In [1]:
```
# To add a new cell, type '# %%'
# To add a new markdown cell, type '# %% [markdown]'
# %% [markdown]
# # Feature Engineering, Baseline Model and Feature Selection
```

Import necessary dependencies

In [2]:
```
import pandas
from matplotlib import pyplot as plt
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
import numpy
from sklearn.feature_selection import chi2
from PIL import Image
from collections import Counter
import re
import sqlite3
from sklearn import decomposition, ensemble
import nltk
from keras.preprocessing import text
from keras.utils import np_utils
from keras.preprocessing import sequence
import pydot
import seaborn as sns
```

```
Using TensorFlow backend.
```

Load in the data from the database

In [3]:
```
dbconn = sqlite3.connect('./data/cleanedtraintest_v2.db')
train_data_df = pandas.read_sql_query('SELECT * FROM train_data', dbconn)
test_data_df = pandas.read_sql_query('SELECT * FROM test_data', dbconn)
dbconn.commit()
dbconn.close()
```

Check the if the data was loaded correctly

In [4]:
```
train_data_df.head()
```

Out[4]:

	index	category	headline	content	headline_cleaned	content_cleaned	content_nosources
0	0	3	Wall St. Bears Claw Back Into the Black (Reuters)	Reuters - Short-sellers, Wall Street's dwindli...	wall bears claw back black	wall street seeing green	Short-sellers, Wall Street's dwindling\band ...
1	1	3	Carlyle Looks Toward Commercial Aerospace (Reu...	Reuters - Private investment firm Carlyle Grou...	carlyle looks toward commercial aerospace	private investment firm carlyle group reputati...	Private investment firm Carlyle Group,\which...
2	2	3	Oil and Economy Cloud Stocks' Outlook (Reuters)	Reuters - Soaring crude prices plus worries\ab...	oil economy cloud stocks outlook	soaring crude prices plus economy outlook earn...	Soaring crude prices plus worries\about the ...
3	3	3	Iraq Halts Oil Exports from Main Southern Pipe...	Reuters - Authorities have halted oil export\f...	iraq halts oil exports main southern pipeline	authorities halted oil main pipeline southern ...	Authorities have halted oil export\flows fro...
4	4	3	Oil prices soar to all-time record, posing new...	AFP - Tearaway world oil prices, toppling reco...	oil prices soar record posing new menace us ec...	tearaway world oil prices toppling records str...	Tearaway world oil prices, toppling records ...

In [5]:
```
train_data_df.drop('index', axis=1, inplace=True)
train_data_df.head()
```

Out[5]:

	category	headline	content	headline_cleaned	content_cleaned	content_nosources
0	3	Wall St. Bears Claw Back Into the Black (Reuters)	Reuters - Short-sellers, Wall Street's dwindli...	wall bears claw back black	wall street seeing green	Short-sellers, Wall Street's dwindling\band ...
1	3	Carlyle Looks Toward Commercial Aerospace (Reu...	Reuters - Private investment firm Carlyle Grou...	carlyle looks toward commercial aerospace	private investment firm carlyle group reputati...	Private investment firm Carlyle Group,\which...
2	3	Oil and Economy Cloud Stocks' Outlook (Reuters)	Reuters - Soaring crude prices plus worries\ab...	oil economy cloud stocks outlook	soaring crude prices plus economy outlook earn...	Soaring crude prices plus worries\about the ...
3	3	Iraq Halts Oil Exports from Main Southern Pipe...	Reuters - Authorities have halted oil export\f...	iraq halts oil exports main southern pipeline	authorities halted oil main pipeline southern ...	Authorities have halted oil export\flows fro...
4	3	Oil prices soar to all-time record, posing new...	AFP - Tearaway world oil prices, toppling reco...	oil prices soar record posing new menace us ec...	tearaway world oil prices toppling records str...	Tearaway world oil prices, toppling records ...

