

Syntactic Formalisms for Parsing Natural Languages

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Study materials

Course materials and homeworks are available on the following web site

<https://is.muni.cz/course/fi/autumn2011/IA161>

Outline

- Introduction to Statistical parsing methods
- Statistical Parsers
 - RASP system
 - Stanford parser
 - Collins parser
 - Charniak parser
 - Berkeley parser

1. Introduction to statistical parsing

- The main theoretical approaches behind modern statistical parsers
 - Over the last 12 years statistical parsing has succeeded significantly!
 - NLP researchers have produced a range of statistical parsers
- wide-coverage and robust parsing accuracy
- They continues to improve the parsers year on year.

Application domains of statistical parsing

- Question answering systems of high precision
- Named entity extraction
- Syntactically based sentence compressions
- Extraction of people's opinion about products
- Improved interaction in computer games
- Helping linguists find data

NLP parsing problem and solution

- The structure of language is ambiguous!

→ local and global ambiguities

- **Classical parsing problem**

→ simple 10 grammar rules can generate 592 parses

→ real size wide-coverage grammar generates millions of parses

NLP parsing problem and solution

NLP parsing solution

We need mechanisms that allow us to find the most likely parses

→ statistical parsing lets us work with very loose grammars that admit millions of parses for sentences but to still quickly find the best parses

Improved methodology for robust parsing

The annotated data: Penn Treebank (early 90's)

- Building a treebank seems a lot slower and less useful than building a grammar
- But it has many helpful things
 - Reusability of the labor
 - Broad coverage
 - Frequencies and distributional information
 - A way to evaluate systems

Characterization of Statistical parsing

- What the grammar which determines the set of legal syntactic structures for a sentence? How is that grammar obtained?
- What is the algorithm for determining the set of legal parses for a sentence?
- What is the model for determining the probability of different parses for a sentence?
- What is the algorithm, given the model and a set of possible parses which finds the best parse?

Characterization of Statistical parsing

$$T_{\text{best}} = \arg \max \text{Score}(T, S)$$

Two components:

- The **model**: a function Score which assigns scores (probabilities) to tree and sentence pairs
- The **parser**: the algorithm which implements the search for T_{best}

Characterization of Statistical parsing

Statistical parsing seen as more of a pattern recognition/Machine Learning problem plus search

The grammar is only implicitly defined by the training data and the method used by the parser for generating hypotheses

Statistical parsing models

Probabilistic approach would suggest the following for the Score function

$$\text{Score}(T, S) = P(T|S)$$

Lots of research on different probability models for Penn Treebank trees

- Generative models, log-linear (maximum entropy) models, ...

2. Statistical parsers

- Many kinds of parsers based on the statistical methods: probability, machine learning
- Different objectives: research, commercial, pedagogical
 - RASP, Stanford parser, Berkeley parser,

RASP system

Robust Accurate Statistical Parsing (2nd release): [Briscoe&Carroll, 2002; Briscoe *et al.* 2006]

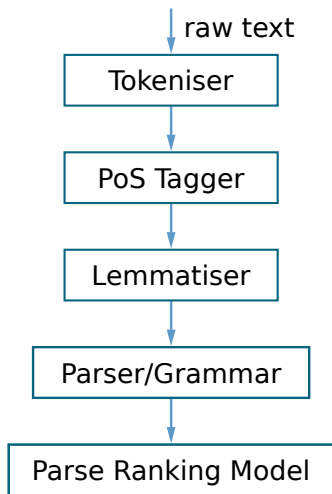
- system for syntactic annotation of free text
- Semantically-motivated output representation
- Enhanced grammar and part-of-speech tagger lexicon
- Flexible and semi-supervised training method for structural parse ranking model

