Topic Modeling

In machine learning and natural language processing, a topic model is a type of statistical model for discovering the abstract "topics" that occur in a colle frequently used text-mining tool for discovery of hidden semantic structures in a text body. Intuitively, given that a document is about a particular topic, o the document more or less frequently: "dog" and "bone" will appear more often in documents about dogs, "cat" and "meow" will appear in documents ab approximately equally in both.

Topic modeling is a technique of extracting hidden topics from a volume of text. Topic modeling is a classic solution to the problem of information retriev technology. Related models and techniques are, among others, latent semantic indexing, independent component analysis, probabilistic latent semantic Gamma-Poisson distribution and Latent Derichlet Allocation (LDA). Source: [wikipedia (https://en.wikipedia.org/wiki/Topic_model)](https://en.wikipedia.org/wiki/Topic_model)

Import required libraries

In [1]:
```
# !pip install pyLDAvis # Uncomment and install this visualization library
```

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
#Data manipulation
import pandas as pd
import numpy as np
from collections import Counter
from pprint import pprint

# Data preprocessing & cleaning
import re
import string
from nltk.corpus import stopwords
from nltk import pos_tag, WordNetLemmatizer
from gensim.utils import simple_preprocess
import gensim.corpora as corpora

# Modeling
import gensim

# Model Evaluation
from gensim.models import CoherenceModel

# Plotting tools
import matplotlib.pyplot as plt
import matplotlib.colors as mcolors
from matplotlib.ticker import FuncFormatter
import seaborn as sns
import pyLDAvis
import pyLDAvis.gensim
```

In [4]:
```
plt.style.use('ggplot')
stop_words=stopwords.words('english')
```

Extend the list of stop words

In [ ]:
```
stop_words.extend(['from', 'subject', 're', 'edu', 'use','know','dont'])
```

Load dataset

In [5]:
```
df=pd.read_csv('datasets/spam.csv')
```

In [6]:
```
df.shape
```

Out[6]:
```
(5572, 5)
```

Check first 5 rows

In [7]:
```
df.head()
```

Out[7]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only ...	NaN	NaN	NaN
1	ham	Ok lar... Joking wif u oni...	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	NaN	NaN	NaN
3	ham	U dun say so early hor... U c already then say...	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro...	NaN	NaN	NaN

Drop unnecessary columns

In [8]:
```
df=df.drop(['Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'],axis=1)
```

Rename columns

In [9]:
```
df.columns=['target','content']
```

In [10]:
```python
df.head()
```

Out[10]:

	target	content
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

In [11]:
```python
df.head()
```

Out[11]:

	target	content
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

Check rows and columns

In [12]:
```python
df.shape
```

Out[12]:
```
(5572, 2)
```

Preprocess Data

Convert the text into lower case

In [13]:
```
def convert_to_lower_case(text):
    return "".join([t.lower() for t in text])
```

In [14]:
```
df['content']=df['content'].apply(lambda x: convert_to_lower_case(x))
```

In [15]:
```
df.head()
```

Out[15]:

	target	content
0	ham	go until jurong point, crazy.. available only ...
1	ham	ok lar... joking wif u oni...
2	spam	free entry in 2 a wkly comp to win fa cup fina...
3	ham	u dun say so early hor... u c already then say...
4	ham	nah i don't think he goes to usf, he lives aro...

Remove emails

In [16]:
```
def remove_emails(text):
    data = ' '.join([item for item in text.split() if '@' not in item])
    return data
```

In [17]:
```
df['content']=df['content'].apply(lambda x: remove_emails(x))
```

In [18]:
```
df.head()
```

Out[18]:

	target	content
0	ham	go until jurong point, crazy.. available only ...
1	ham	ok lar... joking wif u oni...
2	spam	free entry in 2 a wkly comp to win fa cup fina...
3	ham	u dun say so early hor... u c already then say...
4	ham	nah i don't think he goes to usf, he lives aro...

Remove new line characters

In [19]:
```
def remove_line_character(text):
    data=text.rstrip()
    return data
```

In [20]:
```
df['content']=df['content'].apply(lambda x: remove_line_character(x))
```

In [21]:
```
df.head()
```

Out[21]:

	target	content
0	ham	go until jurong point, crazy.. available only ...
1	ham	ok lar... joking wif u oni...
2	spam	free entry in 2 a wkly comp to win fa cup fina...
3	ham	u dun say so early hor... u c already then say...
4	ham	nah i don't think he goes to usf, he lives aro...

Remove single quotes

Alternatively can use punctuation function

In [22]:
```
def remove_single_quotes(text):
    data=text.replace("'", "")
    return data
```

In [23]:
```
df['content']=df['content'].apply(lambda x: remove_single_quotes(x))
```

In [24]:
```
df.head()
```

Out[24]:

	target	content
0	ham	go until jurong point, crazy.. available only ...
1	ham	ok lar... joking wif u oni...
2	spam	free entry in 2 a wkly comp to win fa cup fina...
3	ham	u dun say so early hor... u c already then say...
4	ham	nah i dont think he goes to usf, he lives arou...

Remove Punctuations

In [25]:
```
string.punctuation
```

Out[25]:
```
'!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'
```

In [26]:
```
def remove_punctuation(text):
    return "".join([t for t in text if t not in string.punctuation])
```

In [27]:
```
df['content']=df['content'].apply(lambda x: remove_punctuation(x))
```

In [28]:
```
df.head()
```

Out[28]:

	target	content
0	ham	go until jurong point crazy available only in ...
1	ham	ok lar joking wif u oni
2	spam	free entry in 2 a wkly comp to win fa cup fina...
3	ham	u dun say so early hor u c already then say
4	ham	nah i dont think he goes to usf he lives aroun...

Remove words with less than 3 characters

In [29]:
```
def words_less_than_three_chars(text):
    return " ".join([t for t in text.split() if len(t)>2])
```

In [30]:
```
df['content']=df['content'].apply(lambda x: words_less_than_three_chars(x))
```

In [31]:
```
df.head()
```

Out[31]:

	target	content
0	ham	until jurong point crazy available only bugis ...
1	ham	lar joking wif oni
2	spam	free entry wkly comp win cup final tkts 21st m...
3	ham	dun say early hor already then say
4	ham	nah dont think goes usf lives around here though

Remove digits in data

In [32]:
```
df['content'].replace('\d+', '', regex=True, inplace=True)
```

