

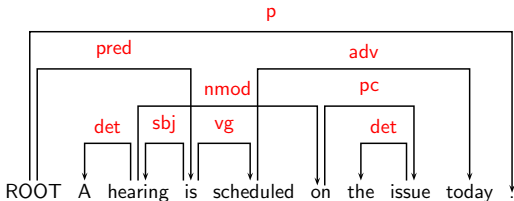
Sorting Out Dependency Parsing

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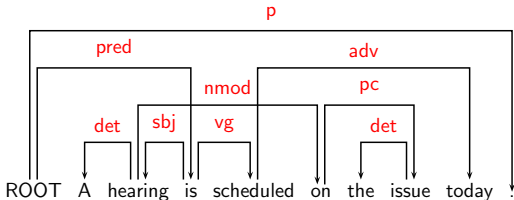
Introduction

- ▶ Syntactic parsing of natural language:
 - ▶ Who does what to whom?
- ▶ Dependency-based syntactic representations
 - ▶ have a natural way of representing discontinuous constructions,
 - ▶ give a transparent encoding of predicate-argument structure,
 - ▶ can be parsed using (simple) data-driven models,
 - ▶ can be parsed efficiently.



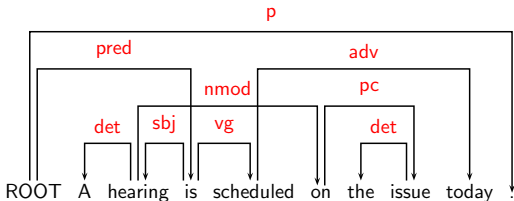
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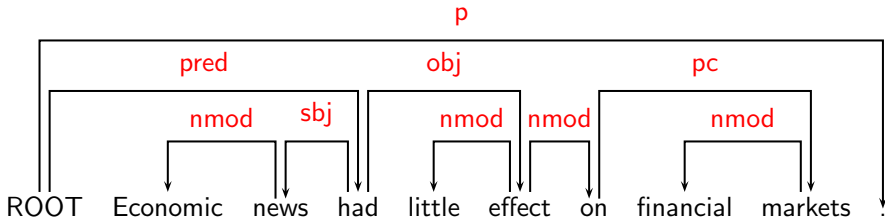
Structure of This Talk

- ▶ Part 1:
 - ▶ Transition-based dependency parsing
 - ▶ Restricted to projective structures
- ▶ Part 2:
 - ▶ Non-projective dependency parsing
 - ▶ Parsing = sorting + projective parsing

Dependency Parsing

Dependency Syntax

- ▶ The basic idea:
 - ▶ Syntactic structure consists of **lexical items**, linked by binary asymmetric relations called **dependencies**.
- ▶ Many different theoretical frameworks

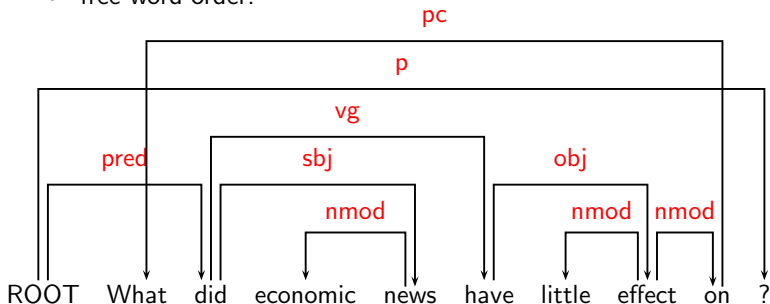


Dependency Trees

- ▶ A dependency structure is a labeled directed tree T , consisting of
 - ▶ a set V of nodes, labeled with words (including ROOT),
 - ▶ a set A of arcs, labeled with dependency types,
 - ▶ a linear precedence order $<$ on V ,with the node labeled ROOT as the unique root.
- ▶ **Note:** Some frameworks do not assume that dependency structures are trees but allow general graphs.

Projectivity

- ▶ A dependency tree T is **projective** iff
 - ▶ for every arc $w_i \rightarrow w_j$ and every node w_k between w_i and w_j in the linear order, there is a (directed) path from w_i to w_k .
- ▶ Most theoretical frameworks do **not** assume projectivity.
- ▶ Non-projective structures are needed to account for
 - ▶ long-distance dependencies,
 - ▶ free word order.



Non-Projectivity in Natural Language

Language	Sentences	Dependencies
Arabic [Maamouri and Bies 2004]	11.2%	0.4%
Basque [Aduriz et al. 2003]	26.2%	2.9%
Czech [Hajič et al. 2001]	23.2%	1.9%
Danish [Kromann 2003]	15.6%	1.0%
Greek [Prokopidis et al. 2005]	20.3%	1.1%
Russian [Boguslavsky et al. 2000]	10.6%	0.9%
Slovene [Džeroski et al. 2006]	22.2%	1.9%
Turkish [Oflazer et al. 2003]	11.6%	1.5%

Data-Driven Dependency Parsing

- ▶ Dependency parsing based on (only) supervised learning from treebank data (annotated sentences)
- ▶ Graph-based [Eisner 1996, McDonald et al. 2005a]
 - ▶ Define a space of candidate dependency trees for a sentence
 - ▶ **Learning:** Induce a model for scoring an entire dependency tree for a sentence
 - ▶ **Inference:** Find the highest-scoring dependency tree, given the induced model
- ▶ Transition-based [Yamada and Matsumoto 2003, Nivre et al. 2004]:
 - ▶ Define a transition system (state machine) for mapping a sentence to its dependency tree
 - ▶ **Learning:** Induce a model for predicting the next state transition, given the transition history
 - ▶ **Inference:** Construct the optimal transition sequence, given the induced model

Transition-Based Dependency Parsing

Overview of the Approach

- ▶ The basic idea:
 - ▶ Define a transition system for dependency parsing
 - ▶ Train a classifier for predicting the next transition
 - ▶ Use the classifier to do parsing as greedy, deterministic search
- ▶ Advantages:
 - ▶ Efficient parsing (linear time complexity)
 - ▶ Robust disambiguation (discriminative classifiers)

Transition System: Configurations

- ▶ A parser configuration is a triple $c = (S, Q, A)$, where
 - ▶ S = a stack $[\dots, w_i]_S$ of partially processed nodes,
 - ▶ Q = a queue $[w_j, \dots]_Q$ of remaining input nodes,
 - ▶ A = a set of labeled arcs (w_i, w_j, l) .

