Foundations of Natural Language Processing

Lecture 1: Introduction

Mirella Lapata

School of Informatics University of Edinburgh

mlap@inf.ed.ac.uk



Slides based on content from: Philipp Koehn, Alex Lascarides, Sharon Goldwater, Shay Cohen, Khalil Sima'an, Ivan Titov

What we'll do today



- Welcome to Foundations of Natural Language Processing!
- Make sure you are in the right class/room.
- We'll cover course logistics.
- We'll get started on what is NLP and why it is hard.

Background needed for this course

We assume you are familiar with most/all of the following:

- Basic Python programming
- Finite-state machines, regular languages, context-free grammars
- Dynamic programming (e.g., edit distance, Viterbi, and/or CKY algorithms)
- Concepts from machine learning (e.g., estimating probabilities, making predictions based on data)
- Probability theory (conditional probabilities, Bayes' Rule, independence and conditional independence, expectations)
- Vectors, logarithms, linear algebra, matrix operations
- Some basic linguistic concepts (e.g., parts of speech)

Where we are headed

INF2-iads discussed ideas and algorithms for NLP from a largely formal, algorithmic perspective. Here we build on that by:

- Focusing on real data with all its complexities.
- Discussing some of the NLP techniques in more depth.
- Introducing many tasks and technologies that didn't fit into the Inf2-iads story.
- By the end of the class, you'll know how to make your own ChatGPT.

Course organization

- Course organizer: Ivan Titov
- Lecturers: Mirella Lapata and Ivan Titov
- 3 lectures per week (Tue, Wed & Fri, 12:10–13.00)
- We will use Learn and Drupal for slides, lectures, labs, assignments, due dates, etc
- Labs: two groups, every two weeks (on Fridays, 13:10–14:30 or 14:30–16.00)
- Tutorials: in small groups, every two weeks (on Thursdays, 12:10–13:00, 13:10–14:30, or 14:30–16:00); tutorials start next week
- Course discussion forum: Piazza.

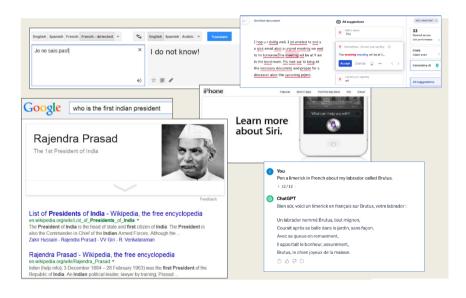
Check Learn for all the links and up-to-date information

Outside work required

In addition to attending lectures, you are expected to keep up with:

- Readings from textbook: Speech and Language Processing, Jurafsky and Martin: 3rd edition (online) and 2nd edition (paperback, International version, for chapters that aren't updated in 3rd ed).
- There will also be links to academic papers (recommended).
- Tutorials and quizzes.
- Lectures are being recorded. The audience is not in shot.
- Two assignments, worth 25%.
- Exam in April/May, worth 75% of final mark.

What is Natural Language Processing?



What is Natural Language Processing?

Applications

- Machine Translation
- Information Retrieval
- Question Answering
- Dialogue Systems
- Information Extraction
- Summarization
- Sentiment Analysis
- ..

Core Technologies

- Language modeling
- Part-of-speech tagging
- Syntactic parsing
- Coreference resolution
- Named-entity recognition
- Word sense disambiguation
- Semantic Role Labeling
- . .

This course

NLP is a big field! We focus mainly on core ideas and methods needed for technologies in the second column (and eventually for applications).

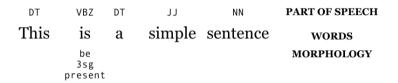
- Core concepts in NLP
- Core linguistic problems and methodologies in NLP
- including machine learning, problem design, and evaluation methods



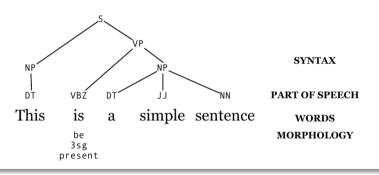
This is a simple sentence words

- Language consists of many levels of structure
- Humans fluently integrate all of these in producing/understanding language
- Ideally, so would a computer!

