Lost in the Woods?

Transition-Based Dependency Parsing with Non-Projective Trees

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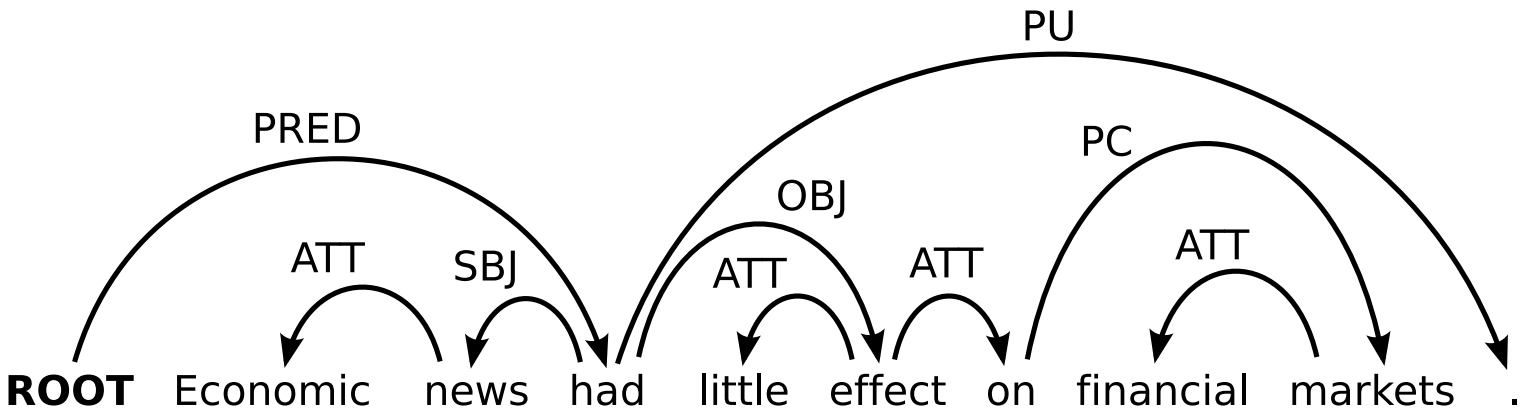
Introduction

- Syntactic parsing of natural language
  - Who does what to whom?
- Dependency-based syntactic representations
  - Long tradition in descriptive and theoretical linguistics
  - Increasingly popular in computational linguistics

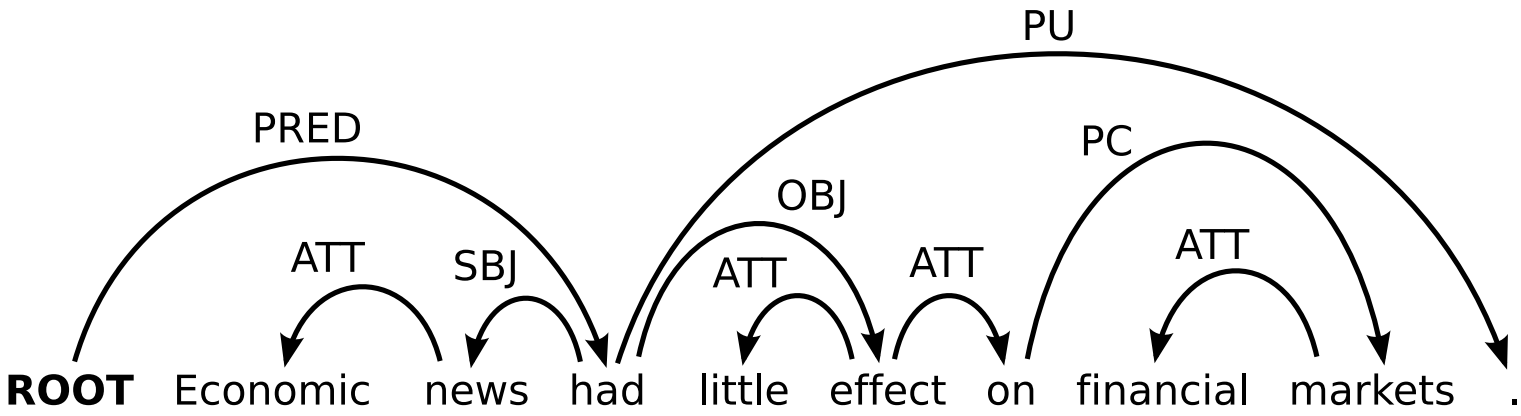


Why Popular?

- Usefulness of dependency structures in applications
  - Transparent encoding of predicate-argument structure
  - Interface from parser to downstream application
- Availability of dependency treebanks
  - Dependency annotation natural for many languages
  - Prague Dependency Treebank as a model
  - Data sets from CoNLL shared tasks (2006–2009)
- Advancement of data-driven dependency parsing
  - Robust and efficient parsing methods
  - High accuracy for many languages

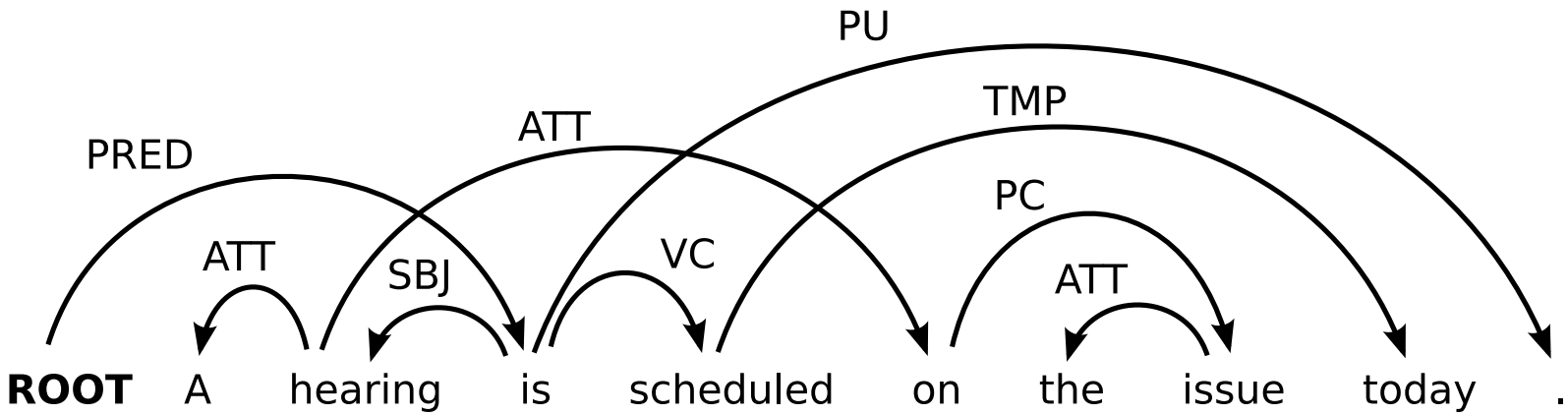
Dependency Syntax

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



Projectivity

- Discontinuous constructions?
  - A dependency tree is projective if every subtree covers a contiguous substring of the sentence.
- Most theoretical frameworks do not assume projectivity (but many parsers do).



