M07 Homework

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In [ ]:

```python
import pandas as pd
import numpy as np
from glob import glob
import re
import nltk
import plotly_express as px
from lib.textparser import TextParser
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer, TfidfTransformer

from numpy.linalg import norm
from scipy.spatial.distance import pdist
import scipy.cluster.hierarchy as sch
import matplotlib.pyplot as plt
from scipy.linalg import eigh
from sklearn.decomposition import PCA
import seaborn as sns
```

In [ ]:

```python
import configparser
config = configparser.ConfigParser()
config.read("../env.ini")
data_home = config['DEFAULT']['data_home']
output_dir = config['DEFAULT']['output_dir']
data_prefix = 'novels'
```

Import the LIB and CORPUS tables from the provided CSV files. The index OHCO for CORPUS is ['book_id','chapter_id','para_num','sent_num','token_num'] The index for LIB is 'book_id'.

In [ ]:

```python
OHCO = ['book_id','chap_id','para_num','sent_num','token_num']
```

In [ ]:

```python
LIB = pd.read_csv(f"{data_home}/{data_prefix}-LIB.csv").set_index('book_id')
CORPUS = pd.read_csv(f"{data_home}/{data_prefix}-CORPUS.csv").set_index(OHCO)
```

In [ ]:

```python
LIB
```

Out[ ]:

	genre_id	author_id
book_id		
secretadversary	d	christie
styles	d	christie
moonstone	d	collins
adventures	d	doyle
baskervilles	d	doyle
scarlet	d	doyle
signoffour	d	doyle
marieroget	d	poe
ruemorgue	d	poe
northangerabbey	g	austen
christmascarole	g	dickens
monk	g	lewis
pitandpendulum	g	poe
reddeath	g	poe
usher	g	poe
udolpho	g	radcliffe
oldenglishbaron	g	reeve
frankenstein	g	shelley
dracula	g	stoker
castleofotranto	g	walpole

In [ ]:

```python
CORPUS
```

Out[ ]:

					pos	term_str
book_id	**chap_id**	**para_num**	**sent_num**	**token_num**		
secretadversary	**1**	**0**	**1**	**0**	DT	the
				1	NNP	young
				2	NNP	adventurers
				3	NNP	ltd
		1	**0**	**0**	JJ	tommy
...	**...**	**...**	**...**	**...**	...	...
baskervilles	**11**	**114**	**1**	**7**	RBR	more
				8	JJ	comfortable
				9	IN	outside
				10	IN	than
				11	NN	in

1500417 rows × 2 columns

Extract a VOCAB table and add max_pos as a feature.

In [ ]:

```python
CORPUS = CORPUS[CORPUS.term_str != '']
CORPUS['pos_group'] = CORPUS.pos.str[:2]


VOCAB = CORPUS.term_str.value_counts().to_frame('n').sort_index()
VOCAB.index.name = 'term_str'
VOCAB['n_chars'] = VOCAB.index.str.len()
VOCAB['p'] = VOCAB.n / VOCAB.n.sum()
VOCAB['i'] = -np.log2(VOCAB.p)

VOCAB['max_pos'] = CORPUS[['term_str','pos']].value_counts().unstack(fill_value=0).idxmax(1)
```

In [ ]:

```python
VOCAB
```

Out[ ]:

	n	n_chars	p	i	max_pos
term_str					
a	28533	1	1.901674e-02	5.716586	DT
aback	9	5	5.998340e-06	17.347005	NN
abaft	2	5	1.332965e-06	19.516930	IN
abandon	44	7	2.932522e-05	15.057499	VB
abandoned	68	9	4.532079e-05	14.429467	VBN
...	...	...	...	...	...
à	3	1	1.999447e-06	18.931968	NNP
æt	1	2	6.664823e-07	20.516930	NN
ætat	1	4	6.664823e-07	20.516930	VBD
ça	2	2	1.332965e-06	19.516930	JJ
émeutes	1	7	6.664823e-07	20.516930	PDT

27396 rows × 5 columns

Compute TFIDF and VOCAB['dfidf'] for the CORPUS using the following parameters:

bag = ['book_id', 'chap_id']

tf_method = 'max'

idf_method = 'standard'

