M08 Homework

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In [ ]:
```
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 sklearn.decomposition import LatentDirichletAllocation as LDA
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 [ ]:
```
import configparser
config = configparser.ConfigParser()
config.read("../env.ini")
data_home = config['DEFAULT']['data_home']
output_dir = config['DEFAULT']['output_dir']
data_prefix = 'novels'
```

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

In [ ]:
```
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 [ ]:
```
nouns = ['NN', 'NNS']

CORPUS = CORPUS.query("pos in @nouns")

CORPUS
```

Out[ ]:

					pos	term_str
book_id	**chap_id**	**para_num**	**sent_num**	**token_num**		
secretadversary	**1**	**1**	**0**	**2**	NN	thing
		2	**0**	**2**	NN	bean
		3	**0**	**3**	NNS	people
				7	NN	affectionately
				15	NN	exit
...	**...**	**...**	**...**	**...**	...	...
baskervilles	**11**	**114**	**0**	**0**	NN	it
				10	NN	well
				13	NN	voice
			1	**0**	NNS	i
				11	NN	in

311851 rows × 2 columns

In [ ]:
```
def join_lists_to_sentence(lst):
    return ' '.join(lst)
```

In [ ]:
```
DOCS = CORPUS.dropna().groupby(OHCO[:3]).term_str.apply(list).to_frame().rename(columns={'term_str':'doc_str'})

DOCS_c = CORPUS.dropna().groupby(OHCO[:2]).term_str.apply(list).to_frame().rename(columns={'term_str':'doc_str'})
```

In [ ]:
```
DOCS['doc_str'] = DOCS['doc_str'].apply(join_lists_to_sentence)

DOCS_c['doc_str'] = DOCS_c['doc_str'].apply(join_lists_to_sentence)
```

In [ ]:
```
n_topics = 20
max_iter = 5

lda_engine = LDA(n_components=n_topics, max_iter=max_iter, learning_offset=50., random_state=0)
lda_engine_c = LDA(n_components=n_topics, max_iter=max_iter, learning_offset=50., random_state=0)
```

In [ ]:
```
count_engine = CountVectorizer(max_features= 4000, ngram_range=(1, 2), stop_words='english')
count_model = count_engine.fit_transform(DOCS.doc_str)
TERMS = count_engine.get_feature_names_out()

count_engine_c = CountVectorizer(max_features= 4000, ngram_range=(1, 2), stop_words='english')
count_model_c = count_engine_c.fit_transform(DOCS_c.doc_str)
TERMS_c = count_engine_c.get_feature_names_out()
```

Theta

Paragraph Topic Models

In [ ]:
```
TNAMES = [f"T{str(x).zfill(len(str(n_topics)))}" for x in range(n_topics)]
```

In [ ]:
```
lda_model = lda_engine.fit_transform(count_model)
THETA = pd.DataFrame(lda_model, index=DOCS.index)
THETA.columns.name = 'topic_id'
THETA.columns = TNAMES
```

In [ ]:
```
THETA
```

Out[ ]:

			T00	T01	T02	T03	T04	T05	T06	T07	T08	T09	T10	T11	T12	
book_id	**chap_id**	**para_num**														
adventures	**1**	**1**	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.0
		2	0.001563	0.266616	0.001563	0.001563	0.001563	0.614620	0.001563	0.001563	0.001563	0.001563	0.001563	0.001563	0.001563	0.
		3	0.001064	0.484450	0.001064	0.001064	0.001064	0.001064	0.001064	0.001064	0.001064	0.001064	0.001064	0.001064	0.001064	0.
		4	0.083195	0.001471	0.001471	0.001471	0.460585	0.001471	0.001471	0.001471	0.001471	0.001471	0.001471	0.001471	0.001471	0.0
		5	0.004167	0.004167	0.360616	0.386463	0.004167	0.004167	0.004167	0.004167	0.004167	0.004167	0.004167	0.004167	0.004167	0.
...	**...**	**...**	...	...	...	...	...	...	...	...	...	...	...	...	...	
usher	**1**	**43**	0.003846	0.003846	0.003846	0.003846	0.003846	0.003846	0.247691	0.003846	0.003846	0.404135	0.003846	0.003846	0.282789	0.0
		44	0.002000	0.002000	0.002000	0.002000	0.002000	0.002000	0.002000	0.002000	0.002000	0.610828	0.002000	0.002000	0.002000	0.0
		45	0.001316	0.055305	0.001316	0.001316	0.001316	0.001316	0.001316	0.001316	0.522070	0.400257	0.001316	0.001316	0.001316	0.
		46	0.001786	0.001786	0.001786	0.001786	0.001786	0.001786	0.001786	0.001786	0.267462	0.367113	0.001786	0.001786	0.001786	0.
		47	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.105991	0.001613	0.001613	0.864977	0.

