# Non-projective Dependency-based Pre-Reordering with Recurrent Neural Network for Machine Translation

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University of Pisa, Italy

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**die Frau hat gekauft die Katze .**
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  - ☺Trained on word alignments, exploit syntax
  - ☹Only **tree-local** swaps, only constituency or **projective** dependency syntax
- Syntax-free statistical [Tromble and Eisner, 2009, ...]
  - ☺Trained on word alignments
  - ☹Don't exploit syntax, only word pair features

# Example

auf diese Weise wird die raffinierte Undurchsichtigkeit geschickt aufrechterhalten ; während der Euro ″ stark und stabil ″ sein sollte und die Währungsreserven anfangs lediglich zur Verteidigung während des Übergangszeitraums ( falls notwendig ) dienen sollten , erweist sich heute , daßweder die eine noch die andere dieser Behauptungen zutreffend waren und sich in Frankfurt überhaupt nichts tut !

*the issue therefore remains skilfully blurred ; while the euro was intended to be ´ strong and stable ´ and the reserve assets were originally intended to provide protection during the transitional period ( should this prove necessary ) , it now appears that neither of these expectations has been fulfilled and Frankfurt is totally deadlocked !*

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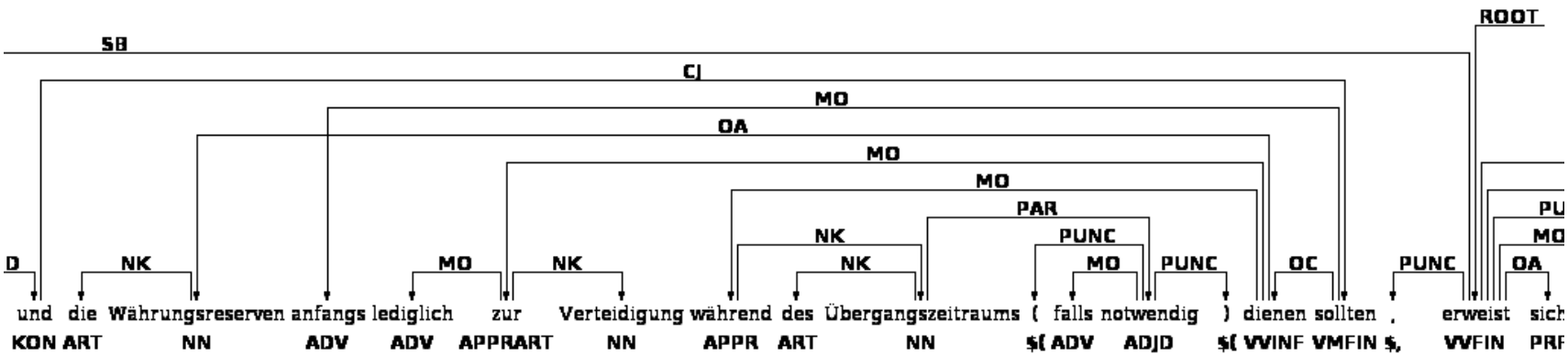


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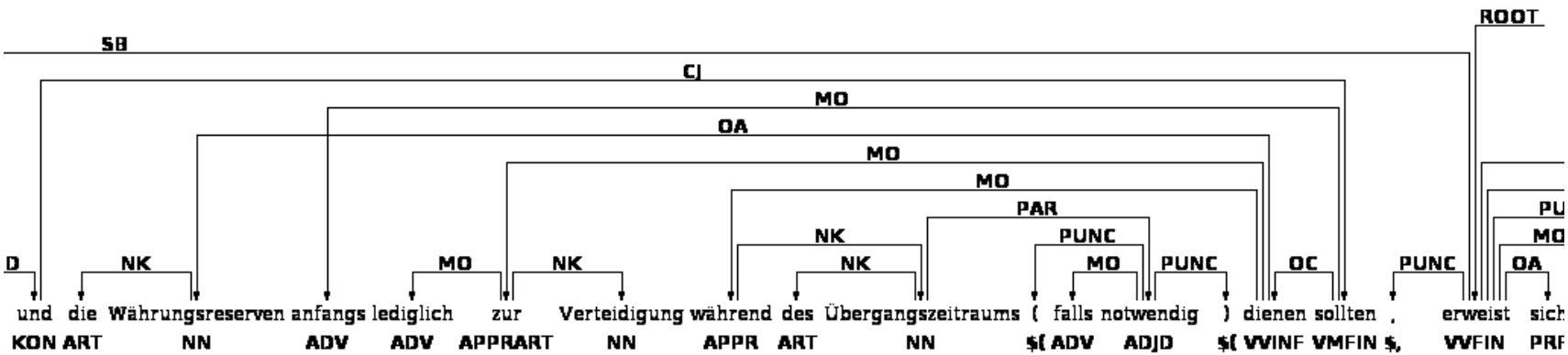