In [6]:
```
test_data_df.head()
```

Out[6]:

	index	category	headline	content	headline_cleaned	content_cleaned	content_nosources
0	0	3	Fears for T N pension after talks	Unions representing workers at Turner Newall...	fears n pension talks	unions representing workers turner newall say ...	Unions representing workers at Turner Newall...
1	1	4	The Race is On: Second Private Team Sets Launc...	SPACE.com - TORONTO, Canada -- A second\team o...	race second private team sets launch date huma...	toronto canada rocketeers competing million an...	TORONTO, Canada -- A second\team of rocketee...
2	2	4	Ky. Company Wins Grant to Study Peptides (AP)	AP - A company founded by a chemistry research...	company wins grant study peptides	company founded chemistry researcher universit...	A company founded by a chemistry researcher ...
3	3	4	Prediction Unit Helps Forecast Wildfires (AP)	AP - It's barely dawn when Mike Fitzpatrick st...	prediction unit helps forecast wildfires	barely dawn mike fitzpatrick starts shift blur...	It's barely dawn when Mike Fitzpatrick start...
4	4	4	Calif. Aims to Limit Farm-Related Smog (AP)	AP - Southern California's smog-fighting agenc...	calif aims limit smog	southern california agency went emissions bovi...	Southern California's smog-fighting agency w...

In [7]:
```
test_data_df.drop('index', axis=1, inplace=True)
test_data_df.head()
```

Out[7]:

	category	headline	content	headline_cleaned	content_cleaned	content_nosources
0	3	Fears for T N pension after talks	Unions representing workers at Turner Newall...	fears n pension talks	unions representing workers turner newall say ...	Unions representing workers at Turner Newall...
1	4	The Race is On: Second Private Team Sets Launc...	SPACE.com - TORONTO, Canada -- A second\team o...	race second private team sets launch date huma...	toronto canada rocketeers competing million an...	TORONTO, Canada -- A second\team of rocketee...
2	4	Ky. Company Wins Grant to Study Peptides (AP)	AP - A company founded by a chemistry research...	company wins grant study peptides	company founded chemistry researcher universit...	A company founded by a chemistry researcher ...
3	4	Prediction Unit Helps Forecast Wildfires (AP)	AP - It's barely dawn when Mike Fitzpatrick st...	prediction unit helps forecast wildfires	barely dawn mike fitzpatrick starts shift blur...	It's barely dawn when Mike Fitzpatrick start...
4	4	Calif. Aims to Limit Farm-Related Smog (AP)	AP - Southern California's smog-fighting agenc...	calif aims limit smog	southern california agency went emissions bovi...	Southern California's smog-fighting agency w...

Sample 4000 rows

In [8]:
```
train_data_sample = train_data_df.sample(n = 4000, replace = False, random_state = 123)
train_data_sample.head()
```

Out[8]:

	category	headline	content	headline_cleaned	content_cleaned	content_nosources
30870	2	NHL on Ice, Maybe for Whole 2004-05 Season (AP)	AP - No shots, no saves, no goals. The Nationa...	nhl ice maybe whole season	shots saves goals national hockey league locke...	No shots, no saves, no goals. The National H...
7738	2	Rowers to be punished for criticism of teammate	ROWER Sally Robbins #39;s teammates are expect...	rowers punished criticism teammate	rower sally robbins teammates expected face di...	ROWER Sally Robbins #39;s teammates are expect...
25351	2	Changing Directions	Over at USA Today -- Slogan: "All the News Tha...	changing directions	slogan news fit print four paragraphs less got...	Over at - Slogan: "All the News That's Fit to...
74309	4	Cassini snapshots murky moon Titan	The Cassini probe got the first close-up photo...	cassini snapshots murky moon titan	cassini probe got first photos saturn murky mo...	The Cassini probe got the first close-up photo...
88347	1	Farewell Yasser Arafat	GAZA CITY, 12 November 2004 - The world will b...	farewell yasser arafat	gaza city world bid farewell abu ammar yasser ...	GAZA CITY, - The world will bid farewell to Ab...

