LSD GAČR project

LSD: Linguistic Structure Representation in Neural Networks

David Mareček, Jindřich Libovický, **Rudolf Rosa**, **Tomáš Musil**

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Charles University
Faculty of Mathematics and Physics
Institute of Formal and Applied Linguistics

Outline

Intro and Motivation

Word Embeddings and Morphology

Multi-head Self-attentions and Syntax

References

Intro and Motivation

Intro and Motivation

- Word embeddings and Deep neural networks perform great
- They do not have any explicit knowledge of linguistic abstractions
- How do they work? What emergent abstractions can we observe in them? How can we interpret them?
- Are the emergent structures and abstractions similar to classical linguistic structures and abstractions?

LSD project

Linguistic **S**tructure representation in **D**eep networks

- National Science Foundation of Czech Republic
- 2018 – 2020

Goals:

- Word embeddings and DNNs perform great.
- They do not have any explicit knowledge linguistic abstractions.
- How do they work? What abstractions can we observe in them? How do we interpret them?
- Are the emergent structures similar to classical linguistic structures?

LSD team

David Mareček

Jindřich Libovický

Rudolf Rosa

Tomáš Musil

Selected LSD results

Inspecting Word Embeddings using Principal Component Analysis (Musil, 2019)

- What features are important for word embeddings of various NLP tasks?

Derivational Morphological Relations in Word Embeddings (Musil et al., 2019)

- Unsupervised clustering of word-embedding differences captures derivational relations.

Neural Networks as Explicit Word-Based Rules (Libovický, 2019)

- We interpret a convolutional network for sentiment classification as word-based rules.

Looking for Syntax in Transformer Self-Attentions (Mareček and Rosa, 2019, 2018)

- Building constituency trees from multi-head self-attentions.

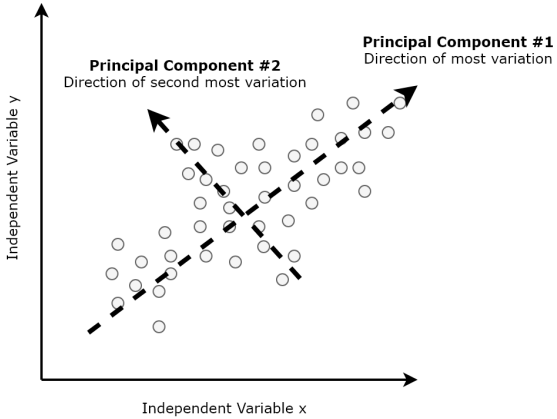
Word Embeddings and Morphology

Word Embeddings

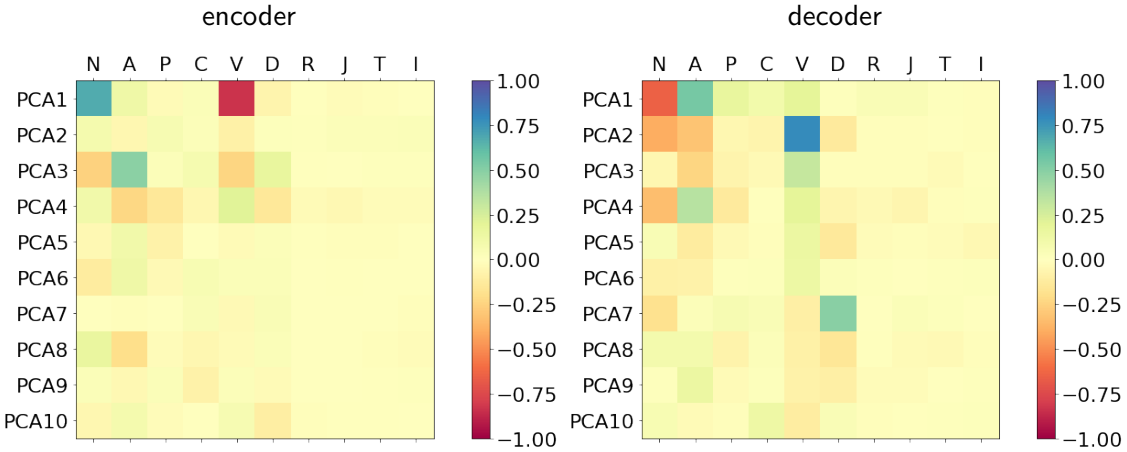
- A vector for each word (e.g. 100 dimensional, i.e. each word associated with a list of 100 real numbers)
- Learned in an unsupervised way from large plaintext corpora
- Observes the distributional hypothesis: words that appear in similar context have similar embeddings

Principal Component Analysis (PCA)

- Transformation to another orthogonal basis set
- 1st principal component has the largest possible variance across the data
- Each other principal component is orthogonal to all preceding components and has the largest possible variance.
- If something correlates with the highest principal components its possibly very important for the NLP task.

