L90: Overview of Natural Language Processing
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1. What does it mean to know a language?
2. Form transformation
3. Why NLP is hard?
4. Scope of NLP based on Ann Copestake's previous lecture

Overview

breadth over depth

Natural Language English, Welsh, Afrikaans, Mandarin, . . .

English as a Second Language, . . .

Sanskrit, . . .

dolphin language
L90: Overview of Natural Language Processing

breadth over depth
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- breadth over depth

- English, Welsh, Afrikaans, Mandarin, ... English as a Second Language, ...
  - Sanskrit, ...
  - ?dolphin language
Lecture 1: Overview of Natural Language Processing

1. What does it mean to know a language?
2. Form transformation
3. Why NLP is hard?
4. Scope of NLP based on Ann Copestake's previous lecture

- breadth over depth
- computational models

Languages: English, Welsh, Afrikaans, Mandarin, ... English as a Second Language, ... Sanskrit, ... ?dolphin language
Lecture 1: Overview of Overview of Natural Language Processing

1. What does it mean to know a language?
2. Form transformation
3. Why NLP is hard?
4. Scope of NLP

based on Ann Copestake’s previous lecture
What does it mean to know a language?
universal translator

🔗 www.youtube.com/watch?v=wtAmPX1Itr0
What does it mean to *know* a language?

Some yinkish dripners blorked quastofically into the nindin with the pidibs.

the example is partly from A Carnie’s *Syntax: A Generative Introduction*
What does it mean to *know* a language?

*Some yinkish dripners blorked quastofically into the nindin with the pidibs.*

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- there was a BLORK event;
What does it mean to *know* a language?

Some yinkish dripners *blorked* quastofically into the nindin with the pidibs.

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- there was a **BLORK** event;
- it happened in the **PAST**;
What does it mean to *know* a language?

**Some yinkish *dripners* blorked *quastofically* into the *nindin* with the *pidibs.***

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- it happened in the **PAST**;
- the **AGENT** of **BLORK** is dripners;
- the dripners were yinkish;
- some but not all dripners blorked;
- **with the pidibs** may talk about **nindin** or **BLORK**;
Structuring a number

01010101010101010101010101010101010101010101010101010101010...
Structuring a number

01010101010101010101010101010101010101010101010101010101010101010101...

0110101000010011100110011111110011101110011001001000...

\sqrt{2} - 1

\frac{3}{24}
Structuring a number

$\sqrt{2} - 1$
Some yinkish dripners blorked quastofically into the nindin with the pidibs
Some yinkish dripners blorked quastofically into the nindin with the pidibs

dripner -s blork -ed pidib -s
Structuring a sentence

Some yinkish dripners blorked quastofically into the nindin with the pidibs

- morphology — the structure of words
Structuring a sentence

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morphology — the structure of words
Structuring a sentence

Some yinkish dripners blorked quastofically into the nindin with the pidibs

- morphology — the structure of words

syntax — the way words are used to form sentences
compositional semantics — the construction of meaning based on syntax
lexical semantics — the meaning of individual words
vectorize words, phrases, sentences, paragraphs
Structuring a sentence

Some yinkish dripners blorked quastofically into the nindin with the pidibs

syntax — the way words are used to form sentences

morphology — the structure of words
Structuring a sentence

Some yinkish dripners blorked quastofically into the nindin with the pidibs — the construction of meaning based on syntax

syntax — the way words are used to form sentences

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Structuring a sentence

lexical semantics — the meaning of individual words

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syntax — the way words are used to form sentences

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Some yinkish dripners blorked quastofically into the nindin with the pidibs

AGENT

Some

ADJ

yinkish

dripners

NOUN

blorked

VERB

quastofically

ADV

into

NOUN

the

nindin

with

the

pidibs

NOUN

pidib

-s

morphology — the structure of words

Some yinkish dripners blorked quastofically into the nindin with the pidibs

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morphology — the structure of words
Structuring a sentence

- **Compositional semantics** — the construction of meaning based on syntax
- **Lexical semantics** — the meaning of individual words
- **Syntax** — the way words are used to form sentences
- **Vectorize words, phrases, sentences, paragraphs**
- **Morphology** — the structure of words
- **Compositional semantics** — the construction of meaning based on syntax
NLP: the computational modelling of human language

- **Morphology** — the structure of words: lecture 2.
- **Syntax** — the way words are used to form phrases: lectures 3, 5 and 6.
- **Semantics**
  - **Compositional semantics** — the construction of meaning based on syntax: lecture 9.
  - **Lexical semantics** — the meaning of individual words: lecture 8 (sort of) and 10.
- **Pragmatics** — meaning in context: lecture 11.
- **Language generation** — lecture 12.

