Multitask Pointer Network for Discontinuous Constituent Parsing

An application to the German language

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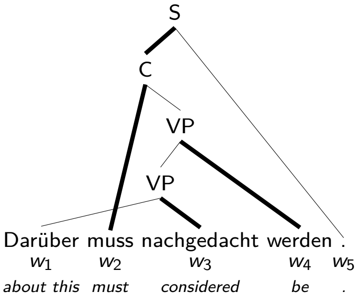
Why use a neural network to model grammar?

Linguistic preliminaries: constituent trees

Let $w = (w_1, \ldots, w_L)$ be a sentence.

Definition

- A *constituent tree* is a rooted tree whose leaves are the words $(w_i)_{i=1}^{L}$ and internal nodes are constituents satisfying some constraints.
- A *constituent* is a triple $(Z, \mathcal{Y}, h)$ containing, respectively, its label, yield, and lexical head.
- A constituent is *discontinuous* if its yield is not contiguous.

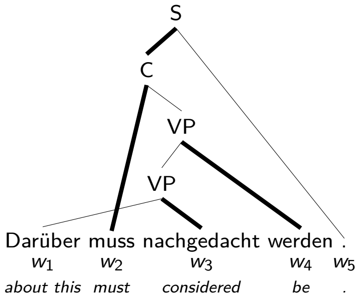


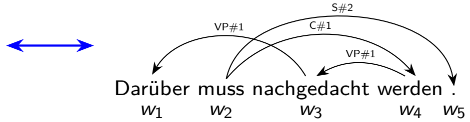
Reduction to dependency parsing

Definition

A *dependency tree* is a rooted tree spanning the words in the sentence $(w_i)_{i=1}^{L}$. Each edge is labelled and connects a *head word* (parent) to a *dependency* (child).

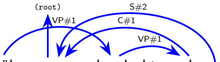
Fernández-González and Martins (2015) show that constituent trees are isomorphic to dependency trees in which the edges contain information about constituent labels and attachment order.





Mathematical formalisation

- Regressor: sentence $(w_i)_{i=1}^{L}$.
- Regressand: dependency tree, parts of speech and morphology.
- Bottom-up approach: think of *arcs* going from every child w_i to its parent $y_i^{\text{arc}} \in w \setminus w_i$.



w	Darüber	muss	nachgedacht	werden	.
	w_1	w_2	w_3	w_4	w_5
y^{arc}	w_3	(root)	w_4	w_2	w_2
y^{lab}	VP	–	VP	C	S
y^{ord}	1	–	1	1	2
y^{pos}	PAV	VM	V	VA	$.
y^{morph}	–	fin	part	inf	–

Denote the regressand by $y = (y_i)_{i=1}^{L}$ where $y_i = (y_i^{\text{arc}}, y_i^{\text{lab}}, y_i^{\text{ord}}, y_i^{\text{pos}}, y_i^{\text{morph}})$ and with mild abuse of notation let $y_{<i} = (y_1, \dots, y_i)$ for each $i = 2, \dots, L$ and $y_{<1} = 0$.

Assumption

For each $i = 1, \dots, L$, the random variables $y_i^{\text{lab}}, y_i^{\text{ord}}, y_i^{\text{pos}}$ and y_i^{morph} are mutually independent conditional on y_i^{arc}, $y_{<i}$ and w.

We can decompose the conditional probability of y given w:

$$
\begin{aligned}
p_w(y) &= \prod_{i=1}^{L} p_w(y_i \mid y_{<i}) \\
&= \prod_{i=1}^{L} \Big\{ p_w(y_i^{\text{arc}} \mid y_{<i}) p_w(y_i^{\text{lab}} \mid y_i^{\text{arc}}, y_{<i}) \\
&\qquad \cdot p_w(y_i^{\text{ord}} \mid y_i^{\text{arc}}, y_{<i}) p_w(y_i^{\text{pos}} \mid y_i^{\text{arc}}, y_{<i}) p_w(y_i^{\text{morph}} \mid y_i^{\text{arc}}, y_{<i}) \Big\}.
\end{aligned}
$$

Encoder-decoder setup

Given an input sentence $w = (w_i)_{i=1}^{L}$ we generate *embeddings* $\boldsymbol{\omega} = (\omega_i)_{i=1}^{L}$, where

$$\omega_i = \textbf{WordEmbed}(w_i) \oplus \textbf{CharEmbed}(w_i) \oplus \textbf{BertEmbed}(w_i).$$

- **CharEmbed** is implemented using a CNN á la Chiu and Nichols (2016).
- BERT model pre-trained on German text by Chan et al. (2020).

