

Lab 3.3 - FMRI, Stat 214, Spring 2025

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1 Introduction

Understanding how the human brain processes natural language remains a central challenge in neuroscience and cognitive science. In previous phases of this project, we developed encoding models to predict voxel-level brain activity from language stimuli using fMRI data from [2]. In Lab 3.1, we compared Bag-of-Words, Word2Vec [3], and GloVe [4] embeddings; in Lab 3.2, we pre-trained a custom encoder using a masked language modeling objective to generate context-aware embeddings. Across both parts, these embeddings were used as inputs to ridge regression models to predict BOLD responses across voxels, providing insight into the relationship between linguistic representations and neural activity.

In this final phase, Lab 3.3, we shift focus to *fine-tuning and interpreting* a large pre-trained language model for our brain prediction task. Specifically, we begin by fine-tuning BERT [1] on the fMRI dataset to better align its embeddings with the neural responses observed during naturalistic story listening. We also explore parameter-efficient fine-tuning strategies such as Low-Rank Adaptation (LoRA) to assess whether we can achieve similar performance gains with reduced computational overhead. These fine-tuned models are then evaluated against the previously tested approaches from Labs 3.1 and 3.2.

In addition to predictive performance, this lab introduces an interpretability dimension. Using SHAP and LIME, we analyze which input words most strongly influence the model’s predictions at well-predicted voxels. By focusing on voxels where prediction accuracy is highest, we aim to uncover linguistically meaningful features that contribute to model output. Comparing the outputs of SHAP and LIME across different stories and subsets of voxels allows us to assess the consistency and plausibility of the explanations provided, offering a new perspective on how language models—and potentially the brain—represent meaning during natural language processing.

2 EDA

In this section, we perform a preliminary exploratory data analysis (EDA) to develop a basic understanding of the dataset. The data consists of fMRI recordings from two subjects, each listening to 101 stories. We divide the dataset into training/validation and test sets: 75 stories (75%) are used for training and validation, while the remaining 26 stories (25%) are reserved for testing. All EDA, embedding, and modeling are performed solely on training/validation data.

2.1 Stories

The stories are stored in a "list of words" format, with each story represented as a list of individual words stripped of punctuation and spacing. Figure 1 shows the distribution of story lengths, measured by word count, for the 75 stories in the training/validation set. The histogram reveals a roughly unimodal distribution with a slight right skew. Most stories cluster around the center, with both the mean and median at 1,893 words. This similarity suggests the skew is relatively mild. Story lengths range from 697 to 3,476 words, indicating substantial variation in stimulus duration.

The excerpt below is a sample passage from one of the stories, with punctuation added for readability, as it is not present in the original data.

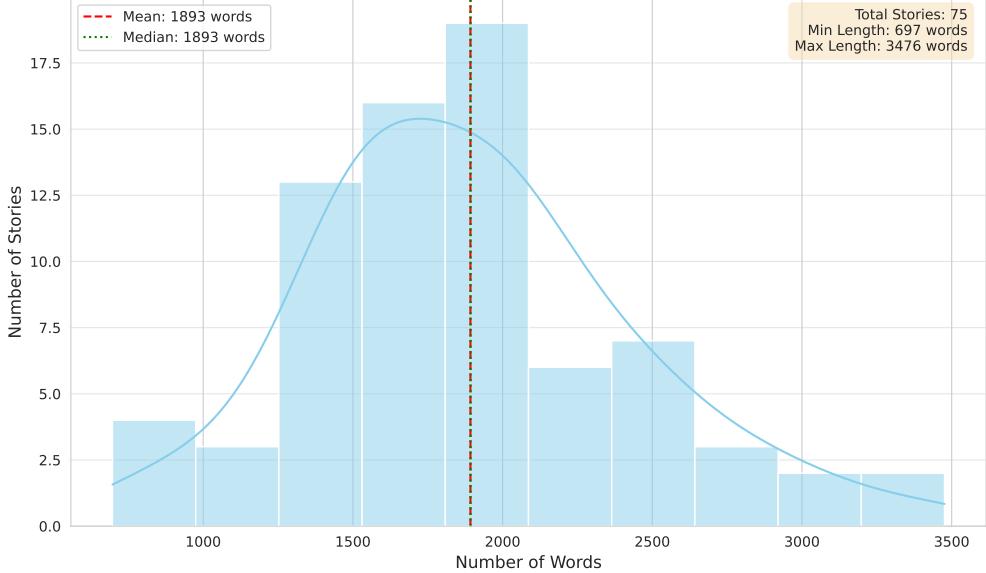


Figure 1: Distribution of story lengths in training/validation dataset.

"My story begins, I am driving my uh silver station Volvo uh from Brooklyn to my mother's house in Rosedale, Queens, on a hot mid-afternoon August day in two thousand and three. My mother uh is a widow. Uh, my father has passed away from lung cancer fifteen years before, nineteen eighty-eight, and she has not resumed dating. She has sworn off men in no uncertain terms. She has told me that, "I am never, ever going to wash another pair of men's underwear again. I am finished with the species. I'm done."

The story is a narrative piece, rich in detail and context. The language is conversational, featuring personal anecdotes and reflections. The presence of filler words like "uh" reflects natural speech patterns, suggesting that the corpus is informal and may differ from the more formal text typically used in NLP tasks.

2.2 fMRI Signals

The fMRI signal data capture the brain's response, measured via the Blood-Oxygen-Level-Dependent (BOLD) signal, as subjects listened to the stories. For each of the 75 stories comprising the training/validation set for a given subject, the data is organized into a two-dimensional numerical array. Each row in this array represents the brain activity across all measured voxels at a specific Time of Repetition (TR), which is the sampling interval of the fMRI scanner. Each column corresponds to a single voxel, with 94,251 voxels for Subject 2 or 95,556 for Subject 3, recorded per subject. Consequently, the dimensions of these arrays are $T \times V$, where V is constant, and T (the number of TRs) varies from story to story, reflecting the differing lengths of the narratives; indeed, as shown in Figure 2, there is a strong positive correlation between the number of words in a story and the duration of its corresponding fMRI recording in TRs.

To understand the basic characteristics of the BOLD signal, we analyzed the distribution of raw signal values across all voxels and time points in the training/validation set. Because plotting every individual reading is impractical, we randomly sampled 10,000 raw signal values from the training data for each subject. Figure 3 shows histograms of these sampled values for Subject 2 and Subject 3. The distributions are highly similar: both are unimodal, approximately Gaussian in shape, and centered near zero. The spread (or variance) of the raw signals also appears comparable across subjects.

