TRAINING LANGUAGE MODELS FOR DEEPER UNDERSTANDING IMPROVES BRAIN ALIGNMENT

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ABSTRACT

Building systems that achieve a deeper understanding of language is one of the central goals of natural language processing (NLP). Towards this goal, recent works have begun to train language models on narrative datasets which require extracting the most critical information by integrating across long contexts. However, it is still an open question whether these models are learning a deeper understanding of the text, or if the models are simply learning a heuristic to complete the task. This work investigates this further by turning to the one language processing system that truly understands complex language: the human brain. We show that training language models for deeper narrative understanding results in richer representations that have improved alignment to human brain activity. We further find that the improvements in brain alignment are larger for character names than for other discourse features, which indicates that these models are learning important narrative elements. Taken together, these results suggest that this type of training can indeed lead to deeper language understanding. These findings have consequences both for cognitive neuroscience by revealing some of the significant factors behind brain-NLP alignment, and for NLP by highlighting that understanding of long-range context can be improved beyond language modeling.

1 INTRODUCTION

Language models that have been trained to predict the next word over millions of text documents have led to large improvements on a range of benchmark tasks in natural language processing (NLP). However, researchers have shown that models may be learning to rely on shallow heuristics to perform these tasks rather than learning a deeper language understanding (McCoy et al., 2019; Min et al., 2020; Linzen, 2020). To build systems with deeper language understanding, recent work has proposed to train language models on narrative datasets which require extracting the most critical information by integrating across long contexts (Kryscinski et al., 2021; Sang et al., 2022; Kočiskỳ et al., 2018). Does this approach truly lead to deeper understanding of language? We investigate this further by turning to the one language processing system that truly understands complex language: the human brain.

Researchers have previously used human brain recordings to interpret representations learned by pretrained language models (LMs) (Søgaard, 2016; Toneva & Wehbe, 2019; Abdou et al., 2021). This is done by evaluating how well representations obtained from a language model can predict representations sampled from the human brain during language comprehension via a brain imaging device, such as functional magnetic resonance imaging (fMRI). If this prediction performance, also known as brain alignment, is determined to be significant via a statistical test, then the LM and specific brain location or timepoint are thought to significantly align in their representations of language. Using these methods, researchers have shown that pretrained language models significantly predict large parts of the brain regions that are thought to underlie language comprehension (Wehbe et al., 2014b; Jain & Huth, 2018; Toneva & Wehbe, 2019; Caucheteux & King, 2020; Schrimpf et al., 2021; Goldstein et al., 2022).

In this work, we draw insights from the human brain in order to investigate whether language models are truly learning deeper language understanding. We do this by analyzing the effect of training an LM for deeper language understanding on its alignment with fMRI recordings of participants reading a chapter of a popular book. A significant improvement in brain alignment would indicate

that the model has learned additional brain-relevant information, which can be then analyzed further to reveal the specific reasons for this improvement.

We specifically investigate 4 pretrained language models (i.e. "base models") and 4 corresponding models which are obtained by training the base models on the BookSum dataset (Kryscinski et al., 2021) to improve the base language model's narrative understanding (i.e. "booksum models"). The BookSum dataset was selected because it is a summarization dataset that requires understanding complex interactions across long narratives, and the 4 models were selected because their architectures were designed to integrate information across long contexts. We evaluate the alignment of the base and booksum models with fMRI recordings of 8 participants reading a chapter of a popular book word-by-word, made publicly available by Wehbe et al. (2014a). This dataset was chosen because it is one of the largest datasets of participants processing a narrative story (5176 words which corresponds to approximately 1300 samples of fMRI recordings per participant).

Our main contributions are as follows:

1. In Section 4, we show that training language models for deeper narrative understanding improves alignment to human brain activity. Also, when increasing the number of words fed to the models, up to 500 words, brain alignment increases. Lastly, for each model, we identify the layers where these improvements in brain alignment occur.
2. In Section 5, we show that improved brain alignment in Section 4 is not due to improved language modeling (LM) ability, a possible confounding factor. By disentangling LM ability's contribution to brain alignment, we present evidence that BookSum-trained models develop deeper language understanding.
3. In Section 6, we present a simple interpretability approach to study what brain-relevant information is gained by language models after training for deeper language understanding. Our results reveal that these models are learning richer representations across all tested discourse features (Characters, Emotions, Motions). Furthermore, they learn more about Characters than Emotions and Motions. This indicates that discourse features are a promising dimension to study brain alignment and deep language understanding.

Combining our contributions from Sections 4, 5, and 6, we present evidence that these NLP models are indeed developing deeper language understanding.

2 Related work on brains and language

Our work relates to a growing body of research on disentangling the contributions of different types of information to the alignment between brain recordings and language models. Toneva et al. (2020) present an approach to disentangle supra-word meaning from lexical meaning in language models and show that the supra-word meaning is predictive of fMRI recordings in two language regions (anterior and posterior temporal lobes). Caucheteux et al. (2021) and Reddy & Wehbe (2021) aim to disentangle alignment due to syntactic and semantic processing. Toneva et al. (2022) examine whether a representations obtained from a language model aligns with different language processing regions in a similar or different ways. Additionally, researchers have suggested that one contributor to the alignment is the language model's ability to predict the next word, with a positive relationship between lower perplexity and higher brain alignment across NLP models (Schrimpf et al., 2021; Goldstein et al., 2022). On the other hand, more recent work shows that no simple relationship exists, and language modeling loss is not a good predictor of brain alignment (Pasquiou et al., 2022). Our work contributes to this research area in two ways: (1) We disentangle the contributions of LM ability from deep language understanding towards brain-NLP alignment. (2) We show that deep language understanding is another factor that contributes to brain-NLP alignment.

Some works have also investigated the alignment with brain recordings of fine-tuned language models. Schwartz et al. (2019) finetuned a pretrained BERT to predict fMRI and MEG recordings of people reading a chapter of a book. The resulting fine-tuned model leads to improved prediction of previously unseen brain recordings, specifically in regions that are known to support language processing. However, it is not clear what type of information has been induced in the fine-tuned BERT model that has contributed to the improved alignment with brain recordings. Oota et al. (2022) investigate the alignment between fMRI recordings of people comprehending language and

BERT that has been fine-tuned on a set of NLP tasks, such as co-reference resolution and question-answering. The authors find that the best aligning task-tuned BERT varies according to whether the brain recordings correspond to reading or listening to the language stimuli. Our approach and research questions are complementary to these previous works.

Additionally, previous works which study the brain alignment of language models use models not specifically designed to integrate rich information across long contexts. Therefore previous work observed that brain alignment worsened as sequence length was increased for many models (Toneva & Wehbe, 2019), or investigate relatively short contexts. On the other hand, our work uses models trained to integrate rich information across long contexts. We show that brain alignment remains high even when supplying sequence lengths of up to 500 words, a finding that adds to prior works.

3 METHODS

3.1 BRAIN REPRESENTATIONS

We use a publicly available brain dataset (Wehbe et al., 2014a) consisting of fMRI recordings of 8 participants reading chapter 9 of the book *Harry Potter and the Sorceror's Stone* (Rowling et al., 1998). The 5176 words in the chapter are presented to participants at a fixed interval of 0.5 seconds, one word at a time. The chapter was divided into four runs of approximately equal length, and participants were allowed a short break at the end of each run. We use this specific dataset for two main reasons: 1) the story is situated within a rich narrative world with characters, emotions and relationships, and 2) it is one of the largest publicly available datasets in terms of samples per participant which improves the reliability of the brain alignment estimate.

The fMRI recordings are sampled at a consistent interval, or repetition time (TR), of 2 seconds. At each TR, the activity level is recorded in each volume pixel (i.e. voxel) in the participant's brain. Hence, the brain representation for each participant is a matrix $Y_i \in \mathbb{R}^{n \times v_i}$, where n is the number of TRs and v_i is the number of voxels in the brain of participant i. The number of voxels differs for each human subject, ranging from $25,000$ to $31,000$.

3.2 NLP REPRESENTATIONS

We extract NLP representations from a total of 8 models. We refer to 4 of them as "base models": BART-base, LED-base, BigBird-base and LongT5-base. We refer to the remaining 4 as "booksum models": BART-booksum, LED-booksum, BigBird-booksum and LongT5-booksum.

Base models. Our 4 "base models" were trained with a language modeling (LM) objective. We use the corresponding pretrained models provided by Hugging Face (Wolf et al., 2020). We provide some important details for each of the 4 pretrained models below and more details in Appendix A.

- BART (Lewis et al., 2019) uses a standard Transformer-based sequence-to-sequence architecture with 12 layers and 768-dimensional representations. It can process sequence lengths up to 1024 tokens. BART was pretrained by corrupting documents and learning to reconstruct the original text, on a combination of books (narratives) and Wikipedia data.
- BigBird (Zaheer et al., 2020) is a Transformer-based model with 32 layers and 1024-dimensional representations. It uses a sparse-attention mechanism that allows it to process sequence lengths up to 4096 tokens. We use the version of BigBird that was pretrained with Masked Language Modeling on books and summarization on the BigPatent dataset, which contains U.S. patent documents alongside human-written summaries.
- Longformer Encoder Decoder (LED) (Beltagy et al., 2020) has an encoder-decoder Transformer architecture with 12 layers and 768-dimensional representations. It uses an efficient local+global attention based on the Longformer, and can process up to 16384 tokens. LED was pretrained with the same procedure as BART above.
- LongT5 (Guo et al., 2021) is an encoder-decoder Transformer with 12 layers and 768-dimensional representations. It can handle long input sequences up to 16384 tokens. We use the version of LongT5 with Transient Global Attention (TGlobal). LongT5 was pretrained by masking and generating sentences on the C4 dataset, a collection of roughly 750 GB of English texts sourced from the public Common Crawl open repository.

Booksum models. Our 4 "booksum models" are first initialized from one of the "base models". All of their parameters are then trained using the BookSum dataset (Kryscinski et al., 2021). The BookSum dataset is described in the paragraph below. We chose base and booksum models that would be useful for investigating our hypothesis. (1) Their architectures are designed to take advantage of long contexts, which is useful for deep understanding. (2) The booksum models have good performance on BookSum, and the base models have good performance on other long-context benchmarks. (3) The base models, except LongT5, were pretrained with language modeling on large narrative datasets, which ensures that base and booksum models were trained on datasets from similar domains, to allow fair comparisons. (4) Our models are sufficiently varied, and we study 4 pairs of models in total, which improves reliability of our results.

BookSum dataset for long-range summarization. The BookSum dataset (Kryscinski et al., 2021) is a challenging dataset for summarizing long narratives. For training, the inputs are chapters from books and the outputs are human-written summaries. The input documents are relatively long, with an average of more than 5000 words, and contain long-range causal and temporal dependencies. The ground-truth output summaries have an average of roughly 500 words. To generate these summaries, NLP models must capture the most critical information by understanding complex interactions across long-range contexts. Some examples from the BookSum dataset are provided in Appendix B. Furthermore, the dataset belongs to the narrative domain, which captures rich discourse structures for characters, emotions and relationships, which is also the case for the Harry Potter stimulus dataset that we use to evaluate brain alignment. The BookSum Dataset also does not include any books from the Harry Potter series, thus preventing train-test overlap.

Extracting NLP representations. Our goal is to extract NLP representations for each of the 5176 words in our Harry Potter fMRI dataset. For each word, we feed the word and its preceding context to a model, and extract its outputs at every layer for the word. We extract NLP representations for all 8 NLP models, all layers for each model, and vary the input sequence lengths between 20 to 1000 words. Each unique combination of (model, layer number, input sequence length) will produce a different set of NLP representations, $X_{l,s}^{m} \in \mathbb{R}^{5176 \times d}$, where d is the embedding size for model m, layer l, sequence length s.

3.3 Aligning Brain and NLP representations.

We follow a general alignment approach that has been previously used in several works (Jain & Huth, 2018; Toneva & Wehbe, 2019; Schrimpf et al., 2021). This approach learns a function to predict the fMRI recordings at every voxel of each participant i using the NLP representations that correspond to the same text read by the participant. Similarly to previous work, we parameterize this function as a linear function, regularized using the ridge penalty. We train the function in a cross-validated way and test its performance on the data that was heldout during training. We select the ridge parameter via nested cross-validation. Since the fMRI data was collected in 4 runs of approximately equal length, we use 4-fold cross validation where each fold corresponds to holding out one run of fMRI data for testing. We also remove 10TRs of fMRI data and the corresponding NLP representations from the ends of each test run to avoid possible train-test overlap. Other details about the alignment approach are provided in Appendix C.

Evaluate brain alignment. We evaluate the brain alignment using two evaluation metrics, computed between the predictions of heldout fMRI recordings $\hat{Y}_i \in \mathbb{R}^{n \times v_i}$ and the true corresponding fMRI data $Y_i \in \mathbb{R}^{n \times v_i}$. Both evaluation metrics are used by prior works and each has its own advantages.