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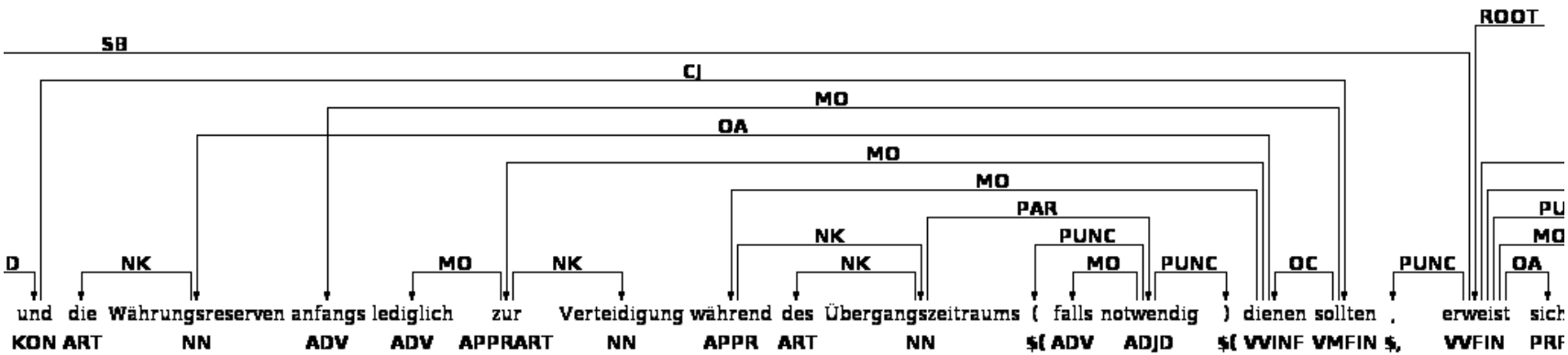


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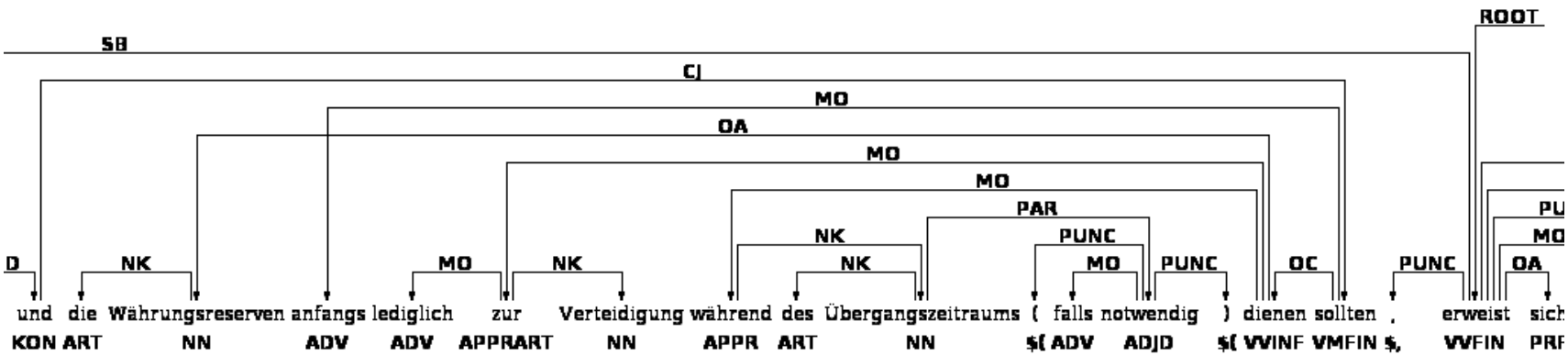


