大模型时代的脑编解码技术综述

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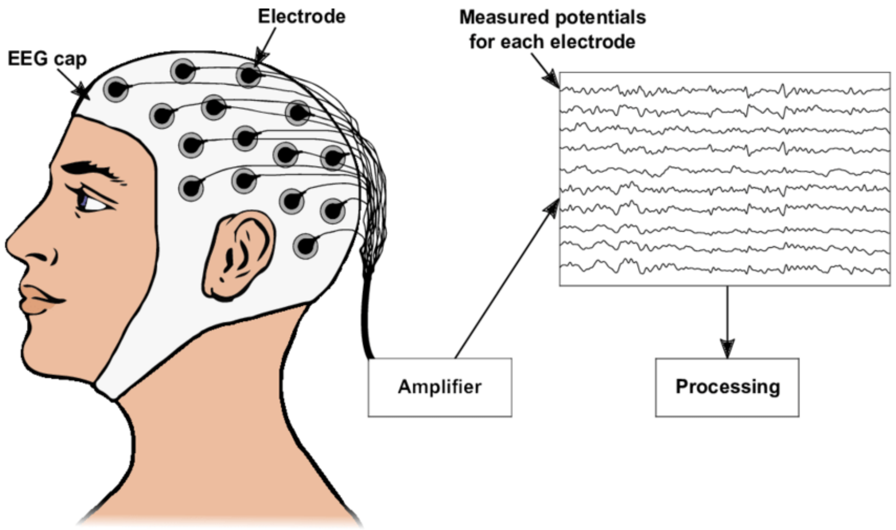
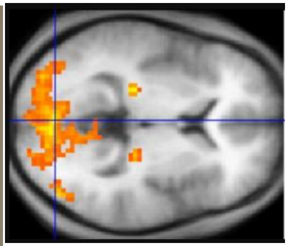
Background

- **Stimulus → Brain activates**



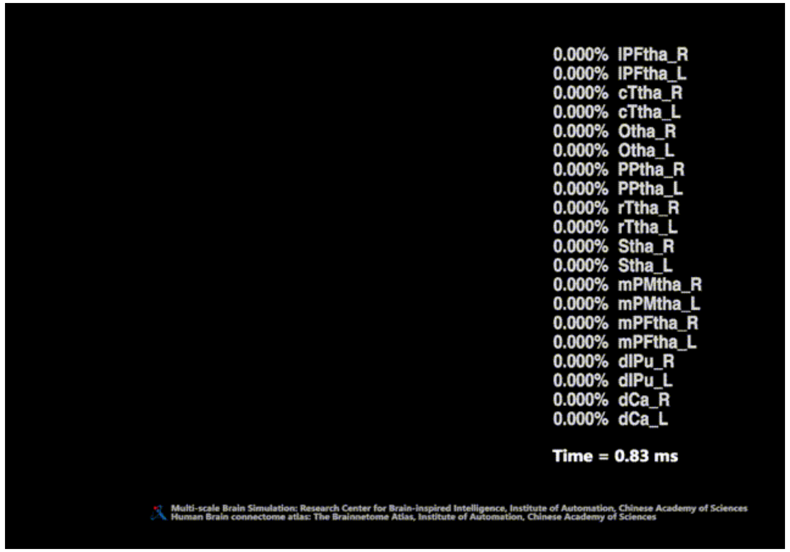
Electroencephalography, EEG



functional magnetic resonance imaging, fMRI

Neural/Brain Encoding and Decoding

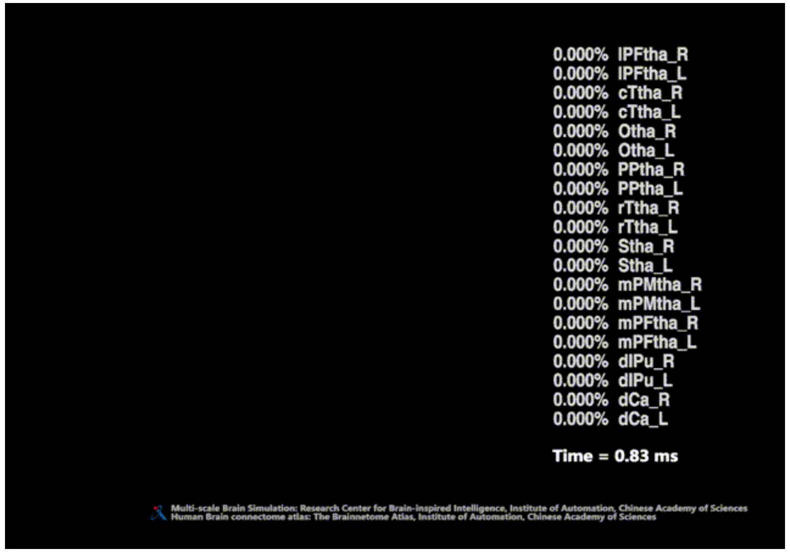
- **Neural encoding** is the study of **how neurons represent information with electrical activity** (action potentials) at the level of individual cells or in networks of neurons. Studies of neural encoding aim to characterize the **relationship between sensory stimuli or behavioural output and neural signals**.



Neural/Brain Encoding and Decoding

- **Neural decoding** is the study of **what information is available in the electrical activity (action potentials)** of individual cells or networks of neurons. Studies of neural decoding aim to identify **what stimulus, event, or desired output elicits a particular pattern of neural activity.**

https://www.nature.com/subjects/neural-decoding

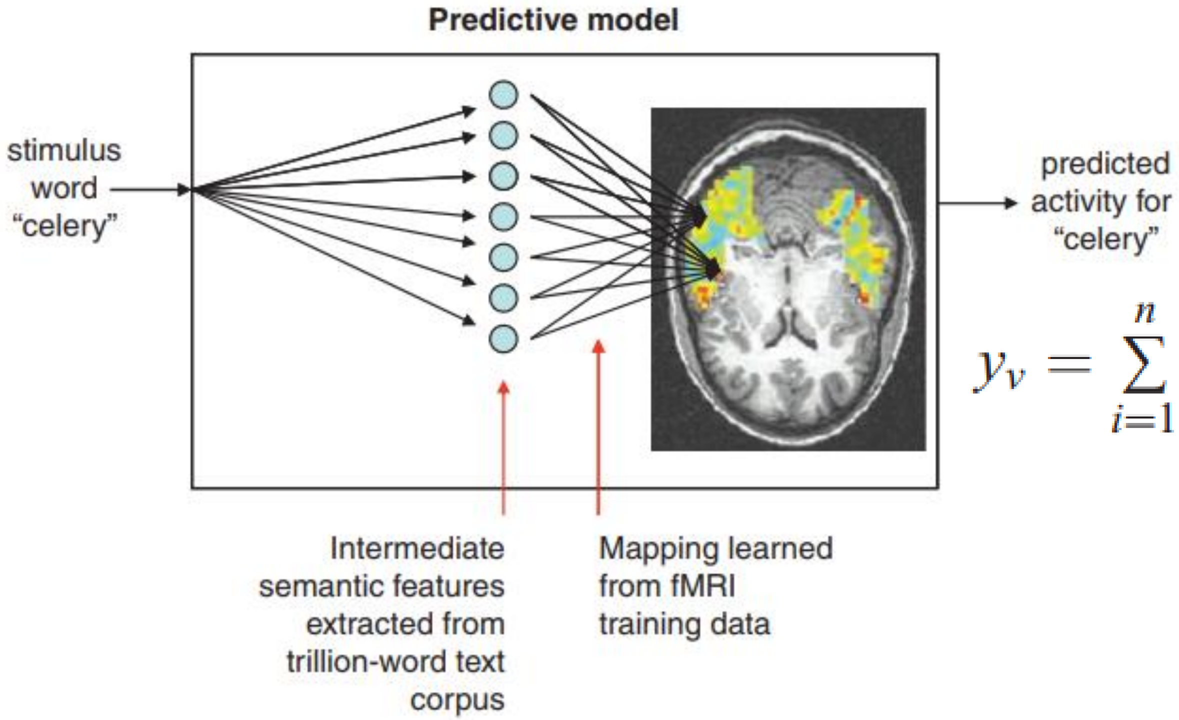


Brain Encoding

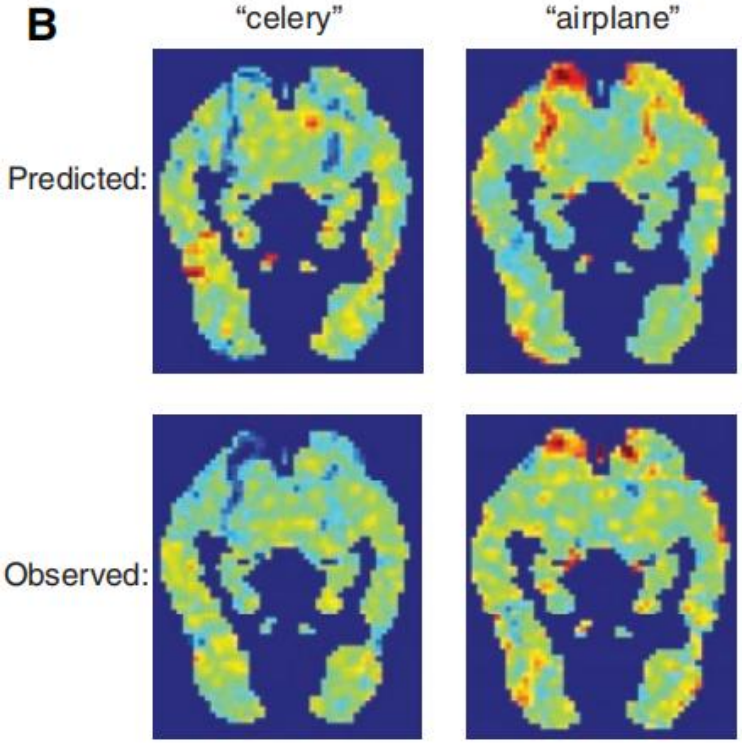
Brain Encoding

Science AAAS

Predicting Human Brain Activity Associated with the Meanings of Nouns
Tom M. Mitchell, *et al.*
Science **320**, 1191 (2008);
DOI: 10.1126/science.1152876

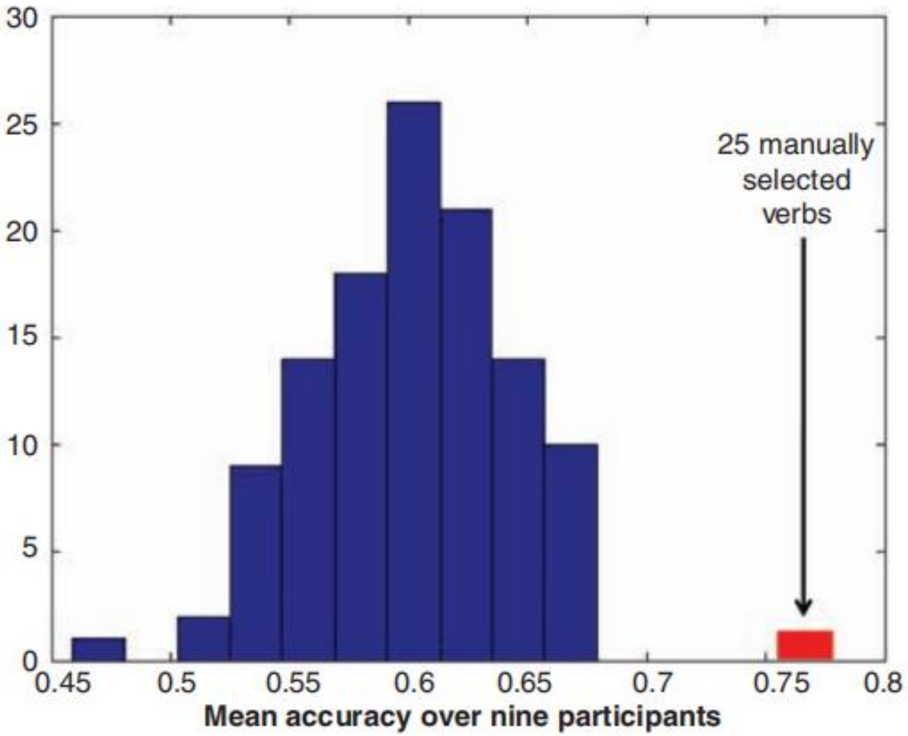


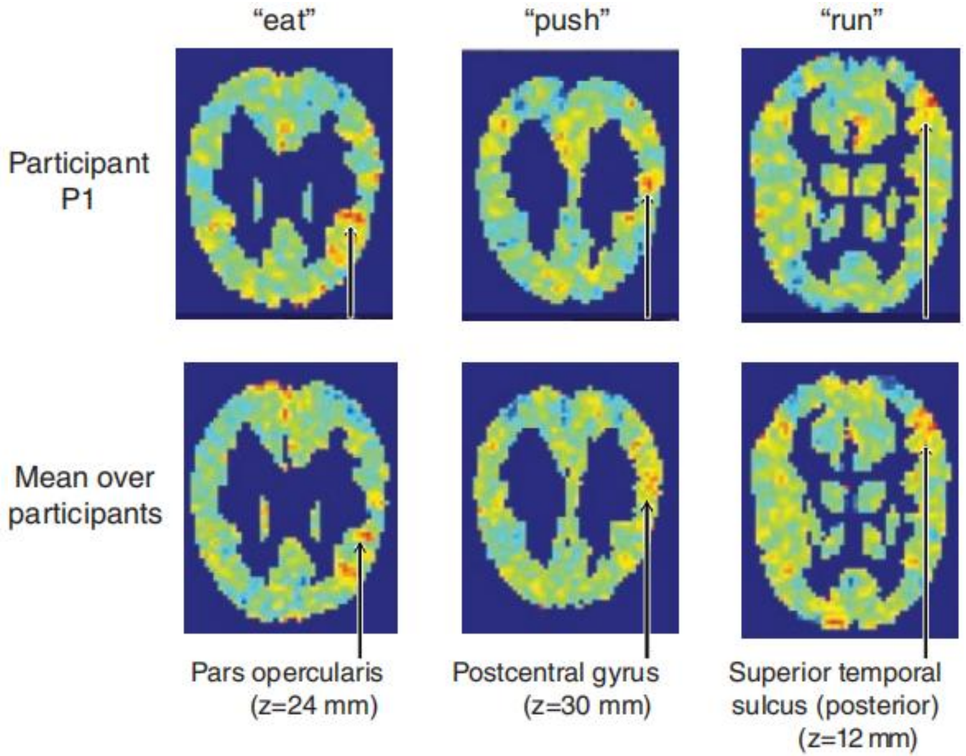
$$y_v = \sum_{i=1}^{n} c_{vi} f_i(w)$$



Brain Encoding

- fMRI data from **9** healthy, college-age **participants** who viewed **60 different word-picture pairs** presented **6 times each**.
- **12 semantic categories** (animals, body parts, buildings, building parts, clothing, furniture, insects, kitchen items, tools, vegetables, vehicles, and other man-made items).



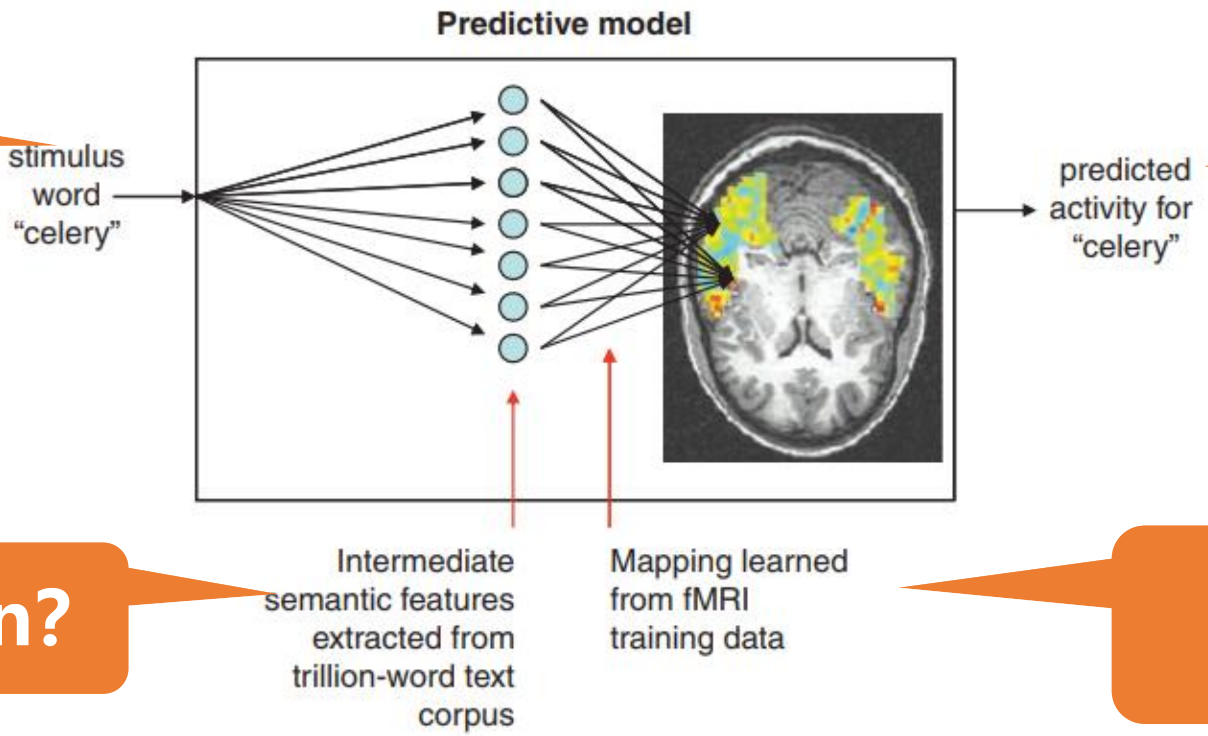


Brain Encoding

Goal/Tasks?

Stimulus?

Evaluation?



Representation?

Mapping Method?

Mitchell TM, Shinkareva SV, Carlson A, Chang KM, Malave VL, Mason RA, Just MA. **Predicting human brain activity associated with the meanings of nouns**. Science. 2008.

Stimulus/Features-Lexical and syntactic

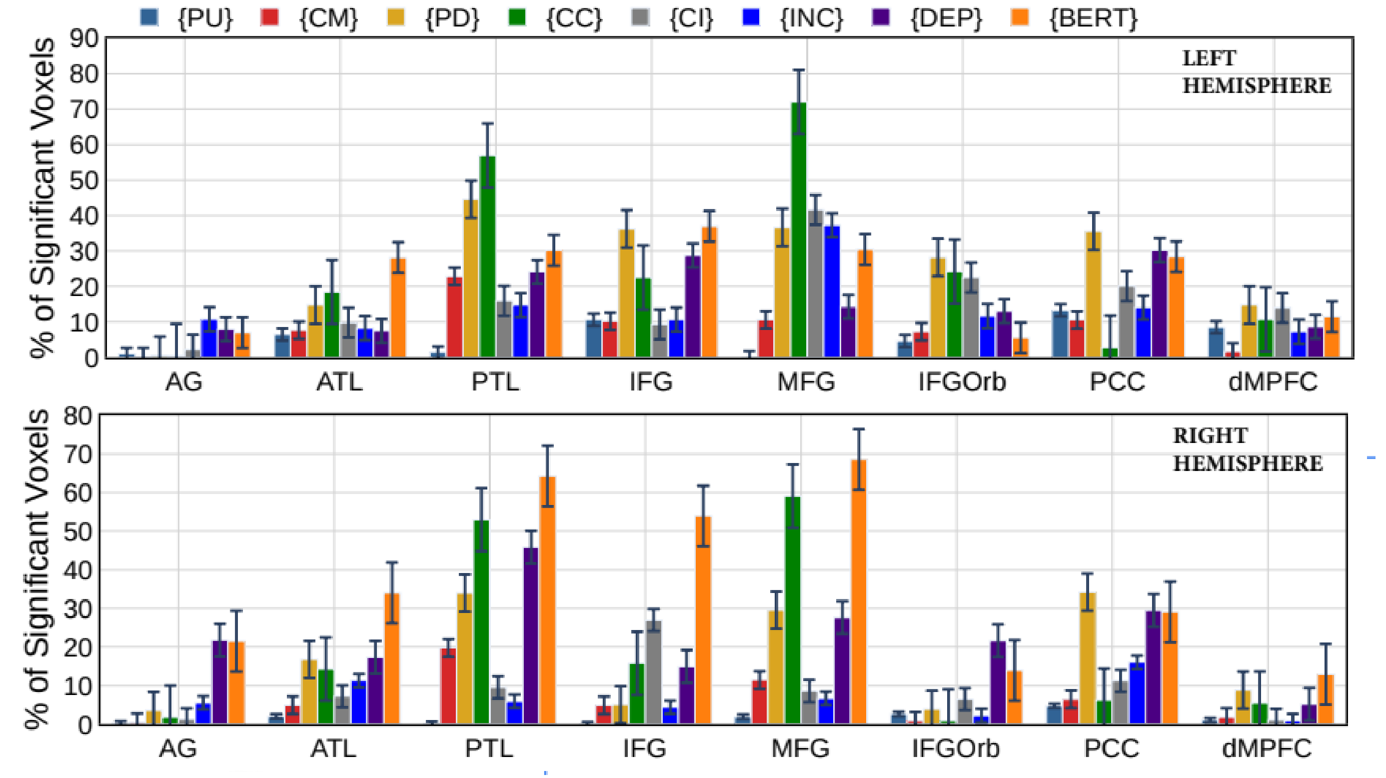
- Kai-min K. Chang, Vladimir L. Cherkassky, Tom M. Mitchell, and Marcel Adam Just. 2009. **Quantitative modeling of the neural representation of adjective-noun phrases to account for fMRI activation**. ACL 2009.

Adjective	Noun	Category
Soft	Bear	Animal
Large	Cat	Animal
Strong	Dog	Animal
Plastic	Bottle	Utensil
Small	Cup	Utensil
Sharp	Knife	Utensil
Hard	Carrot	Vegetable
Cut	Corn	Vegetable
Firm	Tomato	Vegetable
Paper*	Airplane	Vehicle
Model*	Train	Vehicle
Toy*	Truck	Vehicle

Table 1. Word stimuli. Asterisks mark the object-modifying adjectives, as opposed to the ordinary attribute-specifying adjectives.

Findings: Neural activity encodes distinguishable patterns for adjective-noun phrases. Multiplicative models best capture how adjectives modify nouns, while noun-centric processing dominates for attribute-specifying phrases.

- Subba Reddy Oota, Mounika Marreddy, Manish Gupta, and Raju Bapi. 2023. **How does the brain process syntactic structure while listening?**. In Findings of ACL 2023.

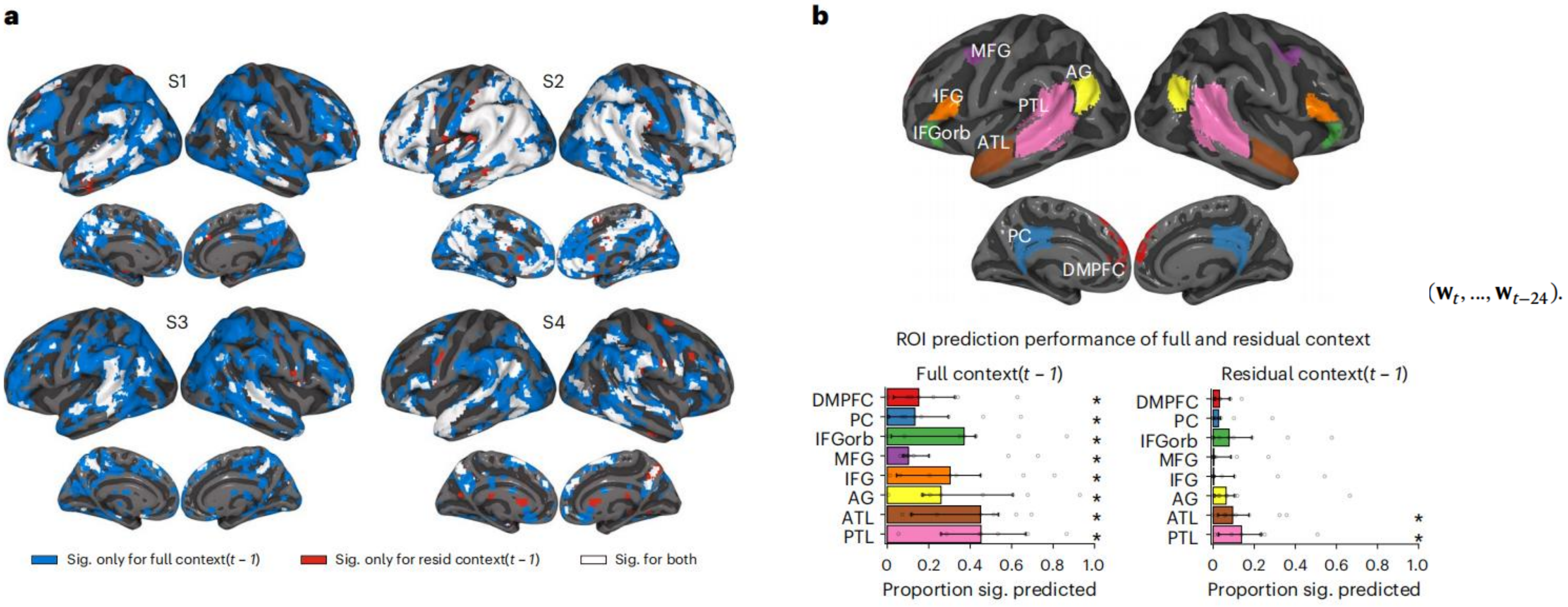


Findings: Constituency parsers (especially CC) better predicted activity in the temporal lobe (ATL, PTL) and middle frontal gyrus (MFG). Dependency parsers (DEP) were more effective in the angular gyrus (AG) and posterior cingulate cortex (PCC)

Stimulus/Features-Meaning Composition

- Mariya Toneva, Tom M. Mitchell & Leila Wehbe. **Combining computational controls with natural text reveals aspects of meaning composition**. Nature Computational Science (2022)

"finished the apple, green banana"



Findings: **Supra-word embeddings significantly predicted activity in the anterior temporal lobe (ATL) and posterior temporal lobe (PTL).**

Stimulus/Features-Meaning Composition

- Changjiang Gao, Jixing Li, Jiajun Chen, and Shujian Huang. **Measuring Meaning Composition in the Human Brain with Composition Scores from Large Language Models**. ACL 2024.

$$
\begin{aligned}
\mathrm{dist}(\mathbf{p}_i^l, \mathbf{p}^l) &= D_{\mathrm{JS}}^{\frac{1}{2}}(\mathbf{p}_i^l \| \mathbf{p}^l) \\
&= \left[\frac{1}{2} D_{\mathrm{KL}}(\mathbf{p}_i^l \| \mathbf{p}_m^l) + \frac{1}{2} D_{\mathrm{KL}}(\mathbf{p}^l \| \mathbf{p}_m^l)\right]^{\frac{1}{2}}
\end{aligned}
$$

$$
S_{\mathrm{comp}}^l = \frac{\min_{1 \le i \le d_m} \mathrm{dist}(\mathbf{p}_i^l, \mathbf{p}^l)}{\max_{1 \le j \le d_m} \mathrm{dist}(\mathbf{p}_j^l, \mathbf{p}^l)}
$$

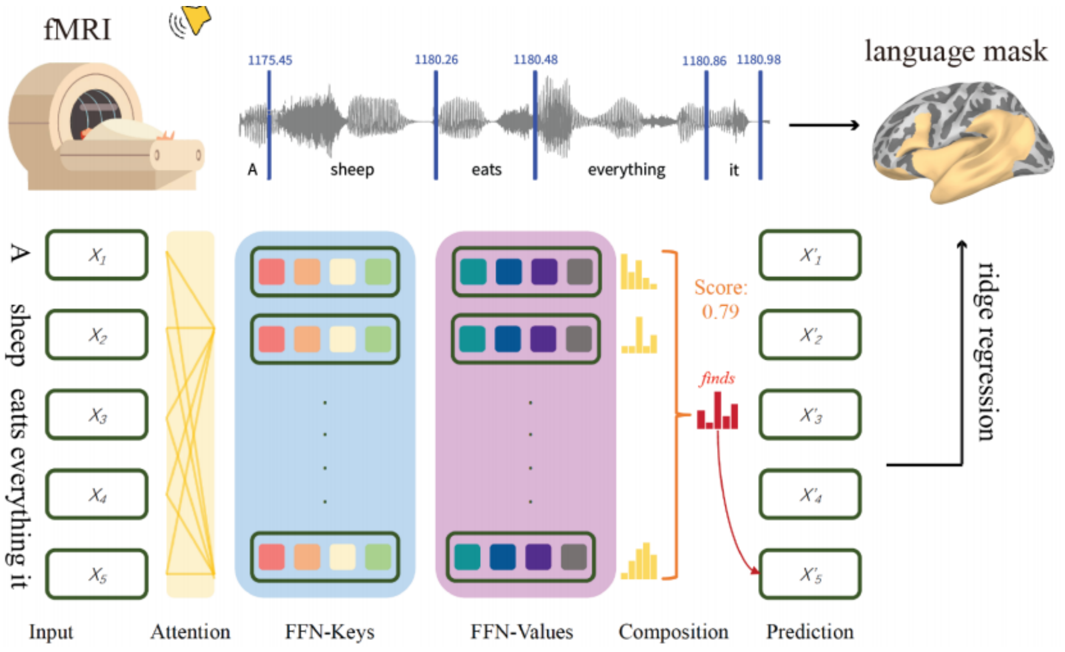


Figure 1: Comparing Composition Scores with fMRI data during naturalistic listening comprehension.