In addition to examining the average fMRI signal across the entire dataset, it is informative to visualize the distribution of signals for each story individually. Figure 4 presents the distribution of several summary statistics (mean, median, interquartile range (IQR), minimum, and maximum) computed from the fMRI signal for each of the 101 stories, where each story is treated as a single data point. The central tendency

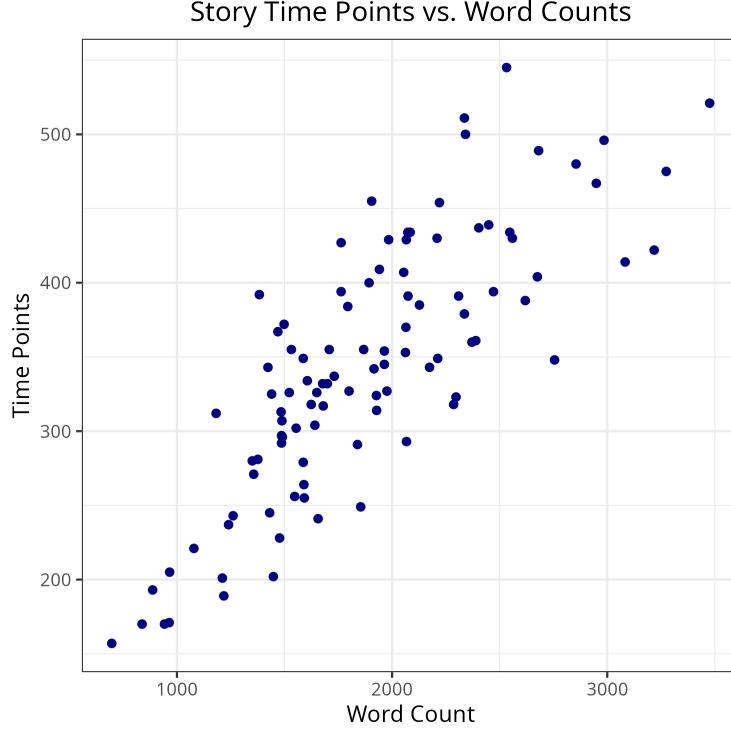


Figure 2: The number of words in a story is strongly correlated with the number of fMRI repetition time points.

and spread (IQR) appear highly consistent across stories, while the minimum and maximum values show much greater variability. This variation in extremes may reflect story-specific events or transient noise artifacts.

Figure 5 offers a more granular view by plotting the mean and IQR of the fMRI signal across all voxels at each time point within selected example stories. This enables a direct comparison of the temporal signal profiles between Subject 2 and Subject 3 over the course of each story. Despite some fluctuations, the mean signal values for both subjects consistently oscillate within a relatively narrow range (approximately -1 to 1), not only in the stories shown here but across the full set.

In stark contrast, the maximum signal value at each time point, shown in Figure 6, reveals substantial variability in peak activity levels over the course of a single story. Although some of this variation may be driven by noise, there appears to be a moderate degree of correlation or shared structure in the timing of peak signal fluctuations between the two subjects listening to the same story.

Another thing to note is that the fMRI signals of Subject 2 contain some NaN values, which are not present in Subject 3. However, the proportion of NaN values is very small, only 5.9×10^{-6} of the total number of values. Due to the small proportion, we simply imputed them with the global mean to prepare the prediction and expect no significant impact on the model performance no matter which imputation method we use.

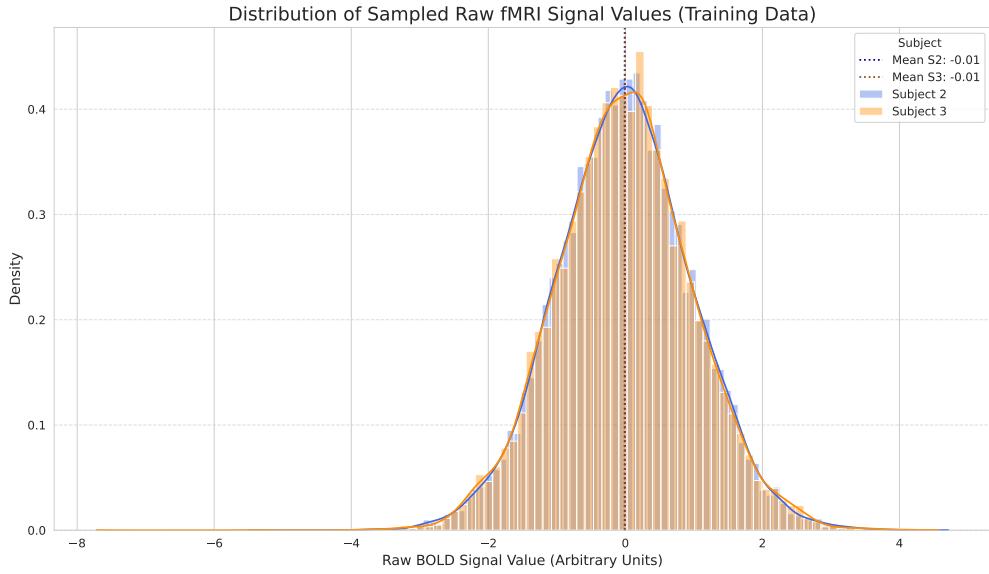


Figure 3: Distribution of fMRI signals in training/validation dataset.

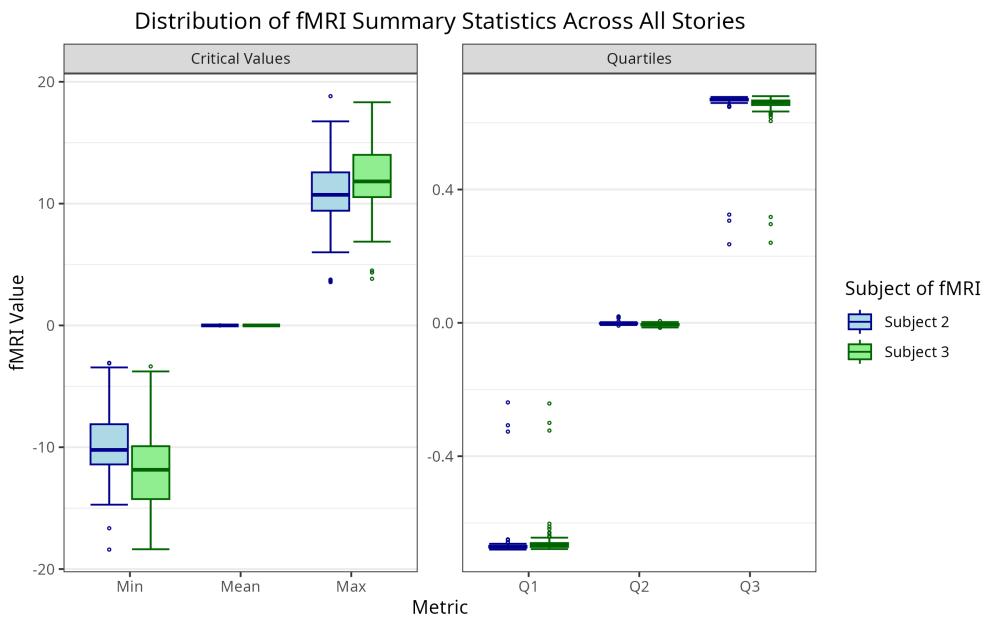


Figure 4: Across all 101 stories, the mean, median, and interquartile range (Q1–Q3) of fMRI signals are tightly distributed, while the minima and maxima show wide variation.

