Intro to NLP

March 19, 2018

1 Brief intro to Natural Language Processing (NLP)

1.1 TL;DR → NLP involves converting words into numbers and doing math on these numbers in order to identify relationships between the words and documents they live in.

```
In [1]: #from IPython.display import Image, display
        import os
        from glob import glob
        import pandas as pd
        cur_dir = os.path.abspath(os.curdir)
        image_dir = os.path.join(cur_dir,'images')
        data_dir = os.path.join(cur_dir,'data')
        output_dir = os.path.join(cur_dir,'output')
```

1.2 Why NLP?

It is a very broad domain that deals with analyzing and understanding human text and words. Some areas of application include the following:

- text classification/clustering (including spam detection & sentiment analysis)
- machine translation
- language modeling (e.g. predicting the next word given the previous words)
- summarizing blocks of text (to find the main topics/topic sentences or concepts)
- caption generation
- speech recognition
- question answering.

Additionally, the input data for NLP is generally unstructured meaning that some of our favorite, go-to tools and approaches won't work without some pre-processing steps and/or thought.

1.3 My experiences with NLP

Over the years I've used NLP/text mining in several projects including the following.

- Characterization of the articles written and posted on a social media site and assign topics to them.

- Identification of Entities (People, Places, Companies, etc.)

- used these to connect articles and recommend content.
- used these to analyze what the articles were being written on in a seasonal way
- used these to identify what brands the authors were writing about

- Assess sentiment and trends in articles.
- Digest/summarize/group weekly status reports.
- Analyze claims notes in order to identify common features in claims and claims processing as well as trends over time.

1.4 CLEARLY this is *too much* to fully cover in a short talk.

1.4.1 Goals for today.

1. Provide an overview of some concepts, terms and methods.
2. Illustrate through a few examples.

1.4.2 First some key terms/phrases

- *Tokenization* (breaking text into smaller pieces: i.e. words and sentences)
- *Stopwords* (non-important words that should be identified and ignored)
- *n-grams* (groupings of adjacent words)
  - 1-grams are single words, 2-grams (bi-grams) are 2 consecutive words, 3-grams are three consecutive words etc.
  - a simple way to capture some of the frequent collocalization of specific words/context
  - computational complexity grows rapidly with increasing n
- *Stemming* & *Lemmatization* (how to collapse similar words to a single representation)
  - stemming is rule-based (such as stripping off suffixes)
  - lemmatization is vocabulary + grammar based (requires passing through a set of steps to id the root form of the word)
  - Often you'll have too many tokens in your document to make sense of things. This is one way to reduce the dimensionality.
  - Common examples include plurals or verbs of different tenses
- *Part-of-Speech (POS) Tagging* (identifying and assigning this meta-data to the words in a sentence)
  - adds information to the document; you can think of it as an additional, derived feature
  - helps distinguish different uses of a particular word
- *Named Entity Recognition (NER)* (identifying people/places/companies/etc.)
  - can be thought of as an additional feature and means to understand what a document is about.
- *corpus* (a set of documents)
  - the input; can be split into test and training sets for ML jobs

1.5 Start Simply : Represent a set of documents (*corpus*) by a vector space defined by the words present.

- Use the words contained within a set of documents to define a basis set (i.e. set of vectors assumed to be orthogonal to one another) in order to locate a given document within in this resulting (word-based) vector space.
  - so if you have N unique words in your set of M documents then your vector space will have a dimensionality of N.
- In this approach we're ignoring each word's context and using unigrams. This is the so-called **Bag-of-Words** approach.
- I'm relying heavily on `python`, especially `sklearn` package.

1.5.1 Toy example with limited vocabulary.

Consider a simple example where there are only 3 words in your set of documents: 'Airplane','Boat','Car' and every sentence or document is constructed only out of these words.

To convert these to an orthogonal basis vector set you can explicitly define

Then you map a given sentence or document into this **vector space**.

```
In [2]: toy_corpus = ["Boat Airplane Airplane Boat Car",
                      "Car Airplane Car Boat Car Airplane",
                      "Car Car Car Airplane Car Airplane Airplane",
                      "Boat Airplane Boat Boat Boat Boat Airplane",
                      "Car Car Car Boat Car Airplane",
                      "Boat Car Car Boat Car Boat",
                      "Car Airplane Boat Airplane Boat Car Airplane"]
```

The easiest way to do this is to define the number of occurrences of each word as the value along that axis for each word. For example the following 'sentences' can be expressed as.

Within this framework, the similarity between two known documents (or a query for a document given a corpus) can be measured by the similarity of these vectors (i.e. the distance). Typically cosine similarity is used for this distance.

This vectorization is implemented in `scikit-learn's CountVectorizer`

```
In [3]: from sklearn.feature_extraction.text import CountVectorizer
        toy_vectorizer = CountVectorizer()
        #print(vectorizer)
        toy_vectorizer.fit(toy_corpus)
        corpus_vec=toy_vectorizer.transform(toy_corpus).toarray()
        print(corpus_vec)
```

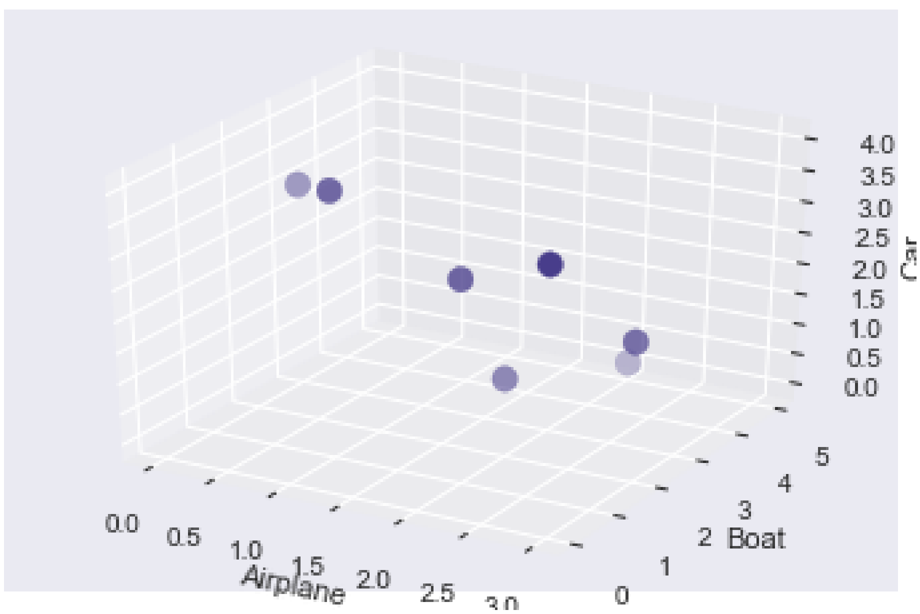
```
[[2 2 1]
 [2 1 3]
 [3 0 4]
 [2 5 0]
 [1 1 4]
 [0 3 3]
 [3 2 2]]
```

1.6 visualize:

```
In [4]: %matplotlib inline
        import matplotlib.pyplot as plt
        import matplotlib
        from cycler import cycler
        import numpy as np
        from mpl_toolkits import mplot3d
        import seaborn as sns
        sns.set()
```

the initial positions of our sentences in this space

```
In [5]: fig = plt.figure()
        ax = plt.axes(projection='3d')

        x = [c[0] for c in corpus_vec]
        y = [c[1] for c in corpus_vec]
        z = [c[2] for c in corpus_vec]
        ax.scatter3D(xs=x,ys=y,s=90,zs=z, color='darkslateblue')

        ax.set_xlabel('Airplane')
        ax.set_ylabel('Boat')
        ax.set_zlabel('Car',rotation=90);
```

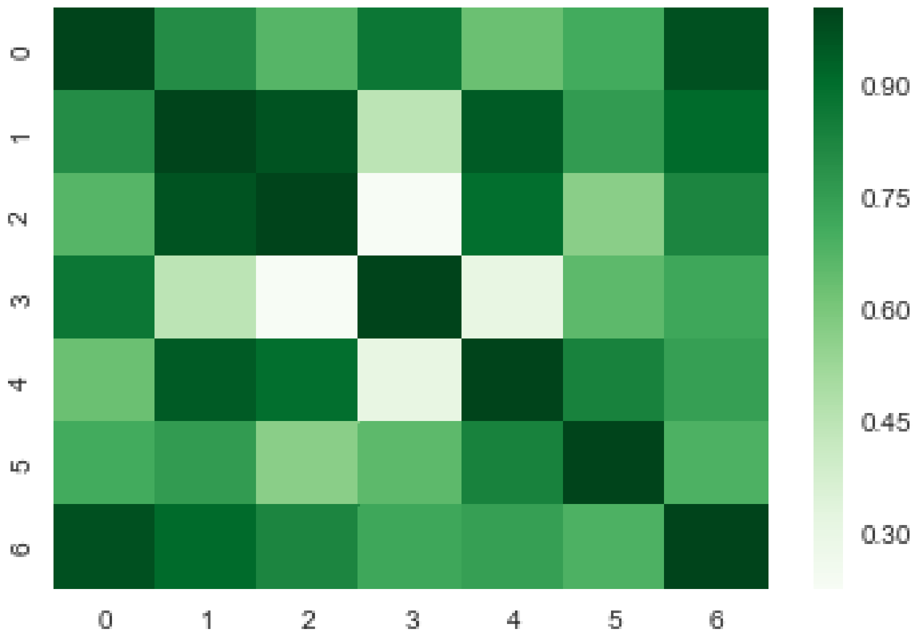


1.7 To compare similarities between 'documents' or sentences: measure distance between pairs of vectors

```
In [6]: from sklearn import metrics
        toy_sim_mat = metrics.pairwise.cosine_similarity(corpus_vec)
```

```
In [7]: sns.heatmap(toy_sim_mat,cmap="Greens")
```

```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x22fdb3fcd30>
```




```
In [8]: toy_sim_mat[2][3], toy_corpus[2], toy_corpus[3], corpus_vec[2],corpus_vec[3]   # most di
```

```
Out[8]: (0.22283440581246222,
         'Car Car Car Airplane Car Airplane Airplane',
         'Boat Airplane Boat Boat Boat Boat Airplane',
         array([3, 0, 4], dtype=int64),
         array([2, 5, 0], dtype=int64))
```

```
In [9]: toy_sim_mat[1][2], toy_corpus[1], toy_corpus[2], corpus_vec[1], corpus_vec[2] #most simi
```

```
Out[9]: (0.9621404708847279,
         'Car Airplane Car Boat Car Airplane',
         'Car Car Car Airplane Car Airplane Airplane',
         array([2, 1, 3], dtype=int64),
         array([3, 0, 4], dtype=int64))
```

1.8 Some possible problems with this Bag of Words approach.

There are several issues with this approach when you consider the entire English dictionary.

- (1) Typically there are words that are very common in general, so they appear in lots of documents. (“the”, “and”, “or” etc..)
  - these are typically referred to as *stopwords*
- (2) Within a given document or corpus, there are usually additional high frequency words that don’t contribute much discriminating information between documents or sentences.
  - These words can overwhelm the mathematical operations required to determine similarities.
  - For example in an article about March Madness words like NCAA or basketball or college don’t provide additional information. We may not want to count repeating words as much.
- (3) When words are used as atomic types for the basis of the vector space, they have no semantic relations (the similarity between them is zero, since they are perpendicular to each other). However, in reality we know that words can be similar in meaning, or even almost identical synonyms.
  - Thus the **bag of words** moniker.
- (4) And of course syntactic structure is completely lost.

2 A more complicated example the text of a book.

- Utilize Project Gutenberg an online library of free eBooks.
- Examine a book to understand what this analysis looks like on a bigger corpus.
- Observe differences between some packages and pre-processing steps.

A couple of helper functions I wrote to download, ingest the raw_text and split it into chapters follows.

```
In [19]: def load_pg_text(my_file):
             try:
                 with open(my_file,'rb') as f:
                     text=f.read()
                     raw_text=text.decode('utf-8')
             except UnicodeDecodeError:
                 with open(my_file) as f:
                     raw_text=f.read()

             # first id the title & author
             tmp = [a.strip('\r') for a in raw_text.split('\n')]
             lines_to_find = ['*** START OF THIS PROJECT GUTENBERG', '*** END OF THIS PROJECT GU
```

```
    ll_to_find = [line for line in tmp if line.startswith(lines_to_find[0]) or line.sta
    try:
        start_idx = tmp.index(ll_to_find[0])
        end_idx = tmp.index(ll_to_find[1])
        title_str = ll_to_find[0].split('EBOOK')[-1].rstrip('***').strip(' ')
        if title_str == 'AROUND THE WORLD IN 80 DAYS':
            title_str=title_str.replace('80','EIGHTY')
        elif title_str == 'A JOURNEY TO THE INTERIOR':
            title_str=title_str.replace('TO THE','INTO THE')

        title_idx = [k for k,line in enumerate(tmp) if line.startswith(title_str)]
        try:
            title_index = max(title_idx)
        except ValueError:
            print("**WARNING** starting at first line; may have excessive intro materia
            title_index = start_idx+1

    except IndexError:
        start_idx = [k for k, line in enumerate(tmp) if line.startswith('*END THE SMALL
        end_idx = [k for k,line in enumerate(tmp) if line.startswith('End of the Projec
        #title_str=" ".join([a for a in tmp[7:12] if a != ""])
        title_index = start_idx

    try:
        last_index = next(i for i,v in zip(range(len(tmp)-1,-1,-1), reversed(tmp)) if '
    except StopIteration:
        last_index = end_idx-1

    return tmp[title_index:last_index]


class Chapter(object):
    """A class to contain chapters from Project Gutenberg text files"""
    def __init__(self, name, title, text, author, book_id, chapter_index, book):
        self.name=name
        self.title=title
        self.text=text
        self.author=author
        self.book_id=book_id
        self.chapter_index=chapter_index
        self.bookname=book


def split_into_chapters(text, book_id, key_word='Chapter ', authorname=None, bookname=N
    if authorname is None:
        authorname = 'unknown'
    if bookname is None:
```

```
        bookname='unknown'
    chapter_idx = [k for k,line in enumerate(text) if key_word in line ]
    #print(len(chapter_idx))
    if key_word == 'THE STRAND MAGAZINE':
        chapter_idx = [c+6 for c in chapter_idx]
    else:
        key_word+=' '

    chapters=[]
    for i,a in enumerate(chapter_idx):
        if i != len(chapter_idx)-1:
            b = chapter_idx[i+1]-1
        else:
            b = len(text)

        chapter_name = text[a]
        chapter_title = text[a+2] #TOD improve this
        chapter_text = ' '.join([line.replace("\'","'") for line in text[a+3:b] if not
        my_chapter = Chapter(chapter_name, chapter_title, chapter_text, authorname, boo
        chapters.append(my_chapter)

    return chapters
```

2.1 Consider an example: Around the World in 80 Days Text

- load the file & parse it
- split it into chapters (throw away other parts of the eBook like table of contents, publisher info, etc.)
- rejoin everything into a single corpus

```
In [119]: raw_text=load_pg_text('data/103.txt')
          chapters= split_into_chapters(raw_text,103, key_word='Chapter ', authorname='Verne')
          print("We split this book into {n} chapters.".format(n=len(chapters)))
          corpus_all_in_one = ' '.join([chap.text for chap in chapters])
          print("The entire book has a length of {n} characters.".format(n=len(corpus_all_in_one
```

```
We split this book into 37 chapters.
The entire book has a length of 364686 characters.
```

3 First consider all the words in this book

3.1 Must tokenize (i.e. split into words)

- the methods to tokenize exist in a number of python packages including `nltk`, `sklearn`, `spaCy`, & the standard library.
- you can also build your own (probably using regex).

