Part 5: Neural Transition-based Methods

Part 5.1: Greedy Parsing

•Neural MaltParser



Transition	Stack	Buffer	A
	[ROOT]	[He has good control .]	Ø
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]	[]	$A \cup \text{root}(\text{ROOT},\text{has})$

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

•ZPar features

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)

 $s_{2}.t \circ s_{1}.t \circ b_{1}.t; s_{2}.t \circ s_{1}.t \circ lc_{1}(s_{1}).t; \\s_{2}.t \circ s_{1}.t \circ rc_{1}(s_{1}).t; s_{2}.t \circ s_{1}.t \circ lc_{1}(s_{2}).t; \\s_{2}.t \circ s_{1}.t \circ rc_{1}(s_{2}).t; s_{2}.t \circ s_{1}.w \circ rc_{1}(s_{2}).t; \\s_{2}.t \circ s_{1}.w \circ lc_{1}(s_{1}).t; s_{2}.t \circ s_{1}.w \circ b_{1}.t$

Yue Zhang and Joakim Nivre. *Transition-Based Dependency Parsing with Rich Non-Local Features*. In proceedings of ACL 2011, short papers. Portland, USA. June.



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

Results

Doroor	De	ev	Te	st	Speed
Faisei	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

Dorcor	De	ev	Te	st	Speed
Faiser	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

CTB (SD)

PTB (SD)

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

• Chen and Manning with richer features



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

Results

System	Method	Representation	Emb	PTB-YM	PTB-SD		CI	ГВ
				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.

• Chen and Manning with less features









• Results

	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

	Development		Te	est
	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

PTB (SD)

CTB (CTB5)

•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 ¹⁴ Words with LSTMs. EMNLP.

• Results

		This	Nork 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

Ballesteros, M., Dyer, C., & Smith, N. A. (2015). Improved Transition-Based Parsing by Modeling Characters instead of JCNLP 2017 Tutorial Words with LSTMs. EMNLP.

Named Entity Recognition

Model CRF Layer 🖌 B-PER) ← E-PER S-LOC 0 **C**1 **c**3 \mathbf{c}_4 **c**₂ **Bi-LSTM** \mathbf{r}_1 \mathbf{r}_2 r₃ r₄ encoder 1 2 3 4 Word embeddings Mark visited Watney Mars

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, Chris Dyer, Neural Architectures for Named Entity Recognition, In Proceedings of NAACL 2016

Named Entity Recognition

- Model
 - Transitions

\mathbf{Out}_t	\mathbf{Stack}_t	Buffer _t	Action	Out_{t+1}	\mathbf{Stack}_{t+1}	\mathbf{Buffer}_{t+1}	Segments
0	S	$(\mathbf{u}, u), B$	SHIFT	0	$(\mathbf{u}, u), S$	B	
0	$(\mathbf{u}, u), \ldots, (\mathbf{v}, v), S$	B	REDUCE(y)	$g(\mathbf{u},\ldots,\mathbf{v},\mathbf{r}_y),O$	S	B	$(u \dots v, y)$
0	S	$(\mathbf{u}, u), B$	OUT	$g(\mathbf{u},\mathbf{r}_{arnothing}),O$	S	B	

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, Chris Dyer, Neural Architectures for Named Entity Recognition, In Proceedings of NAACL 2016

Named Entity Recognition

Results

• English NER results

Model	F ₁
Collobert et al. (2011)*	89.59
Lin and Wu (2009)	83.78
Lin and Wu (2009)*	90.90
Huang et al. (2015)*	90.10
Passos et al. (2014)	90.05
Passos et al. (2014)*	90.90
Luo et al. (2015)* + gaz	89.9
Luo et al. $(2015)^*$ + gaz + linking	91.2
Chiu and Nichols (2015)	90.69
Chiu and Nichols (2015)*	90.77
LSTM-CRF (no char)	90.20
LSTM-CRF	90.94
S-LSTM (no char)	87.96
S-LSTM	90.33

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, Chris Dyer, Neural Architectures for Named Entity Recognition, In Proceedings of NAACL 2016

Dependency and Constituent Parsing

• Decoder



1. Vanilla Decoder

2. Stack-queue Decoder

Jiangming Liu, Yue Zhang, Encoder-Decoder Shift-Reduce Syntactic Parsing. IWPT 2017: 105-114

Dependency and Constituent Parsing

Results

Model	UAS (%)
Dyer et al. (2015)	92.3
Vanilla decoder	88.5
SQ decoder + average pooling	91.9
SQ decoder + attention	92.4
SQ decoder + treeLSTM	92.4

Jiangming Liu, Yue Zhang, Encoder-Decoder Shift-Reduce Syntactic Parsing. IWPT 2017: 105-114

Dependency Parser



Vaswani, A., & Sagae, K. (2016). Efficient Structured Inference for Transition-Based Parsing with Neural Networks and Error States. NAACL.

Dependency Parser



Vaswani, A., & Sagae, K. (2016). Efficient Structured Inference for Transition-Based Parsing with Neural Networks and Error States. NAACL.

