Empirical Methods in Natural Language Processing
Lecture 1
Introduction

(today’s slides based on those of Sharon Goldwater, Philipp Koehn, Alex Lascarides)

31 August 2016
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 modelling
• Part-of-speech tagging
• Syntactic parsing
• Named-entity recognition
• Coreference resolution
• Word sense disambiguation
• Semantic Role Labelling
• ...

NLP lies at the intersection of computational linguistics and artificial intelligence. NLP is (to various degrees) informed by linguistics, but with practical/engineering rather than purely scientific aims. Processing speech (i.e., the acoustic signal) is separate.
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, especially using data ("empirical")
What are your goals?

Why are you here? Perhaps you want to:

- work at a company that uses NLP (perhaps as the sole language expert among engineers)
- use NLP tools for research in linguistics (or other domains where text data is important: social sciences, humanities, medicine, . . . )
- conduct research in NLP (or IR, MT, etc.)
What does an NLP system need to “know”?

• Language consists of many levels of structure

• Humans fluently integrate all of these in producing/understanding language

• Ideally, so would a computer!
Words

This is a simple sentence
This is a simple sentence

be
3sg
present
Parts of Speech

This is a simple sentence

be
3sg
present
Syntax

This is a simple sentence

```
NP
  DT VBZ DT JJ NN
NP
```

SYNTAX

PART OF SPEECH

WORDS

MORPHOLOGY
This is a simple sentence
This is a simple sentence.

But it is an instructive one.
Why is NLP hard?

1. **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*

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

What can we do about 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*.

But the “best” analysis is only good if our probabilities are accurate. Where do they come from?
Statistical NLP

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

- Typically more robust than earlier rule-based methods.
- Relevant statistics/probabilities are learned from data.
- Normally requires lots of data about any particular phenomenon.
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 “word” is a string of letters separated by spaces (a great oversimplification, we’ll return to this issue...)
# Word Counts

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

<table>
<thead>
<tr>
<th>any word</th>
<th>Frequency</th>
<th>Token</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,698,599</td>
<td>the</td>
<td></td>
</tr>
<tr>
<td>849,256</td>
<td>of</td>
<td></td>
</tr>
<tr>
<td>793,731</td>
<td>to</td>
<td></td>
</tr>
<tr>
<td>640,257</td>
<td>and</td>
<td></td>
</tr>
<tr>
<td>508,560</td>
<td>in</td>
<td></td>
</tr>
<tr>
<td>407,638</td>
<td>that</td>
<td></td>
</tr>
<tr>
<td>400,467</td>
<td>is</td>
<td></td>
</tr>
<tr>
<td>394,778</td>
<td>a</td>
<td></td>
</tr>
<tr>
<td>263,040</td>
<td>I</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>nouns</th>
<th>Frequency</th>
<th>Token</th>
</tr>
</thead>
<tbody>
<tr>
<td>124,598</td>
<td>European</td>
<td></td>
</tr>
<tr>
<td>104,325</td>
<td>Mr</td>
<td></td>
</tr>
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<td>92,195</td>
<td>Commission</td>
<td></td>
</tr>
<tr>
<td>66,781</td>
<td>President</td>
<td></td>
</tr>
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<td>62,867</td>
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<td>57,804</td>
<td>Union</td>
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<td>53,683</td>
<td>report</td>
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<td>53,547</td>
<td>Council</td>
<td></td>
</tr>
<tr>
<td>45,842</td>
<td>States</td>
<td></td>
</tr>
</tbody>
</table>
Word Counts

But also, out of 93,638 distinct words (word types), 36,231 occur only once. Examples:

- cornflakes, mathematicians, fuzziness, jumbling
- pseudo-rapporteur, lobby-ridden, perfunctorily,
- Lycketoft, UNCITRAL, H-0695
- policyfor, Commissioneris, 145.95, 27a
Order words by frequency. What is the frequency of $n$th ranked word?
Plotting word frequencies

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

Summarizes 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
Zipf’s law

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Why a line in log-scales? \( fr = k \) \( \Rightarrow \) \( f = \frac{k}{r} \) \( \Rightarrow \) \( \log f = \log k - \log r \)
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.
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 ./.
Why is NLP hard?

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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
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
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?
Traditionally, NLP survey courses cover morphology, then syntax, then semantics and applications. This reflects the traditional form-focused orientation of the field, but this course will be organized differently, with the following units:

- **Introduction** (≈4 lectures): Getting everyone onto the same page with the fundamentals of text processing (Python 3/Unix) and linguistics.

- **Words & BoW: Supervised** (≈4 lectures): Approaches to classification that ignore linguistic structure within a sentence or document, focusing on the individual words/bags of words.

- **N-grams & Sequences: Supervised** (≈5 lectures): Techniques that model sentences as sequences of words, including part-of-speech tagging and lexical semantic tagging.
Organization of Topics (2/2)

- **Hierarchical Sentence Structure** (≈4 lectures): Tree-based models of sentences that capture grammatical phrases and relationships (syntactic structure), as well as structured representations of within-sentence semantic relationships.

- **Unsupervised Learning** (≈3 lectures): Models for characterizing words and text collections based on unlabeled data.

- **Applications** (≈4 lectures): Overviews of language technologies for text such as machine translation and question answering.
This course has enrollment from three different programs:

- Linguistics
- Computer Science
- Data Analytics

This means that there will be a diversity of backgrounds and skills, which is a fantastic opportunity for you to learn from fellow students. It also requires a bit of care to make sure the course is valuable for everyone.
What’s *not* in this course

- Formal language theory
- Computational morphology
- Logic-based compositional semantics
- Speech/signal processing, phonetics, phonology

(But see next 2 slides!)
Some Related Courses (1/2)

In Linguistics:

- Intro to NLP (Amir Zeldes, last semester)
- Signal Processing (Corey Miller, this semester)
- Machine Translation (George Wilson, last semester)
- Computational Semantics and Information Extraction (Anthony Davis, last fall)
- Computational Corpus Linguistics (Zeldes, this semester)
- Computational Discourse Models (Zeldes, this semester)
Some Related Courses (2/2)

In Computer Science:

- Intro to Machine Learning (Mark Maloof, last semester)
- Statistical Machine Learning (Grace Hui Yang, this semester)
- Theory of Computation (Calvin Newport, last semester)
- Automated Reasoning (Maloof, last semester)
- Data Analytics (Lisa Singh, this semester)
- Information Retrieval (Nazli Goharian, this semester)
Course organization

- Instructor: Nathan Schneider
- TA: James Maguire
- Lectures: MW 3:30–4:45, ICC 234 White-Gravenor 213
- Web site: for syllabus, schedule (lecture slides/readings/assignments): http://tiny.cc/enlp
- We will also use Canvas for communication once enrollment is finalized.