

# Dependency Parsing

Tutorial at COLING-ACL, Sydney 2006

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# Why?

- ▶ Increasing interest in dependency-based approaches to syntactic parsing in recent years
  - ▶ New methods emerging
  - ▶ Applied to a wide range of languages
  - ▶ CoNLL-X shared task (June, 2006)
- ▶ Dependency-based methods still less accessible for the majority of researchers and developers than the more widely known constituency-based methods

# For Whom?

- ▶ Researchers and students working on syntactic parsing or related topics within other traditions
- ▶ Researchers and application developers interested in using dependency parsers as components in larger systems

# What?

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

# Outline

## Introduction

- Motivation and Contents

- Basic Concepts of Dependency Syntax

## Parsing Methods

- Dynamic Programming

- Constraint Satisfaction

- Deterministic Parsing

- Non-Projective Dependency Parsing

## Pros and Cons of Dependency Parsing

## Practical Issues

- Parsers

- Treebanks

- Evaluation

## Outlook

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# Dependency Syntax

- ▶ The basic idea:
  - ▶ Syntactic structure consists of **lexical items**, linked by binary asymmetric relations called **dependencies**.
- ▶ In the words of Lucien Tesnière [Tesnière 1959]:
  - ▶ La phrase est un *ensemble organisé* dont les éléments constituants sont les *mots*. [1.2] Tout mot qui fait partie d'une phrase cesse par lui-même d'être isolé comme dans le dictionnaire. Entre lui et ses voisins, l'esprit aperçoit des *connexions*, dont l'ensemble forme la charpente de la phrase. [1.3] Les connexions structurales établissent entre les mots des rapports de *dépendance*. Chaque connexion unit en principe un terme *supérieur* à un terme *inférieur*. [2.1] Le terme supérieur reçoit le nom de *régissant*. Le terme inférieur reçoit le nom de *subordonné*. Ainsi dans la phrase *Alfred parle [...]*, *parle* est le régissant et *Alfred* le subordonné. [2.2]

# Dependency Syntax

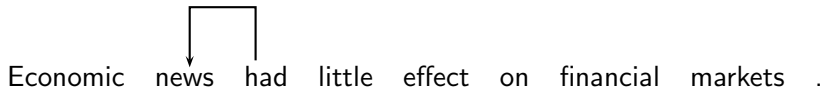
- ▶ The basic idea:
  - ▶ Syntactic structure consists of **lexical items**, linked by binary asymmetric relations called **dependencies**.
- ▶ In the words of Lucien Tesnière [Tesnière 1959]:
  - ▶ The sentence is an *organized whole*, the constituent elements of which are *words*. [1.2] Every word that belongs to a sentence ceases by itself to be isolated as in the dictionary. Between the word and its neighbors, the mind perceives *connections*, the totality of which forms the structure of the sentence. [1.3] The structural connections establish *dependency relations* between the words. Each connection in principle unites a *superior* term and an *inferior* term. [2.1] The superior term receives the name *governor*. The inferior term receives the name *subordinate*. Thus, in the sentence *Alfred parle* [...], *parle* is the governor and *Alfred* the subordinate. [2.2]



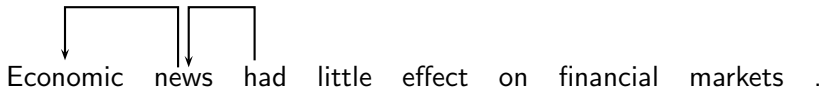
# Dependency Structure

Economic news had little effect on financial markets .

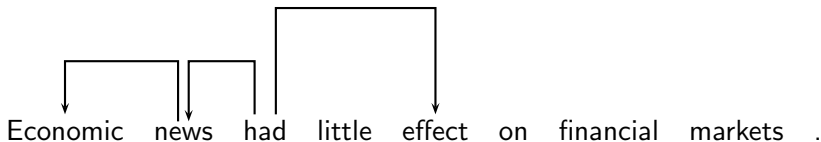
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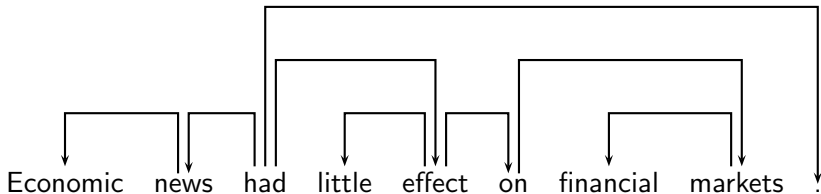
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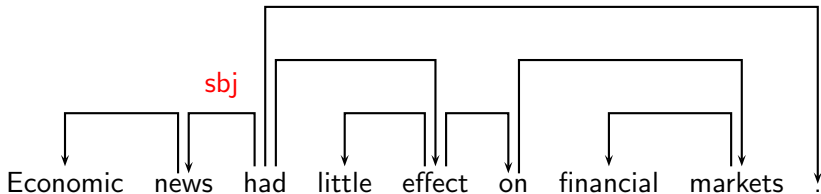
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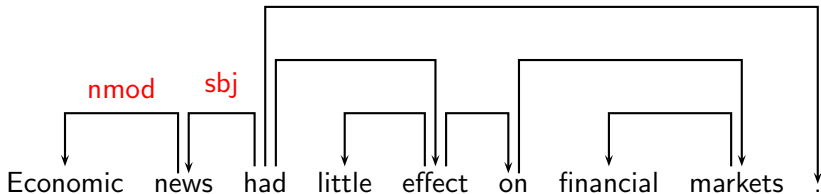
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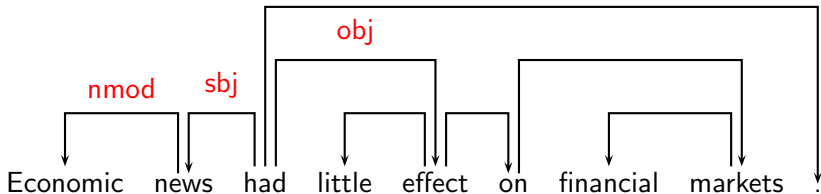
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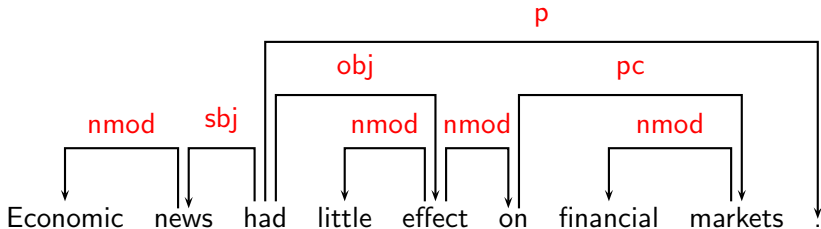


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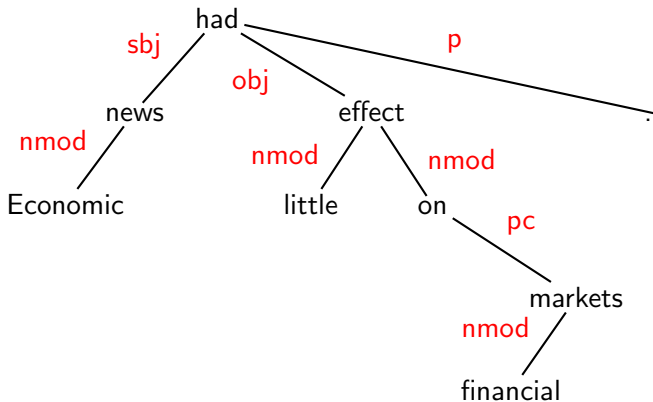
# Terminology

<b>Superior</b>	<b>Inferior</b>
Head	Dependent
Governor	Modifier
Regent	Subordinate
⋮	⋮

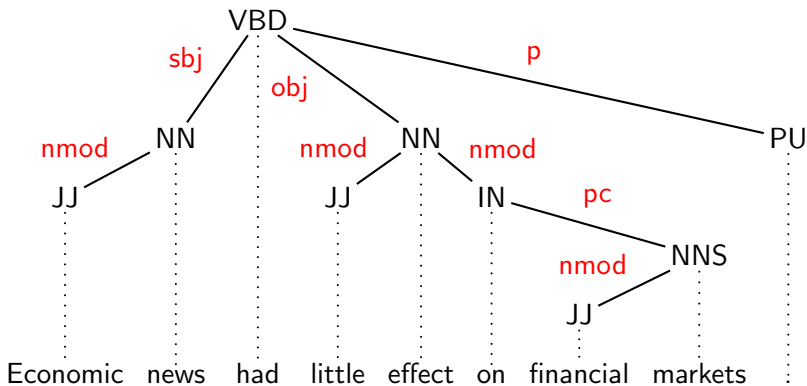
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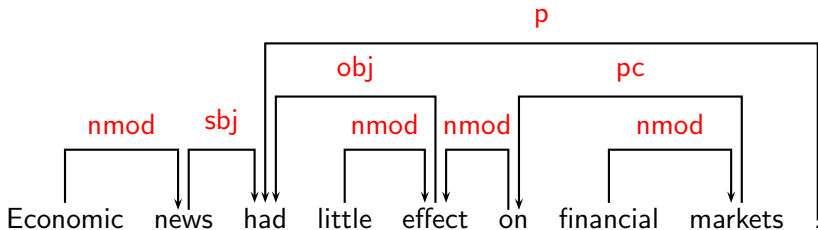
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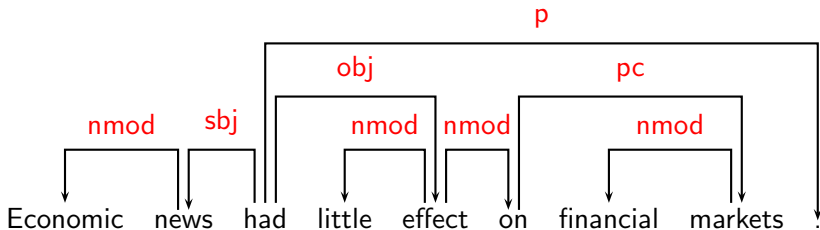
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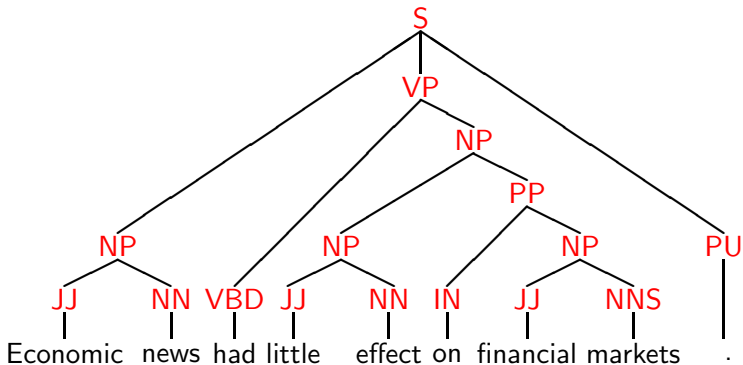
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# Phrase Structure





# Comparison

- ▶ Dependency structures explicitly represent
  - ▶ head-dependent relations (**directed arcs**),
  - ▶ functional categories (**arc labels**),
  - ▶ possibly some structural categories (parts-of-speech).
- ▶ Phrase structures explicitly represent
  - ▶ phrases (**nonterminal nodes**),
  - ▶ structural categories (**nonterminal labels**),
  - ▶ possibly some functional categories (grammatical functions).
- ▶ Hybrid representations may combine all elements.

