# 04_lda_with_sklearn

September 29, 2021

## 0.1 Topic Modeling: Latent Dirichlet Allocation with sklearn

### 0.1.1 Imports

[1]:
```
import warnings
from collections import OrderedDict
from pathlib import Path

import numpy as np
import pandas as pd

# Visualization
from ipywidgets import interact, FloatSlider
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter
import seaborn as sns

import pyLDAvis
from pyLDAvis.sklearn import prepare

from wordcloud import WordCloud
from termcolor import colored

# spacy for language processing
import spacy

# sklearn for feature extraction & modeling
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer,␣
↪TfidfTransformer
from sklearn.decomposition import LatentDirichletAllocation, TruncatedSVD, NMF
from sklearn.model_selection import train_test_split
from sklearn.externals import joblib
```

[3]:
```
%matplotlib inline
plt.style.use('ggplot')
plt.rcParams['figure.figsize'] = (14.0, 8.7)
pyLDAvis.enable_notebook()
warnings.filterwarnings('ignore')
```

```
pd.options.display.float_format = '{:,.2f}'.format
```

[20]:
```
# change to your data path if necessary
DATA_DIR = Path('../data')
data_path = DATA_DIR / 'bbc'
```

[21]:
```
results_path = Path('results')
model_path = Path('results', 'bbc')
if not model_path.exists():
    model_path.mkdir(exist_ok=True, parents=True)
```

## 0.2 Load BBC data

Using the BBC data as before, we use sklearn.decomposition.LatentDirichletAllocation to train an LDA model with five topics.

[6]:
```
files = data_path.glob('**/*.txt')
doc_list = []
for i, file in enumerate(files):
    with open(str(file), encoding='latin1') as f:
        topic = file.parts[-2]
        lines = f.readlines()
        heading = lines[0].strip()
        body = ' '.join([l.strip() for l in lines[1:]])
        doc_list.append([topic.capitalize(), heading, body])
```

### 0.2.1 Convert to DataFrame

[10]:
```
docs = pd.DataFrame(doc_list, columns=['topic', 'heading', 'article'])
docs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2225 entries, 0 to 2224
Data columns (total 3 columns):
topic      2225 non-null object
heading    2225 non-null object
article    2225 non-null object
dtypes: object(3)
memory usage: 52.2+ KB
```

## 0.3 Create Train & Test Sets

[11]:
```
train_docs, test_docs = train_test_split(docs,
                                         stratify=docs.topic,
                                         test_size=50,
                                         random_state=42)
```

[12]:
```
train_docs.shape, test_docs.shape
```

[12]:
```
((2175, 3), (50, 3))
```

[13]:
```
pd.Series(test_docs.topic).value_counts()
```

[13]:
```
Sport            12
Business         11
Tech              9
Politics          9
Entertainment     9
Name: topic, dtype: int64
```

### 0.3.1 Vectorize train & test sets

[14]:
```
vectorizer = TfidfVectorizer(max_df=.2,
                             min_df=.01,
                             stop_words='english')

train_dtm = vectorizer.fit_transform(train_docs.article)
words = vectorizer.get_feature_names()
train_dtm
```

[14]:
```
<2175x2899 sparse matrix of type '<class 'numpy.float64'>'
        with 204945 stored elements in Compressed Sparse Row format>
```

[15]:
```
test_dtm = vectorizer.transform(test_docs.article)
test_dtm
```

[15]:
```
<50x2899 sparse matrix of type '<class 'numpy.float64'>'
        with 4759 stored elements in Compressed Sparse Row format>
```

### 0.3.2 LDA with sklearn

[16]:
```
n_components = 5
topic_labels = ['Topic {}'.format(i) for i in range(1, n_components+1)]
```

[17]:
```
lda_base = LatentDirichletAllocation(n_components=n_components,
                                     n_jobs=-1,
                                     learning_method='batch',
                                     max_iter=10)
lda_base.fit(train_dtm)
```

[17]:
```
LatentDirichletAllocation(batch_size=128, doc_topic_prior=None,
             evaluate_every=-1, learning_decay=0.7,
             learning_method='batch', learning_offset=10.0,
             max_doc_update_iter=100, max_iter=10, mean_change_tol=0.001,
```

```
             n_components=5, n_jobs=-1, n_topics=None, perp_tol=0.1,
             random_state=None, topic_word_prior=None,
             total_samples=1000000.0, verbose=0)
```

**Persist model** The model tracks the in-sample perplexity during training and stops iterating once this measure stops improving. We can persist and load the result as usual with sklearn objects:

[22]:
```python
joblib.dump(lda_base, model_path / 'lda_10_iter.pkl')
```

[22]:
```
['results/bbc/lda_10_iter.pkl']
```

[23]:
```python
lda_base = joblib.load(model_path / 'lda_10_iter.pkl')
lda_base
```

[23]:
```
LatentDirichletAllocation(batch_size=128, doc_topic_prior=None,
             evaluate_every=-1, learning_decay=0.7,
             learning_method='batch', learning_offset=10.0,
             max_doc_update_iter=100, max_iter=10, mean_change_tol=0.001,
             n_components=5, n_jobs=-1, n_topics=None, perp_tol=0.1,
             random_state=None, topic_word_prior=None,
             total_samples=1000000.0, verbose=0)
```

### 0.3.3 Explore topics & word distributions

[24]:
```python
# pseudo counts
topics_count = lda_base.components_
print(topics_count.shape)
topics_count[:5]
```

```
(5, 2899)
```

[24]:
```
array([[13.6484    ,  8.92765995,  1.31418808, …,  1.99495236,
         0.20661246,  0.73422033],
       [ 1.12298041,  0.57822241,  0.89849244, …,  0.90932536,
         0.20011641,  0.21499239],
       [ 3.5594674 ,  0.62943508,  0.64723764, …,  0.34056913,
         0.20001791,  0.30883726],
       [ 0.20017937,  0.20022822,  0.20016096, …,  0.20015571,
        11.59332613,  0.20018161],
       [ 4.56503009,  0.94708874,  2.04736569, …,  0.86563724,
         0.20001157,  5.03625788]])
```

[25]:
```python
topics_prob = topics_count / topics_count.sum(axis=1).reshape(-1, 1)
topics = pd.DataFrame(topics_prob.T,
                      index=words,
                      columns=topic_labels)
topics.head()
```

[25]:

| | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 |
|---|---|---|---|---|---|
| 10 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 100 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 100m | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 11 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

