Multi-subject models of the resting brain

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- extract reproducible inter-subject ICA patterns.
- CanICA = CCA + ICA: a multivariate random effects
- CCA – canonical correlation analyisys
A group model for stable multi-subject ICA on fMRI datasets

Group-variability model:

- Ps - set of subject-specific spatial patterns
- B - group-level

\[ Ps = Ls B + Rs, \]

- Ls a loading matrix giving how much each pattern is represented in subject s,
- and Rs a residual matrix giving the deviation from the group patterns
- For a group: \( P = LB + R \)
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Observation model

- For each acquisition-frame time point the observed data is a combination of different subject specific patterns $P_s$ confounded by observation noise:

$$Y_s = W_s P_s + E_s$$

- $Y_s$ - resulting spatial images fMRI sequences (an $n_{frames} \times n_{voxels}$ matrix)
- $E_s$ - the observation noise
- $W_s$ - a loading matrix
- In group notation: $Y = MA + E$

the mixing matrix can be factored out in a subject-specific matrix and group-level matrix, and the rejected noise is the addition of two terms, a subject-specific one and a group-level one

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Estimation procedure

1. Separate observation noise $E_s$ from subject-specific patterns $P_s$ through principal component analysis (PCA).
2. Canonical correlation analysis to estimate the group-level patterns.

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 Canonical correlation analysis (CCA)

- CCA is used to compare two multivariate datasets by finding components pairs of each dataset that maximize cross-correlation.
- It finds two bases, one for each variable, that are optimal with respect to correlations and, at the same time, it finds the corresponding correlations.
- It finds the two bases in which the correlation matrix between the variables is diagonal and the correlations on the diagonal are maximized.
- The significance threshold on the canonical correlations is set by sampling a bootstrap distribution of the maximum canonical correlation using Es - the subject-level observation noise identified previously.

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Estimation procedure

- 3. Group-level independent components — identifying group-level components B spanning the subspace of common patterns of activation

- The final components are thresholded such that ICA patterns lie in blobs standing out from the background

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Cross-validation of group-level patterns

- Split the group of subjects in two and learn ICA maps from each sub-group
- This yields the sets of patterns $A_1$ and $A_2$.
- Compare the overlap of thresholded maps and reorder one set to match maps by maximum overlap.
- Reproducibility can be quantified by studying the cross-correlation matrix

$$C = A_1^T A_2.$$  

$$C_{i,j} = 1 \text{ if and only if } (A_1)_i \text{ and } (A_2)_j \text{ are identical.}$$

A new approach to neural decoding: acting on the similarities between activation patterns, rather than on the patterns themselves  Rajeev Raizada

- What makes our brains similar is the connections between neurons but not the activity itself.
The neurons inside group A and B are rhythmically synchronized. However, C is in-phase synchronized exclusively to A and not to B.
The strength of gamma-band synchronization is modulated with the phase of lower-frequency rhythms, particularly the theta rhythm.
Attentional modulation of SFC in areas V1, V2, and V4.

On alternating blocks of trials, monkeys were cued to attend to a moving grating either inside (top) or outside (bottom) of the recorded neuron's RF. Red traces represent SFC in each area, with attention directed INTO the neuron's RF. Blue traces represent SFC with attention directed OUT of the RF.

Buffalo E A et al. PNAS 2011;108:11262-11267