MEG Encoding using Neural Language & Speech Models and Shared Context Semantics in Listening Stories

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Summary

- Language models (LMs) predict both text-evoked and speech-evoked brain activity to an impressive degree irrespective of choice of modality.
- Speech-based models (SMs), which would be expected to predict speech-evoked brain activity better, provided they model language processing in the brain well.
- **These findings poses several questions:**
  - Are speech models (SMs) outperform language models (LMs) during speech-evoked brain activity?
  - Do both LMs and SMs combine a new word representation with previous context?
  - What type of information is shared between LMs and SMs that results in improved brain predictivity?
- We investigate these questions using both LMs (GPT2) and SMs (Wav2vec2.0, HuBERT and Data2vec), and observe how these models predict MEG brain recordings acquired while participants listened to the naturalistic stories.
- Language models outperform speech models irrespective of speech-evoked brain activity.
- Both type of models still behind the estimated noise-ceiling performance.
- Like LMs, previous context is important in predicting MEG recordings for SMs

Language Models (LMs) / Speech Models (SMs) are trained to predict missing words/speech

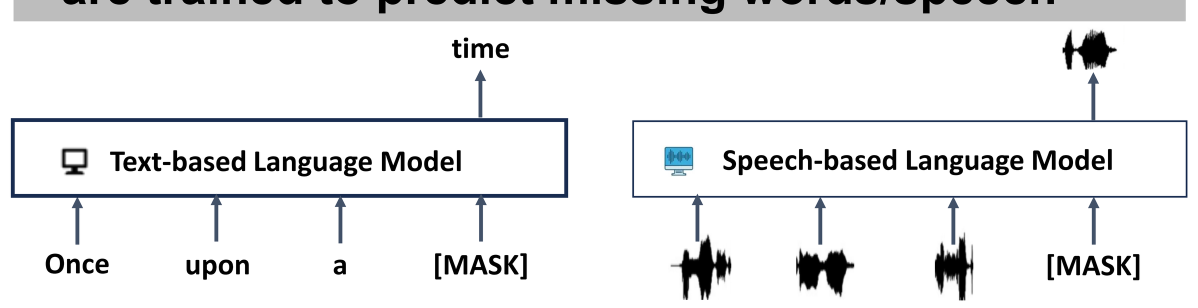


Figure 1: Language Models (LMs) and Speech Models (SMs) have achieved impressive performance across many benchmarks

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

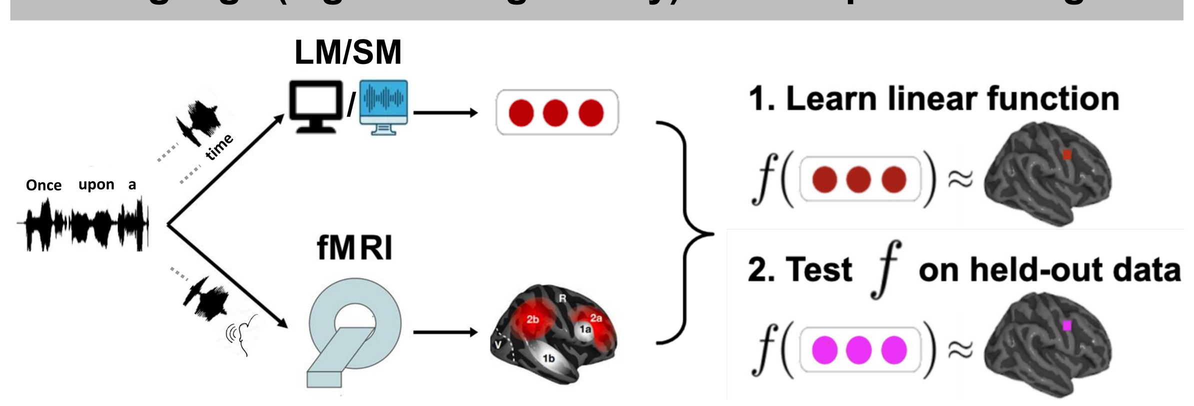
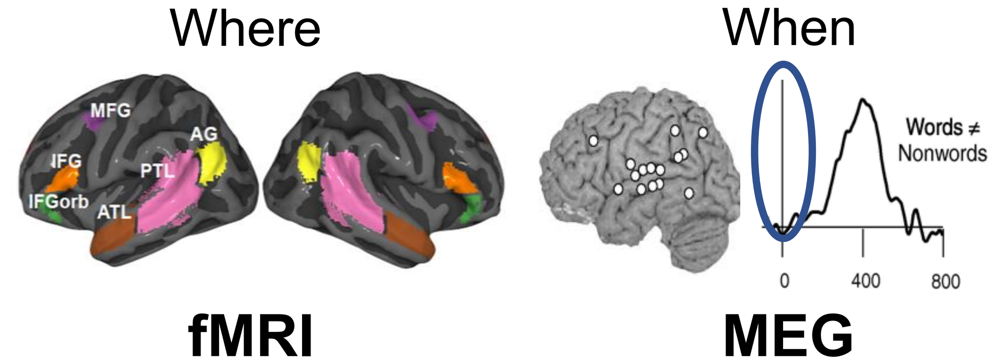


