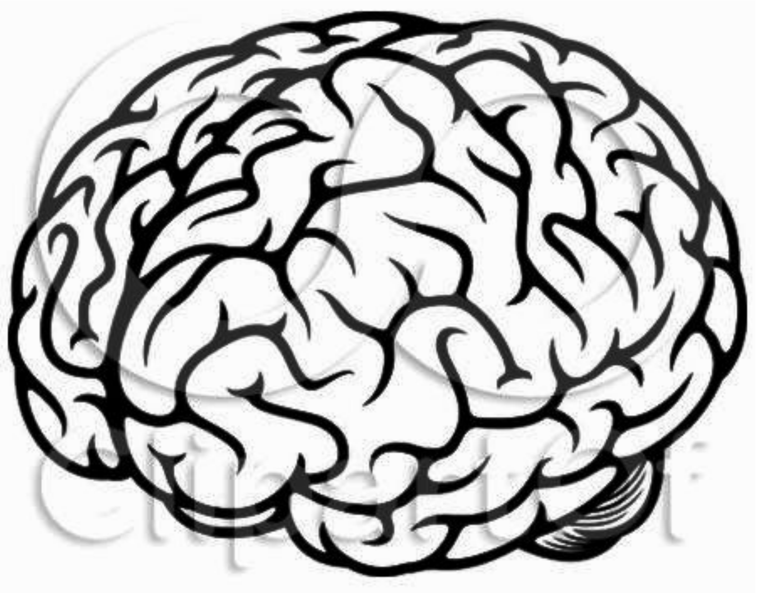
MRI based brain parcellation

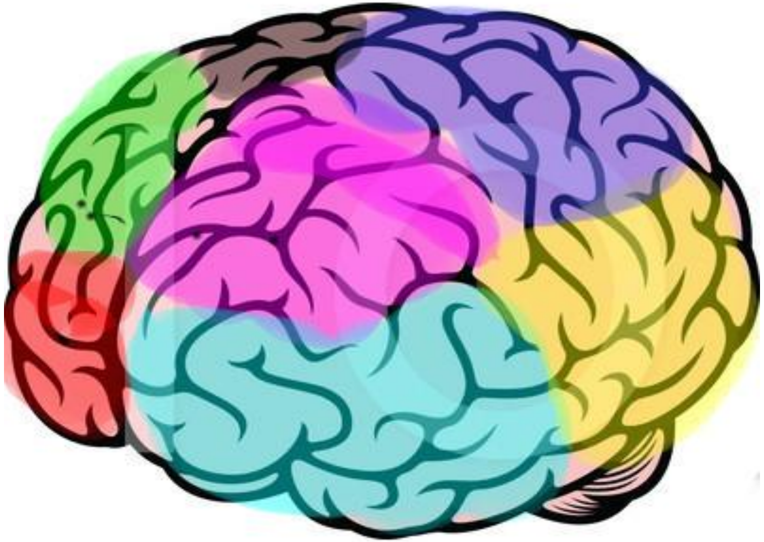
Kurmukov Anvar, 2020

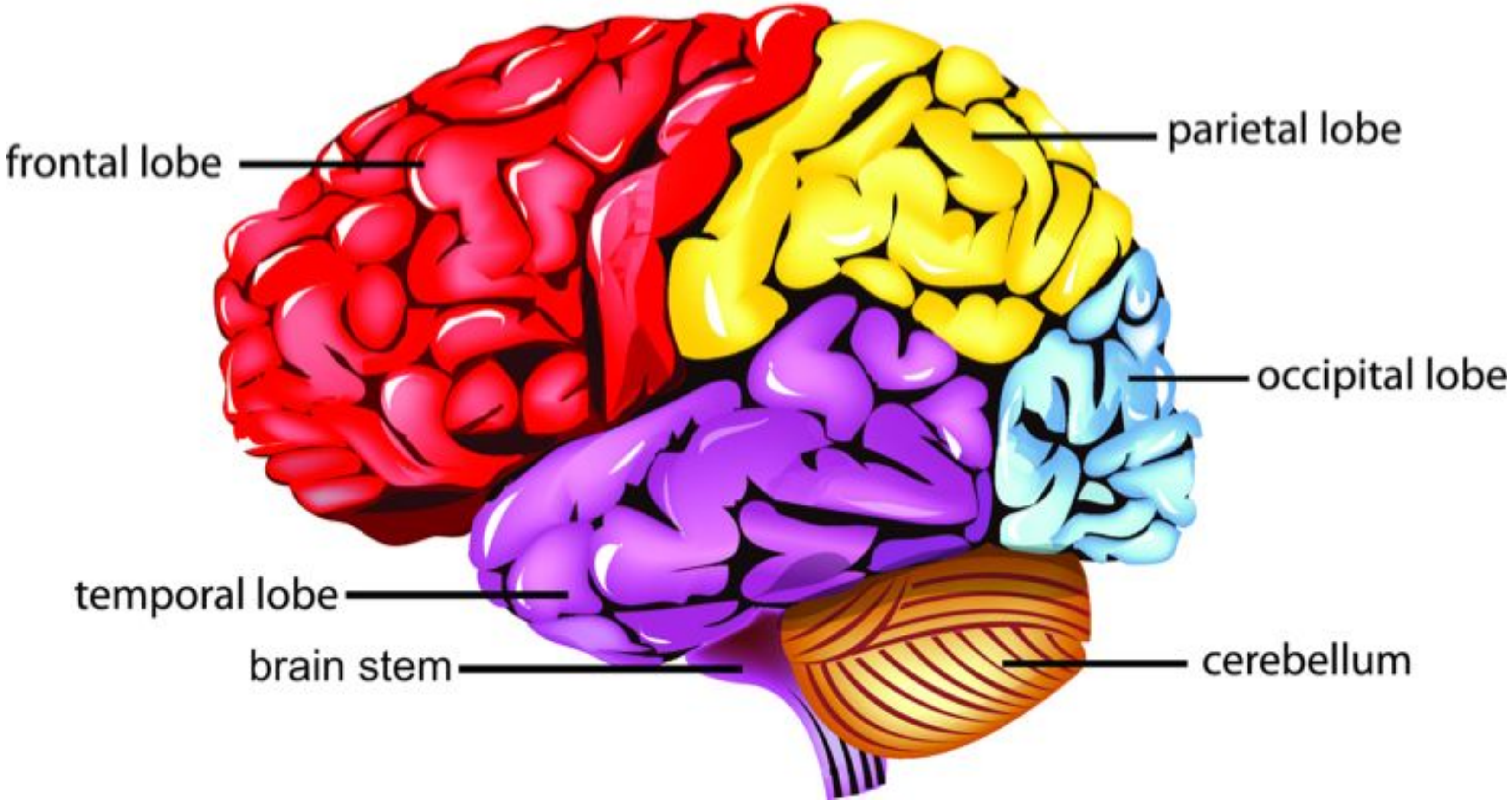
1. What is brain parcellation?

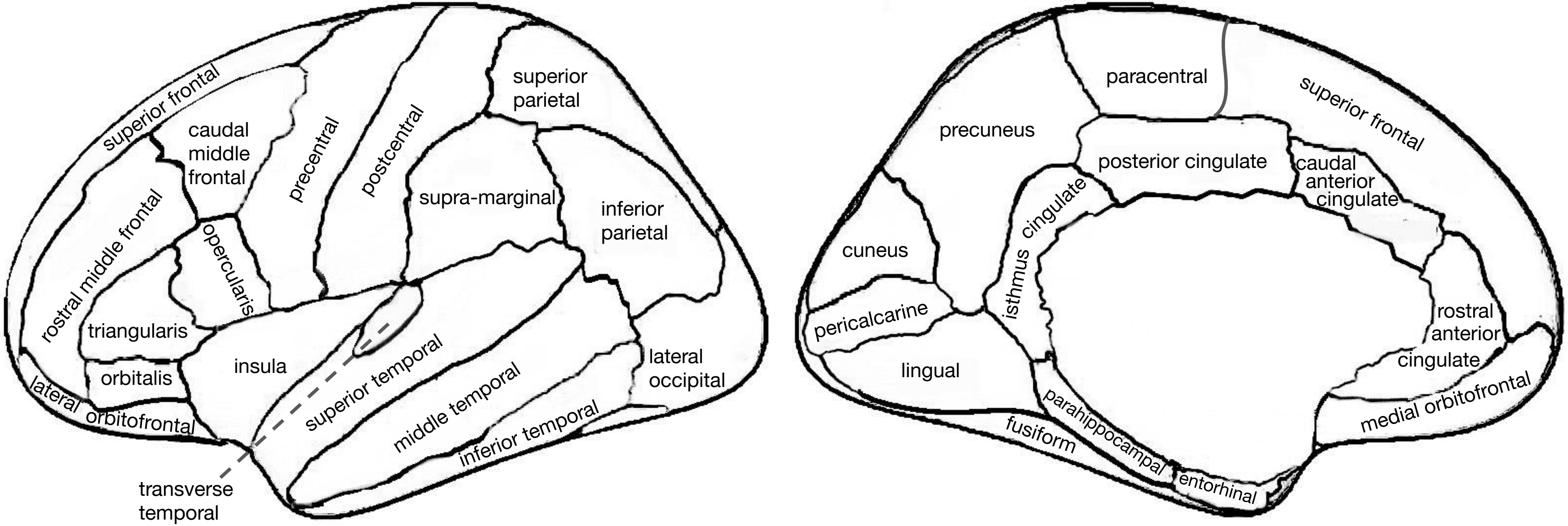
In computational neuroimaging, brain parcellation methods subdivide the brain into individual regions <...> to study its **structure and function.**

