Natural Language Processing

Lecture 1
Introduction

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Course textbooks

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- Dan Jurafsky and James H. Martin,
  Speech and Language Processing 3rd ed.
  Draft available at
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These slides are in large part based on the first, ”Introduction” chapter of the Eisenstein book.

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  - communication: the ability to accept input and produce output in natural language;
  - understanding: being able to access and utilize the informational and emotional content;
  - linguistic assistance: the ability to help humans to express themselves linguistically.

Related fields

Computational linguistics

The scientific study of language using computational methods.

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- Perhaps the closest field to NLP, but with a different focus: NLP is *not* concerned with theoretical insights into natural languages *per se* but only with the design and analysis of methods useful for computational language processing.
- Instead of direct implementations of theoretical ideas, it often provides *architectural inspiration* for NLP systems.

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The above characteristics make especially the AI subfields Knowledge Representation and Reasoning very relevant for NLP.

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- Texts are sequences of discrete symbols, so ML models capable of dealing with this type of input (and output in case of generation) are needed.

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- Speech2text provides input for NLP applications,
- NLP apps provide input for speech synthesis;
- Both processing and synthesizing speech requires linguistic knowledge that is also relevant for NLP: especially *language modeling* has a central role in both areas.

Applications

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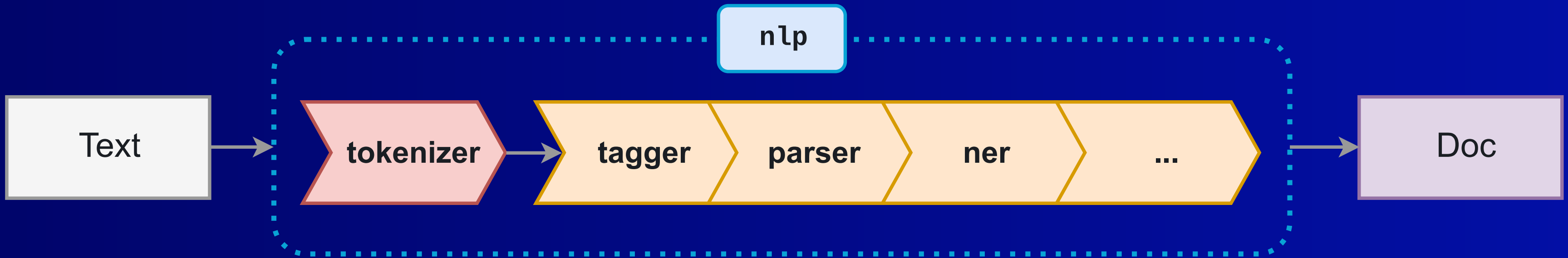
- auto-completion for free-text input,
- document summarization,
- text generation from structured data (from stock exchange news to error messages).

Central themes

Pipeline vs end-to-end architectures

An influential view of NLP considers its core task to provide a pipeline of modules that successively produce general-purpose linguistic analyses, each module building on the outputs of the previous ones:



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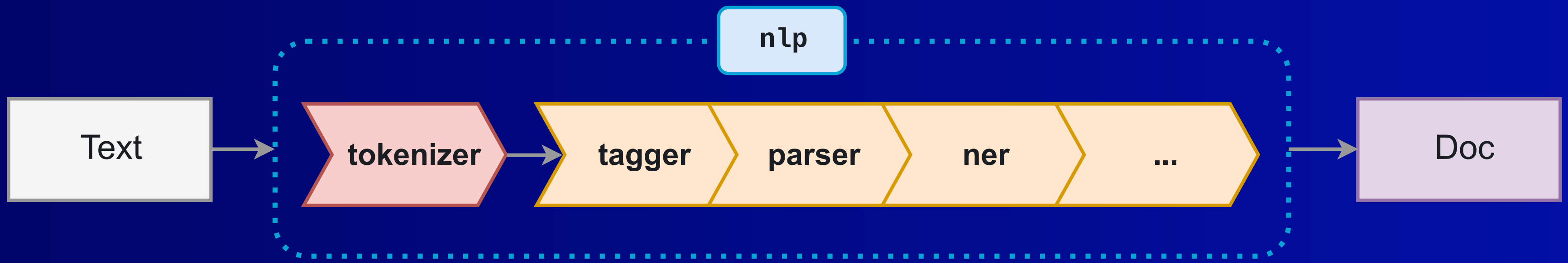

(Figure from the documentation of the spaCy NLP library.)

Specialized NLP applications are then built as relatively simple additions on top of elements of this universal pipeline.

Pipeline vs end-to-end cont.

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State-of-the art NLP applications frequently fall in between these two extremes: they use some universal analyzer modules, e.g., for word segmentation or stemming, and also rely on ML models that skip some of the traditional pipeline steps to produce the required output.

