Lecture 6 - Introduction to Natural Language Processing

Intro2AI-class - ANITI

Chloé Braud, CNRS - IRIT, chloe.braud@irit.fr

12 April 2021

Unfortunately, still no HAL or Marvin

2001, A Space Odysssey

The Hitchhiker's Guide to the Galaxy

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE
TOULOUSE INSTITUTE

Unfortunately, still no HAL or Marvin

The Hitchhiker's Guide to the Galaxy

2001, A Space Odysssey

But we can "talk" with the SNCF…

NLP is used for many applications: mining text

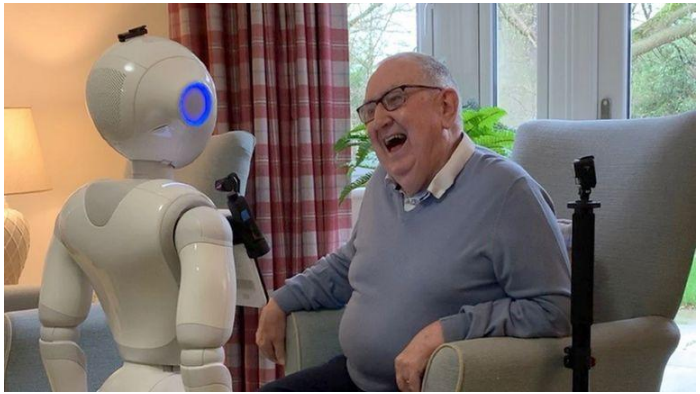
- spam filtering
- spell checking
- automatic translation
- finding information in text / databases
- finding entities and linking them
- classifying text, e.g. topic, fake news ...
- analysing opinion / sentiment in text
- summarizing text
- simplifying text
- profiling users
- detecting mental illness
- ...

More and more companies and other academic fields are interested in NLP techniques

What is Natural Language Processing?

At the **interface between**:

- Linguistics: dealing with natural languages
- Computational Science: algorithms
- Mathematics: statistics, probabilities
- Physics: speech processing



Subdomain of Artificial Intelligence:

- human machine interaction
- human human interaction

= access to information / extract information

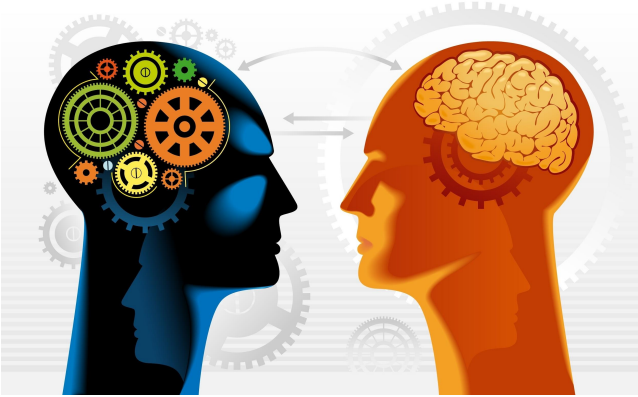
= understanding intelligence through communication

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

What is Natural Language Processing?

Computational techniques to process data in natural language

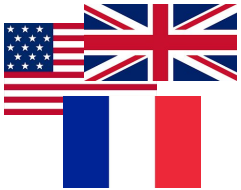
- **Practical**: Creating tools to automatically process data in natural language, i.e. tools to analyse, model, “understand”, generate, save language
- **Theoretical**: Using empirical methods to better understand what is language: how does it work? how people understand each other?



ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

What is Natural Language Processing?

Take data

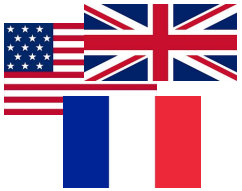


WIKIPÉDIA
L'encyclopédie libre

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

What is Natural Language Processing?

Take data (all)



Doctissimo

WIKIPÉDIA
L'encyclopédie libre

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

What is Natural Language Processing?

Take data (all)

Doctissimo

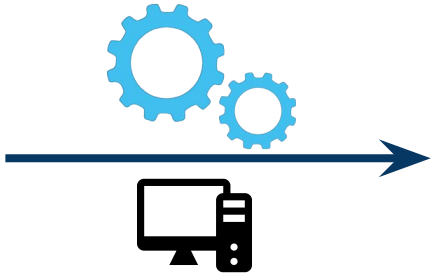
WIKIPÉDIA
L'encyclopédie libre

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

What is Natural Language Processing?

Take data (all)

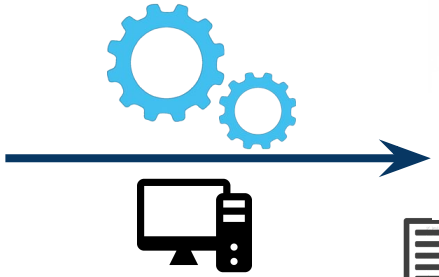
Process



What is Natural Language Processing?

Take data (all)

Process

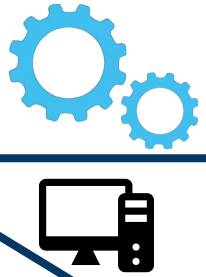


Develop applications

What is Natural Language Processing?

Take data (all)

Process



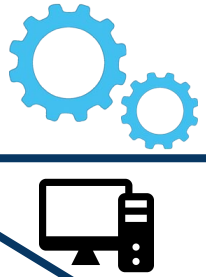
Develop applications

Understand language

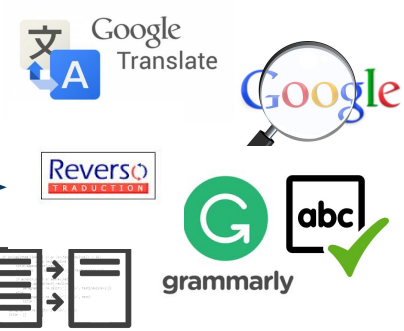
What is Natural Language Processing?

Take data (all)

Process



Develop applications



Understand language

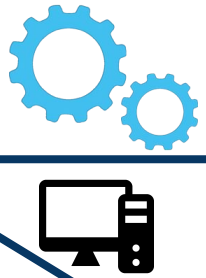
What does it mean?
How we do that?

What is Natural Language Processing?

Take data (all)

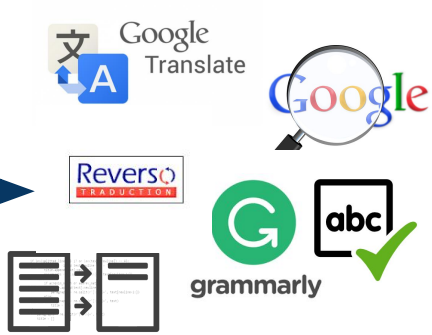
Many challenges!

Process



What does it mean?
How we do that?

Develop applications



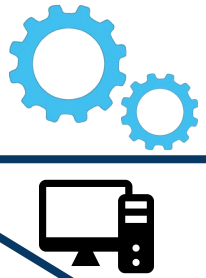
Understand language

What is Natural Language Processing?

Take data (all)

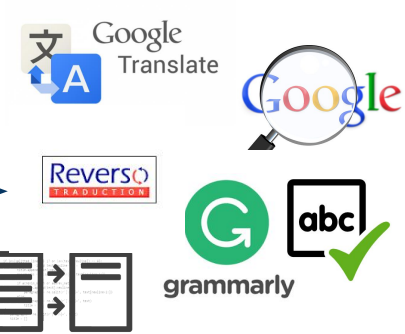
Many challenges!

Process



What does it mean?
How we do that?

Develop **applications**



Understand language

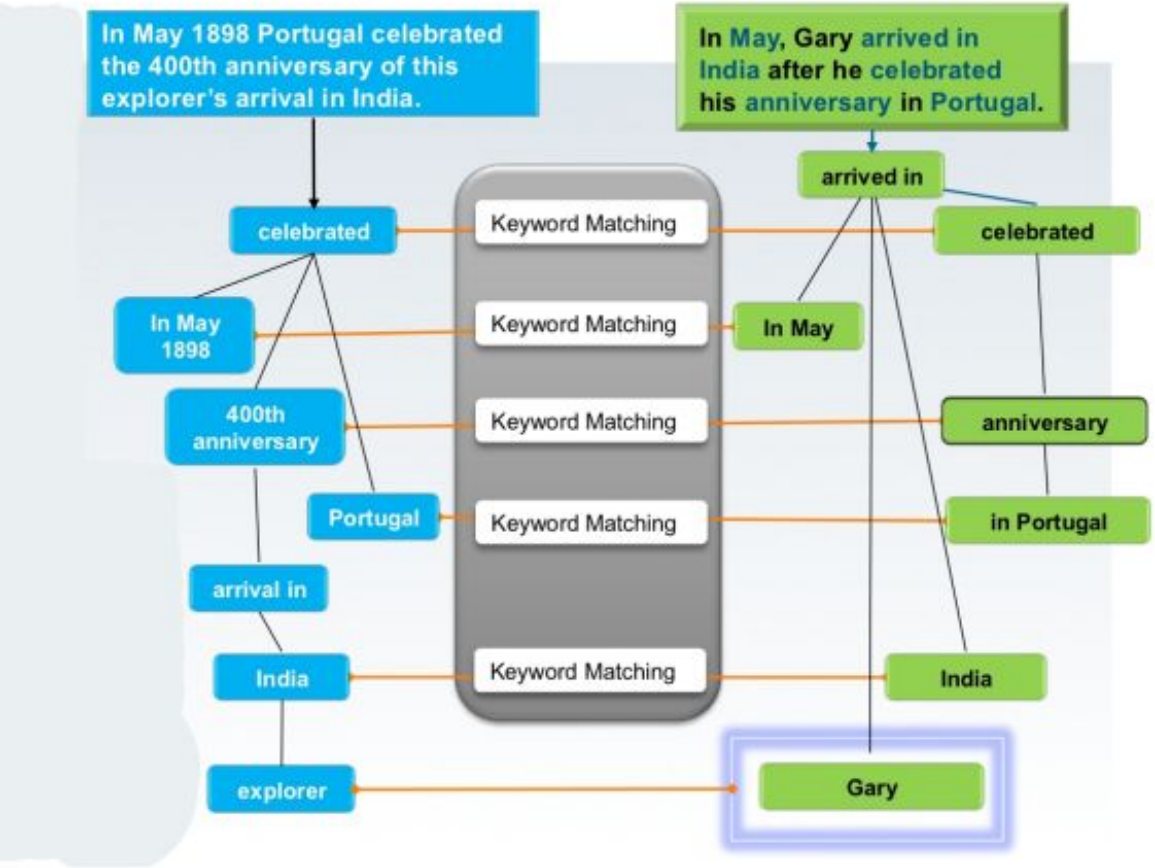
ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Why NLP is hard?

Example: Question-Answering with Watson

Why NLP is hard?

Keyword matching can provide good clues
→ but here, misleading

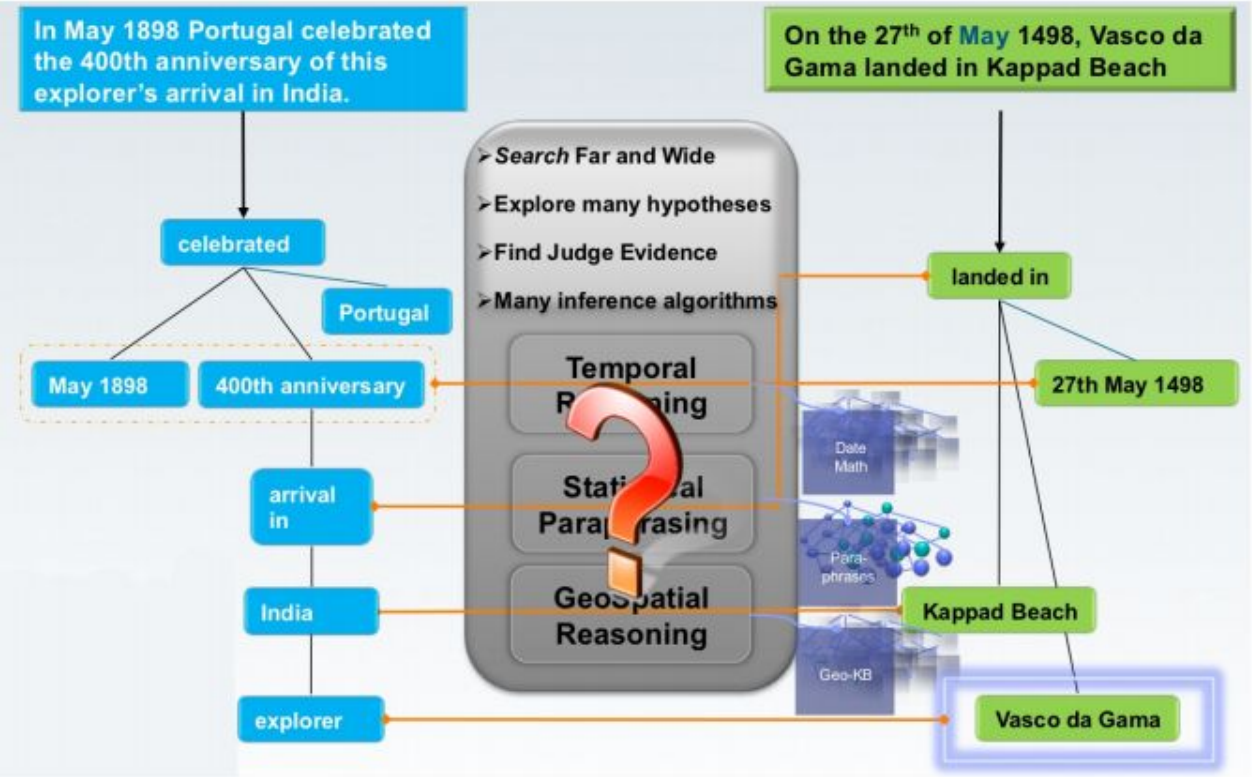


Why NLP is hard?

But it won't be enough most of the time:

→ stronger evidence are much harder to find, relying on:

- fine-grained analysis (e.g. temporal reasoning)
- complex understanding (e.g. paraphrasing)

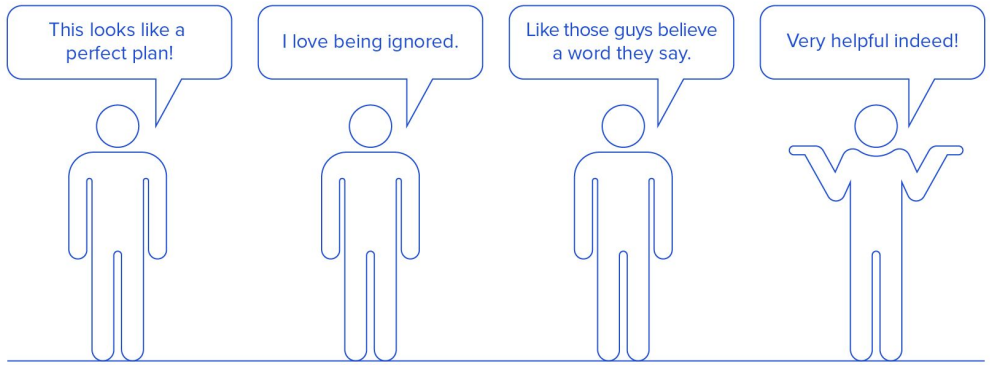


Why NLP is hard?

Many issues:

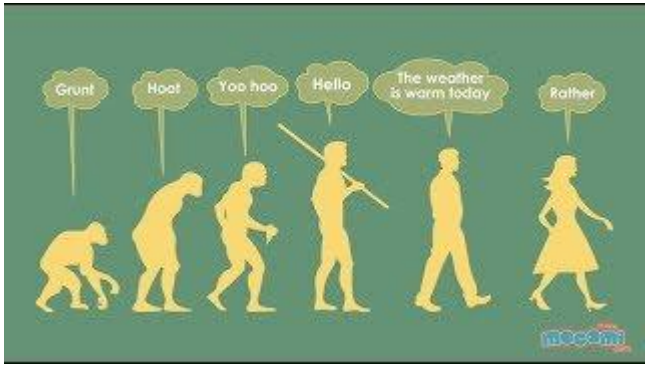
- ambiguity
- coreferent entities
- equivalent forms
- sarcasm
- negation, contrast
- ...

Coronavirus quickly spread worldwide in 2020. The virus mostly affects elderly people. They can easily catch it.



This mouse **is not good** looking, <u>but</u> it works **perfect** and I **like** it.

Why NLP is hard?



Other issues:

- language is evolving
- speakers do not always master their own language...
- speakers are creative:
  - e.g. lol, mdr, yolo, omg ...
  - e.g. cheeeeeerrrsss
  - e.g. love u
  - e.g. <3 :) :D

→ Makes the study of language fascinating but its automatic processing harder (and funnier ;)

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

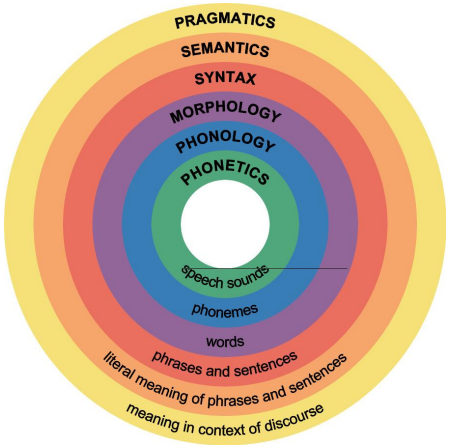
Summary

1. **Fundamentals of linguistics**
   - linguistic levels of analysis
   - ambiguity!
2. **Fundamentals of NLP**
   - Pre-processing
   - Linguistic analysis
3. **Hands-on NLP**
   - Finding data
   - Preparing data
   - Learning from data
4. **More about learning scenario and applications**
   - Classification
   - Sequence labelling
   - Sequence to Sequence
5. **To go further**
   - Limits of classical statistical methods
   - Limits of supervised learning
   - Current challenges in NLP

Practical session: Sentiment analysis

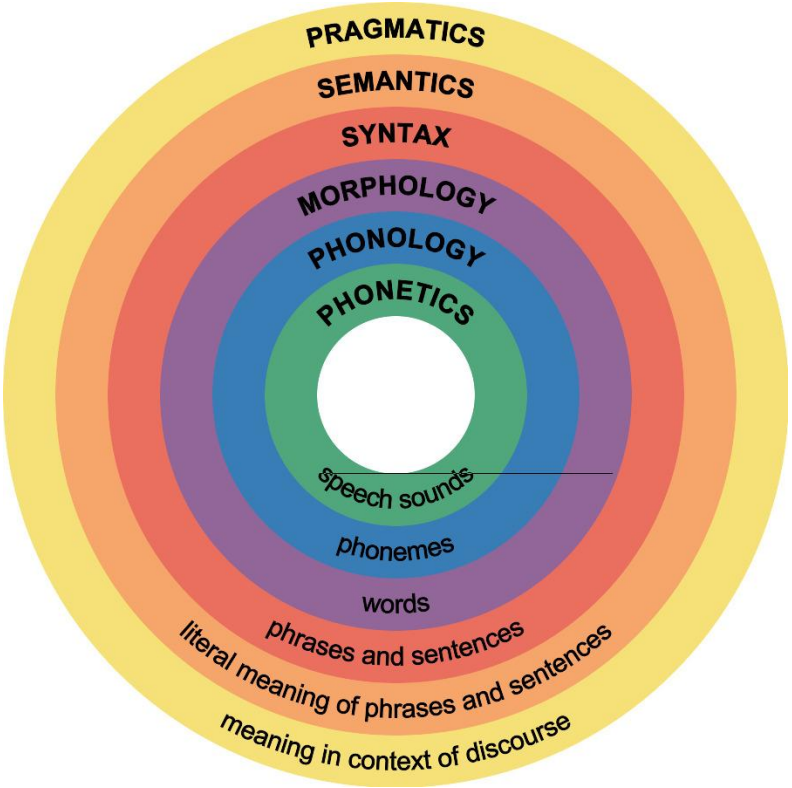
ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Fundamentals of Linguistics



