Sorting Out Dependency Parsing

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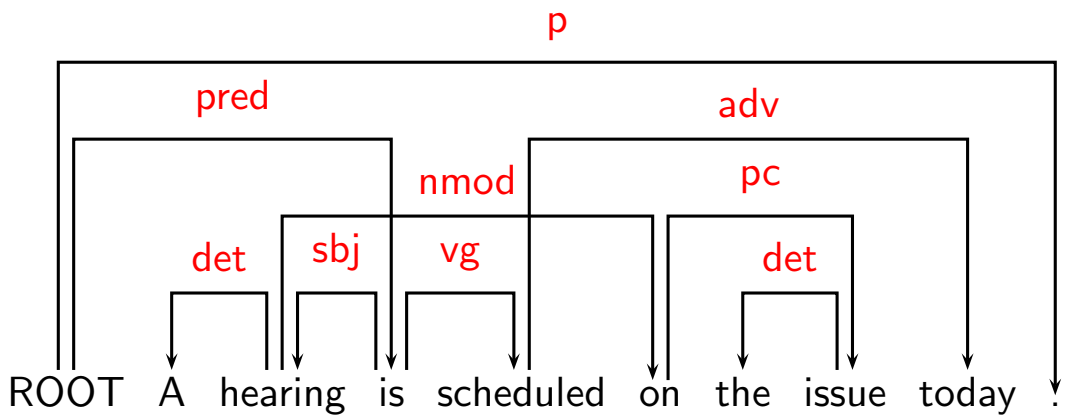
Introduction

- 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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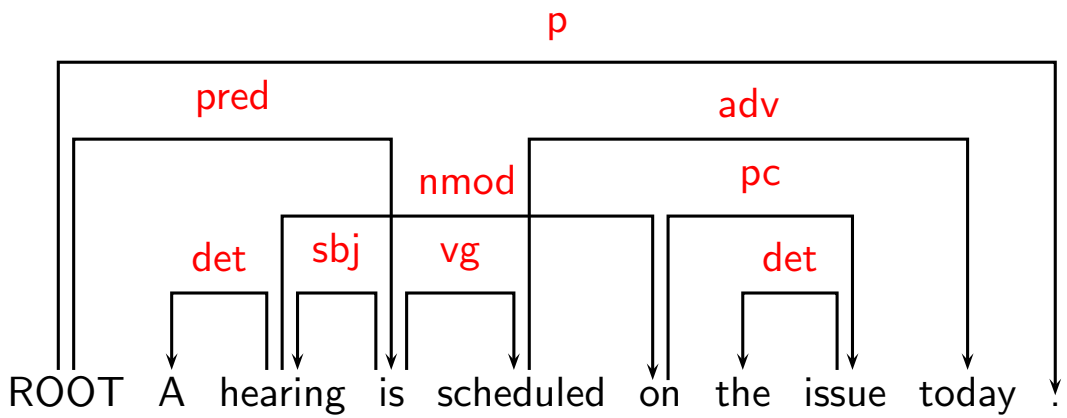

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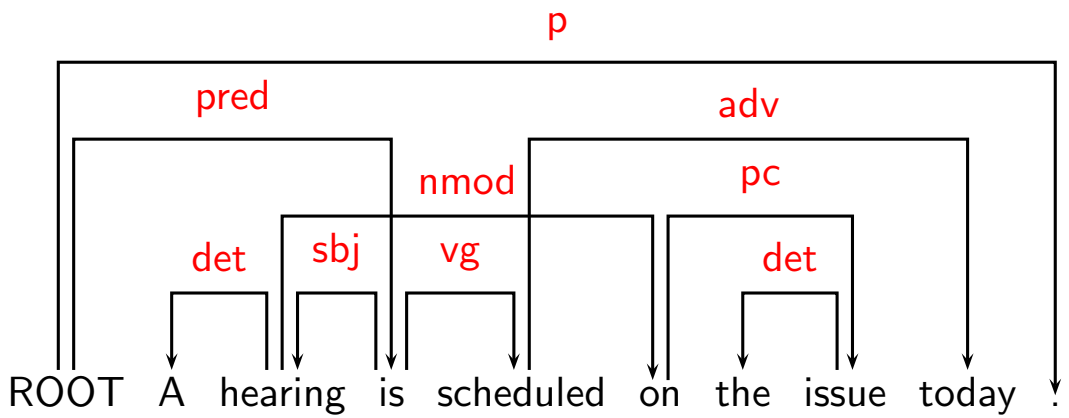


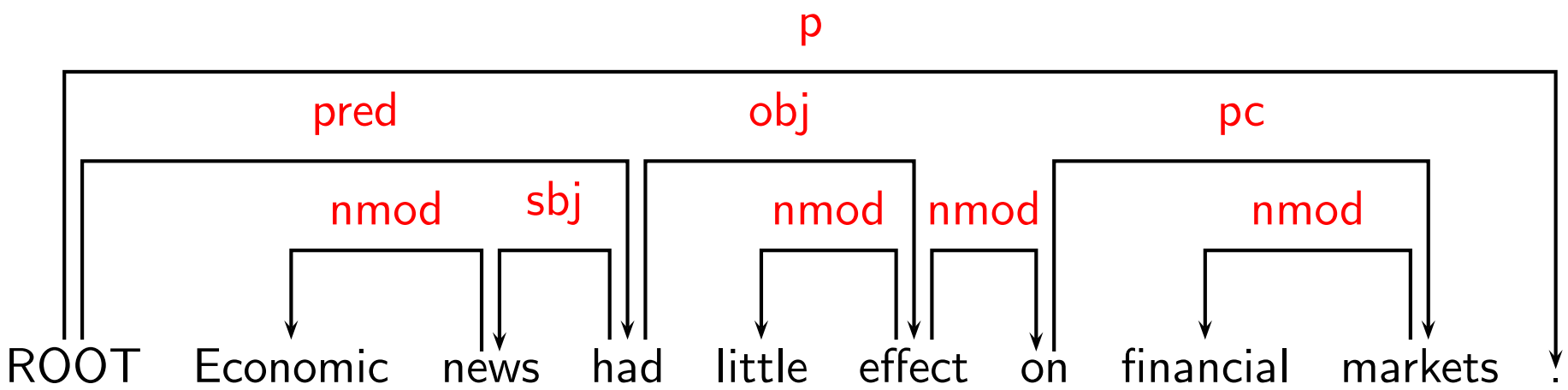
Structure of This Talk

- 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

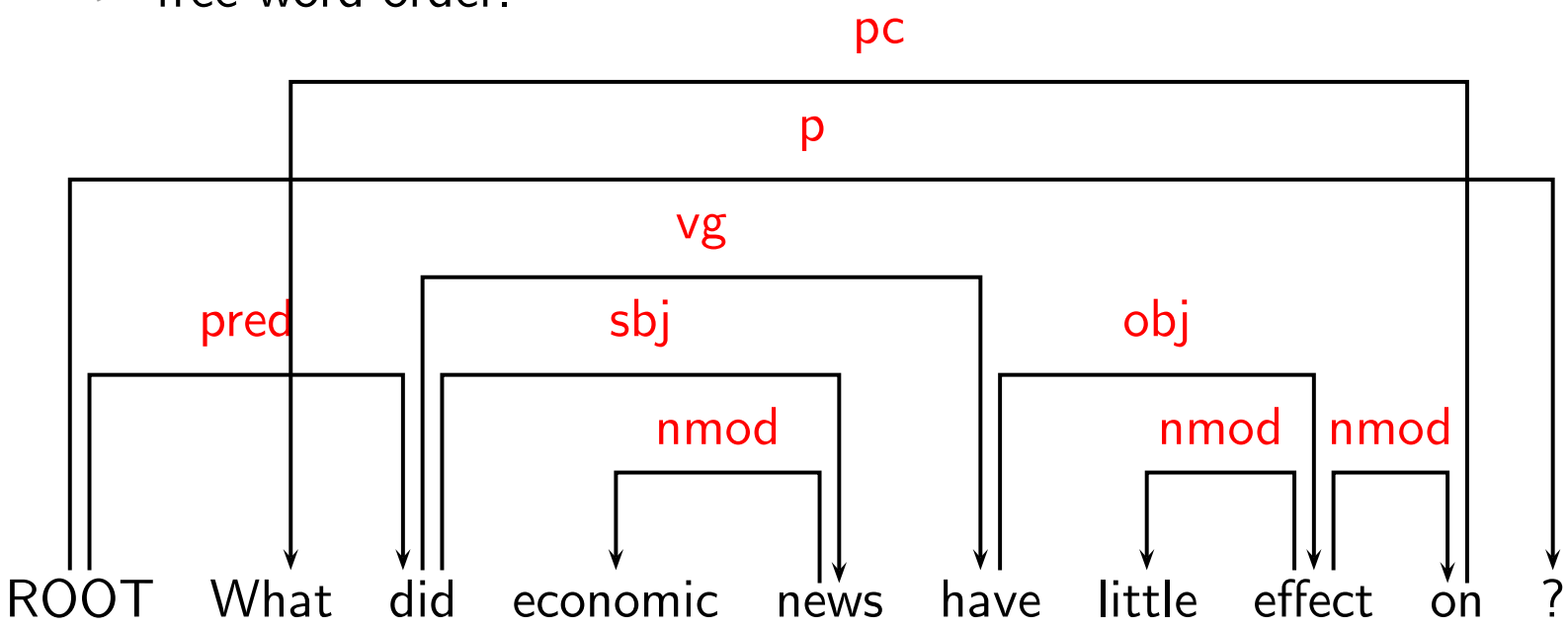


Dependency Graphs

- A dependency structure is a directed graph G, 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.
- Formal conditions on dependency graphs:
  - Rooted: No arcs into ROOT.
  - Connected: G is (weakly) connected.
  - Single-Head: No node with an in-degree > 1.
- **Note:** A rooted, connected, single-head graph is a tree.

Projectivity

- A dependency graph G is projective iff
  - for every arc $w_i \rightarrow w_j$ and every word 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 graphs for a sentence
  - Learning: Induce a model for scoring an entire dependency graph for a sentence
  - Inference: Find the highest-scoring dependency graph, 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 graph
  - 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 $[\ldots, w_i]_S$ of partially processed words,
  - Q = a queue $[w_j, \ldots]_Q$ of remaining input words,
  - A = a set of arcs (w_i, w_j, l).
- Initialization:

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

  NB: $w_0 = \text{ROOT}$
- Termination:

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

Transition System: Transitions

- Left-Arc(l)

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

- Right-Arc(l)

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

- Shift

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

Deterministic Parsing

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

Parse$(w_1, \ldots, w_n)$
1 $c \leftarrow ([w_0]_S, [w_1, \ldots, w_n]_Q, \{\})$
2 **while** Q_c is not empty
3 $c \leftarrow \text{Shift}(c)$
4 $t \leftarrow o(c)$
5 **while** $t \in \{\text{Left-Arc}(l), \text{Right-Arc}(l)\}$
6 $c = t(c)$
7 $t = o(c)$
8 **return** $G = (\{w_0, w_1, \ldots, w_n\}, A_c)$

Example

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

$[\![\text{ROOT}]\!]_S$ $[\![\text{Economic news had little effect on financial markets .}]\!]_Q$

ROOT Economic news had little effect on financial markets .

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

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

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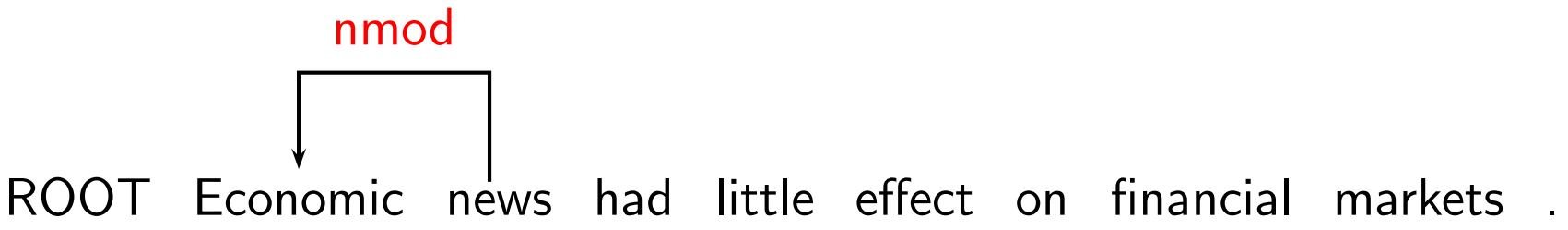
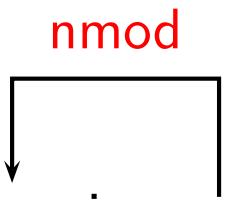


Example

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

$[\![\text{ROOT}\ \ \text{news}\ \ \text{had}]\!]_S\ \ [\![\text{little}\ \ \text{effect}\ \ \text{on}\ \ \text{financial}\ \ \text{markets}\ \ .]\!]_Q$



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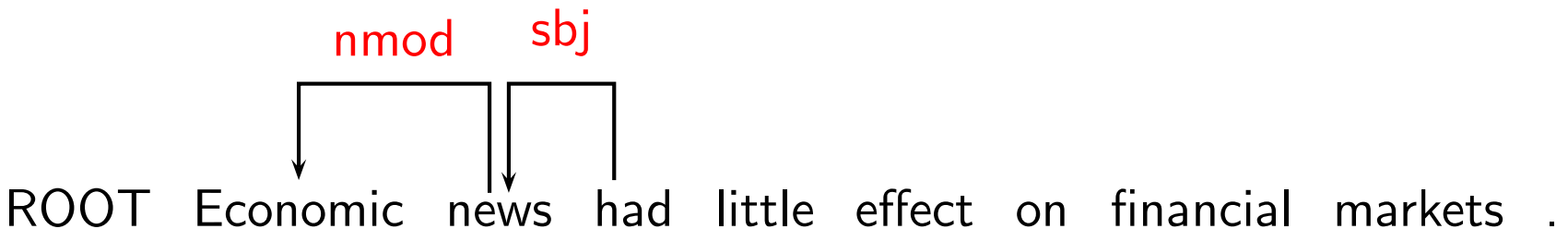

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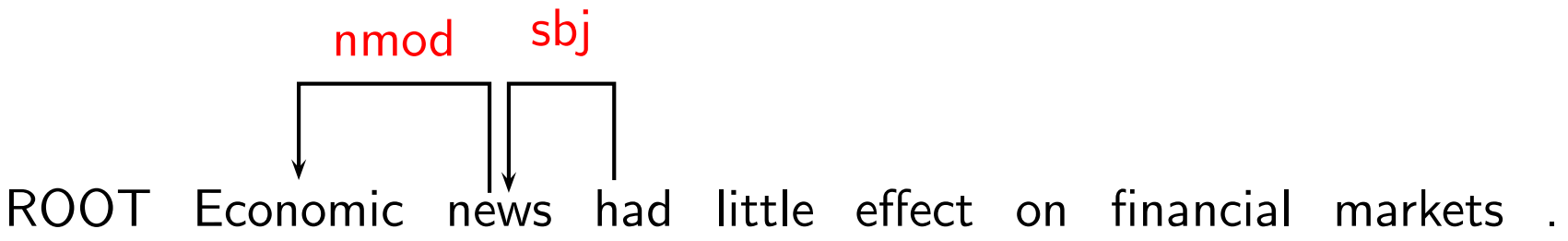

Example

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

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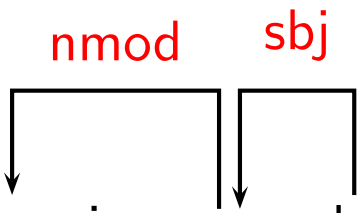

