Improving Constituent Representation with Hypertree Neural Networks

Hao Zhou [1], Gongshen Liu [1], Kewei Tu [2]
[1] School of Electronic Information and Electrical Engineering, Shanghai Jiao Tong University
[2] School of Information Science and Technology, ShanghaiTech University

Motivations

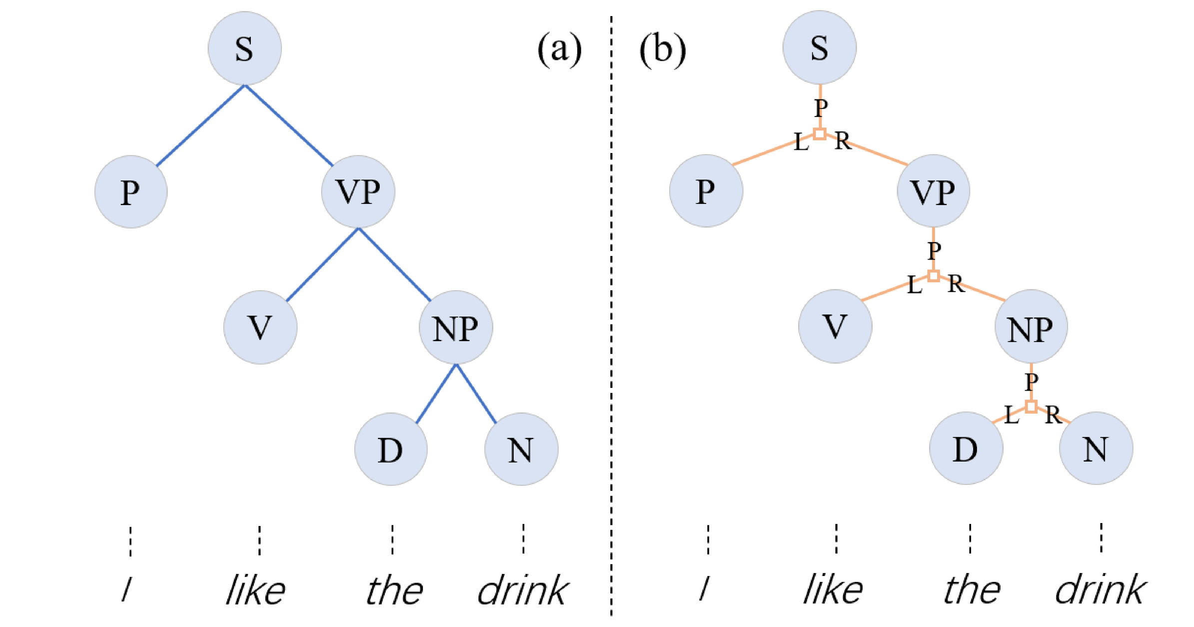
- Distributed span representations are useful in various NLP tasks.
- Existing methods are mostly based on simple derivations from word or sub-word representations.
- We improve span representations using the underlying compositional structures of text, which are often represented with constituency parse trees.

Existing methods

- **Simple derivations:** from word or sub-word representations, such as average, max-pooling. These methods ignore the compositional structures both within and outside text spans.
- **Recursive neural networks (RvNNs)**: recursively compose span representations from their sub-spans but separate the representations computed from both directions and disallow them to directly interact with each other.
- **Graph neural networks (GNNs)**: such as GCN and GAT, represent each composition with multiple edges that become mixed up with edges from other compositions.

Our Method: Hypertree Neural Networks (HTNN)

(1) View A Constituency Parse Tree as A Hypertree



- Each node represents a constituent and each hyperedge is a tuple of multiple nodes representing a composition of smaller child constituents into a larger parent constituent.