In [ ]:

```python
def create_bag_of_words(CORPUS, bag):
    BOW = CORPUS.groupby(bag+['term_str']).term_str.count().to_frame('n')
    return BOW

idf_method = 'standard'

def get_TFIDF(BOW, tf_method):
    DTCM = BOW.n.unstack(fill_value=0)

    DF = DTCM.astype('bool').sum()
    N = len(DTCM)

    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.log2(1 + DTCM.T)

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

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

    TF = TF.T

    if idf_method == 'standard':
        IDF = np.log2(N / DF)

    elif idf_method == 'max':
        IDF = np.log2(DF.max() / DF)

    elif idf_method == 'smooth':
        IDF = np.log2((1 + N) / (1 + DF)) + 1

    return TF * IDF, DF * IDF
```

In [ ]:
```
TFIDF, DFIDF = get_TFIDF(create_bag_of_words(CORPUS, ['book_id', 'chap_id']), 'max')

TFIDF
```

Out[ ]:

	term_str	a	aback	abaft	abandon	abandoned	abandoning	abandons	abasement	abashed	abate	...	zoöphagy	zufalle	zum	zuniga	zusammen	à	æ
book_id	**chap_id**																		
adventures	**1**	0.0	0.0	0.0	0.00000	0.006493	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
	2	0.0	0.0	0.0	0.00000	0.000000	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
	3	0.0	0.0	0.0	0.00000	0.000000	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
	4	0.0	0.0	0.0	0.00000	0.000000	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
	5	0.0	0.0	0.0	0.00000	0.000000	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
...	**...**	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	.
udolpho	**54**	0.0	0.0	0.0	0.00000	0.000000	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
	55	0.0	0.0	0.0	0.00000	0.009341	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
	56	0.0	0.0	0.0	0.00000	0.000000	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
	57	0.0	0.0	0.0	0.00000	0.000000	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.
usher	**1**	0.0	0.0	0.0	0.01253	0.000000	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.

320 rows × 27396 columns

Create a DOC table from the TFIDF index in which each row represents a bag, i.e. a chapter. In other words, it should have ['book_id', 'chap_id'] as its index. This table should have information from the LIB table added to it, so that each chapter is identified with an author, title, and genre. These data will appear in your visualizations. For example, in a scatter plot of documents in the first two principle components, you will want to know the book and chapter of each data point.

In [ ]:
```
DOC = TFIDF.reset_index()[['book_id','chap_id']]
DOC = DOC.merge(LIB, on='book_id', how='left')
DOC.set_index(['book_id','chap_id'],inplace=True)
DOC
```

Out[ ]:

		genre_id	author_id
book_id	**chap_id**		
adventures	**1**	d	doyle
	2	d	doyle
	3	d	doyle
	4	d	doyle
	5	d	doyle
...	**...**	...	...
udolpho	**54**	g	radcliffe
	55	g	radcliffe
	56	g	radcliffe
	57	g	radcliffe
usher	**1**	g	poe

320 rows × 2 columns

Create a reduced version of the TFIDF table with only the top 1000 nouns (i.e. NN and NNS) in descending order of DFIDF.

Do not "collapse" table -- keep the index as (book_id, chap_id).

