

# Natural Language Models and Interfaces

BSc Artificial Intelligence

Lecturer: Wilker Aziz

Institute for Logic, Language, and Computation

2018, week 1, lecture a

Course organisation

Why NLP?

Why is NLP hard?

An overview of problems

An overview of the statistical method

Language data: first contact

# Course

Topic: Statistical Natural Language Processing

Team

- ▶ Instructor: Wilker Aziz
- ▶ Assistants: Miguel Rios, Urja, Evelyne, Nora, Caitlin, Tessa

Attendance

- ▶ lectures: not monitored, but encouraged
- ▶ labs: highly encouraged!

# Course information

## Blackboard

- ▶ course manual
- ▶ weekly materials: readings, slides
- ▶ assignments: exercises, projects

## Textbook

Jurafsky & Martin, *Speech and Language Processing* (2nd edition)

Additional material may be announced in class

# Assessment

- ▶ One exam (individual work): 40%
- ▶ Weekly assignments (in pairs)
  - ▶ practical programming exercises and mini-projects: 40%
  - ▶ theoretical (non-programming) exercises: 20%

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# What about processing language?

It's every where!

- ▶ We talk about things

*I love Paris! All those bridges, the cathedral, the Louvre, oh and of course, the tower!*

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*From Dam square you head north on Damrak till you see it, really, you can't miss it.*

- ▶ We entertain ourselves

Eleanor Ribgy

*... picks up the rice*

*In the church where a wedding has been*

*Lives in a dream*

*Waits at the window, wearing the face*

*That she keeps in a jar by the door*

*Who is it for*

# People infer stuff from text and speech

*I've had a wonderful weekend! I always wanted to buy a melodica. On Saturday, I finally went to that fancy music store in Haarlem. The rest of the weekend, I practised some of my favourite songs on it.*

---

Adapted from A. Louis, S. Goldwater, I. Titov, K. Sima'an, T. Deoskar

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The melodica was bought at that store in Haarlem
- ▶ impressions about speaker/writer style  
The writing is boring or funny or engaging

# All of this understanding plays a role when we

- ▶ Make conversations with other
- ▶ Translate from one language to another
- ▶ Create a summary of a document
- ▶ Find an answer to a question from a text

NLP then is about enabling computers to do some of these tasks

- ▶ How to study/analyse language in computational terms?
- ▶ How to build applications that will do these tasks automatically?

# Goals of NLP

## Scientific

- ▶ Build models of the human use of language

## Engineering

- ▶ Build models that serve in technological applications
  - ▶ machine translation
  - ▶ speech systems
  - ▶ information extraction, etc.



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In this course we

- ▶ draw insights from scientific knowledge
- ▶ but mostly focus on engineering aspects
- ▶ and rely on language data in the form of digital text

# NLP Applications

- ▶ Information retrieval: Google
- ▶ Summarisation: Google News
- ▶ Speech recognition: Siri, Alexa, Google Home
- ▶ Dialogue systems: Amazon chatbot
- ▶ Machine translation: Google translate
- ▶ Image captioning: Microsoft, Facebook
- ▶ Recommendation systems: Amazon reviews
- ▶ Social network analysis: Facebook, Twitter

Course organisation

Why NLP?

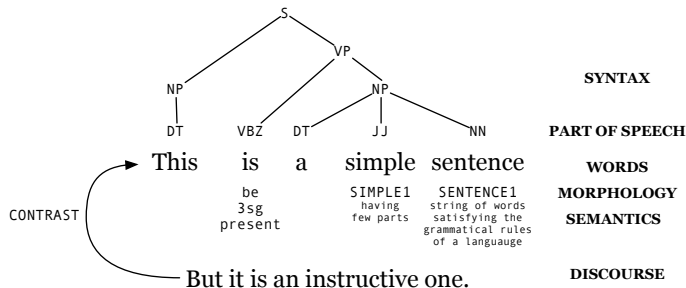
Why is NLP hard?

