Deep Learning and Lexical, Syntactic and Semantic Analysis

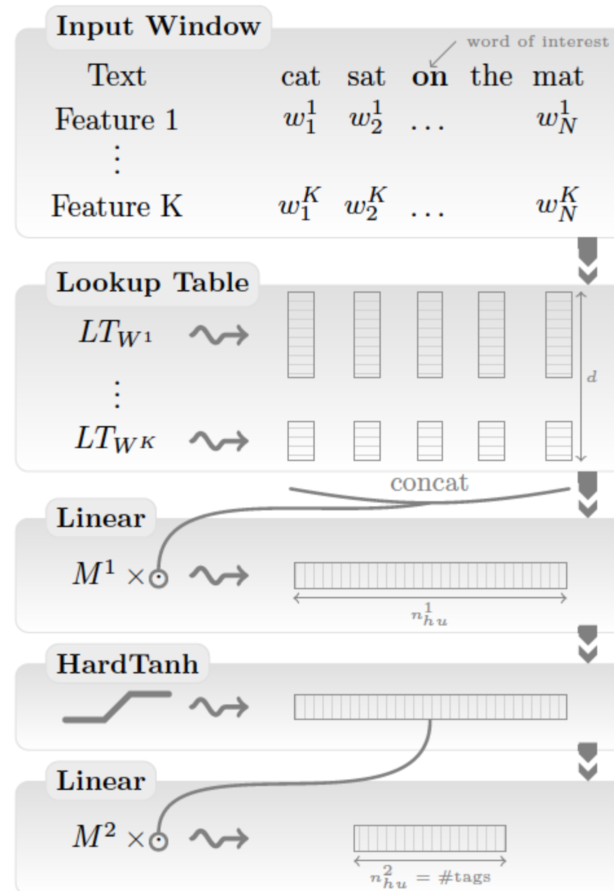
Wanxiang Che (HIT)
Yue Zhang (SUTD)

Part 3: Greedy Decoding

Part 3.1: Greedy Decoding for Tagging

Window Approach

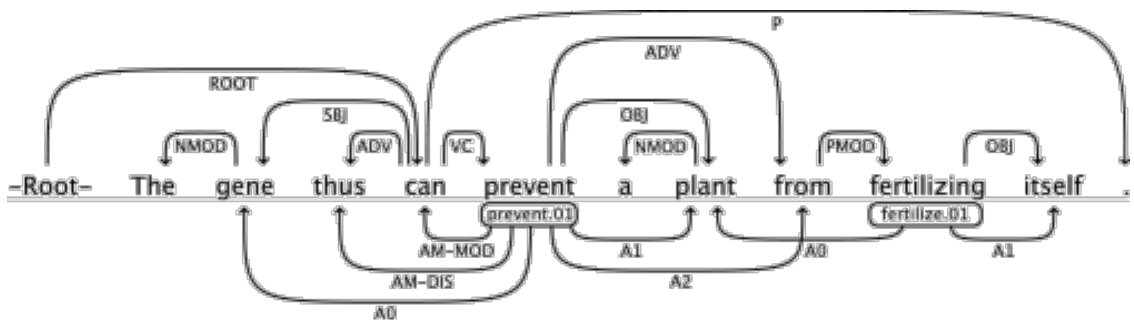
- Tasks
  - POS tagging, Chunking, NER, SRL
- Tag **one word** at a time
- Feed a **fixed-size** window of text around **each word** to tag
- Features
  - Words, POS tags, Suffix, Cascading, …



Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural Language Processing (Almost) from Scratch. J. Mach. Learn. Res. 12, 2493-2537.

Window Approach

- Works fine for most tasks
- How to deal with long-range dependencies?
  - E.g. in SRL, the verb of interest might be outside the window!



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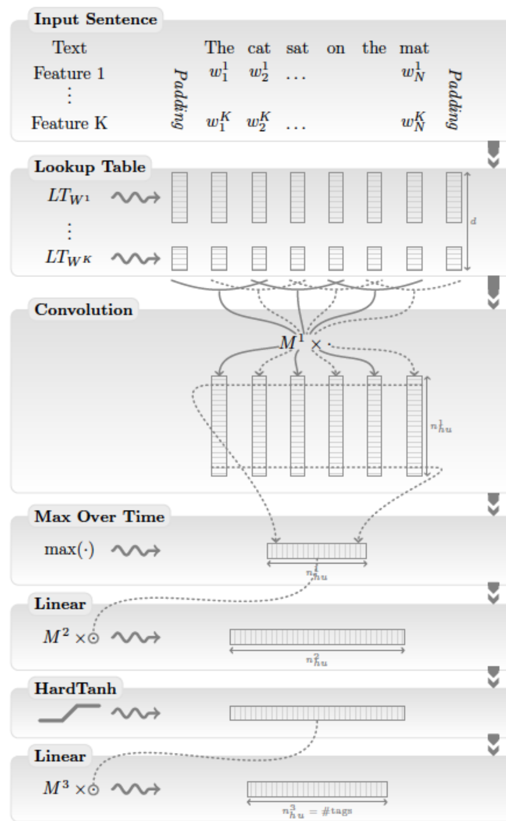
Sentence Approach

- Tag one word at a time
  - add extra **relative position** features
- Feed the **whole sentence** to the network
- Convolutions to handle variable-length inputs
- **Max over** time to capture most relevant features
  - Outputs a fixed-sized feature vector

Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural Language Processing (Almost) from Scratch. J. Mach. Learn. Res. 12, 2493-2537.

Sentence Approach



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Results

Approach	POS (PWA)	Chunking (F1)	NER (F1)	SRL (F1)
Benchmark Systems	97.24	94.29	89.31	77.92
NN+WLL	96.31	89.13	79.53	55.40

- Window approach: POS, Chunking, NER
- Sentence approach: SRL
- WLL: Word-Level Log-Likelihood

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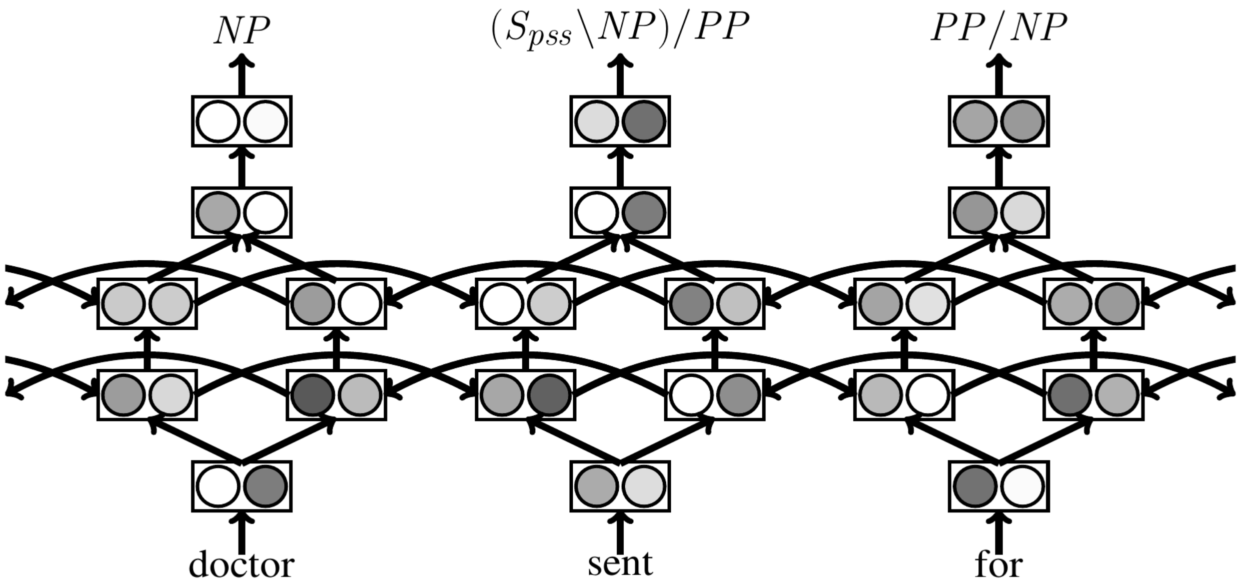
CCG Supertagging



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Lewis, M., Lee, Kenton., & Zettlemoyer, L. (2016). LSTM CCG Parsing. NAACL.

