Exercises

Data

The data for all exercises comes from an fMRI experiment on single finger representations in primary motor cortex, reported as Experiment 1 in Ejaz et al. (2015).
The mat-file contains activation estimates from the motor cortex of 12 hemispheres (6 subjects) during the movement of the contralateral(CONTRA) fingers. We also give the activation patterns for the ipsi-lateteral fingers (IPSI), but we'll mostly concentrate on the contralateral activity.

Note: The activation estimates are already spatially pre-whitened!

Each element of the cell array which contains 3 dimensional "matrix" (a tensor) of size numFing x numVox x numRuns.

For example
`CONTRA{h}(f,p,r):`
Contains the data from the h^{th} hemisphere (12 total) for the f^{th} finger (1-5), the p^{th} voxel and the r^{th} run.

The Models are stored in the structure array model with the fields:

Model(i).RDM = Representational dissimilarity matrix, predicted (squared) distances
Model(i).G = Predicted second moment matrix (in correlation format)
Model(i).G_cent= Centered predicted second moment matrix
Model(i).name = name of Model

Model 1: Derived from correlation of muscular activation patterns during single finger presses
Model 2: Derived from the natural statistic of hand movements (Ingram et al.) - correlations of MCP velocities

Exercise 1 - Encoding

1. Write a function that
   1.1. Extracts the n first eigenvectors of Model(i).G -> X
   1.2. Uses normal linear regression to estimate W on 7 runs
   1.3. Loops over runs -> get predicted values for all runs
   1.4. Evaluate prediction by correlating with observed patterns

2. Fit the model for the 12 hemispheres, 1-4 "synergies", and the two models. Plot the average results separately for the models as a function of number of factors

3. Modify your function, so it takes a regularisation factor and performs Ridge regression instead of normal regression. Repeat task 2 with a lambda = 0.2. How do the results change from 2?

4. Systematically vary lambda from 0.01 to 5. Plot the correlation

4. Calculate the average inter-hemisphere correlation between the vectors of 10 dissimilarities. Which measure yields the highest average between-hemisphere correlation?

5. Calculate the average LDC distance and then use classical multidimensional scaling to plot these distances in 2-d representational graph (see lecture on second moment matrix and classical multi-dimensional scaling).

Exercise 2 - RSA

1. Write a function that takes pre-whitened activity estimates as an input and estimates the cross-validated second-moment matrix and the cross-validated Euclidean distances between any pair of fingers. Plot the cross-validated distance matrix and the representational dissimilarity matrix for each hemisphere.
2. Inspect the cross-validated distance for movements of the ipsilateral fingers. Would you be able to reliably decode movements of the ipsilateral hand?
3. Use the estimated second-moment matrix to plot a classical multi-dimensional scaling plot of the estimated distances. Use the first two eigenvectors. What does the plot look like?
4. Repeat the process, this time removing the baseline. This can be done by
   - subtracting the mean activity pattern for each run
   - centring the estimated SMM, or
   - re-estimating the SMM-matrix from the RDM

   Why does the graph change so much?
5. String the 10 distances out to a vector for each hemisphere.Correlate the distances of each hemisphere with
   - the predicted distances from the the two models
   - the mean of all the subjects (upper noise ceiling)
   - the mean of the left-out subjects (lower noise ceiling)