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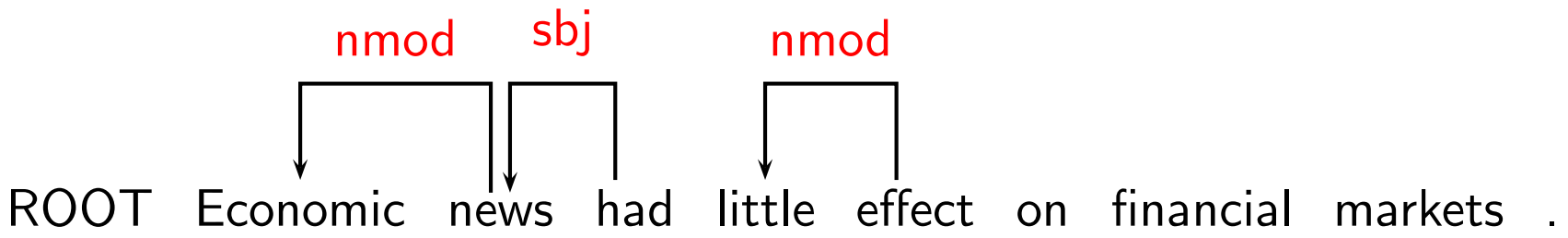

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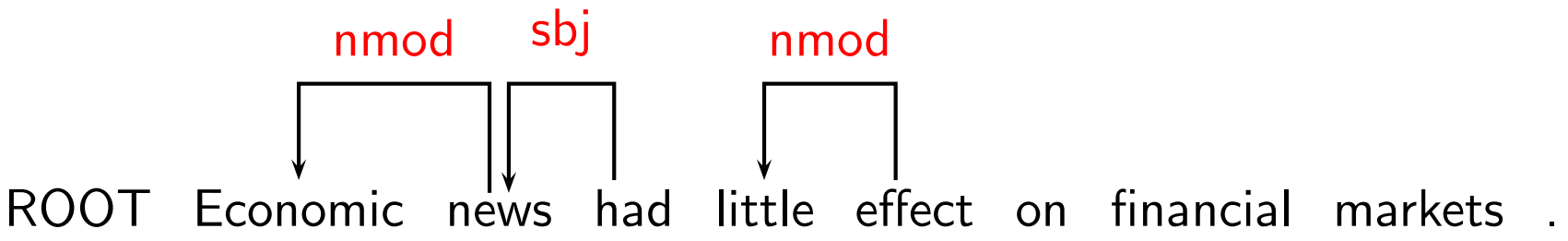

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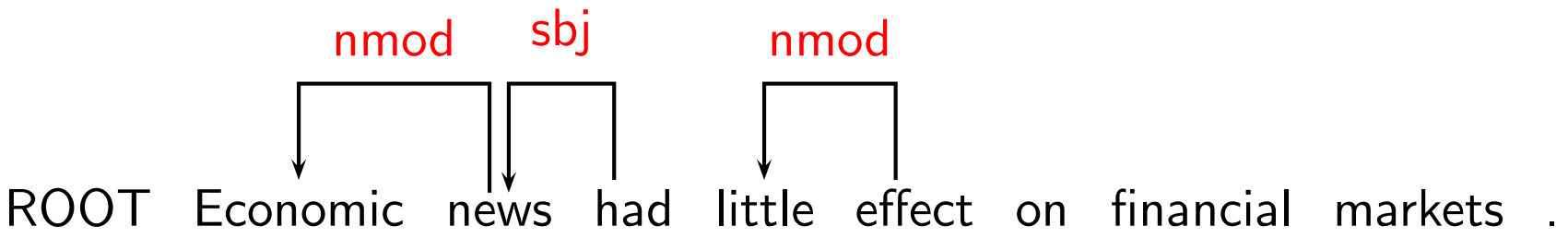

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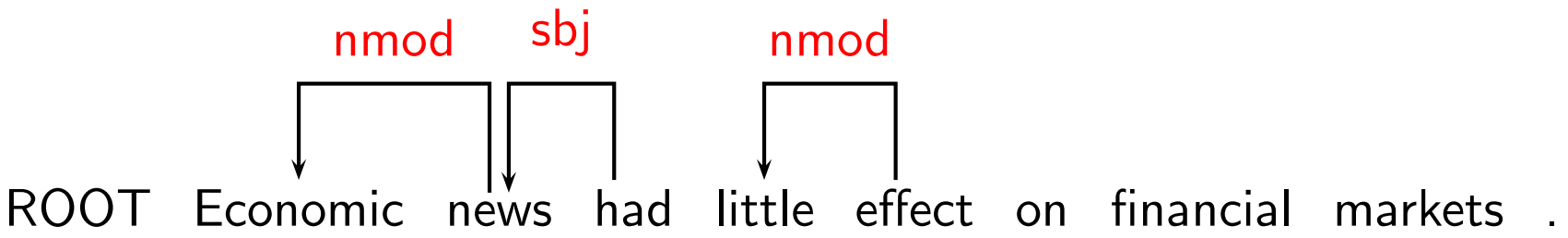
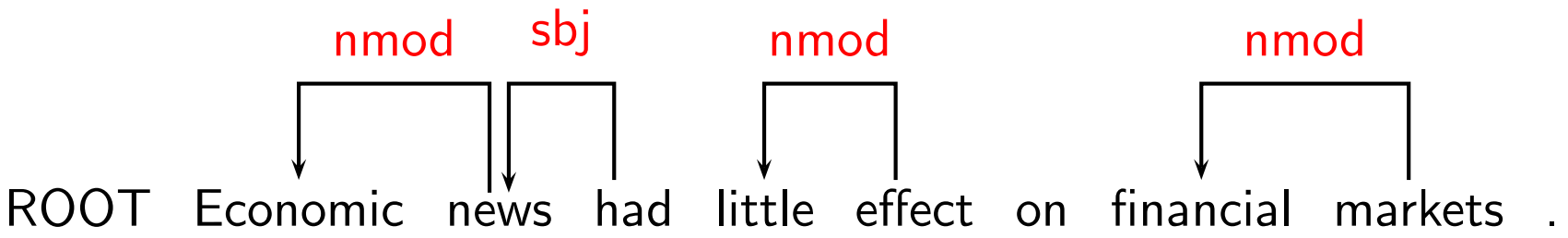


Example

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

$[\![\text{ROOT}\ \ \text{had}\ \ \text{effect}\ \ \text{on}\ \ \text{markets}]\!]_S\ \ [\![.]\!]_Q$



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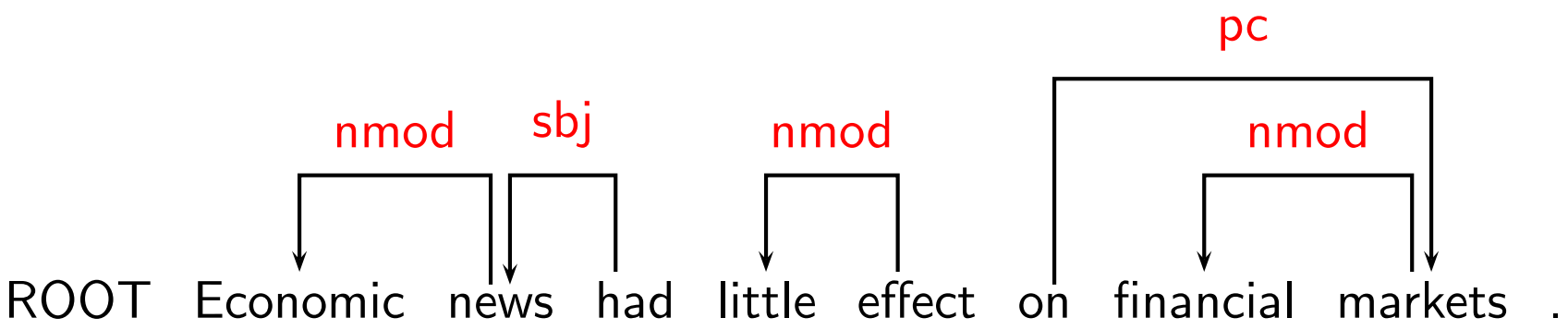
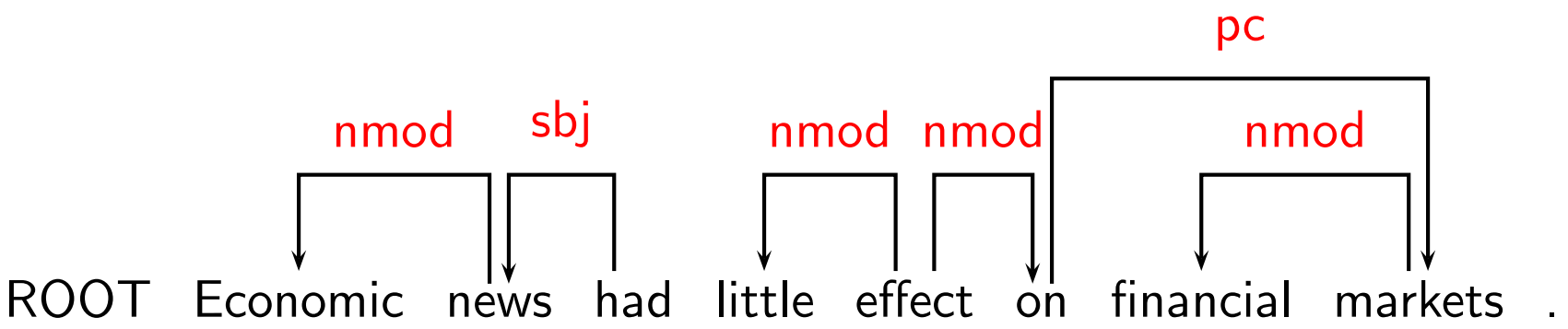


Example

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

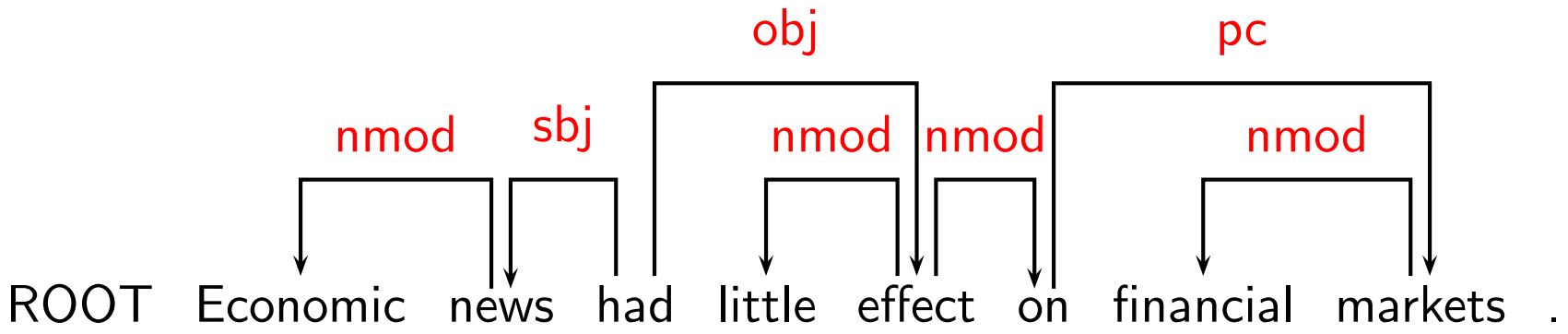
$[\![\text{ROOT}\ \ \text{had}\ \ \text{effect}]\!]_S\ \ [\![.]\!]_Q$



Example

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

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



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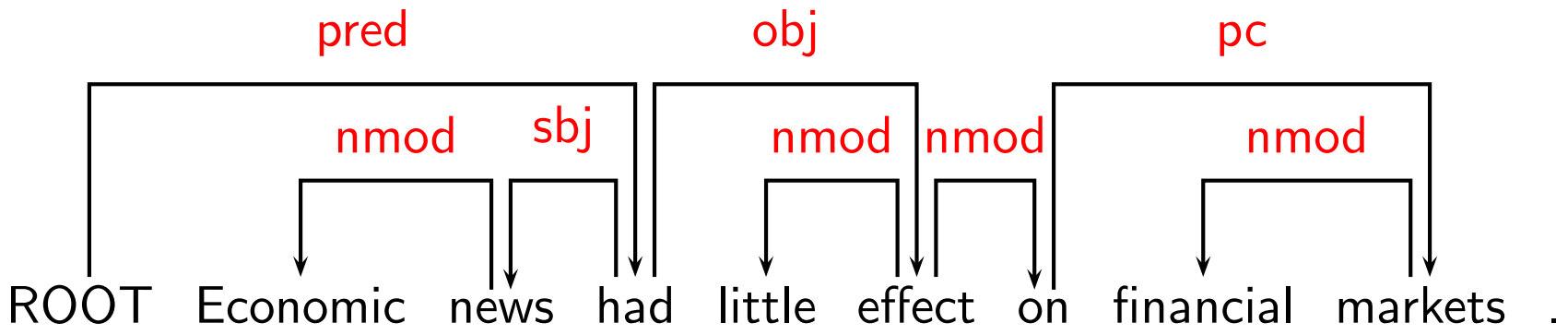
$o(c) = \text{Shift}$

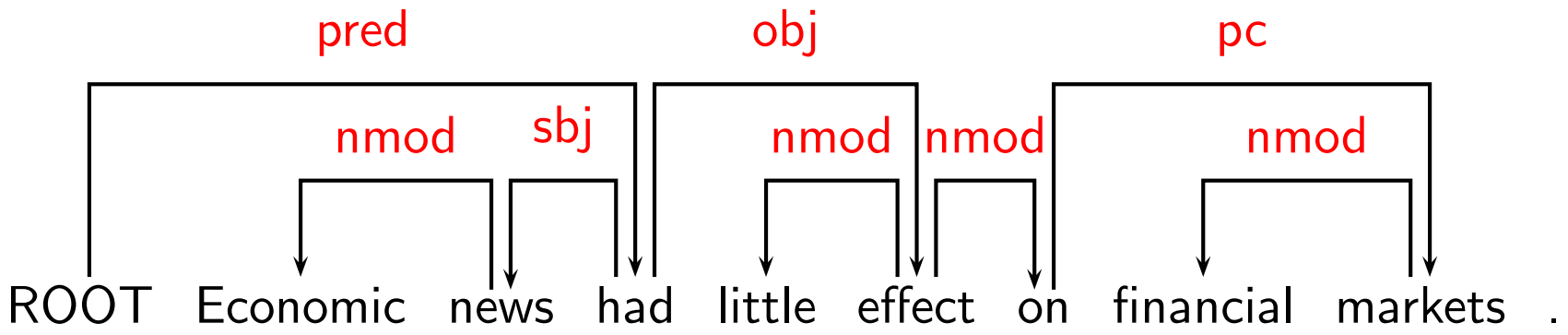
$[\![\text{ROOT}]\!]_S \quad [\![.]\!]_Q$



Example

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

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



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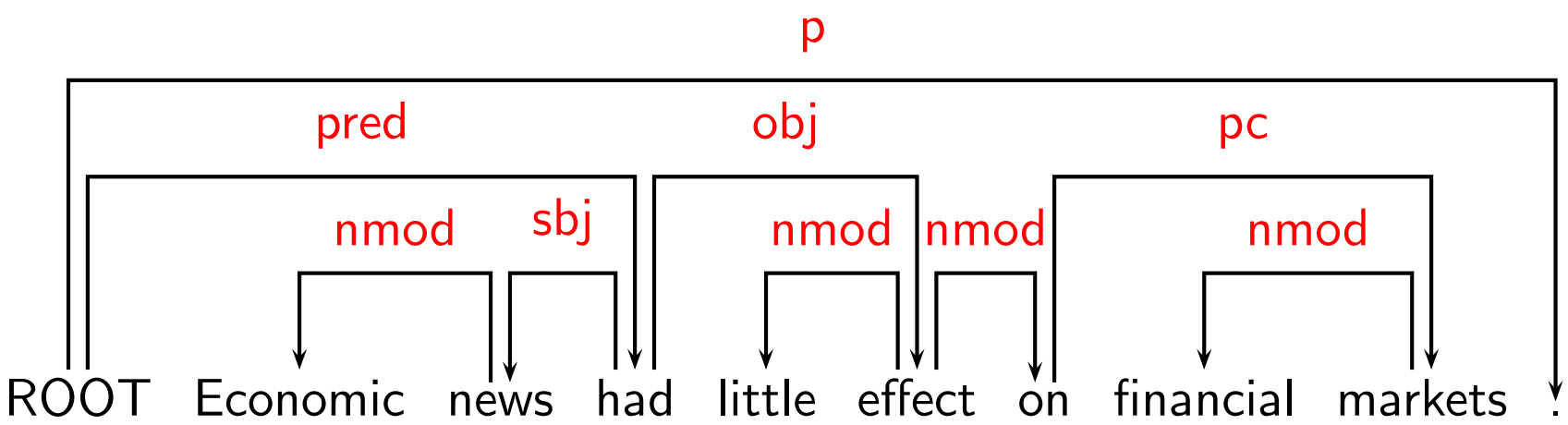


Algorithm Analysis

- 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.