Figure 2: Brain alignment of a LM/SM

With MEG we can analyze sub-word time course

- MEG recording data at very fast temporal resolution
- So, we can look at sub-word process
- fMRI recording data at very high-spatial resolution



Brain encoding schema

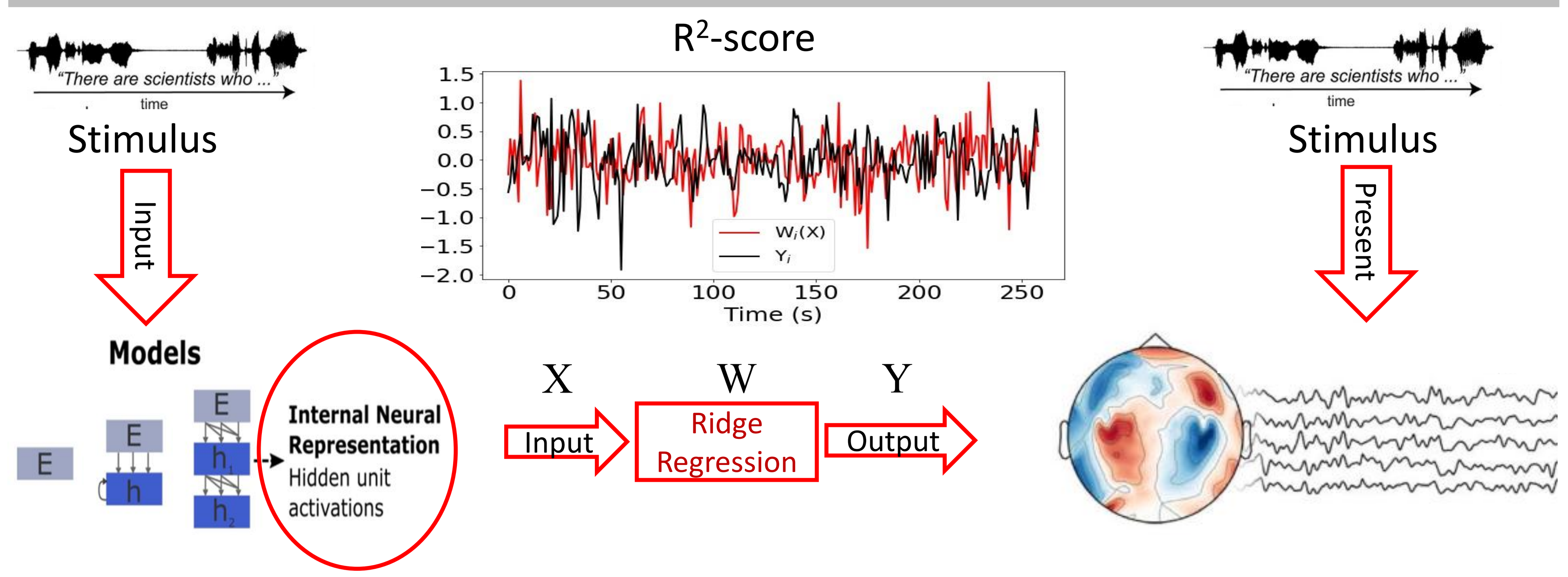
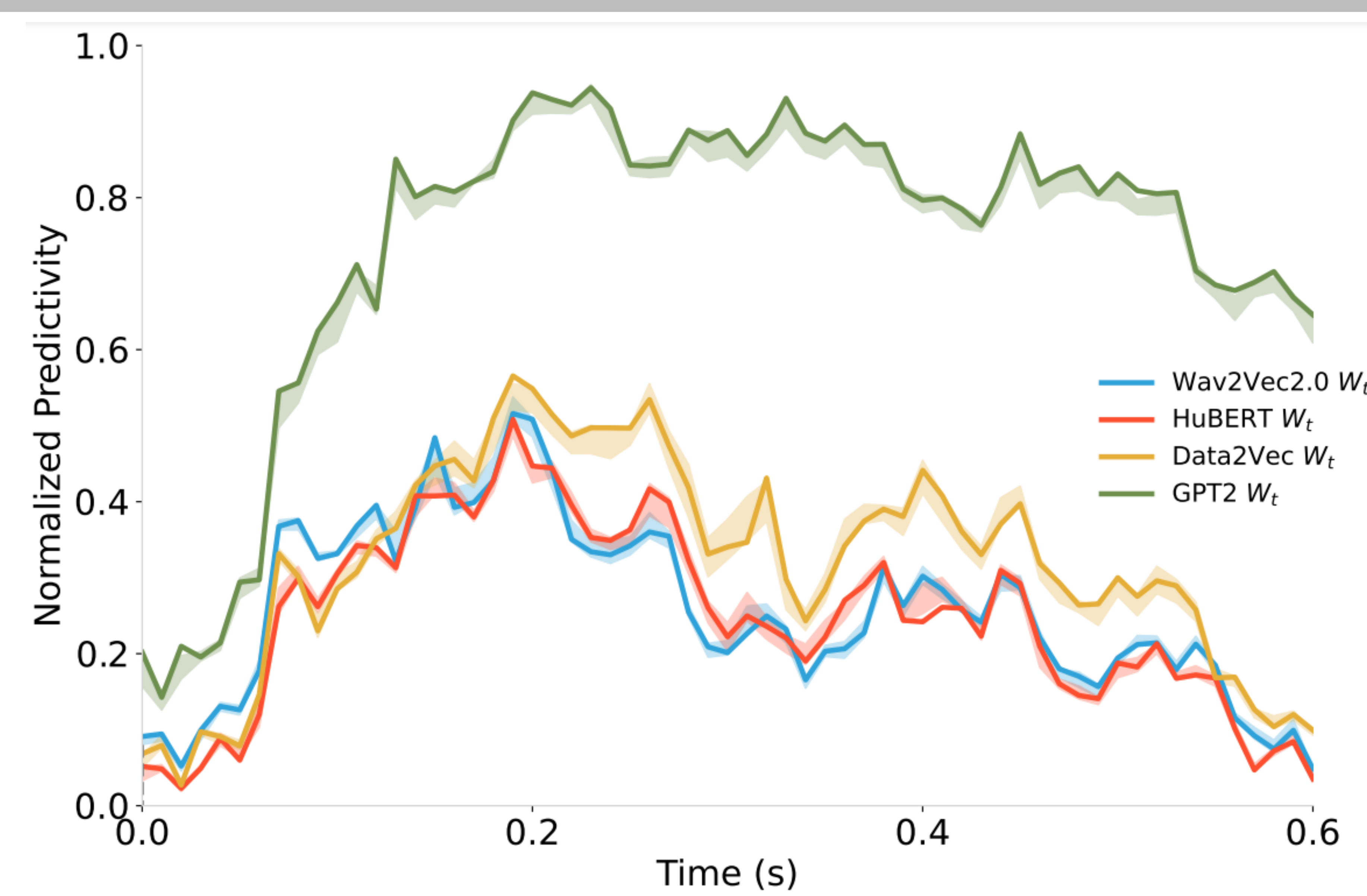
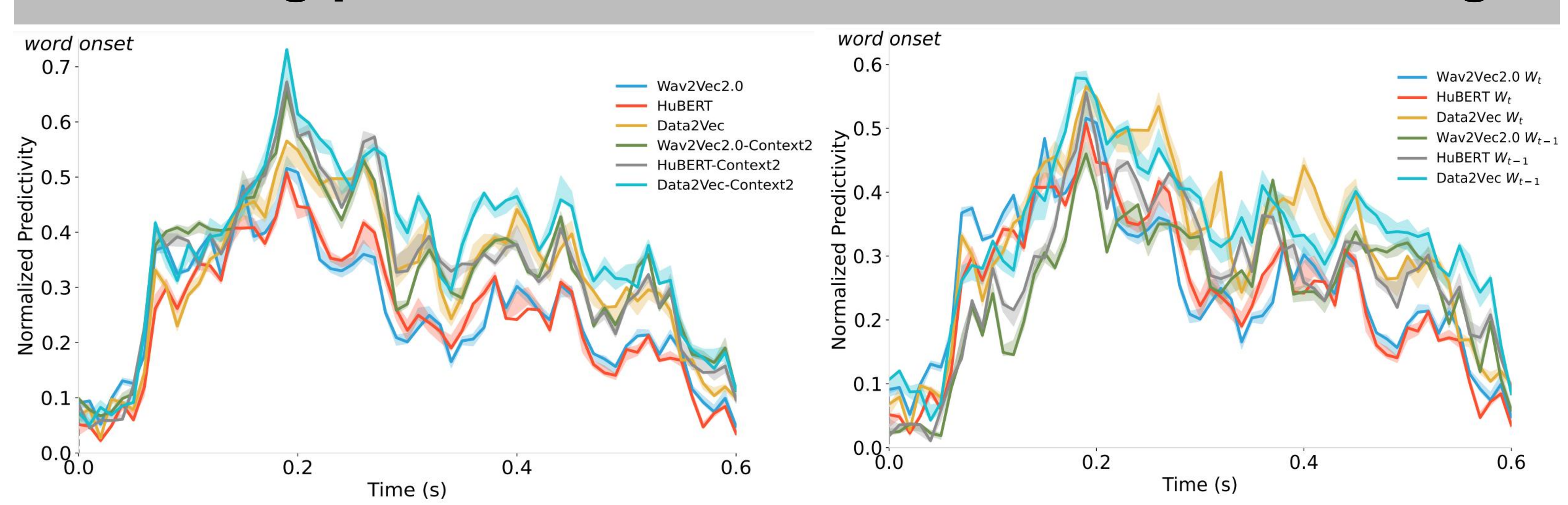


