Generative Adversarial Network (GAN) for Remote Sensing Images unsupervised Learning

Amina Ben Hamida, A Benoit, Patrick Lambert, Chokri Ben Amar

Generative Adversarial Network (GAN) for Remote Sensing Images unsupervised Learning

Amina Ben Hamida[1, 2] Alexandre Benoit[1]
Patrick Lambert[1] Chokri Ben Amar[2]

[1] Univ. Savoie Mont Blanc, LISTIC, F-74000 Annecy, France
[2] REGIM, Ecole Nationale des Ingénieurs de Sfax, 3038 Sfax, Tunisie

amina.ben-hamida@univ-smb.fr

1 Introduction

In the Remote Sensing (RS) field, the main purpose behind the use of classical deep learning approaches is to discover and learn the content of a variety of datasets now freely available (Landsat, Sentinel...). Basically, the most performing deep learning approaches used in this context have been deployed in order to map high-dimensional rich images into class labels or execute per pixel supervised segmentation to obtain semantic maps such as the one detailed in [2] and [3]. Although such architectures have witnessed a striking success, they still are limited in terms of fulfilling non-supervised clustering tasks. However, the serious lack of richly annotated RS datasets combined with the important time dependent variability of its spatial information deflects the interest toward the use of non supervised approaches. Such challenge is emphasized when using the RS data annotations for the analysis of temporal changes.
It goes without saying that the introduction of auto-encoders as an unsupervised learning method, has allowed the extraction of accurate representations of the data via latent codes (the layer about which the network is symmetric) and back-propagation techniques. In fact, Auto-encoders are in general built based on two components, an encoder and a decoder. The encoder will read the input and compress it to a compact representation while the decoder will use this representation to try recreating the input. The goal behind the use of such process in Remote Sensing tasks is to learn interpretable data representations with the minimum reconstruction error possible that can be later on used to perform classical clustering methods such the k-means and be interpreted by human experts. Vanilla Auto-encoders are however hard to train. Recently, Variational Auto-encoders [4] allow us to perform both learning and generating data samples using the latent variables Space. However, their generated samples tend to be slightly blurry and the learned representations are quite in-accurate.

2 Generative Adversarial Networks: GANs

As a remedy to such problem, we propose to use the generative models which were proposed by Ian Goodfellow and al in [1] providing the AI world with a new class of Deep Learning Models which enable not only a non-supervised learning of images content but also a generation of new samples that imitate the available datasets.
The Generative Adversarial Networks (GANs) can learn interpretable representations from Remote Sensing datasets with no required supervision. In fact, such approach introduces the training process as a competition between two separate networks: a Generator network and a second Discriminative. The Generator will try to generate fake images that fool the Discriminator into thinking that they're real while the Discriminator will try to distinguish between a real and a generated image. Every time the discriminator notices a difference between the two samples the generator adjusts its parameters slightly to make more realistic samples. They both get stronger together until the discriminator cannot distinguish between the real and the generated images anymore. After this, the trained generator will be able to reproduce the true data distribution and the discriminator is guessing at random, unable to find a difference. The presented work investigates the use of two main generative adversarial network architectures used for the generation of high-resolution remote sensing RGB images. We first, deploy the Deep convolutional generative adversarial model as detailed in [5] where both the generator and the discriminator are classical-like convolutional neural networks. In that case, the discriminator is used to specify which are the statistics worth matching (Feature matching) in the RS dataset samples. Then, we propose a new version of the Energy Based GAN [6] that enable the generation of high resolution RS images using The UC merced Dataset which consists of images of 21 land-use classes (100 256×256-pixel RGB images for each class). As presented in Fig.1 The generator is a encoder/decoder duet that is trained to produce fake samples while the discriminator takes either real or generated images, and estimates the

energy value accordingly. The output of the discriminator shapes the energy function, attributing low energy to the real data samples and higher energy to the fake ones. Once trained, the discriminator measures then how well an arbitrary image fits into the real image distribution while drawing a boundary between real and fake samples.

