Brain-like computation and intelligence

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This project's aim was to predict neural activity resulting from the vision of a labelled image during an object recognition task in non-human primates. The dataset consists of 2592 images (with each three-channel - RGB) and the corresponding average firing rate (between 70 and 170 ms) of 168 neurons located in the inferior temporal (IT) cortex.

At first, linear regression models that predict neural activity from pixels were investigated. The data were flattened and normalised, then given as input in a ridge regression model and least square regression model (Skylearn library). Yielded results were similar, with an average Correlation (Corr) of 0.17 and an average Explained Variance (EV) of -0.93. As expected, the results are quite bad, as predicting from pixels is very difficult. To avoid overfitting, the first 1000 principal components (PC) were computed with a Principal component analysis (PCA) to obtain Corr of 0.22, and EV of -0.07. Cross-validation (CV) was run for the ridge model to optimize the alpha parameter. The best results were found with an alpha of 463636 and a score of 0.073, with Corr of 0.28 and EV of 0.09. Results across all neurons are plotted in Fig. 1. It is important to notice that a negative EV suggest that the prediction is poorer than a model that would return the mean value of the activities. The cross-validation slightly improves the result but with really high alpha, resulting in a prediction around the mean which is not very informative.

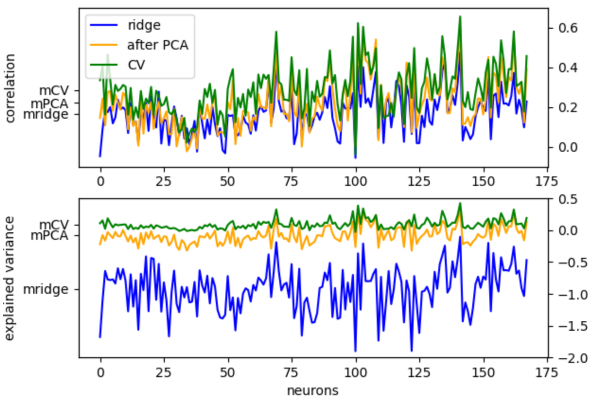

Fig. 1: Linear Model Evaluation before and after PCA, and with crossvalidation

As the linear model did not yield satisfactory results, a task-driven modelling approach was tested. The underlying hypothesis is that training the network to perform a relevant behavioural task leads it to develop a similar pattern of activation to the ones of the biological brain. A pre-trained ResNet50 was loaded and fed with our images. Activation layers were then extracted (conv1, layer 1-4, and avgpool) for the train and validation dataset, and the corresponding first 1000 PCs were computed. We use the precedent ridge linear model to predict neural activities (no CV). Results are significantly better than with a simple linear model which is supporting evidence for the above-stated hypothesis. Performance in order of depth is visualized in Fig. 2.

As expected, the deeper, the more specific the detected features become. Therefore the EV grows until layer 3 while going down in the next layer where specificity becomes too high. We obtain an EV of 0.382 and a Corr of 0.608. The results obtained were compared with the ones from a randomly initialized model. While it performed relatively well for layer 1, EV of 0.446 and Corr of 0.204, the performance then continuously decreased and end the worth.

For the second part, a neural network was trained and optimized in a data-driven approach. A basic shallow neural network with one convolutional layer and two linear layers with Relu activation was chosen as a basis. Learning rates between [0.001 and 0.1] were tried, as well as Adam and stochastic gradient descent (SGD) optimizer. The best results were found with a learning rate of 0.05 and SGD, which yielded a loss of 0.1170. Using tanh instead of Relu improved a bit the result up to a loss of 0.1152. Adding a convolutional layer led to a similar performance. Corr and EV of the best model are plotted in Fig. 3, with a mean Corr of 0.41 and mean

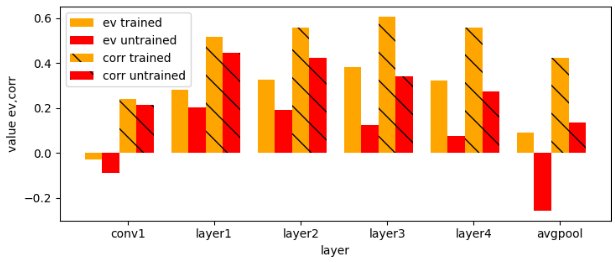

Fig. 2: mean of explained variance and correlation across layers in pre-trained and untrained ResNet50

EV of 0.18, which is worse than the results obtained by the task-driven model.

Another more complex network was designed to mimic brain circuitry, with three convolutional layers that have small kernel size (representing the limited receptive field of each neuron in the lower visual brain fields), normalization and dropout layer (to avoid overfitting and represent the coding sparsity observed in brains) was tried, but it only led to worse results around 0.13. Normalization of the images only led to worse results.

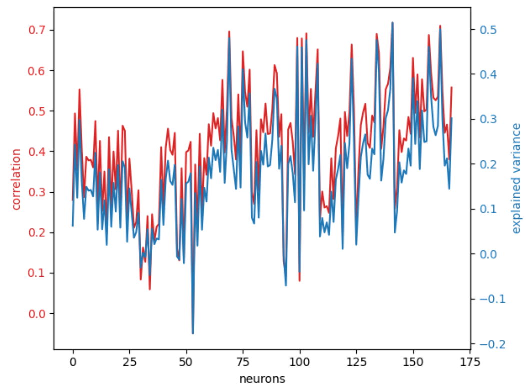

Fig. 3: Correlation and explained Variance for each neuron activity for NN

Research

We tried other pre-trained models in object recognition to compare the results with the ResNet50. VOneNetCornets, for example, is a neural network with an architecture constructed as a model of the ventral pathway of the brain, activated during object recognition. As it has been specifically constructed in a brain-architecture-orientated way, we had much hope of it raising the best results but failed of making it work properly in time. Other popular pre-trained networks were tried, such as densenet169, Inception-v3, MobileNet (small and large) and AlexNet. First, we notice good results with AlexNet in a surprisingly short running time. Finally, we obtain the best result with Inception-v3 on layer Mixed_6d, with EV = 0.409 and Corr = 0.630. All results are plotted in Fig. 4.

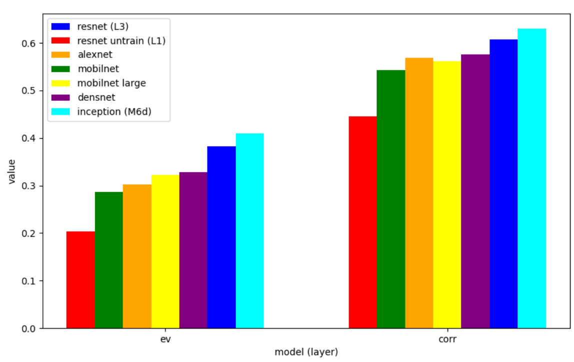

Fig. 4: Result of exploration with pre-trained models