Deep convolutional GANs as parameterization method in data assimilation

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Outline

- **Introduction**
- **Generative adversarial networks**
- **Experiment 1: GANs evaluation**
- **Experiment 2: Assimilation**
- **Conclusions**
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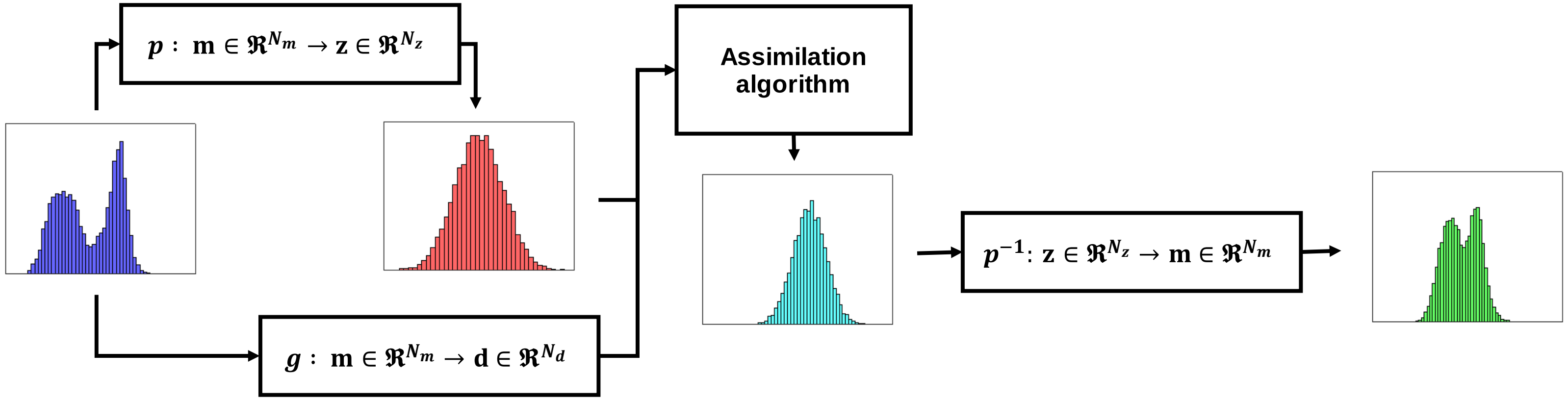
Introduction

- Popular ensemble-based methods rely on Gaussian assumption.
- Many parameters have non-Gaussian behavior
  - Categorical facies
  - Multilevel uncertainties
- The assimilation Vanishes its original distribution.
- How to handle with the non-Gaussianity in ensemble-methods?
  - Parameterization techniques

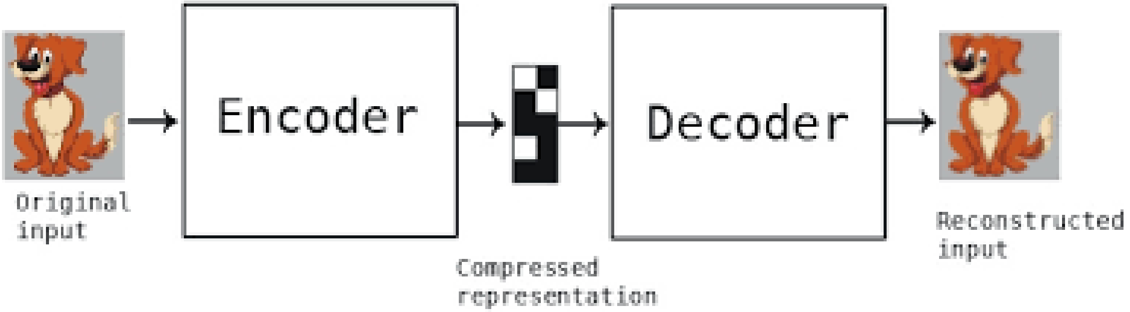


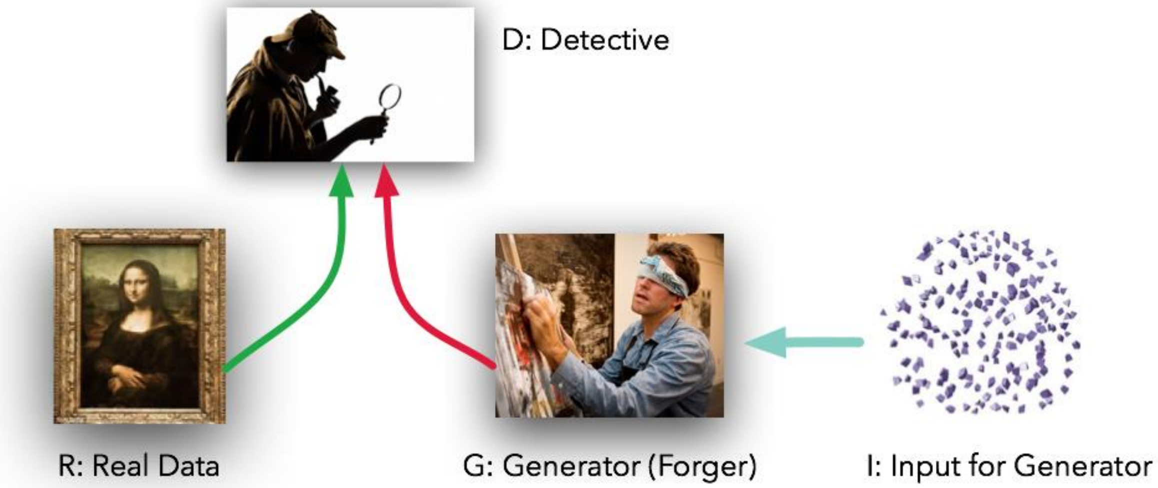
Introduction

- Several parameterization methods.
- Deep learning techniques:
  - Autoencoder (Kim et al., 2020)
  - CNN-PCA (Liu and Durlofsky, 2021)
  - GANs (Canchumuni et al., 2021; Zhang et al., 2022)
- Comparison between GAN and VAE (Bao et al., 2022):
  - VAE performed better in DA
  - GAN resulted in better realizations
- Proceed with investigation of GANs:
  - Evaluate another GAN architecture in DA (Autoencoder Discriminator)

Generative adversarial networks

- GANs (Goodfellow et al., 2014):
  - Composed by a generator and a discriminator:
    - Generator takes a random vector and try to generate new samples.
    - Discriminator try to classify samples as real (from original domain) or fake (generated by generator).
  - Adversarial training:
    - Generator and discriminator must compete against each other.
    - Discriminator is trained to better classify between real and fake.
    - Generator is trained to 'fool' the discriminator.

