Language Generation from Brain Recordings

Ziyi Ye, Qingyao Ai, Yiqun Liu, Maarten de Rijke, Min Zhang, Christina Lioma, and Tuukka Ruotsalo

Abstract-Semantic reconstruction of language from brain recordings has been demonstrated within a classification setup, where a pre-generated language candidate is selected based on how well it matches semantic representations decoded from the brain. Cortical semantic representations in brain recordings are generally employed to identify the most likely semantic candidates, yet decoded representations are not directly involved in the language generation process. Here, we propose a generative language brain-computer interface (BCI) that uses the capacity of a large language model jointly with a semantic brain decoder to directly generate language from functional magnetic resonance imaging (fMRI) input. While a standard large language model (without brain input) can already generate high-quality continuations given a text prompt, we find that the generation output from our proposed model for connecting brain recordings to a language model is more closely aligned with the visual or auditory language stimuli in response to which brain recordings are sampled. This is especially significant in cases where a standard large language model exhibits a lower likelihood of generating the continuation, or in other words, deems the continuation to be unexpected. Our findings demonstrate the feasibility of directly employing non-invasive BCIs in the language generation phase and show that a direct generation approach outperforms previously proposed approaches to connect language generation to brain recordings.

INTRODUCTION

Decoding computational representations of continuous language from non-invasive brain recordings can enhance our understanding of semantic language representations and enable neural communication interfaces for restorative and augmentative applications. Previous work has demonstrated that it is possible to decode meaningful linguistic and semantic information from brain recordings to guide classification tasks, such as selecting a target from a set of words [MSC⁺08], [PBLS11], sentences [PLP+18], [TLJH23], and topics [KvVH+19]. For instance, Moses et al. [MML+21] successfully decoded the target words from a vocabulary of 50 words, using the brain recordings of an anarthria patient with electrodes implanted in the sensorimotor cortex. Pereira et al. [PLP+18] utilized noninvasive functional magnetic resonance imaging (fMRI) data to decode the target sentence from a pair of sentences that were presented as visual stimuli.

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Recently, large language models (LLMs), particularly those based on generative approaches [RWC⁺19], [BMR⁺20], [TLI⁺23], have become a dominant approach in computational language modeling. LLMs are capable of generating continuous language that is semantically and syntactically coherent [TLI+23]. Given a text prompt, LLMs can produce the most likely continuation based on the statistical semantic knowledge they learned from a vast amount of text. Leveraging the powerful generative capabilities of LLMs, recent language brain-computer interfaces (BCIs) [TLJH23], [AEPW20] have successfully used brain recordings to incorporate semantic information into language reconstruction. For example, Tang et. al. [TLJH23] use a LLM to pre-generate a set of possible candidates and then select the best one based on their similarities with the semantic representations decoded from the fMRI data.

The methods listed above consider brain decoding and language generation as two separate phases. Semantic representations extracted from brain recordings are used exclusively in a post-hoc classification phase for selecting the candidates generated with LLM. While LLMs represent a leap forward in mimicking human language, they merely generate the most likely continuations based on their training material, which is typically crawled from the web [RWC+19], [BMR+20]. In other words, there is no guarantee that the language generated by LLMs reflects the semantics decoded from brain recordings. The two-stage process that separates LLM generation from brain decoding has intrinsic limitations, as it simply assumes that LLMs can always generate accurate semantic candidates without any knowledge of the intended semantics of an individual. Therefore, directly incorporating brain recordings into the language generation process is an open problem that has not yet been solved.

Here, we present BrainLLM, an approach in which the semantic representation decoded from brain recordings is directly involved in the generation phase of continuous language. We focus on language generation from non-invasive fMRI recordings of healthy participants perceiving visual or auditory language stimuli. As depicted in Fig. 1, our proposed model generates a continuation of language from a given text prompt. Unlike existing work [TLJH23], [AEPW20], BrainLLM incorporates brain signals directly in the language generation phase, thereby eliminating the need for post-hoc selection among pre-generated language continuation candidates. This paradigm leads to enhanced performance compared to LLM generation with only the text prompt and to existing methods involving pre-generation and post-hoc selection, as it directly guides LLMs to generate language based on brain recordings.

To accomplish this, BrainLLM consists of four key steps illustrated in Fig. 1: (1) brain data is collected and features are extracted, (2) a brain decoder learns an embedding from

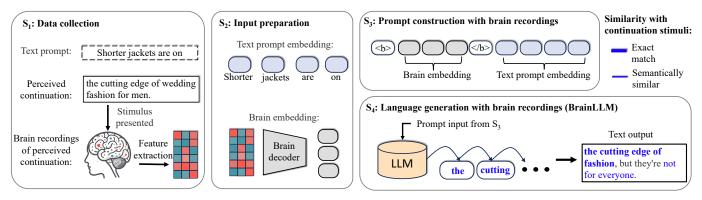


Fig. 1: Language generation with brain recordings (BrainLLM). The generation process has four main stages. S_1 : Brain recordings in response to the perceived continuation are collected for language generation. S_2 : A brain decoder is adopted to extract features from brain recordings and transform them into hidden vectors that match the shape of text embeddings in a standard LLM. S_3 : Brain embedding and text prompt embedding are concatenated as prompt input for the LLM. S_4 : The prompt input is fed into the LLM for language generation. BrainLLM generates content that is an exact match ("the cutting edge of") with, or semantically similar content ("not for everyone") to, the perceived continuation.

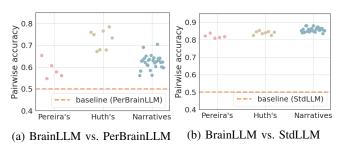


Fig. 2: Pairwise accuracy comparisons: BrainLLM vs. PerBrainLLM and BrainLLM vs. StdLLM. Each dot represents the pairwise accuracy of a single participant in Pereira's dataset (5 participants), Huth's dataset (8 participants), and the Narratives dataset (28 participants). The pairwise accuracy of BrainLLM is significantly higher than PerBrainLLM in Fig. 2a and StdLLM in Fig. 2b at q(FDR) < 0.05 (one-sided non-parametric test) across all datasets and partipants. A comparison between PerBrainLLM and StdLLM is shown in Fig. S12.

the brain recordings, (3) prompts are constructed from brain and text modalities, and (4) language is generated in an autoregressive manner based on a model of the prompt and an LLM. The brain decoder learns to map the space of brain representations onto a space with the same dimensionality as the text embeddings in the LLM. This facilitates the generation based on a prompt representation that integrates both the brain modality and the text modality. A protocol called "prompt tuning" [LZD+23] and a generation-based loss function is adopted to train the brain decoder. This protocol guarantees that the parameters in the LLMs are fixed while only the brain decoder is updated during training. To this end, the model parameters of the decoder can be fully trained with only a limited amount of neurological data compared to the data requirements for training a complete LLM.

TABLE I: Language generation performance averaged across participants in different datasets. The difference between BrainLLM and PerBrainLLM/StdLLM is significant at q(FDR) < 0.05 (one-sided non-parametric test) on all datasets and metrics.

Dataset	Model	Bleu-1(↑)	ROUGE-L(↑)	WER(↓)
Pereira's	StdLLM	0.2415	0.2096	0.8349
	PerBrainLLM	0.3249	0.2771	0.7781
	BrainLLM	0.3333	0.2877	0.7681
Huth's	StdLLM	0.1500	0.1310	0.9200
	PerBrainLLM	0.1668	0.1474	0.9109
	BrainLLM	0.1899	0.1709	0.8946
Narratives	StdLLM	0.0953	0.0829	0.9485
	PerBrainLLM	0.1269	0.1105	0.9311
	BrainLLM	0.1375	0.1209	0.9239

RESULTS

BrainLLM We evaluate **fMRI** using three $[PLP^{+}18], [NLH^{+}21],$ $[LWJ^+23]$ participants perceive visual or auditory language stimuli (see Table S14 and SI appendix for details). We construct a language generation task for each time frame (e.g., a time repetition (TR) of 2s in Huth's dataset) during the fMRI recording process, as depicted in Fig. 1. The preceding text (if any) to a time frame serves as the *text prompt* (see Method). Meanwhile, the presented language stimulus within the time frame is considered as the *perceived continuation*, typically encompassing 3-10 words. Then, the model's generation ability is evaluated by aligning its generation output to the perceived continuation. We trained and evaluated the model for each human participant, involving 5 participants in Pereira's dataset [PLP+18], 8 participants in Huth's dataset [LWJ+23], and 28 participants in the Narratives dataset [NLH⁺21]. We use Llama-2 as the backbone language model [TLI⁺23] because it is one of the best-known and best-performing models among the public-sourced LLMs. A split-by-stimuli protocol is applied (see SI Appendix) to ensure that the language stimuli and the corresponding brain response used during testing have not been seen in the training set.

We compare the generation performance of BrainLLM to that of two control models: (1) language generation from a standard LLM (StdLLM) that makes no use of brain recordings, and (2) language generation from permuted brain recordings (PerBrainLLM). The StdLLM only uses the text prompt to generate language, as in a standard LLM. As illustrated in Fig. S1, PerBrainLLM uses the same procedures as Brain-LLM but with the brain input permuted (see Method). This permutation disrupts the correspondence between the brain recordings and the perceived continuations to serve as another control. As we will see below in our experiments comparing the control models, PerBrainLLM significantly outperforms StdLLM (see SI Appendix for a more detailed comparison). The enhanced performance of PerBrainLLM over StdLLM lies in its ability to generate content that aligns with the common data distribution of language usage in the dataset. Although PerBrainLLM uses brain recordings that are not aligned with stimuli perceived by an individual for a particular continuation, these contents share similar language usage patterns (e.g., all stimuli in Pereira's dataset are Wikipedia-style). Hence, we first present the overall performance of BrainLLM, Per-BrainLLM, and StdLLM, followed by in-depth analyses of BrainLLM and PerBrainLLM to study the performance gain derived from brain recordings sampled from the corresponding data samples.

We evaluate BrainLLM against the two control models defined above from three perspectives: (1) pairwise accuracy: whether BrainLLM has a higher likelihood of generating the perceived continuation than the control model (StdLLM or PerBrainLLM); (2) language similarity metrics (BLEU, ROUGE, and word error rate (WER)): measurements of the similarity between the perceived continuation and the generated language; (3) human preference: show the output of BrainLLM alongside that of the control model, and ask human annotators to judge which is semantically closer to the perceived continuation. In addition to the control model, we also compared BrainLLM against the latest prior work [TLJH23] that pre-generates some candidates and then uses brain recordings for selection.

The averaged pairwise accuracy of BrainLLM versus StdLLM is 84.8%, 82.5%, and 84.1% in Pereira's dataset, Huth's dataset, and the Narratives dataset, respectively (Fig. 2b). This indicates that BrainLLM has a significantly higher likelihood of generating the perceived continuation compared to StdLLM: for the false discovery rate (FDR) we find q(FDR) < 0.05 (one-sided, non-parametric test). BrainLLM also outperforms StdLLM in all language similarity metrics in Table I (q(FDR) < 0.05). We further compare BrainLLM against PerBrainLLM, which permutes the brain input: a significant performance difference is achieved both in terms of pairwise accuracy and language similarity metrics (q(FDR) < 0.05, Fig. 2a and Table I). The highest averaged pairwise accuracy of BrainLLM versus PerBrainLLM, standing at 76.7%, is observed in Huth's dataset, which has the largest size of neurological data samples for each participant. This suggests that increasing the size of neurological training data may improve the model performance. Note that Brain-LLM also leads to a significant improvement when compared with the pre-generation and selection-based method proposed by Huth's [TLJH23] (see Table S12 and Discussion for a detailed comparison). Furthermore, we conducted a human evaluation experiment (detailed in Method) in which 202 annotators recruited from Amazon's Mechanical Turk 1 were asked to make a preference judgment between generation outputs from BrainLLM and PerBrainLLM, or they could opt for "hard to distinguish" if no clear preference emerged. Within the randomly selected sample of 3,000 language pairs generated by BrainLLM and PerBrainLLM from Huth's dataset, the average annotations showed a preference distribution where 48.4% favored BrainLLM, 39.2% favored PerBrainLLM, and 12.4% of the annotators found the pairs indistinguishable. The statistical analysis revealed a significant difference in preference between BrainLLM and PerBrainLLM (p=0.027 using a one-side t-test).

Language generation performance across perceived continuation with different surprise levels

LLMs, by predicting the next token with the highest probability, enable the generation of well-structured, coherent language that is aware of the text prompt. This architecture also provides a unified framework for modeling surprise in text continuations by estimating their prediction-error signals (see SI appendix). For example, the likelihood of "meet you" following "Nice to" is higher than "take chances", which means that "meet you" has a lower surprise to LLMs than "take chances". Typically, a higher level of surprise indicates that the LLM finds it more surprising and challenging to generate the perceived continuation. We test the performance of BrainLLM under different surprise levels. As illustrated in Fig. S2 and Fig. S3, both BrainLLM and PerBrainLLM show a performance decrease as the level of surprise increases in terms of BLEU-1. However, compared to PerBrainLLM, BrainLLM exhibits a more moderate decline in performance. Furthermore, we examine the pairwise accuracy of BrainLLM and PerBrainLLM across perceived continuation with varying levels of surprise, as depicted in Fig. 3. We observe that the pairwise accuracy increases as the surprise levels rise. A significant positive correlation exists between the surprise level and the pairwise accuracy, with Pearson's r = 0.09, 0.15,and 0.08 in Pereira's, Huth's, and the Narratives datasets, respectively (q(FDR) < 0.05 in all datasets). This suggests that when the LLM deems the perceived continuation as unexpected, the information decoded from brain recordings can significantly enhance the generation process.

Effect of text prompt

Typically, LLMs generate language as a continuation of the given text prompt. Existing natural language processing (NLP) research [KMH⁺20] has shown that the generation accuracy improves when given a longer length of text prompt [KMH⁺20]. The integration of brain recordings into LLM generation raises a critical question: How does the length of the text prompt affect the performance of BrainLLM?

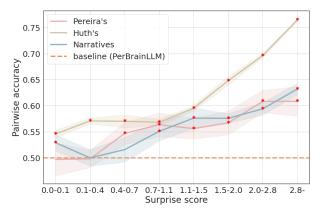


Fig. 3: Pairwise accuracy between BrainLLM and Per-BrainLLM in perceived continuation with different surprise levels. The surprise level quantifies the model's likelihood of generating the continuation stimuli, whereas a higher surprise indicates a greater difficulty of generating the perceived continuation. * indicates the pairwise accuracy is significantly higher than the baseline with q(FDR) < 0.05 (one-sided non-parametric test). The error bars indicate the standard error across participants.

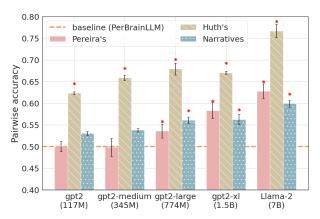


Fig. 4: Pairwise accuracy between BrainLLM and Per-BrainLLM across large language models with different sizes of parameters. \ast indicates the pairwise accuracy is significantly better than the baseline at q(FDR) < 0.05 (one-sided non-parametric test).