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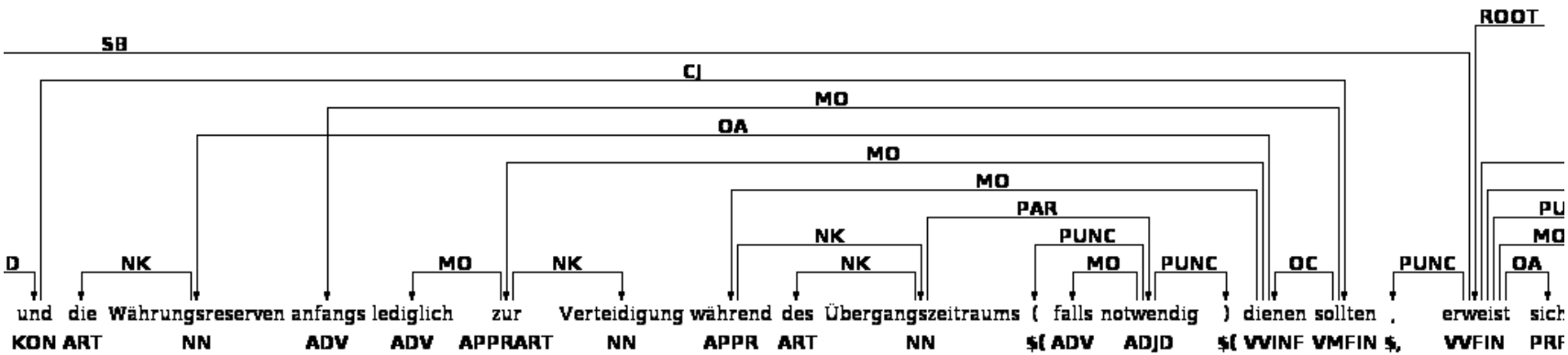


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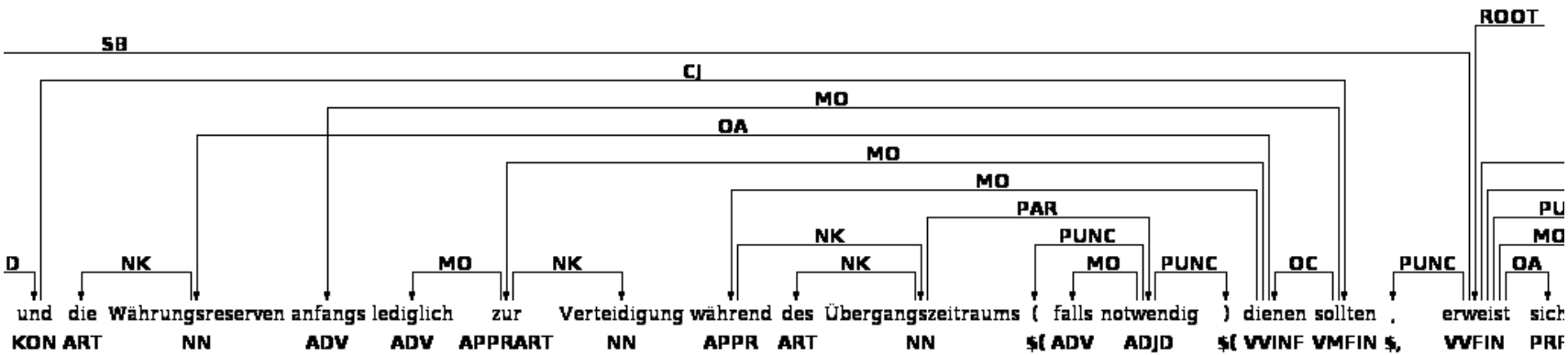


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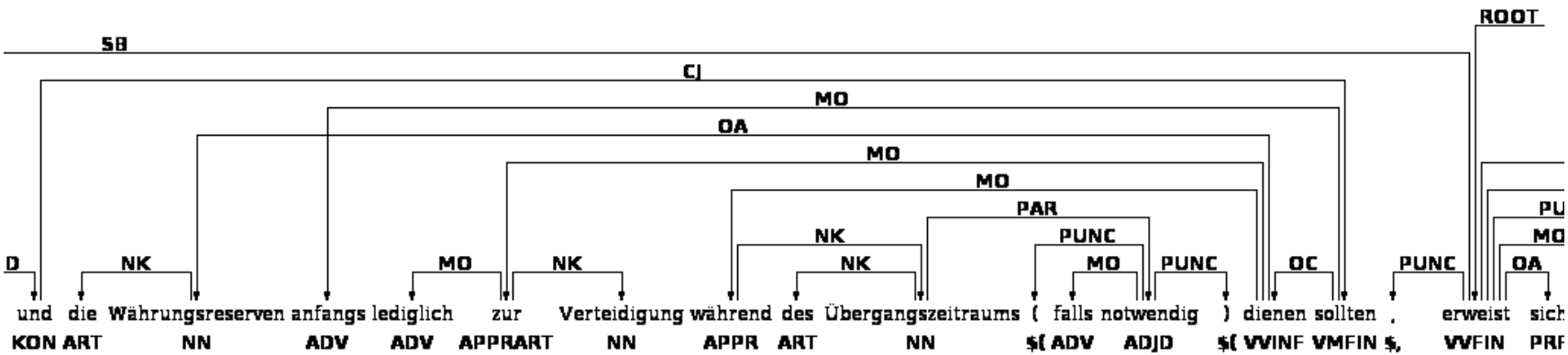