Non-Projectivity in Natural Language

Language	Sentences	Dependencies
Arabic [Hajič et al. 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%

Plan for the Talk

- Part 1:
  - Transition-based dependency parsing
  - Robust and efficient parsing for projective trees
- Part 2:
  - Dealing with non-projective trees
  - Comparison of three methods:
    - Pseudo-projective parsing
    - Extended arc transitions
    - Online reordering

Transition-Based Dependency Parsing

Overview of the Approach

- The basic idea:
  - Define a transition system for dependency parsing
  - Train a model for scoring possible transitions
  - Parse by searching for the optimal transition sequence
- Advantages:
  - Highly efficient parsers with low complexity
  - Rich history-based feature models for disambiguation

Dependency Trees Formally

- A dependency tree for a sentence $S = w_1, \ldots, w_n$, given a set L of labels, is a labeled directed tree T, consisting of
  - a set V of nodes, labeled with words (including **ROOT**),
  - a set $A \subseteq V \times L \times V$ of arcs, labeled with dependency types,
  - a linear precedence order $<$ on V,

  with **ROOT** as the unique root

- Note:
  - An arc (w_i, l, w_j) has head w_i, label l and dependent w_j
  - Alternative notation: $w_i \xrightarrow{l} w_j$ (or $w_i \rightarrow w_j$)

Transition System: Configurations

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

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

  NB: w_0 = **ROOT**
- Termination:

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

Transition System: Transitions

- Left-Arc(l)

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

- Right-Arc(l)

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

- Shift

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

Oracle 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** $Q_c \neq [\,]$ **or** $|S_c| > 1$
3 $\quad t \leftarrow o(c)$
4 $\quad c \leftarrow t(c)$
5 **return** $T = (\{w_0, w_1, \ldots, w_n\}, A_c)$

Parsing Example

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

ROOT Economic news had little effect on financial markets .

Parsing Example

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

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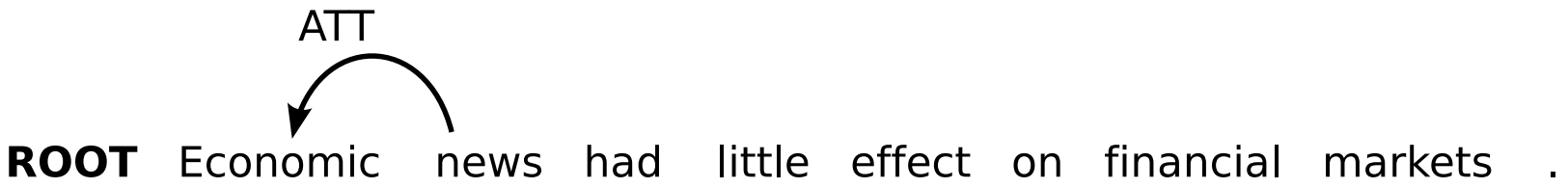

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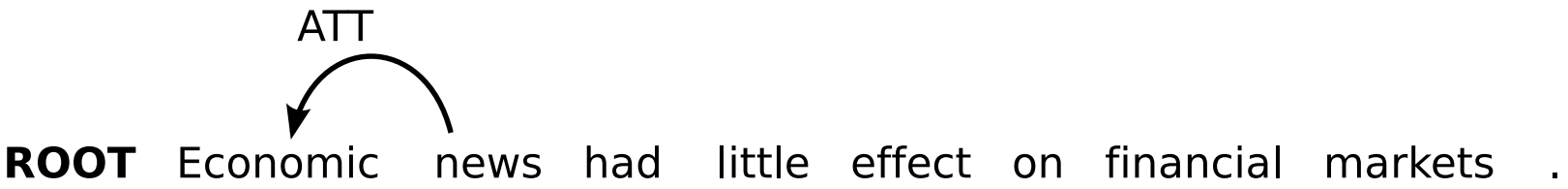

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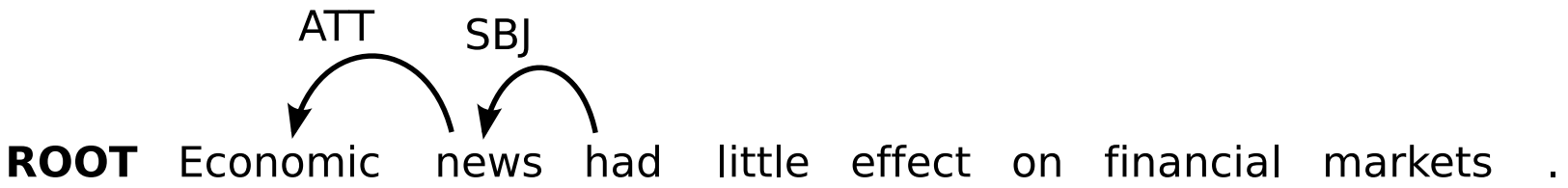

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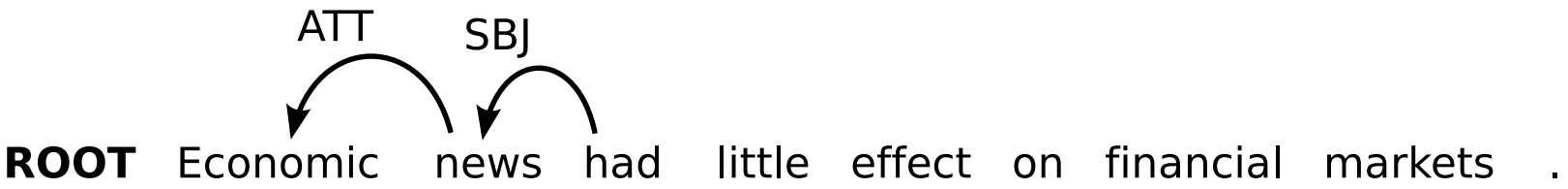

