# Foundations of Natural Language Processing Lecture 1 Introduction

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(Slides based on those of Philipp Koehn, Alex Lascarides, Sharon Goldwater)

14 January 2020



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# What is Natural Language Processing?

#### **Applications**

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

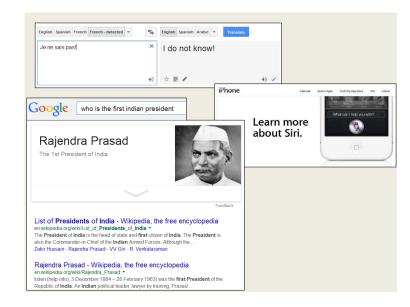
• ...

#### Core technologies

- Language modelling
- Part-of-speech tagging
- Syntactic parsing
- Named-entity recognition
- Coreference resolution
- Word sense disambiguation
- Semantic Role Labelling

• ...

# What is Natural Language Processing?



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#### 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).

- Linguistic facts and issues
- Computational models and algorithms

More advanced methods and specific application areas covered in 4th/5th year courses:

- ullet Natural Language Understanding, Generation and Machine Translation (NLU+)
- Text Technologies
- Automatic Speech Recognition

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# What does an NLP system need to "know"?

Words

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

This is a simple sentence words

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# Morphology

Parts of Speech

This is a simple sentence words

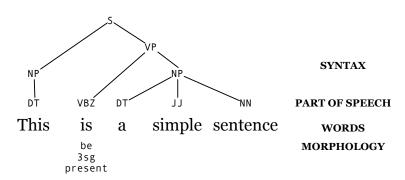
be 3sg present

MORPHOLOGY

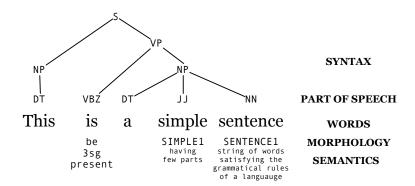
This is a simple sentence words

be 3sg present Morphology

# **Syntax**



#### **Semantics**



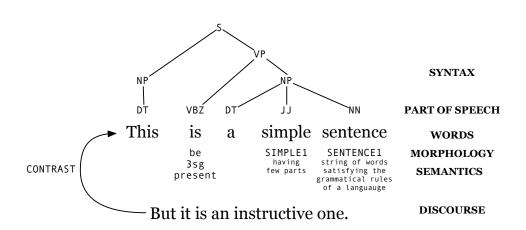
 $\exists y (\textit{this\_dem}(x) \land \textit{be}(e, x, y) \land \textit{simple}(y) \land \textit{sentence}(y))$ 

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#### **Discourse**

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# Why is NLP hard?

- 1. Ambiguity at many levels:
- Word senses: bank (finance or river?)
- Part of speech: chair (noun or verb?)
- $\bullet$  Syntactic structure: I saw a man with a telescope
- $\bullet$  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 cancelled. Nicholas isn't coming to the office today.

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

# **Ambiguity**

Inf2a started to discuss methods of dealing with ambiguity.

- non-probabilistic methods (FSMs for morphology, CKY parsers for syntax) return all possible analyses.
- probabilistic models (HMMs for POS tagging, PCFGs for syntax) and algorithms (Viterbi, probabilistic CKY) return the **best possible analysis**, i.e., the most probable one according to the model.

This "best" analysis is only good if our model's probabilities are accurate. Where do they come from?

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# Why is NLP hard?

- 2. Sparse data due to 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, we'll return to this issue...)

#### Statistical NLP

Like most other parts of AI, NLP today is dominated by statistical methods.

- Typically more robust than earlier rule-based methods.
- Relevant statistics/probabilities are learned from data (cf. Inf2b).
- Normally requires lots of data about any particular phenomenon.

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#### **Word Counts**

Most frequent words (word **types**) in the English Europarl corpus (out of 24m word **tokens**)

any word	
Frequency	Туре
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

Frequency         Type           124,598         European           104,325         Mr           92,195         Commission           66,781         President           62,867         Parliament           57,804         Union           53,683         report	nouns	
104,325         Mr           92,195         Commission           66,781         President           62,867         Parliament           57,804         Union           53,683         report	Frequency	Туре
92,195         Commission           66,781         President           62,867         Parliament           57,804         Union           53,683         report	124,598	European
66,781         President           62,867         Parliament           57,804         Union           53,683         report	104,325	Mr
62,867         Parliament           57,804         Union           53,683         report	92,195	Commission
57,804 Union 53,683 report	66,781	President
53,683 report	62,867	Parliament
	57,804	Union
E0 E47 C '1	53,683	-
53,547 Council	53,547	Council
45,842 States	45,842	States

