# Master student training course

## Unsupervised deep feature learning. Application to epilepsy mapping in multiparametric MRI.

Supervisor : Carole Lartizien
Team : 'images et modèles'
https://www.creatis.insa-lyon.fr/~lartizien

Location : laboratoire CREATIS, Bat Blaise Pascal, campus de la Doua, Villeurbanne

Contact : carole.lartizien@creatis.insa-lyon.fr

**Key-words: machine learning, deep learning, generative adversarial networks (GAN), medical imaging**

**Scientific context:**
In recent years, machine learning has received a lot of attention to explore and structure multidimensional and multi-modality medical imaging data for the purpose of image segmentation, registration or automated detection and characterization of pathology. Among the machine learning tools, deep learning is one approach that is currently focusing increasing attention, since it has been recently shown to outperform traditional approaches in most of the applications cited above.

Deep networks consist of an input layer (that usually consists of the image) and an output layer as well as multiple connected layers of nonlinear processing units. Each successive layer uses the output from the previous layer as input, so that higher level features are derived from lower level features to form a hierarchical representation. The network main architecture defined by the user (including the number of layers) determines a set of learnable parameters which are adapted based on the minimisation of a predefined cost function over the learning data set. The output layer and cost function are defined based on the task at hand.

The vast majority of tasks that have been studied so far, in particular with convolutional networks (as illustrated in fig. 1), are supervised, meaning that the last layer of the network is a classification or regression layer. Training is thus performed on samples consisting of couples of input (image) and output (label for classification or continuous value for regression) values.

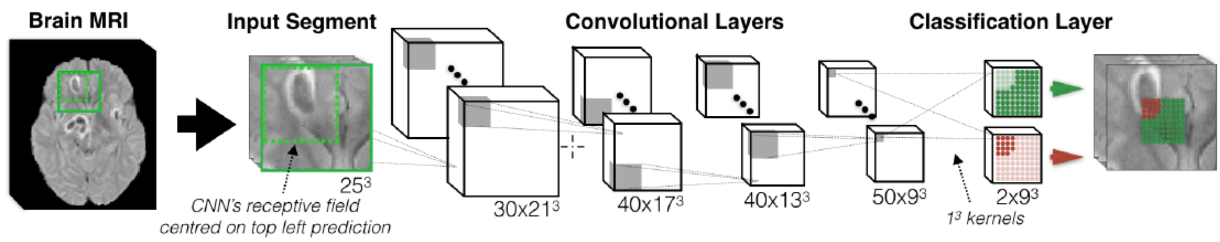


**Figure 1**. Illustrative deep convolutional neural network for the automatic segmentation of brain MRI tumors. The classification layer performs attributes a binary label to each voxel : red = tumor, green =normal tissue. from [Kamnitsas,MEDIA 2017]

As an example, a deep network whose aim is to segment the different structures of the brain (white matter, grey matter..) will require to build an annotated training database where each structure of interest (ie one wants to segment) has been labelled in the image. Even if patient scans can easily be labelled as pathological at the image level, access to this ground truth at the voxel level is very limited since it is based on the consensus manual annotations of clinical experts which are very time and effort demanding.

One alternative to the lack of labelled data is to learn unsupervised representation models, as done by autoencoders for instance, whose cost function consists of the reconstruction error between the input and output units. The advantage of such systems is thus that they don't require any labelled data and can learn feature learning that are not tuned to any particular task. They however may lack of sensitivity to capture the most discriminative features for a specific task.

This topic has been poorly explored in the domain of medical imaging. We recently developed such an approach for neuroimaging applications. We indeed propose to learn efficient unsupervised representations from patches extracted from MR brain acquisitions of normal subjects (see fig.2 (right)) based on a siamese network architecture [Alaverdyan et al,  2016]. This latent representation then serves as input to an outlier detection algorithm to detect epileptogenic lesions in multiparametric brain MR imaging [Alaverdyan et al, 2017]. Promising results were achieved with such architecture as illustrated in fig.2 (left).