Brain parcellation based on information theory





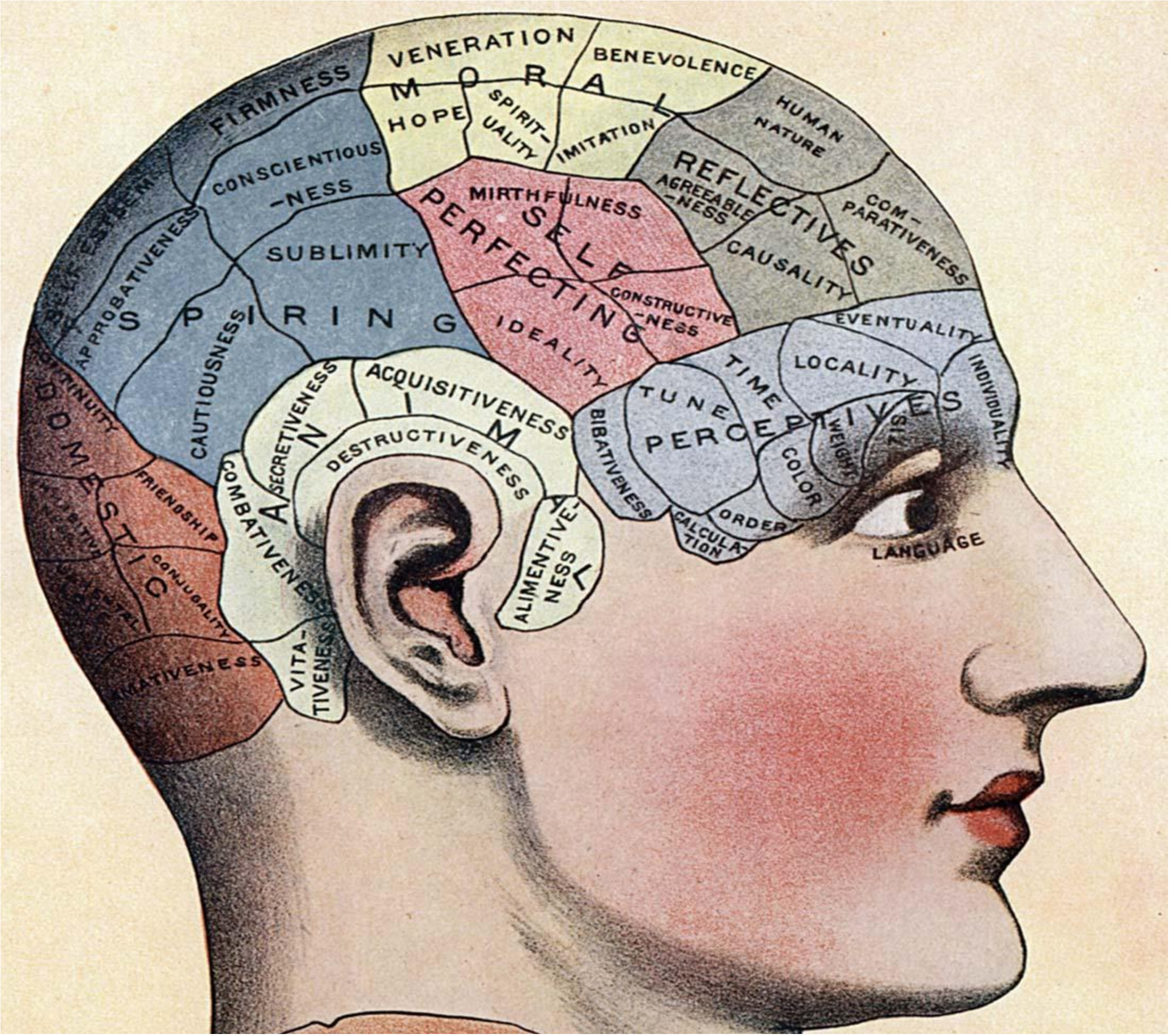

frontal lobe
parietal lobe
occipital lobe
temporal lobe
brain stem
cerebellum



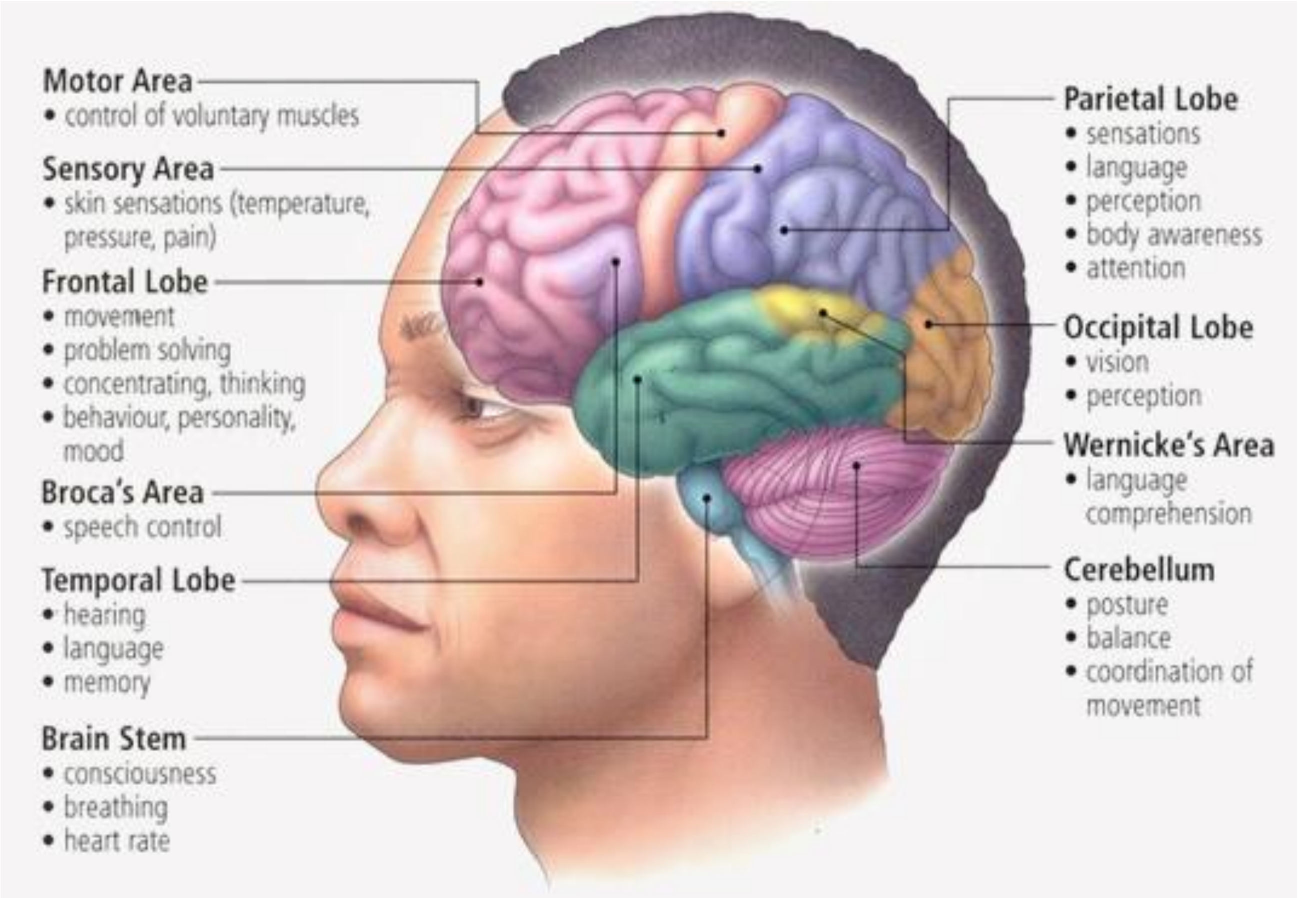
superior frontal
caudal middle frontal
precentral
postcentral
superior parietal
supra-marginal
inferior parietal
rostral middle frontal
opercularis
triangularis
orbitalis
lateral orbitofrontal
insula
superior temporal
middle temporal
inferior temporal
lateral occipital
transverse temporal
paracentral
superior frontal
precuneus
posterior cingulate
caudal anterior cingulate
isthmus cingulate
cuneus
pericalcarine
lingual
rostral anterior cingulate
medial orbitofrontal
fusiform
parahippocampal
entorhinal

2. Why do we need parcellations?

1. Because brain structure is somehow related to its function.
2. Because typical MRI consists of ~10^5 up to ~ 10^7 voxels and typical study has ~10^1 up to ~10^3 observations (dimensionality reduction).
3. Because in multimodal studies we need to have 1 to 1 correspondence between different modalities.
4. Because in population studies we need to have 1 to 1 correspondence between subjects.
5. To build connectomes;)



[Phrenology](#)
(pseudoscience)


Motor Area
• control of voluntary muscles
Sensory Area
• skin sensations (temperature, pressure, pain)
Frontal Lobe
• movement
• problem solving
• concentrating, thinking
• behaviour, personality, mood
Broca's Area
• speech control
Temporal Lobe
• hearing
• language
• memory
Brain Stem
• consciousness
• breathing
• heart rate
Parietal Lobe
• sensations
• language
• perception
• body awareness
• attention
Occipital Lobe
• vision
• perception
Wernicke's Area
• language comprehension
Cerebellum
• posture
• balance
• coordination of movement

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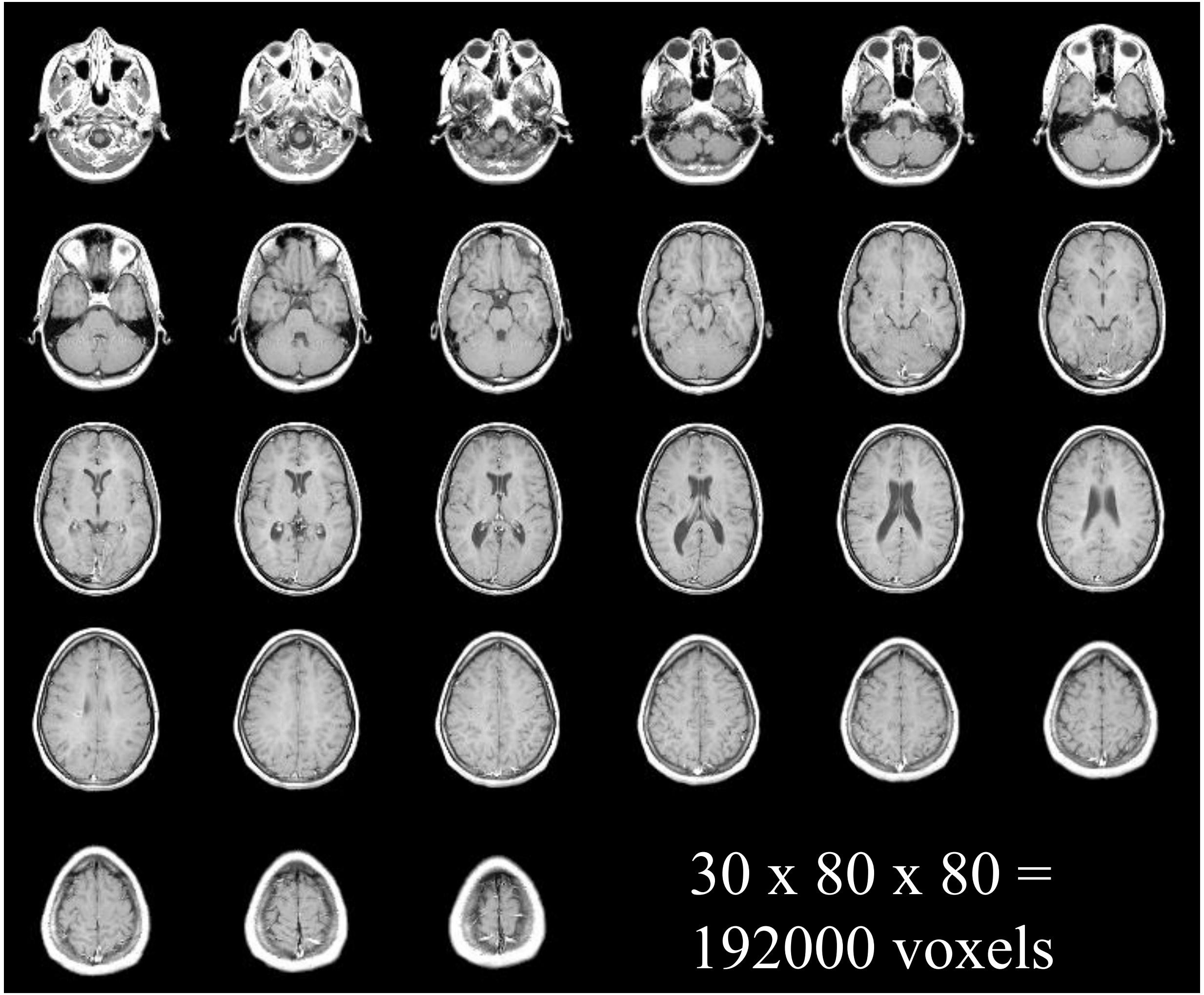
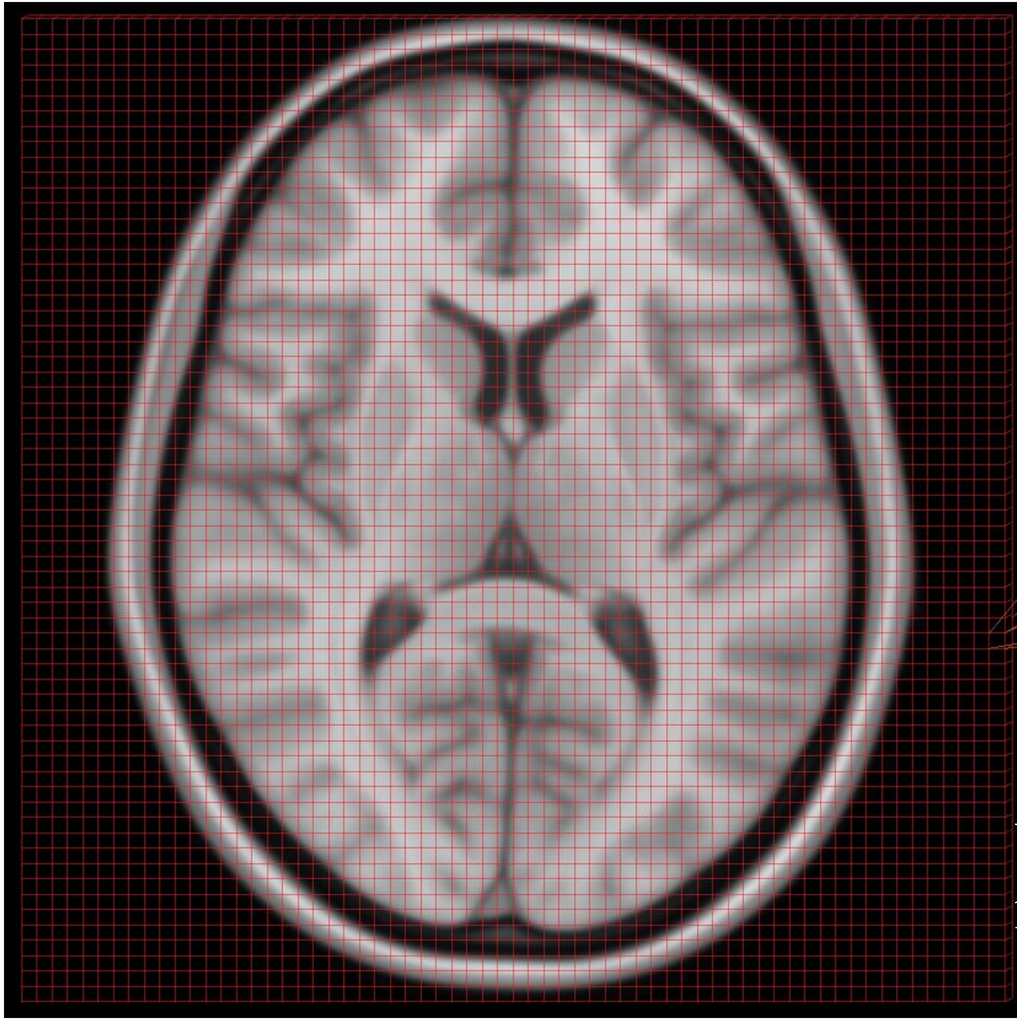

