** Indegence Data Science Assignment **

Text Classification Analysis

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In [49]:

```
# import all required packages
import pandas as pd
#from nltk.tokenize import word_tokenize
#from nltk.corpus import stopwords
#from nltk.stem import PorterStemmer
import matplotlib.pyplot as plt
from wordcloud import WordCloud
from math import log, sqrt
import pandas as pd
import numpy as np
import re

from nltk.corpus import stopwords
from string import punctuation
%matplotlib inline
```

In [50]:

```
# Read the input file
data = pd.read_csv("../data/Data.csv")
```

Count observation for each ADR labels

In [51]:

```
data.ADR_label.value_counts()
```

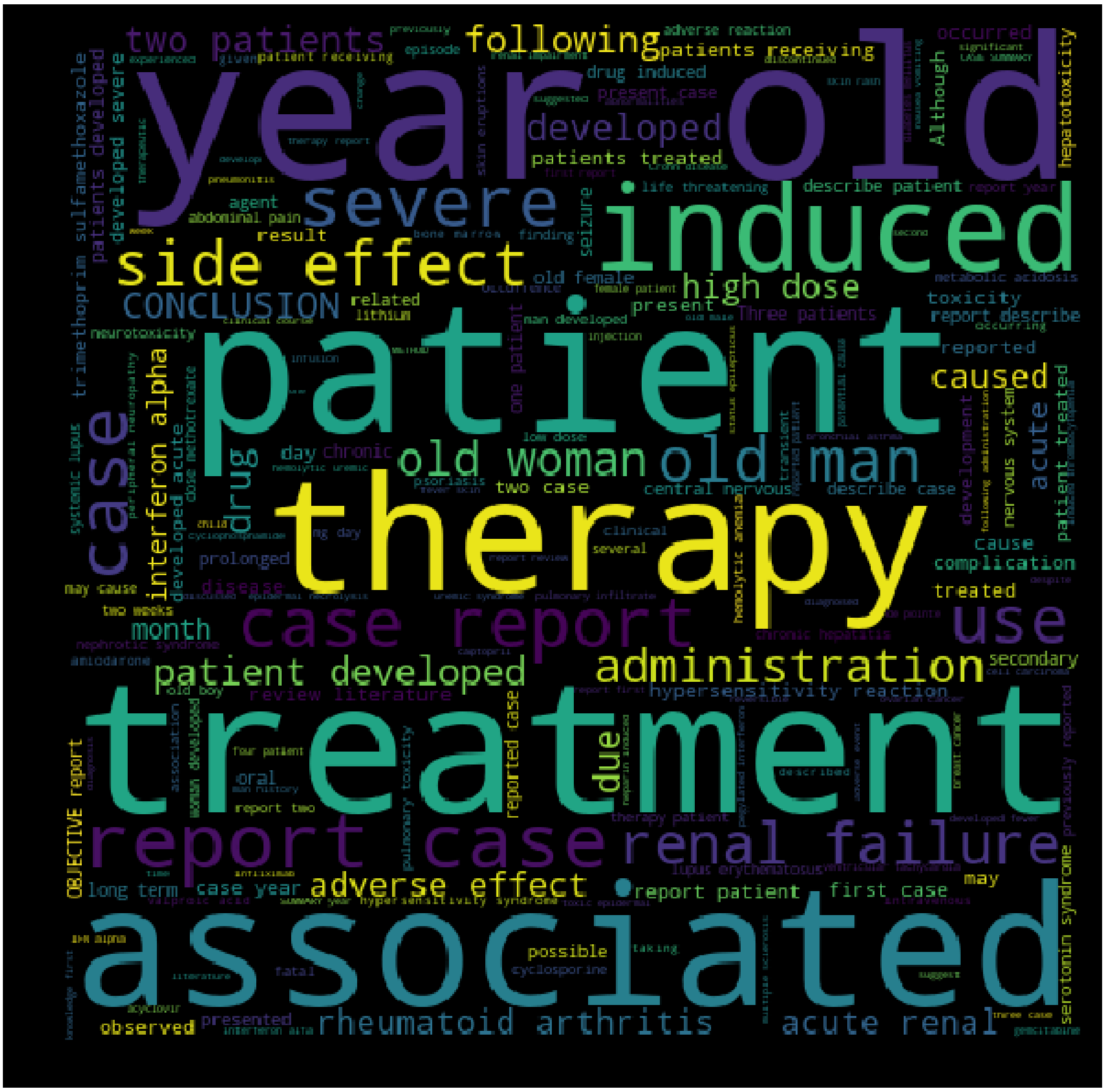
Out[51]:

```
0    16694
1     6822
Name: ADR_label, dtype: int64
```

