Simple topic identification

Puteaux, Fall/Winter 2020-2021

- §1 Introduction to Natural Language Processing in Python
- §1.2 Simple topic identification

1 Word counts with bag-of-words

1.1 What is bag-of-words?

- It is a basic method for finding topics in a text.
- Need first to create tokens using tokenization.
- And then count up all the tokens.
- The more frequent a word, the more important it might be.
- It can be a great way to determine the significant words in a text.

1.2 Code of bag-of-words in Python:

```
[1]: from nltk.tokenize import word_tokenize
from collections import Counter

Counter(
    word_tokenize("""The cat is in the box. The cat likes the box. \
The box is over the cat."""))
```

```
'likes': 1,
    'over': 1})

[2]: counter = Counter(
    word_tokenize("""The cat is in the box. The cat likes the box. \
    The box is over the cat."""))
    counter.most_common(2)

[2]: [('The', 3), ('cat', 3)]
```

1.3 Practice question for bag-of-words picker:

• It's time for a quick check on the understanding of bag-of-words. Which of the below options, with basic NLTK tokenization, map the bag-of-words for the following text?

```
"The cat is in the box. The cat box."

| ('the', 3), ('box.', 2), ('cat', 2), ('is', 1).
| ('The', 3), ('box', 2), ('cat', 2), ('is', 1), ('in', 1), ('.', 1).
| ('the', 3), ('cat box', 1), ('cat', 1), ('box', 1), ('is', 1), ('in', 1).
| ('The', 2), ('box', 2), ('.', 2), ('cat', 2), ('is', 1), ('in', 1), ('the', 1).
| Question-solving method:
| [3]: from nltk.tokenize import word_tokenize from collections import Counter
| Counter(word_tokenize("The cat is in the box. The cat box."))
| [3]: Counter({'The': 2, 'cat': 2, 'is': 1, 'in': 1, 'the': 1, 'box': 2, '.': 2})
```

1.4 Practice exercises for word counts with bag-of-words:

▶ Package pre-loading:

```
[4]: from nltk import word_tokenize
```

▶ Data pre-loading:

```
[5]: article = open('ref1. Wikipedia article - Debugging.txt').read()
```

▶ Bag-of-words Counter building practice:

```
[6]: # Import Counter
from collections import Counter

# Tokenize the article: tokens
```

```
tokens = word_tokenize(article)

# Convert the tokens into lowercase: lower_tokens
lower_tokens = [t.lower() for t in tokens]

# Create a Counter with the lowercase tokens: bow_simple
bow_simple = Counter(lower_tokens)

# Print the 10 most common tokens
print(bow_simple.most_common(10))
```

```
[(',', 151), ('the', 150), ('.', 89), ('of', 81), ("''", 66), ('to', 63), ('a', 60), ('``', 47), ('in', 44), ('and', 41)]
```

- §1 Introduction to Natural Language Processing in Python
- §1.2 Simple topic identification

2 Simple text preprocessing

2.1 Why preprocess?

- When performing machine learning or other statistical methods, it could help make for better input data.
- Examples:
 - tokenization to create a bag of words
 - lowercasing words
- Lemmatization/Stemming:
 - shorten words to their root stems
- Remove stop words, punctuation, or unwanted tokens.
- Good to experiment with different approaches.

2.2 Code of text preprocessing with Python:

```
[7]: from nltk.tokenize import word_tokenize from collections import Counter
```

► Text preprocessing practice:

```
[8]: from nltk.corpus import stopwords
      text = """The cat is in the box. The cat likes the box.
      The box is over the cat."""
      tokens = [w for w in word_tokenize(text.lower()) if w.isalpha()]
      no stops = [t for t in tokens if t not in stopwords.words('english')]
      Counter(no_stops).most_common(2)
 [8]: [('cat', 3), ('box', 3)]
 [9]: from nltk.stem import WordNetLemmatizer
      text = """Cats, dogs and birds are common pets. So are fish."""
      tokens = [w for w in word_tokenize(text.lower()) if w.isalpha()]
      no stops = [t for t in tokens if t not in stopwords.words('english')]
      wordnet_lemmatizer = WordNetLemmatizer()
      lemmatized = [wordnet lemmatizer.lemmatize(t) for t in no stops]
      print(lemmatized)
      ['cat', 'dog', 'bird', 'common', 'pet', 'fish']
     2.3 Practice question for text preprocessing steps:
        • Which of the following are useful text preprocessing steps?
          \square Stems, spelling corrections, lowercase.
          ⊠ Lemmatization, lowercasing, removing unwanted tokens.
          ☐ Removing stop words, leaving in capital words.
          \square Strip stop words, word endings and digits.
     2.4 Practice exercises for simple text preprocessing:
     ▶ Package pre-loading:
[10]: from nltk import word_tokenize
      from collections import Counter
     ▶ Data pre-loading:
[11]: article = open('ref1. Wikipedia article - Debugging.txt').read()
      tokens = word_tokenize(article)
      lower_tokens = [t.lower() for t in tokens]
      stopwords = open('ref2. English stopwords.txt').read()
      english_stops = word_tokenize(stopwords)
```

