Cross-view Brain Decoding

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Abstract

How the brain captures the meaning of linguistic stimuli across multiple views is still a critical open question in neuroscience. Consider three different views of the concept apartment: (1) picture (WP) presented with the target word label, (2) sentence (S) using the target word, and (3) word cloud (WC) containing the target word along with other semantically related words. Unlike previous efforts, which focus only on single view analysis, in this paper, we study the effectiveness of brain decoding in a zero-shot cross-view learning setup. Further, we propose brain decoding in the novel context of cross-view-translation tasks like image captioning (IC), image tagging (IT), keyword extraction (KE), and sentence formation (SF). Using extensive experiments, we demonstrate that cross-view zero-shot brain decoding is practical leading to $\sim 0.68$ average pairwise accuracy across view pairs. Also, the decoded representations are sufficiently detailed to enable high accuracy for cross-view-translation tasks with following pairwise accuracy: IC (78.0), IT (83.0), KE (83.7) and SF (74.5).

Analysis of the contribution of different brain networks reveals exciting cognitive insights: (1) A high percentage of visual voxels are involved in image captioning and image tagging tasks, and a high percentage of language voxels are involved in the sentence formation and keyword extraction tasks. (2) Zero-shot accuracy of the model trained on S view and tested on WC view is better than same-view accuracy of the model trained and tested on WC view.

1 Introduction

Curiosity to know how different cortical regions play a role in understanding the meaning of concepts has driven the study of two fundamental aspects, brain decoding and encoding (Mitchell et al., 2008; Naselaris et al., 2011; Chen et al., 2014). One of the central goals of brain decoding is to build a system that can understand what a subject is thinking, seeing, perceiving by analyzing neural recordings. Thus, in the context of language, it may be beneficial to learn similarity mappings between linguistic representation and the associated brain activation, and how we compose the linguistic meaning from different stimuli such as text (Pereira et al., 2018; Wehbe et al., 2014a), images (Eickenberg et al., 2017; Beliy et al., 2019), videos (Huth et al., 2016; Nishimoto et al., 2011), or speech (Zhao et al., 2014) by analyzing the evoked brain activity. Also, decoding the functional activity of the brain has numerous applications in education and healthcare.

Recent studies have made much progress using functional magnetic resonance imaging (fMRI) brain activity to reconstruct semantic vectors corresponding to linguistic items, including words (Mitchell et al., 2008; Pereira et al., 2018), phrases, sentences, and paragraphs (Wehbe et al., 2014a). Other studies have used fMRI data to classify stimuli into different categories, e.g., classifying fMRI for the “apartment word+picture” stimuli as ‘building’ or ‘tools’ (Mitchell et al., 2008).

Unlike these studies, which focus on single-view brain decoding using traditional feature engineering, in this work, we explore cross-view decoding, propose cross-view translation tasks, and investigate the application of Transformer models (Vaswani et al., 2017). Most of the previous studies have used the dataset from (Pereira et al., 2018) which follows a star schema (concept at the center and specific views like word+picture, sentence, and word cloud around it). To enable cross-view translation tasks, it was critical to build direct pairwise-view relationships (picture-sentence, picture-word cloud and sentence-word cloud). Hence, we augment the dataset in Pereira et al. (2018) with such manually labeled pairwise-view relationships.

Despite the significant progress in learning the representations of linguistic items obtained by de-
coding the fMRI brain activity, there are still many open questions that need to be addressed in mapping the language stimuli and associated brain activation, such as (1) Zero-shot decoding setup: How accurately would a model, trained to decode a concept using a view, perform when inferred using another view? (2) Cross-view translation tasks: Given an fMRI activation corresponding to a view of the linguistic stimuli, how accurately can we decode its another related view? (3) Brain network contributions: What are the different brain regions that are activated in response to different views? Which parts of the brain are involved in cross-view translation tasks like image captioning, image tagging, keyword extraction, and sentence formation?

