

# Hierarchical Modelling of Individual- and Population-Level Resting State Networks from Big fMRI Data

Talks on this poster #1166:

Oral session: Connectivity States and Traits

Symposium: Modern Bayesian Methods in Neuroimaging

## Introduction

- Big fMRI data such as UK Biobank [1,2]
  - > Detailed mapping of the brain function and disorders
  - Functional parcellations and network discovery [3]
  - Functional connectivity in populations and individuals [4]
  - Prediction of cognitive function and disorders in individuals [5].

- Hierarchical modelling of functional networks
  - > Estimation in both individuals and populations
  - Bidirectional hierarchical models [6, 7, 8]; e.g. PROFUMO: Probabilistic Functional Modes [6,7]
  - Application to resting state networks (RSNs)
  - Computationally expensive

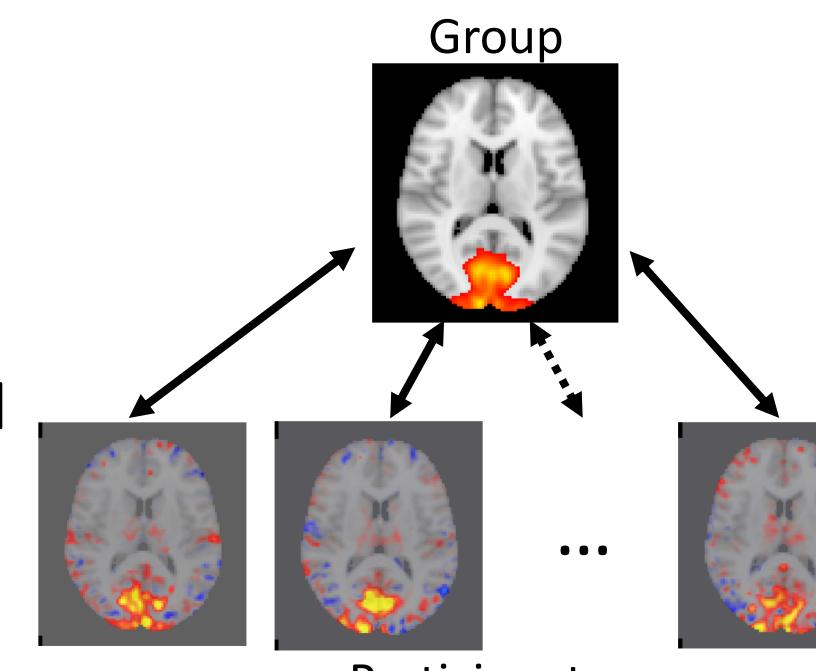


Figure 1 Bidirectional hierarchical models of the functional brain networks

## Materials and Methods

### Proposing Stochastic PROFUMO (sPROFUMO):

- Using stochastic variational inference [9,10] to scale to large-scale datasets (Fig 2).
- Subject-level estimation using group-level Bayesian priors.
- Allow for heterogeneity in the population by retrieving subject-specific memories.
- Iterate between subject and group estimation until convergence.

### Applying model to UK Biobank data:

- 5000 UK biobank subjects
- Volumetric, minimally preprocessed using FSL-FIX, spatial smoothing at 5mm FWHM.
- Characterising 150 RSNs at population and individual-level.
- Comparison to group spatial ICA (FSL's MELODIC) and MELODIC + Dual Regression (DR) for single subjects.

### Predicting cognitive function:

- Comparing prediction accuracies of sPROFUMO and spatial ICA.
- 68 cognitive tests from UK Biobank.
- Each RSN used separately to predict cognitive outcome.
- Imaging confounds regressed out [11].
- Elastic net as classifier.