Encoder: feed embeddings through a multi-layer bi-directional LSTM with skip-connections and dropout:

$$\mathbf{e} = (\mathbf{e}_i)_{i=0,\dots,n} = \textbf{BiLSTM}(\omega).$$

($\mathbf{e}_0$ represents the root pseudo-node.)

Decoder: feed embeddings through a single-layer uni-directional LSTM with dropout:

$$\mathbf{d} = (\mathbf{d}_i)_{i=1,\dots,n} = \textbf{LSTM}(\omega).$$

- Obtain dimension-reduced representations:

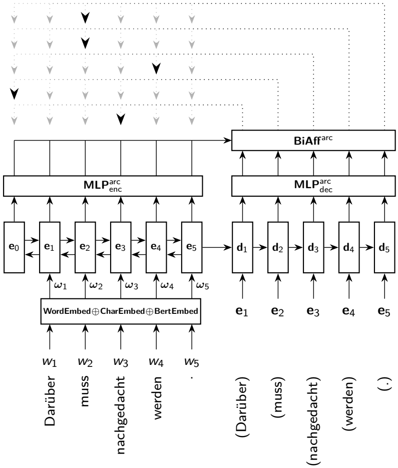
$$\mathbf{e}^{\mathrm{arc}} = \mathbf{MLP}^{\mathrm{arc}}_{\mathrm{enc}}(\mathbf{e}); \quad \mathbf{d}^{\mathrm{arc}} = \mathbf{MLP}^{\mathrm{arc}}_{\mathrm{dec}}(\mathbf{d}).$$

- Obtain *latent features* $\mathbf{v}^{\mathrm{arc}}$:

$$\begin{aligned}\mathbf{v}^{\mathrm{arc}}_{i,j} &= \mathbf{BiAff}^{\mathrm{arc}}(\mathbf{e}^{\mathrm{arc}}_i, \mathbf{d}^{\mathrm{arc}}_j) \\ &:= \mathbf{e}^{\mathrm{arc}\,\mathsf{T}}_i \mathbf{U}^{\mathrm{arc}}_{\text{h-d}} \mathbf{d}^{\mathrm{arc}}_i \\ &\quad + \mathbf{e}^{\mathrm{arc}\,\mathsf{T}}_i \mathbf{U}^{\mathrm{arc}}_{\text{h-h}} \mathbf{e}^{\mathrm{arc}}_i + \mathbf{d}^{\mathrm{arc}\,\mathsf{T}}_i \mathbf{U}^{\mathrm{arc}}_{\text{d-d}} \mathbf{d}^{\mathrm{arc}}_i \\ &\quad + U^{\mathrm{arc}}_{\mathrm{h}} \mathbf{e}^{\mathrm{arc}}_i + U^{\mathrm{arc}}_{\mathrm{d}} \mathbf{d}^{\mathrm{arc}}_i + \mathbf{u}^{\mathrm{arc}}_{\mathrm{bias}}.\end{aligned}$$

- Obtain *attention logits*:

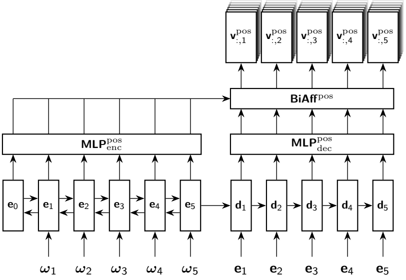
$$s^{\mathrm{arc}}_{i,j} = \mathbf{u}^{\mathrm{arc}\,\mathsf{T}}_{\mathrm{agg}} \tanh(\mathbf{v}^{\mathrm{arc}}_{i,j}).$$



Fixing child w_j, the vector $\mathbf{softmax}(s^{\mathrm{arc}}_{:,j})$ can be interpreted as an estimated probability distribution over potential parents.

$$\hat{p}^{\mathrm{arc}}(w_i \mid y_{<j}, w) = \mathbf{softmax}(s^{\mathrm{arc}}_{:,j})_i.$$

- Encoder and decoder are shared across tasks. The remaining network is separately trained.
- Classification via a bi-affine architecture allows modelling of class probabilities conditional on arcs.



Example: part-of-speech classification.

$$\mathbf{e}^{\text{pos}} = \mathbf{MLP}^{\text{pos}}_{\text{enc}}(\mathbf{e}); \quad \mathbf{d}^{\text{pos}} = \mathbf{MLP}^{\text{pos}}_{\text{dec}}(\mathbf{d}).$$