Average fMRI Signal Across Selected Stories

Mean (line) and IQR (shaded) comparison between **Subject 2** and **Subject 3**.

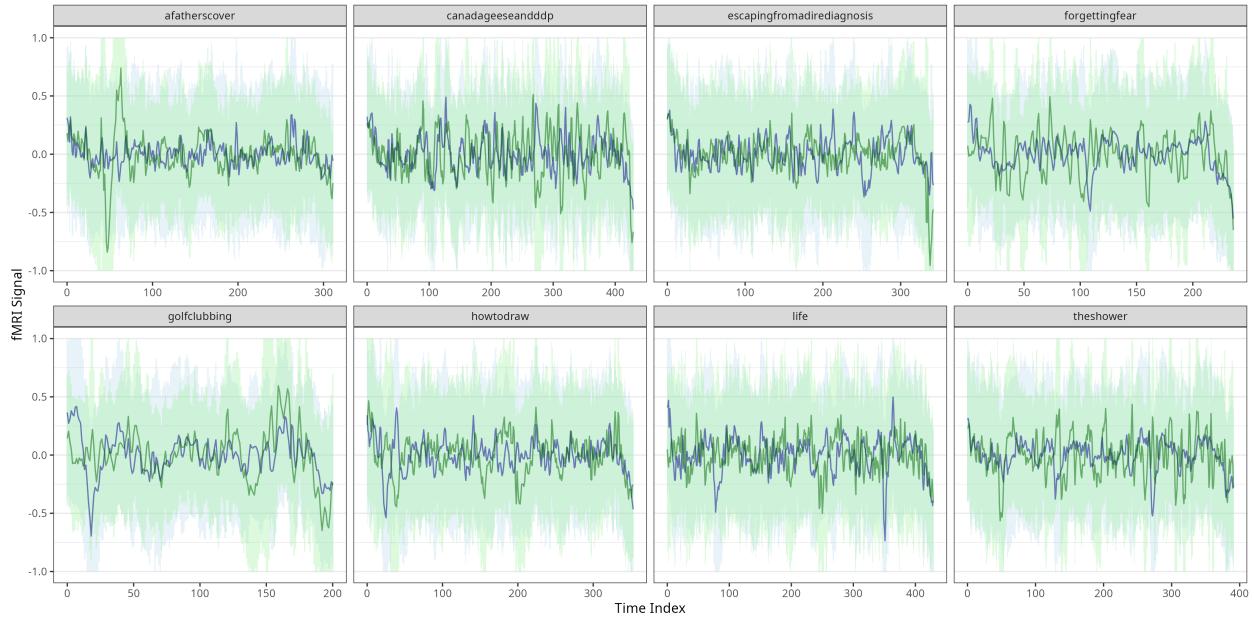


Figure 5: Mean fMRI signal (line) and interquartile range (shaded area) for Subject 2 and Subject 3 at each time point, plotted separately for each story. Mean values for both subjects generally oscillate between -1 and 1 .

Maximum fMRI Signal Across Selected Stories

Comparison between **Subject 2** and **Subject 3**.

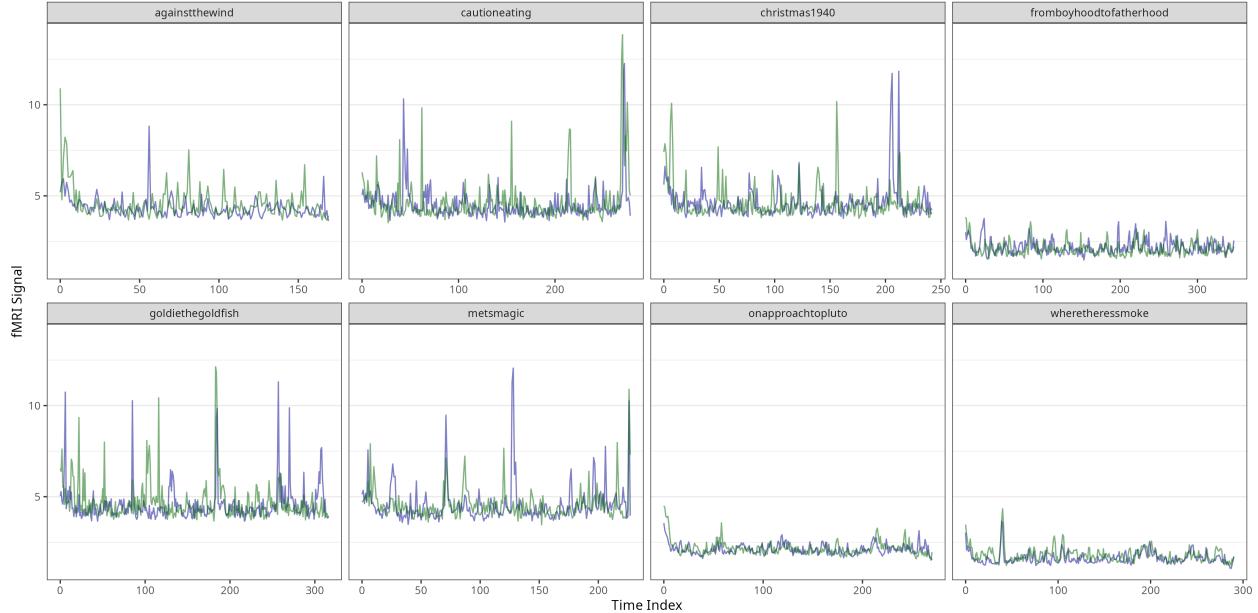


Figure 6: Maximum fMRI signals for Subject 2 and Subject 3 are highly correlated across several stories, despite substantial noise.

3 Interpretation

In this section, we apply SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to interpret the fine-tuned BERT model’s predictions by identifying the most influential words for two different test stories: `buck` and `lawsthatchokecreativity`. Annotated versions of each story, highlighting word-level importances, are included in Appendix B and Appendix C.

3.1 Voxel Selection

Although the fine-tuned model generates predictions for all 94,251 voxels in Subject 2 and 95,556 voxels in Subject 3, we limit our interpretability analysis to the voxels where the model performs well. This selective approach is crucial: methods like SHAP and LIME attempt to assign attribution based on a model’s behavior, so they are only meaningful when the model’s predictions are reliable. Interpreting poorly performing voxels would be misleading because feature attributions would reflect noise rather than a meaningful signal.

