# Natural Language Models and Interfaces

BSc Artificial Intelligence

Lecturer: Wilker Aziz
Institute for Logic, Language, and Computation

2020, week 1, lecture a

# NLMI

# Course

Topic: Statistical Natural Language Processing

Team

- Instructors: Wilker Aziz and Lieuwe Rekker
- Assistants: Daniel, Mitchell, Putri, Puck, Tim, Zarah

Attendance

- lectures: not monitored, but encouraged
- laptopcollege and werkcollege: highly encouraged!
  develop homework (lab assignments and written report)

# Course information

Canvas

- course manual
- weekly materials: readings, slides, exercises
- assignments
- notifications

Textbook

Jurafsky & Martin, *Speech and Language Processing* (3rd edition)

Any additional material will be announced in class and on canvas

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Exams

- Mid-term (individual): 30%
- Final (individual): 30%

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  - to be done in pairs (obligatory)
  - change your partner during the midterm week (obligatory)
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Ungraded quizzes and lists of exercises

# Final grade

$$\text{final grade} = 1 + \frac{9}{10}\left(\underbrace{0.3 \times \text{midterm} + 0.3 \times \text{final exam}}_{\text{exam component}}\right.$$

$$\left. + \underbrace{0.25 \times \text{notebooks} + 0.15 \times \text{report}}_{\text{assignment component}}\right)$$

- your assignment component must be $\geq 5$
- your exam component must be $\geq 5$
- you may only resit your exam component

Rounding

- We round components to the closest half point.
- The *final grade* is rounded to the closest half point, or to the closest point if it falls between $5$ and $6$.

To pass the course your rounded final grade must be $> 5$

# Deadlines

Assignments become available on Tuesday morning
and are due by Friday 6 PM.

- submission through canvas only
  assignments submitted by any other form will be ignored
- these are hard deadlines
- late submissions are not graded and thus score $0$
- exceptions to this rule may be warranted on a per case basis condition on a valid reason: if necessary, reach out to your TA — though note TAs will not decide, instead they will make a case on your behalf, ultimately Lieuwe and I will decide.

# Quizzes and exercises

Exam-type questions

- Quizzes (in class)
  prepare your phone to scan QR codes
  or use the link on the slides
- Lists of exercises (after class)

# NLMI

Course organisation

Why NLP?

Why is NLP hard?

An overview of problems

An overview of the statistical method

Language data: first contact

# What about processing language?

It's everywhere!

- We talk about things
  *I love Paris! All those bridges, the cathedral, the Louvre, oh and of course, the tower!*

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  *I love Paris! All those bridges, the cathedral, the Louvre, oh and of course, the tower!*
- We give instructions
  *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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- impressions about speaker/writer style
  The writing is boring or funny or engaging

---

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# 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?

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

# 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

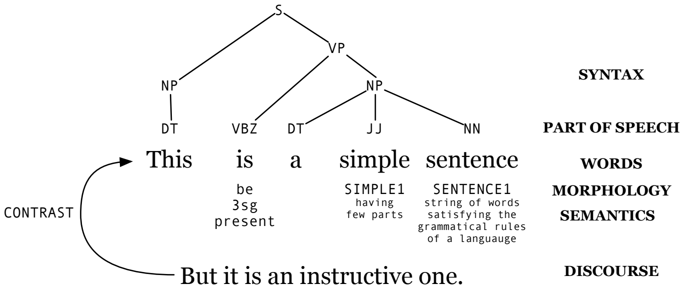
- draw insights from scientific knowledge
- but mostly focus on engineering aspects
- and rely on language data in the form of digital text

# 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

# NLMI

# 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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Adapted from T. Deoskar

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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*

Adapted from T. Deoskar

# 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

Twitter example due to Noah Smith

# 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:

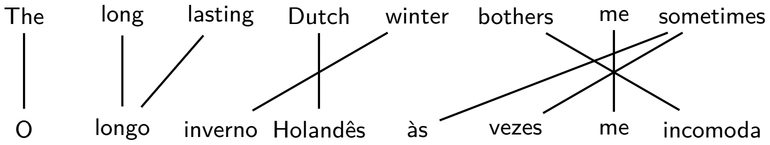
| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 他 | 还 | 提出 | 一 | 系列 | 具体 | 措施 | 和 | 政策 | 要点 | 。 |
| He | also | propose | one | series | concrete | measure | and | policy | essential | . |

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

Example from Xue et al. (2005)

# Why is NLP hard?

Languages have different word orders




Myself (2018)

# Why is NLP hard?

Context dependence

- correct interpretation typically requires context
  and often requires world knowledge
  *Paris is so beautiful,* the city or the celebrity?

