Recent Advances in Dependency Parsing

Tutorial, EACL, April 27th, 2014

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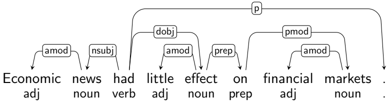
Overview of the Tutorial

- Introduction to Dependency Parsing (Joakim)
- Graph-based parsing post-2008 (Ryan)
- **Transition-based parsing post-2008** (Joakim)
- Summary and final thoughts (Ryan)

Transition-Based Dependency Parsing

Configuration:	(S, B, A)		
Initial:	$([\ ], [0, 1, \ldots, n], \{\ \})$		
Terminal:	$(S, [\ ], A)$		
Shift:	$(S, i\|B, A)$	$\Rightarrow$	$(S\|i, B, A)$
Reduce:	$(S\|i, B, A)$	$\Rightarrow$	(S, B, A)
Right-Arc(k):	$(S\|i, j\|B, A)$	$\Rightarrow$	$(S\|i\|j, B, A \cup \{(i, j, k)\})$
Left-Arc(k):	$(S\|i, j\|B, A)$	$\Rightarrow$	$(S, j\|B, A \cup \{(j, i, k)\})$

$\Leftrightarrow$



Overview

- Improved learning and inference
  - Beam search and structured prediction
  - Dynamic programming
  - Easy-first parsing
  - Dynamic oracles
- Non-projective parsing
  - Online reordering
  - Multiplanar parsing
- Joint morphological and syntactic analysis

The Basic Idea

- Define a transition system for dependency parsing
- Learn a model for scoring possible transitions
- Parse by searching for the optimal transition sequence

Arc-Eager Transition System [Nivre 2003]

Configuration:	(S, B, A)		$[S = \text{Stack}, B = \text{Buffer}, A = \text{Arcs}]$	
Initial:	$([\ ], [0, 1, \ldots, n], \{\ \})$			
Terminal:	$(S, [\ ], A)$			
Shift:	$(S, i\|B, A)$	$\Rightarrow$	$(S\|i, B, A)$	
Reduce:	$(S\|i, B, A)$	$\Rightarrow$	(S, B, A)	$h(i, A)$
Right-Arc(k):	$(S\|i, j\|B, A)$	$\Rightarrow$	$(S\|i\|j, B, A \cup \{(i, j, k)\})$	
Left-Arc(k):	$(S\|i, j\|B, A)$	$\Rightarrow$	$(S, j\|B, A \cup \{(j, i, k)\})$	$\neg h(i, A) \wedge i \neq 0$

Notation:
$S|i$ = stack with top i and remainder S
$j|B$ = buffer with head j and remainder B
$h(i, A)$ = i has a head in A

Example Transition Sequence

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

ROOT	Economic	news	had	little	effect	on	financial	markets	.
	adj	noun	verb	adj	noun	prep	adj	noun	.

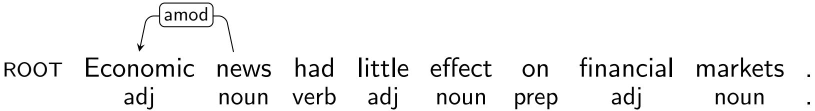
Example Transition Sequence

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

ROOT	Economic	news	had	little	effect	on	financial	markets	.
	adj	noun	verb	adj	noun	prep	adj	noun	.

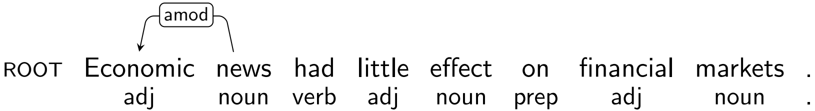
Example Transition Sequence

[ROOT]$_S$ [news, had, little, effect, on, financial, markets, .]$_B$



Example Transition Sequence

[ROOT, news]$_S$ [had, little, effect, on, financial, markets, .]$_B$



Example Transition Sequence

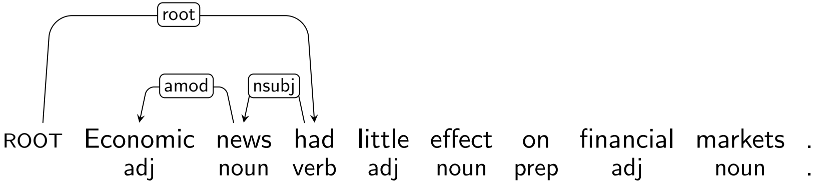
$[\text{ROOT}]_S$ $[\text{had, little, effect, on, financial, markets, .}]_B$

amod nsubj

ROOT	Economic	news	had	little	effect	on	financial	markets	.
	adj	noun	verb	adj	noun	prep	adj	noun	.

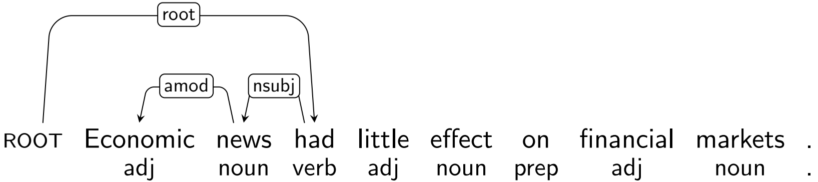
Example Transition Sequence

$[\text{ROOT, had}]_S$ $[\text{little, effect, on, financial, markets, .}]_B$



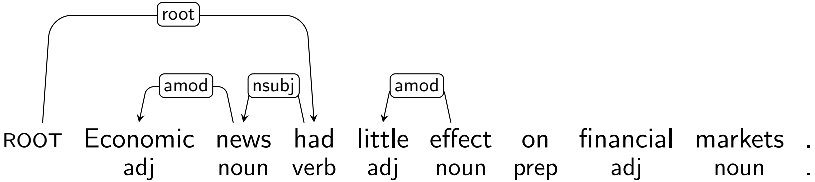
Example Transition Sequence

$[\text{ROOT, had, little}]_S$ $[\text{effect, on, financial, markets, .}]_B$



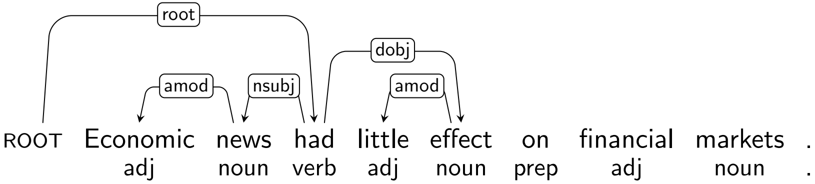
Example Transition Sequence

[ROOT, had]$_S$ [effect, on, financial, markets, .]$_B$



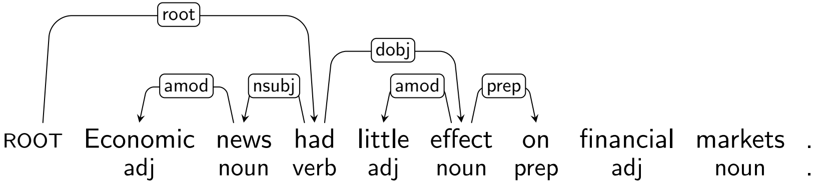
Example Transition Sequence

$[\text{ROOT, had, effect}]_S$ $[\text{on, financial, markets, .}]_B$



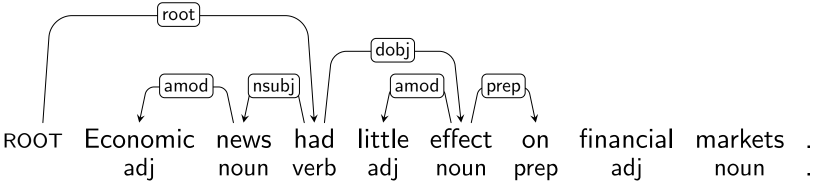
Example Transition Sequence

$[\text{ROOT, had, effect, on}]_S$ $[\text{financial, markets, .}]_B$



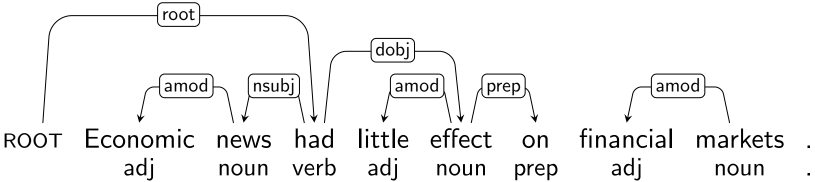
Example Transition Sequence

$[\text{ROOT, had, effect, on, financial}]_S \quad [\text{markets, .}]_B$



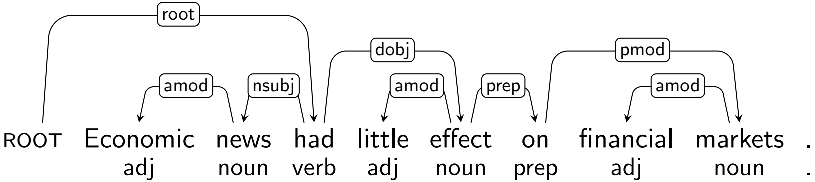
Example Transition Sequence

$[$ROOT, had, effect, on$]_S$ $[$markets, .$]_B$



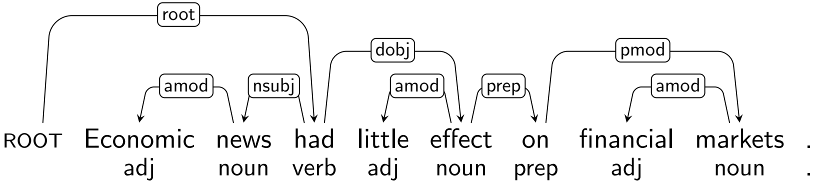
Example Transition Sequence

[ROOT, had, effect, on, markets]$_S$ [.]$_B$



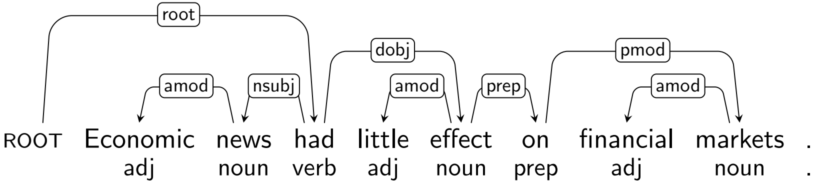
Example Transition Sequence

$[\text{ROOT, had, effect, on}]_S \quad [.]_B$



Example Transition Sequence

[ROOT, had, effect]$_S$ [.]$_B$



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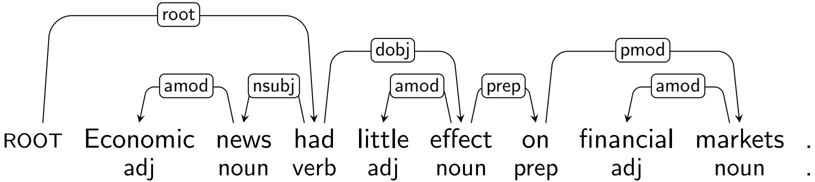
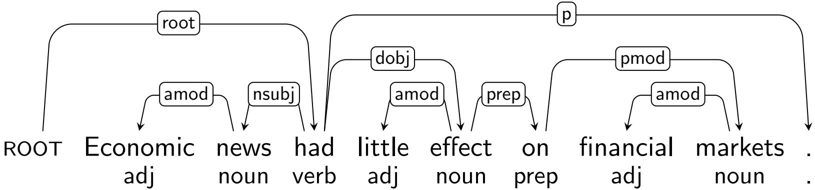
$[\text{ROOT, had}]_S \quad [.]_B$



Example Transition Sequence

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



Arc-Standard Transition System [Nivre 2004]

Configuration: (S, B, A) $[S = \text{Stack}, B = \text{Buffer}, A = \text{Arcs}]$

Initial: $([\ ], [0, 1, \ldots, n], \{\ \})$

Terminal: $([0], [\ ], A)$

Shift: $(S, i|B, A) \Rightarrow (S|i, B, A)$

Right-Arc(k): $(S|i|j, B, A) \Rightarrow (S|i, B, A \cup \{(i, j, k)\})$

Left-Arc(k): $(S|i|j, B, A) \Rightarrow (S|j, B, A \cup \{(j, i, k)\})$ $\quad i \neq 0$

Greedy Inference

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

$$
\begin{array}{l}
\mathrm{Parse}(w_1, \ldots, w_n) \\
\quad c \leftarrow ([\ ]_S, [0, 1, \ldots, n]_B, \{\ \}) \\
\quad \textbf{while } B_c \neq [\ ] \\
\qquad t \leftarrow o(c) \\
\qquad c \leftarrow t(c) \\
\quad \textbf{return } G = (\{0, 1, \ldots, n\}, A_c)
\end{array}
$$

- Complexity given by upper bound on number of transitions
- Parsing in $O(n)$ time for the arc-eager transition system

From Oracles to Classifiers

- An oracle can be approximated by a (linear) classifier:

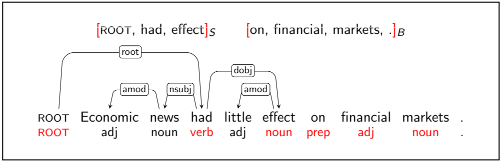
$$o(c) = \underset{t}{\operatorname{argmax}}\, \mathbf{w} \cdot \mathbf{f}(c, t)$$