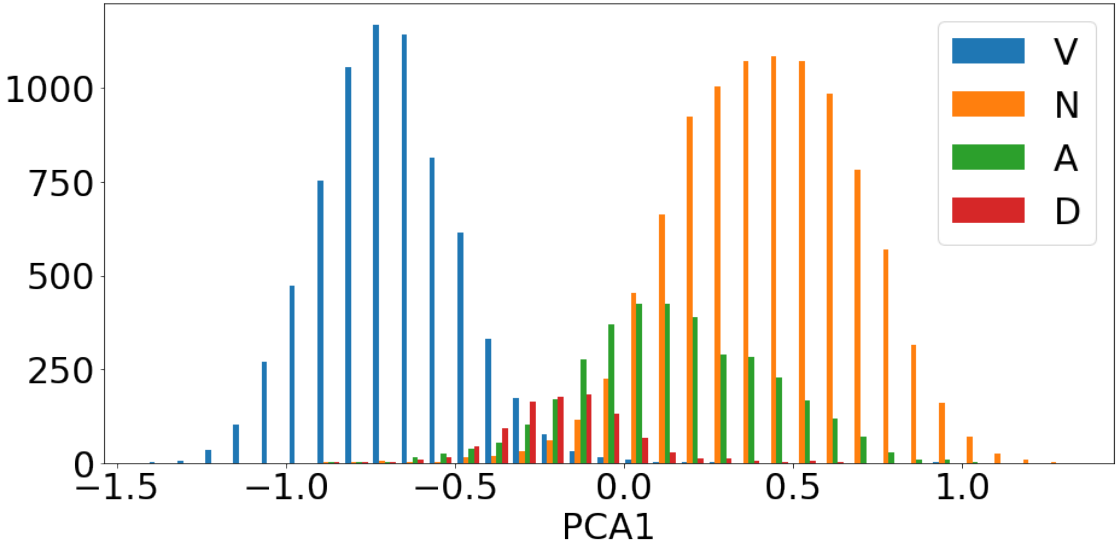


Word-embeddings learned by NMT, correlation with POS tags



N = Nouns, A = Adjectives, P = Pronouns, C = Numerals, V = Verbs,
D = Adverbs, R = Prepositions, J = Conjunctions, T = Particles, I = Interjections