CCG Supertagging

- No POS feature
- Reduce word sparsity
- Global context information

Model	Accuracy	Time
C&C (gold POS)	92.60	-
C&C (auto POS)	91.50	0.57
NN	91.10	21.00
RNN	92.63	-
RNN+dropout	93.07	2.02

Model	**Dev**	**Test**
C&C tagger	91.5	92.0
NN	91.3	91.6
RNN	93.1	93.0
LSTM	94.1	94.3
LSTM + Tri-training	**94.9**	**94.7**

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CCG Supertagging

Supertagger	Accuracy
Bidirectional RNNs	93.4
Forward LSTM only	83.5
Backward LSTM only	89.5
Bidirectional LSTMs	**94.1**

Word Class	NN	LSTM	LSTM+ Tri-training
All	91.32	94.14	**94.90**
Unseen Words	90.39	94.21	**95.26**
Unseen Usages	45.80	59.37	**62.46**
Prepositions	78.11	84.40	**85.98**
Verbs	82.55	87.85	**89.24**
Wh-words	90.47	92.09	**94.16**
Long range	74.80	83.99	**86.31**

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CCG Supertagging

- Parsing results

Model	P	R	F1
C&C	86.2	84.2	85.2
C&C + RNN	87.7	86.4	87.0
EASYCCG	83.7	83.0	83.3
Dependencies	86.5	85.8	86.1
LSTM	87.7	86.7	87.2
LSTM + Dependencies	88.2	87.3	87.8
LSTM + Tri-training	**88.6**	**87.5**	**88.1**
LSTM + Tri-training + Dependencies	88.2	87.3	87.8

Lewis, M., & Steedman, M. (2014). Improved CCG Parsing with Semi-supervised Supertagging. TACL.
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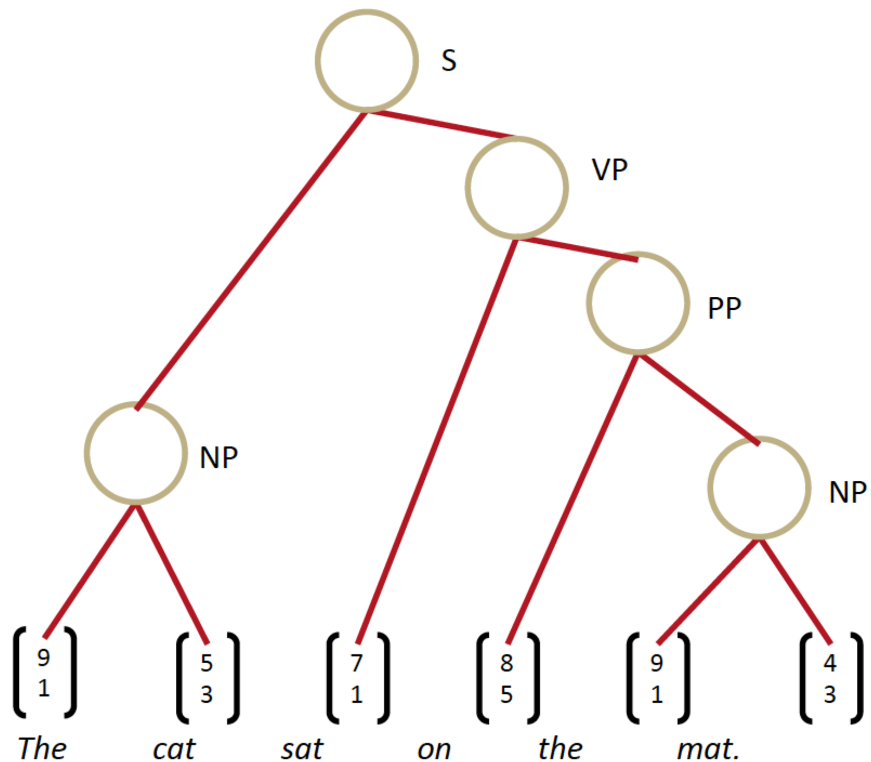
Part 3.2: Greedy Search for Constituent Parsing with RNN

Constituent Parsing with Recursive NN

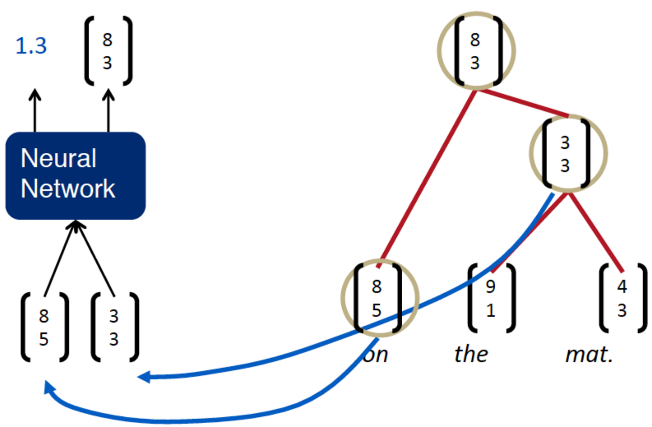
- Our goal



Richard Socher, Cliff Lin, Andrew Y. Ng, and Christopher D. Manning. Parsing Natural Scenes and Natural Language with Recursive Neural Networks. ICML 2011

Recursive NN

- Inputs
  - Two candidate children's representations
- Outputs
  - The semantic representation if the two nodes are merged
  - Score of how plausible the new node would be



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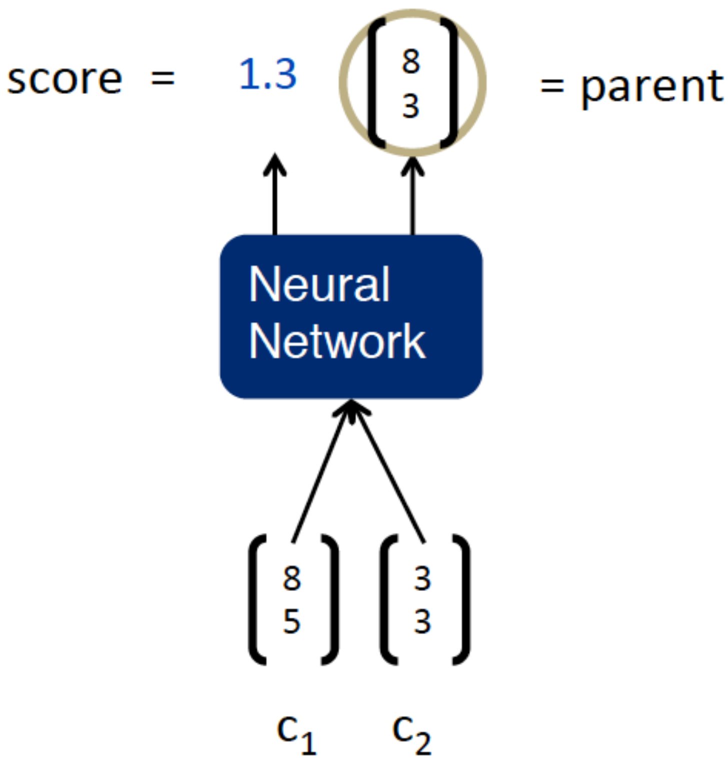
RNN Definition



$$\begin{cases} \text{score} = U^T p \\ p = \tanh\left(W \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + b\right) \end{cases}$$

where *W* at all nodes of the tree are the same

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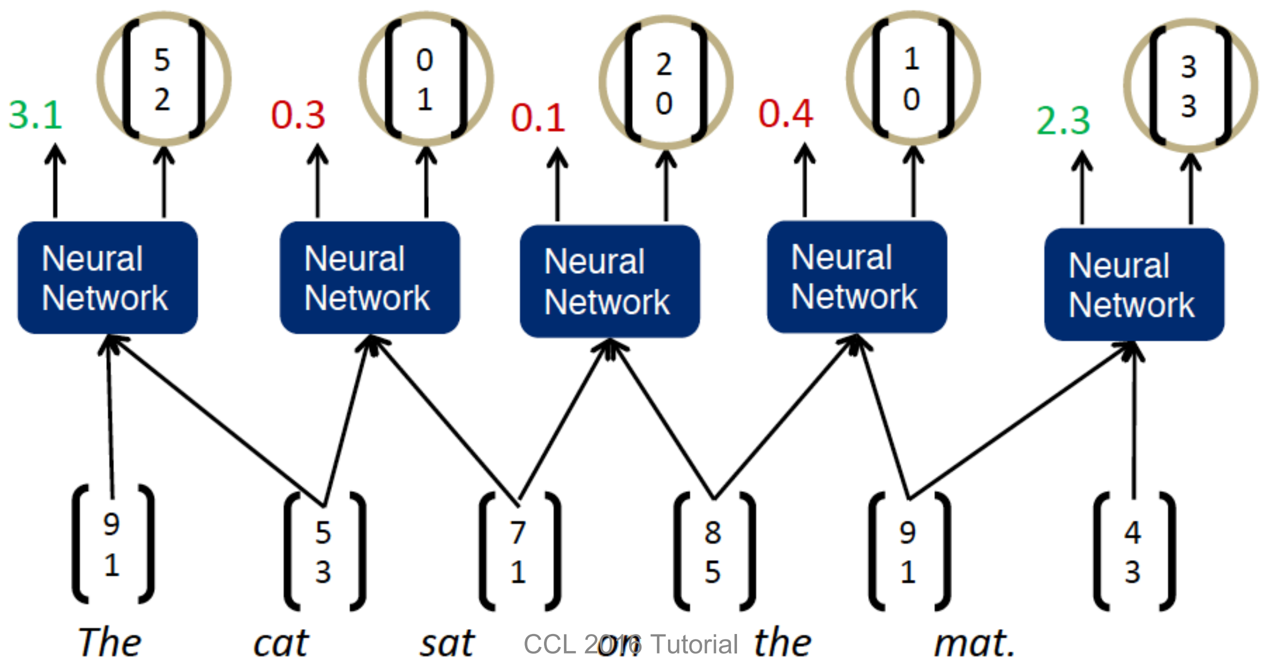
Parsing a sentence with an RNN