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# Basic levels of structure



Slide from S. Goldwater

# Why is NLP hard?

Ambiguity at many levels

- ▶ Word senses: **bank** (finance or river?)
- ▶ Part of speech: **chair** (noun or verb?)
- ▶ Syntactic structure: **I saw a man with a telescope**
- ▶ Quantifier scope: **Every child loves some movie**
- ▶ Multiple: **I saw her duck**

*and ambiguity typically grows with sentence length*

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*and ambiguity typically grows with sentence length*

**Examples from newspaper headlines**

*Iraqi head seeks arms*

*Stolen painting found by tree*

*Teacher strikes idle kids*

# Why is NLP hard?

## Variability (paraphrasing)

- ▶ *Emma burst into tears and he tried to comfort her, saying things to make her smile.*
- ▶ *Emma cried, and he tried to console her, adorning his words with puns.*

---

Example from Barzilay and McKeown (2001)

# Why is NLP hard?

## Different genres

- ▶ Suppose we train a part of speech tagger on the Wall Street Journal

Mr./NNP Vinken/NNP is/VBZ chairman/NN of/IN  
Elsevier/NNP N.V./NNP ,/, the/DT Dutch/NNP  
publishing/VBG group/NN ./.

- ▶ What will happen if we try to use this tagger for social media??

ikr smh he asked fir yo last name



# Why is NLP hard?

## Languages are different

- Chinese sentences do not have delimiters between words

(a) Raw data:

他还提出一系列具体措施和政策要点。

(b) Segmented:

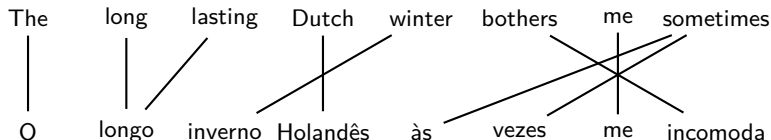
他 还 提出 一 系列 具体 措施 和 政策 要点 。

He also propose one series concrete measure and policy essential .

(He also proposed a series of concrete measures and essentials on policy.)

# Why is NLP hard?

Languages have **different word orders**



# Why is NLP hard?

## Context dependence

- ▶ correct interpretation typically requires context and often requires world knowledge

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## Unknown representation

- ▶ we don't know how humans represent knowledge

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# Sequential prediction

What is the next word? [▶ quiz](#)

- ▶ I slept on my ...
- ▶ Where is the ...
- ▶ Natural language processing is ...

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What is the next word? [▶ quiz](#)

- ▶ I slept on my ...
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not every word is equally likely to continue a certain prefix

- ▶ we typically make meaningful and grammatical sentences



# Sequence segmentation

Some languages are based on *continuous scripts* [Wiki](#)

- ▶ for example Chinese and Thai

In English, words are generally clearly delimited

- ▶ but we still care about **tokenisation**
  - ▶ input: I'm not gonna miss it, neither should ya!
  - ▶ output: I 'm not gonna miss it , neither should ya !

▶ [quiz](#)

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▶ [quiz](#)

It is not necessarily clear what it means to find a segmentation

- ▶ we are either looking for meaning carrying parts
- ▶ or trying to minimise the cost of representation

# Sequence labelling

We are often interested in analysing sentences

- ▶ we can classify words with respect to parts of speech  
apple is a noun
- ▶ and context usually plays a role  
I chair<sub>verb</sub> debates all the time, and usually I do not have a  
chair<sub>noun</sub> to sit on
- ▶ some words may refer to an entity  
Leibniz<sub>Wiki</sub> was a German mathematician