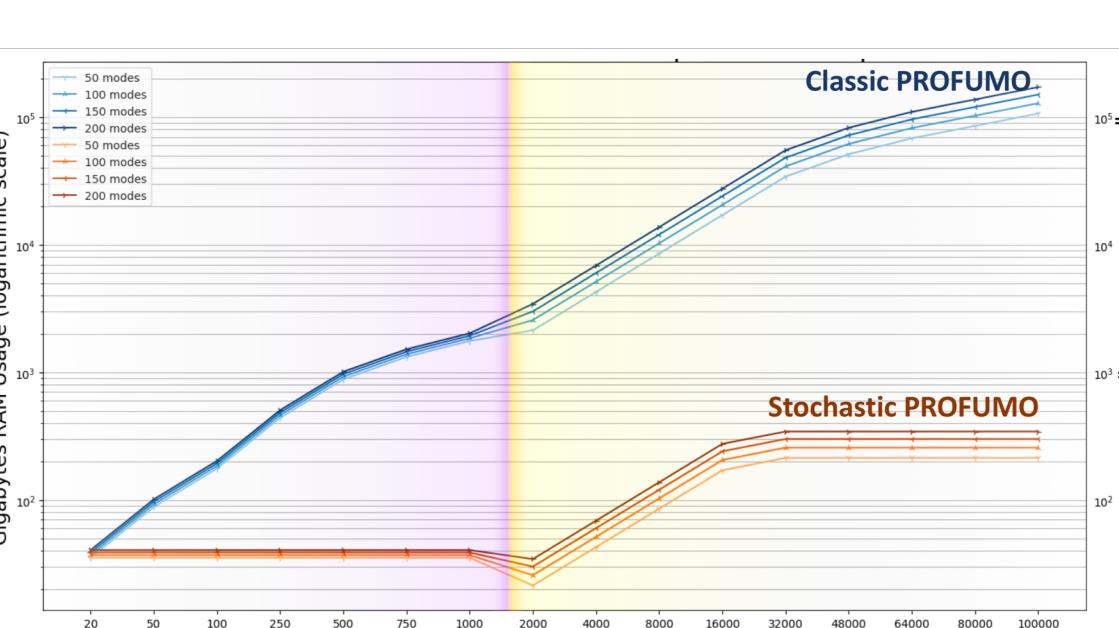


Figure 2 Classic versus stochastic PROFUMO

## Results

### sPROFUMO Resting State Networks

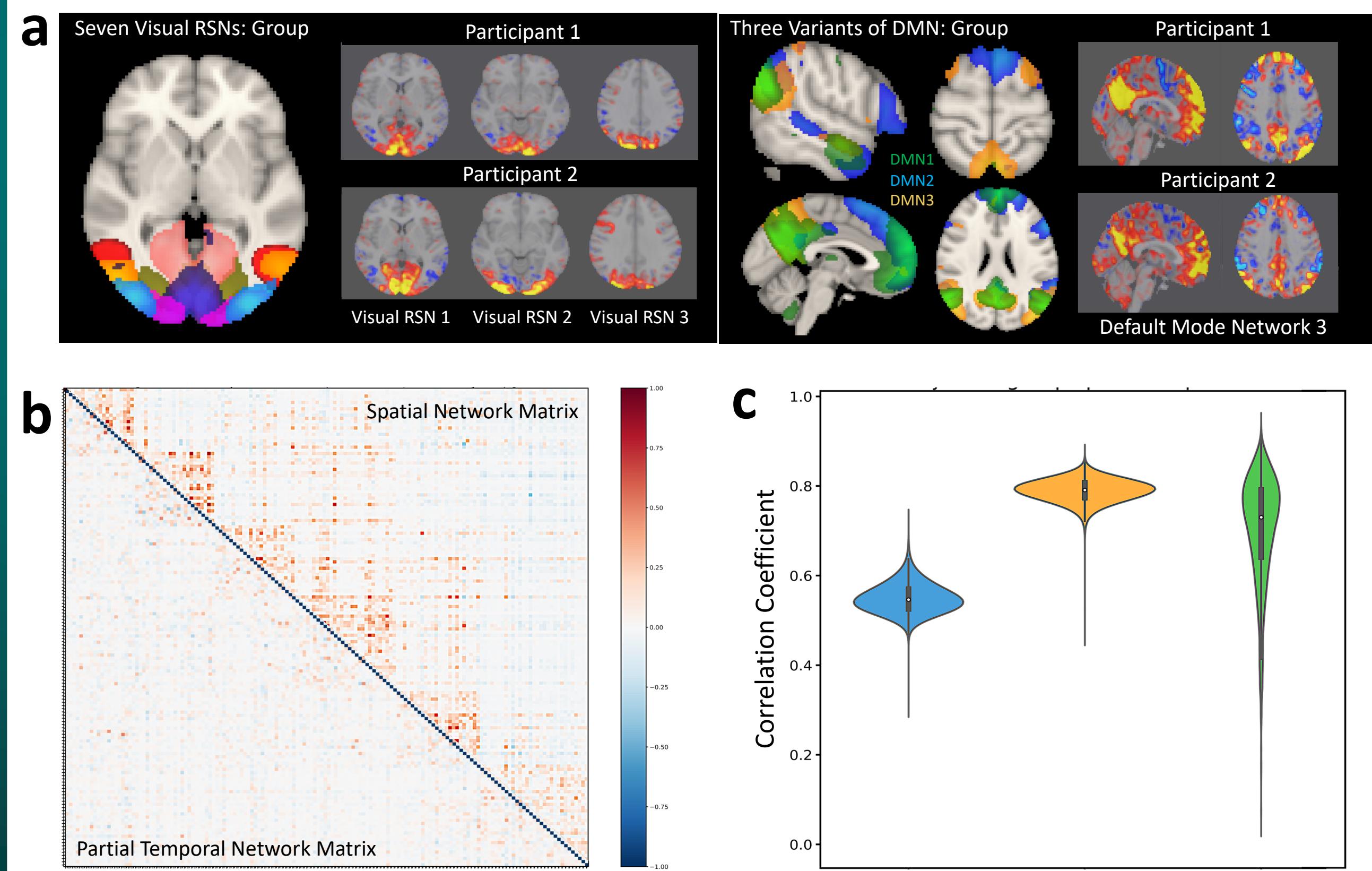


Figure 3 Summary results of RSNs found using sPROFUMO: a) Example visual and default mode networks at population and individual-level. RSNs are overlapping and show rich details of spatial variability; b) connectivity estimated based on partial correlations between time courses (lower triangle) and spatial correlation between spatial layouts (upper triangle) of RSNs. Six distinct clusters were identified based on spatial correlations. c) Cross-subject consistency of spatial RSN layout (SMAP), spatial and partial temporal network matrices (SNET and PTNET).