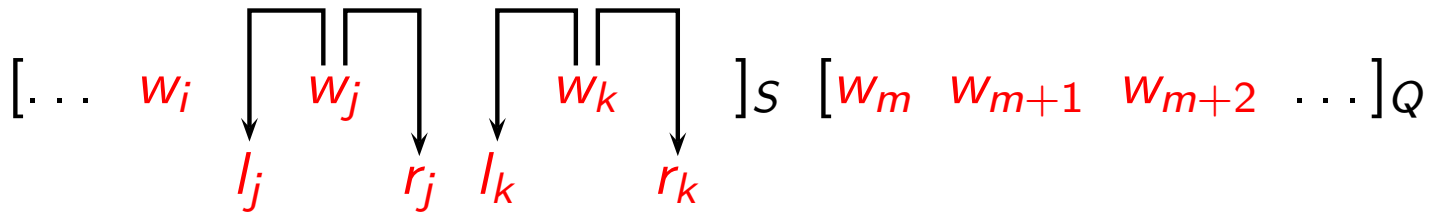
Alternative Parsing Algorithms

- 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 graph (DEPREL)

A Typical Feature Model



FORM			+			+			+			
LEMMA			+			+						
POSTAG		+		+			+			+	+	+
FEATS			+			+						
DEPREL				+		+	+	+				

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 $C_{0,m} = (c_0, c_1, \ldots, c_m)$ 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 graphs
  - Deterministic linear-time parsing with oracle
  - Oracles approximated by classifiers trained on treebank data
- However:
  - Limited to projective dependency graphs
  - What to do with discontinuous constructions?

Non-Projective Dependency Parsing

What's the Problem?

- Non-projective dependency graphs 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

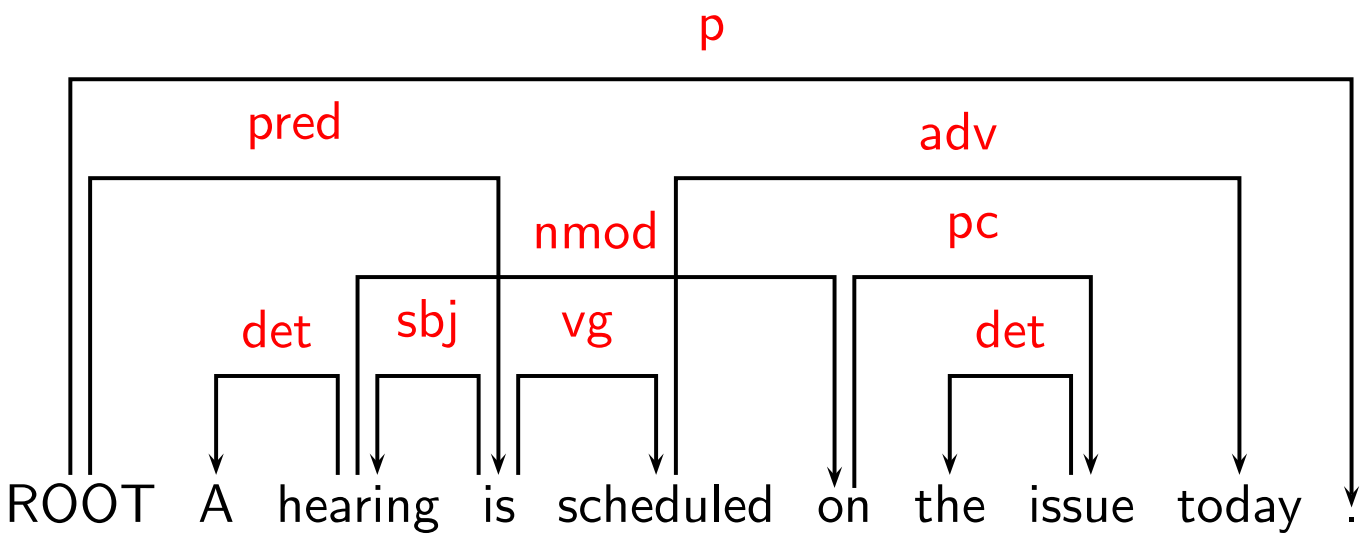
- Algorithms for non-projective dependency parsing:
  - Graph-based parsing using the Chu-Liu-Edmonds algorithm [McDonald et al. 2005b]
  - Transition-based parsing for restricted [Attardi 2006] or arbitrary [Nivre 2007] non-projective structures
- Post-processing of projective dependency graphs:
  - 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 graph only in relation to a particular word order.
- Words can always be reordered to make the graph projective.



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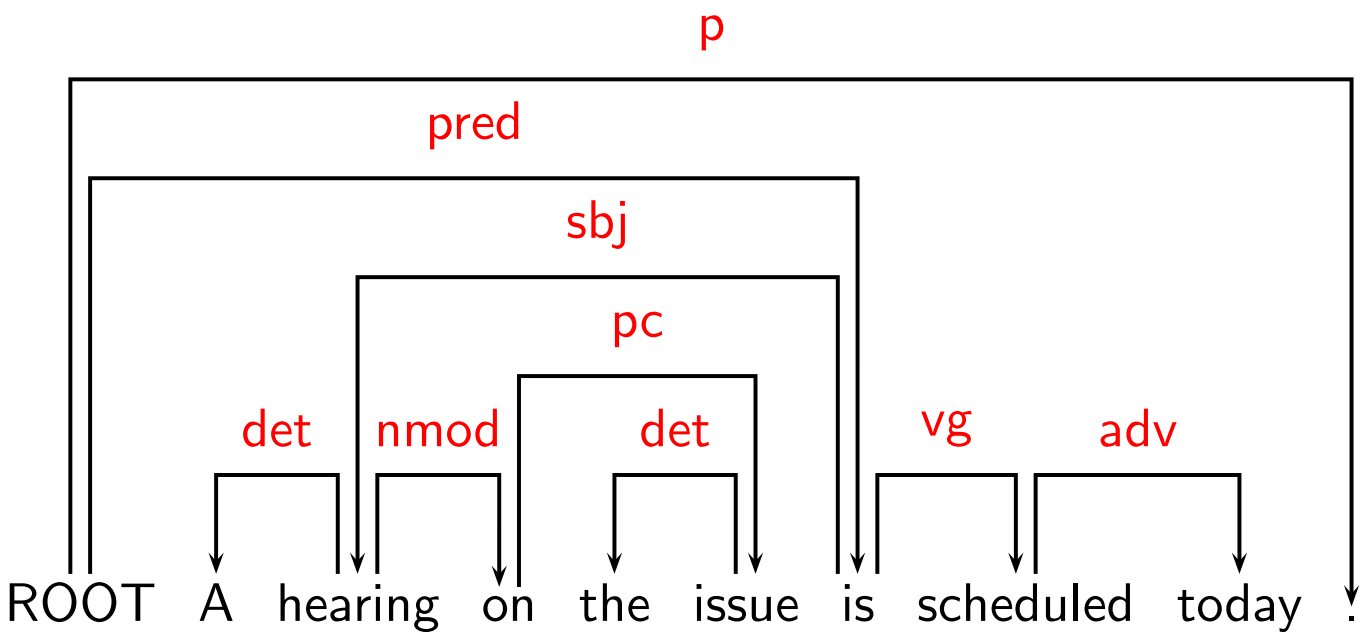
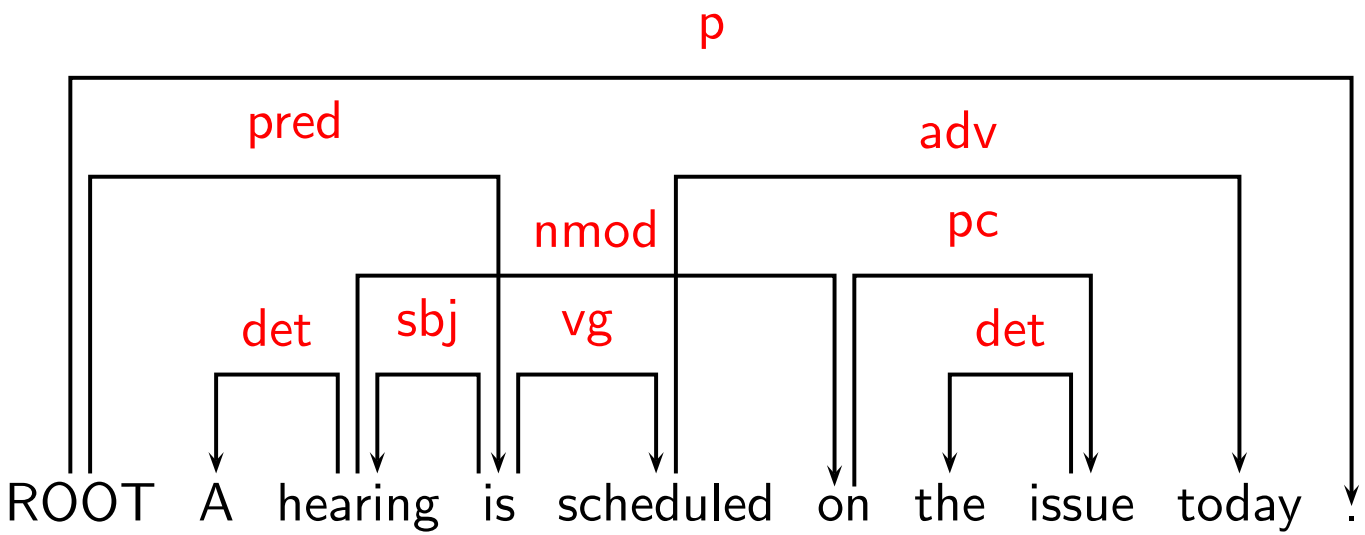


Projective Order

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



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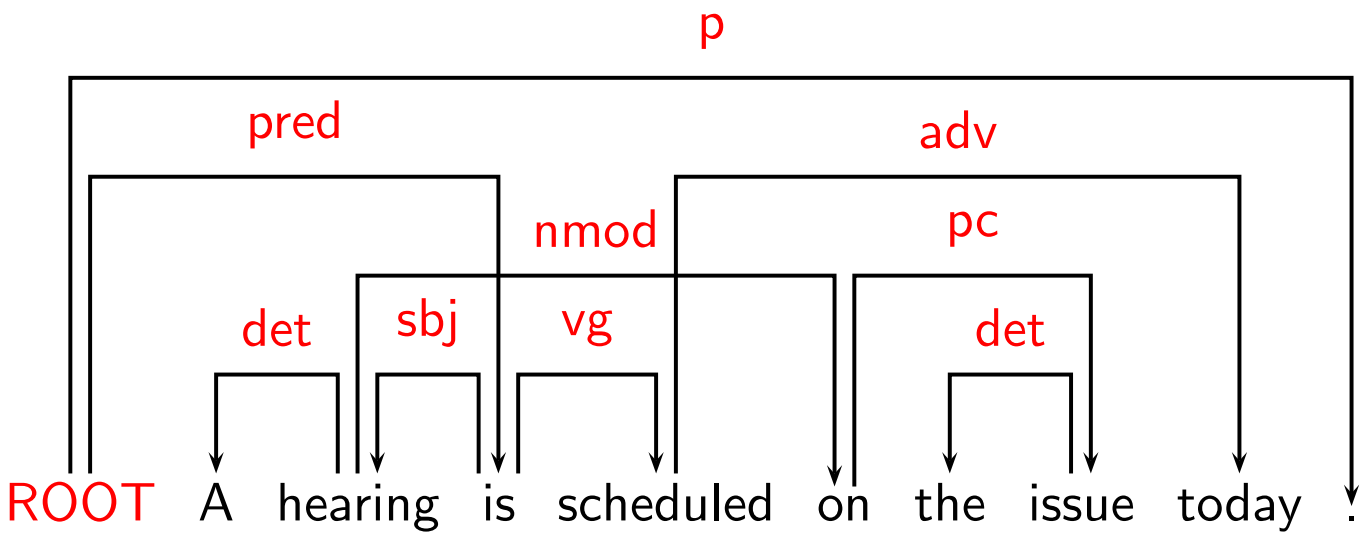

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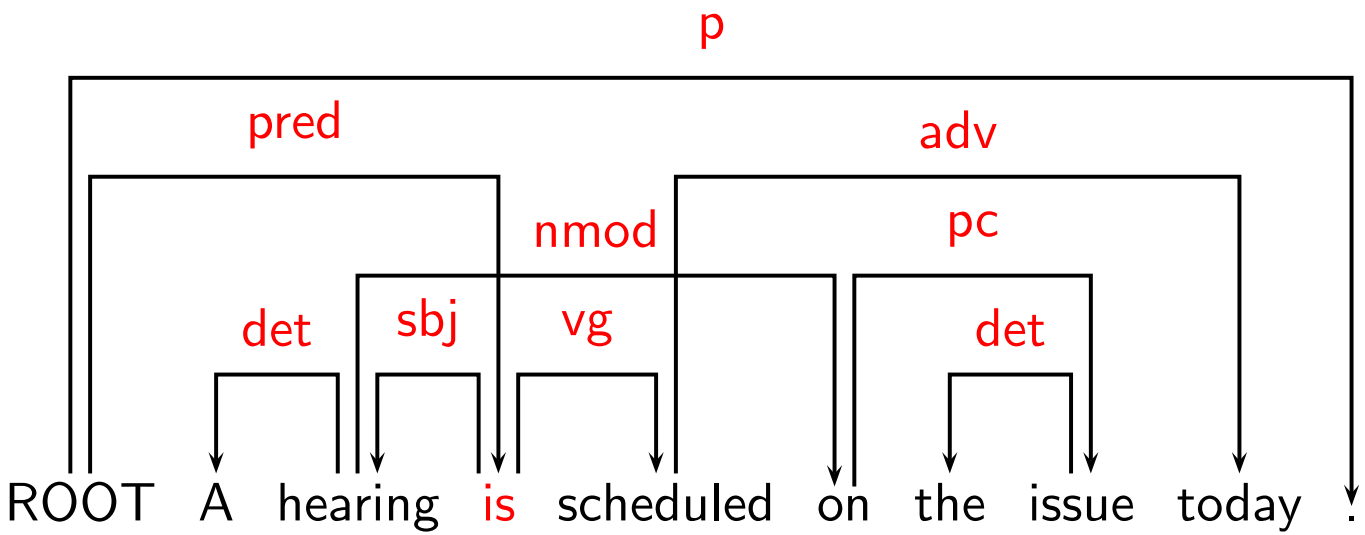

