Joint processing of linguistic properties in brains and language models

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Language models (LMs) predict brain activity evoked by complex language (e.g. listening a story) to an impressive degree



Brain alignment of a LM \Rightarrow how similar its representations are to a human brain's

Jain and Huth. Incorporating context into language encoding models for fMRI. (NeurIPS 2018) Toneva and Wehbe. Interpreting and improving natural-language processing (in machines) with natural language-processing (in the brain). (NeurIPS 2019) Language models (LMs) predict brain activity evoked by complex language (e.g. listening a story) to an impressive degree



Brain alignment of a LM \Rightarrow Why do language models have better brain alignment? What are the reasons?

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Language models (LMs) are trained to predict missing words

	Surface		Syntactic		Semantic							
Layer	SentLen (Surface)	WC (Surface)	TreeDepth (Syntactic)	TopConst (Syntactic)	BShift (Syntactic)	Tense (Semantic)	SubjNum (Semantic)	ObjNum (Semantic)	SOMO (Semantic)	CoordInv (Semantic)		
1	93.9 (2.0)	24.9 (24.8)	35.9 (6.1)	63.6 (9.0)	50.3 (0.3)	82.2 (18.4)	77.6 (10.2)	76.7 (26.3)	49.9 (-0.1)	53.9 (3.9)		
2	95.9 (3.4)	65.0 (64.8)	40.6 (11.3)	71.3 (16.1)	55.8 (5.8)	85.9 (23.5)	82.5 (15.3)	80.6 (17.1)	53.8 (4.4)	58.5 (8.5)		
3	96.2 (3.9)	66.5 (66.0)	39.7 (10.4)	71.5 (18.5)	64.9 (14.9)	86.6 (23.8)	82.0 (14.6)	80.3 (16.6)	55.8 (5.9)	59.3 (9.3)		
4	94.2 (2.3)	69.8 (69.6)	39.4 (10.8)	71.3 (18.3)	74.4 (24.5)	87.6 (25.2)	81.9 (15.0)	81.4 (19.1)	59.0 (8.5)	58.1 (8.1)		
5	92.0 (0.5)	69.2 (69.0)	40.6 (11.8)	81.3 (30.8)	81.4 (31.4)	89.5 (26.7)	85.8 (19.4)	81.2 (18.6)	60.2 (10.3)	64.1 (14.1)		
6	88.4 (-3.0)	63.5 (63.4)	41.3 (13.0)	83.3 (36.6)	82.9 (32.9)	89.8 (27.6)	88.1 (21.9)	82.0 (20.1)	60.7 (10.2)	71.1 (21.2)		
7	83.7 (-7.7)	56.9 (56.7)	40.1 (12.0)	84.1 (39.5)	83.0 (32.9)	89.9 (27.5)	87.4 (22.2)	82.2 (21.1)	61.6 (11.7)	74.8 (24.9)		
8	82.9 (-8.1)	51.1 (51.0)	39.2 (10.3)	84.0 (39.5)	83.9 (33.9)	89.9 (27.6)	87.5 (22.2)	81.2 (19.7)	62.1 (12.2)	76.4 (26.4)		
9	80.1 (-11.1)	47.9 (47.8)	38.5 (10.8)	83.1 (39.8)	87.0 (37.1)	90.0 (28.0)	87.6 (22.9)	81.8 (20.5)	63.4 (13.4)	78.7 (28.9)		
10	77.0 (-14.0)	43.4 (43.2)	38.1 (9.9)	81.7 (39.8)	86.7 (36.7)	89.7 (27.6)	87.1 (22.6)	80.5 (19.9)	63.3 (12.7)	78.4 (28.1)		
11	73.9 (-17.0)	42.8 (42.7)	36.3 (7.9)	80.3 (39.1)	86.8 (36.8)	89.9 (27.8)	85.7 (21.9)	78.9 (18.6)	64.4 (14.5)	77.6 (27.9)		
12	69.5 (-21.4)	49.1 (49.0)	34.7 (6.9)	76.5 (37.2)	86.4 (36.4)	89.5 (27.7)	84.0 (20.2)	78.7 (18.4)	65.2 (15.3)	74.9 (25.4)		
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BERT composes a hierarchy of linguistic signals ranging from surface to semantic features.

The strongest alignment with high-level language brain regions has consistently been observed in middle layers



Across several types of large NLP systems, best alignment with fMRI in middle layers

What are the reasons for this observed brain alignment?

Investigate via a perturbation approach



Does the removal of a linguistic property affects the alignment between language model and the brain across all layers?



Removal of each linguistic property leads to a significant decrease in brain alignment on average across layers.



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Greatest impact on brain alignment in the middle layers



Which linguistic properties have the most influence on the trend of brain alignment across BERT layers?



L 2 3 4 5 6 7 8 9 10 11 12 Layer Depth

Removal of each linguistic property leads to a significant decrease in brain alignment on average across layers.

Greatest impact on brain alignment in the middle layers

 $Corr_{task}$ (Δ probing accuracy_{task}, Δ brain alignment_{task})

	Tasks	AG	ATL	PTL	IFG	IFGOrb	MFG	PCC	dmPFC	Whole Brain
	Word Length	0.261	0.264	0.220	0.355	0.129	0.319	0.143	0.100	0.216
Suntactio	TreeDepth	0.365	0.421	0.458	0.442	0.257	0.436	0.109	0.027	0.443
Syntactic	TopConstituents	0.489	0.421	0.464	0.516	0.453	0.463	0.459	0.463	0.451
	Tense	0.226	0.283	0.307	0.325	0.345	0.339	0.435	0.122	0.248
	Subject Number	0.124	0.201	0.231	0.239	0.285	0.228	0.348	0.237	0.254
Semantic	Object Number	0.306	0.392	0.342	0.313	0.503	0.335	0.328	0.001	0.263

ROI-Level Analysis

Syntactic properties have the largest effect on the trend of brain alignment across model layers

Qualitative Analysis: Effect of each linguistic property



TopConstituent property is more localized to the canonical language regions in the left hemisphere and is more distributed in the right hemisphere.

Conclusions for neuro-Al research field

Artificial Biological

What are the reasons behind better similarity between language models and brains?

1. Al-engineering:

- guide linguistic feature selection,
- facilitate improved transfer learning,
- help in the development of cognitively plausible AI architectures

2. Computational modeling in Neuroscience

 enables cognitive neuroscientists to have more control over using language models as model organisms of language processing

3. Model interpretability

 the addition of linguistic features by our approach can further increase the model interpretability using brain signals (Toneva & Wehbe 2019) Joint Processing of linguistic properties in brains and language models (NeurIPS 2023)



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