# Big Data and Automated Content Analysis (6EC)
# Week 4: »Processing textual data« Monday

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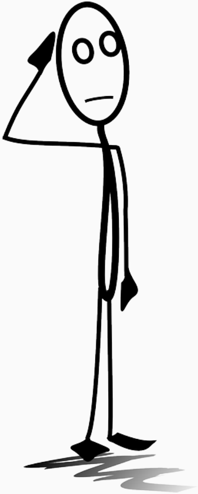
UvA RM Communication Science

# Today



*Everything clear from last week?*

# Main points from last week

**I assume that by now, everybody knows:**

- the relationship between "traditional" statistics and machine learning;
- how to run unsupervised models with scikit-learn;
- how to run supervised models with scikit-learn.

**This week, we will get a general overview of working with textual data. Combining the knowledge from this week with last week gives you all blocks you need to do cool automated content analyses – which we will start with next week.**

# 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. . .

```
# 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

```python
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):
  # do sth with string t here, create new string t2
  return t2

results = [mycleanup(t) for t in allmytexts]
```

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# Pandas string methods as alternative

If you select column with strings from a pandas dataframe, pandas offers a collection of string methods (via `.str.`) that largely mirror standard Python string methods:

```
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.

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# Regular expressions

# Regular expressions

## What is a regexp?

# Regular Expressions: What and why?

## What is a regexp?

- a *very* widespread way to describe patterns in strings
- Think of wildcards like * or operators like `OR`, `AND` or `NOT` in search strings: a regexp does the same, but is *much* more powerful
- You can use them in many editors (!), in the Terminal, in STATA ... and in Python

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# A more powerful tool

## An example

- We want to remove everything but words from a tweet
- We can do so by calling the `.replace()` method multiple times (for each unwanted character)
- We can do so with a join+list comprehension: `"".join([c for c in tweet if c not in listwithunwantedcharacters])`
- But we can also use a regular expression instead: `[^a-zA-Z]` matches anything that is not a letter

## Basic regexp elements

### Alternatives

| | |
|---|---|
| `[TtFf]` | matches either T or t or F or f |
| `Twitter|Facebook` | matches either Twitter or Facebook |
| `.` | matches any character |

### Repetition

| | |
|---|---|
| `?` | the expression before occurs 0 or 1 times |
| `*` | the expression before occurs 0 or more times |
| `+` | the expression before occurs 1 or more times |

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## regexp quizz

### Which words would be matched?

1. `[Pp]ython`
2. `[A-Z]+`
3. `RT ?:? @[a-zA-Z0-9]+`

# regexp quizz

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# What else is possible?

See the table in the book!

# Regular expressions

## Using a regexp in Python

# How to use regular expressions in Python

## The module `re`*

`re.findall("[Tt]witter|[Ff]acebook",testo)` returns a list with all occurances of Twitter or Facebook in the string called `testo`

`re.findall("[0-9]+[a-zA-Z]+",testo)` returns a list with all words that start with one or more numbers followed by one or more letters in the string called `testo`

`re.sub("[Tt]witter|[Ff]acebook","a social medium",testo)` returns a string in which all all occurances of Twitter or Facebook are replaced by "a social medium"

Use the less-known but more powerful module `regex` instead to support all dialects used in the book

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# How to use regular expressions in Python

## The module re

`re.match(" +([0-9]+) of ([0-9]+) points",line)` returns None unless it *exactly* matches the string `line`. If it does, you can access the part between () with the `.group()` method.

Example:

```
line="          2 of 25 points"
result=re.match(" +([0-9]+) of ([0-9]+) points",line)
if result:
   print ("Your points:",result.group(1))
   print ("Maximum points:",result.group(2))
```

Your points: 2

Maximum points: 25

# Possible applications

## Data preprocessing

- Remove unwanted characters, words, . . .
- Identify *meaningful* bits of text: usernames, headlines, where an article starts, . . .
- filter (distinguish relevant from irrelevant cases)

# Possible applications

**Data analysis: Automated coding**

- Actors
- Brands
- links or other markers that follow a regular pattern
- Numbers (!)

