Structured Learning with Inexact Search: Advances in Shift-Reduce CCG Parsing

This work is made possible and fully supported by the Carnegie Trust for the Universities of Scotland and the Cambridge Trust.

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$$y^* = \arg\max_{y \in \mathcal{Y}_x} \sum_{d \in \mathcal{D}(y)} \text{score}(\Phi(d))$$

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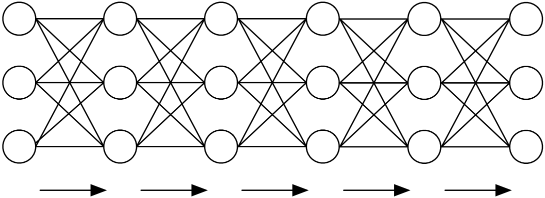
$\mathcal{Y}_x$ is exponentially-sized and prohibitive to enumerate.

Structured Prediction: Sequence Labelling



MEMM [McCallum et al., 2000]

$$p(y_1, \ldots, y_m | x_1, \ldots, x_m)$$

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$$
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&= \prod_{i=1}^{m} p(y_i | y_{i-1}, x_1, \ldots, x_m) \\
&= \prod_{i=1}^{m} \frac{\exp\{\mathbf{w} \cdot \Phi(x_1, \ldots, x_m, i, y_{i-1}, y_i)\}}{\sum_{y_i'} \exp\{\mathbf{w} \cdot \Phi(x_1, \ldots, x_m, i, y_{i-1}, y_i')\}}
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$$

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$$z = \sum_{y_{1:m} \in \mathcal{Y}_x} \exp\{\sum_{i=1}^{m} \sum_{j=1}^{F} \omega_j \phi_j(y_{i-1}, y_i, x, i)\}$$

MEMM and CRF

$$p(y_1, \ldots, y_m | x_1, \ldots, x_m) = \prod_{i=1}^{m} \frac{\exp\{\mathbf{w} \cdot \Phi(x_1, \ldots, x_m, i, y_{i-1}, y_i)\}}{\sum_{y_i'} \exp\{\mathbf{w} \cdot \Phi(x_1, \ldots, x_m, i, y_{i-1}, y_i')\}}$$

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- Feature function: Φ
- Structured output: y
- Search: dynamic programming + Viterbi decoding
- $\arg\max_{y_{1:m}} p(y_1, \ldots, y_m | x_1, \ldots, x_m)$

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The Structured Perceptron [Collins, 2002]

```
w ← 0                                            ▷ the input is the training set {(x_i, y_i)}_{i=1}^n
while not converged do
  for i ← 1, ..., n do
    y* ← arg max_{y∈GEN(x_i)} w · Φ(x_i, y)           ▷ obtain model prediction
    if y* ≠ y_i then                                 ▷ y* not correct
      w ← w + Φ(x_i, y_i) − Φ(x_i, y*)               ▷ online update
```

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while not converged **do**
  for $i \leftarrow 1, \ldots, n$ **do**
    $y^* \leftarrow \arg\max_{y \in \mathrm{GEN}(x_i)} \mathbf{w} \cdot \Phi(x_i, y)$ $\triangleright$ obtain model prediction
    if $y^* \neq y_i$ **then** $\triangleright$ y^* not correct
      $\mathbf{w} \leftarrow \mathbf{w} + \Phi(x_i, y_i) - \Phi(x_i, y^*)$ $\triangleright$ online update

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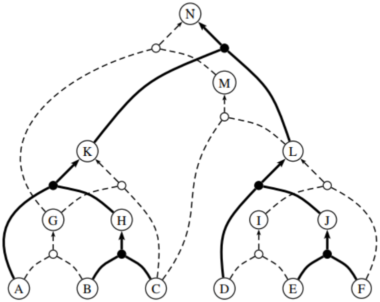
  - beam search (the incremental structured perceptron [Collins and Roark, 2004])
  - dynamic programming + cube pruning [Chiang, 2007]

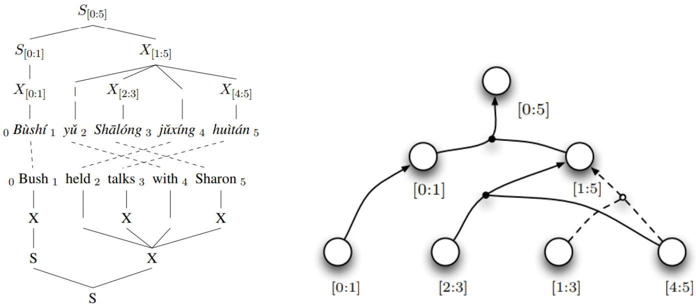
Structured Perceptron with Inexact Search [Huang et al., 2012]



Graph-based dependency parsing

[Zhang and McDonald, 2012; Zhang et al., 2013]

Structured Perceptron with Inexact Search [Huang et al., 2012]



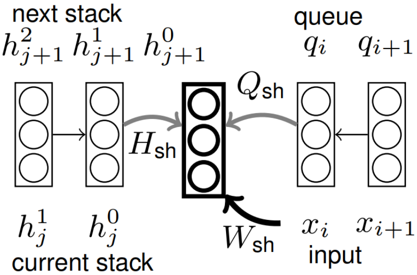
Hierarchical phrase-based translation

[Zhao et al., 2014]

Neural Network Models

- Sequence-to-Sequence [Sutskever et al., 2014]
  - training: per-step cross-entropy
  - test: $p(y_1, \ldots, y_n | x_1, \ldots, x_m) = \prod_{t=1}^{n} p(y_t | y_1 \ldots, y_{t-1}, \mathbf{c})$
  - search: $y^* = \arg\max_{y \in \mathcal{Y}_x} p(y|x)$
- Representation learning: RNN, LSTM, CNN [Gehring et al., 2017]
- Search: greedy, beam search (no search at training time)
- Structured learning: [Ranzato et al., 2016; Wiseman and Rush, 2016]
- most recent: [Edunov et al., 2017]

Neural Network Models + Structured Perceptron-Inspired Updates



Watanabe and Sumita, 2015 uses a variant of Max Violation.

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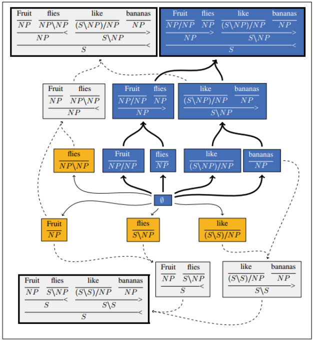

Lee et al., 2016 extends Max Violation to All Violation.

Outline

- Three models for shift-reduce CCG parsing
  - representation learning:
  - structured learning:
  - search:

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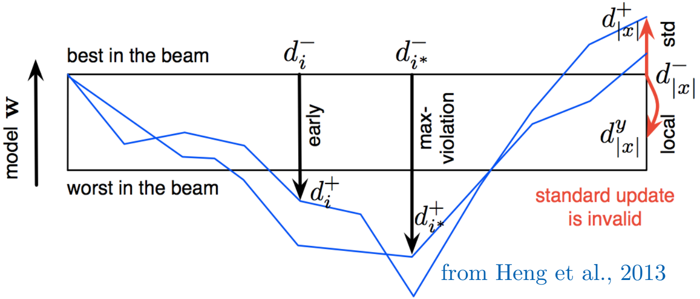

from Heng et al., 2013

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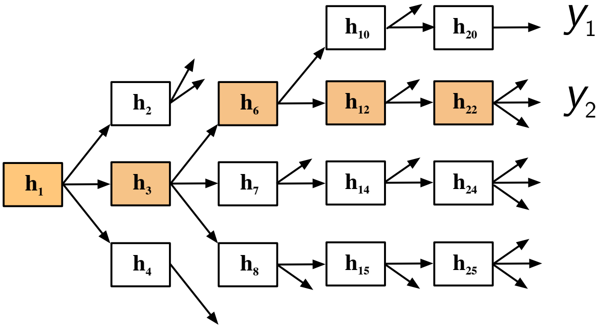
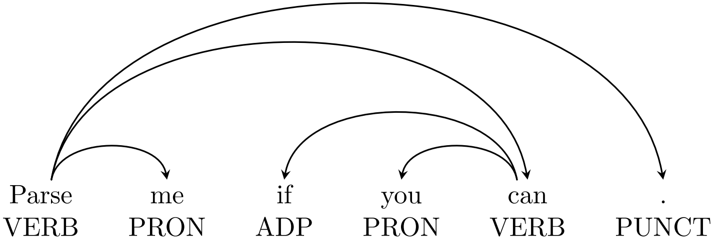
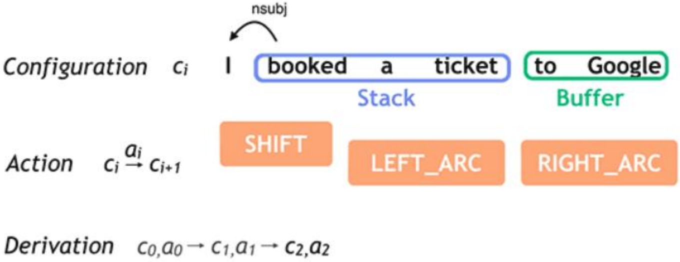


Dependency Parsing



Google SyntaxNet output

Transition-based Dependency Parsing



source: Google SyntaxNet

Shift-Reduce CCG Parsing

- Combinatory Categorial Grammar (CCG)

the books which John likes

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$$\frac{\text{the}}{NP/N} \quad \frac{\text{books}}{N} \quad \frac{\text{which}}{(NP\backslash NP)/(S/NP)} \quad \frac{\text{John}}{NP} \quad \frac{\text{likes}}{(S\backslash NP)/NP}$$

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\multicolumn{2}{c}{\overline{\qquad NP \qquad}{>}} & & &
\end{array}$$

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$$

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\multicolumn{2}{c}{\underline{\qquad\qquad}{>}} & & \underline{\qquad}{>}\mathbf{T} & \\
\multicolumn{2}{c}{NP} & & S/(S\backslash NP) & \\
 & & & \multicolumn{2}{c}{\underline{\qquad\qquad\qquad}{>}\mathbf{B}} \\
 & & & \multicolumn{2}{c}{S/NP}
\end{array}
$$

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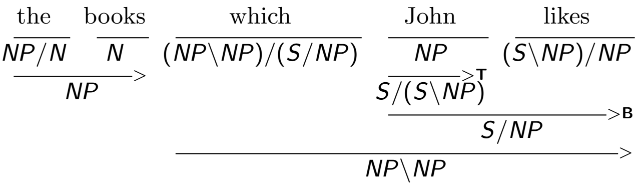

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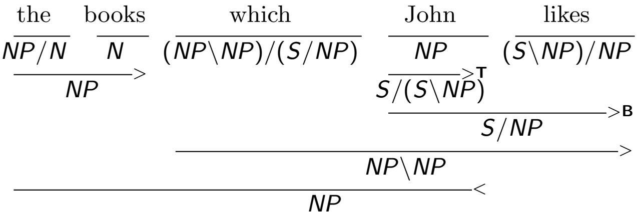

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  - Supertagging (regular language; 1000 tags vs. 50 for CFG)
  - Parsing (mildly context-sensitive; only a dozen rules vs. 500K for CFG [Petrov and Klein, 2007])

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- Dual Decomposition, Belief Propogation [Auli and Lopez, 2011]
- Remains to be the most competitive formalism for recovering "deep" dependencies (from coordination, control, extraction etc.) [Rimell et al., 2009; Nivre et al., 2010]

