Temporal generative neural nets

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Keywords Time series, deep learning, generative neural nets as recurrent neural nets, GANs

This internship will focus on the proposition of novel generative neural networks for time series and the analysis of what information they capture.

In recent years, the interest for generative models in the deep learning community has grown rapidly, with the proposition of Generative Adversarial Networks (GANs) [3] whose aim is to generate examples that mimics the distribution of the original data. Its main idea is to train simultaneously two networks that compete one against the other (see figure 1):

- a generative network (the generator), which generates fake examples from an initial random noise;
- a discriminative network (the discriminator) able to discriminate real examples from fake ones.

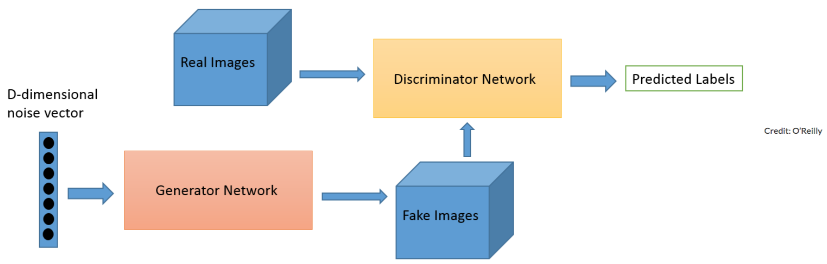

Figure 1: GAN architecture

At each step, the generator produces more and more realistic examples until the point that real and fake examples are indistinguishable. GANs are often used to generate images (see figure 2 for examples), in which both the generator and the discriminator are convolutional neural networks, that is to say deep feed-forward neural networks.

Concerning the specific case of generating sequences, generative Recurrent Neural Networks (RNNs) have been proposed [4], as well as temporal variants

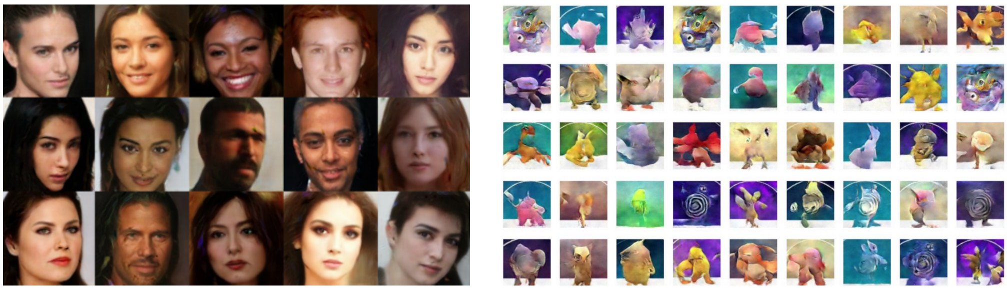

Figure 2: (left) Faces (image from https://blog.heuritech.com/2017/04/11/) and (right) Pokemons (see https://www.youtube.com/watch?v=rs3aI7bACGc) generated by a GAN.

of GANs [5, 2]. RNNs are a class of neural network, whose neurons are equipped with an internal memory, allowing to grasp the sequential nature of the data.

However, both families of models (GANs and RNNs) are likely to suffer from mode collapse [1] (*ie.* learn only the most important mode(s) of the data distribution rather than the full distribution).

The aim of this internship is to study the interest of using generative RNNs as a building block of a GAN model and compare it to the previously cited baselines in terms of distribution coverage. Also, an *a posteriori* analysis of what the obtained generative model has learned (using visualizations inspired from [6], for example) should be performed so as to get better insights regarding (i) the motifs learned by recurrent units and (ii) the temporal horizon that is kept in memory by such models.

Required or appreciated skills. Applicants must be familiar with deep learning. Experience with TensorFlow is a plus.

Context of the internship. The internship will take place within the ANR Jeune Chercheur MATS (machine learning for environemental time series). The internship may be followed by a PhD.

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