Word Embeddings and the Brain

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Git Repository https://github.com/OfriHefetz/Word-Embeddings-and-the-Brain

Abstract

This report comprehensively investigates neural decoding and encoding using sentence representations. This project report contains a structured task, semi-structured tasks, and an open-ended task in the field of sentence decoding and semantic hierarchies within the brain.

In the **structured** task, we compared the results of Homework Assignment 3 question 3 using different static word embeddings, specifically Word2Vec and GloVe. To gain further insights, we reviewed Pereira et al.'s (2018) research and highlighted the similarities and differences between their analyses.

In the **semi-structured** tasks, we trained a decoder model on datasets from analyses 2 and 3 using the non-contextualized original sentence representations and representations from a contextualized word embedding model. Finally, we compared the results of both methods to assess their performance in sentence decoding. Furthermore, we built a brain-encoder model to predict human neural signals from sentence-embedding vector representations. We used linear regression models for each voxel in the dataset related to analyses 2, calculated R^2 scores, and examined the significance of associations between word vectors and neural activity. This analysis was conducted using both non-contextualized and contextualized vector representations.

The **open-ended** task aimed to investigate and compare the uncovering of semantic hierarchies and explore the hierarchical structure of semantic representations between BERT representations and fMRI data. We aim to understand how these two distinct modalities capture and represent semantic information within the brain.

Keywords: machine learning, word embedding, fMRI, BERT, decoder, accuracy scores, PCA, Agglomerative Clustering, Semantics.

Structured Task: Sentence Decoding

Analysis of Different Static Word Embeddings for Sentence Decoding

As part of the structured task, we analyzed Homework Assignment 3 question 3 using Word2Vec and GloVe word embeddings. Initially, we chose Word2Vec as a static word embedding to compare its rank accuracy scores with GloVe's. We believed that Word2Vec's semantic embeddings would result in higher accuracy scores across most folds compared to our results in HW 3 question 3. However, upon examining Figure 1, our initial assumption proved false. In 12 out of 18 folds, the rank accuracy scores with Word2Vec were lower than those with GloVe.

In Homework Assignment 3, question 3, our task involved creating a code to split the data into training and test sets using 18-fold cross-validation. We trained the decoder using the provided code, utilized it to decode semantic vectors, and evaluated the accuracy of the decoded vectors using the average rank method for each fold. Then repeated, the analysis using another type of static word embedding, specifically the "Word2Vec Google News 300," and compared the results to those obtained with GloVe.

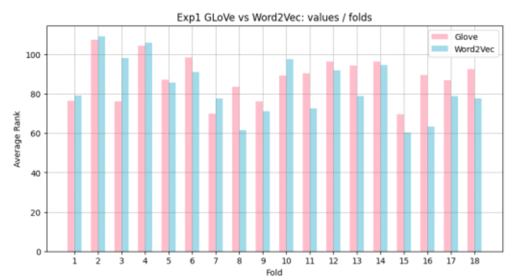

Figure 1: EX1 – GloVe vs. Word2Vec: Values per Fold.

As shown in Figure 1, in most of the 18 folds, the rank accuracy scores with Word2vec were significantly lower than those of the brain decoder with GloVe. This finding was opposite to our initial belief.

Similarities and Differences in Pereira et al., 2018

Pereira et al. (2018)'s research aims to develop a unique system known as a "universal brain decoder." This technology is designed to clarify the meanings of words, phrases, or sentences by analyzing brain activity patterns. This decoder is significant because it can be trained using minimal brain imaging data while working with various themes, including abstract thinking.

The authors conducted three experiments to test their method:

- The first experiment focused on how the brain responds to specific objects, such as dogs or cars. They trained the decoder using data from one person and used 60 words for this purpose.

- The second experiment was focused on discovering how the brain interprets abstract notions such as adjectives and verbs. To do this, the writers deliberately picked terms depending on how similar their meanings were. Then, they trained the decoder using data from four people to test if it could also handle abstract concepts.
- The third experiment was about checking whether the decoder could work with different sets of sentences. The authors trained it using one set of sentences and then tested it on another set. This helped them understand if the decoder could handle various types of language.

Despite these differences, all three experiments shared some things in common:

- They used brain scans taken using a unique imaging technique called fMRI while people read sentences.
- They used algorithms to analyze brain patterns and figure out the meaning of the sentences.
- They used similar sentences about different topics, and the participants read each sentence multiple times.

The research aims to understand better how our brains process language and opens new possibilities for decoding our thoughts using brain scans.

