Statistical Natural Language Processing

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University of Tübingen
Seminar für Sprachwissenschaft

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Why study (statistical) NLP

- Many practical applications (NLP)
- Investigating basic scientific questions, primarily in linguistics and cognitive science (CL)
- NLP is the collection of core methods and applications in a 'computational linguistics' program

Application examples

Just a few examples

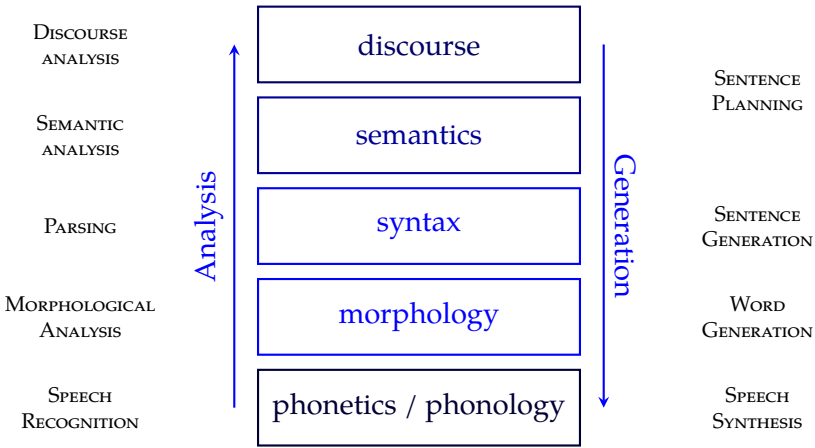
For profit (engineering):

- Machine translation
- Question answering
- Information retrieval
- Dialog systems
- Summarization
- Text classification
- Text mining/analytics
- Speech recognition and synthesis
- Automatic essay grading
- Forensic linguistics

For fun (research):

- Modeling language processing learning
- Investigating language change through time and space
- Aiding language documentation through text processing
- Automatic corpus annotation for linguistic research
- Stylometry, author identification

Layers of linguistic analysis



Annotation layers: an example

From the AP comes this story : →Tokens

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From	the	AP	comes	this	story	:	→Tokens
ADP	DET	PROPN	VERB	DET	NOUN	PUNCT	→POS Tags

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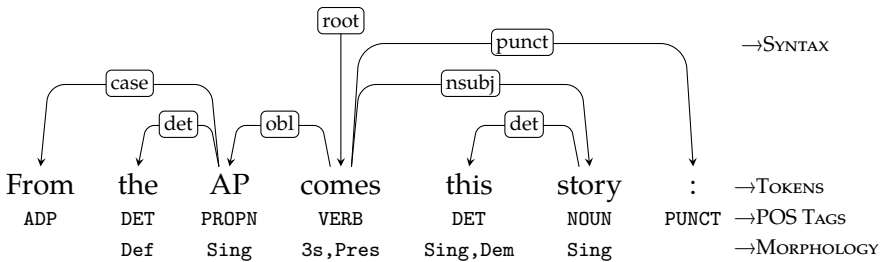
ADP	DET	PROPN	VERB	DET	NOUN	PUNCT	→POS Tags
	Def	Sing	3s,Pres	Sing,Dem	Sing		→Morphology

Annotation layers: an example



Typical NLP pipeline

- Text processing / normalization
- Word/sentence tokenization, segmentation
- POS tagging
- Morphological analysis
- Syntactic parsing
- Semantic parsing
- Named entity recognition
- Coreference resolution

Do we need a pipeline?

- Most "traditional" NLP architectures are based on a pipeline approach:
  - tasks are done individually, results are passed to upper level
- Joint learning (e.g., POS tagging and syntax) often improves the results
- End-to-end learning (without intermediate layers) is another (recent/trending) approach

On the word 'statistical'

> *But it must be recognized that the notion 'probability of a sentence' is an entirely useless one, under any known interpretation of this term.* — *Chomsky (1968)*

- Some linguistic traditions emphasize(d) use of 'symbolic', rule-based methods
- Some NLP systems are based on rule-based systems (esp. from 80's 90's)
- Virtually, all modern NLP systems include some sort of statistical component

What is difficult with NLP?