- ▶ Initialization:

$$([w_0]_S, [w_1, \dots, w_n]_Q, \{\})$$

NB: $w_0 = \text{ROOT}$

- ▶ Termination:

$$([w_0]_S, [], A)$$

Transition System: Transitions

▶ Left-Arc(l)

$$\frac{([\dots, w_i, w_j]_S, Q, A)}{([\dots, w_j]_S, Q, A \cup \{(w_j, w_i, l)\})} \quad [i \neq 0]$$

▶ Right-Arc(l)

$$\frac{([\dots, w_i, w_j]_S, Q, A)}{([\dots, w_i]_S, Q, A \cup \{(w_i, w_j, l)\})}$$

▶ Shift

$$\frac{([\dots]_S, [w_i, \dots]_Q, A)}{([\dots, w_i]_S, [\dots]_Q, A)}$$

Deterministic Parsing

- ▶ Given an **oracle** o that correctly predicts the next transition $o(c)$, parsing is deterministic:

```

Parse( $w_1, \dots, w_n$ )
1   $c \leftarrow ([w_0]_S, [w_1, \dots, w_n]_Q, \{ \})$ 
2  while  $Q_c \neq []$  or  $|S_c| > 1$ 
3       $t \leftarrow o(c)$ 
4       $c \leftarrow t(c)$ 
5  return  $G = (\{w_0, w_1, \dots, w_n\}, A_c)$ 

```


Example

$o(c) = \text{Shift}$

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

ROOT Economic news had little effect on financial markets .

Example

$o(c) = \text{Shift}$

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

ROOT Economic news had little effect on financial markets .

Example

$o(c) = \text{Left-Arc}_{\text{mod}}$

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

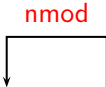
ROOT Economic news had little effect on financial markets .

Example

$o(c) = \text{Shift}$

[[ROOT news]]_S [[had little effect on financial markets .]]_Q

ROOT Economic news had little effect on financial markets .



Example

$o(c) = \text{Left-Arc}_{\text{sbj}}$

[[ROOT news had]]_S [[little effect on financial markets .]]_Q

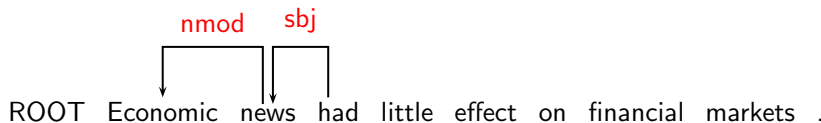
ROOT Economic news had little effect on financial markets .

The diagram illustrates a dependency arc labeled 'nmod' (nominal modifier) in red. The arc starts at the word 'Economic' and ends at the word 'news'. The arc is represented by a horizontal line above the words, with a vertical line extending down from the left end to the word 'Economic' and another vertical line extending down from the right end to the word 'news'. A downward-pointing arrow is attached to the left vertical line.

Example

$o(c) = \text{Shift}$

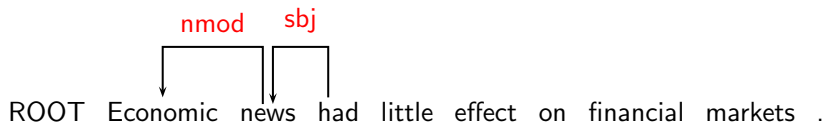
[[ROOT had]]_S [[little effect on financial markets .]]_Q



Example

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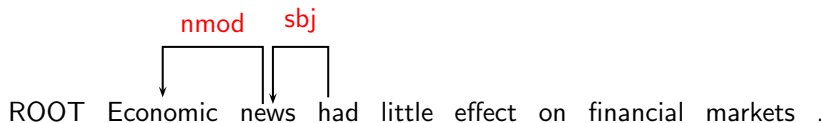
[[ROOT had little]]_S [[effect on financial markets .]]_Q



Example

$o(c) = \text{Left-Arc}_{nmod}$

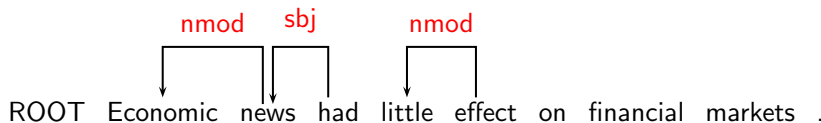
[[ROOT had little effect]]_S [[on financial markets .]]_Q



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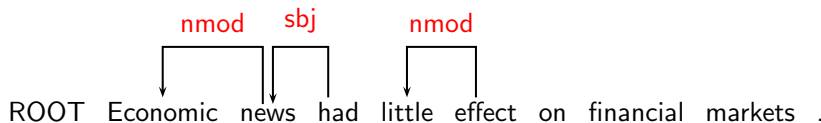
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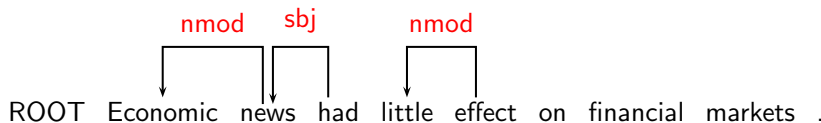
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Example

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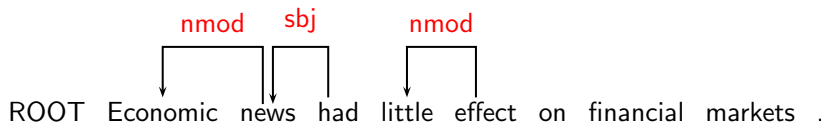
[[ROOT had effect on financial]]_S [[markets .]]_Q



Example

$o(c) = \text{Left-Arc}_{nmod}$

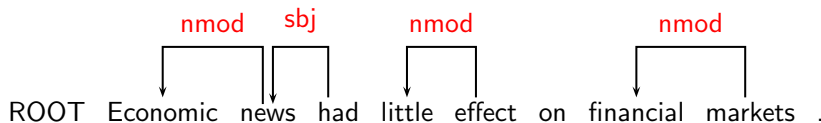
[[ROOT had effect on financial markets]]_S [[.]]_Q



