Combining Probability-guided Contrastive Feature Learning and Graph Neural Networks for Cytoarchitecture Classification in the Human Brain

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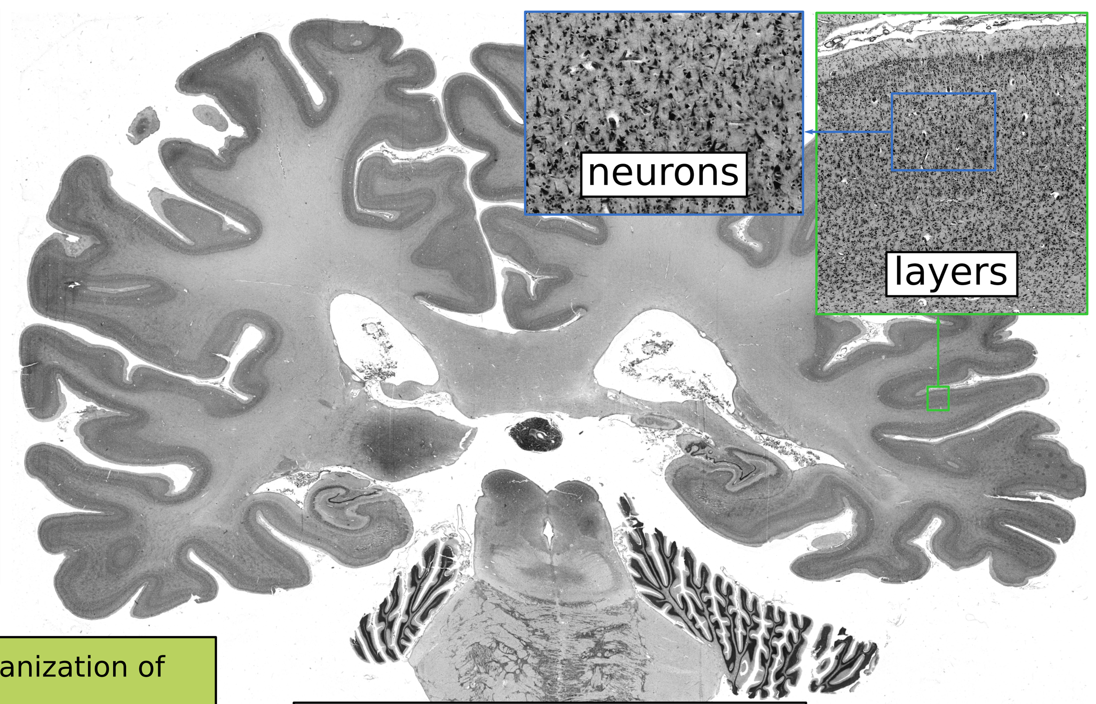
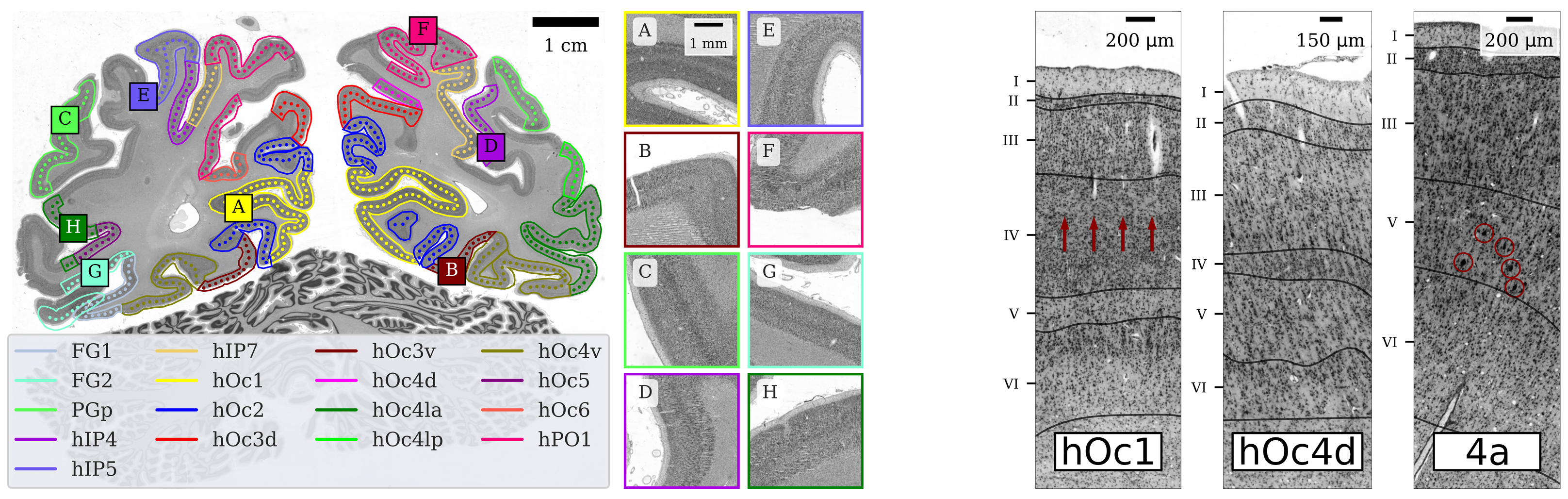
Histological Human Brain Sections

