Week 7 Lab: Text Analytics

This week's assignment will focus on text analysis of BBC News articles.

Our Dataset:

Dataset: bbc.csv(Provided in folder assign_wk7)
Consists of 2225 documents from the BBC news website corresponding to stories in five topical areas from 2004-2005.
Class Labels: 5 (business, entertainment, politics, sport, tech)

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
sns.set()
```

In [2]:
```
news = pd.read_csv('assign_wk7/bbc.csv', header=0, usecols=[1,2], names=['raw_text', 't
news.head(10)
```

Out[2]:

	raw_text	target_names
0	UK economy facing 'major risks'\n \n The UK ma...	business
1	Aids and climate top Davos agenda\n \n Climate...	business
2	Asian quake hits European shares\n \n Shares i...	business
3	India power shares jump on debut\n \n Shares i...	business
4	Lacroix label bought by US firm\n \n Luxury go...	business
5	Insurance bosses plead guilty\n \n Another thr...	business
6	Turkey-Iran mobile deal 'at risk'\n \n Turkey'...	business
7	Parmalat to return to stockmarket\n \n Parmala...	business
8	WorldCom director admits lying\n \n The former...	business
9	Ebbers denies WorldCom fraud\n \n Former World...	business

Text Analytics Lab

Objective: To demostrate all of the text analysis techniques covered int his week's lecture material.

Preparation of the text data for analysis

    * Elimination of stopwords, punctuation, digits, lowercase

In [3]:
```
news.target_names.value_counts()
```

Out[3]:
```
sport            511
business         510
politics         417
tech             401
entertainment    386
Name: target_names, dtype: int64
```

In [4]:
```
print(news.raw_text[3])
```

```
India power shares jump on debut

 Shares in India's largest power producer, National Thermal Power Corp (NTPC) have risen
13% on their stock market debut.

 The government's partial sell-off of NTPC is part of a controversial programme to priva
tise state-run firms. The 865 million share offer, a mix of new shares and sales by the
government, raised 54bn rupees($1.2bn). It was India's second $1bn stock debut in three
months, coming after the flotation by software firm Tata. The share offer was eleven tim
es oversubscribed. "It is a good investment bet," said Suhas Naik, an investment analyst
from ING Mutual Fund. "Power needs in India are set to rise and NTPC will benefit from t
hat." Analysts say the success of the NTPC flotation would encourage the government to r
educe stakes in more power companies. NTPC has said it will use the money from the share
sale to feed the growing needs of the country's energy-starved economy. The firm is the
largest utility company in India, and the sixth largest power producer in the world.
```

In [5]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
le.fit_transform(news['target_names'])
news['target'] = le.transform(news['target_names'])
```

In [6]:
```
news['target_names'] = le.inverse_transform(news['target'])
```

In [7]:
```
news.to_csv('assign_wk7/bbc_renamed.csv', header=True, index=False)
```

In [8]:
```
df = pd.read_csv('assign_wk7/bbc_renamed.csv')
df
```

Out[8]:

	raw_text	target_names	target
0	UK economy facing 'major risks'\n \n The UK ma...	business	0
1	Aids and climate top Davos agenda\n \n Climate...	business	0
2	Asian quake hits European shares\n \n Shares i...	business	0
3	India power shares jump on debut\n \n Shares i...	business	0
4	Lacroix label bought by US firm\n \n Luxury go...	business	0
...	...	...	...
2220	Warning over Windows Word files\n \n Writing a...	tech	4
2221	Fast lifts rise into record books\n \n Two hig...	tech	4

	raw_text	target_names	target
2222	Nintendo adds media playing to DS\n \n Nintend...	tech	4
2223	Fast moving phone viruses appear\n \n Security...	tech	4
2224	Hacker threat to Apple's iTunes\n \n Users of ...	tech	4

2225 rows × 3 columns

In [9]:
```
df['word_cnt'] = df.raw_text.apply(lambda x: len(str(x).split(" ")))
```

In [10]:
```
df['char_cnt'] = df.raw_text.str.len()
```

In [11]:
```
from nltk.corpus import stopwords
stop = stopwords.words('english')

df['stopwords'] = df.raw_text.apply(lambda x: len([x for x in x.split() if x in stop]))
```

In [12]:
```
df['clean_text'] = df.raw_text.apply(lambda x: " ".join(x.lower() for x in x.split()))
```

In [13]:
```
df['clean_text'] = df.clean_text.str.replace('\S+@\S+','') #looking for the case of XXX
df['clean_text'] = df.clean_text.str.replace('http\S+','') #looking for http or https w
df['clean_text'] = df.clean_text.str.replace('\S+.com','') #looking for email addresses
df['clean_text'] = df.clean_text.str.replace('\S+.edu','') #looking for email addresses
```

