Brain-Like Language Processing via a Shallow Untrained Multihead Attention Network



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* Proposed Model

What makes representations induced by architectural priors alone exhibit reasonable alignment to brain data ??

TL;DR

Token
Mixing
(e.g., MHA)

Tokenization
Strategy
(e.g., BPE)

Highlights

Using language units in a Shallow Untrained Multihead Attention (SUMA) model we achieve:

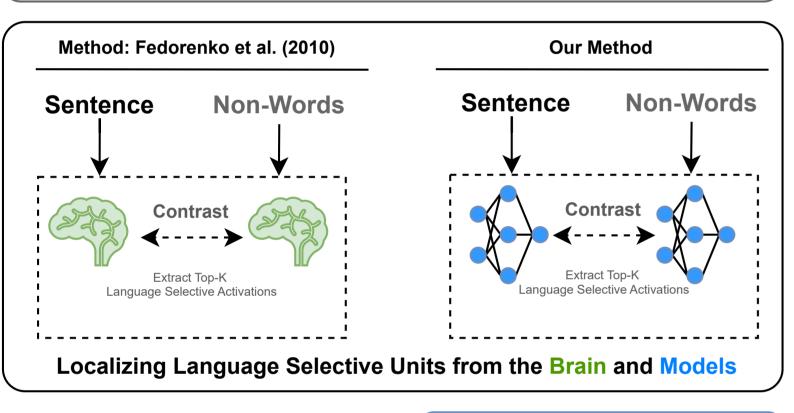
- 1. SoTA on brain benchmarks!
- 2. SoTA on behavioral benchmark!!
- 3. Efficient language modeling !!!

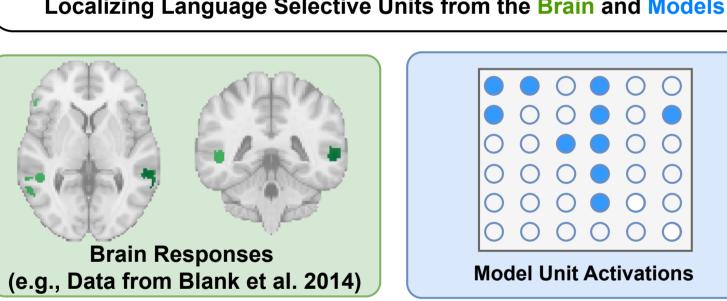
Isolating Critical Components of the Transformer Architecture Tokenization THUN1+M THUN1+A TH

Input Text Tokenize Text Untrained Multihead Attention Localize Lang Units Trained Transformer Blocks Language