```
<input>:1: DeprecationWarning: invalid escape sequence \d
<input>:1: DeprecationWarning: invalid escape sequence \d
<input>:1: DeprecationWarning: invalid escape sequence \d
<ipython-input-32-f2d5817ef051>:1: DeprecationWarning: invalid escape sequence \d
  df['content'].replace('\d+', '', regex=True, inplace=True)
```

Remove rows without data

In [33]:
```
df.drop(df[(df['content']=='') | (df['content']==' ')].index, inplace=True,axis=0)
```

In [34]:
```
df[df['content']=='']
```

Out[34]:

target	content

In [35]:
```
df.shape
```

Out[35]:
```
(5546, 2)
```

Remove non-alpha numeric characters

In [36]:
```
def remove_non_alpha_numerics(text):
    alpha_num=' '.join([word for word in text.split() if word.isalpha()])
    return alpha_num
```

In [37]:
```
df['content']=df['content'].apply(lambda x: remove_non_alpha_numerics(x))
```

In [38]:
```
df.head()
```
Out[38]:

	target	content
0	ham	until jurong point crazy available only bugis ...
1	ham	lar joking wif oni
2	spam	free entry wkly comp win cup final tkts st may...
3	ham	dun say early hor already then say
4	ham	nah dont think goes usf lives around here though

Tokenize the text

In [39]:
```
def text_tokenizaion(text):
    return re.split(' ',text)
```
In [40]:
```
df['content']=df['content'].apply(lambda x: text_tokenizaion(x))
```
In [41]:
```
df.head()
```
Out[41]:

	target	content
0	ham	[until, jurong, point, crazy, available, only,...
1	ham	[lar, joking, wif, oni]
2	spam	[free, entry, wkly, comp, win, cup, final, tkt...
3	ham	[dun, say, early, hor, already, then, say]
4	ham	[nah, dont, think, goes, usf, lives, around, h...

Remove stopword Comment this section when using Extracts Nouns only function

```
In [42]: print(stop_words)
```

```
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours
imself', 'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them', 'their', 'theirs', 'them
hat', "that'll", 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having'
'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between
'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once
'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', '
l', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll', 'm', 'o', 're', 've', 'y', 'ain', 'aren', "aren't", '
esn't", 'hadn', "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', "must
n', "shouldn't", 'wasn', "wasn't", 'weren', "weren't", 'won', "won't", 'wouldn', "wouldn't", 'from', 'subject', 're', 'edu
```

```
In [43]: def remove_stopwords(text):
             return [w for w in text if w not in stop_words]
```

```
In [44]: df['content']=df['content'].apply(lambda x: remove_stopwords(x))
```

```
In [45]: df.head()
```

Out[45]:

	target	content
0	ham	[jurong, point, crazy, available, bugis, great...
1	ham	[lar, joking, wif, oni]
2	spam	[free, entry, wkly, comp, win, cup, final, tkt...
3	ham	[dun, say, early, hor, already, say]
4	ham	[nah, think, goes, usf, lives, around, though]

Extracts Nouns only

```
In [46]: def extract_nouns(text):
             is_noun = lambda pos: pos[:2] == 'NN' or  pos[:2] == 'RB' or  pos[:2] == 'JJ'
             all_nouns = " ".join([word for (word, pos) in pos_tag(text) if is_noun(pos)])
             return all_nouns
```

In [47]:
```
df['content']=df['content'].apply(lambda x: extract_nouns(x))
```

In [48]:
```
df.head()
```

Out[48]:

	target	content
0	ham	jurong point crazy available bugis great world...
1	ham	lar joking wif oni
2	spam	free entry comp win cup final tkts st receive ...
3	ham	dun early hor already
4	ham	nah think usf lives

In [49]:
```
df['content']=df['content'].apply(lambda x: text_tokenizaion(x))
```

Normalize text by Lemmatization

In [50]:
```
def text_lematization(text):
    return [WordNetLemmatizer().lemmatize(w) for w in text]
```

In [51]:
```
df['content']=df['content'].apply(lambda x: text_lematization(x))
```

In [52]:
```
df.head()
```

Out[52]:

	target	content
0	ham	[jurong, point, crazy, available, bugis, great...
1	ham	[lar, joking, wif, oni]
2	spam	[free, entry, comp, win, cup, final, tkts, st,...
3	ham	[dun, early, hor, already]
4	ham	[nah, think, usf, life]

Convert data to list for modeling

In [53]:
```
data = df.content.values.tolist()
tokenized_data = df.content.values.tolist()
```

In [54]:
```
print(tokenized_data[0:2])
```

