Introduction to CIT 831

Natural Language Processing

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CIT 831 Natural Language Processing

1. Why is Natural Language Processing difficult?
2. Structuring the field
3. NLP between system development and science
4. The structure of the course

Readings

- Jurafsky, Daniel S., and James H. Martin (fothcoming) Speech and Language Processing: An Introduction to Natural Language Processing, Speech Recognition, and Computational Linguistics. 3rd edition. Prentice-Hall.
- Goodfellow, Ian, Bengio, Yoshua, and Courville, Aaron: Deep Learning. MIT Press, 2016

Why is Natural Language Processing difficult?

- language is compositional
  - smaller units combine into larger ones
  - the meaning of a complex expression is determined by its structure and the meanings of its constituents (Gottlob Frege, 1879)
- language is complex
  - few elementary units, manifold ways to combine them
  - no upper length limitations for complex utterances

Why is Natural Language Processing difficult?

- language is ambiguous on all levels
  - phonological:
    - The same sound is spelled differently

      $/\text{fi:l}/ \rightarrow$ feel, $/\text{mi:l}/ \rightarrow$ meal
    - The same characters are pronounced differently

      read $\rightarrow /\text{ri:t}/$, read $\rightarrow /\text{r}\epsilon\text{d}/$, bear $\rightarrow /\text{b}\epsilon\text{:r}/$

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      read $\rightarrow$ /ri:t/, read $\rightarrow$ /rϵd/, bear $\rightarrow$ /bϵ:r/
  - morphological:
    - -ed $\rightarrow$ past tense verb vs. past participle (vs. part of the stem)
    - -s $\rightarrow$ 3rd person singular vs. plural noun (vs. part of the stem)

Why is Natural Language Processing difficult?

- language is ambiguous on all levels
  - lexical:

rose/V	She rose from her chair.
	Disapproval rose from the audience.
	(She was afraid to rose.)
rose/N	This rose is beautiful.
	The flowers came in all shades of rose.
rose/A	I'll take the rose flowers.
light/N	I switched on the light.
	(That shed light on the issue.)
	In the light of the current situation ...
light/A	Light pressure might help.
	The light package came today.
light/V	We can light the fire with my matches.

Why is Natural Language Processing difficult?

- language is ambiguous on all levels
  - structural:
    - PP attachment:

      He saw the woman with the telescope.
    - Reduced relative clauses:

      We saw the Eiffel tower flying to Paris.

Why is Natural Language Processing difficult?

- language is flexible
  - the same or similar content can be expressed in very many different ways.
- language is shaped by individual or collective preferences
  - dialects, stylistic variations, ...
- language is dynamic
  - neologisms and dying-out words
  - semantic shift
  - meaning negotiation
- language uses mataphor, vagueness, underspecification, ...

Structuring the field

- applications
- linguistic descriptions
- knowledge acquisition
- system design
- modularization
- data structures
- tasks
- models
- methods and algorithms

Applications of NLP

???

Linguistic Descriptions

Complexity levels vs. semiotic perspectives

	syntax	semantics	pragmatics

Linguistic Descriptions

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	syntax (form)	semantics (meaning)	pragmatics (purpose)

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grammar			

Linguistic Descriptions

Complexity levels vs. semiotic perspectives

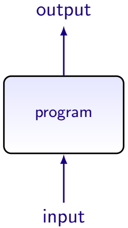
	syntax (form)	semantics (meaning)	pragmatics (purpose)
phonology			
morphology			
grammar			
discourse			

Knowledge acquisition

- manual compilation
  - using a formalism for knowledge representation
- machine learning
  - symbolic, probabilistic, neural, ...
  - supervised, unsupervised, semi-supervised, self-supervised

The history of NLP system design

Rule-based architectures



monolithic programs

1950 – 1970

The history of NLP system design

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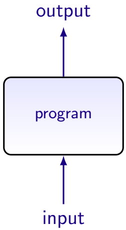