Page 4 of 13

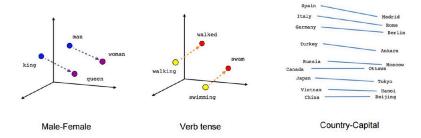
```
[12]: # Import WordNetLemmatizer
     from nltk.stem import WordNetLemmatizer
     # Retain alphabetic words: alpha_only
     alpha_only = [t for t in lower_tokens if t.isalpha()]
     # Remove all stop words: no_stops
     no_stops = [t for t in alpha_only if t not in english_stops]
     # Instantiate the WordNetLemmatizer
     wordnet_lemmatizer = WordNetLemmatizer()
     # Lemmatize all tokens into a new list: lemmatized
     lemmatized = [wordnet_lemmatizer.lemmatize(t) for t in no_stops]
     # Create the bag-of-words: bow
     bow = Counter(lemmatized)
     # Print the 10 most common tokens
     print(bow.most_common(10))
     [('debugging', 40), ('system', 25), ('bug', 17), ('software', 16), ('problem',
     15), ('tool', 15), ('computer', 14), ('process', 13), ('term', 13), ('debugger',
     13)]
    ##
    ## Natural Language Processing in Python
    §1 Introduction to Natural Language Processing in Python
    §1.2 Simple topic identification
```

3 Introduction to gensim

3.1 What is gensim?

- It is a popular open-source NLP library.
- It uses top academic models to perform complex tasks:
 - building document or word vectors
 - performing topic identification and document comparison

3.2 What is a word vector?



3.3 Code of creating a gensim corpus:

```
[13]: from gensim.corpora.dictionary import Dictionary
      from nltk.tokenize import word_tokenize
      my_documents = [
          'The movie was about a spaceship and aliens.',
          'I really liked the movie!',
          'Awesome action scenes, but boring characters.',
          'The movie was awful! I hate alien films.',
          'Space is cool! I liked the movie.',
          'More space films, please!',
[14]: tokenized_docs = [word_tokenize(doc.lower()) for doc in my_documents]
      dictionary = Dictionary(tokenized_docs)
      dictionary.token2id
[14]: {'.': 0,
       'a': 1,
       'about': 2,
       'aliens': 3,
       'and': 4,
       'movie': 5,
       'spaceship': 6,
       'the': 7,
       'was': 8,
       '!': 9,
       'i': 10,
       'liked': 11,
       'really': 12,
       ',': 13,
       'action': 14,
       'awesome': 15,
       'boring': 16,
```

```
'but': 17,
       'characters': 18,
       'scenes': 19,
       'alien': 20,
       'awful': 21,
       'films': 22,
       'hate': 23,
       'cool': 24,
       'is': 25,
       'space': 26,
       'more': 27,
       'please': 28}
[15]: corpus = [dictionary.doc2bow(doc) for doc in tokenized_docs]
      corpus
[15]: [[(0, 1), (1, 1), (2, 1), (3, 1), (4, 1), (5, 1), (6, 1), (7, 1), (8, 1)],
       [(5, 1), (7, 1), (9, 1), (10, 1), (11, 1), (12, 1)],
       [(0, 1), (13, 1), (14, 1), (15, 1), (16, 1), (17, 1), (18, 1), (19, 1)],
       [(0, 1),
        (5, 1),
        (7, 1),
        (8, 1),
        (9, 1),
        (10, 1),
        (20, 1),
        (21, 1),
        (22, 1),
        (23, 1)],
       [(0, 1), (5, 1), (7, 1), (9, 1), (10, 1), (11, 1), (24, 1), (25, 1), (26, 1)],
       [(9, 1), (13, 1), (22, 1), (26, 1), (27, 1), (28, 1)]]
```

3.4 What are the advantages of creating a gensim corpus?

- First of all, gensim models can be easily saved, updated, and reused.
- Secondly, the dictionary created can also be updated.
- Lastly, the more advanced and feature-rich bag-of-words can be used in future exercises.