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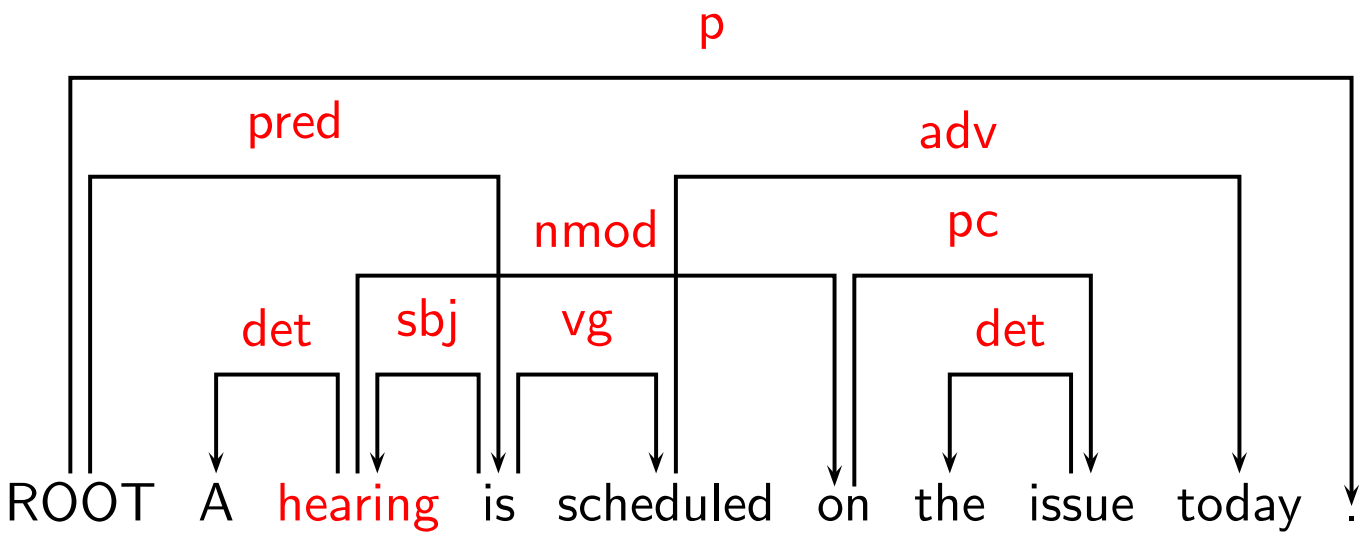

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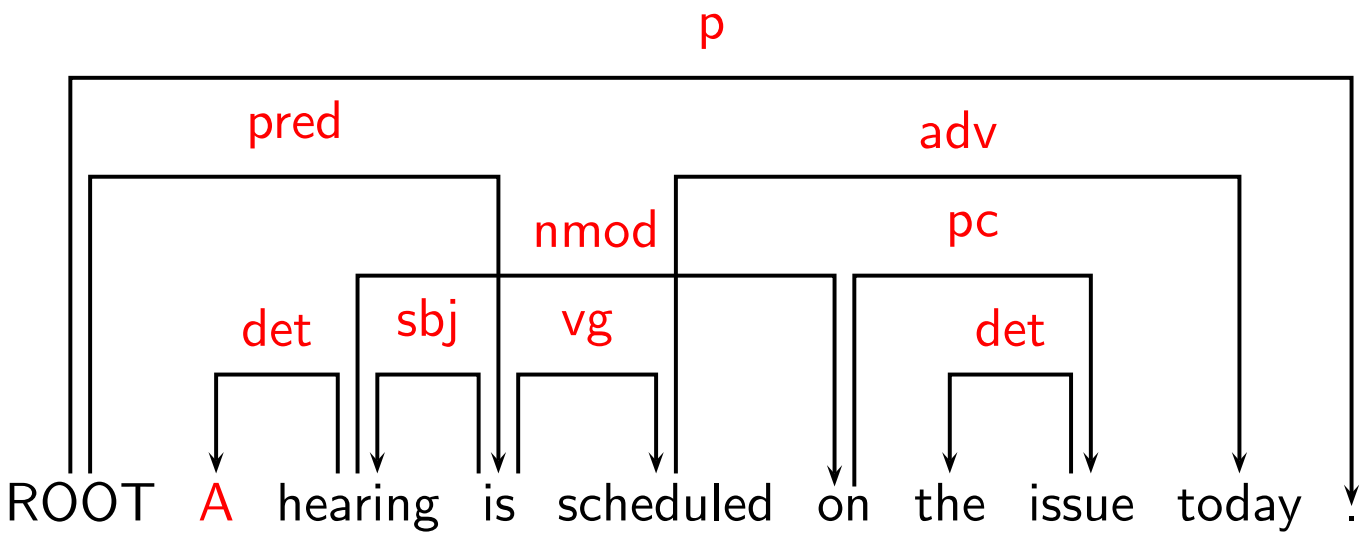
Projective Order

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



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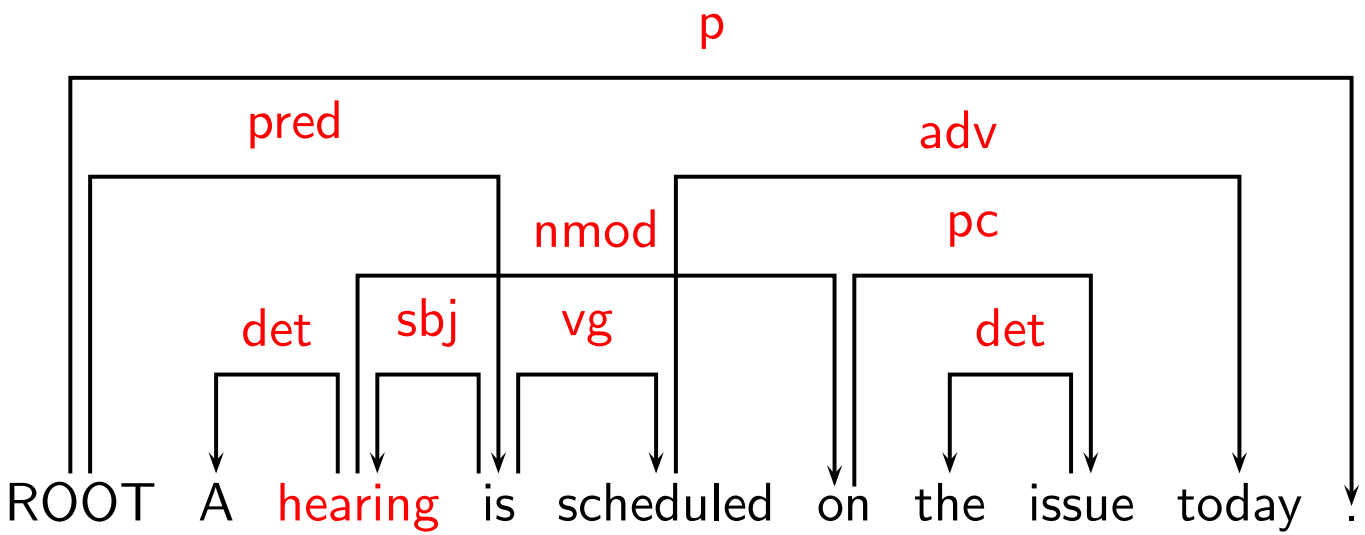

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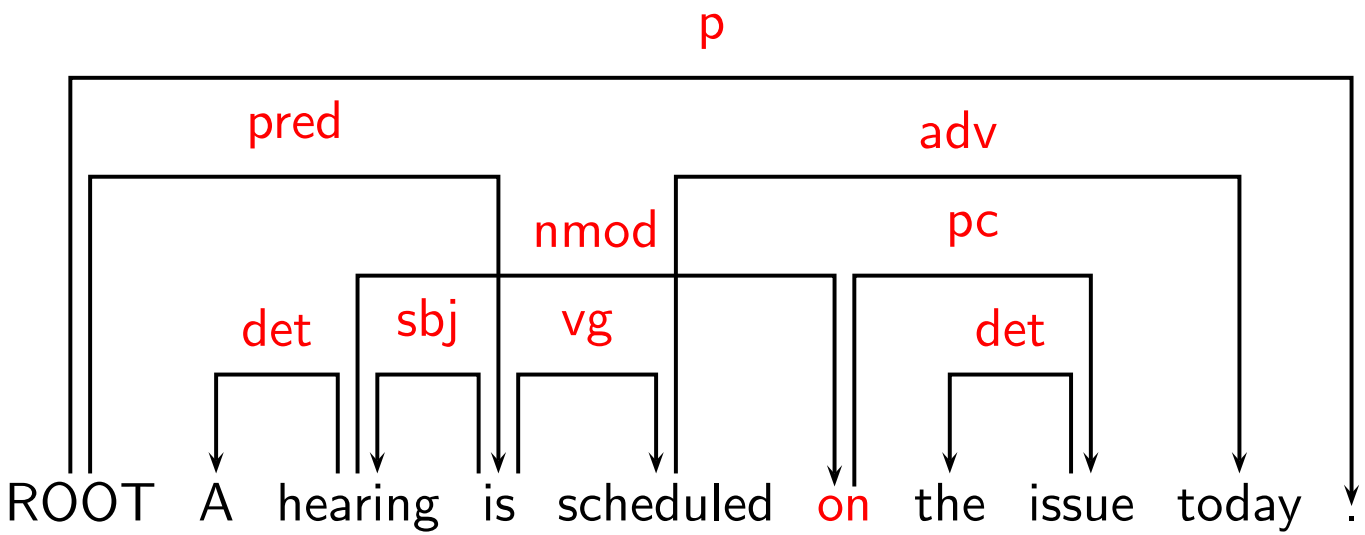

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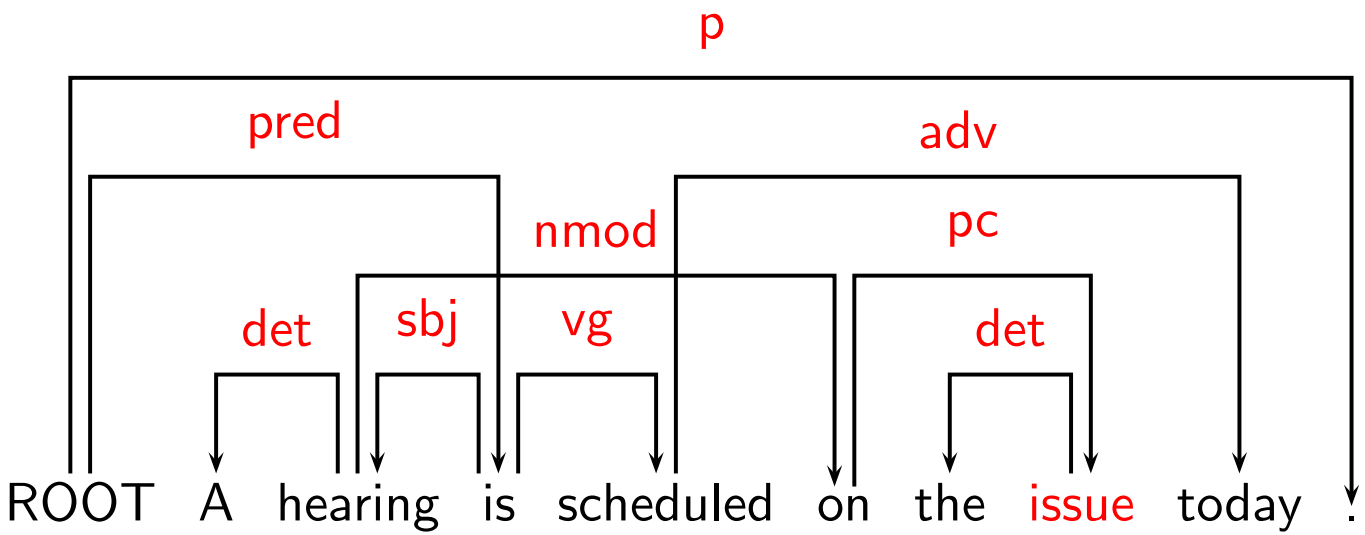

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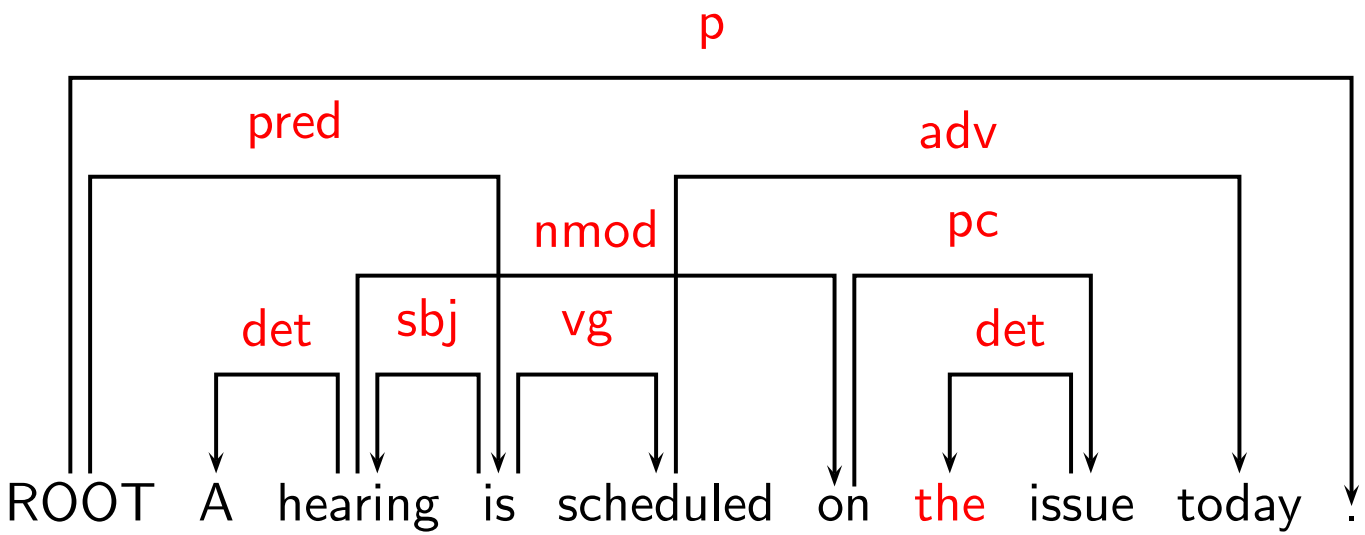

