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

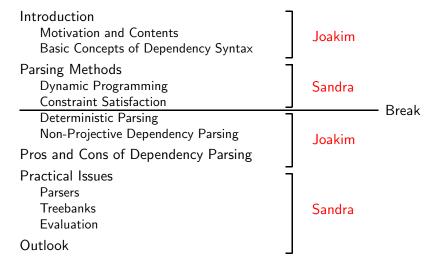
Parsers

Treebanks

Evaluation

Outlook

Outline



Dependency Syntax

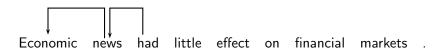
- ► The basic idea:
 - Syntactic structure consists of lexical items, linked by binary asymmetric relations called dependencies.
- ▶ In the words of Lucien Tesnière [Tesnière 1959]:
 - La phrase est un ensemble organisé dont les éléments constituants sont les mots. [1.2] Tout mot qui fait partie d'une 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]

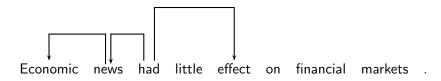
Dependency Syntax

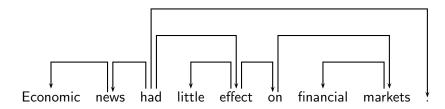
- ► The basic idea:
 - Syntactic structure consists of lexical items, linked by binary asymmetric relations called dependencies.
- ▶ In the words of Lucien Tesnière [Tesnière 1959]:
 - The sentence is an *organized whole*, the constituent elements of which are *words*. [1.2] Every word that belongs to 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]

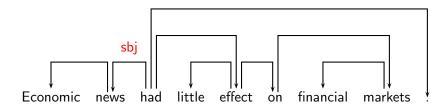
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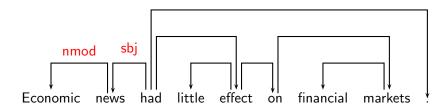
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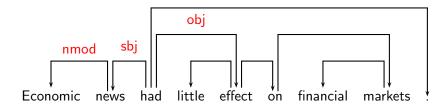


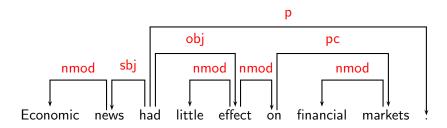










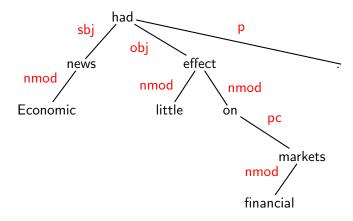


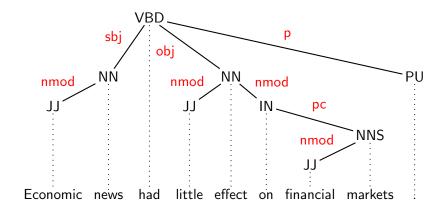
Terminology

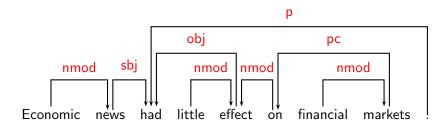
Superior	Inferior
Head	Dependent
Governor	Modifier
Regent	Subordinate
:	:

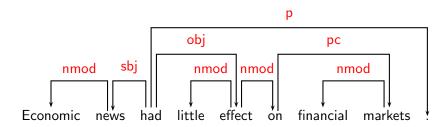
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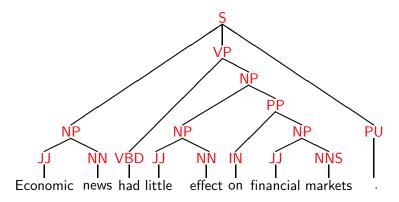








Phrase Structure



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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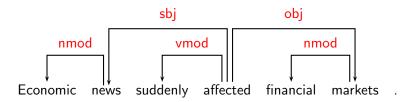
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Criteria for Heads and Dependents

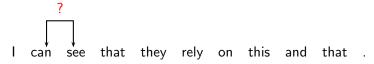
- ► Criteria for a syntactic relation between a head *H* and a dependent *D* in a construction *C* [Zwicky 1985, Hudson 1990]:
 - 1. H determines the syntactic category of C; H can replace C.
 - 2. H determines the semantic category of C; D specifies H.
 - 3. H is obligatory; D may be optional.
 - 4. 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

