Dependency Parsing

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With thanks to Sandra Kübler and Joakim Nivre

Why?

- Increasing interest in dependency-based approaches to syntactic parsing in recent years
  - New methods emerging
  - Applied to a wide range of languages
  - CoNLL shared tasks (2006, 2007)

What?

- Computational methods for dependency-based parsing
  - Syntactic representations
  - Parsing algorithms
  - Machine learning
- Available resources for different languages
  - Parsers
  - Treebanks

Syntactic parsing

- automatically determining the syntactic structure for a given sentence
- Traditionally (for phrase-structure grammars):
  - search through all possible trees for a sentence
  - bottom-up vs top-down approaches

Ambiguities

- more than one possible structure for a sentence
- natural languages are hugely ambiguous
- a very common problem

PoS-ambiguities **Attachment ambiguities**

		VB				
	VBZ	VBP	VBZ			
NNP	NNS	NN	NNS	CD	NN	
Fed	raises	interest	rates	0.5	%	in effort to control inflation

Back in the days (90s)

- Parsers assigned linguistically detailed syntactic structures (based on linguistic theories)
- Grammar-driven parsing: possible trees defined by the grammar
- Problems with **coverage**
  - only around 70% of all sentences were assigned an analysis
- Most sentences were assigned very many analyses by a grammar
  - no way of choosing between them

Enter data-driven (statistical) parsing

- Today data-driven/statistical parsing is available for a range of languages and syntactic frameworks
- Data-driven approaches: possible trees defined by the treebank (may also involve a grammar)
- Produce one analysis (hopefully the most likely one) for any sentence
- And get most of them correct
- Still an active field of research, improvements are still possible!

Statistics in parsing

- classical NLP parsing:
  - symbolic grammar and lexicon
  - proof systems to prove parses from words
- ambiguity problem is very large
  - minimal grammar on previous sentence: 36 parses
  - large broad-coverage grammar: millions of parses
- use probabilities to pick the most likely parse

Treebanks

- need data to estimate probabilities
- collection of sentences manually annotated with the correct parse ⇒ a **treebank**
- Penn Treebank: treebanks from Brown, Switchboard, ATIS og *Wall Street Journal* corpora
- Treebanks for other languages
  - Prague Dependency Treebank (czech)
  - Negra/Tuba-DZ (German)
  - Penn (Chinese)
  - Norwegian Dependency Treebank
  - the CoNLL treebanks (Project A)

Text parsing

- Goal: parse unrestricted text in natural language
  - Given a text $T = (x_1, \ldots, x_2)$ in language L, derive the correct analysis for every sentence $x_i \in T$.
- Challenges:
  - robustness: at least one analysis
  - disambiguation: at most one analysis
  - accuracy: correct analysis (for every sentence)
  - efficiency: reasonable time-and memory usage
- Two different methodological strategies
  - grammar-driven
  - data-driven

Grammar-driven parsing

- A formal grammar G defines
  - the language $L(G)$ that can be parsed
  - the class of analyses returned by the parser
- robustness (analyze any input sentence)
  - some input sentences x_i are not in $L(G)$
  - constraint relaxation, partial parsing
- disambiguation
  - number of analyses assigned by grammar may be very large
  - probabilistic extensions, e.g. PCFG
- accuracy: assumed advantage, but requires joint optimization of robustness and disambiguation

Data-driven parsing

1. formal model M defining possible analyses for sentences in L
2. A sample of annotated text $S = (x_1, \ldots, x_m)$ from L
3. An inductive inference scheme I defining actual analyses for the sentences of a text $T = (x_1, \ldots, x_n)$ in L, relative to M and S.

- S is the **training data:** contains representations satisfying M
- a **treebank**: manually annotated with correct analysis
- I based on **supervised** machine learning

Data-driven parsing

- robustness: depends on M and I, but usually designed such that any input string is assigned at least one analysis.
- disambiguation: severe problem, solved by inductive inference scheme
- improved accuracy represents main challenge
- efficiency: variation

Data-driven dependency parsing

- *M* defined by formal conditions on dependency graphs (labeled directed graphs that are):
  - connected
  - acyclic
  - single-head
  - (projective)
- *I* may be defined in different ways
  - parsing method (deterministic, non-deterministic)
  - machine learning algorithm, feature representations
- Two main approaches: **graph-based** and **transition-based** models [McDonald and Nivre 2007]

Graph-based approaches

- Basic idea:
  - define a space of candidate dependency graphs for a sentence
  - Learning: induce a model for scoring an entire dependency graph for a sentence
  - Parsing: Find the highest scoring dependency graph, given the induced model
- Characteristics:
  - global training
  - exhaustive search

Transition-based approaches

- Basic idea:
  - define a transition system for mapping a sentence to its dependency graph
  - Learning: induce a model for predicting the next state transition, given the transition history
  - Parsing: Construct the optimal transition sequence, given the induced model
- Characteristics:
  - local training
  - greedy search

MSTParser: Maximum Spanning Trees

[McDonald et al. 2005a, McDonald et al. 2005b]

- Score of a dependency tree = sum of scores of dependencies
- Scores are independent of other dependencies.
- Finding the highest scoring dependency tree = finding the maximum spanning tree (MST) in a graph containing all possible graphs
- Two cases:
  - Projective: Use Eisner's parsing algorithm.
  - Non-projective: Use Chu-Liu-Edmonds algorithm for finding the maximum spanning tree in a directed graph [Chu and Liu 1965, Edmonds 1967].
- Use machine learning for determining weight vector $\mathbf{w}$: large-margin multi-class classification (MIRA)

