NX-421: Neural signals and signal processing

MINI PROJECT 1

For this mini-project, we propose 3 variants and you will do only the one your group chose (*or had to choose according to the availability)*.

You should provide us with a report of 3 pages max (including images), single column, font-size 11px in Arial. Make sure to shape the structure in a paper-like format: Introduction, Methods, Results and Discussion sections.

Each of the 3 variants has a practical part that corresponds to your methods and a theoretical part that you should address and integrate in your report and presentations.

All groups have to submit their report by **Thursday 20th October at 18:00**.
Note that this is a sharp deadline, no extensions are allowed.

Groups presenting this mini-projects are:

Variant 1

Description

In this mini-project variant we will have you study the neural processing of emotionally provocative auditory stimuli. A researcher is specifically interested in figuring out what regions of the brain are activated when subjects are listening to positive compared to negative emotional musical and nonmusical stimuli (pure neutral tones) during fMRI scanning.

The dataset that you will use is accessible through openneuro (https://openneuro.org/datasets/ds000171/versions/00001).

Participants listened in blocks of 33 seconds to positive or negative music. Music blocks were interleaved with 33 seconds of pure tone listening, following the paradigm described in Lepping, et al., 2015 (see bibliographical reference [1]). The last 3 seconds of each musical block was used to make sure participants were paying attention, where they had to press a button to indicate if they found the samples to be positive or negative.
The research question is on the difference of processing of music in auditory content.
The acquired dataset was not preprocessed, so take into consideration at least 2 minimum preprocessing steps (motor correction and smoothing).

Your task will be to detect the activation related to the positive and negative emotional music with respect to non-musical stimuli. To this end, you will use a General Linear Model (GLM) as you saw in the lab of week 4.

Practical part

Using what you learnt in the tutorials, tackle the following questions:

1) Apply preprocessing on one subject (minimum steps are motion correction and smoothing, you can decide to apply any other step you deem appropriate).
2) Specify the experimental design matrix to use for this subject and include this matrix in your report.
3) Run the GLM at the level you deem reasonable.
4) Using the results of the GLM analysis and the contrast you chose, create the activation corresponding to the impact of positive and negative music. Please include the contrast you obtain, and report in which brain region you find maximal contrast **based on AAL atlas parcellation**.

(BONUS):

★ Consider 4 more healthy subjects of the same datasets (controls subset), take care to perform normalization!

➔ *Hint:* you can also normalize the contrasts instead of the volumes but do not forget to smooth in all cases the fMRI volumes before your analysis. Nilearn includes a smoothing option in the GLM!

★ *If you have time you can also compare the contrasts or maps with respect to 4 other participants that belong to the subset of subjects with depression.*
➔ *Hint: you should look at folders* `sub-mdd##`

Theoretical part

Answer the following questions:

1) Can you do the first level analysis on this dataset?
2) Can you do the second level analysis on this dataset?
3) Based on your answers, is your model a mixed-effect or fixed-effect model?
4) What contrast should you consider to answer the question?
5) Do you think in this case a block design was appropriate? Would you replace it with an event-related design? If so, why and what would you change?

References

[1] Lepping RJ, Atchley RA, Chrysikou E, Martin LE, Clair AA, et al. (2016) Neural Processing of Emotional Musical and Nonmusical Stimuli in Depression. PLOS ONE 11(6): e0156859. https://doi.org/10.1371/journal.pone.0156859

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Variant 2

Description:

The quality of fMRI data is affected by the subject's motion in the scanner. This can cause signal alterations across fMRI volumes generating spurious results. Hence, motion correction is always an important preprocessing step in fMRI data analysis. In this miniproject variant we will have you study mainly motion correction, alongside learning how to visualise the data and perform brain extraction, another standard preprocessing step.

The dataset that you will use is accessible through openneuroi:
Flanker test https://openneuro.org/datasets/ds000102/versions/00001. A detailed description of the task design and acquisition parameters can also be found here.

Your task in this miniproject is divided into 4 practical parts as listed below. Following that you have to answer some theoretical questions in brief detail.
Reference:

1) Follow the lab tutorials on fMRI preprocessing,
2) FSL is a useful tool to quickly perform several preprocessing steps. Check out FSL commands and their documentation, which might be useful for your implementation here.
3) Check out this paper from Power et al. (2012). This can be useful for your implementation and understanding how motion correction is performed, analysed and presented in neuroimaging research.

Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2012). Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. NeuroImage, 59(3), 2142–2154. https://doi.org/10.1016/j.neuroimage.2011.10.018

Practical Part:

NOTE-You have to perform all the analysis on one subject's functional data only. Check the Paper from Power et al. on how to compute and visualize different motion metrics.

