Wells and context aware diffusion model for geological cross-section generation

G. Shutov [1] B. Belozerov E. Burnaev [1 2] V. Vanovskiy [1]
[1] *Skolkovo Institute of Science and Technology, Moscow, Russia* [2] *Autonomous Non-Profit Organization Artificial Intelligence Research Institute, Moscow, Russia*. Correspondence to: G. Shutov grigoriy.shutov@skoltech.ru.

1. Introduction

Generative models, especially diffusion models [1, 2], have demonstrated remarkable capabilities in various domains, achieving state-of-the-art results in image synthesis and other problems. However, relatively little research has explored the application of diffusion models to physical systems. This emerging field necessitates the development of specialized datasets and novel conditioning strategies to effectively integrate multimodal contextual and measurement information. In this work, we address this gap by applying diffusion models to generate vertical cross-sections of oil reservoir properties, conditioned on both well measurements and the geological context. We demonstrate that such models are capable of generating representations of subsurface heterogeneity that correspond to the conditional data, ultimately contributing to improved reservoir characterization and management.

2. Related work

Research has shown that GANs [3, 4, 5], VAE [6, 7] and graph neural networks [8] are capable of generating oil reservoir properties conditioned on well measurements. Another work uses diffusion models [9] to solve the history matching task and generate facies maps that correspond to the production history. Recent research [10] introduces new conditional strategies for the generation of facies maps that correspond to limited measurements. However, such research utilizes datasets without geological diversity in terms of depositional environment. In real oil reservoir, such properties as collector fraction or geological bodies shapes and alignment vary depending on the reservoir type. We call such properties geological context, and according to our knowledge, there has been no research related to conditioning on such context together with the well measurements.

Our contribution. We develop a diffusion model able to generate vertical cross-sections of oil reservoir properties with conditioning not only on well measurements, but also on geological context as an example of which we took the lateral angle of the cross section to the geographic axes.

3. Data

The initial dataset has been created using geostatistics methods and consists of 3D cubes related to Brugge benchmark [11, 12]. Each cube has three properties: facies type, porosity and permeability, which are crucial for reservoir characterization. The dataset also has 7 vertical wells in which these three properties are interpreted from the well logs data. We slice this dataset into vertical cross-sections (see Fig. 1). Each cross-section goes through some well and has a different angle between itself and X axis.

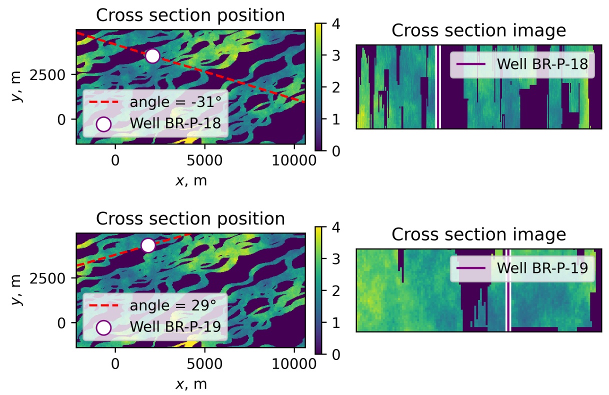

Fig. 1: Top view of 3D cubes (left) with cross-sections positions (red line) and cross-sections images (right). The color corresponds to the permeability k, mD.

Geological context. Note that the angle between cross-section and X axis is a representative example of the cross-section geological context. On one hand, if the angle is negative (Fig. 1, top), the cross-section is orthogonal to the channels and has abrupt structure that consists of channels' sections. On the other hand, if the angle is positive (Fig. 1, bottom), the cross-section is parallel to the the channels and has more or less continuous structure.

We aim to train the generative model which takes angle value and well measurements as a condition and returns cross-section images.

4. Model

We utilize DDPM [1] that is implemented in Diffusers library. [13]. The architecture is conditional 2D UNet with cross-attention layers. To encode the angle, we use linear layer with the activation function, with one input channel for the angle and some number of output channels taken as hyperparameter and corresponding to the cross-attention dimension.

