NSSP Mini Project 1

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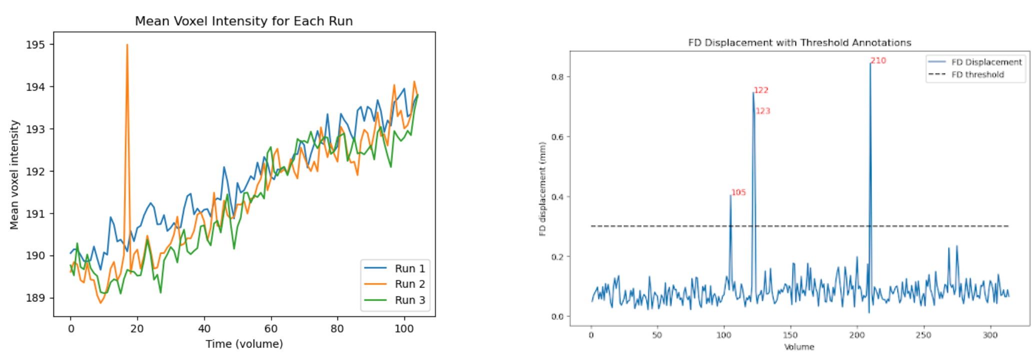
Part 1 – Practicals

This study explores the neural processing of emotional auditory stimuli, aiming to identify brain activation differences when subjects listen to positive versus negative music and neutral tones. Given that the dataset is unprocessed, we applied preprocessing steps, focusing our analysis on control subjects and the ”task-music-run” data.

We first standardized each of the 3 functional runs separately, applying the transformation $\frac{x_i-\mu}{\sigma}$ where x_i represents each sample, μ the mean, and σ the standard deviation of the run. After concatenating the standardized runs, we performed motion correction and applied spatial smoothing with a full width at half maximum (FWHM) of 4 mm, a standard neuroimaging choice that balances noise reduction and spatial detail, validated by visual inspection. Anatomical co-registration was omitted, along with additional anatomical preprocessing, as our GLM analysis focuses on task-related activation patterns where high-resolution functional data alone was deemed sufficient. Problematic volumes were removed directly in the design matrix to avoid shifting.

As shown in Figure 1a, we observed a small, recurring drift in mean voxel intensity, attributed to scanner or physiological fluctuations. To account for this, we added a drift regressor to the design matrix. Additionally, Figure 1b reveals four volumes with significant displacement due to abrupt motion, which can introduce artifacts that distort the BOLD signal, potentially biasing results. To control for these motion outliers, we included individual regressors for each affected volume. The final design matrix, shown in Figure 2, incorporates these adjustments to mitigate confounds.



(a) Mean voxel intensity of each run with the small drift

(b) Frame-wise displacement as aggregate measure of motion

Figure 1: Justification for each additional design matrix columns

Given our single-subject dataset, we performed a first-level GLM analysis. The resulting beta/statistical maps for each regressor are provided in the notebook. To examine the impact of positive versus negative music on neuronal activity, we created a contrast vector $c = [\ldots, 0, 1, -1, 0, \ldots]$ where the values 1 and −1 correspond to the indices for positive and negative music activations, respectively. The resulting image, shown in Figure 3, reveals that the region with the maximal contrast is identified as Vermis 7 according to AAL atlas parcellation, a region associated with cognitive and emotional processing (Figure 3). For more robust results, co-registration would typically be recommended; however, we assumed that our processing pipeline was sufficiently robust to proceed without it.

