The Mindboggle project: feature-based brain labeling

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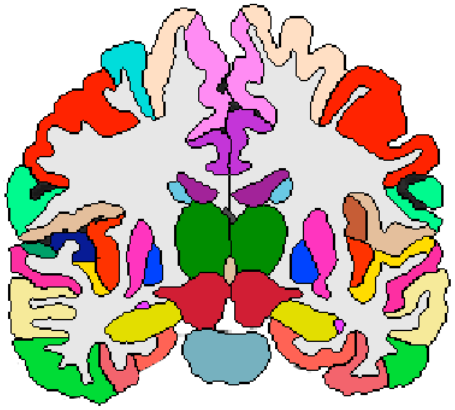
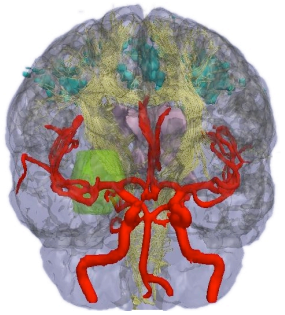


February 11, 2011
University of Pennsylvania

Why label brains?

Labels serve as a visual guide and teaching tool

- teach brain anatomy
- guide neurosurgery



http://www.cbd.ucla.edu/bios/iacoboni.html, http://brainvisa.info/, http://dx.doi.org/10.1126/science.1145876
http://groups.csail.mit.edu/vision/medical-vision/past-projects.html, http://www.spl.harvard.edu/publications/item/view/1265

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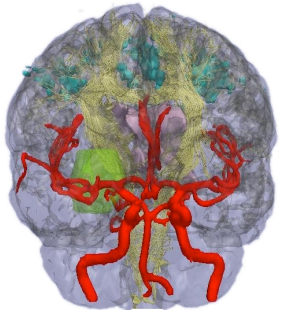
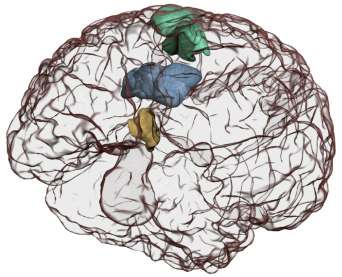


Labels break up data within a brain

- assign results to brain regions
- quantify data by brain region



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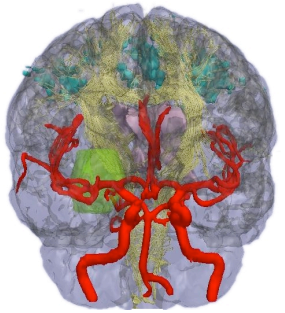

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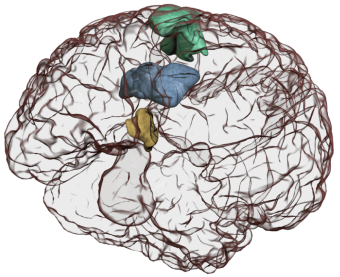
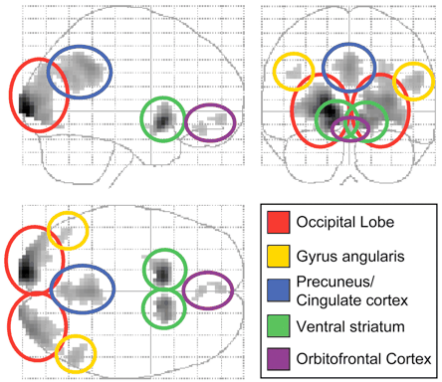


Labels establish correspondences across brains

- compare individuals within and across studies
- communicate results with a common language



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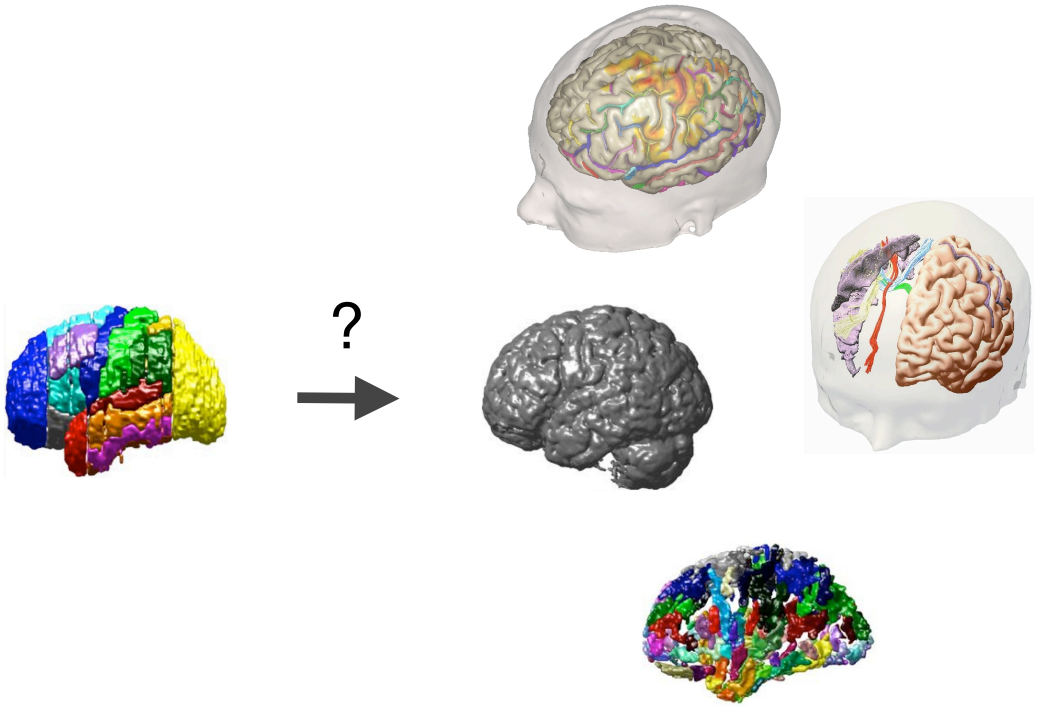
How should we label brains?



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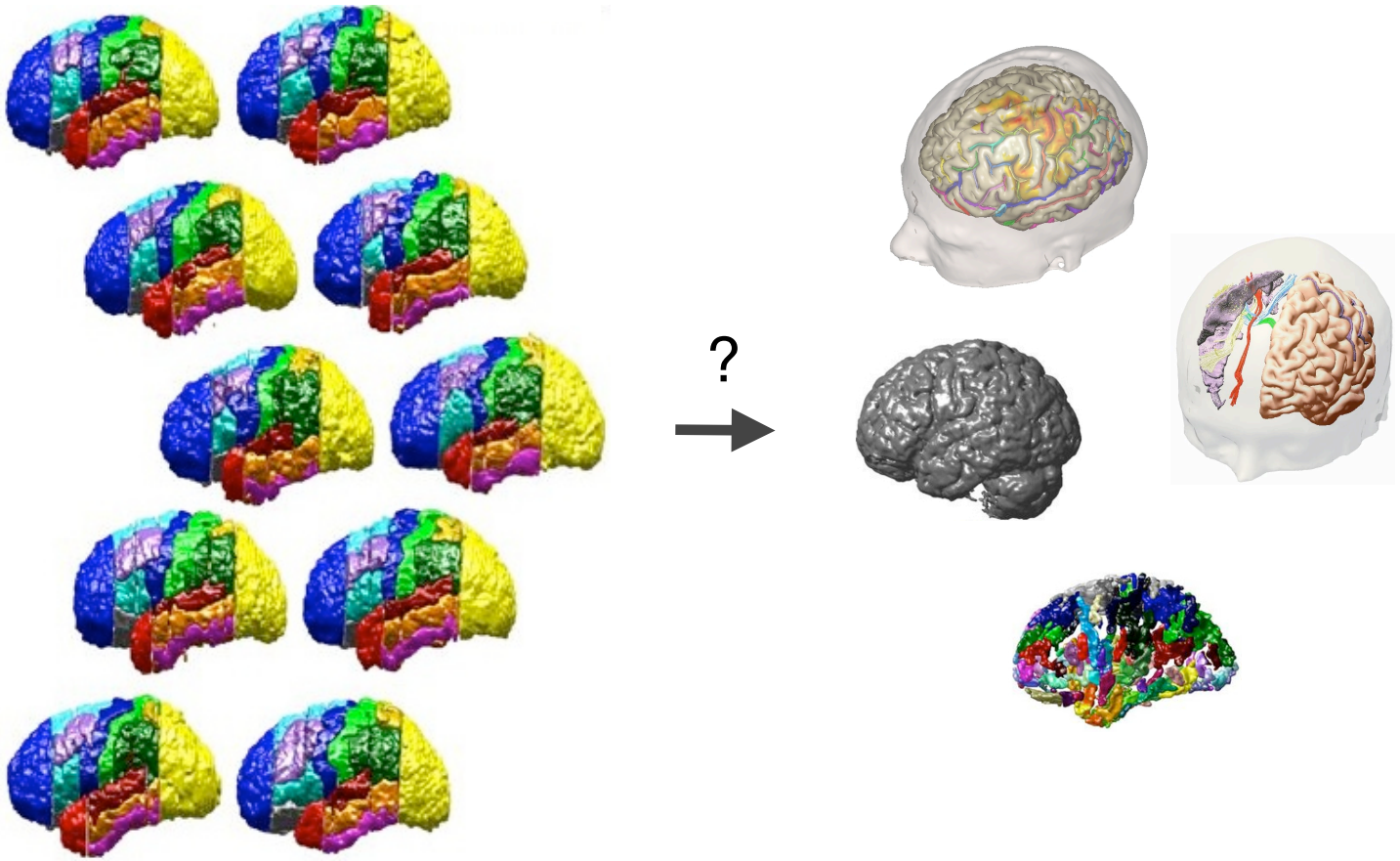
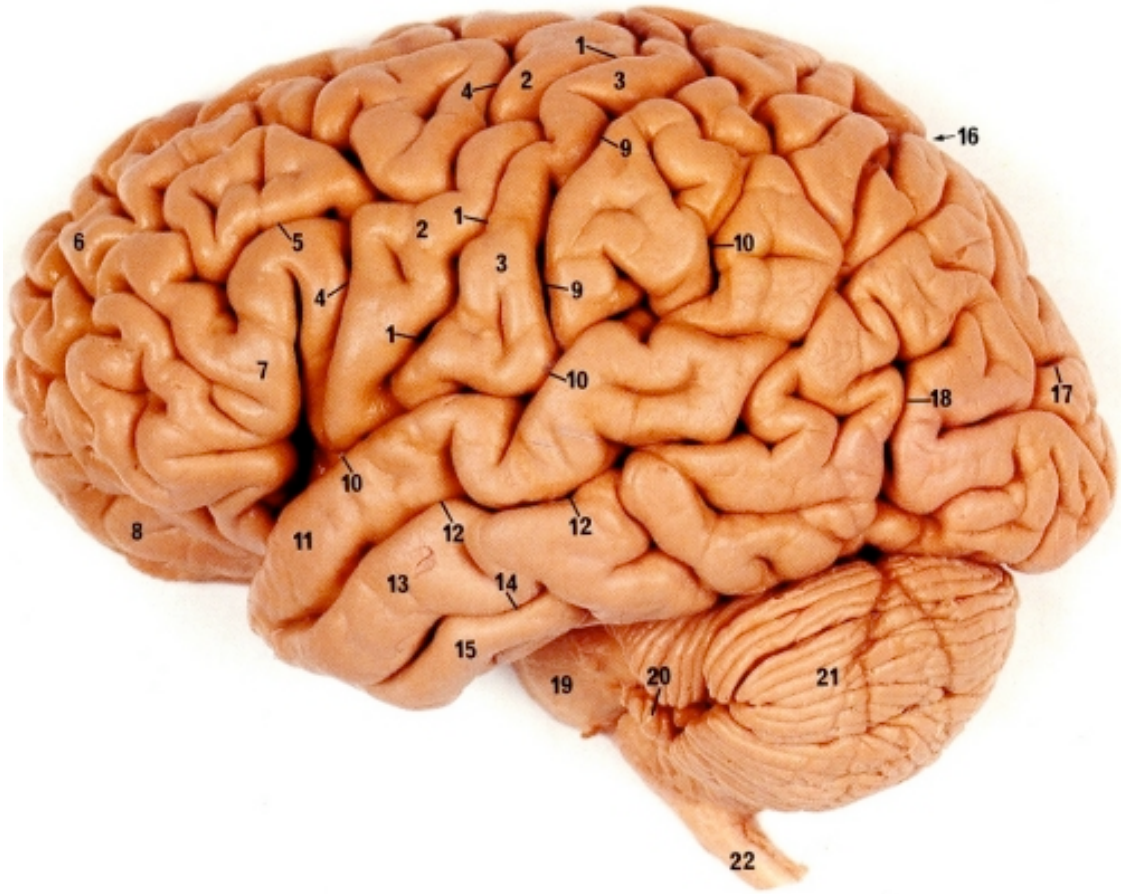
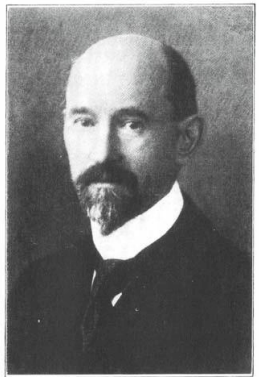


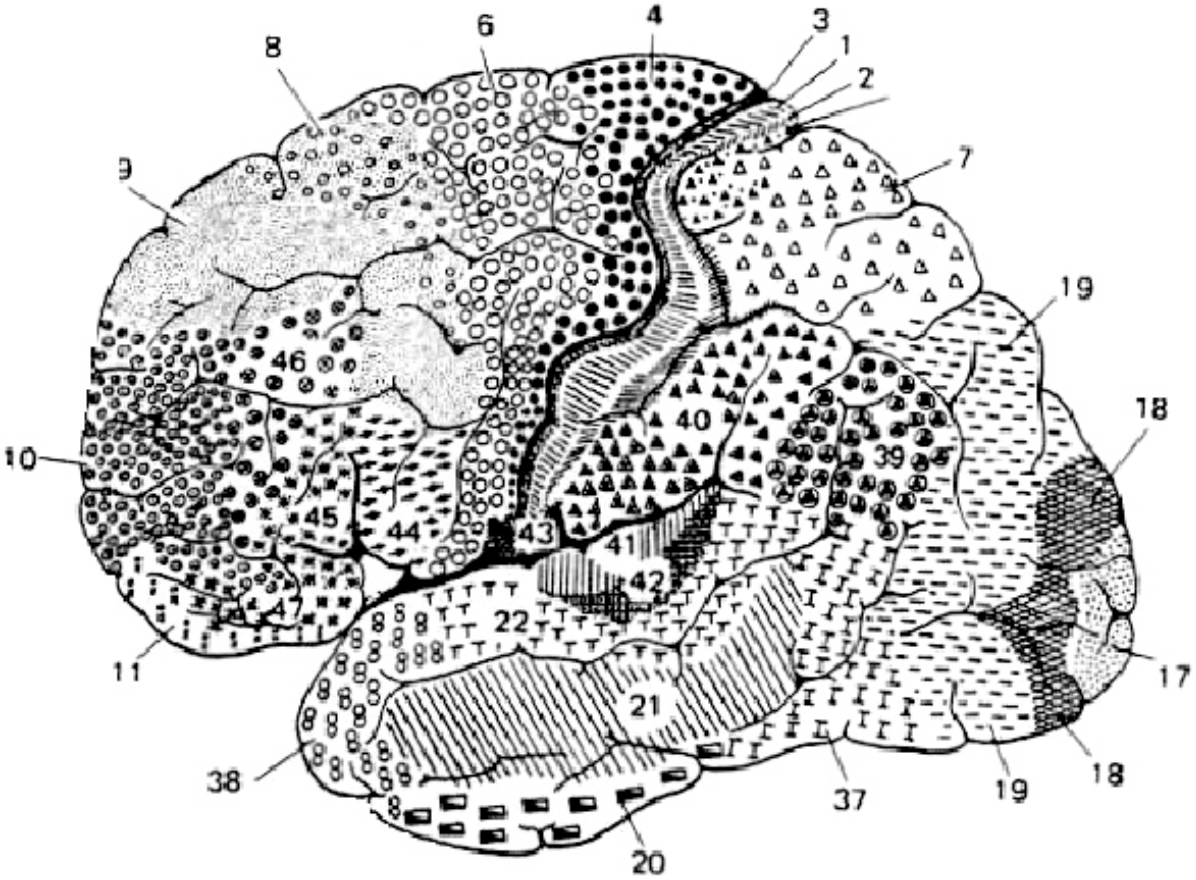
1. Manual labeling

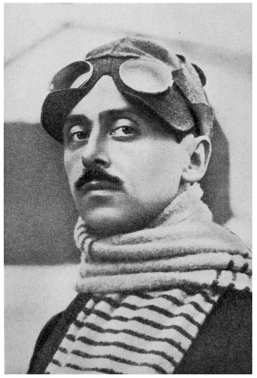




Korbinian Brodmann
(1868-1918)

Cytoarchitectonic boundaries





Constantin von Economo
(1876-1931)

Cytoarchitectonic boundaries

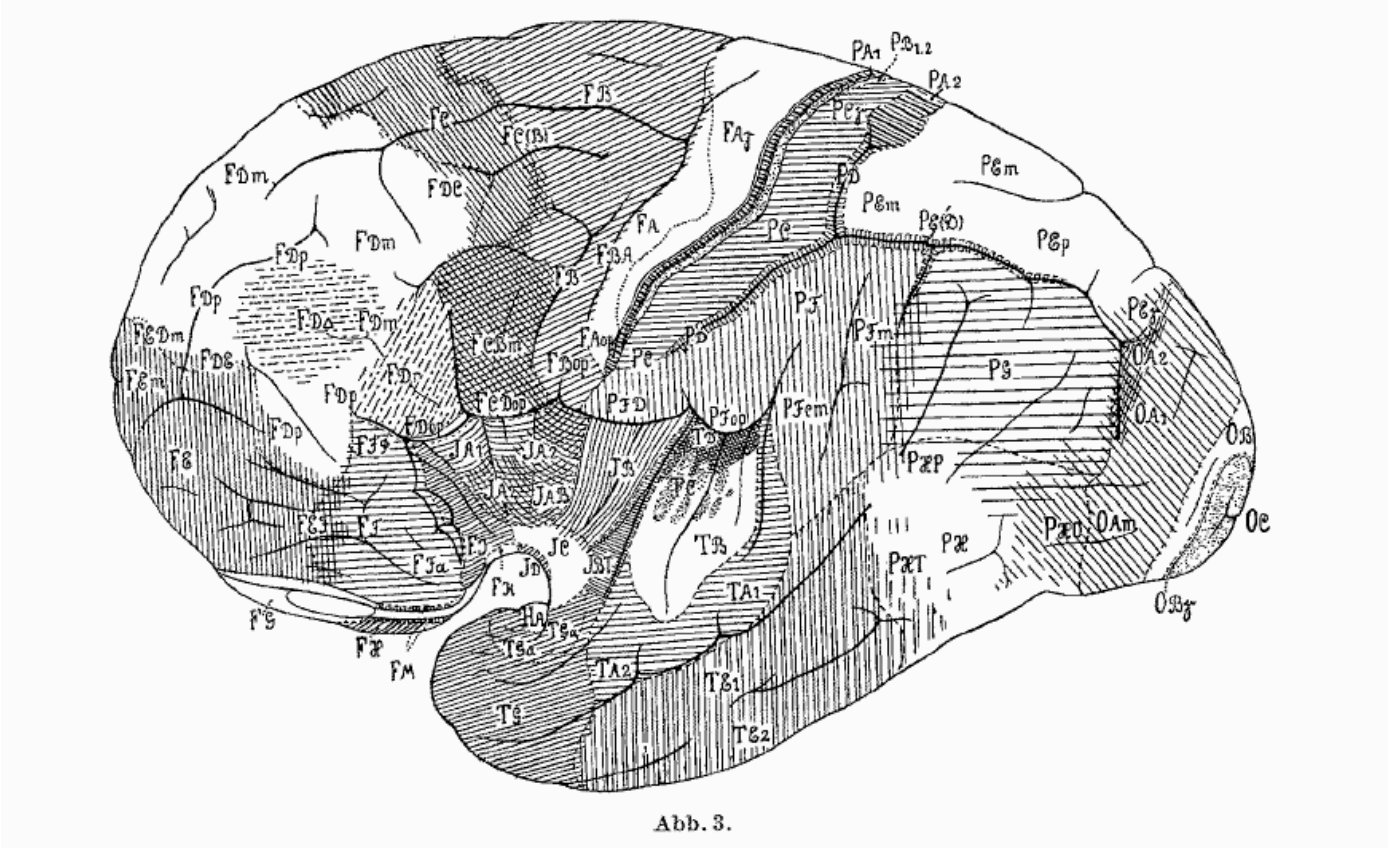
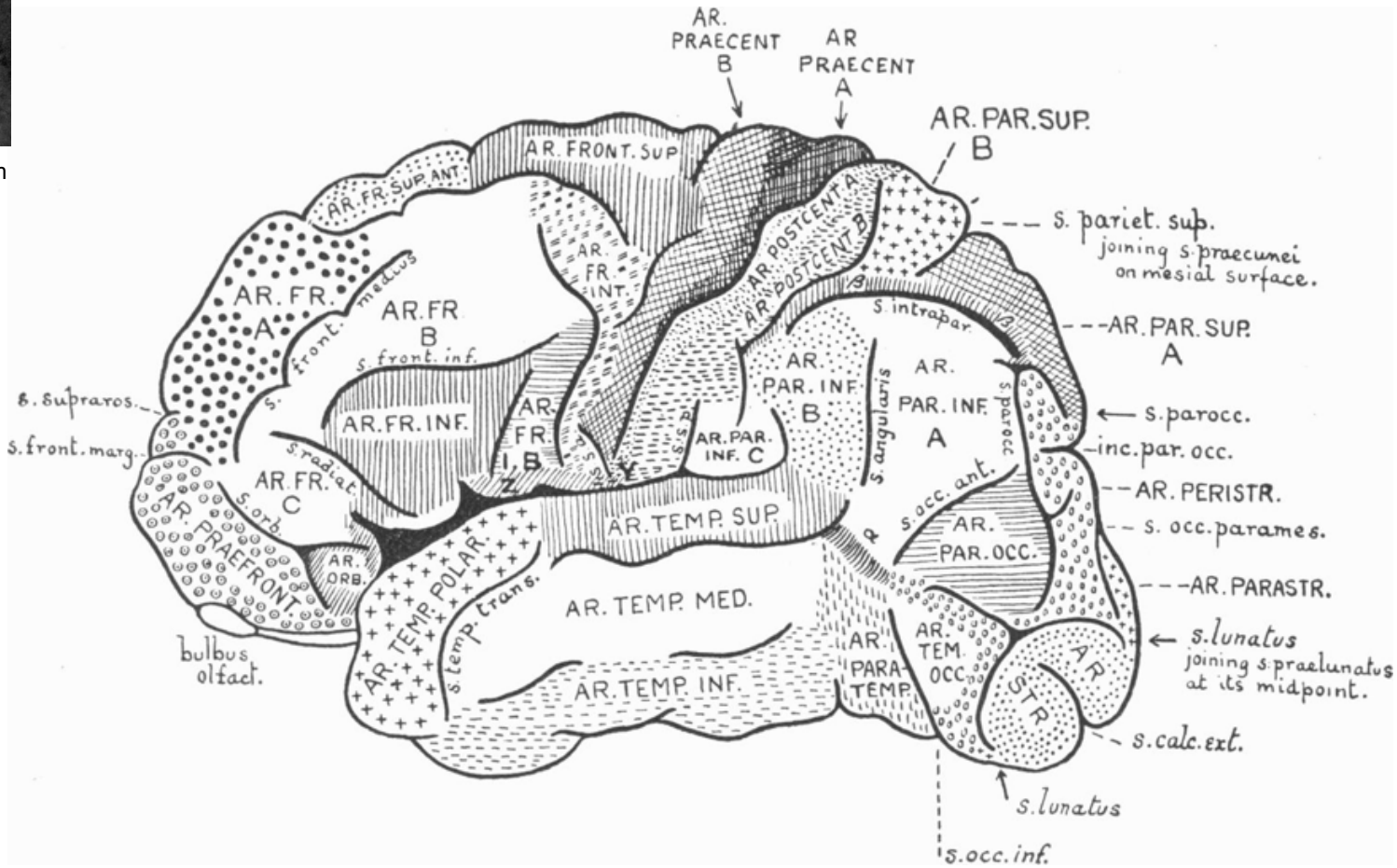


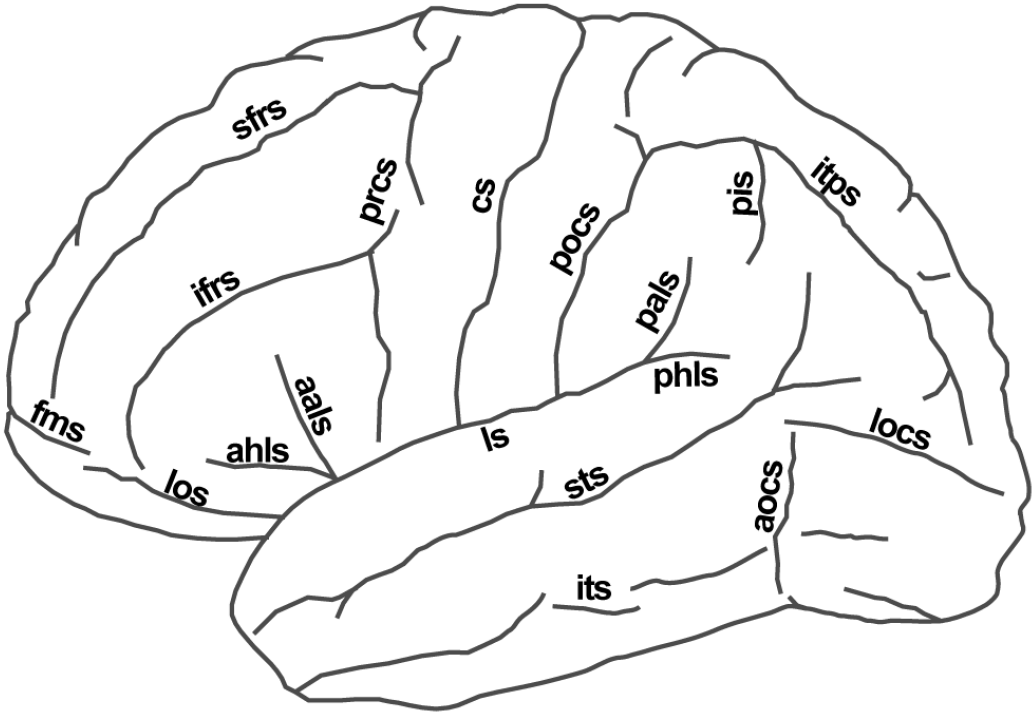
Abb. 3.

Sir Grafton Elliot Smith
(1871-1937)

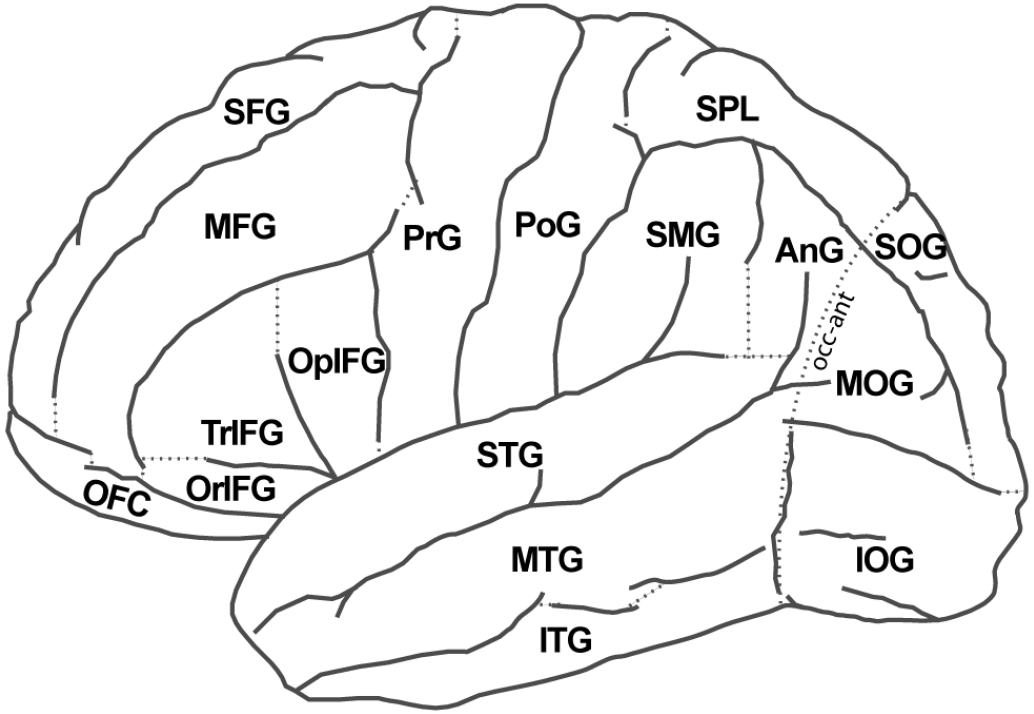
Topographic boundaries

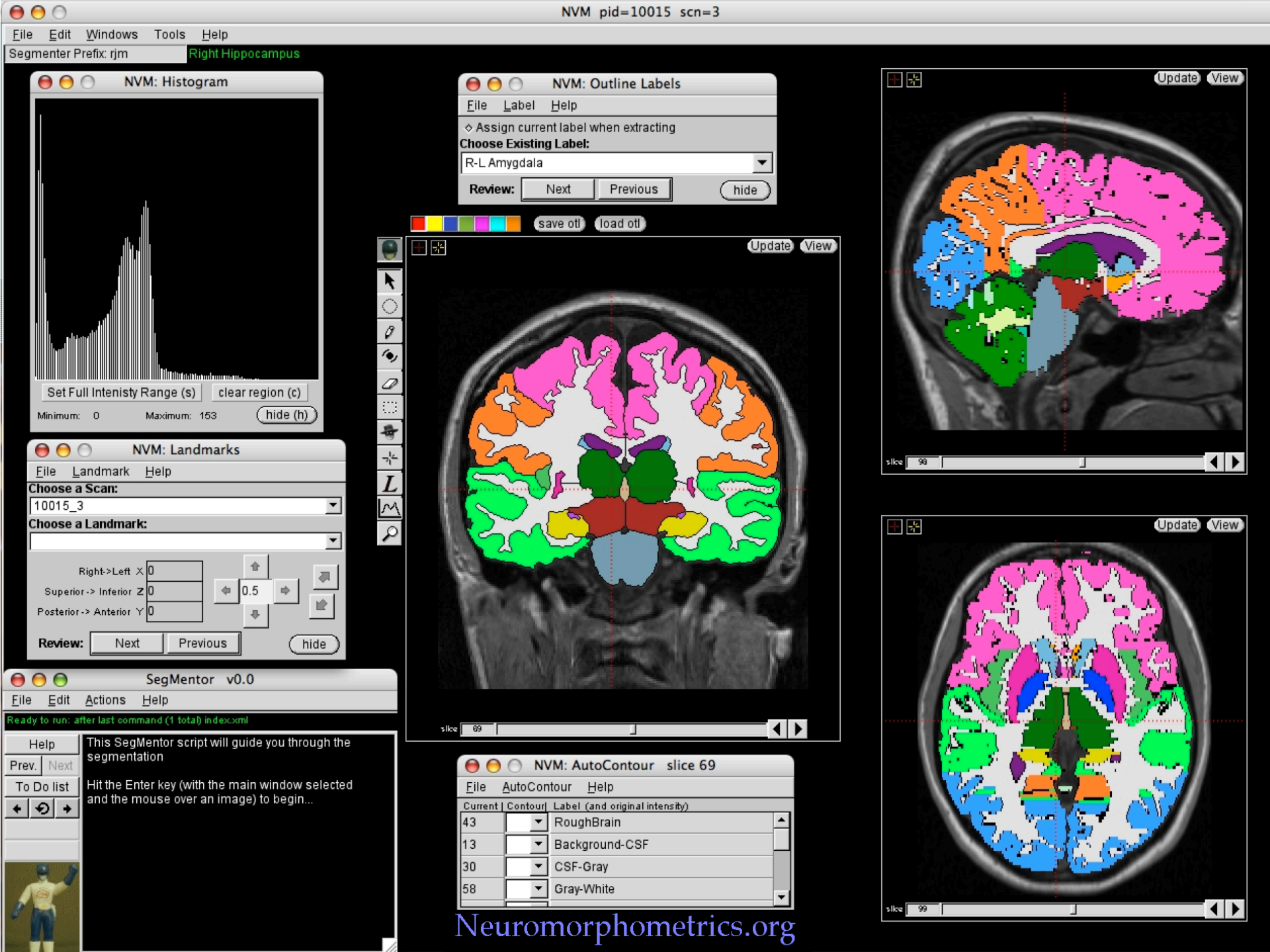


Sulcus definitions



Gyrus definitions

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Right Hippocampus
NVM: Histogram
Set Full Intenisty Range (s)
clear region (c)
Minimum: 0
Maximum: 153
hide (h)
NVM: Outline Labels
File Label Help
◇ Assign current label when extracting
Choose Existing Label:
R-L Amygdala
Review:
Next
Previous
hide
save otl
load otl
Update
View
slice 69
slice 98
slice 99
NVM: Landmarks
File Landmark Help
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10015_3
Choose a Landmark:
Right->Left X 0
Superior -> Inferior Z 0
Posterior -> Anterior Y 0
0.5
Review:
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Previous
hide
SegMentor v0.0
File Edit Actions Help
Ready to run: after last command (1 total) index.xml
Help
Prev.
Next
To Do list
This SegMentor script will guide you through the segmentation
Hit the Enter key (with the main window selected and the mouse over an image) to begin...
NVM: AutoContour slice 69
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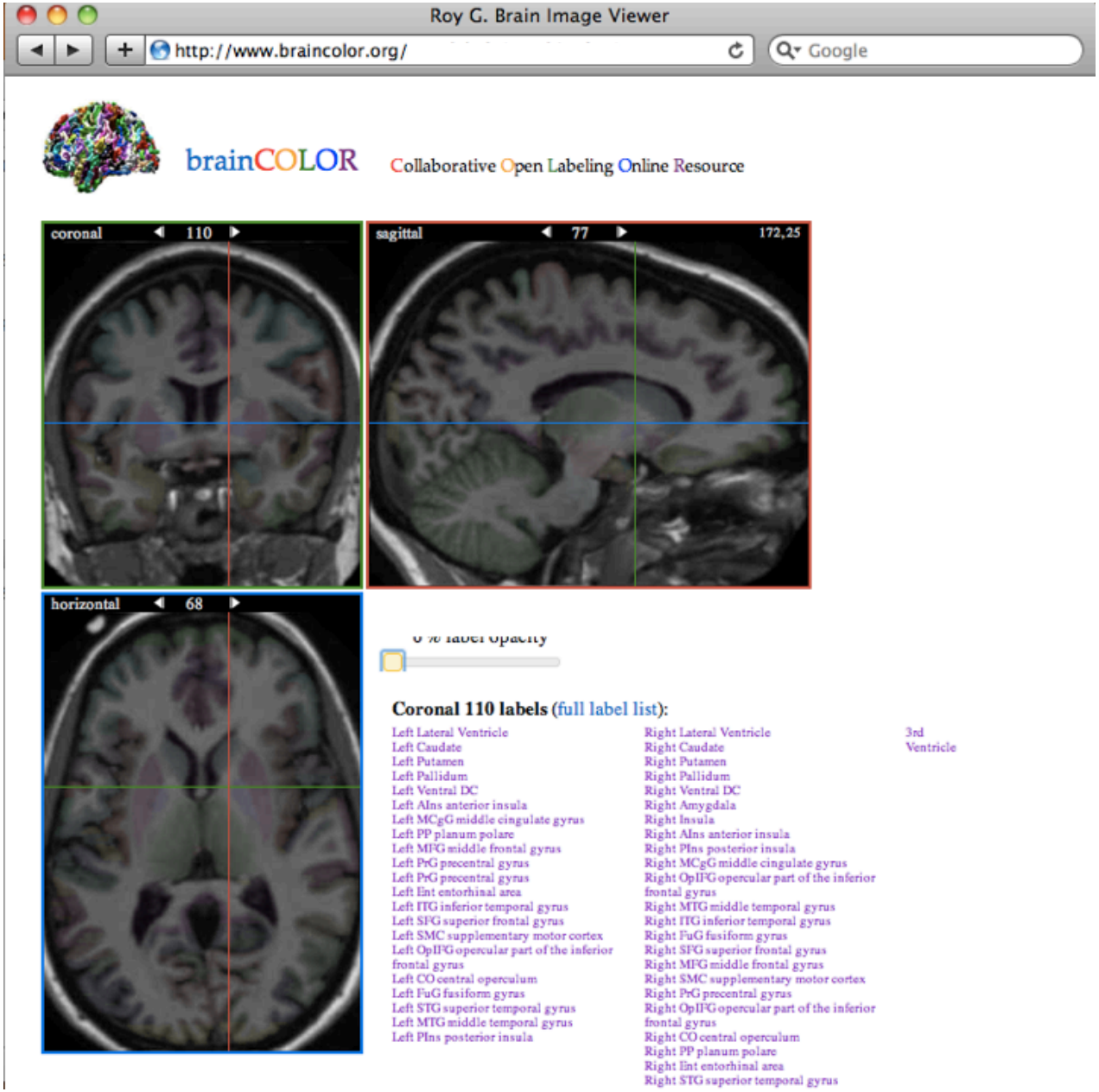
Current
Contour
Label (and original intensity)
43 RoughBrain
13 Background-CSF
30 CSF-Gray
58 Gray-White
Neuromorphometrics.org


Roy G. Brain Image Viewer
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Google
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coronal 110
sagittal 77 172,25
horizontal 68
Coronal 110 labels (full label list):
Left Lateral Ventricle
Left Caudate
Left Putamen
Left Pallidum
Left Ventral DC
Left AIns anterior insula
Left MCgG middle cingulate gyrus
Left PP planum polare
Left MFG middle frontal gyrus
Left PrG precentral gyrus
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Left Ent entorhinal area
Left ITG inferior temporal gyrus
Left SFG superior frontal gyrus
Left SMC supplementary motor cortex
Left OpIFG opercular part of the inferior frontal gyrus
Left CO central operculum
Left FuG fusiform gyrus
Left STG superior temporal gyrus
Left MTG middle temporal gyrus
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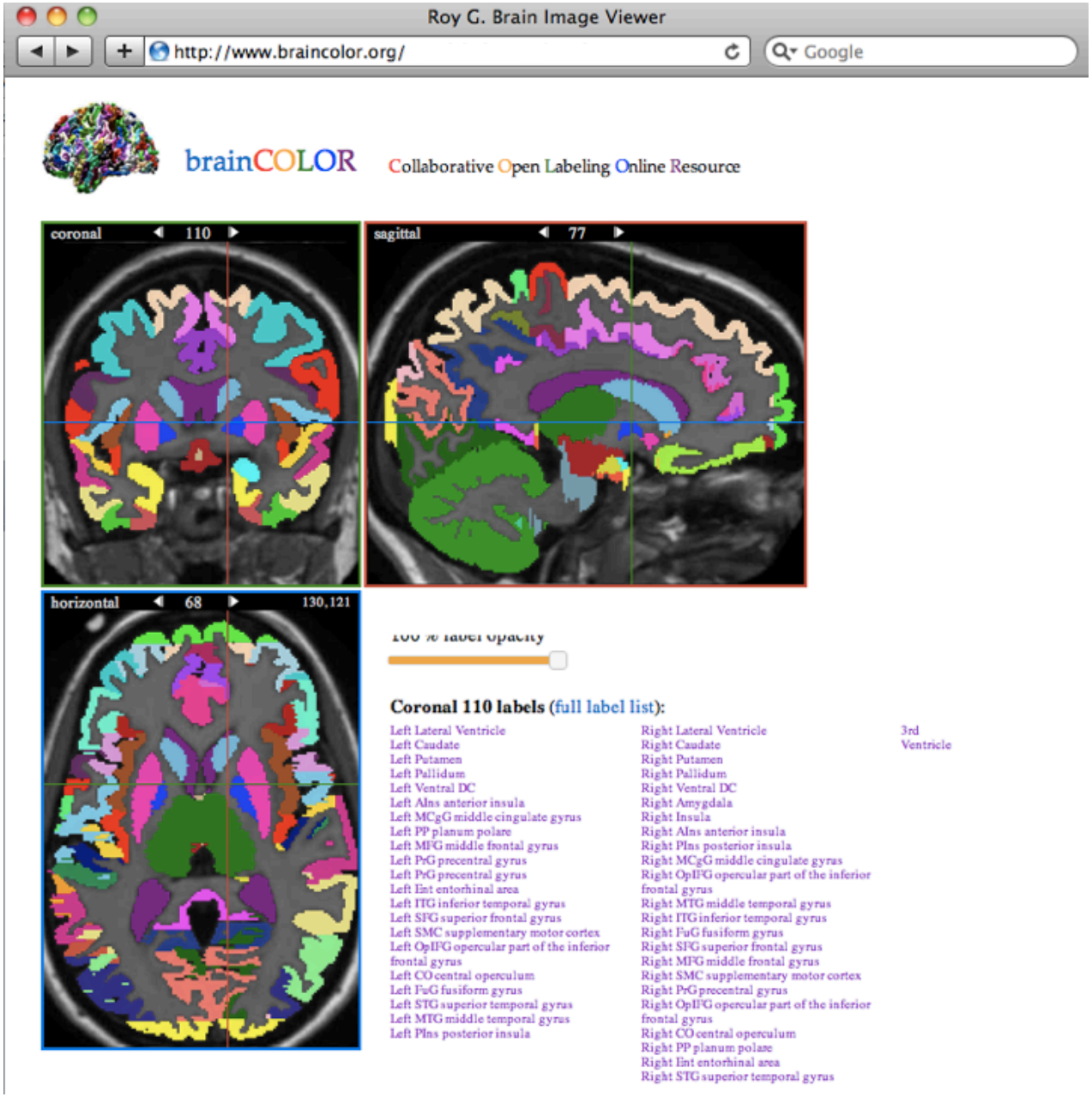
3rd Ventricle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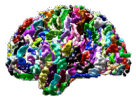


An interactive tool for constructing optimal brain colormaps

Arno Klein — NY State Psych. Inst. Columbia University, NY
Andrew Worth — Neuromorphometrics, Inc., MA
Jason Tourville — Cognitive & Neural Systems Boston University, MA
Bennett Landman — Vanderbilt University Nashville, TN
Tito Dal Canton — NY State Psych. Inst. Columbia University, NY
Satrajit S. Ghosh — Research Laboratory of Electronics, MIT, MA
David Shattuck — Laboratory of NeuroImaging UCLA, CA

Goal

Create a software tool to aid in the construction of optimal colormaps for viewing and labeling brain anatomical images.

Background

The application of color is an indispensible means of visually distinguishing anatomical regions of the brain [1,2]. The need to facilitate visualization of brain images has become particularly urgent with the inception of large-scale anatomical labeling projects, such as the BrainCOLOR project, in which hundreds of MR images of the human brain are being manually labeled (www.braincolor.org/protocols) as well as viewed online (www.braincolor.org/roygbiv).

Choosing a color space

Our colormap must consist of colors that are perceptually distinct, so it is reasonable to choose a color space that is perceptually uniform, where a separation between two colors in the color space is as discriminable as the same separation between two other colors in the color space.
The International Commission on Illumination (CIE) devised a color space in 1931 that facilitates color description (Fig.1). Subsequent improvements led to the CIELAB and CIELUV color spaces, as well as a cylindrical variant, CIELch, all of which attempt to be perceptually uniform.

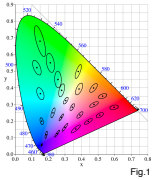


Fig.1

Constructing a colormap

We uniformly sampled hues from the CIELch cylinder (Fig.2) at different distances from the center (70-100% chrominance) and at different lightness values. The resulting colormap (Fig.3) has the same number of colors as regions we wish to color (49 cortical regions in the BrainCOLOR protocol). We intend to expand the number of colors to include subcortical and other regions.

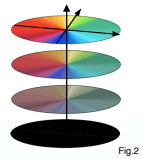


Fig.2

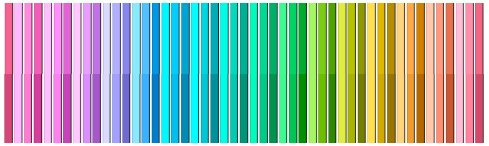


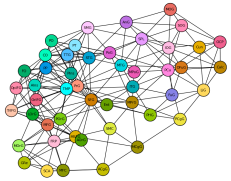
Fig.3

1. Schott GD (2010) Colored illustrations of the brain: some conceptual and contextual issues. Neuroscientist. 16(5):508-18.
2. Schoonover, C (2010) Portraits of the Mind: Visualizing the Brain from Antiquity to the 21st Century. Abrams (ISBN-13: 978-0810990334)

CIE1931 figure: http://en.wikipedia.org/wiki/File:CIExy1931_MacAdam.png
CIELch figure: http://www.colorbasics.com/ColorSpace/

Maximizing discriminability of adjacent regions

To easily distinguish brain regions from each other, we wish to maximize the color difference between adjacent regions. We do this by constructing a graph that represents connections (edges) between regions (nodes).



We define an *optimal mapping* of colors as the combination of colors assigned to nodes with the maximum sum of color differences between connected nodes, defined by the CIE2000 Delta E measure (http://en.wikipedia.org/wiki/Color_difference).
However, we cannot compute 8.8×10^{18} permutations of the 49 colors in the colormap, so we break up the brain into sublobes and compute the permutations of portions of the colormap at a time:

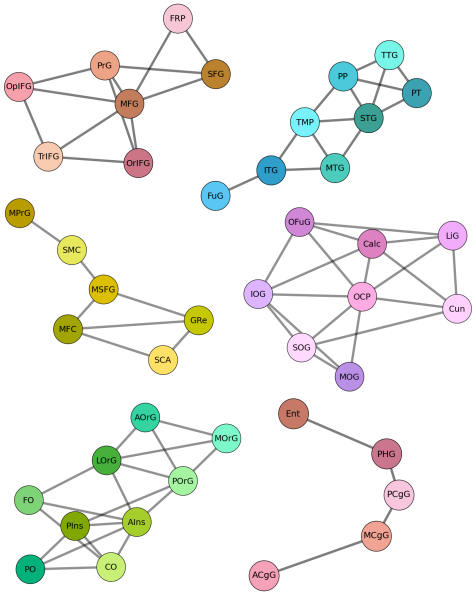
Frontal Lobe (7,6,9):
- Lateral Surface (7)
- Medial Surface (6)
- Inferior Surface (4)
- Opercular Region (3)
- Insular Region (2)

Temporal Lobe (8):
- Lateral Surface (4)
- Supratemporal Surface (3)
- Inferior Surface (1)

Parietal lobe (6):
- Lateral Surface (4)
- Medial Surface (2)

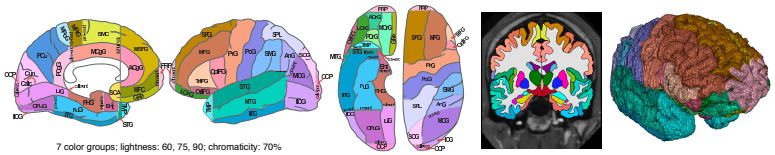
Occipital Lobe (8):
- Lateral Surface (4)
- Inferior Surface (1)
- Medial Surface (3)

Limbic Cortex (5):
- Cingulate Cortex (3)
- Medial Temporal Cortex (2)

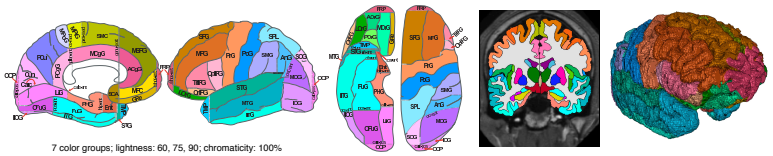


Grouping regions by using similar colors

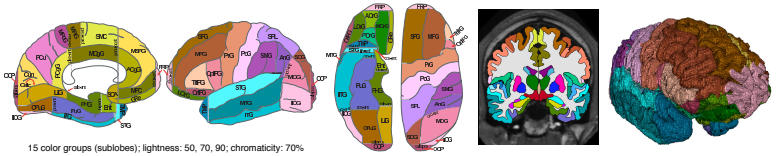
For labeling a brain image, maximum discriminability is paramount. For viewing a brain image, however, it is useful to visually group regions by assigning similar colors to the regions within a group. To create this visual grouping, we colored each subgraph with a neighborhood of colors (sampled within a wedge of the CIELch cylinder).



7 color groups; lightness: 60, 75, 90; chromaticity: 70%



7 color groups; lightness: 60, 75, 90; chromaticity: 100%



15 color groups (sublobes); lightness: 50, 70, 90; chromaticity: 70%

Conclusion and Future Work

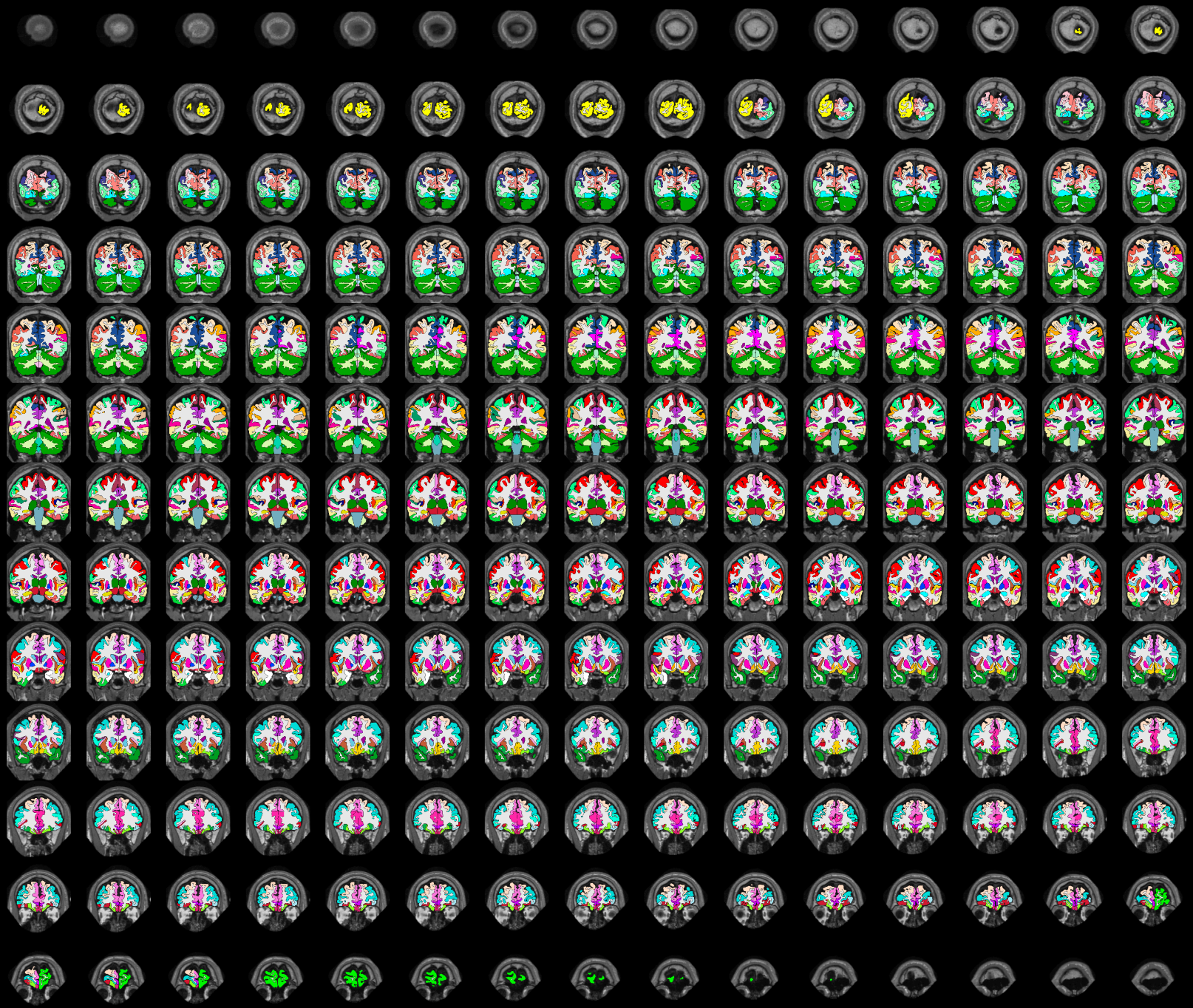
We have created Python software for creating and applying colormaps to brain images.
Download the software from: http://binarybottle.github.com/brainCOLORmap
The software calls the Python libraries: *NumPy, NetworkX, Python-Colormath, Matplotlib, and xlrd*, to:

1. convert a table of adjacent regions (an adjacency matrix) to a weighted graph of colored nodes
2. compute permutations of colors for each subgraph to optimally distinguish colors of adjacent regions
3. apply similar colors to predefined groups of regions

There are many improvements we could pursue. We have targeted the following for future work:

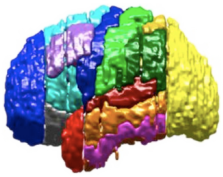
- Develop an optimization algorithm for whole graphs or larger subgraphs.
- Restrict the color space to colors that can be displayed; currently, the CIELch colors that should appear different from one another may appear similar after conversion to SRGB colors.
- Seed color values to better control the range of colors for each group of regions.
- Accommodate visual concerns such as color blindness by adapting the colormap accordingly.

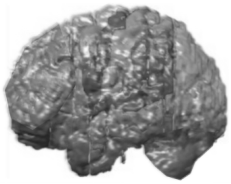
This project is funded as part of NIMH R01 MH084029-02 and NIMH R43 MH084358.



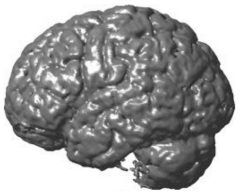
2. Automated labeling

atlas



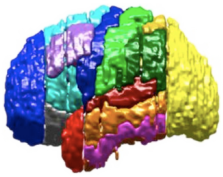


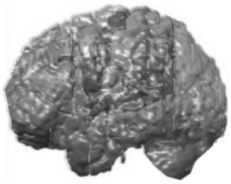
target



Convention: registration-based labeling

atlas

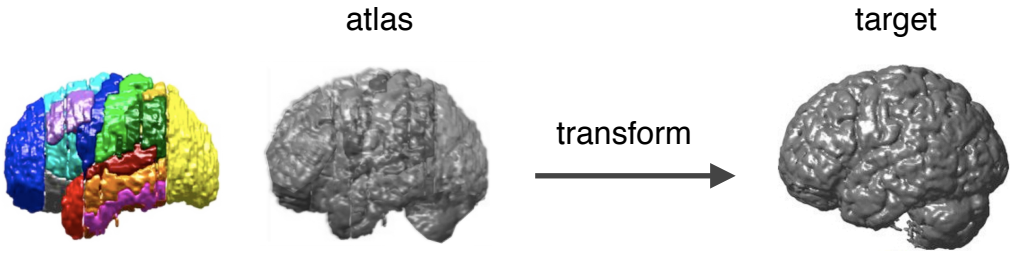




target

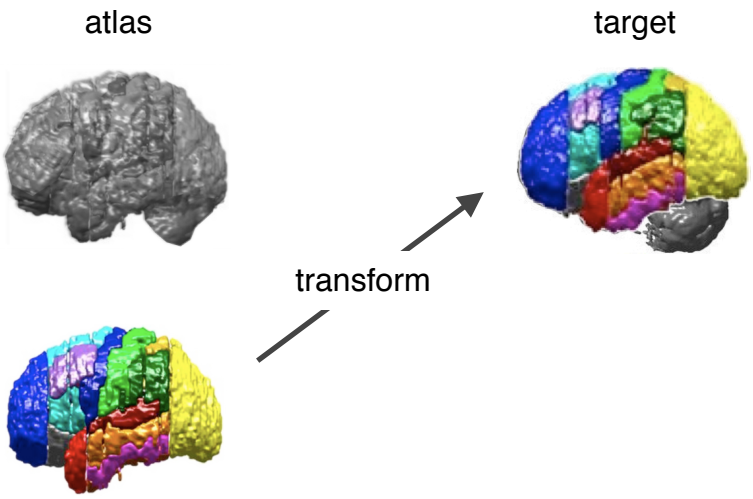
Convention: registration-based labeling

Step 1: compute the registration transform
from the atlas to the target

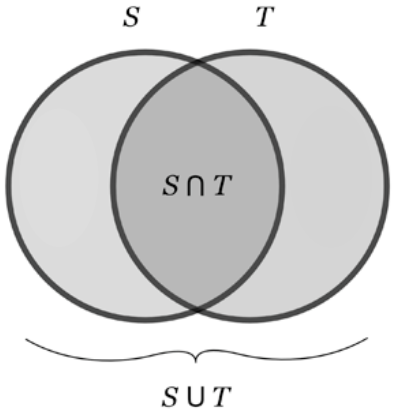


Convention: registration-based labeling

Step 2: apply the transform to the atlas labels



Evaluation



Target overlap: $$TO = \frac{\sum_r |S_r \cap T_r|}{\sum_r |T_r|}$$

Union overlap: $$UO = \frac{\sum_r |S_r \cap T_r|}{\sum_r |S_r \cup T_r|}$$

Mean overlap: $$MO = 2\frac{\sum_r |S_r \cap T_r|}{\sum_r (|S_r| + |T_r|)}$$

Volume similarity: $$VS = 2\frac{\sum_r (|S_r| - |T_r|)}{\sum_r (|S_r| + |T_r|)}$$

Hausdorff Distance Error:

$$DE(S,T) = \sum_r mean(mean_{s \epsilon S_r}(inf_{t \epsilon T_r}(d(s,t))), mean_{t \epsilon T_r}(inf_{s \epsilon S_r}(d(s,t))))$$

"Evaluation of 14 nonlinear deformation algorithms applied to human brain MRI registration"

NeuroImage (2009)

Algorithms:	>14 software packages
Participants:	16 from 11 institutions
Data:	80 brains manually labeled according to 4 different whole-brain labeling protocols (56 to 128 regions)
Registrations:	Each algorithm applied >2,168 times (>45,000 total)
Evaluation:	8 measures (overlap, distance, volume similarity)
Analysis:	3 independent methods (ranking and statistical tests)

"Evaluation of 14 nonlinear deformation algorithms applied to human brain MRI registration" NeuroImage (2009)

Software	Similarity metric	Transformation
SyN	CC	bi-directional diffeomorphism (D)
ART	nCC	FFD based on cubic splines (H, np)
IRTK	nMI	cubic B-splines
SPM5 DARTEL	multinomial model: congealing	FDM of viscosity field (Dc)
JRD-fluid	Jensen-Rényi divergence	viscous fluid; variational calculus (D)
Diffeomorphic Demons	SSD	displacement field (D, np)
FNIRT	SSD	cubic B-splines
ROMEO	displaced frame difference	local affine
ANIMAL	CC	local translations
SICLE	SSD	3-D Fourier series (D)
SPM5 Unified Segment	generative segmentation	discrete cosine transforms
SPM5 "SPM2-type"	MSD	discrete cosine transforms
SPM5 Normalize	MSD	discrete cosine transforms
AIR	MSD	5th-order polynomial warps
FLIRT (linear)	nCR	linear, rigid-body

n = normalized
CC = cross-correlation
CR = correlation ratio
MI = mutual information
MSD = mean of squared differences
SSD = sum of squared differences

D = diffeomorphic
Dc = diffeomorphic, constant over time
FDM = finite difference model
FFD = free-form deformation
H = homeomorphic
np = nonparametric

“Evaluation of volume-based and surface-based brain image registration methods”

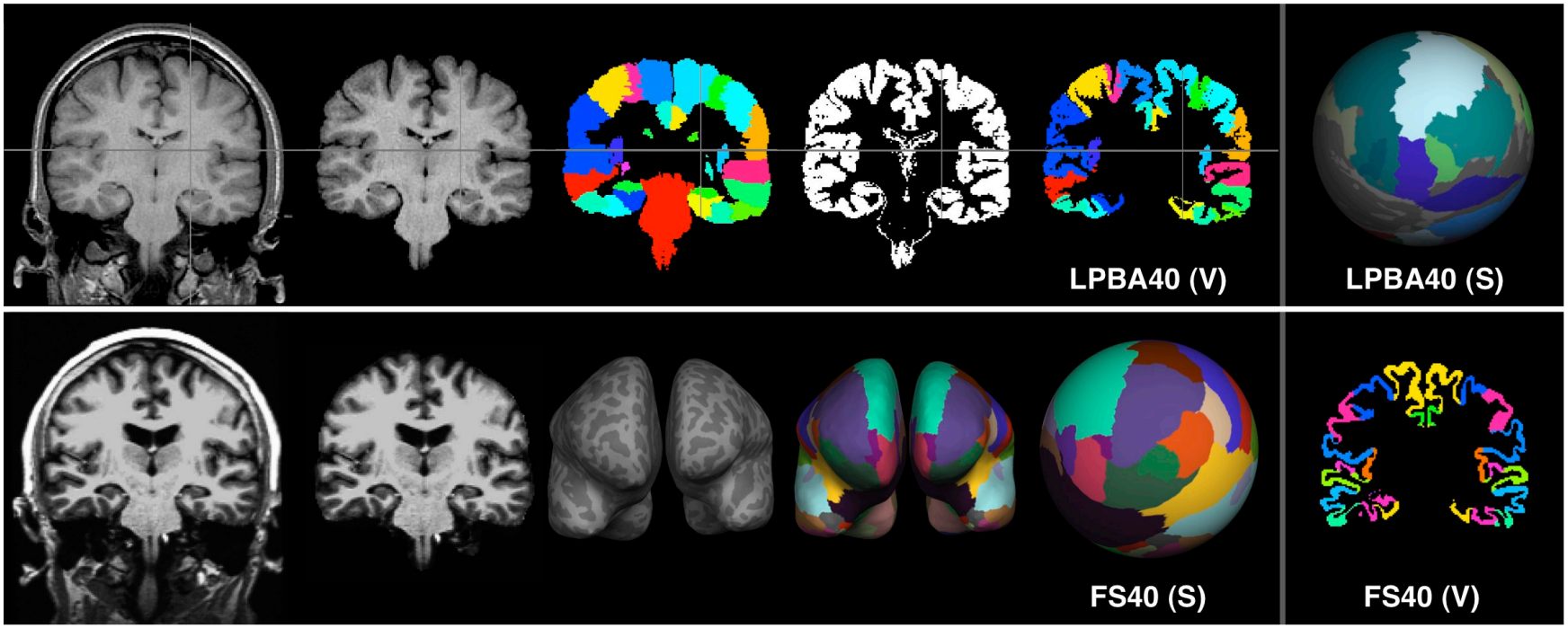
NeuroImage (2010)

Collaborators:	Software:	Space:
Satrajit S. Ghosh		
Brian Avants, James C. Gee	ANTS (SyN)	volume
B.T.T. Yeo	Spherical Demons	surface
Bruce Fischl	FreeSurfer	surface
Babak Ardekani	ART	volume

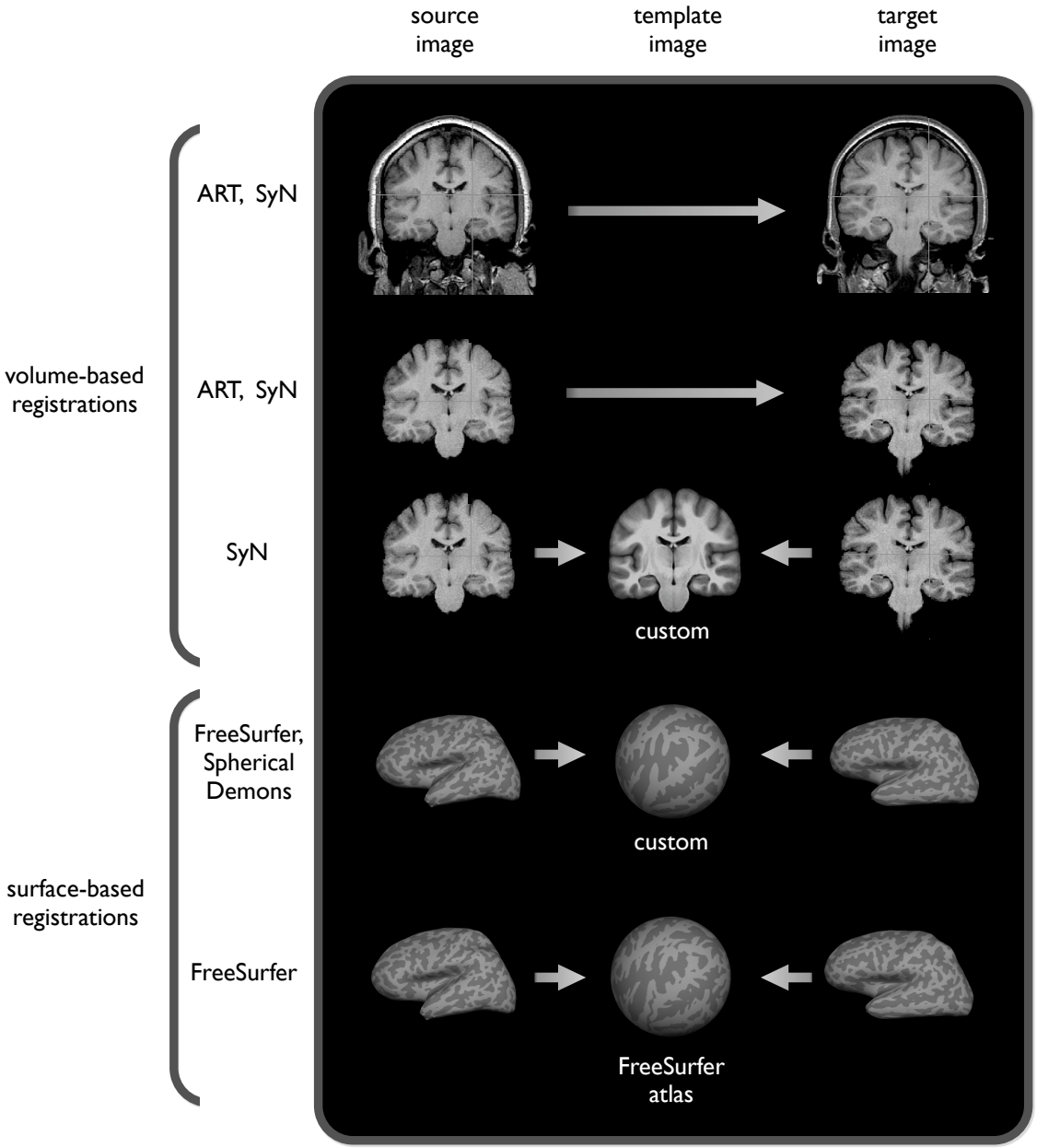
- first study to compare volume and surface registration methods
- first study to compare whole-head and brain-only image registrations
- compares registration accuracy with and without custom templates
- >16,000 registrations
- 80 manually labeled brain images for evaluation
- 2 different brain labeling protocols

Volume and surface data

(labeled in volumes ***and*** surfaces)



registrations

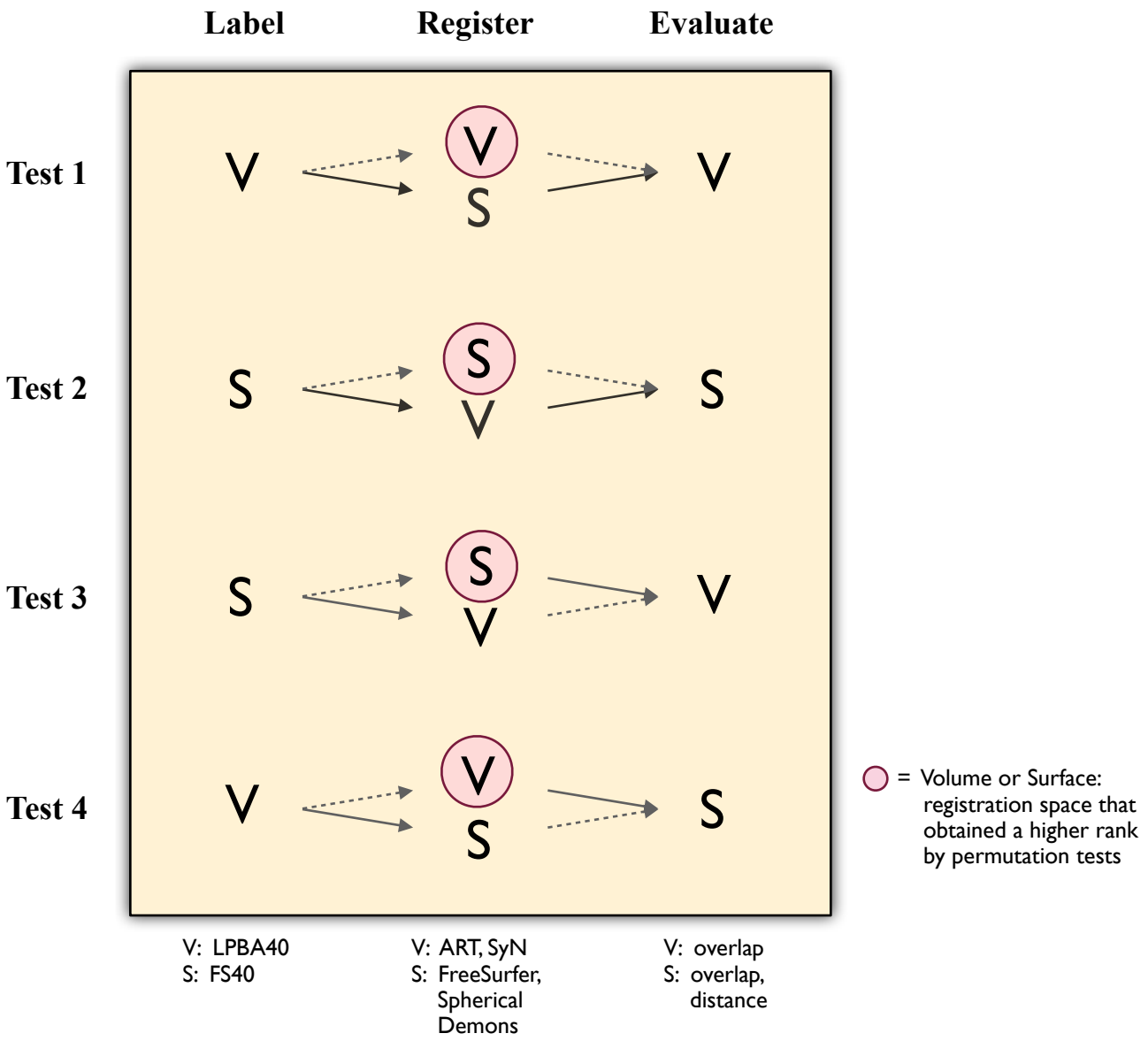


Test 1: permutation test ranks

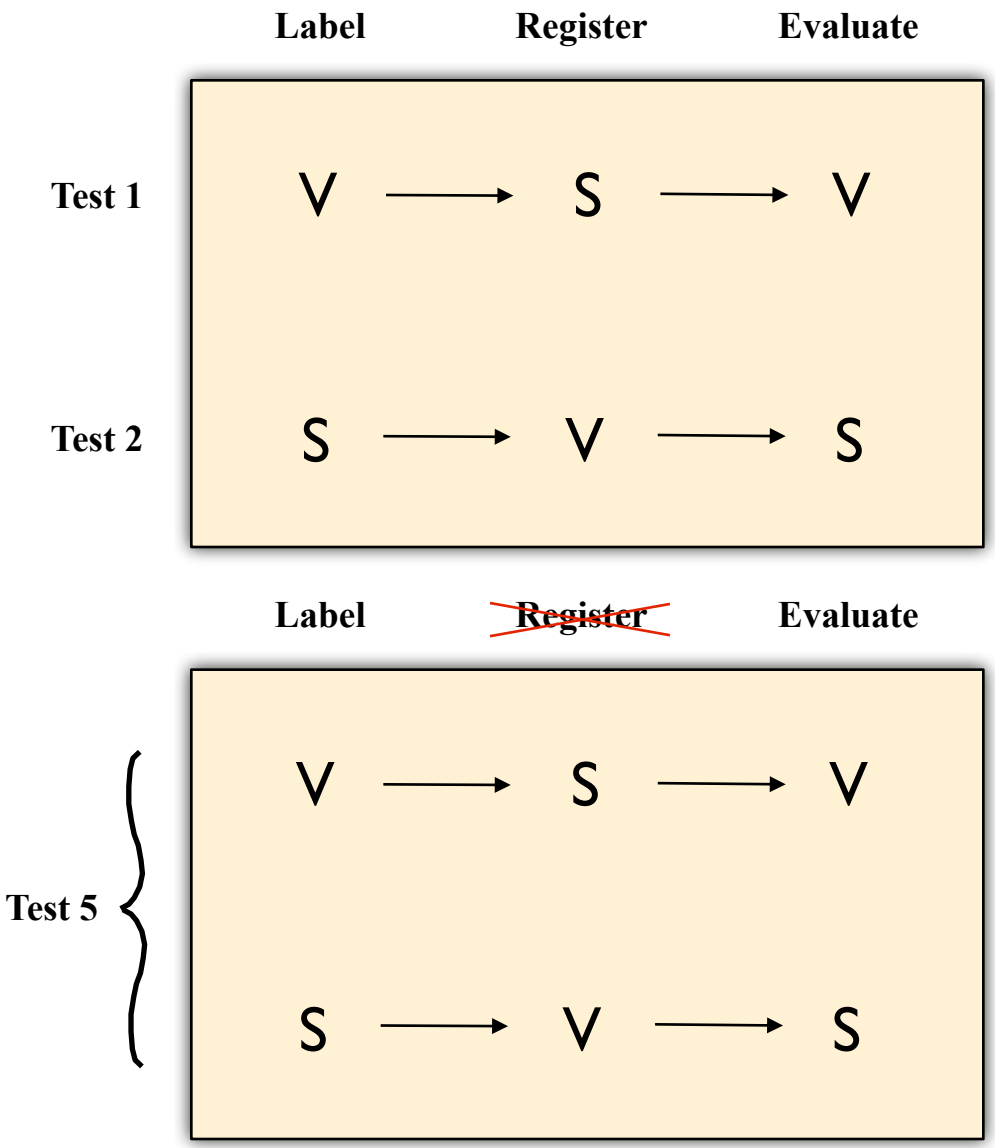
Volume registration methods	
Rank 1	SyN with custom templates
Rank 2	SyN ART

Surface registration methods	
Rank 1	FreeSurfer with custom templates Spherical Demons with custom templates
Rank 2	FreeSurfer with default atlas

Tests 1-4


Label
Register
Evaluate
Test 1
V
V
S
V
Test 2
S
S
V
S
Test 3
S
S
V
V
Test 4
V
V
S
S
= Volume or Surface: registration space that obtained a higher rank by permutation tests
V: LPBA40
S: FS40
V: ART, SyN
S: FreeSurfer, Spherical Demons
V: overlap
S: overlap, distance

Test 5: resampling



Test 5: resampling

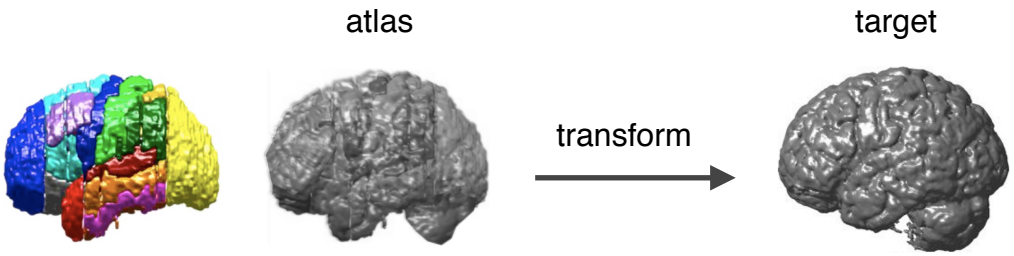
1. Brain extraction aids volume registration.

2. Custom templates improve registration over direct pairwise registration.

3. Resampling volume labels on surfaces *or* surface labels on volumes precludes a fair comparison between surface and volume registration methods.

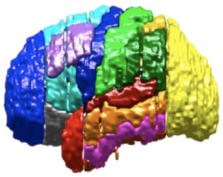
Recommendation:
Construct a custom template from a limited sample drawn from the same or a similar representative population, using the same algorithm used for registering brains to the template.

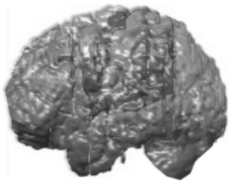
Convention: registration-based labeling



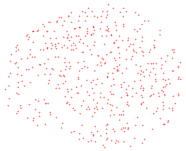
Mindboggle 2: feature-based labeling

atlas



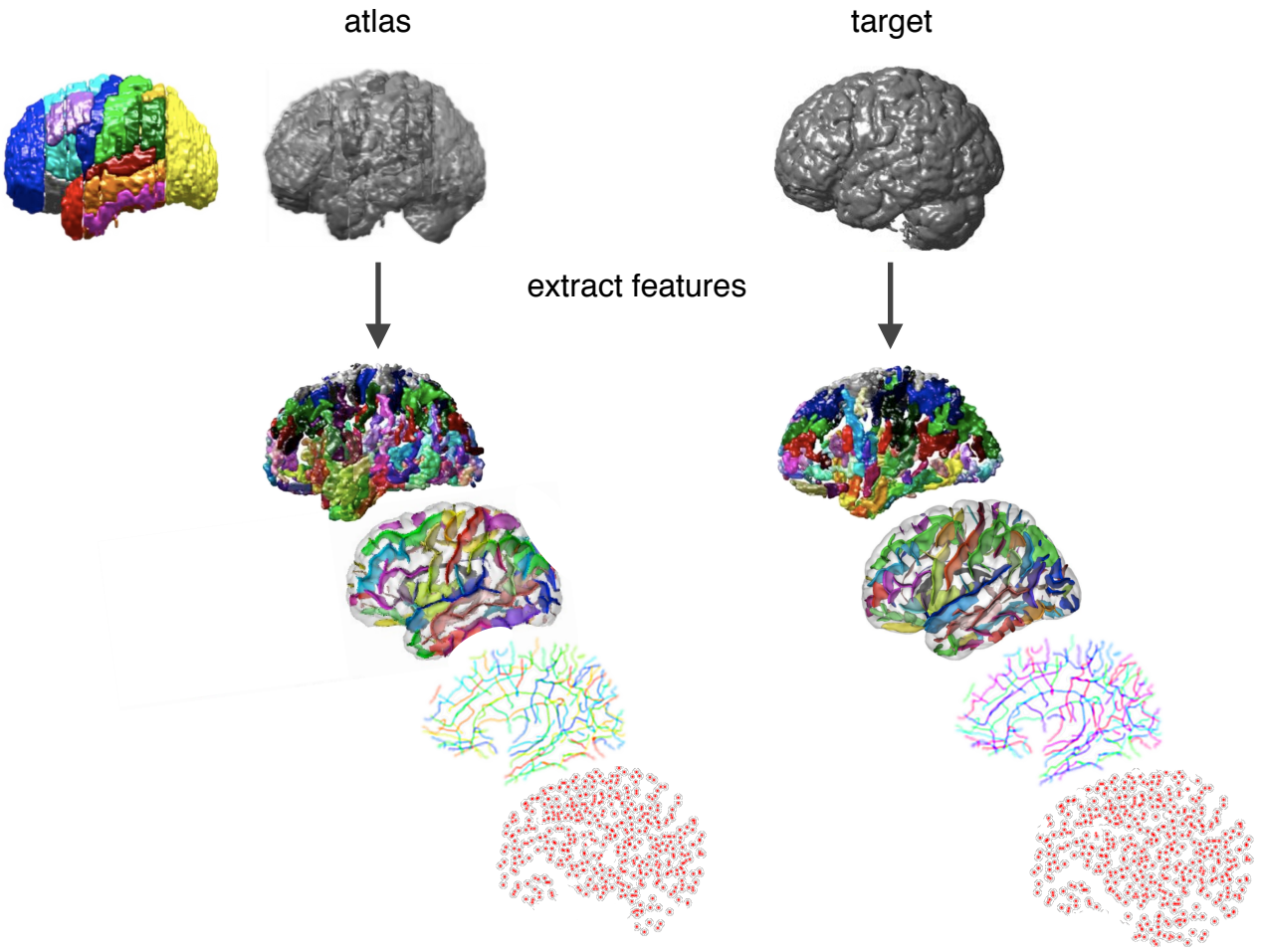


target



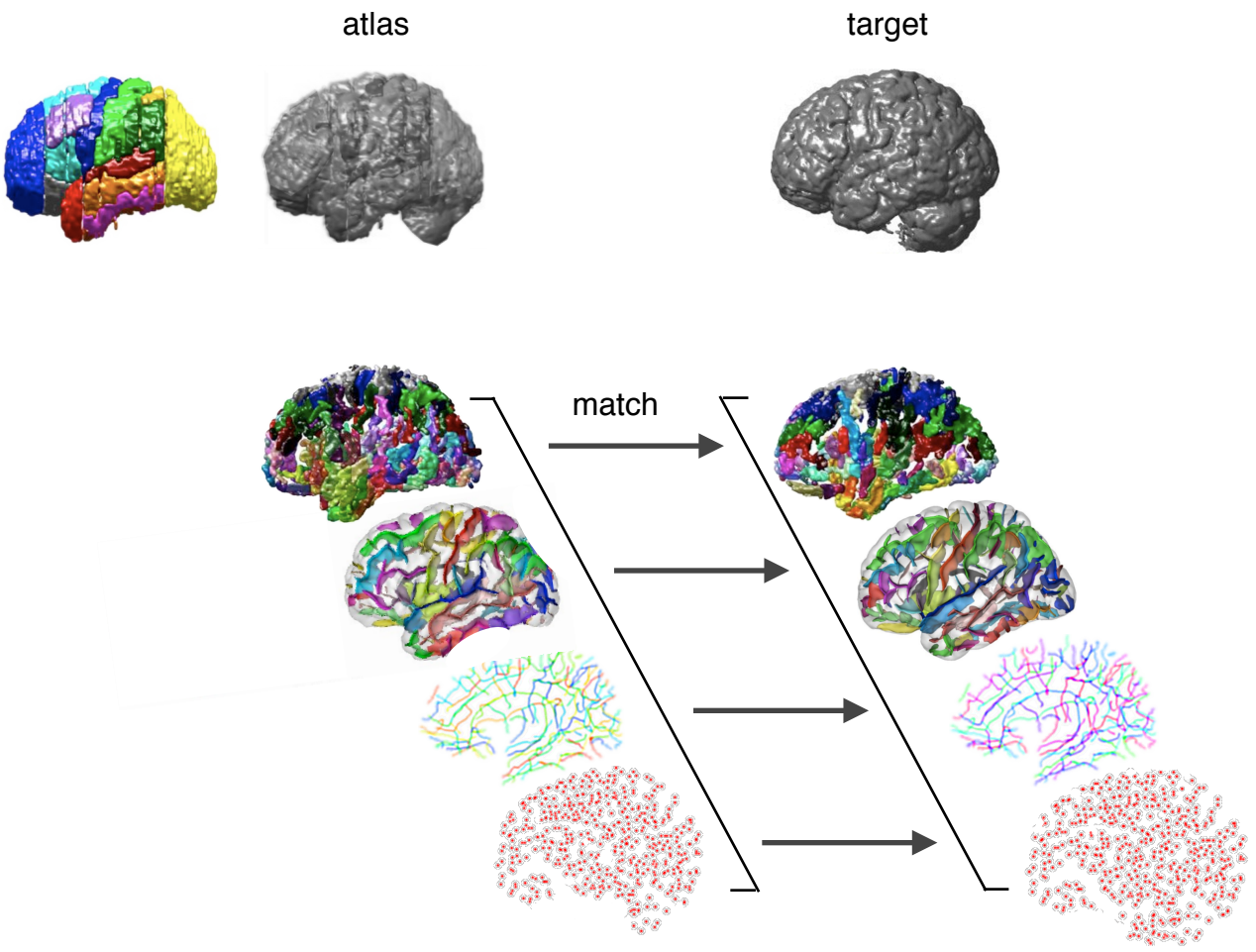
Mindboggle 2: feature-based labeling

Step 1: extract features



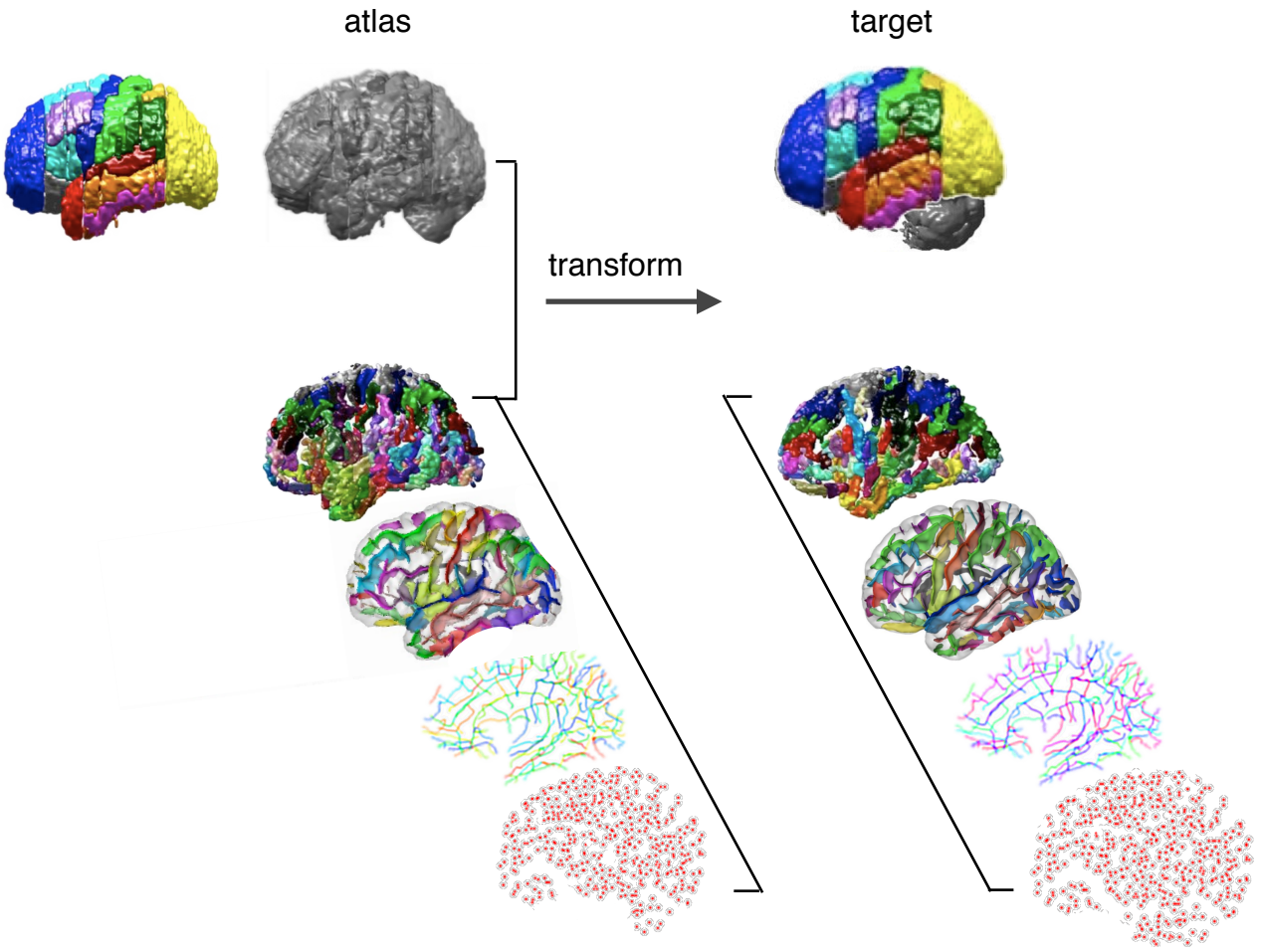
Mindboggle 2: feature-based labeling

Step 2: match atlas and target features



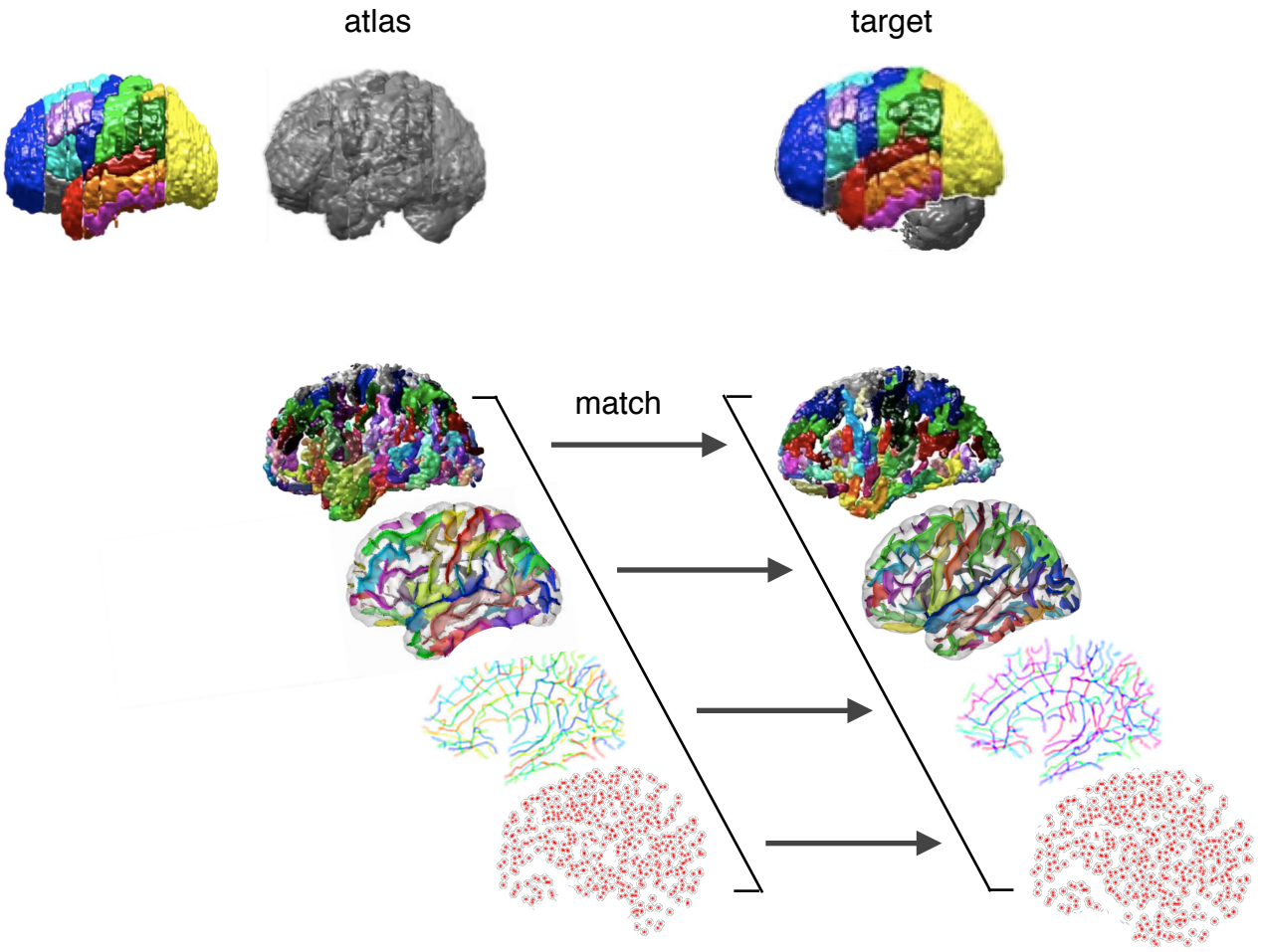
Mindboggle 2: feature-based labeling

Step 3: compute image + landmark-based registration transform from atlas to target



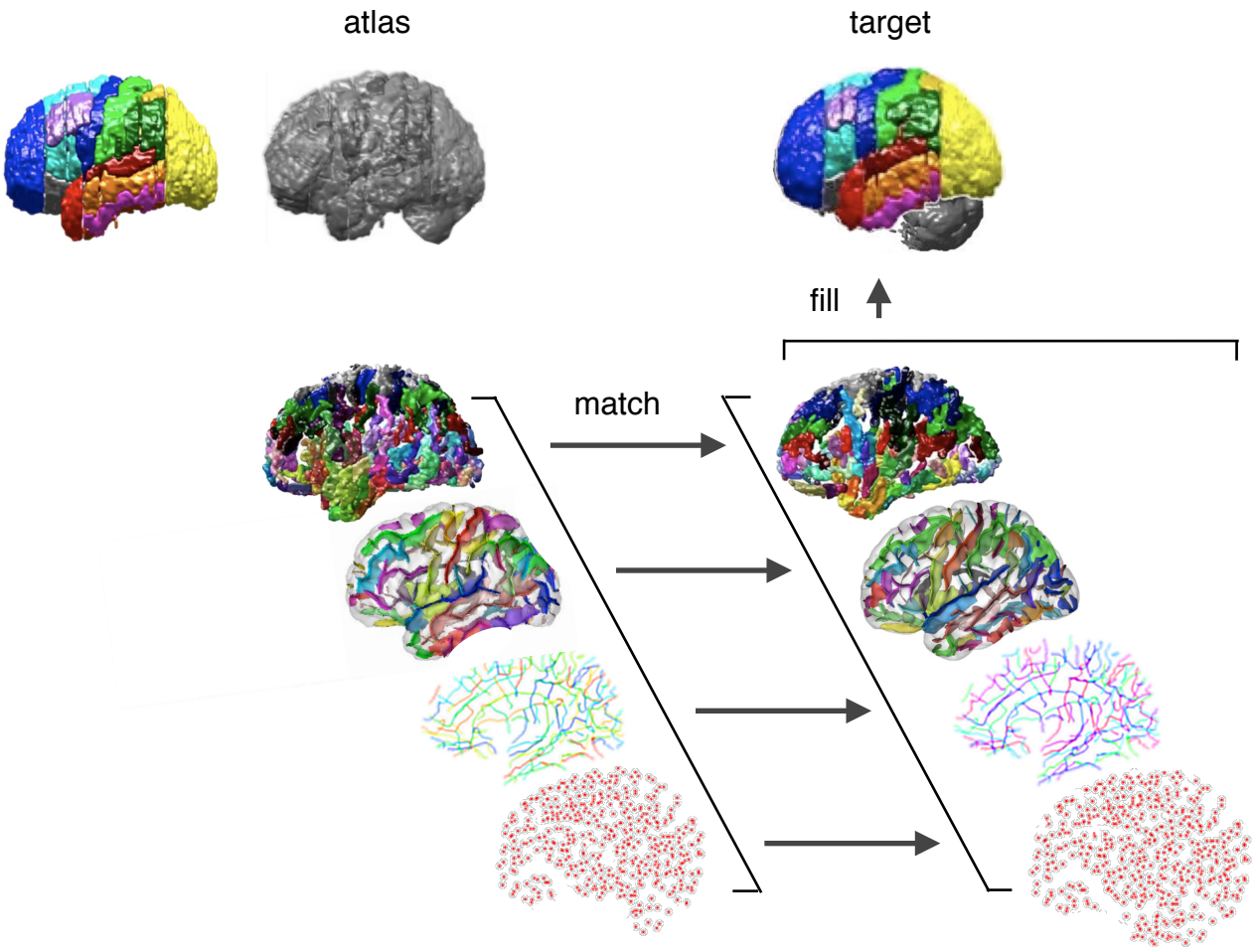
Mindboggle 2: feature-based labeling

Step 2: or match...

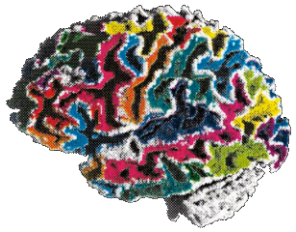


Mindboggle 2: feature-based labeling

Step 3: then propagate labels within inferred label boundaries?



Candidate features

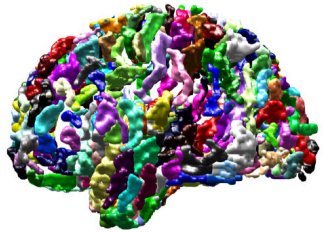


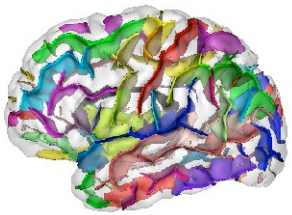
3-D:

labeled **regions** (manual)

sulcal **basins**

sulcal **skeletons**

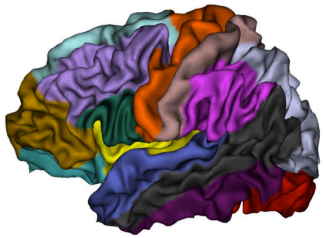


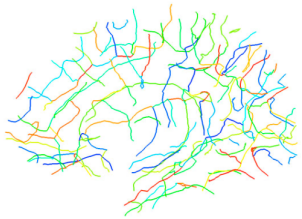


2-D:

sulcal **ribbons**

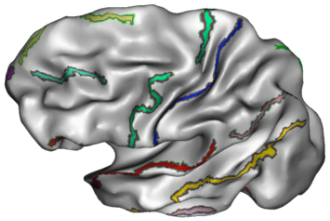
gyral **surfaces**

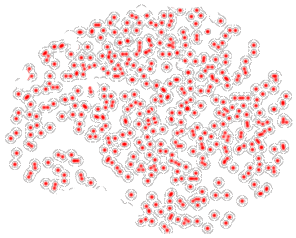




1-D:

sulcal & gyral **curves**

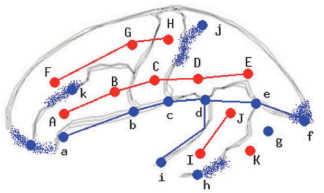




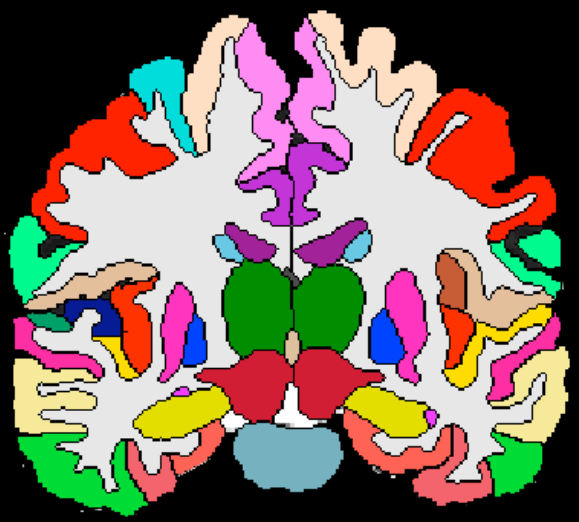
0-D:

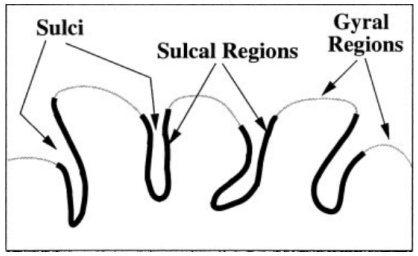
SIFT **points**

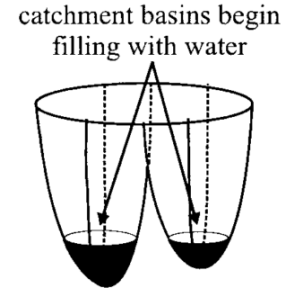
sulcal **pits**

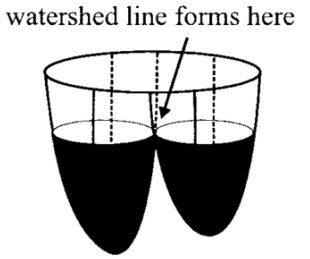


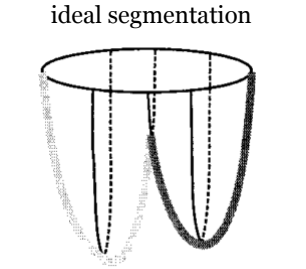
Candidate features in 3-D:
manually labeled **regions**



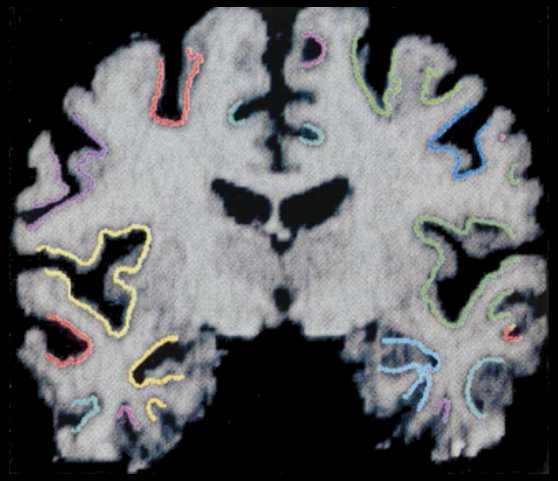


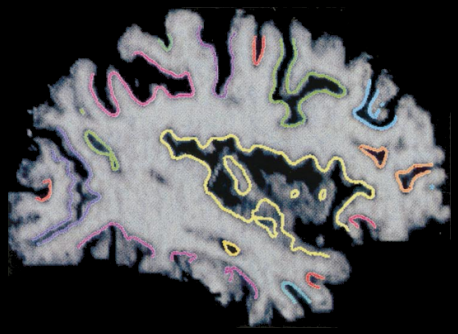




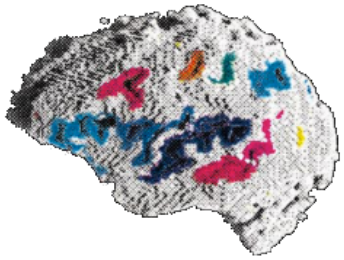


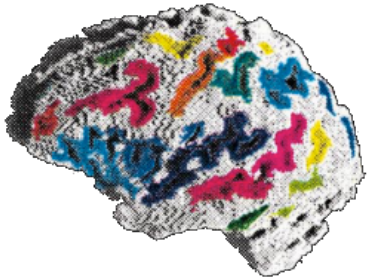
Candidate features in 3-D: sulcal **basins**

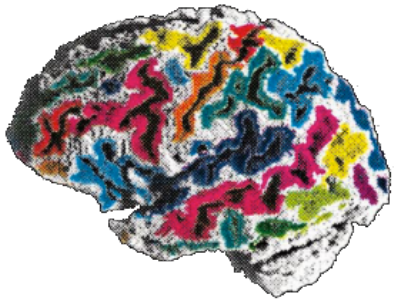


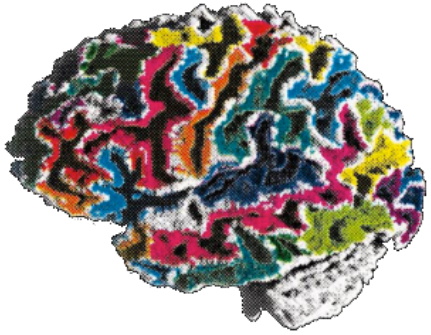


Rettman et al. 2002, Lohmann et al., 2000

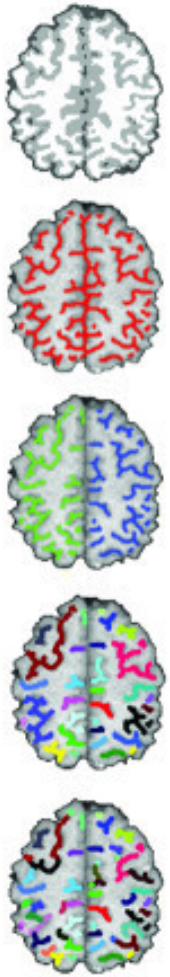


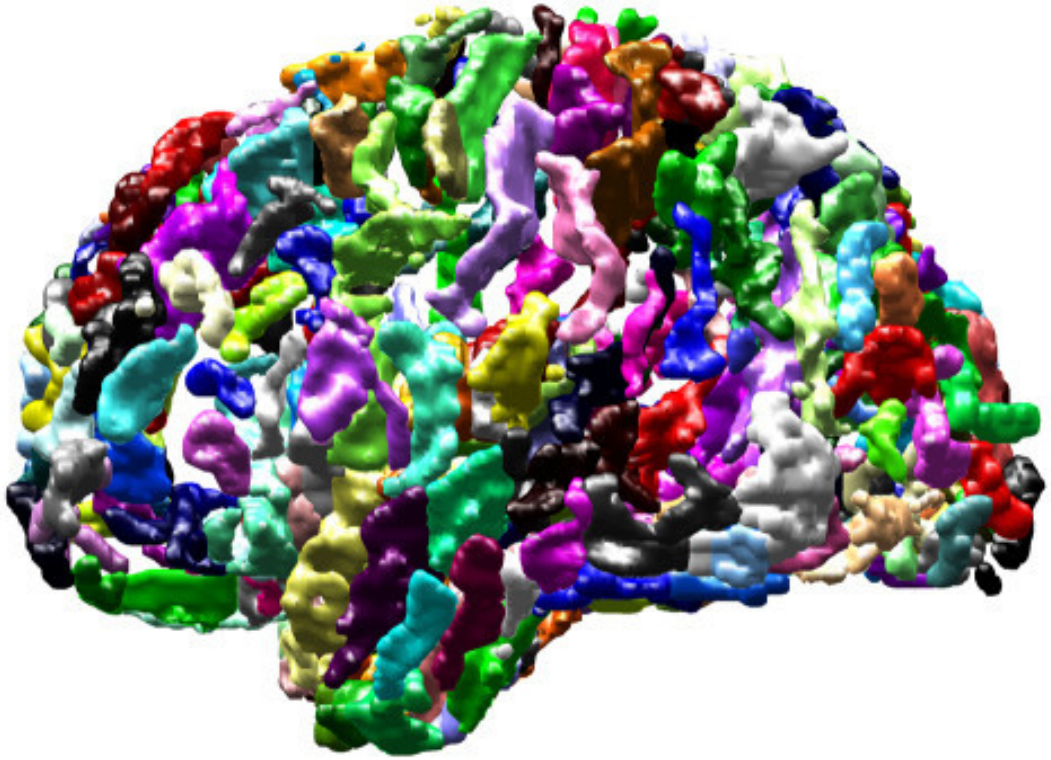




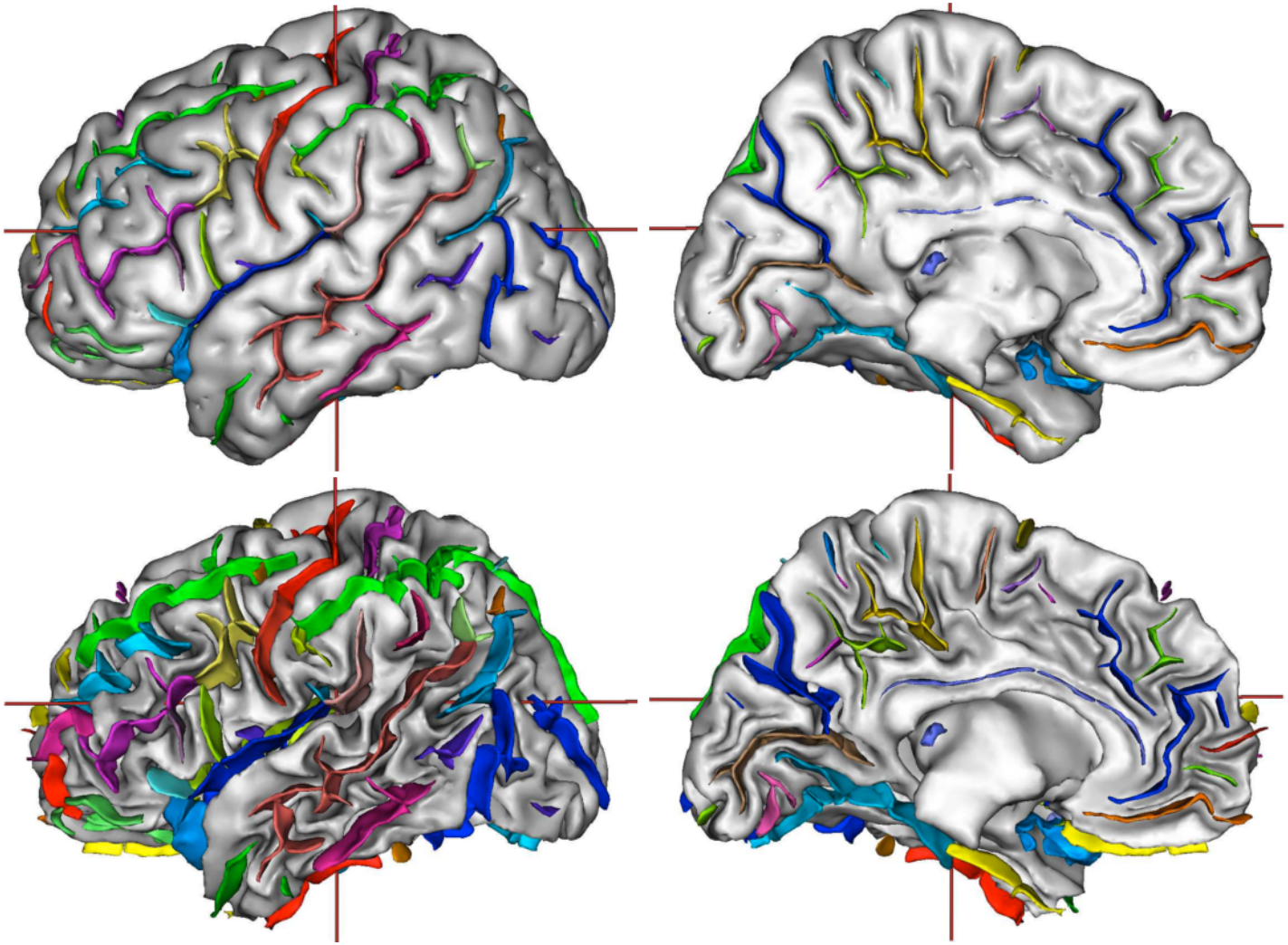


Candidate features in 3-D:
sulcal **skeletons**



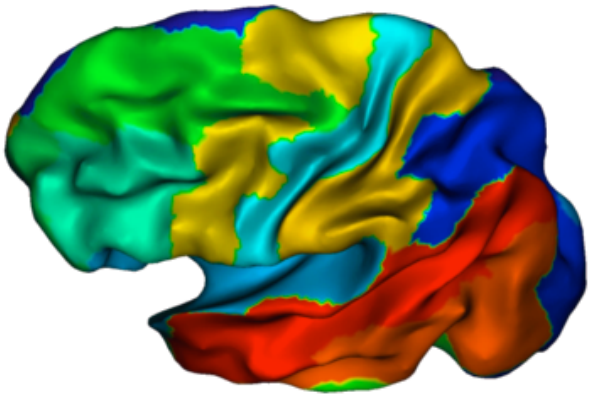


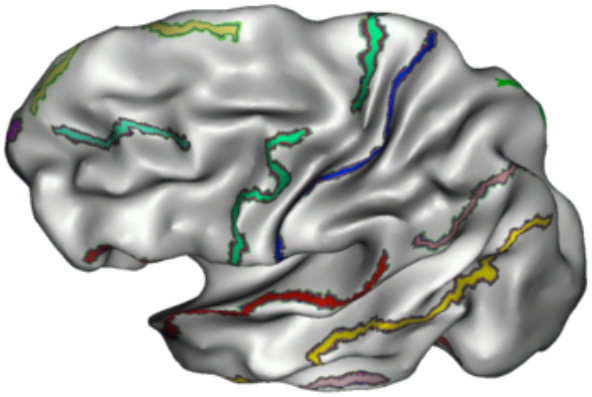
Candidate features in 2-D:
sulcal **ribbons**

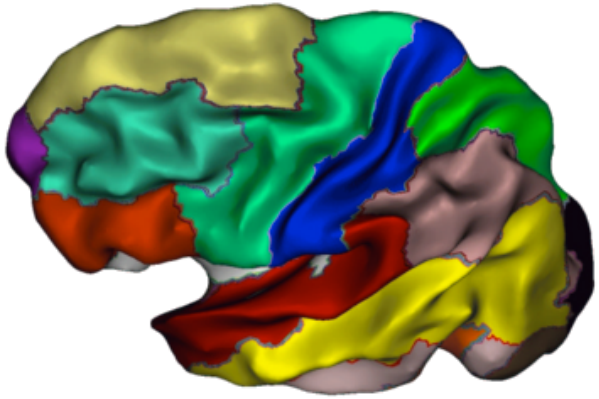


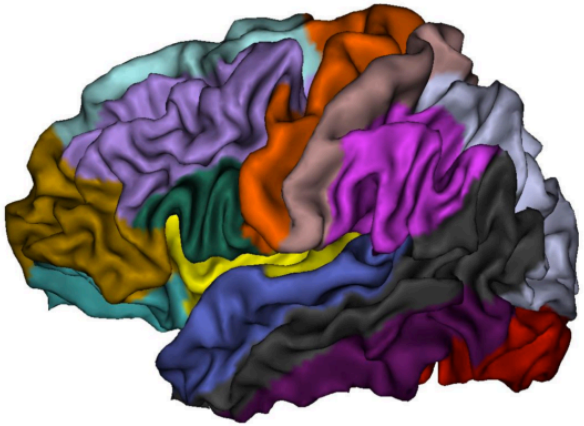
Clouchoux, 2008

Candidate features in 2-D:
sulcal & gyral **surfaces**



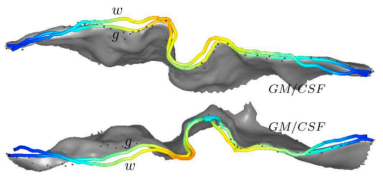


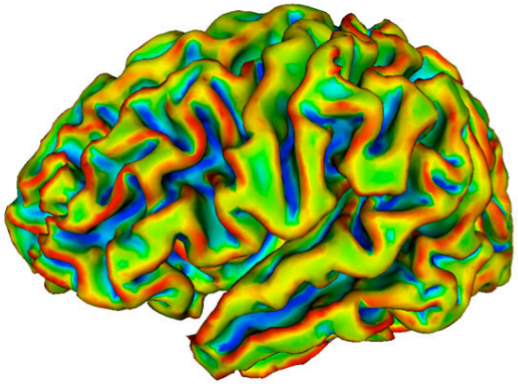


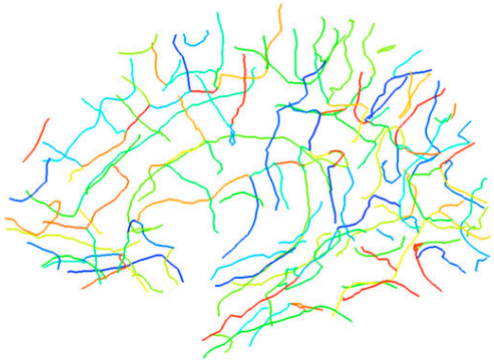


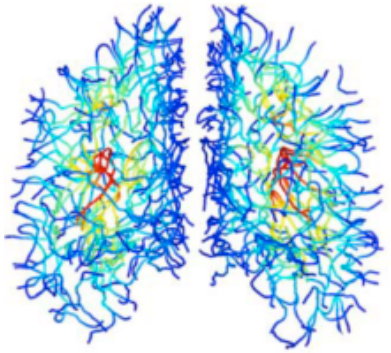
Cachia et al., 2003, Clouchoux et al., 2006

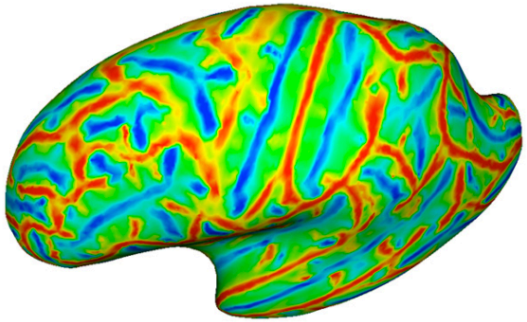
Candidate features in 1-D: sulcal **curves**

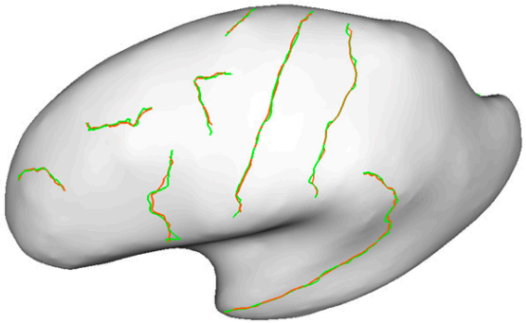


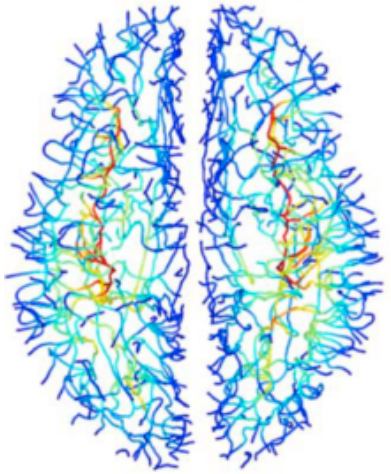






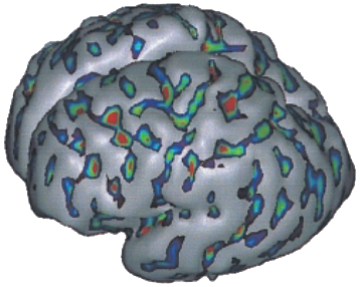


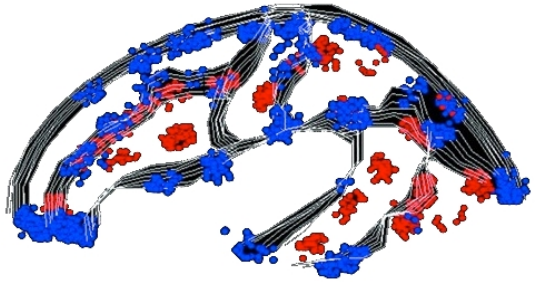


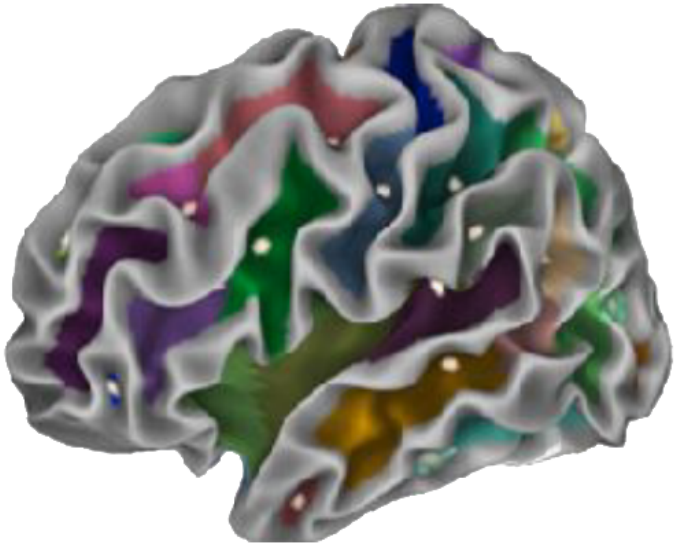


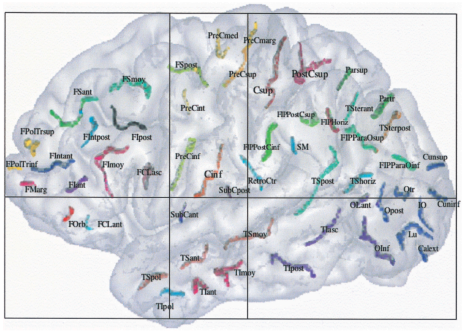
Li et al., 2008, Kao et al., 2007

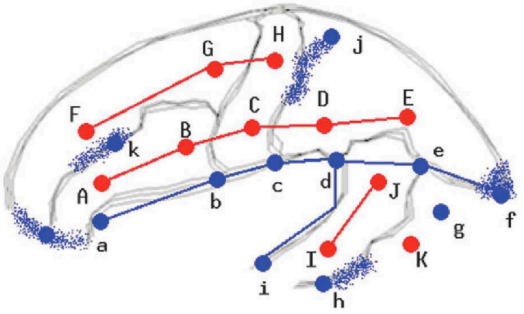
Candidate features in 0-D: sulcal **pits**





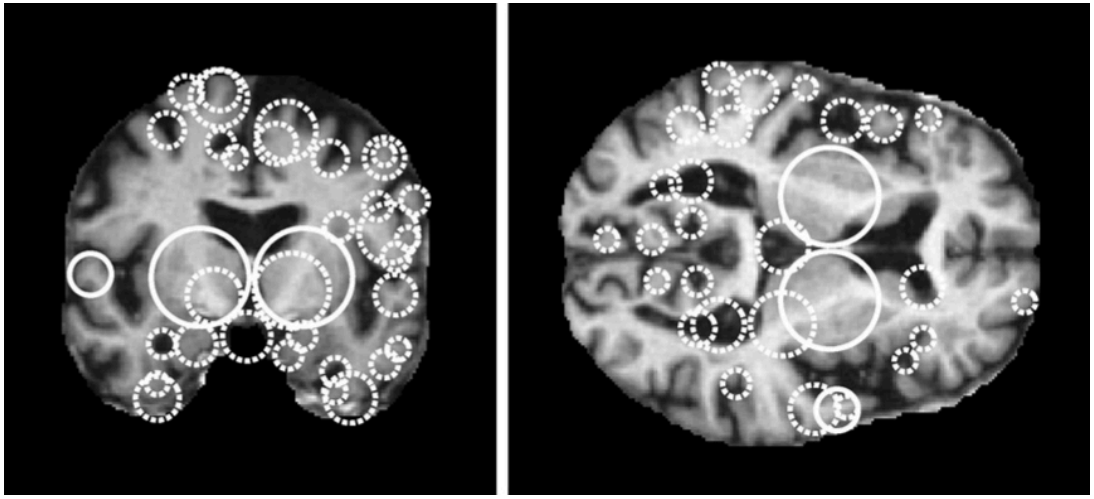






Regis et al., 2005, Im et al., 2010, Lohmann et al., 2007

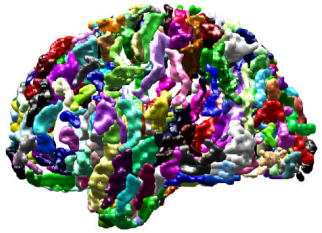
Candidate features in 0-D:
SIFT **points**

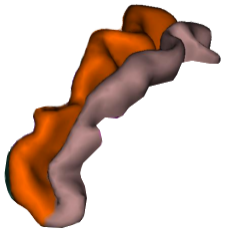


Toews 2008, 2010

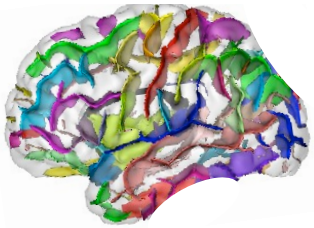
Proposed nested feature hierarchy

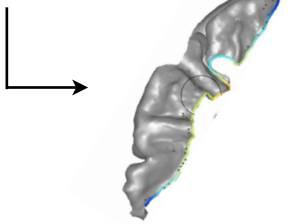
3-D



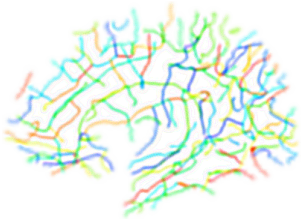


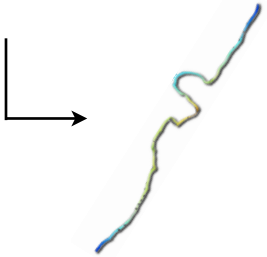
2-D



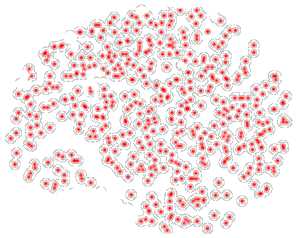


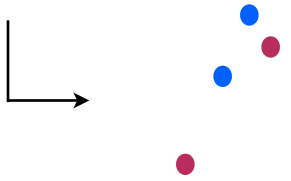
1-D





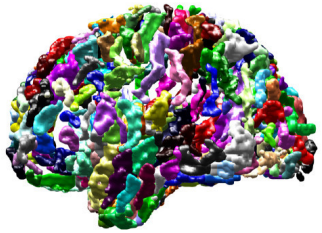
0-D

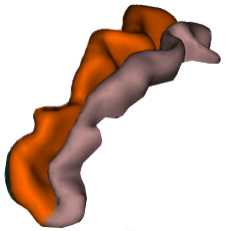




Candidate shape measures

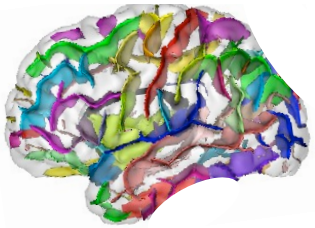
3-D





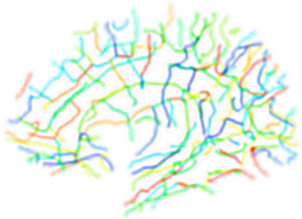
volume
surface area
lengths (thickness)
?

2-D



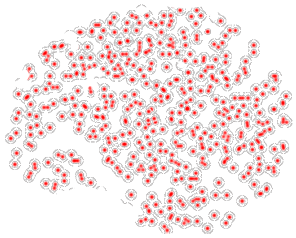
area
curvature
convexity
?

1-D



length
curvature
convexity
?

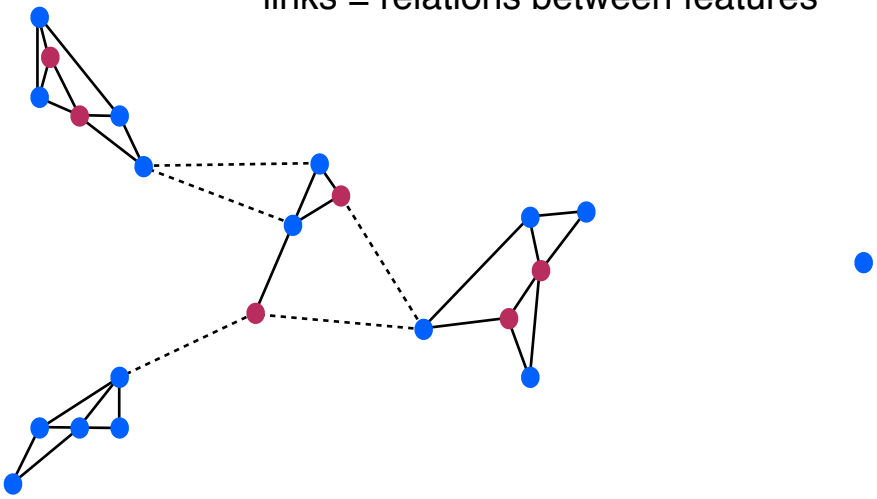
0-D



number of points
3-D convex hull volume
1-D sequence
?

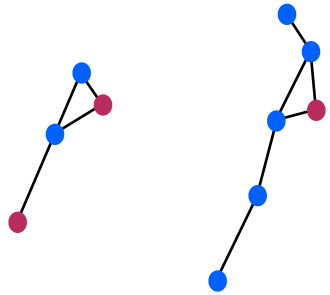
Network analysis measures

nodes = features
links = relations between features

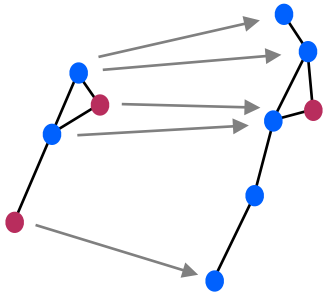


- centrality
- betweenness
- modularity
- ...

Deformation-based morphometry measures

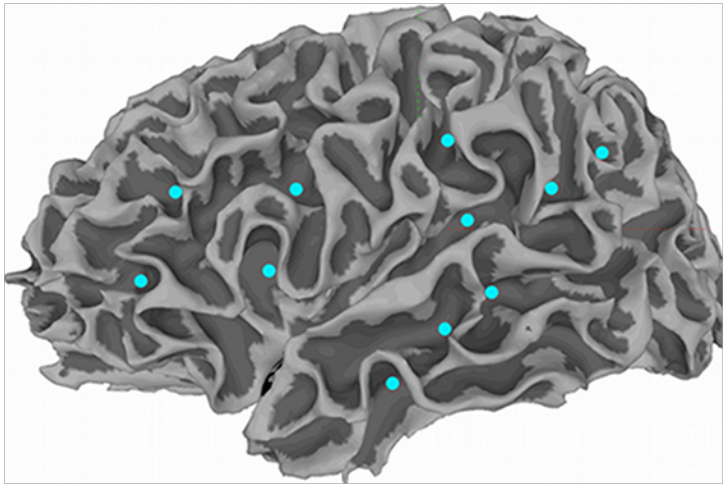


Deformation-based morphometry measures

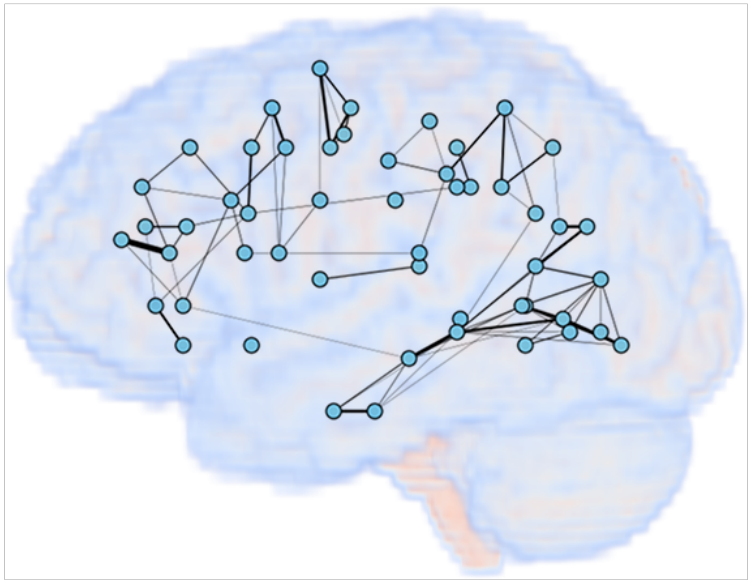


- warp field
- Jacobian
- Haussdorf distance

Multimodal feature graphs

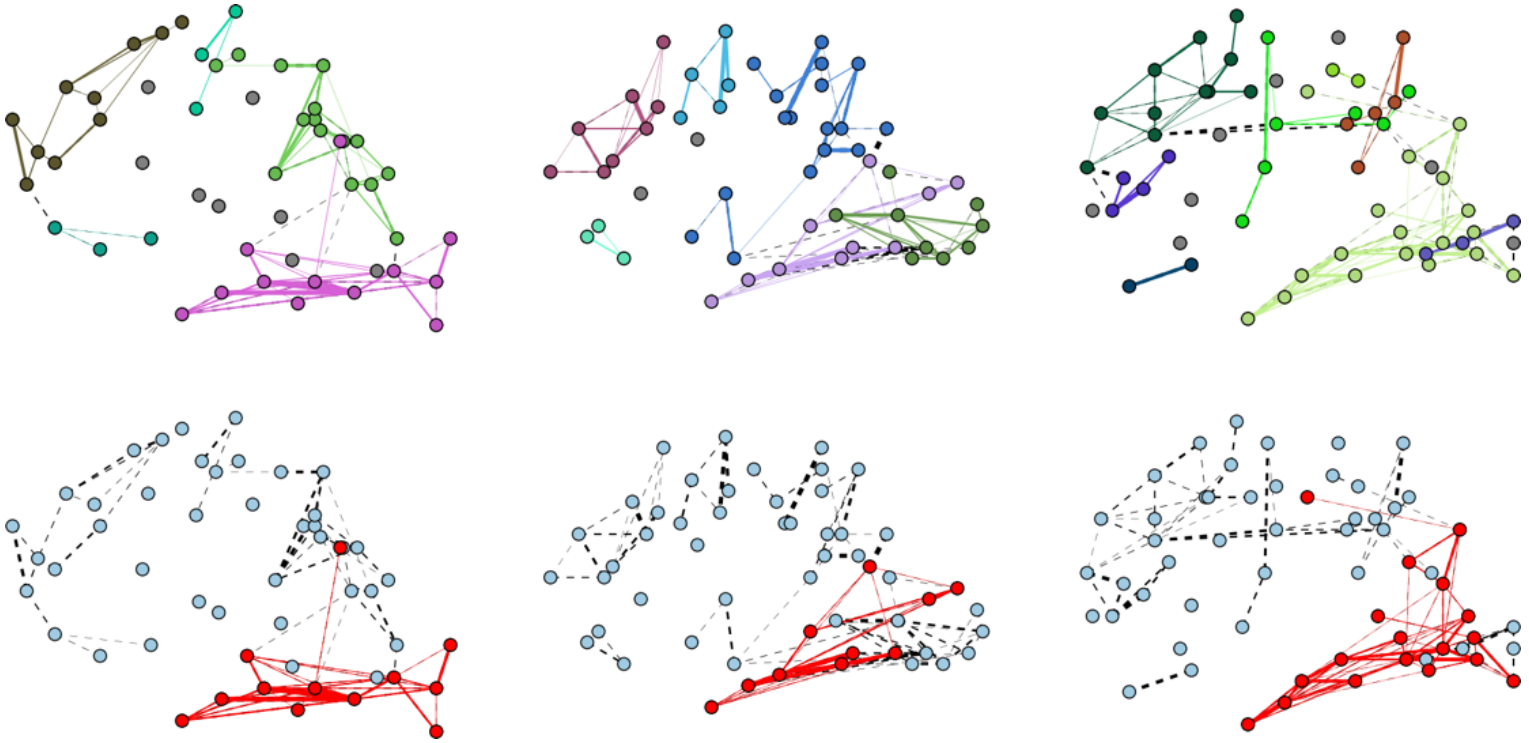


A gray/white matter surface (left lateral view) with visible sulcal pits highlighted (cyan circles). These features go by different names (sulcal roots, buried or annectant gyrii, plis de passage) and may be well conserved structures formed early in development.



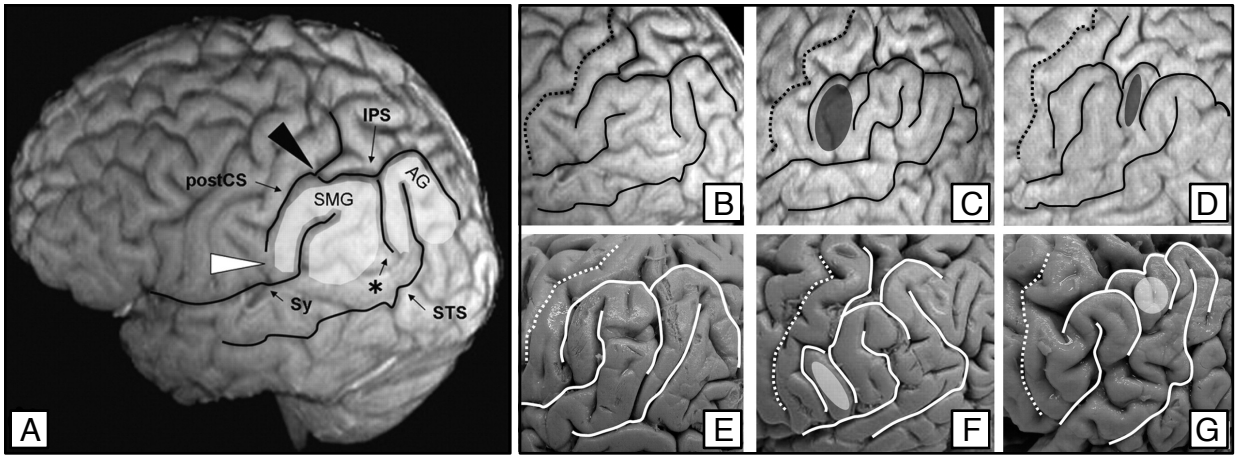
DTI connectivity graph (same subject). Vertices represent all extracted sulcal pits and each edge width indicates a connection probability greater than 0.01 between two vertices (and does not follow a tractography path).

Subgraph matching



Early attempt at subgraph extraction (upper row) and matching (lower row).
These graphs were constructed from (left to right) a remitter, non-remitter, and control subject.
The subgraphs in red in the lower row have the highest small-worldness ratio.

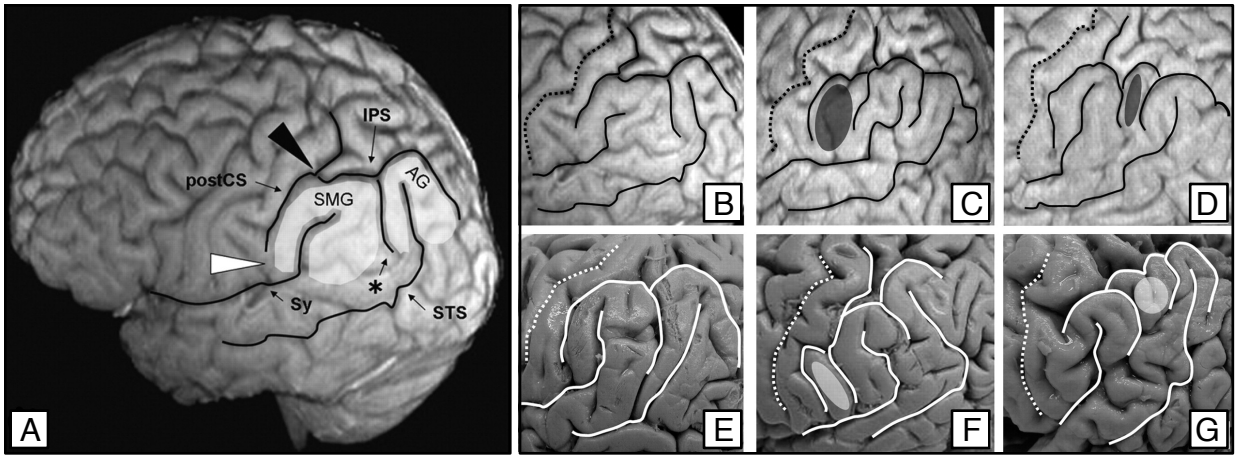
Anatomical variability

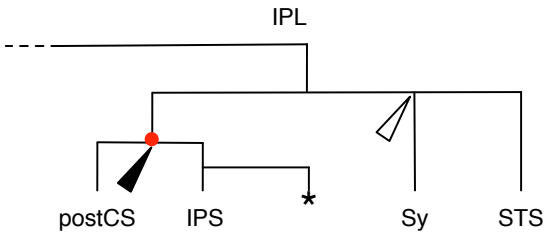


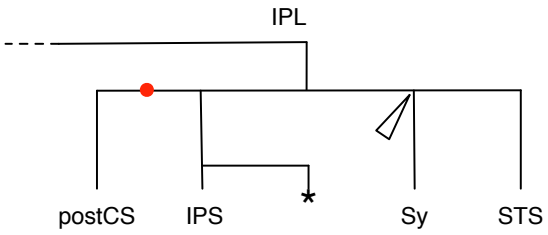
Example of natural morphological variability: left inferior parietal lobule (IPL; Kiriyama et al. 2009).
(A-D) are MRI data and (E-G) are post-mortem specimens.
(A) IPL is highlighted and folds are outlined.
(B,E) Typical folding pattern.
(C,F) PreSMG pattern: an additional gyrus (ellipse) lies between postCS and SMG.
(D,G) PreAG pattern: an additional gyrus (ellipse) lies between SMG and AG.

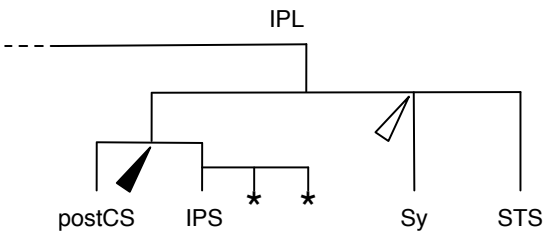
[SMG: supramarginal gyrus; AG: angular gyrus; postCS: postcentral sulcus; IPS: intraparietal sulcus;
Sy: Sylvian fissure, STS: superior temporal sulcus; *sulcus intermedius primus]

Graph-based representation of anatomical development









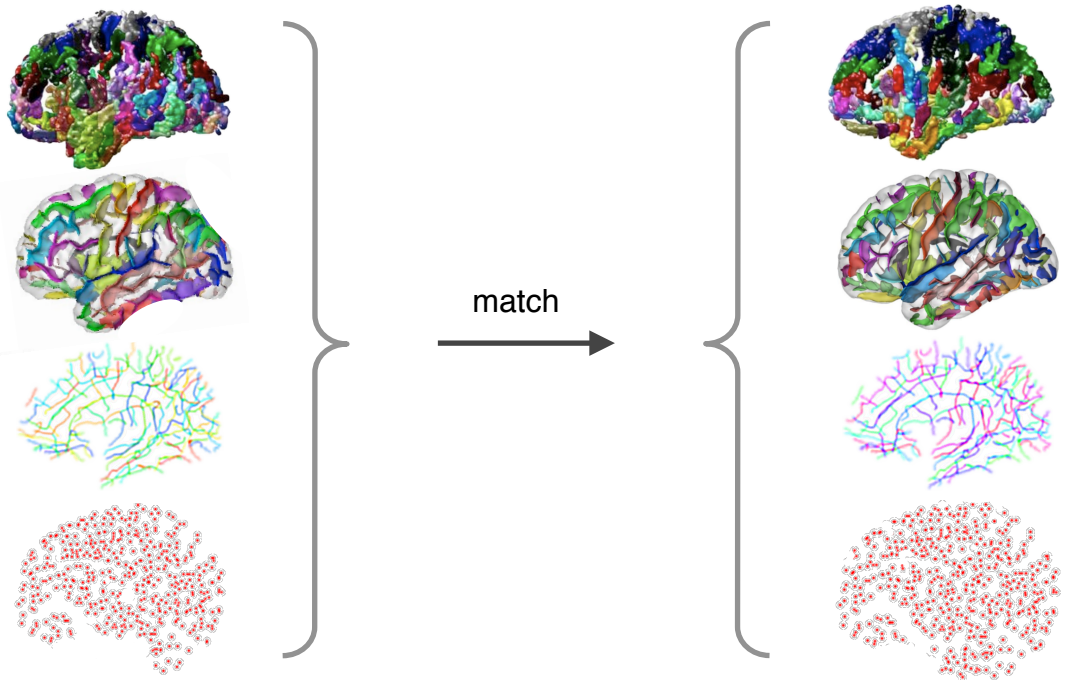
Feature matching

Bayesian face recognition algorithm

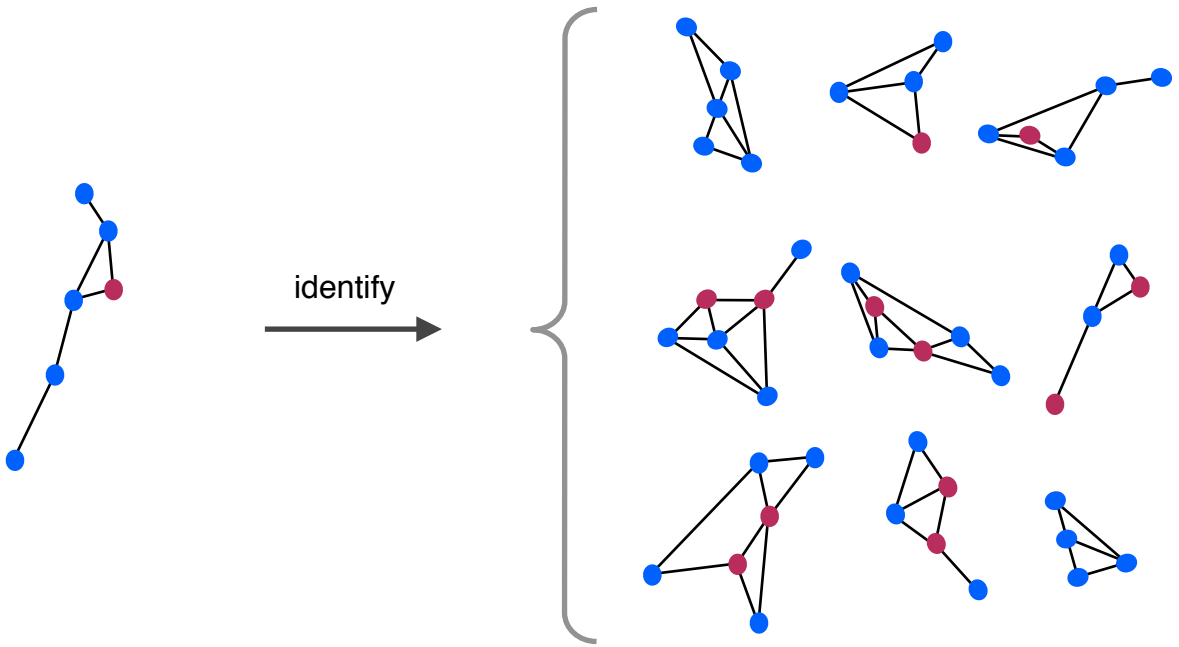
Example: MAP binary classification
(Moghaddam et al., 1998)

Feature matching

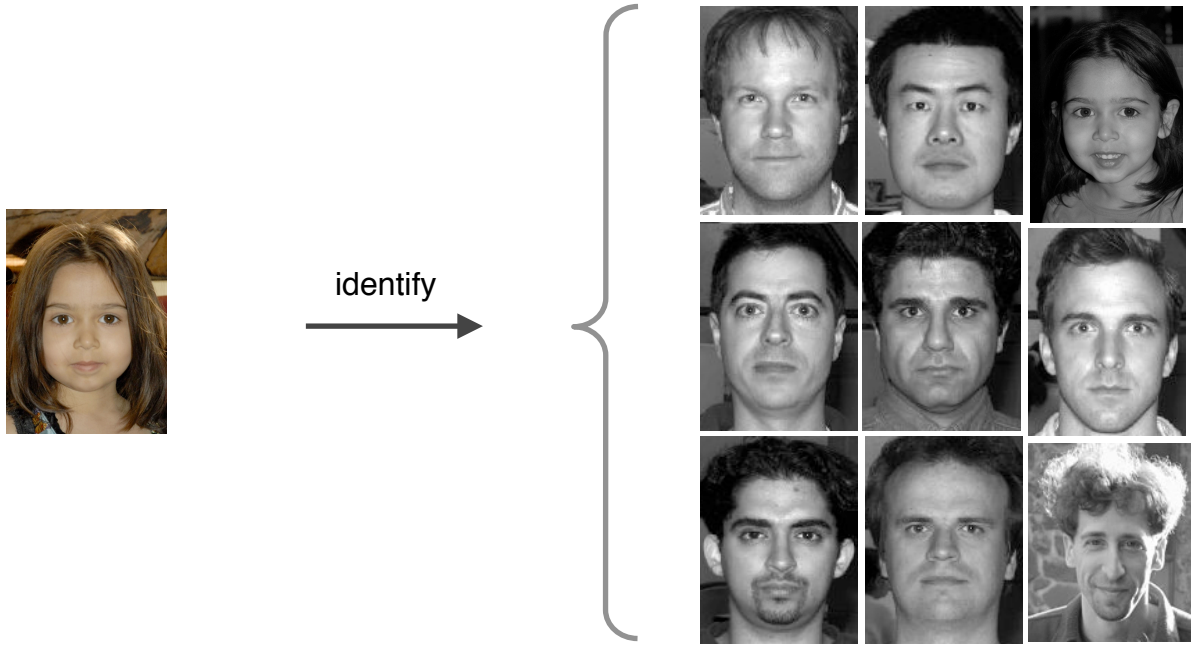
Instead of matching the entire set
of features across whole brains ...



... we can try to identify a group of features within a brain.

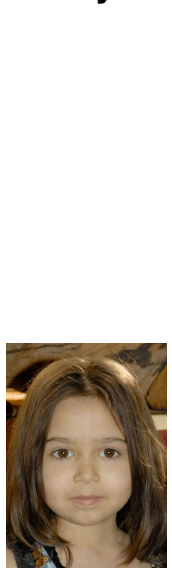


To adapt Bayesian face recognition to this problem, we can think about a set of facial features instead of a group of brain features ...

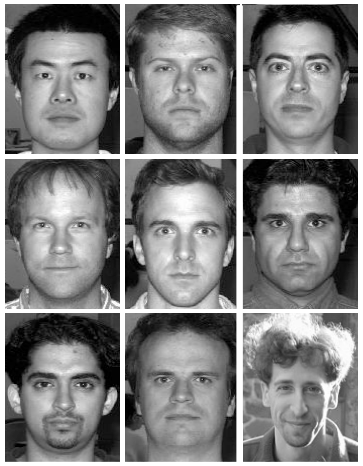


male faces c/o Brian Avants

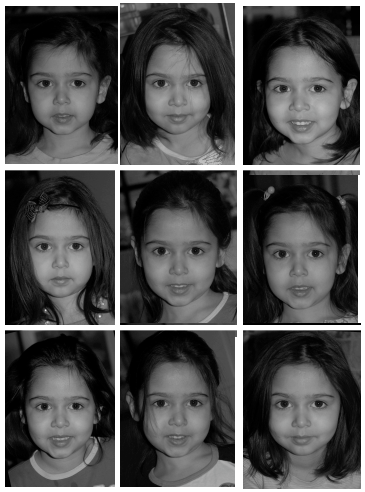
... and perform Bayesian binary classification,
by maximizing the posterior:



Extraclass?

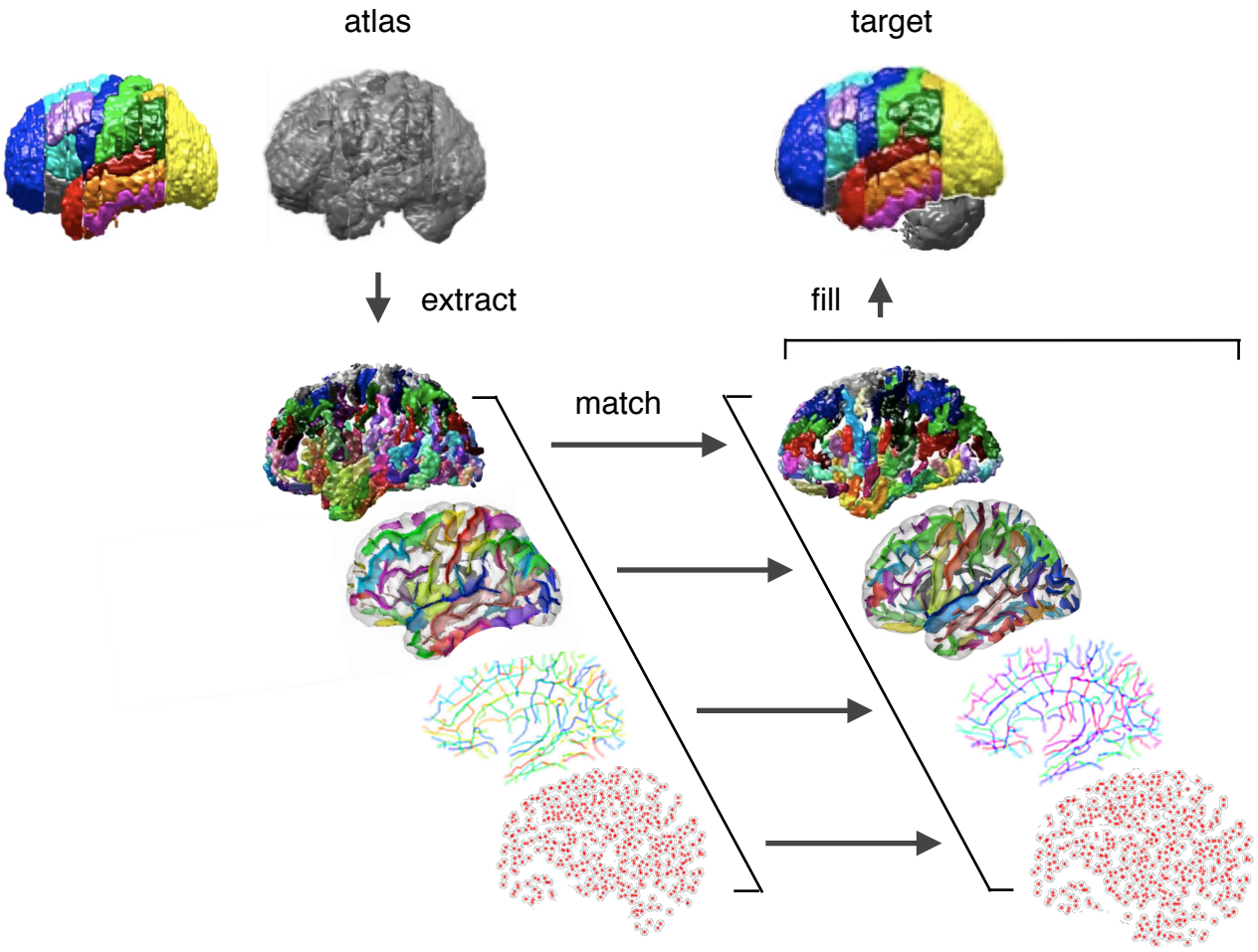


Intraclass?



$$P(\Omega_I|\Delta) = \frac{P(\Delta|\Omega_I)P(\Omega_I)}{P(\Delta|\Omega_I)P(\Omega_I) + P(\Delta|\Omega_E)P(\Omega_E)}$$

Mindboggle 2: feature extraction
feature matching
feature-driven labeling



Denis Peruzzo
DTI tractography

Forrest Bao
(Texas Tech)
Nested feature extraction

Noah Lee
Convolutional neural networks,
distributed database architecture

Ray Razlighi
SIFT algorithm evaluation

Satrajit Ghosh (MIT)
Machine learning,
NiPype software pipeline

Steve Ellis
Computational topology