Stimulus/Features-Meaning Composition

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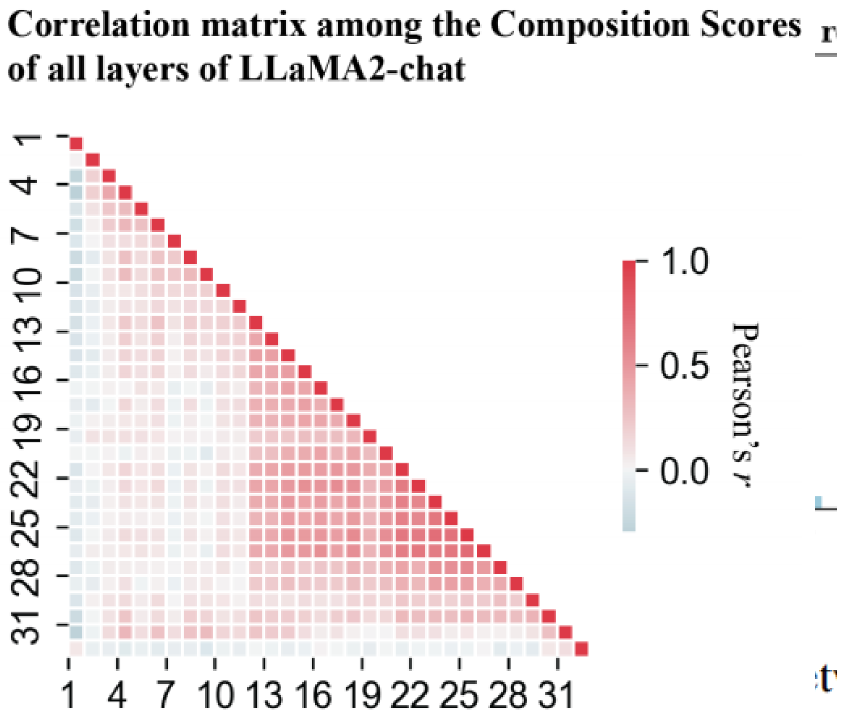
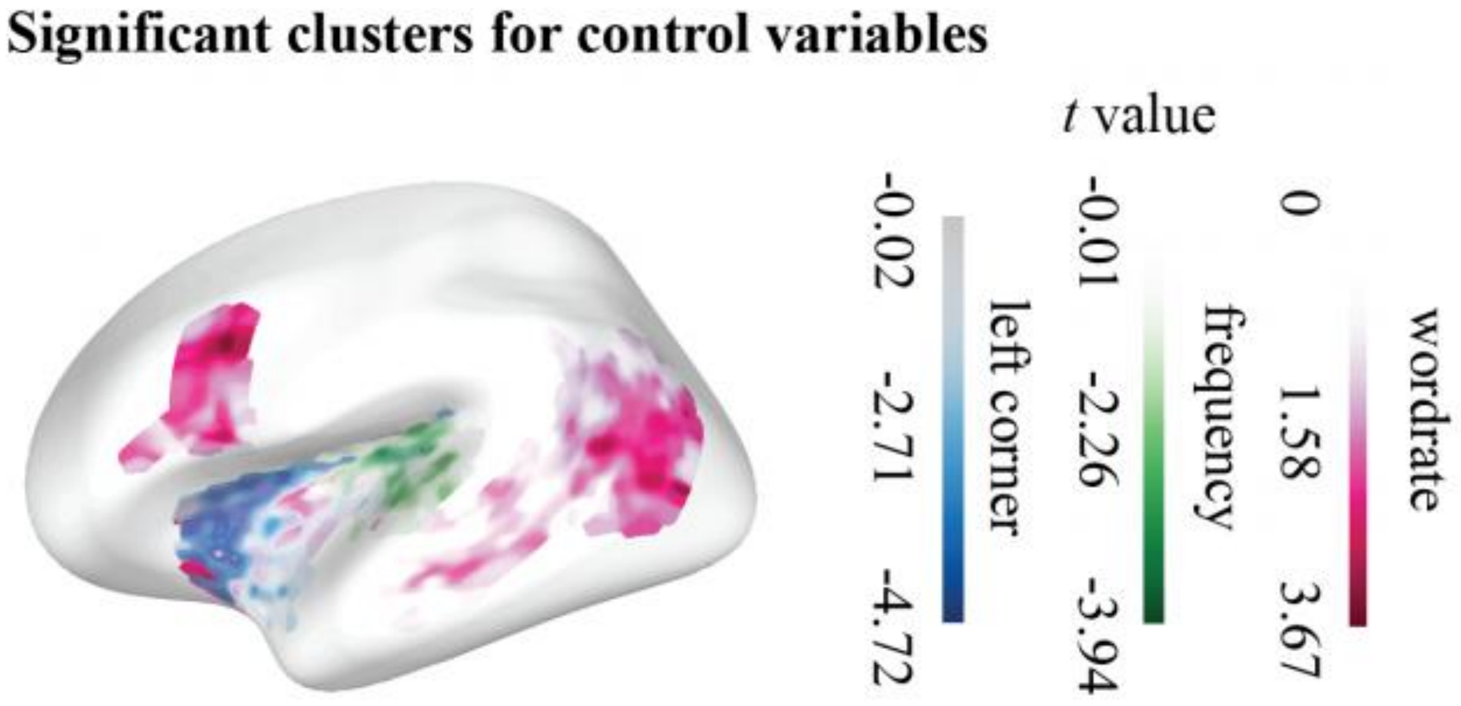
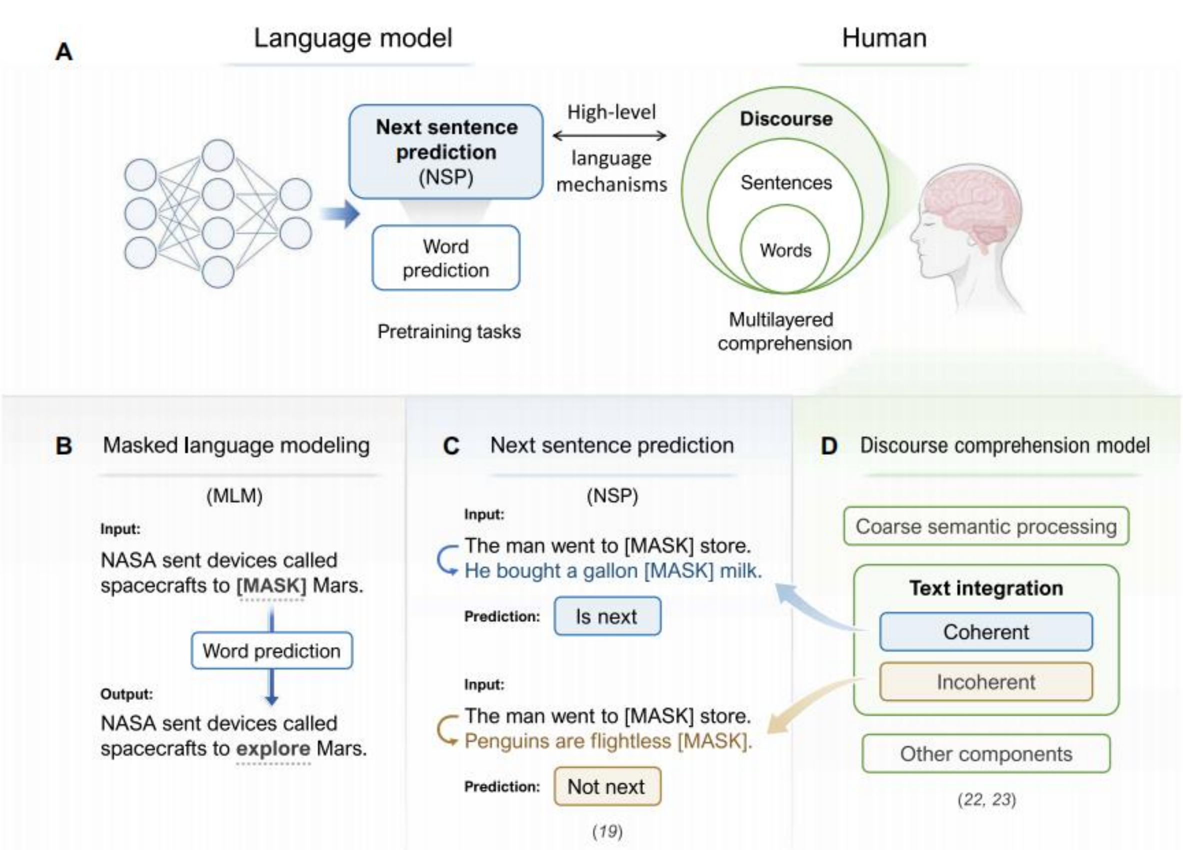


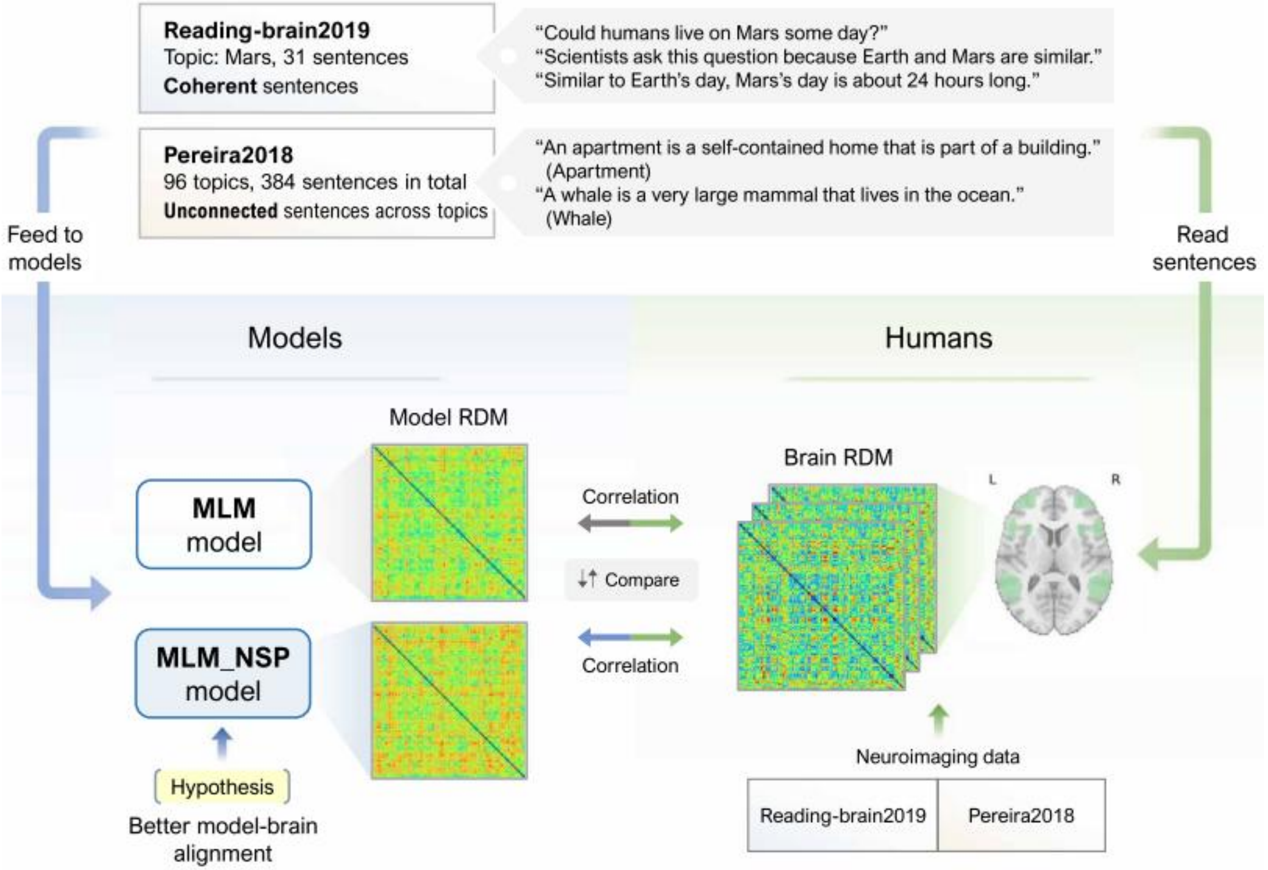


Findings: (1) **Scores vary across layers, with higher layers showing greater compositional complexity; correlations between layers are low, indicating unique information in each layer; (2) The Composition Score correlates with broader brain clusters (left inferior frontal gyrus, left anterior superior temporal gyrus) compared to control variables.**

Stimulus/Features-Discourse Comprehension

Shaoyun Yu, Chanyuan Gu, Kexin Huang, and Ping Li. **Predicting the next sentence (not word) in large language models: What model-brain alignment tells us about discourse comprehension**. Science Advances, 2024.





Stimulus/Features-Discourse Comprehension

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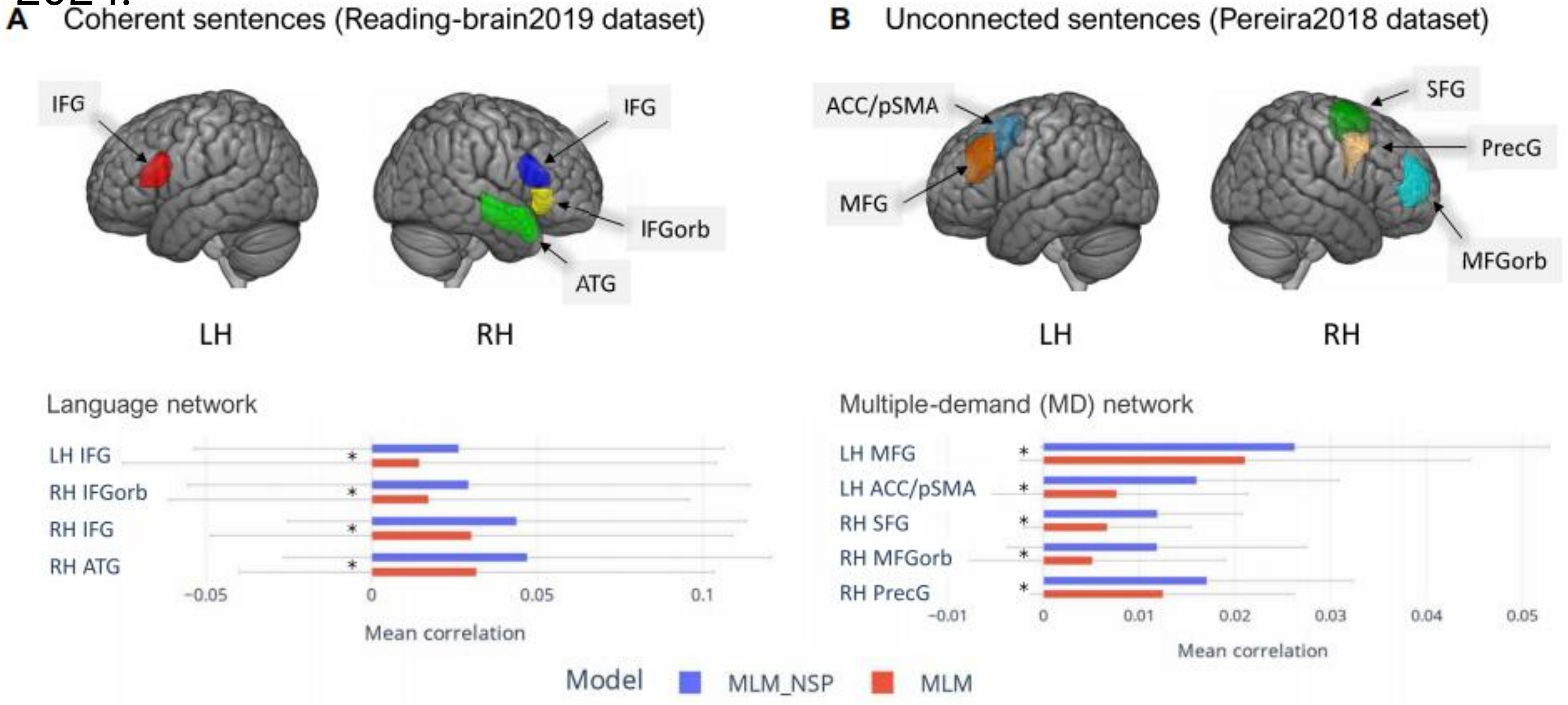
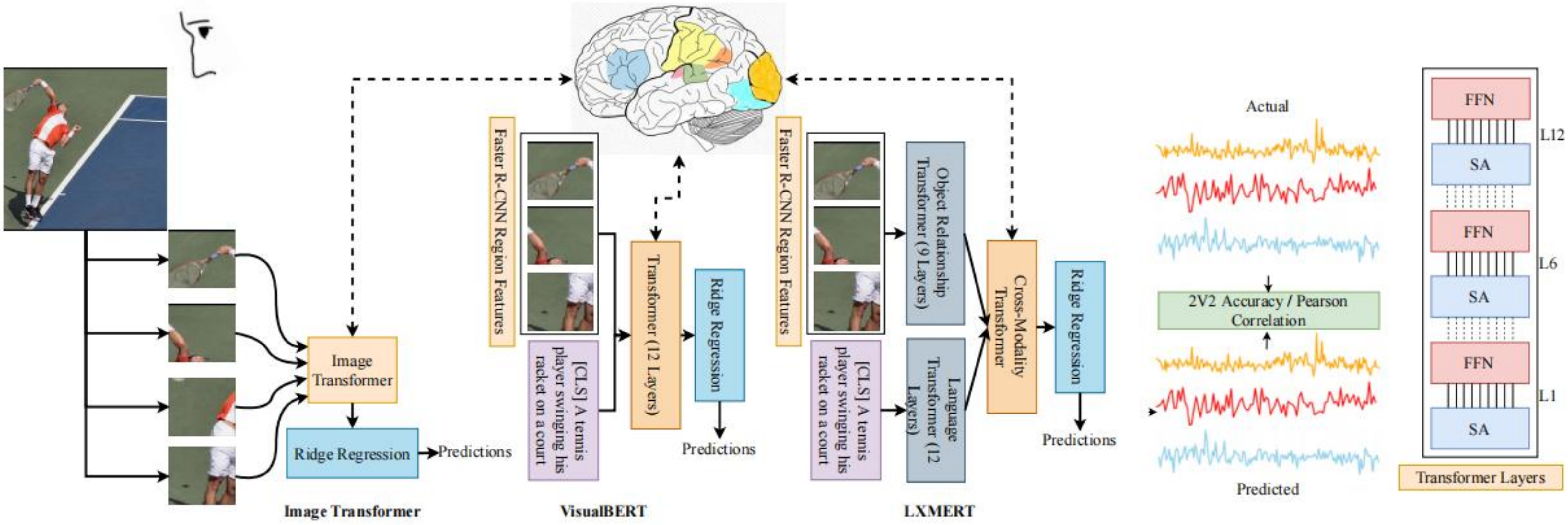


Findings:

For coherent sentences (Reading-brain2019), MLM_NSP showed stronger alignment in right hemisphere language network regions (e.g., right inferior frontal gyrus [IFG], right anterior temporal gyrus [ATG]) .
For unconnected sentences (Pereira2018), MLM_NSP aligned better with the domain-general multiple demand (MD) network, including left middle frontal gyrus (MFG) and right superior frontal gyrus (SFG)

Stimulus/Features-Multimodal

Subba Reddy Oota, Jashn Arora, Vijay Rowtula, Manish Gupta, and Raju S. Bapi. **Visio-Linguistic Brain Encoding**. COLING 2022.



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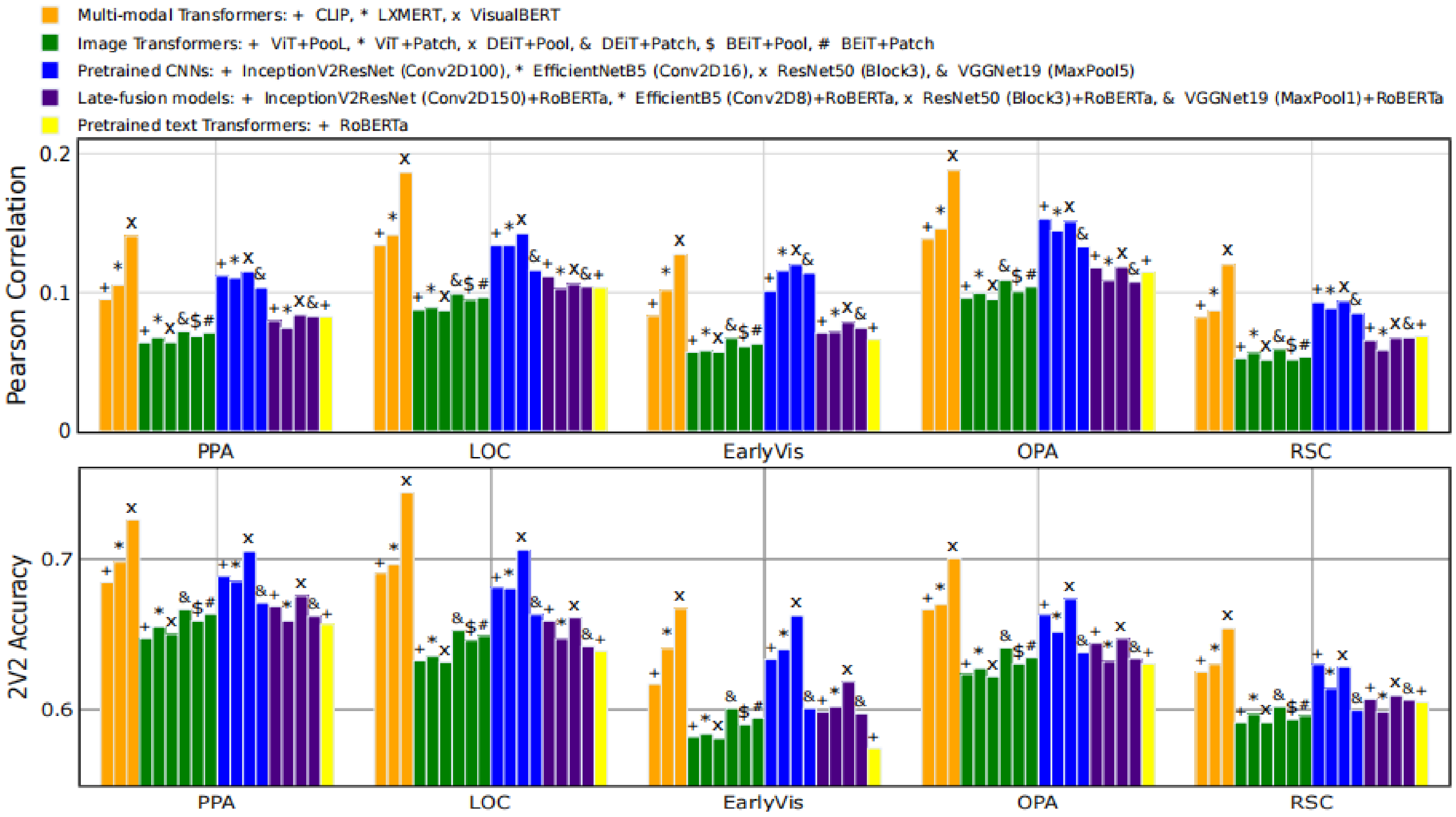
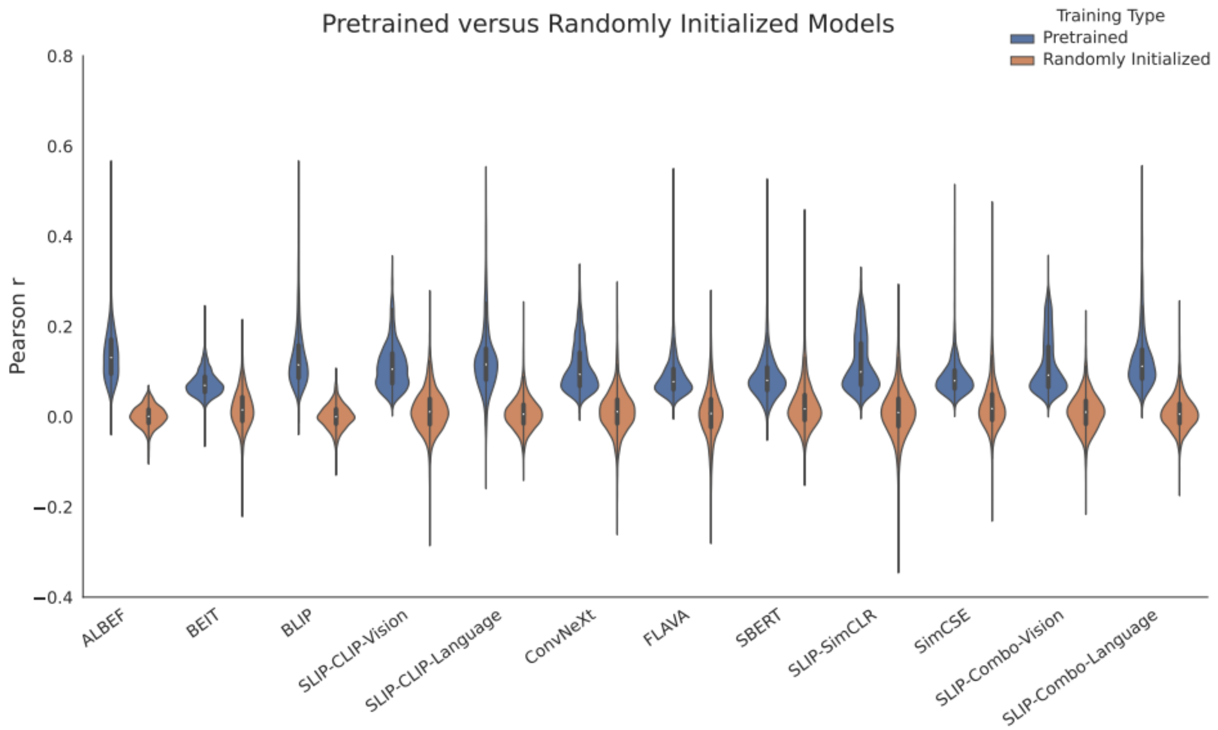


Findings:

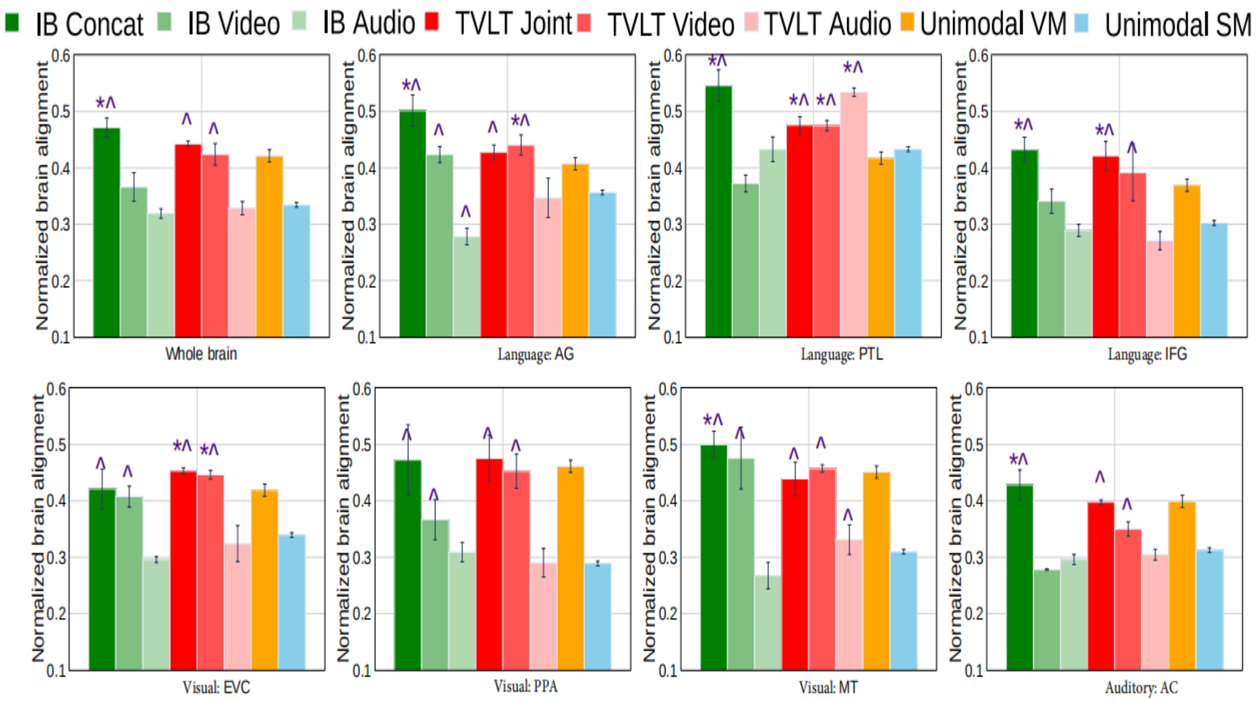
- **VisualBERT outperforms other models**: The multi-modal Transformer VisualBERT achieves state-of-the-art results on both datasets, surpassing single-mode models, image Transformers, and other multi-modal models .
- **Brain region correlations: Regions with dual language and vision functions (e.g., LPTG, LMTG, LIFG, STS)** show higher correlation with multi-modal models, indicating these models better mimic human brain behavior

Stimulus/Features-Multimodal

- Vighnesh Subramaniam, Colin Conwell, Christopher Wang, Gabriel Kreiman, Boris Katz, Ignacio Cases, Andrei Barbu. **Revealing Vision-Language Integration in the Brain with Multimodal Networks**. ICML 2024.
- SUBBA REDDY OOTA, Khushbu Pahwa, mounika marreddy, Maneeesh Singh, Manish Gupta, Raju Surampudi Bapi. **Multi-modal brain encoding models for multi-modal stimuli**. ICLR 2025.