MaltParser: transition-based dependency parsing

- MaltParser is a language-independent system for data-driven dependency parsing which is freely available
- It is based on a **deterministic** parsing strategy in combination with treebank-induced **classifiers** for predicting parsing actions
- MaltParser employs a rich feature history in order to guide parsing
- May easily be extended to take into account new features of the parse history

MaltParser

- Parsing as a set of transitions between parse configurations
- A parse configuration is a triple $\langle S, I, G \rangle$, where
  - S represents the parse stack – a list of tokens which are candidates for dependency arcs
  - I is the queue of remaining input tokens
  - G represents the dependency graph under construction
- The parse *guide* predicts the next parse action (transition), based on the current parse configuration
- The guide is trained employing discriminative machine learning
- Recasts the learning problem as a classification problem: given a parse configuration, predict the next transition

Deterministic Parsing

- Basic idea:
  - Derive a single syntactic representation (dependency graph) through a deterministic sequence of elementary parsing actions
  - Sometimes combined with backtracking or repair
- Motivation:
  - Psycholinguistic modeling
  - Efficiency
  - Simplicity

Shift-Reduce Type Algorithms

- Data structures:
  - Stack $[\ldots, w_i]_S$ of partially processed tokens
  - Queue $[w_j, \ldots]_Q$ of remaining input tokens
- Parsing actions built from atomic actions:
  - Adding arcs ($w_i \rightarrow w_j$, $w_i \leftarrow w_j$)
  - Stack and queue operations
- Restricted to projective dependency graphs

Nivre's Algorithm

- Four parsing actions:

$$\text{Shift}\quad \frac{[\ldots]_S \quad [w_i, \ldots]_Q}{[\ldots, w_i]_S \quad [\ldots]_Q}$$

$$\text{Reduce}\quad \frac{[\ldots, w_i]_S \quad [\ldots]_Q \quad \exists w_k : w_k \rightarrow w_i}{[\ldots]_S \quad [\ldots]_Q}$$

$$\text{Left-Arc}_r\quad \frac{[\ldots, w_i]_S \quad [w_j, \ldots]_Q \quad \neg\exists w_k : w_k \rightarrow w_i}{[\ldots]_S \quad [w_j, \ldots]_Q \quad w_i \stackrel{r}{\leftarrow} w_j}$$

$$\text{Right-Arc}_r\quad \frac{[\ldots, w_i]_S \quad [w_j, \ldots]_Q \quad \neg\exists w_k : w_k \rightarrow w_j}{[\ldots, w_i, w_j]_S \quad [\ldots]_Q \quad w_i \stackrel{r}{\rightarrow} w_j}$$

- Characteristics:
  - Integrated labeled dependency parsing
  - Arc-eager processing of right-dependents