```
[['jurong', 'point', 'crazy', 'available', 'bugis', 'great', 'world', 'buffet', 'cine', 'amore', 'wat'], ['lar', 'joking',
```

Create Data Input to Model

1. Create Dictionary

In [55]:
```
id2word = corpora.Dictionary(tokenized_data)
```

In [56]:
```
id2word
```

Out[56]:
```
<gensim.corpora.dictionary.Dictionary at 0x1fde03d3198>
```

2. Create Corpus (Term Document Frequency)

In [57]:
```
corpus = [id2word.doc2bow(text) for text in tokenized_data]
```

In [58]:
```
print(corpus[0:2])
```

```
[[(0, 1), (1, 1), (2, 1), (3, 1), (4, 1), (5, 1), (6, 1), (7, 1), (8, 1), (9, 1), (10, 1)], [(11, 1), (12, 1), (13, 1), (1
```

Show corpus and frequency

In [59]:
```
print([[(id2word[id], freq) for id, freq in cp] for cp in corpus[:1]])
```

```
[[('amore', 1), ('available', 1), ('buffet', 1), ('bugis', 1), ('cine', 1), ('crazy', 1), ('great', 1), ('jurong', 1), ('p
```

Modeling LDA Topic model

Latent Dirichlet allocation (LDA)

Latent Dirichlet allocation (LDA) is a generative statistical model that allows sets of observations to be explained by unobserved groups that explain why example, if observations are words collected into documents, it posits that each document is a mixture of a small number of topics and that each word's document's topics. LDA is an example of a topic model and belongs to the machine learning toolbox and in wider sense to the artificial intelligence toolb (https://en.wikipedia.org/wiki/Latent_Dirichlet_allocation)

In the LDA model below we specify chunksize which is the number of document to use for each training iteration/chunk. passes is the total number of tra

In [60]:
```
model = gensim.models.ldamodel.LdaModel(corpus=corpus,id2word=id2word,num_topics=6, random_state=100, update_every=1,
                                        chunksize=100,passes=10,alpha='auto',per_word_topics=True)
```

Show topics

Each keyword has a weighted importance value

In [61]:
```
pprint(model.print_topics())
```

