03_document_term_matrix

September 29, 2021

1 From tokens to numbers: the document-term matrix

The bag of words model represents a document based on the frequency of the terms or tokens it contains. Each document becomes a vector with one entry for each token in the vocabulary that reflects the token's relevance to the document.

The document-term matrix is straightforward to compute given the vocabulary. However, it is also a crude simplification because it abstracts from word order and grammatical relationships. Nonetheless, it often achieves good results in text classification quickly and, thus, a very useful starting point.

There are several ways to weigh a token's vector entry to capture its relevance to the document. We will illustrate below how to use sklearn to use binary flags that indicate presence or absence, counts, and weighted counts that account for differences in term frequencies across all documents, i.e., in the corpus.

1.1 Imports & Settings

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
%matplotlib inline

from collections import Counter
from pathlib import Path

import numpy as np
import pandas as pd
from scipy import sparse
from scipy.spatial.distance import pdist

# Visualization
import matplotlib.pyplot as plt
from matplotlib.ticker import ScalarFormatter
import seaborn as sns
from ipywidgets import interact, FloatRangeSlider

# spacy for language processing
import spacy
```

```
# sklearn for feature extraction & modeling
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer,␣
↪TfidfTransformer
from sklearn.model_selection import train_test_split
```

[3]:
```
sns.set_style('white')
```

1.2 Load BBC data

[4]:
```
path = Path('..', 'data', 'bbc')
files = sorted(list(path.glob('**/*.txt')))
doc_list = []
for i, file in enumerate(files):
    topic = file.parts[-2]
    article = file.read_text(encoding='latin1').split('\n')
    heading = article[0].strip()
    body = ' '.join([l.strip() for l in article[1:]]).strip()
    doc_list.append([topic, heading, body])
```

1.2.1 Convert to DataFrame

[5]:
```
docs = pd.DataFrame(doc_list, columns=['topic', 'heading', 'body'])
docs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2225 entries, 0 to 2224
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   topic     2225 non-null   object
 1   heading   2225 non-null   object
 2   body      2225 non-null   object
dtypes: object(3)
memory usage: 52.3+ KB
```

1.2.2 Inspect results

[6]:
```
docs.sample(10)
```

[6]:
```
         topic                             heading  \
1744     sport    Davenport hits out at Wimbledon
1919      tech  California sets fines for spyware
1937      tech    Games maker fights for survival
965   politics  Opposition grows to house arrests
1799     sport      Officials respond in court row
998   politics    Minimum rate for foster parents
```

```
2038      tech  Europe backs digital TV lifestyle
1823     sport  Roddick to face Saulnier in final
57    business   Electrolux to export Europe jobs
345   business  Disaster claims 'less than $10bn'

                                                   body
1744  World number one Lindsay Davenport has critici…
1919  The makers of computer programs that secretly …
1937  One of Britain's largest independent game make…
965   The Conservatives have expressed "serious misg…
1799  Australian tennis' top official has defended t…
998   Foster carers are to be guaranteed a minimum a…
2038  How people receive their digital entertainment…
1823  Andy Roddick will play Cyril Saulnier in the f…
57    Electrolux saw its shares rise 14% on Tuesday …
345   Insurers have sought to calm fears that they f…
```

1.2.3 Data drawn from 5 different categories

[7]:
```
docs.topic.value_counts(normalize=True).to_frame('count').style.format({'count':
 '{:,.2%}'.format})
```

[7]:
```
<pandas.io.formats.style.Styler at 0x7f5c41434b50>
```

1.3 Explore Corpus

1.3.1 Token Count via Counter()

[8]:
```
# word count
word_count = docs.body.str.split().str.len().sum()
print(f'Total word count: {word_count:,d} | per article: {word_count/len(docs):
 ,.0f}')
```

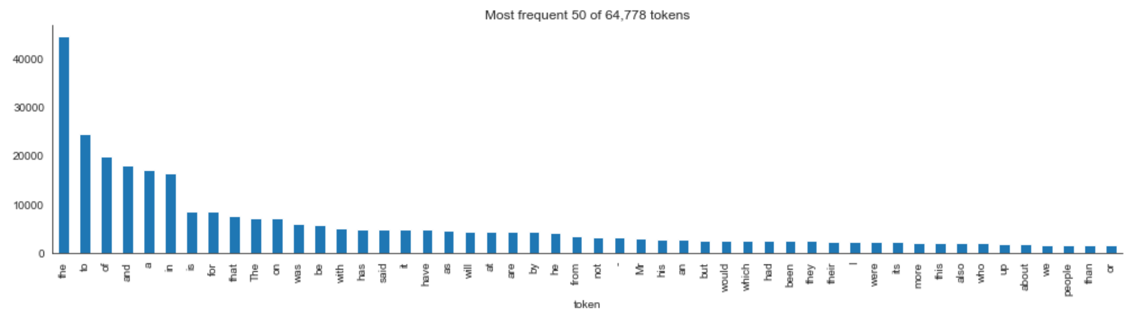
```
Total word count: 842,910 | per article: 379
```

[9]:
```
token_count = Counter()
for i, doc in enumerate(docs.body.tolist(), 1):
    if i % 500 == 0:
        print(i, end=' ', flush=True)
    token_count.update([t.strip() for t in doc.split()])
```

