holybooks

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December 7, 2018

1 Holy Book Similarity Analysis

1.1 CS410 Text Information Systems, Final Project, Fall 2018

Click here to start docker container at mybinder

For browsing (rather than the interactive notebook in mybinder) the main notebook is holybooks.ipynb, and the PDF equivalent is holybooks.pdf

1.1.1 Authors

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John Moran - jfmoran2: Division of Labour, 50% share: sourcing, cleaning, preprocessing data, documentation, voiceover, mybinder setup, repo management.

1.2 Functionality Overview

This Jupyter notebook tool was developed to enable the visualisation of similarities and differences of the major texts from many of the worlds largest religions. It also includes non-religious works from approximately similar periods (of translation) as a benchmark. While the tool is focused on religious works, it is general enough to be applied to be used to visualize the comparison of books from any genre.

The tool, as supplied, consists of a Jupyter notebook and the raw texts downloaded from the websites below. It requires the installation of a fairly standard Python data science stack as described in the installation section below.

1.2.1 Data Sources

All books were sourced from open data sites in accordance with their licensing terms, as follows:

- Christianity: 2.2 billion followers, King James Bible
- Islam: 1.6 billion followers, Quran (Yusuf Ali version)
- Hinduism: 1 billion followers, Bhagavad Gita
- Buddhism: 380 million followers, Tipitaka
- Mormonism: 15 million followers, Book of Mormon
- Judaism: 14 million followers, Torah
- Shakespeare collection
- Jane Austen collecton

1.3 Installation

1.3.1 Option 1: Cloud

There are two options for installation. The first and simplest isnt really installation at all. The Jupyter notebook can be started directly from mybinder. It will take several minutes to start as it copies across file from this github repo, then builds and starts a docker container with the Python required libraries, but in the meantime you can browse the notebook itself.

1.3.2 Option 2: Local Machine

This Jupyter notebook is built on a reasonably standard Python Data Science stack. Perhaps the easiest to install the prerequisites, if they are not already on your Windows, Mac or Linux machine, is to download and install Anaconda (Python version 3) from here, and then "conda install nltk", or refer to the official NLTK website

If you have an existing Python 3.5 or above installation and don't wish to install Anaconda, you can do the following, but you may need to be careful with versions:

```
pip install numpy scipy matplotlib pandas scikit-learn jupyter nltk
```

You will then need to clone or download the GitHub repo from here. This contains the Jupyter notebook, and the raw religious texts in a directory called 'books-raw'.

At a terminal/command line window you then type 'jupyter notebook' in the dorectory that contains the notebook and books-raw directory. This will start the notebook server at port 8888 on your local machine and open a browser window. If you have any problems check this quickstart guide

1.4 Usage

Clicking on holybook.ipynb in the Jupyter notebook file browser window will open this notebook, and putting your cursor in a cell clicking on ">| Run" will run the cell. The processing steps in this notebook are:

1) **Load libraries**, initialize display options, download stopwords
2) **Define utility functions** for displaying similarity map, displaying topic words, and filtering text.
3) **Text Cleaning:** Sections to clean each book by reading the raw text from file(s) in the "books-raw" directory and creating a cleaned file in the 'books' directory. In the case of the old and new testament, a clean file is created for each chapter.
4) **Text Processing:** Stopword removal, stemming and lemmatization
5) **Word Count Vectorisation** using TFIDF
6) **Topic Discovery** using LDA
7) **t-SNE** based similarity mapping
8) **MDS** based similarity mapping

2 Start of Processing

2.1 Load libraries and initialise options and directory

```
In [1]: import re
        import glob
        import lxml.html
        import os

        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import matplotlib.patches as mpatches
        %matplotlib inline

        import nltk
        from nltk.corpus import stopwords
```

```
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.decomposition import LatentDirichletAllocation
from sklearn.manifold import TSNE, MDS

# set Jupyter to display ALL output from a cell (not just last output)
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

# set pandas and numpy options to make print format nicer
pd.set_option("display.width",100)
pd.set_option("display.max_columns",1000)
pd.set_option('display.max_colwidth', -1)
pd.set_option('display.max_rows', 500)
np.set_printoptions(linewidth=120, threshold=5000, edgeitems=10, suppress=True)

seed = 42

# create clean books directory if doesnt already exist
if not os.path.exists('books'):
    os.makedirs('books')

nltk.download('stopwords')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/graham/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /Users/graham/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Out[1]: True

2.2 Utility Functions

In [2]:
```
# plot similarity map and save as png file at good resolution
def plotmap(topics):
    fig, ax = plt.subplots(figsize=(13,12))  # 12,11 or 8,7
    _ = ax.scatter(topics[:,0], topics[:,1], color='black', s=20)
    _ = plt.title('Holy Book Similarity Map', fontsize=20)
    # _ = plt.xlim(-40,60);  _ = plt.ylim(-65,60)
    _ = ax.grid()