Figure 3: Approach to directly test for the alignment between a LM/SM and MEG brain recordings.

Encoding performance of LM and SMs



Encoding performance SMs: Contextual Embeddings



Brain alignment – 4-fold Cross-Validation + Ridge regression

MEG-MASC Dataset

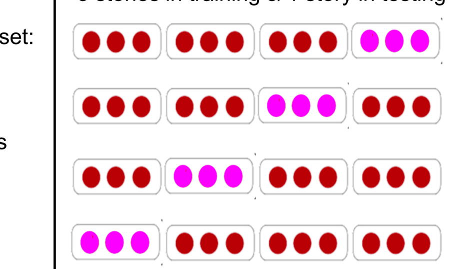
- MEG recordings
- 27 participants
- 2 hours of story listening
- 2 repeated sessions
- structural MRIs
- audio, phonetic and word annotations
- standardised BIDS structure

(1) Naturalistic story listening dataset

- 4 natural stories (11, 002 words) x 768 ⇒ LM/SM representations
- 800ms signal window around word onset: 200ms before (baseline correction), 600ms after
- 208 MEG sensors x 81 time points ⇒ MEG predictions (same dimensions as actual brain activity)
- 18 participants
- 3 Speech language models
  - Wav2vec2.0
  - HuBERT
  - Data2Vec
- 1 Text language Model (GPT2)