Create word cloud for ADR label = 1

In [52]:

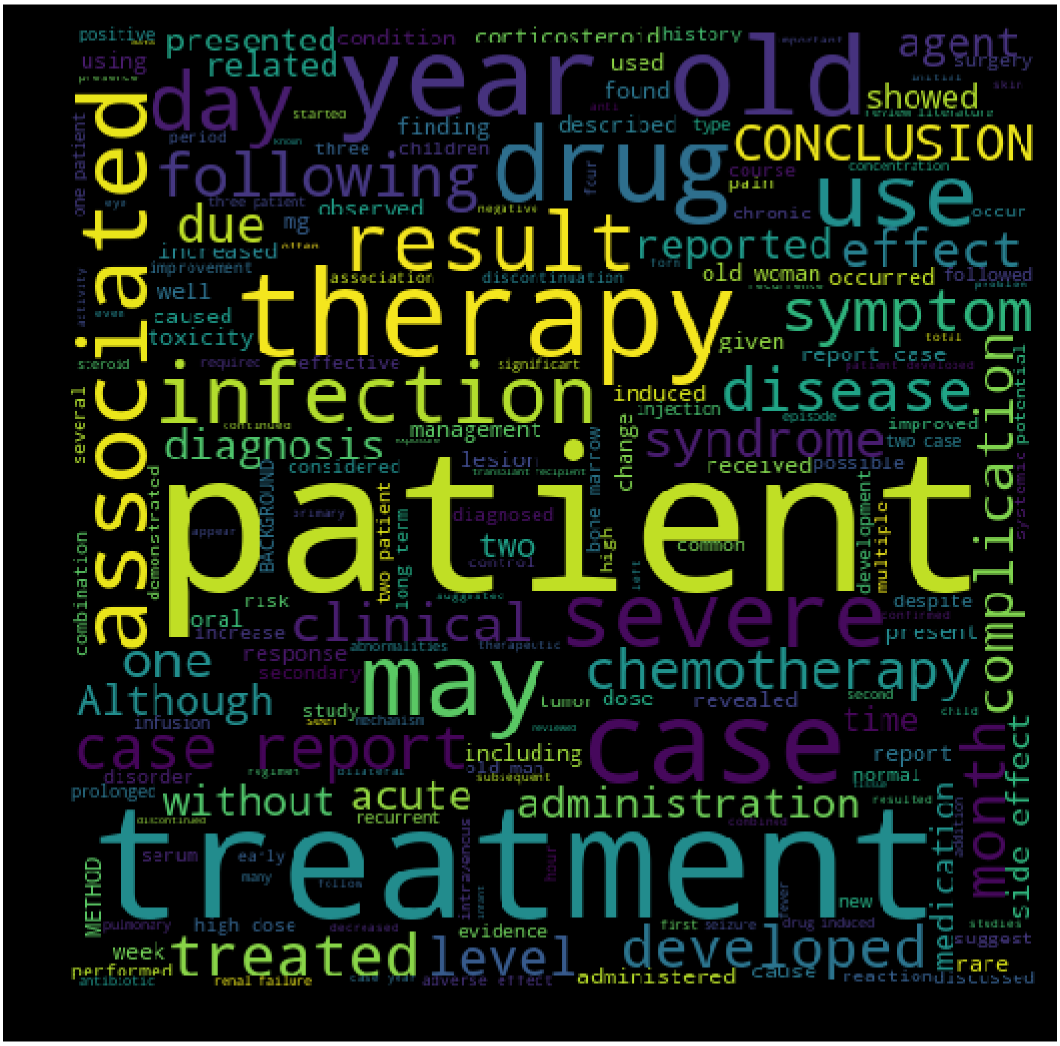
```
data_ADR_1_word = ' '.join(list(data[data['ADR_label'] == 1]['Tweet']))
spam_wc = WordCloud(width = 512,height = 512).generate(data_ADR_1_word)
plt.figure(figsize = (8, 8), facecolor = 'k')
plt.imshow(spam_wc)
plt.axis('off')
plt.tight_layout(pad = 0)
plt.show()
```



Create word cloud for ADR label = 0

In [53]:

```
data_ADR_1_word = ' '.join(list(data[data['ADR_label'] == 0]['Tweet']))
spam_wc = WordCloud(width = 512,height = 512).generate(data_ADR_1_word)
plt.figure(figsize = (7, 7), facecolor = 'k')
plt.imshow(spam_wc)
plt.axis('off')
plt.tight_layout(pad = 0)
plt.show()
```



Find top frequenct terms to create custom stop word list

    * This will help to remove noise word which will harm for the classification.
    * Create custom stop word list with help of top frequent word.