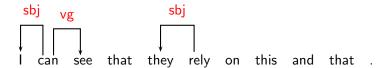
Construction	Head	Dependent
Exocentric	Verb	Subject (sbj)
	Verb	Object (obj)
Endocentric	Verb	Adverbial (vmod)
	Noun	Attribute (nmod)



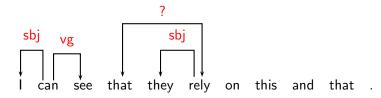
- ► Complex verb groups (auxiliary ↔ main verb)
- ► Subordinate clauses (complementizer ↔ verb)
- ▶ Coordination (coordinator ↔ conjuncts)
- ▶ Prepositional phrases (preposition ← nominal)
- Punctuation



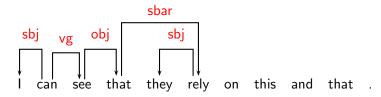
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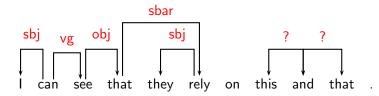
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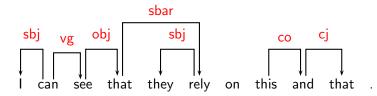
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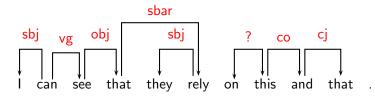
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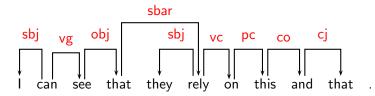
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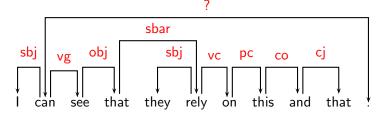
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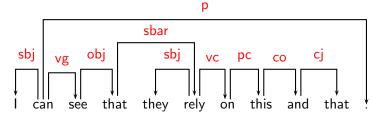
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Dependency Graphs

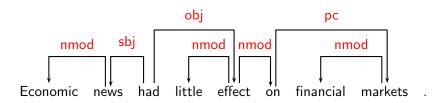
- ► A dependency structure can be defined as a directed graph *G*, consisting of
 - ▶ a set V of nodes.
 - ▶ a set *E* of arcs (edges),
 - \triangleright a linear precedence order < on V.
- ► Labeled graphs:
 - ▶ Nodes in *V* are labeled with word forms (and annotation).
 - Arcs in E are labeled with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

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.

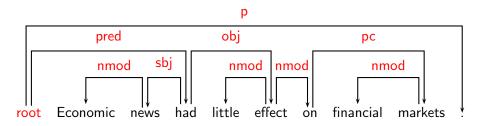
Connectedness, Acyclicity and Single-Head

- 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.



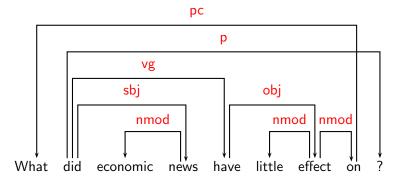
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Projectivity

- 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 $x = w_1, ..., w_n$
 - ▶ 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

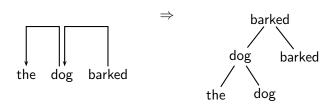
- ► Three main traditions:
 - Dynamic programming
 - ► Constraint satisfaction
 - Deterministic parsing
- ► Special issue:
 - Non-projective dependency parsing

Dynamic Programming

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

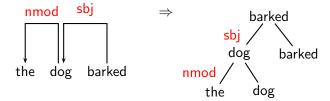
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Dependency Chart Parsing

- 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: $O(n^5)$.

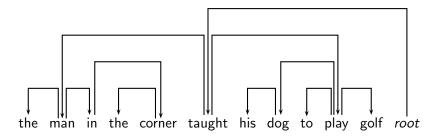
Dynamic Programming Approaches

- ► 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]

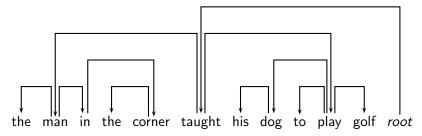
Eisner's Bilexical Algorithm

- ► 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.

