CSAI

Assignment-2

Report

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Calculating Grand mean and normalising data

I calculate the mean value of each voxel across the 4 categories (face, house, cat, and bottle) and then subtracted this mean from the the fMRI data I got for these 4 categories, so as to make their mean value 0.

```
col_means = np.mean(fmri_data[behavioural['labels'].isin(['face','house','cat','bottle'])], axis=0) # grand mean
grand_mean=col_means
face_mask=behavioural['labels'].isin(['face'])
house_mask=behavioural['labels'].isin(['house'])
cats_mask=behavioural['labels'].isin(['cat'])
bottles_mask=behavioural['labels'].isin(['bottle'])
face_data=fmri_data[face_mask]
mean_removed_face_fmri=face_data-col_means
mean_face_data = np.mean(mean_removed_face_fmri, axis=0)
house_data=fmri_data[house_mask]
mean_removed_house_fmri=house_data-col_means
mean_house_data = np.mean(mean_removed_house_fmri, axis=0)
cat_data=fmri_data[cats_mask]
mean_removed_cat_fmri=cat_data-col_means
mean_cat_data = np.mean(mean_removed_cat_fmri, axis=0)
bottle_data=fmri_data[bottles_mask]
mean_removed_bottle_fmri=bottle_data-col_means
mean_bottle_data = np.mean(mean_removed_bottle_fmri, axis=0)
```

Calculating Mean Response

After normalising, I have calculated the mean response for each of the 4 categories separately, as shown in the above code snippet.

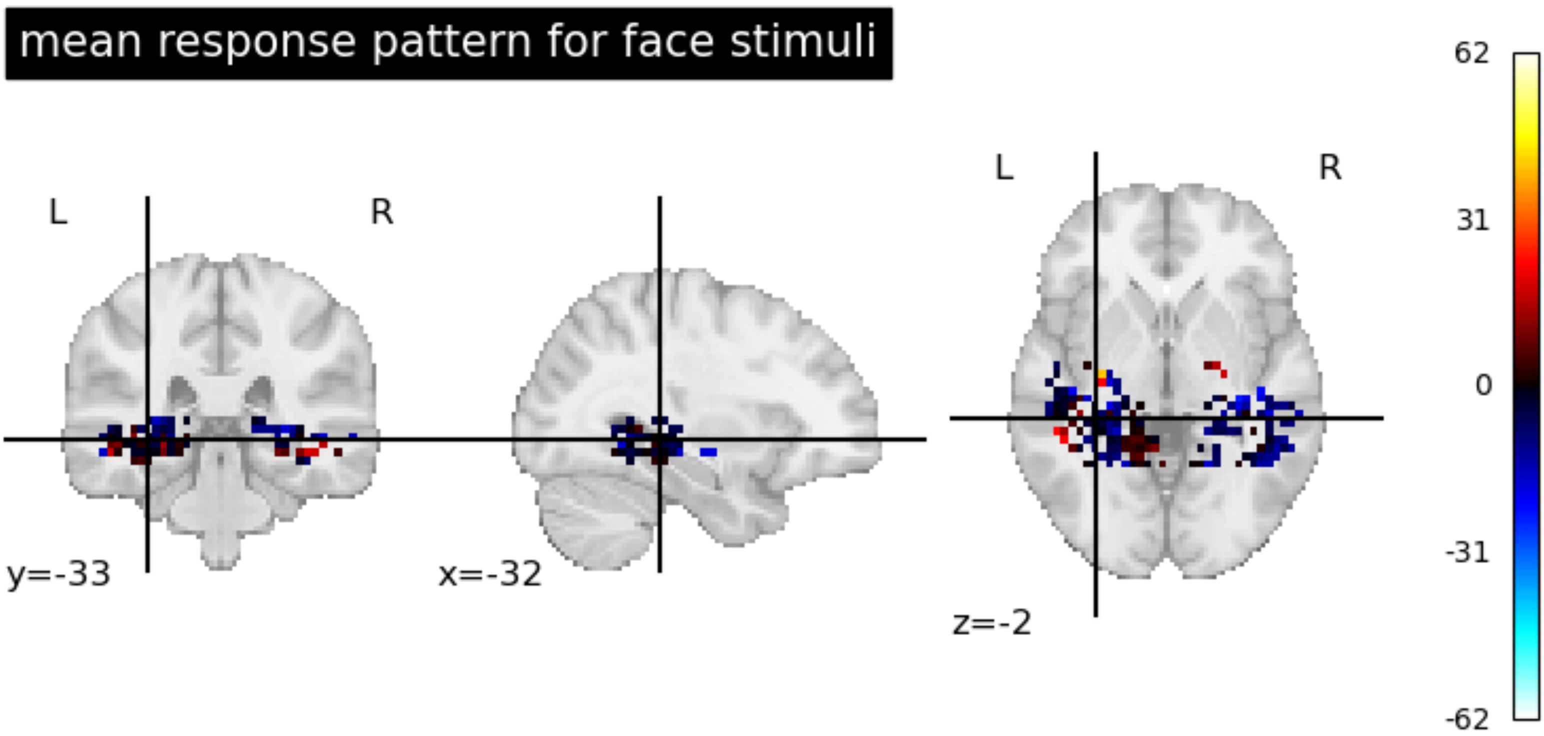
Plotting mean response patterns for each category overlaid (visualised) on the brain (anatomical image)

