Exploratory Data Analysis and Topic Modeling

This section will cover:

- initial exploratory analysis
- grammar and spelling correction
- feature extraction with SpaCy
- topic modeling with latent Dirichlet allocation (LDA).
- automatic scoring with LDA

In [1]:
```
#essential imports
%matplotlib inline

import numpy as np
import pandas as pd
import re
from datetime import datetime
```

In [2]:
```
#visualization
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```
#Text Processing Libraries
import spacy
from spacy.lang.en.stop_words import STOP_WORDS
from string import punctuation
```

In [4]:
```
#ML Libraries
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation
from sklearn.model_selection import train_test_split
```

```python
import joblib
```

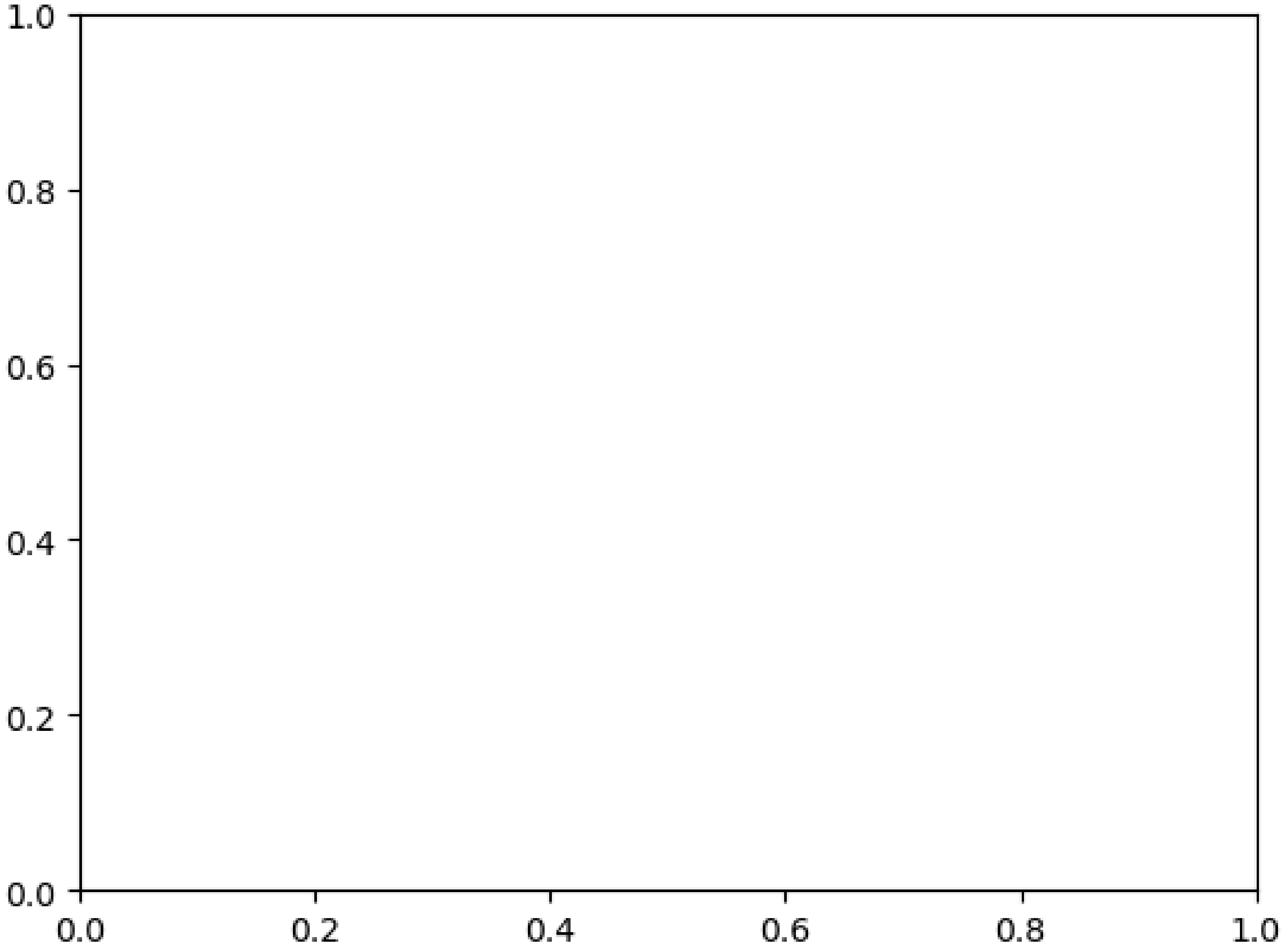
In [5]:
```python
#LDA Visualization
import pyLDAvis.lda_model
from pyLDAvis.lda_model import prepare
```

In [6]:
```python
#matplotlib and pandas config
import seaborn as sns
#plt.style.use('seaborn-colorblind')
palette = sns.color_palette("colorblind")
plt.gca().set_prop_cycle('color', palette)

# Setup Pandas
pd.set_option('display.width', 500)
pd.set_option('display.max_columns', 100)
pd.set_option('display.notebook_repr_html', True)
pd.set_option('display.max_colwidth', 100)

pyLDAvis.enable_notebook()
# plt.rcParams['figure.figsize'] = [8, 5]
plt.rcParams['figure.dpi'] = 100

import warnings
warnings.simplefilter("ignore", DeprecationWarning)
```



In [7]:
```
training_set  = pd.read_csv('training_set_rel3.tsv', sep='\t', encoding = "ISO-8859-1")\
            .rename(columns={'essay_set': 'topic', 'domain1_score': 'target_score', 'domain2_score': 'topi
training_set.sample()
```

Out[7]:

	essay_id	topic	essay	rater1_domain1	rater2_domain1	rater3_domain1	target_score	rater1_domain2	rater
10409	16359	6	The Mooring Mast has two obstacles @CAPS1 the winds on top of the building are constantly shifti...	2	2	NaN	2	NaN	

In [8]:

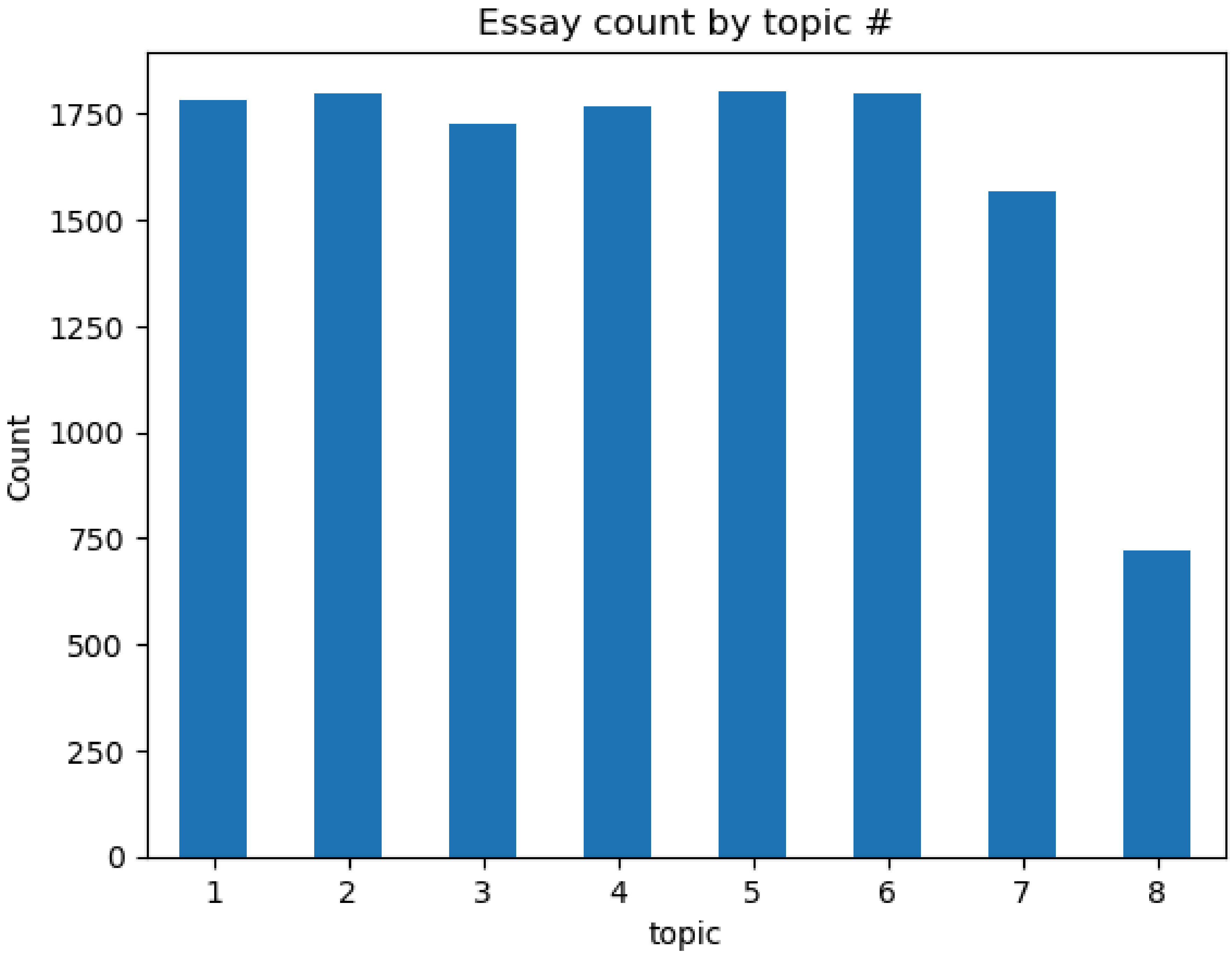
```
training_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12976 entries, 0 to 12975
Data columns (total 28 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   essay_id        12976 non-null  int64
 1   topic           12976 non-null  int64
 2   essay           12976 non-null  object
 3   rater1_domain1  12976 non-null  int64
 4   rater2_domain1  12976 non-null  int64
 5   rater3_domain1  128 non-null    float64
 6   target_score    12976 non-null  int64
 7   rater1_domain2  1800 non-null   float64
 8   rater2_domain2  1800 non-null   float64
 9   topic2_target   1800 non-null   float64
 10  rater1_trait1   2292 non-null   float64
 11  rater1_trait2   2292 non-null   float64
 12  rater1_trait3   2292 non-null   float64
 13  rater1_trait4   2292 non-null   float64
 14  rater1_trait5   723 non-null    float64
 15  rater1_trait6   723 non-null    float64
 16  rater2_trait1   2292 non-null   float64
 17  rater2_trait2   2292 non-null   float64
 18  rater2_trait3   2292 non-null   float64
 19  rater2_trait4   2292 non-null   float64
 20  rater2_trait5   723 non-null    float64
 21  rater2_trait6   723 non-null    float64
 22  rater3_trait1   128 non-null    float64
 23  rater3_trait2   128 non-null    float64
 24  rater3_trait3   128 non-null    float64
 25  rater3_trait4   128 non-null    float64
 26  rater3_trait5   128 non-null    float64
 27  rater3_trait6   128 non-null    float64
dtypes: float64(22), int64(5), object(1)
memory usage: 2.8+ MB
```

In [9]:

```
training_set.groupby('topic').agg('count').plot.bar(y='essay', rot=0, legend=False)
plt.title('Essay count by topic #')
```

```
plt.ylabel('Count')
plt.show()
```