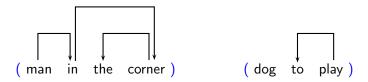
Example



Example



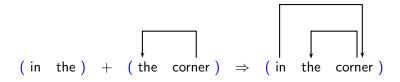
Spans:



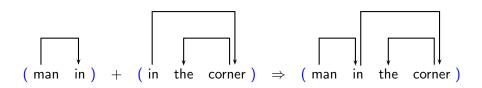
Start by combining adjacent words to minimal spans:

```
(the man) (man in) (in the) ...
```

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

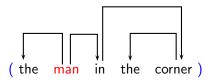


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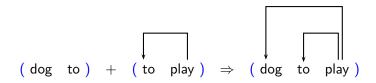


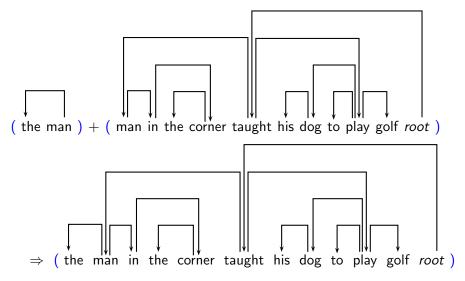
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Invalid span:



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





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
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 - Each word chooses a subcat/supercat frame.
 - Selects an analysis that satisfies all frames if possible.
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 - ► 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

$$\begin{split} & \textit{Pr}(\textit{words}, \textit{tags}, \textit{links}) = \\ & \prod_{1 \leq i \leq n} \left(\prod_{\textit{c}} \textit{Pr}(\textit{tword}(\textit{dep}_{\textit{c}}(\textit{i})) \mid \textit{tag}(\textit{dep}_{\textit{c}-1}(\textit{i})), \textit{tword}(\textit{i})) \right) \\ & \textit{c} = -(1 + \#\textit{left} - \textit{deps}(\textit{i})) \dots 1 + \#\textit{right} - \textit{deps}(\textit{i}), \textit{c} \neq 0 \\ & \textit{or: } \textit{dep}_{\textit{c}+1}(\textit{i}) \textit{ if } \textit{c} < 0 \end{split}$$

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 slo	OW	
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 w: large-margin multi-class classification (MIRA)

Maximum Spanning Trees (2)

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

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

Online Learning

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

1. \mathbf{w} = 0; \mathbf{v} = 0; i = 0;

