Data-Driven Deep Dependency Parsing

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Outline

The Covert Helps Parse the Overt

Semantic Dependency Parsing

Question

HPSG PET, Enju, ACE, ... CCG C&C, ... LFG XLE, ...

PCFG Collins, Charniark&Johnson, Berkeley, ... Data-driven MST, Mate, Malt, SyntaxNet, Stanford, ZPar, RNNG,

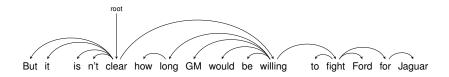
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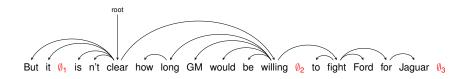
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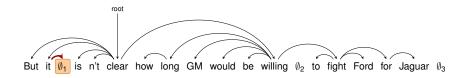
Can deep syntactic information help surface parsing?

PCFG Collins, Charniark&Johnson, Berkeley, ... Data-driven MST, Mate, Malt, SyntaxNet, Stanford, ZPar, RNNG,

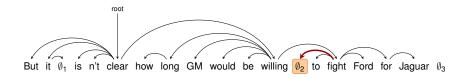




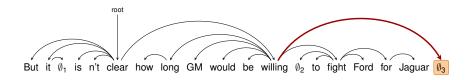
- \emptyset_1 : expletive construction.
- Ø₂: the subject of *fight* is somehow missing because it is *controled* by the subject of *willing*.
- Ø₃: *wh*-movement in which an adjunct of *willing*, i.e. *how long* is moved to the front of the clause.



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But it is n't clear how long GM would be willing to fight Ford for Jaguar

Task

- Predicting empty elements
- Predicting dependencies, including dependencies between normal and empty elements

But it \emptyset_1 is n't clear how long GM would be willing \emptyset_2 to fight Ford for Jaguar \emptyset_3

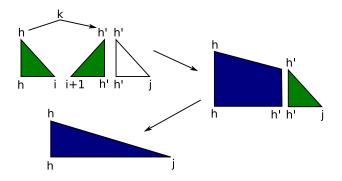
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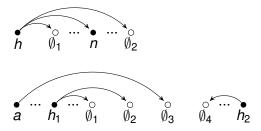
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Prototypes of structures with empty categories

Assumption

Empty nodes can be only dependents.

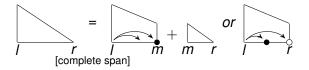




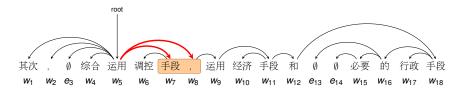
incomplete spans: a dependency and the region between the head and modifier.



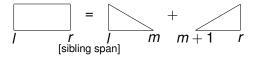
complete spans: a head-word and its descendents on one side



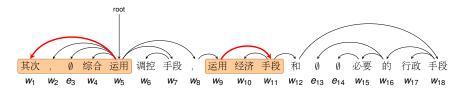
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sibling span: the region between successive modifiers of same head.



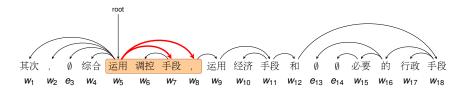
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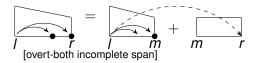
overt-outside incomplete span



incomplete spans: a dependency and the region between the head and modifier.



overt-both incomplete span



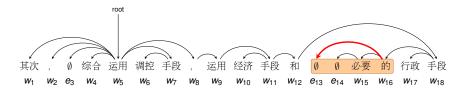
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covert-inside incomplete span



incomplete spans: a dependency and the region between the head and modifier.



covert-ouside incomplete span



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Evaluation

Disambiguation: Global linear model

$$f(\boldsymbol{y}) = \sum_{\boldsymbol{p} \in \boldsymbol{y}} \mathbf{w}_f^\top \phi_f(\boldsymbol{s}, \boldsymbol{p})$$

Results: unlabeled attachment score for all overt words

Model	English	Chinese
second-order	91.73	89.16
$+\emptyset$ (partial)	91.70 (-0.03)	89.20 (+0.04)
$+\emptyset$ (full)	91.72 (-0.01)	89.28 (+0.12)
third-order	92.23	90.00
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Analysis

Two types of errors

- Approximation error
- Estimation error

Information about empty categories is helpful for reducing the approximation error, but brings new challenge for estimation.

