A Practical Introduction to Machine Learning in Python
Day 2 - Tuesday
»From text to features: Natural Language Processing «

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Today

Bottom-up vs. top-down

- Approaches to working with text

Natural Language Processing

- Better tokenization
- Stopword and punctuation removal
- Stemming and lemmatization
- ngrams

From test to large-scale

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

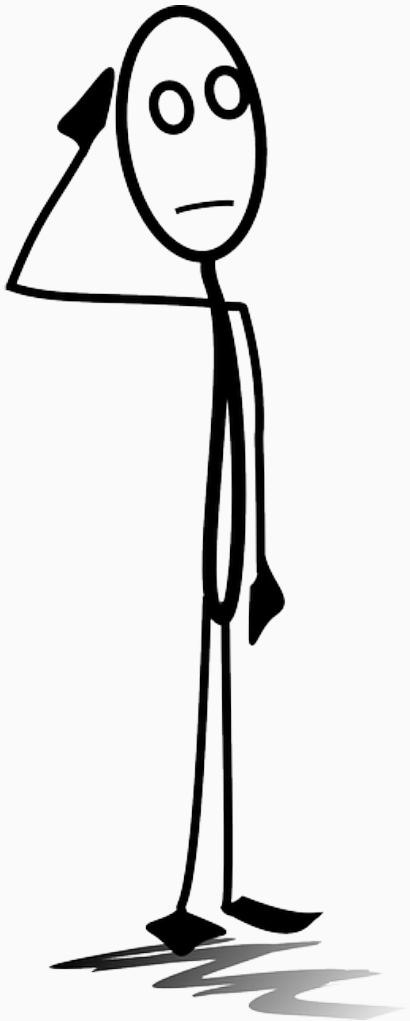
```
1  from collections import Counter
2
3  texts = ["I really really really love him, I do", "I hate him"]
4
5  for t in texts:
6      print(Counter(t.split()).most_common(3))
```

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

A simple top-down approach

```
1  texts = ["I really really really love him, I do", "I hate him"]
2  features = ['really', 'love', 'hate']
3
4  for t in texts:
5      print(f"\nAnalyzing '{t}':")
6      for f in features:
7          print(f"{f} occurs {t.count(f)} times")
```

```
1  Analyzing 'I really really really love him, I do':
2  really occurs 3 times
3  love occurs 1 times
4  hate occurs 0 times
5
6  Analyzing 'I hate him':
7  really occurs 0 times
8  love occurs 0 times
9  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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Bottom-up vs. top-down

Approaches to working with text

The toolbox

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 where "a" is replaced by "b"
- `.count("bla")` counts how often substring "bla" occurs

Use tab completion for more!

Natural Language Processing

Natural Language Processing

NLP: What and why?

Preprocessing steps

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

pruning How can we remove unneccessary words/ punctuation?

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

parse sentences How can identify and encode grammatical functions of tokens?

Natural Language Processing

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)

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

```
1 [['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

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

```
1 [['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.

Natural Language Processing

Stopword and punctuation removal

Stopword removal

The logic of the algorithm is very much related to the one of a simple sentiment analysis!

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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

Stopword removal: What and why?

Why remove stopwords?

- If we want to identify key terms (e.g., by means of a word count), we are not interested in them
- If we want to calculate document similarity, it might be inflated
- If we want to make a word co-occurance graph, irrelevant information will dominate the picture

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]
```

```
1  [['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.

Removing punctuation

```
1 from nltk.tokenize import RegexpTokenizer
2 tokenizer = RegexpTokenizer(r'\w+')
3 tokenizer.tokenize("Hi teachers, what's up!")
```

```
1 ['Hi', 'teachers', 'what', 's', 'up']
```

```
1 from string import punctuation
2 doc = "Today is @Toni's Birthday!!!"
3 "".join([w for w in doc if w not in punctuation])
```

```
1 'Today is Tonis Birthday'
```

Natural Language Processing

Stemming and lemmatization

NLP: What and why?

Why do stemming?

- Because we do not want to distinguish between smoke, smoked, smoking, ...
- Typical preprocessing step (like stopword removal)

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', '!']]
```

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      ', '.', 'second', 'sentence', '!']]
```

Stemming and stopword removal - let's combine them!

```
from nltk.stem.snowball import SnowballStemmer
from nltk.corpus import stopwords
stemmer=SnowballStemmer("english")
mystopwords = stopwords.words("english")
frase="I am running while generously greeting my neighbors"
frasenuevo=""
for palabra in frase.lower().split():
        if palabra not in mystopwords:
                frasenuevo=frasenuevo + stemmer.stem(palabra) + " "
```

Now, `print(frasenuevo)` returns:

```
run generous greet neighbor
```

Perfect! Or:

```
print(" ".join([stemmer.stem(p) for p in frase.lower().split() if p not
    in mystopwords]))
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    in mystopwords]))
```

Natural Language Processing

ngrams

Instead of just looking at single words (unigrams), we can also use adjacent words (bigrams).

ngrams

```
1 import nltk
2 texts = ['This is the first text text text first', 'And another text
      yeah yeah']
3 texts_bigrams = [["_".join(tup) for tup in nltk.ngrams(t.split(),2)] for
       t in texts]
4 print(texts_bigrams)
```

```
[['This_is', 'is_the', 'the_first', 'first_text',
'text_text', 'text_text', 'text_first'],
['And_another', 'another_text', 'text_yeah',
'yeah_yeah']]
```

Typically, we would combine both. What do you think? Why is this useful? (and what may be drawbacks?)

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```

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From test to large-scale

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 ow= function and then use it in the list comprehension:

```
1 def mycleanup(t):
2     # do sth with string t here, create new string t2
3     return t2
4
5 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:

```
1 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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