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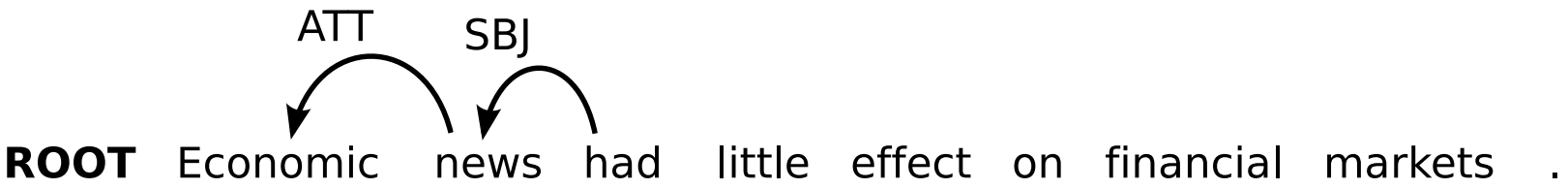

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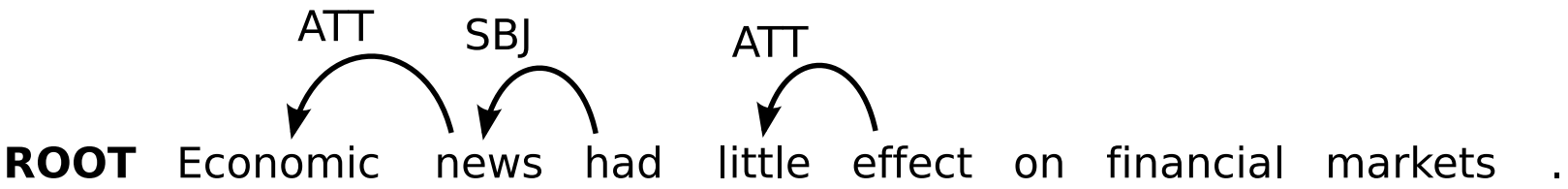

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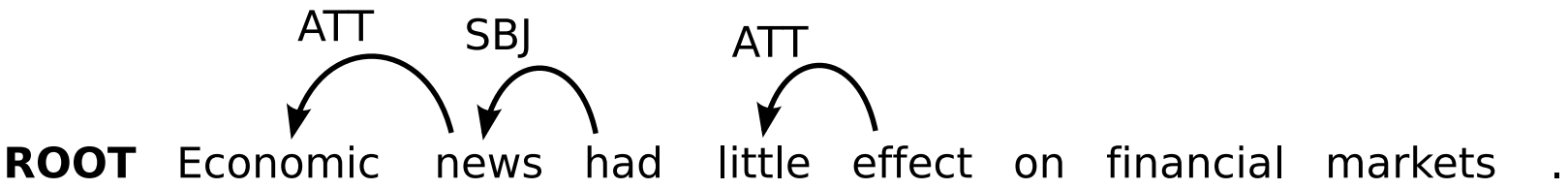

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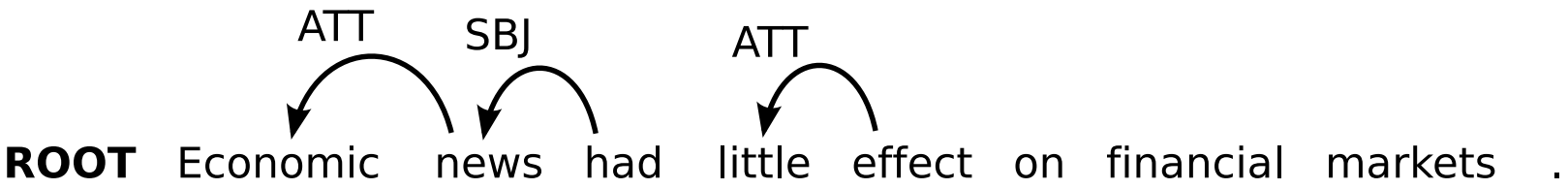

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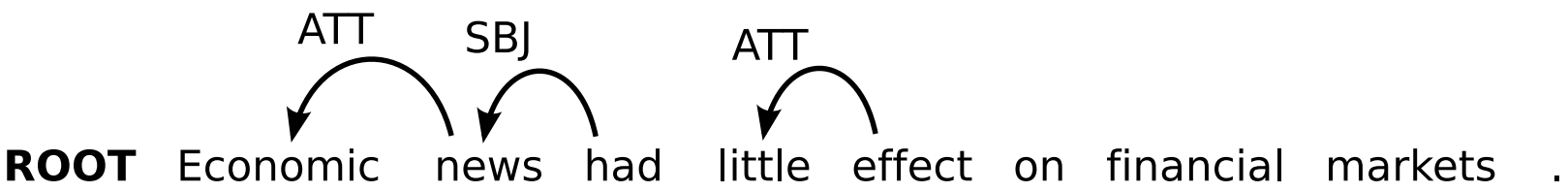

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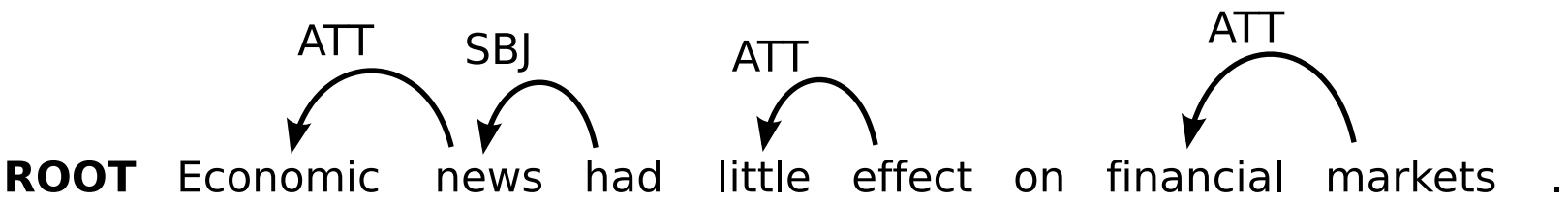