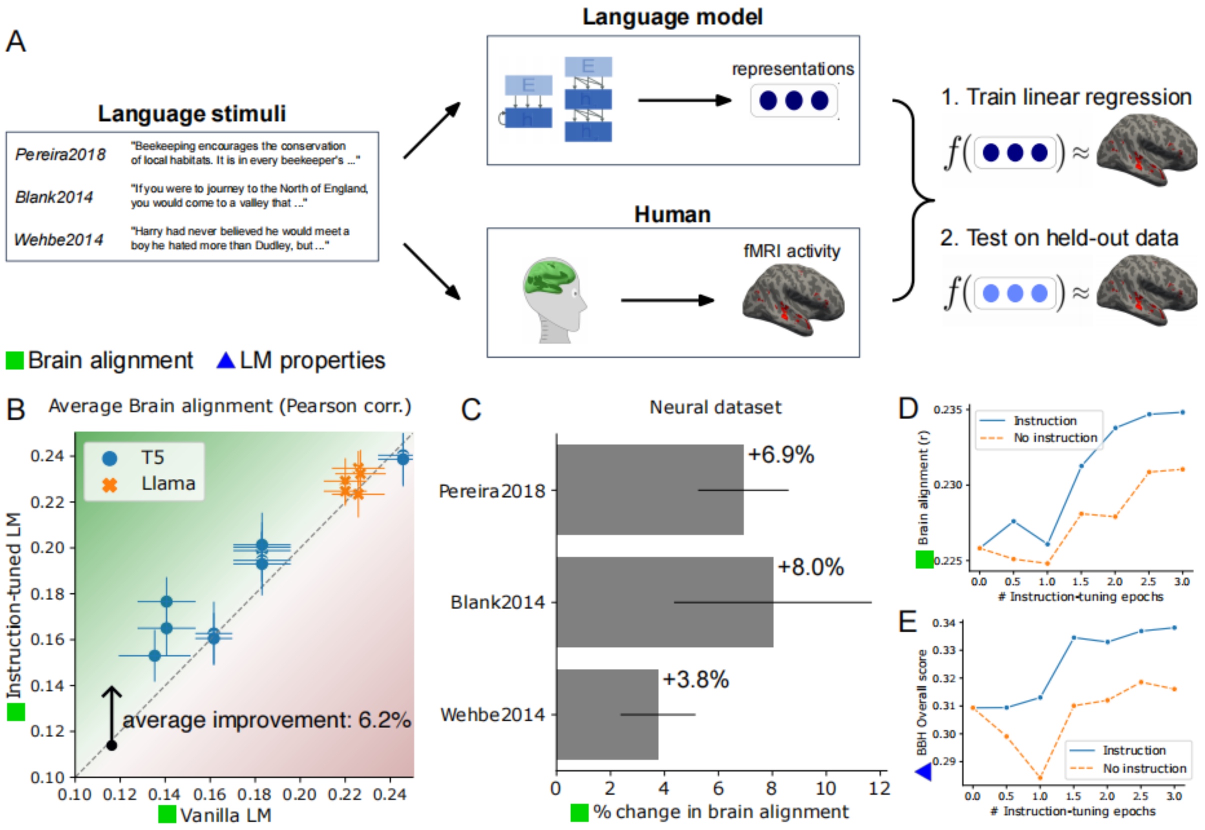
Findings: **Multimodal models, particularly those with CLIP-style training,** are best suited for predicting neural activity in integration sites.

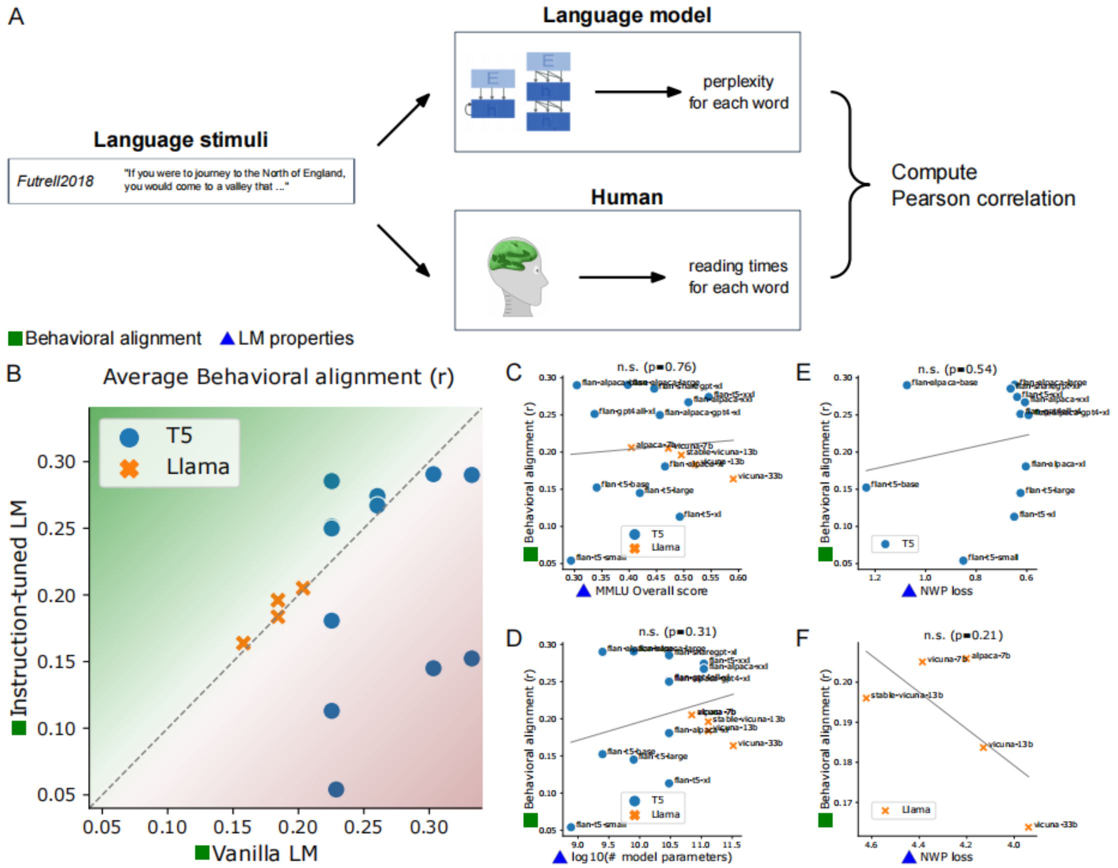


Findings: **Multi-modal models outperform unimodal ones** in alignment with key language (e.g., AG, IFG) and visual (e.g., EVC, MT) regions. **Cross-modal models rely partly on video** for brain alignment; jointly pretrained ones use both video and audio.

Goal/Tasks - SFT

Khai Loong Aw, Syrielle Montariol, Badr AlKhamissi, Martin Schrimpf, Antoine Bosselut. **Instruction-tuning Aligns LLMs to the Human Brain**. COLM 2024.

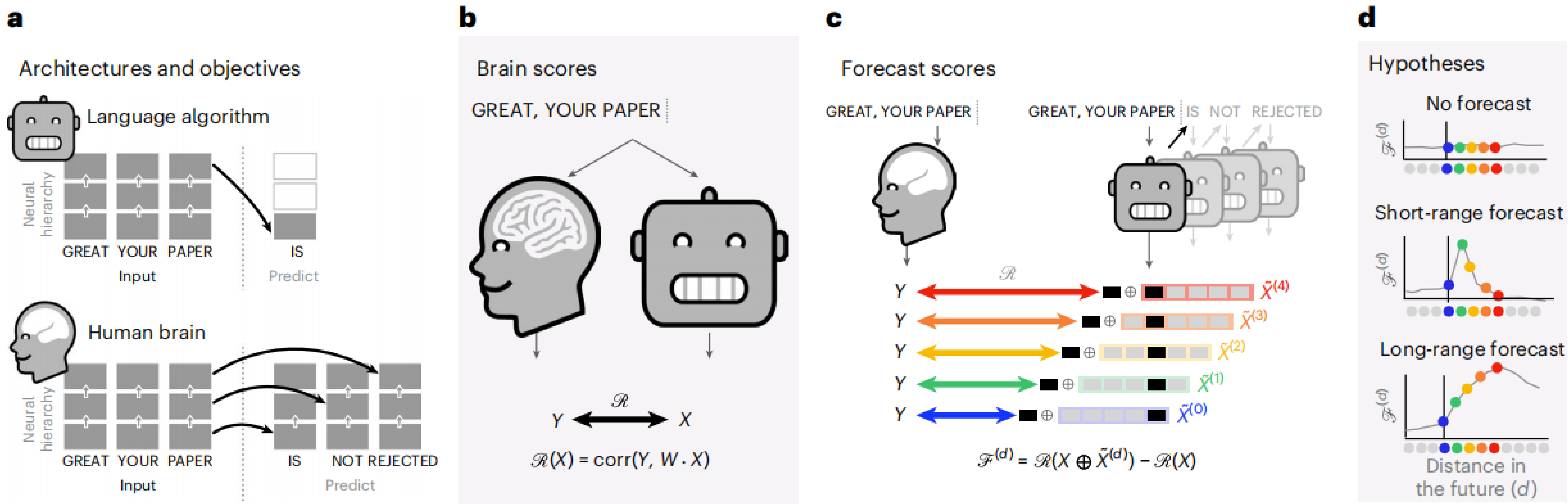




Findings: **Instruction-tuning enhances LLMs' alignment with human brain activity, likely by improving their representation of world knowledge. However, this neural alignment does not translate to stronger behavioral alignment in reading tasks.**

Goal/Tasks - Predictive Coding

Charlotte Caucheteux, Alexandre Gramfort & Jean-Rémi King. **Evidence of a predictive coding hierarchy in the human brain listening to speech**. Nature Human Behaviour (2023).



Goal/Tasks - Predictive Coding

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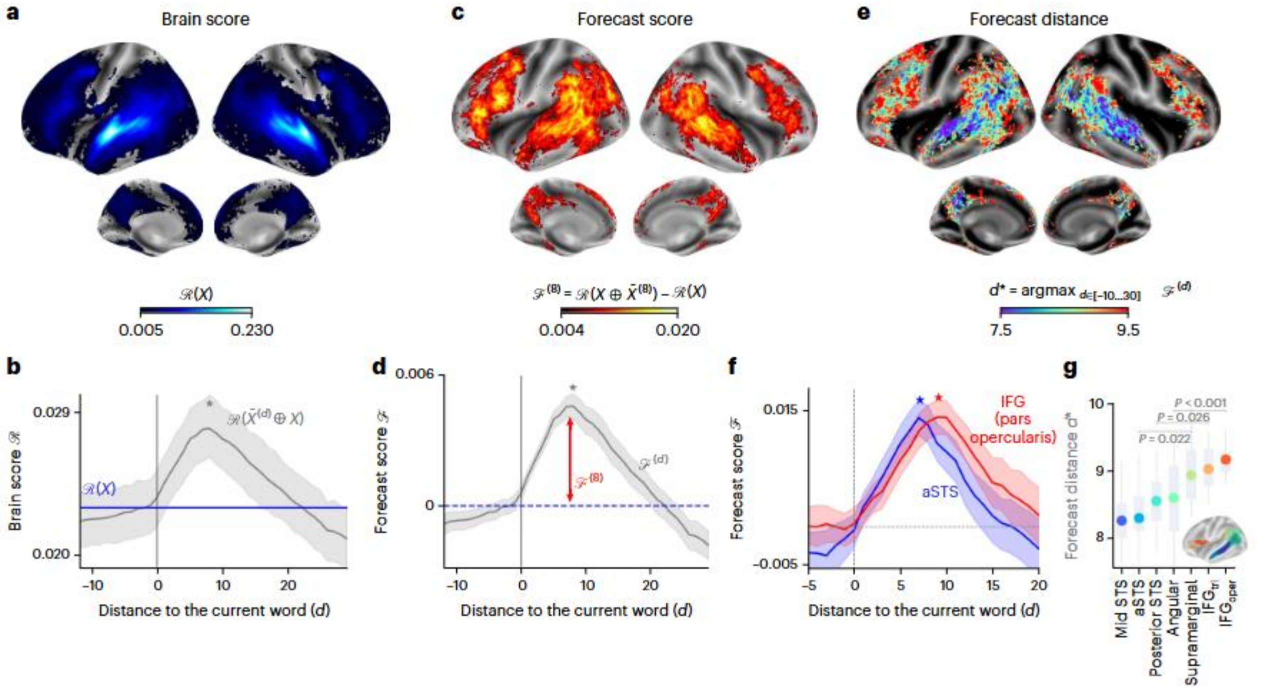
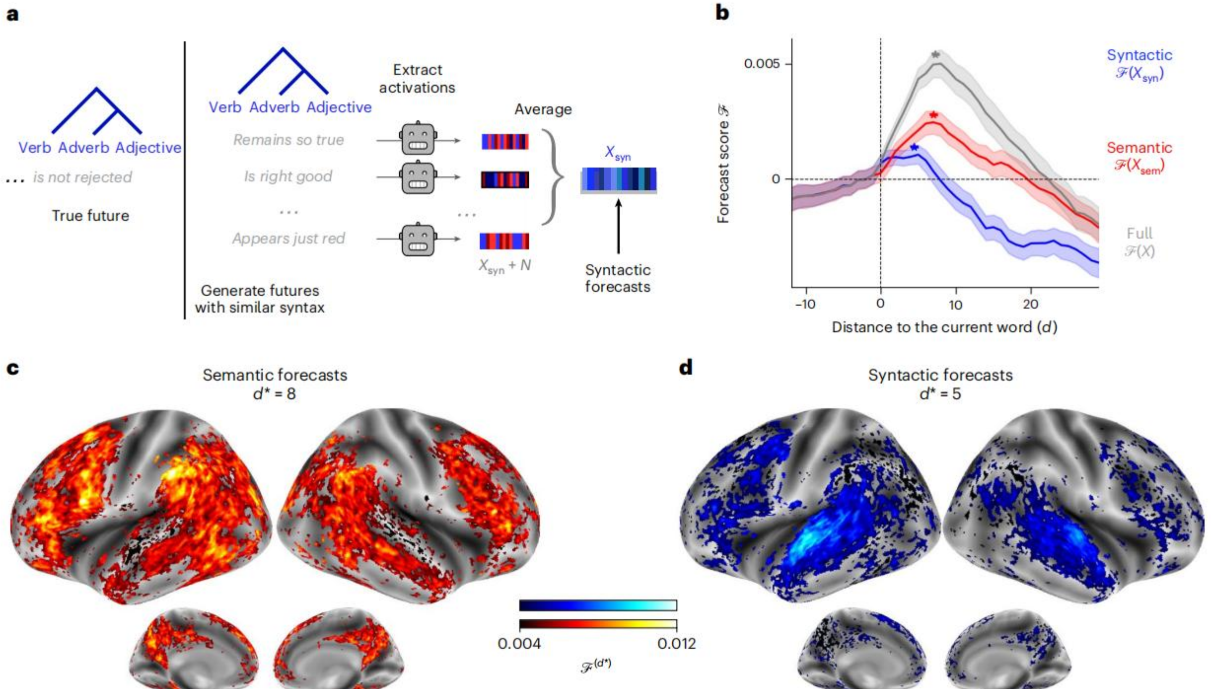
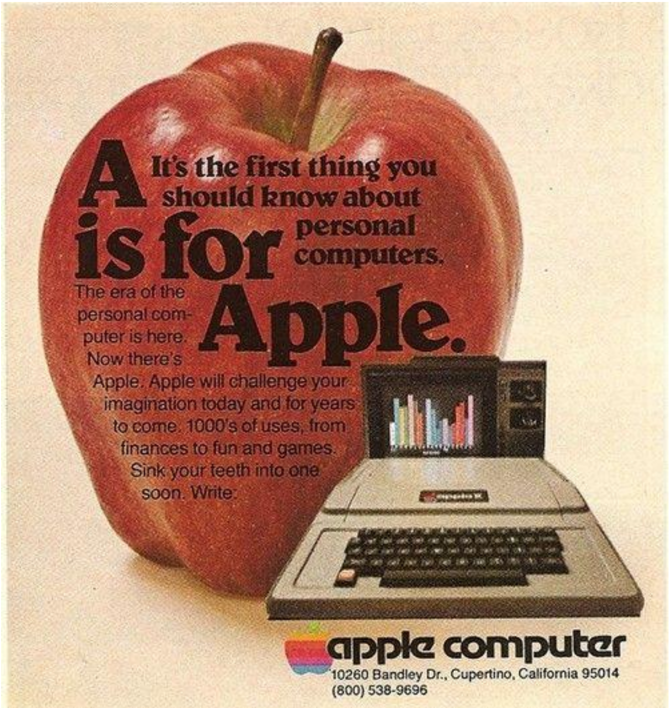




Findings: Modern language models (e.g., GPT-2) linearly map onto brain responses, with this **mapping improving when models include multi-timescale predictions**. Critically, predictions are hierarchically organized: **frontoparietal cortices predict higher-level, longer-range (e.g., 8 words, ~3.15s) and more contextual representations than temporal regions** . Semantic forecasts are long-range, while **syntactic ones are short-range** . These results support hierarchical predictive coding in language processing

Goal/Tasks - Working Memory

Congchi Yin, Yongpeng Zhang, Xuyun Wen, Piji Li. **Improve Language Model and Brain Alignment via Associative Memory.** Findings of ACL 2025.



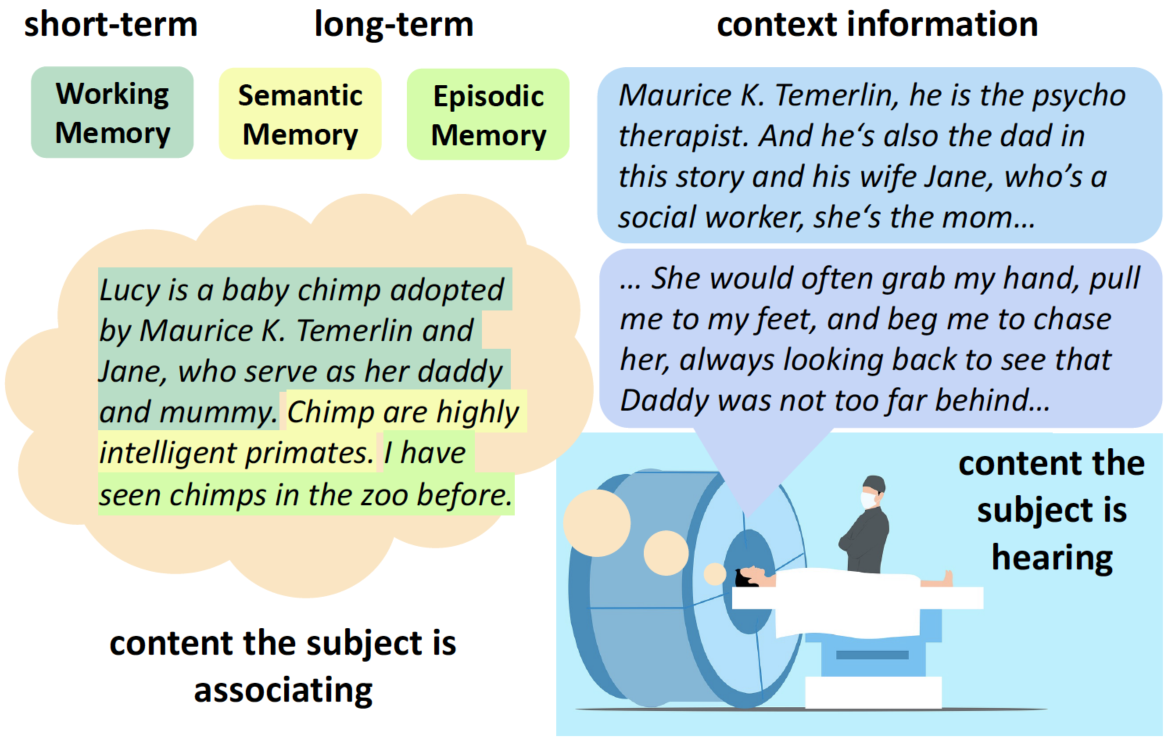


Figure 1: An example of how mental association works when subject is hearing and processing information.

