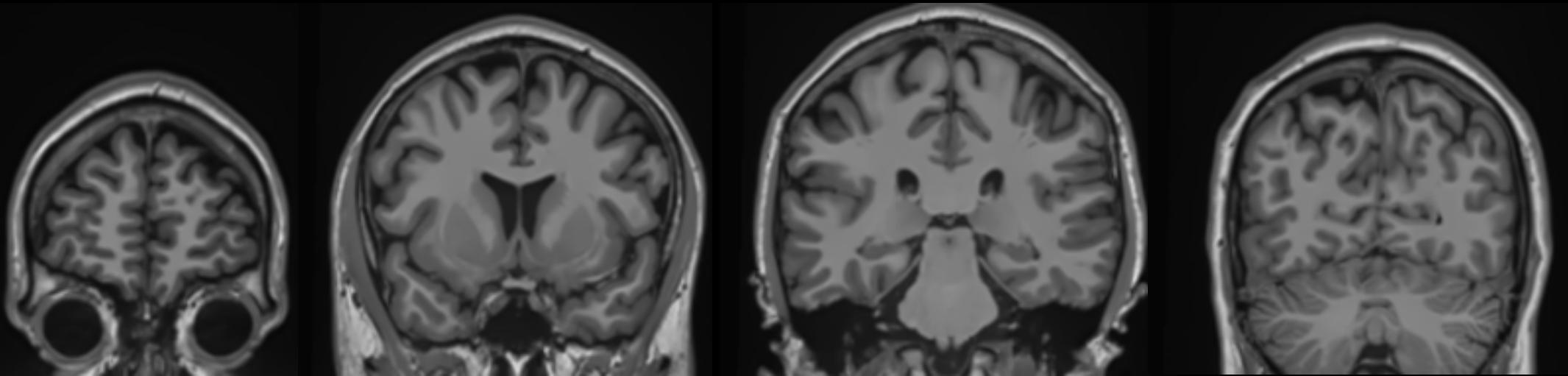


Structural MRI analysis

Boris Bernhardt, PhD
NeuroImaging of Epilepsy Lab
boris@bic.mni.mcgill.ca

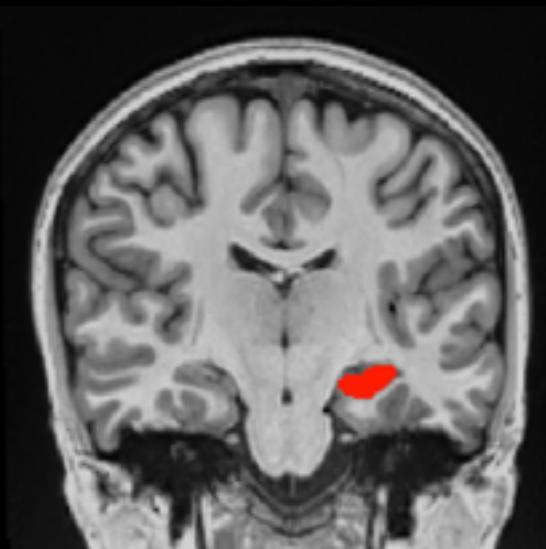


structural MRI

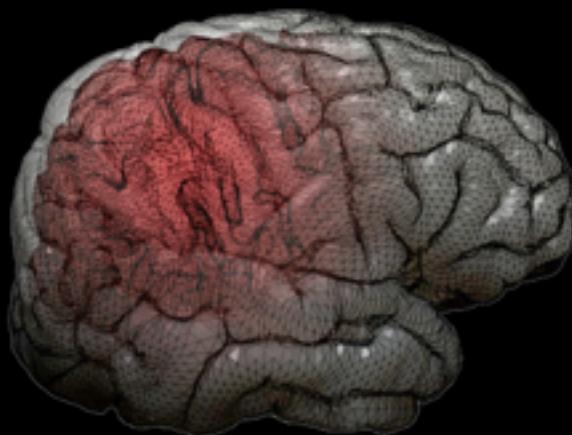


T1-weighted MRI

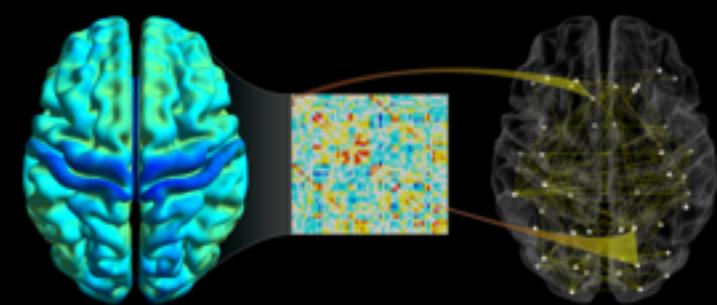
methods



MRI volumetry

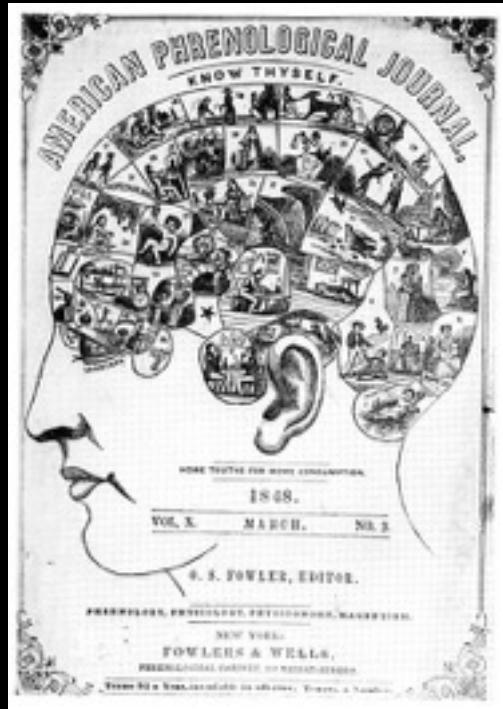


Surface-based analysis



Covariance mapping

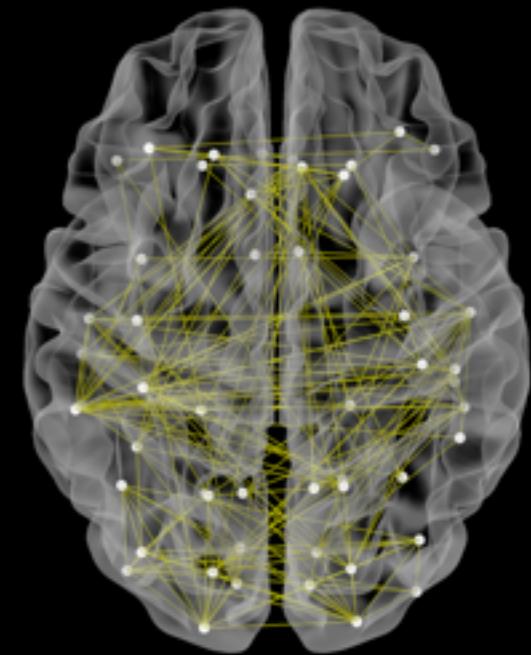
applications



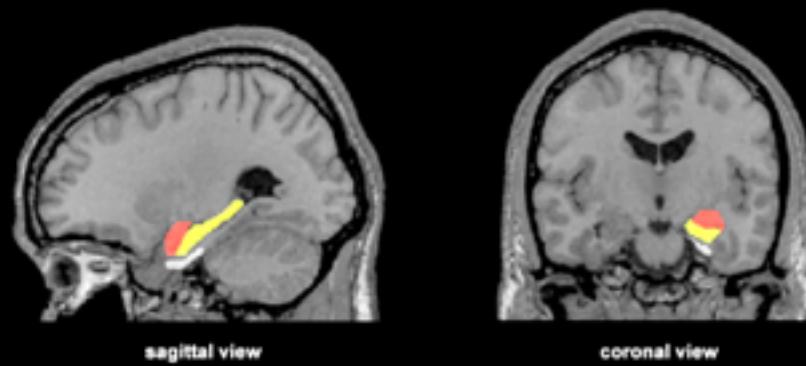
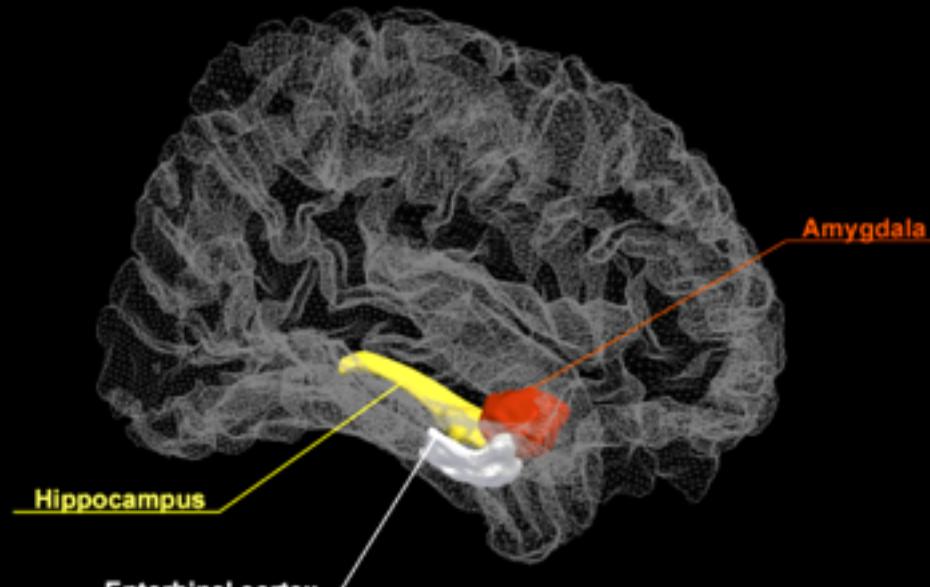
Individual differences



Brain disorders



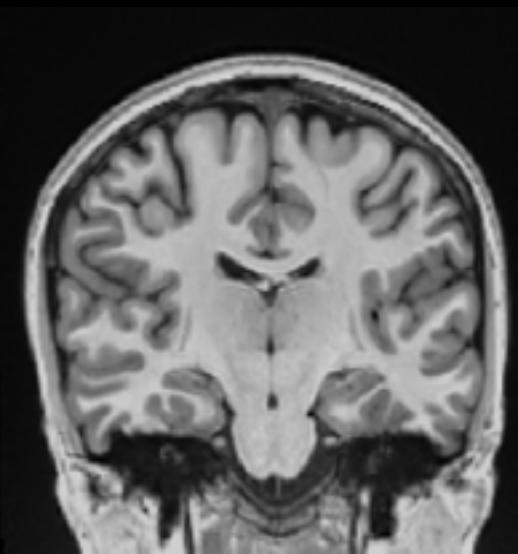
Brain organization



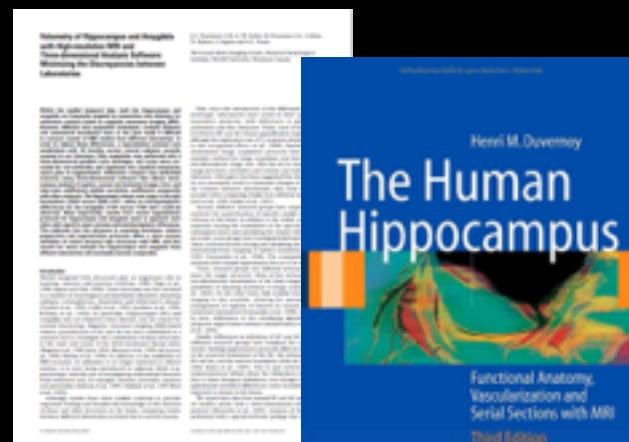
MRI volumetry

idea: trace structure in 3D and count number of voxels

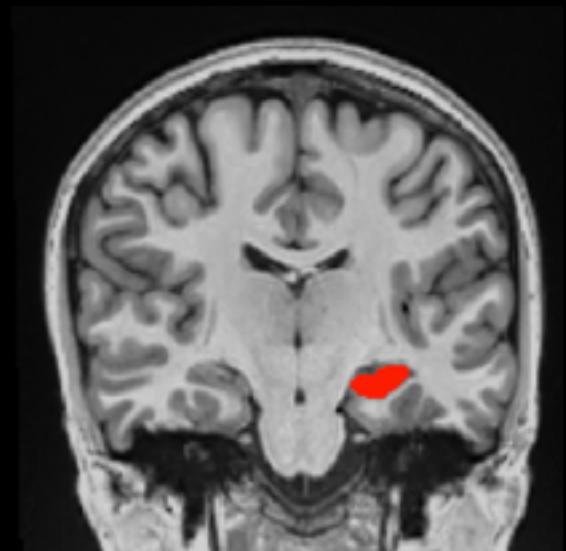
volumetry 'pipeline'



input



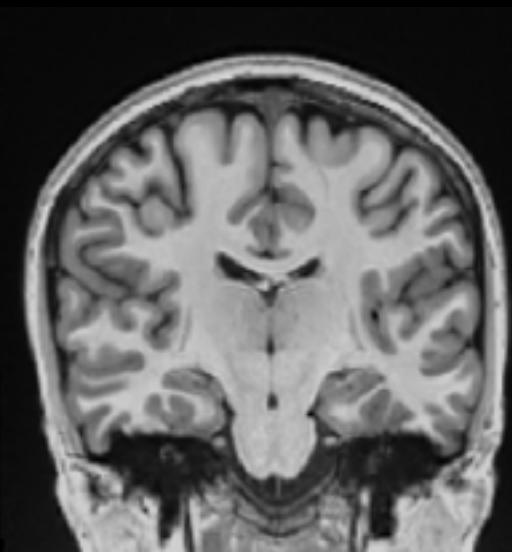
read and become expert



segment



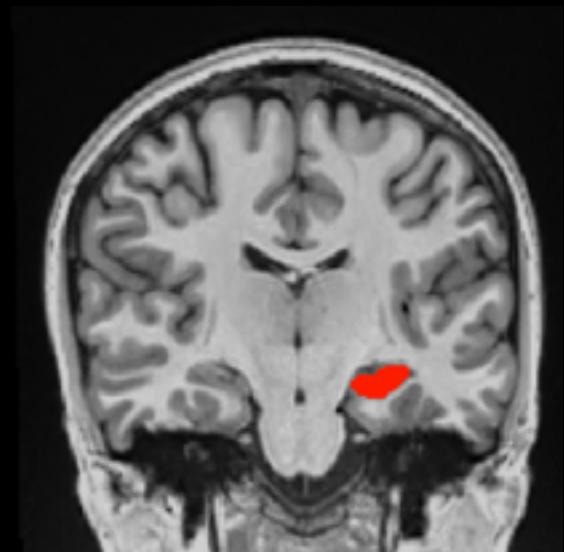
alternative volumetry 'pipeline'