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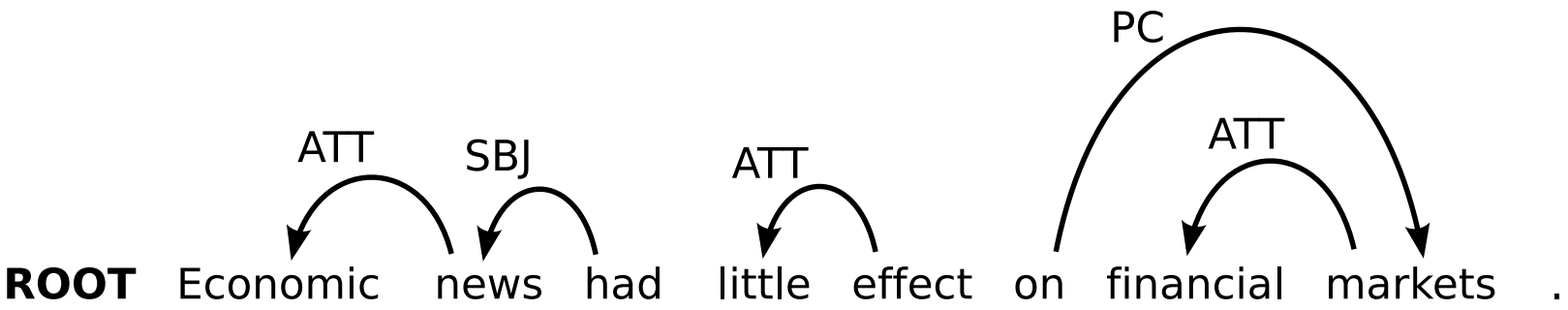

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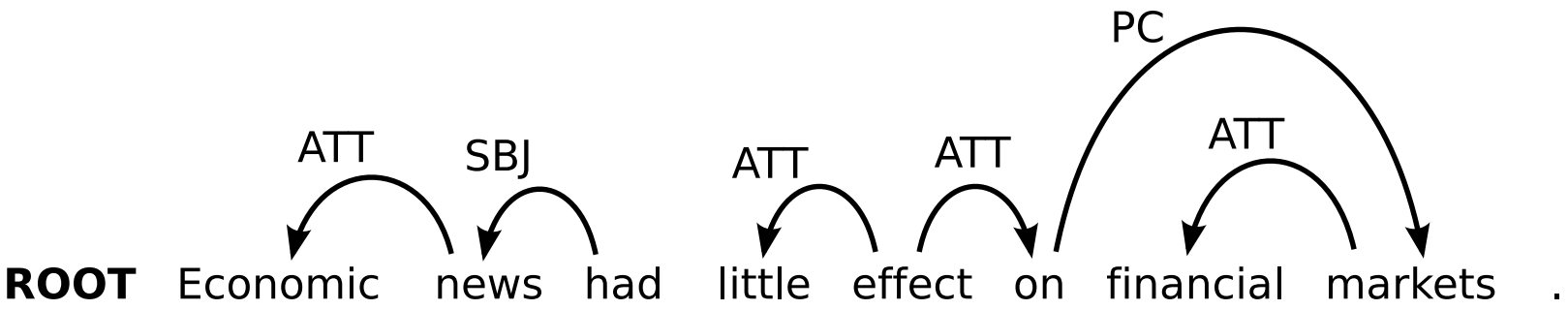

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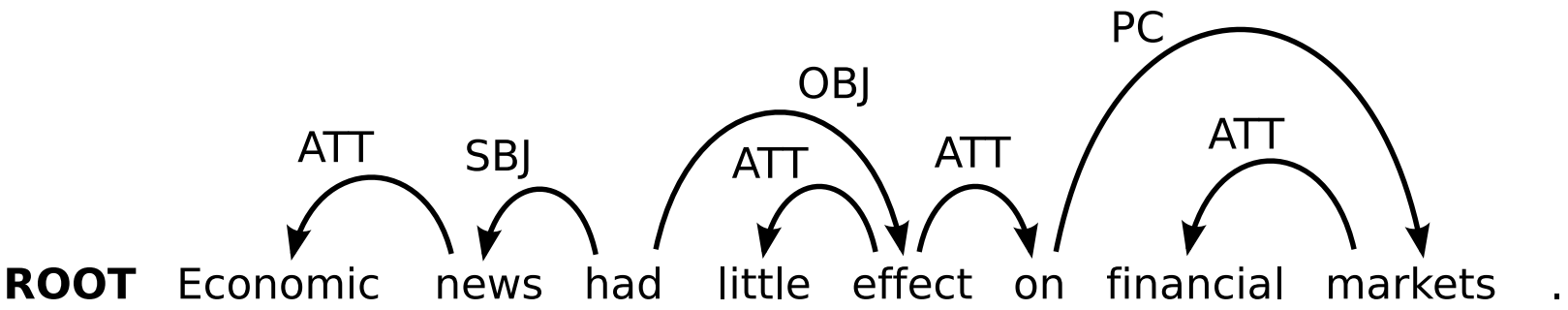

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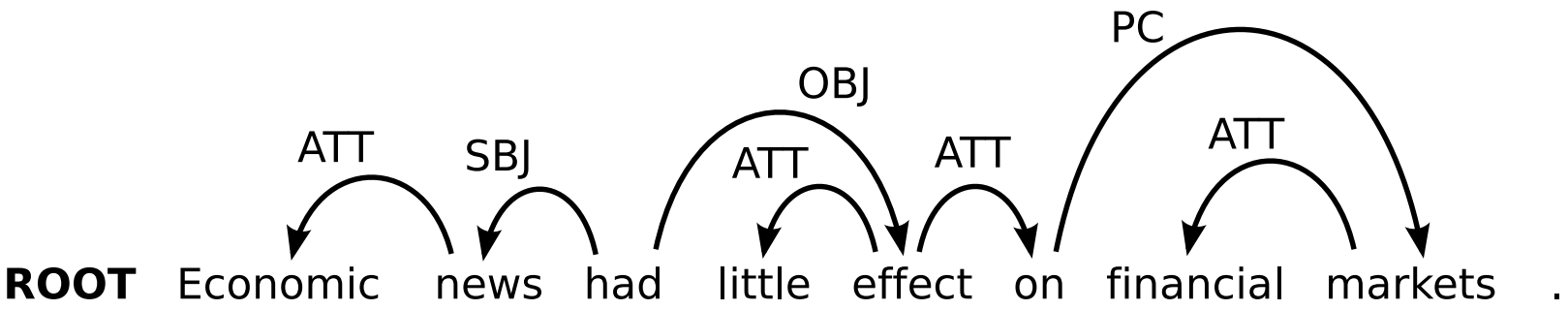

