6.13 Code Exercise 6

Max Ryoo (hr2ee)

Set up

In [1]:
```
import pandas as pd
import numpy as np
import re
from numpy.linalg import norm
from scipy.spatial.distance import pdist
```

In [2]:
```
import seaborn as sns
sns.set(style="ticks")

%matplotlib inline
```

In [3]:
```
OHCO = ['book_id', 'chap_num', 'para_num', 'sent_num', 'token_num']
SENTS = OHCO[:4]
PARAS = OHCO[:3]
CHAPS = OHCO[:2]
BOOKS = OHCO[:1]
```

Import

In [4]:
```
VOCAB = pd.read_csv('../M05/HW_5_DATA/VOCAB.csv').set_index('term_id')
LIB = pd.read_csv('../M05/HW_5_DATA/LIB.csv').set_index('book_id')
TOKEN = pd.read_csv('../M05/HW_5_DATA/TOKEN.csv')
```

Resolve into only Austen's Novels

HINT: You can use your TOKEN file from the previous assignment where you can filter out tokens for Austen's novels using the above LIB data (book_id as join key, think inner join)

In [5]:
```
LIB = LIB[LIB['author'] == 'austen']
```

In [6]:
```
LIB
```

Out[6]:

book_id	book_title	book_file	author	title
158	Emma, by Jane Austen	epubs/AUSTEN_JANE_EMMA-pg158.txt	austen	Emma
946	Lady Susan, by Jane Austen	epubs/AUSTEN_JANE_LADY_SUSAN-pg946.txt	austen	Lady Susan
1212	Love And Freindship And Other Early Works, by ...	epubs/AUSTEN_JANE_LOVE_AND_FREINDSHIP_SIC_-pg1...	austen	Love And Freindship And Other Early Works
141	Mansfield Park, by Jane Austen	epubs/AUSTEN_JANE_MANSFIELD_PARK-pg141.txt	austen	Mansfield Park
121	Northanger Abbey, by Jane Austen	epubs/AUSTEN_JANE_NORTHANGER_ABBEY-pg121.txt	austen	Northanger Abbey
105	Persuasion, by Jane Austen	epubs/AUSTEN_JANE_PERSUASION-pg105.txt	austen	Persuasion
1342	Pride and Prejudice, by Jane Austen	epubs/AUSTEN_JANE_PRIDE_AND_PREJUDICE-pg1342.txt	austen	Pride and Prejudice
161	Sense and Sensibility, by Jane Austen	epubs/AUSTEN_JANE_SENSE_AND_SENSIBILITY-pg161.txt	austen	Sense and Sensibility

In [7]:

```
np.unique(LIB.index.values)
```

Out[7]:

```
array([ 105,  121,  141,  158,  161,  946, 1212, 1342])
```

In [8]:

```
## Filter austen
TOKEN = TOKEN[TOKEN['book_id'].isin(LIB.index.values)]
TOKEN = TOKEN.set_index(OHCO)
```

In [9]:

```
TOKEN
```

Out[9]:

book_id	chap_num	para_num	sent_num	token_num	pos_tuple	pos	token_str	ter
158	1	1	0	0	('Emma', 'NNP')	NNP	Emma	
				1	('Woodhouse,', 'NNP')	NNP	Woodhouse,	wood
				2	('handsome,', 'NN')	NN	handsome,	hand
				3	('clever,', 'NN')	NN	clever,	
				4	('and', 'CC')	CC	and	
...	...	...	...	...	...	...	...	
161	50	21	0	57	('producing', 'VBG')	VBG	producing	proc
				58	('coolness', 'NN')	NN	coolness	co
				59	('between', 'IN')	IN	between	be
				60	('their', 'PRP$')	PRP$	their	
				61	('husbands.', 'NN')	NN	husbands.	hus

795399 rows × 4 columns

In [10]:

```
TOKEN = TOKEN[~TOKEN.term_str.isna()]
VOCAB = VOCAB[~VOCAB.term_str.isna()]
TOKEN['term_id'] = TOKEN.term_str.map(VOCAB.reset_index().set_index('term_str')
```

```
/var/folders/pn/dgy7ckd90nl7mlj6g6rc_1kw0000gn/T/ipykernel_80831/548902373.py:
3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
able/user_guide/indexing.html#returning-a-view-versus-a-copy
  TOKEN['term_id'] = TOKEN.term_str.map(VOCAB.reset_index().set_index('term_st
r').term_id)
```

Add a feature for work year in the LIB table. Use the data provided in the Appendix. You will use these date to interpret your results

- Scholarly side note: This is the publication year in most cases. For works published posthumously, the year refers to when scholars think the work was actually completed

In [11]:

```
austen_work_dates = [
    [158, 1815, 'Emma'],
    [946, 1794, "Lady Susan"],
    [1212, 1790, "Love And Freindship And Other Early Works"],
    [141, 1814, "Mansfield Park"],
```

```
    [121, 1803, "Northanger Abbey"],
    [105, 1818, "Persuasion"],
    [1342, 1813, "Pride and Prejudice"],
    [161, 1811, "Sense and Sensibility"],
]
austen_work_df = pd.DataFrame(austen_work_dates, columns = ['book_id', 'year',
austen_work_df
```

