Lab 5. Topic Modeling

Introduction

In this lab, we will focus on **topic modeling**, which is an important area within natural language processing.

- Topic modeling is a simple way to capture the sense of what a document or a collection of documents is about.
- Topic modeling is mostly done using unsupervised learning algorithms that detect topics on their own.
- Topic-modeling algorithms operate by performing statistical analysis on words or tokens in documents and using those statistics to automatically assign each document to multiple topics.
- Topic modeling is often used as a first step to explore textual data in order to get a feel for the content of the text.

Topic-Modeling Algorithms

Topic-modeling algorithms operate on the following assumptions:

- Topics contain a set of words.
- Documents are made up of a set of topics.

In the upcoming sections, we will cover in detail three topic-modeling algorithms namely LSA, LDA, and HDP.

Note The LDA algorithm builds on the LSA algorithm. In this case, similar acronyms are indicative of this association.

Latent Semantic Analysis (LSA)

Consider that we have a collection of documents, and these documents are made up of words. Our goal is to discover the latent topics in the documents. So, in the beginning, we have a collection of documents that we can represent as a term-to-document matrix. This term-to-document matrix has terms as rows and documents as columns. The following table gives a simplified illustration of a term-to-document matrix:

Term to Document			
	Doc-1	Doc-1	Doc-3
Water			
Dog			
Willow			
Cart			
Pill			
Stone			

Now, we break this matrix down into three separate matrix factors, namely a term-to-topics matrix, a topic-importance matrix, and a topic-to-documents matrix. Let's consider the matrix shown on the left-hand side and the corresponding factor matrices on the right-hand side:

As we can see in this diagram, the rectangular matrix is separated into the product of other matrices. The process takes a matrix, *M*, and splits it, as shown in the following formula:

$$M = U \Sigma V^{T}$$

Exercise 5.01: Analyzing Wikipedia World Cup Articles with Latent Semantic Analysis

In this exercise, you will perform topic modeling using LSA on a Wikipedia World Cup dataset. For this, you will make use of the `LsiModel` class provided by the gensim library. You will use the Wikipedia library to fetch articles, the spaCy engine for the tokenization of the text, and the newline character to separate documents within an article.

Follow these steps to complete this exercise:

1. Open a Jupyter Notebook.
2. Insert a new cell and add the following code to import the necessary libraries:

```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
from gensim import corpora
from gensim.models import LsiModel
from gensim.parsing.preprocessing import preprocess_string
```

3. To clean the text, define a function to remove the non-alphanumeric characters and replace numbers with the `#` character. Replace instances of multiple newline characters with a single newline character. Use the newline character to separate out the documents in the corpus. Insert a new cell and add the following code to implement this:

```
import re
HANDLE = '@\w+'
LINK = 'https?://t\.co/\w+'
SPECIAL_CHARS = '&lt;|&lt;|&amp;|#'
PARA='\n+'
def clean(text):
    text = re.sub(LINK, ' ', text)
```

````
    text = re.sub(SPECIAL_CHARS, ' ', text)
    text = re.sub(PARA, '\n', text)
    return text
```
````

4. Insert a new cell and add the following code to find Wikipedia articles related to the World Cup:

```
import wikipedia
wikipedia.search('Cricket World Cup'),\
wikipedia.search('FIFA World Cup')
```

The code generates the following output:

```
(['Cricket World Cup',
  'Under-19 Cricket World Cup',
  '2019 Cricket World Cup',
  '2023 Cricket World Cup',
  '2015 Cricket World Cup',
  '2011 Cricket World Cup',
  '1996 Cricket World Cup',
  '2020 Under-19 Cricket World Cup',
  '1983 Cricket World Cup',
  "Women's Cricket World Cup"],
 ['2018 FIFA World Cup',
  'FIFA World Cup',
  '2022 FIFA World Cup',
  '2014 FIFA World Cup',
  '2010 FIFA World Cup',
  '2006 FIFA World Cup',
  '2026 FIFA World Cup',
  '2002 FIFA World Cup',
  '1998 FIFA World Cup',
  '1930 FIFA World Cup'])
```

5. Insert a new cell and add the following code fetch the Wikipedia articles about the 2018 FIFA World Cup and the 2019 Cricket World Cup, concatenate them, and show the result:

```
latest_soccer_cricket=['2018 FIFA World Cup',\
                       '2019 Cricket World Cup']
corpus=''
for cup in latest_soccer_cricket:
    corpus=corpus+wikipedia.page(cup).content
corpus
```
```

The code generates the following output:

```
'The 2018 FIFA World Cup was the 21st FIFA World Cup, an international football tournament contested by th
e men\'s national teams of the member associations of FIFA once every four years. It took place in Russia
from 14 June to 15 July 2018. It was the first World Cup to be held in Eastern Europe, and the 11th time t
hat it had been held in Europe. At an estimated cost of over $14.2 billion, it was the most expensive Worl
d Cup. It was also the first World Cup to use the video assistant referee (VAR) system.The finals involved
32 teams, of which 31 came through qualifying competitions, while the host nation qualified automatically.
Of the 32 teams, 20 had also appeared in the previous tournament in 2014, while both Iceland and Panama ma
de their first appearances at a FIFA World Cup. A total of 64 matches were played in 12 venues across 11 c
ities. Germany were the defending champions, but were eliminated in the group stage. Host nation Russia we
re eliminated in the quarter-finals.\nThe final took place on 15 July at the Luzhniki Stadium in Moscow, b
etween France and Croatia. France won the match 4–2 to claim their second World Cup title, marking the fou
rth consecutive title won by a European team.\n\n\n== Host selection ==\n\nThe bidding procedure to host t
```