- **Symbolic models** — finite-state machines and context-free grammars: lecture 2 and 5.
- **Statistical models** — classification: lecture 3.
- **Neural models** — (sequential) classification: lecture 4 and 7.
Form transformation

natural language expressions

comprehension

production

\( R \)  

{ morphological structure, syntactic structure, semantic structure, discourse structure, application-related structure }
Popular representations in NLP

CoNLL shared tasks

- The SIGNLL Conference on Computational Natural Language Learning
- https://www.conll.org/previous-tasks

<table>
<thead>
<tr>
<th>Year</th>
<th>Task Description</th>
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<tbody>
<tr>
<td>2019</td>
<td>Cross-Framework Meaning Representation Parsing</td>
</tr>
<tr>
<td>2018/2017</td>
<td>Multilingual Parsing from Raw Text to Universal Dependencies</td>
</tr>
<tr>
<td>2018/2017</td>
<td>Universal Morphological Reinflection</td>
</tr>
<tr>
<td>2016/2016</td>
<td>(Multilingual) Shallow Discourse Parsing</td>
</tr>
<tr>
<td>2014/2013</td>
<td>Grammatical Error Correction</td>
</tr>
<tr>
<td>2012/2011</td>
<td>Modelling (Multilingual) Unrestricted Coreference in OntoNotes</td>
</tr>
<tr>
<td>2010</td>
<td>Hedge Detection</td>
</tr>
<tr>
<td>2009/2008</td>
<td>Syntactic and Semantic Dependencies in English/Multiple Languages</td>
</tr>
<tr>
<td>2007/2006</td>
<td>Multi-Lingual Dependency Parsing (Domain Adaptation)</td>
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<tr>
<td>2005/2004</td>
<td>Semantic Role Labeling</td>
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<td>2003/2002</td>
<td>Language-Independent Named Entity Recognition</td>
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<tr>
<td>2001</td>
<td>Clause Identification</td>
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<tr>
<td>2000</td>
<td>Chunking</td>
</tr>
<tr>
<td>1999</td>
<td>NP Bracketing</td>
</tr>
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</table>
input words

1 U.N.
2 official
3 Ekeus
4 heads
5 for
6 Baghdad
7 .

input words

1 U.N. NNP
2 official NN
3 Ekeus NNP
4 heads VBZ
5 for IN
6 Baghdad NNP
7 . .
<table>
<thead>
<tr>
<th></th>
<th>Input Words</th>
<th>Part-of-Speech Tags</th>
<th>Syntactic Chunks</th>
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</thead>
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<tr>
<td>1</td>
<td>U.N.</td>
<td>NNP I-NP</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>official</td>
<td>NN I-NP</td>
<td></td>
</tr>
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<td></td>
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<tr>
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<td>VBZ I-VP</td>
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</tr>
<tr>
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<td>IN I-PP</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Baghdad</td>
<td>NNP I-NP</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>.</td>
<td>.</td>
<td>0</td>
</tr>
</tbody>
</table>

This diagram illustrates the input words, part-of-speech tags, and syntactic chunks for a sample sentence.
input words

1. U.N.  NNP  I-NP
2. official  NN  I-NP
3. Ekeus  NNP  I-NP
4. heads  VBZ  I-VP
5. for  IN  I-PP
6. Baghdad  NNP  I-NP
7. .  .  0

part-of-speech tags

syntactic chunks
U.N. I-NP I-ORG
official I-NP 0
Ekeus I-NP I-PER
heads I-VP 0
for I-PP 0
Baghdad I-NP I-LOC

part-of-speech tags

input words

syntactic chunks

named entities
U.N. I-NP I-ORG
official I-NP 0
Ekeus I-NP I-PER
heads I-VP 0
for I-PP 0
Baghdad I-NP I-LOC

