Big Data & Automated Content Analysis
Week 6 – Wednesday: »Text as data«

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Today

How did it go? And some first feedback on the exam.

Everything clear from last week?

The bag-of-words (BOW) model

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General idea

A text as a collections of word

Let us represent a string

```
t = "This this is is is a test test test"
```

like this:

```
from collections import Counter
print(Counter(t.split()))
```

```
Counter({'is': 3, 'test': 3, 'This': 1, 'this': 1, 'a': 1})
```

Compared to the original string, this representation

- is less repetitive
- preserves word frequencies
- but does *not* preserve word order
- can be interpreted as a vector to calculate with (!!!)

Of course, still a lot of stuff to fine-tune. . . (for example, This/this)

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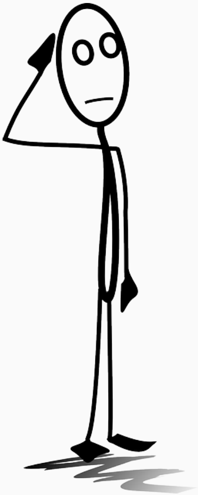
From vector to matrix

If we do this for multiple texts, we can arrange the vectors in a table.

t1 = "This this is is is a test test test"
t2 = "This is an example"

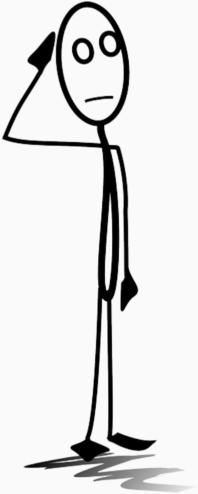
	a	an	example	is	this	This	test
t1	1	0	0	3	1	1	3
t2	0	1	1	1	0	1	0



What can you do with such a matrix?
Why would you want to represent a collection of texts in such a way?

The cell entries: raw counts versus tf·idf scores

- In the example, we entered simple counts (the “term frequency”)



But are all terms equally important?

The cell entries: raw counts versus tf·idf scores

- In the example, we entered simple counts (the "term frequency")
- But does a word that occurs in almost all documents contain much information?
- And isn't the presence of a word that occurs in very few documents a pretty strong hint?
- Solution: Weigh by *the number of documents in which the term occurs at least once) (the "document frequency")*

⇒ we multiply the "term frequency" (tf) by the inverse document frequency (idf)

(usually with some additional logarithmic transformation and normalization applied, see https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfTransformer.html)

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Is tf·idf always better?

It depends.

- Ultimately, it's an empirical question which works better ($\rightarrow$ weeks on machine learning)
- In many scenarios, "discounting" too frequent words and "boosting" rare words makes a lot of sense (most frequent words in a text can be highly un-informative)
- Beauty of raw tf counts, though: interpretability + describes document in itself, not in relation to other documents

Internal representations

Sparse vs dense matrices

- Most are not *not* contained in a given document
- $\rightarrow$ tens of thousands of columns (terms), and one row per document
- Filling all cells is inefficient *and* can make the matrix too large to fit in memory (!!!)
- Solution: store only non-zero values with their coordinates! (sparse matrix)
- dense matrix (or dataframes) not advisable, only for toy examples

Internal representations

Little over-generalizing R vs Python remark

Among R users, it is very common to manually inspect document-term matrices, and many operations are done directly on them. In Python, they are more commonly seen as a means to an end (mostly, as input for machine learning).

Many R modules convert to dense matrices: really problematic for larger datasets!

Getting a clean BOW representation

Room for improvement

tokenization How do we (best) split a sentence into tokens (terms, words)?

pruning How can we remove unneccessary words?

lemmatization How can we make sure that slight variations of the same word are not counted differently?

Getting a clean BOW representation

Better tokenization

OK, good enough, perfect?

.split()

- space → new word
- no further processing whatsoever
- thus, only works well if we do a preprocessing outselves (e.g., remove punctuation)

```
docs = ["This is a text", "I haven’t seen John’s derring-do. Second sentence!"]
tokens = [d.split() for d in docs]
```

```
[['This', 'is', 'a', 'text'], ['I', "haven't", 'seen', "John's", 'derring-do.', 'Second', 'sentence!']]
```

OK, good enough, perfect?