Structure Regularization with joint decoding

$$\begin{array}{ll} \max & \lambda f(\boldsymbol{y}) + (1 - \lambda) g(\boldsymbol{z}) \\ \text{s.t.} & \boldsymbol{y} \in \mathcal{Y}, \boldsymbol{z} \in \mathcal{Z} \\ & \boldsymbol{y}(i,j) = \boldsymbol{z}(i,j), \; \forall (i,j) \in \mathcal{I} \end{array}$$

Results

	Algo	English	Chinese
CM	1+3	91.94 (+0.21)	89.53 (+0.37)
	1+4	91.88 (+0.15)	89.44 (+0.28)
DD	1+3	91.96 (+0.23)	89.53 (+0.37)
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CM	2+5	92.60 (+0.37)	90.35 (+0.35)
DD	2+5	92.71 (+0.48)	90.38 (+0.38)

Two joint decoders

CM Chart merging DD Dual decomposition

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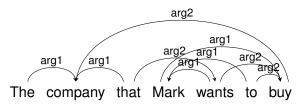
Grammar as an annotator.



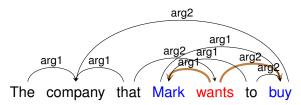
Zhang Yi

Robust Deep Linguistic Processing

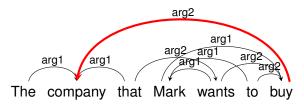
Large-scale Corpus-Driven PCFG Approxmation of an HPSG



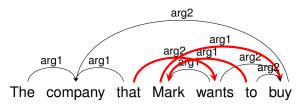
- Predicate-argument analysis, bi-lexical relations
- Long-distance dependencies
- Graph-structured representations, many crossing arcs
- Not a tree: single-headed (X), cycle-free (X)



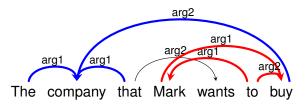
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Parsing approaches

Approaches

- Maximum Subgraph Parsing
- Transition-based Parsing
- Graph Merging

Maximum Subgraph

Input A directed graph G = (V, A)Output Subgraph $G' = (V, A' \subseteq A)$ with maximum total weight such that G' belongs to \mathcal{G}

$$G'(s) = \arg \max_{H \in \mathcal{G}(s,G)} \sum_{p \in H} \mathsf{SCOREPART}(s,p)$$

 Example When G is tree, Maximum Subgraph = Maximum Spanning Tree
 Complexity G and the order of SCOREPART determine the complexity of inference.

Complexity

\mathcal{G}	0	Algo	
Arbitrary	1	$O(n^2)$	
Arbitrary	2	NP-hard	ACL15
Acyclic	1	NP-hard	Kuhlmann & Jonsson
Noncrossing	1	$O(n^3)$	Kuhlmann & Jonsson
Noncrossing	2	$O(n^4)$	ACL17a
1-endpoint-crossing	1	$O(n^5)$	Ongoing work
1-endpoint-crossing	1	$O(n^5)$	ACL17b
pagenumber-2			
1-endpoint-crossing	1	$O(n^4)$	ACL17b
pagenumber-2, C-free			
1-endpoint-crossing	2	$O(n^4)$	EMNLP17
pagenumber-2, C-free			

Transition-based parsing



- Psycholinguistically motivated: Left-to-right, word-by-word
- Partially parsed results (parsing states) constrain parsing of subsequent words
- Usually, perform greedy search to get a *good* parse.