input



automatic segmentation approaches



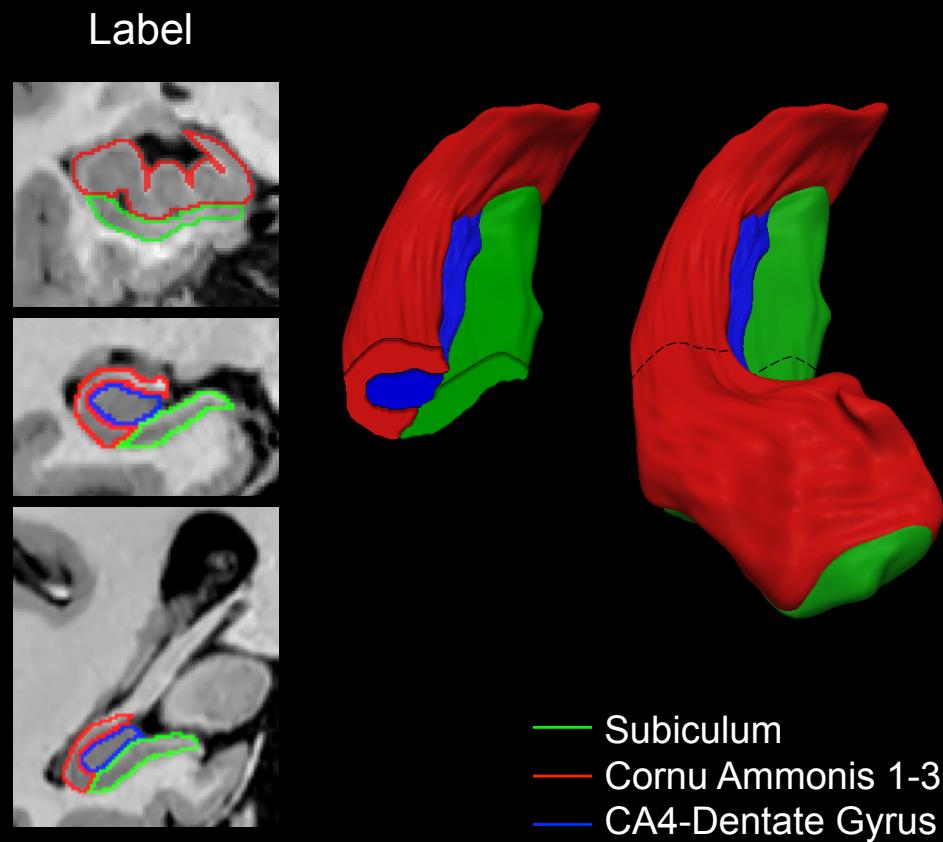
segment

Chupin et al. (2009) *NeuroImage*

Coupe et al. (2010) *MICCAI*

Kim et al. (2011) *MedImaAnal*

subfield volumetry



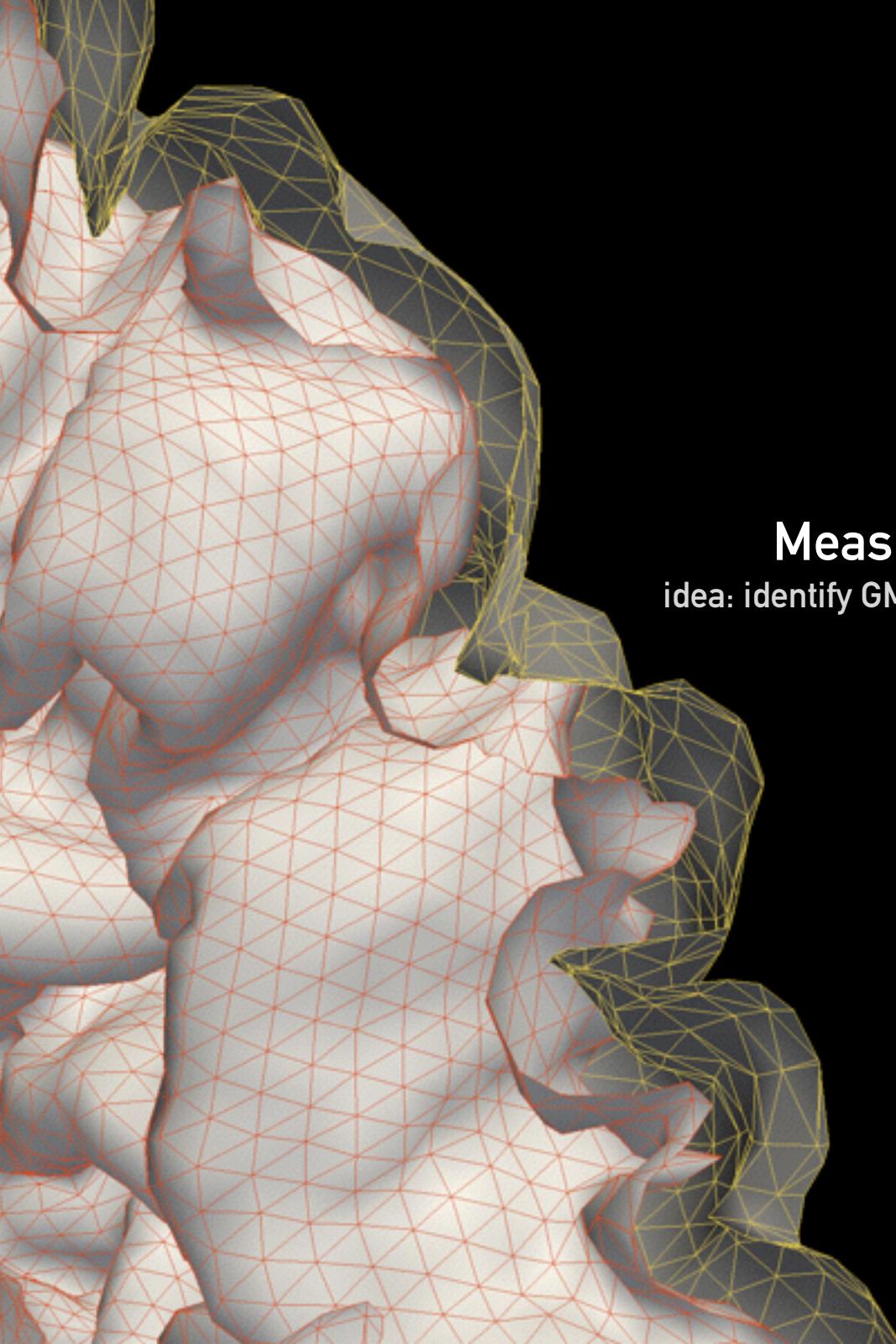
MRI volumetry: pros and cons

Pros

- ▶ focussed, simple methodology
- ▶ biologically and anatomically meaningful
- ▶ clinically well established
- ▶ subregional level of analysis possible

Cons

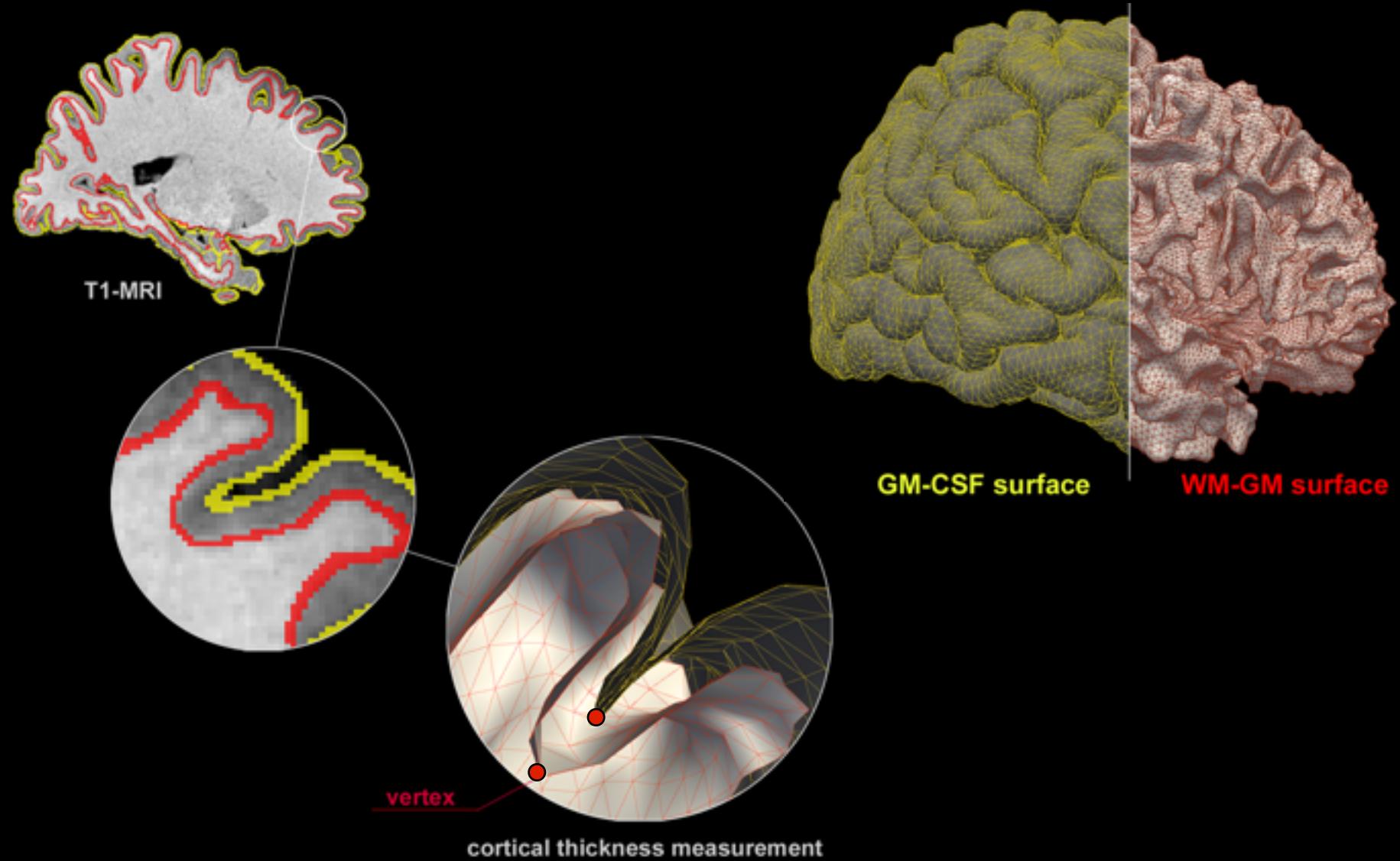
- ▶ labor-intensive manual segmentations are gold standard
- ▶ requires expert anatomical knowledge
- ▶ inter-rater, intra-rater variability, inter-protocol variability
- ▶ limited to individual anatomical regions



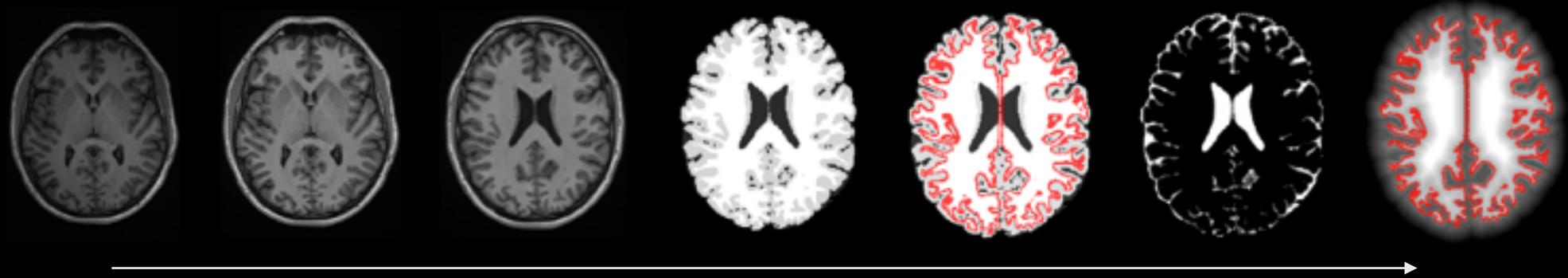
Measuring cortical thickness on MRI

idea: identify GM/WM and GM/CSF, measure their distance

MRI-based cortical thickness measurements



some processing...