In [14]:
```
df['clean_text'] = df.clean_text.str.replace('[^\w\s]', '')
```

In [15]:
```
df['clean_text'] = df.clean_text.str.replace('\d+', '')
```

In [16]:
```
from nltk.corpus import stopwords, words
stop = stopwords.words('english')
df['clean_text'] = df.clean_text.apply(lambda x: " ".join(w for w in x.split() if w not
```

In [17]:
```
df.head()
```

Out[17]:

	raw_text	target_names	target	word_cnt	char_cnt	stopwords	clean_text
0	UK economy facing 'major risks'\n \n The UK ma...	business	0	329	1996	112	uk economy facing major risks uk manufacturing...
1	Aids and climate top Davos agenda\n \n Climate...	business	0	454	2727	161	aids climate top davos agenda climate change f...
2	Asian quake hits European shares\n \n Shares i...	business	0	553	3444	171	asian quake hits european shares shares europe...
3	India power shares jump on debut\n \n Shares i...	business	0	175	1038	55	india power shares jump debut shares indias la...

	raw_text	target_names	target	word_cnt	char_cnt	stopwords	clean_text
4	Lacroix label bought by US firm\n \n Luxury go...	business	0	152	894	47	lacroix label bought us firm luxury goods grou...

Identify the 10 most frequently used words in the text

```
* How about the ten least frequently used words?
* How does lemmatization change the most/least frequent words?
   - Explain and demonstrate this topic
```

In [18]:
```python
import nltk

freq = freq = pd.Series(' '.join(df.clean_text).split()).value_counts().to_dict()

top_10 = list(freq.items())[:10]
bottom_10 = list(freq.items())[-10:]

print("The 10 most frequently used words in the text are: \n\n" + str(top_10))

print("\n The 10 least frequently used words in the text are: \n\n" + str(bottom_10))
```

```
The 10 most frequently used words in the text are:

[('said', 7244), ('mr', 3004), ('would', 2554), ('also', 2141), ('people', 1954), ('ne
w', 1942), ('us', 1901), ('one', 1733), ('year', 1628), ('could', 1505)]

 The 10 least frequently used words in the text are:

[('aniston', 1), ('joeys', 1), ('dispossessed', 1), ('sixyearrun', 1), ('nephew', 1),
('phoebe', 1), ('butlersloss', 1), ('rotten', 1), ('thirteen', 1), ('mu', 1)]
```

1 letter words are no friend of mine.

In [19]:
```python
df['clean_text'] = df.clean_text.apply(lambda x: " ".join(x for x in x.split() if len(x

freq = pd.Series(' '.join(df.clean_text).split()).value_counts().to_dict()
bottom_10 = list(freq.items())[-10:]
print("The 10 least frequently used words in the text are: \n\n" + str(bottom_10))
```

```
The 10 least frequently used words in the text are:

[('tysabritreated', 1), ('restating', 1), ('leukoencephalopathy', 1), ('areconsulting',
1), ('multifocal', 1), ('idecs', 1), ('irelandbased', 1), ('shihabeldin', 1), ('adnan',
1), ('mu', 1)]
```

In [20]:
```python
import nltk
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')

#establish the lemmatizer
wordnet_lemmatizer = WordNetLemmatizer()
```

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

In [21]:
```python
df['clean_text'] = df.clean_text.apply(lambda x: " ".join(wordnet_lemmatizer.lemmatize(
```

In [22]:
```python
df['clean_text'] = df.clean_text.apply(lambda x: " ".join(x for x in x.split() if len(x

freq = pd.Series(' '.join(df.clean_text).split()).value_counts().to_dict()

top_10 = list(freq.items())[:10]
bottom_10 = list(freq.items())[-10:]
print("The 10 most frequently used words in the text are: \n\n" + str(top_10))
print("\n The 10 least frequently used words in the text are: \n\n" + str(bottom_10))
```

```
The 10 most frequently used words in the text are:

[('said', 7244), ('mr', 3045), ('year', 2851), ('would', 2554), ('also', 2141), ('peopl
e', 2029), ('new', 1942), ('one', 1803), ('could', 1505), ('game', 1461)]

 The 10 least frequently used words in the text are:

[('fuck', 1), ('twat', 1), ('malarkey', 1), ('whittle', 1), ('littman', 1), ('circs',
1), ('swears', 1), ('erica', 1), ('congruent', 1), ('mu', 1)]
```

Oh wow hahaha.... to be fair 'malarkey' is a great word. At least they are the least frequently used words ... right?

Lemmetization seemed to remove the words that were a combination of two words. This is because it couldn't recognize a base-word for words like "areconsulting" or "butlersloss".

The most frequent words did not change much except for their notable frequency. Lemmetization detected the word 'years' and converted it to the base-word 'year' before tallying the frequency of the base-word, which caused an increase.