Out[11]:

	book_id	year	title
0	158	1815	Emma
1	946	1794	Lady Susan
2	1212	1790	Love And Freindship And Other Early Works
3	141	1814	Mansfield Park
4	121	1803	Northanger Abbey
5	105	1818	Persuasion
6	1342	1813	Pride and Prejudice
7	161	1811	Sense and Sensibility

In [12]:
```
LIB
```

Out[12]:

book_id	book_title	book_file	author	title
158	Emma, by Jane Austen	epubs/AUSTEN_JANE_EMMA-pg158.txt	austen	Emma
946	Lady Susan, by Jane Austen	epubs/AUSTEN_JANE_LADY_SUSAN-pg946.txt	austen	Lady Susan
1212	Love And Freindship And Other Early Works, by ...	epubs/AUSTEN_JANE_LOVE_AND_FREINDSHIP_SIC_-pg1...	austen	Love And Freindship And Other Early Works
141	Mansfield Park, by Jane Austen	epubs/AUSTEN_JANE_MANSFIELD_PARK-pg141.txt	austen	Mansfield Park
121	Northanger Abbey, by Jane Austen	epubs/AUSTEN_JANE_NORTHANGER_ABBEY-pg121.txt	austen	Northanger Abbey
105	Persuasion, by Jane Austen	epubs/AUSTEN_JANE_PERSUASION-pg105.txt	austen	Persuasion
1342	Pride and Prejudice, by Jane Austen	epubs/AUSTEN_JANE_PRIDE_AND_PREJUDICE-pg1342.txt	austen	Pride and Prejudice
161	Sense and Sensibility, by Jane Austen	epubs/AUSTEN_JANE_SENSE_AND_SENSIBILITY-pg161.txt	austen	Sense and Sensibility

In [13]:
```
LIB = pd.merge(LIB, austen_work_df[['book_id','year']], on="book_id", how="inne
```

Creating TFIDF

In [14]:
```
def get_tfidf(token, ohco_level, count_method, tf_method, idf_method):
    ## "bag" --> ohco_level
    BOW = token.groupby(ohco_level+['term_id']).term_id.count().to_frame().rena
    BOW['c'] = BOW.n.astype('bool').astype('int')

    DTCM = BOW[count_method].unstack().fillna(0).astype('int')

    ## tf_method from params
    if tf_method == 'sum':
        TF = DTCM.T / DTCM.T.sum()

    elif tf_method == 'max':
        TF = DTCM.T / DTCM.T.max()

    elif tf_method == 'log':
        TF = np.log10(1 + DTCM.T)

    elif tf_method == 'raw':
        TF = DTCM.T

    elif tf_method == 'double_norm':
        TF = DTCM.T / DTCM.T.max()
        TF = tf_norm_k + (1 - tf_norm_k) * TF[TF > 0]

    elif tf_method == 'binary':
        TF = DTCM.T.astype('bool').astype('int')

    TF = TF.T

    ## Compute DF
    DF = DTCM[DTCM > 0].count()

    ## Compute IDF
    N = DTCM.shape[0]

    ## idf_method from params
    if idf_method == 'standard':
        IDF = np.log10(N / DF)

    elif idf_method == 'max':
        IDF = np.log10(DF.max() / DF)

    elif idf_method == 'smooth':
        IDF = np.log10((1 + N) / (1 + DF)) + 1

    ## Compute TFIDF
    TFIDF = TF * IDF

    return TFIDF
```

In [15]:
```
TFIDF = get_tfidf(TOKEN, BOOKS, 'n', 'sum', 'standard')
TFIDF
```

Out[15]:

term_id	1	2	3	6	11	14	15	18	
book_id									
105	0.000000	0.000014	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.
121	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.
141	0.000000	0.000000	0.000011	0.000000	0.000000	0.000000	0.000000	0.000000	0.
158	0.000000	0.000000	0.000000	0.000011	0.000000	0.000000	0.000000	0.000000	0.
161	0.000000	0.000005	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.
946	0.000000	0.000000	0.000026	0.000000	0.000000	0.000000	0.000000	0.000000	0.
1212	0.000054	0.000000	0.000000	0.000000	0.000054	0.000027	0.000027	0.000027	0
1342	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.

8 rows × 14727 columns

Create a DOC table

In [16]:
```
DOC = TFIDF.reset_index()['book_id']
```

In [17]:
```
DOC = pd.DataFrame(DOC, columns = ['book_id'])
```

In [18]:
```
DOC
```

Out[18]:

	book_id
0	105
1	121
2	141
3	158
4	161
5	946
6	1212
7	1342

In [19]:
```
DOC.index.name = 'doc_id' # We give the new index a name
```

In [20]:
```
DOC
```

Out[20]:

doc_id	book_id
0	105
1	121
2	141
3	158
4	161
5	946
6	1212
7	1342

In [21]:

```
LIB
```

Out[21]:

