In [162]:
```
pip install scikit-plot
```

```
Requirement already satisfied: scikit-plot in c:\programdata\anaconda3
\lib\site-packages (0.3.7)
Requirement already satisfied: joblib>=0.10 in c:\programdata\anaconda3
\lib\site-packages (from scikit-plot) (0.13.2)
Requirement already satisfied: scikit-learn>=0.18 in c:\programdata\ana
conda3\lib\site-packages (from scikit-plot) (0.21.2)
Requirement already satisfied: matplotlib>=1.4.0 in c:\programdata\anac
onda3\lib\site-packages (from scikit-plot) (3.1.0)
Requirement already satisfied: scipy>=0.9 in c:\programdata\anaconda3\l
ib\site-packages (from scikit-plot) (1.2.1)
Requirement already satisfied: numpy>=1.11.0 in c:\programdata\anaconda
3\lib\site-packages (from scikit-learn>=0.18->scikit-plot) (1.16.4)
Requirement already satisfied: cycler>=0.10 in c:\programdata\anaconda3
\lib\site-packages (from matplotlib>=1.4.0->scikit-plot) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\programdata\anac
onda3\lib\site-packages (from matplotlib>=1.4.0->scikit-plot) (1.1.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1
in c:\programdata\anaconda3\lib\site-packages (from matplotlib>=1.4.0->
scikit-plot) (2.4.0)
Requirement already satisfied: python-dateutil>=2.1 in c:\programdata\a
naconda3\lib\site-packages (from matplotlib>=1.4.0->scikit-plot) (2.8.
0)
Requirement already satisfied: six in c:\programdata\anaconda3\lib\site
-packages (from cycler>=0.10->matplotlib>=1.4.0->scikit-plot) (1.12.0)
Requirement already satisfied: setuptools in c:\programdata\anaconda3\l
ib\site-packages (from kiwisolver>=1.0.1->matplotlib>=1.4.0->scikit-plo
t) (41.0.1)
Note: you may need to restart the kernel to use updated packages.
```

In [163]:
```
pip install wordcloud
```

```
Requirement already satisfied: wordcloud in c:\programdata\anaconda3\li
b\site-packages (1.5.0)
Requirement already satisfied: numpy>=1.6.1 in c:\programdata\anaconda3
```

```
\lib\site-packages (from wordcloud) (1.16.4)
Requirement already satisfied: pillow in c:\programdata\anaconda3\lib\s
ite-packages (from wordcloud) (6.1.0)
Note: you may need to restart the kernel to use updated packages.
```

In [164]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\programdata\anaconda3\lib
\site-packages (0.90)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\si
te-packages (from xgboost) (1.2.1)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\si
te-packages (from xgboost) (1.16.4)
Note: you may need to restart the kernel to use updated packages.
```

In [165]:
```
# Import general useful packages
import numpy as np
import pandas as pd
import re

# Counter elements
from collections import Counter

# Matplot
import matplotlib.pyplot as plt
%matplotlib inline

# nltk
import nltk
from nltk.corpus import stopwords
from  nltk.stem import SnowballStemmer
from nltk.stem import WordNetLemmatizer #word stemmer class
lemma = WordNetLemmatizer()
from wordcloud import WordCloud, STOPWORDS
from nltk import FreqDist

# Import matplotlib for visualisations
import matplotlib.pyplot as plt
import matplotlib.cm as cm
```

```python
import seaborn as sns
import scikitplot as skplt

# Import all machine learning algorithms
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
import xgboost as xgb

# Import other useful subpackage
from sklearn.metrics import confusion_matrix, accuracy_score, classific
ation_report
```

In [166]:
```python
# Required if Uploading data directly into google colab
# from google.colab import files
# df = files.upload()
```

In [167]:
```python
# Calling the Generic Tweets dataset
# import io
# df2 = pd.read_csv(io.BytesIO(df['generic_tweets.txt']))
# df2.head(n=5)
```

Data Import & Cleaning - Generic Tweets

In [168]:
```python
# Importing Generic Tweets to test models.
df2 = pd.read_csv('generic_tweets.txt')
df2.head(n=5)
```

Out[168]:

	class	id	date	query	user	text

	class	id	date	query	user	text
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...
1	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
2	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
3	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
4	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....

In [169]:

```
# Data cleaning and pre-process dataset
nltk.download('stopwords')

# TEXT CLEANING
TEXT_CLEANING_RE = "@\S+|https?:\S+|http?:\S|[^A-Za-z0-9]+"
# A stop word is a commonly used word (such as “the”, “a”, “an”, “in”)
 that a search engine has been programmed to ignore, both when indexing
 entries for searching and when retrieving them as the result of a sear
ch query.
stop_words = stopwords.words("english")
# To reduce words to their root form
stemmer = SnowballStemmer("english")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\rahma\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [170]:

```
# Applying the data cleaning from above
def preprocess(text, stem=False):
    # Remove link,user and special characters
    text = re.sub(TEXT_CLEANING_RE, ' ', str(text).lower()).strip()
    tokens = []
```

```
    for token in text.split():
        if token not in stop_words:
            if stem:
                tokens.append(stemmer.stem(token))
            else:
                tokens.append(token)
    return " ".join(tokens)

df2.text = df2.text.apply(lambda x: preprocess(x))
```

Exporatory Analysis - Generic Tweets

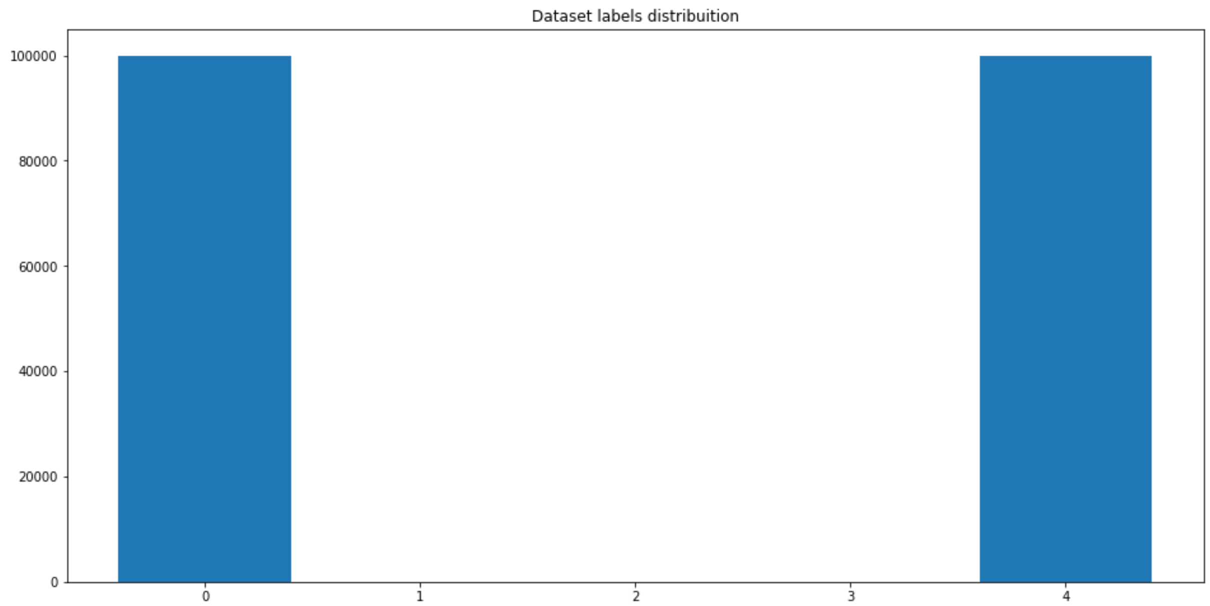
In [171]:

```
# check the data frame info
print(df2.info())
df2.rename(columns={"class": "sentiment"}, inplace=True)

# Get uniques values of sentiment column
df2['sentiment'].unique()

# Find count of individual sentiment and create a bar plot for better v
isualization
sen_cnt = Counter(df2.sentiment)

plt.figure(figsize=(16,8))
plt.bar(sen_cnt.keys(), sen_cnt.values())
plt.title("Dataset labels distribuition")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200000 entries, 0 to 199999
Data columns (total 6 columns):
class    200000 non-null int64
id       200000 non-null int64
date     200000 non-null object
query    200000 non-null object
user     200000 non-null object
text     200000 non-null object
dtypes: int64(2), object(4)
memory usage: 9.2+ MB
```

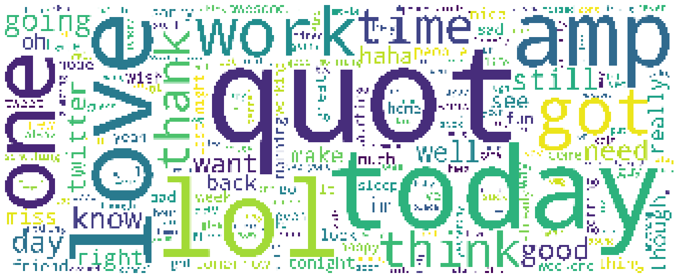
None

Out[171]: Text(0.5, 1.0, 'Dataset labels distribuition')



There is a perfect balance in target variable class in the dataset. This is very suitable for any ML model, as overfitting by the dominant class is avoided, irrespective of the ML model being implemented

In [172]:
```
# all tweets
all_words = " ".join(df2.text)

# Wordcloud of tweets
wordcloud = WordCloud(height=4000, width=10000, stopwords=STOPWORDS, ba
ckground_color='white')
wordcloud = wordcloud.generate(all_words)
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```



Model Preparation (Bag of Words and TFIDF) - Generic Tweets

For both TFIDF and Bag of Words, max_features=1000 will be used for the interest of computation speed. Otherwise, the models could take days to run if not run on big data platforms with shared cluster space.

In [174]:
```
# tokenize all the cleaned tweets in our dataset. Tokens are individual
 terms or words,
# and tokenization is the process of splitting a string of text into to
kens
tokenized_tweet = df2['text'].apply(lambda x: x.split())
tokenized_tweet.head()
```

Out[174]:
```
0    [awww, bummer, shoulda, got, david, carr, thir...
1    [upset, update, facebook, texting, might, cry,...
2    [dived, many, times, ball, managed, save, 50, ...
3              [whole, body, feels, itchy, like, fire]
4                                [behaving, mad, see]
Name: text, dtype: object
```

In [175]:
```
# Stemming is a rule-based process of stripping the suffixes (“ing”, “l
y”, “es”, “s” etc) from a word
from nltk.stem.porter import *
stemmer = PorterStemmer()

tokenized_tweet = tokenized_tweet.apply(lambda x: [stemmer.stem(i) for
```

```
i in x]) # stemming
tokenized_tweet.head()
```

Out[175]:
```
0    [awww, bummer, shoulda, got, david, carr, thir...
1    [upset, updat, facebook, text, might, cri, res...
2    [dive, mani, time, ball, manag, save, 50, rest...
3                 [whole, bodi, feel, itchi, like, fire]
4                                     [behav, mad, see]
Name: text, dtype: object
```

In [176]:
```
# let’s stitch these tokens back together
for i in range(len(tokenized_tweet)):
    tokenized_tweet[i] = ' '.join(tokenized_tweet[i])

df2['text'] = tokenized_tweet
print(df2)
```

```
         sentiment          id                          date     query  \
0                0  1467810369  Mon Apr 06 22:19:45 PDT 2009  NO_QUERY   
1                0  1467810672  Mon Apr 06 22:19:49 PDT 2009  NO_QUERY   
2                0  1467810917  Mon Apr 06 22:19:53 PDT 2009  NO_QUERY   
3                0  1467811184  Mon Apr 06 22:19:57 PDT 2009  NO_QUERY   
4                0  1467811193  Mon Apr 06 22:19:57 PDT 2009  NO_QUERY   
5                0  1467811372  Mon Apr 06 22:20:00 PDT 2009  NO_QUERY   
6                0  1467811592  Mon Apr 06 22:20:03 PDT 2009  NO_QUERY   
7                0  1467811594  Mon Apr 06 22:20:03 PDT 2009  NO_QUERY   
8                0  1467811795  Mon Apr 06 22:20:05 PDT 2009  NO_QUERY   
9                0  1467812025  Mon Apr 06 22:20:09 PDT 2009  NO_QUERY   
```

10	0	1467812416	Mon Apr 06 22:20:16 PDT 2009	NO_QUERY
11	0	1467812579	Mon Apr 06 22:20:17 PDT 2009	NO_QUERY
12	0	1467812723	Mon Apr 06 22:20:19 PDT 2009	NO_QUERY
13	0	1467812771	Mon Apr 06 22:20:19 PDT 2009	NO_QUERY
14	0	1467812784	Mon Apr 06 22:20:20 PDT 2009	NO_QUERY
15	0	1467812799	Mon Apr 06 22:20:20 PDT 2009	NO_QUERY
16	0	1467812964	Mon Apr 06 22:20:22 PDT 2009	NO_QUERY
17	0	1467813137	Mon Apr 06 22:20:25 PDT 2009	NO_QUERY
18	0	1467813579	Mon Apr 06 22:20:31 PDT 2009	NO_QUERY
19	0	1467813782	Mon Apr 06 22:20:34 PDT 2009	NO_QUERY
20	0	1467813985	Mon Apr 06 22:20:37 PDT 2009	NO_QUERY
21	0	1467813992	Mon Apr 06 22:20:38 PDT 2009	NO_QUERY
22	0	1467814119	Mon Apr 06 22:20:40 PDT 2009	NO_QUERY
23	0	1467814180	Mon Apr 06 22:20:40 PDT 2009	NO_QUERY
24	0	1467814192	Mon Apr 06 22:20:41 PDT 2009	NO_QUERY
25	0	1467814438	Mon Apr 06 22:20:44 PDT 2009	NO_QUERY
26	0	1467814783	Mon Apr 06 22:20:50 PDT 2009	NO_QUERY
27	0	1467814883	Mon Apr 06 22:20:52 PDT 2009	NO_QUERY
28	0	1467815199	Mon Apr 06 22:20:56 PDT 2009	NO_QUERY
29	0	1467815753	Mon Apr 06 22:21:04 PDT 2009	NO_QUERY

...	...	...	...	...
199970	4	1693954825	Mon May 04 00:26:55 PDT 2009	NO_QUERY
199971	4	1693954864	Mon May 04 00:26:55 PDT 2009	NO_QUERY
199972	4	1693954878	Mon May 04 00:26:55 PDT 2009	NO_QUERY
199973	4	1693954978	Mon May 04 00:26:57 PDT 2009	NO_QUERY
199974	4	1693954980	Mon May 04 00:26:57 PDT 2009	NO_QUERY
199975	4	1693955032	Mon May 04 00:26:58 PDT 2009	NO_QUERY
199976	4	1693955058	Mon May 04 00:26:58 PDT 2009	NO_QUERY
199977	4	1693955124	Mon May 04 00:26:59 PDT 2009	NO_QUERY
199978	4	1693955159	Mon May 04 00:27:00 PDT 2009	NO_QUERY
199979	4	1693955172	Mon May 04 00:27:00 PDT 2009	NO_QUERY
199980	4	1693955181	Mon May 04 00:27:00 PDT 2009	NO_QUERY
199981	4	1693955229	Mon May 04 00:27:01 PDT 2009	NO_QUERY
199982	4	1693955239	Mon May 04 00:27:01 PDT 2009	NO_QUERY
199983	4	1693955259	Mon May 04 00:27:01 PDT 2009	NO_QUERY
199984	4	1693955313	Mon May 04 00:27:02 PDT 2009	NO_QUERY
199985	4	1693955318	Mon May 04 00:27:02 PDT 2009	NO_QUERY
199986	4	1693955346	Mon May 04 00:27:02 PDT 2009	NO_QUERY
199987	4	1693955449	Mon May 04 00:27:04 PDT 2009	NO_QUERY