Word-embedding space learnt by NMT encoder



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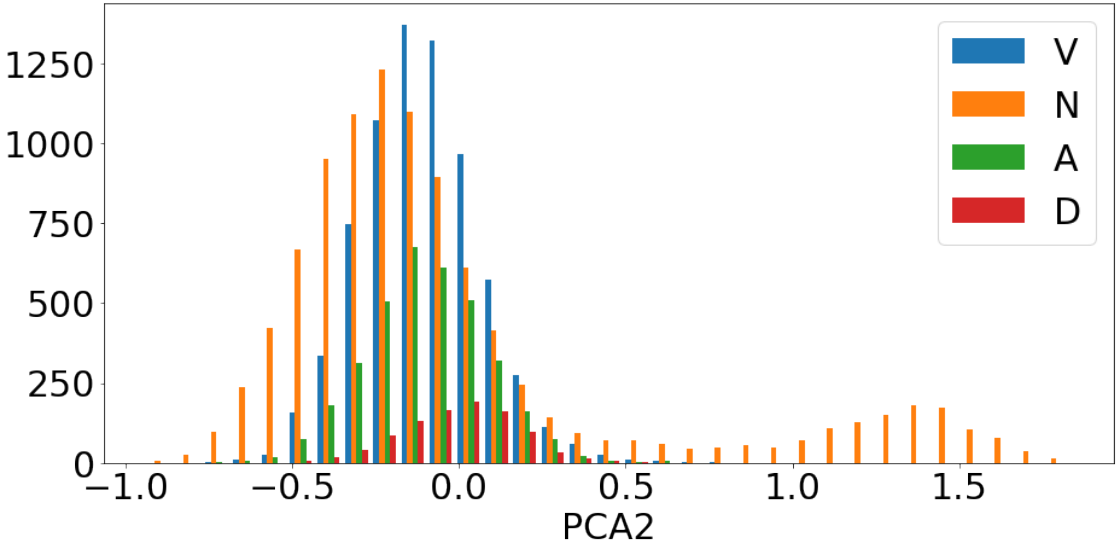
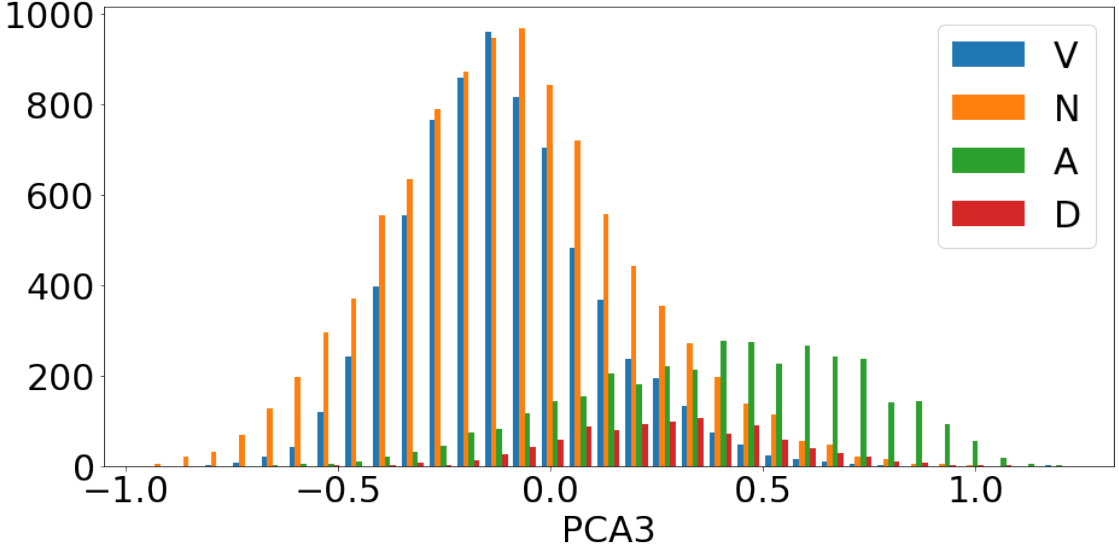


Word-embedding space learnt by NMT encoder



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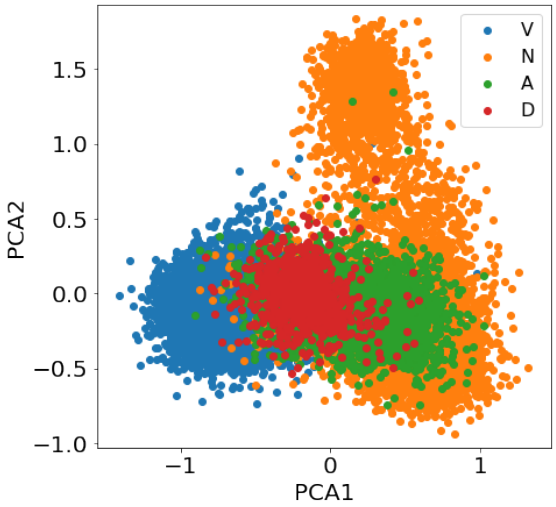
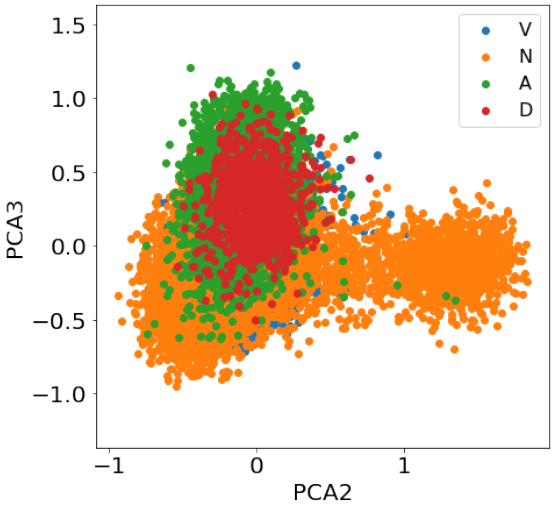
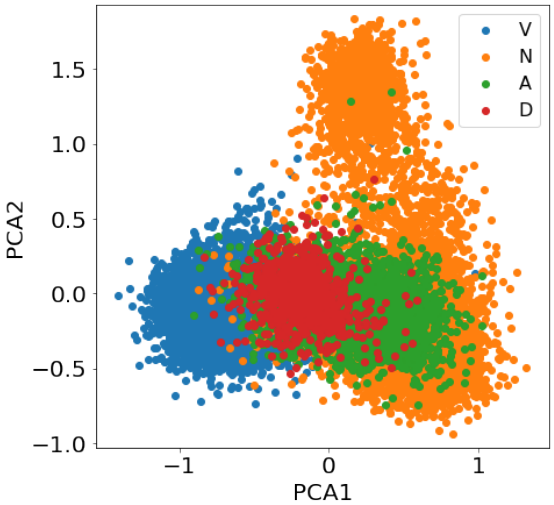