Dependency Parser

System	wsj23-S	wsj23-YM
ErrSt–25–rand	92.17	92.16
ErrSt-25-pre*	93.61	93.21
Chen & Manning*	91.8	_
Huang & Sagae	_	92.1
Zhang & Nivre	93.5	92.9
Weiss et al.*	93.99	_
Zhang & McDonald	93.71	93.57
Martins et al.	92.82	93.07
Koo et al. (dep2c)*	_	93.16

Vaswani, A., & Sagae, K. (2016). Efficient Structured Inference for Transition-Based Parsing with Neural Networks and Error States. NAACL.

Part 5.2: Dependency Parsing with Beam Search

•Zhang & Nivre (2011)

$$y = \arg \max score(y')$$
$$y' \in \operatorname{GEN}(x)$$

$$score(y) = \sum_{a \in y} \theta \cdot \Phi(a)$$

•Chen and Manning (2014)

$$h = (W_1 x + b_1)^3$$

$$p = softmax(o)$$

 $o = W_2 h$

•What does not work

$$s(y) = \sum_{a \in y} \log p_a$$

$$L(\theta) = max(0, \delta - s(y_g) + s(y_p)) + \frac{\lambda}{2} \parallel \theta \parallel^2$$

•Sentence-level log likelihood

$$p(y_i \mid x, \theta) = \frac{e^{f(x, \theta)_i}}{\sum_{y_j \in \text{GEN}(x)} e^{f(x, \theta)_j}}$$

$$f(x, \theta)_i = \sum_{a_k \in y_i} o(x, y_i, k, a_k)$$

Contrastive Estimation

$$L(\theta) = -\sum_{(x_i, y_i) \in (X, Y)} \log p(y_i \mid x_i, \theta)$$
$$= -\sum_{(x_i, y_i) \in (X, Y)} \log \frac{e^{f(x_i, \theta)_i}}{Z(x_i, \theta)}$$
$$= \sum_{(x_i, y_i) \in (X, Y)} \log Z(x_i, \theta) - f(x_i, \theta)_i$$

$$Z(x,\theta) = \sum_{y_j \in \text{GEN}(x)} e^{f(x, \theta)_j}$$

Contrastive Estimation

$$L'(\theta) = -\sum_{(x_i, y_i) \in (X, Y)} \log p'(y_i \mid x_i, \theta)$$
$$= -\sum_{(x_i, y_i) \in (X, Y)} \log \frac{e^{f(x_i, \theta)_i}}{Z'(x_i, \theta)}$$
$$= \sum_{(x_i, y_i) \in (X, Y)} \log Z'(x_i, \theta) - f(x_i, \theta)_i$$
$$Z'(x, \theta) = \sum_{y_j \in \text{BEAM}(x)} e^{f(x, \theta)_j}$$

•Results

Description	UAS				
Baseline	91.63				
	structured	greedy			
beam = 1	74.90	91.63			
beam = 4	84.64	91.92			
beam = 16	91.53	91.90			
beam = 64	93.12	91.84			
beam = 100	93.23	91.81			

•Results

Description	UAS
greedy neural parser	91.47
ranking model	89.08
beam contrastive learning	93.28

•Results

System	UAS	LAS	Speed	
baseline gre	91.47	90.43	0.001	
Huang and	Sagae (2010)	92.10		0.04
Zhang and I	Nivre (2011)	92.90	91.80	0.03
Choi and M	92.96	91.93	0.009	
Ma et al. (2	93.06			
Bohnet and	93.67	92.68	0.4	
Suzuki et al	93.79			
Koo et al. (2	2008)†	93.16		
Chen et al.	93.77			
beam size				
training	decoding			
100	100	93.28	92.35	0.07
100	64	93.20	92.27	0.04
100	16	92.40	91.95	0.01

Google's SyntaxNet

•Andor et al. follows this method

- •Offers theorem
- •More tasks
- •Better results

Training with Beam Search:



Update: maximize P(correct parse) relative to the set of alternatives

Globally Normalized SyntaxNet Architecture (Overview)

Andor, D., Alberti, Chris., Weiss, D., Severyn, A., Presta, A., Ganchev, K., Petrov, S., & Collins, M. (2016). Globally Normalized Transition-Based Neural Networks. ACL.

Google's SyntaxNet

•English Results

	WSJ		Union-News		Union-Web		Union-QTB	
Method	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS
Martins et al. (2013)*	92.89	90.55	93.10	91.13	88.23	85.04	94.21	91.54
Zhang and McDonald (2014)*	93.22	91.02	93.32	91.48	88.65	85.59	93.37	90.69
Weiss et al. (2015)	93.99	92.05	93.91	92.25	89.29	86.44	94.17	92.06
Alberti et al. (2015)	94.23	92.36	94.10	92.55	89.55	86.85	94.74	93.04
Our Local (B=1)	92.95	91.02	93.11	91.46	88.42	85.58	92.49	90.38
Our Local (B=32)	93.59	91.70	93.65	92.03	88.96	86.17	93.22	91.17
Our Global (B=32)	94.61	92.79	94.44	92.93	90.17	87.54	95.40	93.64
Parsey McParseface (B=8)	-	-	94.15	92.51	89.08	86.29	94.77	93.17

Andor, D., Alberti, Chris., Weiss, D., Severyn, A., Presta, A., Ganchev, K., Petrov, S., & Collins, M. (2016). Globally JCNLP 2017 Tutorial Normalized Transition-Based Neural Networks. ACL.