30 x 80 x 80 =
192000 voxels



Matrix size of slice:
64 x 64

Voxel size:
3mm x 3mm x 3mm

voxels are not necessarily squared

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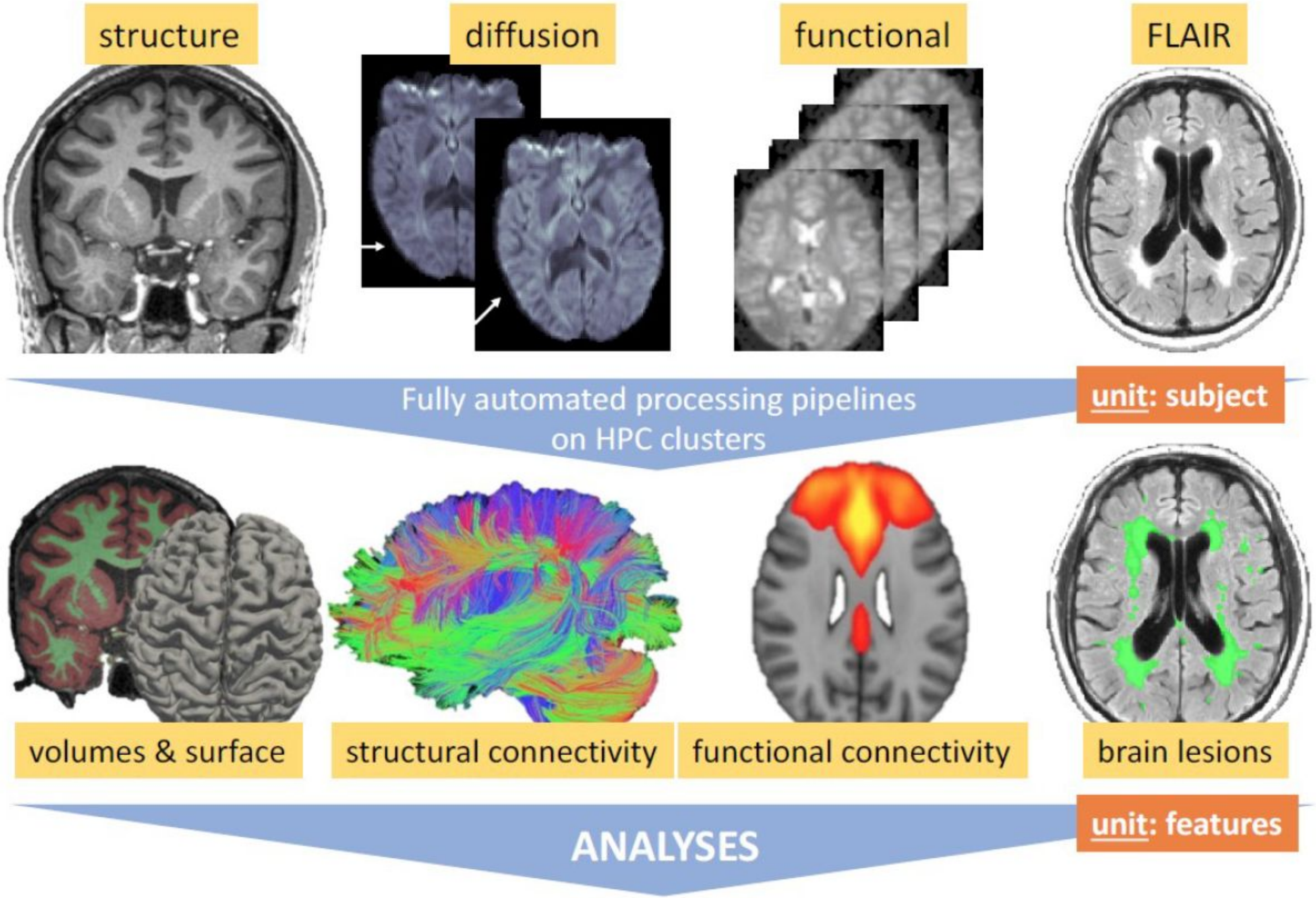
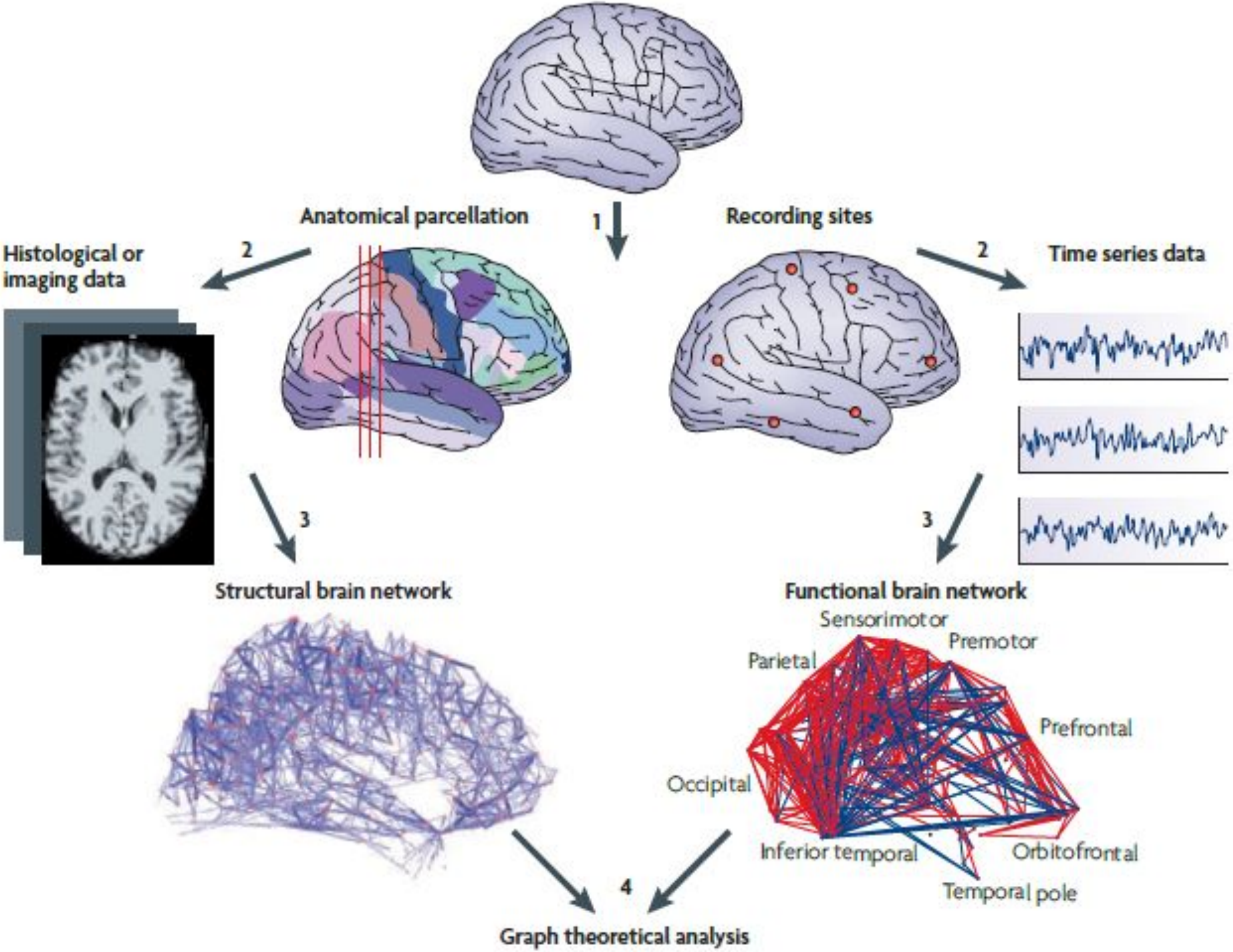

structure
diffusion
functional
FLAIR
Fully automated processing pipelines
on HPC clusters
unit: subject
volumes & surface
structural connectivity
functional connectivity
brain lesions
ANALYSES
unit: features