- History-based feature representation $\mathbf{f}(c, t)$
- Weight vector $\mathbf{w}$ learned from treebank data

Feature Representation

- Features over input tokens relative to S and B

Configuration



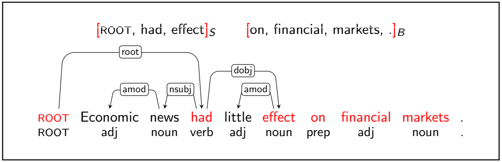
Features

$$
\begin{aligned}
\text{pos}(S_2) &= \text{ROOT} \\
\text{pos}(S_1) &= \text{verb} \\
\text{pos}(S_0) &= \text{noun} \\
\text{pos}(B_0) &= \text{prep} \\
\text{pos}(B_1) &= \text{adj} \\
\text{pos}(B_2) &= \text{noun}
\end{aligned}
$$

Feature Representation

- Features over input tokens relative to S and B

Configuration



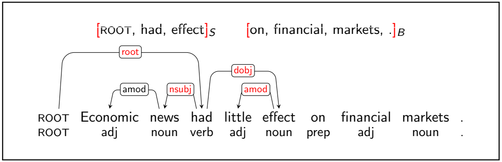
Features

$$
\begin{aligned}
\text{word}(S_2) &= \text{ROOT}\\
\text{word}(S_1) &= \text{had}\\
\text{word}(S_0) &= \text{effect}\\
\text{word}(B_0) &= \text{on}\\
\text{word}(B_1) &= \text{financial}\\
\text{word}(B_2) &= \text{markets}
\end{aligned}
$$

Feature Representation

- Features over input tokens relative to S and B
- Features over the (partial) dependency graph defined by A

Configuration



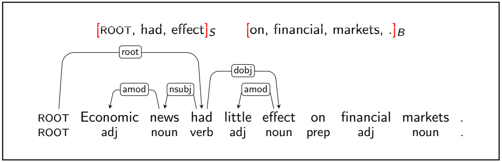
Features

$\text{dep}(S_1)$	$=$	root
$\text{dep}(\text{lc}(S_1))$	$=$	nsubj
$\text{dep}(\text{rc}(S_1))$	$=$	dobj
$\text{dep}(S_0)$	$=$	dobj
$\text{dep}(\text{lc}(S_0))$	$=$	amod
$\text{dep}(\text{rc}(S_0))$	$=$	NIL

Feature Representation

- Features over input tokens relative to S and B
- Features over the (partial) dependency graph defined by A
- Features over the (partial) transition sequence

Configuration



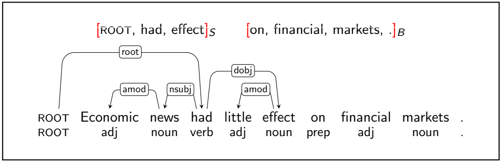
Features

$$
\begin{aligned}
t_{i-1} &= \text{Right-Arc(dobj)} \\
t_{i-2} &= \text{Left-Arc(amod)} \\
t_{i-3} &= \text{Shift} \\
t_{i-4} &= \text{Right-Arc(root)} \\
t_{i-5} &= \text{Left-Arc(nsubj)} \\
t_{i-6} &= \text{Shift}
\end{aligned}
$$

Feature Representation

- Features over input tokens relative to S and B
- Features over the (partial) dependency graph defined by A
- Features over the (partial) transition sequence

Configuration



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t_{i-1} &= \text{Right-Arc(dobj)} \\
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t_{i-3} &= \text{Shift} \\
t_{i-4} &= \text{Right-Arc(root)} \\
t_{i-5} &= \text{Left-Arc(nsubj)} \\
t_{i-6} &= \text{Shift}
\end{aligned}
$$

- Feature representation unconstrained by parsing algorithm

Local Learning

- Given a treebank:
  - Reconstruct oracle transition sequence for each sentence
  - Construct training data set $D = \{(c, t) \mid o(c) = t\}$
  - Maximize accuracy of local predictions $o(c) = t$
- Any (unstructured) classifier will do (SVMs are popular)
- Training is local and restricted to oracle configurations

Greedy, Local, Transition-Based Parsing

- Advantages:
  - Highly efficient parsing – linear time complexity with constant time oracles and transitions
  - Rich history-based feature representations – no rigid constraints from inference algorithm
- Drawback:
  - Sensitive to search errors and error propagation due to greedy inference and local learning
- The major question in transition-based parsing has been how to improve learning and inference, while maintaining high efficiency and rich feature models

Beam Search

- Maintain the k best hypotheses [Johansson and Nugues 2006]:

  Parse($w_1, \ldots, w_n$)
  Beam $\leftarrow \{([\,]_S, [0, 1, \ldots, n]_B, \{\,\})\}$
  while $\exists c \in$ Beam $[B_c \neq [\,]]$
    foreach $c \in$ Beam
      foreach t
        Add($t(c)$, NewBeam)
    Beam $\leftarrow$ Top(k, NewBeam)
  return $G = (\{0, 1, \ldots, n\}, A_{\text{Top}(1,\,\text{Beam})})$

- Note:
  - $\text{Score}(c_0, \ldots, c_m) = \sum_{i=1}^{m} \mathbf{w} \cdot \mathbf{f}(c_{i-1}, t_i)$
  - Simple combination of locally normalized classifier scores
  - Marginal gains in accuracy

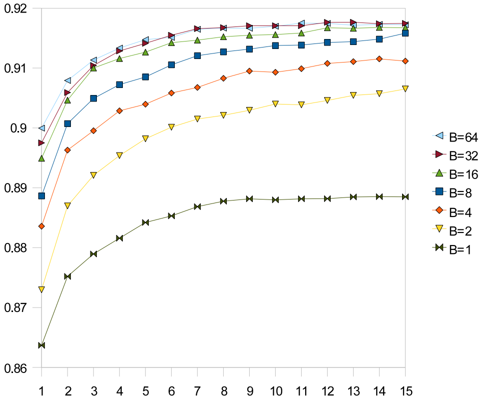
Structured Prediction

- Parsing as structured prediction [Zhang and Clark 2008]:
  - Minimize loss over entire transition sequence
  - Use beam search to find highest-scoring sequence
- Factored feature representations:

$$\mathbf{f}(c_0, \ldots, c_m) = \sum_{i=1}^{m} \mathbf{f}(c_{i-1}, t_i)$$

- Online learning from oracle transition sequences:
  - Structured perceptron [Collins 2002]
  - Early update [Collins and Roark 2004]
  - Max-violation update [Huang et al. 2012]

Beam Size and Training Iterations

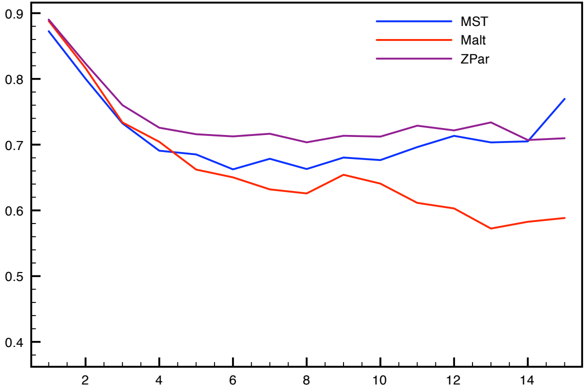


[Zhang and Clark 2008]

The Best of Two Worlds?

- Like graph-based dependency parsing (MSTParser):
  - Global learning – minimize loss over entire sentence
  - Non-greedy search – accuracy increases with beam size
- Like (old school) transition-based parsing (MaltParser):
  - Highly efficient – complexity still linear for fixed beam size
  - Rich features – no constraints from parsing algorithm

Precision by Dependency Length



[Zhang and Nivre 2012]

Even Richer Feature Models

	ZPar	Malt
Baseline	92.18	89.37
+distance	+0.07	–0.14
+valency	+0.24	0.00
+unigrams	+0.40	–0.29
+third-order	+0.18	0.00
+label set	+0.07	+0.06
Extended	93.14	89.00

[Zhang and Nivre 2011, Zhang and Nivre 2012]

- Adding graph-based features may require special techniques
  [Zhang and Clark 2008, Bohnet and Kuhn 2012]

Dynamic Programming

- If beam search reduces search errors, why not exact inference?
- Dynamic programming for transition-based parsers:
  - Using a graph-structured stack [Huang and Sagae 2010]
  - Using push-computations [Kuhlmann et al. 2011]
- Adds constraints on feature representations

Deduction System for Arc-Eager Parsing

Items: $[i^b, j] \quad \Leftrightarrow \quad (S, i|B, A) \Rightarrow^* (S|i, j|B', A')$

$$b = \begin{cases} 1 & \text{if } [\![h(i) \in A']\!] \\ 0 & \text{otherwise} \end{cases}$$

Goal: $[0^0, n+1]$

Axiom: $[0^0, 1]$

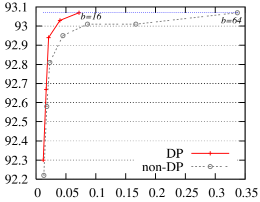
Rules:

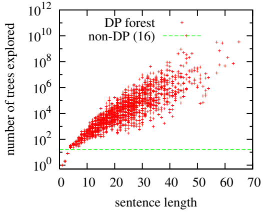
Shift:	$[i^b, j] \Rightarrow [j^0, j+1]$
Reduce:	$[i^b, m] \wedge [m^1, j] \Rightarrow [i^b, j]$
Right-Arc:	$[i^b, j] \Rightarrow [j^1, j+1]$
Left-Arc:	$[i^b, m] \wedge [m^0, j] \Rightarrow [i^b, j]$

[Kuhlmann et al. 2011]

Theory and Practice

- Theoretical results:
  - Arc-eager parsing in $O(n^3)$ time (cf. Eisner)
  - Arc-standard parsing in $O(n^5)$ time (cf. CKY)
- In practice:
  - Results hold only for very simplistic feature models
  - Practical implementations use beam search
  - Benefits from ambiguity packing





[Huang and Sagae 2010]

The Need for Speed

- Beam search helps but slows down the parser
- Dynamic programming in addition constrains feature model
- What can we do to maintain the highest speed?
  - Easy-first parsing – give up left-to-right incremental search
  - Dynamic oracles – learn how to recover from errors
- These two ideas can be combined

Easy-First Non-Directional Parsing

- Process dependencies from easy to hard (not left to right) and from local to global (bottom up) [Goldberg and Elhadad 2010]

Configuration: (L, A) $[L = \text{List}, A = \text{Arcs}]$

Initial: $([0, 1, \ldots, n], \{\ \})$

Terminal: $([0], A)$

Attach-Right(*i*, *k*):

$$([v_1, \ldots, v_m], A) \;\Rightarrow\; ([v_1, \ldots, v_{i-1}, v_{i+1}, \ldots, v_m], A \cup \{(v_{i+1}, v_i, k)\})$$

Attach-Left(*i*, *k*):

$$([v_1, \ldots, v_m], A) \;\Rightarrow\; ([v_1, \ldots, v_i, v_{i+2}, \ldots, v_m], A \cup \{(v_i, v_{i+1}, k)\})$$

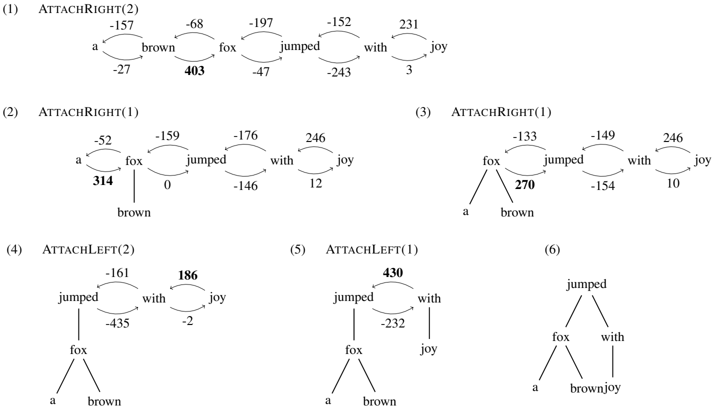
Parsing Algorithm

- Given an oracle o that selects the highest-confidence transition $o(c)$, parsing is deterministic:

Parse$(w_1, \ldots, w_n)$
  $c \leftarrow ([0, 1, \ldots, n], \{\ \})$
  while length$(L_c) > 1$
    $t \leftarrow o(c)$
    $c \leftarrow t(c)$
  return $G = (\{0, 1, \ldots, n\}, A_c)$

- Number of possible transitions grows with sentence length
- Parsing in $O(n \log n)$ time with priority heap

Parsing Example



[Goldberg and Elhadad 2010]

Oracles Revisited

- How do we train the easy-first parser?
- Recall our training procedure for greedy parsers:
  - Reconstruct oracle transition sequence for each sentence
  - Construct training data set $D = \{(c, t) \mid o(c) = t\}$
  - Maximize accuracy of local predictions $o(c) = t$
- Presupposes a unique optimal transition for each configuration
  - Does not make sense for the easy-first parser
  - Turns out to be a bad idea in general

Online Learning with a Conventional Oracle

Learn($\{T_1, \ldots, T_N\}$)