Shift-Reduce CCG Parsing

the books which John likes

Shift-Reduce CCG Parsing

the	books	which	John	likes
NP/N				

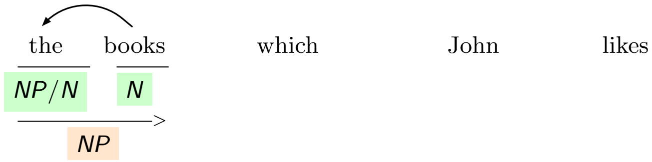
SH

Shift-Reduce CCG Parsing

the	books	which	John	likes
NP/N	N			

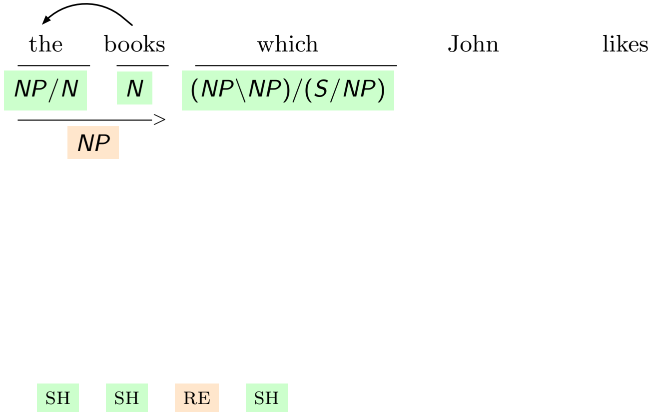
SH SH

Shift-Reduce CCG Parsing



SH SH RE

Shift-Reduce CCG Parsing



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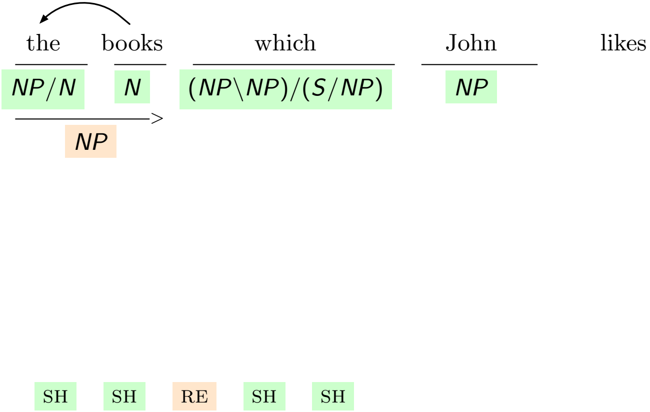

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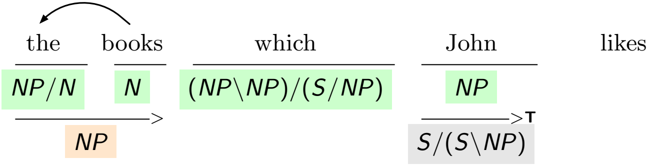
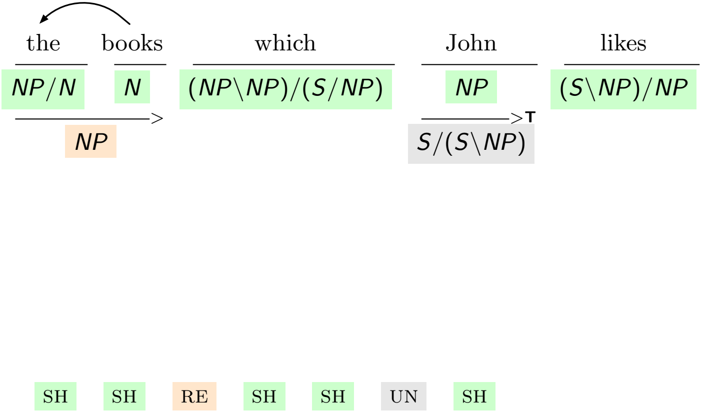


SH SH RE SH SH UN

Shift-Reduce CCG Parsing



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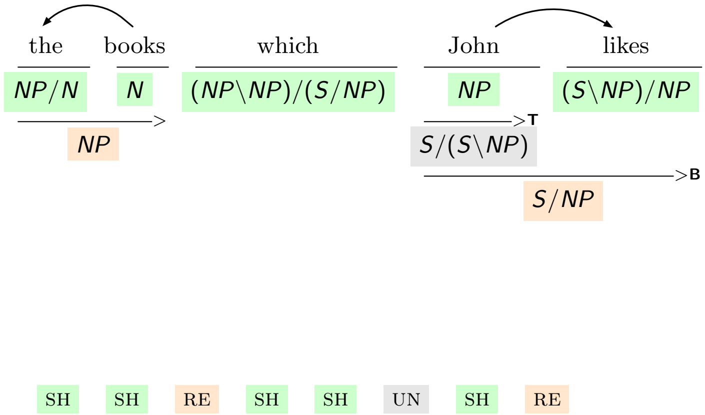

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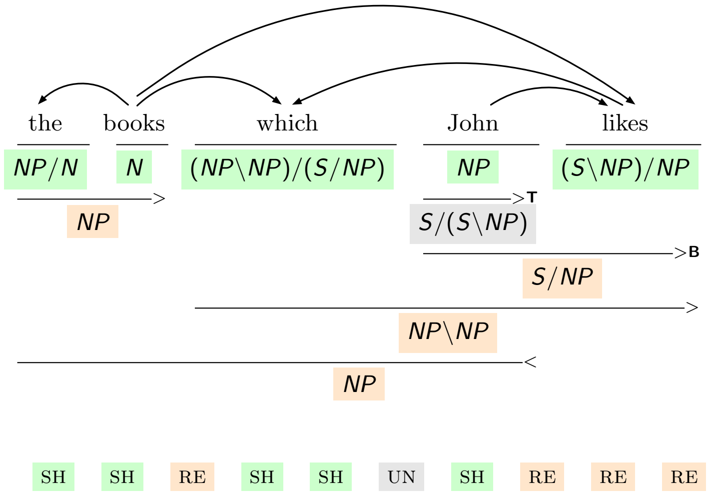
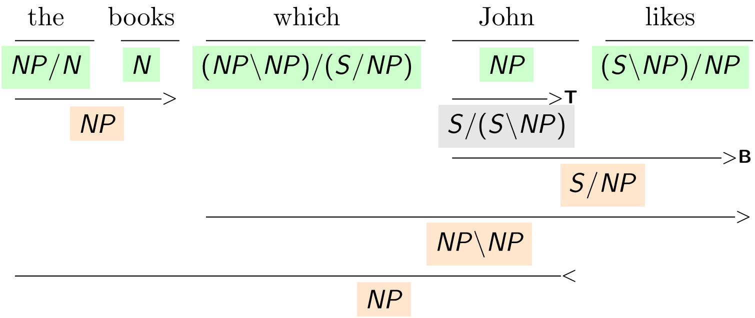


Model 1

[Xu et al., ACL 2014]

Standard Training: Greedy Local Model



SH SH RE SH SH UN SH RE RE RE

Standard Training: Greedy Local Model

- Score of an action $a = \mathbf{w} \cdot \phi(\langle s, q \rangle, a)$
- No search at training time, can use beam search decoding

step	stack $(s_n, \ldots, s_1, s_0)$	queue $(q_0, q_1 \ldots, q_n)$	action
0		Ms. Haag plays Elianti	

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1	N/N	Haag plays Elianti	SHIFT

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1	N/N	Haag plays Elianti	SHIFT
2	N/N N	plays Elianti	SHIFT

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0		Ms. Haag plays Elianti	
1	N/N	Haag plays Elianti	SHIFT
2	$N/N\ N$	plays Elianti	SHIFT
3	N	plays Elianti	REDUCE

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3	N	plays Elianti	REDUCE
4	NP	plays Elianti	UNARY

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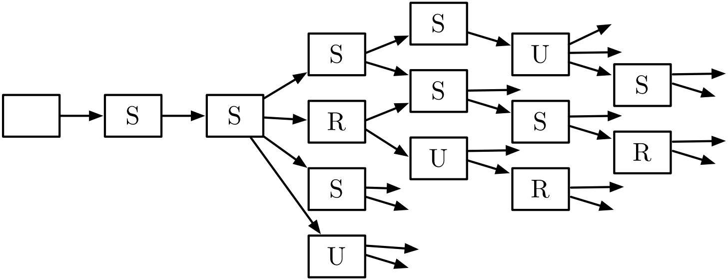
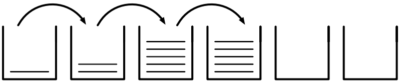
1	N/N	Haag plays Elianti	SHIFT
2	$N/N\ N$	plays Elianti	SHIFT
3	N	plays Elianti	REDUCE
4	NP	plays Elianti	UNARY
5	$NP\ (S[dcl]\backslash NP)/NP$	Elianti	SHIFT
6	$NP\ (S[dcl]\backslash NP)/NP\ N$		SHIFT
7	$NP\ (S[dcl]\backslash NP)/NP\ NP$		UNARY
8	$NP\ S[dcl]\backslash NP$		REDUCE
9	$S[dcl]$		REDUCE

Global Structured Training
[Collins and Roark, 2004]

- Score of an action $a = \mathbf{w} \cdot \phi(\langle s, q \rangle, a)$





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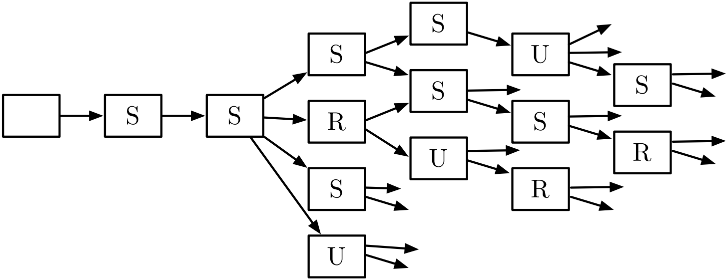

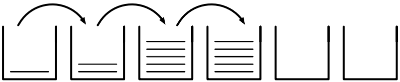

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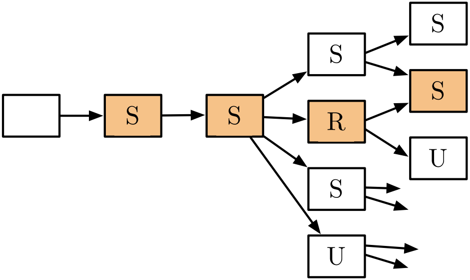
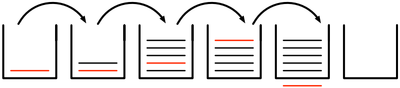
- Structured perceptron update: $\mathbf{w} \leftarrow \mathbf{w} + \phi(x_i, y_{ij}) - \phi(x_i, \mathcal{B}_j[0])$





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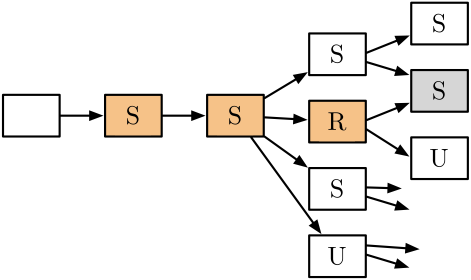

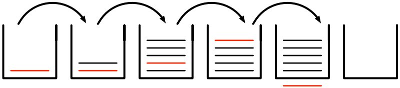

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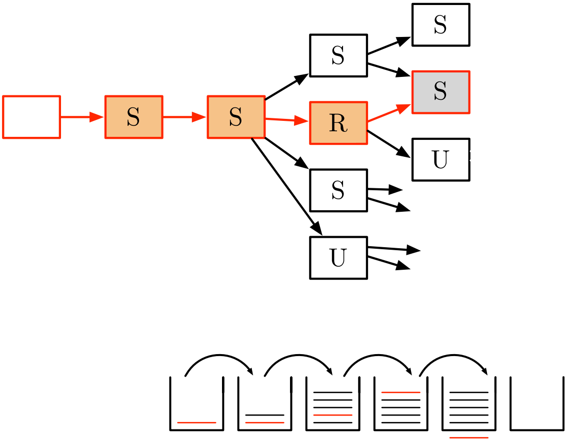

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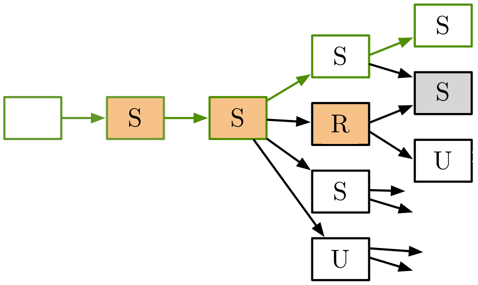
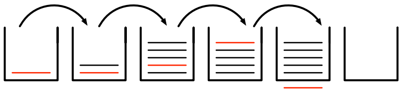
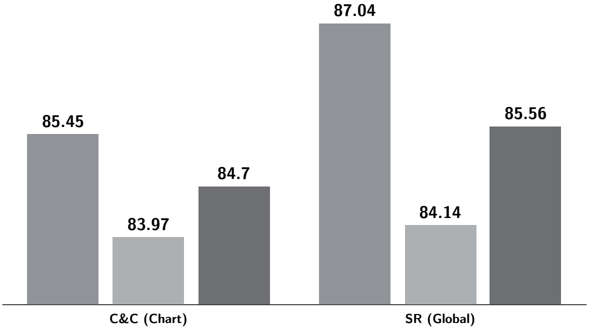


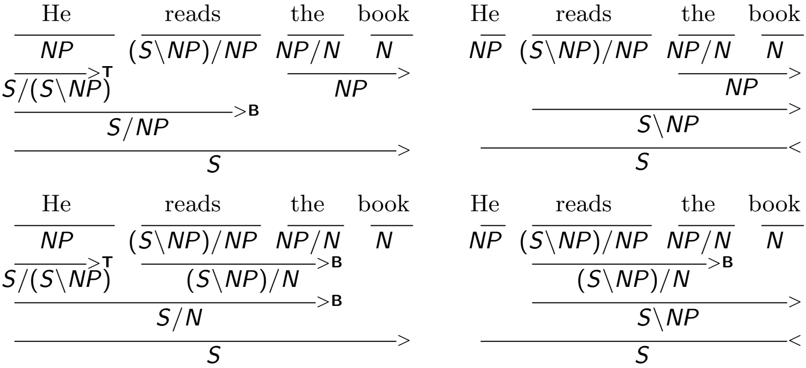


Global Structured Training for CCG
[Zhang and Clark, 2011]

- Conditional log-linear vs. linear
- Dynamic programming vs. beam search



Spurious Ambiguity in CCG



$\langle$*the*, *book*$\rangle$
$\langle$*reads*, *book*$\rangle$
$\langle$*reads*, *he*$\rangle$

In general, exponentially many!