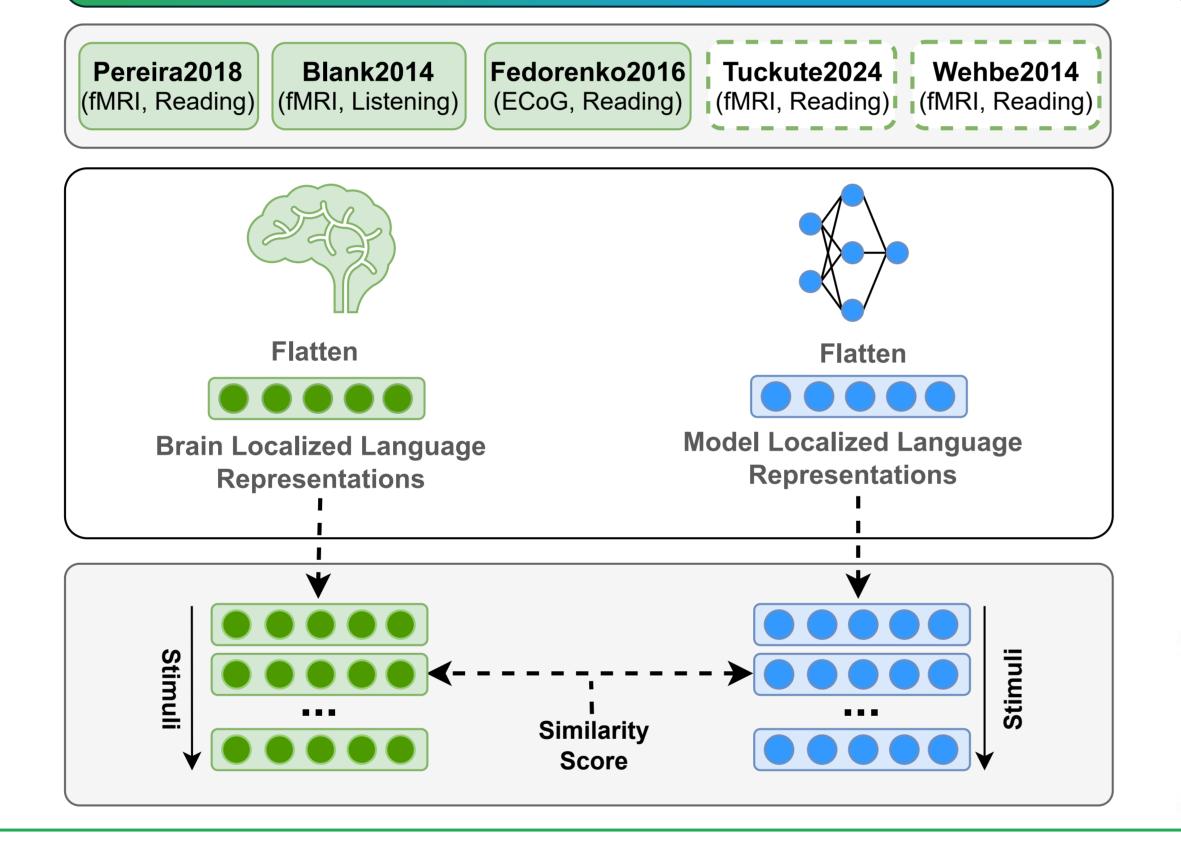
Localization



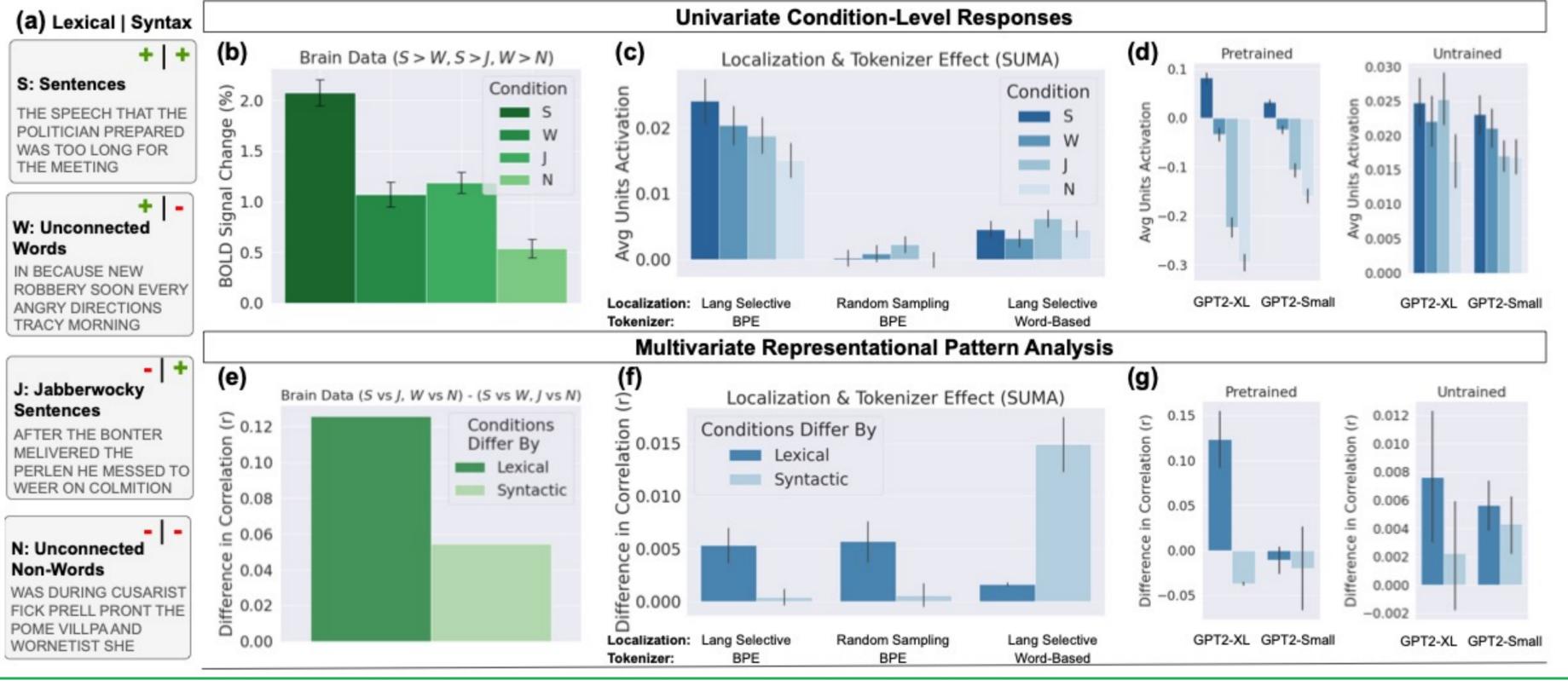




Benchmarking



Language Units Exhibit Similar Response Profiles as the Human Language System



Paper Link





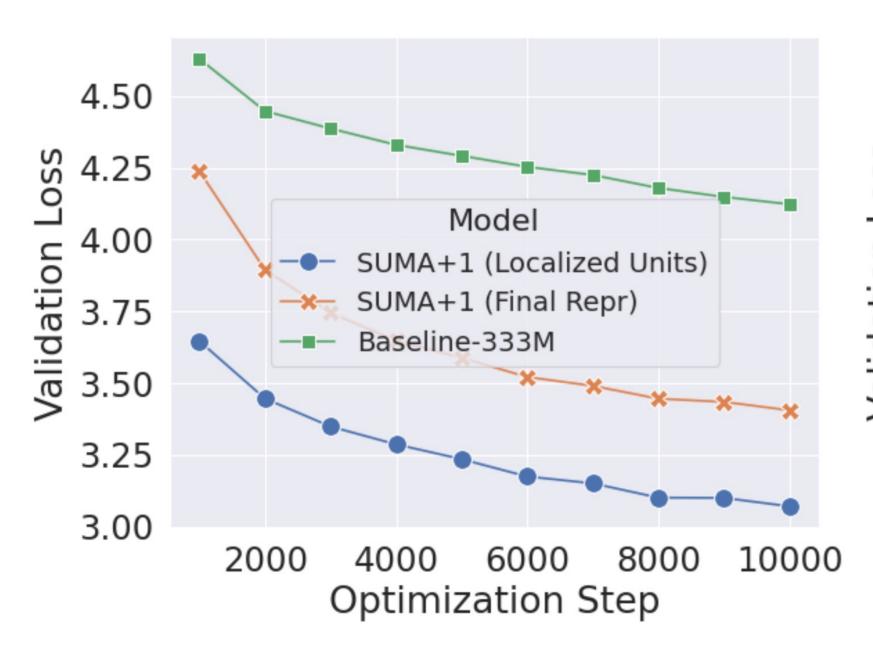


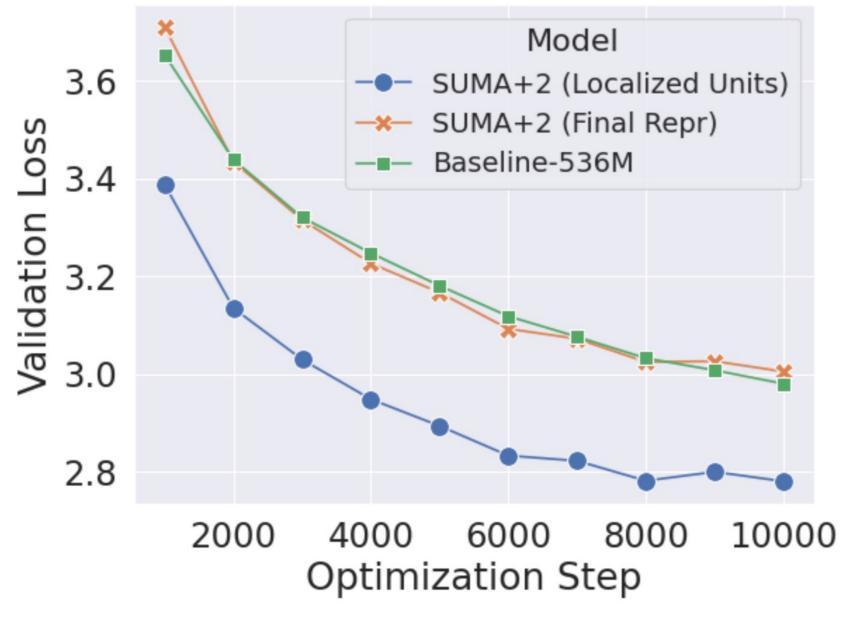
*Equal Supervision

What are the key architectural components underlying the surprising brain alignment of untrained LLMs?

