Teach-the-teacher: Python
Day 4: »Processing textual data // NLP«

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Today

Bottom-up vs. top-down

Automated content analysis can be either **bottom-up** (inductive, explorative, pattern recognition, . . .) or **top-down** (deductive, based on a-priori developed rules, . . .). Or in between.

The ACA toolbox

	Methodological approach		
	Counting and Dictionary	*Supervised Machine Learning*	*Unsupervised Machine Learning*
Typical research interests and content features	visibility analysis sentiment analysis subjectivity analysis	frames topics gender bias	frames topics
Common statistical procedures	string comparisons counting	support vector machines naive Bayes	principal component analysis cluster analysis latent dirichlet allocation semantic network analysis

Boumans2016

Bottom-up vs. top-down

Bottom-up

- Count most frequently occurring words
- Maybe better: Count combinations of words $\Rightarrow$ Which words co-occur together?

We *don't* specify what to look for in advance

Top-down

- Count frequencies of pre-defined words
- Maybe better: patterns instead of words

We *do* specify what to look for in advance

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Top-down

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We *do* specify what to look for in advance

A simple bottom-up approach

```
from collections import Counter

texts = ["I really really really love him, I do", "I hate him"]

for t in texts:
    print(Counter(t.split()).most_common(3))
```

```
[('really', 3), ('I', 2), ('love', 1)]
[('I', 1), ('hate', 1), ('him', 1)]
```

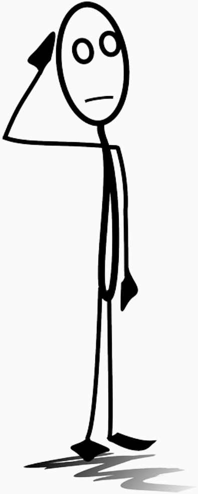
A simple top-down approach

```python
texts = ["I really really really love him, I do", "I hate him"]
features = ['really', 'love', 'hate']

for t in texts:
    print(f"\nAnalyzing '{t}':")
    for f in features:
        print(f"{f} occurs {t.count(f)} times")
```

```
Analyzing 'I really really really love him, I do':
really occurs 3 times
love occurs 1 times
hate occurs 0 times

Analyzing 'I hate him':
really occurs 0 times
love occurs 0 times
hate occurs 1 times
```



When would you use which approach?

Some considerations

- Both can have a place in your workflow (e.g., bottom-up as first exploratory step)
- You have a clear theoretical expectation? Bottom-up makes little sense.
- But in any case: you need to transform your text into something "countable".

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- But in any case: you need to transform your text into something "countable".

Basic string operations

Working with strings

1. string methods that every string has (`"hello".upper()`)
2. functions that take a string as input (`len("hello")`)
3. pandas column string methods (`df["somecolumn"].str.upper()`)
4. applying string methods or functions to a pandas column (`df["somecolumn"].apply(len)` or `df["somecolumn"].apply(lambda x: x.upper())`)

For today, we assume that our data are a list of strings – adapt accordingly for pandas.

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An example says more than 1000 words. . .

```python
# probably read from text file(s) instead, you learned that already...
data = [ "I <b>really</b> liked this movie! It was great.  ", "  What an awful movie", "Awesome!!!"]

data_stripped = [e.strip() for e in data]
data_lower = [e.lower() for e in data_stripped]
data_clean = [e.replace("<b>","").replace("</b>","") for e in data_lower]

# or, more efficient, in one single step:
data_clean2 = [e.strip().lower().replace("<b>","").replace("</b>","") for e in data]
```

Two examples says even more:

```python
from string import punctuation

# punctuation is just the string '!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'

text = "This is a test! Let's get rid (of) punct&"

# we make a list of each character in the text but only if it is not
# a punctuation sign. The, we join the elements of the list directly
# to each other without anything between it ("")
cleantext = "".join([c for c in text if c not in punctuation])
```

Combine both

```
from string import punctuation

def strip_punctuation(text):
    return "".join([c for c in text if c not in punctuation])

data_clean3 = [strip_punctuation(e).strip().lower()\
   .replace("<b>","").replace("</b>","") for e in data]
```

The toolbox at a glance

Slicing

`mystring[2:5]` to get the characters with indices 2,3,4

String methods

- `.lower()` returns lowercased string
- `.strip()` returns string without whitespace at beginning and end
- `.find("bla")` returns index of position of substring “bla” or -1 if not found
- `.replace("a","b")` returns string with `"a"` replaced by `"b"`
- `.count("bla")` counts how often substring “bla” occurs
- `.isdigit()` true if only numbers

Use tab completion for more!

