Appendix 1 to Sato J, Balardin J, Vidal MC, et al. Identification of segregated regions in the functional brain connectome of autistic patients by a combination of fuzzy spectral clustering and entropy analysis. *J Psychiatry Neurosci* 2015.

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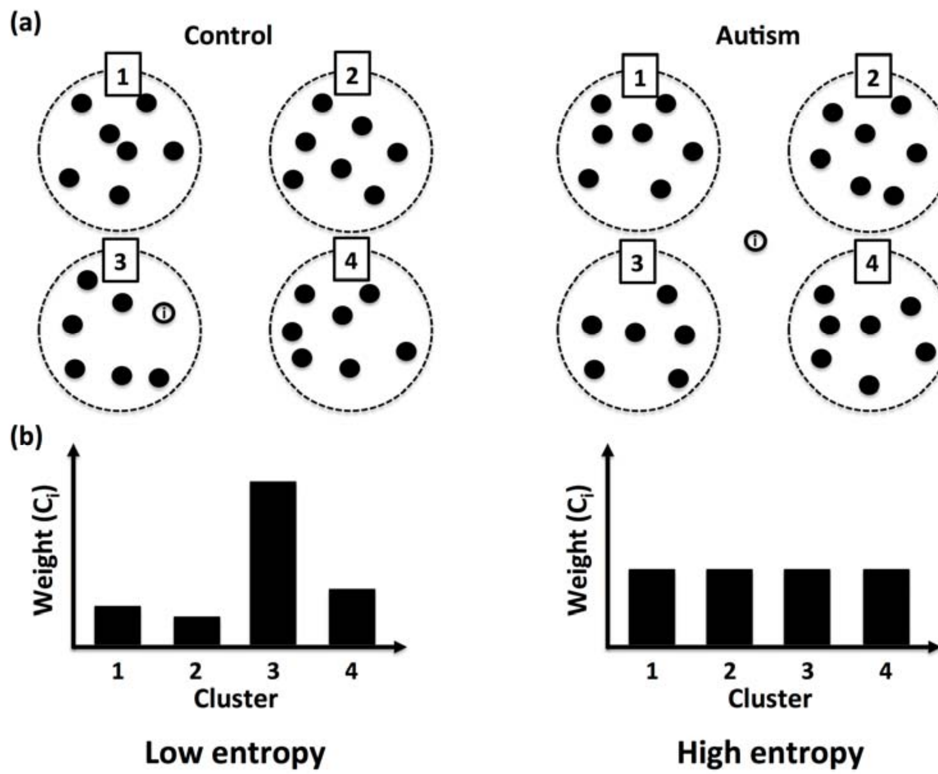

Fig. 1: Illustration of the entropy analysis. (a) Schematic example of one "control subject" and one "patient." The ROIs are represented by black circles and are clustered into 4 groups. In the control, the th ROI (white circle) is clearly assigned to cluster 3, while the same th ROI is equally far from the 4 clusters in the patient, i.e., the th ROI belongs equally to all 4 clusters. (b) The bars represent the extent to which the th ROI belongs to the th cluster (). Note that in the control case, the th ROI exhibits a low Shannon entropy, while in the patient, the same ROI exhibits a high Shannon entropy.

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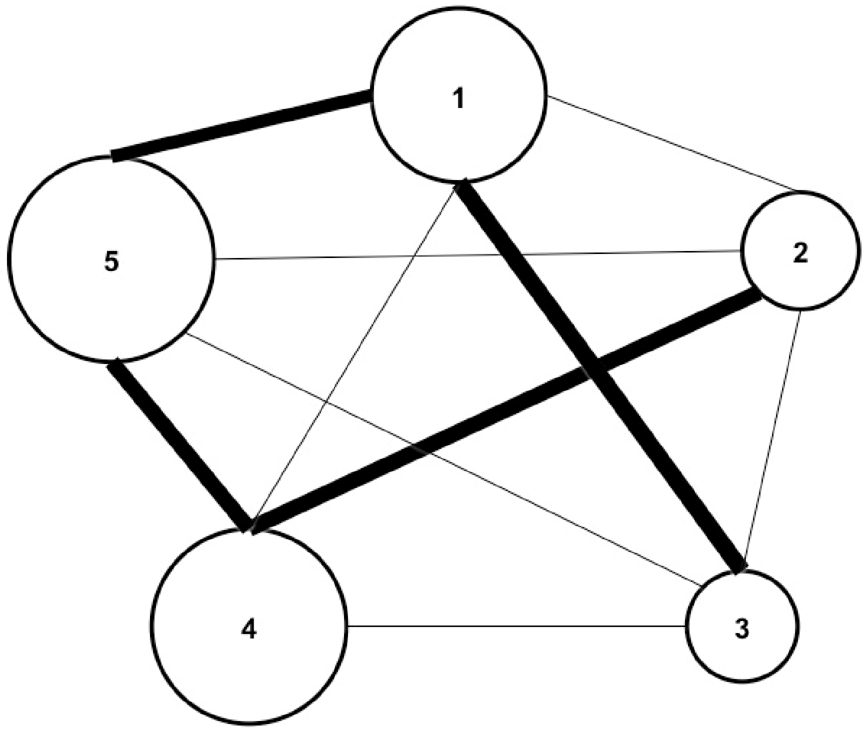

