Neural Language Models with Latent Syntax

Thesis Master of Logic

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May 24, 2019

Institute for Logic, Language and Computation (ILLC)

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Neural Language Models with Latent Syntax

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$\vdots$

The hungry cat meows.

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(S (NP The (ADJP hungry) cat) (VP meows) .)
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- From statistical viewpoint a sentence is a sequence of words

$$\textit{The hungry cat meows} \cong \langle \textit{The}, \textit{hungry}, \textit{cat}, \textit{meows} \rangle$$

from some vocabulary $V = \{cat, dog, a, \ldots, The\}$.

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- Comparatively it makes more sense:

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  Knowing the syntactic structure of the sentence could help.

Syntactic structure

Consider inserting the word apparently in the sentence

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- Idea: use only some of the stuctures y to approximate the sum.
- Which stuctures? Those proposed by a (separate) conditional model $q(y \mid x)$.

Approximate marginal

Solution: rewrite the sum as an expectation under q:

$$p(x) = \sum_{y \in \mathcal{Y}(x)} q(y \mid x) \frac{p_\theta(x, y)}{q(y \mid x)}$$

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- Sample trees $y^{(1)}, \ldots, y^{(K)}$ from $q(y \mid x)$ and estimate

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\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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- A much smaller sum!

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

Key ideas of thesis

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

- competitive language model sensitive to syntactic phenomena
- sum intractable (approximation possible)
- training limited to annotated data

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- allows estimation from data without annotation
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Key ideas of thesis

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

- competitive language model sensitive to syntactic phenomena
- sum intractable (approximation possible)
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Contribution: let $q(y \mid x)$ be a CRF parser

- Strong independence assumptions
- Efficient computation of key quantities

Goal: approximate learning of both with $q(y \mid x)$

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

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Recurrent Neural Network Grammar

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

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Conditions on entire history.

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Stack	Action

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(S	

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Stack			Action
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Parametrization

An RNN encodes the stack, and backtracks upon reduce action

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A composition function computes a single representation

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The RNN updates with the composed representation

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Parametrization

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(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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The RNNG is an RNN that recursively compresses its history.

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

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CRF parser

A globally normalized model

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

where

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

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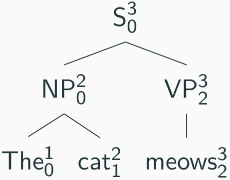
We factorize Ψ over the parts of the tree y_c:

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

- Parts $y_c = (A, i, j)$ are labeled spans, *e.g.* (NP, 0, 2)
- Factorization allows efficient computation of $\sum$!

Factorization



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

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

Scoring parts of tree $\psi(x, y_c)$

Parametrization

- Compute score $\psi(x, y_c)$ with a neural network following Stern et al. [2017]
- Use feedfoward neural network to compute the span score

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

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

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

  where $\mathbf{f}$ and $\mathbf{b}$ forward and backward vectors.
- Very minimalistic setup!

Parametrization

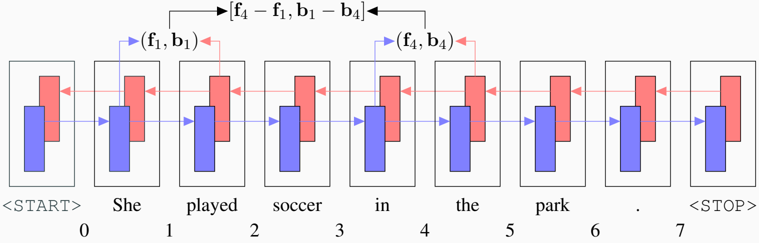


Figure 1: Span representation $\mathbf{s}_{ij}$ from $\mathbf{f}$ and $\mathbf{b}$. Figure by Gaddy et al. [2018].

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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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

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

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 $P(Y \mid X = x)$.

Entropy

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$$\begin{aligned} \mu(v) &:= \sum_{y \in \mathcal{Y}(x)} q(y \mid x)\, \mathbf{1}(v \in y) = \mathbb{E}[\mathbf{1}(v \in Y)] \\ &= \frac{\alpha(A, i, j)\, \beta(A, i, j)}{Z(x)} \end{aligned}$$

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Entropy

The entropy has a nice interpretation:

$$\begin{aligned} H(q(y \mid x)) &= \log Z(x) - \sum_{y \in \mathcal{Y}(x)} q(y \mid x) \sum_{v \in y} \log \psi(x, v) \\ &= \log Z(x) - \sum_{y \in \mathcal{Y}(x)} q(y \mid x) \log \Psi(x, y) \\ &= \log Z(x) - \mathbb{E}_p \left[\log \Psi(x, Y) \right] \end{aligned}$$

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log-weight of all trees

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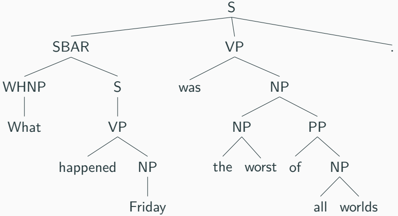
&= \log Z(x) - \mathbb{E}_p \left[\log \Psi(x, Y) \right]
\end{aligned}
$$