```
[(0,
  '0.063*"call" + 0.038*"free" + 0.027*"mobile" + 0.023*"later" + '
  '0.020*"number" + 0.017*"claim" + 0.017*"phone" + 0.017*"sorry" + '
  '0.016*"min" + 0.015*"night"'),
 (1,
  '0.049*"ltgt" + 0.023*"pls" + 0.022*"stop" + 0.020*"really" + 0.018*"friend" '
  '+ 0.017*"message" + 0.017*"next" + 0.014*"" + 0.013*"shit" + '
  '0.013*"problem"'),
 (2,
  '0.033*"time" + 0.019*"still" + 0.018*"ill" + 0.016*"txt" + 0.016*"thats" + '
  '0.014*"cant" + 0.013*"want" + 0.013*"yeah" + 0.013*"soon" + 0.012*"work"'),
 (3,
  '0.025*"back" + 0.023*"great" + 0.023*"well" + 0.022*"new" + 0.016*"please" '
  '+ 0.015*"cash" + 0.013*"havent" + 0.013*"happy" + 0.013*"guy" + '
  '0.012*"wish"'),
 (4,
  '0.034*"day" + 0.026*"good" + 0.024*"text" + 0.024*"lor" + 0.021*"home" + '
  '0.020*"week" + 0.019*"today" + 0.015*"hey" + 0.013*"reply" + 0.013*"yes"'),
 (5,
  '0.022*"thing" + 0.020*"much" + 0.016*"babe" + 0.014*"also" + '
  '0.013*"something" + 0.012*"love" + 0.012*"school" + 0.010*"minute" + '
  '0.010*"malaria" + 0.010*"house"')]
```

Model Evaluation

1. Model perplexity

In information theory, perplexity is a measurement of how well a probability distribution or probability model predicts a sample. It may be used to compar
the probability distribution is good at predicting the sample. [wikipedia (https://en.wikipedia.org/wiki/Perplexity)](https://en.wikipedia.org/wiki/Perplexity)

In [62]:
```
model.log_perplexity(corpus)
```

Out[62]:
```
-8.585864408770574
```

2. Topic Coherence

Topic coherence is a metric that returns the coherene score with is a measure of the degree of semantic similarity between high scoring words in the top

In [63]:
```
model_coherence = CoherenceModel(model=model, texts=tokenized_data, dictionary=id2word, coherence='c_v')
```

In [64]:
```
model_coherence.get_coherence()
```

Out[64]:
```
0.46460550004033324
```

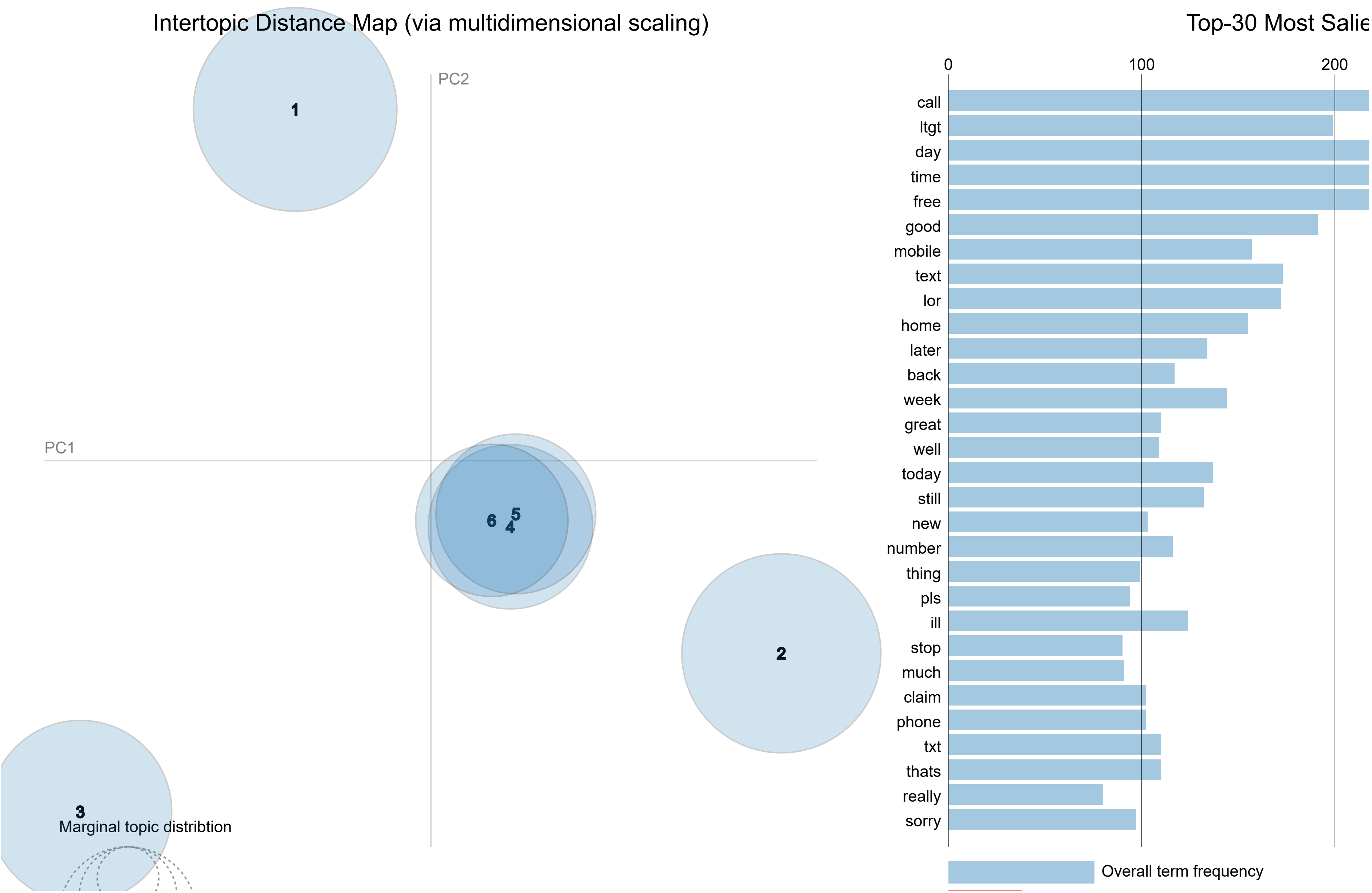
Visualize the topics

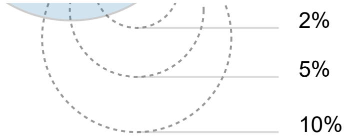
In [65]:
```
pyLDAvis.enable_notebook()
vis=pyLDAvis.gensim.prepare(model, corpus, id2word)
```

In [66]:
```
vis
```
Out[66]:

Selected Topic: 0 | Previous Topic | Next Topic | Clear Topic

Slide to adjust relevance metric:(2)
λ = 1





Estimated term frequency within the selected to

1. saliency(term w) = frequency(w) * [sum_t p(t | w) * log(p(t
2. relevance(term w | topic t) = λ * p(w | t) + (1 - λ) * p(w | t)/

Interpreting the Visual

Each bubble on the left graph represents a topic. The larger the bubble, the more prevalent is that topic. A good topic model will have fairly big, non-ove chart instead of being clustered in one quadrant. A model with too many topics, will typically have many overlaps, small sized bubbles clustered in one r

1. Dominant topic in each sentence

To get the dominant topic in each sentence we compute the percentage contribution of each topic.

In [67]:
```
def topics_in_sentences(model=None, corpus=corpus, texts=data):
    # Initialize an empty dataframe
    sentence_topics_df = pd.DataFrame()

    # Loop through each document and each sentence to get the key topics
    for i, row_list in enumerate(model[corpus]):
        row = row_list[0] if model.per_word_topics else row_list
        row = sorted(row, key=lambda x: (x[1]), reverse=True)
        # For each document extract the topic percentage contribution and keywords
        for j, (topic_num, prop_topic) in enumerate(row):
            if j == 0:  # Dominant topic
                wp = model.show_topic(topic_num)
                topic_keywords = ", ".join([word for word, prop in wp])
                sentence_topics_df = sentence_topics_df.append(pd.Series([int(topic_num), round(prop_topic,4), topic_keywo
            else:
                break
    sentence_topics_df.columns = ['Dominant_Topic', 'Pct_Contribution', 'Topic_Keywords']

    # Append original text to the end of the output
    contents = pd.Series(texts)
    sentence_topics_df = pd.concat([sentence_topics_df, contents], axis=1)
    return(sentence_topics_df)


sentence_topics_keywords_df = topics_in_sentences(model=model, corpus=corpus, texts=tokenized_data)