# Some Theoretical Frameworks

- ▶ Word Grammar (WG) [Hudson 1984, Hudson 1990]
- ▶ Functional Generative Description (FGD) [Sgall et al. 1986]
- ▶ Dependency Unification Grammar (DUG)  
[Hellwig 1986, Hellwig 2003]
- ▶ Meaning-Text Theory (MTT) [Mel'čuk 1988]
- ▶ (Weighted) Constraint Dependency Grammar ([W]CDG)  
[Maruyama 1990, Harper and Helzerman 1995,  
Menzel and Schröder 1998, Schröder 2002]
- ▶ Functional Dependency Grammar (FDG)  
[Tapanainen and Järvinen 1997, Järvinen and Tapanainen 1998]
- ▶ Topological/Extensible Dependency Grammar ([T/X]DG)  
[Duchier and Debusmann 2001, Debusmann et al. 2004]

# Some Theoretical Issues

- ▶ Dependency structure sufficient as well as necessary?
- ▶ Mono-stratal or multi-stratal syntactic representations?
- ▶ What is the nature of lexical elements (nodes)?
  - ▶ Morphemes?
  - ▶ Word forms?
  - ▶ Multi-word units?
- ▶ What is the nature of dependency types (arc labels)?
  - ▶ Grammatical functions?
  - ▶ Semantic roles?
- ▶ What are the criteria for identifying heads and dependents?
- ▶ What are the formal properties of dependency structures?

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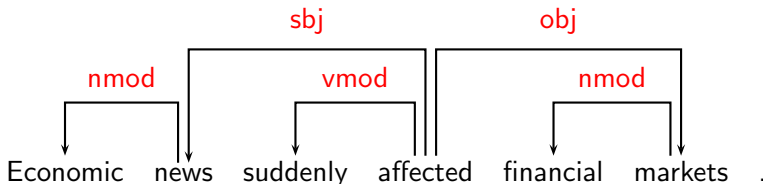
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- ▶ What are the formal properties of dependency structures?

# Criteria for Heads and Dependents

- ▶ Criteria for a syntactic relation between a head  $H$  and a dependent  $D$  in a construction  $C$  [Zwicky 1985, Hudson 1990]:
  1.  $H$  determines the syntactic category of  $C$ ;  $H$  can replace  $C$ .
  2.  $H$  determines the semantic category of  $C$ ;  $D$  specifies  $H$ .
  3.  $H$  is obligatory;  $D$  may be optional.
  4.  $H$  selects  $D$  and determines whether  $D$  is obligatory.
  5. The form of  $D$  depends on  $H$  (agreement or government).
  6. The linear position of  $D$  is specified with reference to  $H$ .
- ▶ Issues:
  - ▶ Syntactic (and morphological) versus semantic criteria
  - ▶ Exocentric versus endocentric constructions

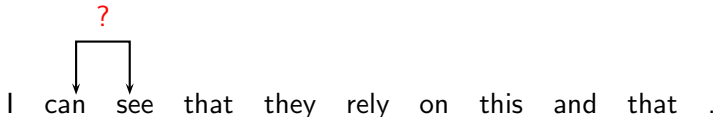
## Some Clear Cases

Construction	Head	Dependent
Exocentric	Verb	Subject ( <b>sbj</b> )
	Verb	Object ( <b>obj</b> )
Endocentric	Verb	Adverbial ( <b>vmod</b> )
	Noun	Attribute ( <b>nmod</b> )



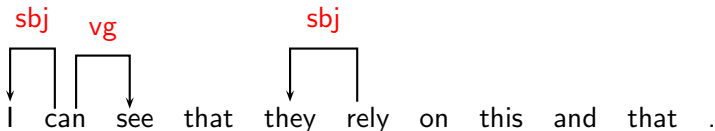
## Some Tricky Cases

- ▶ Complex verb groups (auxiliary  $\leftrightarrow$  main verb)
- ▶ Subordinate clauses (complementizer  $\leftrightarrow$  verb)
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- ▶ Prepositional phrases (preposition  $\leftrightarrow$  nominal)
- ▶ Punctuation



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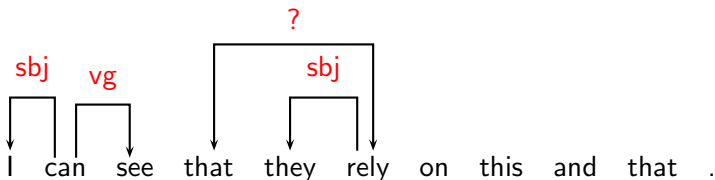
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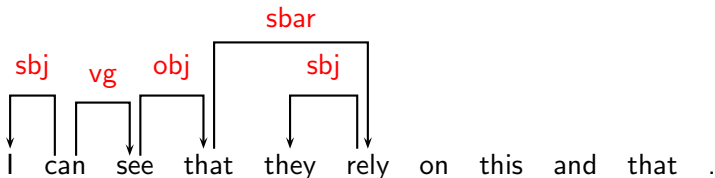
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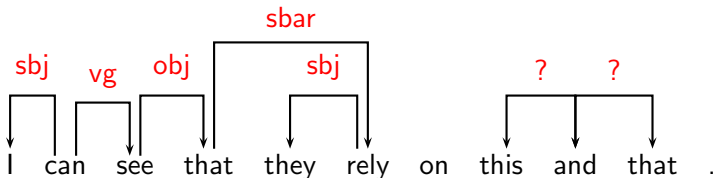
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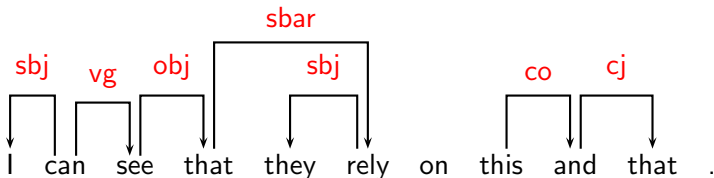
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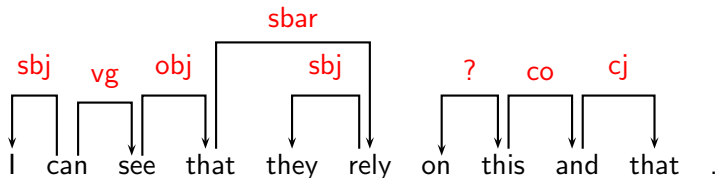
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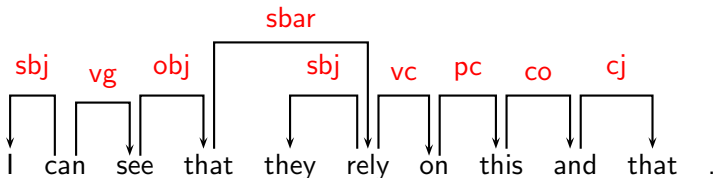
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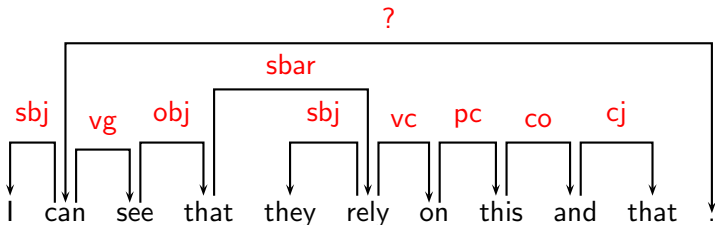
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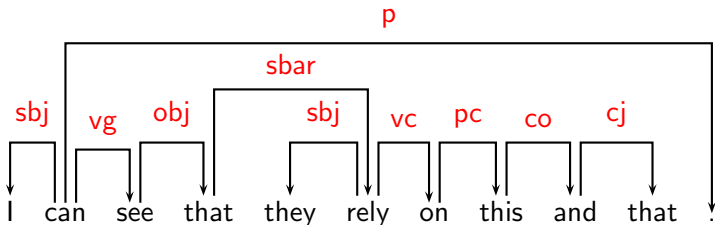
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# Dependency Graphs

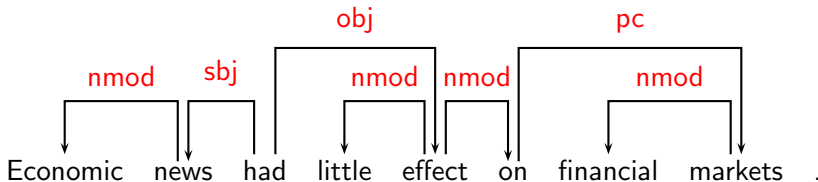
- ▶ A dependency structure can be defined as a directed graph  $G$ , consisting of
  - ▶ a set  $V$  of nodes,
  - ▶ a set  $E$  of arcs (edges),
  - ▶ a linear precedence order  $<$  on  $V$ .
- ▶ Labeled graphs:
  - ▶ Nodes in  $V$  are labeled with word forms (and annotation).
  - ▶ Arcs in  $E$  are labeled with dependency types.
- ▶ Notational conventions ( $i, j \in V$ ):
  - ▶  $i \rightarrow j \equiv (i, j) \in E$
  - ▶  $i \rightarrow^* j \equiv i = j \vee \exists k : i \rightarrow k, k \rightarrow^* j$

# Formal Conditions on Dependency Graphs

- ▶  $G$  is (weakly) **connected**:
  - ▶ For every node  $i$  there is a node  $j$  such that  $i \rightarrow j$  or  $j \rightarrow i$ .
- ▶  $G$  is **acyclic**:
  - ▶ If  $i \rightarrow j$  then not  $j \rightarrow^* i$ .
- ▶  $G$  obeys the **single-head** constraint:
  - ▶ If  $i \rightarrow j$ , then not  $k \rightarrow j$ , for any  $k \neq i$ .
- ▶  $G$  is **projective**:
  - ▶ If  $i \rightarrow j$  then  $i \rightarrow^* k$ , for any  $k$  such that  $i < k < j$  or  $j < k < i$ .

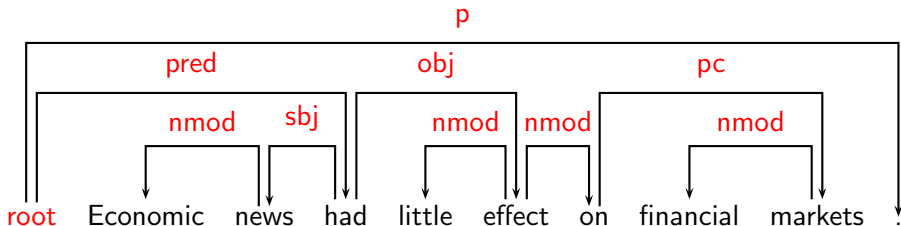
# Connectedness, Acyclicity and Single-Head

- ▶ Intuitions:
  - ▶ Syntactic structure is complete (**Connectedness**).
  - ▶ Syntactic structure is hierarchical (**Acyclicity**).
  - ▶ Every word has at most one syntactic head (**Single-Head**).
- ▶ Connectedness can be enforced by adding a special root node.