Google's SyntaxNet

•Results for other languages

	Catalan	Chinese	Czech	English	German	Japanese	Spanish
Method	UAS LAS	UAS LAS					
Best Shared Task Result	- 87.86	- 79.17	- 80.38	- 89.88	- 87.48	- 92.57	- 87.64
Ballesteros et al. (2015)	90.22 86.42	80.64 76.52	79.87 73.62	90.56 88.01	88.83 86.10	93.47 92.55	90.38 86.59
Zhang and McDonald (2014)	91.41 87.91	82.87 78.57	86.62 80.59	92.69 90.01	89.88 87.38	92.82 91.87	90.82 87.34
Lei et al. (2014)	91.33 87.22	81.67 76.71	88.76 81.77	92.75 90.00	90.81 87.81	94.04 91.84	91.16 87.38
Bohnet and Nivre (2012)	92.44 89.60	82.52 78.51	88.82 83.73	92.87 90.60	91.37 89.38	93.67 92.63	92.24 89.60
Alberti et al. (2015)	92.31 89.17	83.57 79.90	88.45 83.57	92.70 90.56	90.58 88.20	93.99 93.10	92.26 89.33
Our Local (B=1)	91.24 88.21	81.29 77.29	85.78 80.63	91.44 89.29	89.12 86.95	93.71 92.85	91.01 88.14
Our Local (B=16)	91.91 88.93	82.22 78.26	86.25 81.28	92.16 90.05	89.53 87.4	93.61 92.74	91.64 88.88
Our Global (B=16)	92.67 89.83	84.72 80.85	88.94 84.56	93.22 91.23	90.91 89.15	93.65 92.84	92.62 89.95

Andor, D., Alberti, Chris., Weiss, D., Severyn, A., Presta, A., Ganchev, K., Petrov, S., & Collins, M. (2016). Globally JCNLP 2017 Tutorial Normalized Transition-Based Neural Networks. ACL.
Changes of Performance

Test on PTB with Stanford Dependency



UAS LAS

Part 5.3: Other tasks with beam-search

step	action	$buffer(\cdots w_{-1}w_0)$	queue($c_0c_1\cdots$)
0	-	ϕ	中国…
1	SEP	中	国外
2	APP	中国	外 企
3	SEP	中国 外	企业
4	APP	中国 外企	业务
5	SEP	中国 外企 业	务发
6	APP	中国 外企 业务	发展
7	SEP	… 业务 发	展 迅 速
8	APP	… 业务 发展	迅 速
9	SEP	发展 迅	速
10	APP	发展 迅速	ϕ

Feature templates	Action
$c_{-1}c_{0}$	APP, SEP
$w_{-1}, w_{-1}w_{-2}, w_{-1}c_0, w_{-2}len(w_{-1})$	
$start(w_{-1})c_0, end(w_{-1})c_0$	
$start(w_{-1})end(w_{-1}), end(w_{-2})end(w_{-1})$	SEP
$w_{-2}len(w_{-1}), len(w_{-2})w_{-1}$	
w_{-1} , where $len(w_{-1}) = 1$	



Models	P	R	F	
word-based models	•			
discrete	95.29	95.26	95.28	
neural	95.34	94.69	95.01	
combined	96.11	95.79	95.95	
character-based models				
discrete	95.38	95.12	95.25	
neural	94.59	94.92	94.76	
combined	95.63	95.60	95.61	
other models				
Zhang et al. (2014)	N/A	N/A	95.71	
Wang et al. (2011)	95.83	95.75	95.79	
Zhang and Clark (2011)	95.46	94.78	95.13	

Main results on CTB60 test dataset

Models	PKU	MSR	
our word-based models			
discrete	95.1	97.3	
neural	95.1	97.0	
combined	95.7	97.7	
character-based models			
discrete	94.9	96.8	
neural	94.4	97.2	
combined	95.4	97.2	
other models			
Cai and Zhao (2016)	95.5	96.5	
Ma and Hinrichs (2015)	95.1	96.6	
Pei et al. (2014)	95.2	97.2	
Zhang et al. (2013a)	96.1	97.5	
Sun et al. (2012)	95.4	97.4	
Zhang and Clark (2011)	95.1	97.1	
Sun (2010)	95.2	96.9	
Sun et al. (2009)	95.2	97.3	

Main results on PKU and MSR test dataset



Zhang, M., Zhang, Y., & Fu, G. (2016). Transition-Based Neural Word Segmentation. ACL.



Zhang, M., Zhang, Y., & Fu, G. (2016). Transition-Based Neural Word Segmentation. ACL.