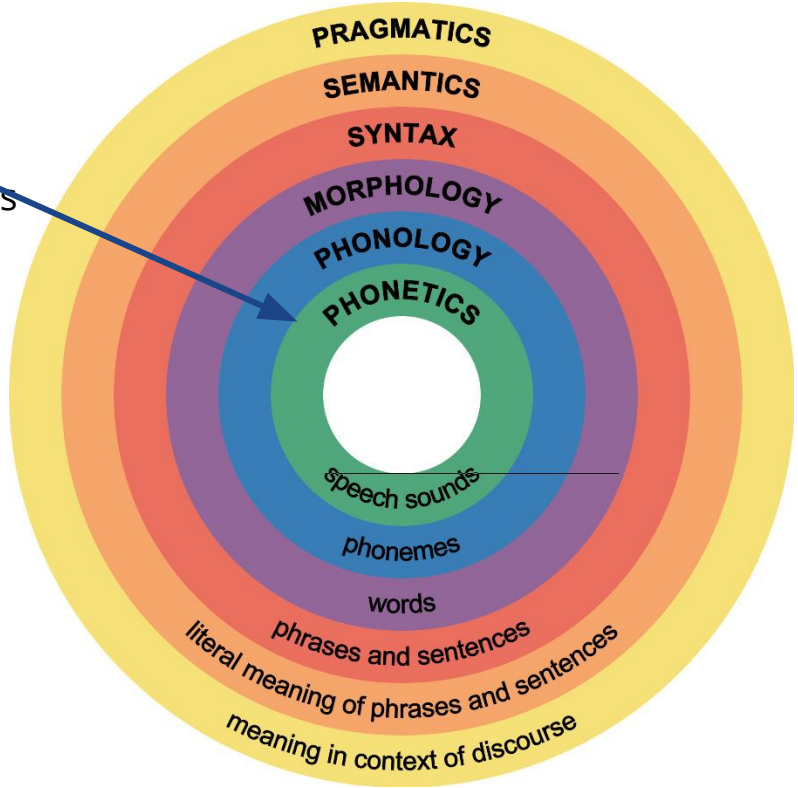
ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Main levels of linguistics structure



Main levels of linguistics structure

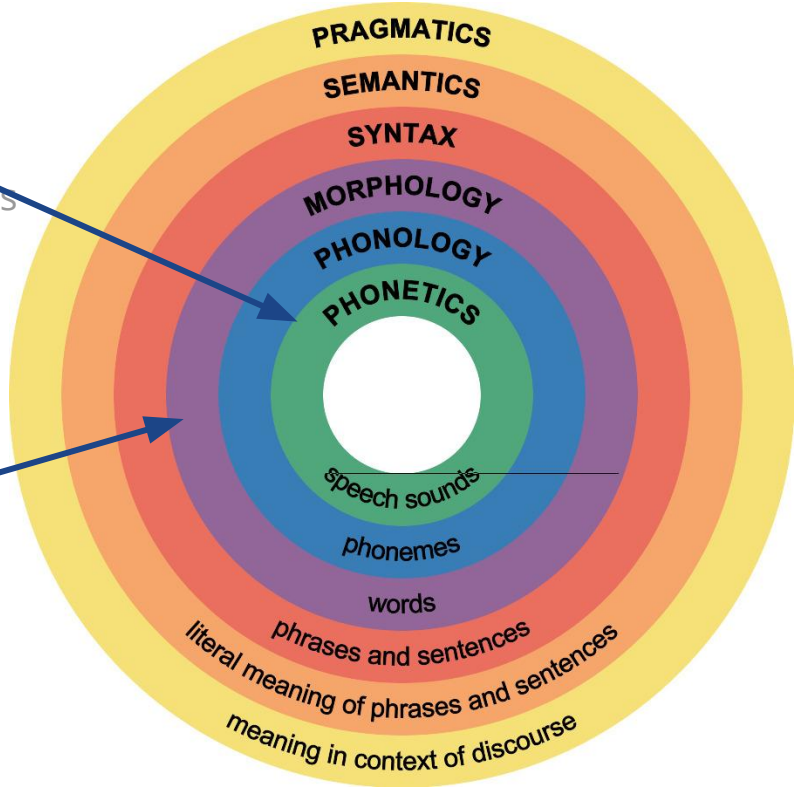
Phonetics-Phonology:
Speech processing is distinct from NLP = focus on text. But NLP researchers work on transcriptions from speech.



Main levels of linguistics structure

Phonetics-Phonology:
Speech processing is distinct from NLP = focus on text. But NLP researchers work on transcriptions from speech.

Morphology:
How words are built. Studies on new words creation: people are very creative!

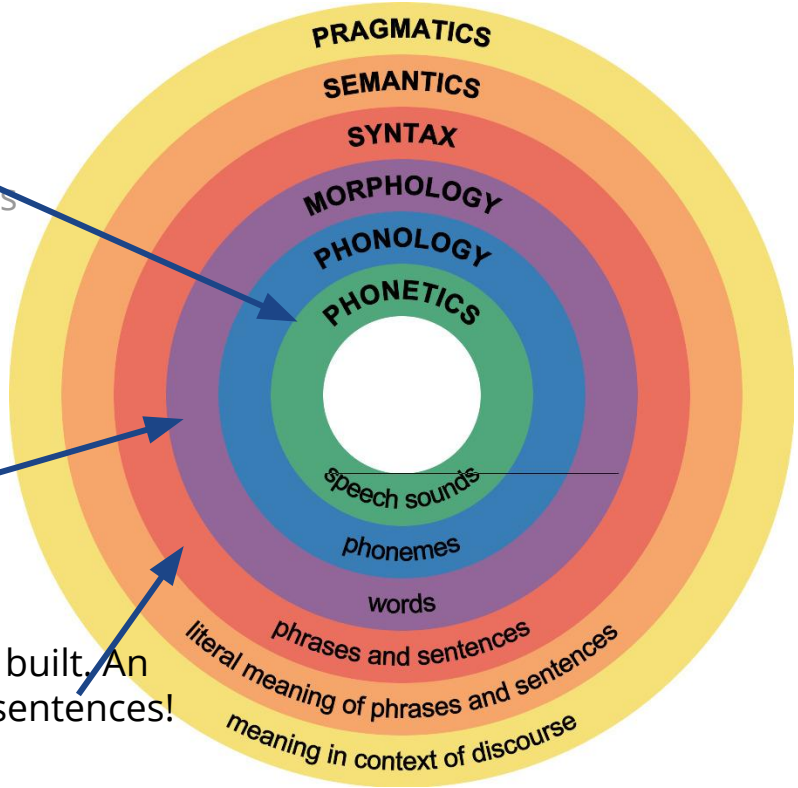


Main levels of linguistics structure

Phonetics-Phonology:
Speech processing is distinct from NLP = focus on text. But NLP researchers work on transcriptions from speech.

Morphology:
How words are built. Studies on new words creation: people are very creative!

Syntax:
How sentences are built. An infinite number of sentences!

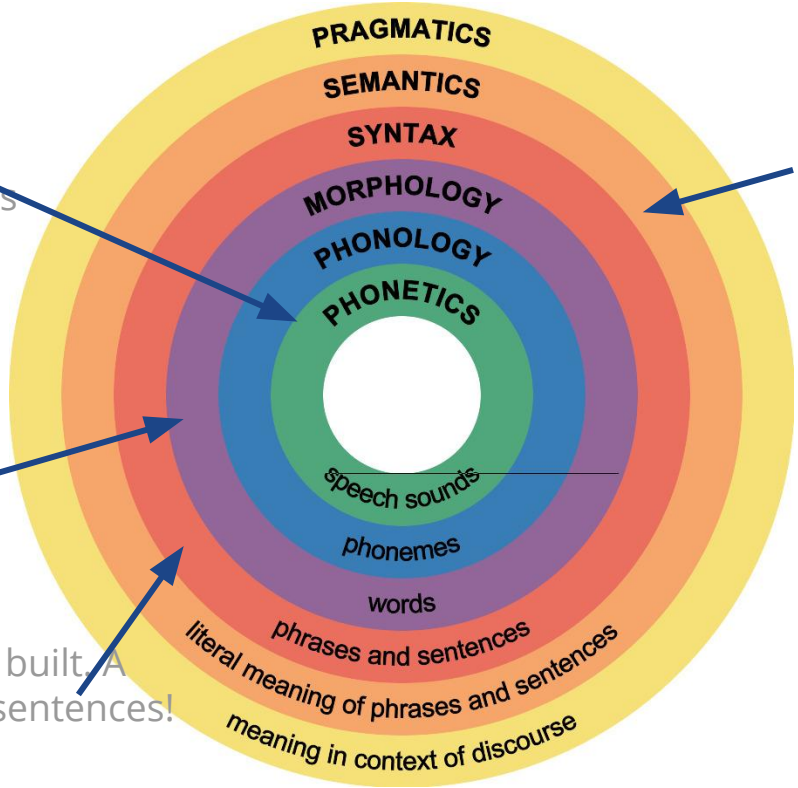


Main levels of linguistics structure

Phonetics-Phonology:
Speech processing is distinct from NLP = focus on text. But NLP researchers work on transcriptions from speech.

Morphology:
How words are built. Studies on new words creation: people are very creative!

Syntax:
How sentences are built. A infinite number of sentences!



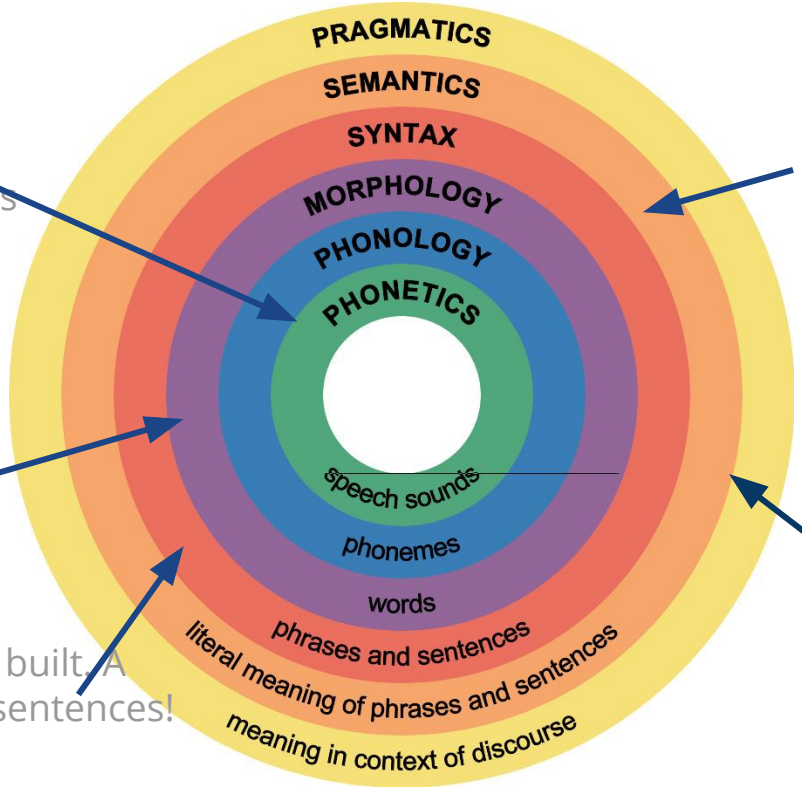
Semantics:
Literal meaning of the words and utterances. What do you mean?

Main levels of linguistics structure

Phonetics-Phonology:
Speech processing is distinct from NLP = focus on text. But NLP researchers work on transcriptions from speech.

Morphology:
How words are built. Studies on new words creation: people are very creative!

Syntax:
How sentences are built. A infinite number of sentences!



Semantics:
Literal meaning of the words and utterances. What do you mean?

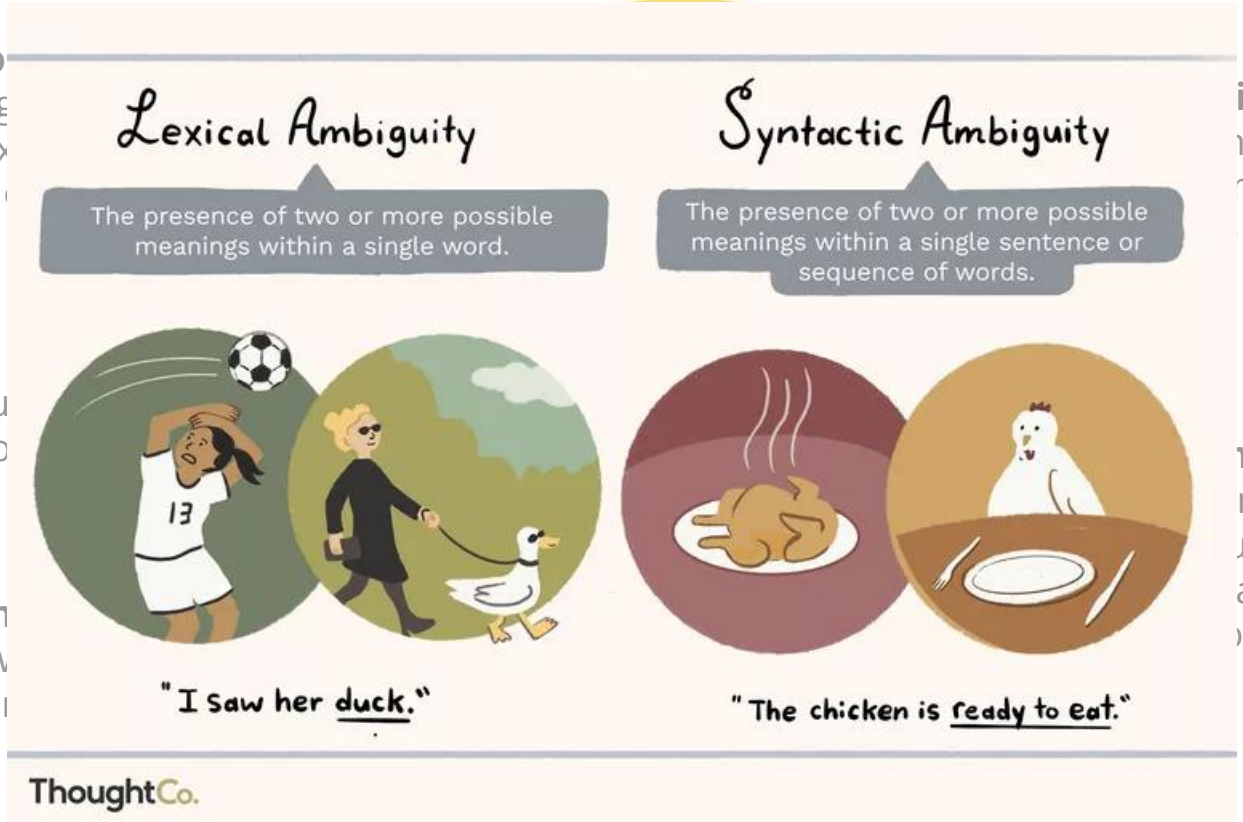
Pragmatics:
Meaning in context. What do you really mean? How can we understand each other?

Main levels of linguistics structure

Phonetics-Phono
Speech processing
NLP = focus on tex
researchers work
from speech.

Morphology:
How words are bu
new words creatio
very creative!

Syn
How
infi



ics:
eaning of the
nd utterances.
you mean?

atics:
ng in context. What
u really mean?
an we understand
other?

Fundamentals of NLP

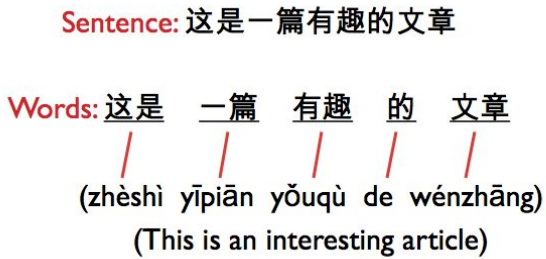
ANITI
ARTIFICIAL & NATURAL INTELLIGENCE
TOULOUSE INSTITUTE

Pre-processing

Basic operations / pre-processing needed for almost any applications:

- tokenisation
- sentence segmentation
- normalization:
  - lower-casing
  - lemmatization, stemming
  - removing stop-words

Words / Tokens



Text = sequences of characters, spaces, punctuation encoded the same way

→ We need to find the words boundaries = **tokenization**

→ Crucial: words are meaningful units, minimal input to NLP systems

What is a word? = sequence of characters separated with a blank (space, line) or punctuation?

- apostroph: ***I don't know*** = 3 or 4 words?
- Multiword expressions: ***in spite of; fleur bleue; perdre la tête*** = how many words?
- Proper nouns: ***San Francisco, Tour Eiffel***
- Other languages:
  - German: ***rindfleischetikettierungsüberwachungsaufgabenübertragungsgesetz*** = "the law for the delegation of monitoring beef labeling."
  - no word boundaries explicitly marked for some languages (= word segmentation)

Sentences

Text = sequences of characters, spaces, punctuation encoded the same way

→ We need to find the sentence boundaries = **sentence segmentation**

→ Crucial: Sentences are the input of many systems; Syntactic analysis is based on sentences

- **'.'** is very ambiguous, a period may denote:
  - an abbreviation (47% of the periods in the Wall Street Journal),
  - decimal point,
  - an ellipsis,
  - an email address
- **?** and **!** are less ambiguous (in English), but they may appear in embedded quotations, emoticons, computer code, and slang

In Oct. 2013, M. Obama will visit Paris. He will meet ministers, deputies, parliamentarians etc. to discuss.

→ Context is crucial to find sentence boundaries

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Sentences

Text = sequences of characters, spaces, punctuation encoded the same way

→ We need to find the sentence boundaries = **sentence segmentation**

→ Crucial: Sentences are the input of many systems; Syntactic analysis is based on sentences

- **'.'** is very ambiguous, a period may denote:
  - an abbreviation (47% of the periods in the Wall Street Journal),
  - decimal point,
  - an ellipsis,
  - an email address
- **?** and **!** are less ambiguous (in English), but they may appear in embedded quotations, emoticons, computer code, and slang

*In **Oct.** 2013, **M.** Obama will visit Paris. He will meet ministers, deputies, parliamentarians **etc.** to discuss.*

→ Context is crucial to find sentence boundaries

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Normalization

Often, we do some normalization on words, to improve generalization:

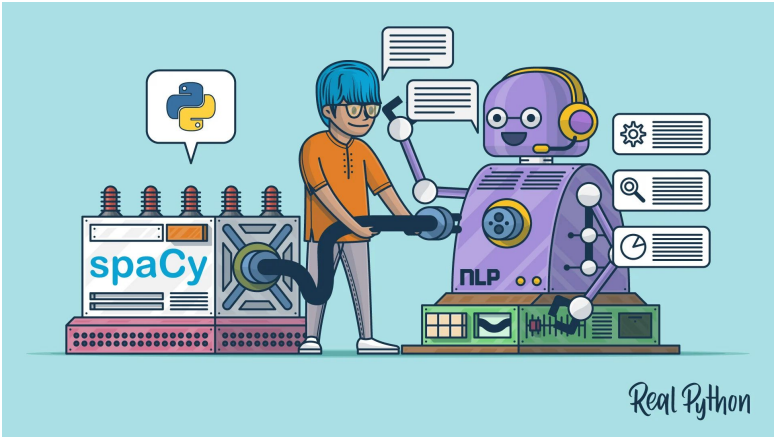
- lower-casing: **“The” → “the”**
- **lemmatization** = reduce to “base form”, remove inflectional endings
  - i.e. “managed” → “manage”, “is/was/were/being” → “be”
  - introduce ambiguity: “changed” → “change” = Verb or Noun
  - no clear base form for some words
    - e.g. pronouns: in Spacy “I” → “PRON”
- removing **stop-words** = very frequent, less meaningful words e.g. **“i, me, the, to, when, …”**

Many lists, see e.g. list in NLTK: https://www.nltk.org/book/ch02.html

Linguistic Analysis

Additional processing that can provide rich information:

- Part-of-Speech (POS) tagging
- Word sense disambiguation
- Named Entity recognition
- Syntactic parsing
- Discourse parsing



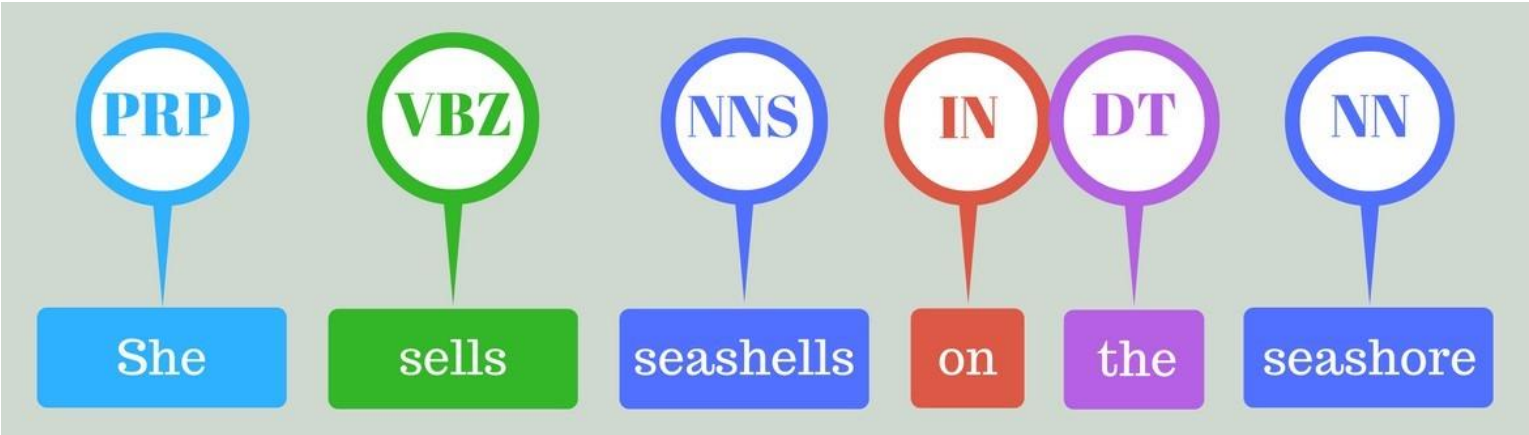
→ statistical models

→ Varied performance, can be very hard especially for high-level tasks (i.e. semantics) and low-resources languages / domains.