2. for n: 1...\mathcal{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}/(\mathcal{N} \cdot \mathcal{T})
```

MIRA

MIRA weight update:

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

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

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

- ► *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)

	English		Czech	
Parser	W	S	W	S
k-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.

▶ Based on [Maruyama 1990]

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- ► Example 1:
 - ▶ $word(pos(x)) = DET \Rightarrow$ (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.

- Based on [Maruyama 1990]
- Example 1:
 - ▶ $word(pos(x)) = DET \Rightarrow$ (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.
- ► 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.

- Based on [Maruyama 1990]
- Example 1:
 - ▶ $word(pos(x)) = DET \Rightarrow$ (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.
- ► 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.
- 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:

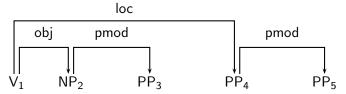
- 1. Form initial constraint network using a "core" grammar.
- 2. Remove local inconsistencies.
- 3. If ambiguity remains, add new constraints and repeat step 2.

Constraint Propagation Example

- Problem: PP attachment
- ▶ Sentence: Put the block on the floor on the table in the room
- ▶ Simplified representation: V₁ NP₂ PP₃ PP₄ PP₅

Constraint Propagation Example

- Problem: PP attachment
- ▶ Sentence: Put the block on the floor on the table in the room
- ▶ Simplified representation: V₁ NP₂ PP₃ PP₄ PP₅
- Correct analysis:



Put the block on the floor on the table in the room

word(pos(x))=PP
 ⇒ (word(mod(x)) ∈ {PP, NP, V}, mod(x) < pos(x))
 A PP modifies a PP, an NP, or a V on the left.

- ▶ 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.
- ▶ word(pos(x))=PP, word(mod(x)) ∈ {PP, NP} ⇒ label(x)=pmod
 - ▶ If a PP modifies a PP or an NP, its label is pmod.

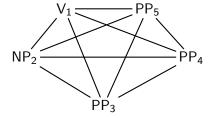
- ► word(pos(x))=PP⇒ (word(mod(x)) ∈ {PP, NP, V}, mod(x) < pos(x))
 - A PP modifies a PP, an NP, or a V on the left.
- ▶ word(pos(x))=PP, word(mod(x)) ∈ {PP, NP} ⇒ label(x)=pmod
 - ▶ If a PP modifies a PP or an NP, its label is pmod.
- $\blacktriangleright \quad word(pos(x)) = PP, \ word(mod(x)) = V \Rightarrow \ label(x) = loc$
 - ▶ If a PP modifies a V, its label is loc.

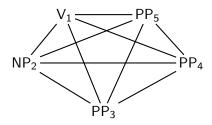
- word(pos(x))=PP
 ⇒ (word(mod(x)) ∈ {PP, NP, V}, mod(x) < pos(x))
 A PP modifies a PP, an NP, or a V on the left.
- ▶ word(pos(x))=PP, $word(mod(x)) \in \{PP, NP\}$ $\Rightarrow label(x)=pmod$
 - ▶ If a PP modifies a PP or an NP, its label is pmod.
- word(pos(x))=PP, word(mod(x))=V ⇒ label(x)=loc
 If a PP modifies a V, its label is loc.
- ▶ 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))=PP⇒ $(word(mod(x)) \in \{PP, NP, V\}, mod(x) < pos(x))$
 - A PP modifies a PP, an NP, or a V on the left.
- ▶ word(pos(x))=PP, $word(mod(x)) \in \{PP, NP\}$ $\Rightarrow label(x)=pmod$
 - ▶ If a PP modifies a PP or an NP, its label is pmod.
- word(pos(x))=PP, word(mod(x))=V ⇒ label(x)=loc
 If a PP modifies a V, its label is loc.
- ▶ word(pos(x))=NP $\Rightarrow (word(mod(x))=V, label(x)=obi, mod(x) < pos(x))$
 - ▶ An NP modifies a V on the left with the label obj.
- \blacktriangleright word(pos(x))=V \Rightarrow (mod(x)=nil, label(x)=root)
 - A V modifies nothing with the label root.

- word(pos(x))=PP
 ⇒ (word(mod(x)) ∈ {PP, NP, V}, mod(x) < pos(x))
 A PP modifies a PP, an NP, or a V on the left.
- ▶ word(pos(x))=PP, $word(mod(x)) \in \{PP, NP\}$ $\Rightarrow label(x)=pmod$
 - ▶ If a PP modifies a PP or an NP, its label is pmod.
- $\blacktriangleright \quad word(pos(x)) = PP, \ word(mod(x)) = V \Rightarrow \ label(x) = loc$
 - If a PP modifies a V, its label is loc.
- ▶ 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.