Word-embedding space learnt by NMT encoder



What is the separated island of Nouns visible in PCA2?

When we take a sample of words from this cluster, it contains almost exclusively named entities:

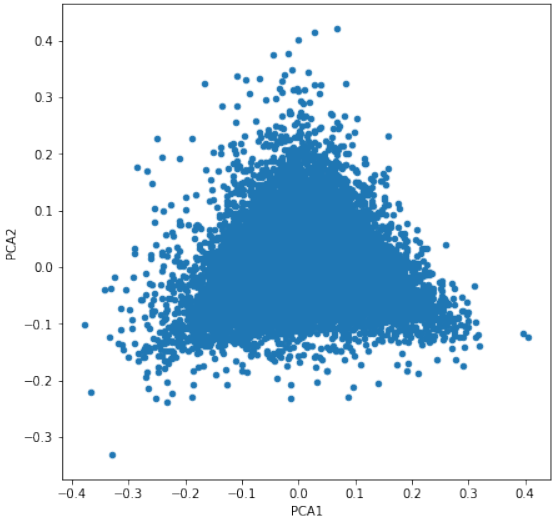
Fang, *Eliáš*, *Jož*, *Aenea*, *Bush*, *Eddie*, *Zlatoluna*, *Gordon*, *Bellondová*, *Hermiona*

Word-embedding space learnt by Sentiment Analysis

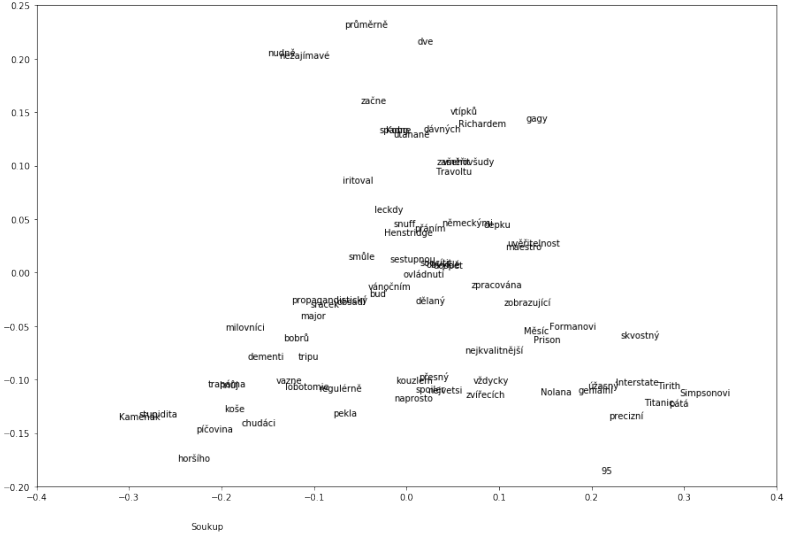
- Task: deciding whether a given text is emotionally positive, negative, or neutral.
- Trained on Czech ČSFD database (`https://www.csfd.cz/`), data were obtained from user comments and rankings of movies.
- Architecture: Convolutional neural network based on Kim (2014).

