

Lecture 6 - Introduction to Natural Language Processing

Intro2AI-class - ANITI



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12 April 2021

Unfortunately, still no HAL or Marvin



2001, A Space Odyssey



The Hitchhiker's Guide to the Galaxy

Unfortunately, still no HAL or Marvin

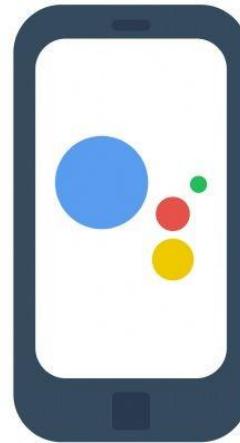


2001, A Space Odyssey

ANITI
ARTIFICIAL INTELLIGENCE
TOULOUSE INSTITUTE



The Hitchhiker's Guide to the Galaxy



Parler avec OUI.sncf

Bien sur. Voici OUI.sncf.

Bonjour, je suis l'assistant OUI.sncf.
Dis-moi où et quand tu veux partir, je m'occupe du reste.



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

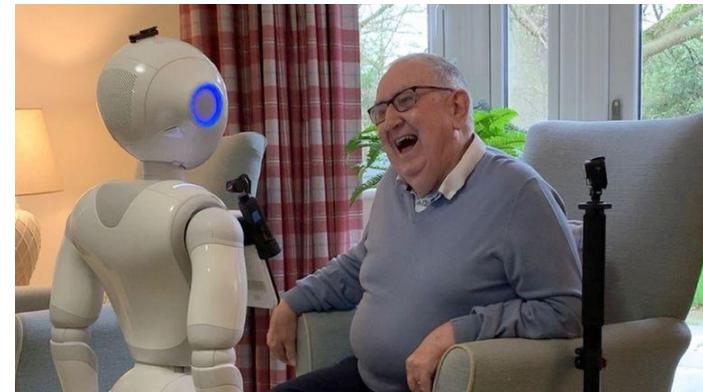
What is Natural Language Processing?

At the **interface between**:

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

Subdomain of Artificial Intelligence:

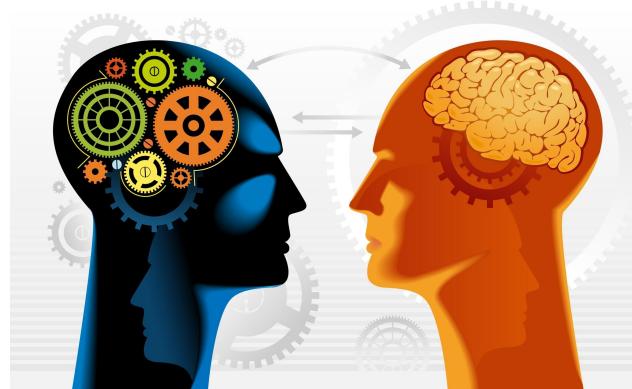
- human machine interaction
- human human interaction
 - = access to information / extract information
 - = understanding intelligence through communication



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?

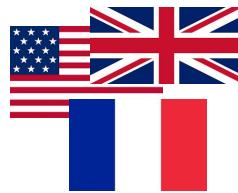


What is Natural Language Processing?

Take data

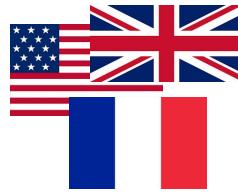


WIKIPÉDIA
L'encyclopédie libre



What is Natural Language Processing?

Take data (all)



[Doctissimo](#)

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What is Natural Language Processing?

Take data (all)



[Doctissimo](#)

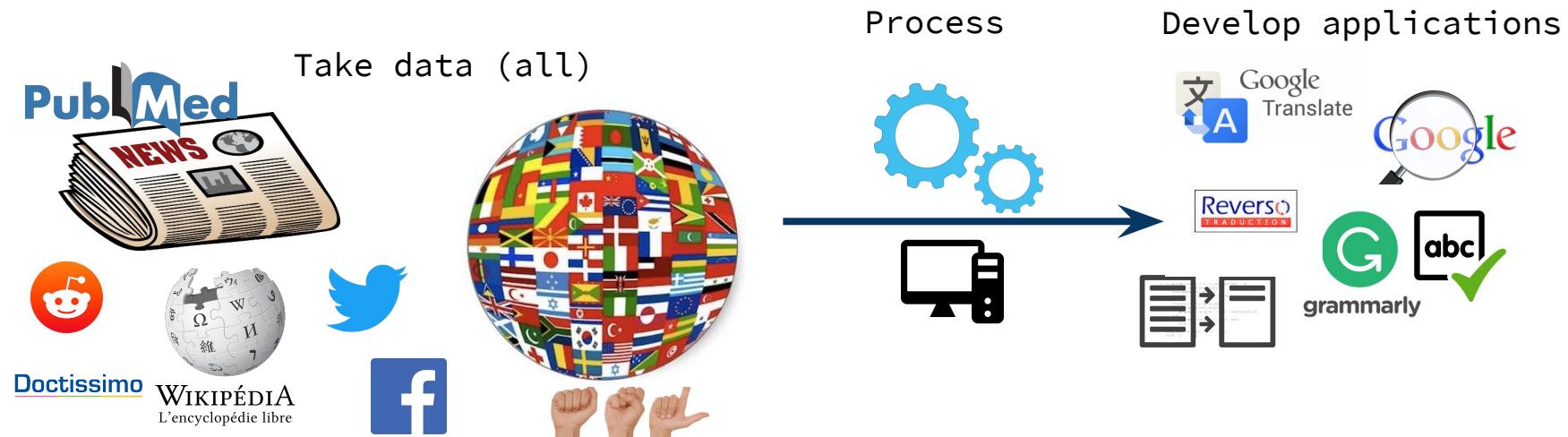
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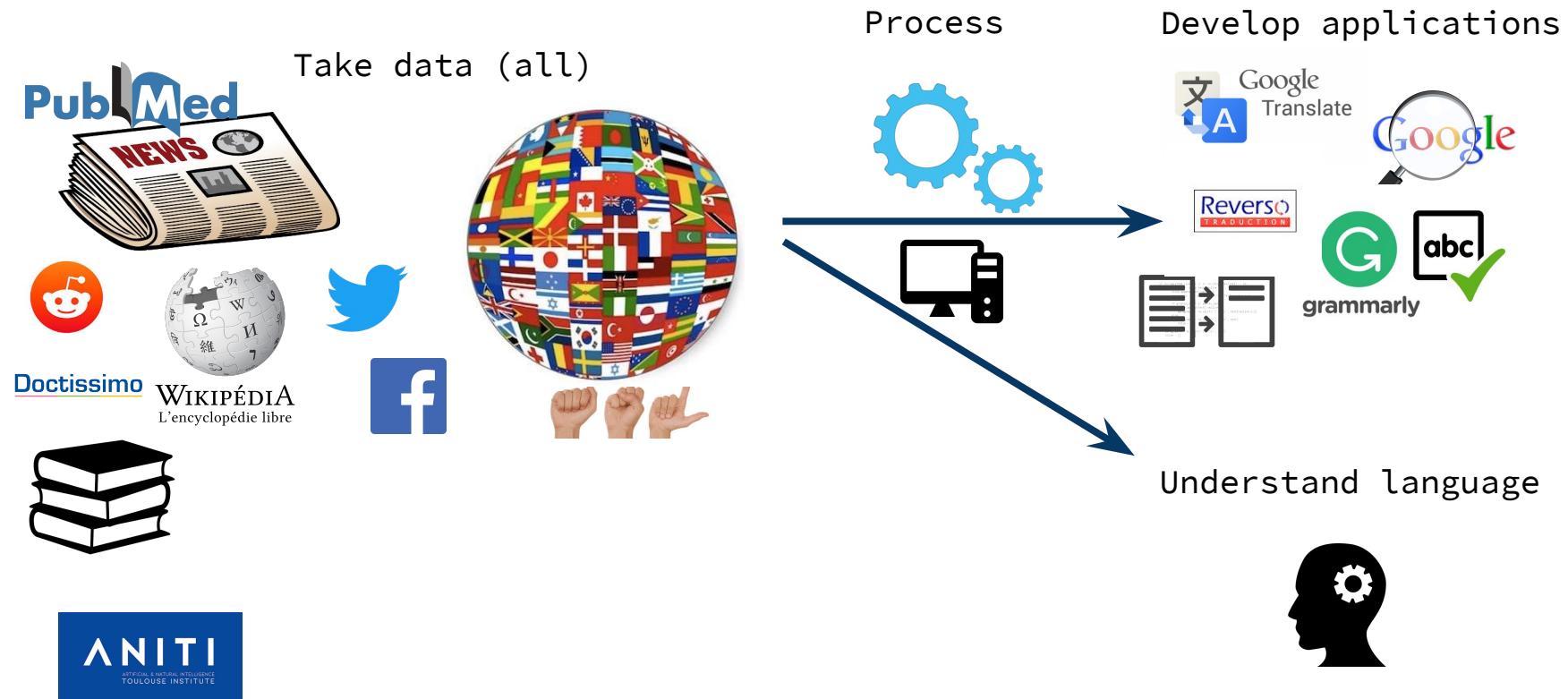
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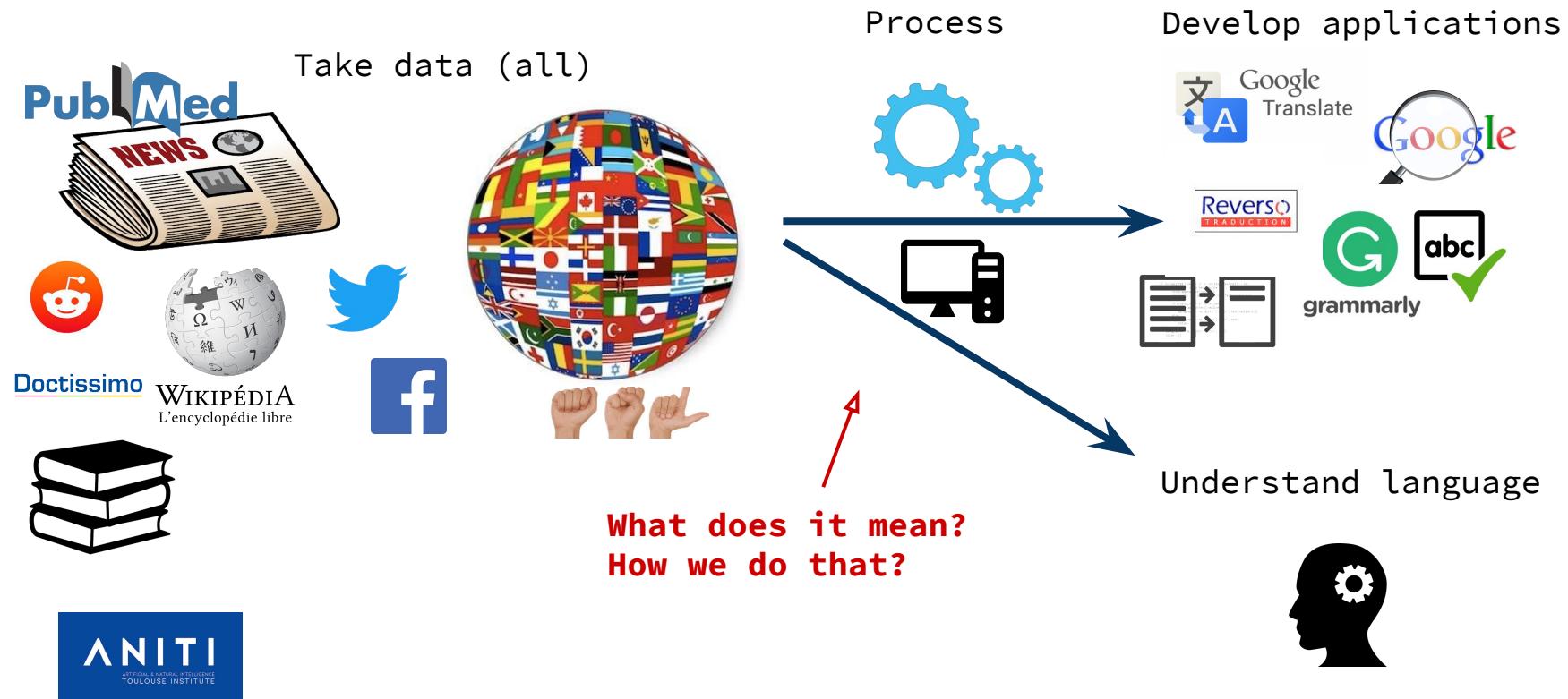
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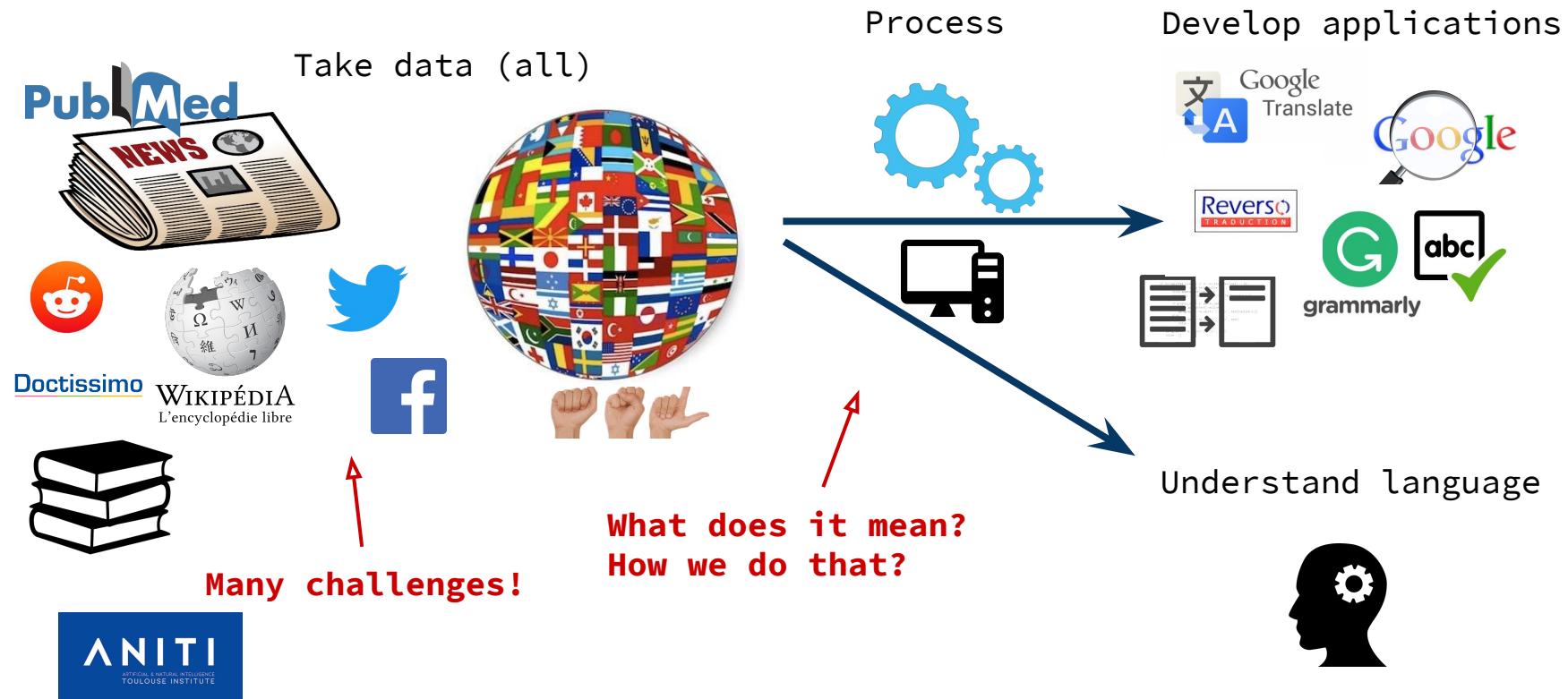
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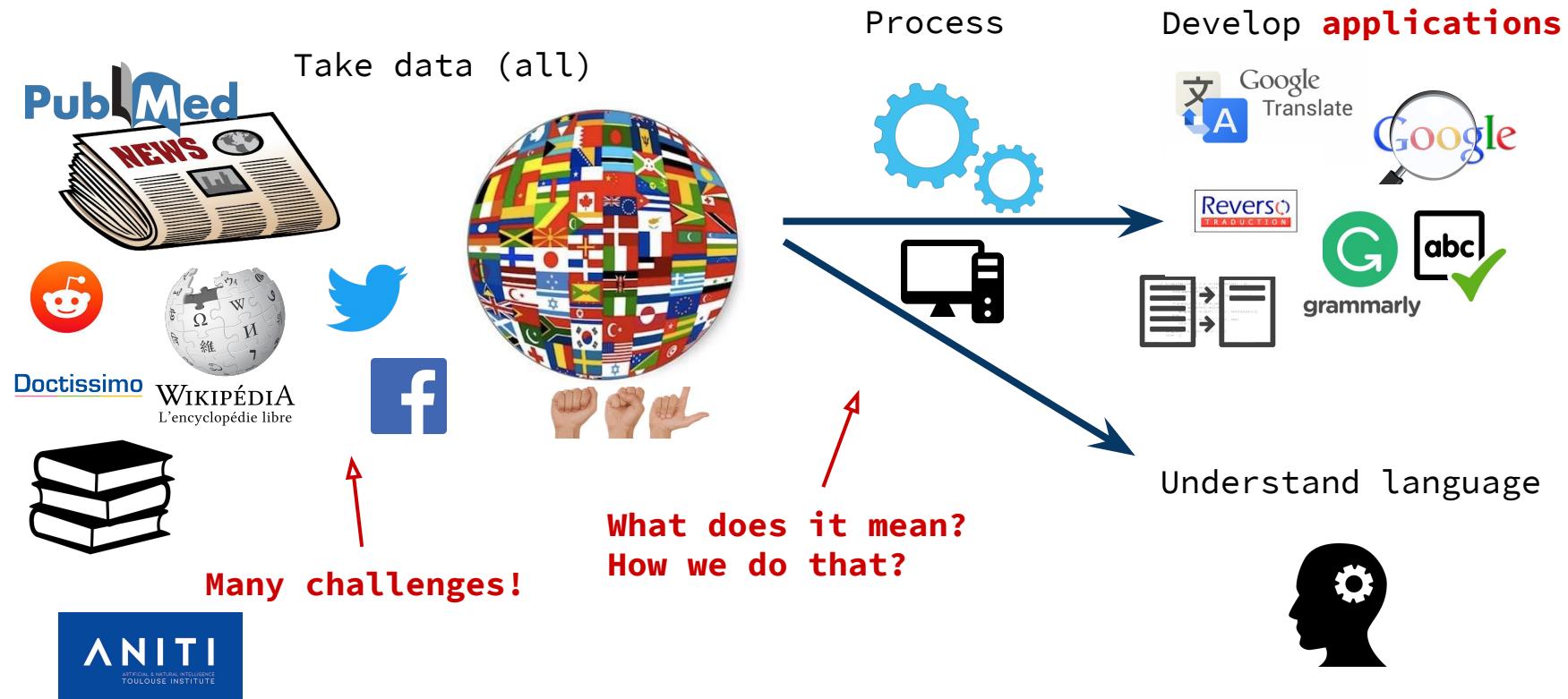
What is Natural Language Processing?