```
500 1000 1500 2000
```

[10]:
```
tokens = (pd.DataFrame(token_count.most_common(), columns=['token', 'count'])
          .set_index('token')
          .squeeze())
```

[11]:
```
n = 50
(tokens
 .iloc[:50]
 .plot
 .bar(figsize=(14, 4), title=f'Most frequent {n} of {len(tokens):,d} tokens'))
sns.despine()
plt.tight_layout();
```



1.4 Document-Term Matrix with `CountVectorizer`

The scikit-learn preprocessing module offers two tools to create a document-term matrix. The CountVectorizer uses binary or absolute counts to measure the term frequency tf(d, t) for each document d and token t.

The TfIDFVectorizer, in contrast, weighs the (absolute) term frequency by the inverse document frequency (idf). As a result, a term that appears in more documents will receive a lower weight than a token with the same frequency for a given document but lower frequency across all documents.

The resulting tf-idf vectors for each document are normalized with respect to their absolute or squared totals (see the sklearn documentation for details). The tf-idf measure was originally used in information retrieval to rank search engine results and has subsequently proven useful for text classification or clustering.

Both tools use the same interface and perform tokenization and further optional preprocessing of a list of documents before vectorizing the text by generating token counts to populate the document-term matrix.

Key parameters that affect the size of the vocabulary include:

- `stop_words`: use a built-in or provide a list of (frequent) words to exclude
- `ngram_range`: include n-grams in a range for n defined by a tuple of (nmin, nmax)
- `lowercase`: convert characters accordingly (default is True)
- `min_df`/ max_df: ignore words that appear in less / more (int) or a smaller / larger share of documents (if float [0.0,1.0])
- `max_features`: limit number of tokens in vocabulary accordingly
- `binary`: set non-zero counts to 1 True

1.4.1 Key parameters

[12]:
```python
print(CountVectorizer().__doc__)
```

```
Convert a collection of text documents to a matrix of token counts

    This implementation produces a sparse representation of the counts using
    scipy.sparse.csr_matrix.

    If you do not provide an a-priori dictionary and you do not use an analyzer
    that does some kind of feature selection then the number of features will
    be equal to the vocabulary size found by analyzing the data.

    Read more in the :ref:`User Guide <text_feature_extraction>`.

    Parameters
    ----------
    input : string {'filename', 'file', 'content'}, default='content'
        If 'filename', the sequence passed as an argument to fit is
        expected to be a list of filenames that need reading to fetch
        the raw content to analyze.

        If 'file', the sequence items must have a 'read' method (file-like
        object) that is called to fetch the bytes in memory.

        Otherwise the input is expected to be a sequence of items that
        can be of type string or byte.

    encoding : string, default='utf-8'
        If bytes or files are given to analyze, this encoding is used to
        decode.

    decode_error : {'strict', 'ignore', 'replace'}, default='strict'
        Instruction on what to do if a byte sequence is given to analyze that
        contains characters not of the given `encoding`. By default, it is
        'strict', meaning that a UnicodeDecodeError will be raised. Other
        values are 'ignore' and 'replace'.

    strip_accents : {'ascii', 'unicode'}, default=None
        Remove accents and perform other character normalization
        during the preprocessing step.
        'ascii' is a fast method that only works on characters that have
        an direct ASCII mapping.
        'unicode' is a slightly slower method that works on any characters.
        None (default) does nothing.

        Both 'ascii' and 'unicode' use NFKD normalization from
        :func:`unicodedata.normalize`.
```

```
    lowercase : bool, default=True
        Convert all characters to lowercase before tokenizing.

    preprocessor : callable, default=None
        Override the preprocessing (string transformation) stage while
        preserving the tokenizing and n-grams generation steps.
        Only applies if ``analyzer is not callable``.

    tokenizer : callable, default=None
        Override the string tokenization step while preserving the
        preprocessing and n-grams generation steps.
        Only applies if ``analyzer == 'word'``.

    stop_words : string {'english'}, list, default=None
        If 'english', a built-in stop word list for English is used.
        There are several known issues with 'english' and you should
        consider an alternative (see :ref:`stop_words`).

        If a list, that list is assumed to contain stop words, all of which
        will be removed from the resulting tokens.
        Only applies if ``analyzer == 'word'``.

        If None, no stop words will be used. max_df can be set to a value
        in the range [0.7, 1.0) to automatically detect and filter stop
        words based on intra corpus document frequency of terms.

    token_pattern : string
        Regular expression denoting what constitutes a "token", only used
        if ``analyzer == 'word'``. The default regexp select tokens of 2
        or more alphanumeric characters (punctuation is completely ignored
        and always treated as a token separator).

    ngram_range : tuple (min_n, max_n), default=(1, 1)
        The lower and upper boundary of the range of n-values for different
        word n-grams or char n-grams to be extracted. All values of n such
        such that min_n <= n <= max_n will be used. For example an
        ``ngram_range`` of ``(1, 1)`` means only unigrams, ``(1, 2)`` means
        unigrams and bigrams, and ``(2, 2)`` means only bigrams.
        Only applies if ``analyzer is not callable``.

    analyzer : string, {'word', 'char', 'char_wb'} or callable,
default='word'
        Whether the feature should be made of word n-gram or character
        n-grams.
        Option 'char_wb' creates character n-grams only from text inside
        word boundaries; n-grams at the edges of words are padded with space.
```

```
    If a callable is passed it is used to extract the sequence of features
    out of the raw, unprocessed input.