(2) Brain Alignment: Dataset Curation

3 stories in training & 1 story in testing



(3) 4-fold Cross-Validation

Layer-wise Performance of SM: Data2vec

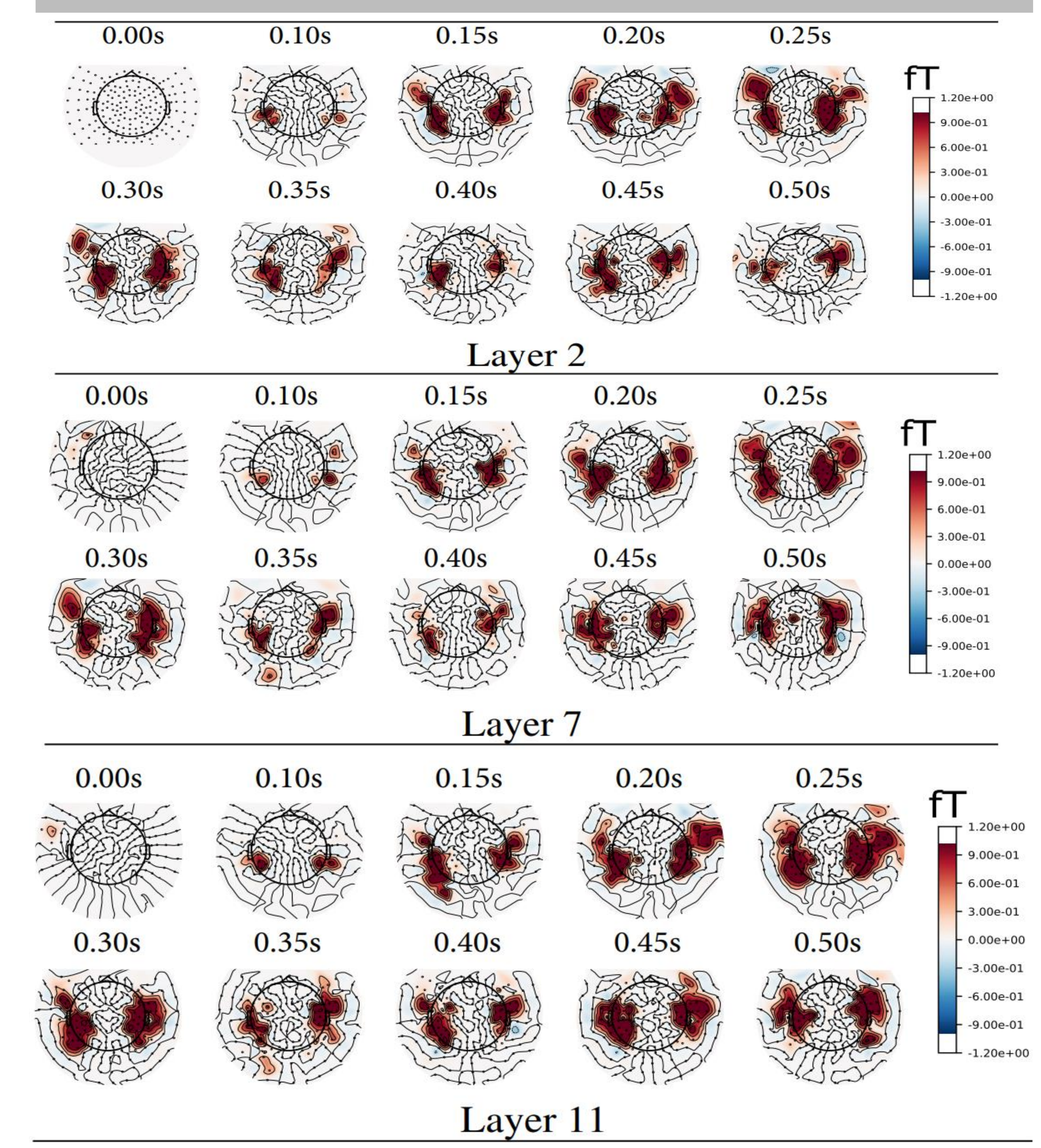


Figure 5: Topo map for Average Normalized predictivity by Data2Vec (across subjects) for MEG activity. Word onset is at 0ms. Layer 2 (top), Layer 7 (middle), and Layer 11 (bottom).

References

[1] Toneva et al. 2019.
Interpreting and improving natural-language processing (in machines) with natural language-processing (in the brain).

[2] Gwilliams et al. 2022.
Meg-masc: a high-quality magneto-encephalography dataset for evaluating natural speech processing.

[3] Oota et al. 2023.
Meg encoding using word context semantics in listening stories.

Acknowledgements

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