- **20v20 classification accuracy.** This metric evaluates the fMRI predictions by using them in a classification task on held-out data in the cross-validation setting. The classification task is to predict which of two sets of words was being read, based on the corresponding NLP representations of these words (Mitchell et al., 2008; Wehbe et al., 2014b). The sets consist of 20 consecutive TRs and the classification is repeated 1000 times within each fold. The final 20v20 accuracy is the average across the folds. This metric was proposed as a way to boost the signal-to-noise ratio in estimating the brain alignment for single-trial data. The Harry Potter data is entirely single-trial (i.e. the participants read the book chapter only once and so each word appears only once in its context) and increasing the number of TRs

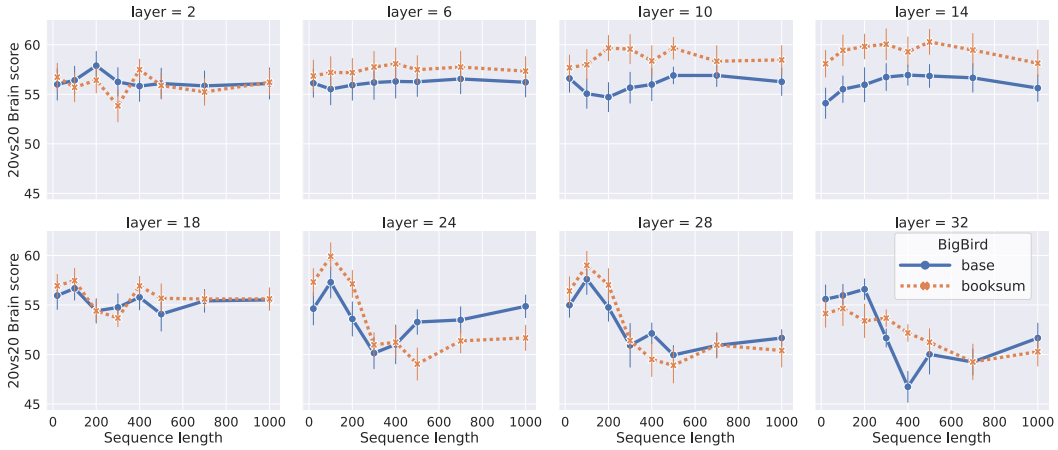

Figure 1: Brain alignment comparisons between BigBird-base and BigBird-booksum, across multiple representative layers and sequence lengths. Each data point represents the average across 8 participants. Training for deeper narrative understanding improves brain alignment significantly in early to middle layers (layers 6-14 out of 32) (paired t-test, FDR corrected for multiple comparisons at significance level 0.05). Results for the remaining models (BART, LED, LongT5) also improve significantly and are presented in Appendix F. These results suggest that long-range and deep understanding is an important contributor to brain representation alignment.

that are classified together up to 20 improves the classification accuracy for this dataset (Wehbe et al., 2014a;b).

- **Pearson correlation.** This metric evaluates the similarity between the fMRI predictions and the corresponding true fMRI data by computing the Pearson correlation between $\hat{y}_{i,j}$ and $y_{i,j}$ for participant i and each voxel $j \in \{1, \ldots v_i\}$. This produces a vector $\in \mathbb{R}^{v_i}$. This metric can be computed efficiently and is widely used in cognitive neuroscience (Huth et al., 2016; Jain & Huth, 2018; Caucheteux et al., 2021; Schrimpf et al., 2021; Goldstein et al., 2022).

4 Training NLP models for Deep Narrative Understanding

Do NLP models trained for deeper understanding of long narratives have improved brain alignment over those trained for language modeling (LM) with shallow understanding? To investigate this question, we evaluate the 20v20 brain alignment scores of 4 booksum models (deeper understanding) against 4 base models, as described in Section 3. We use all 8 NLP models, layers 1 to 12, sequence lengths 20 to 1000, and all 8 human subjects. The results for one of the 4 models for a representative set of layers are presented in Figure 1. The results for the remaining models are presented in Appendix F.

Booksum models are significantly better aligned to brain representations. We suggest that this is due to deeper understanding of text, because of two key facts. (1) The booksum models were trained on the BookSum dataset, which is designed with challenging tasks to learn deeper narrative understanding. It requires understanding complex interactions across long-range contexts and generating summaries that capture the most critical information. (2) Furthermore, these models have architectures that were designed to integrate information across long context lengths. This allowed them to develop deeper understanding when trained on BookSum.

Could the improved brain alignment of booksum models be due to other confounding variables and not deeper language understanding? In this paragraph, we describe how we tried to eliminate possible confounding variables. (1) Both base and booksum models were trained with similar data: large narrative datasets. Hence, improved brain alignment is not simply because booksum models were trained on data from a more similar domain to the brain alignment dataset (Harry Potter). (2) The booksum models and their corresponding base versions support identical sequence lengths,

and were also trained with similar input lengths: all the base models were trained with long input sequences between 1024 and 4096 tokens. Hence, improved brain alignment is not because booksum models were trained on longer input lengths. (3) In Section 5, we show that training NLP models for deep understanding improves brain alignment, but does not improve LM ability. Hence, improved brain alignment is not because booksum models developed better language modeling ability through BookSum-training. Therefore, we argue that improved brain alignment for booksum models is likely not due to these confounding variables.

Brain alignment across models peaks around context length of 500 **words.** Prior work that used earlier language models such as BERT and Transformer-XL found that brain alignment peaked around 50 words (Toneva & Wehbe, 2019). We find a 10-fold increase in the sequence length that results in the peak of brain alignment, across both the base and booksum models. Because this peak is consistent for both types of models, we attribute the 10-fold increase to the fact that the models that we evaluate in this work are specifically designed to integrate longer context than previous models. However, we do not observe an additional benefit beyond 500 words of context, even though the models that we analyze are supposed to incorporate more than 500 words of context (up to 16384 tokens for LED and LongT5).

Booksum finetuning improves brain alignment for different layers across models. Finetuning has been shown to result in greater changes in deeper layers than earlier layers of models (Mosbach et al., 2020). Therefore one might expect that changes in brain alignment that are due to finetuning may emerge primarily in the deeper layers. However, we find that the brain alignment is significantly improved at different layer depths across the 4 models that we test. BigBird and LED improve their alignment with the brain significantly in early to mid layers (layers 6-14 out of 32 in BigBird, and layers 2-8 out of 12 in LED), whereas LongT5 shows significant increases only in the deep layers (layers 8-12 out of 12). BART shows a consistent significant difference throughout most of its layers (layers 2-11 out of 12). These results suggest that the brain-relevant changes may be distributed differently across different models.

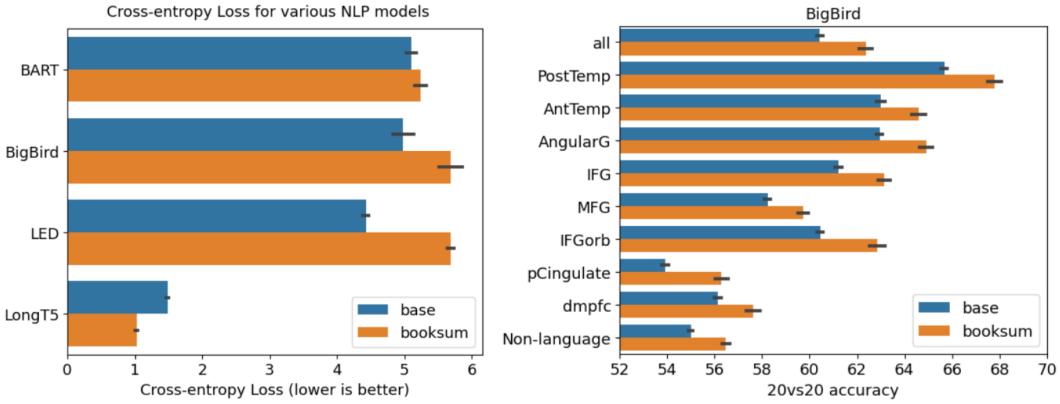

Figure 2: *Left.* Language modeling (LM) ability for various NLP models, represented by cross-entropy loss (lower is better) on the text corresponding to the Harry Potter dataset. We used 4-fold cross-validation. The booksum model has worse LM ability than the base model for BigBird and LED, but better for LongT5. It has no significant difference for BART. Hence, while all 4 booksum models have better brain alignment, most do not have better LM ability. This shows that the improved brain alignment in booksum models (shown in Figure 1) is due to deeper understanding, and not language modeling. *Right.* 20v20 accuracy is significantly higher for the model with deeper understanding (booksum) than LM model (base), across all brain language regions. This suggests that the function of deep understanding is not localized to any one particular region in the brain, and is instead distributed across language regions. Similar results were obtained for all other models (BART, LED, LongT5), shown in Appendix G. Overall, these results suggest the need to supplement training of NLP models beyond LM for improved language understanding.

5 RELATIONSHIP BETWEEN BRAIN ALIGNMENT, LANGUAGE MODELING AND DEEP UNDERSTANDING

Why does training language models on BookSum lead to improved brain alignment, as our results show in Section 4? Is it due to the models developing deeper language understanding, or are there other confounding factors? One possible confounding factor is language modeling (LM) ability, as some works suggest that LM ability contributes to brain-NLP alignment (Schrimpf et al., 2021; Goldstein et al., 2022). This raises the possibility that booksum models have greater brain alignment simply because they developed better language modeling ability through BookSum-training. We conduct experiments to further investigate this possibility.

Our goal is to show that the improved brain alignment is related to deeper understanding, rather than improved LM ability. We show this by demonstrating that training LM models for deep understanding (booksum models) improves brain alignment, but simultaneously does not improve LM ability for 3 of the 4 models.

We evaluate the LM ability of all 8 NLP models (4 base, 4 booksum) on the text corresponding to the same Harry Potter chapter which was used to obtain the brain recordings. First, we split our Harry Potter text dataset into a train and test set (75% and 25% of the text respectively). Next, for each model, we freeze all layers, add a LM head, and train only the head to predict masked words in the train set. Finally, we evaluate each model's cross-entropy loss (LM ability) on the heldout test set. We froze all model weights (other than LM head) to ensure that the representations are preserved, identical to the ones used to evaluate brain alignment. We used the Harry Potter text dataset to ensure that the same dataset is used for measuring both brain alignment and LM ability, to allow for a consistent comparison. We perform 4-fold cross validation to improve reliability, where each fold corresponds to consecutive 25% of the text. The results are presented in Figure 2.

Improved brain alignment is not due to better language modeling (LM) ability. For BigBird and LED, the booksum model achieves significantly higher brain alignment but significantly worse LM performance than the base model. For BART, the booksum model achieves greater brain alignment but does not significantly differ in LM performance. For LongT5, the booksum model has both higher brain and LM performance. Hence, while all 4 booksum models have significantly better brain alignment, the majority of them do not have a better LM performance. This shows that the improved brain alignment for at least 3 of the 4 models is due to deeper understanding and not their ability to predict the next word.

How does brain alignment differ across brain regions? We specifically investigate alignment within the brain regions in the language network, which are thought to underlie language comprehension Fedorenko et al. (2010); Fedorenko & Thompson-Schill (2014). For each region in the brain language network, we compare the average brain alignment for booksum versus base models. To compute these averages per model, we use all layers, sequence lengths, and participants. The results for BigBird are presented in Figure 2, and the results for the remaining models are included in Appendix G.

Across all brain language ROIs, brain alignment is significantly greater for booksum models. This suggests that the brain-relevant information imparted by the training towards deep understanding is not localized to any one particular region in the brain, and is instead distributed across language regions. Furthermore, this shows that models that have significantly better language modeling performance (base $\gg$ booksum for BigBird and LED) do not achieve better alignment in any language region. This further supports the need to complement language modeling with deep understanding for NLP training.

6 INTERPRETING BRAIN ALIGNMENT ACROSS DISCOURSE FEATURES

What are NLP models learning when trained for deeper understanding? Are they learning a deeper understanding of the important narrative elements, such as Characters, Emotions, and Motions in the text? In this section, we present a simple interpretability approach to dive deeper into studying the brain alignment for various discourse features (Characters, Emotions, Motions). We apply this method to understand how the representations of NLP models are changing when they are trained for deeper understanding.

Algorithm 1 Interpretability approach to compare brain alignment across discourse features

Input: fMRI predictions, fMRI activity
for all discourse features **do**
    label words with discourse feature
    map labeled words to fMRI TRs
    extract NLP predictions for discourse TRs
    extract brain activity for discourse TRs
    compute Pearson corr. for discourse TRs
    Result: Pearson corr. for discourse feature
end for
Result: Pearson corr. for all discourse features

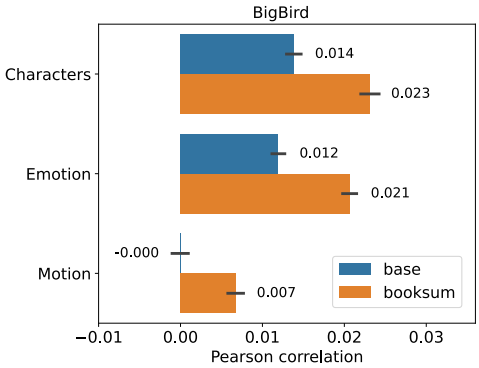

Figure 3: *Left.* Interpretability approach to compare brain alignment across various discourse features. *Right.* Pearson correlation for fMRI repetition times (TRs) corresponding to three discourse features. NLP models achieve greater brain alignment for Characters than other discourse features. When training NLP models for deep understanding, brain alignment significantly improves for all discourse features. However, it improves more for Characters than other discourse features. Note that the correlations reported in this figure are low in magnitude because they are an average that includes a large number of brain voxels that may not be significantly involved in brain-NLP alignment or language processing.