What is Natural Language Processing?



What is Natural Language Processing?



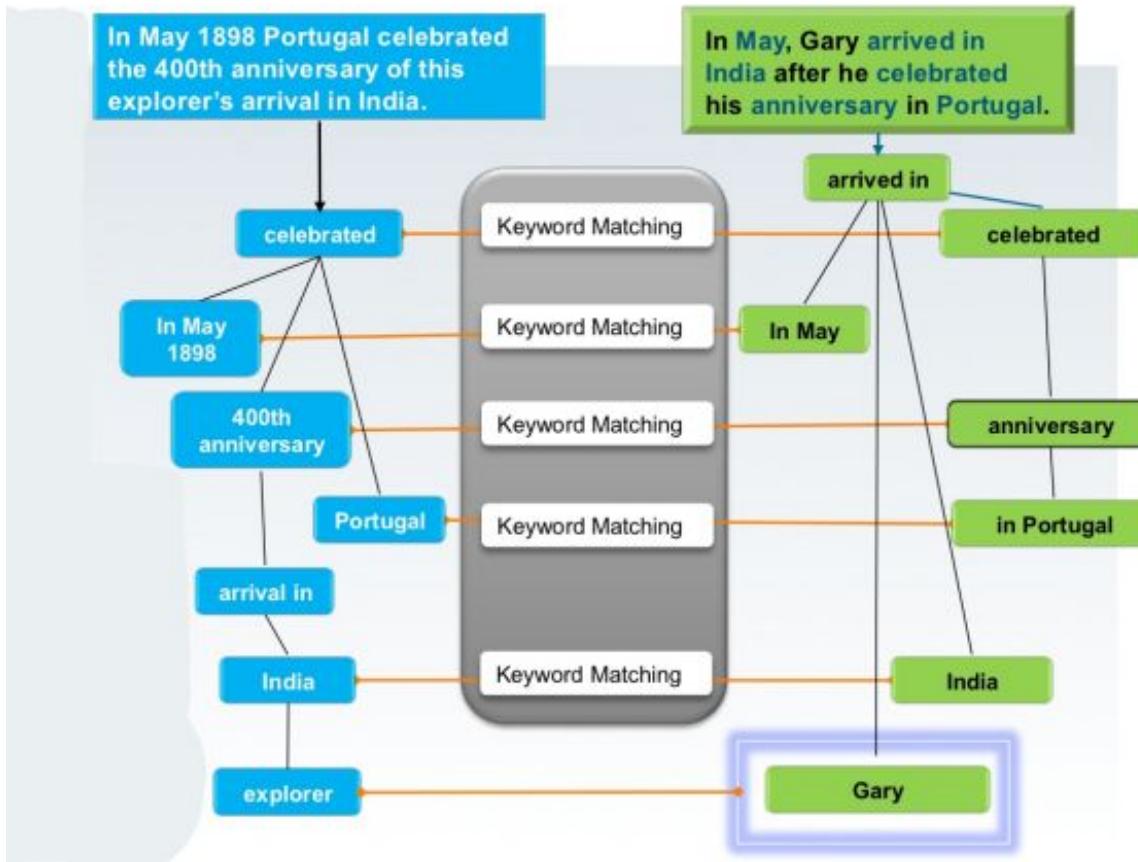
Why NLP is hard?

Example: Question-Answering with Watson



Why NLP is hard?

Keyword matching can provide good clues

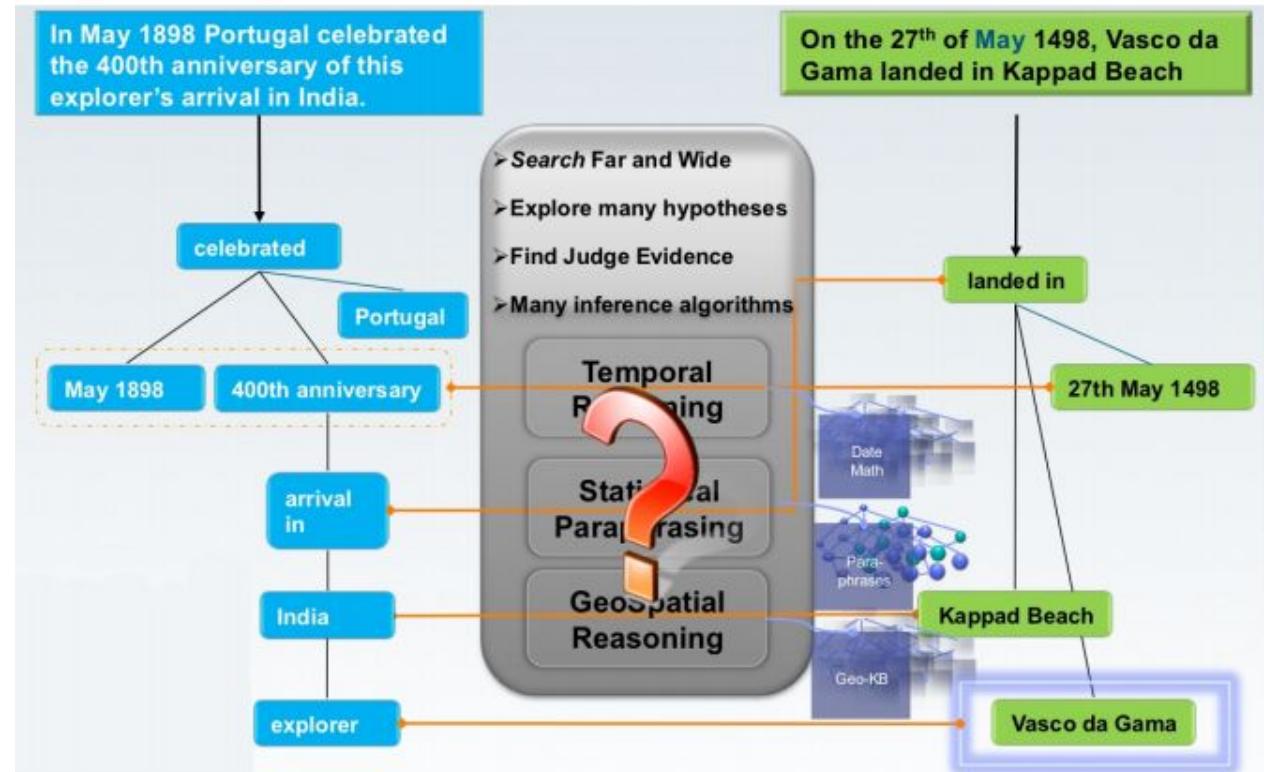


Why NLP is hard?

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)

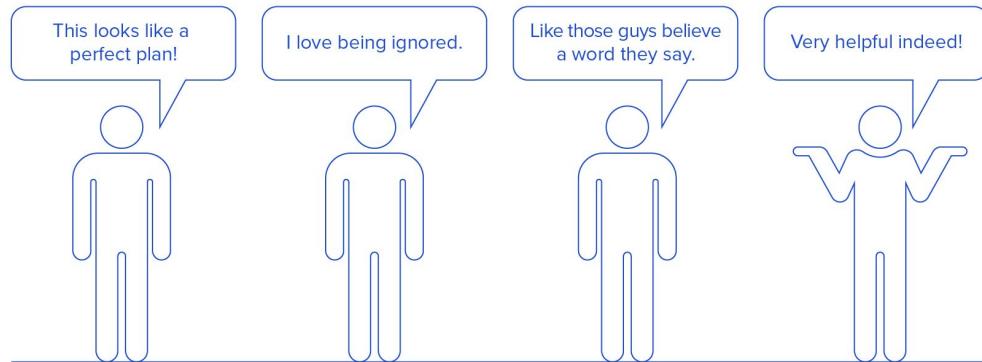


Why NLP is hard?

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.



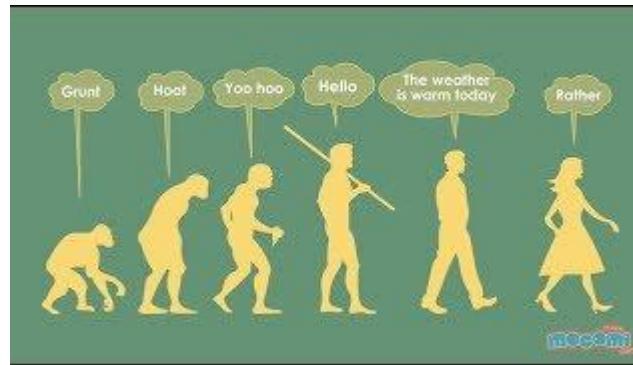
This mouse **is not good** looking, but it works **perfect** and I like it.



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. cheeeeerrrsss
 - e.g. love u
 - e.g. <3 :) :D



 DaBaddest BitchAroun
@ATL_PRINCESS

Sometimes i snap at ppl on twitter bcuz im insecure. Its a defense magnesium

from Inglewood, CA

Reply Retweet Favorite More

RETWEETS 5 FAVORITES 3

8:53 PM - 28 Oct 2013

 Donald J. Trump 
@realDonaldTrump

After having written many best-selling books and somewhat priding myself on my ability to write, it should be noted that the Fake News constantly likes to pore over my tweets looking for a mistake. I capitalize certain words only for emphasis, not b/c they should be capitalized!

