Natural Language Processing – Part 1

NLP

Natural Language Processing (NLP) is the field concerned with computational techniques that allow computers to deal with human language. Linguistics provides a theoretical and historical basis for NLP, but NLP also falls within the realms of computer science and artificial intelligence. Besides text mining, NLP also covers text generation, chat bots, sentiment analysis, speech recognition, digital voice assistants like Siri and more.

This part will cover the basis of text analysis

- **Regular Expression:** RegEx
- **Tokenization:** Determining word units
- **Lemmatization and Stemming:** Returning the base of a word
- **Part-of-speech tagging:** Determining grammatical function of a word
- **Named entity recognition:** Recognizing real-world things (people, places)
- **N-grams:** Grouping words that belong together
- **Parsing:** Syntatic structure of a sentence

Regular expression: RegEx

Regular expression is a very common and wide-used technique for text mining. Using a special syntax to create patterns you can grab certain character groups from text.
RegEx works best for words with distinct patterns such as phone numbers, email addresses or to remove unwanted characters.

```
>>> import re

>>> re.match("cat", "The cat knocked the glass of the table.")
>>> "cat"

>>> re.findall(r'\d+', "We have 3 cats and 2 dogs.")
>>> ['3', '2']
```

Shorthand Character	Regex Equivalent	Description
\w	[A-Za-z0-9_]	Matches any character that is a letter (regardless of case), number, or underscore
\W	[^A-Za-z0-9_]	Matches any character that is **NOT** a letter (regardless of case), number, or underscore
\d	[0-9]	Matches any character that is a digit
\D	[^0-9]	Matches any character that is **NOT** a digit
\s	[\t\r\n\f]	Matches any character that is a whitespace character (spaces, tabs, carriage returns, newlines, and form feeds)
\S	[^ \t\r\n\f]	Matches any character that is **NOT** a whitespace character (spaces, tabs, carriage returns, newlines, and form feeds)

In addition:

```
.       Any character except newline
*       Match 0 or more
+       Match 1 or more
{n}     Match exactly n
{n,}    Match at least n
{n, m}  Match between n and m
```

Other cheetsheets: **https://cheatography.com/mutanclan/cheat-sheets/python-regular-expression-regex/**

In [3]:

```
# Other useful expressions:
# r'(?:...)' <- a non matching group
#(?=...) Positive lookbehind
my_string = "foo bar bar baz"

print("All bar:", re.findall(r'bar', my_string))
print("Only after foo:", re.findall(r'(?:foo\s)(bar)', my_string))
```

```
All bar: ['bar', 'bar']
Only after foo: ['bar']
```

In [4]:

```
re.match    # Try to apply the pattern at
            # the start of the string
re.search   # Scan through string
            # looking for a match to the pattern
re.findall  # Find all matches in a string
re.finditer # Return an iterator over
            # all non-overlapping matches
```

Out[4]:

```
<function re.finditer(pattern, string, flags=0)>
```

More complicated regeular expression can become quite long:

```
"^([a-zA-Z0-9_\-\.]+)@([a-zA-Z0-9_\-\.]+)\.([a-zA-Z]{2,5})$"
```

In [5]:

```python
my_string = "My email address is groothuis.susanne@kpmg.nl"
pattern = "([a-zA-Z0-9_\-\.]+)@([a-zA-Z0-9_\-\.]+)\.([a-zA-Z]{2,5})"
re.search(pattern, my_string)
```

Out[5]:

```
<re.Match object; span=(20, 45), match='groothuis.susanne@kpmg.nl'>
```

In [6]:

```
# You can also use regular expression to split texts:
my_string = """A regular expression (shortened as regex or regexp also referred to as rational expression) is a sequence of characters that define a search pattern. Usually such patterns are used by string-searching

The concept arose in the 1950s when the American mathematician Stephen Cole Kleene formalized the description of a regular language. The concept came into common use with Unix text-processing utilities. Different sy

Regular expressions are used in search engines, search and replace dialogs of word processors and text editors, in text processing utilities such as sed and AWK and in lexical analysis. Many programming languages pr
```

