Generative adversarial networks for modeling reservoirs with permeability anisotropy

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Abstract. The geological model is a main element in describing the characteristics of hydrocarbon reservoirs. These models are usually obtained using geostatistical modeling techniques. Recently, methods based on deep learning algorithms have begun to be applied as a generator of a geologic models. However, there are still problems with how to assimilate dynamic data to the model. The goal of this work was to develop a deep learning algorithm - generative adversarial network (GAN) and demonstrate the process of generating a synthetic geological model:
• Without integrating permeability data into the model
• With data assimilation of well permeability data into the model
The authors also assessed the possibility of creating a pair of generative-adversarial network-ensemble smoother to improve the closed-loop reservoir management of oil field development.

1. Introduction
A key step in the geological modeling process is to predict the spatial distribution of geological facies. This step involves building a realistic numerical model that considers direct measurements available with a small number of direct observations (for example, well logging data). It is the limitedness of direct measurements that leads to the problem of geological uncertainty, which affects the technological processes of the development of oil and gas fields.

Methods of data assimilation [1] can solve the problem of geological uncertainty. However, data assimilation methods are based on Gaussian distributions, so their efficiency are greatly degraded when the prior data is described in terms of complex facies distribution [2].

New deep learning algorithms - generative adversarial networks [3] - will be able to help solve the problem of data assimilation due to their unique ability to recreate objects of varying complexity by learning from similar examples. At the first stage - parameterization for the data assimilation problem - it is the ability to recreate geological facies that will show the effectiveness of GANs.

The goal of this work is to develop and implement a generative adversarial network for:
• Generation of models without direct observation integration
• Generation of models with the integration of direct observations - permeability parameter

This paper is organized as follows: in the next section, we present deep learning in general and GAN, in particular. Next, we review the method of generation of models without direct observation integration. Then, we explain the generation of models with the integration of direct observations procedure. The last section of the paper presents our conclusions and discussion.
2. Deep learning

Machine learning and deep learning are a large group of artificial intelligence methods and algorithms that have the ability to transform various kinds of representations/features into a target result or prediction. But machine learning can be used not only to find a mapping of a representation to a result, but also to define the representation itself. This approach is called feature learning or representation learning [4]. Representation learning often produce much better quality than «hand-crafted» learning. Also it allows AI systems to quickly adapt to new data with minimal human intervention. For a simple problem, the representation learning algorithm can find a good set of features in a few minutes, for complex ones, in a time from several hours to several months.

Designing features manually for a complex problem is time-consuming and can take decades of work by the entire research community. When designing features or feature learning algorithms, our goal is usually to isolate the factors of variation that explain the observed data.

Of course, it can be very difficult to extract such high-level abstract features from the raw data. Many factors of variability, such as local formation anisotropy, can only be identified if there is a very deep, human-like understanding of the nature of the data. But since it is almost as difficult to get an idea as it is to solve the original problem, then learning the representations will help nothing.

Deep learning addresses this central problem of representation learning by introducing representations expressed in terms of other, simpler representations.

2.1. Generative Adversarial Networks

A generative adversarial network (GAN) is a machine learning method with architecture which allows unsupervised learning [3]. There are two components in the designed GAN, both of which are a neural network. The first is the generative network; it can generate a distribution of candidate data with preliminary data. The second is a discriminator network that can distinguish between candidate data distribution and true data distribution. The goal of the GAN is to optimize the discriminator network $D$, which is to maximize the expected logarithmic probability of the true distribution of the data, otherwise it maximizes the probability when input from true observation. Meanwhile, the generative model $G$ learns to minimize distribution of candidate data and accurate distribution of data during training.

The GAN training process is implemented by simultaneously training both networks through optimization of the loss function:

$$
\min_D \max_G L(D, G) = E_{x \sim p_r}[\log (D(x))] + E_{z \sim p_z}[\log (1 - D(G(z)))]$$

$$= E_{x \sim p_r}[\log (D(x))] + E_{z \sim p_g}[\log (1 - D(z))], \tag{1}
$$

where $p_z$ – is the data distribution over noisy input;
$p_g$ – is the probability distribution by generator network.
$p_r$ – is the data distribution over real observations.
$L$ – the loss function.

The ability of GANs to construct representations is reflected in many papers related to petroleum geology. For example, at work [5] authors implemented GAN, which trained on geostatistical models for representing of the distribution of properties of rock for reservoir simulation. In the work in [5] authors present stochastic reconstruction of GAN implementation for image generation of limestone.

3. Generation of models without direct observation integration

To generate geological models, we used a generative adversarial network (GAN) (Figure 1), where the generator ($G$) and discriminator ($D$) are designed in the form of Convolutional Neural Networks (CNNs) based on CNN's powerful image feature extraction capabilities.

A random vector $z$ is fed into the GAN, usually chosen from the normal distribution $z \sim p(z) = N(0, 1)$, and is expected to output a real image $x$ that reproduces the basic properties of the training sample. The generation process is carried out by the generator $G$, which is trained to map samples from $z$ to $x$. The generated image and the real image are then input to $D$, which is trained to estimate a probability indicating that the image is real (from the training dataset) or fake (generated by $G$). $G$ and
$D$ are trained in turn, optimizing the following $\min - \max$ objective function (2) to improve their generating and difference ability:

$$\min_D \max_G \mathbb{E}_{x \sim p_{data}} \{ \log D(x) \} + \mathbb{E}_{z \sim p_z} \{ \log (1 - D(G(z))) \},$$

(2)

where $p_{data}$ and $p_z$ - distribution of training data and latent vectors. $x$ and $z$ represent training models and hidden vectors respectively.

