Learning pipeline-independent statistic maps in fMRI

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Location

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Keywords

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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).
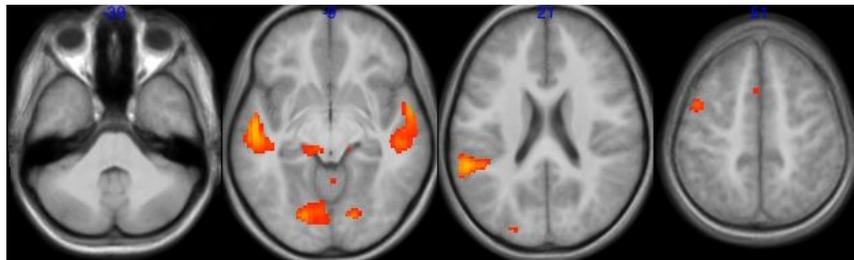

Fig. 1 Example of fMRI activation map for a language task

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

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