Example

[root]$_S$ [Economic news had little effect on financial markets .]$_Q$

Example

[root Economic]$_S$ [news had little effect on financial markets .]$_Q$

Shift

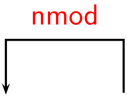
Example

nmod

[root]$_S$ Economic [news had little effect on financial markets .]$_Q$

Left-Arc$_{nmod}$

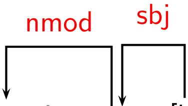
Example



[root Economic news]$_S$ [had little effect on financial markets .]$_Q$

Shift

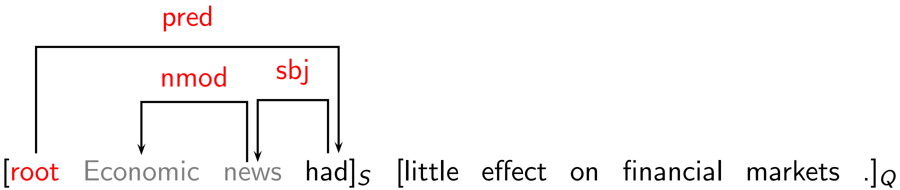
Example



$[$root$]_S$ Economic news $[$had little effect on financial markets .$]_Q$

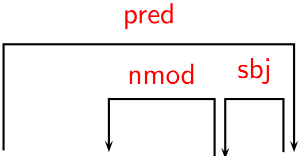
Left-Arc$_{sbj}$

Example



Right-Arc$_{pred}$

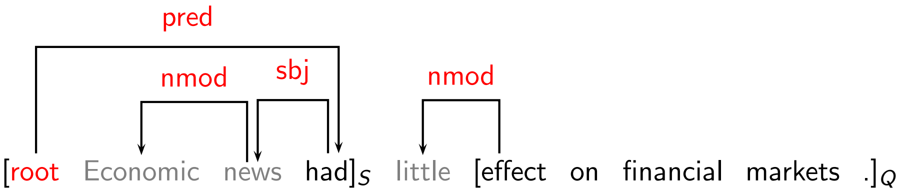
Example



[root Economic news had little]$_S$ [effect on financial markets .]$_Q$

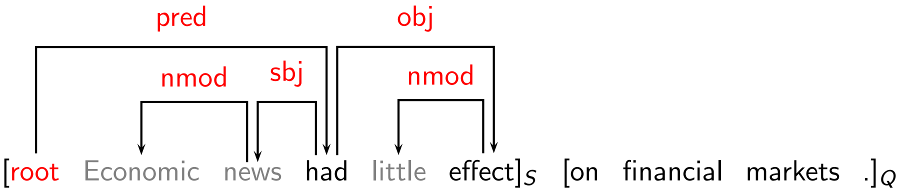
Shift

Example



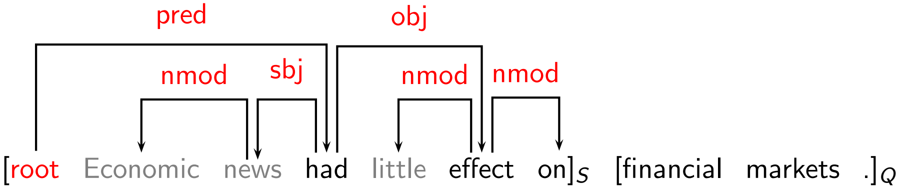
Left-Arc$_{nmod}$

Example



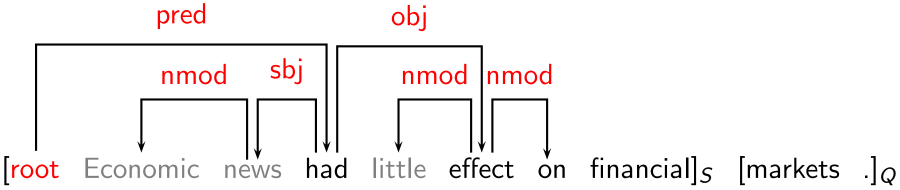
Right-Arc$_{obj}$

Example



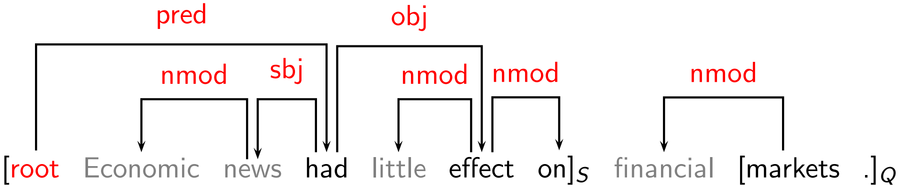
Right-Arc$_{nmod}$

Example



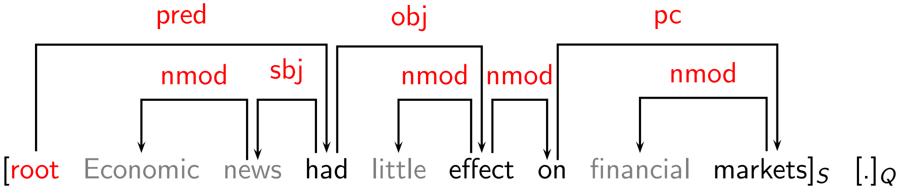
Shift

Example



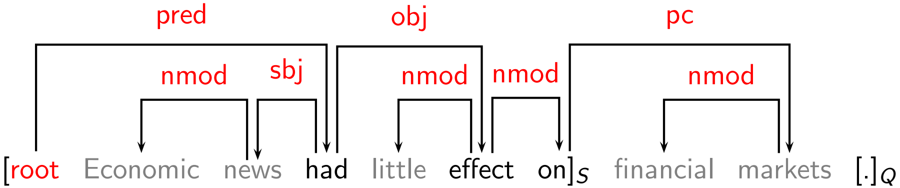
Left-Arc$_{nmod}$

Example



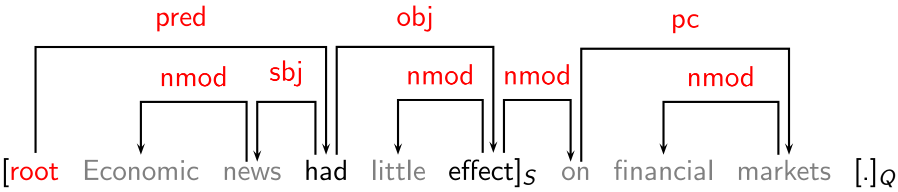
Right-Arc$_{pc}$

Example



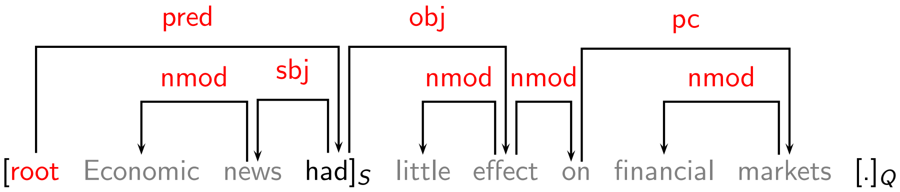
Reduce

Example



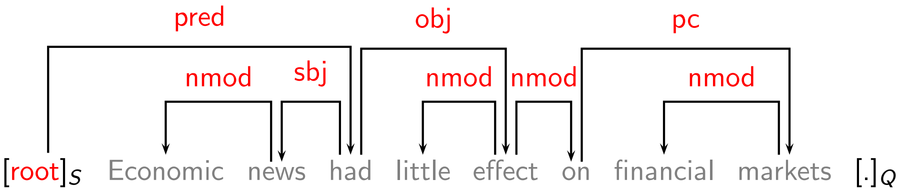
Reduce

Example



Reduce

Example



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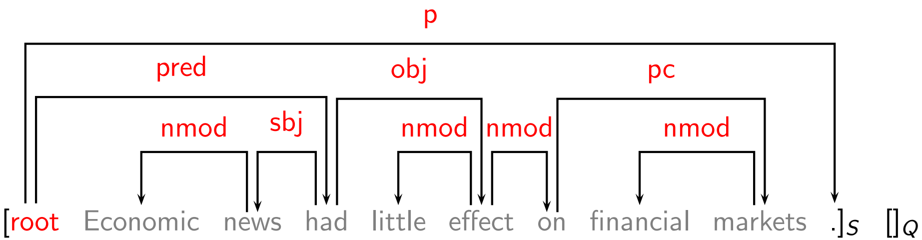