Motivation: Dependency Model

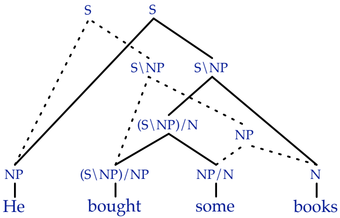
- The derivation is just a “trace” of the semantic interpretation [Steedman, 2000]

Motivation: Dependency Model

- The derivation is just a “trace” of the semantic interpretation [Steedman, 2000]
  - an elegant solution to the spurious ambiguity problem
  - gold-standard data cheaper to obtain
  - optimizing for evaluation

Model 1: The Dependency Model

- Use dependencies as the ground truth
  - encoding exponentially many “correct” paths



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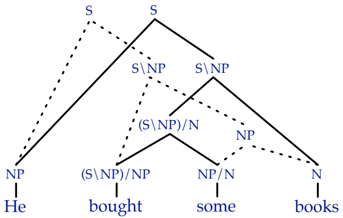
- Beam search – global structured learning

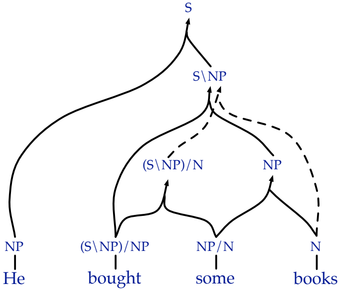
The Dependency Model

	[Clark et al., 2002]	C&C (dep)	Z&C	this work
Shift-Reduce	✗	✗	✓	✓
Dep. Model	✓	✓	✗	✓
Deriv. Feats	✗	✓	✓	✓

CCG Parse Forest

- Compactly represents all derivation and dependency structure pair
- Grouping together equivalent chart entries
  - identical category, head and *unfilled* dependencies
  - individual entries are *conjunctive* nodes and equivalence classes are *disjunctive* nodes





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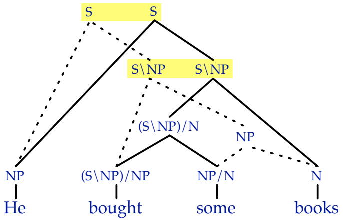
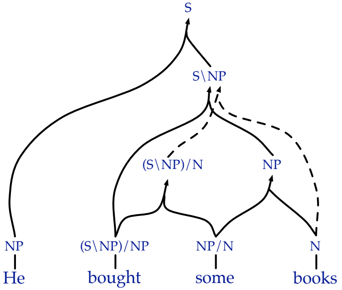
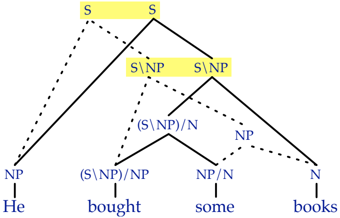




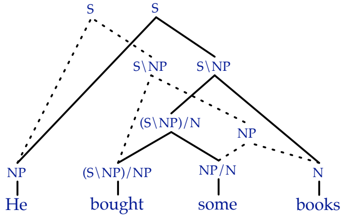
The Oracle Forest

- A **subset** of the **complete** forest
  - consistent with the gold-standard dependency structure
  - exponentially-sized and impossible to enumerate
- A dependency structure decomposes over derivations
  - dependencies are realized on conjunctive nodes
  - can count dependencies on-the-fly



The Oracle Forest

- intution 1: dependencies "live on" conjunctive nodes



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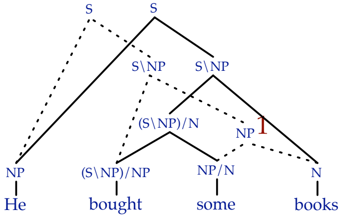

$\langle$*some*, NP/N_1, 1, *books*$\rangle$

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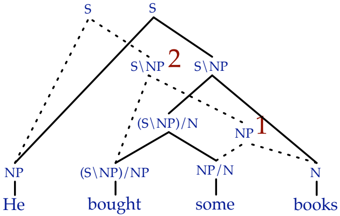

$\langle some, NP/N_1, 1, books \rangle$

$\langle bought, (S\backslash NP_1)/NP_2, 2, books \rangle$

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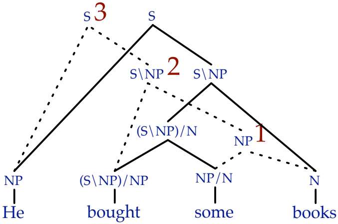

⟨*some*, NP/N_1, 1, *books*⟩

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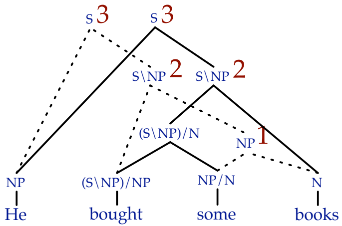

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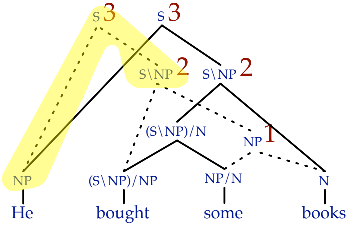

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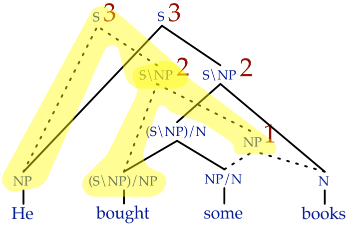

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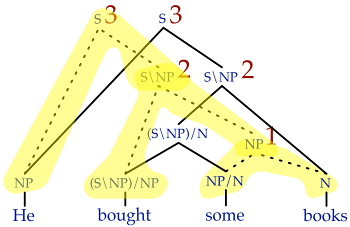

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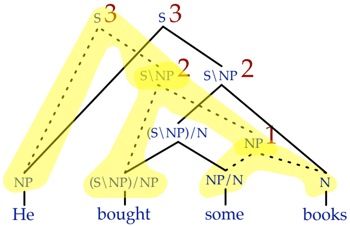
Shift-Reduce Dependency Oracle

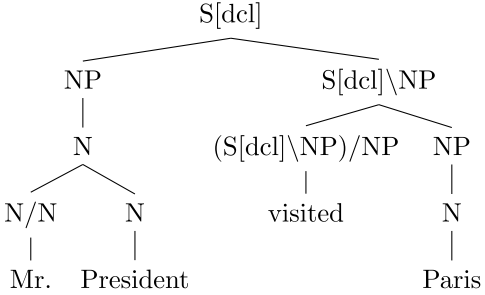
- The dependency oracle

$$f_d(\langle s, q\rangle, (x, c), \Phi_G) = \begin{cases} \textit{true} & \text{if } s' \sim G \text{ or } s' \simeq G \\ \textit{false} & \text{otherwise} \end{cases}$$



The Dependency Model Oracle

Canonical Shift-Reduce is bottom-up post-order traversal



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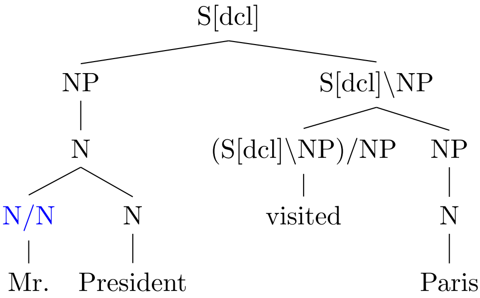
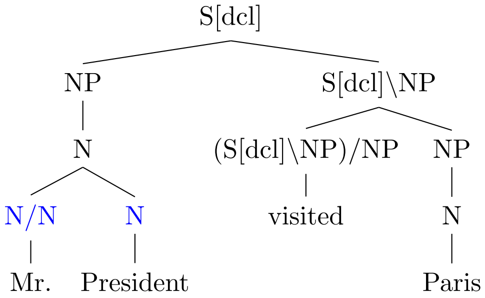


Shift

The Dependency Model Oracle

Canonical Shift-Reduce is bottom-up post-order traversal



Shift Shift

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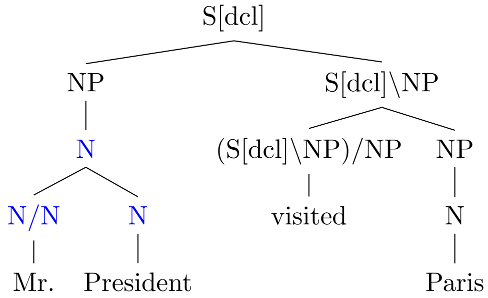

Shift Shift Reduce

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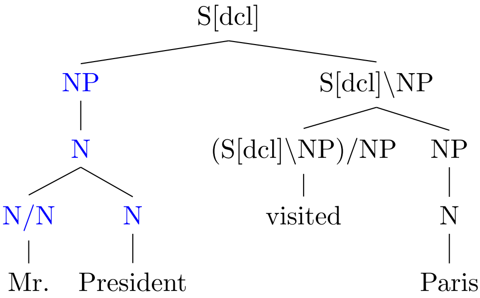

Shift Shift Reduce Unary

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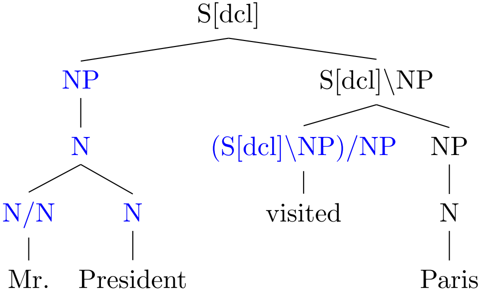

Shift Shift Reduce Unary Shift

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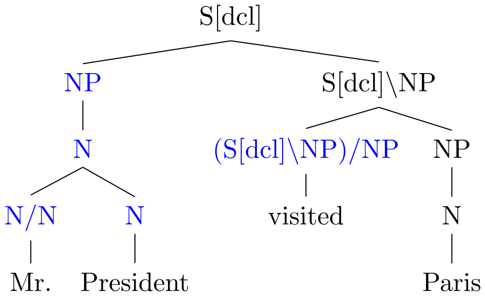
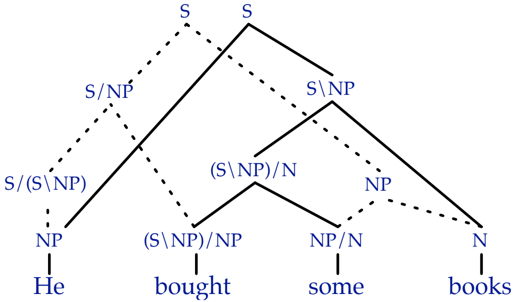


Shift Shift Reduce Unary Shift Shift Unary Reduce Reduce

The Dependency Model Oracle

But this doesn't carry over to an oracle forest



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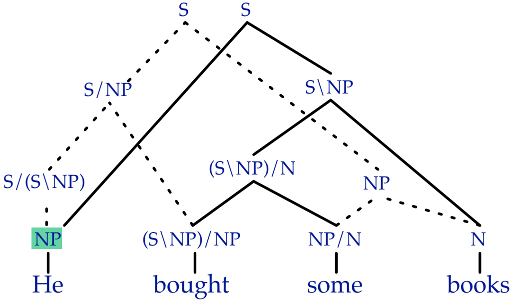

Shift-*NP*

The Dependency Model Oracle

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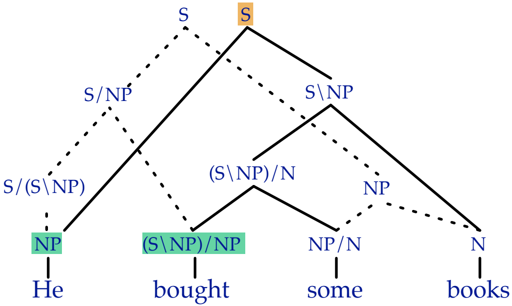