- Combinatorial problems - computational complexity
- Ambiguity
- Data sparseness

NLP and computational complexity

- How many possible parses a sentence may have?
- How many ways can you align two (parallel) sentences?
- How many operations are needed for calculating probability of a sentence from the probabilities of words in it?

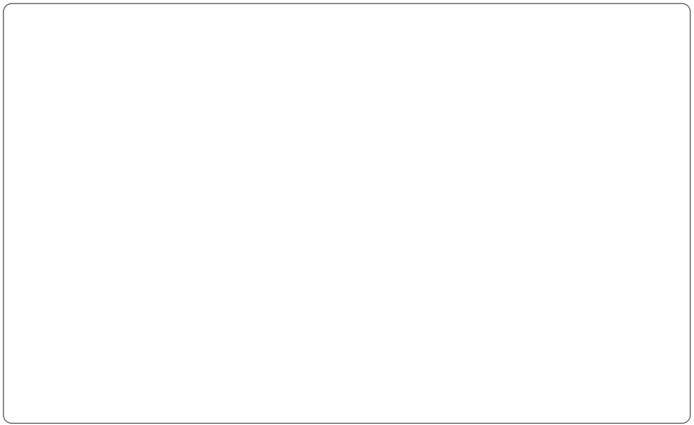
NLP and computational complexity

- How many possible parses a sentence may have?
- How many ways can you align two (parallel) sentences?
- How many operations are needed for calculating probability of a sentence from the probabilities of words in it?
- Many similar questions we deal with have an exponential search space
- Naive approaches often are computationally intractable

Combinatorial problems

A typical linguistic problem: parsing

How many different binary trees can span a sentence of N words?



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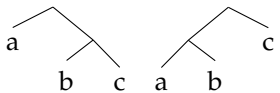

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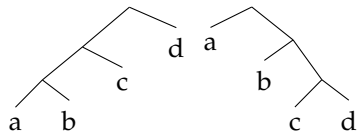

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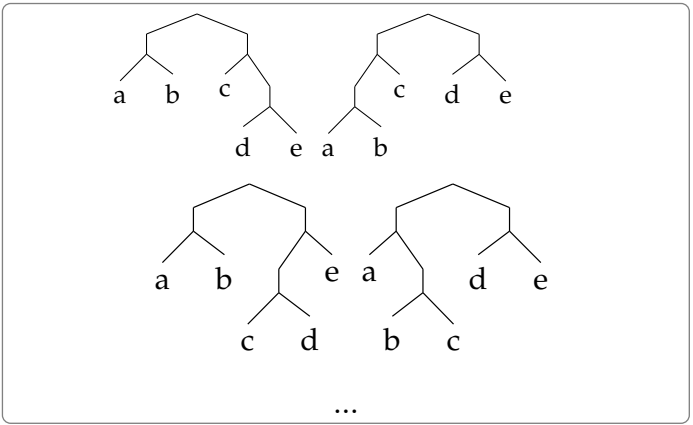

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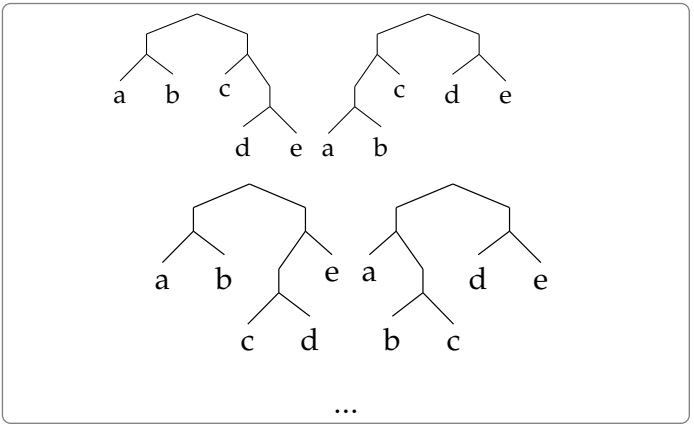


words	trees
2	1
3	2
4	5
5	14
10	4862
20	1 767 263 190
...	...