part-of-speech tags
input words
syntactic chunks
named entities
1. U.N. (NNP, I-NP, I-ORG, 3)
2. official (NN, I-NP, 0, 3)
3. Ekeus (NNP, I-NP, I-PER, 4)
4. heads (VBZ, I-VP, 0, 0)
5. for (IN, I-PP, 0, 6)
6. Baghdad (NNP, I-NP, I-LOC, 4)
7. (., 0, 0, 4)
1. U.N. (NNP, I-NP, I-ORG) 3
2. official (NN, I-NP) 0 3
3. Ekeus (NNP, I-NP, I-PER) 4
4. heads (VBZ, I-VP) 0 0
5. for (IN, I-PP) 0 6
6. Baghdad (NNP, I-NP, I-LOC) 4
7. (.) (.) 0 0 4

part-of-speech tags

syntactic dependencies

syntactic chunks

named entities
## Querying a knowledge base

**User query:** Has my order number 4291 been shipped yet?

**Database:**

<table>
<thead>
<tr>
<th>Order number</th>
<th>Date ordered</th>
<th>Date shipped</th>
</tr>
</thead>
<tbody>
<tr>
<td>4290</td>
<td>2/2/13</td>
<td>2/2/13</td>
</tr>
<tr>
<td>4291</td>
<td>2/2/13</td>
<td>2/2/13</td>
</tr>
<tr>
<td>4292</td>
<td>2/2/13</td>
<td>2/2/13</td>
</tr>
</tbody>
</table>

**USER:** Has my order number 4291 been shipped yet?

**DB QUERY:** order(number=4291,date_shipped=?)

**RESPONSE:** Order number 4291 was shipped on 2/2/13
Instructions

Natural language: Go to the third junction and take a left

Programming language:

```
(do-seq(do-n-times 3
  (move-to forward-loc
   (do-until
    (junction current-loc
     (move-to forward-loc)))))
  (turn-right))
```

Many other application-based representations

Why NLP is hard?
Why is this difficult?

(1) a. How fast is the RTX 30?
   b. How fast will my RTX 30 arrive?
   c. Please tell me when I can expect the RTX 30 I ordered.

similar strings mean different things

different strings mean the same thing
Why is this difficult?

(2) a. Do you sell Sony laptops and disk drives?
   b. Do you sell (Sony (laptops and disk drives))?
   c. Do you sell (Sony laptops) and (disk drives)?

\[ 2 \times (3 + 4) = 2 \times 3 + 2 \times 4 \quad \text{vs} \quad 2 \times 3 + 4 \]
Wouldn’t it be better if . . .?

The properties which make natural language difficult to process are essential to human communication:

- Flexible
- Learnable but compact
- Emergent, evolving systems

Synonymy and ambiguity go along with these properties.

Natural language communication can be indefinitely precise:

- Ambiguity is mostly local (for humans)
Scope of NLP
A typical call-for-paper (1)

ACL (=Annual Meeting of the Association for Computational Linguistics) 2020 has the goal of a broad technical program. Relevant topics for the conference include, but are not limited to, the following areas:

- Theory and Formalism in NLP (Linguistic and Mathematical)
- Machine Learning for NLP
- Cognitive Modeling and Psycholinguistics
- Phonology, Morphology and Word Segmentation
- Syntax: Tagging, Chunking and Parsing
- Semantics: Lexical
- Semantics: Sentence Level
- Semantics: Textual Inference and Other Areas of Semantics
- Discourse and Pragmatics
- Generation
- Resources and Evaluation
- Interpretability and Analysis of Models for NLP
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- Information Extraction
- Information Retrieval and Text Mining
- Machine Translation
- Question Answering
- Dialogue and Interactive Systems
- Summarization
- Sentiment Analysis, Stylistic Analysis, and Argument Mining
- (other) NLP Applications
- Computational Social Science and Social Media
- Ethics and NLP
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Apple iPhone 11 review: The best $700 iPhone Apple has...

Apple iPhone 11 review: The best $700 iPhone Apple has ever made. The good Even faster speed, improved...
Mar 29, 2020 - ★★★★★ Rating: 4.5 - Review by Patrick Holland

iPhone 11 review | TechRadar

May 4, 2020 - The iPhone 11 is something of a surprise - it brings more advanced technology (namely in the camera capabilities and the processing power under the hood) and yet offers it for less than the iPhone XR cost in 2018. It combines a large 6.1-inch display with a premium-feeling body, and comes in an array of colors too.
★★★★★ Rating: 4.5 - Review by Gareth Beavis

Apple iPhone 11 review - YouTube

The Apple iPhone 11 is the cheapest of the three new iPhones but does that mean you are giving up a lot? Our...
Oct 3, 2019 - Uploaded by GSMArena Official
The iPhone 11 is something of a surprise — it brings more advanced technology (namely in the camera capabilities and the processing power under the hood) and yet offers it for less than the iPhone XR cost in 2018. It combines a large 6.1-inch display with a premium-feeling body, and comes in an array of colors too.

