

# Towards automated mapping of cytoarchitectonic areas using Deep Learning

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Mitglied der Helmholtz-Gemeinschaft



**HIBALL**  
HELMHOLTZ International BigBrain  
Analytics & Learning Laboratory



Human Brain Project



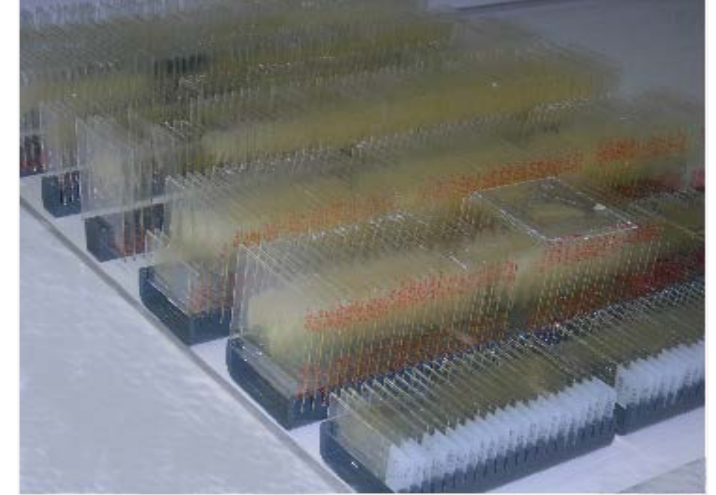
HELMHOLTZAI



**JÜLICH**  
Forschungszentrum

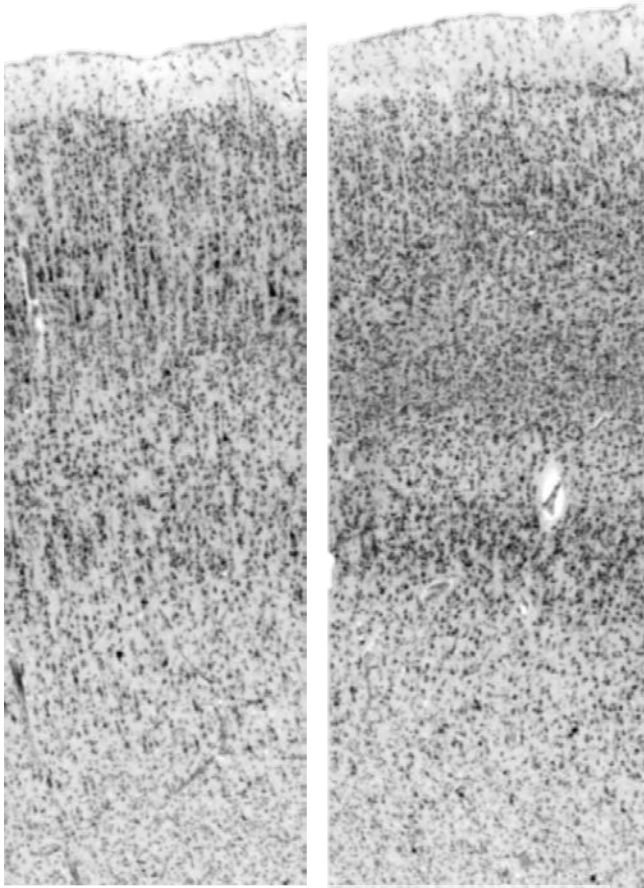


# Production of whole brain sections

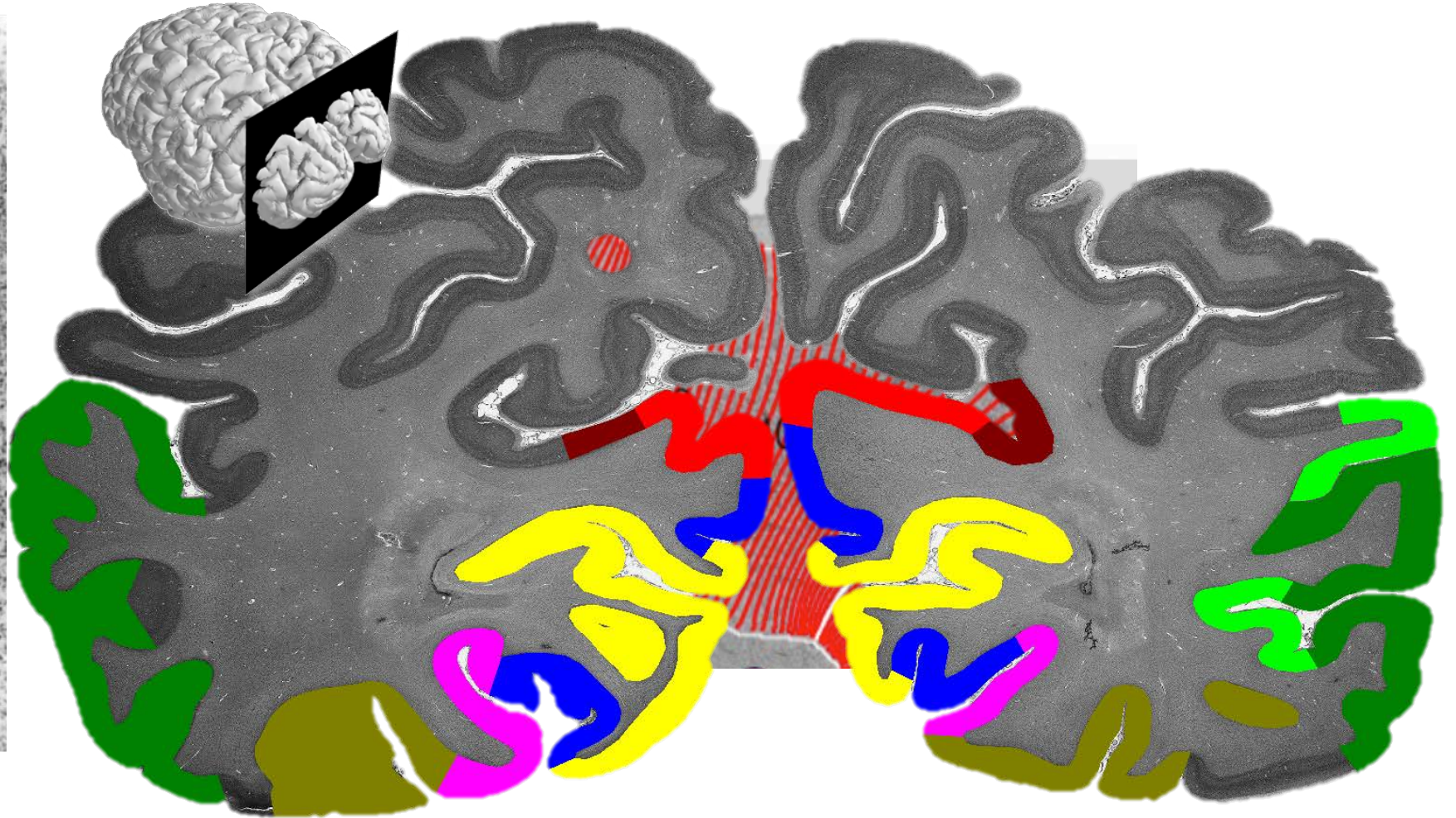




# Cytoarchitectonic mapping in serial sections



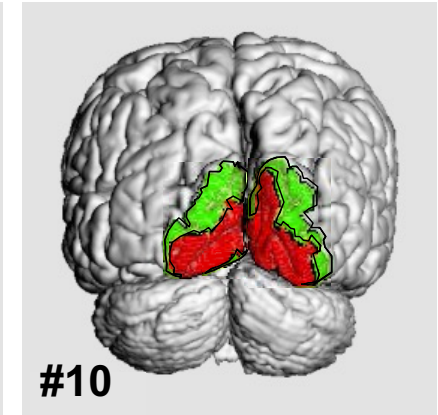
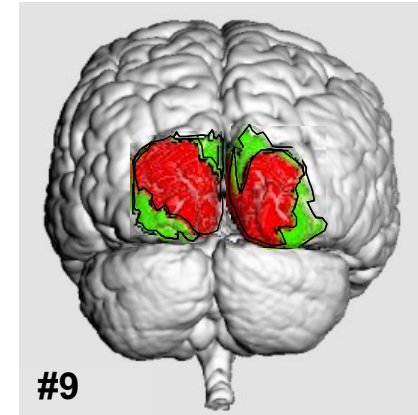
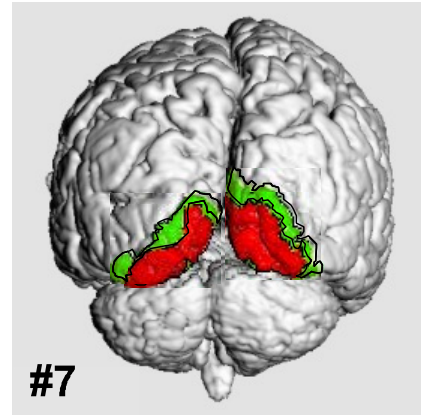
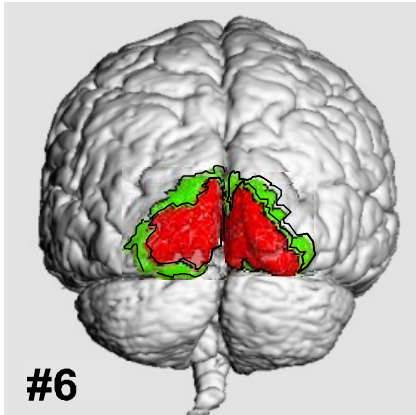
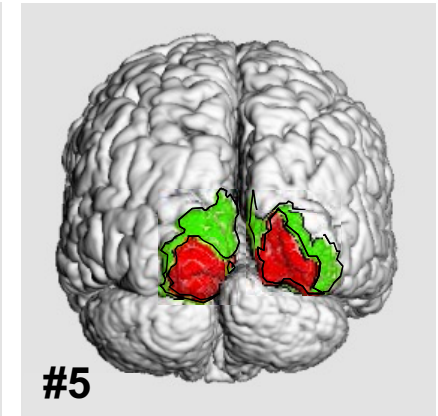
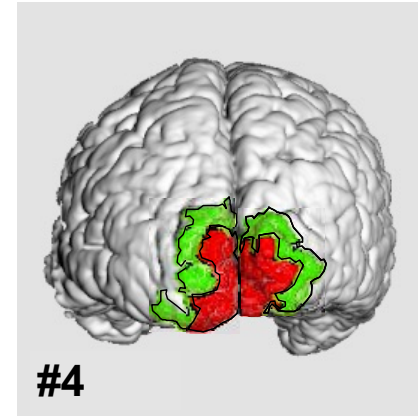
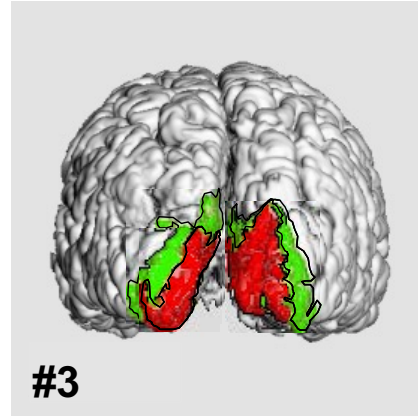