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

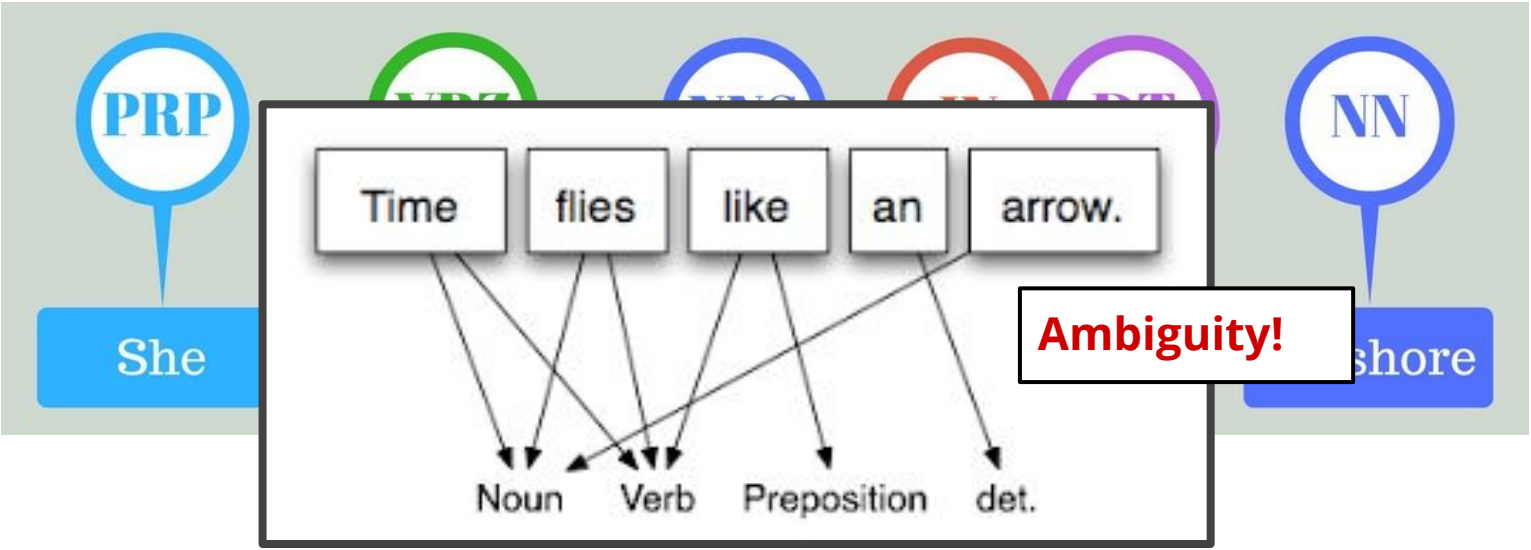
Part-Of-Speech Tagging

= Associating a morpho-syntactic category to each word
→ Noun, Verb, Pronoun, Adjective, Adverb ...



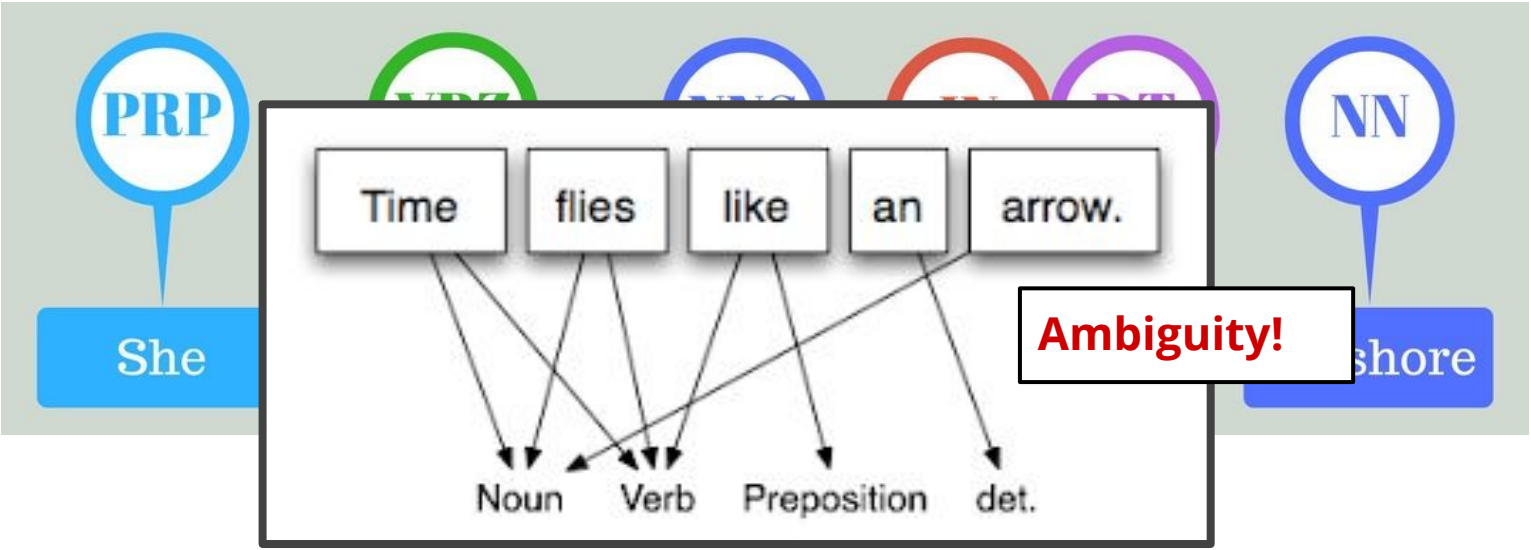
Part-Of-Speech Tagging

= Associating a morpho-syntactic category to each word
→ Noun, Verb, Pronoun, Adjective, Adverb …



Part-Of-Speech Tagging

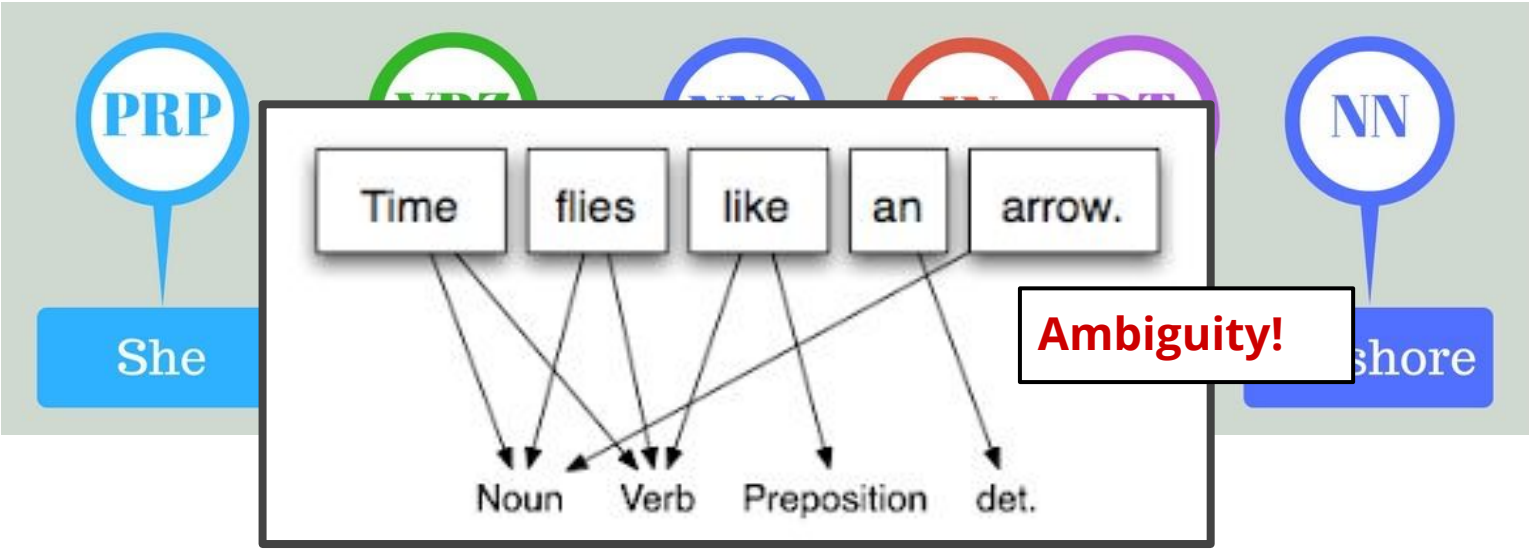
= Associating a morpho-syntactic category to each word
→ Noun, Verb, Pronoun, Adjective, Adverb ...



- useful for syntactic parsing, disambiguation, and many applications
- state-of-the-art: English ≃ 97%

Part-Of-Speech Tagging

= Associating a morpho-syntactic category to each word
→ Noun, Verb, Pronoun, Adjective, Adverb ...



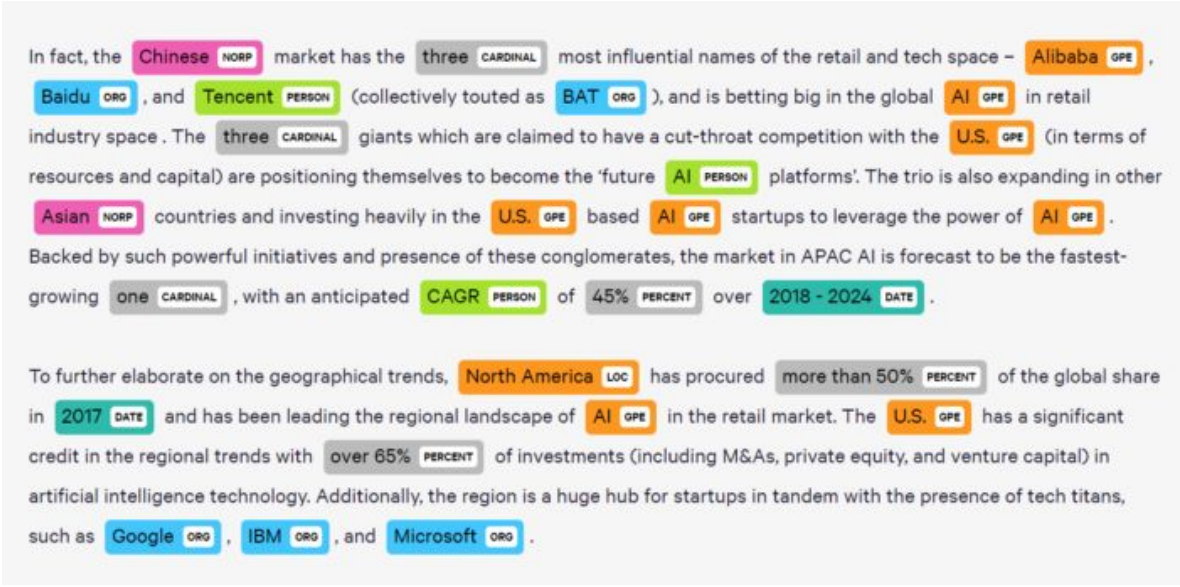
- useful for syntactic parsing, disambiguation, and many applications
- state-of-the-art: English ≃ 97%

Track progress in NLP:
https://github.com/sebastianruder/NLP-progress

Named Entity Recognition (NER)

= Identifying Named Entities, Typing them

- Types: person names, organizations, locations, medical codes, time expressions, quantities, monetary values, percentages
- State-of-the-art: English ≃ 50-94% (depending on the difficulty of the task)



Syntactic analysis

= Grouping words into phrases, and phrases into sentences

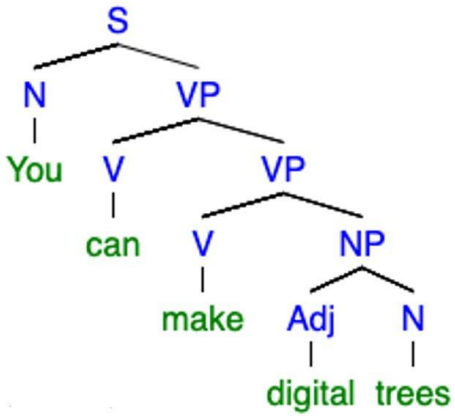
- *You can make **(constituent trees) / (beautiful drawings)**.* → Noun Phrase
- *You can **(make something) / (fly)**.* → Verb Phrase
- You make **(very interesting and well designed)** / **(boring)** presentations → Adjective Phrase

→ Hierarchical organization

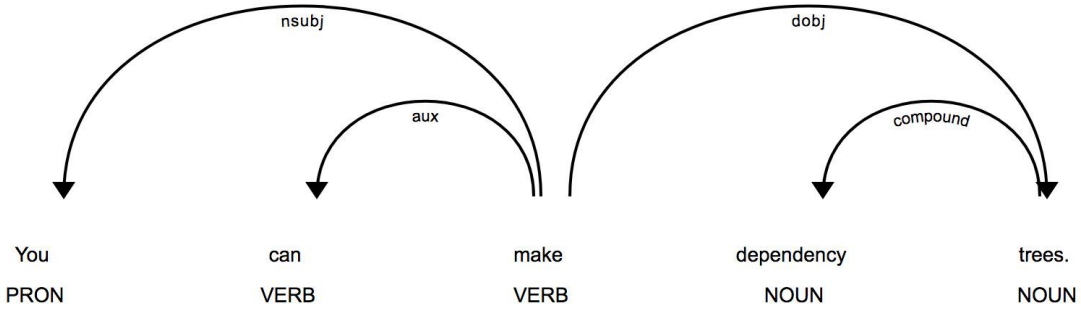
ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Syntactic analysis