Right-Arc$_p$

Classifier-Based Parsing

- Data-driven deterministic parsing:
  - Deterministic parsing requires an oracle.
  - An oracle can be approximated by a classifier.
  - A classifier can be trained using treebank data.
- Learning methods:
  - Support vector machines (SVM)
    [Kudo and Matsumoto 2002, Yamada and Matsumoto 2003, Isozaki et al. 2004, Cheng et al. 2004, Nivre et al. 2006]
  - Memory-based learning (MBL)
    [Nivre et al. 2004, Nivre and Scholz 2004]
  - Maximum entropy modeling (MaxEnt)
    [Cheng et al. 2005]

Feature Models

- Learning problem:
  - Approximate a function from parser configurations, represented by feature vectors to parser actions, given a training set of gold standard derivations.
- Typical features:
  - Tokens:
    - Target tokens
    - Linear context (neighbors in S and Q)
    - Structural context (parents, children, siblings in G)
  - Attributes:
    - Word form (and lemma)
    - Part-of-speech (and morpho-syntactic features)
    - Dependency type (if labeled)
    - Distance (between target tokens)

Feature Models

- Parse configurations are represented by a set of features, which focus on attributes of the *top* of the stack, the *next* input token and neighboring tokens in the stack, input queue and dependency graph

	form	pos	dep
S:*top*	+	+	+
I:*next*	+	+	
G:head of *top*	+		
G:leftmost dependent of *top*			+

Non-Projective Dependency Parsing

- Many parsing algorithms are restricted to projective dependency graphs.
- Is this a problem?
- Statistics from CoNLL-X Shared Task [Buchholz and Marsi 2006]
  - NPD = Non-projective dependencies
  - NPS = Non-projective sentences

Language	**%NPD**	**%NPS**
Dutch	5.4	36.4
German	2.3	27.8
Czech	1.9	23.2
Slovene	1.9	22.2
Portuguese	1.3	18.9
Danish	1.0	15.6

Two Main Approaches

- Algorithms for non-projective dependency parsing:
  - McDonald's spanning tree algorithm [McDonald et al. 2005b]
  - Covington's algorithm [Nivre 2006]
- Post-processing of projective dependency graphs:
  - Pseudo-projective parsing [Nivre and Nilsson 2005]

Non-Projective Parsing Algorithms

- Complexity considerations:
  - Projective (Proj)
  - Non-projective (NonP)

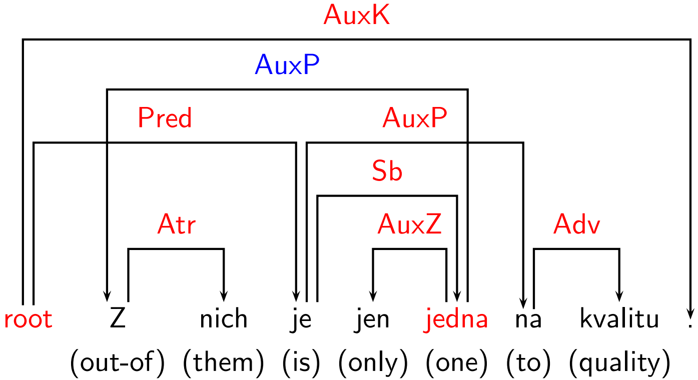
Problem/Algorithm	Proj	NonP
Deterministic parsing [Nivre 2003, Covington 2001]	$O(n)$	$O(n^2)$
First order spanning tree [McDonald et al. 2005b]	$O(n^3)$	$O(n^2)$

Post-Processing

- Two-step approach:
  1. Derive the best projective approximation of the correct (possibly) non-projective dependency graph.
  2. Improve the approximation by replacing projective arcs by (possibly) non-projective arcs.
- Rationale:
  - Most "naturally occurring" dependency graphs are primarily projective, with only a few non-projective arcs.

Pseudo-Projective Parsing

- Projectivize training data:
  - Projective head nearest permissible ancestor of real head
  - Arc label extended with dependency type of real head



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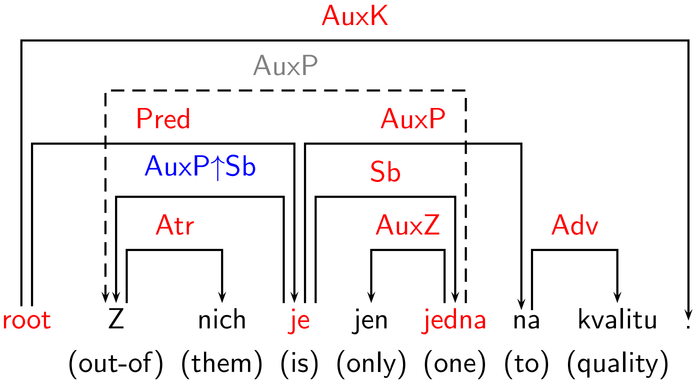
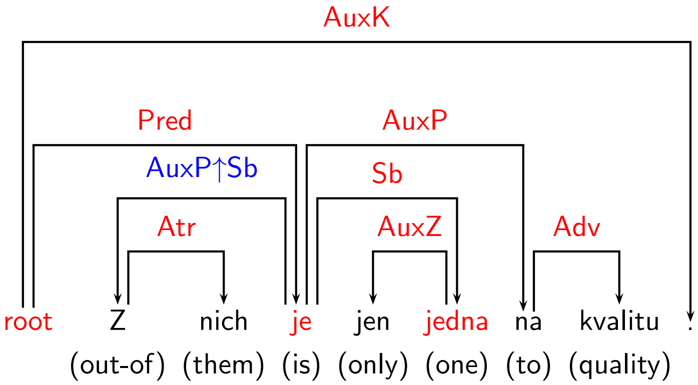