	book_id	book_title	book_file	author	title
0	158	Emma, by Jane Austen	epubs/AUSTEN_JANE_EMMA-pg158.txt	austen	Emma
1	946	Lady Susan, by Jane Austen	epubs/AUSTEN_JANE_LADY_SUSAN-pg946.txt	austen	Lady Susan
2	1212	Love And Freindship And Other Early Works, by ...	epubs/AUSTEN_JANE_LOVE_AND_FREINDSHIP_SIC_-pg1...	austen	Love And Freindship And Other Early Works
3	141	Mansfield Park, by Jane Austen	epubs/AUSTEN_JANE_MANSFIELD_PARK-pg141.txt	austen	Mansfield Park
4	121	Northanger Abbey, by Jane Austen	epubs/AUSTEN_JANE_NORTHANGER_ABBEY-pg121.txt	austen	Northanger Abbey
5	105	Persuasion, by Jane Austen	epubs/AUSTEN_JANE_PERSUASION-pg105.txt	austen	Persuasion
6	1342	Pride and Prejudice, by Jane Austen	epubs/AUSTEN_JANE_PRIDE_AND_PREJUDICE-pg1342.txt	austen	Pride and Prejudice
7	161	Sense and Sensibility, by Jane Austen	epubs/AUSTEN_JANE_SENSE_AND_SENSIBILITY-pg161.txt	austen	Sense and Sensibility

In [22]:

```
DOC['title'] = DOC.book_id.map(LIB.set_index('book_id').author) \
```

```
    + '-' + DOC[['book_id']].apply(lambda x: x.astype('str').str.cat(sep='-'),
    + ': '+ DOC.book_id.map(LIB.set_index('book_id').title) \
    + ': '+ DOC.book_id.map(LIB.set_index('book_id').year.astype(str))
```

In [23]:
```
DOC
```

Out[23]:

doc_id	book_id	title
0	105	austen-105: Persuasion: 1818
1	121	austen-121: Northanger Abbey: 1803
2	141	austen-141: Mansfield Park: 1814
3	158	austen-158: Emma: 1815
4	161	austen-161: Sense and Sensibility: 1811
5	946	austen-946: Lady Susan: 1794
6	1212	austen-1212: Love And Freindship And Other Ear...
7	1342	austen-1342: Pride and Prejudice: 1813

Create Normalized Tables

In [24]:
```
L0 = TFIDF.astype('bool').astype('int')
L1 = TFIDF.apply(lambda x: x / x.sum(), 1)
L2 = TFIDF.apply(lambda x: x / norm(x), 1)
```

Create Doc Pair Table

Create a table to store our results.

Note that `pist()` is a "distance matrix computation from a collection of raw observation vectors stored in a rectangular array".

In [25]:
```
PAIRS = pd.DataFrame(index=pd.MultiIndex.from_product([DOC.index.tolist(), DOC.
PAIRS = PAIRS[PAIRS.level_0 < PAIRS.level_1].set_index(['level_0','level_1'])
PAIRS.index.names = ['doc_a', 'doc_b']
```

In [26]:
```
PAIRS.shape
```

Out[26]:
```
(28, 0)
```

In [27]:
```
PAIRS.head()
```

Out[27]:

doc_a	doc_b
0	1
	2
	3
	4
	5

Compute Distances

In [28]:
```
%time PAIRS['cityblock'] = pdist(TFIDF, 'cityblock')
```
```
CPU times: user 885 µs, sys: 195 µs, total: 1.08 ms
Wall time: 709 µs
```

In [29]:
```
%time PAIRS['euclidean'] = pdist(TFIDF, 'euclidean')
```
```
CPU times: user 1.19 ms, sys: 1.97 ms, total: 3.16 ms
Wall time: 762 µs
```

In [30]:
```
%time PAIRS['cosine'] = pdist(TFIDF, 'cosine')
```
```
CPU times: user 1.71 ms, sys: 1.51 ms, total: 3.22 ms
Wall time: 1.13 ms
```

In [31]:
```
%time PAIRS['jaccard'] = pdist(L0, 'jaccard') # Fast, and similar to js
```
```
CPU times: user 1.5 ms, sys: 2.79 ms, total: 4.3 ms
Wall time: 1.13 ms
```

In [32]:
```
%time PAIRS['dice'] = pdist(L0, 'dice')
```
```
CPU times: user 1.37 ms, sys: 2.25 ms, total: 3.62 ms
Wall time: 926 µs
```

In [33]:
```
%time PAIRS['js'] = pdist(L1, 'jensenshannon') # Turns out to be really slow
```
```
CPU times: user 8.54 ms, sys: 11.2 ms, total: 19.8 ms
Wall time: 5.92 ms
```

In [34]:
```
%time PAIRS['euclidean2'] = pdist(L2, 'euclidean') # Should be the same as cosi
```
```
CPU times: user 1.1 ms, sys: 1.52 ms, total: 2.62 ms
Wall time: 743 µs
```

In [35]:
```
PAIRS.head()
```

Out[35]:

doc_a	doc_b	cityblock	euclidean	cosine	jaccard	dice	js	euclidean2
0	1	0.085579	0.006127	0.993740	0.684479	0.520310	0.749041	1.409780
	2	0.081613	0.006548	0.991765	0.642722	0.473538	0.726978	1.408379
	3	0.085155	0.006899	0.996053	0.653259	0.485067	0.744629	1.411420
	4	0.083070	0.007684	0.997107	0.652180	0.483878	0.747470	1.412167
	5	0.089198	0.008322	0.998408	0.852517	0.742945	0.799245	1.413088