Two main paradigms: constituency and dependency



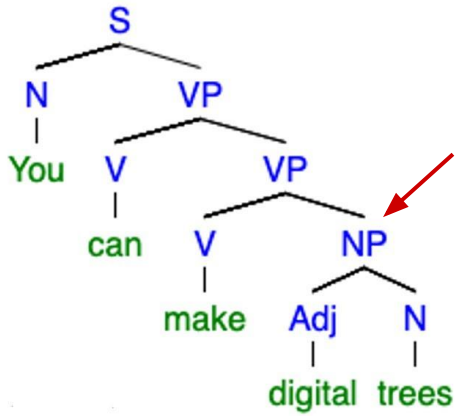
Constituency trees



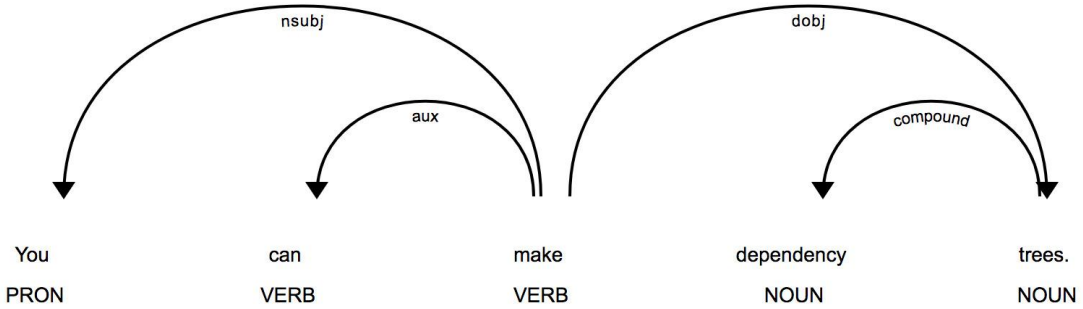
Dependency trees

Syntactic analysis

Two main paradigms: constituency and dependency



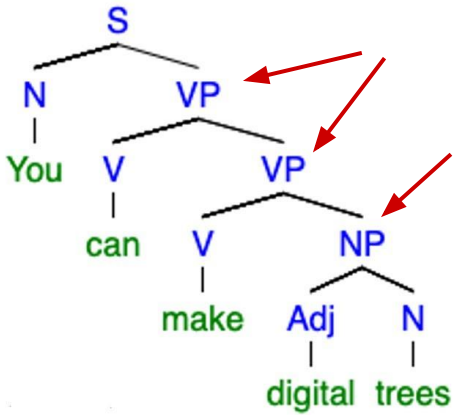
Constituency trees



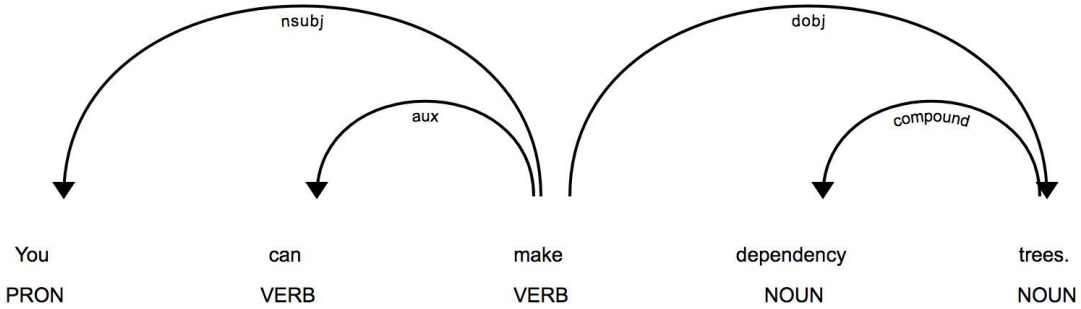
Dependency trees

Syntactic analysis

Two main paradigms: constituency and dependency



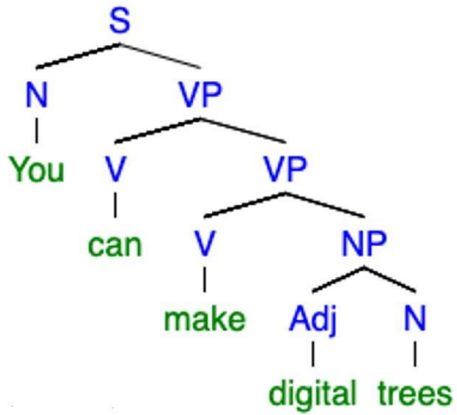
Constituency trees



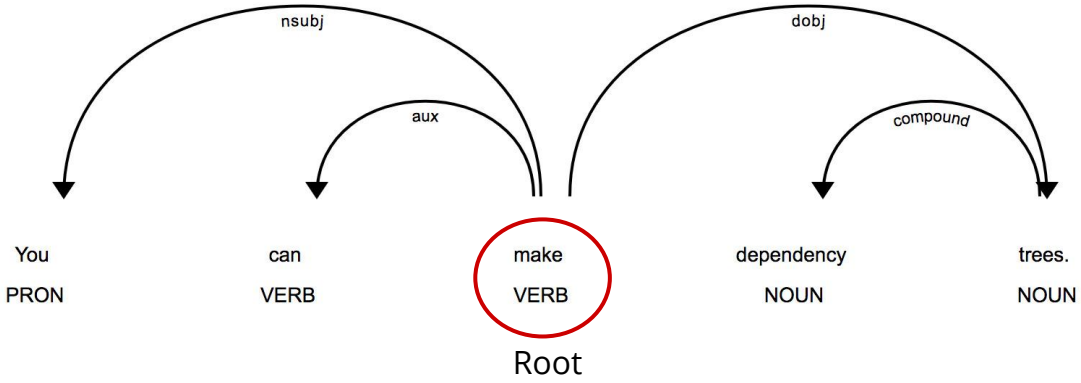
Dependency trees

Syntactic analysis

Two main paradigms: constituency and dependency



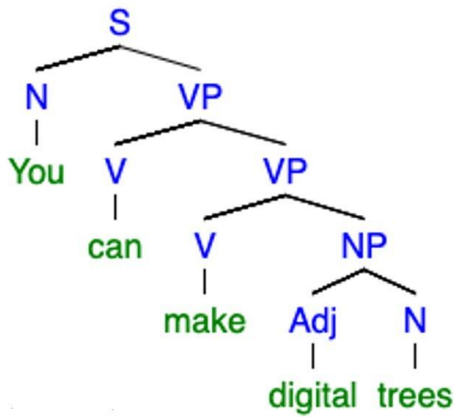
Constituency trees



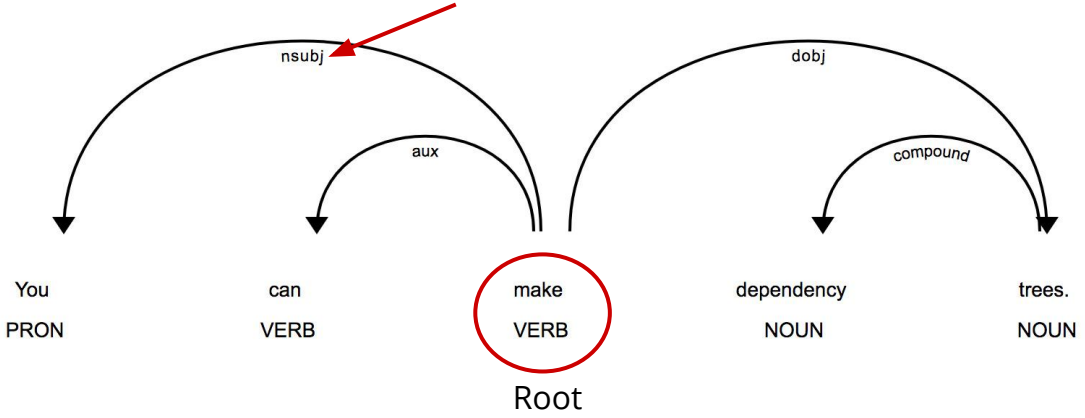
Dependency trees

Syntactic analysis

Two main paradigms: constituency and dependency



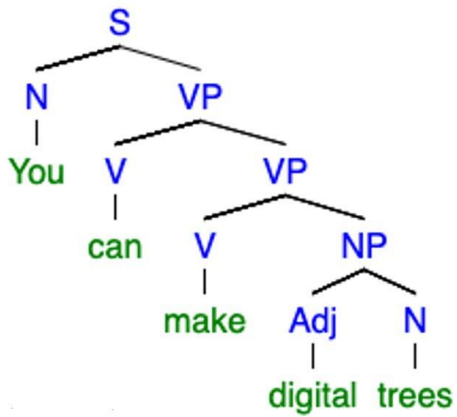
Constituency trees



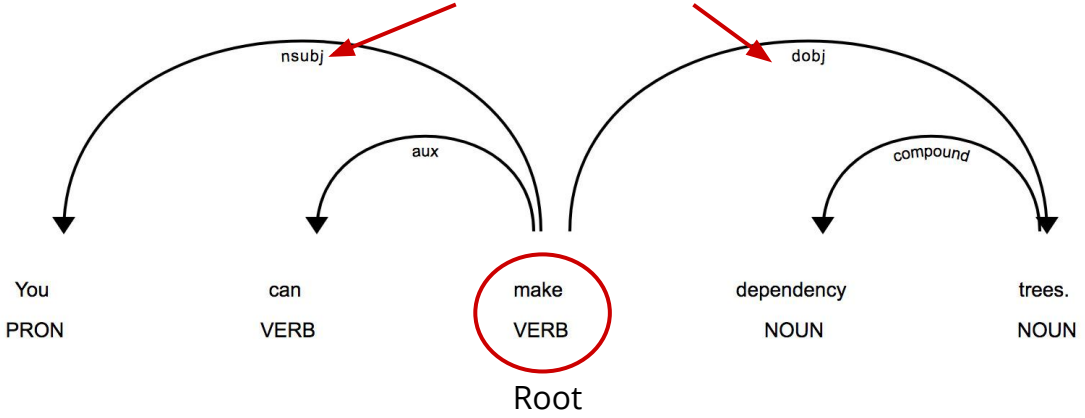
Dependency trees

Syntactic analysis

Two main paradigms: constituency and dependency

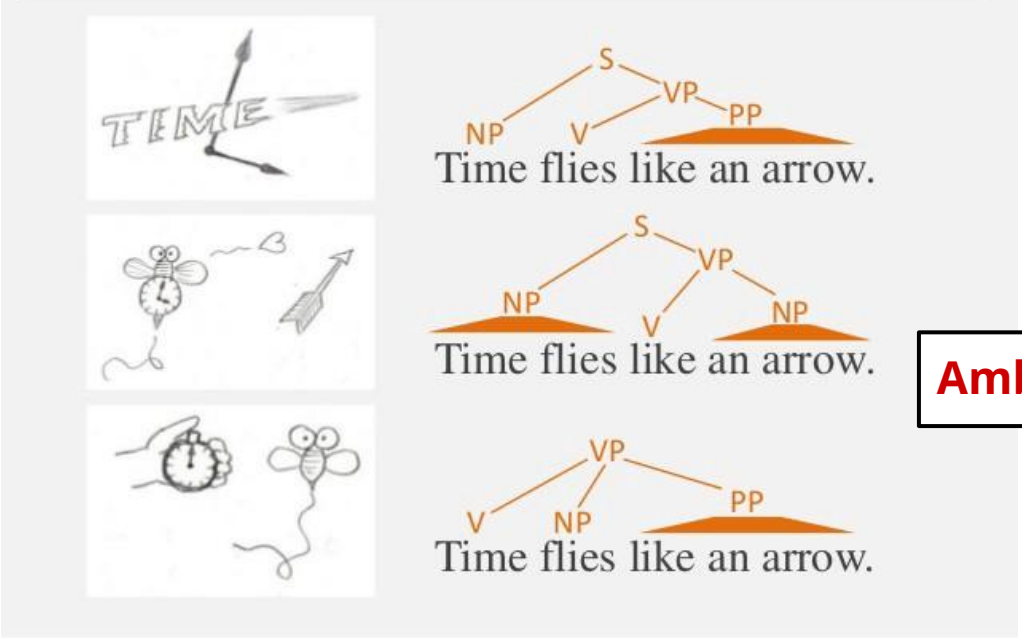


Constituency trees



Dependency trees

Syntactic analysis



Ambiguity!

State-of-the-art system for English Constituency ≃ 96% ; Dependency ≃ 97%

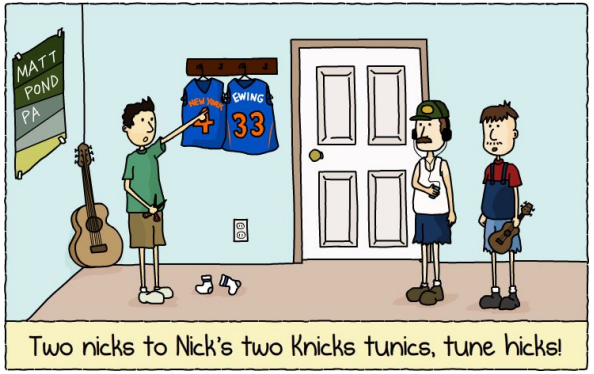
Semantics: Words

Words disambiguation: homophones and homonyms

- Homophones: mostly a problem for speech processing

- Homonyms:
  - makes syntactic analysis harder: Noun or Verb?
  - makes semantic analysis harder: what sense?

- State-of-the-art: English ≃ 73-80% depending on granularity



Semantico-pragmatics: Discourse

Going beyond sentence boundaries

= connecting spans of text into a coherent, meaningful document

= understanding interaction in conversations

- coreference and anaphora
- temporal links
- topics
- discourse / rhetorical relations

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Semantico-pragmatics: Discourse

Going beyond sentence boundaries

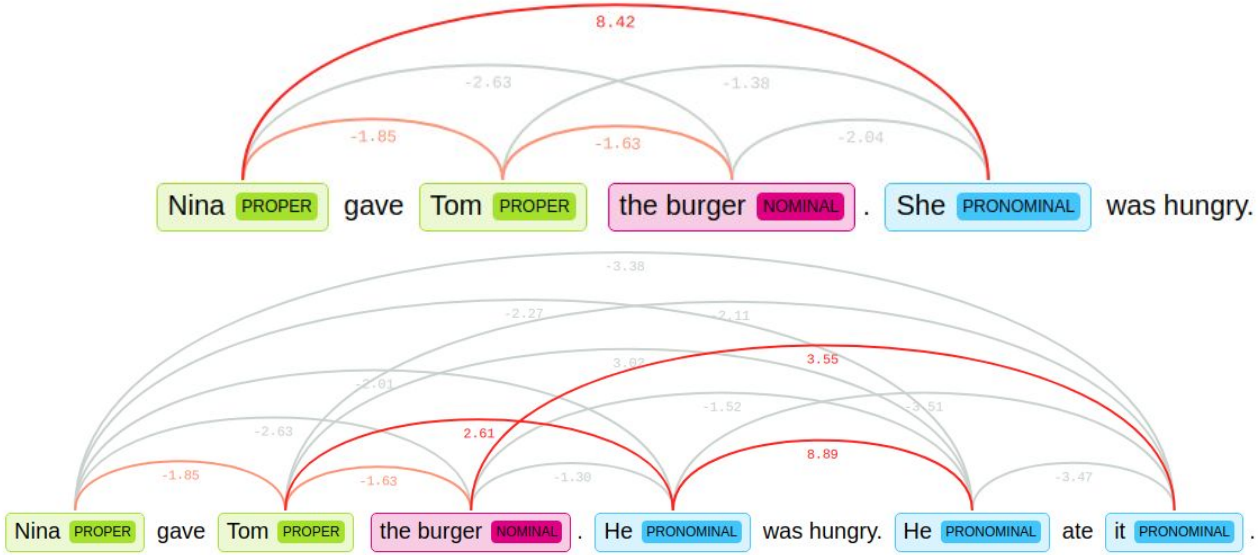
= connecting spans of text into a coherent, meaningful document

= understanding interactions in conversations

- **coreference and anaphora**
- temporal links
- topics
- **discourse / rhetorical relations**

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Coreference



Finding expressions / entities (person, animals, things...) that are linked together:

- nouns to other nouns
- nouns to pronouns
- pronouns to other pronouns

State-of-the-art: English ≃ 80%

Examples from Neuralcoref (by HuggingFace), try it: https://huggingface.co/coref/

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

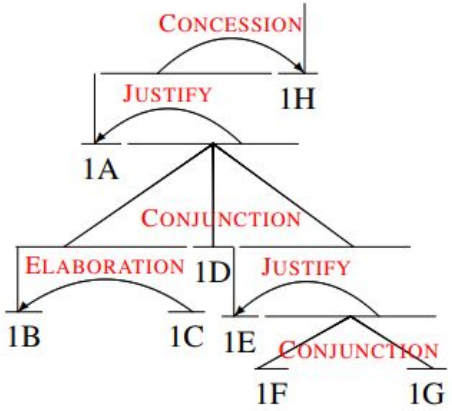
Discourse parsing

= Linking sentences or clauses with semantico-pragmatic relations such as ***Explanation, Result, Contrast…***

- (1) The train derailed. (Result) There were four wounded people. (Explanation) The driver was going too fast.

→ Could help a QA system to answer complex questions:

e.g., why did the train derailed?



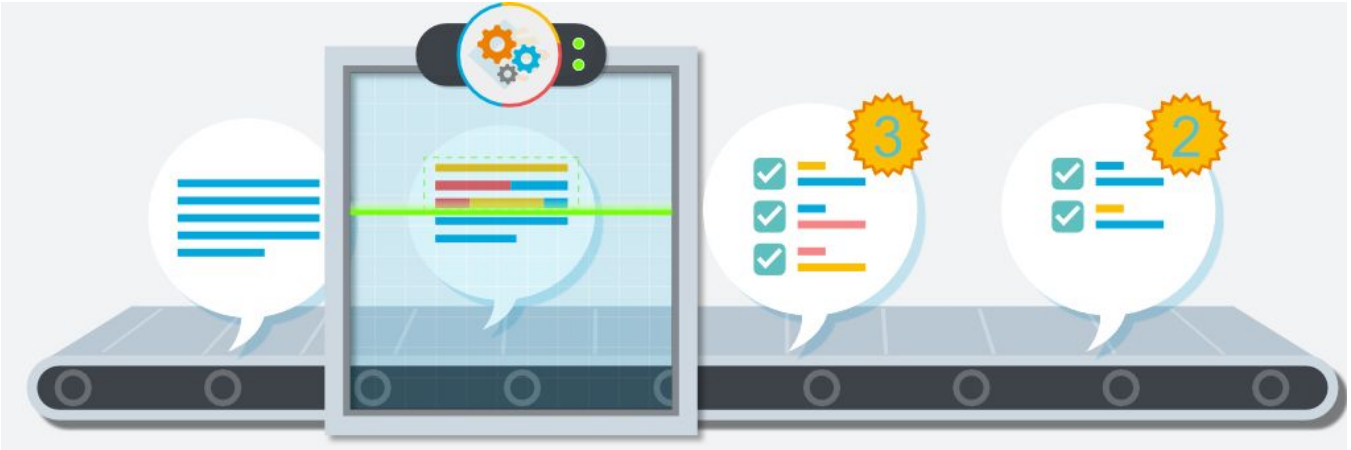
[It could have been a great movie]^{1A} [It does have beautiful scenery,]^{1B} [some of the best since Lord of the Rings.]^{1C} [The acting is well done,]^{1D} [and I really liked the son of the leader of the Samurai.]^{1E} [He was a likable chap,]^{1F} [and I hated to see him die.]^{1G} [But, other than all that, this movie is nothing more than hidden rip-offs.]^{1H}

[Bahtia et al., 2015]

Very hard task: State-of-the-art: English ≃ 57.4%

- (2) Tina gave Tom the burger. (because / Explanation) **He** was hungry.
- (3) Tina gave Tom the burger. (although / Contrast) **She** was hungry.

Hands-on NLP



ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Finding data

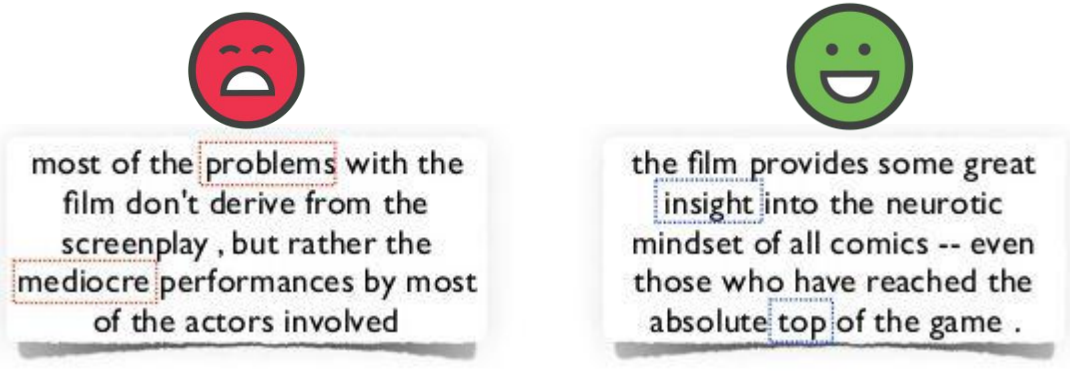
Many datasets available:

- NLTK datasets and lexical resources: https://www.nltk.org/book/ch02.html
- Scikit-learn datasets: https://scikit-learn.org/stable/datasets.html
- Kaggle: https://www.kaggle.com/datasets?tags=13204-NLP
- LDC (charged): https://www.ldc.upenn.edu/
- A list here: https://github.com/niderhoff/nlp-datasets
- Research teams websites
  - https://nlp.stanford.edu/links/statnlp.html#Corpora
  - http://www.llf.cnrs.fr/en/resources

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

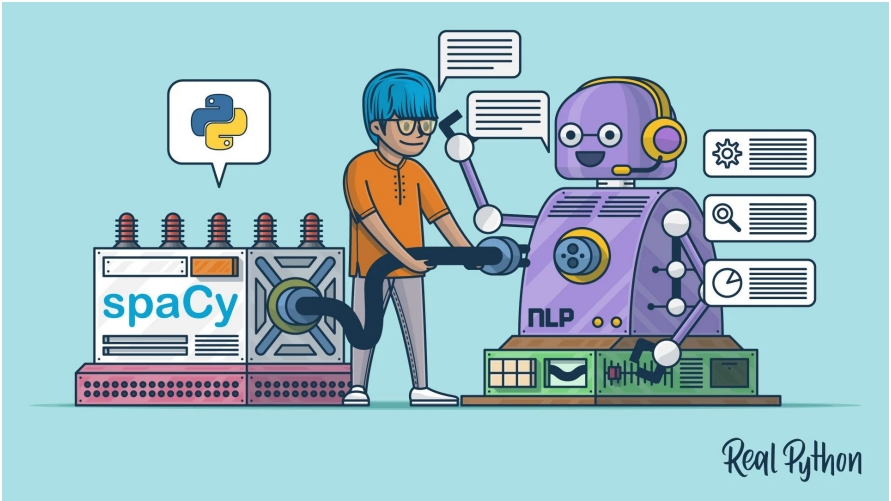
Example: Sentiment analysis with movies reviews

- Reviews are texts of varied size
- Written by anyone
- Describing a sentiment about something (here movies)
- The task: classify each review as positive or negative
  - sometimes, a neutral category is added
  - more fine-grained: retrieve the number of stars / likes



Preprocessing with NLTK or Spacy

https://www.nltk.org/



https://spacy.io/

Example: Tokenisation and sentence segmentation using Spacy

```
[14] import spacy
     nlp = spacy.load('en_core_web_sm')

     # Tokenization
     sentence = 'Nina gave Tom the burger.'

     # Preprocess using spacy's pipeline
     doc = nlp(sentence)

     for token in doc:
       print( token.text )
```

```
Nina
gave
Tom
the
burger
.
```

```
# Sentence segmentation
text = 'Nina gave Tom the burger. He was hungry. She ate it.'

# Preprocess using spacy's pipeline
doc = nlp(text)

# Print the sentences
for i, sent in enumerate( doc.sents ):
  print( i, sent.text.strip() )
```

```
0 Nina gave Tom the burger.
1 He was hungry.
2 She ate it.
```

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Example: Part-Of-Speech Tagging with NLTK or Spacy