To identify the most informative voxels, we rank them by the CC between predicted and actual fMRI responses across time points. We then select voxels whose performance exceeds the 99.5th percentile (i.e., the top 0.5% of correlation scores). Table 1 shows the corresponding CC thresholds for each subject and story. From the eligible voxels, we randomly sample a subset for SHAP and LIME interpretation to keep the analysis computationally manageable.

Table 1: Top 0.5% CC Voxel Thresholds

Story	Subject 2	Subject 3
<code>buck</code>	0.216	0.294
<code>lawsthatchokecreativity</code>	0.159	0.206

3.2 SHAP & LIME Implementation

Both SHAP and LIME explain model predictions by perturbing the input features and measuring how those changes affect the output, attributing influence to each feature accordingly. In our case, the model takes BERT embeddings as input and outputs fMRI predictions, so we define a wrapper function around the model that returns predictions only for a subset of high-performing voxels. This allows SHAP and LIME to focus their explanations on the most informative regions of the brain.

For SHAP, we use `KernelExplainer`, a model-agnostic method that estimates Shapley values by fitting a locally weighted linear model around each prediction. For LIME, we use `LimeTabularExplainer`, which similarly fits local linear models to approximate feature importances. Both methods require a background dataset to serve as a reference distribution for generating perturbed samples. To ensure consistency and interpretability, we use the BERT embeddings from several training set stories as the background.

After applying SHAP and LIME, we obtain a three-dimensional array of explanation values with shape `(num_chunks, embedding_dim, num_voxels)`. To summarize these into word-level importance scores for each voxel, we take the absolute value of the explanation values and then average across the embedding dimension. The result is a matrix of shape `(num_chunks, num_voxels)` that reflects the relative importance of each word chunk to each voxel’s predicted activation.

3.3 Test Story 1: buck

As shown in Figure 7, the word rankings produced by SHAP and LIME for `buck` are fairly consistent between Subject 2 and Subject 3, although the correlation is weaker than that observed for the raw attribution scores. This suggests that both SHAP- and LIME-based word importances are relatively stable across listeners to this story.

Interestingly, Figure 8 indicates that the words most highly ranked by SHAP differ substantially from those most highly ranked by LIME. In fact, their word rankings are weakly negatively correlated, implying that SHAP and LIME emphasize different features of the input when assigning importance. This points to complementary but largely divergent interpretations of model behavior by the two methods and suggests

Cross-Subject Consistency in Word Importance

Comparing SHAP and LIME scores and ranks between Subject 2 and Subject 3

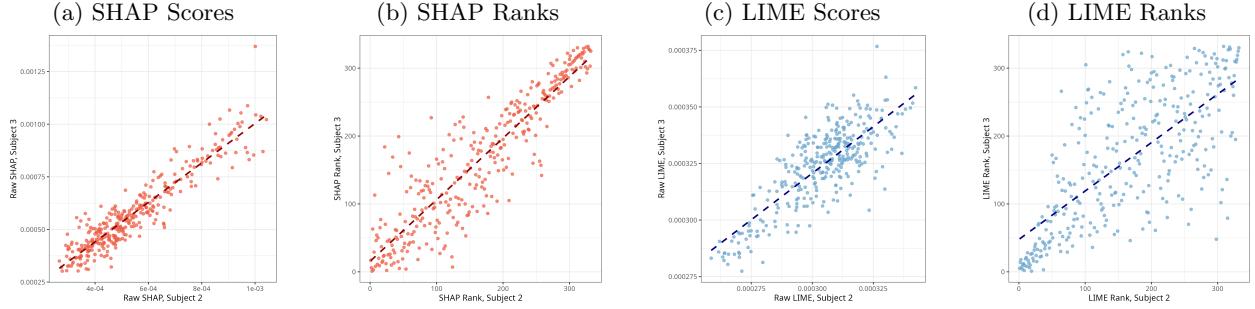


Figure 7: Scatterplots comparing word-level SHAP (red) and LIME (blue) values between Subject 2 and Subject 3. Scores (left) show strong cross-subject agreement, while ranks (right) exhibit greater dispersion—indicating consistency in which words matter, but differences in their relative importance.

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SHAP vs. LIME: Average Word Rank Comparison

Comparing average word ranks across Subject 2 and Subject 3

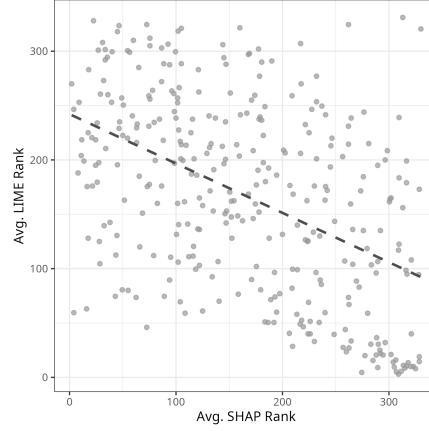


Figure 8: The weak negative correlation $r = -0.35$ between SHAP ranks (x-axis) and LIME ranks (y-axis) suggests that the two methods often prioritize different sets of words, even when averaged across subjects.

In buck, SHAP tends to highlight:

- **Emotional experiences** (e.g., "to eat from this spread", "no one had ever asked me what i want")
- **Prison dynamics** (e.g., "prison", "walk the one gate after another", "hundred guys waiting", "[out] of prison they know you on parole")
- **Identity markers** (e.g., "know this ink work this is prison ink", "now i speak a lot of different gangster languages", "understand blood i even speak a little")
- **Transitional phrases** (e.g., "so", "because for the past ten years", "and leave out of here")

Meanwhile, LIME tends to highlight:

- **Temporal markers** (e.g., "after twenty six years", "corridor for the last time", "through that last gate")
- **Quantitative details** (e.g., "thirty seven eighty seven five report", "with two hundred dollars in it", "no more than eight feet away")
- **Action sequences** (e.g., "they load us on a van", "i get to r and r", "washing dishes my wife says")

Curiously, words identified by both methods almost exclusively involve **interactions with the speaker’s wife** (e.g., “gave her a quick kiss whispered in”, “call out to my wife i said hey babe”, “i could see her she was snapping pictures”, “and he tells my wife wait”).

This pattern suggests that these two methods can provide complementary insights about which textual features drive fMRI responses: SHAP may better capture emotional and thematic elements, while LIME may be more effective at identifying sequentially important narrative details. For a more comprehensive list of words identified by each method, see Appendix B.