    colourmap = {'OldTestmnt': 'dodgerblue', 'NewTestmnt': 'slateblue', 'Torah':'blue', 'Tipitaka':'palevioletr
                 'Quran':'forestgreen', 'SiriGuruGranth':'teal', 'BhagavadGita':'indianred','BookofMormon': 'g
                 'Shakespeare':'darkviolet', 'JaneAusten':'magenta',}
    colours = [colourmap[book[:book.index("-")]] for book in book_names]
    for i, txt in enumerate(book_names):
        _ = ax.annotate(txt, (topics[i,0], topics[i,1]), size=9, ha='center', rotation=0, color=colours[i])

    patchList = []
    for key in colourmap:
            data_key = mpatches.Patch(color=colourmap[key], label=key)
            patchList.append(data_key)
    _ = plt.legend(handles=patchList, fontsize=8)
    _ = plt.tight_layout()
    _ = plt.savefig('holybooksplot', dpi=200)
    _ = plt.show()
#     import mpld3
#     from mpld3 import plugins
#     # mpld3.display(fig)
```

```
#     mpld3.save_html(fig, 'index.html')

def display_topics(model, feature_names, num_top_words): # display words in topic
    for topic_idx, topic in enumerate(model.components_[:-1,:]):
        print("Topic%2d:" % (topic_idx), end='')
        print(",".join([feature_names[i] for i in topic.argsort()[:-num_top_words - 1:-1]]))

# common filtering function used by all books processes below
def stripper(instring):
    outstring = ' '.join(instring.split()).lower()
    outstring = ' '.join(re.findall("[a-zA-Z]+", outstring))
    return outstring

# calculate euclidean distance between two points
from math import hypot
def euclidean_distance(p1,p2):
    x1,y1 = p1
    x2,y2 = p2
    return round(hypot(x2 - x1, y2 - y1),4)

# create dataframe of distances between books
def calc_distances(topics):
    distances = []
    book1 = []
    book2 = []
    for i, vector in enumerate(topics):
        for j in range(i+1,len(topics)):
            book1.append(book_names[i])
            book2.append(book_names[j])
            distances.append(euclidean_distance(topics[i], topics[j]))

    distances_df = pd.DataFrame({'book1': book1, 'book2': book2, 'distance':distances})
    distances_df = distances_df.sort_values('distance')
    return distances_df
```

2.2.1 Process Old Testament

```
In [3]: filename = 'OldTestmnt'
        book = pd.read_csv('books-raw/'+filename+'-raw.txt', sep='~', header=None) # force all into one column
        book['chapter'] = book[0].str.extract('([0-9]?[A-Za-z]*)', expand=False)
        book['content'] = book[0].str.split(' ',1).str[1]
        book.shape

        for chapter in book.chapter.unique():
            content = book[book.chapter==chapter].content.to_string(index=False)
            content = stripper(content)
            with open('books/'+filename+'-'+chapter+'.txt', 'w') as text_file:
                _ = text_file.write(content)
            print(chapter, len(content),', ',end='')
```

```
Out[3]: (23145, 3)
```

```
Ge 190358 , Exo 164531 , Lev 123538 , Num 170811 , Deu 142384 , Josh 97230 , Jdgs 95839 , Ruth 12581 , 1Sm 125340 , 2Sm
```

2.2.2 Process New Testament

```
In [4]: filename = 'NewTestmnt'
        book = pd.read_csv('books-raw/'+filename+'-raw.txt', sep='~', header=None) # force all into one column
        book['chapter'] = book[0].str.extract('([0-9]?[A-Za-z]*)', expand=False)
        book['content'] = book[0].str.split(' ',1).str[1]
        book.shape
```

```
for chapter in book.chapter.unique():
    content = book[book.chapter==chapter].content.to_string(index=False)
    content = stripper(content)
    with open('books/'+filename+'-'+chapter+'.txt', 'w') as text_file:
        _ = text_file.write(content)
    print(chapter, len(content),', ',end='')
```

Out[4]: (7957, 3)