The fMRI brain activity can be decoded to a semantic vector representation of a view (word, sentence, word cloud) using a ridge-regression decoder, as explored in several previous studies (Pereira et al., 2018; Sun et al., 2019). To train this decoder model, earlier works focused on hand-crafted features (Mitchell et al., 2008; Wehbe et al., 2014a), which suffer from these drawbacks: (1) cannot address word sense disambiguation, (2) limited in terms of vocabulary, (3) inability to extract signals for abstract stimuli, and (4) inability to capture the context and sequential aspects of a sentence. Recently, many studies have shown accurate results in mapping the brain activity using neural distributed word embeddings for linguistic stimuli (Anderson et al., 2017; Pereira et al., 2018; Oota et al., 2018; Nishida and Nishimoto, 2018; Sun et al., 2019). To represent meaning, these studies use either word or sentence level embeddings extracted from the models trained on large corpora. Unfortunately, none of these address the open questions around zero-shot cross-view decoding and cross-view translation as discussed above. Recently, Transformer-based models have been explored for brain encoding (Hollenstein et al., 2019), which inspires us to harness Transformer-based models like BERT (Devlin et al., 2019) for our brain decoding tasks.

Our extensive experiments lead us to the following key insights: (1) Training on sentence-view leads to surprisingly improved accuracy for zero-shot word-cloud inference. (2) Although zero-shot inference for word+pictures and sentence views is not as good as inference on view-specific trained models, a universal decoder trained across all views provides comparable inference accuracy for each of the views. (3) High pairwise accuracies of 78.0, 83.0, 83.7, and 74.5 for image captioning, image tagging, keyword extraction, and sentence formation, respectively, enable us to conclude that cross-view translation tasks using fMRI data are practically feasible.

Our main contributions are as follows. (1) We propose multiple cross-view brain decoding tasks like zero-shot cross-view decoding and cross-view translation. (2) We build decoder models using Transformer-based methods and analyze brain network contributions across single-view as well as our proposed cross-view tasks. (3) We augment the popular Pereira et al. (2018)’s dataset with pairwise-view relationships and use it to demonstrate the efficacy of our proposed methods.

2 Related Work

Advances in functional neuroimaging tools such as fMRI have made it easier to study the relationship between language/visual stimuli and functions of brain networks (Constable et al., 2004; Thirion et al., 2006; Fedorenko et al., 2010). 2.1 Brain Decoding

The earlier brain decoding experiments studied the recovery of simple concrete nouns and verbs from fMRI brain activity (Mitchell et al., 2008; Palatucci et al., 2009; Nishimoto et al., 2011; Pereira et al., 2011) where the subject watches either a picture or a word. Unlike the earlier work, Wehbe et al. (2014a); Huth et al. (2016) built a model to decode the text passages instead of individual words. However, these studies used either simple or constrained sets of stimuli, which poses a question of generalization of these models. Recently, Pereira et al. (2018) explicitly decoded both words and sentences when subjects were shown both concrete and abstract stimuli. Affolter et al. (2020) reconstructed the sentences along with categorizing words or predicting the semantic vector representation from fMRI brain activity. Schwartz et al. (2019); Wang et al. (2020a) focused on understanding how multiple tasks activate associated regions in the brain.

With the success of deep learning based word representations, multiple researchers have used distributed word embeddings for brain decoding models in place of carefully hand-crafted feature vectors (Huth et al., 2016; Pereira et al., 2018; Oota et al., 2018; Wang et al., 2020b). Using the distributed sentence representations, Wehbe et al.
Sun et al. (2019) demonstrated that neural sentence representations are better for decoding whole sentences from brain activity patterns. In this paper, we re-analyze multiple results from (Pereira et al., 2018; Sun et al., 2019) to demonstrate how different brain networks are associated with each task using the GloVe word embeddings (Pennington et al., 2014) and representations obtained from BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019). None of the previous studies leverage fMRI data for multiple views to understand different brain network activation and do not explicitly investigate the cross-view decoding or cross-view translation tasks.

2.2 Language Models and the Brain

Recently, the success of contextual and Transformer-based language models has raised the question of whether these models might be able to make an association between brain activation and language. Beinborn et al. (2019) showed the success of the ELMo language model (Peters et al., 2018) in predicting the fMRI brain activation of several datasets. Also, Gauthier and Levy (2019); Toneva and Wehbe (2019) tried to decode the fMRI activations to improve the latent representations of language stimuli using BERT (Devlin et al., 2019). In contrast to earlier works, Affolter et al. (2020) described the language generation with GPT-2 using brain activities. We take inspiration from these pieces of work and experiment with both GloVe as well as BERT for various cross-view brain decoding tasks.