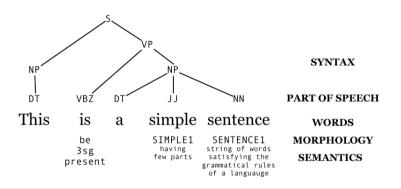
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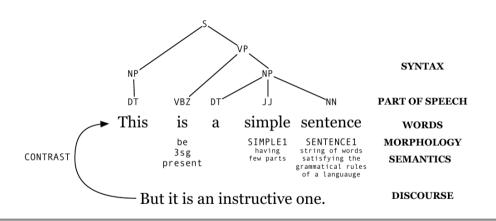
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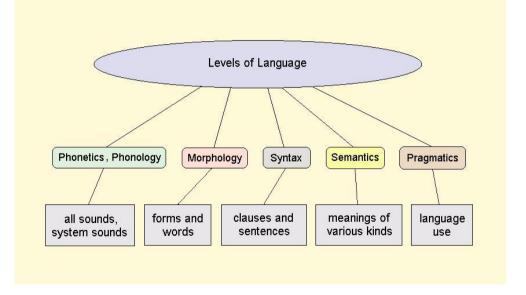


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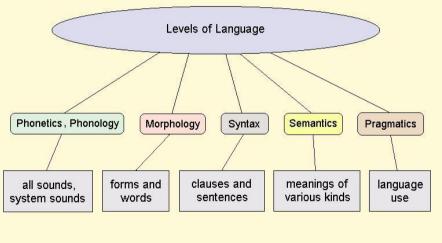
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Levels of Linguistics Analysis



Levels of Linguistics Analysis

Do we really need to model all these levels?



- 1. Who bought a bridge?
- 2. Where will the bridge be re-built?
- 3. How long will it take?

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History of NLP

Linquistic Theories

- * Weaver proposal on machine based translation
- * Chomsky's generative grammar
- * Georgetown exp translating Russian sentences to English

Rule-Based Systems

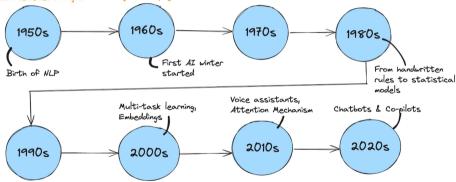
- * ELIZA a chatbot using simple grammar rules * SHRDULU - block language
- * ALPAC report and halt of funding for NLP projects

More Rule-Based Systems

- * Case grammars, semantic networks
- * TALE-SPIN story writing
- * MYCIN diagnose blood infections

Statistical Models

- * Ontologies (i.e. knowledge graphs) and expert systems * Sumbolic models and semantic
- interpretation * Tree-based models



Statistical NLP

- * N-Grams for modeling language
- * LSTM RNNS (1997)
- * HMMs for speech recognition

Neural NLP

- * Deep Learning for NLP * Google Translate (2006) (still using statistical models)
- * Multi-task learning (2008)

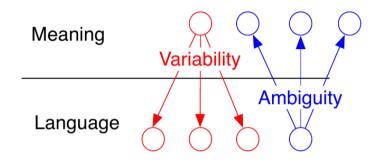
Foundation for LLMs

- * Word2Vec (2013) embeddings
- * Attention (2015), Transformers (2017), BERT (2018)
- * GPT (2018), T5 (2019) language model

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- + GPT-3 (2020)
- * ChatGPT (2022), Bard (2023)
- * GPT-4 (2023), Gemini (2023), Claude (2023), LLaMA-2 (2023). Mixtral 8x7B (2023)

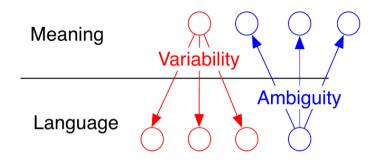
Why is NLP hard?