In [43]:

```
from nltk.stem import WordNetLemmatizer
from collections import Counter
from nltk.tokenize import word_tokenize


custom_words=['\'s','also','',"''",'``','le','.The','--']
stop_words = set(stopwords.words('english') + list(punctuation) + custom_words)
wordnet_lemmatizer = WordNetLemmatizer()

class_corpus = data.groupby('ADR_label').apply(lambda x: x['Tweet'].str.cat())
class_corpus

class_corpus = class_corpus.apply(lambda x: Counter(
    [wordnet_lemmatizer.lemmatize(w)
     for w in word_tokenize(x)
     if w.lower() not in stop_words and not w.isdigit()]
))
whole_text_freq = class_corpus.sum()


label, repetition = zip(*whole_text_freq.most_common(1000))
print(label)
```

```
('patient', 'case', 'treatment', 'report', 'therapy', 'developed', 'ma
y', 'associated', 'treated', 'acute', 'drug', 'severe', 'syndrome', 'ef
fect', 'renal', 'following', 'disease', 'use', 'two', 'day', 'clinica
l', 'symptom', 'reported', 'month', 'reaction', 'woman', 'complicatio
n', 'administration', 'infection', 'cause', 'first', 'due', 'year', 'ch
ronic', 'liver', 'chemotherapy', 'receiving', 'one', 'cell', 'level',
'used', 'describe', 'week', 'present', 'adverse', 'pulmonary', 'man',
'dose', 'presented', 'study', 'induced', 'showed', 'toxicity', 'failur
e', 'agent', 'diagnosis', 'without', 'three', 'child', 'blood', 'hepati
tis', 'rare', 'serum', 'received', 'well', 'course', 'risk', 'pain', 's
ide', 'oral', 'including', 'fever', 'high', 'systemic', 'caused', 'diso
rder', 'skin', 'review', 'intravenous', 'factor', 'combination', 'mg',
'within', 'increased', 'history', 'result', 'literature', 'revealed',
'potential', 'finding', 'cancer', 'normal', 'related', 'secondary', 'po
ssible', 'multiple', 'previously', 'response', 'corticosteroid', 'injec
tion', 'time', 'described', 'lesion', 'leukemia', 'inhibitor', 'infusio
n', 'increase', 'dos', 'acid', 'seizure', 'occurred', 'bone', 'four',
'considered', 'development', 'tumor', 'taking', 'significant', 'sign',
'cardiac', 'experienced', 'known', 'hypersensitivity', 'effective', 'gi
ven', 'change', 'biopsy', 'evidence', 'cutaneous', 'management', 'funct
ion', 'followed', 'mechanism', 'medication', 'second', 'methotrexate',
'later', 'carcinoma', 'administered', 'observed', 'lung', 'common', 'us
ing', 'resolved', 'transplant', 'new', 'marrow', 'association', 'centra
l', 'visual', 'type', 'left', 'concentration', 'hour', 'hepatic', 'disc
ontinuation', 'steroid', 'complete', 'suggest', 'rash', 'male', 'test',
'diagnosed', 'heart', 'period', 'loss', 'found', 'several', 'hypertensi
on', 'topical', 'artery', 'transplantation', 'female', 'respiratory',
'low', 'interferon', 'antibiotic', 'total', 'feature', 'early', 'seriou
s', 'necrosis', 'therapeutic', 'fatal', 'arthritis', 'B', 'lithium', 'e
pisode', 'right', 'author', 'resulted', 'bilateral', 'rheumatoid', 'mil
d', 'system', 'demonstrated', 'improved', 'withdrawal', 'resulting', 'l
ong-term', 'positive', 'potentially', 'C', 'antibody', 'abnormality',
'sodium', 'could', 'eye', 'successfully', 'condition', 'eruption', 'tox
ic', 'five', 'plasma', 'examination', 'progressive', 'occur', 'prolonge
d', 'ventricular', 'peripheral', 'recurrent', 'care', 'often', 'thrombo