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#### **Word Counts**

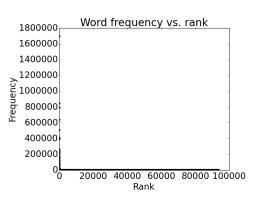
But also, out of 93638 distinct word types, 36231 occur only once. Examples:

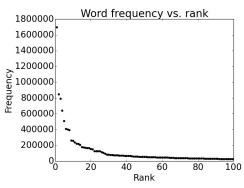
- cornflakes, mathematicians, fuzziness, jumbling
- pseudo-rapporteur, lobby-ridden, perfunctorily,
- Lycketoft, UNCITRAL, H-0695
- policyfor, Commissioneris, 145.95, 27a

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# **Plotting word frequencies**

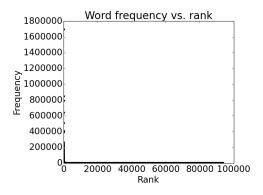
Order words by frequency. What is the frequency of nth ranked word?





# **Plotting word frequencies**

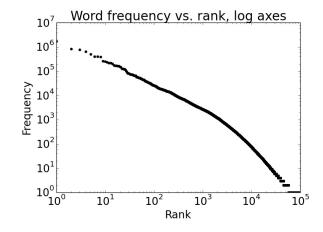
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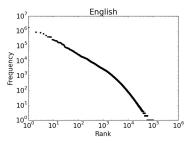
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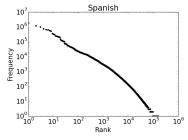
# Rescaling the axes

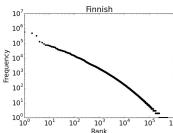
To really see what's going on, use logarithmic axes:

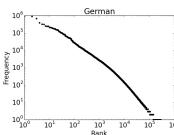


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# Zipf's law

Summarizes the behaviour we just saw:

$$f \times r \approx k$$

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

Why a line in log-scales?  $fr = k \implies f = \frac{k}{r} \implies \log f = \log k - \log r$ 

# Zipf's law

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### 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 in a CFG).
- This means we need to find clever ways to estimate probabilities for things we have rarely or never seen during training.

#### Why is NLP hard?

#### 3. Variation

• 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 ./.

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#### Why is NLP hard?

#### 4. Expressivity

• Not only can one form have different meanings (ambiguity) but the same meaning can be expressed with different forms:

She gave the book to Tom vs. She gave Tom the book Some kids popped by vs. A few children visited Is that window still open? vs Please close the window

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• 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

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#### Why is NLP hard?

#### 5 and 6. Context dependence and Unknown representation

- Last example also shows that correct interpretation is context-dependent and often requires world knowledge.
- Very difficult to capture, since we don't even know how to represent the knowledge a human has/needs: What is the "meaning" of a word or sentence? How to model context? Other general knowledge?

That is, in the limit NLP is hard because AI is hard

• In particular, we've made remarkably little progress on the Knowledge Representation problem...

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# 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 (estimating probabilities, making predictions based on data)
- Probability theory (conditional probabilities, Bayes' Rule, independence and conditional independence, expectations)
- Vectors, logarithms
- Concepts of syntactic structure and semantics and relationship between them (ideally for natural language but at least for programming languages)
- Some basic linguistic concepts (e.g. parts of speech, inflection)

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# **Course organization**

- Lecturers: Alex Lascarides and Shay Cohen
- Lectures: Tue/Fri 10:00-10:50 LTC, DHT.
- Labs: two groups (Mondays and Thursdays at 3:10pm, AT 6.06)
   Choose a lab group and register for it via LEARN
   Labs start next week!
- Web site: for slides, lectures, labs, assignments, due dates, etc http://www.inf.ed.ac.uk/teaching/courses/fnlp/
- Course mailing list: fnlp-students@inf. Register ASAP to get on the list!
- Course discussion forum: Piazza.
   Link for signing up to FNLP's piazza page is on FNLP website.

#### Where we are headed

Informatics 2a 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 some tasks and technologies that didn't fit into the Inf2a story.

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#### **Outside work required**

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

- Readings from textbook: *Speech and Language Processing*, 3rd edition (online) and 2nd edition (paperback, International version), Jurafsky and Martin.
- NLP techniques in Python: Bird, S., E. Klein and E. Loper, *Natural Language Processing with Python*, (2009) O'Reilly Media
- Weekly (unassessed) labs (in Python). To help solidify concepts and give you practical experience. Help and feedback available from lab demonstrator.
- Lectures are being recorded. Recordings will be linked from the lectures page week by week. The audience is *not* in shot.
- Two assignments (in Python)
  - The second worth 30%
- The first will be reviewed and marked, but will not contribute to your final mark
- Exam in May, worth 70% of final mark.

We will also provide some optional further readings/exercises for those who wish to stretch themselves. These will be clearly marked as optional (non-examinable).