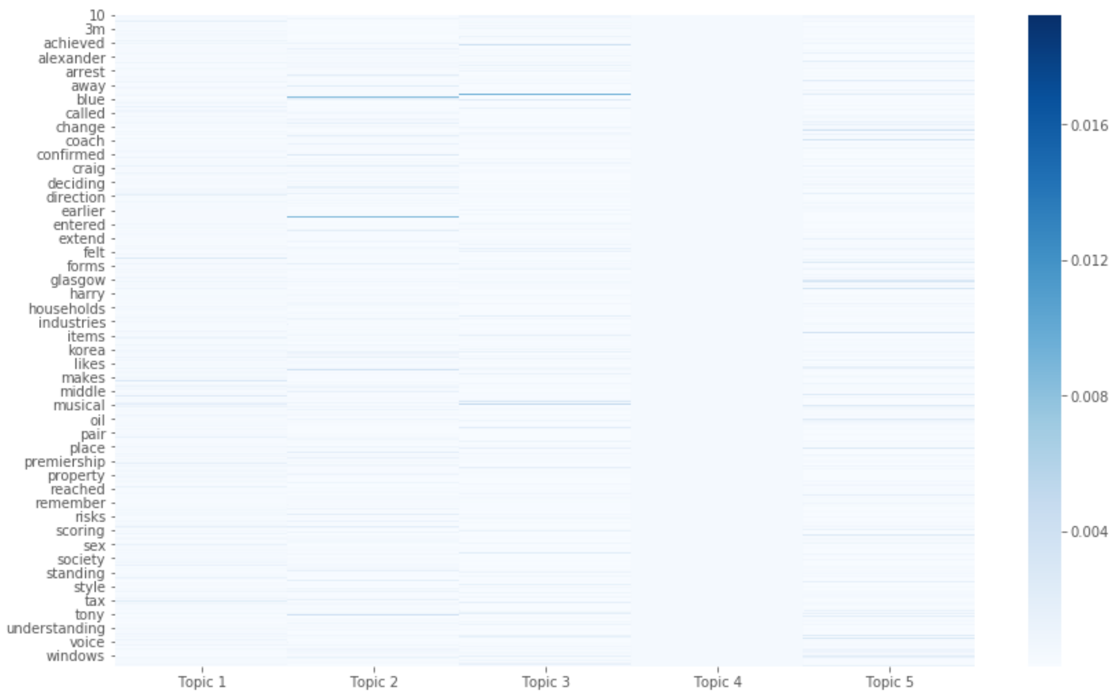
[26]:

```
# all words have positive probability for all topics
topics[topics.gt(0).all(1)].shape[0] == topics.shape[0]
```

[26]: True

[27]:

```
sns.heatmap(topics, cmap='Blues');
```




[28]:

```
top_words = {}
for topic, words_ in topics.items():
    top_words[topic] = words_.nlargest(10).index.tolist()
pd.DataFrame(top_words)
```

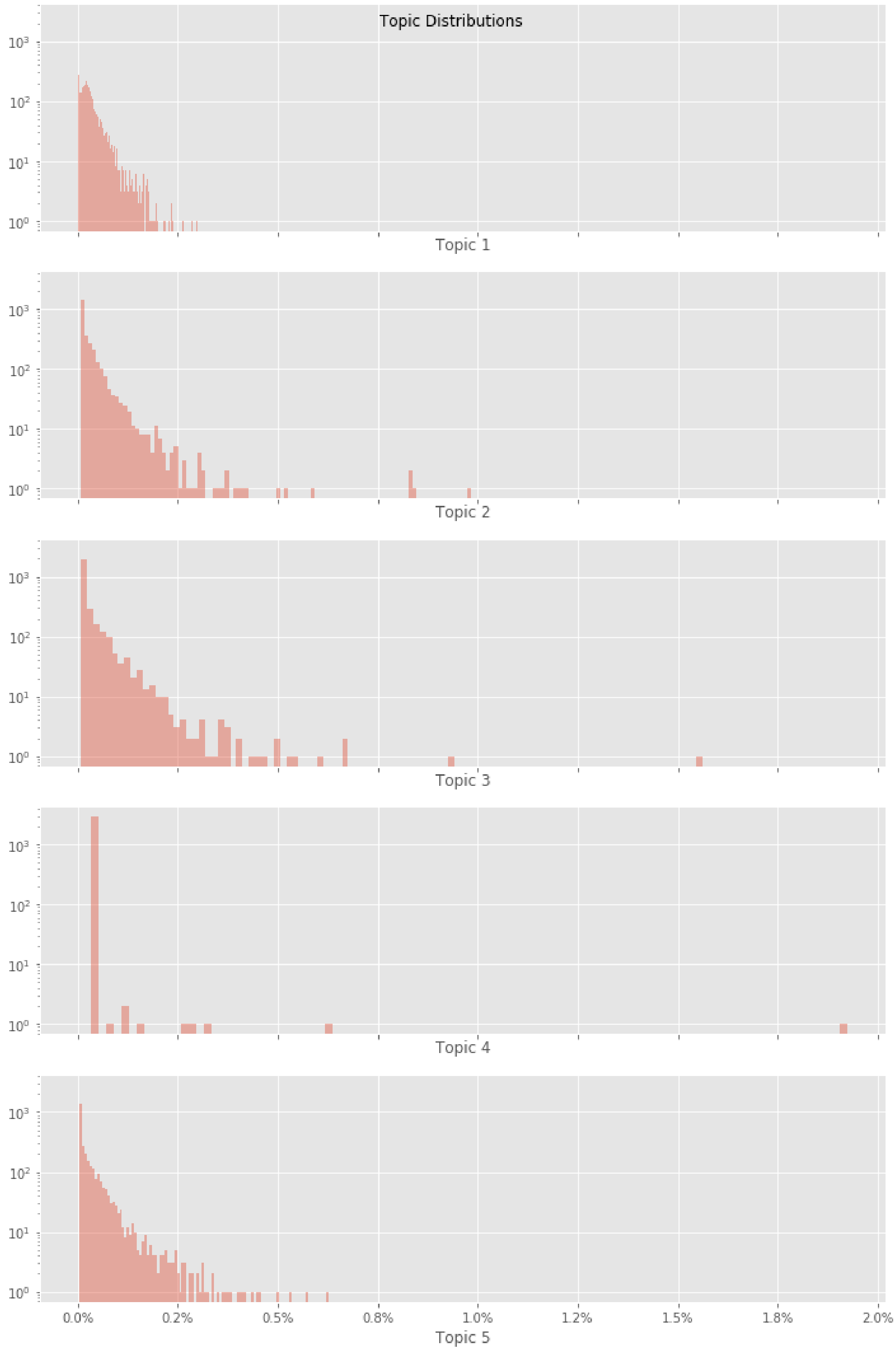
[28]:

| | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 |
|---|---|---|---|---|---|
| 0 | company | labour | film | yukos | game |
| 1 | market | party | best | russian | england |
| 2 | firm | election | awards | sullivan | win |
| 3 | sales | blair | award | auction | club |
| 4 | mobile | brown | band | mikhail | match |

```
5      growth    minister      star      russia      cup
6        2004      howard     album  ambitions     team
7  technology       prime     music  bankruptcy     play
8     economy  chancellor     actor       court  players
9     million        tory  festival       judge   injury
```

[29]:

```
fig, axes = plt.subplots(nrows=5, sharey=True, sharex=True, figsize=(10, 15))
for i, (topic, prob) in enumerate(topics.items()):
    sns.distplot(prob, ax=axes[i], bins=100, kde=False, norm_hist=False)
    axes[i].set_yscale('log')
    axes[i].xaxis.set_major_formatter(FuncFormatter(lambda x, _: '{:.1%}'.
 ↪format(x)))
fig.suptitle('Topic Distributions')
fig.tight_layout()
```


Topic Distributions
Topic 1
Topic 2
Topic 3
Topic 4
Topic 5
0.0%
0.2%
0.5%
0.8%
1.0%
1.2%
1.5%
1.8%
2.0%