### Comparison to Spatial ICA and Dual Regression

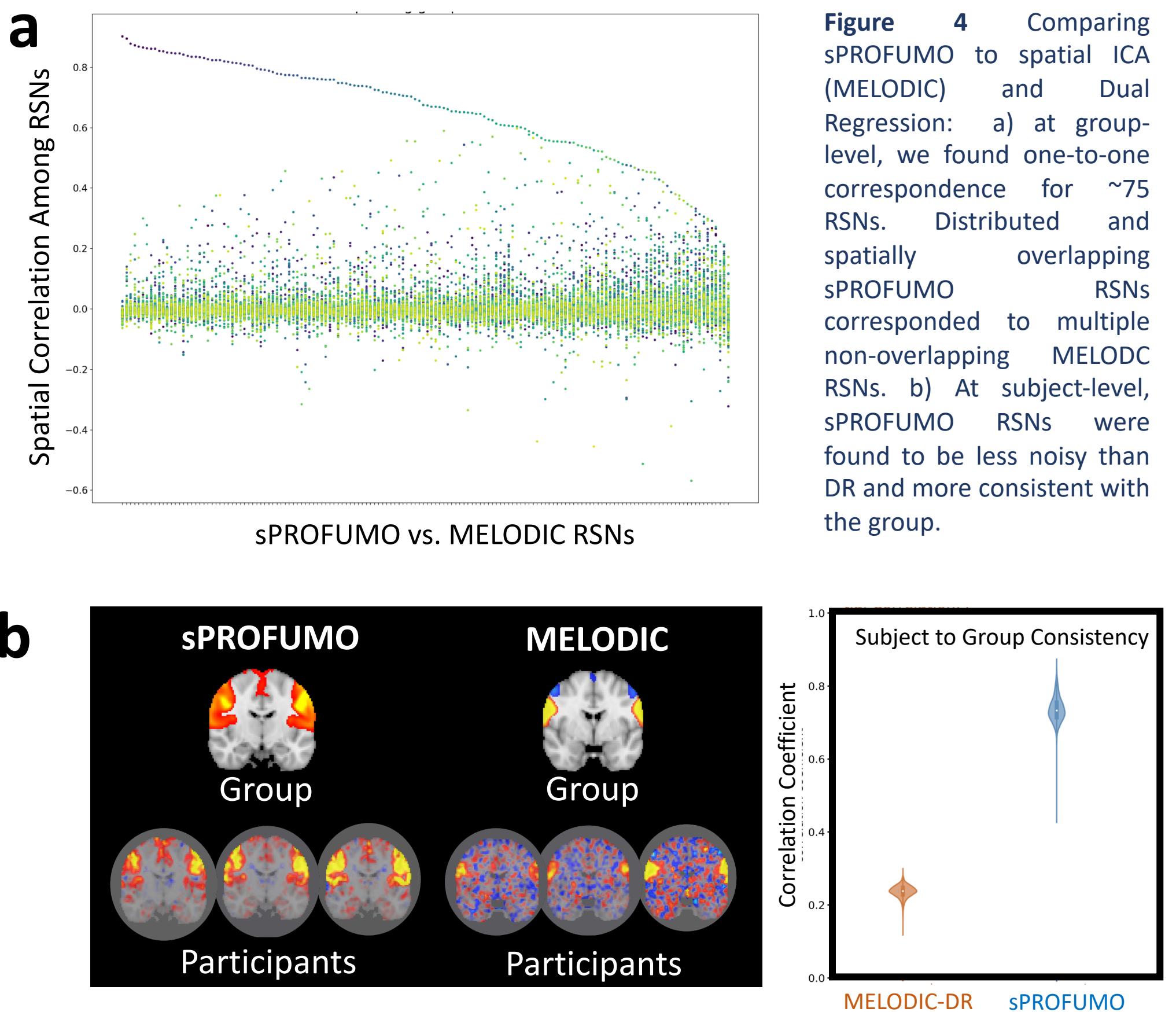


Figure 4 Comparing sPROFUMO to spatial ICA (MELODIC) and Dual Regression: a) at group-level, we found one-to-one correspondence for ~75 RSNs. Distributed and spatially overlapping sPROFUMO RSNs corresponded to multiple non-overlapping MELODIC RSNs. b) At subject-level, sPROFUMO RSNs were found to be less noisy than DR and more consistent with the group.