```
199988          4  1693955535  Mon May 04 00:27:05 PDT 2009  NO_QUERY
199989          4  1693955558  Mon May 04 00:27:05 PDT 2009  NO_QUERY
199990          4  1693955710  Mon May 04 00:27:07 PDT 2009  NO_QUERY
199991          4  1693955809  Mon May 04 00:27:09 PDT 2009  NO_QUERY
199992          4  1693955837  Mon May 04 00:27:10 PDT 2009  NO_QUERY
199993          4  1693956028  Mon May 04 00:27:13 PDT 2009  NO_QUERY
199994          4  1693956082  Mon May 04 00:27:13 PDT 2009  NO_QUERY
199995          4  1693956088  Mon May 04 00:27:13 PDT 2009  NO_QUERY
199996          4  1693956096  Mon May 04 00:27:14 PDT 2009  NO_QUERY
199997          4  1693956099  Mon May 04 00:27:14 PDT 2009  NO_QUERY
199998          4  1693956134  Mon May 04 00:27:14 PDT 2009  NO_QUERY
199999          4  1693956160  Mon May 04 00:27:14 PDT 2009  NO_QUERY

                   user                                              t
ext
0        _TheSpecialOne_       awww bummer shoulda got david carr third
day
1          scotthamilton  upset updat facebook text might cri result sc
h...
2               mattycus    dive mani time ball manag save 50 rest go bo
und
3                ElleCTF                   whole bodi feel itchi like f
ire
4                 Karoli                                     behav mad
see
5               joy_wolf                                        whole c
rew
```

```
6                mybirch                                            need 
hug
7                   coZZ   hey long time see ye rain bit bit lol fine th
ank
8        2Hood4Hollywood                                               n
ope
9                mimismo                                         que mu
era
10          erinx3leannexo                      spring break plain citi s
now
11           pardonlauren                                          pierc 
ear
12                   TLeC                 bear watch thought ua loss embarr
ass
13       robrobbierobert                    count idk either never talk any
mor
14            bayofwolves  would first gun realli though zac snyder douc 
h...
15             HairByJess            wish got watch miss iamlilnicki prem
ier
16         lovesongwriter  holli death scene hurt sever watch film wri d 
i...
17               armotley                                           file 
tax
18             starkissed        ahh ive alway want see rent love soundtr
ack
19              gi_gi_bee                   oh dear drink forgotten tabl dr
ink
20                 quanvu                                     day get much d
one
21             swinspeedx  one friend call ask meet mid valley today tim 
e...
22              cooliodoc                                       bake cake 
ate
23             viJILLante                                        week go h
ope
24             Ljelli3166                               blagh class 8 tomor
row
25          ChicagoCubbie                                  hate call wake pe
```

```
opl
26          KatieAngell                          go cri sleep watch mar
ley
27                gagoo                                 im sad miss li
lli
28              abel209                  ooooh lol lesli ok lesli get 
mad
29      BaptisteTheFool  meh almost lover except track get depress eve
r...
...                 ...                                               
...
199970      Donealready  know stepford wive live st mari island quit l
i...
199971     Simplymelony                                          thank
yu
199972     hiChristiana  updat twitter middl night piss everyon link ph
one
199973    communicating  almost done sunday task includ open sourc cod
e...
199974    vanessaveasley                                          exca
tli
199975         zoealice                go len shop want macro resea
rch
199976       sepiaverse            hai naa also refer obssess impli 
fan
199977      FollanPhoto      upload imag web yep listya amp hendik long
go
199978  RockstarAtHeart  newbi malakai thanh li stir troubl last night
...
199979  benjaminbeckett                                    suck cock to
nit
199980        michaeljek                              red symond prime min
ist
199981      courtneyyy3                                             oh 
say
199982     freocookster  lushi tee interview md sexpo friday nice engl
i...
199983          Barb04s  sorri tweet read tweet right first time would
...
```

```
199984     Hetty4Christ                              pre 2nd brain surgeri s
ong
199985     deadstockric         awwwwwww thank yeah real dope flick c
ome
199986        xtiiiiine                                      wanna laugh sum
mer
199987         pinkpebs  video arch yesterday taken briankerrphoto bai
l...
199988           CWhyte       wow twitter get seriou traffic googl go
buy
199989  sdhawkins_sfasu              destin e harmoni user sometim won
der
199990     BossTycoonLZ                                            u doinn s
exc
199991     KingNick1100  3 ur name anyway hi post someth page empti ok
...
199992         ssoun126                        haha sorri lol btw nice mee
t u
199993       jchavarria                                             ok way w
ork
199994     sheryonstone                                       got kid ladypn
ok
199995       FelineBred                    haha remark matern leav fire li
ttl
199996      softthistle

199997        elysion32  oki doke time escap north massa back turn get
...
199998       fancyjessy                                   finish lesson hoo
ray
199999         noraezan   ppl fuck kp0 cb stop ask laa love boyfriend t
hat

[200000 rows x 6 columns]
```

In [177]:

```
# BAG OF WORDS: Counting number of words per entry/document
# Bag-of-Words features can be easily created using sklearn's CountVect
orizer function.
# We will set the parameter max_features = 1000 to select only top 1000
```

```
 terms ordered by term frequency across the corpus
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer = CountVectorizer(max_df=0.90, min_df=2, max_features=10
00, stop_words='english')
# bag-of-words feature matrix
bow = bow_vectorizer.fit_transform(df2['text'])
print(bow)
```

```
  (0, 225)	1
  (0, 224)	1
  (0, 373)	1
  (0, 74)	1
  (1, 105)	1
  (1, 877)	1
  (1, 735)	1
  (1, 708)	1
  (1, 208)	1
  (1, 860)	1
  (1, 296)	1
  (1, 915)	1
  (1, 917)	1
  (2, 707)	1
  (2, 12)	1
  (2, 730)	1
  (2, 539)	1
  (2, 79)	1
  (2, 874)	1
  (2, 540)	1
  (3, 507)	1
  (3, 313)	1
  (3, 112)	1
  (4, 535)	1
  (6, 434)	1
  :	:
  (199992, 387)	1
  (199992, 594)	1
  (199992, 803)	1
  (199992, 552)	1
  (199992, 517)	1
  (199993, 943)	1
```

```
  (199993, 970) 1
  (199993, 612) 1
  (199994, 477) 1
  (199994, 612) 1
  (199994, 373) 1
  (199995, 513) 1
  (199995, 387) 1
  (199995, 498) 1
  (199997, 422) 1
  (199997, 900) 1
  (199997, 874) 1
  (199998, 501) 1
  (199998, 323) 1
  (199999, 121) 1
  (199999, 347) 1
  (199999, 822) 1
  (199999, 662) 1
  (199999, 61)  1
  (199999, 526) 1
```

In [178]:

```
# TF-IDF: It works by penalizing the common words by assigning them low
er weights while giving
# importance to words which are rare in the entire corpus but appear in
 good numbers
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(max_df=0.90, min_df=2, max_features=
1000, stop_words='english')
# TF-IDF feature matrix
tfidf = tfidf_vectorizer.fit_transform(df2['text'])
```

In [179]:

```
print(tfidf)
```

```
  (0, 74)	0.5914496287582646
  (0, 373)	0.37475504299386675
  (0, 224)	0.635836307151928
  (0, 225)	0.3247432599759005
  (1, 917)	0.36795372005829907
  (1, 915)	0.31387866812306936
```

```
(1, 296)	0.34352598128170037
(1, 860)	0.3429473275559573
(1, 208)	0.3220421724688195
(1, 708)	0.3920093534271115
(1, 735)	0.2626550551630971
(1, 877)	0.20855732210382913
(1, 105)	0.40075047557125837
(2, 540)	0.34331986038588624
(2, 874)	0.2330009288788982
(2, 79)	0.43036810124905645
(2, 539)	0.4115062679365704
(2, 730)	0.39080546940759253
(2, 12)	0.4337805386200754
(2, 707)	0.3638591195476241
(3, 112)	0.7753958305415023
(3, 313)	0.4715532953157644
(3, 507)	0.4199985662543353
(4, 535)	1.0
(6, 590)	0.5590683007766692
:	:
(199992, 552)	0.45383016217641314
(199992, 803)	0.384742436274447
(199992, 594)	0.3792503913801654
(199992, 387)	0.37604527314221436
(199992, 130)	0.5024969127917983
(199993, 612)	0.6580489612219965
(199993, 970)	0.4516419056009819
(199993, 943)	0.6024874718529549
(199994, 373)	0.45933883758831506
(199994, 612)	0.6002770235014732
(199994, 477)	0.6547330198937789
(199995, 498)	0.6132792456414257
(199995, 387)	0.5310623407511952
(199995, 513)	0.5846891114954555
(199997, 874)	0.46626338159418673
(199997, 900)	0.713926148242243
(199997, 422)	0.5224058899365022
(199998, 323)	0.5892661201316681
(199998, 501)	0.8079390073916287
```

```
  (199999, 526) 0.2597076173842374
  (199999, 61)  0.41394399381823177
  (199999, 662) 0.4631981492718444
  (199999, 822) 0.39141855690213634
  (199999, 347) 0.4008531032801404
  (199999, 121) 0.48245010194721943
```

In [180]:
```
# Spliting Data form above reduction dataset for bag of words
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(bow, df2['sentimen
t'], test_size = 0.3, random_state = 3)
```

Model Implementation & Results (Bag of Words and TFIDF) - Generic Tweets

In [181]:
```
# Applying various Classification algorithms without doing variable red
uctions using bag of words
accuracy_scores = np.zeros(7)

# Support Vector Classifier
svm = SVC().fit(X_train, y_train)
prediction1 = svm.predict(X_test)
accuracy_scores[0] = accuracy_score(y_test, prediction1)*100
print('Support Vector Classifier accuracy: {}%'.format(accuracy_scores[
0]))

# Logistic Regression
logis = LogisticRegression().fit(X_train, y_train)
prediction2 = logis.predict(X_test)
accuracy_scores[1] = accuracy_score(y_test, prediction2)*100
print('Logistic Regression accuracy: {}%'.format(accuracy_scores[1]))

# K Nearest Neighbors
knn = KNeighborsClassifier().fit(X_train, y_train)
prediction3 = knn.predict(X_test)
accuracy_scores[2] = accuracy_score(y_test, prediction3)*100
print('K Nearest Neighbors Classifier accuracy: {}%'.format(accuracy_sc
```

```
ores[2]))

# Gaussian Naive Bayes
#clf = GaussianNB().fit(X_train, y_train)
#prediction4 = clf.predict(X_test)
#accuracy_scores[3] = accuracy_score(y_test, prediction4)*100
#print('Gaussian Naive Bayes Classifier accuracy: {}%'.format(accuracy_
scores[3]))

# Decision Tree
#decision = DecisionTreeClassifier().fit(X_train, y_train)
#prediction4 = decision.predict(X_test)
#accuracy_scores[3] = accuracy_score(y_test, prediction4)*100
#print('Decision Tree Classifier accuracy: {}%'.format(accuracy_scores
[3]))


# Random Forest
random = RandomForestClassifier().fit(X_train, y_train)
prediction5 = random.predict(X_test)
accuracy_scores[4] = accuracy_score(y_test, prediction5)*100
print('Random Forest Classifier accuracy: {}%'.format(accuracy_scores[4
]))

# Gradient Boosting
GB = GradientBoostingClassifier().fit(X_train, y_train)
prediction6 = GB.predict(X_test)
accuracy_scores[5] = accuracy_score(y_test, prediction6)*100
print('Gradient Boosting Classifier accuracy: {}%'.format(accuracy_scor
es[5]))

#XGBoosting
xgb_model = xgb.XGBClassifier()
xgb_model.fit(X_train, y_train)
prediction7 = xgb_model.predict(X_test)
accuracy_scores[6] = accuracy_score(y_test, prediction7)*100
print('XGBoost Classifier accuracy: {}%'.format(accuracy_scores[6]))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: Fut
ureWarning: The default value of gamma will change from 'auto' to 'scal
```