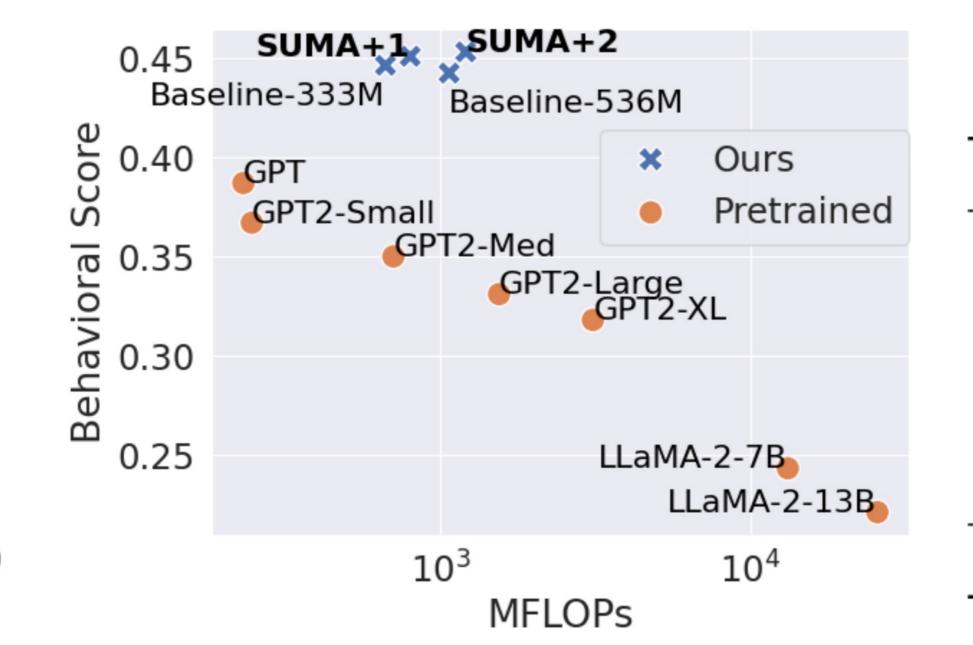


Language Units Improves Language Modeling and Sample Efficiency





SoTA on Human Reading Time Alignment



Language Units Brain Alignment Scores in Pretrained and Untrained Models



Model (MFLOPs)	Pereira2018	Blank2014	Fed2016	Tuckute2024	Wehbe2014	Average
GPT2-Small (170)	0.38/0.16	0.10/0.05	0.27/0.27	0.29/0.21	0.11/0.05	0.23/0.15
GPT2-Med (604)	0.38/0.16	0.10/0.04	0.29/0.26	0.37/0.19	0.11/0.05	0.25/0.14
GPT2-Large (1,420)	0.39/0.16	0.09/0.05	0.30/0.25	0.32/0.21	0.08/0.04	0.23/0.14
GPT2-XL (2,950)	0.34/0.15	0.04/0.04	0.27/0.25	0.34/0.23	0.04/0.04	0.21/0.15
LLaMA-2-7B (12,950)	0.32/0.32	0.01/0.24	0.22/0.34	0.34/0.13	0.02/0.15	0.18/0.24
LLaMA-2-13B (25,380)	0.41/0.28	0.04/0.14	0.26/0.32	0.34/0.17	0.06/0.09	0.22/0.20
SUMA (268)	- / 0.43	- / 0.44	-/0.34	-/0.19	-/0.21	-/0.32