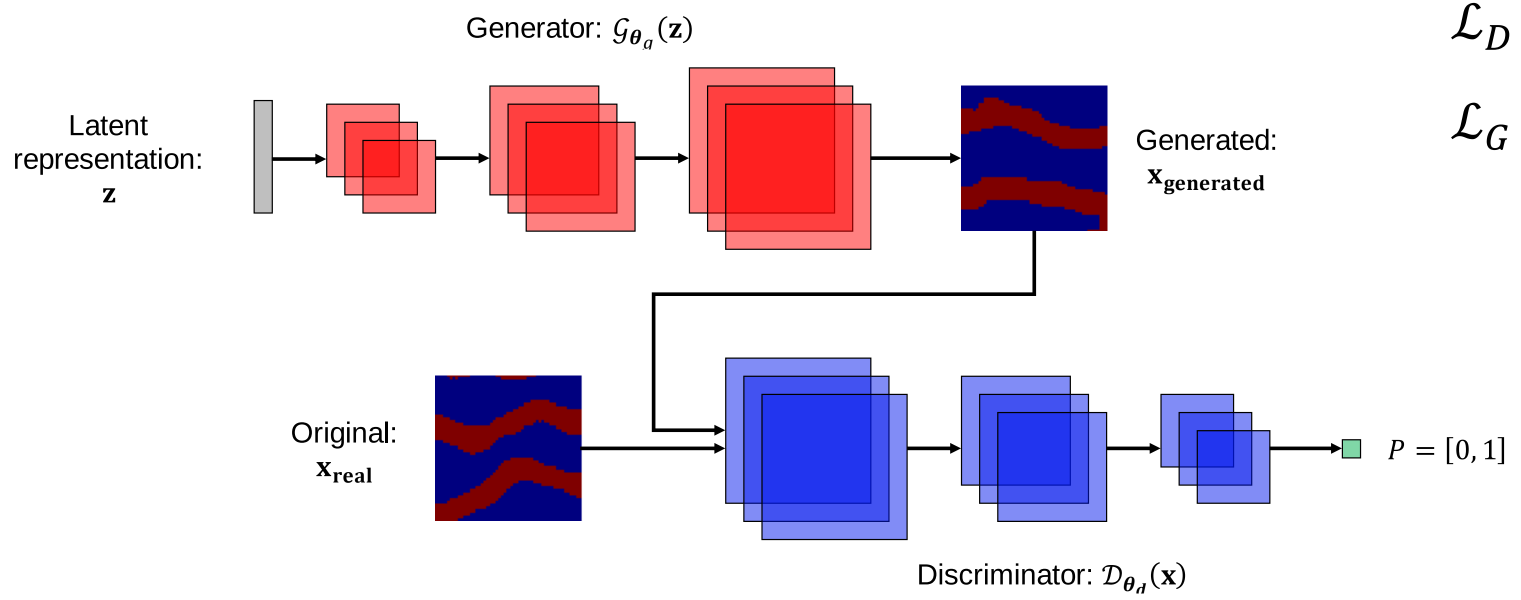




Generative adversarial networks

- DCGAN (Radford et al., 2015):
  - Zero-sum game between $\mathcal{G}$ and $\mathcal{D}$:
  - $\min_{\mathcal{G}} \max_{\mathcal{D}} E_{\mathbf{x}\sim p(\mathbf{x})}[\log \mathcal{D}(\mathbf{x})] + E_{\mathbf{z}\sim p(\mathbf{z})}\left[\log\left(1-\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)\right)\right]$

In Discriminator training: $\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)$ to 0



$$\mathcal{L}_D = \max_{\mathcal{D}} \log \mathcal{D}(\mathbf{x}) + \log\left(1-\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)\right)$$

$$\mathcal{L}_G = \min_{\mathcal{G}} \log\left(1-\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)\right)$$

In generator training: $\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)$ to 1

Generative adversarial networks

- Wasserstein GAN (WGAN)(Arjovsky et al., 2017):
  - Approximates Earth Mover Distance (EMD) (or Wasserstein-1 distance).

  - Discriminator as critic (don't have probabilities):
    - Instead of classifying, discriminator estimates the Wasserstein distance between real and generated distributions: $\mathcal{D}(\cdot) = [0, \infty]$
    - Critic maximizes the distance between its output on real and fake samples
    - Generator minimizes critic output for fake samples
    - $\min_{\mathcal{G}} \max_{\mathcal{D}} E_{\mathbf{x}\sim p(\mathbf{x})}[\mathcal{D}(\mathbf{x})] - E_{\mathbf{z}\sim p(\mathbf{z})}\left[\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)\right]$
  - Seeks for convergence of generator.

In Discriminator training: $\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)$ to 0

$$\mathcal{L}_D = \max_{\mathcal{D}} \mathcal{D}(\mathbf{x}) - \mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)$$

$$\mathcal{L}_G = \min_{\mathcal{G}} -\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)$$

clip $\mathcal{D}(-c, c)$

In Generator training: $\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)$ to ∞

Generative adversarial networks

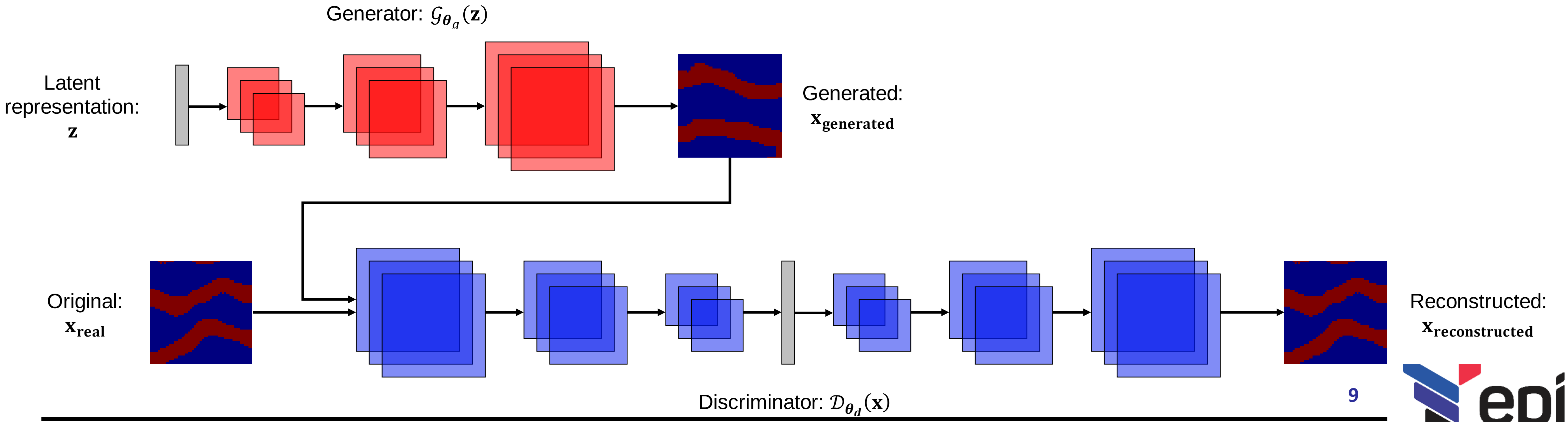
- Wasserstein GAN (WGAN) (Arjovsky et al., 2017):

- Differences:
  - Discriminator output has no constraint (sigmoid in DCGAN because [0, 1])
  - Weight clipping to ensure Lipschitz constraint (w)
  - Need pretrain the discriminator (critic) or train at different rates

- Solved the training failure with cost of convergence speed (Gonog and Zhou, 2019) (also reported in Canchumuni et al., 2021).