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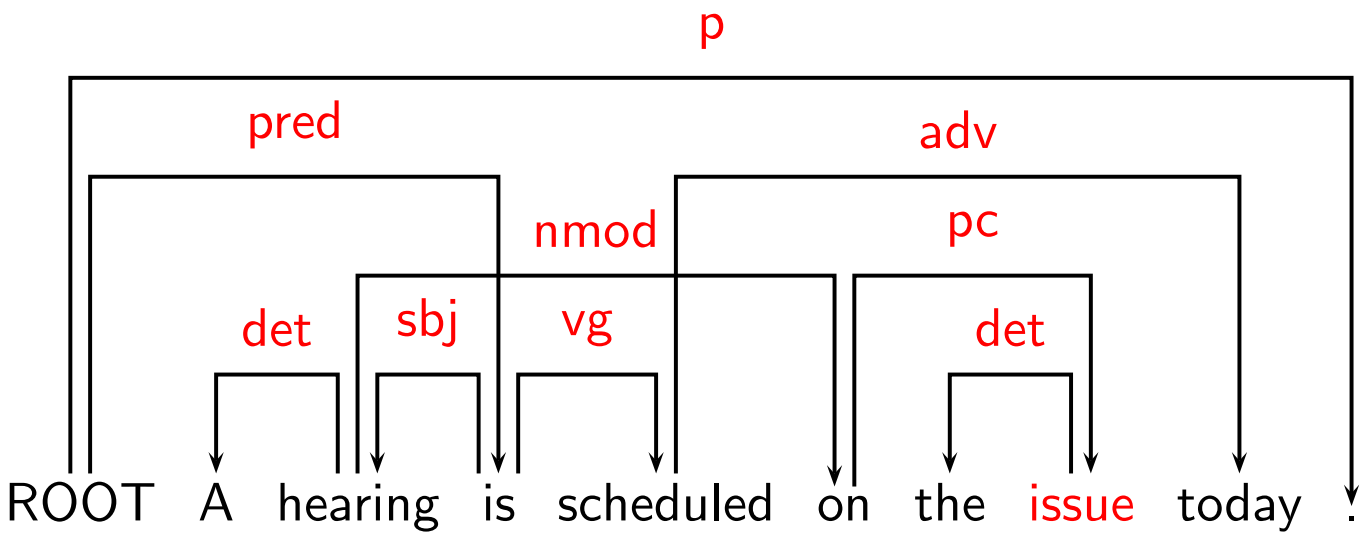

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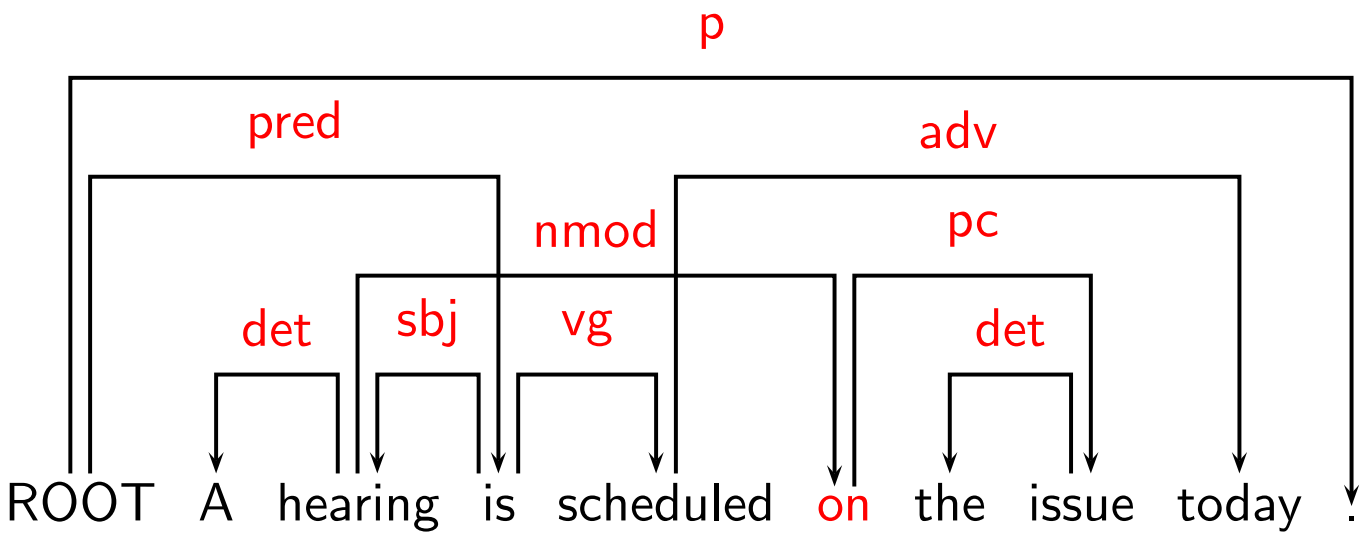

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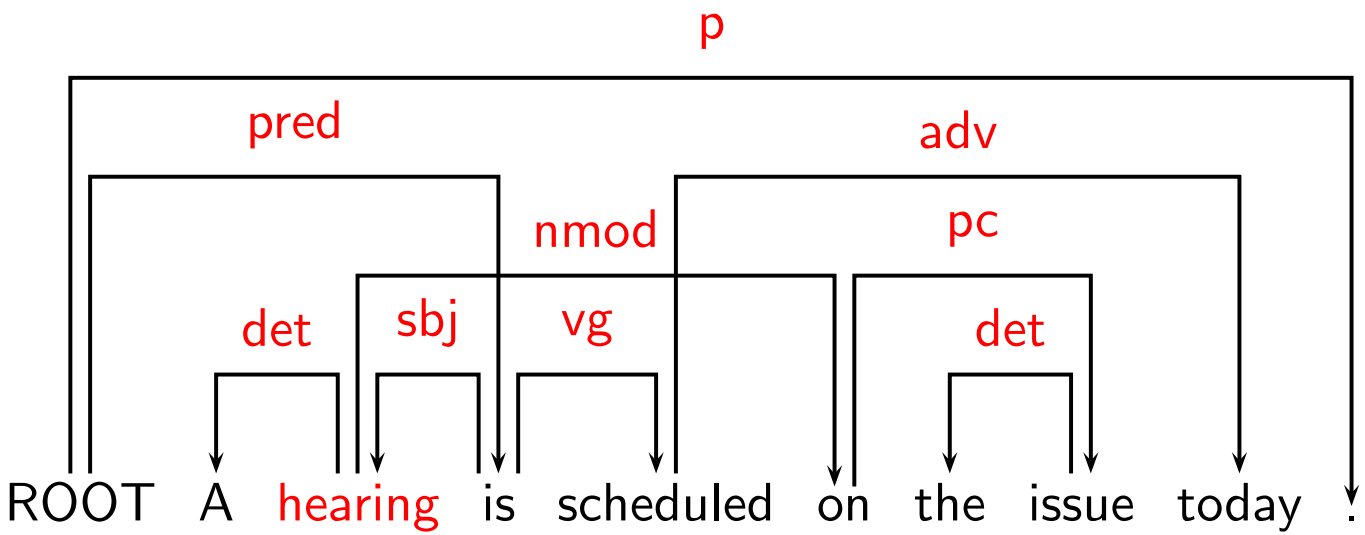

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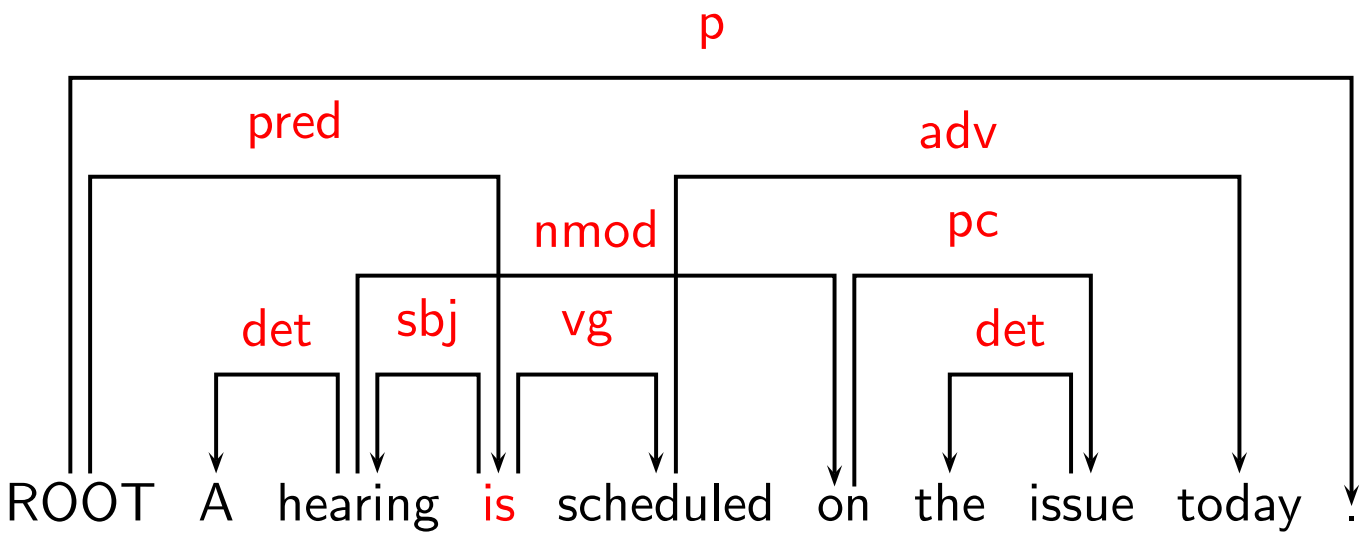

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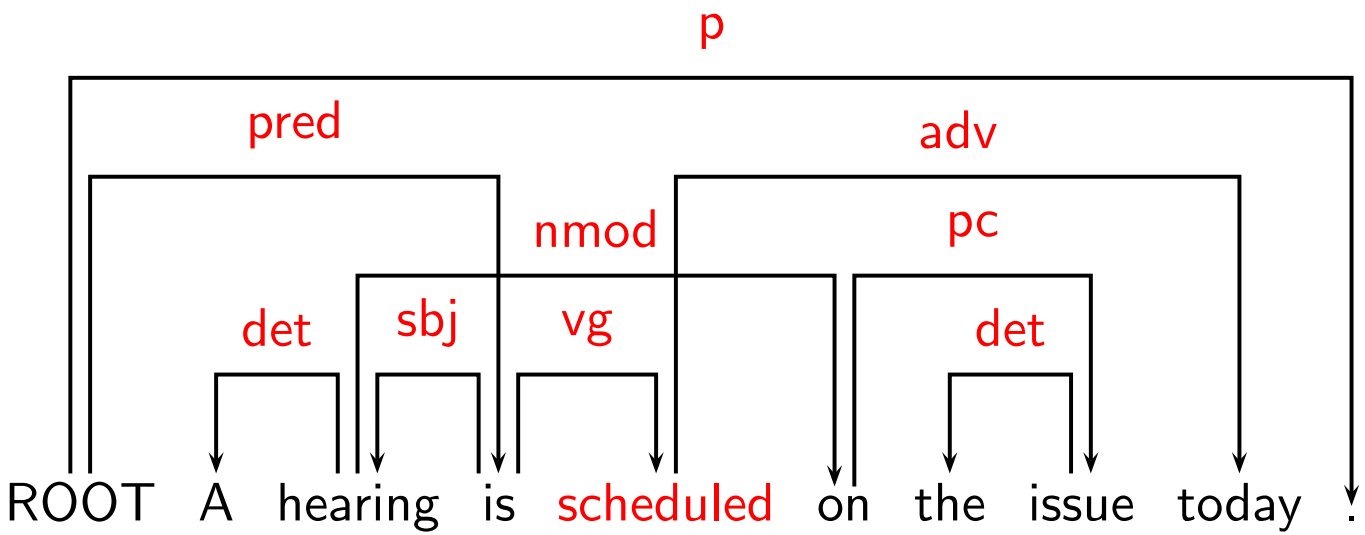

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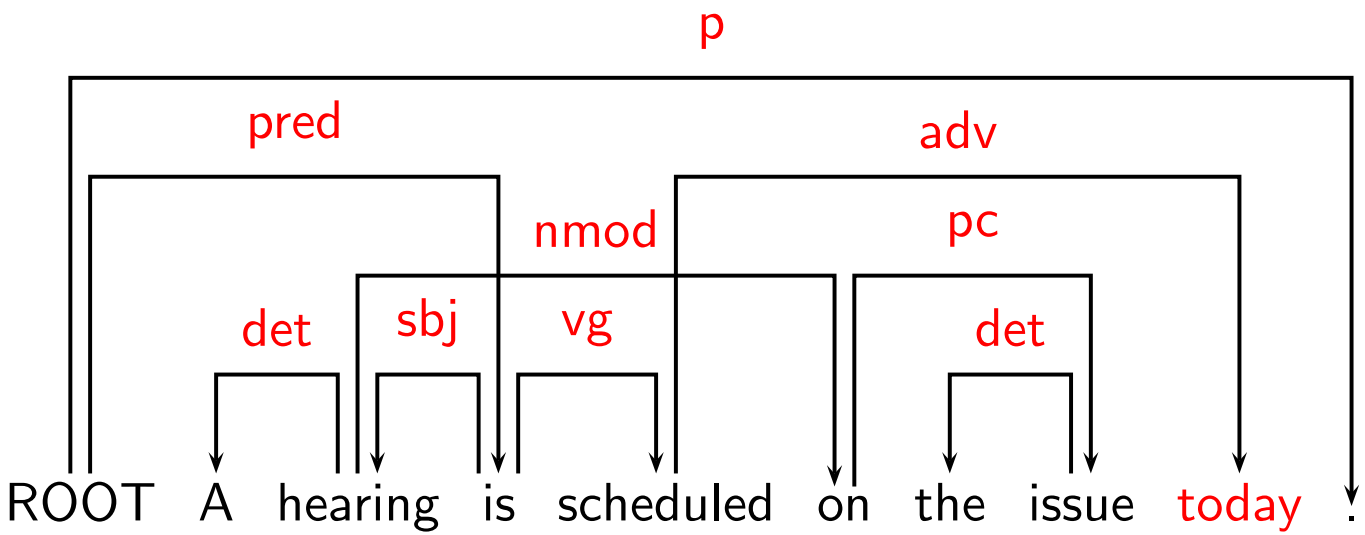

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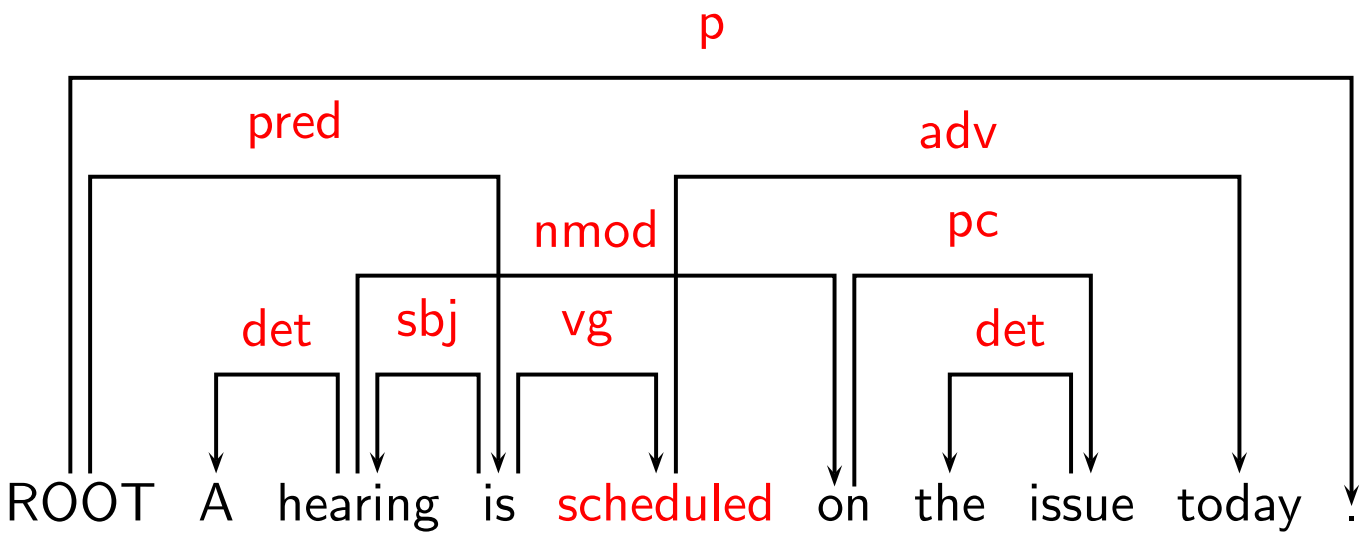

