** Project - Alternus Vera**

** Team: code-monkeys**

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** GitHub: https://github.com/pujakb/ML/tree/master/News_Classifier**

** Data preparation and Distillation :**

** Removing stop words and punchuations**

** lower case implementation**

** stemming, lematizing**

** tokenizing**

** LDA**

** LSA**

** LDA Vs LSA comparision**

** POS**

** tSNE**

** Bokeh clusters**

** Classifiers on model :**

** Decision tree, SVM, Naive Bayes, Random Forest, Logistic regression**

Importing the Libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from tqdm import tqdm
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.pipeline import Pipeline
import nltk
import nltk.corpus
from nltk.tokenize import word_tokenize
import csv
```

Loading the Data

In [2]:

```
training = pd.read_csv('C://PUJAMS//machinelearning//csvfiles//liar_dataset//t
rain.tsv',sep='\t')
testing = pd.read_csv('C://PUJAMS//machinelearning//csvfiles//liar_dataset//te
st.tsv',sep='\t')
validation = pd.read_csv('C://PUJAMS//machinelearning//csvfiles//liar_datase
t//valid.tsv',sep='\t')
vocabulary = pd.read_csv (r'C:\PUJAMS\machinelearning\csvfiles\liar_dataset\se
nsation_dictionary.csv')
```

In [3]:
```
columns = ['id', 'label', 'statement', 'subjects', 'speaker',
         'speaker_job', 'state', 'party', 'barely_true_counts',
         'false_counts', 'half_true_counts', 'mostly_true_counts', 'pants_on_f
ire_counts',
         'context']
training.columns = columns
testing.columns = columns
validation.columns = columns
training.head(5)
```

Out[3]:

	id	label	statement	subjects	speaker	speaker_job	state	
0	10540.json	half-true	When did the decline of coal start? It started...	energy,history,job-accomplishments	scott-surovell	State delegate	Virginia	dem
1	324.json	mostly-true	Hillary Clinton agrees with John McCain "by vo...	foreign-policy	barack-obama	President	Illinois	dem
2	1123.json	false	Health care reform legislation is likely to ma...	health-care	blog-posting	NaN	NaN	non
3	9028.json	half-true	The economic turnaround started at the end of ...	economy,jobs	charlie-crist	NaN	Florida	dem
4	12465.json	true	The Chicago Bears have had more starting quart...	education	robin-vos	Wisconsin Assembly speaker	Wisconsin	repu

In [4]:
```
#data integrity check (missing label values)
#none of the datasets contains missing values therefore no cleaning required
def data_qualityCheck():

    print("Checking data qualitites...")
    training.isnull().sum()
    training.info()

    print("check finished.")

    #below datasets were also used
    testing.isnull().sum()
    testing.info()

    validation.isnull().sum()
    validation.info()

data_qualityCheck()
```

```
Checking data qualitites...
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10239 entries, 0 to 10238
Data columns (total 14 columns):
id                      10239 non-null object
label                   10239 non-null object
statement               10239 non-null object
subjects                10237 non-null object
speaker                 10237 non-null object
speaker_job             7342 non-null object
state                   8031 non-null object
party                   10237 non-null object
barely_true_counts      10237 non-null float64
false_counts            10237 non-null float64
half_true_counts        10237 non-null float64
mostly_true_counts      10237 non-null float64
pants_on_fire_counts    10237 non-null float64
context                 10137 non-null object
dtypes: float64(5), object(9)
memory usage: 1.1+ MB
check finished.
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1266 entries, 0 to 1265
Data columns (total 14 columns):
id                      1266 non-null object
label                   1266 non-null object
statement               1266 non-null object
subjects                1266 non-null object
speaker                 1266 non-null object
speaker_job             941 non-null object
state                   1004 non-null object
party                   1266 non-null object
barely_true_counts      1266 non-null int64
false_counts            1266 non-null int64
half_true_counts        1266 non-null int64
mostly_true_counts      1266 non-null int64
pants_on_fire_counts    1266 non-null int64
context                 1249 non-null object
dtypes: int64(5), object(9)
memory usage: 138.5+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1283 entries, 0 to 1282
Data columns (total 14 columns):
id                      1283 non-null object
label                   1283 non-null object
statement               1283 non-null object
subjects                1283 non-null object
speaker                 1283 non-null object
speaker_job             938 non-null object
state                   1004 non-null object
party                   1283 non-null object
barely_true_counts      1283 non-null int64
false_counts            1283 non-null int64
half_true_counts        1283 non-null int64
mostly_true_counts      1283 non-null int64
pants_on_fire_counts    1283 non-null int64
context                 1271 non-null object
```

```
dtypes: int64(5), object(9)
memory usage: 140.4+ KB
```

Observing the data

In [5]:
```
#data observation
def data_obs():
    print("training dataset size:")
    print(training.shape)
    print(training.head(10))

    #below dataset were used for testing and validation purposes
    print(training.shape)
    print(training.head(10))

    print(validation.shape)
    print(validation.head(10))

data_obs()
```

```
training dataset size:
(10239, 14)
           id        label                                          statement
  \
0  10540.json    half-true  When did the decline of coal start? It started...

1    324.json  mostly-true  Hillary Clinton agrees with John McCain "by vo...

2   1123.json        false  Health care reform legislation is likely to ma...

3   9028.json    half-true  The economic turnaround started at the end of ...

4  12465.json         true  The Chicago Bears have had more starting quart...

5   2342.json  barely-true  Jim Dunnam has not lived in the district he re...

6    153.json    half-true  I'm the only person on this stage who has work...

7   5602.json    half-true  However, it took $19.5 million in Oregon Lotte...

8   9741.json  mostly-true  Says GOP primary opponents Glenn Grothman and ...

9   7115.json  mostly-true  For the first time in history, the share of th...


                             subjects                speaker  \
0        energy,history,job-accomplishments         scott-surovell
1                            foreign-policy           barack-obama
2                               health-care           blog-posting
3                              economy,jobs          charlie-crist
4                                 education              robin-vos
5                      candidates-biography  republican-party-texas
6                                    ethics           barack-obama
7                                      jobs         oregon-lottery
8  energy,message-machine-2014,voting-record          duey-stroebel
9                                 elections        robert-menendez

                 speaker_job       state         party  barely_true_counts
\
0             State delegate    Virginia      democrat                 0.0

1                  President    Illinois      democrat                70.0

2                        NaN         NaN          none                 7.0

3                        NaN     Florida      democrat                15.0

4  Wisconsin Assembly speaker   Wisconsin    republican                 0.0

5                        NaN       Texas    republican                 3.0

6                  President    Illinois      democrat                70.0

7                        NaN         NaN  organization                 0.0

8       State representative   Wisconsin    republican                 0.0
```

```
9               U.S. Senator  New Jersey      democrat                 1.0


   false_counts  half_true_counts  mostly_true_counts  pants_on_fire_counts
\
0           0.0               1.0                 1.0                   0.0

1          71.0             160.0               163.0                   9.0

2          19.0               3.0                 5.0                  44.0

3           9.0              20.0                19.0                   2.0

4           3.0               2.0                 5.0                   1.0

5           1.0               1.0                 3.0                   1.0

6          71.0             160.0               163.0                   9.0

7           0.0               1.0                 0.0                   1.0

8           0.0               0.0                 1.0                   0.0

9           3.0               1.0                 3.0                   0.0


                                 context
0                        a floor speech.
1                                 Denver
2                         a news release
3                    an interview on CNN
4             a an online opinion-piece
5                      a press release.
6  a Democratic debate in Philadelphia, Pa.
7                             a website 
8                         an online video
9                               a speech
(10239, 14)
           id        label                                          statement
  \
0  10540.json    half-true  When did the decline of coal start? It started...

1    324.json  mostly-true  Hillary Clinton agrees with John McCain "by vo...

2   1123.json        false  Health care reform legislation is likely to ma...

3   9028.json    half-true  The economic turnaround started at the end of ...

4  12465.json         true  The Chicago Bears have had more starting quart...

5   2342.json  barely-true  Jim Dunnam has not lived in the district he re...

6    153.json    half-true  I'm the only person on this stage who has work...

7   5602.json    half-true  However, it took $19.5 million in Oregon Lotte...

8   9741.json  mostly-true  Says GOP primary opponents Glenn Grothman and ...
```

```
9   7115.json  mostly-true  For the first time in history, the share of th...

                                   subjects                speaker  \
0       energy,history,job-accomplishments          scott-surovell
1                           foreign-policy            barack-obama
2                              health-care            blog-posting
3                             economy,jobs           charlie-crist
4                                education               robin-vos
5                     candidates-biography  republican-party-texas
6                                   ethics            barack-obama
7                                     jobs           oregon-lottery
8  energy,message-machine-2014,voting-record           duey-stroebel
9                                elections         robert-menendez

                speaker_job       state         party  barely_true_counts
\
0            State delegate    Virginia      democrat                 0.0

1                 President    Illinois      democrat                70.0

2                       NaN         NaN          none                 7.0

3                       NaN     Florida      democrat                15.0

4  Wisconsin Assembly speaker   Wisconsin    republican                 0.0

5                       NaN       Texas    republican                 3.0

6                 President    Illinois      democrat                70.0

7                       NaN         NaN  organization                 0.0

8      State representative   Wisconsin    republican                 0.0

9              U.S. Senator  New Jersey      democrat                 1.0


   false_counts  half_true_counts  mostly_true_counts  pants_on_fire_counts
\
0           0.0               1.0                 1.0                   0.0

1          71.0             160.0               163.0                   9.0

2          19.0               3.0                 5.0                  44.0

3           9.0              20.0                19.0                   2.0

4           3.0               2.0                 5.0                   1.0

5           1.0               1.0                 3.0                   1.0

6          71.0             160.0               163.0                   9.0

7           0.0               1.0                 0.0                   1.0
```

```
8           0.0                0.0                 1.0                   0.0

9           3.0                1.0                 3.0                   0.0


                                       context
0                              a floor speech.
1                                       Denver
2                               a news release
3                          an interview on CNN
4                    a an online opinion-piece
5                             a press release.
6   a Democratic debate in Philadelphia, Pa.
7                                    a website 
8                               an online video
9                                     a speech
(1283, 14)
           id       label                                           statement
\
0    238.json  pants-fire  When Obama was sworn into office, he DID NOT u...

1   7891.json       false  Says Having organizations parading as being so...

