Efficient Discontinuous Phrase-Structure Parsing via the Generalized Maximum Spanning Arborescence

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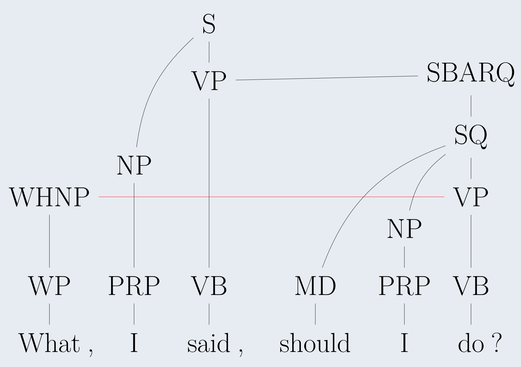
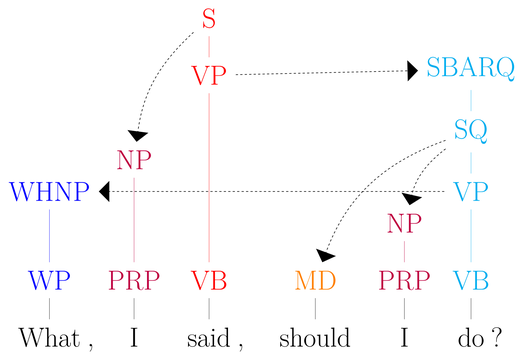
Discontinuous Phrase Structure



Discontinuous Lexicalized Spinal Grammar



Parsing: Joint Problem

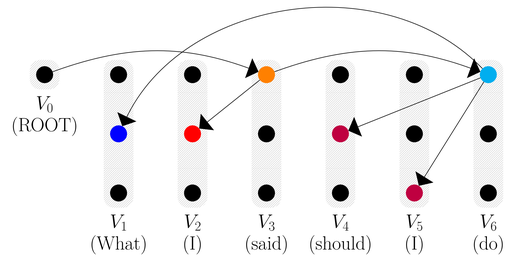
- Spine tagging
- Non-projective dependency parsing

Benefits

- Reduces to a known optimization problem
- Based on two well-studied tasks in NLP

Generalized Maximum Spanning Arborescence

Joint tagging and parsing		**Generalized Spanning Arborescence**
One spine per word	$\Leftrightarrow$	One node per cluster
Non-projective dependencies	$\Leftrightarrow$	Spanning arborescence over clusters



Integer Linear Programming Formulation

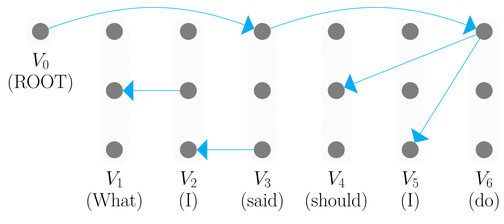
Variables:
- y_a: selection of arc $a \in A$
- x_v: selection of vertex $v \in V$

Optimization program:
- (1): structure with maximum weight under an arc-factored model
- (2)-(4): y is a spanning arborescence over clusters
- (5): vertex x_v included if it is adjacent to an arc in y
- (6): exactly one vertex per cluster

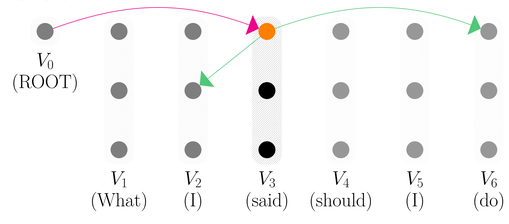
$$\max_{x,y} \quad \phi^\top y \tag{1}$$
$$\text{s.t.} \quad y(\delta^-(V_0)) = 0 \tag{2}$$
$$y(\delta^-(V_k)) = 1 \qquad \forall 1 \leq k \leq n \tag{3}$$
$$y(\delta^-(\bigcup_{V_k \in \pi'} V_k)) \geq 1 \qquad \forall \pi' \subseteq \pi \setminus \{V_0\} \tag{4}$$
$$x_v \geq y_a \qquad \forall v \in V, a \in \delta(v) \tag{5}$$
$$x_v(V_k) = 1 \qquad \forall 0 \leq k \leq n \tag{6}$$

Fast Decoding via Dual Decomposition and Subgradient Descent

Arc variables duplication: 3 copies (1 color per copy) / Subproblems must agree on selected arcs



Maximum Spanning Arborescence over clusters
⇒ No constraint on adjacent vertices



One subproblem per cluster
⇒ Exactly one adjacent vertex per cluster

Neural Parametrization

- $\mathbf{d}$: dependencies — (h, m): a single dependency
- $\mathbf{s}$: spine tags — s_m: a single tag
- $\mathbf{w}$: input sentence

$$P(\mathbf{d}, \mathbf{s}|\mathbf{w}) = P_\alpha(\mathbf{d}|\mathbf{w}) \times P_\nu(\mathbf{s}|\mathbf{d}, \mathbf{w})$$

Assuming stat. independence between variables:

$$\approx \prod_{(h,m)\in\mathbf{d}} P_\alpha(h|m, \mathbf{w}) \times P_\nu(s_m|m, \mathbf{d}, \mathbf{w})$$
$$\approx \prod_{(h,m)\in\mathbf{d}} P_\alpha(h|m, \mathbf{w}) \times P_\nu(s_m|m, h, \mathbf{w})$$

Neural network:
- Stacked bi-LSTMs
- + Biaffine classifiers
- + Softmax

Parameter estimation:
- Log-likelihood max.
- Dropout: 0.5 on inputs

Experimental Results

Discontinuous PTB (English)

	LF	Time
	Short sentences only	
This work	**89.85**	≈ 4
van Cranenburgh *et al.*	87.00	≈ 180
	Full test set	
This work	**89.17**	≈ 5.5

TIGER (German)

	LF	Time
This work	**81.63**	≈ 11
Coavoux *et al.*	81.60	≈ 2.5

Future work

- Max-margin training
- High-order scoring models:
  - Bi-gram
  - Sibling and grand-father
- Application to other joint tagging and parsing problems