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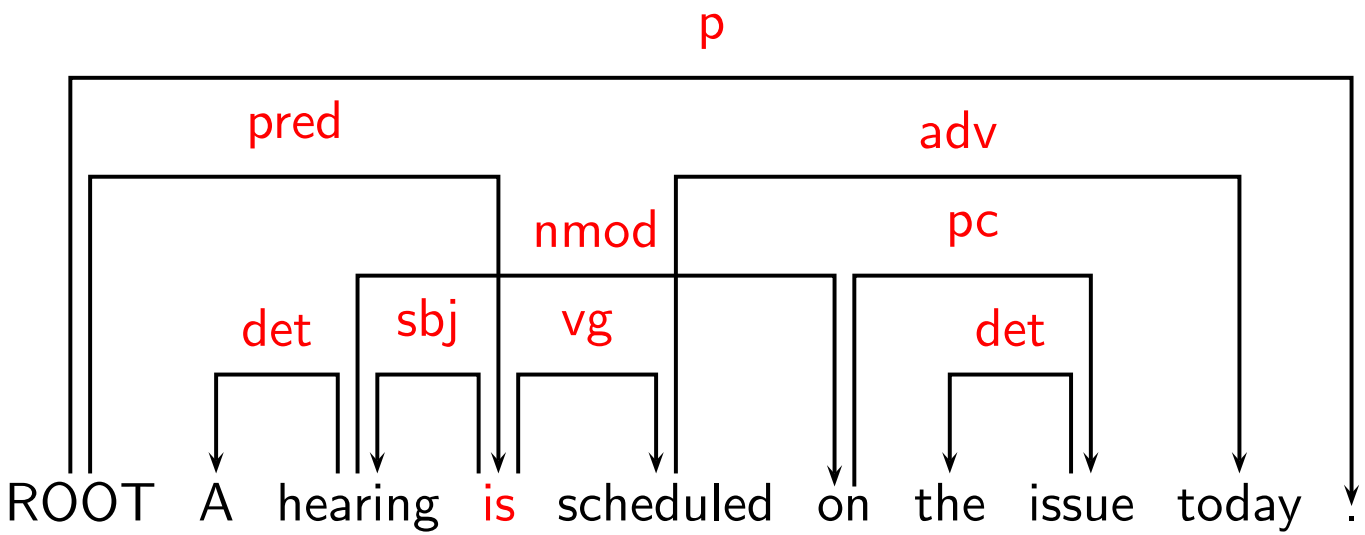

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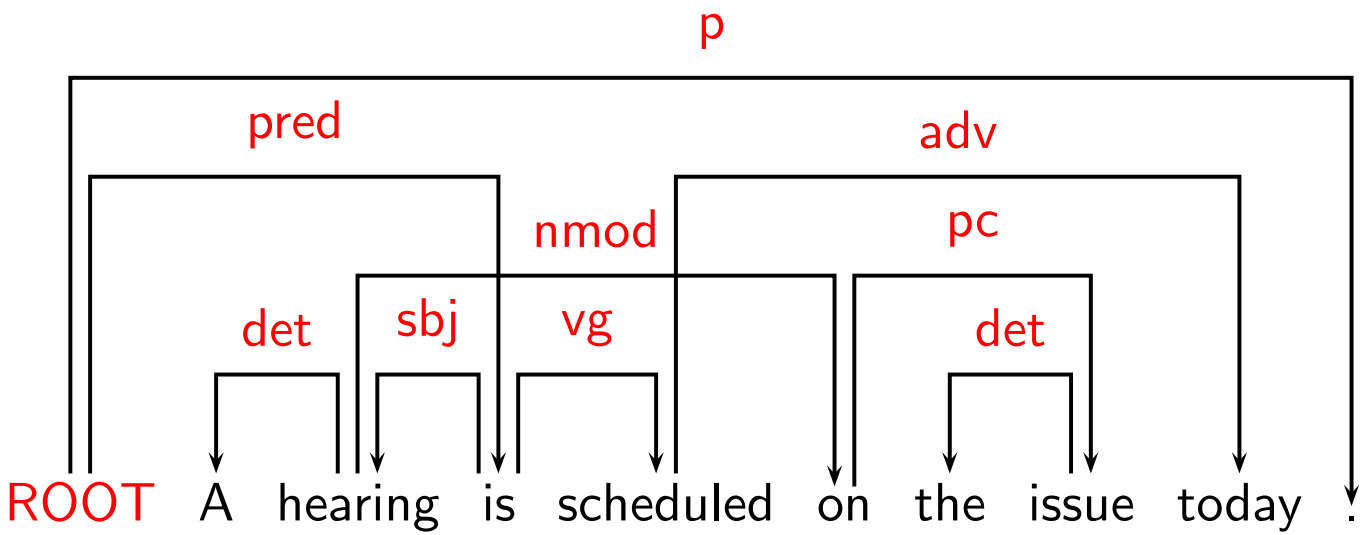

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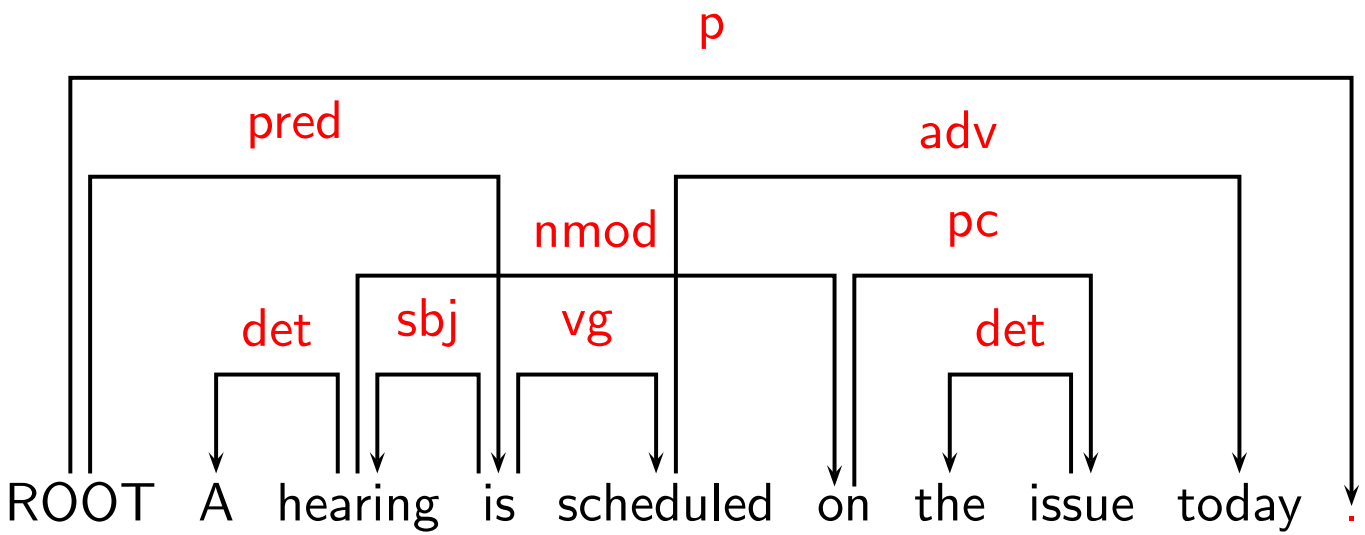

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Sorting into Projective Order

- Basic idea:
  - Combine an algorithm for sorting words according to the projective order $<_p$ with a transition-based algorithm for constructing a projective dependency graph
- 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 $c = (m, S, Q, A)$, where
  - m = a stack index (0 = top),
  - S = a stack $[\ldots, {w_i}^m, \ldots, {w_j}^0]_S$ of partially processed words,
  - Q = a queue $[w_k, \ldots]_Q$ of remaining input words,
  - A = a set of arcs (w_i, w_j, l).
- Initialization:

  $(0, [w_0]_S, [w_1, \ldots, w_n]_Q, \{\})$

  NB: w_0 = ROOT
- Termination:

  $(0, [w_0]_S, []_Q, A)$

Transition System: Transitions

- Swap

$$\frac{(m, \quad [\ldots, w_i{}^{m+1}, w_j{}^{m}, \ldots, w_k{}^{0}]_S, \quad Q, \quad A)}{(m+1, \quad [\ldots, w_j{}^{m+1}, w_i{}^{m}, \ldots, w_k{}^{0}]_S, \quad Q, \quad A)} \; [i \neq 0, Q \neq [\,]]$$

- Left-Arc(l)

$$\frac{(m, \quad [\ldots, w_i{}^{m+1}, w_j{}^{m}, \ldots, w_k{}^{0}]_S, \quad Q, \quad A)}{(m, \quad [\ldots, w_j{}^{m}, \ldots, w_k{}^{0}]_S, \quad Q, \quad A \cup \{(w_j, w_i, l)\})} \; [i \neq 0]$$

- Right-Arc(l)

$$\frac{(m, \quad [\ldots, w_i{}^{m+1}, w_j{}^{m}, \ldots, w_k{}^{0}]_S, \quad Q, \quad A)}{(m, \quad [\ldots, w_i{}^{m}, \ldots, w_k{}^{0}]_S, \quad Q, \quad A \cup \{(w_i, w_j, l)\})}$$

- Shift

$$\frac{(m, \quad [\ldots]_S, \quad [w_i, \ldots]_Q, \quad A)}{(0, \quad [\ldots, w_i{}^{0}]_S, \quad [\ldots]_Q, \quad A)}$$

Deterministic Parsing

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

Parse$(w_1, \ldots, w_n)$
1 $c \leftarrow (0, [w_0]_S, [w_1, \ldots, w_n]_Q, \{\})$
2 **while** Q_c is not empty
3 $c \leftarrow \text{Shift}(c)$
4 $t \leftarrow o(c)$
5 **while** $t = \text{Swap}$
6 $c = t(c)$
7 $t = o(c)$
8 **while** $t \in \{\text{Left-Arc}(l), \text{Right-Arc}(l)\}$
9 $c = t(c)$
10 $t = o(c)$
11 **return** $G = (\{w_0, w_1, \ldots, w_n\}, A_c)$

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

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

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

ROOT A hearing is scheduled on the issue today .

Example

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

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

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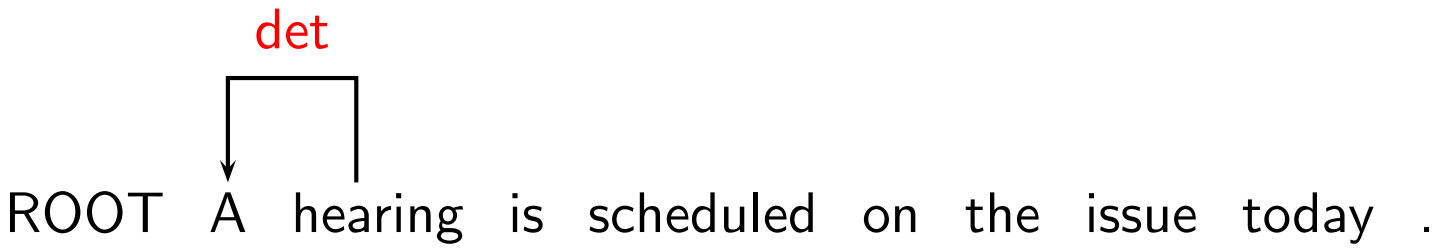
Example

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

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



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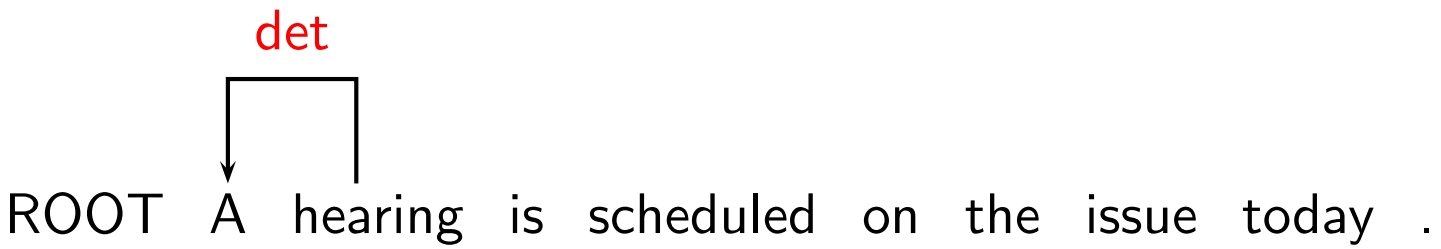

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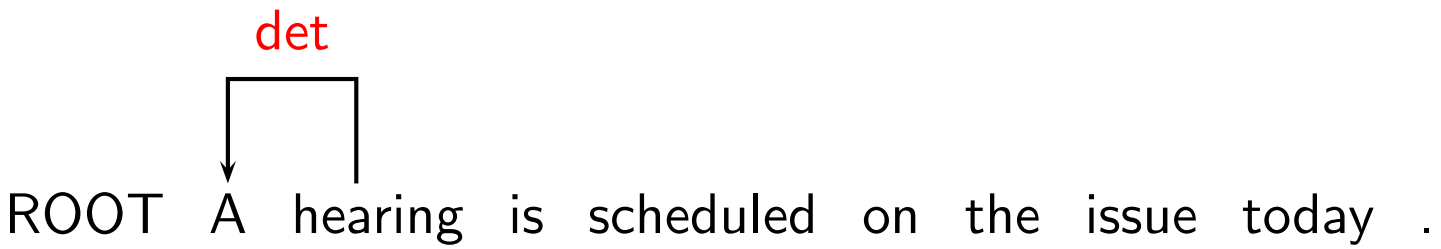

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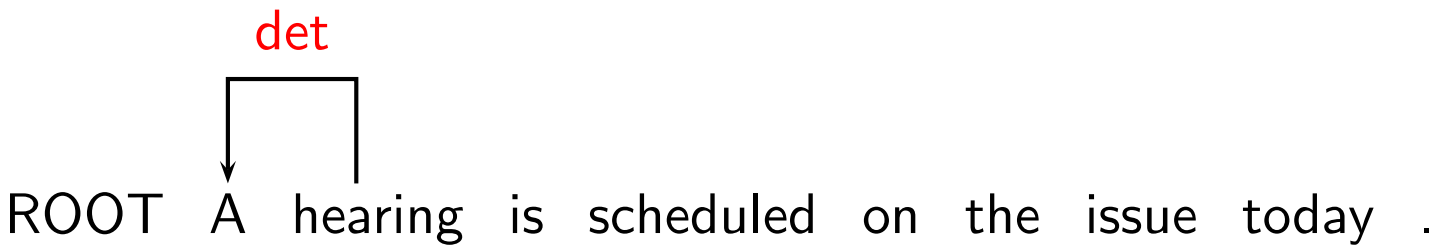