Transfer learning

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- $\hat{y}$ is the predicted output.

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- Learning: Finding the optimal θ parameters. This is typically done by optimizing θ on a large supervised data set $\{\langle x_i, y_i \rangle\}_{i=1}^{N}$ using numerical optimization methods.
- Search: Finding the best scoring y for a specific x, i.e., computing the value of the argmax in the formula. Since the search space $Y(x)$ is often large because the potential ys have a complex structure (think, e.g., of a parse tree), this problem frequently requires combinatorial optimization.

Semantic perspectives: relational

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The relational perspective concentrates on these semantic/conceptual links between the senses of expressions, which together constitute semantic networks:

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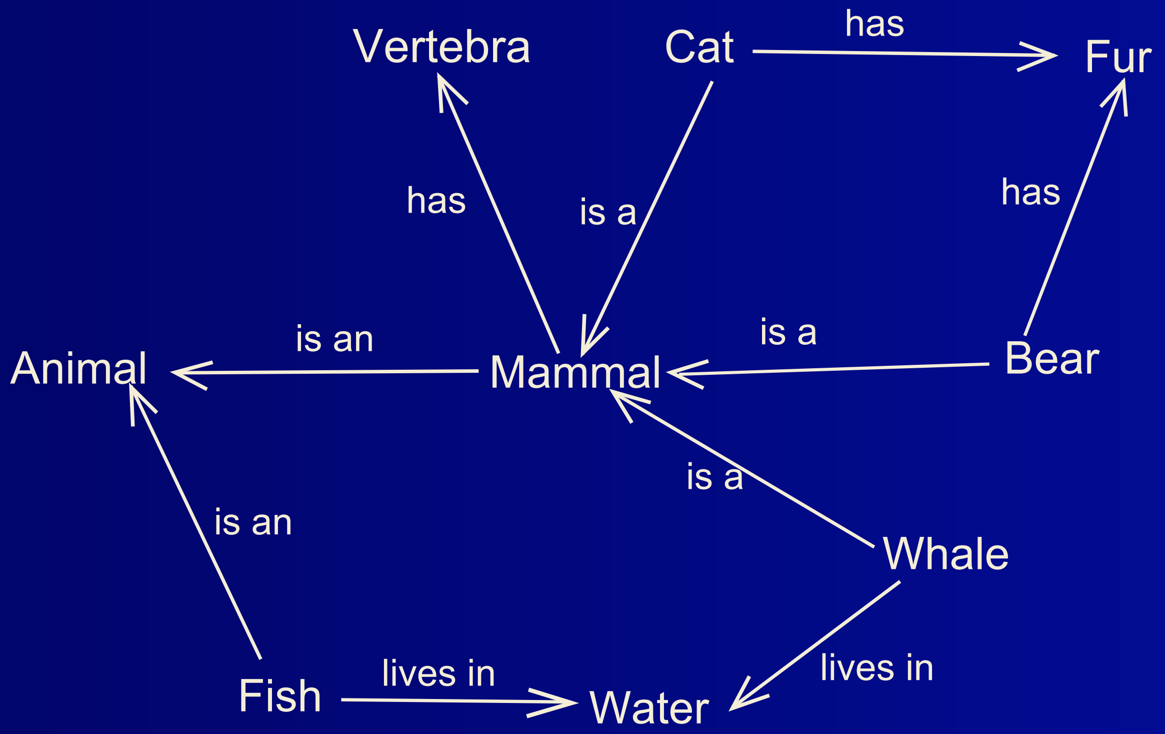

(A semantic network fragment. Figure from Wikipedia: Semantic Networks.)

Lexical semantic ontologies like WordNet and FrameNet are attempts to enumerate the semantic relations between a large number of word senses.

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un|*bear*|*able*|*s*

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allows us to see the meaning of *unbearables* as being composed of the meanings of its parts *un*, *bear*, *able* and *s*.

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The principle can be applied to larger linguistic units than words: sentences or even paragraphs etc. One (traditional) approach is to represent meanings with logical formulas and associate syntactic syntactic rules of combination with semantic/logical ones:

[1] Wikipedia: Principle of Compositionality.

Semantic perspectives: compositionality

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VISITS(JOHN,JULIE)

JOHN $\lambda x.$VISITS$(x,$JULIE$)$

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$\Rightarrow$ Bardiwac is a heavy red alcoholic beverage made from grapes.

[2] The example is from Stefan Evert’s Distributional semantics slides.

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- "Linguistic items with similar distributions have similar meanings." [4]

[3] J.R. Firth, *Papers in Linguistics 1934–1951 (1957).*

[4] Wikipedia: Distributional semantics.

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- learns the similarities without providing any explanation *why* these distributions are similar.