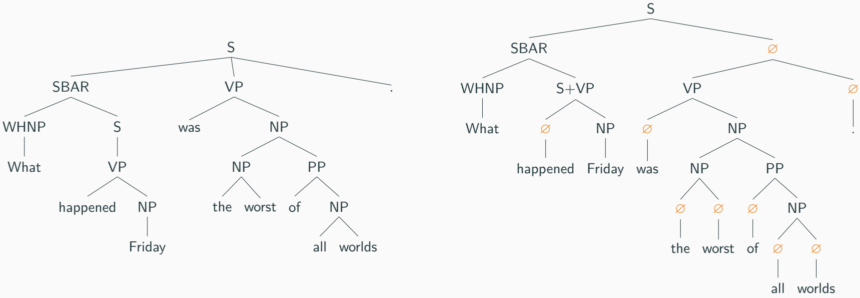
log-weight of all trees

log-weight of the expected tree

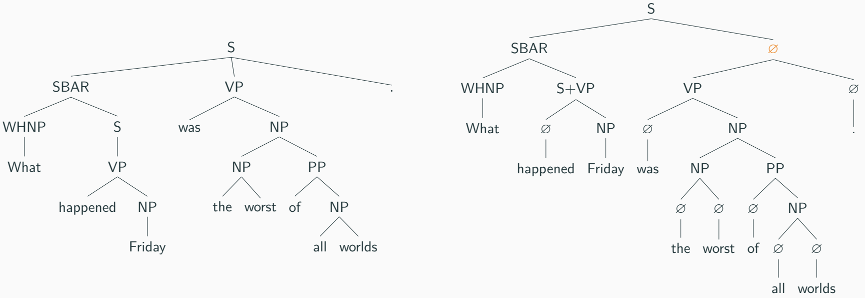
Dealing with *n*-ary trees



Dealing with *n*-ary trees



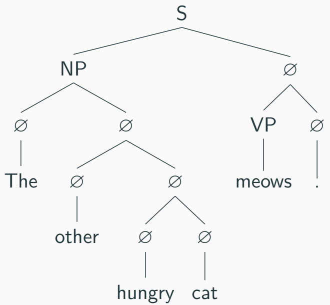
Dealing with *n*-ary trees

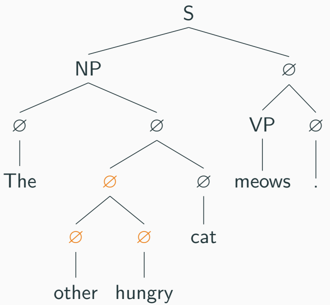


Derivational ambiguity

We treat the dummy label ∅ as any other label

- Absorbing the empty labels gives back an *n*-ary tree
- 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:

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

Can we estimate θ and λ this way?

Unsupervised learning

The objective:

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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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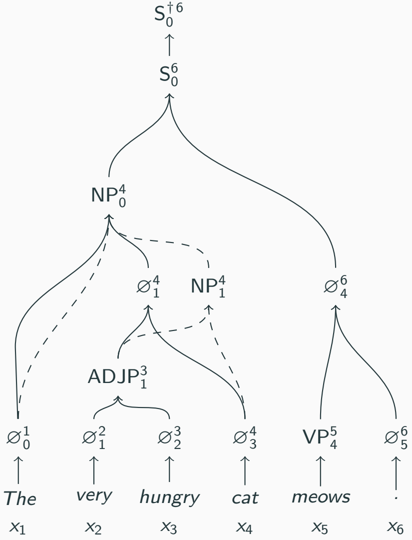
\end{aligned}
$$

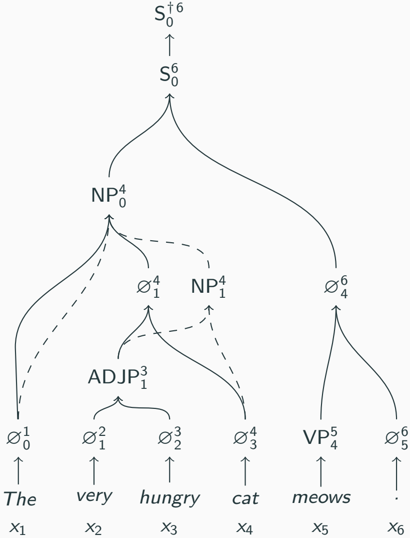
Can we estimate θ and λ this way? Almost there...

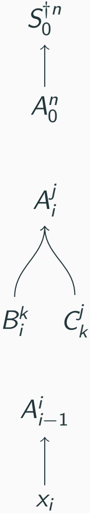
Backup slides

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

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

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

Inside algorithm

$$
\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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\end{aligned}
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\begin{aligned}
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&= \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) \\
&= \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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Inside algorithm

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

Inside algorithm

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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) \\
&= \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) \\
&= \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 algorithm

sum over all *outgoing* edges

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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

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

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

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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.