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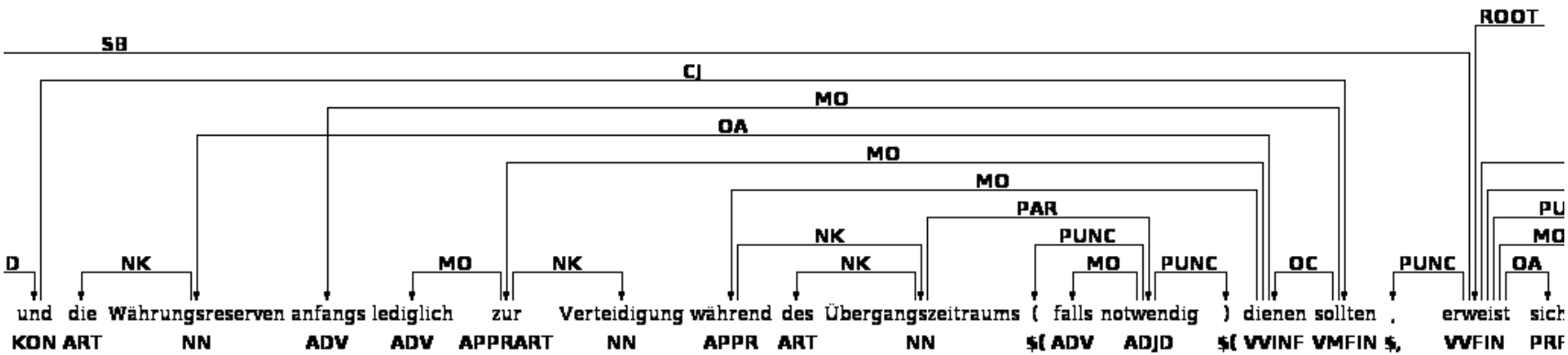


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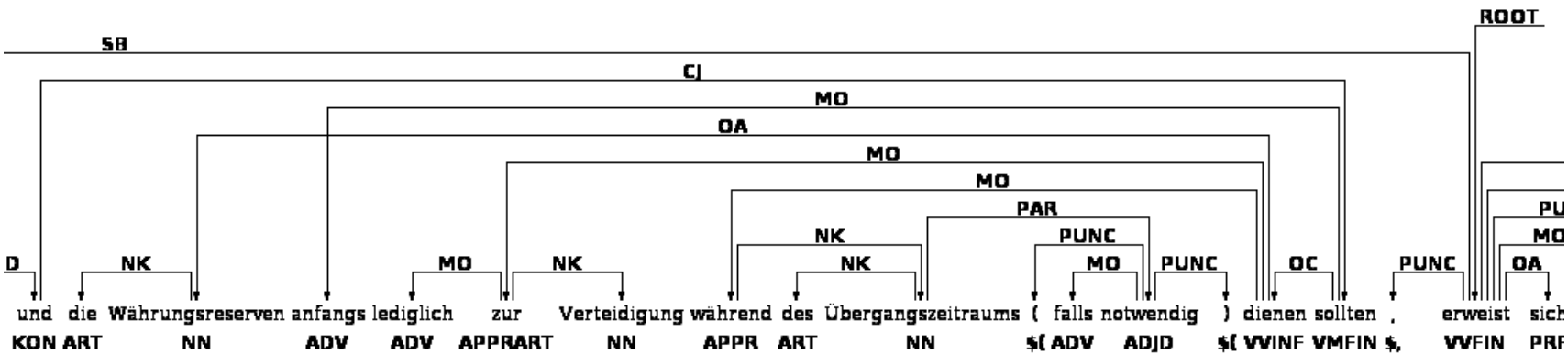


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  - ☺Tried and tested approach [Feng et al. 2010, ...]
  - ☹Positive probability mass to non-permutations
  - ☹NNLMs have performance issues due to normalization over dictionary

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$$
\begin{aligned}
v(t) &= \tau(\Theta^{(1)} \cdot x(t) + \Theta^{REC} \cdot v(t-1)) \\
h_j(t) &= < \tau(\Theta^{(o)} \cdot x_o(j)), \theta^{(2)} \odot v(t-1) > \\
&\quad + \theta^{(\alpha)} \cdot \log(L_f - t) + \theta^{(bias)} \qquad (1) \\
p_j(t) &= \frac{\exp h_j(t)}{\sum_{j'} \exp h_{j'}(t)}
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# Results