    .. versionchanged:: 0.21

    Since v0.21, if ``input`` is ``filename`` or ``file``, the data is
    first read from the file and then passed to the given callable
    analyzer.

max_df : float in range [0.0, 1.0] or int, default=1.0
    When building the vocabulary ignore terms that have a document
    frequency strictly higher than the given threshold (corpus-specific
    stop words).
    If float, the parameter represents a proportion of documents, integer
    absolute counts.
    This parameter is ignored if vocabulary is not None.

min_df : float in range [0.0, 1.0] or int, default=1
    When building the vocabulary ignore terms that have a document
    frequency strictly lower than the given threshold. This value is also
    called cut-off in the literature.
    If float, the parameter represents a proportion of documents, integer
    absolute counts.
    This parameter is ignored if vocabulary is not None.

max_features : int, default=None
    If not None, build a vocabulary that only consider the top
    max_features ordered by term frequency across the corpus.

    This parameter is ignored if vocabulary is not None.

vocabulary : Mapping or iterable, default=None
    Either a Mapping (e.g., a dict) where keys are terms and values are
    indices in the feature matrix, or an iterable over terms. If not
    given, a vocabulary is determined from the input documents. Indices
    in the mapping should not be repeated and should not have any gap
    between 0 and the largest index.

binary : bool, default=False
    If True, all non zero counts are set to 1. This is useful for discrete
    probabilistic models that model binary events rather than integer
    counts.

dtype : type, default=np.int64
    Type of the matrix returned by fit_transform() or transform().

Attributes
----------
```

```
vocabulary_ : dict
    A mapping of terms to feature indices.

fixed_vocabulary_: boolean
    True if a fixed vocabulary of term to indices mapping
    is provided by the user

stop_words_ : set
    Terms that were ignored because they either:

      - occurred in too many documents (`max_df`)
      - occurred in too few documents (`min_df`)
      - were cut off by feature selection (`max_features`).

    This is only available if no vocabulary was given.

Examples
--------
>>> from sklearn.feature_extraction.text import CountVectorizer
>>> corpus = [
…     'This is the first document.',
…     'This document is the second document.',
…     'And this is the third one.',
…     'Is this the first document?',
… ]
>>> vectorizer = CountVectorizer()
>>> X = vectorizer.fit_transform(corpus)
>>> print(vectorizer.get_feature_names())
['and', 'document', 'first', 'is', 'one', 'second', 'the', 'third', 'this']
>>> print(X.toarray())
[[0 1 1 1 0 0 1 0 1]
 [0 2 0 1 0 1 1 0 1]
 [1 0 0 1 1 0 1 1 1]
 [0 1 1 1 0 0 1 0 1]]
>>> vectorizer2 = CountVectorizer(analyzer='word', ngram_range=(2, 2))
>>> X2 = vectorizer2.fit_transform(corpus)
>>> print(vectorizer2.get_feature_names())
['and this', 'document is', 'first document', 'is the', 'is this',
'second document', 'the first', 'the second', 'the third', 'third one',
 'this document', 'this is', 'this the']
 >>> print(X2.toarray())
 [[0 0 1 1 0 0 1 0 0 0 0 1 0]
 [0 1 0 1 0 1 0 1 0 0 1 0 0]
 [1 0 0 1 0 0 0 0 1 1 0 1 0]
 [0 0 1 0 1 0 1 0 0 0 0 0 1]]

See Also
--------
```

```
HashingVectorizer, TfidfVectorizer

Notes
-----
The ``stop_words_`` attribute can get large and increase the model size
when pickling. This attribute is provided only for introspection and can
be safely removed using delattr or set to None before pickling.
```

1.4.2 Document Frequency Distribution

[13]:
```python
binary_vectorizer = CountVectorizer(max_df=1.0,
                                    min_df=1,
                                    binary=True)

