Net2Brain: A Toolbox to compare artificial vision models with human brain responses

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Abstract

We introduce Net2Brain, a graphical and command-line user interface toolbox for comparing the representational spaces of artificial deep neural networks (DNNs) and human brain recordings. While different toolboxes facilitate only single functionalities or only focus on a small subset of supervised image classification models, Net2Brain allows the extraction of activations of more than 600 DNNs trained to perform a diverse range of vision-related tasks (e.g. semantic segmentation, depth estimation, action recognition, etc.), over both image and video datasets. The toolbox computes the representational dissimilarity matrices (RDMs) over those activations and compares them to brain recordings using representational similarity analysis (RSA), weighted RSA, both in specific ROIs and with searchlight search. In addition, it is possible to add a new data set of stimuli and brain recordings to the toolbox for evaluation. We demonstrate the functionality and advantages of Net2Brain with an example showcasing how it can be used to test hypotheses of cognitive computational neuroscience.

Keywords: Toolbox; DNN; CNN; ViT; RSA; fMRI; MEG; Searchlight Analysis

Introduction

Several studies have demonstrated the potential of DNNs to serve as state-of-the-art computational models of the primate visual cortex (Cadieu et al., 2014; Khaligh-Razavi & Kriegeskorte, 2014; Yamins et al., 2014; Guclu & van Gerven, 2015; Cichy, Khosla, Pantazis, Torralba, & Oliva, 2016). In the last decade, DNNs trained to perform visual tasks have successfully been able to resemble, predict and explain neural activity in the visual cortex. Different implementations of these models (varying, for example, their architecture, objective function, or training algorithm) have been compared to uncover the computational principles, algorithms and neurobiological mechanisms behind visual processing (Richards, 2019).

To promote this line of research, new benchmarks, datasets, and challenges relevant to cognitive neuroscience experiments have been developed (Cichy, Roig, Andonian, et al., 2019; Cichy, Roig, & Oliva, 2019; Cichy et al., 2021; Schrimpf et al., 2018). However, to fully take advantage of these models and frameworks, a toolbox for efficiently comparing the representational spaces of state-of-the-art DNNs and brain responses is needed. Some toolboxes have been developed to facilitate the use of DNNs, however, they tend to focus only on a small subset of supervised image classification models, even though studies have shown that DNNs trained for different tasks can also help to provide new information about the visual cortex (Tang, LeBel, & Huth, 2021; Dwivedi, Bonner, Cichy, & Roig, 2021).

We, therefore, introduce Net2Brain, an easy-to-use toolbox that allows neuroscientists to efficiently incorporate over 600 DNN trained for different objective functions, datasets, etc, into their research. We opensource it to promote its continual growth over time.

Related Work

In the past, deep learning models have been adopted across scientific fields to answer domain-specific questions (Raghu & Schmidt, 2020). This was greatly facilitated by open-source software that allows the straightforward usage and development of DNNs, such as PyTorch (Paszke et al., 2019), TensorFlow (Abadi et al., 2015), Caffe (Jia et al., 2014) and Keras (Chollet et al., 2015). With such a variety of libraries at hand and the increasing use of deep learning models in neu-
In the last few years, the field of deep learning has shown that DNNs trained on multi-sensory input, which are capable of creating multimodal representations, achieve better generalization and overall performance. In this context, much debate exists in the field of cognitive neuroscience on the multimodal nature of cortical representations, and the idea that brain areas higher up in the hierarchy might need to encode these types of representations for carrying out more abstract computations (Tang et al., 2021). Combining both fields, this hypothesis could be tested by analyzing if brain representation is more similar to multimodal DNNs than unimodal ones.

As an exploratory work, we used Net2Brain to compare the responses of the multimodal CLIP-ResNet50 and CLIP-ViT-B/32, a self-supervised DNN trained on image-text pairs (Radford et al., 2021), with its unimodal counterparts ResNet50 and ViT-B/32, which are supervised DNN trained to perform object recognition on Imagenet, to human functional magnetic resonance imaging (fMRI) recordings from the dataset by Michael F. Bonner et al. (Bonner & Epstein, 2017).

As illustrated in Fig.1, we found that the multimodal CLIP-ResNet50 has significantly better predictability of the regions of interest (ROIs), which are displayed in Fig. 2, than its unimodal counterpart ResNet50 throughout all presented layers. This can be seen as a prelude toward research that argues whether the inclusion of captions allows encoding spatial relations and how other modalities could improve predictability.

Another pattern that can be observed is that although CLIP-ViT and normal ViT behave similarly, they both have better predictability of the regions than ResNet50. This invites to delve deeper into exploring regions of the brain using other DNNs rather than CNNs, and having different architectures to help understand the structure of the visual cortex.

In sum, Net2Brain facilitates investigating correlations between...
Figure 1: Prediction of brain responses using multimodal DNNs vs their unimodal counterparts in the ROIs in Fig. 2 and a table displaying the layers with the highest correlation. The range from lower to upper noise ceiling is indicated by the gray box and the asterisk above the bars indicates the significance of the calculated data. The error bar represents the standard error across subjects.

Figure 2: Cortical overlay showing locations of cortical regions from the probabilistic atlas used in Fig. 1. 

Conclusion

We have introduced Net2Brain, a toolbox for comparing the responses of artificial neural networks and the human visual cortex using representation similarity analysis. Our toolbox facilitates the adoption of DNNs in cognitive neuroscience research, lowers the knowledge barrier for newcomers that want to implement these tools, and provides users the flexibility to carry out these analyses using their computational models and brain datasets. We have also demonstrated the simplicity of using Net2Brain for testing a hypothesis from cognitive computational neuroscience. In the future, the toolbox will include more brain datasets and functions for carrying out common analyses in neuroscience research, such as variance partitioning analysis and encoding models.

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