The 61st Annual Meeting of the Association for Computational Linguistics Holographic CCG Parsing

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Motivation

> Explicit modeling of phrase structure

Recent CCG supertagging and parsing models demonstrate high performance yet rely on **non-explicit modeling** of dependencies between words through neural networks.

Explicit modeling of phrase structure with neural networks.

> Syntactic phrase-level representation

Compose syntactically rich phrase-level representations while maintaining training efficiency.

> Span-based Parsing

- Store word-level representations.
- Recursively compose phrase-level representations.
- Directly evaluates category assignment to phrases. 3.

Algorithm 1: Span-based CKY parsing 1 $\mathbf{v}_{0:1}, \mathbf{v}_{1:2}, \cdots, \mathbf{v}_{n-1:n} = Encode(w_1, w_2, \cdots, w_n);$ 2 for $i = 0, \dots, n - 1$ do $P_w(i, i+1) = SM(\mathbf{Q}_w \sigma(LN(\mathbf{U}_w \mathbf{v}_{i:i+1} + \mathbf{b}_w)) + \mathbf{c}_w);$ \triangleright Equation (11) for $C \in \{X | P_w(i, i+1)[X] > t_w = 0.1\}$ do $prob[i, i + 1, C] = \log P_w(i, i + 1)[C];$ $vector[i, i+1, C] = \mathbf{v}_{i:i+1};$ 7 for $\ell = 2, \cdots, n$ do for $i = 0, \cdots, n - \ell$ do $j = i + \ell;$ for $k = i + 1, \dots, j - 1$ do for $C_1 \in \{X | prob[i, k, X] > 0\}$ do $\mathbf{v}_{i:k} = vector[i, k, C_1];$ 12 for $C_2 \in \{X | prob[k, j, X] > 0\}$ do 13 $\mathbf{v}_{k:i} = vector[k, j, C_2];$ 14

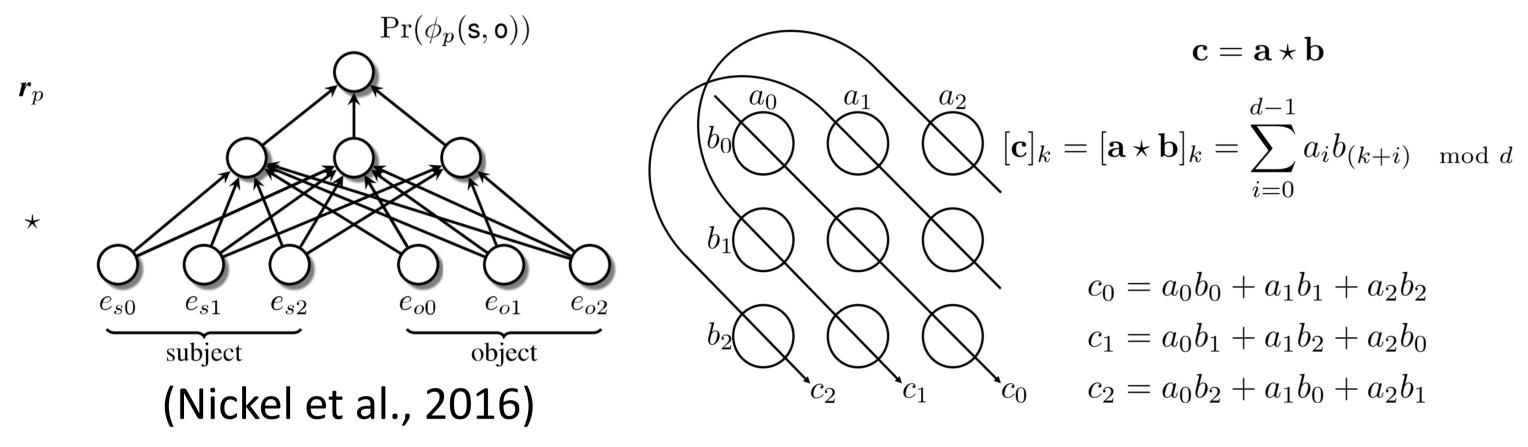


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Holographic CCG

> Holographic Embeddings (Nickel et al., 2016)

