Latent Diffusion Model Conditioned by Segmentation Maps for 2D Geological Facies Generation

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Abstract

In reservoir modeling, it is important to develop geologically sound subsurface models that agree with known spatial information, such as physical measurements at well locations and data from seismic surveys. Along with several methods from two-point and multiple-point geostatistics, generative models are increasingly being adopted for this challenge. Dupont et al. (2018) have demonstrated GANs can overcome some limitations of conventional methods, and more recently, Lee et al. (2023) have used Latent Diffusion Models to sample 2D facies realizations constrained by sparse observations at well locations.

Restricting realizations to a region of interest is also useful for reservoir modeling, as top and bottom horizons are examples of spatial boundaries that should be honored when sampling 2D vertical slices. In this study, we explore the use of Latent Diffusion Models to generate 2D facies realizations conditioned by spatial constraints.

Method

The development of Denoising Diffusion Probabilistic Models by Ho et al. (2020) and Latent Diffusion Models by Rombach et al. (2021) has allowed diffusion models to generate high-quality natural images under reasonable computational requirements.

Lee et al. (2023) adapted Latent Diffusion Models for the task of creating 2D facies realizations conditioned by known facies at well locations. Subsurface horizons can be used to delineate a region of interest, and the production of realistic geological patterns within spatial constraints is an important condition in reservoir modeling as well.

The GAN River-I is a public dataset of 2D horizontal slices of 3D facies models, designed by Sun et al. (2022) to provide a stern test for machine learning and geostatistical tools. The problem of creating 2D realizations conditioned by spatial boundaries can be tackled on this benchmark dataset by applying a mask over facies inside a region of interest. Figure 1 shows a 2D training sample and its corresponding conditional, obtained by masking all facies except “Overbank” (in light green).

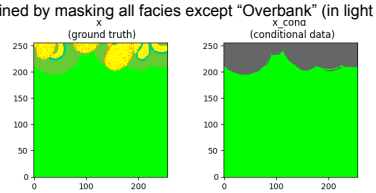

Figure 1: Sample from Training Set (left) and Conditional Data (right)

Conditionally generated samples are expected to display diverse and realistic patterns inside the region of interest while respecting its boundaries.

Results

Figure 2 shows a sample from the test set, its conditional data, and three conditionally generated samples.

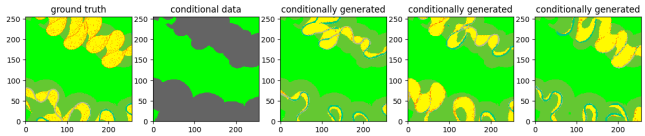

Figure 2: Ground truth, conditional, and generated samples

It can be noted from the visual inspection of Figure 2 that our LDM implementation was able to generate patterns matching the style of the training set to a sensible degree. The generated samples are significantly distinct, suggesting a degree of resilience to mode collapse, a common problem of generative models.

The conditional boundaries were well respected, with 99.22% of pixels from generated samples agreeing with conditional data.

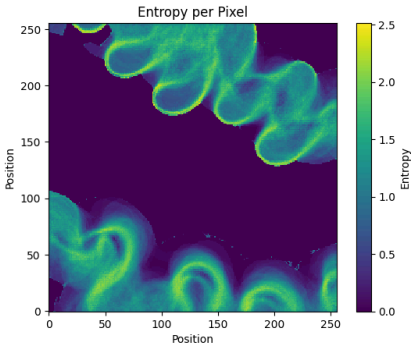

Figure 3: Entropy per pixel (in bits) of samples generated by the same conditional

Figure 3 shows the entropy per pixel for 200 realizations generated for the conditional of Figure 2. It can be seen there is higher uncertainty for facies inside the region of interest, as the realizations are diverse within those boundaries. The entropy is zero almost everywhere outside, meaning the same class (“Overbank") was consistently and correctly placed on the realizations.

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