3.1.1 Let's start by using `nltk` and a simple word count using `collections.Counter`

We are interested in finding: 1. how many times a word occurs across the whole corpus (total number of occurrences) 2. How many documents a word occurs in

```
In [120]: corpus_all_in_one[:100]
```

```
Out[120]: 'THE ONE AS MASTER, THE OTHER AS MAN   Mr. Phileas Fogg lived, in 1872, at No. 7, Savi
```

```
In [12]: from nltk.tokenize import word_tokenize

         try:  # py3
             all_tokens = [t for t in word_tokenize(corpus_all_in_one)]
         except UnicodeDecodeError:  # py27
             all_tokens = [t for t in word_tokenize(corpus_all_in_one.decode('utf-8'))]

         print("Total number of words: {} in {} unique tokens.".format(len(all_tokens), len(set(
         from collections import Counter
         total_term_frequency = Counter(all_tokens)
```

```
Total number of words: 75754 in 7467 unique tokens.
```

```
In [121]: all_tokens[:18]
```

```
Out[121]: ['THE',
           'ONE',
           'AS',
           'MASTER',
           ',',
           'THE',
           'OTHER',
           'AS',
           'MAN',
           'Mr.',
           'Phileas',
           'Fogg',
           'lived',
           ',',
           'in',
           '1872',
           ',',
           'at']
```

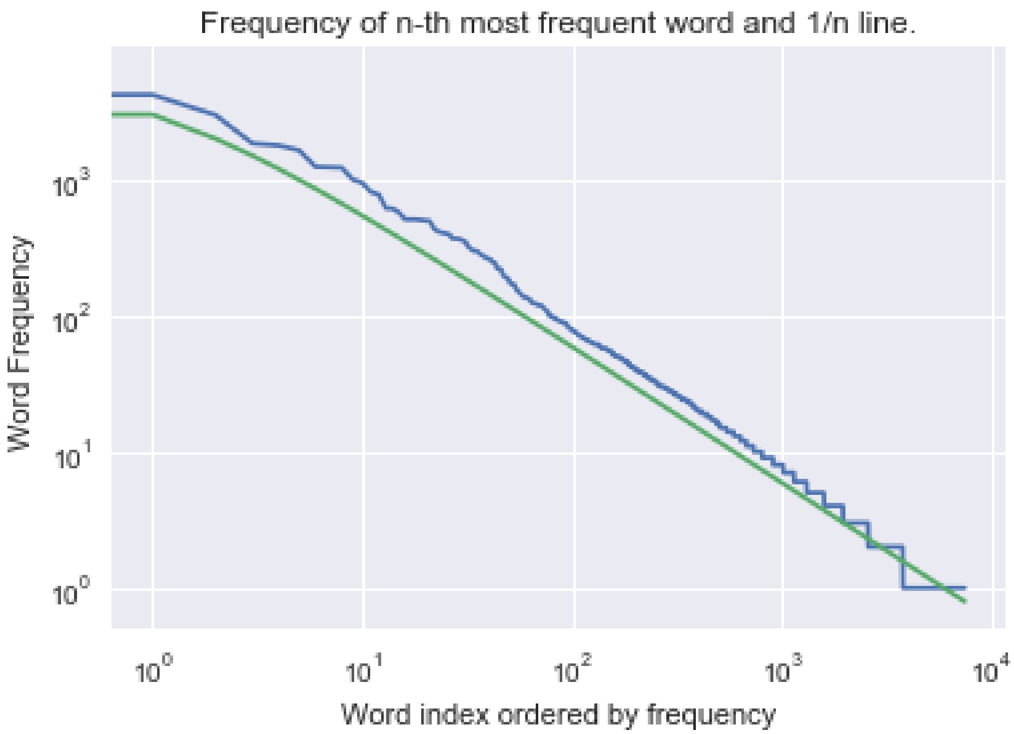
3.1.2 Aside

In 1935, linguist George Zipf noted that in any big text, the nth most frequent word appears with a frequency of about 1/n of the most frequent word. He get's credit for Zipf's Law, even though Felix Auerbach made the same observation in 1913. If we plot the frequency of words, most common first, on a log-log plot, they should come out as a straight line if Zipf's Law holds.

```
In [13]: def plot_ordered_term_frequency(term_freq):
             M = term_freq.most_common(1)[-1][-1]#['the']
             plt.yscale('log'); plt.xscale('log'); plt.title('Frequency of n-th most frequent wo
             plt.plot([c for (w, c) in term_freq.most_common()])
             plt.plot([M/i for i in range(1, len(term_freq)+1)]);
             plt.ylabel('Word Frequency')
             plt.xlabel('Word index ordered by frequency');
             return
```

Here we see that it is a fairly close fit:

```
In [122]: plot_ordered_term_frequency(total_term_frequency)
```




```
In [123]: for word, freq in total_term_frequency.most_common(20):
              print("{w}\t{f}".format(w=word, f=freq))
```

```
,        5945
the        4151
.        2947
and        1829
of        1768
to        1628
``        1232
''        1223
```

```
a        1214
was        995
in        938
his        807
he        770
;        611
Fogg        608
at        568
not        507
with        507
The        506
that        501
```

3.1.3 Wait a lot of these tokens aren't words (punctuation) or are just simple (non-informative words)

- ah we need to remove these stopwords and punctuation marks.
- also this formuation of words as strings is case sensitive. Let's lowercase everything and reasses
- try again, this time splitting into sentences first

```
In [16]: from nltk.tokenize import sent_tokenize
         import string

         all_sentences = sent_tokenize(corpus_all_in_one)
         print("{N} sentences found.".format(N=len(all_sentences)))
```

```
3655 sentences found.
```

```
In [124]: tokens = [word for sent in sent_tokenize(corpus_all_in_one) for word in word_tokenize(
          # remove words that are just punctuation
          no_punct = list(filter(lambda word: word not in string.punctuation, tokens))
          # lowercase everything so
          lc_tokens = [word.lower() for word in no_punct]
          print("Total number of words: {} in {} unique tokens.".format(len(lc_tokens), len(set(
          lc_total_term_frequency = Counter(lc_tokens)
```

```
Total number of words: 65476 in 6931 unique tokens.
```

```
In [125]: for word, freq in lc_total_term_frequency.most_common(20):
              print("{w}\t{f}".format(w=word, f=freq))
```

```
the        4666
and        1894
of        1783
to        1647
```

```
a        1294
``        1232
''        1223
was        1007
he        987
in        978
his        840
at        634
fogg        611
it        577
that        525
on        522
not        519
with        512
had        511
as        437
```

```
In [126]: from nltk.corpus import stopwords
          print(len(stopwords.words('english')))

          print(stopwords.words('english'))
          stop_list = stopwords.words('english')+["--","``","''","...",'mr.',"'s","“","”","'nt",
```

```
179
['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll
```

```
In [127]: #stop_list = stopwords.words('english') + list(my_punct)+["--","``","''","..."]

          tokens_no_stop = [token for token in lc_tokens if token not in stop_list]

          total_term_frequency_no_stop = Counter(tokens_no_stop)
          ntokens = len(total_term_frequency_no_stop.keys())
          print("This reduces our corpus to containing {m} words in {n} unique tokens.".format(m
          for word, freq in total_term_frequency_no_stop.most_common(20):
              print("{w}\t{f}".format(w=word, f=freq))
```

```
This reduces our corpus to containing 31536 words in 6801 unique tokens.
fogg        611
passepartout        399
would        286
fix        245
phileas        222
said        192
one        168
could        140
aouda        136
time        126
```

```
master        123
upon         119
train         119
sir          103
two          101
hundred        97
replied        93
steamer        91
hours         90
thousand        88
```

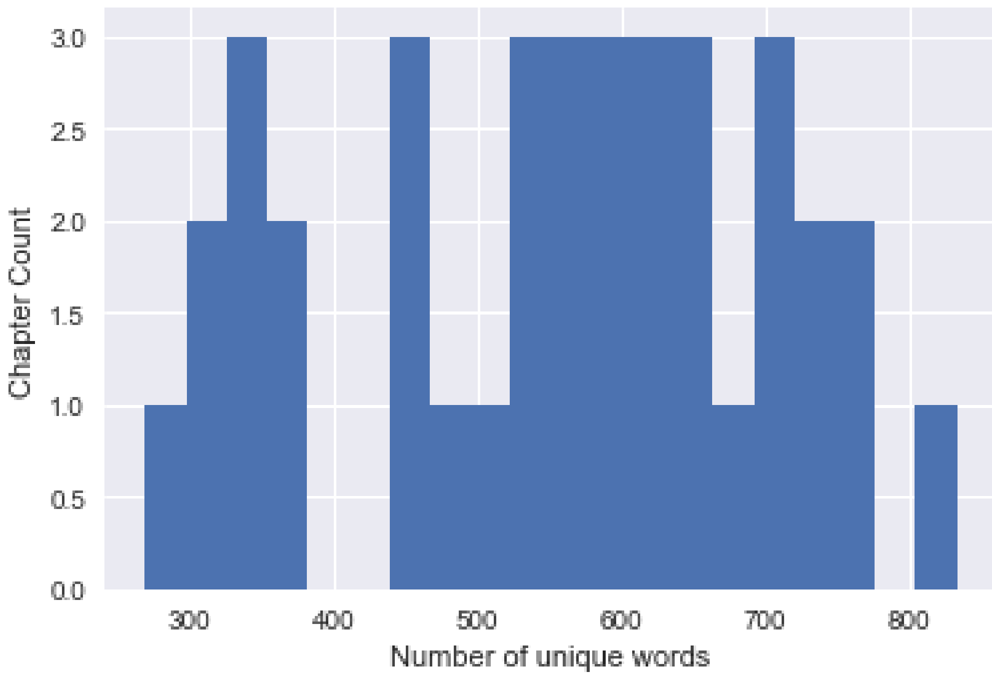
```
In [23]: # wrap this all into a function
         def nltk_tokenize(text, stop_words=stop_list):
             # tokenize
             tokens = [word for sent in sent_tokenize(text) for word in word_tokenize(sent)]
             # remove words that are just punctuation
             no_punct = list(filter(lambda word: word not in string.punctuation, tokens))
             # lowercase everything
             lc_tokens = [word.lower() for word in no_punct]
             # remove stopwords
             tokens_no_stop = [token for token in lc_tokens if token not in stop_words]

             return tokens_no_stop
```

```
In [128]: by_chap_tokens = []
          by_chap_counts = []
          for chapter in chapters:
              ctokens = [t for t in nltk_tokenize(chapter.text)]

              #print(chapter.name,len(ctokens))
              by_chap_tokens.append(ctokens)
              chapCounter = Counter(ctokens)
              by_chap_counts.append(chapCounter)
```

```
In [129]: def get_chapter_stats(chapter_tokens, chapters):
              data = []
              for k, c in enumerate(chapters):
                  nwords = len(by_chap_tokens[k])
                  ntokens = len(set(by_chap_tokens[k]))
                  name = c.name
                  #nchar =
                  data.append([nwords,ntokens,name])
              df = pd.DataFrame(data, columns=['words','tokens','name'])
              return df
```

```
In [130]: chp_stats =get_chapter_stats(by_chap_tokens, chapters)
          chp_stats.tokens.hist(bins=20)
```

```
plt.xlabel('Number of unique words');
plt.ylabel('Chapter Count');
```



In [131]: chp_stats

Out[131]:

	words	tokens	name
0	728	533	Chapter I
1	573	447	Chapter II
2	1029	622	Chapter III
3	491	344	Chapter IV
4	490	359	Chapter V
5	660	454	Chapter VI
6	389	270	Chapter VII
7	516	356	Chapter VIII
8	826	578	Chapter IX
9	817	587	Chapter X
10	1315	832	Chapter XI
11	1103	744	Chapter XII
12	995	595	Chapter XIII
13	999	708	Chapter XIV
14	915	550	Chapter XV
15	802	523	Chapter XVI
16	873	612	Chapter XVII
17	682	440	Chapter XVIII
18	1050	642	Chapter XIX

```
19   857   519      Chapter XX
20  1283   752     Chapter XXI
21  1020   756    Chapter XXII
22   968   639   Chapter XXIII
23   963   604    Chapter XXIV
24  1003   687     Chapter XXV
25   844   565    Chapter XXVI
26  1017   721   Chapter XXVII
27  1250   708  Chapter XXVIII
28  1082   656    Chapter XXIX
29  1038   620     Chapter XXX
30   939   569    Chapter XXXI
31   515   347   Chapter XXXII
32  1220   700  Chapter XXXIII
33   482   319   Chapter XXXIV
34   738   475    Chapter XXXV
35   565   352   Chapter XXXVI
36   499   304  Chapter XXXVII
```

3.2 Question. Can we distinguish or cluster the chapters based upon the words in them?

In [28]:
```
chap_top5 =[]
chap_top5freq =[]
for k,c in enumerate(by_chap_counts):
    top5 = []
    freqtop5 = []
    for word, freq in c.most_common(5):
        top5.append(word)
        freqtop5.append(freq)
    chap_top5.append(top5)
    chap_top5freq.append(freqtop5)
```