3.5 Practice question for word vectors:

• What are word vectors, and how do they help with NLP?

 \Box They are similar to bags of words, just with numbers. You use them to count how many tokens there are.

 \square Word vectors are sparse arrays representing bigrams in the corpora. You can use them to compare two sets of words to one another.

- ⊠ Word vectors are multi-dimensional mathematical representations of words created using deep learning methods. They give us insight into relationships between words in a corpus.
- □ Word vectors don't actually help NLP and are just hype.

3.6 Practice exercises for introduction to gensim:

▶ Package pre-loading:

```
[16]: import zipfile
from nltk import word_tokenize
```

▶ Data pre-loading:

```
file_name = 'ref4. Wikipedia articles.zip'
with zipfile.ZipFile(file_name, 'r') as archive:
    files = [
        archive.read(name) for name in archive.namelist()
        if name.endswith('.txt')
    ]

doc_tokens = [word_tokenize(file.decode("utf-8")) for file in files]

articles = []
stopwords = open('ref2. English stopwords.txt').read()
english_stops = word_tokenize(stopwords)
for i in range(len(doc_tokens)):
    lower_tokens = [t.lower() for t in doc_tokens[i]]
    alphanumeric_only = [t for t in lower_tokens if t.isalnum()]
    no_stops = [t for t in alphanumeric_only if t not in english_stops]
    articles.append(no_stops)
```

▶ Gensim corpus creating and querying practice:

```
[18]: # Import Dictionary
from gensim.corpora.dictionary import Dictionary

# Create a Dictionary from the articles: dictionary
dictionary = Dictionary(articles)

# Select the id for "computer": computer_id
computer_id = dictionary.token2id.get("computer")

# Use computer_id with the dictionary to print the word
print(dictionary.get(computer_id))

# Create a MmCorpus: corpus
corpus = [dictionary.doc2bow(article) for article in articles]
```

```
# Print the first 10 word ids with their frequency counts from the fifth
      \rightarrow document
      print(corpus[4][:10])
     computer
     [(13, 2), (24, 1), (43, 1), (44, 6), (45, 1), (50, 1), (58, 1), (59, 1), (61, 1)]
     7), (75, 1)]
     ▶ Package pre-loading:
[19]: from collections import defaultdict
      import itertools
     ► Gensim bag-of-words practice:
[20]: # Save the fifth document: doc
      doc = corpus[4]
      # Sort the doc for frequency: bow_doc
      bow_doc = sorted(doc, key=lambda w: w[1], reverse=True)
      # Print the top 5 words of the document alongside the count
      for word_id, word_count in bow_doc[:5]:
          print(dictionary.get(word_id), word_count)
      # Create the defaultdict: total_word_count
      total_word_count = defaultdict(int)
      for word_id, word_count in itertools.chain.from_iterable(corpus):
          total_word_count[word_id] += word_count
     language 54
     programming 39
     languages 30
     code 22
     computer 15
[21]: # Save the fifth document: doc
      doc = corpus[4]
      # Sort the doc for frequency: bow_doc
      bow_doc = sorted(doc, key=lambda w: w[1], reverse=True)
      # Print the top 5 words of the document alongside the count
      for word id, word count in bow doc[:5]:
          print(dictionary.get(word_id), word_count)
      # Create the defaultdict: total_word_count
```

```
language 54
programming 39
languages 30
code 22
computer 15
computer 598
software 450
cite 322
ref 259
code 235
##
## Natural Language Processing in Python
                               ##
§1 Introduction to Natural Language Processing in Python
§1.2 Simple topic identification
```

4 Tf-idf with gensim

4.1 What is tf-idf?

- Tf-idf means term frequency inverse document frequency.
- Allow determining the most important words in each document.
- Each corpus may have shared words beyond just stopwords.
- These words should be down-weighted in importance.
- Example:
 - "sky" from the theme of astronomy
- Ensures most common words don't show up as keywords.

• Keep document specific frequent words weighted high.