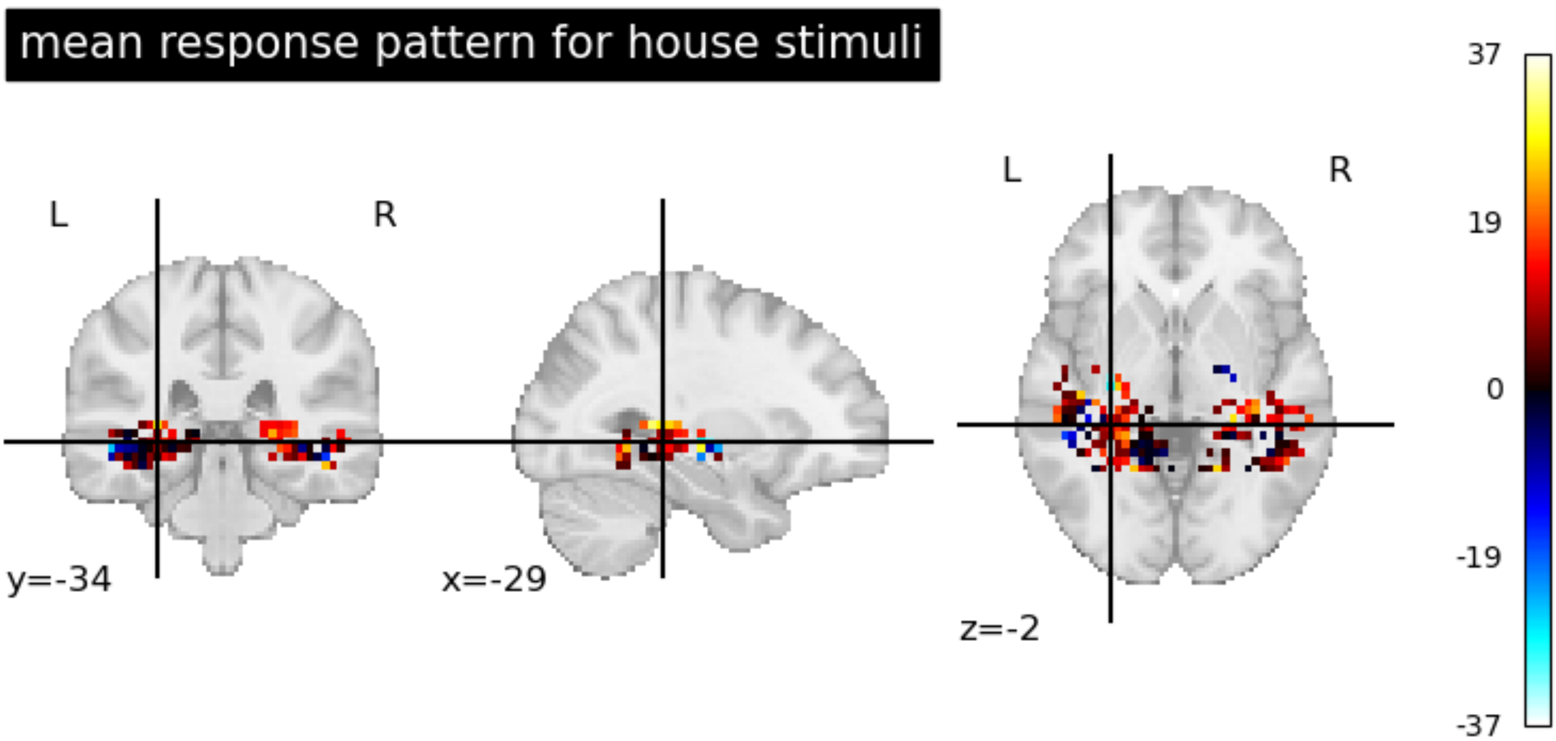
Using the inverse_transform method of NiftiMasker, I get the inverse mean response images for all 4 categories and then plot them using the plotting.plot_stat_map function.