Generative adversarial networks

- Boundary Equilibrium GAN (BEGAN) (Berthelot et al., 2017):
  - Autoencoder discriminator (distribution of errors instead distribution of samples)
  - Stable training.
  - Trade-off between image quality and image diversity.
  - Introduced a convergence measure: $\mathcal{M}$



Generative adversarial networks

- Boundary Equilibrium GAN (BEGAN) (Berthelot et al., 2017):
  - Equilibrium when $E_{\mathbf{x}\sim p(\mathbf{x})}[\mathcal{D}(\mathbf{x})] = E_{\mathbf{z}\sim p(\mathbf{z})}\left[\mathcal{D}\left(\mathcal{G}(\mathbf{z})\right)\right]$
  - Discriminator has two objectives:
    - Auto-encode real images
    - Distinguish between real and fake
  - Relax the equilibrium with $\gamma \in [0, 1]$
  - Defining the pixel-wise loss $\mathcal{L}(v) = |v - \mathcal{D}(v)|$
  - Losses:
    - $$\begin{cases} \mathcal{L}_D = \mathcal{L}(\mathbf{x}) - k_t \mathcal{L}\left(\mathcal{G}(\mathbf{z})\right) \\ \mathcal{L}_G = \mathcal{L}\left(\mathcal{G}(\mathbf{z})\right) \\ k_{t+1} = k_t + \lambda_k \left(\gamma \mathcal{L}(\mathbf{x}) - k_t \mathcal{L}\left(\mathcal{G}(\mathbf{z})\right)\right) \end{cases}$$

Diversity ratio

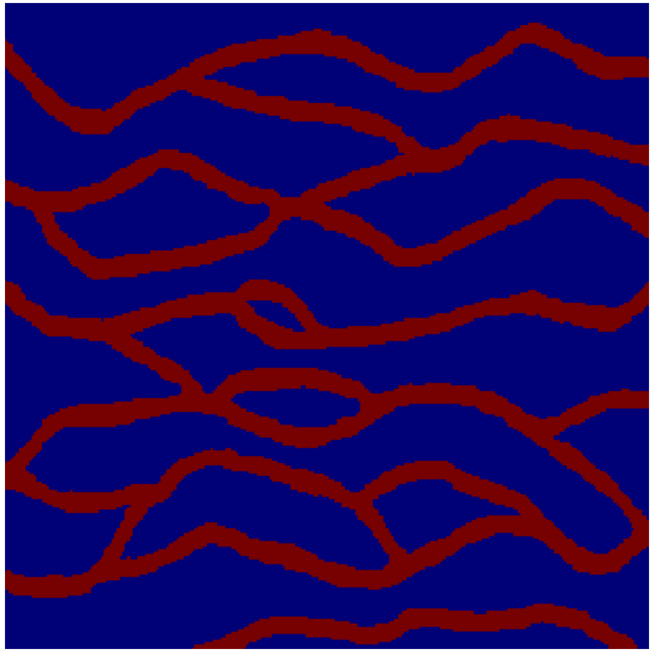
Proportional gain

Samples at varying γ
(Berthelot et al., 2017)

Convergence measure: $\mathcal{M} = \mathcal{L}(\mathbf{x}) + \left|\gamma \mathcal{L}(\mathbf{x}) - \mathcal{L}\left(\mathcal{G}(\mathbf{z})\right)\right|$

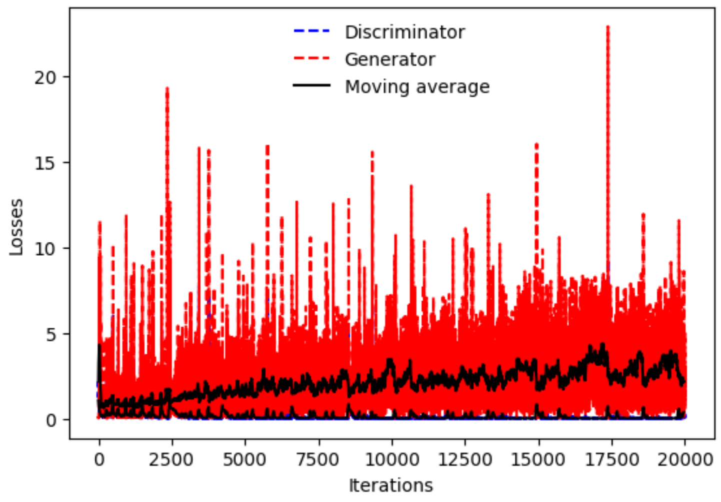
Experiment 1: GANs evaluation

- Channelized reservoir with categorical facies
- 10,000 training samples with SNESIM (Strebelle, 2002)
  - Bao et al. (2022) – 80,000
  - Canchumuni et al. (2021) and Zhang et al. (2022) – 20,000
- 20,000 iterations for all networks (TensorFlow 2.7.0)
- Latent space $N_z = 500$
- 2 channels: [-1, 1] -> final facies is the maximum value Canchumuni et al. (2021)

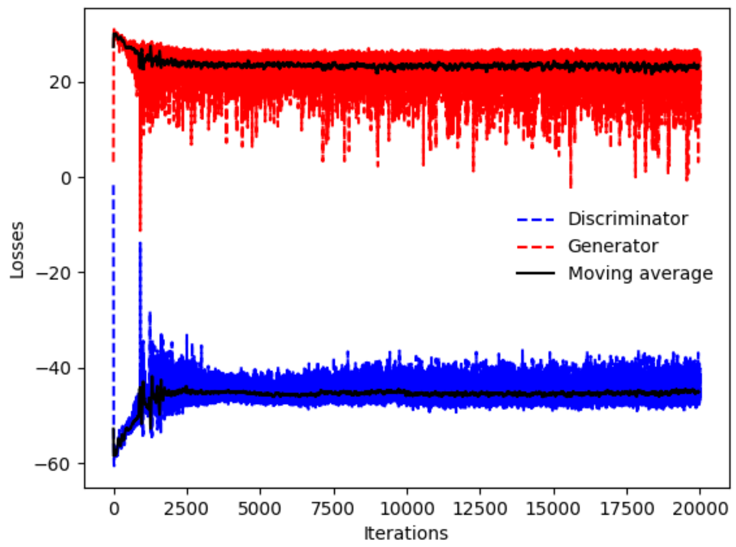


Training image (250x250)