Furthermore, how does the BrainLLM perform in scenarios where there is no text prompt provided? We present the BLEU-1 score of BrainLLM and PerBrainLLM with different lengths of text prompts in Fig. S5 and Fig. S6, and their pairwise accuracy is shown in Fig. S4. A negative correlation exists between the length of the text prompt and the pairwise accuracy, with Pearson's r values of -0.013, -0.059, and -0.060 in Pereira's, Huth's, and the Narratives datasets, respectively. This observation can be partially explained by the fact that longer text prompts provide LLMs with more contextual information, resulting in a lower level of surprise for the perceived continuation [GHL+22], [GZB+22], and consequently reducing the importance of brain input information. The relationship between text length and surprise level is verified in the text stimuli of Pereira's dataset, Huth's dataset,

and Narratives dataset (see Fig. S7).

Furthermore, we investigate language generation from brain recordings without any text prompt. Table S10 presents the performance of BrainLLM and PerBrainLLM for language generation without text prompts. On one hand, we observe that BrainLLM outperforms PerBrainLLM in pairwise accuracy, as well as on all language similarity metrics. The pairwise accuracy (0.8885 in Pereira's dataset, 0.8816 in Huth's dataset, and 0.6728 in the Narratives dataset) is even higher than that of generation with text prompts. This enhanced performance of BrainLLM versus PerBrainLLM can be explained by the high surprise levels for perceived continuations when no text prompt is given. However, we observe that the language similarity metrics for generation without text prompts are much lower than those with text prompts (see Table S10). This indicates that generating language without text prompts is still challenging.

Impact of LLM with different parameter sizes

We conducted our main experiments based on Llama-2 [TLI⁺23], which is one of the state-of-the-art LLMs with a large number of parameters, i.e., 7 billion (7B). To study the impact of LLM with different parameter sizes, we tested a series of generative LLMs constructed with different parameter sizes, including GPT-2 (117M parameters), GPT-2medium (345M parameters), GPT-2-large (774M parameters), GPT-2-xl (1.5B parameters), and the Llama-2 (7B parameters). Across StdLLM, PerBrainLLM, and BrainLLM, language similarity metrics significantly increase as the number of parameters in the LLM increases (see Table S11). This observation aligns with established knowledge: LLMs equipped with more parameters demonstrably excel at language generation [KMH⁺20], [?]. Interestingly, while the performance of PerBrainLLM improves with the increase in the number of parameters (see Table S11), the relative improvement of BrainLLM over PerBrainLLM also increases (see Fig. 4). This indicates that LLMs with an increasing number of parameters exhibit amplified benefits from integrating brain recordings.

Effect of the amount of neurological data for training

We tested BrainLLM on a variable number of neurological data and computed its pairwise accuracy versus PerBrainLLM. As shown in Fig. S9, the language generation performance steadily increases as the model is trained with more neurological data on Huth's dataset and the Narratives dataset. Existing studies [AVH23], [TW19] have found that enlarging the size of neurological datasets can improve the mapping between language representation in the brain and that in the LLM. Our results further suggest that expanding the size of neurological datasets also leads to improved performance when jointly modeling the brain representation with LLM for language generation.

Language generation across cortical regions

In addition to evaluating our model with brain recordings from all cortical regions, we explore how

language can be generated within various cortical regions. Fig. S8 presents the language generation performance in terms of pairwise accuracy of BrainLLM versus PerBrainLLM with Broca's area $[MMG^{+}03],$ precuneus (PrCu) [CSLP04], the the prefrontal cortex (PFC) [GPD98], the auditory cortex (AC) [SSP+99], and the angular gyrus (AG) [VEVML+16], [PBPG15] for one participant randomly selected from Huth's dataset. The pairwise accuracy demonstrates that BrainLLM significantly outperforms PerBrainLLM in all language processing regions, with its highest score of 0.8012 observed in Broca's area. This performance even surpasses the results achieved using responses from all cortical regions. Due to the extremely high dimensionality of fMRI data, we perform dimensionality reduction when using signals from all cortical regions (see Method). This dimensionality reduction may lose some information. However, data reduction is not necessary when using a single cortical region, which suggests that leveraging a single brain region, particularly one associated with language semantics, may yield better decoding performance. Nonetheless, to preclude bias in selecting regions of interest (ROIs), results using responses from all cortical regions are reported in the main findings. Existing research has shown that during language processing, a substantial portion of the cortex is engaged [LHSH11], [BD11]. This suggests that different cortical regions related to language might encode overlapping or similar language representations [KCJ01], potentially facilitating language generation using just a single cortical area. These findings have also been observed in prior research on brain language decoding using classification-based approaches [TLJH23], [CK22].

DISCUSSION

Our study demonstrates that language can be directly generated from brain recordings, rather than through selection from pre-defined or pre-generated language candidates. To accomplish this, we jointly model brain recordings as a representation input that is fed to the LLM. Unlike a standard LLM that generates only the most likely language continuation, the generation output of BrainLLM is more aligned with the text content perceived by human participants. Using prompt tuning techniques [LJF⁺22], [LZD⁺23], BrainLLM has approximately only 6 million trainable parameters, which is much smaller than Llama-2's 7 billion parameters. This parameter size matches existing models like ridge regression commonly used for classifying language candidates with brain recordings (e.g., Tang et al. [TLJH23]; Pereira et al. [PLP+18]), yet achieves direct language generation without restricting selection to a pre-defined pool of candidates.

The generation process of BrainLLM can be considered as selecting the next token each time from the full vocabulary of LLMs (which has 32,000 tokens in our experiments). Across all stimuli in the three datasets that we consider, BrainLLM achieves an average top-1 accuracy of 65.8% in generating the next token when producing a continuation. This top-1 accuracy level is comparable to existing language decoding research [TLJH23], [PLP+18] which typically achieves the

selection from a tiny set of 2–50 word or sentence candidates. Considering that the standard LLM alone can often generate the next token quite reliably when given the text prompt, we further compare the performance of BrainLLM and its controls, i.e., StdLLM and PerBrainLLM. BrainLLM yields an average pairwise accuracy of 83.8% versus StdLLM and 67.6% versus PerBrainLLM, across all datasets. It is important to note that this accuracy was not achieved in a conventional binary or multi-class classification task, but in a generative setting with the full vocabulary of LLMs. This suggests that it is feasible to jointly model brain recordings in language generation with computational generative models.

How can we integrate human brain representations into machine language generation models?

Previous work has only shown that the representations in language models and the human brain can be mapped to each other [TW19], [Ton21], [SBT+21], [HCL+22], [AKB+21], [SWZZ20]. How these representations can be jointly trained within a single framework has not been studied yet. The popular approach in existing work is representation similarity analysis [Ton21], which involves aligning the semantic representations in language models with those in the brain [CGK22]. Key findings from these studies include exploring how training language models can enhance this alignment [AT23], whether brain representations can be used to improve the representations in language models [TW19], and if the human brain possesses the capability to predict the next token similarly to language models [GZB+22]. Our approach differs from the above as the representation alignment between the brain recordings and the language representation in LLMs does not necessarily mean that one can be used to generate the other within a computational framework. Language models typically generate coherent language based on contextualized representations [LJF⁺22] extracted from the text prompt. This implies that what we learn from brain recordings could be used to enrich these contextualized representations, thereby encouraging the LLM to generate language that matches the semantics reflected in brain recordings.

The success of the presented model compared to previous work [ZWZZ21], [XZW⁺23] can be attributed to two factors. Firstly, the information encoded in the human brain often encompasses contextual and situational semantics [GZB⁺22], [PLP+18]. Such information may be leveraged to enrich contextualized representations as input for a LLM. Secondly, as language models have evolved through increasing model parameter sizes, there has been an emergence of "few-shot learning" or "in-context learning" capability [LARC21]. This capability indicates that language models are able to use generative loss functions to effectively backpropagate gradients to the contextualized representations learned from the brain recordings. Our experiments also show that language models with increasing model parameter sizes achieve a greater performance improvement in BrainLLM when compared to PerBrainLLM.

Comparison with previous work

In the majority of existing studies, decoding brain signals has relied on pre-defining a set of semantic candidates (e.g., words [MSC⁺08], concepts [PLP⁺18], sentences [SWZZ19]) and employing a mapping function to determine which candidate best matches the recorded brain activity. The predefinition step implies that these methods are incapable of constructing continuous narratives. An exception is a recent study [TLJH23] that successfully constructs continuous semantic candidates by first pre-generating several continuation candidates and then selecting from the candidates with brain recordings. Our approach is markedly different from this study, as their model is still constrained to selecting from a limited pool of candidates (such as 5, as mentioned in their article). Given that the perceived continuation in the constructed data samples is approximately 3-10 tokens in length, this results in a range of possible combinations from about 3×10^{13} to 1×10^{45} . Such a large number of possible token combinations exceeds the scope of traditional paradigms which utilize brain recordings to classify from a small set of candidates.

To further compare with previous work, we implemented the pre-generation and selection method proposed by Tang et al. [TLJH23] on the same dataset they used (Huth's dataset). The implementation detail is provided in the SI appendix. We observed that their method could outperform the control model (especially under the "without text prompt" setting), yet significantly underperform with respect to BrainLLM in terms of language similarity metrics (see Table S12). To further study the difference between the proposed direct language generation (BrainLLM) approach and Tang et al.'s two-stage approach, we conducted a token-level analysis. The analysis explored how the generation likelihood of tokens in the perceived continuation ranked among all 32,000 tokens. as shown in Fig. S11. Our observations indicate that when using PerBrainLLM models, which lack corresponding brain recordings to the perceived continuation, for the pre-generation stage of Tang et al.'s approach, there exists a 39% probability that the ground truth tokens may not be included among the top-5 candidates, thereby being excluded from Tang et al.'s approach. This implies that this two-stage approach may not always be able to construct the ground truth token when only the top candidates are pre-generated for the post-hoc selection with brain recordings. On the other hand, for the tokens in the perceived continuation that were not ranked among the top-5 by the PerBrainLLM model (comprising 164,107 samples from 3 participants), our model achieved a strictly better ranking among all 32,000 tokens for 68.9% of these data samples. This indicates the advantage of the proposed direct generation approach, as it demonstrates superior efficacy in scenarios where continuations are less likely to be generated, thereby mitigating the risk of discarding potentially accurate tokens during the generation process.

In recent years, many studies in the field of natural language processing have suggested that language-related tasks can be transformed into generative settings. For example, in sentiment analysis, LLMs generate detailed sentiment descriptions instead of selecting from several semantic labels, and in

topic classification, they provide a summary or a series of keywords that encapsulate the main topic. Similarly, neuroscience research has indicated that the human brain exhibits a tendency to predict the next word, a phenomenon supported by various studies [GZB⁺22], [LC15], [Cla13]. Therefore, we believe that the generative approach is a promising direction for language BCIs, where representations decoded from the human brain can be used as a direct input for language generation.

Implications and future extensions

Our study illustrates the feasibility of direct language generation from brain recordings and highlights their differences and superiority over previous classification-based BCIs in scenarios of decoding perceived language (using visual or auditory stimuli). Due to the advantages of the generative paradigm, BrainLLM can serve as a superior alternative to traditional classification-based approaches, especially in BCI applications where the content to be constructed cannot be confined to a pre-defined set. However, several steps are still needed to realize BrainLLM's potential in language decoding. We observe that when a text prompt is provided, the language similarity metrics are high with BrainLLM. However, in situations without a text prompt, even though BrainLLM still outperforms its control models, the language similarity has a low effect size, implying limited usability in realistic BCI scenarios (see Table I and Table S10). Ideally, each generation step could autoregressively serve as the text prompt for the next step [TLJH23], but errors in this process could accumulate. We suggest that our work can be integrated with BCIs that utilize motor representations [WAH⁺21], [ZBGMA10] or attempted language production [ACC19]. The advantage of motor-based BCIs lies in their higher accuracy, though they are only accessible during attempted speech [ACC19] or several paradigms that require user training [ZBGMA10], which requires considerable user effort. In contrast, our approach functions effectively in both visual and auditory perception scenarios, owing to the extracted general semantic representations. The joint operation of two types of BCIs, such as initially generating accurate text prompts based on the motorbased BCIs, followed by language generation without any motor-related effort using our approach, could be a promising direction for generative BCIs.

Furthermore, BrainLLM essentially quantified the generation likelihood of participants' perceived continuation when given a text prompt. Therefore, it can be used to estimate the probability of generating any semantic content rather than a few semantic candidates. This implies that existing paradigms on studying the representation and formation of language in the brain can be extended by BrainLLM. For example, in the neurolinguistic sentence reading paradigm [?], researchers usually manipulate various linguistic characteristics of the sentences to study their effects on brain responses. BrainLLM enables us to simply collect brain data in a more natural reading scenario and allows us to conduct analyses by comparing the generation likelihoods associated with the content with different linguistic characteristics. Possible insights may include

the exploration of whether different populations have varying expectations for the content following a text prompt and which brain regions are more closely related to the generation of specific linguistic aspects. Additionally, existing studies have shown that semantic information in the human brain is context-aware [CK22], e.g., the brain response to "flat" is different in "flat object" and "flat emotion". Since our method is also a context-based (text prompt) generation, it can be used to explore the impact of contextual information and its effect on brain responses. An example is exploring the connections between various brain regions and the contextualized semantic aspects by comparing their generation performance.

Last, several studies show that computational language modeling can gain insights from human responses to language [OWJ⁺22], [SOW⁺20], especially brain responses [Ton21]. Our experiments reveal that content deemed surprising by LLMs could potentially be corrected by recordings in the human brain. This suggests the possibility of training better language models, or at least more effectively personalized models with individual human brain recordings.

METHOD

We formalize the task of language generation from brain recordings and then detail and justify the different components of BrainLLM, followed by describing the datasets, training, and evaluation.

Task formalization

Given a text prompt W composed of a sequence of tokens $\{w_1, w_2, w_3, \dots, w_n\}$, the task objective is to predict its continuation $M = \{m_1, m_2, \dots, m_k\}$ with the participants' brain recordings while they are perceiving the stimuli constructed with the continuation content M. In this paper, we refer to M as the "perceived continuation". The brain recording $B = \{b_1, \dots, b_t\} \in \mathbb{R}^{t \times c}$ is a sequence of features extracted from blood oxygen level dependent (BOLD) signals, with c being the number of neurological features and t being the number of time frames in which brain recordings are collected. We segment t time frames after the stimuli presentation of the perceived continuation. This segmentation takes into account the delayed effect of BOLD signals [MSC $^+$ 08] (t is set to 4, consistent with existing work [TLJH23], [Ton21]). The language generation task aims to learn an autoregressive function F that can generate the perceived continuation Mone token at a time, utilizing the text prompt W and the brain recording B as inputs. This process can be formalized as $\hat{m}_i = F(\{w_1, \dots, w_n, \hat{m}_1, \dots, \hat{m}_{i-1}\}, B; \Theta), \text{ where } \hat{m}_i \text{ is the }$ *i*-th token generated by the model, Θ is the model parameters.

Model

Large language model (LLM): In our study, we have adopted the LLMs released on Hugging-face (https://huggingface.co/models), including Llama-2 (https://huggingface.co/meta-llama/Llama-2-7b) and the GPT-2 series (https://huggingface.co/gpt2). These LLMs function in a similar way. Typically, they first convert the

input tokens into a series of latent vectors with an embedding layer. Then, these vectors are fed into a multi-layer neural network that uses multi-head self-attention to aggregate the representations of each vector in a sequence [VSP+17]. Based on this architecture, for any input sequence of tokens $S = \{s_1, s_2, \dots, s_n\}$ with length n, the LLM can estimate a prior probability distribution $P(s_{n+1} \mid S)$ for the next token s_{n+1} over the given sequence S. This probability estimation function P serves as a mechanism for autoregressive language generation. Conventionally, the input tokens S are text-based. However, in our approach the brain recordings are incorporated into the construction of sequence S, enabling language generation that is aware of the brain input. Additional details regarding the construction, statistics, and abilities of different LLMs are provided in the SI Appendix.