Evaluation of a GloVe-Based Decoder Model for Sentence Decoding

In this section, we present the GloVe-based decoder model trained in Homework Assignment 3, Question 3, on the datasets from Analyses 2 and 3. These datasets consist of sentence representations, which are vector representations obtained by averaging the word vectors in each sentence, along with the corresponding neural data from individual subjects. To evaluate the performance of the decoder model, we used the learned GloVe-based decoder. First, the decoder model decoded the sentence representations and mapped them to the corresponding neural data. Then, to assess the effectiveness of the decoder model, we employed the rank accuracy method, as previously done. This method measures the ability of the decoder to rank the accurate sentence representations. We observed significant differences compared to the results obtained in Analysis 1.

Figure 2 shows that the rank accuracy values achieved for EX2 and EX3 were higher than those obtained for EX1. These findings suggest that additional noise in the decoder word vectors due to the complexity of sentence structures can affect the model's performance. However, despite this challenge, the GloVe-based decoder model demonstrated promising capabilities in accurately decoding sentence representations in Analyses EX2 and EX3.

Figure 2: EX1 vs. EX2 vs. EX3 - Values per Fold.

Topic-Based Performance Analysis of Sentence Decoding using a GloVe-Based Decoder Model

This section analyzes the accuracy scores obtained from the previous section. This was sone to identify the topics where the GloVe-based decoder model was more or less successful in predicting the sentences. To gain insights into the performance of the decoder model, we examined the average accuracy scores for each topic in both Exp2 and Exp3.

Figures 3 and 4 show the average scores for each topic in their respective experiments. We identified specific topics in which the decoder model excelled in predicting the sentences. For example, in Exp2, fish, vehicles, and animal topics showed the best average accuracy scores. Respectively, topics such as owls, blindness, and hurricanes showed excellent accuracy in Exp3.

However, there were topics where the decoder model achieved fairly lower accuracy scores. For example, in Exp2, topics related to music, crime, and profession, and in Exp3, topics such as gambling, opera, and computer graphics. Interestingly, although the topics in both experiments were distinct, some shared a common mega-topic. For example, the topics of owls and fish fall under the broader category of animals, and opera is an aspect of music. These observations led us to hypothesize that our brain decoder performs better in predicting sentences involving concrete concepts, such as specific animals or vehicles, than intangible concepts, like musical genres or professions.

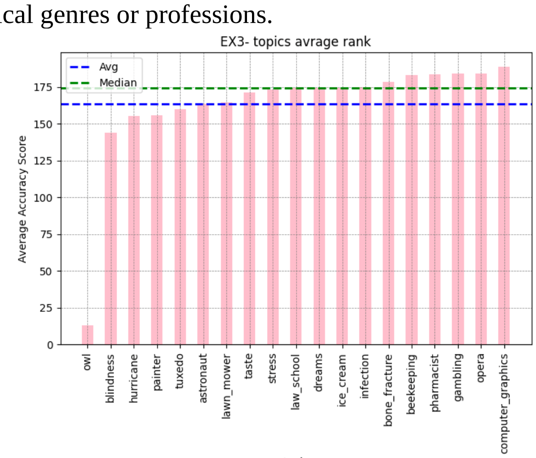

Figure 3: EX3 – Average Rank per Topic.

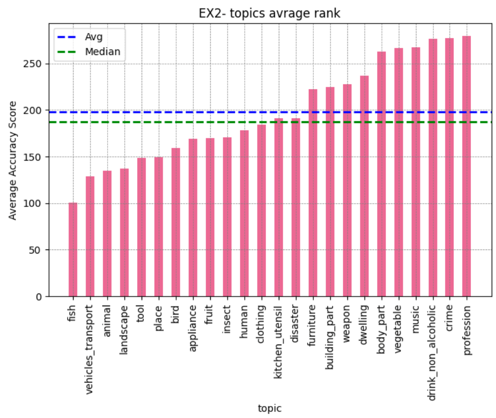

Figure 4: EX2 – Average Rank per Topic.

Semi-Structured Tasks

This section presents the results of two tasks: neural decoding and neural encoding, performed on a dataset related to analysis 2 or 3 from Pereira et al., 2018. The goal of the first task is to train a decoder model to predict sentence identities using different types of sentence representations. The second task involves building a brain-encoder model to predict human neural signals from sentence embedding vectors.

Comparison of Decoder Models Using Different Sentence Representations

In this task, we trained decoder models on the datasets from analysis 2 and 3. We expanded the comparison by including three types of models: the original representations, BERT ("Paraphrase-albert-small-v2" model from the sentence-transformers library), and T5 ("gtr-t5-base" model, which was converted from the TensorFlow model gtr-base-1 to PyTorch).

The evaluation of the decoder models involved analyzing the average rank across 18 folds. The results obtained for analysis 2 (EX2) and analysis 3 (EX3) indicated that the T5 model consistently performed the worst among the three models. On the other hand, the original representations and BERT demonstrated superior performance in terms of average rank.