26481 rows × 20 columns

In [ ]:
```
PHI = pd.DataFrame(lda_engine.components_, columns=TERMS, index=TNAMES)
PHI.index.name = 'topic_id'
PHI.columns.name = 'term_str'
```

In [ ]:
```
PHI
```

Out[ ]:

term_str	**abbess**	**abbey**	**abhorrence**	**abilities**	**ability**	**abode**	**abroad**	**abruptly**	**absence**	**absent**	**...**	**yew**	**yonder**	**youd**	**youll**	**y**
topic_id																
T00	24.535845	0.050000	0.050000	3.206668	1.050000	1.648825	0.050000	0.050000	15.100544	0.050000	...	0.050000	0.050000	0.050000	0.050000	1.40
T01	9.409348	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	2.679206	9.063185	1.877767	...	0.050000	0.050000	13.753684	1.294147	0.05
T02	0.050000	0.131319	0.050000	0.050000	1.318971	0.060615	0.050000	0.551422	0.801228	0.050000	...	0.050000	4.470425	4.122913	0.050000	0.05
T03	0.050000	0.050000	0.050000	0.050000	0.239226	0.050000	0.050000	0.050000	4.715879	0.050000	...	0.050000	0.050000	0.050000	0.050000	0.05
T04	15.084176	7.092118	3.057912	2.328208	0.050000	0.050000	1.130891	2.530501	8.616017	0.050000	...	0.050000	0.050001	0.050000	0.050000	0.05
T05	0.050000	1.702302	0.050000	0.050000	6.661022	0.050000	1.050000	1.067997	4.302003	5.222163	...	0.050000	0.050000	0.050000	0.050000	0.05
T06	0.050000	1.165601	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	5.487454	0.050000	...	0.050000	16.703012	0.061771	24.665989	0.05
T07	0.050000	5.662827	1.142745	0.050000	0.050000	3.546514	0.050000	0.050000	15.122058	0.050000	...	5.391363	0.050000	0.050000	0.050000	2.5
T08	6.782509	0.050000	0.050000	0.050000	0.050000	0.050000	0.054359	0.050000	4.095759	0.050000	...	0.050000	1.577559	0.050000	0.050000	0.05
T09	0.050000	1.768883	7.295480	0.050000	0.050000	0.050000	0.110093	0.050000	3.365551	0.050167	...	1.300758	0.050000	0.050000	0.050000	0.05
T10	0.093738	13.422929	5.703860	0.727190	0.995160	0.050000	0.050000	0.050000	5.539881	0.050000	...	0.050000	0.050000	0.050000	0.050000	0.05
T11	0.305965	0.081295	0.050000	0.050000	0.050000	0.526867	6.302084	0.050000	4.151751	0.050000	...	0.050000	0.050017	1.268381	0.065494	2.5
T12	8.138419	6.138685	0.050000	0.050000	0.050000	3.978350	0.291904	0.050000	2.439587	0.050000	...	0.050000	0.050000	0.050001	0.050000	0.05
T13	0.050000	0.050000	0.050000	1.244644	6.925214	0.051966	0.050000	7.420873	4.144335	0.721995	...	6.393700	0.050001	0.050000	0.050000	0.05
T14	0.050000	0.088812	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.149841	0.050000	...	0.050000	11.446334	0.050000	0.050000	0.05
T15	0.050000	0.050000	0.050000	4.234158	0.050000	0.058975	0.257296	0.050000	9.417309	0.050000	...	1.114178	0.052648	0.050000	0.050000	0.05
T16	0.050000	0.050000	0.050000	1.977291	0.050000	8.941975	0.050000	0.050000	0.762748	7.975099	...	0.050000	0.050000	0.050000	1.174370	17.48
T17	0.050000	1.156518	0.050003	0.050000	1.050000	0.050000	0.050000	0.050000	16.180694	1.886602	...	0.050000	0.050000	0.050995	0.050000	0.05
T18	0.050000	0.050000	0.050000	2.631842	2.160409	9.635914	2.395368	0.050000	16.086318	0.616208	...	0.050000	0.050003	0.050000	0.050000	1.2
T19	0.050000	2.188711	0.050000	0.050000	0.050000	0.050000	3.858005	0.050000	1.457859	0.050000	...	0.050000	0.050000	4.042255	0.050000	0.05