Useful links to RASP

<http://ilexir.co.uk/applications/rasp/download/>

<http://www.informatics.susx.ac.uk/research/groups/nlp/rasp/>

Components of system



■ Input:

unannotated text or transcribed (and punctuated) speech

■ 1st step:

sentence boundary detection and tokenisation modules

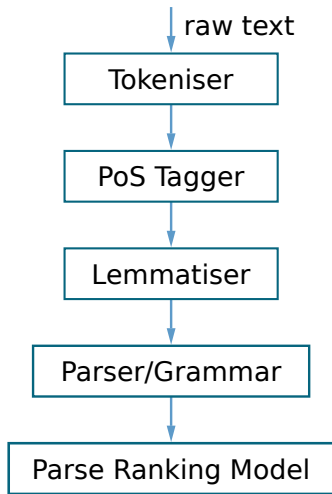
■ 2nd step:

Tokenized text is tagged with one of 150 POS and punctuation labels (derived from the CLAWS tagset)

→ first-order ('bigram') HMM tagger

→ trained on the manually corrected tagged version of the Susanne, LOB and BNC corpora

Components of system



■ 3rd step:

Morphological analyzer

■ 4th step:

Manually developed wide-coverage tag sequence grammar in the parser

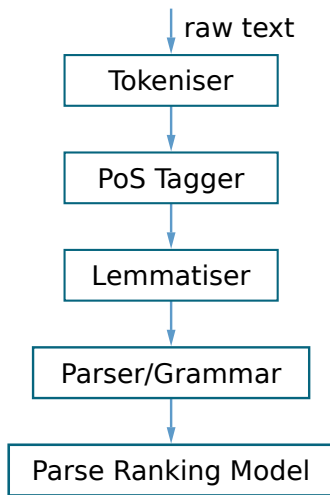
→ 689 unification based phrase structure rules

→ preterminals to this grammar are the POS and punctuation tags

→ terminals are featural description of the preterminals

→ non-terminals project information up the tree using an X-bar scheme with 41 attributes with a maximum of 33 atomic values

Components of system



■ 5th step:

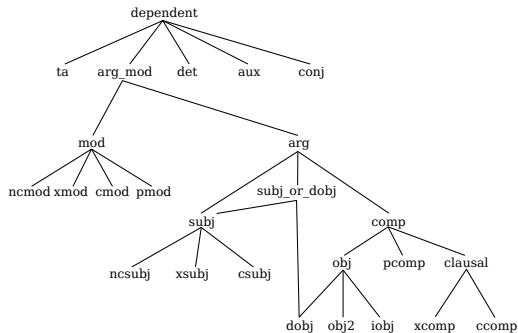
Generalized LR Parser

→ a non-deterministic LALR table is constructed automatically from CF 'backbone' compiled from the featurebased grammar

→ the parser builds a packed parse forest using this table to guide the actions it performs

→ the n-best parses can be efficiently extracted by unpacking sub-analyses, following pointers to contained subanalyses and choosing alternatives in order of probabilistic ranking

Components of system



■ Output:

set of named grammatical relations (GRs)

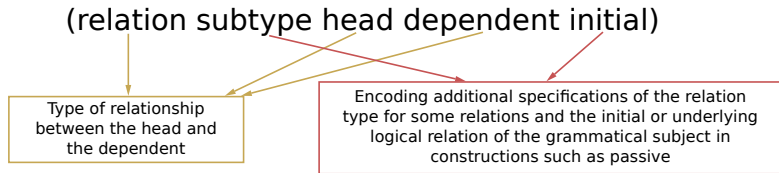
→ resulting set of ranked parses can be displayed or passed on for further processing

→ transformation of derivation trees into a set of named GRs

→ GR scheme captures those aspects of predicate-argument structure

Evaluation

- The system has been evaluated using the re-annotation of the PARC dependency bank (DepBank, King *et al.*, 2003)
- It consists of 560 sentences chosen randomly from section 23 of the WSJ with grammatical relations compatible with RASP system.
- Form of relations



