Analyzing similarities in category specific patterns of brain responses with Haxby dataset

Cognitive Science and AI: Assignment 2

February 22, 2024

1 Instructions for submission

Maximum marks - 100

Deadline: 25th Feb 2024

- You may do the assignment in Jupyter or Colab notebook or a script that executes the code.
- A report should be submitted that includes all the deliverables. Report and code should be included in a folder specified by Roll Number and Name of the student and submitted in Moodle, adhering to the deadline.
- Include the assignment number, your name and roll number in the notebook/script as well for better identity.
- Late submissions are NOT accepted.
- IMPORTANT: Make sure that the assignment that you submit is your own work. Do not copy any part from any source including your friends, seniors. Any breach of this rule could result in serious actions including an F grade in the course.
- Your marks will depend on the correctness / convincing discussion points. In addition, due consideration will be given to the clarity and details of your answers and the legibility and structure of your code.
- Do not copy or plagiarise, if you're caught for plagiarism or copying, penalties are much higher (including an F grade in the course) than simply omitting that question.

2 Objectives

This assignment is based on the experimental categories designed in (Haxby et al. 2001). The list of available categories is: faces, houses, cats, shoes, scissors, chairs, and bottles. The objective is to analyze similarities within and between four different categories and discuss the emerging patterns of similarity/dissimilarity with Pearson correlation and Representational Similarity Analysis (RSA) (Kriegeskorte, Mur, and Bandettini 2008).

The assignment outcome is focused on:

1. Visualizing mean response patterns for each category overlaid (visualized) on the brain (anatomical image). For instance, as in Figure 1.
2. Compute mean correlations within- and between-category to observe similarities and distinctiveness across categories. For instance, refer to the table that displays mean correlations in Figure 2, taken from (Haxby et al. 2001).
3. Representational Similarity Analysis using any one of the distance measures such as cosine, euclidean or any other similar measures of your choice (please indicate why you chose this and its definition, for clarity).

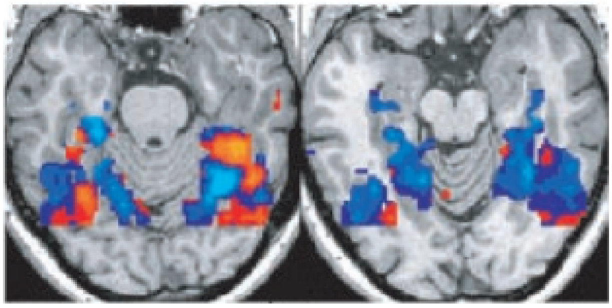

Figure 1: Mean patterns of response related to face category. Picture courtesy: Figure 3. from Haxby et al. (2001) Science paper

Region: all object-selective ventral temporal cortex

Mean correlations (± SE)

	Faces	Houses	Cats	Bottles	Scissors	Shoes	Chairs	Scrambled
Faces	0.74 ± 0.02	-0.41 ± 0.08	0.31 ± 0.04	-0.12 ± 0.06	-0.03 ± 0.1	-0.25 ± 0.06	-0.38 ± 0.1	-0.19 ± 0.05
Houses	-0.39 ± 0.05	0.81 ± 0.05	-0.28 ± 0.06	-0.24 ± 0.04	-0.27 ± 0.11	-0.21 ± 0.07	0 ± 0.09	0.07 ± 0.1
Cats	0.4 ± 0.06	-0.42 ± 0.1	0.47 ± 0.07	-0.11 ± 0.06	-0.05 ± 0.08	-0.03 ± 0.05	-0.15 ± 0.06	-0.32 ± 0.08
Bottles	-0.16 ± 0.11	-0.33 ± 0.08	-0.26 ± 0.05	0.28 ± 0.1	-0.05 ± 0.07	0.16 ± 0.03	-0.14 ± 0.07	-0.13 ± 0.06
Scissors	-0.07 ± 0.08	-0.39 ± 0.07	0.03 ± 0.08	0.11 ± 0.06	0.31 ± 0.1	0.18 ± 0.07	-0.09 ± 0.1	-0.29 ± 0.05
Shoes	-0.16 ± 0.06	-0.24 ± 0.06	-0.22 ± 0.05	0.24 ± 0.08	-0.04 ± 0.13	0.43 ± 0.1	-0.19 ± 0.11	-0.28 ± 0.06
Chairs	-0.47 ± 0.09	0.11 ± 0.05	-0.18 ± 0.08	-0.26 ± 0.08	0.11 ± 0.14	-0.13 ± 0.1	0.4 ± 0.06	0.14 ± 0.07
Scr	-0.33 ± 0.08	0.1 ± 0.09	-0.45 ± 0.05	0.02 ± 0.1	-0.37 ± 0.05	-0.13 ± 0.07	-0.08 ± 0.07	0.6 ± 0.05

