Portfolio

Contents

1 Homeworks

1.1 Homework 1

Please read the book chapter on "Analysis of Functional MRI Data" (see Materials), and answer shortly to the following questions:

1. What are the approximate spatial and temporal resolutions of fMRI data?
   Spatial resolution is typically between 3 and 4 mm, but can vary depending on the magnet used. Temporal resolution depends on BOLD response which has width of around 3s and peaks at around 5-6s, resulting in blurry temporal information.

2. What is the difference between a block and an event-related design?
   Block-related design consists of several trials that are then clustered into blocks each containing the trials of the same condition. Event-related design the trials are not clustered, and are instead presented in a random sequence with sufficient time gaps between the trials in order to separate successive responses.

3. What is the aim of general linear modeling (GLM) of fMRI data?
   GLM aims to fit a model to the time course of each voxel independently. In order to achieve this the fMRI data is processed voxel-wise.

1.2 Homework 2

Please read the review Imaging retinotopic maps in the human brain by Wandell and Winawer, and answer the following questions:

1. What is a cortical visual field map?
   Cortical visual field map is a map of the brain that shows boundaries between visual areas in the visual cortex.

2. How do you measure a visual field map in the human brain?
   Early methods depended on lesions and defects in the visual system (e.g. subjects with homonymous field defect). However, improvements were made and methods based on stimuli creating traveling waves of activity in primary visual cortex were developed allowing us to identify visual field maps.

3. What is functional specialization?
   Functional specialization is a characteristic of the visual cortex where distinct regions are responsible for different functions, e.g. ventral visual stream processes vision for perception, whereas dorsal stream processes visual information for the purpose of executing actions.

1.3 Homework 3

Please read the book chapter Tutorial on Pattern Classification in Functional Imaging by Mur and Kriegeskorte (see Materials), and answer the following questions:

1. What is pattern-information analysis (also called multi-voxel pattern analysis, MVPA)?
   Pattern information analysis is a type of analysis that looks into ROIs (regions of interest) and considers their patterns of activity. This is contrary to conventional methods that take the overall activation of a region into account.

2. What is novel about pattern-information analysis compared to standard (univariate) fMRI analysis?
   Pattern information analysis aims to reveal the representational content by leveraging the fine-grained patterns of activity present in each of the functional regions. This approach also ensures that the high-resolution imagery provided by fMRI is used efficiently.

3. In practice, how would you perform pattern-information analysis on fMRI data?
   Pattern information analysis can be performed through a series of steps. fMRI data first needs to be split (e.g. into a training and test sets) and preprocessed. After that, the subject activity patterns are estimated and voxel regions to be included in analysis are selected. This is then used to train and test the classifier.

1.4 Homework 4

Please read the review Representational geometry: integrating cognition, computation, and the brain by Kriegeskorte and Kievit (see Materials), and answer the following questions:

1. What is representational similarity analysis (RSA)?
   RSA (representational similarity analysis) involves comparisons of representational geometries between regions of brain, stimulus descriptions conceptual and computational models, and behavioral reflections of similarity. It is applicable to either functional imaging data such as fMRI, EEG, MEG, etc. but also neuronal recording data.

2. What is a representational dissimilarity matrix (RDM)?
   RDM (representational dissimilarity matrix) is a matrix constructed by computing the distance between brain-activity patterns within representational space. They also allow us to easily compare different representations by simply computing correlation coefficients between RDMs.

3. Give an example of a research question that could be addressed using RSA. This can be some of the examples given in the paper or you could think of a research question of your own.
   Perhaps this type of analysis could be used to get understanding of how exactly the brain performs mental rotation. Coming from a computer science background, I think that understanding of these mechanisms could further allow us to upgrade artificial neural networks used in deep learning for various purposes.