Shift-NP Shift-$(S\backslash NP)/NP$

The Dependency Model Oracle

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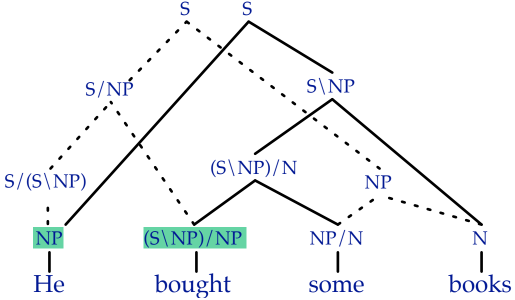

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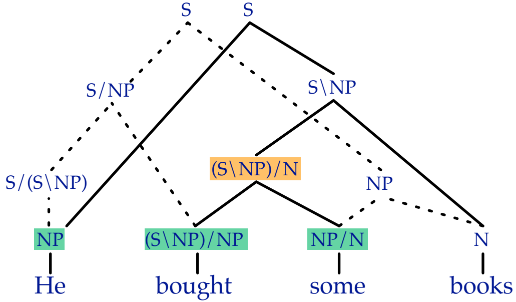

Shift-NP Shift-$(S\backslash NP)/NP$ Shift-NP/N

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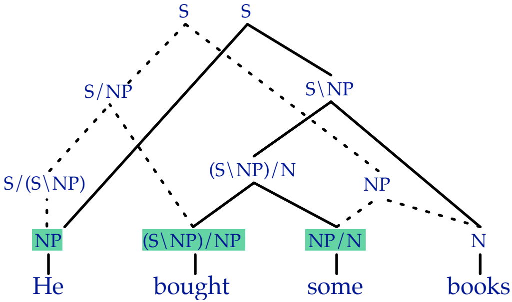

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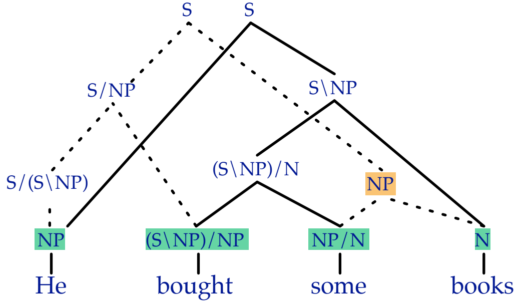

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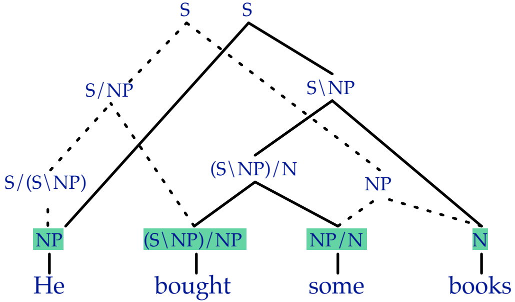

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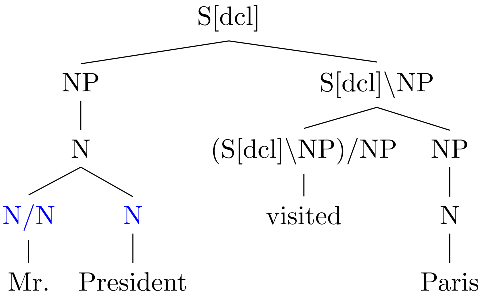
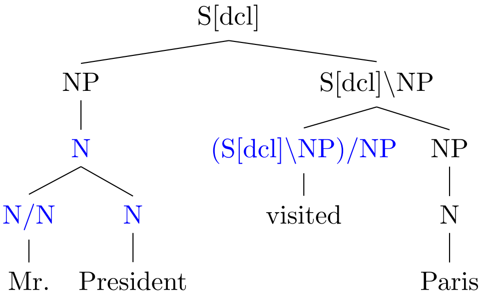
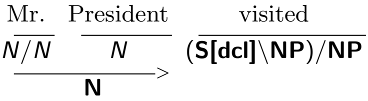


Mr. President

N/N **N**

The Dependency Model Oracle





The Dependency Model Oracle

- The dependency oracle

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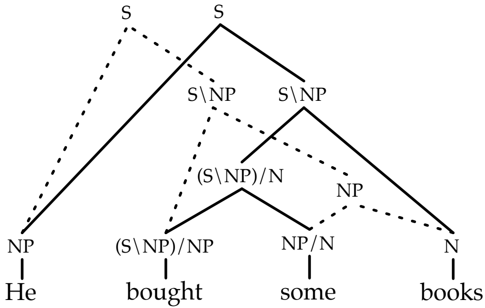
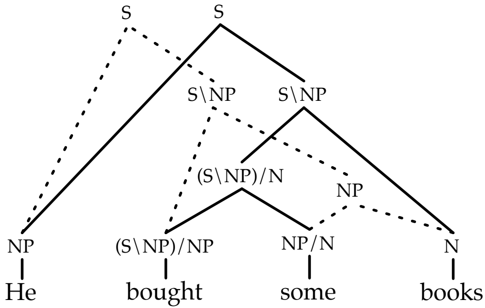
- Shared ancestor set
  - contains possible valid nodes an item should visit
  - is built on-the-fly during decoding for each action type
  - constructed with each *valid* action

The Dependency Model



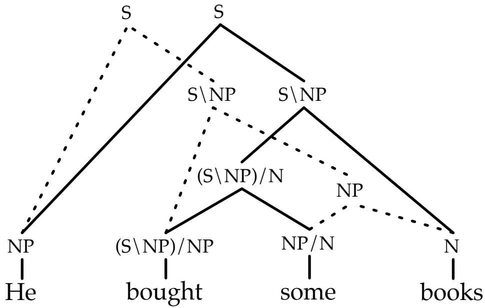
stack $(s_n, ..., s_1, s_0)$	$\mathcal{R}(c_{s_0})$

The Dependency Model



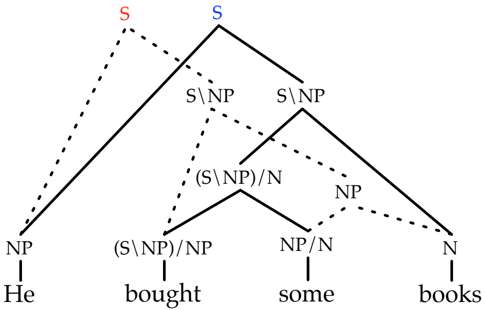
stack ($s_n, ..., s_1, s_0$)	$\mathcal{R}(c_{s_0})$
NP	

The Dependency Model



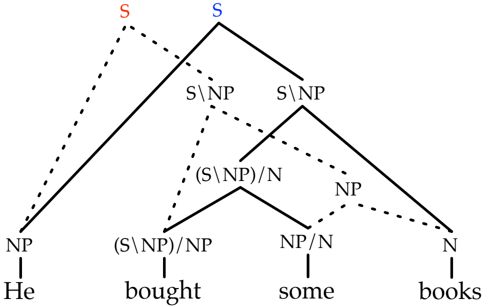
stack $(s_n, ..., s_1, s_0)$	$\mathcal{R}(c_{s_0})$
NP	()

The Dependency Model



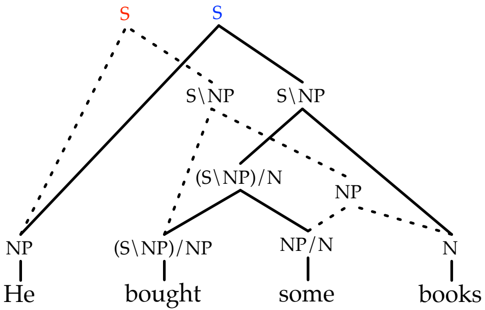
stack ($s_n, ..., s_1, s_0$)	$\mathcal{R}(c_{s_0})$
NP	()
$NP\ (S\backslash NP)/NP$	

The Dependency Model



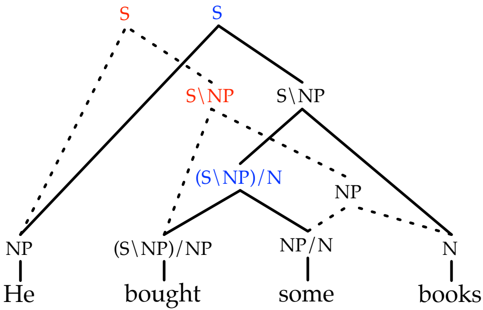
stack $(s_n, \ldots, s_1, s_0)$	$\mathcal{R}(c_{s_0})$
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)

The Dependency Model



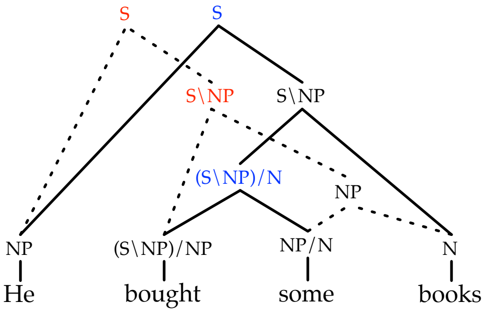
stack $(s_n, \ldots, s_1, s_0)$	$\mathcal{R}(c_{s_0})$
NP	()
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	

The Dependency Model



stack $(s_n, \ldots, s_1, s_0)$	$\mathcal{R}(c_{s_0})$
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	

The Dependency Model



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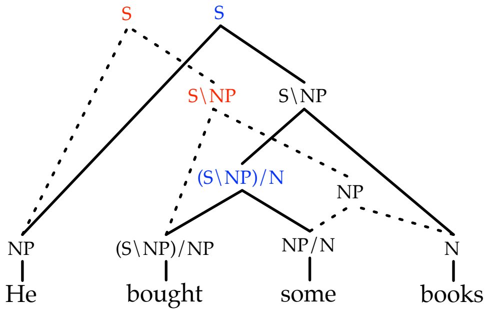
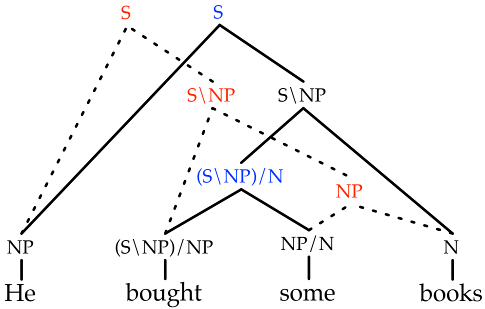
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$

The Dependency Model



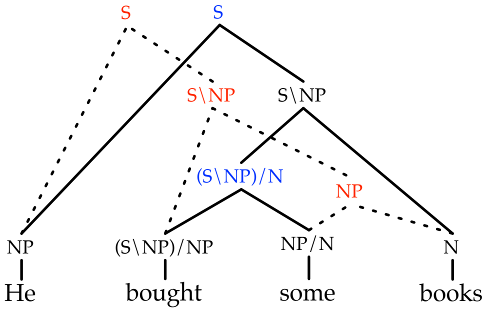
stack $(s_n, \ldots, s_1, s_0)$	$\mathcal{R}(c_{s_0})$
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
$NP\ (S\backslash NP)/NP\ NP/N\ N$	

The Dependency Model



stack $(s_n, ..., s_1, s_0)$	$\mathcal{R}(c_{s_0})$
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
$NP\ (S\backslash NP)/NP\ NP/N\ N$	

The Dependency Model



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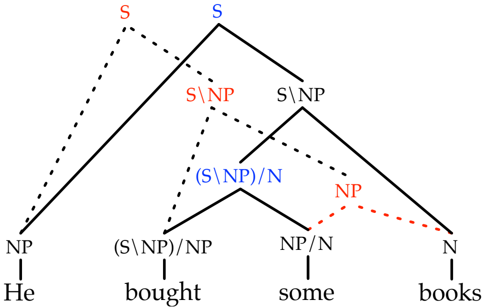
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
$NP\ (S\backslash NP)/NP\ NP/N\ N$	(NP)

The Dependency Model



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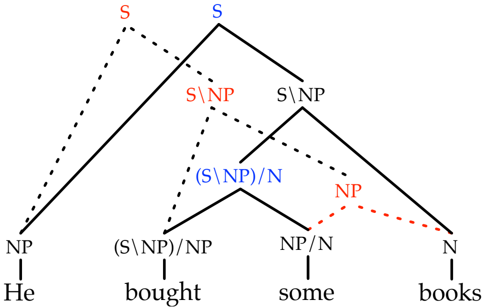
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
$NP\ (S\backslash NP)/NP\ NP/N\ N$	(NP)
$NP\ (S\backslash NP)/NP\ NP$	