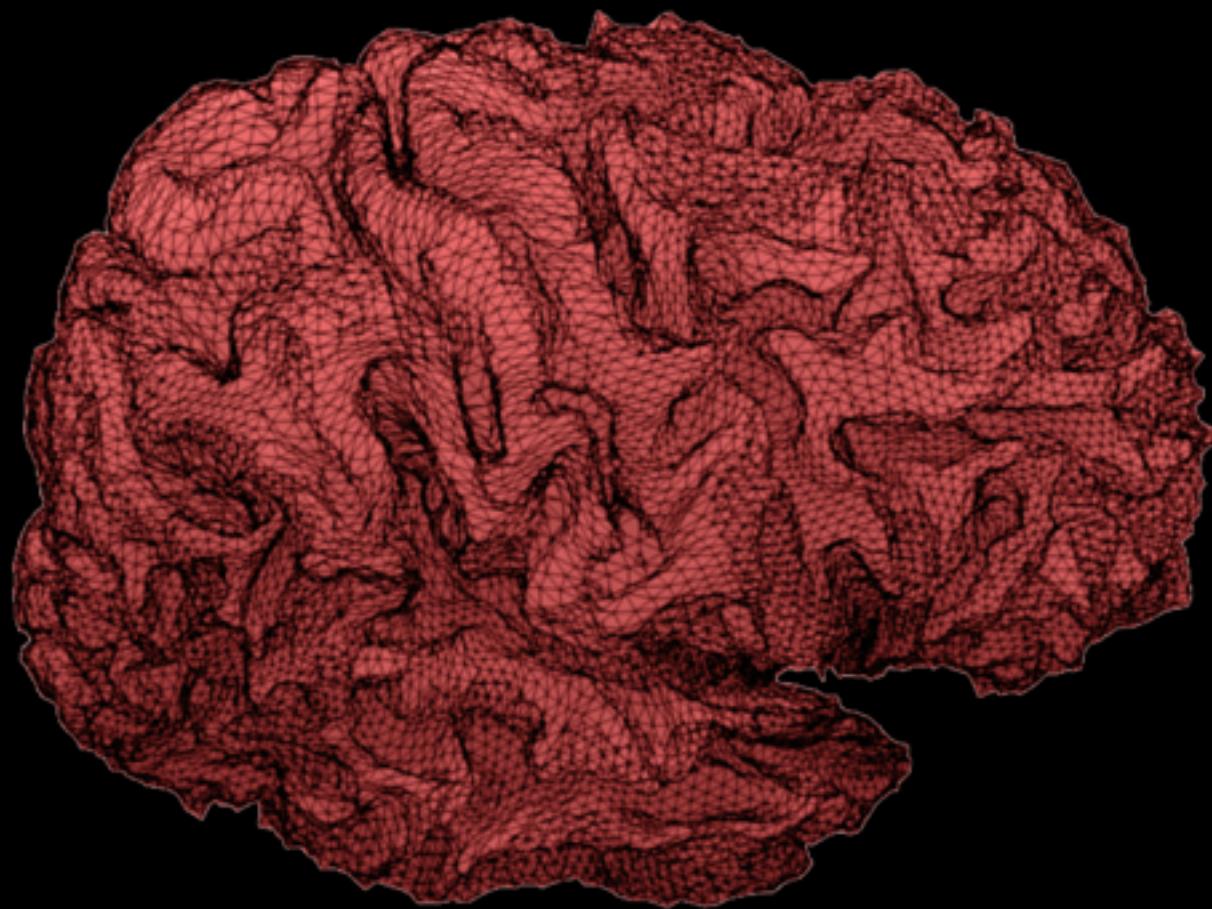
CIVET

OMM: March 17

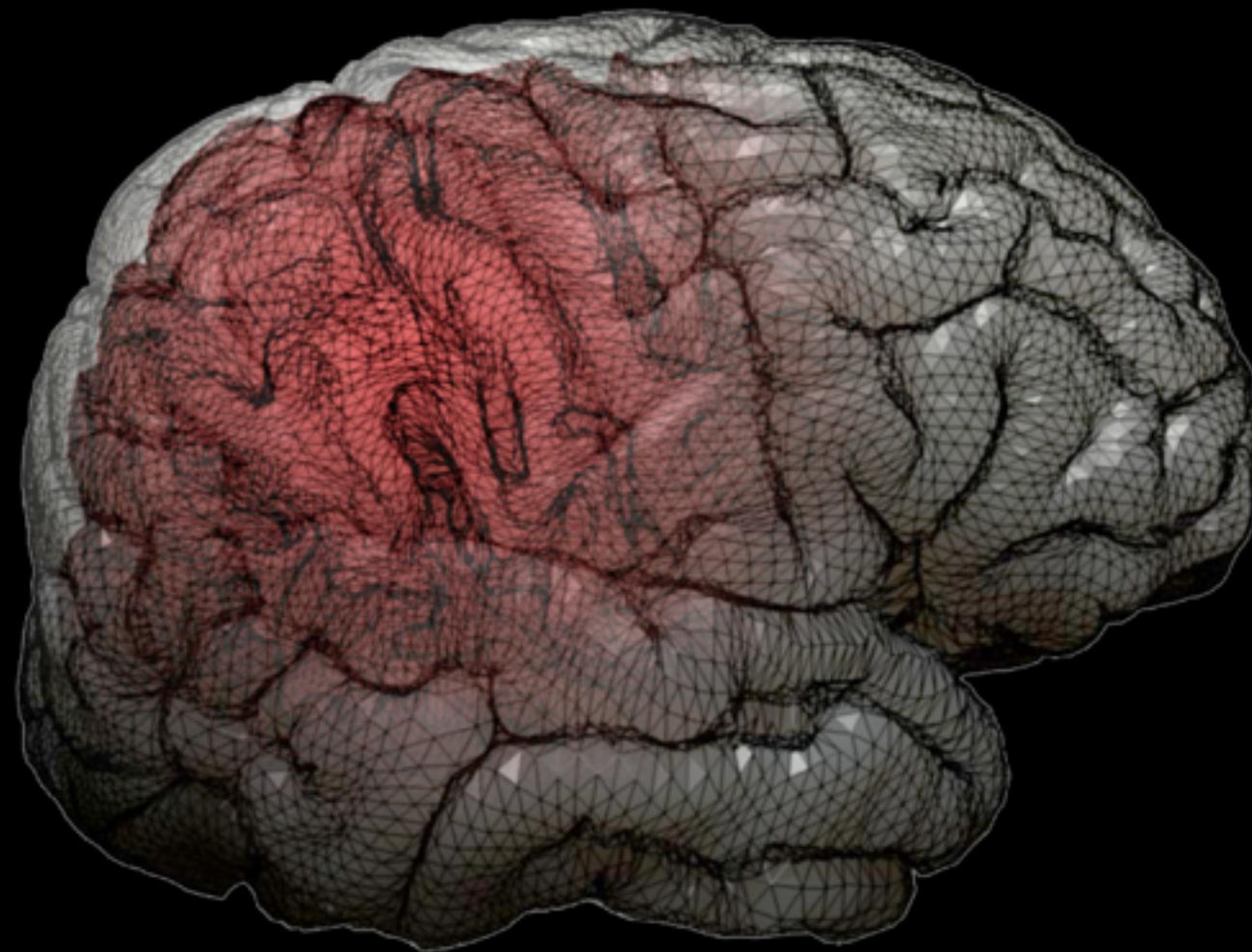
MacDonald et al. (2000) *NeuroImage*

Kim et al. (2005) *NeuroImage*

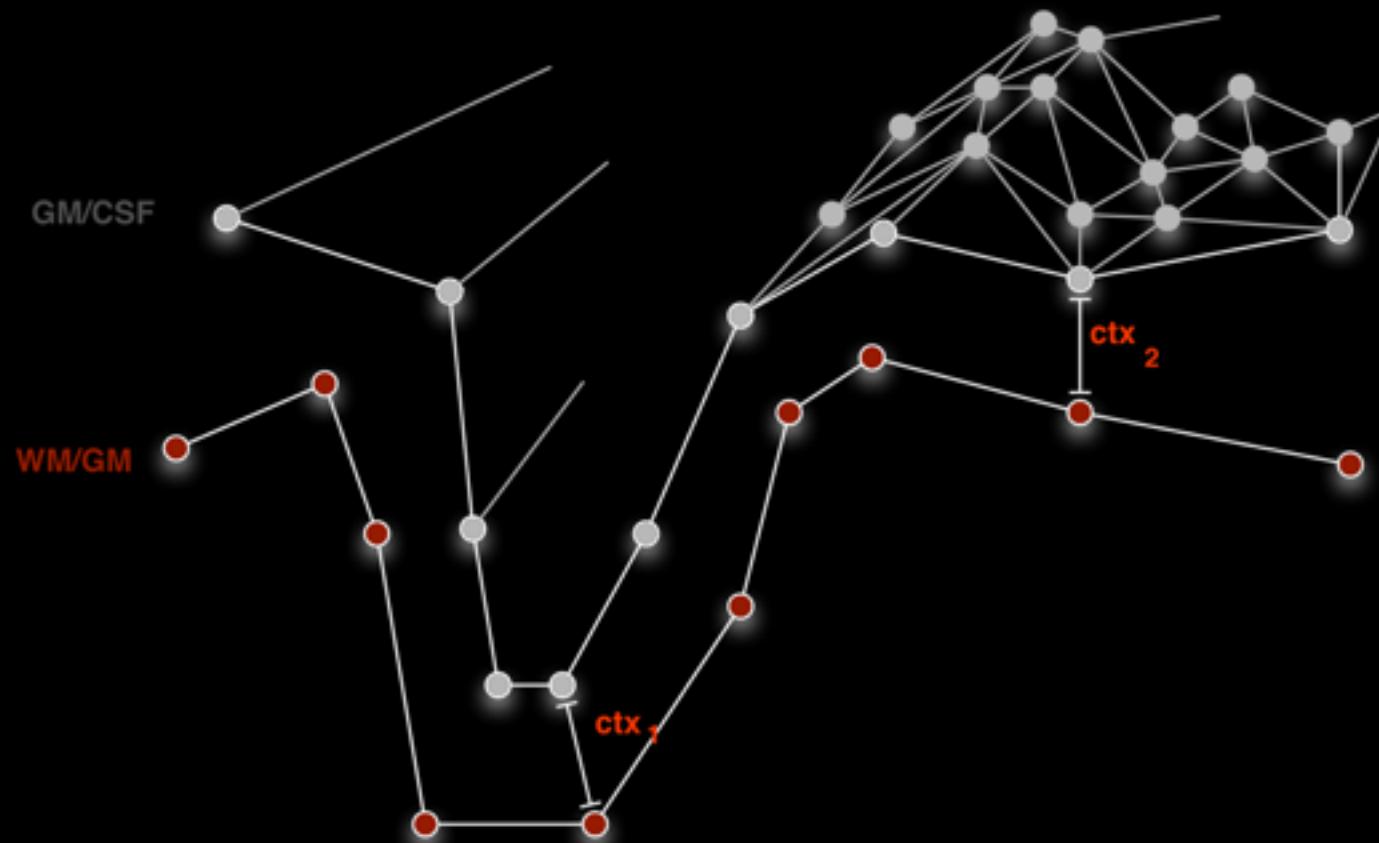
WM surface



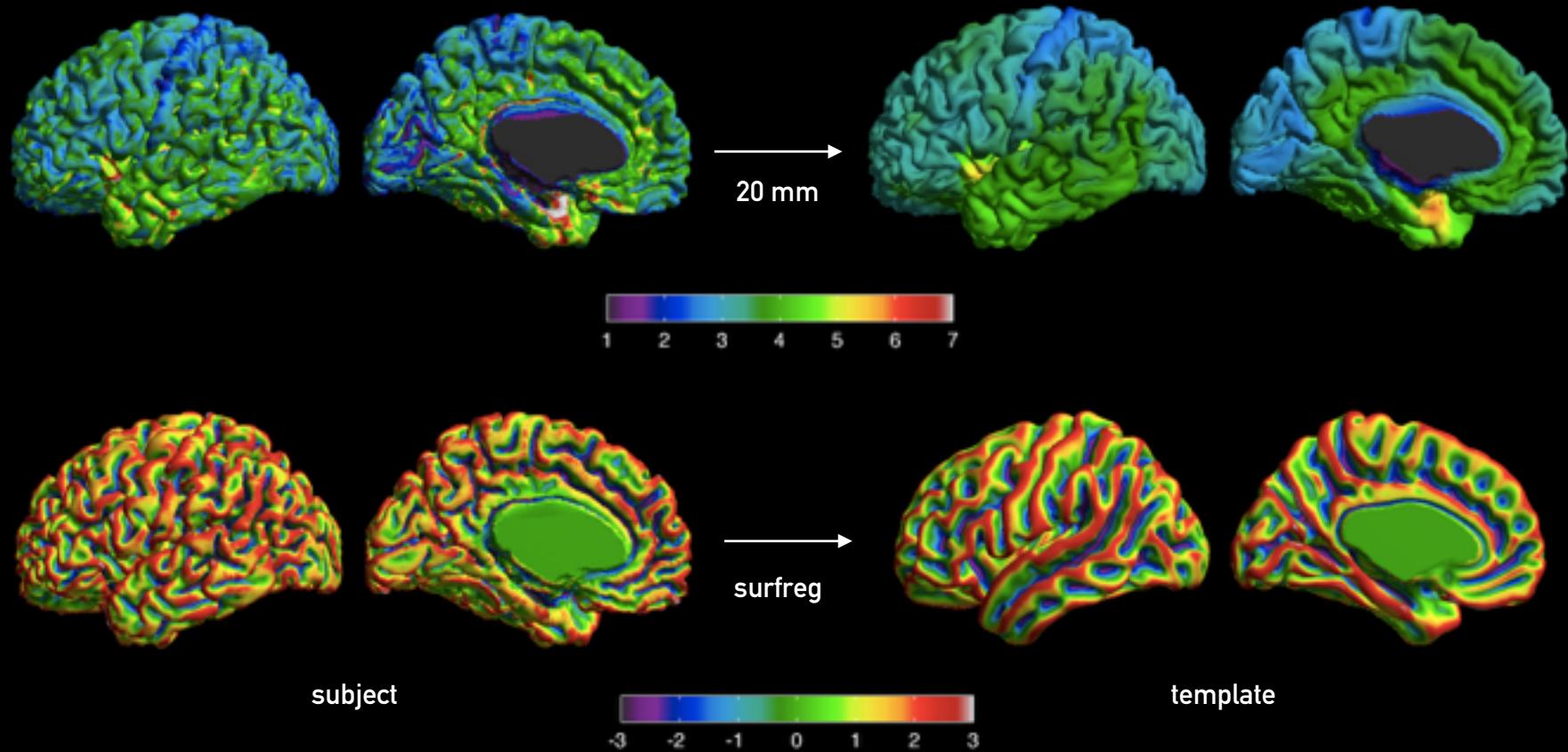
GM surface



measurement of cortical thickness



surface-based processing

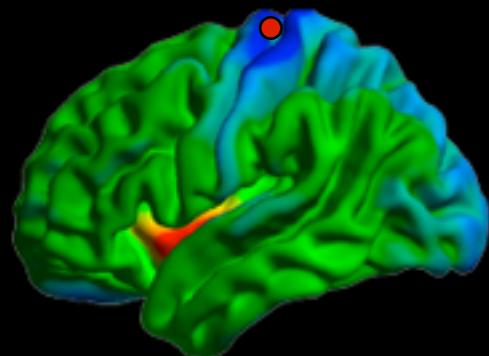


Chung et al. (2003) *NeuroImage*

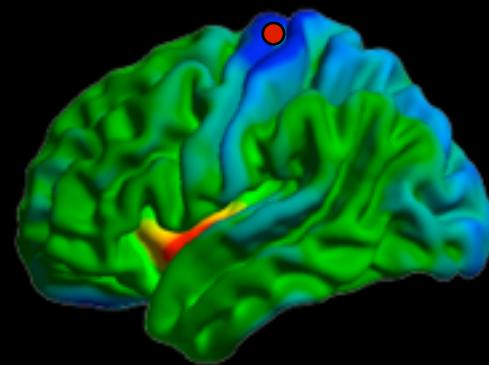
Robbins et al. (2004) *MedImaAnalysis*

statistical analysis using SurfStat

Controls

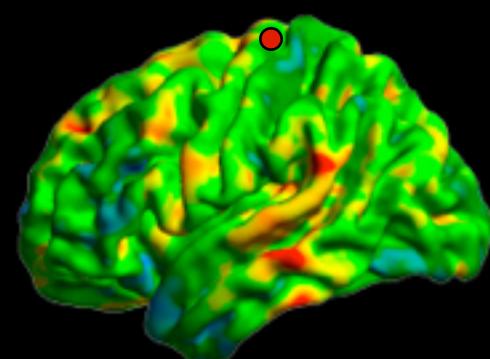


Patients

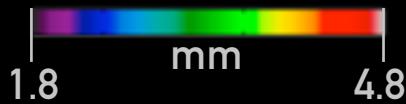
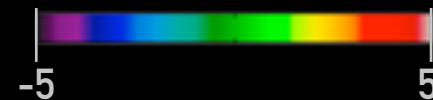
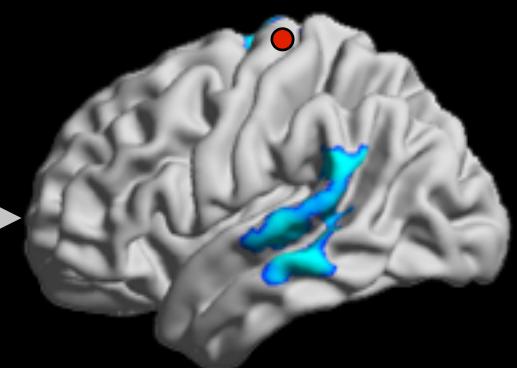


GLM

t-map



p-values



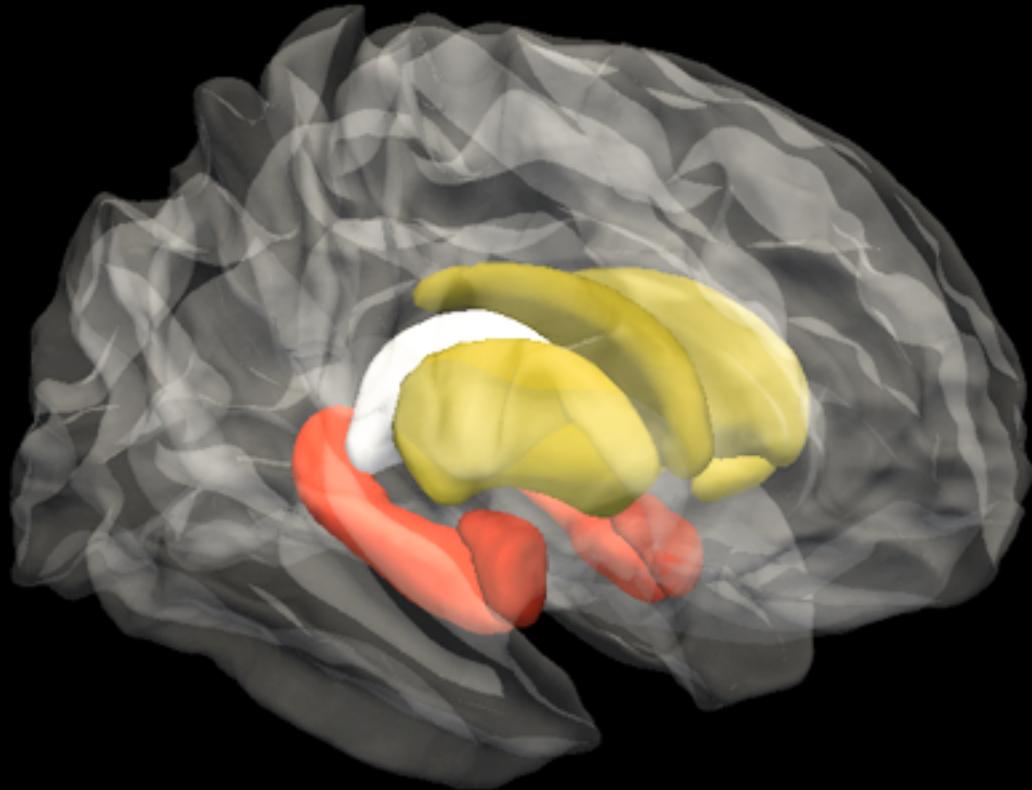
cortical thickness: pros and cons

Pros

- ▶ automated, continuous, whole-cortex
- ▶ processing and measurement respect cortical topology
- ▶ direct, biologically meaningful, mm-measure
- ▶ surface-registration may increase sensitivity

Cons

- ▶ heavy post-processing (4-25 hours/case)
- ▶ dependent on classification
- ▶ manual corrections often necessary
- ▶ limited to (neo)cortex



Surface-based analysis of subcortical shape
idea: take advantage of surface-based framework to assess subregional changes

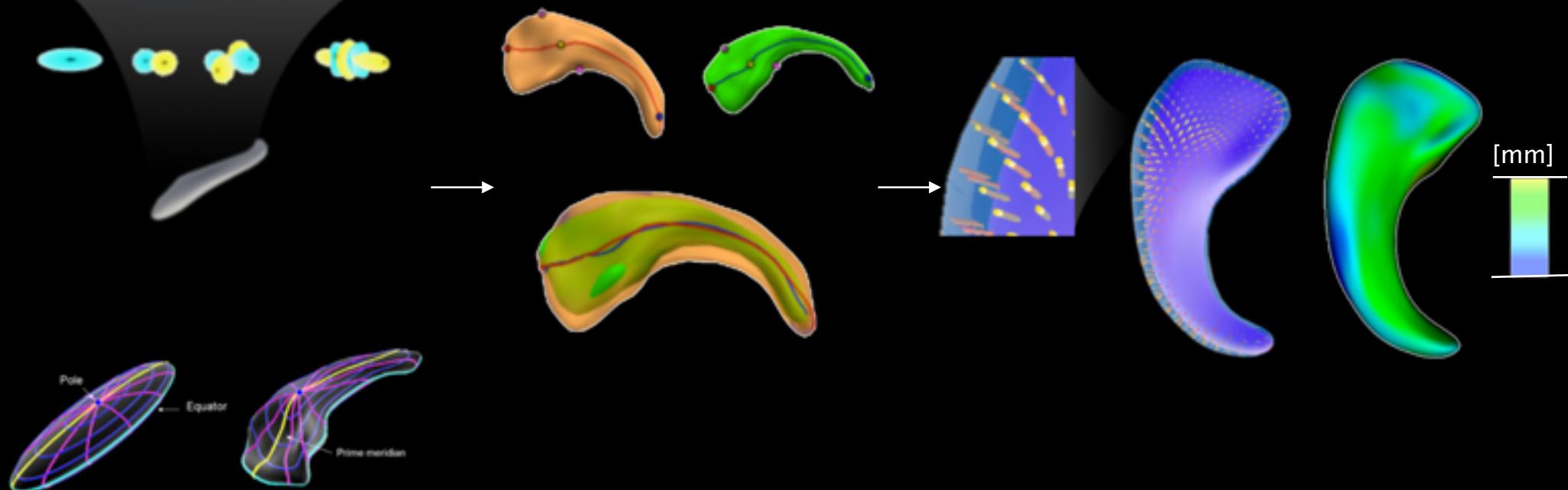
SPHARM-PDM

SPHARM-PDM



Alignment along long axis

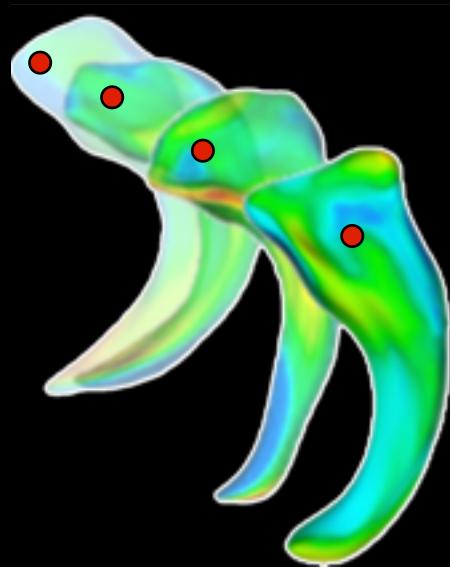
displacement from subject to template



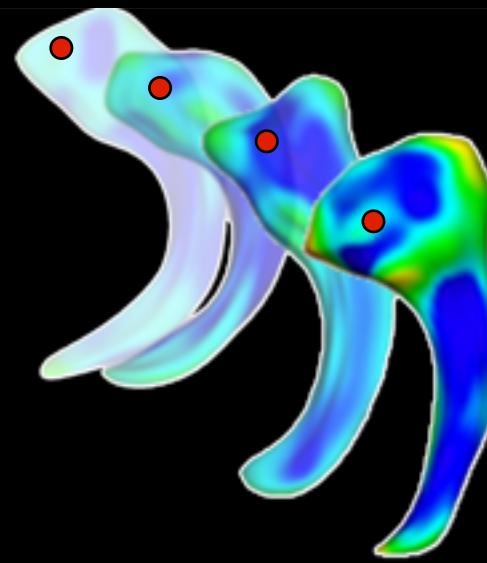
Styner, Gerig et al. (2006), Kim et al. (2008)