Example

$o(c) = \text{Right-Arc}_{pc}$

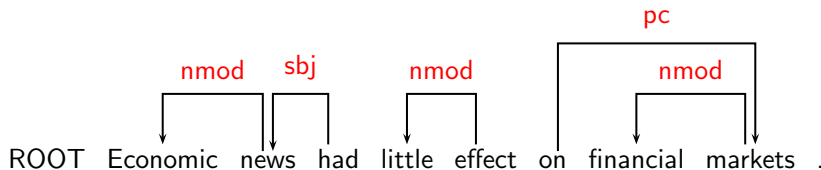
[[ROOT had effect on markets]]_S [[.]]_Q



Example

$o(c) = \text{Right-Arc}_{nmod}$

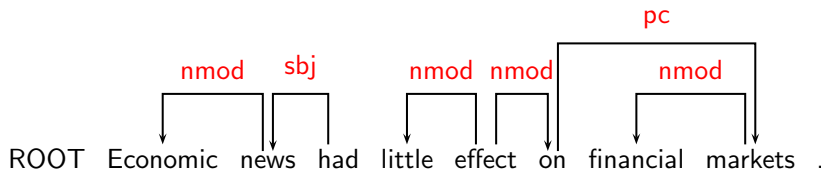
[[ROOT had effect on]]_S [[.]]_Q



Example

$o(c) = \text{Right-Arc}_{obj}$

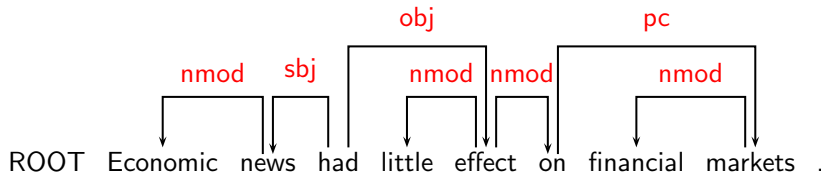
[[ROOT had effect]]_S [[.]]_Q



Example

$o(c) = \text{Right-Arc}_{\text{pred}}$

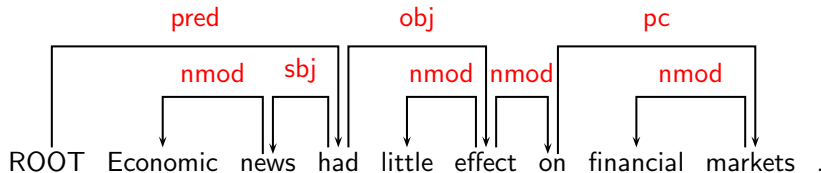
$[[\text{ROOT had}]_S \quad [.]_Q$



Example

$o(c) = \text{Shift}$

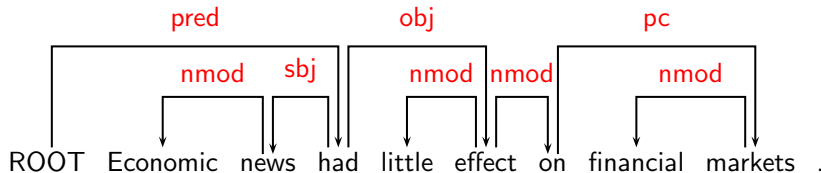
$[[\text{ROOT}]_s \quad [\cdot]_q$



Example

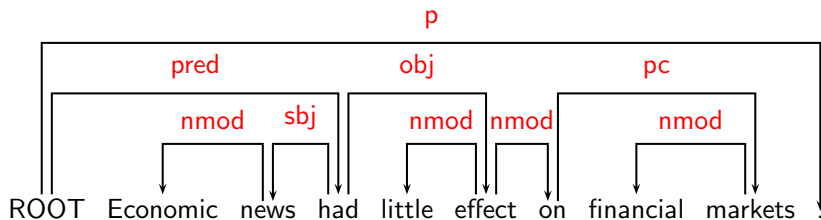
$o(c) = \text{Right-Arc}_p$

$[[\text{ROOT } \cdot]_s \quad []_q$



Example

$[[\text{ROOT}]_s \quad []_q$



Algorithm Analysis

- ▶ Given an input sentence of length n , the parser terminates after exactly $2n$ transitions.
- ▶ The algorithm is sound and complete for projective dependency trees.
- ▶ The algorithm is arguably optimal with respect to
 - ▶ robustness (at least one analysis),
 - ▶ disambiguation (at most one analysis),
 - ▶ efficiency (linear time).
- ▶ Accuracy depends on how well we can approximate oracles using machine learning.

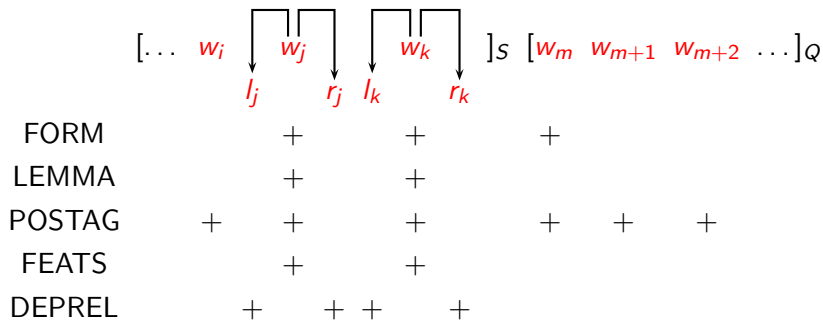
Alternative Parsing Algorithms

- ▶ Alternative transition systems:
 - ▶ Stack-based:
 - ▶ Arc-eager shift-reduce parsing [Nivre 2003]
 - ▶ Arc-standard shift-reduce parsing [Yamada and Matsumoto 2003]
 - ▶ Restricted non-projective parsing [Attardi 2006]
 - ▶ List-based:
 - ▶ Unrestricted non-projective parsing [Covington 2001, Nivre 2007]
- ▶ Alternative search strategies:
 - ▶ Greedy search:
 - ▶ Single-pass [Nivre et al. 2004]
 - ▶ Iterative [Yamada and Matsumoto 2003]
 - ▶ Beam search [Johansson and Nugues 2006, Titov and Henderson 2007]