- **Postmortem** human brains
- Fixation in paraffine
- **Cut** into histological sections
  - 6000-8000 sections per brain
  - Thickness: 20µm
- Staining for **cell bodies**
- **Light-microscopic** imaging
  - Resolution: 1µm/pixel
  - up to 100'000 x 136'000 pixels
  - up to 15 GB per image



Goal: Study the microstructural organization of the human brain to understand its functions.

Cytoarchitectonic Brain Areas



- Areas defined by the spatial organization of neurons into **layers** and **columns**
- Indicators for **connectivity** and **function**
- Microstructural reference for **brain atlases** [1, 2]

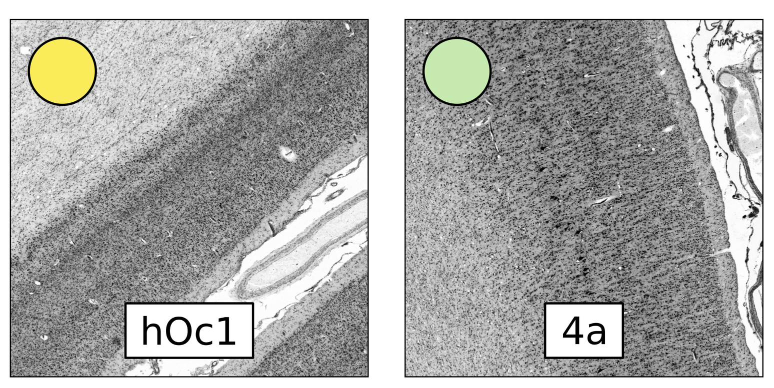
Goal: Automatically identify cytoarchitectonic areas using **deep learning** to enable large-scale analysis

Challenges: limited annotations; complex and ambiguous structures; multi-scale patterns; artifacts

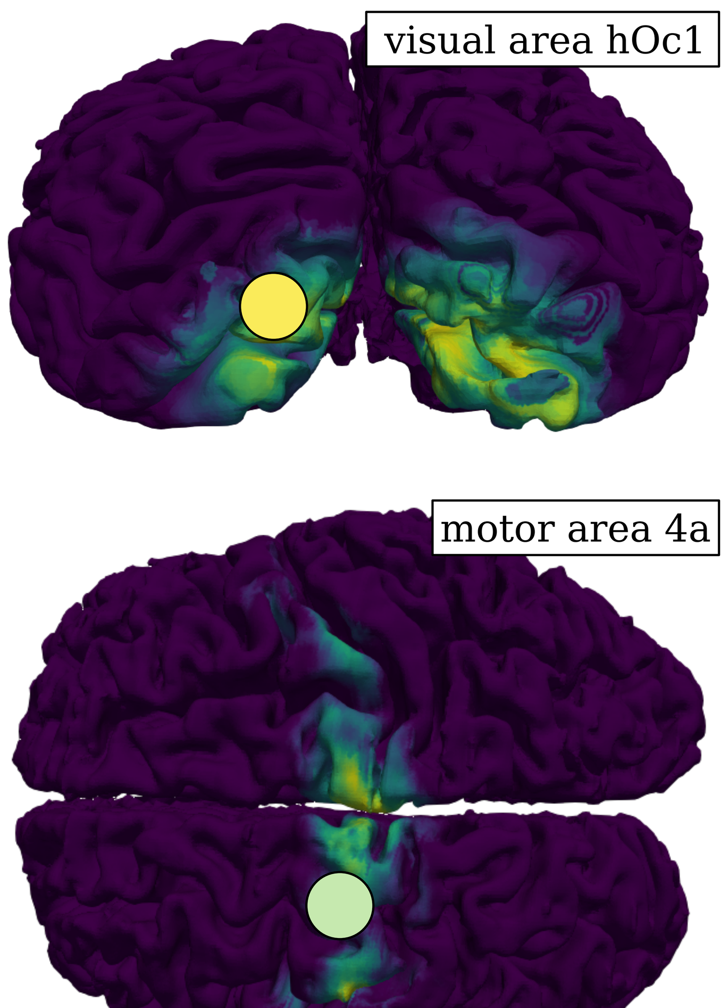
Probability-guided Contrastive Feature Learning

Idea: Train a neural network to map image patches from **similar brain areas** to **similar feature vectors**

Cytoarchitecture Learning



- Extract **image patches** from microscopic images
- Each image patch is associated with a discrete **probability vector** over cytoarchitectonic areas
- Probability vector indicates **how likely** a specific area occurs at a **specific location** in the brain
- Pairwise **similarity weight** is defined as cross-correlation between probability vectors
  - High correlation → similar area → **similar features**
  - Low correlation → different area → **diferent features**
- **Contrastive learning:** Learn by comparing image patches in a training batch [3]
- Learned features enable cytoarchitecture classification



Probabilistic maps from Julich-Brain [1] indicate the occurence probability of areas at different locations

Probabiliy-guided Contrastive Loss

feature vectors encoded by a neural network $z_i = f(X_i)$

$$\mathcal{L}_i = -\frac{1}{\sum_{j=1}^{N} \omega_{ij}} \sum_{j=1}^{N} \mathbb{I}_{i \neq j} \boxed{\omega_{ij}} \log \frac{\exp(\langle \boxed{z_i}, z_j \rangle / \tau)}{\sum_{k=1}^{N} \mathbb{I}_{i \neq k} \exp(\langle z_i, z_k \rangle / \tau)}$$

similarity weight between two probability vectors $\omega_{ij} = \langle p_i, p_j \rangle$

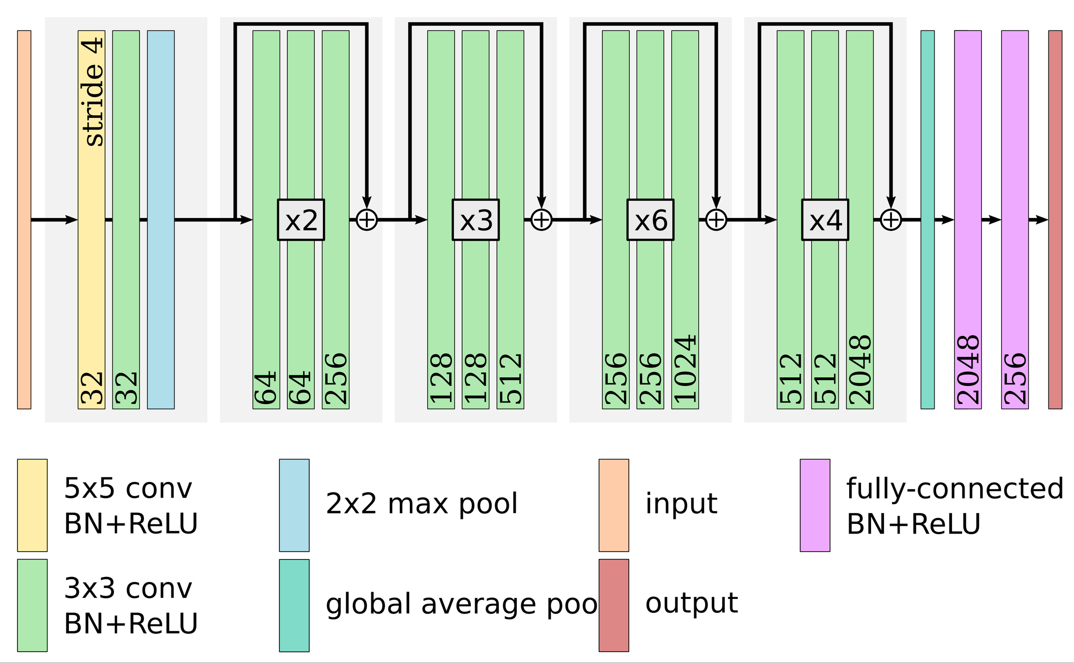
probability vector associated with an image patch $p_i \in \mathbb{R}^P$

number of image patches in a training batch N

image patch extracted from a microscopic brain scan X_i

temperature scaling parameter τ

Training & Neural Network Architecture



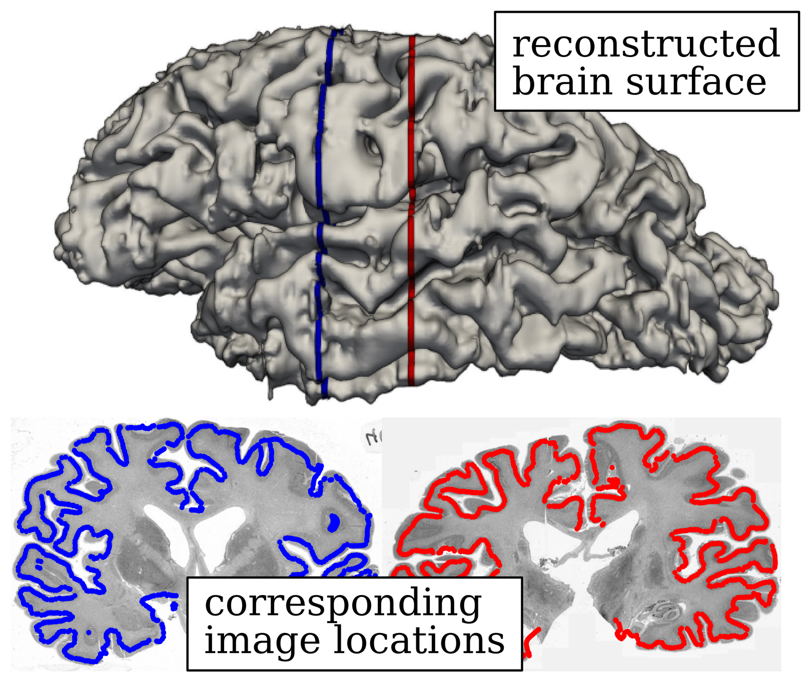
- Based on **ResNet50**
- **Custom head** to account for large input image size
- **Input size:** 2048px@2µm/px
- **Batch size:** 2048 images
- **Projection head** [3]
- 3679 brain sections (8 brains)
- **Hardware configuration**
  - **JURECA-DC** [4] (16 nodes)
  - **GPUs:** 64 NVidia A100
  - **Training time:** 18 hours

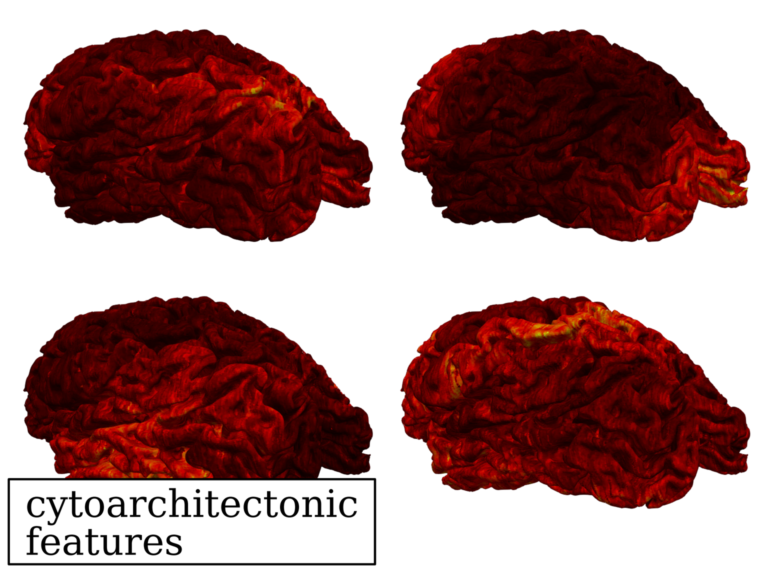
Graph Neural Networks for Cytoarchitecture Classification

Idea: Model cytoarchitecture classification as **graph node classification task** on approximate brain reconstructions

Graph-based Framework

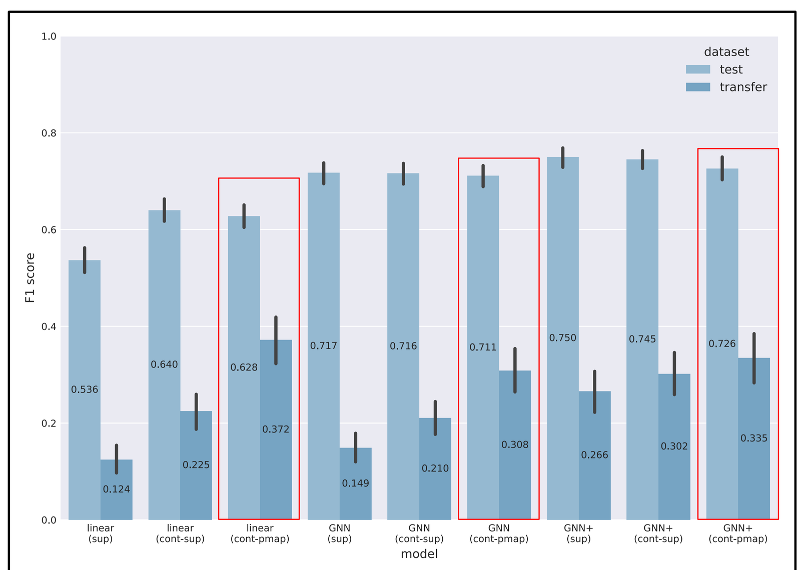
- Approximately reconstruct **brain surface meshes**
- Associate mesh nodes with **image locations**
- Compute **deep cytoarchitectonic features**
- Add **additional features** (location, probabilistic maps, annotations) to graph nodes
- Train **graph neural networks (GNNs)** to classify corresponding **cytoarchitectonic areas** for each node in the graph [5]
- GNNs combine local local **high-resolution image features** with **neighborhood information**





Training & Evaluation

- Training with **categorical cross-entropy** using available expert annotations
- 1860 sections from 7 brains (80% train, 20% test)
- 325 sections from 8th brain (transferability check)
- JURECA-DC [4] (2 nodes, 8 NVidia A100 GPUs)
- **Architecture:** Graph Attention (GAT) [6] (3 layers)
- **Input:** cytoarchitecture features, probability vectors, canonical spatial coordinates [5]
- Performance measurement using **macro-F1 score**



Macro F1-scores for known (test) and unknown (transfer) brains. **sup:** supervised; **cont-sup:** contrastive supervised [5]; **cont-pmap:** contrastive pmap; **linear:** linear classification; **GNN:** GNN w. cytoarchitecture features; **GNN+:** GNN w. cytoarchitecture features, pmaps, and coordinates.

Conclusion & Future Work

- **Probability-guided contrastive learning** enables learning of useful cytoarchitectonic features without annotated training data
- **Graph Neural Networks** efficiently integrate local features from high-resolution images with neighborhood information encoded in graphs
- **Future work**
  - **End-to-end** learning of image and graph features
  - **Cluster analysis** as basis for **data-driven brain parcellation** and knowledge discovery
  - Investigation of **limited transferability** to unseen brains

1. Amunts, K. et al. *Julich-Brain: A 3D probabilistic atlas of the human brain's cytoarchitecture.* Science 369 (2020).
2. Amunts, K. & Zilles, K. *Architectonic Mapping of the Human Brain beyond Brodmann.* Neuron 88 (2015).
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4. Thörnig, P., *JURECA: Data Centric and Booster Modules implementing the Modular Supercomputing Architecture at Jülich Supercomputing Centre.* JLSRF 7 (2021)
5. Schiffer, C. et al. *2D Histology Meets 3D Topology: Cytoarchitectonic Brain Mapping with Graph Neural Networks.* MICCAI (2021)
6. Veličković, P. *Graph Attention Networks*, arXiv:1710.10903 (2018)

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