```
Mat 120355 , Mark 76505 , Luke 130271 , John 94621 , Acts 125980 , Rom 48724 , 1Cor 47424 , 2Cor 31034 , Gal 15737 , Epl
```

2.2.3 Process Bhagavad Gita

In [5]:
```
filename = 'BhagavadGita'
book = pd.read_csv('books-raw/'+filename+'-raw.txt', sep='~', header=None) # force all into one column
book = book[~book[0].str.startswith('This free PDF')]
book = book[book[0].str.len() > 3]
book.shape

content = book[0].to_string(index=False)
content = stripper(content)
with open('books/'+filename+'-None.txt', 'w') as text_file:
    _ = text_file.write(content)
print(filename, len(content))
```

Out[5]: (742, 1)

```
BhagavadGita 105424
```

2.2.4 Process Quran

In [6]:
```
filename = 'Quran'
book = pd.read_csv('books-raw/'+filename+'-raw.txt', sep='~', header=None) # force all into one column
book[0] = book[0].str.split('|',2).str[2]
book.shape

content = book[0].to_string(index=False)
content = stripper(content)
with open('books/'+filename+'-None.txt', 'w') as text_file:
    _ = text_file.write(content)
print(filename, len(content))
```

Out[6]: (6236, 1)

```
Quran 862817
```

2.2.5 Process Shakespeare

In [7]:
```
files = glob.glob("books-raw/Shakespeare*.txt")

for filename in files:
    book = pd.read_csv(filename, sep='~', header=None) # force all into one column
    content = book[0].to_string(index=False)
    content = stripper(content)
    with open('books/'+filename[10:-8]+'.txt', 'w') as text_file:
        _ = text_file.write(content)
    print(filename, len(content))
```

```
books-raw/Shakespeare-RomeoAndJuliet-raw.txt 129473
books-raw/Shakespeare-Othello-raw.txt 139984
books-raw/Shakespeare-Macbeth-raw.txt 93565
books-raw/Shakespeare-HenryV-raw.txt 141725
books-raw/Shakespeare-TamingOfShrew-raw.txt 117007
books-raw/Shakespeare-MidsumNightsDream-raw.txt 88784
books-raw/Shakespeare-Hamlet-raw.txt 165856
books-raw/Shakespeare-TheTempest-raw.txt 105207
```

2.2.6 Process Jane Austen

```
In [8]: files = glob.glob("books-raw/JaneAusten*.txt")

        for filename in files:
            book = pd.read_csv(filename, sep='~', header=None) # force all into one column
            content = book[0].to_string(index=False)
            content = stripper(content)
            with open('books/'+filename[10:-8]+'.txt', 'w') as text_file:
                _ = text_file.write(content)
            print(filename, len(content))
```

```
books-raw/JaneAusten-SenseSensibility-raw.txt 651371
books-raw/JaneAusten-LoveFriendship-raw.txt 179509
books-raw/JaneAusten-LadySusan-raw.txt 123625
books-raw/JaneAusten-Emma-raw.txt 846293
books-raw/JaneAusten-NorthangerAbbey-raw.txt 417609
books-raw/JaneAusten-MansfieldPark-raw.txt 852946
books-raw/JaneAusten-PridePrejudice-raw.txt 659224
```

2.2.7 Process Siri Guru Granth

```
In [9]: filename = 'SiriGuruGranth'
        book = pd.read_csv('books-raw/'+filename+'-raw.txt', sep='~', header=None) # force all into one column
        book.shape
        content = book[0].str.replace('[^\x00-\x7F]','').str.replace('(O+ \d+ O+)','').to_string(index=False)
        content = stripper(content)

        with open('books/'+filename+'-None.txt', 'w') as text_file:
            _ = text_file.write(content)
        print(filename, len(content))
```

```
Out[9]: (4489, 1)
```

```
SiriGuruGranth 4237657
```

2.2.8 Process Torah

```
In [10]: files = glob.glob("books-raw/Torah*.txt")

         for filename in files:
             book = pd.read_csv(filename, sep='~', header=None) # force all into one column

             content = book[0].str.replace('(\d+,\d+)','').str.replace('{P}','').to_string(index=False)
             content = stripper(content)
             with open('books/'+filename[10:-8]+'.txt', 'w') as text_file:
                 _ = text_file.write(content)
             print(filename, len(content))
```