3 Methodology

3.1 Brain Imaging Dataset

We experiment with the popular dataset from (Pereira et al., 2018). It is obtained from 11 subjects (P01, M01, M02, M04, M07, M09, M10, M13, M15, M16, M17) where each subject read 180 concept words (abstract + concrete) in three different paradigms or views while functional magnetic resonance images (fMRI) were acquired. These contain 128 nouns, 22 verbs, 29 adjectives and adverbs, and 1 function word. In paradigm-1, participants were shown concept word along with picture with an aim to observing brain activation when participants retrieved relevant meaning using visual information. In paradigm-2, the concept word presented in a sentence allows us to probe activity in the language areas associated with contextual information and meaning of a sentence. In paradigm-3, the concept word was presented in a word cloud format, surrounded by five semantically similar words. These paradigms provide brain representation of 180 concepts in three different views.

For each of the 180 concepts, the dataset contains five pictures, six sentences each containing the concept word, and a word cloud. However, the dataset follows a star schema (concept at the center and specific views like word+picture, sentence, and word cloud around it). To enable cross-view translation tasks, it was critical to build direct pairwise-view relationships (picture-sentence, picture-word cloud, sentence-word cloud, and word cloud-sentence). In other words, it was necessary to have captions and tags for image-view, keywords for sentence-view, and 3-4 sentences corresponding to wordcloud-view, and hence we manually labeled these and added them to Pereira et al. (2018)’s dataset. Fig. 2 shows the input and output examples for the four cross-view translation tasks. We make the augmented dataset publicly available.

![Figure 1: An Example of Cross-View Zero-shot Concept Decoding, trained on WP-view examples, and tested on “Apartment” WC-view instance. Target is GloVe/BERT representation of “Apartment” concept word.](image)
Word+Picture fMRI
Image tags
GloVe/BERT

Cross-View IC Decoder
A colorful bird sitting on a tree branch.
(A) Image Captioning (IC)

Cross-View IT Decoder
Bird, Colorful, Branch, Sitting, Red, Tree
(B) Image Tagging (IT)

Cross-View SF Decoder
A flock of red birds resting in their nest.
(C) Sentence Formation (SF)

Cross-View KE Decoder
Bird, Snow, Ground, Red, Sitting, Small
(D) Keyword Extraction (KE)

Table 1: CV Translation Task Definitions

| Task               | Input                  | Output          |
|--------------------|------------------------|-----------------|
| Image captioning   | Word+Picture fMRI      | Caption         |
| Image tagging      | Word+Picture fMRI      | Image tags      |
| Keyword extraction | Sentence fMRI          | Keywords        |
| Sentence formation | Word-cloud fMRI        | Sentence        |

Figure 2: Cross-View Translation Task Input, output examples from Pereira et al. (2018)’s dataset.

differ across experiments. We follow K-fold cross-validation, in which all the data samples from K-1 folds were used for training, and the model was tested on samples of the left-out fold. We use GloVe or BERT embeddings for output semantic representations. We also experimented with RoBERTa embeddings, but the results were very similar to BERT, and hence we omit them for lack of space. For BERT, we use the BERT-pooled output for obtaining embeddings. For GloVe, we use bag-of-words averaged embedding.

Cross-View Zero-shot Concept Decoding

For each subject in the dataset, for each of the three input views, we trained 18 models (one for each fold) where each model is trained on the brain activity of 170 concepts and tested on left-out 10 concepts to predict vector representation (GloVe or BERT) of the concept word. The 5000 informative voxels were selected for 170 concepts in each fold, and the same voxel locations were chosen for test datasets. At test time, the input to each model can belong to any of the three views. Thus, for each subject, for each fold, we perform (1) three same-view train-test experiments and (2) six cross-view zero-shot train-test experiments with different input views at train and test time. Target is always fixed as a vector representation of the concept word. Fig. 1 shows an example. We use pairwise accuracy to report results.

Cross-view translation tasks

For each subject in the dataset, we learn model for the following cross-view translation tasks using 18 fold cross-validation. The input and output for each of these tasks is shown in Table 1. Fig. 2 shows an example for each task. As before, we use 5000 informative voxels, computed separately for each of the 11 participants and each of the four tasks. Regression target is semantic vector representation (GloVe or BERT).