20 rows × 4000 columns

In [ ]:
```
TOPICS = PHI.stack().groupby('topic_id')\
    .apply(lambda x: ' '.join(x.sort_values(ascending=False).head(7).reset_index().term_str))\
    .to_frame('top_terms')
TOPICS
```

Out[ ]:

topic_id	top_terms
T00	eyes head girl mother face paper silence
T01	yes oh father good ah man child
T02	sir man coffee dinner moor thank time
T03	case word course time room son papers
T04	door room apartment night chamber hand man
T05	country thing scene world mind day mountains
T06	night castle door way maamselle place time
T07	house voice person family brother surprise words
T08	death aunt story chamber time ha night
T09	moment blood face eyes hand death heart
T10	mind day night hour hope steps time
T11	lady business right matter things years mind
T12	room door light hall air window hand
T13	question money time chair mr things tuppence
T14	hand face time case evidence room man
T15	day time room way night sort thing
T16	letter man lord voice room look lady
T17	man friend hand gentleman eyes life people
T18	time man morning hour way house chance
T19	time work dear box man come police

Chapter Models

In [ ]:

```
lda_model_c = lda_engine_c.fit_transform(count_model_c)
THETA_c = pd.DataFrame(lda_model_c, index=DOCS_c.index)
THETA_c.columns.name = 'topic_id'
THETA_c.columns = TNAMES

THETA_c
```

Out[ ]:

book_id	chap_id	T00	T01	T02	T03	T04	T05	T06	T07	T08	T09	T10	T11	T12	T13	
adventures	1	0.000041	0.453161	0.513976	0.000041	0.000041	0.000041	0.000041	0.012536	0.000041	0.000041	0.019671	0.000041	0.000041	0.000041	0.0
	2	0.000038	0.000038	0.999271	0.000038	0.000038	0.000038	0.000038	0.000038	0.000038	0.000038	0.000038	0.000038	0.000038	0.000038	0.0
	3	0.000052	0.337203	0.346489	0.000052	0.000052	0.000052	0.000052	0.315419	0.000052	0.000052	0.000052	0.000052	0.000052	0.000052	0.0
	4	0.067080	0.337080	0.449709	0.000035	0.000035	0.000035	0.000035	0.099572	0.000035	0.000035	0.000035	0.000035	0.000035	0.000035	0.0
	5	0.000045	0.111001	0.576448	0.000045	0.000045	0.028478	0.000045	0.065585	0.000045	0.000045	0.000045	0.000045	0.217812	0.000045	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
udolpho	54	0.201512	0.000055	0.000055	0.000055	0.053633	0.000055	0.000055	0.000055	0.000055	0.000055	0.633650	0.000055	0.000055	0.000055	0.0
	55	0.333667	0.000071	0.000071	0.000071	0.042286	0.000071	0.000071	0.000071	0.000071	0.000071	0.583647	0.000071	0.000071	0.000071	0.0
	56	0.000108	0.000108	0.000108	0.000108	0.000108	0.000108	0.000108	0.000108	0.000108	0.000108	0.116071	0.000108	0.000108	0.000108	0.0
	57	0.000327	0.000327	0.000327	0.000327	0.000327	0.061416	0.000327	0.000327	0.000327	0.000327	0.236997	0.000327	0.000327	0.000327	0.0
usher	1	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.000043	0.0

320 rows × 20 columns

In [ ]:

```
PHI_c = pd.DataFrame(lda_engine_c.components_, columns=TERMS_c, index=TNAMES)
PHI_c.index.name = 'topic_id'
PHI_c.columns.name = 'term_str'

PHI_c
```