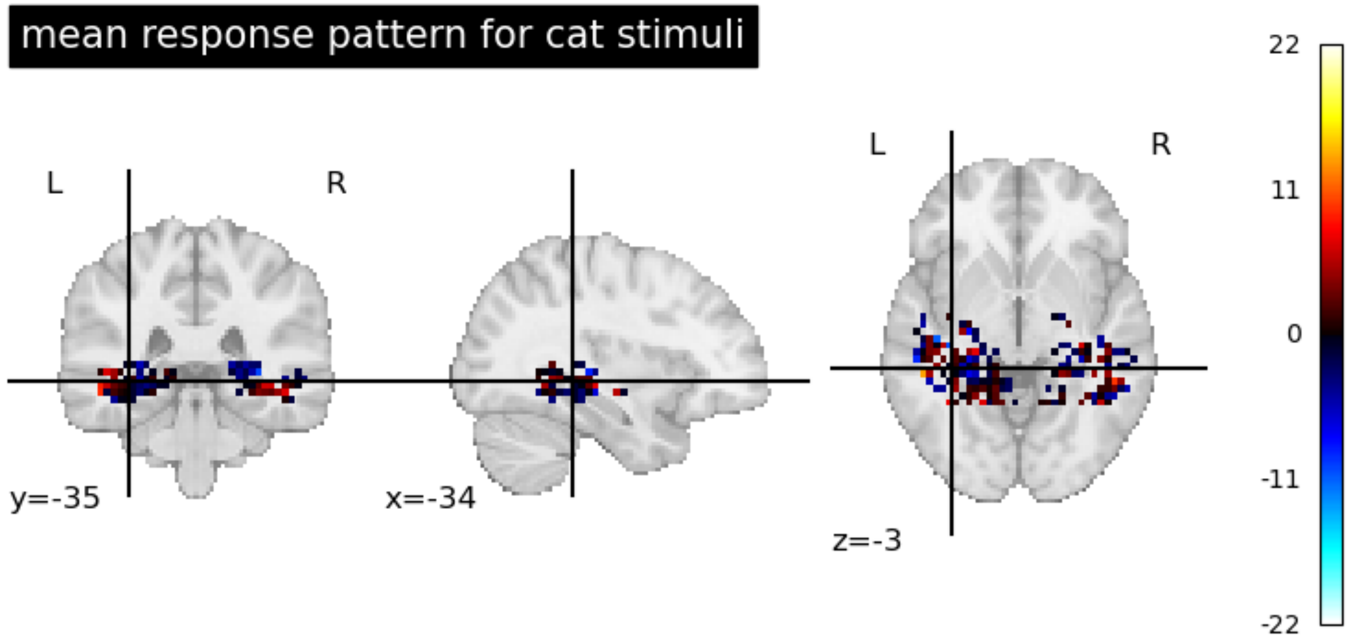
```
inverted_mean_response_face_img=masker.inverse_transform(mean_face_data)
plotting.plot_stat_map(inverted_mean_response_face_img,title='mean response pattern for face stimuli')
inverted_mean_response_house_img=masker.inverse_transform(mean_house_data)
plotting.plot_stat_map(inverted_mean_response_house_img,title='mean response pattern for house stimuli')
inverted_mean_response_cat_img=masker.inverse_transform(mean_cat_data)
plotting.plot_stat_map(inverted_mean_response_cat_img,title='mean response pattern for cat stimuli')
inverted_mean_response_bottle_img=masker.inverse_transform(mean_bottle_data)
plotting.plot_stat_map(inverted_mean_response_bottle_img,title='mean response pattern for bottle stimuli')
plotting.show()
```