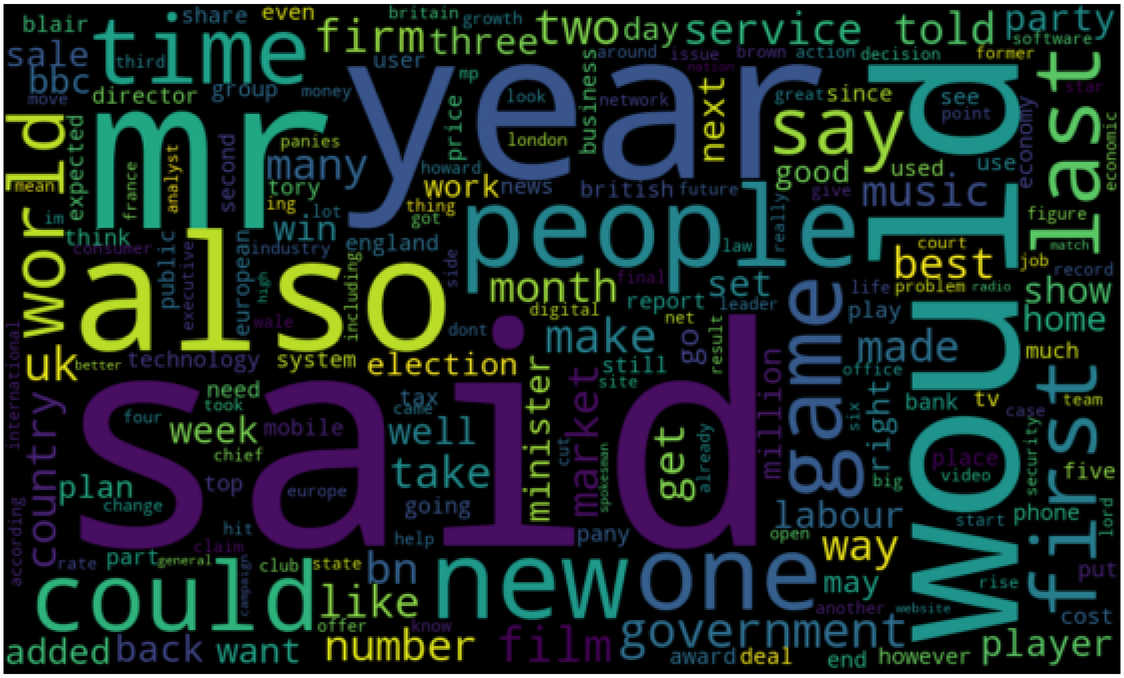
Generate a world cloud for the text

In [23]:
```python
from wordcloud import WordCloud

wc = WordCloud(width=1000, height=600, max_words=200).generate_from_frequencies(freq)
```

In [24]:
```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
plt.imshow(wc, interpolation='bilinear')
plt.axis('off')
plt.show()
```



Demonstrate the generation of n-grams and part of speech tagging

In [25]:
```python
tokens = ' '.join(df.clean_text).split()
```

In [26]:
```python
ngrams_2 = nltk.bigrams(tokens)

freq_2grams = pd.Series(ngrams_2).value_counts().to_dict()
list(freq_2grams.items())[:20]
```

Out[26]:
```
[(('last', 'year'), 498),
 (('said', 'mr'), 363),
 (('told', 'bbc'), 347),
 (('mr', 'blair'), 334),
 (('prime', 'minister'), 317),
 (('mr', 'brown'), 256),
 (('chief', 'executive'), 204),
 (('said', 'would'), 193),
 (('last', 'week'), 188),
 (('tony', 'blair'), 186),
 (('mobile', 'phone'), 182),
 (('bbc', 'news'), 178),
 (('general', 'election'), 174),
 (('new', 'york'), 167),
 (('six', 'nation'), 162),
 (('bn', 'bn'), 162),
 (('year', 'ago'), 160),
 (('mr', 'howard'), 159),
 (('liberal', 'democrat'), 156),
 (('number', 'one'), 146)]
```

In [27]:
```python
ngrams_3 = nltk.trigrams(tokens)

freq_3grams = pd.Series(ngrams_3).value_counts().to_dict()
list(freq_3grams.items())[:20]
```

Out[27]:
```
[(('told', 'bbc', 'news'), 147),
```

```
(('bbc', 'news', 'website'), 97),
(('told', 'bbc', 'radio'), 76),
(('leader', 'michael', 'howard'), 58),
(('mr', 'blair', 'said'), 54),
(('million', 'dollar', 'baby'), 52),
(('radio', 'today', 'programme'), 49),
(('told', 'bbc', 'sport'), 48),
(('bbc', 'radio', 'today'), 47),
(('tory', 'leader', 'michael'), 41),
(('mr', 'howard', 'said'), 41),
(('next', 'general', 'election'), 39),
(('chancellor', 'gordon', 'brown'), 33),
(('prime', 'minister', 'tony'), 32),
(('leader', 'charles', 'kennedy'), 32),
(('minister', 'tony', 'blair'), 32),
(('digital', 'music', 'player'), 30),
(('two', 'year', 'ago'), 28),
(('mr', 'blair', 'told'), 27),
(('world', 'number', 'one'), 27)]
```