2   8169.json   half-true     Says nearly half of Oregons children are poor.

3    929.json   half-true  On attacks by Republicans that various program...

4   9416.json       false  Says when armed civilians stop mass shootings ...

5   6861.json        true  Says Tennessee is providing millions of dollar...

6   1122.json       false  The health care reform plan would set limits s...

7  13138.json        true  Says Donald Trump started his career back in 1...

8   1880.json   half-true  Bill White has a long history of trying to lim...

9  12803.json   half-true  John McCains chief economic adviser during the...


                                  subjects                  speaker  \
0        obama-birth-certificate,religion               chain-email
1         campaign-finance,congress,taxes         earl-blumenauer
2                                  poverty        jim-francesconi
3                        economy,stimulus            barack-obama
4                                     guns              jim-rubens
5                  education,state-budget              andy-berke
6                              health-care             club-growth
7  candidates-biography,diversity,housing         hillary-clinton
8                                 military  republican-party-texas
9                                  economy               tim-kaine

                                speaker_job          state       party
\
0                                      NaN            NaN        none

1                         U.S. representative         Oregon    democrat
```

```
2  Member of the State Board of Higher Education         Oregon        none

3                                       President       Illinois    democrat

4                             Small business owner  New Hampshire  republican

5                         Lawyer and state senator      Tennessee    democrat

6                                              NaN            NaN        none

7                          Presidential candidate       New York    democrat

8                                              NaN          Texas  republican

9                                      U.S. Senator       Virginia    democrat


   barely_true_counts  false_counts  half_true_counts  mostly_true_counts  \
0                  11            43                 8                   5
1                   0             1                 1                   1
2                   0             1                 1                   1
3                  70            71               160                 163
4                   1             1                 0                   1
5                   0             0                 0                   0
6                   4             5                 4                   2
7                  40            29                69                  76
8                   3             1                 1                   3
9                   8             3                15                  15

   pants_on_fire_counts                                            context
0                   105                                                NaN
1                     0                          a U.S. Ways and Means hearing
2                     0                                 an opinion article
3                     9                              interview with CBS News
4                     0            in an interview at gun shop in Hudson, N.H.
5                     0  a letter to state Senate education committee c...
6                     0                                              a TV ad
7                     7                          the first presidential debate
8                     1                                          an e-mail
9                     0  a speech at the Democratic National Convention...
```

In [6]:

```
# training=training[['label','statement']]
# training.head(5)
```

In [7]:
```
training.groupby('label').describe()
```

Out[7]:

	barely_true_counts								false_counts		...
	count	mean	std	min	25%	50%	75%	max	count	mean	...
label											
barely-true	1654.0	11.730351	17.605713	1.0	1.0	3.0	13.0	70.0	1654.0	12.422612	...
false	1992.0	11.610944	19.224930	0.0	0.0	2.0	11.0	70.0	1992.0	15.785643	...
half-true	2114.0	11.848628	19.512656	0.0	0.0	2.0	14.0	70.0	2114.0	12.568117	...
mostly-true	1962.0	11.825688	19.999061	0.0	0.0	2.0	14.0	70.0	1962.0	12.280836	...
pants-fire	839.0	11.050060	17.162980	0.0	0.0	5.0	11.0	70.0	839.0	18.162098	...
true	1676.0	10.754773	18.920702	0.0	0.0	1.0	11.0	70.0	1676.0	10.818616	...

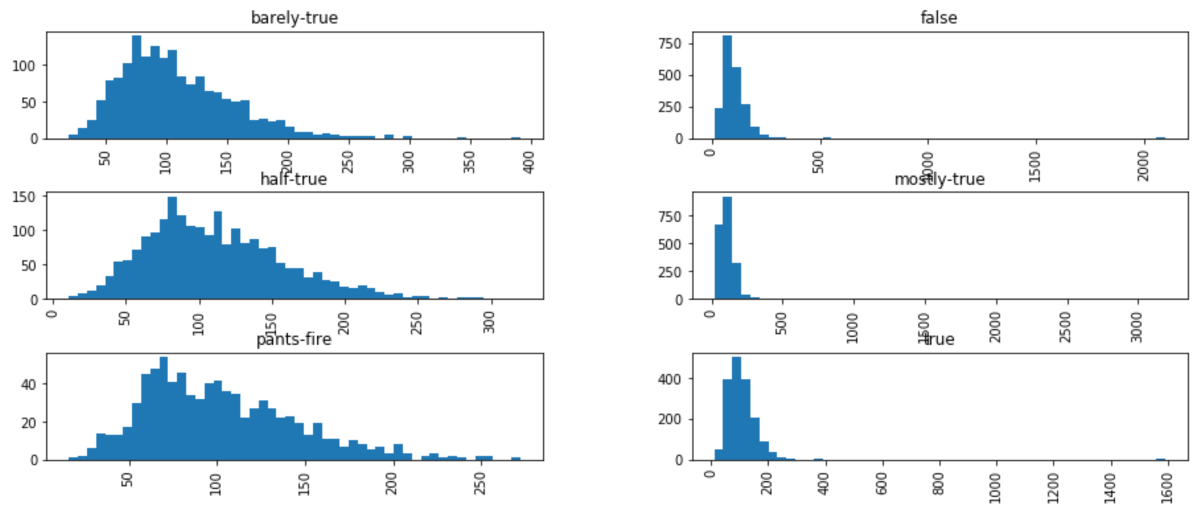
6 rows × 40 columns

In [8]:
```
training.iloc[0]["statement"][:len(training.iloc[0]["statement"])]
```

Out[8]:
```
'When did the decline of coal start? It started when natural gas took off tha
t started to begin in (President George W.) Bushs administration.'
```

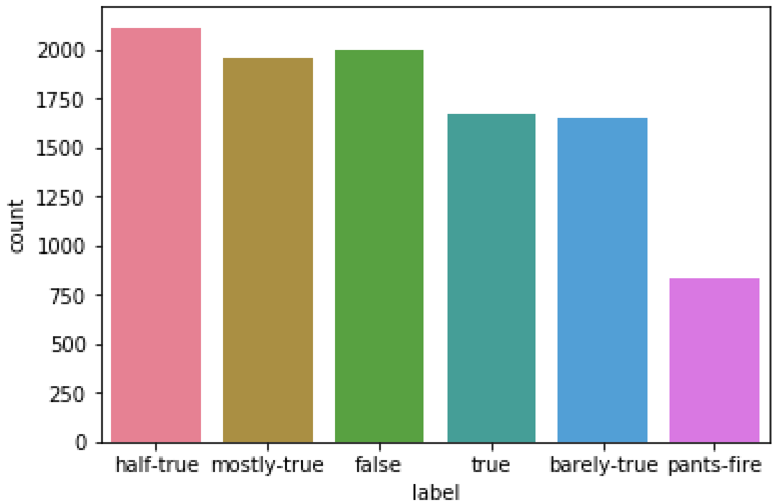
In [9]:
```
training['length'] = training['statement'].apply(len)
training.hist(column='length',by='label',bins=50, figsize=(15,6))
```

Out[9]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000000000BE9BE48>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000BEEE668
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000BF17978>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000BF41A90
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000000000C07ADA0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000000000C07ADD8
>]],
      dtype=object)
```



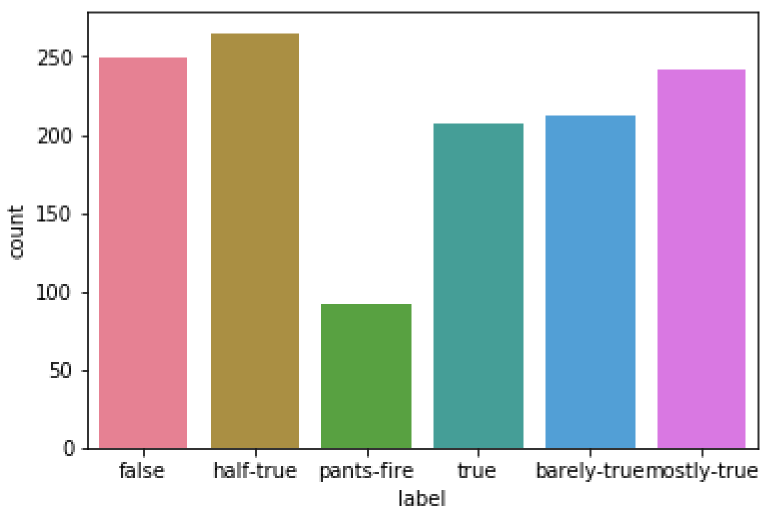
In [10]:
```
#distribution of classes for prediction
def create_distribution(dataFile):

    return sns.countplot(x='label', data=dataFile, palette='husl')


#by calling below we can see that training, test and valid data seems to be fa
ilry evenly distributed between the classes
create_distribution(training)
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0xc23c438>



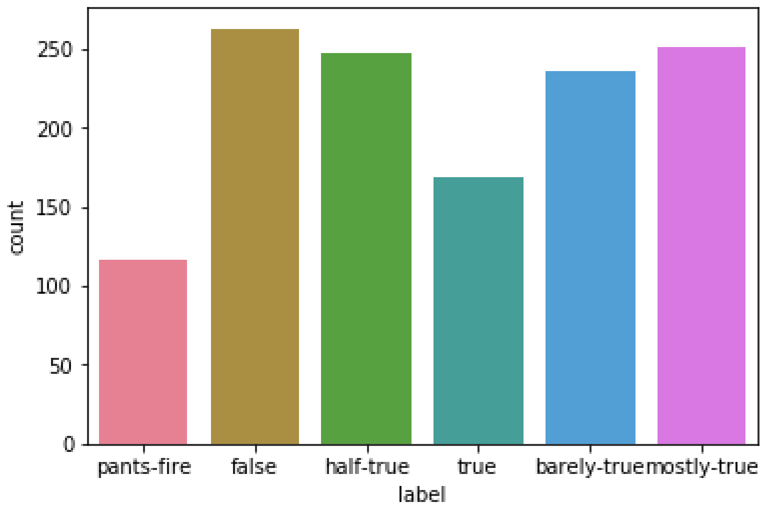
In [11]:
```
create_distribution(testing)
```

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0xc5729e8>



In [12]:
```
create_distribution(validation)
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0xc5cc470>



In [13]:
```
training.label.unique()
```

Out[13]:
```
array(['half-true', 'mostly-true', 'false', 'true', 'barely-true',
       'pants-fire'], dtype=object)
```