source



Source is lost ;(

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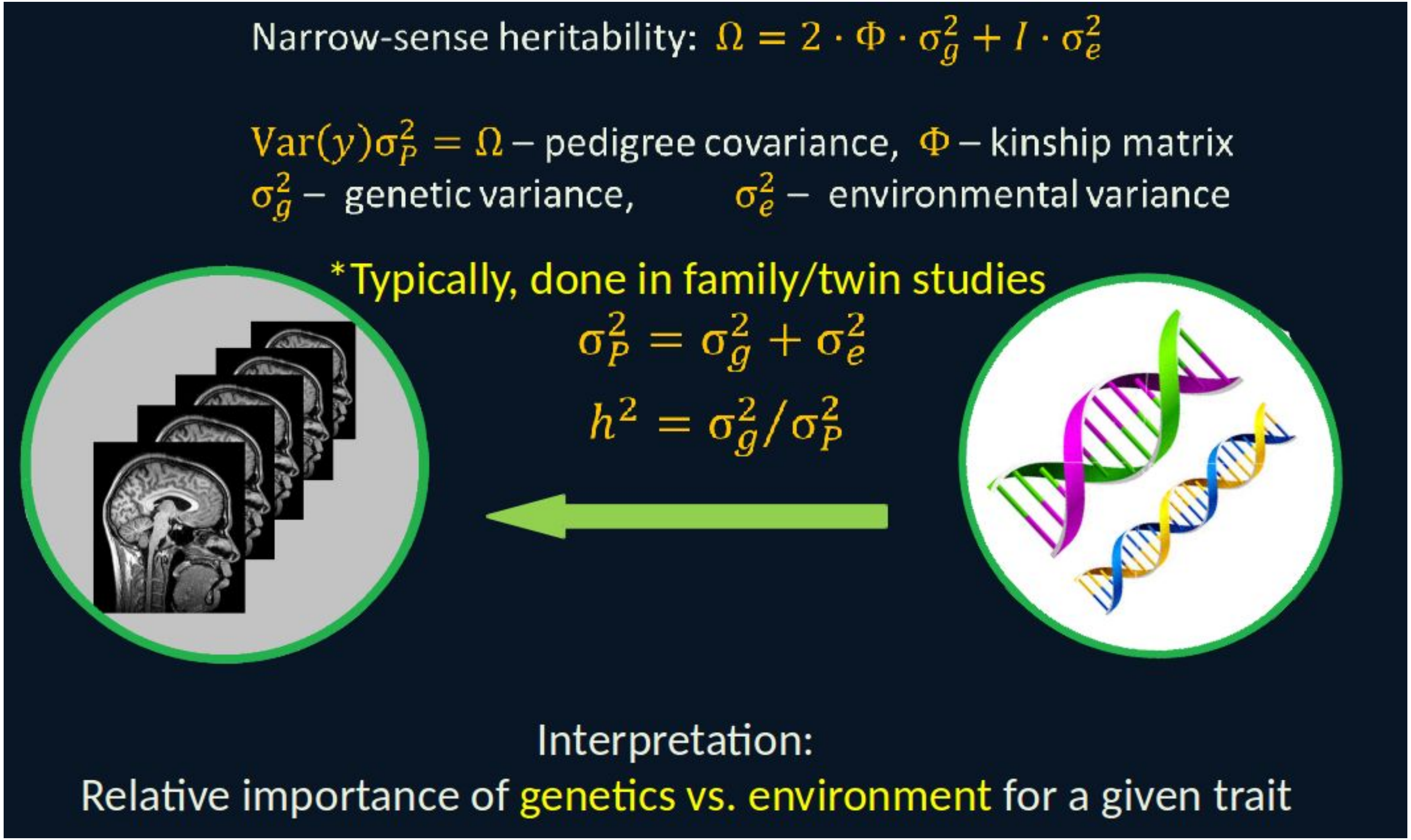
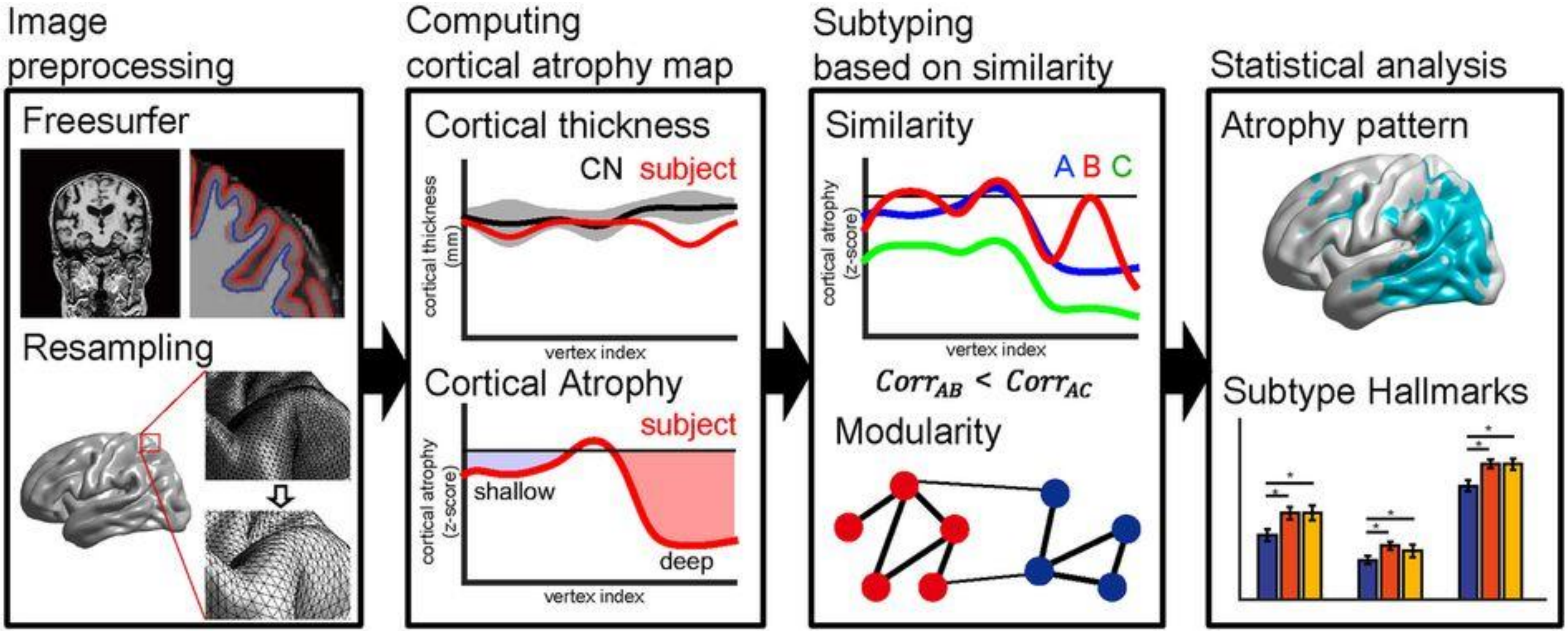
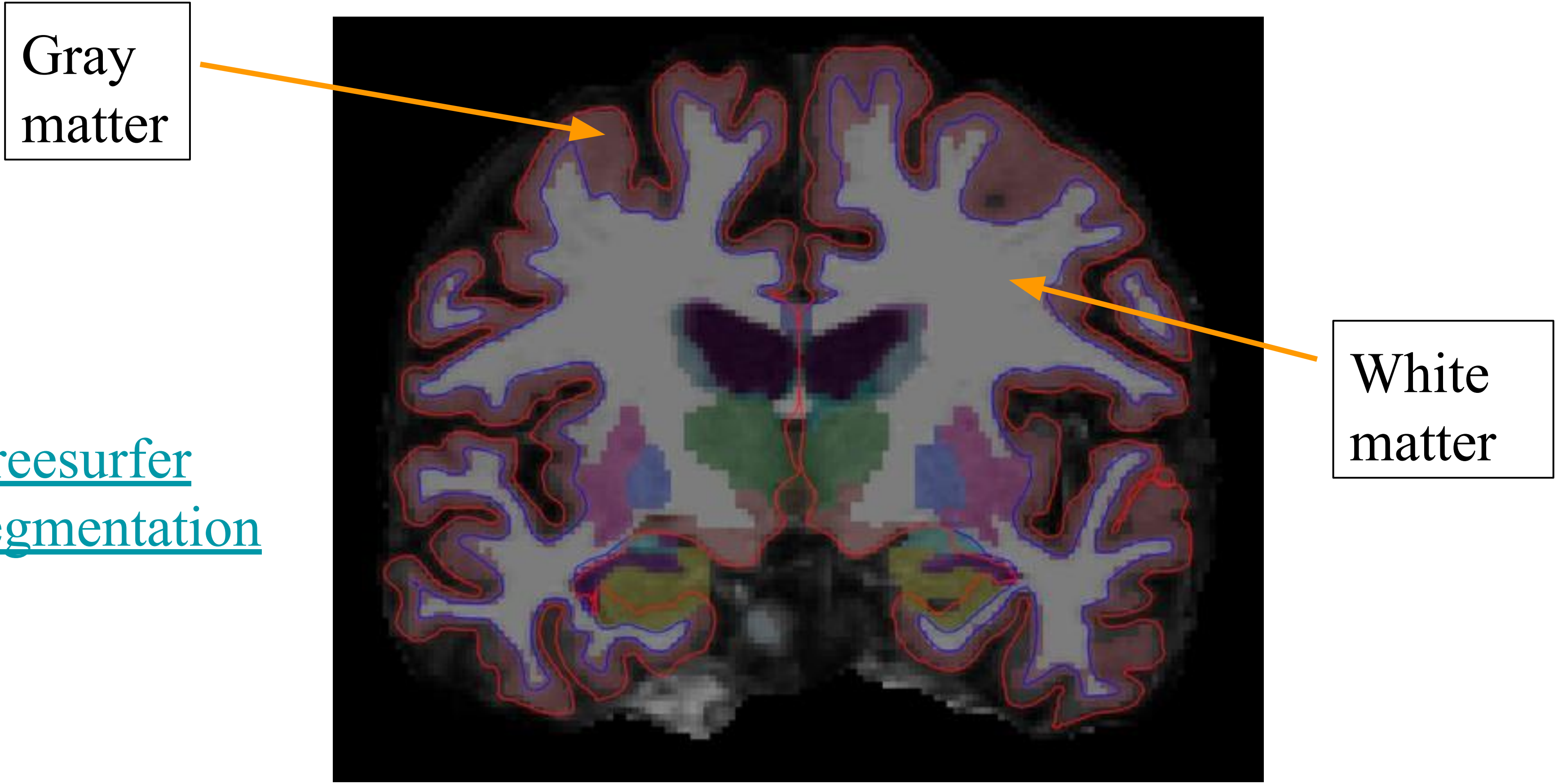
Heritability of the shape of subcortical brain structures in the general population





[Robust Identification of Alzheimer's Disease subtypes based on cortical atrophy patterns]()



[Freesurfer segmentation]

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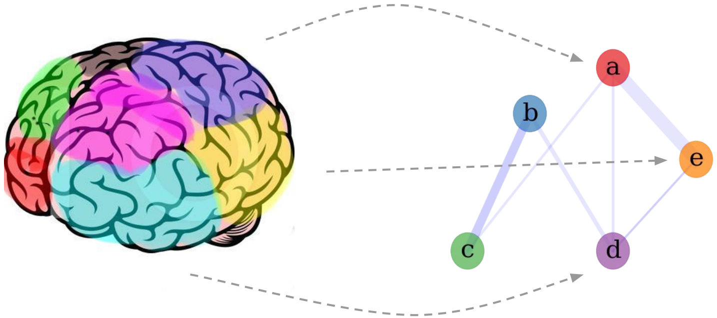
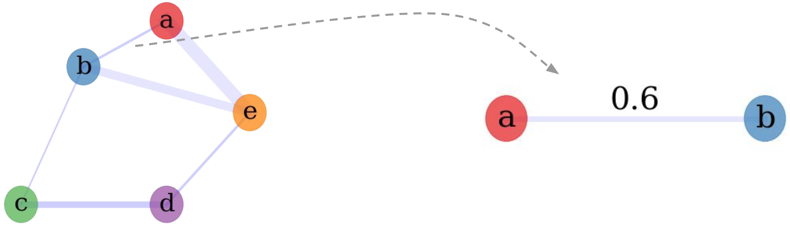
Brain network = Connectome

Brain regions become nodes



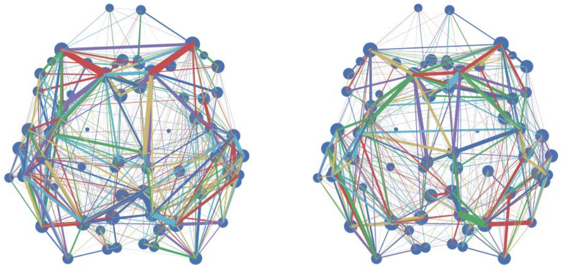
Neural connections between regions become edges



Graph $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E}, \boldsymbol{l}, \boldsymbol{w})$, where

- $\boldsymbol{V}$ is the set of nodes
- $\boldsymbol{E}$ is the set of edges
- $\boldsymbol{l}$ is node's labeling mapping
- $\boldsymbol{w}$ is edge's weighting mapping

is called a brain network or a **connectome**



[Classification of Normal and Pathological Brain Networks Based on Similarity in Graph Partitions]

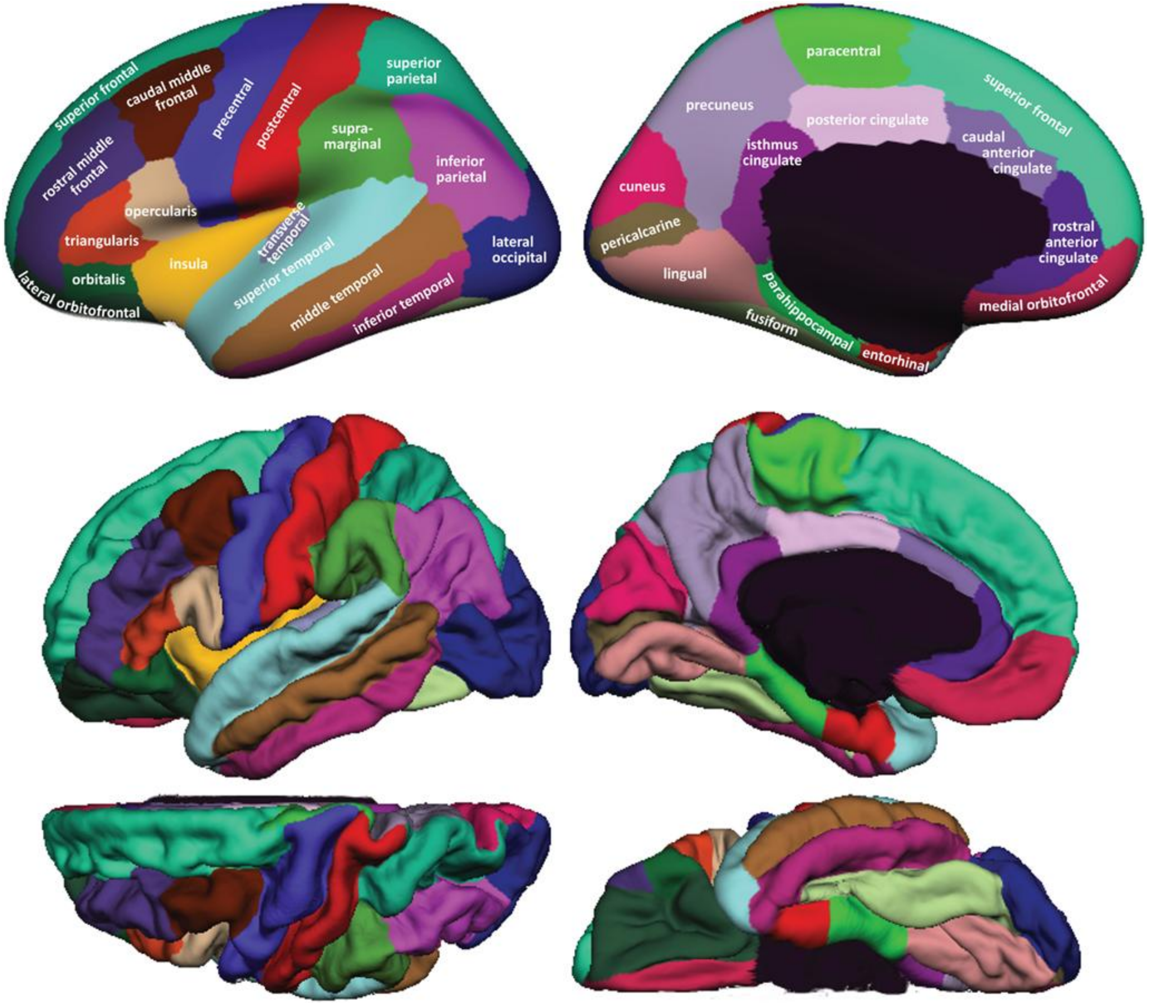
3. Anatomical parcellations

Cortical parcellations = parcellation of the brain surface, popular examples are:

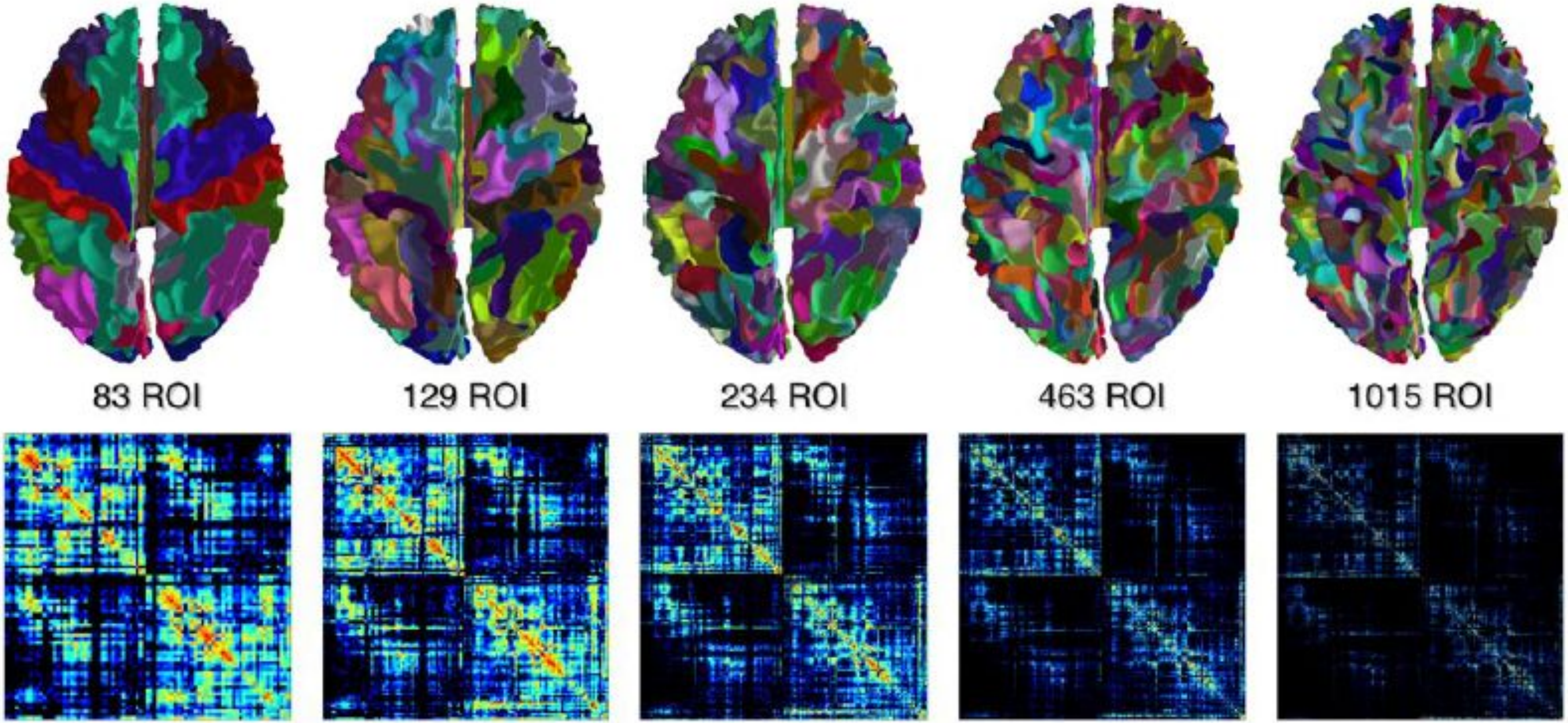
1. Destrieux Atlas
2. Desikan-Killiany Atlas
3. DKT Atlas
4. Lausanne atlas
5. Harvard-Oxford atlas
6. Automated Anatomical Labeling
7. more

[101 labeled brain images and a consistent human cortical labeling protocol]()

They used DKT protocol. Manual segmentation of anatomical areas

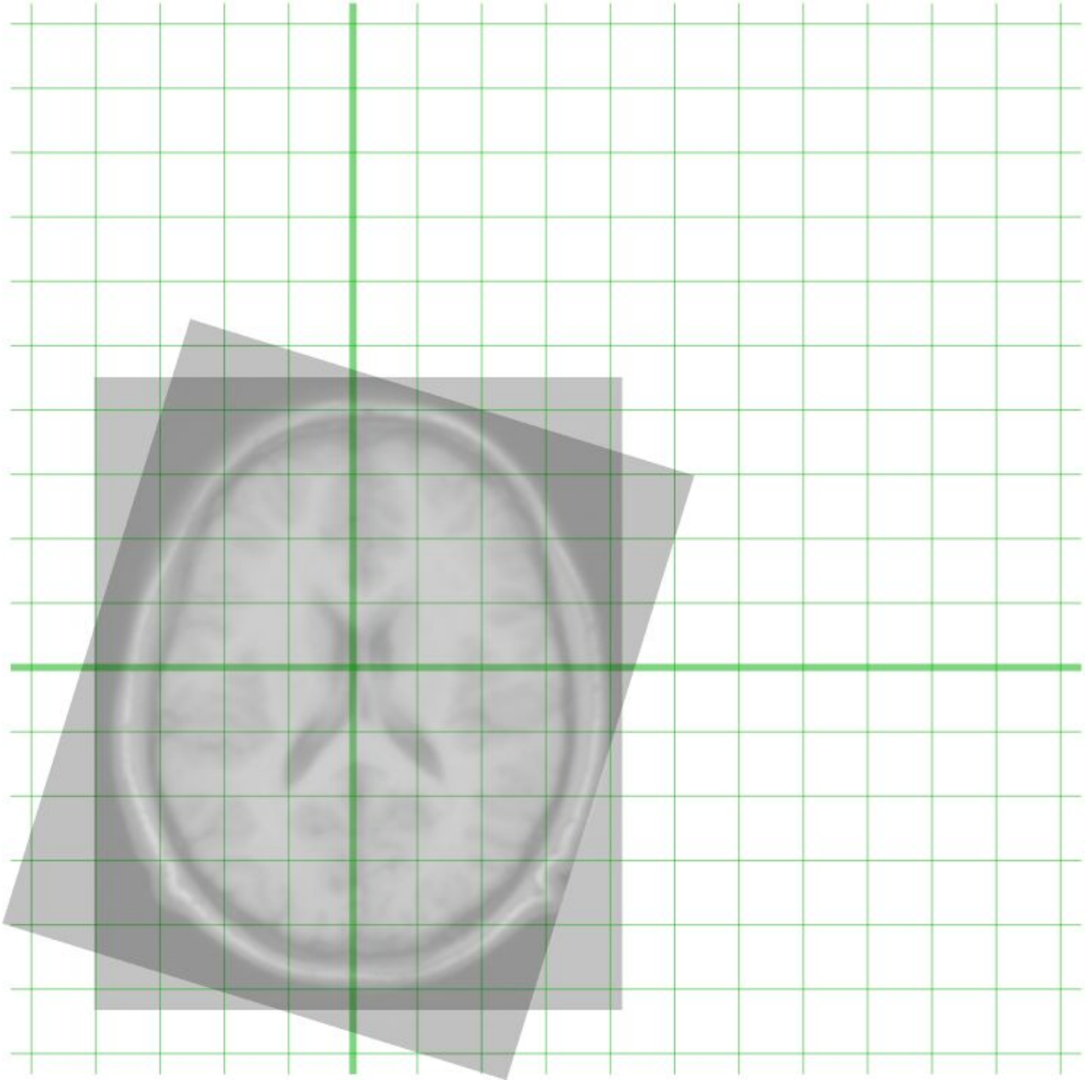


Lausanne atlas



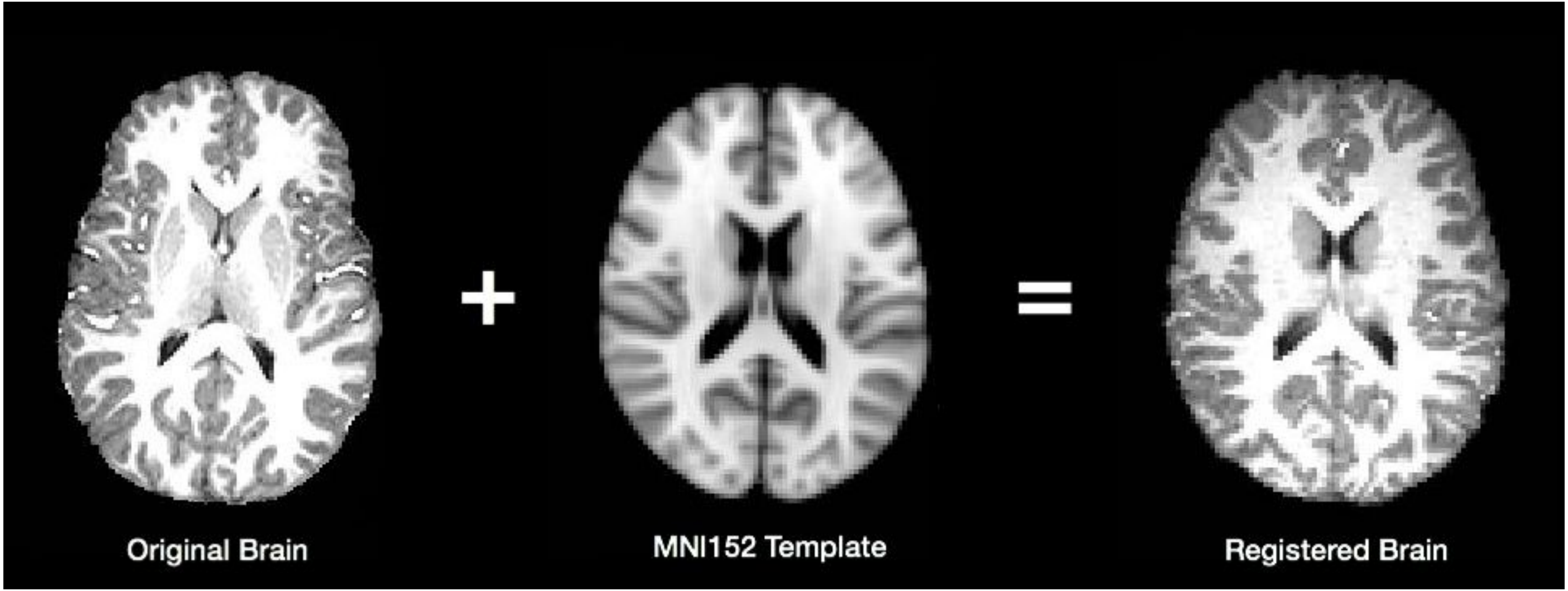
[source](#) [implementation](#)