Neg: *"Very boring. I felt asleep."*

Pos: *"Great movie with super effects!!!"*

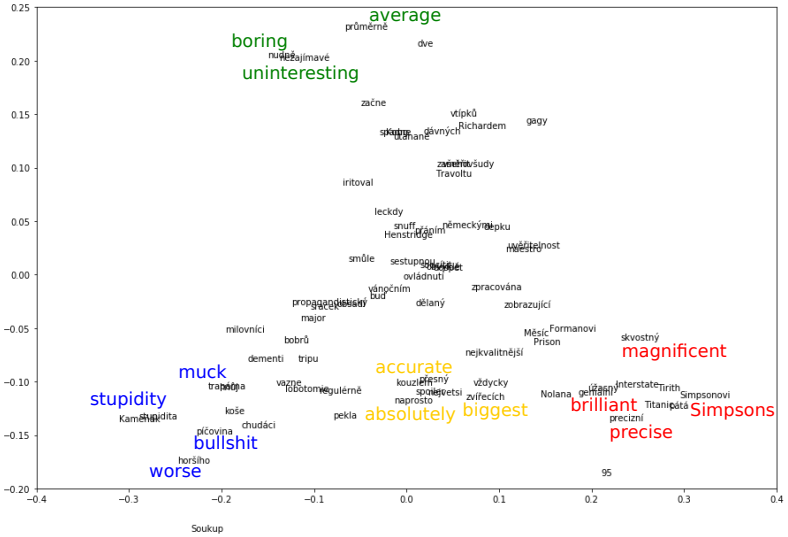


Word-embedding space learnt by Sentiment Analysis



We sampled some words from the vector space...

Word-embedding space learnt by Sentiment Analysis



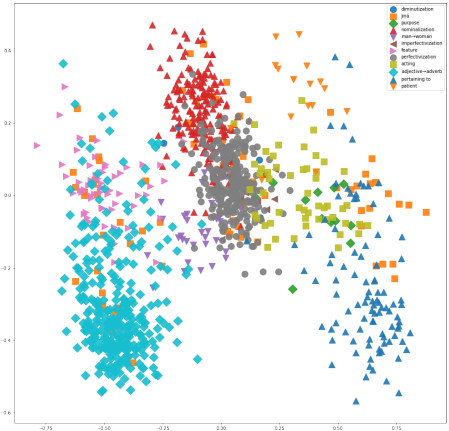
↔ ... polarity of the word

↕ ... intensity of the word

Word embedding space is shaped by the task for which it is trained.

Looking for derivational relations

e.g. kompenzovat – kompenzace (compensate – compensation)



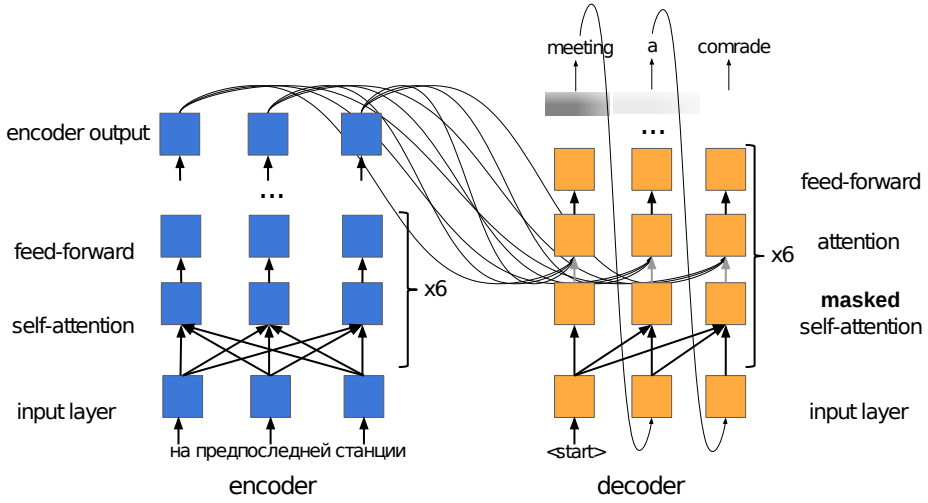
smutný – smutně letní – letně

Looking for ???

- Future work: meaning?