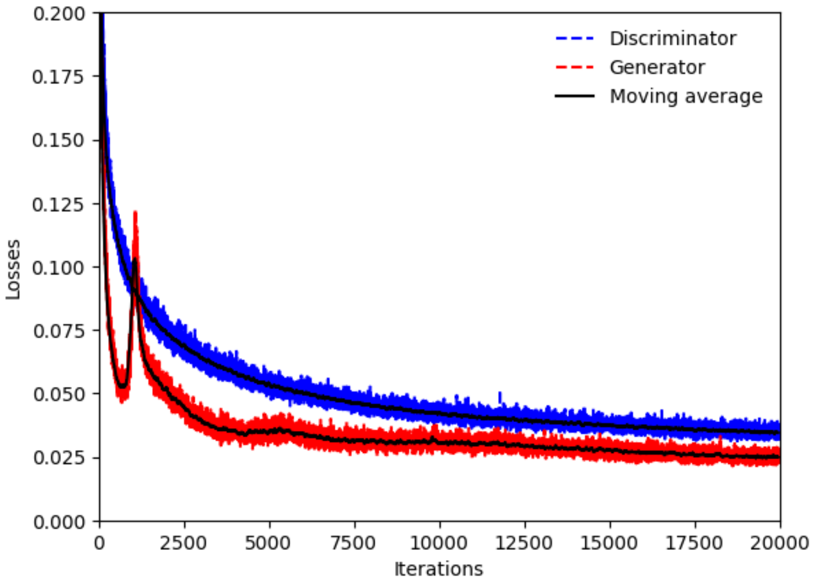
Experiment 1: GANs evaluation



DCGAN



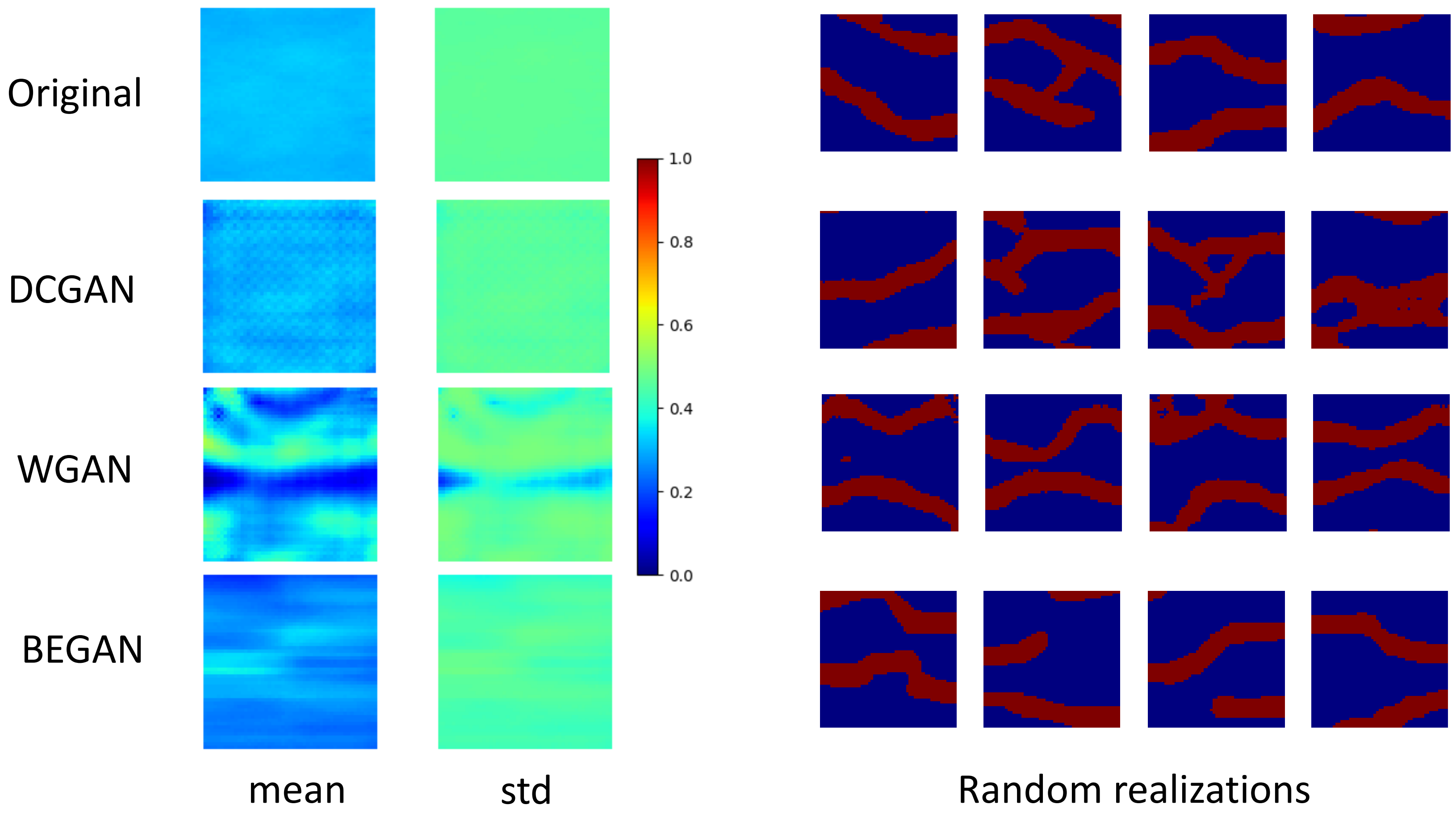
WGAN



BEGAN

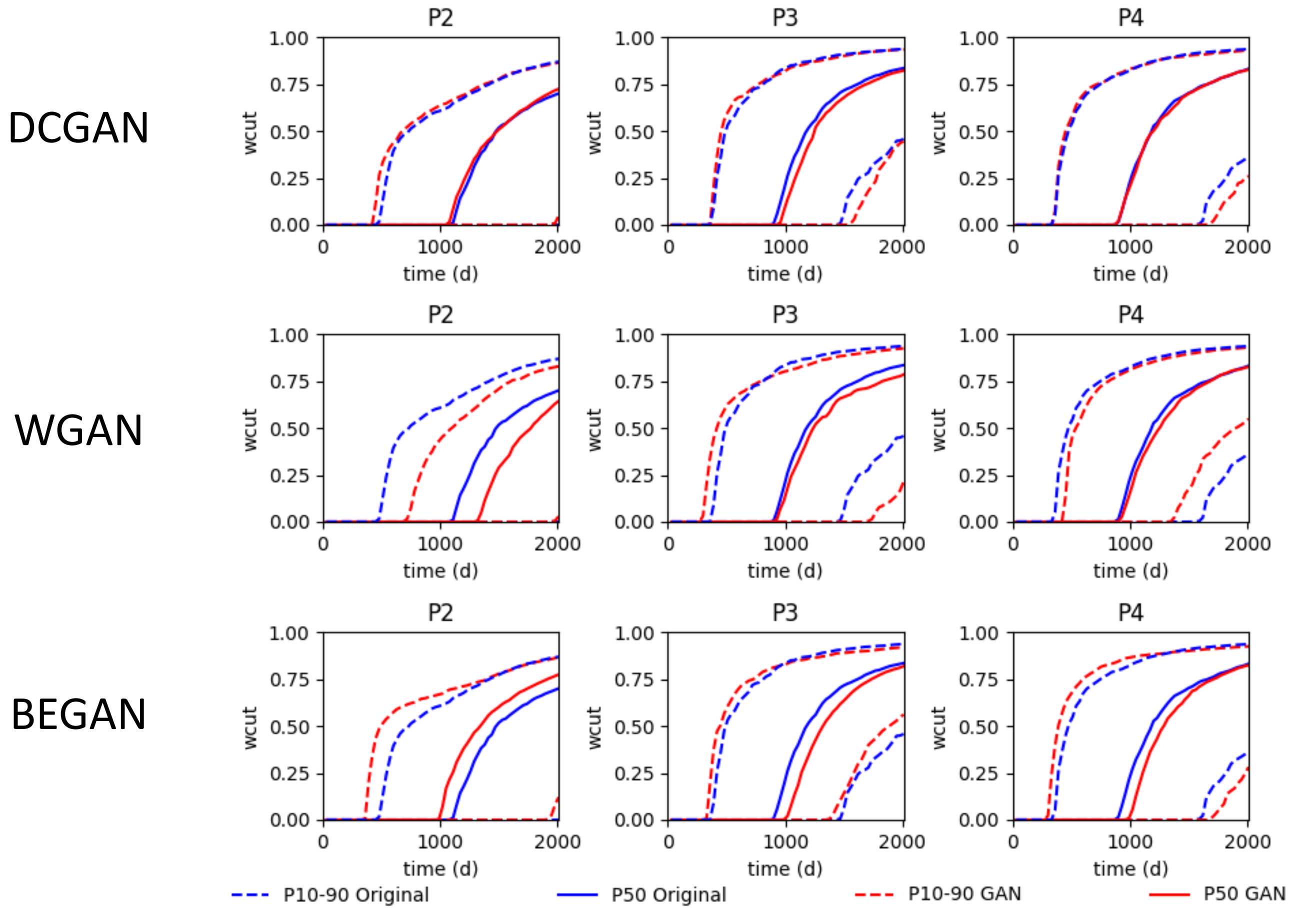
Experiment 1: GANs evaluation

- Random realizations generated with GANs



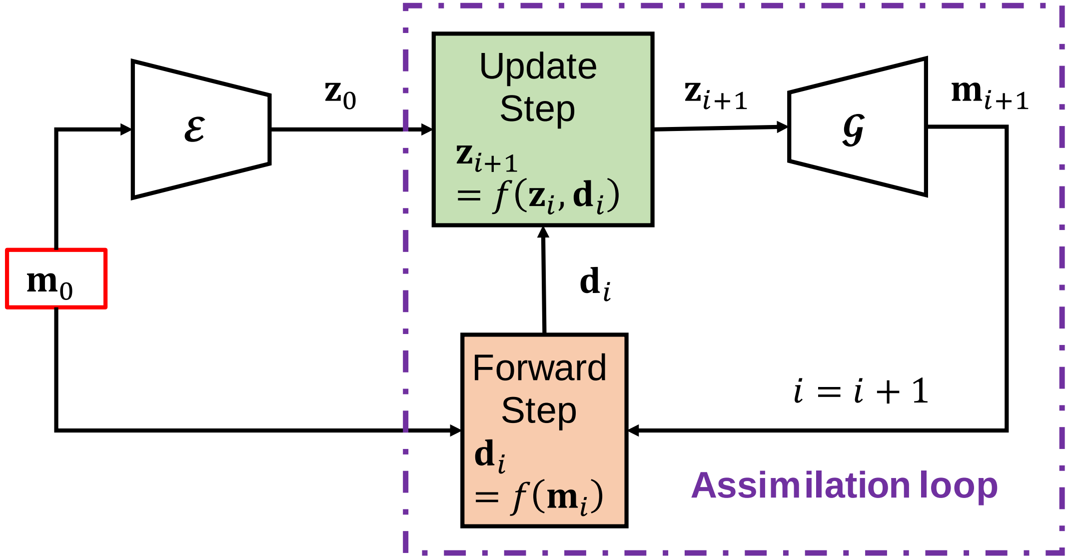
Experiment 1: GANs evaluation

- Percentiles from original and generated ensembles ($N = 200$)

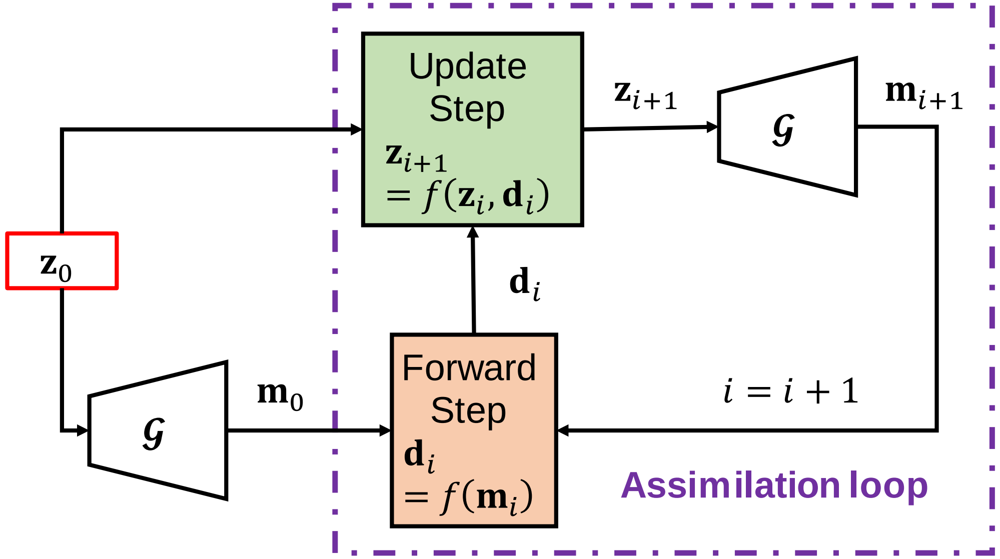


Experiment 2: Assimilation

- Two options:
  - Start by encoding $\{\mathbf{m}_0\}_{j=1}^{N_e}$ to obtain $\{\mathbf{z}_0\}_{j=1}^{N_e}$ (Canchumuni et al., 2021) (encoding)