Interpretability approach to compare brain alignment across various discourse features. For each discourse feature, we compute an average Pearson correlation score for booksum models, and another correlation for base models. This allows us to compare the brain alignment between base and booksum models, separately for each discourse feature. Different discourse features may be present at different frequency in the text. Hence, to enable fair comparisons, we use the same number of samples to compute the correlation for each discourse feature. We present the results and the approach's pseudocode in Figure 3. To compute these averages, we use all 8 models, layers 1 to 12, sequence lengths from 20 to 1000, and all 8 human subjects. We elaborate the details in Appendix D.

When training NLP models for deep understanding, brain alignment improves significantly for all discourse features. This suggests that deep narrative understanding results in richer representations for all discourse features.

NLP models align more to the brain for Characters than other discourse features, and also improve the most for Characters when training for deeper understanding. For Characters, Pearson correlation averaged across all voxels improves by 0.011, which is higher than for other discourse features. Note that the correlations reported in Figure 3 are low in magnitude because they are an average that includes a large number of brain voxels that may not be significantly involved in brain-NLP alignment or language comprehension. Next, we compare the brain plots in rows D and E of Figure 4. Character TRs improve in more voxels (orange regions) than the random TR sample. It is also surprising that booksum-training actually results in significantly worse alignment for some brain voxels (blue regions). One possible reason is that these specific regions may participate in prediction of future words, and as we saw in Section 5, the language modeling performance of BigBird has declined as a consequence of the BookSum-training. The results for significance tests can be found in Appendix H.

Discourse features are a promising dimension to study brain alignment. Our work contributes towards understanding what language models are learning when trained for deeper understanding. We show that brain alignment is higher for Characters than other discourse features. We hypothesize that, for Characters, language models integrate richer information from surrounding context, producing representations with greater alignment to brain representations. On the other hand, NLP representations for other discourse features may be more shallow and less context-dependent. In the future, we hope to dive deep into investigating this hypothesis, which will ultimately generate insights for a better understanding into NLP representations. Furthermore, future work can explore additional discourse features.

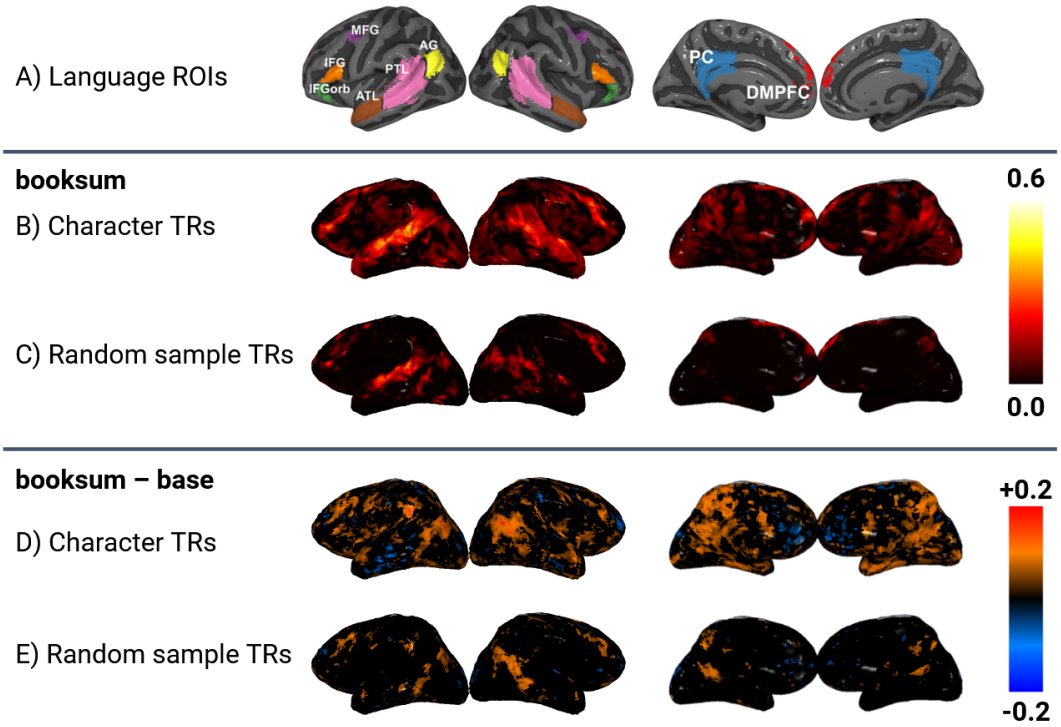

Figure 4: Pearson correlation between fMRI predictions from BigBird and true fMRI activity for one representative participant. (A) Visualization of regions of interest (ROIs) thought to underlie language comprehension. (B) Pearson correlations for booksum models for Character TRs. (C) Same as B, but for an equal number of TRs sampled randomly from all TRs. (D) Difference in Pearson correlations between booksum and base models, for Character TRs. (E) Same as D, but for the random sample. Comparing figure B and C, there is greater brain alignment for Character TRs than for the random sample, both within and outside the language ROIs. Comparing figure D and E, Character TRs improve in more voxels than the random sample TRs. Only voxels with statistically significant results are plotted. Similar results are reported for other participants in Appendix I.

7 Conclusions and Future Work

Conclusions for brain-NLP interdisciplinary field. How and why do brain and NLP representations align? This work contributes the following findings towards this question. (1) Understanding of characters and other discourse features is a significant factor in brain-NLP alignment. (2) Deeper understanding of a text contributes to brain-NLP alignment independently from language modeling (LM) ability. Overall, our work helps to fill in a knowledge gap in the brain-NLP field.

Conclusions for NLP. Language modeling (LM) has achieved great success and popularity. However, is LM sufficient to develop NLP models with language understanding? We present a unique approach to answer this question by drawing insights from human brains. Our results reveal that: (1) LM models achieve poorer representations for Characters and other discourse features, compared to deeper understanding models. (2) Existing training methods for narrative understanding are a first step towards developing language models with deep language understanding. By using results from brain-NLP alignment, we argue for the need to train NLP models with deeper understanding of long-range context, going beyond language modeling.

Future work. There are multiple exciting avenues to build on our work. (1) We showed that brain alignment differs across discourse features. Future work can investigate why these differences exist. (2) We showed that deeper understanding in NLP models improves brain alignment. Future work can explore the mechanisms behind deeper understanding of texts in NLP models.

8 REPRODUCIBILITY STATEMENT

Code available at: `https://github.com/brain-nlp/brain_language_deeper`. In this anonymized repository, we provide the following: (1) Code used to reproduce the results in our paper. (2) README explaining how to install packages, preprocess data, run experiments, and plot visualizations of results. (3) In our paper, we run a large number of experiments (many models, layers, sequence lengths, subjects, discourse features, brain ROIs, etc). Hence, we provide scripts to automate the process of running experiments across the various models, layers, etc. We hope this will make it easy for others to use our code efficiently. (4) After running experiments to obtain data, you can also use our code for plotting the figures in our paper, as well as additional graphs to visualize results. We hope this will allow others to use our code for future projects.

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A NLP MODELS USED IN OUR WORK

For all 4 base models and 4 booksum models, we use pretrained models provided by Hugging Face (Wolf et al., 2020).

- BART (Lewis et al., 2019)
  - Base model: https://huggingface.co/facebook/bart-base
  - Booksum model: https://huggingface.co/KamilAin/bart-base-booksum
- LED (Beltagy et al., 2020)
  - Base model: https://huggingface.co/allenai/led-base-16384
  - Booksum model: https://huggingface.co/pszemraj/led-base-book-summary
- BigBird (Zaheer et al., 2020)
  - Base model: https://huggingface.co/google/bigbird-pegasus-large-bigpatent
  - Booksum model: https://huggingface.co/pszemraj/bigbird-pegasus-large-K-booksum
- LongT5 (Guo et al., 2021)
  - Base model: https://huggingface.co/google/long-t5-tglobal-base
  - Booksum model: https://huggingface.co/pszemraj/long-t5-tglobal-base-16384-book-summary

B EXAMPLES FROM BOOKSUM DATASET

Here, we describe the inputs and outputs used for training models on BookSum (Kryscinski et al., 2021). The input documents are chapters from books. The output summaries are human-written, obtained from various sources such as CliffNotes, SparkNotes, GradeSaver, etc. Below are examples of summaries from BookSum.

Summary of Chapter 18 of "Sense and Sensibility" by Jane Austen.
Edward's reticence became more noticeable as his visit continued. On one occasion Marianne attempted to leave the couple alone together and met with the speedy withdrawal of Edward from the room where she had left them. One day when the sisters and Edward were having breakfast, Marianne noticed "a ring, with a plait of hair in the centre," on one of Edward's fingers. She asked him if it was Fanny's, and Edward answered in the affirmative. Elinor and Marianne, however, believed it was Elinor's, although while Marianne thought it was freely given, Elinor was "conscious it must have been procured by some theft or contrivance unknown to herself." At noon, Sir John and Mrs. Jennings arrived, curious about the guest at the cottage. Realizing that he was the mysterious man with a name beginning with "F," Sir John insisted that they must "drink tea" at Barton Park that night and dine there the following day.

Summary of Chapter 4 of "The Picture of Dorian Gray" by Oscar Wilde.
Over the next several years, Dorian becomes obsessed with the book given to him by Lord Henry. He buys multiple copies of the "first edition, and them bound in different colors so that they might suit his moods." To Dorian, "the whole book...seemed to contain the story of his own life, written before he had lived it." Like the book's young hero, Dorian begins immersing himself in varied interests, including religion, mysticism, music, jewels, ancient tapestries, and the study of his own ancestors. Dorian is, however, quick to change obsessions once they no longer interest him, following the whims of his desire with the passion of an artist. He clings to each current obsession fervently, studying it and acquiring as many fanciful examples of it as he can find. He buys extravagent gowns covered in hundreds of pearls to feed his interest in jewels, and ancient, golden-threaded tapestries to nourish his curiosity about embroidery. As soon as a given subject has exhausted itself in his mind, however, he drops it in favor of his next interest. For the next 18 years, capriciousness is a way of life for Dorian...

Summary of Chapter 6 of "The Brothers Karamazov, Volume 3" by Fyodor Dostoevsky.
When Alyosha enters his father's home, his father and brother Ivan are finishing dinner and the servants attend them in the dining room. Here we're given a little background on Smerdyakov, Stinking Lizaveta's son. A quiet, sullen child, Smerdyakov was discovered to have the "falling

sickness" ; he would fall into fits every month or so. For some reason Fyodor grew quite fond of the boy after his illness was discovered. One day, Smerdyakov was found picking through his soup, and Fyodor decided that Smerdyakov should be trained as a chef. After training in Moscow, Smerdyakov came back to be Fyodor's cook. Now 24, he is just as sullen and silent as ever.

C FURTHER DETAILS ABOUT BRAIN ALIGNMENT APPROACH

In this section, we describe additional details for aligning the word-level NLP representations to human brain activity. We follow a general alignment approach that has been previously used in several works (Jain & Huth, 2018; Toneva & Wehbe, 2019; Schrimpf et al., 2021).

We start with the following variables. NLP representations $\in \mathbb{R}^{5176 \times d}$, where where d is the embedding size. Brain activity $\in \mathbb{R}^{n \times v_i}$, where n is the number of TRs and v_i is the number of voxels in the brain of participant i.

First, we reduce the dimensionality of the word-level NLP representations $\in \mathbb{R}^{5176 \times d}$ using PCA and retain the top 10 principle components (more than 75% of the variance) to result in a matrix $\in \mathbb{R}^{5176 \times 10}$. Next, we next construct TR-level NLP representations by down-sampling the word embeddings (words presented at 0.5 seconds) to the TR rate (2 seconds) by averaging to corresponding word-level NLP representations to result in a matrix $\in \mathbb{R}^{n \times 10}$, where n is the number of TRs. The final NLP representations are constructed by concatenating the TR-level NLP representations corresponding to the previous 4 TRs. The previous TR-level embeddings are included in order to account for the lag in the hemodynamic response that fMRI records. Because the response measured by fMRI is an indirect consequence of brain activity that peaks about 6 seconds after stimulus onset, predictive methods commonly include preceding timepoints (Nishimoto et al., 2011; Wehbe et al., 2014a; Huth et al., 2016). This allows for a data-driven estimation of the hemodynamic response functions (HRFs) for each voxel, which is preferable to assuming one because different voxels may exhibit different HRFs. These steps produce the final NLP inputs to the brain alignment stage $X^m_{l,s} \in \mathbb{R}^{n \times 40}$, for model m, layer l, sequence length s.