•Other Methods

•Cai and Zhao (2016) •Yang et al. (2017)

Cai, D., & Zhao, H. (2016). Neural Word Segmentation Learning for Chinese. ACL. Jie Yang, Yue Zhang, Fei Dong. *Neural Word Segmentation with Rich Pretraining* (ACL). Vancouver, Canada, July.

Model



•Update at max-violation

$$j^* = \operatorname*{arg\,min}_{j} \left\{ \rho_{\boldsymbol{\theta}}(y_0^j) - \max_{\boldsymbol{d} \in B_j} \rho_{\boldsymbol{\theta}}(\boldsymbol{d}) \right\}$$

Using expected loss from all violations

$$L(\boldsymbol{w}, \boldsymbol{y}; \boldsymbol{B}, \boldsymbol{\theta}) = \max\left\{0, 1 - \rho_{\boldsymbol{\theta}}(y_0^{j^*}) + \mathbb{E}_{\tilde{B}_{j^*}}[\rho_{\boldsymbol{\theta}}]\right\}$$

$$\tilde{B}_{j^*} = \left\{ \boldsymbol{d} \in B_{j^*} | \rho_{\boldsymbol{\theta}}(\boldsymbol{d}) > \rho_{\boldsymbol{\theta}}(y_0^{j^*}) \right\}$$
$$p_{\boldsymbol{\theta}}(\boldsymbol{d}) = \frac{\exp(\rho_{\boldsymbol{\theta}}(\boldsymbol{d}))}{\sum_{\boldsymbol{d}' \in \tilde{B}_{j^*}} \exp(\rho_{\boldsymbol{\theta}}(\boldsymbol{d}'))}$$
$$E_{\tilde{B}_{j^*}}[\rho_{\boldsymbol{\theta}}] = \sum_{\boldsymbol{d} \in \tilde{B}_{j^*}} p_{\boldsymbol{\theta}}(\boldsymbol{d})\rho_{\boldsymbol{\theta}}(\boldsymbol{d}).$$

•English Results

parser	test
Collins (Collins, 1997)	87.8
Berkeley (Petrov and Klein, 2007)	90.1
SSN (Henderson, 2004)	90.1
ZPar (Zhu et al., 2013)	90.4
CVG (Socher et al., 2013)	90.4
Charniak-R (Charniak and Johnson, 2005)	91.0
This work: TNCP	90.7

•Chinese Results

parser	test
ZPar (Zhu et al., 2013)	83.2
Berkeley (Petrov and Klein, 2007)	83.3
Joint (Wang and Xue, 2014)	84.9
This work: TNCP	84.3

• Binarization



Actions

– Shift



Actions

– Shift



Actions

– Shift



- Actions
 - Reduce-r-NP



- Actions
 - Reduce-r-NP



Actions

– Shift



Actions

– Shift



Actions

– Shift



- Actions
 - Reduce-r-NP



- Actions
 - Reduce-I-VP



Actions

– Shift



little boy red tomatoes

- Actions
 - Reduce-I-S



- Actions
 - Reduce-r-S



- Actions
 - Terminate



- Bottom-up guidance
 - Rich local features from readily constructed trees
 - Lack of the look-ahead guidance
 - Post-order traversal on the tree



 $(3 \rightarrow 4 \rightarrow 5 \rightarrow 2 \rightarrow 7 \rightarrow 9 \rightarrow 10 \rightarrow 8 \rightarrow 6 \rightarrow 11 \rightarrow 1)$

Model

 Parser Transitions (Top-down)
 Generator Transitions

• Model

• Parser Transitions (Top-down)

- NT(X) introduces an "open nonterminal" X onto the top of the stack.
- SHÌFŤ
- REDUCE

Stack _t	Buffer _t	Open NTs _t	Action	\mathbf{Stack}_{t+1}	\mathbf{Buffer}_{t+1}	Open NTs_{t+1}
S	B	n	NT(X)	$S \mid (X$	B	n+1
S	$x \mid B$	n	SHIFT	$S \mid x$	B	n
$S \mid (X \mid \tau_1 \mid \ldots \mid \tau_\ell)$	B	n	REDUCE	$S \mid (\mathbf{X} \tau_1 \ldots \tau_\ell)$	B	n-1

(a) Parser Transitions

Actions

- NT(S)



Actions

– NT(NP)



Actions

– Shift



Actions

– Shift


Actions

– Shift



• Actions

- Reduce



Actions ۲

- NT(VP)

boy



Actions ۲

– Shift

boy



Actions ۲

- NT(NP)

likes



Actions

– Shift

The

little

boy

likes



Actions

– Shift



Actions

- Reduce



Actions

- Reduce



Actions

– Shift



Actions

- Reduce



- Actions
 - Terminate



- Top-down guidance
 - Non-local information for local decision
 - Strong encoders over the input to predict a constituent hierarchy before its construction
 - Pre-order traversal on the tree



 $1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 8 \rightarrow 9 \rightarrow 10 \rightarrow 11$