- $\blacktriangleright \quad word(pos(x)) = V \Rightarrow (mod(x) = nil, label(x) = root)$
 - A V modifies nothing with the label root.

Modification links do not cross.





Possible values ← unary constraints:

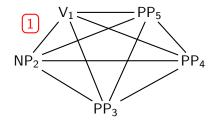
 V_1 : <root, nil>

 NP_2 : <obj, 1>

 PP_3 : <loc, 1>, <pmod, 2>

PP₄: <loc, 1>, <pmod, 2>, <pmod, 3>

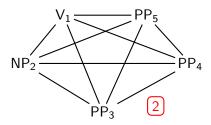
PP₅: <loc, 1>, <pmod, 2>, <pmod, 3>, <pmod,4>



Each arc has a constraint matrix:

For arc 1:

$$\begin{array}{c|c} \downarrow V_1 \setminus \mathsf{NP}_2 \to & \mathsf{} \\ \hline \mathsf{} & 1 \\ \end{array}$$



Each arc has a constraint matrix:

For arc 2:

$_{\downarrow}$ PP ₃ \ PP ₄ \rightarrow	<loc, 1=""></loc,>	<pre><pmod, 2=""></pmod,></pre>	<pmod, 3=""></pmod,>
<loc, 1=""></loc,>	1	0	1
<pmod, $2>$	1	1	1

- ► Still 14 possible analyses.
- ▶ Filtering with binary constraints does not reduce ambiguity.
- ▶ Introduce more constraints:

- Still 14 possible analyses.
- ▶ Filtering with binary constraints does not reduce ambiguity.
- Introduce more constraints:
- ▶ word(pos(x))=PP, on_table ∈ sem(pos(x)) ⇒ ¬(floor ∈ sem(mod(x)))
 - ► A floor is not on the table.

- ▶ Still 14 possible analyses.
- Filtering with binary constraints does not reduce ambiguity.
- ► Introduce more constraints:
- ▶ word(pos(x))=PP, on_table ∈ sem(pos(x)) $\Rightarrow \neg$ (floor ∈ sem(mod(x)))
 - A floor is not on the table.
- ► label(x)=loc, label(y)=loc, mod(x)=mod(y), word(mod(x))=V⇒ x=y
 - No verb can take two locatives.

- Still 14 possible analyses.
- Filtering with binary constraints does not reduce ambiguity.
- Introduce more constraints:
- ▶ word(pos(x))=PP, on_table ∈ sem(pos(x)) ⇒ ¬(floor ∈ sem(mod(x)))
 - A floor is not on the table.
- ► label(x)=loc, label(y)=loc, mod(x)=mod(y), word(mod(x))=V⇒ x=y
 - No verb can take two locatives.
- Each value in the domains of nodes is tested against the new constraints.

Old:

$_{\downarrow} \ PP_{3} \ \backslash \ PP_{4} \ \rightarrow$	<loc, 1=""></loc,>	<pmod, 2=""></pmod,>	<pmod, 3=""></pmod,>
<loc, 1=""></loc,>	1	0	1
<pmod, 2=""></pmod,>	1	1	1

Old:

$_{\downarrow}~PP_{3}~\backslash~PP_{4}~\rightarrow$	<loc, 1=""></loc,>	<pre><pmod, 2=""></pmod,></pre>	<pmod, 3=""></pmod,>
<loc, 1=""></loc,>	1	0	1
<pmod, $2>$	1	1	1

violates first constraint

Old:

\downarrow PP ₃ \ PP ₄ \rightarrow	<loc, 1=""></loc,>	<pmod, 2=""></pmod,>	<pmod, 3=""></pmod,>
<loc, 1=""></loc,>	1	0	1
<pmod, 2=""></pmod,>	1	1	1

After applying first new constraint:

$$\begin{array}{c|cccc} \downarrow \mathsf{PP_3} \setminus \mathsf{PP_4} \to & <\mathsf{loc, 1}> & <\mathsf{pmod, 2}> \\ \hline <\mathsf{loc, 1}> & 1 & 0 \\ <\mathsf{pmod, 2}> & 1 & 1 \\ \end{array}$$

Old:

$\downarrow \ PP_3 \ \backslash \ PP_4 \ \rightarrow$	<loc, 1=""></loc,>	<pmod, 2=""></pmod,>	<pmod, 3=""></pmod,>
<loc, 1=""></loc,>	1	0	1
<pmod, 2=""></pmod,>	1	1	1

After applying first new constraint:

$$\begin{array}{c|cccc} \downarrow \mathsf{PP}_3 \setminus \mathsf{PP}_4 \to & <\mathsf{loc, 1}> & <\mathsf{pmod, 2}> \\ \hline <\mathsf{loc, 1}> & 1 & 0 \\ <\mathsf{pmod, 2}> & 1 & 1 \\ \end{array}$$

violates second constraint

Old:

$\downarrow \ PP_3 \ \backslash \ PP_4 \ \rightarrow$	<loc, 1=""></loc,>	<pre><pmod, 2=""></pmod,></pre>	<pmod, 3=""></pmod,>
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<pmod, 2=""></pmod,>	1	1	1

After applying first new constraint:

$$\begin{array}{c|cccc} \downarrow \mathsf{PP_3} \setminus \mathsf{PP_4} \to & <\mathsf{loc, 1}> & <\mathsf{pmod, 2}> \\ \hline <\mathsf{loc, 1}> & \mathbf{0} & \mathbf{0} \\ <\mathsf{pmod, 2}> & 1 & 1 \\ \end{array}$$

Old:

$\downarrow PP_3 \ \backslash \ PP_4 \ \rightarrow$	<loc, 1=""></loc,>	<pre><pmod, 2=""></pmod,></pre>	<pmod, 3=""></pmod,>
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After applying first new constraint:

$$\begin{array}{c|cccc} \downarrow \mathsf{PP}_3 \setminus \mathsf{PP}_4 \to & <\mathsf{loc}, \ 1> & <\mathsf{pmod}, \ 2> \\ \hline <\mathsf{loc}, \ 1> & 0 & 0 \\ <\mathsf{pmod}, \ 2> & 1 & 1 \\ \end{array}$$

After applying second new constraint:

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 ⇒ 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

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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]:

$$\begin{aligned} &\mathsf{PARSE}(x = (w_1, \dots, w_n)) \\ &1 \quad \text{for } i = 1 \text{ up to } n \\ &2 \quad & \mathsf{for } j = i - 1 \text{ down to } 1 \\ &3 \quad & \mathsf{LINK}(w_i, \, w_j) \end{aligned}$$

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

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

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Shift-Reduce Type Algorithms

- Data structures:
 - ▶ Stack $[..., w_i]_S$ of partially processed tokens
 - ▶ Queue $[w_i, ...]_Q$ 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:

Shift
$$\frac{[\ldots]s \quad [w_i, \ldots]_Q}{[\ldots, w_i]s \quad [\ldots]_Q}$$
Left
$$\frac{[\ldots, w_i, w_j]s \quad [\ldots]_Q}{[\ldots, w_i]s \quad [\ldots]_Q \quad w_i \to w_j}$$
Right
$$\frac{[\ldots, w_i, w_j]s \quad [\ldots]_Q}{[\ldots, w_j]s \quad [\ldots]_Q \quad w_i \leftarrow w_j}$$

- 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 $O(n^2)$

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Nivre's Algorithm

► Four parsing actions:

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

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

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

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

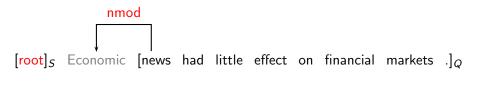
- Characteristics:
 - Integrated labeled dependency parsing
 - Arc-eager processing of right-dependents
 - ▶ Single pass over the input gives time complexity O(n)

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

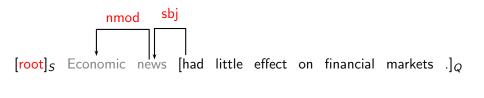
```
[\text{root} \ \text{Economic}]_S [\text{news had little effect on financial markets }.]_Q
```

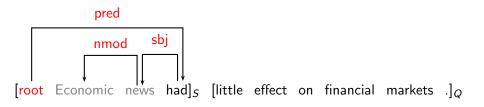
Shift

Left-Arc_{nmod}

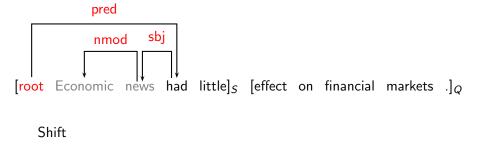


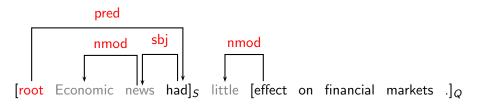
Left-Arc_{sbi}



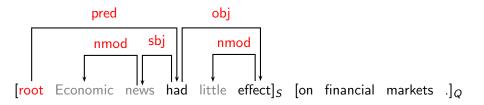


Right-Arc_{pred}

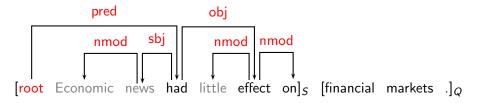




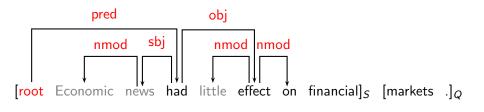
Left-Arc_{nmod}



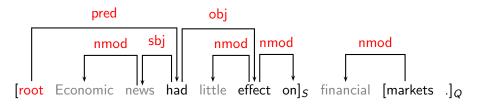
Right-Arcobj



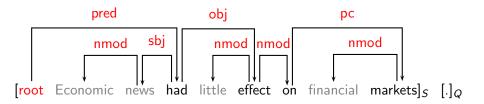
Right-Arc_{nmod}



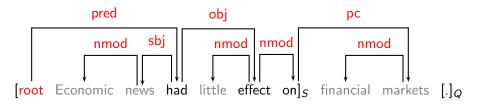
Shift



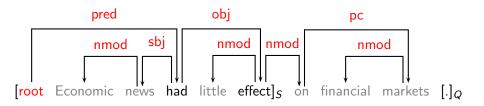
Left-Arc_{nmod}



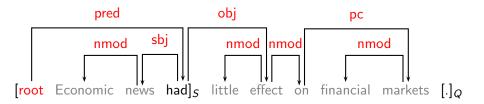
Right-Arc_{pc}



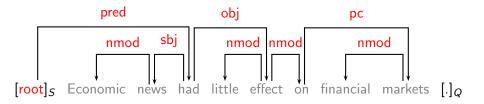
Reduce



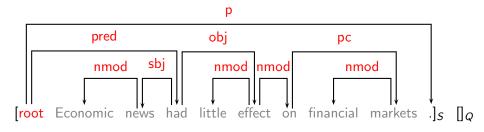
Reduce



Reduce



Reduce



Right-Arcp

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
lsozaki 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)

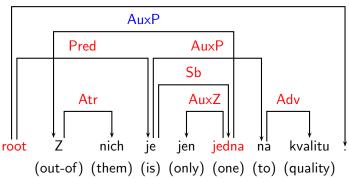
Problem/Algorithm	Proj	NonP
Complete grammar parsing [Gaifman 1965, Neuhaus and Bröker 1997]	Р	<i>NP</i> hard
Deterministic parsing [Nivre 2003, Covington 2001]	O(n)	$O(n^2)$
First order spanning tree [McDonald et al. 2005b]	$O(n^3)$	$O(n^2)$
$\it N$ th order spanning tree ($\it N>1$) [McDonald and Pereira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

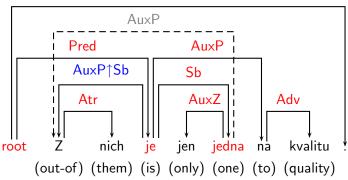
- ▶ Projectivize training data:
 - Projective head nearest permissible ancestor of real head
 - Arc label extended with dependency type of real head

AuxK



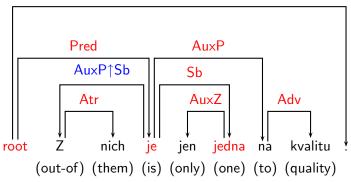
- ▶ Projectivize training data:
 - Projective head nearest permissible ancestor of real head
 - Arc label extended with dependency type of real head

AuxK



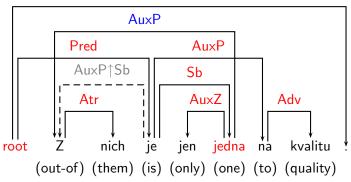
- ► Deprojectivize parser output:
 - ► Top-down, breadth-first search for real head