### Predicting Cognitive Function

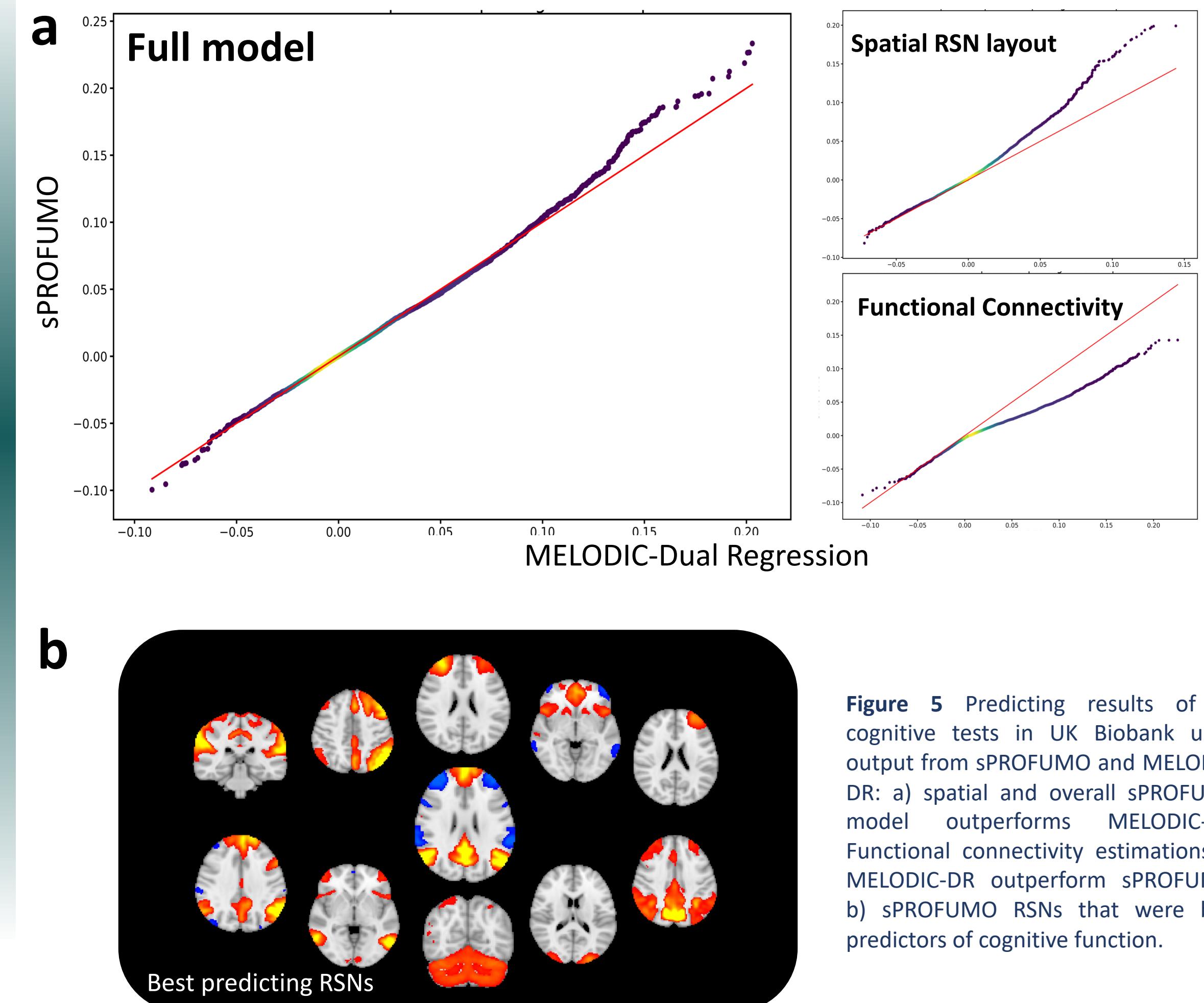


Figure 5 Predicting results of 68 cognitive tests in UK Biobank using output from sPROFUMO and MELODIC-DR: a) spatial and overall sPROFUMO model outperforms MELODIC-DR. Functional connectivity estimations of MELODIC-DR outperform sPROFUMO. b) sPROFUMO RSNs that were best predictors of cognitive function.

## Conclusions

- Stochastic PROFUMO can be used to infer individual and population RSNs from UK-Biobank-sized data.
- Stochastic inference allows for modelling heterogeneity in big data.
- Compared to MELODIC-DR, sPROFUMO more consistent in estimating cross-subject variability of RSNs.
- Compared to MELODIC-DR, sPROFUMO's spatial and overall model better predictors of cognitive tests.
- Compared to sPROFUMO, MELODIC-DR's functional connectivity better predictor of cognitive tests
  - Possibly related to recent discussions about interpretability of functional connectivity [7, 12,13].

- [1] Miller, Smith et al., Nature Neuroscience (2016).
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## References