Goal/Tasks - Working Memory

- Data augmentation score → Association simulation

Original Sentences	Method	Data Augmentation
This is Los Angeles. And it's the height of summer. In a small bungalow off of La Cienega, Clara serves homemade chili and chips in red plastic bowls – wine in blue plastic.	word-level, GPT-4	heat, bustling, cozy, spicy, casual, colorful
	word-level, human	hot, comfortable
	sentence-level, GPT-4	The sun blazes down on a cozy home in LA where a casual summer gathering unfolds.
	sentence-level, human	Clara uses plastic bowls of different colors to make thing in a bungalow.
Louis when I first started here. People told him, "Oh no, no she is white man, she's white, she sounds white she's white," and he, convinced, having never met me, that I was black. Well as it turns out, he was right.	word-level, GPT-4	debate, racial identity, assumptions, voice, community perceptions, prejudice, correctness, self-awareness, revelation
	word-level, human	debate, truth, revelation, surprise, race
	sentence-level, GPT-4	In a St. Louis debate about my ethnicity, a stranger's conviction about my race challenged the assumptions tied to my voice,and he was correct.
	sentence-level, human	Debates about the author being black and white were going on long before he came to St Louis Missouri community.

$$\mathcal{R}(X^{(l)}_{assoc}) = corr(g \circ f(X^{(l)}_{assoc}), \overline{Y_i}).$$

The data augmentation of one specific voxel is defined as the difference between brain score with association and original brain score:

$$\mathcal{F}(X^{(l)}) = \mathcal{R}(X^{(l)}_{assoc}) - \mathcal{R}(X^{(l)}).$$

Goal/Tasks - Working Memory

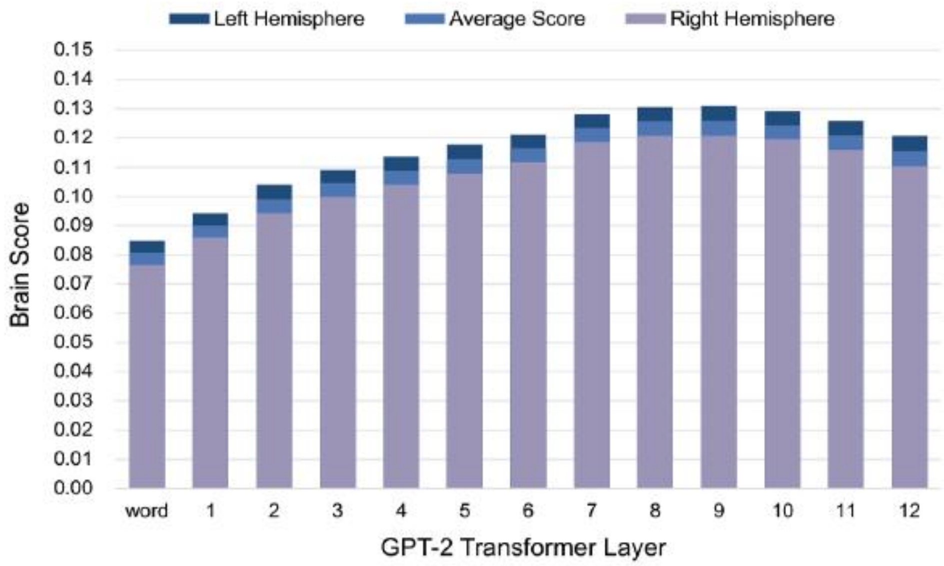
- Empower LLMs to Associate

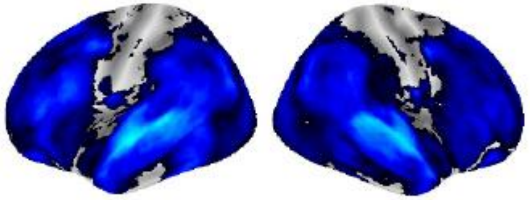
Input		Output
Instruction	**Story Paragraph**	
I'll give you some sentences, you have to perform related association with words.	Sheldon slowly walked into the restaurant, eying the decor suspiciously. His roommate Leonard pushed past him and asked the hostess for a table for two. As they were led to their chairs, Sheldon began to protest yet again.	quirky, cautious, skeptical, friends, dining, impatient
Given some sentences, you are supposed to make related associations and output words.	You know, I think I may have misjudged this restaurant. I won't go out on a limb, but I think we may be looking at my new Tuesday hamburger.	surprise, reconsideration, hamburger, potential favorite
Given a batch of sentences, you need to execute the process of interlinking them based on their relevance with words.	He zipped up Barney's bag and handed it back to him. Quinn followed Barney down the concourse in total confusion. Magic trick? Why wouldn't he tell her what was in the box? She tried to interrogate him as they sat in front of the gate, but he refused to spill the beans.	mystery, secrecy, curiosity, travel, frustration, companionship

$$\mathcal{M}(X^{(l)}) = (\mathcal{R}(X_{sft}^{(l)}) - \mathcal{R}(X^{(l)}))/\mathcal{R}(X^{(l)}).$$

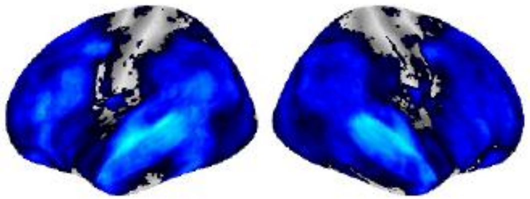
Goal/Tasks - Working Memory

- Brain Score Comparison and Brain Score Ceiling Test

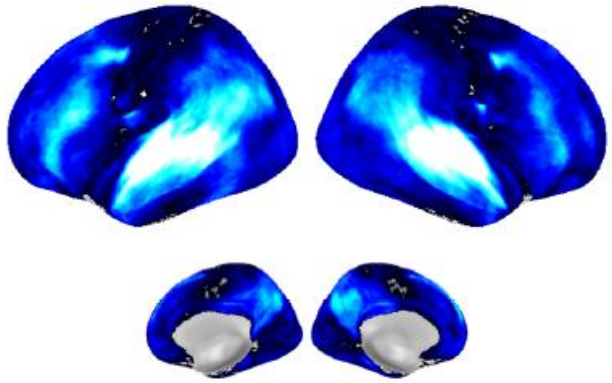




Brain score of GPT-2

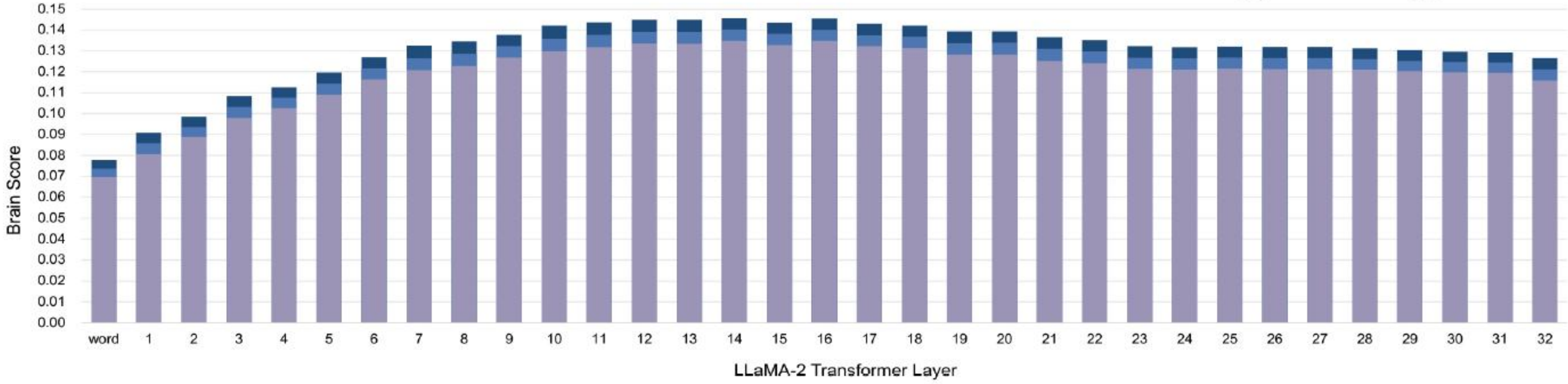


Brain score of LLaMA-2



Brain score ceiling

$$\mathcal{R}(X^{(l)}) = corr(g \circ f(X^{(l)}), \overline{Y_i})$$



Goal/Tasks - Working Memory

- Data Augmentation Score

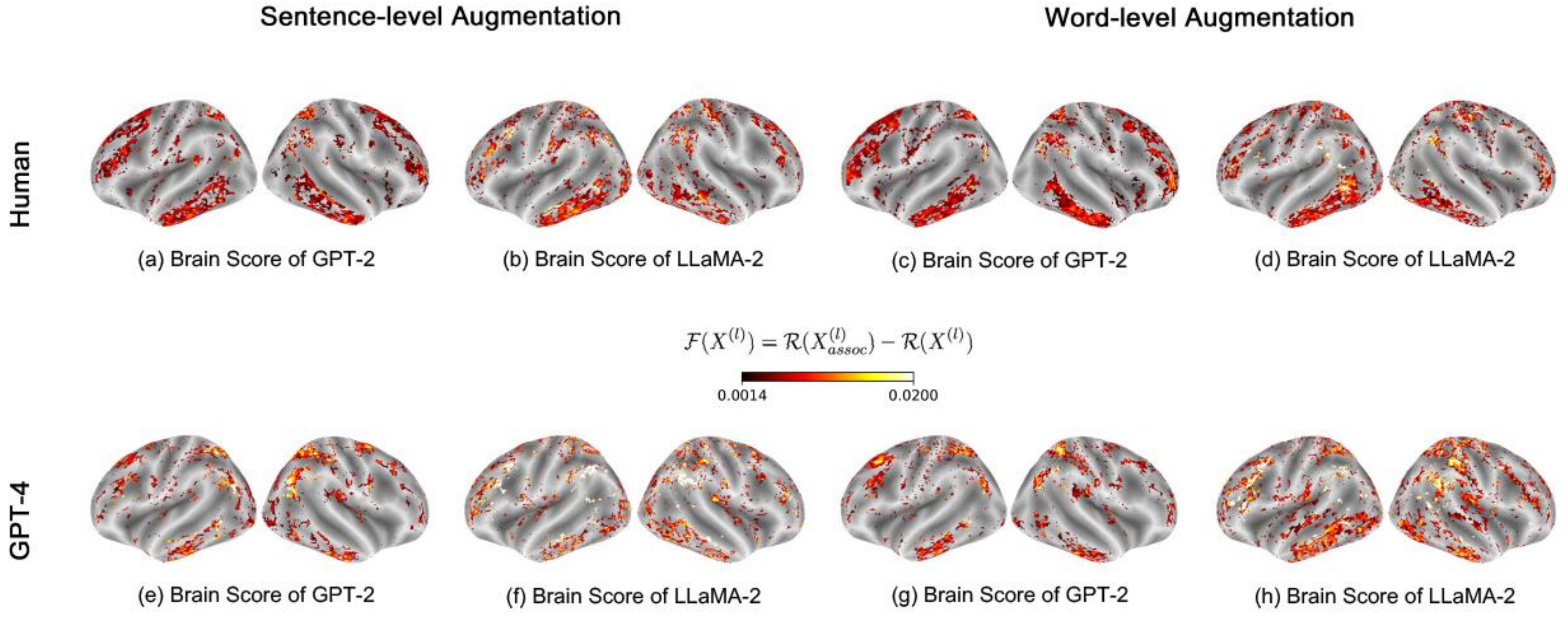
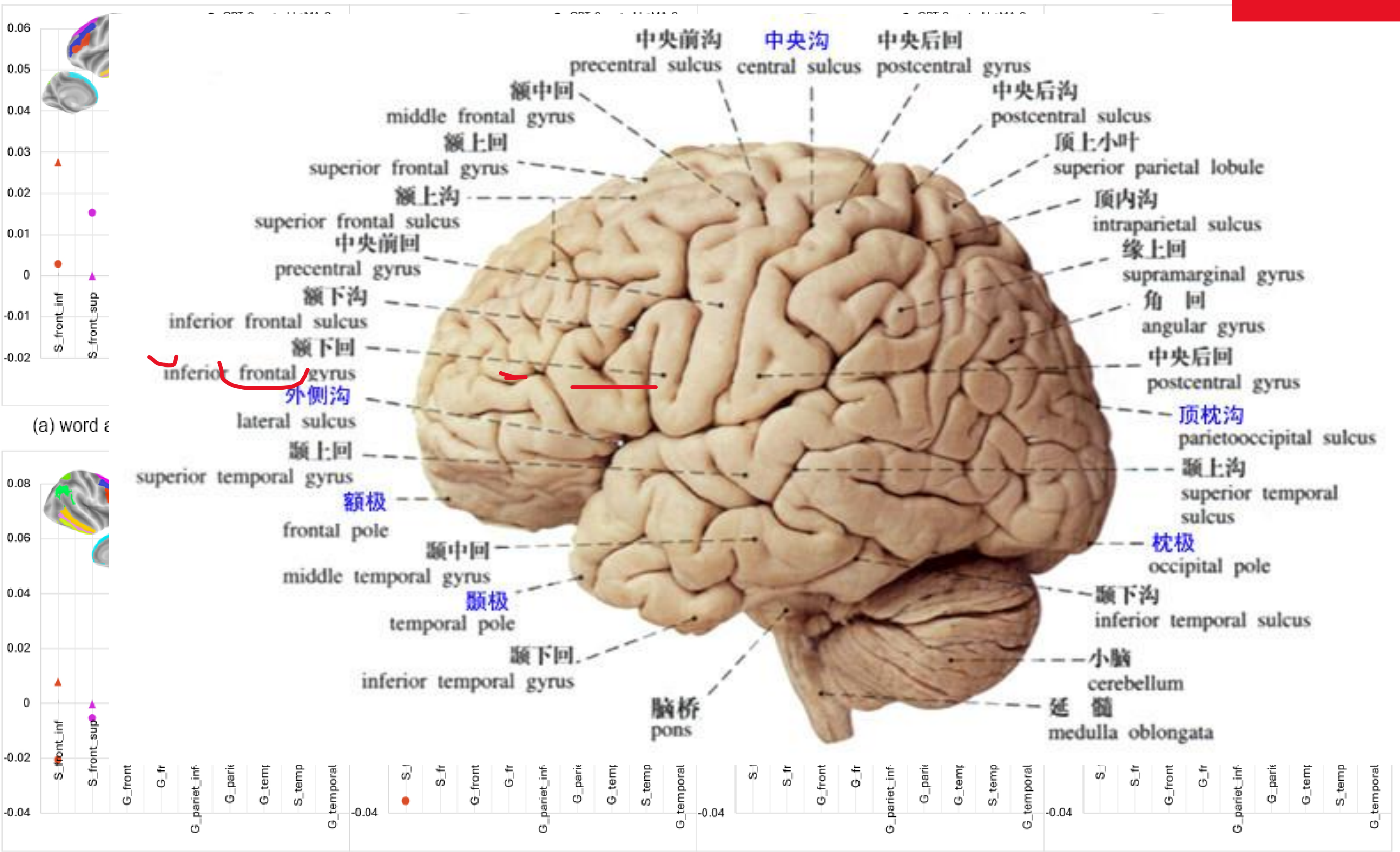


Figure 4: Data augmentation score of sentence-level and word-level mental association.

Goal/Tasks - Working Memory

- Data Augmentation Score of ROIs



(a) word a

(e) word augmentation by GPT-4(R) (f) sentence augmentation by GPT-4(R) (g) word augmentation by human(R) (h) sentence augmentation by human(R)

- **4 ROIs**
- **L/R**

Goal/Tasks - Working Memory

- Mental Association Score

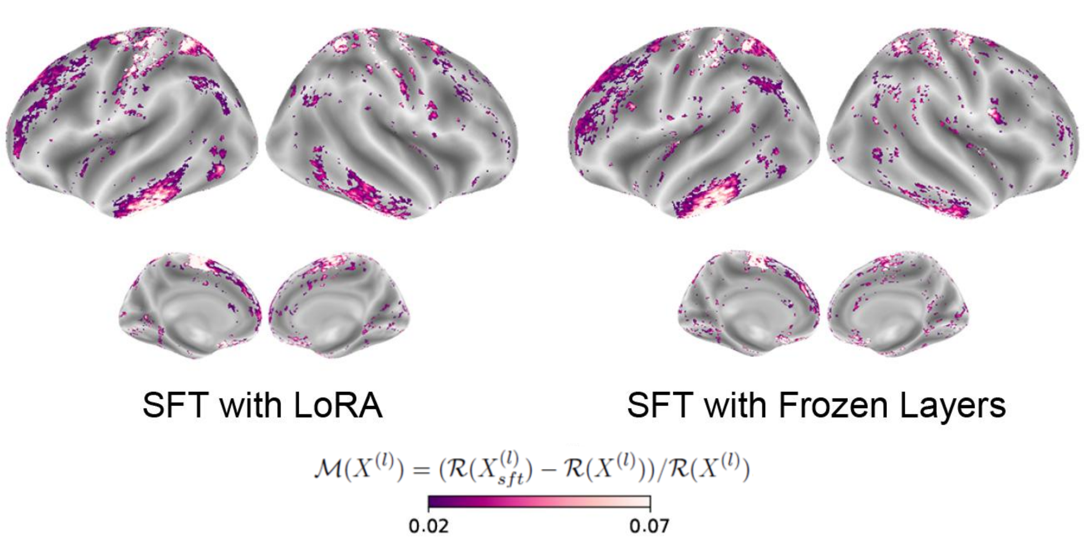
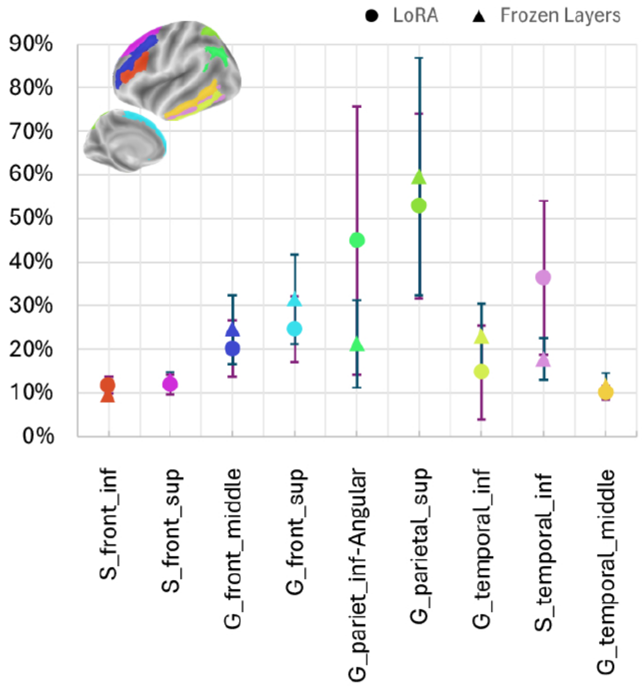
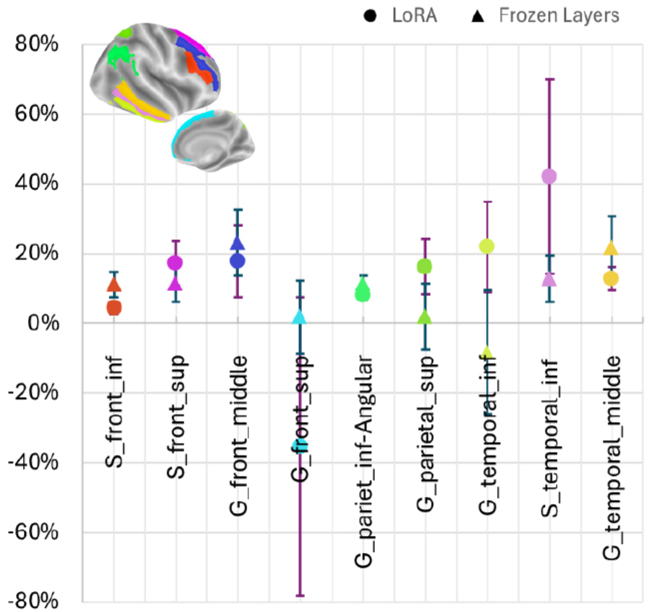


Figure 6: Mental association score after supervised fine-tuning with two different methods.



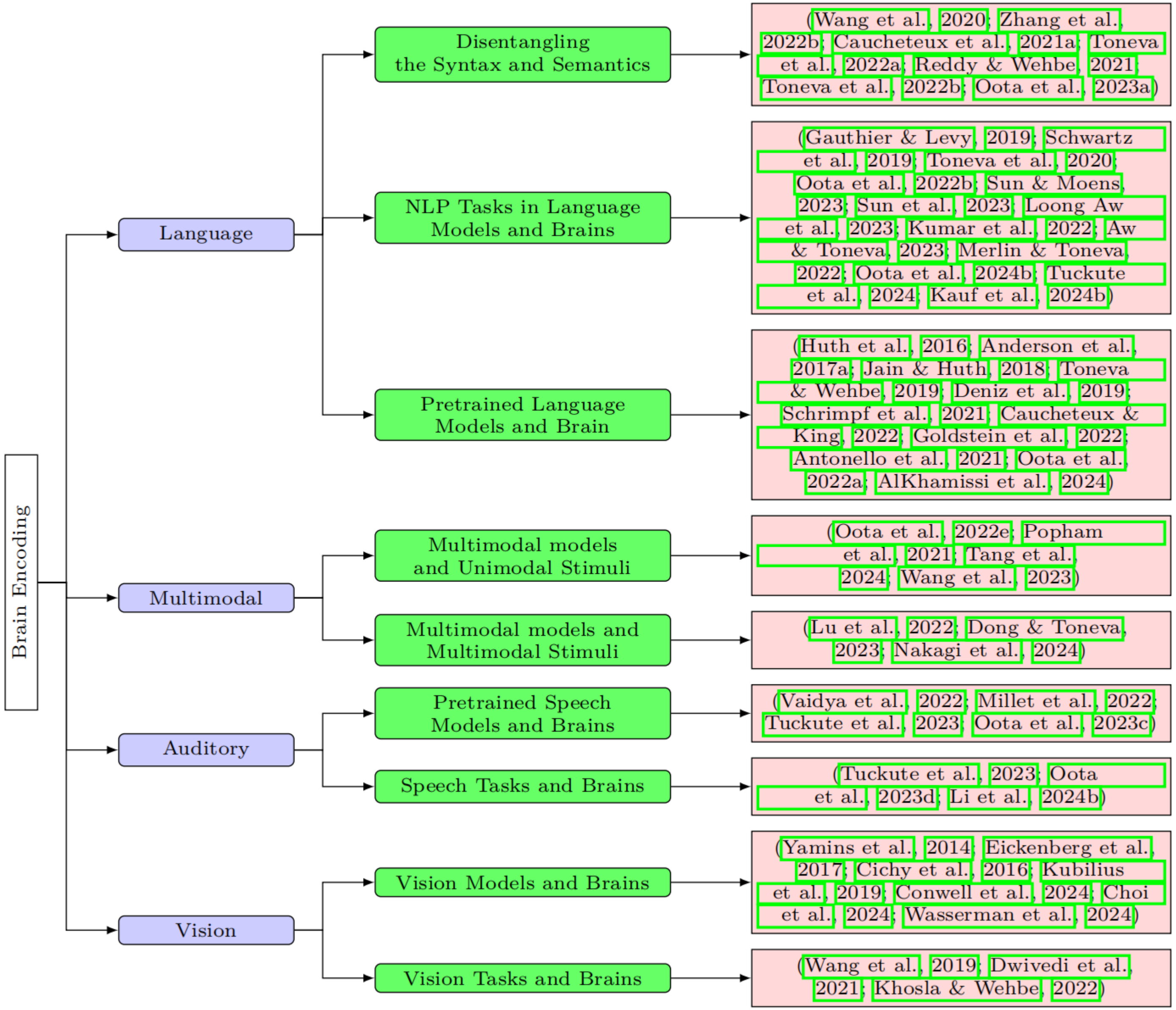
(a) ROI mental association score(L)



(b) ROI mental association score(R)

Brain Encoding - Others

- Li Ji-An, Corey Yi … Mattar. **Linking In-context Learn…** 2024.
- Christina Sartzet… **…d Neural Networks and Brains Watc…**
- Khai Loong Aw, I… **…rratives improves brain alignment…**
- …………



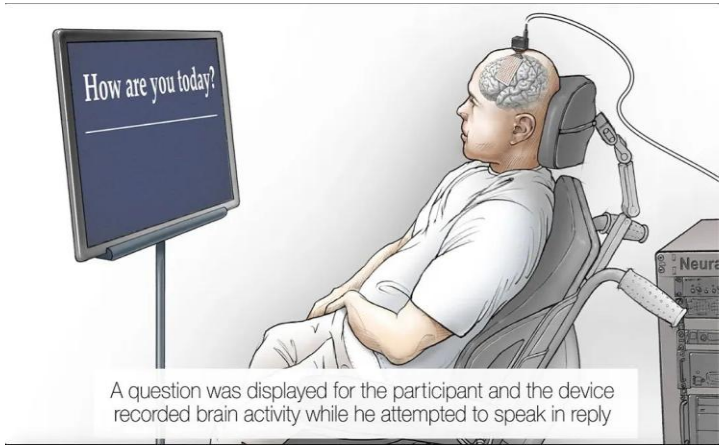
Oota et al (2024)

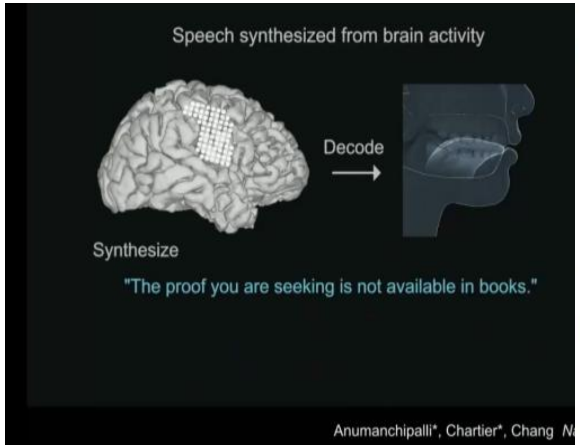
Brain Encoding - Key Takeaways

- Brain encoding can serve as a **special evaluation or verification method or metrics** to analyze grammar, semantics, model structure, model mechanism, and so on.
- How does the brain carry out processes of **representation, compression, memorization, storage, retrieval, and reasoning**?
- It is necessary to **conduct dual verification** of the conclusions from the perspective of **neuroscience**.

Brain Decoding

Brain Decoding





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2024-04-24 18:19 发布于上海 数码领域创作者
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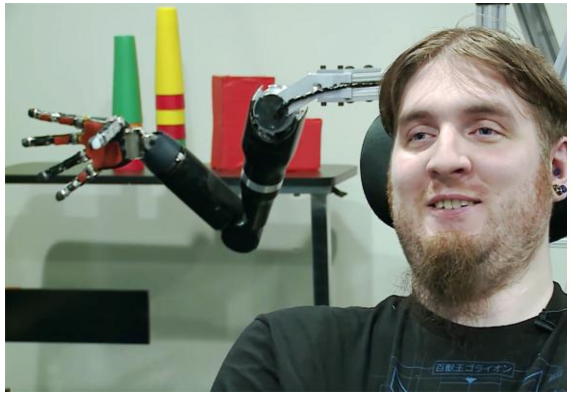
虽然如今提及脑机接口技术，不少人会先想到马斯克的Neuralink，但事实上国内团队也在该领域也取得了不少成果。近日，浙江大学脑机接口团队的最新研究成果在浙江大学医学院附属第二医院发布，成果显示，其脑机接口技术能够使76岁瘫痪老人实现用意念控制机械臂写汉字，且100个常用汉字正确率达到96%。



- **Generation from Signals**

Brain Decoding

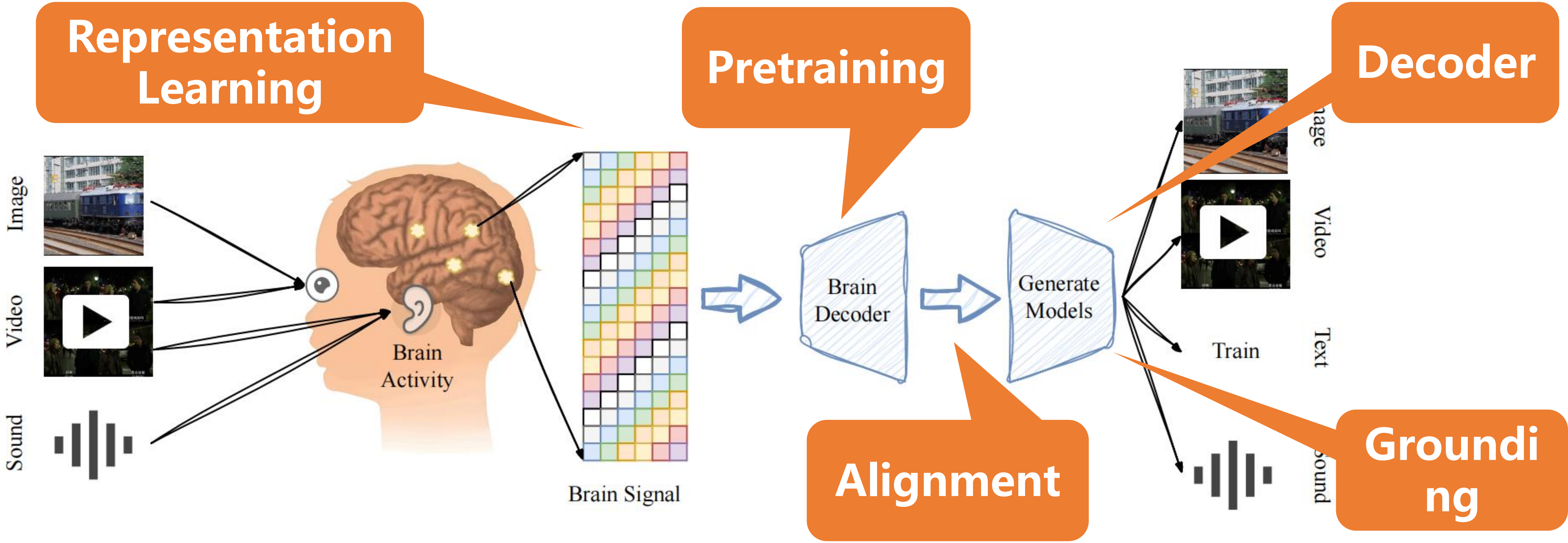


Fig. 1. The basic structure of fMRI-based brain decoding tasks: After the human body receives external stimuli, the brain generates signals in specific regions. By decoding these brain signals and using generative models for reconstruction, the stimulus signals received by the brain are restored.

Pengyu Liu, Guohua Dong, Dan Guo, Kun Li, Fengling Li, Xun Yang, Meng Wang, and Xiaomin Ying. **A Survey on fMRI-based Brain Decoding for Reconstructing Multimodal Stimuli**. *arXiv:2503.15978* (2025).

Brain2Text

Zhenhailong Wang, and Heng Ji. **Open vocabulary electroencephalography-to-text decoding and zero-shot sentiment classification**. AAAI 2022.