  - Start by generating the initial ensemble from $\{\mathbf{z}_0\}_{j=1}^{N_e} \sim \boldsymbol{N}(0, \mathbf{I})$ (random)



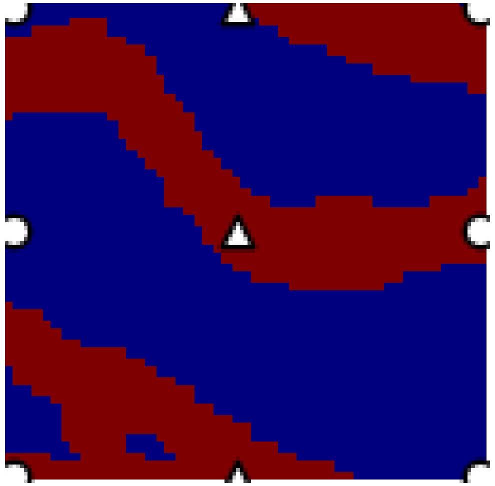
Encoding



Random

Experiment 2: Assimilation

- Test case:



Reference model ($\mathbf{m}_{\text{true}}$)

Size (gridblocks)	51x51x1
Wells	9 (6 producers, 3 injectors)
Data	OPR, WPR, WIR (2500 days) ($N_d = 1005$)
Parameters	Log-Permeability ($N_m = 2601$)
Ensemble size	200
Data assimilation	ES-MDA (Emerick and Reynolds, 2013) with $N_i = \alpha_i = 8$