In [28]:

```python
from nltk.tag import pos_tag

pos_tags = pos_tag(tokens)
pos_tags[:10]
```

Out[28]:

```
[('uk', 'JJ'),
 ('economy', 'NN'),
 ('facing', 'VBG'),
 ('major', 'JJ'),
 ('risk', 'NN'),
 ('uk', 'IN'),
 ('manufacturing', 'VBG'),
 ('sector', 'NN'),
 ('continue', 'VBP'),
 ('face', 'VBP')]
```

In [29]:

```python
from collections import Counter

pos_tags = Counter([j for i,j in pos_tag(tokens)])
```

In [30]:

```python
pos_tags
```

Out[30]:

```
Counter({'JJ': 90251,
         'NN': 225618,
         'VBG': 19788,
         'IN': 7891,
         'VBP': 14085,
         'CD': 6674,
         'VBD': 34253,
         'NNS': 11796,
         'RBS': 129,
         'RB': 23162,
         'VBN': 12475,
         'VB': 10600,
         'JJS': 2392,
         'JJR': 1764,
         'NNP': 993,
         'RBR': 1051,
         'WP$': 120,
         'MD': 5333,
         'VBZ': 3096,
         'DT': 811,
         'CC': 281,
```

```
         'FW': 865,
         'PRP': 250,
         'RP': 387,
         'WP': 69,
         'WRB': 45,
         'WDT': 60,
         'EX': 69,
         'POS': 2,
         'NNPS': 3,
         'PRP$': 15,
         'PDT': 4,
         'TO': 2,
         'UH': 10})
```

In [31]:
```
pos_tags_df = pd.DataFrame.from_dict(pos_tags, orient='index', columns=['qty'])
pos_tags_df.to_csv('assign_wk7/pos_tags.csv')
```

In [32]:
```
postag = pd.read_csv('assign_wk7/pos_tags.csv', header=0, names=['tag', 'qty'])
most_common_pos = postag.sort_values(by='qty', ascending=False)
mcp = most_common_pos.head(-10)
mcp
```

Out[32]:

	tag	qty
1	NN	225618
0	JJ	90251
6	VBD	34253
9	RB	23162
2	VBG	19788
4	VBP	14085
10	VBN	12475
7	NNS	11796
11	VB	10600
3	IN	7891
5	CD	6674
17	MD	5333
18	VBZ	3096
12	JJS	2392
13	JJR	1764
15	RBR	1051
14	NNP	993
21	FW	865
19	DT	811
23	RP	387
20	CC	281

	tag	qty
22	PRP	250
8	RBS	129
16	WP$	120

In [33]:

```python
least_common_pos = postag.sort_values(by='qty', ascending=True)
lcp = least_common_pos.head(10)
lcp
```

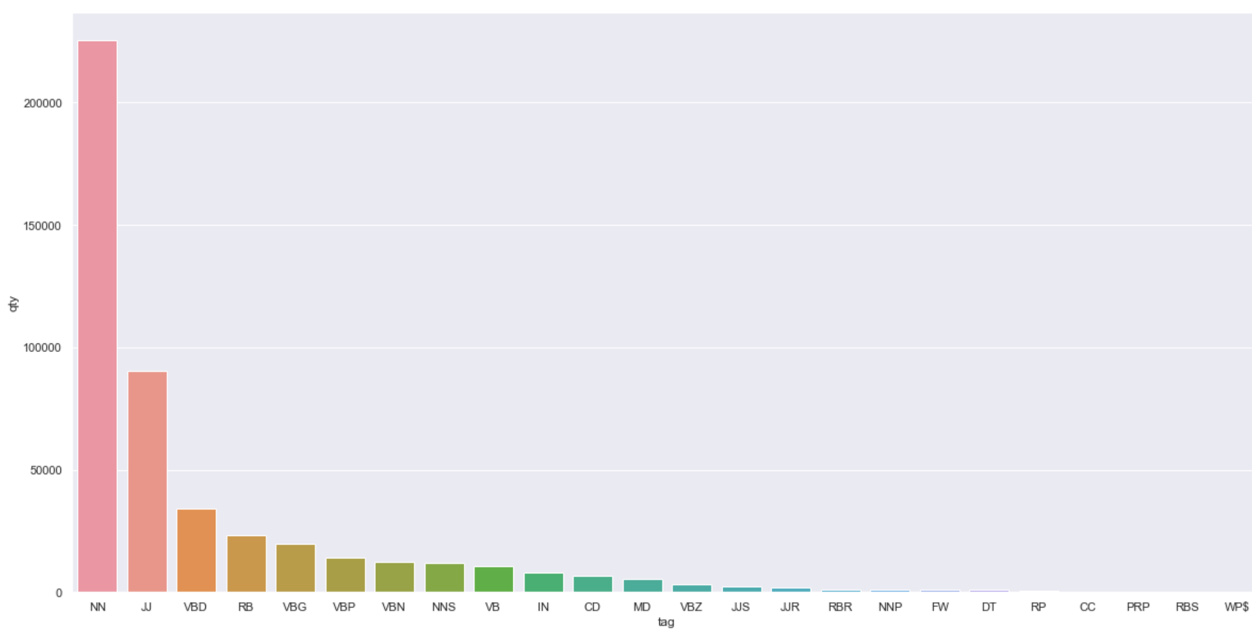
Out[33]:

	tag	qty
28	POS	2
32	TO	2
29	NNPS	3
31	PDT	4
33	UH	10
30	PRP$	15
25	WRB	45
26	WDT	60
27	EX	69
24	WP	69

In [34]:

```python
f, ax = plt.subplots(figsize=(20,10))
sns.barplot(x=mcp['tag'], y=mcp['qty'])
```

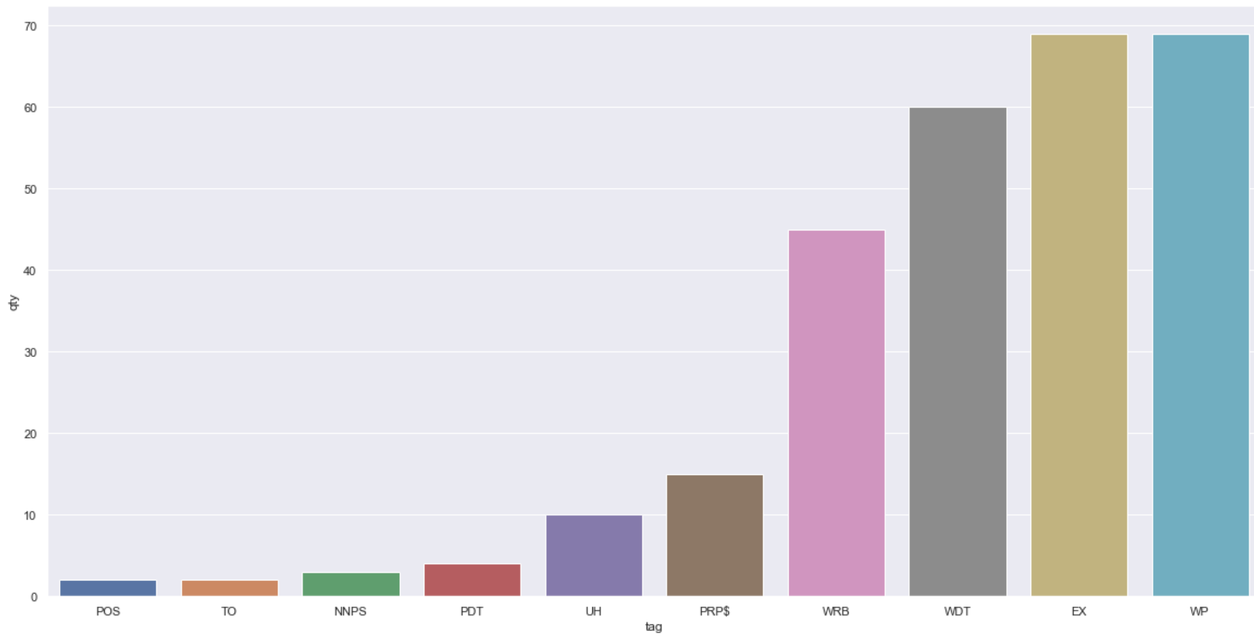
Out[34]: <AxesSubplot:xlabel='tag', ylabel='qty'>



NN (singular nouns) are the greatest.

In [35]:
```
f, ax = plt.subplots(figsize=(20,10))
sns.barplot(x=lcp['tag'], y=lcp['qty'])
```

Out[35]:
```
<AxesSubplot:xlabel='tag', ylabel='qty'>
```



The least common parts of speech are tied with POS (possessive ending like "'s") and TO (prepositions or infinitive markers like 'to').