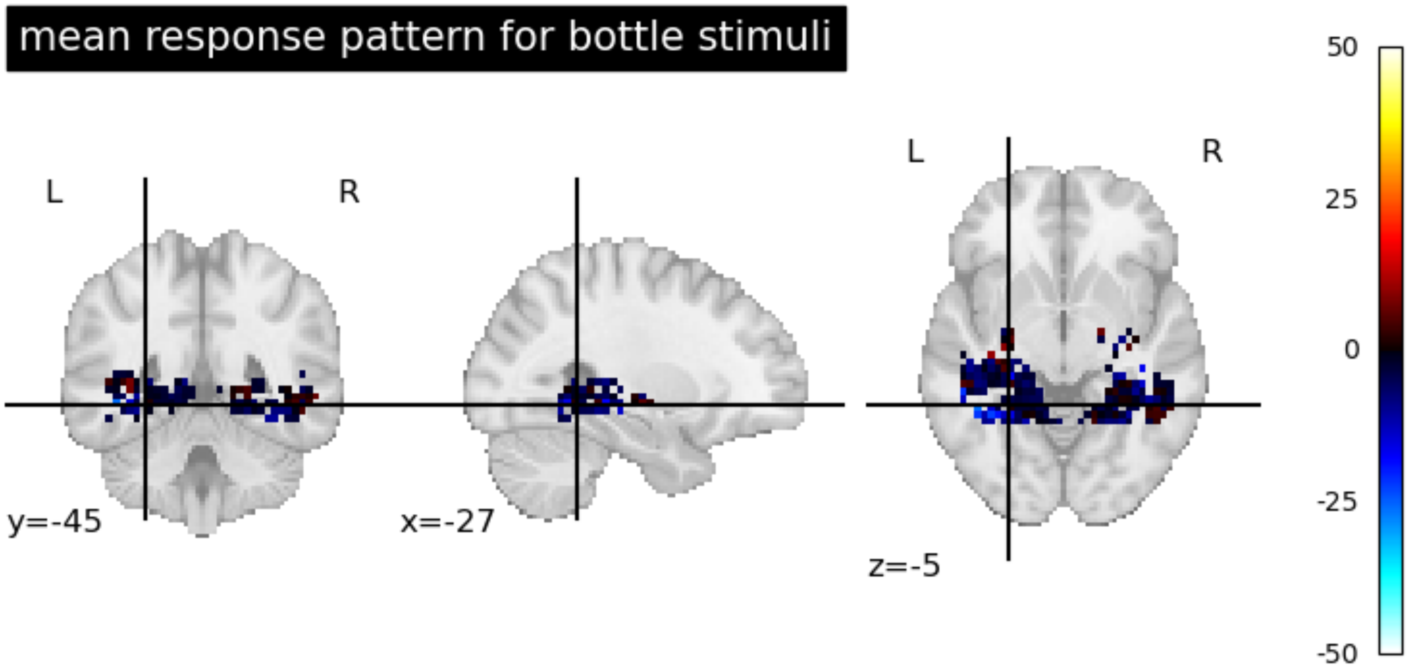
Subject-4, X-Cats, Y-Bottles

Visualising mean response patterns for each category overlaid (visualised) on the brain (anatomical image)









Observations

We are analysing the plot of the activations in the Ventral Temporal region of the brain.

Face: Most of the region is blue/black which means decreased activation of voxels. This decrease is relative to the other conditions.

House: We see increased activations in the plot, shown by red and yellow parts. This increase is relative to others.

Cat: Resembles the plot for face, decreased (relative) activations in voxels (blue).

Bottle: Blue and black patches, showing decreased activations or deactivations in the region, relative to others.

Overall, the most distinct one is for house, with high activations.