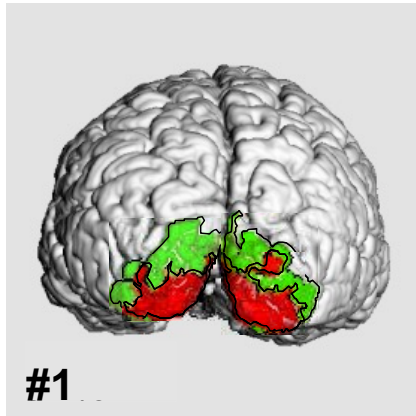
Amunts, K. and K. Zilles, Architectonic Mapping of the Human Brain beyond Brodmann. Neuron 2015. 88(6)





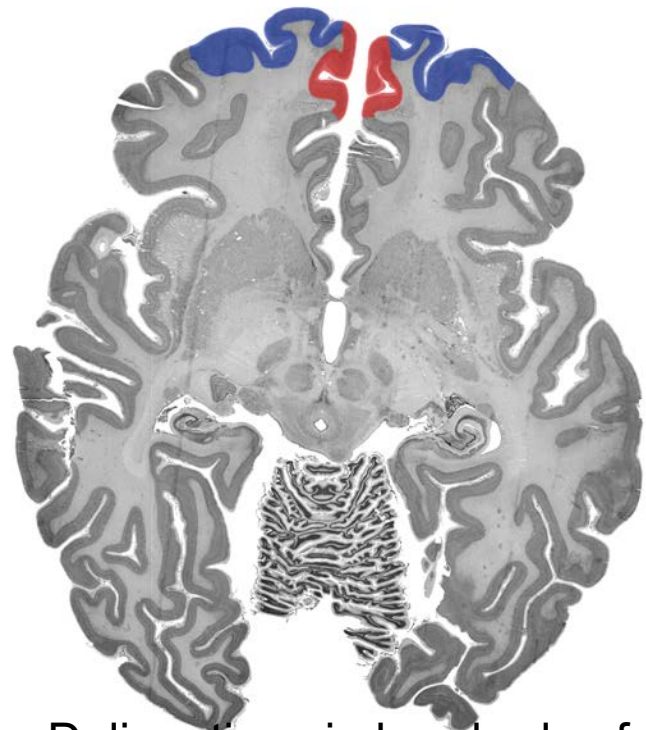
# Capturing intersubject variability

Amunts, Zilles et al.: Brodmann's Areas 17 and 18 Brought into Stereotaxic Space—Where and How Variable?, *NeuroImage*, Volume 11, Issue 1, 2000, Pages 66-84

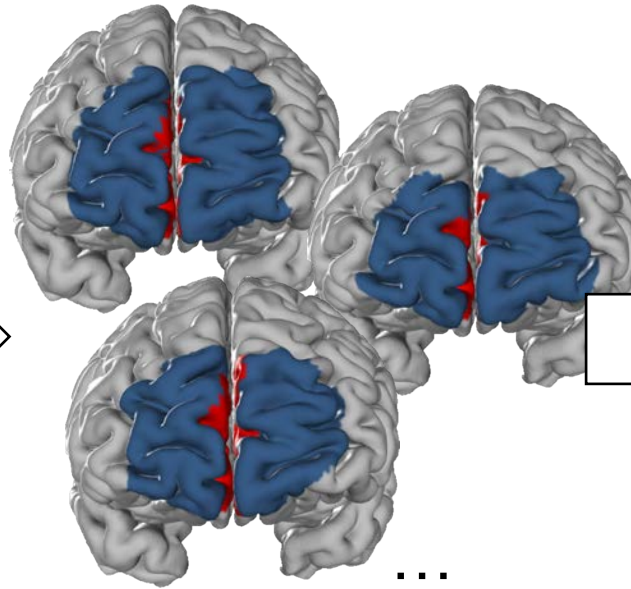
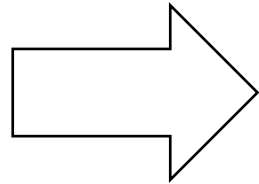




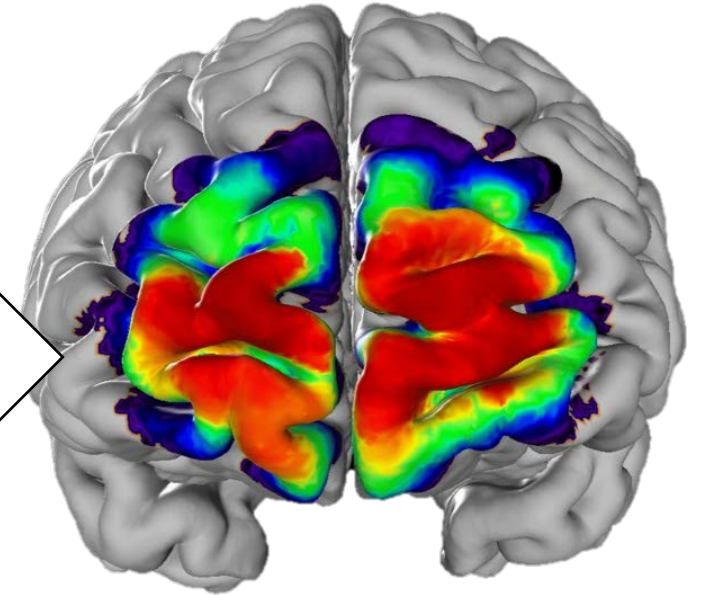
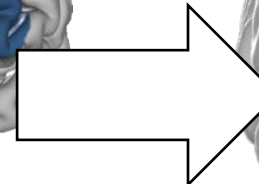
# Julich-Brain: cytoarchitectonic probabilistic maps



Delineations in hundreds of sections in 10 individual brains  
[micrometer scale]



Individual delineations projected to  
MNI reference space  
[mm scale]



Probabilistic map  
[mm scale]