 - Search constrained by extended arc label

AuxK



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

AuxK



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 neighboorhood $N(h_i)$ 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 $argmax_{h'_i} P(h'_i | w_i, N(h_i))$.

Second-Order Non-Projective Parsing

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

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

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]

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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

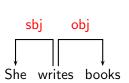
Complexity

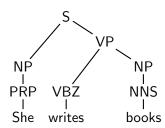
- Practical complexity:
 - Given the Single-Head constraint, parsing a sentence $x = w_1, \dots, w_n$ can be reduced to labeling each token w_i with:
 - ▶ a head word hi.
 - ightharpoonup a dependency type d_i .
- ► Theoretical complexity:
 - By exploiting the special properties of dependency graphs, it is sometimes possible to improve worst-case complexity compared to constituency-based parsing:
 - Lexicalized parsing in $O(n^3)$ time [Eisner 1996b]

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Transparency

▶ Direct encoding of predicate-argument structure





Transparency

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

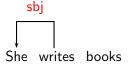




NP I NNS I books

Transparency

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

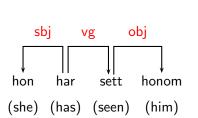


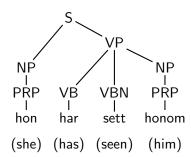


NP | NNS | books

Word Order

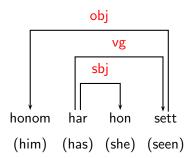
- ▶ Dependency structure independent of word order
- ► Suitable for free word order languages (cf. German results)

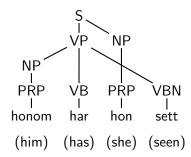




Word Order

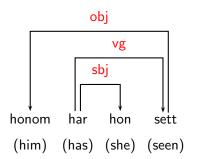
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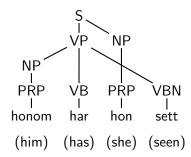




Word Order

- 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

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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
 - 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

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Trainable Parsers (2)

- ▶ loakim 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-Sabanci 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

Dependency Treebanks (4)

- ► Slovene Dependency Treebank
 - ca. 30 000 words
 - Freely downloadable
 - URL: http://nl.ijs.si/sdt/
- ► METU-Sabanci 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.bultreebank.org/
 - Dependency version available from Kiril Simov (kivs@bultreebank.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
- ► 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
 - ▶ 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 (under construction)

Constituent Treebanks (6)

- ► Cast3LB
 - ca 18 000 sentences
 - ▶ URL: 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 ⇒ 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

- ▶ 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.
- Sample entries:

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

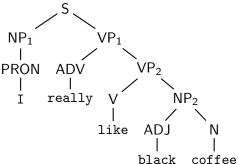
► First line: The head of an S constituent is the first Aux daughter from the right; if there is no Aux, then the first VP, etc.

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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))
```

```
(S
      right-to-left (Aux VP NP AP PP))
(VP
      left-to-right (V VP))
      right-to-left (Pron N NP))
(NP
                                                  head
                                                         lex. head
                                           root
 NP<sub>1</sub>
PRON
        AD
       really
               like
                      black
                               coffee
```

