Multitask Pointer Network for Discontinuous Constituent Parsing

An application to the German language

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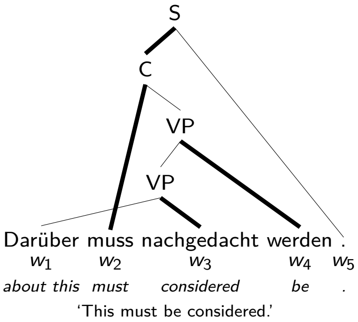
Why use a neural network to model German grammar?

- Constituent trees are a syntactic formalism representing phrasal hierarchy in a sentence.
- Free-order languages like German contain many grammatical discontinuities.
- Discontinuous representations introduce computational complexity but can be more valuable for downstream applications.
- Grammar-less neural network-based models have continually pushed the state of the art.
- My model is based on Fernández-González and Gómez-Rodríguez (2022), who propose an architecture based on pointer neural networks in a multi-task setting.
- I achieve state-of-the-art performance across several metrics.

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.

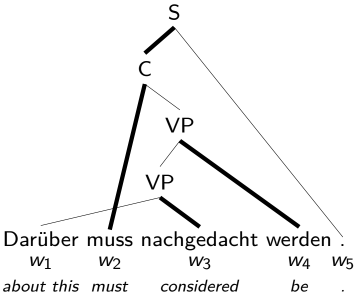


Figure: Constituent tree

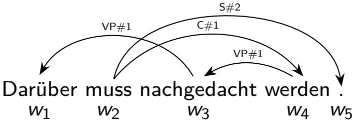
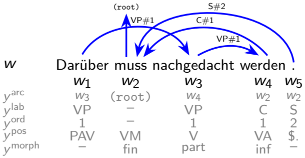


Figure: Dependency tree

Mathematical formalisation

- Regressor: sentence $(w_i)_{i=1}^{L}$.
- Regressand: $y_i = (y_i^{\text{arc}}, y_i^{\text{lab}}, y_i^{\text{ord}}, y_i^{\text{pos}}, y_i^{\text{morph}})$ for each $i = 1, \ldots, L$.
- Bottom-up approach: think of *arcs* going from every child w_i to its parent $y_i^{\text{arc}} \in w \setminus w_i$.



Denote $y = (y_i)_{i=1}^{L}$ and with mild abuse of notation let $y_{<i} = (y_1, \ldots, y_{i-1})$ for each $i = 2, \ldots, L$ and $y_{<1} = 0$.

Assumption (conditional independence)

For each $i = 1, \ldots, L$, 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:[1]

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

[1] For notational simplicity we have written $p_w(\cdot) \equiv p(\cdot \mid w)$ and $p_w(\cdot \mid \cdot) \equiv p(\cdot \mid \cdot, w)$.

Sequence-to-sequence setup

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

$$\boldsymbol{\omega}_i = \mathbf{WordEmbed}(w_i) \oplus \mathbf{CharEmbed}(w_i) \oplus \mathbf{BertEmbed}(w_i).$$

- **WordEmbed** is a simple lookup table.
- **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:

$$\boldsymbol{e} = (\boldsymbol{e}_i)_{i=0,\ldots,L} = \mathbf{BiLSTM}(\boldsymbol{\omega}).$$

($\boldsymbol{e}_0$ is the initial state and represents the root pseudo-node.)

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

$$\boldsymbol{d} = (\boldsymbol{d}_i)_{i=1,\ldots,L} = \mathbf{LSTM}((\mathbf{e}_i)_{i=1,\ldots,L}).$$

(the initial state of the decoder is the final state of the encoder.)

Classification tasks: quadratic classifier

Building on Dozat and Manning (2016).

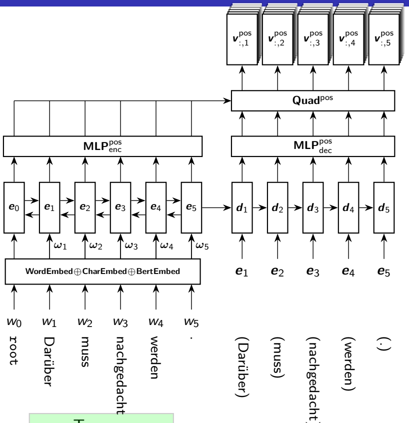
- Model conditional probabilities of y_i^{lab}, y_i^{ord}, y_i^{pos} and y_i^{morph}.
- Encoder and decoder are shared across tasks.

