Neural Language Models with Latent Syntax

Thesis MSc Logic

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The hungry cat meows.

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Knowing the syntactic structure of the sentence could help.

Syntactic structure

Consider inserting the word `apparently` in a sentence.

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- Which stuctures? Those proposed by a separate) conditional model $q(y \mid x)$.

Approximate marginal

Solution: rewrite the sum as an expectation under q:

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- Estimate this expectation with samples from q
- Sample trees $y^{(1)}, \ldots, y^{(K)}$ from $q(\cdot \mid x)$ and form the estimate

$$\mathbb{E}_q \left[\frac{p_\theta(x, y)}{q(y \mid x)} \right] \approx \sum_{k=1}^{K} \frac{p_\theta(x, y^{(k)})}{q(y^{(k)} \mid x)}$$

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- This is an unbiased estimator.
- Choosing K we can make this a much smaller sum!

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- A conditional distribution over trees... A probabilistic parser!

Key ideas of thesis

Choice Let $p_\theta(x, y)$ be an RNNG [Dyer et al., 2016]

- competitive language model sensitive to syntactic phenomena
- sum intractable (but approximation possible)
- training limited to annotated data (e.g. Penn Treebank)

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Goal Learn $p_\theta(x, y)$ by maximizing $p(x)$ directly

- allows estimation from data without annotation
- mix with supervised objective for semi-supervised training
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Contribution A CRF parser as $q_\lambda(y \mid x)$ parametrized by λ

- Efficient computation of key quantities in the unsupervised objective
- Strong independence assumptions guide the posterior during training

$$p(x) = \mathbb{E}_{q_\lambda}\left[\frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right]$$

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Recurrent Neural Network Grammar

Models the sequence of actions $a = (a_1, \ldots, a_T)$ that build sentence x together with tree y

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Decompose using chain rule and condition on entire history.

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Transition system

Stack	Action

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(S	

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Stack	Action
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Parametrization

The RNNG is an RNN that recursively compresses and labels its history.

- An RNN encodes the stack, and backtracks upon reduce action

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- A composition function computes a single representation

  (NP *The hungry cat*) from (NP *The* *hungry* *cat*

Parametrization

The RNNG is an RNN that recursively compresses and labels its history.

- An RNN encodes the stack, and backtracks upon reduce action

  (S (NP *The* *hungry* *cat*

- A composition function computes a single representation

  (NP *The hungry cat*) from (NP *The* *hungry* *cat*

- The RNN updates with the composed representation

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CRF parser

A globally normalized model

$$q_\lambda(y \mid x) = \frac{\Psi(x, y)}{Z(x)},$$

where

- $\Psi(x, y) \geq 0$ scores trees for a sentence
- $Z(x) = \sum_{y \in \mathcal{Y}(x)} \Psi(x, y)$ is a global normalizer

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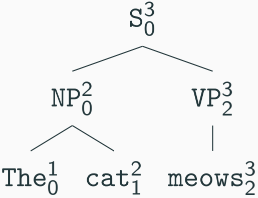
We factorize Ψ over the parts of the tree y_c:

$$\Psi(x, y) = \prod_{c=1}^{C} \psi(x, y_c),$$

- Parts y_c are the labeled spans in the full tree y
- This factorization allows efficient computation of $\sum$!

Factorization



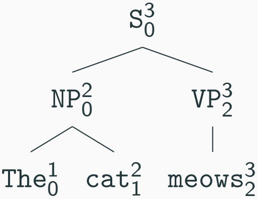
$\Longrightarrow$

(S, 0, 3)
(NP, 0, 2)
(VP, 2, 3)

Scoring entire tree $\Psi(x, y)$

Scoring parts $\psi(x, y_c)$

Factorization



$\Longrightarrow$

$(\mathtt{S},\ 0,\ 3)$
$(\mathtt{NP},\ 0,\ 2)$
$(\mathtt{VP},\ 2,\ 3)$

Scoring entire tree $\Psi(x, y)$

Scoring parts $\psi(x, y_c)$

This is even stronger than then ususual PCFG factorization into anchored rules like

$$(\mathtt{S} \rightarrow \mathtt{NP}\ \mathtt{VP},\ 0,\ 2,\ 3)$$

Parametrization

Compute score $\psi(x, y_c) \geq 0$ with a neural network following Stern et al. [2017]. Let (A, i, j) be a labeled span.