Voxelwise Consistency of SHAP and LIME Word Ranks

Distribution of word rankings across individual voxels and subject-score combinations

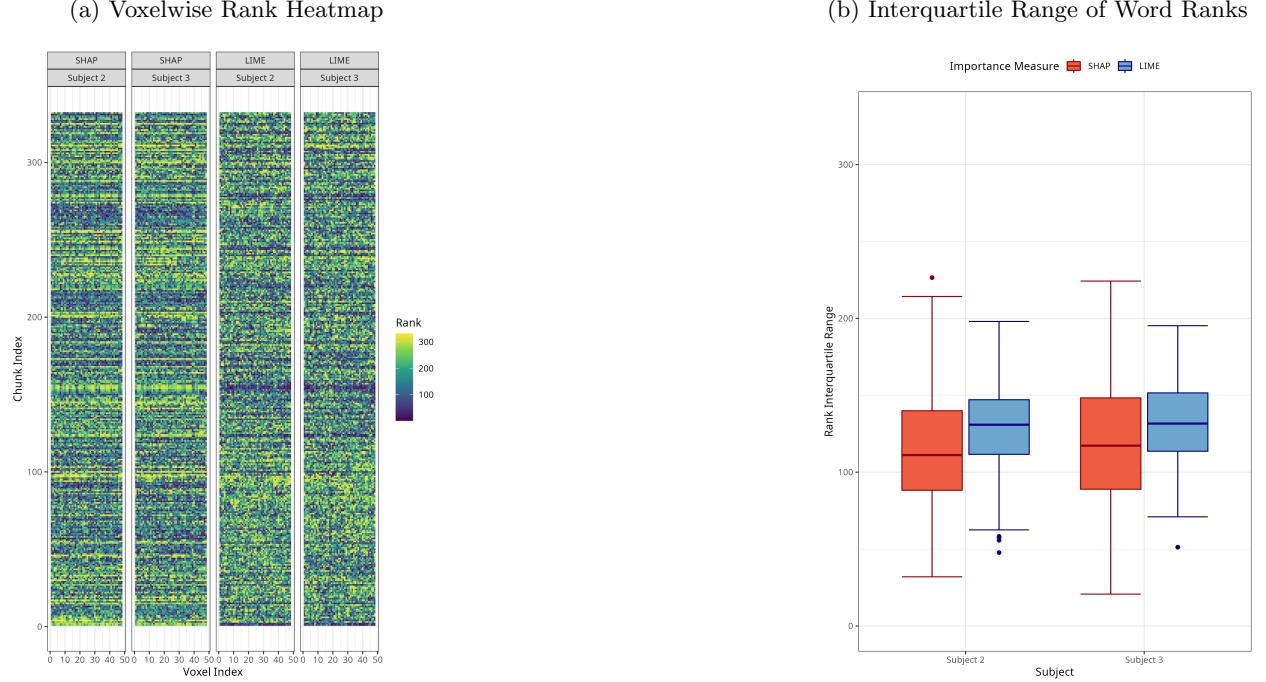


Figure 9: Word ranks assigned by individual voxels show a high degree of consistency within and across subjects. The heatmap (left) displays voxelwise rankings for 332 word chunks, revealing horizontal banding patterns that reflect agreement in word importance. The boxplot (right) summarizes the spread of these ranks within chunks. For the average word, the IQR spans only ~ 125 ranks, suggesting relatively stable importance scores across voxels.

Regarding differences across voxels, Figure 9 reveals visible horizontal banding in the heatmaps for both SHAP and LIME, indicating that word rankings are relatively consistent across voxels within and between subjects. The accompanying boxplot shows that SHAP produces slightly lower median IQRs for word ranks across voxels, suggesting less variability and lower voxel sensitivity for the average word. Conversely, LIME exhibits a tighter distribution of IQR values, indicating that while its average variability may be higher, the spread among the least consistently ranked words is smaller.

3.4 Test Story 2: `lawsthatchokecreativity`

As shown in Figure 10, the word rankings produced by SHAP and LIME for `lawsthatchokecreativity` are fairly consistent between Subject 2 and Subject 3, although the correlation is weaker than that observed for the raw attribution scores. This suggests that both SHAP- and LIME-based word importances are relatively stable across listeners to this story.

Cross-Subject Consistency in Word Importance
Comparing SHAP and LIME scores and ranks between Subject 2 and Subject 3

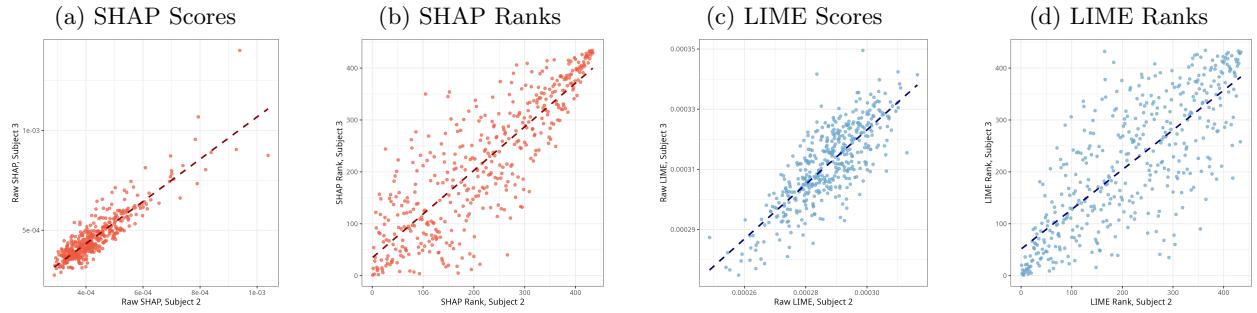


Figure 10: Scatterplots comparing word-level SHAP (red) and LIME (blue) values between Subject 2 and Subject 3. Scores (left) show strong cross-subject agreement, while ranks (right) exhibit greater dispersion—indicating consistency in which words matter, but differences in their relative importance.

Interestingly, Figure 11 indicates that the words most highly ranked by SHAP differ substantially from those most highly ranked by LIME. In fact, their word rankings are weakly negatively correlated, implying that SHAP and LIME emphasize different features of the input when assigning importance. This points to complementary but largely divergent interpretations of model behavior by the two methods.

SHAP vs. LIME: Average Word Rank Comparison
Comparing average word ranks across Subject 2 and Subject 3

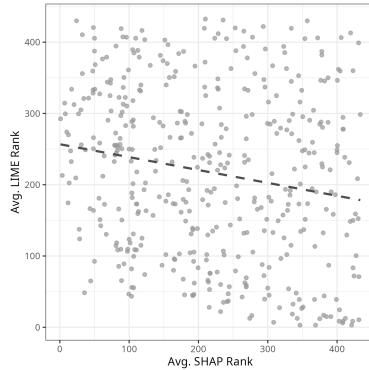


Figure 11: The weak negative correlation $r = -0.12$ between SHAP ranks (x-axis) and LIME ranks (y-axis) suggests that the two methods often prioritize different sets of words, even when averaged across subjects.