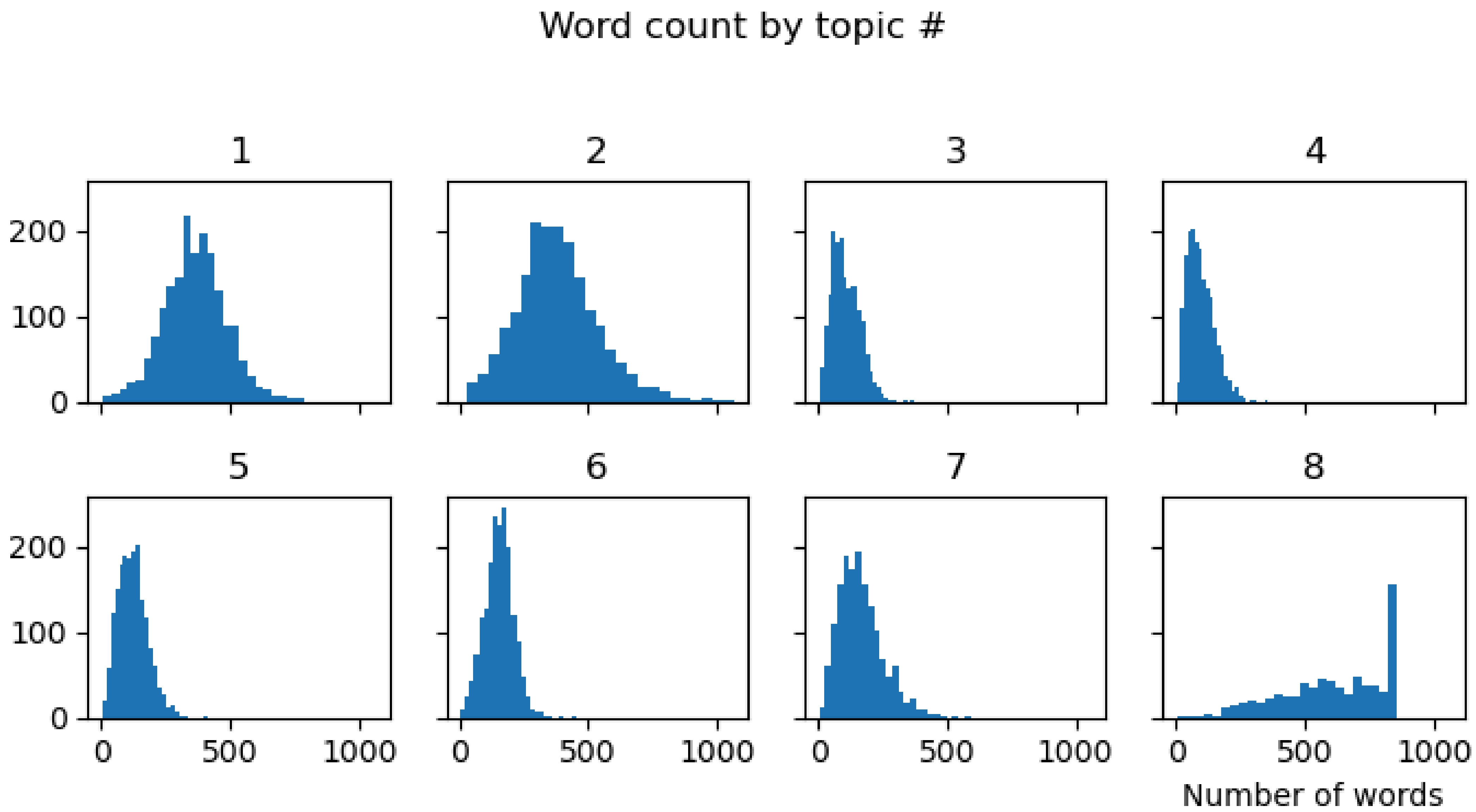


Since topic 8 has the fewest essays and the most distinct scores, it might prove to be the most challenging topic to model.

In [10]:
```
# Count characters and words for each essay
training_set['word_count'] = training_set['essay'].str.strip().str.split().str.len()
```

In [11]:
```
training_set.hist(column='word_count', by='topic', bins=25, sharey=True, sharex=True, layout=(2, 4), figsi
plt.suptitle('Word count by topic #')
```

```
plt.xlabel('Number of words')
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```



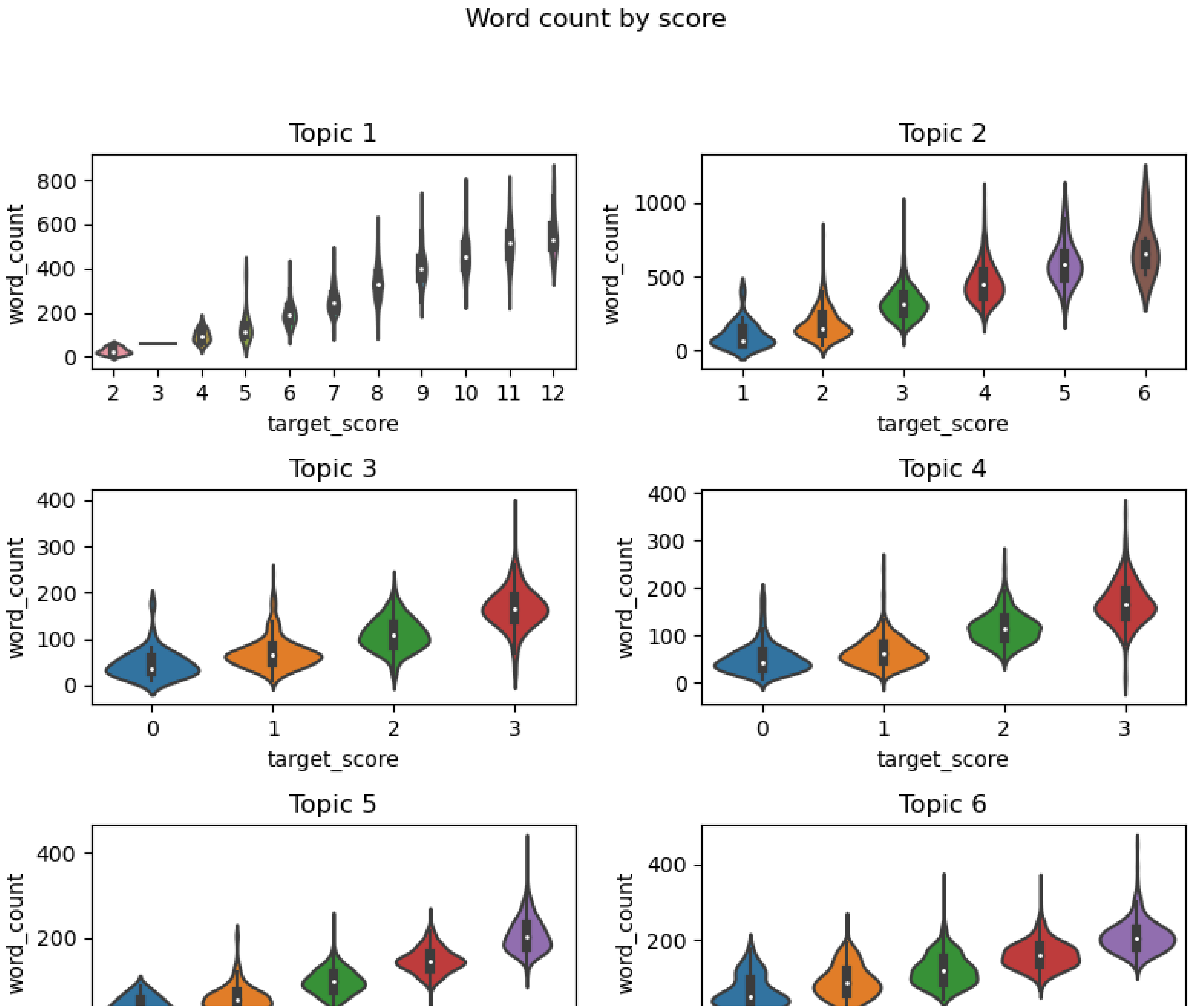
In [12]:
```
training_set.groupby(['topic'])['target_score'].agg(['min','max','count','nunique'])
```

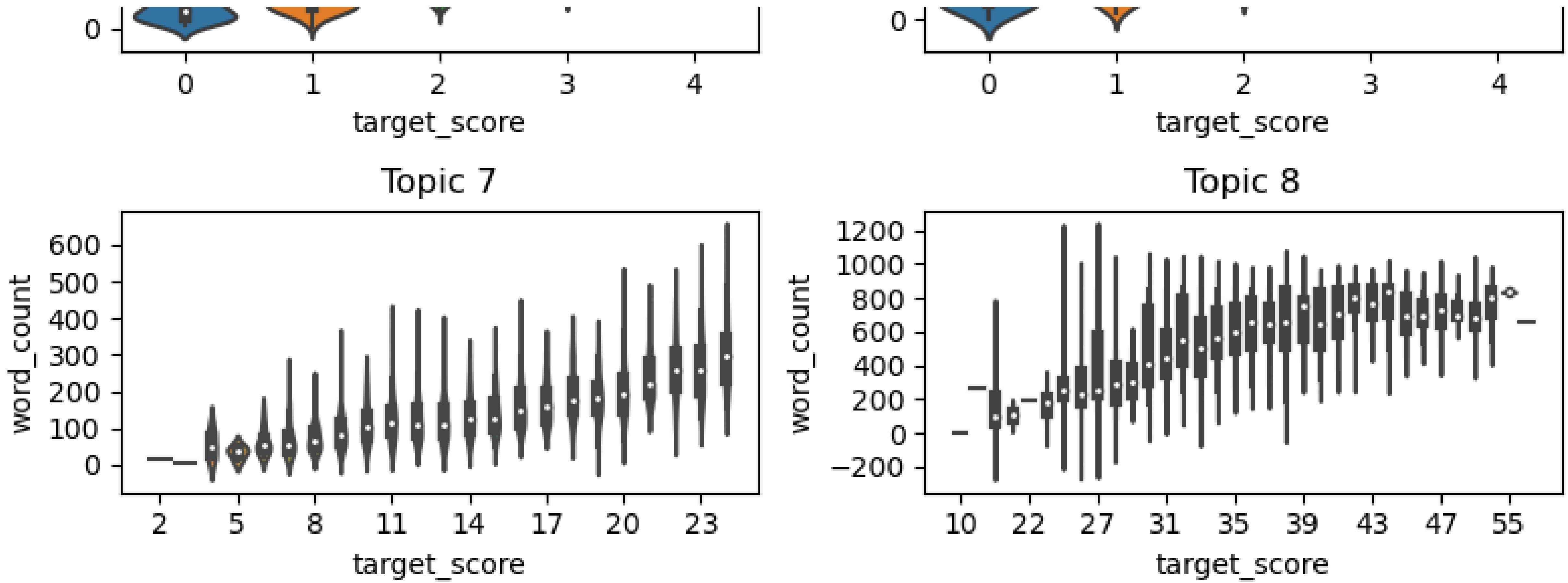
Out[12]:

topic	min	max	count	nunique
1	2	12	1783	11
2	1	6	1800	6
3	0	3	1726	4
4	0	3	1770	4
5	0	4	1805	5
6	0	4	1800	5
7	2	24	1569	23
8	10	60	723	34

In [13]:

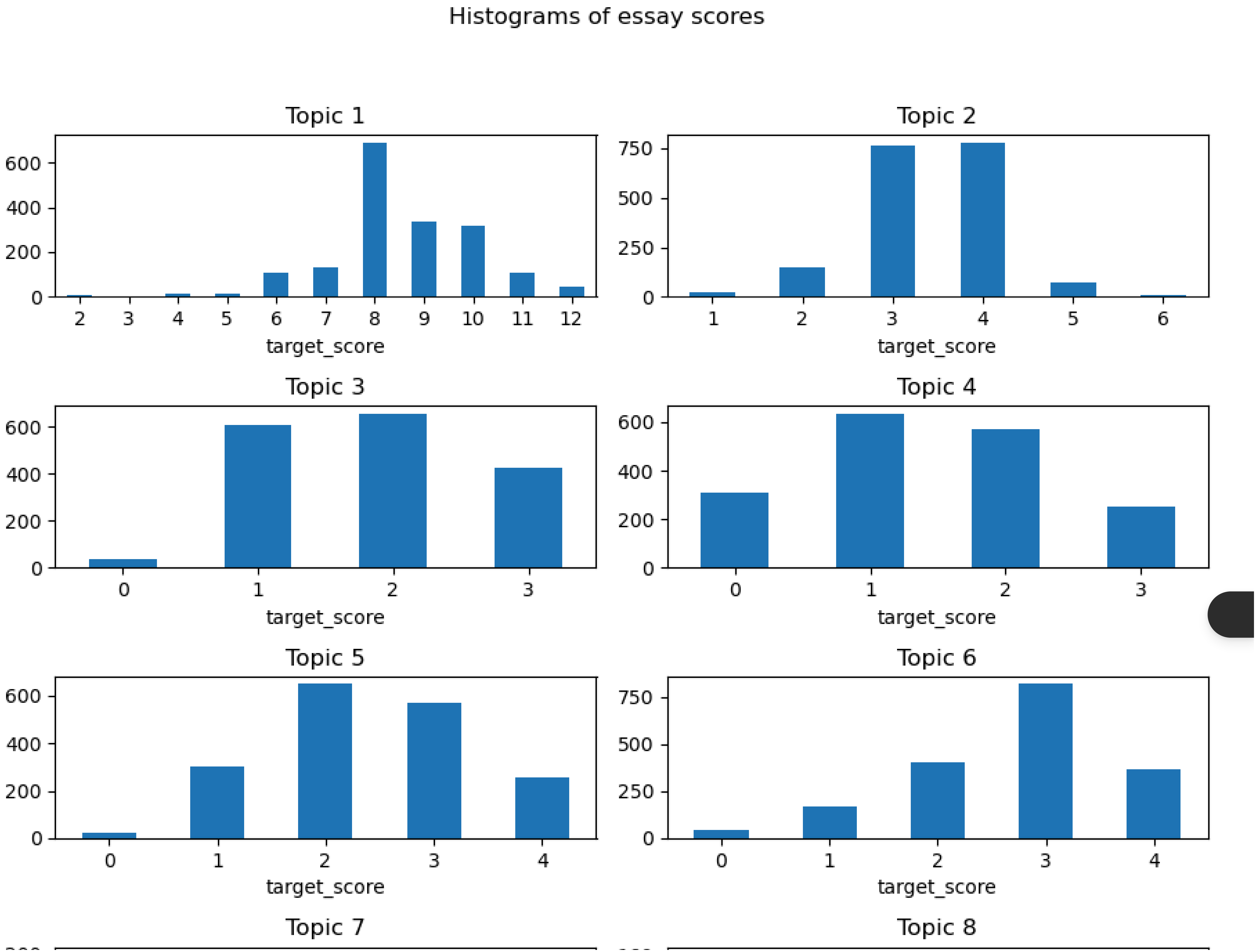
```
topic_number = 0
fig, ax = plt.subplots(4,2, figsize=(8,10))
for i in range(4):
    for j in range(2):
        topic_number += 1
        sns.violinplot(x='target_score', y='word_count', data=training_set[training_set['topic'] == topic_
        ax[i,j].set_title('Topic %i' % topic_number)
ax[3,0].locator_params(nbins=10)
ax[3,1].locator_params(nbins=10)
plt.suptitle('Word count by score')
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