- Embedding knowledge graphs into vector space \bullet for statistical modeling
- Vector composition using **circular correlation** to capture dependencies between entities
- Similarity of knowledge graphs and phrase structures that need to capture dependencies between components



- **Holographic CCG (Hol-CCG)**
- Formulate CCG as a **recursive compositional operation** between

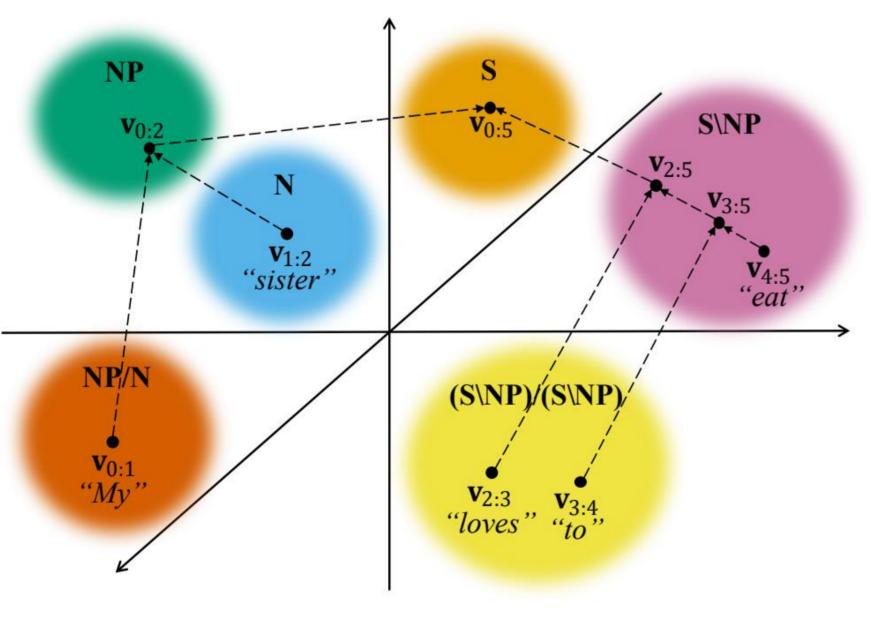
14	$\mathbf{v}_{k:j} = vecior[\kappa, j, \mathbf{C}_2],$	
15	for $C \in \{X C_1 C_2 \rightarrow X \in R\}$ do	
16	$\mathbf{v}_{i:j} = \mathbf{v}_{i:k} \star \mathbf{v}_{k:j} ;$	▷ Equations (4) and (5)
17	$P_s(i,j) = SM(\mathbf{Q}_s\sigma(LN(\mathbf{U}_s\mathbf{v}_{i:j} + \mathbf{b})))$	$(\mathbf{b}_s)) + \mathbf{c}_s); \qquad \triangleright Equation (13)$
18	if $P_s(i, j)[e] > t_s = 0.01$ then	
19	$P_p(i,j) = SM(\mathbf{Q}_p\sigma(LN(\mathbf{U}_p\mathbf{v}_{i:j}$	$(+ \mathbf{b}_p)) + \mathbf{c}_p); \triangleright$ Equation (12)
20	if $P_p(i, j)[C] > t_p = 0.01$ then	
21	$p = \log P_p(i,j)[C] + \log P_s(i,j)[C] + \log P_s(i,$	$j)[e]+prob[i,k,C_1]+prob[k,j,C_2];$
22	if $p > prob[i, j, C]$ then	
23	prob[i, j, C] = p;	
24	backpointer[i, j, C] = (k	$, C_1, C_2);$
25	$vector[i, j, C] = \mathbf{v}_{i:j};$	