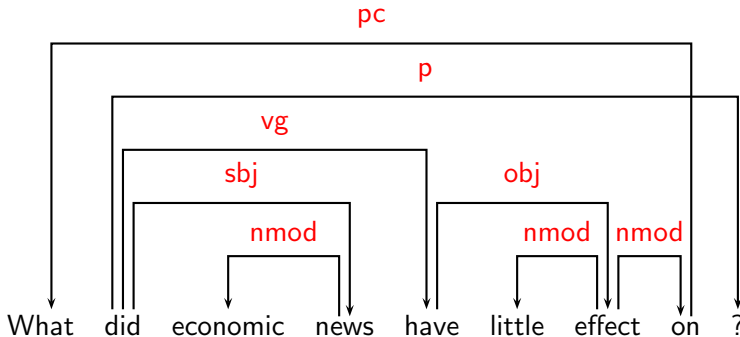
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# Projectivity

- ▶ Most theoretical frameworks do **not** assume projectivity.
- ▶ Non-projective structures are needed to account for
  - ▶ long-distance dependencies,
  - ▶ free word order.



# Scope of the Tutorial

- ▶ Dependency parsing:
  - ▶ Input: Sentence  $x = w_1, \dots, w_n$
  - ▶ Output: Dependency graph  $G$
- ▶ Focus of tutorial:
  - ▶ Computational methods for dependency parsing
  - ▶ Resources for dependency parsing (parsers, treebanks)
- ▶ Not included:
  - ▶ Theoretical frameworks of dependency syntax
  - ▶ Constituency parsers that exploit lexical dependencies
  - ▶ Unsupervised learning of dependency structure

# Parsing Methods

- ▶ Three main traditions:
  - ▶ Dynamic programming
  - ▶ Constraint satisfaction
  - ▶ Deterministic parsing
- ▶ Special issue:
  - ▶ Non-projective dependency parsing

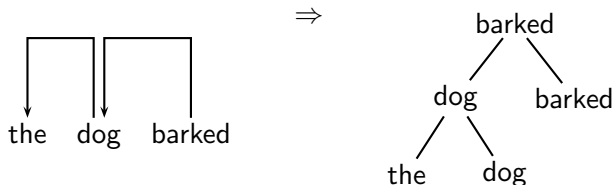
# Dynamic Programming

- ▶ Basic idea: Treat dependencies as constituents.
- ▶ Use, e.g., CYK parser (with minor modifications).
- ▶ Dependencies as constituents:



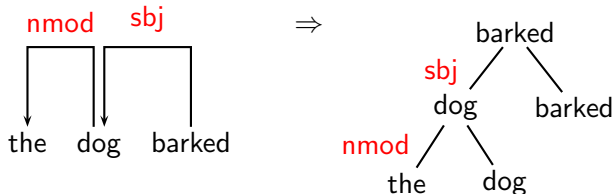
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# Dependency Chart Parsing

- ▶ Grammar is regarded as context-free, in which each node is lexicalized.
- ▶ Chart entries are subtrees, i.e., words with all their left and right dependents.
- ▶ Problem: Different entries for different subtrees spanning a sequence of words with different heads.
- ▶ Time requirement:  $O(n^5)$ .

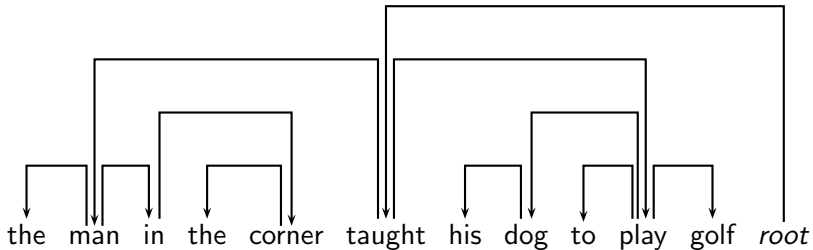
# Dynamic Programming Approaches

- ▶ Original version: [Hays 1964]
- ▶ Link Grammar: [Sleator and Temperley 1991]
- ▶ Earley-style parser with left-corner filtering:  
[Lombardo and Lesmo 1996]
- ▶ Bilexical grammar: [Eisner 1996a, Eisner 1996b, Eisner 2000]
- ▶ Bilexical grammar with discriminative estimation methods:  
[McDonald et al. 2005a, McDonald et al. 2005b]

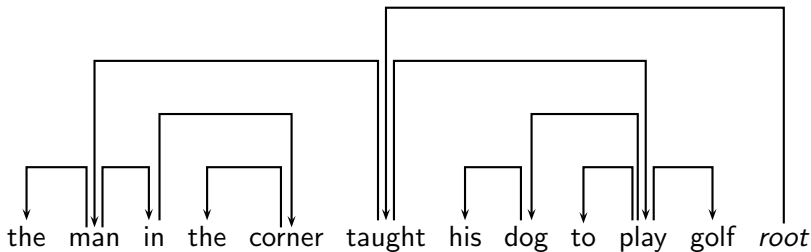
# Eisner's Bilexical Algorithm

- ▶ Two novel aspects:
  - ▶ Modified parsing algorithm
  - ▶ Probabilistic dependency parsing
- ▶ Time requirement:  $O(n^3)$ .
- ▶ Modification: Instead of storing subtrees, store **spans**.
- ▶ Def. span: Substring such that no interior word links to any word outside the span.
- ▶ Underlying idea: In a span, only the endwords are **active**, i.e. still need a head.
- ▶ One or both of the endwords can be active.

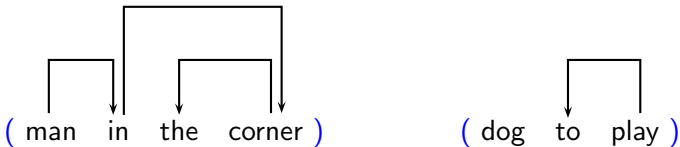
# Example



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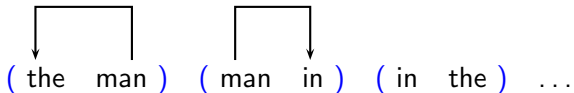


Spans:



# Assembly of Correct Parse

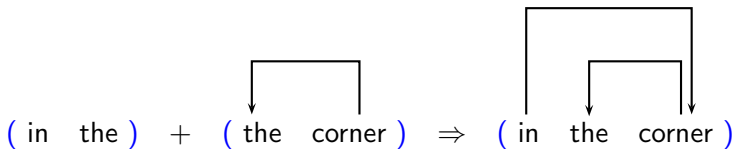
Start by combining adjacent words to minimal spans:





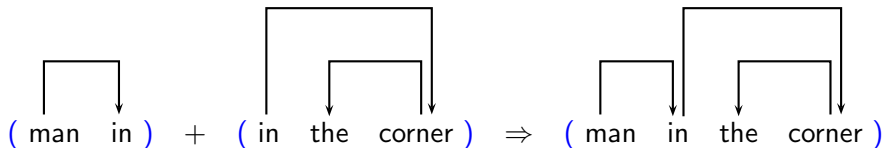
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Combine spans which overlap in one word; this word must be governed by a word in the left or right span.



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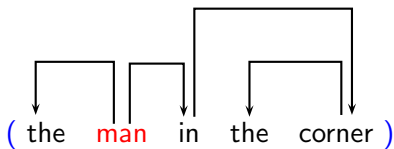
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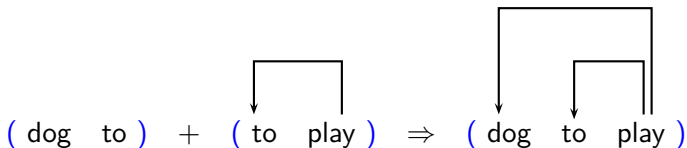
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Invalid span:

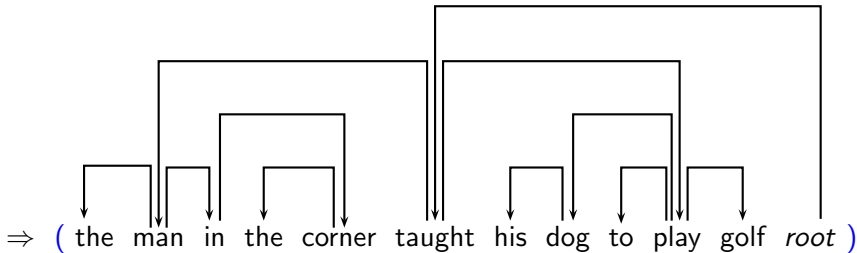
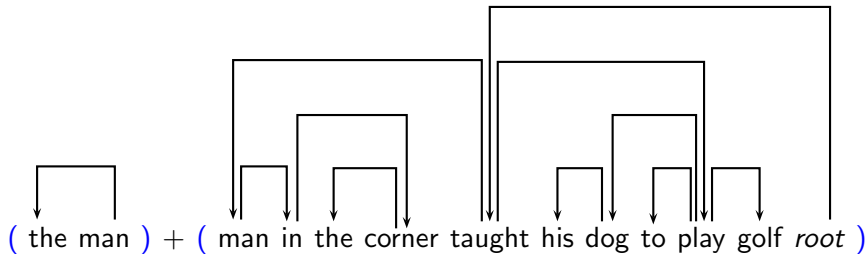


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# Assembly of Correct Parse



# Eisner's Probability Models

- ▶ Model A: Bigram lexical affinities
  - ▶ First generates a trigram Markov model for POS tagging.
  - ▶ Decides for each word pair whether they have a dependency.
  - ▶ Model is leaky because it does not control for crossing dependencies, multiple heads, ...

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- ▶ Model B: Selectional preferences
  - ▶ First generates a trigram Markov model for POS tagging.
  - ▶ Each word chooses a subcat/supercat frame.
  - ▶ Selects an analysis that satisfies all frames if possible.
  - ▶ Model is also leaky because last step may fail.

# Eisner's Probability Models

- ▶ Model A: Bigram lexical affinities
  - ▶ First generates a trigram Markov model for POS tagging.
  - ▶ Decides for each word pair whether they have a dependency.
  - ▶ Model is leaky because it does not control for crossing dependencies, multiple heads, ...
- ▶ Model B: Selectional preferences
  - ▶ First generates a trigram Markov model for POS tagging.
  - ▶ Each word chooses a subcat/supercat frame.
  - ▶ Selects an analysis that satisfies all frames if possible.
  - ▶ Model is also leaky because last step may fail.
- ▶ Model C: Recursive Generation
  - ▶ Each word generates its actual dependents.
  - ▶ Two Markov chains:
    - ▶ Left dependents
    - ▶ Right dependents
  - ▶ Model is not leaky.