Mean correlations within and between categories (with standard error)

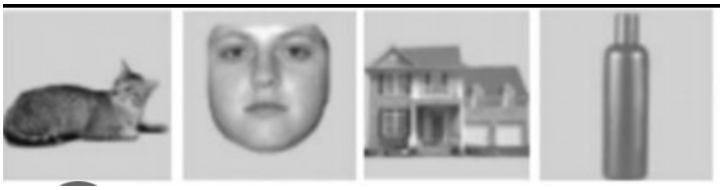
	face	house	cat	bottle
face	0.95+-0.01	-0.77+-0.03	0.34+-0.02	-0.40+-0.02
house	-0.80+-0.02	0.95+-0.01	-0.52+-0.01	-0.11+-0.02
cat	0.15+-0.09	-0.41+-0.09	0.69+-0.03	-0.14+-0.06
bottle	-0.23+-0.06	-0.28+-0.07	-0.22+-0.03	0.83+-0.02

The fMRI data can be divided based on odd and even runs for all categories. So, we have face, house, cat and bottle data for even runs vertically (across rows) and for odd runs horizontally (across columns). So, within a category, we find correlation using data for odd and even runs. Between categories, we find correlation values for odd vs even and even vs odd runs. That is why the matrix is not symmetric and the diagonal elements are not 1.

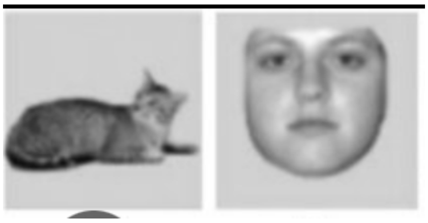
Observations

High within-category correlation for face and house but low for cat and bottle: Within-category correlations were higher for stimuli that were more easily distinguishable or had more distinctive features.
Faces and houses are generally considered to have more distinctive features compared to cats and bottles. Faces have unique configurations of features such as eyes, nose, and mouth, which our brains are highly attuned to recognising. Similarly, houses often have clear structural features such as windows, doors, and roofs that differentiate them from other objects. These distinctive features likely lead to higher within-category correlations because the brain's processing regions involved in recognising faces or houses are more consistently activated by stimuli within the same category.
On the other hand, cats and bottles might be less distinctive or have fewer unique features that the brain can reliably use for categorisation. Cats may vary greatly in appearance (different breeds, colours, sizes) making it harder for the

brain to find consistent patterns across different cat images. Similarly, bottles could vary in shape, size, colour, and content, making it more difficult for the brain to establish consistent patterns of response within the category.