ES-MDA update step:

$$\mathbf{m}_{j,i+1} = \mathbf{m}_{j,i} + \mathbf{C}_{\mathbf{MD}}(\mathbf{C}_{\mathbf{DD}} + \alpha_i \mathbf{C}_{\mathbf{D}})(\mathbf{d}_{\mathbf{obs},j} - \mathbf{d}_{j,i})$$

$$\sum_{i=1}^{N_i} \alpha_i^{-1} = 1$$

$$\mathbf{d}_{\mathbf{obs},j} \sim (\mathbf{d}_{\mathbf{obs}}, \alpha_i \mathbf{C}_{\mathbf{D}})$$

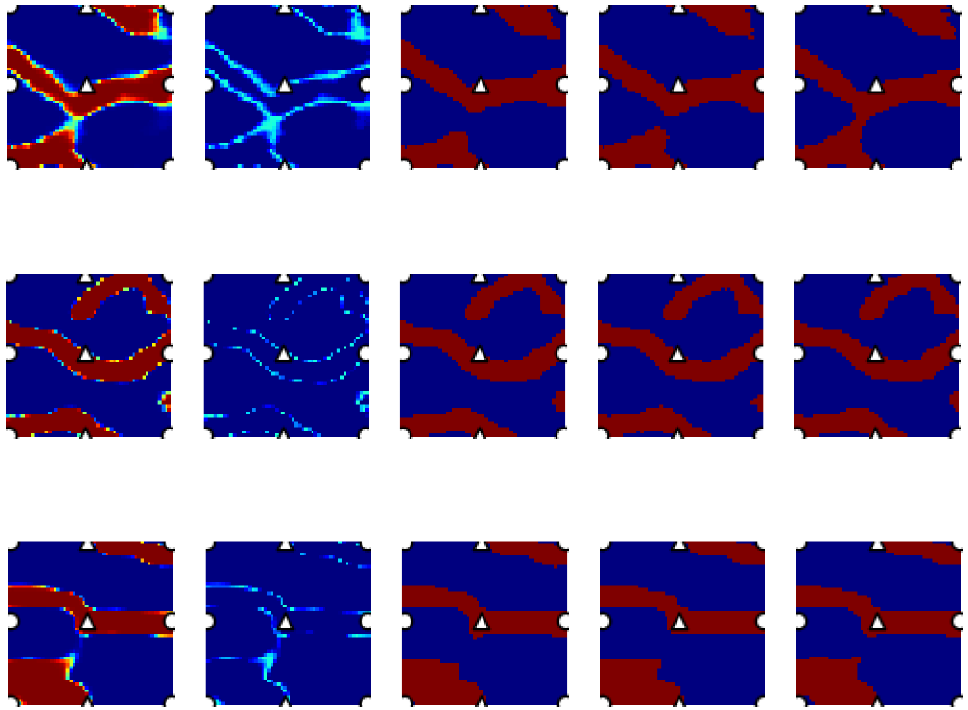
Experiment 2: Assimilation

- Start encoding

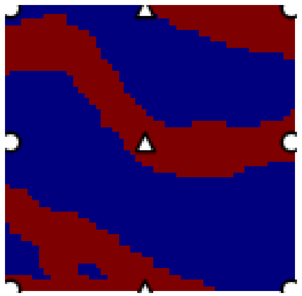
DCGAN

WGAN

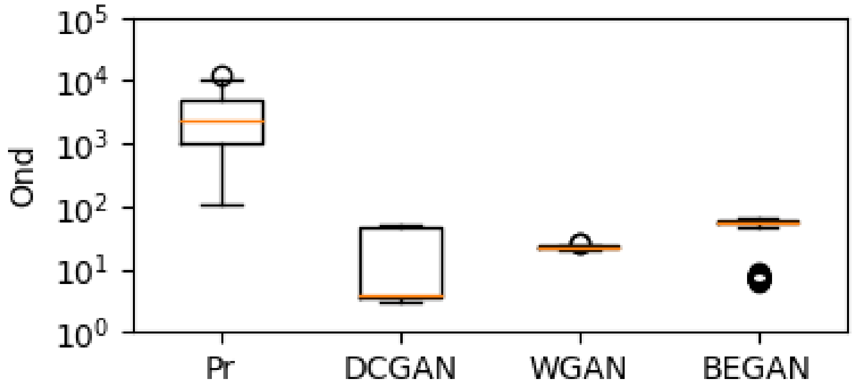
BEGAN



mean std $n = 1$ $n = 2$ $n = 3$



$\mathbf{m}_{\text{true}}$

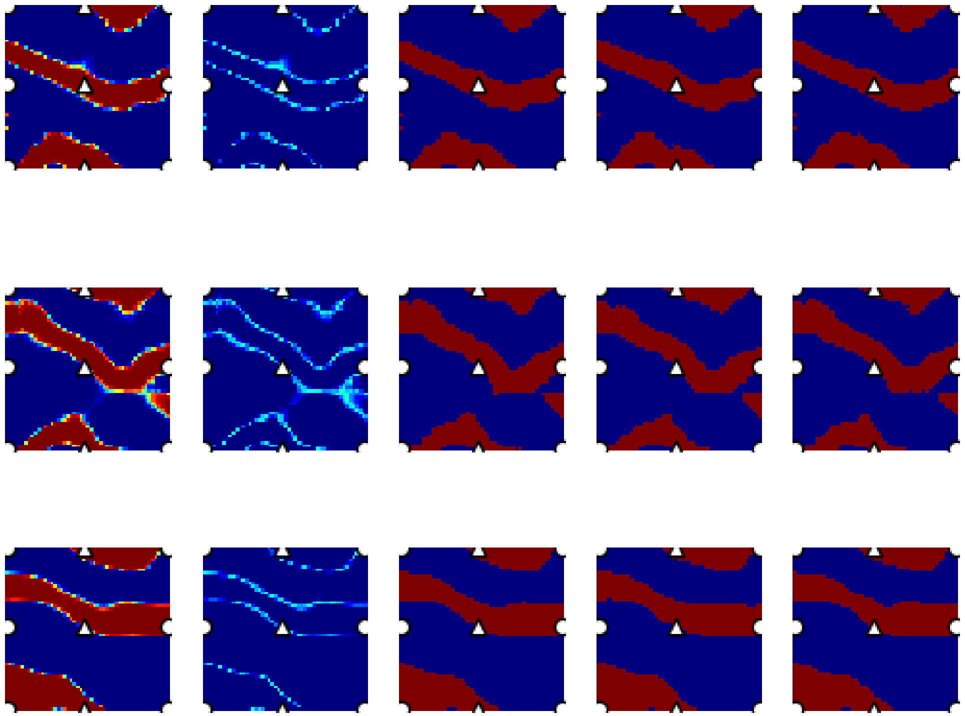


Prior* and posterior data-mismatch for all analyzed cases.