Generative Model

$$p(\boldsymbol{x}, \boldsymbol{y}) = \prod_{t=1}^{|\boldsymbol{a}(\boldsymbol{x}, \boldsymbol{y})|} p(a_t \mid \boldsymbol{a}_{< t})$$
$$= \prod_{t=1}^{|\boldsymbol{a}(\boldsymbol{x}, \boldsymbol{y})|} \frac{\exp \mathbf{r}_{a_t}^\top \mathbf{u}_t + b_{a_t}}{\sum_{a' \in \mathcal{A}_G(T_t, S_t, n_t)} \exp \mathbf{r}_{a'}^\top \mathbf{u}_t + b_{a'}},$$

• Model

Generator Transitions

• GEN(x) operations which generate terminal symbol $x \in \Sigma$ and add it to the top of the stack and the out-put buffer

Stack _t	Terms _t	Open NTs _t	Action	\mathbf{Stack}_{t+1}	$Terms_{t+1}$	Open NTs_{t+1}
S	Т	n	NT(X)	$S \mid (X)$	T	n+1
S	T	n	$\operatorname{GEN}(x)$	$S \mid x$	$T \mid x$	n
$S \mid (X \mid \tau_1 \mid \ldots \mid \tau_\ell)$	T	n	REDUCE	$S \mid (\mathbf{X} \ au_1 \ \dots \ au_\ell)$	T	n-1

(b) Generator Transitions

Generative Model

 Distribution over stack (S_t), output buffer (T_t) and history of actions (a < t)



• English Results

	Model	type	$\mathbf{F_1}$
	Model1Vinyals et al. (2015)* – WSJ only Henderson (2004)Henderson (2004)Socher et al. (2013a) Zhu et al. (2013)Zhu et al. (2013)Petrov and Klein (2007) Bod (2003) Shindo et al. (2012) – single Shindo et al. (2012) – ensembleZhu et al. (2013)	D	88.3
	Henderson (2004)	D	89.4
D=discriminative	Socher et al. (2013a)	D	90.4
G=generative	Zhu et al. (2013)	D	90.4
S=Somi supervised	Petrov and Klein (2007)	G	90.1
S-Semi-supervised	Bod (2003)	G	90.7
	Shindo et al. (2012) – single	G	91.1
	Shindo et al. (2012) – ensemble	G	92.4
	Zhu et al. (2013)	S	91.3
	McClosky et al. (2006)	S	92.1
	Vinyals et al. (2015) – single	S	92.1
	Discriminative, $q(\boldsymbol{y} \mid \boldsymbol{x})$	D	89.8
	Generative, $\hat{p}(\boldsymbol{y} \mid \boldsymbol{x})$	G	92.4

• Chinese Results

	Model	type	$\mathbf{F_1}$
	Zhu et al. (2013)	D	82.6
	Wang et al. (2015)	D	83.2
D=discriminative,	Huang and Harper (2009)	D	84.2
G=generative,	Charniak (2000)	G	80.8
S=Semi-supervised	Bikel (2004)	G	80.6
	Petrov and Klein (2007)	G	83.3
	Zhu et al. (2013)	S	85.6
	Wang and Xue (2014)	S	86.3
	Wang et al. (2015)	S	86.6
	Discriminative, $q(\boldsymbol{y} \mid \boldsymbol{x})$	D	80.7
	Generative, $\hat{p}(\boldsymbol{y} \mid \boldsymbol{x})$	G	82.7

- Trade-off
 - Compromise between bottom-up constituent information and top-down lookahead information

- In-order traversal on the non-binary tree
 - Regard the left-most child as the left branch of the binary tree, and the rest children are traced from left to right.



$$(3 \rightarrow 2 \rightarrow 4 \rightarrow 5 \rightarrow 1 \rightarrow 7 \rightarrow 6 \rightarrow 9 \rightarrow 8 \rightarrow 10 \rightarrow 11)$$

• Actions

– Shift



Actions

- PJ(NP)



Actions

– Shift



Actions

– Shift



• Actions

- Reduce



Actions

– PJ(S)



Actions

– Shift



• Actions

- PJ(VP)



Actions

The

little

boy

likes

– Shift



• Actions

The

little

boy

likes

red

- PJ(NP)



• Actions

– Shift



• Actions

- Reduce



red tomatoes

• Actions

- Reduce



red tomatoes

• Actions

– Shift



red tomatoes

• Actions

- Reduce



- Actions
 - Terminate


Different Transition Systems



- Generalization
 - In-Order system can be generalized into variants by modifying k, the number of leftmost nodes traced before the parent node.
 - If k = 0, top-down system is a special case
 - If k = inf, bottom-up system is a special case

•Models



•Results

•English Constituent Results (on WSJ Section 23)

Model	F 1		
fully-supervision		reranking	
Socher et al. (2013)	90.4	Huang (2008)	91.7
Zhu et al. (2013)	90.4	Charniak and Johnson (2005)	91.5
Vinyals et al. (2015)	90.7	Choe and Charniak (2016)	92.6
Watanabe and Sumita (2015)	90.7	Dyer et al. (2016)	93.3
Shindo et al. (2012)	91.1	Kuncoro et al. (2017)	93.6
Durrett and Klein (2015)	91.1	Top-down parser	93.3
Dyer et al. (2016)	91.2	Bottom-up parser	93.3
Cross and Huang (2016)	91.3	In-order parser	93.6
Liu and Zhang (2017)	91.7	semi-supervised reranking	<u> </u>
Top-down parser	<u>91.2</u>	Choe and Charniak (2016)	93.8
Bottom-up parser	91.3	In-order parser	94.2
In-order parser	91.8	X	1