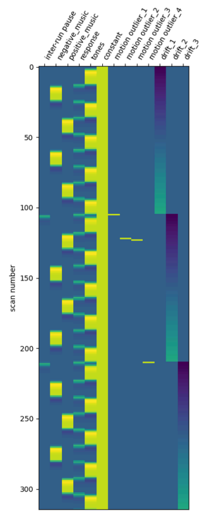


Figure 2: Design matrix for the GLM analysis

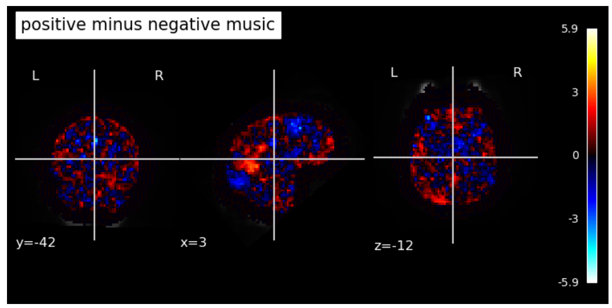


Figure 3: Impact of positive against negative music on neuronal activity

Part 1 – Theoreticals

1

Since we are given a dataset with 20 participants, we can perform a second level analysis, involving group-level statistical testing to identify consistent activation patterns across individuals, allowing us to generalize findings to the population level.

2

We could test a null hypothesis assuming no significant difference in neuronal activity between positive and negative music exposure. A one-sample t-test on the group-level contrast would assess whether the average difference across subjects is significantly different from zero. Due to lack of additional information about the subjects, we cannot separate them into groups (e.g., age, gender) and conduct more sophisticated between-group analyses. This contrast addresses whether positive versus negative music induces distinct brain responses across participants, potentially reflecting differential emotional or cognitive processing of these stimuli.

Part 2 – Practicals (Variant 3)

To apply K-Means clustering to our fMRI data, we first preprocessed it to retain only gray matter voxels as done in [2], using a dataset mask transformed with FLIRT. This step aims to exclude the influence of non-encephalon, cerebrospinal fluid, and white matter voxels, as well as gray matter voxels overlapping with white matter due to slight misalignments introduced during the transformation of the mask, ensuring a more focused clustering on relevant brain areas. This vectorized dataset represents each time point as a row and each voxel as a column. We then subtracted the spatial mean to ensure that each voxel signal has a mean of zero across time, which normalizes the data and allows for a clearer clustering outcome.

The goal of K-Means clustering here is to partition the voxels into groups based on their time series similarity, potentially identifying regions of the brain with similar activity patterns. To determine the optimal number of clusters, we calculated the inertia for a range of cluster numbers, as shown in Figure 4. By examining the inertia curve and applying the elbow method, 6 clusters were selected, as this is the point where the inertia begins to decrease at lower rate.

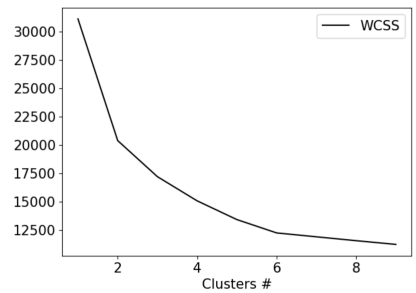


Figure 4: Within-Cluster Sum of Squares for different clusters

Part 2 – Theoreticals

1

Visually, it's difficult to identify specific functional pathways within each cluster, as shown in 5, where activation patterns appear broad and diffuse across different brain regions. To gain further insight, we used the AAL atlas to identify significantly activated areas within each cluster, as displayed in the KM.ipynb file. For example, Cluster 1 showed activation in Heschl's gyrus, cerebellar regions, and the vermis, which are indicative of the Auditory and Somatomotor Networks. Other clusters, such as 3, 4, and 5, involved the amygdala and cerebellar regions, aligning with the Limbic and Somatomotor Networks. However, many clusters include regions not strongly associated with any established functional pathways, and the activation values across clusters are generally low, making it difficult to draw definitive conclusions about their functional significance. This may reflect baseline or 'resting-state' activation, suggesting that these widespread clusters capture ongoing brain dynamics independent of task-specific stimuli.

2

There would be several ways to identify components that are not relevant networks. One way could be to use the CompCor algorithm [4]. It states that principal components derived from noise regions-of-interest (ROI) are able to accurately describe physiological noise processes in gray matter regions. PCA on these noise ROIs yields components added as covariates in a GLM to estimate physiological noise. It would allow the selection of voxels with high temporal standard deviation (tSTD), often corresponding to ventricles, edges, and vessels, without needing anatomical scans.