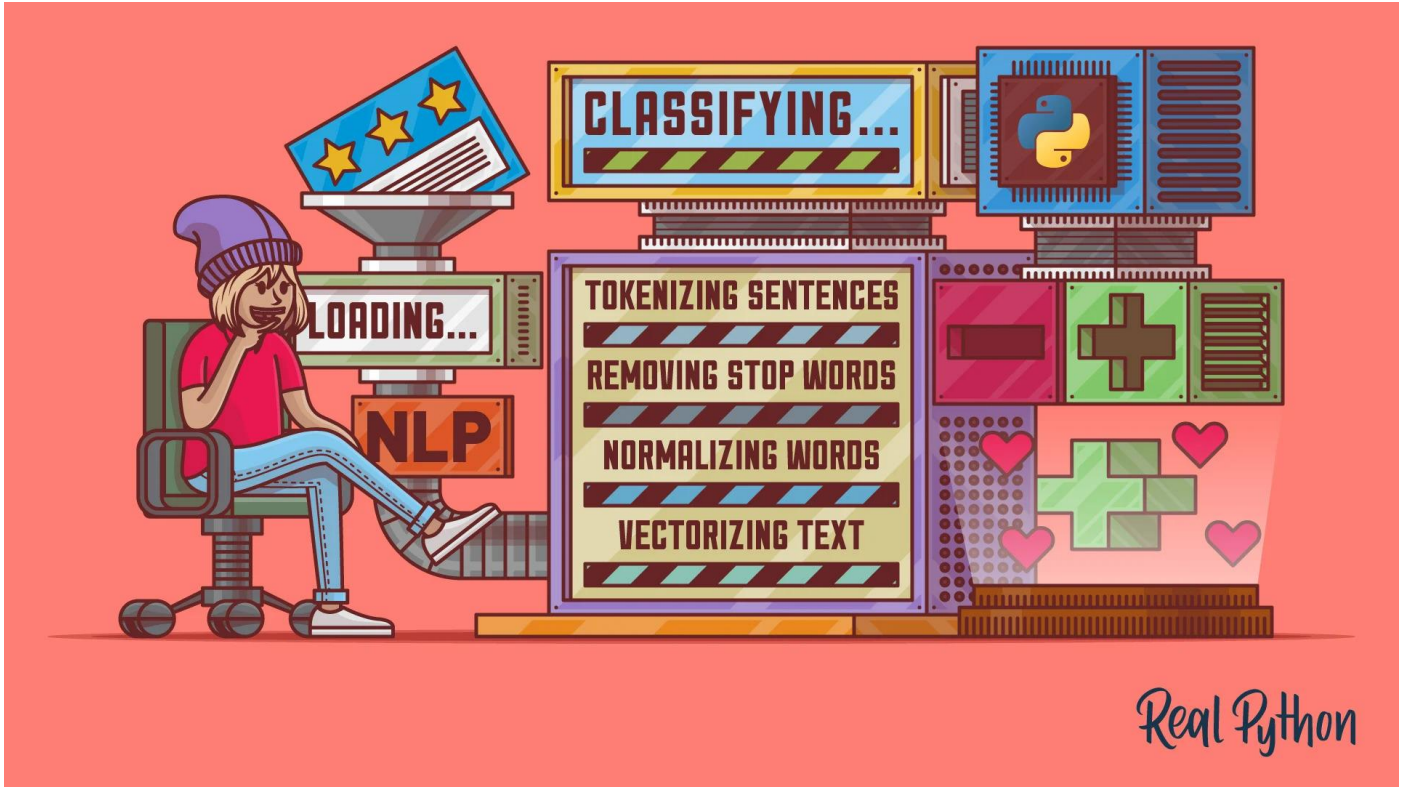
```
[15] sentence = "Time flies like an arrow."
     tokens = nltk.word_tokenize(sentence)
     tagged_tokens = nltk.pos_tag(tokens) # POS tagging
     print(tagged_tokens)

     [('Time', 'NNP'), ('flies', 'NNS'), ('like', 'IN'), ('an', 'DT'), ('arrow', 'NN'), ('.', '.')]
```

```
[16] import spacy
     import pandas as pd
     nlp = spacy.load('en')

     sentence = "Time flies like an arrow."
     nlp_sentence = nlp(sentence)
     spacy_pos_tagged = [(w, w.tag_, w.pos_) for w in nlp_sentence]
     print(spacy_pos_tagged )

     pd.DataFrame(spacy_pos_tagged,
                  columns=['Word', 'POS tag', 'Tag type'])

     [(Time, 'NNP', 'PROPN'), (flies, 'VBZ', 'VERB'), (like, 'IN', 'SCONJ'), (an, 'DT', 'DET'), (arrow, 'NN', 'NOUN'), (., '.', 'PUNCT')]
```

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Try more during the practical session

Playing with data: let's learn something



Learning regularities from textual data

NLP systems are based on:

- 1980's Early approach: Symbolic methods = hand-written rules
  - ex: tokenizer based on regular expressions
  - advantages: based on linguistics expertise, very precise
  - inconvenients: lack of coverage, time consuming
- 1990's Statistical approaches: machine learning algorithms
  - learn rules automatically = (mostly) linear functions
  - rather fast to train, still good baselines
- ≃ 2010 Neural methods
  - combine linear and non-linear functions
  - improved performance (in general)
  - harder to interpret ("black-box")

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Learning regularities from textual data

NLP systems are based on:

- 1980's Early approach: **Symbolic methods** = handwritten rules
  - ex: tokenizer based on regular expressions
  - advantages: based on linguistics expertise, very precise
  - inconvenients: lack of coverage, time consuming
- 1990's Statistical approaches: machine learning algorithms
  - learn rules automatically = (mostly) linear functions
  - rather fast to train, still good baselines
- ≃ 2010 Neural methods
  - combine linear and non-linear functions
  - improved performance (in general)
  - harder to interpret ("black-box")

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Learning regularities from textual data

NLP systems are based on:

- 1980's Early approach: Symbolic methods = handwritten rules
  - ex: tokenizer based on regular expressions
  - advantages: based on linguistics expertise, very precise
  - inconvenients: lack of coverage, time consuming
- 1990's Statistical approaches: **machine learning** algorithms
  - learn rules automatically = (mostly) linear functions
  - rather fast to train, still good baselines
- ≃ 2010 Neural methods
  - combine linear and non-linear functions
  - improved performance (in general)
  - harder to interpret ("black-box")

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Learning regularities from textual data

NLP systems are based on:

- 1980's Early approach: Symbolic methods = handwritten rules
  - ex: tokenizer based on regular expressions
  - advantages: based on linguistics expertise, very precise
  - inconvenients: lack of coverage, time consuming
- 1990's Statistical approaches: machine learning algorithms
  - learn rules automatically = (mostly) linear functions
  - rather fast to train, still good baselines
- ≃ 2010 **Neural methods**
  - combine linear and non-linear functions
  - improved performance (in general)
  - harder to interpret ("black-box")

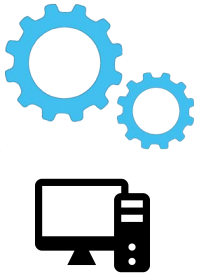
ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Learning from data (reminder, supervised setting)

Input Data / Training set

Data points x	Labels y
	Cat
	Sandwich

Training



building some function f(x) = y

Test set

Use f to predict a label

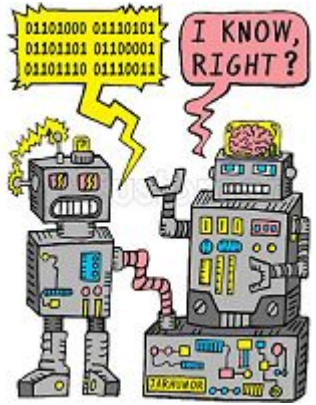
Compute score

CAT ?

20/20

Très bien !

Learning from text data



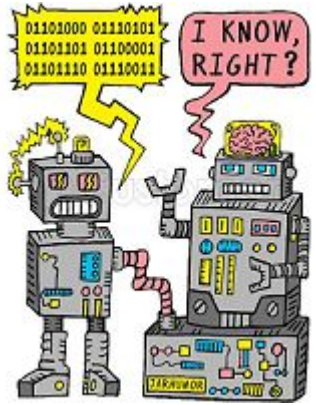
Main issue:

- how to represent text?

e.g. how to transform a sentence into a vector of numerical values?

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Learning from text data



Main issue:

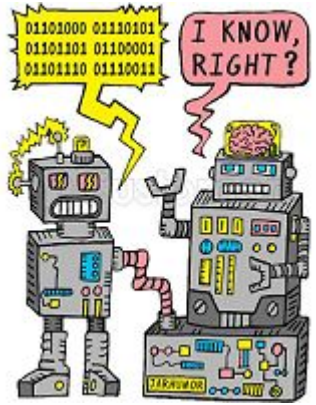
- how to represent text?

e.g. how to transform a sentence into a vector of numerical values?

Bag-of-Words (BOW):

- one vector where each dimension is a word / feature in our vocabulary
- if the word / feature is present in the document, associate a specific value

Learning from text data



Main issue:

- how to represent text?

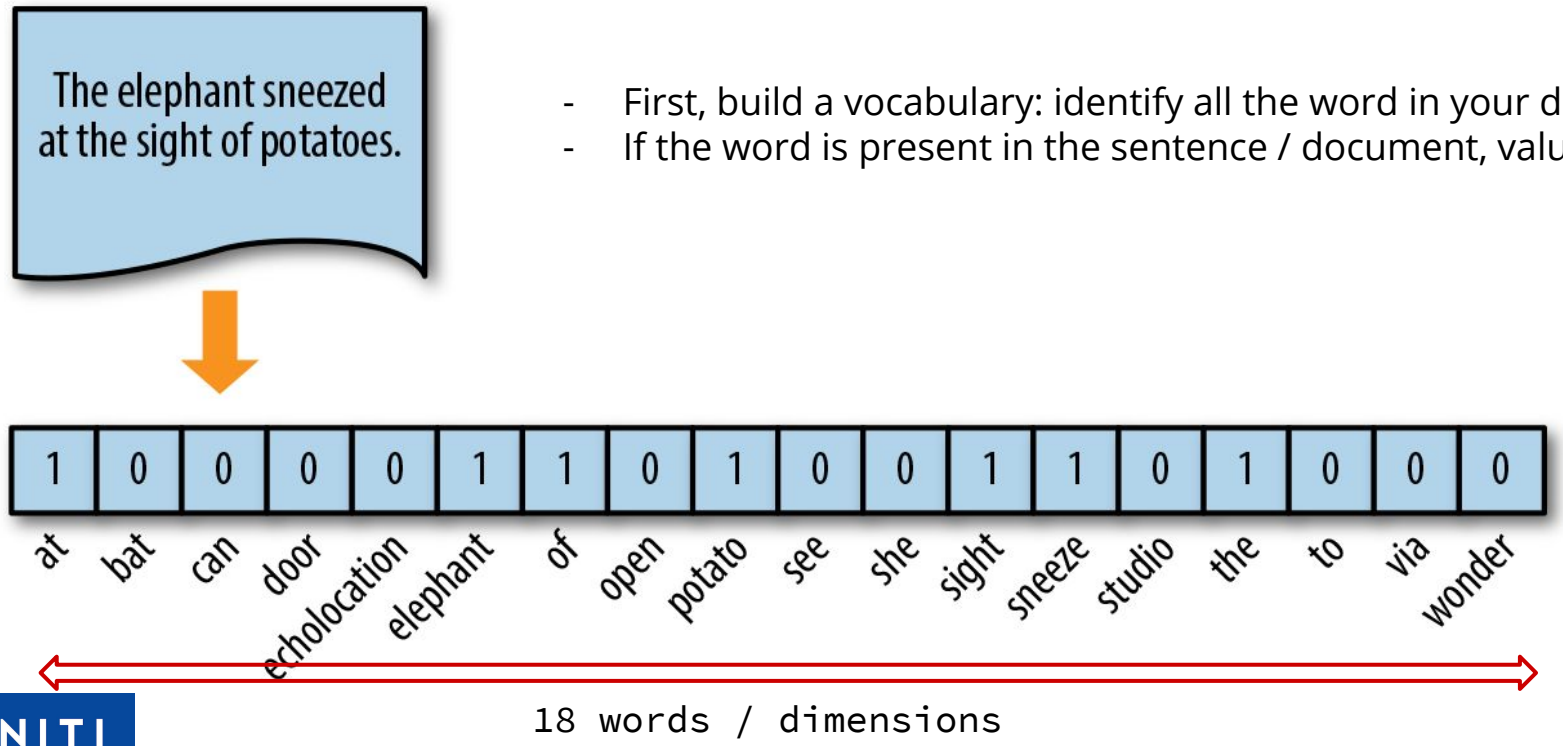
e.g. how to transform a sentence into a vector of numerical values?

Bag-of-Words (BOW):

- one vector where **each dimension is a word / feature in our vocabulary**
- if the word / feature is present in the document, associate a specific value

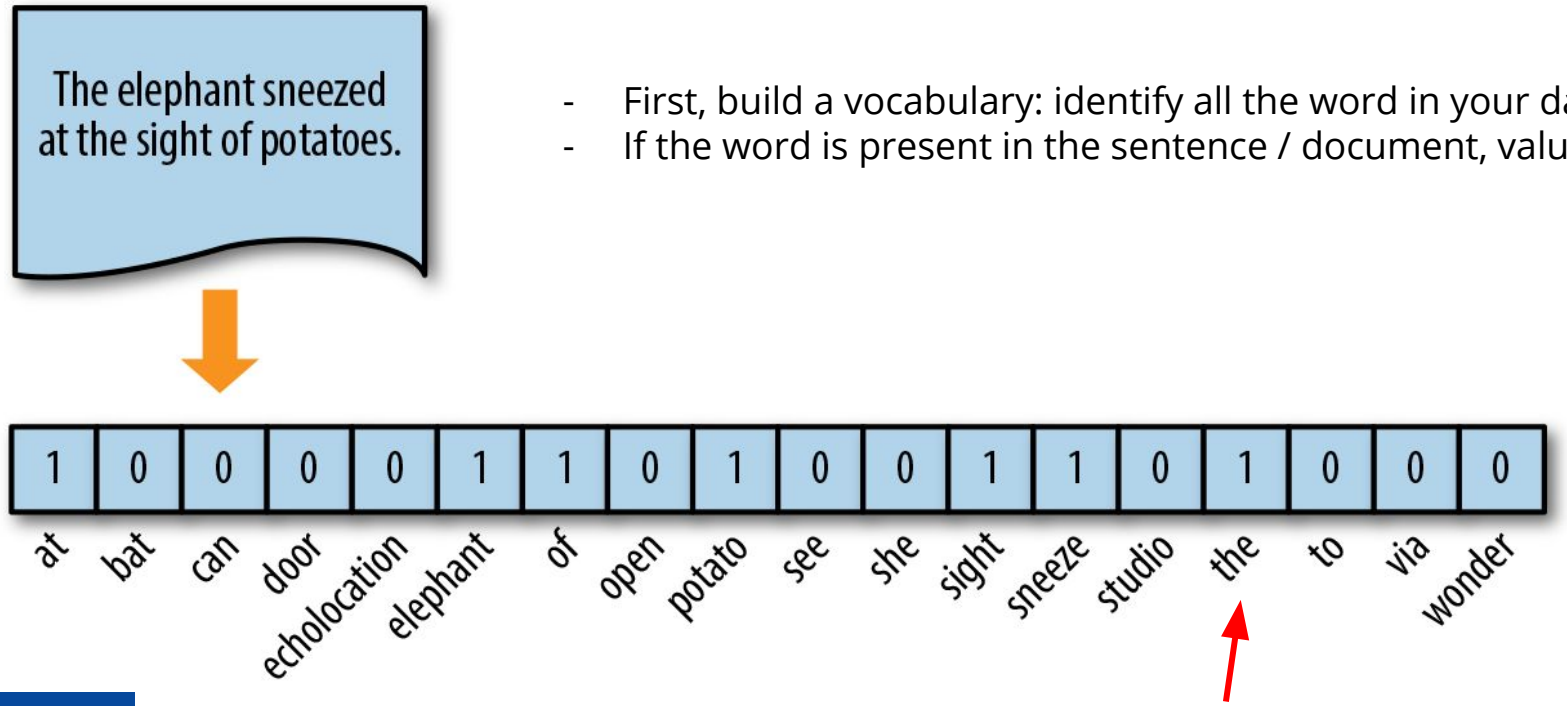
ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

BOW: One-hot encoding



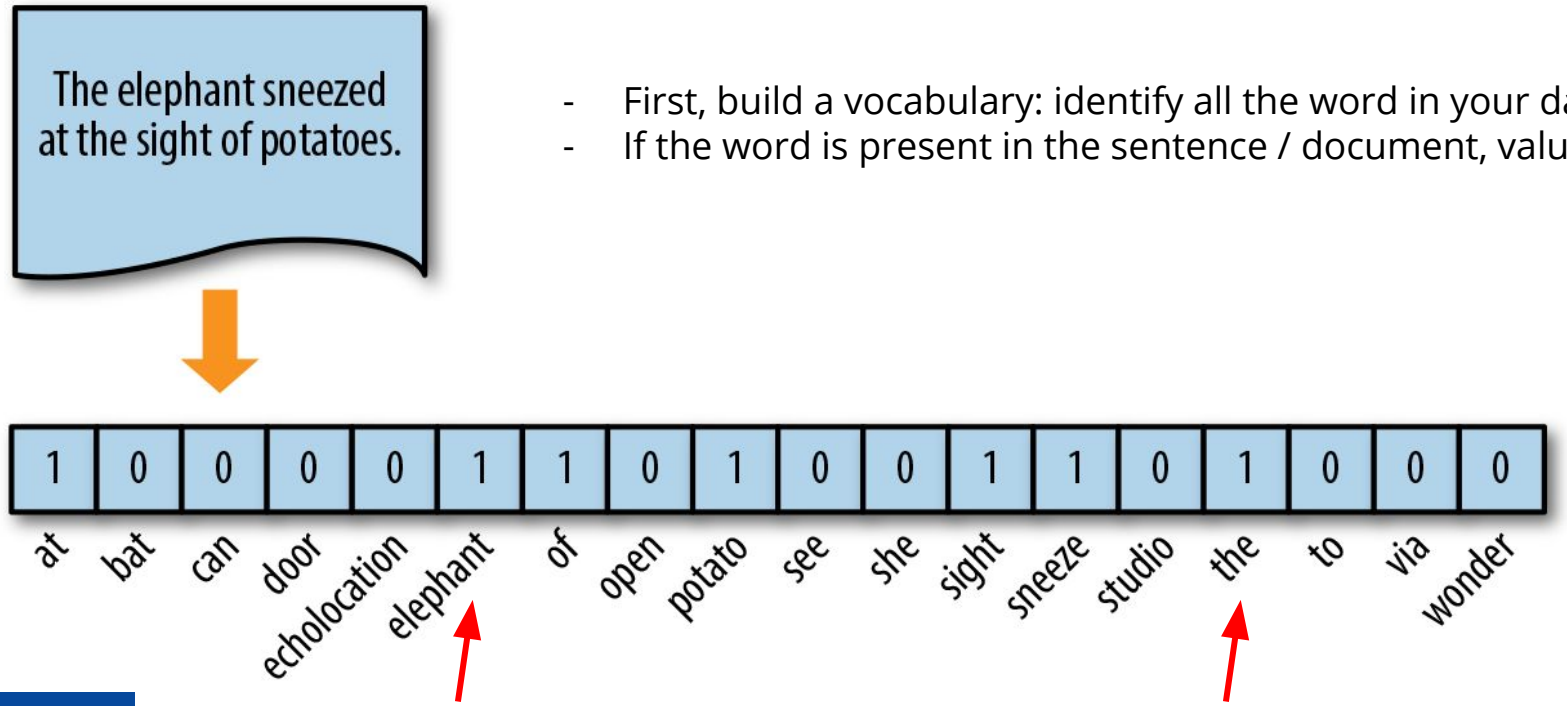
- First, build a vocabulary: identify all the word in your data
- If the word is present in the sentence / document, value = 1