*Prior is the same

Experiment 2: Assimilation

- Start random

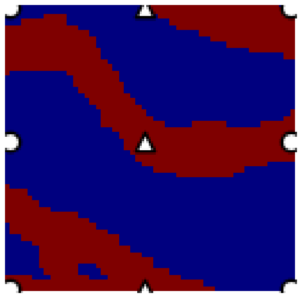


DCGAN

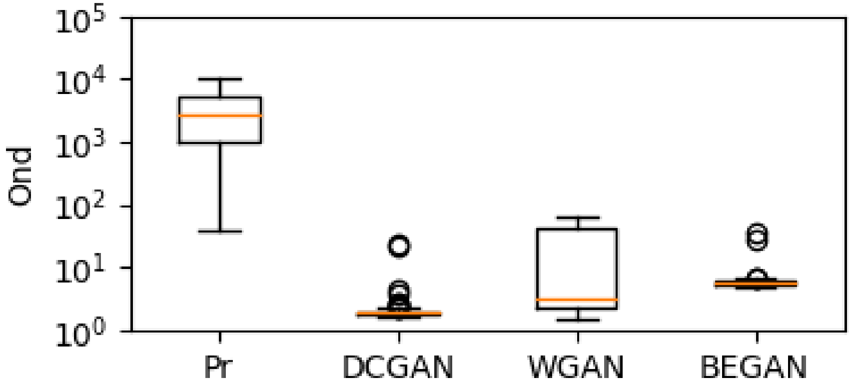
WGAN

BEGAN

mean std $n = 1$ $n = 2$ $n = 3$



$\mathbf{m}_{\mathrm{true}}$



Prior* and posterior data-mismatch for all analyzed cases.