3.3 Informative Voxel Selection

Inspired by the voxel selection method in (Pereira et al., 2018), we chose the informative voxels for our linear regression models as follows. The regression models are trained on each voxel and its 26 neighboring voxels to predict the semantic vector representation. For each voxel in the training part, the mean correlation was calculated between “true” (text-derived) and predicted representations, and the voxels corresponding to the top 5000 mean correlation values were selected as informative voxels. Target semantic representations are word embeddings for cross-view zero-shot concept decoding and ‘word or sentence or word-cloud’ embedding for cross-view translation experiments. Voxel selection provides meaningful cognitive insights across brain networks.

3.4 Model Architecture

We trained a ridge regression based decoding model to predict the semantic vector representation associated with the fMRI informative voxels for a type (view) of each language stimulus. Each dimension is predicted using a separate ridge regression model. Formally, we are given the informative voxel matrix $X \in \mathbb{R}^{N \times V}$ and stimuli vector representation $Y \in \mathbb{R}^{N \times D}$, where $N$ denotes the number of training examples, $V$ denotes the number of informative voxels (we fix it to 5000), and $D$ denotes the embedding dimension of language stimuli. The ridge regression objective function is $f(X_i) = \min_{W} \|Y_o - X_i W_o\|^2_F + \lambda \|W_o\|^2_F$ where, $X_i$ denotes the input voxels for view $i$ (out of {concept+picture, concept+sentence, concept+wordcloud}), $Y_o$ denotes the matrix with embeddings $o$ (out of {word, sentence, word cloud}),
$W_{io}$ denotes the learned weight coefficients for each input view $i$ and output embedding $o$, $\|\cdot\|_F$ denotes the Frobenius norm, and $\lambda > 0$ is a tunable hyper-parameter representing the regularization weight. Besides ridge regression, of course, various other models could be used. However, the goal of this paper is to analyze basic cross-view decoding using the most popular decoding model in neuro-science literature, namely, ridge regression

**Hyper-parameter Setting:** We used sklearn’s ridge-regression with default parameters, 18-fold cross-validation, Stochastic-Average-Gradient Descent Optimizer, Huggingface for BERT, MSE loss function and L2-decay ($\lambda$:1.0). We used WordPiece tokenizer for the Bert-base-uncased model and Spacy-tokenizer for the GloVe model.

### 3.5 Evaluation Metrics

**Pairwise Accuracy** To measure the pairwise accuracy, the first step is to predict all the test stimulus vector representations using a trained decoder model. Let $S = [S_0, S_1, \ldots, S_n], \hat{S} = [\hat{S}_0, \hat{S}_1, \ldots, \hat{S}_n]$ denote the “true” (text-derived) and predicted stimulus representations for $n$ test instances resp. Given a pair $(i, j)$ such that $0 \leq i, j \leq n$, score is 1 if $corr(S_i, \hat{S}_i) + corr(S_j, \hat{S}_j) > corr(S_i, \hat{S}_j) + corr(S_j, \hat{S}_i)$, else 0. Here, $corr$ denotes the Pearson correlation. Final pairwise matching accuracy per participant is the average of scores across all pairs of test instances.

**Rank Accuracy** We compared each decoded vector to all the “true” text-derived semantic vectors and ranked them by their correlation. The classification performance reflects the rank $r$ of the text-derived vector for the correct word: $1 - \frac{r - 1}{\#\text{instances} - 1}$. The final accuracy value for each participant is the average rank accuracy across all instances.

### 3.6 Brain Networks Selection

Inspired by Pereira et al. (2018) and based on the resting-state functional networks, we focused on four brain networks: Default Mode Network (DMN) (linked to the functionality of semantic processing) (Buckner et al., 2008; Binder et al., 2009), Language Network (related to language processing, understanding, word meaning, and sentence comprehension) (Fedorenko et al., 2011), Task Positive Network (related to attention, salience information) (Binder et al., 2009; Duncan, 2010; Power et al., 2011), and Visual Network (related to the processing of visual objects, object recognition) (Buckner et al., 2008; Power et al., 2011). We report the distribution of 5000 informative voxels across the four brain networks across various experiments in the Results Section. Across all participants, voxel distribution across networks is as follows: 4670 (Language), 6490 (DMN), 11630 (TP), and 8170 (Visual). Note that the reported distributions in Section 4 do not add up to 1 because the contribution of the remaining brain networks is not considered.