Oracles as Classifiers

- ▶ Learning problem in transition-based dependency parsing:
 - ▶ Approximate oracle $o(c)$ by classifier $g(c)$
- ▶ History-based feature models:
 - ▶ Parse history $c = (S, Q, A)$ represented by feature vector $\mathbf{x}(c)$
 - ▶ Individual features $\mathbf{x}_i(c)$ defined by properties of words in c , for example:
 - ▶ Lexical properties (FORM or LEMMA)
 - ▶ Part-of-speech tags (POSTAG)
 - ▶ Morphosyntactic features (FEATS)
 - ▶ Labels in the partially built dependency tree (DEPREL)

A Typical Feature Model



Training Data

- ▶ Training instances have the form $(\mathbf{x}(c), t)$, where
 1. $\mathbf{x}(c)$ is a feature vector representation of a configuration c ,
 2. t is the correct transition out of c (i.e., $o(c) = t$).
- ▶ Given a dependency treebank, we can sample the oracle function o as follows:
 - ▶ For each sentence we reconstruct the transition sequence $C_{0,m} = (c_0, c_1, \dots, c_m)$ for the gold standard dependency tree.
 - ▶ For each configuration $c_i (i < m)$, we construct a training instance $(\mathbf{x}(c_i), t_i)$, where $t_i(c_i) = c_{i+1}$.

Learning Algorithms

- ▶ Discriminative models for classification:
 - ▶ Support vector machines (SVM) [Kudo and Matsumoto 2002, Yamada and Matsumoto 2003, Nivre et al. 2006]
 - ▶ Memory-based learning [Nivre et al. 2004, Attardi 2006]
 - ▶ Maximum entropy [Cheng et al. 2005, Attardi 2006]
 - ▶ Perceptron learning [Ciaramita and Attardi 2007]
- ▶ State-of-the-art performance:
 - ▶ Deterministic transition-based parsing with SVM classifiers
 - ▶ CoNLL Shared Task 2006 and 2007
[Buchholz and Marsi 2006, Nivre et al. 2007]

Summing Up

- ▶ The approach so far:
 - ▶ Transition systems for constructing dependency trees
 - ▶ Deterministic linear-time parsing with oracle
 - ▶ Oracles approximated by classifiers trained on treebank data
- ▶ However:
 - ▶ Limited to projective dependency trees
 - ▶ What to do with discontinuous constructions?

Non-Projective Dependency Parsing

What's the Problem?

- ▶ Non-projective dependency trees are required for representational adequacy (discontinuity, transparency).
- ▶ Non-projective dependency parsing is **computationally** hard:
 - ▶ Exact inference is feasible in polynomial time only with drastic independence assumptions (so-called arc-factored models).
 - ▶ Greedy deterministic inference is less efficient than in the projective case ($O(n^2)$ vs. $O(n)$).
- ▶ Non-projective dependency parsing is **empirically** hard:
 - ▶ Non-projective dependencies often span longer distances and are hard to learn with data-driven models.

Previous Work

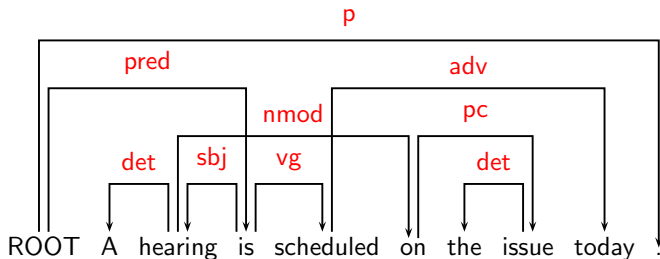
- ▶ Algorithms for non-projective dependency parsing:
 - ▶ Graph-based parsing using the Chu-Liu-Edmonds algorithm [McDonald et al. 2005b]
 - ▶ Transition-based parsing for restricted [Attardi 2006] or arbitrary [Nivre 2007] non-projective structures
- ▶ Post-processing of projective dependency trees:
 - ▶ Pseudo-projective parsing [Nivre and Nilsson 2005]
 - ▶ Corrective modeling [Hall and Novák 2005]
 - ▶ Approximate spanning tree parsing [McDonald and Pereira 2006]

A New Idea

- ▶ Parsing as the result of two interleaved processes:
 - ▶ Sorting the words into a projective order
 - ▶ Parsing the sorted words into a projective dependency tree
- ▶ Potential advantages:
 - ▶ Reduces to projective parsing in the best case
 - ▶ Brings elements of discontinuous constructions together

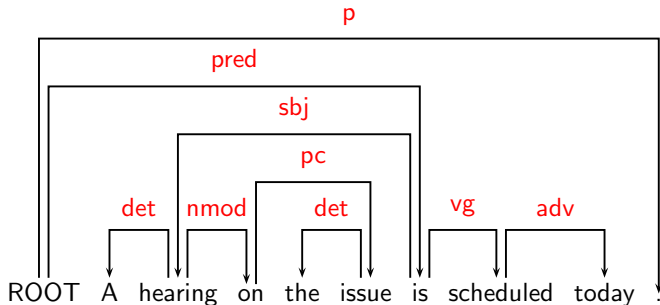
Projectivity and Word Order

- ▶ Projectivity is a property of a dependency tree only in relation to a particular word order.
- ▶ Words can always be reordered to make the tree projective.



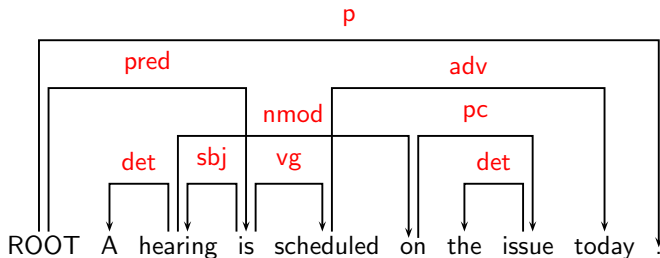
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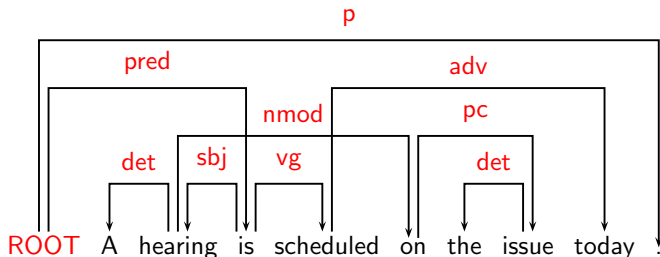
Projective Order

- ▶ Given a dependency tree $T = (V, A, <)$, let the **projective order** $<_p$ be the order defined by an **inorder traversal** of T with respect to $<$.