Experiment

- Dataset: CCGbank (Hockenmaier et al., 2007)
- Calculate the model's prediction error by cross entropy
 - \succ Category assignment to words and phrases: \mathcal{L}_w , \mathcal{L}_p
 - \succ Existence of span: \mathcal{L}_{s}
- Compare models by changing the combination of back-propagating errors (\mathcal{L})
 - \succ Baseline: $\mathcal{L} = \mathcal{L}_{w}$
 - \succ Hol-CCG: $\mathcal{L}=\mathcal{L}_w + \mathcal{L}_p + \mathcal{L}_s$
- Supertagging by Baseline and Hol-CCG
- Parsing using C&C Parser (Clark and Curran, 2007) and Hol-CCG's

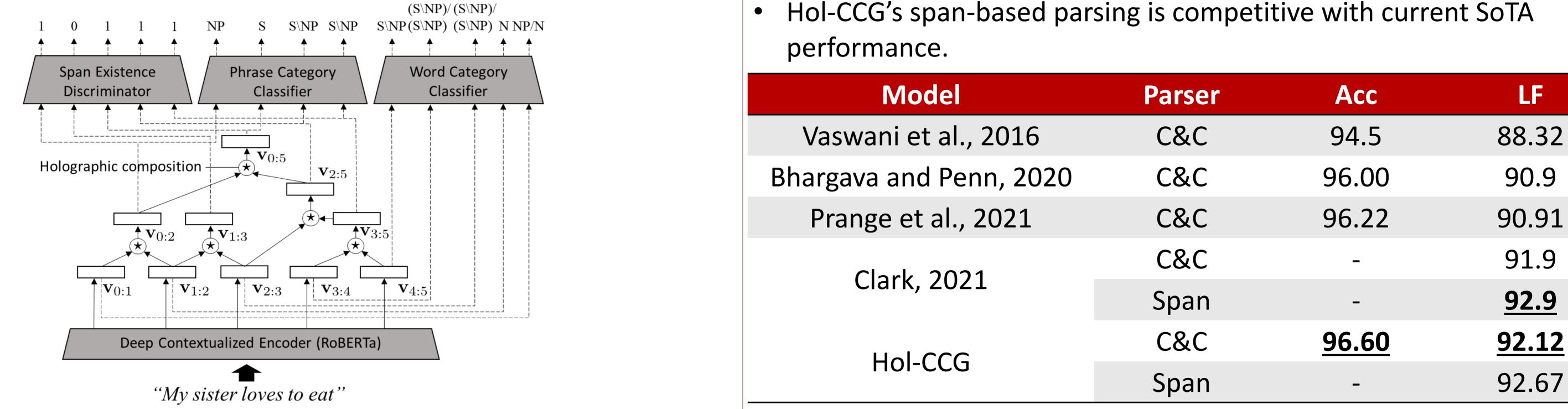
distributed representations in a vector space.

• Applicable to **Supertagging** and **Span-based Parsing**.



> Model Structure

- 1. Encode word sequence into distributed representations.
- 2. Recursively compose phrase-level representations.
- 3. Predict CCG categories and span existence.



span-based parsing

Result & Discussion

- Hol-CCG outperforms baseline.
- Span-based Parsing outperforms C&C Parser.
- Explicit modeling of word/phrase dependencies through composition of phrase representations is effective for both supertagging and parsing.

Training Objectives	Parser	Acc	LF
\mathcal{L}_w (baseline)	C&C	96.41 ± 0.03	91.77 ± 0.03
	C&C	<u>96.59 ± 0.02</u>	<u>92.03 ± 0.04</u>
$\mathcal{L}_w + \mathcal{L}_p + \mathcal{L}_s$ (Hol-CCG)	Span	_	<u>92.61 ± 0.03</u>

- Hol-CCG achieved SoTA in supertagging accuracy and LF with C&C Parser.
- Hol-CCG's span-based parsing is competitive with current SoTA

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