Evaluation of full brain parcellation schemes using the NeuroVault database of statistical maps

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Introduction

The task of dividing the human brain into regions has been captivating scientists for many years. It is particularly difficult due to a plethora of different brain features (cortical thickness, resting state connectivity, structural connectivity etc.) that can be used but also because of biases related to the size of the parcels. In the following work we revisit this challenge and introduce a new evaluation technique that works for both cortical and subcortical parcellations. Our approach is based on data from a diverse set of cognitive experiments that employs nonparametric methods to account for smoothness and parcel size biases.

Methods

Publicly available statistical maps deposited in the NeuroVault.org database [1] were used as the initial dataset. Maps were limited to those that were: group level, fMRI BOLD, task based, unthresholded, and associated with a publication. After additional manual quality control, 430 unthresholded statistical maps from 50 published studies were selected to enter the analysis. To estimate the null distribution of measures of interest (see below) for each statistical map, a set of 200 random maps with matched smoothness was generated for each real map. All of the maps were standardized to zero mean and unitary variance.

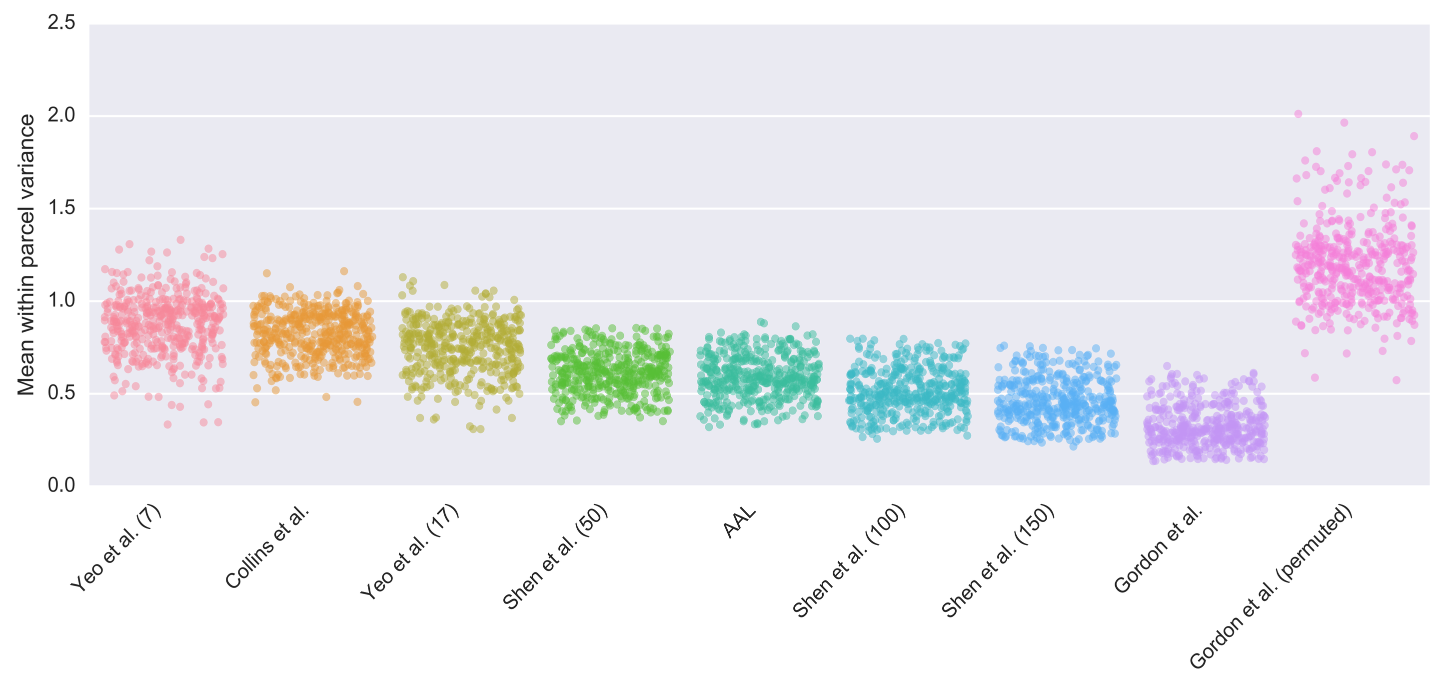
We have selected 5 commonly used parcellations for this comparison: Yeo et al.[2] Collins et al. [3], Shen et al. [4], AAL [5], and Gordon et al. [6]. As an additional sanity check we took the parcellation with the highest number of parcels (Gordon et al.) and permuted its labels. For each atlas and each real statistical map we calculated within and between parcel variance. The same measure was calculated for random maps. Means and standard deviations from those distributions were used to standardize real map measures, removing biases coming from map smoothness as well as number of parcels in each atlas.
Code used to perform the analysis is available at https://github.com/NeuroVault/atlas_analysis.

