École Polytechnique et Fédérale de Lausanne

NX-421 - Neural Signals and Signal Processing

Neural Processing of Emotional Musical and Nonmusical Stimuli

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1 Introduction

This project aims to investigate the neural processing of emotionally provocative auditory stimuli, particularly focusing on the brain regions activated while listening to positive and negative music. The dataset used for this analysis is derived from OpenNeuro [Lep+15], which contains fMRI data collected while subjects listened to emotional music and pure tones. Understanding the differences in brain activation patterns can provide insights into how emotional content in auditory stimuli influences neural processing.

2 Part I

2.1 Preprocessing

To prepare the data for analysis, several preprocessing steps were applied to the fMRI data of the control subjects. First, we performed skull stripping using the Brain Extraction Tool (BET) from FSL, removing non-brain tissue from the anatomical image. Then for each functional run, we loaded the functional images, calculated their mean and standard deviation, and applied the standardization formula to each voxel. This ensured comparability across runs and participants, thereby reducing variability.

After standardization, we applied slice timing correction to address timing differences in the acquisition of individual slices within each volume. This correction was performed using the SliceTimer tool from Nipype, which aligned the data based on slice acquisition timing.

Furthermore, we concatenated all the runs into a single 4D functional image, to allow unified analysis across multiple runs, enhancing the statistical power of our generalized linear model (GLM). To mitigate artifacts that could affect the quality and interpretation of the data, we applied motion correction using the MCFLIRT tool from FSL, which corrects for head movements that may have occurred during scanning. Once normalized to MNI space with FLIRT, the skull-stripped image was then used to coregistrate our fMRI data via EpiReg. Finally, we implemented smoothing by applying a Gaussian filter to the motion-corrected functional image. Smoothing enhances the signal-to-noise ratio and accounts for anatomical variability across subjects, making it easier to detect brain activation.

2.2 Generalized Linear Model

We employed a Generalized Linear Model (GLM) to compare the fMRI signals elicited by positive versus negative emotional musical stimuli during scanning. We initiated the first-level analysis by generating a design matrix based on the fMRI images and the event information from the `all_events` object (which includes events from runs 1, 2, and 3).

The resulting design matrix contains 27 predictors (Figure 1). The two columns `negative_music` and `positive_music` represent the expected response profiles of regions sensitive to auditory stimulation (Figure 2).

For a better interpretability of the results, we only show the maps of the regressors `negative_music`, `positive_music`, `response` and `tones` (Figure 4) in this report. Drift regressors aren't relevant for the interpretation, since they do not correspond to any behavioral or experimental variable, and we exclude the HRF derivative regressors, which do not represent distinct task-related brain activations, but capture signal variations due to delays or shifts in neural response timing.

To isolate the conditions of "positive" and "negative" music, we created a `contrast map` that selectively compares these two columns of the model (Figure 3). Afterward, we computed a t-statistic, which we converted to a z-scale. The resulting map was displayed over the average functional image, with a threshold set at an arbitrary value of 1.96, corresponding to an alpha value of 0.05 in two-sided inference, on the z-scale (Figure 5). We discarded the clusters smaller than 30 voxels to remove any

isolated peak (Figure 6). The maximal contrast is observed in the right calcarine, and two symmetrical clusters are observed in the regions corresponding to the insular cortex.
When trying to control for the expected proportions of false discoveries among the detected activations using the False Discovery Rate (FDR) or to control the family-wise error rate with the Bonferroni method, we ended up with no significant voxel left. This could be due to the fact that we are only considering one subject, making our analysis less robust and very vulnerable to noise.

2.3 Theoretical questions

In this dataset, a second-level analysis can indeed be performed by combining the results from each subject's first-level analysis, where individual Generalized Linear Models (GLMs) assess brain responses to emotional musical stimuli. By aggregating the contrast maps from all subjects, a group-level GLM allows us to evaluate whether the observed effects are consistent and significant across the population, thereby providing more generalizable conclusions about the neural correlates of emotional processing in response to music.

For this second-level analysis, a relevant contrast would be the comparison between depressive and non-depressive patients' brain activation during music listening. This contrast addresses how depression modulates neural responses to emotional music, providing insights into altered emotional processing and brain dynamics in depression. It can help identify brain regions that show differences in activation between the two groups, particularly in areas related to emotional engagement and auditory processing. Together, these analyses can deepen our understanding of brain networks that are universally engaged by music and those that differ across emotional states, shedding light on the neural dynamics underlying auditory emotional processing.

3 Part II

3.1 Independent Component Analysis

Independent Component Analysis (ICA) is a powerful technique for separating a multivariate signal into additive, independent components. It is particularly useful in fMRI studies for identifying spatially independent networks associated with different brain functions. In our analysis, we performed ICA on the preprocessed fMRI data using the CanICA implementation from Nilearn with 10 components to uncover the underlying neural networks activated by emotional musical stimuli (Figure 7, 8).