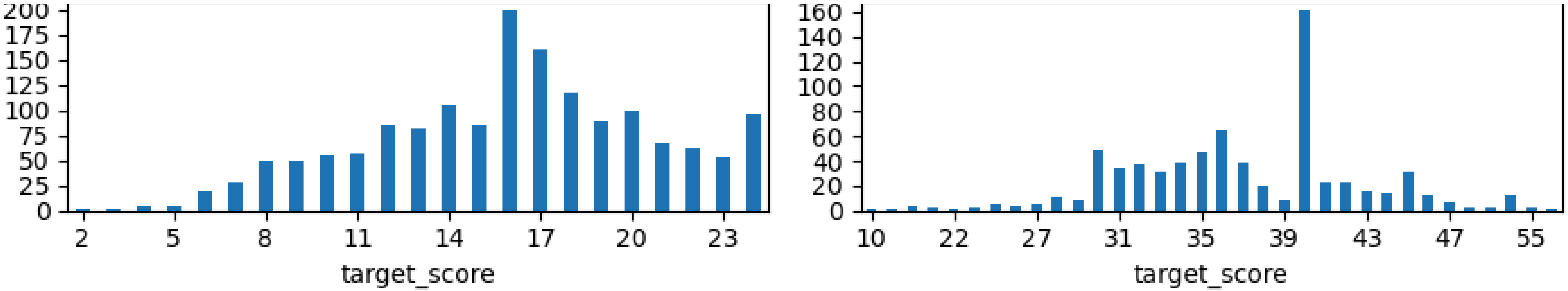

Word count by score
Topic 1
Topic 2
Topic 3
Topic 4
Topic 5
Topic 6
word_count
target_score



We can see a reasonable correlation between word count and score for all but topic 8 where the word count apparently reaches a maximum at the upper third of the scores.

In [14]:
```
topic_number = 0
fig, ax = plt.subplots(4,2, figsize=(9,9), sharey=False)
for i in range(4):
    for j in range(2):
        topic_number += 1
        training_set[training_set['topic'] == topic_number]\
            .groupby('target_score')['essay_id']\
            .agg('count')\
            .plot.bar(ax=ax[i, j], rot=0)
        ax[i,j].set_title('Topic %i' % topic_number)
ax[3,0].locator_params(nbins=10)
ax[3,1].locator_params(nbins=10)
plt.suptitle('Histograms of essay scores')
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```


Histograms of essay scores
Topic 1
600
400
200
0
2
3
4
5
6
7
8
9
10
11
12
target_score
Topic 2
750
500
250
0
1
2
3
4
5
6
target_score
Topic 3
600
400
200
0
0
1
2
3
target_score
Topic 4
600
400
200
0
0
1
2
3
target_score
Topic 5
600
400
200
0
0
1
2
3
4
target_score
Topic 6
750
500
250
0
0
1
2
3
4
target_score
Topic 7
Topic 8



Many scores are underrepresented. Classification could be difficult without rebalancing.

Essay processing:

1. Language correction with languagetool (add number of corrections as feature)
2. Sentence tokenization with Spacy
3. Sentence count and length
4. Word tokenize with Spacy
5. Word token classification (punctuation, stop words and anonymized entities, pos, ent)
6. Document similarity (based on arbitrary high scoring essay for each topic)

Grammar and spelling

As to be expected with student essays, many essays exhibit grammar and spelling errors.

Parts-of-speech (POS) and named-entity-recognition (NER) is hampered in part by the lack of consitent spelling and punctuation. Therefore, the essays will be corrected using languagetool and the nlp parsing will be performed with Spacy on the corrected essays.

In [15]:
```
text = 'Some people are still using Myspoce instead of facdbook'
```

Textblob is an open source nlp package and something to keep an eye on. Unlike Spacy, textblob includes a statistics based spell checker. It only claims 70% accuracy, and in my testing it didn't perform well.

https://textblob.readthedocs.io/en/dev/

In [16]:
```
from textblob import TextBlob
data = TextBlob(text)
print (data.correct())
```

```
Some people are still using Myspoce instead of facdbook
```

Languagetool.org has a python wrapper for spelling and grammatical errors at https://pypi.org/project/language-tool-python/

It appears to work quite well, although it requires intermediate storage of a list of errors ('matches').

In [17]:
```
import language_tool_python
tool = language_tool_python.LanguageTool('en-US')

matches = tool.check(text)
tool.correct(text)
```

Out[17]:
```
'Some people are still using MySpace instead of Facebook'
```

In [18]:
```
text = training_set.essay[1871]
text
```

Out[18]:
```
'I do think that there should be a censorship in not just in libaries, but everywhare.      Personlly, I
think that the way that the libraries have the books are appropite and if the parents do not want thier ch
ildren going any where  that is not privy to them keep a hand lenght away     As for the parents, the pare
nts know the aera that intrest them ,therefor the parents should go there'
```

In [19]:
```
matches = tool.check(text)
tool.correct(text)
```

Out[19]:
```
'I do think that there should be a censorship in not just in libraries, but everywhere.  Personally, I thi
nk that the way that the libraries have the books are appropriate and if the parents do not want their chi
ldren going anywhere that is not privy to them keep a hand length away As for the parents, the parents kno
w the area that interest them, therefor the parents should go there'
```

As seen in the last sentence, languagetool did not correct `",therefor"`. Nonetheless, it should be good enough to proceed.

In [20]:
```
"""
use language tool to correct for most spelling and grammatical errors. Also count the applied corrections.
Using language_check python wrapper for languagetool:
https://pypi.org/project/language-tool-python/
"""
tool = language_tool_python.LanguageTool('en-US')

t0 = datetime.now()

training_set['matches'] = training_set['essay'].apply(lambda txt: tool.check(txt))
training_set['corrections'] = training_set.apply(lambda l: len(l['matches']), axis=1)
training_set['corrected'] = training_set.apply(lambda l: tool.correct(l['essay']), axis=1)

t1 = datetime.now()
print('Processing time: {}'.format(t1 - t0))

# save work
training_set.to_pickle('training_corr.pkl')
```

```
Processing time: 0:27:42.024892
```

Here's a very special example of poor writing skills (or perhaps a digitization error?). None of the spell checkers I tried were able to make much sense out of this.

In [21]:
```
print('Original:')
print(training_set.essay[18])
print('Corrected with languagetool:')
print(training_set.corrected[18])
```

```
Original:
I aegre waf the evansmant ov tnachnolage. The evansmant ov tnachnolige is being to halp fined a kohar froi
alnsas. Tnanchnolage waf ont ot we wod not go to the moon. Tnachnologe evans as we maech at. The people are
in tnacholege to the frchr fror the good ov live. Famas invanyor ues tnacholage leki lena orde dvanse and h
is fling mashine. Tnachologe is the grat
Corrected with languagetool:
I Segre weigh the Evanston of tnachnolage. The Evanston of tnachnolige is being to half fined a Zohar from
Kansas. Tnanchnolage weigh on tot we won not go to the moon. Technology Evans as we match at. The people ar
e in tnacholege to the arch for the good of live. FAMAS inventor UES anchorage Levi Lena order dance and hi
s fling machine. Tnachologe is the great
```

NLP with SpaCy

Although much of the analysis could be performed with other NLP packages, SpaCy was chosen due to its combination of speed and simplicity.

In [22]:
```
training_set = pd.read_pickle('training_corr.pkl')
```

In [23]:
```
sents = []
tokens = []
lemma = []
pos = []
ner = []

stop_words = set(STOP_WORDS)
stop_words.update(punctuation) # remove it if you need punctuation

nlp = spacy.load('en_core_web_sm')

t0 = datetime.now()

# suppress numpy warnings
#np.warnings.filterwarnings('ignore')

for essay in nlp.pipe(training_set['corrected'], batch_size=100):
    if essay.is_parsed:
```