•Results

•English Dependency Results(on WSJ Section 23)

Model	UAS	LAS
Kiperwasser and Goldberg (2016) [†]	93.9	91.9
Cheng et al. (2016) †	94.1	91.5
Andor et al. (2016)	94.6	92.8
Dyer et al. (2016) -re	95.6	94.4
Dozat and Manning (2017) [†]	95.7	94.0
Kuncoro et al. (2017) -re	95.7	94.5
Choe and Charniak (2016) -sre	95.9	94.1
In-order parser	⁻ 94.5 ⁻	93.4
In-order parser -re	95.9	94.9
In-order parser -sre	96.2	95.2

•Results

•Chinese Constituent Results (on CTB Test set)

Parser	F_1
fully-supervision	
Zhu et al. (2013)	83.2
Wang et al. (2015)	83.2
Dyer et al. (2016)	84.6
Liu and Zhang (2017)	85.5
Top-down parser	84.6
Bottom-up parser	85.7
In-order parser	86.1
rerank	
Charniak and Johnson (2005)	82.3
Dyer et al. (2016)	86.9
Top-down parser	86.9
Bottom-up parser	87.5
In-order parser	88.0

•Results

•Chinese Dependency Results(on CTB Test set)

Model	UAS	LAS
Dyer et al. (2016)	85.5	84.0
Ballesteros et al. (2016)	87.7	86.2
Kiperwasser and Goldberg (2016)	87.6	86.1
Cheng et al. (2016) †	88.1	85.7
Dozat and Manning (2017) †	89.3	88.2
In-order parser	87.4	86.4
In-order parser -re	89.4	88.4





Span-Based Constituency Parsing

•Example



Cross, James, and Liang Huang. "Span-based constituency parsing with a structure-label system and provably optimal dynamic oracles." In *EMNLP* (2016).

Span-Based Constituency Parsing



Cross, James, and Liang Huang. "Span-based constituency parsing with a structure-label system and provably optimal dynamic oracles." In *EMNLP* (2016).

Span-Based Constituency Parsing

•Results

Closed Training & Single Model	LR	LP	F_1
Sagae and Lavie (2006)	88.1	87.8	87.9
Petrov and Klein (2007)	90.1	90.3	90.2
Carreras et al. (2008)	90.7	91.4	91.1
Shindo et al. (2012)			91.1
†Socher et al. (2013)			90.4
Zhu et al. (2013)	90.2	90.7	90.4
Mi and Huang (2015)	90.7	90.9	90.8
†Watanabe and Sumita (2015)			90.7
Thang et al. (2015) (A*)	90.9	91.2	91.1
†*Dyer et al. (2016) (discrim.)			89.8
†*Cross and Huang (2016)			90.0
†*static oracle	90.7	91.4	91.0
†*dynamic/exploration	90.5	92.1	91.3

Cross, James, and Liang Huang. "Span-based constituency parsing with a structure-label system and provably optimal dynamic oracles." In *EMNLP* (2016).



Kurita, Shuhei, Daisuke Kawahara, and Sadao Kurohashi. "Neural Joint Model for Transition-based Chinese Syntactic Analysis." In ACL Vol. 1. 2017.

•Models



Kurita, Shuhei, Daisuke Kawahara, and Sadao Kurohashi. "Neural Joint Model for Transition-based Chinese Syntactic Analysis." *In ACL* Vol. 1. 2017.

•Results

•Joint Segmentation and POS tagging

Model	Seg	POS
Hatori+12 SegTag	97.66	93.61
Hatori+12 SegTag(d)	98.18	94.08
Hatori+12 SegTagDep	97.73	94.46
Hatori+12 SegTagDep(d)	98.26	94.64
M. Zhang+14 EAG	97.76	94.36
Y. Zhang+15	98.04	94.47
SegTag(g)	98.41	94.84
SegTag	98.60	94.76

Kurita, Shuhei, Daisuke Kawahara, and Sadao Kurohashi. "Neural Joint Model for Transition-based Chinese Syntactic Analysis." *In ACL* Vol. 1. 2017.

•Results

•Joint Segmentation, POS tagging and Dependency Parsing

Model	Seg	POS	Dep
Hatori+12	97.75	94.33	81.56
M. Zhang+14 EAG	97.76	94.36	81.70
SegTagDep(g)	98.24	94.49	80.15
SegTagDep	98.37	94.83	81.42

Kurita, Shuhei, Daisuke Kawahara, and Sadao Kurohashi. "Neural Joint Model for Transition-based Chinese Syntactic Analysis." *In ACL* Vol. 1. 2017.