4. Couple of words on Image Registration

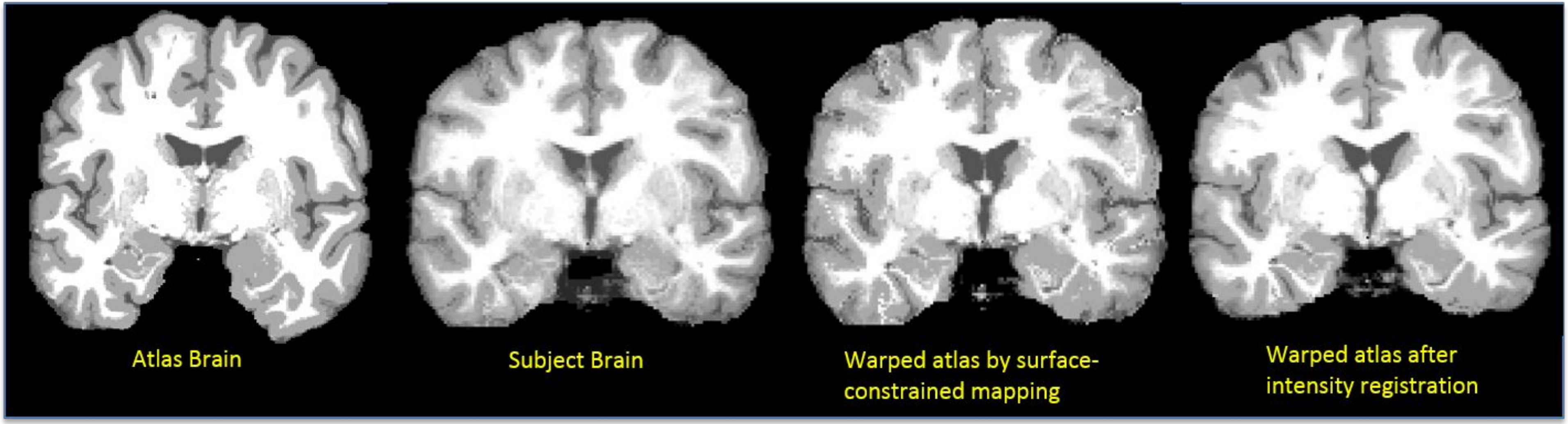


Voxel-wise registration

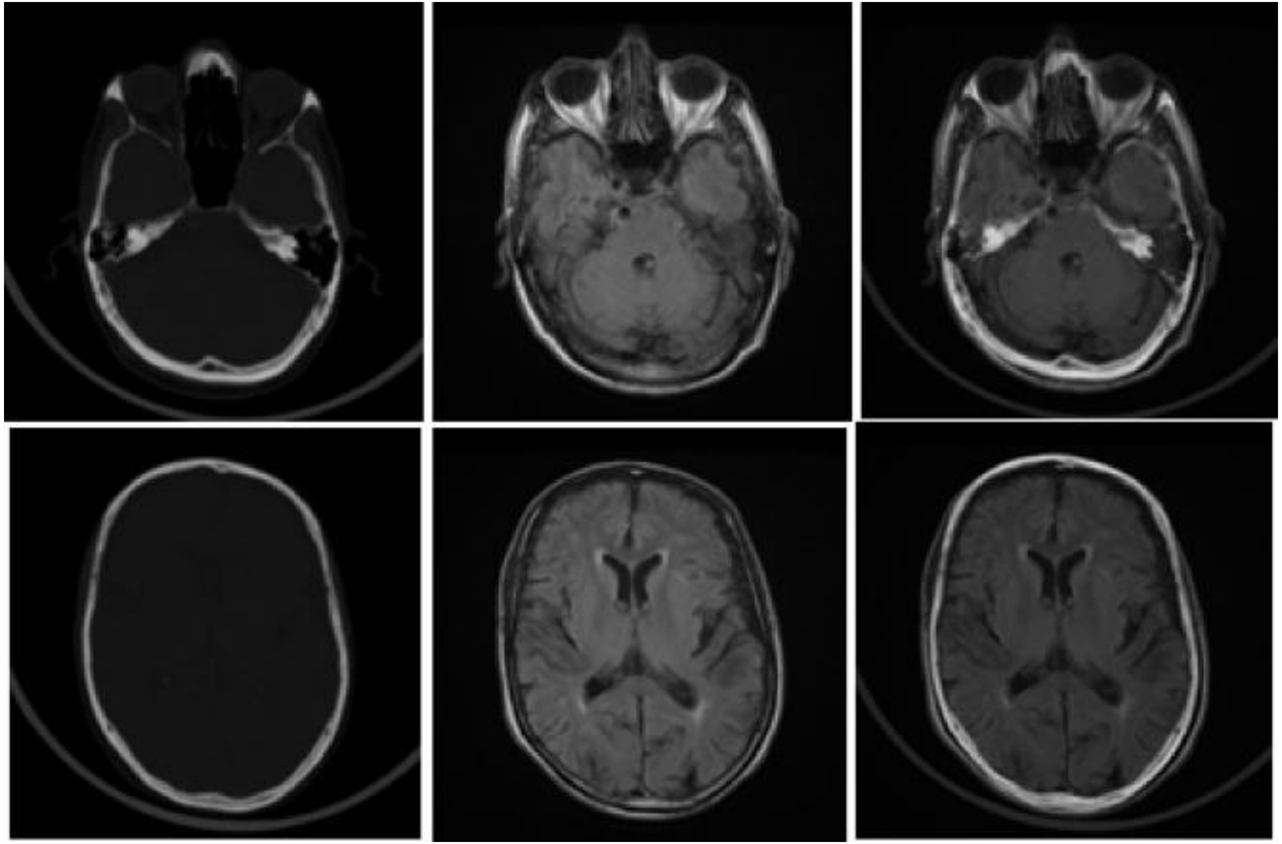
Register on template



[About MNI space]()

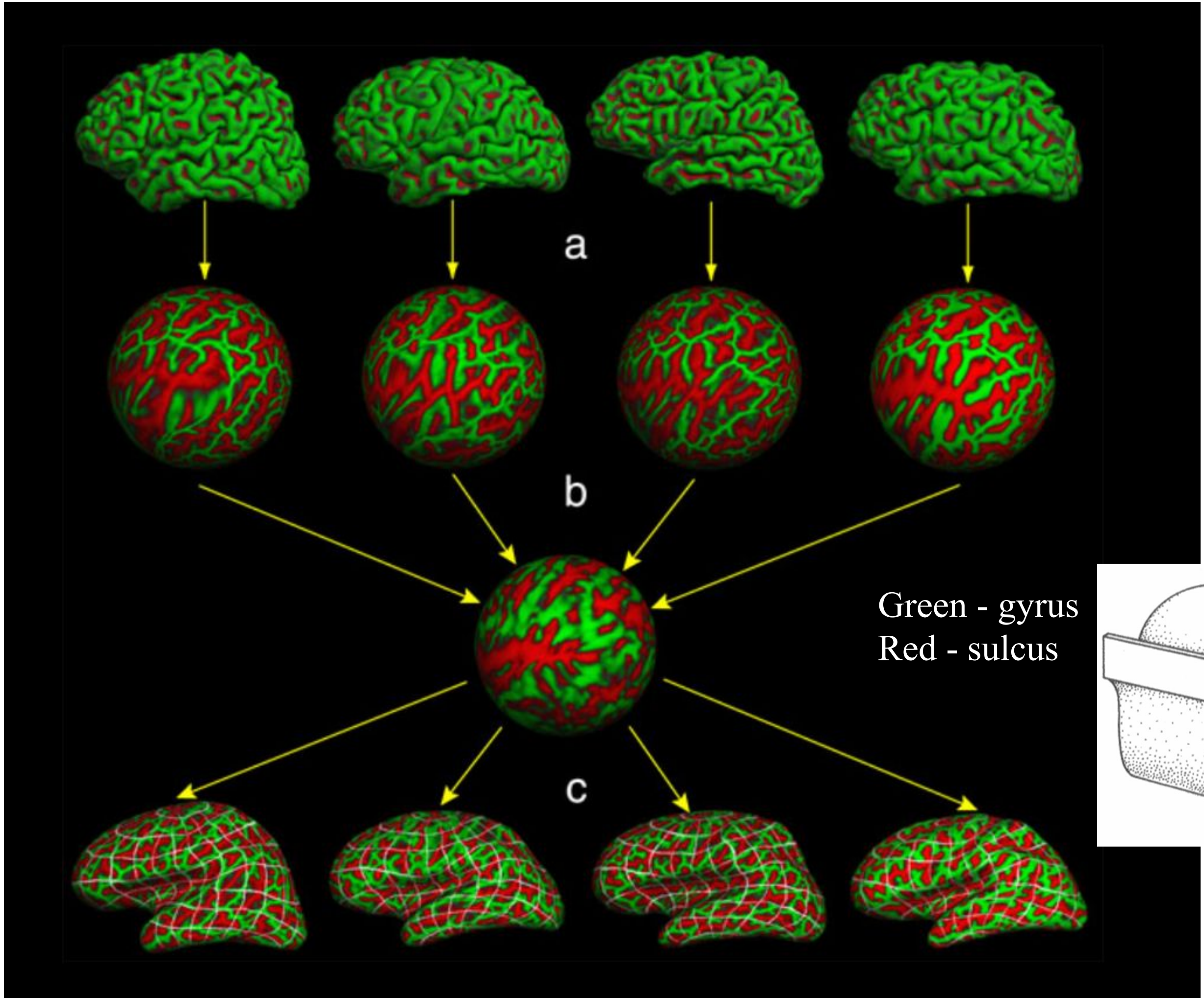

Atlas Brain
Subject Brain
Warped atlas by surface-constrained mapping
Warped atlas after intensity registration

Register on modality

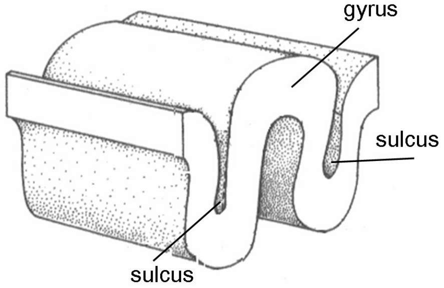


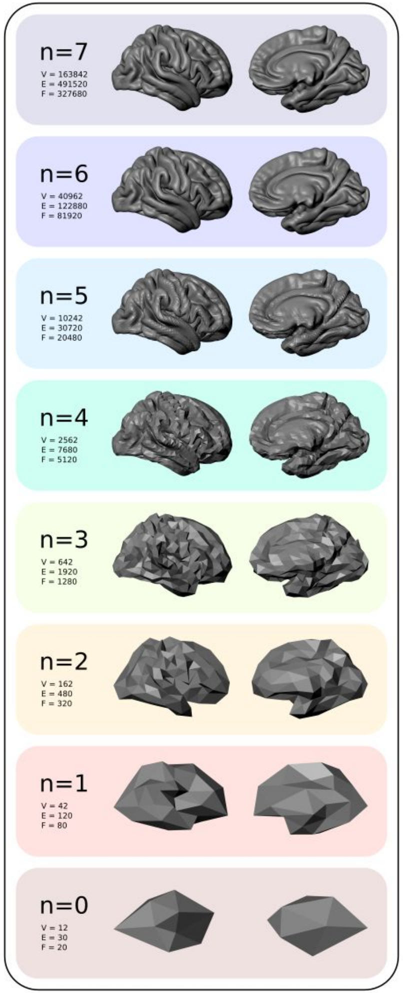
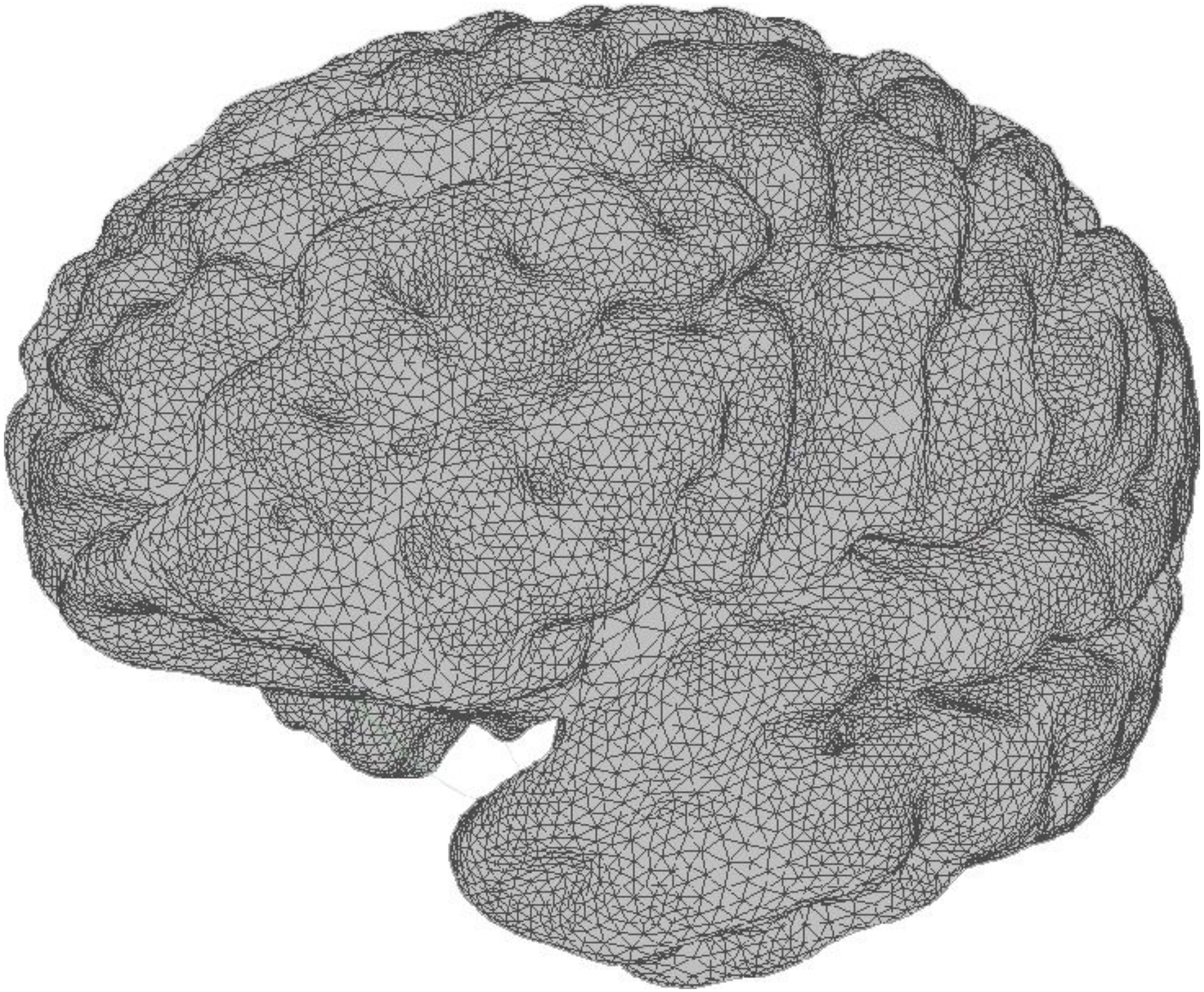
Surface-based registration