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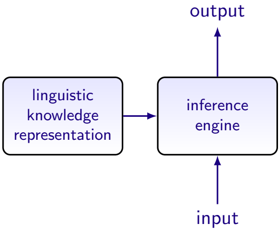
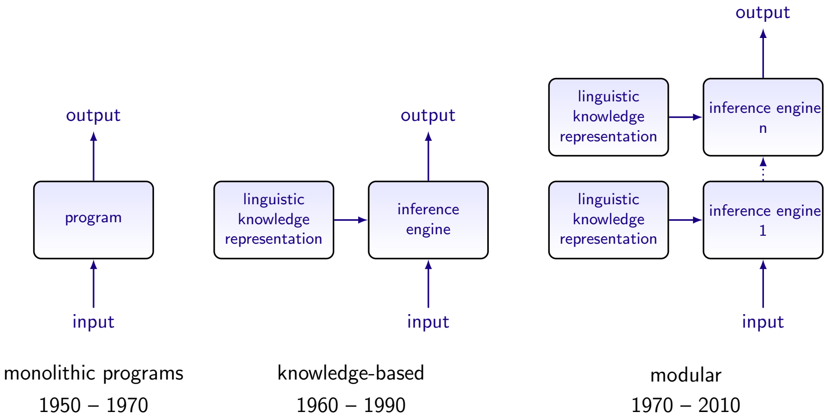


knowledge-based

1960 – 1990

The history of NLP system design

Rule-based architectures



Modularization

- Partial components for modular systems
  - morphological analysis
  - part-of-speech tagging
  - syntactic/semantic parsing
  - pragmatic analysis
  - named entity recognition
  - coreference resolution
  - semantic role labeling
  - text planning
  - text generation
- results are fed as features into a subsequent component

Modularization

(Good) reasons for developing modular systems:

- complexity reduction: simpler solutions for (simpler) partial tasks
- availability of training data: less expensive data collection (and annotation) for simpler tasks

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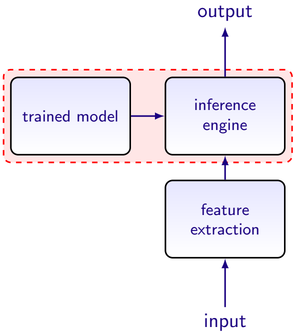
Drawbacks of modular systems

- error percolation: wrong decisions in earlier components might cause severe breakdowns in later ones
- ambiguity percolation: degree of ambiguity may rise exponentially with the number of components in a pipeline
- models are developed (i.e. optimized) separately and need to be fitted

The history of NLP system design

Traditional machine learning (symbolic/stochastic/neural)

often almost indistinguishable



monolithic

1980 – 2000

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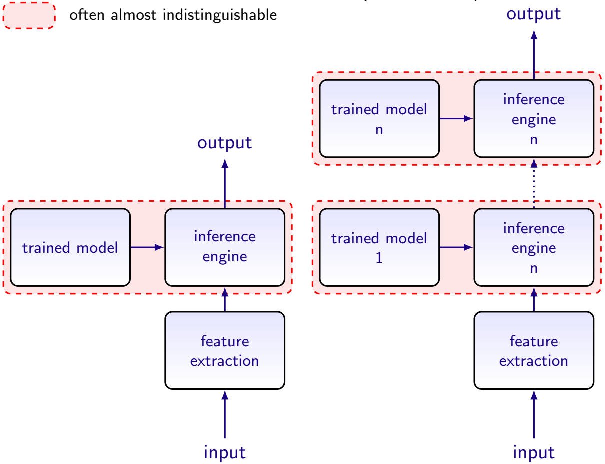