Fig. 2: Illustrative example of the eigenvector centrality. A node in the network is important if it is connected to other important (high eigenvector centrality) nodes 32. The bigger the node, the higher the centrality. The thickness of the edges represents the strength of the functional connectivity among nodes.

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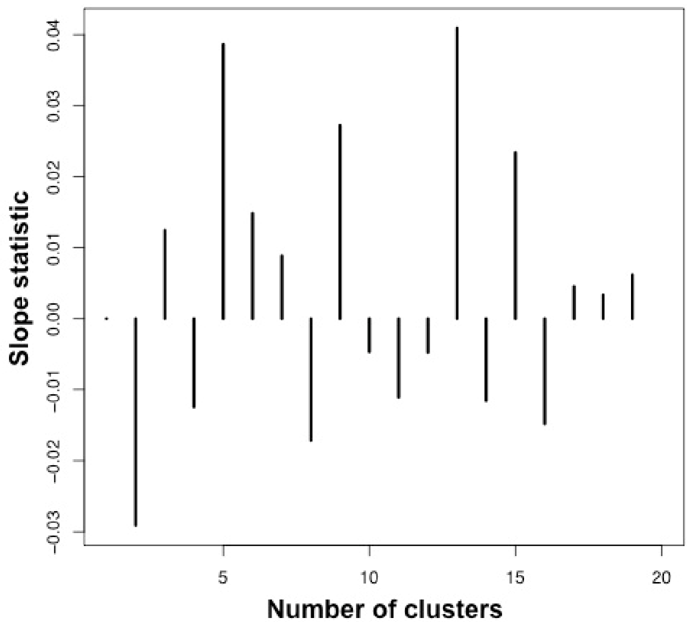

Fig. 3: Selection of the number of clusters. Plot of the number of clusters (X axis) versus the slope statistic (Y axis). The highest slope statistic value suggests that the optimum number of clusters in this data set was 13.

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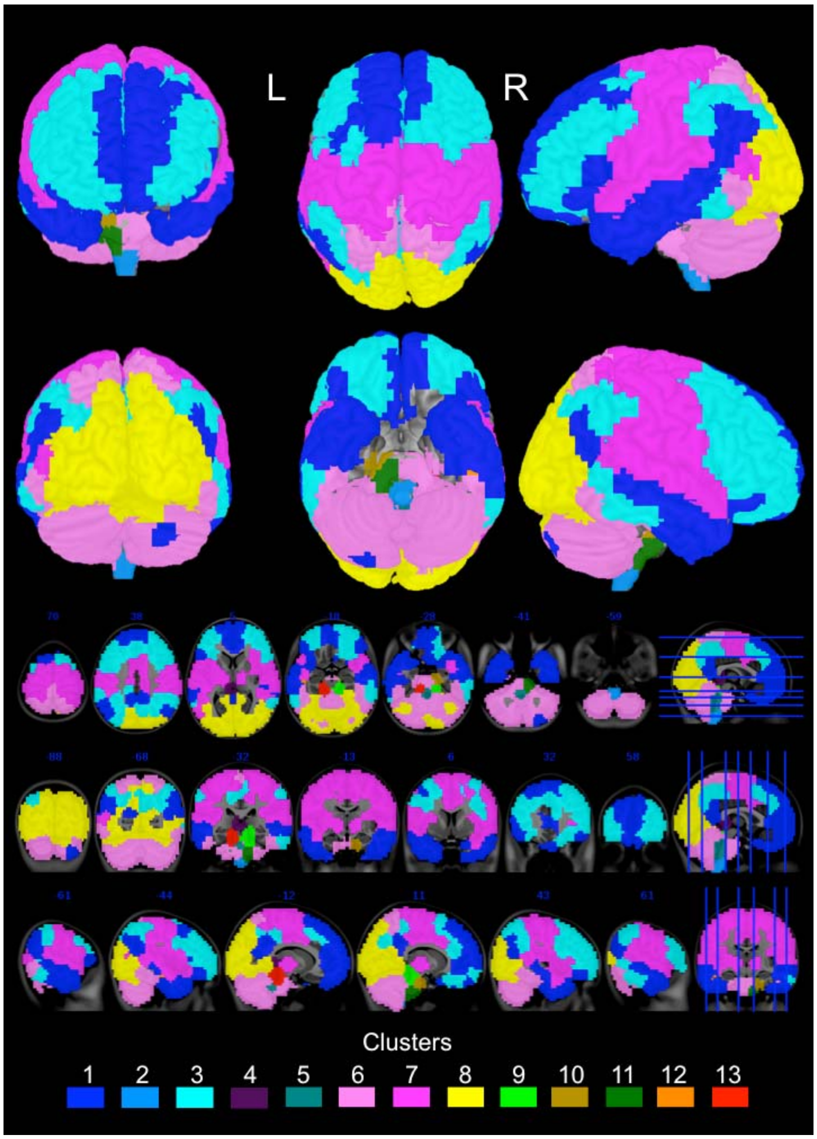