Projective Order

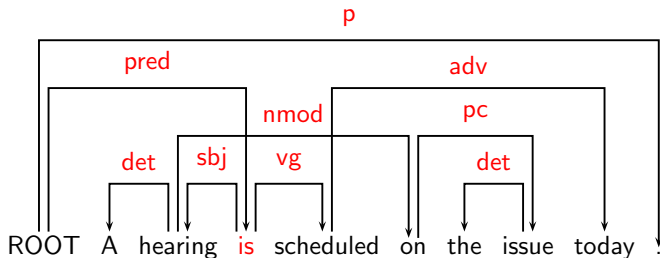
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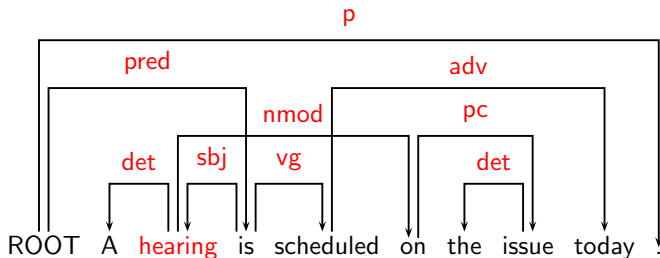
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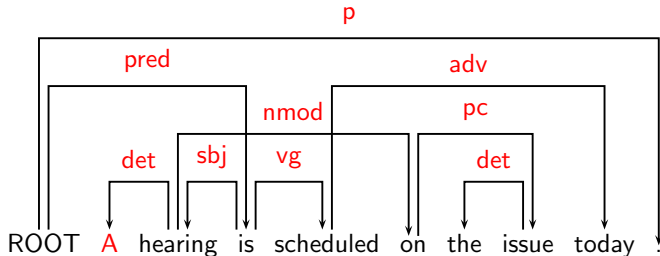
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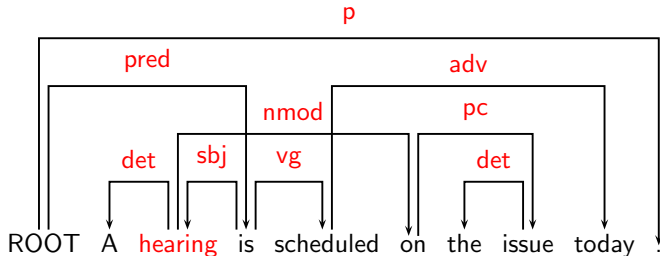
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ROOT A

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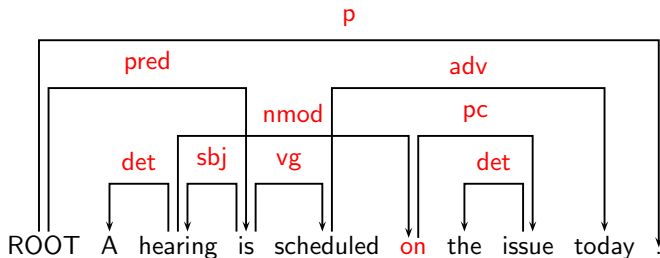
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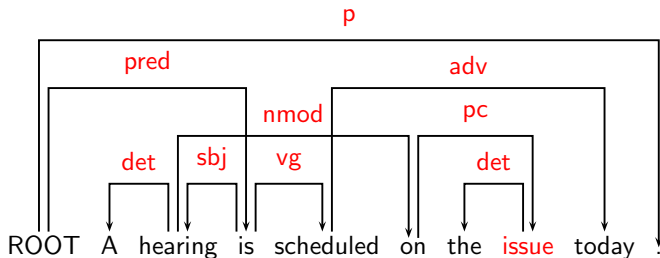
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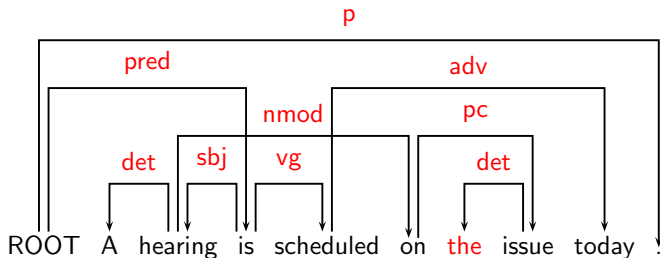
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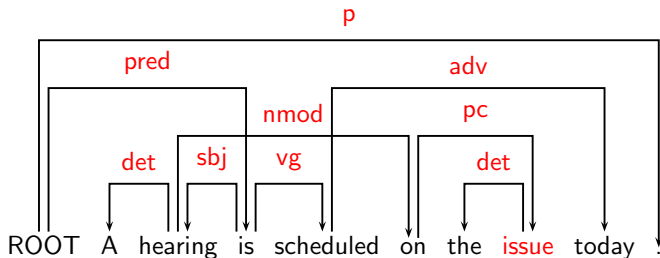
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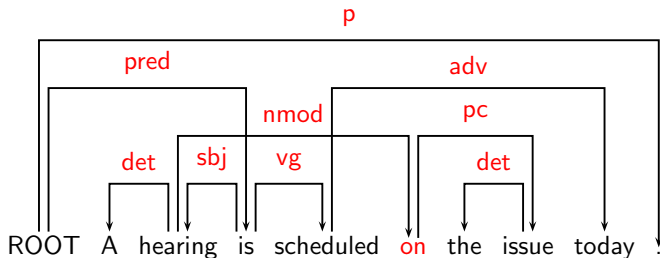
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ROOT A hearing on the issue