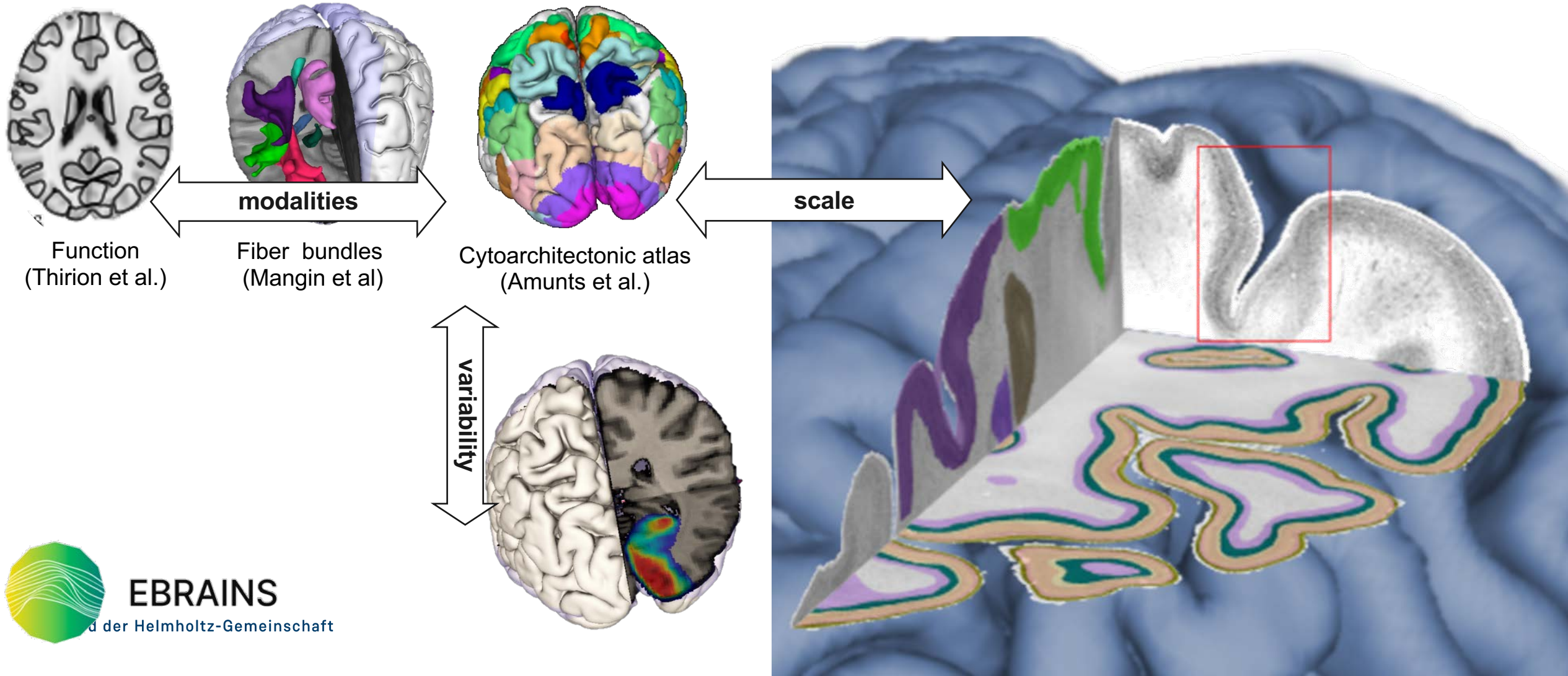
Bludau et al. 2014



# Building a multilevel human brain atlas using BigBrain

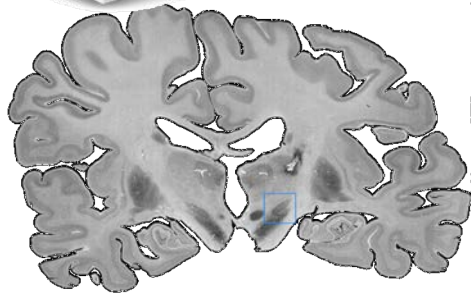
## Region definitions in MNI space

## Region definitions at the microscopic scale in BigBrain space

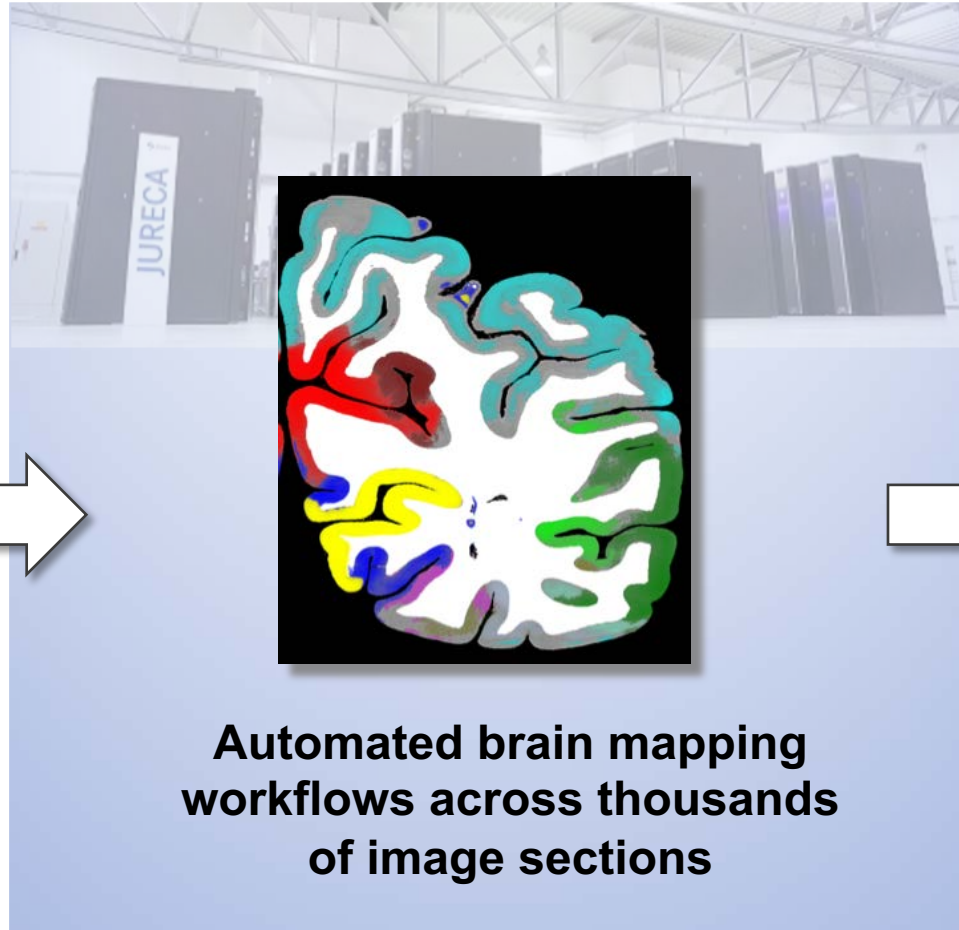




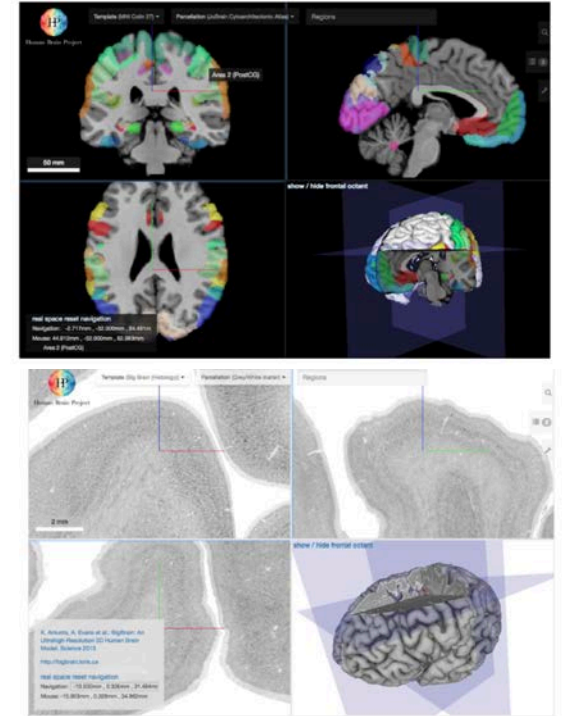
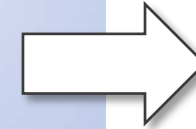
# Aim: From the lab to the web at high throughput using Big Data Analytics on High Performance Computers