Create a Topic model of the text

```
* Find the optimal number of topics
* test the accuracy of your model
* Display your results 2 different ways.
    1) Print the topics and explain any insights at this point.
    2) Graph the topics and explain any insights at this point.
```

In [36]:
```
lem_ls = list(df.clean_text.apply(lambda x: list(x.split())))
print(lem_ls[:2])
```

```
[['uk', 'economy', 'facing', 'major', 'risk', 'uk', 'manufacturing', 'sector', 'continu
e', 'face', 'serious', 'challenge', 'next', 'two', 'year', 'british', 'chamber', 'merc
e', 'bcc', 'said', 'group', 'quarterly', 'survey', 'panies', 'found', 'export', 'picke
d', 'last', 'three', 'month', 'best', 'level', 'eight', 'year', 'rise', 'came', 'despit
e', 'exchange', 'rate', 'cited', 'major', 'concern', 'however', 'bcc', 'found', 'whole',
'uk', 'economy', 'still', 'faced', 'major', 'risk', 'warned', 'growth', 'set', 'slow',
'recently', 'forecast', 'economic', 'growth', 'slow', 'little', 'manufacturer', 'domesti
c', 'sale', 'growth', 'fell', 'back', 'slightly', 'quarter', 'survey', 'firm', 'found',
'employment', 'manufacturing', 'also', 'fell', 'job', 'expectation', 'lowest', 'level',
'year', 'despite', 'positive', 'news', 'export', 'sector', 'worrying', 'sign', 'manufact
uring', 'bcc', 'said', 'result', 'reinforce', 'concern', 'sector', 'persistent', 'inabil
ity', 'sustain', 'recovery', 'outlook', 'service', 'sector', 'uncertain', 'despite', 'in
crease', 'export', 'order', 'quarter', 'bcc', 'noted', 'bcc', 'found', 'confidence', 'in
creased', 'quarter', 'across', 'manufacturing', 'service', 'sector', 'although', 'overal
l', 'failed', 'reach', 'level', 'start', 'reduced', 'threat', 'interest', 'rate', 'incre
ase', 'contributed', 'improved', 'confidence', 'said', 'bank', 'england', 'raised', 'int
erest', 'rate', 'five', 'time', 'november', 'august', 'last', 'year', 'rate', 'kept', 'h
old', 'since', 'amid', 'sign', 'falling', 'consumer', 'confidence', 'slowdown', 'outpu
t', 'pressure', 'cost', 'margin', 'relentless', 'increase', 'regulation', 'threat', 'hig
her', 'tax', 'remain', 'serious', 'problem', 'bcc', 'director', 'general', 'david', 'fro
```

```
st', 'said', 'consumer', 'spending', 'set', 'decelerate', 'significantly', 'next', 'mont
h', 'unlikely', 'investment', 'export', 'rise', 'sufficiently', 'strongly', 'pick', 'sla
ck'], ['aid', 'climate', 'top', 'davos', 'agenda', 'climate', 'change', 'fight', 'aid',
'leading', 'list', 'concern', 'first', 'day', 'world', 'economic', 'forum', 'swiss', 're
sort', 'davos', 'business', 'political', 'leader', 'around', 'globe', 'listen', 'uk', 'p
rime', 'minister', 'tony', 'blair', 'opening', 'speech', 'wednesday', 'mr', 'blair', 'fo
cus', 'africa', 'development', 'plan', 'global', 'warming', 'earlier', 'day', 'came', 'u
pdate', 'effort', 'million', 'people', 'antiaids', 'drug', 'end', 'world', 'health', 'or
ganisation', 'said', 'people', 'poor', 'country', 'lifeextending', 'drug', 'six', 'mont
h', 'earlier', 'amounting', 'million', 'needed', 'bn', 'funding', 'gap', 'still', 'stoo
d', 'way', 'hitting', 'target', 'said', 'theme', 'stressed', 'mr', 'blair', 'whose', 'at
tendance', 'announced', 'last', 'minute', 'want', 'dominate', 'uk', 'chairmanship', 'gro
up', 'industrialised', 'state', 'issue', 'discussed', 'fiveday', 'conference', 'range',
'china', 'economic', 'power', 'iraq', 'future', 'sunday', 'election', 'aside', 'mr', 'bl
air', 'world', 'leader', 'expected', 'attend', 'including', 'french', 'president', 'jacq
ues', 'chirac', 'due', 'speak', 'video', 'link', 'bad', 'weather', 'delayed', 'helicopte
r', 'south', 'african', 'president', 'thabo', 'mbeki', 'whose', 'arrival', 'delayed', 'i
vory', 'coast', 'peace', 'talk', 'ukraine', 'new', 'president', 'viktor', 'yushchenko',
'also', 'newly', 'elected', 'palestinian', 'leader', 'mahmoud', 'abbas', 'showbiz', 'fig
ure', 'also', 'put', 'appearance', 'frontman', 'bono', 'wellknown', 'campaigner', 'trad
e', 'development', 'issue', 'angelina', 'jolie', 'goodwill', 'campaigner', 'un', 'refuge
e', 'unlike', 'previous', 'year', 'protest', 'wef', 'expected', 'muted', 'antiglobalisat
ion', 'campaigner', 'called', 'demonstration', 'planned', 'weekend', 'time', 'people',
'expected', 'converge', 'brazilian', 'resort', 'porto', 'alegre', 'world', 'social', 'fo
rum', 'socalled', 'antidavos', 'campaigner', 'globalisation', 'fair', 'trade', 'many',
'cause', 'contrast', 'davos', 'forum', 'dominated', 'business', 'issue', 'outsourcing',
'corporate', 'leadership', 'boss', 'fifth', 'world', 'panies', 'led', 'attend', 'surve
y', 'published', 'eve', 'conference', 'pricewaterhousecoopers', 'said', 'four', 'ten',
'business', 'leader', 'confident', 'panies', 'would', 'see', 'sale', 'rise', 'asian', 'a
merican', 'executive', 'however', 'much', 'confident', 'european', 'counterpart', 'polit
ical', 'discussion', 'focusing', 'iran', 'iraq', 'china', 'likely', 'dominate', 'mediu
m', 'attention']]
```