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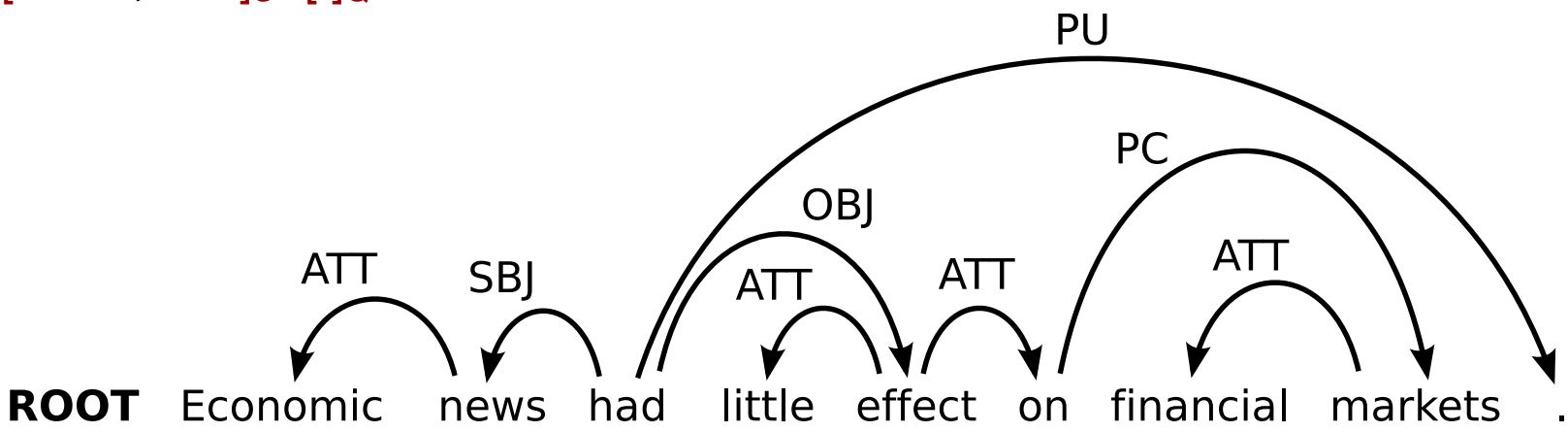

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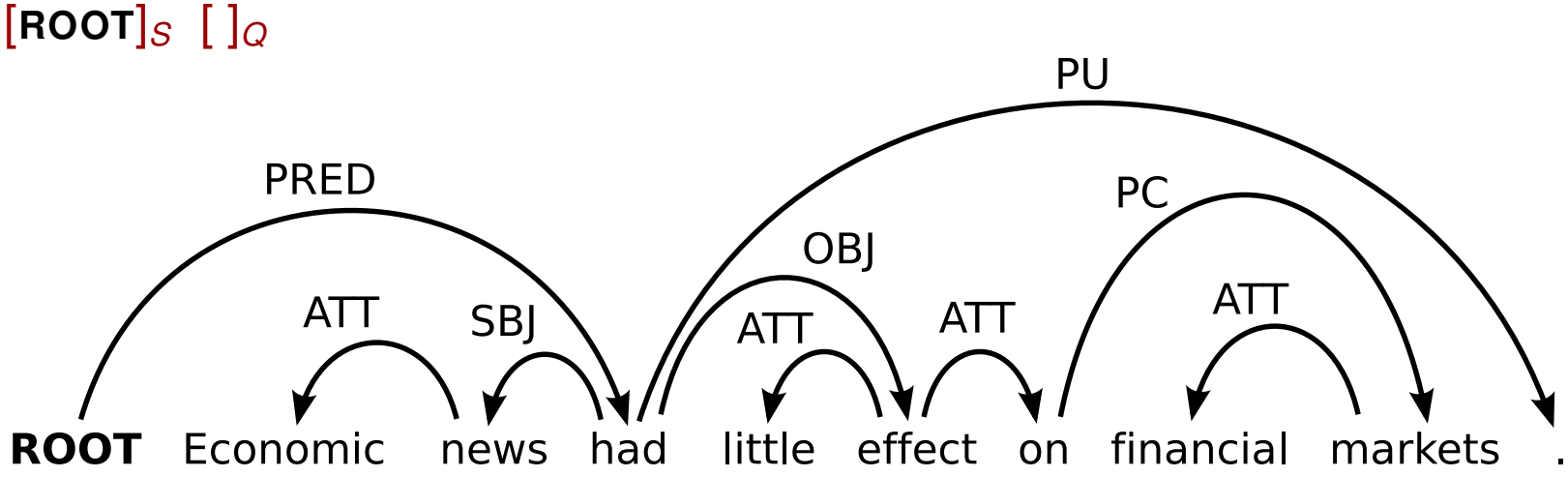


Algorithm Analysis

- 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.

Approximating Oracles

- Feature-based scoring function:

$$\mathcal{S}(c,t) = \sum_{i=1}^{k} \mathbf{w}_i \cdot \mathbf{f}_i(c,t)$$

  where $\mathbf{w}_i$ is the (learned) weight for feature $\mathbf{f}_i(c,t)$

- Rich history-based models:
  - Features over input tokens relative to S and Q
  - Features over the (partial) dependency tree defined by A
  - Features over the (partial) transition sequence $t_1, \ldots, t_i$

  NB: No constraints on scope or combination of features

Typical Features

- Basic features:
  - PoS, Word, PoS+Word for $S_1, \ldots, S_k, Q_1, \ldots, Q_k$
  - PoS, Word, DepLabel for dependents of S_1 and S_2
  - Distance S_1–S_2
  - Left and right valency of S_1 and S_2
  - Left and right dependency label set of S_1 and S_2
- Conjoined features:
  - All pairs of S_1 and S_2 features
  - Triples of PoS features:
    - Trigrams over S and Q
    - Dependents of S_1 and S_2 conjoined with S_1+Q_1
    - Adjacent siblings of S_1 and S_2 conjoined with their head
  - Distance, valency and label sets conjoined with (pairs of) S_1 and S_2 features

Learning and Inference

- Local optimization [Yamada and Matsumoto 2003, Nivre et al. 2004]:

$$o(c) = \underset{t}{\text{argmax}}\ \mathcal{S}(c, t)$$

  - Learning to maximize accuracy of oracle prediction
  - Inference to 1-best configuration at each decision point

- Global optimization [Titov and Henderson 2007, Zhang and Clark 2008]:

$$\textsc{Parse}(w_1, \ldots, w_n) = \underset{T=(V,A_{c_m})}{\text{argmax}} \sum_{i=1}^{m} \mathcal{S}(c_{i-1}, t_i)$$

  - Learning to minimize loss over entire transition sequence
  - Inference to k-best configurations (beam search)

Summing Up

- Transition-based dependency parsing
  - Efficient thanks to low parsing complexity
  - Accurate thanks to rich non-local features
  - State of the art for projective parsing [Zhang and Nivre 2011]
- However:
  - Limited to projective dependency trees
  - What to do with discontinuous constructions?