binary_dtm = binary_vectorizer.fit_transform(docs.body)
```

[14]:
```python
binary_dtm
```

[14]:
```
<2225x29275 sparse matrix of type '<class 'numpy.int64'>'
        with 445870 stored elements in Compressed Sparse Row format>
```

[15]:
```python
n_docs, n_tokens = binary_dtm.shape
```

[16]:
```python
tokens_dtm = binary_vectorizer.get_feature_names()
```

CountVectorizer skips certain tokens by default

[17]:
```python
tokens.index.difference(pd.Index(tokens_dtm))
```

[17]:
```
Index(['!', '"', '""unconscionable,', '"'I', '"'Oh', '"'We', '"'You', '"(When',
       '"…it', '"100%',
       …
       'Â£900m', 'Â£910m).', 'Â£93.6bn)', 'Â£933m', 'Â£947m', 'Â£960m',
       'Â£98)', 'Â£99', 'Â£9m', 'Â£9m,'],
      dtype='object', length=47927)
```

Persist Result

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

[18]:
```python
dtm_path = results_path / 'binary_dtm.npz'
if not dtm_path.exists():
    sparse.save_npz(dtm_path, binary_dtm)
```

[19]:
```
token_path = results_path / 'tokens.csv'
if not token_path.exists():
    pd.Series(tokens_dtm).to_csv(token_path, index=False)
else:
    tokens = pd.read_csv(token_path, header=None, squeeze=True)
```

[20]:
```
doc_freq = pd.Series(np.array(binary_dtm.sum(axis=0)).squeeze()).div(n_docs)
max_unique_tokens = np.array(binary_dtm.sum(axis=1)).squeeze().max()
```

1.4.3 min_df vs max_df: Interactive Visualization

The notebook contains an interactive visualization that explores the impact of the min_df and max_df settings on the size of the vocabulary. We read the articles into a DataFrame, set the CountVectorizer to produce binary flags and use all tokens, and call its .fit_transform() method to produce a document-term matrix:

The visualization shows that requiring tokens to appear in at least 1% and less than 50% of documents restricts the vocabulary to around 10% of the almost 30K tokens. This leaves a mode of slightly over 100 unique tokens per document (left panel), and the right panel shows the document frequency histogram for the remaining tokens.

[21]:
```
df_range = FloatRangeSlider(value=[0.0, 1.0],
                            min=0,
                            max=1,
                            step=0.0001,
                            description='Doc. Freq.',
                            disabled=False,
                            continuous_update=True,
                            orientation='horizontal',
                            readout=True,
                            readout_format='.1%',
                            layout={'width': '800px'})

@interact(df_range=df_range)
def document_frequency_simulator(df_range):
    min_df, max_df = df_range
    keep = doc_freq.between(left=min_df, right=max_df)
    left = keep.sum()

    fig, axes = plt.subplots(ncols=2, figsize=(14, 6))

    updated_dtm = binary_dtm.tocsc()[:, np.flatnonzero(keep)]
    unique_tokens_per_doc = np.array(updated_dtm.sum(axis=1)).squeeze()
    sns.distplot(unique_tokens_per_doc, ax=axes[0], kde=False, norm_hist=False)
    axes[0].set_title('Unique Tokens per Doc')
    axes[0].set_yscale('log')
    axes[0].set_xlabel('# Unique Tokens')
    axes[0].set_ylabel('# Documents (log scale)')
```

```
    axes[0].set_xlim(0, max_unique_tokens)
    axes[0].yaxis.set_major_formatter(ScalarFormatter())

    term_freq = pd.Series(np.array(updated_dtm.sum(axis=0)).squeeze())
    sns.distplot(term_freq, ax=axes[1], kde=False, norm_hist=False)
    axes[1].set_title('Document Frequency')
    axes[1].set_ylabel('# Tokens')
    axes[1].set_xlabel('# Documents')
    axes[1].set_yscale('log')
    axes[1].set_xlim(0, n_docs)
    axes[1].yaxis.set_major_formatter(ScalarFormatter())

    title = f'Document/Term Frequency Distribution | # Tokens: {left:,d} ({left/
↪n_tokens:.2%})'
    fig.suptitle(title, fontsize=14)
    sns.despine()
    fig.tight_layout()
    fig.subplots_adjust(top=.9)
```

```
interactive(children=(FloatRangeSlider(value=(0.0, 1.0), description='Doc. Freq.
↪', layout=Layout(width='800px'…
```

1.4.4 Most similar documents

The CountVectorizer result lets us find the most similar documents using the `pdist()` function for pairwise distances provided by the `scipy.spatial.distance` module.

It returns a condensed distance matrix with entries corresponding to the upper triangle of a square matrix.

We use `np.triu_indices()` to translate the index that minimizes the distance to the row and column indices that in turn correspond to the closest token vectors.

[22]:
```
m = binary_dtm.todense()
pairwise_distances = pdist(m, metric='cosine')
```

[23]:
```
closest = np.argmin(pairwise_distances)
```

[24]:
```
rows, cols = np.triu_indices(n_docs)
rows[closest], cols[closest]
```

[24]:
```
(6, 245)
```

[25]:
```
docs.iloc[6].to_frame(6).join(docs.iloc[245].to_frame(245)).to_csv(results_path␣
↪/ 'most_similar.csv')
```

[26]:
```
docs.iloc[6]
```

```
[26]: topic                                              business
      heading                          Jobs growth still slow in the US
      body       The US created fewer jobs than expected in Jan…
      Name: 6, dtype: object
```

```
[27]: pd.DataFrame(binary_dtm[[6, 245], :].todense()).sum(0).value_counts()
```

```
[27]: 0    28972
      1      265
      2       38
      dtype: int64
```

1.4.5 Baseline document-term matrix

```
[28]: # Baseline: number of unique tokens
      vectorizer = CountVectorizer() # default: binary=False
      doc_term_matrix = vectorizer.fit_transform(docs.body)
      doc_term_matrix
```