BTW: After installing gensim and the dependencies of the library, restart jupyter-notebook or it will not work.

After issues importing the libraries I found the following solution:

MTKnife from StackOverflow said "My problem apparently was trying to import gensim right after installing it, while Jupyter Notebook was running. Restarting Jupyter and Sypder fixed the problems with both environments."

Reference: https://stackoverflow.com/questions/61182206/module-smart-open-has-no-attribute-local-file

In [37]:
```
import smart_open
import gensim
import gensim.corpora as corpora
```

In [38]:
```
id2word = corpora.Dictionary(lem_ls)
corpus = [id2word.doc2bow(post) for post in lem_ls]
```

And....now we wait

In [39]:
```
lda_model = gensim.models.LdaMulticore(corpus=corpus,
                                       id2word=id2word,
                                       num_topics=10,
                                       random_state=42,
                                       chunksize=100,
```

```
                                    passes=10,
                                    per_word_topics=True)
```

In [40]:
```
print(lda_model.print_topics())
```

```
[(0, '0.015*"said" + 0.015*"year" + 0.010*"bn" + 0.009*"market" + 0.008*"sale" + 0.006
*"firm" + 0.006*"price" + 0.006*"bank" + 0.006*"uk" + 0.006*"growth"'), (1, '0.019*"sai
d" + 0.018*"phone" + 0.012*"mobile" + 0.010*"system" + 0.009*"network" + 0.008*"firm" +
0.008*"people" + 0.007*"service" + 0.007*"could" + 0.007*"software"'), (2, '0.025*"musi
c" + 0.011*"cell" + 0.011*"song" + 0.010*"album" + 0.009*"band" + 0.009*"drug" + 0.009
*"pp" + 0.008*"court" + 0.008*"artist" + 0.007*"yukos"'), (3, '0.011*"film" + 0.011*"yea
r" + 0.009*"best" + 0.009*"said" + 0.007*"award" + 0.007*"one" + 0.006*"also" + 0.005*"s
how" + 0.005*"star" + 0.005*"first"'), (4, '0.020*"spyware" + 0.013*"copy" + 0.012*"dvd"
+ 0.009*"fa" + 0.008*"pirated" + 0.007*"ripguard" + 0.006*"orchestra" + 0.006*"macrovisi
on" + 0.006*"chart" + 0.005*"pany"'), (5, '0.012*"oscar" + 0.010*"aviator" + 0.009*"bes
t" + 0.009*"actor" + 0.008*"dollar" + 0.008*"actress" + 0.007*"nomination" + 0.006*"fil
m" + 0.006*"ray" + 0.006*"baby"'), (6, '0.024*"said" + 0.018*"mr" + 0.011*"would" + 0.00
8*"government" + 0.006*"people" + 0.006*"party" + 0.006*"say" + 0.006*"labour" + 0.005
*"minister" + 0.005*"election"'), (7, '0.013*"said" + 0.012*"people" + 0.010*"technolog
y" + 0.008*"game" + 0.007*"user" + 0.006*"mr" + 0.006*"also" + 0.006*"digital" + 0.006
*"music" + 0.005*"new"'), (8, '0.013*"game" + 0.009*"said" + 0.007*"player" + 0.007*"eng
land" + 0.006*"win" + 0.006*"first" + 0.006*"time" + 0.005*"back" + 0.005*"last" + 0.005
*"world"'), (9, '0.004*"evans" + 0.004*"ukraine" + 0.003*"walmart" + 0.003*"hamm" + 0.00
3*"fannie" + 0.002*"ossie" + 0.002*"mae" + 0.002*"borussia" + 0.002*"yushchenko" + 0.002
*"dortmund"')]
```

The top 10 words:

- topic 0: said, year, bn, market, sale, firm, price, bank, growth, share
- topic 1: said, phone, mobile, system, network, firm, could, people, software, service
- topic 2: music, song, album, band, cell, drug, court, artist, pp, yukos
- topic 3: film, year, said, best, one, award, also, show, star, first
- topic 4: spyware, dvd, copy, fa, pirated, riqguard, chart, macrovision, orchestra, osullivan
- topic 5: oscar, aviator, best, actor, dollar, actress, nomination, film, ray, baby
- topic 6: said, mr, would, government, people, party, labour, say, minister, election
- topic 7: said, people, technology, game, user, mr, digital, also, music, mobile
- topic 8: game, said, england, player, win, first, time, back, last, team
- topic 9: evans, ukraine, walmart, fannie, hamm, ossie, mae, borussia, yushchenko, dortmund

In [41]:
```
from gensim.models import CoherenceModel

coherence_model_lda = CoherenceModel(model=lda_model,
                                     texts=lem_ls,
                                     dictionary=id2word,
                                     coherence='c_v')

coherence_lda = coherence_model_lda.get_coherence()

print('\nCoherence Score: ', coherence_lda)
```

```
Coherence Score:  0.507078407675348
```

A coherence schore of .50 can be better so I will now optimize the base model.

In [42]:
```
scores = []
for i in range(2,15):
    print(f'Calcuting for {i} topics')
    lda_model = gensim.models.LdaMulticore(corpus=corpus,
```

```python
                                                id2word=id2word,
                                                num_topics=i,
                                                random_state=42,
                                                chunksize=100,
                                                passes=10,
                                                per_word_topics=True)
    # compute the coherence score
    coherence_model_lda = CoherenceModel(model=lda_model,
                                          texts=lem_ls,
                                          dictionary=id2word,
                                          coherence='c_v')

    # retreive the coherence_scores
    coherence_lda = coherence_model_lda.get_coherence()

    scores.append((i,coherence_lda))
```

```
Calcuting for 2 topics
Calcuting for 3 topics
Calcuting for 4 topics
Calcuting for 5 topics
Calcuting for 6 topics
Calcuting for 7 topics
Calcuting for 8 topics
Calcuting for 9 topics
Calcuting for 10 topics
Calcuting for 11 topics
Calcuting for 12 topics
Calcuting for 13 topics
Calcuting for 14 topics
```

In [43]:

```python
scores
```

Out[43]:

```
[(2, 0.36012557622051056),
 (3, 0.34376659357003775),
 (4, 0.4581386426538785),
 (5, 0.40293895390909357),
 (6, 0.448329903408631),
 (7, 0.4934569426924096),
 (8, 0.49812501043744534),
 (9, 0.4848654306965179),
 (10, 0.5162742843140313),
 (11, 0.4797148479281119),
 (12, 0.503218657218243),
 (13, 0.4973208236121931),
 (14, 0.5194922436809735)]
```

The best model is of 10 topics.

In [44]:

```python
bf_lda_model = gensim.models.LdaMulticore(corpus=corpus,
                                          id2word=id2word,
                                          num_topics=10,
                                          random_state=42,
                                          chunksize=100,
                                          passes=10,
                                          per_word_topics=True)
```

In [45]:

```python
import pyLDAvis.gensim_models
import pickle
import pyLDAvis

# Visualize the topics
```

```python
pyLDAvis.enable_notebook()
LDAvis_prepared = pyLDAvis.gensim_models.prepare(bf_lda_model, corpus, id2word)
pyLDAvis.save_html(LDAvis_prepared,'assign_wk7/news_topic_model_viz.html')
```

```
C:\Users\SCULLY\anaconda3\lib\site-packages\sklearn\decomposition\_lda.py:28: Deprecatio
nWarning: `np.float` is a deprecated alias for the builtin `float`. To silence this warn
ing, use `float` by itself. Doing this will not modify any behavior and is safe. If you
specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/relea
se/1.20.0-notes.html#deprecations
  EPS = np.finfo(np.float).eps
```

Open the html file from the folder outside jupyter-notebook.

Top 10 words for topic 1 from the graphical representation:

said, mr, would, government, people, party, say, labour, minister, election

The following words are found with greatest frequency in topic 1 over all other topics:

Mr, government, party, labour, minister, election, blair, plan, public, law, tory, tax, issue, brown, lord, leader

This is demonstrated by hovering over the words in the barplot on the html and watching that the topic 1 cluster is largest.

This analysis helps to decipher possible topic subjects. Topic 1 may be news articles about the government and politics.

Topic two most frequent words indicates that the topic is about sports.

I really enjoyed this assignment. I may want to take the text analytics course because of this assignment. I can see a lot of use out of Natural Language Processing and creating accessability tools for people in need. I'm very interested in learning more on use oral communications. Using tools like this as well as image clustering can obtain so much data from real life events without much need for expensive study setups. A camera, sound recording, and willing people can bring a lot of insights.