Learning pipeline-independent statistic maps in fMRI

Master 2 internship - 2019

Supervisors

Elisa Fromont, Professor at University of Rennes 1, LACODAM team
elisa.fromont@inria.fr, http://people.irisa.fr/Elisa.Fromont/

Camille Maumet, Research scientist at Inria, VisAGeS team
camille.maumet@inria.fr, http://camillemaumet.com

Location: Rennes - Inria / IRISA

Duration: 4-6 months

Keywords
Unsupervised Deep learning, Metric Learning, Brain imaging, Statistics, fMRI, Pipelines

Context
Researchers and clinicians use functional Magnetic Resonance Imaging (fMRI) to identify which parts of the brain activate when performing a task. fMRI results are represented as 3D images called 'activation map' in which active areas are highlighted and inactive areas are removed (cf. Fig. 1).

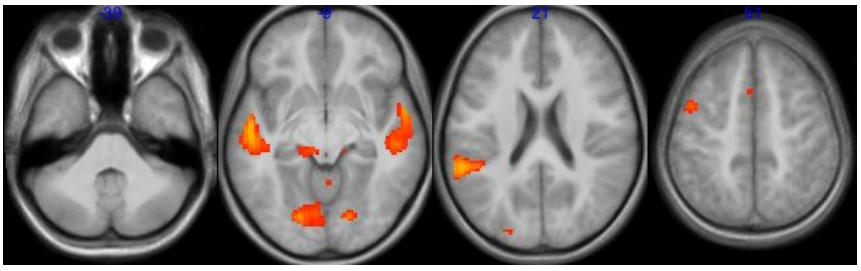

Fig. 1 Example of fMRI activation map for a language task

Researchers process fMRI through an imaging pipeline to transform the raw data supplied by the MRI machine into the final 'activation map'. Each pipeline include: pre-processing steps to clean up the data (e.g. correct for motion, register to a reference space) and a statistical analysis to extract the areas of significant activation.

Many variations on the fMRI pipeline are possible; leading to a huge results space. Parameters that can vary across pipelines include: the type of brain imaging software, the type of method for each step, the parameters used for each algorithm, etc. A brain region can be declared as active with one pipeline and as inactive with another pipeline leading to possible confusions.

The goal of this internship is to eliminate pipeline-induced variations and create pipeline-independent fMRI statistic maps using machine learning.

Detailed description
Deep learning approaches are data-intensive methods that learn unknown structure from the data. Variants of such networks such as autoencoders or generative adversarial networks have been designed to learn latent representation of the data in an unsupervised setting. To learn a representation invariant to the fMRI pipeline, we believe that pair-based or triplet-based metric learning techniques could also be used in conjunction with these unsupervised representation learning approaches (see. (Schroff, Kalenichenko, and Philbin 2015; Mohammadi and Kain 2017; Bhattarai, Sharma, and Jurie 2016)). Applications to the domain of brain imaging (e.g. (Richard et al. 2018)) are still limited in part due to small sample sizes (Poldrack et al. 2017).

In this work, you will take advantage of the largest database of fMRI statistic map: NeuroVault (Gorgolewski et al. 2015) to build an encoder (GAN, autoencoder, …) that will provide a representation of the fMRI statistics in a lower dimensional space.

In a second step, you will take advantage of data from previous work (Bowring, Maumet, and Nichols 2018) with 3 pipelines on 3 fMRI datasets (total of 180 images) to build siamese autoencoders that will generate pipeline-independent fMRI maps.

Required skills

- Some knowledge about computer vision
- Interest in medical imaging
- Interest (even better knowledge) in machine learning in general and deep learning particular
- Good programming skills in Python (for Keras)
- Very good understanding of English

References

Bhattarai, B., G. Sharma, and F. Jurie. 2016. “CP-mtML: Coupled Projection Multi-Task Metric Learning for Large Scale Face Retrieval.” In 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 4226–35.

Bowring, Alexander, Camille Maumet, and Thomas Nichols. 2018. “Exploring the Impact of Analysis Software on Task fMRI Results.” bioRxiv. https://doi.org/10.1101/285585.

Gorgolewski, Krzysztof J., Gael Varoquaux, Gabriel Rivera, Yannick Schwarz, Satrajit S. Ghosh, Camille Maumet, Vanessa V. Sochat, et al. 2015. “NeuroVault.org: A Web-Based Repository for Collecting and Sharing Unthresholded Statistical Maps of the Human Brain.” Frontiers in Neuroinformatics 9 (8). https://doi.org/10.3389/fninf.2015.00008.

Mohammadi, Seyed Hamidreza, and Alexander Kain. 2017. “Siamese Autoencoders for Speech Style Extraction and Switching Applied to Voice Identification and Conversion.” In Interspeech 2017, 1293–97. ISCA: ISCA.

Poldrack, Russell A., Chris I. Baker, Joke Durnez, Krzysztof J. Gorgolewski, Paul M. Matthews, Marcus R. Munafò, Thomas E. Nichols, Jean-Baptiste Poline, Edward Vul, and Tal Yarkoni. 2017. “Scanning the Horizon: Towards Transparent and Reproducible Neuroimaging Research.” Nature Reviews. Neuroscience, January. https://doi.org/10.1038/nrn.2016.167.

Richard, Hugo, Ana Pinho, Bertrand Thirion, and Guillaume Charpiat. 2018. “Optimizing Deep Video Representation to Match Brain Activity.” In CCN 2018 - Conference on Cognitive Computational Neuroscience. https://hal.archives-ouvertes.fr/hal-01868735.

Schroff, F., D. Kalenichenko, and J. Philbin. 2015. “FaceNet: A Unified Embedding for Face Recognition and Clustering.” In 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 815–23.