Figure 2: Mean correlations obtained on the patterns of response within and across categories. Table courtesy: Mean correlations table from Online Supplementary Material Haxby et al. (2001) Science paper

3 Haxby Dataset

The analysis should be done on fMRI timeseries voxels considering only the ventral temporal (VT) mask (in other words patterns of BOLD responses within VT area). ~~This is already provided in Assignment 1~~. Please see Appendix A to extract data from fMRI image.

NOTE: Given data should be normalized to a mean of zero in each voxel across categories by subtracting the mean response across all categories before implementing the tasks. In your report, please indicate clearly how you accomplish this.

4 Tasks

The brain response patterns of similarity/dissimilarity need to be compared for both within- and between-categories: **A)** faces and houses and **B)** "X" and "Y". "X" and "Y" are specified based on the group you are allocated to. For example, it could be chairs and shoes or cats and scissors, etc.

After data is normalized, restrict the analysis to four different categories. On the four assigned categories **A)** and **B)**, the analysis should cover the visualization of mean responses, Mean correlation table, and RSA similarity/dissimilarity map. In all the cases, you must include and discuss your observations, insights, and comments on the results.

5 Deliverables

A brief report and code should be submitted. More weightage in marks will be given for convincing discussion for each figure. Code can be submitted as a separate script or notebook that generate the figures included in the report.

References

Haxby, James V. et al. (2001). "Distributed and Overlapping Representations of Faces and Objects in Ventral Temporal Cortex." In: Science 293.5539, pp. 2425–2430.

Kriegeskorte, Nikolaus, Marieke Mur, and Peter Bandettini (2008). "Representational similarity analysis - connecting the branches of systems neuroscience." In: Frontiers in Systems Neuroscience 2.

A Tutorial

```python
from nilearn.datasets import fetch_haxby
data_files = fetch_haxby(subjects=[2]) # Here subject 2 is fetched, you should replace with your
func_filenames = data_files.func[0]

# Load behavioral data
import pandas as pd

behavioral = pd.read_csv(data_files.session_target[0], sep=" ")
mask = behavioral['labels'].isin(['rest'])
behavioral = behavioral[~mask]

from nilearn.image import index_img

fmri_img = index_img(func_filenames, ~mask)

from nilearn.maskers import NiftiMasker

masker = NiftiMasker(mask_img=data_files['mask_vt'][0])
fmri_data = masker.fit_transform(fmri_img)

# Restrict fmri data of all categories to specific category, follow below:
# First, mask behavioral target to face
face_category = behavioral['labels'].isin(['face'])
# Then, use this mask to restrict to face fMRI responses
face_fmri_data = fmri_data[face_category]

# Remove grand mean or global mean computed across all categories removing 'rest'

mean_removed_face_fmri = face_fmri_data - grand_mean

# Invert the mean removed fmri data to fmri image

inverted_mean_removed_face_fmri_img = masker.inverse_transform(mean_removed_face_fmri)

# Visualize
from nilearn import plotting

plotting.plot_stat_map(inverted_mean_removed_face_fmri_img)

# 2 Compute correlations

# Use numpy corrcoef to compute correlation or scipy.stats.linregress
# to get correlation and standard error

# 3 RSA
# sklearn.metrics.pairwise_distances can be used
```

Figure 3: Snapshot of code demonstrated in Tutorial.