**High throughput  
microscopic imaging  
(Terabytes / day)**



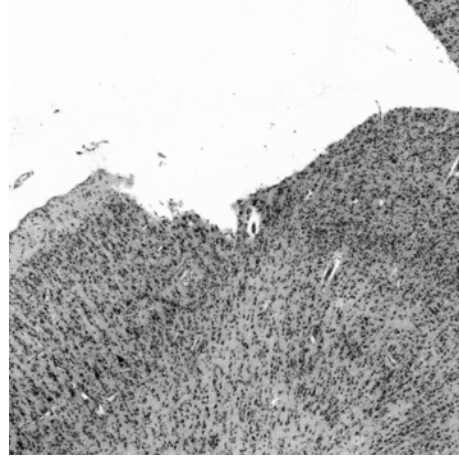
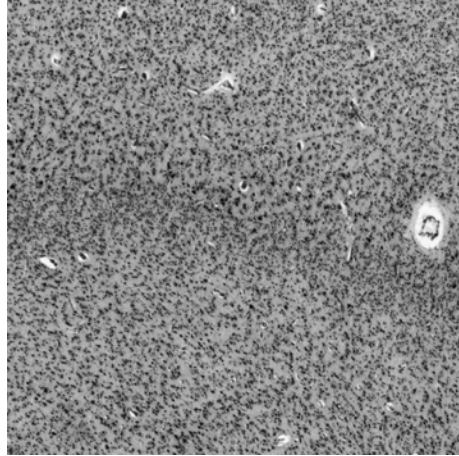
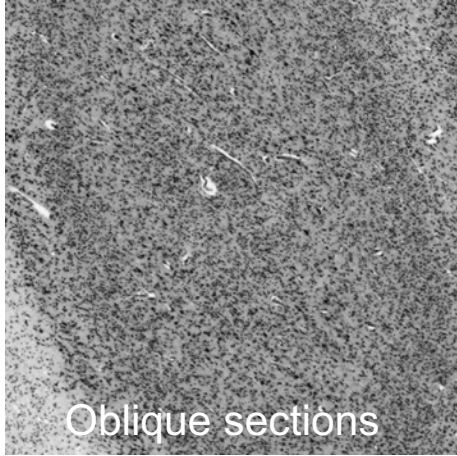
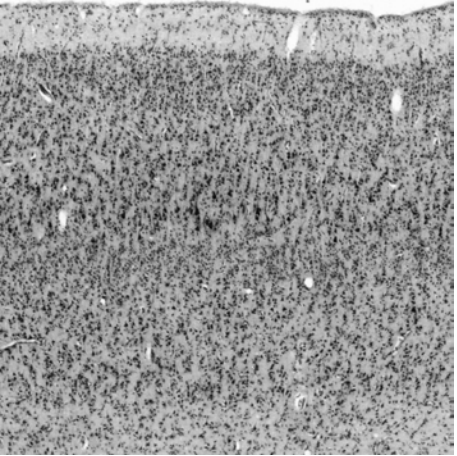
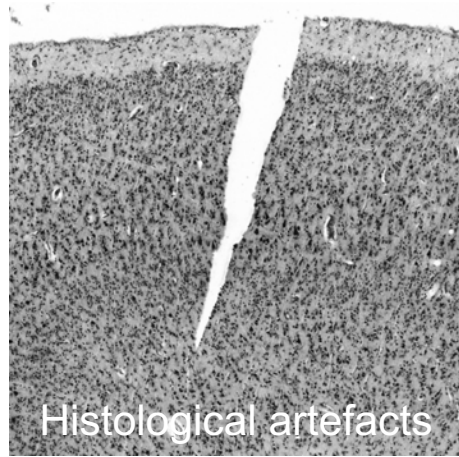
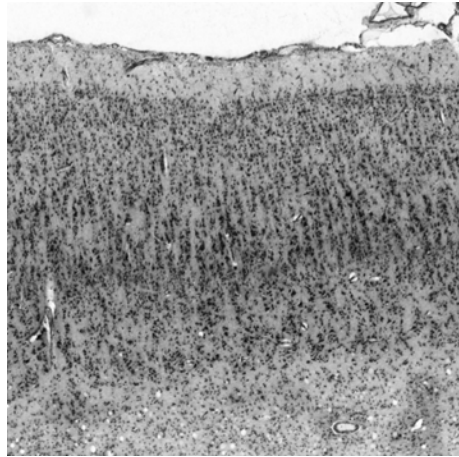
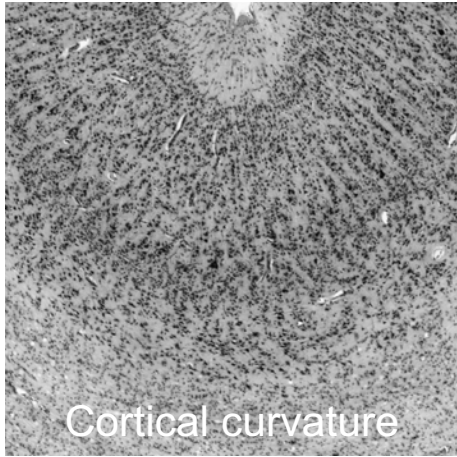
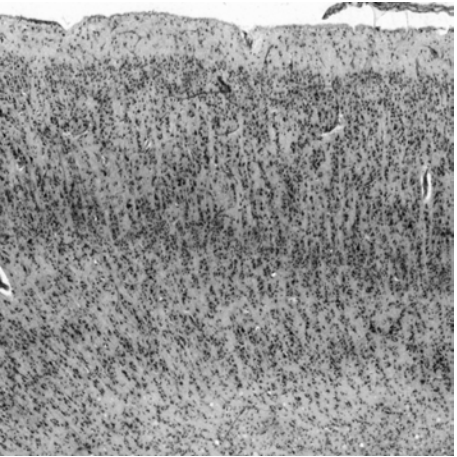
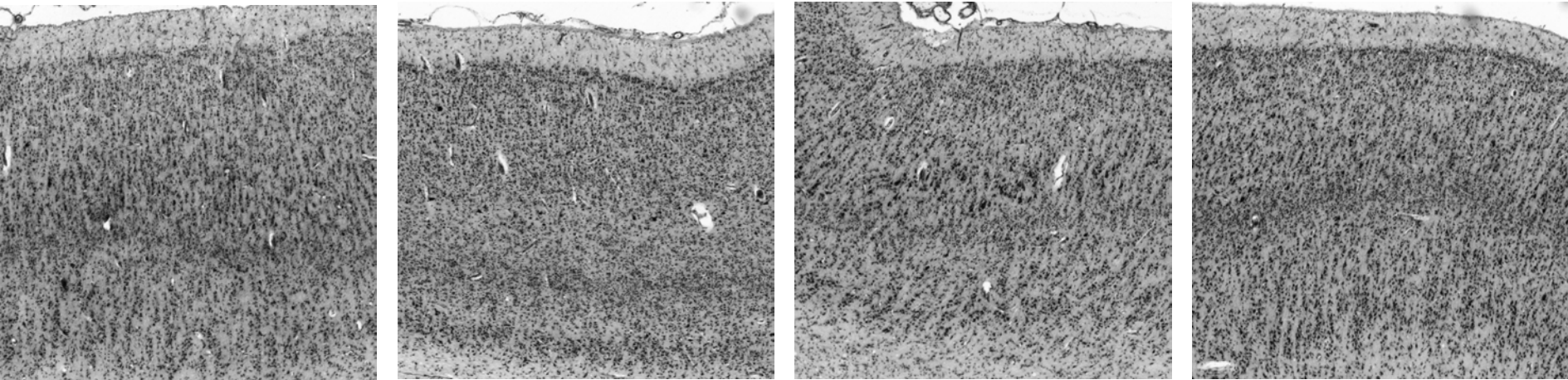
**Automated brain mapping  
workflows across thousands  
of image sections**