### 4 Results and Cognitive Insights

Since we are the first to propose cross-view tasks (decoding as well as translation), unfortunately, there are no baselines to compare with. For same-view experiments using GloVe, our results are in line with those reported in (Pereira et al., 2018). In this section, we present an extensive analysis of our results.

#### 4.1 Cross-View Zero-shot Concept Decoding

Table 2 shows averaged (across subjects) pairwise and rank accuracy results for models trained on word+picture (WP), sentence (S) and word-cloud (WC) views and tested on each of the three views. Figs. 3, 4 and 5 show detailed results for models trained on WP, S and WC views resp. Specifically, Fig. 3 shows results when we infer using voxels corresponding to each of the three views. Ground-truth is GloVe (G) or BERT (B) embedding vector. Thus, (WP, B, R) means input view=WP (Word+picture), embedding=BERT, and metric=Rank (R) accuracy. Table 3 shows distribution of informative voxels across the four brain networks. In this figure, (WP, G, D) means input view=WP (Word+picture), embedding=GloVe, and brain network=DMN (D). Fig. 6 shows the spatial distribution of informative voxels (plotted using nilearn Python library) across models trained on different forms of stimuli (WP, S and WC). The value of each voxel is the fraction of 11 participants for whom that voxel was among the 5000 most informative. Fig. 10 in the Appendix shows distribution of informative voxels across the four brain networks.

**Train on WP view:** We make the following observations from Fig. 3 and Tables 2 and 3: (1) For test
Figure 3: Model trained on Word+Pictures view. Cross-View Concept Decoding Pairwise (PW) and Rank (R) accuracy when tested on Word+Picture (WP)/Sentence (S)/Word-cloud (WC) views using GloVe (G) and BERT (B). Each colored dot represents a subject. The bar plot shows averages.

We make the following observations from Fig. 4 and Tables 2 and 3: (1) For zero-shot test on WP view, wrt pairwise accuracy, GloVe model (0.74) is better than BERT (0.72) (one-sample t-test, 0.05 significance level, p=0.024). (2) For the test on S or WC views, BERT shows better zero-shot performance than GloVe across both metrics. This can be explained by analyzing the brain network distribution differences as follows. (3) We observe that BERT captures a higher percentage of language informative voxels (18%) and DMN voxels (16%) compared to GloVe (12%, 13%), demonstrating the better language understanding with transformer based representations. This result has p=0.003 for language voxels and p=0.021 for DMN using a t-test with 0.05 significance. (4) When the model is trained on WP view (unlike other views), for both embeddings, most informative voxels (about 53%) lie in the visual brain network, which is expected. Also, the location of these voxels was consistent across participants (as illustrated in Fig. 6).

Table 3: Distribution of informative voxels among four brain networks: DMN (D), Visual (V), Language (L), Task Positive (T). Embeddings: GloVe (G), BERT (B). Input views: Word+Picture (WP), Sentence (S), Word-Cloud (WC)

| Embeddings | WP | S | WC |
|------------|----|---|----|
|            |    |   |    |
|            |    |   |    |

Figure 4: Model trained on Sentences view. Cross-View Concept Decoding Pairwise (PW) and Rank (R) accuracy when tested on Word+Picture (WP)/Sentence (S)/Word-cloud (WC) views using GloVe (G) and BERT (B) embeddings. Each colored dot represents a subject. The bar plot shows averages.

Train on S view: We make the following observations from Fig. 4 and Tables 2 and 3: (1) BERT performs better than GloVe. Results are not significant with p=0.401 for test on WC view. Zero-shot results for test on WP and S views are significant with p=0.002, 0.014 using t-test, and 0.05 significance level. (2) The supremacy of BERT can...
be explained by observing that BERT captures a higher percentage of informative voxels from the DMN (14%), Language (19%), and Visual (16%) networks when compared to GloVe (DMN - 11.5%, Language - 12%, Visual - 11.5%) when trained on WC view.