In [29]:
```
chap_top5
```

Out[29]:
```
[['fogg', 'phileas', 'saville', 'row', 'club'],
 ['passepartout', 'fogg', 'one', 'master', 'would'],
 ['fogg', 'stuart', 'phileas', 'thousand', 'said'],
 ['passepartout', 'fogg', 'master', 'good', 'twenty'],
 ['fogg', 'phileas', 'would', 'reform', 'club'],
 ['fix', 'suez', 'consul', 'steamer', 'mongolia'],
 ['consul', 'passport', 'october', 'fix', 'fogg'],
 ['fix', 'passepartout', 'london', 'monsieur', 'watch'],
 ['bombay', 'mongolia', 'fix', 'fogg', 'steamer'],
 ['bombay', 'fogg', 'india', 'calcutta', 'passepartout'],
 ['fogg', 'sir', 'francis', 'passepartout', 'would'],
 ['would', 'fogg', 'sir', 'francis', 'guide'],
 ['fogg', 'guide', 'sir', 'francis', 'parsee'],
```

```
 ['passepartout', 'fogg', 'would', 'phileas', 'guide'],
 ['fogg', 'passepartout', 'judge', 'said', 'phileas'],
 ['hong', 'kong', 'would', 'fix', 'fogg'],
 ['passepartout', 'fix', 'fogg', 'aouda', 'master'],
 ['fogg', 'would', 'passepartout', 'steamer', 'hong'],
 ['passepartout', 'fix', 'fogg', 'said', 'master'],
 ['fogg', 'fix', 'aouda', 'would', 'could'],
 ['fogg', 'would', 'wind', 'miles', 'tankadere'],
 ['passepartout', 'fogg', 'carnatic', 'japanese', 'found'],
 ['passepartout', 'long', 'noses', 'upon', 'japanese'],
 ['passepartout', 'fogg', 'fix', 'would', 'steamer'],
 ['fogg', 'fix', 'aouda', 'passepartout', 'upon'],
 ['train', 'pacific', 'omaha', 'locomotive', 'great'],
 ['passepartout', 'mormon', 'one', 'train', 'elder'],
 ['passepartout', 'fogg', 'train', 'would', 'colonel'],
 ['fogg', 'train', 'colonel', 'car', 'said'],
 ['fogg', 'train', 'aouda', 'fix', 'would'],
 ['fogg', 'sledge', 'passepartout', 'omaha', 'time'],
 ['fogg', 'phileas', 'captain', 'would', 'henrietta'],
 ['fogg', 'captain', 'henrietta', 'speedy', 'phileas'],
 ['fogg', 'fix', 'passepartout', 'phileas', 'would'],
 ['fogg', 'aouda', 'passepartout', 'could', 'master'],
 ['fogg', 'phileas', 'minutes', 'andrew', 'stuart'],
 ['fogg', 'passepartout', 'phileas', 'day', 'minutes']]
```

In [30]:
```
top5overChap = list(set([item for sublist in chap_top5 for item in sublist]))
```

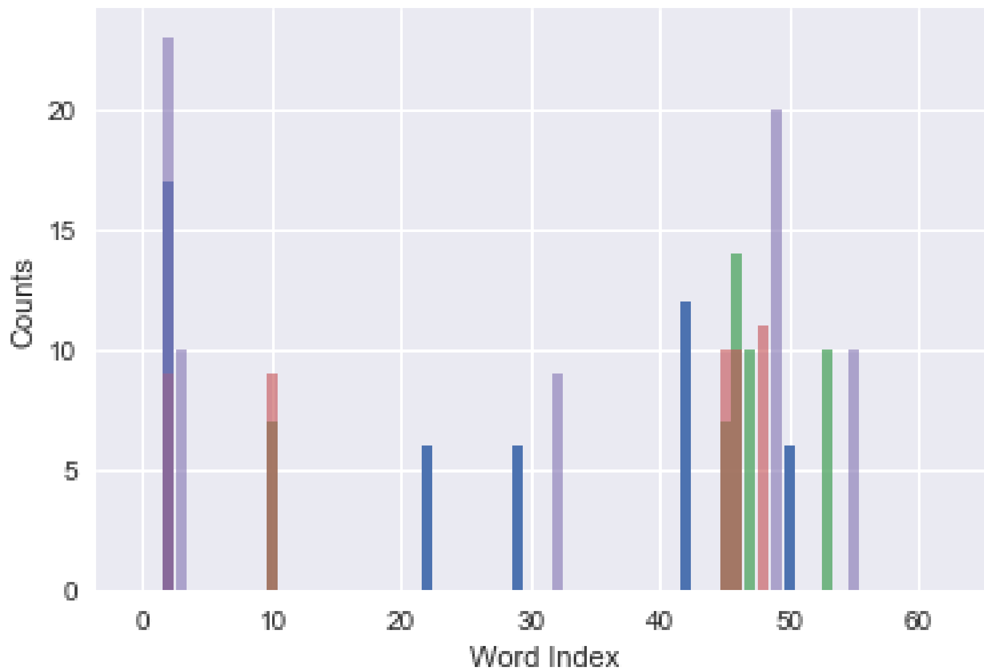
In [132]:
```
n_top_words = len(top5overChap)
n_top_words
```

Out[132]:
```
63
```

In [32]:
```
top5counts = np.zeros((len(chapters),n_top_words))
for j, chp in enumerate(chap_top5):
    for k,word in enumerate(chp):
        val = chap_top5freq[j][k]
        i = top5overChap.index(word)
        #print(j,k,i, word, val)
        top5counts[j][i]=val
```

In [33]:
```
plt.bar(x=range(n_top_words), height=top5counts[0])
plt.bar(x=range(n_top_words), height=top5counts[5], alpha=0.8)
plt.bar(x=range(n_top_words), height=top5counts[8], alpha=0.6)
plt.bar(x=range(n_top_words), height=top5counts[30], alpha=0.6)
print([top5overChap[a] for a in np.where(top5counts[0]>0)[0]])
print([top5overChap[a] for a in np.where(top5counts[5]>0)[0]])
print([top5overChap[a] for a in np.where(top5counts[8]>0)[0]])
print([top5overChap[a] for a in np.where(top5counts[30]>0)[0]])
plt.ylabel('Counts');
plt.xlabel('Word Index');
```

```
['fogg', 'saville', 'club', 'phileas', 'row']
['steamer', 'mongolia', 'fix', 'suez', 'consul']
['fogg', 'steamer', 'mongolia', 'fix', 'bombay']
['fogg', 'omaha', 'time', 'sledge', 'passepartout']
```



4 To approach this more seriously we would want to address the relative importance of our words (i.e. issues (1) and (2) above.

4.1 Enter TF-IDF

4.1.1 Term Frequency Inverse Document Frequency (tf-idf) is a good way to address the concerns of overcounting or overweighting certain words in corpus.

Given t represents a term, d represents a document and D is the set of all documents, the general equation is

$$tf\text{-}idf(t,d,D) = tf(t,d) \cdot idf(t,D) \tag{1}$$

- TF: Term Frequency

How often does a word occur? TF simply counts the number of times a word is in a document -- the most frequently occurring words (especially after stop-words have been removed) give some insight into the content of a particular document.

If the documents you are comparing are of different lengths you probably need to adjust the simplest version (raw count) by document length.

- IDF: (Inverse document frequency)

IDF measures how much information a given word provides. The idea is to **penalize** the total count of a word in a document by how often it appears in all of the documents. The higher this number the less valuable the word is because it contains less information that can distinguish the document. In the extreme case, where the word appears in large fraction of the documents, usually it is even better to completely eliminate the count. These are the stopwords, and/or corpus-specific stopwords.

A good heuristic is

$$idf(t, D) = \log \frac{N}{1 + n_t} \tag{2}$$

where N is the number of documents ($N = |D|$) and n_t is the number of documents where term t appears in it.

```
In [34]: from sklearn.feature_extraction.text import TfidfVectorizer
         vectorizer = TfidfVectorizer()
```

```
In [35]: chap_corpus = [" ".join(a) for a in by_chap_tokens]
```

```
In [36]: vectorizer.fit(chap_corpus)
         chap_corp_vec = vectorizer.transform(chap_corpus)
```

```
In [133]: chap_corp_vec.shape # number of chapters by vocabulary size
```

```
Out[133]: (37, 6637)
```

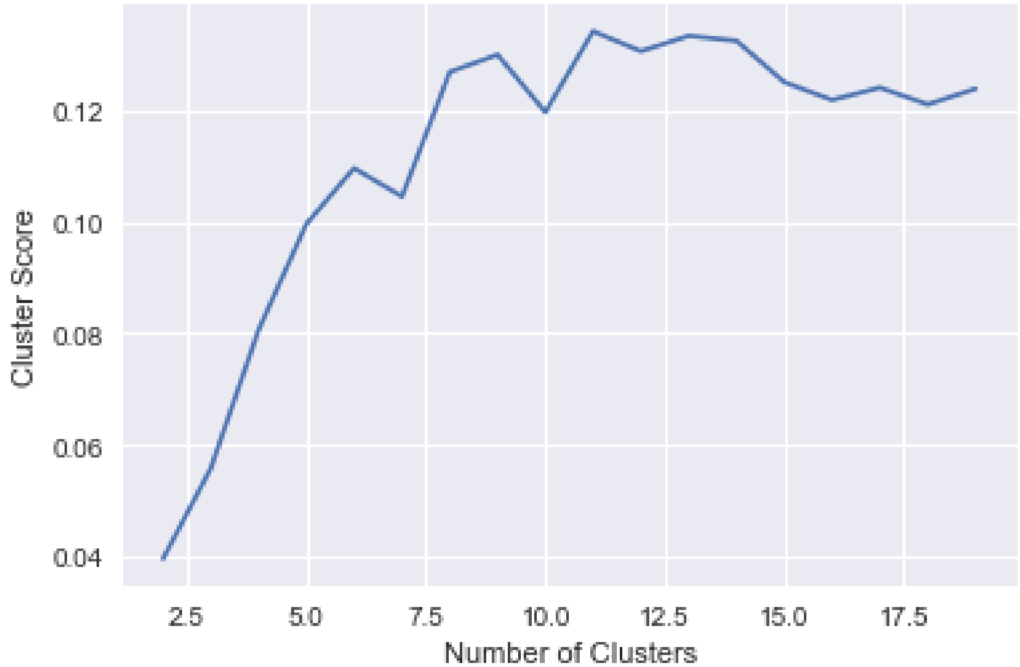
```
In [38]: from sklearn import cluster
         def cluster_text(X,nclusters=6, random_state= 1155, show_plot=True):
             clstr = cluster.KMeans(random_state=random_state, n_clusters=nclusters)
             clstr.fit(X)
             if show_plot:
                 obs_per_cluster = pd.Series(clstr.labels_).value_counts()
                 obs_per_cluster.plot(kind="bar",color='cadetblue')
                 plt.ylabel('Number of Observations')
                 plt.xlabel('Cluster ID')
                 plt.show()
             return clstr
```

```
In [39]: def extract_tfidf_term_fractions(clusters,vectorizor,my_matrix,n_terms = 100):
             vocab = vectorizor.get_feature_names()
             ## get the rows that correspond to a given cluster_label:
             #clust_id = 1
             nclusters = clusters.n_clusters

             clst_labels = pd.Series(clusters.labels_)
             nobs = len(clst_labels.value_counts())
             #print(nclusters,nobs)
```

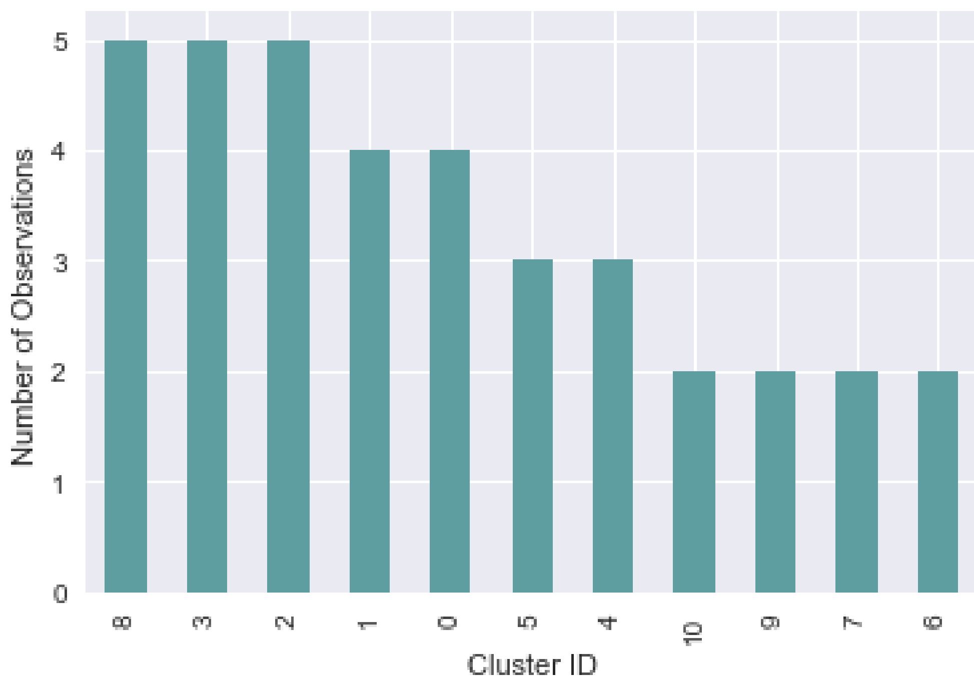
```
    if nobs < nclusters:
        nclusters=nobs


    for k in range(nclusters):
        obs_idx = clst_labels[clst_labels == k].index.tolist()
        # reduce to the average value for each word
        vect_contributions = my_matrix[obs_idx].mean(axis=0).tolist()[0]
        df_vect = pd.Series(vect_contributions,index=vocab)
        if len(vocab)>n_terms:
            df_vect.sort_values(ascending=False,inplace=True)
        # just print all of them as they are
        #
        #    df_vect.plot(kind='bar',color='steelblue',rot=45)
        #else:
        df_vect[:n_terms].plot(kind='bar',color='steelblue',rot=45)
        plt.title("Top terms from Cluster %d (n = %d)" %(k,len(obs_idx)),fontsize=20)
        plt.ylabel('Mean TFIDF value')
        plt.show()


    return

def plot_single_cluster_tfidf_terms(clusters,vectorizor,my_matrix,n_terms = 100, cluste
    vocab = vectorizor.get_feature_names()
    ## get the rows that correspond to a given cluster_label:

    clst_labels = pd.Series(clusters.labels_)

    #for k in range(nclusters):
    obs_idx = clst_labels[clst_labels == cluster_id].index.tolist()
        # reduce to the average value for each word
    vect_contributions = my_matrix[obs_idx].mean(axis=0).tolist()[0]
    df_vect = pd.Series(vect_contributions,index=vocab)
    if len(vocab)>n_terms:
        df_vect.sort_values(ascending=False,inplace=True)
        # just print all of them as they are
        #
        #    df_vect.plot(kind='bar',color='steelblue',rot=45)
        #else:
    df_vect[:n_terms].plot(kind='bar',color='darkslateblue',rot=45)
    plt.title("Top terms from Cluster %d (n = %d)" %(cluster_id,len(obs_idx)),fontsize=
    plt.ylabel('Mean TFIDF value')
    plt.show()


    return
```

In [40]:
```
def create_and_score_clusters(vector, min_size=2,max_size=20,metric='silhouette',show_p
    cluster_score_info ={}
    v2 = vector.dot(vector.T)
    for k in range(min_size,max_size,1):
        tmp_cluster = cluster_text(vector, nclusters=k, show_plot=False, **kwargs)
        if metric == 'silhouette':
            cluster_score_info[k]=metrics.cluster.silhouette_score(v2, labels=tmp_clust
    if show_plot:
        pair = sorted(cluster_score_info.items()) # = [(x,y) for x,y in a.items()]
        x,y = zip(*pair)
        plt.plot(x,y)
        plt.xlabel('Number of Clusters')
        plt.ylabel('Cluster Score')

    return cluster_score_info
```

