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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  - ☺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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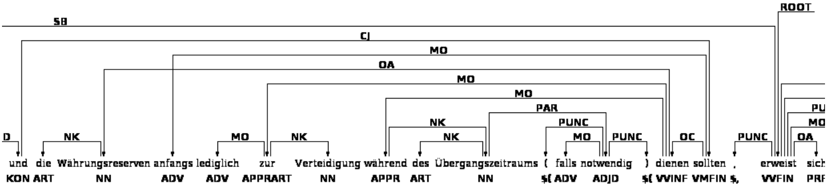

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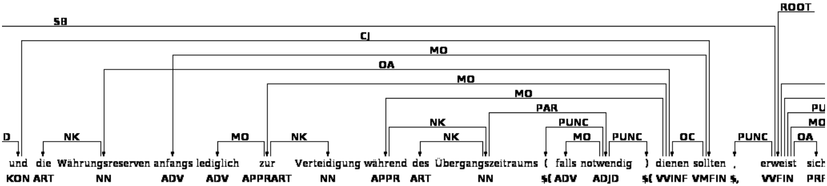

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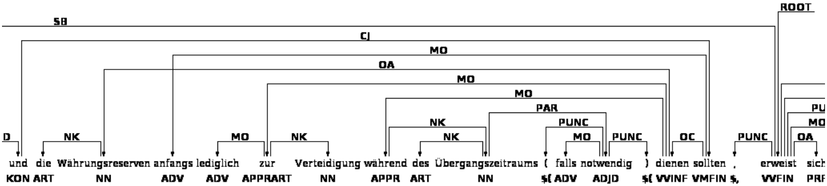

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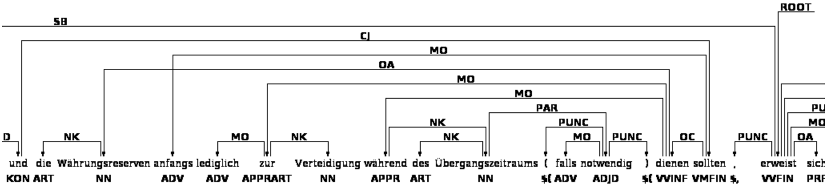

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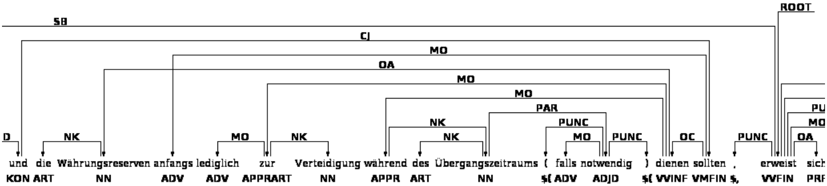

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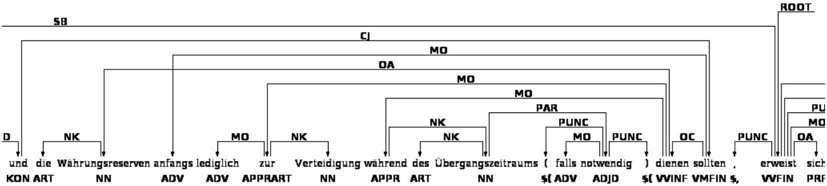

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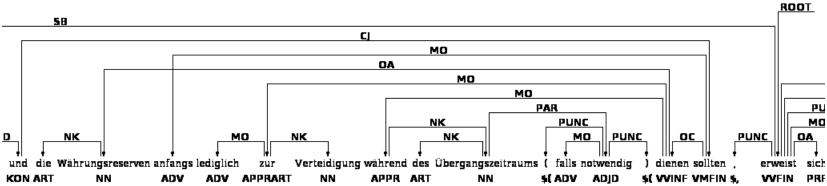

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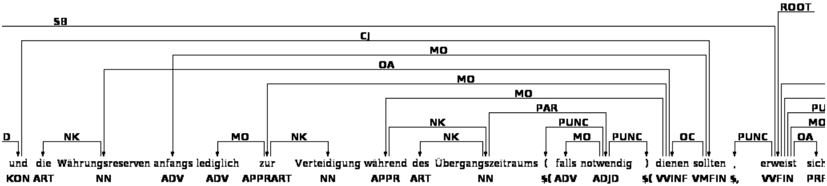

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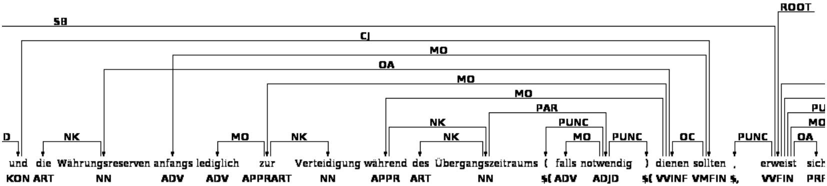

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  - ☹NNLMs have performance issues due to normalization over dictionary

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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)} \\
p_j(t) &= \frac{\exp h_j(t)}{\sum_{j'} \exp h_{j'}(t)}
\end{aligned}
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Reordering	BLEU	improvement
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  - Predict permutation at word level, including fragments as features