# Example 1: Counting actors

```python
import re, csv
from glob import glob
counts1=[]
counts2=[]
filenames = glob("/home/damian/articles/*.txt")

for fn in filenames:
   with open(fn) as fi:
      artikel = fi.read()
      artikel = artikel.replace('\n',' ')

      ↪  counts1.append(len(re.findall('Israel.*(minister|politician.*|[Aa]ut
      counts2.append(len(re.findall('[Pp]alest',artikel)))

output=zip(filenames, counts1, counts2)
with open("results.csv", mode='w',encoding="utf-8") as fo:
    writer = csv.writer(fo)
    writer.writerows(output)
```

# Example 2: Parsing semi-structured data

If your data look like this, you can loop over the lines and use regular expressions to extract the info you need!

```
                          All Rights Reserved

                           2 of 200 DOCUMENTS

                              De Telegraaf

                         21 maart 2014 vrijdag

Brussel bereikt akkoord aanpak probleembanken;
ECB krijgt meer in melk te brokkelen

SECTION: Finance; Blz. 24
LENGTH: 660 woorden

BRUSSEL  Europa heeft gisteren op de valreep een akkoord bereikt
over een saneringsfonds voor banken. Daarmee staat de laatste
```

## Practice yourself!

Take some time to write some regular expressions. Write a script that

- extracts URLS form a list of strings
- removes everything that is not a letter or number from a list of strings

(first develop it for a single string, then scale up)

More tips: http://www.pyregex.com/

# 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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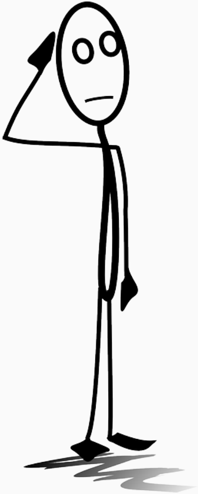
# From vector to matrix

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"

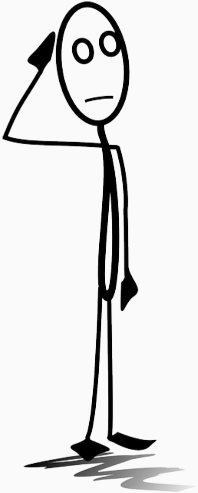
| | a | an | example | is | this | This | test |
|---|---|---|---|---|---|---|---|
| *t1* | 1 | 0 | 0 | 3 | 1 | 1 | 3 |
| *t2* | 0 | 1 | 1 | 1 | 0 | 1 | 0 |



*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")*

$\Rightarrow$ 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)!

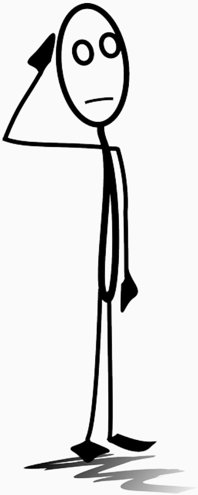
# OK, good enough, perfect?

```python
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!):

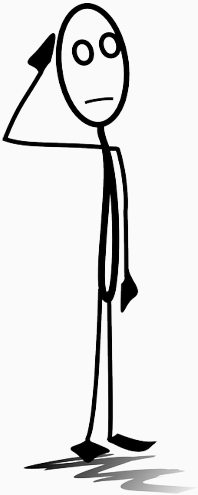
```
myvectorizer = CountVectorizer(tokenizer = TreebankWordTokenizer().
    tokenize, stop_words=mystopwords)
```

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 → drink)
- Lemmatization: find word that you would need to look up in a dictionary (drinking → drink, but also went → 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

- Stemming: reduce words to its stem by removing last part (drinking → drink)
- Lemmatization: find word that you would need to look up in a dictionary (drinking → drink, but also went → 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', '!']]
```

# 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

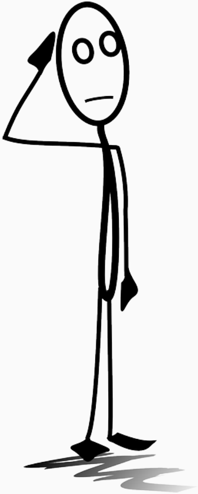
"Remove stopwords, punctuation etc. and store in a string with spaces"

```
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

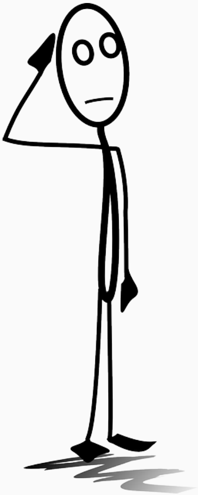
**collocations** *n*grams that appear more frequently than expected

**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.



*Any questions?*

# Next steps

**Make sure you understood all of today's concepts.**

**Re-read the chapters.**

**I prepared exercises to work on (alone or in teams):**

https://github.com/uvacw/teaching-bdaca/blob/main/6ec-course/week04/exercises/

No class on Thursday (Kingsday)

Take-home exam on Monday 8th (after class).The answer sheets and all files have to be handed in no later than Wednesday evening (10–5, 23.59)