sis', 'malignant', 'performed', 'anemia', 'carbamazepine', 'suggests',
'tissue', 'edema', 'infant', 'improvement', 'underwent', 'onset', 'gast
rointestinal', 'decreased', 'control', 'previous', 'coronary', 'additio
n', 'important', 'brain', 'diabetes', 'medical', 'human', 'dysfunctio
n', 'initiation', 'surgery', 'combined', 'daily', 'lower', 'high-dose',
'however', 'surgical', 'regimen', 'status', 'seen', 'insulin', 'atypica
l', 'lupus', 'manifestation', 'role', 'even', 'diffuse', 'large', 'know
ledge', 'complicated', 'muscle', 'started', 'subsequent', 'data', 'radi
ation', 'occurrence', 'characterized', 'rate', 'unusual', 'injury', 'ma
rked', 'interaction', 'enzyme', 'breast', 'abdominal', 'exposure', 'lea
d', 'primary', 'hemorrhage', 'initial', 'pneumonia', 'range', 'need',
'despite', 'treat', 'confirmed', 'continued', 'age', 'usually', 'decrea
se', 'interstitial', 'headache', 'resolution', 'presence', 'thrombocyto
penia', 'tachycardia', 'develop', 'admitted', 'boy', 'nervous', 'descri
bes', 'rapid', 'successful', 'refractory', 'event', 'continuous', 'stan
dard', 'pressure', 'calcium', 'aware', 'especially', 'serotonin', 'incl
uded', 'dosage', 'died', 'hypotension', 'transient', 'catheter', 'eleva
ted', 'bleeding', 'suggested', 'form', 'follow-up', 'small', 'major',
'cerebral', 'required', 'became', 'le', 'clozapine', 'number', 'virus',
'hospital', 'corneal', 'lymphoma', 'although', 'similar', 'consistent',
'adult', 'neuropathy', 'inflammatory', 'eosinophilia', 'cisplatin', 'li
fe-threatening', 'recurrence', 'occurring', 'subsequently', 'many', 'me
tabolic', 'monitoring', 'increasing', 'drug-induced', 'rapidly', 'ocula
r', 'immunosuppressive', 'disseminated', 'hormone', 'heparin', 'fluid',
'mean', 'discontinued', 'activity', 'single', 'old', 'laboratory', 'pri
or', 'deficiency', 'phenytoin', 'advanced', 'death', 'might', 'nephroti
```

```
c', 'count', 'appears', 'myocardial', 'must', 'analysis', 'rarely', 're
mission', 'pregnancy', 'commonly', 'led', 'generalized', 'acidosis', 'o
utcome', '.The', 'clinically', 'nausea', 'experience', 'recovery', 'whi
te', 'body', 'presentation', 'local', 'ovarian', 'reversible', 'possibi
lity', 'site', 'recipient', 'erythema', 'third', 'metastatic', 'antipsy
chotic', 'recently', 'involving', 'probably', 'retinal', 'different',
'neuroleptic', 'relationship', 'girl', 'prescribed', 'spinal', 'diabeti
c', 'complex', 'active', 'made', 'intrathecal', 'neurologic', 'observat
ion', 'abscess', 'receptor', 'fibrosis', 'pediatric', 'arterial', 'show
n', 'amiodarone', 'persistent', 'suspected', 'reduction', 'young', 'hem
olytic', 'erythematosus', 'recovered', 'discus', 'presenting', 'immun
e', 'intoxication', 'undergoing', 'six', 'growth', 'olanzapine', 'MTX',
'noted', 'stem', 'HIV', 'autoimmune', 'absence', 'weight', 'depressio
n', 'evaluation', 'intensive', 'among', 'include', 'infarction', 'probl
em', 'abnormal', 'incidence', 'mg/day', 'vomiting', 'area', 'cyclospori
ne', 'imaging', 'postoperative', 'uncommon', 'atrial', 'reduced', 'stag
e', 'underlying', 'neurological', 'colitis', 'leading', 'movement', 'lo
ng', 'thyroid', 'Crohn', 'h', 'posterior', 'efficacy', 'interval', 'pla