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Monolingual BLEU:

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| none | 62.10 | |
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| Europarl | Collins | 33.52 | +0.52 |
| Europarl | unlex. Base RNN-RM | 33.41 | +0.41 |
| Europarl | lex. Base RNN-RM | 33.38 | +0.38 |
| news2013 | baseline | 18.80 | |
| news2013 | Collins | NA | NA |
| news2013 | unlex. Base RNN-RM | 19.19 | +0.39 |
| news2013 | lex. Base RNN-RM | 19.01 | +0.21 |
| news2009 | baseline | 18.09 | |
| news2009 | **Collins** | 18.74 | **+0.65** |
| news2009 | unlex. Base RNN-RM | 18.50 | +0.41 |
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  - Predict permutation at word level, including fragments as features

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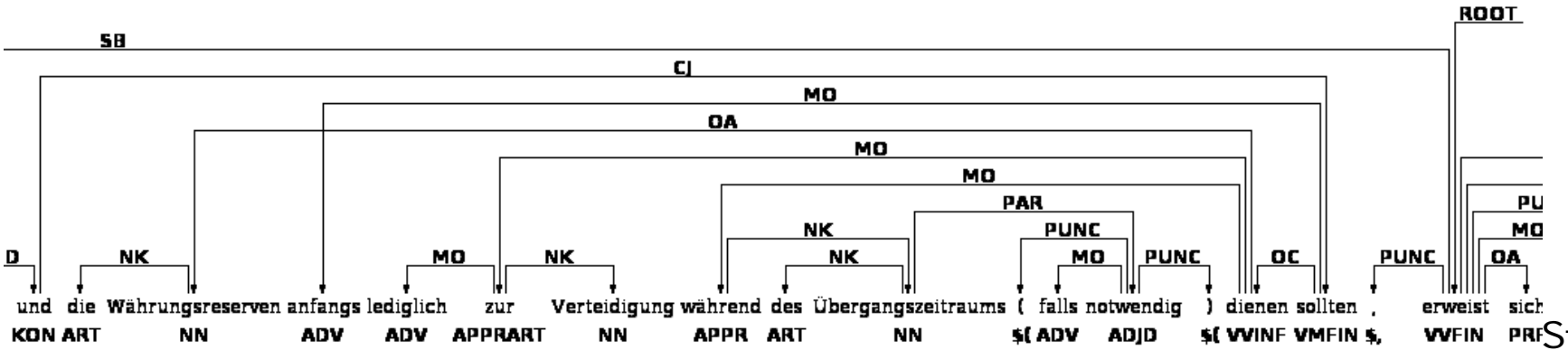


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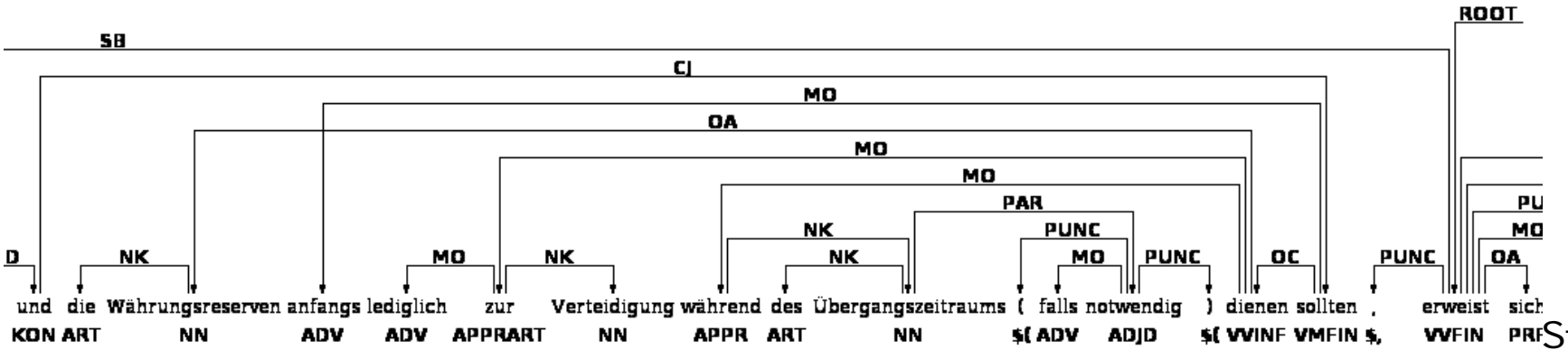