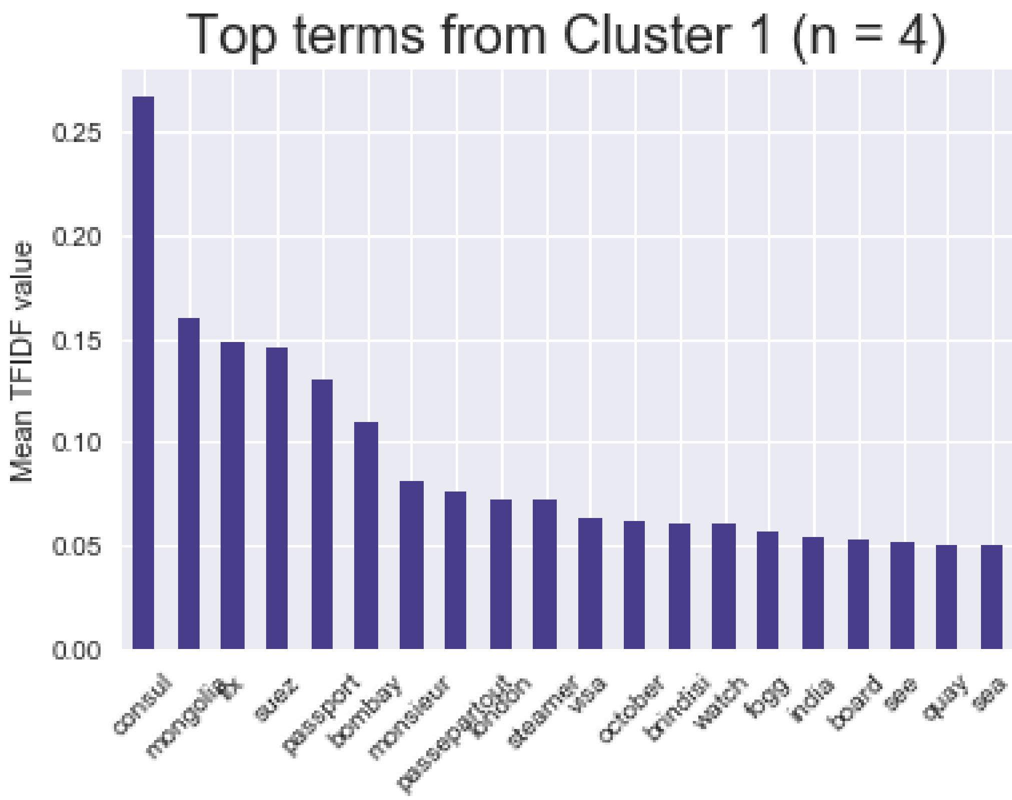
In [41]:
```
a = create_and_score_clusters(chap_corp_vec)
```



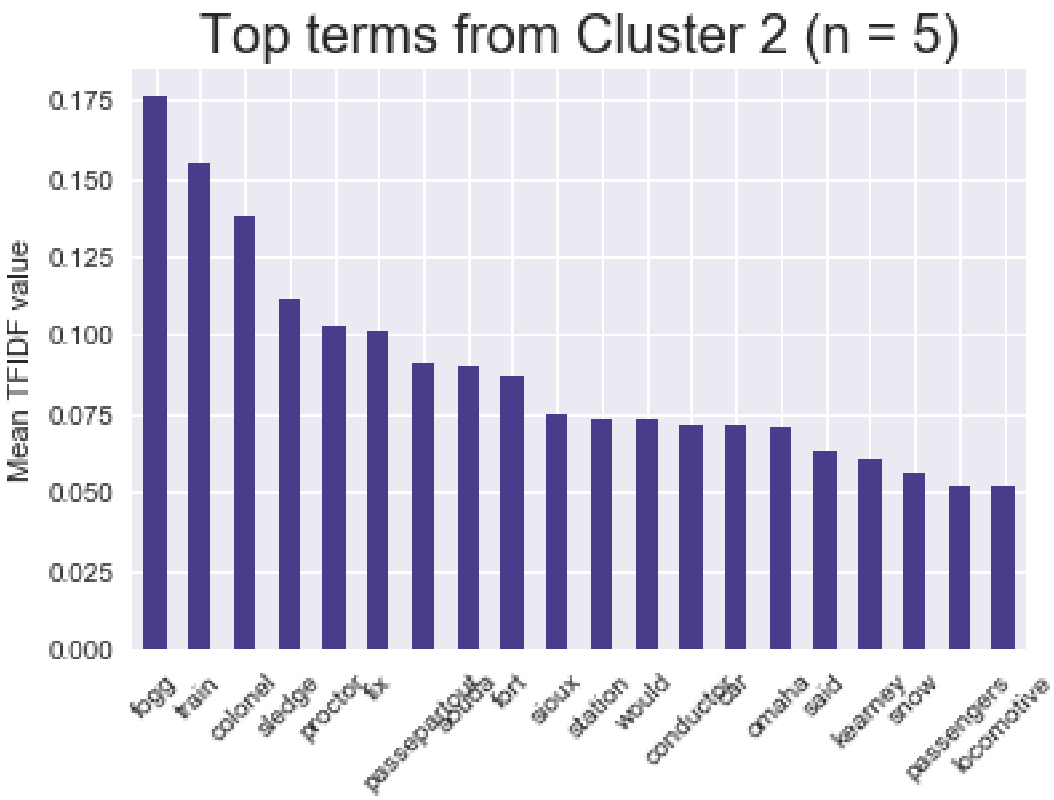
In [43]:
```
c_11 = cluster_text(chap_corp_vec, nclusters=11)
```



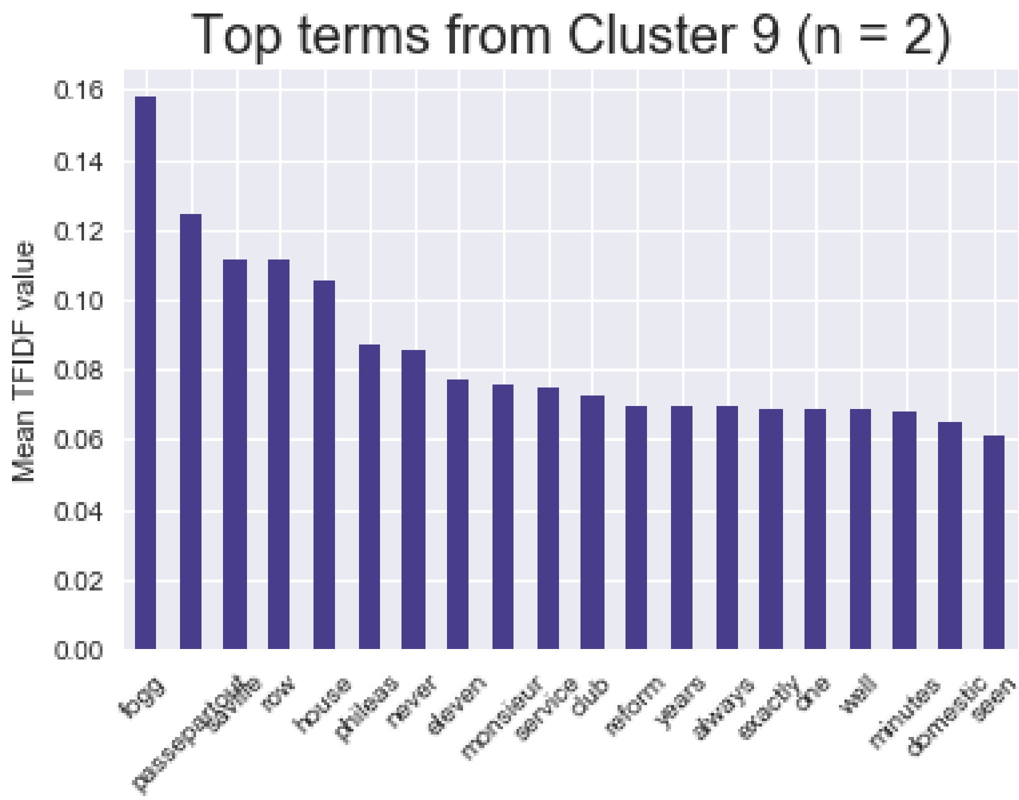

```
In [44]: metrics.cluster.silhouette_score(np.dot(chap_corp_vec,chap_corp_vec.T), labels=c_11.lab

Out[44]: 0.13435737408344714

In [45]: [c_11.labels_[a] for a in [0,5,8, 30 ]]

Out[45]: [9, 1, 1, 2]

In [47]: plot_single_cluster_tfidf_terms(c_11, vectorizer, chap_corp_vec, n_terms=20, cluster_id
```




```
In [48]: plot_single_cluster_tfidf_terms(c_11, vectorizer, chap_corp_vec, n_terms=20, cluster_id
```




```
In [49]: plot_single_cluster_tfidf_terms(c_11, vectorizer, chap_corp_vec, n_terms=20, cluster_id
```



5 Can we compare one document to another?

```
In [50]: def setup_document_list(fname, train=True):
             pg_text = []
             book_chapters = []
             if train:
                 tval = 1
             else:
                 tval = 0
             # ingest meta_file
             df = pd.read_csv(fname)
             for i, row in df[df.train==tval].iterrows():
                 bid = (row.file).split('/')[1].rstrip('.txt').split('-')[0]
                 #print(bid, row.file)
                 raw_text = load_pg_text(row.file)
                 print(len(raw_text), row.author, row.book)
                 chapters = split_into_chapters(raw_text, int(bid), key_word=row.breakword, auth
                 print("We split {b} into {n} chapters.".format(b=row.book, n=len(chapters)))
                 book_chapters.append(len(chapters))
                 pg_text.append(chapters)
```

```
            return pg_text, df, book_chapters
```

```
In [51]: pg_text, df, book_chapters = setup_document_list('document_listing.txt')
```

```
8013 Verne 80days
We split 80days into 37 chapters.
19214 Verne Leagues
We split Leagues into 47 chapters.
13036 Austen Pride
We split Pride into 61 chapters.
16242 Austen Emma
We split Emma into 55 chapters.
12691 Doyle Return
We split Return into 13 chapters.
11942 Doyle Holmes
We split Holmes into 12 chapters.
```

```
In [52]: pg_text_test, df2, bk_ch2 = setup_document_list('document_listing.txt', train=False)
```

```
9595 Verne Journey
We split Journey into 45 chapters.
12822 Austen Sense
We split Sense into 50 chapters.
6833 Doyle Hound
We split Hound into 15 chapters.
```

5.1 Preprocess all the text in each of the chapters to be input into a TF-IDF formulation:

- tokenize
- remove stop words
- remove punctuation

```
In [53]: clean_chapters = []
         clean_corpus = []
         clean_by_book =[]
         book_info = []
         for book in pg_text:
             by_book = []
             for k,ch in enumerate(book):
                 new_text = " ".join([token for token in nltk_tokenize(ch.text)])
                 clean_chapter = Chapter(ch.name,ch.title, new_text, ch.author, ch.book_id, k, c
                 clean_chapters.append(clean_chapter)
                 clean_corpus.append(new_text)
                 by_book.append(new_text)
                 if k == 0:
```

```
                book_info.append([ch.author, ch.bookname, ch.book_id])
        by_book = "".join([line for line in by_book])
        clean_by_book.append(by_book)
```

```
In [54]: len(clean_corpus), len(clean_by_book)
```

```
Out[54]: (225, 6)
```

```
In [134]: clean_by_book[0][:100]
```

```
Out[134]: 'one master man phileas fogg lived 1872 7 saville row burlington gardens house sherida
```

```
In [135]: clean_corpus[85][:60]
```

```
Out[135]: 'bennet among earliest waited bingley always intended visit t'
```

5.2 Two outputs:

1. A corpus that is 1 row for each chapter
2. A corpus that is 1 row for each book

5.3 let's start with the second one and see if we can determine differences between these authors

```
In [62]: #df[df.train==1][['author','book',#
         book_df = pd.DataFrame(book_info, columns=['Author','BookName','BookId'])
         book_df['chapters']=book_chapters
         #book_df
```

5.4 Start with a *tf-idf* vectorizer

```
In [57]: tfidf_vectorizer=TfidfVectorizer()
         tfidf_by_book_vec = tfidf_vectorizer.fit_transform(clean_by_book)
         tfidf_by_book_feature_names = tfidf_vectorizer.get_feature_names()
```

```
In [58]: np.shape(tfidf_by_book_vec), len(tfidf_by_book_feature_names)
```

```
Out[58]: ((6, 22242), 22242)
```

```
In [137]: tf_book_feature_names[-8:]
```

```
Out[137]: ['yards', 'ye', 'yellow', 'yielded', 'york', 'younger', 'youngest', 'youth']
```

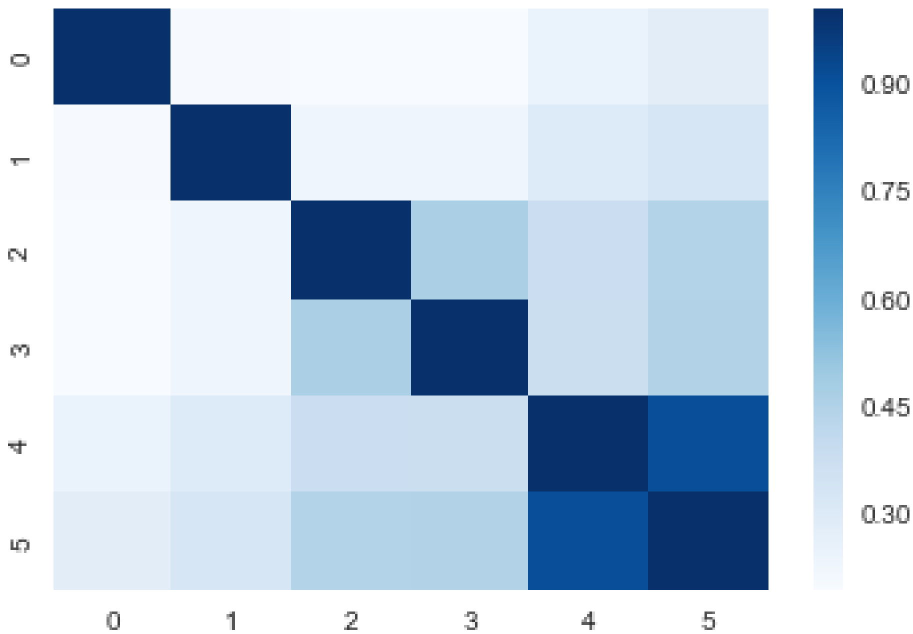
5.5 this is the dimension of our Document to Word matrix

6 by 22242

```
In [59]: b2b_TF_dist = np.dot(tfidf_by_book_vec, tfidf_by_book_vec.T).toarray()
```

```
In [60]: sns.heatmap(b2b_TF_dist,cmap='Blues')
```

Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0x22fdc4734a8>



In [61]: book_df

Out[61]:

	Author	BookName	BookId	chapters
0	Verne	80days	103	37
1	Verne	Leagues	2488	47
2	Austen	Pride	1342	61
3	Austen	Emma	158	55
4	Doyle	Return	221	13
5	Doyle	Holmes	48320	12

If you squint you might be able to guess that 4 & 5 (Doyle) are closest with 2 & 3 (Austen) are next closest.