Dependency Parsing(with feature set)

Positional Features

-	Features	Arc-standard	Arc-hybrid	Arc-eager
	$\{ \vec{s}_{2}, \vec{s}_{1}, \vec{s}_{0}, \vec{b}_{0} \}$	$93.95_{\pm 0.12}$	$94.08_{\pm 0.13}$	$93.92_{\pm 0.04}$
	$\{\stackrel{\rightarrow}{s}_1, \stackrel{\rightarrow}{s}_0, \stackrel{\rightarrow}{b}_0\}$	$94.13_{\pm 0.06}$	94.08 ± 0.05	$93.91_{\pm 0.07}$
	$\{\stackrel{\rightarrow}{s}_{0}, \stackrel{\rightarrow}{b}_{0}\}$	$54.47_{\pm 0.36}$	$94.03_{\pm 0.12}$	93.92 ± 0.07
	$\{\vec{b}_0\}$	$47.11_{\pm 0.44}$	$52.39_{\pm 0.23}$	79.15 ± 0.06
	Min positions	Arc-standard	Arc-hybrid	Arc-eager
-	K&G 2016a	-	4	-
	C&H 2016a	3	-	-
	our work	3	2	2

Shi, Tianze, Liang Huang, and Lillian Lee. "Fast (er) Exact Decoding and Global Training for Transition-Based Dependency Parsing via a Minimal Feature Set." In EMNLP (2017).

Dependency Parsing(with feature set)



Shi, Tianze, Liang Huang, and Lillian Lee. "Fast (er) Exact Decoding and Global Training for Transition-Based Dependency Parsing via a Minimal Feature Set." In EMNLP (2017).

Dependency Parsing with exploration

•Parsing Model

•(1)
$$p(z_t \mid \mathbf{p}_t) = \frac{\exp\left(\mathbf{g}_{z_t}^\top \mathbf{p}_t + q_{z_t}\right)}{\sum_{z' \in \mathcal{A}(S,B)} \exp\left(\mathbf{g}_{z'}^\top \mathbf{p}_t + q_{z'}\right)}$$

•(2)
$$p(\boldsymbol{z} \mid \boldsymbol{w}) = \prod_{t=1}^{|\boldsymbol{z}|} p(z_t \mid \mathbf{p}_t)$$

Miguel Ballesteros, Yoav Goldberg, Chris Dyer, Noah A. Smith. "Training with exploration improves a greedy stack-LSTM parser." *In EMNLP*(2016).

Dependency Parsing with exploration

•Experiments

•Baseline: Dyer et al.(2015)

•Dynamic Oracle: for error states, estimate the best tree from the state, using it for oracle

•Sample negative cases

Chris Dyer, Miguel Ballesteros, Wang Ling, Austin Matthews, Noah A. Smith, Transition-Based Dependency Parsing with Stack Long Short-Term Memory, In Proceedings of the 53rd ACL and the 7th IIJCNLP(2015) Miguel Ballesteros, Yoav Goldberg, Chris Dyer, Noah A. Smith. "Training with exploration improves a greedy stack-LSTM parser." *In EMNLP*(2016).

Dependency Parsing with exploration

•Results

	English		Chi	nese
Method	UAS	LAS	UAS	LAS
Arc-standard (Dyer et al.)	92.40	90.04	85.48	83.94
Arc-hybrid (static)	92.08	89.80	85.66	84.03
Arc-hybrid (dynamic)	92.66	90.43	86.07	84.46
Arc-hybrid (dyn., $\alpha = 0.75$)	92.73	90.60	86.13	84.53
+ pre-training:				
Arc-standard (Dyer et al.)	93.04	90.87	86.85	85.36
Arc-hybrid (static)	92.78	90.67	86.94	85.46
Arc-hybrid (dynamic)	93.15	91.05	87.05	85.63
Arc-hybrid (dyn., $\alpha = 0.75$)	93.56	91.42	87.65	86.21

Miguel Ballesteros, Yoav Goldberg, Chris Dyer, Noah A. Smith. "Training with exploration improves a greedy stack-LSTM parser." *In EMNLP*(2016).

Part 5.4: Hybrid Models

Feature Integration

• Model



Meishan Zhang and Yue Zhang. *Combining Discrete and Continuous Features for Deterministic Transition-based Dependency Parsing*. In proceedings of EMNLP 2015, Lisboa, Portugal, September.

Feature Integration

Results



Meishan Zhang and Yue Zhang. *Combining Discrete and Continuous Features for Deterministic Transition-based Dependency Parsing*. In proceedings of EMNLP 2015, Lisboa, Portugal, September.

Feature Optimization

- Model
 - Combine discrete



Wang, Zhiguo, Haitao Mi, and Nianwen Xue. "Feature Optimization for Constituent Parsing via Neural Networks." ACL (1). 2015.

Feature Optimization

• Chinese Results

Туре	System	F_1
Ours	Supervised*‡ Pretrain-Finetune*‡	83.2 86.6
SI	Petrov and Klein (2007) Wang and Xue (2014)‡	83.3 83.6
SE	Zhu et al. (2013)‡ Wang and Xue (2014)‡	85.6 86.3
RE	Charniak and Johnson (2005) Wang and Zong (2011)	82.3 85.7

Wang, Zhiguo, Haitao Mi, and Nianwen Xue. "Feature Optimization for Constituent Parsing via Neural Networks." ACL (1). 2015.