Reading Task	#Training Sample	BLEU-N(%) $N=1$	$N=2$	$N=3$	$N=4$	ROUGE-1(%) P	R	F
SR v1.0 (half$_{1st}$)	1771	33.5	16.6	7.2	3.4	22.8	21.6	22.0
SR v1.0 (half$_{1st}$) + NR v1.0 (half$_{1st}$)	3129	37.3	20.2	10.2	5.0	27.8	25.4	26.5
SR v1.0 (half$_{1st}$) + NR v1.0 (half$_{2nd}$)	3058	37.4	18.8	8.9	4.0	26.3	25.2	25.5
SR v1.0	3391	34.5	17.2	7.2	3.0	23.9	22.0	22.8
SR v1.0 + NR v1.0	5797	37.1	20.0	10.4	5.3	27.7	26.0	26.8
SR v1.0 + NR v1.0 + TSR v1.0	9169	37.4	20.0	10.5	5.7	27.4	24.6	25.9
SR v1.0 + NR v1.0 + NR v2.0	10710	**40.1**	**23.1**	**12.5**	**6.8**	**31.7**	**28.8**	**30.1**
w/o pretrained weights	10710	24.7	7.3	2.4	1.0	19.4	20.2	18.9

Table 3: EEG-To-Text sequence-to-sequence model evaluation: (half$_{1st}$) and (half$_{2nd}$) indicate using data from the first half of or the second half of the subjects respectively; no parenthesis means using data from all subjects.

Brain2Text

Zhenhailong Wang, and Heng Ji. **Open vocabulary electroencephalography-to-text decoding and zero-shot sentiment classification**. AAAI 2022.

(1)	Ground Truth: He is a prominent **member of** the *Bush family*, the younger brother of **President George W. Bush**...
	Model Output: was a former **member of** the *American family*, and son brother of **President George W. Bush**...
(2)	Ground Truth: Raymond Arrieta (born March 26, 1965 in San Juan, **Puerto Rico**) is considered by many to be one of **Puerto Rico's greatest** comedians.
	Model Output: mond wasaga,19 in 17, 18) New Francisco, **Puerto Rico**) is a one many to be the of the **Rico's greatest** poets.
(3)	Ground Truth: He was first *appointed* to fill the Senate **seat** of Ernest Lundeen who had **died** in office.
	Model Output: was a *elected* to the the position **seat** in the Hemy in **died** died in 18 in
(4)	Ground Truth: Adolf Otto Reinhold Windaus (December 25, 1876 - June 9, 1959) was a significant *German chemist*.
	Model Output: rian Hitler,hardt,eren18 18, 1885 – January 3, 18) was a *German figure*- and
(5)	Ground Truth: It's *not a particularly* **good** film, but neither is it a *monsterous* one.
	Model Output: was a a *bad* **good** story, but it is it *bad bad*. one.

Table 4: EEG-To-Text decoding examples on unseen test sentences. (1-4) are biographical sentences from Wikipedia in NR v1.0, v2.0. (5) is movie review in SR v1.0. **Bold** words indicate exact match, *Italic* words indicate semantic resemblance, and Underline words indicate error match.

Brain2Text

Hyejeong Jo, Yiqian Yang, Juhyeok Han, Yiqun Duan, Hui Xiong, and Won Hee Lee. **Are eeg-to-text models working?** IJCAI workshop 2024. https://github.com/NeuSpeech/EEG-To-Text

Correction on (AAAI 2022) Open Vocabulary EEG-To-Text Decoding and Zero-shot sentiment classification

results and code is updated on master branch

results and code is updated on master branch

results and code is updated on master branch

First of all, we are not pointing at others, we do this correction due to no offense, but a kind reminder of being careful of the string generation process. We repsect Mr. Wang very much, and appreciate his great contribution in this area.

After scrutilizing the original code shared by Wang Zhenhailong, we discovered that the eval method have an unintentional but very serious mistake in generating predicted strings, which is using teacher forcing implicitly.

The code which reaches my concern is:

```
seq2seqLMoutput = model(input_embeddings_batch, input_masks_batch, input_mask_invert_batch, target_ids_
logits = seq2seqLMoutput.logits # bs*seq_len*voc_sz
probs = logits[0].softmax(dim = 1)
values, predictions = probs.topk(1)
predictions = torch.squeeze(predictions)
predicted_string = tokenizer.decode(predictions)
```

Therefore resulting in predictions like below:

```
target string: It isn't that Stealing Harvard is a horrible movie -- if only it were that grand a failu
predicted string:  was't a the. is was a bad place, it it it were a.. movie.
################################################
```

Brain2Text

Hyejeong Jo, Yiqian Yang, Juhyeok Han, Yiqun Duan, Hui Xiong, and Won Hee Lee. **Are eeg-to-text models working?** IJCAI workshop 2024. https://github.com/NeuSpeech/EEG-To-Text

In addition, we noticed that some people are using it as code base which generates concerning results. We are not condemning these researchers, we just want to notice them and maybe we can do something together to resolve this problem.

BELT Bootstrapping Electroencephalography-to-Language Decoding and Zero-Shot SenTiment Classification by Natural Language Supervision

Aligning Semantic in Brain and Language: A Curriculum Contrastive Method for Electroencephalography-to-Text Generation

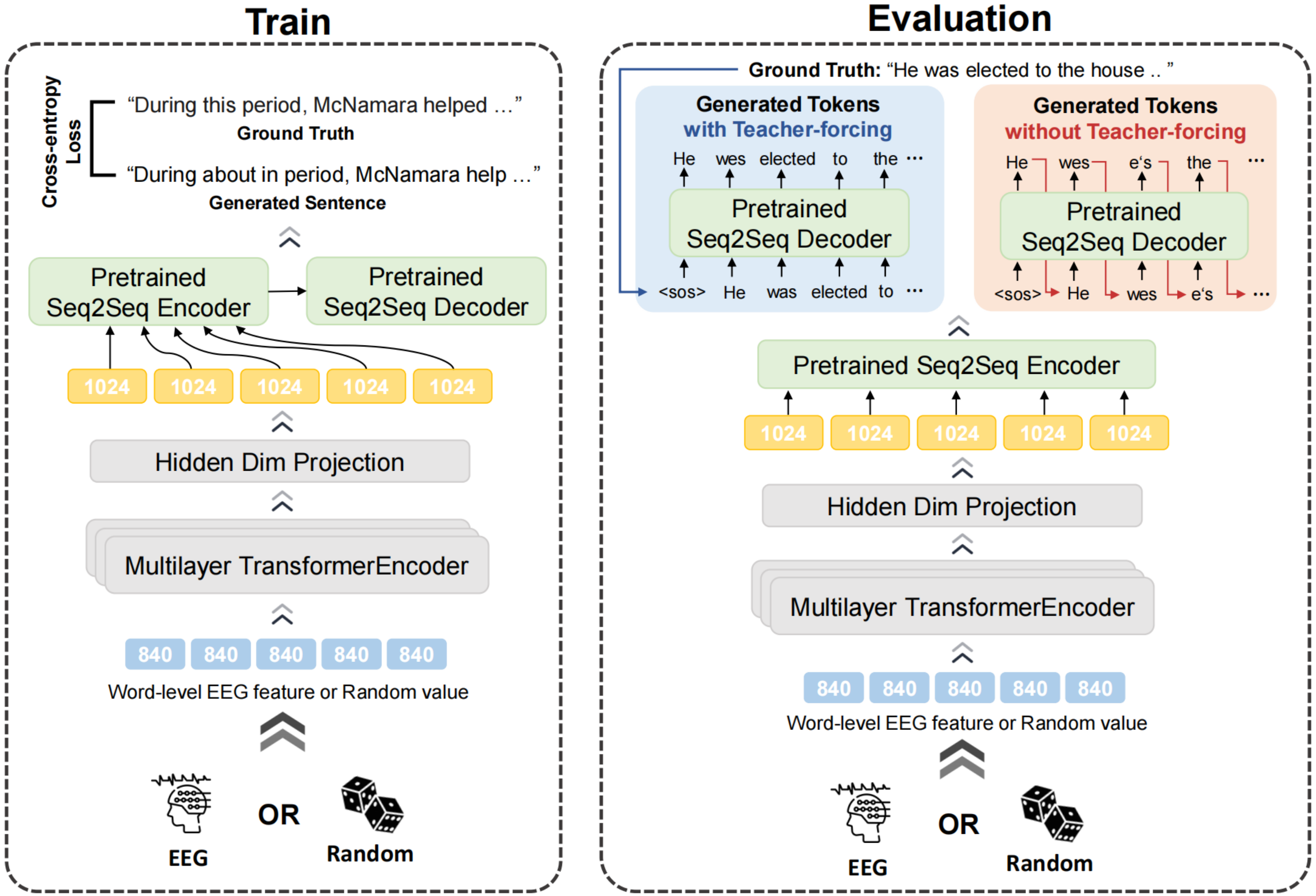
UniCoRN: Unified Cognitive Signal ReconstructioN bridging cognitive signals and human language

Semantic-aware Contrastive Learning for Electroencephalography-to-Text Generation with Curriculum Learning

DeWave: Discrete EEG Waves Encoding for Brain Dynamics to Text Translation

Brain2Text

Hyejeong Jo, Yiqian Yang, Juhyeok Han, Yiqun Duan, Hui Xiong, and Won Hee Lee. **Are eeg-to-text models working?** IJCAI workshop 2024. https://github.com/NeuSpeech/EEG-To-Text



Brain2Text

Hyejeong Jo, Yiqian Yang, Juhyeok Han, Yiqun Duan, Hui Xiong, and Won Hee Lee. **Are eeg-to-text models working?** IJCAI workshop 2024. https://github.com/NeuSpeech/EEG-To-Text

Table 2. EEG-to-Text model evaluation on the ZuCo datasets, incorporating reading tasks from **SR v1.0, NR v1.0, and TSR v1.0**. "*w/tf*" denotes results obtained using teacher-forcing during evaluation as utilized in the original study [1]. In the training and evaluation phases, "EEG" denotes the use of word-level EEG features, while "Random" refers to the employment of random numbers generated from a normal distribution.

Pretrained model	Training	Evaluation	BLEU-N (%) N=1	N=2	N=3	N=4	ROUGE-1 (%) P	R	F	WER (%)
BART	EEG	EEG	13.69	2.97	0.82	0.32	11.98	13.43	11.87	108.43
	EEG	Random	13.87	3.09	0.77	0.25	12.23	13.60	12.14	108.31
	Random	EEG	14.05	3.12	1.00	0.41	11.46	12.37	11.14	110.96
	Random	Random	14.22	3.06	0.93	0.39	11.62	12.29	11.19	110.98
BART *w/tf* [1]	EEG	EEG	39.31	22.09	12.49	7.27	26.41	31.40	28.58	78.08
	EEG	Random	39.34	22.13	12.52	7.29	26.44	31.43	28.61	78.07
	Random	EEG	39.67	22.15	12.49	7.12	26.29	31.00	28.34	78.09
	Random	Random	39.69	22.17	12.50	7.12	26.32	31.03	28.37	78.09
Pegasus	EEG	EEG	8.47	2.48	0.81	0.25	0.00	0.00	0.00	99.69
	EEG	Random	8.58	2.48	0.78	0.00	0.00	0.00	0.00	99.89
	Random	EEG	9.12	2.70	0.91	0.23	0.00	0.00	0.00	98.73
	Random	Random	9.06	2.60	0.84	0.00	0.00	0.00	0.00	99.24
Pegasus *w/tf*	EEG	EEG	38.18	21.04	11.50	6.09	26.72	30.51	28.38	78.57
	EEG	Random	38.30	21.09	11.57	6.12	26.84	30.65	28.51	78.56
	Random	EEG	39.10	21.74	11.97	6.17	27.43	31.26	29.11	78.09
	Random	Random	39.17	21.70	11.96	6.18	27.41	31.34	29.14	78.10
T5	EEG	EEG	16.64	5.80	1.96	0.81	12.28	12.88	11.85	111.13
	EEG	Random	15.42	4.78	1.57	0.65	10.57	11.45	10.35	112.00
	Random	EEG	15.95	5.71	2.01	0.91	11.90	12.61	11.47	111.37
	Random	Random	15.54	5.22	1.70	0.67	11.48	12.23	11.10	111.74
T5 *w/tf*	EEG	EEG	43.50	25.50	15.18	8.69	22.92	28.23	25.11	81.39
	EEG	Random	43.53	25.56	15.15	8.68	22.76	27.82	24.87	81.43
	Random	EEG	43.47	25.34	15.03	8.67	23.02	27.96	25.06	81.64
	Random	Random	43.63	25.57	15.23	8.78	23.36	28.40	25.45	81.46

Table 4. Decoding examples of EEG-to-Text models [1]. "EEG" and "Random" represent that the model is trained and tested on word-level EEG features and random numbers, respectively. BART is used as the pretrained seq2seq model for all models. "*w/tf*" denotes results obtained using teacher-forcing during evaluation, as utilized in the original study [1]. **Bold** indicates words exactly matching the ground truth. Underline denotes words consistently generated by models without teacher-forcing.

Ground truth	It's not a particularly **good** film, **but** neither **is it** a monsterous **one**.
EEG *w/tf* [1]	's a a bad **good** movie, **but** it **is it** bad bad. **one**.
Random *w/tf*	's a a bad **good** movie, **but** it **is it** bad bad. **one**.
EEG	He was elected to the United States House of Representatives in 1946.
Random	He was educated at the University of Virginia, where he earned a Bachelor of Arts degree in political science.
Ground truth	Everything its title **implies**, a standard-**issue** crime **drama** spat out from the Tinseltown assembly **line**.
EEG *w/tf* [1]	about predecessor **implies** is and movie,**issue**, **drama**. between of the depthsseltown set **line**.
Random *w/tf*	about predecessor **implies** is and movie,**issue**, **drama**. between of the sameseltown set..
EEG	He was a member of the Democratic National Committee (DNC) from 1952 until his death in 1968.
Random	He was educated at Trinity College, Cambridge and the University of Oxford.
Ground truth	Joseph H. Ball (November 3, 1905 - December 18, **1993) was an American** politician.
EEG *w/tf* [1]	was. Smith (born 23, 18 - April 23, **1993) was an American** actor,
Random *w/tf*	wasux W (born 23, 18 - April 23, 1977) **was an American** actor.
EEG	He was elected to the United States House of Representatives in 1920.
Random	He was educated at the University of Wisconsin-Madison, and received a Bachelor of Arts degree in English literature from Stony Brook University.

Data Contamination Issues in Brain-to-Text Decoding

- Data splittng methods may cause information leakage.

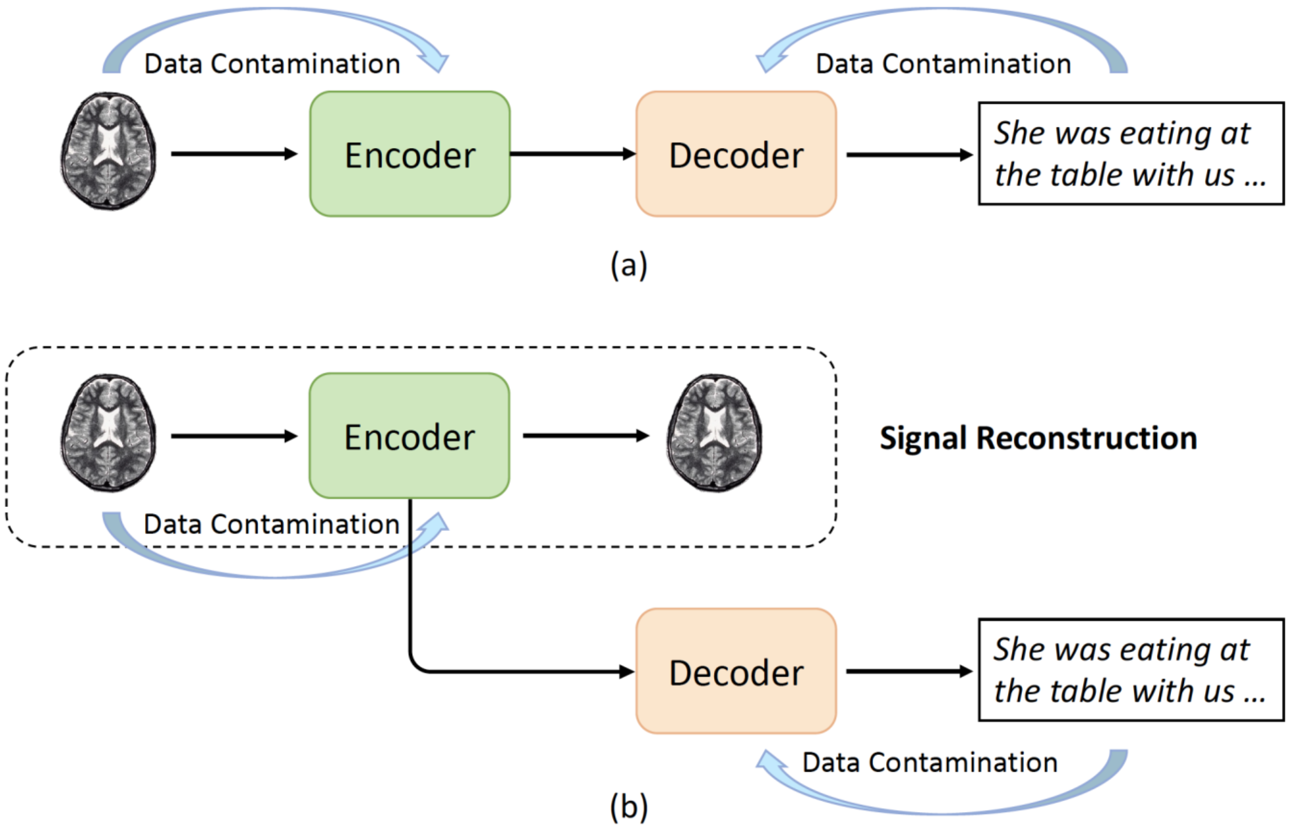


Figure 1: General frameworks of brain-to-text decoding and possible situations of data contamination.

Data Contamination Issues in Brain-to-Text Decoding

- Data splittng methods may cause information leakage.

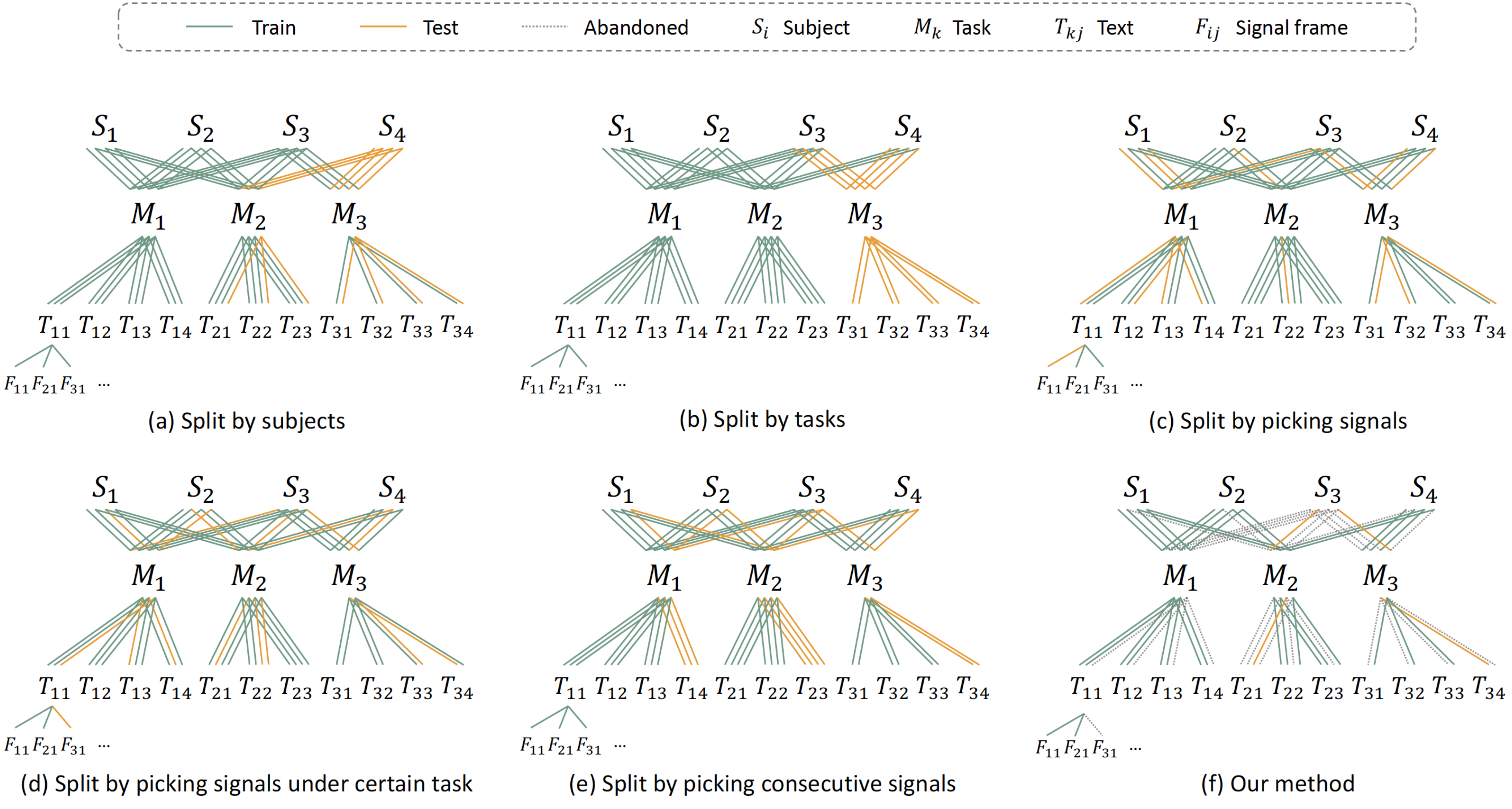


Figure 2: Different splitting methods for cognitive dataset. (Color printing is preferred.)

Data Contamination Issues in Brain-to-Text Decoding

- Leakage Rate

Type	Method	Narratives / ZuCo				Average
		seed1	seed2	seed3	seed4	
CSLR(%)	(a)	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**
	(b)	6.73 / -	6.32 / -	7.7 / -	17.93 / -	9.67 / -
	(c)	12.55 / 12.52	12.52 / 12.55	12.48 / 12.48	12.44 /12.46	12.50 / 12.50
	(d)	12.81 / 12.60	12.8 / 12.58	12.78 / 12.56	12.79 / 12.61	12.795 / 12.59
	(e)	12.28 / -	12.27 / -	12.26 / -	12.27 / -	12.27 / -
	(f)	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**
TSLR(%)	(a)	100.00 / 23.43	100.00 / 20.25	100.00 / 23.38	100.00 / 22.95	100.00 / 22.50
	(b)	**0.00** / -	**0.00** / -	**0.00** / -	**0.00** / -	**0.00** / -
	(c)	100.00 / 13.21	100.00 / 13.06	100.00 / 12.91	100.00 / 13.1	100.00 / 13.07
	(d)	99.93 / **0.00**	99.81 / **0.00**	99.54 / **0.00**	99.99 / **0.00**	99.82 / **0.00**
	(e)	9.19 / -	9.31 / -	9.36 / -	9.29 / -	9.29 / -
	(f)	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**	**0.00 / 0.00**

Table 1: Results of Cognitive Signal Leakage Rate (CSLR) and Text Stimuli Leakage Rate (TSLR).

Data Contamination Issues in Brain-to-Text Decoding

- Leakage verification

Model	Epoch+lr+Method	BLEU-N (%)				ROUGE-1 (%)		
		$N=1$	$N=2$	$N=3$	$N=4$	F	P	R
UniCoRN	10+1e-3+(a)	49.56	30.49	21.07	15.49	44.83	50.41	40.65
	10+1e-3+(b)	26.37	7.50	2.48	0.99	22.28	25.99	19.62
	10+1e-3+(c)	**50.24**	**30.83**	**21.23**	**15.60**	44.68	49.44	41.01
	10+1e-3+(d)	49.63	30.29	20.85	15.32	**45.06**	**50.47**	**41.03**
	10+1e-3+(e)	28.94	9.39	4.07	1.53	21.68	24.64	19.49
UniCoRN*	20+1e-4+(a)	50.19	34.25	25.98	21.00	46.59	50.36	43.62
	30+1e-4+(a)	**55.46**	**40.99**	**32.85**	**27.56**	**52.08**	**55.02**	**49.68**
	20+1e-4+(b)	**25.91**	**8.80**	**3.84**	**1.66**	**20.65**	**27.74**	**16.57**
	30+1e-4+(b)	**25.91**	**8.80**	**3.84**	**1.66**	**20.65**	**27.74**	**16.57**
	20+1e-4+(c)	72.44	60.84	53.35	47.88	70.52	74.10	67.53
	30+1e-4+(c)	**72.82**	**61.42**	**53.95**	**48.44**	**71.24**	**74.41**	**68.57**
	20+1e-4+(d)	65.31	51.02	42.54	36.72	62.76	67.09	59.29
	30+1e-4+(d)	**66.56**	**53.00**	**44.75**	**39.02**	**63.89**	**67.51**	**60.95**
	20+1e-4+(e)	**32.15**	**12.34**	**5.57**	**2.45**	**24.28**	**30.43**	**20.35**
	30+1e-4+(e)	**32.15**	**12.34**	**5.57**	**2.45**	**24.28**	**30.43**	**20.35**

Table 2: Generation quality of UniCoRN model for fMRI under different training settings. Here UniCoRN* indicates the encoder of UniCoRN is randomly initialized instead of pre-trained through signal reconstruction task.

Data Contamination Issues in Brain-to-Text Decoding

- Leakage verification

Model	Epoch+lr+Method	BLEU-N (%)				ROUGE-1 (%)		
		$N=1$	$N=2$	$N=3$	$N=4$	F	P	R
UniCoRN	50+1e-4+(a)	58.09	49.23	43.23	**38.43**	63.88	61.12	67.50
	80+1e-4+(a)	**60.88**	**50.52**	**43.42**	37.84	**65.17**	**61.16**	**70.72**
	50+1e-4+(c)	52.30	42.89	36.80	32.17	57.39	51.09	67.29
	80+1e-4+(c)	**60.78**	**55.92**	**53.18**	**51.10**	**84.64**	**63.16**	**71.50**
	50+1e-4+(d)	**22.90**	**7.36**	**2.71**	**0.95**	**17.73**	**19.90**	**17.33**
	80+1e-4+(d)	**22.90**	**7.36**	**2.71**	**0.95**	**17.73**	**19.90**	**17.33**
EEG2Text	50+1e-4+(a)	51.22	33.83	22.99	16.05	46.40	46.85	46.58
	80+1e-4+(a)	**63.32**	**52.52**	**45.19**	**39.50**	**65.96**	**64.74**	**68.01**
	50+1e-4+(c)	53.83	38.99	29.57	23.01	53.64	54.19	53.56
	80+1e-4+(c)	**65.42**	**57.56**	**52.56**	**48.60**	**73.00**	**69.99**	**77.01**
	50+1e-4+(d)	**23.92**	**8.16**	**3.21**	**1.20**	**20.78**	**19.96**	**23.89**
	80+1e-4+(d)	**23.92**	**8.16**	**3.21**	**1.20**	**20.78**	**19.96**	**23.89**

Table 3: Generation quality of UniCoRN and EEG2Text model for EEG under different training settings.

Data Contamination Issues in Brain-to-Text Decoding

- Our splitting methods

Dataset	Model	BLEU-N (%)				ROUGE-1 (%)		
		$N=1$	$N=2$	$N=3$	$N=4$	F	P	R
Narratives	UniCoRN	**22.83**	**5.69**	**1.43**	**0.48**	**15.55**	**24.80**	**19.04**
ZuCo	UniCoRN	23.32	**7.78**	**3.01**	**1.09**	18.47	20.00	17.92
	EEG2Text	**24.49**	7.49	2.28	0.62	**23.98**	**23.95**	**25.74**

Table 4: A fair benchmark for evaluating brain-to-text decoding.

Congchi Yin, Qian Yu, Zhiwei Fang, Jie He, Changping Peng, Zhangang Lin, Jingping Shao, and Piji Li. **Cross-Subject Data Splitting for Brain-to-Text Decoding**. *arXiv:2312.10987* (2023).