5.5.1 Retry at Chapter-level

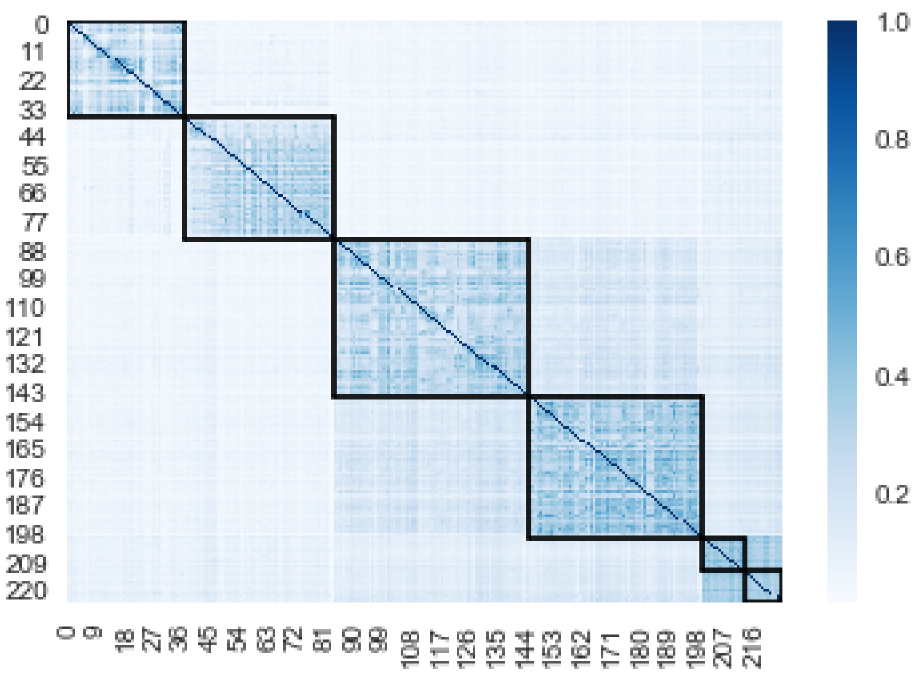
In [63]:
```
chapter_tfidf_vectorizer=TfidfVectorizer()
chapter_tfidf_vec = chapter_tfidf_vectorizer.fit_transform(clean_corpus)
chapter_tfidf_feature_names = chapter_tfidf_vectorizer.get_feature_names()
```

In [64]:
```
len(chapter_tfidf_feature_names)
```

Out[64]: 22032

In [65]:
```
c2c_TF_dist = np.dot(chapter_tfidf_vec, chapter_tfidf_vec.T).toarray()
sns.heatmap(c2c_TF_dist,cmap='Blues')
```

```
ch_boundaries = book_df.chapters.cumsum().values.tolist()
ch_boundaries.insert(0,0)
total = max(ch_boundaries)
for i,v in enumerate(ch_boundaries):
    if v != total:
        w = ch_boundaries[i+1]
        #for v in book_df.chapters.cumsum().values():

        plt.axhline(y=v, xmin=v/total, xmax=w/total,color='k')
        plt.axhline(y=w, xmin=v/total, xmax=w/total,color='k')
        plt.axvline(x=v, ymin=1-v/total, ymax=1-w/total,color='k')
        plt.axvline(x=w, ymin=1-v/total, ymax=1-w/total,color='k')
```



5.6 This is cool → chapters of contiguous books are more self-similar

5.7 But harder to see similarities between authors (particularly Verne)

6 This is all well and good.

- I've shown that I can group text into similar clusters and identify the top words (features) in each cluster.

6.1 However is there more we can do?

6.2 What about Topic Modeling ?

Topic Modeling attempts to use machine learning to infer some sort of abstract "topics" within a collection of documents. It works by identifying informative collocation on our bag of words corpus. There are different ways to approach determining these topics. Two of the most common are *LDA* and *NMF*. The Topic Modeling process thus assigns documents to a mixture of these topics and thus words can be associated to varying degrees into these different topics.

6.2.1 LDA: Latent Dirichlet Allocation is a probabalistic graphical model

- Note in ML LDA can also represent not to be confused with Linear Discriminate Analysis which is a method to characterize/distinguish between multiple classes.
- Latent Dirichlet allocation (LDA) is a generative probabilistic model of a corpus. The basic idea is that documents are represented as random mixtures over latent topics, where each topic is characterized by a distribution over words.

  -- Blei, Ng & Jordan J Machine Learning Research 3 (2003) 993-1022 Latent Dirichlet Allocation
- In `python`, LDA is implemented in the goto ML library, `sklearn`. However the best python implementation (in terms of speed and scalability) is `Gensim`.

6.2.2 NMF: Non-negative Matrix Factorization just uses straightforward linear algebra

- Implemented in `sklearn`
- The document-word matrix, $\mathbf{D}$, is factorized into two matrices:, $\mathbf{T}$ and $\mathbf{W}$ as

$$\mathbf{D} = \mathbf{TW} \tag{3}$$

- Effectively one can think of this as a dimensional reduction, projecting the document-word matrix $\mathbf{D}$ into a document-topic matrix $\mathbf{T}$ useful for assessing similarities and gaining some idea of what the document is about and topic-word matrix $\mathbf{W}$ is generated in the process.

6.2.3 What is the catch? You have to specify the number of topics to assign.

6.3 Apply both

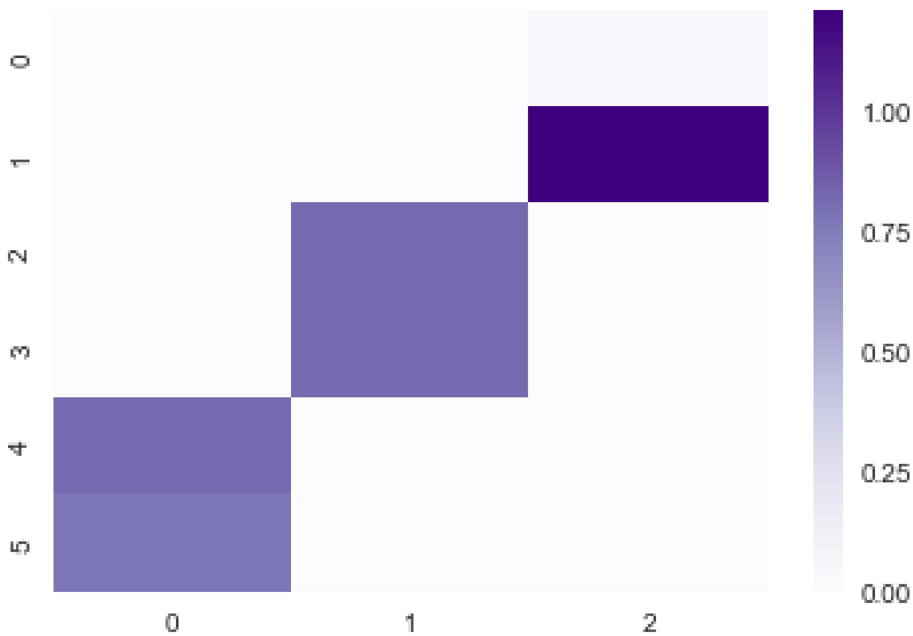
In [85]:
```
n_features=2000

# Use it-idf
tfidf_vectorizer=TfidfVectorizer(max_df=0.95, min_df=2,max_features=n_features)
tfidf_book_vec = tfidf_vectorizer.fit_transform(clean_by_book)
tfidf_book_feature_names = tfidf_vectorizer.get_feature_names()

# LDA can only use raw term counts for LDA because it is a probabilistic graphical mode

tf_vectorizer = CountVectorizer(max_df=0.95, min_df=2, max_features=n_features, stop_wo
tf_book_vec = tf_vectorizer.fit_transform(clean_by_book)
tf_book_feature_names = tf_vectorizer.get_feature_names()
```

```
In [67]: tfidf_book_vec.shape, tf_book_vec.shape

Out[67]: ((6, 1000), (6, 1000))

In [86]: from sklearn.decomposition import NMF, LatentDirichletAllocation

         no_topics = 3

         # Run NMF
         nmf = NMF(n_components=no_topics, random_state=1, alpha=.1, l1_ratio=.5, init='nndsvd')

         # Run LDA
         lda = LatentDirichletAllocation(n_components=no_topics, max_iter=25, learning_method='o
                                         learning_offset=50.,random_state=121).fit(tf_book_vec)

In [87]: def display_topics(model, feature_names, no_top_words):
             for topic_idx, topic in enumerate(model.components_):
                 print("Topic {d}:".format(d=topic_idx))
                 print (" ".join([feature_names[i]
                                 for i in topic.argsort()[:-no_top_words - 1:-1]]))

         no_top_words = 10
         print("\n NMF topics")
         display_topics(nmf, tfidf_book_feature_names, no_top_words)
         print("\n Now for LDA topics")
         display_topics(lda, tf_book_feature_names, no_top_words)


 NMF topics
Topic 0:
holmes watson sherlock shall lestrade street chair police cried crime
Topic 1:
mrs elizabeth jane harriet shall sister mother pleasure frank aunt
Topic 2:
ned canadian replied professor ocean surface waves seas ve 000

 Now for LDA topics
Topic 0:
mrs elizabeth jane harriet shall sister mother pleasure frank feelings
Topic 1:
holmes shall watson cried street sherlock chair lestrade police station
Topic 2:
ned replied canadian professor surface seas ocean 000 waves waters


In [88]: nmf_doctopic = nmf.transform(tfidf_book_vec)
         nmf_doctopic#/np.sum(nmf_doctopic,axis=1,keepdims=True)

Out[88]: array([[0.        , 0.        , 0.042202  ],
                [0.        , 0.        , 1.20962826],
```

```
       [0.        , 0.82576388, 0.        ],
       [0.        , 0.82298039, 0.        ],
       [0.82384161, 0.        , 0.        ],
       [0.778778  , 0.        , 0.        ]])
```

In [89]:
```
sns.heatmap(nmf_doctopic,cmap='Purples')#plt.xticks([1,2,3],['Topic 0', 'Topic 1','Topi
```

Out[89]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22fdfce38d0>
```

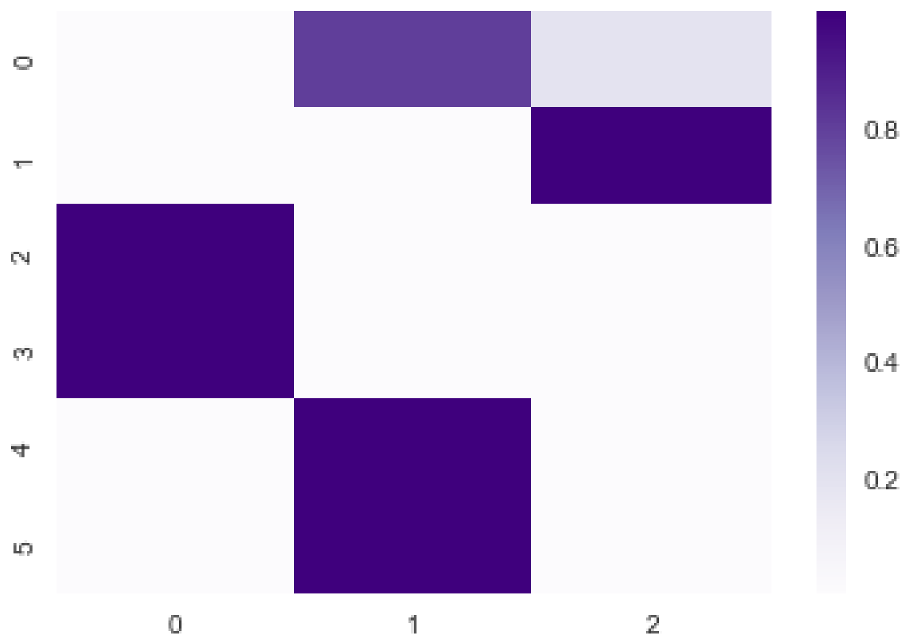


In [90]:
```
lda_doctopic = lda.transform(tf_book_vec)
[np.round(x,2) for x in lda_doctopic]#/np.sum(lda_doctopic,axis=1,keepdims=True)
```

Out[90]:
```
[array([0.  , 0.81, 0.19]),
 array([0., 0., 1.]),
 array([1., 0., 0.]),
 array([1., 0., 0.]),
 array([0., 1., 0.]),
 array([0., 1., 0.])]
```

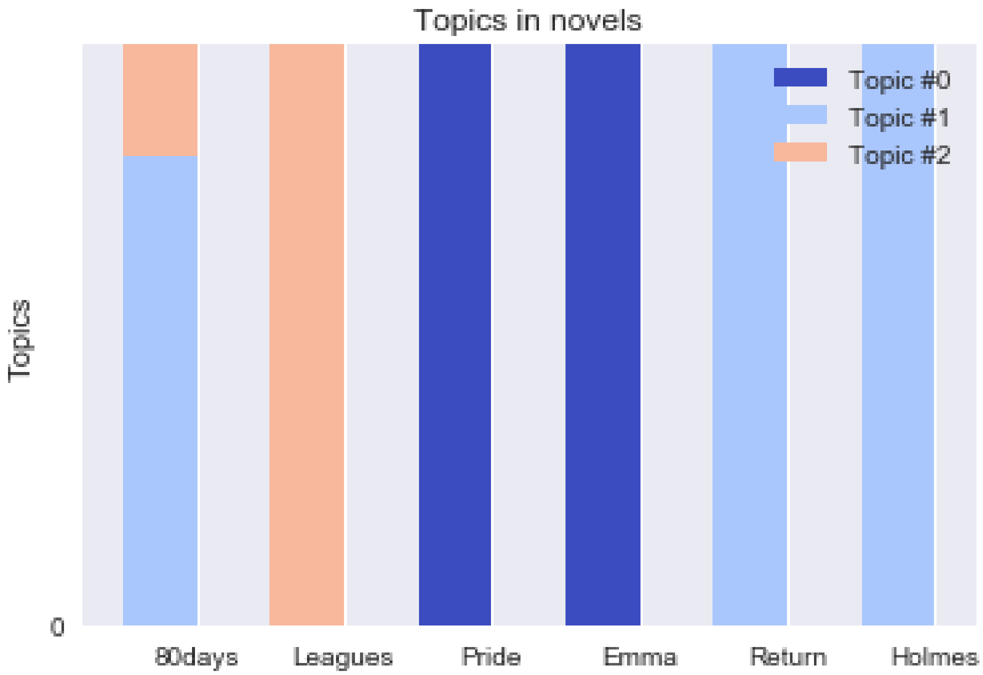
In [91]:
```
sns.heatmap(lda_doctopic,cmap='Purples')#plt.xticks([1,2,3],['Topic 0', 'Topic 1','Topi
```

Out[91]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22fde6c46d8>
```