<http://pages.stat.wisc.edu/~mchung/research/amygdala/>

statistical analysis with SurfStat



Group 1



Group 2

$$\text{disp} = 1 + \text{GROUP} + \varepsilon$$

$$\text{disp} = 1 + \text{AGE} + \varepsilon$$

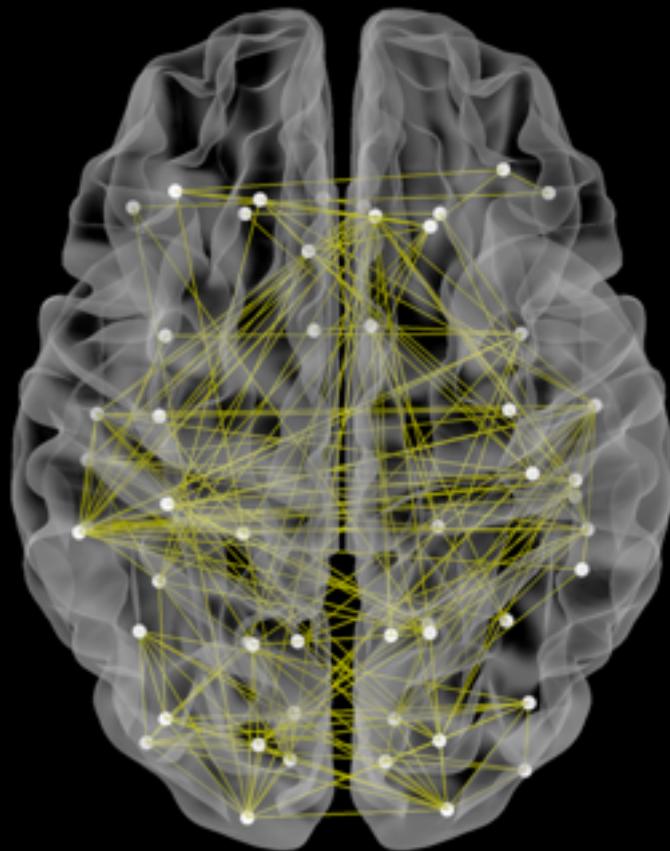
subcortical shape modeling: pros and cons

Pros

- ▶ **subnuclear assessment possible**
- ▶ **intrinsic shape correspondence**

Cons

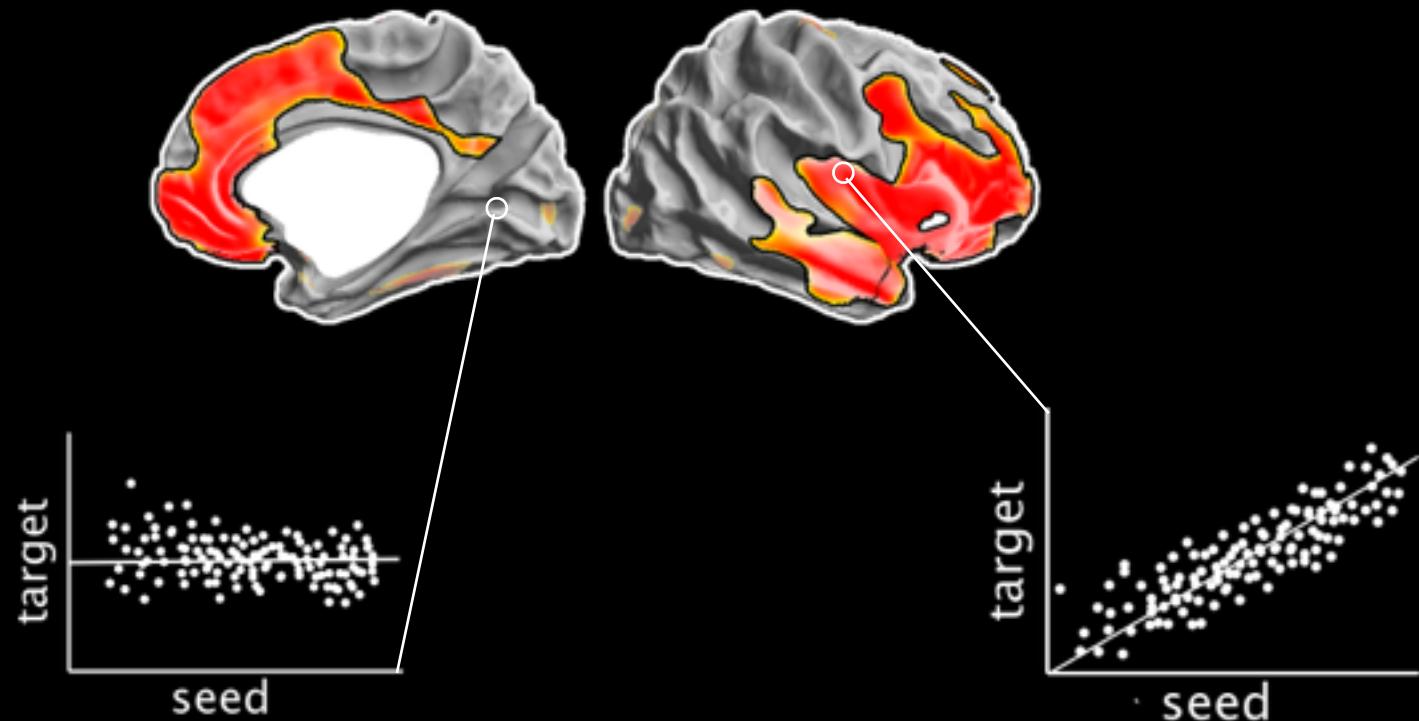
- ▶ **good segmentations necessary (see volumetry)**
- ▶ **volumetric analysis limited to boundary regions**



Structural covariance network mapping

idea: connections = structural correlations between regions across subjects

structural covariance network mapping

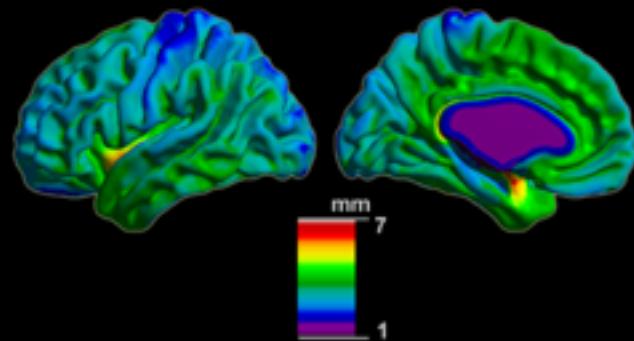


Lerch et al. (2006) *NeuroImage*

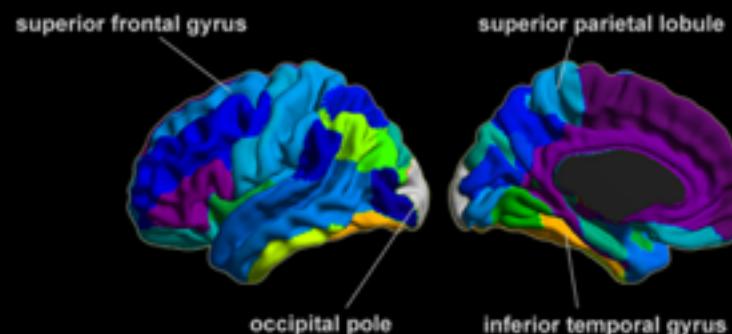
Alexander-Bloch et al. (2013) *Nat Rev Neurosci*

covariance network construction

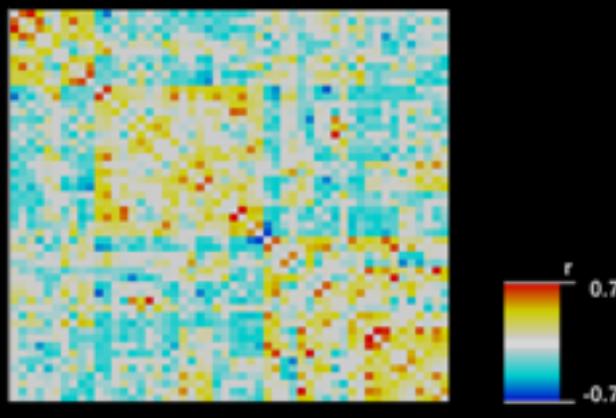
A Cortical thickness measurements



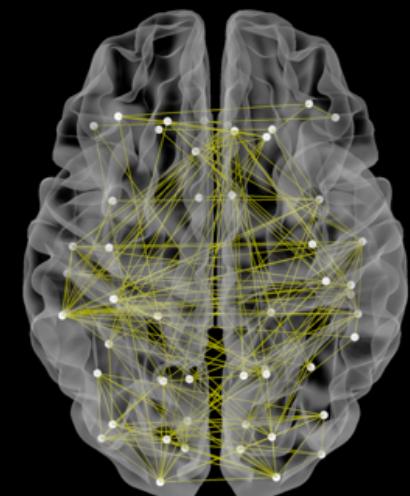
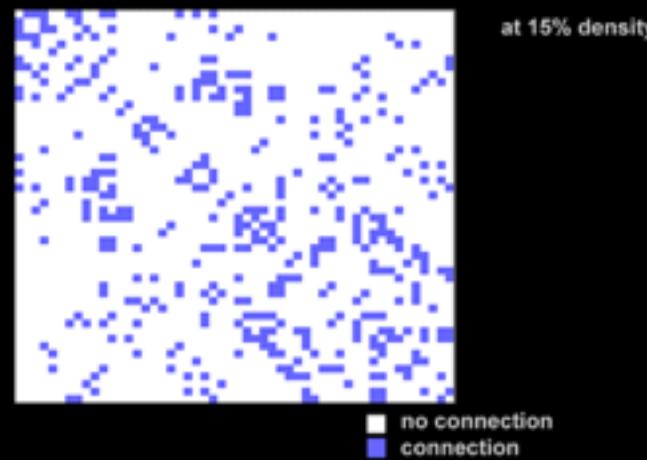
B Anatomical segmentation



C Correlation matrix

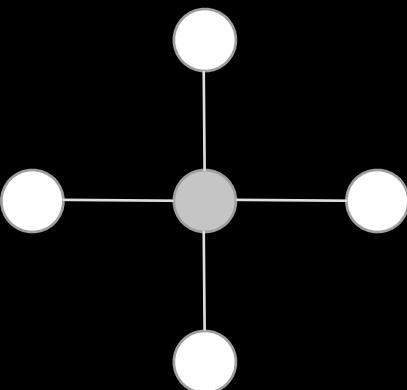


D Connectivity matrix

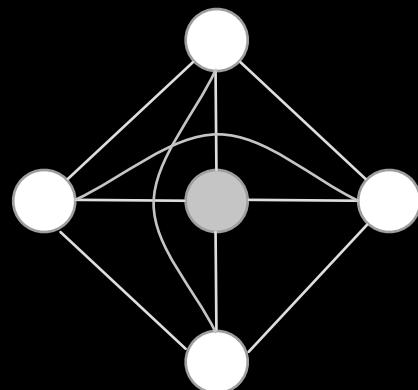


graph-theoretical network metrics

Clustering coefficient (C)

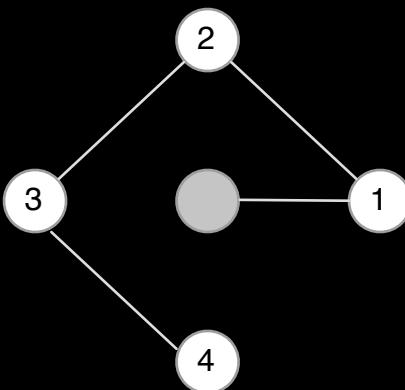


$C = \text{low}$

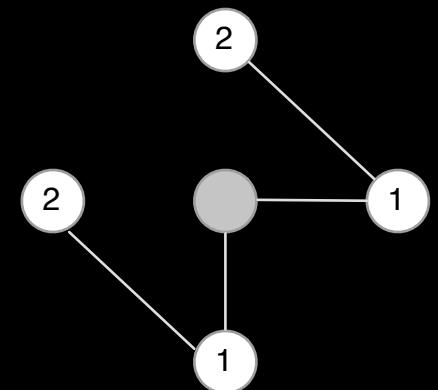


$C = \text{high}$

Characteristic path length (C)



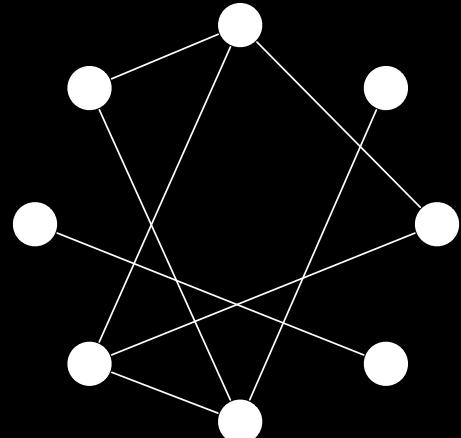
$L = \text{high}$



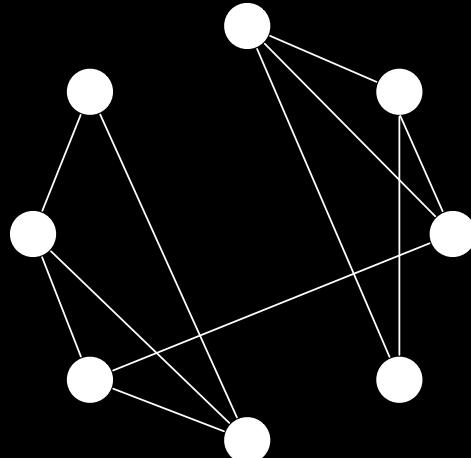
$L = \text{low}$

network topology

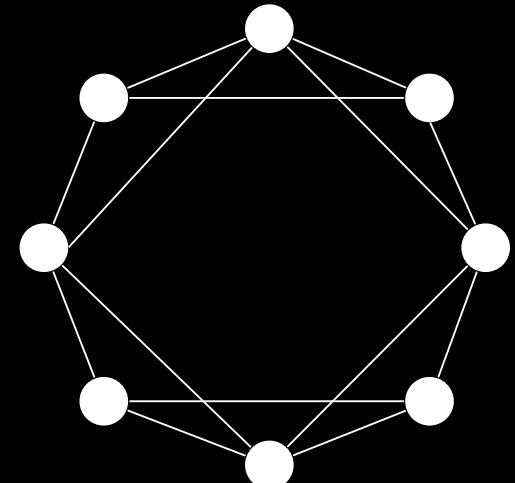
random network



small-world regime



regular lattice network



\downarrow LP \downarrow CP

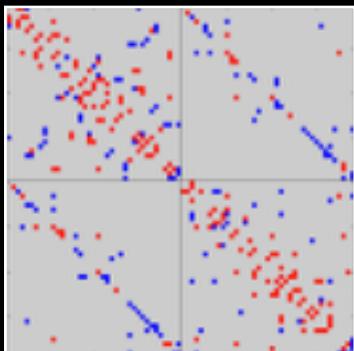
\downarrow LP \uparrow CP

\uparrow LP \uparrow CP

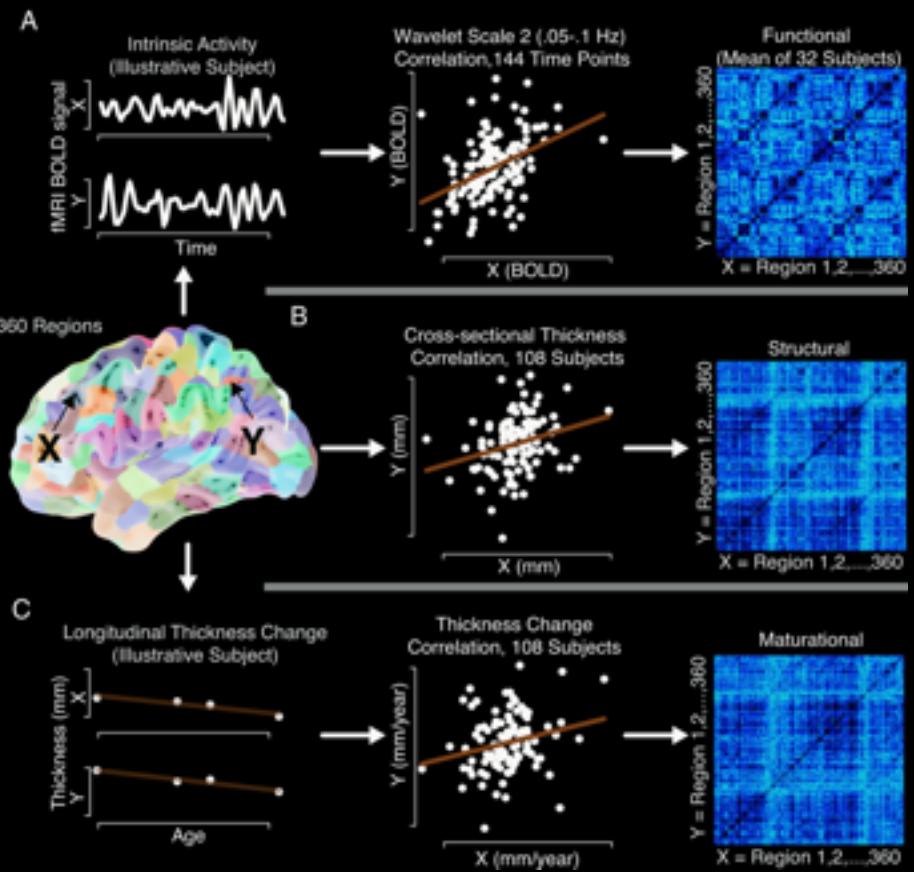
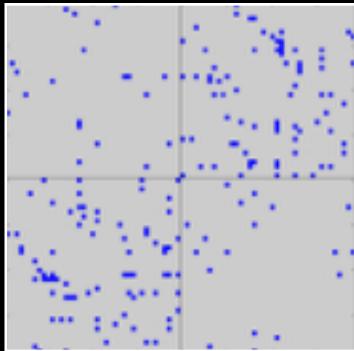
Watts and Strogatz (1998) Nature
Bullmore and Sporns (2009) Nat Rev Neurosci