Input preparation: First, the text prompt is directly fed to the LLM's embedding layer f_w to transform the tokens into latent vectors $V^W = \{v_1^W, \dots, v_n^W\} \in \mathbb{R}^{n \times d}$, where n is the number of tokens, d is the embedding size (see Table S13 for the value of d corresponding to different LLMs). Second, a brain decoder f_b is devised to embed the brain recording into the same latent space with the dimension d. Specifically, for each $b_i \in B$, the decoder embeds it into the space \mathbb{R}^d , which can be formulated as $v_i^B = f_b(b_i)$. Last, the brain embedding V^B and the text embedding V^W are concatenated together, allowing the LLM to perceive modalities from the brain and the text in a unified representation. To differentiate between the two modalities effectively, we introduce two special tokens, i.e., $\langle brain \rangle$ and $\langle /brain \rangle$, to indicate the beginning and end of the brain embedding. The special tokens are randomly initialized as one-dimensional vectors $v^{\langle brain \rangle}$ and $v^{\langle brain \rangle}$, respectively. These vectors have the same number of dimensions d as the token embeddings in LLM. As a result, the input sequence I can be formulated as $I = \{v^{\langle brain \rangle}, v_1^B, \dots, v_t^B, v^{\langle brain \rangle}, v_1^W, \dots, v_n^W\}.$

Brain decoder: The brain decoder is a deep neural network f_b , with the brain recording $B = \{b1, \ldots, b_t\} \in \mathbb{R}^{t \times c}$ as input and the brain embedding $V^B = \{v_1^B, \ldots, v_t^B\} \in \mathbb{R}^{t \times d}$ as output, where d is the LLM's embedding size. The architecture of f_b comprises (1) a position embedding $P = \{p_1, \dots, p_t\} \in$ $\mathbb{R}^{t imes c}$ that captures and represents the chronological order during the collection of BOLD signals, and (2) a multilayer perceptron network f_m designed to transform the brain representation into the latent space that is shared with the text modalities. The position embedding is initialized using a uniform distribution and set to be trainable. Element-wise addition is applied where each position embedding $p_i \in P$ is added to its corresponding BOLD features $b_i \in B$. The multilayer perceptron network f_m is constructed with an input layer and two hidden layers that have the same dimensionality c as the input fMRI features, as well as the output layer with the dimensionality of d. A ReLU [Fuk80] is used as the activation function. Formally, the BOLD features corresponding to the ith time frame, i.e., b_i , is input into the brain decoder f_b , which can be expressed as $v_i^B = f_b(b_i) = f_m(p_i + b_i)$. The output vector embedding v_i^B , with its dimensionality tailored to the LLM's embedding size, can be further adopted to construct

the input with the text modalities.

Training objective: Inspired by the prompt tuning technique [LYF+23], the training of our proposed model involves a warm-up step, followed by a main training step. The warm-up step aims to align the distribution of the brain embedding with that of the text token's embeddings, ensuring that the brain embedding is primed for integration with the text prompt embedding. To streamline the process and enable training without leaking information about the perceived continuation, each $v_i^B \in V^B$ is simply mapped to the mean value of the corresponding text prompt embeddings, i.e., $\frac{1}{n} \sum_{j=1}^n v_j^W$. The mean square error (MSE) loss is adopted during the training process of the warm-up step:

$$L_{MSE} = \frac{1}{t} \sum_{i=1}^{t} (v_i^B - \frac{1}{n} \sum_{j=1}^{n} v_j^W)^2$$

Then, we construct the input sequence I combined with both brain and text modalities. The LLM utilizes a transformer architecture for autoregressive generation based on the input sequence I. The main training target is selected as maximizing the generation likelihood of the perceived continuation:

$$\max_{\Theta} \sum_{i=1,2,...,k} \log(P(m_i \mid I, \{m_1,...,m_{i-1}\}; \Theta))$$

where $\Theta = \{\Theta^{LLM}, \Theta^{f_b}, \Theta^{sp}\}$ is the model parameters, $\Theta^{LLM}, \Theta^{f_b}$, and Θ^{sp} are the parameters of the LLM, the brain decoder, and the special tokens $\langle brain \rangle$ and $\langle \langle brain \rangle$, respectively. During the main step, we retain the inherent knowledge of the LLM while learning useful information from a limited number of data samples with the "prompt tuning" technique [LZD+23]. This technique involves keeping the parameters of the LLM unchanged, and instead, fine-tuning only the input representation, i.e., Θ^{f_b} , and Θ^{sp} in our task. By doing so, the brain decoder learns to decode information from the human brain recordings for guiding the LLM to generate outputs that closely resemble the perceived continuation.

Datasets & preprocessing

We test BrainLLM on three public fMRI datasets, Pereira's dataset [PLP+18], Huth's dataset [LWJ+23], and the Narratives dataset [NLH⁺21]. All datasets, along with their associated studies, received approval from ethics committees and are accessible for basic research. Informed consent was secured from every human research participant. Pereira's dataset collects participants' BOLD signals while viewing visual stimuli composed of Wikipedia-style sentences. Consistent with previous work [LXX22], the brain data of participants who both participated in experiments 2 and 3 were selected in this paper. This involves 5 participants, each responding to 627 sentences. The released beta coefficient brain images (see the original paper [PLP+18]) corresponding to each sentence are adopted in our study. Huth's dataset and the Narratives dataset contain BOLD responses recorded while participants listened to auditory language stimuli of narrative stories. The officially released preprocessed motion-corrected version of these datasets is adopted in our study (https://openneuro.org/datasets/ds003020/ and https://openneuro.org/datasets/ds002345/). Huth's dataset includes data from 8 participants, each listening to 27 stories. Consequently, each participant contributed 6 hours of neural data, amounting to a total of 9,244 TRs. The Narratives dataset initially included 365 participants, but we only selected 28 individuals who engaged in at least 3 stories due to the extremely large computational demand. Among them, eight participants took part in 4 stories, while 20 participants took part in 3 stories, with an average of 1,733 TRs collected from each participant. Additional details regarding the statistics, approvals, pre-processing, and language stimuli for these datasets are provided in the SI Appendix.

To efficiently manage and analyze the fMRI data, we consistently apply dimensionality reduction to c = 1000 dimensions across all datasets for the whole-brain BOLD features. The dimensionality reduction is obtained by applying principal component analysis [AW10] to the preprocessed BOLD features. When conducting analysis on a single brain region, the original signal was directly used without dimensionality reduction. Consequently, we constructed the data samples for the language generation task with the BOLD features in each time frame, corresponding stimuli presented to the participant (perceived continuation), and the text prompt (if any) that preceded the stimuli. Pereira's dataset consists of participants' brain recordings of individual sentences, each presented without overlap. We split each sentence into three parts with equal length. Two unique data samples are constructed by treating the first third as the text prompt and the second third as the perceived continuation as well as combining the first two thirds as the text prompt and using the last third as the perceived continuation. For Huth's dataset and the Narratives dataset, the language stimuli were presented to the participants continuously. Therefore, we split the dataset by treating each TR (2s in Huth's dataset and 1.5s in the Narratives dataset) as a time frame. The perceived content during each time frame is selected as a perceived continuation. Then we used a sliding window ranging from 1 to 3 TRs to select the language stimuli preceding the appearance of the perceived content as the text prompt. This step created 3 data samples for each time frame. The creation of data samples aims to construct as many samples as possible with limited neurological data and ensure that the model is adept at handling text prompts of varying lengths. After that, the data samples are split into training, validation, and testing sets with a size roughly proportional to 3:1:1, respectively. The splitting ensured that there was no overlap of perceived continuation and brain recordings among the training, testing, and validation sets. Additional details and examples for the dataset construction are provided in SI Appendix.

Training protocols

We trained BrainLLM with the Adam optimizer [KB14] using a learning rate of 1×10^{-4} and a batch size of 8. The learning rate is selected from $\{1\times 10^{-3}, 1\times 10^{-4}, 1\times 10^{-5}\}$ based on the experimental performance on Pereira's dataset. These parameters were then directly applied to other datasets without additional hyperparameter tuning to ensure consistency and prevent potential overfitting. The batch size is set

to 8 as the significant graphics memory demands of the LLM preclude the use of a bigger batch size. The training of the warm-up step was stopped after ten epochs. The training of the main step was stopped when no improvement was observed on the validation set for ten epochs, while the test set was never used during the training process. The entire training process was conducted on 16 A100 graphics processing units with 40 GB of memory and took approximately 14 hours to complete. Additional details regarding the training process are provided in SI Appendix.

Measurements

Pairwise accuracy and language similarity metrics are adopted as measurements in our study. Pairwise accuracy is measured by comparing the likelihood of generating the perceived continuation for BrainLLM and its controls. Given a sequence of words, autoregressive LLMs induce a distribution of probabilities for the continuations. We use the cross entropy of the perceived continuation in this distribution as the measure of the likelihood [DB20], [GZB+22]. Then, the pairwise accuracy quantifies the proportion of data samples in which the proposed model demonstrates a higher likelihood of generating the perceived continuation compared to the control model. The negative logarithm of this likelihood is also known as perplexity or surprise, which is widely used in natural language processing. For example, a higher surprise indicates that it is more unlikely for the LLM to generate the continuation. In our analysis of the relationship between surprise and model performance, we utilize the surprise derived from the PerBrainLLM model, which represents surprise estimated by the language model without corresponding brain recordings. Furthermore, the language similarity metrics adopted in our study include BLEU [PRWZ02], ROUGE [Lin04], and WER [KP02]. BLEU (Bilingual Evaluation Understudy) compares n-grams of the generation output with n-grams from the perceived continuation and counts the number of matches. We used the unigram variant BLEU-1. ROUGE (Recall-Oriented Understudy for Gisting Evaluation) is a set of metrics that work by computing overlap measures of n-grams. We adopted the unigram variant and the longest common subsequence variant of ROUGE, namely, ROUGE-1 and ROUGE-L, respectively. WER (word error rate) calculates the ratio of the total number of errors (substitutions, deletions, and insertions) between the generation output and the perceived continuation. In general, higher scores in BLEU and ROUGE, coupled with a lower score in WER, indicate higher language similarity.

Human evaluation

Participants were recruited from Amazon's Mechanical Turk ² with the stipulation of U.S. residents (based on ownership of a U.S. bank account). Non-U.S. residents were excluded as the language stimuli were in English. Selected participants were required to have maintained at least a 90% approval rate on their previous HITs and to have had a minimum of 1,000 HITs approved historically. As a result,

²https://www.mturk.com/

202 participants were engaged in the human evaluation. The human evaluation task is selected as a preference judgment between generation output from BrainLLM and PerBrainLLM. PerBrainLLM is selected as the control of BrainLLM in the human evaluation study, as their comparison directly demonstrates the impact of utilizing brain recordings corresponding to the perceived continuation. We randomly sampled 3,000 pairs of generation output from BrainLLM and PerBrainLLM in Huth's dataset for the task. To mitigate the order effect, each pair of language contents generated from BrainLLM and PerBrainLLM are randomly assigned as "Text1" and "Text2." As shown in Fig. S10, participants are required to judge which one in a pair ("Text1" and "Text2") is semantically closer to the perceived continuation (namely "Base Text"). Participants were paid \$1.0 for approximately 15 minutes. This rate of pay (\$4.0 per hour) is above the median hourly wage for MTurk HITs. All results are included in our analyses. A onesample t-test is implemented to statistically assess the disparity in the preference counts for BrainLLM and PerBrainLLM. In this analysis, instances categorized as "hard to distinguish" are assigned a midpoint value, equidistant between the two options. This approach recognizes the option of "hard to distinguish" as representing a balanced or neutral preference.

Data & Software Availability

The data from Pereira et al. [PLP+18] is available under the CC BY 4.0 license. The Huth's data [LWJ+23] is provided (in part) by the University of Texas at Austin with a "CCO" license. The Narratives dataset [NLH+21] is available under the same universal license. All audio or visual files were provided by the authors of each dataset. The code for our paper can be found at https://github.com/YeZiyi1998/Brainlanguage-generation. All code and materials used in the analysis are available under the CC-NC-BY 4.0 license.

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Supplementary Information

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MATERIALS

Three publicly available functional magnetic resonance imaging (fMRI) datasets are used in the experiments:: Pereira's dataset [PLP⁺18], Huth's dataset [LWJ⁺23], and the Narratives dataset [NLH⁺21]. The statistics of these datasets are listed in Table S14.

Pereira's dataset

Pereira's dataset [PLP+18] consists of recordings from 16 participants' fMRI data while they are watching visual content comprising single words and sentences structured in a style akin to Wikipedia. There are data from three fMRI experiments in their study. We selected data from experiments 2 and 3, in which participants were asked to watch the sentence-based visual contents attentively, with each sentence in the passage presented at one time. To mitigate the overlap issue of BOLD signals between adjacent stimuli, a four-second fixation period was implemented following the presentation of each sentence. Structural and functional MRI data were collected on a whole-body 3-Tesla Siemens Trio scanner with a 32-channel head coil at the Athinoula A. Martinos Imaging Center at the McGovern Institute for Brain Research at MIT or at the Scully Center for the Neuroscience of Mind and Behavior at Princeton University. Each participant did 3 repetitions for each sentence and the averaged beta coefficient brain images (see the original paper [PLP+18] for the definition of beta coefficient brain images) corresponding to each sentence are adopted as brain input in our study. Consistent with previous work focusing on sentence decoding [LXX22], the cognitive data of participants who both participated in experiments 2 and 3 were selected in this paper. In summary, experiments 2 and 3 involved five participants who each responded to 168 passages, with an average of 3.7 sentences per passage.

We use the officially pre-processed beta coefficient images released in the dataset's website (https://osf.io/crwz7). Structural and functional MRI data were analyzed using FSL (http://fsl.fmrib.ox.ac.uk/fsl/) and custom MATLAB scripts. The fMRI data from each scanning session underwent slice timing correction, motion correction, bias field inhomogeneity correction, and high-pass filtering (cutoff: 100 seconds).

Huth's dataset

Huth's dataset [LWJ⁺23], also known as the natural language dataset, contains BOLD fMRI responses recorded from 8 participants each listening to 27 complete, natural, narrative stories (6 hours in total). The stories were sourced from podcasts, including "The Moth Radio Hour," "Modern Love," and "The Anthropocene Reviewed." Each story, lasting approximately 10-15 minutes, was presented during a separate fMRI scan. Participants were instructed to listen to the stories attentively and were not required to provide any responses. At the same time, the MRI data were collected on a 3T Siemens Skyra scanner at The University of Texas at Austin Biomedical Imaging Center using a 64-channel Siemens volume coil.

We use the officially pre-processed version of the dataset. Each functional run underwent motion correction using the FMRIB Linear Image Registration Tool (FLIRT) followed by averaging to generate a high-quality template volume. In the user experiment of Huth's dataset, BOLD signals are collected synchronously with the auditory stimulus presentation. Hence, it is imperative to account for the delay effect inherent in the BOLD signals. In alignment with established precedents in previous research, we consider the 1st to 4th post-stimulus TR periods as the window for capturing the participant's neural response to the stimulus. To mitigate the effects of onset artifacts and suboptimal detrending at the scan's beginning and end, the first and last 5 TRs of each story are removed. As a result, each participant had 9,244 TRs of functional data.