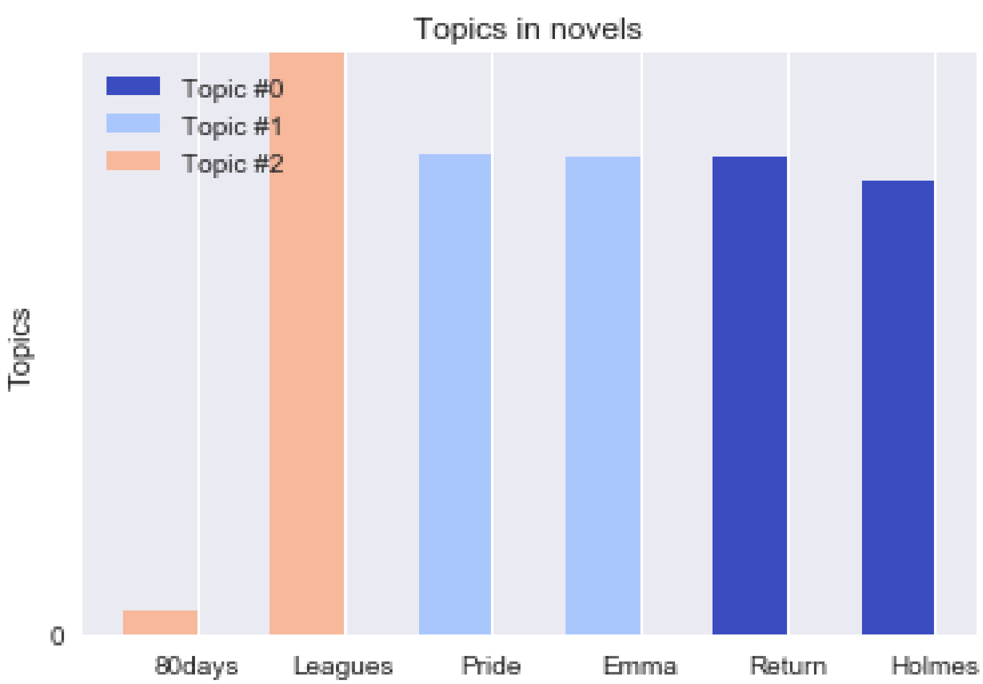


In [76]:
```
def stack_plot_topics_per_instance(doctopic,doclist):
    plots = []
    N,K = doctopic.shape
    ind = np.arange(N)
    width=0.5
    full_height=np.zeros(N)
    for k in range(K):
        color = plt.cm.coolwarm(k/K, 1)
        if k == 0:
            p = plt.bar(ind, doctopic[:, k], width, color=color)
        else:
            p = plt.bar(ind, doctopic[:, k], width, bottom=full_height, color=color)
        full_height += doctopic[:, k]
        plots.append(p)
    plt.ylim((0,1))
    plt.ylabel('Topics')
    plt.title('Topics in novels')
    plt.xticks(ind+width/2, doclist)
    plt.yticks(np.arange(0, 1, 10))
    topic_labels = ['Topic #{}'.format(k) for k in range(K)]
    plt.legend([p[0] for p in plots], topic_labels)
    plt.show()
```

In [92]:
```
stack_plot_topics_per_instance(lda_doctopic,book_df.BookName.values.tolist())
```



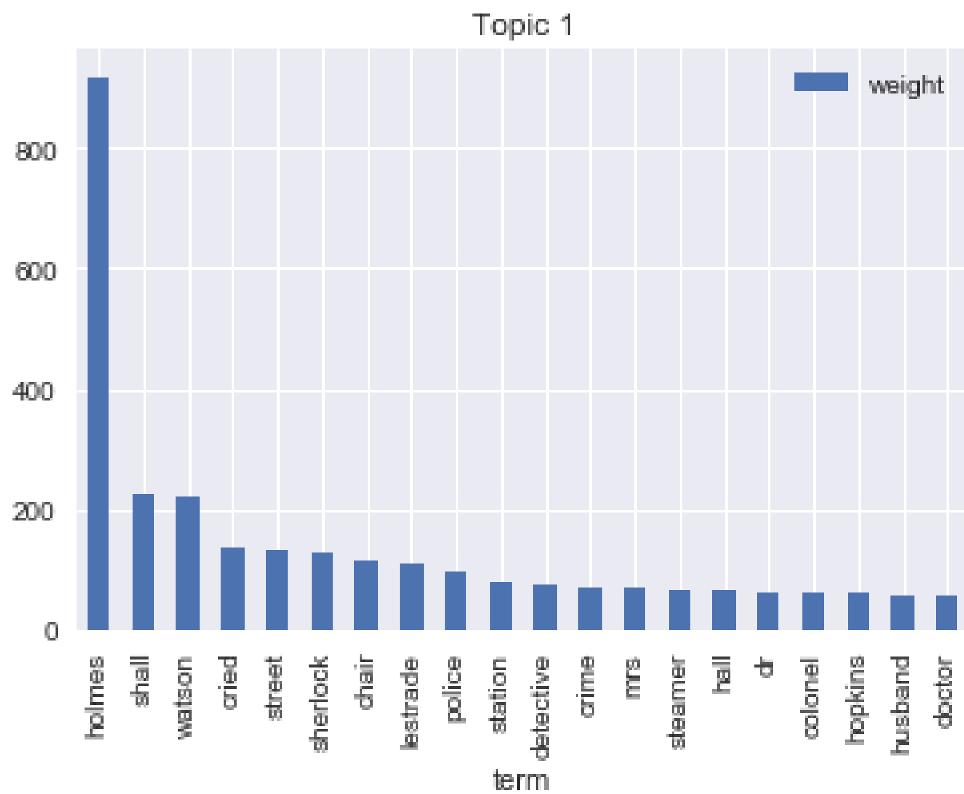

```
In [93]: stack_plot_topics_per_instance(nmf_doctopic, book_df.BookName.values.tolist())
```



In [80]:
```
def plot_lda_topic_words(lda, topic_id, n_terms=20, terms=None):
    #if type(lda)=="<class 'gensim.models.ldamodel.LdaModel'":
    try:
        df = pd.DataFrame(lda.show_topic(topic_id,n_terms), columns=['term','weight']).

    except AttributeError:
        data = [(terms[i],lda.components_[topic_id][i] ) for i in lda.components_[topic
        df =pd.DataFrame(data, columns=['term','weight']).set_index('term')

    df.plot(kind='bar')
    plt.title('Topic {d}'.format(d=str(topic_id)))
    #else:
    #    print("sorry not operational for type {} yet".format(type(lda)))

    return df
```

In [95]:
```
plot_lda_topic_words(lda, 1, n_terms=20, terms=tf_book_feature_names)
```

Out[95]:
```
                weight
term
holmes      919.073024
shall       223.424685
watson      220.020867
cried       137.107710
street      133.245540
sherlock    127.475222
chair       114.710897
lestrade    108.705065
police       97.813462
station      79.997092
detective    72.311506
crime        71.226452
mrs          67.554938
steamer      65.816871
hall         62.924260
dr           62.821747
colonel      60.294946
hopkins      59.125400
husband      58.318395
doctor       56.171464
```