1.5 Homework 5

Please read the review Encoding and decoding in fMRI by Naselaris et al (see Materials), and answer the following questions:

1. What are the differences between decoding and encoding models?
   Encoding models use stimuli to predict activity of the brain, while decoding uses activity to predict information about stimuli.

2. What are the main advantages of using an encoding model?
   The main advantage of encoding models is the fact that they can easily be compared to one another. Besides that, they're explainable and interpretable. Moreover, encoding models are better than decoding models when it comes to determining which set of features is preferentially represented within an ROI.

3. What might be the reasons why decoding models are much more common in fMRI than encoding models?
   Perhaps because it is much easier to present the subject with stimuli, take measurements, then infer information about the stimuli themselves. Rather than predicting the brain activity based solely on a stimulus, as this would require really good understanding of the brain. Besides that, decoding models have some advantages over encoding models. They can be used to assess whether the activity in an ROI is related to behavioral performance. Encoding models, unlike decoding, are also capable of providing a complete functional description of an ROI.

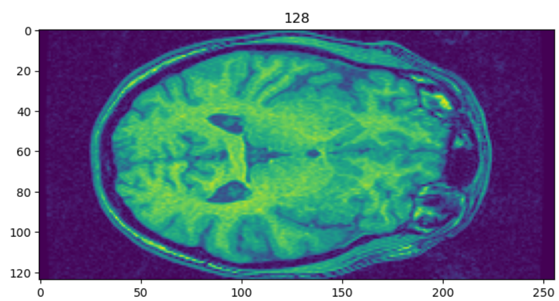
2 Project Work

2.1 Introduction

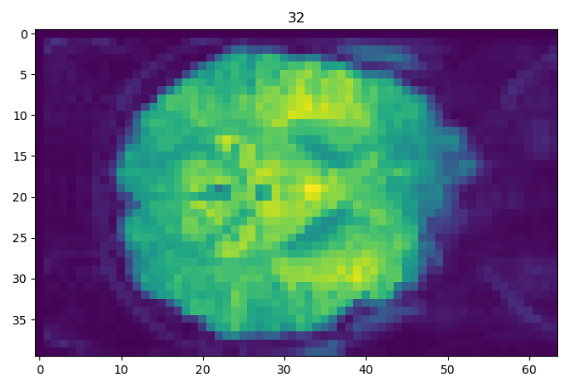
Goal of this project work is to perform various analysis of fMRI data, including GLM model fitting, ROI (region of interest) analysis, classification analysis as well as RSA (representational similarity analysis). These are some of the key methods used for analyzing fMRI data for purposes of mapping various functionalities in the brain, but also decoding or encoding and modelling of the brain.

2.2 Data

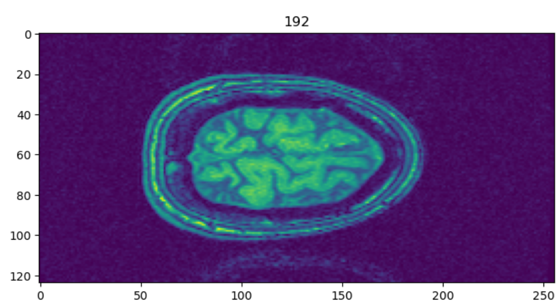
The dataset we are going to analyze contains fMRI data from multiple subjects, but for the purpose of the project we will be focusing on the data from Subject 1. Anatomic imagery of the brain coupled with their BOLD fMRI scans can be seen in Figure 1. Besides that, we are also able to visualize signal captured in a single voxel, e.g. at a position $(20, 25, 60)$ as shown in Figure 2.



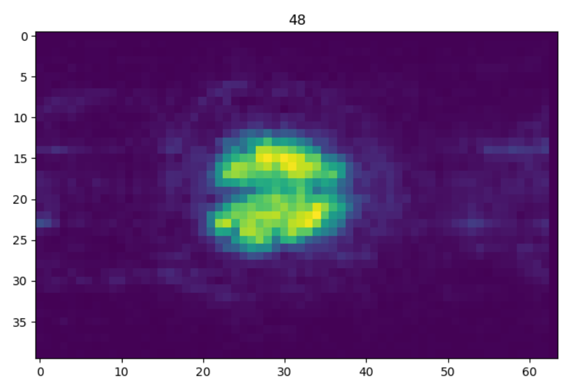
(a) Anatomic image of slice 128 along z axis.