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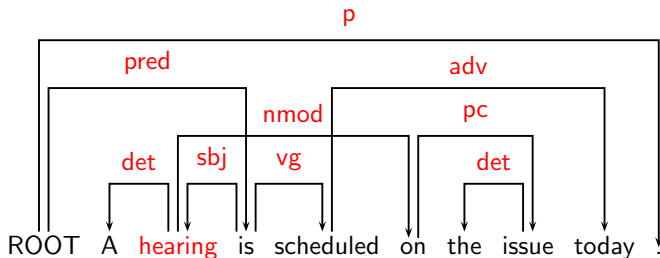
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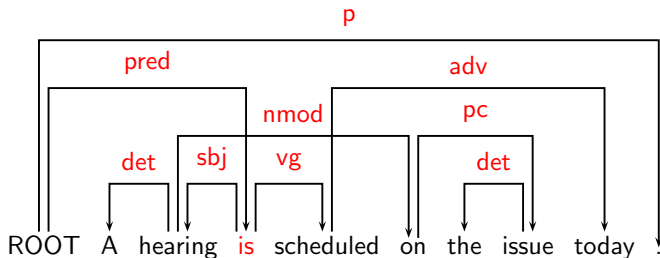
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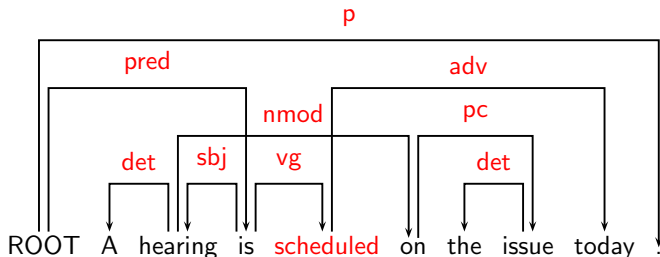
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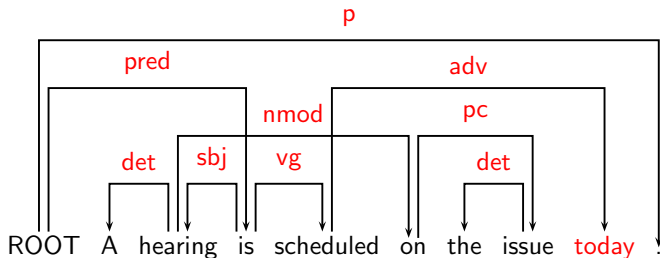
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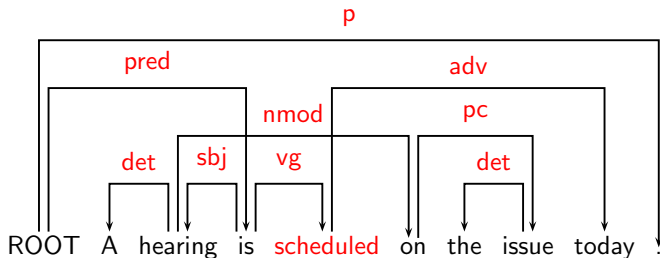
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ROOT A hearing on the issue is scheduled today

Projective Order

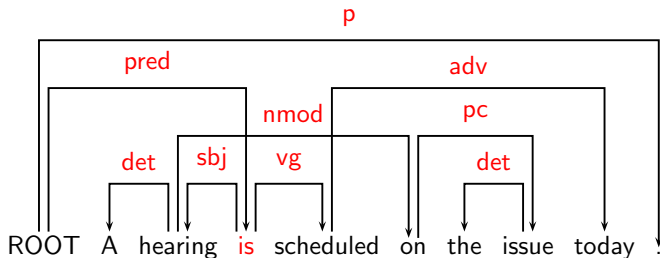
- Given a dependency tree $T = (V, A, <)$, let the **projective order** $<_p$ be the order defined by an **inorder traversal** of T with respect to $<$.



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Projective Order

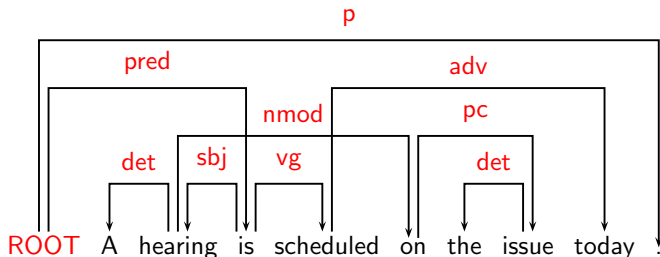
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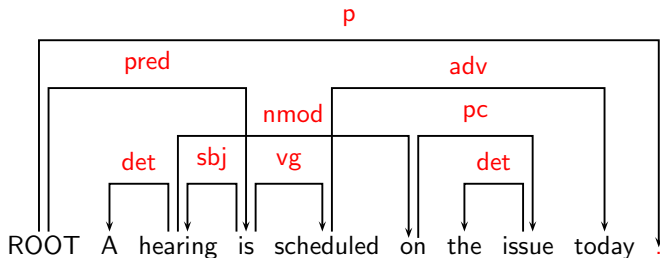
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Sorting into Projective Order

- ▶ Basic idea:
 - ▶ Combine an algorithm for sorting words according to the projective order $<_p$ with a transition-based algorithm for constructing a projective dependency tree
- ▶ Requirements on sorting algorithm:
 - ▶ Online algorithm (sorts in a single left-to-right pass)
 - ▶ Exchange sort (sorts by swapping elements)
 - ▶ Comparison of adjacent elements (cf. parsing algorithm)
- ▶ The simplest sorting algorithm:
 - ▶ Gnome sort – insertion sort with only adjacent swaps

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Transition System: Configurations

- ▶ A parser configuration is a triple $c = (S, Q, A)$, where
 - ▶ $S =$ a stack $[\dots, w_i]_S$ of partially processed nodes,
 - ▶ $Q =$ a stack $[w_j, \dots]_Q$ of remaining input nodes,
 - ▶ $A =$ a set of arcs (w_i, w_j, l) .