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

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

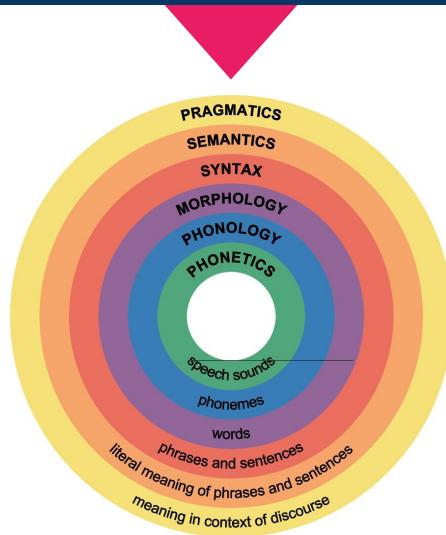
- Classification
- Sequence labelling
- Sequence to Sequence

5. To go further

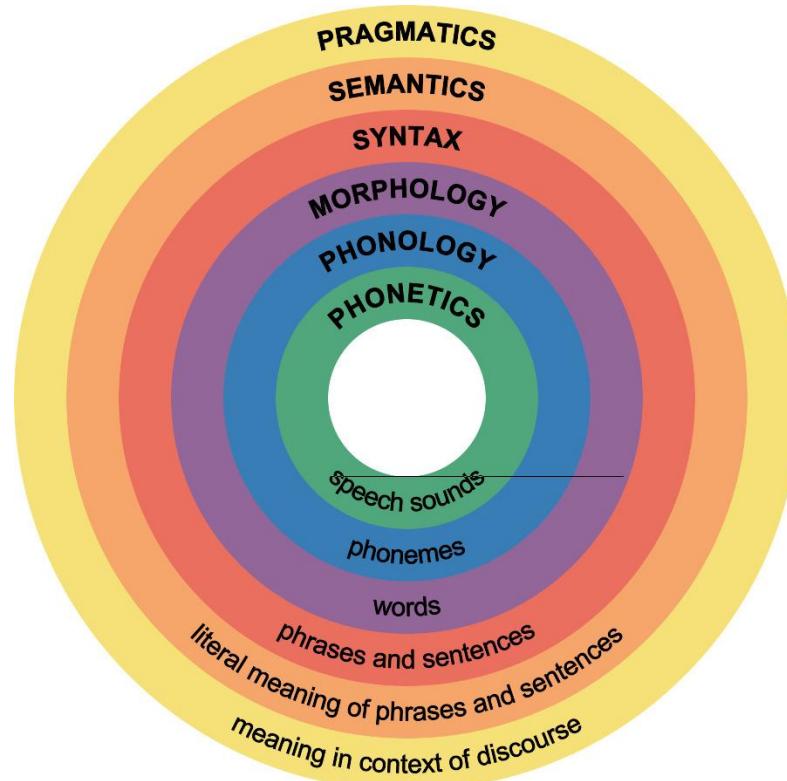
- Limits of classical statistical methods
- Limits of supervised learning
- Current challenges in NLP

Practical session: Sentiment analysis

Fundamentals of Linguistics



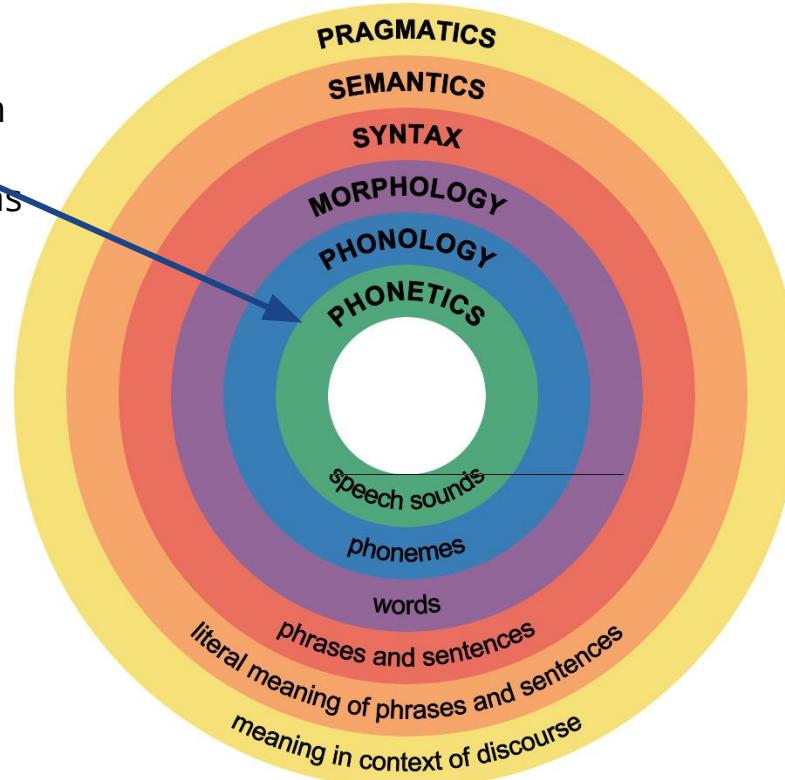
Main levels of linguistics structure



Main levels of linguistics structure

Phonetics-Phonology:

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



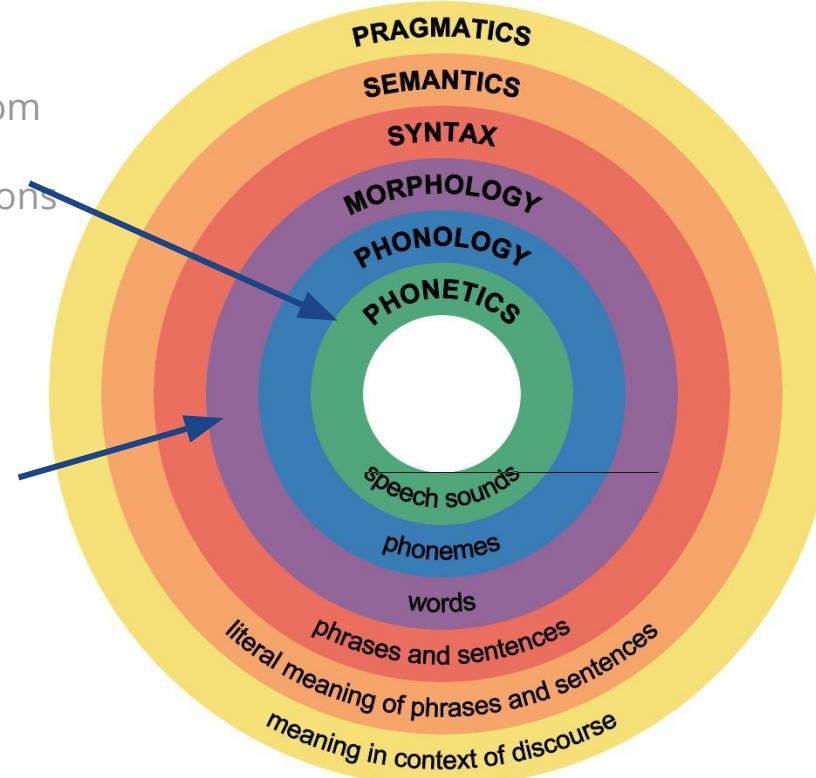
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Morphology:

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



Main levels of linguistics structure

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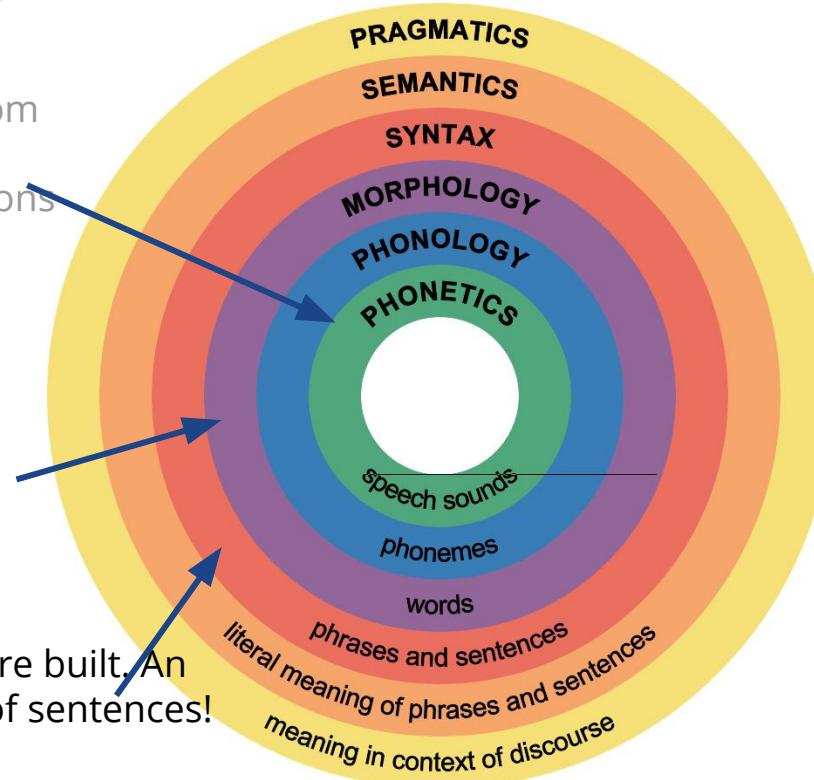
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Syntax:

How sentences are built. An infinite number of sentences!



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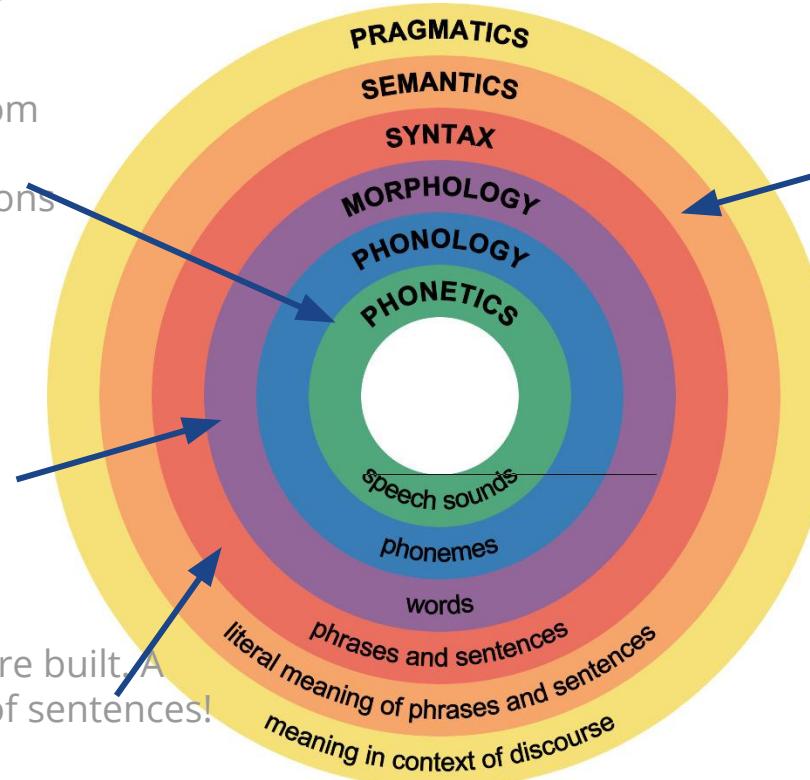
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Semantics:

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

Main levels of linguistics structure

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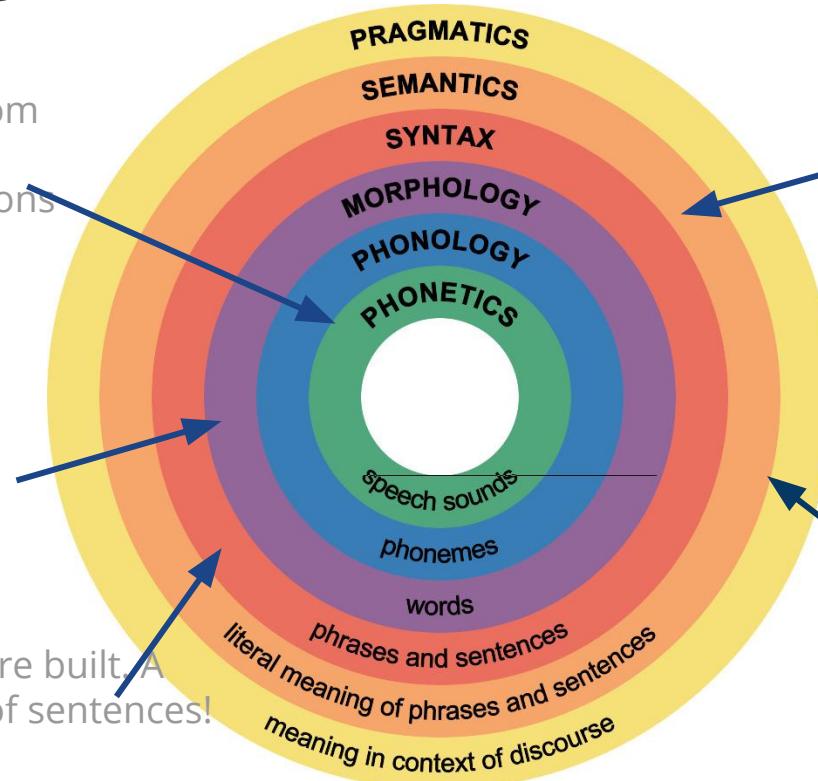
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Semantics:

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 text
researchers work
from speech.

Morphology:

How words are built
new words creation
very creative!

Syntax

How words are put
infinite possibilities

Lexical Ambiguity

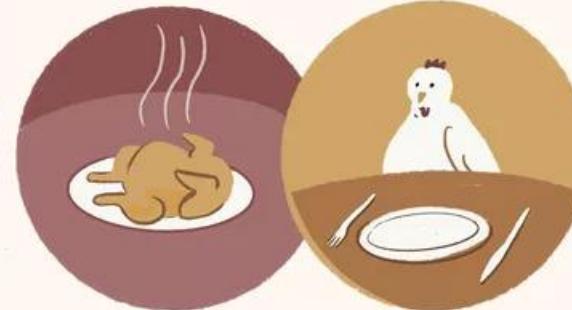
The presence of two or more possible meanings within a single word.



"I saw her duck."

Syntactic Ambiguity

The presence of two or more possible meanings within a single sentence or sequence of words.