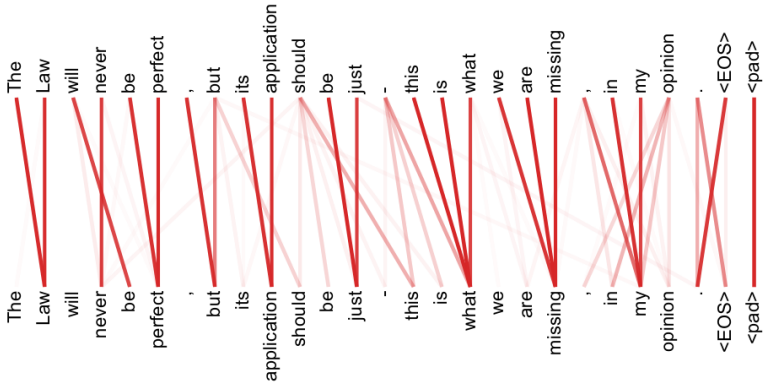
Multi-head Self-attentions and Syntax

Transformer NMT



Multi-headed Self-attention Mechanism

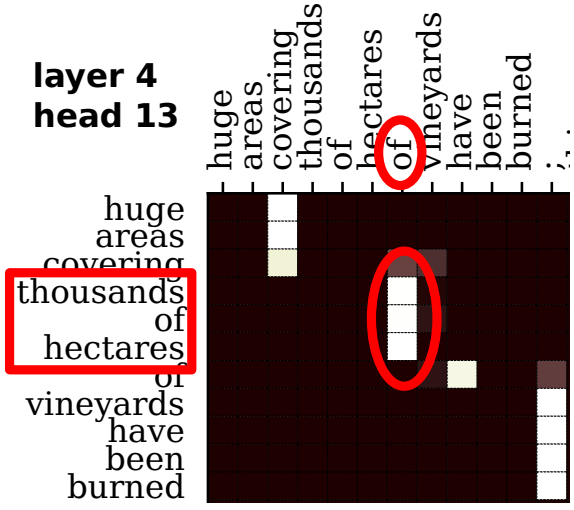
- Encoder: 16 attention heads $\times$ 6 layers
- Attention = weighted sum of "all" "words"
  - "word": contextual representation of word position from previous layer
  - "all": usually focused on just one word



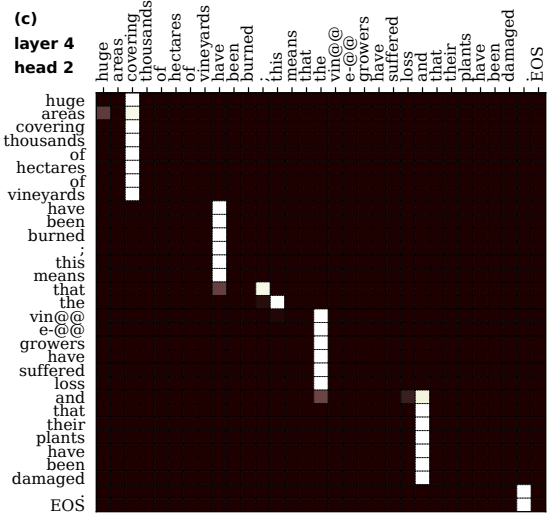
Source: Attention is all you need (Vaswani et al., 2017)

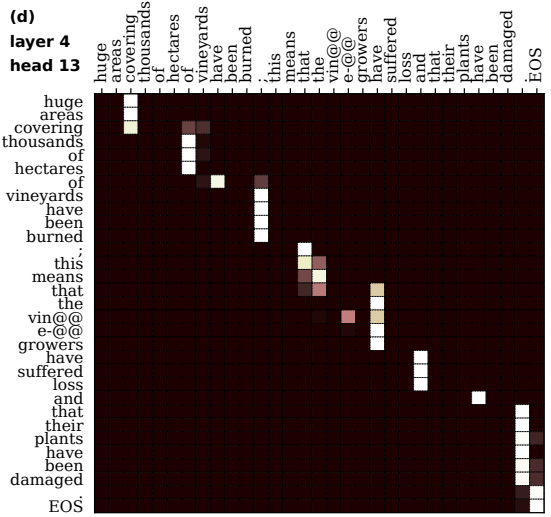
Observation

- Visualisation: matrix of attention weights
- Common pattern: balustrade
  - Baluster: continuous sequence of words attending to the same position
  - Looks like a syntactic phrase
  - Usually attends to phrase boundary
- Research questions
  - Is that syntactic?
  - To what extent?
  - What kind of syntax?