**Table 4**: For each pair of views and each brain network, we show coverage ratios (second task on first/first task on second) of the voxels.

| Network  | WP-S | WC-S | WP-WC |
|----------|------|------|-------|
| DMN      | 0.24/0.17 | 0.23/0.16 | 0.14/0.16 |
| Visual   | 0.11/0.29 | 0.28/0.20 | 0.08/0.25 |
| Language | 0.25/0.25 | 0.22/0.26 | 0.15/0.20 |
| Task Positive | 0.09/0.05 | 0.09/0.07 | 0.06/0.03 |

**Overlapping Voxels**: Given the distribution of informative voxels across four brain networks, we further examine how these voxels from one view overlap with those from another view for the BERT model. Table 4 shows that (1) In the WC-S pair, the language network has very high overlap compared to other brain networks. (2) 29% (and 25%) of visual voxels for S (and WC) view are shared with visual voxels of WP view. This makes sense since a large percentage of informative voxels for WP view are from the visual network.

### 4.2 Cross-View Translation

Fig. 7 (and Table 6 in the Appendix) illustrate pairwise and rank accuracy for Image Captioning (IC), Image Tagging (IT), Sentence Formation (SF) and Keyword Extraction (KE) using GloVe (G) and BERT (B) embeddings. Further, Fig. 8 shows the distribution of informative voxels among four brain networks across all four tasks. Finally, Fig. 9 shows the spatial distribution of informative voxels (plotted using nilearn Python library) across models trained on different translation tasks. The value of each voxel is the fraction of 11 participants for whom that voxel was among the 5000 most informative.

We observe that (1) For all the four tasks, pairwise accuracy is ~75%, and rank-based accuracy is ~70% (except for sentence formation), which shows that cross-view translation is possible with good accuracy. (2) As expected, a high percentage of visual voxels are involved in image captioning and image tagging tasks, and a high percentage of language voxels are involved in the sentence formation and keyword extraction tasks. (3) Image captioning involves relatively higher language voxels compared to image tagging. This could be because generating a caption involves a higher level of language (sequence) skills than generating a set of keywords. (4) The brain maps (see Fig. 9) corre-
Figure 9: Brain Maps for Cross-View Translation Tasks (plotted using nilearn Python library).

Table 5: For each pair of cross-view translation tasks and each brain network, we show coverage ratios (second task on first/first task on second) of the voxels. IC = Image Captioning, IT = Image Tagging, SF = Sentence Formation, KE = Keyword Extraction.

5 Conclusion

We studied brain decoding in the context of cross-view tasks – zero-shot concept decoding and cross-view translation. We studied four cross-view translation tasks: image captioning, image tagging, sentence formation, and keyword extraction. We show that cross-view translation is feasible with good accuracy. Brain network distribution analysis reveals insights about the importance of various parts of the brain for each of these tasks.

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Table 6 illustrates pairwise and rank accuracy for Image Captioning (IC), Image Tagging (IT), Sentence Formation (SF) and Keyword Extraction (KE) using GloVe (G) and BERT (B) embeddings.

|          | GloVe (PW) | GloVe (R) | BERT (PW) | BERT (R) |
|----------|------------|-----------|-----------|----------|
| IC       | 0.789      | 0.696     | 0.799     | 0.672    |
| IT       | 0.830      | 0.685     | 0.820     | 0.656    |
| SF       | 0.745      | 0.615     | 0.717     | 0.622    |
| KE       | 0.837      | 0.715     | 0.805     | 0.711    |

A Cross-View Translation

B Cross-View Zero-shot Concept Decoding

Fig. 10 shows distribution of informative voxels across the four brain networks. In this figure, (WP, G, D) means input view=WP (Word+picture), embedding=GloVe and brain network=DMN (D). The figure clearly shows that a lot of informative voxels belong to the visual brain region for the WP view for both GloVe as well as BERT embeddings. Also, for sentence view, a large percentage of informative voxels are from the language region.
Figure 10: Distribution of informative voxels among four brain networks: DMN (D), Visual (V), Language (L), Task Positive (T). Embeddings: GloVe (G), BERT (B). Input views: Word+Picture (WP), Sentence (S), Word-Cloud (WC)