$\mathbf{w} \leftarrow 0.0$
for i in $1..K$
    for j in $1..N$
        $c \leftarrow ([\ ], [0, 1, \ldots, n_j], \{\ \})$
        while $B_c \neq [\ ]$
            $t^* \leftarrow \text{argmax}_t\, \mathbf{w} \cdot \mathbf{f}(c, t)$
            $t_o \leftarrow o(c, T_i)$
            if $t^* \neq t_o$
                $\mathbf{w} \leftarrow \mathbf{w} + \mathbf{f}(c, t_o) - \mathbf{f}(c, t^*)$
            $c \leftarrow t_o(c)$
return w

Online Learning with a Conventional Oracle

Learn($\{T_1, \ldots, T_N\}$)

$\mathbf{w} \leftarrow 0.0$
for i in $1..K$
  for j in $1..N$
    $c \leftarrow ([\ ], [0, 1, \ldots, n_j], \{\ \})$
    while $B_c \neq [\ ]$
      $t^* \leftarrow \text{argmax}_t\, \mathbf{w} \cdot \mathbf{f}(c, t)$
      $t_o \leftarrow o(c, T_i)$
      if $t^* \neq t_o$
        $\mathbf{w} \leftarrow \mathbf{w} + \mathbf{f}(c, t_o) - \mathbf{f}(c, t^*)$
      $c \leftarrow t_o(c)$
return w

- Oracle $o(c, T_i)$ returns the optimal transition for c and T_i

Conventional Oracle for Arc-Eager Parsing

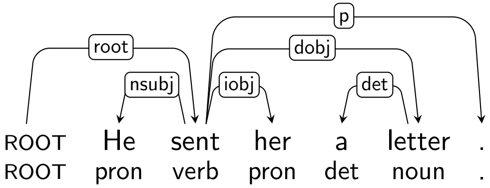
$$o(c, T) = \begin{cases} \text{Left-Arc} & \text{if } \text{top}(S_c) \leftarrow \text{first}(B_c) \text{ in } T \\ \text{Right-Arc} & \text{if } \text{top}(S_c) \rightarrow \text{first}(B_c) \text{ in } T \\ \text{Reduce} & \text{if } \exists v < \text{top}(S_c) : v \leftrightarrow \text{first}(B_c) \text{ in } T \\ \text{Shift} & \text{otherwise} \end{cases}$$

- Correct:
  - Derives T in a configuration sequence $C_{o,T} = c_0, \ldots, c_m$
- Problems:
  - Deterministic: Ignores other derivations of T
  - Incomplete: Valid only for configurations in $C_{o,T}$

Oracle Parse

Transitions:

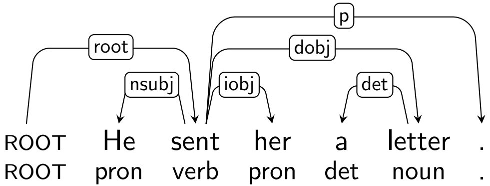
Stack	**Buffer**	**Arcs**
[ ]	[ROOT, He, sent, her, a, letter, .]	



Oracle Parse

Transitions: SH

Stack	**Buffer**	**Arcs**
[ROOT]	[He, sent, her, a, letter, .]	



Oracle Parse

Transitions: SH-RA

Stack

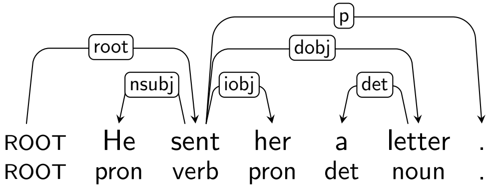
[ROOT, He]

Buffer

[sent, her, a, letter, .]

Arcs

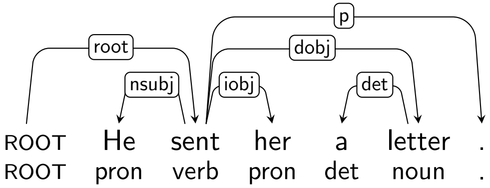
ROOT $\xrightarrow{\text{root}}$ sent



Oracle Parse

Transitions: SH-RA-LA

Stack	**Buffer**	**Arcs**
[ROOT]	[sent, her, a, letter, .]	ROOT $\xrightarrow{\text{root}}$ sent
		He $\xleftarrow{\text{sbj}}$ sent



Oracle Parse

Transitions: SH-RA-LA-SH

Stack

[ROOT, sent]

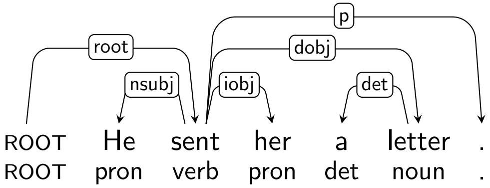
Buffer

[her, a, letter, .]

Arcs

$\text{ROOT} \xrightarrow{\text{root}} \text{sent}$

$\text{He} \xleftarrow{\text{sbj}} \text{sent}$



Oracle Parse

Transitions: SH-RA-LA-SH-RA

Stack

[ROOT, sent, her]

Buffer

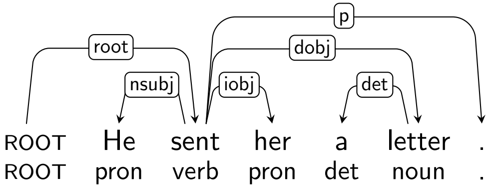
[a, letter, .]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her



Oracle Parse

Transitions: SH-RA-LA-SH-RA-SH

Stack

[ROOT, sent, her, a]

Buffer

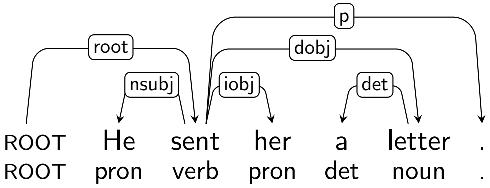
[letter, .]

Arcs

$\text{ROOT} \xrightarrow{\text{root}} \text{sent}$

$\text{He} \xleftarrow{\text{sbj}} \text{sent}$

$\text{sent} \xrightarrow{\text{iobj}} \text{her}$



Oracle Parse

Transitions: SH-RA-LA-SH-RA-SH-LA

Stack

[ROOT, sent, her]

Buffer

[letter, .]

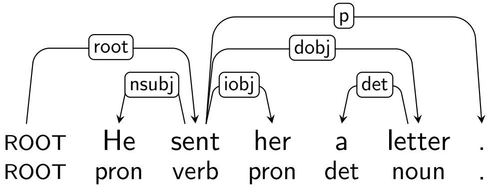
Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her

a $\xleftarrow{\text{det}}$ letter



Oracle Parse

Transitions: SH-RA-LA-SH-RA-SH-LA-RE

Stack

[ROOT, sent]

Buffer

[letter, .]

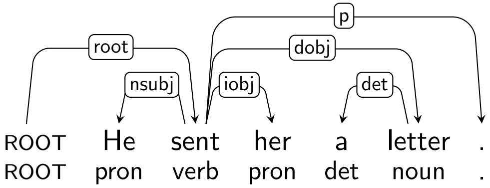
Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her

a $\xleftarrow{\text{det}}$ letter

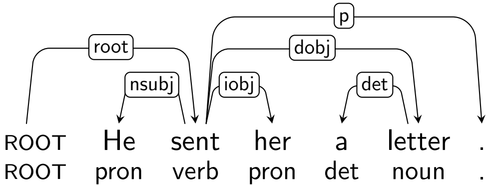


Oracle Parse

Transitions: SH-RA-LA-SH-RA-SH-LA-RE-RA

Stack **Buffer**

[ROOT, sent, letter] [.]



Arcs

$\text{ROOT} \xrightarrow{\text{root}} \text{sent}$

$\text{He} \xleftarrow{\text{sbj}} \text{sent}$

$\text{sent} \xrightarrow{\text{iobj}} \text{her}$

$\text{a} \xleftarrow{\text{det}} \text{letter}$

$\text{sent} \xrightarrow{\text{dobj}} \text{letter}$

Oracle Parse

Transitions: SH-RA-LA-SH-RA-SH-LA-RE-RA-RE

Stack

[ROOT, sent]

Buffer

[.]

Arcs

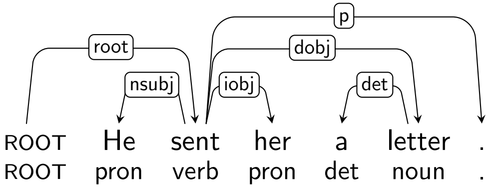
ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her

a $\xleftarrow{\text{det}}$ letter

sent $\xrightarrow{\text{dobj}}$ letter



Oracle Parse

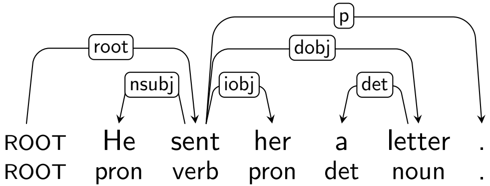
Transitions: SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

Stack

[ROOT, sent, .]

Buffer

[ ]



Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her

a $\xleftarrow{\text{det}}$ letter

sent $\xrightarrow{\text{dobj}}$ letter

sent $\xrightarrow{\text{p}}$.

Non-Determinisim

Transitions: SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA
SH-RA-LA-SH-RA

Stack

[ROOT, sent, her]

Buffer

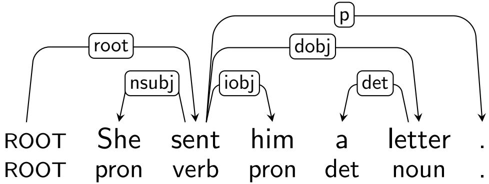
[a, letter, .]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her



Non-Determinisim

Transitions:

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

SH-RA-LA-SH-RA-RE

Stack

[ROOT, sent]

Buffer

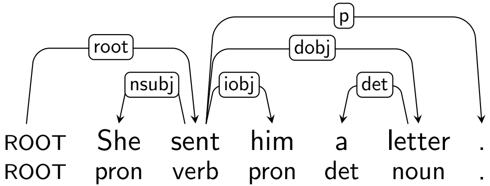
[a, letter, .]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her



Non-Determinisim

Transitions: SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA
SH-RA-LA-SH-RA-RE-SH

Stack

[ROOT, sent, a]

Buffer

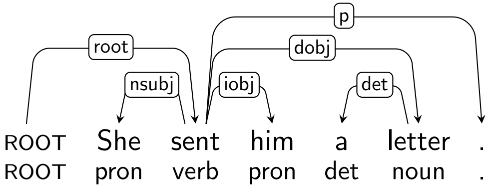
[letter, .]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her



Non-Determinisim

Transitions: SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

SH-RA-LA-SH-RA-RE-SH-LA

Stack

[ROOT, sent]

Buffer

[letter, .]

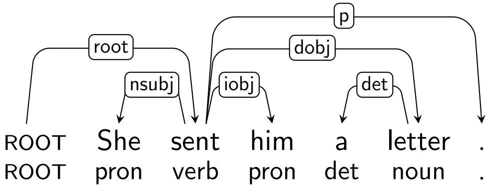
Arcs

$\text{ROOT} \xrightarrow{\text{root}} \text{sent}$

$\text{He} \xleftarrow{\text{sbj}} \text{sent}$

$\text{sent} \xrightarrow{\text{iobj}} \text{her}$

$\text{a} \xleftarrow{\text{det}} \text{letter}$



Non-Determinisim

Transitions:

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

SH-RA-LA-SH-RA-RE-SH-LA-RA

Stack

[ROOT, sent, letter]

Buffer

[.]

Arcs

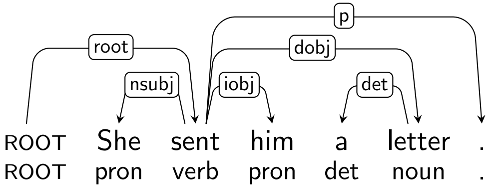
ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her

a $\xleftarrow{\text{det}}$ letter

sent $\xrightarrow{\text{dobj}}$ letter



Non-Determinisim

Transitions: SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA
SH-RA-LA-SH-RA-RE-SH-LA-RA-RE

Stack

[ROOT, sent]

Buffer

[.]

Arcs

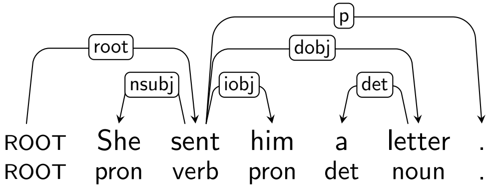
ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

sent $\xrightarrow{\text{iobj}}$ her

a $\xleftarrow{\text{det}}$ letter

sent $\xrightarrow{\text{dobj}}$ letter



Non-Determinisim

Transitions:

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA
SH-RA-LA-SH-RA-RE-SH-LA-RA-RE-RA

Stack

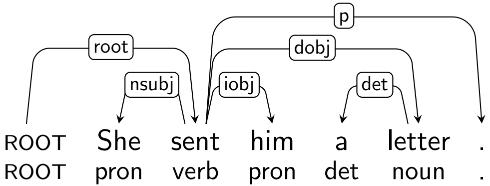
[ROOT, sent, .]

Buffer

[ ]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent
He $\xleftarrow{\text{sbj}}$ sent
sent $\xrightarrow{\text{iobj}}$ her
a $\xleftarrow{\text{det}}$ letter
sent $\xrightarrow{\text{dobj}}$ letter
sent $\xrightarrow{\text{p}}$.