# Eisner's Model C

$$Pr(words, tags, links) = \prod_{1 \leq i \leq n} \left( \prod_c Pr(tword(dep_c(i)) \mid tag(dep_{c-1}(i)), tword(i)) \right)$$

$$c = -(1 + \#left - deps(i)) \dots 1 + \#right - deps(i), c \neq 0$$

$$\text{or: } dep_{c+1}(i) \text{ if } c < 0$$

## Eisner's Results

- ▶ 25 000 Wall Street Journal sentences
- ▶ Baseline: most frequent tag chosen for a word, each word chooses a head with most common distance
- ▶ Model X: trigram tagging, no dependencies
- ▶ For comparison: state-of-the-art constituent parsing, Charniak: 92.2 F-measure

Model	Non-punct	Tagging
Baseline	41.9	76.1
Model X	–	93.1
Model A	too slow	
Model B	83.8	92.8
Model C	86.9	92.0

# 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.
- ▶ If scores are available, parsing can be formulated as maximum spanning tree problem.
- ▶ 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 online learning for determining weight vector  $\mathbf{w}$ : large-margin multi-class classification (MIRA)

## Maximum Spanning Trees (2)

- ▶ Complexity:
  - ▶ Projective (Eisner):  $O(n^3)$
  - ▶ Non-projective (CLE):  $O(n^2)$

$$\text{score}(\text{sent}, \text{deps}) = \sum_{(i,j) \in \text{deps}} \text{score}(i,j) = \sum_{(i,j) \in \text{deps}} \mathbf{w} \cdot f(i,j)$$

# Online Learning

Training data:  $\mathcal{T} = (sent_t, deps_t)_{t=1}^{\mathcal{T}}$

1.  $\mathbf{w} = 0; \mathbf{v} = 0; i = 0;$
2. for  $n : 1..N$
3.     for  $t : 1..\mathcal{T}$
4.          $\mathbf{w}^{(i+1)} = \text{update } \mathbf{w}^{(i)} \text{ according to } (sent_t, deps_t)$
5.          $\mathbf{v} = \mathbf{v} + \mathbf{w}^{(i+1)}$
6.          $i = i + 1$
7.  $\mathbf{w} = \mathbf{v} / (N \cdot \mathcal{T})$

# MIRA

MIRA weight update:

$\min ||\mathbf{w}^{(i+1)} - \mathbf{w}^{(i)}||$  so that

$$score(sent_t, deps_t) - score(sent_t, deps') \geq L(deps_t, deps')$$

$$\forall deps' \in dt(sent_t)$$

- ▶  $L(deps, deps')$ : loss function
- ▶  $dt(sent)$ : possible dependency parses for sentence

## Results by McDonald et al. (2005a, 2005b)

- ▶ Unlabeled accuracy per word (W) and per sentence (S)

Parser	English		Czech	
	W	S	W	S
<i>k</i> -best MIRA Eisner	90.9	37.5	83.3	31.3
best MIRA CLE	90.2	33.2	84.1	32.2
factored MIRA CLE	90.2	32.2	84.4	32.3

- ▶ New development (EACL 2006):
  - ▶ Scores of dependencies are not independent any more
  - ▶ Better results
  - ▶ More later

# Parsing Methods

- ▶ Three main traditions:
  - ▶ Dynamic programming
  - ▶ **Constraint satisfaction**
  - ▶ Deterministic parsing
- ▶ Special issue:
  - ▶ Non-projective dependency parsing



# Constraint Satisfaction

- ▶ Uses *Constraint Dependency Grammar*.
- ▶ Grammar consists of a set of boolean constraints, i.e. logical formulas that describe well-formed trees.
- ▶ A constraint is a logical formula with variables that range over a set of predefined values.
- ▶ Parsing is defined as a constraint satisfaction problem.
- ▶ Parsing is an *eliminative* process rather than a *constructive* one such as in CFG parsing.
- ▶ Constraint satisfaction removes values that contradict constraints.

# Examples for Constraints

- ▶ Based on [Maruyama 1990]

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  - ▶  $word(pos(x)) = DET \Rightarrow (label(X) = NMOD, word(mod(x)) = NN, pos(x) < mod(x))$
  - ▶ A determiner (DET) modifies a noun (NN) on the right with the label NMOD.

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  - ▶ A determiner (DET) modifies a noun (NN) on the right with the label NMOD.
- ▶ Example 2:
  - ▶  $word(pos(x)) = NN \Rightarrow$   
 $(label(x) = SBJ, word(mod(x)) = VB, pos(x) < mod(x))$
  - ▶ A noun modifies a verb (VB) on the right with the label SBJ.

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  - ▶ A noun modifies a verb (VB) on the right with the label SBJ.
- ▶ Example 3:
  - ▶  $word(pos(x)) = VB \Rightarrow$   
 $(label(x) = ROOT, mod(x) = nil)$
  - ▶ A verb modifies nothing, its label is ROOT.

# Constraint Satisfaction Approaches

- ▶ Constraint Grammar: [Karlsson 1990, Karlsson et al. 1995]
- ▶ Constraint Dependency Grammar:  
[Maruyama 1990, Harper and Helzerman 1995]
- ▶ Functional Dependency Grammar: [Järvinen and Tapanainen 1998]
- ▶ Topological Dependency Grammar: [Duchier 1999, Duchier 2003]
- ▶ Extensible Dependency Grammar: [Debusmann et al. 2004]
- ▶ Constraint Dependency Grammar with defeasible constraints:  
[Foth et al. 2000, Foth et al. 2004, Menzel and Schröder 1998,  
Schröder 2002]

# Constraint Satisfaction

- ▶ Constraint satisfaction in general is *NP complete*.
- ▶ Parser design must ensure practical efficiency.
- ▶ Different approaches to do constraint satisfaction:
  - ▶ Maruyama applies constraint propagation techniques, which ensure local consistency (arc consistency).
  - ▶ Weighted CDG uses transformation-based constraint resolution with anytime properties [Foth et al. 2000, Foth et al. 2004, Menzel and Schröder 1998, Schröder 2002].
  - ▶ TDG uses constraint programming [Duchier 1999, Duchier 2003].

# Maruyama's Constraint Propagation

Three steps:

1. Form initial constraint network using a “core” grammar.
2. Remove local inconsistencies.
3. If ambiguity remains, add new constraints and repeat step 2.

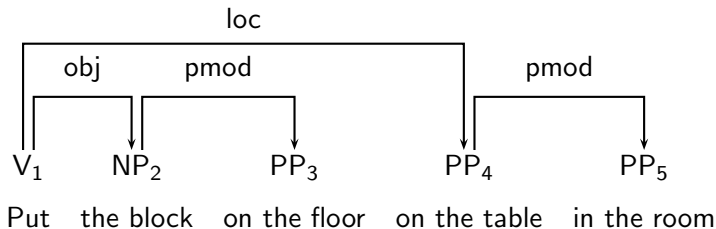


# Constraint Propagation Example

- ▶ Problem: PP attachment
- ▶ Sentence: *Put the block on the floor on the table in the room*
- ▶ Simplified representation:  $V_1$   $NP_2$   $PP_3$   $PP_4$   $PP_5$

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- ▶ Problem: PP attachment
- ▶ Sentence: *Put the block on the floor on the table in the room*
- ▶ Simplified representation:  $V_1 \ NP_2 \ PP_3 \ PP_4 \ PP_5$
- ▶ Correct analysis:



# Initial Constraints

- ▶  $word(pos(x)) = PP$   
 $\Rightarrow (word(mod(x)) \in \{PP, NP, V\}, mod(x) < pos(x))$
- ▶ A PP modifies a PP, an NP, or a V on the left.

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 $\Rightarrow label(x)=pmod$
- ▶ If a PP modifies a PP or an NP, its label is pmod.

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- ▶ ▶  $word(pos(x))=NP$   
 $\Rightarrow (word(mod(x))=V, label(x)=obj, mod(x) < pos(x))$ 
  - ▶ An NP modifies a V on the left with the label obj.

# Initial Constraints

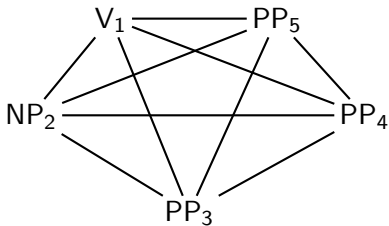
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- ▶ ▶  $word(pos(x))=NP$   
 $\Rightarrow (word(mod(x))=V, label(x)=obj, mod(x) < pos(x))$ 
  - ▶ An NP modifies a V on the left with the label obj.
- ▶ ▶  $word(pos(x))=V \Rightarrow (mod(x)=nil, label(x)=root)$ 
  - ▶ A V modifies nothing with the label root.

# Initial Constraints

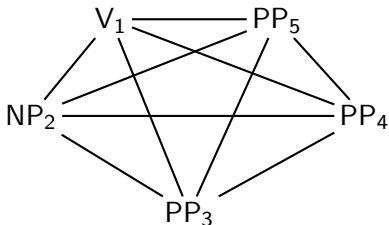
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- ▶ ▶  $word(pos(x))=V \Rightarrow (mod(x)=nil, label(x)=root)$ 
  - ▶ A V modifies nothing with the label root.
- ▶ ▶  $mod(x) < pos(y) < pos(x) \Rightarrow mod(x) \leq mod(y) \leq pos(x)$ 
  - ▶ Modification links do not cross.



# Initial Constraint Network



# Initial Constraint Network



Possible values  $\Leftarrow$  unary constraints:

$V_1$ :  $\langle \text{root}, \text{nil} \rangle$

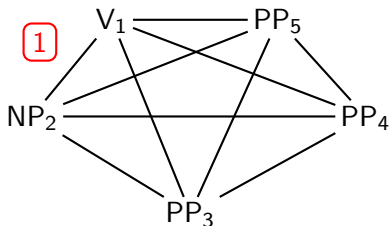
$NP_2$ :  $\langle \text{obj}, 1 \rangle$

$PP_3$ :  $\langle \text{loc}, 1 \rangle, \langle \text{pmod}, 2 \rangle$

$PP_4$ :  $\langle \text{loc}, 1 \rangle, \langle \text{pmod}, 2 \rangle, \langle \text{pmod}, 3 \rangle$

$PP_5$ :  $\langle \text{loc}, 1 \rangle, \langle \text{pmod}, 2 \rangle, \langle \text{pmod}, 3 \rangle, \langle \text{pmod}, 4 \rangle$

# Initial Constraint Network

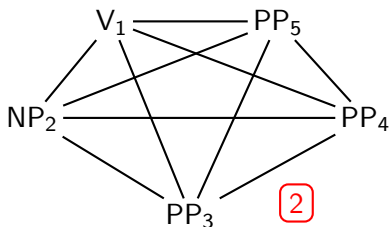


Each arc has a constraint matrix:

For arc **1**:

$\downarrow V_1 \setminus NP_2 \rightarrow$	$\langle \text{obj}, 1 \rangle$
$\langle \text{root}, \text{nil} \rangle$	1

# Initial Constraint Network



Each arc has a constraint matrix:

For arc 2:

$\downarrow$ PP <sub>3</sub> \ PP <sub>4</sub> $\rightarrow$	$\langle \text{loc}, 1 \rangle$	$\langle \text{pmod}, 2 \rangle$	$\langle \text{pmod}, 3 \rangle$
$\langle \text{loc}, 1 \rangle$	1	0	1
$\langle \text{pmod}, 2 \rangle$	1	1	1

# Adding New Constraints

- ▶ Still 14 possible analyses.
- ▶ Filtering with binary constraints does not reduce ambiguity.
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    - ▶ A floor is not on the table.
  - ▶  $label(x)=loc, label(y)=loc, mod(x)=mod(y), word(mod(x))=V$   
 $\Rightarrow x=y$ 
    - ▶ No verb can take two locatives.