**Interactive online access  
to maps and image data**



# Automating cytoarchitectonic mapping with Deep Learning

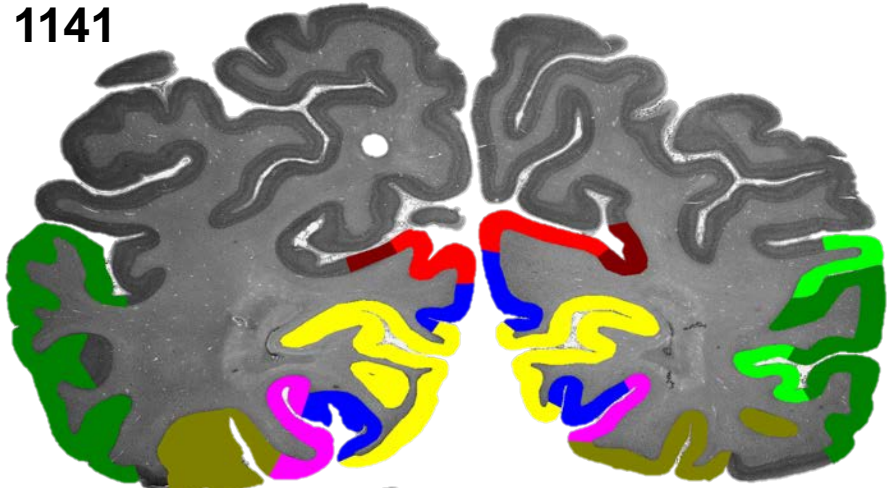


**Which brain area is depicted?**

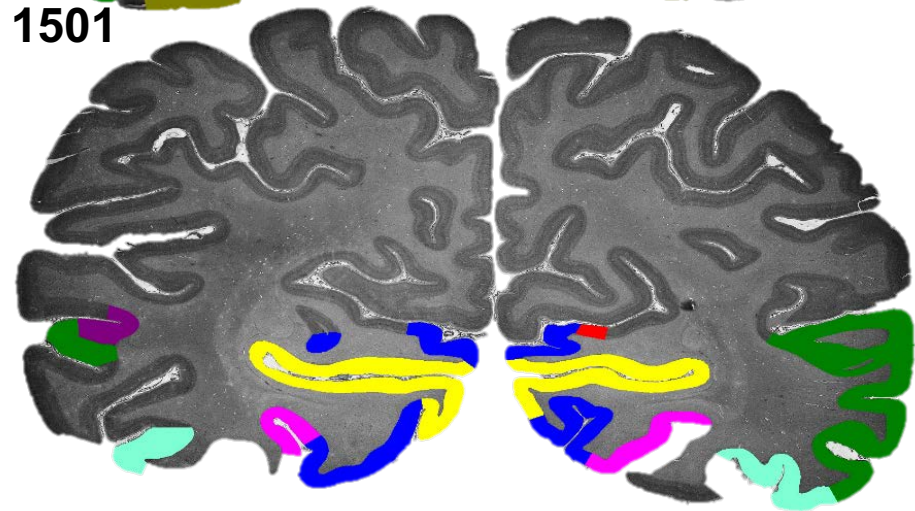


# Fully supervised multi-area segmentation in the visual system using modified U-Nets (2016)

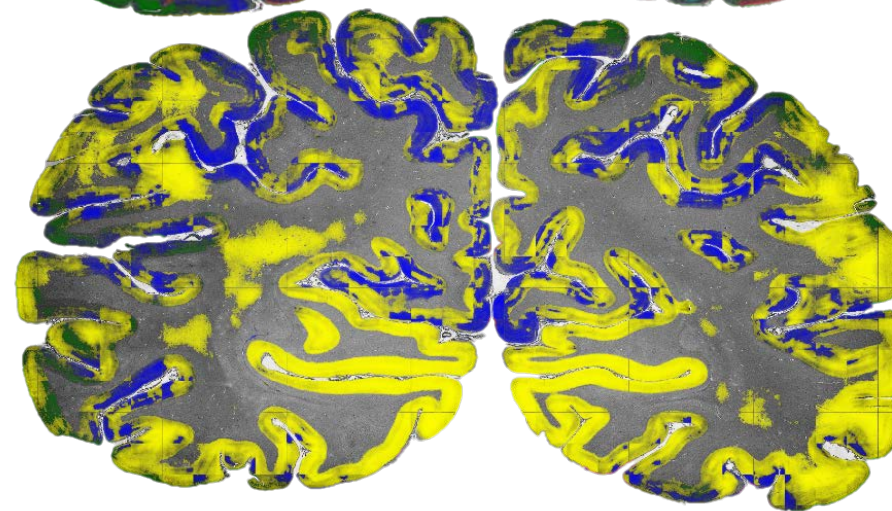
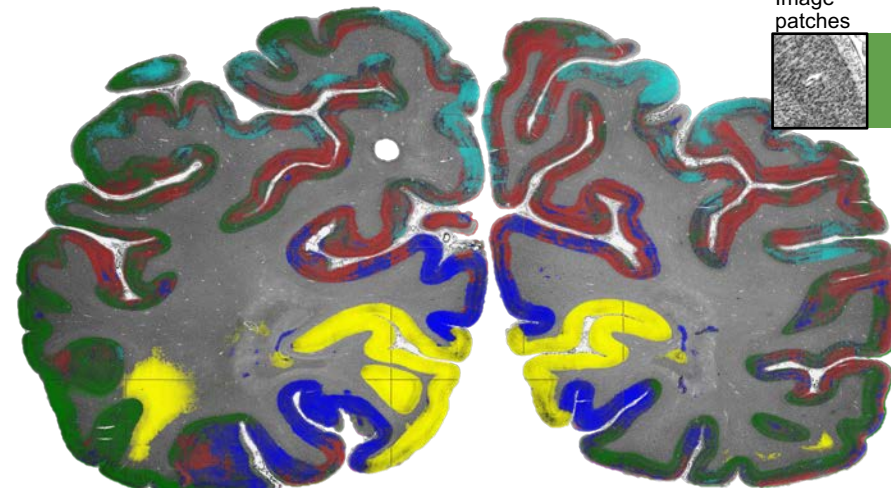
1141



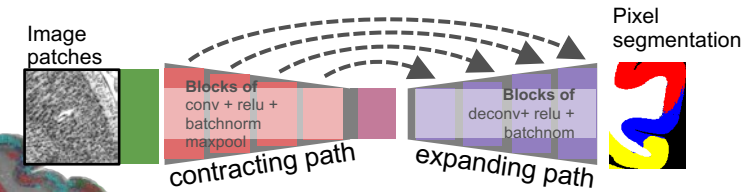
1501



Expert (many hours per image)



Deep Learning (few minutes)

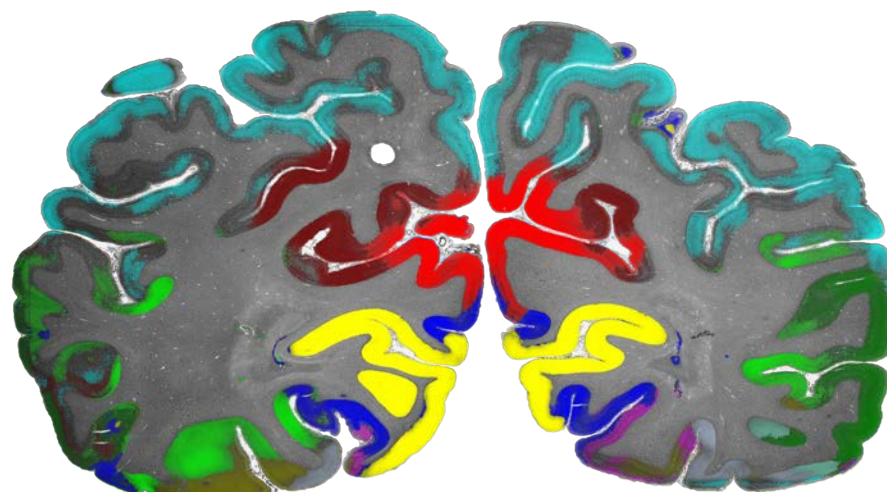
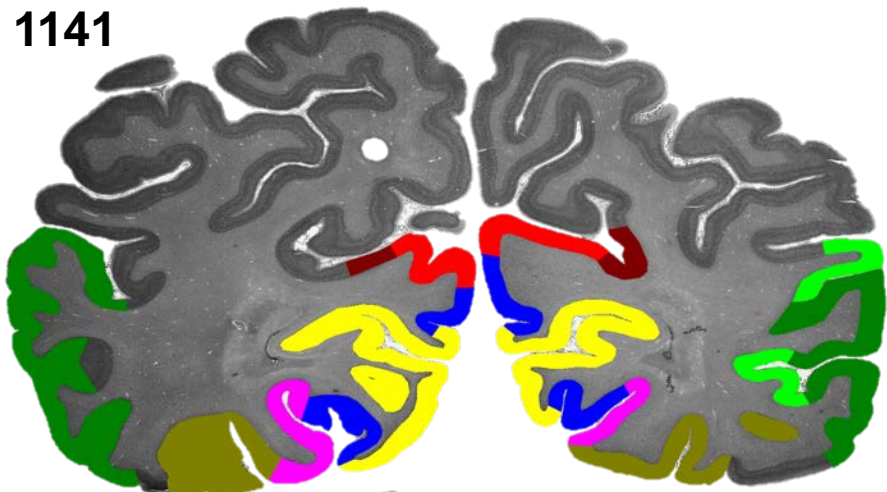


Spitzer, Caspers, Amunts, Dickscheid et al..  
**Feasibility of deep learning for automatic parcellation of cortical regions in histological sections.** OHBM 2016

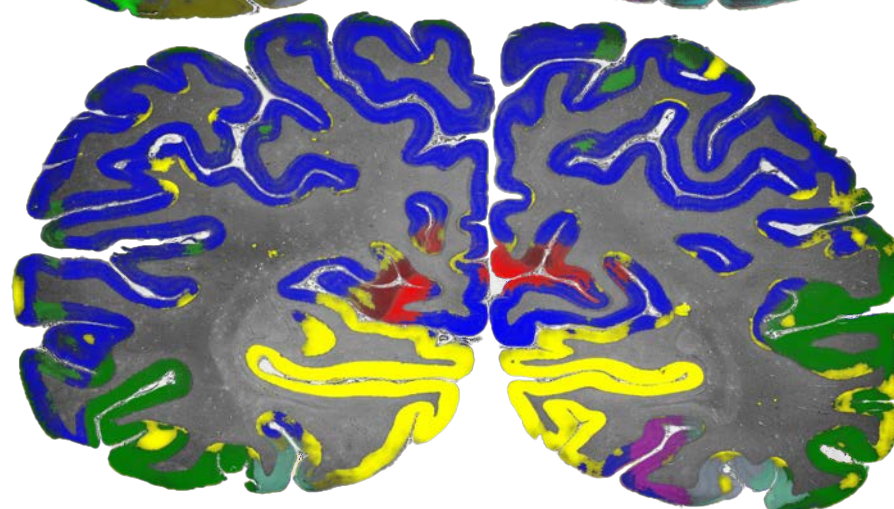
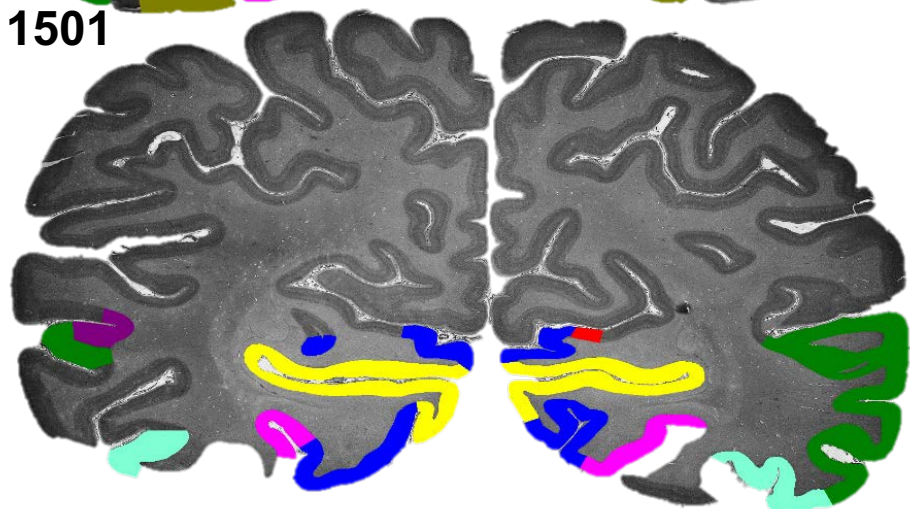