Figure 5 illustrates the comparison of the model's performance on analysis 2, where the original representations and BERT achieved better rankings compared to the T5 model. Similarly, Figure 6 depicts the results for analysis 3, showing that the original representations and BERT outperformed the T5 model regarding average rank.

These findings indicate that, for the given tasks, the original representations and BERT offer more favorable outcomes regarding model performance. The T5 model, despite being a pre-trained sentence-transformers model, did not exhibit competitive results in our experiments.

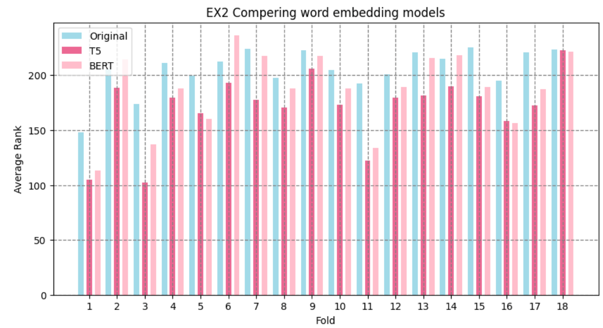

Figure 5: EX2 – Word Embedding Models (Comparison).

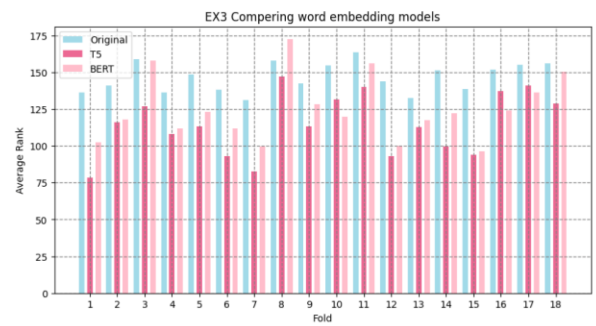

Figure 6: EX3 – Word Embedding Models (Comparison).

Brain Encoder Model for Neural Encoding Analysis

In this task, we aimed to build a brain-encoder model to predict human neural signals from the embedding vector representations of sentences, known as neural encoding. Instead of neural decoding, where sentence identities are predicted using neural signals, we adopted a different approach inspired by the concept of a neural encoder described in Huth et al.'s 2016 paper. We aimed to fit separate linear regression models for each voxel in the dataset related to analysis 2 (384 sentences) from Pereira et al.'s 2018 study, which included 180 concepts.

For each voxel in the dataset, we calculated the R^2 score to assess the relationship between the information embedded in the word vectors and neural activity. We performed this analysis using three methods: once using the original non-contextualized vector representations mentioned in the paper and twice using the contextualized representations extracted from T5 and BERT.

The results in Figures 11 to 19 in the appendix showed interesting differences among the three methods. The T5 and BERT models achieved significantly higher average R^2 scores than the original method. The T5-based representations achieved an average R^2 score of 0.999999999989945, while the BERT-based representations achieved an average R^2 score of 0.9999999999841246. In contrast, the original vector representations had a lower average R^2 score of 0.8029728106604146.

Furthermore, the number of significantly associated voxels varied among the three methods. The T5-based representations showed a significant association with 159,173 voxels, while the BERT-based representations showed a significant association with 30,742 voxels. In contrast, the original vector representations exhibited no significant associations with the voxels.

Considering these findings, it is evident that both the T5 and BERT models outperformed the original vector representations in capturing the relationship between the word vectors and the neural signals. Compared to the original method, the significantly higher average R^2 scores and many significantly associated voxels in the T5 and BERT models indicate their effectiveness in capturing and explaining the neural activity patterns.

The comparison between the three methods is depicted in Figures 11 to 19. Figure 11 compares the number of significantly associated voxels, indicating the effectiveness of each representation in capturing concept associations. Figure 12 compares average ranks, assessing the accuracy and consistency of rankings for the concepts. Figure 13 compares average R^2 scores, providing insights into the explained variance in the voxel data. Figure 14 compares the percentage of voxels with positive R^2 scores, indicating the ability of each representation to capture and explain underlying patterns in the data. Figures 15 to 17 show the distributions of R^2 scores for the original, T5, and BERT representations. Lastly, Figure 18 presents a boxplot comparison of the R^2 scores across the representations, while Figure 19 visualizes the relationship between R^2 scores and average ranks for each representation.

These findings contribute to interpreting and analyzing the neural encoding results obtained from the original non-contextualized T5 and BERT representations. The subsequent sections delve into further analysis and discuss the potential implications and insights derived from the neural encoding analysis.

Open-Ended Task: Uncovering Semantic Hierarchies

Introduction

This project aims to investigate and compare the uncovering of semantic hierarchies and explore the hierarchical structure of semantic representations between BERT representations and fMRI data. We aim to understand how these two distinct modalities capture and represent semantic information within the brain.

