

Probing BERT for German Compound Semantics

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Motivation

- Noun compounds are ubiquitous yet challenging to model
- variable degrees of compositionality
 - cross-lingual differences in productivity & structures

We replicate a prior probing study of English BERT
(Miletić & Schulte im Walde, 2023)

- More challenging scenario of German
- closed spelling
 - higher compounding productivity
 - higher constituent-level ambiguity

Experimental setup

Corpus: DECOW16 → 11.6bn tokens
(Schäfer & Bildhauer, 2012; Schäfer, 2015)

Gold standard: GhoSt-NN → 868 NN compounds
(Schulte im Walde et al., 2016b)

Compound	Modifier	Head
<i>Erbensuppe</i> <i>pea soup</i>	<i>Erbse</i> <i>pea</i> 5.3	<i>Suppe</i> <i>soup</i> 5.3
<i>Eifersucht</i> <i>jealousy</i>	<i>Eifer</i> <i>zeal</i> 2.0	<i>Sucht</i> <i>addiction</i> 2.1

Sample compounds and ratings (scale 1–6)
for modifier and head compositionality

Models: German BERT {cased, uncased}
Tokens: modif, head, comp, cont, cls
Layers: all contiguous spans

Compositionality estimation:

- direct — pairwise cosine
- composite — ADD, MULT, COMB

Can BERT
capture degrees of
noun compound
compositionality
in German?

How does German BERT compare to prior work?

Approach	Modif.	Head
Our best result	0.332	0.433
Schulte im Walde et al. (2016a) LMI vectors; same data	0.490	0.590
Miletić & Schulte im Walde (2023) same method; English data	0.553	0.645

Best results in our study and related prior work (Spearman's ρ)

- Why the performance drop?
- inherently higher difficulty of the task for German
 - less efficient learning of semantics due to ambiguity
 - dataset differences, e.g. constituent family sets

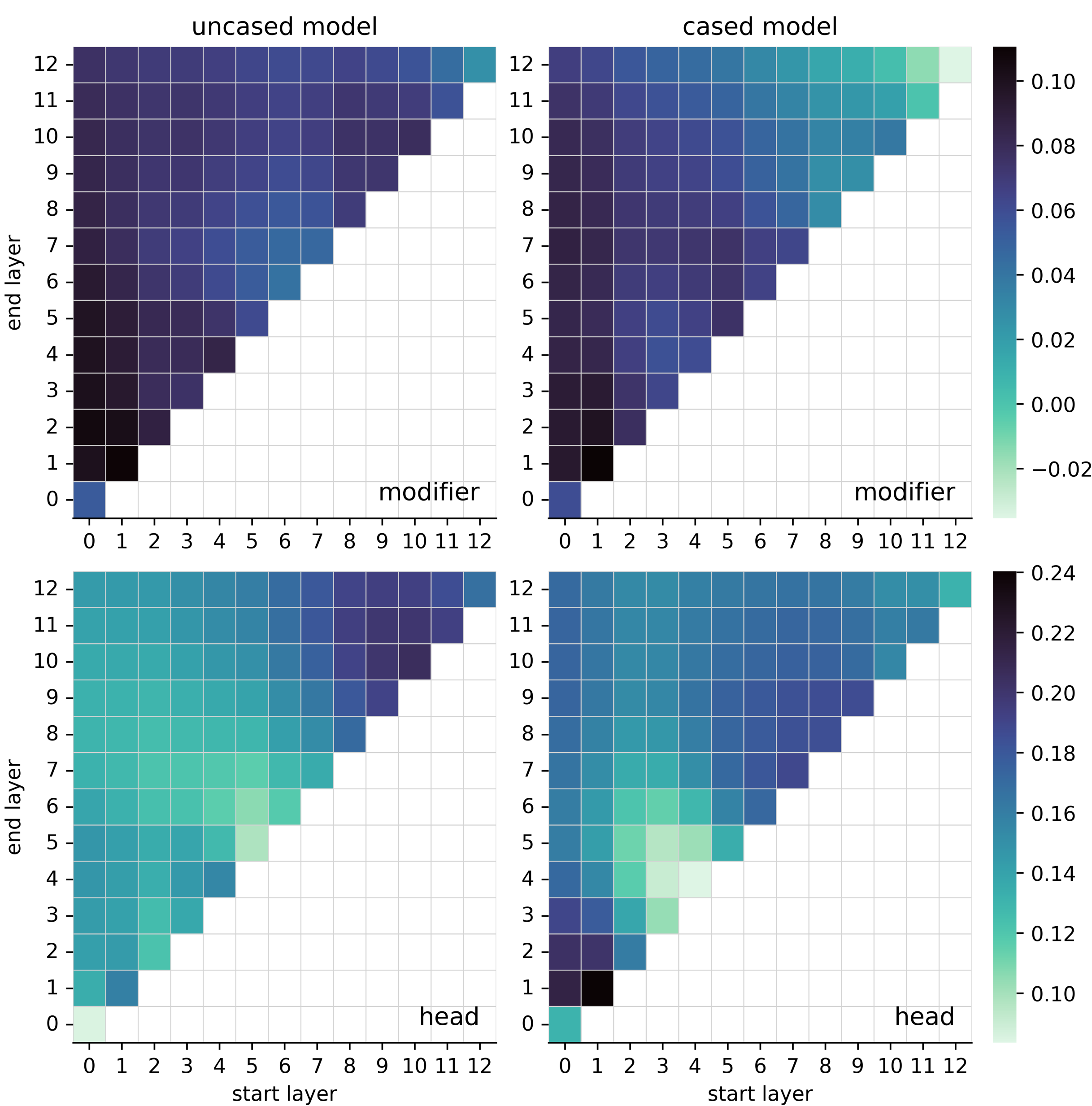
How do modeled tokens affect predictions?

Modifier		mod	head	comp	cont	cls
	mod		0.170	0.174	0.332	0.266
	head	0.170		0.130	0.019	0.024
	comp	0.174	0.130		0.154	0.113
	cont	0.332	0.019	0.154		0.123
Head	cls	0.266	0.024	0.113	0.123	
	mod		0.327	0.202	0.178	0.084
	head	0.327		0.290	0.433	0.246
	comp	0.202	0.290		0.318	0.149
	cont	0.178	0.433	0.318		0.096
	cls	0.084	0.246	0.149	0.096	

Best individual results obtained using direct comparisons of pairs of embeddings for modifier predictions (top) and head predictions (bottom).
Bold values are best in a column; shaded values are best overall.

Example: given the compound *Obstsajt*, we obtain predictions
comp-mod: $\cos(\text{Obstsajt}, \text{Obst})$; comp-head: $\cos(\text{Obstsajt}, \text{Sajt})$; etc.

Which layers & models best encode compositionality information?



Mean performance across contiguous spans of layers, defined by the start layer (x-axis) and end layer (y-axis). Left: uncased model; right: cased model.
Top: modifier predictions; bottom: head predictions.

References

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