# Introducing a weak atlas prior for multi-area segmentation (2017)

1141



1501



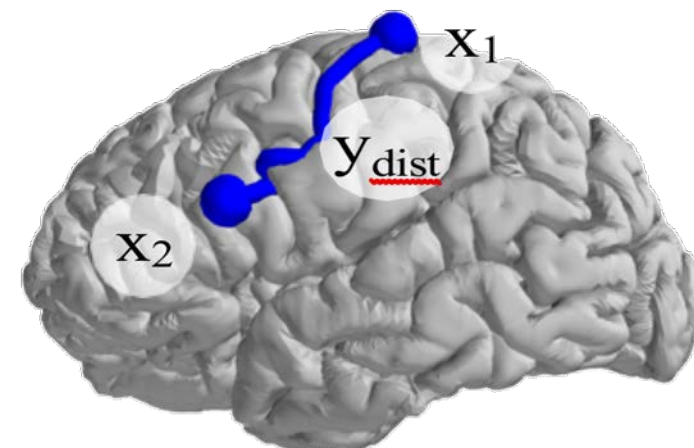
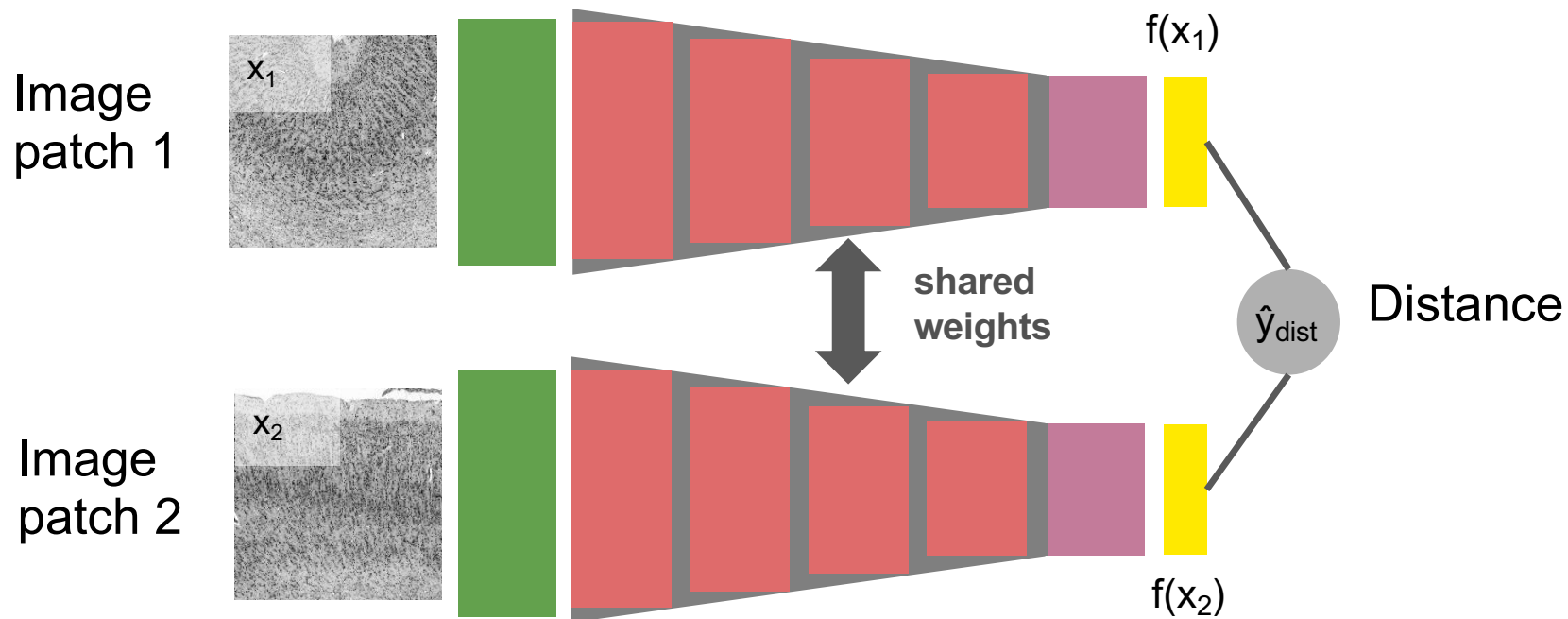
Expert (many hours per image)

Deep Learning (few minutes)

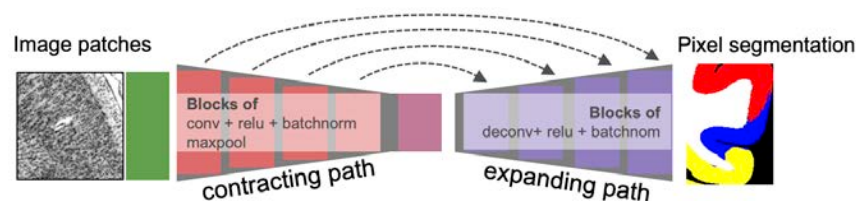
Spitzer, Amunts, Harmeling, Dickscheid. **Parcellation of visual cortex on high-resolution histological brain sections using convolutional neural networks.** ISBI 2017



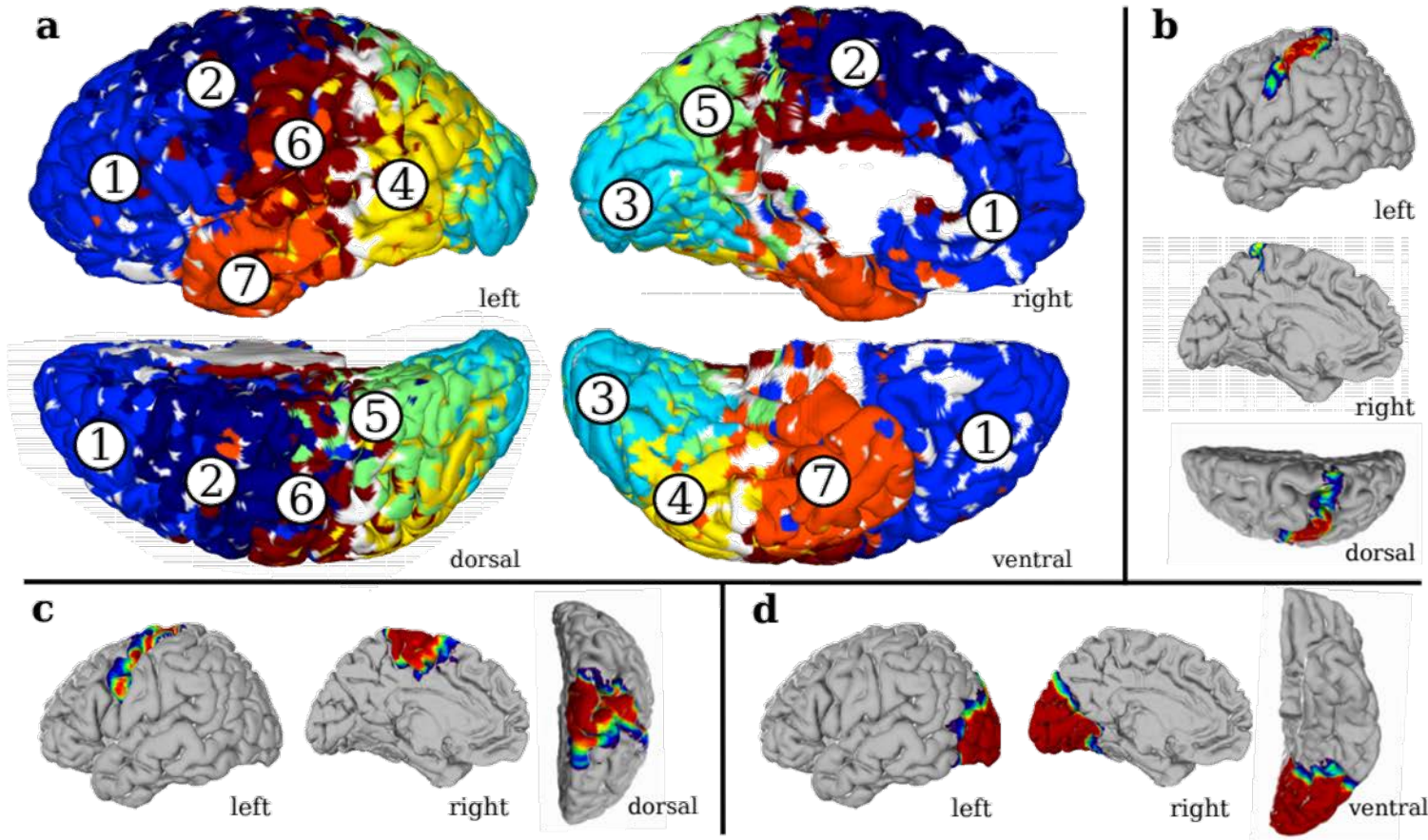
# Self-supervision: A siamese network predicts geodesic distance between pairs of image patches