We utilized the BERT model, as determined in the previous section, as it demonstrated superior performance for our data. Through its language modeling capabilities, BERT provides a powerful framework for extracting and representing semantic information from textual data.

The project encompasses a comprehensive multi-step analytic pipeline, which includes data collection and preprocessing, exploratory data analysis, dimensionality reduction, clustering analysis, statistical analysis, and additional subcluster analysis. These steps allow us to systematically analyze the fMRI data and BERT representations, uncovering the underlying semantic structures in each modality.

Overall, this project aims to thoroughly examine the hierarchical structure of semantic representations in BERT and fMRI data, offering insights into the neural mechanisms underlying language cognition and semantic processing in different modalities.

Data Selection

We selected the EXP2 dataset for its focus on investigating the brain's interpretation of abstract notions, such as adjectives and verbs. This dataset intentionally includes terms with similar meanings to explore how the decoder model handles abstract concepts.

In contrast, EXP1 primarily studied the brain's response to specific objects like dogs or cars, which does not directly address semantic categories or levels of abstraction. EXP3 aimed to assess the decoder's generalizability across different sentence contexts but did not specifically target semantic hierarchies or abstract concepts. Considering our research objectives, the EXP2 data aligns more closely with our goals.

Dimensionality Reduction

Dimensionality reduction techniques were employed to analyze and compare the uncovering of semantic hierarchies between BERT representations and fMRI data. We applied Principal Component Analysis (PCA) to both the BERT representations and fMRI data to reduce the high-dimensional feature space to a lower-dimensional representation.

Through experimentation, we determined that using three principal components yielded the most informative representation for both BERT and fMRI data. This allowed us to capture the key semantic information while visualizing the data in a three-dimensional space.

Clustering Analysis

Following dimensionality reduction, we performed clustering analysis on the BERT representations and fMRI data separately to identify patterns and hierarchical structures within the data. Two clustering algorithms, Agglomerative Clustering, and K-means Clustering were applied.

In the case of Agglomerative Clustering, the BERT representations exhibited a silhouette score of 0.2889 for eight clusters. However, we did not observe distinct visual clusters. On the other hand, the fMRI data achieved a silhouette score of 0.3875, indicating the presence of two connected and distinct visual clusters. This suggests that the fMRI data may display more noticeable hierarchical patterns than the BERT representations.

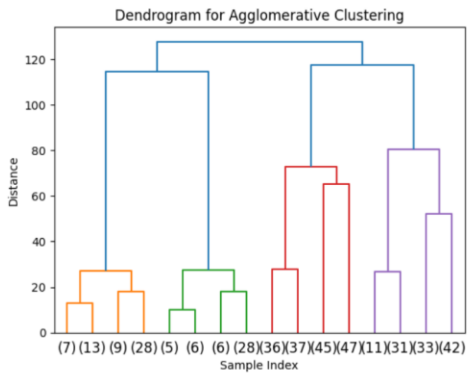

Figure 7: BERT Dendrogram for Agglomerative Clustering.

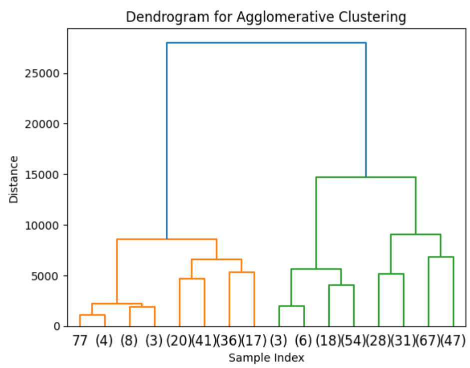

Figure 8: fMRI Dendrogram for Agglomerative Clustering.

For K-means Clustering, the BERT representations obtained a silhouette score of 0.3223 for eight connected but not distinct visual clusters. Similarly, the fMRI data yielded a silhouette score 0.3935 for two connected distinct visual clusters. These results further support that the fMRI data may exhibit clearer hierarchical structures than the BERT representations.