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 $\Rightarrow x=y$ 
    - ▶ No verb can take two locatives.
- ▶ Each value in the domains of nodes is tested against the new constraints.



# Modified Tables

Old:

$\downarrow PP_3 \setminus PP_4 \rightarrow$	$\langle loc, 1 \rangle$	$\langle pmod, 2 \rangle$	$\langle pmod, 3 \rangle$
$\langle loc, 1 \rangle$	1	0	1
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After applying first new constraint:

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$\langle loc, 1 \rangle$	0	0
$\langle pmod, 2 \rangle$	1	1

After applying second new constraint:

$\downarrow PP_3 \setminus PP_4 \rightarrow$	$\langle loc, 1 \rangle$	$\langle pmod, 2 \rangle$
$\langle pmod, 2 \rangle$	1	1

# Weighted Constraint Parsing

- ▶ Approach by [Foth et al. 2004, Foth et al. 2000, Menzel and Schröder 1998, Schröder 2002]
- ▶ Robust parser, which uses soft constraints
- ▶ Each constraint is assigned a weight between 0.0 and 1.0
- ▶ Weight 0.0: hard constraint, can only be violated when no other parse is possible
- ▶ Constraints assigned manually (or estimated from treebank)
- ▶ Efficiency: uses a heuristic transformation-based constraint resolution method

# Transformation-Based Constraint Resolution

- ▶ Heuristic search
- ▶ Very efficient
- ▶ Idea: first construct arbitrary dependency structure, then try to correct errors
- ▶ Error correction by transformations
- ▶ Selection of transformations based on constraints that cause conflicts
- ▶ Anytime property: parser maintains a complete analysis at any time  $\Rightarrow$  can be stopped at any time and return a complete analysis



## Menzel et al.'s Results

- ▶ Evaluation on NEGRA treebank for German
- ▶ German more difficult to parse than English (free word order)
- ▶ Constituent-based parsing: labeled F measure including grammatical functions: 53.4 [Kübler et al. 2006], labeled F measure: 73.1 [Dubey 2005].
- ▶ Best CoNLL-X results: unlabeled: 90.4, labeled: 87.3 [McDonald et al. 2006].

Data	Unlabeled	Labeled
1000 sentences	89.0	87.0
< 40 words	89.7	87.7

# Parsing Methods

- ▶ Three main traditions:
  - ▶ Dynamic programming
  - ▶ Constraint satisfaction
  - ▶ **Deterministic parsing**
- ▶ Special issue:
  - ▶ Non-projective dependency parsing

# 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

# Covington's Incremental Algorithm

- Deterministic incremental parsing in  $O(n^2)$  time by trying to link each new word to each preceding one [Covington 2001]:

PARSE( $x = (w_1, \dots, w_n)$ )

1   **for**  $i = 1$  **up to**  $n$

2       **for**  $j = i - 1$  **down to** 1

3           LINK( $w_i, w_j$ )

$$\text{LINK}(w_i, w_j) = \begin{cases} E \leftarrow E \cup (i, j) & \text{if } w_j \text{ is a dependent of } w_i \\ E \leftarrow E \cup (j, i) & \text{if } w_i \text{ is a dependent of } w_j \\ E \leftarrow E & \text{otherwise} \end{cases}$$

- Different conditions, such as **Single-Head** and **Projectivity**, can be incorporated into the LINK operation.

# Shift-Reduce Type Algorithms

- ▶ Data structures:
  - ▶ Stack  $[\dots, w_i]_S$  of partially processed tokens
  - ▶ Queue  $[w_j, \dots]_Q$  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
- ▶ Left-to-right parsing in  $O(n)$  time
- ▶ Restricted to **projective** dependency graphs

# Yamada's Algorithm

- ▶ Three parsing actions:

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

$$\text{Left} \quad \frac{[\dots, w_i, w_j]_S \quad [\dots]_Q}{[\dots, w_i]_S \quad [\dots]_Q} \quad w_i \rightarrow w_j$$

$$\text{Right} \quad \frac{[\dots, w_i, w_j]_S \quad [\dots]_Q}{[\dots, w_j]_S \quad [\dots]_Q} \quad w_i \leftarrow w_j$$

- ▶ Algorithm variants:
  - ▶ Originally developed for Japanese (strictly head-final) with only the **Shift** and **Right** actions [Kudo and Matsumoto 2002]
  - ▶ Adapted for English (with mixed headedness) by adding the **Left** action [Yamada and Matsumoto 2003]
  - ▶ Multiple passes over the input give time complexity  $O(n^2)$

# Nivre's Algorithm

- Four parsing actions:

$$\begin{array}{lcl}
 \text{Shift} & \frac{[\dots]_S \quad [w_i, \dots]_Q}{[\dots, w_i]_S \quad [\dots]_Q} & \\
 \text{Reduce} & \frac{[\dots, w_i]_S \quad [\dots]_Q \quad \exists w_k : w_k \rightarrow w_i}{[\dots]_S \quad [\dots]_Q} & \\
 \text{Left-Arc}_r & \frac{[\dots, w_i]_S \quad [w_j, \dots]_Q \quad \neg \exists w_k : w_k \rightarrow w_i}{[\dots]_S \quad [w_j, \dots]_Q \quad w_i \xleftarrow{r} w_j} & \\
 \text{Right-Arc}_r & \frac{[\dots, w_i]_S \quad [w_j, \dots]_Q \quad \neg \exists w_k : w_k \rightarrow w_j}{[\dots, w_i, w_j]_S \quad [\dots]_Q \quad w_i \xrightarrow{r} w_j} & 
 \end{array}$$

- Characteristics:

- Integrated labeled dependency parsing
- Arc-eager processing of right-dependents
- Single pass over the input gives time complexity  $O(n)$

# Example

[root]<sub>S</sub> [Economic news had little effect on financial markets .]<sub>Q</sub>

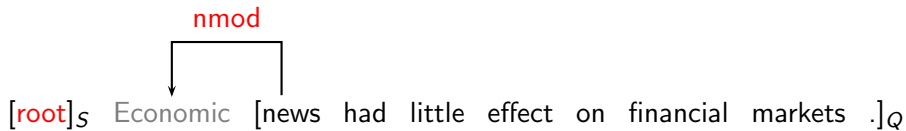


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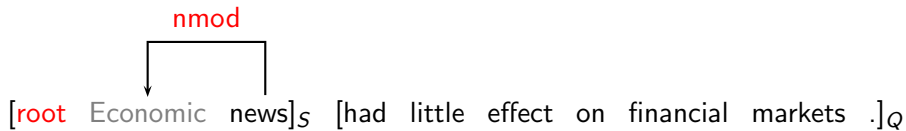
Shift