Ambiguity and natural languages

with pretty pictures

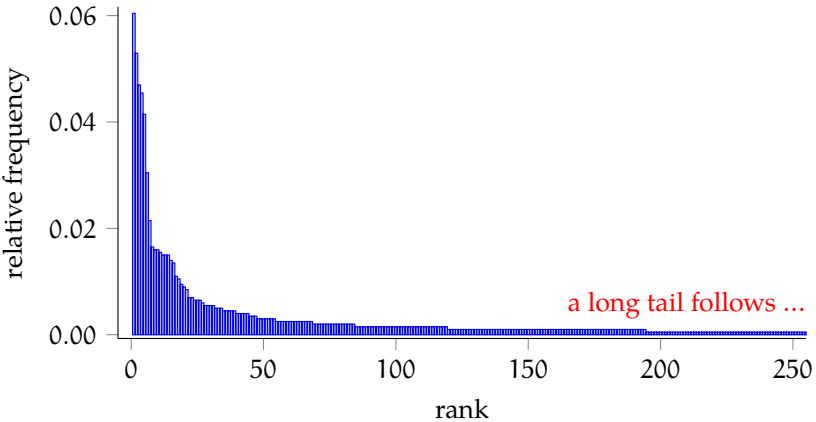
Cartoon Theories of Linguistics, SpecGram Vol CLIII, No 4, 2008. http://specgram.com/CLIII.4/school.gif

Statistical methods and data sparsity

- Statistical methods (machine learning) are the best way we know to deal with ambiguities
- Even for rule-based approaches, a statistical disambiguation component is often needed
- We need (annotated) data to learn, but ...

Languages are full of rare events

word frequencies in a small corpus



What is difficult in CL?

and how can machine learning help?

- Combinatorial problems - computational complexity
  - Often we resort to approximate methods: the answer to 'what is a good approximation?' comes from ML.
- Ambiguity
  - The answer to 'what is the best choice?' comes from ML.
- Data sparseness
  - Even here, ML can help.

What is in this course

- Quick introduction / refreshers on important prerequisites
- The computational linguist's toolbox: basic methods and tools in NLP
- Some applications of NLP

What is in this course

Preliminaries

- Linear algebra, some concepts from calculus
- Probability theory
- Information theory
- Machine learning methods
  - Regression & classification
  - Sequence learning
  - Unsupervised learning

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  - ... but what about ‘deep learning’?

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Preliminaries

- Linear algebra, some concepts from calculus
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- Machine learning methods
  - Regression & classification
  - Sequence learning
  - Unsupervised learning
  - ... but what about 'deep learning'?
  - Short answer: we will cover the basics

What is in this course

NLP Tools and techniques

- Tokenization, normalization, segmentation
- Language models
- Part of speech tagging
- Statistical parsing
- Distributed representations (of words, and other linguistic objects)

What is in this course

Applications

- Text classification
  - sentiment analysis
  - language detection
  - authorship attribution
  - ...

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Applications

- Text classification
  - sentiment analysis
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  - authorship attribution
  - ...

If time allows

- Statistical machine translation
- Named entity recognition
- Text summarization
- Dialog systems
- ...

What is not in this course

- Cutting edge, latest methods & applications
- In-depth treatment of particular topics
- Introduction to terms / concepts from linguistics

Logistics

- Lectures: Mon/Wed 12:15
- Practical sessions: Fri 12:15
- Office hours: Mon 14:00-15:00 ~~(room 1.09)~~ by appointment (email ccoltekin@sfs.uni-tuebingen.de)
- Course web page: `https://snlp2021.github.io/`
- We will use GitHub classroom in this class (more on this soon)