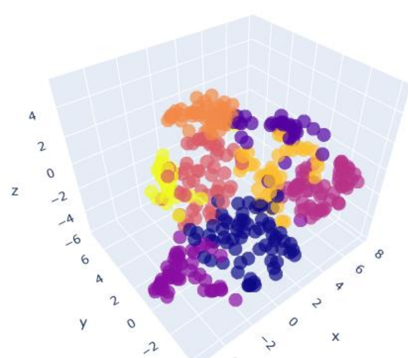

Figure 9: BERT t-SNE 3D Visualization of K-Means Clusters

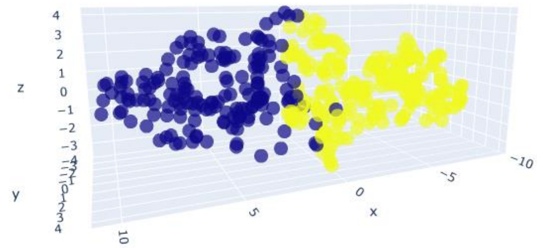

Figure 10: fMRI t-SNE 3D Visualization of K-Means Clusters

We also applied DBSCAN for clustering analysis on the BERT representations and fMRI data. Still, the outcomes were unsatisfactory, revealing only one cluster for both datasets (figures 20-21 – in the appendix), which lacked meaningful insights. This poor performance suggests that the data may exhibit characteristics more amenable to linear transformations and compact cluster structures than density-based clustering. Consequently, it implies the existence of a clear underlying hierarchical structure in the semantic representations within the brain.

Selection of Cluster Algorithm for Further Analysis

Based on the performance and visual patterns observed in the previous analysis, we have chosen to move forward with the Agglomerative Clustering algorithm for further analysis. This decision is based on its higher silhouette score for BERT representations and its potential to capture hierarchical relationships and explore semantic categories within the data. The dendrogram analysis also revealed distinct colors, indicating potential hierarchical structures with Agglomerative Clustering.

By selecting Agglomerative Clustering as our primary algorithm, we can delve deeper into uncovering semantic hierarchies and exploring the hierarchical structure of semantic representations. This algorithm will provide valuable insights into how the brain represents and processes linguistic content, particularly abstract concepts such as adjectives and verbs.

Moving forward with Agglomerative Clustering will allow us to conduct a more focused analysis, building upon the initial findings and exploring the intricate details of semantic hierarchies within the brain. We will leverage the strengths of this algorithm to gain a comprehensive understanding of the hierarchical organization of semantic representations.

Cluster Interpretation in the Context of Semantics

To understand the semantic characteristics of the clusters, we conducted semantic similarity calculations, visualization of semantic relationships, and cluster coherence analysis.

Semantic Similarity The similarity matrices for BERT representations and fMRI data revealed important insights. BERT clusters displayed larger sections in the similarity matrix with the same colors, indicating higher semantic similarity within the clusters. This suggests cohesive semantic properties among data points, as reflected by similarity scores ranging from -1 to 1 (Figure 22 – in the appendix). Similarly, fMRI data exhibited smaller sections in the matrix with the same colors, representing subsets of highly similar data points (Figure 23 – in the appendix). These findings highlight the presence of coherent semantic structures within both data representations.

Visualization of Semantic Relationships Analysis of the clusters showed interesting patterns. BERT data points formed six distinct clusters, with two clusters containing outlier nodes, indicating some variability. In contrast, fMRI data exhibited one tightly grouped cluster and another with scattered nodes along the edges, indicating varying degrees of cohesion. These observations provide insights into the structural organization of the data and highlight differences between the two representations in cluster formation and cohesion.

Cluster Coherence Analysis We performed cluster coherence analysis on BERT representations and fMRI data. Among the eight BERT clusters, Cluster 1 showed the highest within-cluster similarity (0.913), indicating strong coherence. Overall, BERT clusters demonstrated positive within-cluster similarity and negative between-cluster similarity, suggesting distinct semantic separation. The two fMRI clusters exhibited lower within-cluster similarity than BERT but still showed negative between-cluster similarity, indicating some overlap or similarity. These findings highlight BERT's superior ability to capture and organize semantic information compared to fMRI data, which showed a less distinct semantic hierarchy within the clusters.

Conclusion Our analysis provides insights into the semantic characteristics and coherence of the clusters in BERT representations and fMRI data. BERT clusters exhibited higher semantic similarity within clusters, visually represented by larger color-coded sections in the similarity matrix. BERT clusters formed six distinct groups, while fMRI data displayed one tightly grouped cluster and another with scattered nodes. Cluster coherence analysis further supported these findings, with BERT clusters showing stronger coherence than fMRI. These results suggest that BERT representations capture and represent semantic information more effectively, particularly in hierarchical organizations. This study contributes to our understanding of semantic hierarchies and the potential advantages of BERT representations in studying neural processing of semantics.

Statistical Analysis

A comprehensive analysis was conducted to establish the statistical significance of the observed semantic relationships within the clusters. The primary objective was to determine whether these patterns of semantic similarity were statistically significant, indicating a meaningful organization of semantic information in the brain's activity patterns.

Null Hypothesis: The observed mean within-cluster similarity for both BERT representations and fMRI data is not significantly different from random permutations.