- ▶ Initialization:

$$([w_0]_S, [w_1, \dots, w_n]_Q, \{\})$$

NB: $w_0 = \text{ROOT}$

- ▶ Termination:

$$([w_0]_S, [], A)$$

Transition System: Transitions

► Swap

$$\frac{([\dots, w_i, w_j]_S, [\dots]_Q, A) \quad [i \neq 0, i < j]}{([\dots, w_j]_S, [w_i, \dots]_Q, A)}$$

► Left-Arc(l)

$$\frac{([\dots, w_i, w_j]_S, Q, A) \quad [i \neq 0]}{([\dots, w_j]_S, Q, A \cup \{(w_j, w_i, l)\})}$$

► Right-Arc(l)

$$\frac{([\dots, w_i, w_j]_S, Q, A)}{([\dots, w_i]_S, Q, A \cup \{(w_i, w_j, l)\})}$$

► Shift

$$\frac{([\dots]_S, [w_i, \dots]_Q, A)}{([\dots, w_i]_S, [\dots]_Q, A)}$$

Deterministic Parsing

- ▶ Given an **oracle** o that correctly predicts the next transition $o(c)$, parsing is deterministic:

```

Parse( $w_1, \dots, w_n$ )
1   $c \leftarrow ([w_0]_S, [w_1, \dots, w_n]_Q, \{\})$ 
2  while  $Q_c \neq []$  or  $|S_c| > 1$ 
3       $t \leftarrow o(c)$ 
4       $c \leftarrow t(c)$ 
5  return  $G = (\{w_0, w_1, \dots, w_n\}, A_c)$ 

```


Example

$o(c) = \text{Shift}$

$[[\text{ROOT}]_S \text{ [A hearing is scheduled on the issue today .]}_Q]$

ROOT A hearing is scheduled on the issue today .

Example

$o(c) = \text{Shift}$

[[ROOT A]]_S [[hearing is scheduled on the issue today .]]_Q

ROOT A hearing is scheduled on the issue today .

Example

$o(c) = \text{Left-Arc}_{det}$


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


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


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


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Example

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[[ROOT hearing is scheduled on]]_S [[the issue today .]]_Q




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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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


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


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


 ROOT A hearing is scheduled on the issue today .

Example

$o(c) = \text{Left-Arc}_{det}$

[[ROOT hearing on the issue]]_S [[is scheduled today .]]_Q

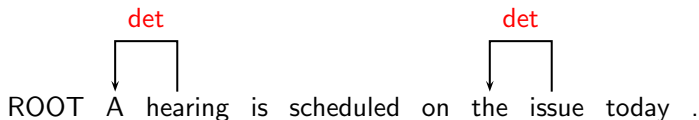


 ROOT A hearing is scheduled on the issue today .

Example

$o(c) = \text{Right-Arc}_{pc}$

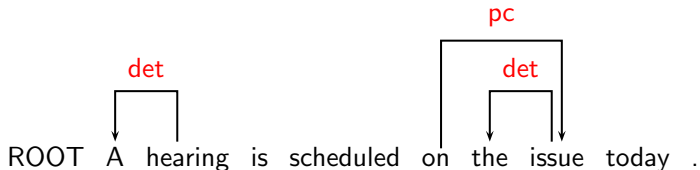
[[ROOT hearing on issue]]_S [[is scheduled today .]]_Q



Example

$o(c) = \text{Right-Arc}_{nmod}$

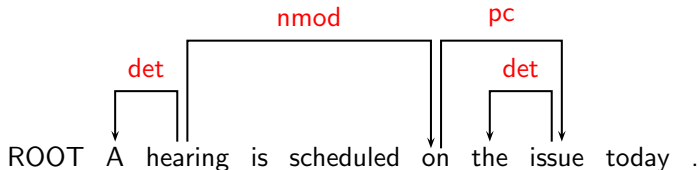
[[ROOT hearing on]]_S [[is scheduled today .]]_Q



Example

$o(c) = \text{Shift}$

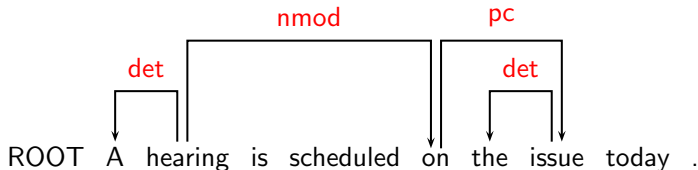
[[ROOT hearing]]_S [[is scheduled today .]]_Q



Example

$o(c) = \text{Left-Arc}_{sbj}$

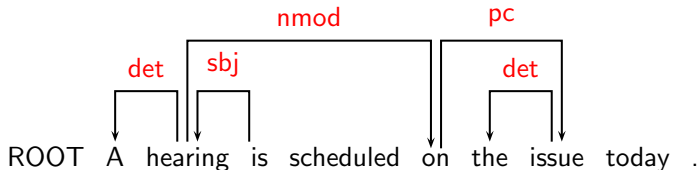
[[ROOT hearing is]]_S [[scheduled today .]]_Q



Example

$o(c) = \text{Shift}$

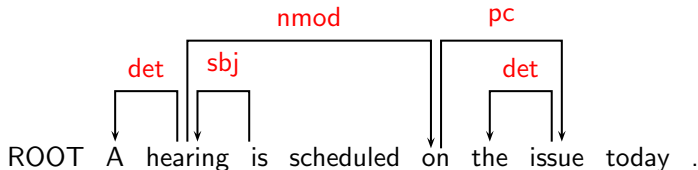
[[ROOT is]]_S [[scheduled today .]]_Q



Example

$o(c) = \text{Shift}$

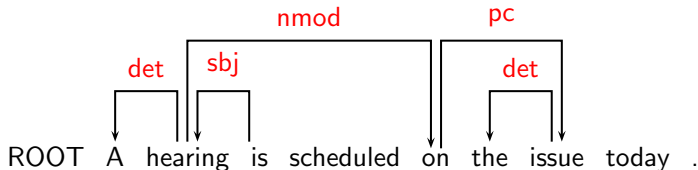
[[ROOT is scheduled]]_S [[today .]]_Q



Example

$o(c) = \text{Right-Arc}_{adv}$

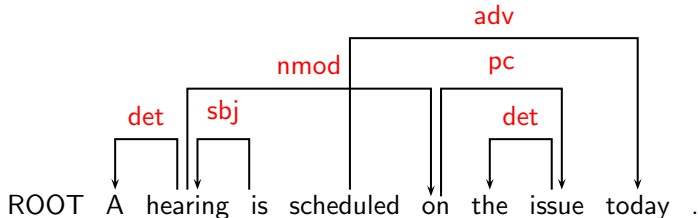
[[ROOT is scheduled today]]_S [[.]]_Q



Example

$o(c) = \text{Right-Arc}_{vg}$

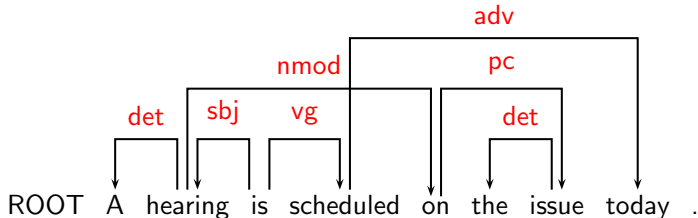
$[[\text{ROOT is scheduled}]_s \quad [.]_Q$