Feature Optimization

• English Results

Туре	System	F_1
Ours	Supervised*‡ Pretrain-Finetune*‡	83.2 86.6
SI	Petrov and Klein (2007) Wang and Xue (2014)‡	83.3 83.6
SE	Zhu et al. (2013)‡ Wang and Xue (2014)‡	85.6 86.3
RE	Charniak and Johnson (2005) Wang and Zong (2011)	82.3 85.7

Wang, Zhiguo, Haitao Mi, and Nianwen Xue. "Feature Optimization for Constituent Parsing via Neural Networks." ACL (1). 2015.

Google Hybrid Model

Dependency parsing



Weiss, D., Alberti, C., Collins, M., & Petrov, S. (2015). Structured Training for Neural Network Transition-Based Parsing. ACL.

Google Hybrid Model

•Using Chen and Manning features for perceptron training

•Back-propagation pre-training

$$L(\Theta) = -\sum_{j} \log P(y_j \mid c_j, \Theta) + \lambda \sum_{i} ||\mathbf{W}_i||_2^2$$

Structured perceptron training

$$(h_1, h_2, P(y))$$

Weiss, D., Alberti, C., Collins, M., & Petrov, S. (2015). Structured Training for Neural Network Transition-Based Parsing. ACL.

Google Hybrid Model

•Results

Method	UAS	LAS	Beam
Graph-based			
Bohnet (2010)	92.88	90.71	n/a
Martins et al. (2013)	92.89	90.55	n/a
Zhang and McDonald (2014)	93.22	91.02	n/a
Transition-based			
*Zhang and Nivre (2011)	93.00	90.95	32
Bohnet and Kuhn (2012)	93.27	91.19	40
Chen and Manning (2014)	91.80	89.60	1
S-LSTM (Dyer et al., 2015)	93.20	90.90	1
Our Greedy	93.19	91.18	1
Our Perceptron	93.99	92.05	8
Tri-training			
*Zhang and Nivre (2011)	92.92	90.88	32
Our Greedy	93.46	91.49	1
Our Perceptron	94.26	92.41	8

Weiss, D., Alberti, C., Collins, M., & Petrov, S. (2015). Structured Training for Neural Network Transition-Based Parsing. ACL.

Model



Model



• Model



• Results

Parser	LR	LP	F_1	Ensemble			
Fully-supervised				Shindo et al. (2012)	N/A	N/A	92.4
Ratnaparkhi (1997)	86.3	87.5	86.9	Vinyals et al. (2015)*	N/A	N/A	90.5
Charniak (2000)	89.5	89.9	89.5	Rerank			
Collins (2003)	88.1	88.3	88.2	Charniak and Johnson (2005)	91.2	91.8	91.5
Sagae and Lavie (2005) [†]	86.1	86.0	86.0	Huang (2008)	92.2	91.2	91.7
Sagae and Lavie (2006)†	87.8	88.1	87.9	Semi supervised			
Petrov and Klein (2007)	90.1	90.2	90.1			~~~~	
Carreras et al. (2008)	90.7	91.4	91.1	McClosky et al. (2006)	92.1	92.5	92.3
Shindo et al. (2012)	N/A	N/A	91.1	Huang and Harper (2009)	91.1	91.6	91.3
Zhu et al. (2013)†	90.2	90.7	90.4	Huang et al. (2010)	91.4	91.8	91.6
Socher et al. (2013)*	N/A	N/A	90.4	Zhu et al. (2013)†	91.1	91.5	91.3
Vinyals et al. (2015)*	N/A	N/A	88.3	Durrett and Klein (2015)*	N/A	N/A	91.1
This work	91.3	92.1	91.7	Dyer et al. (2016)*†	N/A	N/A	92.4

Results

Parser	LR	LP	F_1
Fully-supervised			
Charniak (2000)	79.6	82.1	80.8
Bikel (2004)	79.3	82.0	80.6
Petrov and Klein (2007)	81.9	84.8	83.3
Zhu et al. (2013)†	82.1	84.3	83.2
Wang et al. (2015)‡	N/A	N/A	83.2
This work	85.2	85.9	85.5
Rerank			
Charniak and Johnson (2005)	80.8	83.8	82.3
Semi-supervised			
Zhu et al. (2013)†	84.4	86.8	85.6
Wand and Xue (2014)‡	N/A	N/A	86.3
Wang et al. (2015)‡	N/A	N/A	86.6
Dyer et al. (2016)*†	N/A	N/A	82.7

Results

Parser	#Sent/Second
Ratnaparkhi (1997)	Unk
Collins (2003)	3.5
Charniak (2000)	5.7
Sagae and Lavie (2005)	3.7
Sagae and Lavie (2006)	2.2
Petrov and Klein (2007)	6.2
Carreras et al. (2008)	Unk
Zhu et al. (2013)	89.5
This work	79.2