Tokenizers from the NLTK pacakge

- multiple improved tokenizers that can be used instead of .split()
- e.g., Treebank tokenizer:
    - split standard contractions ("don't")
    - deals with punctuation

```
from nltk.tokenize import TreebankWordTokenizer
tokens = [TreebankWordTokenizer().tokenize(d) for d in docs]
```

```
[['This', 'is', 'a', 'text'], ['I', 'have', "n't", 'seen', 'John', "'s", 'derring-do.', 'Second
    ', 'sentence', '!']]
```

Notice the failure to split the . at the end of the first sentence in the second doc. That's because TreebankWordTokenizer expects *sentences* as input. See book for a solution.

OK, so we can tokenize with a list comprehension (and that's often a good idea!). But what if we want to *directly* get a DTM instead of lists of tokens?

OK, good enough, perfect?

scikit-learn's CountVectorizer (default settings)

- applies lowercasing
- deals with punctuation etc. itself
- minimum word length > 1
- more technically, tokenizes using this regular expression: `r"(?u)\b\w\w+\b"` [1]

```
from sklearn.feature_extraction.text import CountVectorizer
cv = CountVectorizer()
dtm_sparse = cv.fit_transform(docs)
```

[1] ?u = support unicode, \b = word boundary

OK, good enough, perfect?

CountVectorizer supports more

- stopword removal
- custom regular expression
- or even using an external tokenizer
- ngrams instead of unigrams

see https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html

Best of both worlds

Use the Count vectorizer with a NLTK-based external tokenizer! (see book)

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Getting a clean BOW representation

Stopword removal

Stopword removal

What are stopwords?

- Very frequent words with little inherent meaning
- `the, a, he, she, ...`
- context-dependent: if you are interested in gender, `he` and `she` are no stopwords.
- Many existing lists as basis

When using the CountVectorizer, we can simply provide a stopword list.

But we can also remove stopwords "by hand" (next slide):

Stopword removal

```
1  from nltk.corpus import stopwords
2  mystopwords = stopwords.words("english")
3  mystopwords.extend(["test", "this"])
4
5  def tokenize_clean(s, stoplist):
6      cleantokens = []
7      for w in TreebankWordTokenizer().tokenize(s):
8          if w.lower() not in stoplist:
9              cleantokens.append(w)
10     return cleantokens
11
12 tokens = [tokenize_clean(d, mystopwords) for d in docs]
```

```
[['text'], ["n't", 'seen', 'John', 'derring-do.', 'Second', 'sentence', '!']]
```

You can do more!

For instance, in line 8, you could add an or statement to also exclude punctuation.

Getting a clean BOW representation

Pruning

General idea

- Idea behind both stopword removal and tf·idf: too frequent words are uninformative
- (possible) downside stopword removal: a priori list, does not take empirical frequencies in dataset into account
- (possible) downside tf·idf: does not reduce number of features

Pruning: remove all features (tokens) that occur in less than X or more than X of the documents

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Pruning: remove all features (tokens) that occur in less than X or more than X of the documents

CountVectorizer, only stopword removal

```
from sklearn.feature_extraction.text import CountVectorizer,
    TfidfVectorizer
myvectorizer = CountVectorizer(stop_words=mystopwords)
```

CountVectorizer, better tokenization, stopword removal (pay attention that stopword list uses same tokenization!):

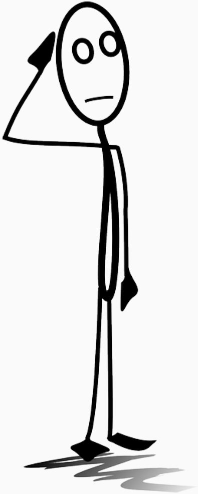
```
myvectorizer = CountVectorizer(tokenizer = TreebankWordTokenizer().
    tokenize, stop_words=mystopwords)
```

Additionally remove words that occur in more than 75% or less than $n = 2$ documents:

```
myvectorizer = CountVectorizer(tokenizer = TreebankWordTokenizer().
    tokenize, stop_words=mystopwords, max_df=.75, min_df=2)
```

All togehter: tf·idf, explicit stopword removal, pruning

```
myvectorizer = TfidfVectorizer(tokenizer = TreebankWordTokenizer().
    tokenize, stop_words=mystopwords, max_df=.75, min_df=2)
```



What is "best"? Which (combination of) techniques to use, and how to decide?