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

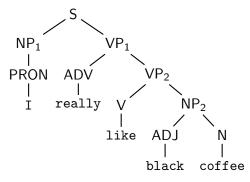


root head lex. head S VP₁ ??

```
(S
      right-to-left (Aux VP NP AP PP))
      left-to-right (V VP))
(VP
(NP
      right-to-left (Pron N NP))
                                               head
                                                      lex. head
                                         root
 NP_1
                                         VP₁
                                               VP_2
                                                      ??
PRON
        ADV
       really
              like
                     black
                             coffee
```

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

Dependency Parsing 96(103)

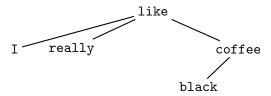
Lin's Conversion - Example (2)

- ▶ 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

Dependency Parsing 97(103)

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



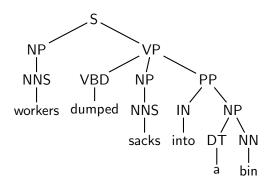
Dependency Parsing 97(103)

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 $\langle Y_d, X, Y_h \rangle$

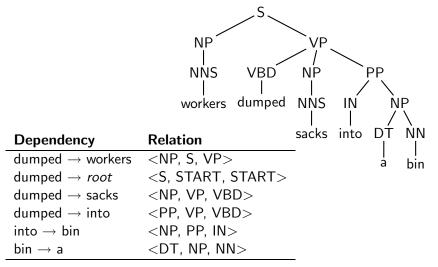
Dependency Parsing 98(103)

Collins' Example



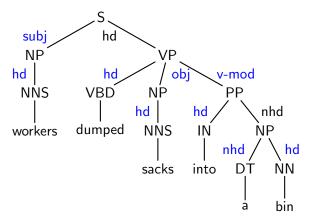
Dependency Parsing 99(103)

Collins' Example



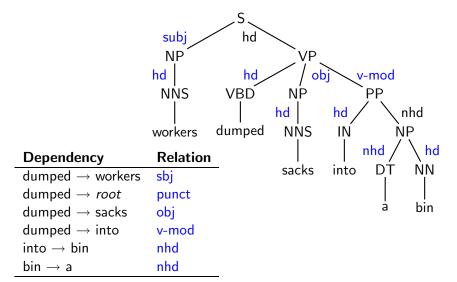
Dependency Parsing 99(103)

Example with Grammatical Functions



Dependency Parsing 100(103)

Example with Grammatical Functions



Dependency Parsing 100(103)

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
 - $ightharpoonup F_{\beta}$ measure
- correct root percentage of sentences that have the correct root

Dependency Parsing 101(103)

evaluation scores:

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Dependency Parsing 101(103)

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Dependency Parsing 101(103)

evaluation scores:

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- ► For single dependency types (labels):
 - Precision
 - ► Recall
 - $ightharpoonup F_{\beta}$ 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



Dependency Parsing 102(103)

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
 - Nth-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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