In [7]:

```
re.split('\.\s',my_string)
```

Out[7]:

```
['A regular expression (shortened as regex or regexp also referred to as rational expres
sion) is a sequence of characters that define a search pattern',
 'Usually such patterns are used by string-searching algorithms for "find" or "find and
replace" operations on strings, or for input validation',
 'It is a technique developed in theoretical computer science and formal language theor
y',
 '\nThe concept arose in the 1950s when the American mathematician Stephen Cole Kleene f
ormalized the description of a regular language',
 'The concept came into common use with Unix text-processing utilities',
 'Different syntaxes for writing regular expressions have existed since the 1980s, one b
eing the POSIX standard and another, widely used, being the Perl syntax',
 '\nRegular expressions are used in search engines, search and replace dialogs of word p
rocessors and text editors, in text processing utilities such as sed and AWK and in lexi
cal analysis',
 'Many programming languages provide regex capabilities either built-in or via librarie
s.']
```

Tokenization

Tokenization is, generally, an early step in the NLP process, a step which splits longer strings of text into smaller pieces, or tokens. Larger chunks of text can be tokenized into sentences (“sentence tokens”), sentences can be tokenized into words (“word tokens”), etc.

In [8]:

```
sentence = "We've tokenized this sentence into words."
sentence.split(' ')
```

Out[8]:

```
["We've", 'tokenized', 'this', 'sentence', 'into', 'words.']
```

There are tokenizers that split up sentences based on punctuation

In [9]:

```
tok = tokenize.PunktSentenceTokenizer()
tokens = tok.tokenize(my_string)
print(f"There are {len(tokens)} sentences.")
tokens
```

```
There are 8 sentences.
```

Out[9]:

```
['A regular expression (shortened as regex or regexp also referred to as rational expres
sion) is a sequence of characters that define a search pattern.',
 'Usually such patterns are used by string-searching algorithms for "find" or "find and
replace" operations on strings, or for input validation.',
 'It is a technique developed in theoretical computer science and formal language theor
y.',
 'The concept arose in the 1950s when the American mathematician Stephen Cole Kleene for
malized the description of a regular language.',
 'The concept came into common use with Unix text-processing utilities.',
 'Different syntaxes for writing regular expressions have existed since the 1980s, one b
eing the POSIX standard and another, widely used, being the Perl syntax.',
 'Regular expressions are used in search engines, search and replace dialogs of word pro
cessors and text editors, in text processing utilities such as sed and AWK and in lexica
l analysis.',
 'Many programming languages provide regex capabilities either built-in or via librarie
s.']
```

Other split all words and punctuations as seperate tokens

In [32]:

```
tok = tokenize.NLTKWordTokenizer()
tokens = tok.tokenize(my_string)
print(f"There are {len(tokens)} tokens")
tokens[:10]
```

```
There are 166 tokens
```

Out[32]:

```
['A',
 'regular',
 'expression',
 '(',
 'shortened',
 'as',
 'regex',
 'or',
 'regexp',
 'also']
```

Or you can define your own tokenizer using regular expression

This tokenizer only keeps tokens that match to the regular expression. As you can see the numbers and special characters are no longer in the list of tokens.

In [31]:

```
pattern = '\w+'
tok = tokenize.RegexpTokenizer(pattern)
tokens = tok.tokenize(my_string)
print(f"There are {len(tokens)} tokens")
tokens[:10]
```

```
There are 156 tokens
```

Out[31]:

```
['A',
 'regular',
 'expression',
 'shortened',
 'as',
 'regex',
 'or',
 'regexp',
 'also',
 'referred']
```

Other popular packages such as spacy use tokenizers in it's backend

In [30]:

```
import spacy
nlp = spacy.load('en_core_web_sm')
doc = nlp(my_string)
tokens = [tok for tok in doc]
print(f"There are {len(tokens)} tokens")
tokens[:10]
```

```
There are 181 tokens
```

Out[30]:

```
[A, regular, expression, (, shortened, as, regex, or, regexp, also]
```

Stemming and Lemmatization

Stemming and Lemmatization are two forms of reducing words to a basic form that captures the family of that word. Stemming usually cuts off a word to a base:

> ***Words*** *and* ***wording*** *become* ***word Democracies*** *become* ***Democraci***

Lemmatization tries to return the token to the base of the word:

> ***Democracies*** *becomes* ***Democracy***

Withing both lemmatization and stemming are different algoritms that can be applied, and obviously they also vary for different languages.
The most common stemming algorithms can be found in NLTK, which are the PorterStemmer and the Snowball Stemmer.
Neither application is necessarily the best, they both have different advantages and disadvantages. You need to make a decision on which one to use depending on the application you have in mind.

Let's see an example of the differences between lemmatization and stemming, by comparing the lemmatizer of spacy and the SnowballStemmer from NLTK.