In [ ]:
```
nouns = ['NN', 'NNS']
top1000 = VOCAB.merge(DFIDF.to_frame('DFIDF'), on='term_str').query("max_pos in @nouns").sort_values('DFIDF', ascending=False).head(1000).inde
TFIDF = TFIDF[[col for col in top1000]]
TFIDF
```

```
Out[ ]:
                     term_str     yours     reply     order curiosity    memory   company  feelings opportunity      book    spirit  ...  humanity      rank  contempt  appreh
            book_id   chap_id
         adventures         1  0.006454  0.000000  0.003227  0.003227  0.006400  0.006400  0.000000    0.000000  0.003282  0.003282  ...  0.000000  0.000000  0.000000       0
                            2  0.009346  0.000000  0.009346  0.000000  0.006178  0.000000  0.000000    0.000000  0.000000  0.000000  ...  0.000000  0.000000  0.000000       0
                            3  0.004089  0.008178  0.000000  0.000000  0.004054  0.008109  0.000000    0.000000  0.004159  0.000000  ...  0.000000  0.000000  0.000000       0
                            4  0.002721  0.002721  0.005442  0.000000  0.002698  0.000000  0.000000    0.002767  0.000000  0.000000  ...  0.000000  0.000000  0.000000       0
                            5  0.003043  0.000000  0.003043  0.003043  0.003017  0.000000  0.000000    0.000000  0.006190  0.000000  ...  0.000000  0.000000  0.000000       0
                ...       ...       ...       ...       ...       ...       ...       ...       ...         ...       ...       ...  ...       ...       ...       ...
            udolpho        54  0.007676  0.003838  0.003838  0.003838  0.003806  0.003806  0.007611    0.007808  0.000000  0.000000  ...  0.017027  0.000000  0.000000       0
                           55  0.000000  0.000000  0.000000  0.004643  0.000000  0.004604  0.000000    0.000000  0.000000  0.004722  ...  0.000000  0.000000  0.010299       0
                           56  0.000000  0.007822  0.000000  0.000000  0.000000  0.015512  0.000000    0.000000  0.000000  0.015912  ...  0.000000  0.000000  0.017351       0
                           57  0.000000  0.000000  0.000000  0.000000  0.033189  0.000000  0.000000    0.000000  0.000000  0.000000  ...  0.000000  0.000000  0.000000       0
              usher         1  0.000000  0.002566  0.002566  0.000000  0.002544  0.000000  0.005088    0.002610  0.005219  0.015657  ...  0.005691  0.011382  0.000000       0

320 rows × 1000 columns
```

Write a function that computes PCA from a given document-term count matrix (this included weighted counts, such a tfidf). It should return three dataframes: LOADINGS (the term-component matrix), DCM (the document-component matrix), COMPINF (the component information table). Give it the following parameters:

X # The input matrix

k # The number of components to generate

norm_docs # True or False

center_by_mean # True of False

center_by_variance # True or False

Compute PCA from the feature-reduced TFIDF table using your function. Use the following parameter values: X = TFIDF_REDUCED Or whatever you called your reduced TFIDF table k=10 norm_docs = True center_by_mean = False center_by_variance = False Visualize your results using scatter plots and box plots.

```
In [ ]:
def get_PCA(X, k, norm_docs = True, center_by_mean = True, center_by_variance = True):
    if norm_docs:
        X = (X.T / np.linalg.norm(X, 2, axis=1)).T

    if center_by_mean:
        X = X - X.mean(axis=0)

    if center_by_variance:
        X = X / X.std(axis=0)

    pca = PCA(n_components=k)
    pca.fit(X)

    loadings = pd.DataFrame(pca.components_.T, index=X.columns)
    loadings.columns = [f'PC{i+1}' for i in range(k)]

    dcm = pd.DataFrame(pca.transform(X), index=X.index)
    dcm.columns = [f'PC{i+1}' for i in range(k)]

    comp = pd.DataFrame({
        'EVR': pca.explained_variance_ratio_,
        'CEVR': np.cumsum(pca.explained_variance_ratio_)
    }, index=[f'PC{i+1}' for i in range(k)])

    return loadings, dcm, comp

LOADINGS, DCM, COMPINF = get_PCA(X=TFIDF, k=10, norm_docs=True, center_by_mean=False, center_by_variance=False)
DCM = DOC.join(DCM)
```