In [9]:
```
test_data_sample = test_data_df.sample(n = 4000, replace = False, random_state = 123)
test_data_sample.head()
```

Out[9]:

	category	headline	content	headline_cleaned	content_cleaned	content_nosources
646	1	Panama pardons Castro 'plotters'	Four men accused of planning to kill Cuba's Fi...	panama pardons castro	four men accused planning kill cuba fidel cast...	Four men accused of planning to kill Cuba's Fi...
2616	4	Elephant DNA Could Help Stem Ivory Trade (AP)	AP - Analyzing the DNA of elephants may help t...	elephant dna could help stem ivory trade	analyzing dna elephants may help trace origins...	Analyzing the DNA of elephants may help trac...
2300	1	Job-Loss Panic Rises in Western Europe (AP)	AP - Stephane Zervos first suspected his job w...	panic rises western europe	stephane zervos first suspected job threatened...	Stephane Zervos first suspected his job was ...
4764	1	Remark on Homosexuality Delays Seating of Euro...	The European Union #39;s normally yawn-inducin...	remark homosexuality delays seating european p...	european union normally institutions raised ey...	The European Union #39;s normally yawn-inducin...
3617	3	Linux: Paris weighs a shift to open-source camp	PARIS The open-source computer system known as...	linux paris weighs shift camp	paris computer system known linux tough battle...	PARIS The open-source computer system known as...

Let's make a Bag of Words

In [10]:
```
# Use countvectorizer to get a vector of words
cv = CountVectorizer(min_df = 2, lowercase = True,
                     token_pattern=r'\b[A-Za-z]{2,}\b', ngram_range = (1, 1))
cv_matrix = cv.fit_transform(train_data_sample.content_cleaned).toarray()

# get all unique words in the corpus
vocab = cv.get_feature_names()

# produce a dataframe including the feature names
headline_bagofwords_df = pandas.DataFrame(cv_matrix, columns=vocab)
headline_bagofwords_df.head()
```

Out[10]:

	aaron	ab	abandon	abandoned	abandons	abbas	abc	abducted	abduction	abductions	...	zaragoza	zdnet	zealand	zee	zero	zimbabwe	zone	zook
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0

5 rows × 6873 columns

We have bag of words already, let's make a Bag of N-Grams

In [11]:
```
# Use countvectorizer to get a vector of ngrams
cv = CountVectorizer(min_df = 2, lowercase = True,
                     token_pattern=r'\b[A-Za-z]{2,}\b', ngram_range = (2, 3))
cv_matrix = cv.fit_transform(train_data_sample.content_cleaned).toarray()

# get all unique words in the corpus
vocab = cv.get_feature_names()

# produce a dataframe including the feature names
headline_bagofngrams_df = pandas.DataFrame(cv_matrix, columns=vocab)
headline_bagofngrams_df.head()
```

Out[11]:

	ab billion	abducted militants	abductions foreigners	abductions foreigners iraq	aboard international	aboard international space	abu ghraib	abu ghraib prison	abu musab	ac milan	...	yukos said	yukos said would	zdnet survey	zdnet survey professionals	zealand biggest	zee tv
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0

