

Tree-Planted Translation for Free-Order, Case-Marking Languages

Motivation

- **Free-order, case-marking languages** tend to require more for adequate machine translation.^{[1][2]}
- Many languages do not have the scale of data required to **implicitly** pick up this more fluid morphosyntactic structure.
- **Can we explicitly teach syntactic structure?**

Method

- Supervised attention through **Tree-Planting**^[3]
- Model dependency graph and train attention head on distance
- Claim: **training efficiency** of syntactic language models with **inference efficiency** of transformers

[1] Arianna Bisazza, Ahmet Üstün, Stephan Sportel; On the Difficulty of Translating Free-Order Case-Marking Languages. *Transactions of the Association for Computational Linguistics* 2021; 9 1233–1248.

[2] Gabriele Sarti, Arianna Bisazza, Ana Guerbero-Arenas, and Antonio Toral. 2022. DivEMT: Neural Machine Translation Post-Editing Effort Across Typologically Diverse Languages. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 7795–7816, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

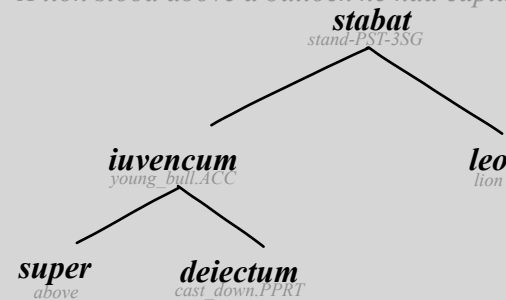
[3] Ryo Yoshida, Taiga Someya, and Yohei Oseki. 2024. Tree-Planted Transformers: Unidirectional Transformer Language Models with Implicit Syntactic Supervision. In *Findings of the Association for Computational Linguistics: ACL 2024*, pages 5120–5134, Bangkok, Thailand. Association for Computational Linguistics.

[4] Gil Rosenthal. 2023. Machina cognoscens: Neural machine translation for latin, a case-marked free-order language.

[5] Milan Straka, Jana Straková, and Federica Gamba. 2024. ÚFAL LatinPipe at EvaLatin 2024: Morphosyntactic Analysis of Latin. In *Proceedings of the Third Workshop on Language Technologies for Historical and Ancient Languages (LT4HALA) @ LREC-COLING-2024*, pages 207–214, Torino, Italia. ELRA and ICCL.

[6] Shikhar Murty, Pratyusha Sharma, Jacob Andreas & Christopher D. Manning. 2023. Characterizing intrinsic compositionality in language models with tree projections. In *ICLR 2023: The eleventh International Conference on Learning Representations*. Kigali.

Super iuvenum stabat deiectum leo.
A lion stood above a bullock he had captured.



	<i>super</i>	<i>iuvenum</i>	<i>stabat</i>	<i>deiectum</i>	<i>leo</i>
<i>super</i>	0.59	0.21	0.081	0.081	0.029
<i>iuvenum</i>	0.16	0.44	0.164	0.164	0.06
<i>stabat</i>	0.06	0.18	0.498	0.067	0.183
<i>deiect</i>	0.08	0.21	0.081	0.592	0.029
<i>leo</i>	0.03	0.08	0.23	0.031	0.624

↓(softmax)

	<i>super</i>	<i>iuvenum</i>	<i>stabat</i>	<i>deiectum</i>	<i>leo</i>
<i>super</i>	0.592	0.217	0.081	0.081	0.029
<i>iuvenum</i>	0.164	0.446	0.164	0.164	0.06
<i>stabat</i>	0.067	0.183	0.498	0.067	0.183
<i>deiect</i>	0.081	0.217	0.081	0.592	0.029
<i>leo</i>	0.031	0.084	0.23	0.031	0.624

Example

Construction of an attention supervision matrix for a short example sentence.

We convert the tree to an $\ell \times \ell$ **matrix** capturing the **syntactic distance between all word pairs**. We then convert the rows to a **probability distribution** using softmax.

The subword attention native to the model is converted to word-level attention by **averaging over the attention of all tokens within a word**.

This produces **two** $\ell \times \ell$ **matrices** which can then be **directly compared** using their KL Divergence - our loss function!

Results

† : baseline comparison

	BLEU	METEOR
Google Translate†	19.4	0.467
Rosenthal (2024)†	22.43	-
Finetune (10 epochs)	17.855	0.387
Finetune (30 epochs)	15.950	0.366
Tree-Planted	14.070	0.341

Experiments

- **Data:**
~100k **Classical Latin-English parallel sentences**^[4] and automatically-generated^[5] **dependency parses**
- **Baseline Model:**
Helsinki-NLP it-en finetuned for 30 epochs on **parallel sentences only**
- **Tree-Planted Model:**
Helsinki-NLP it-en finetuned for 10 epochs on **parallel sentences**, 20 epochs **both parallel sentences and trees**

Discussion

Tree-Planting seemed to **impede performance**. Potential causes:

- Syntactic knowledge may be implicitly encoded across neurons rather than within one head.
Next step: Probe model weights for implicit tree structure^[6] - is it impeding hierarchies, or are hierarchies not useful?
- Implementation may not be optimal. Italian tokenizer may not capture Latin morphology.
Next step: Train a tokenizer on Latin text specifically. Tune hyperparameters and tree-planted head configuration.