Non-Optimality

Transitions: SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

SH-RA-LA-SH

Stack

[ROOT, sent]

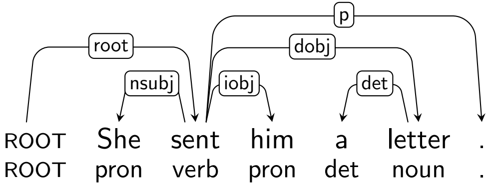
Buffer

[her, a, letter, .]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent



Non-Optimality

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

Transitions: SH-RA-LA-SH-SH

Stack

[ROOT, sent, her]

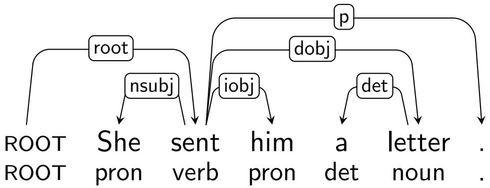
Buffer

[a, letter, .]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent



Non-Optimality

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

Transitions: SH-RA-LA-SH-SH-SH

Stack

[ROOT, sent, her, a]

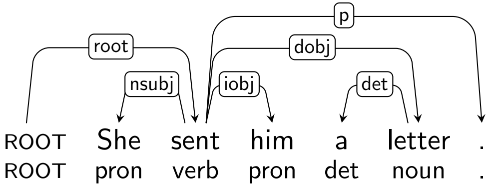
Buffer

[letter, .]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent



Non-Optimality

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

Transitions: SH-RA-LA-SH-SH-SH-LA

Stack

[ROOT, sent, her]

Buffer

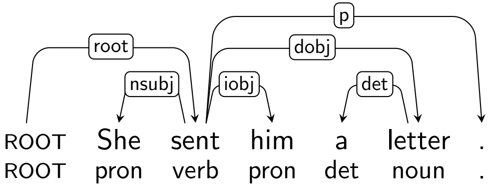
[letter, .]

Arcs

$\text{ROOT} \xrightarrow{\text{root}} \text{sent}$

$\text{He} \xleftarrow{\text{sbj}} \text{sent}$

$\text{a} \xleftarrow{\text{det}} \text{letter}$



Non-Optimality

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

Transitions: SH-RA-LA-SH-SH-SH-LA-SH

Stack

[ROOT, sent, her, letter]

Buffer

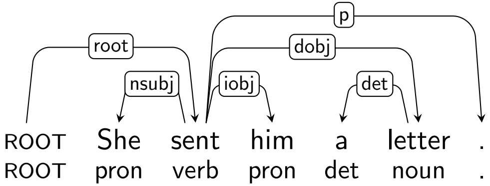
[.]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

a $\xleftarrow{\text{det}}$ letter



Non-Optimality

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

Transitions: SH-RA-LA-SH-SH-SH-LA-SH-SH [3/6]

Stack

[ROOT, sent, letter, .]

Buffer

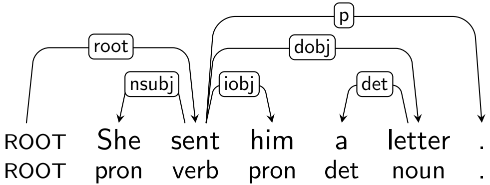
[ ]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

a $\xleftarrow{\text{det}}$ letter



Non-Optimality

	SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA	
Transitions:	SH-RA-LA-SH-SH-SH-LA-SH-SH	[3/6]
	SH-RA-LA-SH-SH-SH-LA	

Stack

[ROOT, sent, her]

Buffer

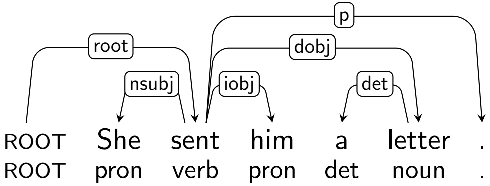
[letter, .]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

a $\xleftarrow{\text{det}}$ letter



Non-Optimality

Transitions:

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

SH-RA-LA-SH-SH-SH-LA-SH-SH [3/6]

SH-RA-LA-SH-SH-SH-LA-LA

Stack

[ROOT, sent]

Buffer

[letter, .]

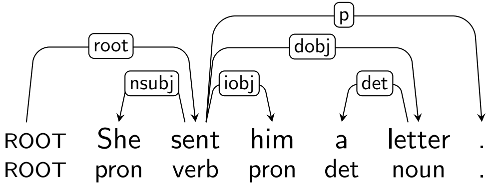
Arcs

ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

a $\xleftarrow{\text{det}}$ letter

her $\xleftarrow{?}$ letter



Non-Optimality

	SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA	
Transitions:	SH-RA-LA-SH-SH-SH-LA-SH-SH	[3/6]
	SH-RA-LA-SH-SH-SH-LA-LA-RA	

Stack

[ROOT, sent, letter]

Buffer

[.]

Arcs

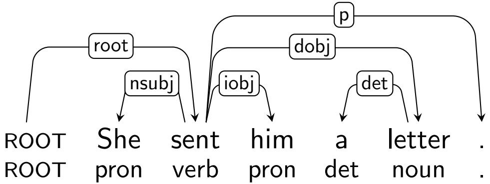
ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

a $\xleftarrow{\text{det}}$ letter

her $\xleftarrow{?}$ letter

sent $\xrightarrow{\text{dobj}}$ letter



Non-Optimality

Transitions:

SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA

SH-RA-LA-SH-SH-SH-LA-SH-SH [3/6]

SH-RA-LA-SH-SH-SH-LA-LA-RA-RE

Stack

[ROOT, sent]

Buffer

[.]

Arcs

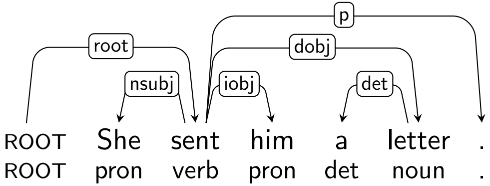
ROOT $\xrightarrow{\text{root}}$ sent

He $\xleftarrow{\text{sbj}}$ sent

a $\xleftarrow{\text{det}}$ letter

her $\xleftarrow{?}$ letter

sent $\xrightarrow{\text{dobj}}$ letter



Non-Optimality

	SH-RA-LA-SH-RA-SH-LA-RE-RA-RE-RA
Transitions:	SH-RA-LA-SH-SH-SH-LA-SH-SH [3/6]
	SH-RA-LA-SH-SH-SH-LA-LA-RA-RE-RA [5/6]

Stack

[ROOT, sent, .]

Buffer

[ ]

Arcs

ROOT $\xrightarrow{\text{root}}$ sent

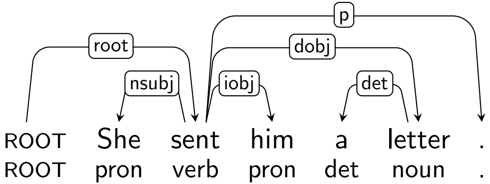
He $\xleftarrow{\text{sbj}}$ sent

a $\xleftarrow{\text{det}}$ letter

her $\xleftarrow{?}$ letter

sent $\xrightarrow{\text{dobj}}$ letter

sent $\xrightarrow{\text{p}}$.



Dynamic Oracles

- Optimality:
  - A transition is optimal if the best tree remains reachable
  - Best tree $= \text{argmin}_{T'} \mathcal{L}(T, T')$
- Oracle:
  - Boolean function $o(c, t, T) =$ **true** if t is optimal for c and T
  - Non-deterministic: More than one transition can be optimal
  - Complete: Correct for all configurations
- New problem:
  - How do we know which trees are reachable?

Reachability for Arcs and Trees

- Arc reachability:
  - An arc $w_i \rightarrow w_j$ is reachable in c iff $w_i \rightarrow w_j \in A_c$, or $w_i \in S_c \cup B_c$ and $w_j \in B_c$ (same for $w_i \leftarrow w_j$)
- Tree reachability:
  - A (projective) tree T is reachable in c iff every arc in T is reachable in c
- Arc-decomposable systems [Goldberg and Nivre 2013]:
  - Tree reachability reduces to arc reachability
  - Holds for some transition systems but not all
    - Arc-eager and easy-first are arc-decomposable
    - Arc-standard is not decomposable

Oracles for Arc-Decomposable Systems

$$o(c, t, T) = \begin{cases} \textbf{true} & \text{if } [\mathcal{R}(c) - \mathcal{R}(t(c))] \cap T = \emptyset \\ \textbf{false} & \text{otherwise} \end{cases}$$

$$\text{where } \mathcal{R}(c) \equiv \{a \mid a \text{ is an arc reachable in } c\}$$

Arc-Eager

$$o(c, \text{LA}, T) = \begin{cases} \textbf{false} & \text{if } \exists w \in B_c : s \leftrightarrow w \in T \text{ (except } s \leftarrow b) \\ \textbf{true} & \text{otherwise} \end{cases}$$

$$o(c, \text{RA}, T) = \begin{cases} \textbf{false} & \text{if } \exists w \in S_c : w \leftrightarrow b \in T \text{ (except } s \rightarrow b) \\ \textbf{true} & \text{otherwise} \end{cases}$$

$$o(c, \text{RE}, T) = \begin{cases} \textbf{false} & \text{if } \exists w \in B_c : s \rightarrow w \in T \\ \textbf{true} & \text{otherwise} \end{cases}$$

$$o(c, \text{SH}, T) = \begin{cases} \textbf{false} & \text{if } \exists w \in S_c : w \leftrightarrow b \in T \\ \textbf{true} & \text{otherwise} \end{cases}$$

Notation: s = node on top of the stack S
b = first node in the buffer B

Online Learning with a Dynamic Oracle

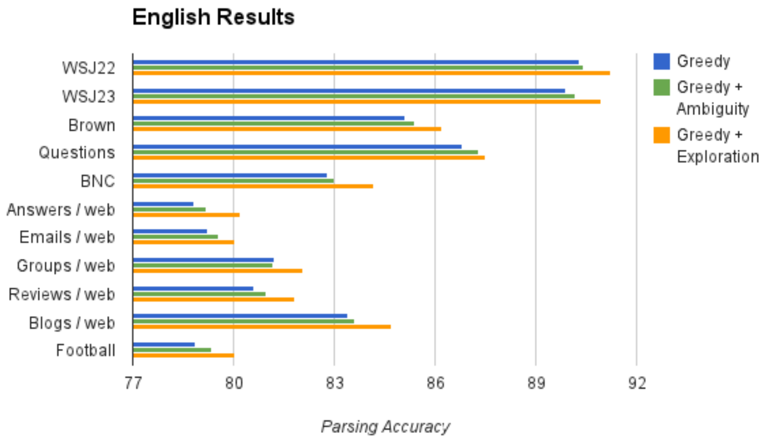
Learn($\{T_1, \ldots, T_N\}$)
    $\mathbf{w} \leftarrow 0.0$
    for i in $1..K$
        for j in $1..N$
            $c \leftarrow ([\ ]_S, [w_1, \ldots, w_{n_j}]_B, \{\ \})$
            while $B_c \neq [\ ]$
                $t^* \leftarrow \text{argmax}_t\, \mathbf{w} \cdot \mathbf{f}(c, t)$
                $t_o \leftarrow \text{argmax}_{t \in \{t | o(c,t,T_i)\}}\, \mathbf{w} \cdot \mathbf{f}(c, t)$
                if $t^* \neq t_o$
                    $\mathbf{w} \leftarrow \mathbf{w} + \mathbf{f}(c, t_o) - \mathbf{f}(c, t^*)$
                $c \leftarrow \text{choice}(t_o(c), t^*(c))$
    return w

Online Learning with a Dynamic Oracle

Learn($\{T_1, \ldots, T_N\}$)

$$
\begin{array}{l}
\mathbf{w} \leftarrow 0.0 \\
\textbf{for } i \text{ in } 1..K \\
\quad \textbf{for } j \text{ in } 1..N \\
\quad\quad c \leftarrow ([\,]_S, [w_1, \ldots, w_{n_j}]_B, \{\,\}) \\
\quad\quad \textbf{while } B_c \neq [\,] \\
\quad\quad\quad t^* \leftarrow \text{argmax}_t\, \mathbf{w} \cdot \mathbf{f}(c, t) \\
\quad\quad\quad t_o \leftarrow \text{argmax}_{t \in \{t \mid o(c,t,T_i)\}}\, \mathbf{w} \cdot \mathbf{f}(c, t) \\
\quad\quad\quad \textbf{if } t^* \neq t_o \\
\quad\quad\quad\quad \mathbf{w} \leftarrow \mathbf{w} + \mathbf{f}(c, t_o) - \mathbf{f}(c, t^*) \\
\quad\quad\quad c \leftarrow \text{choice}(t_o(c), t^*(c)) \\
\textbf{return } \mathbf{w}
\end{array}
$$

- Ambiguity: use model score to break ties
- Exploration: follow model prediction even if not optimal



[Goldberg and Nivre 2012]

Ambiguity and Exploration

- Lessons from dynamic oracles:
  - Do not hide spurious ambiguity from the parser – exploit it
  - Let the parser explore the consequences of its own mistakes
- Related work:
  - Bootstrapping [Choi and Palmer 2011]
  - Selectional branching [Choi and McCallum 2013]
  - Non-monotonic parsing [Honnibal et al. 2013]
  - Dynamic parsing strategy [Sartorio et al. 2013]