```
books-raw/Torah-Genesis-raw.txt 191113
books-raw/Torah-Exodus-raw.txt 165019
books-raw/Torah-Numbers-raw.txt 170648
books-raw/Torah-Leviticus-raw.txt 123213
books-raw/Torah-Deuteronomy-raw.txt 143169
```

2.2.9 Process Tipitaka

```
In [11]: files = glob.glob("books-raw/tipitaka/*.html")
         content = ''
         for filename in files:
             with open(filename,'r') as infile:
                 raw_text = infile.read() # read entire data file into a string
             root = lxml.html.document_fromstring(raw_text)
             for html_class in ['chapter', 'freeverse']:
                 parent = root.find_class(html_class)
                 if len(parent) > 0:
                     parent = parent[0].getchildren()
                     for child in parent:
                         content += '' if child.text is None else child.text

         content = stripper(content)
         with open('books/Tipitaka-None.txt', 'w') as text_file:
             _ = text_file.write(content)
         print('books/Tipitaka-None.txt', len(content))
```

```
books/Tipitaka-None.txt 3491208
```

2.2.10 Process Book of Mormon

```
In [12]: filename = 'BookofMormon'
         book = pd.read_csv('books-raw/'+filename+'-raw.txt', sep='~', header=None) # force all into one column
         book.shape
         content = book[0].to_string(index=False)
         content = stripper(content)

         with open('books/'+filename+'-None.txt', 'w') as text_file:
             _ = text_file.write(content)
         print(filename, len(content))
```

```
Out[12]: (32947, 1)
```

```
BookofMormon 1428514
```

2.3 Prepare Text for Analysis

Create a list of all stopword using NLTK's English stopwords and appending a number of old-English words

```
In [13]: all_stopwords = ['one','thy','thou','thee','shall','unto','hath','let','ye','shalt','hast','thee','upon','said
                          'thine','come','speak','without','us','also','ay','without','name','tis','st',
                         'saith','thus','thereof','put','may']

         all_stopwords.extend(stopwords.words('english'))
         all_stopwords = set(all_stopwords)
```

Create a list "all_books" where each element is the cleaned text of a book with stopwords removed, and create a list of book names where each element is the name of the book.

```
In [14]: all_books = []
         # book_files = glob.glob("books/*.txt")
         book_files = ['books/OldTestmnt-Hos.txt', 'books/JaneAusten-Emma.txt', 'books/OldTestmnt-Ge.txt', 'books/NewTes
         for book_file in book_files:
             with open(book_file, 'r') as text_file:
                 book_text = text_file.read()
                 tokens = [word for word in book_text.split() if word not in all_stopwords]
                 book_text = ' '.join(tokens)
                 all_books.append(book_text)

         book_names = [book[6:-4] for book in book_files]
         print(book_names)
```

```
['OldTestmnt-Hos', 'JaneAusten-Emma', 'OldTestmnt-Ge', 'NewTestmnt-1Cor', 'OldTestmnt-2Ki', 'OldTestmnt-Num', 'NewTestmn
```

2.4 Pre-process Word Tokens (optional)

The following section apply either stemming lemmatization or no pre-processing. It was found that pre-processing did not have any significant benefit for topic identification so this is turned off by default. To turn on change either of the following variables (but not both) to True

```
In [15]: %%time
         stem = False
         lemmatize = True


         if stem:
             stemmer = nltk.stem.PorterStemmer()

             for i, book_text in enumerate(all_books):
                 tokens = [stemmer.stem(word) for word in book_text.split()]
                 all_books[i] = ' '.join(tokens)


         if lemmatize:
             lemma = nltk.wordnet.WordNetLemmatizer()

             for i, book_text in enumerate(all_books):
                 tokens = [lemma.lemmatize(word) for word in book_text.split()]
                 all_books[i] = ' '.join(tokens)
```

```
CPU times: user 6.35 s, sys: 108 ms, total: 6.45 s
Wall time: 6.49 s
```

2.5 Word Count Vectorization

The following section applies Term Frequency Inverse Document Frequency (TFIDF) word count vectorization to all_books. It also filters stop-words, uses both unigrams and bigrams, and omits words that occur in less than 5% of books, or more than 90% of books.

It creates a numpy array 'wc_vectors' with one row for each book, and one column for each word in the vocabulary, the dimensions of which are output below. It also creates a list of the feature_names of each of these columns, of which a sample is shown. Note that TFIDF vectorization was found to be more stable that simple word count vectorization (included for reference but commented out).