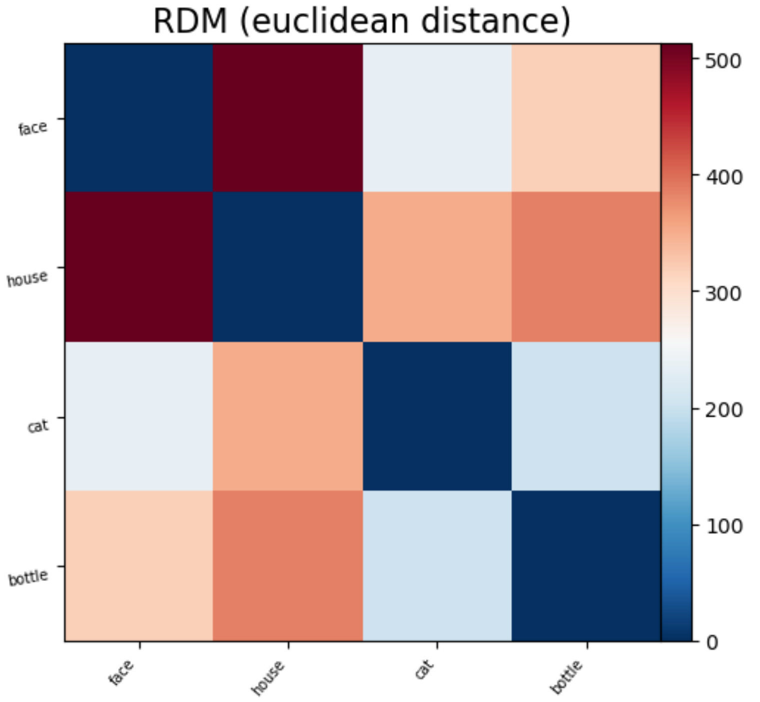


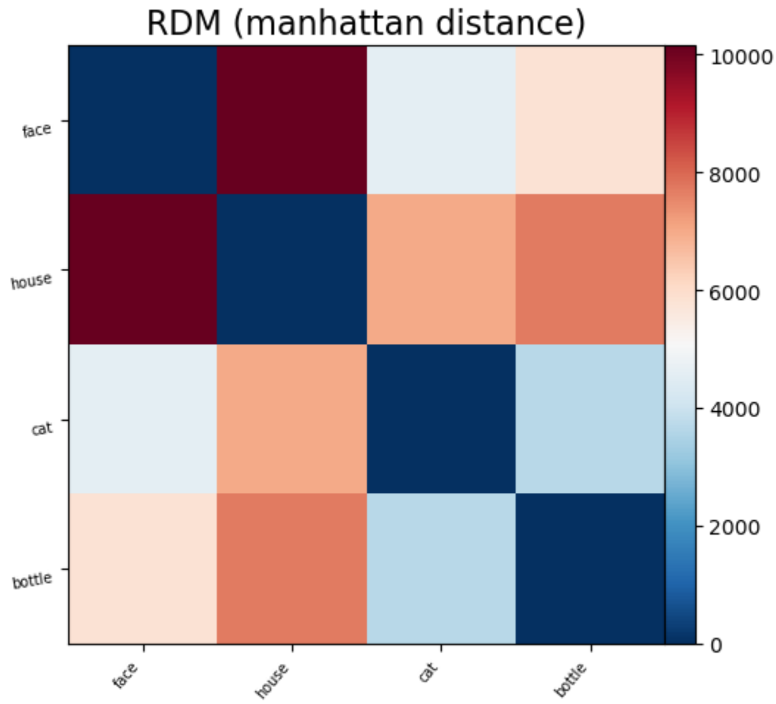
Moderate to high negative correlation values (between face and house, cat and bottle, house and cat, house and bottle, etc.) : Faces and houses are processed in different regions of the brain, typically associated with the Fusiform Face Area (FFA) for faces and the Parahippocampal Place Area (PPA) for houses. These regions may exhibit competitive interactions, where activation in one area inhibits activation in the other. Thus, when faces are strongly represented, activity related to houses might be suppressed, and vice versa, leading to a negative correlation. Similarly, the regions for processing other categories may also differ, causing the negative correlation.