Because the well measurements are spatially aligned with the cross-sections, we use them as a masked tensor that we then concatenate with the input of the DDPM.

5. Results and discussion

We demonstrate the examples of the generated cross-sections on Fig. 2.

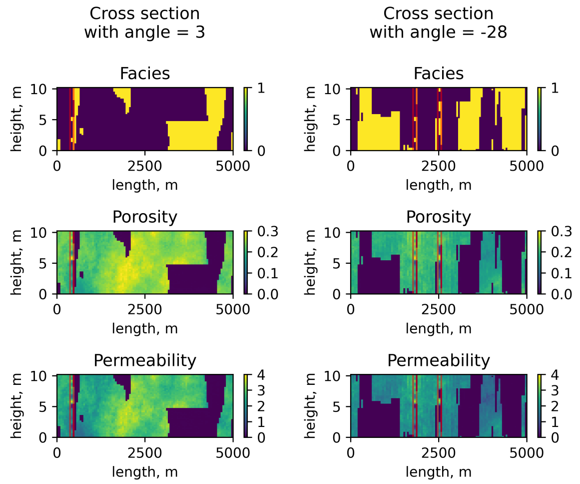

Fig. 2: Example of generated cross-sections with positive angle (left) and negative angle (right). The red lines indicate the wells.

We observe that in these examples the cross-section with positive angle is more continuous than the cross-section with negative angle. However, such correspondence of the generated data to the geological context should be validated statistically. We perform such validation by computing the variograms across 100 generated samples and 100 samples from dataset with same context (see Fig. 3). In addition, we compute the collector fraction (as the fraction of facies of the collector type) and compare its distributions in generated and training samples.

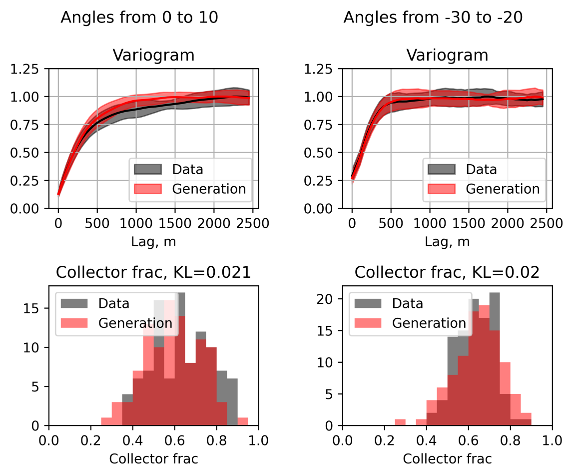

Fig. 3: Variograms and collector fraction distribution comparison for training (gray) and generated (red) samples with positive angle (left) and negative angle (right).

First, one may note that the variograms of the positive angles go lower than variograms of negative angles, meaning that positive angles correspond to more continuous data as expected. Second, the collector fraction distribution is broader for the positive angles cross-sections. This is due to cases when cross-sections go through entire channel (collector fraction close to 1) and cases when cross-sections go through non-conductive field (collector fraction close to 0). Such cases are impossible for cross-sections with negative angles, because they are always orthogonal to the channels (see Fig. 1). Therefore, we observe the lower variance in collectors' fraction. Finally, we note that the distribution of collector fraction as well as variograms of generated samples are very close to those of training samples. We can conclude that the trained model has successfully learned the geological context based on the angle value.

We also need to validate the correspondence of the generated data to the well measurements. To do so, we compute R^2 and MAPE between actual well measurements and generated data in wells positions (see Fig. 4)

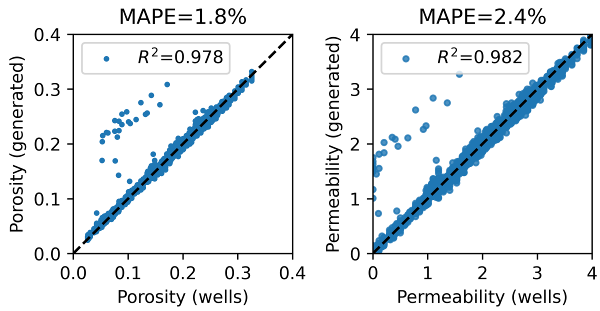

Fig. 4: Porosity (left) and permeability (right) cross-plots of conditional (X-axis) vs generated (Y-axis) data over 100 samples.