```
[28]: <2225x29275 sparse matrix of type '<class 'numpy.int64'>'
              with 445870 stored elements in Compressed Sparse Row format>
```

```
[29]: doc_term_matrix.shape
```

```
[29]: (2225, 29275)
```

1.4.6 Inspect tokens

```
[30]: # vectorizer keeps words
      words = vectorizer.get_feature_names()
      words[:10]
```

```
[30]: ['00',
       '000',
       '0001',
       '000bn',
       '000m',
       '000s',
       '000th',
       '001',
       '001and',
       '001st']
```

1.4.7 Inspect doc-term matrix

[31]:
```
# from scipy compressed sparse row matrix to sparse DataFrame
doc_term_matrix_df = pd.DataFrame.sparse.from_spmatrix(doc_term_matrix,␣
↪columns=words)
doc_term_matrix_df.head()
```

[31]:
```
   00  000  0001  000bn  000m  000s  000th  001  001and  001st  …  zooms  \
0   0    1     0      0     0     0      0    0       0      0  …      0
1   0    0     0      0     0     0      0    0       0      0  …      0
2   0    0     0      0     0     0      0    0       0      0  …      0
3   0    1     0      0     0     0      0    0       0      0  …      0
4   0    0     0      0     0     0      0    0       0      0  …      0

   zooropa  zornotza  zorro  zubair  zuluaga  zurich  zutons  zvonareva  \
0        0         0      0       0        0       0       0          0
1        0         0      0       0        0       0       0          0
2        0         0      0       0        0       0       0          0
3        0         0      0       0        0       0       0          0
4        0         0      0       0        0       0       0          0

   zvyagintsev
0            0
1            0
2            0
3            0
4            0

[5 rows x 29275 columns]
```

1.4.8 Most frequent terms

[32]:
```
word_freq = doc_term_matrix_df.sum(axis=0).astype(int)
word_freq.sort_values(ascending=False).head()
```

[32]:
```
the      52574
to       24767
of       19930
and      18574
in       17553
dtype: int64
```

1.4.9 Compute relative term frequency

[33]:
```
vectorizer = CountVectorizer(binary=True)
doc_term_matrix = vectorizer.fit_transform(docs.body)
doc_term_matrix.shape
```

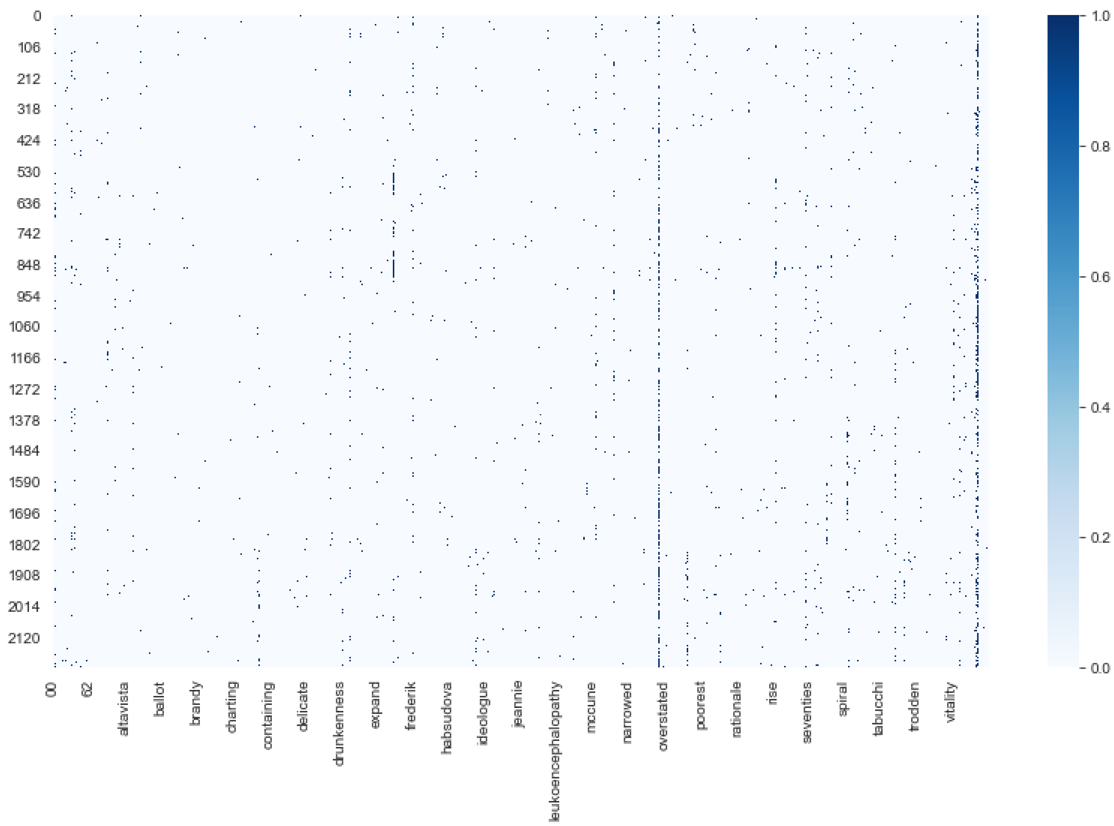
[33]:
```
(2225, 29275)
```

[34]:
```
words = vectorizer.get_feature_names()
word_freq = doc_term_matrix.sum(axis=0)