Narratives dataset

The "Narratives" dataset collection aggregates a variety of fMRI datasets collected while human participants listened to naturalistic spoken stories. The dataset includes 345 participants, 891 functional scans, and 27 diverse stories of varying duration totaling 4.6 hours of unique stimuli. Story stimuli encompass a diverse range of media, including commercially produced radio and internet broadcasts, readings of written works, live performances by professional storytellers, etc. Similar to the collection procedures used in Huth's dataset, participants were instructed to listen to the stories attentively and were not required to provide any responses. All MRI data were collected at the Princeton Neuroscience Institute Scully Center for Neuroimaging. The MRI devices include two 3 T Siemens Magnetom Prisma each with a 64-channel head coil. The vast majority of participants only participated in one fMRI experiment, so the average scan duration for each participant was only 21 minutes. However, some participants engaged in multiple scans, contributing to a larger number of MRI data samples for the training the language generation experiments in a within-participant setup. Therefore, we selected all participants

1

in the Narratives dataset who had participated in at least three fMRI scans for our experiment. This criterion selects 28 participants whose ids are: sub-016,sub-026,sub-034,sub-041,sub-052,sub-055,sub-058,sub-059,sub-060,sub-061,sub-065,sub-066,sub-075,sub-084,sub-106,sub-111,sub-132,sub-133,sub-134,sub-135,sub-136,sub-137,sub-140,sub-141,sub-142,sub-143,sub-144, and sub-145.

The "Narrative" fMRI dataset was released with various preprocessed versions, e.g., AFNI-smooth, AFNI. We use the AFNI-smooth version of the released data. Similar to the pre-processing of Huth's dataset, we treat the 1-st to 4-th TR after a user receives a stimulus as the response. For the fMRI sequence of a participant, the volumes before the onset and after the end of the story stimuli are discarded. The time series of each voxel is normalized to have zero mean and unit standard deviation.

Comparative analysis of different datasets

Huth's dataset and the Narratives dataset use similar settings such as the selection of natural story stimuli, experimental task description, etc. However, the statistics of the natural language dataset and the Narratives dataset are quite different. The Narratives dataset contains neuroimaging data from a large number of participants, i.e., 345, but the data collected from each participant is only 21 minutes on average. On the other hand, Huth's dataset involves only 8 participants, but the recorded time is much longer than that in the Narratives dataset, i.e., 6 hours for each participant. Therefore, we conducted experiments to analyze the effect of different training data sizes on the model performance within Huth's dataset and the Narratives dataset. We found that the average performance in terms of pairwise accuracy of BrainLLM versus PerBrainLLM of the two datasets was very close when using the same training data size (see Fig. S9). However, as Huth's dataset contains more data samples, the averaged performance in Huth's dataset is better than that in the Narratives dataset when using all data for training.

On the other hand, Pereira's dataset exhibits several distinct characteristics when compared with Huth's dataset and the Narratives dataset. Notable differences include the employment of visual stimuli, the non-continuous presentation of stimulation, and the utilization of diverse language styles. We observe that the performance metrics associated with Pereira's dataset diverge significantly from those observed in Huth's and the Narratives dataset, even with the same training data size (see Fig. S9). This variation in performance can primarily be attributed to the disparate settings employed in Pereira's datasets.

METHODS

A. Large language model (LLM)

In our study, we utilized large language models (LLMs) from the GPT-2 series [RWC⁺19] and the Llama-2 model [TLI⁺23]. The model parameters for these LLMs were sourced from their officially released versions on the Hugging Face platform (https://huggingface.co/models). These LLMs are trained and function in a similar manner, i.e., a next token prediction task. They utilize sequential ordering inherent in natural language, with the objective of learning joint probabilities across tokens by conceptualizing them as a product of conditional probabilities:

$$p(x) = \prod_{i=1}^{n} p(s_n \mid s_1, \dots, s_{n-1}),$$

where $S = \{s_1, \ldots, s_n\}$ is natural language consisting of a sequence of tokens. The GPT-2 series and Llama-2 were selected for our experiment due to their open-source accessibility and extensive utilization in the realm of LLMs. As of December 2023, they are among the top 10 most downloaded text generation models on Hugging Face.¹

The main differences between the GPT-2 and the Llama-2 are in their architecture, training data, and training process. (1) In terms of architecture, both models are composed of stacked transformers, but the number of layers and the dimensions of the hidden layers are different, which leads to different sizes of total parameters (see Table S13). Besides, the selection of normalization layers and activation functions, which are adopted for connecting the stacked transform layers, differs between the GPT-2 and the Llama-2 [TLI+23]. (2) They are also different in the construction of training data. The training data of the GPT-2 series were 8 million web pages and a total of 40 GB of text crawled by OpenAI ², while Llama-2 is trained on 2 trillion tokens of text data collected by Meta ³. (3) The training process of the GPT-2 series is entirely unsupervised, focusing solely on the task of predicting the next token. In contrast, the training regimen for the Llama-2 model is more multifaceted. It not only involves the unsupervised next token prediction task but also incorporates several supervised fine-tuning tasks, as well as reward modeling based on human feedback. This implies that Llama-2 not only learns the knowledge of generating continuous language from a large text corpus but also undergoes model correction to some extent through supervised knowledge and feedback involving human participation. Due to its large parameter size, efficient training data, and human involvement in tuning, Llama-2 is currently the strongest open-source model on many benchmarks, and it has comparable capabilities to several commercial-licensed language models [TLI+23].

 $^{^{1}} https://hugging face.co/models?pipeline_tag=text-generation \& sort=downloads$

²https://openai.com/

³https://about.meta.com/

B. Experimental dataset construction

We constructed the data samples for the language generation task with the blood oxygen level dependent (BOLD) features, corresponding stimuli presented to the participant (perceived continuation), and the text prompt (if any) that preceded the stimuli. For Pereira's dataset, brain responses are collected within the corresponding time frames for each sentence. Notably, each sentence is presented three times, and the averaged signals are utilized for analysis (for detailed experimental settings, refer to the original paper [PLP+18]). We split the sentence P corresponding to the fMRI signals into three parts with equal length, i.e., P_1 , P_2 , and P_3 . Two unique data samples are generated by treating the first third (P_1) as the text prompt and the second third (P_2) as the perceived continuation as well as combining the first two-thirds (P_1 and P_2) as the text prompt and using the last third (P_3) as the perceived continuation. At the same time, the brain response to sentence P is adopted for generating the perceived continuation with BrainLLM in these two data samples. The construction of such data samples serves three primary objectives. First, it allows the model to adapt to text prompts of different lengths, so that we can study the impact of prompt length and surprise levels on the language generation performance with BrainLLM. Second, it allows us to construct as many data samples as possible with limited data. Last, segmenting the data into three parts allows the perceived continuation to be distributed between 3 and 10 words, which is consistent with the settings of Huth's dataset and the Narratives dataset that will be introduced later.

For Huth's and the Narratives dataset, the language stimuli were presented to the participants continuously. Therefore, we split the dataset according to the TRs (2s in Huth's dataset and 1.5s in the Narratives dataset). The BOLD features and the corresponding perceived continuation are first selected from each TR. Then we used a slide window ranging from 1 to 3 TRs to pick the language stimuli before the perceived continuation appeared as the text prompt. This step constructed 3 data samples for each TR. This is an example of how we construct the data samples for Huth's dataset and the Narratives dataset. Given a series of TRs, i.e., TR_1 , TR_2 , TR_3 , TR_4 , ..., TR_n , and the corresponding language stimuli P_i for each TR_i ($i \in \{1, 2, ..., n\}$), we generate a series of decoding tasks including:

- $\{W = P_1, M = P_2\}; \{W = P_2, M = P_3\}; \{W = P_3, M = P_4\}; \dots$
- $\{W = \text{concatenate}(P_1, P_2), M = P_3\}; \{W = \text{concatenate}(P_2, P_3), M = P_4]\}; \dots$
- $\{W = \text{concatenate}(P_1, P_2, P_3), M = P_4\}; \{W = \text{concatenate}(P_2, P_3, P_4), M = P_5\}; \dots$

where W is the text prompt and M is the perceived continuation that we aim to generate. Similarly, the construction of data samples aims to create as many samples as possible with limited neurological data and ensure that the model is adept at handling text prompts of varying lengths.

After that, the constructed data samples are split using a split-by-stimuli protocol. The stimuli (i.e., perceived continuation) as well as its corresponding brain recordings are randomly shuffled and split into training, validation, and test sets with a size roughly proportional to 3:1:1, respectively. The splitting ensured that there was no overlap of perceived continuation and brain recordings among the training, validation, and test sets. Besides this split-by-stimuli protocol, we also test the split-by-story splitting protocol in Huth's dataset (Huth's data set contains 27 stories as stimuli for each participant and thus is more suitable for this protocol). The experimental observations using a split-by-story splitting protocol on Huth's dataset were in line with that achieved by using the split-by-stimuli protocol. Please refer to our code repository (https://github.com/YeZiyi1998/Brainlanguage-generation) for data partitioning options and all the experimental results on the Huth's dataset.

C. Control model

Our study employs a generative modeling approach to reconstruct language from brain recordings, which differs from previous classification-based approaches. This necessitates the design of control models to compare the approach to empirical lower-bound models. While it is possible to quantify accuracy like existing classification-based approaches to a certain degree, such as reporting a 65.8% probability of generating the next word from the vocabulary of 32,000 each time, this accuracy stems from a combination of brain input and the provided text prompt. Therefore, it is necessary to compare it with the control model based only on the text prompt to study and analyze the effect of brain input. The model based only on the text prompt employs only a standard LLM without external decoded input and thus quantifies the baseline performance of the LLM independently of the brain recordings input. It has been verified to be powerful in continuous language generation [TLI⁺23]. However, the LLM outputs are based solely on the knowledge learned from the training data crawled from the Web, which may not align with the individual's perception. Hence, we intend to examine the impact of brain input on language generation by comparing our proposed model to control models and probing whether brain input modeling can facilitate language generation that aligns more closely with the content perceived by human participants.

The first control model is a standard LLM which only has the text prompt input (StdLLM). In this comparison, the input of BrainLLM is the brain embedding, two special tokens for decoration the brain embedding, and the text prompt embedding. The input of StdLLM is only the text prompt embedding.

However, BrainLLM has more input tokens than StdLLM, and these tokens are either the output of a trainable brain decoder (brain embedding) or are themselves trainable tokens (special tokens). Hence, during the training process, the additional tokens in BrainLLM may encode information about the data distribution of token usage. This phenomenon, extensively studied in the context of prompt tuning [LZD+23], [CNK+23], is effectively employed to generate language that mirrors the style

observed in the training set. Although we have meticulously ensured that the stimuli in the training, validation, and test sets are entirely non-overlapping, they may still share a common data distribution of token usage due to their shared origin. For instance, all stimuli in Pereira's dataset adhere to a Wikipedia-style format and exhibit a token usage distribution akin to that of Wikipedia. Another way to interpret this effect is that even if the brain response is not sampled from the currently perceived continuation, it can still guide the language model to generate the language content that it is sampled from. This indicates that it may guide the LLM to generate content that is sampled from a single dataset and may exhibit similarities to the currently perceived continuation.

Therefore, the difference between BrainLLM and StdLLM may not only lie in the information about the currently perceived continuation that may be decoded from the brain but also in the effect brought by the information of token usage encoded in additional learnable tokens. In order to eliminate these effects, we permutated the brain inputs as additional baseline PerBrainLLM. In PerBrainLLM, the brain input does not necessarily correspond to the currently perceived continuation but may be sampled from participants' responses to any language content in the dataset. This allows us to study the impact of the semantic information about the currently perceived continuation contained in the brain while mitigating the effect of adding additional tokens. In this paper, we predominantly employed PerBrainLLM as the baseline across most of the analysis, as our primary focus lies in the effect of the information from brain recordings on the currently perceived continuation.

To further explain the difference between BrainLLM and its control models, we include a comparison of them from a probability perspective. As we have addressed in the Method section, in the generation task, the expected output is the perceived continuation $M = \{m_1, \ldots, m_k\}$, the input information is the brain input B, and the text prompt input $W = \{w_1, \ldots, w_n\}$. Hence, the task can be simplified as estimating the generation likelihood of M as $P(M \mid B, W)$. When no brain input is given, the generation likelihood of M is $P_{LLM}(M|W) = q(M_{LLM} \mid W_{LLM})$, $q(M_{LLM} \mid W_{LLM})$ is the prior distribution of language generation in the standard LLM. When brain input is given, the generation likelihood with brain input is $P_{BrainLLM}(M \mid B, W)$, and its marginal probability is $P_{BrainLLM,M}(M \mid W) = \sum_b P(M_{dataset}, B = b \mid W_{dataset}) = q(M_{dataset} \mid W_{dataset})$, where $q(M_{dataset} \mid W_{dataset})$ is the distribution of language generation in the given dataset (textual stimuli). $q(M_{dataset} \mid W_{dataset})$ is different from $q(M_{LLM} \mid W_{LLM})$ as the text distribution is different in the given dataset and the dataset to train the standard LLM. Therefore, when B is permuted as B and may not provide information regarding the currently perceived continuation, we can assume that B and M are independent. Thus, the posterior probability is have the posterior probability of $P_{PerBrainLLM}(M \mid B, W)$ as follows:

$$P_{PerBrainLLM}(M \mid \tilde{B}, W) = \frac{P(\tilde{B}, W \mid M)P(M)}{P(\tilde{B}, W)} = \frac{P(B)P(W \mid M)P(M)}{P(B, W)} \propto q(M_{\text{dataset}} \mid W_{\text{dataset}}) = P_{BrainLLM, M}(W \mid M) = \frac{P(B)P(W \mid M)P(M)}{P(B, W)} = \frac{P(B)P(W \mid M)P(W)}{P(B, W)} = \frac{P(B)P(W \mid M)P(W)}{P(B,$$

This indicates that $P_{PerBrainLLM}(M \mid B^*, W)$ is in direct proportion to the marginal probability of $P_{BrainLLM}(M \mid W)$. Hence, the performance difference between BrainLLM and PerBrainLLM is solely due to the information gained from selecting brain samples corresponding to the perceived continuation, and is not related to the learned data distribution of token usage $q(M_{\text{dataset}} \mid W_{\text{dataset}})$ obtained during the training process.

D. The pre-generation followed by post-hoc selection approach [TLJH23]

Tang et al. [TLJH23] propose a pre-generation followed by post-hoc selection approach to reconstruct continuous language from BOLD signals. They used a standard GPT model and an encoder as independent post-hoc models for language reconstruction. Building upon the publicly available GPT (or GPT-1) model [RNSS18], they further refined its capabilities by fine-tuning it on a corpus encompassing Reddit comments (exceeding 200 million words in total) and 240 autobiographical narratives from The Moth Radio Hour and Modern Love. A brain encoder is trained to estimate a set of weights that quantify the impact of the perceived continuation (represented by GPT embeddings) on the BOLD signal in each voxel. With the GPT model and the brain encoder, they reconstruct the language with the following process. First, the GPT model is used to pre-generate the top-5 tokens that could be the next token when given the text prompt. This pre-generation process incrementally builds up a sequence of tokens as the continuation of the given text prompt, based on the top-5 tokens generated by the GPT model at each generation step. Using a beam search algorithm with a width of 200, the continuation candidates can be pre-generated with the GPT model. Second, to avoid exponential combinations during the generation process (e.g., the n-th power of 5 when pre-generating n tokens), the model selects and keeps the candidate continuations within the size of the beam width by measuring how well the recorded brain responses match the brain responses predicted by the pre-generated candidates. To tackle the challenge of generating text with a vast vocabulary, they employed a restricted subset of 6,867 tokens extracted from the training set. The generated outputs from their approach are then compared to those from a standard LLM (i.e., GPT in their paper) in terms of language similarity metrics.