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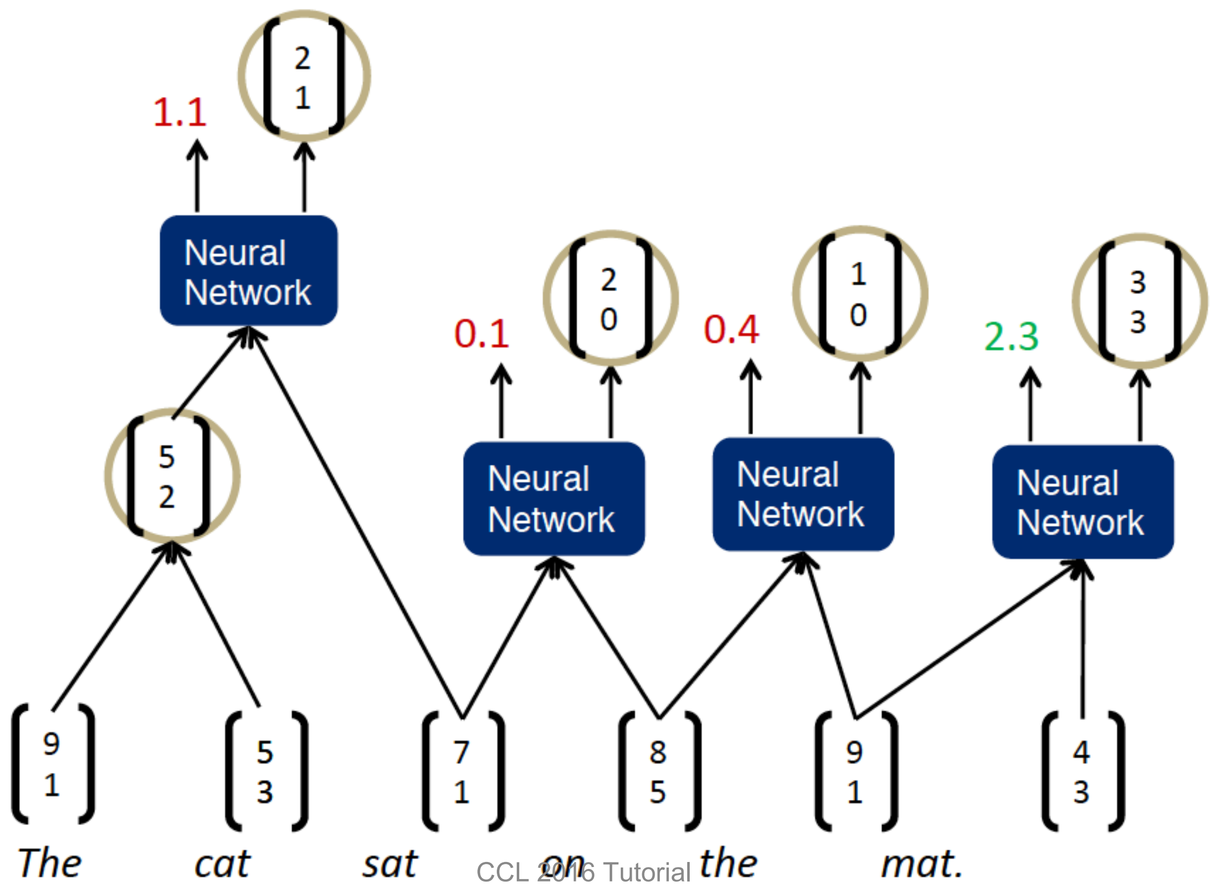
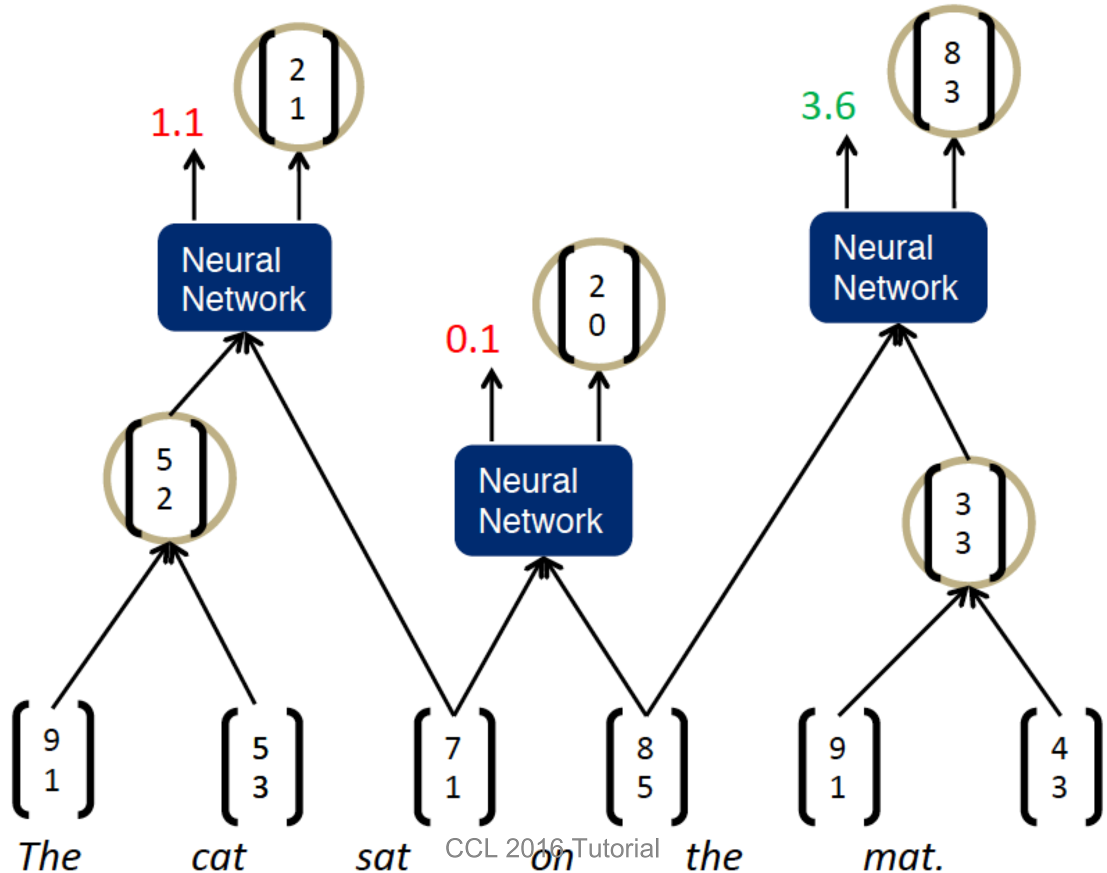
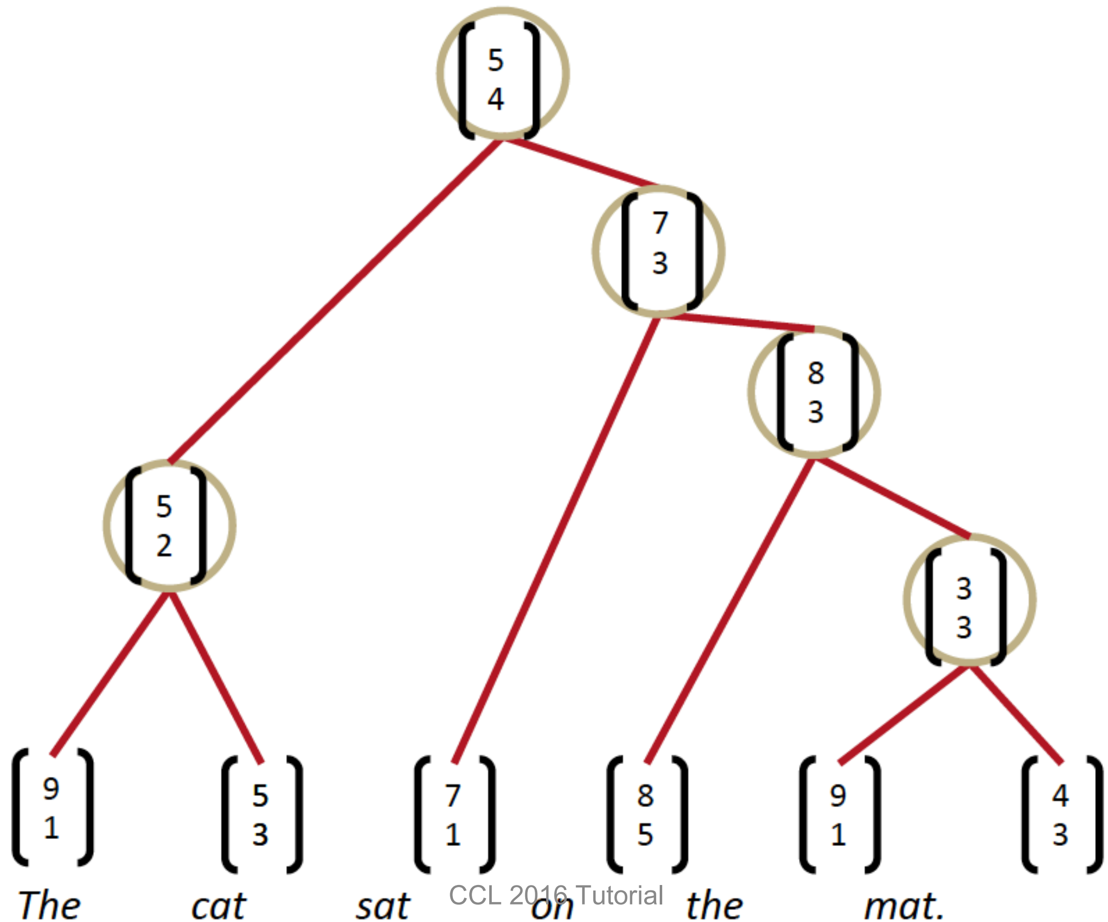