Getting a clean BOW representation

Stemming and lemmatization

Stemming and lemmatization

- Stemming: reduce words to its stem by removing last part (drinking $\rightarrow$ drink)
- Lemmatization: find word that you would need to look up in a dictionary (drinking $\rightarrow$ drink, but also went $\rightarrow$ go)
- stemming is simpler than lemmatization
- lemmatization often better

Example below: tokenization and lemmatization with spacy in one go:

```
import spacy
nlp = spacy.load('en') # potentially you need to install the language
    model first
lemmatized_tokens = [[token.lemma_ for token in nlp(doc)] for doc in
    docs]
```

```
[['this', 'be', 'a', 'text'], ['-PRON-', 'have', 'not', 'see', 'John', "'s", 'derring', '-', 'do
    ', '.', 'second', 'sentence', '!']]
```

Stemming and lemmatization

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```

The order of preprocessing steps

Option 1

Preprocessing only through Vectorizer

"Just use CountVectorizer or Tfidfvectorizer with the appropriate options."

- pro: No double work, efficient if your main goal is a sparse matrix (for ML?) anyway
- con: you cannot "see" the preprocessed texts

Option 2

Extensive preprocessing without Vectorizer

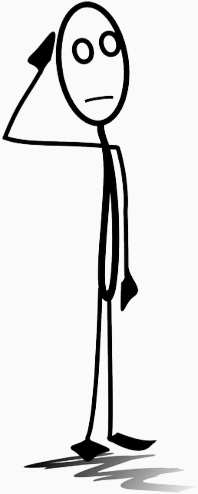
"Remove stopwords, punctuation etc. and store in a string with spaces"

```
cleaneddocs = [" ".join(re.findall(r"\w\w+", d)).lower() for d in docs]
cleaneddocswithoutstopwords = [" ".join([w for w in d.split() if w not
    in mystopwords]) for d in cleaneddocs]
```

```
['this is text', 'haven seen john derring do second sentence']
['text', 'seen john derring second sentence']
```

Yes, this list comprehension looks scary – you can make a more elaborate for loop instead

- pro: you can read (and store!) the preprocessed docs
- pro: even the most stupid vectorizer (or wordcloud tool) can split the resulting string later on
- con: potentially double work (for you *and* the computer)



How would you do it?

I tend to go for Option 2 because

- I like to inspect a sample of the documents
- I can re-use the cleaned docs irrespective of the Vectorizer

But sometimes, I opt of Option 1 instead because

- I want to systematically compare the effect of different choices in a machine learning pipeline (then I can simply vary the vectorizer instead of the data)
- I want to use techniques that are geared towards little or no preprocessing (deep learning)

How further?

Main takeaway

- It matters how you transform your text into numbers ("vectorization").
- Preprocessing matters, be able to make informed choices.
- Keep this in mind when we will discuss Machine Learning! It will come back throughout Part II!

- Once you vectorized your texts, you can do all kinds of calculations (random example: get the cosine similarity between two texts)

More NLP

***n*-grams** Consider using *n*-grams instead of unigrams

collocations *n*grams that appear more frequently than expected

POS-tagging grammatical function (“part-of-speach”) of tokens

NER named entity recognition (persons, organizations, locations)

More NLP

I **really** recommend looking into spacy (https://spacy.io) for advanced natural language processing, such as part-of-speech-tagging and named entity recogntion.

Friday

Based on today's lecture and Chapter 10...

Try to take some of the data from last week and

- preprocess them (in different ways)
- vectorize them
- give a (tabular and/or graphical) overview of tokens (unigrams, bigrams, collocations).

Then,

- compare that bottom-up approach with a top-down (keyword or regular-expression based) approach