This null hypothesis assumes no significant differences in the hierarchical organization of semantic representations between BERT representations and fMRI data. It suggests that the observed mean within-cluster similarity for both data types is similar to what would be expected by chance, indicating no distinct differences in uncovering semantic hierarchies.

A permutation test was employed to compare the observed mean within-cluster similarity of BERT representations and fMRI data to random permutations. The permutation test results indicated a p-value of 0.0000 for the BERT data, proving that the observed mean within-cluster similarity significantly differs from random permutations. Contrarily, the fMRI data obtained a p-value of 1.0000, suggesting that the observed mean within-cluster similarity is not significantly different from random permutations. In addition to the permutation test, a t-test was performed. The t-test resulted in a p-value of 0.0000 for the BERT data and 0.0733 for the fMRI data. These findings further support that uncovering semantic hierarchies differs between BERT representations and fMRI data.

Based on these results, BERT representations may capture more informative semantic structures in a hierarchical organization than fMRI data. This highlights the potential advantage of using BERT representations for studying semantic hierarchies in neural processing.

Further Analysis (Sub-Clustering)

A sub-clustering analysis was conducted to gain deeper insights into the semantic organization of the brain activity patterns and explore finer semantic distinctions within each cluster. This analysis aimed to uncover more nuanced relationships between subgroups of data points within the clusters.

The sub-clustering study revealed important details regarding the semantic arrangement of the clusters. Each primary cluster was subdivided, and the average similarity within each subcluster was computed. The total average similarity among the subclusters was 0.864, suggesting that the data points within each subcluster were somewhat comparable. Similarly, the main clusters had an average similarity of 0.874, indicating considerable coherence and similarity across data points inside each main cluster.

These findings shed light on the hierarchical structure and semantic relationships present within the BERT representations. The sub-clustering analysis allowed for a more detailed examination of the data, revealing finer distinctions, and providing a deeper understanding of the semantic organization within each cluster.

Limitations and Future Directions

It is important to acknowledge some limitations of this study. First, the analysis focused on a specific dataset (EXP2) and the chosen clustering algorithms. Different datasets or alternative clustering methods may yield different results. Additionally, using BERT representations and fMRI data alone may not capture the full complexity of semantic hierarchies in the brain.

Future research could explore other language models or neural network architectures to compare their ability to uncover semantic hierarchies. Incorporating other modalities, such as EEG or eye-tracking data, could provide complementary insights into the hierarchical structure of semantic representations.

Furthermore, additional analyses could investigate the relationship between the hierarchical structures identified in the BERT representations and fMRI data. Comparative studies could be conducted to determine how BERT representations align with the neural activity patterns observed in fMRI data during language processing tasks.

Conclusion

In conclusion, this project aimed to investigate and compare the uncovering of semantic hierarchies and explore the hierarchical structure of semantic representations between BERT representations and fMRI data. Through a comprehensive analytic pipeline, including dimensionality reduction, clustering analysis, statistical tests, and sub-clustering analysis, we gained insights into the organization of semantic information within each modality.

According to the findings, BERT representations exhibit significant within-cluster similarity, demonstrating the presence of semantic hierarchies. On the other hand, the fMRI data showed no significant differences from random permutations, showing that the fMRI representation lacked discrete semantic hierarchies.

It is important to remember that this study has limitations. The outcomes are based on a specific dataset and clustering algorithms, and alternative datasets or methodologies may provide different outcomes. Furthermore, BERT representations and fMRI data may need to accurately capture the true complexity of semantic hierarchies in the brain.

Overall, the project enhances our understanding of the structure of semantic representations across various modalities and sheds light on the brain processes underpinning language comprehension and semantic processing. The findings have ramifications for natural language processing, cognitive neuroscience, and artificial intelligence and pave the way for more research into semantic hierarchies.

Conclusions

This report explored various aspects of neural decoding and encoding using sentence representations, focusing on word embeddings and their relationship to the brain.

In the **structured** task, we compared the performance of different static word embeddings, Word2Vec and GloVe, in sentence decoding. Surprisingly, GloVe outperformed Word2Vec in most of the analyzed folds, contrary to our initial expectations. We also examined the similarities and differences between our analysis and Pereira et al.'s (2018) research, which aimed to develop a universal brain decoder.

In the **semi-structured** tasks, we trained decoder models on datasets from Pereira et al.'s analyses and compared different sentence representations, including original representations, BERT, and T5 models. The results indicated that the original representations and BERT consistently outperformed the T5 model regarding average rank accuracy. Additionally, we built a brain-encoder model to predict neural signals from sentence embeddings, and the results showed that both the T5 and BERT models achieved significantly higher R^2 scores than the original method.

We investigated semantic hierarchies in BERT representations and fMRI data in the **open-ended** task. We explored the hierarchical structures within each modality through a multi-step analytic pipeline, including dimensionality reduction and clustering analysis.