Parsing a sentence with an RNN

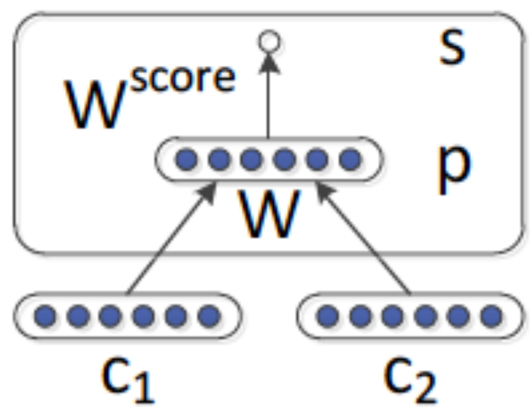


Parsing a sentence with an RNN



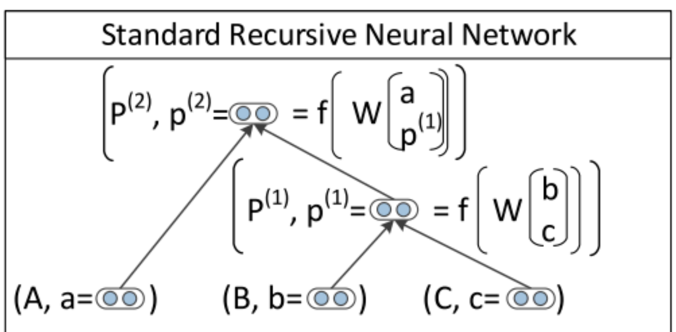
Discussion on Simple RNN

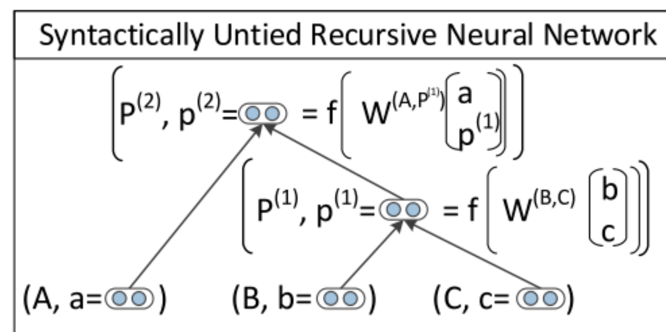
- The composition function with single weight matrix is the same for all categories, punctuation, etc.
- It could capture some phenomena but not adequate for more complex, higher order composition



Solution: Syntactically-Untied RNN (SU-RNN)

- Intuition
  - Condition the composition function on the syntactic categories
- Allows for different composition functions for pairs of syntactic categories, e.g. Adv + AdjP, VP + NP

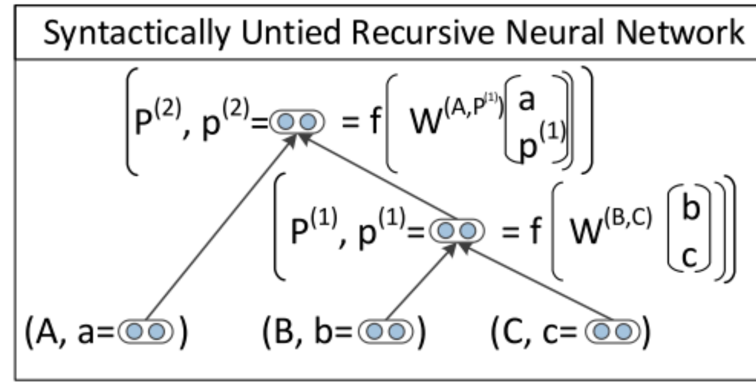




Richard Socher, John Bauer, Christopher D. Manning and Andrew Y. Ng. Parsing with Compositional Vector Grammars. ACL 2013.

Compositional Vector Grammars (CVG)

- PCFG + SU-RNN
- PCFG
  - Produce: k-best parsing trees
- SU-RNN
  - Re-ranking with SU-RNN



$$p^{(1)} = f\left(W^{(B,C)}\begin{bmatrix} b \\ c \end{bmatrix}\right)$$

$$s\left(p^{(1)}\right) = \left(v^{(B,C)}\right)^T p^{(1)} + \log P(P_1 \rightarrow B\ \ C)$$

$$s(\texttt{CVG}(\theta, x, \hat{y})) = \sum_{d \in N(\hat{y})} s\left(p^d\right)$$

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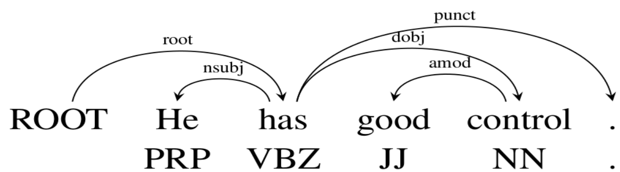
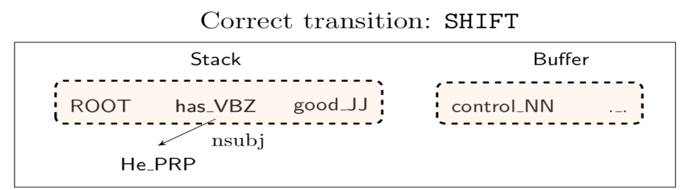
Part 3.3: Transition-based Dependency Parsing with Greedy Search

Dependency Parsing

- Neural MaltParser





Transition	Stack	Buffer	A
	[ROOT]	[He has good control .]	$\emptyset$
SHIFT	[ROOT He]	[has good control .]	
SHIFT	[ROOT He has]	[good control .]	
LEFT-ARC(nsubj)	[ROOT has]	[good control .]	$A\cup$ nsubj(has,He)
SHIFT	[ROOT has good]	[control .]	
SHIFT	[ROOT has good control]	[.]	
LEFT-ARC(amod)	[ROOT has control]	[.]	$A\cup$amod(control,good)
RIGHT-ARC(dobj)	[ROOT has]	[.]	$A\cup$ dobj(has,control)
...	...	...	...
RIGHT-ARC(root)	[ROOT]	[]	$A\cup$ root(ROOT,has)

Chen, D., & Manning, C. D. (2014). A Fast and Accurate Dependency Parser using Neural Network. ACL.