Example

$o(c) = \text{Right-Arc}_{\text{pred}}$

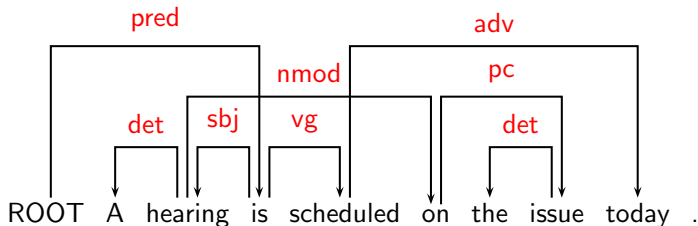
$[[\text{ROOT is}]_S \quad [.]_Q$



Example

$o(c) = \text{Shift}$

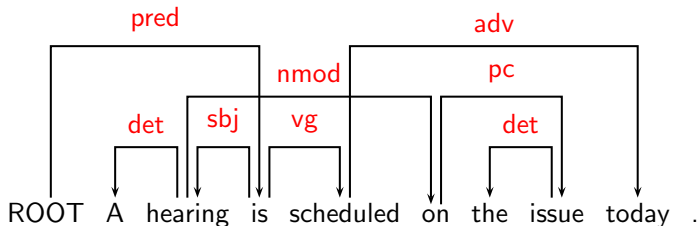
$[[\text{ROOT}]_s \quad [\cdot]_q$



Example

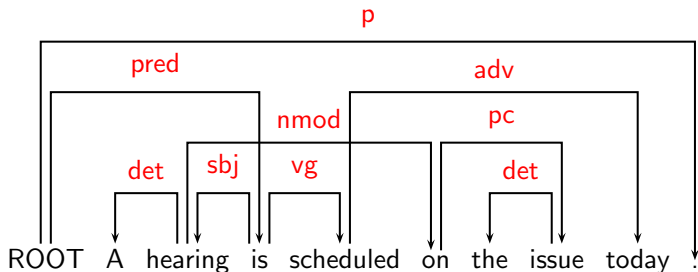
$o(c) = \text{Right-Arc}_p$

$[[\text{ROOT } \cdot]_s \quad []_q]$



Example

$[[\text{ROOT}]_s \quad []_q$



Algorithm Analysis

- ▶ Time complexity of parsing:
 - ▶ $O(n^2)$ in the worst case ($\frac{n(n-1)}{2}$ swaps)
 - ▶ $O(n)$ in the best case (0 swaps)
 - ▶ Average case \approx best case?
- ▶ Conjecture:
 - ▶ Sound and complete for non-projective dependency trees
- ▶ Crucial question:
 - ▶ Can we train classifiers to do sorting as well as parsing?

Experimental Evaluation

- ▶ Data from the CoNLL shared tasks
[Buchholz and Marsi 2006, Nivre et al. 2007]:
 - ▶ Prague Arabic Dependency Treebank (2007) (2.9k, 10.1%)
 - ▶ Prague Dependency Treebank (2007) (25.4k, 23.2%)
 - ▶ Slovene Dependency Treebank (2006) (1.5k, 22.2%)
 - ▶ Metu-Sabancı Turkish Treebank (2007) (5.6k, 33.3%)
- ▶ Classifiers:
 - ▶ Support vector machines with polynomial kernel (degree 2)
 - ▶ Feature models optimized on development set
- ▶ Evaluation metric:
 - ▶ Labeled attachment score (LAS): Percentage of words that are assigned the correct head and dependency label

Preliminary Results

Parser	Arabic	Czech	Slovene	Turkish	Average
Projective					
Pseudo-projective					
Non-projective					
MaltParser 06/07					
Top score 06/07					

Preliminary Results

Parser	Arabic	Czech	Slovene	Turkish	Average
Projective	75.8	74.0	73.3	79.0	75.5
Pseudo-projective					
Non-projective					
MaltParser 06/07					
Top score 06/07					

Preliminary Results

Parser	Arabic	Czech	Slovene	Turkish	Average
Projective	75.8	74.0	73.3	79.0	75.5
Pseudo-projective	76.1	78.2	74.6	79.6	77.1
Non-projective					
MaltParser 06/07					
Top score 06/07					

Preliminary Results

Parser	Arabic	Czech	Slovene	Turkish	Average
Projective	75.8	74.0	73.3	79.0	75.5
Pseudo-projective	76.1	78.2	74.6	79.6	77.1
Non-projective	76.2	79.2	75.4	79.6	77.6
MaltParser 06/07					
Top score 06/07					

Preliminary Results

Parser	Arabic	Czech	Slovene	Turkish	Average
Projective	75.8	74.0	73.3	79.0	75.5
Pseudo-projective	76.1	78.2	74.6	79.6	77.1
Non-projective	76.2	79.2	75.4	79.6	77.6
MaltParser 06/07	74.8	77.2	70.3	79.2	75.4
Top score 06/07	76.5	80.2	73.4	79.8	77.5

Conclusion

- ▶ Transition-based dependency parsing:
 - ▶ Efficient thanks to greedy, deterministic search
 - ▶ Accurate thanks to powerful discriminative classification
- ▶ Novel approach to non-projective dependency parsing:
 - ▶ Interleaved sorting and parsing
 - ▶ Efficiency maintained
 - ▶ Promising empirical results

Acknowledgments

- ▶ My students and co-developers of MaltParser:
 - ▶ Johan Hall and Jens Nilsson
- ▶ Useful comments from:
 - ▶ John Carroll, Carlos Gómez-Rodríguez, Marco Kuhlmann, Ryan McDonald, Paola Merlo, Jamie Henderson, Peter Ljunglöf, Bengt Nordström, Kenji Sagae, David Weir and three anonymous reviewers

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