- Obtain class *logits* $\mathbf{v}^{\text{pos}}$:

$$\begin{aligned}\mathbf{v}^{\text{pos}}_{i,j} &= \mathbf{BiAff}^{\text{pos}}(\mathbf{e}^{\text{pos}}_i, \mathbf{d}^{\text{pos}}_j) \\ &:= \mathbf{e}^{\text{pos}\,\mathsf{T}}_i \mathbf{U}^{\text{pos}}_{\text{h-d}} \mathbf{d}^{\text{pos}}_i + \mathbf{e}^{\text{pos}\,\mathsf{T}}_i \mathbf{U}^{\text{pos}}_{\text{h-h}} \mathbf{e}^{\text{pos}}_i + U^{\text{pos}}_{\text{h}} \mathbf{e}^{\text{pos}}_i \\ &\quad + \mathbf{d}^{\text{pos}\,\mathsf{T}}_i \mathbf{U}^{\text{pos}}_{\text{d-d}} \mathbf{d}^{\text{pos}}_i + U^{\text{pos}}_{\text{d}} \mathbf{d}^{\text{pos}}_i + \mathbf{u}^{\text{pos}}_{\text{bias}}.\end{aligned}$$

Fixing child w_j, the vector $\mathbf{softmax}(\mathbf{v}^{\text{pos}}_{i,j})$ can be interpreted as an estimated probability distribution over its parts-of-speech conditional on having an arc to w_i over potential parents.

$$\hat{p}^{\text{pos}}(c \mid w_i, y_{<j}, w) = \mathbf{softmax}(\mathbf{v}^{\text{pos}}_{i,j})_c.$$

Inference and Training

Inference

Given $w = (w_i)_{i=1}^{L}$, estimate $y = (y_i)_{i=1}^{L}$ via *maximum likelihood*:

$$\hat{y} = \arg\max_{y} \left\{ \prod_{i=1}^{L} \left\{ \hat{p}_w(y_i^{\mathrm{arc}} \mid y_{<i}) \hat{p}_w(y_i^{\mathrm{lab}} \mid y_i^{\mathrm{arc}}, y_{<i}) \cdot \hat{p}_w(y_i^{\mathrm{ord}} \mid y_i^{\mathrm{arc}}, y_{<i}) \hat{p}_w(y_i^{\mathrm{pos}} \mid y_i^{\mathrm{arc}}, y_{<i}) \hat{p}_w(y_i^{\mathrm{morph}} \mid y_i^{\mathrm{arc}}, y_{<i}) \right\} \right\}.$$

The feasible region is very large, so the maximisation is approximated via *beam search*.

Training

The training process involves minimising the *cross-entropy* between the estimated distribution $\hat{p}$ and the empirical distribution present in the dataset $(w^n, y^n)_{n=1}^{N}$.

$$\min_{\hat{p}} \left\{ \sum_{n=1}^{N} \log \prod_{i=1}^{L_n} \left\{ \hat{p}_w(y_i^{n\mathrm{arc}} \mid y_{<i}^{n}) \hat{p}_w(y_i^{n\mathrm{lab}} \mid y_i^{n\mathrm{arc}}, y_{<i}^{n}) \cdot \hat{p}_w(y_i^{n\mathrm{ord}} \mid y_i^{n\mathrm{arc}}, y_{<i}^{n}) \hat{p}_w(y_i^{n\mathrm{pos}} \mid y_i^{n\mathrm{arc}}, y_{<i}^{n}) \hat{p}_w(y_i^{n\mathrm{morph}} \mid y_i^{n\mathrm{arc}}, y_{<i}^{n}) \right\} \right\}$$

$$= \min_{\hat{p}} \left\{ \mathrm{loss}^{\mathrm{arc}} + \mathrm{loss}^{\mathrm{lab}} + \mathrm{loss}^{\mathrm{ord}} + \mathrm{loss}^{\mathrm{pos}} + \mathrm{loss}^{\mathrm{morph}} \right\}.$$

This is approximated via *SGD* with *Nesterov momentum*.

Performance metrics

The TIGER treebank is a widely-used corpus of ∼50 000 constituency trees. Its main textual basis is the *Frankfurter Rundschau*.

- 97 % of the dataset is usable as training examples, with train/dev/test split of 80/10/10 %.

Model (with BERT)	**F1**	**Disc. F1**
F.-González & G.-Rodríguez (2022)	89.8	71.0
Corro (2020)	**90.0**	62.1
Chen & Komachi (2023)	89.6	70.9
This work	89.5	**82.2**

Table: Comparison of overall F1-score and F1-score measured only on discontinuous constituents (Disc. F1), calculated using `disco-dop` as standard practice

Model	`pos`	`morph` (avr)
Kondratyuk et al. (2018)	98.58	98.97
Müller et al. (2013)	98.20	98.27
Schnabel & Schütze (2014)	97.50	97.76
This work	**99.16**	**99.54**

Table: Comparison of part-of-speech (`pos`) and morphology accuracies (%). Morphology accuracies are the average of accuracies for `case`, `degree`, `gender`, `mood`, `number`, `person` and `tense`.

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