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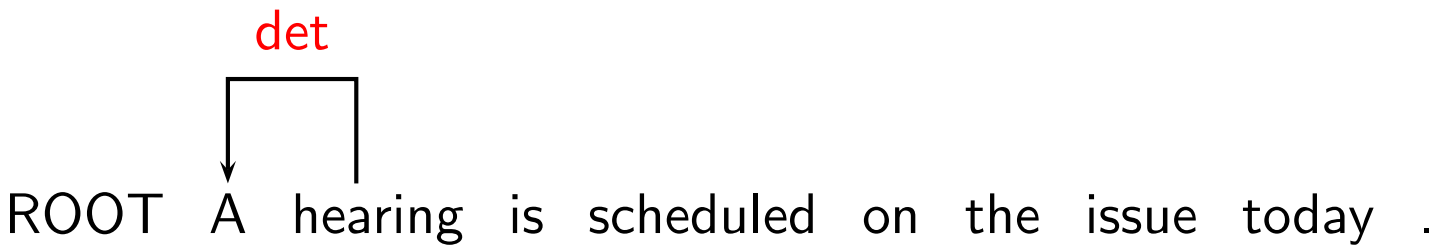

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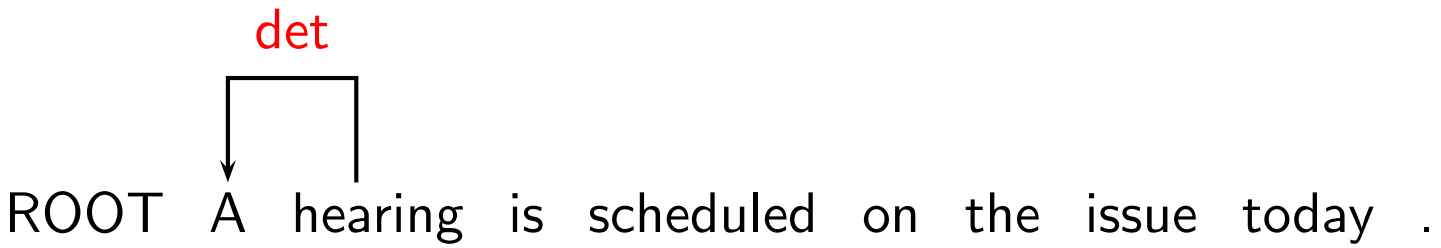

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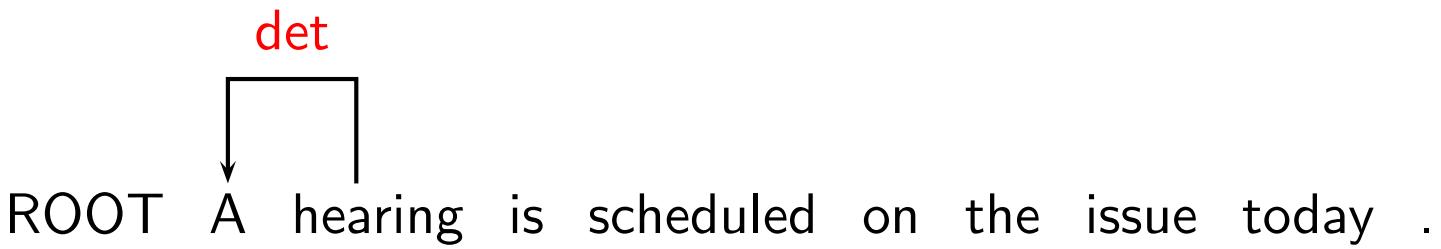

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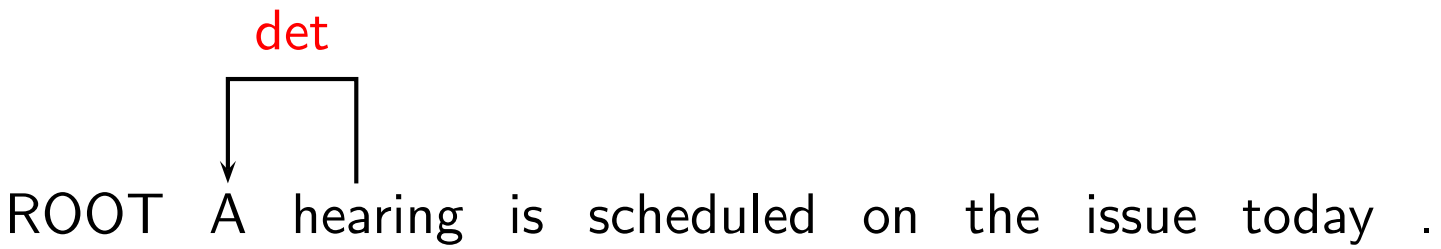

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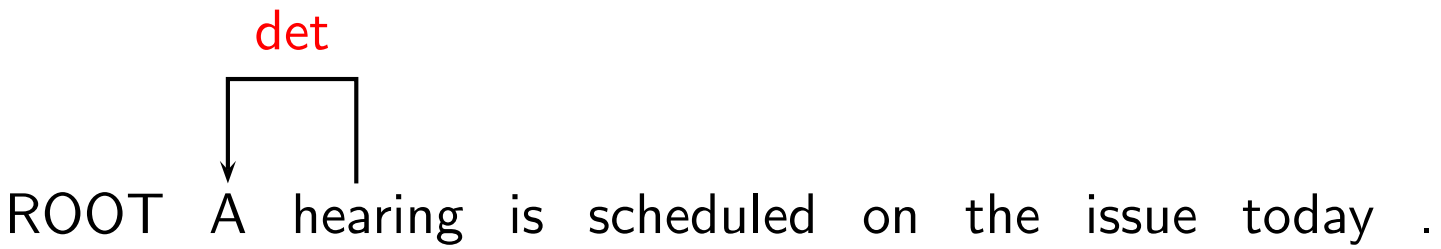

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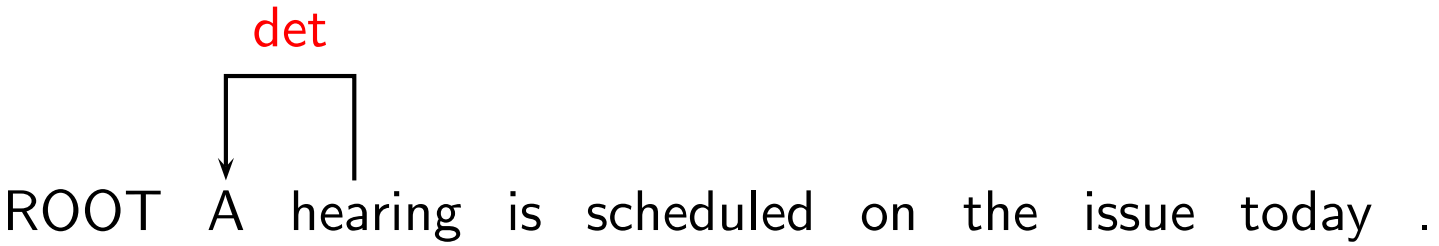

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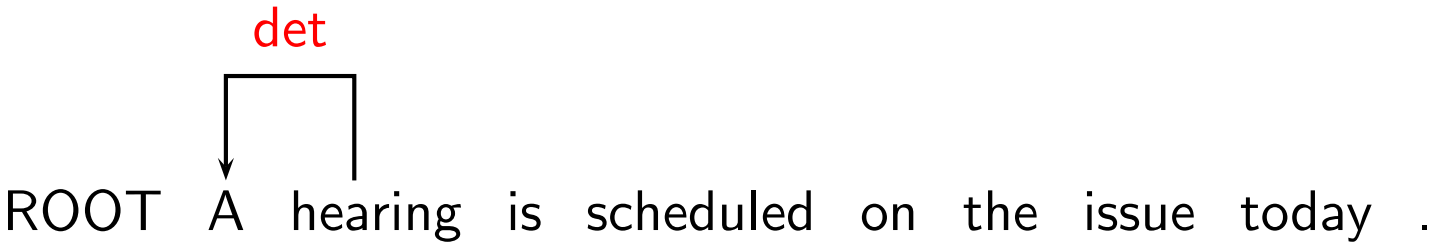
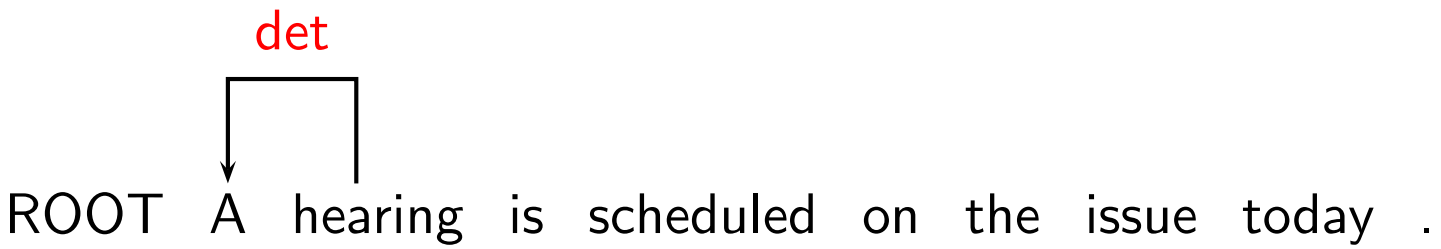


Example

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

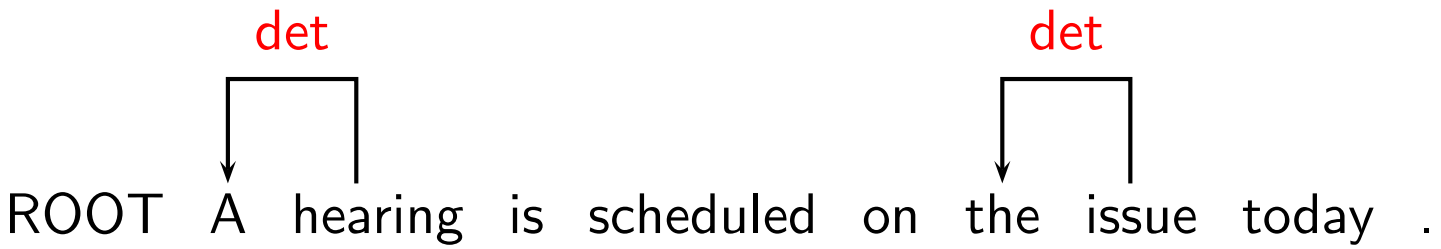
$[\![\text{ROOT hearing on the issue is scheduled}]\!]_S$ $[\![\text{today .}]\!]_Q$



Example

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

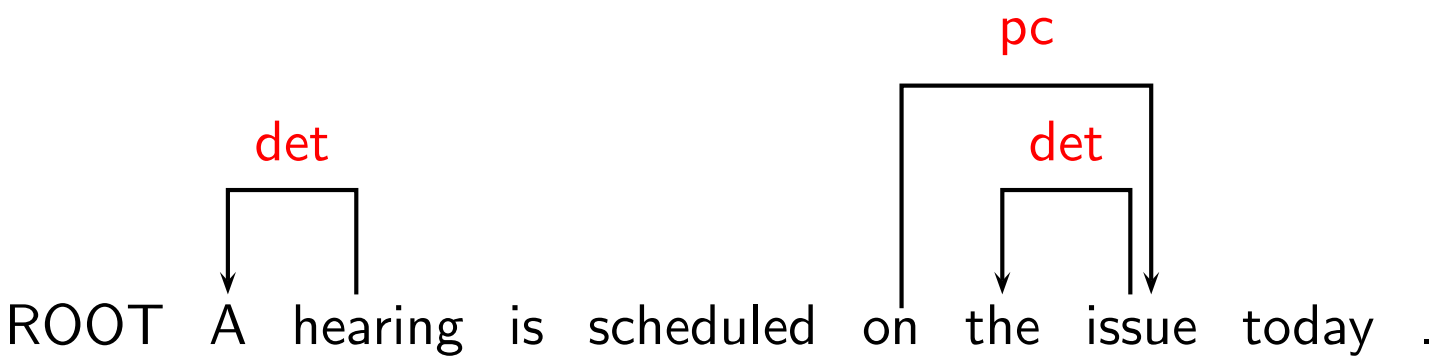
$[\![\text{ROOT hearing on issue}]\!]_S \; [\![\text{is scheduled}]\!]_Q \; [\![\text{today .}]\!]_{Q'}$



Example

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

$[\![\text{ROOT} \quad \text{hearing} \quad \text{on} \quad \text{is} \quad \text{scheduled}]\!]_S \quad [\![\text{today} \quad .]\!]_Q$



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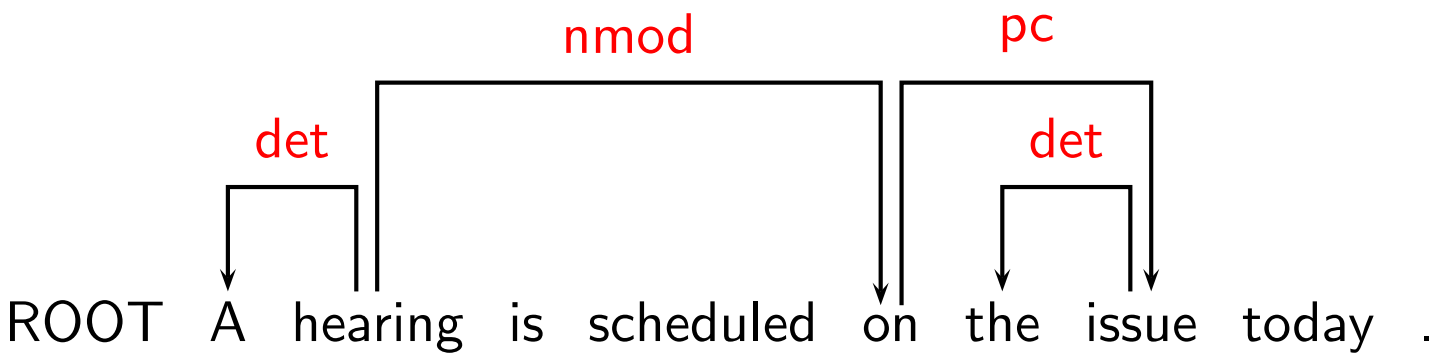
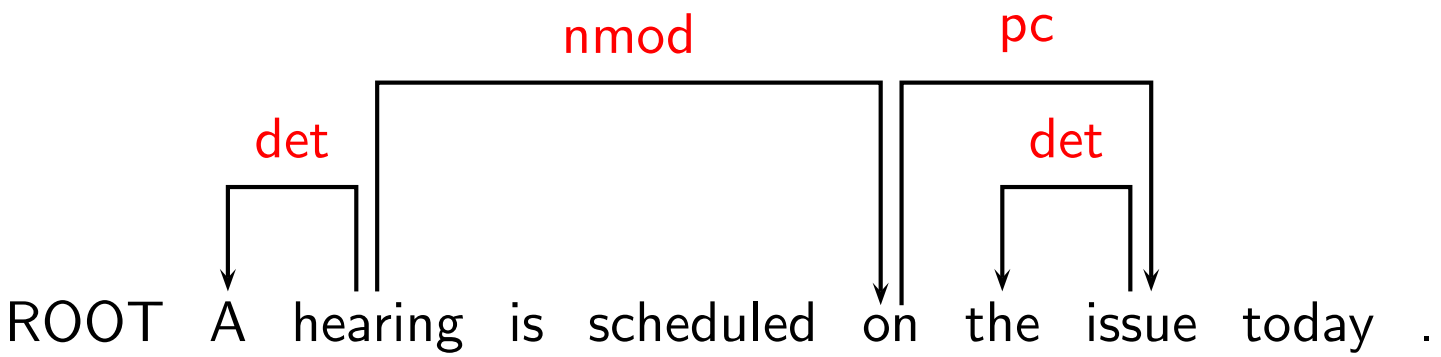