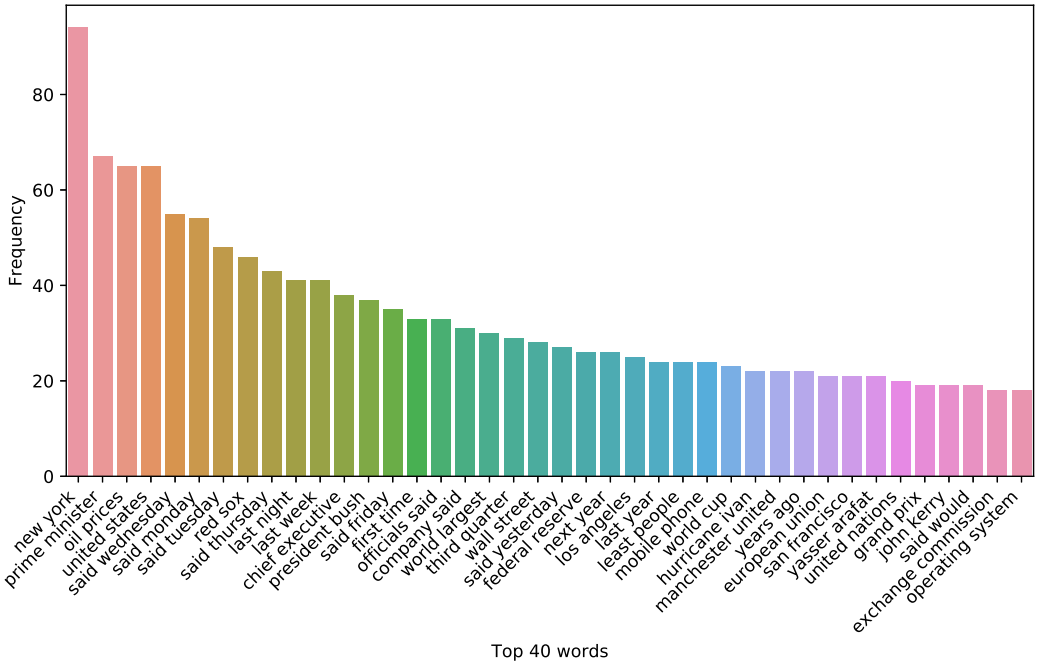
5 rows × 5929 columns

Let's explore the data we got through plots and tables

In [15]:

```
word_count_dict = {}
for word in vocab:
    word_count_dict[word] = int(sum(headline_bagofngrams_df.loc[:, word]))

counter = Counter(word_count_dict)

freq_df = pandas.DataFrame.from_records(counter.most_common(40),
                                        columns=['Top 40 words', 'Frequency'])

plt.figure(figsize=(10,5))
chart = sns.barplot(
    data=freq_df,
    x='Top 40 words',
    y='Frequency'
)

chart.set_xticklabels(
    chart.get_xticklabels(),
    rotation=45,
    horizontalalignment='right',
    fontweight='light'
)
```

Out[15]: [Text(0, 0, 'new york'),
Text(0, 0, 'prime minister'),
Text(0, 0, 'oil prices'),
Text(0, 0, 'united states'),
Text(0, 0, 'said wednesday'),
Text(0, 0, 'said monday'),
Text(0, 0, 'said tuesday'),
Text(0, 0, 'red sox'),
Text(0, 0, 'said thursday'),
Text(0, 0, 'last night'),
Text(0, 0, 'last week'),
Text(0, 0, 'chief executive'),
Text(0, 0, 'president bush'),
Text(0, 0, 'said friday'),
Text(0, 0, 'first time'),
Text(0, 0, 'officials said'),
Text(0, 0, 'company said'),
Text(0, 0, 'world largest'),
Text(0, 0, 'third quarter'),
Text(0, 0, 'wall street'),
Text(0, 0, 'said yesterday'),
Text(0, 0, 'federal reserve'),
Text(0, 0, 'next year'),
Text(0, 0, 'los angeles'),
Text(0, 0, 'last year'),
Text(0, 0, 'least people'),
Text(0, 0, 'mobile phone'),
Text(0, 0, 'world cup'),
Text(0, 0, 'hurricane ivan'),
Text(0, 0, 'manchester united'),
Text(0, 0, 'years ago'),
Text(0, 0, 'european union'),
Text(0, 0, 'san francisco'),
Text(0, 0, 'yasser arafat'),
Text(0, 0, 'united nations'),
Text(0, 0, 'grand prix'),
Text(0, 0, 'john kerry'),
Text(0, 0, 'said would'),
Text(0, 0, 'exchange commission'),
Text(0, 0, 'operating system')]



TF/IDF

Unigram TF/IDF

In [16]:
```
tfidf_vect = TfidfVectorizer(sublinear_tf = True, min_df = 2, ngram_range = (1, 1),
                             use_idf = True, token_pattern=r'\b[A-Za-z]{2,}\b')
tfidf_unigram = tfidf_vect.fit_transform(train_data_sample.content_cleaned).toarray()
# get all unique words in the corpus
vocab = tfidf_vect.get_feature_names()

tfidf_unigram = pandas.DataFrame(numpy.round(tfidf_unigram, 2), columns = vocab)
tfidf_unigram.head()
```

Out[16]:

	aaron	ab	abandon	abandoned	abandons	abbas	abc	abducted	abduction	abductions	...	zaragoza	zdnet	zealand	zee	zero	zimbabwe	zone	zook
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 6873 columns