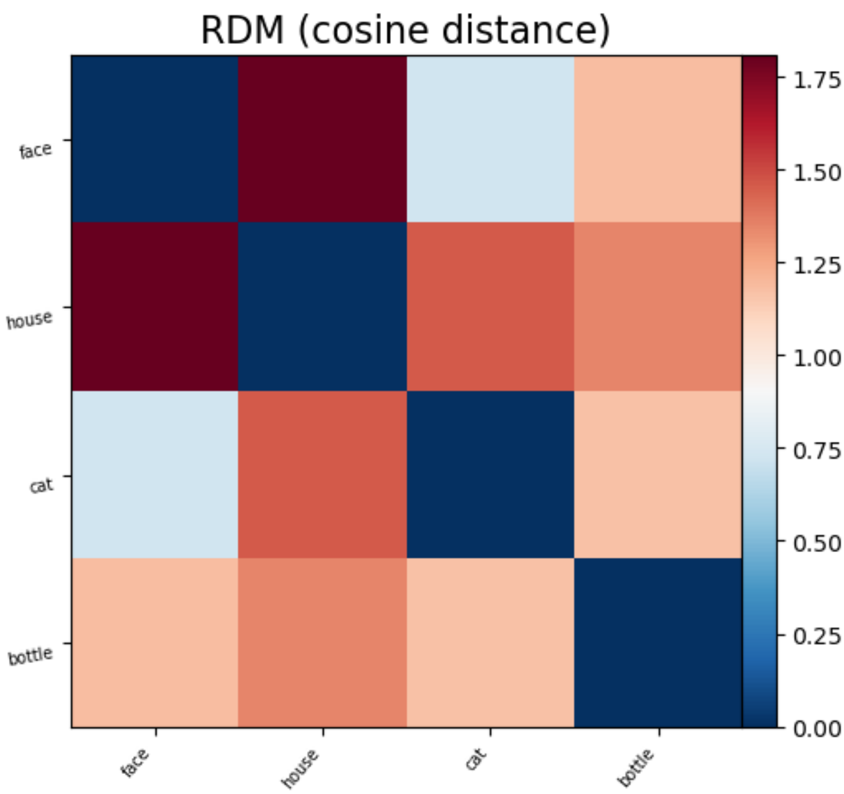


High/moderate positive correlation between face and cat: Faces and cats share certain visual features or characteristics that elicit similar neural responses. For example, both categories may involve processing of complex visual patterns, such as contours, textures, and spatial arrangements, which could lead to overlapping activation patterns in visual processing regions of the brain. Also, faces and cats could have strong semantic associations or shared conceptual representations in participants' minds. For instance, cats are living creatures and face is of a living human, both categories are commonly encountered in daily life and have rich semantic meanings, including social significance (faces) and familiarity (cats). These shared semantic associations could result in similar patterns of neural activation when processing face and cat stimuli.

Representational Similarity Analysis (RSA) using different distance measures

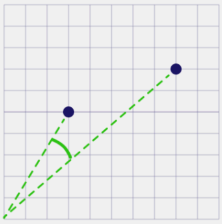






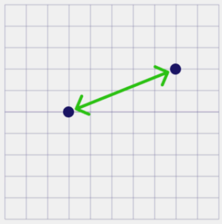
Observations:

In RDMs, low value of dissimilarity indicates that the patterns of brain activity evoked by two different stimulus categories are similar or alike. The value 0 for diagonal entries is there because the data vectors are the same so distance between them is 0 (so dissimilarity is 0). We are comparing, intuitively, is the represented information, not the activity patterns themselves.



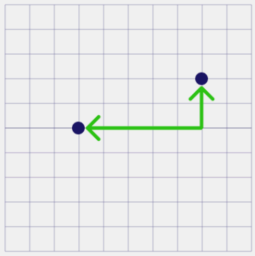
Cosine Distance

$$1 - \frac{A \cdot B}{||A|| \quad ||B||}$$



Squared Euclidean (L2 Squared)

$$\sum_{i=1}^{n} (x_i - y_i)^2$$



Manhattan (L1)

$$\sum_{i=1}^{n} |x_i - y_i|$$

Euclidean and Manhattan distances are both measures of the straight-line distance between two points in a multidimensional space. In the context of comparing patterns of brain activity (as represented by fMRI data), Euclidean and Manhattan distances consider both the magnitude and direction of differences between the neural representations of different stimulus categories.

Euclidean distance combines sensitivity to pattern shape, spatial-mean activity level, and variability across space.

Cosine similarity measures the cosine of the angle between two vectors in a multidimensional space. Cosine distance, which is complementary to cosine similarity, is calculated as 1 minus the cosine similarity. Hence, higher cosine similarity implies lower cosine distance. Cosine similarity focuses more on the direction or orientation of vectors rather than their magnitude. It measures the similarity in the directional relationships between the dimensions rather than the absolute differences in values.

Cats and Bottles highly dissimilar for euclidean and Manhattan distances but not for cosine distance: It seems that the patterns of brain activity evoked by "cat" and "bottle" are significantly different in terms of both magnitude and direction across the brain regions analysed, and so the Euclidean and Manhattan distances yield high dissimilarity between these two categories.
The patterns of brain activity evoked by "cat" and "bottle" have similar directional relationships across brain regions, even if their magnitudes differ. So, cosine similarity would indicate high similarity between these categories, leading to lower cosine distance.

High value of dissimilarity for face and house using all distance measures: The reasons for this are similar to the ones given for the high negative correlation value for face and house in the previous task. The brain regions involved in processing faces are specialised for facial recognition, while those involved in processing houses are specialised for scene perception. Also, faces and houses typically engage different neural circuits and brain regions. So, intuitively, the represented information for face and house and not the activity patterns themselves are quite different.