Example

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

$[\![\text{ROOT hearing is scheduled today}]\!]_S \; [\![.]\!]_Q$



Example

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

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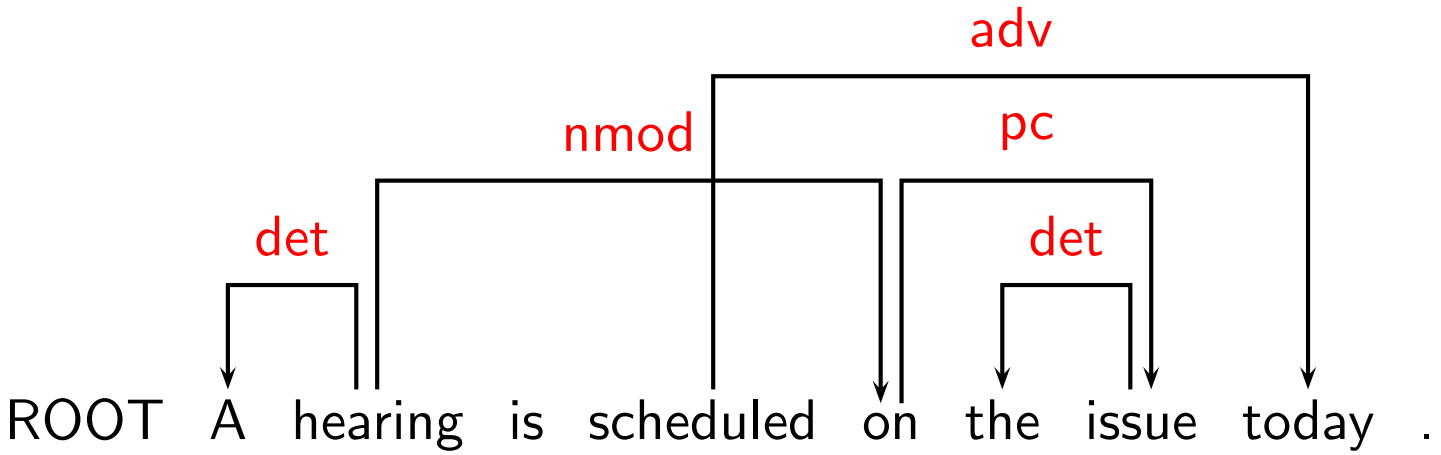
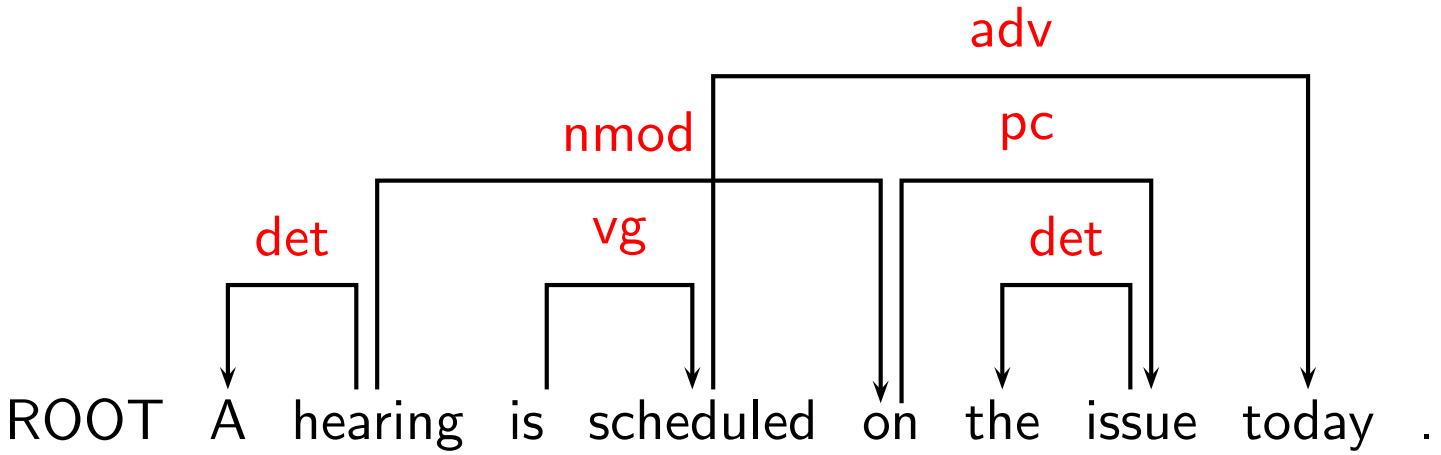


Example

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

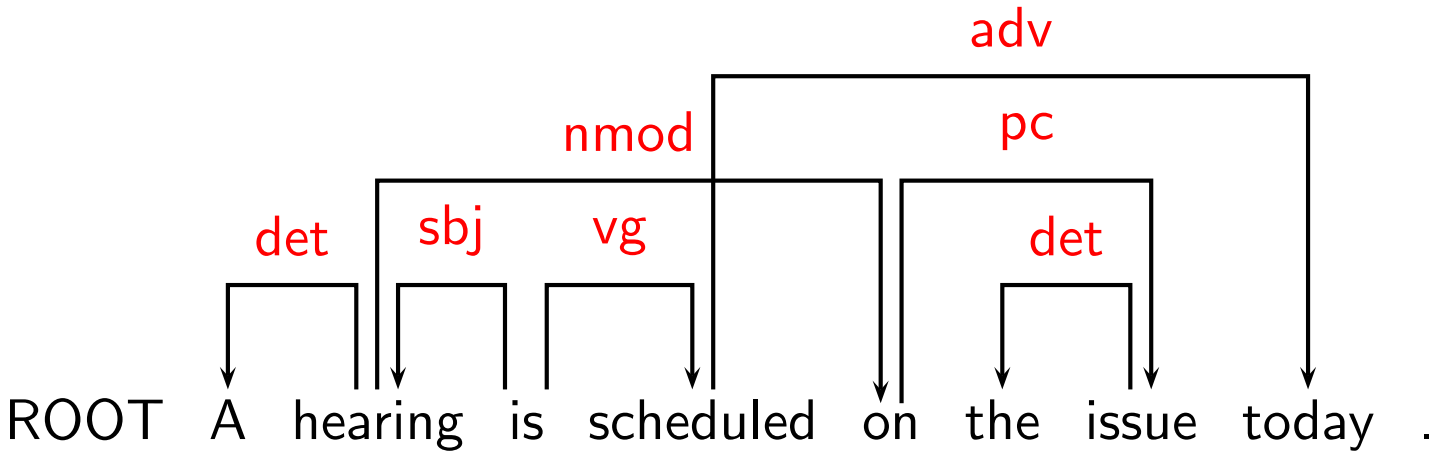
$[\![\text{ROOT} \quad \text{hearing} \quad \text{is}]\!]_S \quad [\![.]\!]_Q$



Example

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

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



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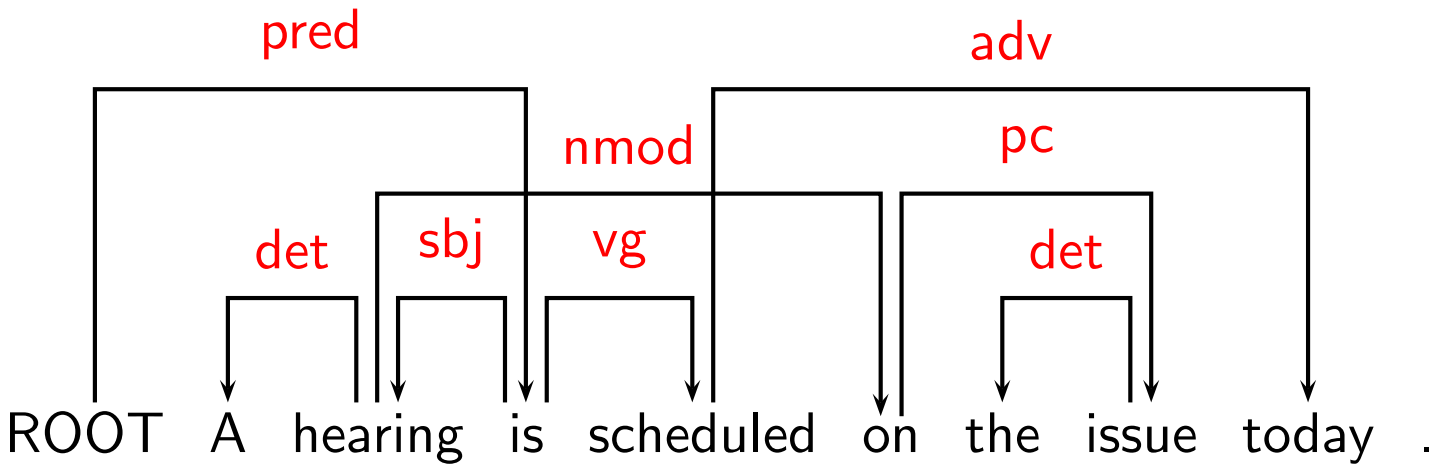
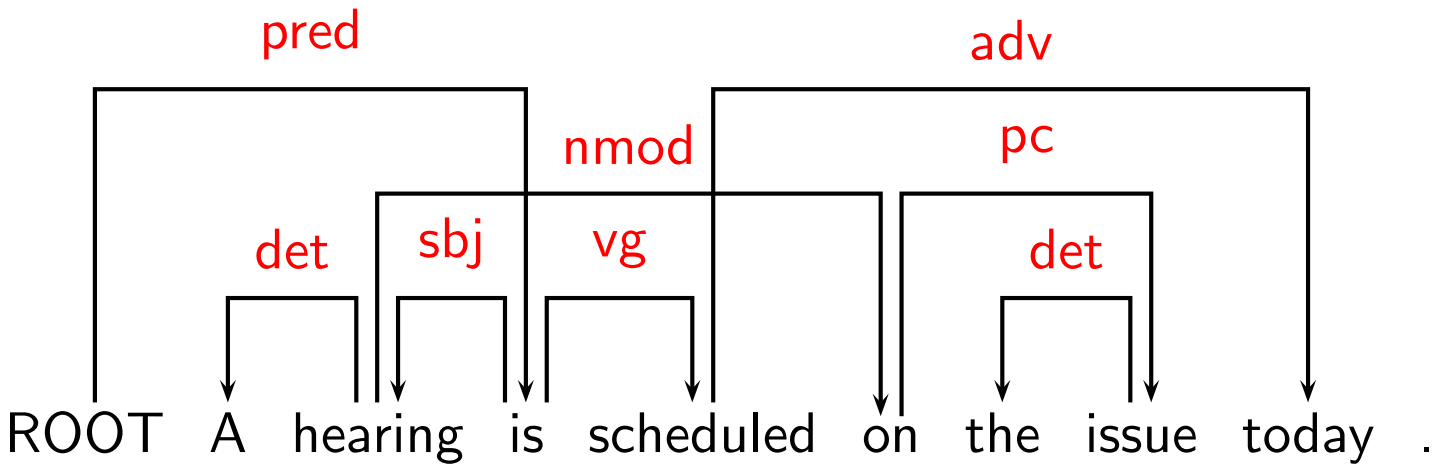
$[\![\text{ROOT}]\!]_s \quad [\![\cdot]\!]_Q$



Example

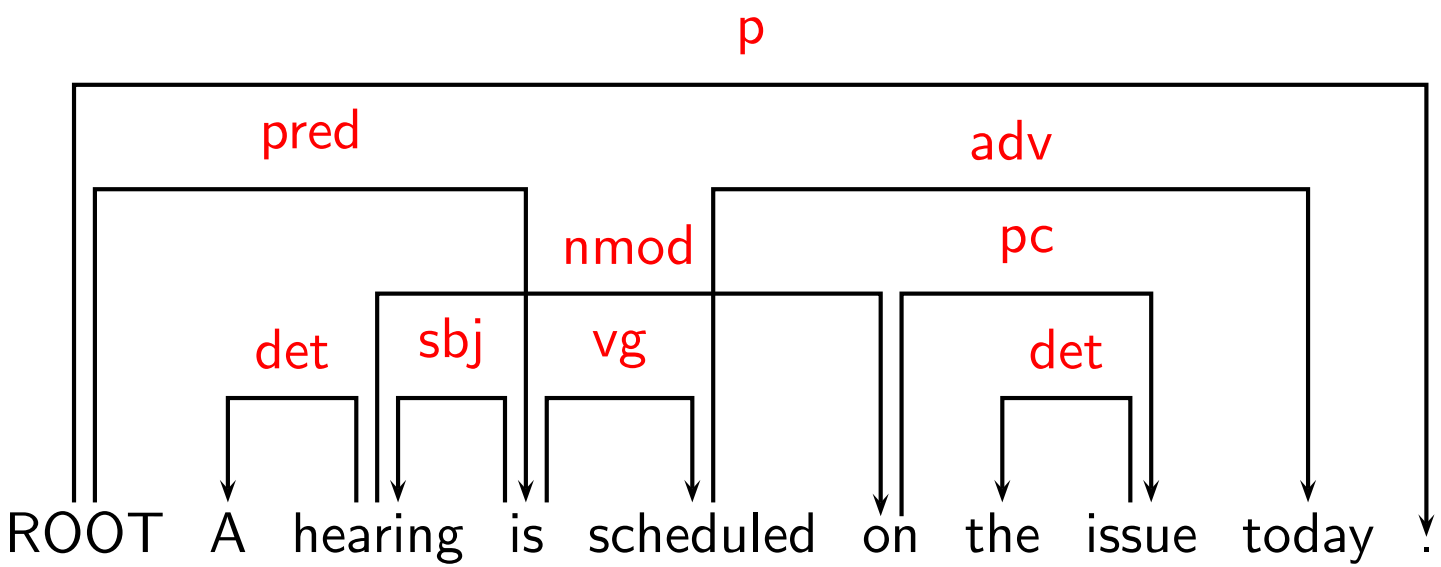
$o(c) = \text{Right-Arc}_p$

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



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-X shared task [Buchholz and Marsi 2006]:
  - Prague Arabic Dependency Treebank (1.5k, 11.2%)
  - Slovene Dependency Treebank (1.5k, 22.2%)
  - Metu-Sabancı Turkish Treebank (5k, 11.6%)
- 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	Slovene	Turkish	Average
Projective				
Pseudo-projective				
Non-projective				
MSTParser 2006				
MaltParser 2006				

Preliminary Results

Parser	Arabic	Slovene	Turkish	Average
Projective	65.8	72.0	64.7	67.5
Pseudo-projective				
Non-projective				
MSTParser 2006				
MaltParser 2006				

Preliminary Results

Parser	Arabic	Slovene	Turkish	Average
Projective	65.8	72.0	64.7	67.5
Pseudo-projective	66.0	71.9	64.7	67.5
Non-projective				
MSTParser 2006				
MaltParser 2006				

Preliminary Results

Parser	Arabic	Slovene	Turkish	Average
Projective	65.8	72.0	64.7	67.5
Pseudo-projective	66.0	71.9	64.7	67.5
Non-projective	67.5	74.8	65.9	69.4
MSTParser 2006				
MaltParser 2006				

Preliminary Results

Parser	Arabic	Slovene	Turkish	Average
Projective	65.8	72.0	64.7	67.5
Pseudo-projective	66.0	71.9	64.7	67.5
Non-projective	67.5	74.8	65.9	69.4
MSTParser 2006	66.9	73.4	63.2	67.8
MaltParser 2006	66.7	70.3	65.7	67.6

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

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