monolithic

1980 – 2000

modular components

1970 – 2010

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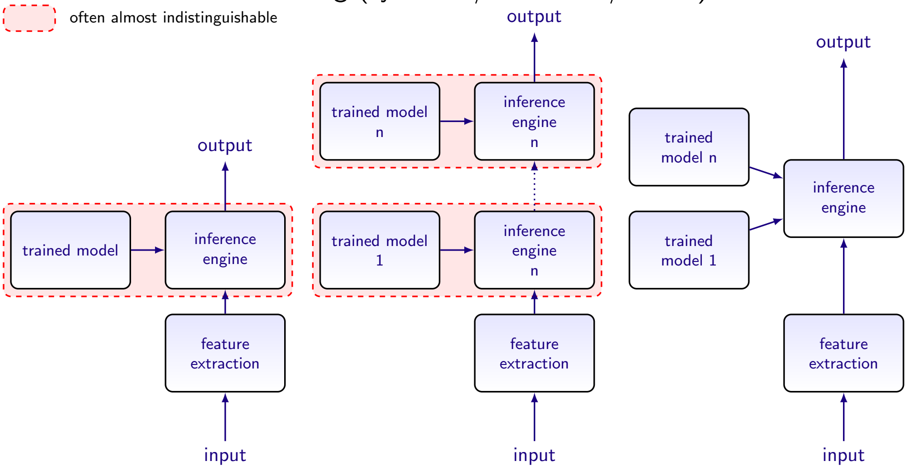


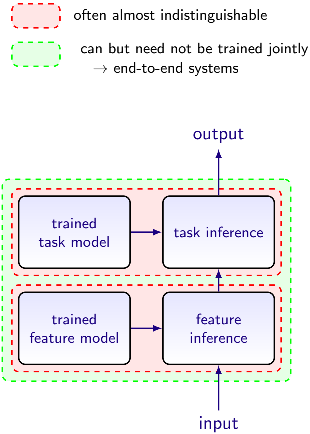
monolithic
1980 – 2000

modular components
1970 – 2010

modular models
1980 – 2020

The history of NLP system design

Representation learning (mainly neural architectures)



shallow

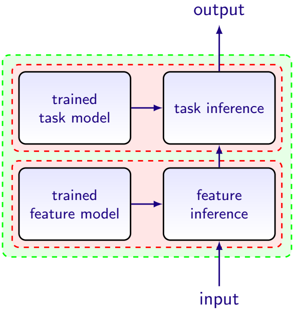
2010 –

The history of NLP system design

Representation learning (mainly neural architectures)

often almost indistinguishable

can but need not be trained jointly
→ end-to-end systems



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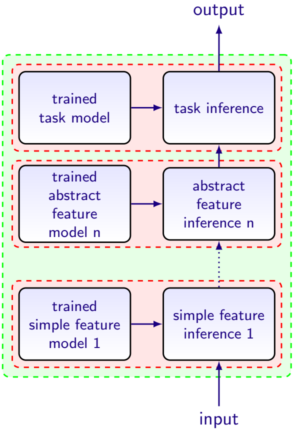

deep

2020 –

The history of NLP system design

1950 - 1970	monolithic systems: single program end-to-end
1960 - 2010	modularized systems: several cooperating components, most often arranged in a pipeline
2000 -	monolithic systems: trained end-to-end

Some terminology

- (Applications of NLP)
- Representations for NLP
- NLP tasks
- Models for NLP
- Methods/Algorithms for NLP

Input/Output Representations for NLP

- symbolic:
  - strings
  - ???

NLP tasks

- classification

  NL item $\mapsto$ category
- ???

Models

- classification/prediction
  - (naive) Bayes classifier
  - support vector machines
  - decision trees
  - multi-layer perceptrons
- measuring complexity
  - (linear) regression models
  - (multilayer) perceptron
- measuring similarity
  - cosine similarity (vectors)
  - alignments (strings, trees, graphs)

Models

- sequence-to-sequence transformation
  - finite state machines
  - (transformation) rules
  - hidden Markov models
  - recurrent neural networks
- structural prediction
  - context-free, dependency, unification-based and constraint-based grammars
- discourse planning, generation
  - special purpose formalisms

Important methods/algorithms

- symbolic
    - search (mostly for optimization)
        - systematic (taboo) search
        - (randomized) gradient descend
        - beam search, best first search
    - alignment
        - dynamic programming
    - structured prediction
        - (model specific) parsing algorithms (Earley, CYK, ...)
        - dynamic programming
        - term/graph unification
        - stochastic and neural classifiers
        - (stochastic) constraint satisfaction
    - probabilistic inference, argmax
- subsymbolic
    - backpropagation
    - softmax

NLP between system development and science

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- but it should not be reduced to system development

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  - How?