Overall, this report provides insights into the performance of word embeddings in sentence decoding, the effectiveness of different decoder and encoder models, and the exploration of semantic hierarchies in BERT representations and fMRI data. These findings contribute to our understanding of language processing in the brain and the potential applications of word embeddings in neural decoding and encoding tasks.

References

Pereira, F., Lou, B., Pritchett, B., Ritter, S., Gershman, S. J., Kanwisher, N., Botvinick, M., & Fedorenko, E. (2018). Toward a universal decoder of linguistic meaning from brain activation. Nature communications, 9 (1), 1–13.

Huth, A. G., De Heer, W. A., Griffiths, T. L., Theunissen, F. E., & Gallant, J. L. (2016). Natural speech reveals the semantic maps that tile human cerebral cortex. Nature, 532 (7600), 453–458.

Shrager, J., & Langley, P. (Eds.) (1990). *Computational models of scientific discovery and theory formation*. San Mateo, CA: Morgan Kaufmann.

Appendix

Semi-Structured Tasks

Brain Encoder Model for Neural Encoding Analysis

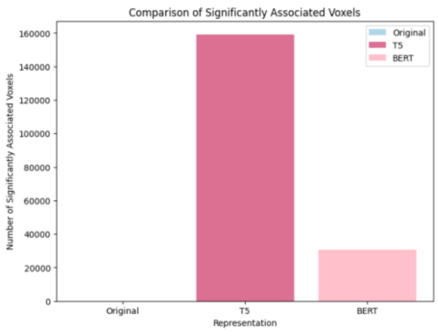

Figure 11: Word Embedding Models – Comparison of Significantly Associated Voxel.

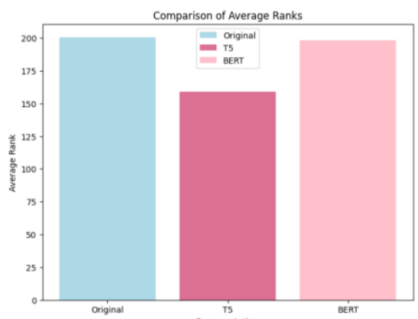

Figure 12: Word Embedding Models – Comparison of Average Ranks.

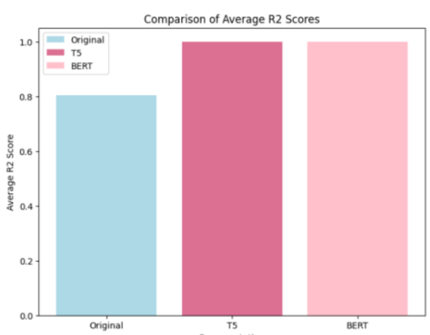

Figure 13: Word Embedding Models – Comparison of R2 Scores.

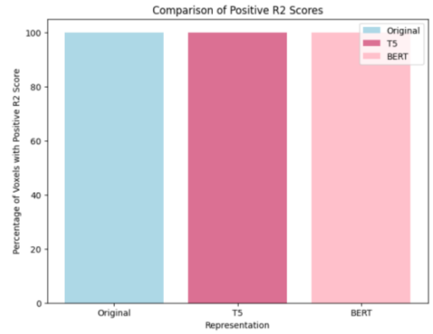

Figure 14: Word Embedding Models – Comparison of Positive R2 Scores.

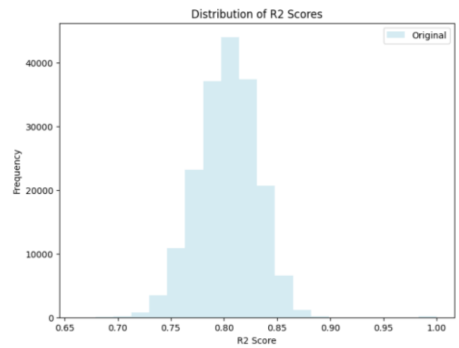

Figure 15: Original Dataset - Distribution of R2 Scores.

Figure 16: BERT - Distribution of R2 Scores.

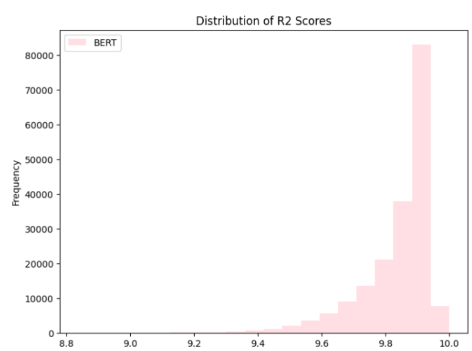

Figure 17: T5 - Distribution of R2 Scores.