```
            tokens.append([e.text for e in essay])
            sents.append([sent.text.strip() for sent in essay.sents])
            pos.append([e.pos_ for e in essay])
            ner.append([e.text for e in essay.ents])
            lemma.append([n.lemma_ for n in essay])
        else:
            # We want to make sure that the lists of parsed results have the
            # same number of entries of the original Dataframe, so add some blanks in case the parse fails
            tokens.append(None)
            lemma.append(None)
            pos.append(None)
            sents.append(None)
            ner.append(None)

training_set['tokens'] = tokens
training_set['lemma'] = lemma
training_set['pos'] = pos
training_set['sents'] = sents
training_set['ner'] = ner

t1 = datetime.now()
print('Processing time: {}'.format(t1 - t0))
```

```
/opt/anaconda3/lib/python3.9/site-packages/spacy/util.py:910: UserWarning: [W095] Model 'en_core_web_sm'
(3.0.0) was trained with spaCy v3.0.0 and may not be 100% compatible with the current version (3.7.4). If y
ou see errors or degraded performance, download a newer compatible model or retrain your custom model with
the current spaCy version. For more details and available updates, run: python -m spacy validate
  warnings.warn(warn_msg)
Processing time: 0:04:38.625142
```

In [24]:
```
training_set.to_pickle('training_spacy.pkl')
```

In [25]:
```
training_set = pd.read_pickle('training_spacy.pkl')
```

In [26]:
```
training_set[['tokens', 'pos', 'sents', 'ner']].head()
```

Out[26]:

	tokens	pos	sents	ner
0	[Dear, local, newspaper, ,, I, think, effects, computers, have, on, people, are, great, learning...	[ADJ, ADJ, NOUN, PUNCT, PRON, VERB, NOUN, NOUN, VERB, ADP, NOUN, AUX, ADJ, NOUN, NOUN, SYM, NOUN...	[Dear local newspaper, I think effects computers have on people are great learning skills/affect...	[@ORGANIZATION2, @CAPS1, @DATE1, @CAPS2]
1	[Dear, @CAPS1, @CAPS2, ,, I, believe, that, using, computers, will, benefit, us, in, many, ways,...	[PROPN, PROPN, PROPN, PUNCT, PRON, VERB, SCONJ, VERB, NOUN, AUX, VERB, PRON, ADP, ADJ, NOUN, ADP...	[Dear @CAPS1 @CAPS2, I believe that using computers will benefit us in many ways like talking an...	[Dear @CAPS1 @CAPS2, millions, one, millions, @LOCATION3, @LOCATION2, Million, @NUM1 hours, a lo...
2	[Dear, ,, @CAPS1, @CAPS2, @CAPS3, More, and, more, people, use, computers, ,, but, not, everyone...	[ADJ, PUNCT, PROPN, PROPN, PROPN, ADJ, CCONJ, ADJ, NOUN, VERB, NOUN, PUNCT, CCONJ, PART, PRON, V...	[Dear, @CAPS1 @CAPS2 @CAPS3 More and more people use computers, but not everyone agrees that thi...	[today, @CAPS4, a thousand]
3	[Dear, Local, Newspaper, ,, @CAPS1, I, have, found, that, many, experts, say, that, computers, d...	[PROPN, PROPN, PROPN, PUNCT, PROPN, PRON, AUX, VERB, SCONJ, ADJ, NOUN, VERB, SCONJ, NOUN, AUX, P...	[Dear Local Newspaper, @CAPS1 I have found that many experts say that computers do not benefit o...	[Dear Local Newspaper, @PERSON1, @PERCENT2, @PERCENT3, @PERCENT2, A+, @CAPS7, Newspaper, Newspap...
4	[Dear, @LOCATION1, ,, I, know, having, computers, has, a, positive, effect, on, people, ., The, ...	[ADJ, PROPN, PUNCT, PRON, VERB, VERB, NOUN, VERB, DET, ADJ, NOUN, ADP, NOUN, PUNCT, DET, NOUN, V...	[Dear @LOCATION1, I know having computers has a positive effect on people., The computers connec...	[First, @NUM1 hours, one, Secondly, one, only one, @CAPS1]

Topic Modeling with Latent Dirichlet Allocation

Latent Dirichlet Allocation, or **LDA**, uses probabilities to allocate any number of documents to a pre-defined number of topics. A very good explanation is given here:

https://tedunderwood.com/2012/04/07/topic-modeling-made-just-simple-enough/

The *Hewlett ASAP* essays are already labeled as belonging to one of eight topics. A baseline excercise will determine how well essays are allocated to a topic using LDA.

A second experiment will be performed using LDA to assign scores.

Another important remark is that LDA is based on probability distributions. Probing these distributions introduces randomness so the results of running this notebook might not exactly match the comments or annotations.

To minimize confusion between the *LDA* derived topics and the *Hewlett ASAP* given topics, the given topic numbers will be replaced with a one-word summary.

LDA uses the probability of finding certain words associated with documents. Stop words will not be very helpful, for example, the word "the" is going to have a high probability across all topics. In order to refine the word list, we'll also use the lemma generated by SpaCy instead of the regular essay. As a reminder, the lemma were generated on language corrected essays.

In [27]:
```
# Replace topic numbers with meaningful one-word summary:
topic_dict = {'topic':{1: 'computer',
                       2: 'censorship',
                       3: 'cyclist',
                       4: 'hibiscus',
                       5: 'mood',
                       6: 'dirigibles',
                       7: 'patience',
                       8: 'laughter'}}

training_set.replace(topic_dict, inplace=True)

# Lemmatized essays re-joined (list to essay)
training_set['l_essay'] = training_set['lemma'].apply(' '.join)
```

Convert essays to a matrix of token (lemma) counts:

In [31]:
```
# Baseline: number of unique lemma
vectorizer = CountVectorizer(max_df=.2,
                             min_df=3,
                             stop_words=list(STOP_WORDS),
                             max_features=2000) # default: binary=False
doc_term_matrix = vectorizer.fit_transform(training_set.l_essay) # using lemmatized essays

# Most frequent tokens:
words = vectorizer.get_feature_names_out()
doc_term_matrix_df = pd.DataFrame(doc_term_matrix.toarray(), columns=words)
word_freq = doc_term_matrix_df.sum(axis=0).astype(int)
word_freq.sort_values(ascending=False).head(10)
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/feature_extraction/text.py:409: UserWarning: Your stop_w
ords may be inconsistent with your preprocessing. Tokenizing the stop words generated tokens ['ll', 've'] n
ot in stop_words.
  warnings.warn(
```

Out[31]:
```
computer     20385
book         13976
building      7837
library       7631
dirigible     6250
read          6127
child         5767
help          5169
offensive     5117
talk          4981
dtype: int64
```

Apply LDA on the word frequency matrix.

In [32]:
```
lda_base = LatentDirichletAllocation(n_components=8,
                                     n_jobs=-1,
                                     learning_method='batch',
                                     max_iter=40,
                                     perp_tol=0.01,
                                     verbose=1,
```

```
                                     evaluate_every=5)
lda_base.fit(doc_term_matrix)

# save base model
joblib.dump(lda_base, 'lda_baseline.pkl')
```

```
iteration: 1 of max_iter: 40
iteration: 2 of max_iter: 40
iteration: 3 of max_iter: 40
iteration: 4 of max_iter: 40
iteration: 5 of max_iter: 40, perplexity: 377.7940
iteration: 6 of max_iter: 40
iteration: 7 of max_iter: 40
iteration: 8 of max_iter: 40
iteration: 9 of max_iter: 40
iteration: 10 of max_iter: 40, perplexity: 375.1996
iteration: 11 of max_iter: 40
iteration: 12 of max_iter: 40
iteration: 13 of max_iter: 40
iteration: 14 of max_iter: 40
iteration: 15 of max_iter: 40, perplexity: 374.8480
iteration: 16 of max_iter: 40
iteration: 17 of max_iter: 40
iteration: 18 of max_iter: 40
iteration: 19 of max_iter: 40
iteration: 20 of max_iter: 40, perplexity: 374.7384
iteration: 21 of max_iter: 40
iteration: 22 of max_iter: 40
iteration: 23 of max_iter: 40
iteration: 24 of max_iter: 40
iteration: 25 of max_iter: 40, perplexity: 374.6739
iteration: 26 of max_iter: 40
iteration: 27 of max_iter: 40
iteration: 28 of max_iter: 40
iteration: 29 of max_iter: 40
iteration: 30 of max_iter: 40, perplexity: 374.6351
iteration: 31 of max_iter: 40
iteration: 32 of max_iter: 40
iteration: 33 of max_iter: 40
iteration: 34 of max_iter: 40
iteration: 35 of max_iter: 40, perplexity: 374.6091
iteration: 36 of max_iter: 40
iteration: 37 of max_iter: 40
iteration: 38 of max_iter: 40
```