New transition systems

A naive idea

PARSE
$$(x = (w_1, ..., w_n))$$

1 for $j = 1..n$
2 for $k = j - 1..1$
3 Link (j, k)

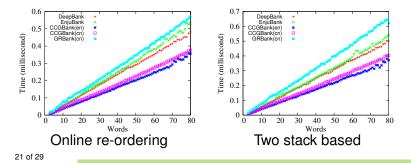
New transition systems

G	System
Arbitrary graphs	Two-stack-based
Arbitrary graphs	Non-incremental online reordering
Supersets of	Incremental K-permutation
noncrossing graphs	

Real running time

Naive spanning runs in time of $\Theta(n^2)$ 1 for j = 1..n2 for k = j - 1..13 Link(j, k)

New systems



A new framework

Challenge of graph parsing

- Complex graphs are difficult to construct for its complex structure.
- Simple graphs can be solved more easily, but the coverage is not satisfactory.

Graph merging

Constructing a complex structure via constructing simple partial structures.



A new framework

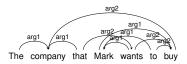
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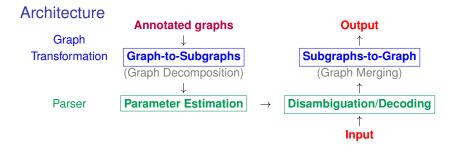
22 of 29

Constructing a complex structure via constructing simple partial structures.

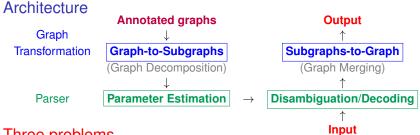




Workflow



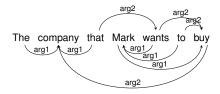
Workflow



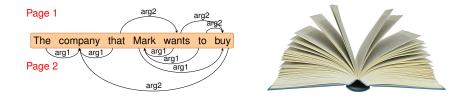
Three problems

- **Training** How to decompose a complex graph into noncrossing graphs?
- Parsing How to construct simple graphs?
- Parsing How to merge subgraphs into a coherent complex graph?

Book embedding



Book embedding



book embedding

A book embedding *B* of *G* satisfies the following conditions.

- 1. Every vertex of *G* is depicted as a point on the spine of *B*.
- 2. Every edge of *G* is depicted as a curve that lies within a single page of *B*.
- 3. Every page of *B* does not have any edge crossings.

Book embedding

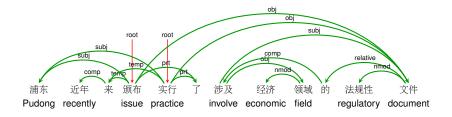


book embedding

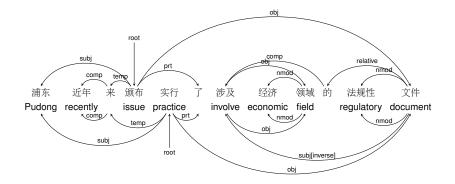
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Tree + Tree + ...



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Decomposing and combining subgraphs

Decomposition as Optimization

$$\begin{array}{ll} \max. & \sum_{k} \boldsymbol{s}_{k}(\boldsymbol{y}_{k}) \\ \text{s.t.} & \boldsymbol{y}_{k} \text{ belongs to } \mathcal{G}_{k} \\ & \sum_{k} \boldsymbol{y}_{k}(i,j) \geq \boldsymbol{y}(i,j), \forall i,j \end{array}$$

Combination as Optimization

$$\begin{array}{ll} \text{min.} & -f_A(\mathbf{g}_A) - f_B(\mathbf{g}_B) \\ \text{s.t.} & \mathbf{g}_A \text{ belongs to } \mathcal{G}_A, \mathbf{g}_B \text{ belongs to } \mathcal{G}_B \\ & A\mathbf{g}_A + B\mathbf{g}_B \leq 0 \end{array}$$

Usually, we can employ Lagrangian Relaxation for solutions.

Data-driven models can produce high-quality deep dependency analysis.

Another experience



Game Over