7 Better visualization: pyLDAvis

```
In [83]: import pyLDAvis as vis
         vis.enable_notebook()
         import pyLDAvis.sklearn
         import pyLDAvis.gensim

In [96]: pyLDAvis.sklearn.prepare(lda, tf_book_vec, tf_vectorizer)

C:\Users\ARADER\Continuum\anaconda3\lib\site-packages\pyLDAvis\_prepare.py:387: DeprecationWarni
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
  topic_term_dists = topic_term_dists.ix[topic_order]


Out[96]: PreparedData(topic_coordinates=            Freq  cluster  topics         x         y
         topic
```

```
1      36.298829        1       1  0.018856 -0.130429
0      35.294468        1       2 -0.218989  0.056413
2      28.406703        1       3  0.200133  0.074016, topic_info=     Category
term
886   Default  1143.000000     holmes  1143.000000  30.0000  30.0000
1181  Default  1066.000000        mrs  1066.000000  29.0000  29.0000
601   Default   602.000000  elizabeth   602.000000  28.0000  28.0000
1002  Default   566.000000       jane   566.000000  27.0000  27.0000
1196  Default   433.000000        ned   433.000000  26.0000  26.0000
860   Default   482.000000    harriet   482.000000  25.0000  25.0000
255   Default   226.000000   canadian   226.000000  24.0000  24.0000
1938  Default   275.000000     watson   275.000000  23.0000  23.0000
1771  Default   190.000000    surface   190.000000  22.0000  22.0000
1601  Default   637.000000      shall   637.000000  21.0000  21.0000
1235  Default   178.000000      ocean   178.000000  20.0000  20.0000
1576  Default   182.000000       seas   182.000000  19.0000  19.0000
1388  Default   245.000000  professor   245.000000  18.0000  18.0000
1491  Default   547.000000    replied   547.000000  17.0000  17.0000
1939  Default   169.000000      waves   169.000000  16.0000  16.0000
0     Default   170.000000        000   170.000000  15.0000  15.0000
1937  Default   162.000000     waters   162.000000  14.0000  14.0000
724   Default   164.000000       fish   164.000000  13.0000  13.0000
1654  Default   271.000000     sister   271.000000  12.0000  12.0000
481   Default   143.000000    degrees   143.000000  11.0000  11.0000
1614  Default   159.000000   sherlock   159.000000  10.0000  10.0000
707   Default   189.000000   feelings   189.000000   9.0000   9.0000
1618  Default   164.000000       ship   164.000000   8.0000   8.0000
767   Default   225.000000      frank   225.000000   7.0000   7.0000
1908  Default   177.000000         ve   177.000000   6.0000   6.0000
1335  Default   223.000000   pleasure   223.000000   5.0000   5.0000
1063  Default   136.000000   lestrade   136.000000   4.0000   4.0000
997   Default   123.000000     island   123.000000   3.0000   3.0000
915   Default   116.000000        ice   116.000000   2.0000   2.0000
146   Default   139.000000       aunt   139.000000   1.0000   1.0000
...       ...          ...        ...          ...      ...      ...
481    Topic3   136.463928    degrees   143.983399   1.2049  -4.9545
1937   Topic3   153.687210     waters   162.155984   1.2049  -4.8357
1939   Topic3   160.585453      waves   169.636375   1.2037  -4.7918
32     Topic3    51.108406     aboard    53.995058   1.2036  -5.9366
1771   Topic3   180.090052    surface   190.361056   1.2031  -4.6771
0      Topic3   161.172721        000   170.665072   1.2013  -4.7881
1627   Topic3    56.372707      shore    59.722134   1.2008  -5.8386
725    Topic3    27.639827  fishermen    29.363579   1.1980  -6.5513
1628   Topic3    35.722606     shores    37.954462   1.1979  -6.2948
1607   Topic3    38.235084     sharks    40.757812   1.1947  -6.2268
915    Topic3   108.985439        ice   116.516244   1.1917  -5.1794
724    Topic3   153.539959       fish   164.992022   1.1866  -4.8366
848    Topic3    54.167689       gulf    57.806879   1.1935  -5.8785
```

```
997    Topic3   113.344453     island   123.222979   1.1750  -5.1402
89     Topic3   107.584119     animal   118.427724   1.1625  -5.1923
495    Topic3    73.997701     depths    80.514036   1.1741  -5.5665
1619   Topic3    54.857438      ships    58.756356   1.1899  -5.8658
1618   Topic3   140.848651       ship   164.639522   1.1025  -4.9229
1388   Topic3   196.865788  professor   245.948375   1.0359  -4.5881
1908   Topic3   143.326189         ve   177.819607   1.0429  -4.9055
1333   Topic3    84.942661   platform    97.506692   1.1206  -5.4286
892    Topic3    67.811572    horizon    75.767736   1.1476  -5.6539
1491   Topic3   321.330581    replied   547.808492   0.7251  -4.0981
1367   Topic3    68.013247   pressure    76.657972   1.1389  -5.6509
595    Topic3    75.379173   electric    88.032344   1.1034  -5.5481
201    Topic3    93.332456      board   129.435911   0.9315  -5.3344
332    Topic3    69.801293      coast    85.125225   1.0601  -5.6249
1150   Topic3    68.344393      midst    93.577391   0.9443  -5.6460
1766   Topic3    69.773114        sun   103.916400   0.8602  -5.6253
718    Topic3    72.414927    finally   126.518434   0.7006  -5.5882

[191 rows x 6 columns], token_table=      Topic       Freq        Term
term
0          1  0.041016         000
0          2  0.017578         000
0          3  0.943368         000
18         1  0.023339       _her_
18         2  0.956890       _her_
18         3  0.023339       _her_
22         1  0.036278        _me_
22         2  0.943220        _me_
22         3  0.036278        _me_
25         1  0.025580       _she_
25         2  0.946449       _she_
25         3  0.025580       _she_
26         1  0.020539      _that_
26         2  0.965313      _that_
26         3  0.020539      _that_
29         1  0.020149       _you_
29         2  0.967163       _you_
29         3  0.020149       _you_
32         1  0.037040      aboard
32         2  0.018520      aboard
32         3  0.944531      aboard
33         1  0.018509     abraham
33         2  0.018509     abraham
33         3  0.962484     abraham
46         1  0.051615  acquainted
46         2  0.946276  acquainted
46         3  0.017205  acquainted
53         1  0.034922     admired
```

```
53         2  0.942907     admired
53         3  0.034922     admired
...      ...       ...         ...
1766       1  0.259824         sun
1766       2  0.067362         sun
1766       3  0.673618         sun
1771       1  0.047279     surface
1771       2  0.005253     surface
1771       3  0.945572     surface
1806       1  0.967826    terrible
1806       2  0.020592    terrible
1806       3  0.020592    terrible
1878       1  0.228092       uncle
1878       2  0.763232       uncle
1878       3  0.008773       uncle
1908       1  0.185581          ve
1908       2  0.005624          ve
1908       3  0.804186          ve
1937       1  0.043168      waters
1937       2  0.012334      waters
1937       3  0.949703      waters
1938       1  0.982627      watson
1938       2  0.007252      watson
1938       3  0.010878      watson
1939       1  0.047160       waves
1939       2  0.005895       waves
1939       3  0.949089       waves
1953       1  0.035786       whale
1953       2  0.017893       whale
1953       3  0.948322       whale
1965       1  0.925460      wilson
1965       2  0.035595      wilson
1965       3  0.035595      wilson

[465 rows x 3 columns], R=30, lambda_step=0.01, plot_opts={'xlab': 'PC1', 'ylab': 'PC2'
```

```
In [97]: pyLDAvis.sklearn.prepare(nmf, tfidf_book_vec, tfidf_vectorizer)
```

```
C:\Users\ARADER\Continuum\anaconda3\lib\site-packages\pyLDAvis\_prepare.py:387: DeprecationWarni
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
  topic_term_dists = topic_term_dists.ix[topic_order]
C:\Users\ARADER\Continuum\anaconda3\lib\site-packages\pyLDAvis\_prepare.py:223: RuntimeWarning:
  kernel = (topic_given_term * np.log((topic_given_term.T / topic_proportion).T))
```

```
C:\Users\ARADER\Continuum\anaconda3\lib\site-packages\pyLDAvis\_prepare.py:240: RuntimeWarning:
  log_lift = np.log(topic_term_dists / term_proportion)
C:\Users\ARADER\Continuum\anaconda3\lib\site-packages\pyLDAvis\_prepare.py:241: RuntimeWarning:
  log_ttd = np.log(topic_term_dists)
```

```
Out[97]: PreparedData(topic_coordinates=           Freq  cluster  topics         x         y
         topic
         2      43.999799        1       1 -0.402615 -0.051229
         0      28.255070        1       2  0.252137 -0.278720
         1      27.745131        1       3  0.150478  0.329949, topic_info=     Category       F
         term
         877   Default  11.000000      holmes  11.000000  30.0000  30.0000
         1172  Default   4.000000         mrs   4.000000  29.0000  29.0000
         596   Default   3.000000   elizabeth   3.000000  28.0000  28.0000
         1188  Default   5.000000         ned   5.000000  27.0000  27.0000
         998   Default   2.000000        jane   2.000000  26.0000  26.0000
         846   Default   2.000000     harriet   2.000000  25.0000  25.0000
         1937  Default   1.000000      watson   1.000000  24.0000  24.0000
         263   Default   2.000000    canadian   2.000000  23.0000  23.0000
         1597  Default   1.000000    sherlock   1.000000  22.0000  22.0000
         1380  Default   1.000000   professor   1.000000  21.0000  21.0000
         1585  Default   2.000000       shall   2.000000  20.0000  20.0000
         1231  Default   1.000000       ocean   1.000000  19.0000  19.0000
         1056  Default   0.000000    lestrade   0.000000  18.0000  18.0000
         1760  Default   1.000000     surface   1.000000  17.0000  17.0000
         1938  Default   1.000000       waves   1.000000  16.0000  16.0000
         1638  Default   0.000000      sister   0.000000  15.0000  15.0000
         1560  Default   1.000000        seas   1.000000  14.0000  14.0000
         1907  Default   1.000000          ve   1.000000  13.0000  13.0000
         1481  Default   2.000000     replied   2.000000  12.0000  12.0000
         0     Default   1.000000         000   1.000000  11.0000  11.0000
         1730  Default   0.000000      street   0.000000  10.0000  10.0000
         1601  Default   0.000000        ship   0.000000   9.0000   9.0000
         721   Default   0.000000        fish   0.000000   8.0000   8.0000
         1936  Default   0.000000      waters   0.000000   7.0000   7.0000
         292   Default   0.000000       chair   0.000000   6.0000   6.0000
         1335  Default   0.000000      police   0.000000   5.0000   5.0000
         1161  Default   0.000000      mother   0.000000   4.0000   4.0000
         993   Default   0.000000      island   0.000000   3.0000   3.0000
         1330  Default   0.000000    pleasure   0.000000   2.0000   2.0000
         760   Default   0.000000       frank   0.000000   1.0000   1.0000
         ...       ...        ...         ...        ...      ...      ...
         345    Topic3   0.086209     colonel   0.086209   1.2821  -5.5243
         464    Topic3   0.255421    daughter   0.255421   1.2821  -4.4382
         465    Topic3   0.043404   daughters   0.043404   1.2821  -6.2105
         796    Topic3   0.064929        girl   0.064929   1.2821  -5.8078
         846    Topic3   2.784621     harriet   2.784621   1.2821  -2.0492
```

```
1876   Topic3   0.102422       uncle   0.102422   1.2821  -5.3520
992    Topic3   0.103659   isabella   0.103659   1.2821  -5.3400
83     Topic3   0.006441     amiable   0.006441   1.2821  -8.1183
998    Topic3   2.821775        jane   2.821775   1.2821  -2.0359
153    Topic3   0.432376        aunt   0.432376   1.2821  -3.9118
1106   Topic3   0.078664    marriage   0.078664   1.2821  -5.6159
1841   Topic3   0.202315     towards   0.202315   1.2821  -4.6712
1161   Topic3   0.507694      mother   0.507694   1.2821  -3.7512
1655   Topic3   0.075183       smith   0.075183   1.2821  -5.6611
1330   Topic3   0.492185    pleasure   0.492185   1.2821  -3.7822
1639   Topic3   0.242067     sisters   0.242067   1.2821  -4.4918
1417   Topic3   0.227180    randalls   0.227180   1.2821  -4.5553
67     Topic3   0.051876   agreeable   0.051876   1.2821  -6.0322
139    Topic3   0.062413      assure   0.062413   1.2821  -5.8473
1638   Topic3   0.824070      sister   0.824070   1.2821  -3.2668
1090   Topic3   0.129236       lucas   0.129236   1.2821  -5.1194
143    Topic3   0.148198  attachment   0.148198   1.2821  -4.9825
760    Topic3   0.472396       frank   0.472396   1.2821  -3.8232
1108   Topic3   0.120723      martin   0.120723   1.2821  -5.1876
596    Topic3   3.734359   elizabeth   3.734359   1.2821  -1.7557
1172   Topic3   4.379426         mrs   4.552105   1.2434  -1.5964
1585   Topic3   1.163964       shall   2.506901   0.5149  -2.9215
436    Topic3   0.356958       cried   0.816165   0.4551  -4.1034
1481   Topic3   0.397623     replied   2.471881  -0.5451  -3.9956
997    Topic3   0.129947          it   0.429489   0.0866  -5.1139

[158 rows x 6 columns], token_table=      Topic      Freq       Term
term
0          1  0.862837        000
263        1  1.131586   canadian
292        2  1.869273      chair
353        1  1.491648  commander
483        1  1.428376    degrees
596        3  1.071134  elizabeth
721        1  1.159517       fish
846        3  1.077346    harriet
877        2  1.011127     holmes
993        1  1.267080     island
994        1  1.565556    islands
998        3  1.063160       jane
1056       2  1.058506   lestrade
1161       3  1.969690     mother
1172       3  0.878714        mrs
1188       1  1.084216        ned
1231       1  1.328249      ocean
1335       2  1.922616     police
1380       1  1.072385  professor
1481       1  0.809101    replied
```

```
1560      1  0.788211       seas
1585      2  0.398899      shall
1585      3  0.398899      shall
1597      2  0.721263   sherlock
1601      1  1.070841       ship
1638      3  1.213489     sister
1681      1  1.959140    species
1730      2  1.546888     street
1760      1  0.745231    surface
1907      1  0.847476         ve
1936      1  1.195937     waters
1937      2  1.027553     watson
1938      1  0.747615      waves, R=30, lambda_step=0.01, plot_opts={'xlab': 'PC1', 'yl
```

7.1 ingest the test data & compare

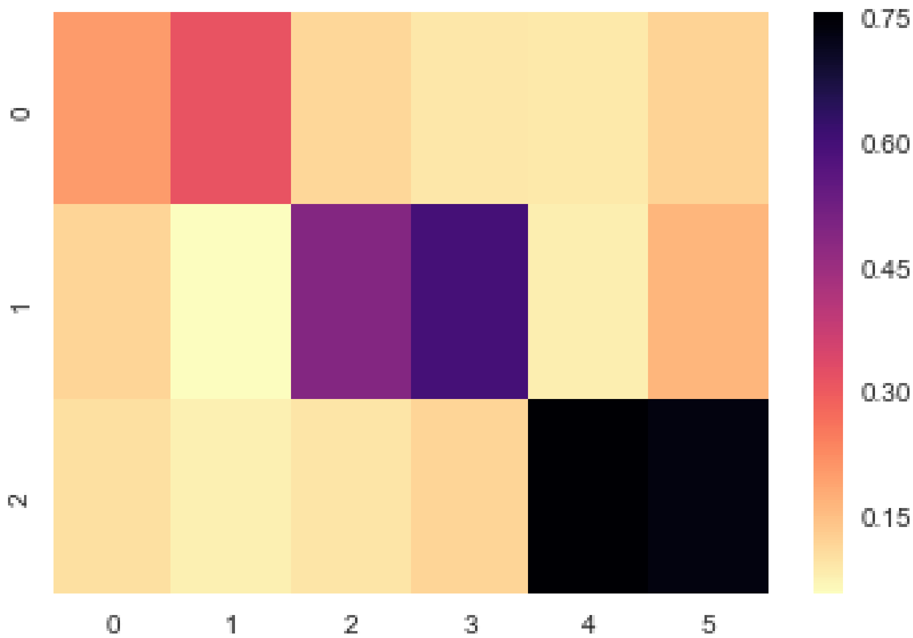
```
In [101]: testclean_chapters = []
          testclean_corpus = []
          testclean_by_book =[]
          #book_info = []
          for book in pg_text_test:
              test_by_book = []
              for k,ch in enumerate(book):
                  new_text = " ".join([token for token in nltk_tokenize(ch.text)])
                  testclean_chapter = Chapter(ch.name,ch.title, new_text, ch.author, ch.book_id,
                  testclean_chapters.append(testclean_chapter)
                  testclean_corpus.append(new_text)
                  test_by_book.append(new_text)
                  if k == 0:
                      print(ch.bookname, ch.author)

              test_by_book = "".join([line for line in test_by_book])
              testclean_by_book.append(test_by_book)
```

```
Journey Verne
Sense Austen
Hound Doyle
```

```
In [102]: test_by_book_vec = tfidf_vectorizer.transform(testclean_by_book)
```

```
In [103]: sns.heatmap(np.dot(test_by_book_vec,tfidf_book_vec.T).todense(),cmap='magma_r')
```

```
Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0x22fdfe01748>
```