Summary: Learning and Inference

- Beam search and structured prediction:
  - Explores a larger search space at training and parsing time
  - Can be combined with dynamic programming
- Dynamic oracles:
  - Explores a larger search space only at training time
  - Can be combined with selectional branching and with flexible transition systems (easy-first, dynamic, non-monotonic)

Non-Projective Parsing

- So far only projective parsing models
- Non-projective parsing harder even with greedy inference
  - Non-projective: $n(n-1)$ arcs to consider – $O(n^2)$
  - Projective: at most $2(n-1)$ arcs to consider – $O(n)$
- Also harder to construct dynamic oracles
  - Conjecture: arc-decomposability presupposes projectivity

Previous Approaches

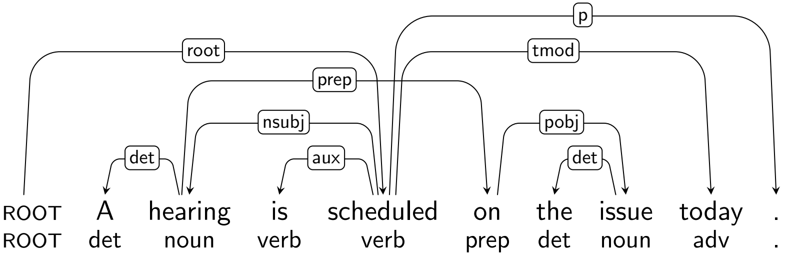
- Pseudo-projective parsing [Nivre and Nilsson 2005]
  - Preprocess training data, post-process parser output
  - Approximate encoding with incomplete coverage
  - Relatively high precision but low recall
- Extended arc transitions [Attardi 2006]
  - Transitions that add arcs between non-adjacent subtrees
  - Upper bound on arc degree (limited to local relations)
  - Exact dynamic programming algorithm [Cohen et al. 2011]
- List-based algorithms [Covington 2001, Nivre 2007]
  - Consider all word pairs instead of adjacent subtrees
  - Increases parsing complexity (and training time)
  - Improved accuracy and efficiency by adding "projective transitions" [Choi and Palmer 2011]

Novel Approaches

- Online reordering [Nivre 2009, Nivre et al. 2009]:
  - Reorder words during parsing to make tree projective
  - Add a special transition for swapping adjacent words
  - Quadratic time in the worst case but linear in the best case
- Multiplanar parsing [Gómez-Rodríguez and Nivre 2010]:
  - Factor dependency trees into k planes without crossing arcs
  - Use k stacks to parse each plane separately
  - Linear time parsing with constant k

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
  - 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 $<$ [Veselá et al. 2004]



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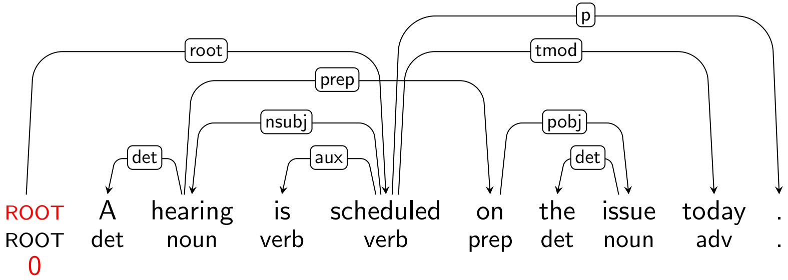

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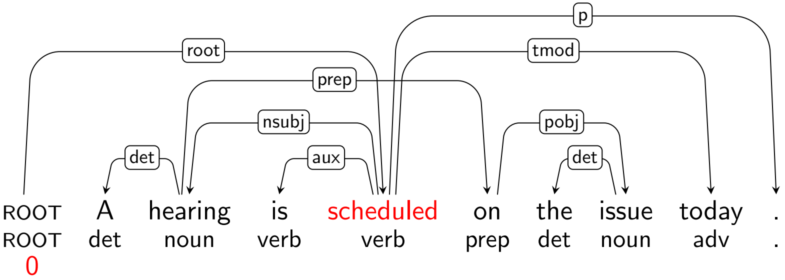

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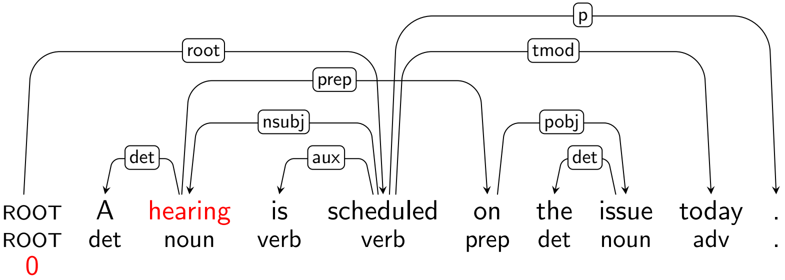

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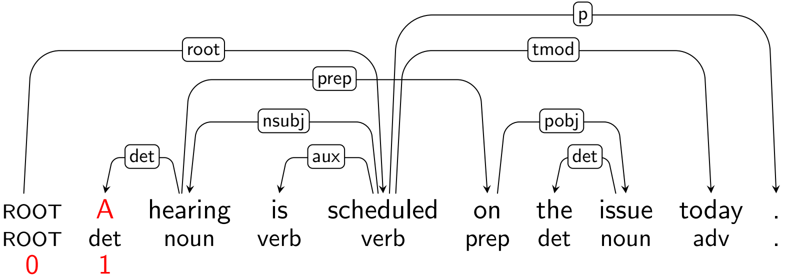

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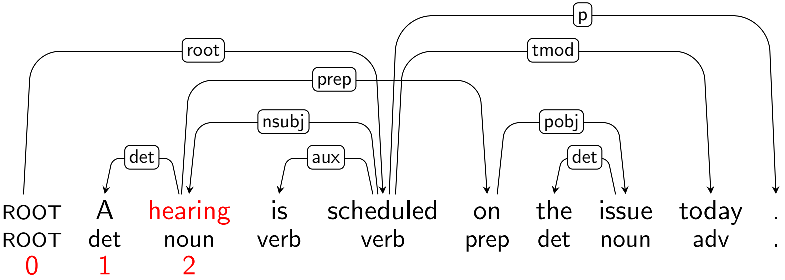

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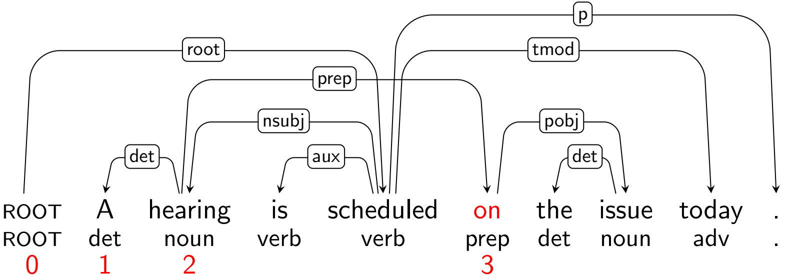

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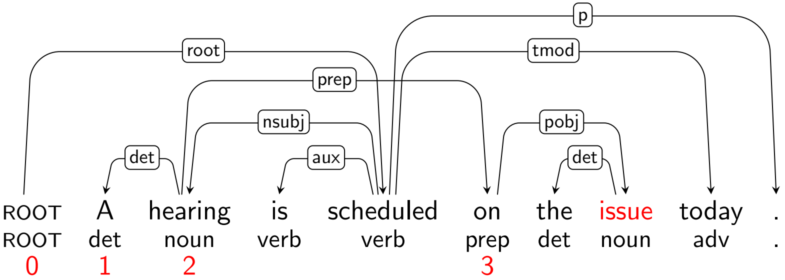

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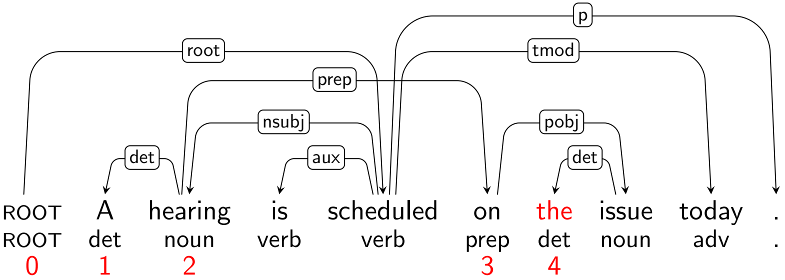

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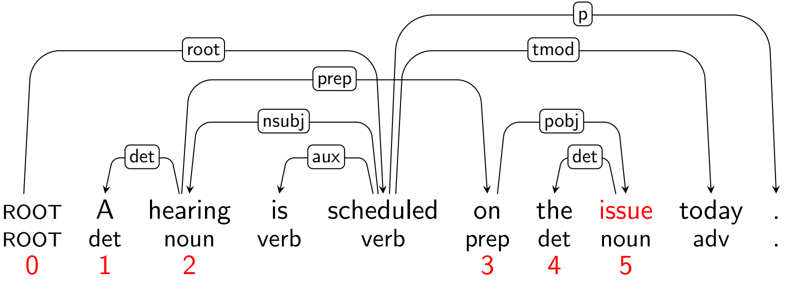

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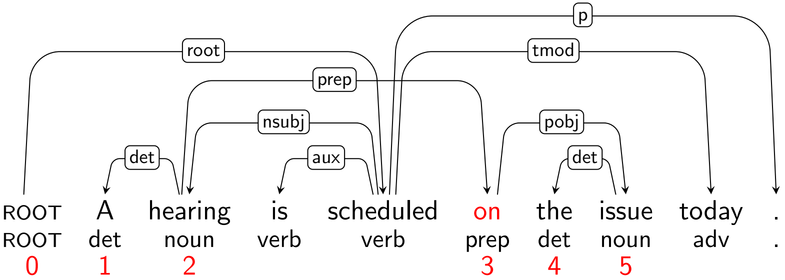

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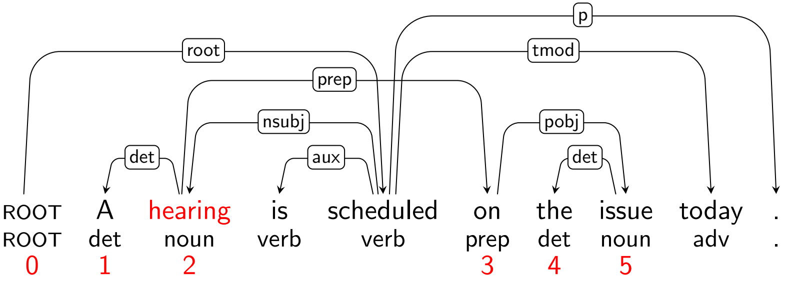

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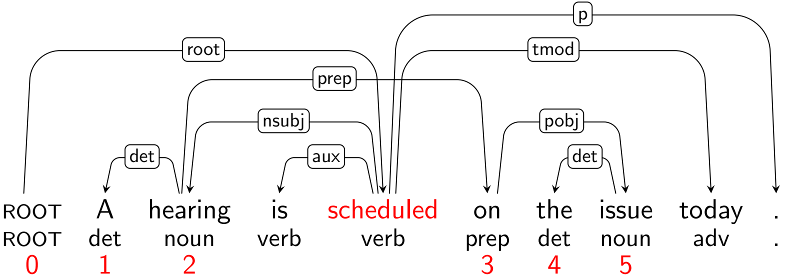

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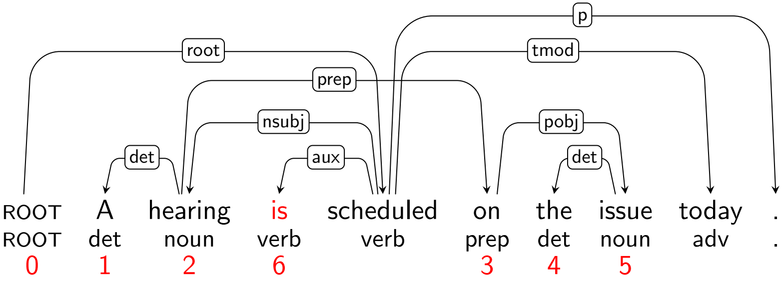

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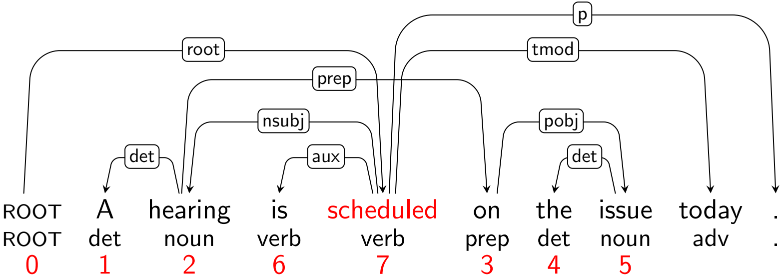