"The chicken is ready to eat."

ics:
meaning of the
nd utterances.
you mean?

atics:
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Fundamentals of NLP



Pre-processing

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

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



Sentence: 这是一篇有趣的文章

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:
- Multiword expressions:
- Proper nouns:
- Other languages:
 - German: **rindfleischetikettierungsüberwachungsaufgabenübertragungsgesetz** = "the law for the delegation of monitoring beef labeling."
 - no word boundaries explicitly marked for some languages (= word segmentation)

Words: 这是 一篇 有趣 的 文章

(zhèshì yīpiān yǒuqù de wénzhāng)

(This is an interesting article)

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

Sentences



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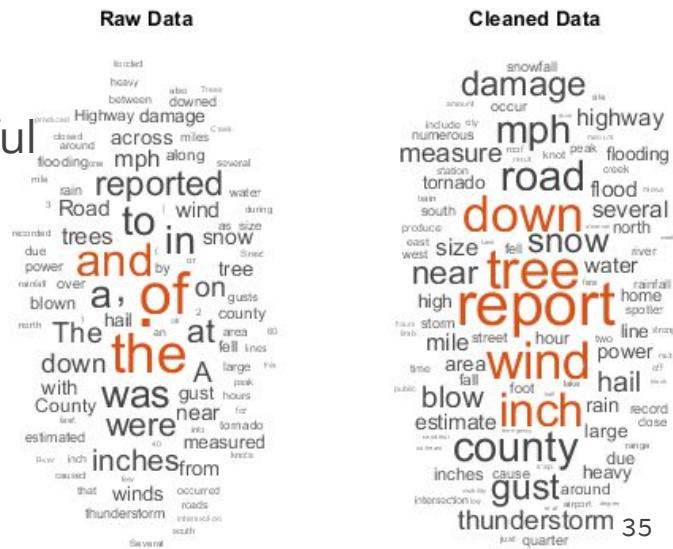
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Normalization

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>



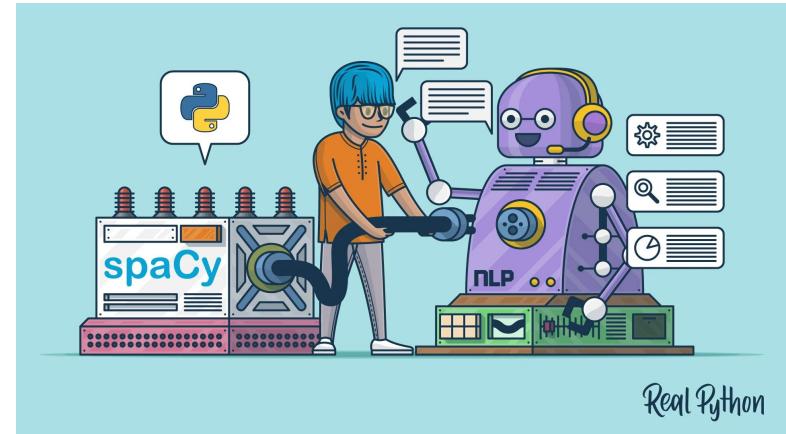
Linguistic Analysis

Additional processing that can provide rich information:

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

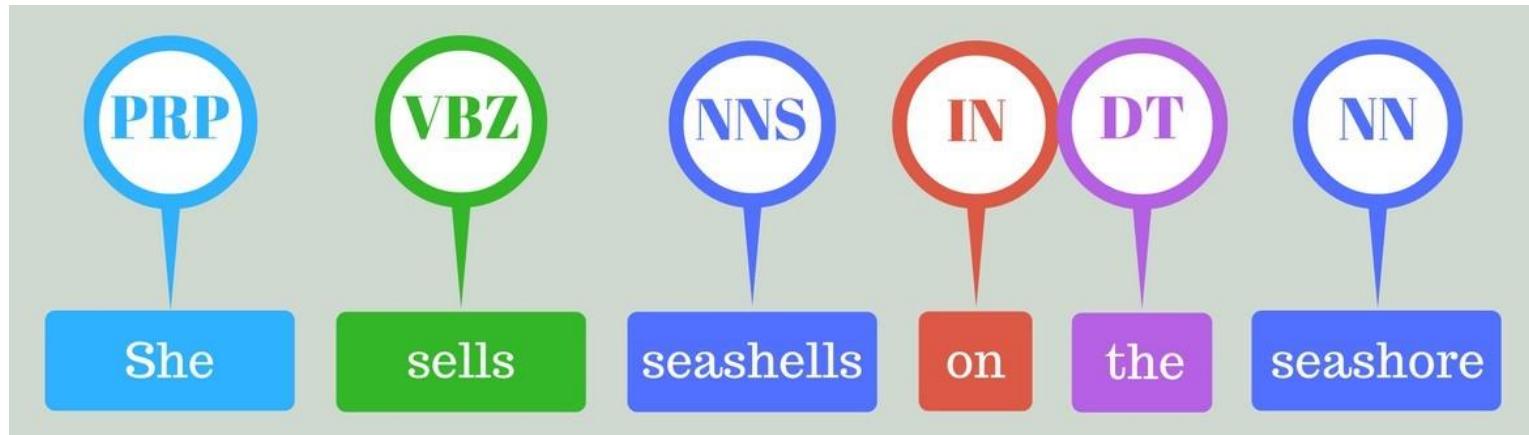
→ statistical models

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



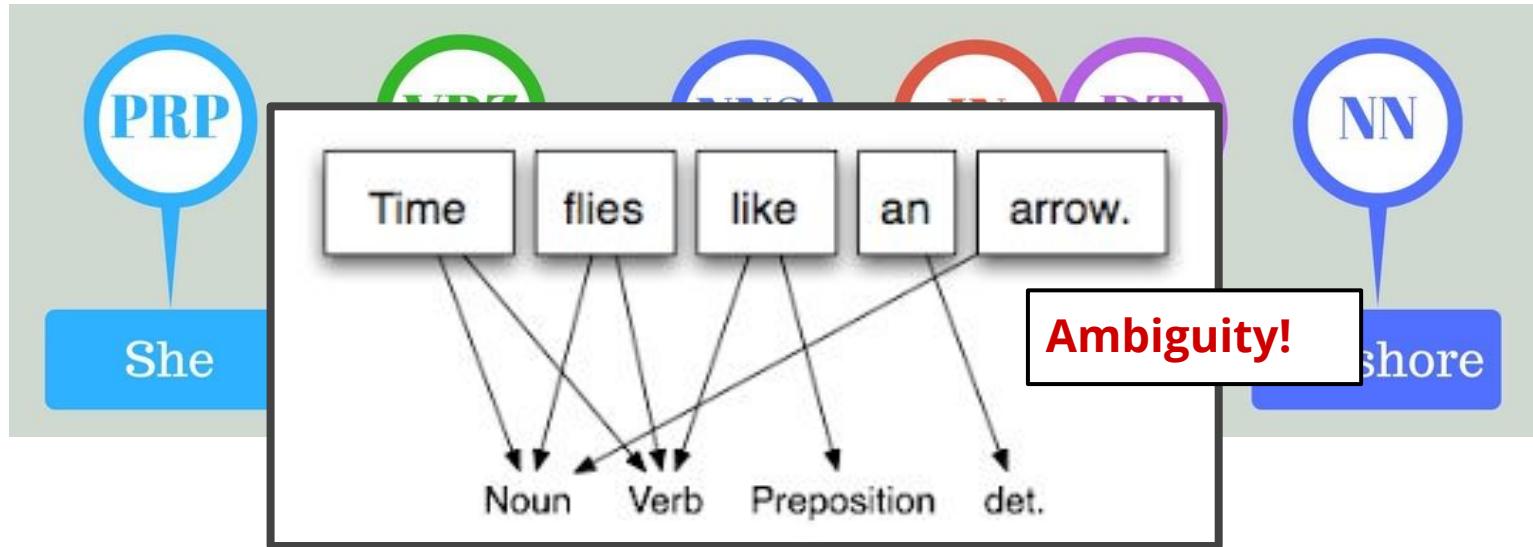
Part-Of-Speech Tagging

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



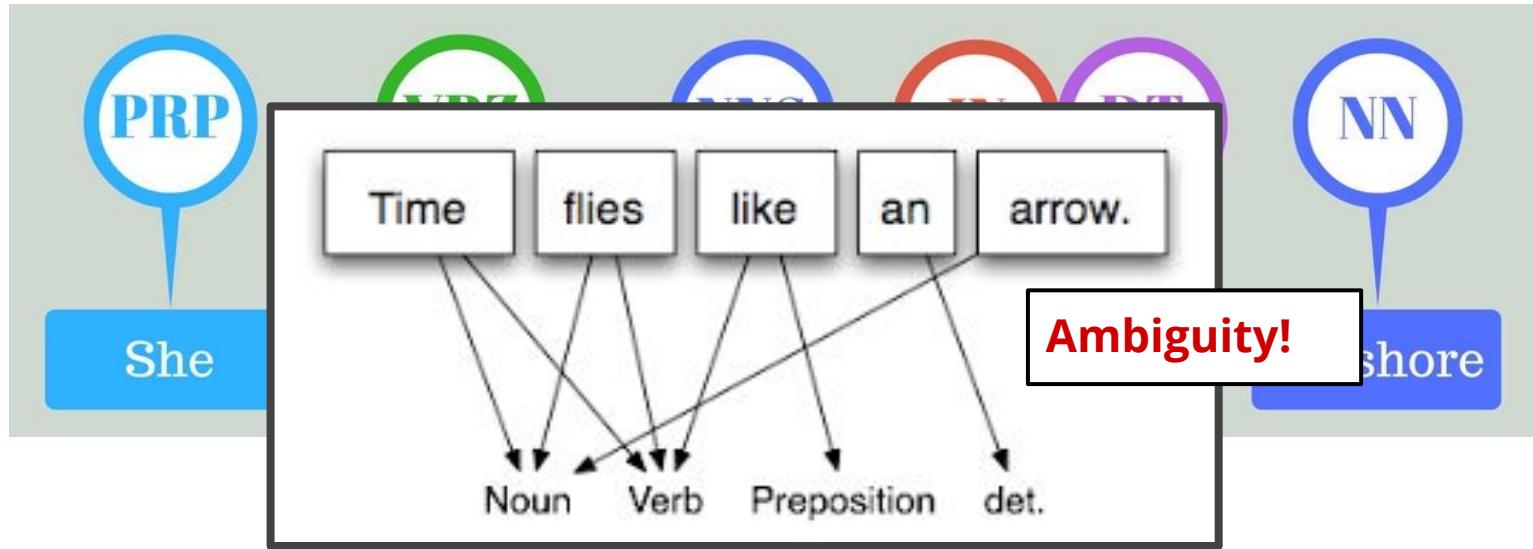
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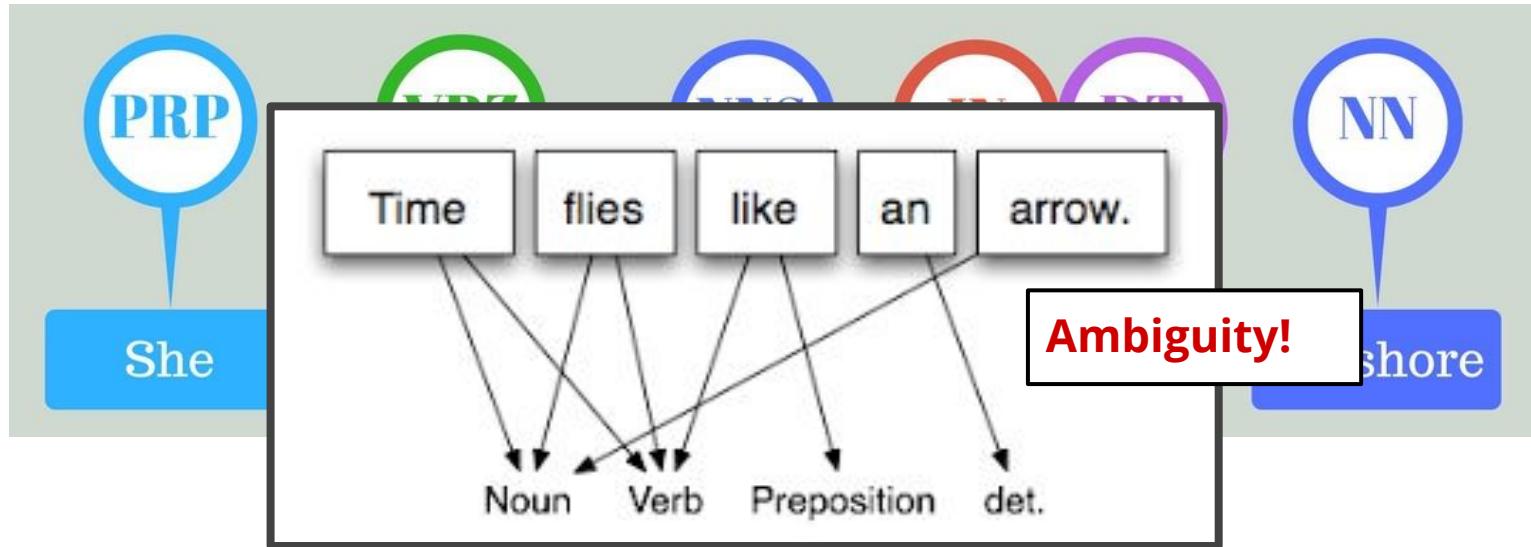
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- state-of-the-art: English ≈ 97%

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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)

In fact, the Chinese NORP market has the three CARDINAL most influential names of the retail and tech space – Alibaba GPE, Baidu ORG, and Tencent PERSON (collectively touted as BAT ORG), and is betting big in the global AI GPE in retail industry space. The three CARDINAL giants which are claimed to have a cut-throat competition with the U.S. GPE (in terms of resources and capital) are positioning themselves to become the 'future AI PERSON platforms'. The trio is also expanding in other Asian NORP countries and investing heavily in the U.S. GPE based AI GPE startups to leverage the power of AI GPE. Backed by such powerful initiatives and presence of these conglomerates, the market in APAC AI is forecast to be the fastest-growing one CARDINAL, with an anticipated CAGR PERSON of 45% PERCENT over 2018 - 2024 DATE.

To further elaborate on the geographical trends, North America LOC has procured more than 50% PERCENT of the global share in 2017 DATE and has been leading the regional landscape of AI GPE in the retail market. The U.S. GPE has a significant credit in the regional trends with over 65% PERCENT of investments (including M&As, private equity, and venture capital) in artificial intelligence technology. Additionally, the region is a huge hub for startups in tandem with the presence of tech titans, such as Google ORG, IBM ORG, and Microsoft ORG.

Syntactic analysis

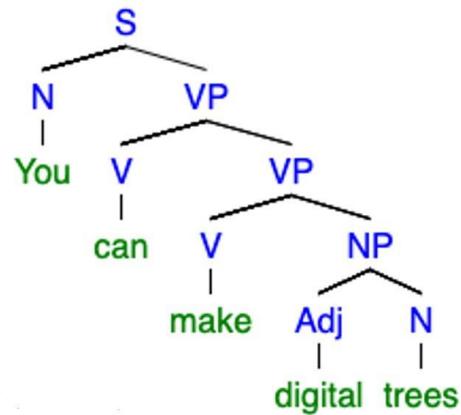
= Grouping words into phrases, and phrases into sentences