In [15]:
```
# This is in case we want to conduct binary classification
# Our focus is to develop a multi-classification model

# train_news['label']=np.where(train_news['label']=='half-true','true',train_news['label'])
# train_news['label']=np.where(train_news['label']=='mostly-true','true',train_news['label'])
# train_news['label']=np.where(train_news['label']=='barely-true','false',train_news['label'])
# train_news['label']=np.where(train_news['label']=='pants-fire','false',train_news['label'])
# train_news['label']=np.where(train_news['label']=='TRUE','true',train_news['label'])
# train_news['label']=np.where(train_news['label']=='FALSE','false',train_news['label'])

# plt.title('statement count Vs label')
# train_news.groupby(['label']).size().plot(kind='bar', color='blue')
# plt.xlabel('count')
# plt.show()
```

In [16]:
```
import re
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from nltk.tokenize import word_tokenize
nltk.download('punkt')

def TextCleansing(txt):
    rem = re.sub('[^a-zA-Z]', ' ', txt)
    rem = rem.lower()
    rem = rem.split()
    ps = PorterStemmer()
    rem = [ps.stem(word) for word in rem if not word in set(stopwords.words('e
nglish'))]
    rem = ' '.join(rem)
    return rem
```

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

In [17]:
```
stop_words=set(stopwords.words('english'))
print(stop_words)
```

```
{'to', 'of', 'once', 'he', 'into', 't', 'ours', 'doing', "weren't", "should'v
e", 'if', 'through', 'yours', 'am', 'during', 'out', "aren't", "wouldn't", 'd
id', "won't", 'wouldn', 'all', 'they', 'below', 'do', 'few', 'been', 'can',
'isn', 'by', 'against', 'i', 'why', 've', 'whom', 'now', 'himself', 'and', 'o
r', 'we', 'in', 'couldn', "mightn't", 'you', 'being', 'own', 'other', 'aren',
'who', 'was', 'are', 'shouldn', 'mightn', "don't", 'what', 'for', 'mustn', 'd
own', "you'll", 'a', 'their', 'than', 'most', "doesn't", 'its', 'very', 'wer
e', 'won', "couldn't", 'some', 'about', 'same', 'on', 'your', 'herself', 'bu
t', 'ma', 'while', 'when', 'have', "shouldn't", "hadn't", 'more', 'my', "yo
u'd", 'over', 'haven', 'not', "hasn't", "you're", 'be', 'is', 'just', 'her',
"she's", 'from', 'him', 'because', 'above', 'there', 'those', 'which', 'sha
n', "wasn't", 'it', 'll', 'his', "haven't", 'further', 'hers', 'weren', 'unti
l', 'ain', 'our', 'doesn', 'before', 'd', "mustn't", 'only', 'both', 'me', "d
idn't", 'after', 'this', 'between', 'hasn', 'myself', "it's", 'has', 'y', 'to
o', "shan't", 'themselves', 'with', 'again', 'itself', 'under', "that'll", 's
he', 'didn', 'the', 'an', 'then', 'don', 'that', 'up', 're', 'such', 'where',
'hadn', 'as', "isn't", 'ourselves', 'will', 'o', 'wasn', 'how', 'each', 'an
y', "needn't", 'had', 'needn', 'at', 'yourself', "you've", 'yourselves', 'n
o', 'nor', 'theirs', 'm', 'here', 'does', 'these', 'them', 'should', 'havin
g', 'so', 'off', 's'}
```

In [19]:
```
training_head = training[['statement']]
training_head['index'] = training_head.index
documents = training_head
```

```
C:\Users\PB\Anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWithC
opyWarning:
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-docs/st
able/indexing.html#indexing-view-versus-copy
```

In [20]:
```
print(len(documents))
print(documents[:5])
```

```
10239
                                           statement  index
0  When did the decline of coal start? It started...      0
1  Hillary Clinton agrees with John McCain "by vo...      1
2  Health care reform legislation is likely to ma...      2
3  The economic turnaround started at the end of ...      3
4  The Chicago Bears have had more starting quart...      4
```

Data Preprocessing

In [21]:
```
import gensim
from gensim.utils import simple_preprocess
from gensim.parsing.preprocessing import STOPWORDS
from nltk.stem import WordNetLemmatizer, SnowballStemmer
from nltk.stem.porter import *
import numpy as np
np.random.seed(2018)
import nltk
nltk.download('wordnet')
```

```
C:\Users\PB\Anaconda3\lib\site-packages\gensim\utils.py:1212: UserWarning: de
tected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

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

Out[21]: True

In [22]:
```
from nltk.stem import PorterStemmer,WordNetLemmatizer
def text_preprocessing(df_base):
    df=df_base.copy()
    # Lowercase the text
    df['statement']=df['statement'].str.lower()
    # word tokenization
    df['statement']=df['statement'].map(lambda x: nltk.word_tokenize(x))
    # remove stop words and non alphanumeric charaters
    df['statement']=df['statement'].map(lambda x: [w for w in x if (not w in s
top_words) and w.isalpha()])
    # Lemmatization
    wordnet_lemmatizer = WordNetLemmatizer()
    df['statement']=df['statement'].map(lambda x: [ wordnet_lemmatizer.lemmati
ze(w) for w in x])
    # stemming
    porter = PorterStemmer()
    df['statement']=df['statement'].map(lambda x: [porter.stem(w) for w in x]
)
    return df
```

In [23]:
```
processed =text_preprocessing(training)
processed.head()
```

Out[23]:

	id	label	statement	subjects	speaker	speaker_job	state	
0	10540.json	half-true	[declin, coal, start, start, natur, ga, took, ...	energy,history,job-accomplishments	scott-surovell	State delegate	Virginia	de
1	324.json	mostly-true	[hillari, clinton, agre, john, mccain, vote, g...	foreign-policy	barack-obama	President	Illinois	de
2	1123.json	false	[health, care, reform, legisl, like, mandat, f...	health-care	blog-posting	NaN	NaN	nc
3	9028.json	half-true	[econom, turnaround, start, end, term]	economy,jobs	charlie-crist	NaN	Florida	de
4	12465.json	true	[chicago, bear, start, quarterback, last, year...	education	robin-vos	Wisconsin Assembly speaker	Wisconsin	re

Word2Vec

Word2vec is a two-layer neural net that processes text. Its input is a text corpus and its output is a set of vectors: feature vectors for words in that corpus.it turns text into a numerical form that deep nets can understand

In [24]:
```
import gensim
from gensim.models.word2vec import Word2Vec
from gensim.models.doc2vec import TaggedDocument
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
```

In [25]:
```
LabeledSentence = gensim.models.doc2vec.LabeledSentence
```

In [26]:
```
def labelled_sentences(articles, label_type):
    labelledSentences = []
    for i,_d in enumerate(articles):
        labelledSentences.append(LabeledSentence(_d, label_type[i]))
    return labelledSentences
```

In [27]:
```
processed_labelled=labelled_sentences(processed['statement'],processed['label'
])
processed_labelled[1]
```

Out[27]:
```
LabeledSentence(words=['hillari', 'clinton', 'agre', 'john', 'mccain', 'vot
e', 'give', 'georg', 'bush', 'benefit', 'doubt', 'iran'], tags='mostly-true')
```

In [28]:
```
tagged = [TaggedDocument(words=_d, tags=[str(i)]) for i, _d in enumerate(proce
ssed['statement'])]
```

In [29]:
```
tagged_words=[x.words for x in tagged]
tagged_words_1D=[]
for row in range(len(tagged_words)):
    for col in range(len(tagged_words[row])):
        tagged_words.append(tagged_words[row][col])

n_dim=300
w2v = Word2Vec(size=n_dim, min_count=0)
w2v.build_vocab(tagged_words)
w2v.train(tagged_words,total_examples=w2v.corpus_count,epochs=w2v.epochs)
```

Out[29]:
```
(1043861, 3317680)
```

In [30]:
```
w2v.most_similar('war')
```

Out[30]:
```
[('rapid', 0.9978175759315491),
 ('longest', 0.9975180625915527),
 ('fundrais', 0.9974884986877441),
 ('incid', 0.997333824634552),
 ('extrem', 0.9971774816513062),
 ('watch', 0.9971362948417664),
 ('jump', 0.9971160292625427),
 ('gasolin', 0.9970066547393799),
 ('happen', 0.996982216835022),
 ('document', 0.9969084858894348)]
```

In [31]:
```
processed_statements=processed[['statement','label']]
processed_statements_vectorized=processed_statements['statement'].map(lambda x
: [w2v[w] for w in x])

processed_statements['statement']=processed_statements_vectorized

from sklearn import preprocessing
le = preprocessing.LabelEncoder()
# list(le.inverse_transform(processed_statements['label']))
processed_statements['label']=le.fit_transform(processed_statements['label'])

processed_statements.head()
```

Out[31]:

	statement	label
0	[[0.08882012, 0.052362617, 0.044050723, 0.0263...	2
1	[[0.23452127, -0.103835195, -0.14599872, 0.228...	3
2	[[0.73109084, 0.56986696, -0.44808704, -0.1760...	1
3	[[0.22355153, 0.084662944, 0.04774518, 0.07887...	2
4	[[0.09246858, 0.02514211, 0.0040849606, 0.0322...	5

In [32]:
```
def document_vector(doc):
    return np.mean(doc, axis=0)

for row_idx in range(len(processed_statements['statement'])):
    for col_idx in range(len(processed_statements['statement'][row_idx])):
        processed_statements['statement'][row_idx][col_idx]=document_vector(pr
ocessed_statements['statement'][row_idx][col_idx])