Spitzer, Kiwitz, Amunts, Harmeling, Dickscheid: Improving cytoarchitectonic segmentation of human brain areas with self-supervised siamese networks. MICCAI 2018



# The CNNs learns a compact encoding of cytoarchitecture – more than border detection



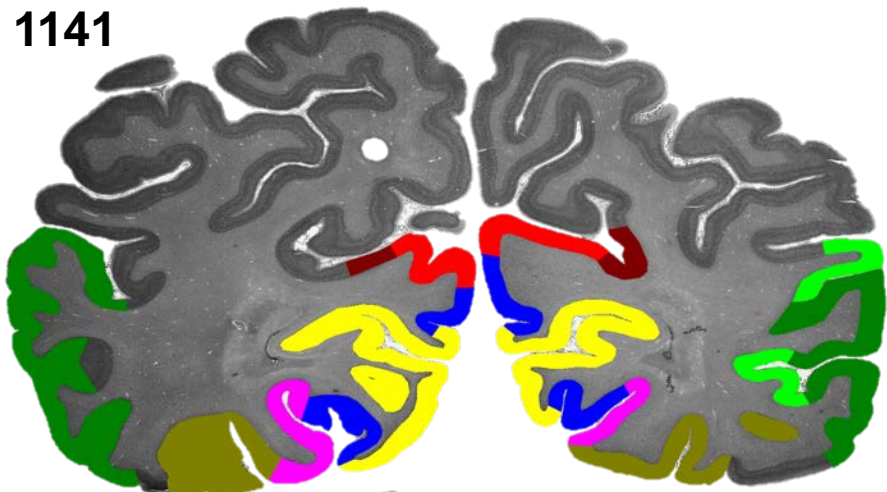
Clustering of the latent features learned by the siamese network

*Spitzer, Amunts, Harmeling, Dickscheid: Compact feature representations for human brain cytoarchitecture using self-supervised learning. MIDL 2018*

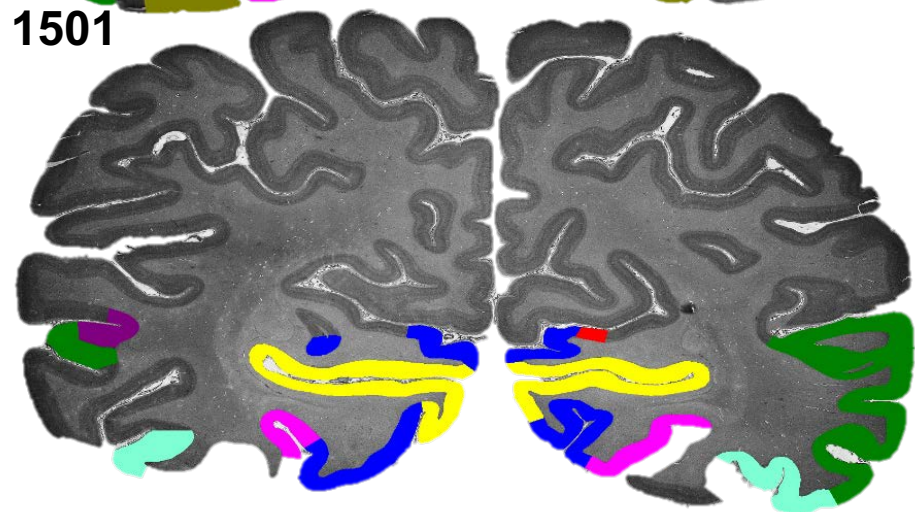


# Initializing multi-area segmentation from the self-supervised task (2018)

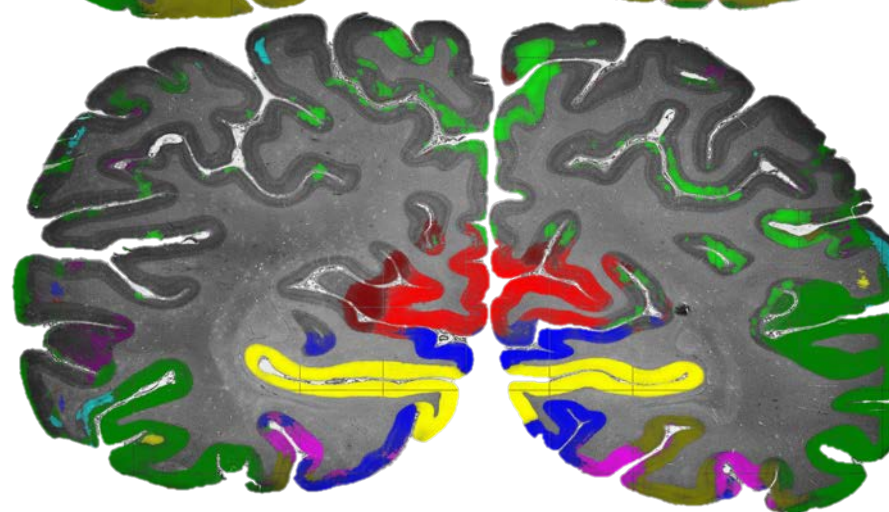
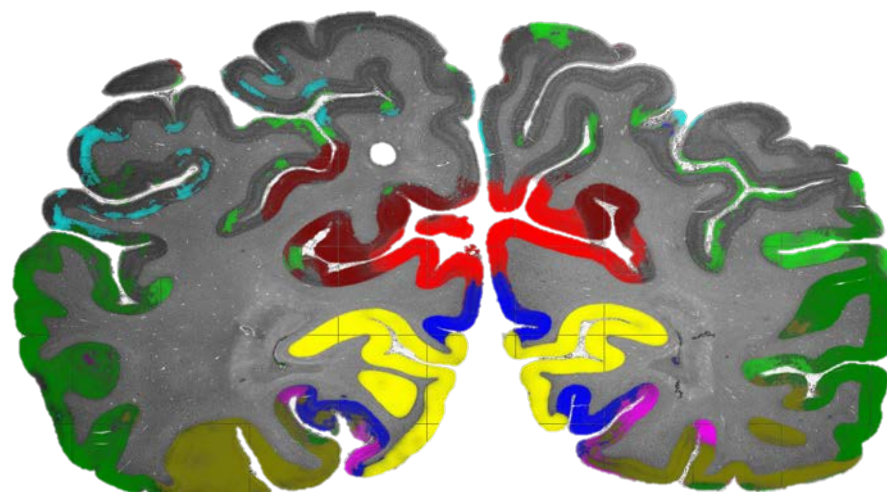
1141



1501



Expert (many hours per image)



Deep Learning (few minutes)

Spitzer, Kiwitz,  
Amunts, Harmeling,  
Dickscheid.  
**Improving  
cytoarchitectonic  
segmentation of  
human brain areas  
with self-supervised  
siamese networks.**  
MICCAI 2018



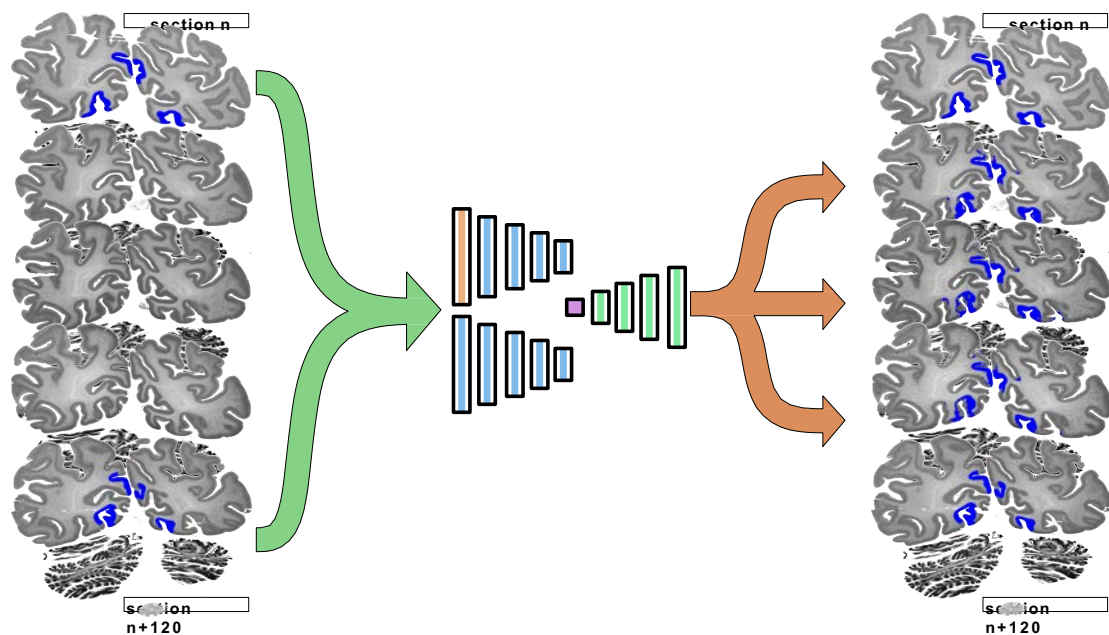
# Interpreting learned features for brain mapping