In `lawsthatchokecreativity`, SHAP tends to highlight:

- **Concrete entities and specific references** (e.g., "john philip sousa", "united states capitol", "four hundred and forty eight percent", "supreme court considered")
- **Technical legal terminology** (e.g., "will be eliminated by a process of evolution", "copyright law at its core regulates", "judgement of fair use")
- **Action-oriented phrases** (e.g., "singing the songs", "take sounds and images", "traveled to this place")

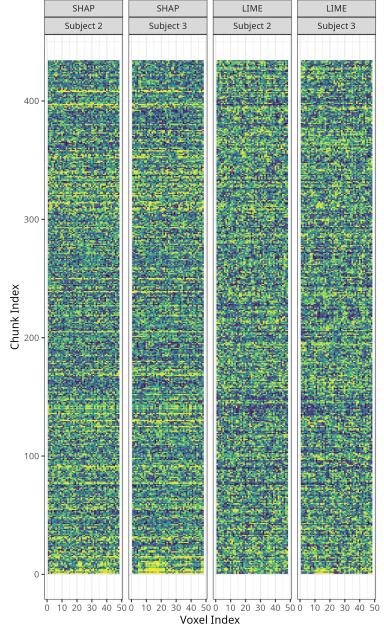
Meanwhile, LIME tends to highlight:

- **Abstract concepts** (e.g., "a culture which is top down owned", "it is a literacy", "weird time it's kind of age of prohibitions")
- **Temporal and spatial references** (e.g., "across the country well in nineteen forty five", "at that time this legal", "and in nineteen forty one")
- **Cultural commentary** (e.g., "this is a picture of culture", "celebrating amateur culture", "it is how our kids think")
- **Technology-related expressions** (e.g., "with access to a fifteen hundred dollar computer", "instinct the technology produces", "can't stop our kids from using")

Voxelwise Consistency of SHAP and LIME Word Ranks

Distribution of word rankings across individual voxels and subject-score combination

(a) Voxelwise Rank Heatmap



(b) Interquartile Range of Word Ranks

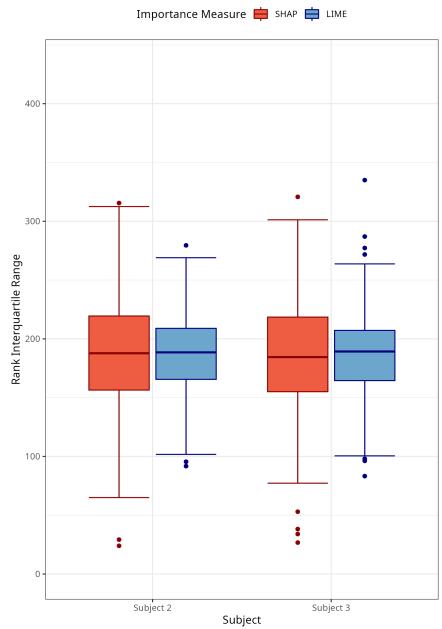


Figure 12: Word ranks assigned by individual voxels show a high degree of consistency within and across subjects. The heatmap (left) displays voxelwise rankings for 434 word chunks, revealing horizontal banding patterns that reflect agreement in word importance. The boxplot (right) summarizes the spread of these ranks within chunks. For the average word, the IQR spans only ~ 180 ranks, suggesting relatively stable importance scores across voxels.

However, words identified by both methods include:

- **Key thesis statements** (e.g., "i'm gonna tell you three stories", "now so instead what we need is")
- **Narrative transitions** (e.g., "and that's where the story of", "extremism on the other a fact we should have many many")
- **Opinion indicators** (e.g., "i think much more important much", "to fight for i as any good")

This pattern suggests that fMRI responses may be driven by both specific semantic content (captured by SHAP) and broader narrative structure (captured by LIME), reflecting the multi-level processing that occurs in the brain during language comprehension. For a more comprehensive list of words identified by each method, see Appendix C.

Regarding differences across voxels, Figure 12 reveals visible horizontal banding in the heatmaps for both SHAP and LIME, indicating that word rankings are relatively consistent across voxels within and between subjects. The accompanying boxplot shows that SHAP produces slightly lower median IQRs for word ranks across voxels, suggesting less variability and lower voxel sensitivity for the average word. Conversely, LIME exhibits a tighter distribution of IQR values, indicating that while its average variability may be higher, the spread among the least consistently ranked words is smaller.

4 Conclusion

This lab demonstrated the efficacy of leveraging pre-trained language models for predicting fMRI responses to narrative stimuli. Our experiments focused on utilizing BERT, first with static embeddings and then through parameter-efficient fine-tuning using LoRA.

The results indicate that embeddings from the pre-trained BERT model significantly outperform those from earlier labs (custom encoders or simpler static embeddings like Bag-of-Words) for Subject 2, and show competitive results for Subject 3. This highlights the benefit of the rich contextual representations learned by larger models. Furthermore, fine-tuning these BERT embeddings with LoRA provided an additional, albeit modest, improvement in predictive accuracy across both subjects, underscoring the value of task-specific adaptation even with limited trainable parameters. The choice of LoRA rank ($r = 8$) and initializing regression heads from prior experiments proved beneficial.

Interpretability analysis using SHAP and LIME on the fine-tuned LoRA-BERT model identified words relevant to the narrative content that influenced predictions for well-modeled voxels. While SHAP and LIME offered somewhat divergent perspectives—SHAP often emphasizing thematic content and LIME highlighting structural or specific details—their combined insights suggest that the model attends to various meaningful linguistic features. Word importance showed reasonable consistency across subjects and voxels, indicating some shared neural processing patterns captured by the model.

In summary, this work confirms that pre-trained transformers, further refined with techniques like LoRA, provide a robust framework for modeling neural language processing. They offer improved predictive power and, through interpretability methods, can shed light on the linguistic features driving brain activity.

References

- [1] Jacob Devlin et al. “Bert: Pre-training of deep bidirectional transformers for language understanding”. In: *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*. 2019, pp. 4171–4186.
- [2] Shailee Jain and Alexander Huth. “Incorporating context into language encoding models for fMRI”. In: *Advances in neural information processing systems* 31 (2018).
- [3] Tomas Mikolov et al. “Efficient estimation of word representations in vector space”. In: *arXiv preprint arXiv:1301.3781* (2013).
- [4] Jeffrey Pennington, Richard Socher, and Christopher D Manning. “Glove: Global vectors for word representation”. In: *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*. 2014, pp. 1532–1543.

A Academic honesty

A.1 Statement

We affirm that the work in this report is entirely my own. We have not copied from any unauthorized sources, and all contributions from classmates, external sources, or tools are acknowledged. Academic research honesty is necessary because it ensures fairness, builds trust in scholarly work, and reflects personal integrity. Misrepresenting work undermines academic standards and disrespects the time and effort of peers and educators. Maintaining honesty in research fosters a learning environment where collaboration and progress can thrive authentically.

A.2 LLM Usage

We used ChatGPT to assist in clarifying concepts, creating visualizations, checking grammar, and improving the structure of our explanations. No content of the report or code was generated by the LLM without our review, editing, and refinement. We ensured that all content was written and understood by us, and the LLM was used as a tool to enhance our work rather than replace our understanding, we take full responsibility for all content in the report.