#df_train_statements['statement']=df_train_statements['statement'].map(documen
t_vector)
processed_statements.drop(index=4497,inplace=True)
processed_statements.reset_index(drop=True)
```

Out[32]:

	statement	label
0	[0.0015531193, 0.0030009032, 0.0048259343, 0.0...	2
1	[0.005818305, 0.010304897, 0.0036140848, 0.007...	3
2	[0.0039481856, 0.018210806, 0.00598304, 0.0067...	1
3	[0.0058103004, 0.001316087, 0.0048259343, 0.00...	2
4	[0.0027394965, 0.002334294, 0.0048259343, -2.0...	5
5	[0.0051740645, 8.1900405e-05, 0.007307156, 0.0...	0
6	[0.0063952627, 0.003622454, 0.0065158713, 0.00...	2
7	[0.0009564376, 0.0042650383, 0.006832938, 0.00...	2
8	[0.0073591056, 0.004535676, 0.0032518224, 0.00...	3
9	[0.004452211, 0.0056764404, 0.0058674715, 0.00...	3
10	[0.00523225, 0.006501026, 0.006832938, 0.00713...	2
11	[0.0046875635, 0.0063856672, 0.006251499, 0.00...	1
12	[0.005886208, 0.00011750842, 0.0055083116, 0.0...	3
13	[0.0020381382, 0.018210806, 0.0046027345, 0.00...	0
14	[0.0048613134, 0.0055349213, 0.0010576568, 0.0...	2
15	[0.002692792, 0.0048573655, 0.0063228006, 0.00...	5
16	[0.0025115563, 0.0054791453, 0.0026679575, 0.0...	0
17	[0.007653927, 0.009440354, 8.842249e-06, 0.002...	2
18	[0.005894712, 0.007918409, 0.005161361, 0.0018...	3
19	[0.0074008037, 0.0042240904, 0.007807286, 0.00...	1
20	[0.019988174, 0.013930908, 0.0056922636, 0.004...	3
21	[0.0055046654, 0.007970379, 0.003117077, 0.006...	3
22	[0.0073591056, 0.0065401616, 0.006110296, 0.00...	2
23	[0.0073591056, 0.0046875635, 0.0063856672, 0.0...	0
24	[0.0060428553, 0.00692223, 0.00022820162, 0.00...	1
25	[0.0025243398, 0.006544179, 0.007132008, 0.006...	3
26	[0.00528491, 0.0038272997, 0.005425787, 0.0061...	2
27	[0.007084581, 0.0053566354, 0.0017373619, 0.00...	1
28	[0.0011862061, 0.0064320765, 0.0042735455, 0.0...	3
29	[0.0073591056, 0.0037955025, 0.0019614815, 0.0...	5
...	...	...
10208	[0.00523225, 0.0020381382, 0.018210806, 0.0046...	5

	statement	label
10209	[0.0043656705, 0.005894712, 0.0040787444, 0.00...	5
10210	[0.0053095864, 0.0073591056, 0.00654957, 0.006...	2
10211	[0.0049790507, 0.0012464045, 0.0074034277, 0.0...	0
10212	[0.0048613134, 0.007970379, 0.0039481856, 0.01...	1
10213	[0.018964062, -0.0027135627, 0.004326349, 0.00...	0
10214	[0.0023030671, 0.0054027964, 0.0053100125, 0.0...	1
10215	[0.003786529, 0.018964062, -0.0027135627, 0.00...	2
10216	[0.0043705986, 0.008069582, 0.004581774, 0.003...	1
10217	[0.007304689, 0.007270716, 0.006722042, 0.0034...	2
10218	[0.0073591056, 0.0046875635, 0.0063856672, 0.0...	3
10219	[0.0062789354, 0.0053005423, 0.0064634476, 0.0...	1
10220	[0.004452211, 0.0056764404, 0.00523225, 0.0018...	5
10221	[0.0073591056, 0.00528491, 0.0038272997, 0.005...	3
10222	[0.013930908, 0.0064594317, 0.0042387014, 0.00...	0
10223	[0.00654957, 0.0071791466, 0.006127811, 0.0068...	2
10224	[0.00024483484, 0.001080337, 0.0016555116, 0.0...	3
10225	[0.0040249764, 0.0032681953, 0.005939055, 0.00...	4
10226	[0.00600365, 0.00079215714, 0.0013603992, 0.00...	0
10227	[0.0038574457, 0.00045269995, 0.0059986347, 0....	3
10228	[0.005329299, 0.008814389, 0.0025323606, 0.003...	0
10229	[0.007026281, 0.013930908, 0.0030334643, 0.009...	2
10230	[0.0010748486, 0.0067132316, 0.0023030671, 0.0...	2
10231	[0.007120289, 0.0010893724, 0.0052630813, 0.00...	4
10232	[0.0073080175, 0.005329299, 0.008814389, 0.006...	2
10233	[0.00342068, 0.0074034277, 0.00023298124, 0.00...	3
10234	[0.008069582, 0.0048294296, 0.0071791466, 0.00...	3
10235	[0.0073591056, 0.0006689055, 0.004880984, 0.00...	2
10236	[0.0011983047, 0.0010808384, 0.0012000249, 0.0...	1
10237	[0.008196405, 0.004830276, 0.0021933161, 0.000...	4

10238 rows × 2 columns

In [33]:

```
texts=[]
for x in processed_statements['statement'].values:
    texts.append(x)
X=pd.DataFrame(texts)
X=X.fillna(0)
y=processed_statements[['label']]
X_train,X_test,y_train,y_test=train_test_split(X, y,test_size = .2, random_sta
te = 1)
X_train.head()
```

Out[33]:

	0	1	2	3	4	5	6	7	
8892	0.005431	0.001999	0.007128	0.002360	0.006550	0.007985	0.004348	0.007403	0.
2933	0.007359	0.009108	0.013931	0.003614	0.002833	0.002692	0.013931	0.001240	0.
3933	0.003033	0.007970	0.005704	0.006502	0.004355	0.006663	0.002504	0.001453	0.
3406	0.007359	-0.003100	0.018964	0.001833	0.003709	0.002651	0.000533	0.005263	0.
7210	0.006073	0.005896	0.003588	0.001695	0.006648	0.005372	0.001766	0.000000	0.

5 rows × 245 columns

Classifiers :

1) Logistic Regression

2) Decision Tree

3) GNB - Gaussian Naive Bayes

4) Random Forest Classifier

In [34]:
```
from sklearn import metrics
from sklearn.metrics import accuracy_score

from sklearn.model_selection import train_test_split
from sklearn import linear_model

lm = linear_model.LogisticRegression(verbose=1)
model = lm.fit(X_train, y_train)
print (model)
predictions = lm.predict(X_test)

print ("Score:", model.score(X_test, y_test))

print(metrics.classification_report(y_test,predictions))
```

```
[LibLinear]LogisticRegression(C=1.0, class_weight=None, dual=False, fit_inter
cept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=1, warm_start=False)
Score: 0.2109375
             precision    recall  f1-score   support

          0       0.00      0.00      0.00       309
          1       0.00      0.00      0.00       396
          2       0.21      1.00      0.35       432
          3       0.00      0.00      0.00       392
          4       0.00      0.00      0.00       171
          5       0.00      0.00      0.00       348

avg / total       0.04      0.21      0.07      2048
```

In [35]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import  LogisticRegression

clf_gini = DecisionTreeClassifier(criterion = "gini", random_state = 100,
                               max_depth=3, min_samples_leaf=5)
clf_gini.fit(X_train, y_train)
dec_pred = clf_gini.predict(X_test)
print ("Score:", clf_gini.score(X_test, y_test))

print(metrics.classification_report(y_test,dec_pred))
```

```
Score: 0.2099609375
             precision    recall  f1-score   support

          0       0.00      0.00      0.00       309
          1       0.26      0.12      0.16       396
          2       0.23      0.23      0.23       432
          3       0.20      0.73      0.31       392
          4       0.00      0.00      0.00       171
          5       0.00      0.00      0.00       348

avg / total       0.14      0.21      0.14      2048
```

In [36]:
```
import numpy as np
from sklearn import metrics
from sklearn.metrics import accuracy_score

from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB().fit(X_train, y_train)
gnb_pred = gnb.predict(X_test)

print ("Score:", gnb.score(X_test, y_test))
print(metrics.classification_report(y_test,gnb_pred))
```

```
Score: 0.08935546875
             precision    recall  f1-score   support

          0       0.25      0.00      0.01       309
          1       0.00      0.00      0.00       396
          2       0.32      0.03      0.05       432
          3       0.00      0.00      0.00       392
          4       0.09      1.00      0.16       171
          5       0.00      0.00      0.00       348

avg / total       0.11      0.09      0.02      2048
```

In [37]:
```
from sklearn.ensemble import RandomForestClassifier
num_trees=200

rf=RandomForestClassifier(n_estimators=num_trees)
rf.fit(X_train, y_train)
rf_pred=rf.predict(X_test)

print ("Score:", rf.score(X_test, y_test))
print(metrics.classification_report(y_test,rf_pred))
```

```
Score: 0.2177734375
             precision    recall  f1-score   support

          0       0.19      0.16      0.17       309
          1       0.23      0.25      0.24       396
          2       0.22      0.35      0.27       432
          3       0.22      0.26      0.24       392
          4       0.14      0.01      0.02       171
          5       0.21      0.12      0.15       348

avg / total       0.21      0.22      0.20      2048
```

From above we can conclude that Logistic regression and Decision Tree classifier are performing better that the other classifiers.

Visualization:

A popular method for visualizing document similarity is to use t-distributed stochastic neighbor embedding, t-SNE.