It's similar to sequence prediction, but with additional context

▶ quiz

# Morphological disambiguation

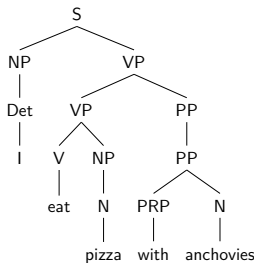
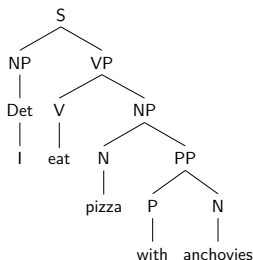
Words have meaning carrying and functional parts

- ▶ English **-ly** usually *derives* an adverb from an adjective
- ▶ less often English can use *agglutination* or *compounding* to make new words  
**wrongdoing** is **wrong** + **doing**
- ▶ there are ambiguities
  - ▶ **s** marks plural in *cats*, third person in *it marks*, nothing in *news*
  - ▶ with a verb **un** means “reversal”, e.g. *untie*  
with an adjective **un** means “not”, e.g. *unwise*
- ▶ other languages are far more complex [▶ Wiki](#)

# Syntactic parsing

We can take the idea of sequence labelling and push it a bit farther

- ▶ label every “coherent” substring in a sentence — a **constituent**
- ▶ and we can do so **recursively**



which one has a **funny** interpretation?

---

Stanford parser demo

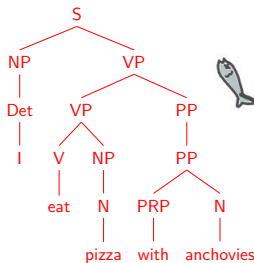
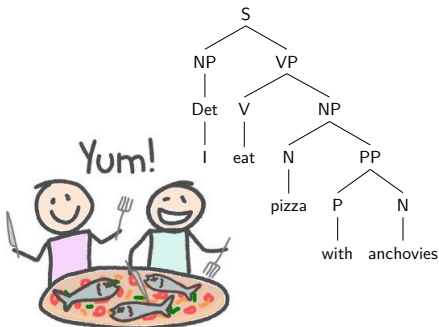
▶ Try it out!

Drawings from James Constable — CC 2.5

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**nesting** tells us about syntactic **dependencies**

Stanford parser demo [▶ Try it out!](#)

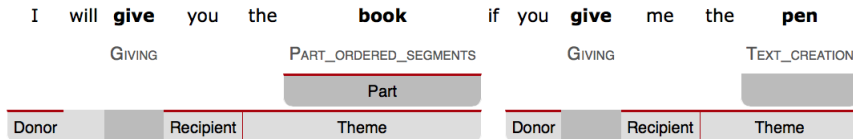
Drawings from James Constable — CC 2.5

# Semantic parsing

We may be interested in the **semantic role** of constituents with respect to a **predicate** rather than their syntactic function

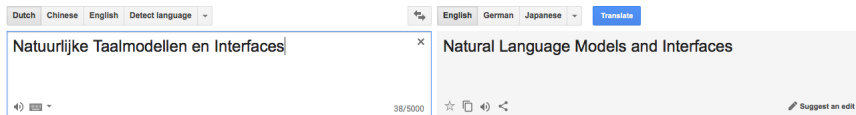
Answer questions such as

- ▶ *who did what to whom, when and why?*



# Text-to-text transformation

We can combine sequential prediction with sequence labelling and a few more things to **translate**



or **summarise**



# Much more

- ▶ coreference resolution
- ▶ discourse analysis
- ▶ question answering
- ▶ paraphrasing
- ▶ translation equivalence
- ▶ word alignment

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# But how can we do that?