# Example



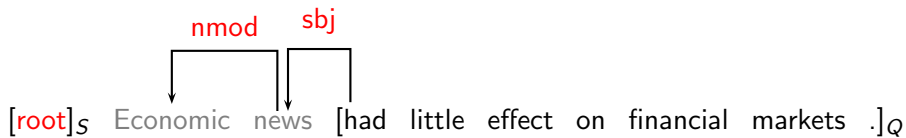
Left-Arc<sub>nmod</sub>

# Example



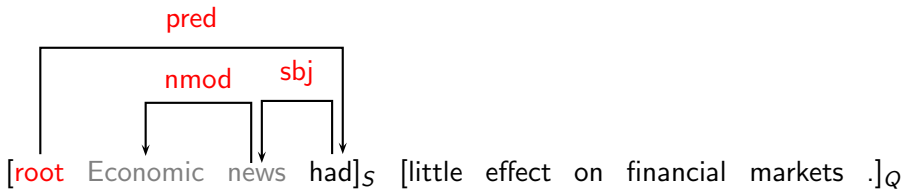
Shift

# Example



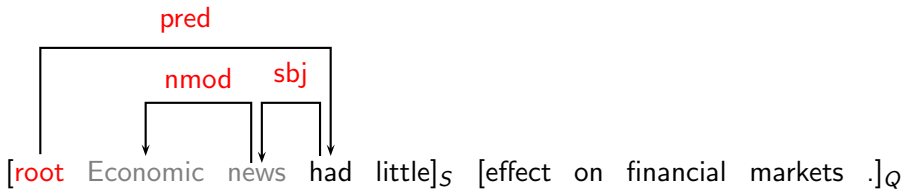
Left-Arc<sub>subj</sub>

# Example



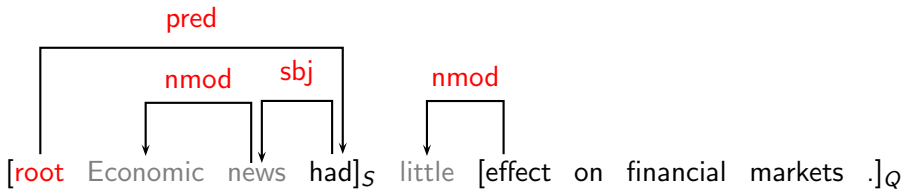
Right-Arc<sub>pred</sub>

# Example



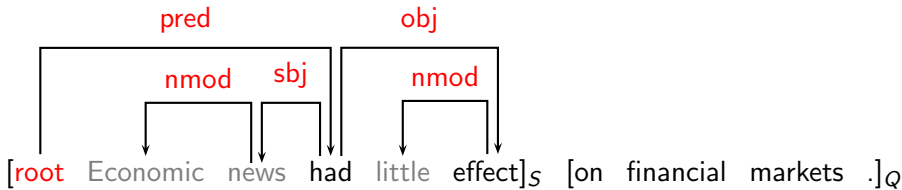
Shift

# Example



Left-Arc<sub>*nmod*</sub>

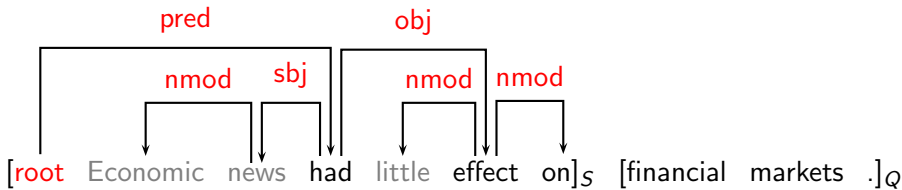
# Example



Right-Arc<sub>obj</sub>

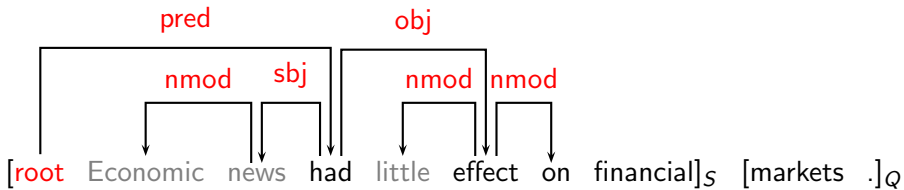


# Example



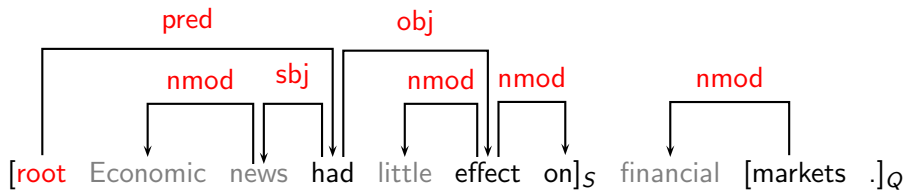
Right-Arc *nmod*

# Example



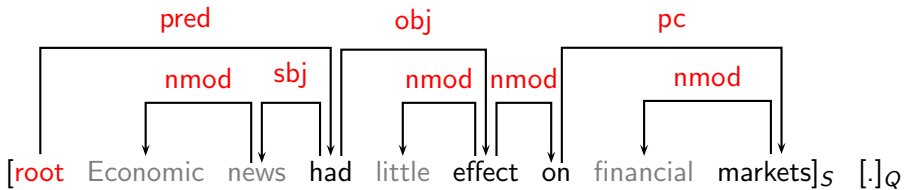
Shift

# Example



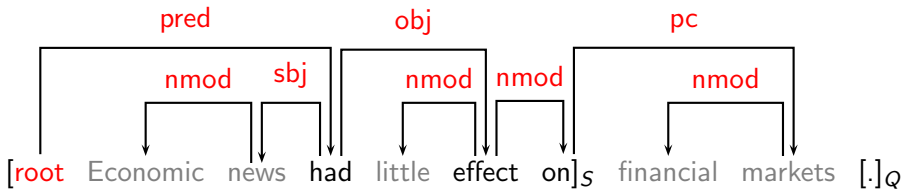
Left-Arc<sub>nmod</sub>

# Example



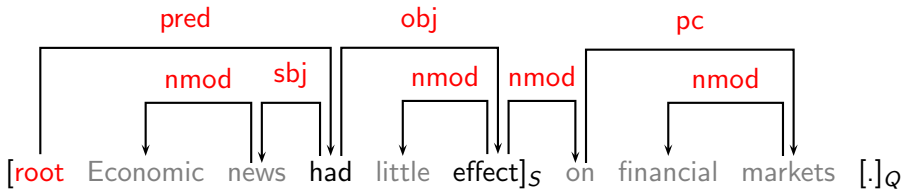
Right-Arc<sub>pc</sub>

# Example



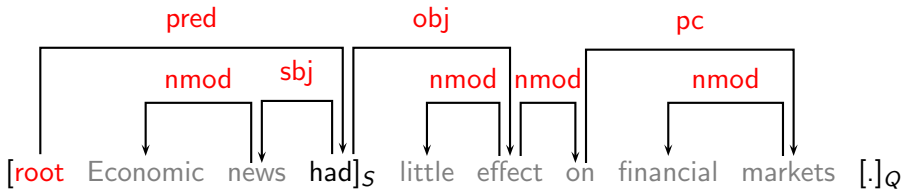
Reduce

# Example



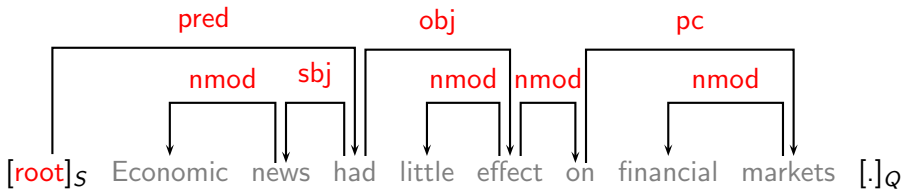
Reduce

# Example



Reduce

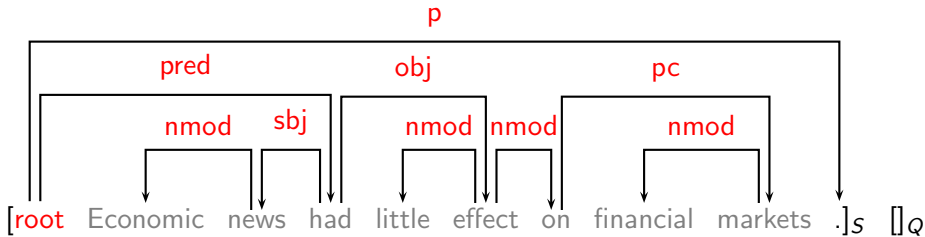
# Example



Reduce



# Example



Right-Arc<sub>p</sub>

# 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 states**, 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)

# State of the Art – English

## ► Evaluation:

- Penn Treebank (WSJ) converted to dependency graphs
- Unlabeled accuracy per word (W) and per sentence (S)
  - **Deterministic classifier-based parsers**  
[Yamada and Matsumoto 2003, Isozaki et al. 2004]
  - **Spanning tree parsers with online training**  
[McDonald et al. 2005a, McDonald and Pereira 2006]
  - Collins and Charniak parsers with same conversion

Parser	W	S
Charniak	92.2	45.2
Collins	91.7	43.3
McDonald and Pereira	91.5	42.1
Isozaki et al.	91.4	40.7
McDonald et al.	91.0	37.5
Yamada and Matsumoto	90.4	38.4

# Comparing Algorithms

- ▶ Parsing algorithm:
  - ▶ Nivre's algorithm gives higher accuracy than Yamada's algorithm for parsing the Chinese CKIP treebank [Cheng et al. 2004].
- ▶ Learning algorithm:
  - ▶ SVM gives higher accuracy than MaxEnt for parsing the Chinese CKIP treebank [Cheng et al. 2004].
  - ▶ SVM gives higher accuracy than MBL with lexicalized feature models for three languages [Hall et al. 2006]:
    - ▶ Chinese (Penn)
    - ▶ English (Penn)
    - ▶ Swedish (Talbanken)

# Parsing Methods

- ▶ Three main traditions:
  - ▶ Dynamic programming
  - ▶ Constraint satisfaction
  - ▶ Deterministic parsing
- ▶ Special issue:
  - ▶ Non-projective dependency parsing

# 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:
  - ▶ Constraint satisfaction methods [Tapanainen and Järvinen 1997, Duchier and Debusmann 2001, Foth et al. 2004]
  - ▶ 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]
  - ▶ Corrective modeling [Hall and Novák 2005]
  - ▶ Approximate non-projective parsing [McDonald and Pereira 2006]



# Non-Projective Parsing Algorithms

► Complexity considerations:

- Projective (**Proj**)
- Non-projective (**NonP**)

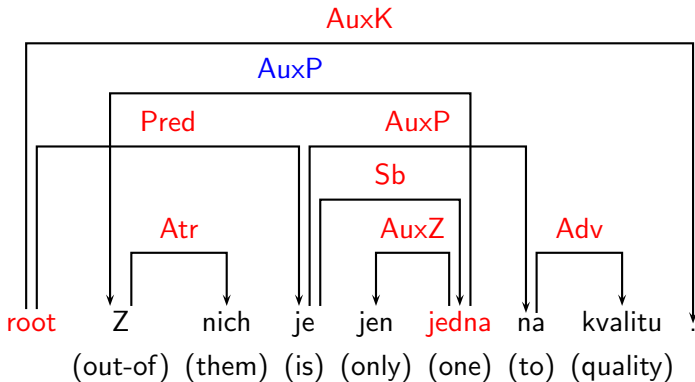
Problem/Algorithm	<b>Proj</b>	<b>NonP</b>
Complete grammar parsing [Gaifman 1965, Neuhaus and Bröker 1997]	$P$	$NP$ hard
Deterministic parsing [Nivre 2003, Covington 2001]	$O(n)$	$O(n^2)$
First order spanning tree [McDonald et al. 2005b]	$O(n^3)$	$O(n^2)$
$N$ th order spanning tree ( $N > 1$ ) [McDonald and Pereira 2006]	$P$	$NP$ hard

# 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.
- ▶ Approaches:
  - ▶ Pseudo-projective parsing [Nivre and Nilsson 2005]
  - ▶ Corrective modeling [Hall and Novák 2005]
  - ▶ Approximate non-projective parsing [McDonald and Pereira 2006]

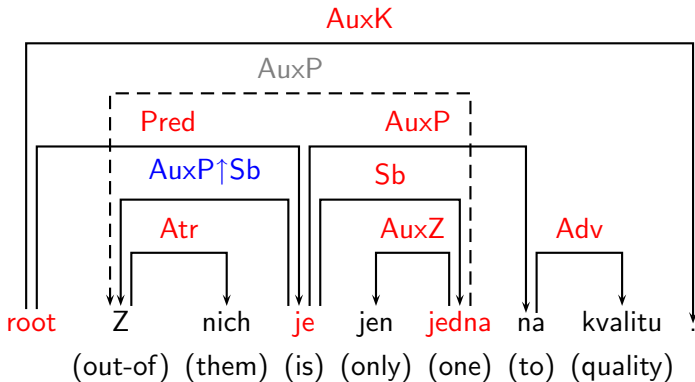
# Pseudo-Projective Parsing

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



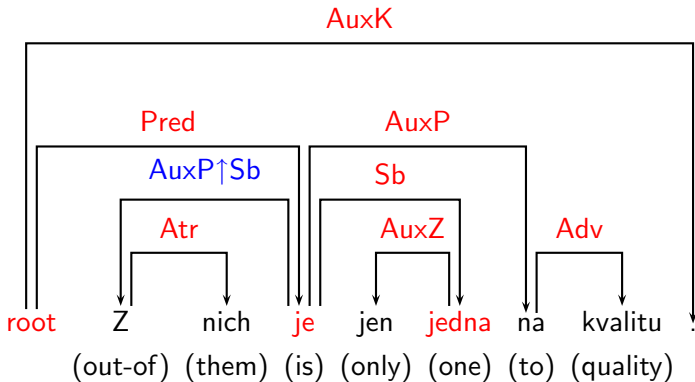
# Pseudo-Projective Parsing

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



# Pseudo-Projective Parsing

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





# Corrective Modeling

- ▶ Conditional probability model

$$P(h'_i | w_i, N(h_i))$$

for correcting the head  $h_i$  of word  $w_i$  to  $h'_i$ , restricted to the local neighborhood  $N(h_i)$  of  $h_i$

- ▶ Model trained on parser output and gold standard parses (MaxEnt estimation)
- ▶ Post-processing:
  - ▶ For every word  $w_i$ , replace  $h_i$  by  $\operatorname{argmax}_{h'_i} P(h'_i | w_i, N(h_i))$ .

## Second-Order Non-Projective Parsing

- ▶ The score of a dependency tree  $y$  for input sentence  $x$  is

$$\sum_{(i,k,j) \in y} s(i,k,j)$$

where  $k$  and  $j$  are adjacent, same-side children of  $i$  in  $y$ .