Compare Distributions

In [36]:

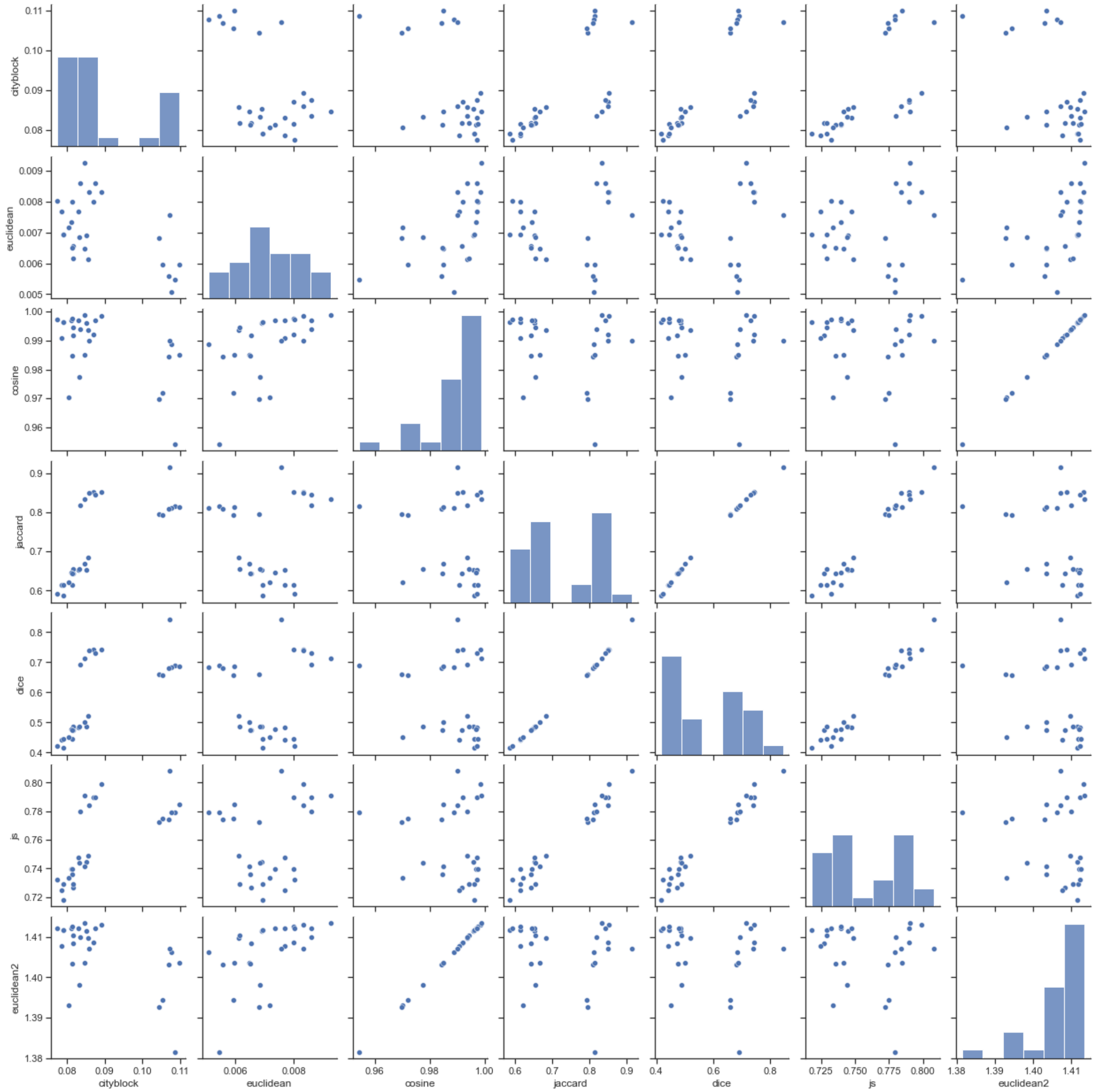
```
if PAIRS.shape[0] > 1000:
    SAMPLE = PAIRS.sample(1000)
else:
    SAMPLE = PAIRS
```

In [37]:

```
sns.pairplot(SAMPLE)
```

Out[37]:

```
<seaborn.axisgrid.PairGrid at 0x15034a5b0>
```



In [38]:

```
PAIRS.sort_values('cosine').head(20).style.background_gradient('YlGn')
```

Out[38]:

doc_a	doc_b	cityblock	euclidean	cosine	jaccard	dice	js	euclidean2
0	6	0.108579	0.005461	0.954275	0.815468	0.688431	0.779452	1.381502
4	6	0.104384	0.006806	0.969851	0.794752	0.659409	0.772317	1.392732
3	7	0.080522	0.007163	0.970280	0.620422	0.449719	0.733672	1.393040
6	7	0.105395	0.005945	0.972049	0.793417	0.657573	0.774967	1.394309
0	7	0.083164	0.006849	0.977539	0.654391	0.486315	0.744135	1.398241
2	6	0.106921	0.005570	0.984302	0.809091	0.679389	0.774153	1.403069
1	7	0.081250	0.006498	0.984756	0.643080	0.473927	0.735702	1.403393
	3	0.084651	0.006484	0.984914	0.667950	0.501445	0.741518	1.403506
3	6	0.109871	0.005963	0.984969	0.813691	0.685902	0.784579	1.403545
1	6	0.107733	0.005074	0.988726	0.811157	0.682309	0.779250	1.406219
5	6	0.107093	0.007562	0.990078	0.915267	0.843772	0.808017	1.407180
2	5	0.085936	0.008310	0.990092	0.850234	0.739484	0.783991	1.407190
	4	0.078507	0.007682	0.990750	0.613689	0.442678	0.724551	1.407658
0	2	0.081613	0.006548	0.991765	0.642722	0.473538	0.726978	1.408379
1	5	0.087071	0.007988	0.992212	0.851427	0.741292	0.789655	1.408696
0	1	0.085579	0.006127	0.993740	0.684479	0.520310	0.749041	1.409780
5	7	0.083544	0.008603	0.993846	0.818652	0.692981	0.780040	1.409855
1	2	0.081578	0.006157	0.994470	0.654541	0.486482	0.729374	1.410298
0	3	0.085155	0.006899	0.996053	0.653259	0.485067	0.744629	1.411420
2	3	0.078923	0.006924	0.996304	0.586344	0.414771	0.717959	1.411598

Create Clusters

Hiearchical

In [39]:

```
import scipy.cluster.hierarchy as sch
import matplotlib.pyplot as plt
```

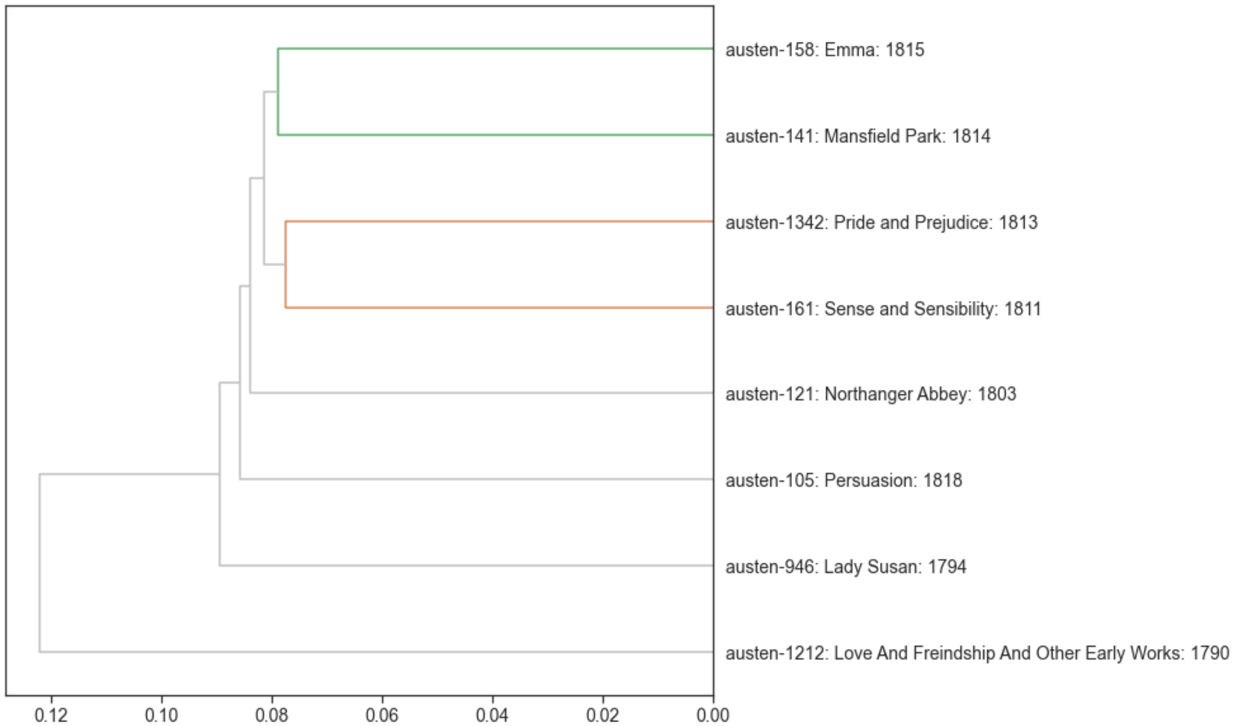
In [40]:

```
def hca(sims, linkage_method='ward', color_thresh=.3, figsize=(10, 10)):
    tree = sch.linkage(sims, method=linkage_method)
    labels = DOC.title.values
    plt.figure()
    fig, axes = plt.subplots(figsize=figsize)
    dendrogram = sch.dendrogram(tree,
                                labels=labels,
                                orientation="left",
                                count_sort=True,
                                distance_sort=True,
                                above_threshold_color='.75',
                                color_threshold=color_thresh
```

```
                            )
    plt.tick_params(axis='both', which='major', labelsize=14)
```