```
In [16]: %%time
         # vect = CountVectorizer(stop_words=all_stopwords, ngram_range=(1,2), min_df=0.05, max_df=0.9)
         vect = TfidfVectorizer(stop_words=all_stopwords, ngram_range=(1,2), min_df=0.05, max_df=0.9)
         wc_vectors = vect.fit_transform(all_books)
```

```
feature_names = vect.get_feature_names()
wc_vectors.shape
print('Sample feature names:',feature_names[0:20])
```

```
Sample feature names: ['aaron', 'aaron brother', 'aaron came', 'aaron died', 'aaron eleazar', 'aaron garment', 'aaron lo
CPU times: user 4.23 s, sys: 136 ms, total: 4.37 s
Wall time: 4.38 s
```

2.6 Topic Discovery

Latent Dirichlet Allocation (LDA) is used to identify the specified number of topics from the TFIDF vectors supplied. It returns a numpy array with one row for each book, and one column for each topic weight, with dimensions shown below. The most heavily weighted few words are shown for each topic in the model.

```
In [17]: %%time
lda_model = LatentDirichletAllocation(n_components=28, learning_method = 'batch', random_state=seed)
X_topics = lda_model.fit_transform(wc_vectors)
X_topics.shape

display_topics(lda_model, feature_names, 8)
```

```
Topic 0:king,israel,people,house,land,came,go,lord god
Topic 1:joab,supreme,action,universe,intellect,sage,bliss,attain
Topic 2:beloved,myrrh,lily,roe,real,spouse,spice,mistaken
Topic 3:spake,pharaoh,abraham,tabernacle,joseph,send,ark,vanity
Topic 4:love,heart,faith,way,see,spirit,would,forth
Topic 5:ungodly,reserved,lasciviousness,gomorrha,enoch,lord rebuke,prophesied saying,disputed
Topic 6:unclean,aaron son,atonement,make atonement,made fire,pause,offering made,penalty
Topic 7:hamlet,deceiver,jehu,elect,abideth,began reign,speed,king syria
Topic 8:christ,jesus,jesus christ,world,lord jesus,glory,grace,mind
Topic 9:miss,dear,however,edward,replied,nurse,affection,soon
Topic10:gourd,great city,tarshish,god prepared,cast forth,doest well,cause evil,tempestuous
Topic11:lust,knowing,subject,saviour,conversation,exhort,god saviour,sober