Many latent features resemble classical brain mapping “rules”





# CNNs support the neuroanatomist: Single-area segmentation across full serial stacks

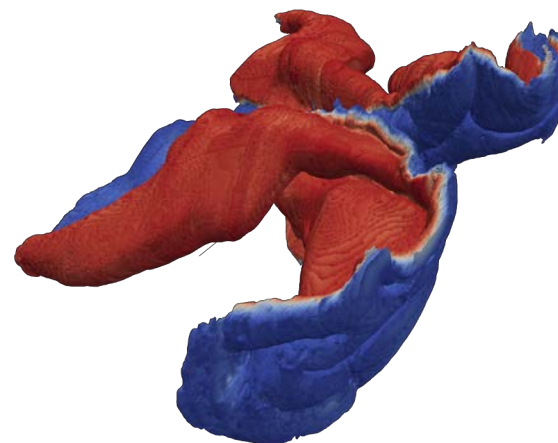
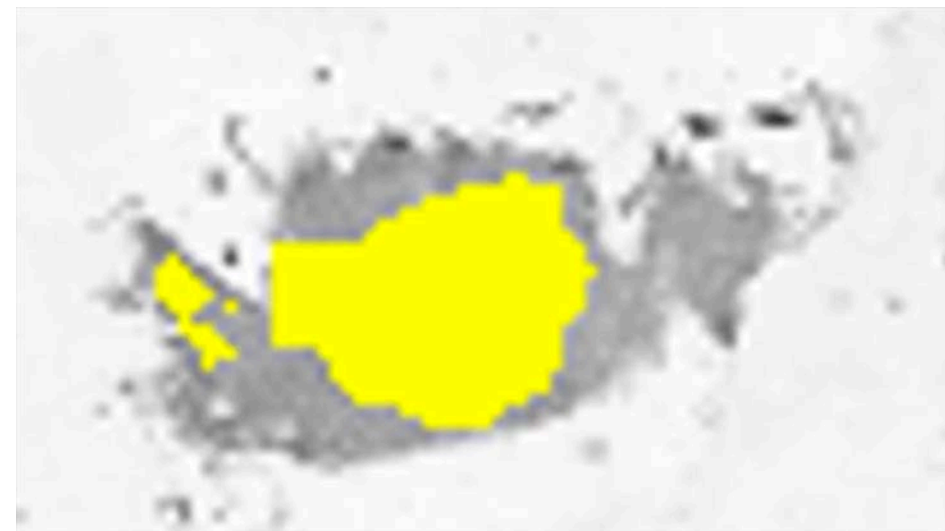


**Training: 2 sections**

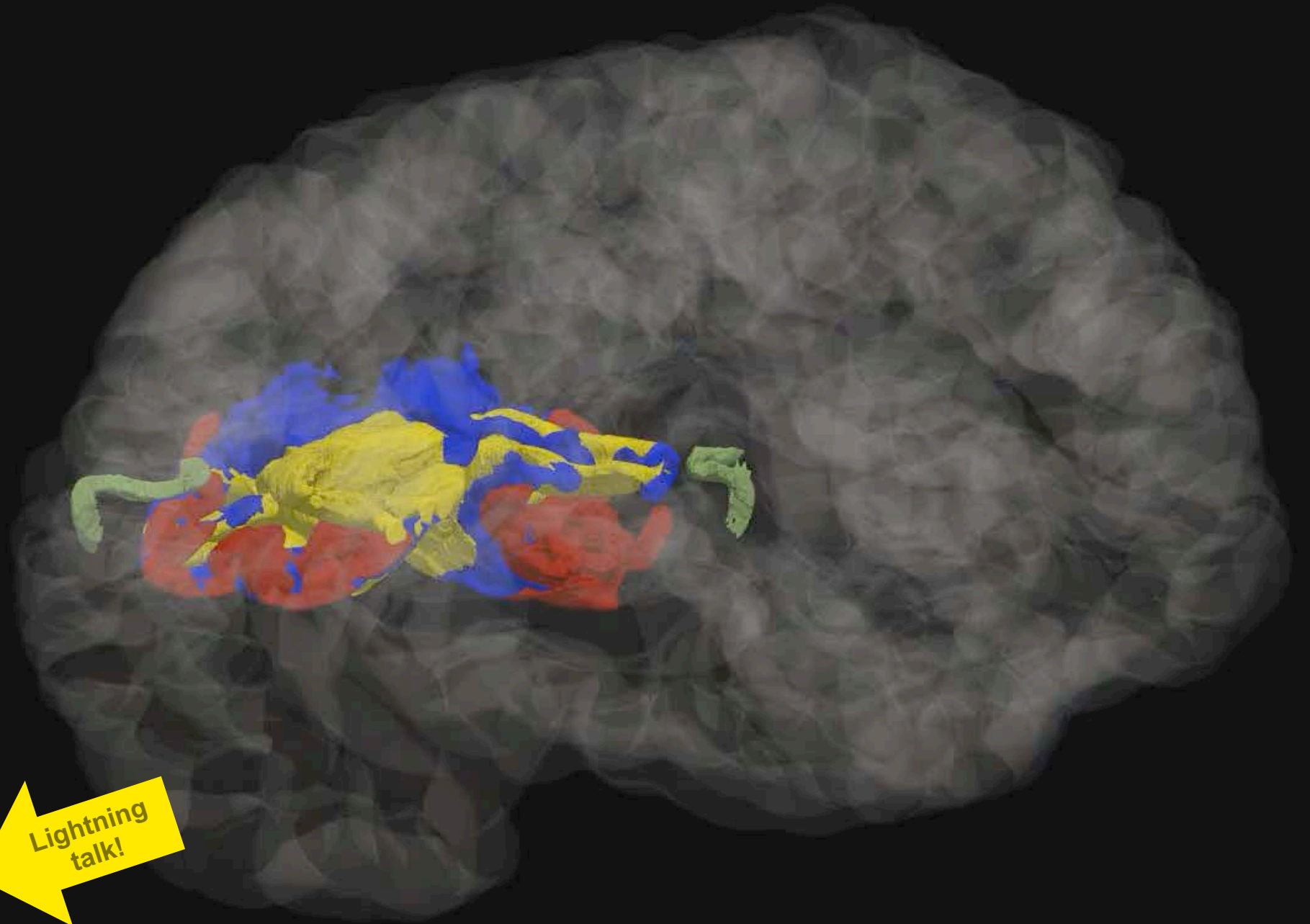
**Inference: >100 sections in between**

Schiffer, Amunts, Dickscheid et al.: **Deep learning speeds up gapless cytoarchitectonic mapping in serial histological sections.** *OHBM 2019*

Area hOc1: ~2400 1 micron sections



3D reconstruction  
in BigBrain space



**3D maps of areas hOc1,  
hOc2, hOc3v and hOc5**  
Based on precise 1 micron  
segmentations in ~2300  
histological sections using  
Deep Learning

Christian Schiffer et al., in prep  
Mitglied der Helmholtz

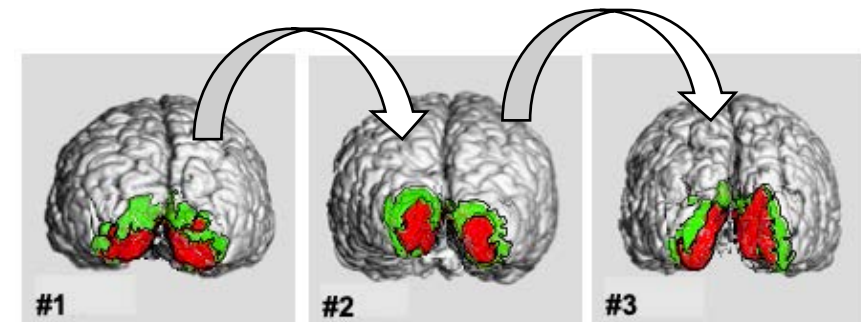
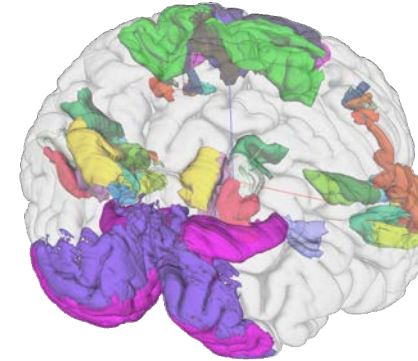




Where are we going from here?

# Where are we going from here?

- Use the single-area CNN as a tool to map more areas in BigBrain
- Transfer learning - propagate maps from BigBrain to a new brain sample, overcoming biological variability and different imaging devices
- Develop learning strategies to build a general (interpretable?) multi-area segmentation model for the whole brain





## **INM, Juelich**

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Svenja Caspers  
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Dirk Pleiter

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Xiao Gui  
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Lyuba Zehl  
Sara Zafarnia

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Jan Bjaalie

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Konrad Wagstyl  
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Blake Richards  
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# Thank You