Different from our experiments, Tang et al. [TLJH23] did not test and analyze the model performance regarding text prompts with varying lengths. They based their approach on several pre-defined initials consisting of only one token (e.g., "I", "He") as text prompts, followed by continuous generation based on content that has been previously generated. These initials provide limited information and may not necessarily be the same as the actual text prompts. Hence, their setting is more similar to the setting of language generation without any text prompts in our experimental setup, which also provides a few text prompts

for language generation. On the other hand, the token combination of the perceived continuation may not be within the beam search width during the beam search process used in their approach. As illustrated in their article, their model is typically unable to generate content that is entirely identical to the perceived continuation. This also implies that their model can not estimate the generation probabilities of the perceived continuation, as the sequences including the perceived continuation are often pruned during the beam search process. As a result, they could not use pairwise accuracy as a metric for evaluation in the same way as we do in our evaluation, but only used a language similarity metric.

To make a fair comparison between Tang et al. [TLJH23]'s model and ours, we reproduce their model with the same configurations for the LLM selection, token vocabulary, evaluation dataset construction, and metrics as ours. The differences between our reproducibility and their original proposed approach are listed below: Firstly, instead of using a private GPT model, the PerBrainLLM based on a publicly available Llama-2 is used for pre-generating candidates. No restriction is applied to the size of the vocabulary (they use a restricted vocabulary), and thus the whole token vocabulary of 32,000 is adopted in the generation process. Using PerBrainLLM for pre-generating candidates means that the method reproduced in our experiments may have a stronger performance than the originally proposed method. Secondly, instead of generating from some pre-defined initial tokens, generation with and without the actual text prompts are both adopted in our comparison for analysis. Thirdly, their model calculates the language similarity metric over the entire text content perceived by the participant during an fMRI recording, approximately 16,400 tokens. This means that, as their paper states, the content generated at any time frame may have shared similar tokens with the perceived content in the other time frame, thus leading to higher language similarity metrics. We, on the other hand, only consider the current time frame in which participants usually perceived about 3-10 tokens, and use the generation output with corresponding brain recordings to calculate the language similarity metrics. This makes the results more targeted, even though they may appear lower on the metric. Finally, due to the infeasibility of estimating the generation probabilities of perceived continuation, only the language similarity metrics (i.e., Bleu-1, ROUGE-1, ROUGE-L, and WER) are used in comparisons involving their models.

E. Surprise measurements and pairwise accuracy

Given a sequence of tokens, LLM induces a distribution of probabilities for all possible following continuations. The likelihood of a possible continuation is the multiplicative product of the probabilities of generating each token in the continuation. Derived from the concept of likelihood, perplexity and surprise stand as two prevalent metrics utilized for assessing the quality of text generated by a language model. Typically, the negative logarithmic cross-entropy likelihood of the perceived continuation in this distribution is adopted as the surprise measurement [MC21]:

surprise =
$$-\sum_{i=0,1,...,k} \log(P(s_{n+k} \mid \{s_{n-1+k},...,s_1)\})$$

where $\{s_n, \ldots, s_{n+k}\}$ is the continuation of $\{s_{n-1+k}, \ldots, s_1\}$. Based on the surprise, perplexity is measured by:

$$perplexity = 2^{surprise}$$

The surprise and perplexity scores focus on the conformity between the continuation generated by the language model and expectations. The higher surprise and perplexity indicate the language model deems the continuation as more unexpected. Our analysis utilizes PerBrainLLM's surprise measurement to examine the impact of surprise on generation performance. This is because the surprise of PerBrainllm represents the surprise of the language model for the perceived continuation when brain recordings corresponding to the perceived continuation are not obtained.

Based on this definition, a more effective language generation model should deem the perceived continuation less surprising. Consequently, to assess the relative performance of the proposed BrainLLM and its control models, PerBrainLLM and LLM, we compare their surprise scores for each perceived continuation within the constructed data sample. This evaluation metric is known as pairwise accuracy and has been extensively utilized for performance comparison in brain decoding and encoding research [MSC+08], [PLP+18].

F. Language similarity metrics

Many language similarity metrics are available in natural language processing research. We adopt Bleu (Bilingual evaluation understudy), ROUGE (Recall-Oriented Understudy for Gisting Evaluation), and Word Error Rate (WER) as our metrics, which are frequently used to measure language similarity, especially in machine translation research [CD22]. To avoid potential bias introduced by relying on language representations from LLMs, we refrain from employing metrics such as BertScore [ZKW+19], which utilize LLM-derived representations. Bleu is a metric for measuring the similarity between two text sequences, and is based on the n-gram precision between the generated sequence and reference sequence. The Bleu score is computed as by:

$$\mathsf{Bleu} = \frac{\mathsf{BP}}{(\mathsf{BP} + (1 - \mathsf{BP}) * (1 - e^{-\ln(r_n)/\ln(m)}))}$$

where r_n is the n-gram precision, which is the number of n-grams that match between the generated sequence and the reference sequence, m is the number of possible n-grams in the reference sequence, BP is the brevity penalty, which is a measure of how much shorter the generated sequence is than the reference sequence, which can be measured by:

$$BP = \begin{cases} 1 & \text{if } r < c \\ e^{1-r/c} & \text{if } r \ge c \end{cases}$$

We used the unigram variant BLEU-1 in our paper. Word Error Rate (WER) is calculated as the number of words that are incorrectly recognized divided by the total number of words in the reference sequence, which is measured by:

WER =
$$(substitutions + deletions + insertions)/m$$

where m is the number of possible n-grams in the reference sequence, substitutions, deletions, and insertions are the number of substitutions, deletions, and insertions while transforming the generated sequence to the reference sequence. ROUGE (Recall-Oriented Understudy for Gisting Evaluation) is another metric for measuring the similarity between two text sequences. It is based on the recall of the n-grams in the generated sequence:

ROUGE-N =
$$\frac{r_n}{m}$$

where r_n is the n-gram recall, which is the number of n-grams that match between the generated sequence and the reference sequence divided by the total number of n-grams in the reference sequence, m is the number of possible n-grams in the reference sequence. We use the unigram variant and the longest common subsequence variant of ROUGE. The longest common subsequence variant of ROUGE is computed as by:

$$\text{ROUGE-L} = \frac{\text{RLCS}}{m}$$

where RLCS is the length of the longest common subsequence between the generated sequence and the reference sequence.

G. Human evaluation

To compare the proposed BrainLLM and its control PerBrainLLM, we conducted a human evaluation. We select PerBrainLLM as the control in the human evaluation study, as their comparison directly demonstrates the impact of utilizing brain recordings corresponding to the perceived continuation. In total, 202 participants were recruited from Amazon's Mechanical Turk 4 and engaged in the human evaluation. All participants have stipulations of U.S. residents (based on ownership of a U.S. bank account). These participants were required to have maintained at least a 90% approval rate on their previous HITs and to have had a minimum of 1,000 HITs approved historically. We randomly sampled 3,000 pairs of generation output from BrainLLM and PerBrainLLM in Huth's dataset. In the random sampling, stratification was taken into account as follows. We randomly sampled 375 language pairs generated by BrainLLM and PerBrainLLM from the data of each participant in the dataset, with a total of 8 participants. To mitigate the order effect, each pair of language contents generated from BrainLLM and PerBrainLLM are randomly assigned as "Text1" and "Text2". As shown in Fig. S10, participants are required to judge which one in a pair ("Text1" and "Text2") is semantically closer to the perceived continuation (namely "Base Text"). This preference judgment is accomplished by selecting from "Text1 is better" and "Text2 is better", or the participant can select "hard to distinguish" if they find it difficult to judge or deem "Text1" and "Text2" as equally good. On average, the participants were paid \$1.0 for each 15 minutes they spent. This rate of pay (\$4.0 per hour) is above the median hourly wage for MTurk HITs. Since it is not possible to guarantee which samples each annotator will label in the annotation of Mechanical Turk (AMT), we can not use some data points to detect whether the annotator has completed the task seriously. Hence, we uphold trust in their annotations and preserve all annotation outcomes, given the annotator's historical approval rate of at least 90%. A one-sided t-test was used to statistically assess the disparity in the preference counts for BrainLLM and PerBrainLLM. In this analysis, instances categorized as "hard to distinguish" are assigned a midpoint value, equidistant between the two options of "Text1 is better" and "Text2 is better". This approach recognizes the option of "hard to distinguish" as representing a balanced or neutral preference.

H. Ethical issues

The development of BCI technology to reconstruct language from the human brain raised significant concerns about privacy and informed consent. The capability to directly access and decode brain signals could facilitate covert monitoring of individuals' thoughts, challenging the deeply ingrained notion of the mind as a private sanctuary, solely accessible to its owner. While this technology has the potential to revolutionize communication, self-expression, and mutual understanding, it also raises concerns about privacy, manipulation, and the very essence of free will [RMC⁺20]. Although such technology is currently at a very early stage where such applications feel a long way off, several existing studies have already discussed the associated

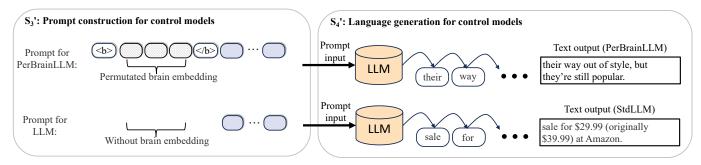


Fig. S1: The schematic diagram for language generation with permuted brain recordings (PerBrainLLM) and without brain recordings (StdLLM). c'. The prompt input for PerBrainLLM adopts a permutation of the correspondence between the sample of brain recordings and the perceived continuation. The prompt input for StdLLM is only the text prompt embedding, which acts as a standard LLM and generates the most likely continuations based on its training on internet-based data. d'. The content generated by PerBrainLLM and StdLLM maintains coherence with the text prompt but fails to align semantically with the perceived continuation.

concerns [MH19], [TLJH23], [RMC⁺20]. For example, Mecacci [MH19] developed several criteria to measure the ethical issue. Tang et al. [TLJH23] observe that participant cooperation is required for language BCIs, which indicates that participants can consciously resist the language decoding process.

Nevertheless, existing language decoding methods follow a pre-definition [PLP+18], [DCR+23] or pre-generation step [TLJH23] to construct semantic candidates within limited topics before incorporating brain recordings to identify the most likely candidate from the pool. As the semantic candidate's pool could be safe and controllable under human heuristics, thoughts that may involve personal information can be precluded from the pre-definition or pre-generation step. However, this control is only effective if the pre-selection process is not subject to malicious attacks. It is still possible for illegal usage such as semantic decoding that may involve sensitive candidates. On the other hand, the proposed direct language generation approach does not have a human-controllable pre-definition or pre-generation stage. This implies that the entire generation process is completely motivated by the representations in the participants' brain and the LLM. Furthermore, the reconstructed language could be anything that is reflected in the brain responses. These features empower our model with greater freedom to generate personalized content compared to previous methods, but they also introduce the potential for decoding contents that participants may wish to keep private.

We believe that the following aspects can be considered to mitigate this concern. Firstly, it may be necessary to avoid the generation of private content from the machine model's perspective. Considering the inherent complexity and lack of explainability of the LLM and the human brain, an applicable approach at this stage involves processing the output content with hand-crafted rules [HZHL20]. Secondly, rather than relying solely on post-hoc filtering for privacy information, we suggest preventing the model from accessing privacy content in the first place by designing and training a safe brain decoder. This approach can be accomplished by machine learning techniques such as feature selection and can ensure the model only generates task-relevant and non-private semantic information in the human brain. Finally, before it is fully ensured that the model will not output private content, the output should be reviewed by the participants. This review process may merely involve the participants deciding whether or not to share such content, thus requiring minimal user effort.

I. Reproducibility

Our experiments use open-source datasets (Pereira's dataset [PLP+18], Huth's dataset [LWJ+23], and the Narratives dataset [NLH+21], which can be downloaded from the paper websites or OpenNeuro⁵), released open-source code (github link: https://github.com/YeZiyi1998/B language-generation), and provide preprocessed datasets (Tsinghua Cloud link: https://cloud.tsinghua.edu.cn/d/04e8cfe6c9c743c69f08/). Third-party researchers can run the example datasets on our code, or download the preprocessed datasets and run them to reproduce our results and analysis.

⁵https://openneuro.org/

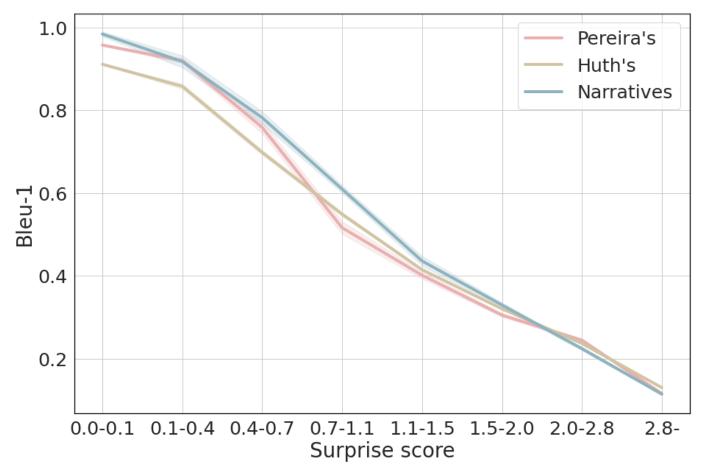


Fig. S2: Bleu-1 score of BrainLLM across perceived continuation with different surprise levels. The Pearson's coefficient r between the surprise levels and the Bleu-1 score in Pereira's dataset, Huth's dataset and Narratives dataset are -0.66 -0.52, and -0.56, respectively. This observation suggests that with an increased surprise level, it becomes more difficult for the LLM to generate the perceived continuations. However, the negativity of this coefficient is smaller than that of PerBrainLLM, indicating that as the surprise level increases, the performance of BrainLLM decreases less than that of PerBrainLLM.

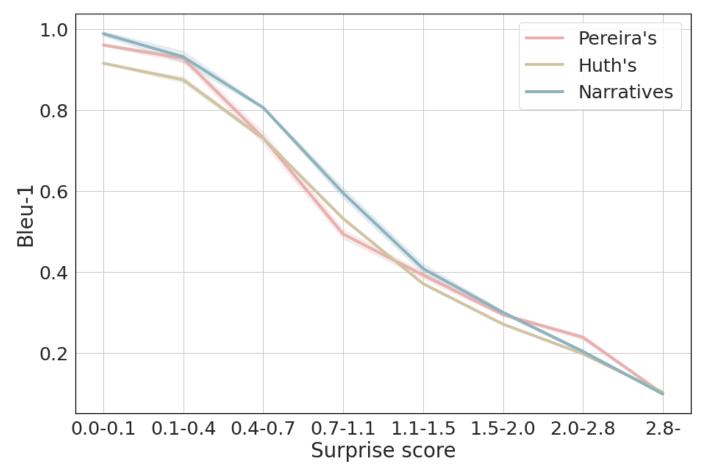


Fig. S3: Bleu-1 score of PerBrainLLM across perceived continuation with different surprise levels. The Pearson's coefficient r between the surprise levels and the Bleu-1 score in Pereira's dataset, Huth's dataset, and Narratives dataset are -0.67 -0.54, and -0.58, respectively. This observation suggests that with an increased surprise level, it becomes more difficult for the LLM to generate the perceived continuations.