Logistics

online classes

- Interaction is important
  - Do not hesitate to ask questions during the online lectures
  - Asynchronous discussion via 'issues' at `https://github.com/snlp2021/snlp`
- Please fill in the 'beginning of semester survey' at `https://moodle.zdv.uni-tuebingen.de/course/view.php?id=1645`
- The online setup is still new to all of us, we learn how to handle it as we go
- Please provide feedback, suggestions

Reading material

- Daniel Jurafsky and James H. Martin (2009). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. second. Pearson Prentice Hall. ISBN: 978-0-13-504196-3
  - Draft chapters of the third edition is available at `http://web.stanford.edu/~jurafsky/slp3/`
- Trevor Hastie, Robert Tibshirani, and Jerome Friedman (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Second. Springer series in statistics. Springer-Verlag New York. ISBN: 9780387848587. URL: `http://web.stanford.edu/~hastie/ElemStatLearn/`
- Course notes for some lectures
- Other online references

Grading / evaluation

As a BA course (Proseminar)

- 7 graded assignments (6-best counts, 10 % each)
- Final exam (40 %)
- Quizzes with T/F or multiple choice questions (on Moodle)
  - Weekly, covering topics from the previous week
  - You have to get all questions correct
  - You have unlimited trials
  - If you complete all, you get 5 bonus points, each quiz missed reduces the bonus by one point

Grading / evaluation

For master's students

- You can take the class as a 'Proseminar' for 6ECTS, with the same requirements
- You can take the class as a 'Hauptseminar' (HS) for (only) 9ECTS with an additional project/paper related to the topics taught in the class
- If you choose the HS option, contact me with your project ideas as soon as you get some ideas

Assignments

- For distribution and submission of assignments, we will use GitHub Classroom
- The amount of `git` usage required is low, but learning/using `git` well is strongly recommended
- You are encouraged work on the assignments in pairs, but **you can work with the same person only once**
- Late assignments up to one week will be graded up to half points indicated
- The solutions will be discussed in the tutorial session after one week from deadline
- We have a match-making system for working in random groups

Practical sessions

- Starting from the first week of May
- Make sure you have a working Python 3 interpreter
- You are encouraged to ask questions about the exercises during practical sessions
- The solutions will be discussed during tutorial sessions

Further git/GitHub usage

- After you complete the survey on Moodle, you will get an invitation to the 'class organization' `snlp2021`
- The GitHub access is needed for
  - private course material
  - assignment links
  - news and announcements

  (through the repository at `https://github.com/snlp2021/snlp`)
- Make sure you are watching this repository
- You are also encouraged to use 'issues' in this repository as a place to discuss course topics, ask questions about the material and assignments

Next

Fri Mathematical preliminaries (some linear algebra and bits from calculus)

Mon Probability theory

References / additional reading material


Bishop, Christopher M. (2006). *Pattern Recognition and Machine Learning*. Springer. ISBN: 978-0387-31073-2.


Chomsky, Noam (1968). "Quine's empirical assumptions". In: *Synthese* 19.1, pp. 53–68. DOI: 10.1007/BF00568049.


Hastie, Trevor, Robert Tibshirani, and Jerome Friedman (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Second. Springer series in statistics. Springer-Verlag New York. ISBN: 9780387848587. URL: http://web.stanford.edu/~hastie/ElemStatLearn/.


Jurafsky, Daniel and James H. Martin (2009). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition*. second. Pearson Prentice Hall. ISBN: 978-0-13-504196-3.


Manning, Christopher D. and Hinrich Schütze (1999). *Foundations of Statistical Natural Language Processing*. MIT Press. ISBN: 9780262133609.

NLP and ambiguity

fun with newspaper headlines

FARMER BILL DIES IN HOUSE

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TEACHER STRIKES IDLE KIDS

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PROSTITUTES APPEAL TO POPE

More ambiguities

we do not recognize many of them at first read

- Time flies like an arrow
- Outside of a dog, a book is a man's best friend
- One morning I shot an elephant in my pajamas
- Don't eat the pizza with knife and fork

More ambiguities

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- Time flies like an arrow;
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- Don't eat the pizza with knife and fork;
  the one with anchovies is better.