(b) BOLD fMRI image of slice 32 along z axis.



(c) Anatomic image of slice 192 along z axis.



(d) BOLD fMRI image of slice 32 along z axis.

Figure 1: Anatomic images and corresponding BOLD fMRI recordings at the same positions.

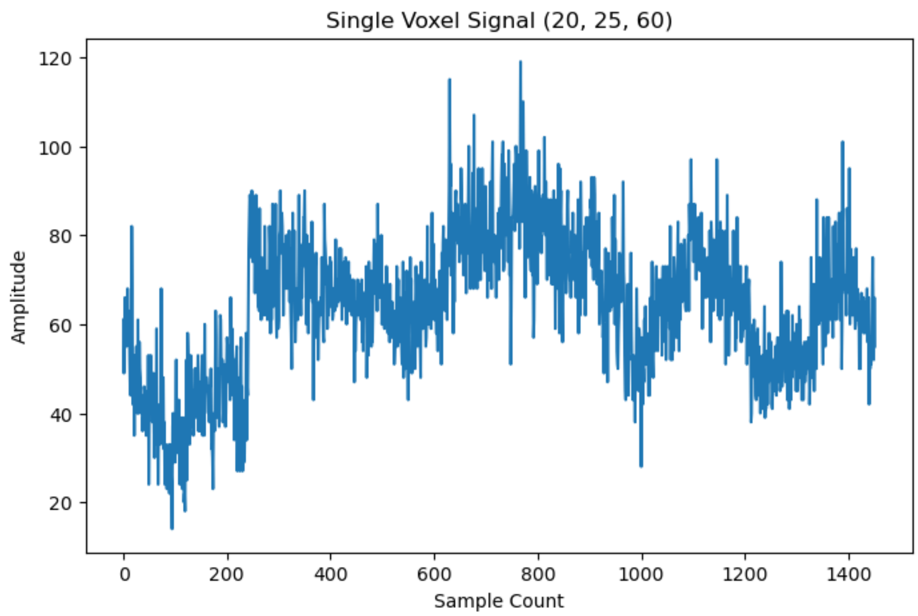


Figure 2: Signals captured at a single voxel position (20, 25, 60) across all timestamps.

2.3 HRF & GLM

In order to fit the GLM (Generalized Linear Model) to our data, we need to obtain the design matrices first. We do so by using the data containing time intervals and order of each stimulus that was presented to the subject. Thereafter, we convolve the matrix with the HRF (Figure 3) to obtain the final design matrix used for fitting the model.