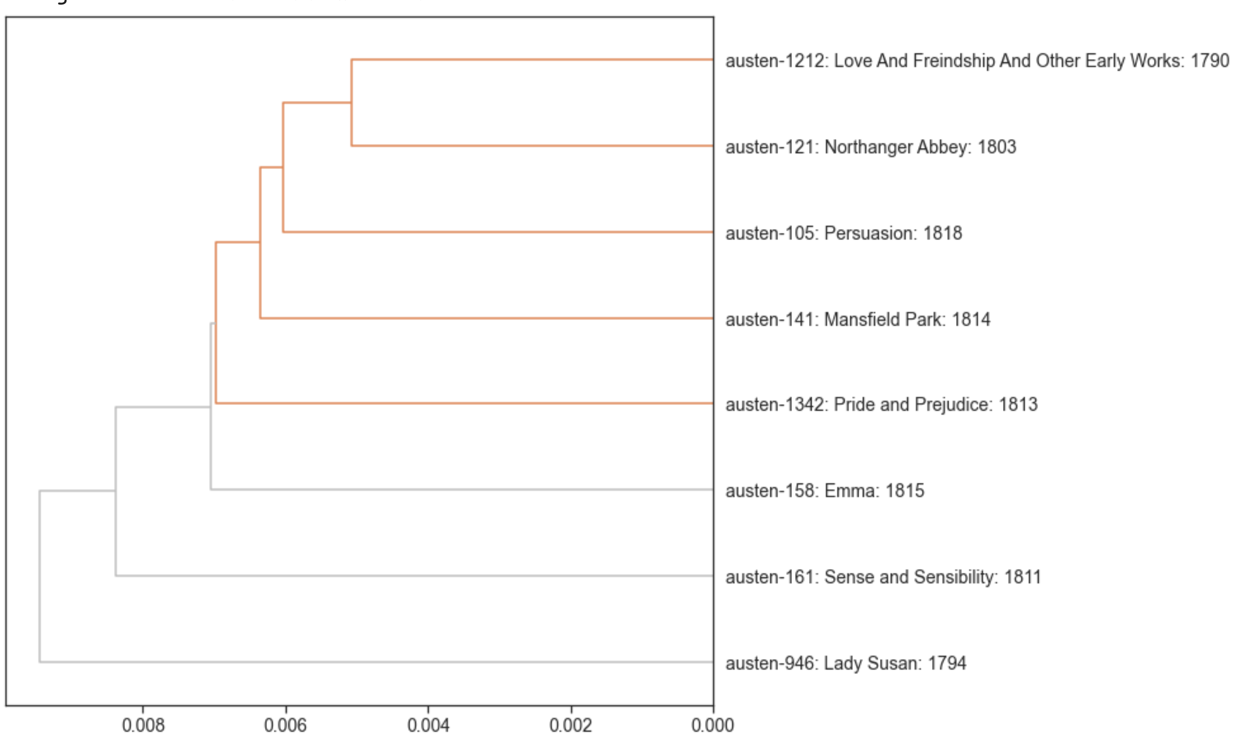
In [41]:
```
hca(PAIRS.cityblock, color_thresh=.08)
```

<Figure size 432x288 with 0 Axes>



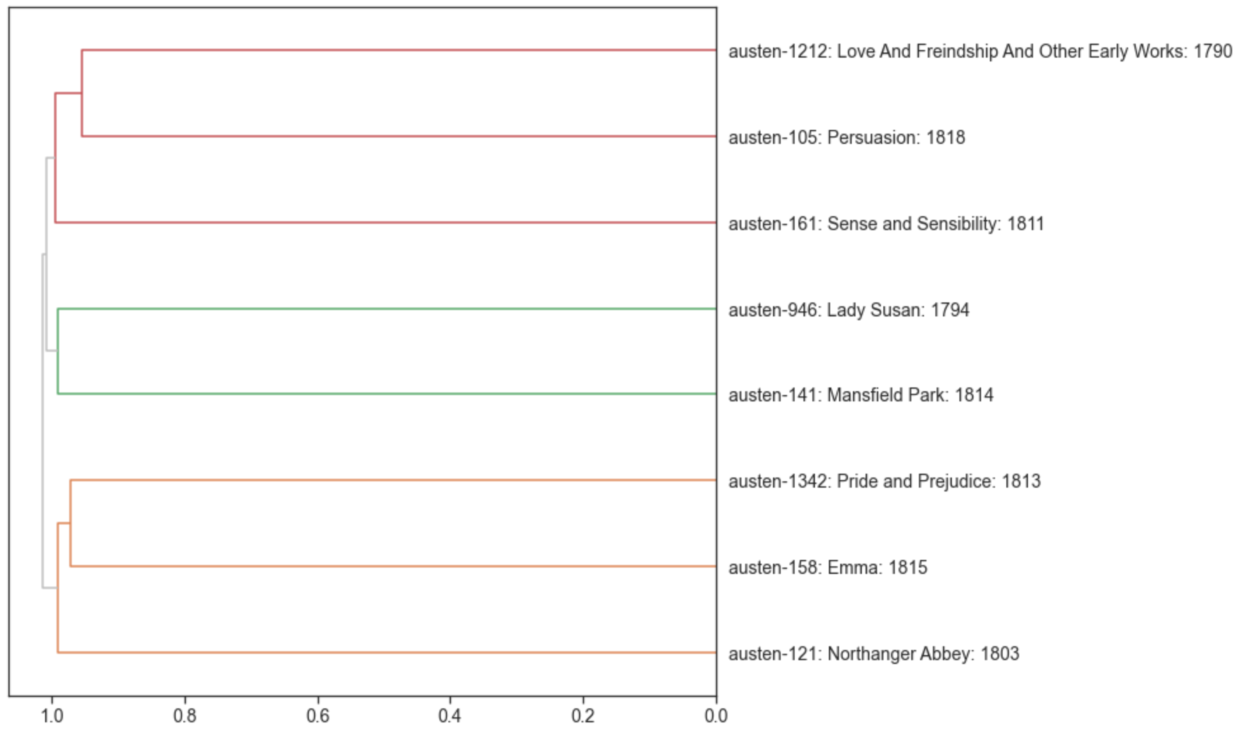
In [42]:
```
hca(PAIRS.euclidean, color_thresh=.007)
```