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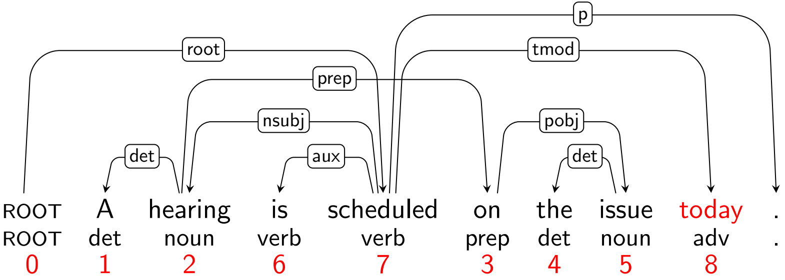

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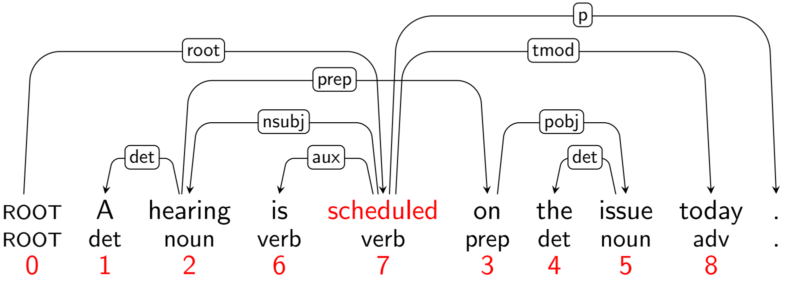

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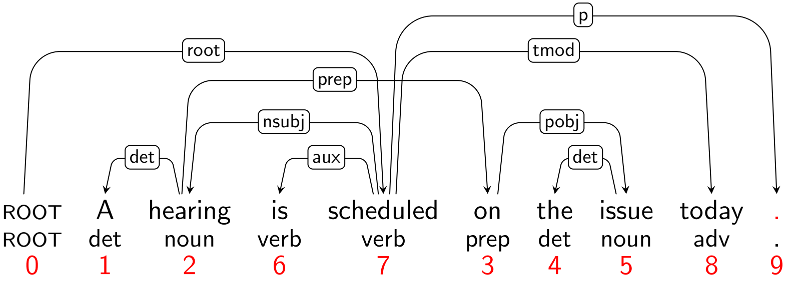

Transition System for Online Reordering

Configuration:	(S, B, A)	$[S = \text{Stack},\ B = \text{Buffer},\ A = \text{Arcs}]$		
Initial:	$([\ ], [0, 1, \ldots, n], \{\ \})$			
Terminal:	$([0], [\ ], A)$			
Shift:	$(S, i\vert B, A)$	$\Rightarrow$	$(S\vert i, B, A)$	
Right-Arc(k):	$(S\vert i\vert j, B, A)$	$\Rightarrow$	$(S\vert i, B, A \cup \{(i, j, k)\})$	
Left-Arc(k):	$(S\vert i\vert j, B, A)$	$\Rightarrow$	$(S\vert j, B, A \cup \{(j, i, k)\})$	$i \neq 0$
Swap:	$(S\vert i\vert j, B, A)$	$\Rightarrow$	$(S\vert j, i\vert B, A)$	$0 < i < j$

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Swap:	$(S\|i\|j, B, A)$	$\Rightarrow$	$(S\|j, i\|B, A)$	$0 < i < j$

- Transition-based parsing with two interleaved processes:
  1. Sort words into projective order $<_p$
  2. Build tree T by connecting adjacent subtrees
- T is projective with respect to $<_p$ but not (necessarily) $<$

Example Transition Sequence

$[\ ]_S$ [ROOT, A, hearing, is, scheduled, on, the, issue, today, .$]_B$

ROOT	A	hearing	is	scheduled	on	the	issue	today	.
ROOT	det	noun	verb	verb	prep	det	noun	adv	.

Example Transition Sequence

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

ROOT	A	hearing	is	scheduled	on	the	issue	today	.
ROOT	det	noun	verb	verb	prep	det	noun	adv	.

Example Transition Sequence

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

ROOT	A	hearing	is	scheduled	on	the	issue	today	.
ROOT	det	noun	verb	verb	prep	det	noun	adv	.

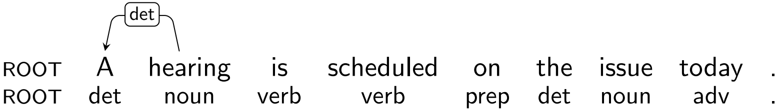
Example Transition Sequence

$[$ROOT, A, hearing$]_S$ $[$is, scheduled, on, the, issue, today, .$]_B$

ROOT	A	hearing	is	scheduled	on	the	issue	today	.
ROOT	det	noun	verb	verb	prep	det	noun	adv	.

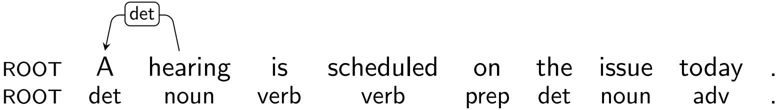
Example Transition Sequence

[ROOT, hearing]$_S$ [is, scheduled, on, the, issue, today, .]$_B$



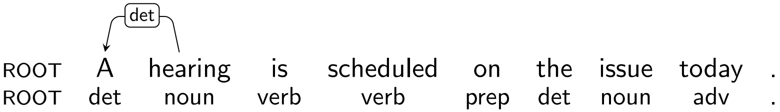
Example Transition Sequence

$[$ROOT, hearing, is$]_S$ $[$scheduled, on, the, issue, today, .$]_B$



Example Transition Sequence

[ROOT, hearing, is, scheduled]$_S$ [on, the, issue, today, .]$_B$



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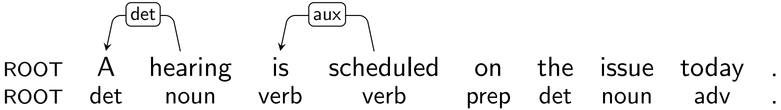
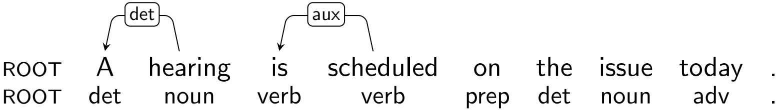


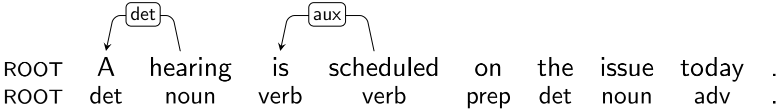
Example Transition Sequence

$[\text{ROOT, hearing, scheduled, on}]_S$ $[\text{the, issue, today, .}]_B$



Example Transition Sequence

[ROOT, hearing, scheduled, on, the]$_S$ [issue, today, .]$_B$



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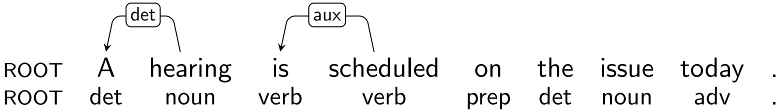

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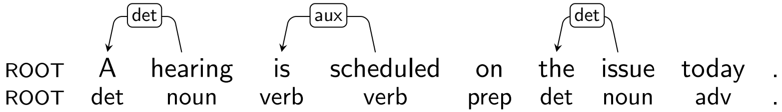

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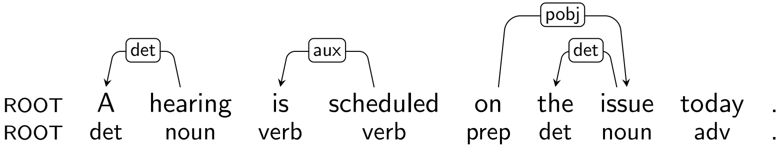

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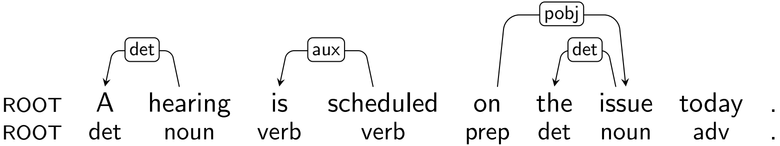

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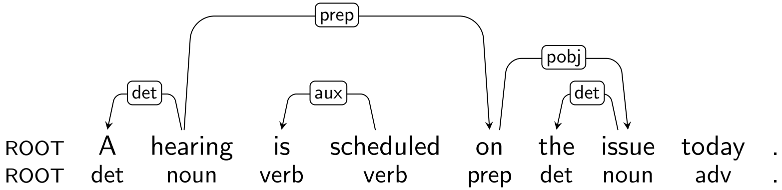

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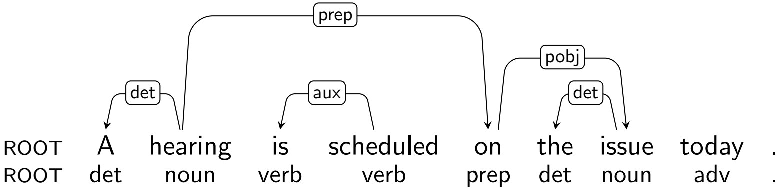

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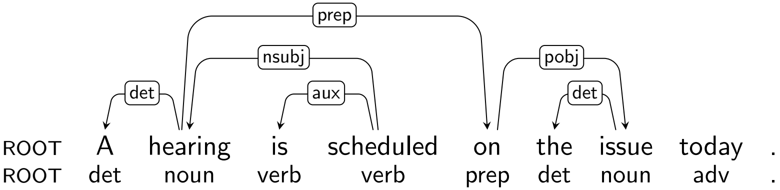

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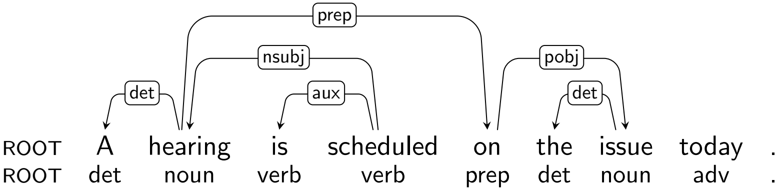

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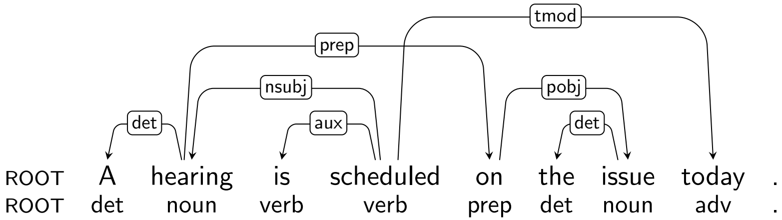

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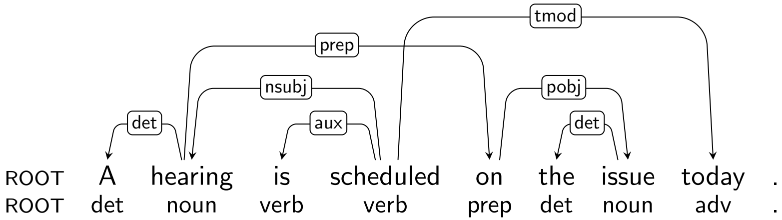

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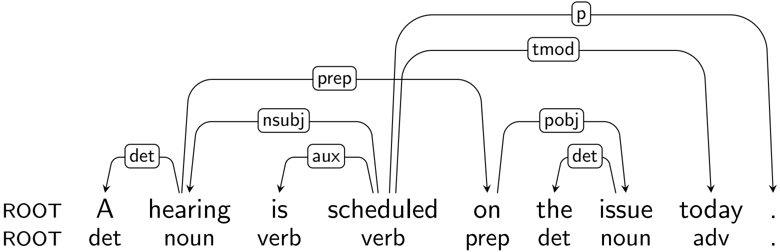

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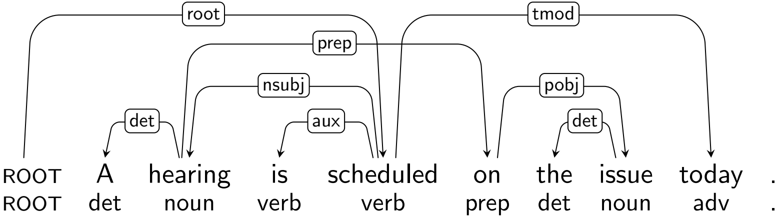


Analysis

- Correctness:
  - Sound and complete for the class of non-projective trees
- Complexity for greedy or beam search parsing:
  - Quadratic running time in the worst case
  - Linear running time in the average case
- Works well with beam search and structured prediction

	Czech		German	
	LAS	UAS	LAS	UAS
Projective	80.8	86.3	86.2	88.5
Reordering	83.9	89.1	88.7	90.9

[Bohnet and Nivre 2012]

Multiplanarity

- Multiplanarity is based on the notion of planarity:
  - A dependency graph is planar if it has no crossing arcs
  - A dependency graph is k-planar if it can be decomposed into (at most) k planar graphs [Yli-Jyrä 2003]
- In most treebanks, well over 99% of the trees are at most 2-planar [Gómez-Rodríguez and Nivre 2010]
- We can parse k-planar graphs in linear time using k stacks