Pseudo-Projective Parsing

- Deprojectivize parser output:
  - Top-down, breadth-first search for real head
  - Search constrained by extended arc label



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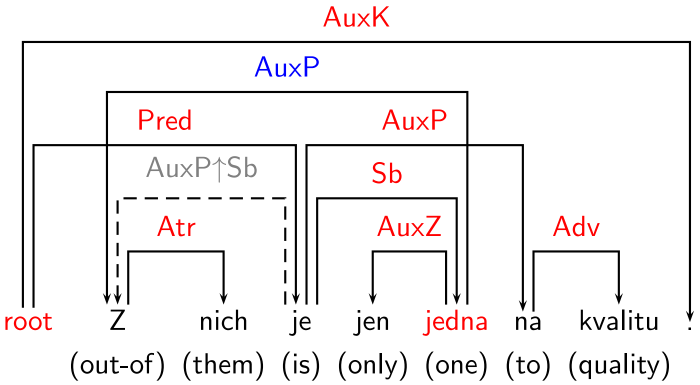


Pros and Cons of Dependency Parsing

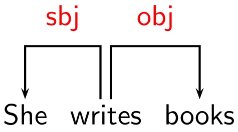
- What are the advantages of dependency-based methods?
- What are the disadvantages?
- Four types of considerations:
  - Complexity
  - Transparency
  - Word order
  - Expressivity

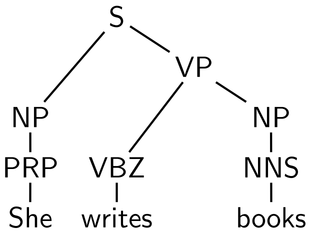
Complexity

- Practical complexity:
  - Given the Single-Head constraint, parsing a sentence $x = w_1, \ldots, w_n$ can be reduced to labeling each token w_i with:
    - a head word h_i,
    - a dependency type d_i.
- Theoretical complexity:
  - By exploiting the special properties of dependency graphs, it is sometimes possible to improve worst-case complexity compared to constituency-based parsing

Transparency

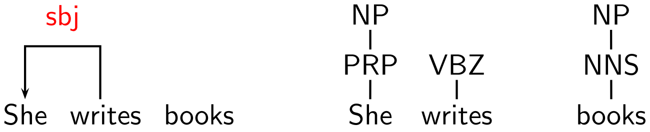
- Direct encoding of predicate-argument structure





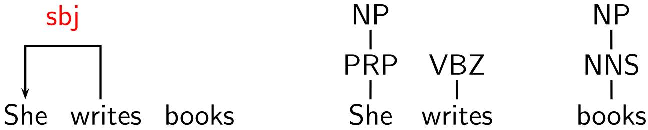
Transparency

- Direct encoding of predicate-argument structure
- Fragments directly interpretable



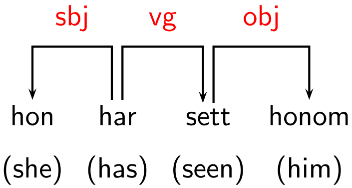
Transparency

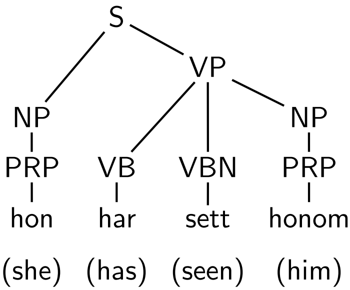
- Direct encoding of predicate-argument structure
- Fragments directly interpretable
- But only with labeled dependency graphs



Word Order

- Dependency structure independent of word order
- Suitable for free word order languages (cf. German results)





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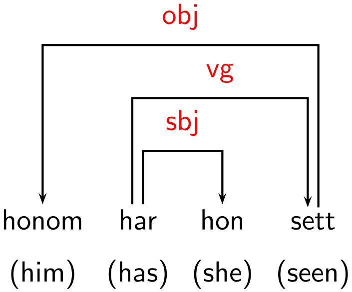

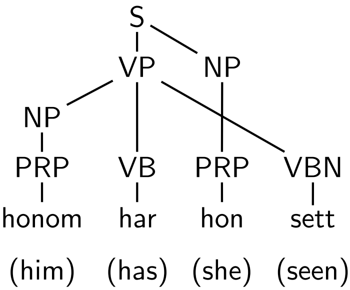

Word Order

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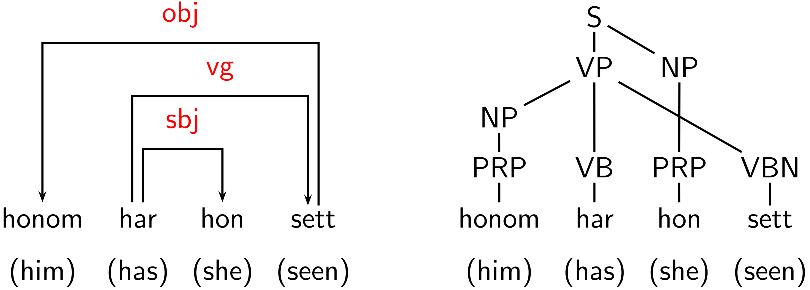
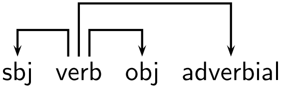
- But only with non-projective dependency graphs



Expressivity

- Limited expressivity:
  - Every projective dependency grammar has a strongly equivalent context-free grammar, but not vice versa [Gaifman 1965].
  - Impossible to distinguish between phrase modification and head modification in unlabeled dependency structure [Mel'čuk 1988].



