Span-Based Constituency Parsing with Provably Optimal Dynamic Oracles

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Dependency vs. Constituency





	search	UAS
Zhang & Nivre 2011	beam	92.9
Chen & Manning 2014	greedy	91.8
Zhou et al. (2015)	beam	93.3
Weiss et al. (2015)	beam	94.0
our work (ACL 2016)	greedy	93.4
Andor et al. (2016)	beam	94.4

	search	F1
Carreras et al. (2008)	cubic	91.1
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Vinyals et al. (2015) (WSJ)	beam	90.5

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This Work	greedy	91.3

Outline

- Span-Based Constituency Parsing
- Bi-Directional LSTM Span Features
- Provably Optimal Dynamic Oracle
- Experiments

Span-Based Parsing

- Previous work uses tree structures on stack
- We simplify to operate directly on sentence spans
- Simple-to-implement linear-time parsing





Structural	Shift	NP VP
(even step)	Combine	PRP MD VBP S
Label	Label-X	I do like VP VBG NP
(odd step)	No-Label	eating NN
		fish





















		S
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		fish
0 I/PRP do/MD	2 like/VBP 3 eating/VBG	4 $t = \{0NP_1\}$
	Combine	
0 I/PRP 1 do/MD	like/VBP	4 fish/NN 5 No-Label $t = \{0, NP_1\}$
	Shift	
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		\mathbf{S}
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Structural (even step)	Shift Combine	S NP VP PRP MD VBP S
Label (odd step)	Label- <i>X</i> No-Label	I do like VP VBG NP eating NN fish
0 I/PRP 1 do/MD	<pre>like/VBP</pre>	$4 fish/NN 5 t = {_0NP_1, _4NP_5}$

0 I/PRP

do/MD

1

like/VBP

eating/VBG fish/NN

5

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	3 Combine	4 <u>5</u>
0 I/PRP do/MD	like/VBP	fish/NN 5 $Label-S-VP$ $t = \{0NP_1, 4NP_5, 3S_5, 3VP_5\}$









Advantages of Span-Based System

- Linear-time and fixed number of steps (well-suited for beam search)
- Separates prediction of structure and labels
- Predicts rules of arbitrary arity with no binarization



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Q: How to decide which action to take? What features represent spans?

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Bi-LSTM Span Features



Sentence segment "eating fish" represented by two vectors:

- Forward component: $f_5 f_3$ (Wang and Chang, ACL 2016)
- Backward component: *b*₃ *b*₅

Span Features for Structure Action

to predict: *Combine*



4 bi-LSTM span features

(no tree-structure information used)

Span Features for Label Action



3 bi-LSTM span features

(no tree-structure information used)

Training Scheme: Local

- Every parser state is paired with a correct action
- Separate multilayer perceptron for each action type
- Baseline training scheme (static oracle) uses canonical order with short-stack preference



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Dynamic Oracle: Motivation

- Static oracle training assumes all correct actions
- What to do after decoding mistakes?



Dynamic Oracle: Motivation

- Static oracle training assumes all correct actions
- What to do after decoding mistakes?
- Need a way to decide best action in arbitrary state:
 Dynamic Oracle (everywhere-defined optimal policy)









smallest reachable gold bracket incl. *s*₀



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- Structure actions depend on next <u>reachable</u> bracket in gold tree
- All non-bracket label states —> No-Label
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Dynamic Oracle: Optimality/Complexity

- First provably optimal oracle for constituency parsing (optimal in both precision and recall)
- After each action next reachable may (or may not) be updated by tracing parent link in gold tree
- Also O(n) steps, thus amortized O(1) time
- Dependency parsing oracle (arc-std): worst case $O(n^3)$ per step



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Static Oracle	91.34	91.43	91.38

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Dynamic + Exploration	91.07	92.22	91.64

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Architecture



- 50-dim word and 20-dim tag embeddings
- No pre-training
- Each LSTM layer 200 units each direction
- 200 ReLU units for each of structure and label predictors

Results on Penn Treebank

Parser	Search	Recall	Prec.	F ₁
Carreras et al. (2008)	cubic	90.7	91.4	91.1
Shindo et al. (2012)	cubic			91.1
Thang et al. (2015)	~cubic			91.1
Watanabe et al. (2015)	beam			90.7
Static Oracle	greedy	90.7	91.4	91.0
Dynamic + Exploration	greedy	90.5	92.1	91.3

 State of the art despite: simple system with greedy actions and small embeddings trained from scratch

Parsing Morphologically Rich Languages



Results on French Treebank

- Morphological feature embeddings (10 dim. each)
- Additional input to recurrent network
- For French, we used SPMRL 2014 predicted features

Parser	Recall	Prec.	F1
Björkelund et al. (2014)			82.53
Static Oracle	83.50	82.87	83.18
Dynamic + Exploration	81.90	84.77	83.31

Summary

- Simple, easy-to-implement span-based parsing system
- No tree/label information in features (good candidate for dynamic programming)
- Linear time parsing with greedy decoding
- No pre-trained embeddings, small architecture, and minimal hyper-parameter tuning (trained on CPU)
- First optimal dynamic oracle for constituency parsing