Fig. 4: ROIs clustering. ROIs clustered into 13 modules. Each colour represents one module/cluster. The clusters highlight some specific and well-established networks, such as the default-mode (cluster 1), control (cluster 3), somatomotor (cluster 7), visual (cluster 8), and cerebellar (cluster 6) clusters.

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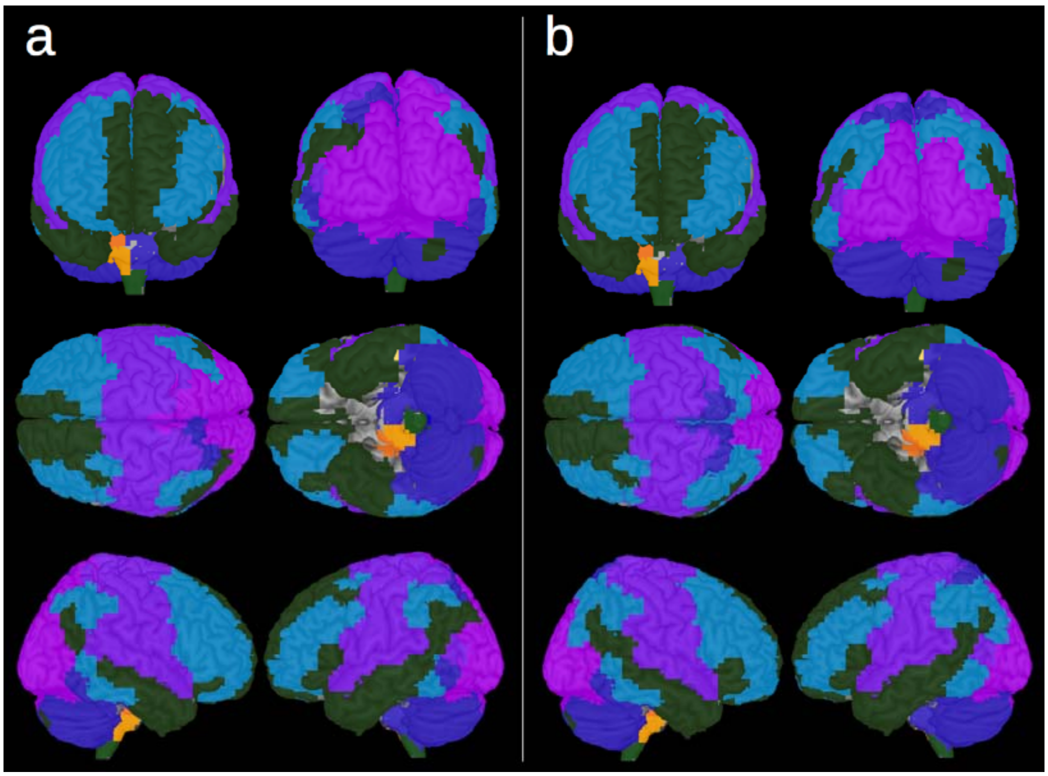

Fig. 5: Clustering of the controls (a) and ASD (b), separately. It is possible to see that controls and ASD cluster similarly.