The Dependency Model



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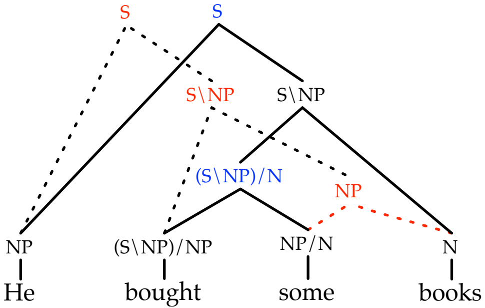
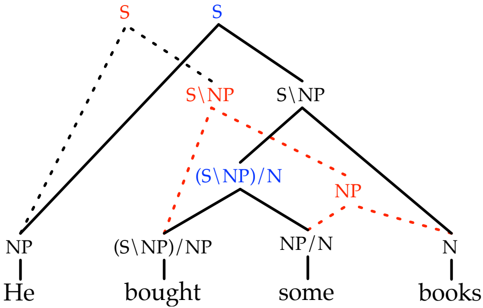
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$ ◄
$NP\ (S\backslash NP)/NP\ NP/N\ N$	(NP)
$NP\ (S\backslash NP)/NP\ NP$	

The Dependency Model



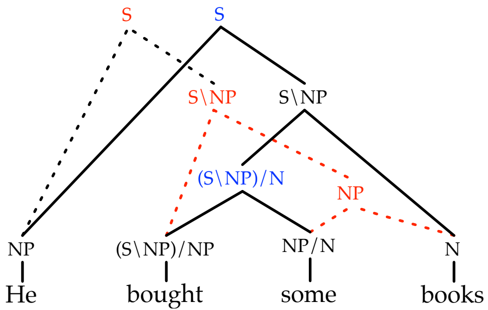
stack $(s_n, ..., s_1, s_0)$	$\mathcal{R}(c_{s_0})$
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
$NP\ (S\backslash NP)/NP\ NP/N\ N$	(NP)
$NP\ (S\backslash NP)/NP\ NP$	$(S\backslash NP)$

The Dependency Model



stack $(s_n, \ldots, s_1, s_0)$	$\mathcal{R}(c_{s_0})$
NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
$NP\ (S\backslash NP)/NP\ NP/N\ N$	(NP)
$NP\ (S\backslash NP)/NP\ NP$	$(S\backslash NP)$
$NP\ S\backslash NP$	

The Dependency Model



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NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S) ◀
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
$NP\ (S\backslash NP)/NP\ NP/N\ N$	(NP)
$NP\ (S\backslash NP)/NP\ NP$	$(S\backslash NP)$
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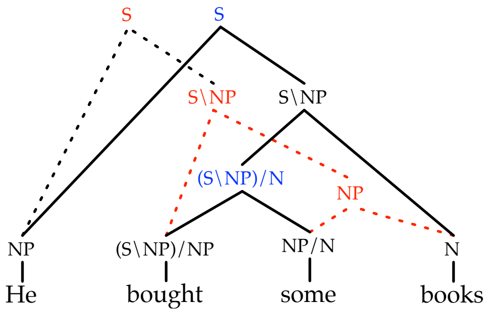

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NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
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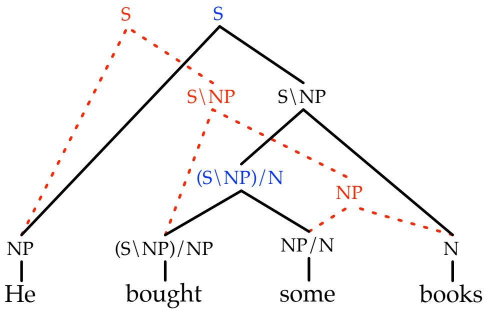
The Dependency Model



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NP	$()$
$NP\ (S\backslash NP)/NP$	(S, S)
$NP\ (S\backslash NP)/NP\ NP/N$	$(S\backslash NP, (S\backslash NP)/N)$
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S	$()$

Training: Chart-based Dependency Model

- Exponentially many derivations ω consistent with a dependency structure π [Clark and Curran, 2007]

$$P(\pi|S) = \sum_{\omega \in \Delta(\pi)} P(\omega, \pi|S)$$

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$$\begin{aligned}
L'(\Lambda) &= L(\Lambda) - G(\Lambda) \\
&= \log \prod_{j=1}^{m} P_\Lambda(\pi_j|S_j) - \sum_{i=1}^{n} \frac{\lambda_i^2}{2\sigma_i^2} \\
&= \sum_{j=1}^{m} \log \frac{\sum_{d \in \Delta(\pi_j)} e^{\boldsymbol{\lambda}.\boldsymbol{f}(d,\pi_j)}}{\sum_{\omega \in \rho(S_j)} e^{\boldsymbol{\lambda}.\boldsymbol{f}(\omega)}} - \sum_{i=1}^{n} \frac{\lambda_i^2}{2\sigma_i^2}
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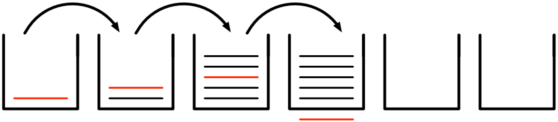
\end{aligned}$$

- Requires summing over all ω

Online Training

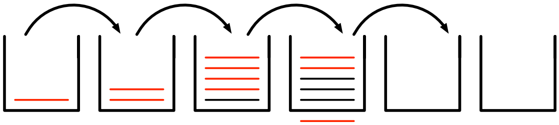
- The normal-form model uses the perceptron with early update
  - only one correct sequence
  - "violation" is guaranteed [Huang et al., 2012]



$$y^* \leftarrow \underset{y \in \mathrm{GEN}(x_i)}{\arg\max}\ \mathbf{w} \cdot \Phi(x_i, y)$$

Online Training

- Standard early update no longer valid for the dependency model
  - multiple correct items possible in each beam
  - "violation" is *not* guaranteed [Huang et al, 2012]



Online Training

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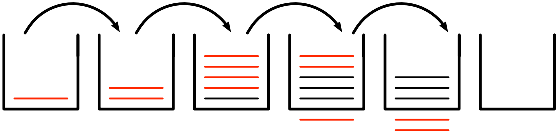
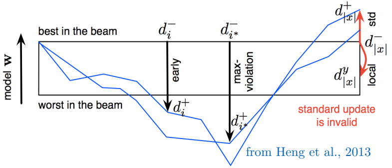
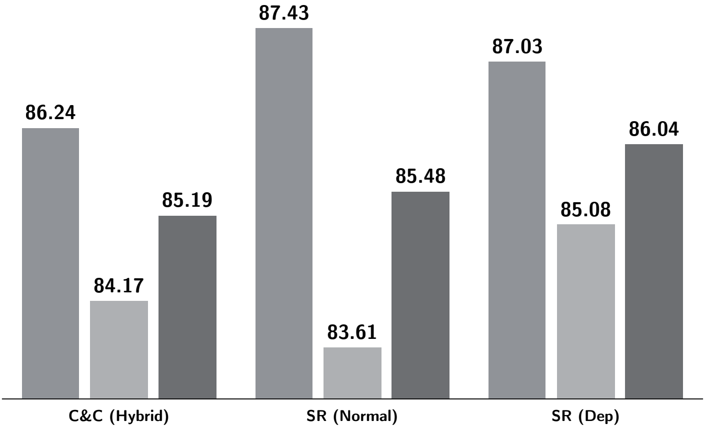
  - "violation" is *not* guaranteed [Huang et al, 2012]
  - $\mathbf{w} \leftarrow \mathbf{w} + \phi(\Pi_G[0]) - \phi(\mathcal{B}_i[0])$

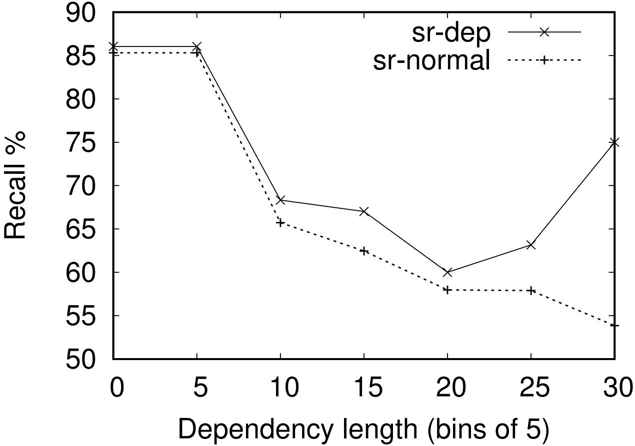




Results


86.24
84.17
85.19
87.43
83.61
85.48
87.03
85.08
86.04
C&C (Hybrid)
SR (Normal)
SR (Dep)

Results



sr-dep
sr-normal
Recall %
90
85
80
75
70
65
60
55
50
0
5
10
15
20
25
30
Dependency length (bins of 5)

Model 2

[Xu et al., NAACL 2016]

Shift-Reduce Parsing

- Linear model (struct. perceptron, SVM etc.)
  - $score(y_i) = \mathbf{w} \cdot \phi(\langle s, q \rangle, y_i)$
  - $score(y) = \sum_{i=1}^{|y|} score(y_i)$
  - $y^* = \arg\max_{y \in \mathcal{Y}_x} score(y)$

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  - sparse and expensive to compute
- [Yamada and Matsumoto, 2003; Huang and Sagae, 2010; Zhang and Clark, 2011; Zhang and Nivre, 2011; Goldberg and Nivre, 2012; Bohnet et al., 2013; Zhu et al., 2013]

Sparse Features

	feature templates
1	S_0wp, S_0c, S_0pc, S_0wc, S_1wp, S_1c, S_1pc, S_1wc, S_2pc, S_2wc, S_3pc, S_3wc,
2	Q_0wp, Q_1wp, Q_2wp, Q_3wp,
3	S_0Lpc, S_0Lwc, S_0Rpc, S_0Rwc, S_0Upc, S_0Uwc, S_1Lpc, S_1Lwc, S_1Rpc, S_1Rwc, S_1Upc, S_1Uwc,
4	S_0wcS_1wc, S_0cS_1w, S_0wS_1c, S_0cS_1c, S_0wcQ_0wp, S_0cQ_0wp, S_0wcQ_0p, S_0cQ_0p, S_1wcQ_0wp, S_1cQ_0wp, S_1wcQ_0p, S_1cQ_0p,
5	$S_0wcS_1cQ_0p$, $S_0cS_1wcQ_0p$, $S_0cS_1cQ_0wp$, $S_0cS_1cQ_0p$, $S_0pS_1pQ_0p$, $S_0wcQ_0pQ_1p$, $S_0cQ_0wpQ_1p$, $S_0cQ_0pQ_1wp$, $S_0cQ_0pQ_1p$, $S_0pQ_0pQ_1p$, $S_0wcS_1cS_2c$, $S_0cS_1wcS_2c$, $S_0cS_1cS_2wc$, $S_0cS_1cS_2c$, $S_0pS_1pS_2p$,
6	$S_0cS_0HcS_0Lc$, $S_0cS_0HcS_0Rc$, $S_1cS_1HcS_1Rc$, $S_0cS_0RcQ_0p$, $S_0cS_0RcQ_0w$, $S_0cS_0LcS_1c$, $S_0cS_0LcS_1w$, $S_0cS_1cS_1Rc$, $S_0wS_1cS_1Rc$.

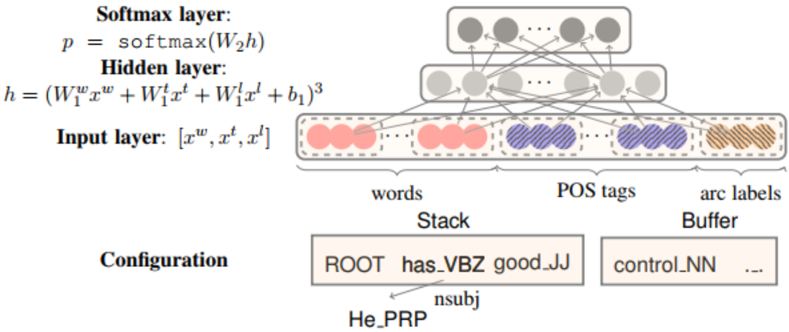
Table 1: Feature templates.