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    - How?
    - Why?

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Typical research questions (about methods)

- Feasibility: Is method A well suited to solve problem B?
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  - What are the problems expected or observed?
- Evaluation: How reliable does method A solve problem B
  - formal measures (e.g. string, tree or graph similarity)
  - comparison with human judgements (e.g. translation, relevance of documents)
- Comparison: Is method A better suited than method B to solve problem C?
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Typical research questions (about methods, continued)

- Complexity: How expensive it is to apply method A to problem B?
  - theoretical/empirical complexity results
  - worst case, typical case, ...

NLP between system development and science

Typical research questions (about methods, continued)

- Complexity: How expensive it is to apply method A to problem B?
  - theoretical/empirical complexity results
  - worst case, typical case, ...
- Explanation: What are the reasons for success / failure of a method?

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- Model complexity: e.g. how many dimensions are needed?

The structure of the course

Learning goals:

- learning of fundamental concepts of contemporary NLP tasks, tools and applications
- training of elementary techniques of scientific work, i.e.
  - formulating research questions,
  - conducting literature studies,
  - presenting scientific results and
  - writing a scientific text in its different phases: drafting, revising, reviewing

The structure of the course

Two major components:

- the reading club:
  reading, discussing and understanding novel concepts
- the writing club:
  presenting, discussing and publishing research questions and insights

The structure of the course

The reading club:

- home: read commonly agreed upon chapters of (Jurafsky and Martin, forthcoming)
- home: formulate your questions about
    - missing foundations
    - difficulties to understand
    - relationships to other concepts from NLP and CS
    - comparison of different methods
    - transfer of ideas to other problems or languages
    - ...
- home: post your questions on the Etherpad for the course
- meeting: cooperative attempts to answer the questions
- home: try to answer the questions still open

How to read a paper/book?

Reading via iterative refinement and selection

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Reading via iterative refinement and selection

- Preselection: Is the paper worth considering?
  - Who is the author?
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  - What the paper is about?
  - What kind of paper is it?
    - Review
    - Tutorial about solutions, evaluation methods, tools, models, or data sets
    - Research paper

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    - Research paper
  - How well does it fit my personal research interests?
  - Is it interesting? Is it of general interest?
  - Are the reported results promising?

How to read a paper/book?

- Shallow understanding: Does the paper contribute important ideas to my research?
  - What was the goal of the research reported?
  - What are the methods/tools applied?
  - What other methods they are based on?
  - What is the novel contribution?
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  - What is the novel contribution?
  - Are the results better to alternative approaches?
- Deep understanding: How does the approach really work?
  - What are the differences to alternative approaches?
  - Could I replicate the results?
  - Could I adapt the approach to my problem?
  - Which aspects of the solution contributed most to its success?
  - Can these aspects be ported to my problem/approach?

How to read a paper?

- Postprocessing/Documentation:
  - Add the paper to your personal data base.
  - Write a short summary of the paper.
  - Re-read the paper after having seen related ones.
  - Revise the summary if necessary.

The structure of the course

The writing club:

- home: formulate one or several (research) questions which might be of interest to the other participants of the course
- home: collect material needed to answer the question(s)
- meeting: give a talk about the question(s) and the answer(s) found
- meeting: discuss the content of the presentation
- meeting: provide feedback to the quality of the presentation
- home: write an essay about your "research" question(s)
  - motivate the question (What was unclear and why? etc.)
  - provide the background information required to understand the question(s)
  - provide your answer(s) and justifying its/their appropriateness
  - put your answers into perspective (What remains to be found out? How important are your findings? etc.)

The structure of the course

The writing club (continued):

- home: write of a review about the essay of another participant with the goal to given her/him helpful feedback on how to improve the essay?
- home: revise your essay according to the feedback received
- home: write a review about the essay of another participant with the goal to inform a fictional program committee of a conference (or the editorial board of a journal) about the strengths and weaknesses of the essay