Dependency Parsing

Softmax layer:

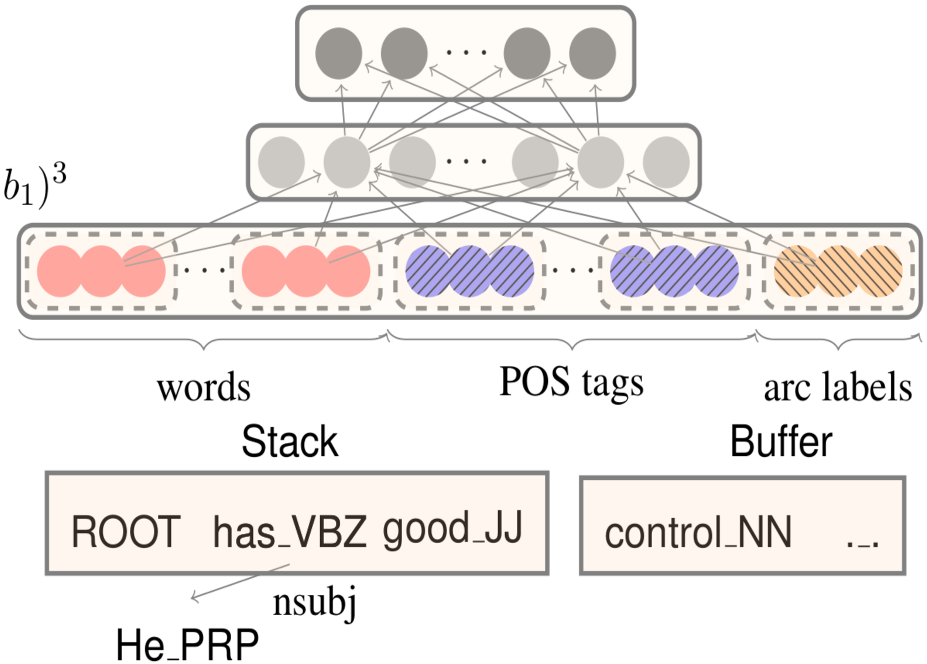
$$p = \texttt{softmax}(W_2 h)$$

Hidden layer:

$$h = (W_1^w x^w + W_1^t x^t + W_1^l x^l + b_1)^3$$

Input layer: $[x^w, x^t, x^l]$

Configuration



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Dependency Parsing

- ZPar features (Zhang and Nivre, ACL 2011)

Single-word features (9)
$s_1.w$; $s_1.t$; $s_1.wt$; $s_2.w$; $s_2.t$; $s_2.wt$; $b_1.w$; $b_1.t$; $b_1.wt$
Word-pair features (8)
$s_1.wt \circ s_2.wt$; $s_1.wt \circ s_2.w$; $s_1.wts_2.t$; $s_1.w \circ s_2.wt$; $s_1.t \circ s_2.wt$; $s_1.w \circ s_2.w$ $s_1.t \circ s_2.t$; $s_1.t \circ b_1.t$
Three-word feaures (8)
$s_2.t \circ s_1.t \circ b_1.t$; $s_2.t \circ s_1.t \circ lc_1(s_1).t$; $s_2.t \circ s_1.t \circ rc_1(s_1).t$; $s_2.t \circ s_1.t \circ lc_1(s_2).t$; $s_2.t \circ s_1.t \circ rc_1(s_2).t$; $s_2.t \circ s_1.w \circ rc_1(s_2).t$; $s_2.t \circ s_1.w \circ lc_1(s_1).t$; $s_2.t \circ s_1.w \circ b_1.t$

Chen, D., & Manning, C. D. (2014). A Fast and Accurate Dependency Parser using Neural Network. ACL.

Dependency Parsing

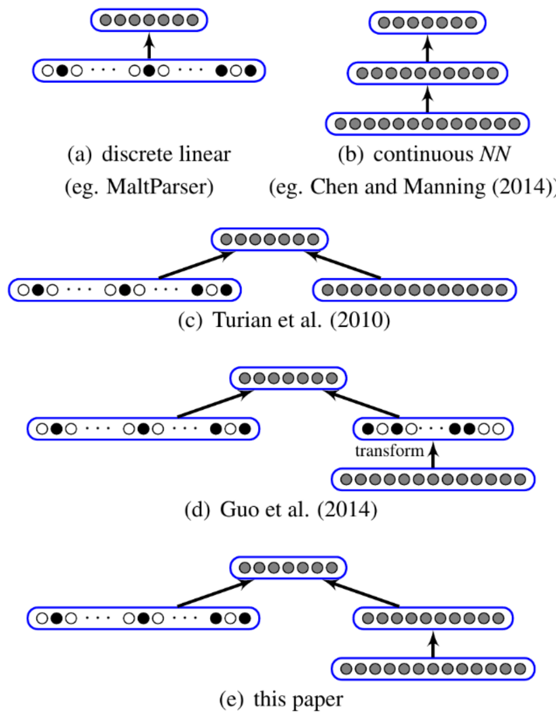
Parser	Dev		Test		Speed
	UAS	LAS	UAS	LAS	(sent/s)
standard	90.2	87.8	89.4	87.3	26
eager	89.8	87.4	89.6	87.4	34
Malt:sp	89.8	87.2	89.3	86.9	469
Malt:eager	89.6	86.9	89.4	86.8	448
MSTParser	91.4	88.1	90.7	87.6	10
Our parser	**92.0**	**89.7**	**91.8**	**89.6**	**654**

Parser	Dev		Test		Speed
	UAS	LAS	UAS	LAS	(sent/s)
standard	82.4	80.9	82.7	81.2	72
eager	81.1	79.7	80.3	78.7	80
Malt:sp	82.4	80.5	82.4	80.6	420
Malt:eager	81.2	79.3	80.2	78.4	393
MSTParser	**84.0**	82.1	83.0	81.2	6
Our parser	**84.0**	**82.4**	**83.9**	**82.4**	**936**

Chen, D., & Manning, C. D. (2014). A Fast and Accurate Dependency Parser using Neural Network. ACL.

Dependency Parsing

- Chen and Manning with combined features



Zhang, M., & Zhang, Y. (2015). Combining Discrete and Continuous Features for Deterministic Transition-based Dependency Parsing. EMNLP.

Dependency Parsing

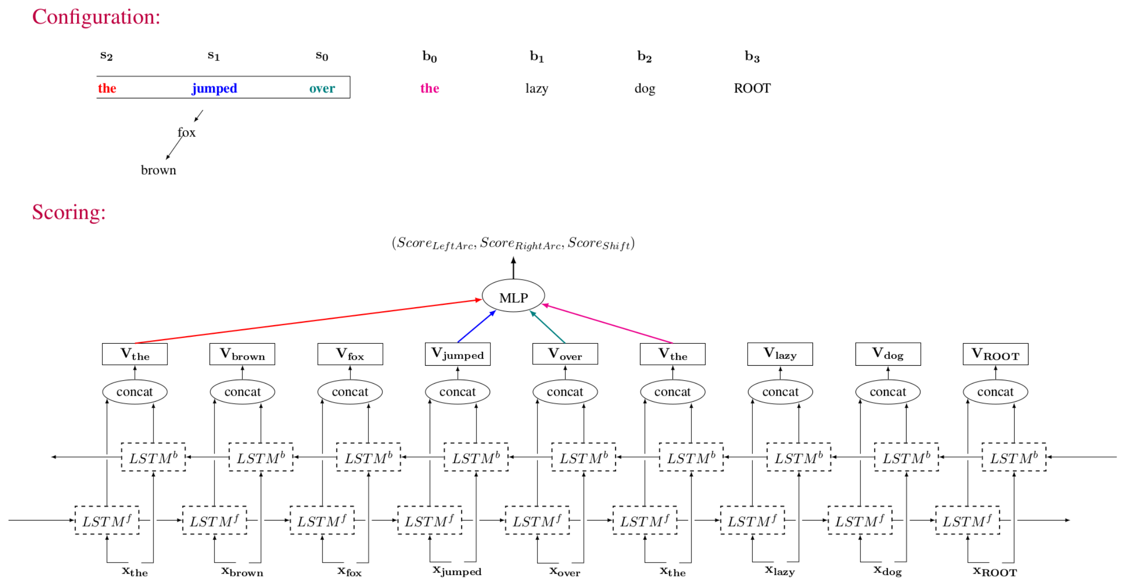
- Chen and Manning with combined features

System	UAS	LAS
L	89.36	88.33
NN	91.15	90.04
This	**91.80**	**90.68**
ZPar-local	89.94	88.92
Ma et al. (2014a)	90.38	–
Chen and Manning (2014)	91.17	89.99
Honnibal et al. (2013)	91.30	90.00
Ma et al. (2014a)*	91.32	–

Zhang, M., & Zhang, Y. (2015). Combining Discrete and Continuous Features for Deterministic Transition-based Dependency Parsing. EMNLP.

