2D Stochastic Structural Geomodeling with Deep Generative Adversarial Networks

Charlie GARAYT[1, 3], Nicolas DESASSIS[1], Samy BLUSSEAU[2], Jean LANGANAY[3], Pierre-Marie GIBERT[3], Thomas ROMARY[1]

[1] Centre for geosciences and geoengineering, Mines Paris, PSL University
[2] Center for Mathematical Morphology (CMM), Mines Paris, PSL University
[3] Geovariances

This work aims to simulate 2D structural geological models, or geomodels, that respect given knowledge and data. By definition, geomodeling is an ill-posed problem due to the limited quantity and quality of available data. Current geomodeling methods struggle to both characterize uncertainties and produce realistic geomodels.

To achieve this goal, a deep generative adversarial network (GAN) has been implemented. GANs, which are usually used in image generation, need a large training dataset. For instance the ImageNet dataset contains more than 1.5 million images. In geomodeling, such a large real dataset does not exist. Fortunately, geological structures are a consequence of physical and chemical processes, so creating a synthetic dataset is feasible from the simulation of these processes.

The training dataset is created from Noddy, which can be viewed as an object-based simulator. The use of advanced GANs like Least-Square GAN (LSGAN) and Wasserstein GAN allows training a deep neural network called the Generator. The Generator defines an implicit distribution of geological models. This is a function that transforms a random vector into a geomodel similar to the training dataset.

However, the Generator produces unconstrained geomodels. A variational Bayesian approach is used in order to train a Sampler, which enables the generation of geomodels that fulfill constraints, or conditioned geomodels. Thanks to the versatility of the variational Bayes approach, constraints can be of different types and quality, for instance rock type, rock orientation or geophysical data. The goal of the Sampler is to find the posterior distribution where the Generator produces the desired conditioned geomodels. Using a variational Bayesian approach makes it possible to take into account different types of data, with their own quantity and quality without re-training the Generator.

Finally, the combination of the Sampler and the GAN allows the generation of conditioned geomodels. In addition, this approach enables handling uncertainties and to perform computation, since the resulting generator produces an implicit distribution of conditioned geomodels.