In [13]:

```
from nltk.stem import SnowballStemmer
import pandas as pd
stemmer = SnowballStemmer('english')
out =[]

sentence = 'Interesting sentences contain various variations wording words of interest'
doc2 = nlp(sentence)
for token in doc2:
    out.append({'token': token.text, 'lemma': token.lemma_, 'stem':stemmer.stem(token.text)})

pd.DataFrame.from_dict(out)
```

Out[13]:

	token	lemma	stem
0	Interesting	interesting	interest
1	sentences	sentence	sentenc
2	contain	contain	contain
3	various	various	various
4	variations	variation	variat
5	wording	wording	word
6	words	word	word
7	of	of	of
8	interest	interest	interest

Part of speech tagging

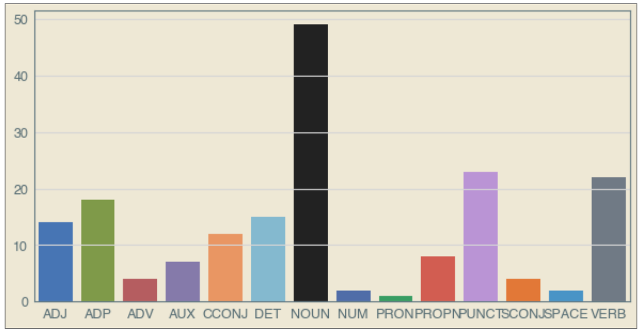
In part of speech tagging we assing each token it's grammatical purpose in the sentence. This means we tag verbs as verbs, and nouns as nouns.

In [29]:

```
pos_tags, counts = np.unique([t.pos_ for t in tokens], return_counts=True)
plt.figure(figsize=(10,5))
sns.barplot(x=pos_tags, y=counts)
```

Out[29]:

```
<AxesSubplot:>
```



In [15]:

```
print_tags(tokens, 'pos', 'Set2', with_tags=False)
```

Out[15]:

A regular expression (shortened as regex or regexp also referred to as rational expression) is a sequence of characters that define a search pattern . Usually such patterns are used by string - searching algorithms for " find " or " find and replace " operations on strings , or for input validation . It is a technique developed in theoretical computer science and formal language theory . The concept arose in the 1950s when the American mathematician Stephen Cole Kleene formalized the description of a regular language . The concept came into common use with Unix text - processing utilities . Different syntaxes for writing regular expressions have existed since the 1980s , one being the POSIX standard and another , widely used , being the Perl syntax . Regular expressions are used in search engines , search and replace dialogs of word processors and text editors , in text processing utilities such as sed and AWK and in lexical analysis . Many programming languages provide regex capabilities either built - in or via libraries .

LEGEND:

adjective: **ADJ** adposition: **ADP** adverb: **ADV** auxiliary: **AUX** coordinating conjunction: **CCONJ** determiner: **DET** noun: **NOUN**

numeral: **NUM** pronoun: **PRON** proper noun: **PROPN** subordinating conjunction: **SCONJ** space: **SPACE** verb: **VERB**

In [16]:

```
for tag in pos_tags:
    print(tag, ':', spacy.explain(tag))
```

```
ADJ : adjective
ADP : adposition
ADV : adverb
AUX : auxiliary
CCONJ : coordinating conjunction
DET : determiner
NOUN : noun
NUM : numeral
PRON : pronoun
PROPN : proper noun
PUNCT : punctuation
SCONJ : subordinating conjunction
SPACE : space
VERB : verb
```

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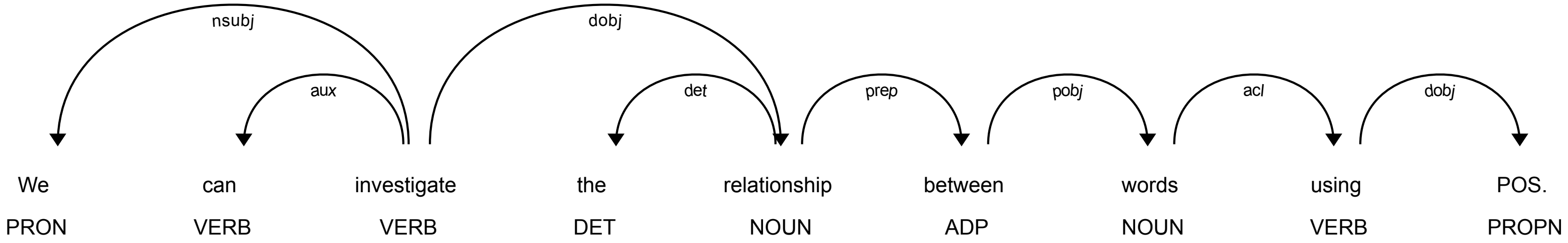
In [17]:

```
new_sentence = "We can investigate the relationship between words using POS."
doc = nlp(new_sentence)
displacy.render(doc, style='dep')
```



In [18]:

```
dep_tags = np.unique([t.dep_ for t in doc])
for tag in dep_tags:
    print(tag, ':', spacy.explain(tag))
```

```
ROOT : None
acl : clausal modifier of noun (adjectival clause)
aux : auxiliary
det : determiner
dobj : direct object
nsubj : nominal subject
pobj : object of preposition
prep : prepositional modifier
punct : punctuation
```

In [19]:

```
print_tags(doc, 'dep')
```

Out[19]:

We **NSUBJ** can **AUX** investigate **ROOT** the **DET** relationship **DOBJ** between **PREP** words **POBJ** using **ACL** POS **DOBJ** . **PUNCT**

Named entity Recognition

Named entity regognition (or NER) is all about identifying words that relate to real-life things such as people, places, organisations etc.

In [20]:

```
txt = """Ginsburg was born and grew up in Brooklyn, New York.
Her older sister died when she was a baby, and her mother died shortly before Ginsburg
graduated from high school. She earned her bachelor's degree at Cornell University
and married Martin D. Ginsburg, becoming a mother before starting law school at Harvard,
where she was one of the few women in her class. Ginsburg transferred to Columbia Law School,
where she graduated joint first in her class. After law school, Ginsburg entered academia.
She was a professor at Rutgers Law School and Columbia Law School, teaching civil
procedure as one of the few women in her field."""

doc = nlp(txt)
displacy.render(doc, style='ent')
```

Ginsburg PERSON was born and grew up in Brooklyn GPE , New York GPE .

Her older sister died when she was a baby, and her mother died shortly before Ginsburg PERSON

graduated from high school. She earned her bachelor's degree at Cornell University ORG

and married Martin D. Ginsburg PERSON , becoming a mother before starting law school at Harvard ORG ,

where she was one CARDINAL of the few women in her class. Ginsburg PERSON transferred to Columbia Law School ORG ,

where she graduated joint first ORDINAL in her class. After law school, Ginsburg PERSON entered academia.

She was a professor at Rutgers Law School ORG and Columbia Law School ORG , teaching civil procedure as one of the few women in her field.

In [21]:

```
for ent in np.unique([t.ent_type_ for t in doc]):
    print(ent,':', spacy.explain(ent))
```

```
 : None
CARDINAL : Numerals that do not fall under another type
GPE : Countries, cities, states
ORDINAL : "first", "second", etc.
ORG : Companies, agencies, institutions, etc.
PERSON : People, including fictional
```

In [22]:

```
txt = """After the extermination of the Luan clan by Duke Ding's great-grandfather Duke Ping,
the state of Jin had been dominated by the six powerful clans – Fan, Han, Zhao, Wei, Zhonghang, and Zhi.
In 497 BC a dispute broke out between Zhao Yang (趙鞅), the leader
of the Zhao clan, and the Fan and Zhonghang clans."""

doc = nlp(txt)
displacy.render(doc, style='ent')
```

After the extermination of the Luan ORG clan by Duke Ding's PERSON great-grandfather Duke Ping PERSON ,

the state of Jin ORG had been dominated by the six CARDINAL powerful clans NORP – Fan, Han NORP , Zhao GPE , Wei PERSON , Zhonghang PERSON , and Zhi PERSON .

In 497 CARDINAL BC a dispute broke out between Zhao Yang PERSON (趙鞅), the leader

of the Zhao GPE clan, and the Fan PERSON and Zhonghang GPE clans.

In [23]:

```
txt = """Giethoorn used to be a pedestrian precinct, but nowadays exceptions are made.
It became locally famous, especially after 1958, when the Dutch film maker Bert Haanstra
made his famous comedy Fanfare there. In the old part of the village, there were no roads
(though a cycling path was eventually added), and all transport was done by water
over one of the many canals. The lakes in Giethoorn were formed by peat unearthing.

Giethoorn was a separate municipality until 1973, when it became part of
Brederwiede, which lost its municipality status in 2001 to merge with Steenwijk.
"""

doc = nlp(txt)
displacy.render(doc, style='ent')
```

Giethoorn **ORG** used to be a pedestrian precinct, but nowadays exceptions are made.

It became locally famous, especially after 1958 **DATE** , when the Dutch **NORP** film maker Bert Haanstra **PERSON**

made his famous comedy Fanfare **GPE** there. In the old part of the village, there were no roads

(though a cycling path was eventually added), and all transport was done by water

over one of the many canals. The lakes in Giethoorn **GPE** were formed by peat unearthing.

Giethoorn was a separate municipality until 1973 **DATE** , when it became part of

Brederwiede, which lost its municipality status in 2001 **DATE** to merge with Steenwijk **GPE** .

In [24]:

```python
# nlp = spacy.load('nl_core_news_md')
import nl_core_news_md
nlp = nl_core_news_md.load()
```

In [25]:

```python
txt = """Giethoorn (Stellingwerfs: Gietern) is een waterstreekdorp in de kop van Overijssel, in de gemeente Steenwijkerland in de Nederlandse provincie Overijssel en ligt tussen
Steenwijk en Meppel.

Bert Haanstra nam in Giethoorn in 1958 zijn speelfilmdebuut Fanfare op, een film over twee rivaliserende fanfares in het fictieve dorpje Lagerwiede. Na het verschijnen van de film Fanfare nam het toerisme sterk toe.

doc = nlp(txt)
displacy.render(doc, style='ent')
```

Giethoorn GPE (Stellingwerfs LANGUAGE : Gietern GPE) is een waterstreekdorp in de kop van Overijssel, in de gemeente Steenwijkerland GPE in de Nederlandse NORP provincie Overijssel GPE en ligt tussen
Steenwijk GPE en Meppel GPE .

Bert Haanstra PERSON nam in Giethoorn GPE in 1958 DATE zijn speelfilmdebuut Fanfare PERSON op, een film over twee CARDINAL rivaliserende fanfares in het fictieve dorpje Lagerwiede GPE . Na het verschijnen van de film Fanfare nam het toerisme sterk toe.

N-Grams

If you payed attention you noticed I skipped over n-grams. N-grams, however, are simply words grouped together. You can do this arbitrarily, and make of every possible combination of consecutive words an n-gram:

In [26]:

```
for n in window([t.text for t in doc][:10], 2):
    print(n)
```

```
('Giethoorn', '(')
('(', 'Stellingwerfs')
('Stellingwerfs', ':')
(':', 'Gietern')
('Gietern', ')')
(')', 'is')
('is', 'een')
('een', 'waterstreekdorp')
('waterstreekdorp', 'in')
```

You usually want to do something smarter, and group them based on what makes sense, or has semantic meaning. An example of this is already the NER we did above.

We can display the results from spacy in two different ways, and see that spacy already does some 'Chucking' (as it's called) to create semantic meaningful n-grams:

With n-grams

No n-grams

In [27]:

```
displacy.render(doc, 'ent')
```

Giethoorn GPE (Stellingwerfs LANGUAGE : Gietern GPE) is een waterstreekdorp in de kop van Overijssel, in de gemeente Steenwijkerland GPE in de Nederlandse NORP provincie Overijssel GPE en ligt tussen
Steenwijk GPE en Meppel GPE .

Bert Haanstra PERSON nam in Giethoorn GPE in 1958 DATE zijn speelfilmdebuut Fanfare PERSON op, een film over twee CARDINAL rivaliserende fanfares in het fictieve dorpje Lagerwiede GPE . Na het verschijnen van de film Fanfare nam het toerisme sterk toe.

In [28]:

```
print_tags(doc, 'ent_type')
```

Out[28]:

Giethoorn GPE (Stellingwerfs LANGUAGE : Gietern GPE) is een waterstreekdorp in de kop van Overijssel , in de gemeente GPE Steenwijkerland GPE in de Nederlandse NORP provincie GPE Overijssel GPE en ligt tussen Steenwijk GPE en Meppel GPE . Bert PERSON Haanstra PERSON nam in Giethoorn GPE in 1958 DATE zijn speelfilmdebuut Fanfare PERSON op , een film over twee CARDINAL rivaliserende fanfares in het fictieve dorpje Lagerwiede GPE . Na het verschijnen van de film Fanfare nam het toerisme sterk toe .

Exercise time

Go to datacamp.com and practice with regex and NER