### 0.3.4 Evaluate Fit on Train Set

[30]:
```
train_preds = lda_base.transform(train_dtm)
train_preds.shape
```

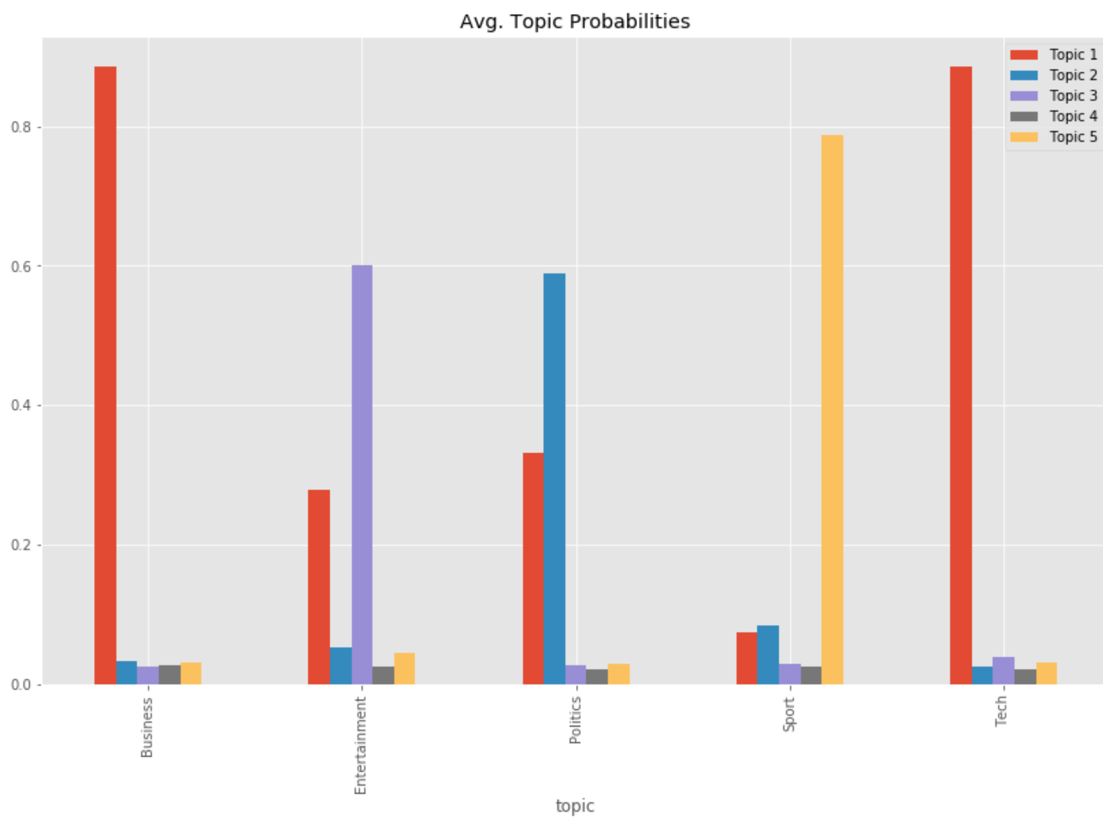
[30]: (2175, 5)

[31]:
```
train_eval = pd.DataFrame(train_preds, columns=topic_labels, index=train_docs.
    ↪topic)
train_eval.head()
```

[31]:

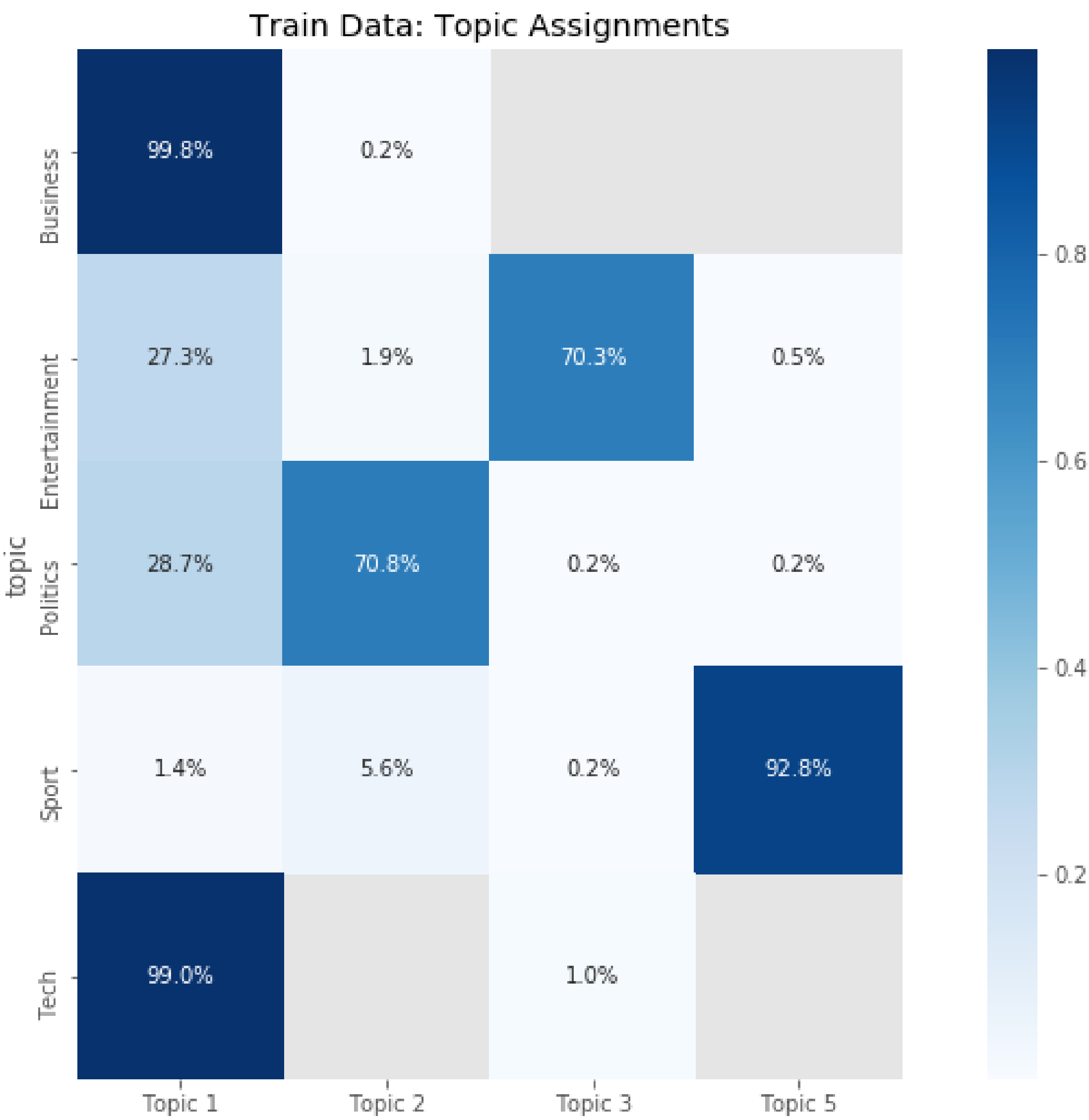
| topic | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 |
|---|---|---|---|---|---|
| Entertainment | 0.72 | 0.20 | 0.03 | 0.03 | 0.03 |
| Tech | 0.92 | 0.02 | 0.02 | 0.02 | 0.02 |
| Entertainment | 0.15 | 0.03 | 0.77 | 0.03 | 0.03 |
| Business | 0.91 | 0.02 | 0.02 | 0.02 | 0.02 |
| Sport | 0.03 | 0.91 | 0.02 | 0.02 | 0.02 |