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Unknown representation

- we don't know how humans represent knowledge

# NLMI

# Sequence prediction

What is the next word? quiz

# Sequence prediction

What is the next word? ▸ quiz

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 am not missing it, neither should ya!
  - output: I am not missing it , neither should ya !

quiz

# Sequence segmentation

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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$_{\text{verb}}$ debates all the time, and usually I do not have a chair$_{\text{noun}}$ to sit on
- some words may refer to an entity
  *Leibniz* ▸ Wiki *was a German mathematician*

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

▸ quiz

- it may require far more knowledge of the world

# Morphological disambiguation

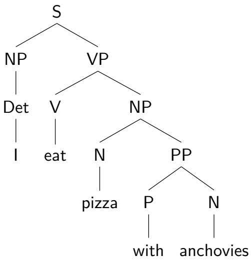
Words have meaning carrying and functional parts

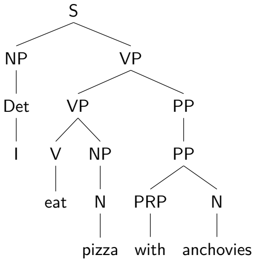
- English -ly usually *derives* an adverb from an adjective
- less often English can use *agglutination* or *compounding* to make new words
  wrongdoing is wrong + doing
- there are ambiguities
  - s marks plural in *cats*, third person in *it marks*, nothing in *news*
  - with a verb un means "reversal", e.g. un*tie*
    with an adjective un means "not", e.g. un*wise*
- 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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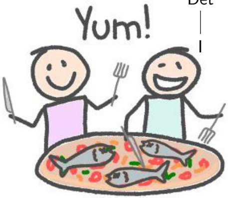


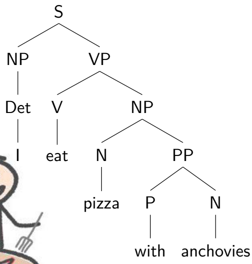


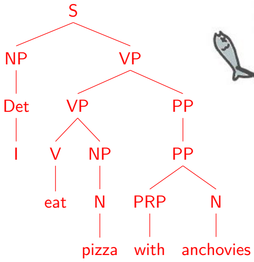


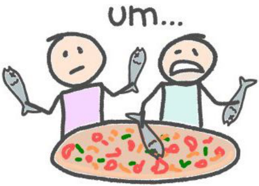


which one has a funny interpretation?

nesting tells us about syntactic dependencies

---

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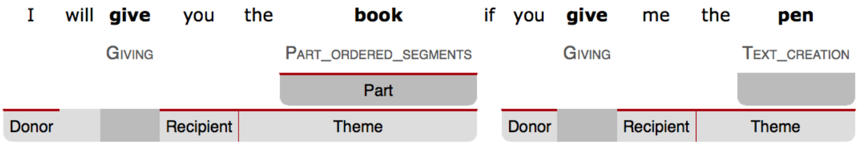
# Semantic parsing

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

Answer questions such as

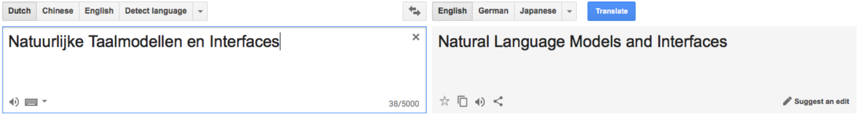
- *who* did *what* to *whom*, *when* and *why*?




ARK's Syntactic & Semantic Parsing Demo ▸ Try it out!

# Text-to-text transformation

We can combine sequence prediction with sequence labelling and a few more things to translate ▸ seq2seq




▸ quiz

or summarise

Google seq2seq

# Much more

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

# NLMI

# But how can we do that?

Statistical approach

- or the "probabilistic pipeline"

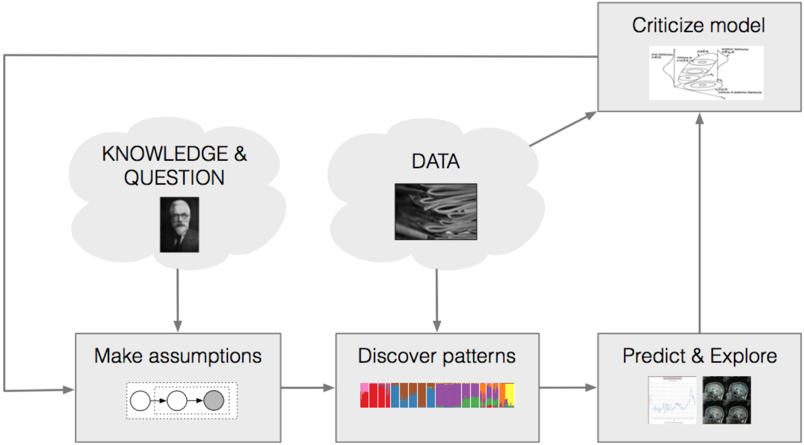



Image by David Blei

# Pipeline

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

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

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- 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?