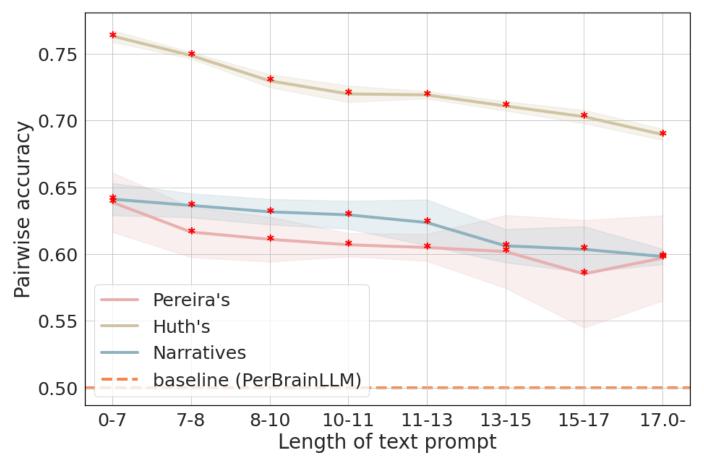


Fig. S4: Pairwise accuracy between BrainLLM and PerBrainLLM across text prompt with different lengths. The Pearson's coefficient r between the length of text prompt and the pairwise accuracy in Huth's dataset and Narratives dataset are significant -0.059 and -0.060, respectively. Both coefficients are statistically significant with p-values of $5e^{-77}$ and $5e^{-40}$, respectively. However, Pearson's coefficient r is not significant in Pereira's dataset (-0.02 with p-values 0.13). This observation could be attributed to the limited sample size of the Pereira dataset, resulting in a scarcity of text prompts of varying lengths.

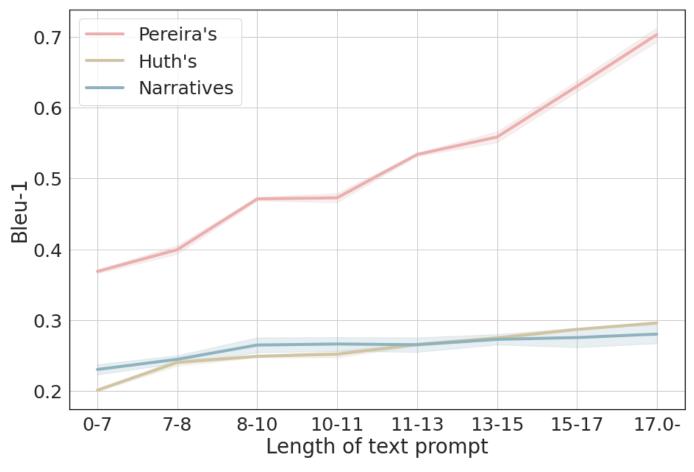


Fig. S5: Bleu-1 score of BrainLLM across text prompt with different lengths. The Pearson's coefficient r between the length of text prompt and the Bleu-1 score in Pereira's dataset, Huth's dataset and Narratives dataset are significant at 0.27, 0.03, and 0.05, respectively. Pereira's dataset is constructed from Wikipedia and is more similar to the training dataset of a standard LLM than the other two datasets based on speech-style content. Therefore, both the overall performance regarding Bleu-1 and correlation coefficients in Pereira's dataset are higher than the other two datasets.

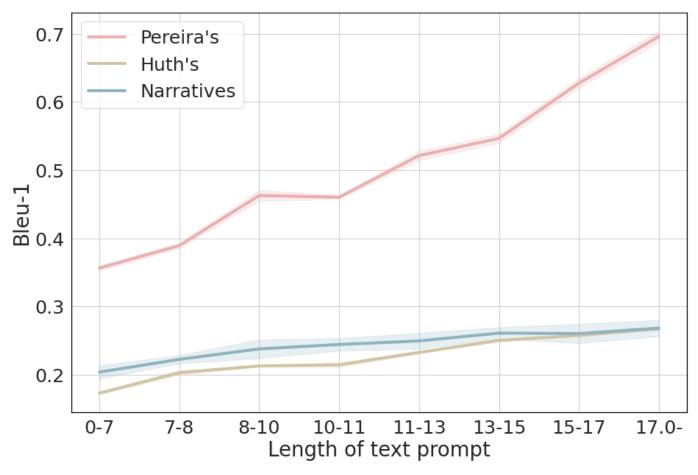


Fig. S6: Bleu-1 score of PerBrainLLM in text prompt with different lengths. The Pearson's coefficient r between the surprise levels and the Bleu-1 score in Pereira's dataset, Huth's dataset and Narratives dataset are significant at 0.27, 0.02, and 0.03, respectively.

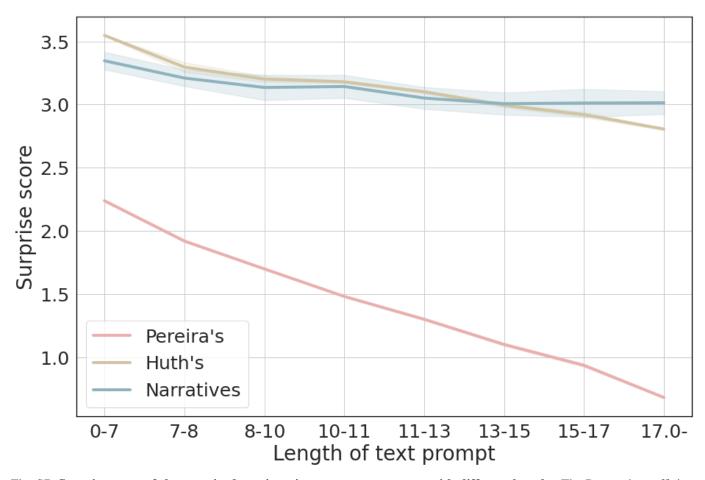


Fig. S7: Surprise score of the perceived continuation across text prompt with different lengths. The Pearson's coefficient r between the surprise levels and the length of text prompts in Pereira's dataset, Huth's dataset and Narratives dataset are significant with p < 0.05 at -0.37, -0.14, and -0.04, respectively.

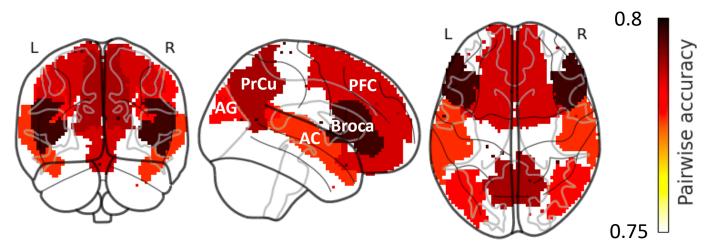


Fig. S8: Language generation performance in terms of pairwise accuracy across cortical regions between BrainLLM and PerBrainLLM from a single participant (participant 1 in Huth's dataset). Brain data (colored regions) used for language generation with BrainLLM were partitioned into the Broca's area, the precuneus (PrCu), the prefrontal cortex (PFC), the auditory cortex (AC), and the angular gyrus (AG).

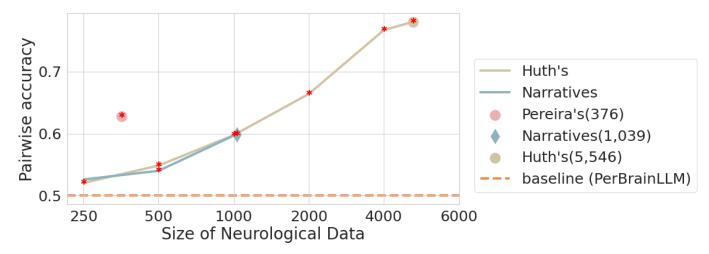


Fig. S9: Language generation performance in terms of pairwise accuracy with various amounts of neurological data for training. The overall amounts of neurological data in Pereira's dataset, Huth's dataset, and Narratives dataset are 376, 1,039, and 5,546 (averaged across participants), respectively.



Fig. S10: Screenshot examples of the human evaluation task. "Text1" and "Text2" are randomly assigned as language generation output from BrainLLM and PerBrainLLM, respectively. "Base Text" is the corresponding perceived continuation. The text prompt is concatenated in front of "Text1", "Text2", and "Base Text" to provide a better context for judging semantic similarity.

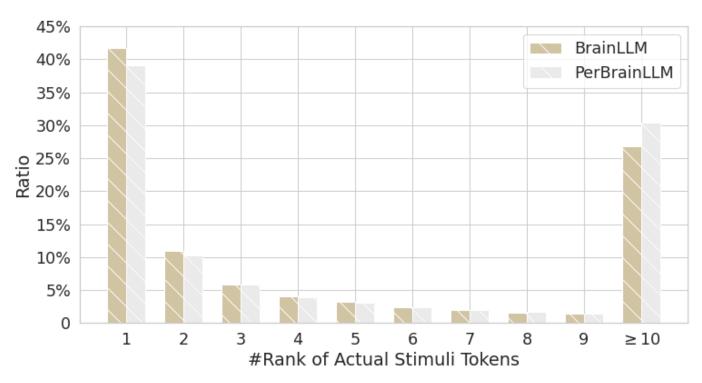


Fig. S11: Rank of token-level perceived continuation in the language generation process with BrainLLM and PerBrainLLM in Huth's dataset. A lower rank indicates that the language model considers the token in the perceived continuation as more likely to be generated. Rank 1 indicates that the model accurately predicts the next token.

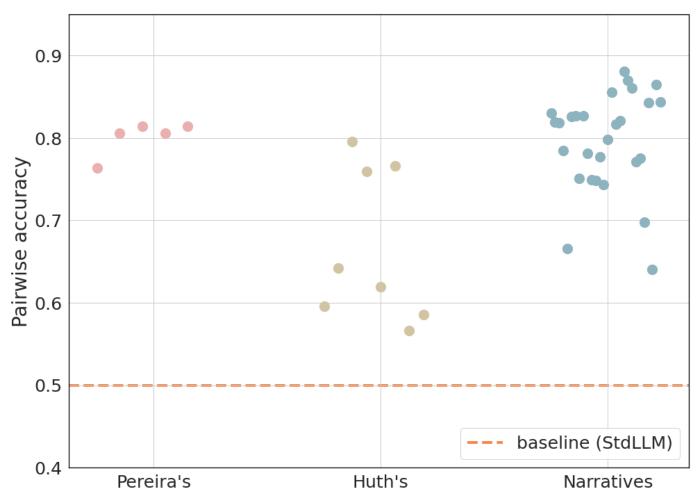


Fig. S12: **Pairwise accuracy comparisons: PerBrainLLM vs. LLM.** Each dot represents the pairwise accuracy of a single participant in Pereira's dataset (5 participants), Huth's dataset (8 participants), and Narratives dataset (28 participants).

TABLE S1. Examples of language generation output from BrainLLM and PerBrainLLM in Pereira's dataset (visual stimuli from Wikipedia content) across various participants. Blue text indicates the generation output and the perceived continuation are exact match.

Text prompt	s where BrainLLM outperforms Pe Perceived continuation	rBrainLLM: Differences in the surpris Generation with BrainLLM (sur- prise)	e scores within the top third. Generation with PerBrainLLM (surprise)	Subject ID	
Electric lawnmowers are better	for the environment because	for the environment than gas- powered mowers. (0.7809)	than gasoline-powered ones be- cause they are quieter and don't (1.7245)	P01	
Drunk driving is the	act of driving under	crime of driving under the influence of alcohol. (1.5430)	most common cause of alcohol- related deaths. (3.3885)	P01	
The wind from the	hurricane shook the house, shattering	hurricane was so strong that it blew the car off (1.7734)	north is cold and dry, while the wind from the (2.8519)	P01	
A wall is a	Il is a solid structure that defines structure that defines and vertical structure mad		vertical structure made of stone, brick or concrete. (2.2302)	M02	
Over the past generation, there has been a	dramatic expansion of legalized gambling.	dramatic increase in the number of children born to women (1.8443)	huge increase in the number of women pilots. (2.6174)	M02	
A scientist studies and produces new knowledge	about the physical world.	about the natural world. (0.6094)	about the world. (1.0747)	M02	
A wall is a	solid structure that defines	solid structure that defines and sometimes protects an area. (0.6725)	structure that separates two spaces. (1.6014)	M04	
They recorded if they recalled	any dreams, and described each	the dream, and if so, what it was about. (2.7073)	the information later. (3.3868)	M04	
Coffee is a popular	drink in many countries,	drink in many parts of the world. Coffee beans (1.0633)	drink around the world. Coffee beans are roasted and (1.6215)	M04	
Performances are typically given	in an opera house	in concert halls or opera houses. (1.2981)	in theaters or concert halls. (2.0215)	M07	
Television content can	be broadcast or received	be broadcast live or pre-recorded. (1.8579)	be entertainment, news or education. (2.4874)	M07	
That is, a taste bud on the tip of the tongue would respond	only if you were eating something sweet.	to sweet, sour, salty, bitter, or umami. (1.9426)	to a sour taste. (2.2187)	M07	
Farms usually have a	house for farmers, a	house for the farmer and his or her family. (1.8633)	fence around them to keep live- stock in and predators (2.1109)	Mī5	
The polar bear will crawl	quietly forward and freeze in	on its stomach and forelimbs to get closer to the (3.3112)	on its stomach to get closer to its prey. (3.5129)	Mī5	
Female mosquitoes bite people	and animals and suck	and animals to suck their blood. (1.5983)	more often than males. (1.7417)	Mī5	

TABLE S2. Examples of language generation output from BrainLLM and PerBrainLLM in Pereira's dataset (visual stimuli from Wikipedia content) across various participants. Blue text indicates the generation output and the perceived continuation are exact match.

Text prompt	e BrainLLM & PerBrainLLM pery Perceived continuation	form similarly: Differences in the surp Generation with BrainLLM (sur- prise)	rise scores within the middle third. Generation with PerBrainLLM (surprise)	Subject ID
Assault rifles can fire in bursts and are	the standard infantry weapon.	used by infantry and special forces. (0.9271)	used by infantry and special forces. (1.0300)	P01
Tomatoes can be used	to make salads, soup or	to make sauces, ketchup and tomato juice. (1.8311)	to make sauces, ketchup, salsa and chutney. (1.9277)	P01
Spectacular castles in dramatic locations provide a record of the	stormy history of many regions.	power and wealth of medieval rulers. (2.9403)	power and wealth of their builders. (3.0320)	P01
Scrubbing a wound with soap or alcohol delays healing, which	increases the risk of infection.	can lead to infection. (0.5653)	can lead to infection. (0.6313)	M02
A sweater is a heavy garment worn on	the torso for warmth.	the upper body. (1.0327)	the upper body to keep warm in cold weather. (1.0961)	M02
An elephant has a long nose called a trunk, which	can grab things or food.	it uses for eating and drinking. (3.3345)	it uses for eating, drinking and breathing. (3.3956)	M02
Disposable rubber or latex	gloves are used to shield	gloves are used to protect the hands from germs. (1.3808)	gloves are used to protect the hands. (1.4422)	M04
We poured the cream mixture into a frozen tub, then start turning the	crank to expose it to the cold.	ice cream maker crank. (2.2776)	ice cream maker on. (2.3339)	M04
Floors may be made	of bare concrete, tile,	of wood, stone, tile or carpet. (1.8595)	of wood, stone or concrete. (1.9154)	M04
valid -¿ best features of its predecessors. It incorporates many of the	elements of spoken theatre, such	best features of other sports, such as soccer and basketball. (2.9760)	best features of its predecessors. (3.0300)	M07
A glove is a	piece of clothing that	covering for the hand. (0.7395)	piece of leather or cloth that covers the hand. (0.7931)	M07
Piranhas are small,	ferocious fish that live	razor-toothed fish that live in South America. (1.0150)	carnivorous fish with razor-sharp teeth. (1.0666)	
A swamp is covered with shallow	water, mud and vegetation.	water and dense vegetation. (1.1008)	water and dense vegetation. A swamp can be freshwater (1.1441)	Mī5
An igloo is a type of shelter made from	blocks of snow by Inuit.	blocks of snow. An igloo is usually dome-shaped. (1.6890)	blocks of snow and ice. An igloo has a dome-shaped (1.7306)	Mī5
Walls delineate a building,	support the roof, and	protect it from the elements, and can be decorated. (1.7052)	protecting it from the elements and intruders. (1.7460)	Mī5

TABLE S3. Examples of language generation output from BrainLLM and PerBrainLLM in Pereira's dataset (visual stimuli from Wikipedia content) across various participants. Blue text indicates the generation output and the perceived continuation are exact match.