Brain2Text

- *Jilong Li, Zhenxi Song, Jiaqi Wang, Meishan Zhang, Honghai LIU, et al.* **BrainECHO: Semantic Brain Signal Decoding through Vector-Quantized Spectrogram Reconstruction for Whisper-Enhanced Text Generation. ACL 2025.**

			BLEU-N (%) ↑				ROUGE-1 (%)↑			WER (%) ↓
Split	**Input**	**Method**	N=1	N=2	N=3	N=4	P	R	F	
Subject	Noise	NeuSpeech (Yang et al., 2024b)	8.45	1.78	0.43	0	10.26	21.61	13.02	198.31
	Noise	BrainECHO	4.75	1.10	0.28	0	11.25	7.81	8.52	105.27
	EEG feature	EEG-to-Text (Wang and Ji, 2022)	8.82	3.15	1.90	1.44	10.13	21.61	13.12	233.99
	EEG	NeuSpeech (Yang et al., 2024b)	85.31	84.38	83.98	83.75	82.60	82.73	82.64	16.97
	EEG	MAD (Yang et al., 2024c)	80.34	79.10	78.46	78.15	81.00	**90.76**	83.79	42.14
	EEG	BrainECHO	**89.78**	**89.06**	**88.74**	**88.55**	**87.05**	87.27	**87.13**	**11.72**
	EEG	BrainECHO *w/ tf*	**98.82**	**98.74**	**98.68**	**98.64**	**98.45**	**98.44**	**98.45**	**1.18**
Sentence	EEG	BrainECHO	**89.24**	**88.52**	**88.18**	**88.01**	**85.56**	**85.78**	**85.63**	**12.34**

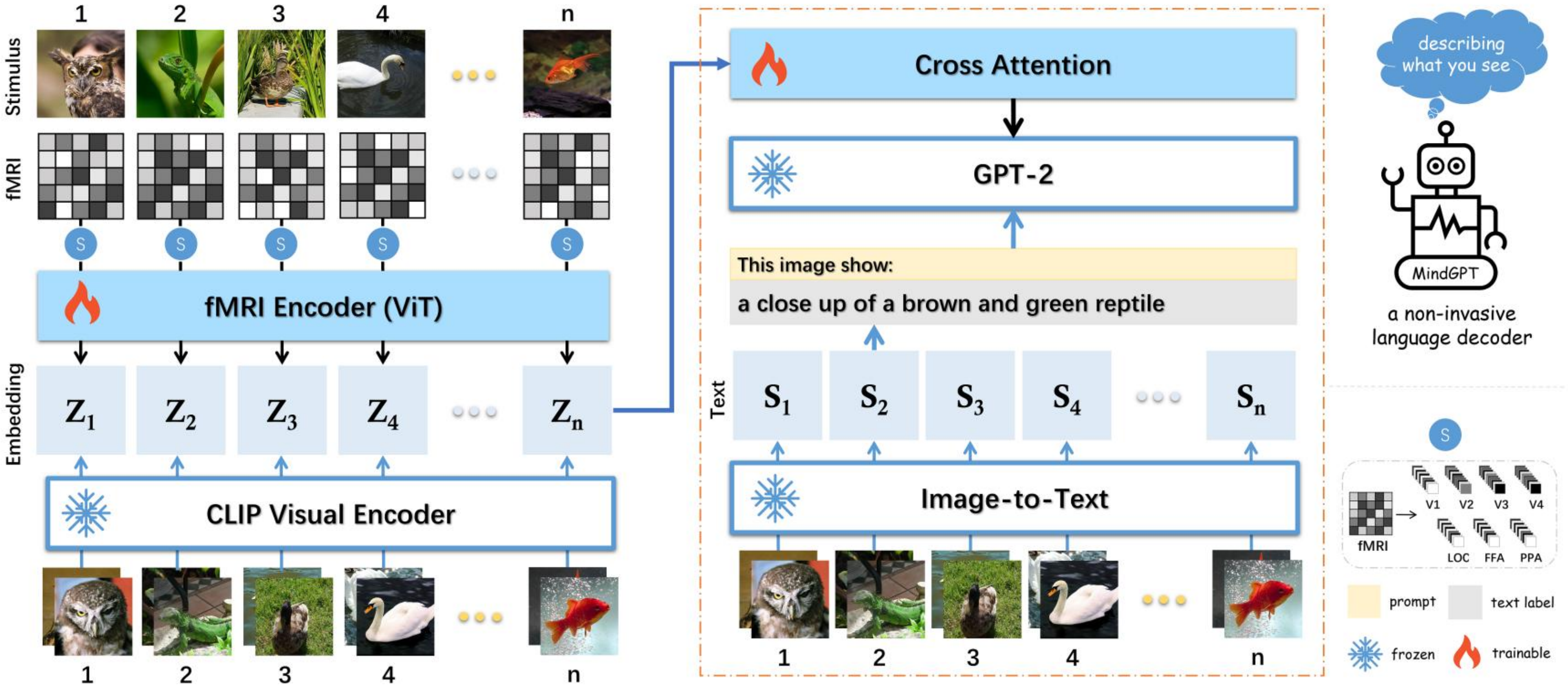
Table 1: Overall comparison of decoding performance on the *Brennan* dataset.

			BLEU-N (%) ↑				ROUGE-1 (%)↑			WER (%) ↓
Split	**Input**	**Method**	N=1	N=2	N=3	N=4	P	R	F	
Random Shuffling	MEG feature	EEG-to-Text (Wang and Ji, 2022)	9.21	2.13	0.57	0.14	9.74	10.73	11.38	118.25
	MEG	NeuSpeech (Yang et al., 2024b)	50.49	46.85	44.42	42.55	46.39	52.48	47.10	71.17
	MEG	NeuSpeech (Original results)	60.3	55.26	51.24	47.78	60.88	59.76	58.73	56.63
	MEG	MAD (Yang et al., 2024c)	3.93	0.42	0	0	8.98	6.85	7.26	105.33
	MEG	BrainECHO	**73.35**	**72.66**	**72.46**	**72.42**	**69.66**	**70.12**	**69.73**	**31.44**
Session	MEG	NeuSpeech (Yang et al., 2024b)	53.16	-	-	-	-	-	-	-
	MEG	BrainECHO	**75.24**	**74.57**	**74.34**	**74.27**	**72.94**	**72.84**	**72.78**	**29.59**
Sentence	MEG	BrainECHO	**73.58**	**72.99**	**72.82**	**72.79**	**70.38**	**70.75**	**70.73**	**31.11**
Subject	MEG	BrainECHO	**75.05**	**74.38**	**74.18**	**74.14**	**71.83**	**72.02**	**71.72**	**29.80**

Table 2: Overall comparison of decoding performance on the *GWilliams* dataset.

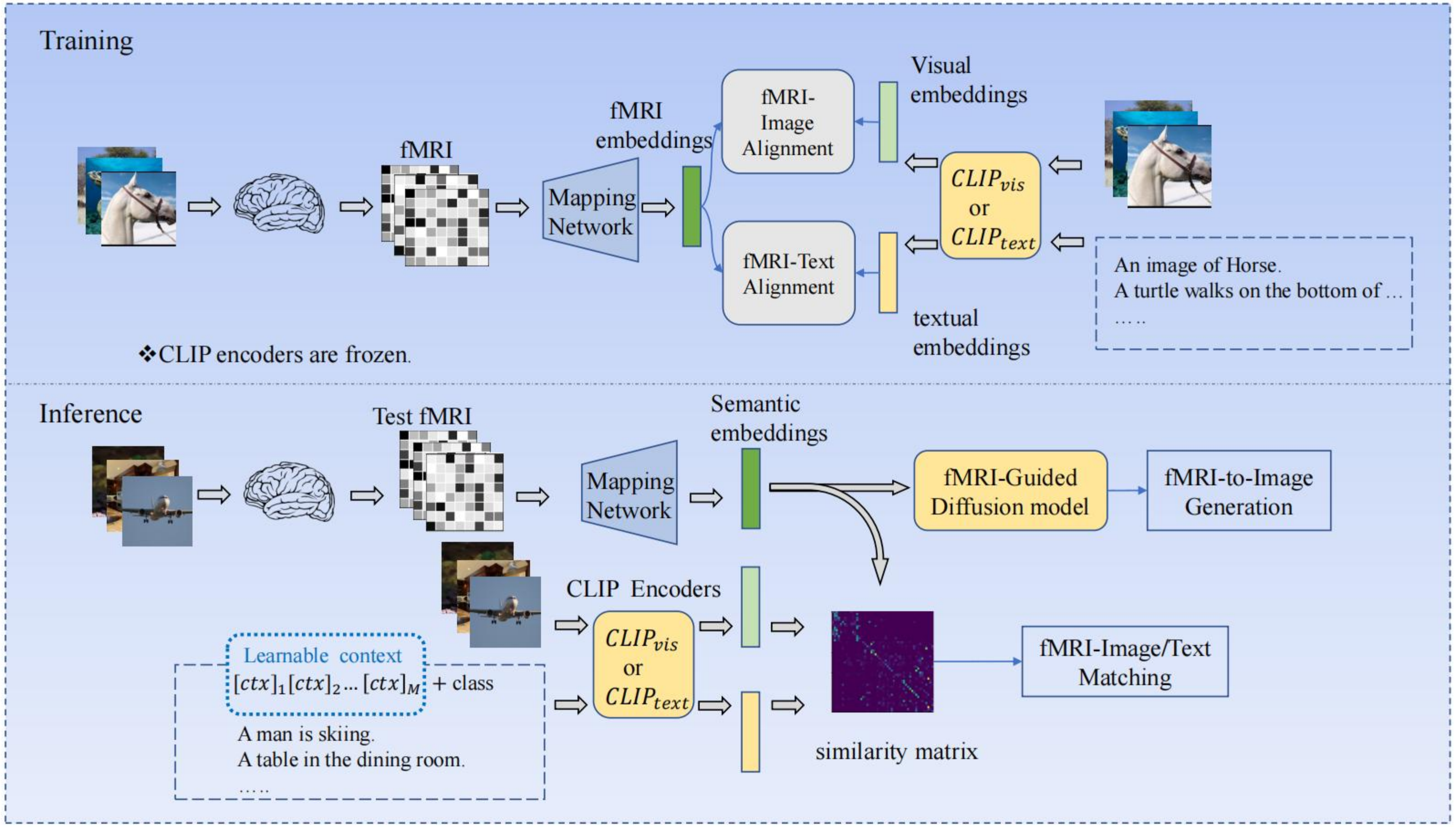
Brain2Text

Jiaxuan Chen, Yu Qi, Yueming Wang, and Gang Pan. **MindGPT: Interpreting what you see with non-invasive brain recordings**. arxiv 2023. *IEEE Transactions on Image Processing* (2025).



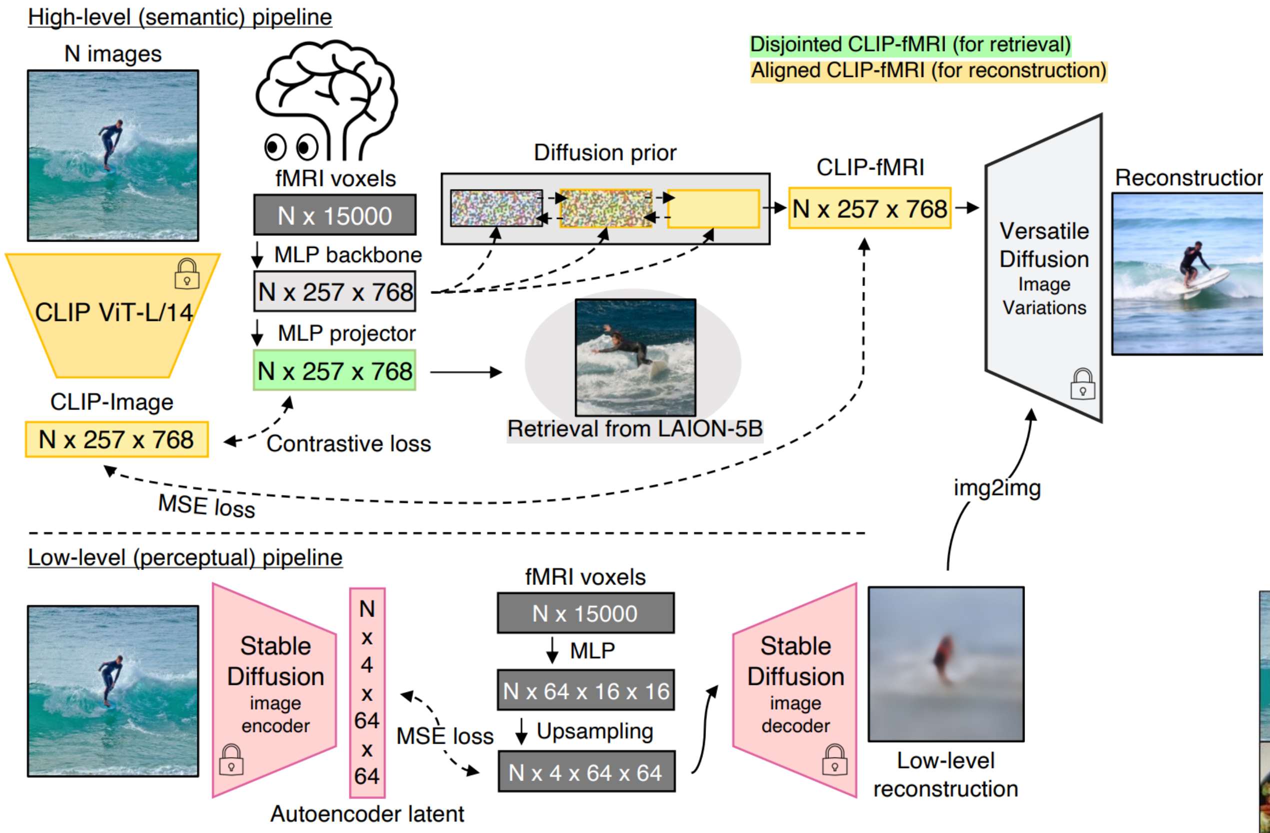
Brain2Image

- Yulong Liu, Yongqiang Ma, Wei Zhou, Guibo Zhu, and Nanning Zheng. **Brainclip: Bridging brain and visual-linguistic representation via clip for generic natural visual stimulus decoding**. arXiv preprint arXiv:2302.12971 (2023).



Brain2Image

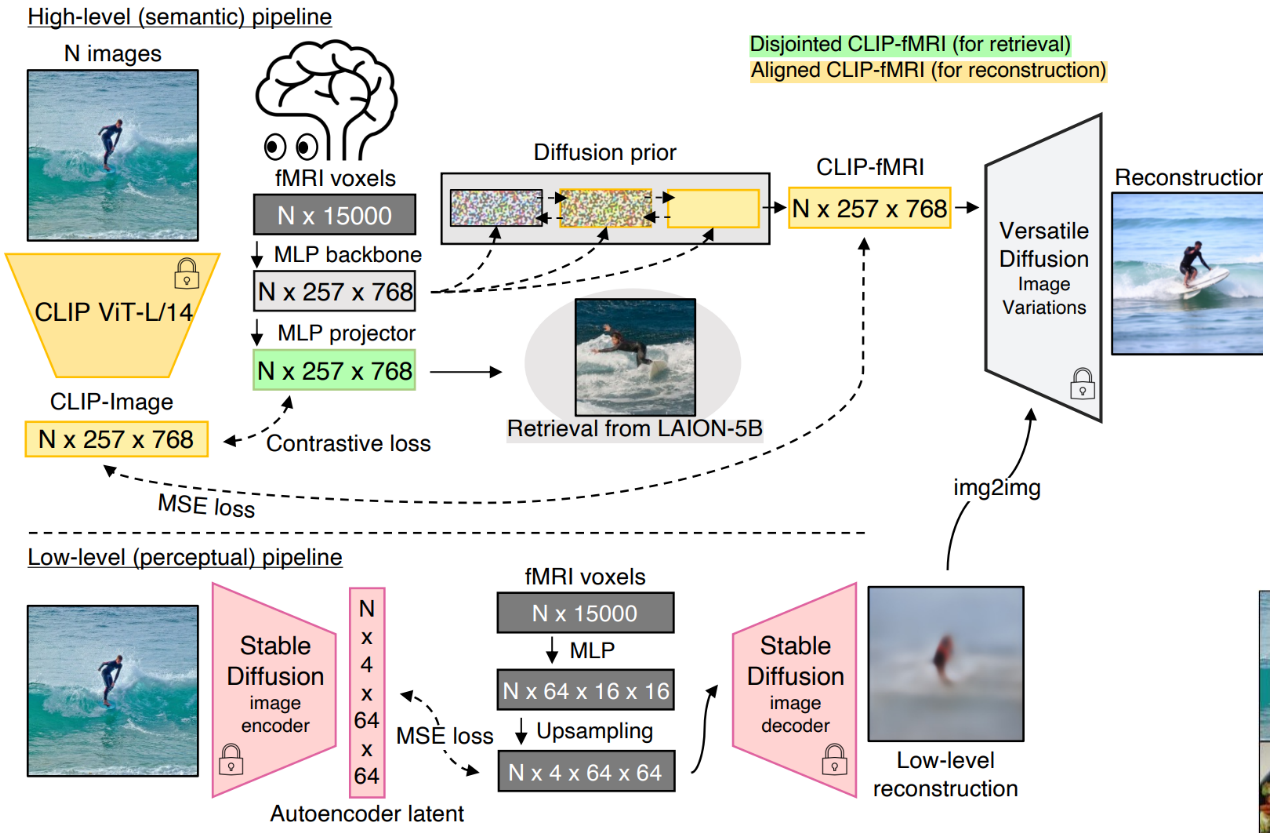
Paul Steven Scotti, Atmadeep Banerjee, Jimmie Goode, Stepan Shabalin, Alex Nguyen, Cohen Ethan, Aidan James Dempster, Nathalie Verlinde, Elad Yundler, David Weisberg, Kenneth Norman, Tanishq Mathew Abraham. **Reconstructing the Mind's Eye: fMRI-to-Image with Contrastive Learning and Diffusion Priors**. NeurIPS 2023.



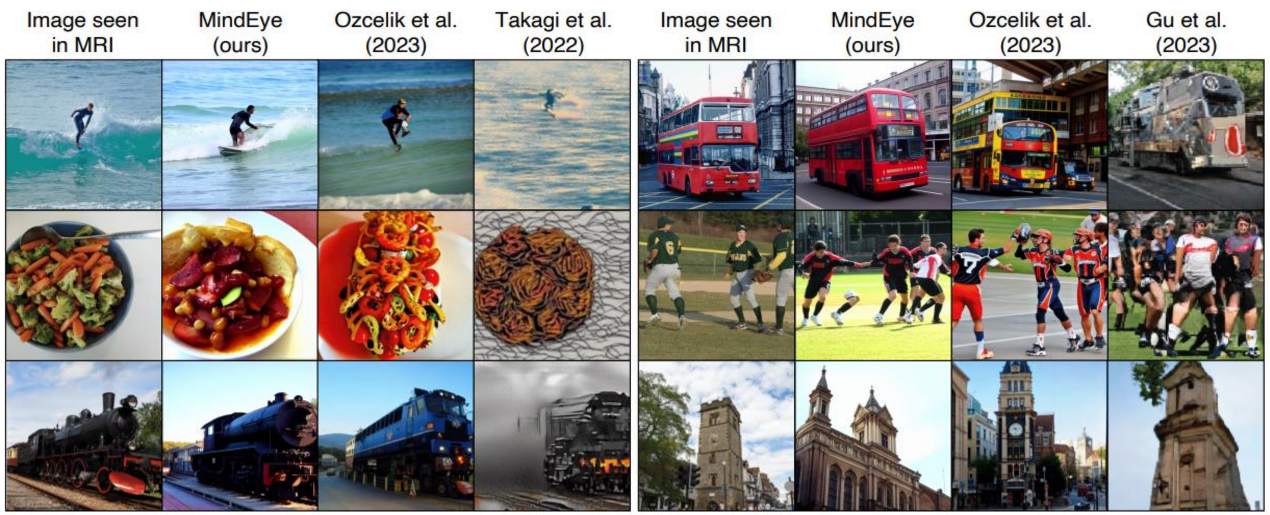
Method	PixCorr ↑	SSIM ↑	Alex(2) ↑	Alex(5) ↑	Incep ↑	CLIP ↑	Eff ↓	SwAV ↓	Image ↑	Brain ↑
	Low-Level				High-Level				Retrieval	
Lin et al. [11]	–	–	–	–	78.2%	–	–	–	11.0%	49.0%
Takagi... [3]	–	–	83.0%	83.0%	76.0%	77.0%	–	–	–	–
Gu et al. [28]	.150	.325	–	–	–	–	.862	.465	–	–
Ozcelik... [4]	.254	**.356**	94.2%	96.2%	87.2%	91.5%	.775	.423	21.1%	30.3%
MindEye	**.309**	.323	**94.7%**	**97.8%**	**93.8%**	**94.1%**	**.645**	**.367**	**93.6%**	**90.1%**
MindEye (Low-Level)	**.360**	**.479**	78.1%	74.8%	58.7%	59.2%	1.00	.663	–	–
MindEye (High-Level)	.194	.308	**91.7%**	**97.4%**	**93.6%**	**94.2%**	**.645**	**.369**	**93.6%**	**90.1%**
MindEye (LAION)	.130	.308	84.0%	92.6%	86.9%	86.1%	.778	.477	–	–
Ozcelik... (Low-, S1)	.358	.437	**97.7%**	**97.6%**	**77.0%**	**71.1%**	**.906**	**.581**	–	–
MindEye (Low-, S1)	**.456**	**.493**	87.1%	84.1%	61.6%	62.4%	.992	.638	–	–

Brain2Image

Paul Steven Scotti, Atmadeep Banerjee, Jimmie Goode, Stepan Shabalin, Alex Nguyen, Cohen Ethan, Aidan James Dempster, Nathalie Verlinde, Elad Yundler, David Weisberg, Kenneth Norman, Tanishq Mathew Abraham. **Reconstructing the Mind's Eye: fMRI-to-Image with Contrastive Learning and Diffusion Priors**. NeurIPS 2023.

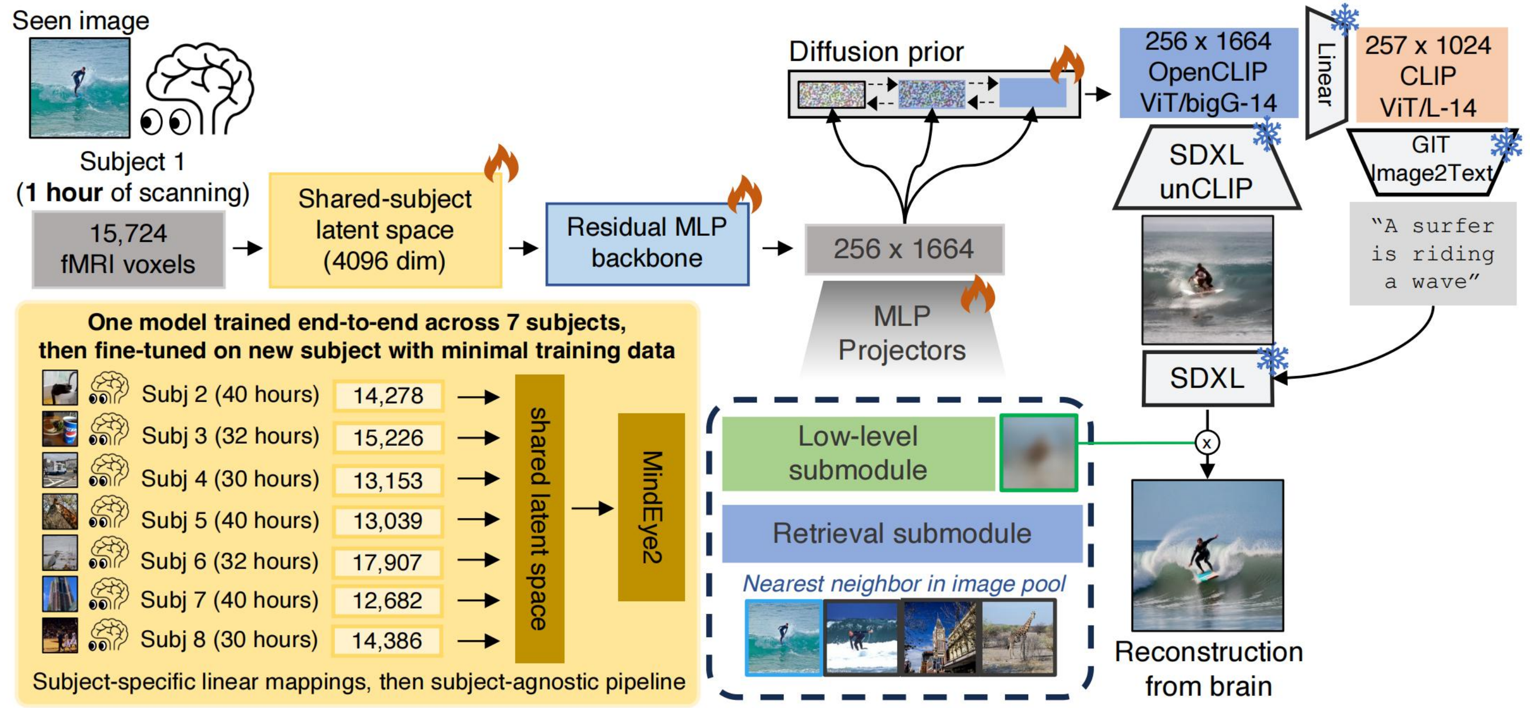


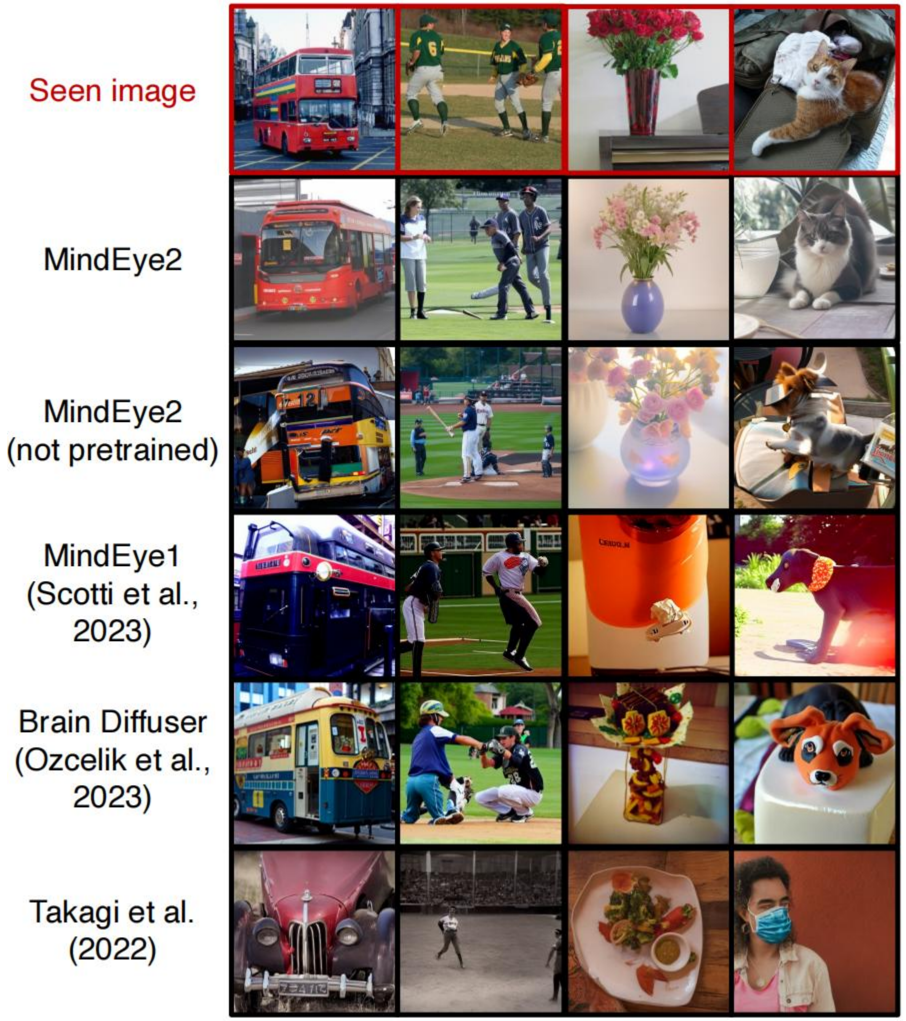
Method	Low-Level				High-Level				Retrieval	
	PixCorr ↑	SSIM ↑	Alex(2) ↑	Alex(5) ↑	Incep ↑	CLIP ↑	Eff ↓	SwAV ↓	Image ↑	Brain ↑
Lin et al. [11]	–	–	–	–	78.2%	–	–	–	11.0%	49.0%
Takagi... [3]	–	–	83.0%	83.0%	76.0%	77.0%	–	–	–	–
Gu et al. [28]	.150	.325	–	–	–	–	.862	.465	–	–
Ozcelik... [4]	.254	**.356**	94.2%	96.2%	87.2%	91.5%	.775	.423	21.1%	30.3%
MindEye	**.309**	.323	**94.7%**	**97.8%**	**93.8%**	**94.1%**	**.645**	**.367**	**93.6%**	**90.1%**
MindEye (Low-Level)	**.360**	**.479**	78.1%	74.8%	58.7%	59.2%	1.00	.663	–	–
MindEye (High-Level)	.194	.308	**91.7%**	**97.4%**	**93.6%**	**94.2%**	**.645**	**.369**	**93.6%**	**90.1%**
MindEye (LAION)	.130	.308	84.0%	92.6%	86.9%	86.1%	.778	.477	–	–
Ozcelik... (Low-, S1)	.358	.437	**97.7%**	**97.6%**	**77.0%**	**71.1%**	**.906**	**.581**	–	–
MindEye (Low-, S1)	**.456**	**.493**	87.1%	84.1%	61.6%	62.4%	.992	.638	–	–



Brain2Image

Paul Scotti, Mihir Tripathy, Cesar Kadir Torrico Villanueva, Reese Kneeland, Tong Chen, Ashutosh Narang, Charan Santhirasegaran, Jonathan Xu, Thomas Naselaris, Kenneth Norman, Tanishq Abraham. **MindEye2: Shared-Subject Models Enable fMRI-To-Image With 1 Hour of Data**. ICML 2024.