Out[ ]:

term_str topic_id	abbess	abbey	abhorrence	abilities	ability	abode	abroad	abruptly	absence	absent	...	yew	yonder	youd	youll	yo
T00	0.054394	0.050000	4.543722	1.860506	0.050000	11.138735	0.050000	3.933571	26.958365	3.381302	...	0.050000	2.805261	0.05000	0.050000	4.174
T01	0.050000	0.050000	0.050000	0.050000	1.728533	0.050000	3.833001	6.162345	12.052522	1.056956	...	0.050000	0.050000	22.04276	11.857174	5.231
T02	0.050000	2.203163	0.752520	2.663744	2.753082	2.527354	1.124571	0.050000	7.104123	0.448911	...	0.050000	4.084648	0.05724	11.764928	3.540
T03	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	12.276826	0.050000	...	0.050000	0.050000	0.05000	0.050000	0.050
T04	0.050000	1.048341	0.050000	0.664028	1.173877	6.671228	0.050000	0.050000	4.743707	3.402281	...	0.050000	0.050005	0.05000	0.050000	2.022
T05	0.050000	0.050000	5.330374	0.050000	0.055884	0.050000	0.079961	0.050000	0.828215	0.050000	...	0.050000	0.050000	0.05000	1.830231	0.050
T06	0.050000	2.050000	0.050000	0.050000	0.050000	1.050000	0.050000	0.050000	1.263061	0.050000	...	0.050000	0.050000	0.05000	0.050000	0.050
T07	0.050000	0.050000	1.347480	1.643311	5.370616	3.860223	6.747598	0.050000	9.294362	0.050000	...	1.206550	1.450529	0.05000	0.414697	0.083
T08	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	...	0.050000	0.050000	0.05000	0.050000	0.050
T09	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.565240	...	1.081698	0.050003	1.05000	0.050000	4.033
T10	29.657817	25.519488	1.459835	8.543420	0.050000	0.064099	2.464869	1.119373	36.055323	3.476658	...	0.050000	0.050000	0.05000	0.050000	4.355
T11	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	...	0.050000	0.050000	0.05000	0.050000	0.050
T12	0.050000	6.133807	0.050000	0.050000	0.050605	0.050000	0.050000	0.050000	0.050000	0.050000	...	11.861752	8.527620	0.05000	0.050000	0.547
T13	0.050000	0.554887	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	0.262874	0.050000	...	0.050000	0.050000	0.05000	0.050000	0.415
T14	0.050000	0.050000	0.050000	0.921276	0.050000	0.050000	0.050000	0.050000	0.050000	0.050000	...	0.050000	1.427235	0.05000	0.050000	0.050
T15	0.050000	0.050000	0.838955	0.050000	4.592003	0.050224	0.050000	2.984711	2.254125	1.063488	...	0.050000	0.050000	0.05000	0.156891	0.050
T16	18.372882	0.061183	1.473475	0.053714	3.675399	3.038136	0.050000	0.050000	9.009967	2.033002	...	0.050000	10.921466	0.05000	0.050000	0.061
T17	16.114907	0.050000	0.050000	0.050000	0.050000	0.050000	1.050000	0.050000	2.763305	3.022163	...	0.050000	2.842806	0.05000	0.050000	0.050
T18	0.050000	0.050000	0.569724	0.050000	0.050000	0.050000	0.050000	0.050000	3.433755	0.050000	...	0.050000	0.050000	0.05000	1.276079	1.083
T19	0.050000	2.829131	1.133916	0.050000	1.050000	0.050000	0.050000	0.050000	2.449470	0.050000	...	0.050000	2.340428	0.05000	0.050000	0.050

20 rows × 4000 columns

In [ ]:

```
TOPICS_c = PHI_c.stack().groupby('topic_id')\
    .apply(lambda x: ' '.join(x.sort_values(ascending=False).head(7).reset_index().term_str))\
    .to_frame('top_terms')
TOPICS_c
```