correspondence to other MRI networks

positive correlation



negative correlation



structural covariance analysis: pros and cons

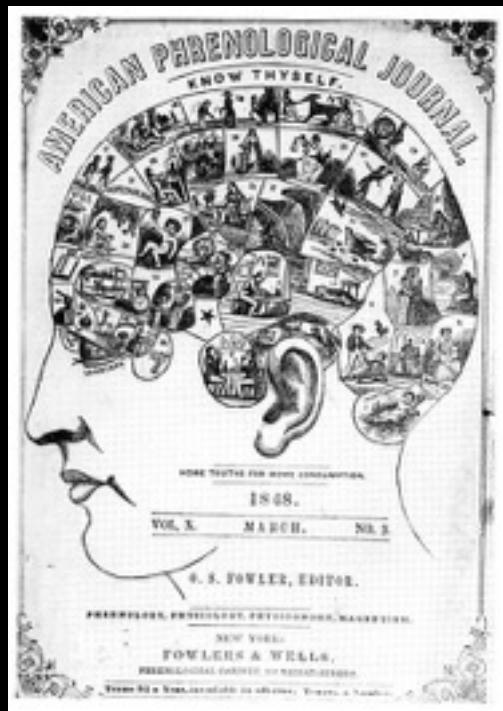
Pros

- ▶ relatively straightforward modeling
- ▶ seeding from within grey matter regions
- ▶ T1w-MRI less artifacts than epi-MRIs, higher resolution

Cons

- ▶ no direct correspondence with anatomical connections
 - ▶ however: process-based interpretation (e.g., maturation)
- ▶ restricted to group-level analysis (but see, Tijms et al. 2011)
- ▶ reviewers often request relatively large samples

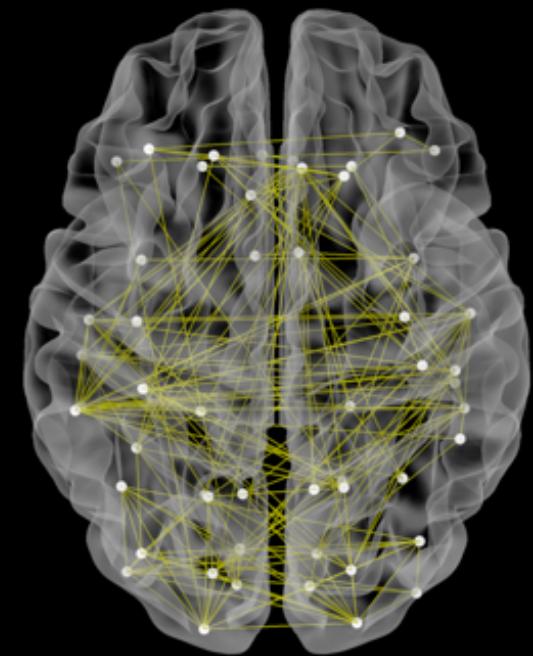
applications



Individual differences



Brain disorders



Brain organization



Structural substrates of individual differences in cognitive functioning



MAX-PLANCK-GESELLSCHAFT

cognitive neuroscience

- assessed brain correlates of cognitive and affective processes
 - task-based
 - using functional MRI
 - localization of function
 - individual differences in cognitive skills
- however:
 - the biological basis of such differences incompletely understood
 - structural MRI has been underused to study cognition
 - off-task thought (aka mind-wandering) less frequently studied

mind-wandering

we constantly receive perceptual information; yet, we mind-wander

- can derail performance in challenging situations
- however: can be beneficial when demands of external world are low

previous work has shown links between mind-wandering and

... creativity, future thinking, and economic decision making (Smallwood et al.)

off-task thought relates to mPFC activity (Christoff 2009 PNAS)

mPFC activity also shown to relate to planning and temporal discounting
(Kable and Glimcher 2007 Nature; Schacter 2010 Neuron; Buckner 2009 TICS)

methods

to assess possibly adaptive mind-wandering

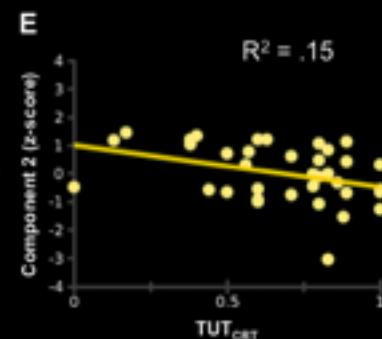
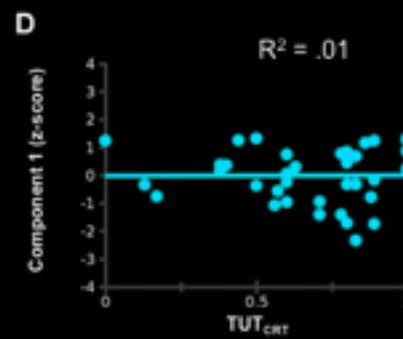
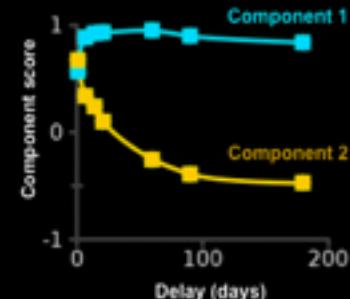
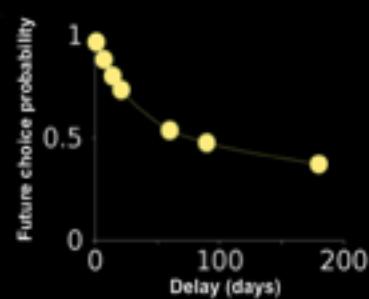
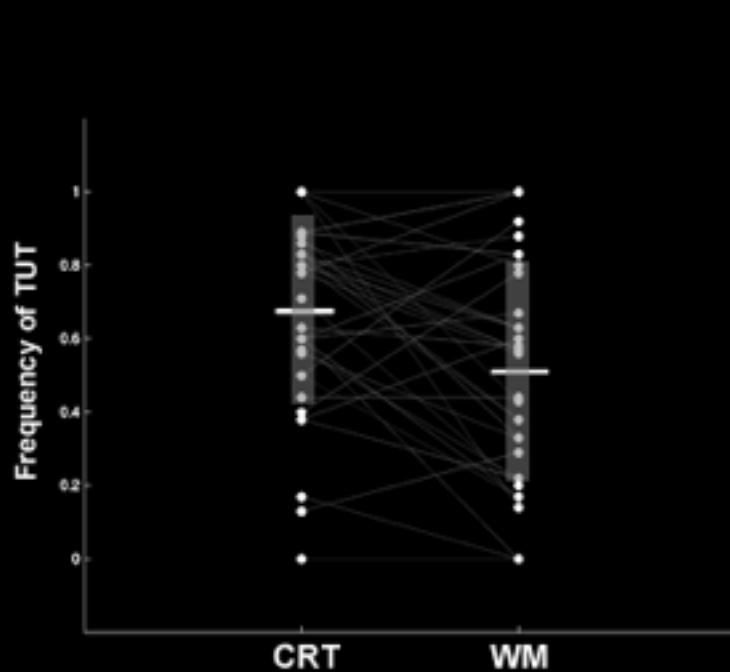
- ▶ task-unrelated thought during easy task (CRT) compared to hard task (WM)
- ▶ measure discounting as marker of patient decision-making

structural substrates of individual differences in tut and discounting

37 healthy controls; behavioral analysis; correlation with cortical thickness

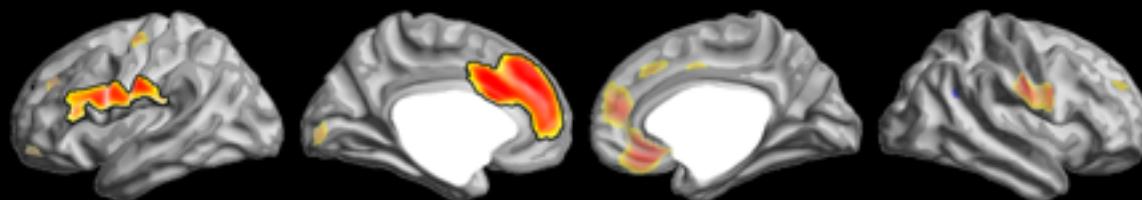
mind-wandering and temporal discounting

n=37

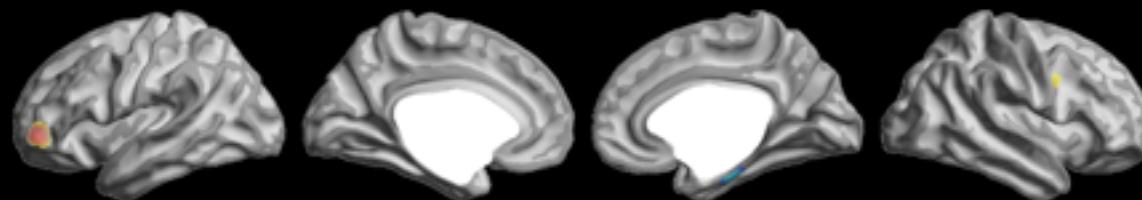


substates of TUT

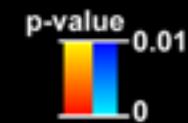
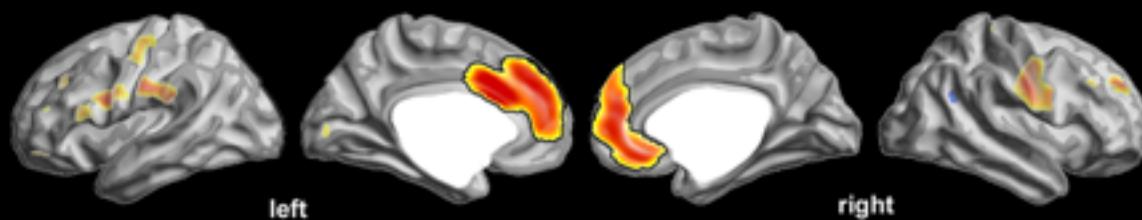
A Effects of TUT_{CRT}



B Effects of TUT_{WM}

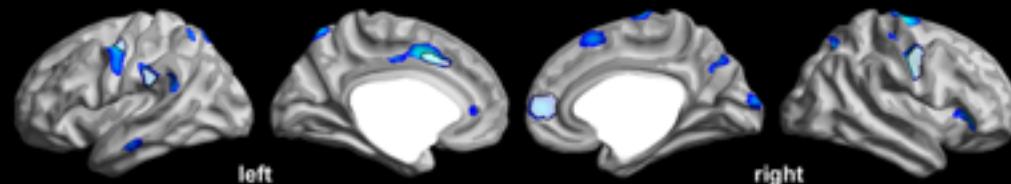


C Effects of TUT_{CRT} , controlled for TUT_{WM}

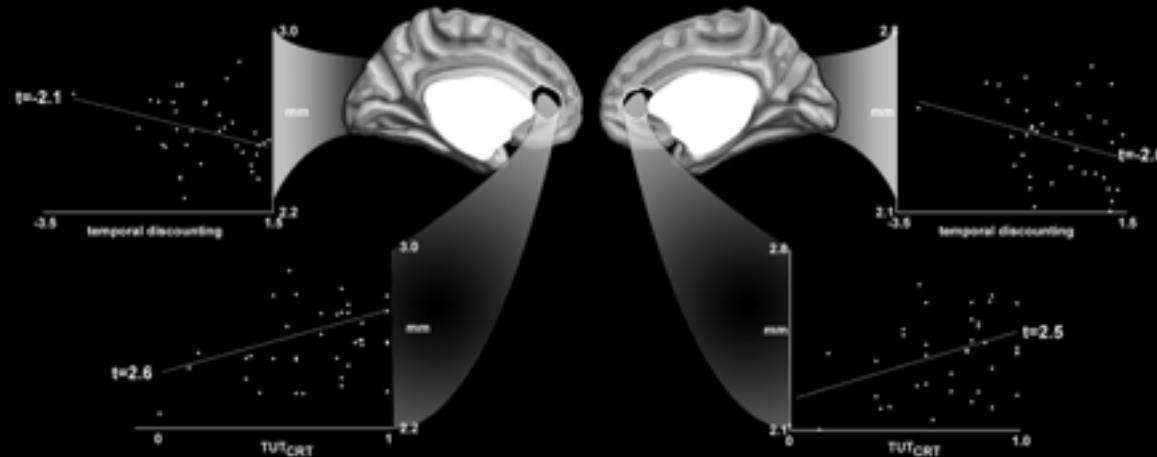


overlap with substrates of discounting

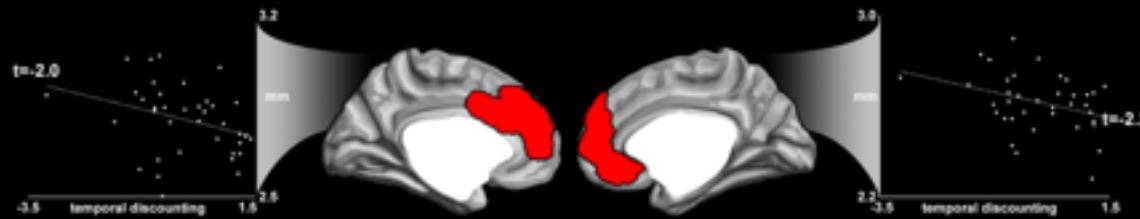
A Whole brain analysis: Effects of TD (blue) and overlap with TUT-CRT (white)



B Region-of-interest analysis: Kable and Glimcher (2007)