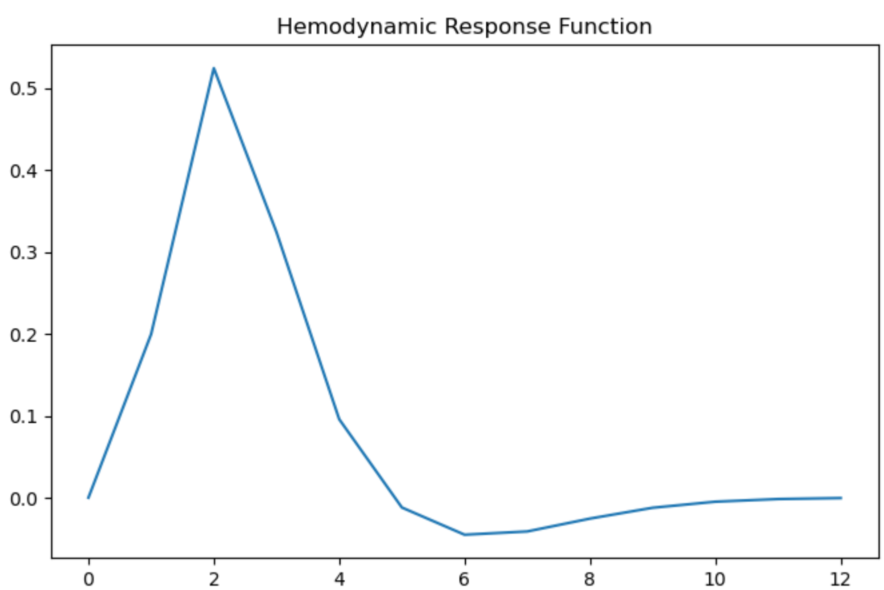
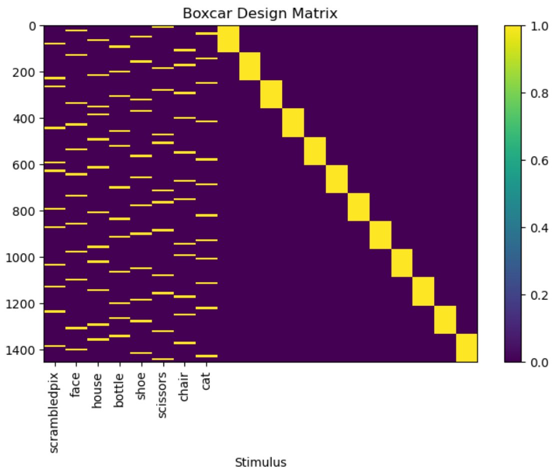


Figure 3: Hemodynamic response function.

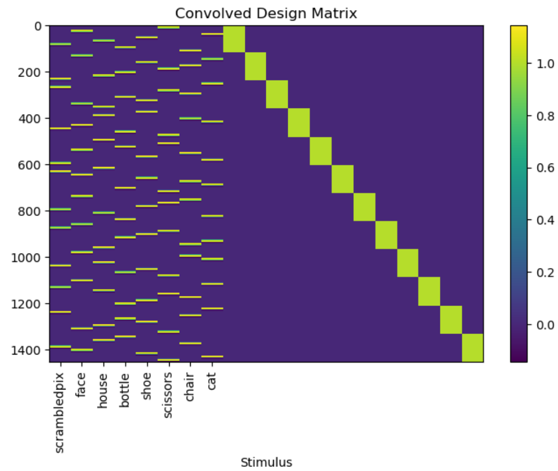
Both matrices can be seen in Figure 4. This allows us to compute t-statistics which we can use to visualize activity at different voxel positions. The t-statistic is computed using the following formula:

$$t = \frac{c^T \hat{\beta}}{\sqrt{\hat{\sigma}^2 c^T (X^T X)^{-1} c}}$$

where X is the design matrix, c is a one-hot vector indicating stimulus position, $\hat{\sigma}$ is the standard deviation of the residual and $\hat{\beta}$ are the linear coefficients.



(a) Base design matrix.



(b) Base design matrix convolved with HRF.

Figure 4: Original and convolved design matrices.

Having fitted the model to the data, we can visualize T-maps. This can be seen in Figure 5 for slice 27 of our data.