Out[ ]:

topic_id	top_terms
T00	son father man heart time hand chamber
T01	room yes man time door face way
T02	man time way hand room day night
T03	corpse body murder evidence period thicket river
T04	eyes heart hand moment bosom oh voice
T05	man eyes life time day men death
T06	case home friends friend evidence innocence aunt
T07	time way house man room sir place
T08	regardless pauses vaults infamy hastily le ind...
T09	night time hand face dear day way
T10	time heart friend family brother moment room
T11	daughter faith rumours stories answer women farm
T12	moor man night face time eyes window
T13	tm work works terms agreement tm works donations
T14	mountains way guides light sound gate man
T15	room door house time hand bed voice
T16	woods mind air scene heart voice chateau
T17	lady door room servants night castle maamselle
T18	time way house place door night man
T19	castle door chamber room night voice moment

1.Use the PHI table from each model to compute the entropy H of the distribution over topics. Which bag generates a lower entropy distribution? Hint: To get H work with the L1 normalized vector of word weight sums by topic in the PHI table.

In [ ]:

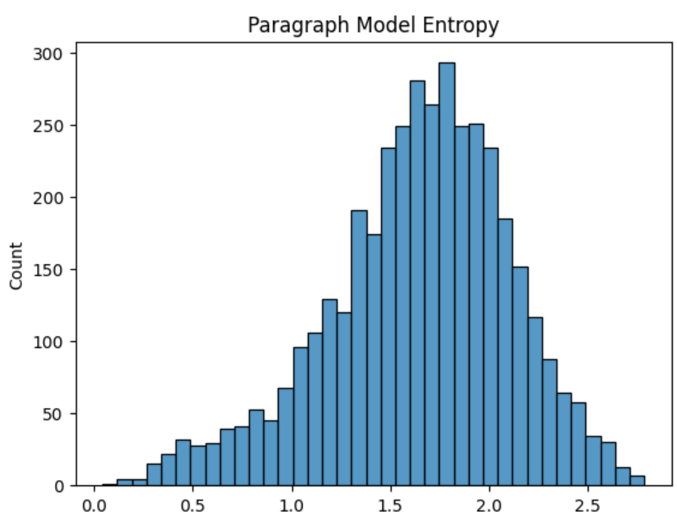
```
phi_normalized = PHI.div(PHI.sum(axis=0), axis=1)

entropy = -phi_normalized * np.log(phi_normalized)
entropy = entropy.sum(axis=0)

entropy
```

```
Out[ ]: term_str
abbess        1.588854
abbey         1.962299
abhorrence    1.467981
abilities     2.021271
ability       1.805479
                ...
youre         0.406246
youth         2.348950
youths        1.885616
youve         1.963727
zeal          1.761813
Length: 4000, dtype: float64
```

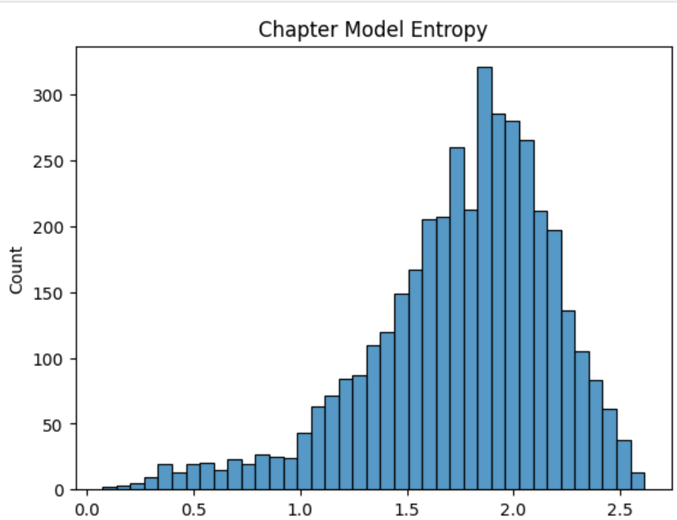
```
In [ ]: phi_c_normalized = PHI_c.div(PHI_c.sum(axis=0), axis=1)

        entropy_c = -phi_c_normalized * np.log(phi_c_normalized)
        entropy_c = entropy_c.sum(axis=0)

        entropy_c
```

```
Out[ ]: term_str
abbess        1.155104
abbey         1.330576
abhorrence    2.049463
abilities     1.629895
ability       1.957611
                ...
youre         0.794967
youth         1.749475
youths        0.835849
youve         1.332307
zeal          1.820260
Length: 4000, dtype: float64
```

```
In [ ]: sns.histplot(entropy)
        plt.title("Paragraph Model Entropy")
        plt.show()
```




```
In [ ]: sns.histplot(entropy_c)
        plt.title("Chapter Model Entropy")
        plt.show()
```



It appears that the paragraph document model entropy distribution is lower than the chapter model entropy in general.