# Format
dominant_topic_df = sentence_topics_keywords_df.reset_index()
dominant_topic_df.columns = ['Document_No', 'Dominant_Topic', 'Topic_Pct_Contribution', 'Keywords', 'Text']
```

In [68]:
```
dominant_topic_df.head()
```

Out[68]:

	Document_No	Dominant_Topic	Topic_Pct_Contribution	Keywords	Text
0	0	3.0	0.4184	back, great, well, new, please, cash, havent, ...	[jurong, point, crazy, available, bugis, great...
1	1	2.0	0.3167	time, still, ill, txt, thats, cant, want, yeah...	[lar, joking, wif, oni]
2	2	2.0	0.6296	time, still, ill, txt, thats, cant, want, yeah...	[free, entry, comp, win, cup, final, tkts, st,...
3	3	3.0	0.2648	back, great, well, new, please, cash, havent, ...	[dun, early, hor, already]
4	4	2.0	0.3209	time, still, ill, txt, thats, cant, want, yeah...	[nah, think, usf, life]

2. The most representative sentence for each topic

In [69]:
```
# pd.options.display.max_colwidth = 100

sorted_sentence_topics_df = pd.DataFrame()
grouped_sentence_topics_df = sentence_topics_keywords_df.groupby('Dominant_Topic')

for i, grp in grouped_sentence_topics_df:
    sorted_sentence_topics_df = pd.concat([sorted_sentence_topics_df,
                                            grp.sort_values(['Pct_Contribution'], ascending=False).head(1)],
                                           axis=0)

# Reset Index
sorted_sentence_topics_df.reset_index(drop=True, inplace=True)

# Format columns
sorted_sentence_topics_df.columns = ['Topic_Num', "Topic_Pct_Contrib", "Keywords", "Representative Text"]
```

In [70]:
```
sorted_sentence_topics_df.head(10)
```

Out[70]:

	Topic_Num	Topic_Pct_Contrib	Keywords	Representative Text
0	0.0	0.7251	call, free, mobile, later, number, claim, phon...	[december, mobile, mths, update, latest, colou...
1	1.0	0.6478	ltgt, pls, stop, really, friend, message, next...	[space, invader, chance, orig, arcade, game, c...
2	2.0	0.7499	time, still, ill, txt, thats, cant, want, yeah...	[height, confidence, aeronautics, professor, c...
3	3.0	0.6096	back, great, well, new, please, cash, havent, ...	[urgent, please, landline, complimentary, lux,...
4	4.0	0.7132	day, good, text, lor, home, week, today, hey, ...	[eerie, nokia, tone, tone, title, tone, dracul...
5	5.0	0.6270	thing, much, babe, also, something, love, scho...	[need, presnts, always, cant, mi, love, jeevit...

3. Topic distribution across documents

In [71]:
```
# Number of Documents for Each Topic
topic_counts = sentence_topics_keywords_df['Dominant_Topic'].value_counts()