- Use bidirectional RNN to compute span represenations $\mathbf{s}_{ij}$

$$\mathbf{s}_{ij} = [\mathbf{f}_j - \mathbf{f}_i; \mathbf{b}_i - \mathbf{b}_j],$$

  where **f** and **b** forward and backward vectors.
- Use feedfoward neural network to compute the span score

$$\log \psi(x, y_c) = [\textsc{ffn}(\mathbf{s}_{ij})]_A.$$

- Very minimalistic setup!

Parametrization

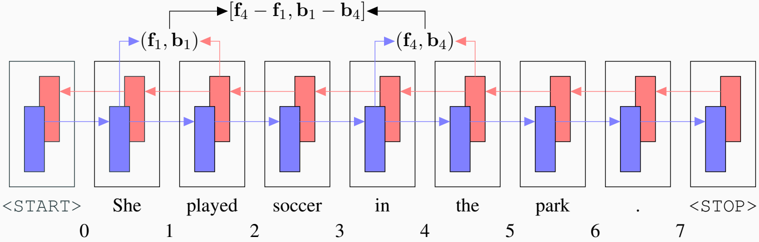


Figure 1: Span representation $\mathbf{s}_{ij}$ from $\mathbf{f}$ and $\mathbf{b}$. Figure by Gaddy et al. [2018].

Inference

The factorization over spans model allows efficient solutions to four related problems:

- Compute normalizer $Z(x) = \sum_y \Psi(x, y)$
- Obtain best parse $\hat{y} = \arg\max_y q(y \mid x)$
- Sample a tree $y \sim q(y \mid x)$
- Compute the entropy $\mathrm{H}(q(y \mid x))$

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- Compute the entropy $\mathrm{H}(q(y \mid x))$

These problems involve either search or summation over all trees!

- Can be solved efficiently by the inside-outside algorithm.

Entropy

$$H(q(y \mid x)) := -\sum_{y \in \mathcal{Y}(x)} q(y \mid x) \log q(y \mid x)$$

Entropy

$$
\begin{aligned}
H(q(y \mid x)) &:= -\sum_{y \in \mathcal{Y}(x)} q(y \mid x) \log q(y \mid x) \\
&= \log Z(x) - \sum_{y \in \mathcal{Y}(x)} q(y \mid x) \sum_{v \in y} \log \psi(x, v)
\end{aligned}
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&= \log Z(x) - \sum_{v \in \mathcal{V}(x)} \log \psi(x, v) \sum_{y \in \mathcal{Y}(x)} \mathbf{1}(v \in y) q(y \mid x)
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&= \log Z(x) - \sum_{v \in \mathcal{V}(x)} \log \psi(x, v) \sum_{y \in \mathcal{Y}(x)} \mathbf{1}(v \in y) q(y \mid x) \\
&= \log Z(x) - \sum_{v \in \mathcal{V}(x)} \log \psi(x, v) \mu(v).
\end{aligned}
$$

Entropy

$$H(q(y \mid x)) = \log Z(x) - \sum_{v \in \mathcal{V}(x)} \log \psi(x, v) \mu(v)$$

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The marginal of a node $v = (A, i, j)$

$$\mu(v) := \sum_{y \in \mathcal{Y}(x)} q(y \mid x) \, \mathbf{1}(v \in y) = \mathbb{E}[\mathbf{1}(v \in Y)]$$

is the probability that v appears in y, according to $P(Y \mid X = x)$.