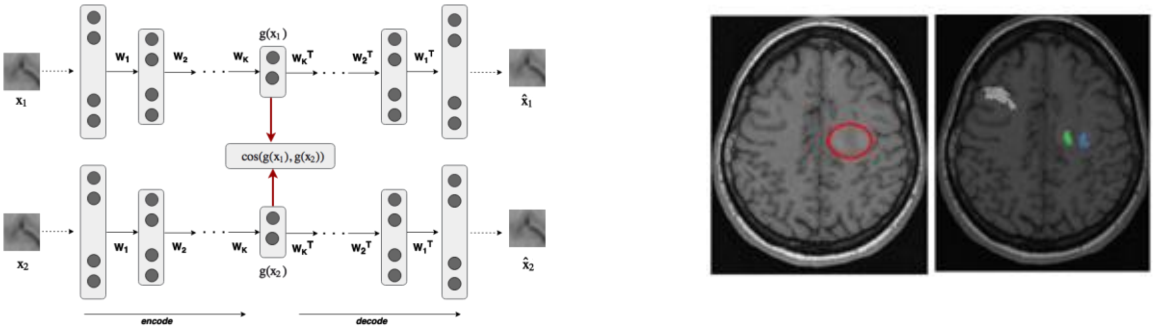


**Figure 2**. Left : unsupervised siamese network proposed in [Alaverdyan et al 2016]. Right: Example Maximum intensity projection (MIP) of a cluster map estimated by the siamese network overlaid on the MRI transverse slices of a patient (The lesion location is highlighted in red circle on the left figure). The grey cluster corresponds to a false detection [Alaverdyan et al 2017].

**Objective**

The objective of this project is to further investigate the potential of unsupervised deep medical imaging feature learning. We propose to explore the performance of generative adversarial networks (GAN) architecture to learn more discriminant feature representation than that achieved with the siamese architecture developed in [Alaverdyan, 2016]. We will start by implementing and optimizing a standard GAN architecture and then focus on more complex models that can embed contextual information with the aim to improve the discriminative power of the learned representation. The medical application domain will be the detection of epileptogenic lesions in multiparametric brain magnetic resonance imaging (MRI) [El Azami et al., 2016].

**Program outline**

The candidate will need to address the following tasks:

- Reviewing the state of the art literature in the domain of unsupervised deep learning algorithms and GANs more specifically
- Designing and implementing one or more specific GAN architectures
- Evaluating the performance of these GAN architectures based on the brain MRI epilepsy patients datasets.
- Designing and implementing a strategy to encode the global and local contextual information within the GAN
- Evaluating this contextual GAN model on the epilepsy MRI dataset.

**Collaboration**

The candidate will be supervised by Carole Lartizien in close collaboration with Zaruhi Alaverdyan as part of her PhD work.  He (She) will be part of collaboration with the LIMOS lab in Clermont-Ferrand as part of the CIGAIL project funded by CNRS. Expertise will be shared between the LIMOS and CREATIS partners to define different possible encoding configurations of the contextual information.

**Skills**

Good knowledge in deep learning is required.

Strong knowledge in at least one of the following fields is required:

- machine learning (deep learning/ outlier detection);
- Signal processing
- Applied mathematics

The available code is written in Python.
The successful candidate is expected to be autonomous and show strong motivation and interest in multidisciplinary research (image processing and machine learning in a medical context).

**Applications**
Interested applicants are required to send a cover letter, CV and any other relevant documents (reference letter, recent transcripts of marks,...) to carole.lartizien@creatis.insa-lyon.fr

**References**

[El Azami, 2016] El Azami, M., A. Hammers, J. Jung, N. Costes, R. Bouet and C. Lartizien. *Detection of Lesions Underlying Intractable Epilepsy on T1-Weighted MRI as an Outlier Detection Problem*. PLoS ONE, 11(9): e0161498, 2016.

[Alaverdyan, 2017] Z. Alaverdyan et C. Lartizien. Feature extraction with regularized siamese networks for outlier detection: application to epilepsy lesion detection. Conférence sur l'apprentissage automatique (CAp 2017), Grenoble, France, 2017.

[Alaverdyan, 2016] Z. Alaverdyan, C. Lartizien. Automatic extraction of representations for outlier detection in medical imaging. Réunion du GDR ISIS- thème A : Apprentissage de représentations : méthodologies et applications, Paris, Oct 2016.

**Gratuity**
~550 euros/mois.

**Contact**
carole.lartizien@creatis.insa-lyon.fr