Variability:

He drew the house
He made a sketch of the house
He showed me his drawing of the house
He portrayed the house in his paintings
He drafted the house in his sketchbook

Why is NLP hard?



Ambiguity:

She drew a picture of herself cart drawn by two horses...

He drew crowds wherever he went ...

The driver slowed as he drew even with me

The officer drew a gun and pointed it at ...

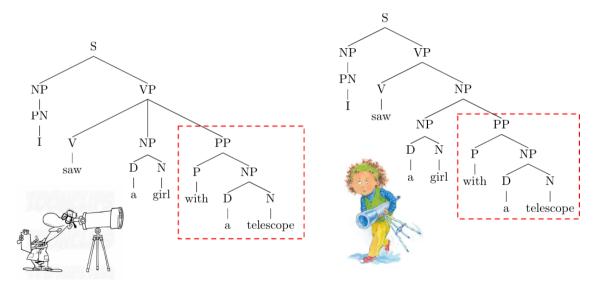
- ~ sketched, made a drawing of
- ~ pulled
- ~ attracted
- ~ proceeded
- ~ took out, produced

Why is NLP hard? Ambiguity at many levels

- Homophones: blew and blue
- Word senses: bank (finance or river?)
- Part of speech: chair (noun or verb?)
- Syntactic structure: I saw a girl with a telescope
 - We'll look into this in more detail!
- Quantifier scope: Every child loves some movie
- Multiple: I saw her duck
- Reference: John dropped the goblet onto the glass table and it broke.
- Discourse: The meeting is canceled. Emily isn't coming to the office today.

How can we model ambiguity, and choose the correct analysis in context?

Syntactic Ambiguity: Prepositional Phrase Attachment



Syntactic Ambiguity

Example with 3 preposition phrases, 5 interpretations:

- Put the block ((in the box on the table) in the kitchen)
- Put the block (in the box (on the table in the kitchen))
- Put ((the block in the box) on the table) in the kitchen
- Put (the block (in the box on the table)) in the kitchen
- Put (the block in the box) (on the table in the kitchen)

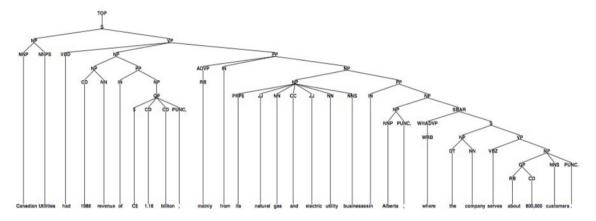
The number of parses is an integer series, known as the Catalan numbers!

$$Cat_n = {2n \choose n} - {2n \choose n-1} \sim \frac{4^n}{n^{3/2}\sqrt{\pi}}$$

1, 2, 5, 24, 42, 132, 429, 1430, 4862, 16796, 58786, ...

Syntactic Ambiguity

A typical tree from a standard dataset (Penn treebank WSJ)



Canadian Utilities had 1988 revenue of \$ 1.16 billion, mainly from its natural gas and electric utility businesses in Alberta, where the company serves about 800.000 customers.

4/26

Real Newspaper Headlines



On Thursday, September 9, Gorman School hosted the first annual Grandparent's Day.

All Grandparents were invited to a school wide pancake breakfast. Upper grade students served as excellent chefs, as well as taking responsibility for serving the food and the clean up after

- Ban on Nude Dancing on Governor's Desk
- Iraqi Head Seeks Arms
- Local High School Dropouts Cut in Half
- Red Tape Holds Up New Bridges
- Juvenile Court to Try Shooting Defendant
- Kids Make Nutritious Snacks

Collected by Chris Manning

Summary

- Course logistics
- What is Natural Language Processing (Al rock star!)
- Language consists of many levels of structure
- NLP is hard due to ambiguity at many levels

Next lecture: we discuss NLP challenges some more, and probabilistic modeling.