Statistical Natural Language Processing

Çağrı Çöltekin
/tʃaːɾˈɯ tʃœltecˈɪn/
ccoltekin@sfs.uni-tuebingen.de

University of Tübingen
Seminar für Sprachwissenschaft

Summer Semester 2018

Why study (statistical) NLP

- (Most of) you are studying in a 'computational linguistics' program
- Many practical applications
- Investigating basic questions in linguistics and cognitive science (and more)

Application examples

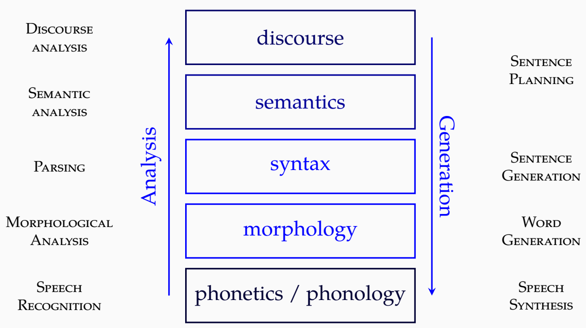
For profit (engineering):

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

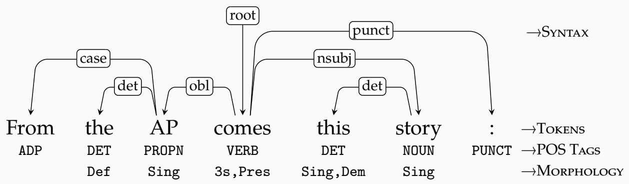
For fun (research):

- Modeling cognitive/social behavior
- Authorship attribution
- Investigating language change through time and space
- (Automatic) corpus annotation for linguistic research

Layers of linguistic analysis



Annotation layers: example



Typical NLP pipeline

- Text processing / normalization
- Word/sentence tokenization
- 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 to calculate probability of sentence based on the probabilities of words in it?
- Many similar questions we deal with have an exponential search space
- Naive approaches often are computationally intractable

NLP and ambiguity
fun with newspaper headlines

- FARMER BILL DIES IN HOUSE
- TEACHER STRIKES IDLE KIDS
- SQUAD HELPS DOG BITE VICTIM
- BAN ON NUDE DANCING ON GOVERNOR'S DESK
- PROSTITUTES APPEAL TO POPE
- KIDS MAKE NUTRITIOUS SNACKS
- DRUNK GETS NINE MONTHS IN VIOLIN CASE
- MINERS REFUSE TO WORK AFTER DEATH

More ambiguities
we do not recognize many of them at first read

- Time flies like an arrow; fruit flies like a banana.
- Outside of a dog, a book is a man's best friend; inside it's too hard to read.
- One morning I shot an elephant in my pajamas. How he got in my pajamas, I don't know.
- Don't eat the pizza with knife and fork ; the one with anchovies is better.
- Hearing voices? Then you're not alone!
- No parking on both sides.
- They are canning peas.
- My job was keeping him alive.
- We watched another fly.
- Double job pay.
- He fed her cat food.

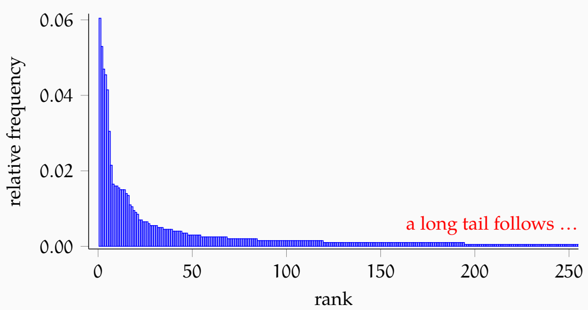
Even more ambiguities
with pretty pictures

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 necessary
- Machine learning methods require (annotated) data
- But …

Languages are full of rare events
word frequencies in a small corpus



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
- Statistical inference
- Some topics from machine learning
  - Regression & classification
  - Sequence learning (HMMs)
  - Neural networks and deep learning
  - Unsupervised learning

What is in this course
NLP Tools and techniques

- Tokenization, normalization, segmentation
- N-gram 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
  - …

If time allows

- Statistical machine translation
- Named entitiy 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/Fri 12:15 at Hörsaal 0.02
- Practical sessions: Wed 10:15 at Hörsaal 0.02
- Office hours: Wed 12:00-14:00 (room 1.09), or by appointment (email ccoltekin@sfs.uni-tuebingen.de)
- Course web page: `http://sfs.uni-tuebingen.de/~ccoltekin/courses/snlp`
- We will use GitHub classroom in this class (more on this soon)

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/`

Grading / evaluation

- Seven graded homework assignments (5 % each)
- Final exam (70 %)
- Attendance
  - 5 % (bonus) if you miss only one or two classes
  - you lose one bonus point for each additional class you miss
- Up to 5 % additional bonus points for Easter eggs:
  - first person finding intentional trivial mistakes in the course material gets 1 %

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 to pair up for the assignments, but you cannot pair with the same person twice
- 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

Assignment 0

- Your first assignment is already posted on the web page
- You need to follow the URL on the print version of the syllabus
- By completing assignment 0, you will
  - register for the course
  - have access to the non-public course material
  - exercise with how later assignments will work
  - provide some data for future exercises
- The repository created for assignment 0 is private, and can only be accessed you and the instructors

Practical sessions

- Tutor: Verena Blaschke ⟨`verena.blaschke@student.uni-tuebingen.de`⟩
- We will start with two sessions on Python tutorial/refresher
- You need to bring your own computer, make sure you have a working Python interpreter
- You are encouraged to ask questions about the exercises during practical sessions
- You are encouraged to ask questions about the assignments
- The solutions will be discussed during tutorial sessions

Further git/GitHub usage

- Once you complete Assignment 0, you will be a member of the 'organization' `snlp2018`
- You will get access to
  - private course material
  - assignment links
  - news and announcements

  through the repository at `https://github.com/snlp2018/snlp2018`
- Make sure to watch 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 (this week) a hands-on introduction to Python

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

Wed Python tutorial (continued)

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.