C Region-of-interest analysis: effects of TD in clusters of TUT-CRT findings



conclusion

substrates of ability to adaptively decouple from here and now

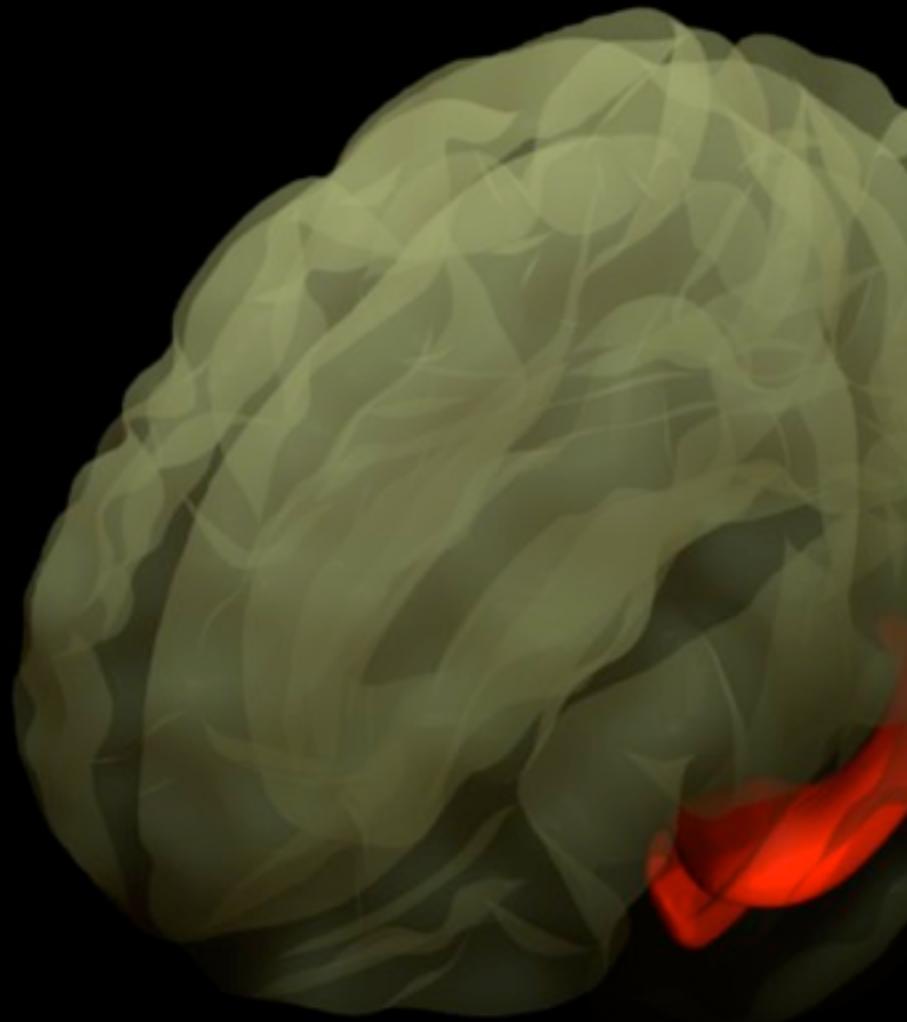
- mind-wandering during easy but not hard task
- patient economic decision making

overlap in mPFC/ACC

- confirm functional MRI showing role of these regions in decoupled thought
- role in control / evaluation of information from memory
- self-projection (Buckner and Carroll 2009 TICS)
- mPFC/ACC strongly interconnected with mesiotemporal memory systems



Structural MRI analyses in temporal lobe epilepsy

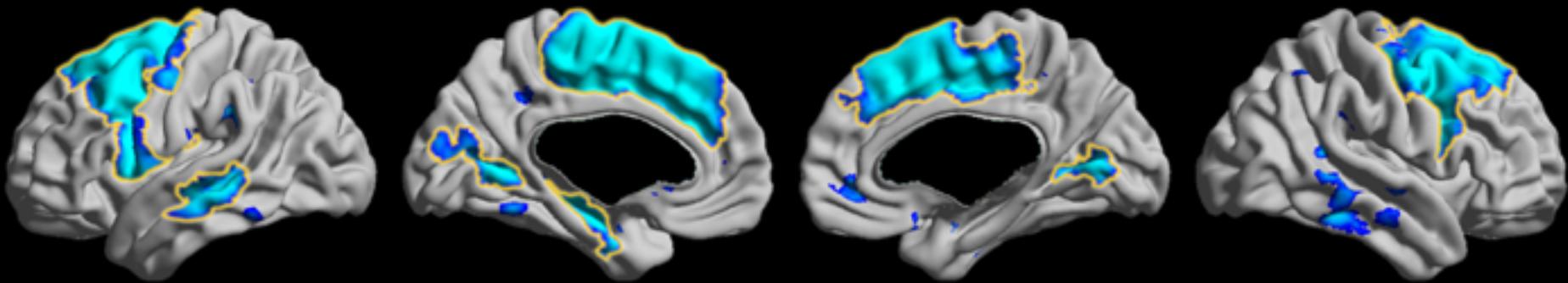


TLE

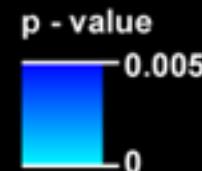
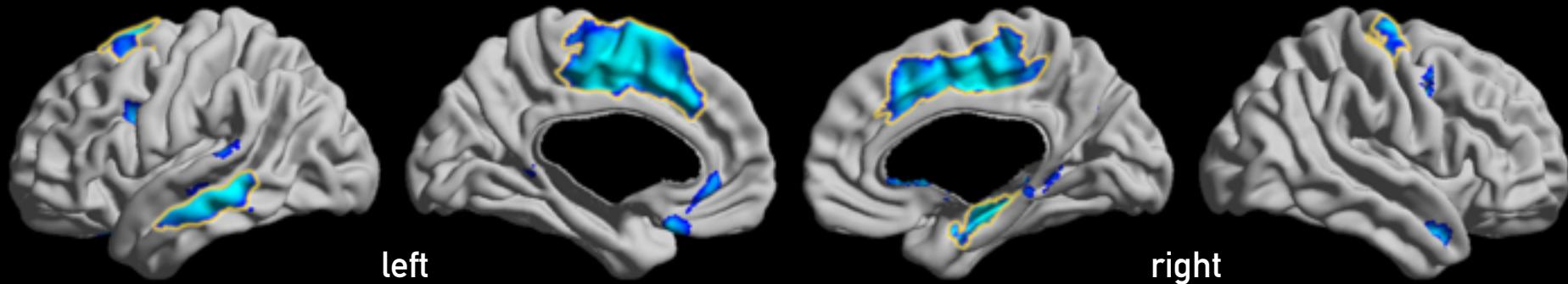
- ▶ temporal lobe epilepsy (TLE) most common drug-resistant epilepsy in adults
 - ▶ seizures originate in TL, pathology often shows mesiotemporal sclerosis (MTS)
 - ▶ hippocampal atrophy on MRI marker of MTS, lateralizes focus in 70%
 - ▶ HA diagnosis: better chances of seizure-free surgical outcome
-
- ▶ long-term seizure-freedom in 50-80% of patients
 - ▶ outcome prediction challenging
 - ▶ outcome likely relates to brain damage outside mesiotemporal lobe

cortical thinning in TLE

A. LTLE (n=52)



B. RTLE (n=53)



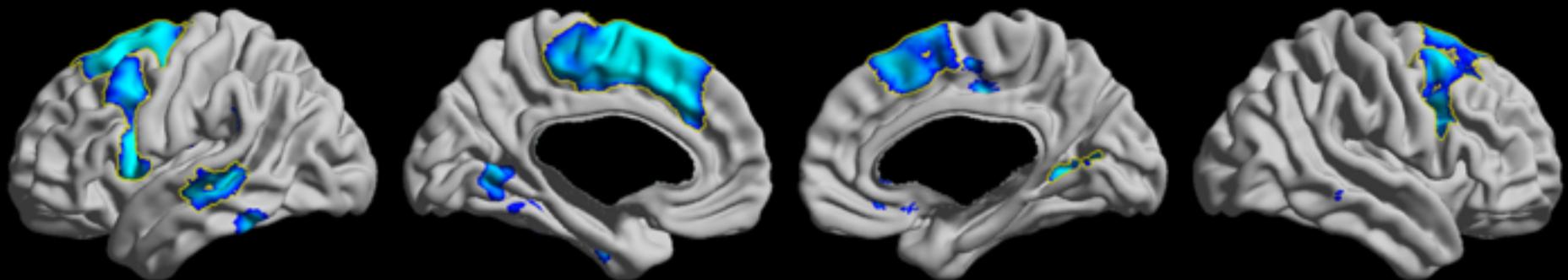
— random field theory
— significant cluster

left

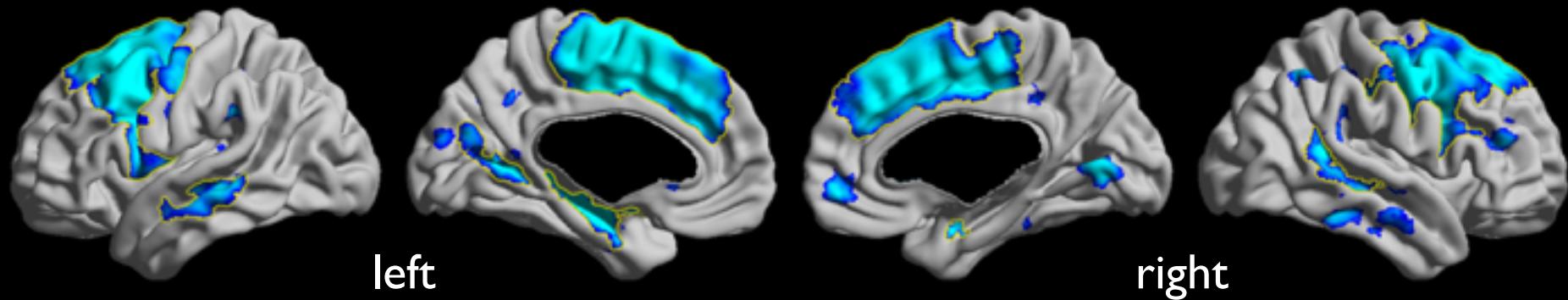
right

influence of hippocampal atrophy

A. LTLE-NV (n = 24)



B. LTLE-HA (n = 28)



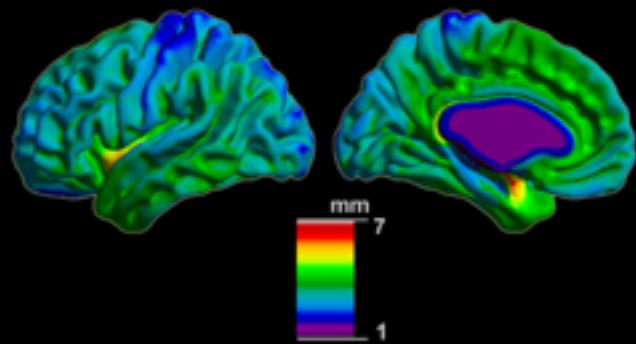
p - value
— random field theory
— significant cluster

interim conclusion 1

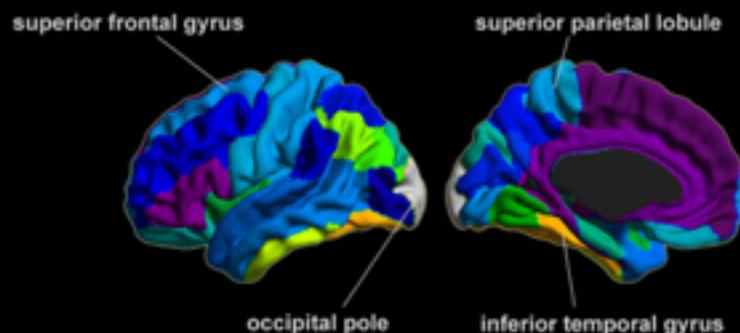
- ▶ cortical thinning in fronto-central and lateral temporal neocortex
 - ▶ seen across the spectrum of TLE
 - ▶ seen at 1.5T, 3T, with CLASP and FreeSurfer (McDonald 2008 Epilepsia; Mueller 2010 NIMH)
 - ▶ consistent with pathological examination (Blanc 2011 Epilepsia)
-
- ▶ widespread pathology indicative of system-level network alterations
 - ▶ motivation for graph theoretical network analysis

addressing system pathology in TLE

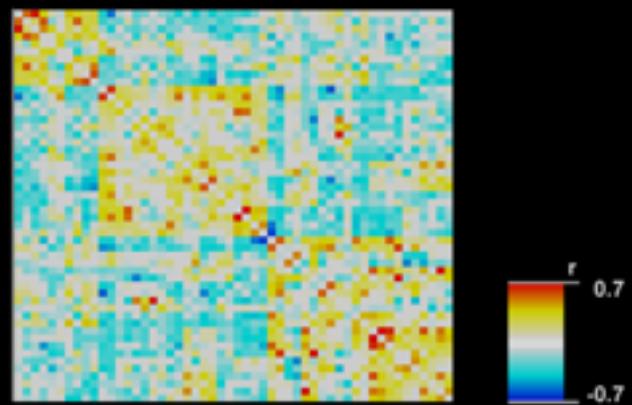
A Cortical thickness measurements



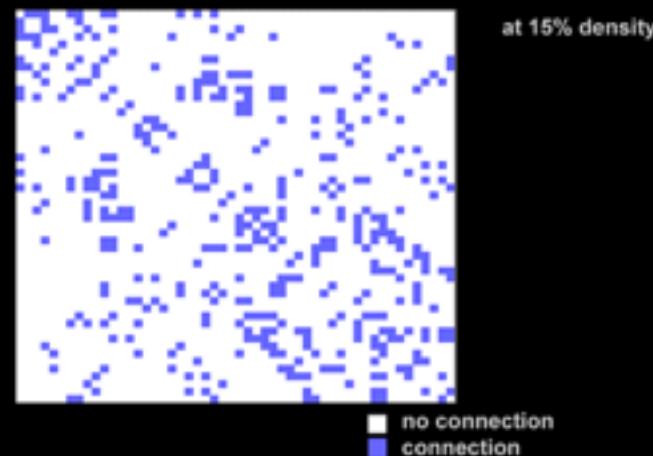
B Anatomical segmentation



C Correlation matrix



D Connectivity matrix

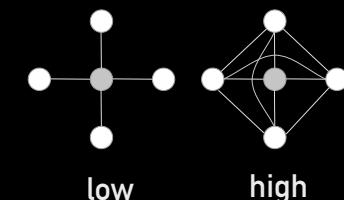
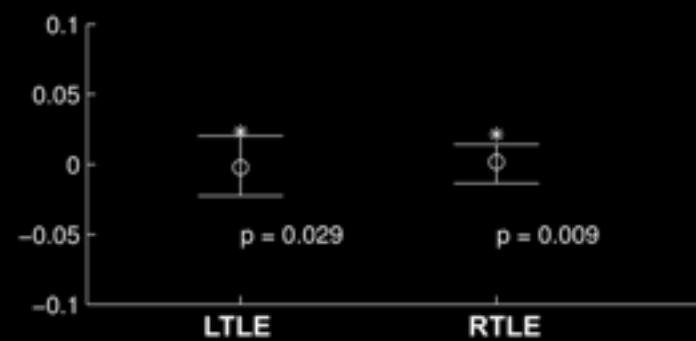


n=63 LTLE, 59 RTLE, 47 controls

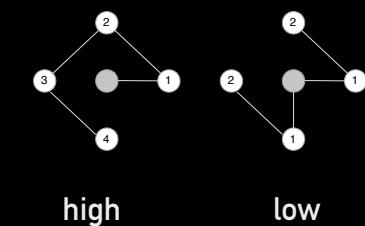
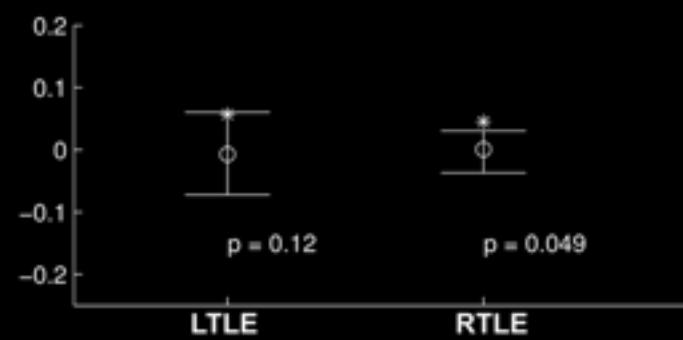
Bernhardt et al. (2011) CerCor

network regularization in TLE

A Clustering coefficient (C)

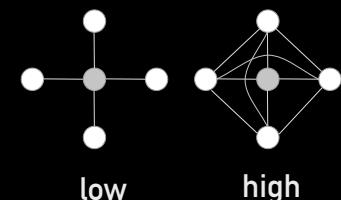
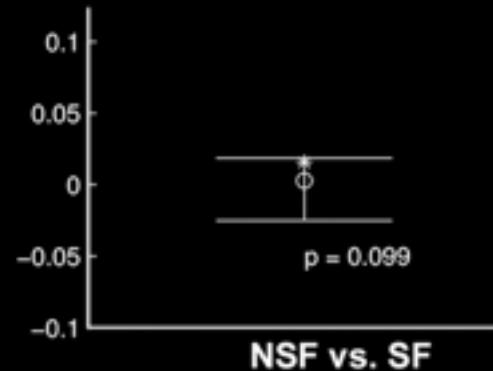


B Path length (P)

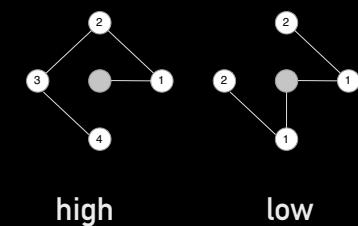
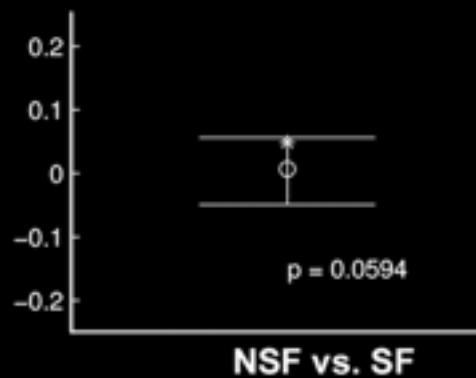


relationship to outcome

A Clustering coefficient (C)



B Path length (P)