1-Planar Transition System

Configuration:	(S, B, A)	$[S = \text{Stack}, B = \text{Buffer}, A = \text{Arcs}]$		
Initial:	$([\ ], [0, 1, \ldots, n], \{\ \})$			
Terminal:	$(S, [\ ], A)$			
Shift:	$(S, i\vert B, A)$	$\Rightarrow$	$(S\vert i, B, A)$	
Reduce:	$(S\vert i, B, A)$	$\Rightarrow$	(S, B, A)	
Right-Arc(k):	$(S\vert i, j\vert B, A)$	$\Rightarrow$	$(S\vert i, j\vert B, A \cup \{(i, j, k)\})$	$\neg h(j, A)$
Left-Arc(k):	$(S\vert i, j\vert B, A)$	$\Rightarrow$	$(S\vert i, j\vert B, A \cup \{(j, i, k)\})$	$\neg h(i, A) \wedge i \neq 0$

- Similar to the arc-eager system except:
  - **Reduce** does not require popped node to have a head
  - **Left-Arc**/**Right-Arc** do not affect S or B

2-Planar Transition System

Configuration: (S_1, S_2, B, A) $[S_1 = \text{Stack 1}, S_2 = \text{Stack 2}]$

Initial: $([\ ], [\ ], [0, 1, \ldots, n], \{\ \})$

Terminal: $(S_1, S_2, [\ ], A)$

Shift:	$(S_1, S_2, i\|B, A)$	$\Rightarrow$	$(S_1\|i, S_2\|i, B, A)$	
Reduce:	$(S_1\|i, S_2, B, A)$	$\Rightarrow$	(S_1, S_2, B, A)	
Right-Arc(k):	$(S_1\|i, S_2, j\|B, A)$	$\Rightarrow$	$(S_1\|i, S_2, j\|B, A \cup \{(i, j, k)\})$	$\neg h(j, A)$
Left-Arc(k):	$(S_1\|i, S_2, j\|B, A)$	$\Rightarrow$	$(S_1\|i, S_2, j\|B, A \cup \{(j, i, k)\})$	$\neg h(i, A) \wedge i \neq 0$
Switch:	(S_1, S_2, B, A)	$\Rightarrow$	(S_2, S_1, B, A)	

- Similar to 1-planar system except:
  - **Shift** pushes a node to both stacks
  - **Left-Arc**/**Right-Arc**/**Reduce** only affect S_1
  - **Switch** swaps S_1 and S_2

Example Transition Sequence

$[\ ]_{S_1}$ $[$ROOT, A, hearing, is, scheduled, on, the, issue, today, .$]_B$

$[\ ]_{S_2}$

ROOT	A	hearing	is	scheduled	on	the	issue	today	.
ROOT	det	noun	verb	verb	prep	det	noun	adv	.

Example Transition Sequence

$[\text{ROOT}]_{S_1}$ $[\text{A, hearing, is, scheduled, on, the, issue, today, .}]_B$

$[\text{ROOT}]_{S_2}$

ROOT	A	hearing	is	scheduled	on	the	issue	today	.
ROOT	det	noun	verb	verb	prep	det	noun	adv	.

Example Transition Sequence

$[\text{ROOT, A}]_{S_1}$ $[\text{hearing, is, scheduled, on, the, issue, today, .}]_B$

$[\text{ROOT, A}]_{S_2}$

ROOT	A	hearing	is	scheduled	on	the	issue	today	.
ROOT	det	noun	verb	verb	prep	det	noun	adv	.

Example Transition Sequence

$[\text{ROOT}, \text{A}]_{S_1}$ $[\text{hearing}, \text{is}, \text{scheduled}, \text{on}, \text{the}, \text{issue}, \text{today}, .]_B$

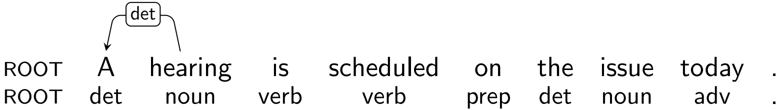
$[\text{ROOT}, \text{A}]_{S_2}$

ROOT	A	hearing	is	scheduled	on	the	issue	today	.
ROOT	det	noun	verb	verb	prep	det	noun	adv	.

Example Transition Sequence

$[\text{ROOT}]_{S_1}$ $[\text{hearing, is, scheduled, on, the, issue, today, .}]_B$

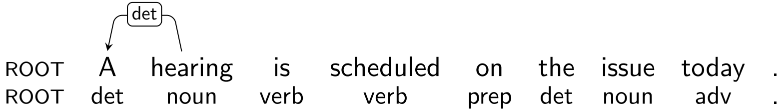
$[\text{ROOT, A}]_{S_2}$



Example Transition Sequence

$[\text{ROOT, hearing}]_{S_1}$ $[\text{is, scheduled, on, the, issue, today, .}]_B$

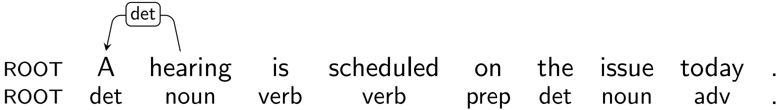
$[\text{ROOT, A, hearing}]_{S_2}$



Example Transition Sequence

[ROOT, hearing, is]$_{S_1}$ [scheduled, on, the, issue, today, .]$_{B}$

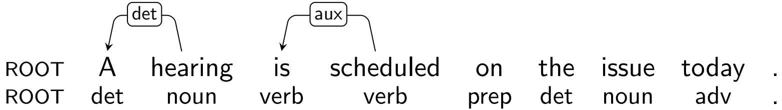
[ROOT, A, hearing, is]$_{S_2}$



Example Transition Sequence

$[\text{ROOT, hearing, is}]_{S_1}$ $[\text{scheduled, on, the, issue, today, .}]_{B}$

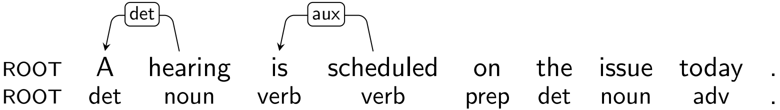
$[\text{ROOT, A, hearing, is}]_{S_2}$



Example Transition Sequence

$[\text{ROOT, hearing}]_{S_1}$ $[\text{scheduled, on, the, issue, today, .}]_B$

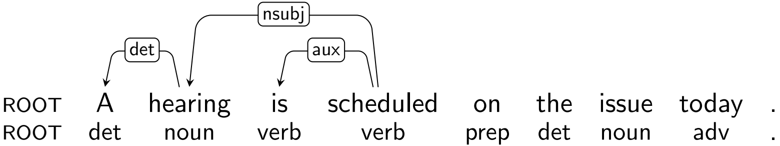
$[\text{ROOT, A, hearing, is}]_{S_2}$



Example Transition Sequence

[ROOT, hearing]$_{S_1}$ [scheduled, on, the, issue, today, .]$_{B}$

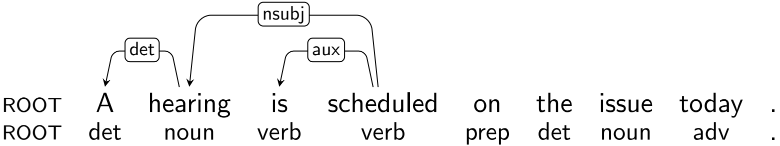
[ROOT, A, hearing, is]$_{S_2}$



Example Transition Sequence

$[\text{ROOT}]_{S_1}$ $[\text{scheduled, on, the, issue, today, .}]_B$

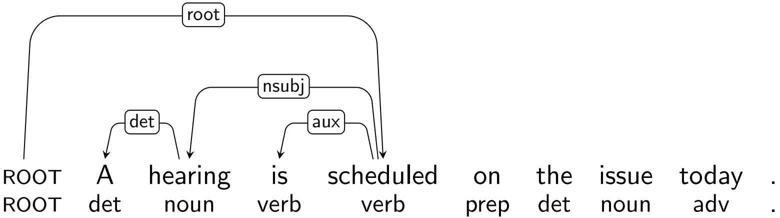
$[\text{ROOT, A, hearing, is}]_{S_2}$



Example Transition Sequence

$[\text{ROOT}]_{S_1}$ $[\text{scheduled, on, the, issue, today, .}]_B$

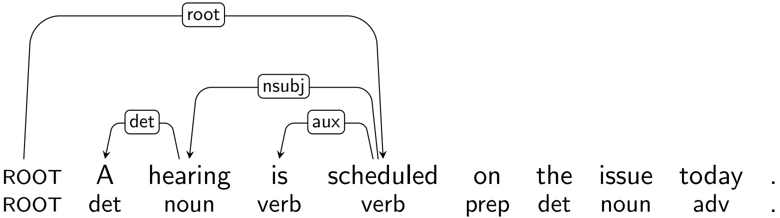
$[\text{ROOT, A, hearing, is}]_{S_2}$



Example Transition Sequence

$[\text{ROOT, scheduled}]_{S_1}$ $[\text{on, the, issue, today, .}]_B$

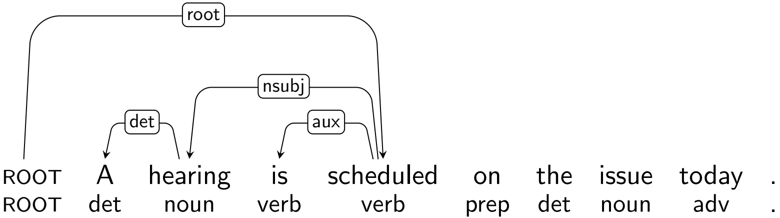
$[\text{ROOT, A, hearing, is, scheduled}]_{S_2}$



Example Transition Sequence

$[\text{ROOT, A, hearing, is, scheduled}]_{S_1}$ $[\text{on, the, issue, today, .}]_B$

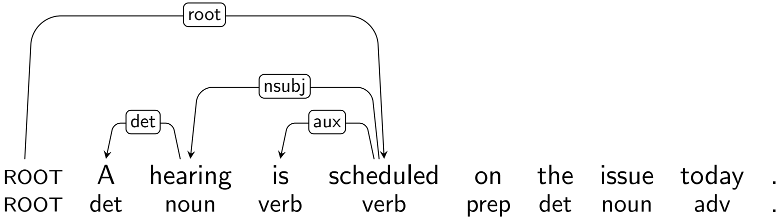
$[\text{ROOT, scheduled}]_{S_2}$



Example Transition Sequence

[ROOT, A, hearing, is]$_{S_1}$ [on, the, issue, today, .]$_{B}$

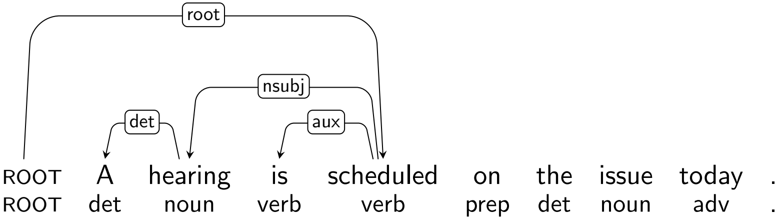
[ROOT, scheduled]$_{S_2}$



Example Transition Sequence

$[\text{ROOT, A, hearing}]_{S_1}$ $[\text{on, the, issue, today, .}]_B$

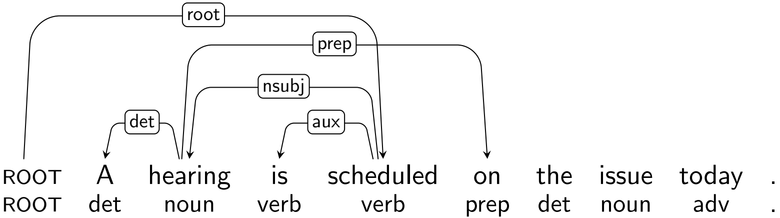
$[\text{ROOT, scheduled}]_{S_2}$



Example Transition Sequence

[ROOT, A, hearing]$_{S_1}$ [on, the, issue, today, .]$_B$

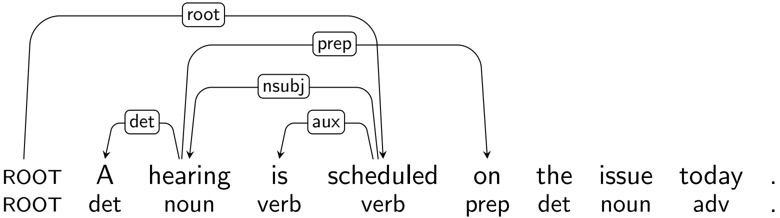
[ROOT, scheduled]$_{S_2}$



Example Transition Sequence

[ROOT, A, hearing, on]$_{S_1}$ [the, issue, today, .]$_B$

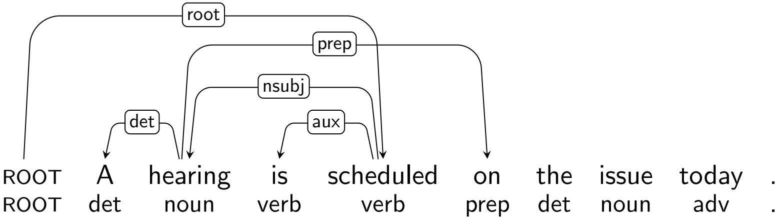
[ROOT, scheduled, on]$_{S_2}$



Example Transition Sequence

[ROOT, A, hearing, on, the]$_{S_1}$ [issue, today, .]$_B$

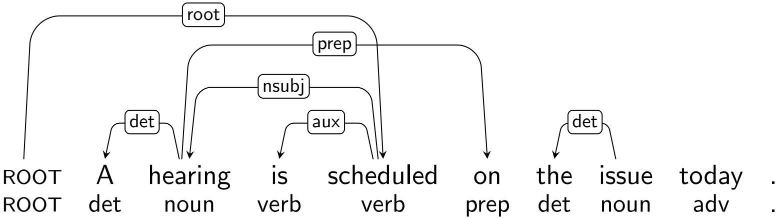
[ROOT, scheduled, on, the]$_{S_2}$



Example Transition Sequence

$[\text{ROOT, A, hearing, on, the}]_{S_1}$ $[\text{issue, today, .}]_B$

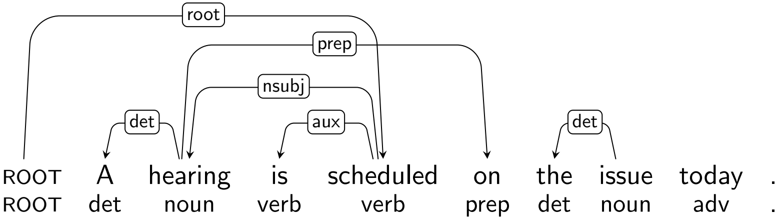
$[\text{ROOT, scheduled, on, the}]_{S_2}$