3.2 Theoretical questions

In our analysis, we identified several components, some of which correspond to known functional brain networks, while others appear to be artifacts. For instance, components such as 5 and 8 likely represent motion artifacts, as they are located peripherally and do not correspond to any specific functional network. However, other components do match relevant functional brain networks. Component 0 appears to represent the visual cortex, while component 7 likely relates to sensory processing in the parietal lobe, which could correspond to auditory processing regions. Additionally, component 1 may align with the brainstem.[Lep+16].

Components that are not relevant networks often capture artifacts like head motion, physiological fluctuations, and scanner drift. These components lack consistent spatial patterns associated with brain networks and typically exhibit irregular time series unrelated to neural activity. To identify components that are not relevant networks, we can use ICA-AROMA and CompCor. ICA-AROMA employs Independent Component Analysis (ICA) to separate fMRI signals into spatially independent components, allowing for the identification and removal of motion-related artifacts to enhance data quality while preserving the autocorrelation structure of the data [Pru+15]. Similarly, CompCor captures physiological noise, such as respiratory and cardiac fluctuations, and enhances quality by isolating these non-neural components [Beh+07].

We notice a similarity between the regions obtained with the GLM procedure and component 0 of the ICA, but they are not exactly on the same level of the z-axis. Given the original objective—to identify which brain regions are activated in response to specific events, the GLM method is preferable because it models brain responses with respect to task timing, allowing for clear statistical testing of event-driven hypotheses. GLM is thus optimal for identifying task-specific activations. In contrast, ICA excels in revealing independent, large-scale networks that are not directly tied to event timing, making it ideal for exploring underlying brain network structure and separating noise from signal. Therefore, GLM would be best applied when investigating task-specific brain activation, while ICA would be more suitable for broader network identification and noise isolation in fMRI data.

4 Conclusion

In this project, we investigated the neural processing of emotional auditory stimuli, focusing on the brain regions activated by positive and negative music. Using the Generalized Linear Model (GLM), we identified significant activation in the left amygdala, consistent with its role in emotional processing. Independent Component Analysis (ICA) also revealed relevant brain networks, such as those associated with auditory and sensory processing. Together, these methods enhanced our understanding of how the brain responds to emotional music, highlighting the importance of both task-related and network-based analyses in fMRI studies.

5 Figures

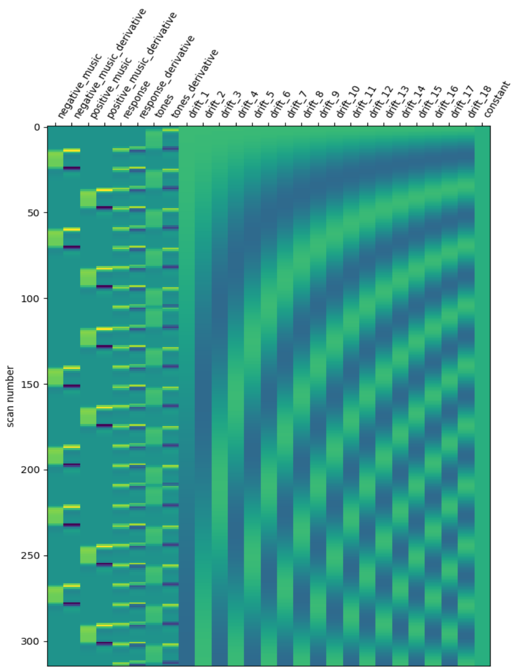

Figure 1: GLM Design Matrix

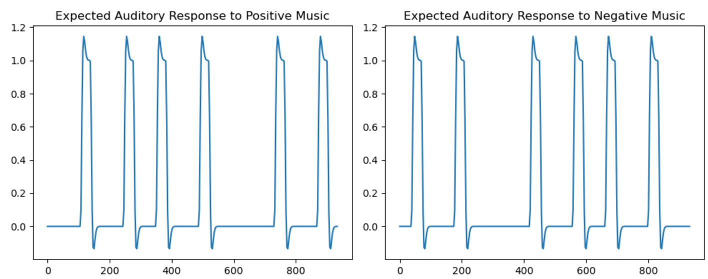

Figure 2: Expected Auditory Response to Positive and Negative Music

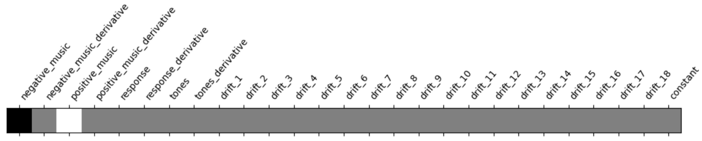

Figure 3: Coefficients of the contrast map, indexed by the names of the columns of the design matrix