6. Insert a new cell and add the following code to clean the text, using the spaCy English language model to tokenize the corpus and exclude all tokens that are not detected as nouns:

```
text=clean(corpus)
import spacy
nlp = spacy.load('en_core_web_sm')
doc=nlp(text)
pos_list=['NOUN']
preproc_text=[]
preproc_sent=[]
for token in doc:
    if token.text!='\n':
        if not(token.is_stop) and not(token.is_punct) \
        and token.pos_ in pos_list:
            preproc_sent.append(token.lemma_)
    else:
        preproc_text.append(preproc_sent)
        preproc_sent=[]
#last sentence
preproc_text.append(preproc_sent)
print(preproc_text)
```

The code generates the following output:

```
[['football', 'tournament', 'man', 'team', 'member', 'association', 'year', 'place', 'time', 'cost', 'vide
o', 'assistant', 'referee', 'system', 'final', 'team', 'competition', 'host', 'nation', 'team', 'tournamen
t', 'appearance', 'total', 'match', 'venue', 'city', 'champion', 'group', 'stage', 'host', 'nation', 'quar
ter', 'final'], ['place', 'match', 'title', 'title', 'team'], ['host', 'selection'], ['bidding', 'procedur
e', 'tournament', 'association', 'interest', 'country', 'bid', 'proceeding', 'bid', 'government', 'lette
r', 'bid', 'bidding', 'process', 'nation', 'bid', 'nation', 'bid', 'bid', 'bid'], ['host', 'tournament',
```

7. Insert a new cell and add the following code to convert the corpus into a list in which each token corresponds to a number for more efficient representation, as gensim requires it in this form. Then, find the topics in the corpus:

```
dictionary = corpora.Dictionary(preproc_text)
corpus = [dictionary.doc2bow(text) for text in preproc_text]
NUM_TOPICS=3
lsamodel=LsiModel(corpus, num_topics=NUM_TOPICS, \
                  id2word = dictionary)
lsamodel.print_topics()
```

The code generates the following output:

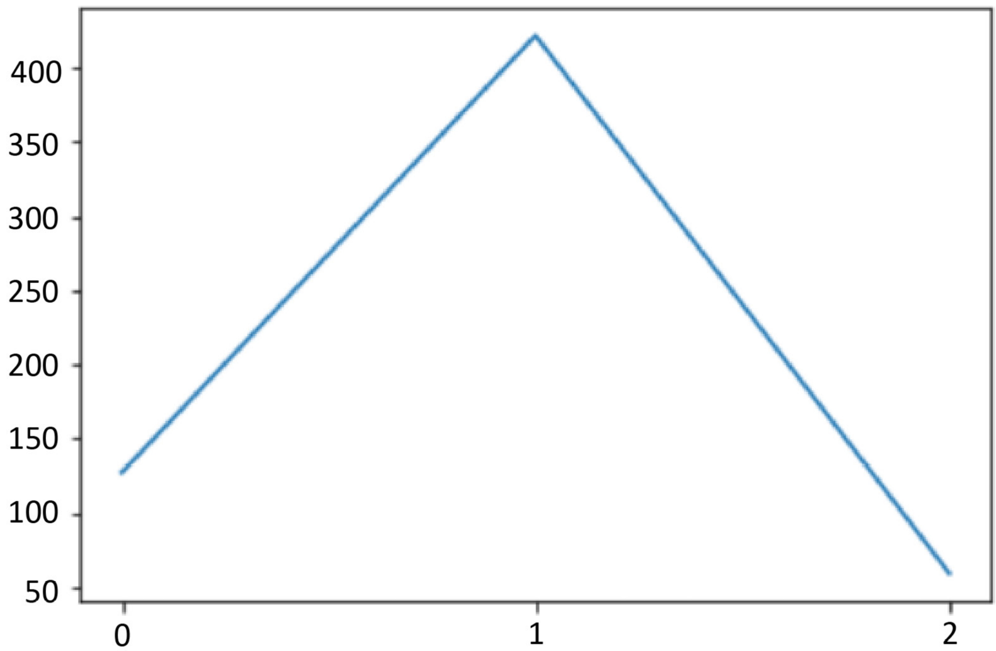
```
[(0,
  '0.554*"wicket" + 0.533*"run" + 0.288*"match" + 0.204*"tournament" + 0.177*"victory" + 0.169*"century" + 
0.168*"over" + 0.138*"partnership" + 0.131*"score" + 0.127*"ball"'),
 (1,
  '0.444*"team" + 0.376*"match" + 0.356*"tournament" + 0.304*"time" + -0.246*"wicket" + -0.230*"run" + 0.1
71*"right" + 0.130*"country" + 0.124*"stage" + 0.124*"broadcast"'),
 (2,
  '-0.451*"match" + 0.389*"team" + -0.353*"right" + 0.315*"time" + -0.260*"broadcast" + -0.133*"viewer" + 
-0.128*"rightsholder" + 0.117*"stage" + 0.115*"final" + 0.114*"nation"')]
```

```
To create our `LsiModel`, we had to decide up front how
many topics we wanted. This would not necessarily match the number
of topics that are actually in the corpus.
```

8. To determine which topics have the highest weight for a document, insert a new cell and add the following code:

```
model_arr = np.argmax(lsamodel.get_topics(),axis=0)
y, x = np.histogram(model_arr, bins=np.arange(NUM_TOPICS+1))
fig, ax = plt.subplots()
plt.xticks(ticks=np.arange(NUM_TOPICS),\
           labels=np.arange(NUM_TOPICS+1))
ax.plot(x[:-1], y)
fig.show()
```

The code generates the following output:



We can see that topic `1` and topic `0` have the highest weight in almost all the documents.