7.2 Not so bad at assigning the best similarity for each author

7.3 Let's retry with each chapter

use clean_corpus

```
In [104]: ctf_vectorizer = CountVectorizer(max_df=0.95, min_df=2, max_features=n_features)
          ctf_book_vec = ctf_vectorizer.fit_transform(clean_corpus)
          ctf_book_feature_names = ctf_vectorizer.get_feature_names()
```

```
In [149]: chap_lda14 = LatentDirichletAllocation(n_components=14, max_iter=25, learning_method='
                                                                 learning_offset=50.,ra
```

```
In [150]: chap_lda_doctopic = chap_lda14.transform(ctf_book_vec)
          #[np.round(x,2) for x in chap_lda_doctopic]
          #chap_lda_doctopic
```

```
In [151]: pyLDAvis.sklearn.prepare(chap_lda14,  ctf_book_vec, ctf_vectorizer)
```

```
C:\Users\ARADER\Continuum\anaconda3\lib\site-packages\pyLDAvis\_prepare.py:387: DeprecationWarni
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#ix-indexer-is-deprecated
  topic_term_dists = topic_term_dists.ix[topic_order]
```

```
Out[151]: PreparedData(topic_coordinates=            Freq  cluster  topics         x         y
          topic
          8      41.252844        1       1 -0.132750 -0.041642
          2      28.606987        1       2 -0.082923  0.063313
          4      19.607530        1       3  0.099369  0.079991
          11      8.331041        1       4  0.001584  0.120740
          0       2.140351        1       5 -0.134695  0.013408
          13      0.006805        1       6  0.030449 -0.007636
          9       0.006805        1       7  0.028330 -0.016589
          12      0.006805        1       8  0.019943 -0.026375
          7       0.006805        1       9  0.028108 -0.019769
          10      0.006805        1      10  0.022268 -0.029206
          3       0.006805        1      11  0.024928 -0.027785
          1       0.006805        1      12  0.027525 -0.030509
          6       0.006805        1      13  0.033876 -0.038150
          5       0.006805        1      14  0.033988 -0.039792, topic_info=     Category
          term
          1513  Default  2329.000000       said  2329.000000  30.0000  30.0000
          244   Default   849.000000    captain   849.000000  29.0000  29.0000
          1184  Default   647.000000   nautilus   647.000000  28.0000  28.0000
          1169  Default  1138.000000        mrs  1138.000000  27.0000  27.0000
          1139  Default   995.000000       miss   995.000000  26.0000  26.0000
          852   Default  1219.000000     holmes  1219.000000  25.0000  25.0000
          533   Default   573.000000  elizabeth   573.000000  24.0000  24.0000
          1038  Default  1128.000000     little  1128.000000  23.0000  23.0000
          1173  Default  1411.000000       must  1411.000000  22.0000  22.0000
          1869  Default  1130.000000         us  1130.000000  21.0000  21.0000
          1929  Default  1361.000000       well  1361.000000  20.0000  20.0000
          1082  Default  1340.000000        man  1340.000000  19.0000  19.0000
          1170  Default  1133.000000       much  1133.000000  18.0000  18.0000
          1867  Default  1223.000000       upon  1223.000000  17.0000  17.0000
          682   Default   598.000000       fogg   598.000000  16.0000  16.0000
          1849  Default   985.000000        two   985.000000  15.0000  15.0000
          353   Default   482.000000    conseil   482.000000  14.0000  14.0000
          971   Default  1050.000000       know  1050.000000  13.0000  13.0000
          1195  Default   491.000000       nemo   491.000000  12.0000  12.0000
          537   Default   937.000000       emma   937.000000  11.0000  11.0000
          575   Default   981.000000      every   981.000000  10.0000  10.0000
          948   Default   590.000000       jane   590.000000   9.0000   9.0000
          1791  Default  1008.000000      think  1008.000000   8.0000   8.0000
          1546  Default  1054.000000        see  1054.000000   7.0000   7.0000
          1809  Default  1056.000000       time  1056.000000   6.0000   6.0000
          1025  Default   853.000000       like   853.000000   5.0000   5.0000
          1535  Default   521.000000        sea   521.000000   4.0000   4.0000
          1199  Default   948.000000      never   948.000000   3.0000   3.0000
          772   Default  1003.000000       good  1003.000000   2.0000   2.0000
          1050  Default   757.000000       long   757.000000   1.0000   1.0000
          ...       ...          ...        ...          ...      ...      ...
```

```
1184  Topic14     0.016654   nautilus   647.383162  -0.9728  -6.8708
797   Topic14     0.009782       gulf    60.126371   0.8715  -7.4030
1126  Topic14     0.012217     meters   204.591124  -0.1307  -7.1806
1195  Topic14     0.014083       nemo   491.227595  -0.8645  -7.0385
87    Topic14     0.010976     animal   124.119425   0.2619  -7.2878
649   Topic14     0.012113       feet   218.742464  -0.2062  -7.1892
1942  Topic14     0.013002      whose   395.117097  -0.7266  -7.1184
1469  Topic14     0.013222    replied   571.098657  -1.0782  -7.1016
1917  Topic14     0.011162     waters   170.402935  -0.0382  -7.2709
1173  Topic14     0.014834       must  1411.029775  -1.8677  -6.9866
1025  Topic14     0.013857       like   853.294225  -1.4328  -7.0547
1849  Topic14     0.013574        two   985.014139  -1.5970  -7.0753
1869  Topic14     0.013773         us  1130.865121  -1.7205  -7.0607
1538  Topic14     0.011043       seas   193.568327  -0.1763  -7.2817
1075  Topic14     0.012806       made   750.634756  -1.3836  -7.1336
1882  Topic14     0.010946         ve   186.870330  -0.1500  -7.2905
1699  Topic14     0.012393      still   599.385148  -1.1913  -7.1663
612   Topic14     0.012107       eyes   488.838272  -1.0108  -7.1897
575   Topic14     0.012736      every   981.582980  -1.6572  -7.1390
1050  Topic14     0.012287       long   757.982720  -1.4347  -7.1750
1513  Topic14     0.013366       said  2329.552989  -2.4733  -7.0908
1082  Topic14     0.012698        man  1340.144332  -1.9716  -7.1420
244   Topic14     0.012282    captain   849.233050  -1.5488  -7.1754
143   Topic14     0.012018       back   621.197932  -1.2578  -7.1971
1038  Topic14     0.012217     little  1128.850169  -1.8386  -7.1806
1809  Topic14     0.011978       time  1056.635203  -1.7923  -7.2004
1929  Topic14     0.011990       well  1361.924869  -2.0451  -7.1994
1921  Topic14     0.011721        way   656.421822  -1.3380  -7.2221
1488  Topic14     0.011450      right   461.174713  -1.0083  -7.2454
1079  Topic14     0.011491       make   646.458646  -1.3425  -7.2419

[1112 rows x 6 columns], token_table=      Topic      Freq          Term
term
0         2  0.022173           000
0         3  0.964525           000
0         4  0.005543           000
1         2  0.046762           100
1         3  0.911855           100
1         5  0.023381           100
3         2  0.028627           500
3         3  0.944707           500
10        3  0.912149        aboard
10        4  0.071541        aboard
11        3  0.982902       abraham
18        1  0.475090  accomplished
18        2  0.045247  accomplished
18        3  0.135740  accomplished
18        4  0.316726  accomplished
```

```
20         1  0.274074   accordingly
20         3  0.630371   accordingly
20         4  0.082222   accordingly
28         1  0.362320        active
28         2  0.461135        active
28         3  0.098815        active
28         4  0.065876        active
36         1  0.807488        admire
36         2  0.064599        admire
36         3  0.064599        admire
36         5  0.064599        admire
45         1  0.811554      affected
45         2  0.101444      affected
45         3  0.033815      affected
45         4  0.033815      affected
...      ...       ...           ...
1968       1  0.991896     woodhouse
1968       5  0.005869     woodhouse
1970       1  0.287691         words
1970       2  0.280314         words
1970       3  0.361457         words
1970       4  0.051637         words
1970       5  0.014753         words
1972       1  0.194990        worked
1972       2  0.454976        worked
1972       3  0.129993        worked
1972       4  0.227488        worked
1983       1  0.457239       written
1983       2  0.345717       written
1983       3  0.044609       written
1983       4  0.033457       written
1983       5  0.111522       written
1986       2  0.893249          yard
1986       4  0.048284          yard
1986       5  0.048284          yard
1991       1  0.313265           yes
1991       2  0.410266           yes
1991       3  0.170149           yes
1991       4  0.071558           yes
1991       5  0.034984           yes
1994       2  0.024413      yokohama
1994       4  0.976530      yokohama
1995       1  0.041568          york
1995       2  0.041568          york
1995       3  0.290976          york
1995       4  0.602736          york

[1670 rows x 3 columns], R=30, lambda_step=0.01, plot_opts={'xlab': 'PC1', 'ylab': 'PC
```

```
In [ ]: import en_core_web_sm as spacy_en
        nlp = spacy_en.load()
```

```
In [112]: def rejoin_chapter_text(raw_text):
              bookname = raw_text[0].bookname
              by_chapter_text = [ch.text for ch in raw_text]
              print("Confirming that there were {n} chapters in {b}.".format(n=len(by_chapter_te
              book_text = " ".join([chapt for chapt in by_chapter_text])
              book_doc = nlp(book_text)
              #How many sentences are in the book ?
              sentences = [s for s in book_doc.sents]
              #league_character_offsets = get_character_offsets(leagues_doc)
              print("{M} sentences in this book.".format(M=len(sentences)))
              return book_doc
```

```
In [113]: hound_doc = rejoin_chapter_text(pg_text_test[2])
```

```
Confirming that there were 15 chapters in Hound.
3936 sentences in this book.
```

```
In [114]: from collections import defaultdict
          NUM_BINS=30
          def get_character_offsets(doc):
              """
              For every character in a `doc` collect all the occurrences offsets and store them
              The function returns a dictionary that has actor lemma as a key and list of occure
              :param doc: Spacy NLP parsed document
              :return: dict object in form
                  {'elizabeth': [123, 543, 4534], 'darcy': [205, 2111]}
              """

              character_offsets = defaultdict(list)
              for ent in doc.ents:
                  if ent.label_ == 'PERSON' and ent.lemma_!= '':
                      character_offsets[ent.lemma_].append(ent.start)

              return dict(character_offsets)



          def plot_character_timeseries(character_offsets, character_labels, normalization_const
              """
              Plot characters' personal names specified in `character_labels` list as time serie
              :param character_offsets: dict object in form {'elizabeth': [123, 543, 4534], 'dar
              :param character_labels: list of strings that should match some of the keys in `ch
              :param normalization_constant: int
              """
```

```
        x = [character_offsets[character_label] for character_label in character_labels]

        with plt.style.context('fivethirtyeight'):
            plt.figure()
            n, bins, patches = plt.hist(x, NUM_BINS, label=character_labels)
            plt.clf()

            ax = plt.subplot(111)
            for i, a in enumerate(n):
                ax.plot([float(x) / (NUM_BINS - 1) for x in range(len(a))], a, label=chara

            matplotlib.rcParams['axes.prop_cycle'] = cycler(color=['r', 'k', 'c', 'b', 'y'
            ax.legend(loc='center left', bbox_to_anchor=(1, 0.5))

    def get_character_adjectives(doc, character_lemma):
        """
        Find all the adjectives related to `character_lemma` in `doc`
        :param doc: Spacy NLP parsed document
        :param character_lemma: string object
        :return: list of adjectives related to `character_lemma`
        """

        adjectives = []
        for ent in doc.ents:
            if ent.lemma_ == character_lemma:
                for token in ent.subtree:
                    if token.pos_ == 'ADJ':  # Replace with if token.dep_ == 'amod':
                        adjectives.append(token.lemma_)

        for ent in doc.ents:
            if ent.lemma_ == character_lemma:
                if ent.root.dep_ == 'nsubj':
                    for child in ent.root.head.children:
                        if child.dep_ == 'acomp':
                            adjectives.append(child.lemma_)

        adjectives = filter(lambda word: word != '-PRON-', adjectives)

        adj = Counter(adjectives)


        return adj
```

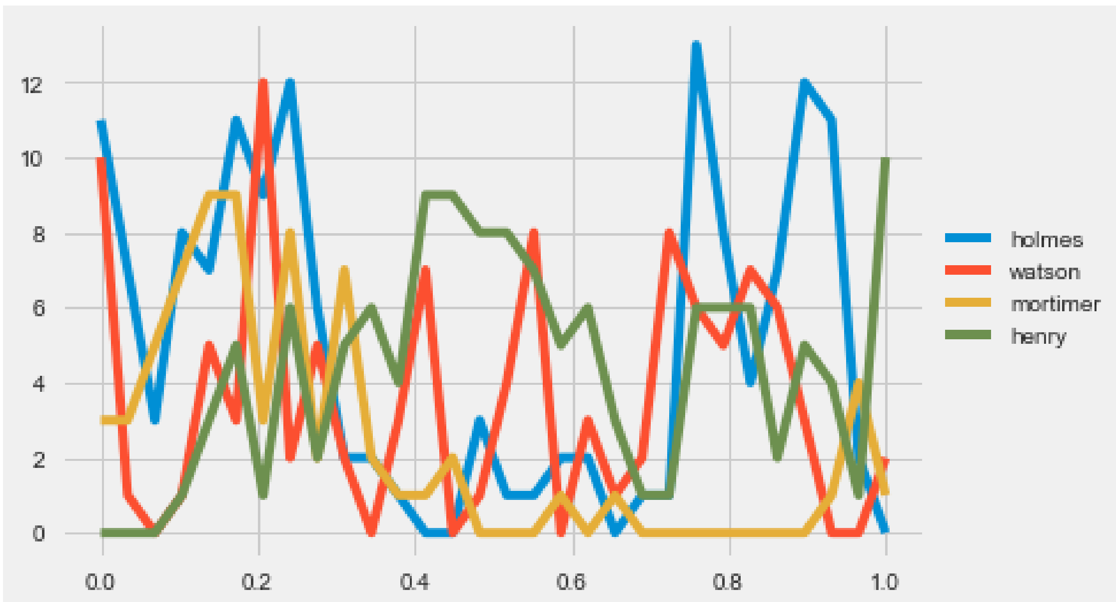
```
In [115]: hound_characters = get_character_offsets(hound_doc)
```

```
In [116]: [(k,len(v)) for k,v in hound_characters.items() if len(v) > 20]
```

```
Out[116]: [('sherlock holmes', 31),
           ('watson', 107),
```

```
('holmes', 147),
('mortimer', 70),
('charles', 78),
('henry baskerville', 23),
('stapleton', 49),
('henry', 130)]
```

```
In [117]: plot_character_timeseries(hound_characters, ['holmes','watson','mortimer','henry'])
```



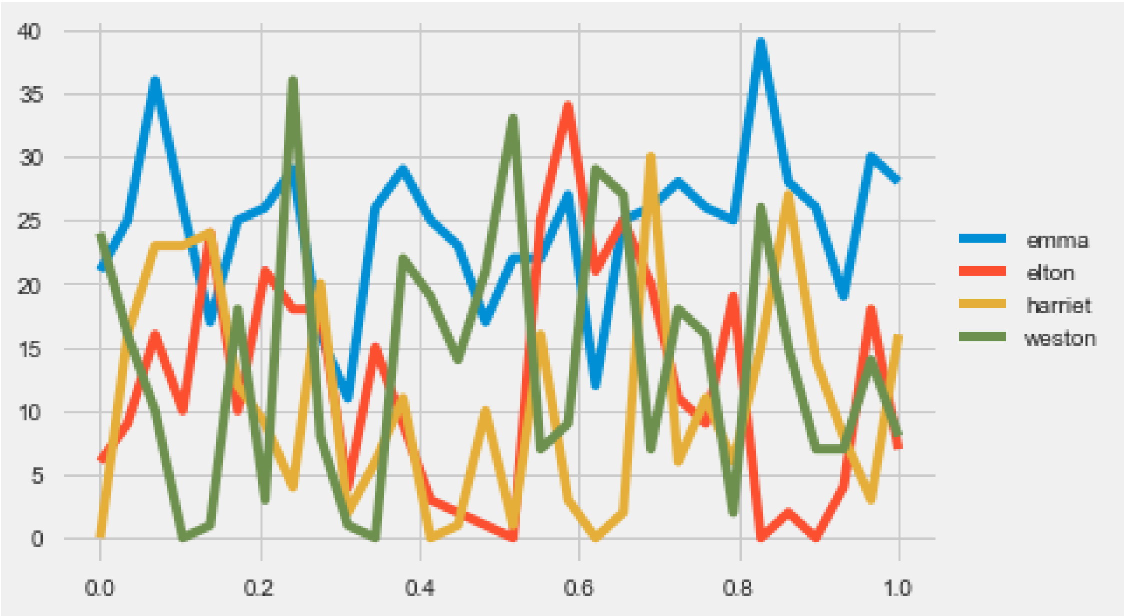

```
In [118]: for character in ['holmes', 'watson','mortimer','henry']:
              print(character)
              print(get_character_adjectives(hound_doc, character).keys())
```

```
holmes
dict_keys(['dear', 'all', 'next', 'silent', 'afoot'])
watson
dict_keys(['dear', 'which', 'alternative', 'long', 'short', 'quick', 'honest', 'ugly', 'dangerou
mortimer
dict_keys(['several', 'strong', 'round', 'visible'])
henry
dict_keys(['queer', 'old', 'which', 'angry', 'other', 'secret', 'particular', 'deep', 'unprotect
```

```
In [140]: emma_doc = rejoin_chapter_text(pg_text[3])
          emma_characters = get_character_offsets(emma_doc)
```

```
Confirming that there were 55 chapters in Emma.
11961 sentences in this book.
```

```
In [142]: [(k,len(v)) for k,v in emma_characters.items() if len(v) > 60]

Out[142]: [('woodhouse', 138),
           ('emma', 735),
           ('weston', 418),
           ('isabella', 67),
           ('knightley', 298),
           ('elton', 361),
           ('churchill', 65),
           ('frank churchill', 137),
           ('perry', 79),
           ('miss bates', 96),
           ('harriet', 319),
           ('jane fairfax', 76),
           ('jane', 178)]

In [148]: plot_character_timeseries(emma_characters, ['emma', 'elton','harriet', 'weston'])
```




```
In [ ]: from gensim import models,  similarities, corpora
        # gensim model uses a corpus and dictionary
        dictionary = corpora.Dictionary([a.split() for a in clean_corpus])
        corpus = [dictionary.doc2bow(text) for text in [a.split() for a in clean_corpus]]
        #corpus = " ".join([word for word in by_book_vec if word in tf_feature_names])
        lda_model = models.LdaModel(corpus, id2word=dictionary, num_topics=20 )

In [ ]: test_dictionary = corpora.Dictionary([a.split() for a in testclean_corpus])
        test_corpus = [test_dictionary.doc2bow(text) for text in [a.split() for a in testclean_c

In [ ]: pyLDAvis.gensim.prepare(lda_model, corpus, dictionary)
```