NEUROVAULT

Results

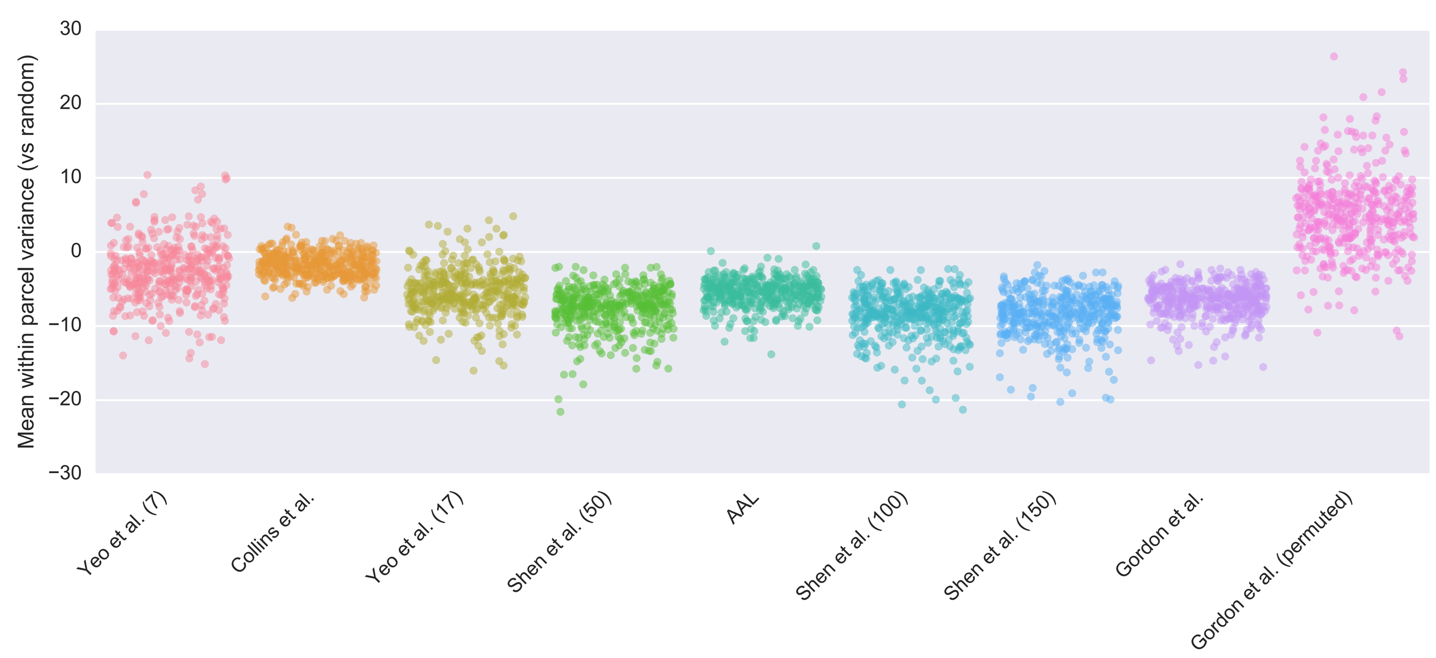
- Small parcels lead to low within parcel variance (Fig. 1)
- Empirically based null distribution can be used to account for parcel size (Fig. 2 and 4)
- Between/within parcel variance ratio determines the balance between number of parcels and model fit (Fig. 3)
- Yeo et al. parcellations outperform Collins et al.
- Gordon et al. parcellation performs similarly to Shen et al.

2



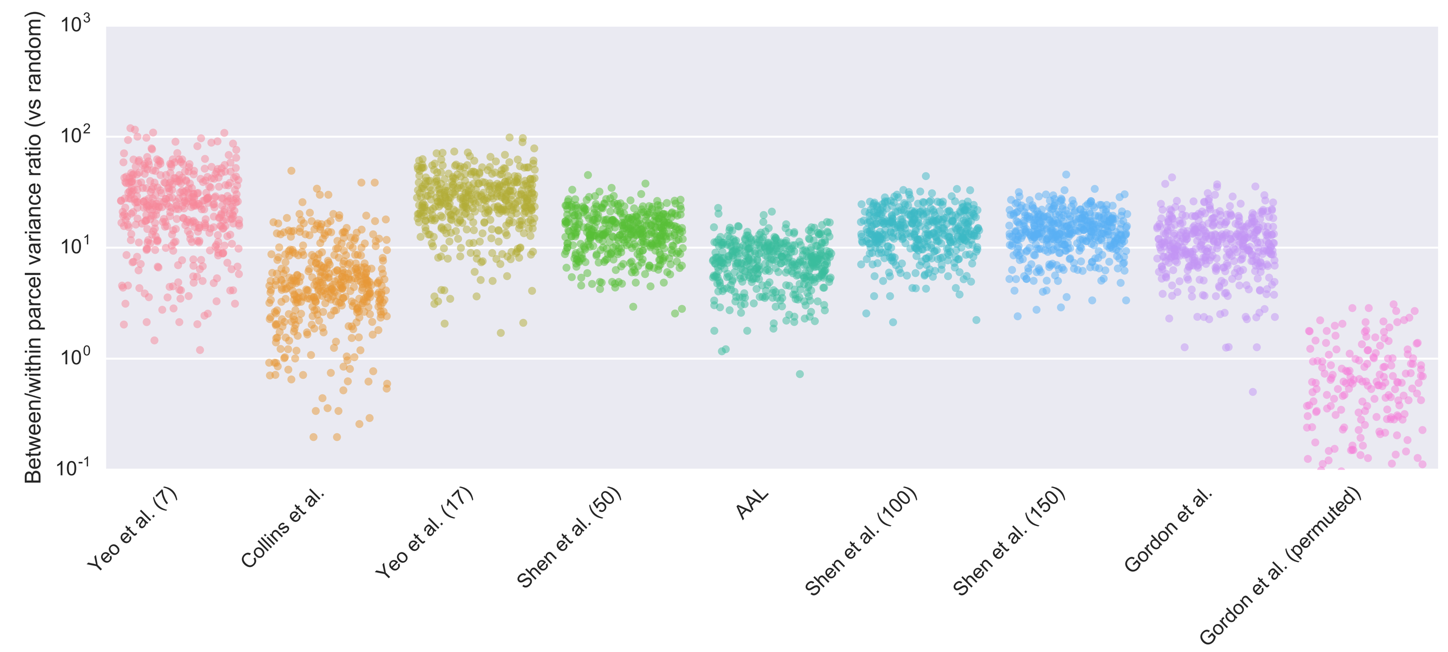
Comparison of parcellation schemes in terms of within parcel variance. Parcellations are ordered by increasing number of parcels. Each dot represents a measurement from one statistical map.