telet', 'neurotoxicity', 'elderly', 'upper', 'likely', 'damage', 'encep
halopathy', 'venous', 'remained', 'allergic', 'per', 'cessation', 'pneu
monitis', 'lymphoblastic', 'nerve', 'particularly', 'negative', 'specif
ic', 'and/or', 'occurs', 'psoriasis', 'impairment', 'weakness', 'safe',
'conventional', 'additional', 'involvement', '5-FU', 'overdose', 'asthm
a', 'prednisone', 'elevation', 'cyclophosphamide', 'ischemic', 'extensi
ve', 'useful', 'frequently', 'cycle', 'anterior', 'documented', 'leg',
'general', 'lymphadenopathy', 'alternative', 'requiring', 'kidney', 'bl
ock', 'macular', 'developing', 'massive', 'procedure', 'amphotericin',
'keratitis', 'responded', 'another', 'induce', 'various', 'physician',
'prevent', '.We', 'spontaneous', 'recombinant', 'intravitreal', 'patter
n', 'identified', 'chest', 'completely', 'infliximab', 'warfarin', 'sta
rting', 'trial', 'agitation', 'available', 'appeared', 'viral', 'urinar
y', 'reviewed', 'recommended', 'contact', 'induction', 'bowel', 'opti
c', 'dermatitis', 'seven', 'manifested', 'cord', 'emergency', 'SUMMAR
Y', 'returned', 'relatively', 'method', 'vascular', 'diagnostic', 'grou
p', 'still', 'appropriate', 'epidermal', 'stopped', 'scan', 'epidural',
'late', 'possibly', 'organ', 'vein', 'tuberculosis', 'widely', 'importa
nce', 'recent', 'dizziness', 'antidepressant', 'safety', 'alpha', 'typi
cal', 'eosinophilic', 'approximately', 'vitamin', 'sinus', 'phenomeno
n', 'selective', 'whose', 'symptomatic', 'concomitant', 'partial', 'adm
ission', 'taken', 'valve', 'support', 'diarrhea', 'myeloid', 'defect',
'insufficiency', 'IFN', 'aggressive', 'either', 'obtained', 'achieved',
'since', 'therefore', 'thought', 'alone', 'de', 'suffered', 'disturbanc
e', 'QT', 'agranulocytosis', 'article', 'value', 'sudden', 'generally',
'immunodeficiency', 'responsible', 'immunosuppression', 'immunoglobuli
n', 'higher', 'acuity', 'characteristic', 'controlled', 'leukopenia',
'culture', 'tamoxifen', 'investigation', 'rhabdomyolysis', 'dialysis',
'pancreatitis', 'malignancy', 'infectious', 'frequency', 'good', 'inges
tion', 'idiopathic', 'ulcer', 'protein', 'swelling', 'risperidone', 'dy
spnea', 'produce', 'shunt', 'hemorrhagic', 'vision', 'series', 'resista
nt', 'remains', 'cytotoxic', 'vincristine', 'detected', 'inflammation',
'immediate', 'progression', 'schizophrenia', 'dyskinesia', '5-fluoroura
cil', 'hepatotoxicity', 'pancreatic', 'direct', 'tract', 'replacement',
'action', 'therapy.The', 'immediately', 'pathogenesis', 'tomography',
'facial', 'recognized', 'CMV', 'show', 'healthy', 'shortly', 'mass', 's
arcoma', 'eight', 'began', 'part', 'lymphocyte', 'probable', 'subcutane
ous', 'psychiatric', 'vasculitis', 'treating', 'lymphocytic', 'curren
t', 'repeated', 'worsening', 'every', 'bleomycin', 'focal', 'clinicia
n', 'delayed', 'rituximab', 'duration', 'obstruction', 'effusion', 'cla
rithromycin', 'appearance', 'meningitis', 'tumour', 'extremity', 'discu
ssed', 'complicating', 'avoid', 'lens', 'psychosis', 'compared', 'appro
ach', 'duct', 'unit', 'sepsis', 'mainly', 'neutropenia', 'pleural', 'se
```

```
ems', 'phosphate', 'confusion', 'cervical', 'suggesting', 'intracrania