V, VP or S modification?

Practical Issues

- Where to get the software?
  - Dependency parsers
  - Conversion programs for constituent-based treebanks
- Where to get the data?
  - Dependency treebanks
  - Treebanks that can be converted into dependency representation
- How to evaluate dependency parsing?
  - Evaluation scores

Parsers

- Trainable parsers

Parsers

- Trainable parsers
- Concentrate on freely available parsers

Trainable Parsers

- Ryan McDonald's **MSTParser**
  - Based on the algorithms of [McDonald et al. 2005a, McDonald et al. 2005b]
  - URL: `sourceforge.net/projects/mstparser`
  - Written in JAVA

Trainable Parsers (2)

- Joakim Nivre's **MaltParser**
  - Inductive dependency parser with memory-based learning and SVMs
  - URL: `http://maltparser.org`
  - Executable versions are available for Solaris, Linux, Windows, and MacOS, open source
  - Written in JAVA

Trainable Parsers (3)

- Many others
  - **Mate**: `https://code.google.com/p/mate-tools/`
  - **Turbo**: `http://www.cs.cmu.edu/~ark/TurboParser/`
  - **Spacy**: `http://spacy.io/`

Treebanks

- Genuine dependency treebanks
- Treebanks for which conversions to dependencies exist

- See also CoNLL-X Shared Task
  URL: `http://nextens.uvt.nl/~conll/`

- Conversion strategy from constituents to dependencies

Dependency Treebanks

- Arabic: Prague Arabic Dependency Treebank
- Czech: Prague Dependency Treebank
- Danish: Danish Dependency Treebank
- Portuguese: Bosque: Floresta sintá(c)tica
- Slovene: Slovene Dependency Treebank
- Turkish: METU-Sabanci Turkish Treebank

Dependency Treebanks (2)

- Norwegian Dependency Treebank
  - Around 300 000 tokens of Bokmål and 300 000 tokens of Nynorsk, released in 2014
  - Freely downloadable (Språkbanken, Nasjonalbiblioteket)

Constituent Treebanks

- English: Penn Treebank
- Bulgarian: BulTreebank
- Chinese: Penn Chinese Treebank, Sinica Treebank
- Dutch: Alpino Treebank for Dutch
- German: TIGER/NEGRA, TüBa-D/Z
- Japanese: TüBa-J/S
- Spanish: Cast3LB
- Swedish: Talbanken05

Conversions to dependency structures exist for all of these

Conversion from Constituents to Dependencies

- Conversion from constituents to dependencies is possible
- Needs head/non-head information
- If no such information is given $\Rightarrow$ heuristics
- Conversion for Penn Treebank to dependencies: e.g., Magerman, Collins, Lin, Yamada and Matsumoto ...
- Conversion restricted to structural conversion, no labeling
- Concentrate on Lin's conversion: [Lin 1995, Lin 1998]

Lin’s Conversion

- Idea: Head of a phrase governs all sisters.
- Uses **Tree Head Table**: List of rules where to find the head of a constituent.
- An entry consists of the node, the direction of search, and the list of possible heads.

Lin's Conversion

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- Uses **Tree Head Table**: List of rules where to find the head of a constituent.
- An entry consists of the node, the direction of search, and the list of possible heads.
- Sample entries:

(S	right-to-left	(Aux VP NP AP PP))
(VP	left-to-right	(V VP))
(NP	right-to-left	(Pron N NP))

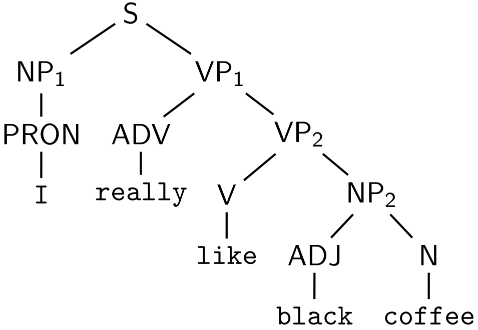
- First line: The head of an S constituent is the first Aux daughter from the right; if there is no Aux, then the first VP, etc.

Lin's Conversion - Example

(S	right-to-left	(Aux VP NP AP PP))
(VP	left-to-right	(V VP))
(NP	right-to-left	(Pron N NP))

Lin's Conversion - Example

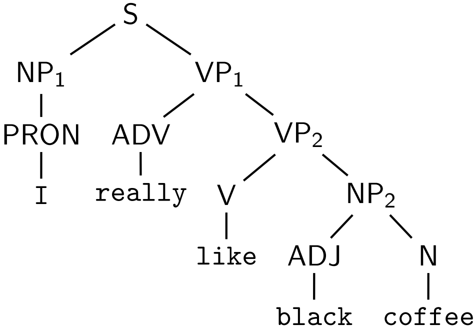
(S	right-to-left	(Aux VP NP AP PP))
(VP	left-to-right	(V VP))
(NP	right-to-left	(Pron N NP))



root	head	lex. head

Lin's Conversion - Example

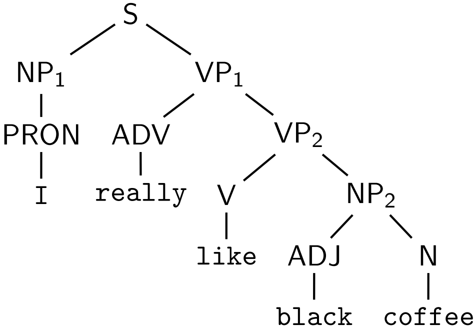
(S right-to-left (Aux VP NP AP PP))
(VP left-to-right (V VP))
(NP right-to-left (Pron N NP))



root	head	lex. head
S	VP_1	??