Method	Low-Level				High-Level				Retrieval	
	PixCorr ↑	SSIM ↑	Alex(2) ↑	Alex(5) ↑	Incep ↑	CLIP ↑	Eff ↓	SwAV ↓	Image ↑	Brain ↑
MindEye2	**0.322**	**0.431**	**96.1%**	98.6%	95.4%	93.0%	**0.619**	0.344	**98.8%**	**98.3%**
MindEye2 (unrefined)	0.278	0.328	95.2%	**99.0%**	**96.4%**	**94.5%**	0.622	**0.343**	–	–
MindEye1	0.319	0.360	92.8%	96.9%	94.6%	93.3%	0.648	0.377	90.0%	84.1%
Ozcelik and VanRullen (2023)	0.273	0.365	94.4%	96.6%	91.3%	90.9%	0.728	0.421	18.8%	26.3%
Takagi and Nishimoto (2023)	0.246	0.410	78.9%	85.6%	83.8%	82.1%	0.811	0.504	–	–
MindEye2 (low-level)	0.399	0.539	70.5%	65.1%	52.9%	57.2%	0.984	0.673	–	–
MindEye2 (1 hour)	0.195	0.419	84.2%	90.6%	81.2%	79.2%	0.810	0.468	79.0%	57.4%

Brain2Image

Original Image

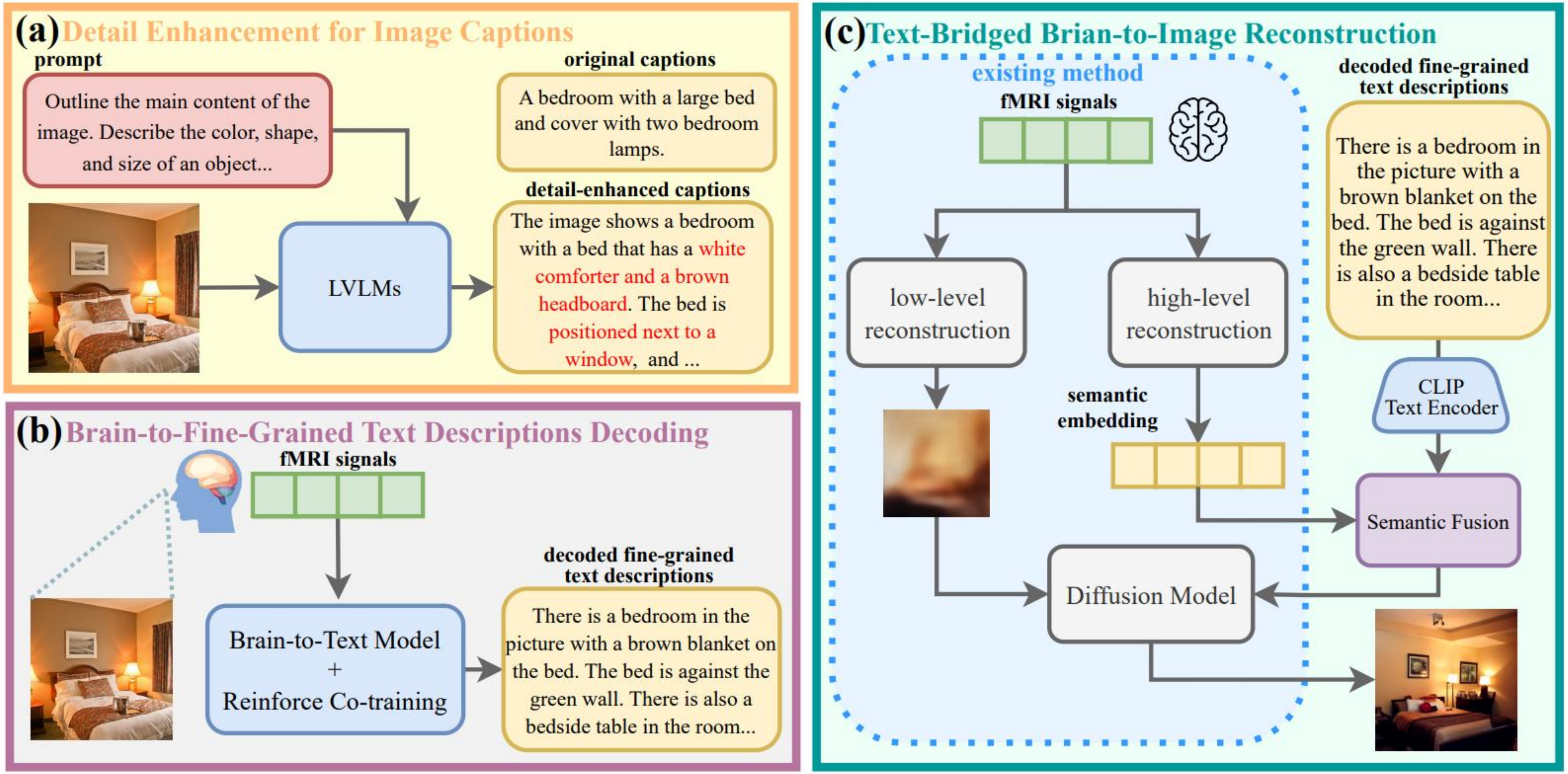
MindEye (NeurIPS2023)

The reconstructed visual stimuli often **lack fine-grained details** due to insufficient semantic information, such as **losing some objects** from the original stimuli.

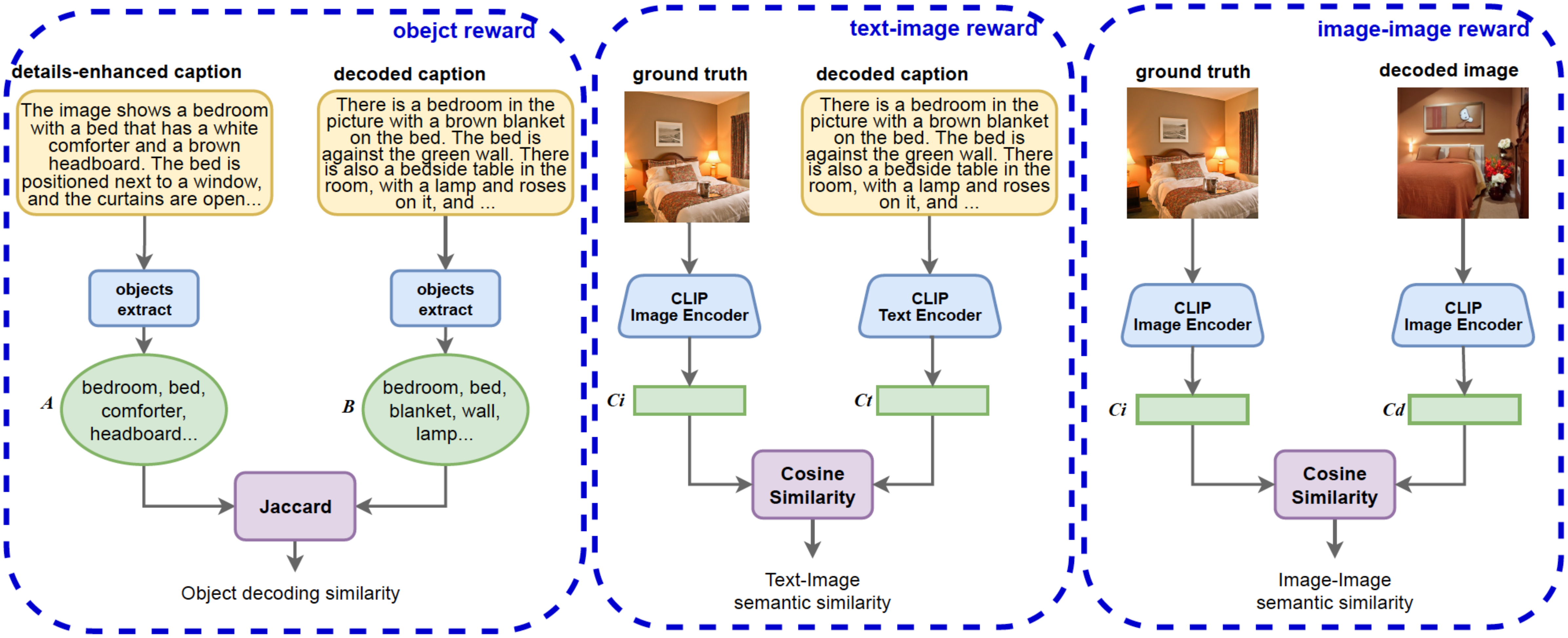
Runze Xia, Shuo Feng, Renzhi Wang, Congchi Yin, Xuyun Wen, and Piji Li. **Improving Brain-to-Image Reconstruction via Fine-Grained Text Bridging**. *CogSci'2025*

Brain2Image

- Details enhancement
- Reconstruction



Brain2Image



$$\mathcal{L}(\theta) = \sum_{t=1}^{T} r_t \log p(a_t | s_t; \theta)$$

$$\mathcal{L} = \mathcal{L}_{CE} + \alpha\mathcal{L}_1 + \beta\mathcal{L}_2 + \gamma\mathcal{L}_3$$

Brain2Image

Method	Low-Level				High-Level			
	PixCorr↑	SSIM↑	Alex(2)↑	Alex(5)↑	Incep↑	CLIP↑	Eff↓	SwAV↓
LDM	/	/	83.0%	83.0%	76.0%	77.0%	/	/
LDM+DE	/	/	84.6%	85.1%	77.3%	79.4%	/	/
BrainDiffuser	.254	.356	**94.2%**	96.2%	87.2%	**91.5%**	.775	**.423**
BrainDiffuser+DE	**.255**	**.357**	93.6%	**96.3%**	**91.1%**	**91.5%**	**.737**	**.423**

Table 1: The reconstruction evaluation of detail-enhancement (denoted as DE in the table) on the LDM (Takagi & Nishimoto, 2023) and BrainDiffuser (Ozcelik & VanRullen, 2023) methods, using the same evaluation metrics as theirs. The values presented in the table are the mean of the assessment results from four participants.

Method	Low-Level				High-Level			
	PixCorr↑	SSIM↑	Alex(2)↑	Alex(5)↑	Incep↑	CLIP↑	Eff↓	SwAV↓
LDM	/	/	83.0%	83.0%	76.0%	77.0%	/	/
LDM+Ours	/	/	81.1%	88.3%	85.6%	86.2%	/	/
BrainDiffuser	.254	.356	94.2%	96.2%	87.2%	91.5%	.775	.423
BrainDiffuser+Ours	.260	.371	93.9%	96.4%	92.4%	92.2%	.710	.409
MindEye	**.309**	.323	94.7%	**97.8%**	93.8%	**94.1%**	.645	.367
MindEye+Ours	.305	**.354**	**94.8%**	**97.8%**	**94.3%**	93.8%	**.637**	**.360**

Table 2: A comparison of the reconstruction results for LDM (Takagi & Nishimoto, 2023), BrainDiffuser (Ozcelik & VanRullen, 2023), and MindEye (Scotti et al., 2023) methods combined with FgB2I's fine-grained text descriptions, using the same evaluation metrics as theirs. The values presented in the table are the mean of the assessment results from four participants.

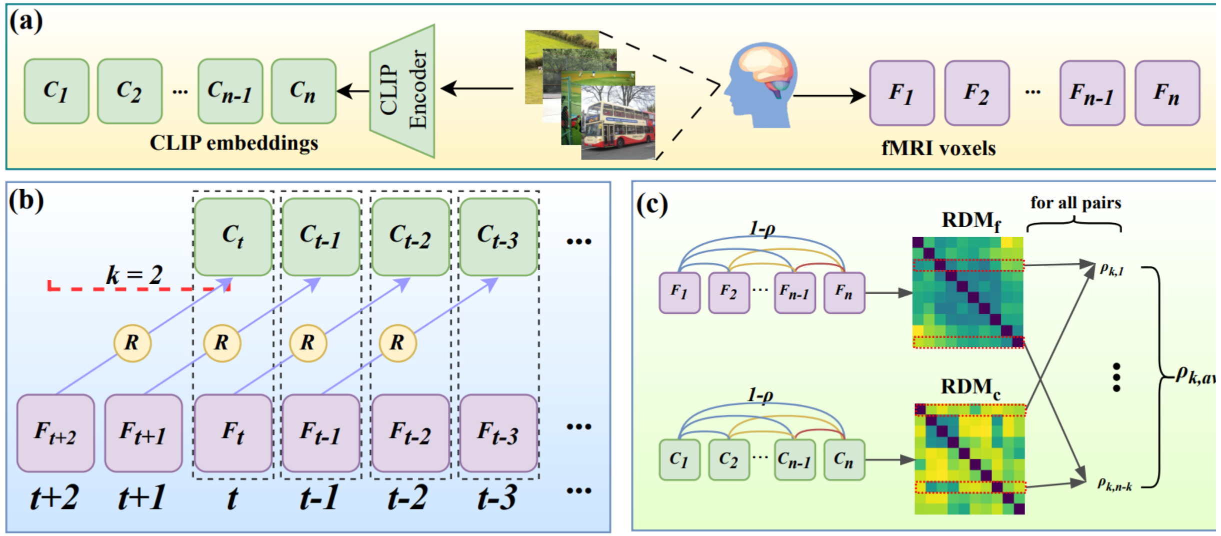
Brain2Image

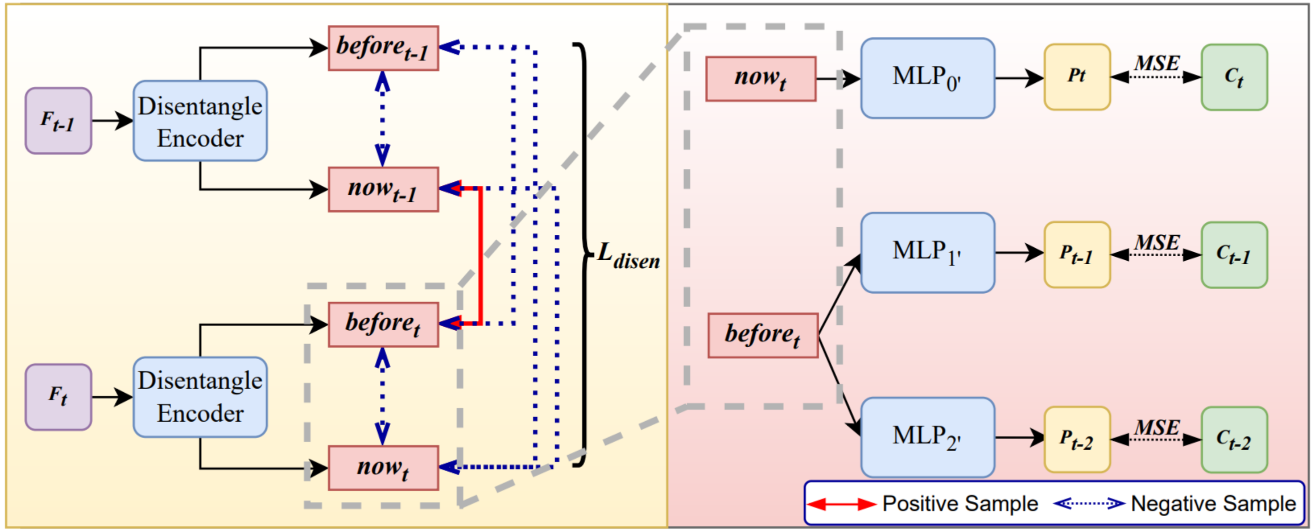
Figure 5: Additional Reconstruction Results. The top section of the figure illustrates semantically coherent reconstructions, whereas the bottom section displays examples with notable discrepancies.

Reason?

Brain2Image

Runze Xia, Congchi Yin and **Piji Li**. **Decoding the Echoes of Vision from fMRI: Memory Disentangling for Past Semantic Information.** EMNLP 2024.





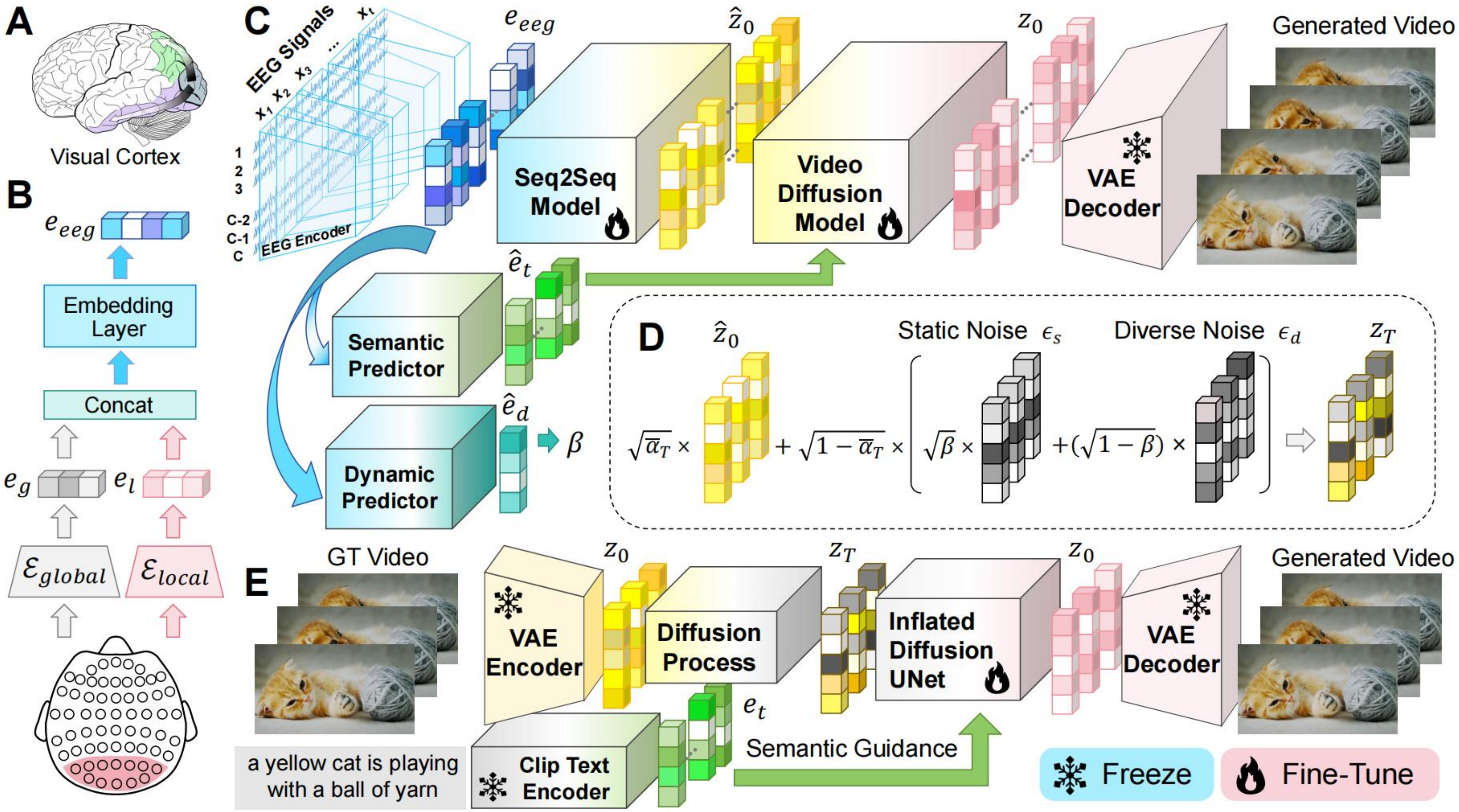
Metrics	α \ k	CIDEr(%) 0	CIDEr(%) 1	CIDEr(%) 2	METEOR(%) 0	METEOR(%) 1	METEOR(%) 2	SPICE(%) 0	SPICE(%) 1	SPICE(%) 2
SF	_	$34.3_{\pm 3.16}$	$12.9_{\pm 2.25}$	$11.0_{\pm 0.99}$	$11.3_{\pm 0.41}$	$\mathbf{8.52_{\pm 0.28}}$	$8.24_{\pm 0.17}$	$8.68_{\pm 1.06}$	$2.85_{\pm 0.92}$	$1.91_{\pm 0.45}$
Ours	0	$35.1_{\pm 4.46}$	$\mathbf{13.4_{\pm 0.70}}$	$\mathbf{11.7_{\pm 0.40}}$	$11.3_{\pm 0.55}$	$8.14_{\pm 0.42}$	$8.23_{\pm 0.11}$	$9.31_{\pm 1.09}$	$\mathbf{3.21_{\pm 0.40}}$	$\mathbf{2.29_{\pm 0.36}}$
Ours	0.01	$\mathbf{39.9_{\pm 2.11}}$	$12.6_{\pm 1.76}$	$11.5_{\pm 1.0}$	$\mathbf{11.7_{\pm 0.35}}$	$8.24_{\pm 0.33}$	$8.15_{\pm 0.32}$	$\mathbf{9.95_{\pm 0.64}}$	$2.84_{\pm 0.52}$	$2.25_{\pm 0.51}$
Ours	0.1	$38.5_{\pm 6.91}$	$10.9_{\pm 0.99}$	$11.7_{\pm 0.94}$	$11.4_{\pm 0.73}$	$8.18_{\pm 0.2}$	$\mathbf{8.27_{\pm 0.29}}$	$9.45_{\pm 1.11}$	$1.80_{\pm 0.53}$	$1.83_{\pm 0.60}$

Brain2Image

- **MindAligner: Explicit Brain Functional Alignment for Cross-Subject Visual Decoding from Limited fMRI Data**. Yuqin Dai, Zhouheng Yao, Chunfeng Song, Qihao Zheng, Weijian Mai, Kunyu Peng, Shuai Lu, Wanli Ouyang, Jian Yang, Jiamin Wu. **ICML 2025.**
- **MindCustomer: Multi-Context Image Generation Blended with Brain Signal.** Muzhou Yu, Shuyun Lin, Lei Ma, Bo Lei, Kaisheng Ma. **ICML 2025.**
- **Human-Aligned Image Models Improve Visual Decoding from the Brain.** Nona Rajabi, Antonio Ribeiro, Miguel Vasco, Farzaneh Taleb, Mårten Björkman, Danica Kragic. **ICML 2025.**
- Visual Decoding and Reconstruction via EEG Embeddings with Guided Diffusion. Dongyang Li, Chen Wei, Shiying Li, Jiachen Zou, Quanying Liu. **NeurIPS 2024**.
- **……**

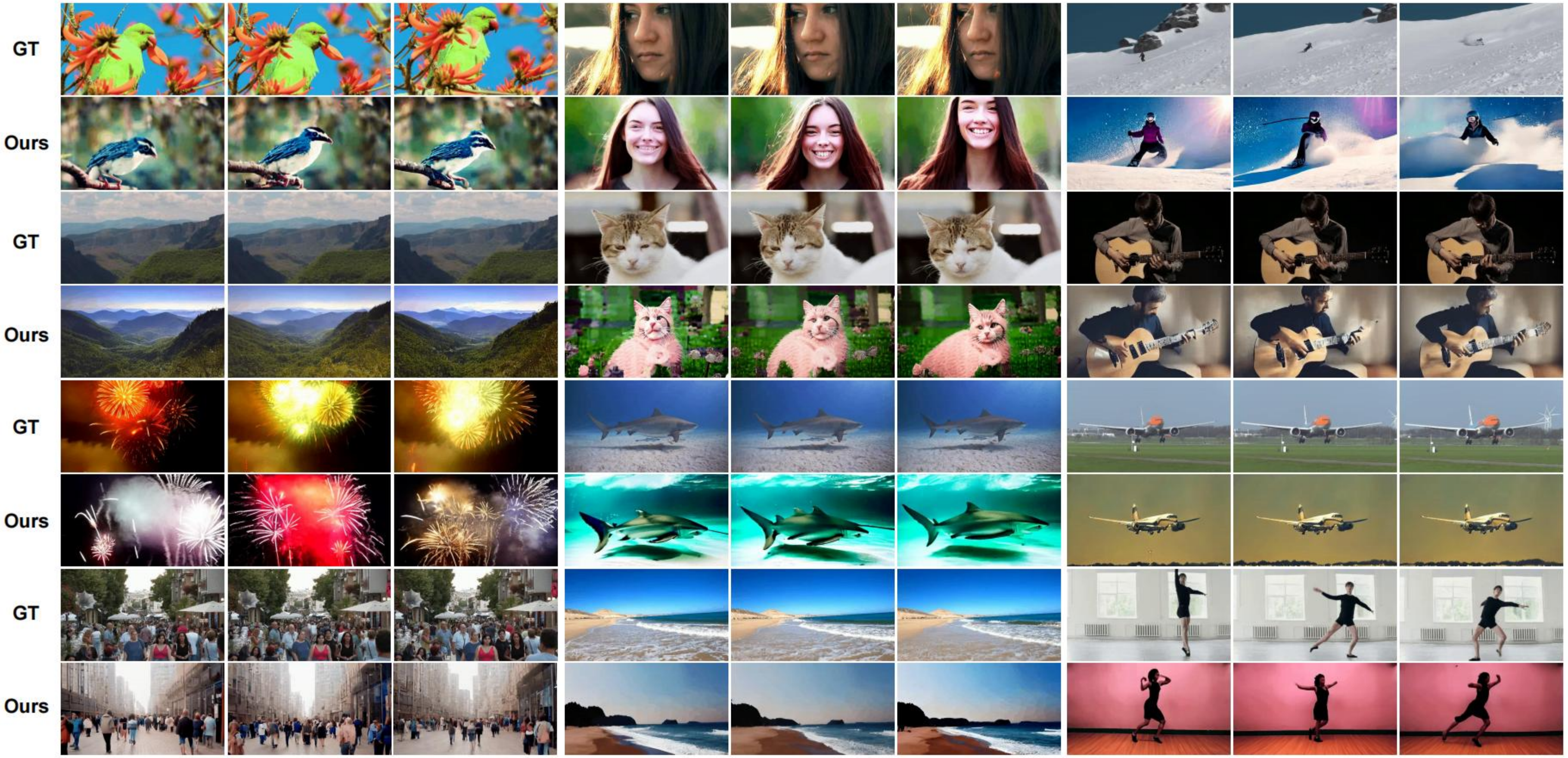
Brain2Video

- Xuan-Hao Liu, Yan-Kai Liu, Yansen Wang, Kan Ren, Hanwen Shi, Zilong Wang, Dongsheng Li, Bao-Liang Lu, Wei-Long Zheng. **EEG2Video: Towards Decoding Dynamic Visual Perception from EEG Signals**. NeurIPS 2024.