Evaluation

Relation	Precision	Recall	F ₁	std	GRs
dependent	79.76	77.49	78.61		10696
aux	93.33	91.00	92.15		400
conj	72.39	72.27	72.33		595
ta	42.61	51.37	46.58		292
det	87.73	90.48	89.09		1114
arg_mod	79.18	75.47	77.28		8295
mod	74.43	67.78	70.95		3908
ncmod	75.72	69.94	72.72		3550
xmod	53.21	46.63	49.70		178
cmod	45.95	30.36	36.56		168
pmod	30.77	33.33	32.00		12
arg	77.42	76.45	76.94		4387
subj_or_dobj	82.36	74.51	78.24		3127
subj	78.55	66.91	72.27		1363
ncsubj	79.16	67.06	72.61		1354
xsubj	33.33	28.57	30.77		7
csubj	12.50	50.00	20.00		2
comp	75.89	79.53	77.67		3024
obj	79.49	79.42	79.46		2328
dobj	83.63	79.08	81.29		1764
obj2	23.08	30.00	26.09		20
iobj	70.77	76.10	73.34		544
clausal	60.98	74.40	67.02		672
xcomp	76.88	77.69	77.28		381
ccomp	46.44	69.42	55.55		291
pcomp	72.73	66.67	69.57		26
macroaverage	62.12	63.77	62.94		
microaverage	77.66	74.98	76.29		

Parsing accuracy on DepBank [Briscoe et al., 2006]

- Micro-averaged precision, recall and F₁ score are calculated from the counts for all relations in the hierarchy
- Macro-averaged scores are the mean of the individual scores for each relation
- Micro-averaged F₁ score of 76.3% across all relations

Stanford parser

Java implementation of probabilistic natural language parsers (version 1.6.9)

: [Klein and Manning, 2003]

- Parsing system for English and has been used in Chinese, German, Arabic, Italian, Bulgarian, Portuguese
- Implementation, both highly optimized PCFG and lexicalized dependency parser, and lexicalized PCFG parser
- Useful links

<http://nlp.stanford.edu/software/lex-parser.shtml>

<http://nlp.stanford.edu:8080/parser/>

Stanford parser

■ Input

various form of plain text

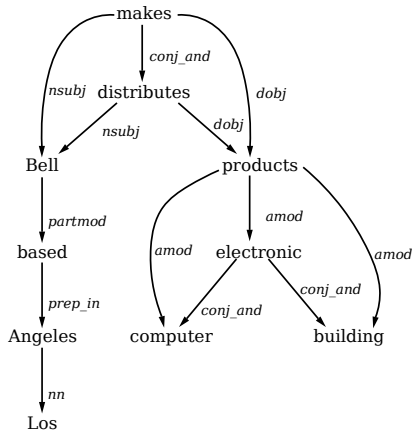
■ Output

Various analysis formats

→ Stanford Dependencies (SD): typed dependencies as GRs

→ phrase structure trees

→ POS tagged text



Graphical representation of the SD for the sentence

"Bell, based in Los Angeles, makes and distributes electronic, computer and building products."

Stanford typed dependencies [De Marmette and Manning, 2008]

- provide a simple description of the grammatical relationships in a sentence
- represents all sentence relationships uniformly as typed dependency relations
- quite accessible to non-linguists thinking about tasks involving information extraction from text and is quite effective in relation extraction applications.

Stanford typed dependencies [De Marnette and Manning, 2008]

For an example sentence:

Bell, based in Los Angeles, makes and distributes electronic, computer and building products.

Stanford Dependencies (SD) representation is:

	conj_and(makes-8, distributes-10)
	amod(products-16, electronic-11)
nsubj(makes-8, Bell-1)	conj_and(electronic-11, computer-13)
nsubj(distributes-10, Bell-1)	amod(products-16, computer-13)
partmod(Bell-1, based-3)	conj_and(electronic-11, building-15)
nn(Angeles-6, Los-5)	amod(products-16, building-15)
prep_in(based-3, Angeles-6)	dobj(makes-8, products-16)
root(ROOT-0, makes-8)	dobj(distributes-10, products-16)

Output

A lineup of masseurs was waiting to take the media in hand.