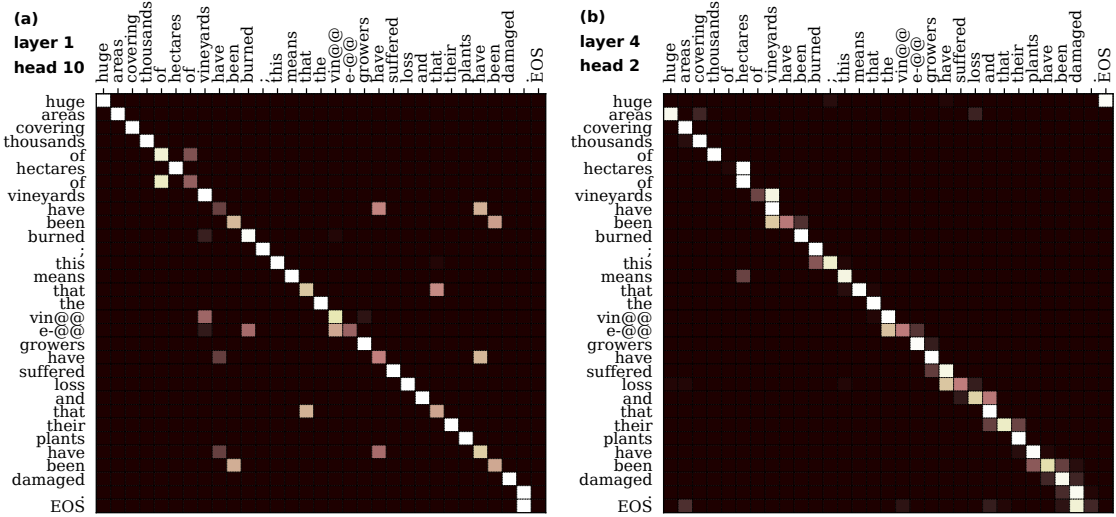


Balustrades (70% of the attention heads)

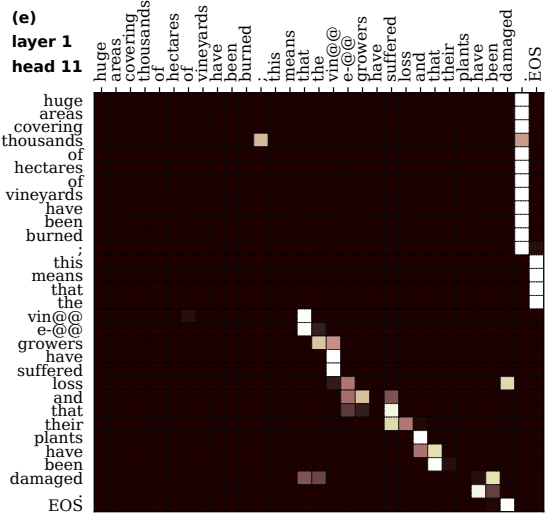


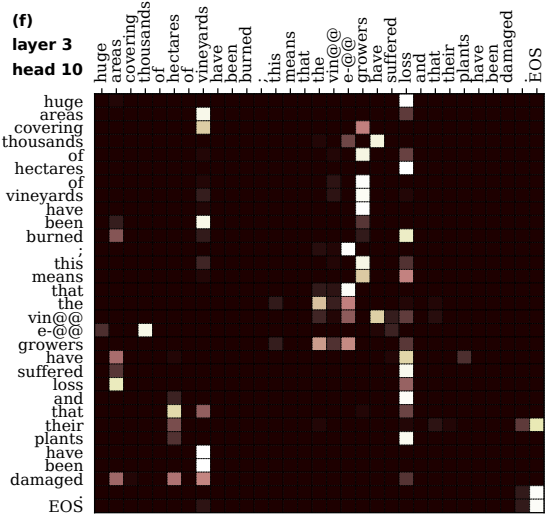


Diagonals (especially 1st layer)



Attend to end, mixed, scattered...