```
e' in version 0.22 to account better for unscaled features. Set gamma e
xplicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

```
Support Vector Classifier accuracy: 71.74000000000001%
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logisti
c.py:432: FutureWarning: Default solver will be changed to 'lbfgs' in
0.22. Specify a solver to silence this warning.
  FutureWarning)
```

```
Logistic Regression accuracy: 74.19333333333333%
K Nearest Neighbors Classifier accuracy: 66.84833333333333%
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:2
45: FutureWarning: The default value of n_estimators will change from 1
0 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

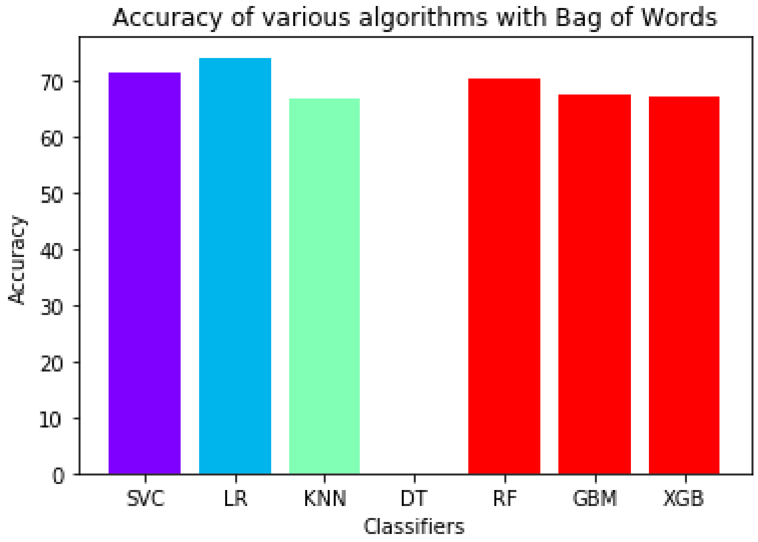
```
Random Forest Classifier accuracy: 70.52000000000001%
Gradient Boosting Classifier accuracy: 67.76333333333334%
XGBoost Classifier accuracy: 67.39666666666668%
```

In [182]:

```
# Accuracy comparison of various algorithms for bag of words
colors = cm.rainbow(np.linspace(0, 2, 9))
labels = ['SVC', 'LR', 'KNN', 'DT', 'RF', 'GBM', 'XGB']
plt.bar(labels,
        accuracy_scores,
        color = colors)
plt.xlabel('Classifiers')
plt.ylabel('Accuracy')
plt.title('Accuracy of various algorithms with Bag of Words')
```

Out[182]:

```
Text(0.5, 1.0, 'Accuracy of various algorithms with Bag of Words')
```



In [183]:

```
# Spliting Data form above reduction dataset for tfidf
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(tfidf, df2['sentime
nt'], test_size = 0.3, random_state = 3)
```

In [184]:

```
# Applying various Classification algorithms without doing variable red
uctions using tfidf
accuracy_scores = np.zeros(7)

# Support Vector Classifier
svm = SVC().fit(X_train, y_train)
prediction1 = svm.predict(X_test)
accuracy_scores[0] = accuracy_score(y_test, prediction1)*100
print('Support Vector Classifier accuracy: {}%'.format(accuracy_scores[
0]))

# Logistic Regression
logis = LogisticRegression().fit(X_train, y_train)
prediction2 = logis.predict(X_test)
accuracy_scores[1] = accuracy_score(y_test, prediction2)*100
print('Logistic Regression accuracy: {}%'.format(accuracy_scores[1]))
```

```
# K Nearest Neighbors
knn = KNeighborsClassifier().fit(X_train, y_train)
prediction3 = knn.predict(X_test)
accuracy_scores[2] = accuracy_score(y_test, prediction3)*100
print('K Nearest Neighbors Classifier accuracy: {}%'.format(accuracy_sc
ores[2]))

# Gaussian Naive Bayes
#clf = GaussianNB().fit(X_train, y_train)
#prediction4 = clf.predict(X_test)
#accuracy_scores[3] = accuracy_score(y_test, prediction4)*100
#print('Gaussian Naive Bayes Classifier accuracy: {}%'.format(accuracy_
scores[3]))

# Decision Tree
#decision = DecisionTreeClassifier().fit(X_train, y_train)
#prediction4 = decision.predict(X_test)
#accuracy_scores[3] = accuracy_score(y_test, prediction4)*100
#print('Decision Tree Classifier accuracy: {}%'.format(accuracy_scores
[3]))


# Random Forest
random = RandomForestClassifier().fit(X_train, y_train)
prediction5 = random.predict(X_test)
accuracy_scores[4] = accuracy_score(y_test, prediction5)*100
print('Random Forest Classifier accuracy: {}%'.format(accuracy_scores[4
]))

# Gradient Boosting
GB = GradientBoostingClassifier().fit(X_train, y_train)
prediction6 = GB.predict(X_test)
accuracy_scores[5] = accuracy_score(y_test, prediction6)*100
print('Gradient Boosting Classifier accuracy: {}%'.format(accuracy_scor
es[5]))

#XGBoosting
xgb_model = xgb.XGBClassifier()
```

```
xgb_model.fit(X_train, y_train)
prediction7 = xgb_model.predict(X_test)
accuracy_scores[6] = accuracy_score(y_test, prediction7)*100
print('XGBoost Classifier accuracy: {}%'.format(accuracy_scores[6]))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\svm\base.py:193: FutureWarning: The default value of gamma will change from 'auto' to 'scale' in version 0.22 to account better for unscaled features. Set gamma e

xplicitly to 'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

```
Support Vector Classifier accuracy: 71.87666666666667%
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:432: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

```
Logistic Regression accuracy: 74.10666666666667%
K Nearest Neighbors Classifier accuracy: 65.68833333333333%
```

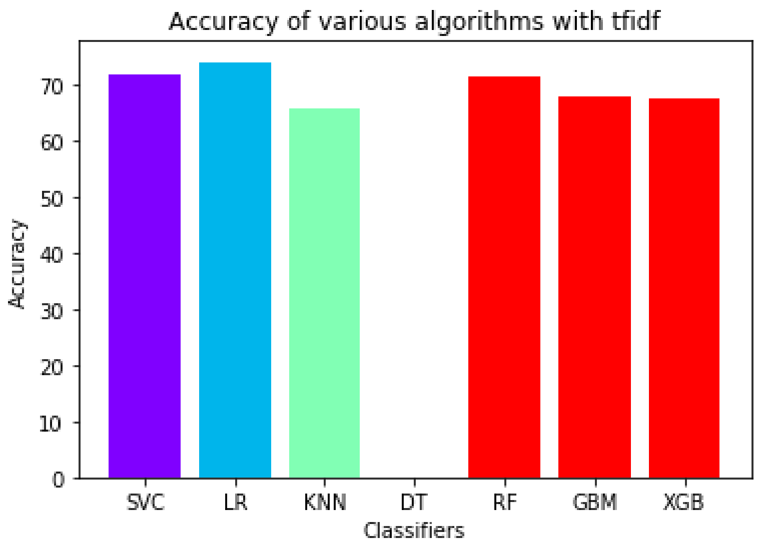
```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
Random Forest Classifier accuracy: 71.51333333333334%
Gradient Boosting Classifier accuracy: 68.06166666666667%
XGBoost Classifier accuracy: 67.42666666666666%
```

In [185]:

```
# Accuracy comparison of various algorithms for bag of words
colors = cm.rainbow(np.linspace(0, 2, 9))
labels = ['SVC', 'LR', 'KNN', 'DT', 'RF', 'GBM', 'XGB']
plt.bar(labels,
        accuracy_scores,
        color = colors)
plt.xlabel('Classifiers')
plt.ylabel('Accuracy')
plt.title('Accuracy of various algorithms with tfidf')
```

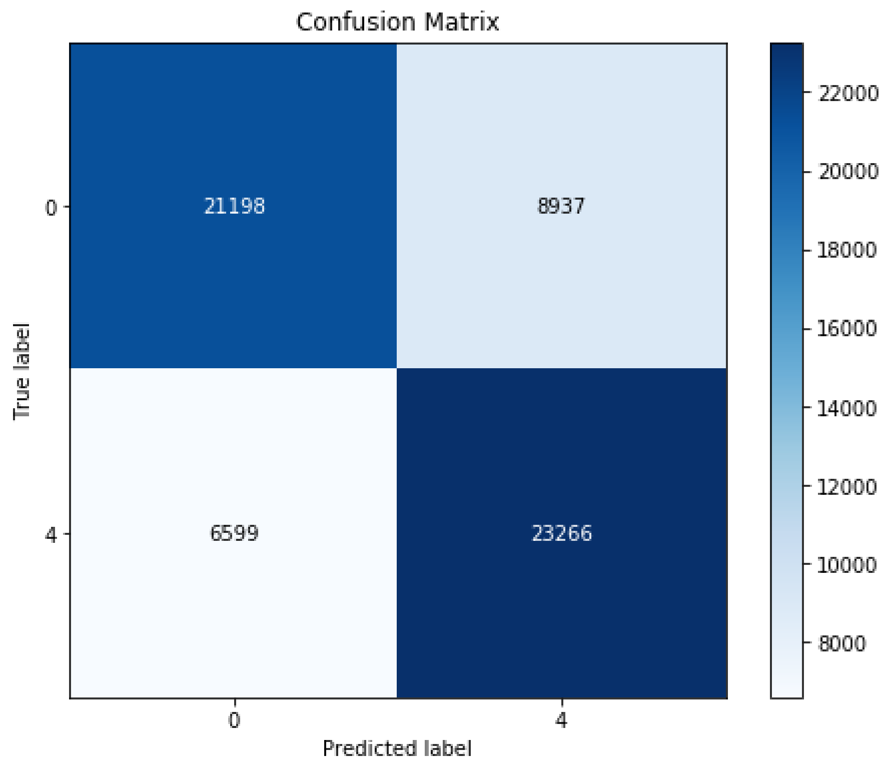
Out[185]: Text(0.5, 1.0, 'Accuracy of various algorithms with tfidf')



In [186]:

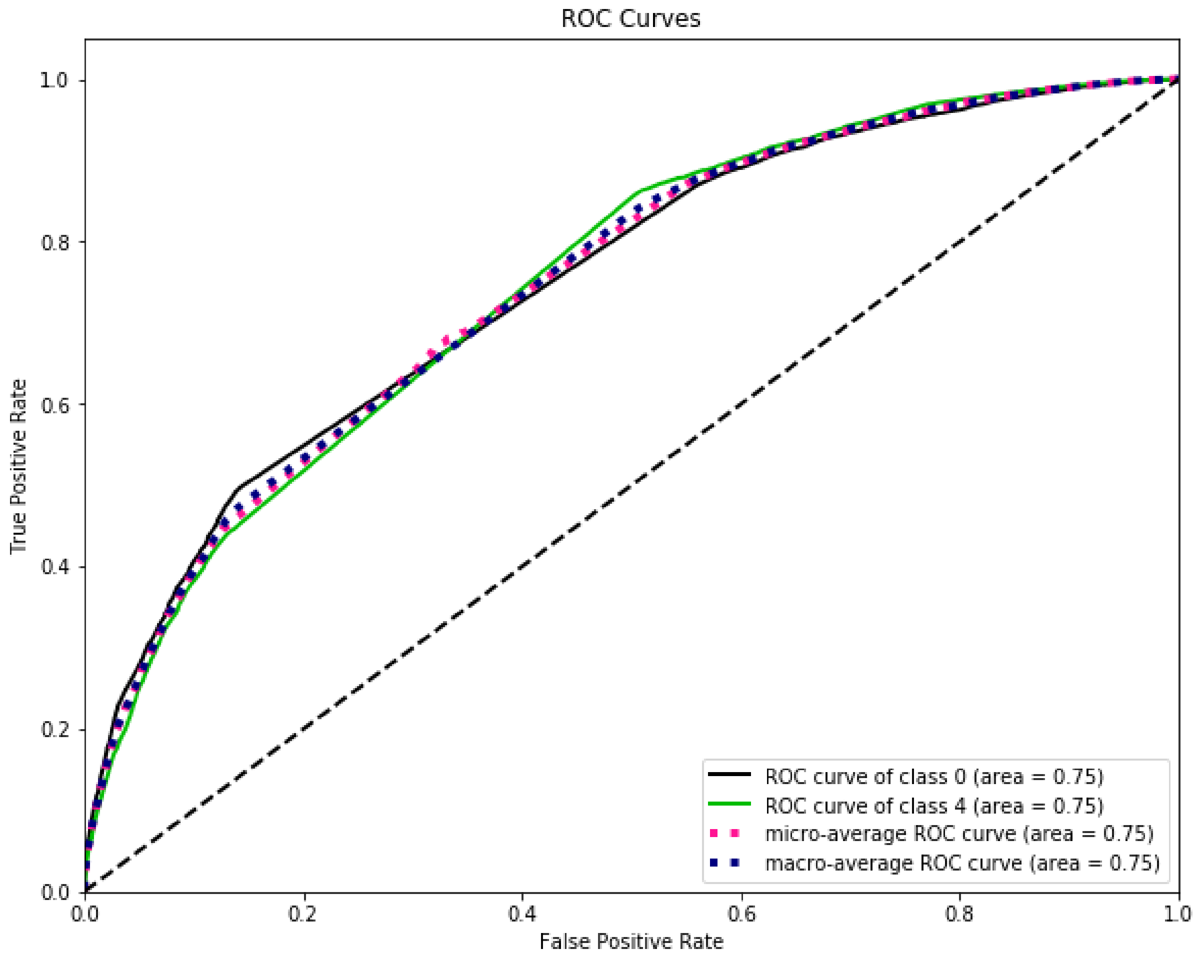
```
# check validation statistics (Classification Summary)
print(classification_report(y_test, prediction2)) # from confusion matr
ix Logistics Regression perform well
# Plot confusion Matrix
skplt.metrics.plot_confusion_matrix(y_test, prediction2, figsize=(8, 6
))
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.76      0.70      0.73     30135
           4       0.72      0.78      0.75     29865

    accuracy                           0.74     60000
   macro avg       0.74      0.74      0.74     60000
weighted avg       0.74      0.74      0.74     60000
```



In [187]:

```
# ROC Curves
y_probas = xgb_model.predict_proba(X_test)
skplt.metrics.plot_roc(y_test, y_probas, figsize=(10, 8)) # Plot ROC Cu
rve
plt.show()
```



Based on the above, for both bag of words and tfidf, it is evident that the top 3 performing models are Logistic Regression, SVC and Random Forest. Between bag of words and tfidf, tfidf performs marginally better. Logistic Regression performs the best, with one of its strengths being good for binary classification models such as this problem. These three models will be used for the Canadian Elections csv and the top performing model for that will be picked for further hyperparameter tuning.

Data Import & Cleaning - Canadian Elections

In [188]:
```
candf2 = pd.read_csv('Canadian_elections_2019.csv')
candf2.head(n=5)
```

Out[188]:

	sentiment	negative_reason	text
0	negative	Women Reproductive right and Racism	b"@RosieBarton So instead of your suggestion, ...
1	positive	NaN	b"#AllWomanSpacewalk it's real!\n@Space_Statio...
2	negative	Economy	b"#Brantford It's going to cost YOU $94 BILLIO...
3	positive	NaN	b"#Canada #CanadaElection2019 #CanadaVotes \n#...
4	negative	Economy	b"#Canada #taxpayers are sick & tired of h...

In [189]:
```
# Data cleaning and pre-process dataset
nltk.download('stopwords')

# TEXT CLENAING
TEXT_CLEANING_RE = "@\S+|https?:\S+|http?:\S|[^A-Za-z0-9]+"
stop_words = stopwords.words("english")
stemmer = SnowballStemmer("english")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\rahma\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

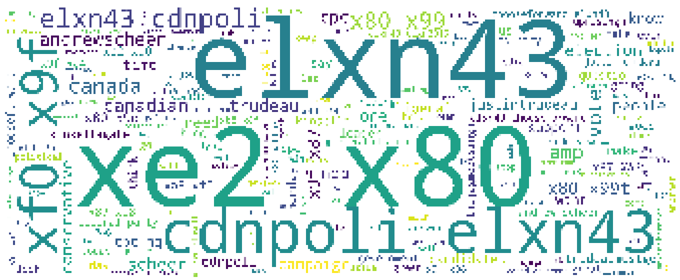
In [190]:
```
def preprocess(text, stem=False):
    # Remove link,user and special characters
    text = re.sub(TEXT_CLEANING_RE, ' ', str(text).lower()).strip()
    tokens = []
    for token in text.split():
        if token not in stop_words:
            if stem:
                tokens.append(stemmer.stem(token))
            else:
```

```
                tokens.append(token)
    return " ".join(tokens)

candf2.text = candf2.text.apply(lambda x: preprocess(x))
```

Exporatory Analysis - Canadian Elections

In [191]:

```
# all tweets
all_words = " ".join(candf2.text)

# Wordcloud of tweets
wordcloud = WordCloud(height=4000, width=10000, stopwords=STOPWORDS, background_color='white')
wordcloud = wordcloud.generate(all_words)
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```



Below, we will attempt to count the number of times there has been a positive tweet about any of the three major parties (NDP, Liberals or Conservatives) as well as negative tweets to determine if we can obtain any insights into the final results

In [192]:

```
print('Number of positive mention for NDP or Jagmeet Singh')
print(candf2[(candf2['text'].str.contains('ndp|singh|jagmeet'))&(candf2['sentiment'] == 'positive')].shape[0])
```

```
Number of positive mention for NDP or Jagmeet Singh
```

161

In [193]:
```
print('Number of positive mention for Liberals or Trudeau')
print(candf2[(candf2['text'].str.contains('liberal|trudeau|justin'))&(candf2['sentiment'] == 'positive')].shape[0])
```

```
Number of positive mention for Liberals or Trudeau
244
```

In [194]:
```
print('Number of positive mention for Conservatives or Andrew Scheer')
print(candf2[(candf2['text'].str.contains('conservative|andrew|scheer'))&(candf2['sentiment'] == 'positive')].shape[0])
```

```
Number of positive mention for Conservatives or Andrew Scheer
192
```

Interestingly, the ratio of positive tweets for Liberals:Conservatives (244:192 = 1.27:1) is very close to the actual ratio of number of seats won between the two during the 2019 Federal Elections (157:121 = 1.3:1). The public opinion on social media correlates incredibly well with the actual results of the election.

In [195]:
```
print('Number of negative mention for NDP or Jagmeet Singh')
print(candf2[(candf2['text'].str.contains('ndp|singh|jagmeet'))&(candf2['sentiment'] == 'negative')].shape[0])
```

```
Number of negative mention for NDP or Jagmeet Singh
100
```

In [196]:
```
print('Number of negative mention for Liberals or Trudeau')
print(candf2[(candf2['text'].str.contains('liberal|trudeau|justin'))&(candf2['sentiment'] == 'negative')].shape[0])
```

```
Number of negative mention for Liberals or Trudeau
292
```

In [197]:
```
print('Number of negative mention for Conservatives or Andrew Scheer')
print(candf2[(candf2['text'].str.contains('conservative|andrew|scheer'
```

```
))&(candf2['sentiment'] == 'negative')].shape[0])
```

```
Number of negative mention for Conservatives or Andrew Scheer
381
```

Interestingly, the ratio of negative tweets between Conservatives/Andrew Scheer and Liberal/Justin Trudeau is also 1.3:1, which is the ratio of seats won by Liberals:Conservatives. The negative public opinions on social media correlates incredibly well with the actual results of the election as well.

Model Preparation - Canadian Elections

In [198]:

```
# Replacing the class value to integer
candf2.sentiment.replace(('positive', 'negative'), (4, 0), inplace=True
)
print(candf2)
```

```
      sentiment                         negative_reason  \
0             0  Women Reproductive right and Racism
1             4                                     NaN
2             0                                 Economy
3             4                                     NaN
4             0                                 Economy
5             0                                  Others
6             4                                     NaN
7             4                                     NaN
8             0                                  Others
9             0                                 Scandal
10            4                                     NaN
11            4                                     NaN
12            4                                     NaN
13            4                                     NaN
14            0                                  Others
15            0                              Tell lies
16            4                                     NaN
17            4                                     NaN
18            4                                     NaN
```

```
19          0                               Scandal
20          0                                Others
21          0                                Others
22          4                                   NaN
23          4                                   NaN
24          0                                Others
25          4                                   NaN
26          0                               Scandal
27          0                                Others
28          4                                   NaN
29          0                             Tell lies
...       ...                                   ...
2103        0                             Tell lies
2104        4                                   NaN
2105        0                             Tell lies
2106        0                               Economy
2107        4                                   NaN
2108        0                             Tell lies
2109        0                                Others
2110        4                                   NaN
2111        4                                   NaN
2112        0                             Tell lies
2113        4                                   NaN
2114        0                                Others
2115        0                               Economy
2116        4                                   NaN
2117        4                                   NaN
2118        0  Women Reproductive right and Racism
2119        0  Women Reproductive right and Racism
2120        4                                   NaN
2121        0                                Others
2122        0                             Tell lies
2123        4                                   NaN
2124        0                             Tell lies
2125        0                                Others
2126        0                       Climate Problem
2127        4                                   NaN
2128        0                               Scandal
2129        0                               Scandal
2130        4                                   NaN
```

```
2131          0  Women Reproductive right and Racism
2132          4                                  NaN

                                                   text
0     b rosiebarton instead suggestion agree canadia...
1     b allwomanspacewalk real n n etobicokenorth ci...
2     b brantford going cost 94 billion next 4 years...
3     b canada canadaelection2019 canadavotes n elxn...
4     b canada taxpayers sick amp tired hard earned ...
5     b canadavotes2019 elxn43 cdnpoli facts blastfr...
6     b cdnmedia elxn43 cdnpoli ppc rocky dong hands...
7     b cdnpoli elxn43 liberals double promised 2015...
8     b chooseforward cdnpoli elxn43 ncanada make am...
9     b cpckinsellagate nlet see receipts pays warre...
10    b elxn43 two days away voting e day read prime...
11    b elxn43 prediction justin trudeau lpc loses m...
12    b icymi analysis ford nation respond renata fo...
13    b icymi analysis ford nation respond renata fo...
14    b kinsella runs deep w cpc lyingandy crazed an...
15    b lyingandy history answering embarrassing que...
16    b threadalert nhere study sheet unfit candidat...
17    b uprisingh definitely looking forward asian p...
18    b uptoyouth cdnpoli elxn43 today youth smart s...
19    b urgent please watch video david haskell peop...
20    b policy comment illegal immoral nefarious act...
21    b andrewscheer fit hold public office let alon...
22    b yorkuhealth prof mary wiktorowicz weighs hea...
23    b 222minutes part leftist justinjournos virtue...
24    b alan poirier alberta saskatchewan ontario pr...
25    b alanthomasdoyle hi alan wondering could put ...
26    b alternatespunky electionscan e electionson c...
27    b althiaraj justintrudeau justintrudeau using ...
28    b althiaraj justintrudeau well yeah jam n nask...
29    b althiaraj ask questions hypotheticals n cdnp...
...                                                 ...
2103  b wow lot bigger lying insurance broker folks ...
2104  b wow supposed quick whistle stop turned hundr...
2105  b wowsers nlooks like cbc globe relied liberal...
2106  b wrong n nyou xe2 x80 x99re one using alberta...
```

```
2107  b wrote intro piece us readers via thenation n...
2108  b yay cbckatie nice see pushback lies attempts...
2109  b yes want affordable future justintrudeau can...
2110  b yes ready xf0 x9f xa7 xa1 xf0 x9f xa7 xa1 el...
2111  b yes us think votendp like many like minded p...
2112            b yes andrewscheer story elxn43 cdnpoli
2113  b yes free tuition key plank platform cant kee...
2114  b yes doubt busy schedule last minute liberal ...
2115  b yes liberals xe2 x80 x99t get majority ndp a...
2116  b yes xe2 x80 x99s endorsement n nbut importan...
2117  b yes encouraged one another cast ballots poll...
2118  b yet andrew scheer maintains expects us belie...
2119  b yet another example constant danger conserva...
2120  b absolutely correct priya canadian media unfa...
2121  b sort betraying memory fought freedom cdnpoli...
2122  b always tell person good campaigning stupid s...
2123  b miltonon make cancer sexy lady lraitt embarr...
2124  b vote dishonest slandering politicians always...
2125  b xe2 x80 x99t supervillain election failed jo...
2126  b care limiting climatechange wondering party ...
2127  b heard first head figure aligns best values v...
2128  b know good enough job smearing campaign right...
2129  b missed comment deflecting issue answer best ...
2130  b daily reminder n endorses strategic voting n...
2131  b yup going reopen abortion debate xf0 x9f x98...
2132                                b zing n ndp elxn43

[2133 rows x 3 columns]
```

In [199]:

```
# tokenize all the cleaned tweets in our dataset. Tokens are individual
 terms or words,
# and tokenization is the process of splitting a string of text into to
kens
tokenized_tweet = candf2['text'].apply(lambda x: x.split())
tokenized_tweet.head()
```

Out[199]:

```
0    [b, rosiebarton, instead, suggestion, agree, c...
1    [b, allwomanspacewalk, real, n, n, etobicokeno...
2    [b, brantford, going, cost, 94, billion, next,...
```

```
3    [b, canada, canadaelection2019, canadavotes, n...
4    [b, canada, taxpayers, sick, amp, tired, hard,...
Name: text, dtype: object
```

In [200]:

```
# Stemming is a rule-based process of stripping the suffixes (“ing”, “l
y”, “es”, “s” etc) from a word
from nltk.stem.porter import *
stemmer = PorterStemmer()

tokenized_tweet = tokenized_tweet.apply(lambda x: [stemmer.stem(i) for
i in x]) # stemming
tokenized_tweet.head()
```

Out[200]:

```
0    [b, rosiebarton, instead, suggest, agre, canad...
1    [b, allwomanspacewalk, real, n, n, etobicokeno...
2    [b, brantford, go, cost, 94, billion, next, 4,...
3    [b, canada, canadaelection2019, canadavot, n, ...
4    [b, canada, taxpay, sick, amp, tire, hard, ear...
Name: text, dtype: object
```

In [201]:

```
# let’s stitch these tokens back together
for i in range(len(tokenized_tweet)):
    tokenized_tweet[i] = ' '.join(tokenized_tweet[i])

candf2['text'] = tokenized_tweet
print(candf2)
```

```
      sentiment                      negative_reason  \
0             0  Women Reproductive right and Racism
1             4                                  NaN
2             0                              Economy
3             4                                  NaN
4             0                              Economy
5             0                               Others
6             4                                  NaN
7             4                                  NaN
8             0                               Others
9             0                              Scandal
```

```
10      4                                 NaN
11      4                                 NaN
12      4                                 NaN
13      4                                 NaN
14      0                              Others
15      0                           Tell lies
16      4                                 NaN
17      4                                 NaN
18      4                                 NaN
19      0                             Scandal
20      0                              Others
21      0                              Others
22      4                                 NaN
23      4                                 NaN
24      0                              Others
25      4                                 NaN
26      0                             Scandal
27      0                              Others
28      4                                 NaN
29      0                           Tell lies
...   ...                                 ...
2103    0                           Tell lies
2104    4                                 NaN
2105    0                           Tell lies
2106    0                             Economy
2107    4                                 NaN
2108    0                           Tell lies
2109    0                              Others
2110    4                                 NaN
2111    4                                 NaN
2112    0                           Tell lies
2113    4                                 NaN
2114    0                              Others
2115    0                             Economy
2116    4                                 NaN
2117    4                                 NaN
2118    0  Women Reproductive right and Racism
2119    0  Women Reproductive right and Racism
2120    4                                 NaN
```

```
2121         0                              Others
2122         0                           Tell lies
2123         4                                 NaN
2124         0                           Tell lies
2125         0                              Others
2126         0                     Climate Problem
2127         4                                 NaN
2128         0                             Scandal
2129         0                             Scandal
2130         4                                 NaN
2131         0  Women Reproductive right and Racism
2132         4                                 NaN