After reducing the dimensionality of NLP representations, we learn a function that uses NLP representations $X^m_{l,s} \in \mathbb{R}^{n \times 40}$ to predict brain activity $\in \mathbb{R}^{n \times v_i}$. Similarly to previous work, we parameterize this function as a linear function, regularized using the ridge penalty. We train the function in a cross-validated way and test its performance on the data that was heldout during training. We select the ridge parameter via nested cross-validation. Since the fMRI data was collected in 4 runs of approximately equal length, we use 4-fold cross validation where each fold corresponds to holding out one run of fMRI data for testing. We also remove 10TRs of fMRI data and the corresponding NLP representations from the ends of each test run to avoid possible train-test overlap.

Finally, we evaluate the alignment between the NLP predictions and the true fMRI activity, as described in the main paper.

D INTERPRETABILITY APPROACH TO COMPARE BRAIN ALIGNMENT ACROSS VARIOUS DISCOURSE FEATURES

Algorithm 2 Interpretability approach to compare brain alignment across discourse features

Input: NLP encoding predictions, fMRI activity ▷ Both $\in \mathbb{R}^{n\ TRs \times v_i\ voxels}$
for all discourse features **do**
    label words with discourse feature ▷ One-hot vector $\in \mathbb{R}^{5176\ words}$
    map labeled words to fMRI TRs labeled with discourse feature ▷ One-hot vector $\in \mathbb{R}^{n}$
    extract NLP encoding predictions for TRs with the discourse feature ▷ $\mathbb{R}^{160 \times v_i}$
    extract actual brain activity for TRs with the discourse feature ▷ $\mathbb{R}^{160 \times v_i}$
    compute Pearson correlation between extracted NLP predictions and brain activity ▷ $\mathbb{R}^{v_i}$
    Result: Pearson correlation score for discourse feature, for each voxel ▷ $\mathbb{R}^{v_i}$
end for
Result: Pearson score for all discourse features

We present the pseudocode for our interpretability approach in Algorithm 2, and elaborate here.

The Pearson correlation score is computed between a pair of NLP encoding predictions and actual brain activity. Both $\in \mathbb{R}^{n \times v_i}$, where n is the number of TRs and v_i is the number of voxels in the brain of participant i. (Line 1)

For each discourse feature (Line 2), we first label the words in the Harry Potter chapter that correspond to the discourse feature, producing a one-hot vector $\in \mathbb{R}^{5176}$. (Line 3) Then, we apply the mapping from the words to fMRI TRs, because fMRI values are recorded once for every few words. This produces a one-hot vector $\in \mathbb{R}^{n}$, which labels the TRs which contain the discourse feature. (Line 4)

Different discourse features will have different number of TRs labeled, e.g. Characters has 236 TRs labeled, whereas Emotions has 170 TRs labeled. For each discourse feature, we sample 160 TRs out of the TRs labeled. We do this to ensure that the same number of TRs are used for each discourse feature, which will allow a fair comparison of Pearson correlation scores between discourse features. Hence, we have a one-hot vector $\in \mathbb{R}^{160}$.

We extract the NLP encoding predictions and brain activity for only the TRs containing Characters, both $\mathbb{R}^{160 \times v_i}$ (Line 5 and 6). Finally, we compute their Pearson correlation, producing a vector $\mathbb{R}^{v_i}$. This produces one Pearson correlation score for each brain voxel (Line 7). To get the Pearson score for the Characters discourse feature, we take the average across all v_i voxels.

Earlier, we mentioned that for each discourse feature, words in the Harry Potter chapter have been labeled. For example, the word "Draco" is marked with the Character feature, and the word "climbed" with the Motion feature. We used discourse feature labels from Wehbe et al. (2014a).

For each discourse feature, we computed the average Pearson correlation for booksum and base models. To compute these averages, we use all 8 models, layers 1 to 12, sequence lengths from 20 to 1000, and all 8 human subjects. The results are reported in 15.

E STATISTICAL TESTS AND FALSE DISCOVERY RATE (FDR) CORRECTION USING THE BENJAMINI–HOCHBERG (BH) PROCEDURE

We perform t-tests to identify which results are statistically significant (and not simply due to chance). As our paper performs a large number of statistical tests, we obtain a large number of p-values. Thus, some will have p-values below 0.05 purely by chance. To correct for this problem of false discovery, we adjust the false discovery rate (FDR) using the Benjamini-Hochberg (BH) procedure. For each original p-value, this produces an new, adjusted p-value. Finally, we compare the adjusted p-value against a significance level of 0.05 to identify results that are statistically significant. For our paper, we report only statistically significant results after FDR-BH correction.

F RESULTS FOR 20V20 ACCURACY ACROSS SEQUENCE LENGTHS AND LAYERS

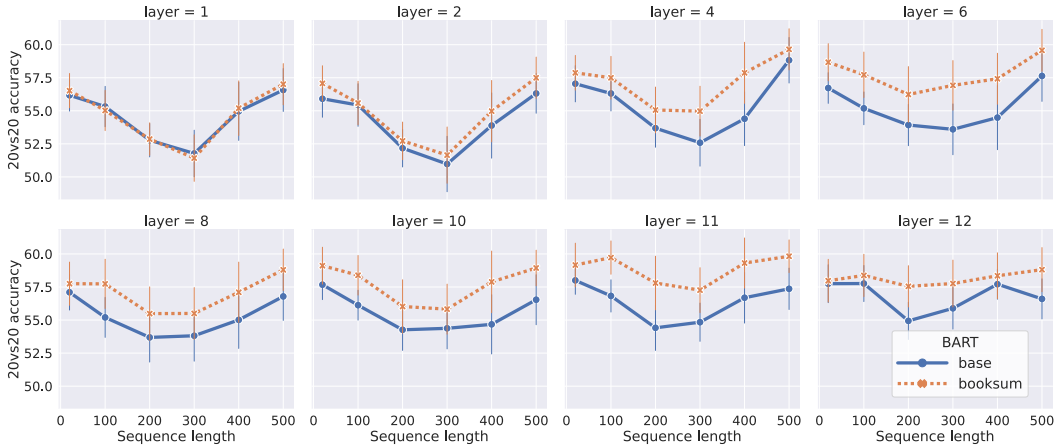

Figure 5: Comparing 20v20 classification accuracy between BART-base and BART-booksum

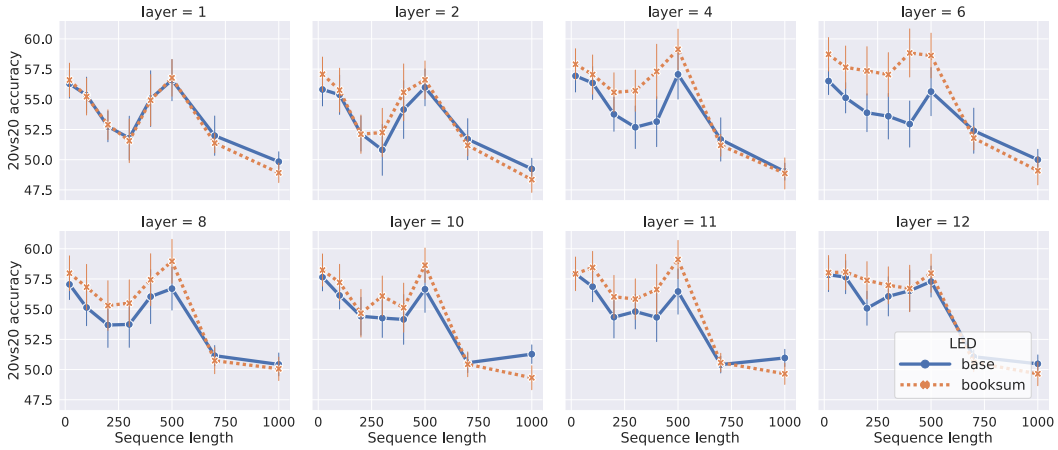

Figure 6: Comparing 20v20 classification accuracy between LED-base and LED-booksum

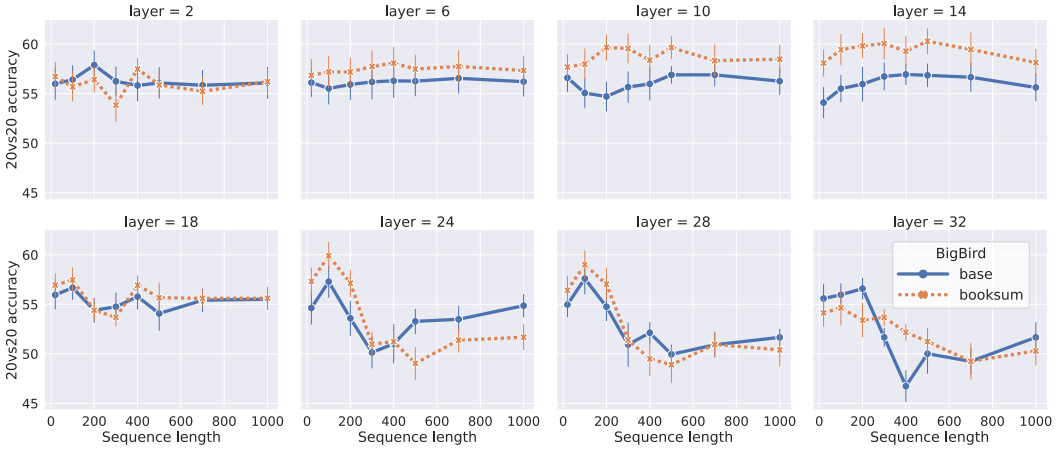

Figure 7: Comparing 20v20 classification accuracy between BigBird-base and BigBird-booksum

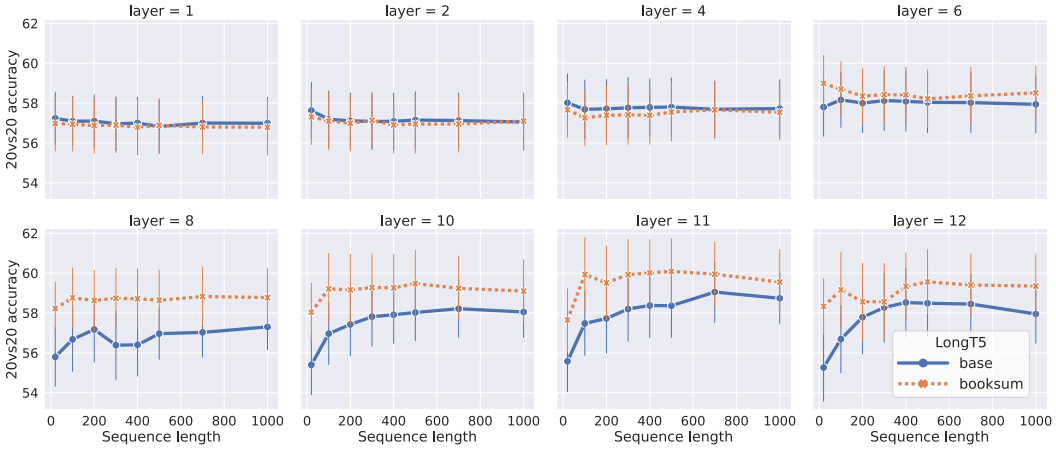

Figure 8: Comparing 20v20 classification accuracy between LongT5-base and LongT5-booksum

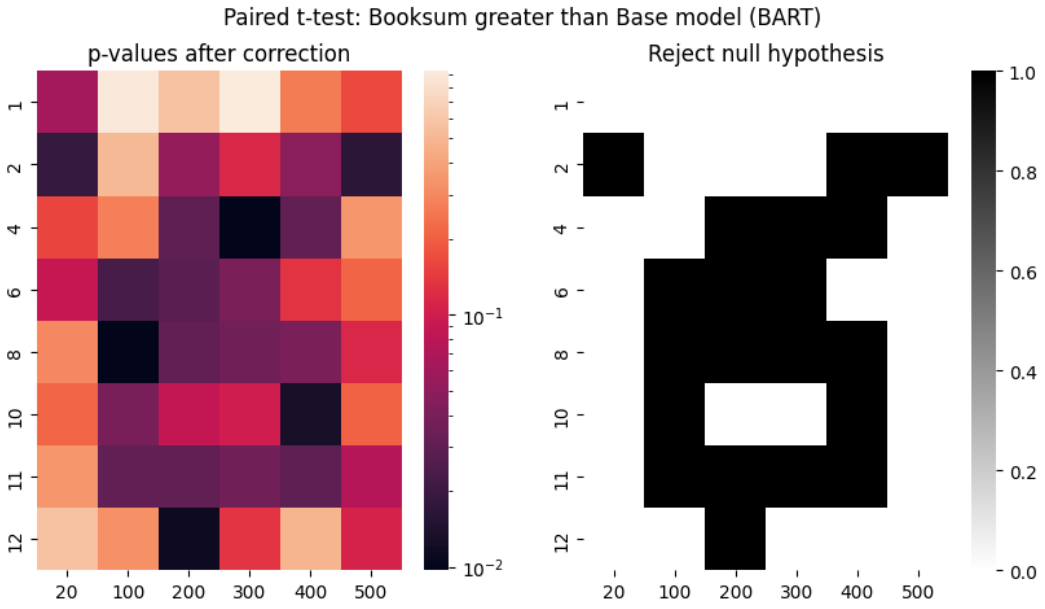

Figure 9: For BART, paired t-test was performed to identify the layers and sequence lengths where the booksum model has greater brain alignment than the base model, with statistical significance. *Left.* p-values obtained from paired t-test, after false discovery rate (FDR) correction using the Benjamini–Hochberg (BH) procedure. *Right.* At significance level 0.05, the layers and sequence lengths labeled in black are those where the booksum model has significantly greater brain alignment than the base model.