Dirichlet Process and Dirichlet Distribution

The Dirichlet distribution is a special case of the Dirichlet process, in which the number of topics needs to be specified explicitly. It is used for the LDA topic-modeling algorithm.

Latent Dirichlet Allocation (LDA)

To understand how LDA works, let's look at a simple example. We have four documents that contain only three unique words: **Cat**, **Dog**, and **Hippo**. The following figure shows the documents and the number of times each word is found in each document:

	Cat	Dog	Hippo
Document 1	10	0	0
Document 2	0	10	0
Document 3	0	0	10
Document 4	10	10	10

As we can see in the figure, the word **Cat** is found **10** times in **Document 1** and **Document 4** and **0** times in documents **2** and **3**. **Document 4** contains all three words **10** times each. For its analysis, LDA maintains two probability tables. The first table tracks the probability of selecting a specific word when sampling a specific topic. The second table keeps track of the probability of selecting a specific topic when sampling a particular document:

Words vs Topics

	Topic 1	Topic 2	Topic 3
Cat	0.00	0.00	0.99
Dog	0.99	0.00	0.00
Hippo	0.00	0.99	0.00

Documents vs Topics

	Topic 1	Topic 2	Topic 3
Document 1	0.030	0.030	0.939
Document 2	0.939	0.030	0.030
Document 3	0.030	0.939	0.030
Document 4	0.33	0.33	0.33

The parameters that we use for tomotopy are as follows:

- `corpus`: This refers to text that we want to analyze.
- Number of topics: This is the number of topics that the corpus contains.
- `iter`: This refers to the number of iterations that the model considers the corpus.
- `α`: This is associated with document generation.
- `η`: This is associated with topic generation.
- `seed`: This helps with fixing the initial randomization.

Measuring the Predictive Power of a Generative Topic Model

The predictive power of a generative topic model can be measured by analyzing the distribution of the generated corpus. Perplexity is a measure of how close the distribution of the words in the generated corpus is to reality. Log perplexity is a more convenient measure for this closeness. The formula for log perplexity is as follows:

$$\log perplexity = -\frac{1}{n}\sum_{k=0}^{n} \log P(w)$$

Exercise 5.02: Finding Topics in Canadian Open Data Inventory Using the LDA Model

In this exercise, we will use the tomotopy LDA model to analyze the Canadian Open Data Inventory. For simplicity, we will consider that the corpus has twenty topics.

The following steps will help you complete this exercise:

1. Open a Jupyter Notebook.
2. Insert a new cell and add the following code to import the necessary libraries:

````
```
import pandas as pd
pd.set_option('display.max_colwidth', 800)
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```
````

3. Insert a new cell and add the following code to read from a download of the Canadian Open Data Inventory, and clean the text:

````
```
OPEN_DATA_URL = '../data/canada-open-data/inventory.csv'
import re
HANDLE = '@\w+'
LINK = 'https?://t\.co/\w+'
SPECIAL_CHARS = '<|<|&|#'
PARA='\n+'
def clean(text):
    text = re.sub(LINK, ' ', text)
    text = re.sub(SPECIAL_CHARS, ' ', text)
    text = re.sub(PARA, '\n', text)
    return text
catalog['description_en'].sample(frac=0.25,replace=False,\
                                 random_state=0).to_c \
                                 sv(OPEN_DATA_URL,\
                                 encoding='utf-8')
file='../data/canada-open-data/catalog.txt'
f=open(file,'r',encoding='utf-8')
text=f.read()
f.close()
text = clean(text)
```
````

4. Insert a new cell and add the following code to clean the text, using the spaCy English language model to tokenize the corpus and to exclude all tokens that are not detected as nouns:

```
import spacy
nlp = spacy.load('en_core_web_sm')
doc=nlp(text)
```

```
pos_list=['NOUN']
preproc_text=[]
preproc_sent=[]
for token in doc:
    if token.text!='\n':
        if not(token.is_stop) and not(token.is_punct) \
        and token.pos_ in pos_list:
            preproc_sent.append(token.lemma_)
    else:
        preproc_text.append(preproc_sent)
        preproc_sent=[]
#last sentence
preproc_text.append(preproc_sent)
print(preproc_text)
```

The code generates the following output:

```
[[], ['crop', 'residue', 'year', 'census'], ['investment', 'transit', 'infrastructure', 'city', 'communit
y', 'funding', 'environment', 'greenhouse', 'gas', 'emission', 'traffic', 'congestion', 'funding', 'provin
ce', 'territory', 'capita', 'basis'], ['need', 'background', 'soil', 'datum', 'assessment', 'site', 'regio
n', 'data', 'region', 'background', 'soil', 'concentration', 'metal', 'area', 'concentration', 'soil', 'qu
ality', 'guideline', 'jurisdiction', 'soil', 'database', 'database', 'region', 'background', 'soil', 'scre
ening', 'site', 'datum', 'background', 'range'], ['vegetable', 'storage', 'factory'], ['report', 'accoun
t'], ['facility', 'region', 'location', 'truck', 'trip', 'end', 'storage', 'handling', 'facility', 'busine
ss', 'dg'], ['park', 'pitcher', 'plant', 'morpology', 'availability', 'nitrogen', 'pitcher', 'plant', 'dev
elopment'], ['innovation', 'business', 'strategy', 'product', 'good', 'service', 'enterprise', 'market',
```