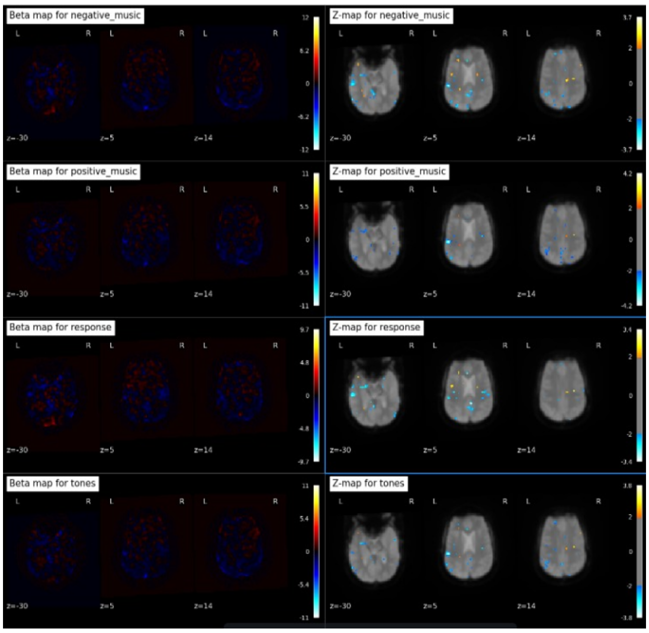

Figure 4: Beta and statistical maps of the relevant regressors

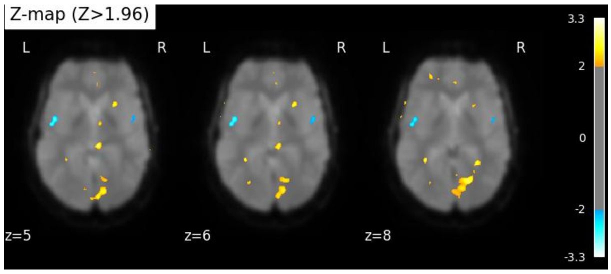

Figure 5: z-score map of the beta coefficients of positive music minus negative music

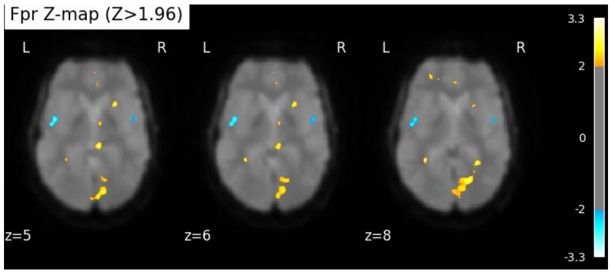

Figure 6: z-score map after applying clustering threshold of 30 voxels

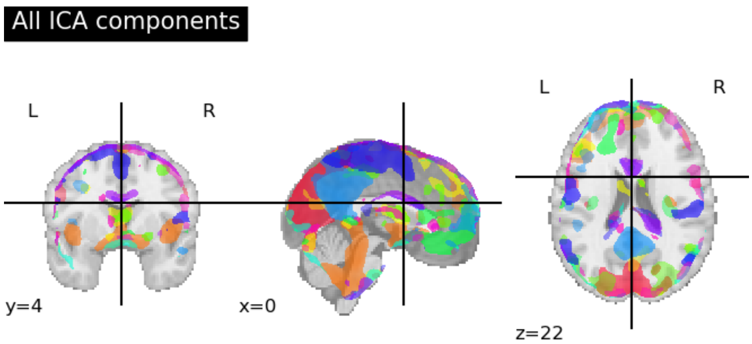

Figure 7: All 10 ICA components

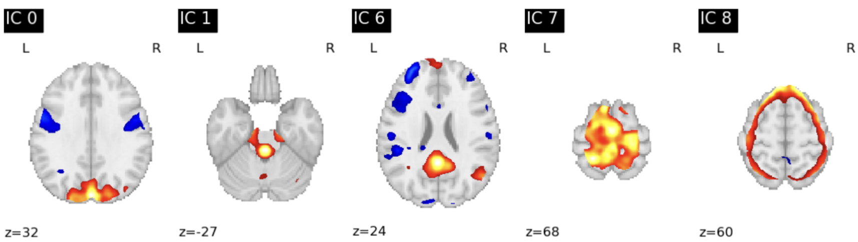

Figure 8: 5 Components of interest

6 Bibliography

References

[Beh+07] Y. Behzadi et al. "A component based noise correction method (CompCor) for BOLD and perfusion based fMRI". In: *NeuroImage* 37.1 (2007), pp. 90–101. DOI: 10.1016/j.neuroimage.2007.04.042. URL: https://doi.org/10.1016/j.neuroimage.2007.04.042.

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