BOW: One-hot encoding



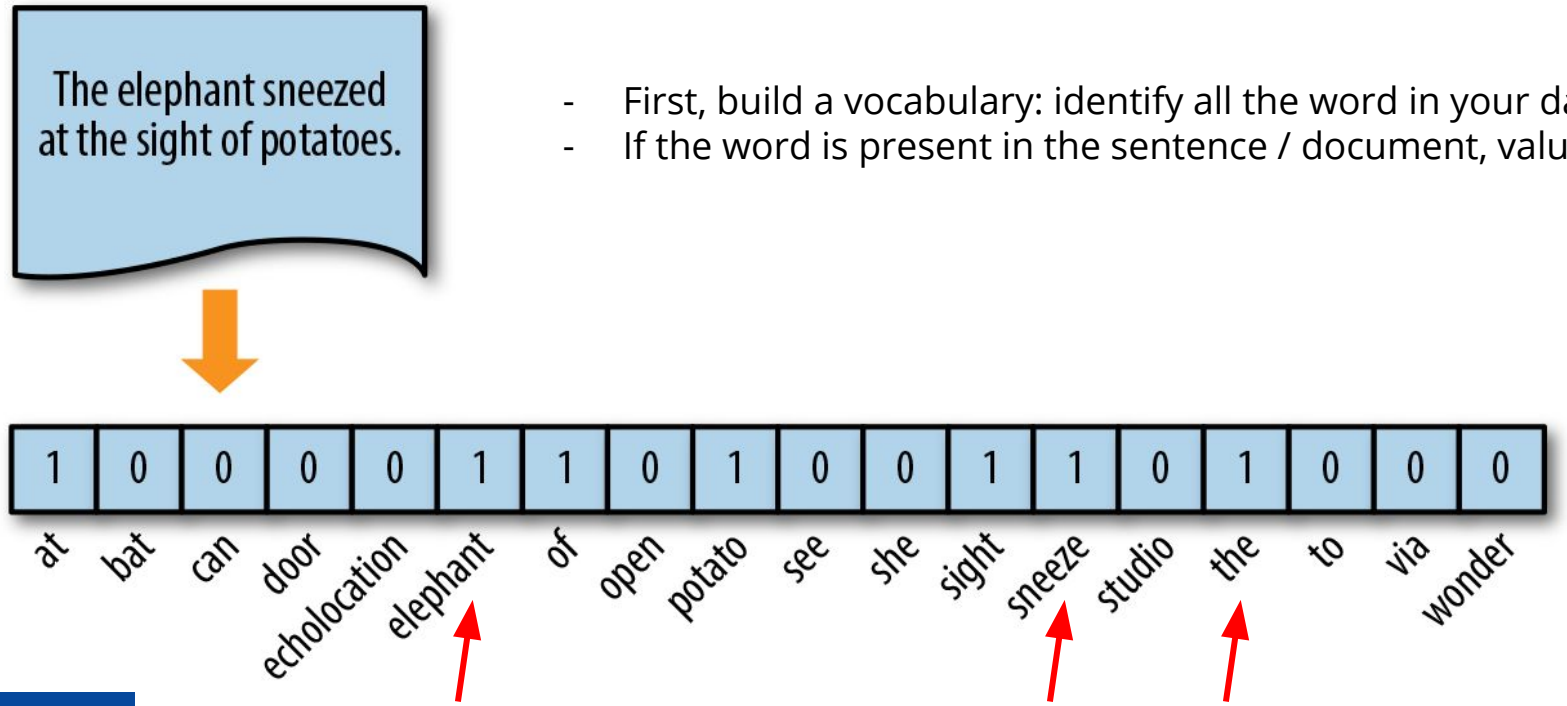
- First, build a vocabulary: identify all the word in your data
- If the word is present in the sentence / document, value = 1

BOW: One-hot encoding



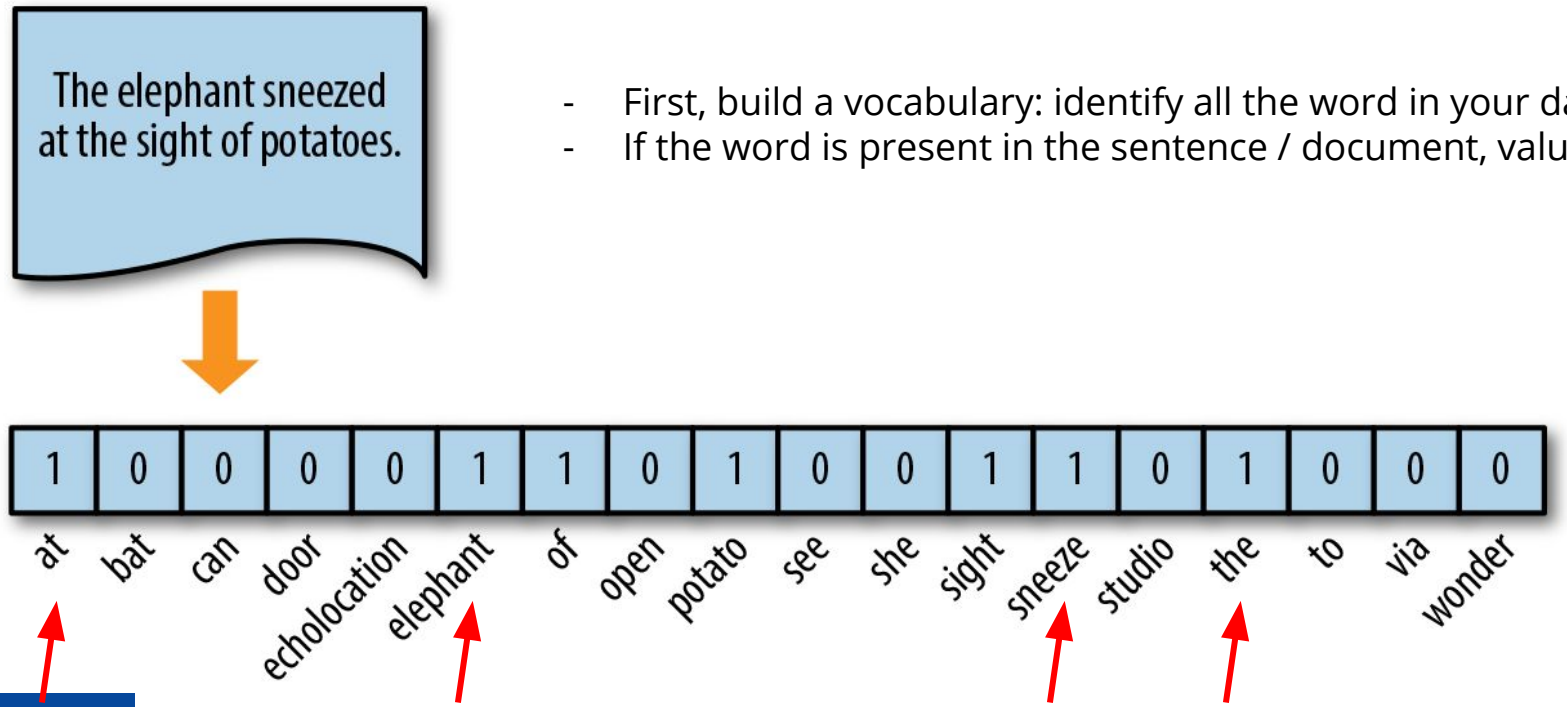
- First, build a vocabulary: identify all the word in your data
- If the word is present in the sentence / document, value = 1

BOW: One-hot encoding



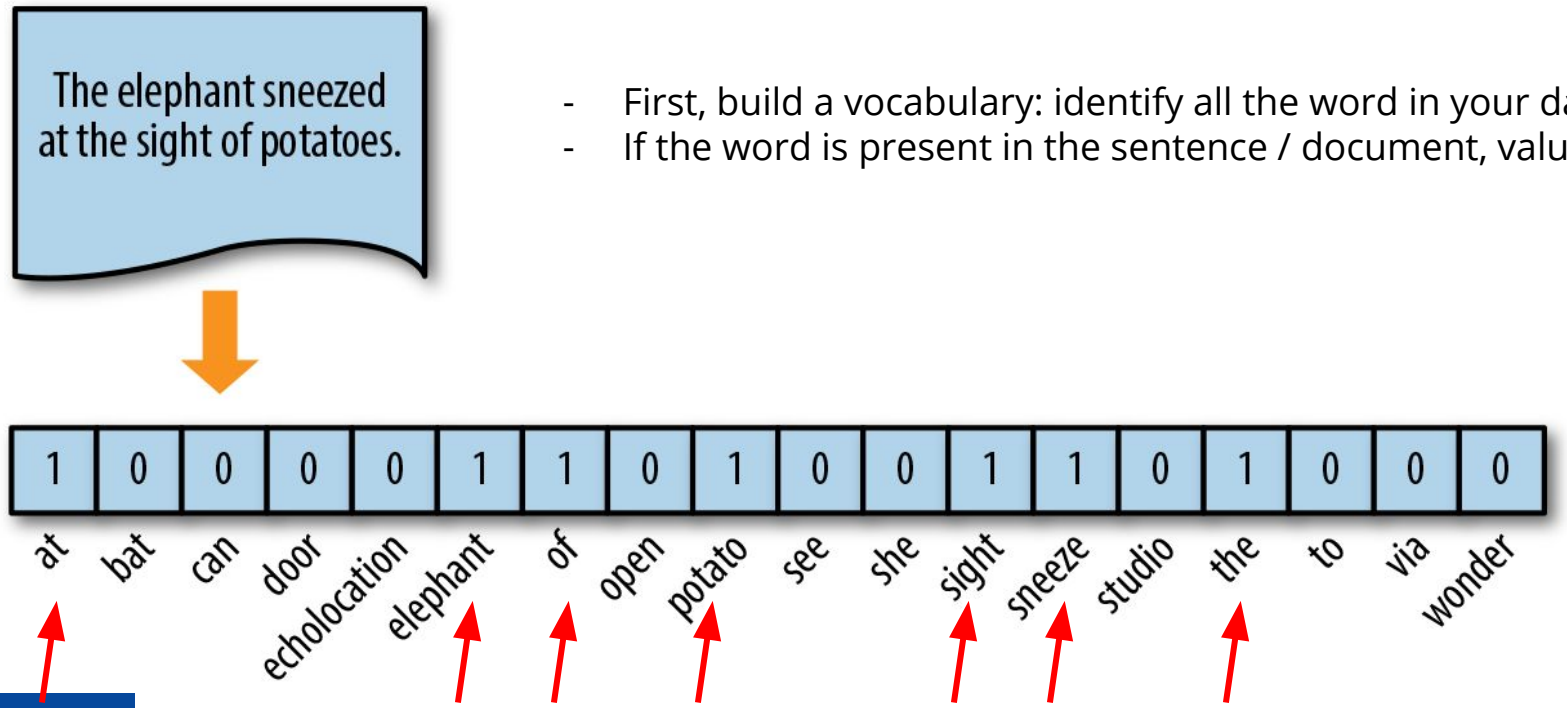
- First, build a vocabulary: identify all the word in your data
- If the word is present in the sentence / document, value = 1

BOW: One-hot encoding



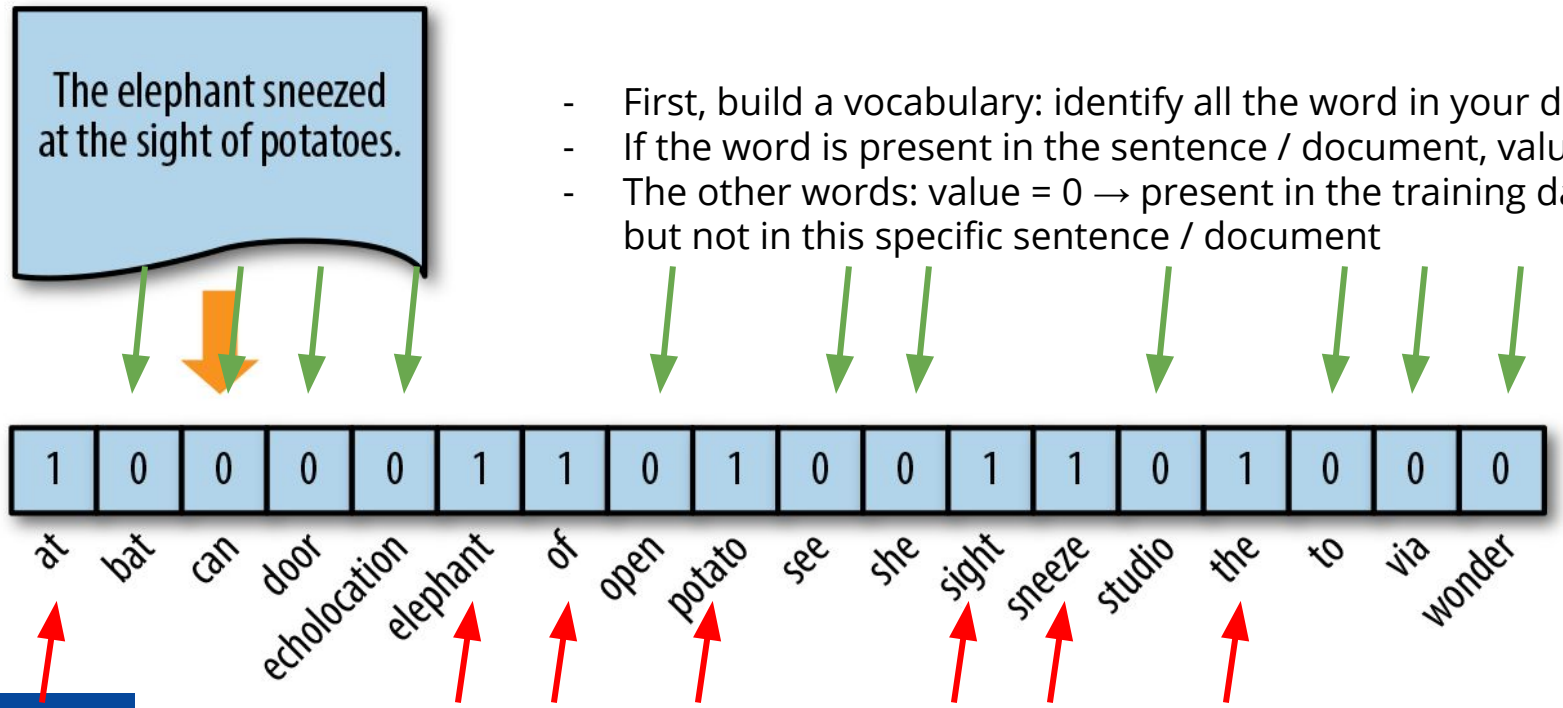
- First, build a vocabulary: identify all the word in your data
- If the word is present in the sentence / document, value = 1

BOW: One-hot encoding



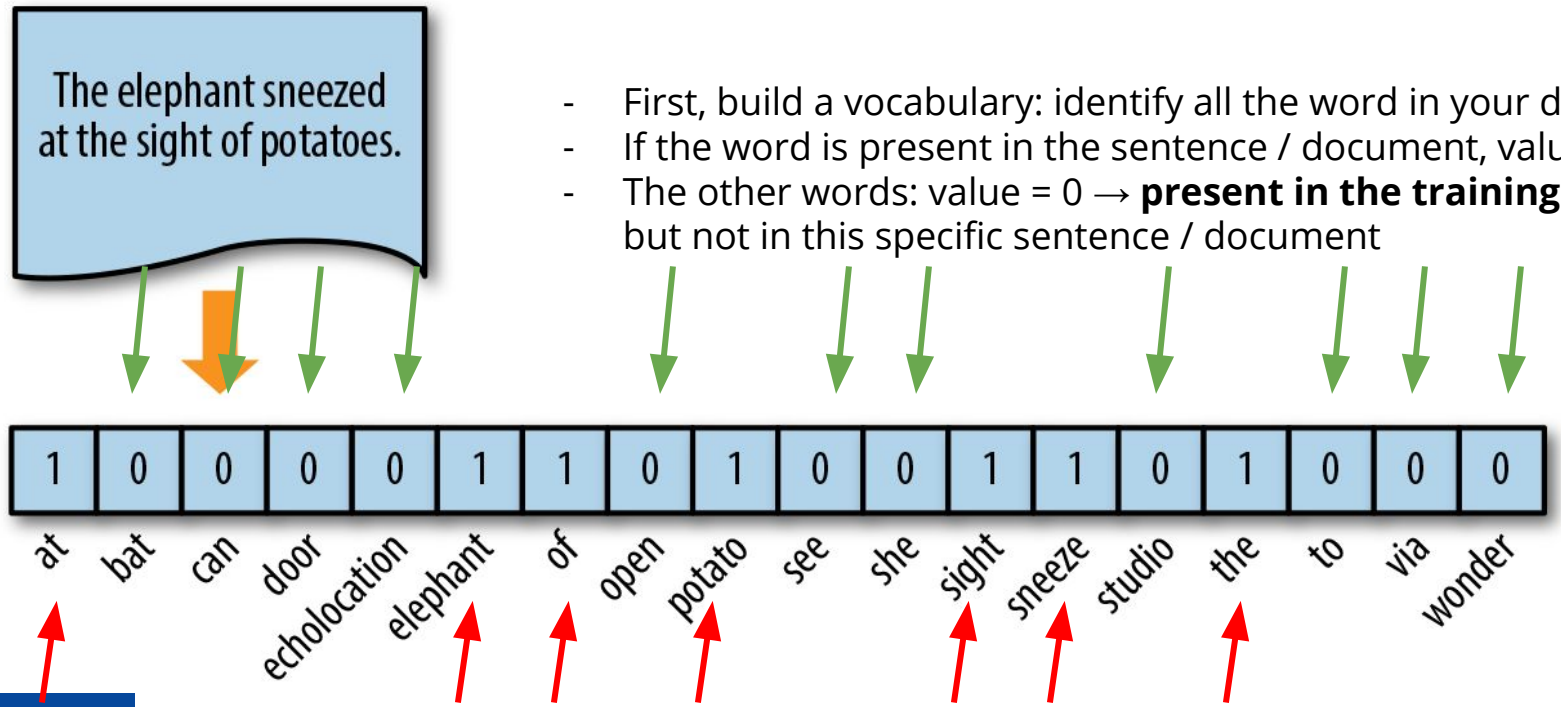
- First, build a vocabulary: identify all the word in your data
- If the word is present in the sentence / document, value = 1

BOW: One-hot encoding



- First, build a vocabulary: identify all the word in your data
- If the word is present in the sentence / document, value = 1
- The other words: value = 0 → present in the training data, but not in this specific sentence / document

BOW: One-hot encoding



- First, build a vocabulary: identify all the word in your data
- If the word is present in the sentence / document, value = 1
- The other words: value = 0 → **present in the training data**, but not in this specific sentence / document

Bag-of-Words

- Easy to use: now the computer can “read” your sentence

The elephant sneezed at the sight of potatoes.

<1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0>

Varied flavors:

- **Binary**
- Raw frequencies: some words are repeated = more important
- Normalizing with TF-IDF: take into account the distribution of the words in the entire corpus
  - “the”: very frequent but not very crucial
  - “magnificent”: rare, but crucial

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Bag-of-Words

- Easy to use: now the computer can “read” your sentence

The elephant sneezed at the sight of potatoes.

<1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 2, 0, 0, 0>

‘the’

Varied flavors:

- Binary
- **Raw frequencies**: some words are repeated = more important
- Normalizing with TF-IDF: take into account the distribution of the words in the entire corpus
  - “the”: very frequent but not very crucial
  - “magnificent”: rare, but crucial

Bag-of-Words

- Easy to use: now the computer can “read” your sentence

The elephant sneezed at the sight of potatoes.