```
iteration: 39 of max_iter: 40
iteration: 40 of max_iter: 40, perplexity: 374.5841
```

Out[32]: ['lda_baseline.pkl']

Topic probabilities for all words. The numbered topics are generated from the latent Dirichlet allocation.

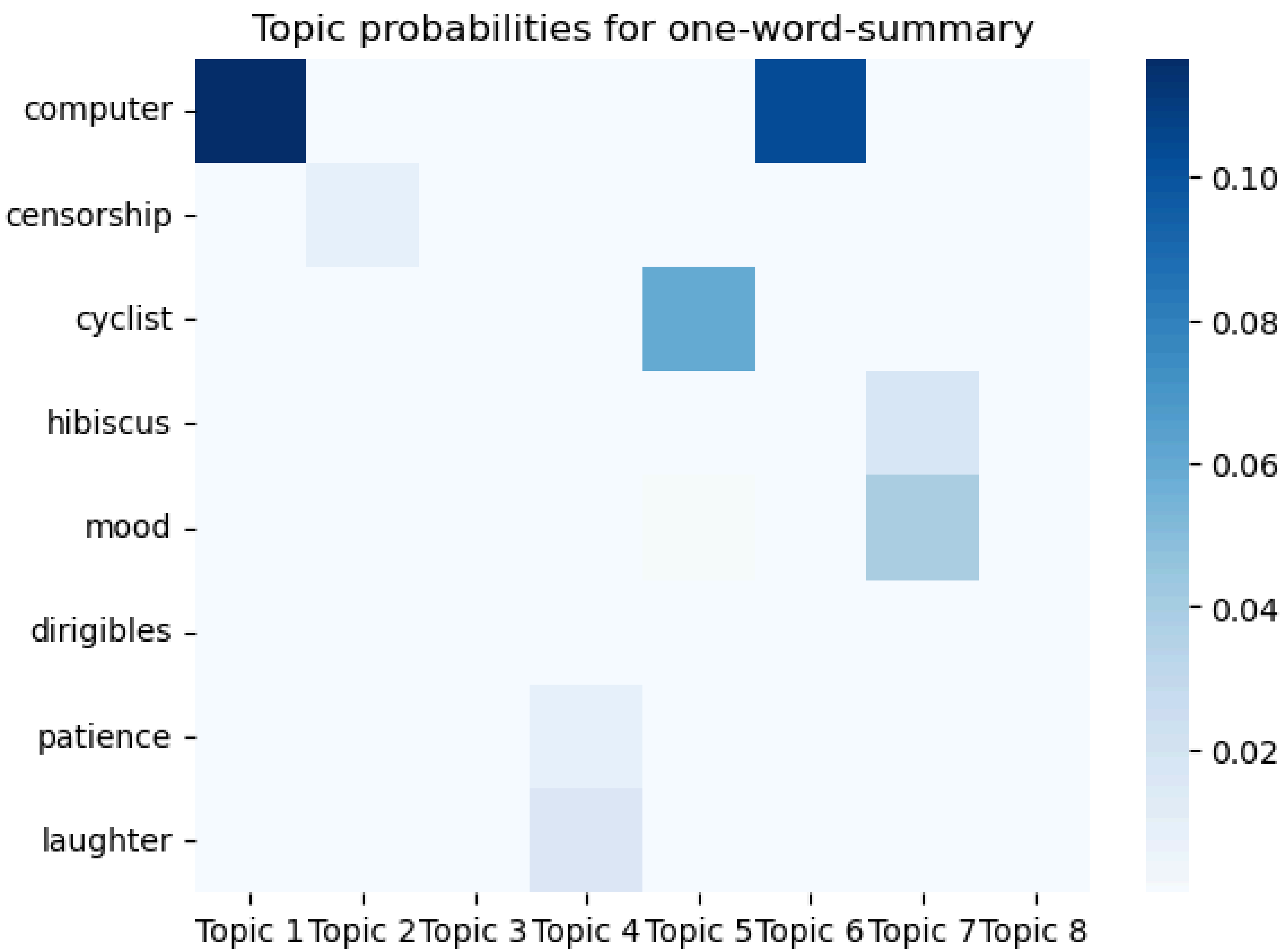
In [33]:
```
topic_labels = ['Topic {}'.format(i) for i in range(1, 9)]
topics_count = lda_base.components_
topics_prob = topics_count / topics_count.sum(axis=1).reshape(-1, 1)
topics = pd.DataFrame(topics_prob.T,
                      index=words,
                      columns=topic_labels)
topics.sample(10)
```

Out[33]:

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
grocery	0.000002	3.566629e-05	0.000001	1.010732e-04	0.000002	1.257325e-04	0.000001	0.000302
police	0.000002	3.451077e-05	0.000001	7.776651e-07	0.000002	2.157998e-04	0.000001	0.000302
increase	0.001493	6.085201e-05	0.000079	7.780401e-07	0.000388	6.794965e-04	0.000001	0.000003
luckily	0.000002	6.669756e-07	0.000014	2.208253e-04	0.000171	1.546135e-05	0.000001	0.000319
view	0.000375	3.671822e-03	0.000001	8.634331e-05	0.000465	2.554657e-04	0.000065	0.000003
network	0.000236	3.106371e-05	0.000020	7.771717e-07	0.000002	3.937072e-04	0.000001	0.000003
dangle	0.000002	6.663237e-07	0.002127	7.771105e-07	0.000002	9.935113e-07	0.000001	0.000003
box	0.000233	2.573980e-05	0.000001	5.207573e-04	0.000002	1.149679e-04	0.000001	0.000235
personality	0.000002	1.358855e-04	0.000001	2.775626e-04	0.000002	4.071248e-05	0.000068	0.000003
scare	0.000034	6.989508e-05	0.000001	2.343085e-04	0.000250	9.946539e-07	0.000001	0.000559

In [34]:
```
one_word = list(topic_dict['topic'].values())
sns.heatmap(topics.reindex(one_word), cmap='Blues')
```

```
plt.title('Topic probabilities for one-word-summary')
plt.show()
```



The heatmap suggests assignments for all but 1 topics.

Below are the most probable words for each topic. We can already see our one-word summaries of the actual topic near the top of the list.

In [35]:
```
top_words = {}
for topic, words_ in topics.items():
```

```
    top_words[topic] = words_.nlargest(10).index.tolist()
pd.DataFrame(top_words)
```

Out[35]:

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
0	computer	book	building	laugh	cyclist	computer	mood	caps3
1	spend	library	dirigible	patient	water	help	love	caps4
2	exercise	read	obstacle	wait	setting	learn	paragraph	caps5
3	kid	offensive	empire	laughter	affect	talk	memoir	caps6
4	outside	child	mast	mom	feature	online	test	person1
5	bad	movie	builder	tell	road	information	sang	person2
6	nature	shelf	face	start	hill	place	hibiscus	caps7
7	play	music	dock	patience	desert	hand	narcissa	organization1
8	reason	material	mooring	person1	hot	reason	create	caps8
9	enjoy	magazine	wind	hour	ride	internet	grateful	caps9

Now we can assign LDA topic probabilities to each essay and aggregate. It is now clear that, for example, LDA allocated topic 3 is aligned with the given topic "computers".

In [36]:

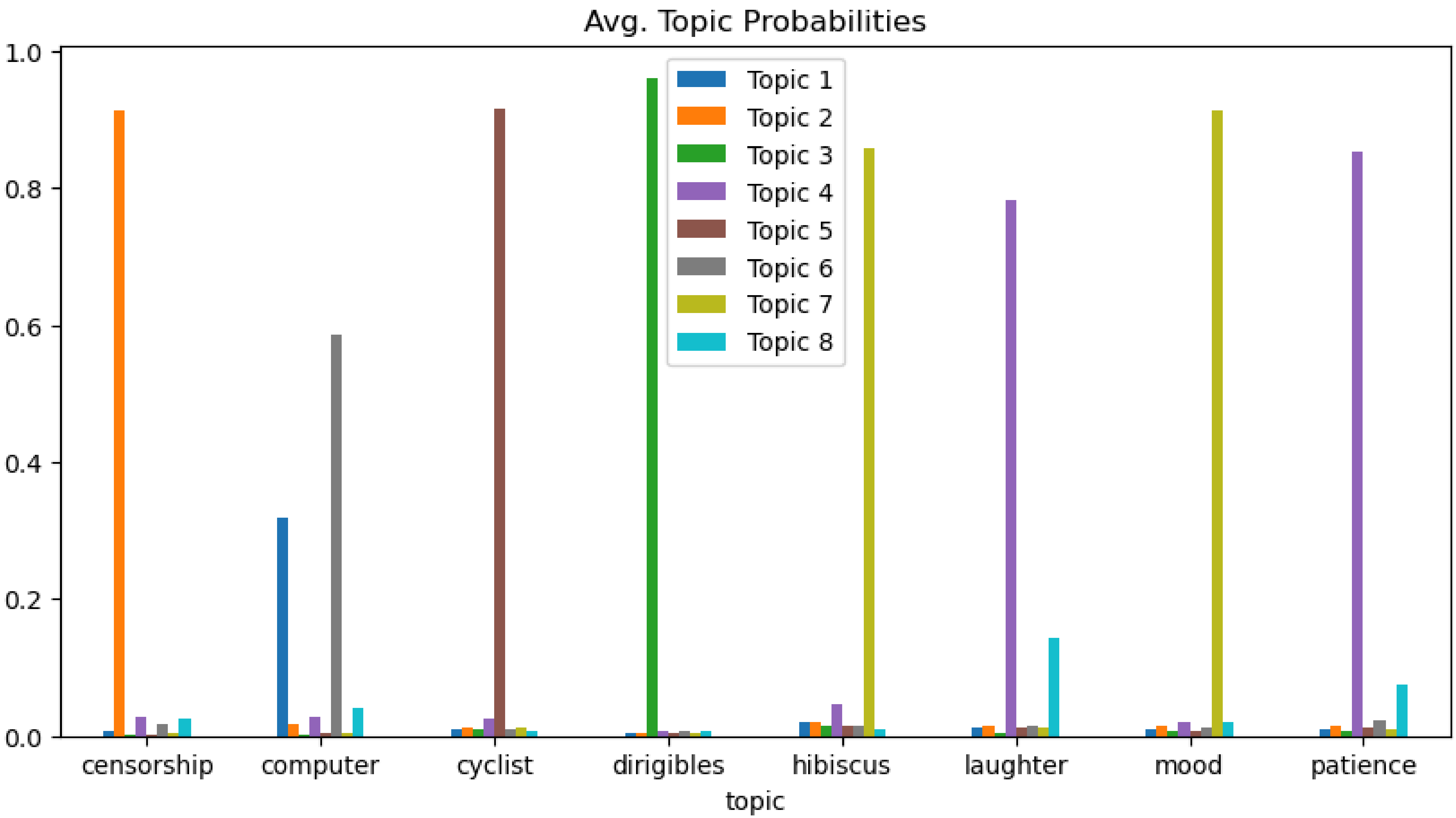
```
train_preds = lda_base.transform(doc_term_matrix)
train_eval = pd.DataFrame(train_preds, columns=topic_labels, index=training_set.topic)
train_eval.sample(10)
```

Out[36]:

topic	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
censorship	0.001192	0.991660	0.001191	0.001192	0.001191	0.001192	0.001191	0.001191
laughter	0.000596	0.043366	0.000597	0.764957	0.000596	0.051134	0.075495	0.063259
mood	0.006258	0.006254	0.006251	0.006257	0.006253	0.006263	0.956209	0.006254
dirigibles	0.001406	0.001405	0.990163	0.001405	0.001405	0.001405	0.001406	0.001405
censorship	0.001017	0.992883	0.001017	0.001017	0.001017	0.001017	0.001017	0.001016
hibiscus	0.003382	0.003381	0.003380	0.003387	0.041978	0.003380	0.937727	0.003385
laughter	0.076853	0.001391	0.001389	0.794300	0.001390	0.001392	0.001390	0.121895
dirigibles	0.007821	0.007817	0.656216	0.007823	0.007814	0.296871	0.007814	0.007823
censorship	0.002018	0.985875	0.002017	0.002018	0.002017	0.002020	0.002018	0.002017
censorship	0.000745	0.994784	0.000745	0.000746	0.000745	0.000745	0.000745	0.000745

In [37]:

```
train_eval.groupby(level='topic').mean().plot.bar(title='Avg. Topic Probabilities', rot=0, colormap='tab10
```



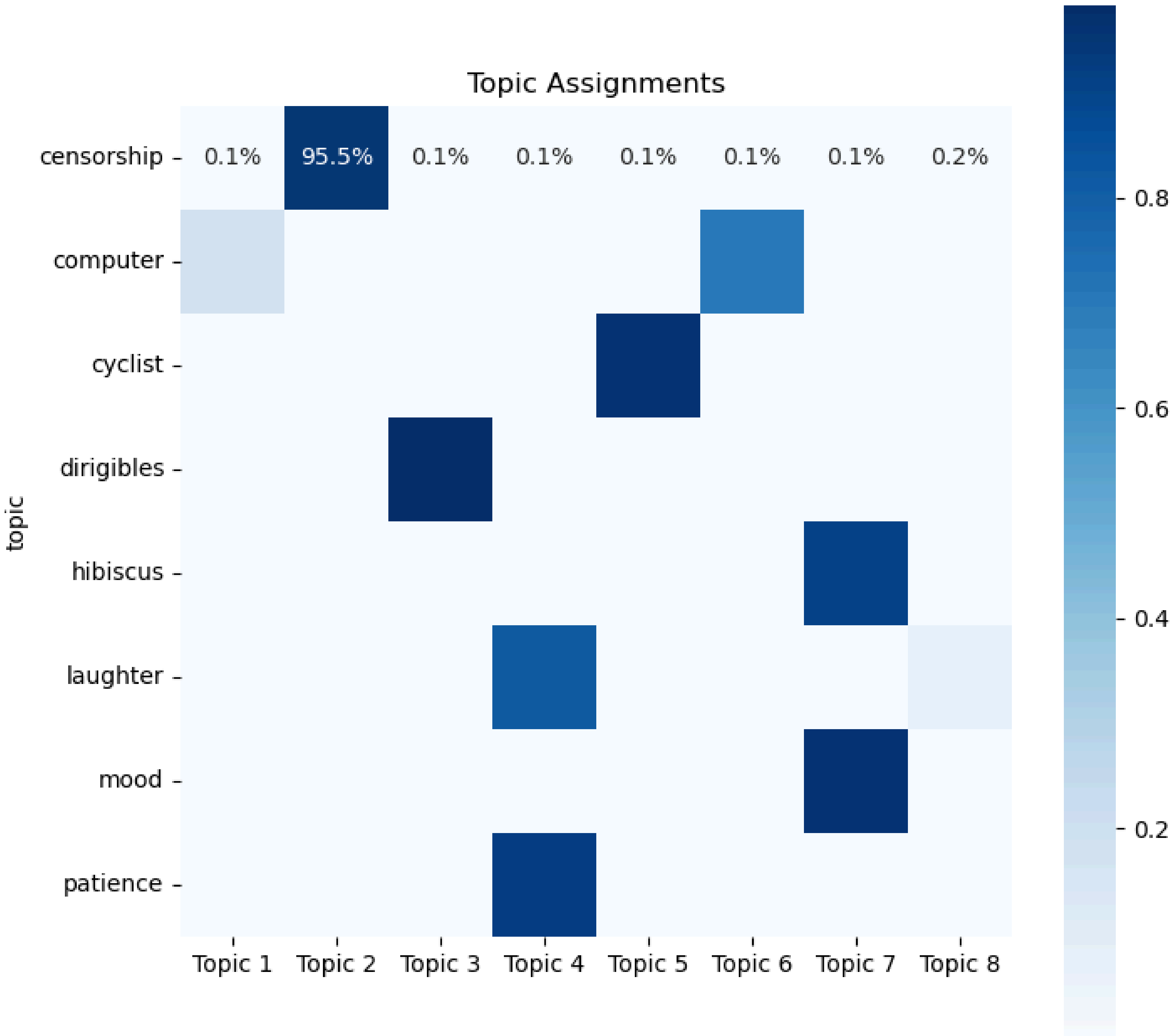
The baseline model was successful in that each given topic is allocated with high probability to an LDA topic:

In [38]:
```
df = train_eval.groupby(level='topic').agg('median')
fig, ax = plt.subplots(figsize=(8,8))
g = sns.heatmap(df, annot=True, fmt='.1%', annot_kws={"size": 10}, cmap='Blues', square=True)
loc, labels = plt.yticks()
g.set_yticklabels(labels, rotation=0)
g.set_title('Topic Assignments');
```

```
df = train_eval\
            .idxmax(axis=1)\
            .reset_index()\
            .groupby('topic', as_index=False)\
            .agg(lambda x:x.value_counts().index[0])\
            .rename(columns={0:'assignment'})
df
```

Out[38]:

	topic	assignment
0	censorship	Topic 2
1	computer	Topic 6
2	cyclist	Topic 5
3	dirigibles	Topic 3
4	hibiscus	Topic 7
5	laughter	Topic 4
6	mood	Topic 7
7	patience	Topic 4


Topic Assignments
censorship
computer
cyclist
dirigibles
hibiscus
laughter
mood
patience
topic
0.1%
95.5%
0.1%
0.1%
0.1%
0.1%
0.1%
0.2%
Topic 1
Topic 2
Topic 3
Topic 4
Topic 5
Topic 6
Topic 7
Topic 8
0.8
0.6
0.4
0.2

Visualization with PyLDAVis

Lambda

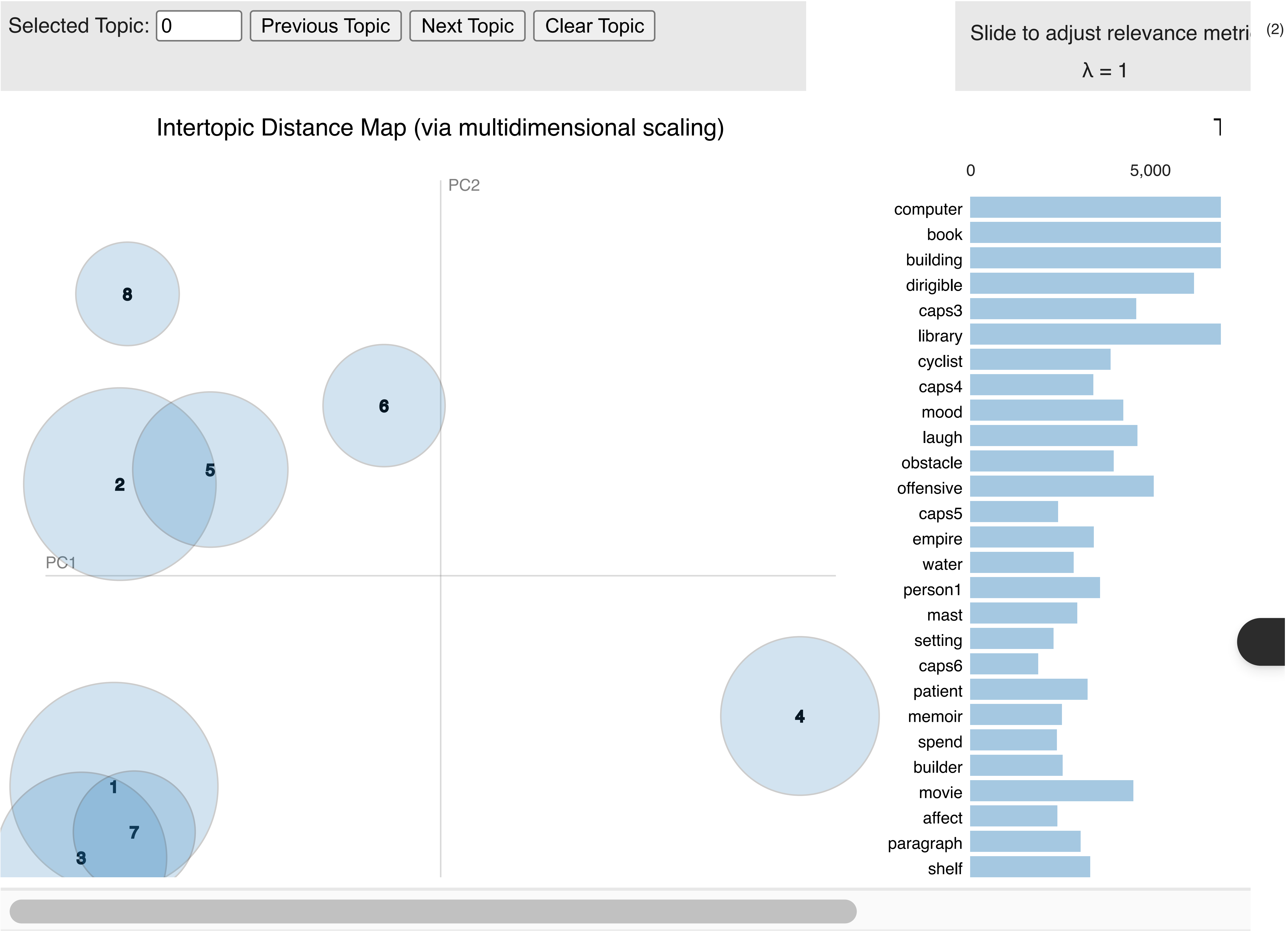
- λ **= 0**: how probable is a word to appear in a topic - words are ranked on lift P(word | topic) / P(word)
- λ **= 1**: how exclusive is a word to a topic - words are purely ranked on P(word | topic)

The ranking formula is $\lambda * P(\text{word}|\text{topic}) + (1-\lambda) * \text{lift}$

User studies suggest $\lambda = 0.6$ works for most people.

In [39]:
```
prepare(lda_base, doc_term_matrix, vectorizer)
```

Out[39]:


Selected Topic: 0
Previous Topic
Next Topic
Clear Topic
Slide to adjust relevance metri (2)
λ = 1
Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
8
6
2
5
4
1
7
3
0
5,000
computer
book
building
dirigible
caps3
library
cyclist
caps4
mood
laugh
obstacle
offensive
caps5
empire
water
person1
mast
setting
caps6
patient
memoir
spend
builder
movie
affect
paragraph
shelf

"Score Allocation"

Can we take this to the next level and assign target scores based on word probabilities? To keep it simple, we'll limit the essays to topic number 4, "hibiscus". This topic has only four target scores and a reasonably balanced distribution.

In [40]:
```
hibiscus = training_set[training_set.topic == 'hibiscus']

# Split essays into training and test sets
train_essays, test_essays = train_test_split(hibiscus,
                                             stratify=hibiscus.target_score,
                                             test_size=0.2,
                                             random_state=42)
```

In [42]:
```
vectorizer = CountVectorizer(max_df=.2,
                             min_df=3,
                             stop_words=list(STOP_WORDS),
                             max_features=400) # limit to account for smaller set of essays

# Train and test doc-term matrices
train_dtm = vectorizer.fit_transform(train_essays.l_essay)
test_dtm = vectorizer.fit_transform(test_essays.l_essay)
```

```
/opt/anaconda3/lib/python3.9/site-packages/sklearn/feature_extraction/text.py:409: UserWarning: Your stop_w
ords may be inconsistent with your preprocessing. Tokenizing the stop words generated tokens ['ll', 've'] n
ot in stop_words.
  warnings.warn(
```

In [43]:
```
lda_score = LatentDirichletAllocation(n_components=4,
                                      n_jobs=-1,
                                      learning_method='batch',
                                      evaluate_every=5,
                                      verbose=1,
                                      max_iter=500)
lda_score.fit(train_dtm)
```

```
# save training model
joblib.dump(lda_score, 'lda_score.pkl')
```

```
iteration: 1 of max_iter: 500
iteration: 2 of max_iter: 500
iteration: 3 of max_iter: 500
iteration: 4 of max_iter: 500
iteration: 5 of max_iter: 500, perplexity: 284.7708
iteration: 6 of max_iter: 500
iteration: 7 of max_iter: 500
iteration: 8 of max_iter: 500
iteration: 9 of max_iter: 500
iteration: 10 of max_iter: 500, perplexity: 276.5026
iteration: 11 of max_iter: 500
iteration: 12 of max_iter: 500
iteration: 13 of max_iter: 500
iteration: 14 of max_iter: 500
iteration: 15 of max_iter: 500, perplexity: 273.2062
iteration: 16 of max_iter: 500
iteration: 17 of max_iter: 500
iteration: 18 of max_iter: 500
iteration: 19 of max_iter: 500
iteration: 20 of max_iter: 500, perplexity: 271.5828
iteration: 21 of max_iter: 500
iteration: 22 of max_iter: 500
iteration: 23 of max_iter: 500
iteration: 24 of max_iter: 500
iteration: 25 of max_iter: 500, perplexity: 270.6663
iteration: 26 of max_iter: 500
iteration: 27 of max_iter: 500
iteration: 28 of max_iter: 500
iteration: 29 of max_iter: 500
iteration: 30 of max_iter: 500, perplexity: 270.0328
iteration: 31 of max_iter: 500
iteration: 32 of max_iter: 500
iteration: 33 of max_iter: 500
iteration: 34 of max_iter: 500
iteration: 35 of max_iter: 500, perplexity: 269.6751
iteration: 36 of max_iter: 500
iteration: 37 of max_iter: 500
iteration: 38 of max_iter: 500
```