Dependency Parsing

- Chen and Manning with richer features



- 11 more LSTMs

Keperwasser, E., & Goldberg, Y. (2016). Simple and Accurate Dependency Parsing Using Bidirectional LSTM Feature Representations. TACL.

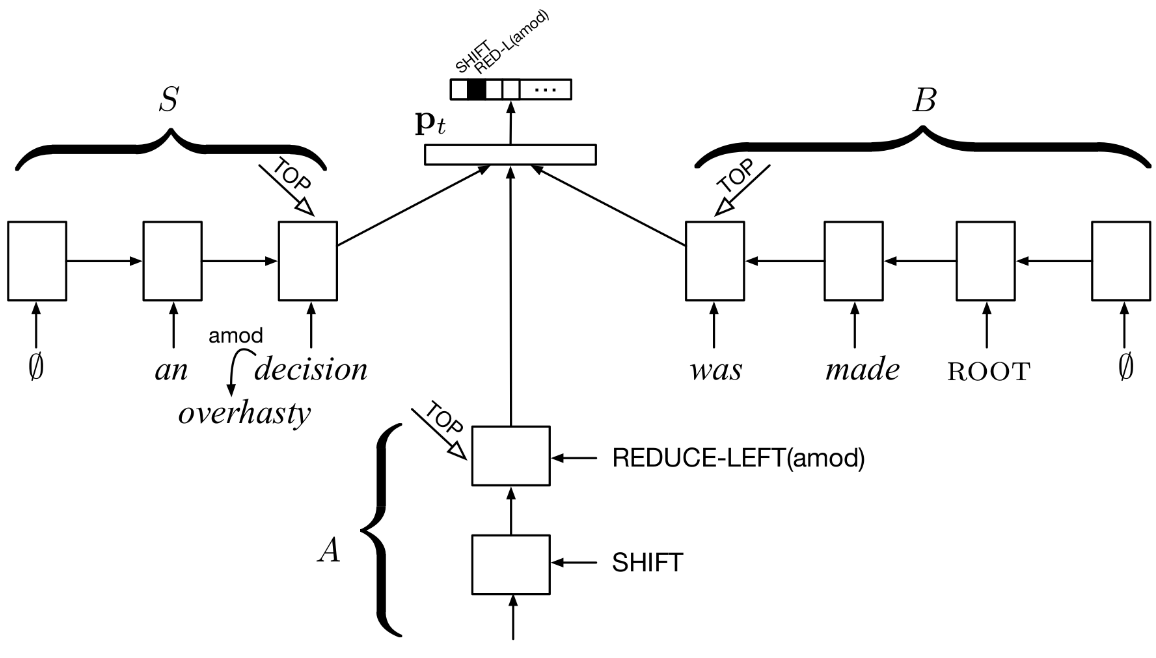
Dependency Parsing

System	Method	Representation	Emb	PTB-YM	PTB-SD		CTB	
				UAS	UAS	LAS	UAS	LAS
This work	graph, 1st order	2 BiLSTM vectors	–	–	93.1	91.0	**86.6**	**85.1**
This work	transition (greedy, dyn-oracle)	4 BiLSTM vectors	–	–	93.1	91.0	86.2	85.0
This work	transition (greedy, dyn-oracle)	11 BiLSTM vectors	–	–	**93.2**	**91.2**	86.5	84.9
ZhangNivre11	transition (beam)	large feature set (sparse)	–	92.9	–	–	86.0	84.4
Martins13 (TurboParser)	graph, 3rd order+	large feature set (sparse)	–	92.8	93.1	–	–	–
Pei15	graph, 2nd order	large feature set (dense)	–	93.0	–	–	–	–
Dyer15	transition (greedy)	Stack-LSTM + composition	–	–	92.4	90.0	85.7	84.1
Ballesteros16	transition (greedy, dyn-oracle)	Stack-LSTM + composition	–	–	92.7	90.6	86.1	84.5
This work	graph, 1st order	2 BiLSTM vectors	YES	–	93.0	90.9	86.5	84.9
This work	transition (greedy, dyn-oracle)	4 BiLSTM vectors	YES	–	93.6	91.5	87.4	85.9
This work	transition (greedy, dyn-oracle)	11 BiLSTM vectors	YES	–	93.9	91.9	**87.6**	86.1
Weiss15	transition (greedy)	large feature set (dense)	YES	–	93.2	91.2	–	–
Weiss15	transition (beam)	large feature set (dense)	YES	–	**94.0**	**92.0**	–	–
Pei15	graph, 2nd order	large feature set (dense)	YES	93.3	–	–	–	–
Dyer15	transition (greedy)	Stack-LSTM + composition	YES	–	93.1	90.9	87.1	85.5
Ballesteros16	transition (greedy, dyn-oracle)	Stack-LSTM + composition	YES	–	93.6	91.4	**87.6**	**86.2**
LeZuidema14	reranking /blend	inside-outside recursive net	YES	93.1	93.8	91.5	–	–
Zhu15	reranking /blend	recursive conv-net	YES	93.8	–	–	85.7	–

Keperwasser, E., & Goldberg, Y. (2016). Simple and Accurate Dependency Parsing Using Bidirectional LSTM Feature Representations. TACL.

Dependency Parsing

- Chen and Manning with less features



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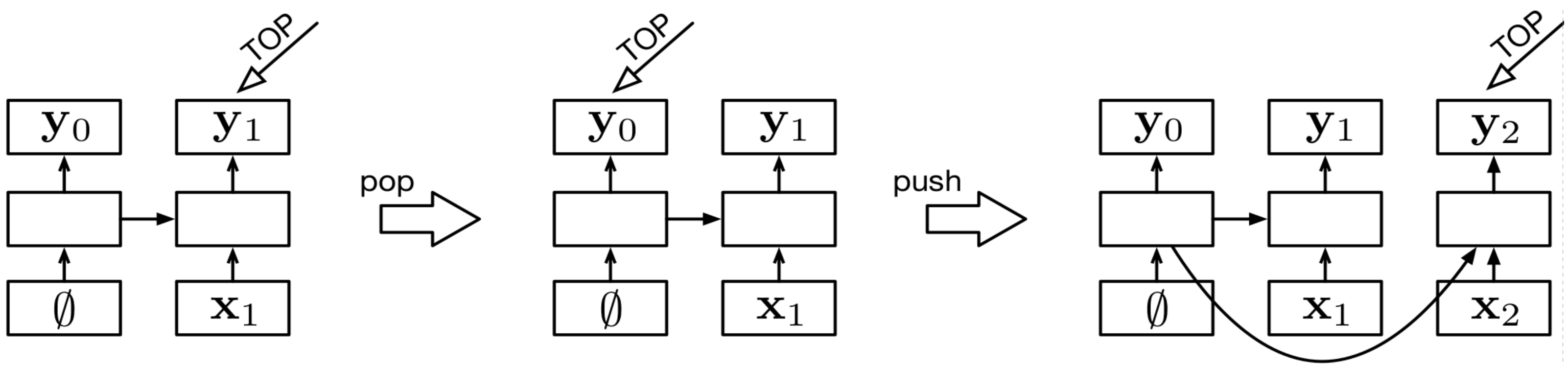
Dependency Parsing