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- $DOWN_{dienen}$ $DOWN_{Wahr...}$ $DOWN_{die}$ *EMIT* **die**

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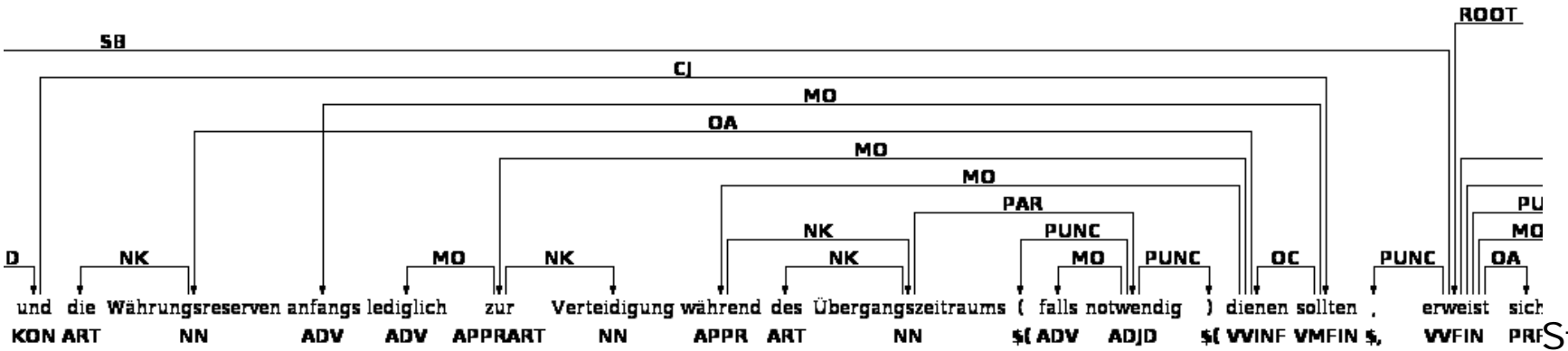


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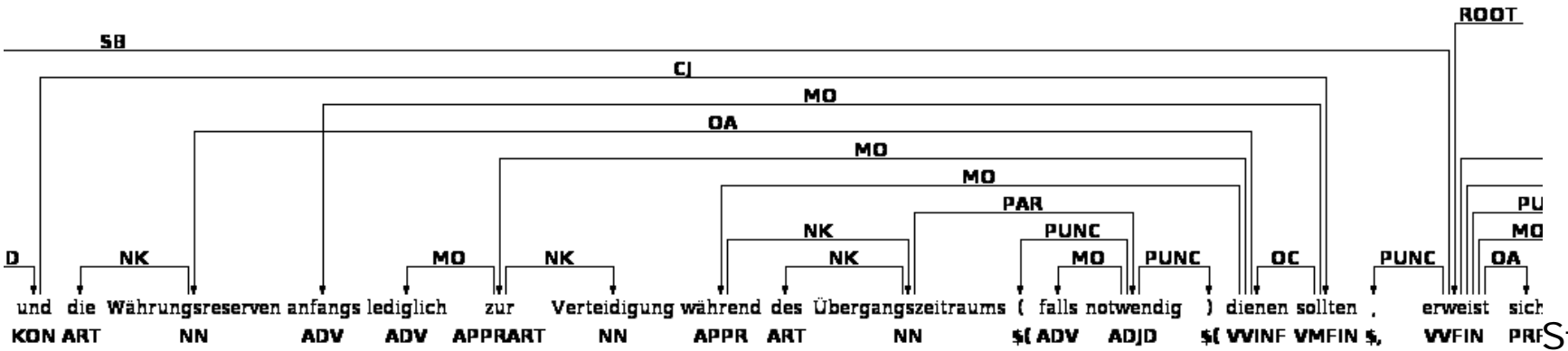