```
The pandas DataFrame was sampled. 25% of the dataset has been
considered so that the memory restrictions related to spaCy can be
addressed, since this is a fairly large sample.
```

5. Insert a new cell and add the following code to see how the negative log likelihood varies by the number of iterations:

```
import tomotopy as tp
NUM_TOPICS=20
mdl = tp.LDAModel(k=NUM_TOPICS,seed=1234)
for line in preproc_text:
    mdl.add_doc(line)
for i in range(0, 110, 10):
    mdl.train(i)
    print('Iteration: {}\tLog-likelihood: {}'.\
          format(i, mdl.ll_per_word))
```

The code generates the following output:

```
Iteration: 0    Log-likelihood: -11.093217577268552
Iteration: 10   Log-likelihood: -6.8822797912226115
Iteration: 20   Log-likelihood: -6.317129241581733
Iteration: 30   Log-likelihood: -6.157586638884254
Iteration: 40   Log-likelihood: -6.073628903605757
Iteration: 50   Log-likelihood: -6.0291570377492905
Iteration: 60   Log-likelihood: -6.005991344426762
Iteration: 70   Log-likelihood: -5.975599517879777
Iteration: 80   Log-likelihood: -5.959173736422274
Iteration: 90   Log-likelihood: -5.939598846671805
Iteration: 100  Log-likelihood: -5.935156891936913
```

iterations

6. Insert a new cell and add the following code to train a topic model with ten iterations and to show the inferred topics:

```
mdl.train(10)
for k in range(mdl.k):
    print('Top 10 words of topic #{}'.format(k))
    print(mdl.get_topic_words(k, top_n=7))
```

The code generates the following output:

```
Top 10 words of topic #0
[('polygon', 0.36050185561180115), ('dataset', 0.0334757782722234726),
('information', 0.03004324994981289), ('soil', 0,029185116291046143), ('area',
0,026610717177391052), ('surface', 0.025752583518624306), ('map',
0.024036318063735962)]
```

7. Insert a new cell and add the following code to see the probability distribution of topics if you consider the entire dataset as a single document:

```
bag_of_words=[word for sent in preproc_text for word in sent]
doc_inst = mdl.make_doc(bag_of_words)
mdl.infer(doc_inst)[0]
np.argsort(np.array(mdl.infer(doc_inst)[0]))[::-1]
```

The code generates the following output:

```
array([11,17,14,19,12,  7,  4, 13, 10,  2,  3, 15,  1, 18, 16,  9,  0,
        6,  8,  5], dtype=int64)
```

8. Insert a new cell and add the following code to see the probability distribution of topic 11:

```
print(mdl.get_topic_words(11, top_n=7))
```

The code generates the following output

```
[('table', 0.24849626421928406), ('census', 0.1265643984079361), ('level',
0.06526772677898407), ('series', 0.06306280940771103), ('topic',
0.062401335686445236), ('geography', 0.062401335686445236), ('country',
0.06218084320425987)]
```

9. Insert a new cell and add the following code to see the probability distribution of topic 17:

   ```
   print(mdl.get_topic_words(17, top_n=7))
   ```

   The code generates the following output:

   ```
   [('datum', 0.0603327676653862), ('information', 0.057247743010520935), ('year',
   0.03462424501776695), ('dataset', 0.03291034325957298), ('project',
   0.017828006289734993), ('website', 0.014057422056794167), ('activity',
   0.012000739574432373)]
   ```

10. Insert a new cell and add the following code to see the probability distribution of topic 5:

   ```
   print(mdl.get_topic_words(5, top_n=7))
   ```

   The code generates the following output:

   ```
   [('survey', 0.04966237023472786), ('catch', 0.03862873837351799), ('sponge',
   0.0364220105111599), ('sea', 0.0342152863740921), ('datum',
   0.028698472306132317), ('fishing', 0.02759511023759842), ('matter',
   0.026491746306419373)]
   ```

Topic 11, topic 17, and topic 5 seem to be interpretable. One could say that topic 11, topic 17, and topic 5 seem to be broadly about geographical data, internet data, and marine life data respectively.

Note

In general, the topics found are extremely sensitive to randomization in both gensim and tomotopy. While setting a `random_state` in gensim could help in reproducibility, in general, the topics found using tomotopy are superior from the perspective of interpretability.

Activity 5.01: Topic-Modeling Jeopardy Questions

Jeopardy is a popular TV show that covers a variety of topics. In this show, participants are given answers and then asked to frame questions. The purpose of this activity is to give a real-world feel to some of the complexity associated with topic modeling. In this activity, you will do topic modeling on a dataset of Jeopardy questions.

Note

The dataset to be used for this activity can be found at

Follow these steps to complete this activity:

1. Open a Jupyter Notebook.
2. Insert a new cell and import pandas and other necessary libraries.
3. Load the dataset into a pandas DataFrame.
4. Clean the data by dropping the DataFrame rows where the `Question` column has empty cells.
5. Find the unique number of categories based on the `Category` column.

6. Randomly select 4% of the questions. Tokenize the text using spaCy. Select tokens that are nouns/verbs/adjectives or a combination.
7. Train a tomotopy LDA model with 1,000 topics.
8. Print the log perplexity.
9. Find the probability distribution on the entire dataset.
10. Sample a few topics and check for interpretability.

Hierarchical Dirichlet Process (HDP)

HDP is a non-parametric variant of LDA. It is called "non-parametric" since the number of topics is inferred from the data, and this parameter isn't provided by us. This means that this parameter is learned and can increase (that is, it is theoretically unbounded).

The gensim and the scikit-learn libraries use variational inference, while the tomotopy library uses collapsed Gibbs sampling.For the tomotopy library, the following parameters are used:

`iter`: This refers to the number of iterations that the model considers the corpus.

`α`: This concentration parameter is associated with document generation.

`η`: This concentration parameter is associated with topic generation.

`seed`: This fixes the initial randomization.

`min_cf`: This helps eliminate those words that occur fewer times than the frequency specified by us.

To get a better understanding of this, let's perform some simple exercises.

Exercise 5.03: Topics in Around the World in Eighty Days

In this exercise, we will make use of the tomotopy HDP model to analyze the text file for Jules Verne's *Around the World in Eighty Days*, available from the Gutenberg Project. We will use the `min_cf` hyperparameter that is used to ignore words that occur fewer times than the specified frequency and discuss its impact on the interpretability of topics.

1. Open a Jupyter Notebook.
2. Insert a new cell and add the following code to import the necessary libraries:

````
```
import pandas as pd
pd.set_option('display.max_colwidth', 800)
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```
````

3. Insert a new cell and add the following code to read from a download of the Gutenberg Project's *Around the World in Eighty Days* by Jules Verne, and clean the text:

```
OPEN_DATA_URL = '../data/aroundtheworld/pg103.txt'
f=open(OPEN_DATA_URL,'r',encoding='utf-8')
text=f.read()
f.close()
import re
```

```
HANDLE = '@\w+'
LINK = 'https?://t\.co/\w+'
SPECIAL_CHARS = '&lt;|&lt;|&amp;|#'
PARA='\n+'
def clean(text):
    text = re.sub(LINK, ' ', text)
    text = re.sub(SPECIAL_CHARS, ' ', text)
    text = re.sub(PARA, '\n', text)
    return text
text = clean(text)
text
```

The code generates the following output:

```
'\ufeffThe Project Gutenberg EBook of Around the World in 80 Days, by Jules Verne\nThis eBook is for the u
se of anyone anywhere at no cost and with\nalmost no restrictions whatsoever.  You may copy it, give it aw
ay or\nre-use it under the terms of the Project Gutenberg License included\nwith this eBook or online at w
ww.gutenberg.net\nTitle: Around the World in 80 Days\nAuthor: Jules Verne\nRelease Date: May 15, 2008 [EBo
ok  103]\nLast updated: February 18, 2012\nLast updated: May 5, 2012\nLanguage: English\n*** START OF THIS
PROJECT GUTENBERG EBOOK AROUND THE WORLD IN 80 DAYS ***\nAROUND THE WORLD IN EIGHTY DAYS\nCONTENTS\nCHAPTE
R\n      I  IN WHICH PHILEAS FOGG AND PASSEPARTOUT ACCEPT EACH OTHER, THE\n         ONE AS MASTER, THE OTH
ER AS MAN\n     II  IN WHICH PASSEPARTOUT IS CONVINCED THAT HE HAS AT LAST FOUND\n         HIS IDEAL\n
III  IN WHICH A CONVERSATION TAKES PLACE WHICH SEEMS LIKELY TO COST\n         PHILEAS FOGG DEAR\n     IV
IN WHICH PHILEAS FOGG ASTOUNDS PASSEPARTOUT, HIS SERVANT\n      V  IN WHICH A NEW SPECIES OF FUNDS, UNKNOW
```

4. Insert a new cell and add the following code to import the necessary libraries, clean the text (using the spaCy English language model to tokenize the corpus), and exclude all tokens that are not detected as nouns:

```
import spacy
nlp = spacy.load('en_core_web_sm')
doc=nlp(text)
pos_list=['NOUN']
preproc_text=[]
preproc_sent=[]
for token in doc:
    if token.text!='\n':
        if not(token.is_stop) and not(token.is_punct) \
        and token.pos_ in pos_list:
            preproc_sent.append(token.lemma_)
    else:
        preproc_text.append(preproc_sent)
        preproc_sent=[]
preproc_text.append(preproc_sent) #last sentence
print(preproc_text)
```

The code generates the following output:

```
[['ebook', 'day'], ['use', 'cost'], ['restriction'], ['term'], [], ['title', 'world', 'day'], ['author'],
['date'], [], [], [], ['START', 'ebook', 'world', 'day'], ['days'], [], ['chapter', 'fogg', 'PASSEPARTOU
T', 'PASSEPARTOUT', 'convinced', 'ideal', 'iii', 'conversation', 'takes', 'LIKELY', 'astound', 'PASSEPARTO
UT', 'v', 'species', 'fund', 'man', 'change', 'DETECTIVE', 'viii', 'PASSEPARTOUT', 'ix', 'prove', 'design
s', 'X', 'PASSEPARTOUT', 'xi', 'means', 'price', 'xii', 'companion', 'forest', 'ensued', 'PASSEPARTOUT',
'proof', 'fortune', 'favors', 'xiv', 'fogg', 'length', 'thinking', 'xv', 'bag', 'banknote', 'thousand', 'p
ound', 'xvi', 'fix', 'happened', 'voyage', 'xviii', 'FIX', 'xix', 'takes', 'interest', 'master', 'xx', 'xx
i', 'master', 'risk', 'losing', 'reward', 'pound', 'XXII', 'PASSEPARTOUT', 'money', 'XXIII', 'passepartou
t', 'xxiv', 'glimpse', 'xxvii', 'passepartout', 'undergoe', 'speed', 'mile', 'hour', 'course', 'history',
```