- 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

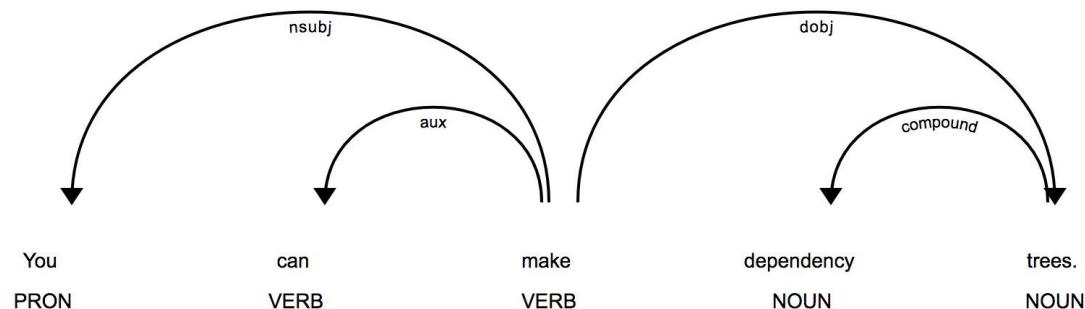
→ Hierarchical organization

Syntactic analysis

Two main paradigms: constituency and dependency



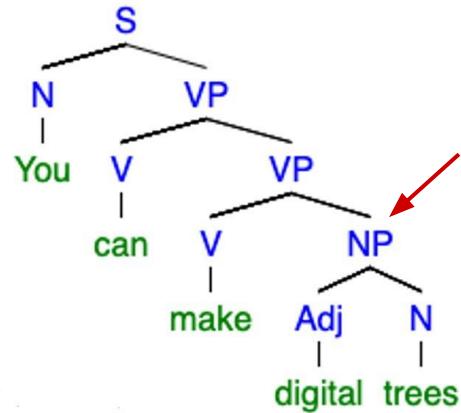
Constituency trees



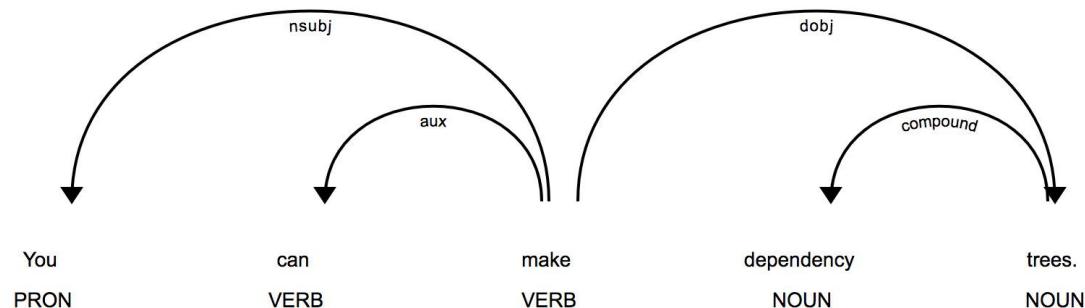
Dependency trees

Syntactic analysis

Two main paradigms: constituency and dependency



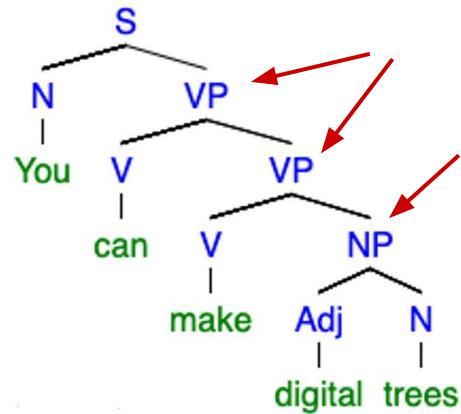
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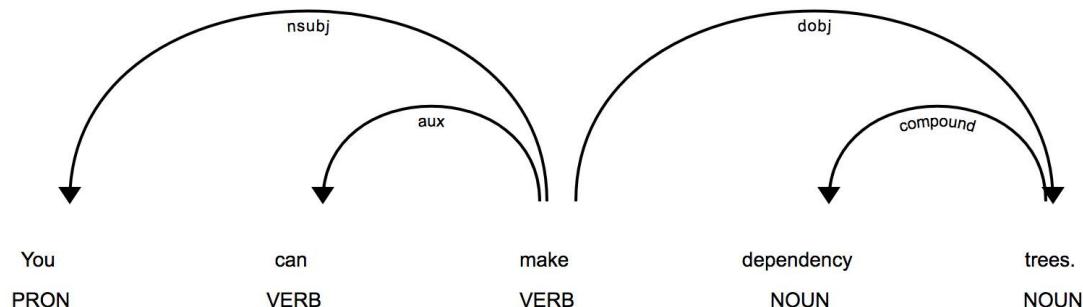
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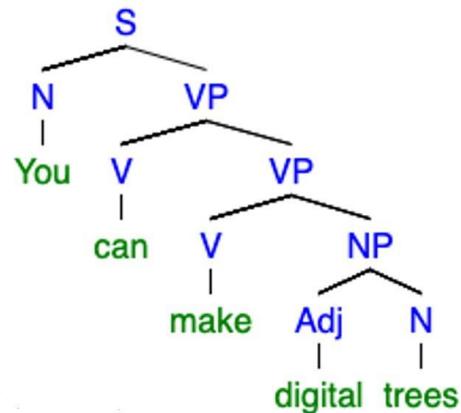
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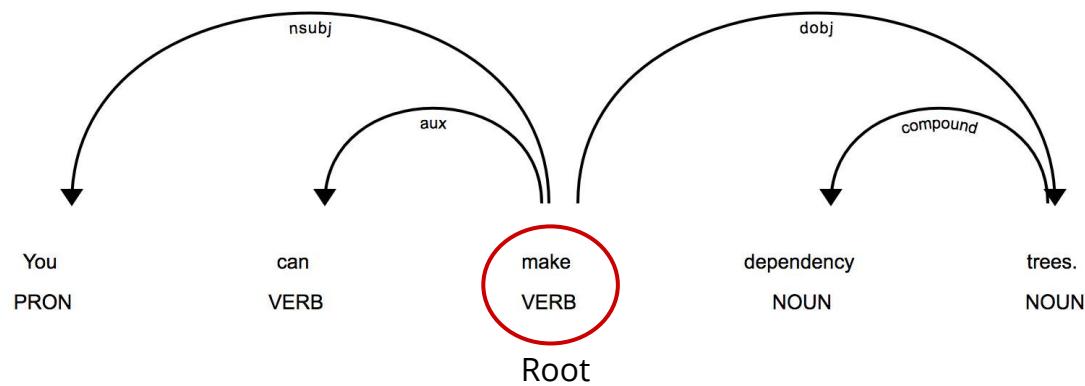
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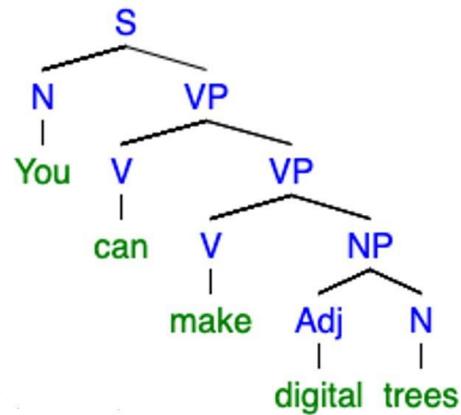
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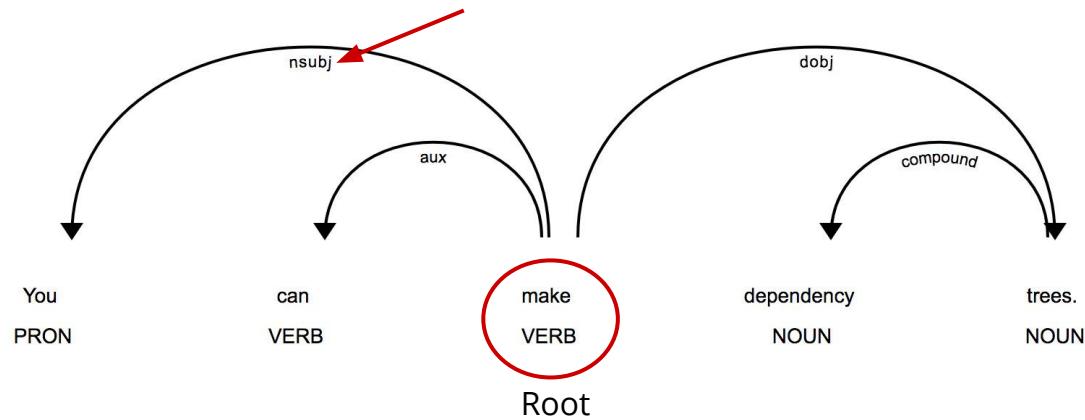
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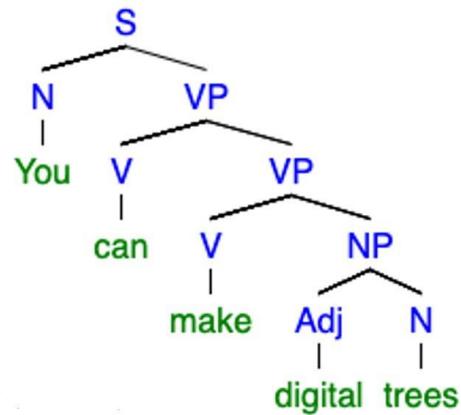
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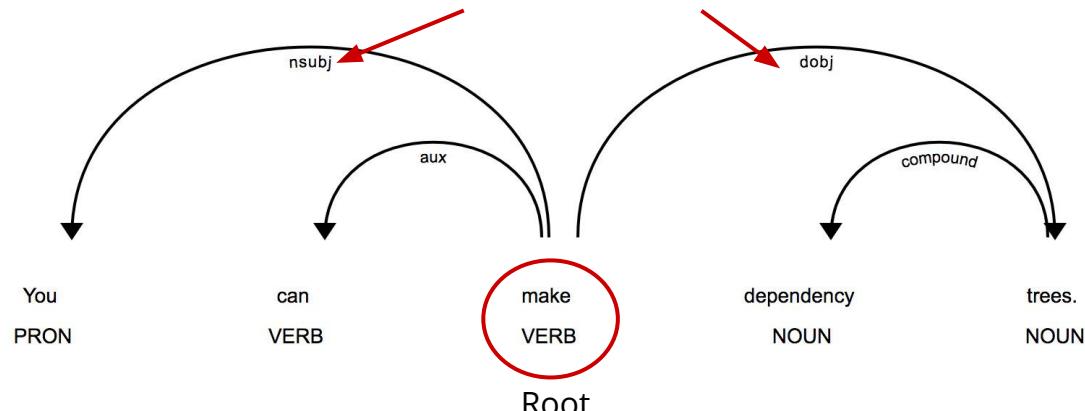
Dependency trees

Syntactic analysis

Two main paradigms: constituency and dependency



Constituency trees



Dependency trees

Syntactic analysis

The slide illustrates the concept of syntactic ambiguity through three panels. The top panel shows a hand-drawn illustration of a clock with the word 'TIME' written next to it. The middle panel shows a fly with a clock on its back, and the bottom panel shows a fly with a hand holding a clock. To the right of these illustrations are three parse trees for the sentence "Time flies like an arrow." Each tree uses orange lines to connect the words into grammatical structures:

- Tree 1:** S → NP VP → TIME flies like an arrow. This structure suggests that "Time" is the subject, "flies" is the verb, and "like an arrow" is a prepositional phrase modifying the verb.
- Tree 2:** S → NP VP → NP V NP → Time flies like an arrow. This structure suggests that "Time" is a noun phrase, "flies" is the verb, and "like an arrow" is another noun phrase.
- Tree 3:** S → V NP PP → flies Time like an arrow. This structure suggests that "flies" is the verb, "Time" is the direct object, and "like an arrow" is a prepositional phrase modifying the verb.

A red box on the right contains the text "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



Semantico-pragmatics: Discourse

Going beyond sentence boundaries

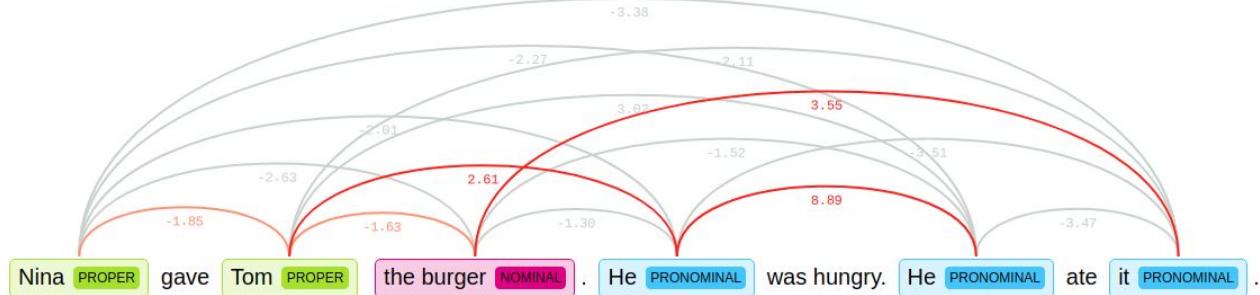
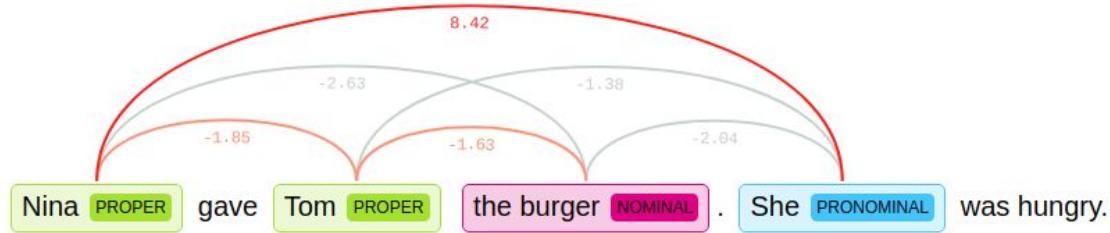
= connecting spans of text into a coherent, meaningful document

= understanding interactions in conversations

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



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/>



Discourse parsing

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

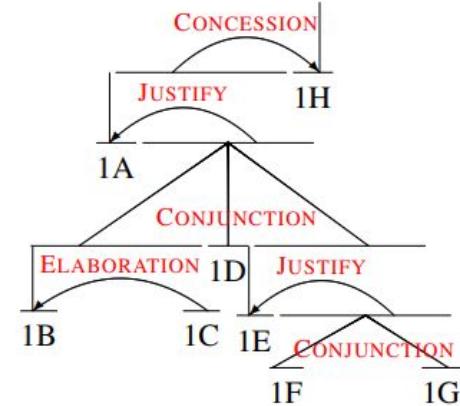
- (1) The train derailed. (Result) There were four wounded people. (Explanation) The driver was going too fast.

→ Could help a QA system to answer complex questions:

e.g., why did the train derailed?

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

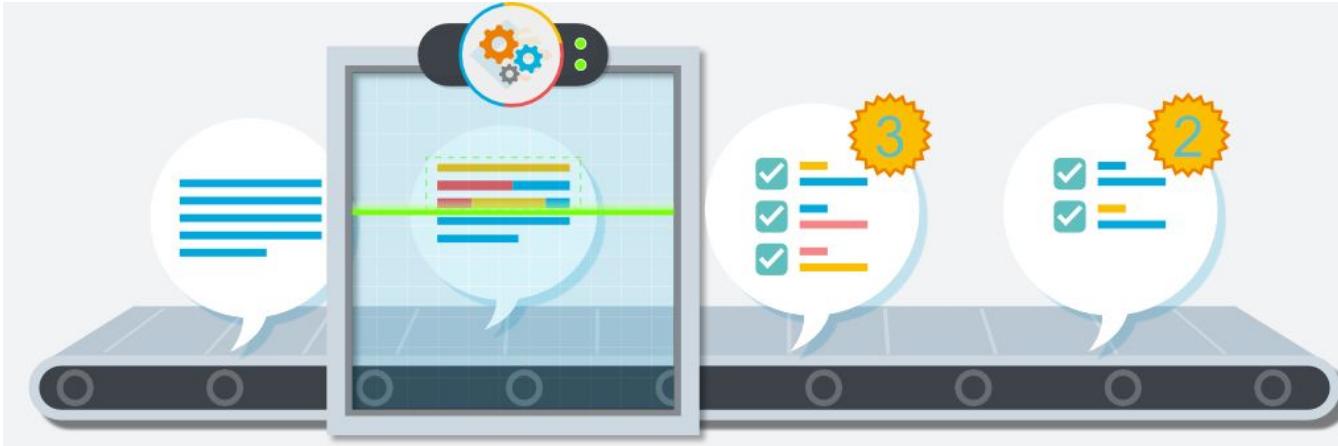
- (2) Tina gave Tom the burger. (because / Explanation) **He** was hungry.
- (3) Tina gave Tom the burger. (although / Contrast) **She** was hungry.