[32]:
```
train_eval.groupby(level='topic').mean().plot.bar(title='Avg. Topic␣
    ↪Probabilities');
```



[33]:

```python
df = train_eval.groupby(level='topic').idxmax(
    axis=1).reset_index(-1, drop=True)
sns.heatmap(df.groupby(level='topic').value_counts(normalize=True)
            .unstack(-1), annot=True, fmt='.1%', cmap='Blues', square=True)
plt.title('Train Data: Topic Assignments');
```



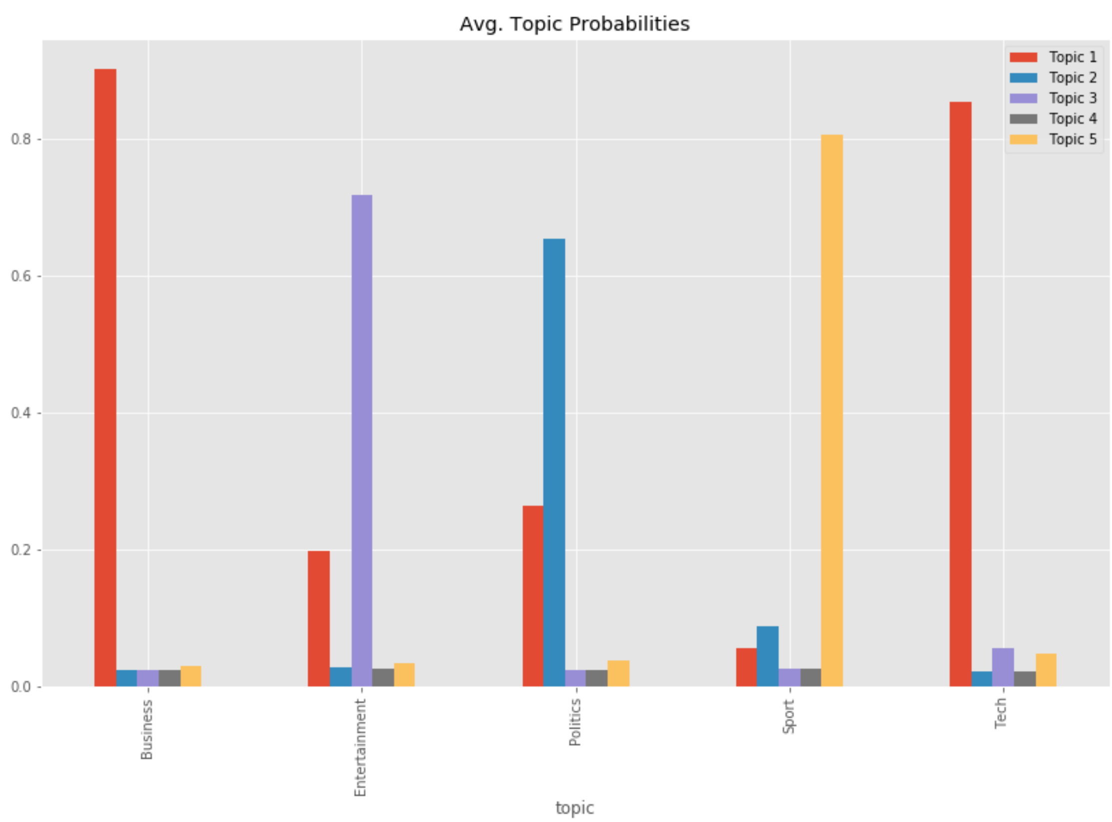
### 0.3.5 Evaluate Fit on Test Set

[34]:
```
test_preds = lda_base.transform(test_dtm)
test_eval = pd.DataFrame(test_preds, columns=topic_labels, index=test_docs.
 ↪topic)
test_eval.head()
```

[34]:

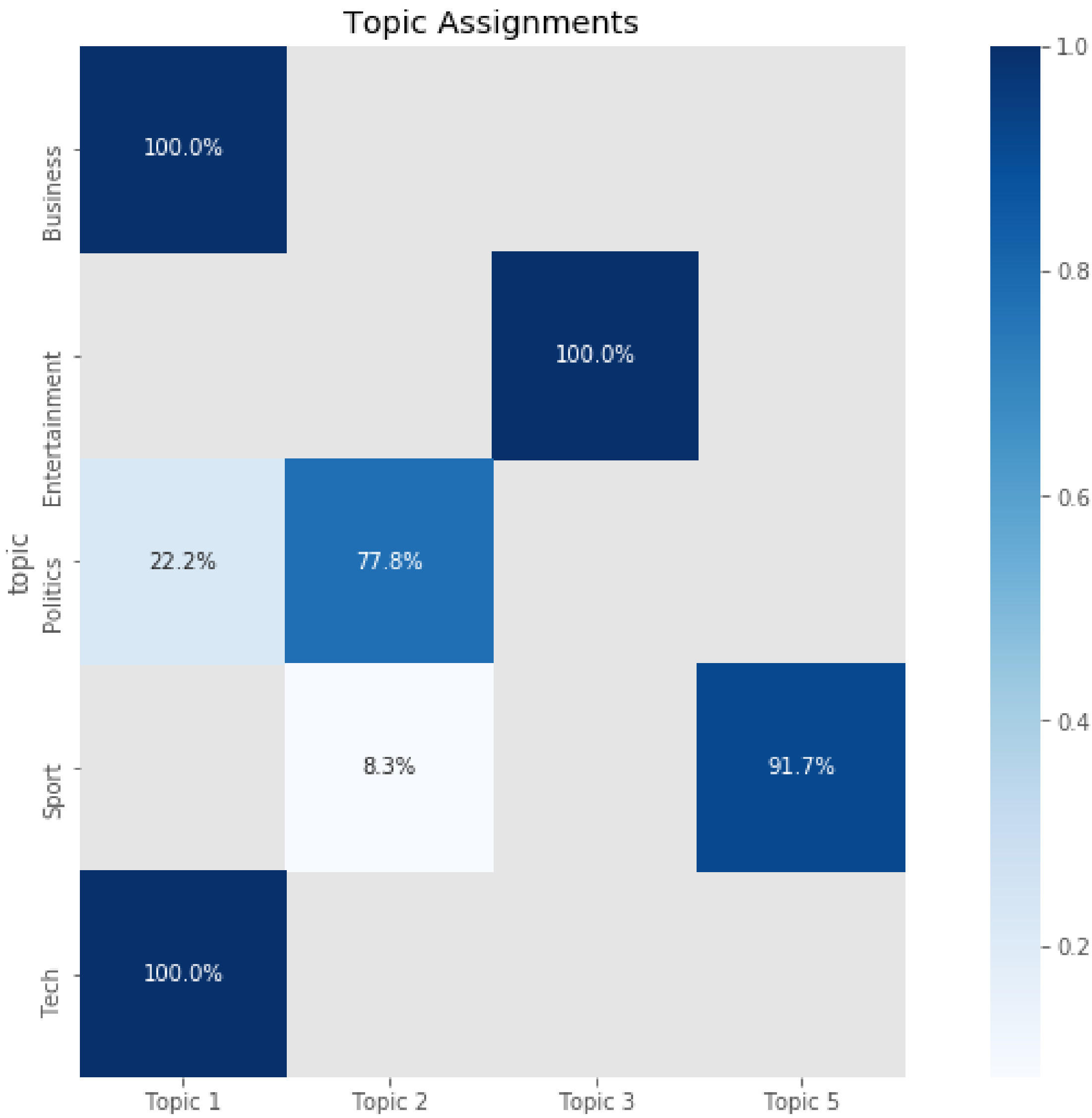
| | Topic 1 | Topic 2 | Topic 3 | Topic 4 | Topic 5 |
|---|---|---|---|---|---|
| topic | | | | | |
| Entertainment | 0.03 | 0.03 | 0.87 | 0.03 | 0.03 |
| Tech | 0.89 | 0.03 | 0.03 | 0.03 | 0.03 |
| Tech | 0.70 | 0.02 | 0.14 | 0.02 | 0.12 |
| Business | 0.91 | 0.02 | 0.02 | 0.02 | 0.03 |
| Sport | 0.03 | 0.03 | 0.02 | 0.02 | 0.90 |