Example Transition Sequence

[ROOT, A, hearing, on]$_{S_1}$ [issue, today, .]$_B$

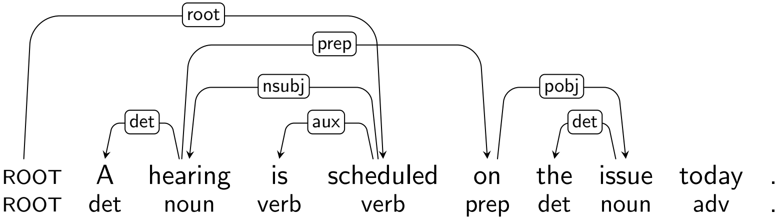
[ROOT, scheduled, on, the]$_{S_2}$



Example Transition Sequence

$[\text{ROOT, A, hearing, on}]_{S_1}$ $[\text{issue, today, .}]_{B}$

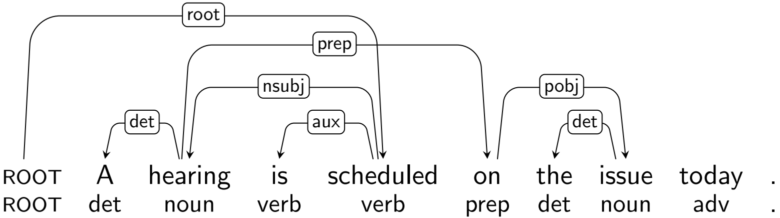
$[\text{ROOT, scheduled, on, the}]_{S_2}$



Example Transition Sequence

$[\text{ROOT, A, hearing, on, issue}]_{S_1}$ $[\text{today, .}]_B$

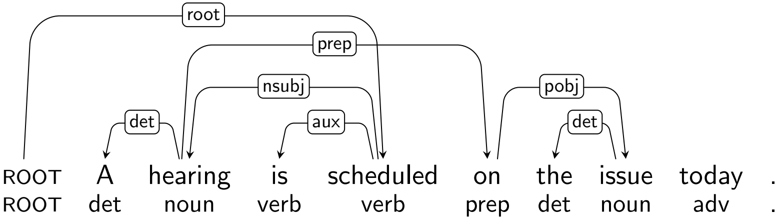
$[\text{ROOT, scheduled, on, the, issue}]_{S_2}$



Example Transition Sequence

$[\text{ROOT, scheduled, on, the, issue}]_{S_1}$ $[\text{today, .}]_B$

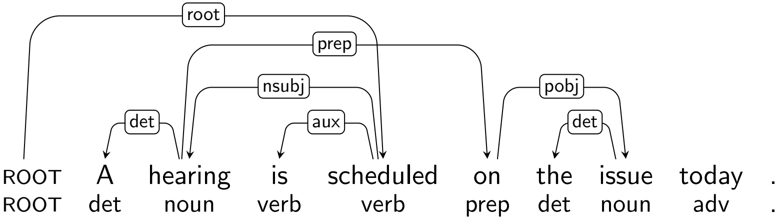
$[\text{ROOT, A, hearing, on, issue}]_{S_2}$



Example Transition Sequence

$[\text{ROOT, scheduled, on, the}]_{S_1}$ $[\text{today, .}]_B$

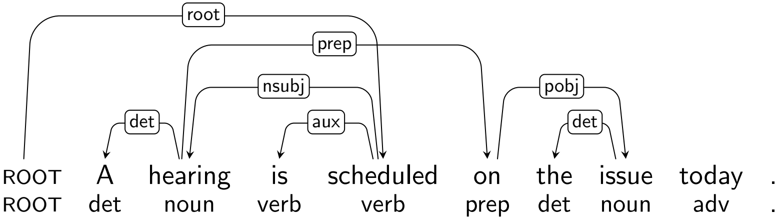
$[\text{ROOT, A, hearing, on, issue}]_{S_2}$



Example Transition Sequence

$[\text{ROOT, scheduled, on}]_{S_1}$ $[\text{today, .}]_B$

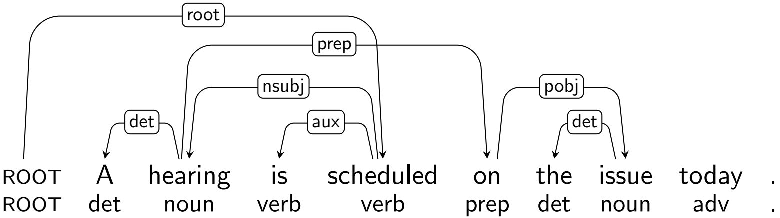
$[\text{ROOT, A, hearing, on, issue}]_{S_2}$



Example Transition Sequence

[ROOT, scheduled]$_{S_1}$ [today, .]$_B$

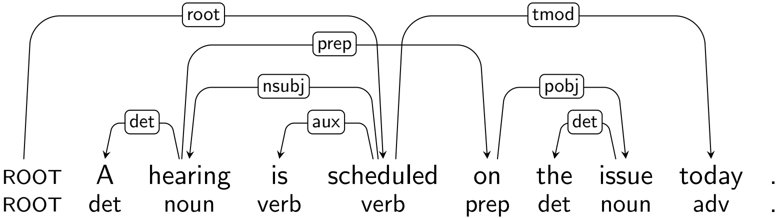
[ROOT, A, hearing, on, issue]$_{S_2}$



Example Transition Sequence

$[\text{ROOT, scheduled}]_{S_1}$ $[\text{today, .}]_B$

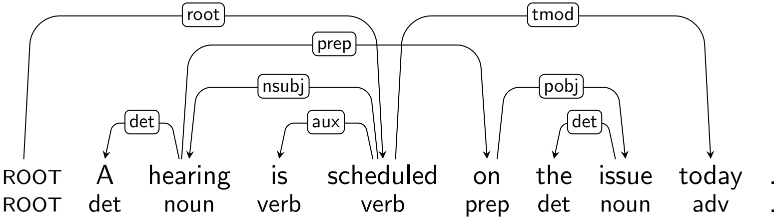
$[\text{ROOT, A, hearing, on, issue}]_{S_2}$



Example Transition Sequence

[ROOT, scheduled, today]$_{S_1}$ [.]$_B$

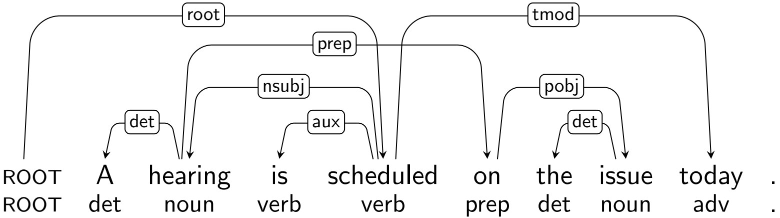
[ROOT, A, hearing, on, issue, today]$_{S_2}$



Example Transition Sequence

[ROOT, scheduled]$_{S_1}$ [.]$_B$

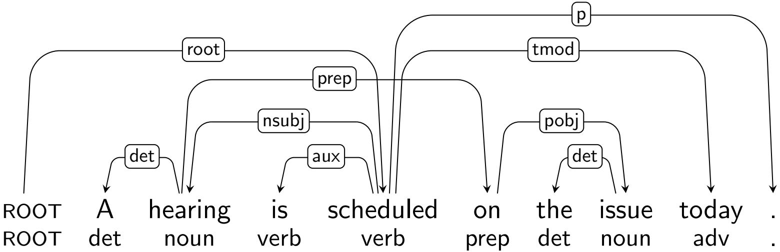
[ROOT, A, hearing, on, issue, today]$_{S_2}$



Example Transition Sequence

[ROOT, scheduled]$_{S_1}$ [.]$_B$

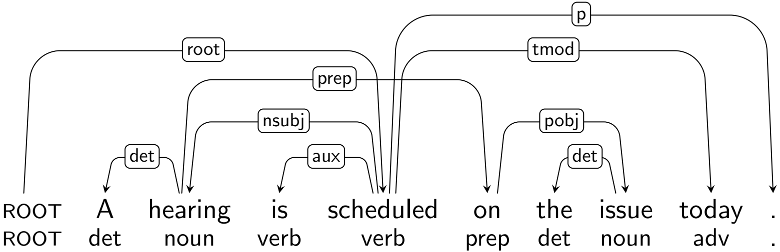
[ROOT, A, hearing, on, issue, today]$_{S_2}$



Example Transition Sequence

$[\text{ROOT, scheduled, .}]_{S_1}$ $[\,]_B$

$[\text{ROOT, A, hearing, on, issue, today, .}]_{S_2}$



Morphology and Syntax

- Morphological analysis in dependency parsing:
  - Crucially assumed as input, not predicted by the parser
  - Pipeline approach may lead to error propagation
  - Most PCFG-based parsers at least predict their own tags
- Recent interest in joint models for morphology and syntax:
  - Graph-based [McDonald 2006, Lee et al. 2011, Li et al. 2011]
  - Transition-based [Hatori et al. 2011, Bohnet and Nivre 2012]
- Can improve both morphology and syntax

Transition System for Morphology and Syntax

Configuration: (S, B, M, A) $[M = \text{Morphology}]$

Initial: $([\ ], [0, 1, \ldots, n], \{\ \}, \{\ \})$

Terminal: $([0], [\ ], M, A)$

Shift(p):	$(S, i\|B, M, A)$	$\Rightarrow$	$(S\|i, B, M \cup \{(i, m)\}, A)$	
Right-Arc(k):	$(S\|i\|j, B, M, A)$	$\Rightarrow$	$(S\|i, B, M, A \cup \{(i, j, k)\})$	
Left-Arc(k):	$(S\|i\|j, B, M, A)$	$\Rightarrow$	$(S\|j, B, M, A \cup \{(j, i, k)\})$	$i \neq 0$
Swap:	$(S\|i\|j, B, M, A)$	$\Rightarrow$	$(S\|j, i\|B, M, A)$	$0 < i < j$

Transition System for Morphology and Syntax

Configuration:	(S, B, M, A) $\quad [M = \text{Morphology}]$			
Initial:	$([\,], [0, 1, \ldots, n], \{\,\}, \{\,\})$			
Terminal:	$([0], [\,], M, A)$			
Shift(p):	$(S, i\|B, M, A)$	$\Rightarrow$	$(S\|i, B, M \cup \{(i, m)\}, A)$	
Right-Arc(k):	$(S\|i\|j, B, M, A)$	$\Rightarrow$	$(S\|i, B, M, A \cup \{(i, j, k)\})$	
Left-Arc(k):	$(S\|i\|j, B, M, A)$	$\Rightarrow$	$(S\|j, B, M, A \cup \{(j, i, k)\})$	$i \neq 0$
Swap:	$(S\|i\|j, B, M, A)$	$\Rightarrow$	$(S\|j, i\|B, M, A)$	$0 < i < j$

- Transition-based parsing with three interleaved processes:
  - Assign morphology when words are shifted onto the stack
  - Optionally sort words into projective order $<_p$
  - Build dependency tree T by connecting adjacent subtrees

Parsing Richly Inflected Languages

- Full morphological analysis: lemma + postag + features
  - Beam search and structured predication
  - Parser selects from k best tags + features
  - Rule-based morphology provides additional features
- Evaluation metrics:
  - PM = morphology (postag + features)
  - LAS = labeled attachment score

	Czech		Finnish		German		Hungarian		Russian	
	PM	LAS	PM	LAS	PM	LAS	PM	LAS	PM	LAS
Pipeline	93.0	83.1	88.8	79.9	89.1	91.8	96.1	88.4	92.6	87.4
Joint	94.4	83.5	91.6	82.5	91.2	92.1	97.4	89.1	95.1	88.0

[Bohnet et al. 2013]

Summary

- Transition-based parsing:
  - Efficient parsing using heuristic inference
  - Unconstrained history-based feature models
- Recent advances in synergy:
  - Beam search and structured prediction
  - Easy-first parsing and dynamic oracles
  - Online reordering for non-projective trees
  - Joint morphological and syntactic analysis

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