Brain2Video

- Xuan-Hao Liu, Yan-Kai Liu, Yansen Wang, Kan Ren, Hanwen Shi, Zilong Wang, Dongsheng Li, Bao-Liang Lu, Wei-Long Zheng. **EEG2Video: Towards Decoding Dynamic Visual Perception from EEG Signals**. NeurIPS 2024.



Brain2Speech

- **The Brain's Bitter Lesson: Scaling Speech Decoding With Self-Supervised Learning.** Dulhan Jayalath, Gilad Landau, Brendan Shillingford, Mark Woolrich, ʻŌiwi Parker Jones. **ICML 2025.**

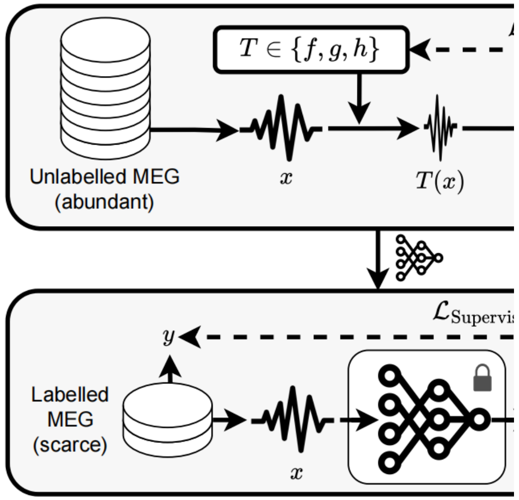
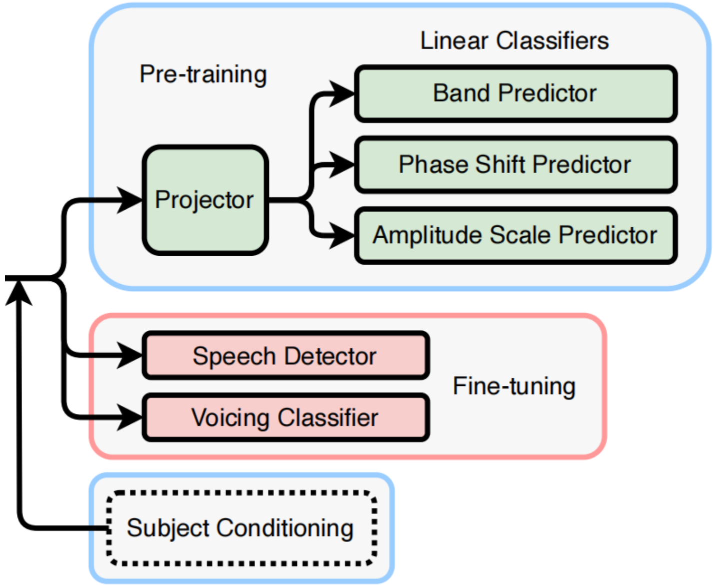


Figure 1: **Leveraging unlabelled dat**
for speech decoding. We pre-train a

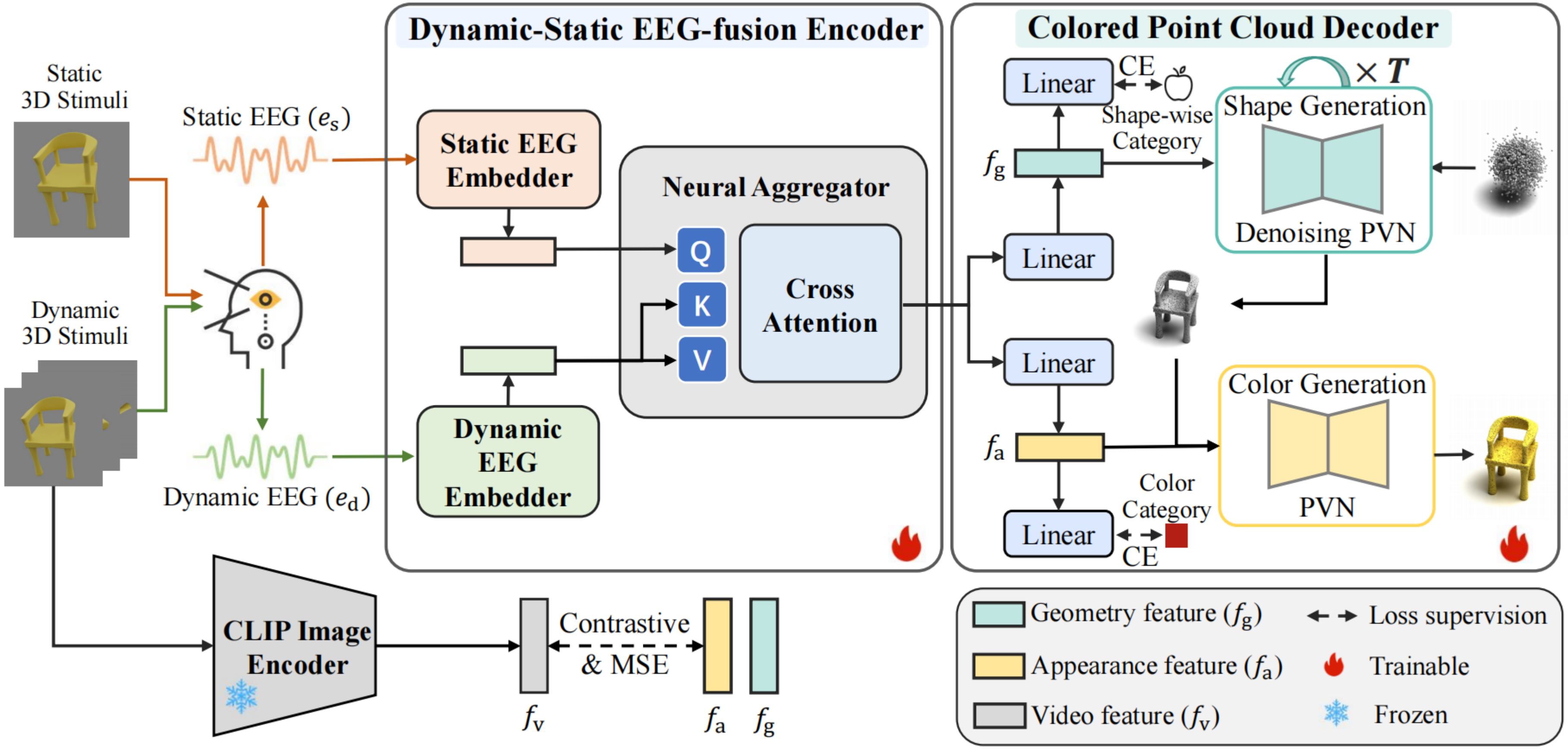
Part	ID	Model		ROC AUC
A	0	Random select		.500
	1	Linear		$.539_{\pm.002}$
B	2	**Ours**	No pre-train.	$.519_{\pm.002}$
	3	+ linear	$\text{Amp}_{(\rho\,=\,0.2)}$	$.624_{\pm.001}$
	4		$\text{Phase}_{(\rho\,=\,0.5)}$	$.615_{\pm.001}$
	5		Band	$.588_{\pm.001}$
	6		All tasks	$.630_{\pm.000}$
	7		+ smoothing	$\mathbf{.700}_{\pm.002}$
C*	8	BIOT[1] + linear		$.615_{\pm.002}$
	9	BrainBERT[2] + linear		$.556_{\pm.007}$
	10	EEGPT[3] + linear		$.602_{\pm.006}$
	11	**Ours** (best) + linear		$\mathbf{.705}_{\pm.003}$
	12	BrainBERT[2] + lin. (surgical)		$.71_{\pm.06}$

[1]Yang et al. (2023) [2]Wang et al. (2023) [3]Wang et al. (2024)



Brain-to-3D

- Zhanqiang Guo · Jiamin Wu · Yonghao Song · Jiahui Bu · Weijian Mai · Qihao Zheng · Wanli Ouyang · Chunfeng Song. **Neuro-3D: Towards 3D Visual Decoding from EEG Signals**. CVPR 2025.



Brain-to-3D

- Zhanqiang Guo · Jiamin Wu · Yonghao Song · Jiahui Bu · Weijian Mai · Qihao Zheng · Wanli Ouyang · Chunfeng Song. **Neuro-3D: Towards 3D Visual Decoding from EEG Signals**. CVPR 2025.

Figure 4. The qualitative results reconstructed by Neuro-3D with two different samplings trials, and the corresponding ground truth.

Method	Object Type		Color Type	
	top-1	top-5	top-1	top-2
Chance level	1.39	6.94	16.67	33.33
DeepNet (2017) [60]	3.70	9.90	20.95	49.71
EEGNet (2018) [35]	3.82	9.72	18.35	46.47
Conformer (2023) [65]	4.05	10.30	18.27	35.81
TSConv (2024) [66]	4.05	10.13	31.13	59.49
Neuro-3D	**5.91**	**16.30**	**39.93**	**61.40**

Table 2. Comparison results on two classification tasks.

Method	Average		Top-1 of 5 samples			
	(2, 1)	(10, 3)	(2, 1)	(10, 3)	CD	F1
Static	51.64	32.39	68.75	55.14	6.75	67.61
Dynamic	50.86	31.50	71.25	54.30	6.40	69.42
Concat	53.22	34.11	69.72	56.53	5.84	73.47
w/o De.	53.94	34.42	65.00	48.54	5.81	73.36
Full	**55.81**	**35.89**	**72.08**	**57.64**	**5.35**	**77.01**

Table 4. Quantitative results of 3D reconstruction, where (N, t) indicates (N-way top-K) result of reconstructed samples.

Brain Decoding: Multimodal

Andrew Luo, Margaret Marie Henderson, Michael J. Tarr, and Leila Wehbe. **BrainSCUBA: Fine-Grained Natural Language Captions of Visual Cortex Selectivity**. ICLR 2024.

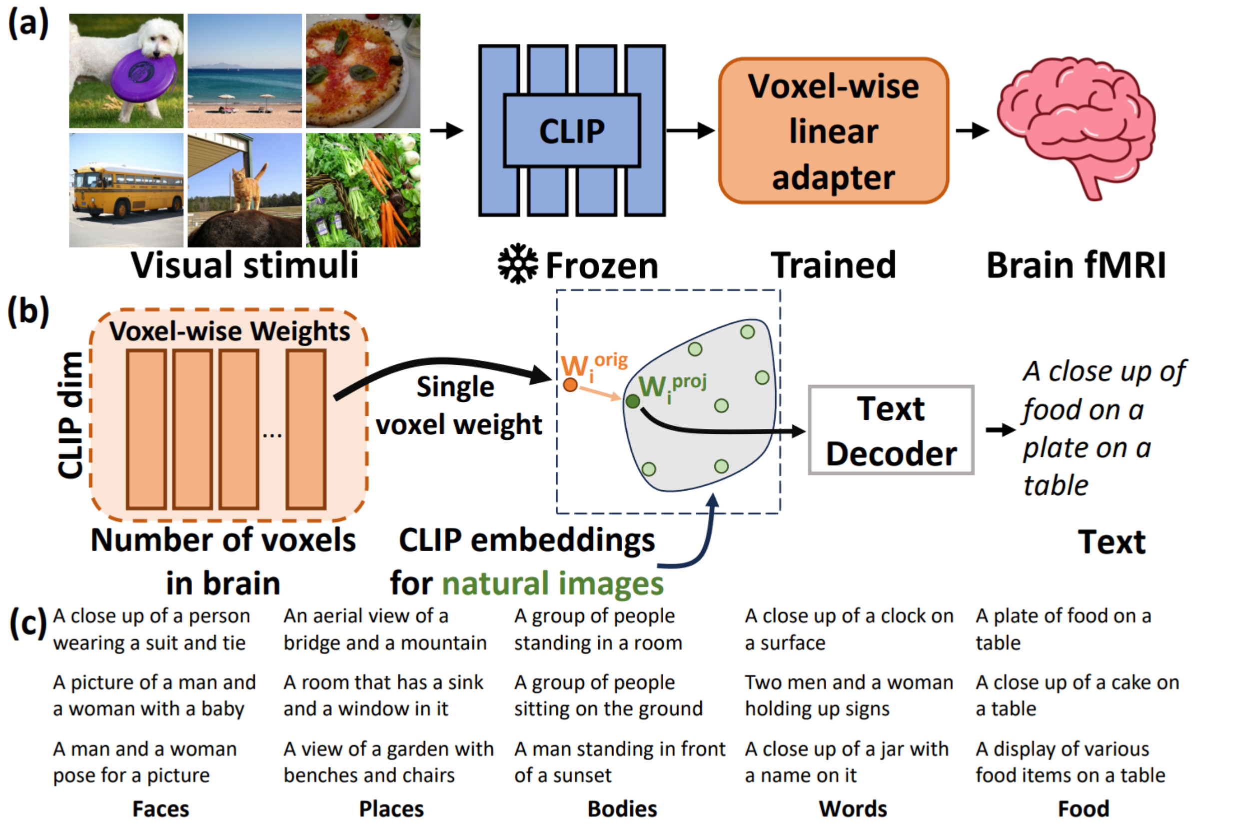
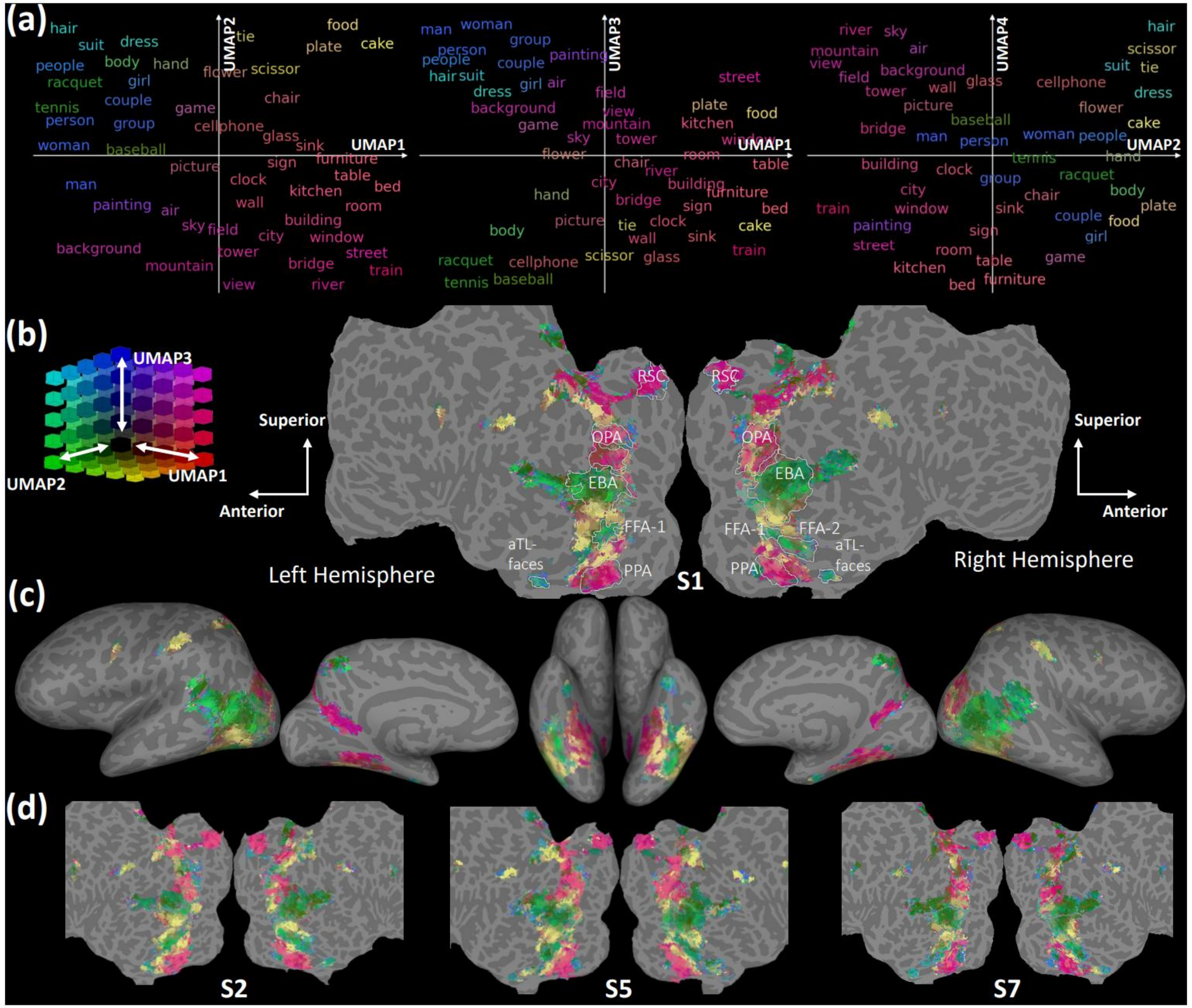


Figure 1: **Architecture of BrainSCUBA.** **(a)** Our framework relies on an fMRI encoder trained to map from images to voxel-wise brain activations. The encoder consists of a frozen CLIP image network with a unit norm output and a linear probe. **(b)** We decode the voxel-wise weights by projecting the weights into the space of CLIP embeddings for natural images followed by sentence generation. **(c)** Select sentences from each region, please see experiments for a full analysis.



Brain Decoding: Foundation Models

- Jiaxuan Chen, Yu Qi, Yueming Wang, and Gang Pan. **MindGPT: Interpreting what you see with non-invasive brain recordings**. *IEEE Transactions on Image Processing* (2025). [Not FM, for text generation]

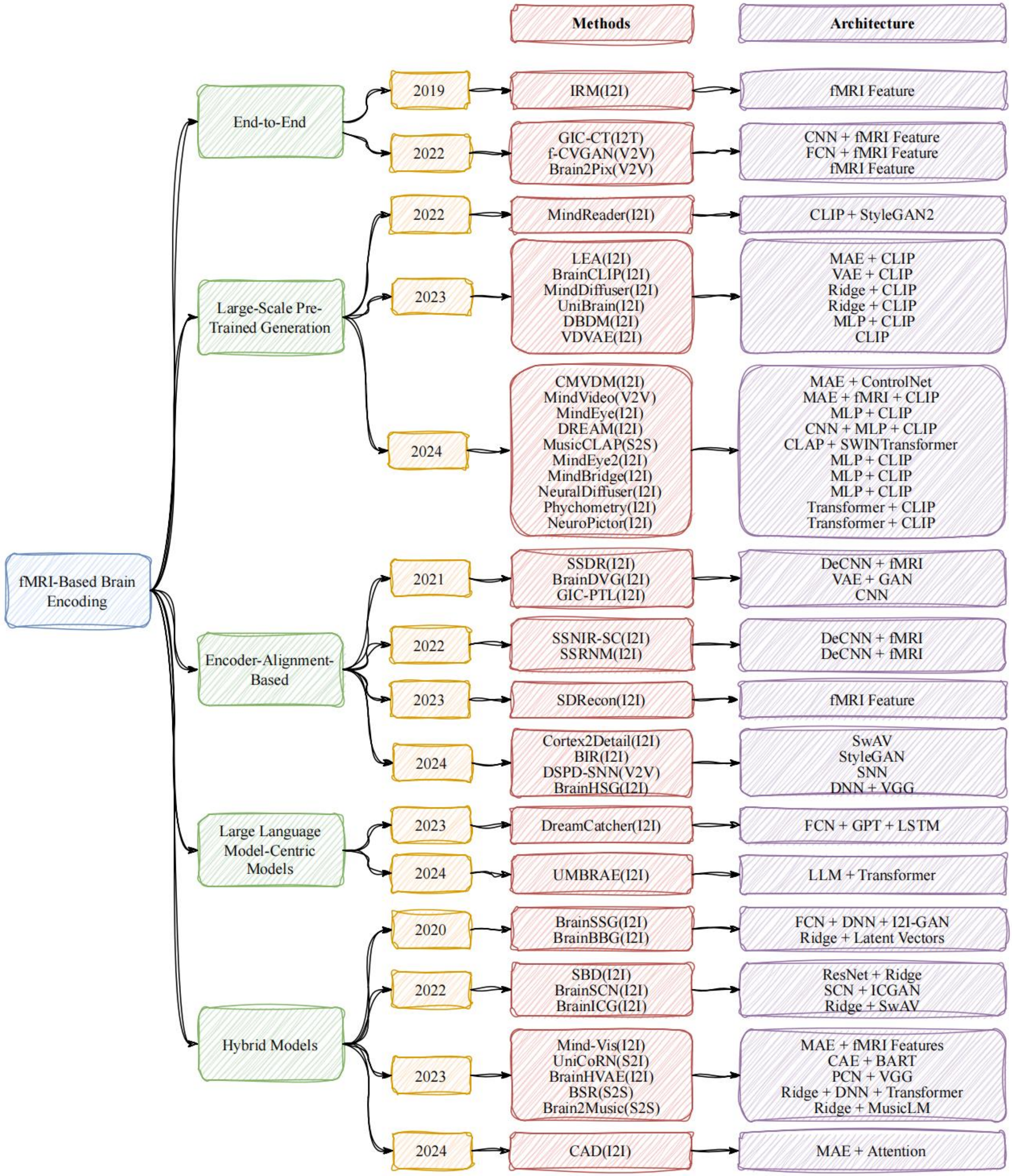
- Josue Ortega Caro, Antonio Henrique de Oliveira Fonseca, Syed Rizvi, Matteo Rosati, Christopher Averill, James Cross, Prateek Mittal, Emanuele Zappala, Rahul Dhodapkar, Chadi Abdallah, David Dijk. **BrainLM: A foundation model for brain activity recordings**. ICLR 2024.

- Yiqian Yang, Yiqun Duan, Hyejeong Jo, Qiang Zhang, Renjing Xu, Oiwi Parker Jones, Xuming Hu, Chin-teng Lin, and Hui Xiong. **NeuGPT: Unified multi-modal neural gpt**. arXiv preprint arXiv:2410.20916 (2024).

- Guangyu Wang, Wenchao Liu, Yuhong He, Cong Xu, Lin Ma, Haifeng Li. **EEGPT: Pretrained Transformer for Universal and Reliable Representation of EEG Signals**. NeurIPS 2024.

Brain Decoding: Key Takeaways

- Drawing on approaches from the **generative domain**, with targeted optimization **tailored to brain decoding**.
- Considering other factors **beyond function mapping, memory, retrieval, thinking, reasoning.**
- Achieve **brain distillation**, **clone its structure and content**, migrate from carbon-based to non-carbon-based, and realize **digital immortality**.



Liu et al (2025)

Papers

Papers – ACL 2025

- **BrainECHO: Semantic Brain Signal Decoding through Vector-Quantized Spectrogram Reconstruction for Whisper-Enhanced Text Generation**
  Jilong Li, Zhenxi Song, Jiaqi Wang, Meishan Zhang, Honghai LIU, Min zhang, Zhiguo Zhang

- **Improve Language Model and Brain Alignment via Associative Memory** *Congchi Yin, Yongpeng Zhang, Xuyun Wen, Piji Li*

Papers – ACL 2024

- **Speech language models lack important brain-relevant semantics**
  SUBBA REDDY OOTA, Emin Çelik, Fatma Deniz, Mariya Toneva

- **Measuring Meaning Composition in the Human Brain with Composition Scores from Large Language Models**
  Changjiang Gao, Jixing Li, Jiajun Chen, Shujian Huang

- **Multipath parsing in the brain**
  Berta Franzluebbers, Donald Dunagan, Miloš Stanojević, Jan Buys, John T. Hale

- **Enhancing EEG-to-Text Decoding through Transferable Representations from Pre-trained Contrastive EEG-Text Masked Autoencoder**
  Jiaqi Wang, Zhenxi Song, Zhengyu Ma, Xipeng Qiu, Min zhang, Zhiguo Zhang

Papers – EMNLP 2024

- **Language models and brains align due to more than next-word prediction and word-level information**
  Gabriele Merlin, Mariya Toneva

- **Unveiling Multi-level and Multi-modal Semantic Representations in the Human Brain using Large Language Models**
  Yuko Nakagi, Takuya Matsuyama, Naoko Koide-Majima, Hiroto Q. Yamaguchi, Rieko Kubo, Shinji Nishimoto, Yu Takagi

- **Decoding the Echoes of Vision from fMRI: Memory Disentangling for Past Semantic Information**
  Runze Xia, Congchi Yin, Piji Li

Papers – NAACL 2025

- **Thought2Text: Text Generation from EEG Signal using Large Language Models (LLMs)**
  Abhijit Mishra, Shreya Shukla, Jose Torres, Jacek Gwizdka, Shounak Roychowdhury

Papers – NAACL 2024

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-
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- Nature Machine Intelligence volume 6, pages1467–1477 (2024)

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- npj Science of Learning volume 10, Article number: 46 (2025)

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- Nature Neuroscience volume 27, pages988–999 (2024

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- Nature Human Behaviour volume 8, pages544–561 (2024)

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- Nature Communications volume 15, Article number: 5523 (2024)

- Better models of human high-level visual cortex emerge from natural language supervision with a large and diverse dataset
- Aria Y. Wang, Kendrick Kay, Thomas Naselaris, Michael J. Tarr & Leila Wehbe
- Nature Machine Intelligence volume 5, pages1415–1426 (2023)

- Alignment of brain embeddings and artificial contextual embeddings in natural language points to common geometric patterns
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- Nature Communications volume 15, Article number: 2768 (2024)

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- Nature Communications volume 15, Article number: 9383 (2024)

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- Large language models surpass human experts in predicting neuroscience results
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- Nature Human Behaviour volume 9, pages305–315 (2025)

- Conversational content is organized across multiple timescales in the brain
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- Nature Human Behaviour (2025)

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- Nature Human Behaviour (2025)

- Differences in regional brain structure in toddlers with autism are related to future language outcomes
- Kuaikuai Duan, Lisa Eyler, Karen Pierce, Michael V. Lombardo, Michael Datko, Donald J. Hagler, Vani Taluja, Javad Zahiri, Kathleen Campbell, Cynthia Carter Barnes, Steven Arias, Srinivasa Nalabolu, Jaden Troxel, Peng Ji & Eric Courchesne
- Nature Communications volume 15, Article number: 5075 (2024)

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- Nature Communications volume 16, Article number: 2258 (2025)

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- Nature Communications volume 16, Article number: 6356 (2025)

- Language is widely distributed throughout the brain
- Linda Drijvers, Steven L. Small & Jeremy I. Skipper
- Nature Reviews Neuroscience volume 26, page189 (2025

- A streaming brain-to-voice neuroprosthesis to restore naturalistic communication
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- Nature Neuroscience volume 28, pages902–912 (2025)

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- Nature (2025)

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- Nature Computational Science volume 5, pages534–546 (2025)

- EEG reveals the cognitive impact of polarized content in short video scenarios
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- Scientific Reports volume 15, Article number: 18277 (2025)

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