Final Project Step 3 Dendograms

```
Course:   DS 5001
Module:   Final
Date:     8 May 2022
Author:   Thomas McIntyre gem5cm@virginia.edu
Purpose:  This notebook will utlize the data created in step 2 to begin
creatin and visualizing dendo grams.
```

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import nltk
from numpy.linalg import norm
sns.set()
from scipy.spatial.distance import pdist
import scipy.cluster.hierarchy as sch
import matplotlib.pyplot as plt
```

In [2]:

```
data_home = "data"
local_lib = "code"
OHCO = ['book_id', 'chap_num', 'para_num', 'sent_num', 'token_num']
SENTS = OHCO[:4]
PARAS = OHCO[:3]
CHAPS = OHCO[:2]
BOOKS = OHCO[:1]
```

Dendograms

In [3]:

```
LIB = pd.read_csv(f"{data_home}/LIB.csv").set_index(OHCO[:1])
CORPUS = pd.read_csv(f"{data_home}/CORPUS.csv").set_index(OHCO)
VOCAB = pd.read_csv(f"{data_home}/VOCAB.csv").set_index("term_str")
BOW = pd.read_csv(f"{data_home}/BOW.csv").rename(columns = {"Unnamed: 2": "term_str"}).
TFIDF = pd.read_csv(f"{data_home}/TFIDF.csv").set_index(CHAPS)
DOC = pd.read_csv(f"{data_home}/DOC.csv").set_index(CHAPS)
```

In [4]:

```
top2000 = VOCAB.loc[VOCAB["max_pos"].isin(["NN","NNS", "VB", "VBD", "VBG", "VBN", "VBP"
top2000
```

Out[4]:

	n	tfidf_mean	df	dfidf	p	i	max_pos	n_pos	stop
term_str									
easy	264	0.003811	196	282.883248	0.000305	11.676997	JJ	10.0	0
present	359	0.005527	197	282.880161	0.000415	11.233551	JJ	9.0	0
fool	388	0.005420	195	282.878975	0.000449	11.121478	NN	10.0	0
big	489	0.006594	195	282.878975	0.000566	10.787701	JJ	6.0	0
loved	381	0.005573	195	282.878975	0.000441	11.147744	VBD	9.0	0
...	...	...	...	...	...	...	...	...	...
footsteps	72	0.001811	53	176.493777	0.000083	13.551466	NNS	5.0	0

	n	tfidf_mean	df	dfidf	p	i	max_pos	n_pos	stop
term_str									
wretch	80	0.001917	53	176.493777	0.000093	13.399463	NN	7.0	0
yielded	67	0.001791	53	176.493777	0.000078	13.655302	VBN	7.0	0
bench	99	0.002380	53	176.493777	0.000115	13.092035	NN	4.0	0
mocking	59	0.001500	53	176.493777	0.000068	13.838748	NN	3.0	0

2000 rows × 9 columns

In [5]:

```
TFIDF = TFIDF[top2000.index]
TFIDF = TFIDF.groupby(["book_id"]).mean()
TFIDF
```

Out[5]:

	easy	present	fool	big	loved	darkness	steps	shut	age	liv
book_id										
1	0.004083	0.001266	0.007018	0.007183	0.006815	0.007443	0.008497	0.002683	0.006253	0.002
2	0.004564	0.001065	0.012901	0.011203	0.006092	0.005780	0.009275	0.003651	0.003900	0.004
3	0.003920	0.001722	0.009380	0.016399	0.004820	0.005722	0.008983	0.002936	0.002885	0.003
4	0.003743	0.006236	0.002390	0.006358	0.001431	0.014794	0.003828	0.007132	0.002822	0.006
16	0.003126	0.004115	0.000000	0.007385	0.008047	0.004034	0.000000	0.008710	0.001726	0.002
730	0.002316	0.003051	0.001227	0.001212	0.001822	0.003502	0.003346	0.005030	0.004587	0.003
768	0.002808	0.015923	0.005726	0.000773	0.007676	0.002370	0.004932	0.010804	0.005991	0.011
1260	0.005670	0.013803	0.002717	0.000788	0.008189	0.004000	0.006244	0.010322	0.008154	0.007
1400	0.004430	0.010641	0.000795	0.000408	0.003380	0.002407	0.001643	0.006785	0.002659	0.004
1727	0.001627	0.012887	0.002397	0.000989	0.002455	0.007677	0.001586	0.003635	0.006704	0.006
6130	0.003350	0.006425	0.000202	0.001852	0.012782	0.005715	0.005253	0.001206	0.016230	0.007
26654	0.003482	0.004080	0.000000	0.007784	0.007965	0.003997	0.000000	0.007183	0.001689	0.002

12 rows × 2000 columns

In [6]:

```
L0 = TFIDF.astype('bool').astype('int') # Binary (Pseudo L)
L1 = TFIDF.apply(lambda x: x / x.sum(), 1) # Manhattan
L2 = TFIDF.apply(lambda x: x / norm(x), 1) # Euclidean

PAIRS = 1 - TFIDF.T.corr().stack().to_frame('corr-raw') # 1 - corr() is considered a di
PAIRS.index.names = ['doc_a','doc_b']
PAIRS = PAIRS.query("doc_a > doc_b") #

combos  = [
    (TFIDF, 'cityblock', 'cityblock-raw'),
    (TFIDF, 'cosine', 'cosine-raw'),
    (L2, 'euclidean', 'euclidean-l2'),
    (L0, 'jaccard', 'jaccard-l0'),
    (L1, 'jensenshannon', 'jensenshannon-l1'),
]

for X, metric, label in combos:
    PAIRS[label] = pdist(X, metric)

PAIRS
```

Out[6]:

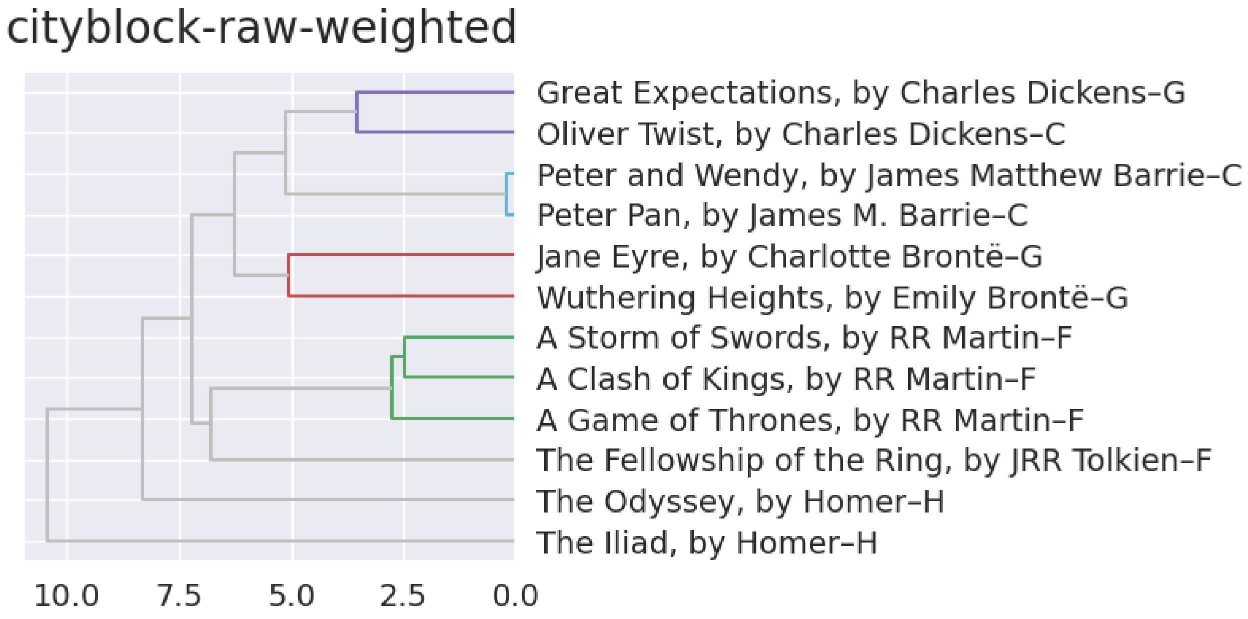
		corr-raw	cityblock-raw	cosine-raw	euclidean-l2	jaccard-l0	jensenshannon-l1
doc_a	**doc_b**						
2	**1**	0.129255	2.694847	0.064280	0.358553	0.019202	0.158872
3	**1**	0.164671	2.806215	0.082284	0.405671	0.017650	0.177303
	2	0.114413	6.651375	0.429195	0.926494	0.096076	0.395412
4	**1**	0.750748	6.702633	0.558086	1.056490	0.266968	0.469951
	2	0.756606	6.399848	0.525179	1.024869	0.108500	0.441777
...	**...**	...	...	...	...	...	...
26654	**768**	0.731766	10.271389	0.729901	1.208223	0.281813	0.572818
	1260	0.724278	5.171052	0.470130	0.969670	0.250784	0.420600
	1400	0.713360	10.379747	0.594158	1.090099	0.283971	0.517599
	1727	0.780301	7.859302	0.577729	1.074922	0.316901	0.486979
	6130	0.991243	10.064711	0.744780	1.220476	0.386203	0.586406

66 rows × 6 columns

In [7]:

```
exec(open("code/methods.py").read())
print(combos[0][-1])
hca(PAIRS[combos[0][-1]],"cityblock-raw-weighted", linkage_method = "weighted")
```

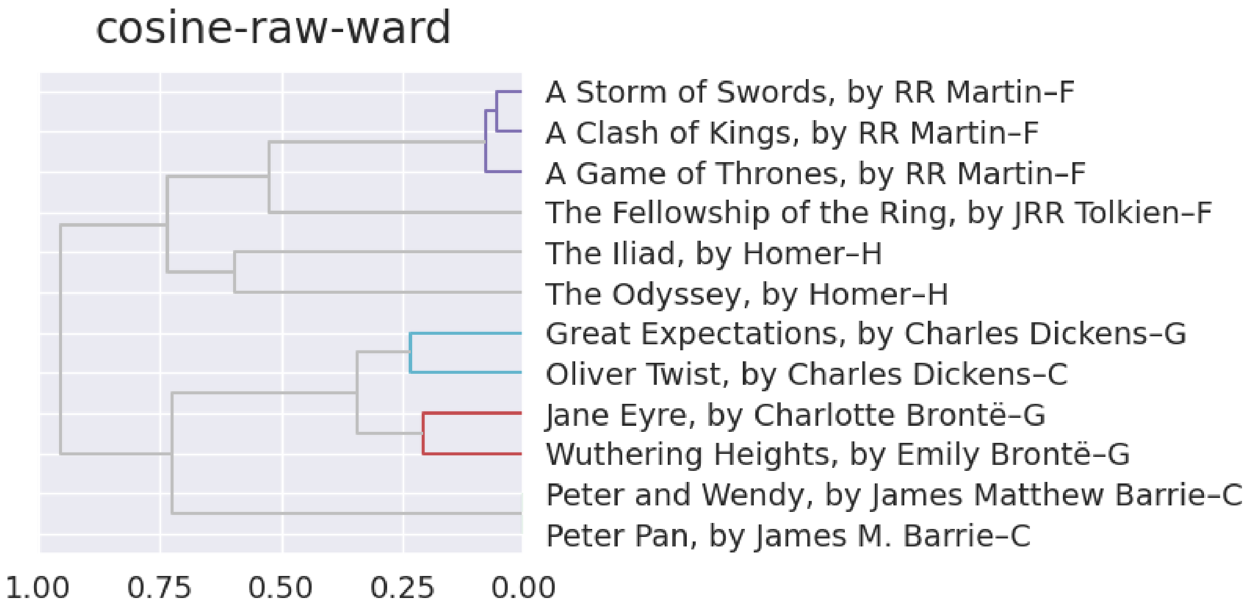
```
cityblock-raw
<Figure size 640x480 with 0 Axes>
```



In [8]:

```
print(combos[1][-1])
hca(PAIRS[combos[1][-1]],"cosine-raw-ward", linkage_method = "ward")
```

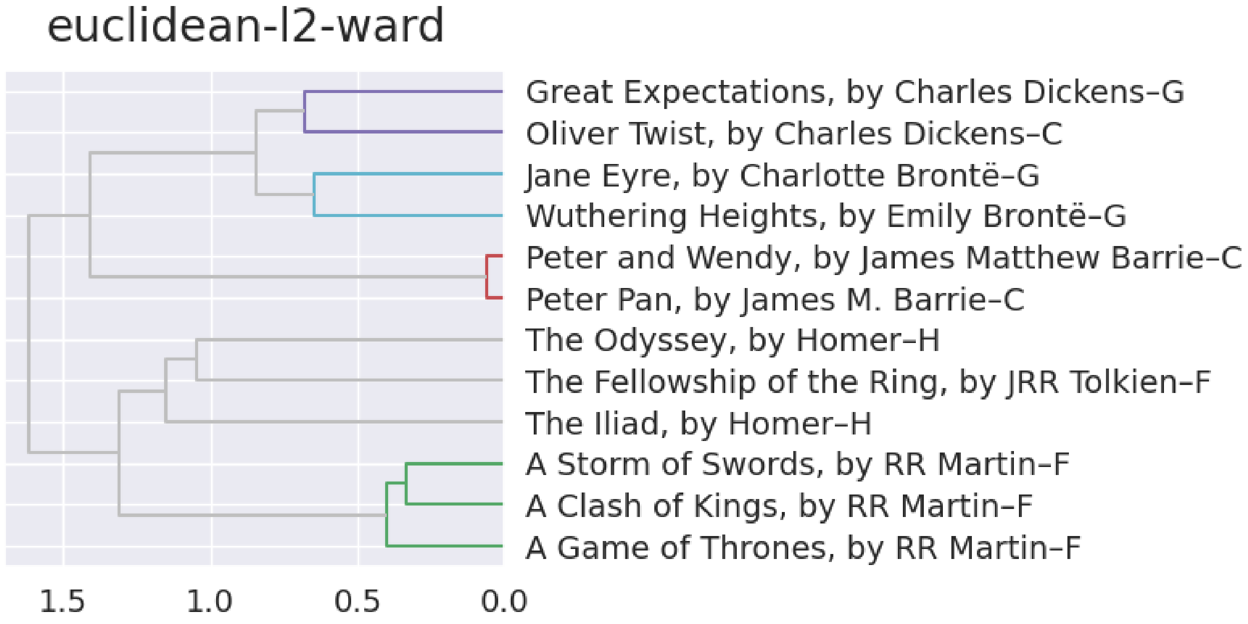
```
cosine-raw
<Figure size 640x480 with 0 Axes>
```



In [9]:

```
print(combos[2][-1])
hca(PAIRS[combos[2][-1]],"euclidean-l2-ward", linkage_method = "ward")
```

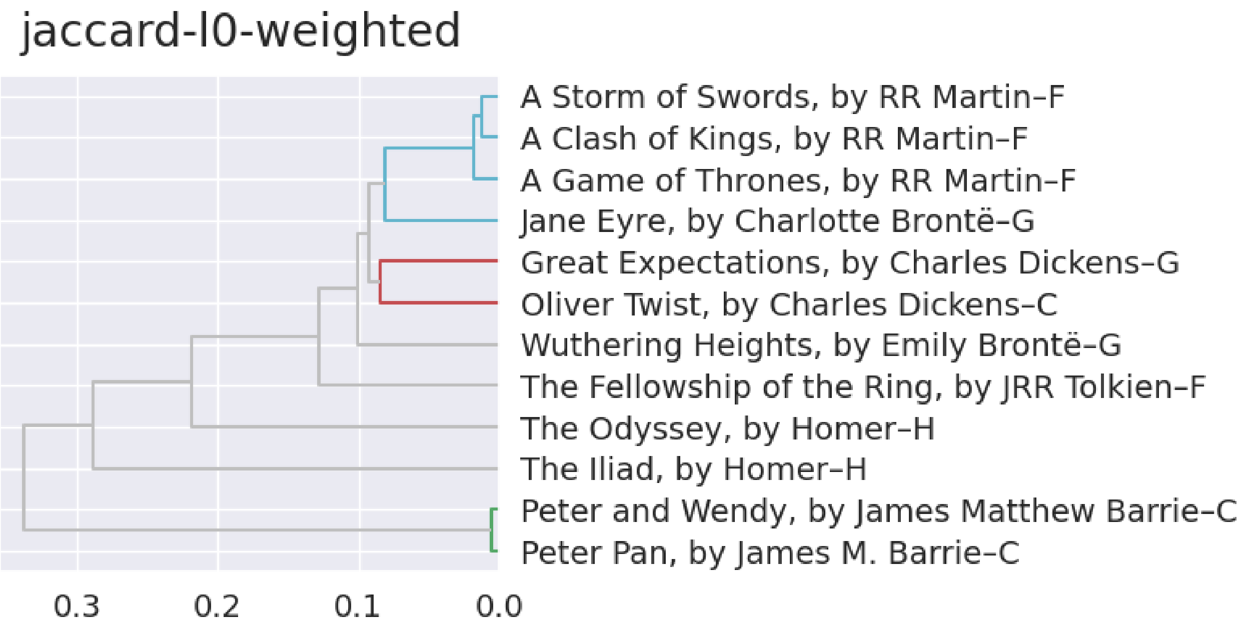
```
euclidean-l2
<Figure size 640x480 with 0 Axes>
```



In [10]:

```
print(combos[3][-1])
hca(PAIRS[combos[3][-1]],"jaccard-l0-weighted", linkage_method = "weighted")
```

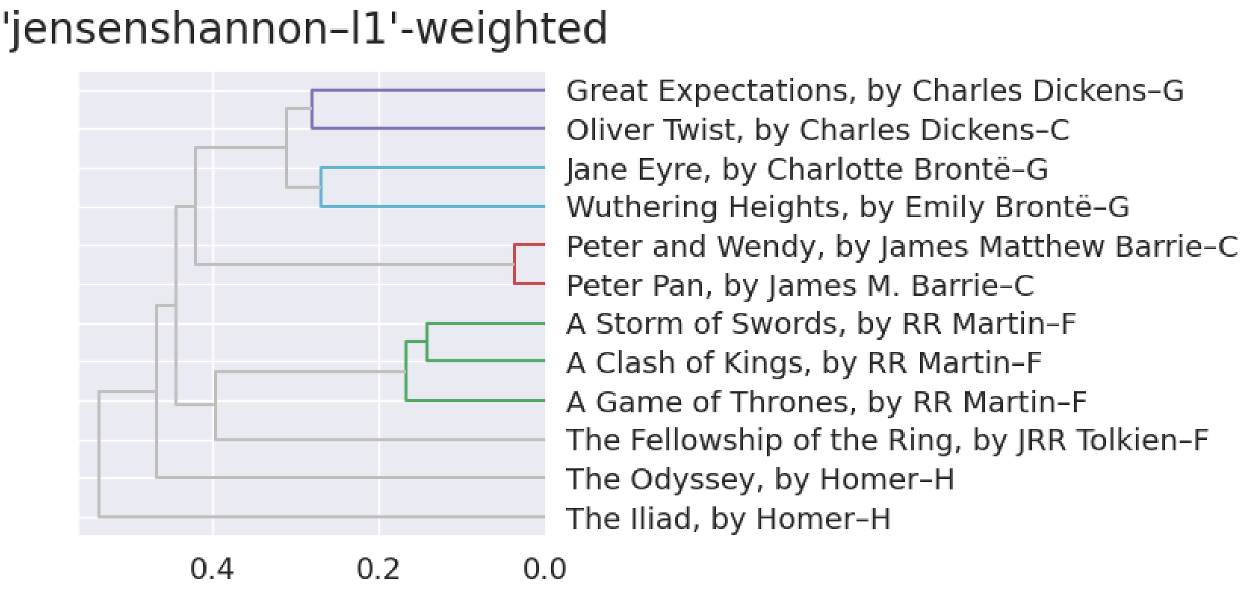
```
jaccard-l0
<Figure size 640x480 with 0 Axes>
```



In [11]:

```
print(combos[4][-1])
hca(PAIRS[combos[4][-1]],"'jensenshannon-l1'-weighted", linkage_method = "weighted")
```

```
jensenshannon-l1
<Figure size 640x480 with 0 Axes>
```



In [12]:

```
PAIRS.to_csv("data/PAIRS.csv")
```

In [19]:

```
LIB
```

Out[19]:

	book_title	book_file	chap_regex	book_le
book_id				
1	A Game of Thrones, by RR Martin	corpus/MARTIN_A_GAME_OF_THRONES-pg1.txt	[A-Z]+[A-Z]+[A-Z]+	29

book_id	book_title	book_file	chap_regex	book_le
2	A Clash of Kings, by RR Martin	corpus/MARTIN_A_CLASH_OF_KINGS-pg2.txt	[A-Z]+[A-Z]+[A-Z]+	32
3	A Storm of Swords, by RR Martin	corpus/MARTIN_A_STORM_OF_SWORDS-pg3.txt	[A-Z]+[A-Z]+[A-Z]+	41
4	The Fellowship of the Ring, by JRR Tolkien	corpus/TOLKIEN_THE_FELLOWSHIP_OF_THE_RING-pg4.txt	_Chapter	18
16	Peter Pan, by James M. Barrie	corpus/BARRIE_PETER_PAN-pg16.txt	((Chapter)\s+\D+)	4
730	Oliver Twist, by Charles Dickens	corpus/DICKENS_OLIVER_TWIST-pg730.txt	((CHAPTER)\s+\D+)	16
768	Wuthering Heights, by Emily Brontë	corpus/BRONTE_WUTHERING_HEIGHTS-pg768.txt	((CHAPTER)\s+\D+)	11
1260	Jane Eyre, by Charlotte Brontë	corpus/BRONTE_JANE_EYRE-pg1260.txt	((CHAPTER)\s+\D+)|PREFACE	19
1400	Great Expectations, by Charles Dickens	corpus/DICKENS_GREAT_EXPECTATIONS-pg1400.txt	((Chapter)\s+\D+)	18
1727	The Odyssey, by Homer	corpus/HOMER_THE_ODYSSEY-pg1727.txt	((BOOK)\s+\D+)	11
6130	The Iliad, by Homer	corpus/HOMER-THE-ILIAD-pg6130.txt	((BOOK)\s+\D+)	15
26654	Peter and Wendy, by James Matthew Barrie	corpus/BARRIE_PETER_AND_WENDY-pg26654.txt	((CHAPTER)\s+\D+)	4

In [18]:

```
PAIRS.style.background_gradient()
```

Out[18]:

doc_a	doc_b	corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
2	1	0.129255	2.694847	0.064280	0.358553	0.019202	0.158872
3	1	0.164671	2.806215	0.082284	0.405671	0.017650	0.177303

		corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
doc_a	doc_b						
	2	0.114413	6.651375	0.429195	0.926494	0.096076	0.395412
4	1	0.750748	6.702633	0.558086	1.056490	0.266968	0.469951
	2	0.756606	6.399848	0.525179	1.024869	0.108500	0.441777
	3	0.771711	8.101119	0.485017	0.984903	0.111612	0.433520
16	1	0.879844	7.583657	0.479037	0.978813	0.083000	0.423842
	2	0.895652	6.490708	0.497365	0.997361	0.091546	0.434171
	3	0.892253	8.363868	0.503809	1.003802	0.197680	0.461599
	4	0.787261	10.124618	0.615819	1.109792	0.267137	0.529219
730	1	0.910884	6.641639	0.558243	1.056639	0.264957	0.469321
	2	0.947610	2.455607	0.055561	0.333350	0.012633	0.142676
	3	0.948544	6.950274	0.424607	0.921528	0.097941	0.394734
	4	0.831134	7.109066	0.559466	1.057796	0.266834	0.470660
	16	0.704133	6.934831	0.535454	1.034847	0.107500	0.447166
768	1	0.928432	8.470164	0.495796	0.995787	0.111556	0.438945
	2	0.972868	7.967502	0.486543	0.986452	0.082000	0.428645
	3	0.962114	7.005722	0.500801	1.000801	0.090545	0.437098
	4	0.798964	8.425893	0.479291	0.979072	0.196672	0.451190
	16	0.732622	10.327463	0.596899	1.092611	0.261748	0.520302
	730	0.527749	7.045716	0.559612	1.057934	0.264824	0.469684
1260	1	0.943370	6.897704	0.435253	0.933009	0.093373	0.402995
	2	0.983680	6.702485	0.559854	1.058163	0.263924	0.472025
	3	0.984662	6.547354	0.539088	1.038353	0.102000	0.451072
	4	0.739076	8.307844	0.493948	0.993929	0.106053	0.440951
	16	0.725076	7.798362	0.490856	0.990813	0.076500	0.432593
	730	0.505519	6.682931	0.507098	1.007073	0.085043	0.441893
	768	0.399325	8.212558	0.500806	1.000805	0.194766	0.454224
1400	1	0.923260	10.072329	0.617486	1.111293	0.259708	0.527069
	2	0.951391	6.628066	0.559292	1.057631	0.261917	0.471038
	3	0.956820	6.684073	0.534151	1.033587	0.268548	0.451581
	4	0.777770	6.482629	0.522529	1.022281	0.137755	0.429364
	16	0.715998	7.965483	0.465739	0.965131	0.135246	0.419524
	730	0.384325	7.159720	0.422456	0.919191	0.120366	0.398601

		corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
doc_a	doc_b						
	768	0.539747	6.490958	0.464005	0.963332	0.127162	0.418480
	1260	0.459056	8.466121	0.549912	1.048725	0.220786	0.466086
1727	1	0.757993	10.537205	0.674407	1.161385	0.297269	0.545138
	2	0.726105	6.640421	0.534361	1.033790	0.267363	0.451701
	3	0.759207	5.118680	0.481349	0.981172	0.250396	0.419827
	4	0.785734	7.302442	0.475141	0.974824	0.255679	0.430029
	16	0.781576	6.692296	0.464154	0.963488	0.247525	0.416477
	730	0.816794	5.235185	0.471909	0.971503	0.251960	0.422019
	768	0.715136	7.921016	0.578737	1.075860	0.319068	0.488190
	1260	0.765269	10.146295	0.744465	1.220217	0.387500	0.586721
	1400	0.748044	0.212942	0.001913	0.061855	0.005355	0.037433
6130	1	0.915830	5.822443	0.312698	0.790820	0.096285	0.312638
	2	0.897099	5.342485	0.294995	0.768108	0.087384	0.307994
	3	0.927083	3.546550	0.232822	0.682381	0.084331	0.280693
	4	0.948808	7.939565	0.574578	1.071987	0.224574	0.474170
	16	0.990714	9.852420	0.724311	1.203587	0.298300	0.561365
	730	1.014291	5.031188	0.477950	0.977702	0.249208	0.417667
	768	1.029609	5.065571	0.208733	0.646116	0.091568	0.270006
	1260	0.974342	5.823409	0.298142	0.772195	0.105318	0.321741
	1400	1.061282	8.688633	0.482467	0.982311	0.222395	0.448635
	1727	0.774705	11.852360	0.697434	1.181046	0.295549	0.563702
26654	1	0.880289	7.261920	0.474511	0.974178	0.253566	0.428451
	2	0.896098	5.240287	0.248071	0.704374	0.086667	0.305711
	3	0.891503	8.538342	0.508198	1.008164	0.203809	0.448270
	4	0.787705	10.762914	0.652393	1.142272	0.270242	0.534799
	16	0.002646	6.647411	0.463570	0.962881	0.245440	0.415309
	730	0.699231	7.795619	0.510257	1.010205	0.211747	0.459843
	768	0.731766	10.271389	0.729901	1.208223	0.281813	0.572818
	1260	0.724278	5.171052	0.470130	0.969670	0.250784	0.420600
	1400	0.713360	10.379747	0.594158	1.090099	0.283971	0.517599
	1727	0.780301	7.859302	0.577729	1.074922	0.316901	0.486979
	6130	0.991243	10.064711	0.744780	1.220476	0.386203	0.586406

In [22]:

```
PAIRS.xs(1, level=1, drop_level=False).style.background_gradient()
```

Out[22]:

		corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
doc_a	**doc_b**						
2	**1**	0.129255	2.694847	0.064280	0.358553	0.019202	0.158872
3	**1**	0.164671	2.806215	0.082284	0.405671	0.017650	0.177303
4	**1**	0.750748	6.702633	0.558086	1.056490	0.266968	0.469951
16	**1**	0.879844	7.583657	0.479037	0.978813	0.083000	0.423842
730	**1**	0.910884	6.641639	0.558243	1.056639	0.264957	0.469321
768	**1**	0.928432	8.470164	0.495796	0.995787	0.111556	0.438945
1260	**1**	0.943370	6.897704	0.435253	0.933009	0.093373	0.402995
1400	**1**	0.923260	10.072329	0.617486	1.111293	0.259708	0.527069
1727	**1**	0.757993	10.537205	0.674407	1.161385	0.297269	0.545138
6130	**1**	0.915830	5.822443	0.312698	0.790820	0.096285	0.312638
26654	**1**	0.880289	7.261920	0.474511	0.974178	0.253566	0.428451

In [23]:

```
PAIRS.xs(2, level=1, drop_level=False).style.background_gradient()
```

Out[23]:

		corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
doc_a	**doc_b**						
3	**2**	0.114413	6.651375	0.429195	0.926494	0.096076	0.395412
4	**2**	0.756606	6.399848	0.525179	1.024869	0.108500	0.441777
16	**2**	0.895652	6.490708	0.497365	0.997361	0.091546	0.434171
730	**2**	0.947610	2.455607	0.055561	0.333350	0.012633	0.142676
768	**2**	0.972868	7.967502	0.486543	0.986452	0.082000	0.428645
1260	**2**	0.983680	6.702485	0.559854	1.058163	0.263924	0.472025
1400	**2**	0.951391	6.628066	0.559292	1.057631	0.261917	0.471038
1727	**2**	0.726105	6.640421	0.534361	1.033790	0.267363	0.451701
6130	**2**	0.897099	5.342485	0.294995	0.768108	0.087384	0.307994
26654	**2**	0.896098	5.240287	0.248071	0.704374	0.086667	0.305711

In [24]:

```
PAIRS.xs(3, level=1, drop_level=False).style.background_gradient()
```

Out[24]:

		corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
doc_a	**doc_b**						
4	**3**	0.771711	8.101119	0.485017	0.984903	0.111612	0.433520
16	**3**	0.892253	8.363868	0.503809	1.003802	0.197680	0.461599
730	**3**	0.948544	6.950274	0.424607	0.921528	0.097941	0.394734

		corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
doc_a	**doc_b**						
768	**3**	0.962114	7.005722	0.500801	1.000801	0.090545	0.437098
1260	**3**	0.984662	6.547354	0.539088	1.038353	0.102000	0.451072
1400	**3**	0.956820	6.684073	0.534151	1.033587	0.268548	0.451581
1727	**3**	0.759207	5.118680	0.481349	0.981172	0.250396	0.419827
6130	**3**	0.927083	3.546550	0.232822	0.682381	0.084331	0.280693
26654	**3**	0.891503	8.538342	0.508198	1.008164	0.203809	0.448270

```
In [25]: PAIRS.loc[1260].style.background_gradient()
```

Out[25]:

	corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
doc_b						
1	0.943370	6.897704	0.435253	0.933009	0.093373	0.402995
2	0.983680	6.702485	0.559854	1.058163	0.263924	0.472025
3	0.984662	6.547354	0.539088	1.038353	0.102000	0.451072
4	0.739076	8.307844	0.493948	0.993929	0.106053	0.440951
16	0.725076	7.798362	0.490856	0.990813	0.076500	0.432593
730	0.505519	6.682931	0.507098	1.007073	0.085043	0.441893
768	0.399325	8.212558	0.500806	1.000805	0.194766	0.454224

```
In [26]: PAIRS.xs(1260, level=1, drop_level=False).style.background_gradient()
```

Out[26]:

		corr–raw	cityblock–raw	cosine–raw	euclidean–l2	jaccard-l0	jensenshannon–l1
doc_a	**doc_b**						
1400	**1260**	0.459056	8.466121	0.549912	1.048725	0.220786	0.466086
1727	**1260**	0.765269	10.146295	0.744465	1.220217	0.387500	0.586721
6130	**1260**	0.974342	5.823409	0.298142	0.772195	0.105318	0.321741
26654	**1260**	0.724278	5.171052	0.470130	0.969670	0.250784	0.420600

```
In [ ]:
```