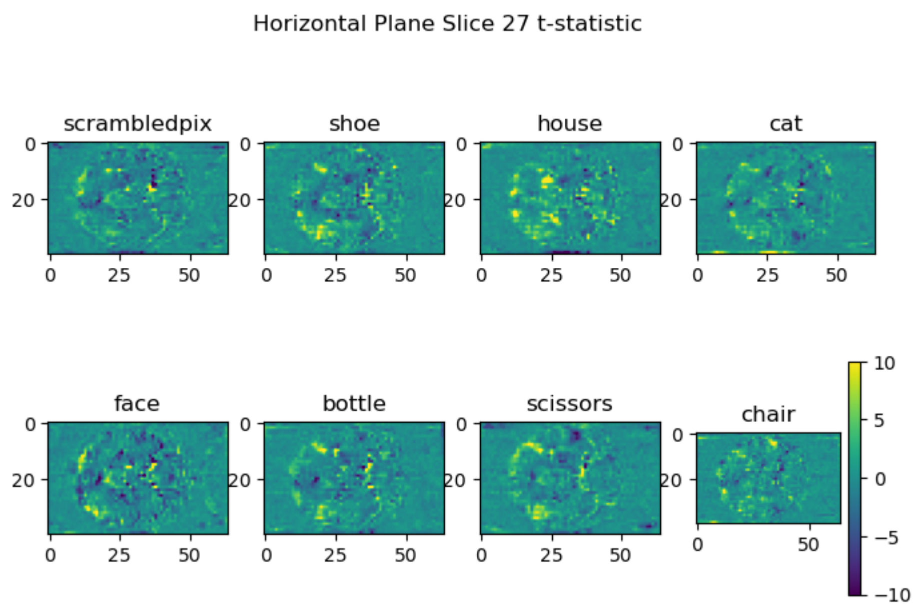
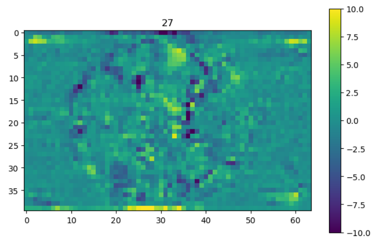


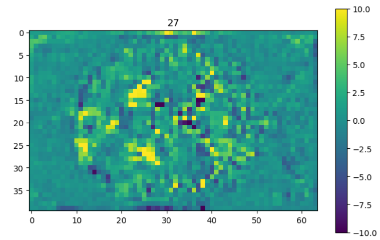
Figure 5: T-map for 27th slice of the horizontal plane.

2.4 Stimulus Contrasting

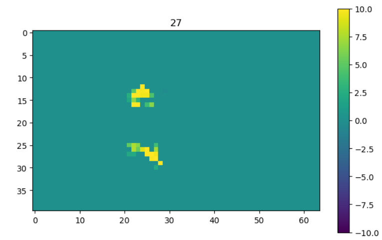
In order to analyze stimulus contrasting we can fit a GLM model same as before, but instead of c being one-hot vector, we put -1 and 1 in the positions of stimuli that we want to contrast. We can see the results in Figure 6a and Figure 6b. Moreover, we are able to apply ROI (region of interest) masking to the contrasted data as shown in Figure 6c.



(a) Scissors and cat stimuli responses contrasted.



(b) Face and house stimuli responses contrasted.



(c) Face and house stimuli contrasts masked using house mask.

Figure 6: Visualization of stimulus contrasting.

2.5 ROI (Region of Interest) Analysis

To get a better insight on how response strength varies depending on the stimulus and particular ROI, we can average the signal and overlay it over stimulus onset times as shown in Figure 7. We can see that for that particular ROI the response to the house stimulus is clearly the strongest. Moreover, if we average t-map values we can see how the response strength changes depending whether the ROI mask is applied or not as shown in Figure 8. It is once again visible that the response for house is the strongest for that particular ROI.

