['top_words_used'].apply(lambda x: len(x))
# punctuation count and ratio in a tweet
data['punc_count'] = df['tweet'].apply(lambda t: len(list(filter(lambda c: c in
data['punc_ratio'] = df['punc_count'] / df['tweet_length']

data['word_count'] = df['clean_tokens'].apply(lambda words: len(words))
data['unique_ratio'] = df['tweet_no_punc'].apply(lambda x: unique_word_ratio(x)
```

In [184]:

```
q = pd.DataFrame(list(df['pos_tags']))[['VB', 'NN', 'JJ']].fillna(0)
data = pd.concat([data, q], axis=1)
```

In [185]:

```
np.where(np.isnan(q))
```

Out[185]:

```
(array([], dtype=int64), array([], dtype=int64))
```

In [193]:

```
df['top_words_used'].head(5)
```

Out[193]:

```
0                                   []
1                          [cristiano]
2                                 [im]
3    [new, learning, deeplearning, nlproc]
4                                   []
Name: top_words_used, dtype: object
```

In [191]:

```
target = df['author'].astype('category').cat.codes
#data = data.drop(['author'], axis=1)
data = df[['source', 'word_count', 'punc_count',
       'punc_ratio', 'day_of_year', 'year', 'has_mentions', 'unique_ratio', 'to
data = data.fillna(0)
```

In [192]:

```
for k, v in classifiers.items():
    results = cross_val_score(v, data, target, cv=5)
    print(k)
    print(results)
```

```
dummy
[0.10567177 0.10034527 0.1027412  0.11530987 0.10542234]
linear_regression
[0.21176501 0.195283   0.19114178 0.18815081 0.2077455 ]
gnb
[0.59629071 0.60271903 0.60198575 0.58928957 0.59472888]
random_forest
[0.79857667 0.80729391 0.79602849 0.79442885 0.79390797]
XGB
[0.81216304 0.81333621 0.80984243 0.80954437 0.81227047]
```