<Figure size 432x288 with 0 Axes>



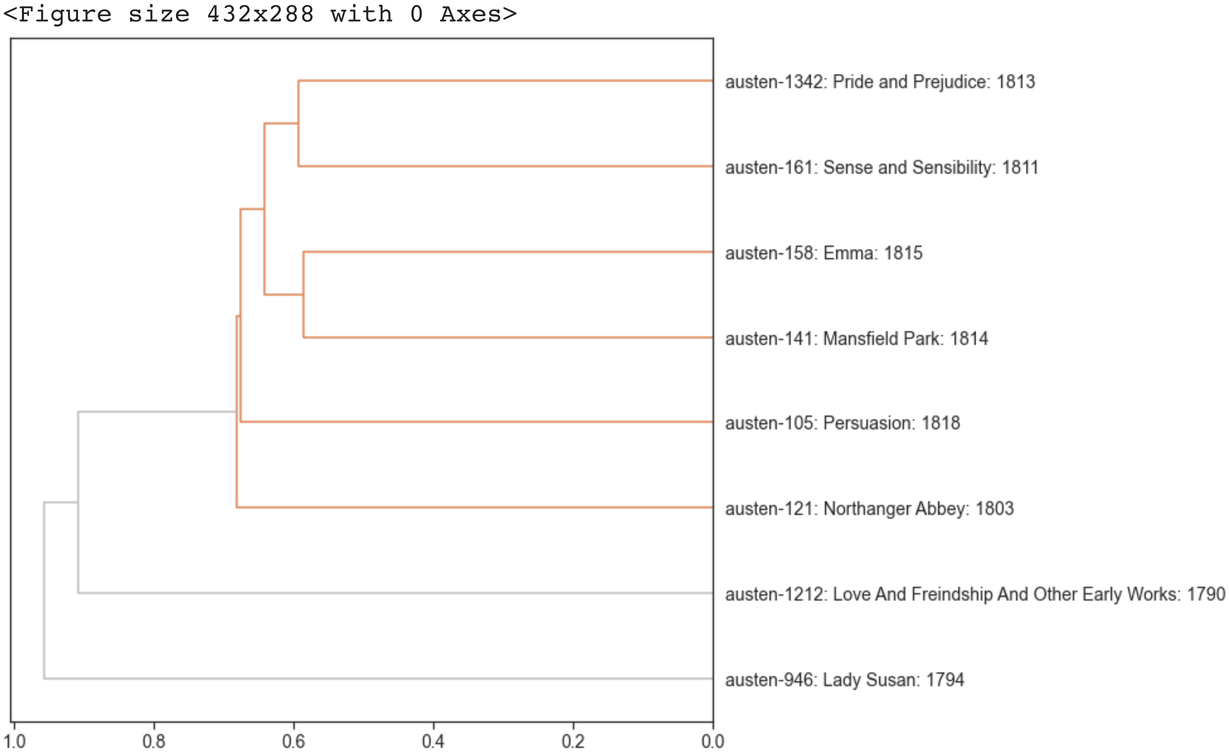
In [43]:
```
hca(PAIRS.cosine, color_thresh=1)
```