# Percentage of Documents for Each Topic
topic_contribution = round(topic_counts/topic_counts.sum(), 4)

# Topic Number and Keywords
topic_num_keywords = sentence_topics_keywords_df[['Dominant_Topic', 'Topic_Keywords']]

# Concatenate Column wise
dominant_topics_df = pd.concat([topic_num_keywords, topic_counts, topic_contribution], axis=1)

# Change Column names
dominant_topics_df.columns = ['Dominant_Topic', 'Topic_Keywords', 'Num_Documents', 'Pct_Documents']
```

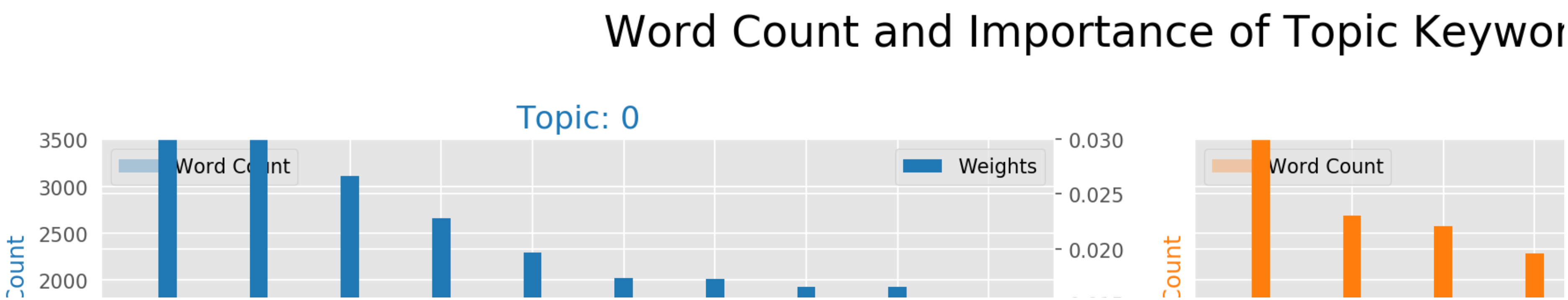
In [72]:
```
dominant_topics_df.head()
```

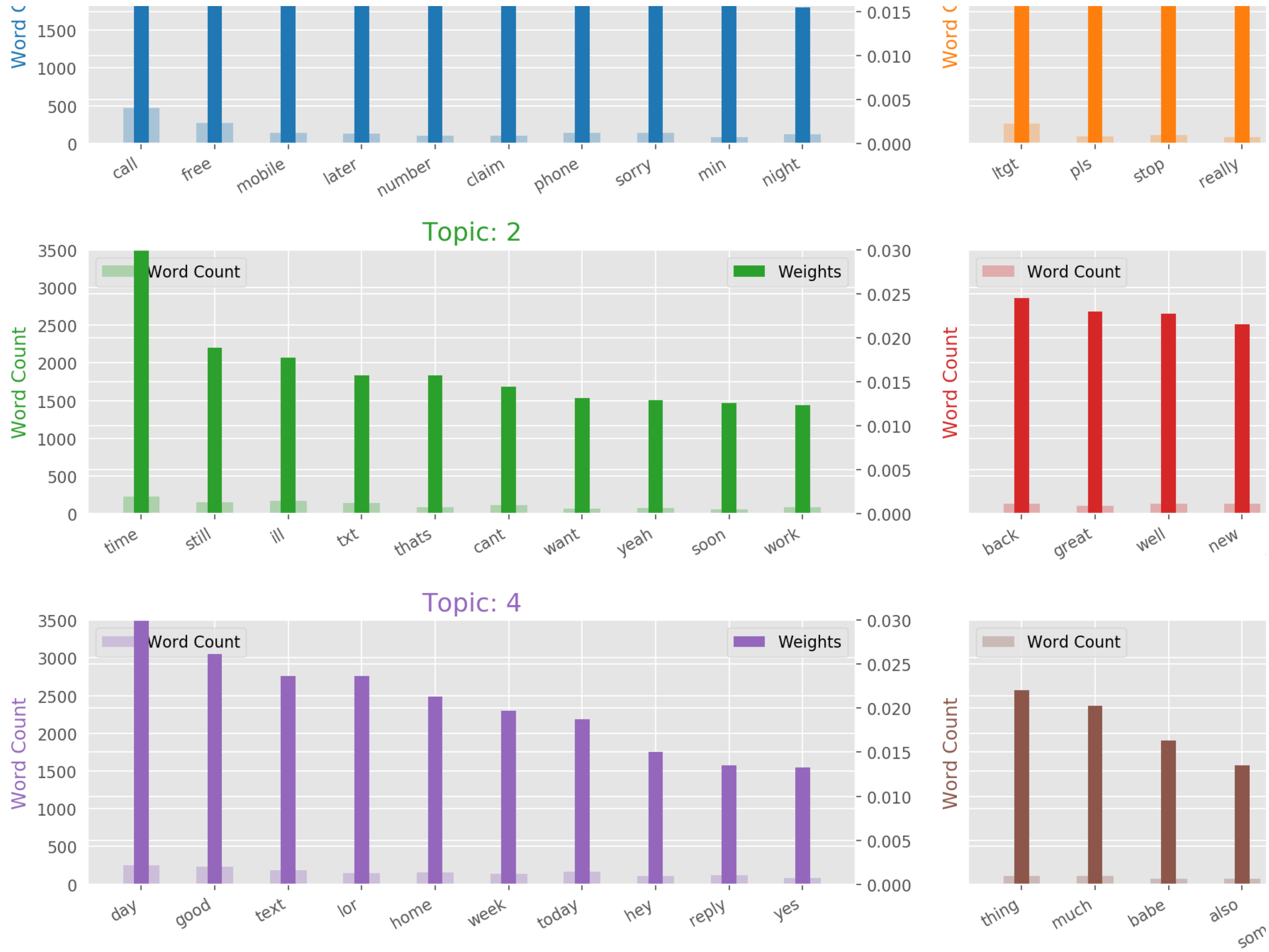
Out[72]:

	Dominant_Topic	Topic_Keywords	Num_Documents	Pct_Documents
0	3.0	back, great, well, new, please, cash, havent, ...	850.0	0.1533
1	2.0	time, still, ill, txt, thats, cant, want, yeah...	504.0	0.0909
2	2.0	time, still, ill, txt, thats, cant, want, yeah...	1776.0	0.3202
3	3.0	back, great, well, new, please, cash, havent, ...	581.0	0.1048
4	2.0	time, still, ill, txt, thats, cant, want, yeah...	1237.0	0.2230

4. Word Clouds of Top N Keywords in Each Topic

In [73]:
```python
topics = model.show_topics(formatted=False)
data_flat = [w for w_list in tokenized_data for w in w_list]
counter = Counter(data_flat)

out = []
for i, topic in topics:
    for word, weight in topic:
        out.append([word, i , weight, counter[word]])

word_cloud_df = pd.DataFrame(out, columns=['word', 'topic_id', 'importance', 'word_count'])

# Plot Word Count and Weights of Topic Keywords
fig, axes = plt.subplots(3, 2, figsize=(16,10), sharey=True, dpi=160)
cols = [color for name, color in mcolors.TABLEAU_COLORS.items()]
for i, ax in enumerate(axes.flatten()):
    ax.bar(x='word', height="word_count", data=word_cloud_df.loc[word_cloud_df.topic_id==i, :], color=cols[i], width=0.5,
    ax_twin = ax.twinx()
    ax_twin.bar(x='word', height="importance", data=word_cloud_df.loc[word_cloud_df.topic_id==i, :], color=cols[i], width=
    ax.set_ylabel('Word Count', color=cols[i])
    ax_twin.set_ylim(0, 0.030); ax.set_ylim(0, 3500)
    ax.set_title('Topic: ' + str(i), color=cols[i], fontsize=16)
    ax.tick_params(axis='y', left=False)
    ax.set_xticklabels(word_cloud_df.loc[word_cloud_df.topic_id==i, 'word'], rotation=30, horizontalalignment= 'right')
    ax.legend(loc='upper left'); ax_twin.legend(loc='upper right')

fig.tight_layout(w_pad=2)
fig.suptitle('Word Count and Importance of Topic Keywords', fontsize=22, y=1.05)
plt.show()
```

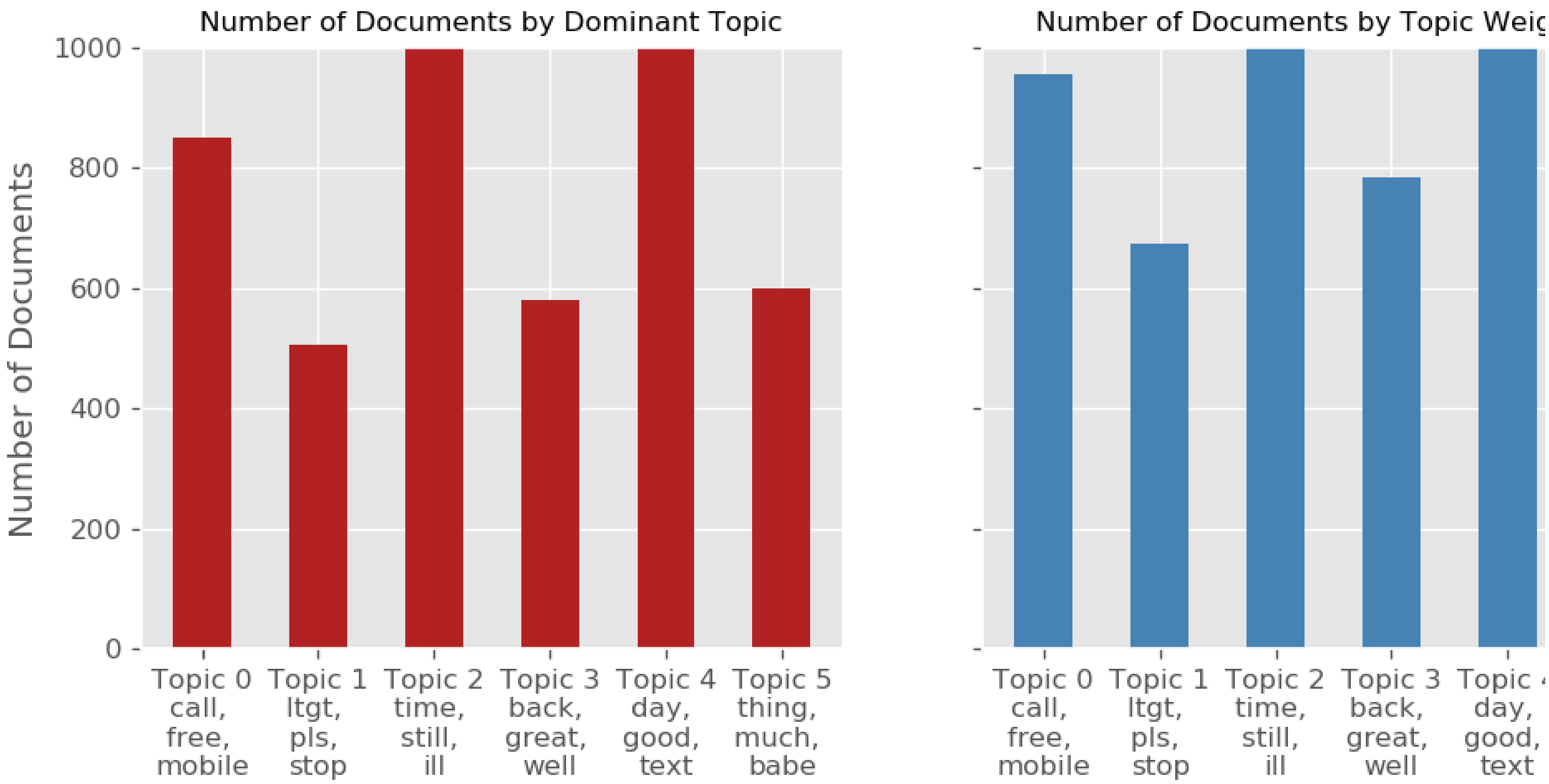



Topic: 2
Topic: 4
Word Count
Weights
call
free
mobile
later
number
claim
phone
sorry
min
night
ltgt
pls
stop
really
time
still
ill
txt
thats
cant
want
yeah
soon
work
back
great
well
new
day
good
text
lor
home
week
today
hey
reply
yes
thing
much
babe
also

5. Most discussed topics in the documents

In [74]:
```
def topics_per_document(model, corpus, start=0, end=1):
    corpus_sel = corpus[start:end]
    dominant_topics = []
    topic_percentages = []
    for i, corp in enumerate(corpus_sel):
        topic_percs, wordid_topics, wordid_phivalues = model[corp]
        dominant_topic = sorted(topic_percs, key = lambda x: x[1], reverse=True)[0][0]
        dominant_topics.append((i, dominant_topic))
        topic_percentages.append(topic_percs)
    return(dominant_topics, topic_percentages)

dominant_topics, topic_percentages = topics_per_document(model=model, corpus=corpus, end=-1)