                                                   text
0     b rosiebarton instead suggest agre canadian wo...
1     b allwomanspacewalk real n n etobicokenorth ci...
2     b brantford go cost 94 billion next 4 year ask...
3     b canada canadaelection2019 canadavot n elxn43...
4     b canada taxpay sick amp tire hard earn donat ...
5     b canadavotes2019 elxn43 cdnpoli fact blastfro...
6     b cdnmedia elxn43 cdnpoli ppc rocki dong hand ...
7     b cdnpoli elxn43 liber doubl promis 2015 natio...
8     b chooseforward cdnpoli elxn43 ncanada make am...
9     b cpckinsellag nlet see receipt pay warren kin...
10    b elxn43 two day away vote e day read primer l...
11    b elxn43 predict justin trudeau lpc lose monda...
12    b icymi analysi ford nation respond renata for...
13    b icymi analysi ford nation respond renata for...
14    b kinsella run deep w cpc lyingandi craze anti...
15    b lyingandi histori answer embarrass question ...
16    b threadalert nhere studi sheet unfit candid n...
17    b uprisingh definit look forward asian paramil...
18    b uptoyouth cdnpoli elxn43 today youth smart s...
19    b urgent pleas watch video david haskel peopl ...
20    b polici comment illeg immor nefari activ cpc ...
21    b andrewsch fit hold public offic let alon pm ...
22    b yorkuhealth prof mari wiktorowicz weigh heal...
23    b 222minut part leftist justinjourno virtu sig...
24    b alan poirier alberta saskatchewan ontario pr...
```

```
25    b alanthomasdoyl hi alan wonder could put quic...
26    b alternatespunki electionscan e electionson c...
27    b althiaraj justintrudeau justintrudeau use 5 ...
28    b althiaraj justintrudeau well yeah jam n nask...
29    b althiaraj ask question hypothet n cdnpoli el...
...                                                 ...
2103  b wow lot bigger lie insur broker folk elxn201...
2104  b wow suppos quick whistl stop turn hundr show...
2105  b wowser nlook like cbc globe reli liber oper ...
2106  b wrong n nyou xe2 x80 x99re one use alberta p...
2107  b wrote intro piec us reader via thenat nabout...
2108  b yay cbckati nice see pushback lie attempt an...
2109  b ye want afford futur justintrudeau canada be...
2110  b ye readi xf0 x9f xa7 xa1 xf0 x9f xa7 xa1 elx...
2111  b ye us think votendp like mani like mind peop...
2112              b ye andrewsch stori elxn43 cdnpoli
2113  b ye free tuition key plank platform cant keep...
2114  b ye doubt busi schedul last minut liber troll...
2115  b ye liber xe2 x80 x99t get major ndp ask pipe...
2116  b ye xe2 x80 x99 endors n nbut import thing ex...
2117  b ye encourag one anoth cast ballot poll close...
2118  b yet andrew scheer maintain expect us believ ...
2119  b yet anoth exampl constant danger conserv pos...
2120  b absolut correct priya canadian media unfairl...
2121  b sort betray memori fought freedom cdnpoli el...
2122  b alway tell person good campaign stupid state...
2123  b miltonon make cancer sexi ladi lraitt embarr...
2124  b vote dishonest slander politician alway choo...
2125  b xe2 x80 x99t supervillain elect fail job n n...
2126  b care limit climatechang wonder parti vote el...
2127  b heard first head figur align best valu vote ...
2128  b know good enough job smear campaign right an...
2129  b miss comment deflect issu answer best respon...
2130  b daili remind n endors strateg vote n elxn43 ...
2131  b yup go reopen abort debat xf0 x9f x98 x8f n ...
2132                              b zing n ndp elxn43

[2133 rows x 3 columns]
```

In [202]:

```
# Bag-of-Words features can be easily created using sklearn’s CountVect
orizer function.
# We will set the parameter max_features = 1000 to select only top 1000
 terms ordered by term frequency across the corpus
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer = CountVectorizer(max_df=0.90, min_df=2, max_features=10
00, stop_words='english')
# bag-of-words feature matrix
bow = bow_vectorizer.fit_transform(candf2['text'])
print(bow)
```

```
  (0, 18)	1
  (0, 107)	1
  (0, 131)	1
  (0, 453)	1
  (0, 723)	1
  (0, 918)	1
  (0, 664)	1
  (0, 348)	1
  (0, 176)	1
  (0, 56)	1
  (0, 867)	1
  (0, 919)	1
  (0, 111)	1
  (0, 40)	1
  (0, 812)	1
  (0, 408)	1
  (0, 725)	1
  (1, 591)	1
  (1, 691)	1
  (1, 131)	1
  (2, 428)	1
  (2, 66)	1
  (2, 992)	1
  (2, 87)	1
  (2, 188)	1
  :	:
  (2129, 390)	1
  (2129, 59)	1
  (2129, 194)	1
```

```
  (2129, 83)    1
  (2129, 109)   1
  (2129, 66)    1
  (2129, 131)   1
  (2130, 350)   1
  (2130, 801)   1
  (2130, 269)   1
  (2130, 706)   1
  (2130, 266)   1
  (2130, 479)   1
  (2130, 892)   1
  (2130, 538)   1
  (2130, 131)   1
  (2131, 214)   1
  (2131, 951)   1
  (2131, 736)   1
  (2131, 735)   1
  (2131, 944)   1
  (2131, 963)   1
  (2131, 988)   1
  (2131, 18)    1
  (2132, 538)   1
```

In [203]:

```
# TF-IDF works by penalizing the common words by assigning them lower w
eights while giving
# importance to words which are rare in the entire corpus but appear in
 good numbers
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(max_df=0.90, min_df=2, max_features=
1000, stop_words='english')
# TF-IDF feature matrix
tfidf = tfidf_vectorizer.fit_transform(candf2['text'])
```

As we saw from the Genric Tweets analysis, TFIDF performed marginally better than Bag of Words. Therefore, in the interest of processing time, TFIDF will be used for Canadian Elections.

In [204]:

```
# Spliting Data form above reduction dataset
```

```
from sklearn.model_selection import train_test_split
X_train, X_valid, y_train, y_valid = train_test_split(tfidf, candf2['se
ntiment'], test_size = 0.3, random_state = 3)
```

Model Implementation & Results - Canadian Elections

In [205]:

```
#predicting various Classification algorithms
accuracy_scores = np.zeros(3)

# Support Vector Classifier
prediction_svm = svm.predict(X_valid)
accuracy_scores[0] = accuracy_score(y_valid, prediction_svm)*100
print('Support Vector Classifier accuracy: {}%'.format(accuracy_scores[
0]))

# Logistic Regression
prediction_logit = logis.predict(X_valid)
accuracy_scores[1] = accuracy_score(y_valid, prediction_logit)*100
print('Logistic Regression accuracy: {}%'.format(accuracy_scores[1]))

# Random Forest
prediction_random = random.predict(X_valid)
accuracy_scores[2] = accuracy_score(y_valid, prediction_random)*100
print('Random Forest Classifier accuracy: {}%'.format(accuracy_scores[2
]))
```

```
Support Vector Classifier accuracy: 52.03124999999999%
Logistic Regression accuracy: 48.90625%
Random Forest Classifier accuracy: 50.46874999999999%
```

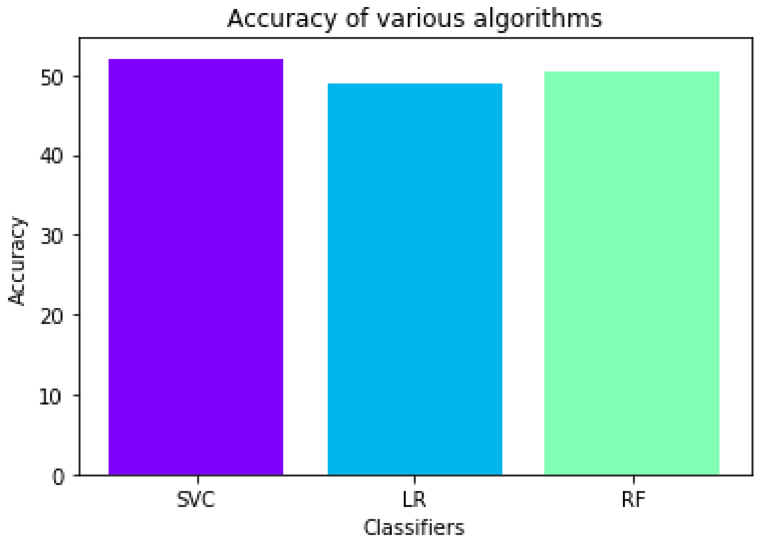
Similar to the Generic Tweets file, Logistic Regrssion appears to perform slightly better for Canadian Elections as well. This model will be selected going forward for further hyperparameter tuning in order to improve the accuracy.

In [206]:

```
# Accuracy comparison of various algorithms
colors = cm.rainbow(np.linspace(0, 2, 9))
```

```
labels = ['SVC', 'LR', 'RF']
plt.bar(labels,
        accuracy_scores,
        color = colors)
plt.xlabel('Classifiers')
plt.ylabel('Accuracy')
plt.title('Accuracy of various algorithms')
```

Out[206]:
```
Text(0.5, 1.0, 'Accuracy of various algorithms')
```



In [207]:
```
#SVC hyperparameter tuning
param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
              'kernel': ['rbf']}

grid = GridSearchCV(SVC(), param_grid, refit = True, verbose = 3)

# fitting the model for grid search
grid.fit(X_train, y_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_spl
it.py:1978: FutureWarning: The default value of cv will change from 3 t
```

```
o 5 in version 0.22. Specify it explicitly to silence this warning.
  warnings.warn(CV_WARNING, FutureWarning)
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent
workers.
```

```
Fitting 3 folds for each of 25 candidates, totalling 75 fits
[CV] C=0.1, gamma=1, kernel=rbf ......................................
[CV] .......... C=0.1, gamma=1, kernel=rbf, score=0.524, total=   0.2s
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s remaining:
    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.2s remaining:
    0.0s
```

```
[CV] C=0.1, gamma=1, kernel=rbf ......................................
[CV] .......... C=0.1, gamma=1, kernel=rbf, score=0.524, total=   0.2s
[CV] C=0.1, gamma=1, kernel=rbf ......................................
[CV] .......... C=0.1, gamma=1, kernel=rbf, score=0.523, total=   0.2s
[CV] C=0.1, gamma=0.1, kernel=rbf ....................................
[CV] ........ C=0.1, gamma=0.1, kernel=rbf, score=0.524, total=   0.2s
[CV] C=0.1, gamma=0.1, kernel=rbf ....................................
[CV] ........ C=0.1, gamma=0.1, kernel=rbf, score=0.524, total=   0.2s
[CV] C=0.1, gamma=0.1, kernel=rbf ....................................
[CV] ........ C=0.1, gamma=0.1, kernel=rbf, score=0.523, total=   0.2s
[CV] C=0.1, gamma=0.01, kernel=rbf ...................................
[CV] ....... C=0.1, gamma=0.01, kernel=rbf, score=0.524, total=   0.2s
[CV] C=0.1, gamma=0.01, kernel=rbf ...................................
[CV] ....... C=0.1, gamma=0.01, kernel=rbf, score=0.524, total=   0.2s
[CV] C=0.1, gamma=0.01, kernel=rbf ...................................
[CV] ....... C=0.1, gamma=0.01, kernel=rbf, score=0.523, total=   0.2s
[CV] C=0.1, gamma=0.001, kernel=rbf ..................................
[CV] ...... C=0.1, gamma=0.001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=0.1, gamma=0.001, kernel=rbf ..................................
[CV] ...... C=0.1, gamma=0.001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=0.1, gamma=0.001, kernel=rbf ..................................
[CV] ...... C=0.1, gamma=0.001, kernel=rbf, score=0.523, total=   0.2s
[CV] C=0.1, gamma=0.0001, kernel=rbf .................................
[CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=0.1, gamma=0.0001, kernel=rbf .................................
[CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.524, total=   0.3s
```

```
[CV] C=0.1, gamma=0.0001, kernel=rbf ................................
[CV] ..... C=0.1, gamma=0.0001, kernel=rbf, score=0.523, total=   0.2s
[CV] C=1, gamma=1, kernel=rbf ........................................
[CV] ........... C=1, gamma=1, kernel=rbf, score=0.663, total=   0.3s
[CV] C=1, gamma=1, kernel=rbf ........................................
[CV] ........... C=1, gamma=1, kernel=rbf, score=0.695, total=   0.3s
[CV] C=1, gamma=1, kernel=rbf ........................................
[CV] ........... C=1, gamma=1, kernel=rbf, score=0.684, total=   0.2s
[CV] C=1, gamma=0.1, kernel=rbf ......................................
[CV] .......... C=1, gamma=0.1, kernel=rbf, score=0.637, total=   0.3s
[CV] C=1, gamma=0.1, kernel=rbf ......................................
[CV] .......... C=1, gamma=0.1, kernel=rbf, score=0.629, total=   0.3s
[CV] C=1, gamma=0.1, kernel=rbf ......................................
[CV] .......... C=1, gamma=0.1, kernel=rbf, score=0.644, total=   0.3s
[CV] C=1, gamma=0.01, kernel=rbf .....................................
[CV] ......... C=1, gamma=0.01, kernel=rbf, score=0.524, total=   0.2s
[CV] C=1, gamma=0.01, kernel=rbf .....................................
[CV] ......... C=1, gamma=0.01, kernel=rbf, score=0.524, total=   0.2s
[CV] C=1, gamma=0.01, kernel=rbf .....................................
[CV] ......... C=1, gamma=0.01, kernel=rbf, score=0.523, total=   0.2s
[CV] C=1, gamma=0.001, kernel=rbf ....................................
[CV] ........ C=1, gamma=0.001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=1, gamma=0.001, kernel=rbf ....................................
[CV] ........ C=1, gamma=0.001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=1, gamma=0.001, kernel=rbf ....................................
[CV] ........ C=1, gamma=0.001, kernel=rbf, score=0.523, total=   0.2s
[CV] C=1, gamma=0.0001, kernel=rbf ...................................
[CV] ....... C=1, gamma=0.0001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=1, gamma=0.0001, kernel=rbf ...................................
[CV] ....... C=1, gamma=0.0001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=1, gamma=0.0001, kernel=rbf ...................................
[CV] ....... C=1, gamma=0.0001, kernel=rbf, score=0.523, total=   0.2s
[CV] C=10, gamma=1, kernel=rbf .......................................
[CV] .......... C=10, gamma=1, kernel=rbf, score=0.667, total=   0.2s
[CV] C=10, gamma=1, kernel=rbf .......................................
[CV] .......... C=10, gamma=1, kernel=rbf, score=0.663, total=   0.2s
[CV] C=10, gamma=1, kernel=rbf .......................................
[CV] .......... C=10, gamma=1, kernel=rbf, score=0.684, total=   0.2s
[CV] C=10, gamma=0.1, kernel=rbf .....................................
```