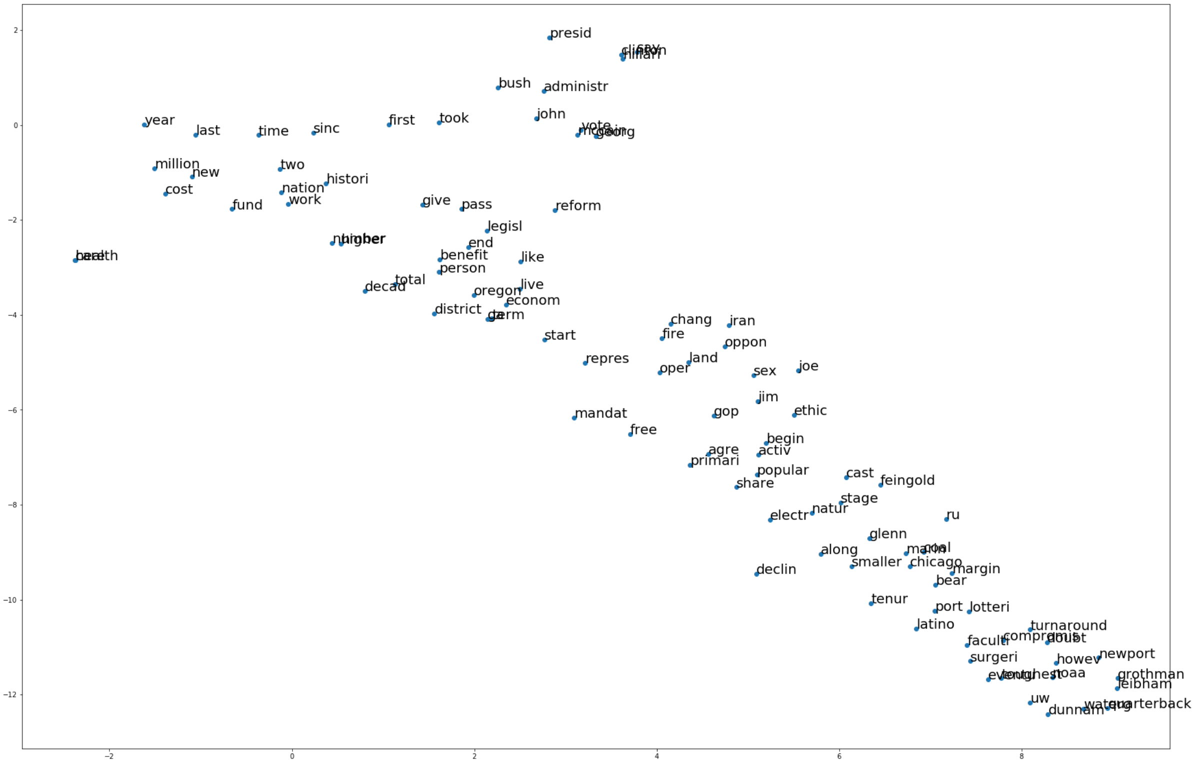
1) Load the corpus and vectorize the text using TF-IDF.

2) Once the corpus is vectorized we visualize it, showing the distribution of classes.

reference:http://www.scikit-yb.org/en/latest/api/text/tsne.html (http://www.scikit-yb.org/en/latest/api/text/tsne.html)

In [38]:
```
# Import libraries
from sklearn.manifold import TSNE
import matplotlib as mpl
import matplotlib.pyplot as plt
warnings.filterwarnings("ignore",category=RuntimeWarning)

# List of vocabulary.

vocab = list(w2v.wv.vocab)

# index vector values by corresponding vocab list

X = w2v[vocab]

print("Total Number of Vocab:", len(X))
print()
print(X[0][:10])

# Visualize only 100 words.

tsne = TSNE(n_components = 2)
X_tsne = tsne.fit_transform(X[:100,:])

df = pd.DataFrame(X_tsne, index = vocab[:100], columns = ['X','Y'])
df.head()

fig = plt.figure()
fig.set_size_inches(30,20)

ax = fig.add_subplot(1,1,1)
ax.scatter(df['X'], df['Y'])

# Put the label on each point.
for word, pos in df.iterrows():
    ax.annotate(word, pos, fontsize = 20)
plt.show()
```

```
Total Number of Vocab: 7539

[ 0.08882012  0.05236262  0.04405072  0.02633099  0.08770611 -0.09703708
  0.02267416 -0.05655846 -0.10878675  0.05518287]
```



In [44]:
```
import numpy as np
import pandas as pd
from IPython.display import display
from tqdm import tqdm
from collections import Counter
import ast

import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import seaborn as sb

%matplotlib inline

raw_data = training

reindexed_data = raw_data['statement']
reindexed_data.index = raw_data['label']

display(raw_data.head())
```

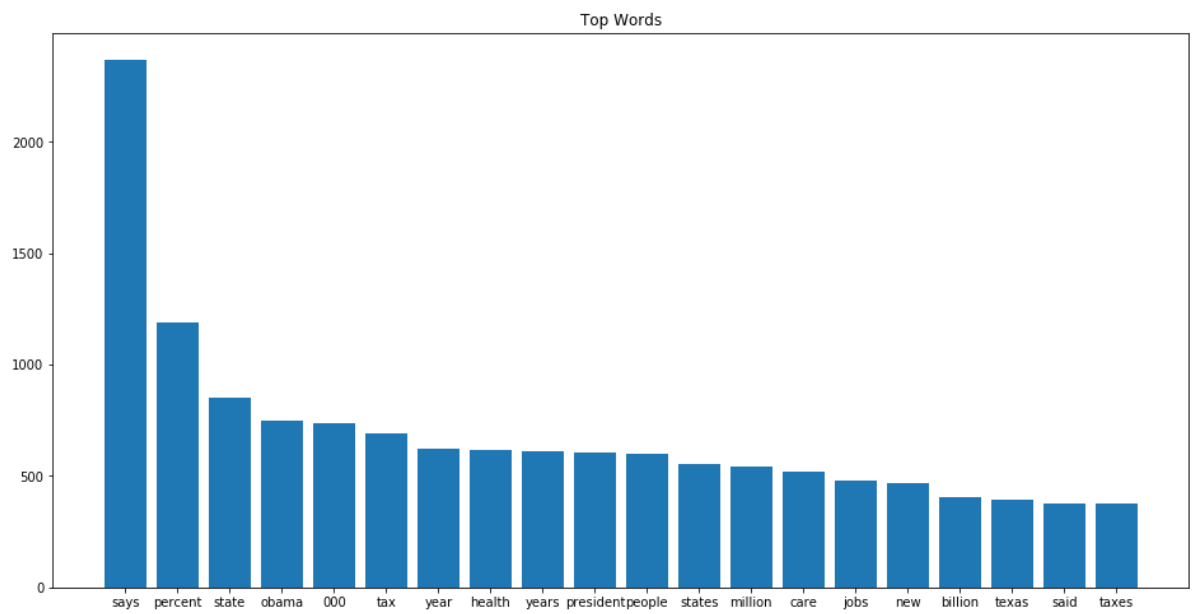
	id	label	statement	subjects	speaker	speaker_job	state	
0	10540.json	half-true	When did the decline of coal start? It started...	energy,history,job-accomplishments	scott-surovell	State delegate	Virginia	dem
1	324.json	mostly-true	Hillary Clinton agrees with John McCain "by vo...	foreign-policy	barack-obama	President	Illinois	dem
2	1123.json	false	Health care reform legislation is likely to ma...	health-care	blog-posting	NaN	NaN	non
3	9028.json	half-true	The economic turnaround started at the end of ...	economy,jobs	charlie-crist	NaN	Florida	dem
4	12465.json	true	The Chicago Bears have had more starting quart...	education	robin-vos	Wisconsin Assembly speaker	Wisconsin	repu

Developing list of the top words used in the statements of Liar Liar dataset, . Stop words are removed from the dataset to avoid any trivial conjunctions, prepositions, etc.

In [45]:
```
# Define helper functions
def get_top_n_words(n_top_words, count_vectorizer, text_data):
    '''returns a tuple of the top n words in a sample and their accompanying c
ounts, given a CountVectorizer object and text sample'''
    vectorized_headlines = count_vectorizer.fit_transform(text_data.as_matrix
())

    vectorized_total = np.sum(vectorized_headlines, axis=0)
    word_indices = np.flip(np.argsort(vectorized_total)[0,:], 1)
    word_values = np.flip(np.sort(vectorized_total)[0,:],1)

    word_vectors = np.zeros((n_top_words, vectorized_headlines.shape[1]))
    for i in range(n_top_words):
        word_vectors[i,word_indices[0,i]] = 1

    words = [word[0].encode('ascii').decode('utf-8') for word in count_vectori
zer.inverse_transform(word_vectors)]

    return (words, word_values[0,:n_top_words].tolist()[0])
```

In [46]:
```
from sklearn.feature_extraction.text import CountVectorizer

count_vectorizer = CountVectorizer(stop_words='english')
words, word_values = get_top_n_words(n_top_words=20, count_vectorizer=count_ve
ctorizer, text_data=reindexed_data)

fig, ax = plt.subplots(figsize=(16,8))
ax.bar(range(len(words)), word_values)
ax.set_xticks(range(len(words)))
ax.set_xticklabels(words)
ax.set_title('Top Words')
```

Out[46]: Text(0.5,1,'Top Words')



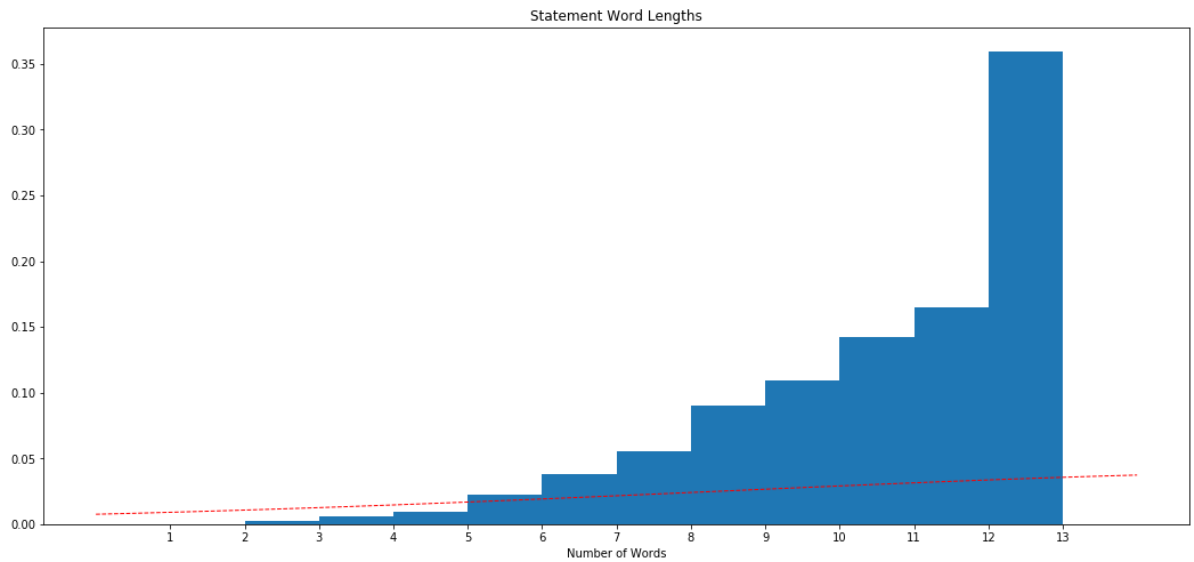
Part Of Speech Tagging

Below is the histogram of statement word lengths, and (POS) part-of-speech tagging to understand the types of words used across the corpus. This requires first converting all headline strings to TextBlobs and calling the pos_tags method on each, yielding a list of tagged words for each headline. A complete list of such word tags is available here.