Freesurfer



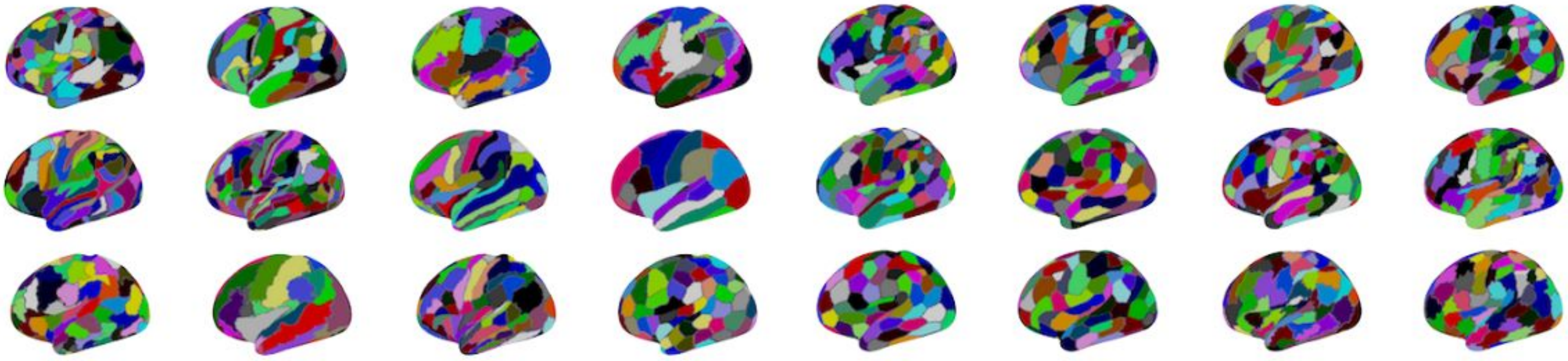
Green - gyrus
Red - sulcus




n=7
V = 163842
E = 491520
F = 327680
n=6
V = 40962
E = 122880
F = 81920
n=5
V = 10242
E = 30720
F = 20480
n=4
V = 2562
E = 7680
F = 5120
n=3
V = 642
E = 1920
F = 1280
n=2
V = 162
E = 480
F = 320
n=1
V = 42
E = 120
F = 80
n=0
V = 12
E = 30
F = 20


4. Data driven brain parcellations

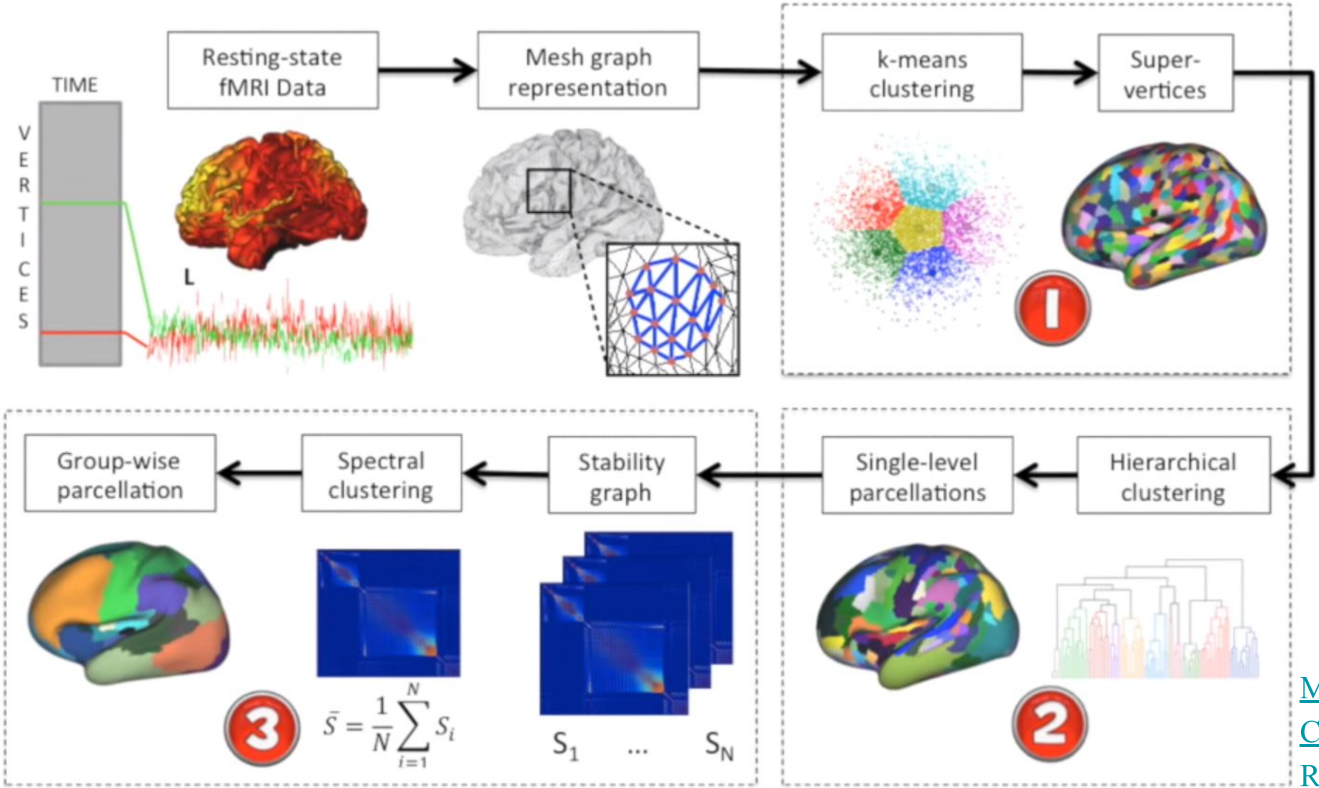
Dozens (or even hundreds) of them



[Human Brain Mapping: A Systematic Comparison of Parcellation Methods for the Human Cerebral Cortex]

1. 2015 Multi-Level Parcellation of the Cerebral Cortex Using Resting-State fMRI, Salim Arslan, Daniel Rueckert https://www.doc.ic.ac.uk/~sa1013/pub/2015_S_Arslan_MICCAI.pdf
    a. 100 HCP subjects. Initial parcellation using k-means, distance is a combination of geodesic distance and time series correlation (from fMRI) -> hierarchical (agglomerative) clustering of these supervertices into larger ones -> Construct meta-graph edges - #times vertices co-occur in the same community -> Cluster this graph using n-cut
2. 2015 A Continuous Flow-Maximisation Approach to Connectivity-driven Cortical Parcellation, Sarah Parisot, Martin Rajchl, Jonathan Passerat-Palmbach, Daniel Rueckert, 2015
    a. Start with random parcellation (spatially constrained) -> Update parcel centers seeking for a point with maximum correlation with all other nodes in a parcel (correlation from fMRI) -> Attach each node to a parcel with the highest correlation (s.t. Spatially smoothness constraints) -> Repeat until convergence.
    b. 25 HCP Subjects
3. 2008 Normalized Cut Group Clustering of Resting-State fMRI Data, Martijn van den Heuvel ,Rene Mandl, Hilleke Hulshoff Pol, 2008, https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0002001#s2
    a. 2-level procedure. 1 construct subject level parcellation from fMRI (correlation, 0.4 cutoff) - 20 clusters (authors call them resting-state networks RSNs). Individual graph consist of 8500-9500 nodes. Use ncut clustering, no spatial constraints. Construct group graph edge +1 between 2 nodes if they were in the same cluster (for a subject). Finally group graph was clustered using ncut. 26 fMRI subjects.
4. 2012 A whole brain fMRI atlas generated via spatially constrained spectral clustering, R. Cameron Craddock, G. Andrew James,Paul E. Holtzheimer, Xiaoping P. Hu, and Helen S. Mayberg, 2012
    a. Build a network from fMRI, such that every node is a voxel and an edge between two nodes exist only if they are in 3D neighborhood (for every voxel there are 26 neighborhood voxels), the weight on an edge is a correlation. Cluster it using ncut, group atlas generated either by averaging subject networks and cluster an averaged one, or by using the same technique as in [3] (Martijn van den Heuvel, 2008)
5. 2014 OPTIMIZING BRAIN CONNECTIVITY NETWORKS FOR DISEASE CLASSIFICATION USING EPIC Gautam Prasad, Shantanu H. Joshi, and Paul M. Thompson https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4232940/
    a. Start with Desikan atlas proposed algorithm combine separate regions into bigger ones, recompute connectivity matrix and run a classification algorithm on it (using PCA as prep step). In such a way authors find “optimal” in terms of classification (AD vs NC) brain parcellation. The search of best combination of regions is done in a probabilistic manner (simulated annealing/random search).

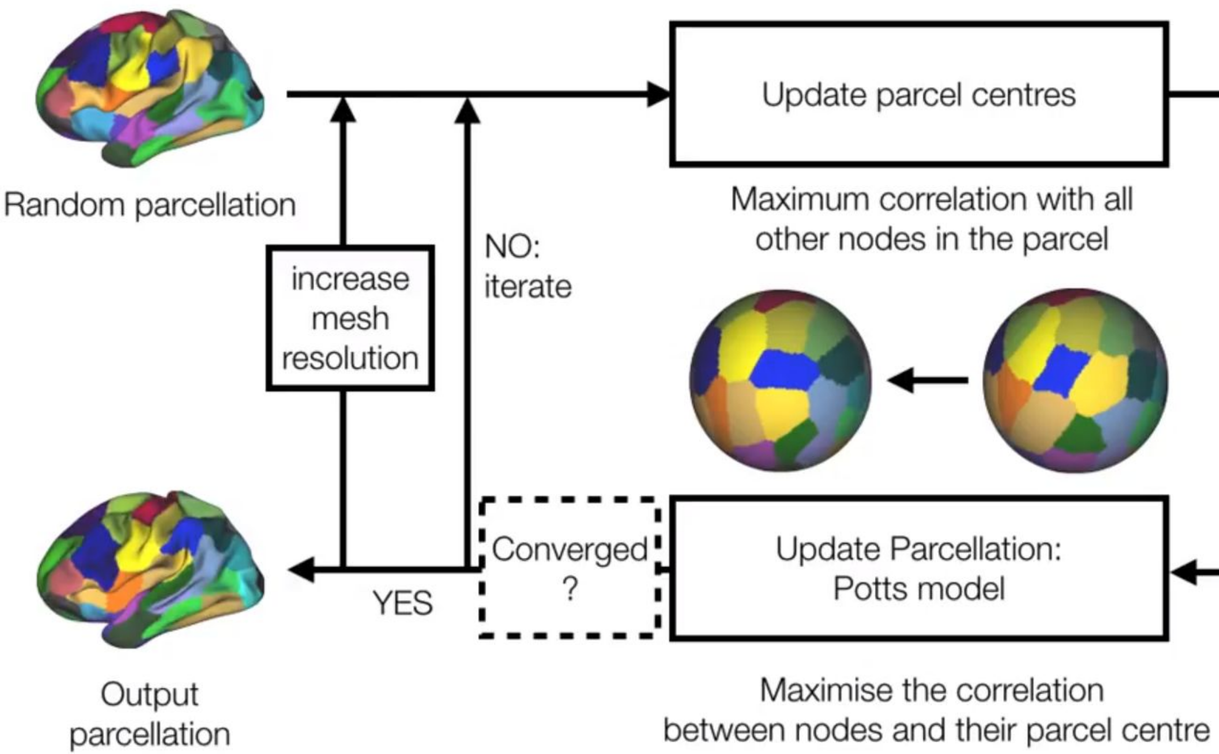
Methodology



[Short presentation video]

[Multi-Level Parcellation of the Cerebral Cortex Using Resting-State fMRI]

