# TOWARDS A DEEP LEARNING APPROACH TO BRAIN PARCELLATION

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## Introduction

**Problem**
Establishing correspondences across structural and functional brain images via labeling, or parcellation, is an important and challenging task for clinical neuroscience and cognitive psychology.

Limitations of existing approaches are that they i) possess shallow architectures, ii) are based on heuristic manual feature engineering, and iii) assume the validity of the designed feature model.

**Objective**
We advocate a deep learning and inference approach to automate brain parcellation.

**Approach**
We present a novel application of convolutional networks to build discriminative features for brain parcellation, which are automatically learned from labels provided by human experts.

## Methods

### The convolutional network architecture

Convolutional networks (CN) belong to the class of artificial cortical network models and are an extension of the classical multi-layer perceptrons (MLPs) model.

They consist of a multi-layer hierarchical architecture of feature maps as depicted in Fig. 1.

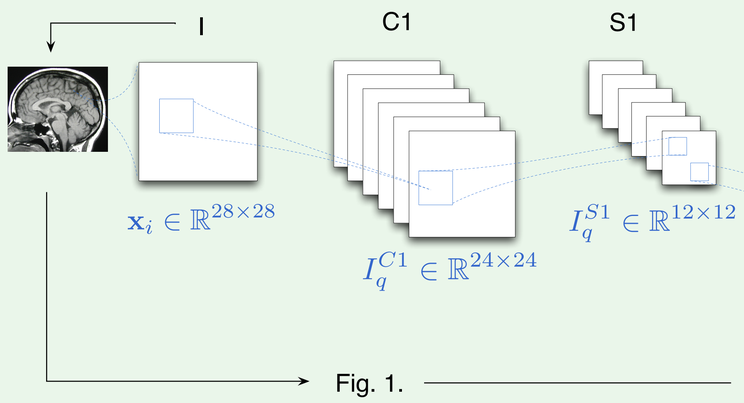


Fig. 1.

I = Input
C1 = Convolution layer 1
S1 = Subsampling layer 1
F = Full connection layer
O = Output layer

The learned model $\theta = \{w, b\}$ includes convolutional operators w and bias term b, which in combination with a nonlinear activation function $\gamma$ (e.g. sigmoid or hyperbolic tangent), form so-called "activity feature maps" $I_q^k$, where k indexes a CN layer and q a particular feature map of layer k.

### Deep learning and inference

The general learning and inference scheme consists of the following steps

1. Forward propagation
2. Compute error
3. Backward propagation
4. Compute gradient

Iterate until certain error criterion reached

The feature maps in each convolutional layer (C1, C2) are computed through a recursive forward dynamic of the form

$$\mathbf{I}_q^k = \gamma(\mathbf{u}_q^k)$$

$$\mathbf{u}_q^k = b_q^k + (\sum_p \mathbf{w}_{q,p}^k \otimes \mathbf{I}_p^{k-1})$$

where $\gamma$ denotes a smooth nonlinearity to ensure differentiability, $\mathbf{u}_q^k$ a pre-activation image, $\mathbf{I}_p^{k-1}$ the feature image at layer k – 1, $\mathbf{w}_{q,p}^k$ a directed convolution kernel from map p to q, and $b_q^k$ a bias term.

Given a deep CN model and training data (xi,y), we automatically learn discriminative features of parcellation units by solving an optimization problem via recursive error back-propagation.

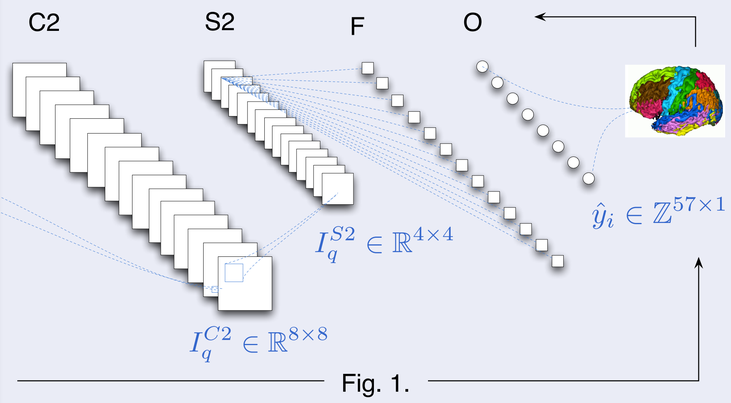


Fig. 1.