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| Game | Life | Film | Book | Wine |
| Season | Know | Movie | Life | Street |
| Team | School | Show | Books | Hotel |
| Coach | Street | Life | Novel | House |
| Play | Man | Television | Story | Room |
| Points | Family | Films | Man | Night |
| Games | Says | Director | Author | Place |
| Giants | House | Man | House | Restaurant |
| Second | Children | Story | War | Park |
| Players | Night | Says | Children | Garden |

| 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|
| Bush | Building | Won | Yankees | Government |
| Campaign | Street | Team | Game | War |
| Clinton | Square | Second | Mets | Military |
| Republican | Housing | Race | Season | Officials |
| House | House | Round | Run | Iraq |
| Party | Buildings | Cup | League | Forces |
| Democratic | Development | Open | Baseball | Iraqi |
| Political | Space | Game | Team | Army |
| Democrats | Percent | Play | Games | Troops |
| Senator | Real | Win | Hit | Soldiers |

| 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|
| Children | Stock | Church | Art | Police |
| School | Percent | War | Museum | Yesterday |
| Women | Companies | Women | Show | Man |
| Family | Fund | Life | Gallery | Officer |
| Parents | Market | Black | Works | Officers |
| Child | Bank | Political | Artists | Case |
| Life | Investors | Catholic | Street | Found |
| Says | Funds | Government | Artist | Charged |
| Help | Financial | Jewish | Paintings | Street |
| Mother | Business | Pope | Exhibition | Shot |

Topics found in 1.8M articles from the New York Times

[Hoffman+ JMLR 2013]

# NLMI

# Let's start with the frequency of words

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

Adapted from T. Deoskar

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> *the frequency of any word is inversely proportional to its rank in the frequency table. Thus the most frequent word will occur approximately twice as often as the second most frequent word, three times as often as the third most frequent word, etc.*

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- 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)

Adapted from T. Deoskar

# 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

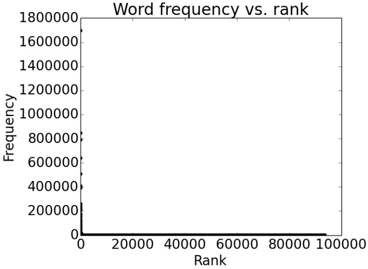
Out of 93638 distinct words (word types), 36231 occur only once!

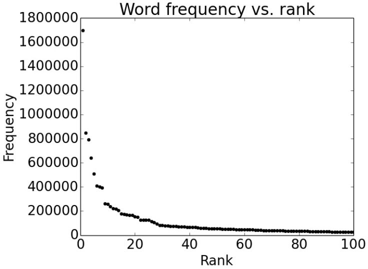
Examples:

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

# Plotting word frequencies

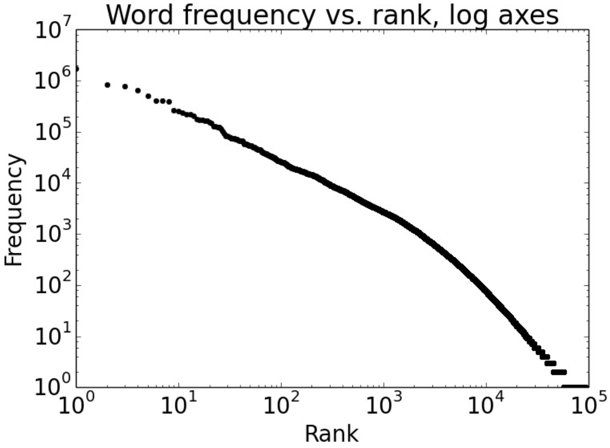
If we order words by frequency,
what is the frequency of $n$th ranked word?



# Rescaling the axes

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



# Zipf's law

Summarises the behaviour we just saw:

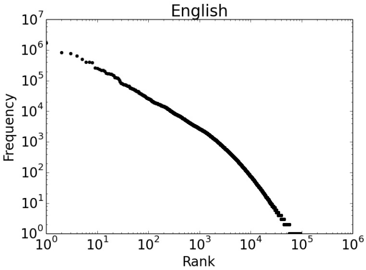
$$f \times r \approx k$$

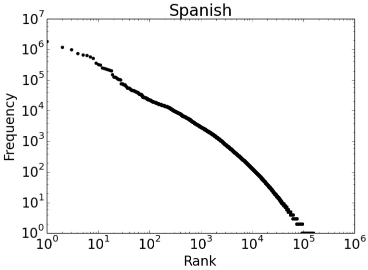
- $f$ = frequency of a word
- $r$ = rank of a word (if sorted by frequency)
- $k$ = a constant

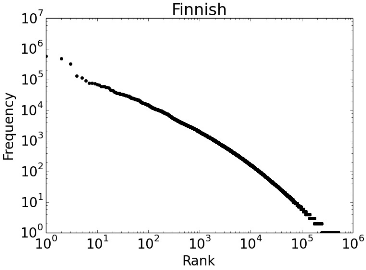
Why a line in log-scales?

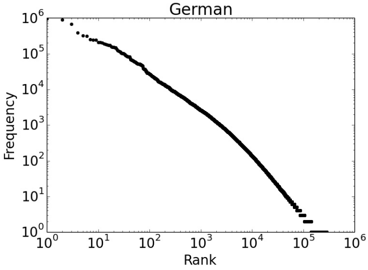
- $fr = k \quad \Rightarrow \quad f = \frac{k}{r} \quad \Rightarrow \quad \log f = \log k - \log r$

# 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

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

See you next time for

- a review of probabilities and parameter estimation

# 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.