Example: part-of-speech classification.

$$\boldsymbol{e}_i^{\text{pos}} = \textbf{MLP}_{\text{enc}}^{\text{pos}}(\boldsymbol{e}_i); \quad \boldsymbol{d}_j^{\text{pos}} = \textbf{MLP}_{\text{dec}}^{\text{pos}}(\boldsymbol{d}_j).$$

- Obtain class *logits* $\boldsymbol{v}_{i,j}^{\text{pos}}$:

$$\boldsymbol{v}_{i,j}^{\text{pos}} = \textbf{Quad}^{\text{pos}}(\boldsymbol{e}_i^{\text{pos}}, \boldsymbol{d}_j^{\text{pos}})$$



$$:= \boldsymbol{e}_i^{\text{pos}\mathsf{T}} \mathbf{U}_{\text{h-d}}^{\text{pos}} \boldsymbol{d}_j^{\text{pos}} + \boldsymbol{e}_i^{\text{pos}\mathsf{T}} \mathbf{U}_{\text{h-h}}^{\text{pos}} \boldsymbol{e}_i^{\text{pos}} + U_{\text{h}}^{\text{pos}} \boldsymbol{e}_i^{\text{pos}} + \boldsymbol{d}_j^{\text{pos}\mathsf{T}} \mathbf{U}_{\text{d-d}}^{\text{pos}} \boldsymbol{d}_j^{\text{pos}} + U_{\text{d}}^{\text{pos}} \boldsymbol{d}_j^{\text{pos}} + \boldsymbol{u}_{\text{bias}}^{\text{pos}}.$$

Fixing child w_j, the vector $\textbf{softmax}(\boldsymbol{v}_{i,j}^{\text{pos}})$ can be interpreted as a probability distribution over its parts of speech conditional on having an arc to w_i:

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

The pointer network: quadratic attention mechanism

Building on Dozat and Manning (2016)'s bi-affine mechanism and drawing from Vinyals et al. (2015).

- Obtain dimension-reduced representations:

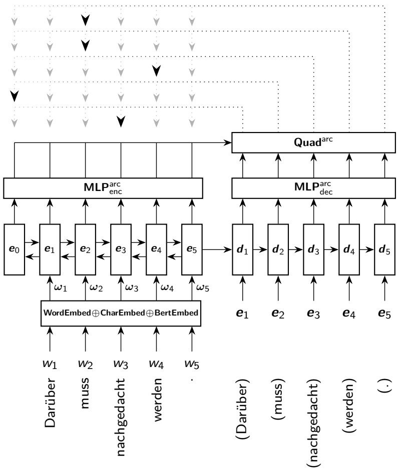
$$\boldsymbol{e}_i^{\text{arc}} = \mathbf{MLP}^{\text{arc}}_{\text{enc}_i}(\boldsymbol{e}_i); \quad \boldsymbol{d}_j^{\text{arc}} = \mathbf{MLP}^{\text{arc}}_{\text{dec}}(\boldsymbol{d}_j).$$

- Obtain *latent features* $\boldsymbol{v}_{i,j}^{\text{arc}}$:

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

- Obtain *attention logits* $s_{i,j}^{\text{arc}}$:

$$s_{i,j}^{\text{arc}} = \boxed{{\boldsymbol{u}^{\text{arc}}_{\text{agg}}}^{\mathsf{T}} \tanh(\boldsymbol{v}_{i,j}^{\text{arc}}).}$$



- Fixing child w_j, the vector $\mathbf{softmax}(\boldsymbol{s}_{:,j}^{\text{arc}})$ can be interpreted as a probability distribution over potential parents:

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

Inference and Training

Training

We find $\hat{p}$ using *SGD* with *Nesterov momentum*, finding a suitably low *cross-entropy* between the model p and the empirical distribution present in the dataset $(w^n, y^n)_{n=1}^N$:

$$
\begin{aligned}
&-\sum_{n=1}^{N} \log \prod_{i=1}^{L_n} \Big\{ p_w(y_i^{n\,\mathrm{arc}} \mid y_{<i}^n) p_w(y_i^{n\,\mathrm{lab}} \mid y_i^{n\,\mathrm{arc}}, y_{<i}^n) p_w(y_i^{n\,\mathrm{ord}} \mid y_i^{n\,\mathrm{arc}}, y_{<i}^n) \\
&\qquad \cdot p_w(y_i^{n\,\mathrm{pos}} \mid y_i^{n\,\mathrm{arc}}, y_{<i}^n) p_w(y_i^{n\,\mathrm{morph}} \mid y_i^{n\,\mathrm{arc}}, y_{<i}^n) \\
&= \mathrm{loss}^{\mathrm{arc}} + \mathrm{loss}^{\mathrm{lab}} + \mathrm{loss}^{\mathrm{ord}} + \mathrm{loss}^{\mathrm{pos}} + \mathrm{loss}^{\mathrm{morph}}.
\end{aligned}
$$

Inference

Given $w = (w_i)_{i=1}^L$, estimate $y = (y_i)_{i=1}^L$ by maximising the estimated conditional probability:

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

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

Model evaluation

The TIGER treebank is a widely-used corpus of ∼50 000 constituent 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 %.
- `PARSEVAL` metrics initially proposed by Black et al. (1991):

$$P = \frac{\#\text{ of correct constituents in prediction}}{\#\text{ of total constituents in prediction}}; \quad R = \frac{\#\text{ of correct constituents in prediction}}{\#\text{ of total constituents in reference}}.$$

Model	F1	Disc. F1
Coavoux et al. (2019)	82.7	55.9
Corro (2020)	90.0	62.1
F.-González & G.-Rodríguez (2022)	89.8	71.0
Chen & Komachi (2023)	89.6	70.9
This work	**90.59**	**84.74**

Table: Comparison of overall F1-score (%) and F1-score measured only on discontinuous constituents (disc. F1). Calculated using `disco-dop` (Van Cranenburgh et al., 2016) as standard practice. All models configured with BERT.

Model	`pos`	`morph` (avr)
Müller et al. (2013)	98.20	98.27
Schnabel & Schütze (2014)	97.50	97.76
Kondratyuk et al. (2018)	98.58	98.97
This work	**99.21**	**99.60**

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`.

Appendix: Mathematical justification for quadratic classifier

Notation has been simplified for presentational clarity. Single c is multinoulli and

$$\begin{bmatrix} \boldsymbol{e}_i \\ \boldsymbol{d}_j \end{bmatrix} \Bigg| \, c \sim \mathcal{N}\left(\begin{bmatrix} \boldsymbol{\mu}_c \\ \phi_c \end{bmatrix}, \begin{bmatrix} A_c & Q_c^\top \\ Q_c & B_c \end{bmatrix}^{-1} \right) \implies \mathbf{d}_j \mid c \sim \mathcal{N}\left(\phi_c, P_c^{-1}\right).$$

The conditional log-probability of c is the following affine quadratic form:

$$\begin{aligned} \log p(c \mid \boldsymbol{e}_i, \boldsymbol{d}_j) &= k_c - \frac{1}{2}\Big((\boldsymbol{e}_i - \boldsymbol{\mu}_c) + A_c^{-1} Q_c^\top (\boldsymbol{d}_j - \phi_c)\Big)^\top A_c \Big((\boldsymbol{e}_i - \boldsymbol{\mu}_c) + A_c^{-1} Q_c^\top (\boldsymbol{d}_j - \phi_c)\Big) \\ &\quad - \frac{1}{2}(\mathbf{d}_j - \phi_j)^\top P_c (\mathbf{d}_j - \phi_j) - \log p(\mathbf{e}_i, \mathbf{d}_j) \end{aligned}$$

$$\begin{aligned} = &- \boxed{\boldsymbol{e}_i^\top Q_c^\top \boldsymbol{d}_j} - \boxed{\frac{1}{2}\boldsymbol{e}_i^\top A_c \boldsymbol{e}_i} - \boxed{\frac{1}{2}\boldsymbol{d}_j^\top (P_c + Q_c A_c^{-1} Q_c^\top) \boldsymbol{d}_j} + \boxed{\left(\boldsymbol{\mu}_c^\top A_c + \phi_c^\top Q_c\right)\boldsymbol{e}_i} \\ &+ \boxed{(\phi_c^\top Q_c A_c^{-1} Q_c^\top \phi^\top P_c + \boldsymbol{\mu}_c^\top Q_c^\top)\boldsymbol{d}_j} \\ &\boxed{\begin{aligned} &-\boldsymbol{\mu}_c^\top Q_c^\top \phi_c - \frac{1}{2}\boldsymbol{\mu}_c^\top A_c \boldsymbol{\mu}_c \\ &-\frac{1}{2}\phi^\top (P_c + Q_c A_c^{-1} Q_c^\top)\phi + k_c \end{aligned}} \\ &\boxed{- \log p(\mathbf{e}_i, \mathbf{d}_j)} \end{aligned}$$

$$= c\text{th row of } \boldsymbol{e}_i^\top \mathbf{U}_{\text{h-d}} \boldsymbol{d}_j + \boldsymbol{e}_i^\top \mathbf{U}_{\text{h-h}} \boldsymbol{e}_i + \boldsymbol{d}_j^\top \mathbf{U}_{\text{d-d}} \boldsymbol{d}_j + U_{\text{h}} \boldsymbol{e}_i + U_{\text{d}} \boldsymbol{d}_j + \boldsymbol{u}_{\text{bias}}.$$

constant in c
so throw away

Memory-efficient implementation: assuming conditional normality:

$$v_{i,j}^c = k^c - \| W_1^c \boldsymbol{e}_i + W_2^c \boldsymbol{d}_j + \boldsymbol{w}_3^c \|_2^2.$$

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