[35]:
```
test_eval.groupby(level='topic').mean().plot.bar(title='Avg. Topic␣
 ↪Probabilities');
```




[36]:
```
df = test_eval.groupby(level='topic').idxmax(
    axis=1).reset_index(-1, drop=True)
sns.heatmap(df.groupby(level='topic').value_counts(normalize=True)
            .unstack(-1), annot=True, fmt='.1%', cmap='Blues', square=True)
```

```
plt.title('Topic Assignments');
```




#### 0.3.6 Retrain until perplexity no longer decreases

[37]:
```
lda_opt = LatentDirichletAllocation(n_components=5,
                                    n_jobs=-1,
                                    max_iter=500,
                                    learning_method='batch',
                                    evaluate_every=5,
                                    verbose=1,
                                    random_state=42)
lda_opt.fit(train_dtm)
```

```
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: 5307.4876
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: 5138.1714
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: 5053.3613
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: 4979.2082
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: 4942.3991
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: 4905.8883
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: 4855.0633
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: 4748.0643
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: 4688.7965
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: 4680.3516
iteration: 51 of max_iter: 500
iteration: 52 of max_iter: 500
iteration: 53 of max_iter: 500
iteration: 54 of max_iter: 500
iteration: 55 of max_iter: 500, perplexity: 4677.8205
iteration: 56 of max_iter: 500
iteration: 57 of max_iter: 500
iteration: 58 of max_iter: 500
iteration: 59 of max_iter: 500
iteration: 60 of max_iter: 500, perplexity: 4677.2711
iteration: 61 of max_iter: 500
iteration: 62 of max_iter: 500
iteration: 63 of max_iter: 500
iteration: 64 of max_iter: 500
iteration: 65 of max_iter: 500, perplexity: 4677.1106
iteration: 66 of max_iter: 500
iteration: 67 of max_iter: 500
iteration: 68 of max_iter: 500
iteration: 69 of max_iter: 500
iteration: 70 of max_iter: 500, perplexity: 4677.0012
iteration: 71 of max_iter: 500
iteration: 72 of max_iter: 500
iteration: 73 of max_iter: 500
iteration: 74 of max_iter: 500
iteration: 75 of max_iter: 500, perplexity: 4676.9818
```

[37]:
```
LatentDirichletAllocation(batch_size=128, doc_topic_prior=None,
             evaluate_every=5, learning_decay=0.7, learning_method='batch',
             learning_offset=10.0, max_doc_update_iter=100, max_iter=500,
             mean_change_tol=0.001, n_components=5, n_jobs=-1,
             n_topics=None, perp_tol=0.1, random_state=42,
             topic_word_prior=None, total_samples=1000000.0, verbose=1)
```

[38]:
```
joblib.dump(lda_opt, model_path / 'lda_opt.pkl')
```

[38]:
```
['results/bbc/lda_opt.pkl']
```

[39]:
```
lda_opt = joblib.load(model_path / 'lda_opt.pkl')
```

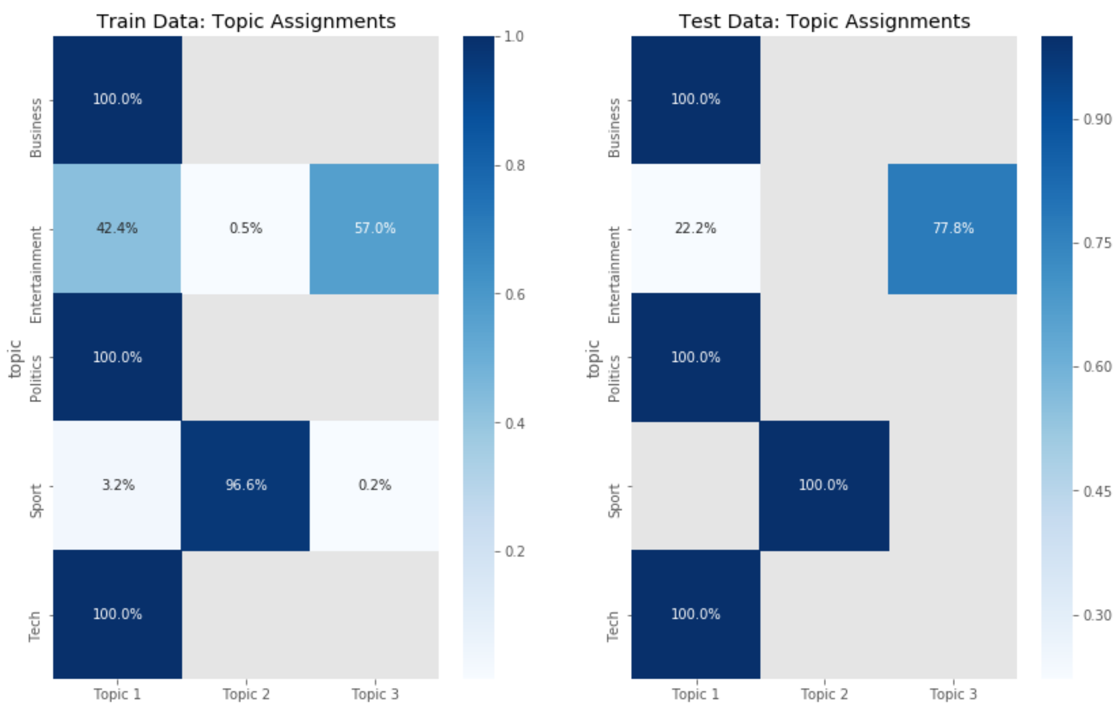
[40]:
```
train_opt_eval = pd.DataFrame(data=lda_opt.transform(train_dtm),
                              columns=topic_labels,
                              index=train_docs.topic)
```

[41]:
```
test_opt_eval = pd.DataFrame(data=lda_opt.transform(test_dtm),
                             columns=topic_labels,
```

```
                                index=test_docs.topic)
```