Dealing with Non-Projective Trees

A Hard Problem

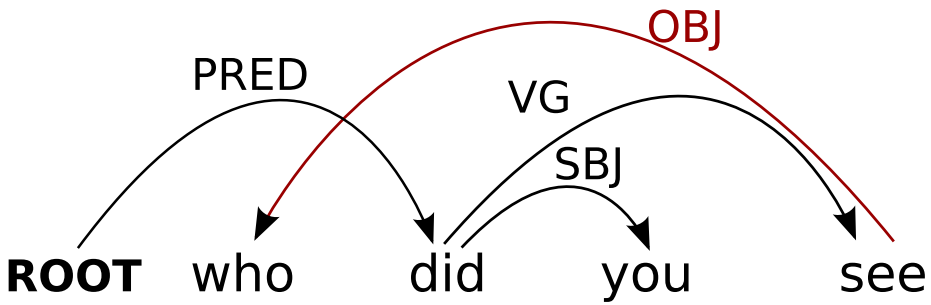
- Intractability results for parsing with non-projective trees:
  - Grammars with ID/LP separation [Neuhaus and Bröker 1997]
  - Weighted constraint grammars [Buch-Kromann 2006]
  - Spanning tree parsing with markovization or valency [McDonald and Pereira 2006, McDonald and Satta 2007]
- Complexity of deterministic parsing [Nivre 2008]:
  - $O(n)$ with projective trees, $O(n^2)$ with arbitrary trees
- Source of difficulty:
  - Word order unconstrained by tree structure (permutation)
  - Trees composed of non-adjacent subtrees (discontinuity)

Approaches

- Pseudo-projective parsing [Nivre and Nilsson 2005]
  - Preprocess training data, post-process parser output
- Extended arc transitions [Attardi 2006]
  - Transitions that add arcs between non-adjacent subtrees
- Online reordering [Nivre 2009]
  - Transitions that perform word order permutations

Pseudo-Projective Parsing

- Pseudo-projective transform [Nivre and Nilsson 2005]:
  - Attach non-projective arcs higher in the tree
  - Encode transformation in arc labels
  - Projective tree with augmented arc labels



- Data-driven parsing:
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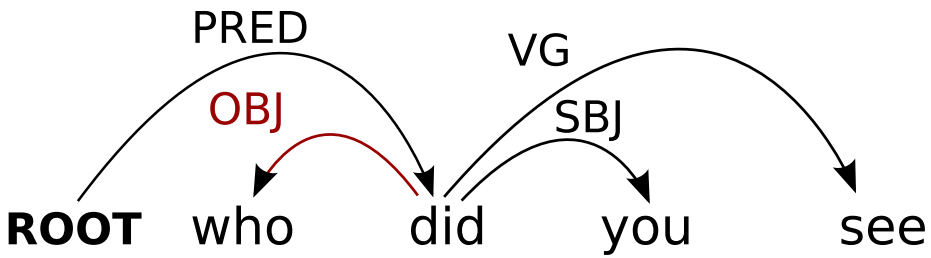

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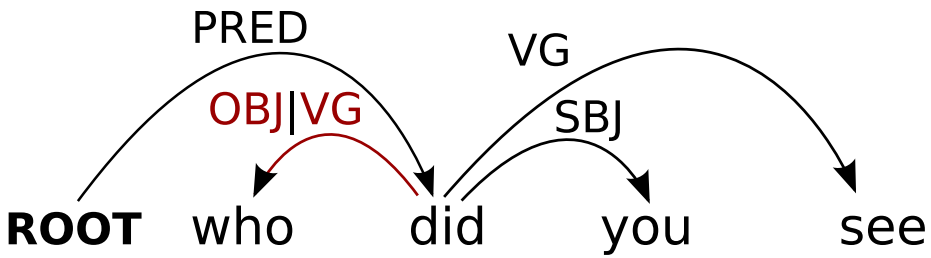

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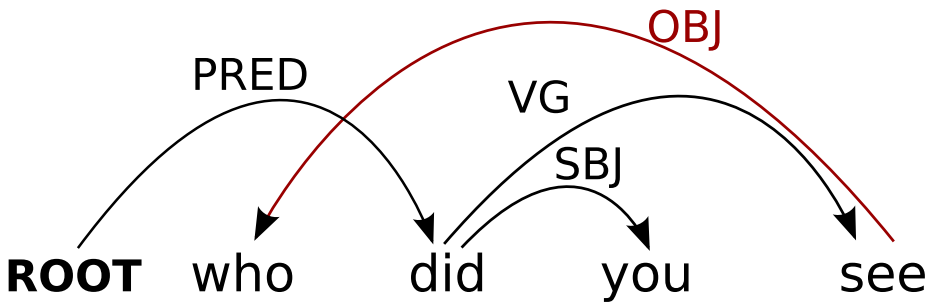

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Extended Arc Transitions

- Add transitions for non-projective arcs [Attardi 2006]:
  - Left-Arc2(l) $\dfrac{([\ldots, w_i, w_j, w_k]_S, \quad Q, \quad A)}{([\ldots, w_j, w_k]_S, \quad Q, \quad A \cup \{(w_k, l, w_i)\})}$ $[i \neq 0]$
  - Right-Arc2(l) $\dfrac{([\ldots, w_i, w_j, w_k]_S, \quad Q, \quad A)}{([\ldots, w_i, w_j]_S, \quad Q, \quad A \cup \{(w_i, l, w_k)\})}$

$[\textbf{ROOT}]_S$ $[\text{who, did, you, see}]_Q$

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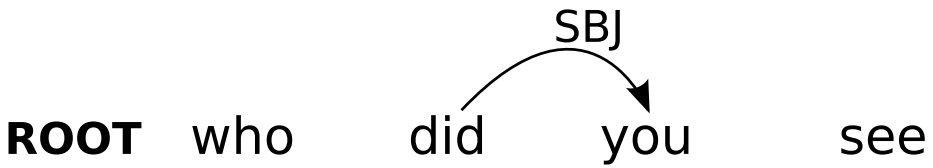