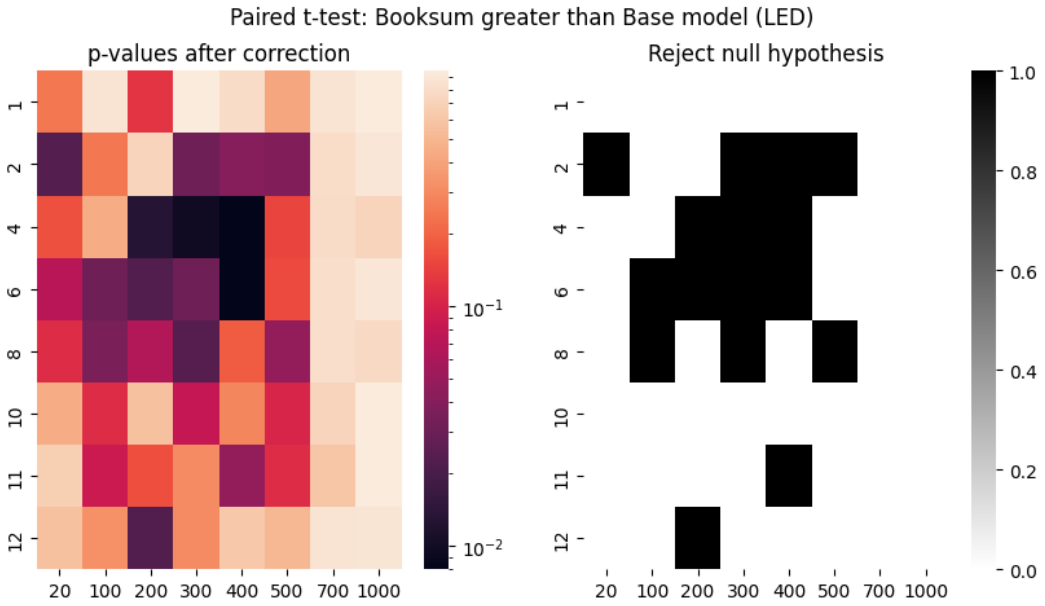

Figure 10: For LED, paired t-test was performed to identify the layers and sequence lengths where the booksum model has greater brain alignment than the base model, with statistical significance. *Left.* p-values obtained from paired t-test, after false discovery rate (FDR) correction using the Benjamini–Hochberg (BH) procedure. *Right.* At significance level 0.05, the layers and sequence lengths labeled in black are those where the booksum model has significantly greater brain alignment than the base model.

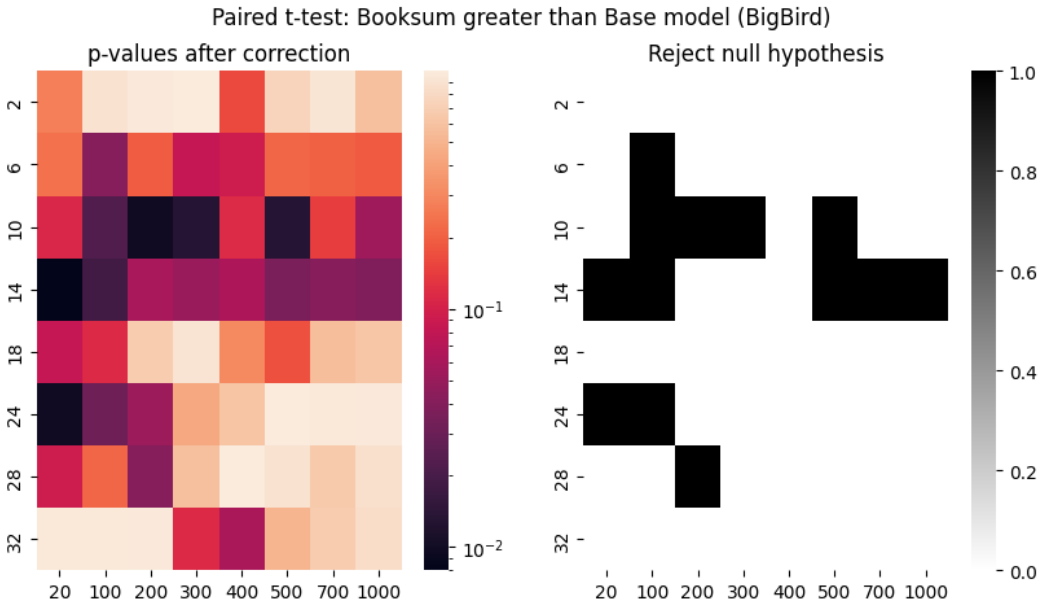

Figure 11: For BigBird, paired t-test was performed to identify the layers and sequence lengths where the booksum model has greater brain alignment than the base model, with statistical significance. *Left.* p-values obtained from paired t-test, after false discovery rate (FDR) correction using the Benjamini–Hochberg (BH) procedure. *Right.* At significance level 0.05, the layers and sequence lengths labeled in black are those where the booksum model has significantly greater brain alignment than the base model.

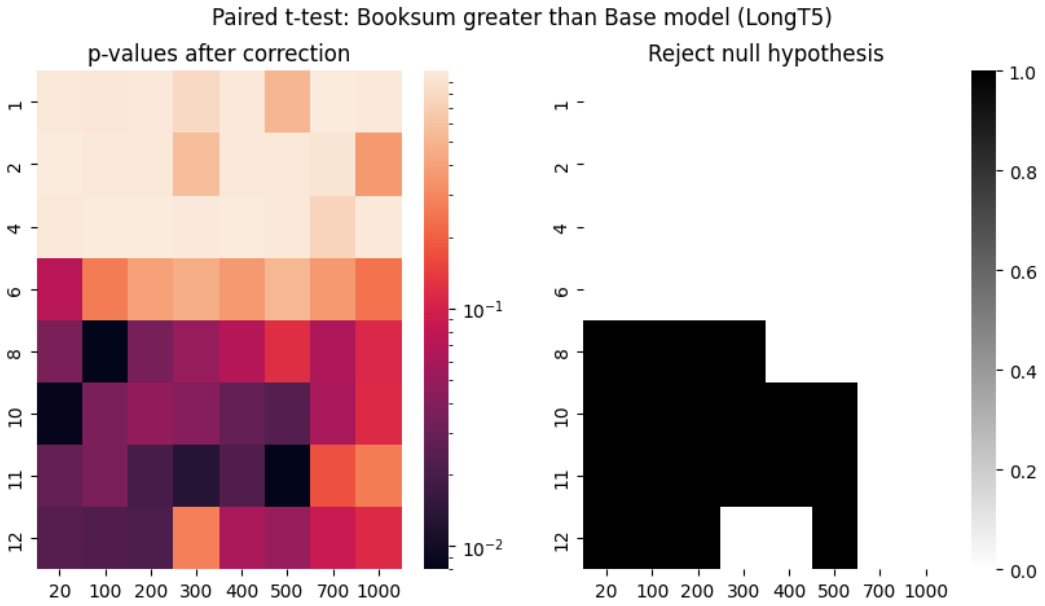

Figure 12: For LongT5, paired t-test was performed to identify the layers and sequence lengths where the booksum model has greater brain alignment than the base model, with statistical significance. *Left.* p-values obtained from paired t-test, after false discovery rate (FDR) correction using the Benjamini–Hochberg (BH) procedure. *Right.* At significance level 0.05, the layers and sequence lengths labeled in black are those where the booksum model has significantly greater brain alignment than the base model.

G RESULTS FOR BRAIN REGIONS OF INTEREST (ROIS)

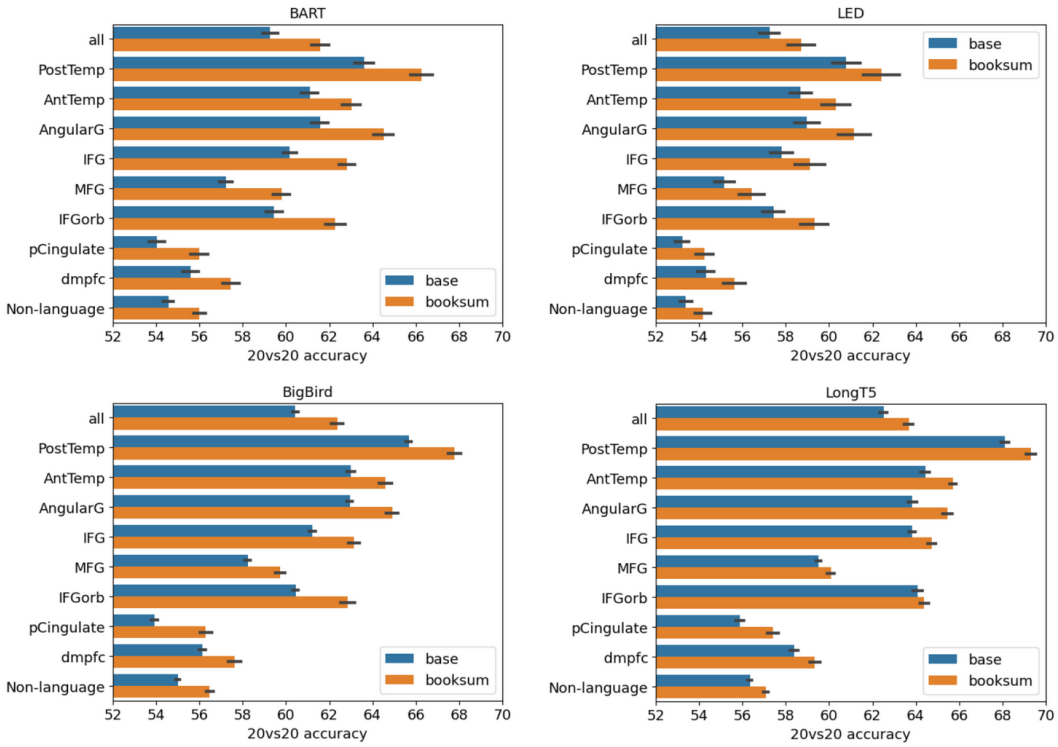

Figure 13: 20v20 accuracy for various brain Regions of Interest (ROIs), for each of the 4 models.

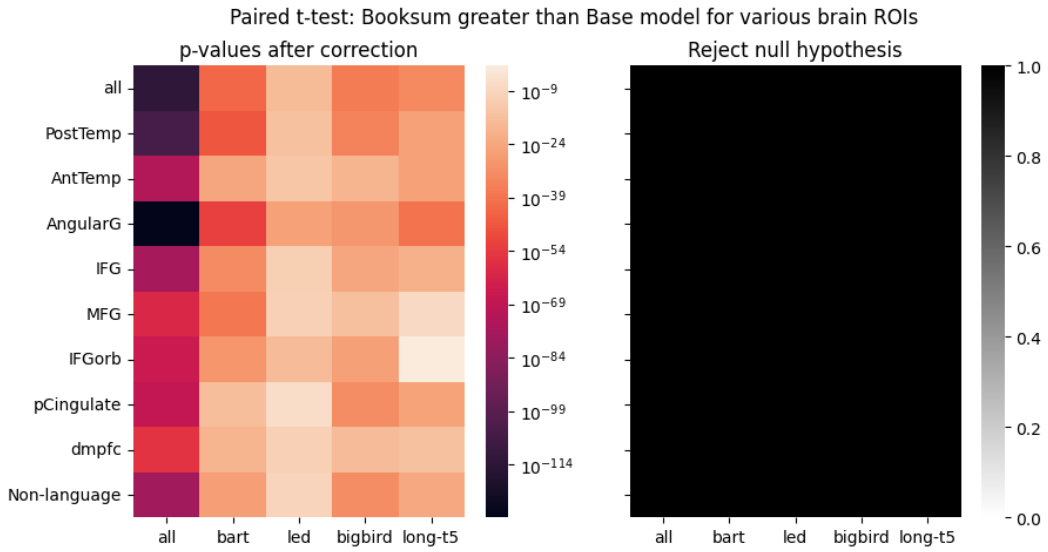

Figure 14: For each of the 4 models, paired t-test was performed to identify the brain ROIs where the booksum model has greater brain alignment than the base model, with statistical significance. We also perform the t-test for all the models combined together, labeled "all". *Left.* p-values obtained from paired t-test, after false discovery rate (FDR) correction using the Benjamini–Hochberg (BH) procedure. *Right.* At significance level 0.05, the brain ROIs labeled in black are those where the booksum model has significantly greater brain alignment than the base model.