### 0.3.7 Compare Train & Test Topic Assignments

[42]:
```
fig, axes = plt.subplots(ncols=2)
source = ['Train', 'Test']
for i, df in enumerate([train_opt_eval, test_opt_eval]):
    df = df.groupby(level='topic').idxmax(
    axis=1).reset_index(-1, drop=True)
    sns.heatmap(df.groupby(level='topic').value_counts(normalize=True)
            .unstack(-1), annot=True, fmt='.1%', cmap='Blues', square=True,␣
 ↪ax=axes[i])
    axes[i].set_title('{} Data: Topic Assignments'.format(source[i]));
```




### 0.3.8 Explore misclassified articles

[43]:
```
test_assignments = test_opt_eval.groupby(level='topic').idxmax(axis=1)
test_assignments = test_assignments.reset_index(-1, drop=True).
 ↪to_frame('predicted').reset_index()
test_assignments['heading'] = test_docs.heading.values
test_assignments['article'] = test_docs.article.values
test_assignments.head()
```

[43]:
```
       topic predicted                                   heading  \
0   Business   Topic 1    Brits return Keane to number one
1   Business   Topic 1      Anti-spam screensaver scrapped
2   Business   Topic 1  The Force is strong in Battlefront
3   Business   Topic 1    Rover deal 'may cost 2,000 jobs'
4   Business   Topic 1    Sculthorpe wants Lions captaincy

                                             article
0   Brits success has helped return Keane's award…
1   A contentious campaign to bump up the bandwid…
2   The warm reception that has greeted Star Wars…
3   Some 2,000 jobs at MG Rover's Midlands plant …
4   Paul Sculthorpe has admitted he would love to…
```

[44]:
```
misclassified = test_assignments[(test_assignments.topic == 'business') & (
    test_assignments.predicted == 'Topic 3')]
misclassified.heading
```

[44]:
```
Series([], Name: heading, dtype: object)
```

[45]:
```
misclassified.article.tolist()
```

[45]:
```
[]
```

### 0.3.9 PyLDAVis

LDAvis helps you interpret LDA results by answer 3 questions:

1. What is the meaning of each topic?
2. How prevalent is each topic?
3. How do topics relate to each other?

Topic visualization facilitates the evaluation of topic quality using human judgment. pyLDAvis is a python port of LDAvis, developed in R and D3.js. We will introduce the key concepts; each LDA implementation notebook contains examples.

pyLDAvis displays the global relationships among topics while also facilitating their semantic evaluation by inspecting the terms most closely associated with each individual topic and, inversely, the topics associated with each term. It also addresses the challenge that terms that are frequent in a corpus tend to dominate the multinomial distribution over words that define a topic. LDAVis introduces the relevance r of term w to topic t to produce a flexible ranking of key terms using a weight parameter 0<= <=1.

With $\phi_{wt}$ as the model's probability estimate of observing the term w for topic t, and as the marginal probability of w in the corpus:

$$r(w, k|\lambda) = \lambda \log(\phi_{kw}) + (1-\lambda) \log \frac{\phi_{kw}}{p_w}$$

The first term measures the degree of association of term t with topic w, and the second term measures the lift or saliency, i.e., how much more likely the term is for the topic than in the corpus.

The tool allows the user to interactively change to adjust the relevance, which updates the ranking of terms. User studies have found that =0.6 produces the most plausible results.

**Refit using all data**

[46]:
```
vectorizer = CountVectorizer(max_df=.5,
                             min_df=5,
                             stop_words='english',
                             max_features=2000)
dtm = vectorizer.fit_transform(docs.article)
```

[47]:
```
lda_all = LatentDirichletAllocation(n_components=5,
                                    max_iter=500,
                                    learning_method='batch',
                                    evaluate_every=10,
                                    random_state=42,
                                    verbose=1)
lda_all.fit(dtm)
```

```
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
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: 1022.6552
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
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: 1007.1868
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
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: 1003.1695
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
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: 997.6211
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
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: 996.7851
iteration: 51 of max_iter: 500
iteration: 52 of max_iter: 500
iteration: 53 of max_iter: 500
iteration: 54 of max_iter: 500
iteration: 55 of max_iter: 500
iteration: 56 of max_iter: 500
iteration: 57 of max_iter: 500
iteration: 58 of max_iter: 500
iteration: 59 of max_iter: 500
iteration: 60 of max_iter: 500, perplexity: 995.8875
iteration: 61 of max_iter: 500
iteration: 62 of max_iter: 500
iteration: 63 of max_iter: 500
iteration: 64 of max_iter: 500
iteration: 65 of max_iter: 500
iteration: 66 of max_iter: 500
iteration: 67 of max_iter: 500
iteration: 68 of max_iter: 500
iteration: 69 of max_iter: 500
iteration: 70 of max_iter: 500, perplexity: 995.6225
iteration: 71 of max_iter: 500
iteration: 72 of max_iter: 500
iteration: 73 of max_iter: 500
iteration: 74 of max_iter: 500
iteration: 75 of max_iter: 500
iteration: 76 of max_iter: 500
iteration: 77 of max_iter: 500
```

```
iteration: 78 of max_iter: 500
iteration: 79 of max_iter: 500
iteration: 80 of max_iter: 500, perplexity: 995.5889
```

[47]:
```
LatentDirichletAllocation(batch_size=128, doc_topic_prior=None,
                          evaluate_every=10, learning_decay=0.7,
                          learning_method='batch', learning_offset=10.0,
                          max_doc_update_iter=100, max_iter=500, mean_change_tol=0.001,
                          n_components=5, n_jobs=None, n_topics=None, perp_tol=0.1,
                          random_state=42, topic_word_prior=None,
                          total_samples=1000000.0, verbose=1)
```

[48]:
```python
joblib.dump(lda_all, model_path /'lda_all.pkl')
```

[48]:
```
['results/bbc/lda_all.pkl']
```

[49]:
```python
lda_all = joblib.load(model_path / 'lda_all.pkl')
```

#### Lambda

- $\lambda = \mathbf{0}$: how probable is a word to appear in a topic - words are ranked on lift P(word | topic) / P(word)
- $\lambda = \mathbf{1}$: 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.

[50]:
```python
prepare(lda_all, dtm, vectorizer)
```

[50]:
```
PreparedData(topic_coordinates=           x     y  topics  cluster  Freq
topic
2       0.07  0.08       1        1 25.51
3       0.09 -0.10       2        1 21.82
0       0.14  0.01       3        1 20.96
4      -0.14  0.14       4        1 18.70
1      -0.17 -0.13       5        1 13.01, topic_info=     Category     Freq
Term    Total  loglift  logprob
1200   Default 2,987.00         mr 2,987.00    30.00    30.00
724    Default   838.00       film   838.00    29.00    29.00
230    Default   960.00       best   960.00    28.00    28.00
1022   Default   770.00     labour   770.00    27.00    27.00
780    Default   855.00       game   855.00    26.00    26.00
817    Default 1,151.00 government 1,151.00    25.00    25.00
1206   Default   810.00      music   810.00    24.00    24.00
619    Default   630.00   election   630.00    23.00    23.00
1305   Default   624.00      party   624.00    22.00    22.00
1177   Default   521.00     mobile   521.00    21.00    21.00
1788   Default   553.00 technology   553.00    20.00    20.00
```