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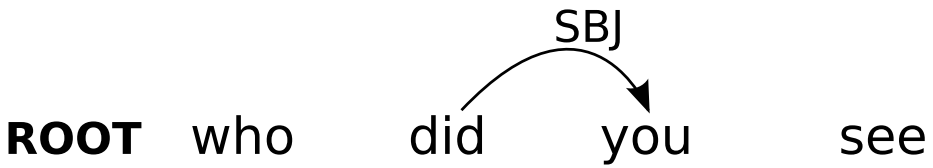

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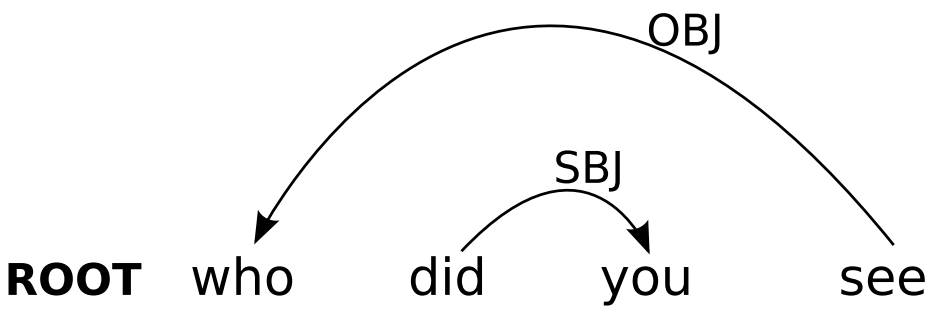

Extended Arc Transitions

- Add transitions for non-projective arcs [Attardi 2006]:
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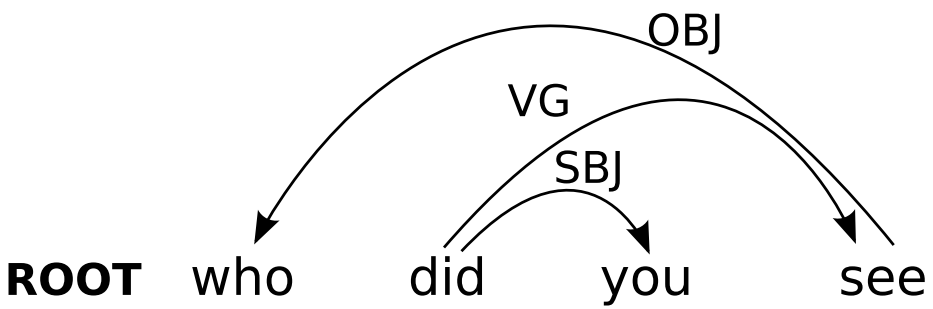

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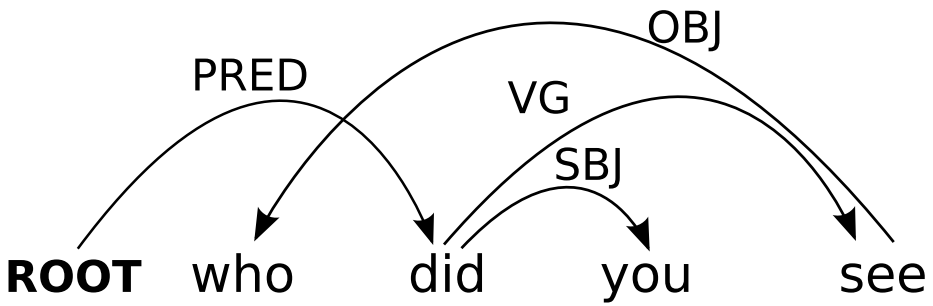

Online Reordering

- Add transition for reordering words [Nivre 2009]:
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$[\textbf{ROOT}]_S$ [who, did, you, see]$_Q$

ROOT who did you see

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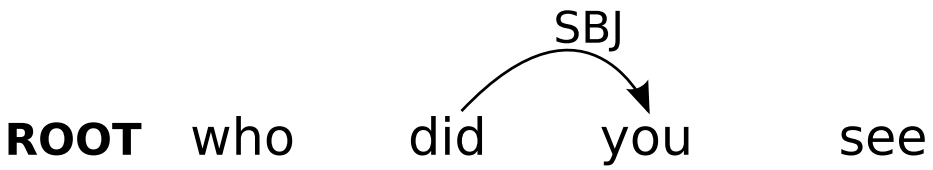

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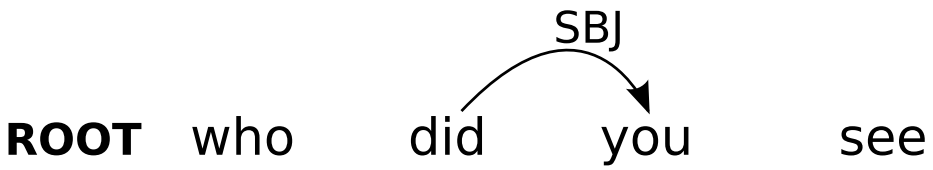

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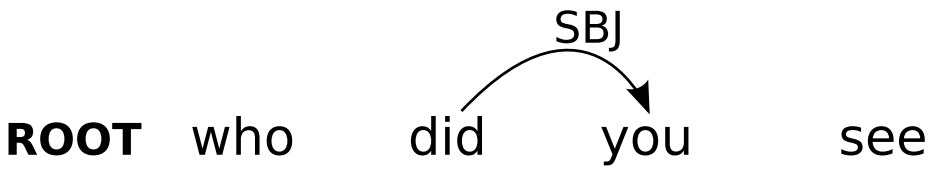

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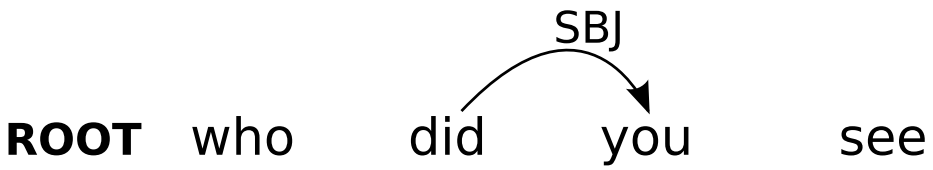