l', 'setting', 'potassium', 'added', 'along', 'published', 'fulminant',
'x', 'mental', 'indicated', 'technique', 'arrhythmia', 'infiltrates',
'intraocular', 'based', 'intervention', 'mg/m2', 'tardive', 'methylpred
nisolone', 'ribavirin', 'low-dose', 'resonance', 'attention', 'acyclovi
r', 'II', 'variety', 'bladder', 'thrombus', 'recognition', 'fibrillatio
n', 'CT', 'SLE', 'exposed', 'gastric', 'asymptomatic', 'adenocarcinom
a', 'tubular', 'tolerated', 'red', 'failed', '.A', 'relapse', 'peritone
al', 'illness', 'suffering', 'short', 'RA', 'population', 'metabolism',
'glucose', 'cytomegalovirus', 'therapy.We', 'initially', 'affected', 'a
nticonvulsant', 'limb', 'differential', 'degree', 'poor', 'maintenanc
e', 'graft', 'thrombolytic', 'mellitus', 'least', 'bile', 'inappropriat
e', 'antagonist', 'irreversible', 'exacerbation', 'severity', 'ataxia',
'removal', 'proteinuria', 'free', 'computed', 'epilepsy', 'vitro', 'sig
nificantly', 'together', 'consequence', 'congenital', 'etiology', 'valp
roate', 'parenteral', 'specimen', 'prophylaxis', 'challenge', 'vancomyc
in', 'hyponatremia', 'valproic', 'measure', 'best', 'leukoencephalopath
y', 'almost', 'testing', 'particular', 'immunocompromised', 'cough', 'l
ight', 'supportive', 'containing', 'transfusion', 'cataract', 'would',
'sertraline', 'minor', 'triamcinolone', 'complained', 'necessary', 'acq
uired', 'urine', 'DNA', 'illustrates', 'product', 'prompt', 'frequent',
'solution', 'certain', 'lamotrigine', 'gemcitabine', 'preparation', 're
garding', 'glaucoma', 'leukaemia', 'conclude', 'granulocyte', 'antiretr
oviral', 'tacrolimus', 'fungal', 'twice', 'phenobarbital', '+/-', 'whet
her', 'alcohol', 'hematologic', 'involved', 'cardiovascular', 'endometr
ial', 'formation', 'evaluated', 'disappeared', 'HUS', 'application', 'd
istress', 'anticoagulant', 'mg/kg', 'nasal', 'determined', 'minimal',
'extremely', 'Staphylococcus', 'hemodialysis', 'highlight', 'essentia
l', 'ethambutol', 'state', 'deep', 'citalopram', 'myelosuppression', 's
ecretion', 'gold', 'family', 'dopamine', 'causing', 'reactivation', 'ba
cterial', 'prednisolone', 'established', 'benign', 'AML', 'aureus', 'be
come', 'CNS', 'antigen', 'nephritis', 'paper', 'necrolysis', 'appear',
'order', 'past', 'reuptake', 'highly', 'isolated', 'coma', 'neck', 'mot
or', 'creatinine', 'histological', 'CBZ', 'arrest', 'itraconazole', 'IF
N-alpha', 'jaundice', 'acetate', 'myasthenia', 'respond', 'persisted',
'gradually', 'managed', 'radiotherapy', 'phase', 'limited', 'monitore
d', 'hand', 'extrapyramidal', 'suggestive', 'herpes', 'moderate', 'opti
on', 'deterioration', 'desensitization', 'mitral', 'spectrum', 'improv
e', 'theophylline', 'clearance', 'difficulty', 'endophthalmitis', 'attr
ibuted', 'main', 'dental', 'upon', 'pulse', 'bradycardia', 'glucocortic
oid', 'magnetic', 'infiltrate', 'benefit', 'magnesium', 'believe', 'car
boplatin', 'sclerosis', 'potent', 'brief', 'mixed', 'trimethoprim-sulfa
methoxazole', 'invasive', 'difficult', 'AIDS', 'B-cell', 'SIADH', 'appa
rent', 'delay', 'last', 'squamous', 'poisoning', 'temporal', 'bronchia
l', 'head', 'coagulation', 'produced', 'hypoglycemia', 'anti-inflammato
ry', 'markedly', 'myeloma', 'contrast', 'adjuvant', 'life')
```