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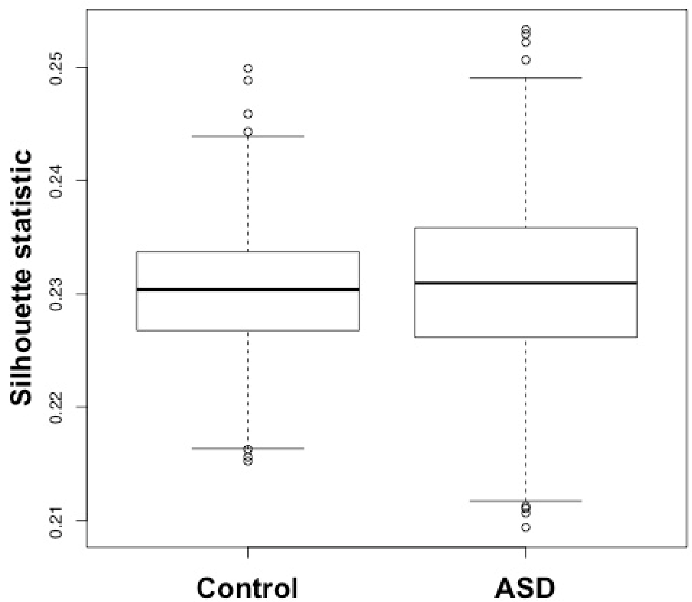

Fig. 6: Boxplots for the silhouette statistics. Boxplots of the average silhouette statistics for controls and ASD by using the labels of the clustering obtained by applying the FSC algorithm on the entire data set.

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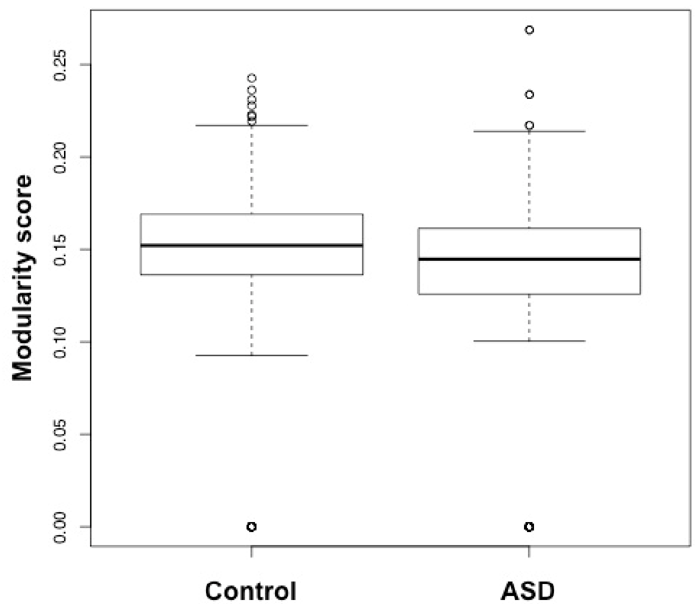

Fig. 7: Boxplot of the modularity scores. The modularities (a measure the appropriateness the partition of the ROIs given their clustering labels) of the functional brain networks of the control subjects and those with ASD. The functional brains of the subjects with autism were less modular than those of the controls ($p < 0.001$).

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Spectral Cluttering

```
################################################################################

## Spectral clustering with c-means (fuzzy clustering)

## Input:
## W: adjacency matrix of the graph
## k: number of clusters

## Output
## C: c-means object (hard clustering labels and weights)

spectral.clustering <- function(W, k) {
  n <- ncol(W)

  ## Diagonal matrix with the degrees in the main diagonal
  D <- matrix(0, n, n)
  for (i in 1:n) {
    D[i,i] <- sum(abs(W[i,]))
  }

  ## Unnormalized Laplacian
  L <- D - W
  U <- (eigen(L)$vectors)[,((n-k+1):n)]
  ## uses the result of k-means as a seed for the fuzzy clustering
  C <- kmeans(U, centers=k, nstart=200)
  Cf <- cmeans(U,centers=C$centers,verbose=FALSE,method="ufcl")

  ## finds the clustering structure that maximizes the silhouette statistic
  ## OBS.: both k-means and the optimization of the silhouette statistic are
  ## done to avoid local optimum clusters.
  tmpf <- mean(silhouette(Cf$cluster, dist(U))[,3])
  for(i in 1:100) {
    C_ <- cmeans(U,centers=C$centers,verbose=FALSE,method="ufcl")
    tmp <- mean(silhouette(C$cluster, dist(U))[,3])
    if(tmp > tmpf) {
      Cf <- C_
      tmpf <- tmp
    }
  }
  return(Cf)
}

################################################################################
```