Part-1: Visualising data

Visualise the anatomical scan and functional scan. Make an animation of the anatomical scan and functional scan

Part-2: Brain extraction

Perform brain extraction on the anatomical image using FSL. Perform brain extraction for different fractional intensity threshold and comment on your observations

Part-3: Motion correction

1) Compute and visualize the motion parameters for 6-dof, i.e., 3 Rotations + 3 Translations across all the volumes.
2) Compute and visualize the Framewise Displacement (FD) for all the volumes

3) Apply motion correction on your data (mcflirt settings: use default cost function, reference volume as middle volume) and visualize the result for a volume of your choice (other than the middle volume).
4) For original data and motion-corrected data, visualise the time series for a voxel and report the differences you observe (if any) between the two.
5) Bonus questions [optional]
    a) Use a FSL command to generate a mean functional image and then use it as a reference image for motion correction
    b) Pick two more subjects. Compare motion correction results (motion parameters and FD) between the 3 subjects and report your observations

Part-4: Outlier volumes detection

1) For the original data, detect the volumes with large motion with another metric called DVARS, that computes the BOLD signal intensity change across the volumes. Plot the DVARS values for all the volumes.
2) Define a threshold of outlier volumes as you deem appropriate, either through a fixed value or through statistical deviation and comment on your observations.

Theoretical Part:

Answer the following questions:

1) What is a flanker test? How is it linked to human cognition? Design an illustration of an experimental design followed in the given dataset.
2) What is the difference between an anatomical scan and a functional scan?
3) What are the typical artefacts observed in functional and anatomical scan? Can they be identified by visual inspection?
4) What are different types of cost functions used in FSL's motion correction? Choose one of your preferences and explain how it works.
5) Why would we still need to perform outlier volume detection after motion correction?

Variant 3

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Imagine that we are interested in identifying which region of the brain is involved in processing faces. We can explore this question by showing participants different types of faces where each face represents one trial. If we scanned someone with this design, we could expect to see any region involved in processing faces increase in activation around the time of the face presentation. To understand which of these regions process faces we would need to add at least one other condition/visual stimulus that will serve as a visual control. It's usually a visual stimulus that has similar properties to a face in terms of luminance and colour. In this mini-project, we'll see how the general linear model (GLM) can be used to make inferences about brain responses in a single subject. Given the simulated time series for a single voxel that resembles real data, we can evaluate how well we can recover the true signal using a general linear model.

Practical Part:

1) First, specify a fake sequence of stimuli events. To this end, create a series of presentations of faces against visual control, each individual presentation lasting 2 seconds. You are free to choose the total duration of the experiment as well as the TR for this timeseries. In other words you will have to "simulate" a time series for a single voxel.
2) The brain has a delayed hemodynamic response to events that have a particular shape, so we will need to convolve these events with an appropriate HRF function. Code from scratch the definition of the HRF function considering the double-gamma definition (seen in class) and convolve the time course with the following HRF function [1]:

$$h(t) = A\left(\frac{t^{\alpha_1-1}\beta_1^{\alpha_1}e^{-\beta_1 t}}{\Gamma(\alpha_1)} - c\frac{t^{\alpha_2-1}\beta_2^{\alpha_2}e^{-\beta_2 t}}{\Gamma(\alpha_2)}\right)$$

Where α_1 = 6, α_2 = 16, $\beta_1 = \beta_2$ = 1 and c=⅙. Here, Γ stands for the gamma function. A is the amplitude of the HRF (which in the case of the GLM is what you try to recover through model fitting!).
You can use both the mathematical definition above or the library `scipy.stats` to generate the gamma distribution.

3) Change the HRF function parameters (α_1 and α_2) of the gamma distributions to obtain slightly different shapes and perform comparisons.

4) In reality, the data is much noisier and the noise comes from low-frequency drift, autocorrelation, or possibly some aliased physiological artefacts. Choose any HRF

model and add Gaussian noise with a sigma of 0.15. The goal of this part is to generate simulated activity from a voxel.

5) Recover the original signal using a general linear model in the form of: $Y = X\beta + \epsilon$, where Y is our observed voxel time series, X is our model or design matrix, and is where we will specify a predicted response to each condition. β is a vector of values that we will estimate to scale our model and ϵ is independent Gaussian noise. Build a design matrix X using an intercept, and a regressor indicating the onset of each condition, convolved with the hemodynamic response function (HRF).
6) Estimate $\hat{\beta}$ using the Ordinary Least Squares (OLS) estimator. Quantify the degree to which your model is accurately predicting the observed data by calculating the residual $residual = Y - \hat{Y}$.
7) Perform a hypothesis test to evaluate if any of the regressors are statistically different from zero.
8) Show a graphical representation of the design matrix and the contrast between the face and object condition.
9) BONUS: Repeat the practical steps 1-6) using the dataset that is accessible through openneuroi: https://openneuro.org/datasets/ds000105/versions/00001

Theoretical Part:

Answer the following questions:

1) What happens when we vary the signal amplitude? How does the model fit change when the signal amplitudes are stronger and weaker?
2) What happens when we vary the noise? How does the amount of noise in the data impact our model fit?
3) A common question in experimental design is determining the optimal number of trials. How many trials do we need?
4) BONUS: What if one condition simply results in processes that systematically take longer than the other condition? What do you think would happen to the β estimates?

References

[1] Lindquist, Martin A., et al. "Modeling the hemodynamic response function in fMRI: efficiency, bias and mis-modeling." *Neuroimage* 45.1 (2009): S187-S198.