We note that despite several outliers, the model has generated the cross-sections with high correspondence to the well measurements.

6. Conclusion

In this work, we verified the important hypothesis that the diffusion models can generate geological data taking into account both geological context and well measurements. The generated data corresponds to selected geologic context variable (angle of the cross-section) both qualitatively and statistically, while also corresponding to the local well measurements. Our results show the high potential of using the generative models for oil reservoir characterization and modeling.

Future developments. Given the promising results of this study, future work will focus on extending our diffusion model to generate 3D reservoir property distributions. Furthermore, we plan to incorporate a wider range of geological context, such as sedimentation environment parameters.

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References

[1] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *Advances in neural information processing systems*, 33:6840–6851, 2020.

[2] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 10684–10695, 2022.

[3] Qiang Zheng, Lingzao Zeng, Zhendan Cao, and George Em Karniadakis. Physics-informed semantic inpainting: Application to geostatistical modeling, 2019.

[4] Shing Chan and Ahmed H Elsheikh. Exemplar-based synthesis of geology using kernel discrepancies and generative neural networks. *arXiv preprint arXiv:1809.07748*, 2018.

[5] Shing Chan and Ahmed H Elsheikh. Parametric generation of conditional geological realizations using generative neural networks. *Computational Geosciences*, 23(5):925–952, 2019.

[6] Smith WA Canchumuni, Alexandre A Emerick, and Marco Aurélio C Pacheco. Towards a robust parameterization for conditioning facies models using deep variational autoencoders and ensemble smoother. *Computers & Geosciences*, 128:87–102, 2019.

[7] Smith WA Canchumuni, Jose DB Castro, Júlia Potratz, Alexandre A Emerick, and Marco Aurelio C Pacheco. Recent developments combining ensemble smoother and deep generative networks for facies history matching. *Computational Geosciences*, 25:433–466, 2021.

[8] Michael Hillier, Florian Wellmann, Boyan Brodaric, Eric de Kemp, and Ernst Schetselaar. Three-dimensional structural geological modeling using graph neural networks. *Mathematical geosciences*, 53(8):1725–1749, 2021.

[9] Guido Di Federico and Louis J Durlofsky. Latent diffusion models for parameterization and data assimilation of facies-based geomodels. *arXiv preprint arXiv:2406.14815*, 2024.

[10] Daesoo Lee, Oscar Ovanger, Jo Eidsvik, Erlend Aune, Jacob Skauvold, and Ragnar Hauge. Latent diffusion model for conditional reservoir facies generation. *Computers amp; Geosciences*, 194:105750, January 2025.

[11] E Peters, RJ Arts, GK Brouwer, CR Geel, Stan Cullick, Rolf J Lorentzen, Yan Chen, KNB Dunlop, Femke C Vossepoel, Rong Xu, et al. Results of the brugge benchmark study for flooding optimization and history matching. *SPE Reservoir Evaluation & Engineering*, 13(03):391–405, 2010.

[12] Elisabeth Peters, Yunxia Chen, O Leeuwenburgh, and DS Oliver. Extended brugge benchmark case for history matching and water flooding optimization. *Computers & Geosciences*, 50:16–24, 2013.

[13] Patrick von Platen, Suraj Patil, Anton Lozhkov, Pedro Cuenca, Nathan Lambert, Kashif Rasul, Mishig Davaadorj, Dhruv Nair, Sayak Paul, Steven Liu, William Berman, Yiyi Xu, and Thomas Wolf. Diffusers: State-of-the-art diffusion models.