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Entropy

The entropy has a nice interpretation:

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H(q(y \mid x)) &= \log Z(x) - \sum_{y \in \mathcal{Y}(x)} q(y \mid x) \sum_{v \in y} \log \psi(x, v) \\
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$$

log-weight of all trees

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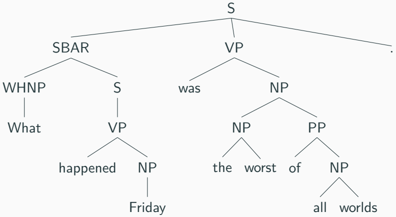
&= \log Z(x) - \mathbb{E}_{p} \left[\log \Psi(x, Y) \right]
\end{aligned}
$$

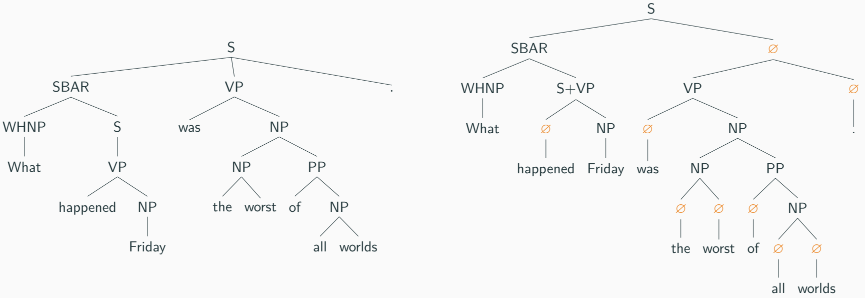
log-weight of all trees

log-weight of the expected tree

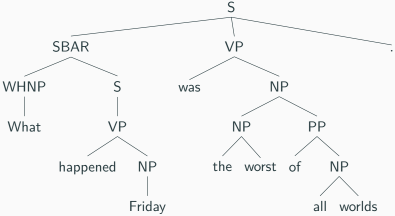
Dealing with *n*-ary trees

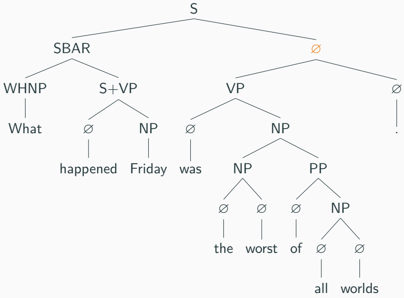


Dealing with *n*-ary trees



Dealing with *n*-ary trees

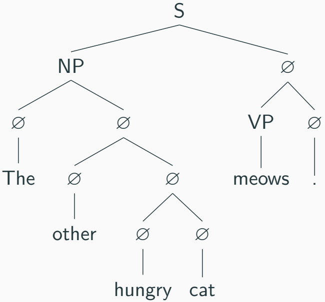


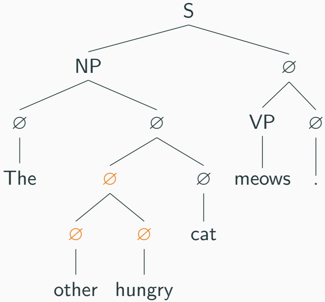


Derivational ambiguity

We treat the dummy label $\varnothing$ as any other label:

- Absorbing the empty labels gives back an *n*-ary tree, but...
- causes derivational ambiguity!





`(S (NP The other hungry cat) (VP meows) .)`

$$p(x) = \mathbb{E}_{q_\lambda}\left[\frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right]$$

$$\log p(x) = \log \mathbb{E}_{q_\lambda} \left[\frac{p_\theta(x, y)}{q_\lambda(y \mid x)} \right]$$

$$\mathcal{L}(\theta, \lambda) = \log p(x) = \log \mathbb{E}_{q_\lambda}\left[\frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right]$$

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$$\begin{aligned}\mathcal{L}(\theta, \lambda) = \log p(x) &= \log \mathbb{E}_{q_\lambda}\left[\frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right] \\ &\geq \mathbb{E}_{q_\lambda}\left[\log \frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right]\end{aligned}$$