<Figure size 432x288 with 0 Axes>



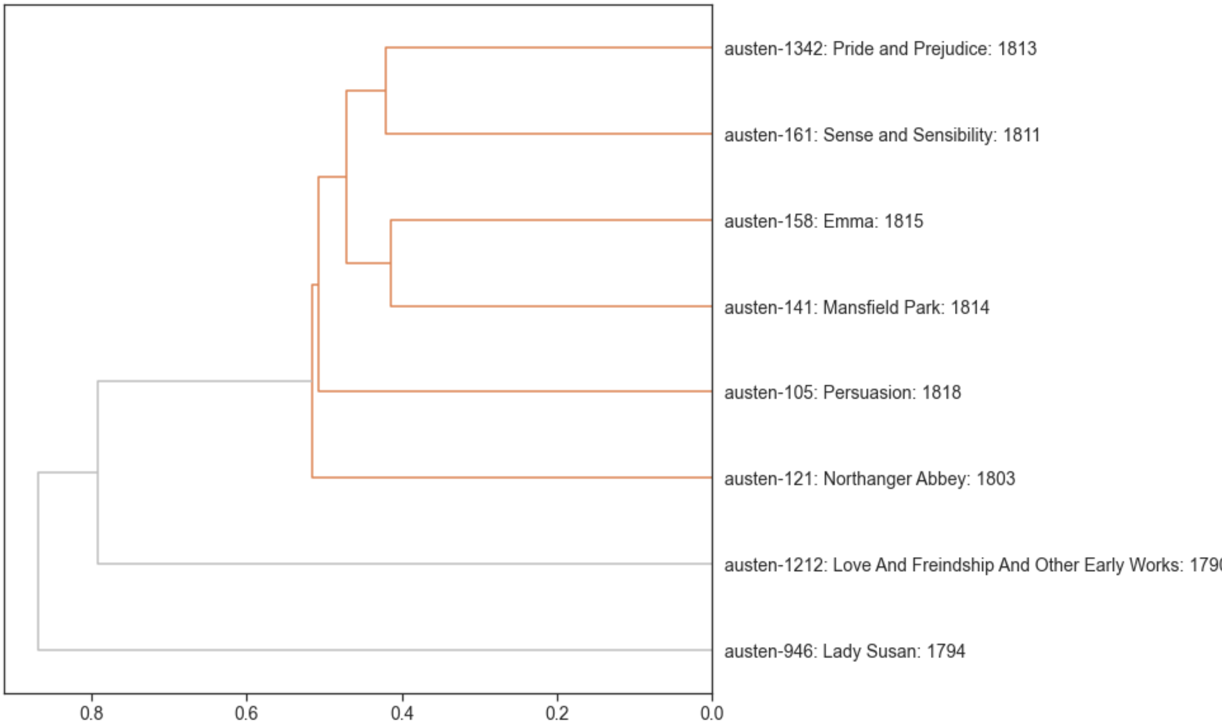
In [44]:
```
hca(PAIRS.jaccard, color_thresh=.8)
```

```
<Figure size 432x288 with 0 Axes>
```



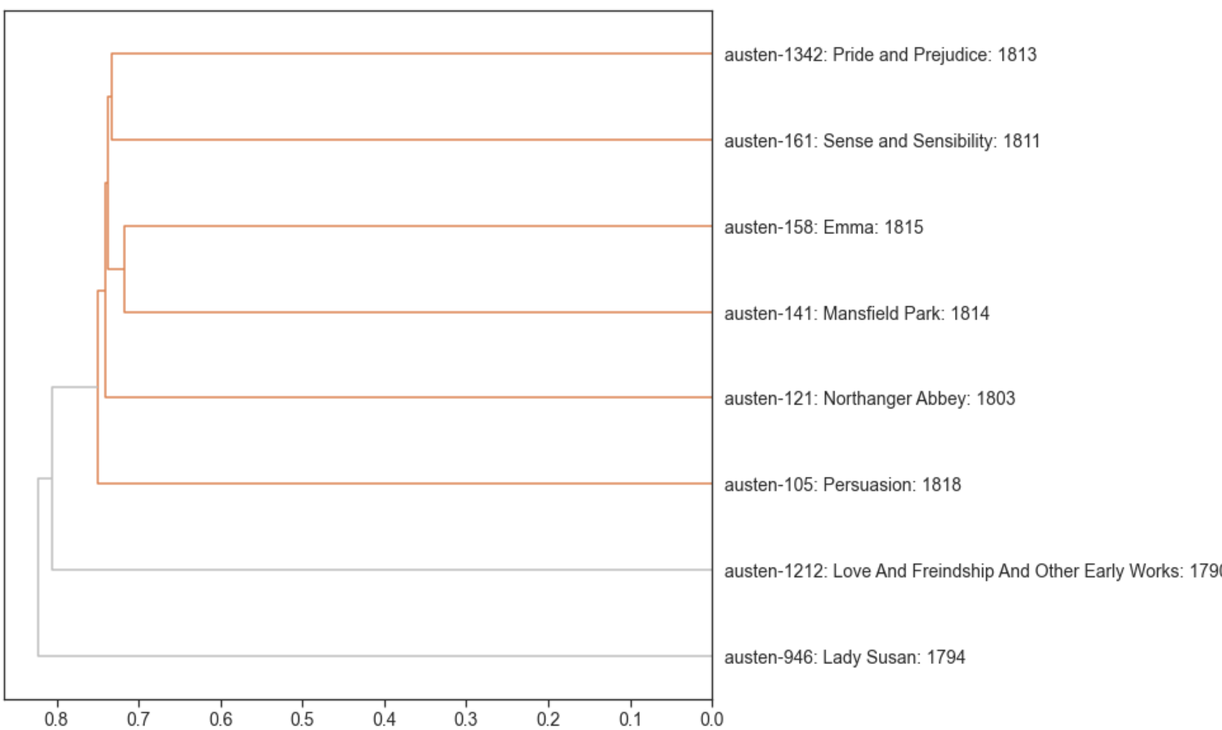
In [45]:
```
hca(PAIRS.dice, color_thresh=.6)
```

```
<Figure size 432x288 with 0 Axes>
```



In [46]:
```
hca(PAIRS.js, color_thresh=.8)
```

```
<Figure size 432x288 with 0 Axes>
```



Given the dendrograms, it seems that the js and dice seems to cluster well based on year. The majority of 1800+ are grouped togther while the later 1790,1794 are seperated out. The other metrics did not perform this well, which is why js and dice seems to be the best ones to consider for clustering.

In [ ]: