

# Large-scale Deep Learning for Cytoarchitecture Classification in the Human Brain

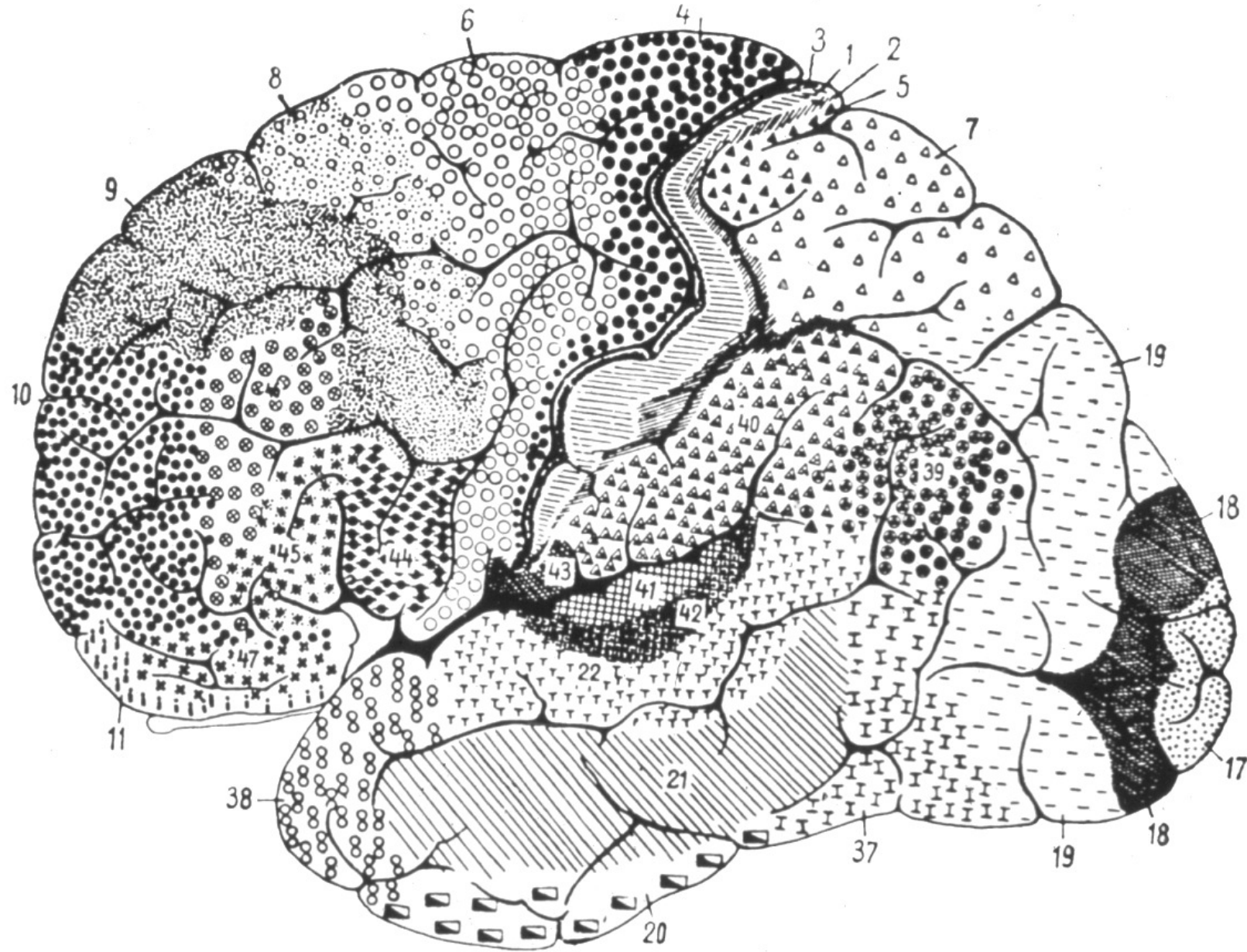
10 Year Anniversary Workshop - NVIDIA Application Lab Jülich

21.06.2022 | Christian Schiffer - Big Data Analytics - INM-1 - Forschungszentrum Jülich

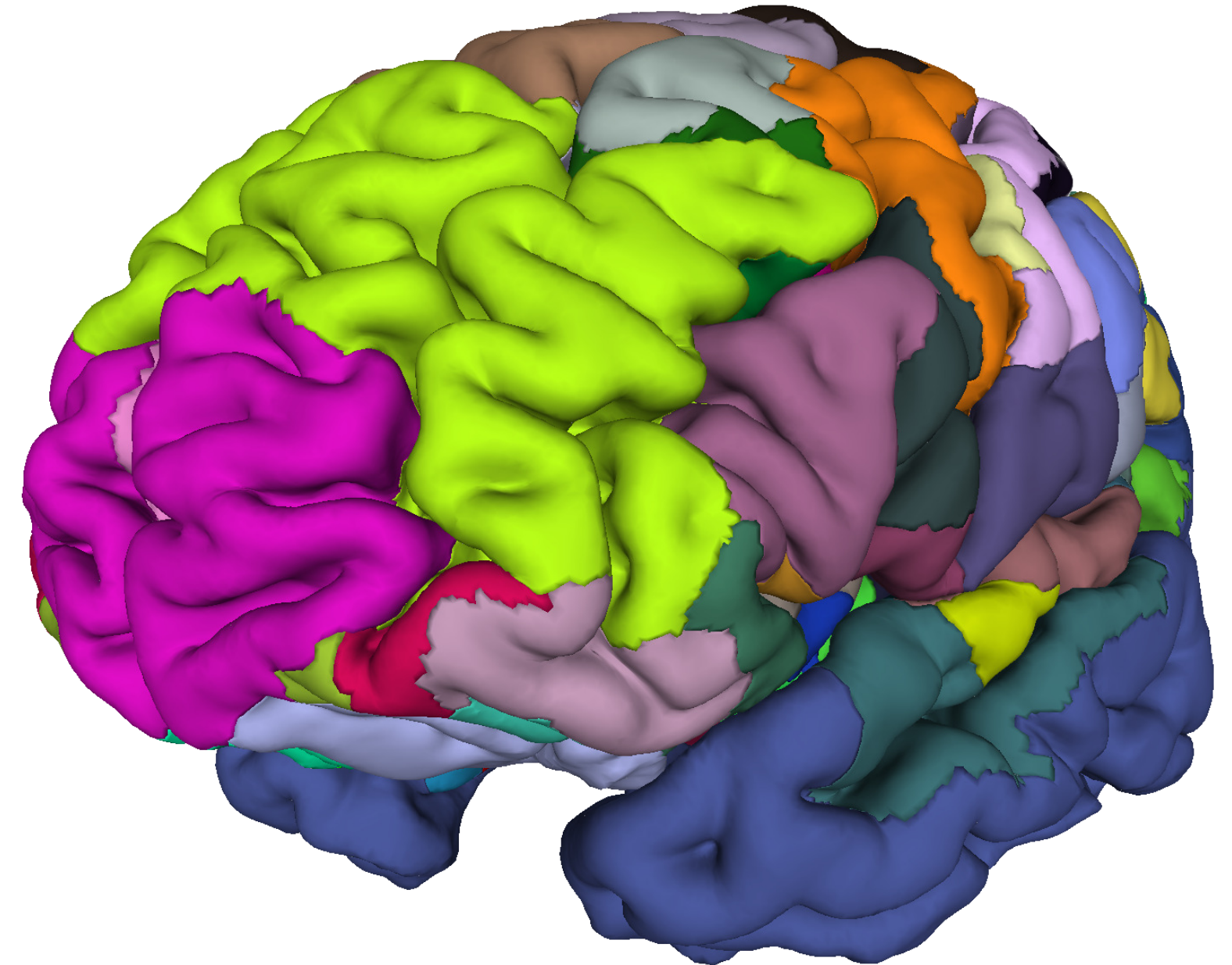




# Building a Human Brain Atlas for Cytoarchitecture



*Brodman, 1909*

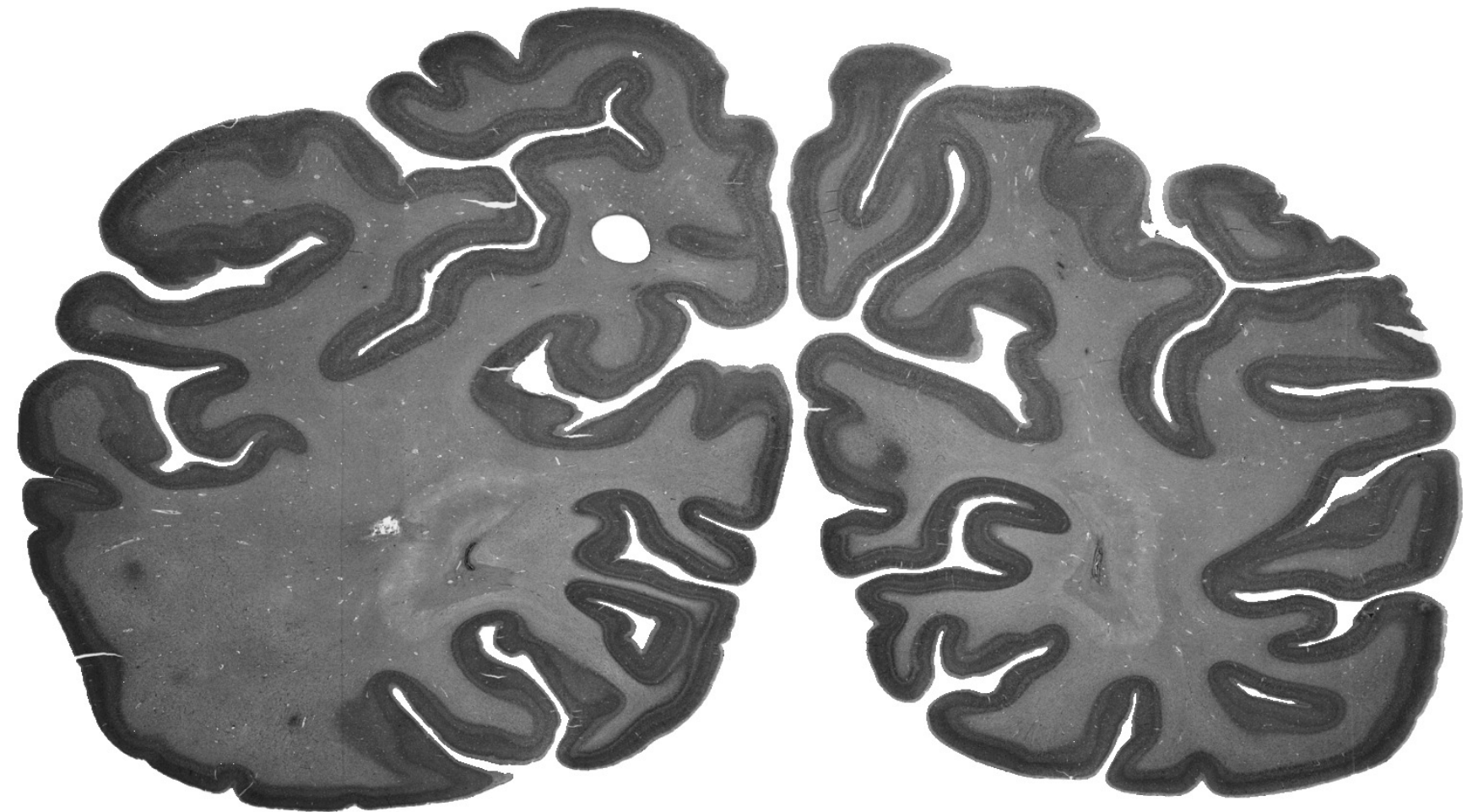


*Amunts et al., 2020*



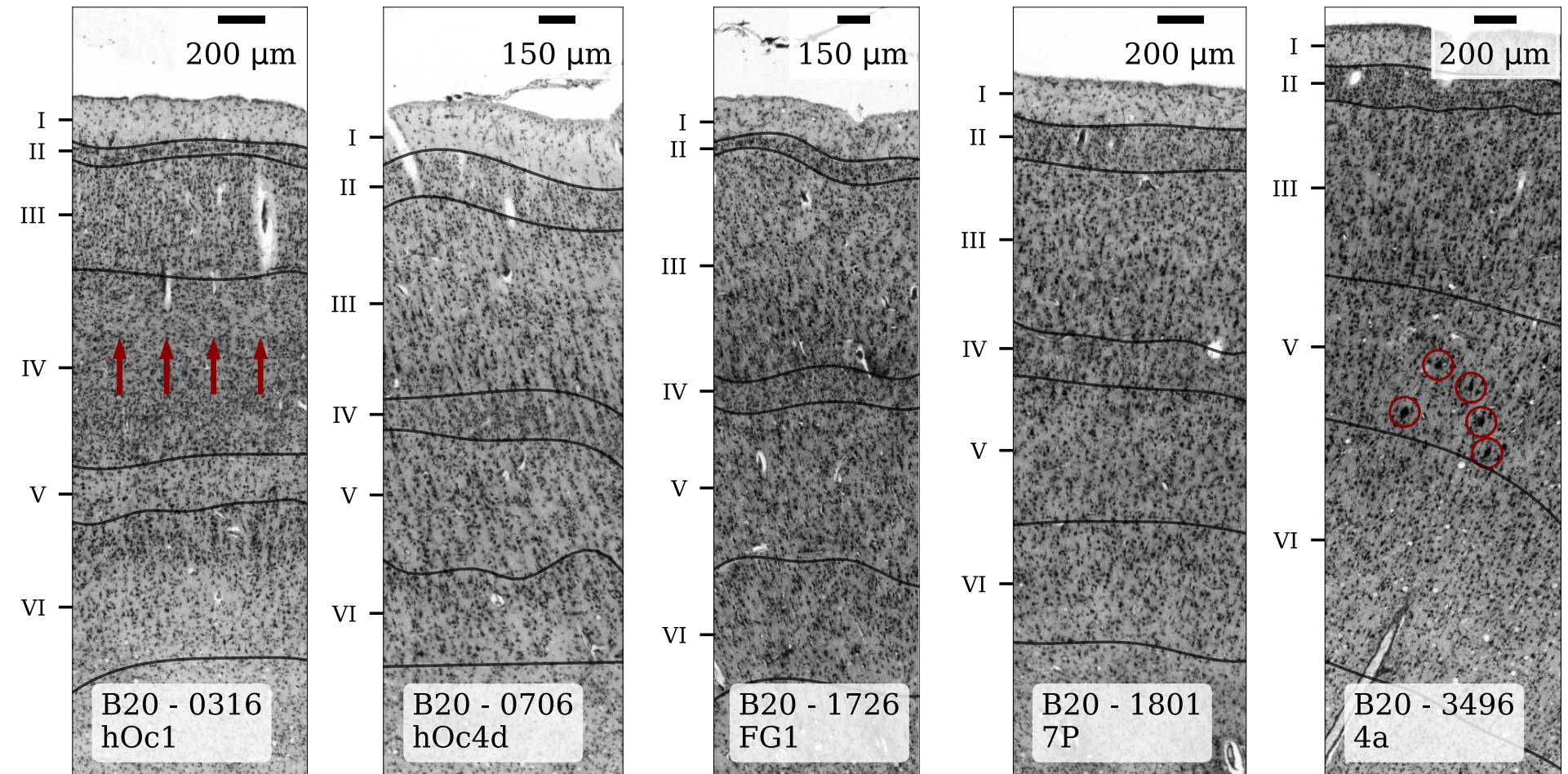
# Histological Human Brain Sections

- Postmortem human brains
- Fixate and **cut** into histological sections
  - 6000-8000 sections per brain
  - Thickness:  $20\mu m$
- Stain for **cell bodies**
- Microscopic imaging at  $1\mu m$  pixel resolution
- **Cerebral cortex**: Outer layer of the cerebrum



# Cytoarchitecture

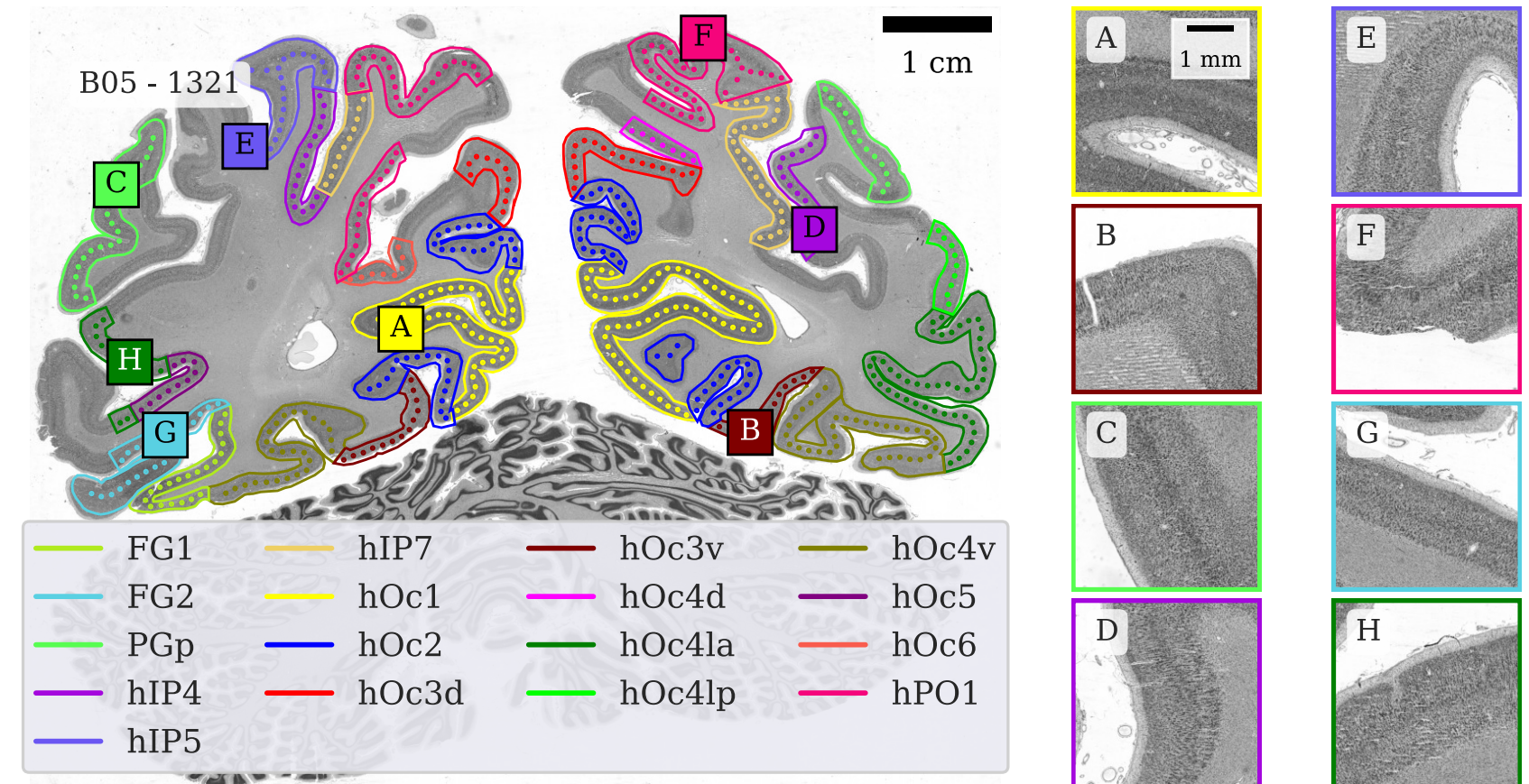
- **Cytoarchitecture:** Distribution, shape, and type of neuronal cells
- Organization into **cortical layers**
- Regional differences define **cortical areas**
- Indicators for **connectivity** and **function**





# Cytoarchitectonic Brain Mapping

- Brain mapping: Identify cytoarchitectonic areas
- Gold standard method: [Schleicher et al., 1999](#)
  - Statistical image analysis
  - Reproducible and observer-independent
  - Time intensive:  $\geq 30\text{-}60$  min/section/area
- **Goal:** Automated cytoarchitectonic mapping to enable large-scale cytoarchitecture analysis
- Train deep neural networks to predict areas from images



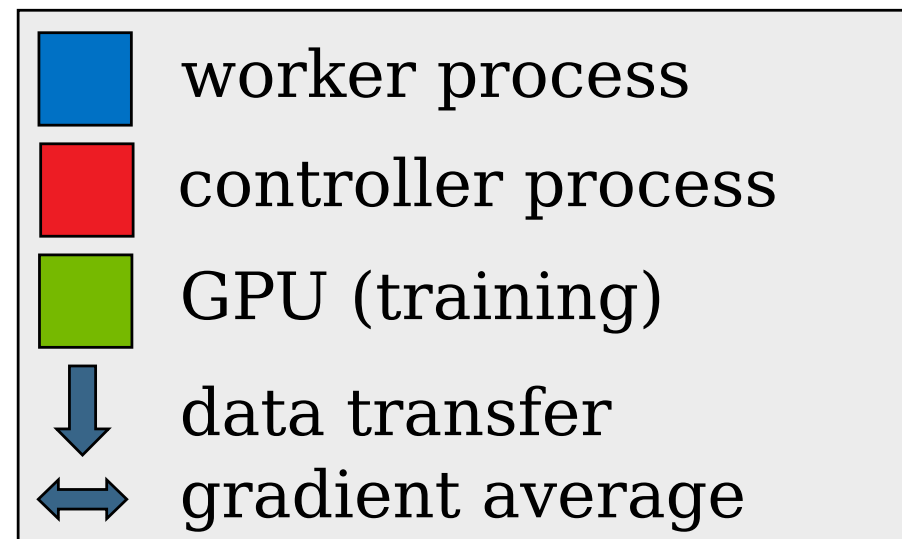


# Distributed Deep Learning on HPC

- Dataset size
  - Large images:  $\sim 80,000 \times 100,000$  px ( $> 8$  GB)
  - Many images: 6000-8000 images per brain
  - Large patches:  $2048 \times 2048$  px/patch ( $4\text{mm}^2 @ 2\mu\text{m}/\text{px}$ )
- Technical challenges
  - I/O: Random access to patches  $\rightarrow$  **flash-based storage**
  - Preprocessing: Augmenting large image patches  $\rightarrow$  **CPUs**
  - Training: Data parallel deep learning  $\rightarrow$  **GPUs**



# Distributed Deep Learning on HPC

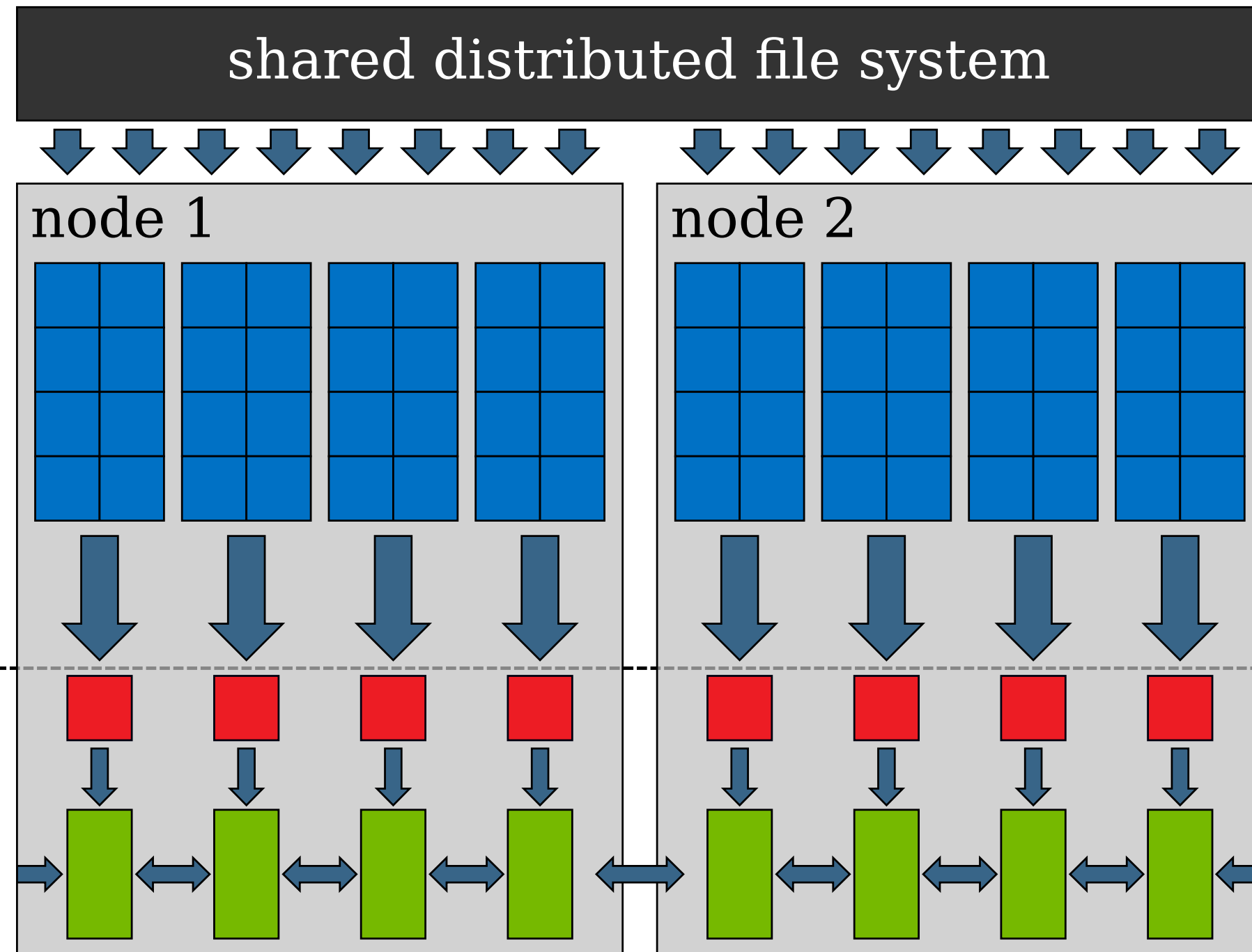


## data stage

- read data
- data augmentation
- transfer to masters

## training stage

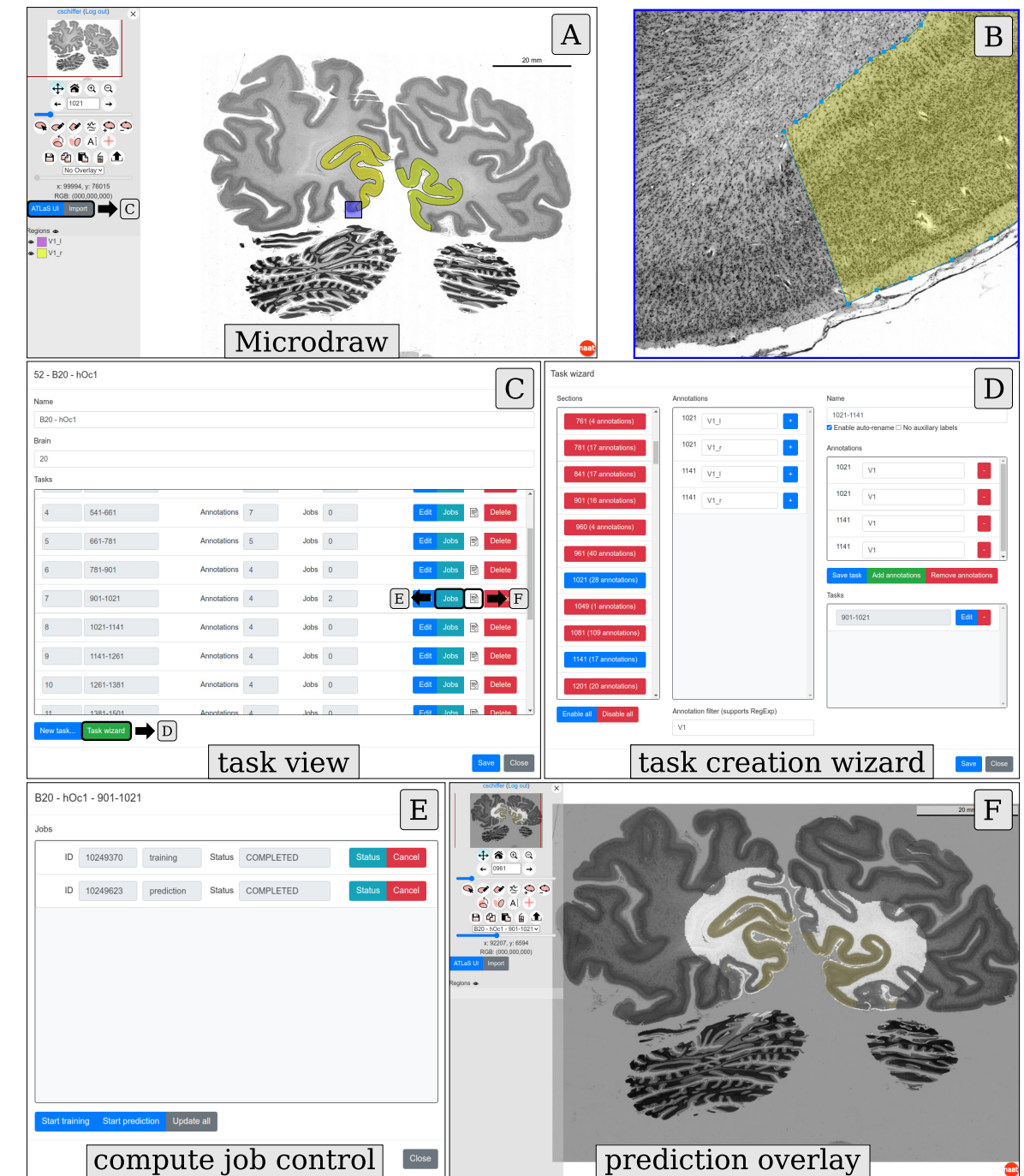
- receive data
- transfer to GPU
- parameter update





# Application 1: Supporting Cytoarchitectonic Mapping with Deep Learning

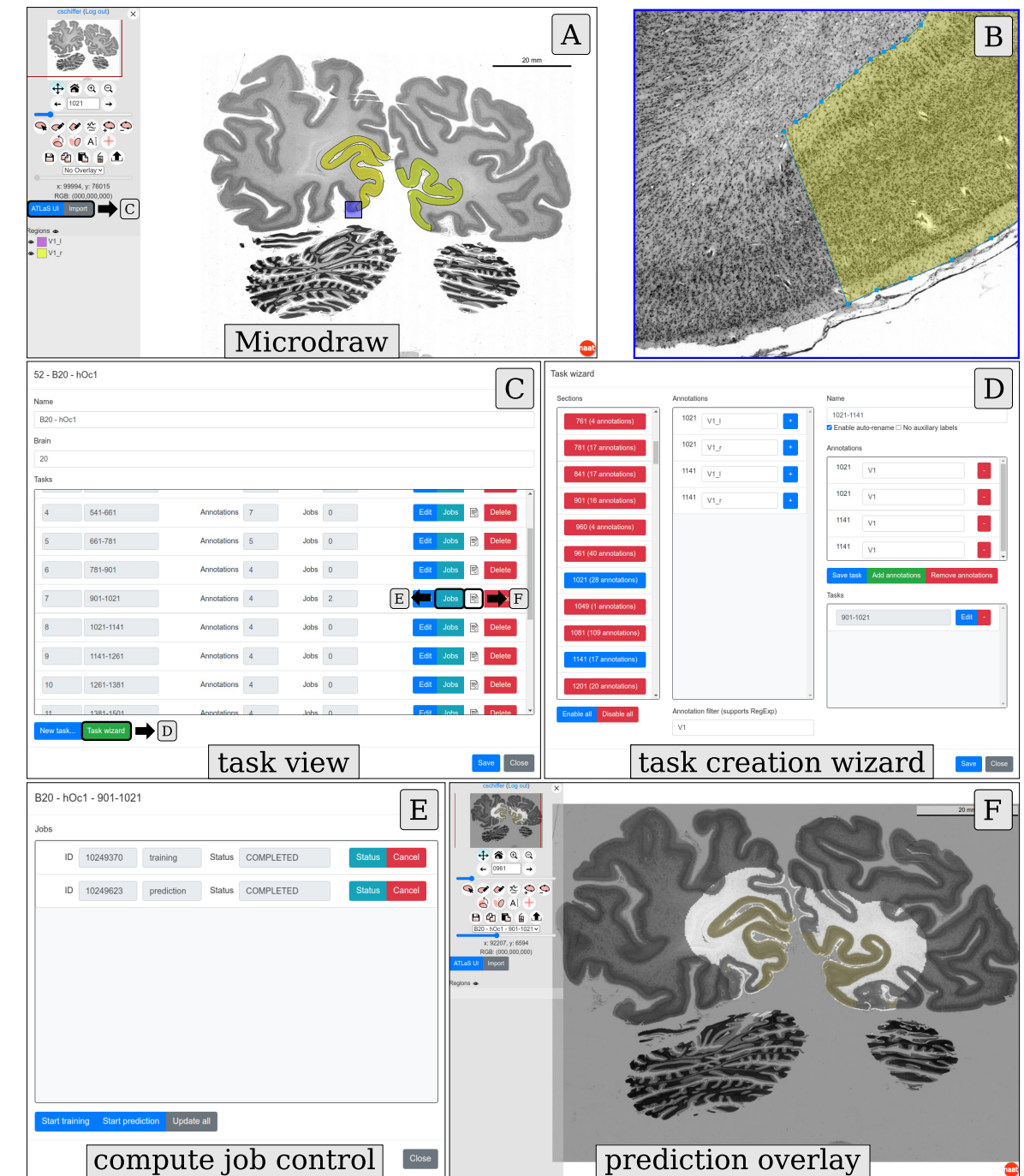
- **Goal:** Interactive workflow to support brain mapping
- **Idea:** Train specialized models using few annotations
  - Provide annotation on **every n-th** brain section
  - Train model on pairs of adjacent annotated sections
  - Apply model to **fill the gaps** between annotations
- **Web interface** for visualization, annotation, configuration





# Application 1: Computational requirements

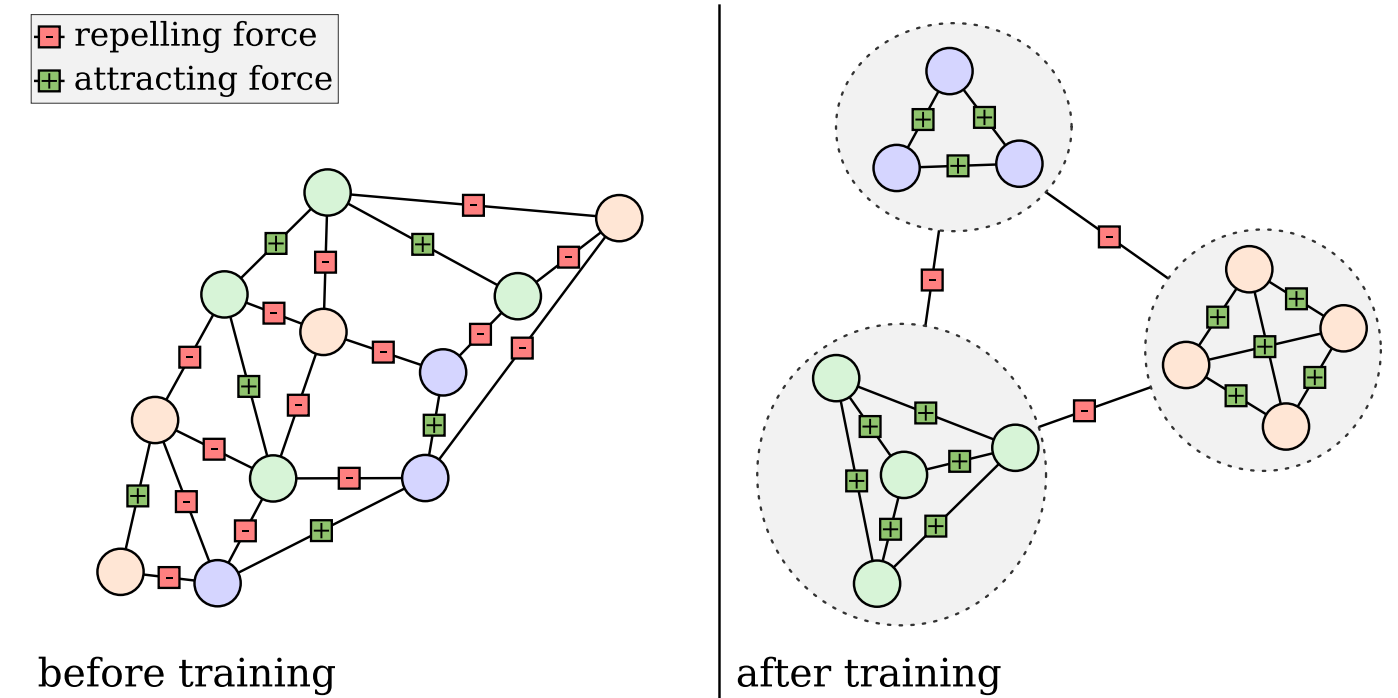
- Users define and submit **training** and **prediction** jobs
- Training and prediction on **JURECA-DC**, each job using...
  - Four **A100 GPUs** ( $4 \times 40\text{GB}$ )
  - **64 MPI ranks**, four threads per rank (256 total)
- Number of models depends on area size ( $\leq 20$ )
- **Runtime: 10-15min** → **Interactive use**





# Application 2: Contrastive Cytoarchitectonic Feature Learning at Large Scale

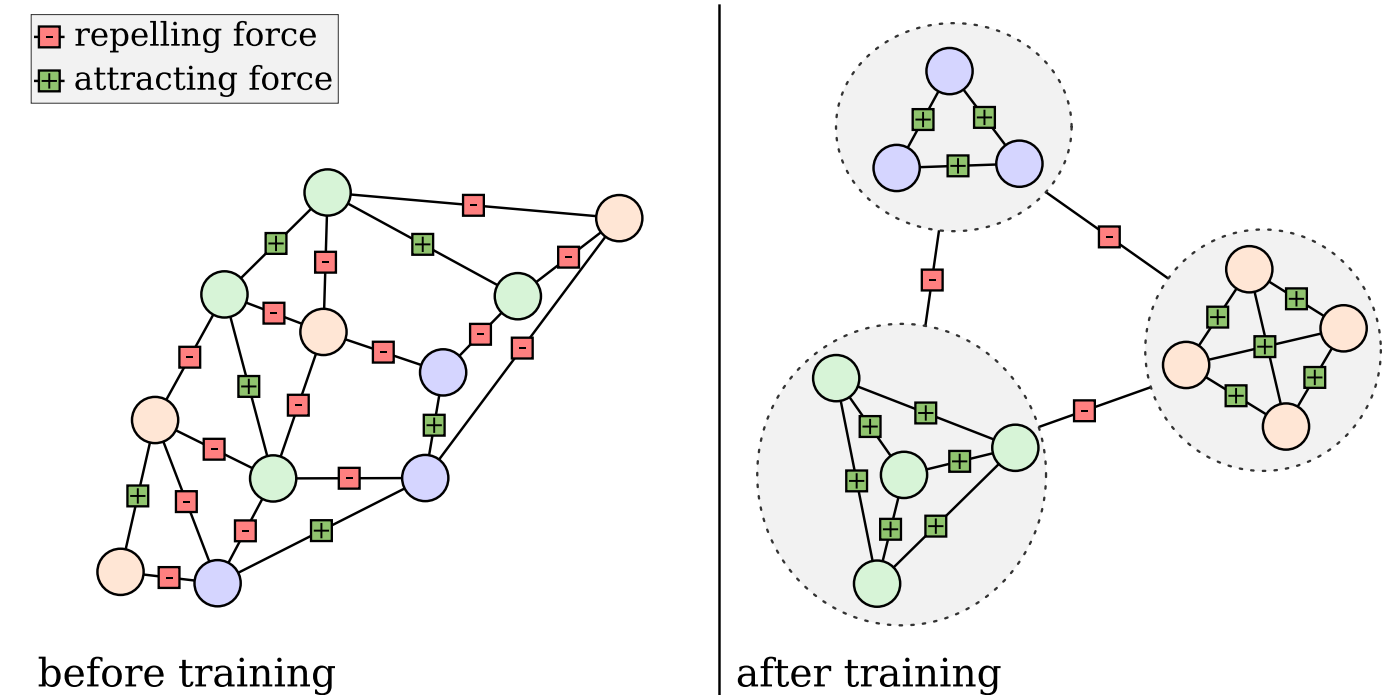
- **Goal:** General model for cytoarchitecture classification
- **Approach:** Contrastive learning
  - Learn features by **comparison**
  - Make features of **similar images** similar
  - Make features of **dissimilar images** *dissimilar*
- **Similarity** based on **labels** or **probabilities**
- Learned features enable **classification** and **clustering**





# Application 2: Computational requirements

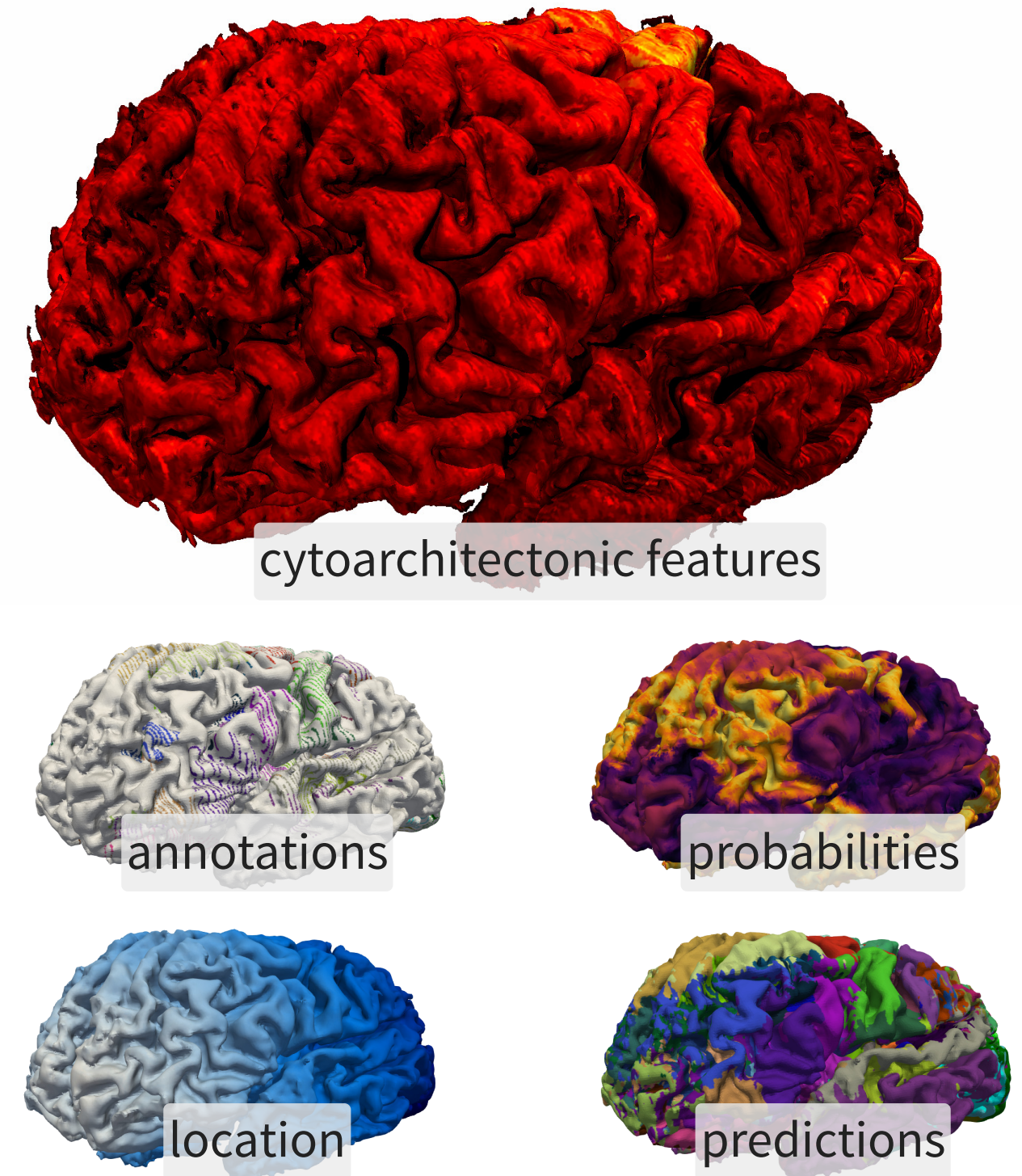
- **Challenge:** Large batch size for comparison
- Training on JURECA-DC
- **Contrastive training configuration**
  - 64 A100 GPUs (16 nodes)
  - 1024 MPI ranks, four threads per rank (4096 total)
  - 16 images per GPU (total GPU memory: 2.5 TB)
  - Total data read:  $\geq 155$  TB
  - Runtime:  $\geq 6$ h
- Methods using **more data** in development





# Application 3: Graph Neural Networks for Cytoarchitecture Classification

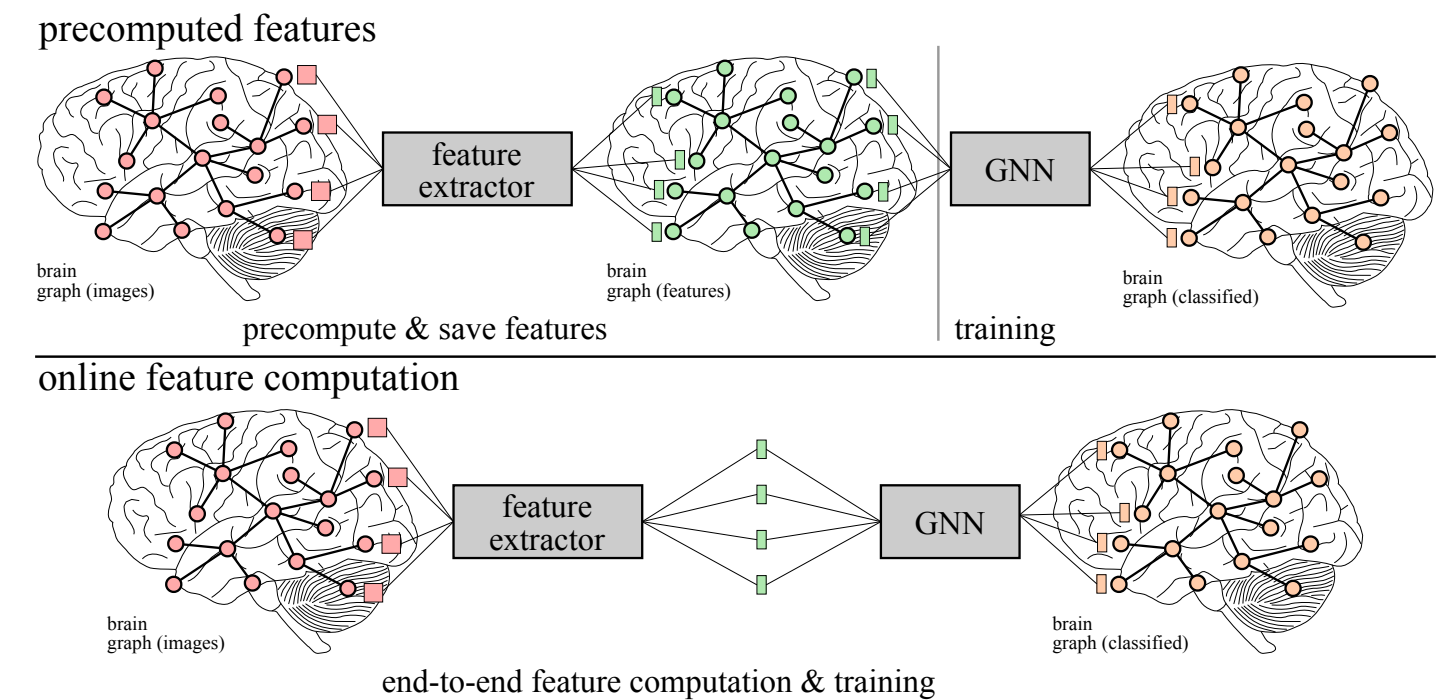
- Previously: Classify individual images
  - **Ill-defined:** Classification often requires context
  - Directly providing context (e.g., 3D) is **infeasible**
- **Idea:** Model brain as a graph
  - Coarse brain reconstruction to obtain a **mesh/graph**
  - Assign **image features** to graph nodes
  - Apply **graph neural networks (GNNs)** to classify nodes
- Improves performance by combining high-resolution **image features** with **context encoded in the graphs**





# Application 3: Computational requirements

- Currently: **Pre-computed features**
- Training on JURECA-DC
- **Graph neural network training configuration**
  - 8 A100 GPUs (2 nodes)
  - 128 MPI ranks, four threads per rank (256 total)
  - **Runtime: 20 - 120 min**
  - Pre-computed attributed graphs: **~60 GB**
- **End-to-end feature and graph learning in development**



# Future work

- Advanced feature learning methods
  - Use **non-annotated data** (self-supervised learning)
  - Compute requirements grow **linearly** with data
- **End-to-end feature and graph learning**
  - End-to-end learning
  - Enable **data augmentation** for robustness
  - Potentially combination with **contrastive learning**
  - **Challenge:** I/O and compute requirements **grow exponentially** with model depth

Christian Schiffer

Mail: [c.schiffer@fz-juelich.de](mailto:c.schiffer@fz-juelich.de)

Phone: +49 2461 61-3678

Team *Big Data Analytics*

Institute of Neuroscience and Medicine (INM-1)

Forschungszentrum Jülich