The most eye-catching feature of the new iPhone is to the imaging capabilities: with two sensors on the rear, you can now take wider-angle snaps alongside the ‘normal’ main images. These sensors are 12MP each, and are raised from the rear of the phone in a square glass enclosure — which we’re not enamored with visually.

The night mode is the most impressive part of the iPhone 11 imaging quality, bringing brightness and clarity to impossibly dark scenes, and the Portrait mode, defocusing the background, is improved on the new iPhone too.
Opinion mining: what do they think about me?

Scan documents (webpages, tweets etc) for positive and negative opinions on people, products, etc.

Find all references to entity in some document collection: list as positive, negative (possibly with strength) or neutral.

Construct summary report plus examples (text snippets).

Fine-grained classification:
  e.g., for phone, opinions about: design, performance, camera, battery life
  ...
Sentiment classification: the research task

Full task
Information retrieval, cleaning up text structure, named entity recognition, identification of relevant parts of text. Evaluation by humans.

Example

Movie review corpus (Pang et al, 2002): strongly positive or negative reviews from IMDb, 50:50 split, with rating score.

Ooooo. Scary.
The old adage of the simplest ideas being the best is once again demonstrated in this, one of the most entertaining films of the early 80's, and almost certainly Jon Landis' best work to date. The script is light and witty, the visuals are great and the atmosphere is top class. Plus there are some great freeze-frame moments to enjoy again and again. Not forgetting, of course, the great transformation scene which still impresses to this day.

In Summary: Top banana
Sentiment classification: the research task

Full task
Information retrieval, cleaning up text structure, named entity recognition, identification of relevant parts of text. Evaluation by humans.

Research task
Preclassified documents, topic known, opinion in text along with some straightforwardly extractable score.

Example
Movie review *corpus* (Pang et al, 2002): strongly positive or negative reviews from IMDb, 50:50 split, with rating score.

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**Bag of words technique**

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- Treat the reviews as collections of individual words.
Bag of words technique

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- Treat the reviews as collections of individual words.
- Classify reviews according to positive or negative words.
Rating: 9/10

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- Treat the reviews as collections of individual words.
- Classify reviews according to positive or negative words.
- Could use word lists prepared by humans, but machine learning based on a portion of the corpus (training set) is preferable.
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**In Summary:** Top banana

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- Could use word lists prepared by humans, but machine learning based on a portion of the corpus (training set) is preferable.
- Use human rankings for training and evaluation.
Bag of words technique

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</table>

In Summary: Top banana

- Treat the reviews as collections of individual words.
- Classify reviews according to positive or negative words.
- Could use word lists prepared by humans, but machine learning based on a portion of the corpus (training set) is preferable.
- Use human rankings for training and evaluation.
- Pang et al (2002): Chance success is 50% (corpus artificially balanced), bag-of-words gives 80%.
Some sources of errors for bag-of-words

- Negation:
  
  *Ridley Scott has never directed a bad film.*
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- Overfitting the training data:
  e.g., if training set includes a lot of films from before 2005, *Ridley* may be a strong positive indicator, but then we test on reviews for ‘Kingdom of Heaven’?
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  *Ridley Scott has never\(\text{\ding{45}}\) directed a bad\(\text{\ding{43}}\) film.*

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- Comparisons and contrasts.
This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it can’t hold up.
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AN AMERICAN WEREWOLF IN PARIS is a failed attempt ... Julie Delpy is far too good for this movie. She imbues Serafine with spirit, spunk, and humanity. This isn’t necessarily a good thing, since it prevents us from relaxing and enjoying AN AMERICAN WEREWOLF IN PARIS as a completely mindless, campy entertainment experience. Delpy’s injection of class into an otherwise classless production raises the specter of what this film could have been with a better script and a better cast ... She was radiant, charismatic, and effective ...
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- Morphology, syntax and compositional semantics: who is talking about what, what terms are associated with what, tense …
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- Getting all this to work well on arbitrary text is very hard.
- Ultimately the problem is AI-complete, but can we do well enough for NLP to be useful?
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