Topic12:mr,sir,lady,de,th,exeunt,wish,exit
Topic13:principality,rich glory,lest man,forgiveness sin,forbearing,day heard,sailed,beguile
Topic14:twelve thousand,great city,heaven saying,voice heaven,know work,four twenty,god almighty,angel came
Topic15:feeling,whatever,consciousness,quality,perception,view,remains,sense
Topic16:banquet,month month,king house,thirteenth,every people,twelfth month,medium,published
Topic17:scripture,suffered,longsuffering,virtue,ever amen,whereby,ungodly,dumb
Topic18:day lord,house lord,daniel,dream,run,rain,glad,governor
Topic19:job,verily say,desolation,doest,coast,receiveth,punish,house judah
Topic20:esau,shouldest,persia,day calamity,begot,obadiah,benaiah,entered gate
Topic21:saul,joshua,suburb,jeroboam,ahab,samuel,fairy,jonathan
Topic22:dead,angel,husband,begat,promise,oh,verily,sat
Topic23:socket,board,curtain,blue purple,chaldean,zedekiah,pure gold,magician
Topic24:disciple,peter,pharisee,john,simon,synagogue,chief priest,galilee
Topic25:bowel,sly,tailor,sirrah,yet love,might much,servant brother,though might
Topic26:mount olive,mitre,wave sea,heaped,david house,boy girl,set men,resemblance
CPU times: user 7.68 s, sys: 1.21 s, total: 8.89 s
Wall time: 2.39 s
```

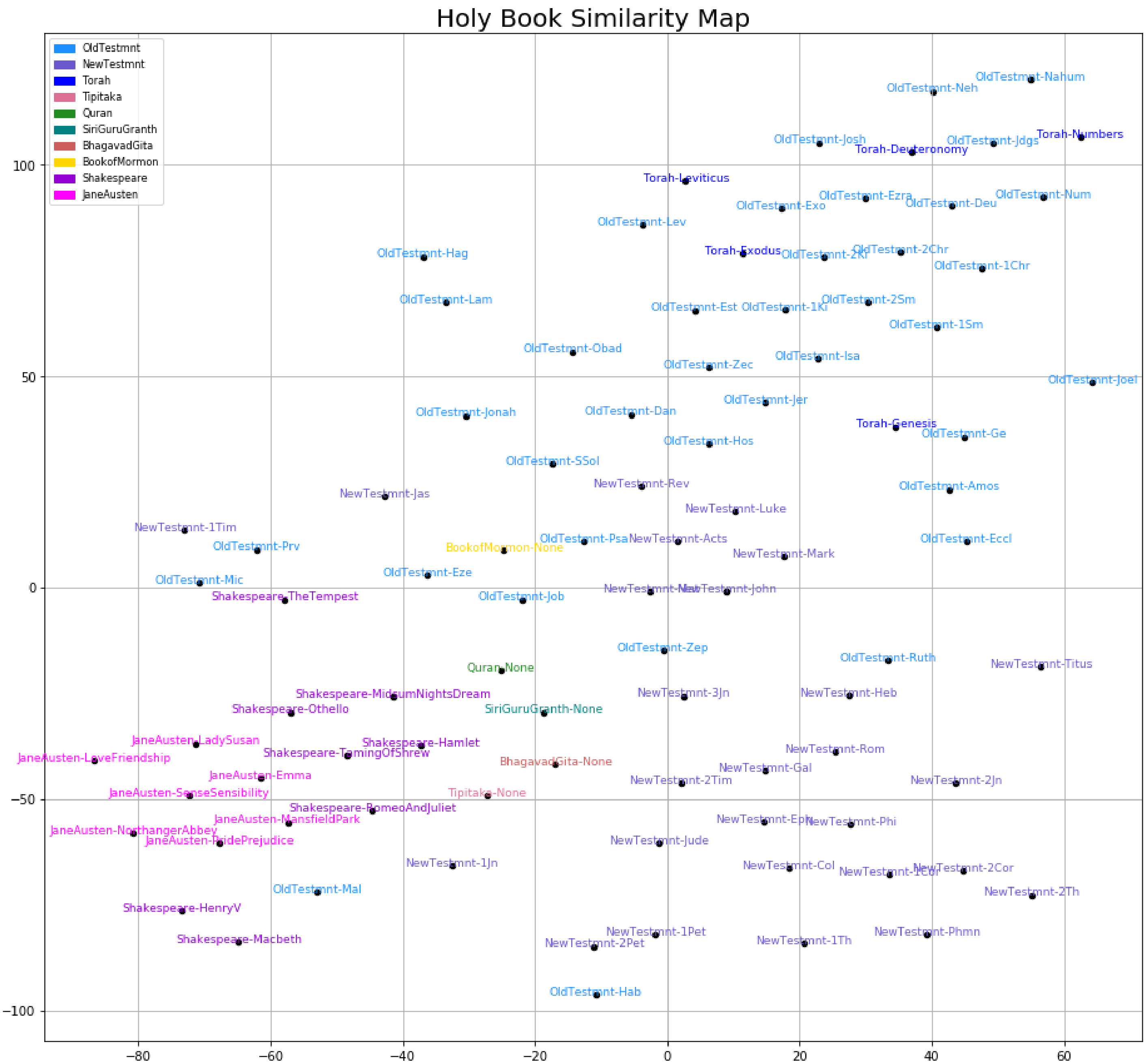
2.7 Apply t-SNE to LDA topics to map to 2-D and plot similarity map

t-Distributed Stochastic Neighbor Embedding projects the multidimensional topic model generated by LDA onto two dimensions to enable plotting. It has two main tunable parameters, perplexity which losely is a way of balancing between local and global elements of the data, and early_exaggeration controls the tightness of clustering. Tuning t-SNE to get the clearest separation requires some experimentation with the parameters. It provides a better visual separation of the data points than MDS (below), but it more sensitive to small changes in the input data.

Further information is available at https://distill.pub/2016/misread-tsne/