N-Gram TF/IDF

In [17]:
```
tfidf_vect = TfidfVectorizer(sublinear_tf = True, min_df = 2, ngram_range = (2, 3),
                             use_idf = True, token_pattern=r'\b[A-Za-z]{2,}\b')
tfidf_ngram = tfidf_vect.fit_transform(train_data_sample.content_cleaned).toarray()

# get all unique words in the corpus
vocab = tfidf_vect.get_feature_names()

tfidf_ngram = pandas.DataFrame(numpy.round(tfidf_ngram, 2), columns = vocab)
tfidf_ngram.head()
```

Out[17]:

	ab billion	abducted militants	abductions foreigners	abductions foreigners iraq	aboard international	aboard international space	abu ghraib	abu ghraib prison	abu musab	ac milan	...	yukos said	yukos said would	zdnet survey	zdnet survey professionals	zealand biggest	zee tv
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 5929 columns

Character TF/IDF

In [18]:
```
tfidf_vect = TfidfVectorizer(analyzer = 'char', sublinear_tf = True, min_df = 2,
                             ngram_range = (2, 3), use_idf = True,
                             token_pattern=r'\b[A-Za-z]{2,}\b')
tfidf_char = tfidf_vect.fit_transform(train_data_sample.content_cleaned).toarray()
tfidf_fit = tfidf_vect.fit_transform(train_data_sample.content_cleaned)

# get all unique words in the corpus
vocab = tfidf_vect.get_feature_names()

tfidf_char = pandas.DataFrame(numpy.round(tfidf_char, 2), columns = vocab)
tfidf_char.head()
```

Out[18]:

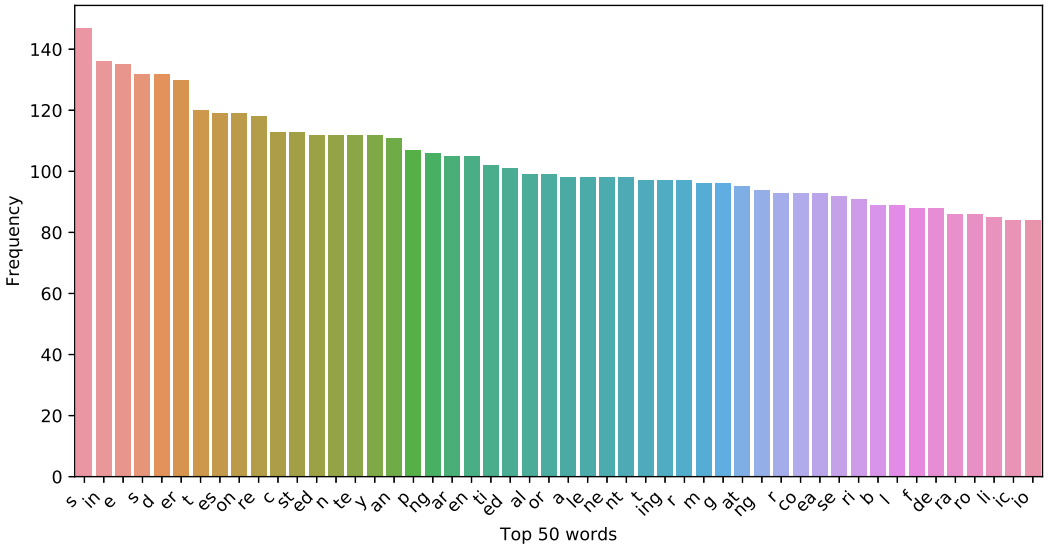
	a	aa	ab	ac	ad	ae	af	ag	ah	ai	...	zur	zv	zvo	zy	zy	zz	zz	zza	zzi	zzl
0	0.00	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0
1	0.03	0.0	0.00	0.07	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0
2	0.03	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0
3	0.00	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.13	0.14	0.0	0.0	0.0	0.0	0.0
4	0.06	0.0	0.07	0.00	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.00	0.00	0.0	0.0	0.0	0.0	0.0