```
[CV] ......... C=10, gamma=0.1, kernel=rbf, score=0.653, total=   0.1s
[CV] C=10, gamma=0.1, kernel=rbf .....................................
[CV] ......... C=10, gamma=0.1, kernel=rbf, score=0.663, total=   0.2s
[CV] C=10, gamma=0.1, kernel=rbf .....................................
[CV] ......... C=10, gamma=0.1, kernel=rbf, score=0.668, total=   0.2s
[CV] C=10, gamma=0.01, kernel=rbf ....................................
[CV] ........ C=10, gamma=0.01, kernel=rbf, score=0.647, total=   0.2s
[CV] C=10, gamma=0.01, kernel=rbf ....................................
[CV] ........ C=10, gamma=0.01, kernel=rbf, score=0.639, total=   0.2s
[CV] C=10, gamma=0.01, kernel=rbf ....................................
[CV] ........ C=10, gamma=0.01, kernel=rbf, score=0.662, total=   0.2s
[CV] C=10, gamma=0.001, kernel=rbf ...................................
[CV] ....... C=10, gamma=0.001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=10, gamma=0.001, kernel=rbf ...................................
[CV] ....... C=10, gamma=0.001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=10, gamma=0.001, kernel=rbf ...................................
[CV] ....... C=10, gamma=0.001, kernel=rbf, score=0.523, total=   0.2s
[CV] C=10, gamma=0.0001, kernel=rbf ..................................
[CV] ...... C=10, gamma=0.0001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=10, gamma=0.0001, kernel=rbf ..................................
[CV] ...... C=10, gamma=0.0001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=10, gamma=0.0001, kernel=rbf ..................................
[CV] ...... C=10, gamma=0.0001, kernel=rbf, score=0.523, total=   0.2s
[CV] C=100, gamma=1, kernel=rbf ......................................
[CV] .......... C=100, gamma=1, kernel=rbf, score=0.671, total=   0.2s
[CV] C=100, gamma=1, kernel=rbf ......................................
[CV] .......... C=100, gamma=1, kernel=rbf, score=0.663, total=   0.2s
[CV] C=100, gamma=1, kernel=rbf ......................................
[CV] .......... C=100, gamma=1, kernel=rbf, score=0.684, total=   0.2s
[CV] C=100, gamma=0.1, kernel=rbf ....................................
[CV] ........ C=100, gamma=0.1, kernel=rbf, score=0.631, total=   0.2s
[CV] C=100, gamma=0.1, kernel=rbf ....................................
[CV] ........ C=100, gamma=0.1, kernel=rbf, score=0.620, total=   0.2s
[CV] C=100, gamma=0.1, kernel=rbf ....................................
[CV] ........ C=100, gamma=0.1, kernel=rbf, score=0.662, total=   0.2s
[CV] C=100, gamma=0.01, kernel=rbf ...................................
[CV] ....... C=100, gamma=0.01, kernel=rbf, score=0.663, total=   0.1s
[CV] C=100, gamma=0.01, kernel=rbf ...................................
[CV] ....... C=100, gamma=0.01, kernel=rbf, score=0.661, total=   0.1s
```

```
[CV] C=100, gamma=0.01, kernel=rbf ...................................
[CV] ....... C=100, gamma=0.01, kernel=rbf, score=0.660, total=   0.1s
[CV] C=100, gamma=0.001, kernel=rbf ..................................
[CV] ...... C=100, gamma=0.001, kernel=rbf, score=0.645, total=   0.2s
[CV] C=100, gamma=0.001, kernel=rbf ..................................
[CV] ...... C=100, gamma=0.001, kernel=rbf, score=0.647, total=   0.2s
[CV] C=100, gamma=0.001, kernel=rbf ..................................
[CV] ...... C=100, gamma=0.001, kernel=rbf, score=0.662, total=   0.2s
[CV] C=100, gamma=0.0001, kernel=rbf .................................
[CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=100, gamma=0.0001, kernel=rbf .................................
[CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.524, total=   0.2s
[CV] C=100, gamma=0.0001, kernel=rbf .................................
[CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.523, total=   0.2s
[CV] C=1000, gamma=1, kernel=rbf .....................................
[CV] ......... C=1000, gamma=1, kernel=rbf, score=0.671, total=   0.2s
[CV] C=1000, gamma=1, kernel=rbf .....................................
[CV] ......... C=1000, gamma=1, kernel=rbf, score=0.663, total=   0.2s
[CV] C=1000, gamma=1, kernel=rbf .....................................
[CV] ......... C=1000, gamma=1, kernel=rbf, score=0.684, total=   0.2s
[CV] C=1000, gamma=0.1, kernel=rbf ...................................
[CV] ....... C=1000, gamma=0.1, kernel=rbf, score=0.629, total=   0.2s
[CV] C=1000, gamma=0.1, kernel=rbf ...................................
[CV] ....... C=1000, gamma=0.1, kernel=rbf, score=0.631, total=   0.2s
[CV] C=1000, gamma=0.1, kernel=rbf ...................................
[CV] ....... C=1000, gamma=0.1, kernel=rbf, score=0.668, total=   0.2s
[CV] C=1000, gamma=0.01, kernel=rbf ..................................
[CV] ...... C=1000, gamma=0.01, kernel=rbf, score=0.635, total=   0.2s
[CV] C=1000, gamma=0.01, kernel=rbf ..................................
[CV] ...... C=1000, gamma=0.01, kernel=rbf, score=0.614, total=   0.2s
[CV] C=1000, gamma=0.01, kernel=rbf ..................................
[CV] ...... C=1000, gamma=0.01, kernel=rbf, score=0.658, total=   0.2s
[CV] C=1000, gamma=0.001, kernel=rbf .................................
[CV] ..... C=1000, gamma=0.001, kernel=rbf, score=0.663, total=   0.1s
[CV] C=1000, gamma=0.001, kernel=rbf .................................
[CV] ..... C=1000, gamma=0.001, kernel=rbf, score=0.659, total=   0.1s
[CV] C=1000, gamma=0.001, kernel=rbf .................................
[CV] ..... C=1000, gamma=0.001, kernel=rbf, score=0.658, total=   0.1s
[CV] C=1000, gamma=0.0001, kernel=rbf ................................
```

```
[CV] .... C=1000, gamma=0.0001, kernel=rbf, score=0.645, total=   0.2s
[CV] C=1000, gamma=0.0001, kernel=rbf ...............................
[CV] .... C=1000, gamma=0.0001, kernel=rbf, score=0.649, total=   0.2s
[CV] C=1000, gamma=0.0001, kernel=rbf ...............................
[CV] .... C=1000, gamma=0.0001, kernel=rbf, score=0.664, total=   0.2s
```

```
[Parallel(n_jobs=1)]: Done  75 out of  75 | elapsed:   13.7s finished
```

Out[207]:
```
GridSearchCV(cv='warn', error_score='raise-deprecating',
             estimator=SVC(C=1.0, cache_size=200, class_weight=None, co
ef0=0.0,
                           decision_function_shape='ovr', degree=3,
                           gamma='auto_deprecated', kernel='rbf', max_i
ter=-1,
                           probability=False, random_state=None, shrink
ing=True,
                           tol=0.001, verbose=False),
             iid='warn', n_jobs=None,
             param_grid={'C': [0.1, 1, 10, 100, 1000],
                         'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
                         'kernel': ['rbf']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fa
lse,
             scoring=None, verbose=3)
```

In [208]:
```
print(grid.best_params_)
```

```
{'C': 1, 'gamma': 1, 'kernel': 'rbf'}
```

The tuned hyperparameters for SVC is pretty much its default values. Hence, lets explore Logistic Regression instead for hyperparameter tuning and evaluate if there is an imporvement in accuracy.

In [209]:
```
# taking logistic regression as the final model (stable and higher accu
racy)
dual=[True,False]
max_iter=[100,110,120,130,140]
```

```
C = [1.0,1.5,2.0,2.5]
param_grid = dict(dual=dual,max_iter=max_iter,C=C)
```

In [210]:
```
#Logsitic Regression hyperparameter tuning
from sklearn.model_selection import GridSearchCV
lr = LogisticRegression(penalty='l2')
grid = GridSearchCV(estimator=lr, param_grid=param_grid, cv = 3, n_jobs
=-1)
#Model after tuning
grid_result = grid.fit(X_train, y_train)
# Summarize results
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_
params_))
```

```
Best: 0.687207 using {'C': 1.0, 'dual': True, 'max_iter': 100}
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logisti
c.py:432: FutureWarning: Default solver will be changed to 'lbfgs' in
0.22. Specify a solver to silence this warning.
  FutureWarning)
```

In [211]:
```
# Logistic Regression accuracy after hypertuning
prediction_logit_new = grid_result.predict(X_valid)
accuracy_scores_logit_new = accuracy_score(y_valid, prediction_logit_ne
w)*100
print('Logistic Regression accuracy after hyperparameter tuning: {}%'.f
ormat(accuracy_scores_logit_new))
```

```
Logistic Regression accuracy after hyperparameter tuning: 73.90625%
```

In the datasets used in this exercise, the sentiments were binary i.e. either positive or negative. Often times, the sentiment obtained from the tweet is more of a fact than a clear binary choice between positive and negative. In such cases, the sentiment of the tweet assigned is entirely subjective upon the human assigning the sentiment class. For sentiment analysis cases with continuous variables assigned to each sentiment (happiness, sadness, anger, etc.), the mixture of sentiment (i.e. emotion) is much better relayed than a clear binary assignment of a human's emotion, such as in this case. Therefore, a discrete classification of sentiment comes with its own pitfalls. Therefore, doing a continuous variable sentiment analysis is preferred over discrete binary assignment.

For predicting the class of negative_reasons, oftentimes the reason itself can be a combination of two different reasons. For example, some of the negative sentiments are a combination of "Economy" and "Tell Lies" where the tweet states lies or incorrect statements made by the political party with respect to the economy. Similar cases exist for other pair of negative_reasons as well. Therefore, the assignment of classes in this case as well might not be totally representative of the actual negative_reason if there are multiple reasons. One of the suggestions would be re-classifying these negative_reasons with the options of adding a secondary reason to it as well. This will, however, increase the number of target variable classes.

Classification of Negative Reasons

In [243]:
```
candf3 = candf2.dropna(axis=0, subset=['negative_reason'])
candf3.head()
```

Out[243]:

	sentiment	negative_reason	text
0	0	Women Reproductive right and Racism	b rosiebarton instead suggest agre canadian wo...
2	0	Economy	b brantford go cost 94 billion next 4 year ask...
4	0	Economy	b canada taxpay sick amp tire hard earn donat ...
5	0	Others	b canadavotes2019 elxn43 cdnpoli fact blastfro...
8	0	Others	b chooseforward cdnpoli elxn43 ncanada make am...

In [244]:
```
# Data cleaning and pre-process dataset
nltk.download('stopwords')

# TEXT CLENAING
TEXT_CLEANING_RE = "@\S+|https?:\S+|http?:\S|[^A-Za-z0-9]+"
stop_words = stopwords.words("english")
stemmer = SnowballStemmer("english")
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\rahma\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [245]:

```
def preprocess(text, stem=False):
    # Remove link,user and special characters
    text = re.sub(TEXT_CLEANING_RE, ' ', str(text).lower()).strip()
    tokens = []
    for token in text.split():
        if token not in stop_words:
            if stem:
                tokens.append(stemmer.stem(token))
            else:
                tokens.append(token)
    return " ".join(tokens)

candf3.text = candf3.text.apply(lambda x: preprocess(x))
candf3
```

```
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\generic.py:5096:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  self[name] = value
```

Out[245]:

	sentiment	negative_reason	text
0	0	Women Reproductive right and Racism	b rosiebarton instead suggest agre canadian wo...
2	0	Economy	b brantford go cost 94 billion next 4 year ask...
4	0	Economy	b canada taxpay sick amp tire hard earn donat ...
5	0	Others	b canadavotes2019 elxn43 cdnpoli fact blastfro...
8	0	Others	b chooseforward cdnpoli elxn43 ncanada make am...

	sentiment	negative_reason	text
9	0	Scandal	b cpckinsellag nlet see receipt pay warren kin...
14	0	Others	b kinsella run deep w cpc lyingandi craze anti...
15	0	Tell lies	b lyingandi histori answer embarrass question ...
19	0	Scandal	b urgent pleas watch video david haskel peopl ...
20	0	Others	b polici comment illeg immor nefari activ cpc ...
21	0	Others	b andrewsch fit hold public offic let alon pm ...
24	0	Others	b alan poirier alberta saskatchewan ontario pr...
26	0	Scandal	b alternatespunki electionscan e electionson c...
27	0	Others	b althiaraj justintrudeau justintrudeau use 5 ...
29	0	Tell lies	b althiaraj ask question hypothet n cdnpoli el...
30	0	Scandal	b althiaraj surpris n justintrudeau answer q y...
33	0	Scandal	b andrewsch warren jwr yell us new stori invol...
34	0	Privilege	b andrewsch life also gotten expens republican...
35	0	Others	b anthonyromo17 phil rack peterdiane01 andrews...
36	0	Others	b artonfurnitur fender bender make bc suprem c...
37	0	Scandal	b asestritsyn yvan baker justintrudeau liber p...
39	0	Scandal	b baldjam cpc hq investig elxn43 donat petrole...
40	0	Economy	b barkoh crippledu kennuck start basic legal p...
41	0	Tell lies	b bcrealiti ontarioisproud serious west coast ...
42	0	Others	b ben johnson even n n cdnpoli yyj qcpoli onpo...
46	0	Tell lies	b c resist gill godwin name one elect sinc har...
47	0	Others	b camrclark natnewswatch one leader give answe...
48	0	Scandal	b canadiangreen soniafurstenau campaign hire w...