Statistical approach

- or the “probabilistic pipeline”

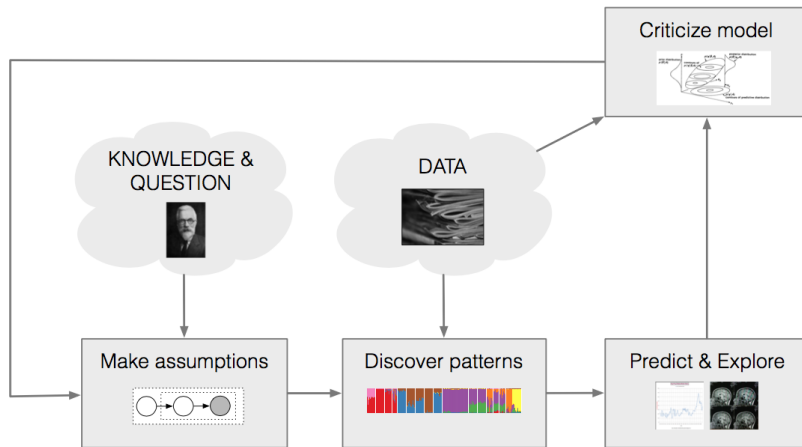


Image by David Blei

# Pipeline

We have knowledge about the world and we have questions we want to answer

- ▶ so we can design a model: encodes our knowledge and assumptions

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We have data that by assumptions is somewhat complies with our assumptions

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# Pipeline

We have knowledge about the world and we have questions we want to answer

- ▶ so we can design a model: encodes our knowledge and assumptions

We have data that by assumptions is somewhat complies with our assumptions

- ▶ so we can use statistics to discover patterns in data

We typically want to predict things or explore things

- ▶ again statistics can help us make decisions
- ▶ predict future outcomes
- ▶ organise unstructured data in some structured way

# What do people talk about in the Wall Street Journal?



Topics found in 1.8M articles from the New York Times

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# Let's start with the frequency of words

There are always phenomena which are important but have rare evidence in data: **Zipf's Law**.

- ▶ To illustrate, let's look at the frequencies of different words in a large text corpus.
- ▶ Assume a “word” is a string of letters separated by spaces (a great oversimplification as we know by now)

# Word Counts

Most frequent words in the English Europarl corpus  
out of 24 million **tokens**

## any word

Frequency	Token
1,698,599	the
849,256	of
793,731	to
640,257	and
508,560	in
407,638	that
400,467	is
394,778	a
263,040	I

## nouns

Frequency	Token
124,598	European
104,325	Mr
92,195	Commission
66,781	President
62,867	Parliament
57,804	Union
53,683	report
53,547	Council
45,842	States

# Word Counts

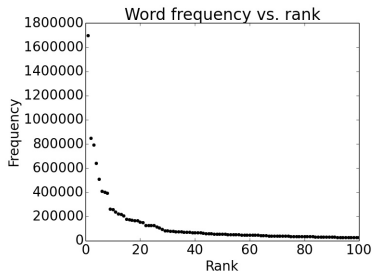
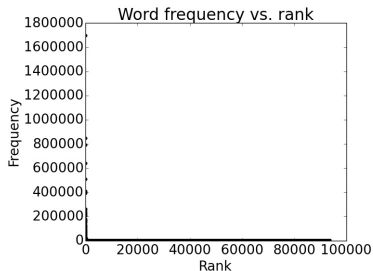
Out of 93638 distinct words (word types), 36231 occur **only once!**

Examples:

- ▶ cornflakes, mathematicians, fuzziness, jumbling
- ▶ pseudo-rapporteur, lobby-ridden, perfunctorily,
- ▶ Lycketoft, UNCITRAL, H-0695
- ▶ policyfor, Commissioneris, 145.95, 27a

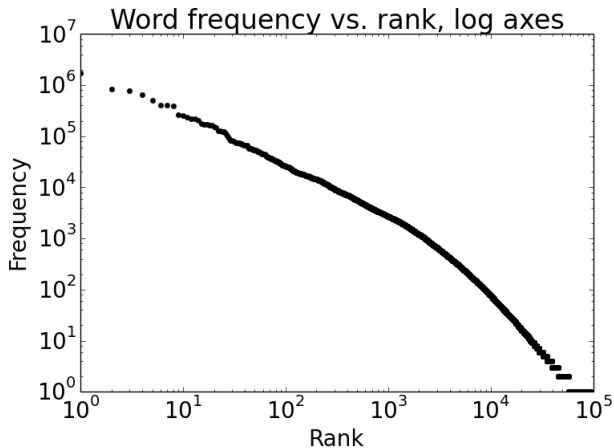
# Plotting word frequencies

If we order words by frequency,  
what is the frequency of  $n$ th ranked word?