```
iteration: 39 of max_iter: 500
iteration: 40 of max_iter: 500, perplexity: 269.4668
iteration: 41 of max_iter: 500
iteration: 42 of max_iter: 500
iteration: 43 of max_iter: 500
iteration: 44 of max_iter: 500
iteration: 45 of max_iter: 500, perplexity: 269.2546
iteration: 46 of max_iter: 500
iteration: 47 of max_iter: 500
iteration: 48 of max_iter: 500
iteration: 49 of max_iter: 500
iteration: 50 of max_iter: 500, perplexity: 269.1696
```

Out[43]: ['lda_score.pkl']

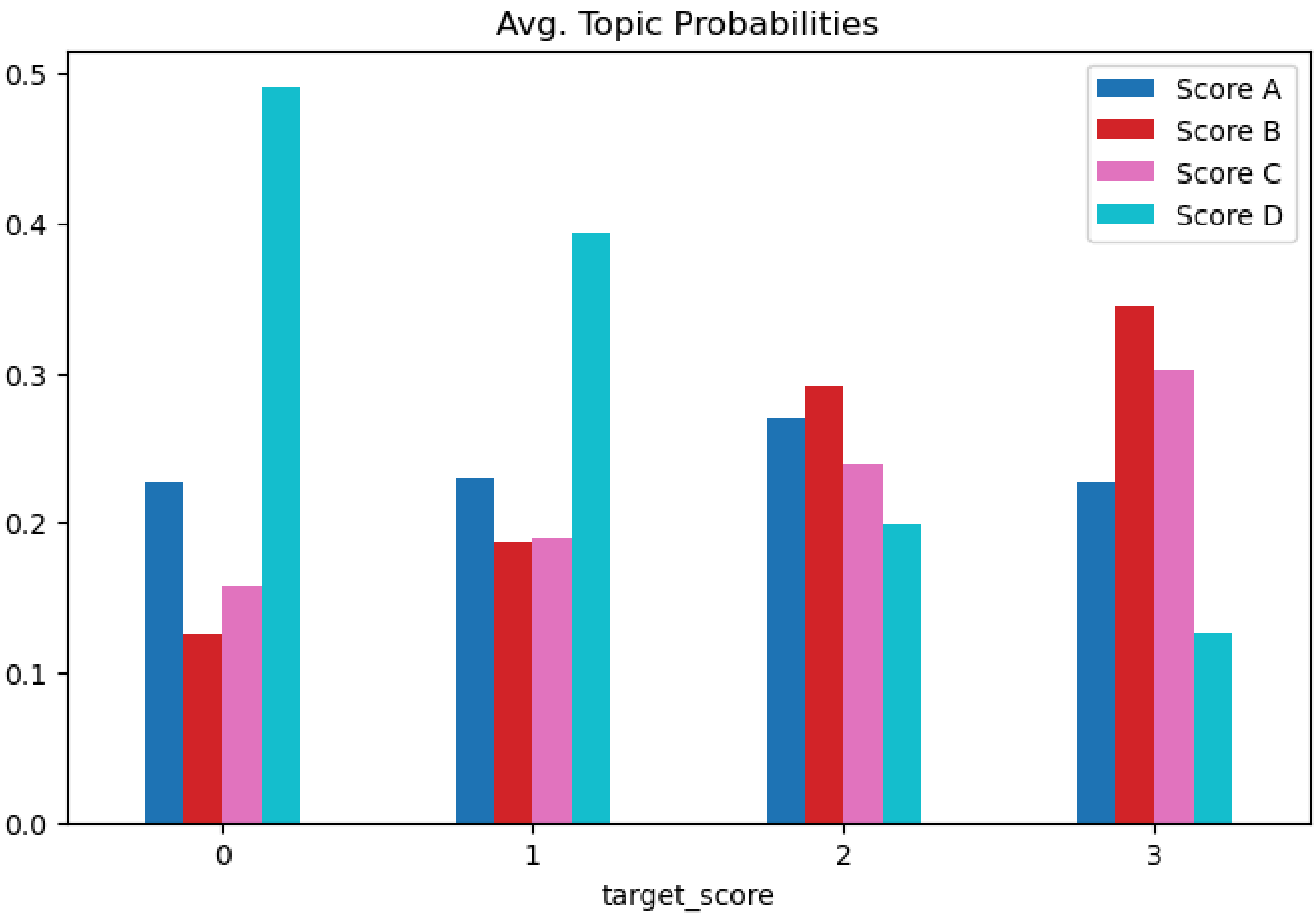
In [44]:
```
topic_labels = ['Score A', 'Score B', 'Score C', 'Score D'] #.format(i) for i in range(1, 5)]

train_preds = lda_score.transform(train_dtm)
train_eval = pd.DataFrame(train_preds, columns=topic_labels, index=train_essays.target_score)
train_eval.sample(5)
```

Out[44]:

target_score	Score A	Score B	Score C	Score D
1	0.013395	0.193333	0.683054	0.110218
2	0.032944	0.033714	0.900212	0.033131
0	0.250000	0.250000	0.250000	0.250000
1	0.494167	0.047301	0.042709	0.415824
1	0.364097	0.028443	0.029704	0.577757

In [45]:
```
train_eval.groupby(level='target_score')\
             .mean()\
             .plot\
             .bar(title='Avg. Topic Probabilities', rot=0, colormap='tab10', figsize=(8,5));
```



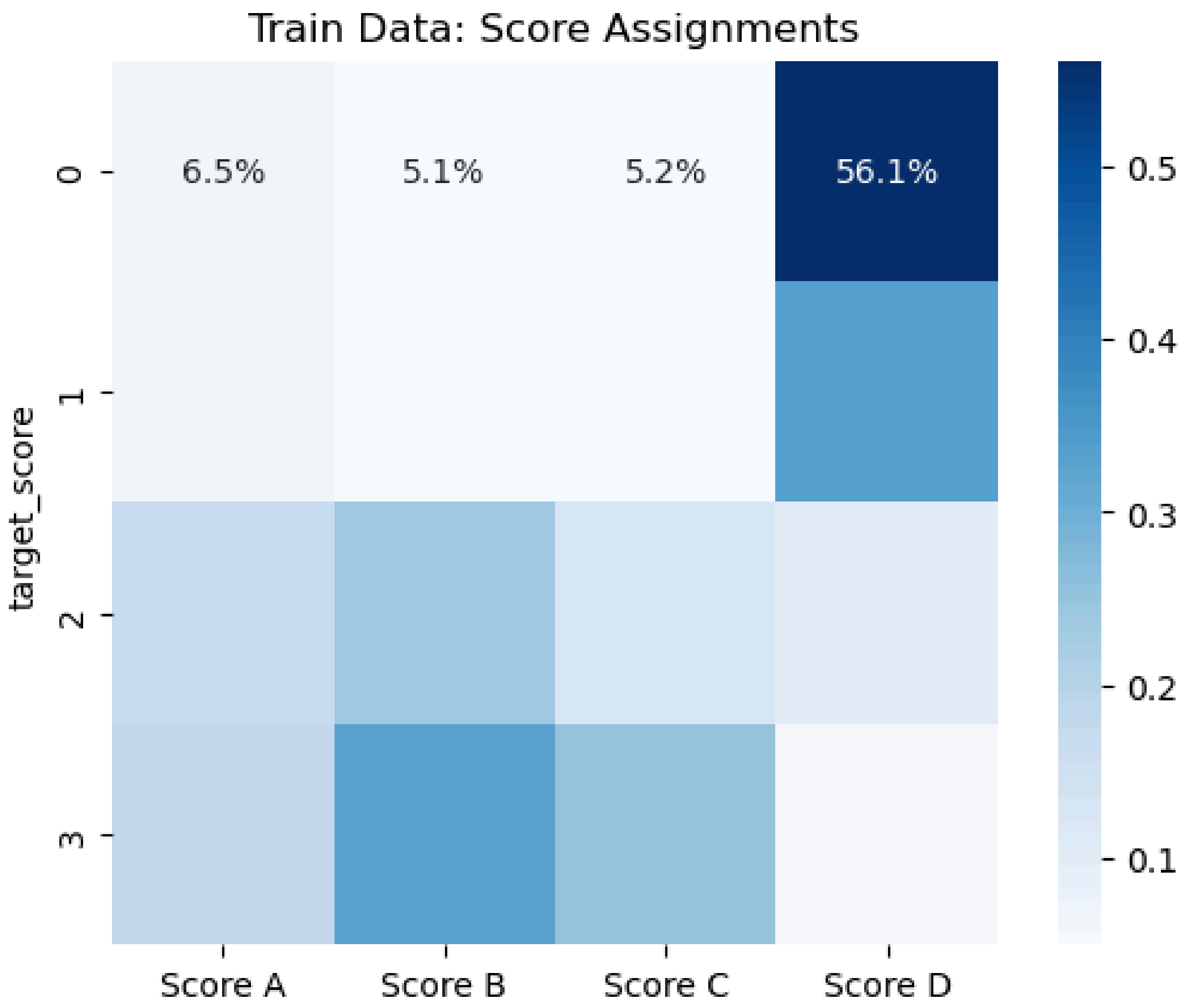
In [46]:
```
df = train_eval.groupby(level='target_score').agg('median')
sns.heatmap(df, annot=True, fmt='.1%', cmap='Blues', square=True)
plt.title('Train Data: Score Assignments');

df = train_eval\
            .idxmax(axis=1)\
            .reset_index()\
            .groupby('target_score', as_index=False)\
            .agg(lambda x:x.value_counts().index[0])\
```