3



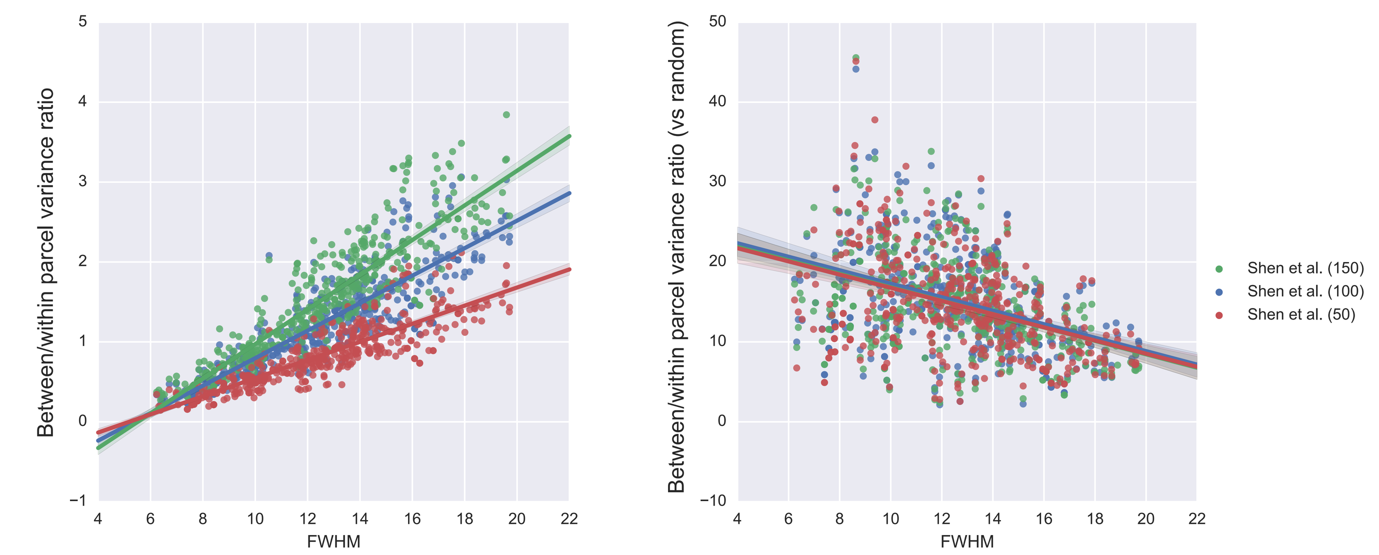
Comparison of parcellation schemes in terms of within parcel variance - normalized by corresponding null models. Parcellations are ordered by increasing number of parcels. Each dot represents a measurement from one statistical map standardized using mean and standard deviation obtained from a null distribution of measurement based on random statistical maps matched in terms of smoothness. A mean within parcel variance score of zero corresponds to parcel homogeneity no different than random.

4



Comparison of parcellation schemes in terms of the ratio of within and between parcel variance - normalized by corresponding null models. Parcellations are ordered by increasing number of parcels. Each dot represents a measurement from one statistical map standardized using mean and standard deviation obtained from a null distribution of measurements based on random statistical maps matched in terms of smoothness. A between/within parcel variance ratio of zero corresponds to measurement level no different than random.

5



Interaction between smoothness and parcel size. Smoothness of the input data has different effect on a parcellation scheme depending on the size of the parcels (left). In contrast to schemes with small parcels (Shen et al. 150 in green) schemes with big parcels (Shen et al. (50) in red) exhibit smaller correlation between smoothness and between/within parcel variance score. Standardization with null distributions derived from data matched for smoothness removes this effect (right).

References

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