4.2 What is the tf-idf formula?

```
• w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)

- w_{i,j} = \text{tf-idf} weight for token i in document j

- tf_{i,j} = \text{number of occurences of token } i in document j

- df_i = \text{number of documents that contain token } i

- N = \text{total number of documents}
```

4.3 Code of tf-idf with gensim:

```
[22]: from gensim.corpora.dictionary import Dictionary
      from nltk.tokenize import word_tokenize
      my_documents = [
          'The movie was about a spaceship and aliens.',
          'I really liked the movie!',
          'Awesome action scenes, but boring characters.',
          'The movie was awful! I hate alien films.',
          'Space is cool! I liked the movie.',
          'More space films, please!',
      ]
      tokenized_docs = [word_tokenize(doc.lower()) for doc in my_documents]
      dictionary = Dictionary(tokenized docs)
      corpus = [dictionary.doc2bow(doc) for doc in tokenized_docs]
[23]: from gensim.models.tfidfmodel import TfidfModel
      tfidf = TfidfModel(corpus)
      tfidf[corpus[1]]
[23]: [(5, 0.1746298276735174),
```

```
[23]: [(5, 0.1746298276735174),
(7, 0.1746298276735174),
(9, 0.1746298276735174),
(10, 0.29853166221463673),
(11, 0.47316148988815415),
(12, 0.7716931521027908)]
```

4.4 Practice question for what is tf-idf:

• To calculate the tf-idf weight for the word "computer", which appears five times in a document containing 100 words. Given a corpus containing 200 documents, with 20 documents mentioning the word "computer", so tf-idf can be calculated by multiplying term frequency with inverse document frequency.

- Notes:
 - term frequency = percentage share of the word compared to all tokens in the document
 - inverse document frequency = logarithm of the total number of documents in a corpus divided by the number of documents containing the term
- Which of the below options is correct?

```
\boxtimes (5 / 100) * log(200 / 20)

\square (5 * 100) / log(200 * 20)

\square (20 / 5) * log(200 / 20)

\square (200 * 5) * log(400 / 5)
```

4.5 Practice exercises for tf-idf with gensim:

► Package pre-loading:

```
[24]: import zipfile

from nltk import word_tokenize

from gensim.corpora.dictionary import Dictionary
from gensim.models.tfidfmodel import TfidfModel
```

▶ Data pre-loading:

```
[25]: file_name = 'ref4. Wikipedia articles.zip'
     with zipfile.ZipFile(file_name, 'r') as archive:
         files = [
              archive.read(name) for name in archive.namelist()
              if name.endswith('.txt')
         1
     doc_tokens = [word_tokenize(file.decode("utf-8")) for file in files]
     articles = []
     stopwords = open('ref2. English stopwords.txt').read()
     english_stops = word_tokenize(stopwords)
     for i in range(len(doc_tokens)):
         lower_tokens = [t.lower() for t in doc_tokens[i]]
          alphanumeric_only = [t for t in lower_tokens if t.isalnum()]
         no_stops = [t for t in alphanumeric_only if t not in english_stops]
         articles.append(no_stops)
     dictionary = Dictionary(articles)
     corpus = [dictionary.doc2bow(article) for article in articles]
     doc = corpus[4]
```

▶ **Wikipedia tf-idf practice:

abstraction 0.1745698215843137 intermediate 0.16521194176980647

```
[26]: # Create a new TfidfModel using the corpus: tfidf
      tfidf = TfidfModel(corpus)
      # Calculate the tfidf weights of doc: tfidf_weights
      tfidf_weights = tfidf[doc]
      # Print the first five weights
      print(tfidf_weights[:5])
     [(13, 0.021411676334320492), (24, 0.01738903055915624), (43,
     0.00805356588388867), (45, 0.021821227698039212), (50, 0.01376766181415054)]
[27]: # Create a new TfidfModel using the corpus: tfidf
      tfidf = TfidfModel(corpus)
      # Calculate the tfidf weights of doc: tfidf weights
      tfidf_weights = tfidf[doc]
      # Print the first five weights
      print(tfidf_weights[:5])
      # Sort the weights from highest to lowest: sorted_tfidf_weights
      sorted_tfidf_weights = sorted(tfidf_weights, key=lambda w: w[1], reverse=True)
      # Print the top 5 weighted words
      for term_id, weight in sorted_tfidf_weights[:5]:
          print(dictionary.get(term_id), weight)
     [(13, 0.021411676334320492), (24, 0.01738903055915624), (43,
     0.00805356588388867), (45, 0.021821227698039212), (50, 0.01376766181415054)]
     compiled 0.2182122769803921
     compilation 0.21353333707313848
     eiffel 0.17794444756094874
```

Page 13 of 13