NX-414 Mini project

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I. Introduction

A better understanding of the brain visual processing can be achieved by building artificial models that match how the brain works, which in turn also helps building better models. This project aims at predicting the activity of IT neurons from images that were presented to monkeys.

Data was derived from *Majaj et al. Journal of Neuroscience 2015* and consists of 2592 pictures and 168 activity profiles of neurons recorded in IT.

II. Part 1

At first, the prediction was made in the simplest **data driven** way by predicting the neural activity from the pixels. The prediction was made using an either unregularized or regularized (lasso, ridge, elastic net) linear regression on the first 1000 principal components of each image. This methods only tries to fit the pixels to the neural activity which is far from what the brain actually does, and is in turn reflected in the poor results.

Moving on to a better suited **task driven** approach, images were passed into a Resnet50 network pre-trained for image classification. The activation of certain of its layers was used to predict the IT neurons' activity through PC extraction and the same models as before.

The most relevant results can be found in Table I, all other results, graph and parameters can be found in the first notebook.

III. Part 2

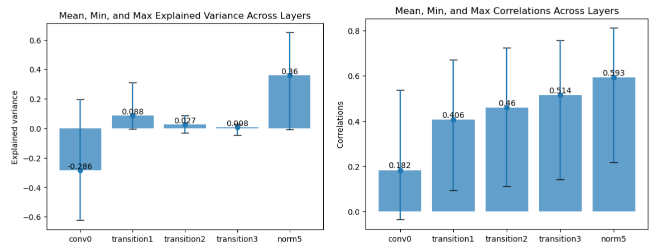
Another **data driven** approach was implemented by training a simple convolutional neural network to predict the neuronal activity from the images. The CNN is composed of two convolution-pooling layers and a linear output layer. Results are shown in Table I, all parameters and histograms can be seen in the second notebook.

The obtained results are better that the **data driven** approach of II because the convolution is able to extract relevant features from the pixel activation. However they are not satisfying enough and **task driven** approaches seem to suit the task better.

IV. Part 3

In accordance with previous results, it was decided to further explore the **task driven** approach from before through another neural network trained for object recognition. Motivated by the presentation of *Schrimpf et al. Neuron 2020* during the course, the Densenet169 network was chosen as it achieves the highest brain score, and better performances are expected for predicting neural activity on networks that are more "brain-like". Similar to II, the images were passed through a pre-trained Densenet169 network, the first 1000 PCs were extracted from the activation of some layers and passed through a linear model to predict the IT neurons' activity. Explained variance and correlations of the predictions for each layer and each linear model in V. Alternatively, more work was done to build a deeper and more complex CNN than the one from III but this yielded less good results which are not presented here.

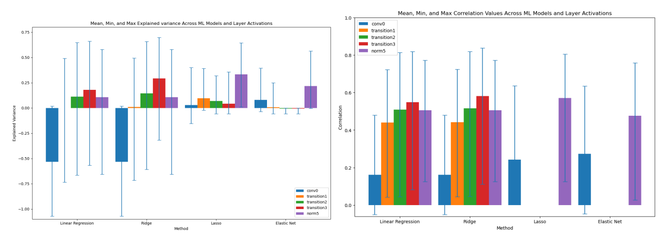
V. Results



(a) Explained variance

(b) Correlations

Figure 1: Performance across layers using Densenet-169 and a layer specifically tuned Ridge regression



(a) Explained variance

(b) Correlations

Figure 2: Performance across layers and models for Densenet-169 : Mean, Min and Max

Model	Mean correlation	Mean EV
II Linear Regression - Ridge	0.22	-0.08
II Resnet50 - Lasso - layer2	0.54	0.30
III Simple CNN	0.40	0.16
IV Densenet169 - Ridge - norm5 layer	0.59	0.36

Table I: Summary of relevant results for each model

VI. Conclusion

From 1a and 1b it is clear that using the activation of deep layers of neural network trained for object recognition works best to predict the activity of IT neurons. These results are aligned with findings from *Zhuang et al. PNAS 2020* who found that activation of deeper layers correlates better with neurons recording of higher visual brain areas. As stated in the data specs, the multi-electrodes array did not only cover the IT region of the brain but also V4, furthermore, the electrodes sites were mostly recording multi-unit activity and not single units, leading to a spatial smoothing of the signal and loss of relevant data.

Better results could be achieved by using more accurate brain-like neural networks trained for object recognition, but also by improving the neurons' recording.