Unsupervised learning

The objective:

$$\mathcal{L}(\theta, \lambda) \geq \mathbb{E}_{q_\lambda}\left[\log \frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right]$$

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Unsupervised learning

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$$\begin{aligned}\mathcal{L}(\theta, \lambda) &\geq \mathbb{E}_{q_\lambda}\left[\log \frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right] \\ &= \mathbb{E}_{q_\lambda}[\log p_\theta(x, y)] - \mathbb{E}_{q_\lambda}[\log q_\lambda(y \mid x)]\end{aligned}$$

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\mathcal{L}(\theta, \lambda) &\geq \mathbb{E}_{q_\lambda}\left[\log \frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right] \\
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&= \underbrace{\mathbb{E}_{q_\lambda}[\log p_\theta(x, y)]}_{\text{estimate with samples}} - \underbrace{\mathrm{H}(q_\lambda(y \mid x))}_{\text{exact computation with CRF!}}
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$$\begin{aligned}\mathcal{L}(\theta, \lambda) &\geq \mathbb{E}_{q_\lambda}\left[\log \frac{p_\theta(x, y)}{q_\lambda(y \mid x)}\right] \\ &= \mathbb{E}_{q_\lambda}[\log p_\theta(x, y)] - \mathbb{E}_{q_\lambda}[\log q_\lambda(y \mid x)] \\ &= \underbrace{\mathbb{E}_{q_\lambda}[\log p_\theta(x, y)]}_{\text{estimate with samples}} - \underbrace{\mathrm{H}(q_\lambda(y \mid x))}_{\text{exact computation with CRF!}}\end{aligned}$$

Also called the expectation lower bound (ELBO).

Gradients

Objective

$$\mathcal{E}(\theta, \lambda) = \mathbb{E}_{q_\lambda}[\log p_\theta(x, y)] - \mathrm{H}(q_\lambda(y \mid x))$$

With respect to θ

- $\nabla_\theta \, \mathrm{H}(q_\lambda(y \mid x))$
- $\nabla_\theta \, \mathbb{E}_{q_\lambda}[\log p_\theta(x, y)]$

With respect to λ

- $\nabla_\lambda \, \mathrm{H}(q_\lambda(y \mid x))$
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Gradients

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With respect to θ

- $\nabla_\theta \mathrm{H}(q_\lambda(y \mid x)) = 0$
- $\nabla_\theta \mathbb{E}_{q_\lambda}[\log p_\theta(x, y)] = \mathbb{E}_{q_\lambda}[\nabla_\theta \log p_\theta(x, y)]$

With respect to λ

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Gradients

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- $\nabla_\lambda \, \mathrm{H}(q_\lambda(y \mid x))$ autodiff...
- $\nabla_\lambda \, \mathbb{E}_{q_\lambda}[\log p_\theta(x, y)] = \overbrace{\mathbb{E}_{q_\lambda}[\log p_\theta(x, y) \nabla_\lambda q_\lambda(y \mid x)]}^{\text{Score function estimator}}$

Backup slides

Syntactic evaluation

Targeted syntactic evaluation with the dataset of Marvin and Linzen [2018]. Three main categories:

1. Agreement
   - The author next to the guards smiles.
   - *The author next to the guards smile.
2. Reflexives
   - The mechanics said the author hurt himself.
   - *The mechanics said the author hurt themselves.
3. Negative polarity items (NPIs)
   - No authors have ever been popular.
   - *The authors have ever been popular.

Syntactic evaluation

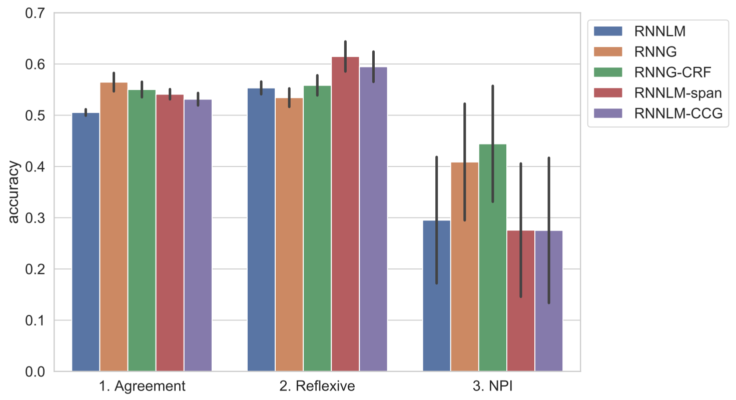


Figure 2: Syneval results averaged over the three main categories.