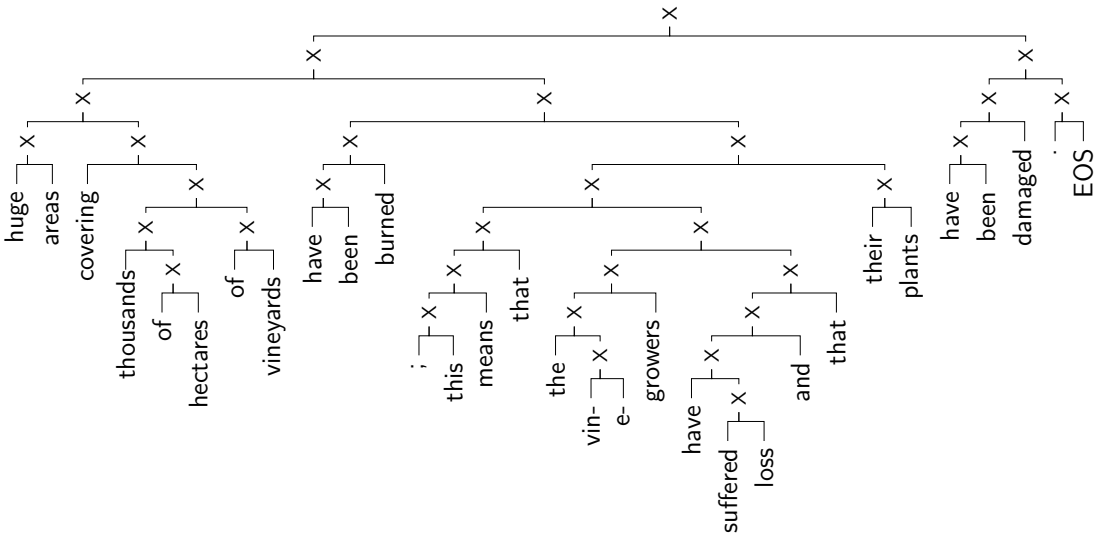




Approach

1. Transformer NMT: French $\leftrightarrow$ English, German $\leftrightarrow$ English, French $\leftrightarrow$ German
2. Balusters $\rightarrow$ phrase candidates
   - Phrase score: average attention weight (summed and equalized)
3. Phrase candidates $\rightarrow$ binary constituency tree
   - Linguistically uninformed algorithm
   - Tree score = sum of phrase scores
   - CKY: find tree with maximal score
4. Compare to standard constituency syntactic trees
   - Penn Treebank, French Treebank, Negra Corpus (via Stanford parser)
   - we observe a 40% match
   - baseline has a 30% match (right-aligned balanced binary tree)

Results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Analysis of results

- The emergent structures can be seen as syntactic to some extent
- Shorter phrases are often captured
- Sentence clauses are often captured

Summary

1. Word embeddings and neural networks are trained without linguistic information.
2. Examine emergent abstractions and structures!
3. Some morphology is captured.
4. Some syntax is captured.

https://ufal.cz/grants/lsd

References

Yoon Kim. Convolutional neural networks for sentence classification. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1746–1751, 2014. doi: 10.3115/v1/d14-1181. URL http://dx.doi.org/10.3115/v1/d14-1181.

Jindrich Libovický. Neural networks as explicit word-based rules. *CoRR*, abs/1907.04613, 2019. URL http://arxiv.org/abs/1907.04613.

David Mareček and Rudolf Rosa. Extracting syntactic trees from transformer encoder self-attentions. In *Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 347–349, Brussels, Belgium, November 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-5444. URL https://www.aclweb.org/anthology/W18-5444.

David Mareček and Rudolf Rosa. From balustrades to pierre vinken: Looking for syntax in transformer self-attentions. In *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 263–275, Florence, Italy, August 2019. Association for Computational Linguistics. URL https://www.aclweb.org/anthology/W19-4827.

Tomáš Musil. Examining structure of word embeddings with pca. In Kamil Ekštein, editor,

Text, Speech, and Dialogue, pages 211–223, Cham, 2019. Springer International Publishing. ISBN 978-3-030-27947-9.

Tomáš Musil, Jonáš Vidra, and David Mareček. Derivational morphological relations in word embeddings. In *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 173–180, Florence, Italy, August 2019. Association for Computational Linguistics. URL `https://www.aclweb.org/anthology/W19-4818`.