Text Transforamtion into vector form

```
* Convert text into vectorized form using tfidf.
* Tfidf uses to define term weight in corpus.
* Remove all english words, punctuation and custom stop words before applying
 Tf-idf.
* Using Bigram to create document term matric.
```

In [54]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

custom_words=['\'s','also','',"''",'``','le','.The','--']
stop_words = set(stopwords.words('english') + list(punctuation) + custom_words)

vectorizer = TfidfVectorizer(lowercase=True,stop_words=stop_words,analyzer = "word",
ngram_range=(1,2))
X = vectorizer.fit_transform(data['Tweet'])
```

Find top weighted terms after tfidf

```
* Manually check top weighted bigram terms that it's useful for the classific
ation or not.
* If bigram terms are impacting to give worng classification prediction then
 remove the terms from corpus.
```

In [45]:

```
indices = np.argsort(vectorizer.idf_)[::-1]
features = vectorizer.get_feature_names()
top_n = 50
top_features = [features[i] for i in indices[:top_n]]
print (top_features)
```

```
['justice greater', 'iliocaval', 'ileus caused', 'ileus common', 'ileus
due', 'ileus neostigmine', 'ileus peripheral', 'ileus resulting', 'ileu
s spontaneously', 'ileus triggered', 'iliac arteries', 'anthracostenosi
s describes', 'iliac dissection', 'iliac dissections', 'iliac vein', 'i
liocaval manifestations', 'il opium', 'ill adolescent', 'ill adults',
'ill defined', 'ill developing', 'ill effect', 'ill inadvertently', 'il
l looking', 'ill neonates', 'anthony fire', 'anthony', 'ill persons',
'ill schizophrenic', 'ill young', 'ileus bortezomib', 'ileus administra
tion', 'ileum urinary', 'ileum together', 'il production', 'il safe',
'il serum', 'il sole', 'il4', 'il4 cd4', 'anthracyclines rituximab', 'i
ld diagnosed', 'ild patient', 'ild patients', 'ild sufficient', 'ilds',
'ilds idiopathic', 'ile', 'ile reduced', 'anthracyclines methotrexate']
```

Split the data into taining and test

```
* Taking 30% test data from input data
```

In [55]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,data["ADR_label"], test_size = 0.
3, random_state = 10)
```

Apply all classification algorithm

```
* Check which classification is giving better result among all classification
 algorithm
```

In [78]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score


#svc = SVC(kernel='sigmoid', gamma=1.0,probability=True)
svc = SVC(kernel='rbf', gamma=0.1,C=10,probability=True)
knc = KNeighborsClassifier(n_neighbors=49)
mnb = MultinomialNB(alpha=0.2)
dtc = DecisionTreeClassifier(min_samples_split=7, random_state=111)
lrc = LogisticRegression(solver='liblinear', penalty='l1')
rfc = RandomForestClassifier(n_estimators=31, random_state=111)
abc = AdaBoostClassifier(n_estimators=62, random_state=111)
bc = BaggingClassifier(n_estimators=9, random_state=111)
etc = ExtraTreesClassifier(n_estimators=9, random_state=111)

clfs = {'SVC' : svc,'KN' : knc, 'NB': mnb, 'DT': dtc, 'LR': lrc, 'RF': rfc, 'AdaBoos
t': abc, 'BgC': bc, 'ETC': etc}


def train_classifier(clf, feature_train, labels_train):
    clf.fit(feature_train, labels_train)


def predict_labels(clf, features):
    return (clf.predict(features))

def score(y_test,pred,average):
    f_score = f1_score(y_test,pred,average=average)
    precision=precision_score(y_test,pred,average=average)
    recall = recall_score(y_test,pred,average=average)
    return precision,recall,f_score

pred_scores = []
for k,v in clfs.items():
    train_classifier(v, X_train, y_train)
    pred = predict_labels(v,X_test)
    precision,recall,fscore =score(y_test,pred,average ='binary')
    res = {'Model':k,'Score':accuracy_score(y_test,pred),'Precision':precision,'Reca
ll':recall,'F_Score':fscore}
    #pred_scores.append((k, [accuracy_score(y_test,pred)],[precision],[recall],[fsco
re]))
    pred_scores.append(res)

#df3 = pd.DataFrame.from_items(pred_scores,orient='index', columns=['Score','Precisi
on,Recall,F_Score'])
df3 = pd.DataFrame(pred_scores)
```

Below result comes after using 'unigram' in Tf-idf

In [13]:

```
df
```

Out[13]:

	Score
SVC	0.866194
KN	0.794189
NB	0.858682
DT	0.833735
LR	0.853154
RF	0.880227
AdaBoost	0.802126
BgC	0.854713
ETC	0.872147

Below result comes after using 'Bigram' in Tf-idf

In [10]:

```
df1
```

Out[10]:

	Score
SVC	0.892700
KN	0.790078
NB	0.880085
DT	0.836003
LR	0.838129
RF	0.873423
AdaBoost	0.810064
BgC	0.854429
ETC	0.871155

Below result comes after using 'Trigram' in tf-idf

In [14]:

```
df2
```

Out[14]:

	Score
SVC	0.890007
KN	0.787243
NB	0.882353
DT	0.843515
LR	0.827498
RF	0.871580
AdaBoost	0.806378
BgC	0.857973
ETC	0.864777

Below result comes after using 'Bigram' with remove noise data from input file in Tf-idf

In [23]:

```
df3
```

Out[23]:

	Score
SVC	0.895252
KN	0.790787
NB	0.884763
DT	0.845216
LR	0.840964
RF	0.869880
AdaBoost	0.813466
BgC	0.857548
ETC	0.868037

Check above result with adding more stop words and calculate precision, recall and F-score

In [80]:

```
df3.set_index('Model', inplace=True)
df3
```

Out[80]:

	F_Score	Precision	Recall	Score
Model				
SVC	0.823870	0.897480	0.761419	0.905032
KN	0.547193	0.749155	0.431001	0.791921
NB	0.796606	0.818881	0.775510	0.884479
DT	0.729009	0.734583	0.723518	0.843090
LR	0.684107	0.812291	0.590865	0.840822
RF	0.732335	0.953978	0.594266	0.873281
AdaBoost	0.605886	0.745739	0.510204	0.806378
BgC	0.748796	0.782724	0.717687	0.859532
ETC	0.738302	0.910256	0.620991	0.871580

Calculate the confusion matric for random forest model

In [14]:

```
from sklearn.metrics import confusion_matrix
train_classifier(rfc, X_train, y_train)
pred = predict_labels(rfc,X_test)
confu_mat = confusion_matrix(y_test,pred)
```

In [15]:

```
confu_mat
```

Out[15]:

```
array([[4864,  133],
       [ 712, 1346]])
```

SVM is giving better result than other model so caculate the confusion matrix for that.

In [79]:

```
from sklearn.metrics import confusion_matrix
svc = SVC(kernel='rbf', gamma=0.1,C=10,probability=True)
train_classifier(svc, X_train, y_train)
pred = predict_labels(svc,X_test)
precision,recall,fscore =score(y_test,pred,average ='binary')
accuracy_score(y_test,pred)
confu_mat = confusion_matrix(y_test,pred)
print(accuracy_score(y_test,pred))
print(precision,recall,fscore)
print(confu_mat)
```

```
0.9050318922749823
0.8974799541809851 0.761418853255588 0.8238696109358571
[[4818  179]
 [ 491 1567]]
```

Looks like support vector machine and Naive bayes model is working better than other classification model

Now do fine tuning parameter for SVM model :

- Grid search will be used to fine tune parameter.
- Using cross validation on that so that overfitting won't happened.

In [81]:

```
# SVM Parameter Tuning

from sklearn import svm
from sklearn.model_selection import GridSearchCV
def svc_param_selection(X, y, nfolds=5):
    Cs = [0.001,0.01, 0.1, 1, 10]
    #Cs = [10]
    gammas = [0.001, 0.01, 0.1, 1]
    #gammas = [0.01]
    kernel = ['rbf','sigmoid','linear']
    param_grid = {'C': Cs, 'gamma' : gammas,'kernel':kernel}
    grid_search = GridSearchCV(svm.SVC(), param_grid, cv=nfolds)
    #grid_search = GridSearchCV(svm.SVC(), param_grid, cv=nfolds)
    grid_search.fit(X, y)
    grid_search.best_params_
    return grid_search.best_params_

svm_best_prama = svc_param_selection(X_test,y_test)
```

In [82]:

```
svm_best_prama
```

Out[82]:

```
{'C': 10, 'gamma': 0.01, 'kernel': 'rbf'}
```

Now create AUC curve for the model SVM to check how much the model is fit with the data set.

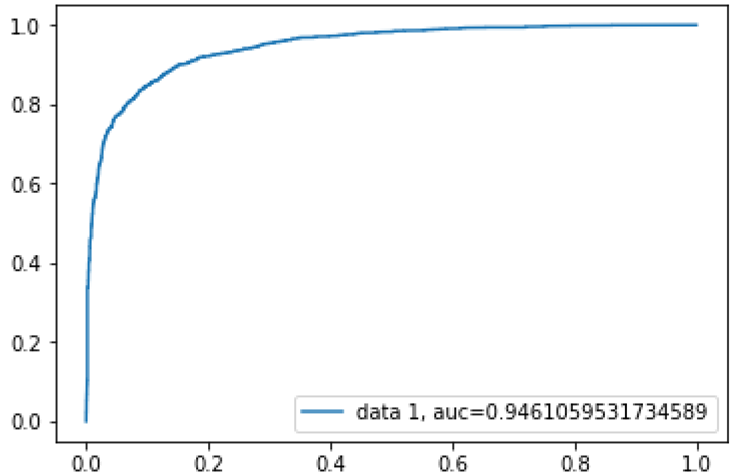
In [59]:

```
# Looks like support vector machine model is working better than other classificatio
n model

from sklearn.metrics import confusion_matrix
from sklearn import metrics

train_classifier(svc, X_train, y_train)
#pred = predict_labels(svc,X_test)

y_pred_proba = svc.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



- Above AUC result is giving the 94.61%. It means model is fitted very good for the input data set.

Conclusion:

- From all classification machine Learning model SVM and Naive Bayes model are good fit with the given data set.
- Support vector machine model is fitting best model on the input data set after calculating F1 score and AUC.
- We can even increase more accuracy after fine tuning parameters and cross validation.
- I have used Tf-idf to define the weight of every term in the tweet.
- Neural Net model can also be created for predicting ADR labels using LSTM.