[Zhang and Clark, 2011]

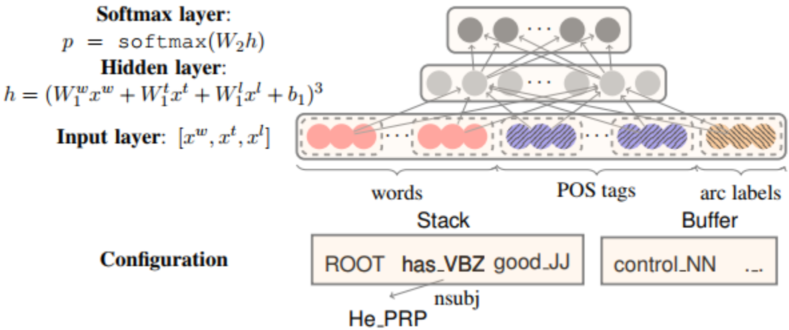
Kernel Features [Chen and Manning, 2014]

s_0.w	s_1.w	s_2.w	s_3.w
s.w$_0$	$s_.$w$_1$	s.w$_2$	s.w$_3$
s_0.l.w	s_1.l.w	s_o.r.w	s_1.r.w
q_0.w	q_1.w	q_2.w	q_3.w
s_0.c	s_0.l.c	s_0.r.c	
s_1.c	s_1.l.c	s_1.r.c	
s_2.c	s_3.c		

Kernel Features [Chen and Manning, 2014]



Kernel Features [Chen and Manning, 2014]



State-of-the-art results at the time!

Local Normalization

$$p(y_t | \langle s, q \rangle_y^{t-1}; \theta) = \frac{\exp\{\gamma(y_t, \langle s, q \rangle_y^{t-1}; \theta)\}}{Z_L\left(\langle s, q \rangle_y^{t-1}\right)}$$

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$$Z_L(\langle \alpha, \beta\rangle_y^{t-1}) = \sum_{{y_t}' \in \mathcal{T}\left(\langle \alpha, \beta\rangle_y^{t-1}\right)} \exp\{\gamma({y_t}', \langle \alpha, \beta\rangle_y^{t-1}; \theta)\}$$

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$$p(y|\theta) = \prod_{t=1}^{|y|} p(y_t|(\langle\alpha,\beta\rangle_y^{t-1});\theta) = \frac{\exp\{\sum_{t=1}^{|y|}\gamma(y_t,\langle\alpha,\beta\rangle_y^{t-1};\theta)\}}{\prod_{t=1}^{|y|} Z_L(\langle\alpha,\beta\rangle_y^{t-1})}$$

Global Normalization (CRF)

$$p(y|\theta) = \frac{\exp\{\sum_{t=1}^{|y|} \gamma(y_t, \langle \alpha, \beta \rangle_y^{t-1}; \theta)\}}{Z_G}$$

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$$Z_G = \sum_{y' \in \mathcal{S}_{|y|}} \exp \sum_{t=1}^{|y|} \gamma(y'_t, \langle \alpha, \beta \rangle_{y'}^{t-1}; \theta)$$

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$$\boxed{y^* = \arg\max_{y' \in \mathcal{S}_{|y|}} \sum_{t=1}^{|y|} \gamma(y'_t, \langle \alpha, \beta \rangle_{y'}^{t-1}; \theta)}$$

[Zhou et al., 2015; Andor et al., 2016]

Local vs. Global Normalization

$$Z_L(\langle\alpha,\beta\rangle_y^{t-1}) = \sum_{y_t{}' \in \mathcal{T}\left(\langle\alpha,\beta\rangle_y^{t-1}\right)} \exp\{\gamma(y_t{}', \langle\alpha,\beta\rangle_y^{t-1}; \theta)\}$$

$$Z_G = \sum_{y' \in \mathcal{S}_{|y|}} \exp \sum_{t=1}^{|y|} \gamma(y'_t, \langle\alpha,\beta\rangle_{y'}^{t-1}; \theta)$$

The label bias problem [Bottou et al., 1997; Le Cun et al., 1998; Lafferty et al., 2001];
Andor et al., 2016 showed that $\mathcal{P}_L \subset \mathcal{P}_G$ (assuming no lookahead)

Expected F-measure Training for Shift-Reduce Parsing with RNNs

	NN	Beam (Train)	Beam (Test)	global
C&M, 2014	✓	✗	✓	✗

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	NN	Beam (Train)	Beam (Test)	global
C&M, 2014	✓	✗	✓	✗
present model	✓	✓	✓	✓

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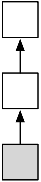
	NN	Beam (Train)	Beam (Test)	global
C&M, 2014	✓	✗	✓	✗
present model	✓	✓	✓	✓

At the same time, the model is optimized towards the final evaluation metric ✓

Expected F-Measure Training: Step 1

❶ Train a baseline model using a cross-entropy loss (pretraining)



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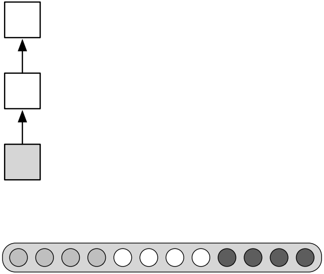

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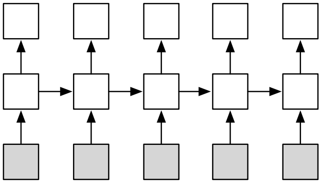
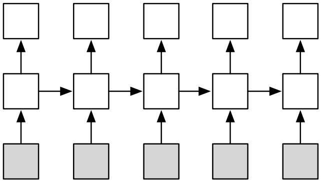


Expected F-Measure Training: Step 1

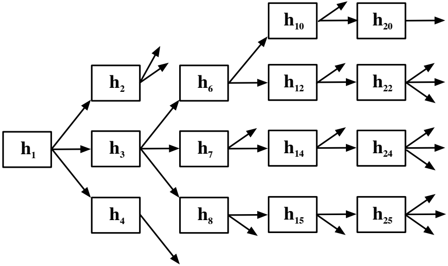
❶ Train a baseline model using a cross-entropy loss (pretraining)



$$L(\theta_B) = -\sum_{k}^{T_i} p(t_k|\theta_B), \qquad \theta_B = \{\mathbf{U}, \mathbf{V}, \mathbf{W}\}$$

Expected F-Measure Training: Step 2

❷ Let $\theta = \theta_B$, and parse each sentence in the training data with beam search



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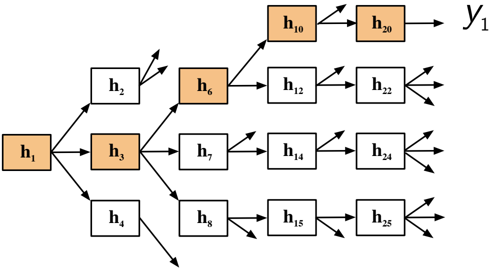

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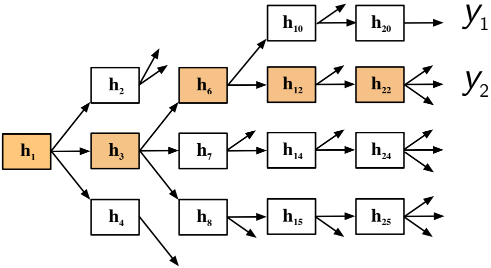

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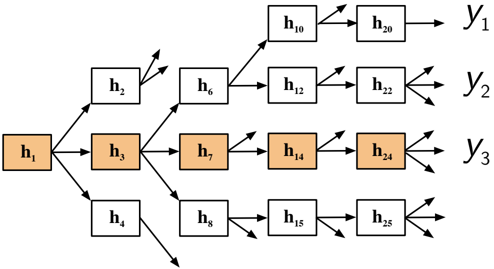

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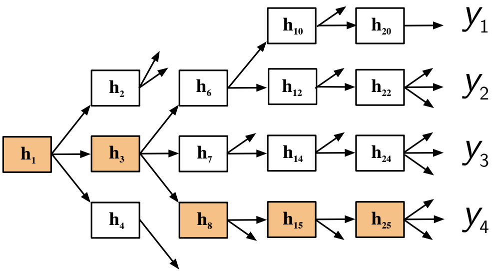

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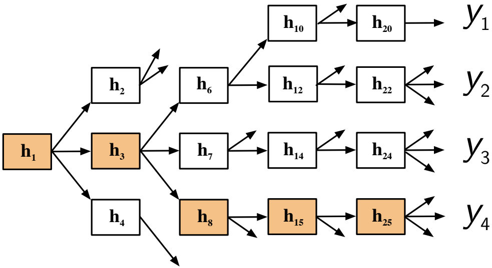

$$\gamma(y_i) = \sum_{j=1}^{|y_i|} \log s_\theta(y_{ij})$$

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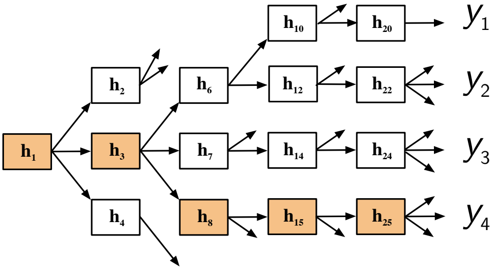

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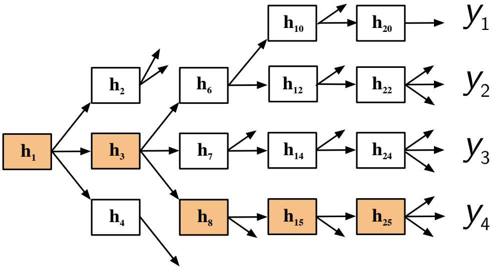

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Expected F-Measure Training: Step 3

3. Compute the -XF1 loss for each sentence, do SGD update and iterate

$$J(\theta) = -\text{XF1}(\theta) = -\sum_{y_i \in \Lambda(x_n)} p(y_i|\theta)\text{F1}(\Delta_{y_i}, \Delta_{x_n}^G),$$

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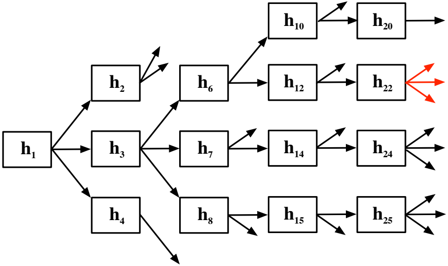

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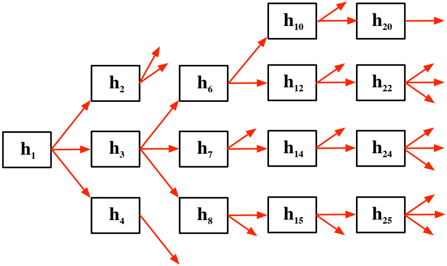

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Expected F-Measure Training

output	action sequence	$\gamma(y_i)$	F1
y_1	$y_{11}\ y_{12} \dots y_{1i}$	-0.60	0.67
y_2	$y_{21}\ y_{22} \dots y_{2j}$	-1.5	0.81
y_3	$y_{31}\ y_{32} \dots y_{3k}$	-4.96	0.90

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output	action sequence	$\gamma(y_i)$	F1
z_1	$z_{11}\ z_{12} \ldots z_{1i}$	-0.90	0.71
z_2	$z_{21}\ z_{22} \ldots z_{2j}$	-0.99	0.72
z_3	$z_{31}\ z_{32} \ldots z_{3k}$	-3.76	0.73

Expected F-Measure Training

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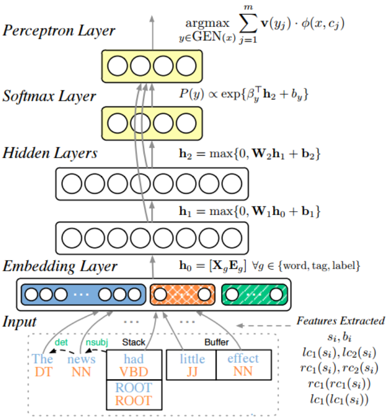
Related Work



[Weiss et al., 2015]

Related Work

- Watanabe and Sumita, 2015
  - max-margin based objective
  - max-violation updates [Huang et al., 2012]

- Zhou et al., 2015
  - based on Chen and Manning, 2014
  - CRF [Bottou et al., 1997; Le Cun et al., 1998; Lafferty et al., 2001]

- Andor et al., 2016
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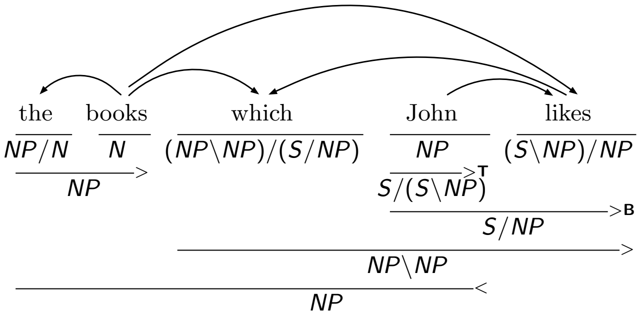
- Optimizing task-specific metrics for parsing
  - e.g., Goodman, 1996; Smith and Eisner, 2006; Auli and Lopez, 2011