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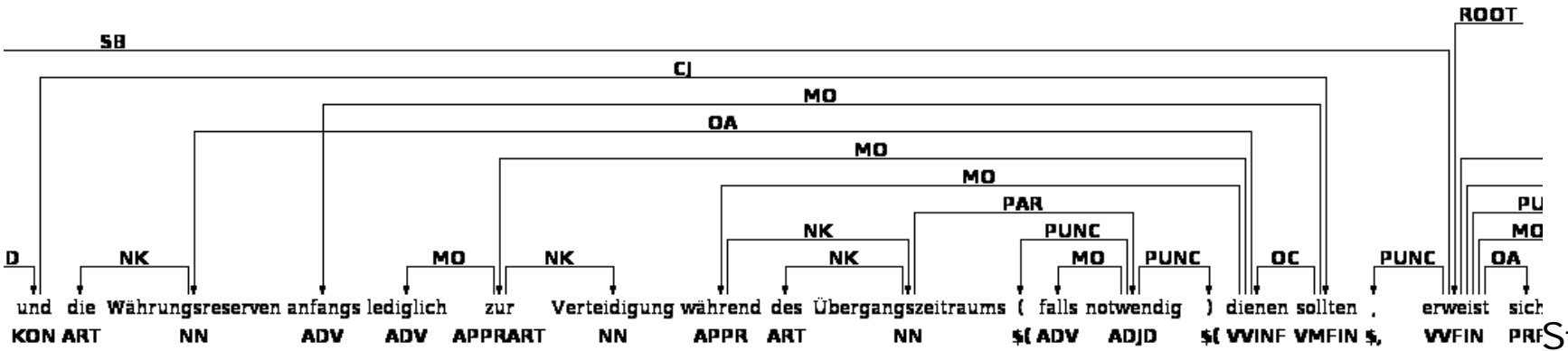


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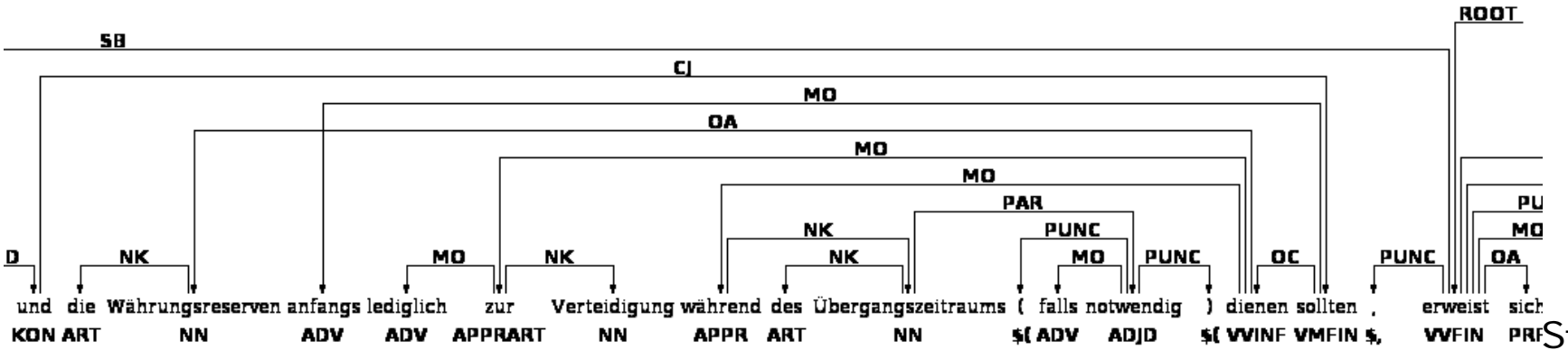


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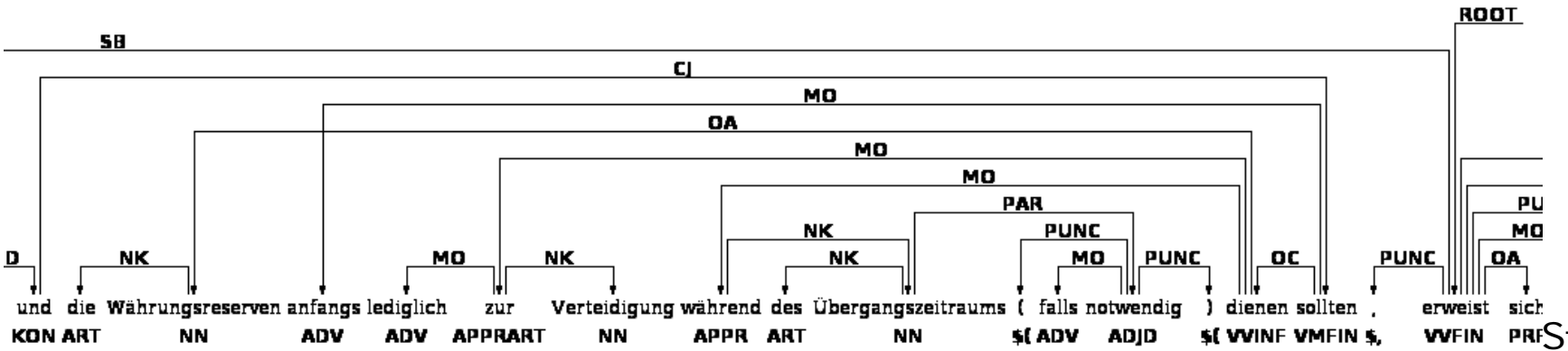