2.Sort the topics in each model's PHI table by topic entropy in descending order. Are the first topics in the two models about the same? In other words, do they yield similar interpretations?

In [ ]:
```
entropy.to_frame('entropy').sort_values('entropy', ascending=False)
```

Out[ ]:

term_str	entropy
reason	2.785186
hands	2.770548
place	2.770185
minutes	2.767588
way	2.761362
...	...
dr	0.164493
rampart	0.138116
know	0.138085
yes sir	0.127967
yes	0.042574

4000 rows × 1 columns

In [ ]:
```
entropy_c.to_frame('entropy_c').sort_values('entropy_c', ascending=False)
```

Out[ ]:

term_str	entropy_c
forth	2.611146
death	2.603228
lives	2.600021
fear	2.592563
grave	2.589092
...	...
ami	0.204586
launch	0.178408
tuppence	0.141986
strychnine	0.127967
tm	0.075675

4000 rows × 1 columns

No, we see that the two different models have different top topics with high entropy. As a result, they do not yield similar interpretations

3.What topic from each model is most strongly associated with each genre? Note that your answer have four parts.

In [ ]:
```
def associated_topic(THETA):
    topics3 = {}
    for genre in LIB['genre_id'].unique():
        topics3[genre] = THETA.loc[LIB[LIB['genre_id'] == genre].index].mean().idxmax()
    return topics3

print(f"paragraph model: {associated_topic(THETA)}")
print(f"chapter model: {associated_topic(THETA_c)}")
```

```
paragraph model: {'d': 'T11', 'g': 'T10'}
chapter model: {'d': 'T01', 'g': 'T10'}
```

We can see that T10 is most associated with the gothic genre for both models, whereas T11 and T01 are the topics most associated with the detective genre respectively

4.Using the THETA table from the Chapters model, get the mean topic weights for each book. Which book is most strongly associated with the gothic genre g, based on the weight of that genre's most representative topic (as discovered in the previous question)?

In [ ]:
```
THETA_c_genres = THETA_c.reset_index().merge(LIB.reset_index()[['book_id', 'genre_id']], on='book_id', how='left')


THETA_c_genres.reset_index().groupby(['book_id', 'genre_id']).sum().iloc[:, 2:].mean(axis=1).sort_values(ascending=False).head(1)
```

Out[ ]:
```
book_id  genre_id
udolpho  g           2.85
dtype: float64
```

The book most associated with the gothic genre is Udolpho

5.How would you characterize the subject matter of the two genres based on their topic models? Consider the words associated with the dominant topics from each model, but also the models overall.

Detective genre:

In [ ]:
```
PHI.loc['T11'].nlargest(7)
```

Out[ ]:
```
term_str
lady        274.983311
business    199.550071
right       188.345697
matter      164.018505
things      138.384200
years       134.472541
mind        126.842663
Name: T11, dtype: float64
```

In [ ]:
```
PHI.loc['T01'].nlargest(7)
```

Out[ ]:
```
term_str
yes       676.605430
oh        423.182329
father    289.463296
good      144.867072
ah        134.824644
man       134.602039
child     131.759456
Name: T01, dtype: float64
```

Gothic genre:

In [ ]:
```
PHI.loc['T10'].nlargest(7)
```

Out[ ]:
```
term_str
mind     301.708298
day      202.957130
night    165.136368
hour     154.804071
hope     151.783386
steps    131.884725
time     124.084483
Name: T10, dtype: float64
```

In [ ]:
```
PHI_c.loc['T10'].nlargest(7)
```

Out[ ]:
```
term_str
time       257.078311
heart      203.006853
friend     187.664125
family     161.686605
brother    158.124586
moment     158.111128
room       157.680791
Name: T10, dtype: float64
```

We can see that both genres and topic models are heavily characterized by themes of family and relationships. However, we can see that the gothic genre is also defined by times such as night, and themes such as hope. In contrast, the detective genre is defined a bit more ambiguously and mysteriously with words such as business, matter, and things, which also makes sense in the context of the genre.