5. Insert a new cell and add the following code to create HDP models in which tokens that occur fewer than five times are ignored, and then show how the negative log likelihood varies according to the number of iterations:

```
import tomotopy as tp
mdl = tp.HDPModel(min_cf=5,seed=0)
for line in preproc_text:
    mdl.add_doc(line)
for i in range(0, 100, 10):
    mdl.train(i)
    print('Iteration: {}\tLog-likelihood: {}'.\
          format(i, mdl.ll_per_word))
for k in range(mdl.k):
    print('Top 10 words of topic #{}'.format(k))
    print(mdl.get_topic_words(k, top_n=7))
```

The code generates the following output:

```
Iteration: 0    Log-likelihood: -6.929488035114073
Iteration: 10   Log-likelihood: -6.5324189802807116
Iteration: 20   Log-likelihood: -6.564015251147695
Iteration: 30   Log-likelihood: -6.90579612594132
Iteration: 40   Log-likelihood: -7.206281552678545
Iteration: 50   Log-likelihood: -7.352613202015137
Iteration: 60   Log-likelihood: -7.337697058844141
Iteration: 70   Log-likelihood: -7.364130322712162
Iteration: 80   Log-likelihood: -7.329386253940604
Iteration: 90   Log-likelihood: -7.356350772885065
```

iterations

6. Insert a new cell and add the following code to see the probability distribution of topics if you consider the entire dataset as a single document:

```
bag_of_words=[word for sent in preproc_text for word in sent]
doc_inst = mdl.make_doc(bag_of_words)
np.argsort(np.array(mdl.infer(doc_inst)[0]))[::-1]
```

The code generates the following output:

```
array([ 33,  21,  70,  82,  68,  80,  69,  81,  83,  71,  72,  84,  23,
        35,  22,  34,  32,  20, 106, 165,  60,  48,  12, 228, 164, 138,
        96, 116, 276, 324, 310, 278, 198, 166, 244,  62,  14,  98, 352,
       196, 292,   0,   1, 180,  41,  40,  89,  88, 354, 184, 296, 104,
       312, 136, 248, 216, 168, 120, 232, 264, 280, 200, 152, 328,  17,
        65,  95, 146, 194, 258, 306, 114, 322, 226, 130, 178, 242, 274,
       290, 162, 338, 210, 308, 148, 132, 250, 377, 364, 345, 348, 374,
```

dataset is considered

7. Insert a new cell and add the following code to see the probability distribution of topic 33:

```
print(mdl.get_topic_words(33, top_n=7))
```

The code generates the following output:

```
[('danger', 0.1534954458475113), ('hour', 0.0015197568573057652), ('time',
0.0015197568573057652), ('train', 0.0015197568573057652), ('master',
0.0015197568573057652), ('man', 0.0015197568573057652), ('steamer',
0.0015197568573057652)]
```

8. Insert a new cell and add the following code to see the probability distribution of topic 21:

```
print(mdl.get_topic_words(21, top_n=7))
```

The code generates the following output:

```
[('hour', 0.1344495415687561), ('minute', 0.1232500821352005), ('day',
0.08405196666717529), ('quarter', 0.07285250723361969), ('moment',
0.07285250723361969), ('clock', 0.005605331063270569), ('card',
0.039254117757081985)]
```

9. Insert a new cell and add the following code to see the probability distribution of topic 70:

```
print(mdl.get_topic_words(70, top_n=7))
```

The code generates the following output:

```
[('event', 0.12901155650615692), ('midnight', 0.12901155650615692),
('detective', 0.06482669711112976), ('bed', 0.06482669711112976), ('traveller',
0.06482669711112976), ('watch', 0.06482669711112976), ('clown',
0.06482669711112976)]
```

10. Insert a new cell and add the following code to see the probability distribution of topic 4:

```
print(mdl.get_topic_words(4, top_n=7))
```

The code generates the following output:

```
[('house', 0.20237493515014648), ('opium', 0.10131379961967468), ('town',
0.07604850828647614), ('brick', 0.07604850828647614), ('mansion',
0.07604850828647614), ('glimpse', 0.50783220678567886), ('ball',
0.050783220678567886)]
```

We can see that ignoring tokens that occur fewer than five times significantly improves the interpretability of the topic model. Also, we have 378 topics in all, many of which are not likely to be interpretable. So, what does this mean? Let's analyze a corpus from another classic and then return to these questions.

Exercise 5.04: Topics in The Life and Adventures of Robinson Crusoe by Daniel Defoe

In this exercise, we will make use of the tomotopy HDP model to analyze a text corpus taken from the text file for Daniel Defoe's *The Life and Adventures of Robinson Crusoe*, available on the Gutenberg Project website. Here, we will take the value of α as 0.8 and experiment with selecting tokens based on different combinations of parts of speech, before training the model.