[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]

Hands-on NLP



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>

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



most of the problems with the film don't derive from the screenplay , but rather the mediocre performances by most of the actors involved



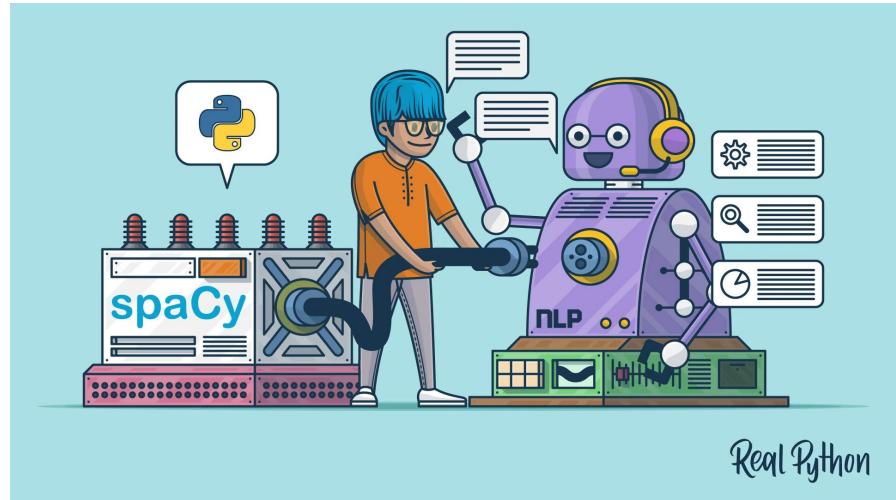
the film provides some great insight into the neurotic mindset of all comics -- even those who have reached the absolute top of the game .

Preprocessing with NLTK or Spacy



Natural Language Analysis
with Python NLTK

<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.
```

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')]
```

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")

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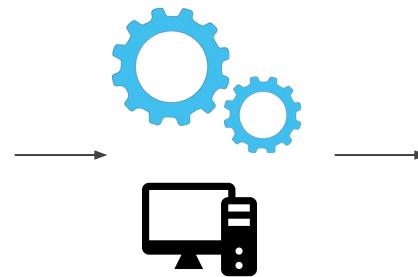


Learning from data (reminder, supervised setting)

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 !

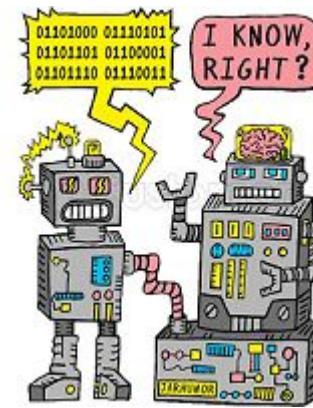


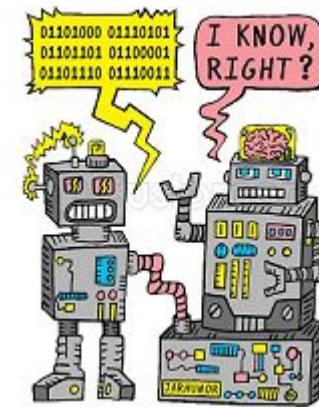
Learning from text data

Main issue:

- how to represent text?

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





Learning from text data

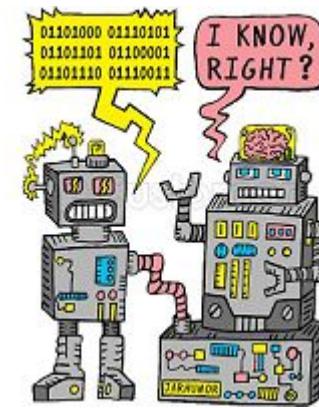
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Bag-of-Words (BOW):

- 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



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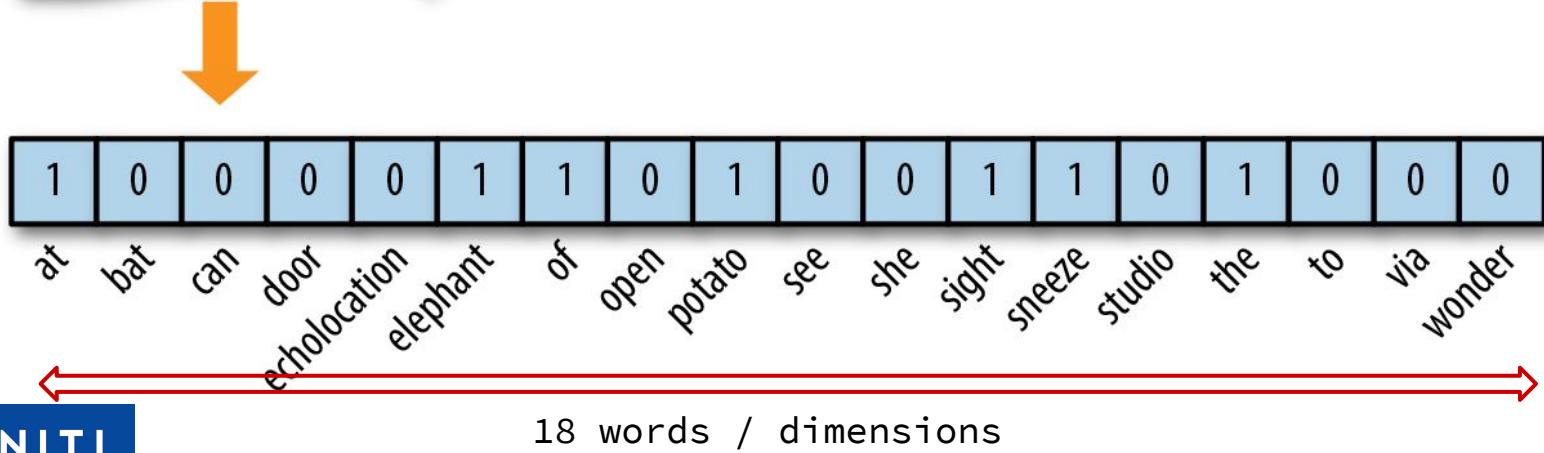
Bag-of-Words (BOW):

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BOW: One-hot encoding

The elephant sneezed
at the sight of potatoes.

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

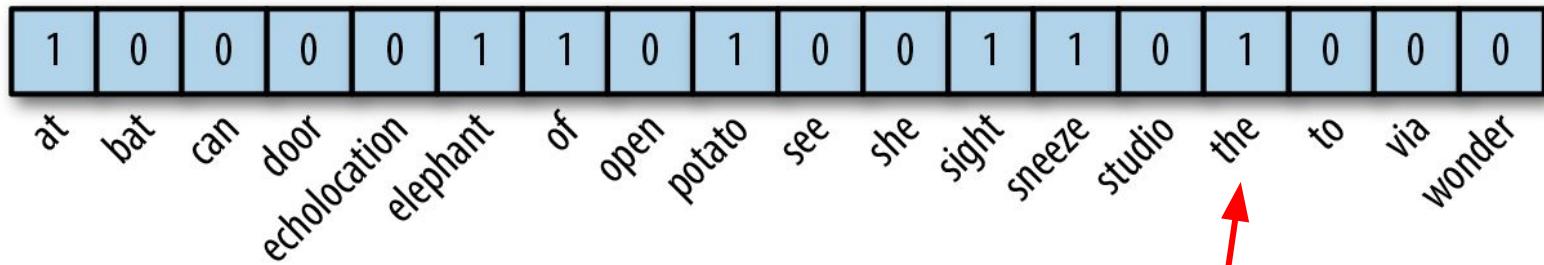


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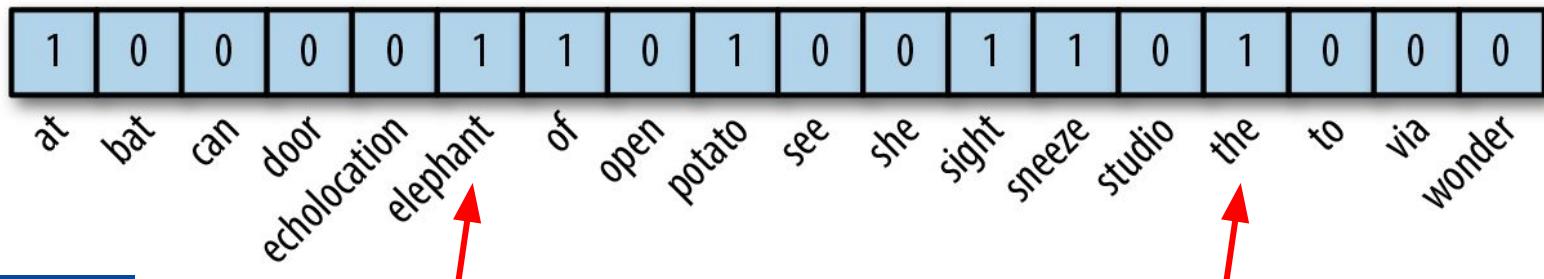


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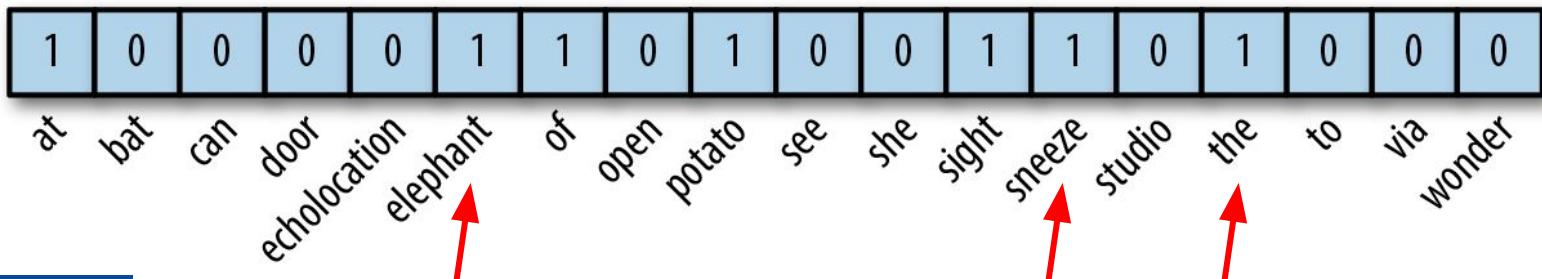


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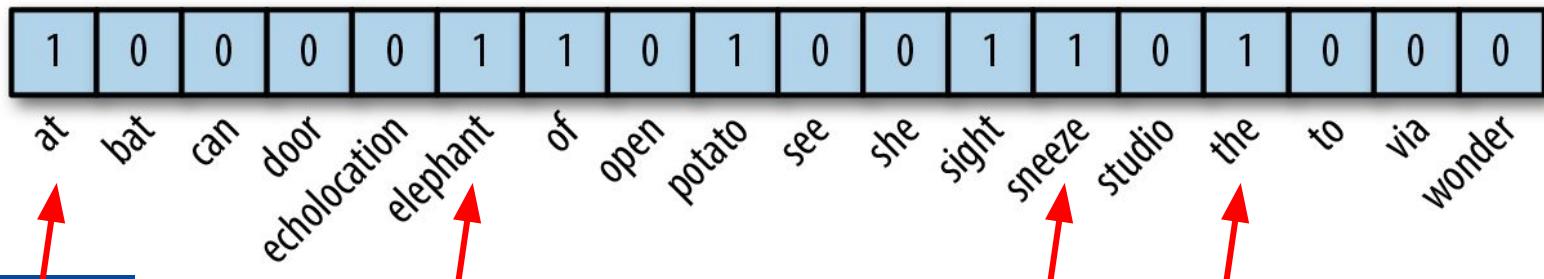


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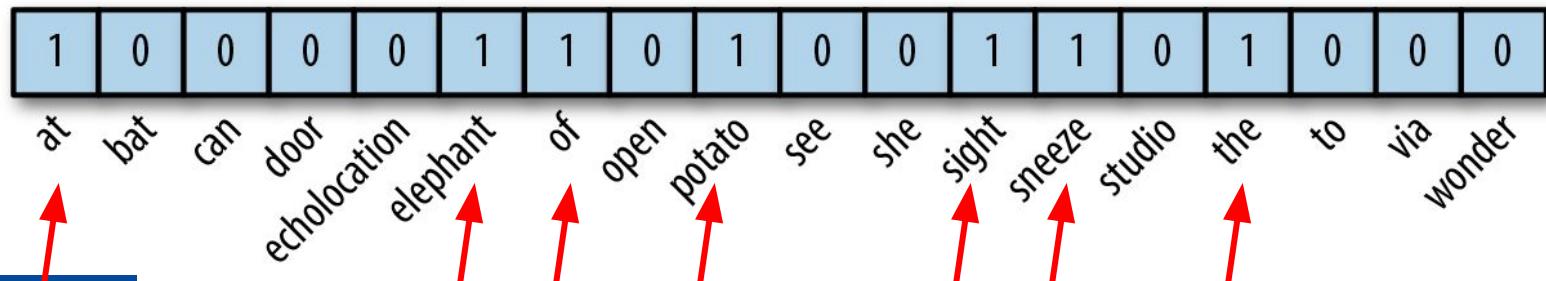