# Distribution of Dominant Topics in Each Document
df = pd.DataFrame(dominant_topics, columns=['Document_Id', 'Dominant_Topic'])
dominant_topic_in_each_doc = df.groupby('Dominant_Topic').size()
df_dominant_topic_in_each_doc = dominant_topic_in_each_doc.to_frame(name='count').reset_index()

# Total Topic Distribution by actual weight
topic_weightage_by_doc = pd.DataFrame([dict(t) for t in topic_percentages])
df_topic_weightage_by_doc = topic_weightage_by_doc.sum().to_frame(name='count').reset_index()

# Top 3 Keywords for each Topic
topic_top3words = [(i, topic) for i, topics in model.show_topics(formatted=False)
                                 for j, (topic, wt) in enumerate(topics) if j < 3]

df_top3words_stacked = pd.DataFrame(topic_top3words, columns=['topic_id', 'words'])
df_top3words = df_top3words_stacked.groupby('topic_id').agg(', \n'.join)
df_top3words.reset_index(level=0,inplace=True)
```

In [75]:
```
# Plot
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 4), dpi=120, sharey=True)

# Topic Distribution by Dominant Topics
ax1.bar(x='Dominant_Topic', height='count', data=df_dominant_topic_in_each_doc, width=.5, color='firebrick')
ax1.set_xticks(range(df_dominant_topic_in_each_doc.Dominant_Topic.unique().__len__()))
tick_formatter = FuncFormatter(lambda x, pos: 'Topic ' + str(x)+ '\n' + df_top3words.loc[df_top3words.topic_id==x, 'words'
ax1.xaxis.set_major_formatter(tick_formatter)
ax1.set_title('Number of Documents by Dominant Topic', fontdict=dict(size=10))
ax1.set_ylabel('Number of Documents')
ax1.set_ylim(0, 1000)

# Topic Distribution by Topic Weights
ax2.bar(x='index', height='count', data=df_topic_weightage_by_doc, width=.5, color='steelblue')
ax2.set_xticks(range(df_topic_weightage_by_doc.index.unique().__len__()))
ax2.xaxis.set_major_formatter(tick_formatter)
ax2.set_title('Number of Documents by Topic Weightage', fontdict=dict(size=10))
plt.show()
```



Model Tuning

Getting most optimal number of topics

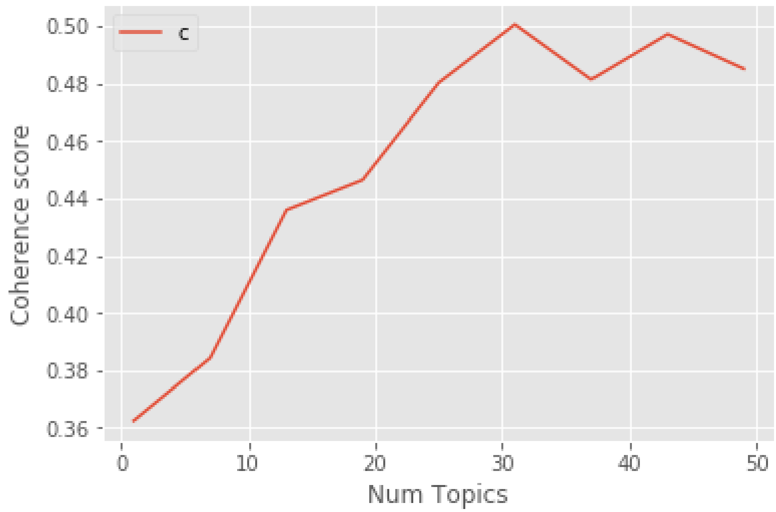
In [76]:
```
limit=50;
start=1;
step=6;
```

In [77]:
```
def compute_optimal_topics(dictionary, corpus, texts, limit, start=2, step=3):
    coherence_values = []
    model_list = []
    for num_topics in range(start, limit, step):
        model = gensim.models.ldamodel.LdaModel(corpus=corpus, num_topics=num_topics, id2word=id2word)
        model_list.append(model)
        coherencemodel = CoherenceModel(model=model, texts=texts, dictionary=dictionary, coherence='c_v')
        coherence_values.append(coherencemodel.get_coherence())

    return model_list, coherence_values
```

In [78]:
```
model_list, coherence_values = compute_optimal_topics(dictionary=id2word, corpus=corpus, texts=tokenized_data, start=start
```

Vsualize

In [79]:
```
x = range(start, limit, step)
plt.plot(x, coherence_values)
plt.xlabel("Num Topics")
plt.ylabel("Coherence score")
plt.legend(("coherence_values"), loc='best')
plt.show()
```



Show topics and coherence values

In [80]:
```
for m, cv in zip(x, coherence_values):
    print("Num Topics =", m, " is having Coherence Value of", round(cv, 4))
```

```
Num Topics = 1  is having Coherence Value of 0.3625
Num Topics = 7  is having Coherence Value of 0.3843
Num Topics = 13  is having Coherence Value of 0.4359
Num Topics = 19  is having Coherence Value of 0.4464
Num Topics = 25  is having Coherence Value of 0.4802
Num Topics = 31  is having Coherence Value of 0.5005
Num Topics = 37  is having Coherence Value of 0.4814
Num Topics = 43  is having Coherence Value of 0.4971
Num Topics = 49  is having Coherence Value of 0.4851
```

Conclusion

How to improve the model:

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1. Improve on text processing.
2. The variety of topics the text talks about.
3. Topic modeling algorithm to use.
4. The number of topics to be retrieved from the algorithm.
5. The Model hyperparameter tuning.