**Figure 1.** Generative adversarial network used in the work.

The training image was an image generated using multiple point statistics [6]. The training image (Figure 2) is a synthetic section of the reservoir with anisotropy in permeability: white background - low permeability, black lines - high-permeability areas.

**Figure 2.** The training image used in experiment.
As an GAN algorithm, we used a CNN [7,8] with the following main parameters (Table 1).

**Table 1.** CNN used in experiment

| Layer (type) | Output Shape   | Number |
|--------------|----------------|--------|
| Dense        | (-, 4096)      | 413696 |
| Reshape      | (-, 8, 8, 64)  | 0      |
| Conv2DTr     | (-, 16, 16, 32)| 32800  |
| Batch        | (-, 16, 16, 32)| 128    |
| Activation   | (-, 16, 16, 32)| 0      |
| Conv2DTr     | (-, 32, 32, 16)| 8208   |
| Batch        | (-, 32, 32, 16)| 64     |
| Activation   | (-, 32, 32, 16)| 0      |
| Conv2DTr     | (-, 64, 64, 8 )| 2056   |
| Batch        | (-, 64, 64, 8 )| 32     |
| Activation   | (-, 64, 64, 8 )| 0      |
| Conv2DTr     | (-, 128, 128, 4)| 516    |
| Batch        | (-, 128, 128, 4)| 16     |
| Activation   | (-, 128, 128, 4)| 0      |
| Conv2D       | (-, 128, 128, 1)| 37     |
| Activation   | (-, 128, 128, 1)| 0      |

At the first step, we chose one of the training image realizations for comparing results. Figure 3 shows the process of generating reservoir realization through epochs. Figure 4 shows the 9 generated reservoir realization. These figures show that network was able to generate realistic facies realizations with the same characteristics of realizations from the training image.

Thus, it can be seen that highly complex physical processes such as reservoir permeability anisotropy and complex facies distribution can be successfully recreated using GANs algorithms.

It can also be noted that approximately at 20 000 epochs the algorithm finds a very similar realization of the facies distribution.
Figure 3. The process of generating reservoir realization through epochs.
4. Generation of models with the integration of direct observations - permeability parameter
In this experiment, we implemented an already trained model that was described in the previous section and applied it to a synthetic sample of «permeability interpretation of well logging» - extracted from one GAN generated realization of a sample of a reservoir section (Figure 5).

Figure 4. Generated reservoir realization.

Figure 5. The training image used in experiment and sample of a reservoir section.
The result of the experiment showed the recovery of a section of the formation with some features of the permeability distribution; however, it is far from a strong similarity with the original training image. Figure 6 shows the 20 generated reservoir realization.

![Generated reservoir realization with the integration of direct observations.](image)

**Figure 6.** Generated reservoir realization with the integration of direct observations.

5. **Conclusion**

The authors of the work have shown the effectiveness of deep learning algorithms - generative adversarial networks in solving the problem of reconstructing of complex reservoir systems with anisotropy of properties and in subsequent parameterization for data assimilation due to their unique ability to recreate objects of varying complexity, learning from similar examples.

A solution to the problem was presented for two cases:

- Generation of models without direct observation integration
- Generation of models with the integration of direct observations - permeability parameter

In the future, authors are planning to modify the algorithm to solve the problem with a more obvious uncertainty of geological properties, which is shown by the results of the experiment of generation of models with the integration of direct observations - permeability parameter. Also, many authors [5,9] point to the significant effectiveness of the coupling GANs with data assimilation methods. In the future, the authors of this article are planning experiments to implement the algorithm into data assimilation problem with model-based dynamic optimization of the waterflooding process, which can improve the economic life-cycle performance of oil fields [1,10,11].
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References
[1] Guliev R and Zolotukhin A 2019 Field development optimization of waterflooding process using data assimilation methods *IOP Conf. Ser. Mater. Sci. Eng.* 700 012054
[2] Canchumun S W A, Castro J D B, Potratz J, Emerick A A and Pacheco M A C 2020 Recent Developments Combining Ensemble Smoother and Deep Generative Networks for Facies History Matching
[3] Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, Courville A and Bengio Y 2020 Generative adversarial networks *Commun. ACM* 63 139–44
[4] Bengio Y, Courville A and Vincent P 2013 Representation Learning: A Review and New Perspectives *IEEE Trans. Pattern Anal. Mach. Intell.* 35 1798–828
[5] Mosser L, Dubrule O and Blunt M J 2019 DeepFlow: History Matching in the Space of Deep Generative Models
[6] Daya Sagar B S, Cheng Q and Agterberg F 2018 *Handbook of Mathematical Geosciences* (Cham: Springer International Publishing)
[7] Sun R and Sessions C 2000 Self-segmentation of sequences: automatic formation of hierarchies of sequential behaviors *IEEE Trans. Syst. Man Cybern. Part B* 30 403–18
[8] Russakovsky O, Deng J, Su H, Krause J, Satheesh S, Ma S, Huang Z, Karpathy A, Khosla A, Bernstein M, Berg A C and Fei-Fei L 2014 ImageNet Large Scale Visual Recognition Challenge
[9] Emerick A A and Reynolds A C 2013 Ensemble smoother with multiple data assimilation *Comput. Geosci.* 55 3–15
[10] Chen Y, Oliver D S, Zhang D and California S 2008 SPE 112873 Efficient Ensemble-Based Closed-Loop Production Optimization 19–23
[11] Brouwer D R and Jansen J D 2004 Dynamic Optimization of Waterflooding With Smart Wells Using Optimal Control Theory *SPE J.* 9 391–402