Eval: F1 over Labeled, Directed CCG Deps



$$\langle \textit{the},\ NP/N_1,\ 1,\ \textit{books},\rangle$$
$$\langle \textit{likes},\ (S\backslash NP_1)/NP_2,\ 1,\ \textit{John}\rangle$$
$$\langle \textit{which},\ (NP/NP_1)/(S/NP)_2,\ 2,\ \textit{likes}\rangle$$
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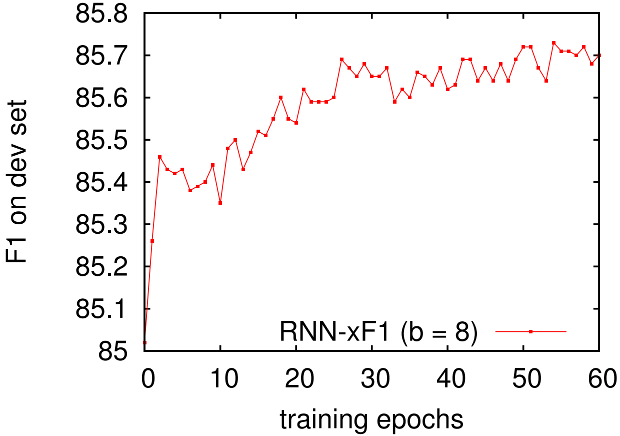
$$\langle \textit{likes},\ (S\backslash NP_1)/NP_2,\ 2,\ \textit{books}\rangle$$

The Greedy Model and Beam Search (Dev)

beam	F1
$b = 1$	84.61
$b = 2$	84.94
$b = 4$	85.01
$b = 6$	85.02
$b = 8$	85.02
$b = 16$	85.01

$b \in \{6, 8\}$ gives $+0.41\%$ F1 over $b = 1$

XF1 Model Dev F1 vs. Training Epochs



Test Set Parsing Results

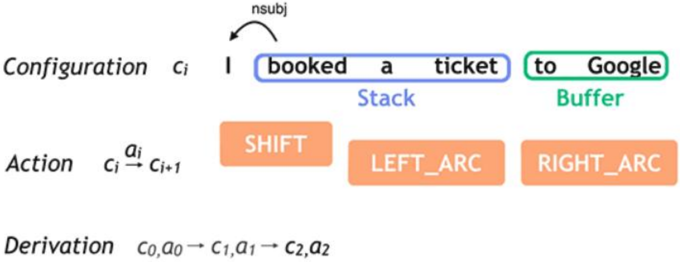
Model	LP	LR	LF	CAT	Speed
C&C (normal)	85.45	83.97	84.70	92.83	97.90
C&C (hybrid)	86.24	84.17	85.19	93.00	95.25
Zhang11 ($b = 16$)	87.04	84.14	85.56	92.95	49.54
Xu14 ($b = 128$)	87.03	85.08	86.04	93.10	12.85
Am16 ($b = 1$)	-	-	83.27	91.89	350.00
Am16 ($b = 16$)	-	-	85.57	92.86	10.00
RNN-greedy ($b = 1$)	88.53	81.65	84.95	93.57	337.45
RNN-greedy ($b = 6$)	88.54	82.77	85.56	93.68	96.04
RNN-XF1 ($b = 8$)	88.74	84.22	86.42	93.87	67.65

- Zhang11 = Zhang and Clark, 2011*, Xu14 = [Xu et al., 2014]; AM16 = Ambati et al., 2016 (NN + Struct. Percep [Weiss et al., 2015])
- The XF1 model improves LR by 2.57% and LF by 1.47% over RNN-greedy ($b = 1$)

Model 3

[Xu, EMNLP 2016]

Transition-based Dependency Parsing



source: Google SyntaxNet

Models

- Local linear (e.g., SVM)

Models

- Local linear (e.g., SVM) $\Rightarrow$ global linear (e.g., struct. perceptron)

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step	stack $(s_n, \ldots, s_1, s_0)$	queue $(q_0, q_1 \ldots, q_n)$	action
0		Ms. Haag plays Elianti	

No "global" sensitivity to parser states

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Solution: Stack-LSTM [Dyer et al., 2015]

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0		Ms. Haag plays Elianti	
1	N/N	Haag plays Elianti	SHIFT
2	N/N N	plays Elianti	SHIFT
3	N	plays Elianti	REDUCE
4	NP	plays Elianti	UNARY
5	NP $(S[dcl]\backslash NP)/NP$	Elianti	SHIFT
6	NP $(S[dcl]\backslash NP)/NP$ N		SHIFT
7	NP $(S[dcl]\backslash NP)/NP$ NP		UNARY
8	NP $S[dcl]\backslash NP$		REDUCE
9	$S[dcl]$		REDUCE

Stack-LSTM [Dyer et al., 2015]

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8	NP $S[dcl]\backslash NP$		REDUCE
9	$S[dcl]$		REDUCE

LSTM-stack , LSTM-queue , LSTM-action

Stack-LSTM [Dyer et al., 2015]

It showed promise

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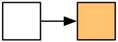

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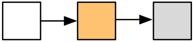

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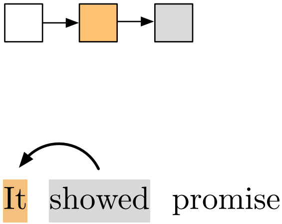

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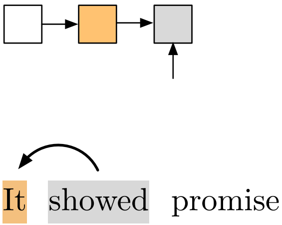

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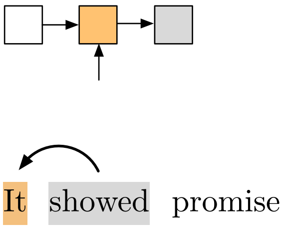

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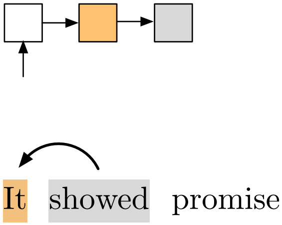

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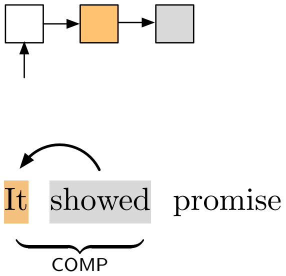

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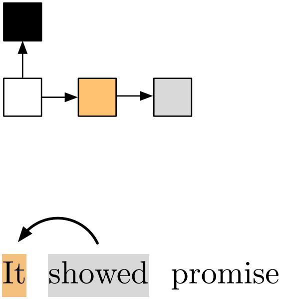

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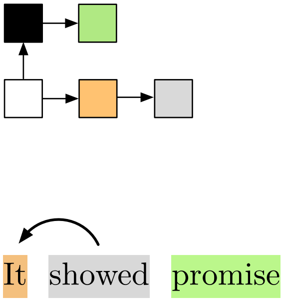
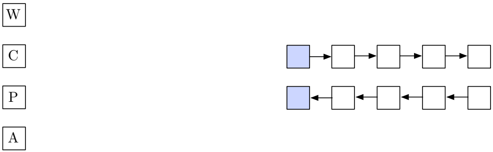


LSTM Shift-Reduce CCG Parsing

the books which John likes



LSTM Shift-Reduce CCG Parsing

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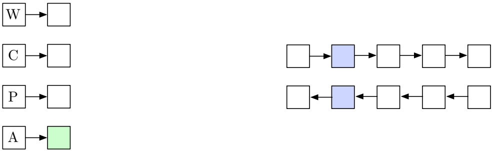
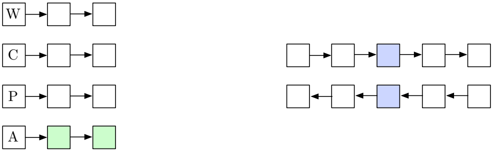
NP/N



LSTM Shift-Reduce CCG Parsing

the	books	which	John	likes
NP/N	N			



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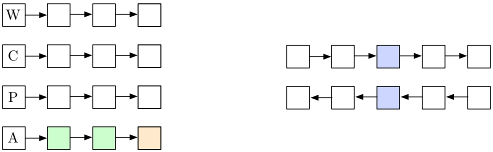
NP/N N

$>$

NP



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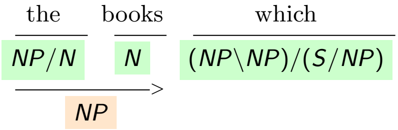
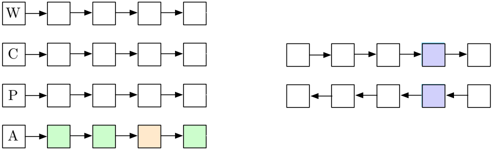
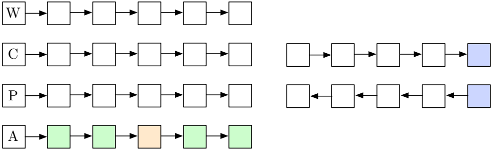




LSTM Shift-Reduce CCG Parsing

the	books	which	John	likes
NP/N	N	$(NP\backslash NP)/(S/NP)$	NP	
NP (>)				



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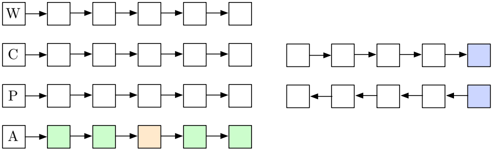

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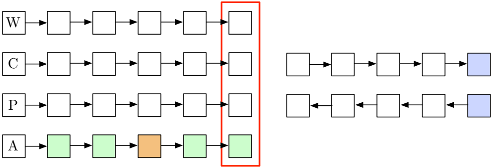
$$\delta_t = [\mathbf{h}_t^{\mathsf{W}}; \mathbf{h}_t^{\mathsf{C}}; \mathbf{h}_t^{\mathsf{P}}; \mathbf{h}_t^{\mathsf{A}}]$$



LSTM Shift-Reduce CCG Parsing

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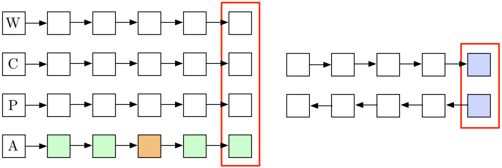
$$\mathbf{b}_t = f(\mathbf{B}[\delta_t; \mathbf{Q}_j] + \mathbf{r})$$



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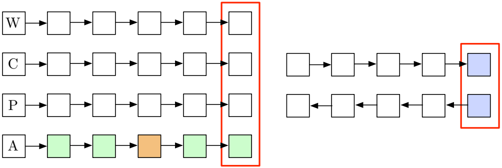
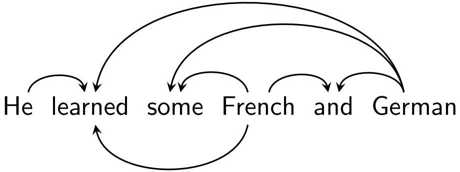
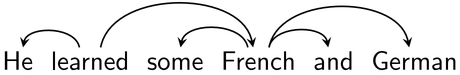
$$\mathbf{a}_t = f(\mathbf{A}\mathbf{b}_t + \mathbf{s})$$