- ▶ The highest scoring projective dependency tree can be computed exactly in  $O(n^3)$  time using Eisner's algorithm.
- ▶ The highest scoring non-projective dependency tree can be approximated with a greedy post-processing procedure:
  - ▶ While improving the global score of the dependency tree, replace an arc  $h_i \rightarrow w_i$  by  $h'_i \rightarrow w_i$ , greedily selecting the substitution that gives the greatest improvement.



# State of the Art – Czech

## ► Evaluation:

- Prague Dependency Treebank (PDT)
- Unlabeled accuracy per word (W) and per sentence (S)
  - **Non-projective spanning tree parsing** [McDonald et al. 2005b]
  - **Corrective modeling** on top of the Charniak parser [Hall and Novák 2005]
  - **Approximate non-projective parsing** on top of a second-order projective spanning tree parser [McDonald and Pereira 2006]
  - **Pseudo-projective parsing** on top of a deterministic classifier-based parser [Nilsson et al. 2006]

Parser	W	S
McDonald and Pereira	85.2	35.9
Hall and Novák	85.1	—
Nilsson et al.	84.6	37.7
McDonald et al.	84.4	32.3
Charniak	84.4	—

# State of the Art – Multilingual Parsing

- ▶ CoNLL-X Shared Task: 12 (13) languages
- ▶ Organizers: Sabine Buchholz, Erwin Marsi, Yuval Krymolowski, Amit Dubey
- ▶ Main evaluation metric: Labeled accuracy per word
- ▶ Top scores ranging from 91.65 (Japanese) to 65.68 (Turkish)
- ▶ Top systems (over all languages):
  - ▶ Approximate second-order non-projective spanning tree parsing with online learning (MIRA) [McDonald et al. 2006]
  - ▶ Labeled deterministic pseudo-projective parsing with support vector machines [Nivre et al. 2006]

# Pros and Cons of Dependency Parsing

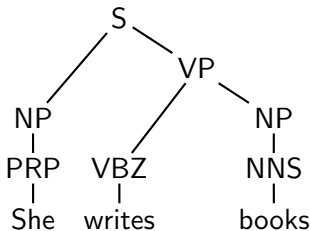
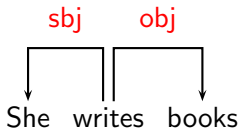
- ▶ What are the advantages of dependency-based methods?
- ▶ What are the disadvantages?
- ▶ Four types of considerations:
  - ▶ Complexity
  - ▶ Transparency
  - ▶ Word order
  - ▶ Expressivity

# Complexity

- ▶ Practical complexity:
  - ▶ Given the **Single-Head** constraint, parsing a sentence  $x = w_1, \dots, w_n$  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:
    - ▶ Lexicalized parsing in  $O(n^3)$  time [Eisner 1996b]

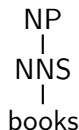
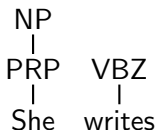
# Transparency

- Direct encoding of predicate-argument structure



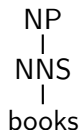
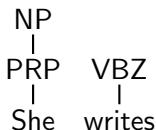
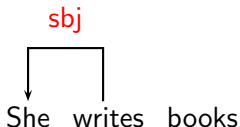
# Transparency

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



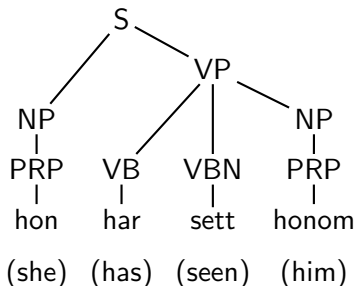
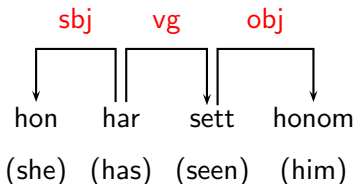
# Transparency

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



# Word Order

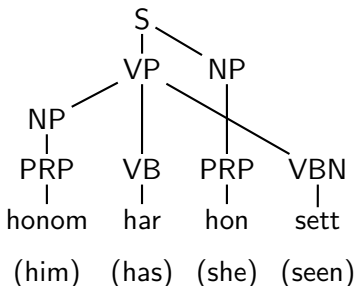
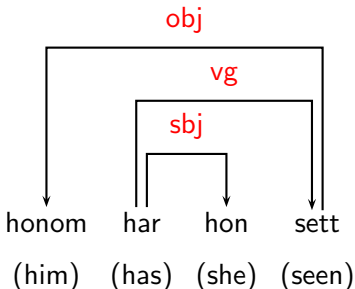
- ▶ Dependency structure independent of word order
- ▶ Suitable for free word order languages (cf. German results)





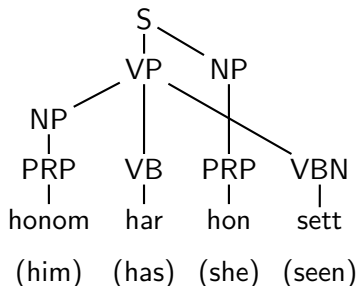
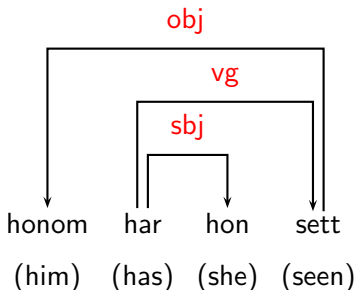
# Word Order

- ▶ Dependency structure independent of word order
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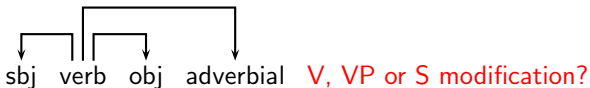
# Word Order

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



- ▶ What about **labeled non-projective** dependency structures?

# 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
- ▶ Where to get help and information?
  - ▶ Dependency parsing wiki

# Parsers

- ▶ Trainable parsers
- ▶ Parsers with manually written grammars

# Parsers

- ▶ Trainable parsers
- ▶ Parsers with manually written grammars
  
- ▶ Concentrate on freely available parsers

# Trainable Parsers

- ▶ Jason Eisner's **probabilistic dependency parser**
  - ▶ Based on bilexical grammar
  - ▶ Contact Jason Eisner: [jason@cs.jhu.edu](mailto:jason@cs.jhu.edu)
  - ▶ Written in LISP
- ▶ Ryan McDonald's **MSTParser**
  - ▶ Based on the algorithms of  
[McDonald et al. 2005a, McDonald et al. 2005b]
  - ▶ URL:  
<http://www.seas.upenn.edu/~ryantm/software/MSTParser/>
  - ▶ Written in JAVA

## Trainable Parsers (2)

- ▶ Joakim Nivre's **MaltParser**

- ▶ Inductive dependency parser with memory-based learning and SVMs
- ▶ URL:  
`http://w3.msi.vxu.se/~nivre/research/MaltParser.html`
- ▶ Executable versions are available for Solaris, Linux, Windows, and MacOS (open source version planned for fall 2006)



# Parsers for Specific Languages

- ▶ Dekang Lin's **Minipar**

- ▶ Principle-based parser
- ▶ Grammar for English
- ▶ URL: <http://www.cs.ualberta.ca/~lindek/minipar.htm>
- ▶ Executable versions for Linux, Solaris, and Windows

- ▶ Wolfgang Menzel's **CDG Parser**:

- ▶ Weighted constraint dependency parser
- ▶ Grammar for German, (English under construction)
- ▶ Online demo:  
<http://nats-www.informatik.uni-hamburg.de/Papa/ParserDemo>
- ▶ Download:  
<http://nats-www.informatik.uni-hamburg.de/download>

## Parsers for Specific Languages (2)

- ▶ Taku Kudo's **CaboCha**
  - ▶ Based on algorithms of [Kudo and Matsumoto 2002], uses SVMs
  - ▶ URL: <http://www.chasen.org/~taku/software/cabocha/>
  - ▶ Web page in Japanese
- ▶ Gerold Schneider's **Pro3Gres**
  - ▶ Probability-based dependency parser
  - ▶ Grammar for English
  - ▶ URL: <http://www.ifi.unizh.ch/CL/gschneid/parser/>
  - ▶ Written in PROLOG
- ▶ Daniel Sleator's & Davy Temperley's **Link Grammar Parser**
  - ▶ Undirected links between words
  - ▶ Grammar for English
  - ▶ URL: <http://www.link.cs.cmu.edu/link/>

# 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-Sabancı Turkish Treebank

## Dependency Treebanks (2)

- ▶ Prague Arabic Dependency Treebank
  - ▶ ca. 100 000 words
  - ▶ Available from LDC, license fee  
(CoNLL-X shared task data, catalogue number LDC2006E01)
  - ▶ URL: <http://ufal.mff.cuni.cz/padt/>
- ▶ Prague Dependency Treebank
  - ▶ 1.5 million words
  - ▶ 3 layers of annotation: morphological, syntactical, tectogrammatical
  - ▶ Available from LDC, license fee  
(CoNLL-X shared task data, catalogue number LDC2006E02)
  - ▶ URL: <http://ufal.mff.cuni.cz/pdt2.0/>

## Dependency Treebanks (3)

- ▶ Danish Dependency Treebank
  - ▶ ca. 5 500 trees
  - ▶ Annotation based on Discontinuous Grammar [Kromann 2005]
  - ▶ Freely downloadable
  - ▶ URL: <http://www.id.cbs.dk/~mtk/treebank/>
- ▶ Bosque, Floresta sintá(c)tica
  - ▶ ca. 10 000 trees
  - ▶ Freely downloadable
  - ▶ URL:  
[http://acdc.linguateca.pt/treebank/info\\_floresta\\_English.html](http://acdc.linguateca.pt/treebank/info_floresta_English.html)

## Dependency Treebanks (4)

- ▶ Slovene Dependency Treebank
  - ▶ ca. 30 000 words
  - ▶ Freely downloadable
  - ▶ URL: <http://nl.ijs.si/sdt/>
- ▶ METU-Sabancı Turkish Treebank
  - ▶ ca. 7 000 trees
  - ▶ Freely available, license agreement
  - ▶ URL: <http://www.ii.metu.edu.tr/~corpus/treebank.html>

# 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



## Constituent Treebanks (2)

- ▶ Penn Treebank
  - ▶ ca. 1 million words
  - ▶ Available from LDC, license fee
  - ▶ URL: <http://www.cis.upenn.edu/~treebank/home.html>
  - ▶ Dependency conversion rules, available from e.g. [Collins 1999]
  - ▶ For conversion with arc labels: Penn2Malt:  
<http://w3.msi.vxu.se/~nivre/research/Penn2Malt.html>
- ▶ BulTreebank
  - ▶ ca. 14 000 sentences
  - ▶ URL: <http://www.bulreebank.org/>
  - ▶ Dependency version available from Kiril Simov  
([kivs@bulreebank.org](mailto:kivs@bulreebank.org))