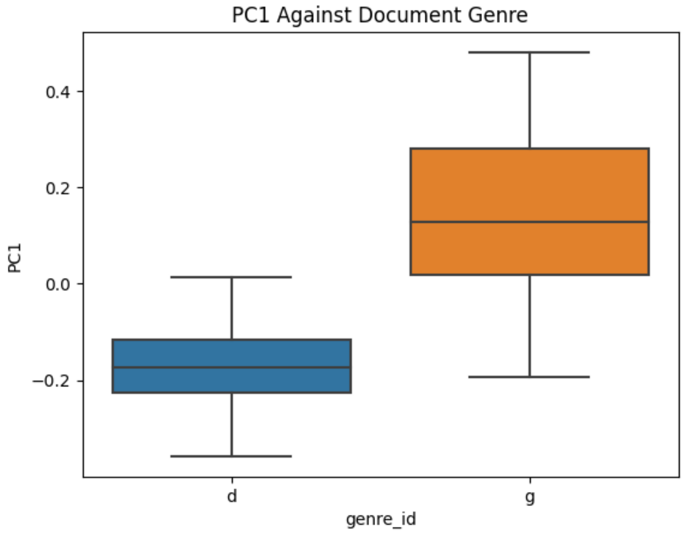
```
In [ ]: DCM
```

```
Out[ ]:
                        genre_id  author_id        PC1        PC2        PC3        PC4        PC5       PC6        PC7        PC8        PC9       PC10
            book_id  chap_id
         adventures        1         d      doyle  -0.237319   0.038768   0.092062   0.029442  -0.191567  0.093441  -0.118399   0.011765  -0.021905  -0.028254
                           2         d      doyle  -0.295389   0.074901   0.035613   0.001857  -0.204501  0.066934  -0.111104  -0.109326  -0.020459   0.026691
                           3         d      doyle  -0.291923  -0.074162   0.035053   0.008414  -0.149578  0.112748  -0.103293  -0.041946   0.000359   0.040192
                           4         d      doyle  -0.162984  -0.025831   0.026673   0.081026  -0.141952  0.057792  -0.204866  -0.071068   0.158094   0.085781
                           5         d      doyle  -0.186560   0.049075   0.012450   0.066207  -0.145323  0.097464  -0.043226  -0.144036   0.006083   0.152767
                ...      ...       ...        ...        ...        ...        ...        ...        ...       ...        ...        ...        ...        ...
            udolpho       54         g  radcliffe   0.379714  -0.132359  -0.030655  -0.065428   0.040511  0.206042  -0.063613  -0.036247   0.028850  -0.000011
                          55         g  radcliffe   0.303586  -0.185496   0.050914   0.036115   0.065106  0.181303  -0.023661  -0.113286   0.074211  -0.011379
                          56         g  radcliffe   0.391705   0.145064  -0.276399  -0.235498  -0.109495  0.141362   0.046051   0.030292  -0.016949   0.121353
                          57         g  radcliffe   0.286226   0.017426  -0.042757  -0.112652   0.019443  0.009336  -0.095355  -0.012079  -0.051540   0.123404
              usher        1         g        poe   0.132124   0.119597   0.032166   0.126673  -0.018076  0.044846  -0.036131  -0.058944  -0.032415  -0.193522

320 rows × 12 columns
```

1. Looking at the documents plotted against the first principle component (PC), which genre has the more narrow range, i.e. distance between the minimum and maximum values? This can be seen using a box plot

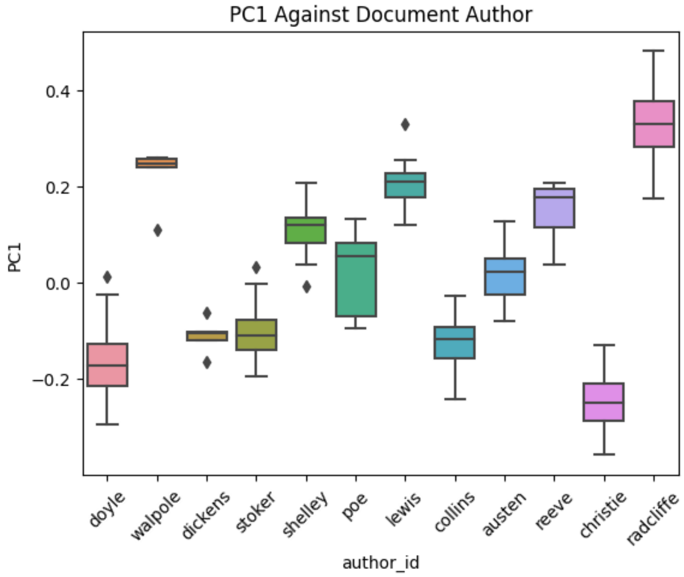
```
In [ ]: sns.boxplot(data=DCM, x = 'genre_id', y = 'PC1')
        plt.title('PC1 Against Document Genre')
        plt.show()
```



We can see from the boxplot above for the first principle component that the **d (detective)** genre has a more narrow range between the minimum and maximum values for the first principle component.