H RESULTS FOR DISCOURSE FEATURES

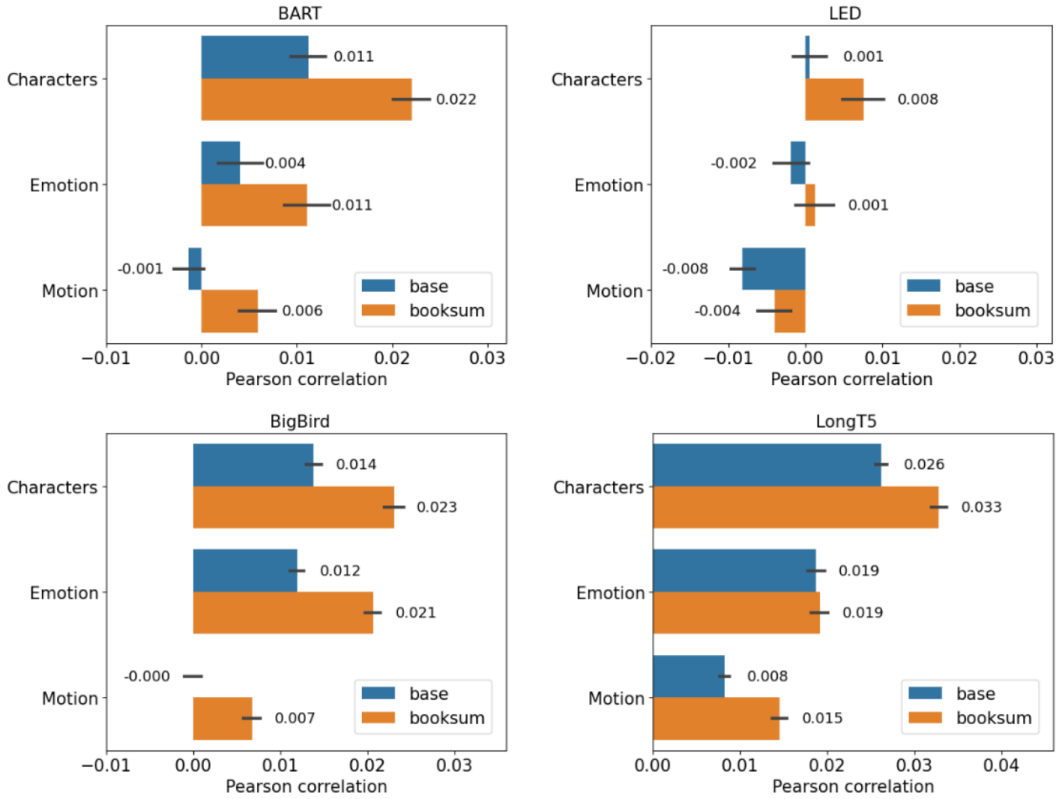

Figure 15: Pearson correlation for various discourse features, for each of the 4 models.

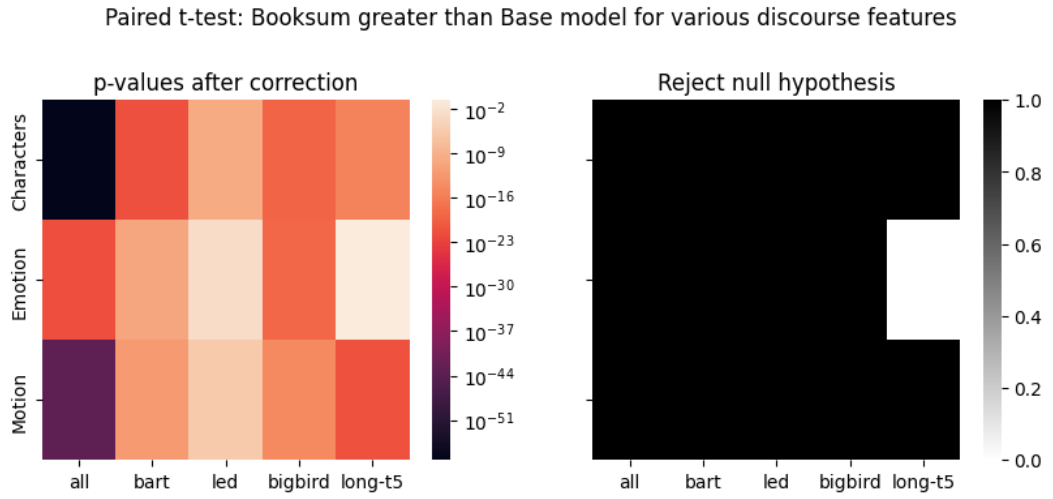

Figure 16: For each of the 4 models, paired t-test was performed to identify the discourse features where the booksum model has greater brain alignment than the base model, with statistical significance. We also perform the t-test for all the models combined together, labeled "all". *Left.* p-values obtained from paired t-test, after false discovery rate (FDR) correction using the Benjamini–Hochberg (BH) procedure. *Right.* At significance level 0.05, the discourse features labeled in black are those where the booksum model has significantly greater brain alignment than the base model.

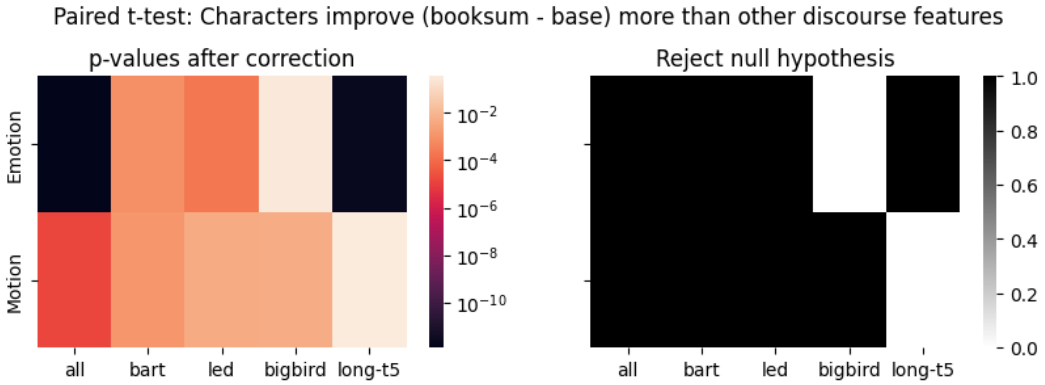

Figure 17: For each of the 4 models, paired t-test was performed to identify whether there were greater improvements for Characters than other discourse features, with statistical significance. We also perform the t-test for all the models combined together, labeled "all". *Left.* p-values obtained from paired t-test, after false discovery rate (FDR) correction using the Benjamini–Hochberg (BH) procedure. *Right.* At significance level 0.05, the brain ROIs labeled in black are those where the booksum model has significantly greater brain alignment than the base model.

I RESULTS FOR BRAIN PLOTS

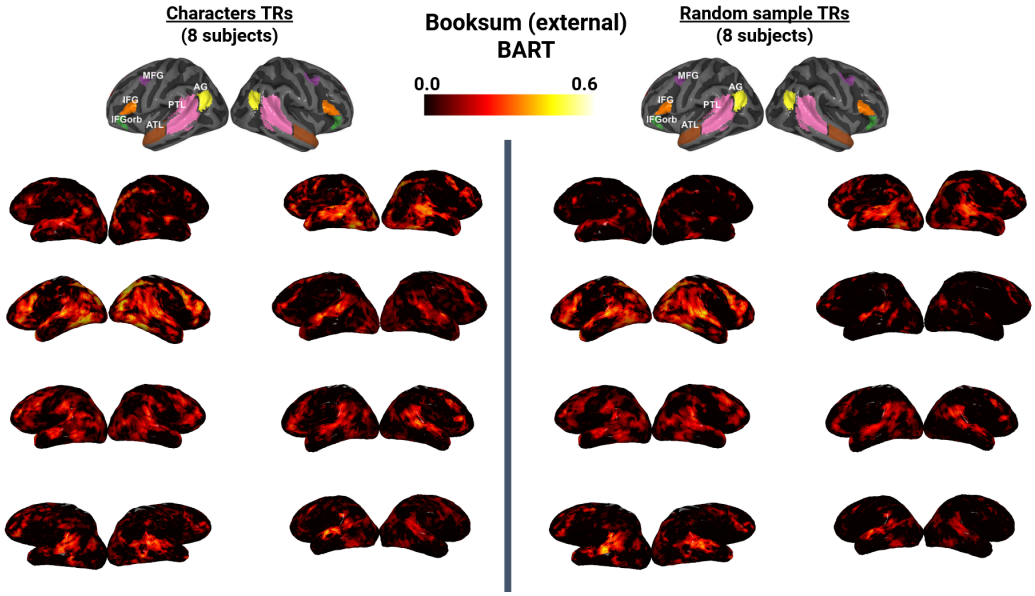

Figure 18: Pearson correlation scores of BART-booksum across brain voxels on the external brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

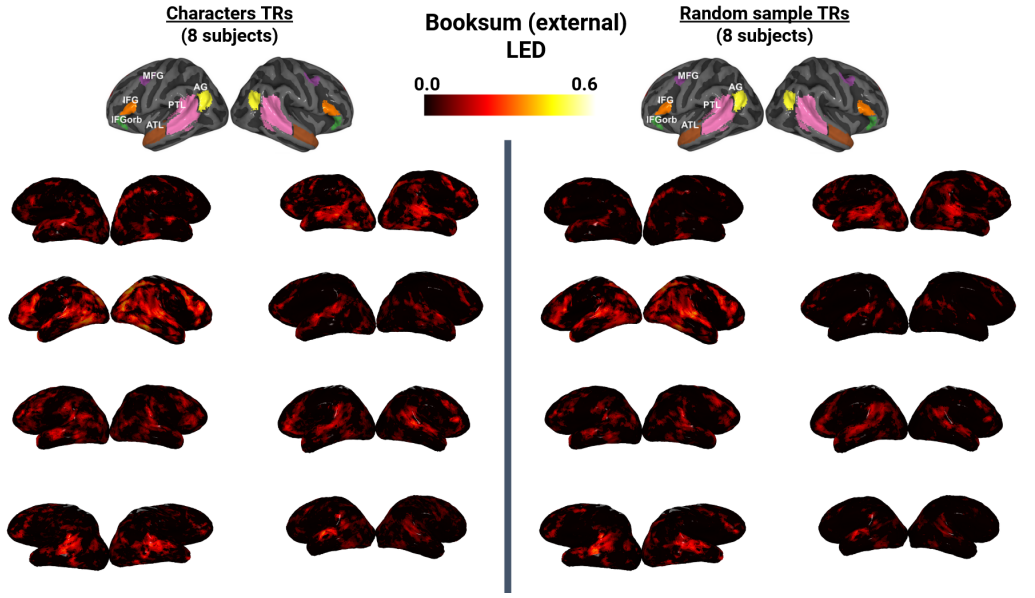

Figure 19: Pearson correlation scores of LED-booksum across brain voxels on the external brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

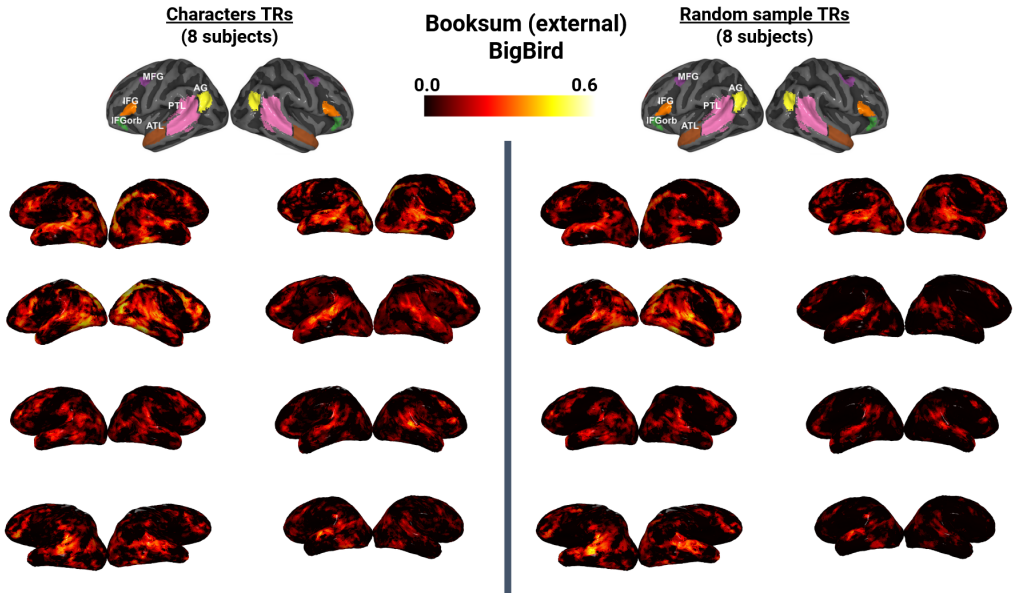

Figure 20: Pearson correlation scores of BigBird-booksum across brain voxels on the external brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