```
In [21]: tsne = TSNE(n_components=2, perplexity=27, early_exaggeration=12, init='pca',verbose=0, random_state=seed)
         tsne_topics = tsne.fit_transform(X_topics)
         plotmap(tsne_topics)

         distances_df = calc_distances(tsne_topics)
         topmost = 12
         print('\nTop {} most related books'.format(topmost))
         distances_df[:topmost]
         print('\nTop {} least related books'.format(topmost))
         distances_df[-topmost:]
```



Top 12 most related books

Out[21]:

	book1	book2	distance
572	NewTestmnt-2Pet	NewTestmnt-1Pet	9.7490
3194	NewTestmnt-Heb	OldTestmnt-Ruth	10.2963
186	OldTestmnt-Ge	Torah-Genesis	10.5483
322	NewTestmnt-1Cor	NewTestmnt-2Cor	11.1878
155	JaneAusten-Emma	JaneAusten-MansfieldPark	11.2134
3406	NewTestmnt-3Jn	OldTestmnt-Zep	11.2162
1152	OldTestmnt-Lam	OldTestmnt-Hag	11.2363
3186	NewTestmnt-Luke	NewTestmnt-Acts	11.2522
2069	Shakespeare-HenryV	Shakespeare-Macbeth	11.3434
3827	JaneAusten-MansfieldPark	JaneAusten-PridePrejudice	11.3757
2857	Shakespeare-TamingOfShrew	Shakespeare-Hamlet	11.4013
608	NewTestmnt-2Pet	OldTestmnt-Hab	11.4544

Top 12 least related books

Out[21]:

	book1	book2	distance
2065	Shakespeare-HenryV	OldTestmnt-Jdgs	219.0368
3274	OldTestmnt-Neh	OldTestmnt-Hab	219.4833
1349	OldTestmnt-Nahum	OldTestmnt-Mal	220.3487
4007	OldTestmnt-Jdgs	Shakespeare-Macbeth	220.6499
1346	OldTestmnt-Nahum	JaneAusten-NorthangerAbbey	223.9295
2037	Shakespeare-HenryV	OldTestmnt-Neh	224.4646
1393	OldTestmnt-Nahum	OldTestmnt-Hab	226.1138
3265	OldTestmnt-Neh	Shakespeare-Macbeth	226.7845
2052	Shakespeare-HenryV	Torah-Numbers	227.8430
3760	Torah-Numbers	Shakespeare-Macbeth	228.9460
1329	OldTestmnt-Nahum	Shakespeare-HenryV	234.6922
1384	OldTestmnt-Nahum	Shakespeare-Macbeth	236.4643

2.8 Apply MDS to LDA topics to map to 2-D and plot similarity map

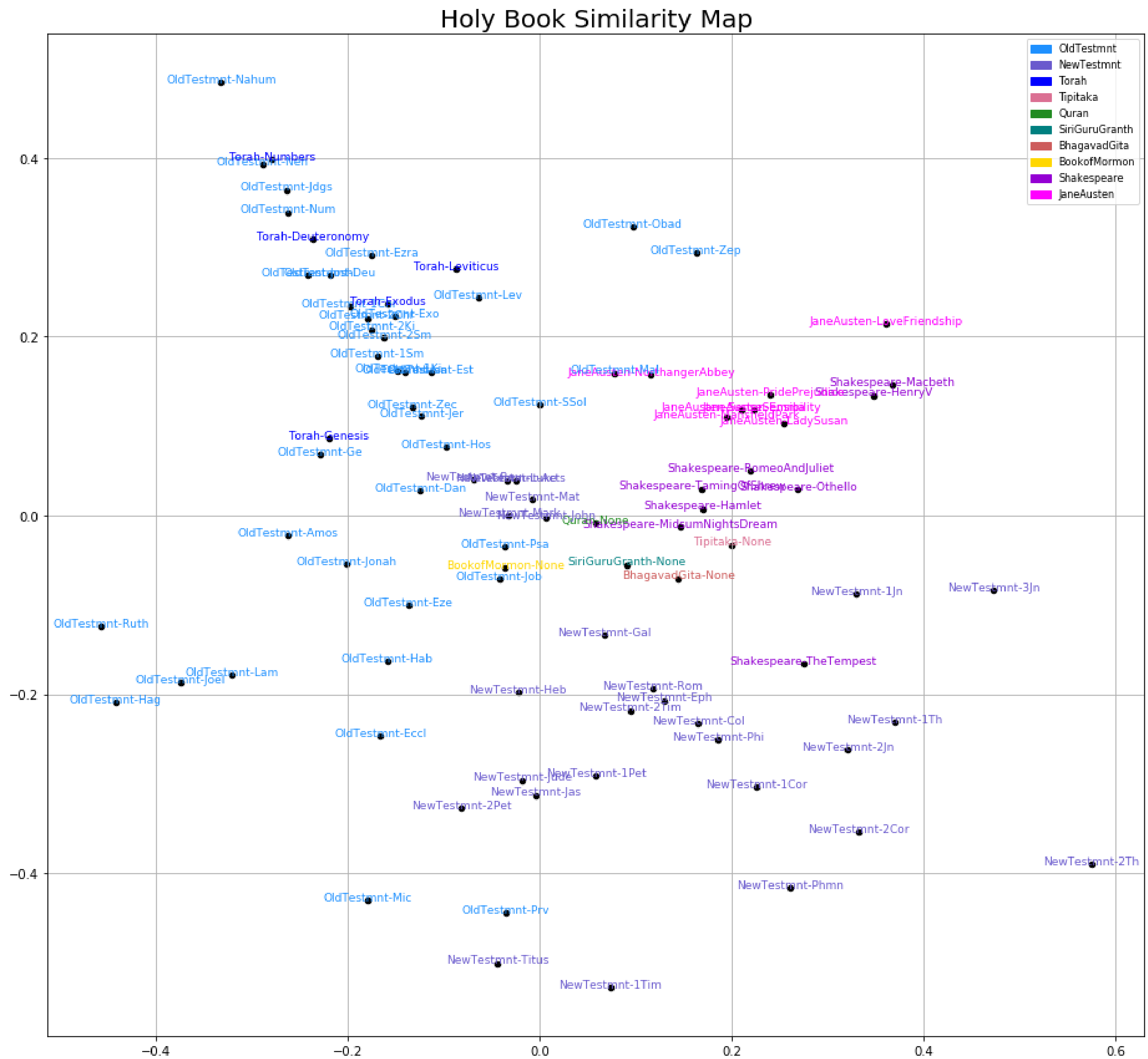
Multidimensial Scaling (MDS) is a conceptually simpler approach than t-SNE to project the multidimensional topics onto two dimensional space. This results in more visual clutter (as the points are not 'forced' apart as in the t-SNE method) and a lower clustering clustering accuracy. i.e. the most and least related books are not as intuitive.

Therefore the t-SNE approach is preferred however this section is included for completeness and reference.

In [22]:
```
mds = MDS(n_components=2, metric=True, verbose=0, random_state=seed)
mds_topics = mds.fit_transform(X_topics)
plotmap(mds_topics)