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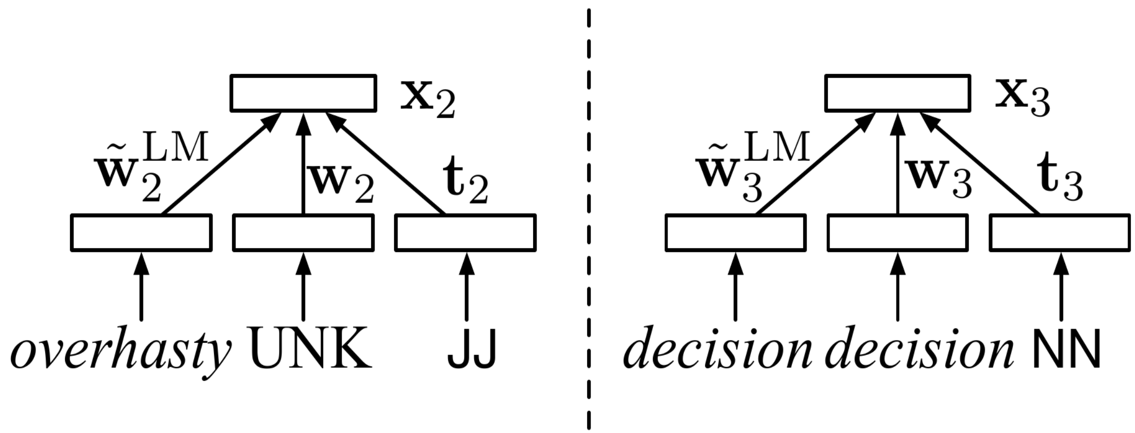
Dependency Parsing



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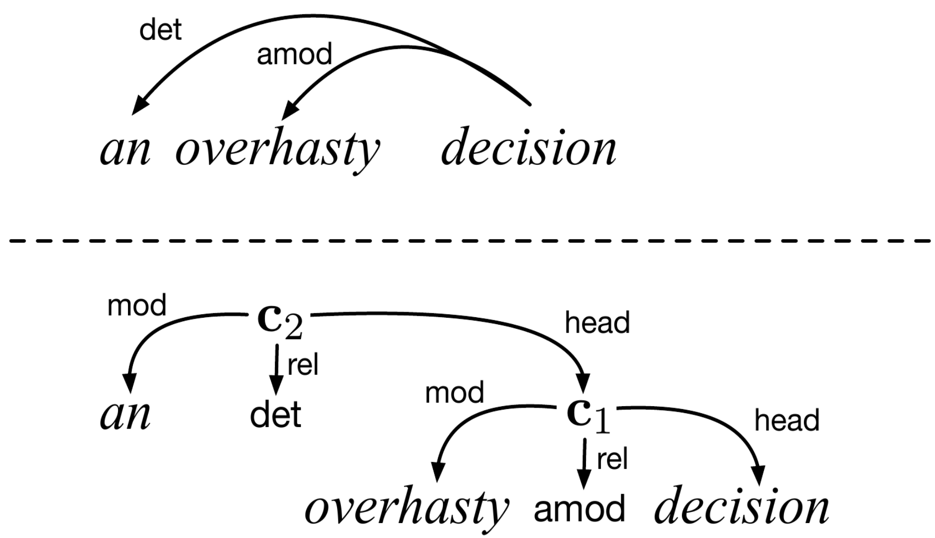


Dyer, C., Ballesteros, M., Ling, W., Matthews, A., & Smith, N. A. (2015). Transition-Based Dependency Parsing with Stack Long Short-Term Memory. ACL.

Dependency Parsing

	Development		Test	
	UAS	LAS	UAS	LAS
S-LSTM	**93.2**	**90.9**	**93.1**	**90.9**
−POS	93.1	90.4	92.7	90.3
−pretraining	92.7	90.4	92.4	90.0
−composition	92.7	89.9	92.2	89.6
S-RNN	92.8	90.4	92.3	90.1
C&M (2014)	92.2	89.7	91.8	89.6

English parsing results (SD)

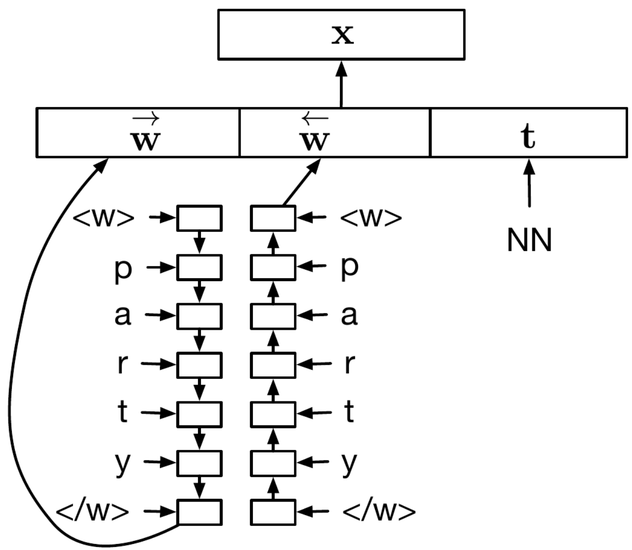
	Development		Test	
	UAS	LAS	UAS	LAS
S-LSTM	**87.2**	**85.9**	**87.2**	**85.7**
−POS	82.8	79.8	82.2	79.1
−pretraining	86.3	84.7	85.7	84.1
−composition	85.8	84.0	85.3	83.6
S-RNN	86.3	84.7	86.1	84.6
C&M (2014)	84.0	82.4	83.9	82.4

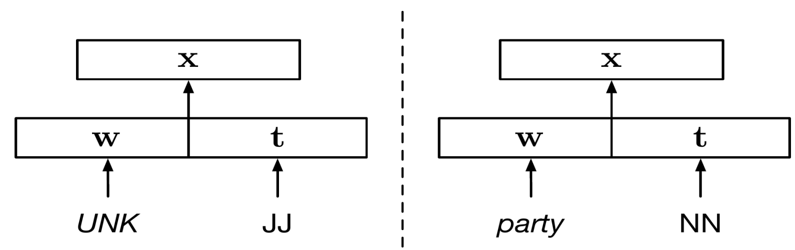
Chinese parsing results (CTB5)

Dyer, C., Ballesteros, M., Ling, W., Matthews, A., & Smith, N. A. (2015). Transition-Based Dependency Parsing with Stack Long Short-Term Memory. ACL.

Dependency Parsing

- Dyer et al. with character based word vector





Ballesteros, M., Dyer, C., & Smith, N. A. (2015). Improved Transition-Based Parsing by Modeling Characters instead of Words with LSTMs. EMNLP.

Dependency Parsing

UAS

Language	Words	Chars	Words + POS	Chars + POS
Arabic	86.14	**87.20**	**87.44**	87.07
Basque	78.42	**84.97**	83.49	**85.58**
French	84.84	**86.21**	**87.00**	86.33
German	88.14	**90.94**	91.16	**91.23**
Hebrew	79.73	**79.92**	**81.99**	80.76
Hungarian	72.38	**80.16**	78.47	**80.85**
Korean	78.98	**88.98**	87.36	**89.14**
Polish	73.29	**85.69**	**89.32**	88.54
Swedish	73.44	**75.03**	**80.02**	78.85
Turkish	71.10	**74.91**	77.13	**77.96**
Chinese	79.43	**80.36**	**85.98**	85.81
English	91.64	**91.98**	**92.94**	92.49
Average	79.79	**83.86**	85.19	**85.38**

LAS

Language	Words	Chars	Words + POS	Chars + POS
Arabic	82.73	**84.34**	**84.81**	84.36
Basque	67.08	**78.22**	74.31	**79.52**
French	80.32	**81.70**	**82.71**	81.51
German	85.36	**88.68**	**89.04**	88.83
Hebrew	69.42	**70.58**	**74.11**	72.18
Hungarian	62.14	**75.61**	69.50	**76.16**
Korean	67.48	**86.80**	83.80	**86.88**
Polish	65.13	**78.23**	**81.84**	80.97
Swedish	64.77	**66.74**	**72.09**	69.88
Turkish	53.98	**62.91**	62.30	**62.87**
Chinese	75.64	**77.06**	**84.36**	84.10
English	88.60	**89.58**	**90.63**	90.08
Average	71.89	**78.37**	79.13	**79.78**

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Dependency Parsing

UAS

Language	Words	Chars	Words + POS	Chars + POS
Arabic	85.21	**86.08**	86.05	**86.07**
Basque	77.06	**85.19**	82.92	**85.22**
French	83.74	**85.34**	**86.15**	85.78
German	82.75	**86.80**	**87.33**	87.26
Hebrew	77.62	**79.93**	**80.68**	80.17
Hungarian	72.78	**80.35**	78.64	**80.92**
Korean	78.70	**88.39**	86.85	**88.30**
Polish	72.01	**83.44**	**87.06**	85.97
Swedish	76.39	**79.18**	**83.43**	83.24
Turkish	71.70	**76.32**	75.32	**76.34**
Chinese	79.01	**79.94**	**85.96**	85.30
English	91.16	**91.47**	**92.57**	91.63
Average	79.01	**85.36**	84.41	**84.68**