# reduce to 1D array
word_freq_1d = np.squeeze(np.asarray(word_freq))

pd.Series(word_freq_1d, index=words).div(
    docs.shape[0]).sort_values(ascending=False).head(10)
```

[34]:
```
the     1.000000
to      0.995056
of      0.991461
and     0.991011
in      0.990562
for     0.930337
on      0.906517
is      0.862472
it      0.858427
said    0.848539
dtype: float64
```

1.4.10 Visualize Doc-Term Matrix

[35]:
```
sns.heatmap(pd.DataFrame(doc_term_matrix.todense(), columns=words),␣
 ↪cmap='Blues')
plt.gcf().set_size_inches(14, 8);
```



1.4.11 Using thresholds to reduce the number of tokens

[36]:
```
vectorizer = CountVectorizer(max_df=.2, min_df=3, stop_words='english')
doc_term_matrix = vectorizer.fit_transform(docs.body)
doc_term_matrix.shape
```

[36]: (2225, 12789)

1.4.12 Use CountVectorizer with Lemmatization

Building a custom tokenizer for Lemmatization with spacy

[37]:
```
nlp = spacy.load('en')
def tokenizer(doc):
    return [w.lemma_ for w in nlp(doc)
                if not w.is_punct | w.is_space]
```

[38]:
```
vectorizer = CountVectorizer(tokenizer=tokenizer, binary=True)
doc_term_matrix = vectorizer.fit_transform(docs.body)
doc_term_matrix.shape
```

[38]: (2225, 25665)

[39]:
```
lemmatized_words = vectorizer.get_feature_names()
word_freq = doc_term_matrix.sum(axis=0)
word_freq_1d = np.squeeze(np.asarray(word_freq))
word_freq_1d = pd.Series(word_freq_1d, index=lemmatized_words).div(docs.
 ↪shape[0])
word_freq_1d.sort_values().tail(20)
```

[39]:
```
from      0.702022
but       0.732135
as        0.742022
by        0.765843
at        0.792809
with      0.824719
that      0.830562
say       0.881798
's        0.896629
on        0.906517
for       0.930337
have      0.972584
in        0.990562
and       0.991011
of        0.991461
a         0.992809
-PRON-    0.993708
to        0.995056
be        0.998202
the       1.000000
dtype: float64
```

Unlike verbs and common nouns, there's no clear base form of a personal pronoun. Should the lemma of "me" be "I", or should we normalize person as well, giving "it" — or maybe "he"? spaCy's solution is to introduce a novel symbol, -PRON-, which is used as the lemma for all personal pronouns.

1.5 Document-Term Matrix with `TfIDFVectorizer`

The TfIDFTransfomer computes the tf-idf weights from a document-term matrix of token counts like the one produced by the CountVectorizer.

The TfIDFVectorizer performs both computations in a single step. It adds a few parameters to the CountVectorizer API that controls the smoothing behavior.

1.5.1 Key Parameters

The `TfIDFTransformer` builds on the `CountVectorizer` output; the `TfIDFVectorizer` integrates both

[40]:
```python
print(TfidfTransformer().__doc__)
```

```
Transform a count matrix to a normalized tf or tf-idf representation

    Tf means term-frequency while tf-idf means term-frequency times inverse
    document-frequency. This is a common term weighting scheme in information
    retrieval, that has also found good use in document classification.

    The goal of using tf-idf instead of the raw frequencies of occurrence of a
    token in a given document is to scale down the impact of tokens that occur
    very frequently in a given corpus and that are hence empirically less
    informative than features that occur in a small fraction of the training
    corpus.

    The formula that is used to compute the tf-idf for a term t of a document d
    in a document set is tf-idf(t, d) = tf(t, d) * idf(t), and the idf is
    computed as idf(t) = log [ n / df(t) ] + 1 (if ``smooth_idf=False``), where
    n is the total number of documents in the document set and df(t) is the
    document frequency of t; the document frequency is the number of documents
    in the document set that contain the term t. The effect of adding "1" to
    the idf in the equation above is that terms with zero idf, i.e., terms
    that occur in all documents in a training set, will not be entirely
    ignored.
    (Note that the idf formula above differs from the standard textbook
    notation that defines the idf as
    idf(t) = log [ n / (df(t) + 1) ]).

    If ``smooth_idf=True`` (the default), the constant "1" is added to the
    numerator and denominator of the idf as if an extra document was seen
    containing every term in the collection exactly once, which prevents
    zero divisions: idf(t) = log [ (1 + n) / (1 + df(t)) ] + 1.

    Furthermore, the formulas used to compute tf and idf depend
    on parameter settings that correspond to the SMART notation used in IR
    as follows:

    Tf is "n" (natural) by default, "l" (logarithmic) when
    ``sublinear_tf=True``.
    Idf is "t" when use_idf is given, "n" (none) otherwise.
    Normalization is "c" (cosine) when ``norm='l2'``, "n" (none)
    when ``norm=None``.