Unsupervised RNNG

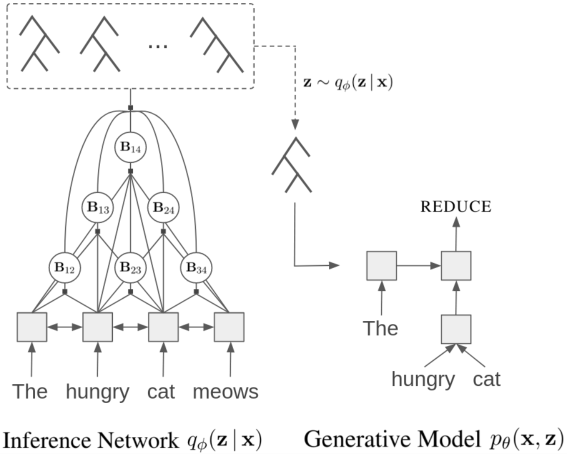
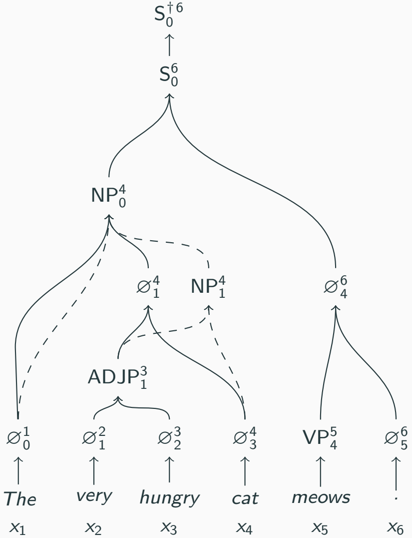
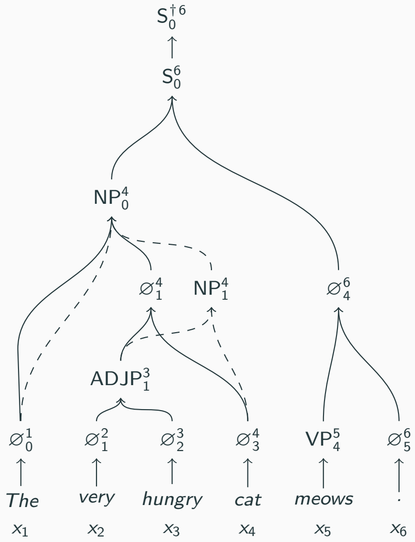


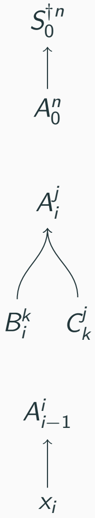
Figure 3: Unsupervised RNNG [Kim et al., 2019].

Compact parse forest



Compact parse forest





Inside algorithm

$$\alpha(A, i, j) = \bigoplus_{e \in I(v)} \omega(e) \otimes \bigotimes_{u \in T(e)} \alpha(u)$$

Inside algorithm

sum over all incoming edges

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$$\alpha(A,i,j) = \bigoplus_{e \in I(v)} \omega(e) \otimes \bigotimes_{u \in T(e)} \alpha(u)$$

weight of edge

Inside algorithm

sum over all incoming edges

$$\alpha(A, i, j) = \bigoplus_{e \in I(v)} \omega(e) \otimes \bigotimes_{u \in T(e)} \alpha(u)$$

weight of edge

product of inside scores of the nodes in the tail of the edge

Inside algorithm

$$\alpha(A,i,j) = \bigoplus_{e \in I(v)} \omega(e) \otimes \bigotimes_{u \in T(e)} \alpha(u)$$

$$= \bigoplus_{B \in \Lambda} \bigoplus_{C \in \Lambda} \bigoplus_{k=i+1}^{j-1} \omega(A,i,j) \otimes \alpha(B,i,k) \otimes \alpha(C,k,j)$$