<1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 2, 0, 0, 0>

Varied flavors:

- Binary
- Raw frequencies: some words are repeated = more important
- **Normalizing with TF-IDF**: take into account the distribution of the words in the entire corpus
  - “the”: very frequent but not very crucial
  - “magnificent”: rare, but crucial

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right)$$

TF-IDF

Term x within document y

$tf_{x,y}$ = frequency of x in y

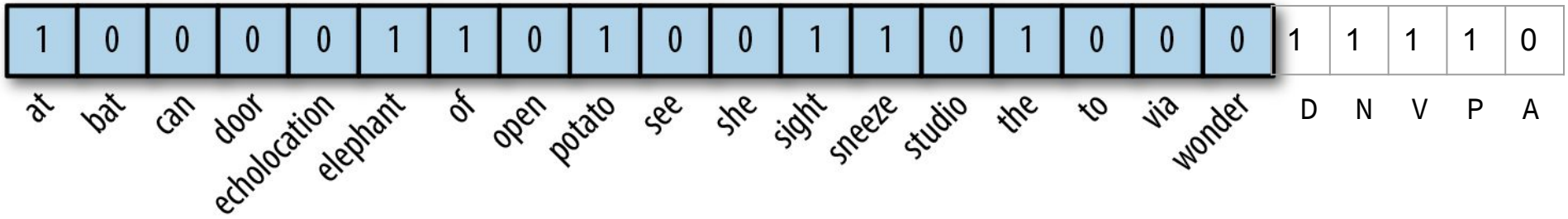
df_x = number of documents containing x

N = total number of documents

Bag of any features

Can be used to take into account any information, e.g. POS tags:

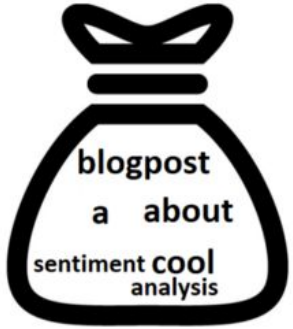
The/D elephant/N sneezed/V at/P the/D sight/N of/P potatoes/N



We can encode any information:

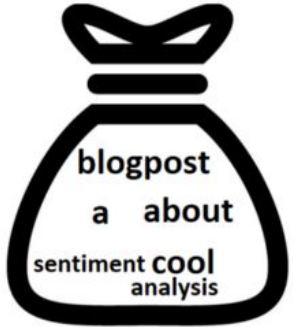
- presence of a syntactic relation
- presence of a Named Entity
- word associated to a sense if disambiguated
- words in the next sentence
- ...

Problems and extensions



1. **Very high dimensional**:
    - 18 dimensions for the previous sentence but could be 100k dimensions!
        - Curse of dimensionality: makes learning hard, prone to overfitting
    - Solutions:
        - ignoring specific words, e.g. stop words
        - keeping only the most frequent / highest TF-IDF
        - grouping words: semantic categories, clusters (Brown)

Problems and extensions



1. Very high dimensional:
   - 18 dimensions for the previous sentence but could be 100k dimensions!
     - Curse of dimensionality: makes learning hard, prone to overfitting
   - Solutions:
     - ignoring specific words, e.g. stop words
     - keeping only the most frequent / highest TF-IDF
     - grouping words: semantic categories, clusters (Brown)
2. Bag-of-Words representation **ignores word ordering and context**
   - crucial:
     - *"I don't know why **I like this movie**."* vs *"**I don't like this movie** and I know why."*
   - solutions: n-grams, i.e. use combination of multiple words
     - e.g. trigrams such as "do not like", "like this movie"
     - but even more dimensions!

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Playing with data (without neurons): scikit-learn

Toolkit for machine learning in Python (developed at INRIA):

- Contains the implementation of many algorithms:
  - Naive Bayes
  - Logistic Regression
  - SVM
  - Decision Trees
  - Perceptron
  - Passive-agressive
  - ...
- Makes also easy to:
  - pre-process / vectorize text data
  - optimize and evaluate models
  - select features
- Classification, clustering, regression

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

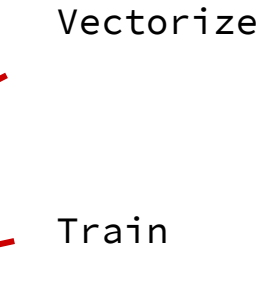
Classification with Scikit-Learn

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report

vectorizer = CountVectorizer( )
train_data_features = vectorizer.fit_transform( train )
test_data_features = vectorizer.transform( test )

classifier = LogisticRegression(max_iter=200)
classifier.fit( train_data_features, train_labels )

preds = classifier.predict( test_data_features )

print( classification_report( test_labels, preds ) )
```


Vectorize

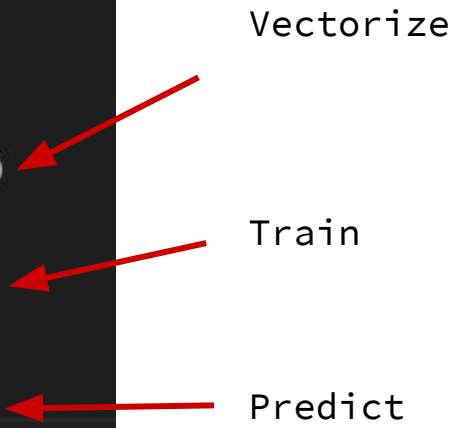
Classification with Scikit-Learn

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report

vectorizer = CountVectorizer( )
train_data_features = vectorizer.fit_transform( train )
test_data_features = vectorizer.transform( test )

classifier = LogisticRegression(max_iter=200)
classifier.fit( train_data_features, train_labels )

preds = classifier.predict( test_data_features )

print( classification_report( test_labels, preds ) )
```



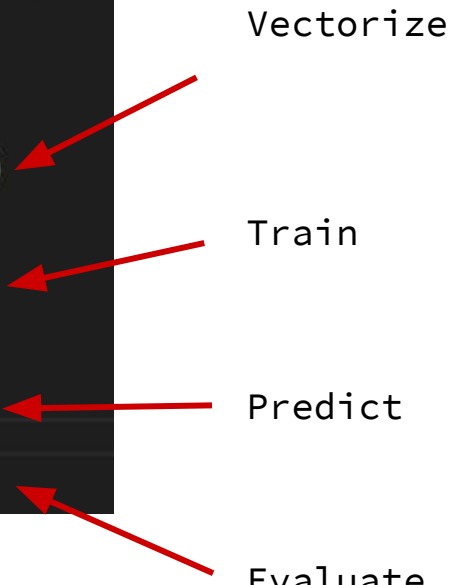
Classification with Scikit-Learn

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report

vectorizer = CountVectorizer( )
train_data_features = vectorizer.fit_transform( train )
test_data_features = vectorizer.transform( test )

classifier = LogisticRegression(max_iter=200)
classifier.fit( train_data_features, train_labels )

preds = classifier.predict( test_data_features )

print( classification_report( test_labels, preds ) )
```



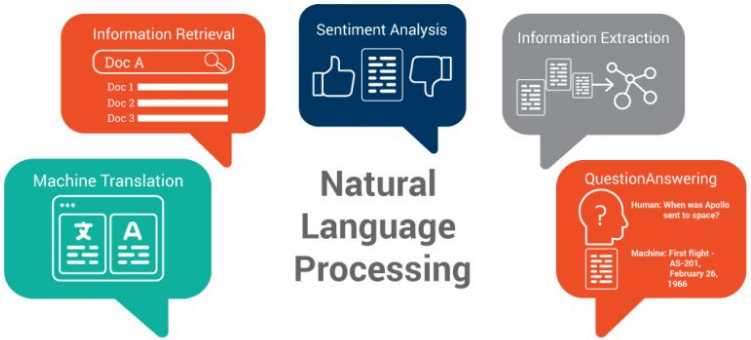
Classification with Scikit-Learn

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report

vectorizer = CountVectorizer( )
train_data_features = vectorizer.fit_transform( train )
test_data_features = vectorizer.transform( test )

classifier = LogisticRegression(max_iter=200)
classifier.fit( train_data_features, train_labels )

preds = classifier.predict( test_data_features )

print( classification_report( test_labels, preds ) )
```



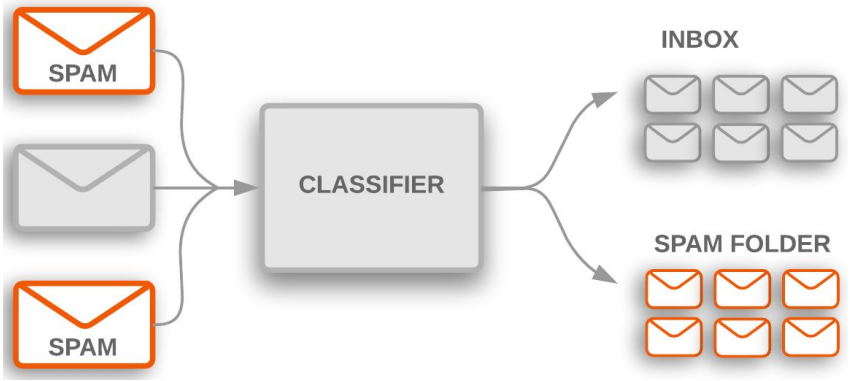
See more during the practical

NLP: tasks and applications



ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Classification



Idea: assign a (known) category to an object

- Word Sense disambiguation
- Classification of books: by genre, author, topic...
- Sentiment analysis: classification of books, tweets, ...
- Fake news detection
- Language detection
- Lie and fraud detection (e.g. in scientific publications...)
- Genre, Political side ... detection
- Psychological trouble detection
- ....

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Sequence Labelling

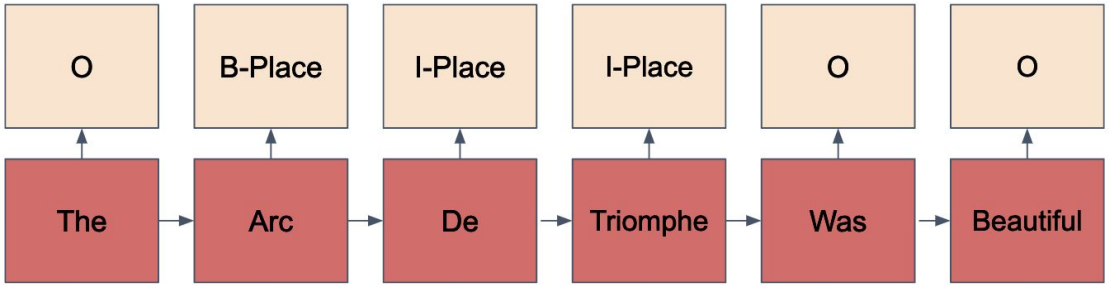
Idea: we want to take into account context, e.g. surrounding words

⟶ making the optimal label for a given element dependent on the choices of nearby elements

- POS tagging
- Named Entity Recognition

⟶ Without neurons: = CRF, HMMs …

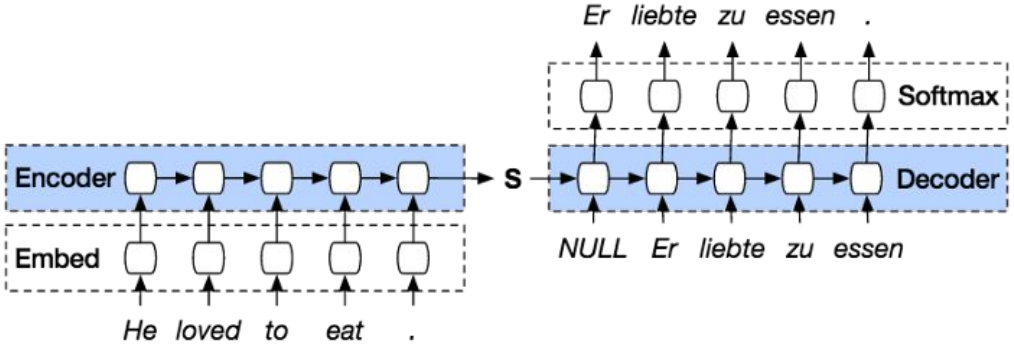
⟶ Now: e.g. with Recurrent Neural Network + CRF

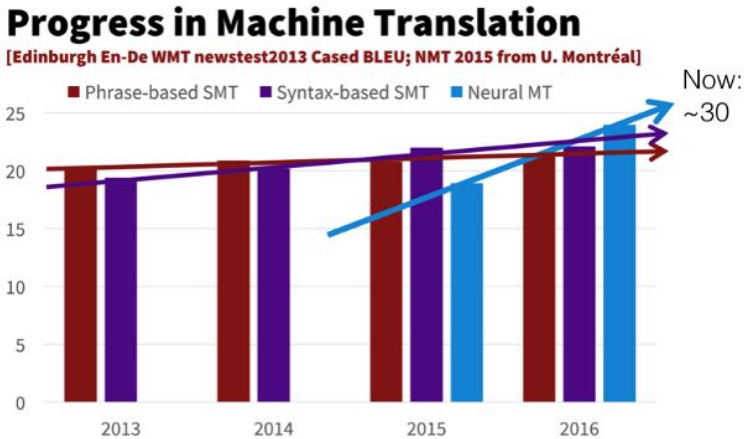


Sequence to Sequence

Idea: we want to take a sequence as input, and to output another sequence

- Machine translation
- Question-answering
- Summarization
- Generation, e.g. generating subtitles, captions, poetry...



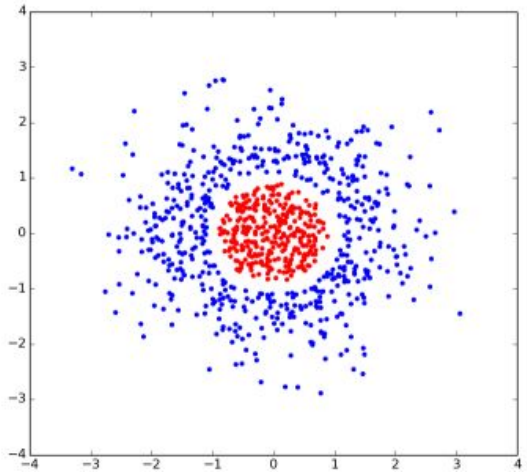


To go further...

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Limits of classical statistical methods

1. Linearity → Neural methods, see next lectures!
2. Data representation: “Feature engineering”
3. Word similarity



ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Data representation

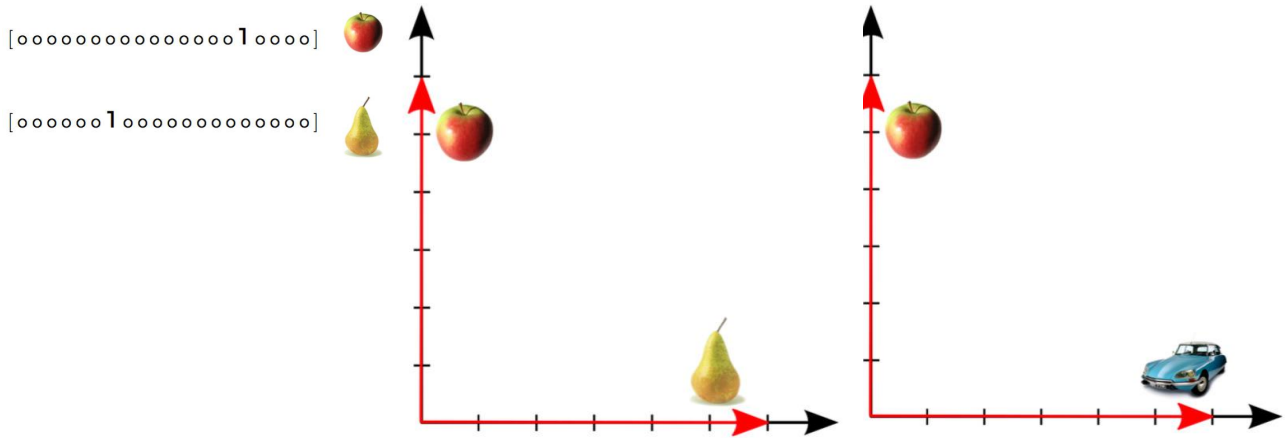
- Defining features has to be done **manually**: require expertise and tests
- A word is represented with a **one-hot vector**: easy to implement

[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]

[0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]

Data representation

- Defining features has to be done manually: require expertise and tests
- A word is represented with a one-hot vector: easy to implement
- But representing the meaning of words?→ **no notion of similarity**

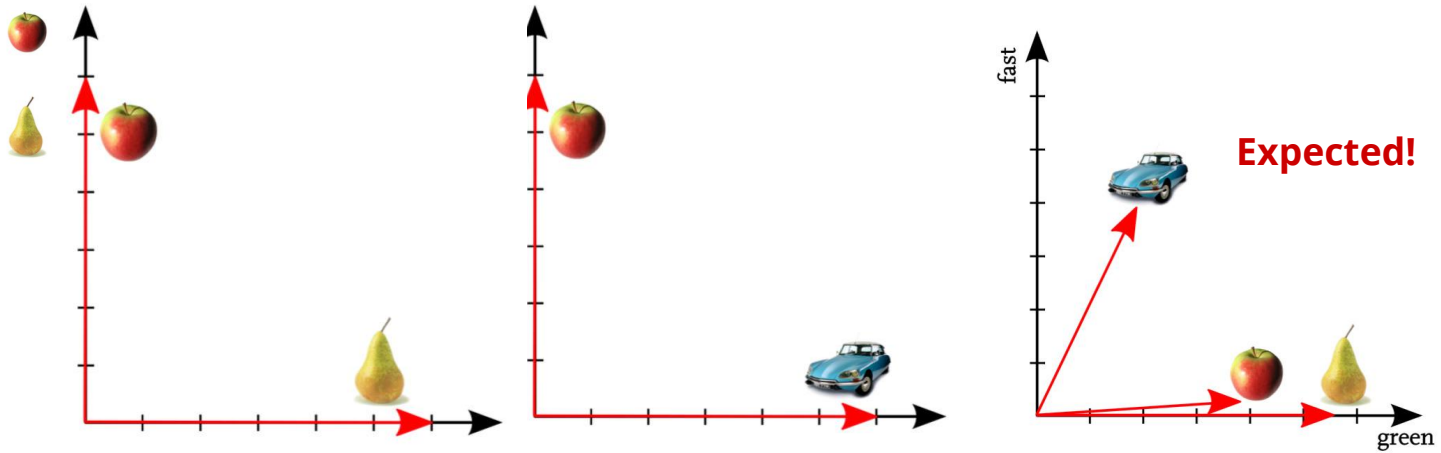


Data representation

- Defining features has to be done manually: require expertise and tests
- A word is represented with a one-hot vector: easy to implement
- But representing the meaning of words?→ **no notion of similarity**
-

[ooooooooooooooloooo]

[oooooolooooooooooooo]



Word distribution

"You shall know a word by the company it keeps."

—J.R. Firth

- Rather old idea: **distributional hypothesis** → 1957!

Example (from Tim van der Cruys):

- delicious *sooluceps*
- sweet *sooluceps*
- stale *sooluceps*
- freshly baked *sooluceps*

→ Guess what is a *sooluceps* ?

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Word distribution

"You shall know a word by the company it keeps."

—J.R. Firth

- Rather old idea: **distributional hypothesis** → 1957!

Example (from Tim van der Cruys):

- delicious *sooluceps*
- sweet *sooluceps*
- stale *sooluceps*
- freshly baked *sooluceps*

Food!

→ Guess what is a *sooluceps* ?

Looking at the context of use of a word, you can guess its meaning

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Word embeddings

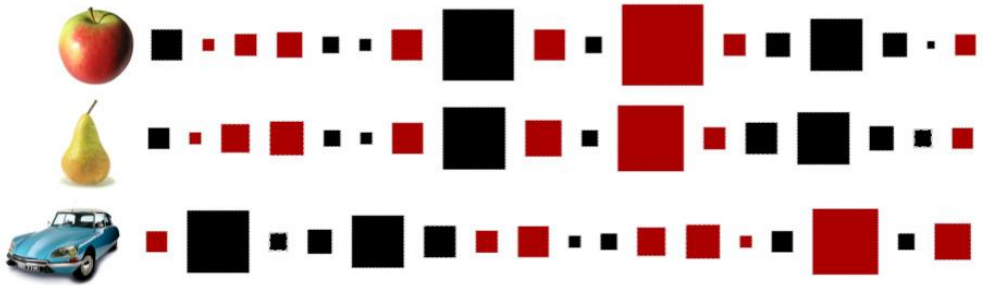
Many studies on representing the meaning of words using context

Before neural networks:

- build a matrix over all the words appearing in a corpus
- count the number of time words appear together
- reduce the dimensions (e.g. PCA)

Now: **Train a neural network to build a representation** / language model

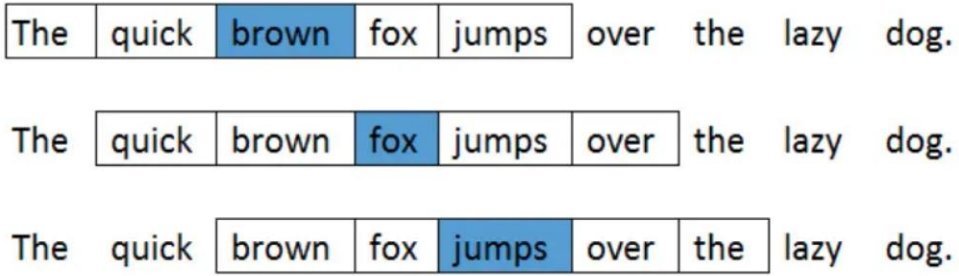
- massive amount of data
- task = predicting a linguistic unit (word, sentence...)



ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Word2vec

For each target word (blue), consider some context words (here, window = 5)



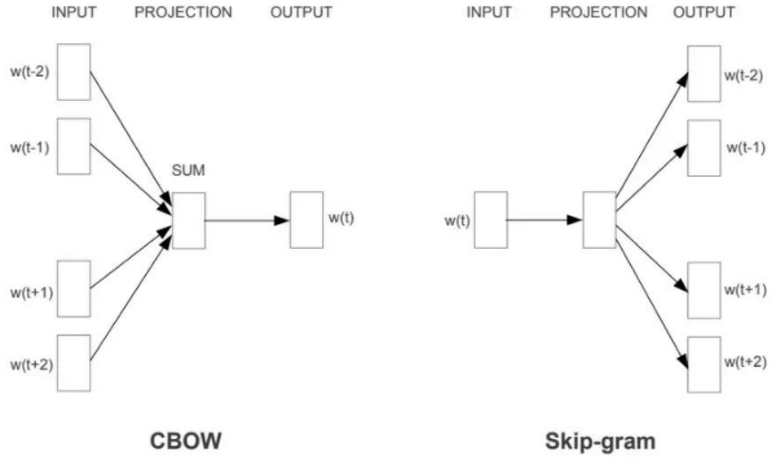
CBOW:

- predict the target word given the context

Skip-gram:

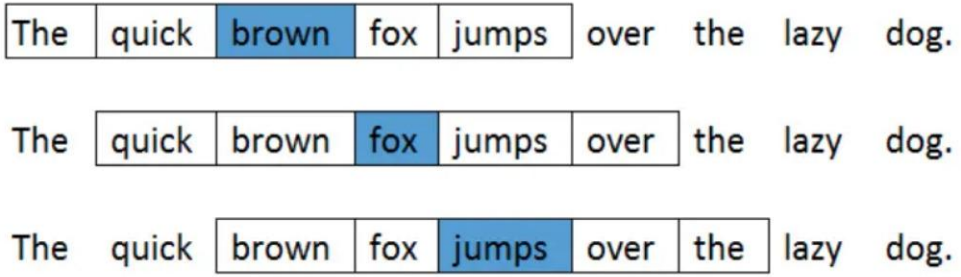
- predict the context words given the target word

→ the hidden layer is used as the representation of the target word



Word2vec

For each target word (blue), consider some context words (here, window = 5)



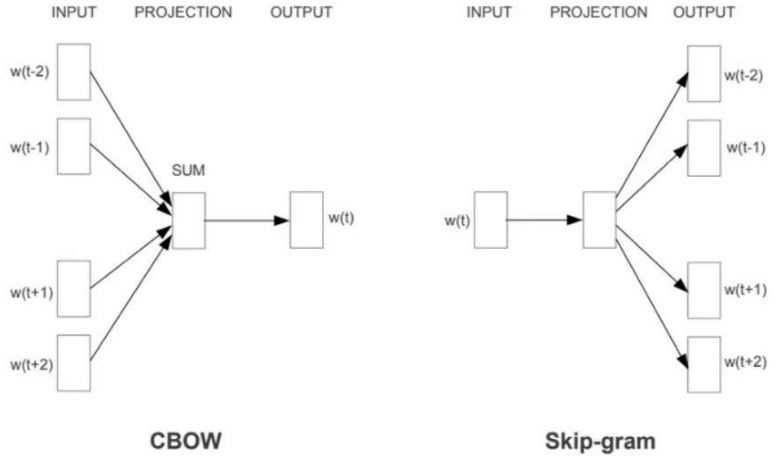
CBOW:

- predict the target word given the context

Skip-gram:

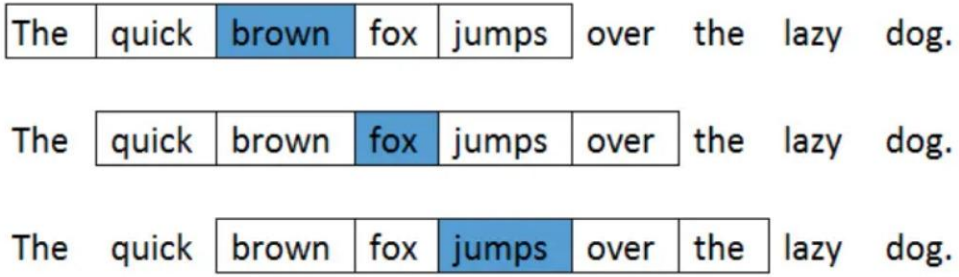
- predict the context words given the target word

→ the hidden layer is used as the representation of the target word



Word2vec

For each target word (blue), consider some context words (here, window = 5)



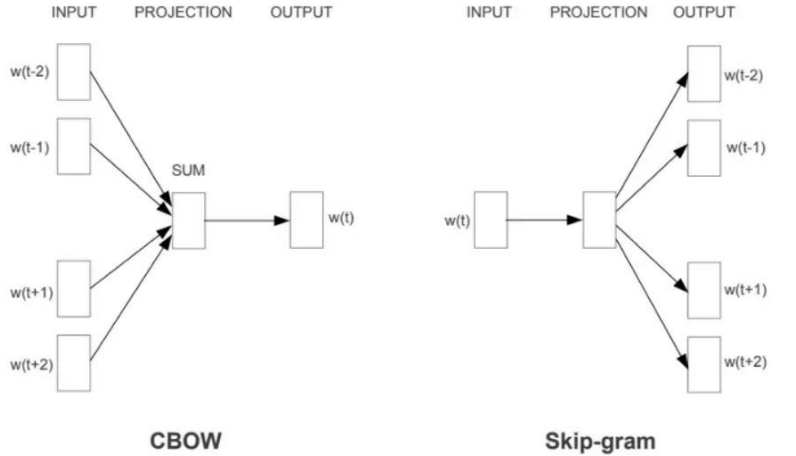
CBOW:

- predict the target word given the context

Skip-gram:

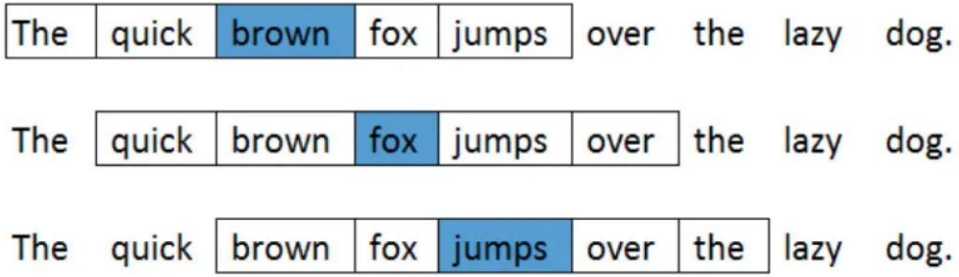
- predict the context words given the target word

→ the hidden layer is used as the representation of the target word



Word2vec

For each target word (blue), consider some context words (here, window = 5)



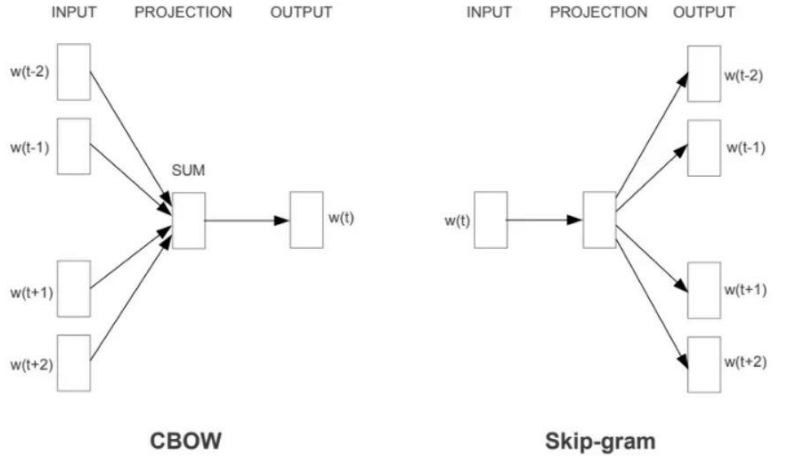
CBOW:

- predict the target word given the context

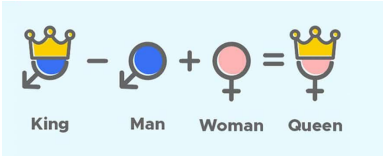
Skip-gram:

- predict the context words given the target word

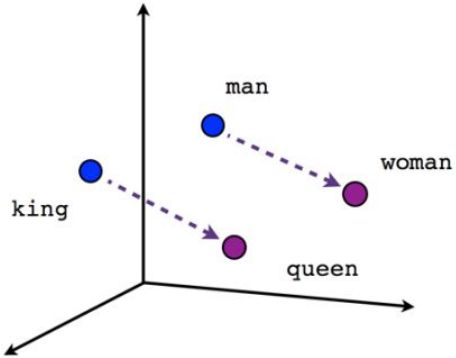
→ **the hidden layer** is used as the representation of the target word



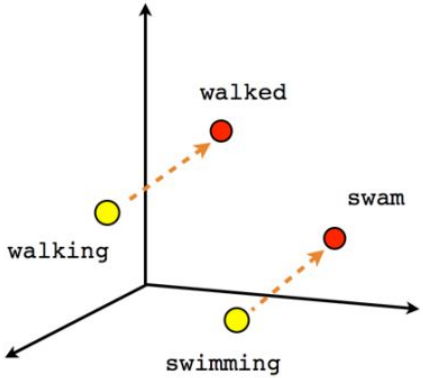
Word2vec



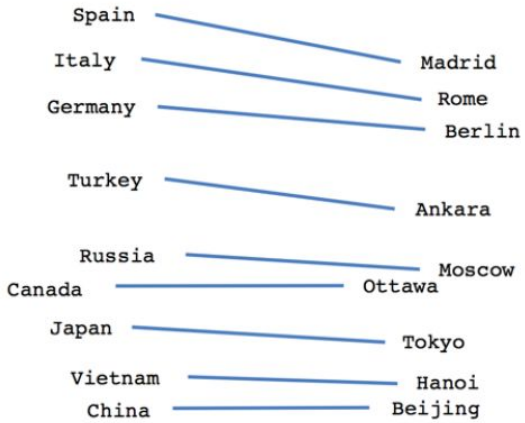
Allow inference:



Male-Female



Verb tense



Country-Capital

Let’s try out during the practical session!

Data representation

- Before NN: expertise needed to find good data representations
- Now: feed your NN with word embeddings! but....
  - which ones? GloVe, FastText, Word2Vec, ELMO, BeRT, RobeRTa, GPT-2, GPT-3, XLNet...
  - which size? and other settings (e.g. window size, number of iterations, built on which data)
  - how to combine them into a sentence / document?
  - and what about other information: character embeddings / POS embeddings / syntactic embeddings / sense embeddings?
  - what about different languages and domains?

→ expertise still needed

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Limits of supervised learning

Annotating data is hard, expensive, time-consuming (but necessary!)

→ Limited amount of annotated data, many proposed solutions e.g.:

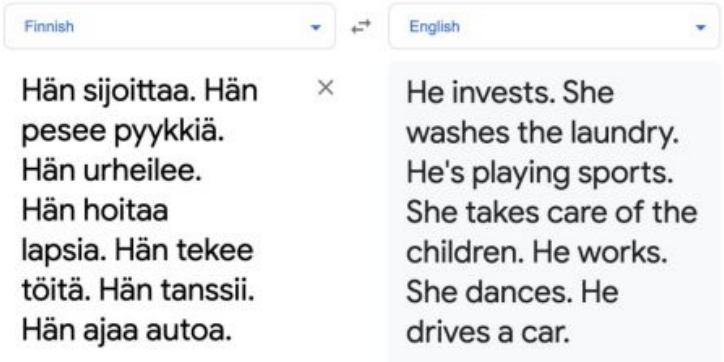
- distant learning: for example use emojis as annotation of sentiments in Tweets = noisy labels, but free annotation
- transfer learning: for example, with multitask learning, transfer knowledge from varied related tasks
- domain adaptation:
  - build a model on a large set of available data in one domain
  - optimize on a small set of annotated data for a target domain
- semi-supervised learning: for example, use word embeddings built on a massive amount of unannotated data to feed your neural network

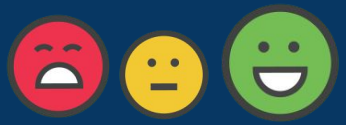
ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Current challenges in NLP

1. Low-resourced languages / domains
2. Interpretability / explainability → very active domain
   - Saliency Map / Allen Interpret (Wallace et al., 2019) https://allennlp.org/interpret
3. Cost of training very large models
   - Energy and Policy Considerations for Deep Learning in NLP https://www.aclweb.org/anthology/P19-1355.pdf
   - On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? http://faculty.washington.edu/ebender/papers/Stochastic_Parrots.pdf
4. Bias and fairness in NLP data / models

Consumption	CO_2e (lbs)
Air travel, 1 person, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experiments	78,468
Transformer (big)	192
w/ neural arch. search	626,155





Practical session

1. Spacy: pre-processing and analysing text data
2. Scikit: sentiment analysis, classifying movie reviews
3. Word2vec: generating word embeddings
4. (Advanced) PyTorch: sentiment analysis using NN

NLP courses, slides, interesting websites (and sources)

- https://dair.ai/notebooks/nlp/2020/03/19/nlp_basics_tokenization_segmentation.html
- https://www.slideshare.net/dinel/new-trends-in-nlp-applications
- https://www.infoq.com/presentations/nlp-practitioners/
- https://github.com/sebastianruder/NLP-progress

+ Thanks to: Tim Van Der Cruys and Philippe Muller who shared their materials (Courses in M2 Info, UPS and M1 Droit, UT3)

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Other sources

- Morphology:
  - https://www.slideserve.com/flynn/natural-language-processing-morphology
  - https://theweek.com/articles/463500/8-favorite-ridiculously-long-german-words
  -
- Tokenisation:
  - https://www.thoughtvector.io/blog/subword-tokenization/
  - http://tm-town-nlp-resources.s3.amazonaws.com/ch2.pdf
  - https://towardsdatascience.com/tokenization-for-natural-language-processing-a179a891bad4
  - https://pythonprogramming.net/tokenizing-words-sentences-nltk-tutorial/
  - https://blog.ekbana.com/pre-processing-text-in-python-ad13ea544dae
- Sentence segmentation:
  - https://www.tm-town.com/blog/is-segmentation-solved-problem
- NER:
  - http://nlpprogress.com/english/named_entity_recognition.html
  -
- Spacy:
  - https://pypi.org/project/visualise-spacy-tree/
  - https://towardsdatascience.com/getting-to-grips-with-parse-trees-6e19e7cd3c3c
- Vectorization:
  - https://towardsdatascience.com/representing-text-in-natural-language-processing-1eead30e57d8
  - https://towardsdatascience.com/the-magic-behind-embedding-models-part-1-974d539f21fd
  -
- Sentiment Analysis:
  - Bhatia, P., Ji, Y., & Eisenstein, J. (2015, September). Better Document-level Sentiment Analysis from RST Discourse Parsing. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing* (pp. 2212-2218).

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE

Sources of pictures

- https://news.sky.com/story/talking-robots-could-be-used-in-uk-care-homes-to-ease-loneliness-and-improve-mental-health-12066296
- https://blog.lecko.fr/machine-learning-lordinateur-a-t-il-vraiment-besoin-de-nous/
- https://fr.m.wikipedia.org/wiki/Fichier:Major_levels_of_linguistic_structure.svg
- https://realpython.com/sentiment-analysis-python/
- https://realpython.com/natural-language-processing-spacy-python/
- https://www.dw.com/en/linguist-theres-a-difference-between-learning-words-and-learning-a-language/a-18602460
- https://numberdyslexia.com/100-orton-gillingham-red-words-list/
- https://sites.google.com/a/sheffield.ac.uk/aal2013/branches/syntax/why-is-syntax-studied
- https://www.bangkokpost.com/life/social-and-lifestyle/1757224/word-wise
- https://blog.aaronccwong.com/2019/building-a-bigram-hidden-markov-model-for-part-of-speech-tagging/
- https://divyagodayal.github.io/2018/06/08/An-introduction-to-part-of-speech-tagging-and-the-Hidden-Markov-Model-953d45338f24/
- https://www.youtube.com/watch?v=CeuhO3s-Iss
- https://analyticsindiamag.com/10-most-used-databases-by-developers-in-2020/
- https://www.erdil.fr/blog/2017/09/26/traitement-automatique-langues-erdil/
- https://www.thoughtco.com/ambiguity-language-1692388
- http://katbailey.github.io/ml/#/title
- https://towardsdatascience.com/representing-text-in-natural-language-processing-1ead30e57d8
- https://towardsdatascience.com/representing-text-in-natural-language-processing-1ead30e57d8
- https://www.wolfram.com/language/12/natural-language-processing/
- https://medium.com/swlh/text-cleaning-43fe4062952b
- https://twitter.com/yoavgo/status/1318576449985662977/photo/1
- http://jetpaper.web.fc2.com/reweiws/page-5462805.html
- https://www.slj.com/?detailStory=can-we-talk-librarians-lead-new-push-civics-education-focusing-discourse
- https://www.toptal.com/deep-learning/4-sentiment-analysis-accuracy-traps
- https://nativeenglishspain.blogspot.com/2013/10/wise-wednesday-grammar-homonym.html
- https://www.eltconcourse.com/training/inservice/lexicogrammar/polysemy.html
- https://medium.com/@umagunturi789/everything-you-need-to-know-about-named-entity-recognition-2a136f38c08f
- https://activewizards.com/blog/top-nlp-algorithms-and-concepts/
- https://medium.com/@laura.mondoloni/ironhack-sketch-exercise-kata-rocket-9ee72879d0d9
- https://www.youtube.com/watch?v=hTIFghkLdhYhttps://www.thepoke.co.uk/2014/05/21/the-25-worst-best-spelling-mistakes-on-twitter/
- http://www.igfasouza.com/blog/check-tweets-spelling/
- https://www.sergent-tobogo.com/dessins/marvin-droopy/
- https://www.relationclientmag.fr/Thematique/strategies-1255/Breves/chatbot-oui-sncf-devient-premier-gagnant-Best-Robot-Experience-330102.htm
- https://developers.google.com/machine-learning/guides/text-classification
- https://medium.com/mosaix/deep-text-representation-for-sequence-labeling-2f2e605ed9d
- https://medium.com/swlh/we-need-to-talk-about-sentiment-analysis-9d1f20f2ebfb
- https://medium.com/@pierre_guillou/nlp-fastai-sequence-to-sequence-model-seq2seq-38d9984cf271
- http://www.bigdatalab.ac.cn/~junxu/publications/KG4IR2017-keynote.pdf
- https://datascientest.com/nlp-word-embedding-word2vec
- https://www.datacamp.com/community/tutorials/simplifying-sentiment-analysis-python
- https://medium.com/@suneelpatel.in/nlp-guide-101-nlp-evolution-past-present-and-future-fcc573629da3

ANITI
ARTIFICIAL & NATURAL INTELLIGENCE TOULOUSE INSTITUTE