B buck Full Text

Words discovered by SHAP in red, LIME in blue, or both in bold. Threshold based on 75th percentile word ranks.

so as i sit down to eat from this spread that has been given in my honor i can't help but to f notice the two feelings that i'm having one i'm a little nervous two i'm very excited because you see in the morning i'll be paroling from state prison after twenty six years this spread is given to me not as like to say hey homie we appreciate you nah it was a spread to say we don't never wanna see your ass in here again and they broke out the finest of the finest top ramen chili in a can uh roast beef in a can you know this this top line of stuff right so after the spread has been had it's time for me to give away some property such as my tv my radio and some self help books that helped me a lot so they'll be better utilized left behind nine o'clock rolls around it's lights out you don't have to go to sleep but you do gotta get off the day room floor it's cool by me i'm leaving in the morning so i may have gotten like three hours worth of sleep that night i slept ready roll and that means i slept with my clothes on so once they call my name i'm out of there bye see you later so five forty five rolls around the night man says cyprien d thirty seven eighty seven five report to r and r i walk down that corridor for the last time walk the one gate after another till i get to r and r and that's receiving and release and i'm on the release end at this point i get to r and r and there's about seven to six other guys waiting for the same thing they start fingerprinting me mugshots and everything i'm cool like time to go so they load us on a van and we drive through one gate after another gate till we get to the final gate the cop says alright everybody off the van you'll step to the man at the base of the tower there and you'll give him some personal information so we did and he gave each man an envelope with two hundred dollars in it better known as gate money we all got back onto the van and drove through that last gate we made it around to the visitor's parking lot and he asked is there anyone with a ride i do i was the only one to get off the van these other guys that two hundred dollar gate money they had to spend it on buying their bus tickets maybe back to southern california or even further up north but i was the lucky one my wife was waiting there with her camera i could see her she was snapping pictures of me like a paparazzi i walk briskly towards her gave her a quick kiss whispered in her ear let's get out of here before they say we made a mistake we got in the car drove away i saw a seven eleven i was like hey babe pull over lemme i wanna go in and get something so i went in and i grabbed a pack of big red gum i hadn't had chewing gum in twenty six years big red was my favorite we got back in the car drove away we were on the road for about thirty to forty five minutes and i spotted a target i said hey babe that's target i saw that on the uh tv pull over lemme i wanna go in there so we did the first thing that caught my eye was how big the shopping basket was it was bigger than the space that i had to store my personal property while in prison i grabbed the basket and went down the aisle grabbing various things such as underwear socks t-shirt toothbrush toothpaste you name it i grabbed it well there goes that two hundred dollar gate money so back in the car my wife says so what do you want for dinner whoa she's stumped me with that one because for twenty six years no one had ever asked me what do i want for dinner my dinner came through a thirteen by thirteen hole in the wall you stick your hand in there and pull out a tray and what's ever on there that's what you eat so she says i know what to fix so she drove we made it to the grocery store went into the grocery store this gigantic store berkeley bowl so i made it to the produce section i'm stuck there are so many oranges to choose from and the reason and i'm stuck just looking at the oranges is because for the past ten years in prison they had taken oranges away from us because they were used to make wine so there's like a bumpy orange a smooth orange a navel orange i even met my first blood orange and at the same time this wave hit me of alone and feeling like i don't know a nervous feeling hit me like i'm the only person in this store who's paroled from a prison today after twenty six years i'm a little stuck a little so i'm looking around and i spot this ink work it's not the typical ink work that i see out here now like with colors no i know this ink work this is prison ink he has a prison guard tower on him a mictic clock with time i know that work i've seen that many times so i walk over to him and i whisper so what yard did you parole from he said oh me i got i paroled from pelican bay like four months ago i'm like and they know you got out of prison they know you on parole aw yeah they not tripping here this is berkeley man nah nobody's tripping well i walked away from him with the understanding that if he can get a job so can i so i met my wife at the checkout once again there's another stunned moment for me there are twelve checkout lines and there's somebody on the other end bagging the groceries in prison there was one window maybe thirteen by thirteen again and there was like three hundred guys waiting to get into this one window with their lists i didn't have to worry about an alarm going off or anything no getting down we're gonna get our groceries and leave out of here that was my thought cool so we made it through the made it through the checkout went back to the car got in the car and we're on the road and we come to a stoplight and this homeless guy had a sign that says anything will help so my wife reaches into the cup holder and gets ready to hand him some change and all of a sudden he gets a phone call and he tells my wife wait i gotta take this call and my thoughts was like uh if he got a cellphone i gotta get one so we drive away and my wife uh she just drives real fast right and we make it to the neighborhood just as fast as we got to the store and she pulls into the neighborhood and she points out the various neighbors' house um this is where fred and mike live the brewers live here and i'm like okay and we get to our house and she said this is us and we live at the edge of the forest i'm like cool cool and so we went inside and she gives me the grand tour and so she says well i'm gonna prepare this dinner i said cool so she made steak and lobster with small potatoes nothing out of a can folks nothing out of a packet either she made this meal we sat down we ate and i had my first glass of wine with my meal not them i'm not saying i've never had wine before i've never had wine with a meal this is some grown folks' shit i thought right so after the meal was finished we're cleaning up washing dishes my wife says you wanna get further acclimated i'm like yeah she said take out the garbage no problem i reach down tie that garbage bag up throw it over my shoulder and out to the front door i go when i open up the door no more than eight feet away from me was a ten point buck just standing there looking at me look at it standing staring at me now had we been on a prison yard me and this buck woulda had issues now i speak a lot of different gangster languages i'm fluent in crip i understand blood i even speak a little sh olo vato loco but i don't speak deer so i shut the door i call out to my wife i said hey babe there's somebody here to see you she came to the door opened it and saw there was the buck she grabbed the trashbag and walked right past it i said damn she speaks deer she came back and we both look out the door together at this buck who's still standing there just looking just majestic as could be and my wife says you don't need to trip him he's just one neighbor coming to welcome you to the neighborhood cool i thought like well the fellas aren't gonna believe this shit when i tell them this

C lawsthatchokecreativity Full Text

Words discovered by SHAP in red, LIME in blue, or both in bold. Threshold based on 75th percentile word ranks.