| | | | | | | |
|---|---|---|---|---|---|---|
| 240 | Default | 551.00 | blair | 551.00 | 19.00 | 19.00 |
| 631 | Default | 593.00 | england | 593.00 | 18.00 | 18.00 |
| 1319 | Default | 2,030.00 | people | 2,030.00 | 17.00 | 17.00 |
| 1129 | Default | 683.00 | market | 683.00 | 16.00 | 16.00 |
| 1884 | Default | 406.00 | users | 406.00 | 15.00 | 15.00 |
| 551 | Default | 404.00 | digital | 404.00 | 14.00 | 14.00 |
| 195 | Default | 291.00 | awards | 291.00 | 13.00 | 13.00 |
| 194 | Default | 280.00 | award | 280.00 | 12.00 | 12.00 |
| 1658 | Default | 373.00 | software | 373.00 | 11.00 | 11.00 |
| 205 | Default | 360.00 | bank | 360.00 | 10.00 | 10.00 |
| 832 | Default | 443.00 | growth | 443.00 | 9.00 | 9.00 |
| 1170 | Default | 552.00 | minister | 552.00 | 8.00 | 8.00 |
| 1329 | Default | 373.00 | phone | 373.00 | 7.00 | 7.00 |
| 1968 | Default | 589.00 | won | 589.00 | 6.00 | 6.00 |
| 403 | Default | 678.00 | company | 678.00 | 5.00 | 5.00 |
| 1346 | Default | 513.00 | players | 513.00 | 4.00 | 4.00 |
| 1957 | Default | 580.00 | win | 580.00 | 3.00 | 3.00 |
| 380 | Default | 364.00 | club | 364.00 | 2.00 | 2.00 |
| 608 | Default | 421.00 | economy | 421.00 | 1.00 | 1.00 |
| … | … | … | … … | … | … | |
| 575 | Topic5 | 56.72 | doping | 57.52 | 2.03 | -6.48 |
| 387 | Topic5 | 130.06 | comedy | 131.91 | 2.03 | -5.65 |
| 724 | Topic5 | 818.47 | film | 838.10 | 2.02 | -3.81 |
| 1661 | Topic5 | 171.90 | song | 177.54 | 2.01 | -5.38 |
| 204 | Topic5 | 211.33 | band | 223.18 | 1.99 | -5.17 |
| 1395 | Topic5 | 148.73 | prize | 158.69 | 1.97 | -5.52 |
| 325 | Topic5 | 102.17 | ceremony | 107.12 | 1.99 | -5.90 |
| 1705 | Topic5 | 127.00 | stars | 137.86 | 1.96 | -5.68 |
| 1703 | Topic5 | 249.12 | star | 292.57 | 1.88 | -5.00 |
| 230 | Topic5 | 698.84 | best | 960.17 | 1.72 | -3.97 |
| 1456 | Topic5 | 101.37 | ray | 108.11 | 1.98 | -5.90 |
| 725 | Topic5 | 211.01 | films | 254.01 | 1.85 | -5.17 |
| 316 | Topic5 | 95.88 | category | 102.16 | 1.98 | -5.96 |
| 1206 | Topic5 | 404.05 | music | 810.44 | 1.34 | -4.52 |
| 1194 | Topic5 | 127.67 | movie | 158.77 | 1.82 | -5.67 |
| 1968 | Topic5 | 290.56 | won | 589.23 | 1.33 | -4.85 |
| 556 | Topic5 | 230.87 | director | 426.78 | 1.43 | -5.08 |
| 266 | Topic5 | 224.16 | british | 533.06 | 1.17 | -5.11 |
| 920 | Topic5 | 182.56 | including | 404.97 | 1.24 | -5.31 |
| 1238 | Topic5 | 228.73 | number | 748.61 | 0.85 | -5.09 |
| 1992 | Topic5 | 232.24 | years | 991.66 | 0.59 | -5.07 |
| 1224 | Topic5 | 285.88 | new | 1,896.89 | 0.15 | -4.87 |
| 1863 | Topic5 | 176.87 | tv | 481.87 | 1.04 | -5.35 |
| 1866 | Topic5 | 210.95 | uk | 1,047.95 | 0.44 | -5.17 |
| 216 | Topic5 | 162.82 | bbc | 747.90 | 0.52 | -5.43 |
| 1081 | Topic5 | 145.36 | london | 454.66 | 0.90 | -5.54 |
| 1816 | Topic5 | 158.76 | time | 1,303.51 | -0.07 | -5.45 |

```
1607   Topic5   136.04      series   252.07     1.42    -5.61
1977   Topic5   147.68       world 1,173.24    -0.03    -5.53
1165   Topic5   135.86     million   574.09     0.60    -5.61

[353 rows x 6 columns], token_table=      Topic  Freq      Term
term
0         1  0.27       000
0         2  0.22       000
0         3  0.38       000
0         4  0.01       000
0         5  0.12       000
26        1  0.04      2004
26        2  0.17      2004
26        3  0.58      2004
26        4  0.05      2004
26        5  0.17      2004
27        1  0.03      2005
27        2  0.28      2005
27        3  0.53      2005
27        4  0.08      2005
27        5  0.08      2005
47        3  0.99       3bn
55        2  0.03       5bn
55        3  0.96       5bn
65        3  0.99       8bn
85        5  1.00     actor
87        5  1.00   actress
117       2  0.01   airline
117       3  0.97   airline
118       3  0.99  airlines
120       5  1.00     album
134       2  0.20  analysts
134       3  0.80  analysts
137       5  0.99   angeles
148       2  0.99     apple
158       4  1.00   arsenal
…     …   …       …
1935      2  0.99       web
1937      2  1.00  websites
1955      4  0.83  williams
1955      5  0.17  williams
1957      1  0.09       win
1957      2  0.02       win
1957      3  0.01       win
1957      4  0.73       win
1957      5  0.15       win
1958      2  1.00   windows
```

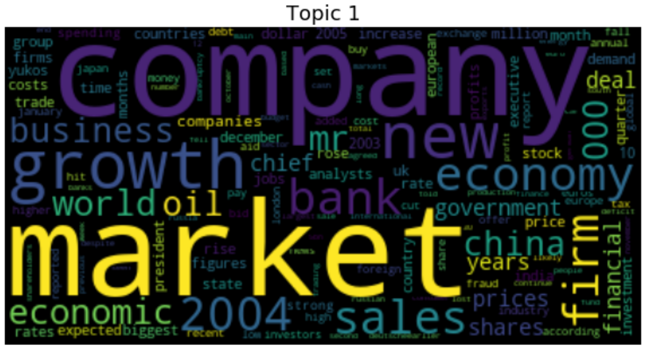
```
1965       2  1.00  wireless
1968       1  0.06       won
1968       2  0.02       won
1968       3  0.04       won
1968       4  0.38       won
1968       5  0.49       won
1977       1  0.07     world
1977       2  0.19     world
1977       3  0.26     world
1977       4  0.36     world
1977       5  0.13     world
1978       3  0.99  worldcom
1992       1  0.19     years
1992       2  0.12     years
1992       3  0.27     years
1992       4  0.19     years
1992       5  0.23     years
1997       3  0.99   yugansk
1998       3  1.00     yukos
1999       4  0.99   zealand

[671 rows x 3 columns], R=30, lambda_step=0.01, plot_opts={'xlab': 'PC1',
'ylab': 'PC2'}, topic_order=[3, 4, 1, 5, 2])
```