Lin's Conversion - Example

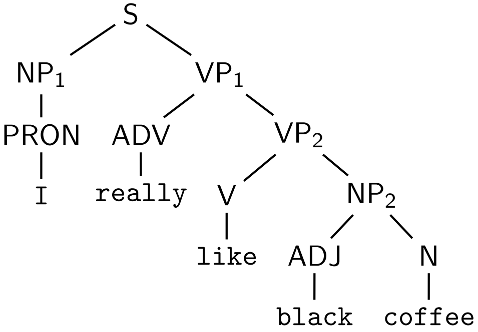
(S	right-to-left	(Aux VP NP AP PP))
(VP	left-to-right	(V VP))
(NP	right-to-left	(Pron N NP))



root	head	lex. head
VP_1	VP_2	??

Lin's Conversion - Example

(S right-to-left (Aux VP NP AP PP))
(VP left-to-right (V VP))
(NP right-to-left (Pron N NP))



root	head	lex. head
S	VP_1	`like`
VP_1	VP_2	`like`
VP_2	V	`like`

Lin's Conversion - Example (2)

- The head of a phrase dominates all sisters.
- VP_1 governs NP_1 $\Rightarrow$ *like* governs *I*
- VP_2 governs ADV $\Rightarrow$ *like* governs *really*

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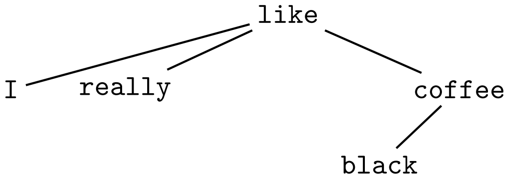
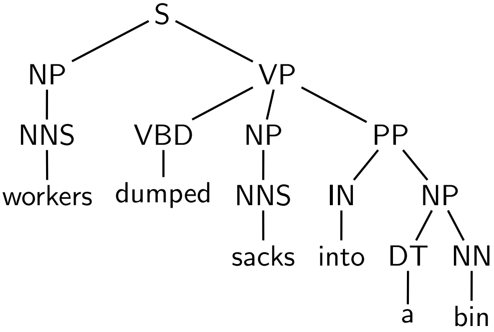


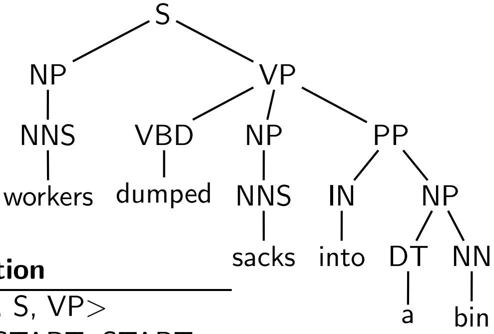
From Structural to Labeled Conversion

- Conversion so far gives only pure dependencies from head to dependent.
- Collins uses combination of constituent labels to label relation [Collins 1999]:
  - Idea: Combination of mother node and two subordinate nodes gives information about grammatical functions.
  - If *headword*$(Y_h) \rightarrow$ *headword*(Y_d) is derived from rule $X \rightarrow Y_1 \ldots Y_n$, the relation is $<Y_d, X, Y_h>$

Collins' Example

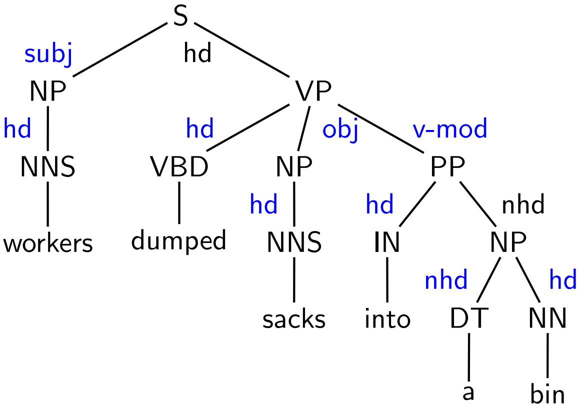


Collins' Example

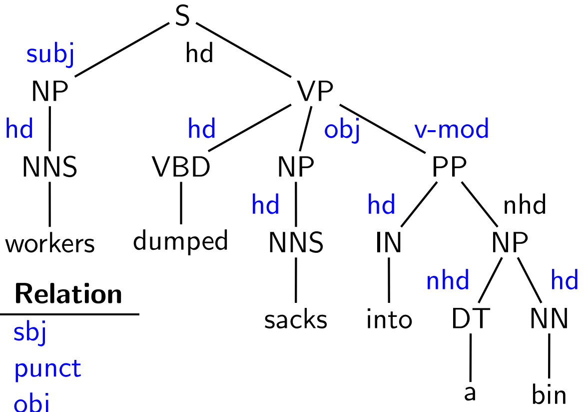


Dependency	**Relation**
dumped $\rightarrow$ workers	<NP, S, VP>
dumped $\rightarrow$ *root*	<S, START, START>
dumped $\rightarrow$ sacks	<NP, VP, VBD>
dumped $\rightarrow$ into	<PP, VP, VBD>
into $\rightarrow$ bin	<NP, PP, IN>
bin $\rightarrow$ a	<DT, NP, NN>