50 SF versus 40 NSF

Bernhardt et al. (2011) CerCor

interim conclusion 2

TLE system disorder

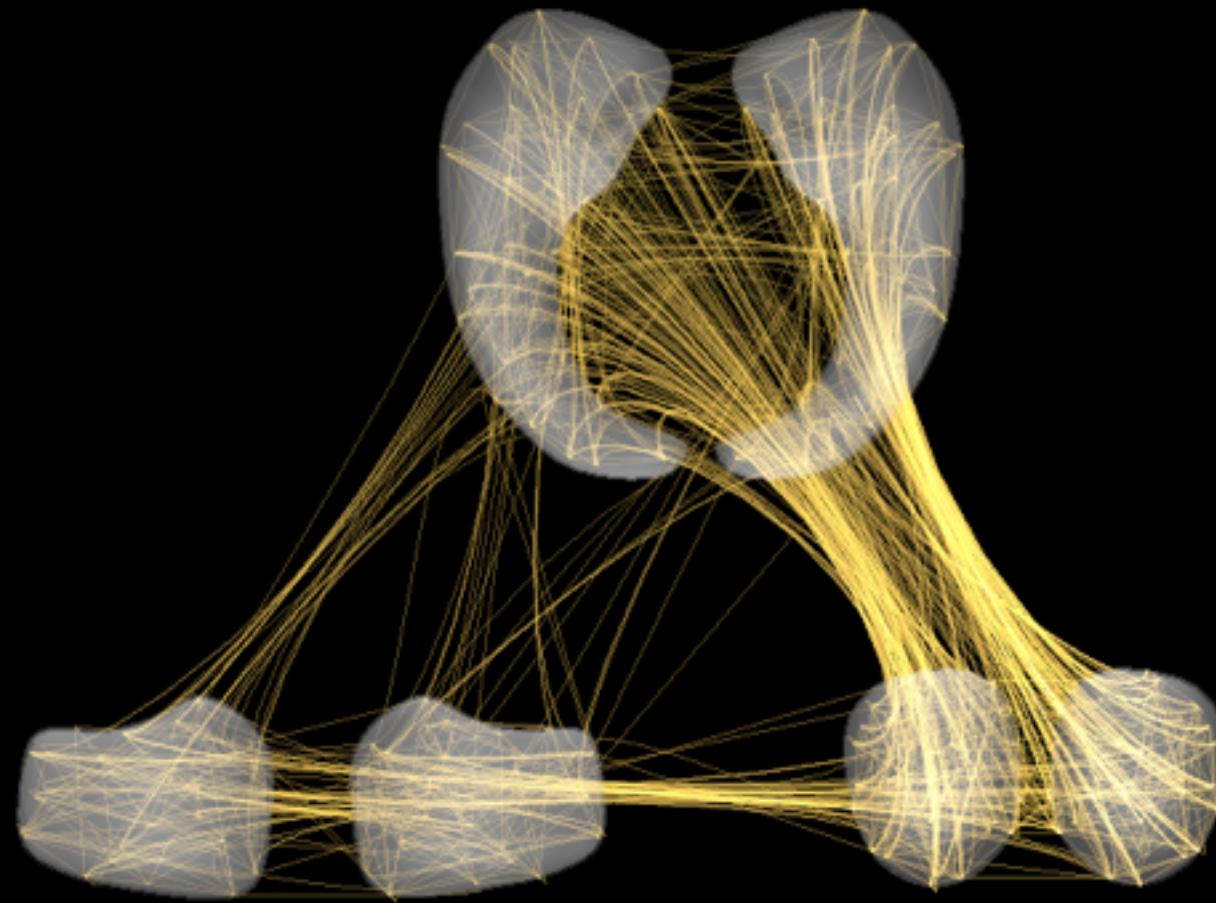
- **cortico-cortical network regularization ($\uparrow P$, $\uparrow C$)**
- **degree of network pathology relates to outcome**

$\uparrow P$

- **likely indicative of disruptions in cortico-cortical connections**
(Concha 2005 Annals Neurology; Focke 2008 NIMH)
- **may relate to cognitive impairments in TLE**

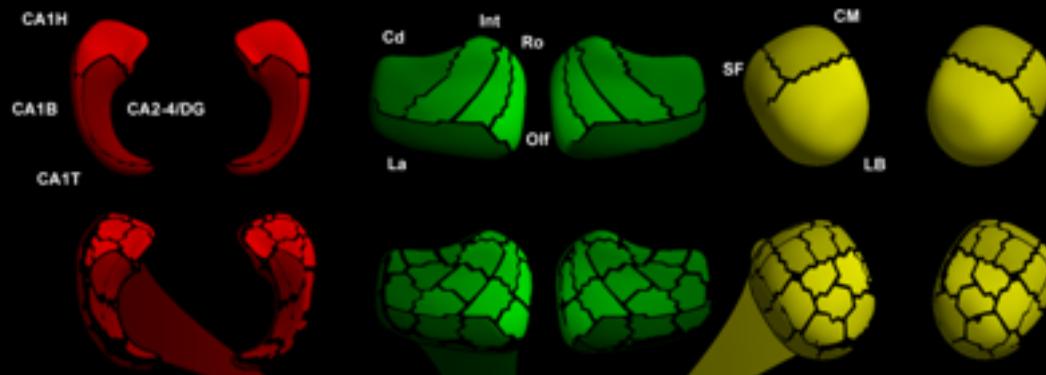
$\uparrow C$

- **increased pathological coupling in affected subnetworks**
- **possibly indicative of shared sensitivity to insults**

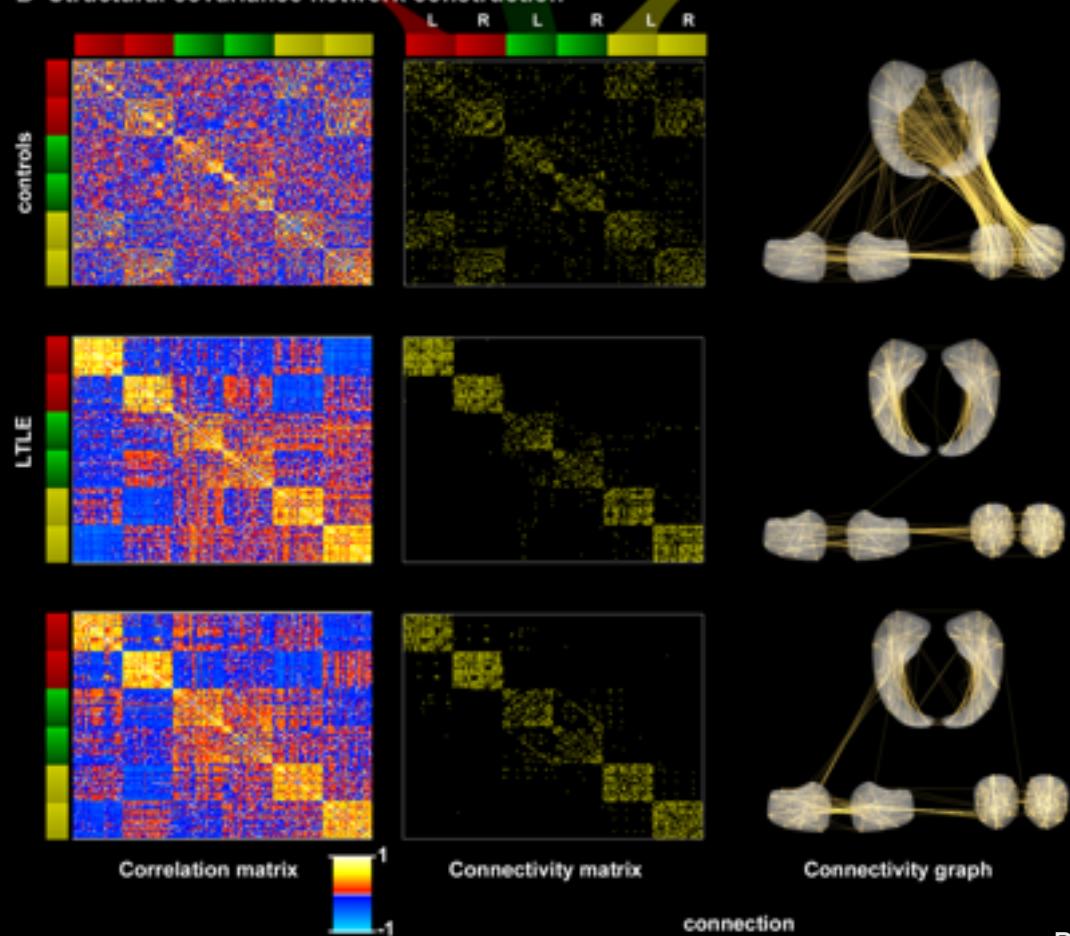


Structural network generation

A Parcels

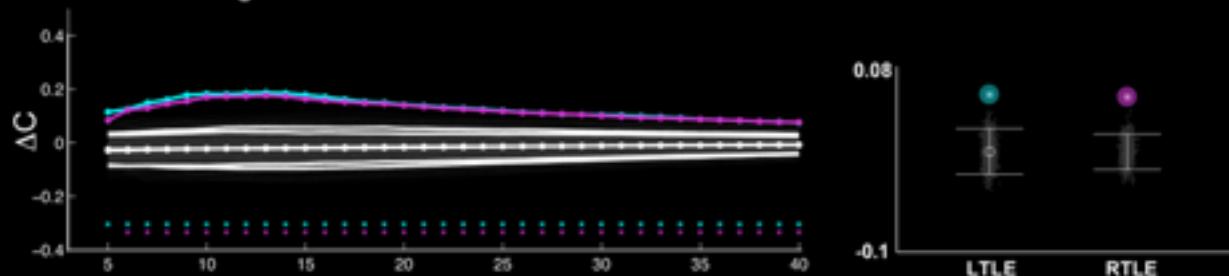


B Structural covariance network construction

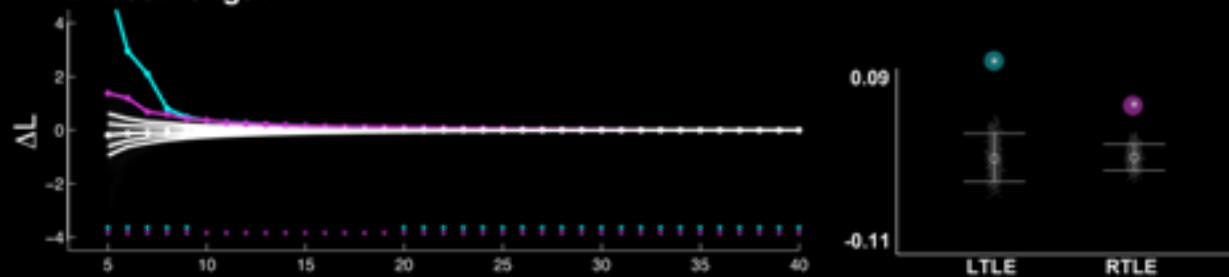


Topological network regularization in TLE

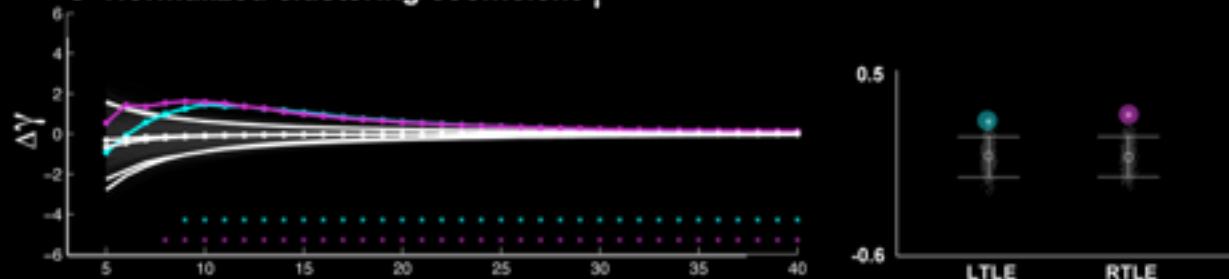
A Clustering coefficient



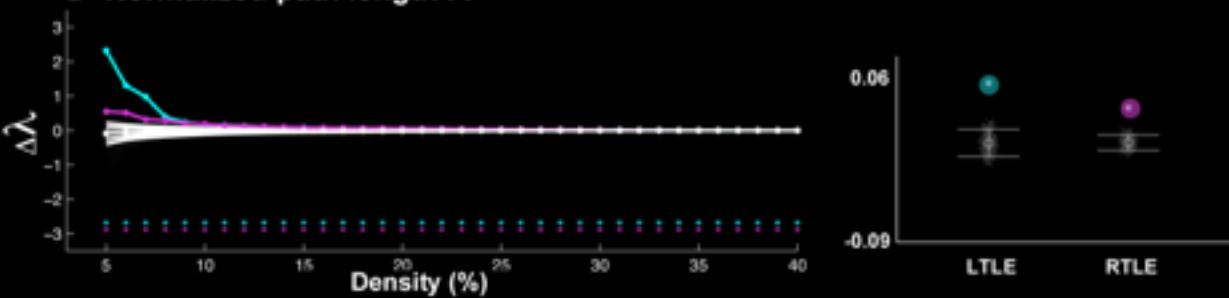
B Path length



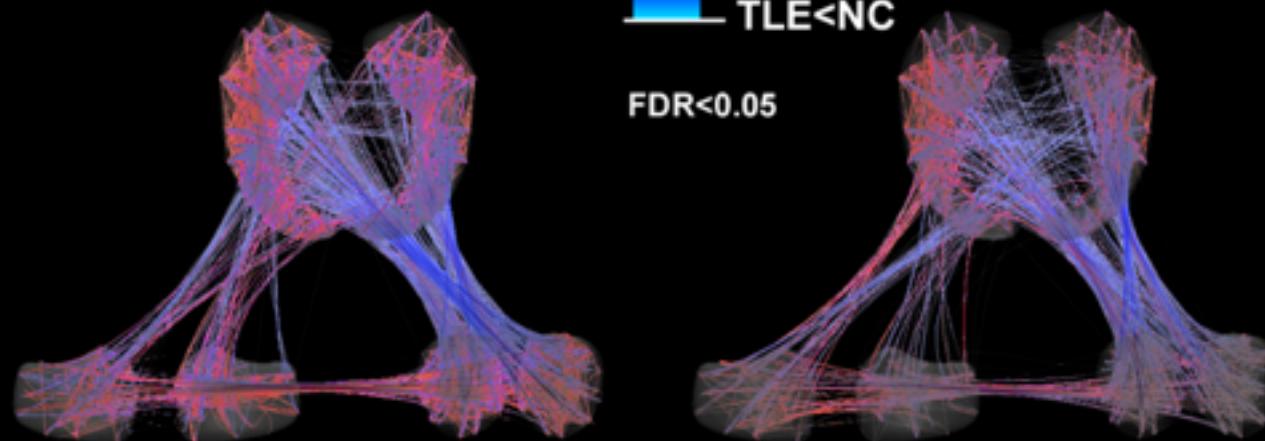
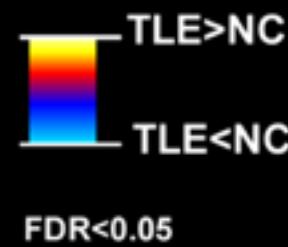
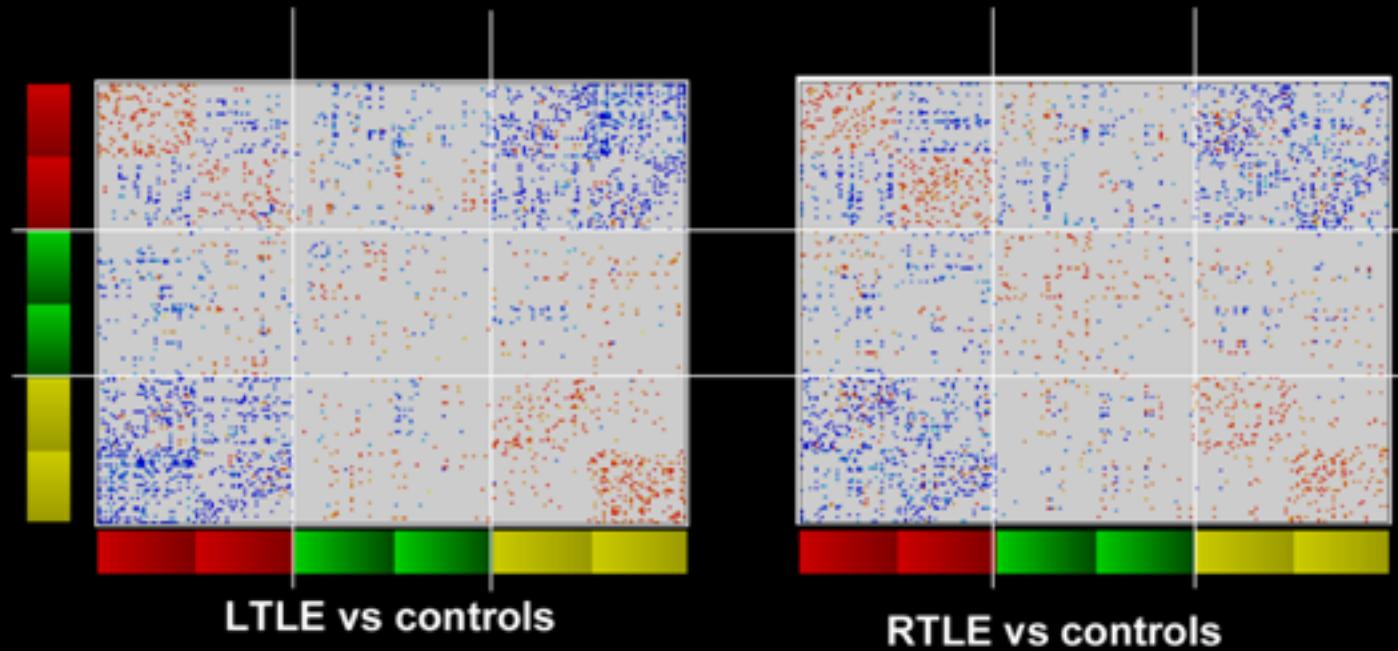
C Normalized clustering coefficient γ