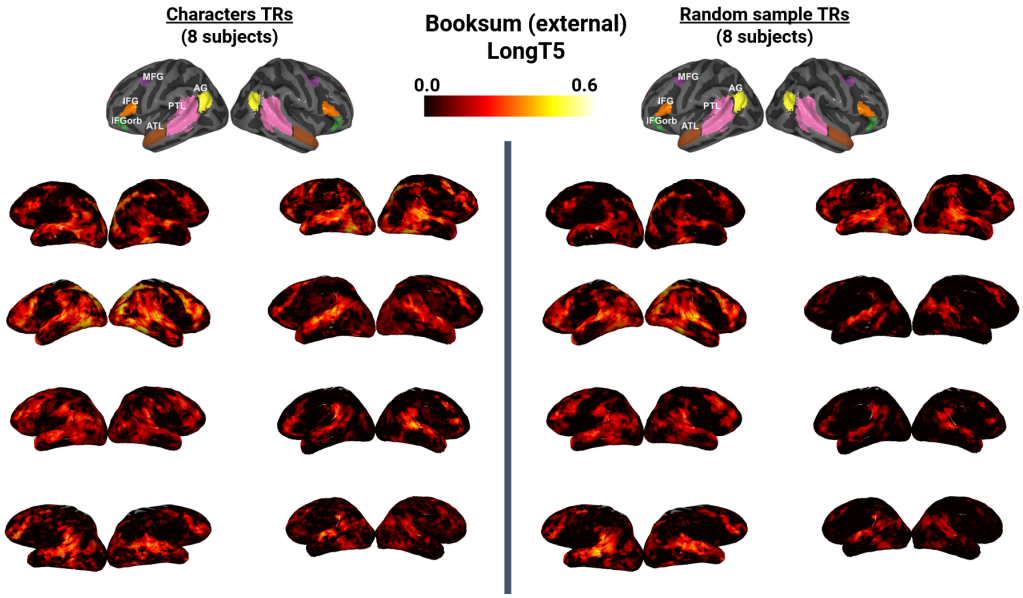

Figure 21: Pearson correlation scores of LongT5-booksum across brain voxels on the external brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

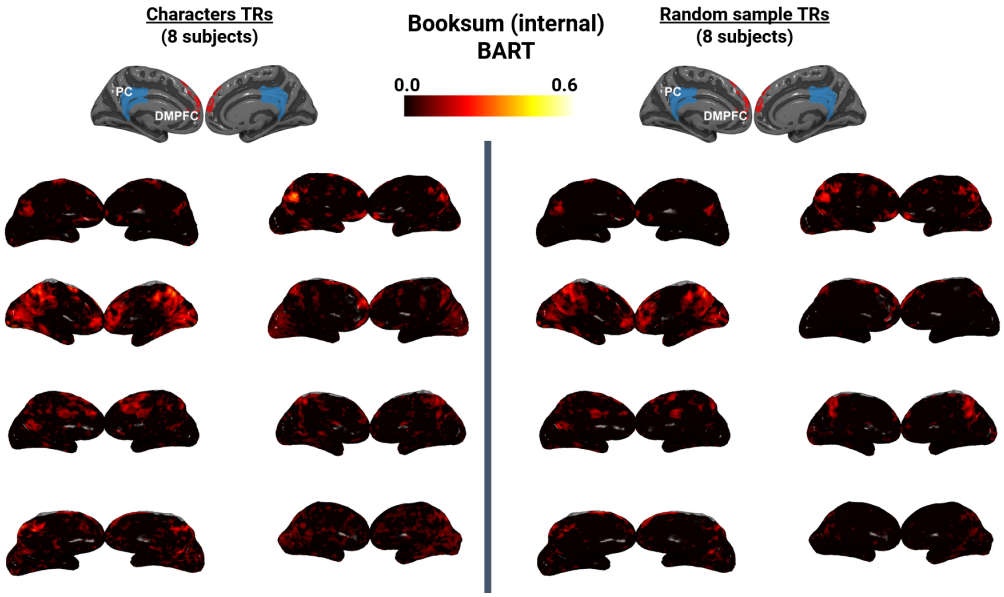

Figure 22: Pearson correlation scores of BART-booksum across brain voxels on the internal brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

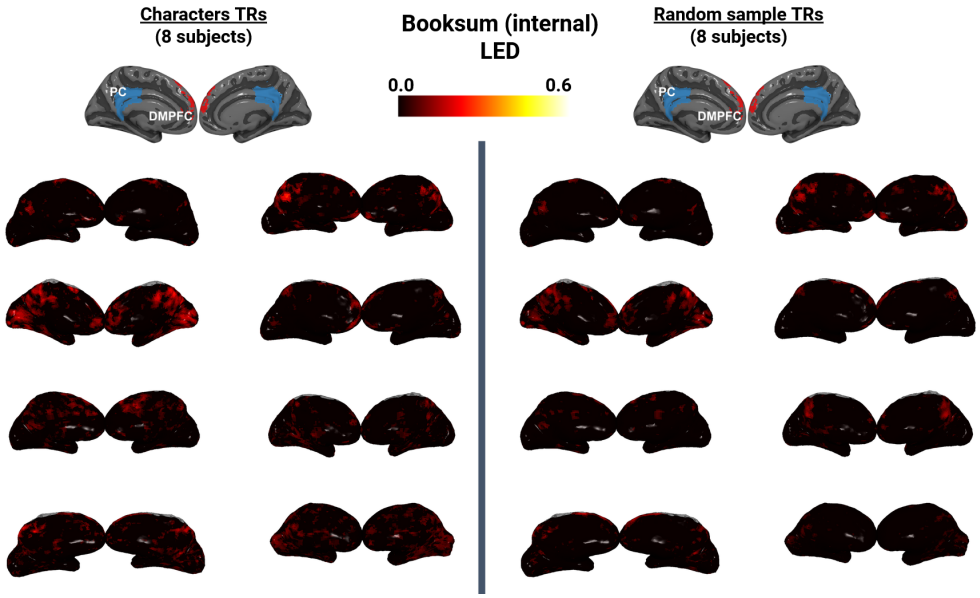

Figure 23: Pearson correlation scores of LED-booksum across brain voxels on the internal brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

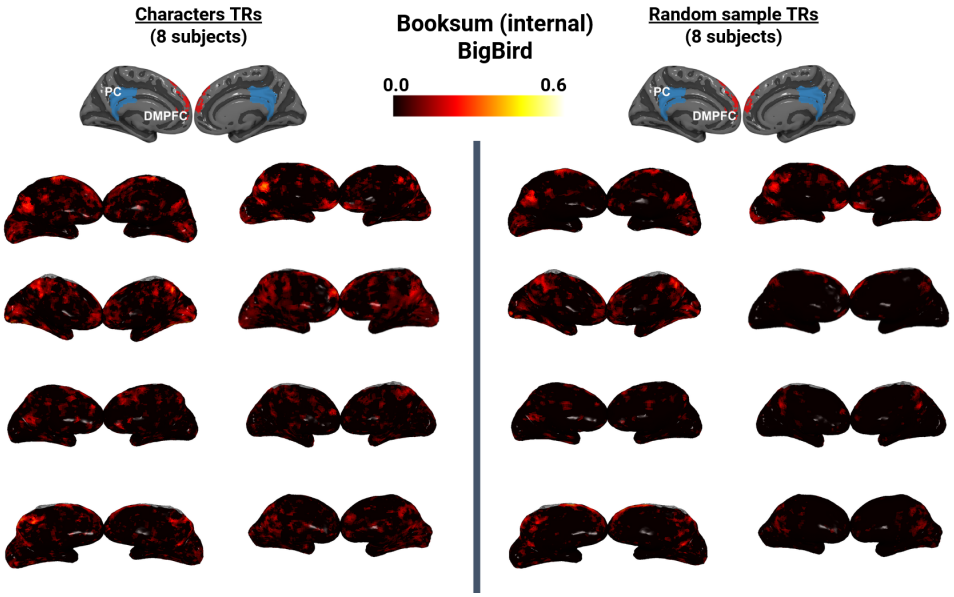

Figure 24: Pearson correlation scores of BigBird-booksum across brain voxels on the internal brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

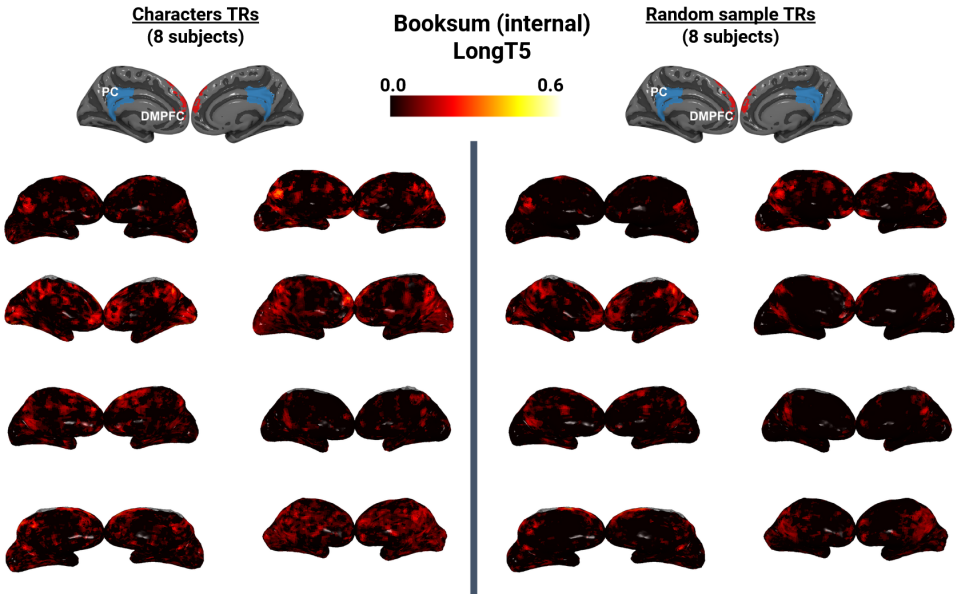

Figure 25: Pearson correlation scores of LongT5-booksum across brain voxels on the internal brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

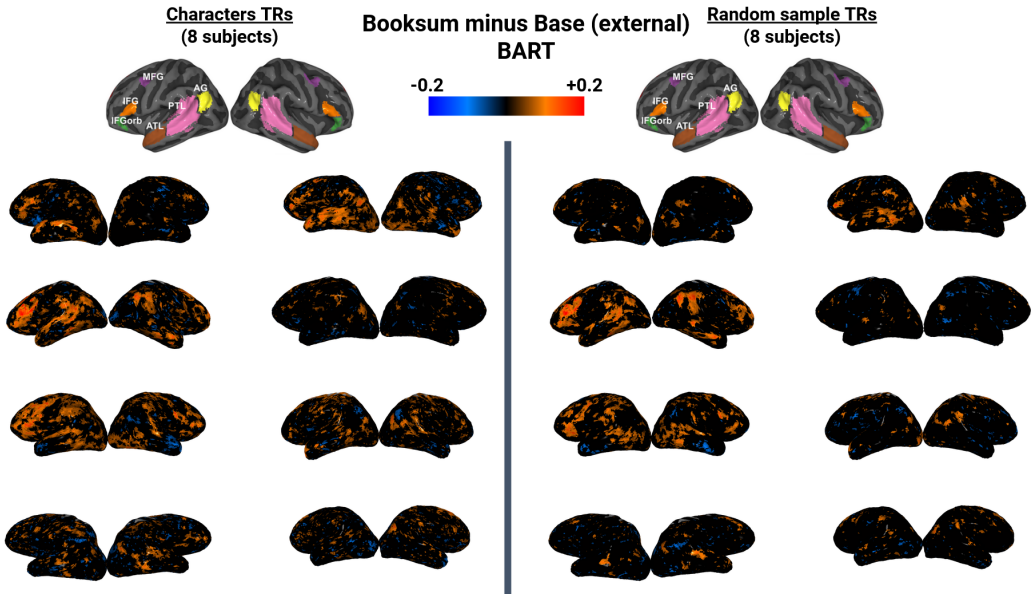

Figure 26: Difference in Pearson correlation scores between BART-booksum and BART-base across brain voxels on the external brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

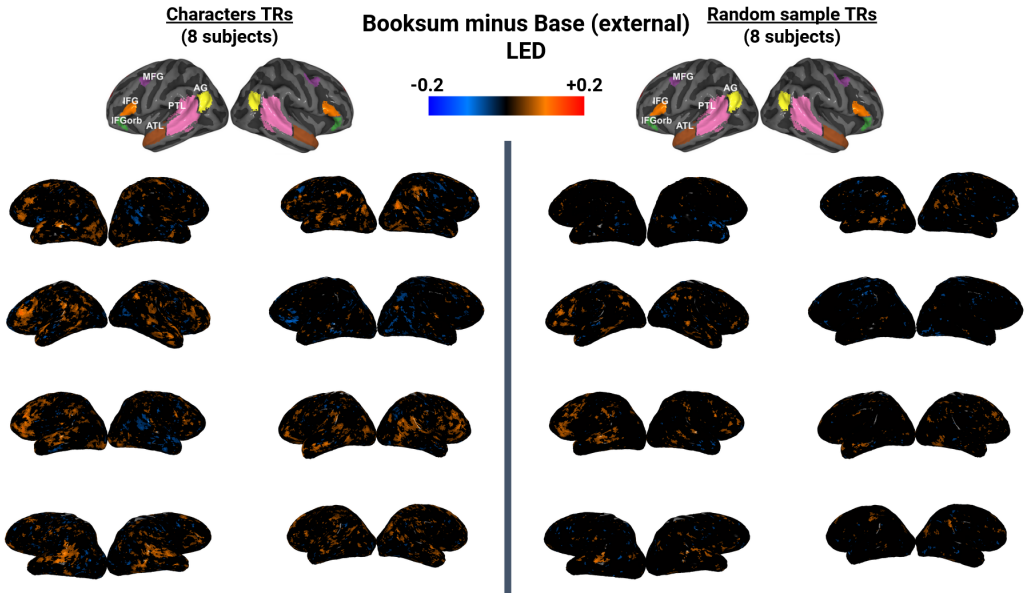

Figure 27: Difference in Pearson correlation scores between LED-booksum and LED-base across brain voxels on the external brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