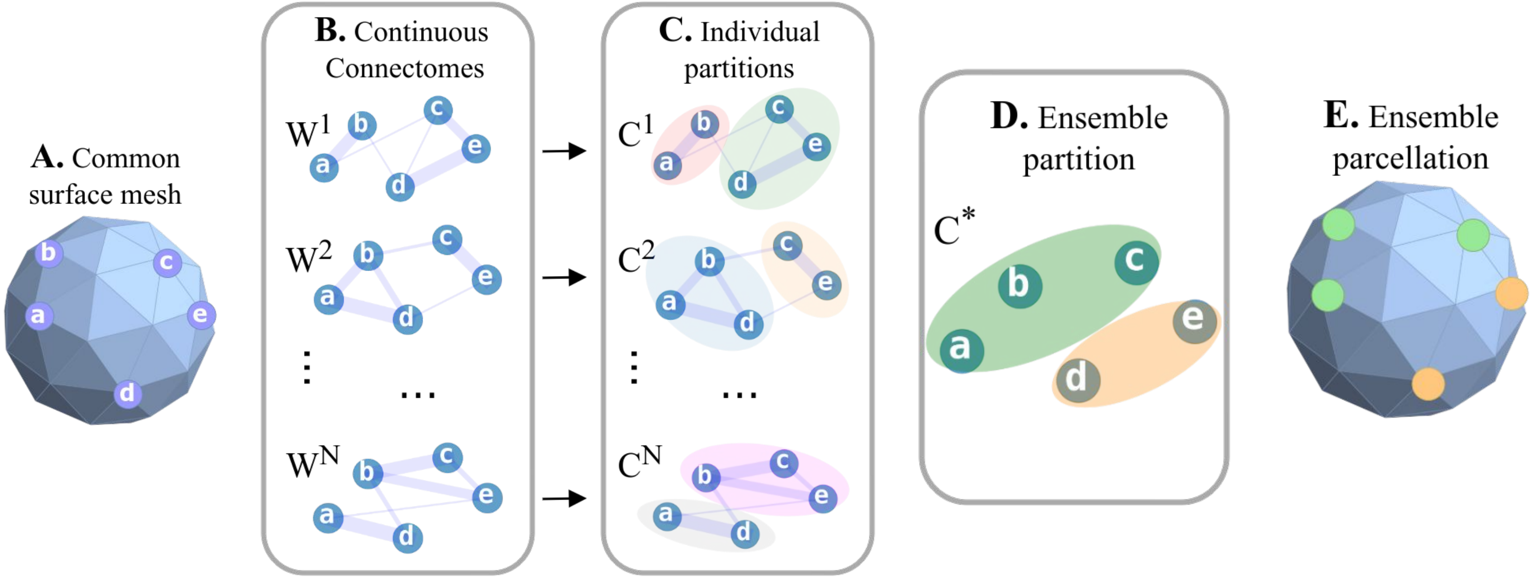
Method Overview



[Short presentation video]

[A Continuous Flow-Maximisation Approach to Connectivity-driven Cortical Parcellation]

Connectivity-Driven Brain Parcellation via Consensus Clustering

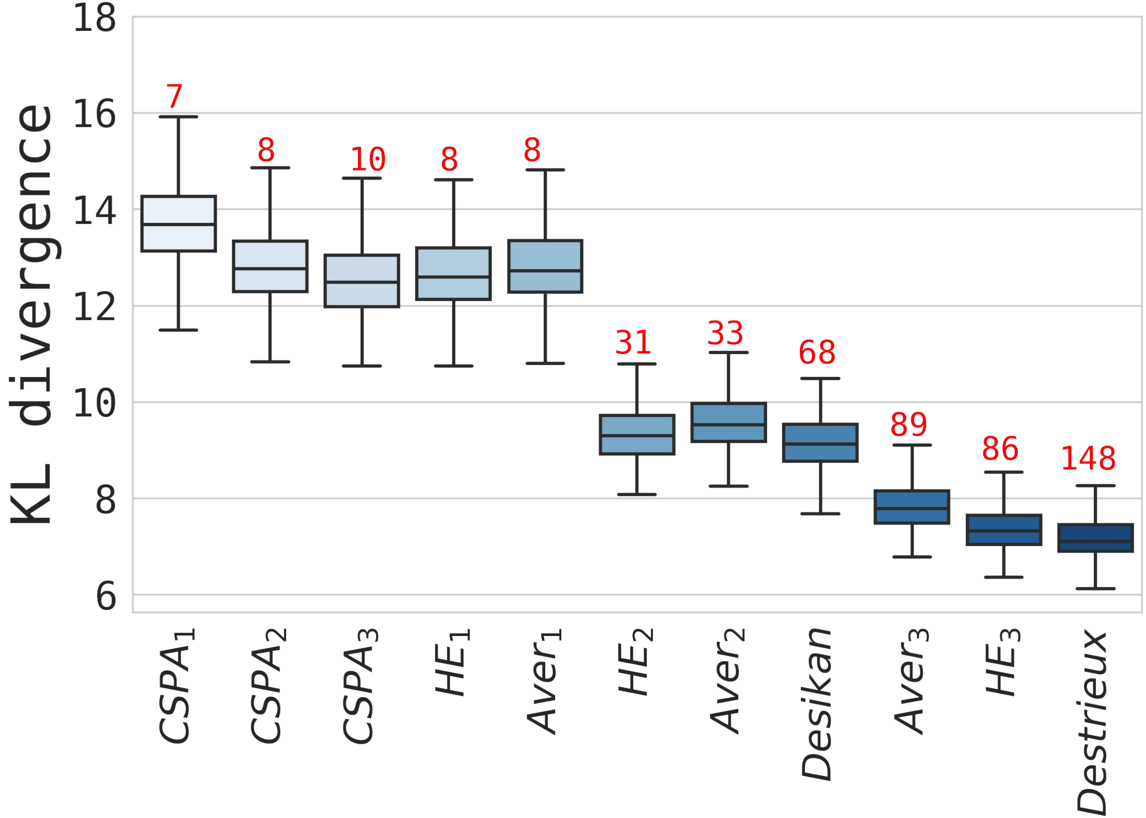


[Connectivity-Driven Brain Parcellation via Consensus Clustering]

Features

- Obtained parcellation is highly symmetrical (left vs right hemisphere)
- Has substantial intersection with classical gyral based parcellations
- Spatially continuous without specific spatial constraints
- Arbitrar subject to clustering approach and averaging approach
- Could be used for subject or group analysis

Network connections preservervation



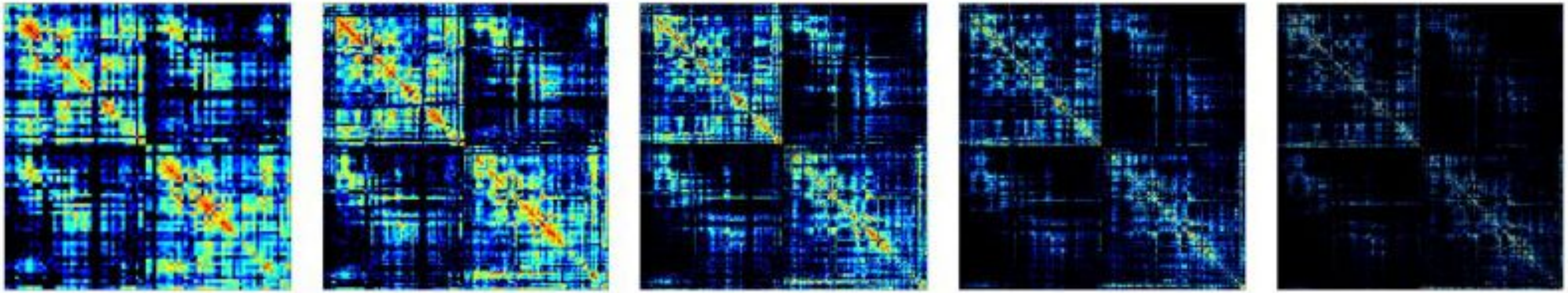
$$KL(\lambda, \gamma) = \int_{-\infty}^{+\infty} \lambda(u) \log \frac{\lambda(u)}{\gamma(u)} du,$$

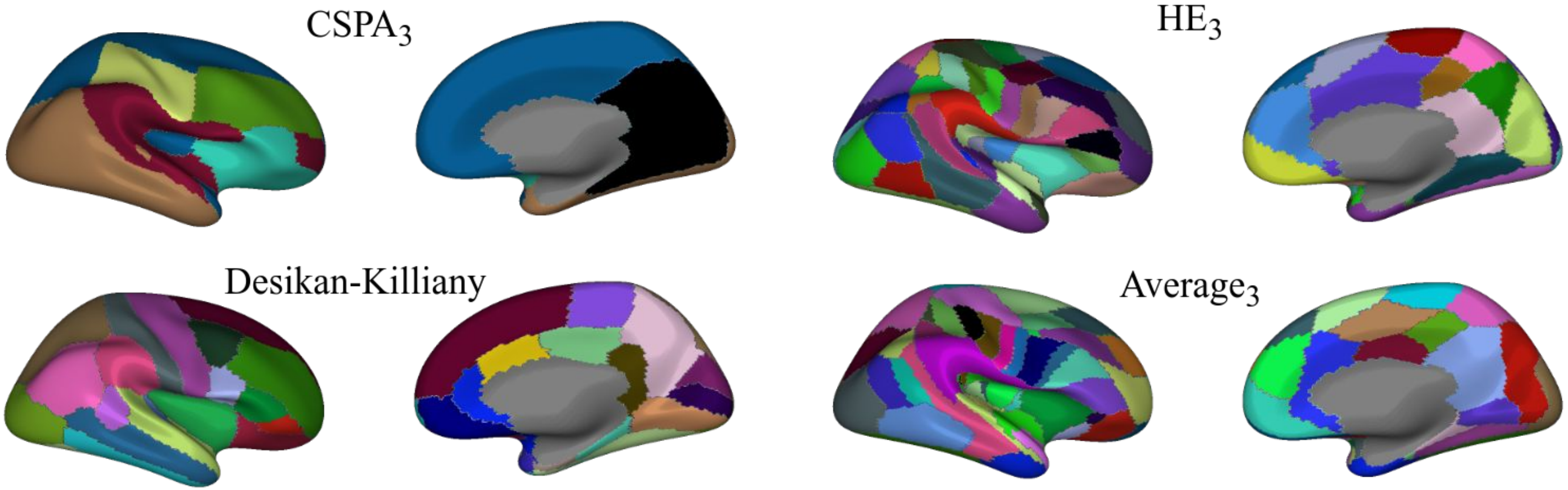
Нестрогая интуиция почему это важно

Szemerédi regularity lemma

From Wikipedia, the free encyclopedia

In mathematics, **the Szemerédi regularity lemma** states that every large enough graph can be divided into subsets of about the same size so that the edges between different subsets behave almost randomly. Szemerédi (1975) introduced a weaker version of this lemma, restricted to bipartite graphs, in order to prove Szemerédi's theorem,[1] and in (Szemerédi 1978) he proved the full lemma.[2] Extensions of the regularity method to hypergraphs were obtained by Rödl and his collaborators[3][4][5] and Gowers.[6][7]





CSPA$_3$
HE$_3$
Desikan-Killiany
Average$_3$

Conclusion

- Problems:
  - Huge amount of different parcellation approaches
  - No obvious way to choose amongst them
- Solution:
  - Use common sense
  - Use anatomical parcellations, they are good enough in most cases.
  - Do not use parcellation at all (if possible).
  - In case of structural connectomes use Connectivity-driven parcellation!

Picture sources

1. http://www.clipartpanda.com/clipart_images/black-and-white-human-brain-3-29489506
2. https://braintumor.org/brain-tumor-information/signs-and-symptoms/brain-illustration/
3. https://www.britannica.com/topic/phrenology
4. https://www.humanbrainfacts.org/basic-structure-and-function-of-human-brain.php
5. http://cs.wellesley.edu/~cs112/courseMaterials/assignments/assign5/assign5.html
6. https://miykael.github.io/nipype-beginner-s-guide/neuroimaging.html
7. http://www.clinica.run/doc/Pipelines/T1_FreeSurfer/
8. https://fcp-indi.github.io/docs/user/anat.html
9. http://brainsuite.org/processing/svreg/details/
10. https://en.wikipedia.org/wiki/Image_registration
11. https://www.spiedigitallibrary.org/conference-proceedings-of-spie/10133/1/Multi-atlas-based-CT-synthesis-from-conventional-MRI-with-patch/10.1117/12.2254571.short?SSO=1
12. https://www.sciencedirect.com/science/article/pii/S2319417017300653
13. https://www.semanticscholar.org/paper/Shape-analysis-of-the-human-brain.-Nitzken-Joseph/c47a238ce4a943a30da38f1047c01580a47fab7d/figure/63
14. https://www.semanticscholar.org/paper/Shape-analysis-of-the-human-brain.-Nitzken-Joseph/c47a238ce4a943a30da38f1047c01580a47fab7d
15. https://brainder.org/2016/05/31/downsampling-decimating-a-brain-surface/