In [47]:
```
from textblob import TextBlob

while True:
    try:
        tagged_headlines = pd.read_csv('abcnews-pos-tagged.csv', index_col=0)
        word_counts = []
        pos_counts = {}

        for headline in tagged_headlines[u'tags']:
            headline = ast.literal_eval(headline)
            word_counts.append(len(headline))
            for tag in headline:
                if tag[1] in pos_counts:
                    pos_counts[tag[1]] += 1
                else:
                    pos_counts[tag[1]] = 1

    except IOError:
        tagged_headlines = [TextBlob(reindexed_data[i]).pos_tags for i in rang
e(reindexed_data.shape[0])]

        tagged_headlines = pd.DataFrame({'tags':tagged_headlines})
        tagged_headlines.to_csv('abcnews-pos-tagged.csv')
        continue
    break

print('Total number of words: ', np.sum(word_counts))
print('Mean number of words per headline: ', np.mean(word_counts))
```

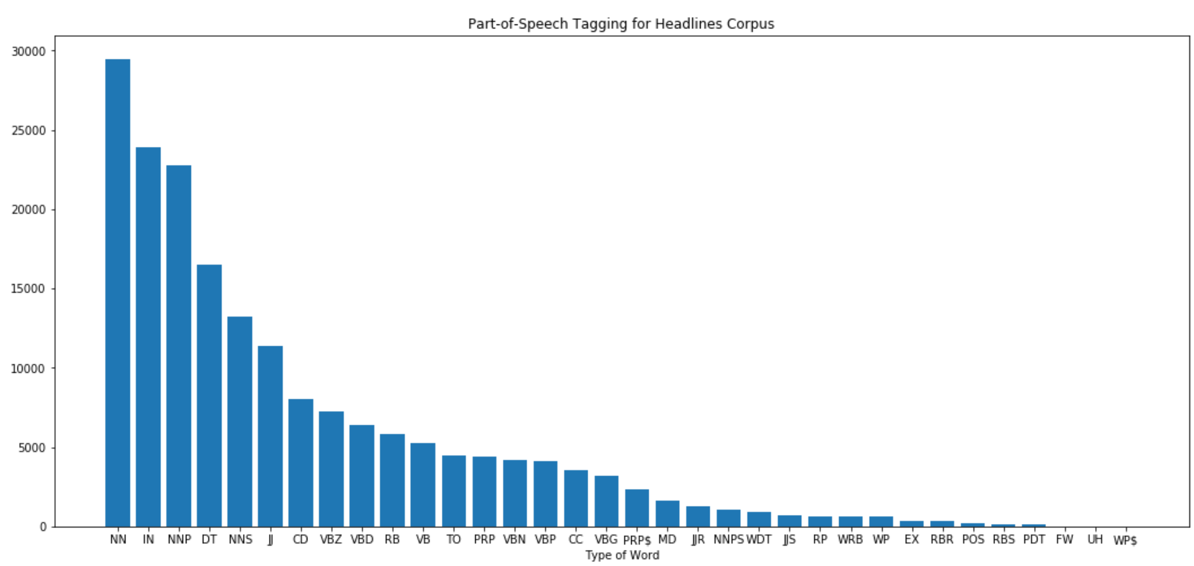
```
Total number of words:  184817
Mean number of words per headline:  18.05029788065241
```

In [48]:
```
fig, ax = plt.subplots(figsize=(18,8))
ax.hist(word_counts, bins=range(1,14), normed=1)
ax.set_title('Statement Word Lengths')
ax.set_xticks(range(1,14))
ax.set_xlabel('Number of Words')
y = mlab.normpdf( np.linspace(0,14,50), np.mean(word_counts), np.std(word_coun
ts))
l = ax.plot(np.linspace(0,14,50), y, 'r--', linewidth=1)
```



In [49]:
```
pos_sorted_types = sorted(pos_counts, key=pos_counts.__getitem__, reverse=True
)
pos_sorted_counts = sorted(pos_counts.values(), reverse=True)

fig, ax = plt.subplots(figsize=(18,8))
ax.bar(range(len(pos_counts)), pos_sorted_counts)
ax.set_xticks(range(len(pos_counts)))
ax.set_xticklabels(pos_sorted_types)
ax.set_title('Part-of-Speech Tagging for Headlines Corpus')
ax.set_xlabel('Type of Word')
```

Out[49]: `Text(0.5,0,'Type of Word')`



Topic Modelling

Now, lets apply clustering algorithm to the statements in order to study the focus of topic of all the news contained. I had experimented this with a small subsample of the dataset in order to determine which of the two potential clustering algorithms is most appropriate.

Preprocessing - Feature Construction; where I would take the sample of text headlines and represent them in feature space. It nothing but, converting each string to a numerical vector. To do this I used, CountVectorizer from SKLearn, which yields an n×K document-term matrix where K is the number of distinct words across the n headlines in our sample with less stop words and with a limit of max_features.

In [50]:
```
small_count_vectorizer = CountVectorizer(stop_words='english', max_features=40
000)
small_text_sample = reindexed_data.sample(n=10000, random_state=0).as_matrix()

print('Headline before vectorization: ', small_text_sample[123])

small_document_term_matrix = small_count_vectorizer.fit_transform(small_text_s
ample)

print('Headline after vectorization: \n', small_document_term_matrix[123])
```

```
Headline before vectorization:  (U.S. Reps.) Paul Ryan, Sean Duffy and Reid R
ibble are shutting down town hall meetings, or making their constituents pay
to attend them.
Headline after vectorization:
   (0, 1232)    1
  (0, 2644)     1
  (0, 6811)     1
  (0, 5028)     1
  (0, 10809)    1
  (0, 9729)     1
  (0, 9117)     1
  (0, 8856)     1
  (0, 3668)     1
  (0, 9488)     1
  (0, 9288)     1
  (0, 8979)     1
  (0, 7812)     1
  (0, 7823)     1
  (0, 6599)     1
```

Now I would apply the clustering algorithm.
1)Latent Semantic Analysis, OR
2)Latent Dirichilet Allocation.
Both will take document-term matrix as input and yield an n×N topic matrix as output, where N is the number of topic categories, a parameter we can say. which would be 8 in this case.

In [51]:
```
n_topics = 8
```

Latent Semantic Analysis

LSA is a technique in natural language processing, in particular distributional semantics, of analyzing relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms. LSA assumes that words that are close in meaning will occur in similar pieces of text

In [52]:
```
# Taking the  argmax  of each headline in this topic matrix will give the pred
icted topics of each headline in the sample.
# We can then sort these into counts of each topic.
# Define helper functions
def get_keys(topic_matrix):
    '''returns an integer list of predicted topic categories for a given topic
 matrix'''
    keys = []
    for i in range(topic_matrix.shape[0]):
        keys.append(topic_matrix[i].argmax())
    return keys

def keys_to_counts(keys):
    '''returns a tuple of topic categories and their accompanying magnitudes f
or a given list of keys'''
    count_pairs = Counter(keys).items()
    categories = [pair[0] for pair in count_pairs]
    counts = [pair[1] for pair in count_pairs]
    return (categories, counts)
```

In [53]:
```
from sklearn.decomposition import TruncatedSVD

lsa_model = TruncatedSVD(n_components=n_topics)
lsa_topic_matrix = lsa_model.fit_transform(small_document_term_matrix)

lsa_keys = get_keys(lsa_topic_matrix)
lsa_categories, lsa_counts = keys_to_counts(lsa_keys)
```

In [54]:
```
# Define helper functions
def get_top_n_words(n, keys, document_term_matrix, count_vectorizer):
    '''returns a list of n_topic strings, where each string contains the n mos
t common
        words in a predicted category, in order'''
    top_word_indices = []
    for topic in range(n_topics):
        temp_vector_sum = 0
        for i in range(len(keys)):
            if keys[i] == topic:
                temp_vector_sum += document_term_matrix[i]
        temp_vector_sum = temp_vector_sum.toarray()
        top_n_word_indices = np.flip(np.argsort(temp_vector_sum)[0][-n:],0)
        top_word_indices.append(top_n_word_indices)
    top_words = []
    for topic in top_word_indices:
        topic_words = []
        for index in topic:
            temp_word_vector = np.zeros((1,document_term_matrix.shape[1]))
            temp_word_vector[:,index] = 1
            the_word = count_vectorizer.inverse_transform(temp_word_vector)[0]
[0]
            topic_words.append(the_word.encode('ascii').decode('utf-8'))
        top_words.append(" ".join(topic_words))
    return top_words
```

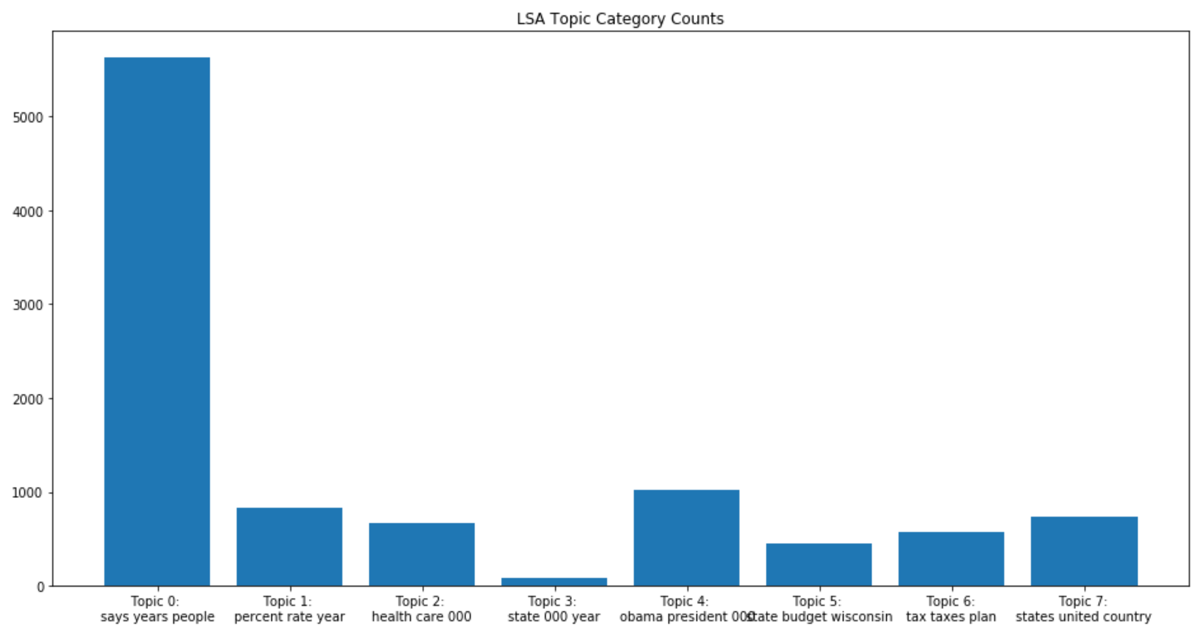
In [55]:
```
top_n_words_lsa = get_top_n_words(10, lsa_keys, small_document_term_matrix, sm
all_count_vectorizer)

for i in range(len(top_n_words_lsa)):
    print("Topic {}: ".format(i), top_n_words_lsa[i])
```

```
Topic 0:  says years people texas voted said new million state obama
Topic 1:  percent rate year people 40 10 years unemployment state income
Topic 2:  health care 000 million insurance law year people plan government
Topic 3:  state 000 year jobs new georgia 10 million billion dollars
Topic 4:  obama president 000 jobs barack year years administration bush crea
ted
Topic 5:  state budget wisconsin florida republican years billion rhode texas
georgia
Topic 6:  tax taxes plan income cuts billion increase cut middle class
Topic 7:  states united country world republican million people countries hal
f senate
```

Thus now I converted the small subset of statements into a list of predicted topic categories, where each category is characterised by its most frequent words.