## Constituent Treebanks (3)

- ▶ Penn Chinese Treebank
  - ▶ ca. 4 000 sentences
  - ▶ Available from LDC, license fee
  - ▶ URL: <http://www.cis.upenn.edu/~chinese/ctb.html>
  - ▶ For conversion with arc labels: Penn2Malt:  
<http://w3.msi.vxu.se/~nivre/research/Penn2Malt.html>
- ▶ Sinica Treebank
  - ▶ ca. 61 000 sentences
  - ▶ Available Academia Sinica, license fee
  - ▶ URL:  
<http://godel.iis.sinica.edu.tw/CKIP/engversion/treebank.htm>
  - ▶ Dependency version available from Academia Sinica

## Constituent Treebanks (4)

### ▶ Alpino Treebank for Dutch

- ▶ ca. 150 000 words
- ▶ Freely downloadable
- ▶ URL: <http://www.let.rug.nl/vannoord/trees/>
- ▶ Dependency version downloadable at [http://nextens.uvt.nl/~conll/free\\_data.html](http://nextens.uvt.nl/~conll/free_data.html)

### ▶ TIGER/NEGRA

- ▶ ca. 50 000/20 000 sentences
- ▶ Freely available, license agreement
- ▶ TIGER URL:  
<http://www.ims.uni-stuttgart.de/projekte/TIGER/TIGERCorpus/>
- ▶ NEGRA URL:  
<http://www.coli.uni-saarland.de/projects/sfb378/negra-corpus/>
- ▶ Dependency version of TIGER is included in release

# Constituent Treebanks (5)

- ▶ TüBa-D/Z
  - ▶ ca. 22 000 sentences
  - ▶ Freely available, license agreement
  - ▶ URL: [http://www.sfs.uni-tuebingen.de/en\\_tuebadz.shtml](http://www.sfs.uni-tuebingen.de/en_tuebadz.shtml)
  - ▶ Dependency version available from Sfs Tübingen
- ▶ TüBa-J/S
  - ▶ Dialog data
  - ▶ ca. 18 000 sentences
  - ▶ Freely available, license agreement
  - ▶ Dependency version available from Sfs Tübingen
  - ▶ URL: [http://www.sfs.uni-tuebingen.de/en\\_tuebajs.shtml](http://www.sfs.uni-tuebingen.de/en_tuebajs.shtml)  
(under construction)

# Constituent Treebanks (6)

## ▶ Cast3LB

- ▶ ca. 18 000 sentences
- ▶ URL: [http://www.dlsi.ua.es/projectes/3lb/index\\_en.html](http://www.dlsi.ua.es/projectes/3lb/index_en.html)
- ▶ Dependency version available from Toni Martí (amarti@ub.edu)

## ▶ Talbanken05

- ▶ ca. 300 000 words
- ▶ Freely downloadable
- ▶ URL:  
<http://w3.msi.vxu.se/~nivre/research/Talbanken05.html>
- ▶ Dependency version also available

# 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.

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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

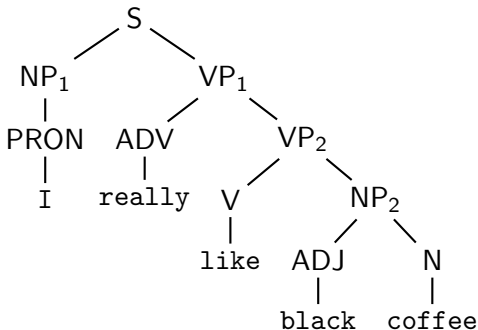
(S    right-to-left    (Aux VP NP AP PP))  
(VP   left-to-right    (V VP))  
(NP   right-to-left    (Pron N NP))

# 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))



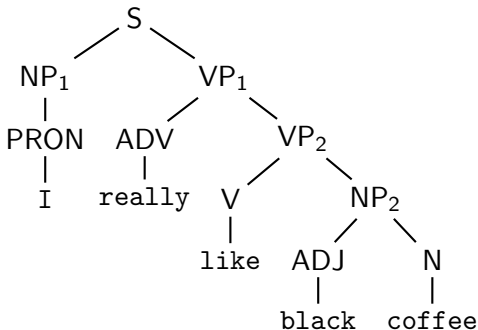
root	head	lex. head
------	------	-----------

# 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))



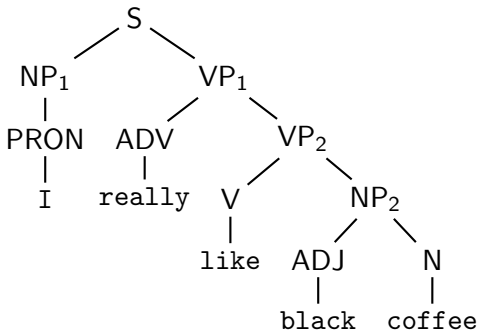
root	head	lex. head
S	VP <sub>1</sub>	??

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

(VP left-to-right (V VP))

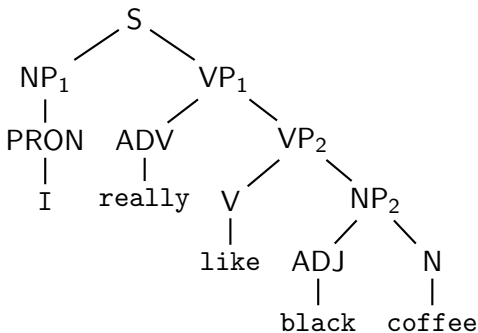
(NP right-to-left (Pron N NP))



root	head	lex. head
VP <sub>1</sub>	VP <sub>2</sub>	??

# 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))



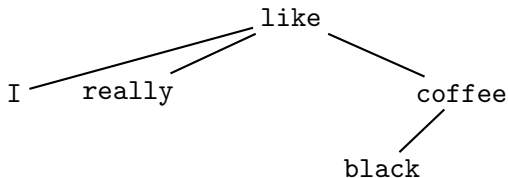
root	head	lex. head
S	VP <sub>1</sub>	like
VP <sub>1</sub>	VP <sub>2</sub>	like
VP <sub>2</sub>	V	like

## 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*

## Lin's Conversion - Example (2)

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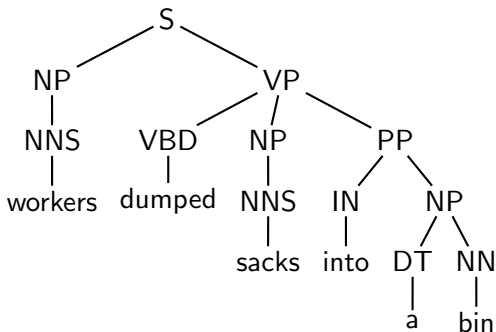


# From Structural to Labeled Conversion

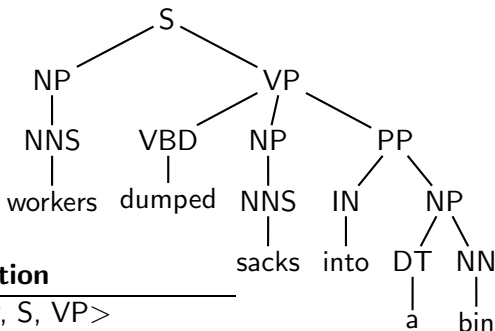
- ▶ Conversion so far gives only pure dependencies from head to dependent.
- ▶ Collins uses combination of constituent labels to label relation [Collins 1999]:
  - ▶ Idea: Combination of mother node and two subordinate nodes gives information about grammatical functions.
  - ▶ If  $headword(Y_h) \rightarrow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



## Collins' Example

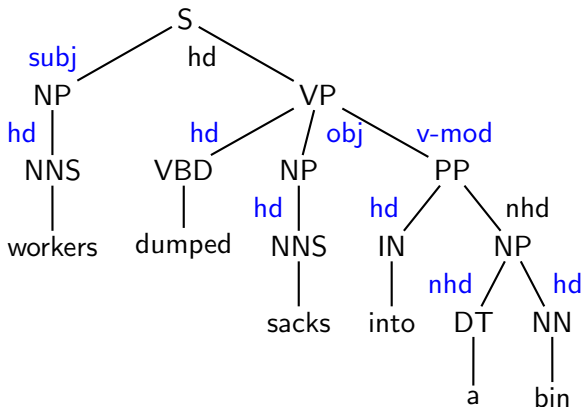


# Collins' Example

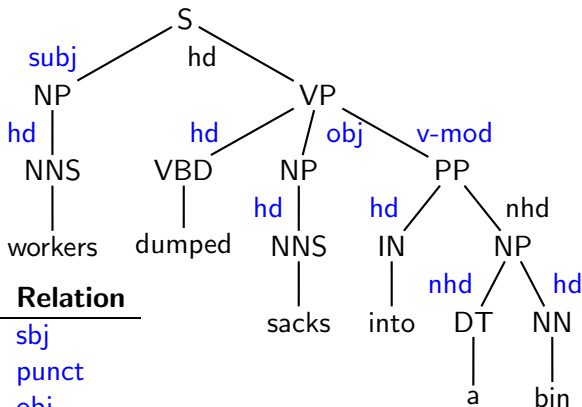


Dependency	Relation
dumped → workers	<NP, S, VP>
dumped → <i>root</i>	<S, START, START>
dumped → sacks	<NP, VP, VBD>
dumped → into	<PP, VP, VBD>
into → bin	<NP, PP, IN>
bin → a	<DT, NP, NN>

## Example with Grammatical Functions



## Example with Grammatical Functions



Dependency	Relation
dumped → workers	sbj
dumped → <i>root</i>	punct
dumped → sacks	obj
dumped → into	v-mod
into → bin	nhd
bin → a	nhd

# Evaluation

evaluation scores:

- ▶ *Exact match* (= S)  
percentage of correctly parsed sentences
- ▶ *Attachment score* (= W)  
percentage of words that have the correct head
- ▶ For single dependency types (labels):
  - ▶ *Precision*
  - ▶ *Recall*
  - ▶  $F_\beta$  *measure*
- ▶ *correct root*  
percentage of sentences that have the correct root

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- ▶ For single dependency types (labels):
  - ▶ *Precision*
  - ▶ *Recall*
  - ▶  $F_\beta$  *measure*
- ▶ *correct root*  
percentage of sentences that have the correct root
- ▶ All labeled and unlabeled



## Further Information

- ▶ Dependency parsing wiki  
<http://depparse.uvt.nl>
- ▶ Book by Joakim: *Inductive Dependency Parsing*



# Outlook

- ▶ Future trends (observed or predicted):
  - ▶ Multilingual dependency parsing
    - ▶ CoNLL Shared Task
    - ▶ Comparative error analysis
    - ▶ Typological diversity and parsing methods
  - ▶ Non-projective dependency parsing
    - ▶ Non-projective parsing algorithms
    - ▶ Post-processing of projective approximations
    - ▶ Other approaches
  - ▶ Global constraints
    - ▶ Grammar-driven approaches
    - ▶  $N$ th-order spanning tree parsing
    - ▶ Hybrid approaches [Foth et al. 2004]
  - ▶ Dependency and constituency
    - ▶ What are the essential differences?
    - ▶ Very few theoretical results

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