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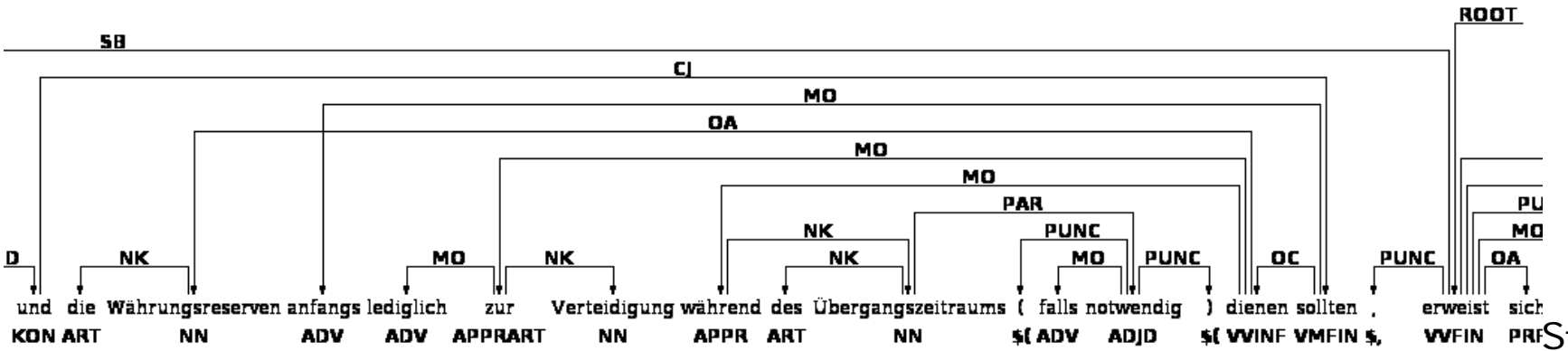


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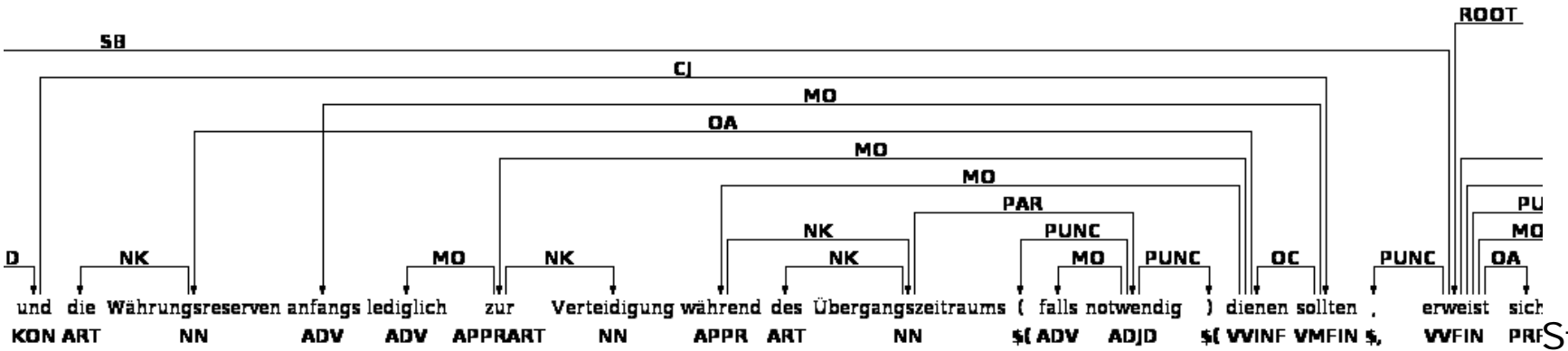


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$$
\begin{aligned}
v_{rst}(t) &= \pi(\Theta^{(1)}_{rst} \cdot x(t) + \Theta^{REC}_{rst} \cdot v(t-1)) \\
v_{upd}(t) &= \pi(\Theta^{(1)}_{upd} \cdot x(t) + \Theta^{REC}_{upd} \cdot v(t-1)) \\
v_{raw}(t) &= \tau(\Theta^{(1)} \cdot x(t) + \Theta^{REC} \cdot v(t-1) \odot v_{upd}(t)) \\
v(t) &= v_{rst}(t) \odot v(t-1) + (1 - v_{rst}(t)) \odot v_{raw}(t)
\end{aligned}
\tag{3}
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| news2013 | **unlex. Base GRU-RM** | 19.28 | **+0.48** |
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Thanks for your attention

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Thanks for your attention
Questions?