#### 0.3.10 Topics as WordClouds

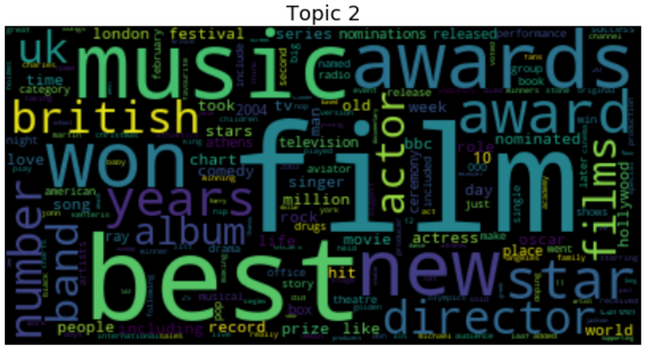
[51]:
```
topics_prob = lda_all.components_ / lda_all.components_.sum(axis=1).reshape(-1,␣
 ↪1)
topics = pd.DataFrame(topics_prob.T,
                      index=vectorizer.get_feature_names(),
                      columns=topic_labels)
```

[52]:
```
w = WordCloud()
fig, axes = plt.subplots(nrows=5, figsize=(15, 30))
axes = axes.flatten()
for t, (topic, freq) in enumerate(topics.items()):
    w.generate_from_frequencies(freq.to_dict())
    axes[t].imshow(w, interpolation='bilinear')
    axes[t].set_title(topic, fontsize=18)
    axes[t].axis('off')
```

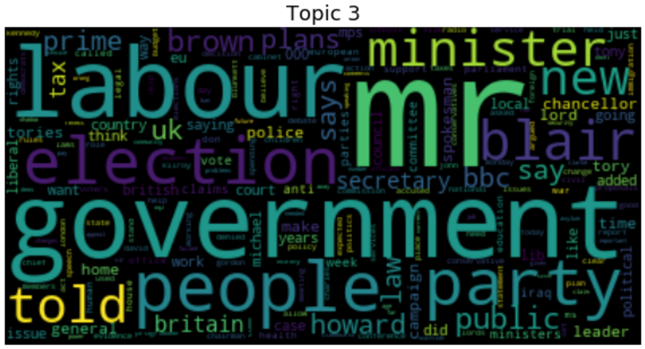
Topic 1



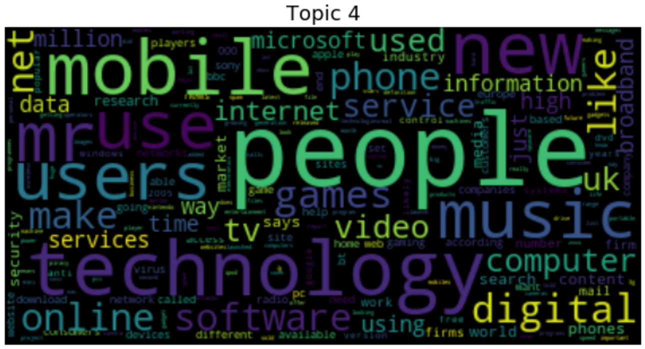

Topic 2



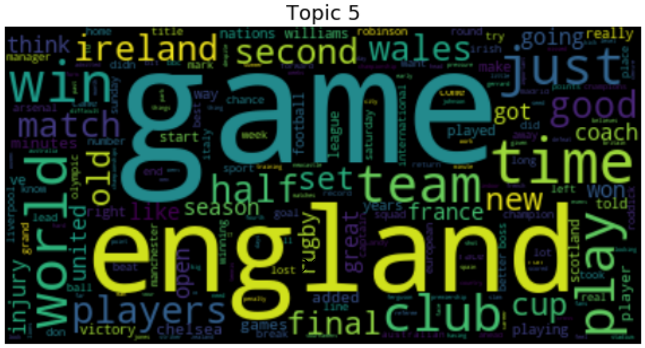

Topic 3




Topic 4




Topic 5



### 0.3.11 Visualize topic-word assocations per document

[53]:
```
dtm_ = pd.DataFrame(data=lda_all.transform(dtm),
                    columns=topic_labels,
                    index=docs.topic)
```

[54]:
```
color_dict = OrderedDict()
color_dict['Topic 1'] = {'color': 'white', 'on_color': 'on_blue'}
color_dict['Topic 2'] = {'color': 'white', 'on_color': 'on_green'}
color_dict['Topic 3'] = {'color': 'white', 'on_color': 'on_red'}
color_dict['Topic 4'] = {'color': 'white', 'on_color': 'on_magenta'}
color_dict['Topic 5'] = {'color': 'blue', 'on_color': 'on_yellow'}
```

[55]:
```
dtm_['article'] = docs.article.values
dtm_['heading'] = docs.heading.values
sample = dtm_[dtm_[topic_labels].gt(.1).all(1)]
sample
```

[55]:
```
               Topic 1  Topic 2  Topic 3  Topic 4  Topic 5  \
topic
Entertainment     0.14     0.28     0.23     0.23     0.11

                                                          article  \
topic
Entertainment   Women in the UK film industry earn less than …

                                         heading
topic
Entertainment  Women in film 'are earning less'
```

[57]:
```
colored_text = []
for word in sample.iloc[0, 5].split():
    try:
        topic = topics.loc[word.strip().lower()].idxmax()
        colored_text.append(colored(word, **color_dict[topic]))
    except:
        colored_text.append(word)

print(' '.join([colored(k, **v) for k, v in color_dict.items()]))
print('\n',sample.iloc[0, 6], '\n')
text = ' '.join(colored_text)
print(text)
```

```
Topic 1 Topic 2 Topic 3
Topic 4 Topic 5
```

Women in film 'are earning less'

Women in the UK film
industry earn less than their male counterparts
despite being better qualified,
according to a study released on
Wednesday. Only 16% of women earn more than Â£50,000,
compared with 30% of men. Women make
up a third of the workforce. The research was
carried out jointly by the UK Film
Council and industry training
body Skillset. It also found that women in the
industry were less likely than men to
be married or have dependant children. The study, which claims to
be the most in-depth so far conducted, found 60% of
women in the film industry
hold degrees, compared with 39% of men. Whilst 17%
of men in the industry had no qualifications, this
was true for only five per cent of women. In the
lower salary bracket, 35% of women earn less than
Â£20,000 a year, compared to only 18% of men. The
research found very few women worked
in the camera, sound, electrical and construction departments, but they made up
a majority of those working in make-up and
hairdressing. UK Film Council
chief executive John
Woodward said: "Whilst the UK has benefited
hugely from its highly-qualified film
production workforce there are still many barriers
facing people who want to get in and
stay in the industry." "Developing the film
production workforce must be underpinned with a commitment to
diversity as well as training." The workforce is largely focused around London,
with 78% in the industry based in the
capital and the south east of England.
The industry depends heavily on word of mouth, with
81% being recruited in that way. In total, only five percent of the workforce is
made up of ethnic minorities, although in London the
figure rises to 24%. The necessity of completing
unpaid work experience to get into the workforce has
also shot up, from 5% before the 1980s, to 45% after 2000.