	sentiment	negative_reason	text
49	0	Tell lies	b candicemalcolm heshmatalavi well known rafid...
50	0	Climate Problem	b cathmckenna give us greenhous ga reduct stra...
...	...	...	...
2082	0	Tell lies	b would mckenna think chr xc3 xa9tien could sa...
2083	0	Others	b would elect night star war trailer elxn43
2084	0	Others	b rosi barton cri air monday night n n elxn43 ...
2088	0	Others	b conserv see get star nand get littl elxn43 c...
2089	0	Others	b except peopl deep throe polit derang syndrom...
2091	0	Scandal	b woke news appar total ok hire firm slander d...
2092	0	Tell lies	b wonder scheer campaign xe2 x80 x99t take que...
2096	0	Economy	b would mr scheer ask thought harper decis cut...
2097	0	Scandal	b xe2 x80 x99t better polit parti xe2 x80 x9cd...
2099	0	Scandal	b wow sheila sound like defam n nimagin think ...
2100	0	Others	b wow elizabeth may like stupid tweet cdnpoli ...
2102	0	Scandal	b wow horgan sight wonder long would tri bask ...
2103	0	Tell lies	b wow lot bigger lie insur broker folk elxn201...
2105	0	Tell lies	b wowser nlook like cbc globe reli liber oper ...
2106	0	Economy	b wrong n nyou xe2 x80 x99re one use alberta p...
2108	0	Tell lies	b yay cbckati nice see pushback lie attempt an...
2109	0	Others	b ye want afford futur justintrudeau canada be...
2112	0	Tell lies	b ye andrewsch stori elxn43 cdnpoli
2114	0	Others	b ye doubt busi schedul last minut liber troll...
2115	0	Economy	b ye liber xe2 x80 x99t get major ndp ask pipe...
2118	0	Women Reproductive right and Racism	b yet andrew scheer maintain expect us believ ...

	sentiment	negative_reason	text
2119	0	Women Reproductive right and Racism	b yet anoth exampl constant danger conserv pos...
2121	0	Others	b sort betray memori fought freedom cdnpoli el...
2122	0	Tell lies	b alway tell person good campaign stupid state...
2124	0	Tell lies	b vote dishonest slander politician alway choo...
2125	0	Others	b xe2 x80 x99t supervillain elect fail job n n...
2126	0	Climate Problem	b care limit climatechang wonder parti vote el...
2128	0	Scandal	b know good enough job smear campaign right an...
2129	0	Scandal	b miss comment deflect issu answer best respon...
2131	0	Women Reproductive right and Racism	b yup go reopen abort debat xf0 x9f x98 x8f n ...

1007 rows × 3 columns

In [246]:

```
# Combining healthcare and marijuana and healthcare into one
candf3['negative_reason'] = candf3['negative_reason'].str.replace('Heal
thcare and Marijuana','Healthcare')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
```

In [247]:

```
candf3.drop(candf3.index[candf3['negative_reason'] == 'Others'], inplac
e = True)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\frame.py:3940: S
ettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame
```

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy
  errors=errors)
```

In [248]:
```
candf3
```

Out[248]:

	sentiment	negative_reason	text
0	0	Women Reproductive right and Racism	b rosiebarton instead suggest agre canadian wo...
2	0	Economy	b brantford go cost 94 billion next 4 year ask...
4	0	Economy	b canada taxpay sick amp tire hard earn donat ...
9	0	Scandal	b cpckinsellag nlet see receipt pay warren kin...
15	0	Tell lies	b lyingandi histori answer embarrass question ...
19	0	Scandal	b urgent pleas watch video david haskel peopl ...
26	0	Scandal	b alternatespunki electionscan e electionson c...
29	0	Tell lies	b althiaraj ask question hypothet n cdnpoli el...
30	0	Scandal	b althiaraj surpris n justintrudeau answer q y...
33	0	Scandal	b andrewsch warren jwr yell us new stori invol...
34	0	Privilege	b andrewsch life also gotten expens republican...
37	0	Scandal	b asestritsyn yvan baker justintrudeau liber p...
39	0	Scandal	b baldjam cpc hq investig elxn43 donat petrole...
40	0	Economy	b barkoh crippledu kennuck start basic legal p...
41	0	Tell lies	b bcrealiti ontarioisproud serious west coast ...
46	0	Tell lies	b c resist gill godwin name one elect sinc har...
48	0	Scandal	b canadiangreen soniafurstenau campaign hire w...
49	0	Tell lies	b candicemalcolm heshmatalavi well known rafid...

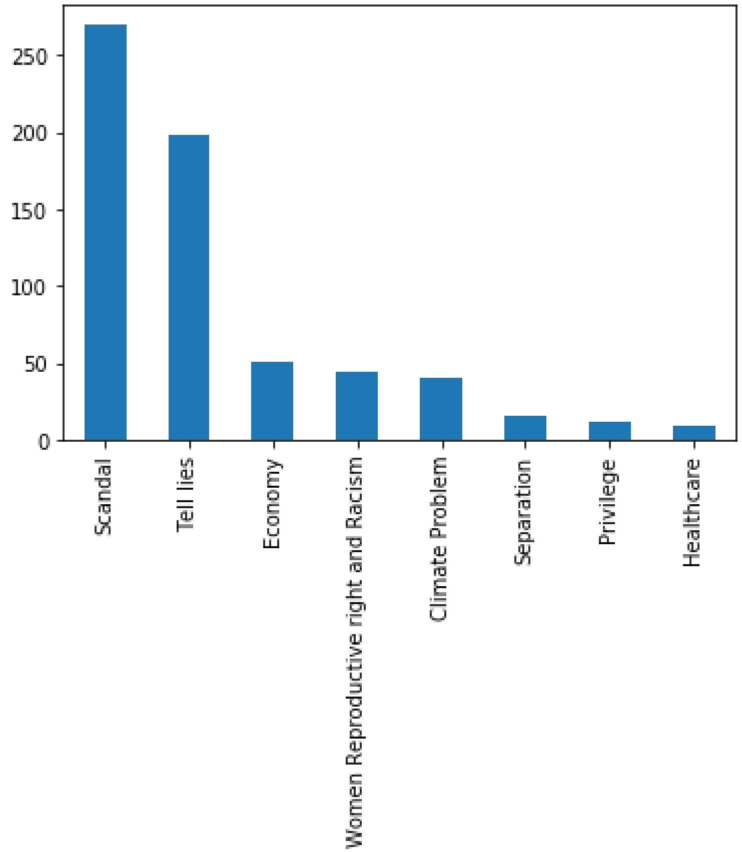
	sentiment	negative_reason	text
50	0	Climate Problem	b cathmckenna give us greenhous ga reduct stra...
52	0	Scandal	b cbcalert andi transpar elect expect transpar...
53	0	Healthcare	b cbconthecoast coalit gov might get us evid b...
54	0	Tell lies	b charliekuss roy woodhal nunnya16 yukon stron...
55	0	Tell lies	b christinainyeg grumpi granni andrewsch began...
57	0	Scandal	b costellodaniel1 paola dec1231 zitaastrava ev...
59	0	Scandal	b cpc hq candid appar troubl swallow andrewsch...
60	0	Scandal	b ctvnew conserv parti spend campaign distanc ...
63	0	Scandal	b deceitindrug abblib long daze joannecang gla...
65	0	Tell lies	b dpalmier sheila copp puglaa janephilpott ref...
69	0	Tell lies	b electionscan e heyday big money go defend po...
74	0	Tell lies	b gill godwin andrewsch real name lie constitu...
...	...	...	...
2057	0	Tell lies	b even support question honesti integr elxn43 ...
2062	0	Scandal	b jt show sock know feel good bad sign liber t...
2063	0	Scandal	b peopl say mainstream media liber bias n n el...
2064	0	Scandal	b think kinsella toronto sun keep mind n nthe ...
2066	0	Scandal	b work opinion columnist report newspap ethic ...
2073	0	Scandal	b canadian cdnmedia shock andrewsch hire kinse...
2074	0	Economy	b canadian pay telfordk pmo spew rubbish amp d...
2076	0	Healthcare	b mani peopl want guy pm nhe proven underhand ...

	sentiment	negative_reason	text
2079	0	Scandal	b thejagmeetsingh next prime minist canada n n...
2082	0	Tell lies	b would mckenna think chr xc3 xa9tien could sa...
2091	0	Scandal	b woke news appar total ok hire firm slander d...
2092	0	Tell lies	b wonder scheer campaign xe2 x80 x99t take que...
2096	0	Economy	b would mr scheer ask thought harper decis cut...
2097	0	Scandal	b xe2 x80 x99t better polit parti xe2 x80 x9cd...
2099	0	Scandal	b wow sheila sound like defam n nimagin think ...
2102	0	Scandal	b wow horgan sight wonder long would tri bask ...
2103	0	Tell lies	b wow lot bigger lie insur broker folk elxn201...
2105	0	Tell lies	b wowser nlook like cbc globe reli liber oper ...
2106	0	Economy	b wrong n nyou xe2 x80 x99re one use alberta p...
2108	0	Tell lies	b yay cbckati nice see pushback lie attempt an...
2112	0	Tell lies	b ye andrewsch stori elxn43 cdnpoli
2115	0	Economy	b ye liber xe2 x80 x99t get major ndp ask pipe...
2118	0	Women Reproductive right and Racism	b yet andrew scheer maintain expect us believ ...
2119	0	Women Reproductive right and Racism	b yet anoth exampl constant danger conserv pos...
2122	0	Tell lies	b alway tell person good campaign stupid state...
2124	0	Tell lies	b vote dishonest slander politician alway choo...
2126	0	Climate Problem	b care limit climatechang wonder parti vote el...
2128	0	Scandal	b know good enough job smear campaign right an...
2129	0	Scandal	b miss comment deflect issu answer best respon...
2131	0	Women Reproductive right and Racism	b yup go reopen abort debat xf0 x9f x98 x8f n ...

642 rows × 3 columns

In [249]:
```
candf3['negative_reason'].value_counts().plot(kind='bar')
```

Out[249]: <matplotlib.axes._subplots.AxesSubplot at 0x201c6f8bc88>



As we can see, the target variable class is heavily imbalanced. Additionally, the two dominant classes "Scandal" and "Tell Lies" are similar type of reasons. However, those will not be combined into one as it will further increase the imbalance of the dataset.

In [232]:
```
# tokenize all the cleaned tweets in our dataset. Tokens are individual
```

```
 terms or words,
# and tokenization is the process of splitting a string of text into to
kens
tokenized_tweet = candf3['text'].apply(lambda x: x.split())
tokenized_tweet.head()
```

Out[232]:
```
0     [b, rosiebarton, instead, suggest, agre, canad...
2     [b, brantford, go, cost, 94, billion, next, 4,...
4     [b, canada, taxpay, sick, amp, tire, hard, ear...
9     [b, cpckinsellag, nlet, see, receipt, pay, war...
15    [b, lyingandi, histori, answer, embarrass, que...
Name: text, dtype: object
```

In [233]:
```
# Stemming is a rule-based process of stripping the suffixes ("ing", "l
y", "es", "s" etc) from a word
from nltk.stem.porter import *
stemmer = PorterStemmer()

tokenized_tweet = tokenized_tweet.apply(lambda x: [stemmer.stem(i) for
i in x]) # stemming
tokenized_tweet.head()
```

Out[233]:
```
0     [b, rosiebarton, instead, suggest, agr, canadi...
2     [b, brantford, go, cost, 94, billion, next, 4,...
4     [b, canada, taxpay, sick, amp, tire, hard, ear...
9     [b, cpckinsellag, nlet, see, receipt, pay, war...
15    [b, lyingandi, histori, answer, embarrass, que...
Name: text, dtype: object
```

In [234]:
```
# Bag-of-Words features can be easily created using sklearn's CountVect
orizer function.
# We will set the parameter max_features = 1000 to select only top 1000
 terms ordered by term frequency across the corpus
from sklearn.feature_extraction.text import CountVectorizer
bow_vectorizer = CountVectorizer(max_df=0.90, min_df=2, max_features=10
00, stop_words='english')
# bag-of-words feature matrix
bow = bow_vectorizer.fit_transform(candf3['text'])
print(bow)
```

```
(0, 17)       1
(0, 130)      1
(0, 153)      1
(0, 471)      1
(0, 707)      1
(0, 934)      1
(0, 658)      1
(0, 371)      1
(0, 193)      1
(0, 50)       1
(0, 881)      1
(0, 935)      1
(0, 134)      1
(0, 36)       1
(0, 827)      1
(0, 425)      1
(0, 710)      1
(1, 445)      1
(1, 69)       1
(1, 995)      1
(1, 99)       1
(1, 201)      1
(1, 130)      1
(1, 153)      1
(2, 279)      1
:      :
(640, 284)    1
(640, 940)    1
(640, 132)    1
(640, 95)     1
(640, 695)    1
(640, 453)    1
(640, 184)    1
(640, 478)    1
(640, 234)    2
(640, 378)    1
(640, 398)    1
(640, 408)    1
(640, 204)    1
```

```
  (640, 53)	1
  (640, 69)	1
  (640, 153)	1
  (641, 954)	1
  (641, 689)	1
  (641, 960)	1
  (641, 227)	1
  (641, 724)	1
  (641, 723)	1
  (641, 972)	1
  (641, 991)	1
  (641, 17)	1
```

In [235]:

```
# TF-IDF works by penalizing the common words by assigning them lower w
eights while giving
# importance to words which are rare in the entire corpus but appear in
 good numbers
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(max_df=0.90, min_df=2, max_features=
1000, stop_words='english')
# TF-IDF feature matrix
tfidf = tfidf_vectorizer.fit_transform(candf3['text'])
```

In [236]:

```
# Spliting Data form above reduction dataset
from sklearn.model_selection import train_test_split
X_train, X_valid, y_train, y_valid = train_test_split(tfidf, candf3['ne
gative_reason'], test_size = 0.3, random_state = 3)
```

In [237]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix, accuracy_score, classific
ation_report

# taking logistic regression as a final model (stable accuracy on new d
ata)
dual=[True,False]
max_iter=[100,110,120,130,140]
```

```
C = [1.0,1.5,2.0,2.5]
param_grid = dict(dual=dual,max_iter=max_iter,C=C)

#Model hypertune
from sklearn.model_selection import GridSearchCV
lr = LogisticRegression(penalty='l2')
grid = GridSearchCV(estimator=lr, param_grid=param_grid, cv = 3, n_jobs
=-1)
#Model after tuning
grid_result = grid.fit(X_train, y_train)
# Summarize results
#print("Best: %f using %s" % (grid_result.best_score, grid_result.best_
params))

# Logistic Regression accuracy after hypertuning
prediction_logit_new = grid_result.predict(X_valid)
accuracy_scores_logit_new = accuracy_score(y_valid, prediction_logit_ne
w)*100
print('Logistic Regression accuracy: {}%'.format(accuracy_scores_logit_
new))
```

```
Logistic Regression accuracy: 59.58549222797927%
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_sea
rch.py:813: DeprecationWarning: The default of the `iid` parameter will
change from True to False in version 0.22 and will be removed in 0.24.
This will change numeric results when test-set sizes are unequal.
  DeprecationWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logisti
c.py:432: FutureWarning: Default solver will be changed to 'lbfgs' in
0.22. Specify a solver to silence this warning.
  FutureWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logisti
c.py:469: FutureWarning: Default multi_class will be changed to 'auto'
in 0.22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)
```