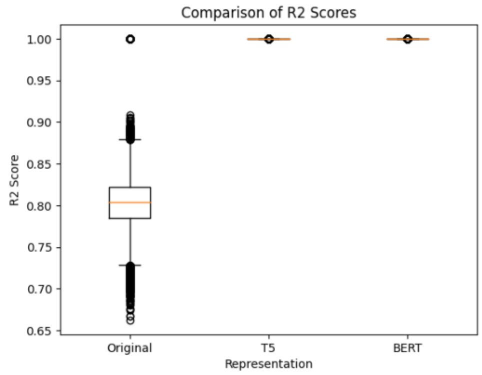

Figure 18: Word Embedding Models – Comparison of R2 Scores.

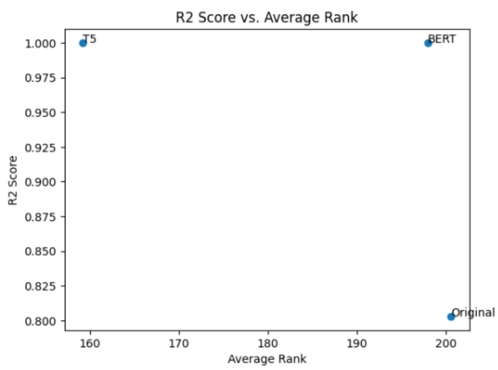

Figure 19: Word Embedding Models – Comparison of R2 Scores vs. Average Rank.

Open-Ended Task: Uncovering Semantic Hierarchies

Clustering Analysis

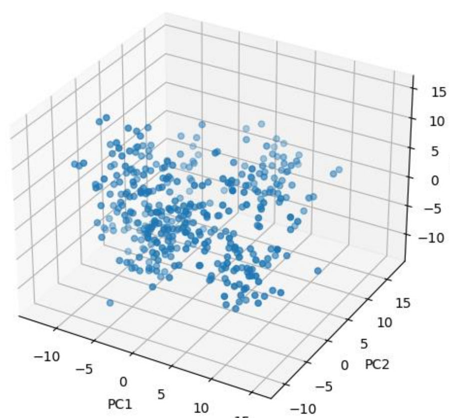

Figure 20: BERT - DBSCAN Clustering in 3D

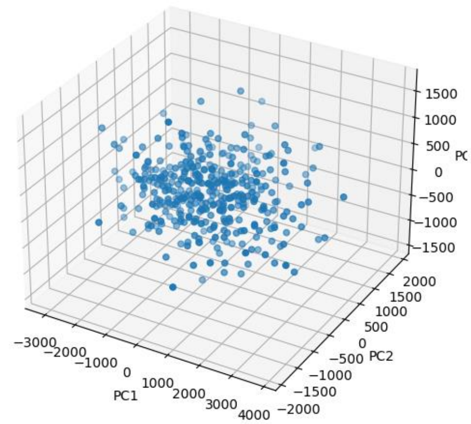

Figure 21: fMRI - DBSCAN Clustering in 3D

Cluster Interpretation in the Context of Semantics

Semantic Similarity

Semantic Similarity

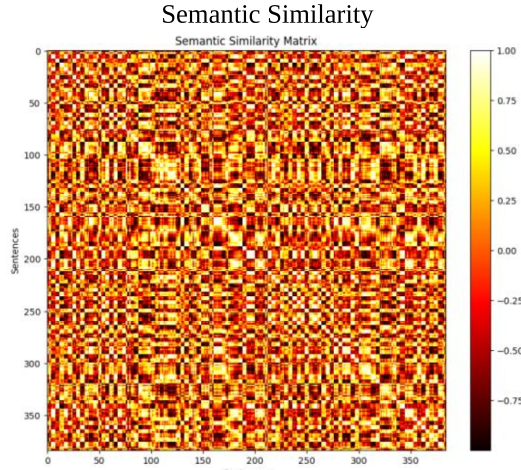

Figure 22: BERT - Semantic Similarity Matrix

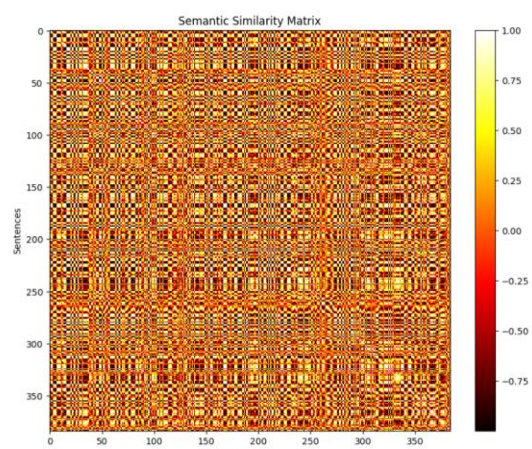

Figure 23: fMRI - Semantic Similarity Matrix