Text prompt	where BrainLLM underperforms Perceived continuation	erBrainLLM: Differences in the surpri. Generation with BrainLLM (surprise)	se scores within the final third. Generation with PerBrainLLM (surprise)	Subject ID
Cats can hunt mice	or birds, but are	, rats, birds and other small animals. (1.8762)	, rats and other small animals. (1.7944)	P01
The piano repertoire is large and famous pianists	can give solo concerts.	have written many original compositions. (2.3033)	often perform in concerts. (2.2118)	P01
Retaining walls provide a	barrier to movement of	barrier against erosion and flooding. (1.9046)	barrier against erosion and flooding. (1.8184)	P01
A sweater that opens down the front	is called a cardigan.	is called a cardigan. (0.3550)	is called a cardigan. (0.2818)	M02
Raspberries are eaten	by themselves or cooked	fresh or used to make jams and desserts. (2.4154)	fresh or made into jams, pies and other desserts. (2.3410)	M02
A horse is a	large hoofed mammal with	large mammal with four legs and a long tail. (0.7095)	large, hoofed mammal with a long neck and mane. (0.6265)	M02
Blenders have a glass	or plastic container with a	or plastic container with a rotating blade. (0.7227)	or plastic container with a rotating blade. (0.6573)	M04
A glove is a	piece of clothing that	covering for the hand, usually made of leather. (0.8059)	covering for the hand. It can be made of (0.7375)	M04
Some patients go there	for specialist diagnosis or	voluntarily, while others are invol- untarily committed. (2.3428)	for treatment of chronic diseases. (2.2665)	M04
A sweater is a heavy garment worn on	the torso for warmth.	the upper body. (0.9449)	the upper body to keep warm. (0.8729)	M07
During times of attack, peasants,	livestock, and property could be brought	merchants and priests would flee. (2.6384)	merchants and craftsmen could be conscripted. (2.5643)	M07
The type of forest	depends on temperature and	is determined by climate, soil and topography. (2.1033)	depends on the climate and the type of trees (2.0256)	M07
Cruise ships are floating hotels that	take people between cities.	travel the world's oceans and seas. (3.6322)	travel the world's oceans and seas. (3.5694)	M15
Lettuce is considered fairly	easy to grow and	low in nutritional value, but it is a good (0.7081)	low in calories and is a good source of (0.6411)	M15
The market for admission to law school and for	new lawyers could eventually crash.	lawyers is very competitive. (3.1436)	jobs as lawyers is very competitive. (3.0660)	M15

TABLE S4. Randomly sampled examples of language generation with BrainLLM and PerBrainLLM in Huth's dataset. Blue text indicates the generation output and the perceived continuation are exact match. These samples were selected from participants 1, 2, and 3.

Text prompt	es where BrainLLM outperforms Perceived continuation	PerBrainLLM: Differences in the surpr Generation with BrainLLM (sur- prise)	rise scores within the top third. Generation with PerBrainLLM (surprise)	Subject ID
you see in the morning I'll be paroling from	state prison after twenty	the state penitentiary where I've been incarcerated for a (2.4710)	the beach and I'll see you then thank you (4.5921)	1
around and we sort of spent the morning like this and it was all really um just	fine and then um	very peaceful and then in the after- noon we went (2.2719)	being in awe of what we were seeing and (5.3981)	<u>1</u>
nee use to know the mortality rates hence tell you how	much premium you need to pay	long you're going to live and hence how much money you need to pay (1,3060)	long you're gonna live uh and i was like eighty per (3.5567)	<u>I</u>
was trying to make my mom look bad in front of the teachers to like deflect	um y you know	the blame um and uh you know it was (3.1762)	some of the blame from her onto me and (5.9958)	<u>1</u>
let it come wait for it wait for it i	see the horizon coming up my feet get a little	'm at the top of the arc i'm over the ocean i'm looking down and (2.9004)	was like no i'm not gonna wait for it and he said well then you (5.1265)	<u>1</u>
would come pick us up and we had to do that twice and if you did that twice	successfully you pass the water	you were out of the navy and i didn't want (3.9887)	in a row you were uh suspended from school uh (6.7814)	<u>2</u>
where i pick up my bag	and i replace the handset	and my phone and i walk out of the shop (2.4662)	and i'm gonna go back to new york um and (4.9229)	
that everything happened in slow motion	the voice in my head asks me	and then all of a sudden i look up and i see (2.5491)	nd um and so i was in the hospital for a couple (4.9326)	2
was because it was also where we kept	all of the family photos	all of our family pictures and i had a lot (1.6215)	the goats and the pigs and the chickens and the (3.8364)	2
with forty three other new astronauts but we weren't re-	astronauts yet we were	astronauts yet we were trainee astronauts and we had (0.2619)	talking about that we were talking about the fact (2.4186)	
been tough immediately we start to reminisce about our thirty second relationship i didn't think that was gonna happen	me neither oh man that was close	i didn't think that was gonna happen but it did and we (4.5486)	but it did and then we start to reminisce about the fact (5.7116)	3
what insurance companies	nee use to know	don't want you to know is that if you (5.6416)	don't do is they don't tell you what to (6.5533)	3
but no you had to be topless for an entire	song and i'm like oh no but	day and i'm like well that's not gonna work for me so i (1.7108)	day and then you had to be nude for an entire day and (2.5826)	3
requests so we said that	we preferred a boy	we'd be happy to do that and then we (3.9074)	's great we'd love to do that and he (4.7590)	3
of the organization it doesn't mean that every storm trooper gets personal one on one time	so i try to	with luke skywalker and so i'm like you know (2.9701)	with darth vader but it does mean that every (3.7780)	3

TABLE S5. Randomly sampled examples of language generation with BrainLLM and PerBrainLLM in Huth's dataset. Blue text indicates the generation output and the perceived continuation are exact match. These samples were selected from participants 1, 2, and 3.

Text prompt	Perceived continuation	perform similarly: Differences in the su. Generation with BrainLLM (sur- prise)	Generation with PerBrainLLM (surprise)	Subject ID
saleswoman and it started to get confusing like which hat i was wearing at which time until	one day i was in	one day i'm in the dressing room and there's a (1.2526)	finally i realized that i was the patient and she (1.7785)	1
and it's late spring and i go visit some	friends at princeton and yet again i get	friends in new york city and i'm staying with a friend of a (2.6285)	of my cousins and they're all like oh my god it's so great (3.1530)	I
mine sends me lolita which i had never read before which is not the best sort of	reading material when there's like twelve and	lolita to read because it's the one that's all about nymphets and (3.2295)	book to read when you're going through something like this but i (3.7540)	<u>1</u>
into a raft signal for help and they	would come pick us up and we had to do that twice	're going to come and rescue me and i'm going to be fine and i'm going to (2.0334)	're not going to be able to hear you over the sound of your own screaming but (2.5564)	<u>1</u>
in full gear flight	suit boots and helmet	suit helmet oxygen mask goggles gloves boots parachute and (1.2413)	suits helmets goggles oxygen masks and all the rest (1.3972)	1
because i i would i would like to say because of the uh incredible amount of love	that you have for them but that's not	that my parents had for me but i think it was more because (1.4390)	and affection that i had for her but it was probably more because (1.8998)	2
assistants to madame diof who had all gathered around and we sort of spent the morning like this	and it was all really um just	and then we went back to the hotel and had lunch and (3.2112)	and then we had lunch and then we sort of spent the (3.6719)	2
the artist never quite pinned down never	quite in a relationship and and you have	quite figured out what was wrong with me but i knew that there (3.4595)	quite figured out what was wrong with me and i think that's probably (3.9192)	2
headphones still there are the headphones still there i i'm on the verge of a nervous	breakdown when finally one of the president's aides	breakdown and then i hear a knock on the door it's the president (1.8259)	breakdown i'm on the verge of a nervous breakdown i'm on the verge (2.2814)	2
they inject something into your ankle like an iodine so- lution and then you they lay you	on a table and you get slid into	down on a table and they cut you open from your pubic area (2.0988)	down on a table and you're strapped to the table and then they (2.2224)	
and and bird watching camps there's	even a camp where you can dress up in armor	all kinds of camps out there and i went to a lot of them and (2.1303)	also a nature center that's open to the public and it's run by volunteers so (2.2510)	3
and the smith corona my smith corona even and to put them all in the front yard next to the rock	garden not too close to the maple tree	ing chair and i'm sitting in the rocking chair with my smith corona (3.0263)	ing chair on the front porch and i'm sitting in the rocking chair (3.1943)	3
what to do when a woman taps you on the	shoulder at a crowded restaurant and demands	shoulder and tells you that she's the first lady of the united (2.0442)	shoulder and she's like oh my god i'm so sorry i didn't (2.2111)	3
their income their status all of our fortunes were tied in together	and i thought but is this	and so it was a very intimate experience and i think (3.1160)	and so i'm sitting there and i'm like oh my god (3.2820)	3
problem i reach down tie that garbage bag up throw it over my	shoulder and out to the front door i	shoulder and i'm walking out of the house when all of a sudden (2.1623)	shoulder and i walk out of the house and i get in my (2.1793)	3

TABLE S6. Randomly sampled examples of language generation with BrainLLM and PerBrainLLM in Huth's dataset. Blue text indicates the generation output and the perceived continuation are exact match. These samples were selected from participants 1, 2, and 3.

Examples Text prompt	where BrainLLM underperform Perceived continuation	as PerBrainLLM: Differences in the surp Generation with BrainLLM (sur- prise)	rise scores within the final third. Generation with PerBrainLLM (surprise)	Subject ID
fist bump in the hallway or someone else got invited up to play cards on air force one a and the moral was	always the same any mo- ment could be the	don't get your hopes up the white house is a big place and (2.5582)	always the same you never know when it's going to be your last (2.0025)	1
it's like embarrassing you know i mean	_	i don't know if you've ever been in this situation (4.5028)	it's embarrassing that i'm crying but i couldn't help it (3.9436)	I
but a lot	of them are adults	of people who work in washington don't know what (3.8812)	of people have asked me over the years why (3.2763)	<u>1</u>
but i can see myself in my kid and	i can see myself sitting at the	i can see my dad in my kid and it's just a beautiful (2.7459)		<u>1</u>
stick figures every forty five seconds because that's how fast the poses are	every forty five seconds and	changing and i'm thinking if i can do this then (2.1718)	so i'm doing stick figures every forty five seconds for (1.4118)	<u>1</u>
i did a sold out	reading at foyles in london	show in new york and then i went to london (2.7226)	show at carnegie hall in new york city and i (2.1535)	
weber's farmhouse i met a very pretty girl	she was his assistant and she gave me her phone	who was a photographer's assistant and uh we fell in love and she had an (3.2647)	who was the daughter of the man who owned the farm and she told me (2.6886)	
center he was away on work experience and he'd given me the keys to his flat which was great for me	because i lived off main campus	because i'd been living in a hostel for the last couple (4.3534)	because i'd never been in a flat before uh and he'd (3.7667)	
and clothes from the salva- tion army i had moral obliga	um objections to wearing make up	tions but i didn't have a lot of money to spend (3.6350)	i had a moral obligation to tell her that she was (3.0323)	2
like you know well i don't think it's worth	doing but you know i	the risk so we're gonna have to go with plan (2.5767)	it you know i don't think it's worth it and (2.2407)	3
fully immersed and then my uncle al who never	ever played with us ever	swam a day in his life comes up to me (3.9922)	smoked a cigarette in his life he's like you know (3.6355)	3
out to yell at us but they start fake smiling and trying to act all normal	and my aunt momo	and i'm like oh my god they're trying to (4.3839)	and i'm like oh my god they're not gonna (4.0172)	3
going to ruin it i wanted to be him	and then when they leave	i wanted to be like him i wanted to be (3.8429)	i wanted to be that guy and so i'm like (3.4656)	3
mediums with which they excel	and i'm just standing there like	and so i'm sitting in my office one day and i (2.1645)	and i'm like oh my god this is the best thing (1.7781)	3

TABLE S7. Randomly sampled examples of language generation with BrainLLM and PerBrainLLM in Narratives dataset. These samples were selected from participants who have participated in at least 4 fMRI scans, including 016, 052, 065, 066, 075, 084, 106, and 111. Blue text indicates the generation output and the perceived continuation are exact match.

Text prompt	es where BrainLLM outperforms Perceived continuation	s PerBrainLLM: Differences in the surpr Generation with BrainLLM (sur- prise)	rise scores within the top third. Generation with PerBrainLLM (surprise)	Subject ID
how illegal that probably was	and she says	and she says (1.396)	for him to (4.923)	016
um um she was like petite i could have	folded her up and put her my pocket she looked	picked her up with one hand and put her in the trunk of my car (2.3750)	put her in the trunk of my car and driven her to work every day (2.6931)	016
stop that's what kills you and so i	lock eyes with her and i	'm standing there and i'm looking at this guy and i'm (2.4197)	did and then i went back to my apartment which was (2.6821)	052
yeah she quickly learned to hold her own bottle at	two months her eyes would	the age of six months and she's been drinking cow's (3.4729)	arm's length and drink from it without spilling a drop (3.9846)	
hand and will not let it go	I'm so glad you're	T'm so glad you're (2.835)	I'm sorry I'm so (4.054)	065
stop that's what kills you and so i	lock eyes with her and i	'm standing there and i'm looking at her and she's looking (2.5705)	'm not going to stop i'm going to keep right on (3.6535)	065
I think several days of the	study and then she	experiment and then we $(\overline{3}.181)$	same thing I think (5.854)	066
romanian gymnast	and she says you know okay y you	and she's in her early twenties and she's very attractive and she's wearing (3.6662)	ics what do you mean romanian gymnastics we've been doing roma- nian gymnastics for (5.5957)	066
um fruit carts and stuff	and then um he	like that and then um he's just kind of (1.5774)	margaret says i don't know what you're talking about (5.2690)	075
wait no not yet this time he is sent to give	uh her like the	her a message um and so sherlock tells him (2.7693)	a speech at columbia he's on the front page (6.0884)	075
somewhere so she's home what a rat	race honest to god	what a rat i'm going to kill that god (3.1600)	in new york you know she's like a rat (4.4346)	084
very tough situation the guy's obviously going through absolute the phone	suddenly rang the gray	rang agony and he's got to get out of (4.2608)	's ringing agony and he picks up the phone (5.2294)	084
tell the truth	is it going to do you any good	i don't know what you're going to do about it but i'm not (1.9322)	you know i've been in new york for thirty five years and i've (2.9949)	106
tight her open eye very how- ever large	and so blue as to appear	and very blue she said you know what i'm going to (2.7501)	and i'm not sure if it's a good thing or a (3.7188)	106
situation the guy's obviously going through absolute the phone	suddenly rang the gray	the gray haired man said i don't know what (2.5783)	and he's like i'm going insanity you know the (7.6719)	111
wake you the gray haired man glanced	briefly left at the girl	over his shoulder at the gray haired woman who had (3.6355)	up at me and he said you know i've been (5.2840)	111

TABLE S8. Randomly sampled examples of language generation with BrainLLM and PerBrainLLM in Narratives dataset. These samples were selected from participants who have participated in at least 4 fMRI scans, including 016, 052, 065, 066, 075, 084, 106, and 111. Blue text indicates the generation output and the perceived continuation are exact match.