```
              .rename(columns={0:'assignment'})
df
```

Out[46]:

	target_score	assignment
0	0	Score D
1	1	Score D
2	2	Score B
3	3	Score B

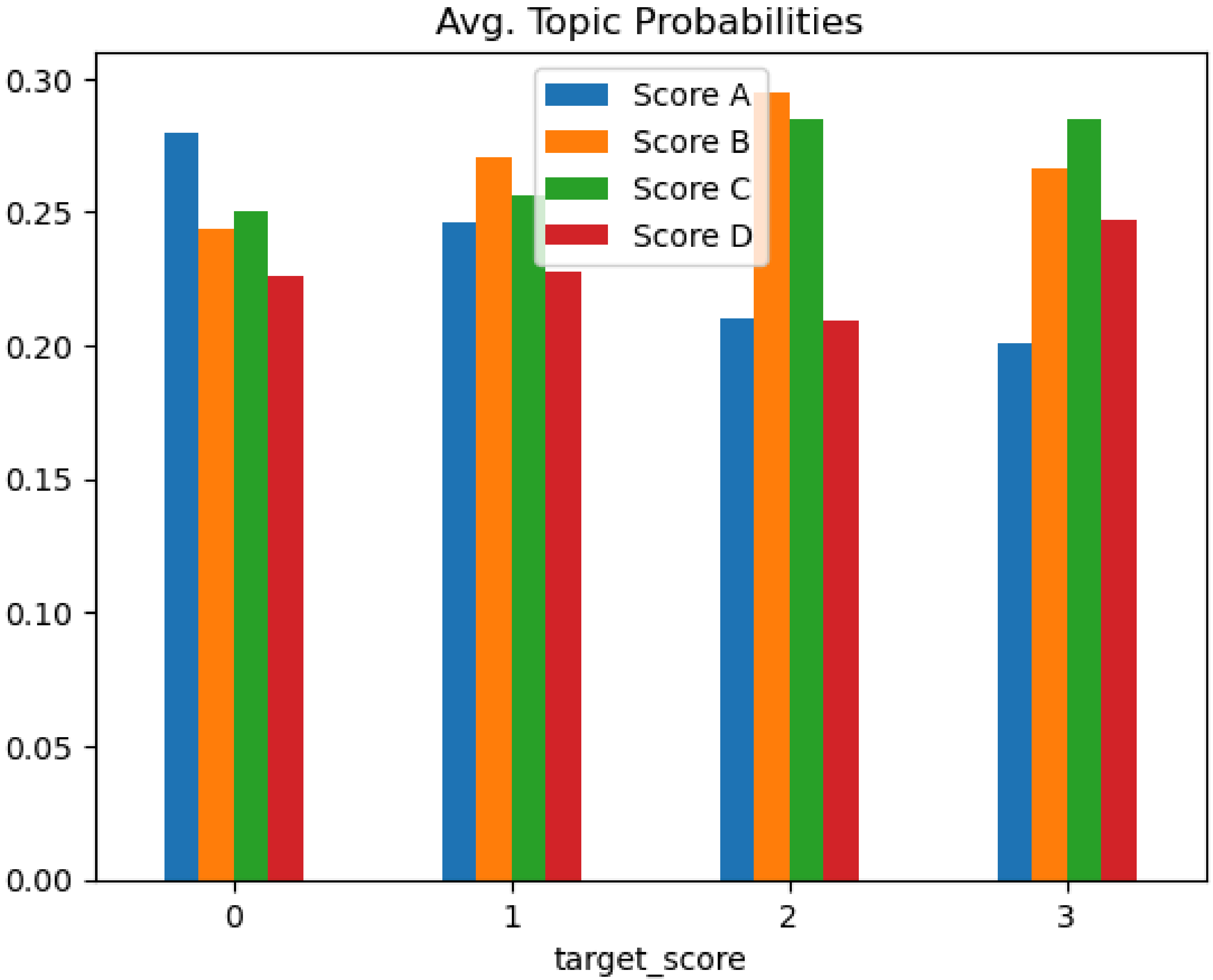


In [47]:
```
test_preds = lda_score.transform(test_dtm)
test_eval = pd.DataFrame(test_preds, columns=topic_labels, index=test_essays.target_score)
test_eval.head()
```

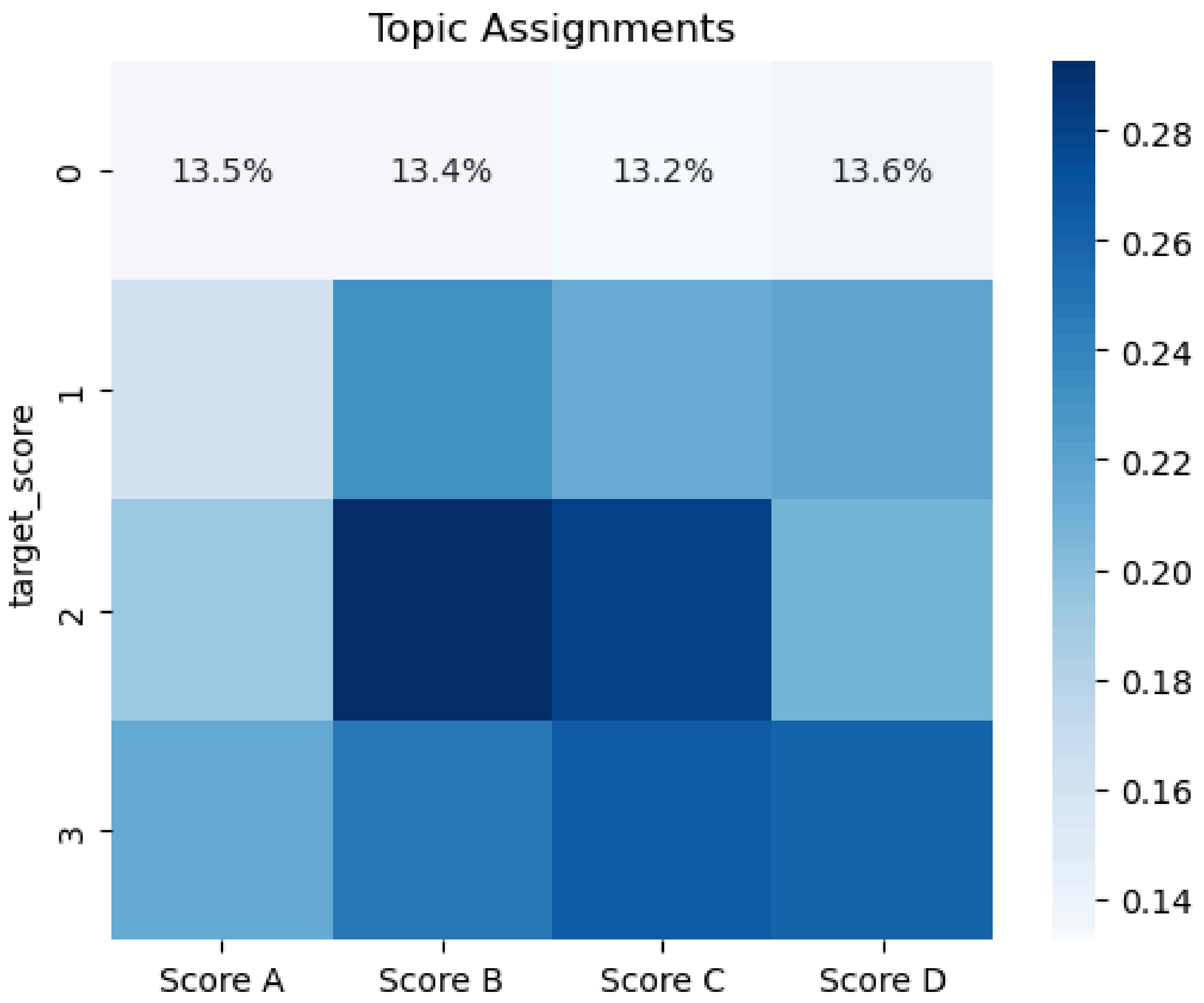
Out[47]:

target_score	Score A	Score B	Score C	Score D
2	0.269809	0.256387	0.398377	0.075428
3	0.131576	0.298208	0.217197	0.353020
0	0.375829	0.037287	0.419204	0.167680
1	0.465458	0.231958	0.217381	0.085203
1	0.914477	0.028287	0.028804	0.028433

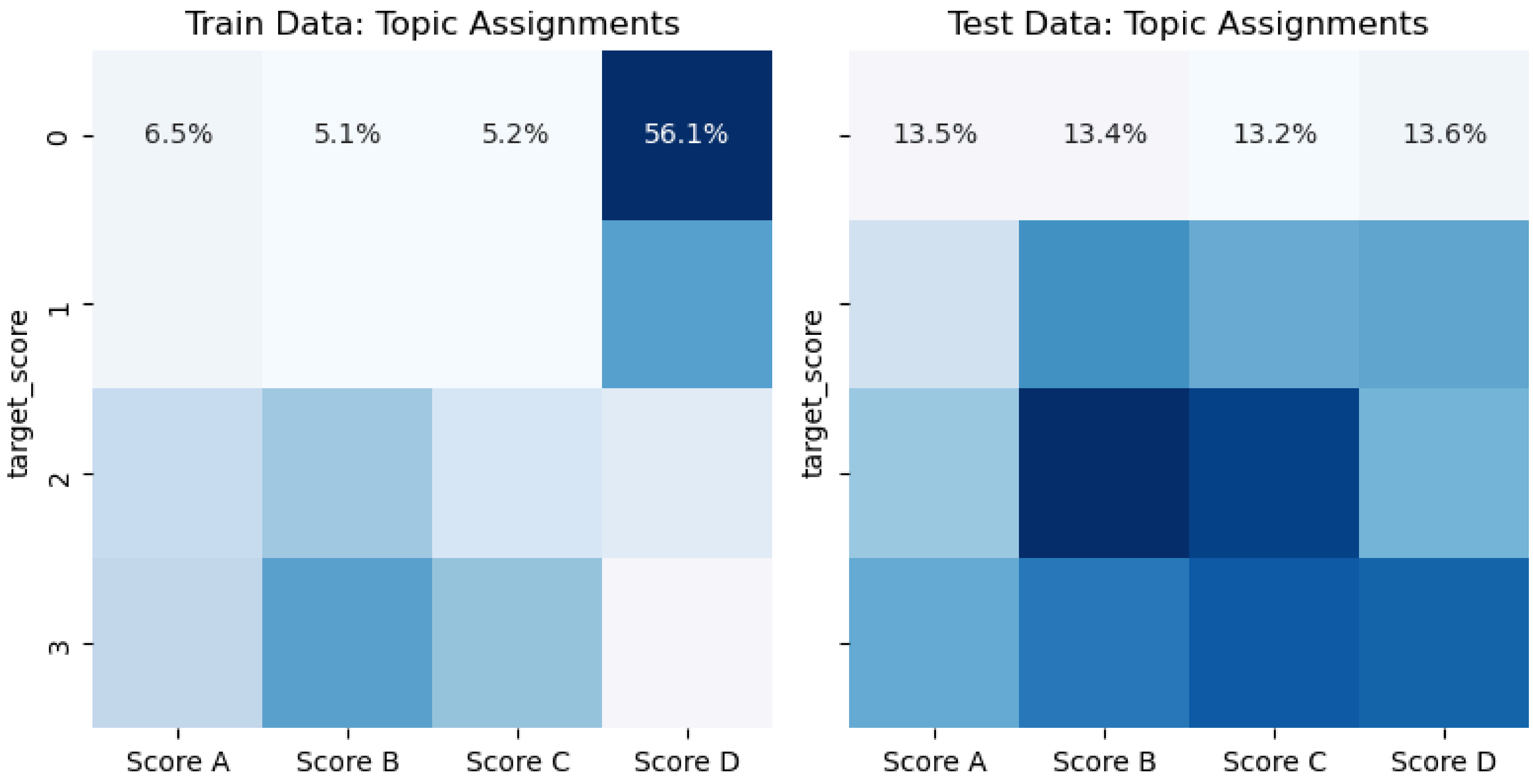
In [48]:
```
test_eval.groupby(level='target_score')\
            .mean()\
            .plot\
            .bar(title='Avg. Topic Probabilities', rot=0);
```



In [49]:
```
df = test_eval.groupby(level='target_score').agg('median')
sns.heatmap(df, annot=True, fmt='.1%', cmap='Blues', square=True)
plt.title('Topic Assignments')
plt.show()
```



In [50]:
```python
fig, axes = plt.subplots(ncols=2, figsize=(8,6), sharey=True)
source = ['Train', 'Test']
for i, df in enumerate([train_eval, test_eval]):
    df = df.groupby(level='target_score').agg('median')
    sns.heatmap(df, annot=True, fmt='.1%', cmap='Blues', square=True, ax=axes[i], cbar=False)
    axes[i].set_title('{} Data: Topic Assignments'.format(source[i]))
plt.tight_layout()
plt.show()
```



While the charts above are very similar to a confusion matrix, the ordering of the LDA derived topics (A,B,C,D) doesn't necessarily match the human-labeled topic ordering (0,1,2,3). Thus, the high percentages, shown here as deep blues, are not expected to be found along the diagonal. Instead the goal is to find topic distinction, indicated by a single dark square in each column, and model accuracy, indicated by identical color patterns between train and test data sets.

As seen above, there is some agreement between train and test data that essays with highest and lowest scores are distinct and assigned "Score A" and "Score B" respectively. Overall, both topic distinction and model accuracy are rather poor. It is highly improbable this approach could be extended to any of the other topics due to the larger range of scores and class imbalance.

Furthermore, repeated LDA runs show a lack of reproducability, which is a sign of poor distinction of topics. In summary, topic modelling, or more specifically using word frequencies and probabilities is not a useful tool to grade student essays. In the next notebook we'll continue with machine learning algorithms.

In [ ]:

```

```