distances_df = calc_distances(mds_topics)

topmost = 12
print('\nTop {} most related books'.format(topmost))
distances_df[:topmost]
print('\nTop {} least related books'.format(topmost))
distances_df[-topmost:]
```



Top 12 most related books

Out[22]:

	book1	book2	distance
1999	OldTestmnt-1Ki	OldTestmnt-Isa	0.0077
3186	NewTestmnt-Luke	NewTestmnt-Acts	0.0095
3248	OldTestmnt-Neh	Torah-Numbers	0.0109
171	JaneAusten-Emma	JaneAusten-SenseSensibility	0.0132
371	OldTestmnt-2Ki	OldTestmnt-2Chr	0.0136
2553	OldTestmnt-Jer	OldTestmnt-Zec	0.0137
1178	BookofMormon-None	OldTestmnt-Job	0.0139
357	OldTestmnt-2Ki	OldTestmnt-2Sm	0.0156

3632	Torah-Exodus	OldTestmnt-Exo	0.0159
3056	NewTestmnt-Rom	NewTestmnt-Eph	0.0176
3834	JaneAusten-MansfieldPark	JaneAusten-SenseSensibility	0.0176
186	OldTestmnt-Ge	Torah-Genesis	0.0205

```
Top 12 least related books
```

Out[22]:

	book1	book2	distance
3517	NewTestmnt-2Th	OldTestmnt-Hag	1.0333
3504	NewTestmnt-2Th	OldTestmnt-Josh	1.0496
3319	OldTestmnt-Ruth	NewTestmnt-2Th	1.0666
1362	OldTestmnt-Nahum	NewTestmnt-2Cor	1.0696
3500	NewTestmnt-2Th	Torah-Deuteronomy	1.0711
1331	OldTestmnt-Nahum	NewTestmnt-Phmn	1.0778
1341	OldTestmnt-Nahum	NewTestmnt-1Tim	1.0899
490	OldTestmnt-Num	NewTestmnt-2Th	1.1105
3520	NewTestmnt-2Th	OldTestmnt-Jdgs	1.1274
3507	NewTestmnt-2Th	Torah-Numbers	1.1627
3240	OldTestmnt-Neh	NewTestmnt-2Th	1.1653
1359	OldTestmnt-Nahum	NewTestmnt-2Th	1.2595