    Read more in the :ref:`User Guide <text_feature_extraction>`.

    Parameters
    ----------
    norm : {'l1', 'l2'}, default='l2'
```

```
    Each output row will have unit norm, either:
    * 'l2': Sum of squares of vector elements is 1. The cosine
    similarity between two vectors is their dot product when l2 norm has
    been applied.
    * 'l1': Sum of absolute values of vector elements is 1.
    See :func:`preprocessing.normalize`

use_idf : bool, default=True
    Enable inverse-document-frequency reweighting.

smooth_idf : bool, default=True
    Smooth idf weights by adding one to document frequencies, as if an
    extra document was seen containing every term in the collection
    exactly once. Prevents zero divisions.

sublinear_tf : bool, default=False
    Apply sublinear tf scaling, i.e. replace tf with 1 + log(tf).

Attributes
----------
idf_ : array of shape (n_features)
    The inverse document frequency (IDF) vector; only defined
    if  ``use_idf`` is True.

    .. versionadded:: 0.20

Examples
--------
>>> from sklearn.feature_extraction.text import TfidfTransformer
>>> from sklearn.feature_extraction.text import CountVectorizer
>>> from sklearn.pipeline import Pipeline
>>> import numpy as np
>>> corpus = ['this is the first document',
…           'this document is the second document',
…           'and this is the third one',
…           'is this the first document']
>>> vocabulary = ['this', 'document', 'first', 'is', 'second', 'the',
…               'and', 'one']
>>> pipe = Pipeline([('count', CountVectorizer(vocabulary=vocabulary)),
…                  ('tfid', TfidfTransformer())]).fit(corpus)
>>> pipe['count'].transform(corpus).toarray()
array([[1, 1, 1, 1, 0, 1, 0, 0],
       [1, 2, 0, 1, 1, 1, 0, 0],
       [1, 0, 0, 1, 0, 1, 1, 1],
       [1, 1, 1, 1, 0, 1, 0, 0]])
>>> pipe['tfid'].idf_
array([1.        , 1.22314355, 1.51082562, 1.        , 1.91629073,
       1.        , 1.91629073, 1.91629073])
```

```
>>> pipe.transform(corpus).shape
(4, 8)

References
----------

.. [Yates2011] R. Baeza-Yates and B. Ribeiro-Neto (2011). Modern
               Information Retrieval. Addison Wesley, pp. 68-74.

.. [MRS2008] C.D. Manning, P. Raghavan and H. Schütze  (2008).
               Introduction to Information Retrieval. Cambridge University
               Press, pp. 118-120.
```

1.5.2 How Term Frequency - Inverse Document Frequency works

The TFIDF computation works as follows for a small text sample

[41]:
```python
sample_docs = ['call you tomorrow',
                'Call me a taxi',
                'please call me... PLEASE!']
```

Compute term frequency

[42]:
```python
vectorizer = CountVectorizer()
tf_dtm = vectorizer.fit_transform(sample_docs).todense()
tokens = vectorizer.get_feature_names()
```

[43]:
```python
term_frequency = pd.DataFrame(data=tf_dtm,
                              columns=tokens)
print(term_frequency)
```

```
   call  me  please  taxi  tomorrow  you
0     1   0       0     0         1    1
1     1   1       0     1         0    0
2     1   1       2     0         0    0
```

Compute document frequency

[44]:
```python
vectorizer = CountVectorizer(binary=True)
df_dtm = vectorizer.fit_transform(sample_docs).todense().sum(axis=0)
```

[45]:
```python
document_frequency = pd.DataFrame(data=df_dtm,
                                  columns=tokens)
print(document_frequency)
```

```
   call  me  please  taxi  tomorrow  you
0     3   2       1     1         1    1
```

Compute TfIDF

[46]:
```
tfidf = pd.DataFrame(data=tf_dtm/df_dtm, columns=tokens)
print(tfidf)
```

```
       call   me  please  taxi  tomorrow  you
0  0.333333  0.0     0.0   0.0       1.0  1.0
1  0.333333  0.5     0.0   1.0       0.0  0.0
2  0.333333  0.5     2.0   0.0       0.0  0.0
```

The effect of smoothing The TfidfVectorizer uses smoothing for document and term frequencies: - `smooth_idf`: add one to document frequency, as if an extra document contained every token in the vocabulary once to prevents zero divisions - `sublinear_tf`: scale term Apply sublinear tf scaling, i.e. replace tf with 1 + log(tf)

[47]:
```
vect = TfidfVectorizer(smooth_idf=True,
                       norm='l2',            # squared weights sum to 1 by␣
 ↪document
                       sublinear_tf=False,   # if True, use 1+log(tf)
                       binary=False)
print(pd.DataFrame(vect.fit_transform(sample_docs).todense(),
             columns=vect.get_feature_names()))
```