Another way would focus on an ICA-based strategy for removing motion artifacts from fMRI data [3].ICA-AROMA consists of three steps: first, probabilistic ICA on preprocessed fMRI data; second, identification of motion-related components using four discriminative features and classification; and third, removal of these components from the fMRI time-series via linear regression.

3

In the GLM procedure, we could observe specific activations for each contrasts and regressors used. For instance, in the positive vs negative setup (Fig. 3), we saw activation in regions related to emotional processing (Vermis 7). Given that music can evoke strong emotions, the activation in this region aligns with expectations for a contrast between positive and negative emotional tones. On the other hand, the MVPA aproach showed more spread and broader regions in each clusters. The GLM analysis provides a straightforward approach for linking stimuli to brain responses by identifying task-related activation, highlighting regions significantly activated for each condition. This method is well-suited for questions like “Which regions are activated by positive vs. negative music?”

In contrast, multivariate pattern analysis (MVPA) identifies intrinsic similarity patterns in brain activation without reference to task conditions. It groups data based on activation patterns across time points, potentially capturing distributed brain networks or shared functional responses. As a decoding model, MVPA clusters are not explicitly tied to specific tasks.

Thus, for our goal of comparing auditory processing of music across conditions, the **GLM offers a direct, interpretable comparison of conditions, specifically highlighting emotional processing of these stimuli and providing statistically significant results related to the experimental question.**

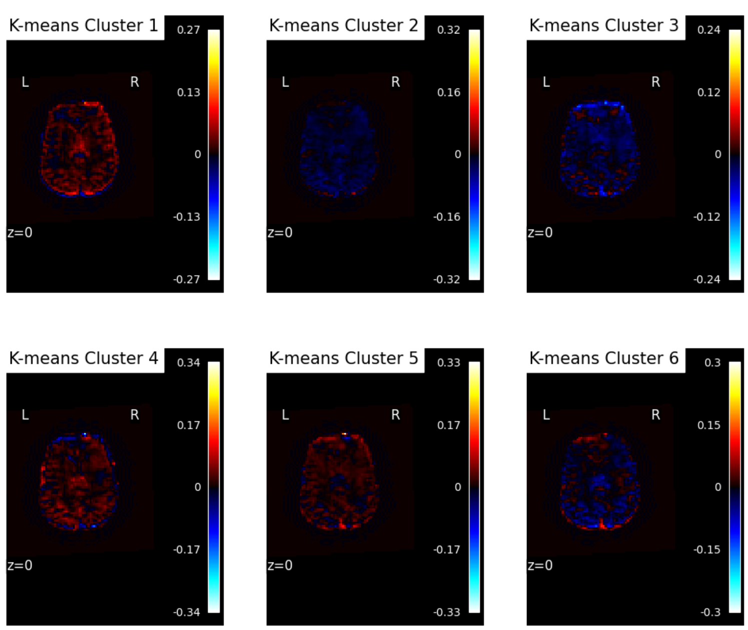
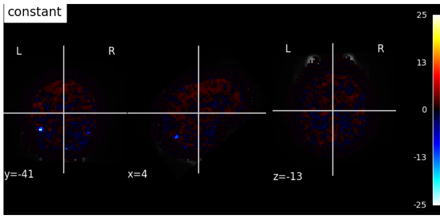
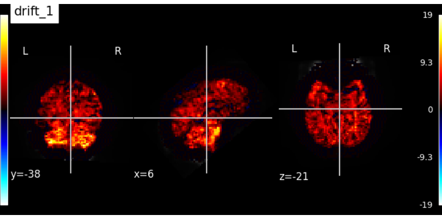


Figure 5: K-means clustering.