From test to large-scale analysis: General approach

1. Take a single string and test your idea

```
t = "This is a test test test."
print(t.count("test"))
```

2a. You'd assume it to return 3. If so, scale it up:

```
results = []
for t in listwithallmytexts:
    r = t.count("test")
    print(f"{t} contains the substring {r} times")
    results.append(r)
```

2b. If you *only* need to get the list of results, a list comprehension is more elegant:

```
results = [t.count("test") for t in listwithallmytexts]
```

General approach

Test on a single string, then make a for loop or list comprehension!

Own functions

If it gets more complex, you can write your own function and then use it in the list comprehension:

```
def mycleanup(t):
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Pandas string methods as alternative

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```
df['newcoloumnwithresults'] = df['columnwithtext'].str.count("bla")
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To pandas or not to pandas for text?

Partly a matter of taste.

Not-too-large dataset with a lot of extra columns? Advanced statistical analysis planned? Sounds like pandas.

It's mainly a lot of text? Wanna do some machine learning later on anyway? It's large and (potentially) messy? Doesn't sound like pandas is a good idea.

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The BOW

The BOW

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 (!!!)

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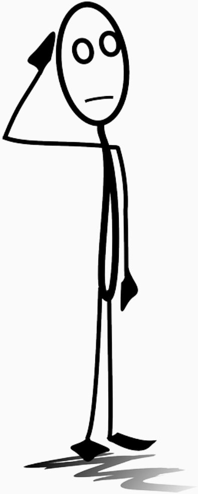
From vector to matrix

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"

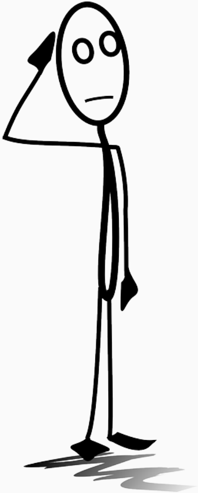
	a	an	example	is	this	This	test
t1	1	0	0	3	1	1	3
t2	0	1	1	1	0	1	0



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 terms 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 many R users, it is 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[1] convert to dense matrices: really problematic for larger datasets!

[1] Things have become a bit better recently

The BOW

A cleaner 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?

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
  - BUT: Assumes lists of *sentences*.
- Solution: Build an own (combined) tokenizer (next slide)!

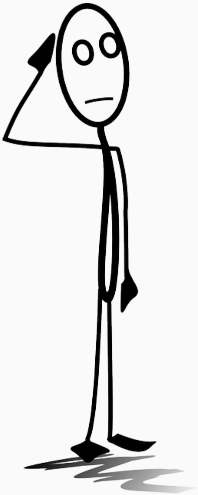
OK, good enough, perfect?

```
import nltk
import regex

class MyTokenizer:
    def tokenize(self, text):
        tokenizer = nltk.tokenize.TreebankWordTokenizer()
        result = []
        word = r"\p{letter}"
        for sent in nltk.sent_tokenize(text):
            tokens = tokenizer.tokenize(sent)
            tokens = [t for t in tokens
                      if regex.search(word, t)]
            result += tokens
        return result

mytokenizer = MyTokenizer()
tokens = [mytokenizer.tokenize(d) for d in docs]
```

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



Can you (try to) explain the code?

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"` [2]

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

[2] ?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 the custom NLTK-based external tokenizer we created before! `cv = CountVectorizer(tokenizer=mytokenizer.tokenize)`

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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" of course using either a for loop (like we did for punctuation removal) or by modifying the tokennizer (try it!).

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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CountVectorizer, only stopword removal

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

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

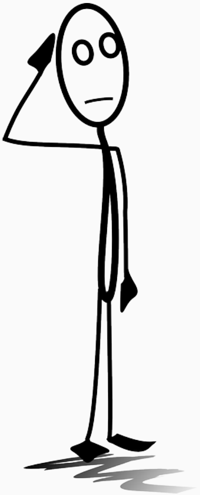
```
myvectorizer = CountVectorizer(tokenizer = TreebankWordTokenizer().tokenize, stop_words=mystopwords)
```

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?

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
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```

The BOW

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

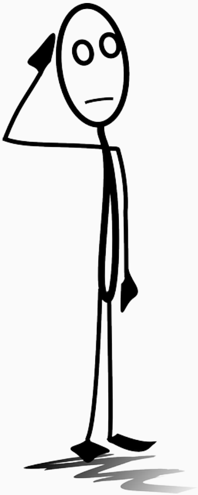
"Remove stopwords, punctuation etc. and store in a string with spaces"

```
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?

Sometimes, I 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 at other times, 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)

The BOW

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.

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Own functions

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```
df['newcoloumnwithresults'] = df['columnwithtext'].str.count("bla")
```

To pandas or not to pandas for text?

Partly a matter of taste.

Not-too-large dataset with a lot of extra columns? Advanced statistical analysis planned? Sounds like pandas.

It's mainly a lot of text? Wanna do some machine learning later on anyway? It's large and (potentially) messy? Doesn't sound like pandas is a good idea.