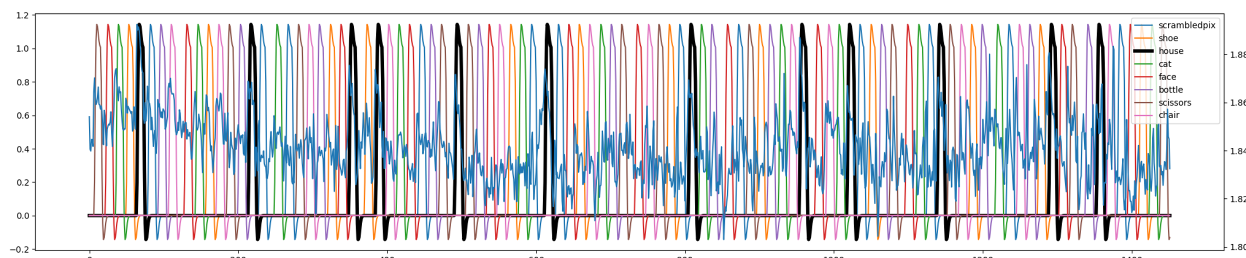
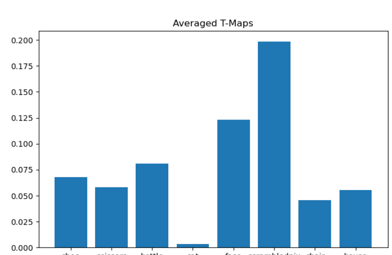
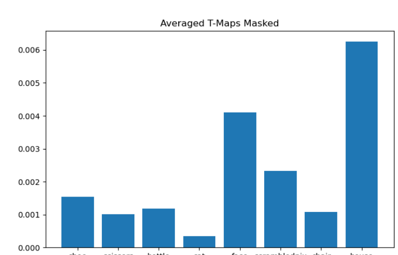


Figure 7: Averaged house ROI signal overlayed with stimulus onset times.



(a) T-maps averaged.



(b) Masked t-maps averaged.

Figure 8: Bar plots of averaged t-maps.

2.6 Classification Analysis

For classification analysis we will applying pattern-correlation classifier. First, we split the data as well as design matrices into train and test sets - for this purpose we will be splitting the data into even and odd runs. Thereafter, we fit the GLM model to train and test data for every possible stimulus combination and compute correlation between masked t-maps (we use the ventral temporal mask). To compute the correlations we use Pearson correlation coefficient given by the following formula:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}.$$

We obtain the correlation matrix shown in Figure 9. (**NB** only positive coefficients are shown as absolute value was taken at the end of processing.)

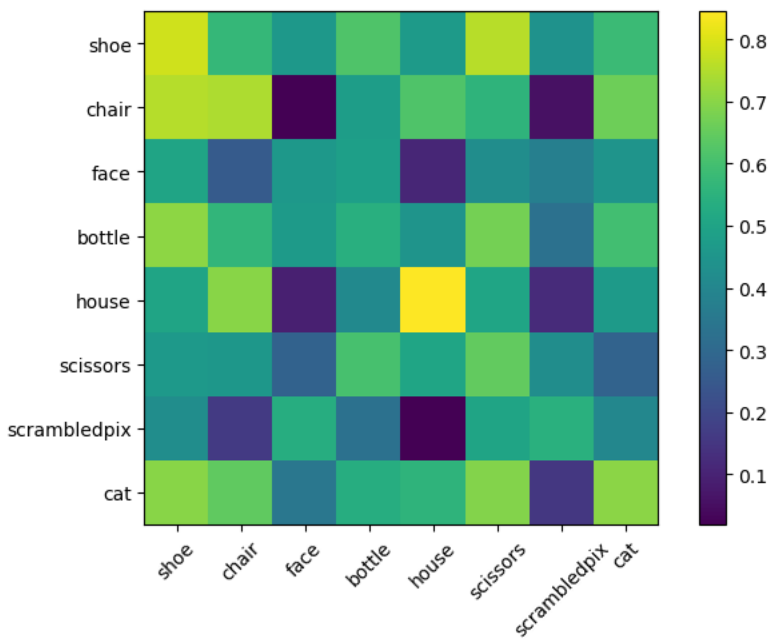


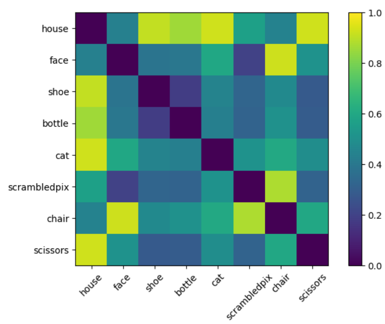
Figure 9: Correlation coefficients computed on masked t-maps between stimuli categories.