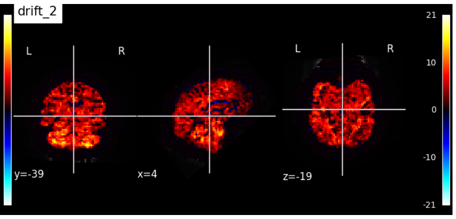
Appendix



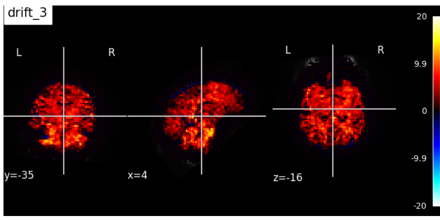
(a) Constant



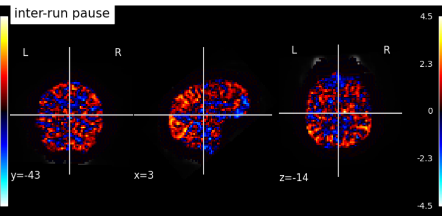
(b) Drift 1



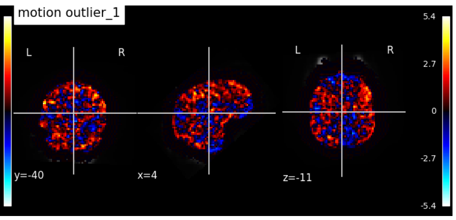
(c) Drift 2



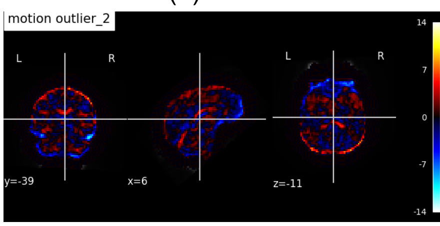
(d) Drift 3



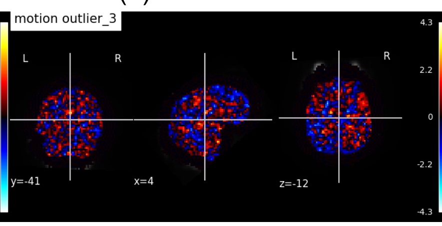
(e) Inter-run Pause



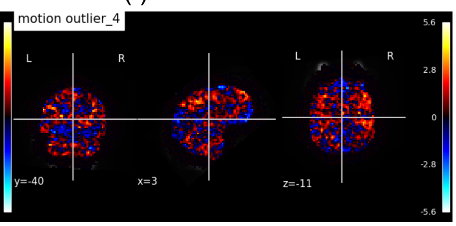
(f) Motion Outlier 1



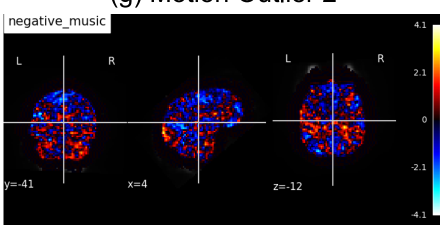
(g) Motion Outlier 2



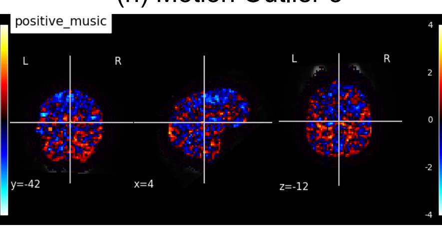
(h) Motion Outlier 3



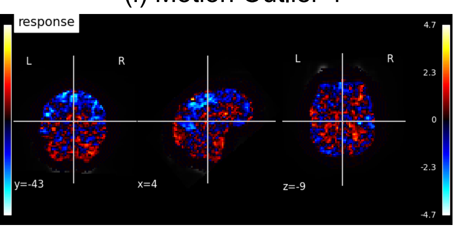
(i) Motion Outlier 4



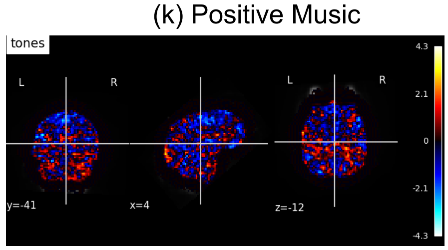
(j) Negative Music



(k) Positive Music



(l) Response



(m) Tones

Figure 6: Statistical maps of all the regressors used in the design matrix