LAS

Language	Words	Chars	Words + POS	Chars + POS
Arabic	82.05	**83.41**	**83.46**	83.40
Basque	66.61	**79.09**	73.56	**78.61**
French	79.22	**80.92**	**82.03**	81.08
German	79.15	**84.04**	**84.62**	84.49
Hebrew	68.71	**71.26**	**72.70**	72.26
Hungarian	61.93	**75.19**	69.31	**76.34**
Korean	67.50	**86.27**	83.37	**86.21**
Polish	63.96	**76.84**	**79.83**	78.24
Swedish	67.69	**71.19**	**76.40**	74.47
Turkish	54.55	**64.34**	61.22	**62.28**
Chinese	74.79	**76.29**	**84.40**	83.72
English	88.42	**88.94**	**90.31**	89.44
Average	71.22	**78.15**	78.43	**79.21**

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Dependency Parsing

	This Work			Best Greedy Result			Best Published Result		
Language	**UAS**	**LAS**	**System**	**UAS**	**LAS**	**System**	**UAS**	**LAS**	**System**
Arabic	86.08	83.41	**Chars**	84.57	81.90	B'13	88.32	86.21	B+'13
Basque	85.22	78.61	**Chars + POS**	84.33	78.58	B'13	89.96	85.70	B+'14
French	86.15	82.03	**Words + POS**	83.35	77.98	B'13	89.02	85.66	B+'14
German	87.33	84.62	**Words + POS**	85.38	82.75	B'13	91.64	89.65	B+'13
Hebrew	80.68	72.70	**Words + POS**	79.89	73.01	B'13	87.41	81.65	B+'14
Hungarian	80.92	76.34	**Chars + POS**	83.71	79.63	B'13	89.81	86.13	B+'13
Korean	88.39	86.27	**Chars**	85.72	82.06	B'13	89.10	87.27	B+'14
Polish	87.06	79.83	**Words + POS**	85.80	79.89	B'13	91.75	87.07	B+'13
Swedish	83.43	76.40	**Words + POS**	83.20	75.82	B'13	88.48	82.75	B+'14
Turkish	76.32	64.34	**Chars**	75.82	65.68	N+'06a	77.55	n/a	K+'10
Chinese	85.96	84.40	**Words + POS**	87.20	85.70	D+'15	87.20	85.70	D+'15
English	92.57	90.31	**Words + POS**	93.10	90.90	D+'15	94.08	92.19	W+'15

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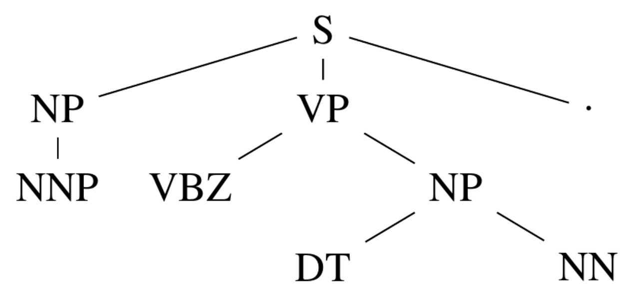
Part 3.4: Sequence to Sequence with Greedy Search

Constituent Parsing

- Sequence to sequence

John has a dog . $\rightarrow$



John has a dog . $\rightarrow$ $(S\ (NP\ NNP\ )_{NP}\ (VP\ VBZ\ (NP\ DT\ NN\ )_{NP}\ )_{VP}\ .\ )_{S}$

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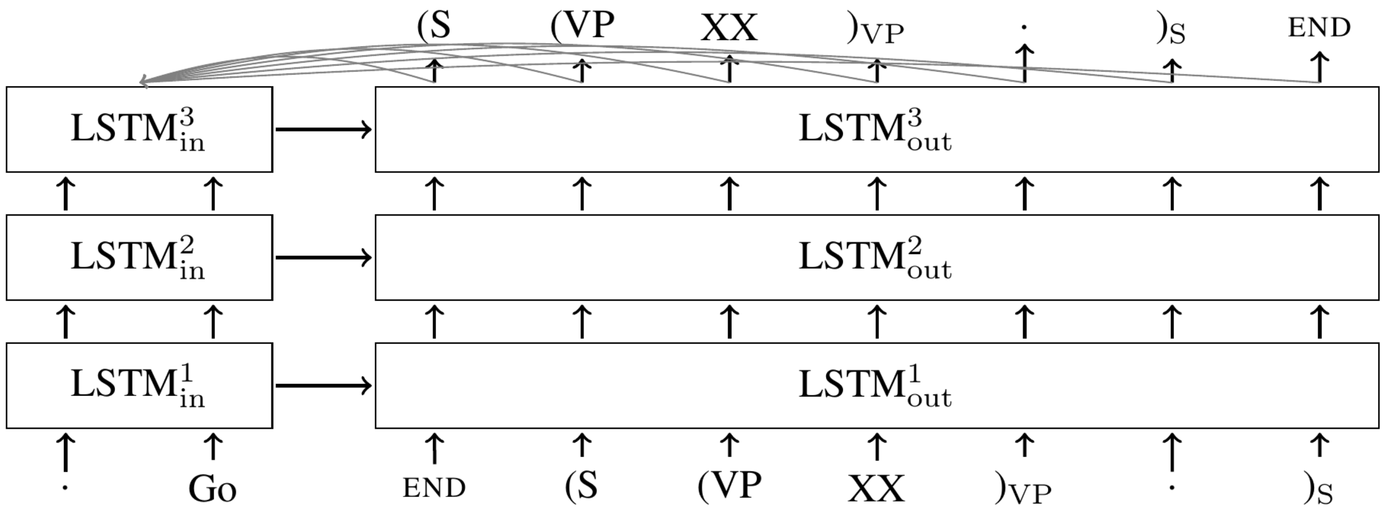
Constituent Parsing



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Constituent Parsing

Parser	**Training Set**	**WSJ 22**	**WSJ 23**
baseline LSTM+D	WSJ only	< 70	< 70
LSTM+A+D	WSJ only	88.7	88.3
LSTM+A+D ensemble	WSJ only	90.7	90.5
baseline LSTM	BerkeleyParser corpus	91.0	90.5
LSTM+A	high-confidence corpus	**92.8**	**92.1**
Petrov et al. (2006) [12]	WSJ only	91.1	90.4
Zhu et al. (2013) [13]	WSJ only	N/A	90.4
Petrov et al. (2010) ensemble [14]	WSJ only	92.5	91.8
Zhu et al. (2013) [13]	semi-supervised	N/A	91.3
Huang & Harper (2009) [15]	semi-supervised	N/A	91.3
McClosky et al. (2006) [16]	semi-supervised	92.4	**92.1**

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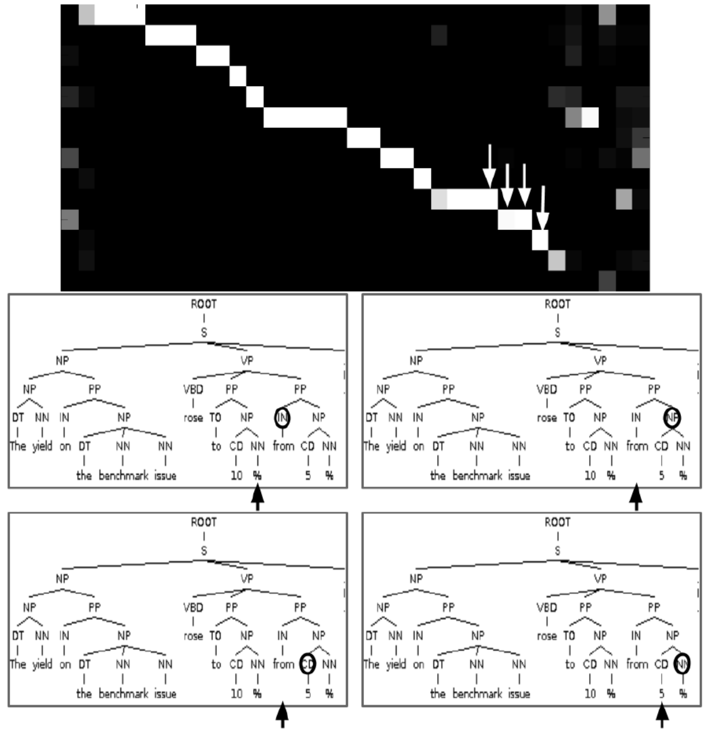
Constituent Parsing



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