(2) Initialization of Node Representation

- For a span s = [i, j], we use attention pooling method to initialize the representations

$$\mathbf{s}_{ij} = \sum_{k=i}^{j-1} a_k \cdot \mathbf{e}_k \qquad a_k = \mathbf{Softmax}(\mathbf{v}_1^T \cdot \mathbf{e}_k)$$

- Concatenate with constituent tag embedding

$$\mathbf{s}'_{ij} = \mathbf{Concat}([\mathbf{s}_{ij}; \mathbf{Embedding}(tag)])$$

(3) Composition within Hyperedge

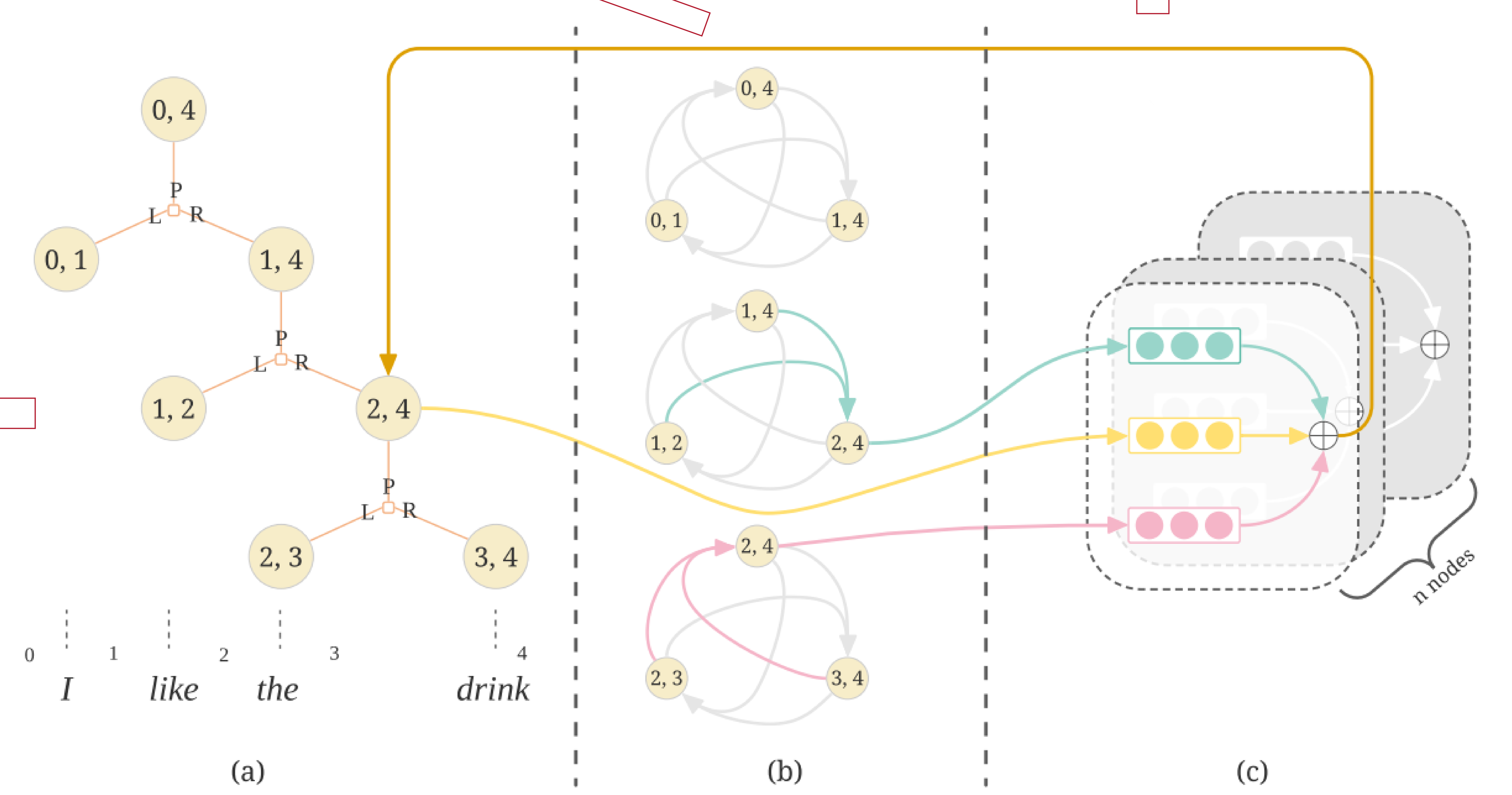
- Any node can be computed from the others within each hyperedge.
- The composition function is inspired by TreeLSTM