Example with Grammatical Functions



Example with Grammatical Functions



Dependency	**Relation**
dumped $\rightarrow$ workers	sbj
dumped $\rightarrow$ *root*	punct
dumped $\rightarrow$ sacks	obj
dumped $\rightarrow$ into	v-mod
into $\rightarrow$ bin	nhd
bin $\rightarrow$ a	nhd

Evaluation

- Internal evaluation: compare **accuracy** of model output to gold standard
- External evaluation (task-based evaluation):
  - quantify whether model output improves performance on a dependent task

Evaluation: data-driven dependency parsing

evaluation scores:

- *Attachment score* percentage of words that have the correct head (and label)
- Labeled and unlabeled
- For single dependency types (labels):
  - *Precision*
  - *Recall*
  - *F measure*

Part I: Data-driven dependency parsing

- Dependency grammar (last Monday)
- Dependency parsing (today)
- Project A released today
- Experimental methodology (Thursday)
- Project A (written report due **Oct. 23rd**):
  - training and evaluation of parsers for several languages
  - CoNLL-X (2006, 2007)
  - MaltParser: freely available software for data-driven dependency parsing

- Sabine Buchholz and Erwin Marsi. 2006.
  CoNLL-X shared task on multilingual dependency parsing. In *Proceedings of the Tenth Conference on Computational Natural Language Learning*.
- Yuchang Cheng, Masayuki Asahara, and Yuji Matsumoto. 2004.
  Determinstic dependency structure analyzer for Chinese. In *Proceedings of the First International Joint Conference on Natural Language Processing (IJCNLP)*, pages 500–508.
- Yuchang Cheng, Masayuki Asahara, and Yuji Matsumoto. 2005.
  Machine learning-based dependency analyzer for Chinese. In *Proceedings of International Conference on Chinese Computing (ICCC)*, pages ?–?
- Y. J. Chu and T. J. Liu. 1965.
  On the shortest arborescence of a directed graph. *Science Sinica*, 14:1396–1400.
- Michael Collins. 1999.
  Head-Driven Statistical Models for Natural Language Parsing. Ph.D. thesis, University of Pennsylvania.
- Michael A. Covington. 2001.
  A fundamental algorithm for dependency parsing. In *Proceedings of the 39th Annual ACM Southeast Conference*, pages 95–102.
- J. Edmonds. 1967.

Optimum branchings. *Journal of Research of the National Bureau of Standards*, 71B:233–240.

- Haim Gaifman. 1965.
  Dependency systems and phrase-structure systems. *Information and Control*, 8:304–337.
- Hideki Isozaki, Hideto Kazawa, and Tsutomu Hirao. 2004.
  A deterministic word dependency analyzer enhanced with preference learning. In *Proceedings of the 20th International Conference on Computational Linguistics (COLING)*, pages 275–281.
- Taku Kudo and Yuji Matsumoto. 2002.
  Japanese dependency analysis using cascaded chunking. In *Proceedings of the Sixth Workshop on Computational Language Learning (CoNLL)*, pages 63–69.
- Dekang Lin. 1995.
  A dependency-based method for evaluating broad-coverage parsers. In *Proceedings of IJCAI-95*, pages 1420–1425.
- Dekang Lin. 1998.
  A dependency-based method for evaluating broad-coverage parsers. *Natural Language Engineering*, 4:97–114.
- Ryan McDonald and Joakim Nivre. 2007.

Characterizing the errors of data-driven dependency parsing models. In *Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*.

- Ryan McDonald, Koby Crammer, and Fernando Pereira. 2005a.
  Online large-margin training of dependency parsers. In *Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 91–98.
- Ryan McDonald, Fernando Pereira, Kiril Ribarov, and Jan Hajič. 2005b.
  Non-projective dependency parsing using spanning tree algorithms. In *Proceedings of the Human Language Technology Conference and the Conference on Empirical Methods in Natural Language Processing (HLT/EMNLP)*, pages 523–530.
- Igor Mel'čuk. 1988.
  Dependency Syntax: Theory and Practice. State University of New York Press.
- Joakim Nivre and Jens Nilsson. 2005.
  Pseudo-projective dependency parsing. In *Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics (ACL)*, pages 99–106.
- Joakim Nivre and Mario Scholz. 2004.
  Deterministic dependency parsing of English text. In *Proceedings of the 20th International Conference on Computational Linguistics (COLING)*, pages 64–70.
- Joakim Nivre, Johan Hall, and Jens Nilsson. 2004.

Memory-based dependency parsing. In Hwee Tou Ng and Ellen Riloff, editors, *Proceedings of the 8th Conference on Computational Natural Language Learning (CoNLL)*, pages 49–56.

- Joakim Nivre, Johan Hall, Jens Nilsson, Gülsen Eryiğit, and Svetoslav Marinov. 2006.
  Labeled pseudo-projective dependency parsing with support vector machines. In *Proceedings of the Tenth Conference on Computational Natural Language Learning (CoNLL)*.
- Joakim Nivre. 2003.
  An efficient algorithm for projective dependency parsing. In Gertjan Van Noord, editor, *Proceedings of the 8th International Workshop on Parsing Technologies (IWPT)*, pages 149–160.
- Joakim Nivre. 2006.
  Constraints on non-projective dependency graphs. In *Proceedings of the 11th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, pages 73–80.
- Hiroyasu Yamada and Yuji Matsumoto. 2003.
  Statistical dependency analysis with support vector machines. In Gertjan Van Noord, editor, *Proceedings of the 8th International Workshop on Parsing Technologies (IWPT)*, pages 195–206.