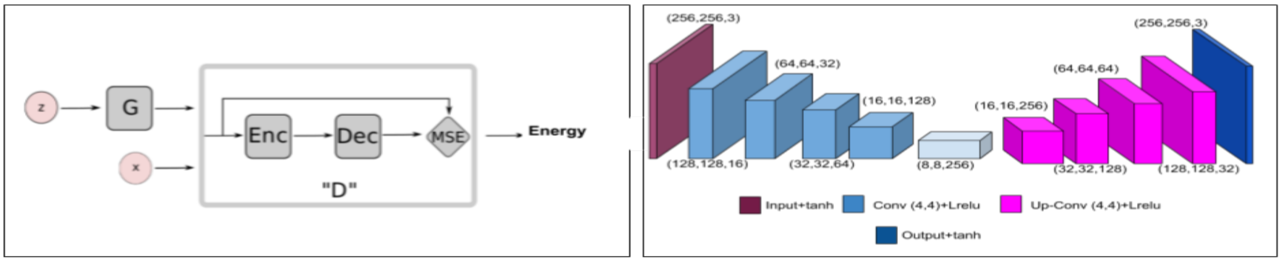

Figure 1 – Right: Overview of the Energy Based GAN (EBGAN) architecture. Left: Zoom into the Discriminator Encoder/Decoder networks

3 Discussion

The proposed Generative Adversarial Networks provide effective learning of data representations with the hallmark of extracting interesting features as seen in the generated results presented in Fig.2.

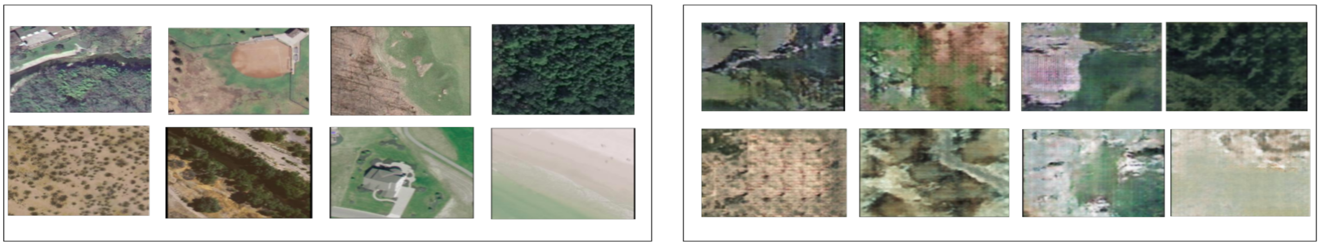

Figure 2 – Sample images. (a) Random images from UC-Merced data set. (b) Exemplary images produced by generator trained on UC-Merced based the EBGAN architecture

Upon convergence, such features can be used for the sake of different image analysis applications namely unsupervised data clustering tasks. For example, a k-means clustering method can be used behind the generative adversarial networks to enable the automatic identification of terrain types clusters present in a multispectral dataset. Furthermore, the use of the GANs could be extended to time series image analysis for changes detection.

References

[1] Goodfellow, Ian, et al. *"Generative adversarial nets" ,* Advances in neural information processing systems. 2014.

[2] A. Ben Hamida, A. Benoit, P. Lambert and C. Ben Amar, *"3-D Deep Learning Approach for Remote Sensing Image Classification",* in IEEE Transactions on Geoscience and Remote Sensing, 2018.,

[3] Audebert, Nicolas, Bertrand Le Saux, and Sébastien Lefévre. *"Semantic segmentation of earth observation data using multimodal and multi-scale deep networks."* Asian Conference on Computer Vision. Springer, Cham, 2016.

[4] Sonderby, Casper Kaae, et al. *"Ladder variational autoencoders."* Advances in neural information processing systems, 2016.

[5] Lin, Daoyu, et al. *"MARTA GANs: Unsupervised Representation Learning for Remote Sensing Image Classification."* IEEE Geoscience and Remote Sensing Letters, 2017

[6] hao, Junbo, Michael Mathieu, and Yann LeCun. *"Energy-based generative adversarial network."* ,2016.