# Rescaling the axes

To really see what's going on, use logarithmic axes:



# Zipf's law

Summarises the behaviour we just saw:

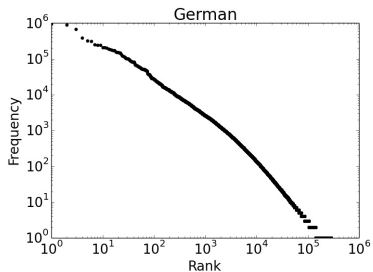
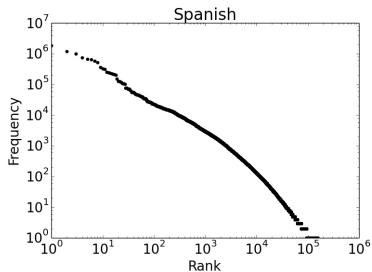
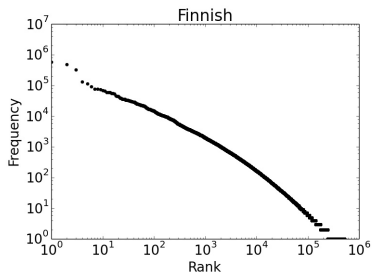
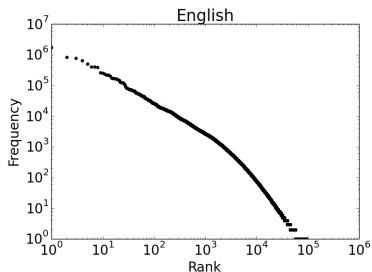
$$f \times r \approx k$$

- ▶  $f$  = frequency of a word
- ▶  $r$  = rank of a word (if sorted by frequency)
- ▶  $k$  = a constant

Why a line in log-scales?

$$\text{▶ } fr = k \Rightarrow f = \frac{k}{r} \Rightarrow \log f = \log k - \log r$$

# What about other languages?



# Implications of Zipf's Law

- ▶ Regardless of how large our corpus is, there will be a lot of infrequent (and zero-frequency!) words.
- ▶ In fact, the same holds for many other levels of linguistic structure (e.g., syntactic rules).
- ▶ This means we need to find clever ways to estimate probabilities for things we have rarely or never seen.



# Scope of the course

In this course you will learn about

- ▶ probabilistic modelling
- ▶ statistical inference and estimation
- ▶ how to represent language data
- ▶ discovering patterns in text collections

# Topics

- ▶ Markov models: including language models and sequence prediction
- ▶ Mixture models: sequence labelling and PCFGs
- ▶ Models of distributional semantics: word representation
- ▶ Translation equivalence: learning dictionaries

# References I

- Regina Barzilay and Kathleen R. McKeown. Extracting paraphrases from a parallel corpus. In *Proceedings of 39th Annual Meeting of the Association for Computational Linguistics*, pages 50–57, Toulouse, France, July 2001. Association for Computational Linguistics. doi: 10.3115/1073012.1073020. URL <http://www.aclweb.org/anthology/P01-1008>.
- Naiwen Xue, Fei Xia, Fu-dong Chiou, and Marta Palmer. The penn chinese treebank: Phrase structure annotation of a large corpus. *Nat. Lang. Eng.*, 11(2):207–238, June 2005. ISSN 1351-3249. doi: 10.1017/S135132490400364X. URL <https://doi.org/10.1017/S135132490400364X>.