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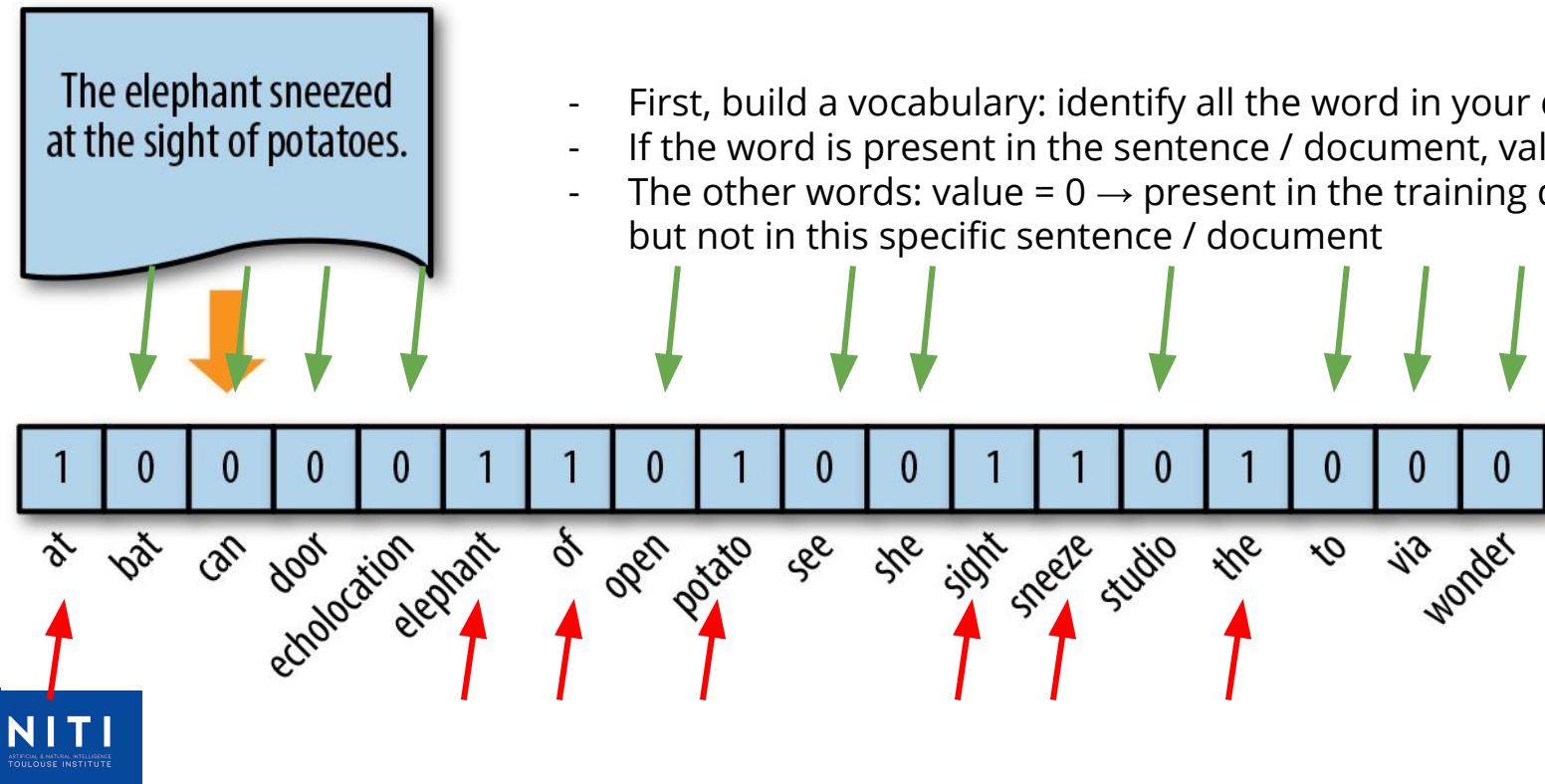
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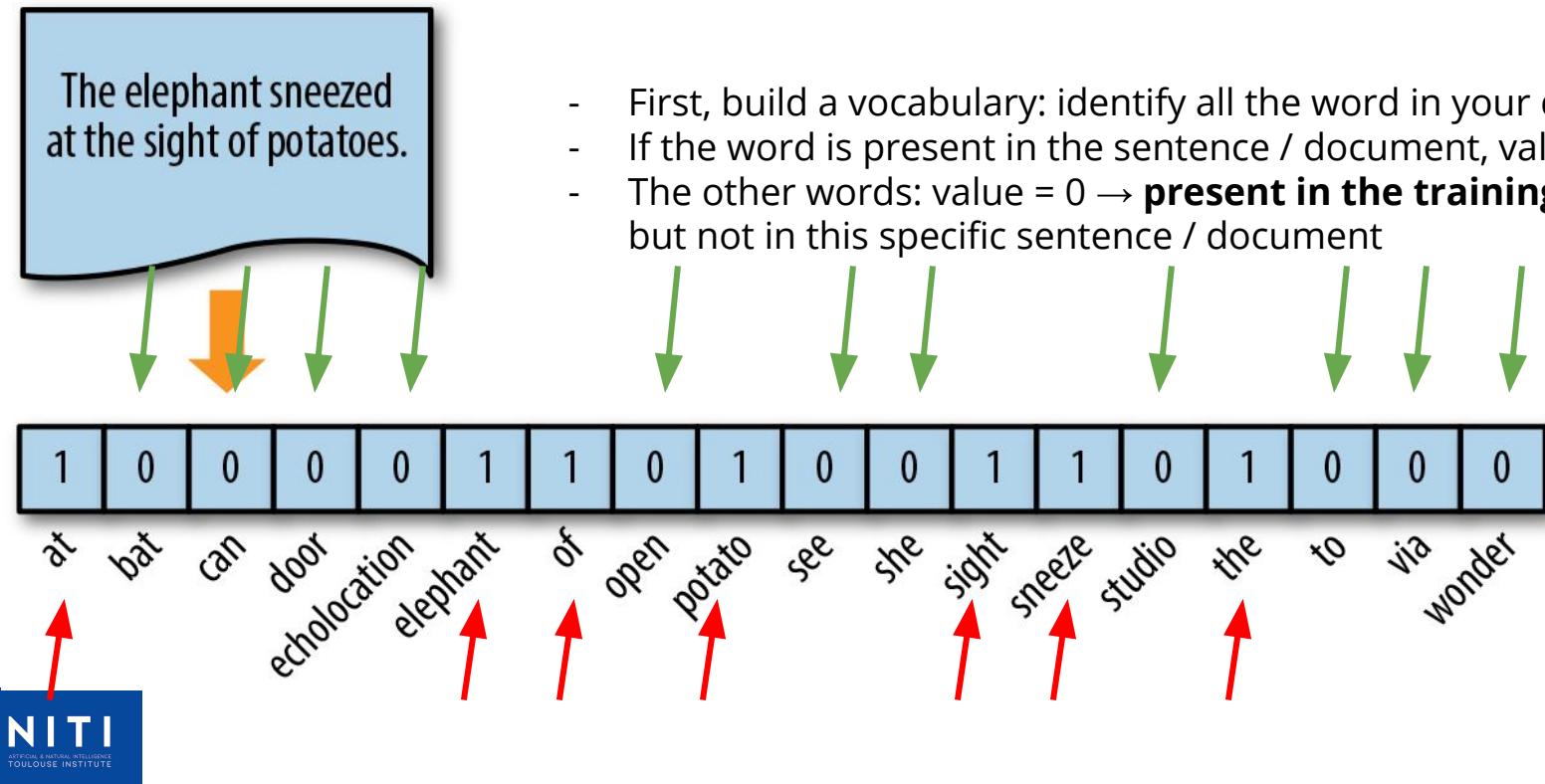
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BOW: One-hot encoding



BOW: One-hot encoding



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

Bag-of-Words

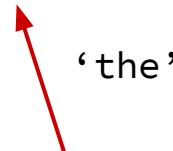
- Easy to use: now the computer can “read” your sentence



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>**

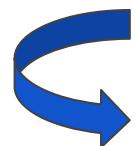
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$$w_{x,y} = tf_{x,y} \times \log \left(\frac{N}{df_x} \right)$$

TF-IDF

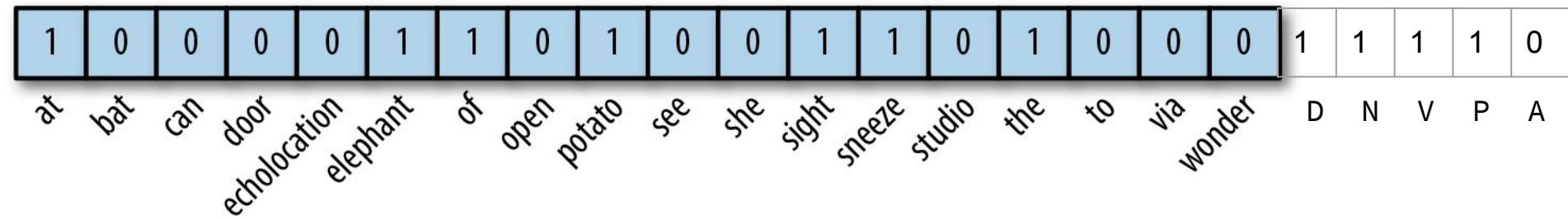
Term x within document y

$tf_{x,y}$ = frequency of x in y
 df_x = number of documents containing x
 N = total number of documents

Bag of any features

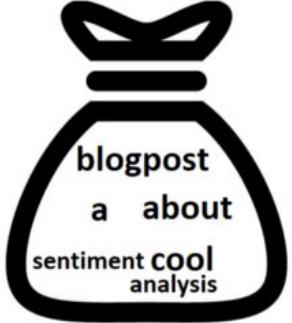
Can be used to take into account any information, e.g. POS tags:

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



We can encode any information:

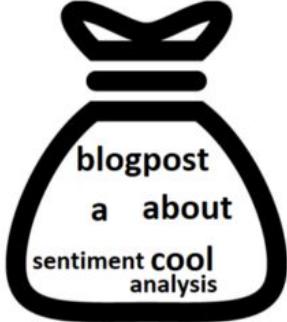
- presence of a syntactic relation
- presence of a Named Entity
- word associated to a sense if disambiguated
- words in the next sentence
- ...



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)



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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!

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-aggressive
 - ...
- Makes also easy to:
 - pre-process / vectorize text data
 - optimize and evaluate models
 - select features
- Classification, clustering, regression



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



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Vectorize

Train

Classification with Scikit-Learn



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Vectorize

Train

Predict

Classification with Scikit-Learn



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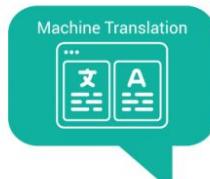
Predict

Evaluate

See more during the practical

NLP: tasks and applications

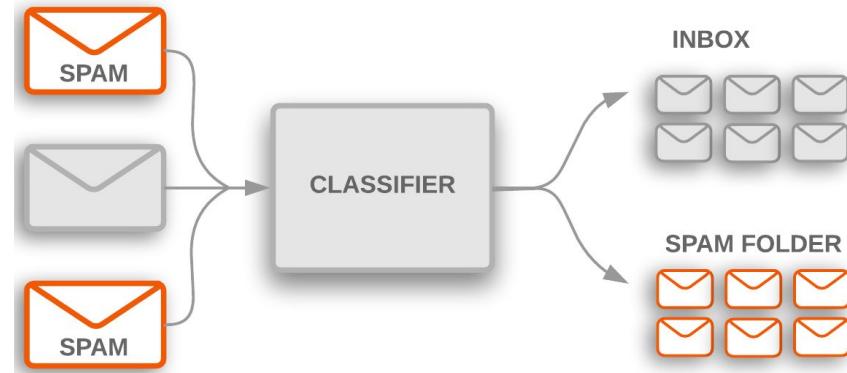
Natural
Language
Processing



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
-



Sequence Labelling

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

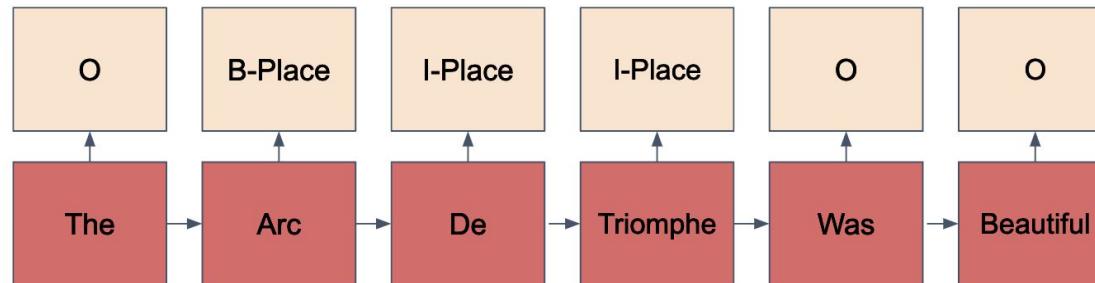
→ making the optimal label for a given element dependent on the choices of nearby elements

- POS tagging
- Named Entity Recognition

→ Without neurons: = CRF, HMMs ...

$$P(H|O) = \frac{P(O|H)P(H)}{P(O)}$$

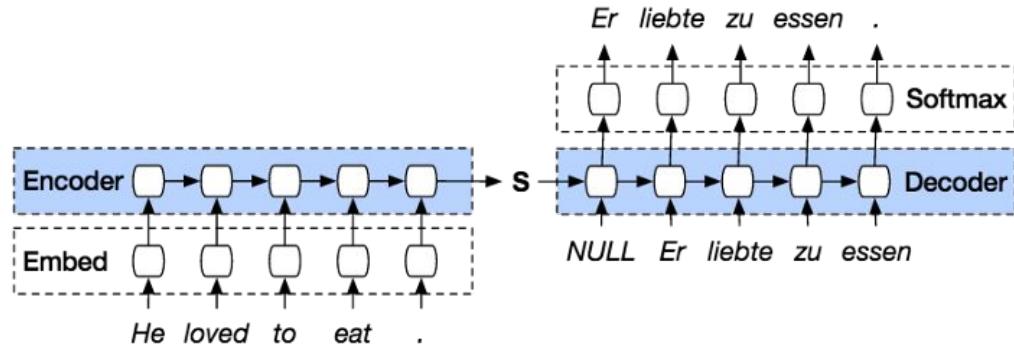
→ Now: e.g. with Recurrent Neural Network



Sequence to Sequence

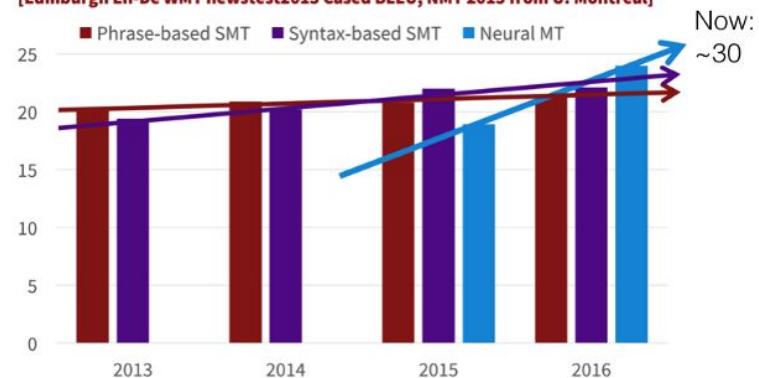
Idea: we want to take a sequence as input, and to output another sequence

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

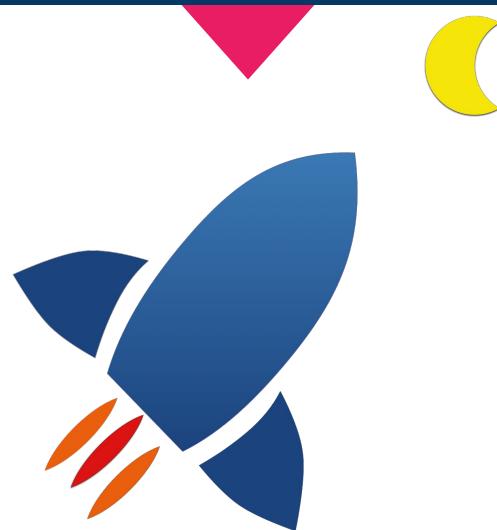


Progress in Machine Translation

[Edinburgh En-De WMT newstest2013 Cased BLEU; NMT 2015 from U. Montréal]

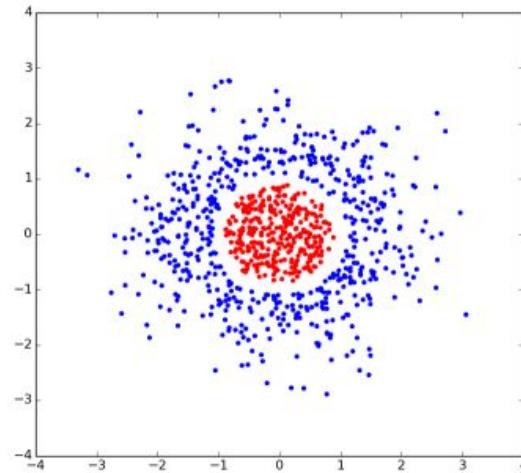


To go further...