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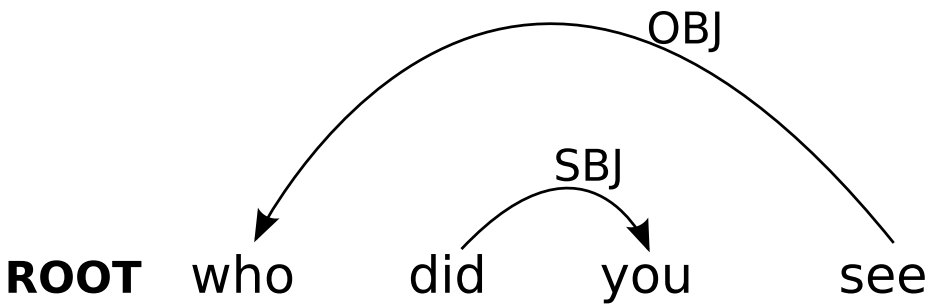

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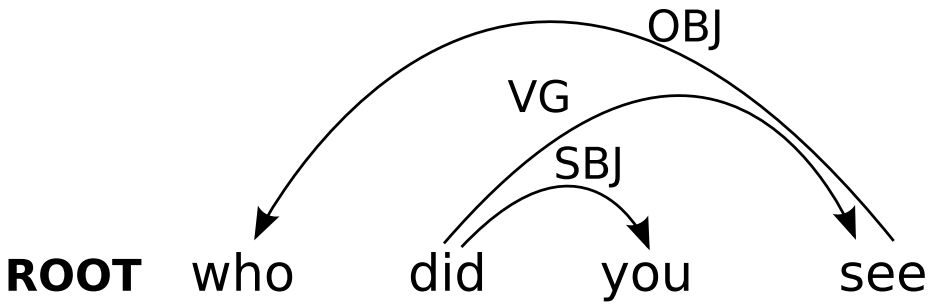

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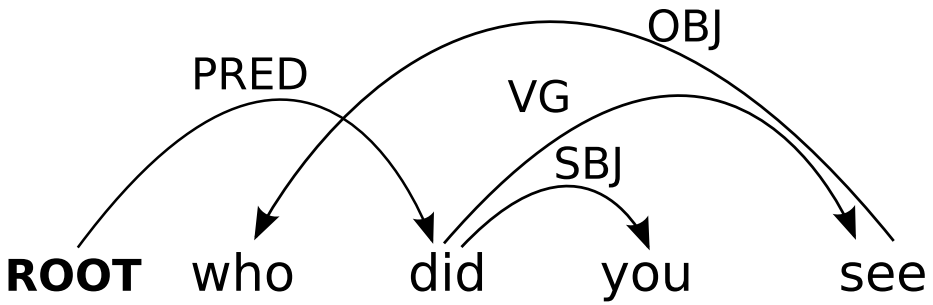

Comparison

	PProj	**EArc**	**Swap**
Completeness	no	no	yes
Parsing complexity	$O(n)^*$	$O(n)$	$O(n^2)$
Post-processing	yes	no	no

Empirical Evaluation

- Comparative evaluation [Kuhlmann and Nivre 2010]:
  - Theoretical coverage (oracle parsing)
  - Empirical performance (trained parser models)
- Data sets from CoNLL 2009 [Hajič et al. 2009]:
  - Czech: Prague Dependency Treebank [Hajič et al. 2001]
  - English: Penn Treebank [Marcus et al. 1993]
  - German: Tiger [Brants et al. 2002]
- Implementation: MaltParser [Nivre et al. 2006]

Training Set Statistics

	NPSent	NPArcs	NPLen	PLen
Czech	22.4	1.9	4.5	3.6
English	7.6	0.4	8.2	3.4
German	28.1	2.3	10.6	3.9

NPSent = Percentage of sentences with a non-projective tree
NPArcs = Percentage of arcs that are non-projective
NPLen = Average length of non-projective arcs
PLen = Average length of projective arcs

Theoretical Coverage

	Czech		English		German	
	LAS	**LEM**	**LAS**	**LEM**	**LAS**	**LEM**
Proj	98.0	76.9	99.7	93.7	97.7	73.1
PProj	99.8	97.9	*100.0	99.6	99.8	97.9
EArc	99.6	98.9	99.6	98.3	98.5	96.0
Swap	100.0	100.0	100.0	100.0	100.0	100.0

LAS = Labeled attachment score
LEM = Labeled exact match

Theoretical Coverage

	Czech		English		German	
	LAS	**LEM**	**LAS**	**LEM**	**LAS**	**LEM**
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PProj	99.8	97.9	*100.0	99.6	99.8	97.9
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Swap	100.0	100.0	100.0	100.0	100.0	100.0

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Swap	100.0	100.0	100.0	100.0	100.0	100.0

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Empirical Performance

	Czech		English		German	
	LAS	**LEM**	**LAS**	**LEM**	**LAS**	**LEM**
Proj	79.7	27.9	84.9	17.8	83.3	31.9
PProj	80.6	30.7	85.0	18.5	84.1	34.7
EArc	80.6	31.9	84.6	16.6	82.8	32.5
Swap	80.7	31.3	85.0	18.6	83.7	34.6

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Empirical Performance

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	LAS	**LEM**	**LAS**	**LEM**	**LAS**	**LEM**
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Empirical Performance: Non-Projective Arcs

	Czech		English		German	
	LP	**LR**	**LP**	**LR**	**LP**	**LR**
Proj	–	5.0	–	8.4	–	4.2
PProj	76.1	53.5	63.2	47.4	71.1	43.6
EArc	79.7	65.0	62.5	46.3	69.1	49.7
Swap	77.9	65.5	55.8	49.5	61.2	48.9

LP = Labeled precision on non-projective arcs output by the parser
LR = Labeled recall on non-projective arcs in gold standard

Empirical Performance: Non-Projective Arcs

	Czech		English		German	
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Discussion

- Overall parsing accuracy (LAS, LEM):
  - Significant improvement if non-projective dependencies are frequent enough (Czech and German but not English)
- Non-projective dependencies (LP, LR):
  - Precision relatively high (60–80), sometimes almost equivalent to projective dependencies modulo length
  - Recall generally lower (45–65) and language-dependent (better for Czech than for English and German)
- Comparing methods:
  - Very similar results for all three methods
  - EArc harmful if non-projective dependencies are longer (English and German but not Czech)

Conclusion

Conclusion

- Transition-based parsing:
  - Efficient parsing using greedy inference or beam search
  - Unconstrained history-based feature models
- Non-projective dependencies:
  - Three transition-based techniques:
    - Pseudo-projective parsing
    - Extended arc transitions
    - Online reordering (swap)
  - High precision, moderate recall
- Future work on non-projective dependencies:
  - Study the effect of global optimization
  - Compare with other kinds of dependency parsers

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