2. Looking at the documents plotted against the first PC, which author has the highest absolute value, in terms of both mean and range? In other words, which author is farthest from 0? Again, the box plots of each author are useful here.

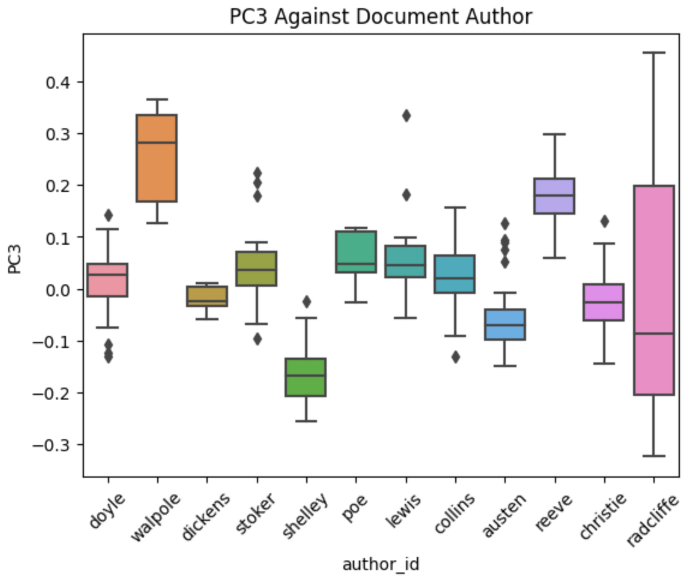
```
In [ ]: sns.boxplot(data=DCM, x = 'author_id', y = 'PC1')
        plt.title('PC1 Against Document Author')
        plt.xticks(rotation=45)
        plt.show()
```



We can see from the boxplot above for the first principle component that the author **Radcliffe** has both the highest absolute mean value of mean and range.

3. In the third PC, which author has, by far, the maximum range?

```
In [ ]: sns.boxplot(data=DCM, x = 'author_id', y = 'PC3')
        plt.title('PC3 Against Document Author')
        plt.xticks(rotation=45)
        plt.show()
```



We can see from the boxplot above for the third principle component that the author **Radcliffe** has the highest maximum range by far

4. Looking at the loadings for the second PC, how would you characterize the opposition, based on the top three words at each pole?

```
In [ ]: LOADINGS['PC2'].sort_values(ascending=False).to_frame().head(3)
```

Out[ ]:

	PC2
term_str	
mountains	0.176642
woods	0.140543
sea	0.103898

```
In [ ]: LOADINGS['PC2'].sort_values(ascending=True).to_frame().head(3)
```

Out[ ]:

	PC2
term_str	
brother	-0.153843
engagement	-0.115630
father	-0.113204

For the loadings of the second principle component, we can see that there is a the strongest positive terms are related to nature. In contrast, we can see that the strongest negative terms are all related to family. We can see a potential contrast here for the opposition between nature and family

5. Recompute the principle components with center_by_variance set to True. This will change the words that appear at the extremes of the first PC. Does this change your interpretation in the previous question?

```
In [ ]: LOADINGS5, DCM5, COMPINF5 = get_PCA(X=TFIDF, k=10, norm_docs=True, center_by_mean=False, center_by_variance=True)
        DCM5 = DOC.join(DCM5)
```

```
In [ ]: LOADINGS5['PC1'].sort_values(ascending=False).to_frame().head(3)
```

Out[ ]:

	PC1
term_str	
countenance	0.095031
length	0.094551
melancholy	0.087428

```
In [ ]: LOADINGS5['PC1'].sort_values(ascending=True).to_frame().head(3)
```

Out[ ]:

	PC1
term_str	
matter	-0.085165
anything	-0.082012
course	-0.075488

instructions unclear, recomputing PCA and examining extremes at first PC. Compared to the previous question, we do not see clear themes of family or nature. Rather, the extremes of the first PC do not have as much of an association with eachother that we can discern when we are centered by variance.