### Context-aware feature learning

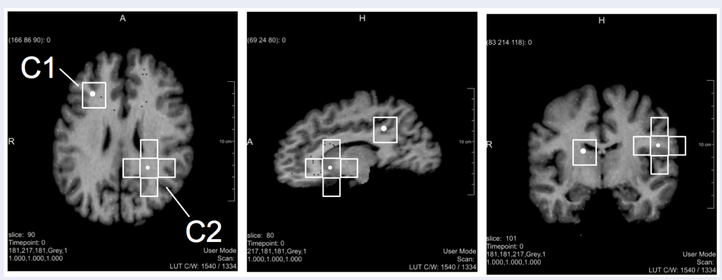


Fig. 2.

We built two different kinds of context-aware feature configurations. For each voxel we considered a large neighborhood of surrounding image data, providing discriminative contextual information to determine the class label in a given location.

## Experiments & Results

We used 40 brain images and their labels (56 structures + background) from the LONI Probabilistic Brain Atlas (LPBA40).

We performed two sets of experiments to assess the performance of our approach using feature configuration C1 and C2. 25,000 random patches from subject 1 within a central slice were used for model training and validation (50:50). Testing was performed for the remaining subjects. The table below shows the parcellation performance when using C1 in terms of the sensitivity and specificity for 4 subjects. Using feature configuration C2 did not yield performance improvements.

| | Subject 4 | Subject 13 | Subject 39 | Subject 2 |
|---|---|---|---|---|
| Sensitivity | 0.9836 | 0.9723 | 0.9786 | 0.9609 |
| Specificity | 0.9386 | 0.8475 | 0.9135 | 0.7791 |

Human labels vs machine predicted labels

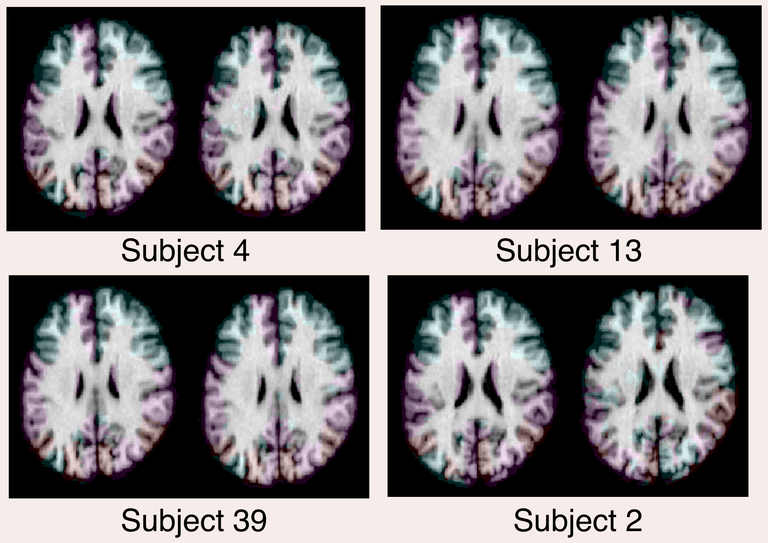


Fig. 3.

## Conclusion

We were able to demonstrate parcellation of the cerebral cortex, without human intervention to build handcrafted features or to provide other prior knowledge. Given the limited training data it is remarkable how well the CN model is able to learn discriminative features from parcellation labels provided by human experts.

## Acknowledgements

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## References

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