$$[\mathbf{h}'_p; \mathbf{c}'_p] = \mathbf{Compose}(\mathbf{h}_p, \mathbf{h}_l, \mathbf{h}_r, \mathbf{c}_l, \mathbf{c}_r)$$
$$[\mathbf{h}'_l; \mathbf{c}'_l] = \mathbf{Compose}(\mathbf{h}_l, \mathbf{h}_p, \mathbf{h}_r, \mathbf{c}_p, \mathbf{c}_r)$$
$$[\mathbf{h}'_r; \mathbf{c}'_r] = \mathbf{Compose}(\mathbf{h}_r, \mathbf{h}_p, \mathbf{h}_l, \mathbf{c}_p, \mathbf{c}_l)$$

(4) Aggregation of Multiple Representations

- A node in the HTNN is connected with two hyperedges, resulting in two different representations for the node.
- A third representation is from the previous layer.

$$a_i = \mathbf{Softmax}(\mathbf{v}_2^T \mathbf{tanh}(\mathbf{W}[\mathbf{h}'_0; \mathbf{h}'_i]))$$
$$\mathbf{h}' = \sum_i a_i \cdot \mathbf{h}'_i, \quad i \in \{0, 1, 2\}$$



Experiments & Results

(1) Probing Experiments

	NEL		SRC		COREF		AVG	
	F1-const	F1-all	F1-const	F1-all	F1-const	F1-all	F1-const	F1-all
Pooling	96.18	**96.07**	93.08	93.05	92.99	93.01	94.08	94.04
TreeLSTM	95.05	94.22	90.02	89.88	90.07	89.70	91.71	91.27
Bi-TreeLSTM	95.25	94.42	90.49	90.35	90.33	89.96	92.02	91.58
SentiBERT	92.98	92.84	95.92	95.09	96.01	95.64	94.97	94.52
GAT	96.01	95.18	93.41	93.26	96.13	95.76	95.18	94.73
GCN	96.03	95.20	93.51	93.37	96.22	95.85	95.25	94.81
GAT-sib	95.79	94.96	92.85	92.71	95.66	95.29	94.77	94.32
GCN-sib	95.87	95.04	93.27	93.13	95.68	95.31	94.94	94.50
HTNN	**96.28**	95.45	**93.88**	**93.74**	**96.33**	**95.96**	**95.50**	**95.05**

- HTNN shows strong performance on Named entity labeling (NEL), Semantic role classification (SRC), Coreference arc prediction (COREF)

(2) Semantic Role Labeling (SRL) Experiments

	CONLL12		CONLL05 WSJ		CONLL05 BROWN	
	F1-const	F1-all	F1-const	F1-all	F1-const	F1-all
Pooling	82.36	82.23	82.82	81.90	71.51	70.43
SentiBERT	75.31	75.18	74.52	73.69	66.52	65.51
GAT	85.29	85.16	84.69	83.74	73.32	72.24
GCN	87.91	87.77	88.06	87.08	79.22	78.09
GAT-sib	76.41	76.29	78.34	77.46	62.52	61.58
GCN-sib	88.40	88.27	88.45	87.46	80.03	79.87
HTNN	**89.94**	**89.81**	**90.77**	**89.76**	**82.88**	**81.68**
Wang et al. (2019)†	-	84.21	-	85.23	-	75.36
Fei et al. (2021)*	-	87.35	-	88.81	-	81.27

- **HTNN achieves the best performance on all the three datasets.** SRL is more challenging than the probing tasks.

Conclusions & Future Work

- We propose hypertree neural networks (HTNN) to generate better representations of constituent spans following constituency parse tree structures.
- In the future, we plan to tackle two related issues of our approach, namely its reliance on high-quality constituency parses and its inability to represent distituent spans (some of which may nonetheless be important).