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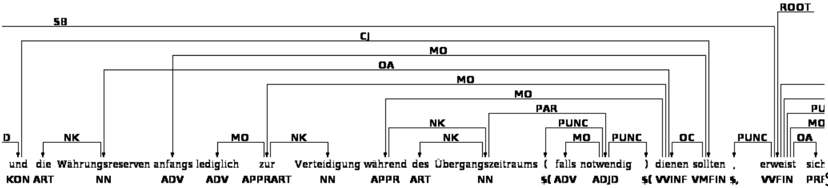

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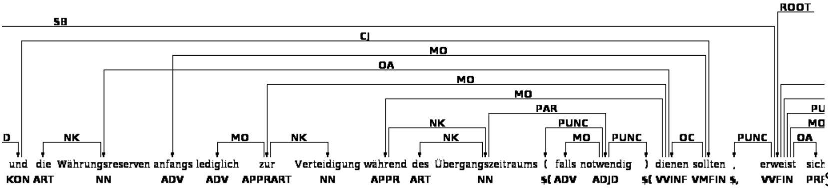

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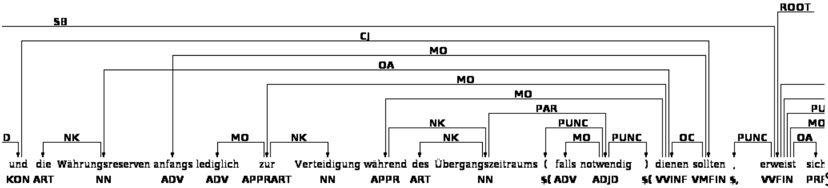

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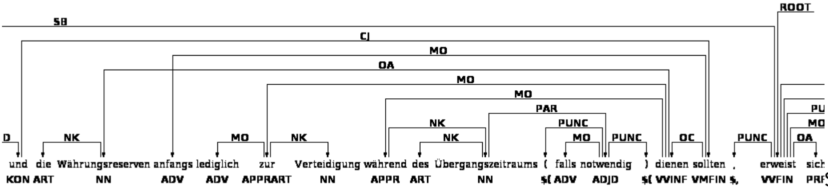

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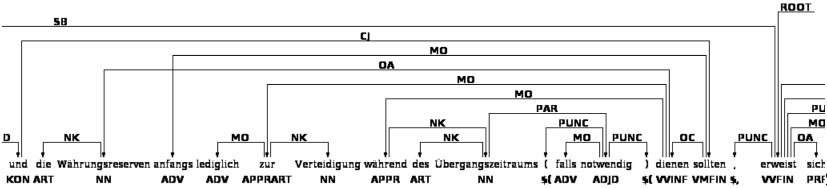

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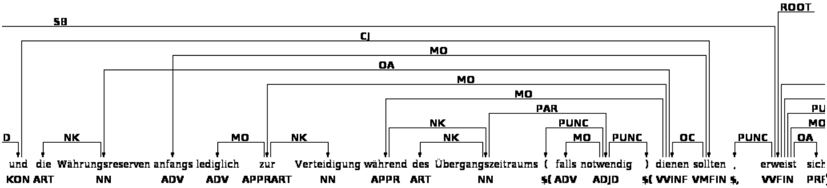

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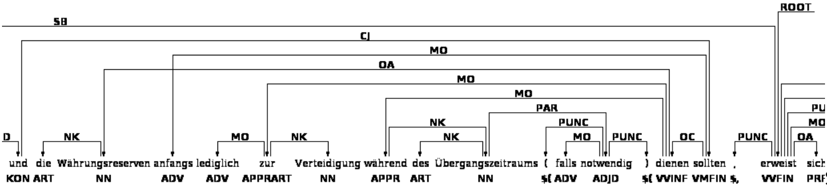

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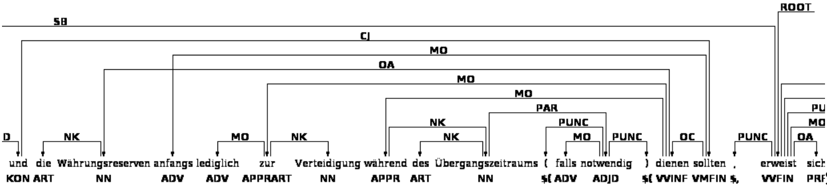

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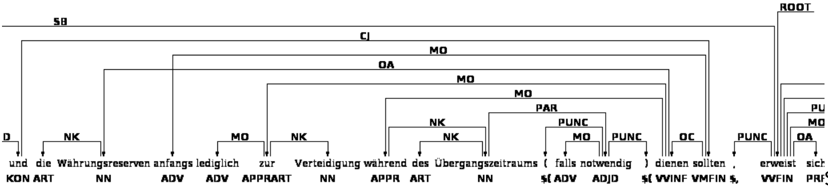

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Translation BLEU:

Test set	system	BLEU	improvement
Europarl	baseline	33.00	
Europarl	"oracle"	41.80	+8.80
Europarl	Collins	33.52	+0.52
Europarl	unlex. Base RNN-RM	33.41	+0.41
Europarl	lex. Base RNN-RM	33.38	+0.38
Europarl	unlex. Fragment RNN-RM	33.54	+0.54
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
news2013	unlex. Fragment RNN-RM	19.27	+0.47
news2009	baseline	18.09	
news2009	**Collins**	18.74	**+0.65**
news2009	unlex. Base RNN-RM	18.50	+0.41
news2009	lex. Base RNN-RM	18.44	+0.35
news2009	unlex. Fragment RNN-RM	18.60	+0.51

☹Slow! $O(L^3)$.

Results

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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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Questions?