Examples who	ere BrainLLM & PerBrainLLM Perceived continuation	perform similarly: Differences in the su Generation with BrainLLM (sur- prise)	rprise scores within the middle third. Generation with PerBrainLLM (surprise)	Subject ID
and bob still	lived in our building i would	to this day doesn't know what i was talking about but (3.2736)	to this day is the only person i've ever met who (3.3426)	016
work for the new york times and i was working a story one time about money	laundering on a little	laundering in the cayman islands and i was talking (1.9536)	laundering in the cayman islands and so i went (2.0190)	016
over looked at it like antarc- tica but of course	that's my space was always	i didn't know any of this at the time and (3.5026)	i'd never been to antarctica so i didn't know what (3.5060)	052
that the movement didn't quite look perfunctory	she cleared her hair back	i mean it looked as if she were really trying (4.5558)	i mean it didn't look as if she was just (4.6744)	052
they probably all hopped in a cab and went	down to the village for a couple of	home to their wives and kids and the next morning they got up (1.8726)	home the next morning when i got to work there was a note (2.0255)	
maybe there really was some sort of explosion that started this dreaming	well there will be an explo- sion down at	business but i don't think so i think it's all part of some(3.1162)	but i don't think so i think it's the same thing that's been (3.2655)	065
me and toward the end of this run i was out at a	bar one night and i saw	bar with a bunch of my friends and we're all drinking (1.4914)	bar and i was drinking with a bunch of my friends (1.6697)	066
jim we were just talking	about how you always	about the fact that you're going to be a (2.2731)	about this the other day and i said to (2.4484)	
walked out of a marriage or something or	is an alcoholic or both	walked out of a relationship or something like that and (2.7615)	someone i don't know margaret says she doesn't want to (3.1711)	075
tense interaction	there he asks uh	between the two of them and then uh there's (2.8394)	between the two of them and then um sherlock (3.2370)	075
and then	she says don't worry i'll	he says you know what i'm going to do is (1.8448)	he said you know what i'm going to do i'm (1.9885)	084
get this guy so we took the very brief eight and a start chatting and it's like half minute ride from	unbelievable and uh stand- ing still on the ground to	new york to boston and i'm sitting there and i'm talking to this guy (3.1790)	bob's apartment to my apartment and we're chatting away and he says you know (3.3136)	084
i say this in all sincerity will you get undressed and get into	bed like a good guy	bed and i'll be there in a few minutes he (2.8405)	the shower and i'll be there in a couple of (2.9818)	
very nearly do every	night when i get home	single one of them and i think that's what makes (2.5423)	single one of those things and i'm not going to (2.6685)	106
to teach you how to do a drop and roll which is this maneuver you do when you land it's where you	basically it's what it sounds like you drop and	land on your side and you roll out of the way so that you (1.8660)	land on your side and then you roll away from the impact so that (2.1725)	111
hop on the bus gus and i	think nice we have some- thing in	'm like oh my god he's going to kill me i'm (5.0009)	'm like you know what i'm going to do i'm going (5.3027)	111

TABLE S9. Randomly sampled examples of language generation with BrainLLM and PerBrainLLM in Narratives dataset. These samples were selected from participants who have participated in at least 4 fMRI scans, including 016, 052, 065, 066, 075, 084, 106, and 111. Blue text indicates the generation output and the perceived continuation are exact match.

Examples Text prompt	where BrainLLM underperform Perceived continuation	as PerBrainLLM: Differences in the surp Generation with BrainLLM (sur- prise)	rise scores within the final third. Generation with PerBrainLLM (surprise)	Subject ID
killed they had this guy shot you know one of those sto- ries	the guy's found dead under a	that's and i was like you know it's kind of hard (2.8172)	that's just too good to be true and so i called (2.6888)	016
without a for most of it as far as i'm	concerned and i i	concerned you know i'm not going to be able (2.3960)	concerned you know i'm not going to be able (2.2632)	016
and said god i don't know	i mean what do you think	i don't know what to make of it mr henry you're (2.0291)	what's the matter with me i don't know what's the matter (1.9017)	052
intellectual that's the funny part that's the hilarious part	she reads the theatrical	that's the god damn funniest part of all i (4.6749)	that's the funniest thing i've ever heard in my (4.5382)	052
tell the truth is it going to do you any good	to sit around and stew	i don't know what you're trying to do but it (3.0622)	to tell the truth you're not going to believe me (2.9767)	065
won't you let me	buy some of them for you huh	tell you what's going to happen first of all they're going to (3.4254)	get a word in edgewise will you just let me tell you (3.3369)	
know i'm not sure i was looking for a fuse and i thought maybe i'd dropped one	under the boathouse so i scratched	on the floor but i didn't find one and then all (3.7047)	on the floor or something and i was looking for it (3.5558)	066
place the gray haired	man said and slowly moved his	man looked up from his typewriter and said good morning i'm (2.9905)	man's voice came out of the darkness he was standing in (2.7964)	
on the way there	they have a conversation in the cab	and then uh he's talking to her about the case that they're (3.1337)	um sherlock and watson are talking about this case that they've been (2.9230)	075
flier elated graduating and gown and all they tape his	face next to the weathered	diploma to the refrigerator i'm so proud of you margaret (3.9406)	flier to the bulletin board in the lobby of her (3.7263)	
ceiling uh didn't she leave with you no christ you didn't see	her leave at all then w	her you didn't see her at all did you no i (3.8462)	her did you she didn't come back with you i don't (3.7091)	
trouble and only things like	um and bob realized alpine mountains or	that and so i said you know what i'm going to do (4.8688)	that you know and so i'm sitting there and i'm looking at (4.7052)	084
and get away with it because it's written into the	constitution that you can't prosecute	constitution of the united states that you can't kill somebody (1.3103)	constitution of the united states that you can't be tried (1.1602)	
i'm the one who put him away crawled up	inside squeezed inside this	to the top of the building and looked down (4.1327)	on the ceiling and crawled out of the apartment (3.9751)	
tub doing standing	with all this water and why are	up in the tub doing standing up in the tub doing standing (4.2724)	up in the bathtub and i was like oh my god this (4.0076)	
and i guess i	didn't know the protocol of	don't know if this is true or not but one (2.9560)	don't know if this is true or not but i (2.6666)	

TABLE S10. Performance of language generation without text prompt (averaged across participants) in different datasets. The comparison between BrainLLM and PerBrainLLM are significant at q(FDR) < 0.05 (one-sided non-parametric test) on all datasets and metrics, respectively.

Dataset	Model	BLEU-1(↑)	ROUGE-1(↑)	ROUGE-L(↑)	WER(↓)	Pairwise accuracy (with PerBrainLLM)
Pereira's	PerBrainLLM	0.0787	0.0553	0.0540	0.9726	0.5000
	BrainLLM	0.1025	0.0788	0.0749	0.9610	0.8885
Huth's	PerBrainLLM	0.0960	0.0817	0.0779	0.9703	0.5000
	BrainLLM	0.1356	0.1160	0.1099	0.9541	0.8816
Narratives	PerBrainLLM	0.1270	0.1133	0.1092	0.9328	0.5000
	BrainLLM	0.1320	0.1184	0.1145	0.9283	0.6728

TABLE S11. Performance of language generation with LLM with different sizes of parameters in different datasets (averaged across participants). As we focus on the performance comparison between BrainLLM and Per-BrainLLM, we did not show experiments with StdLLM here. But you can find more results on StdLLM in our github repository (https://github.com/YeZiyi1998/Brain-language-generation). * denotes a significant difference with BrainLLM using a Wilcoxon test with q(FDR) < 0.5 under the same model and the same dataset.

Dataset	LLM backbone	Model	BLEU-1(↑)	ROUGE-1(↑)	$\textbf{ROUGE-L}(\uparrow)$	$WER(\downarrow)$
	Llama-2 (7B)	LLM PerBrainLLM BrainLLM	0.2415* 0.3249* 0.3333	0.2133* 0.2875* 0.2987	0.2096* 0.2771* 0.2877	0.8349* 0.7781* 0.7681
Pereira's	GPT-2-xl (1.5B)	PerBrainLLM BrainLLM	0.2772 0.2814*	0.234 0.2378*	0.2256 0.2292*	0.8246 0.8239*
	GPT-2-large (774M)	PerBrainLLM BrainLLM	0.2605* 0.2655	0.213* 0.2182	0.2057* 0.2106	0.8404* 0.8395
	GPT-2-medium (345M)	PerBrainLLM BrainLLM	0.2100 0.2118	0.1649* 0.1672	0.1605 0.1626	0.8774 0.8779
	GPT-2 (117M)	PerBrainLLM BrainLLM	0.1866 0.1846	0.1456 0.1445	0.1426 0.1414	0.8968 0.8973
Huth's	Llama-2 (7B)	LLM PerBrainLLM BrainLLM	0.1500* 0.1668 0.1899	0.1360* 0.1536 0.1780	0.1310* 0.1474 0.1709	0.92* 0.9109 0.8946
	GPT-2-xl (1.5B)	PerBrainLLM BrainLLM	0.1708* 0.1791	0.1652* 0.1729	0.1581* 0.1656	0.909 * 0.9022
	GPT-2-large (774M)	PerBrainLLM BrainLLM	0.1657* 0.1762	0.1584* 0.1693	0.1516* 0.1616	0.9132* 0.9049
	GPT-2-medium (345M)	PerBrainLLM BrainLLM	0.164* 0.1667	0.1549* 0.1578	0.1489* 0.1514	0.914* 0.9126
	GPT-2 (117M)	PerBrainLLM BrainLLM	0.1088* 0.1096	0.1059* 0.1065	0.0997* 0.1011	0.9516* 0.952
Narratives	Llama-2 (7B)	LLM PerBrainLLM BrainLLM	0.0953* 0.1269* 0.1375	0.0858* 0.1144* 0.1249	0.0829* 0.1105* 0.1209	0.9485* 0.9311* 0.9239
	gpt-xl (1.5B)	PerBrainLLM BrainLLM	0.1248* 0.1298	0.1171* 0.122	0.1121* 0.1168	0.9340* 0.9319
	gpt-large (774M)	PerBrainLLM BrainLLM	0.1202* 0.1237	0.1124* 0.1159	0.1074* 0.1104	0.9402* 0.9401
	gpt-medium (345M)	PerBrainLLM BrainLLM	0.1056* 0.1063	0.0993* 0.0999	0.095* 0.0956	0.9472* 0.9463
	gpt (117M)	PerBrainLLM BrainLLM	0.1099* 0.1111	0.1032* 0.1047	0.098* 0.0997	0.9509* 0.9506

TABLE S12. Comparison of language generation performance (averaged across participants) of BrainLLM and the pregeneration followed by post-hoc selection model [TLJH23] in Huth's dataset. $\dagger/*$ denotes a significant difference with BrainLLM/PerBrainLLM using a Wilcoxon test with q(FDR) < 0.5 under the setting (with or without text prompt). The pairwise accuracy for the PerBrainLLM+selection model is not available as the selection-based method can not get the possibilities of generating the perceived continuation. The original work proposed by Huth's et al. [TLJH23] utilizes settings similar to generation without any text prompts. Hence, we present their performance comparison in both settings.

Setting	Model	BLEU-1(↑)	ROUGE-1(↑)	ROUGE-L(↑)	WER(↓)	Pairwise accuracy (with PerBrainLLM)
with text prompt	PerBrainLLM	0.1668*	0.1536*	0.1474*	0.9200*	0.5000*
	PerBrainLLM+selection [TLJH23]	0.1675*	0.1537*	0.1483*	0.9197*	-
	BrainLLM	0.1899 †	0.178 [†]	0.1709 †	0.8946 †	0.7667 †
without text prompt	PerBrainLLM	0.0960*	0.0817*	0.0779*	0.9703*	0.5000*
	PerBrainLLM+selection [TLJH23]	0.0967 [†] ,*	0.0818*	0.0788 [†] ,*	0.9700 [†] ,*	-
	BrainLLM	0.1356 [†]	0.1160 †	0.1099 [†]	0.9541 [†]	0.8816 [†]

TABLE S13. **Statistics of the LLMs adopted in our experiments.** These statistics are gathered from the original paper [TLI⁺23], [RWC⁺19] and the public sourced repositories (https://huggingface.co/meta-llama/Llama-2-7b and https://huggingface.co/gpt2).

Model	#Parameters	#Transformer layers	Embedding size	Vocabulary size	Quantization	#Max input tokens
Llama-2	7B	32	4,096	32,000	float16	4,096
GPT-2-x1	1.5B	48	1,600	50,257	float32	1,024
GPT-2-large	774M	36	1,280	50,257	float32	1,024
GPT-2-medium	345M	24	1,024	50,257	float32	1,024
GPT-2	117M	12	768	50,257	float32	1,024

TABLE S14. Overall statistics of neuroimaging datasets.

Dataset	Signals	#participants	#Total Duration	#Duration per participant	#Total TRs	#TRs per participant	#Total words	#Words per participant
Pereira's	fMRI (visual stimuli)	5	7.0 h	1.4 h	3135	627	38650	7730
Huth's	fMRI (auditory stimuli)	8	3.5 days	10 h	122992	15374	427296	53412
Narratives	fMRI (auditory stimuli)	28	21.0h	45 min	48496	1732	230460	8231

TABLE S15. Language generation performance averaged across participants in different datasets. The difference between BrainLLM and PerBrainLLM/StdLLM are significant at q(FDR) < 0.05 (one-sided non-parametric test) on all datasets and metrics, respectively.

Dataset	Model	Bleu-1(↑)	ROUGE-1(↑)	ROUGE-L(↑)	WER(↓)
	StdLLM	0.2415	0.2133	0.2096	0.8349
Pereira's	PerBrainLLM BrainLLM	0.3249 0.3333	0.2875 0.2987	0.2771 0.2877	0.7781 0.7681
	StdLLM	0.1500	0.1360	0.1310	0.9200
Huth's	PerBrainLLM	0.1668	0.1536	0.1474	0.9109
	BrainLLM	0.1899	0.1780	0.1709	0.8946
	StdLLM	0.0953	0.0858	0.0829	0.9485
Narratives	PerBrainLLM	0.1269	0.1144	0.1105	0.9311
	BrainLLM	0.1375	0.1249	0.1209	0.9239

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