In [56]:
```
top_3_words = get_top_n_words(3, lsa_keys, small_document_term_matrix, small_c
ount_vectorizer)
labels = ['Topic {}: \n'.format(i) + top_3_words[i] for i in lsa_categories]

fig, ax = plt.subplots(figsize=(16,8))
ax.bar(lsa_categories, lsa_counts)
ax.set_xticks(lsa_categories)
ax.set_xticklabels(labels)
ax.set_title('LSA Topic Category Counts')
```

Out[56]:
```
Text(0.5,1,'LSA Topic Category Counts')
```



In order to properly differentiate LSA with LDA , lets try using dimensionality-reduction technique called t -SNE, which will also serve to better illuminate the success of the clustering process.

In [57]:
```
from sklearn.manifold import TSNE

tsne_lsa_model = TSNE(n_components=2, perplexity=50, learning_rate=100,
                        n_iter=2000, verbose=1, random_state=0, angle=0.75)
tsne_lsa_vectors = tsne_lsa_model.fit_transform(lsa_topic_matrix)
```

```
[t-SNE] Computing 151 nearest neighbors...
[t-SNE] Indexed 10000 samples in 0.023s...
[t-SNE] Computed neighbors for 10000 samples in 1.360s...
[t-SNE] Computed conditional probabilities for sample 1000 / 10000
[t-SNE] Computed conditional probabilities for sample 2000 / 10000
[t-SNE] Computed conditional probabilities for sample 3000 / 10000
[t-SNE] Computed conditional probabilities for sample 4000 / 10000
[t-SNE] Computed conditional probabilities for sample 5000 / 10000
[t-SNE] Computed conditional probabilities for sample 6000 / 10000
[t-SNE] Computed conditional probabilities for sample 7000 / 10000
[t-SNE] Computed conditional probabilities for sample 8000 / 10000
[t-SNE] Computed conditional probabilities for sample 9000 / 10000
[t-SNE] Computed conditional probabilities for sample 10000 / 10000
[t-SNE] Mean sigma: 0.021052
[t-SNE] KL divergence after 250 iterations with early exaggeration: 68.492363
[t-SNE] Error after 2000 iterations: 0.961622
```

Now we have two-dimensional representations ready !! lets plot the clusters using Bokeh. It will be useful to derive the centroid location of each topic before that. This would add context to the visualization.

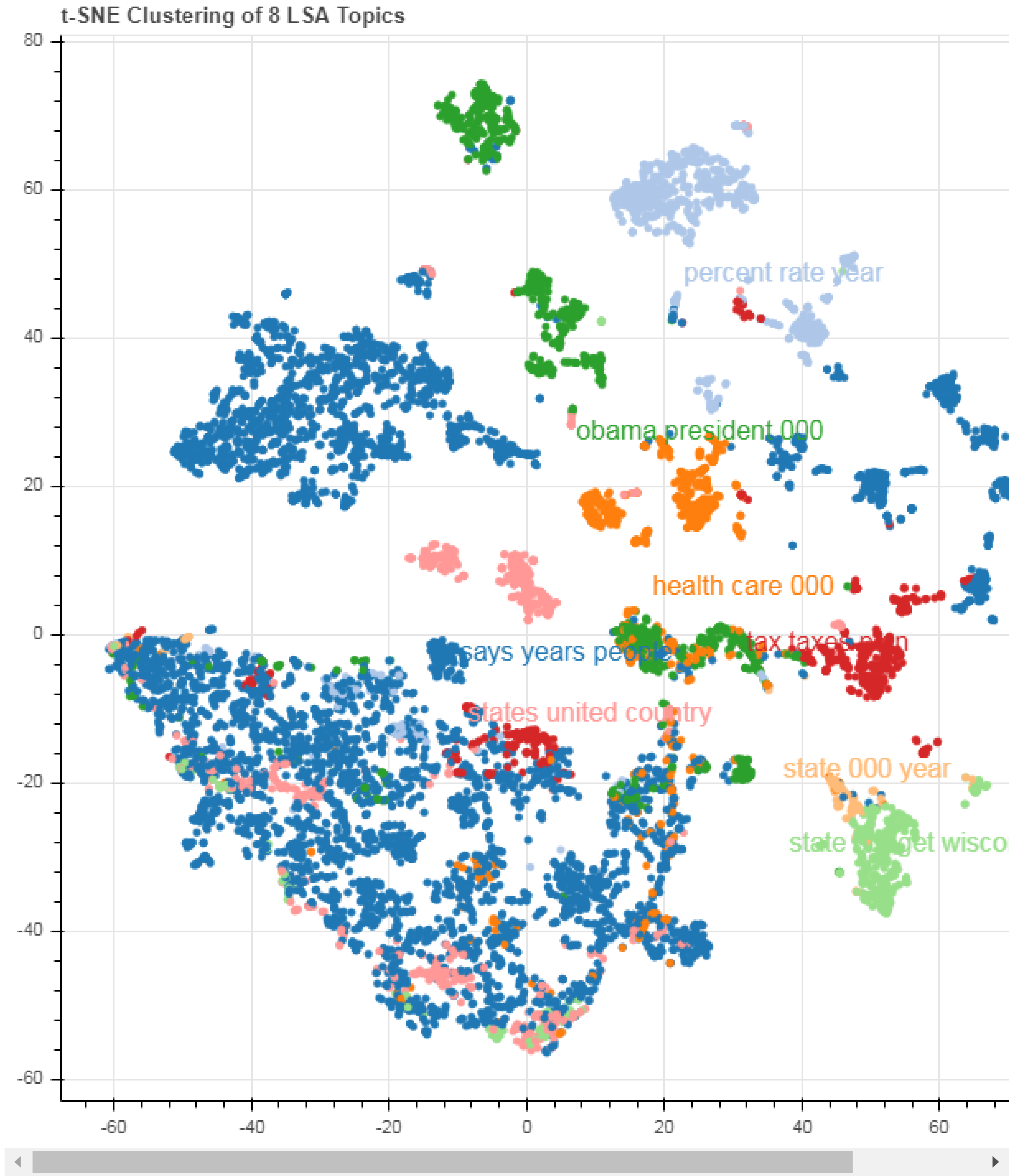
In [58]:
```
# Define helper functions
def get_mean_topic_vectors(keys, two_dim_vectors):
    '''returns a list of centroid vectors from each predicted topic categor
y'''
    mean_topic_vectors = []
    for t in range(n_topics):
        articles_in_that_topic = []
        for i in range(len(keys)):
            if keys[i] == t:
                articles_in_that_topic.append(two_dim_vectors[i])

        articles_in_that_topic = np.vstack(articles_in_that_topic)
        mean_article_in_that_topic = np.mean(articles_in_that_topic, axis=0)
        mean_topic_vectors.append(mean_article_in_that_topic)
    return mean_topic_vectors
```

In [59]:
```
from bokeh.plotting import figure, output_file, show
from bokeh.models import Label
from bokeh.io import output_notebook
output_notebook()

colormap = np.array([
    "#1f77b4", "#aec7e8", "#ff7f0e", "#ffbb78", "#2ca02c",
    "#98df8a", "#d62728", "#ff9896", "#9467bd", "#c5b0d5",
    "#8c564b", "#c49c94", "#e377c2", "#f7b6d2", "#7f7f7f",
    "#c7c7c7", "#bcbd22", "#dbdb8d", "#17becf", "#9edae5" ])
colormap = colormap[:n_topics]
```

(https://bokeh.pydata.org) BokehJS 0.12.16 successfully loaded.

Now lets plot the cluster and see..Also we have included top 3 words in the cluster, that are located on the centriod of that topic.

In [61]:
```
top_3_words_lsa = get_top_n_words(3, lsa_keys, small_document_term_matrix, sma
ll_count_vectorizer)
lsa_mean_topic_vectors = get_mean_topic_vectors(lsa_keys, tsne_lsa_vectors)

plot = figure(title="t-SNE Clustering of {} LSA Topics".format(n_topics), plot
_width=700, plot_height=700)
plot.scatter(x=tsne_lsa_vectors[:,0], y=tsne_lsa_vectors[:,1], color=colormap[
lsa_keys])

for t in range(n_topics):
    label = Label(x=lsa_mean_topic_vectors[t][0], y=lsa_mean_topic_vectors[t][
1],
                  text=top_3_words_lsa[t], text_color=colormap[t])
    plot.add_layout(label)

show(plot)
```



As we can see above plot is not very convincing. not much separation of topics is achieved , and it is difficult to tell whether this can be attributed to the LSA decomposition or instead the t -SNE dimensionality reduction process.

Latent Dirichilet Allocation

Below process is same. Just that, instead of using LSA, I used LDA. LDA is instead a generative probabilistic process, designed with the specific goal of uncovering latent topic structure in text corpora.