5 rows × 5834 columns

In [19]:

```
word_count_dict = {}
for word in vocab:
    word_count_dict[word] = int(sum(tfidf_char.loc[:, word]))

counter = Counter(word_count_dict)

freq_df = pandas.DataFrame.from_records(counter.most_common(50),
                                        columns=['Top 50 words', 'Frequency'])

plt.figure(figsize=(10,5))
chart = sns.barplot(
    data=freq_df,
    x='Top 50 words',
    y='Frequency'
)

chart.set_xticklabels(
    chart.get_xticklabels(),
    rotation=45,
    horizontalalignment='right',
    fontweight='light'
)
```

Out[19]: [Text(0, 0, 's '),
Text(0, 0, 'in'),
Text(0, 0, 'e '),
Text(0, 0, ' s'),
Text(0, 0, 'd '),
Text(0, 0, 'er'),
Text(0, 0, 't '),
Text(0, 0, 'es'),
Text(0, 0, 'on'),
Text(0, 0, 're'),
Text(0, 0, ' c'),
Text(0, 0, 'st'),
Text(0, 0, 'ed'),
Text(0, 0, 'n '),
Text(0, 0, 'te'),
Text(0, 0, 'y '),
Text(0, 0, 'an'),
Text(0, 0, ' p'),
Text(0, 0, 'ng'),
Text(0, 0, 'ar'),
Text(0, 0, 'en'),
Text(0, 0, 'ti'),
Text(0, 0, 'ed '),
Text(0, 0, 'al'),
Text(0, 0, 'or'),
Text(0, 0, ' a'),
Text(0, 0, 'le'),
Text(0, 0, 'ne'),
Text(0, 0, 'nt'),
Text(0, 0, ' t'),
Text(0, 0, 'ing'),
Text(0, 0, 'r '),
Text(0, 0, ' m'),
Text(0, 0, 'g '),
Text(0, 0, 'at'),
Text(0, 0, 'ng '),
Text(0, 0, ' r'),
Text(0, 0, 'co'),
Text(0, 0, 'ea'),
Text(0, 0, 'se'),
Text(0, 0, 'ri'),
Text(0, 0, ' b'),
Text(0, 0, 'l '),
Text(0, 0, ' f'),
Text(0, 0, 'de'),
Text(0, 0, 'ra'),
Text(0, 0, 'ro'),
Text(0, 0, 'li'),
Text(0, 0, 'ic'),
Text(0, 0, 'io')]



Document Similarity

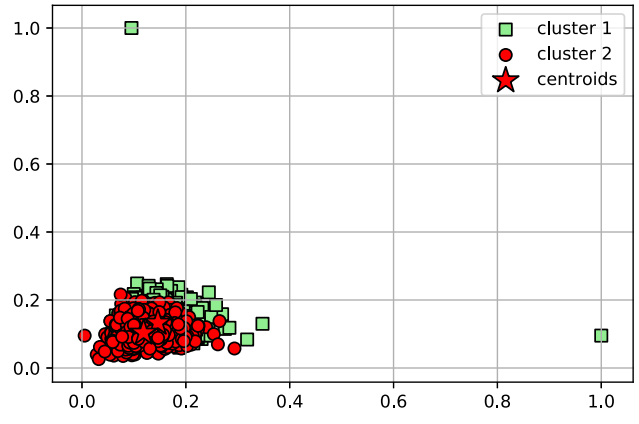
In [21]:
```
from sklearn.metrics.pairwise import cosine_similarity

similarity_matrix = cosine_similarity(tfidf_fit)
similarity_df = pandas.DataFrame(similarity_matrix)
similarity_df
```

Out[21]:

	0	1	2	3	4	5	6	7	8	9	...	3990	3991	3992	3993	3994
0	1.000000	0.095259	0.164343	0.136964	0.085002	0.106770	0.161383	0.151646	0.166582	0.101963	...	0.130839	0.118731	0.125330	0.112532	0.146402
1	0.095259	1.000000	0.074602	0.092086	0.190149	0.159834	0.158358	0.099680	0.119509	0.168387	...	0.057014	0.141423	0.138974	0.113837	0.088554
2	0.164343	0.074602	1.000000	0.135493	0.129496	0.132866	0.150840	0.143989	0.150554	0.077022	...	0.117931	0.114257	0.109056	0.110385	0.148440
3	0.136964	0.092086	0.135493	1.000000	0.100380	0.099874	0.113398	0.112133	0.111077	0.090205	...	0.147588	0.090534	0.162916	0.106458	0.138141
4	0.085002	0.190149	0.129496	0.100380	1.000000	0.150315	0.140680	0.115041	0.114895	0.120666	...	0.102981	0.119532	0.156242	0.107706	0.155334
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
3995	0.128665	0.141727	0.074880	0.128705	0.141434	0.096627	0.158732	0.186491	0.193820	0.095237	...	0.157934	0.143463	0.162309	0.099097	0.134725
3996	0.100010	0.126414	0.140385	0.071895	0.118277	0.114325	0.134758	0.081212	0.083704	0.101485	...	0.117732	0.144555	0.072108	0.073279	0.096205
3997	0.108122	0.085801	0.095980	0.121315	0.105968	0.054475	0.139955	0.119577	0.122685	0.109679	...	0.082717	0.072371	0.137245	0.097474	0.071417
3998	0.136546	0.147084	0.129208	0.150548	0.122254	0.103778	0.181423	0.119995	0.147895	0.110204	...	0.122925	0.085255	0.169854	0.075314	0.129028
3999	0.077240	0.092092	0.089120	0.133394	0.081994	0.073494	0.203616	0.093117	0.182370	0.074369	...	0.077919	0.139014	0.149045	0.094292	0.081787

4000 rows × 4000 columns

In [22]:
```
from sklearn.cluster import KMeans

km = KMeans(
    n_clusters=2, init='random',
    n_init=10, max_iter=300,
    tol=1e-04, random_state=0
)
y_km = km.fit_predict(similarity_df)

#Convert to array for clustering to work
similarity_df_array = numpy.array(similarity_df)

# plot the 3 clusters
plt.scatter(
    similarity_df_array[y_km == 0, 0], similarity_df_array[y_km == 0, 1],
    s=50, c='lightgreen',
    marker='s', edgecolor='black',
    label='cluster 1'
)

plt.scatter(
    similarity_df_array[y_km == 1, 0], similarity_df_array[y_km == 1, 1],
    s=50, c='red',
    marker='o', edgecolor='black',
    label='cluster 2'
)

# plt.scatter(
#     similarity_df_array[y_km == 2, 0], similarity_df_array[y_km == 2, 1],
#     s=50, c='lightblue',
#     marker='v', edgecolor='black',
#     label='cluster 3'
# )

#plt.scatter(
#    w2v_feature_array[y_km == 2, 0], w2v_feature_array[y_km == 2, 1],
#    s=50, c='red',
#    marker='h', edgecolor='black',
#    label='cluster 4'
#)

# plot the centroids
plt.scatter(
    km.cluster_centers_[:, 0], km.cluster_centers_[:, 1],
    s=250, marker='*',
    c='red', edgecolor='black',
    label='centroids'
)
plt.legend(scatterpoints=1)
plt.grid()
plt.show()
```



Using gensim to build Word2Vec

In [24]:
```
from gensim.models import word2vec

# tokenize sentences in corpus
wpt = nltk.WordPunctTokenizer()
tokenized_corpus = [wpt.tokenize(document) for document in train_data_df.headline_cleaned]

# Set values for various parameters
feature_size = 100    # Word vector dimensionality
window_context = 20          # Context window size
workers = 10
min_word_count = 5   # Minimum word count
sample = 1e-3   # Downsample setting for frequent words

w2v_model = word2vec.Word2Vec(tokenized_corpus, size=feature_size,
                          window=window_context, min_count=min_word_count,
                          sample=sample, iter=500)
```

Visualize Word Embedding

In [32]:
```
from sklearn.manifold import TSNE
words = w2v_model.wv.index2word
wvs = w2v_model.wv[words]
tsne = TSNE(n_components=2, random_state=0, n_iter=500, perplexity=2)
numpy.set_printoptions(suppress=True)
T = tsne.fit_transform(wvs)
labels = words
plt.figure(figsize=(12, 6))
plt.scatter(T[:, 0], T[:, 1], c='orange', edgecolors='r')
for label, x, y in zip(labels, T[:, 0], T[:, 1]):
 plt.annotate(label, xy=(x+1, y+1), xytext=(0, 0), textcoords='offset points')
```