D Normalized path length λ



Low-Level network differences



interim conclusion 3

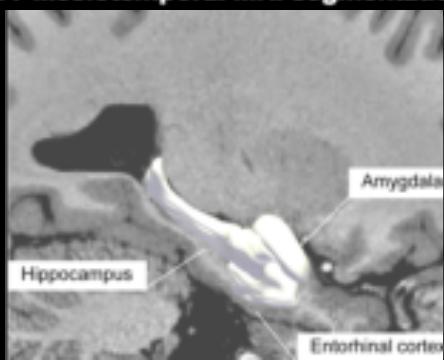
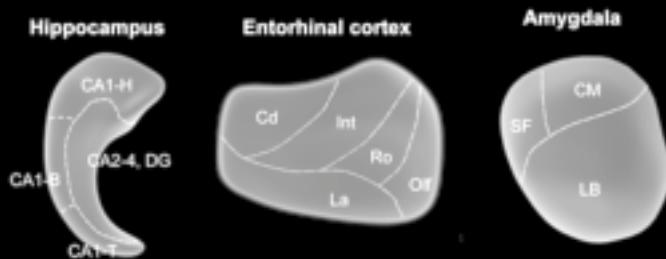
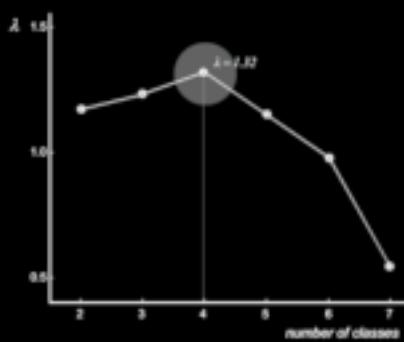
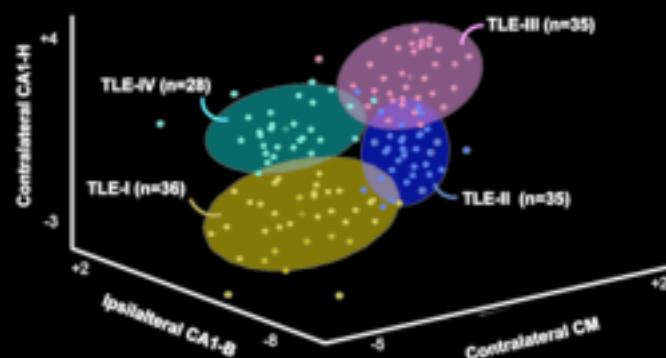
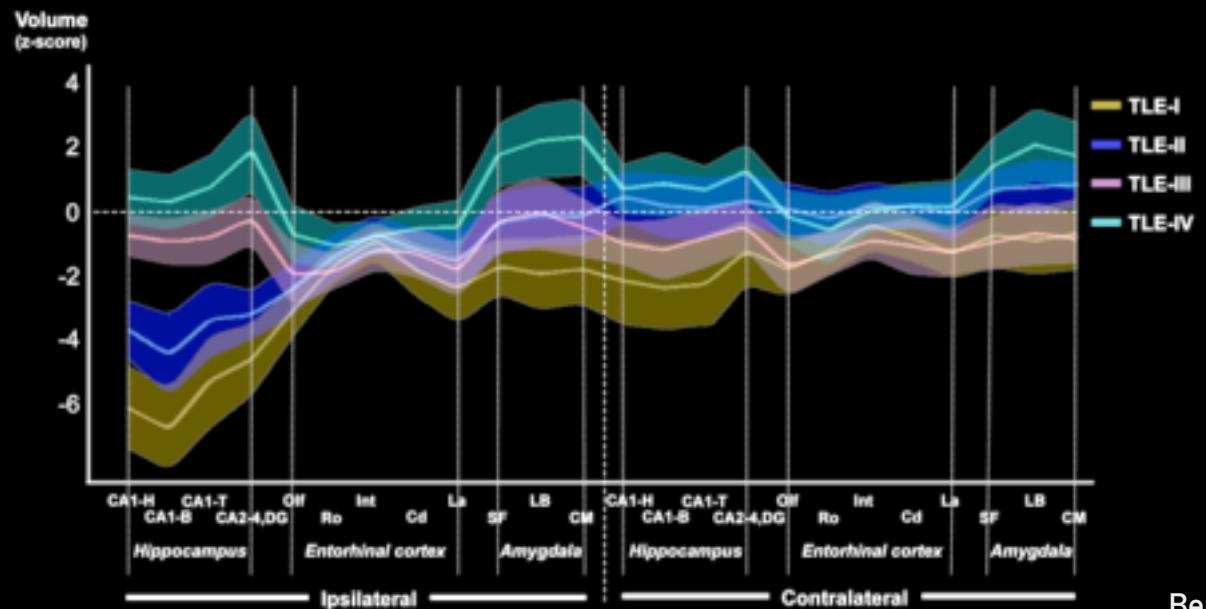
- subregional network regularization ($\uparrow P$ and $\uparrow C$)
 - \uparrow within-structure covariance (possibly related to sprouting)
 - \downarrow between-structure covariance (possibly related to disconnection)
 - $\uparrow P$ in HA vs NV
- however: $\uparrow P$ in SF vs NSF, controlling for HA diagnosis
 - Divergence between neocortical and mesiotemporal pathology wrt outcome
- network measures possible group-level biomarker

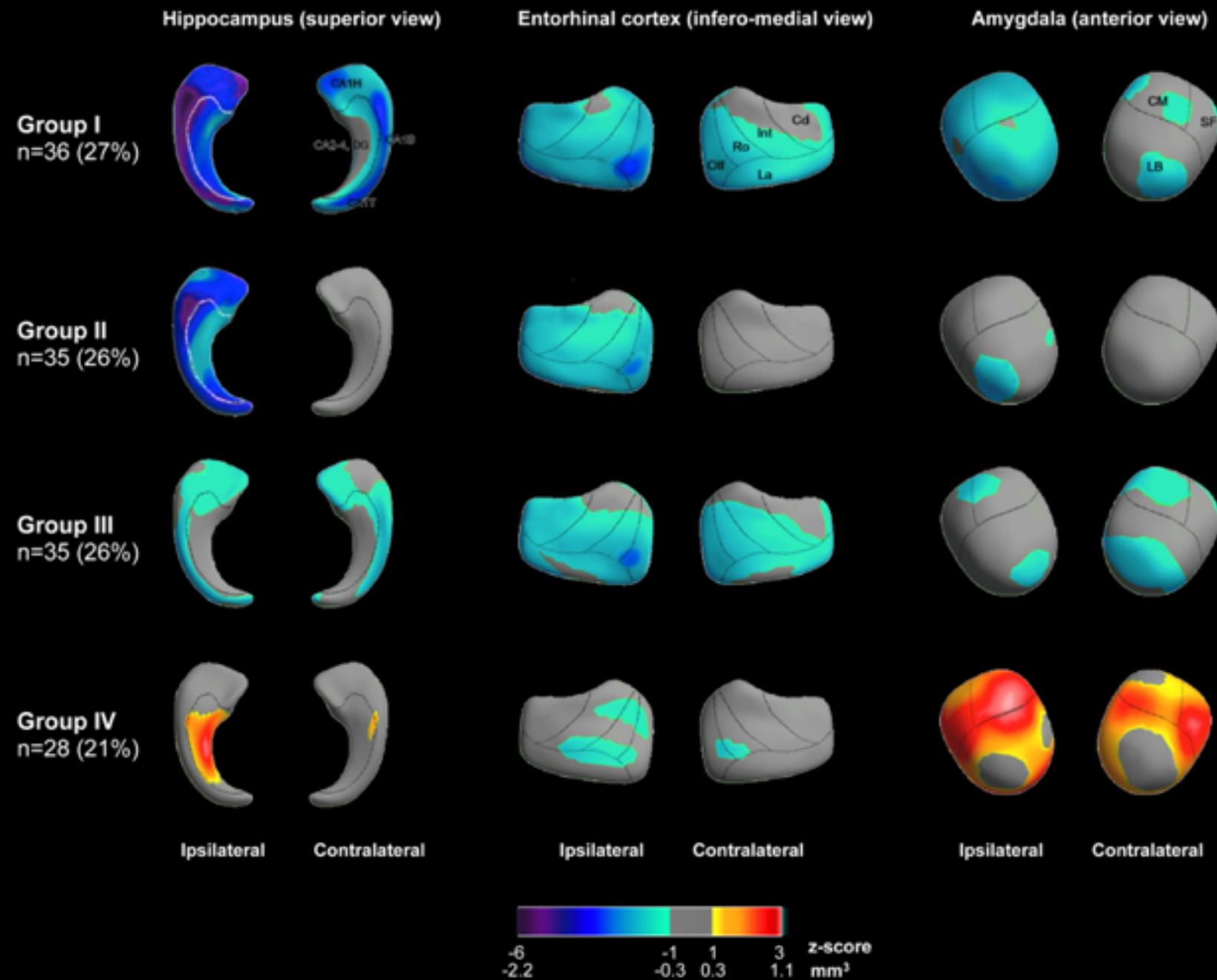
biomarkers

- ▶ prognostic biomarkers
 - ▶ may reveal clinical subpopulations of TLE

goal: extend spectrum of TLE-HA vs TLE-NV
 - ▶ should ideally work on a patient-specific level

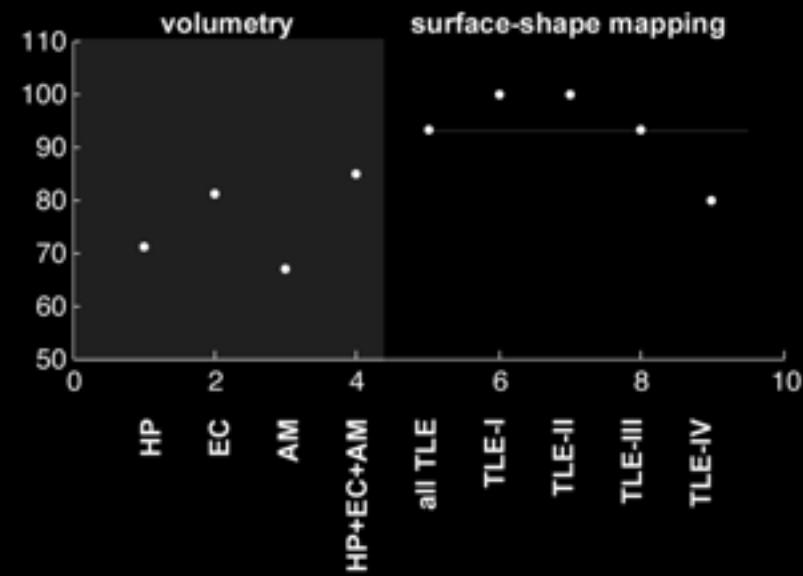
goal: lateralize focus and predict outcome
- ▶ machine-learning lends appropriate tools for both goals
 - ▶ unsupervised clustering
 - ▶ supervised prediction

A Mesiotemporal MRI segmentation**B Surface-shape maps and parcellation****C Establishing number of classes****D Exemplary clustering solution****E Mesiotemporal profiles**

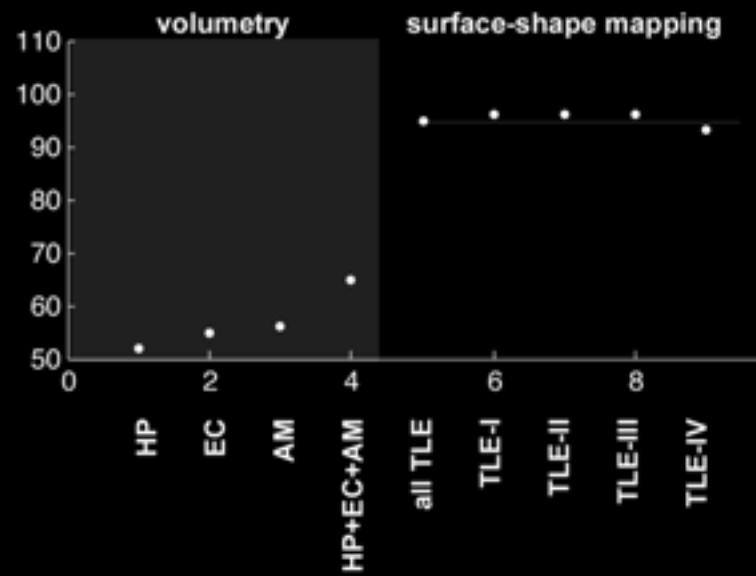


Clinical utility of mesiotemporal surface-shape mapping

A Seizure focus lateralization accuracy

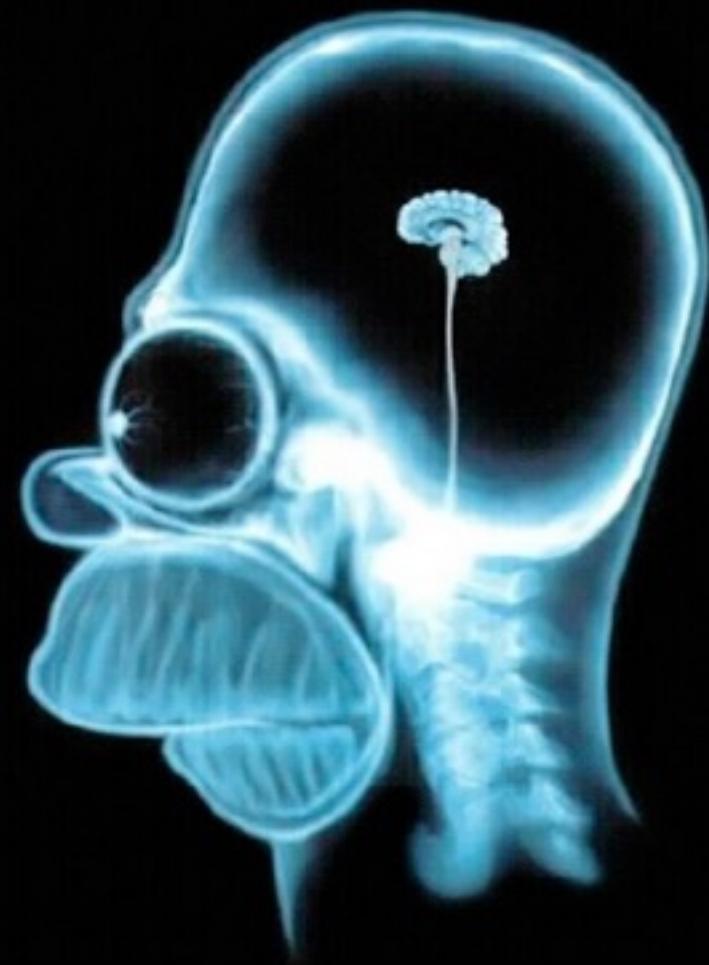


C Surgical outcome prediction accuracy



conclusions

- ▶ MRI profiling provides nuanced characterization of TLE spectrum
 - ▶ consistent anterior entorhinal subfield atrophy
 - ▶ gradation of hippocampal-amygda changes (atrophy >> hypertrophy)
- ▶ high level of clinical validity
 - ▶ 95% accurate prediction of outcome (conventional volumetry: 52%)
 - ▶ 93% accurate lateralization (conventional volumetry: 71%)
- ▶ promising biomarker for presurgical workup in drug-resistant TLE



overall summary

overall summary

structural MRI permits

- ▶ mapping substrates individual differences
- ▶ brain network analysis
- ▶ assessing brain pathology and biomarker discovery

complimentary tools can be used for meaningful analysis

- ▶ MRI volumetry
- ▶ surface-based methods
- ▶ structural MRI covariance analysis

merci!

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Benoit Caldairou

Min Liu

Luis Concha

Dewi Schrader

Alan Evans

Jason Lerch

Yong He

John Chen

Sebastian Dery

Jeanne Timmins Costello Fellowship (MNI)

Savoy Foundation

DAAD

Studienstiftung

CIHR

Tania Singer

Jonathan Smallwood

Sofie Valk

Nikolaus Steinbeis

Daniel Margulies

Giorgia Silani

Geoffrey Bird

Uta Frith



MAX-PLANCK-GESELLSCHAFT