In [62]:
```
from sklearn.decomposition import LatentDirichletAllocation

lda_model = LatentDirichletAllocation(n_components=n_topics, learning_method=
'online',
                                          random_state=0, verbose=0)
lda_topic_matrix = lda_model.fit_transform(small_document_term_matrix)
```

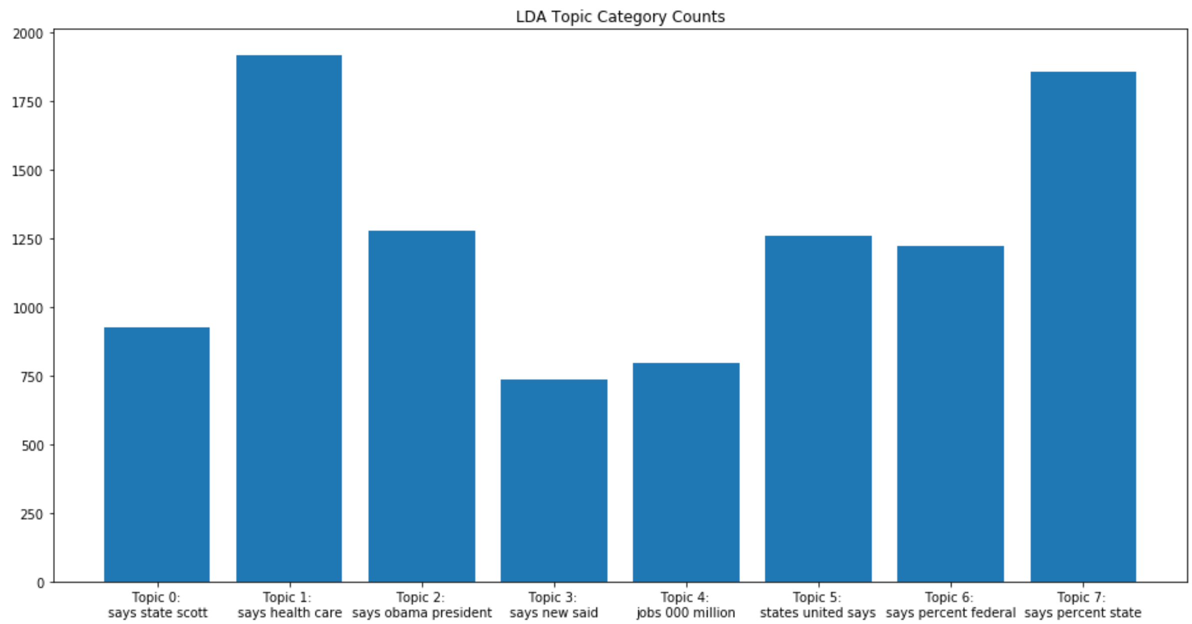
In [63]:
```
lda_keys = get_keys(lda_topic_matrix)
lda_categories, lda_counts = keys_to_counts(lda_keys)
```

In [64]:
```
top_n_words_lda = get_top_n_words(10, lda_keys, small_document_term_matrix, sm
all_count_vectorizer)

for i in range(len(top_n_words_lda)):
    print("Topic {}: ".format(i), top_n_words_lda[i])
```

```
Topic 0:  says state scott gov federal rick government court wisconsin walker
Topic 1:  says health care percent tax taxes people voted obama plan
Topic 2:  says obama president barack clinton said hillary trump donald campa
ign
Topic 3:  says new said obama state administration water make government texa
s
Topic 4:  jobs 000 million new says job health created insurance sector
Topic 5:  states united says rate percent years year country state people
Topic 6:  says percent federal people year state illegal tax american america
ns
Topic 7:  says percent state 000 billion tax year years budget texas
```

In [65]:
```
top_3_words = get_top_n_words(3, lda_keys, small_document_term_matrix, small_c
ount_vectorizer)
labels = ['Topic {}: \n'.format(i) + top_3_words[i] for i in lda_categories]

fig, ax = plt.subplots(figsize=(16,8))
ax.bar(lda_categories, lda_counts)
ax.set_xticks(lda_categories)
ax.set_xticklabels(labels)
ax.set_title('LDA Topic Category Counts')
```

Out[65]:
```
Text(0.5,1,'LDA Topic Category Counts')
```

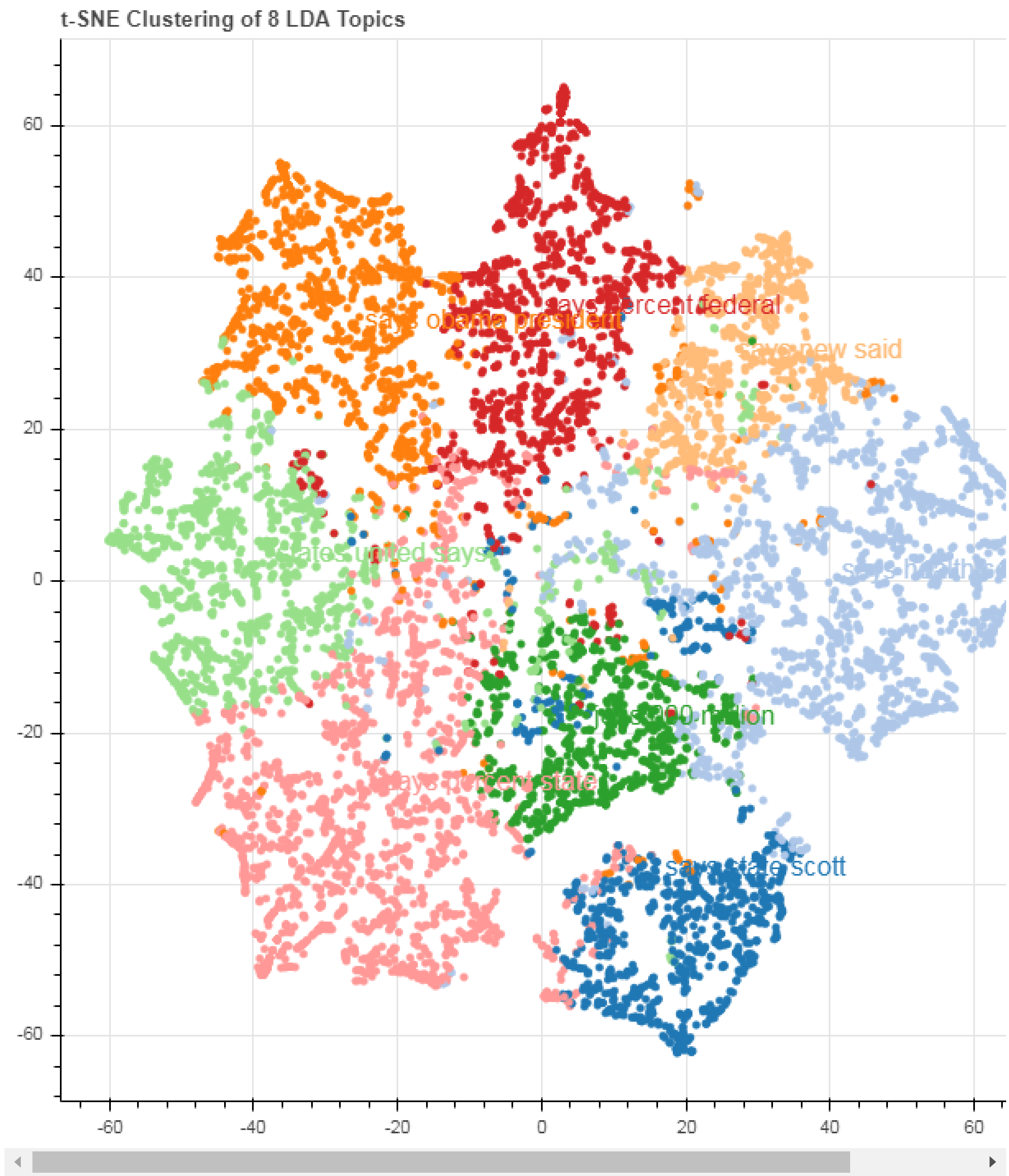


To achieve better comparison, we again take this topic matrix and project it into two dimensions with t -SNE.

In [66]:
```
from sklearn.manifold import TSNE

tsne_lda_model = TSNE(n_components=2, perplexity=50, learning_rate=100,
                        n_iter=2000, verbose=1, random_state=0, angle=0.75)
tsne_lda_vectors = tsne_lda_model.fit_transform(lda_topic_matrix)
```

```
[t-SNE] Computing 151 nearest neighbors...
[t-SNE] Indexed 10000 samples in 0.016s...
[t-SNE] Computed neighbors for 10000 samples in 1.522s...
[t-SNE] Computed conditional probabilities for sample 1000 / 10000
[t-SNE] Computed conditional probabilities for sample 2000 / 10000
[t-SNE] Computed conditional probabilities for sample 3000 / 10000
[t-SNE] Computed conditional probabilities for sample 4000 / 10000
[t-SNE] Computed conditional probabilities for sample 5000 / 10000
[t-SNE] Computed conditional probabilities for sample 6000 / 10000
[t-SNE] Computed conditional probabilities for sample 7000 / 10000
[t-SNE] Computed conditional probabilities for sample 8000 / 10000
[t-SNE] Computed conditional probabilities for sample 9000 / 10000
[t-SNE] Computed conditional probabilities for sample 10000 / 10000
[t-SNE] Mean sigma: 0.090871
[t-SNE] KL divergence after 250 iterations with early exaggeration: 85.454643
[t-SNE] Error after 2000 iterations: 1.739634
```

In [67]:
```
top_3_words_lda = get_top_n_words(3, lda_keys, small_document_term_matrix, sma
ll_count_vectorizer)
lda_mean_topic_vectors = get_mean_topic_vectors(lda_keys, tsne_lda_vectors)

plot = figure(title="t-SNE Clustering of {} LDA Topics".format(n_topics), plot
_width=700, plot_height=700)
plot.scatter(x=tsne_lda_vectors[:,0], y=tsne_lda_vectors[:,1], color=colormap[
lda_keys])

for t in range(n_topics):
    label = Label(x=lda_mean_topic_vectors[t][0], y=lda_mean_topic_vectors[t][
1],
                  text=top_3_words_lda[t], text_color=colormap[t])
    plot.add_layout(label)

show(plot)
```



Now that impressive! Its evident that LDA has had much more succcess than LSA in distinguishing the topic categories. Therefore, LDA is an appropriate algorithm for our case.