1. Open a Jupyter Notebook.
2. Insert a new cell and add the following code to import the necessary libraries:

````
```
import pandas as pd
pd.set_option('display.max_colwidth', 800)
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```
````

3. Insert a new cell and add the following code to read from a download of the Gutenberg Project's *The Life and Adventures of Robinson Crusoe* by Daniel Defoe, and clean the text:

```
OPEN_DATA_URL = '../data/robinsoncrusoe/521-0.txt'
f=open(OPEN_DATA_URL,'r',encoding='utf-8')
text=f.read()
f.close()
import re
HANDLE = '@\w+'
LINK = 'https?://t\.co/\w+'
SPECIAL_CHARS = '&lt;|&lt;|&amp;|#'
PARA='\n+'
def clean(text):
    text = re.sub(LINK, ' ', text)
    text = re.sub(SPECIAL_CHARS, ' ', text)
    text = re.sub(PARA, '\n', text)
    return text
text = clean(text)
text
```

The code generates the following output:

```
'\ufeffThe Project Gutenberg eBook, The Life and Adventures of Robinson Crusoe,\nby Daniel Defoe\nThis eBo
ok is for the use of anyone anywhere in the United States and most\nother parts of the world at no cost an
d with almost no restrictions\nwhatsoever.  You may copy it, give it away or re-use it under the terms of
\nthe Project Gutenberg License included with this eBook or online at\nwww.gutenberg.org.  If you are not
located in the United States, you\'ll have\nto check the laws of the country where you are located before
using this ebook.\nTitle: The Life and Adventures of Robinson Crusoe\nAuthor: Daniel Defoe\nRelease Date:
September 7, 2015  [eBook  521]\nThis file was first posted on February 28, 1996\nLast Updated: November 1
6, 2016\nLanguage: English\nCharacter set encoding: UTF-8\n***START OF THE PROJECT GUTENBERG EBOOK THE LIF
E AND ADVENTURES OF\nROBINSON CRUSOE***\nTranscribed from the 1919 Seeley, Service & Co. edition by David
Price,\nemail ccx074@pglaf.org\n                                   The\n                            Life an
d Adventures\n                                    of\n                              Robinson Crusoe\n
By\n                             Daniel Defoe\n                               * * * * *\n
_With Illustrations by H. M. Brock_\n                               * * * * *\n
London\n                      Seeley, Service & Co. Limited\n                         38 Great Russell Str
```

4. Insert a new cell and add the following code to import the necessary libraries. Clean the text using the spaCy English language model to tokenize the corpus and to exclude all tokens that are not detected as nouns:

```
import spacy
nlp = spacy.load('en_core_web_sm')
doc=nlp(text)
"""
We can experiment with other or a combinations of parts of speech
['NOUN','ADJ','VERB','ADV'] #['NOUN','ADJ']
"""
pos_list=['NOUN']
preproc_text=[]
preproc_sent=[]
for token in doc:
    if token.text!='\n':
        if not(token.is_stop) and not(token.is_punct) \
        and token.pos_ in pos_list:
            preproc_sent.append(token.lemma_)
    else:
        preproc_text.append(preproc_sent)
        preproc_sent=[]
preproc_text.append(preproc_sent) #last sentence
print(preproc_text)
```

The code generates the following output:

```
[[], [], ['use'], ['part', 'world', 'cost', 'restriction'], ['term'], [], [], ['law', 'country', 'ebook'],
['title'], ['author'], ['ebook'], ['file'], [], [], [], ['START', 'PROJECT'], [], ['edition'], ['email'],
[], ['year', 'city', 'family'], ['country', 'father', 'foreigner'], ['estate', 'merchandise'], ['trade'],
['mother', 'relation', 'family'], ['country'], ['corruption', 'word'], ['Crusoe', 'companion'], [], ['brot
her', 'lieutenant'], ['regiment', 'foot', 'flander'], ['battle'], ['brother'], ['father', 'mother'], ['so
n', 'family', 'trade', 'head'], ['thought', 'father'], ['share', 'learning'], ['education', 'country', 'sc
hool'], ['law', 'sea'], ['inclination'], ['command', 'father', 'entreaty', 'persuasion'], ['mother', 'frie
nd'], ['propensity', 'nature', 'life', 'misery'], [], ['father', 'man', 'counsel'], ['design', 'morning'],
['chamber', 'gout'], ['subject', 'reason'], ['inclination', 'house'], ['country', 'prospect'], ['fortune',
```

5. Insert a new cell and add the following code to import the necessary libraries. Create an HDP model with the `α` concentration parameter as `0.8` and see how the negative log likelihood varies with the number of iterations:

```
import tomotopy as tp
mdl = tp.HDPModel(alpha=0.8,seed=0)
for line in preproc_text:
    mdl.add_doc(line)
for i in range(0, 110, 10):
    mdl.train(i)
    print('Iteration: {}\tLog-likelihood: {}'.\
          format(i, mdl.ll_per_word))
for k in range(mdl.k):
    print('Top 10 words of topic #{}'.format(k))
    print(mdl.get_topic_words(k, top_n=7))
```

The code generates the following output:

```
Iteration: 0    Log-likelihood: -7.90226765159165
Iteration: 10   Log-likelihood: -7.371047840028124
Iteration: 20   Log-likelihood: -7.37652709605804
Iteration: 30   Log-likelihood: -7.428692292874718
Iteration: 40   Log-likelihood: -7.40457823874009
Iteration: 50   Log-likelihood: -7.4007174035615515
Iteration: 60   Log-likelihood: -7.397126200841502
Iteration: 70   Log-likelihood: -7.386784886923981
Iteration: 80   Log-likelihood: -7.3724504423195345
Iteration: 90   Log-likelihood: -7.387830544015653
Iteration: 100  Log-likelihood: -7.375331385114747
```

6. Insert a new cell and add the following code to save the topic model:

````
```
mdl.save('../data/robinsoncrusoe/hdp_model.bin')
```
````

7. Insert a new cell and add the following code to load the topic model:

````
```
mdl = tp.HDPModel.load('../data/robinsoncrusoe/'\
                       'hdp_model.bin')
```
````

8. Insert a new cell and add the following code to see the probability distribution of topics if you consider the entire dataset as a single document:

```
bag_of_words=[word for sent in preproc_text for word in sent]
doc_inst = mdl.make_doc(bag_of_words)
mdl.infer(doc_inst)[0]
np.argsort(np.array(mdl.infer(doc_inst)[0]))[::-1]
```

The code generates the following output:

```
array([163, 103,  28,  64, 124,  40, 160, 100, 162, 102, 161, 101,   0,
         1,  49,  48, 169, 168,  72,  73,  35,  47,  43, 107,  45,  69,
        71,  67,  83,  81,  79,  77, 167, 165,  97,  96,  95,   2,  14,
        26,  38,  50,  62,  74,  86,  98, 110, 122, 134, 146, 158, 194,
        18, 114, 138,   6, 183,  32,  92, 184, 186, 119,  11, 113,  17,
         5,  23, 143, 137,  89,  53,  54, 179,  52,  51,  55, 180,  57,
        56,  70, 181,  58,  59,  60,  68,  66,  65,  63,  61,  39, 185,
        46, 192,   3,   7,   8,   9,  12,  13,  15,  19,  20,  21,  24,
        25,  27, 191,  29,  30,  31,  33,  34,  36,  37,  41,  42, 188,
        44, 187, 178, 176,  75, 117,  76, 123, 164, 125, 126, 127, 128,
       129, 130, 131, 132, 133, 135, 139, 140, 141, 144, 145, 147, 148,
       149, 150, 151, 152, 153, 154, 155, 156, 157, 120, 121, 193,  87,
        90,  91,  84, 174,  93,  94, 116,  82, 175, 173, 172, 171, 170,
       104, 105, 106, 166, 108, 109, 111,  80,  78, 115, 177,  85,  99,
       159, 190, 182, 189,  10, 142,  22, 118,  16, 136,   4, 112,  88],
      dtype=int64)
```

considered

9. Insert a new cell and add the following code to see the probability distribution of topic 163:

```
print(mdl.get_topic_words(163, top_n=7))
```

The code generates the following output:

```
[('horse', 0.13098040223121643), ('way', 0.026405228301882744), ('mankind',
0.26405228301882744), ('fire', 0.026405228301882744), ('object',
0.026405228301882744), ('bridle', 0.026405228301882744), ('distress',
0.026405228301882744)]
```

10. Insert a new cell and add the following code to see the probability distribution of topic 103:

```
print(mdl.get_topic_words(103, top_n=7))
```

The code generates the following output:

```
[('manor', 0.03706422075629234), ('inheritance', 0.03706422075629234), ('lord',
0.03706422075629234), ('man', 0.0003669724682377309), ('shore',
0.0003669724682377309), ('ship',0.0003669724682377309)]
```

11. Insert a new cell and add the following code to see the probability distribution of topic 28:

```
print(mdl.get_topic_words(28, top_n=7))
```

The code generates the following output:

```
[('thought', 0.07716038823127747), ('mind', 0.045609116554260254), ('word',
0.038597721606492996), ('face', 0.03509202599525452), ('terror',
0.03509202599525452), ('tear', 0.3158633038401604), ('apprehension',
0.3158633038401604)]
```

Activity 5.02: Comparing Different Topic Models

The **Consumer Financial Protection Bureau** (**CFPB**) publishes consumer complaints made against organizations in the financial sector. This original dataset is available at https://www.consumerfinance.gov/data-research/consumer-complaints/#download-the-data. In this activity, you will qualitatively compare how HDP and LDA models perform on the interpretability of topics by analyzing student loan complaints.

Follow these steps to complete this activity:

1. Open a Jupyter Notebook.
2. Import the `pandas` library and load the dataset from a text file produced by partially processing the dataset from the CFPB website mentioned at the beginning of this section.
3. Tokenize the text using spaCy. Select tokens that may be a part of speech (noun/verb/adjective or a combination).
4. Train an HDP model.
5. Save and load the HDP model. To save a topic model, use the following line of code:

   ```
   mdl.save('../data/consumercomplaints/hdp_model.bin')
   ```

   To load a topic model, use the following:

   ```
   mdl = tp.HDPModel.load('../data/consumercomplaints/hdp_model.bin')
   ```

6. Determine the topics in the entire set of complaints. Sample a few topics and check for interpretability.
7. Repeat steps 3-8 for an LDA model instead of an HDP model. Consider the number of topics in the LDA model to around the number of topics found in the HDP model.
8. Select the qualitatively better model from the HDP and LDA models trained in this activity. Also, compare these two models quantitatively.

   Note: The full solution to this activity in the current directory

Summary

In this lab, we discussed topic modeling in detail. Without delving into advanced statistics, we reviewed various topic-modeling algorithms (such as LSA, LDA, and HDP) and how they can be used for topic modeling on a given dataset. We explored the challenges involved in topic modeling, how experimentation can help address those challenges, and, finally, broadly discussed the current state-of-the-art approaches to topic modeling.

In the next lab, we will learn about vector representation of text, which helps us convert text into a numerical format to make it more easily understandable by machines.