Two Simple Motivations: I



this parser



Google SyntaxNet and Stanford

Two Simple Motivations: II

input : $w_0 \ldots w_{n-1}$

axiom : $0 : (0, \epsilon, \beta, \phi)$

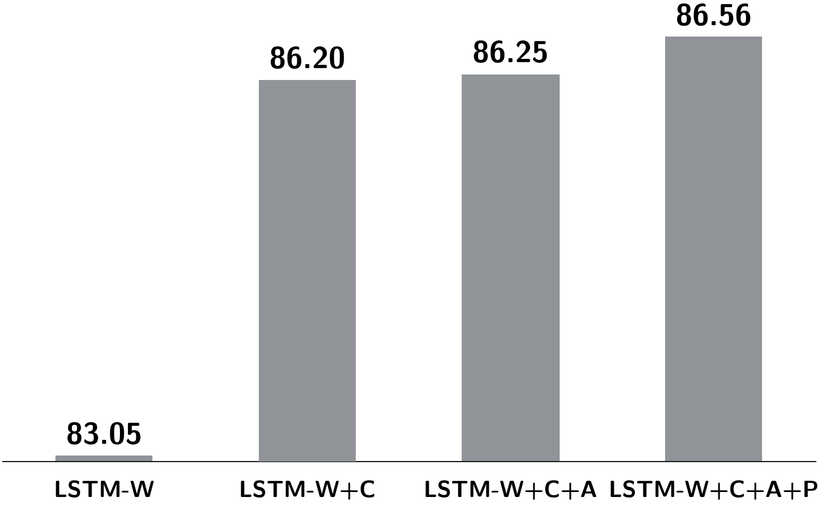
goal : $2n - 1 + \mu : (n, \delta, \epsilon, \Delta)$

$$\frac{\omega : (j, \delta, x_{w_j}|\beta, \Delta)}{\omega + 1 : (j+1, \delta|x_{w_j}, \beta, \Delta)} \qquad (\textsc{shift}; 0 \leq j < n)$$

$$\frac{\omega : (j, \delta|s_1|s_0, \beta, \Delta)}{\omega + 1 : (j, \delta|x, \beta, \Delta \cup \langle x \rangle))} \qquad (\textsc{reduce}; s_1 s_0 \rightarrow x)$$

$$\frac{\omega : (j, \delta|s_0, \beta, \Delta)}{\omega + 1 : (j, \delta|x, \beta, \Delta)} \qquad (\textsc{unary}; s_0 \rightarrow x)$$

Results: Locally Normalized Models



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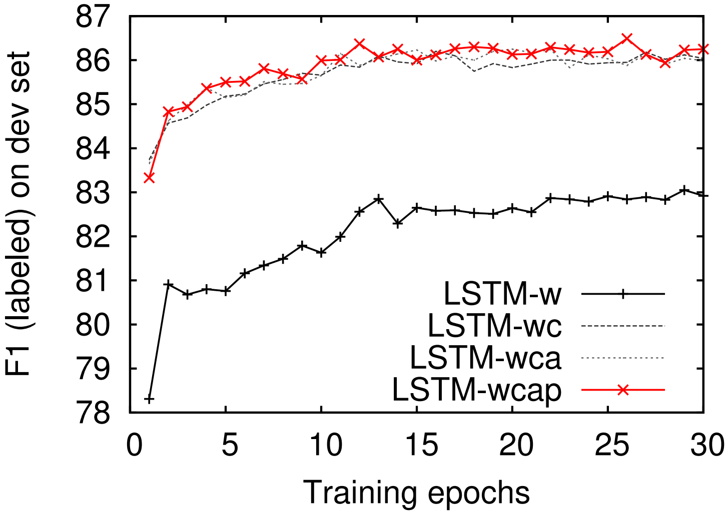

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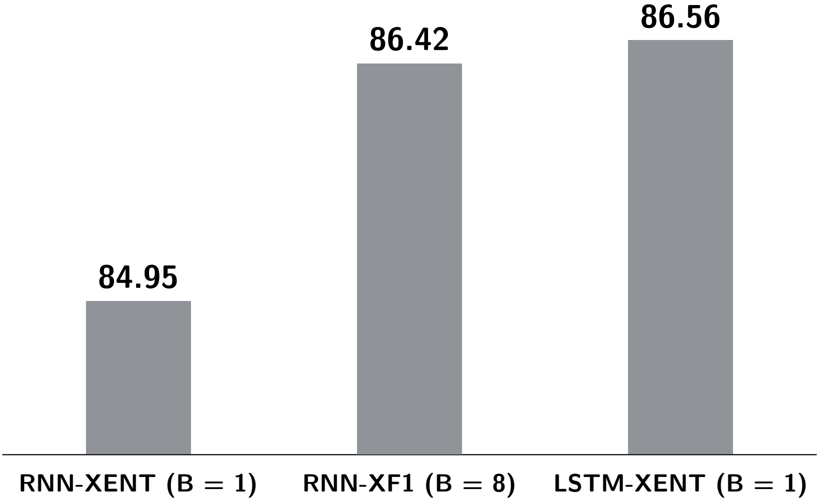

The Label Bias Problem [Bottou et al., 1997; LeCun et al., 1998; Lafferty et al., 2001]

$$p(y_t | \langle s, q \rangle_y^{t-1}; \theta) = \frac{\exp\{\gamma(y_t, \langle s, q \rangle_y^{t-1}; \theta)\}}{Z_L\left(\langle s, q \rangle_y^{t-1}\right)}$$

$$Z_L(\langle \alpha, \beta \rangle_y^{t-1}) = \sum_{y_t{}' \in \mathcal{T}\left(\langle \alpha, \beta \rangle_y^{t-1}\right)} \exp\{\gamma(y_t{}', \langle \alpha, \beta \rangle_y^{t-1}; \theta)\}$$

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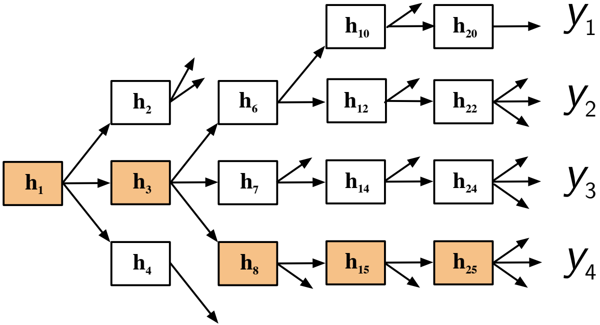
Andor et al., (2016) showed that $\mathcal{P}_L \subset \mathcal{P}_G$ and label bias is irrespective of the scoring function γ

XF1 Training



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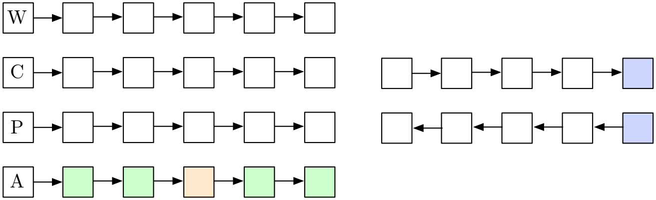
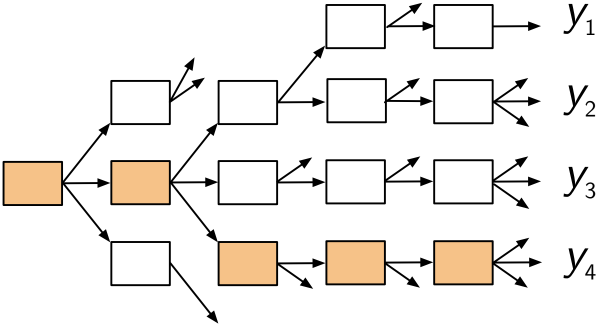
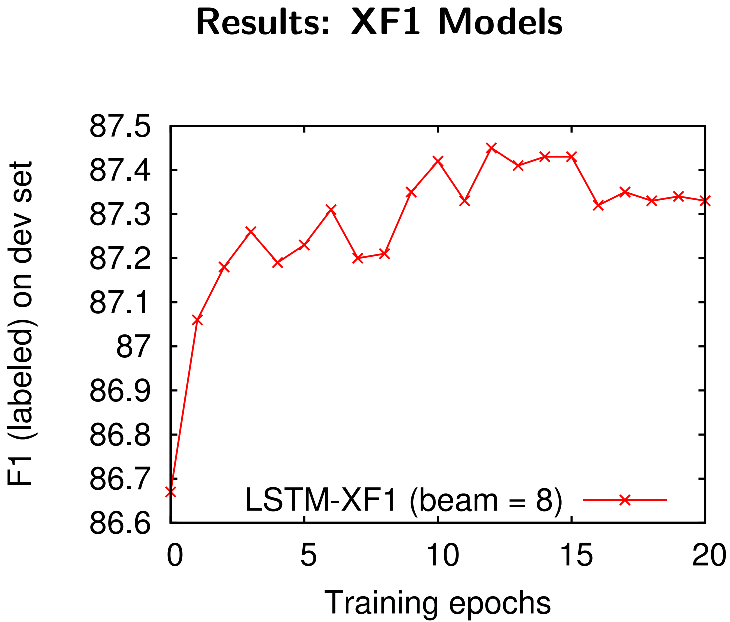
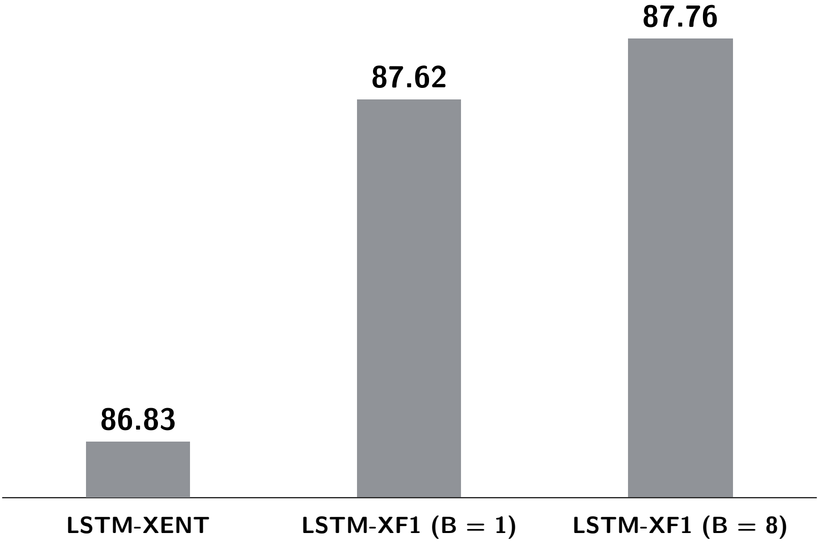


XF1 Training

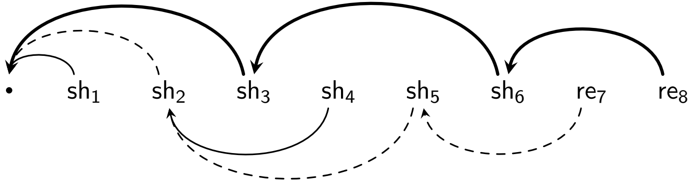



Results: XF1 Models
F1 (labeled) on dev set
87.5
87.4
87.3
87.2
87.1
87
86.9
86.8
86.7
86.6
0
5
10
15
20
Training epochs
LSTM-XF1 (beam = 8)

Results: XF1 Models



Impl.: Tree-Structured Stack + Dynamically Structured Graph



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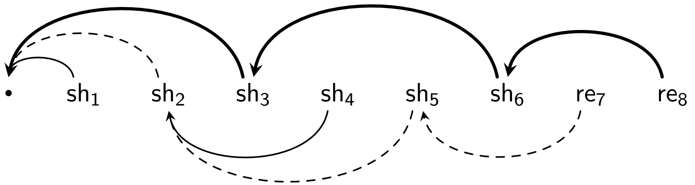

$$
\begin{aligned}
\boldsymbol{\delta}^{a}_{s_r} &= \mathsf{BPTS}(s_r.\mathcal{A}) \\
&= \sum_{m \in s_r.\mathcal{A}.keys} \sum_{i \in s_r.\mathcal{A}[m]} \boldsymbol{\delta}_m \boldsymbol{\delta}_{im} \\
&= \sum_{m \in s_r.\mathcal{A}.keys} \sum_{i \in s_r.\mathcal{A}[m]} \boldsymbol{\delta}_m \underbrace{p(y_i|\theta)(\mathsf{XF1}(\theta) - \mathsf{F1}(\Delta_{y_i}, \Delta^{G}_{x_n}))\frac{1}{z_m}}_{\text{XF1 gradient per action}}
\end{aligned}
$$

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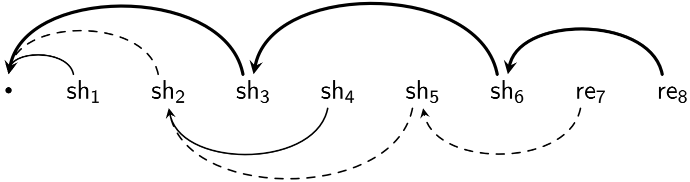

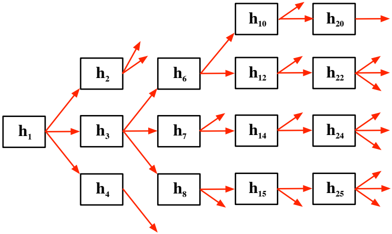

CNN $\Rightarrow$ DyNet

Conclusions

- Global normal-form

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- Global normal-form $\Rightarrow$ global dependency model with a hidden variable (with the struct. perceptron)

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- Beam search $\Rightarrow$ struct. perceptron, RNN, and LSTM $\Rightarrow$ global structured learning