```
       call        me    please      taxi  tomorrow       you
0  0.385372  0.000000  0.000000  0.000000  0.652491  0.652491
1  0.425441  0.547832  0.000000  0.720333  0.000000  0.000000
2  0.266075  0.342620  0.901008  0.000000  0.000000  0.000000
```

1.5.3 TfIDF with new articles

Due to their ability to assign meaningful token weights, TFIDF vectors are also used to summarize text data. E.g., reddit's autotldr function is based on a similar algorithm.

[48]:
```
tfidf = TfidfVectorizer(stop_words='english')
dtm_tfidf = tfidf.fit_transform(docs.body)
tokens = tfidf.get_feature_names()
dtm_tfidf.shape
```

[48]:
```
(2225, 28980)
```

[49]:
```
token_freq = (pd.DataFrame({'tfidf': dtm_tfidf.sum(axis=0).A1,
                            'token': tokens})
              .sort_values('tfidf', ascending=False))
```

[50]:
```
token_freq.head(10).append(token_freq.tail(10)).set_index('token')
```

[50]:
```
                tfidf
token
said        87.251494
```

```
mr            58.220783
year          41.982178
people        37.303707
new           34.197388
film          29.728250
government    28.792651
world         27.031199
time          26.358319
best          26.304266
baked          0.014186
pavlovian      0.014186
buzzcocks      0.014186
sisterhood     0.014186
siouxsie       0.014186
sioux          0.014186
bane           0.014186
biassed        0.014186
duetted        0.014186
speechless     0.014186
```

1.5.4 Summarizing news articles using TfIDF weights

Select random article

[51]:
```python
article = docs.sample(1).squeeze()
article_id = article.name
```

[52]:
```python
print(f'Topic:\t{article.topic.capitalize()}\n\n{article.heading}\n')
print(article.body.strip())
```

```
Topic:  Business

France Telecom gets Orange boost

Strong growth in subscriptions to mobile phone network Orange has helped boost
profits at owner France Telecom.  Orange added more than five million new
customers in 2004, leading to a 10% increase in its revenues. Increased take-up
of broadband telecoms services also boosted France Telecom's profits, which
showed a 5.5% rise to 18.3bn euros ($23.4bn; Â£12.5bn). France Telecom is to
spend 578m euros on buying out minority shareholders in data services provider
Equant.  France Telecom, one of the world's largest telecoms and internet
service providers, saw its full-year sales rise 2.2% to 47.2bn euros in 2004.
Orange enjoyed strong growth outside France and the United Kingdom - its core
markets - swelling its subscriber base to 5.4 million. France Telecom's
broadband customers also increased, rising to 5.1 million across Europe by the
end of the year. The firm said it had met its main strategic objectives of
growing its individual businesses and further reducing its large debt. An ill-
fated expansion drive in the late 1990s saw France Telecom's debt soar to 72bn
```

```
euros by 2002. However, this has now been reduced to 43.9bn euros. "Our results
for 2004 allow us to improve our financial structure while focusing on the
innovation that drives our strategy," said chief executive Thierry Breton.
Looking ahead, the company forecast like-for-like sales growth of between 3% and
5% over the next three years. France Telecom is consolidating its interest in
Equant, which provides telecoms and data services to businesses. Subject to
approval by shareholders of the two firms, it will buy the shares in Equant it
does not already own. France Telecom said it would fund the deal by selling an
8% stake in telephone directory company PagesJaunes.
```

Select most relevant tokens by tfidf value

[53]:
```python
article_tfidf = dtm_tfidf[article_id].todense().A1
article_tokens = pd.Series(article_tfidf, index=tokens)
article_tokens.sort_values(ascending=False).head(10)
```

[53]:
```
telecom         0.540529
france          0.341326
equant          0.261060
euros           0.244469
orange          0.186060
telecoms        0.160378
services        0.108252
growth          0.106366
shareholders    0.102073
businesses      0.097149
dtype: float64
```

Compare to random selection

[54]:
```python
pd.Series(article.body.split()).sample(10).tolist()
```

[54]:
```
['our',
 'in',
 'at',
 'Breton.',
 'and',
 'the',
 'improve',
 'to',
 'subscriber',
 'in']
```

1.6 Create Train & Test Sets

1.6.1 Stratified train_test_split

[55]:
```
train_docs, test_docs = train_test_split(docs,
                                         stratify=docs.topic,
                                         test_size=50,
                                         random_state=42)
```

[56]:
```
train_docs.shape, test_docs.shape
```

[56]:
```
((2175, 3), (50, 3))
```

[57]:
```
pd.Series(test_docs.topic).value_counts()
```

[57]:
```
sport            12
business         11
entertainment     9
politics          9
tech              9
Name: topic, dtype: int64
```

1.6.2 Vectorize train & test sets

[58]:
```
vectorizer = CountVectorizer(max_df=.2,
                             min_df=3,
                             stop_words='english',
                             max_features=2000)

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

[58]:
```
<2175x2000 sparse matrix of type '<class 'numpy.int64'>'
        with 178765 stored elements in Compressed Sparse Row format>
```

[59]:
```
test_dtm = vectorizer.transform(test_docs.body)
test_dtm
```

[59]:
```
<50x2000 sparse matrix of type '<class 'numpy.int64'>'
        with 4043 stored elements in Compressed Sparse Row format>
```