In Figure 10 we show the above correlation matrix in form of bar plots for easier and more accurate legibility. We can see that the correlations are the highest for stimuli within the same category. Moreover, we can also see that the correlation for response on "house" stimulus is especially high and strongly correlated. This indicates that objects from the same stimulus group cause similar brain activity, indicating that their representations in the brain are potentially similar.

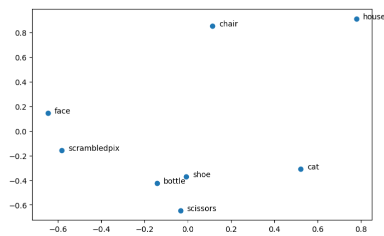
Figure 10: Correlations for each of the stimuli in form of a bar plot.

2.7 RSA (Representational Similarity Analysis)

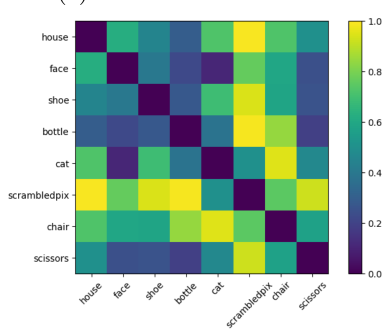
To perform RSA we need to compute RDM (Representational Dissimilarity Matrix). We will be focusing on between-mask RDMs and between-subject RDMs. Dissimilarity can be computed by subtracting correlation from 1. Once again, we want to compare t-maps obtained from all combinations of stimuli - either using different masks (e.g. face mask against house mask) or different subject data. Results of comparisons are shown in Figure 11.



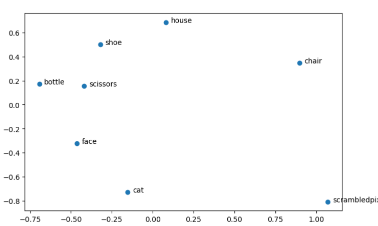
(a) RDM for house mask.



(b) Multidimensionally scaled representation.



(c) RDM for face mask.



(d) Multidimensionally scaled representation.

Figure 11: RSA performed on two different masks for Subject 1.

From the obtained data we can see that RDMs are relatively similar and consistent across different masks for the same subject.

2.8 vRF (Voxel Receptive Field) Modelling

vRF modelling would involve usage of encoding models. Therefore, instead of trying to tell stimuli from fMRI data, like we did so far, it would be needed to create an encoding model that would be able to predict brain activity, i.e. voxel BOLD levels based on stimuli. To make use of Haxby data, this would require fitting a linearized encoding model to training data where inputs would be images and outputs would be voxel activity predictions. For this purpose, we could also make use of more complex, nonlinear models such as deep neural networks. It is worth noting that vRF modelling requires significant amounts of data - therefore making Haxby dataset potentially not suitable as the amount of data would not be sufficient for our model to generalize well.

2.9 Conclusion

Through this project work we have shown how to perform analysis of fMRI data by applying different techniques, such as GLM fitting, stimulus contrasting, ROI analysis, classification analysis as well as RSA. All of these techniques are powerful tools for drawing conclusions about the fMRI data and performing various types of analysis such as mapping functionalities to different brain areas or decoding brain activity and extracting information. Information about the source code and the implementation can be down below.

2.10 Source Code and Implementation Details

Analysis was performed using Python in combination with NiBabel, SciPy, NumPy, scikit-learn and matplotlib. For the source code and implementation details please refer to: https://github.com/bronemos/mapping-decoding-modelling-human-brain/blob/main/project-work.ipynb.