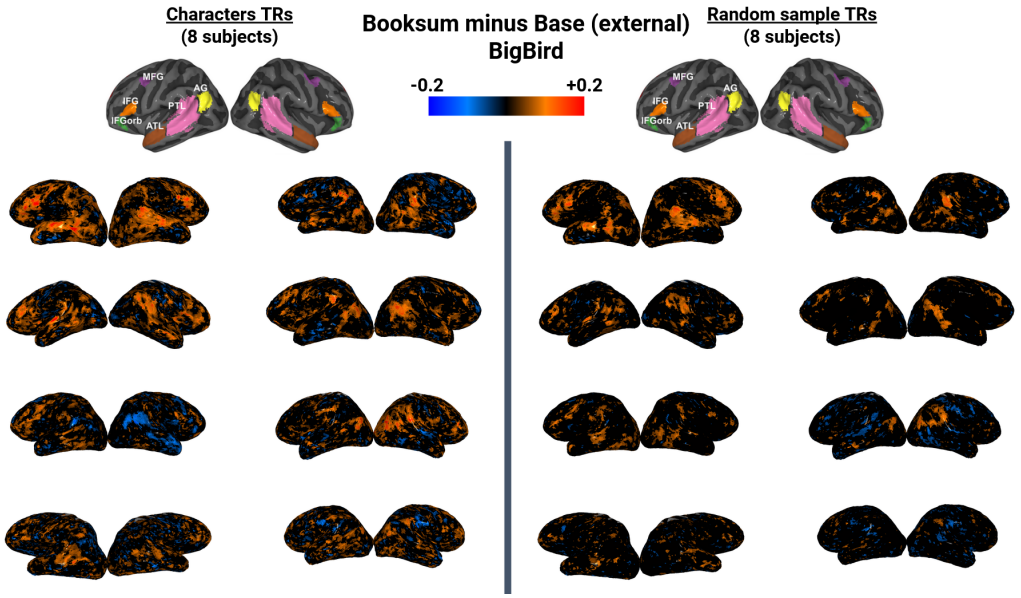

Figure 28: Difference in Pearson correlation scores between BigBird-booksum and BigBird-base across brain voxels on the external brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

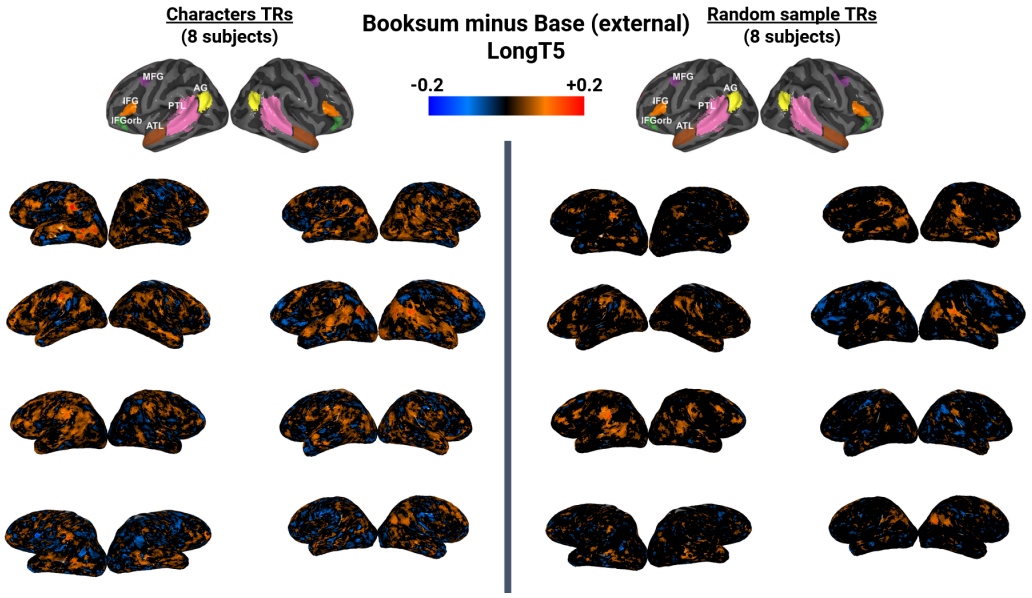

Figure 29: Difference in Pearson correlation scores between LongT5-booksum and LongT5-base across brain voxels on the external brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

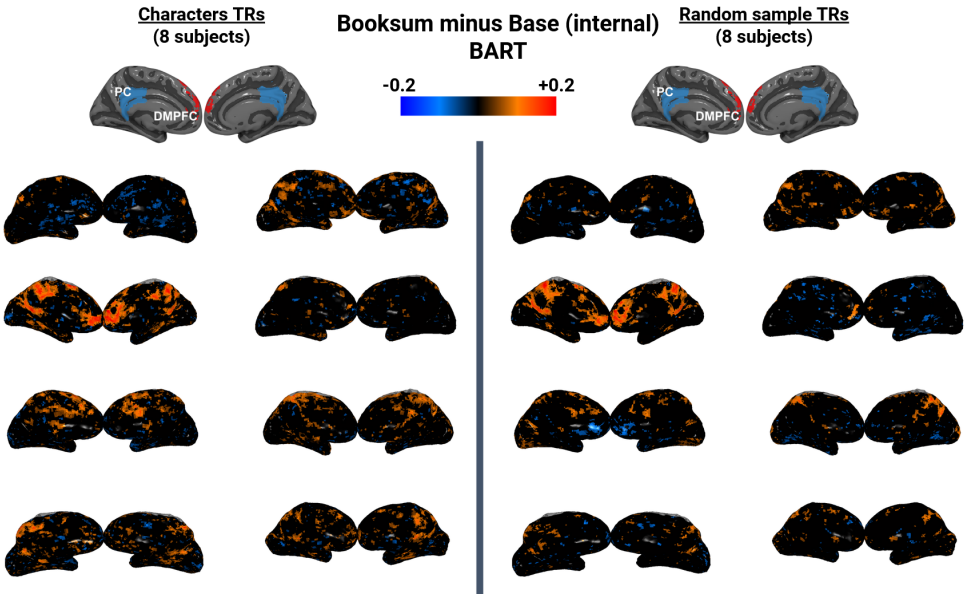

Figure 30: Difference in Pearson correlation scores between BART-booksum and BART-base across brain voxels on the internal brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

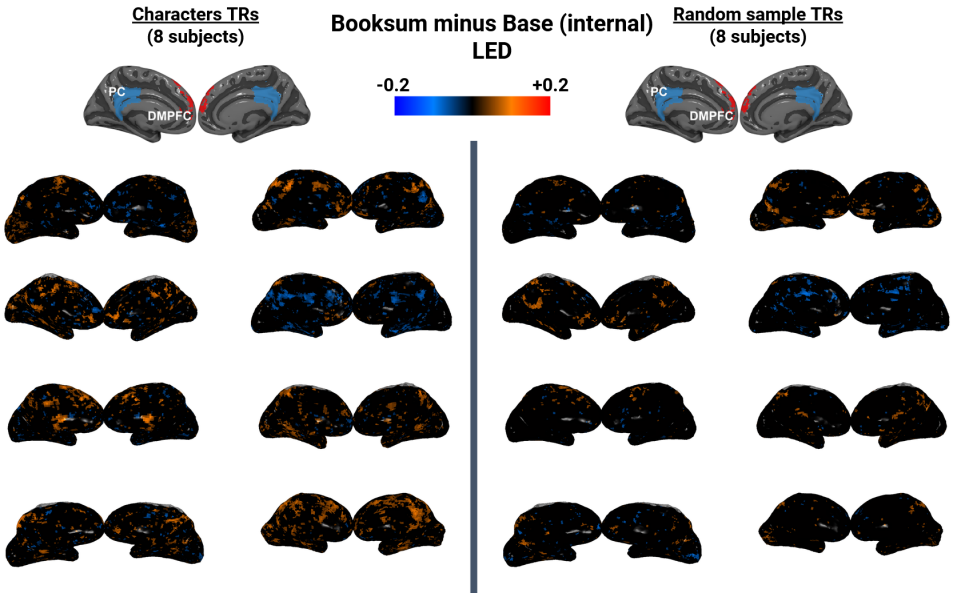

Figure 31: Difference in Pearson correlation scores between LED-booksum and LED-base across brain voxels on the internal brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

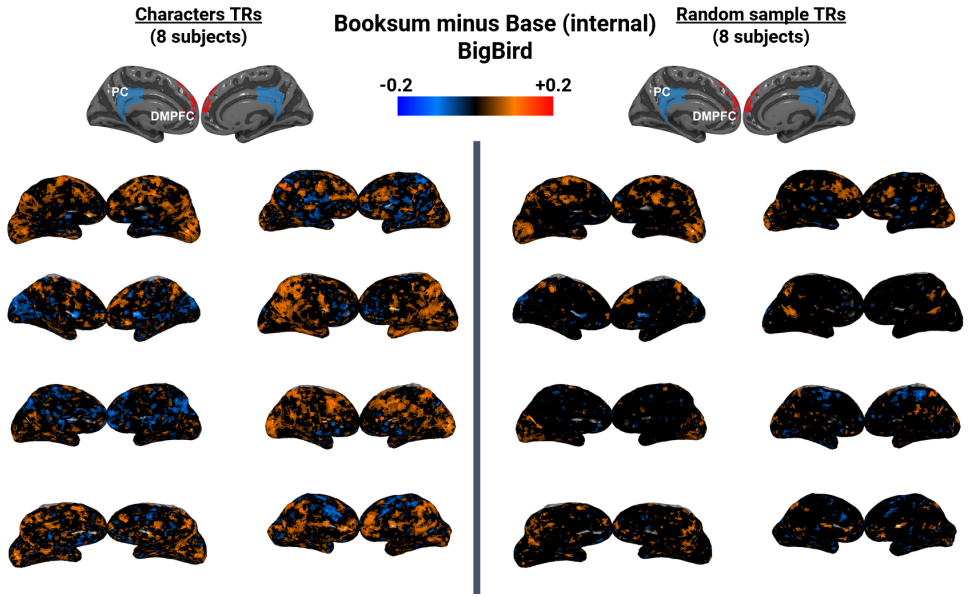

Figure 32: Difference in Pearson correlation scores between BigBird-booksum and BigBird-base across brain voxels on the internal brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.

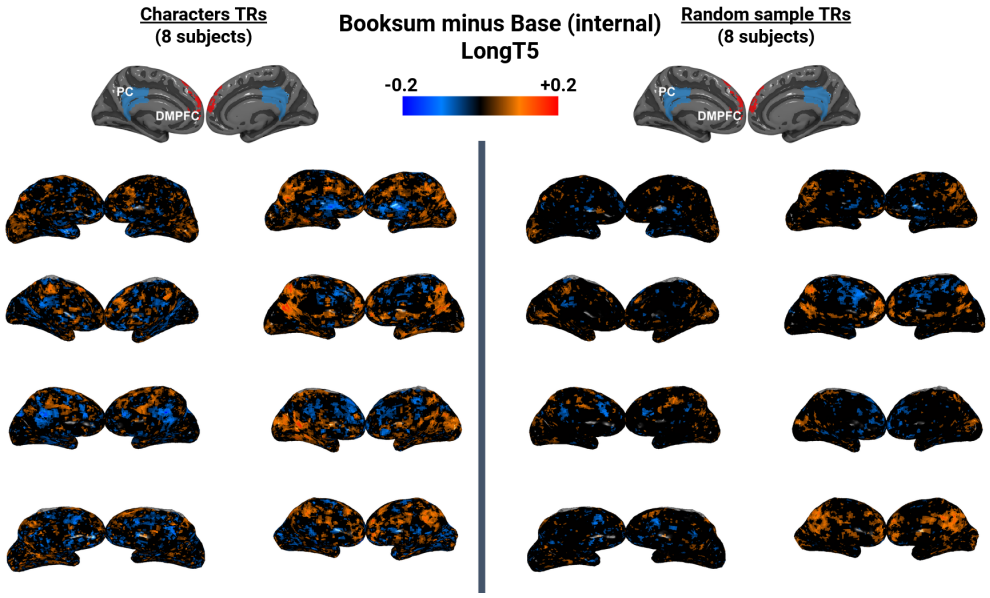

Figure 33: Difference in Pearson correlation scores between LongT5-booksum and LongT5-base across brain voxels on the internal brain surfaces of 8 human subjects. *Left.* Pearson correlation scores computed for only TRs which contain Characters. *Right.* Same as Left, but for an equal number of TRs sampled randomly from all TRs.