Limits of classical statistical methods

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

[oooooooooooooooooooo1oooo]

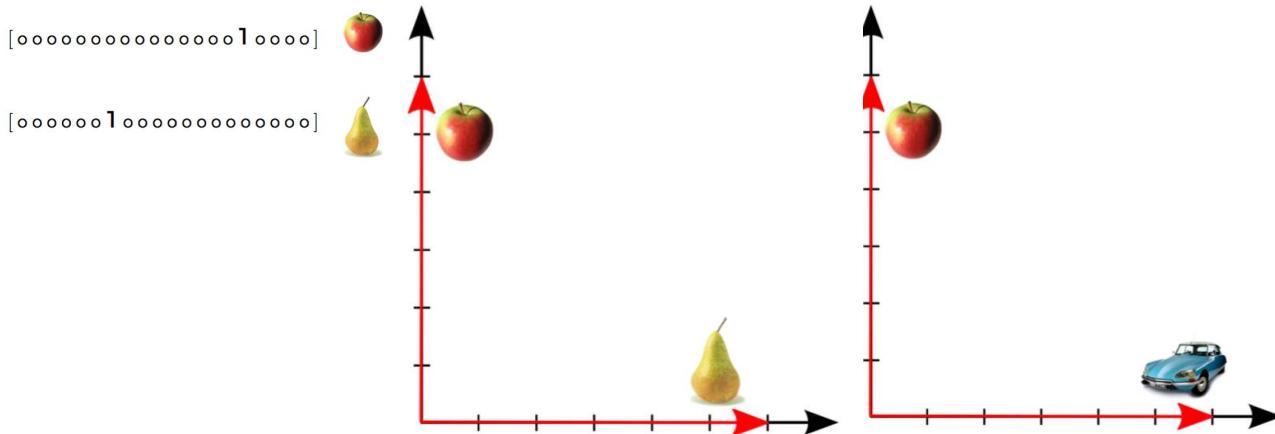


[oooooooo1ooooooooooooooo]



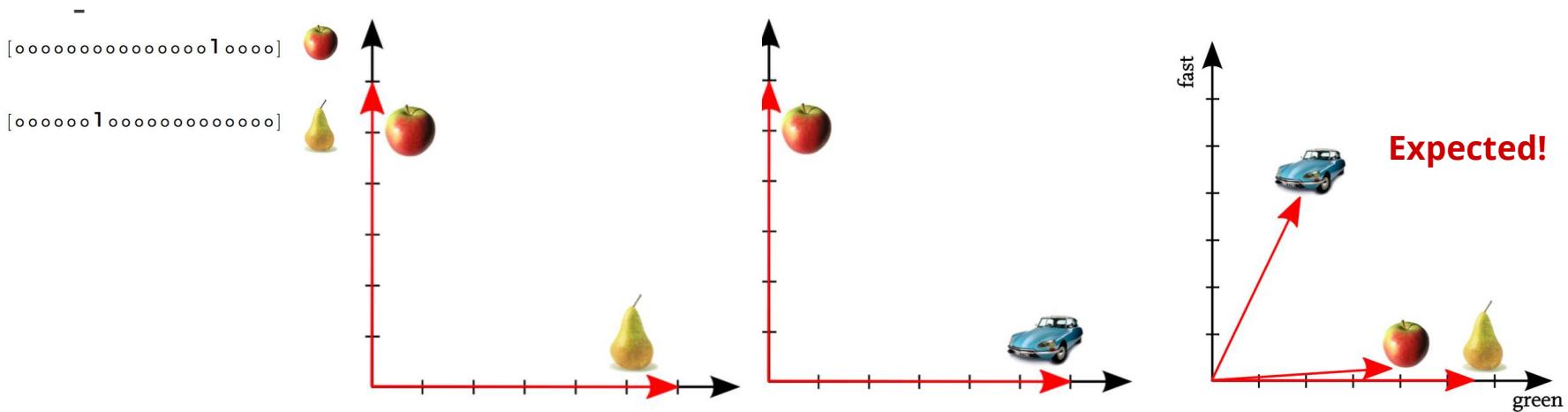
Data representation

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- A word is represented with a one-hot vector: easy to implement
- But representing the meaning of words? → **no notion of similarity**



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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* ?

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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



Word embeddings

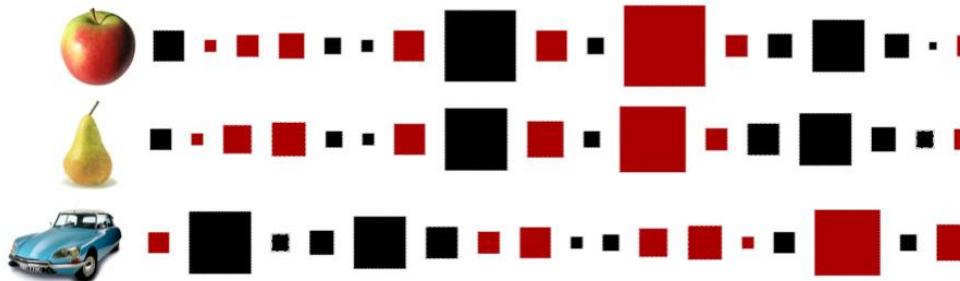
Many studies on representing the meaning of words using context

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...)



Word2vec

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

CBOW:

- predict the target word given the context

Skip-gram:

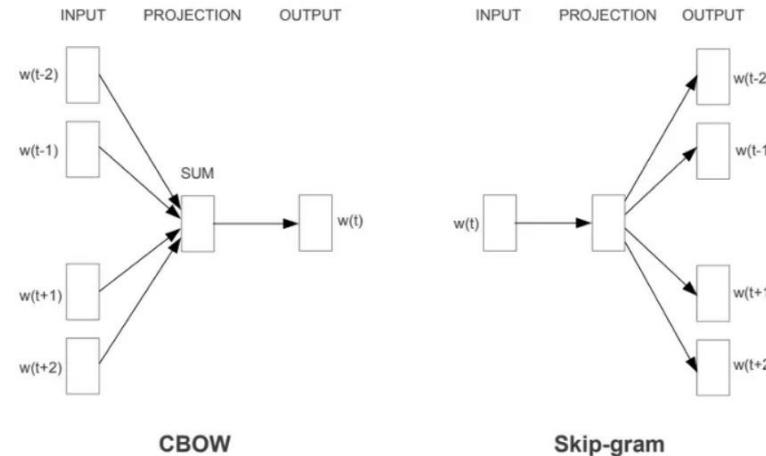
- predict the context words given the target word

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

The quick brown fox jumps over the lazy dog.

The quick brown fox jumps over the lazy dog.

The quick brown fox jumps over the lazy dog.



Word2vec

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

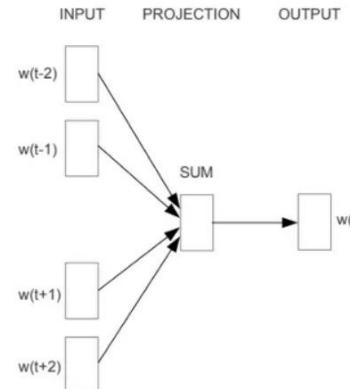
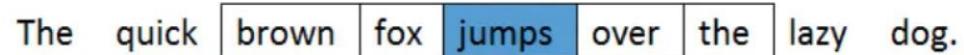
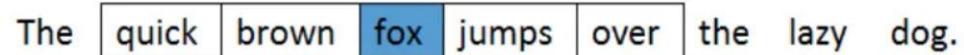
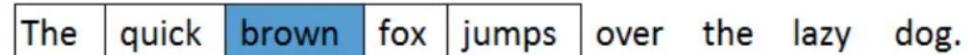
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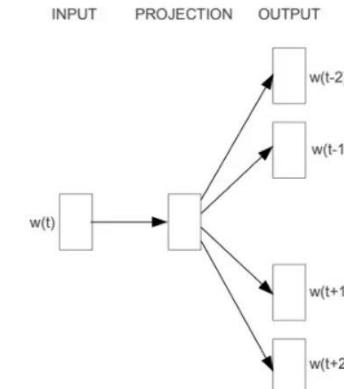
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CBOW



Skip-gram

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CBOW:

- predict the target word given the context

Skip-gram:

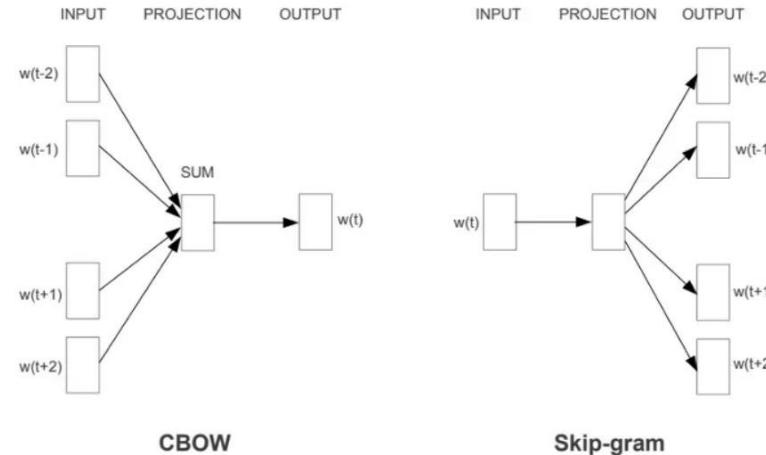
- predict the context words given the target word

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

The quick brown fox jumps over the lazy dog.

The quick brown fox jumps over the lazy dog.

The quick brown fox jumps over the lazy dog.



Word2vec

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

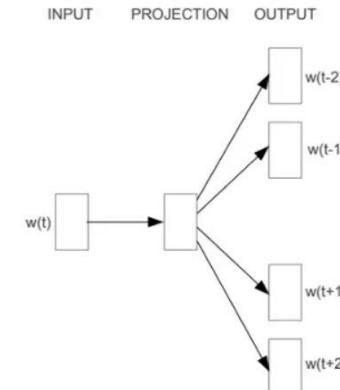
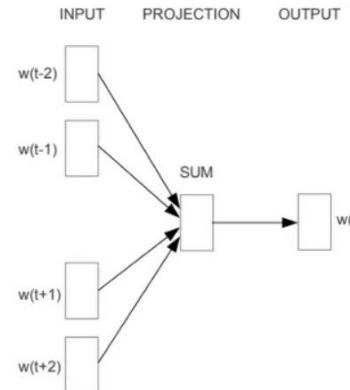
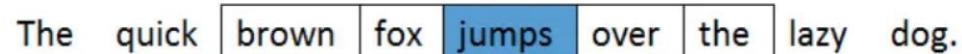
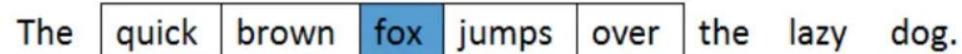
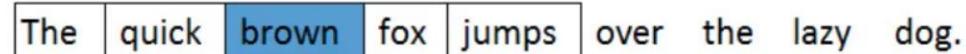
CBOW:

- predict the target word given the context

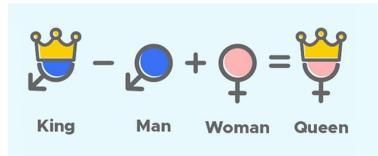
Skip-gram:

- predict the context words given the target word

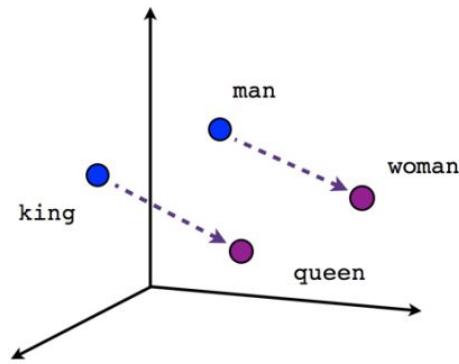
→ **the hidden layer** is used as the representation of the target word



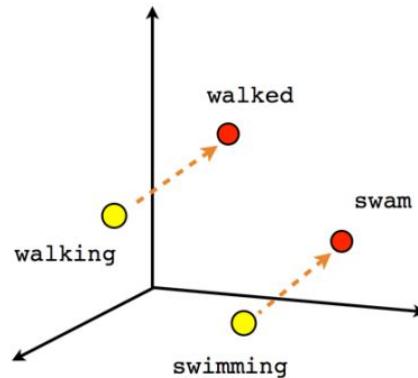
Word2vec



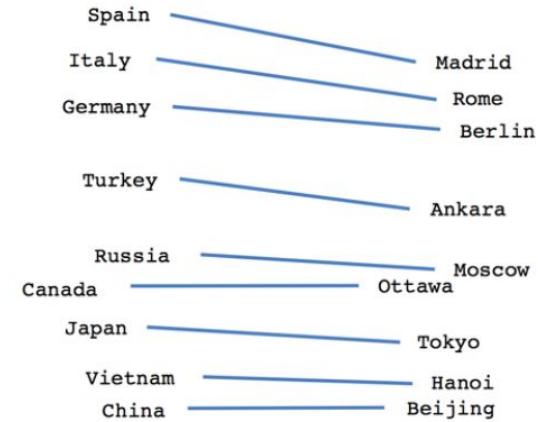
Allow inference:



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

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

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 ₂ e (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

Finnish	↔	English
Hän sijoittaa. Hän pesee pyykiä.	×	He invests. She washes the laundry.
Hän urheilee.		He's playing sports.
Hän hoitaa lapsia. Hän tekee töitä. Hän tanssii.		She takes care of the children. He works. She dances. He
Hän ajaa autoa.		drives a car.



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://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)

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
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- 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-1eedad30e57d8>
 - <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).

Sources of pictures

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- <https://www.dw.com/en/linguist-theres-a-difference-between-learning-words-and-learning-a-language/a-18602460>
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- <https://nativeenglishspain.blogspot.com/2013/10/wise-wednesday-grammar-homonym.html>
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- <https://medium.com/@umadantuun/789/everything-you-need-to-know-about-trained-entity-recognition-2a136f38c08f>
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- <http://www.jefasouza.com/blog/check-tweets-spelling/>
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- <https://developers.google.com/machine-learning/guides/text-classification>
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- <https://medium.com/swlh/we-need-to-talk-about-sentiment-analysis-9d1f20f2ebfb>
- https://medium.com/@jeremie_guillou/nlp-fastai-sequence-to-sequence-model-seq2seq-38d9984cf271
- <http://www.bigdatalab.ac.cn/~jxnxu/publications/KG4IR2017-keynote.pdf>
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