i'm gonna tell you three stories on the way to one argument that's going to tell you a little bit about how we open user generated content up for business so here's the first story nineteen oh six this man john philip souza traveled to this place the united states capitol to talk about this technology what he called the quote talking machines souza was not a fan of the talking machines this is what he had to say these talking machines are going to ruin artistic development of music in this country when i was a boy in front of every house in the summer evenings you would find young people together singing the songs of the day or the old songs today you hear these infernal machines going night and day we will not have a vocal cord left souza said the vocal cords will be eliminated by a process of evolution as was the tail of man when he came from the ape this is a picture of culture we could describe it using modern computer terminology as a kind of read write culture it's a culture where people participate in the creation and the re creation of their culture in that sense it's read write souza's fear was that we would lose that capacity because of these quote infernal machines they would take it away and in its place we'd have the opposite of read write culture what we could call read only culture culture where creativity was consumed but the consumer is not a creator a culture which is top down owned where the vocal cords of the millions have been lost now as you look back at the twentieth century at least in what we think of as the quote developed world hard not to conclude that souza was right never before in the history of human culture had it been as professionalized never before as concentrated never before has creativity of the millions been as effectively displaced and displaced because of these quote infernal machines the twentieth century was that century where at least for those places we know the best culture moved from this read write to read only existence so second cg land is a kind of property is property it's protected by law as lord blackstone described it land is protected by trespass law for most of the history of trespass law by presuming it protects the land all the way down below and to an indefinite extent upwards now that was a pretty good system for most of the history of the regulation of land until this technology came along and people began to wonder were these instruments trespassers as they flew over land without clearing the rights of the farms below as they traveled across the country well in nineteen forty five supreme court got a chance to address that question two farmers thomas lee and tinnie causby who raised chickens had a significant complaint because of these technologies the complaint was that their chickens followed the pattern of the airplanes and flew themselves into the walls of the barn when the airplanes flew over the land and so they appealed to lord blackstone to say these airplanes were trespassing since time immemorial the law had said you can't fly over the land without permission of the landowner so this flight must stop well the supreme court considered this hundred years tradition and said in an opinion written by justice douglas that the causbys must lose the supreme court said the doctrine protecting land all the way to the sky has no place in the modern world otherwise every transcontinental flight would be subject would subject the operator to countless trespass suits common sense a rare idea in the law but here it was common sense revolts at the idea common sense cg finally cg before the internet the last great terror to rain down on the content industry was a terror created by this technology broadcasting a new way to spread content and therefore a new battle over the control of the businesses that would spread content now at that time the entity the legal cartel that controlled the performance rights for most of the music that would be broadcast using these technologies was ascap they had an excus exclusive license on the most popular content and they exercised it in a way that tried to demonstrate to the broadcasters who really was in charge so between nineteen thirty one and nineteen thirty nine they raised rates by some four hundred and forty eight percent until the broadcasters finally got together and said okay enough of this and in nineteen thirty nine a lawyer sydney kaye started something called broadcast music incorporated know it as bmi and bmi was much more democratic in the art that it would include within its repertoire including african american music for the first time in the uh repertoire but most important was that bmi took public domain works and made arrangements of them which they gave away for free to their subscribers so that in nineteen forty when ascap threatened to double their rates the majority of broadcasters switched to bmi now ascap said they didn't care the people will revolt they predicted because the very best music was no longer available because they had shifted to the second best public domain provided by bmi well they didn't revolt and in nineteen forty one ascap cracked and the important point to recognize is that even though these broadcasters were broadcasting something you would call second best that competition was enough to break at that time this legal cartel over access to music okay three stories here's the argument in my view the most significant thing to recognize about what this internet is doing is its opportunity to revive the read write culture that souza romanticized digital technology is the opportunity for the revival of these vocal cords that he spoke so passionately to congress about user generated content spreading in businesses in extraordinarily valuable ways celebrating amateur culture by which i don't mean amateurish culture i mean culture where people produce for the love of what they're doing and not for the money i mean the culture that your kids are producing all the time for when you think of what souza romanticized in the young people together singing the songs of the day of the old songs you should recognize what your kids are doing right now taking the songs of the day and the old songs and remixing them to make them something different it's how they understand access to this culture i'm not talking about nor justifying people taking other people's content in wholesale and distributing it without the permission of the copyright owner i'm talking about people taking and recreating using other people's content using digital technologies to say things differently it is now anybody with access to a fifteen hundred dollar computer who can take sounds and images from the culture around us and use it to say things differently these tools of creativity have become tools of speech it is a literacy for this generation this is how our kids speak it is how our kids think it is what your kids are as they increasingly understand digital technologies and their relationship to themselves now in response to this new use of culture using digital technologies the law has not greeted this souza revival with very much common sense instead the architecture of copyright law and the architecture of digital technologies as they interact have produced the presumption that these activities are illegal because if copyright law at its core regulates something called copies then in the digital world the one fact we can't escape is that every single use of culture produces a copy every single use therefore requires permission without permission you are a trespasser common sense here though has not yet revolted in response to this response that the law has offered to these forms of creativity instead what we've seen is something much worse than a revolt there's a growing extremism that comes from both sides in this debate in response to this conflict between the law and the use of these technologies one side builds new technologies such as one recently announced that will enable them to automatically take down from sites like youtube any content that has any copyrighted content in it whether or not there's a judgment of fair use that might be applied to the use of that content and on the other side among our kids there's a growing copyright abolitionism a generation that rejects the very notion of what copyright is supposed to do rejects copyright and believes that the law is nothing more than an ass to be ignored and to be fought at every opportunity possible the extremism on one side begets extremism on the other a fact we should have learned many many times over and both extremes in this debate are just wrong now the balance that i try to fight for is as any good liberal try to fight for first by looking to the government total mistake right looked first to the courts and the legislatures to try to get them to do something to make the system make more sense it failed partly because the courts are too passive partly because the legislatures are corrupted by which i don't mean that there's bribery operating to stop real change but more the economy of influence that governs how congress functions means that policymakers here will not understand this until it's too late to fix it so we need something different we need a different kind of solution and the solution here in my view is a private solution a solution that looks to legalize what it is to be young again and to realize the economic potential of that and that's where the story of bmi becomes relevant because as bmi demonstrated competition here can achieve some form of balance the same thing can happen now we don't have a public domain to draw upon now so instead what we need is two types of changes first that artists and creators embrace the idea choose that their work be made available more freely so for example they can say their work is available freely for non commercial this amateur type of use but not freely for any commercial use and second we need the businesses that are building out this read write culture to embrace this opportunity expressly to enable it so that this ecology of free content or freer content can grow on a neutral platform where they both exist simultaneously so that more free can compete with less free and the opportunity to develop the creativity in that competition can teach one the lessons of the other now i would talk about one particular such plan that i know something about but i don't want violate ted's first commandment of selling so i'm not gonna talk about this at all i'm instead just gonna remind you of the point that bmi teaches us that artist choice is the key for new technology having an opportunity to be open for business and we need to build artist choice here if these new technologies are to have that opportunity but let me end with something i think much more important much more important than business it's the point about how this connects to our kids we have to recognize they're different from us it is technology that has made them different and as we see what this technology can do we need to recognize you can't kill the instinct the technology produces we can only criminalize it we can't stop our kids from using it we can only drive it underground we can't make our kids passive again we can only make them quote pirates and is that good we live in this weird time it's kind of age of prohibitions where in many areas of our life we live life constantly against the law ordinary people live life against the law and that's what i we are doing to our kids they live life knowing