POS tagged text

Parsing [sent. 4 len. 13]: [A, lineup, of, masseurs, was, waiting, to, take, the, media, in, hand, .]

CFPSG representation

```
(ROOT
  (S
    (NP
      (NP (DT A) (NN lineup))
      (PP (IN of)
        (NP (NNS masseurs))))
    (VP (VBD was)
      (VP (VBG waiting)
        (S
          (VP (TO to)
            (VP (VB take)
              (NP (DT the) (NNS media))
              (PP (IN in)
                (NP (NN hand))))))))
    (. .)))
```

Typed dependencies representation

```
det(lineup2, A1)
nsubj(waiting6, lineup2)
xsubj(take8, lineup2)
prep_of(lineup2, masseurs4)
aux(waiting6, was5)
root(ROOT0, waiting6)
aux(take8, to7)
xcomp(waiting6, take8)
det(media10, the9)
dobj(take8, media10)
prep_in(take8, hand12)
```

Berkeley parser

Learning PCFGs, statistical parser (release 1.1, version 09.2009)

: [Petrov *et al.*, 2006; Petrov and Klein, 2007]

- Parsing system for English and has been used in Chinese, German, Arabic, Bulgarian, Portuguese, French
- Implementation of unlexicalized PCFG parser
- Useful links

<http://nlp.cs.berkeley.edu/>

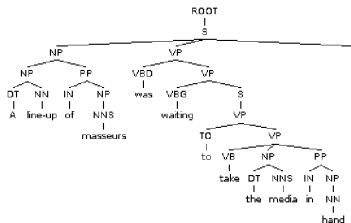
[http://tomato.banatao.berkeley.edu:
8080/parser/parser.html](http://tomato.banatao.berkeley.edu:8080/parser/parser.html)

<http://code.google.com/p/berkeleyparser/>

Comparison of parsing an example sentence

A lineup of masseurs was waiting to take the media in hand.

```
(ROOT
 (S
  (NP
   (NP (DT A) (NN line-up))
   (PP (IN of)
    (NP (NNS masseurs))))
  (VP (VBD was)
   (VP (VBG waiting)
    (S
     (VP (TO to)
      (VP (VB take)
       (NP (DT the) (NNS media))
       (PP (IN in)
        (NP (NN hand))))))))
   (. .)))
```



Berkeley parser

```
Parsing [sent. 4 len. 13]: [A, line-up, of, masseurs, was, waiting, to,
(ROOT
 (S
  (NP
   (NP (DT A) (NN line-up))
   (PP (IN of)
    (NP (NNS masseurs))))
  (VP (VBD was)
   (VP (VBG waiting)
    (S
     (VP (TO to)
      (VP (VB take)
       (NP (DT the) (NNS media))
       (PP (IN in)
        (NP (NN hand))))))))
   (. .)))
```

Stanford parser

charniak parser

Probabilistic LFG F-Structure Parsing : [Charniak, 2000; Bikel, 2002]

- Parsing system for English
- PCFG based wide coverage LFG parser
- Useful links

`http://nclt.computing.dcu.ie/demos.html`

`http://lfg-demo.computing.dcu.ie/lfgparser.html`

Collins parser

Head-Driven Statistical Models for natural language parsing (Release 1.0, version 12.2002) : [Collins, 1999]

- Parsing system for English
- Useful links

<http://www.cs.columbia.edu/~mcollins/code.html>

Bikel's parser

Multilingual statistical parsing engine (release 1.0, version 06.2008)

: [Charniak, 2000; Bikel, 2002]

- Parsing system for English, Chinese, Arabic, Korean

<http://www.cis.upenn.edu/~dbikel/#stat-parser>

<http://www.cis.upenn.edu/~dbikel/software.html>

Comparing parser speed on section 23 of WSJ Penn Treebank

Parser	Time (min.)
Collins	45
Charniak	28
Sagae	11
CCG	1.9