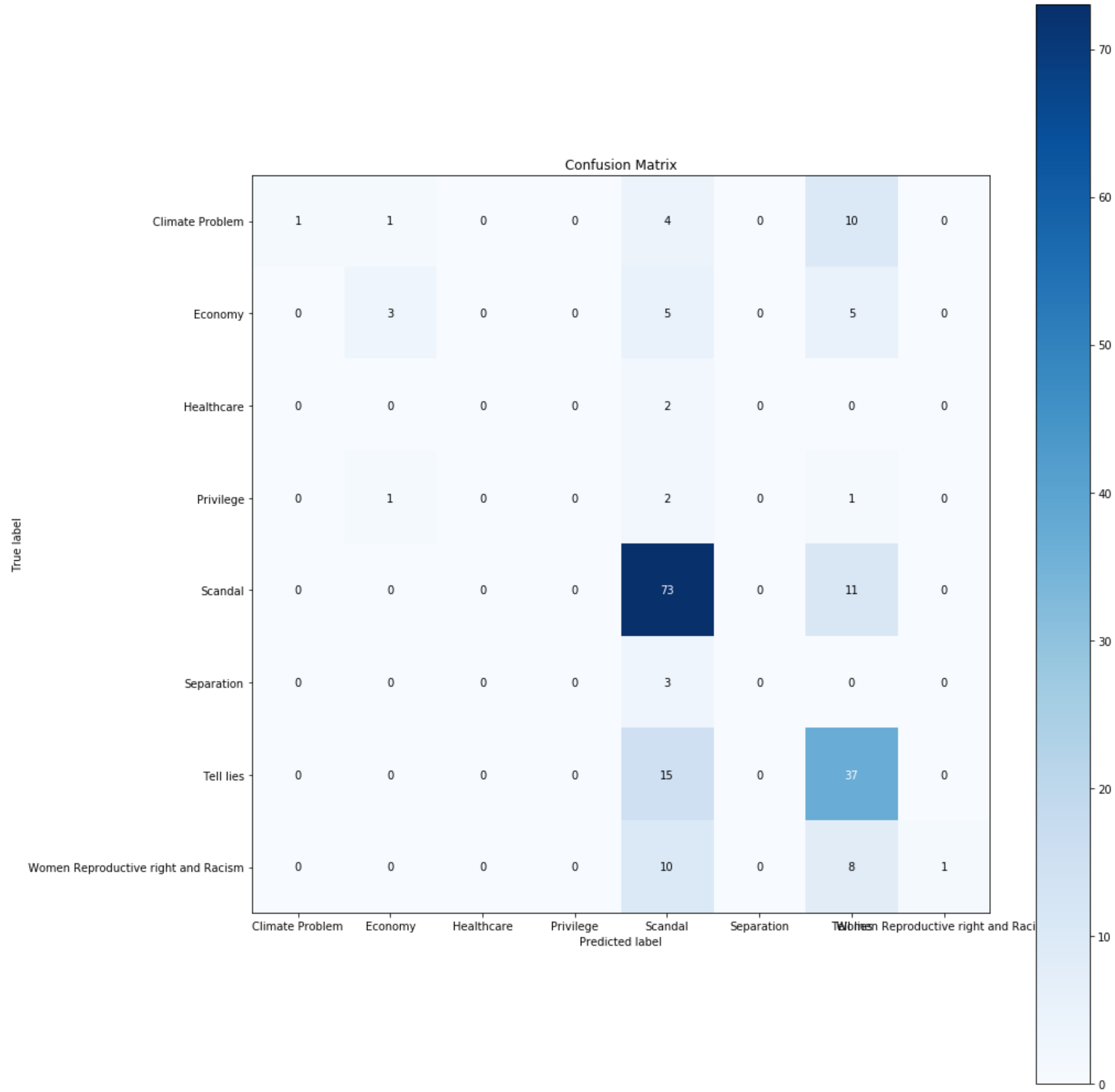
In [238]:

```
# check validation statistics (Classification Summary) for TDIDF
import scikitplot as skplt
```

```
print(classification_report(y_valid, prediction_logit_new)) # from confusion matrix Logistics Regression perform well
# Plot confusion Matrix
skplt.metrics.plot_confusion_matrix(y_valid, prediction_logit_new, figsize=(15, 18))
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:1437: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

```
                                precision    recall  f1-score   support

                Climate Problem       1.00      0.06      0.12        16
                        Economy       0.60      0.23      0.33        13
                     Healthcare       0.00      0.00      0.00         2
                      Privilege       0.00      0.00      0.00         4
                        Scandal       0.64      0.87      0.74        84
                     Separation       0.00      0.00      0.00         3
                      Tell lies       0.51      0.71      0.60        52
Women Reproductive right and Racism       1.00      0.05      0.10        19

                       accuracy                           0.60       193
                      macro avg       0.47      0.24      0.24       193
                   weighted avg       0.64      0.60      0.52       193
```


Confusion Matrix
True label
Predicted label
Climate Problem
Economy
Healthcare
Privilege
Scandal
Separation
Tell lies
Women Reproductive right and Racism
1 1 0 0 4 0 10 0
0 3 0 0 5 0 5 0
0 0 0 0 2 0 0 0
0 1 0 0 2 0 1 0
0 0 0 0 73 0 11 0
0 0 0 0 3 0 0 0
0 0 0 0 15 0 37 0
0 0 0 0 10 0 8 1
70
60
50
40
30
20
10
0

In [239]:
```
# Spliting Data form above reduction dataset
from sklearn.model_selection import train_test_split
X_train, X_valid, y_train, y_valid = train_test_split(bow, candf3['nega
tive_reason'], test_size = 0.3, random_state = 3)
```

In [240]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix, accuracy_score, classific
ation_report

# taking logistic regression as a final model (stable accuracy on new d
ata)
dual=[True,False]
max_iter=[100,110,120,130,140]
C = [1.0,1.5,2.0,2.5]
param_grid = dict(dual=dual,max_iter=max_iter,C=C)

#Model hypertune
from sklearn.model_selection import GridSearchCV
lr = LogisticRegression(penalty='l2')
grid = GridSearchCV(estimator=lr, param_grid=param_grid, cv = 3, n_jobs
=-1)
#Model after tuning
grid_result = grid.fit(X_train, y_train)
# Summarize results
#print("Best: %f using %s" % (grid_result.best_score, grid_result.best_
params))

# Logistic Regression accuracy after hypertuning
```

```
prediction_logit_new = grid_result.predict(X_valid)
accuracy_scores_logit_new = accuracy_score(y_valid, prediction_logit_ne
w)*100
print('Logistic Regression accuracy: {}%'.format(accuracy_scores_logit_
new))
```

```
Logistic Regression accuracy: 62.17616580310881%
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\model_selection\_sea
rch.py:813: DeprecationWarning: The default of the `iid` parameter will
change from True to False in version 0.22 and will be removed in 0.24.
This will change numeric results when test-set sizes are unequal.
  DeprecationWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logisti
c.py:432: FutureWarning: Default solver will be changed to 'lbfgs' in
0.22. Specify a solver to silence this warning.
  FutureWarning)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\logisti
c.py:469: FutureWarning: Default multi_class will be changed to 'auto'
in 0.22. Specify the multi_class option to silence this warning.
  "this warning.", FutureWarning)
```

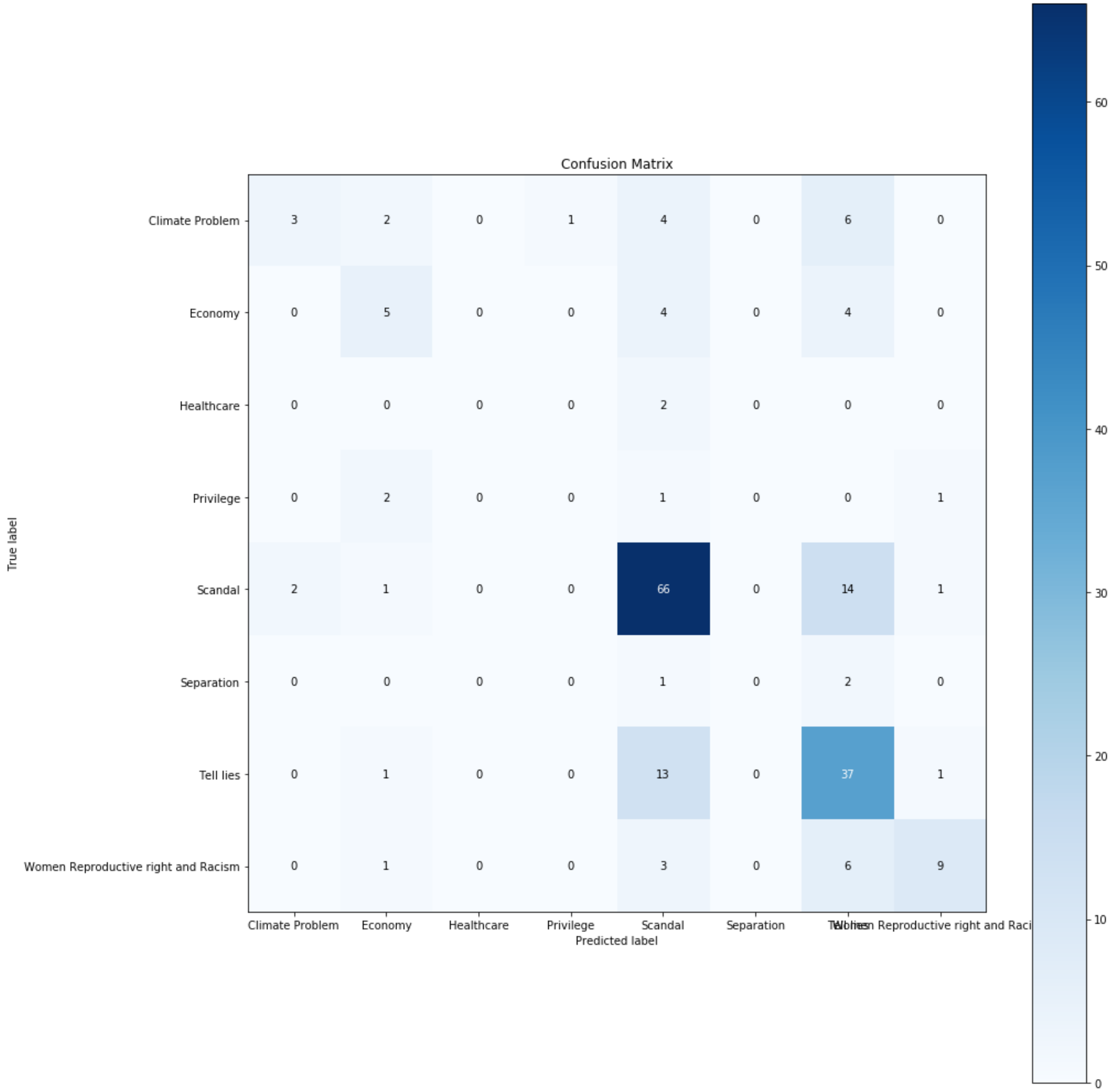
In [241]:

```
# check validation statistics (Classification Summary) for Bag of Words
import scikitplot as skplt
print(classification_report(y_valid, prediction_logit_new)) # from conf
usion matrix Logistics Regression perform well
# Plot confusion Matrix
skplt.metrics.plot_confusion_matrix(y_valid, prediction_logit_new, figs
ize=(15, 18))
plt.show()
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\classificati
on.py:1437: UndefinedMetricWarning: Precision and F-score are ill-defin
ed and being set to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

```
                                     precision    recall  f1-score   su
pport

                    Climate Problem       0.60      0.19      0.29
```

```
16
                              Economy       0.42      0.38      0.40
13
                           Healthcare       0.00      0.00      0.00
 2
                            Privilege       0.00      0.00      0.00
 4
                              Scandal       0.70      0.79      0.74
84
                           Separation       0.00      0.00      0.00
 3
                            Tell lies       0.54      0.71      0.61
52
Women Reproductive right and Racism       0.75      0.47      0.58
19

                             accuracy                           0.62
193
                            macro avg       0.38      0.32      0.33
193
                         weighted avg       0.60      0.62      0.60
193
```


Confusion Matrix
True label
Predicted label
Climate Problem
Economy
Healthcare
Privilege
Scandal
Separation
Tell lies
Women Reproductive right and Racism
3 2 0 1 4 0 6 0
0 5 0 0 4 0 4 0
0 0 0 0 2 0 0 0
0 2 0 0 1 0 0 1
2 1 0 0 66 0 14 1
0 0 0 0 1 0 2 0
0 1 0 0 13 0 37 1
0 1 0 0 3 0 6 9
60
50
40
30
20
10
0

As aforementioned, sentiment analysis is best used when there is one or multiple moods that can be assignmed as part of the sentiment rather than just binary assignment of positive or negative. Most real life election sentiment analysis of social media involves these mood labels which helps better understand the depth of sentiment of the voter and reduces the subjectivity of the human assigning the binary sentiment reading the tweet.

Therefore, it is critical that the training model is well balanced and the negative_reason cateogires are carefully determined to minimize any potential overlap in their meaning. As we can see from the confusion matrix above, "Scandal" is often confused with "Tell Lies" as we predicted earlier and causes the highest degree of error. If we were to combine these two into one target variable, it will definitely improve the accuracy of the model but will lead to a heavily imbalanced data set.