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$$\begin{aligned}
\alpha(A,i,j) &= \bigoplus_{e \in I(v)} \omega(e) \otimes \bigotimes_{u \in T(e)} \alpha(u) \\
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&= \omega(A,i,j) \otimes \bigoplus_{k=i+1}^{j-1} \bigoplus_{B \in \Lambda} \alpha(B,i,k) \otimes \bigoplus_{C \in \Lambda} \alpha(C,k,j)
\end{aligned}$$

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&= \omega(A,i,j) \otimes \bigoplus_{k=i+1}^{j-1} \bigoplus_{B \in \Lambda} \alpha(B,i,k) \otimes \bigoplus_{C \in \Lambda} \alpha(C,k,j) \\
&= \omega(A,i,j) \otimes \bigoplus_{k=i+1}^{j-1} \sigma(i,k) \otimes \sigma(k,j)
\end{aligned}
$$

Outside algorithm

$$\beta(A, i, j) = \bigoplus_{e \in O(v)} \omega(e) \otimes \beta(H(e)) \otimes \bigotimes_{\substack{w \in T(e) \\ w \neq u}} \alpha(w)$$

Outside algorithm

sum over all *outgoing* edges

$$\beta(A,i,j) = \bigoplus_{e \in O(v)} \omega(e) \otimes \beta(H(e)) \otimes \bigotimes_{\substack{w \in T(e) \\ w \neq u}} \alpha(w)$$

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weight of edge

outside value of node
in the head of the edge

Outside algorithm

sum over all *outgoing* edges

$$\beta(A, i, j) = \bigoplus_{e \in O(v)} \omega(e) \otimes \beta(H(e)) \otimes \bigotimes_{\substack{w \in T(e) \\ w \neq u}} \alpha(w)$$

weight of edge

outside value of node
in the head of the edge

sum over inside values of
the sibling nodes

Inside and Outside algorithms

The final recursions are

$$\alpha(A,i,j) = \omega(A,i,j) \otimes \bigoplus_{k=i+1}^{j-1} \sigma(i,k) \otimes \sigma(k,j)$$

$$\beta(A,i,j) = \bigoplus_{k=1}^{i-1} \sigma'(k,j) \otimes \sigma(k,i) \oplus \bigoplus_{k=j+1}^{n} \sigma'(i,k) \otimes \sigma(j,k),$$

where

$$\sigma(i,j) = \bigoplus_{A \in \Lambda} \alpha(A,i,j),$$

$$\sigma'(i,j) = \bigoplus_{A \in \Lambda} \omega(A,i,j)\beta(A,i,j).$$

References

Chris Dyer, Adhiguna Kuncoro, Miguel Ballesteros, and Noah A. Smith. Recurrent neural network grammars. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 199–209. Association for Computational Linguistics, 2016.

References II

David Gaddy, Mitchell Stern, and Dan Klein. What's going on in neural constituency parsers? an analysis. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 999–1010. Association for Computational Linguistics, 2018.

Yoon Kim, Alexander M Rush, Lei Yu, Adhiguna Kuncoro, Chris Dyer, and Gábor Melis. Unsupervised recurrent neural network grammars. *arXiv preprint arXiv:1904.03746*, 2019.

Rebecca Marvin and Tal Linzen. Targeted syntactic evaluation of language models. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1192–1202. Association for Computational Linguistics, 2018.

References III

Mitchell Stern, Jacob Andreas, and Dan Klein. A minimal span-based neural constituency parser. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 818–827, Vancouver, Canada, July 2017. Association for Computational Linguistics.