*All cases resulted in similar values

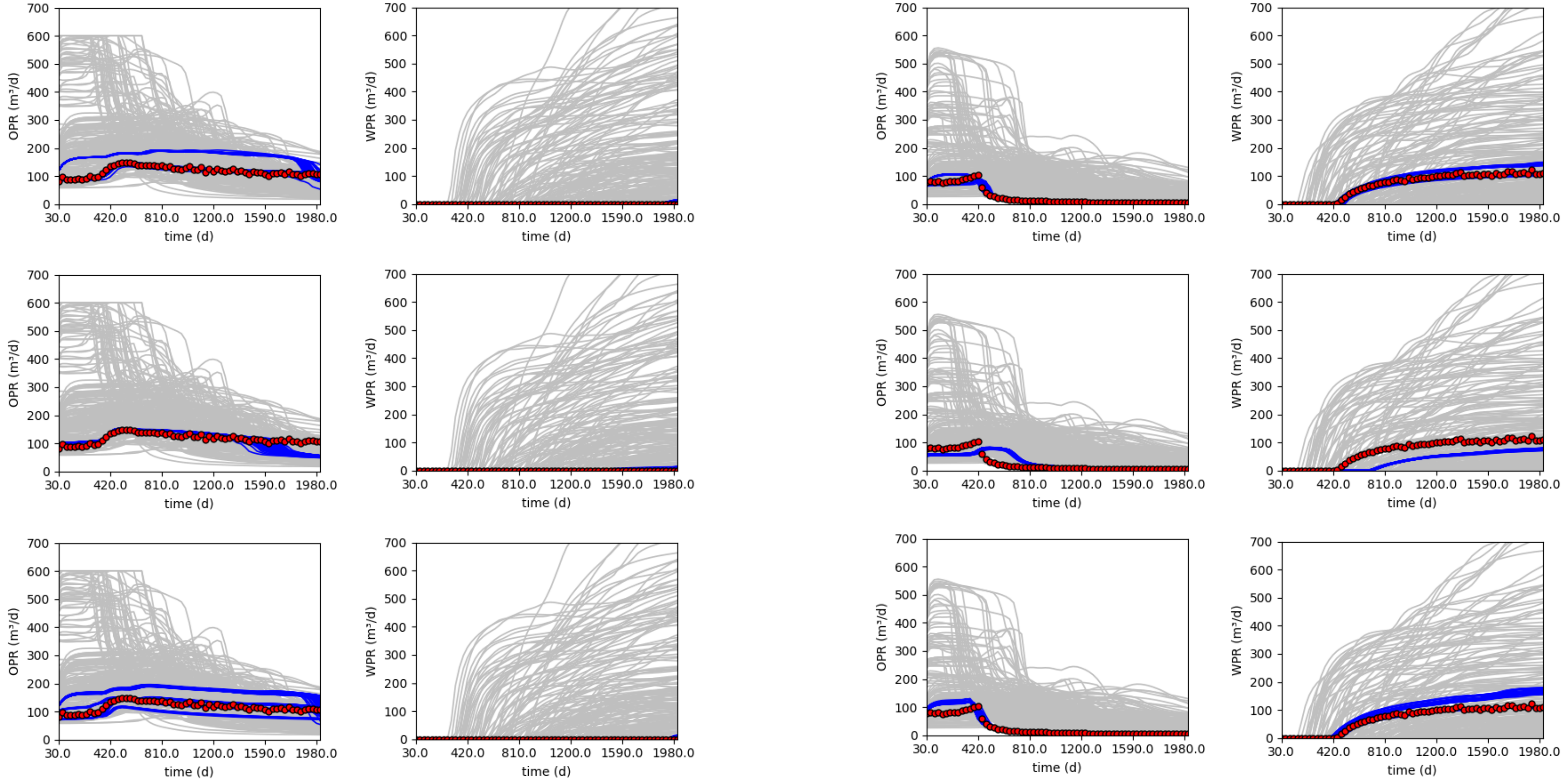
Experiment 2: Assimilation

- Start encoding

DCGAN

WGAN

BEGAN



P2

P4

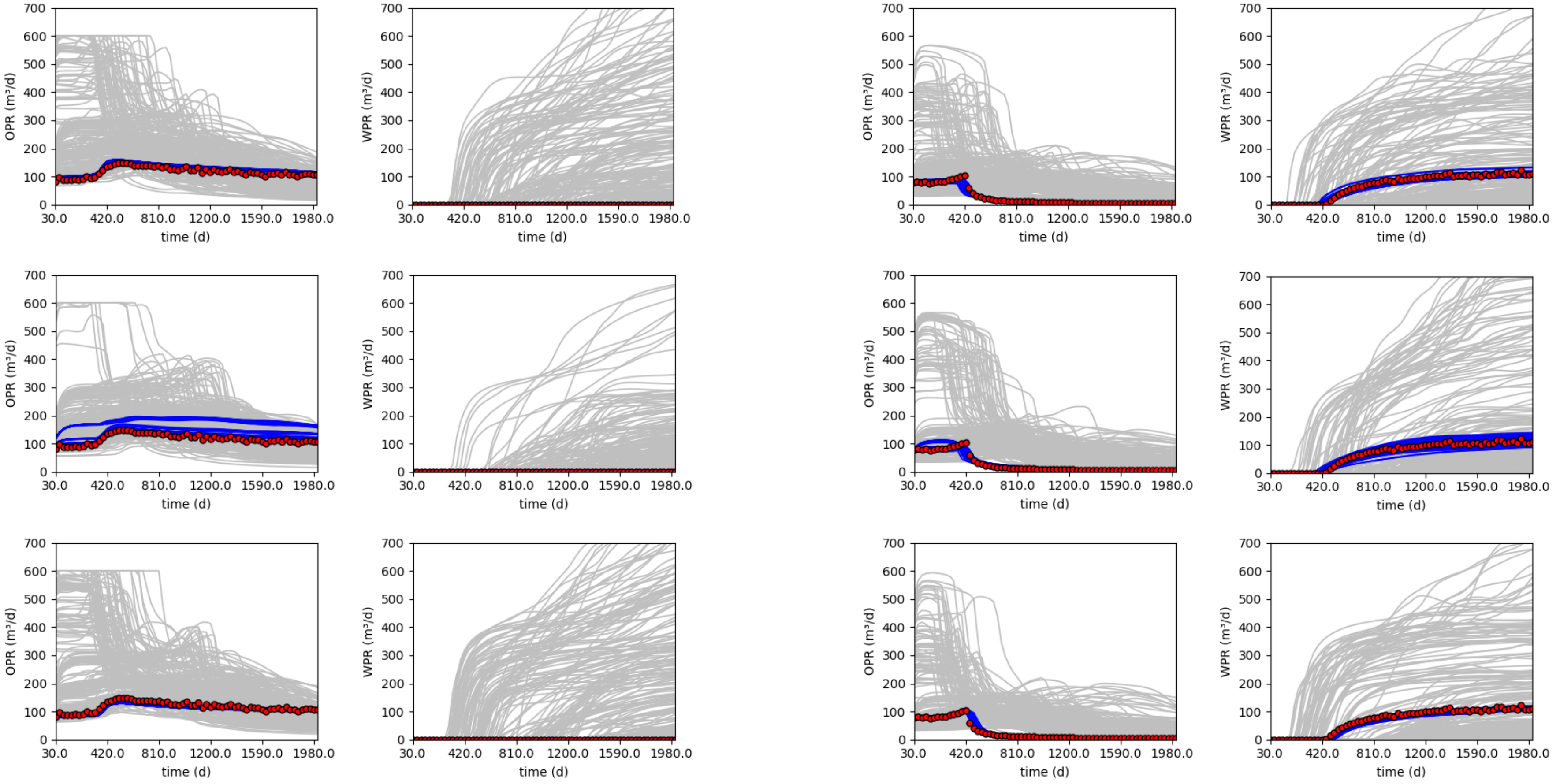
Experiment 2: Assimilation

- Start random

DCGAN

WGAN

BEGAN



P2

P4

Conclusions

- BEGAN resulted in stable training (convergence in loss functions)
- Generated images without discontinuities with ensemble mean and std closer to original ensemble in comparison with WGAN
- Equivalent assimilation results with BEGAN

- Next steps/improvements:
  - Evaluation of hyperparameters effect (γ, N_z)
  - Analysis of different BEGAN architectures (e.g. BEGAN-E) (Xie et al., 2022)
  - Parameterization/generation of 3D reservoirs with GANs stills an open problem

Acknowledgments

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Conclusions

Thank you

for your attention!

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Appendix: Structures

- Networks Architecture:

DCGAN/WGAN

Generator	Config. - Output - Activ.
Input	[500]
Fully-conected	7x7x8n
Reshape	[7x7x8n]
2D conv. Transpose	filters = 8n, size=(5,5), strides=(2,2), padding=same - [14x14x128] - ReLU
Resize	Bilinear - [13x13x2n]
2D conv. Transpose	filters = 4n, size=(5,5), strides=(2,2), padding=same - [26x26x64] - ReLU
2D conv. Transpose	filters = 2n, size=(5,5), strides=(2,2), padding=same - [52x52x32] - ReLU
Resize	Bilinear - [51x51xn]
2D conv. Transpose	filters = 2, size=(5,5), strides=(1,1), padding=same - [51x51x2] - tanh

Discriminator	Config. - Output - Activ.
Input	[51x51x2]
2D conv.	filters = n, size=(4,4), strides=(2,2), padding=same - [26x26x32] - LeakyReLU
2D conv.	filters = 2n, size=(4,4), strides=(2,2), padding=same - [13x13x64] - LeakyReLU
2D conv.	filters = 4n, size=(4,4), strides=(2,2), padding=same - [7x7x128] - LeakyReLU
2D conv.	filters = 8n, size=(4,4), strides=(1,1), padding=same - [7x7x256] - LeakyReLU
Flatten	-
Fully-conected	1 - sigmoid/linear

BEGAN

Encoder	Config. - Output - Activ.
Input	[51x51x2]
2D conv.	filters = n, size=(3,3), strides=(1,1), padding=same - [51x51x32] - LeakyReLU
2D conv.	filters = n, size=(3,3), strides=(2,2), padding=same - [26x26x32] - LeakyReLU
2D conv.	filters = 2n, size=(3,3), strides=(1,1), padding=same - [26x26x64] - LeakyReLU
2D conv.	filters = 2n, size=(3,3), strides=(2,2), padding=same - [13x13x64] - LeakyReLU
2D conv.	filters = 3n, size=(3,3), strides=(1,1), padding=same - [13x13x96] - LeakyReLU
2D conv.	filters = 3n, size=(3,3), strides=(2,2), padding=same - [7x7x96] - LeakyReLU
2D conv.	filters = 4n, size=(3,3), strides=(1,1), padding=same - [7x7x128] - LeakyReLU
2D conv.	filters = 4n, size=(3,3), strides=(1,1), padding=same - [7x7x128] - LeakyReLU
Flatten	-
Fully-conected	[500] - tanh

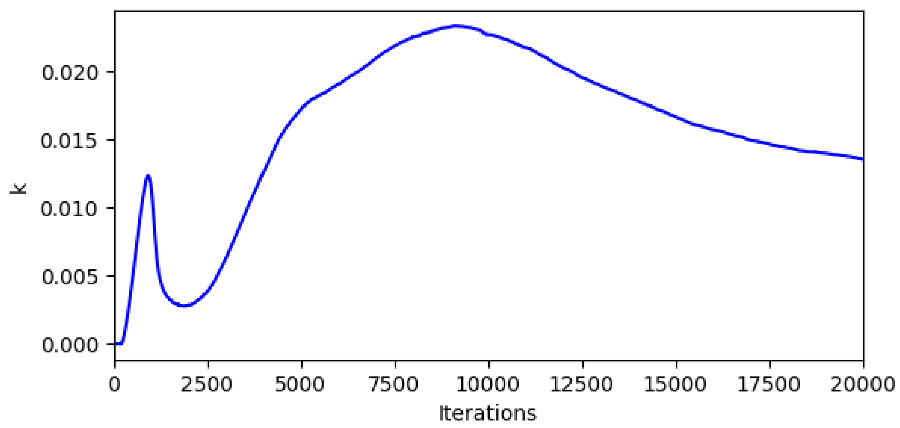
Decoder/Generator	Config. - Output - Activ.
Input	[500]
Fully-conected	7x7xn
Reshape	[7x7xn]
2D conv.	filters = n, size=(3,3), strides=(1,1), padding=same - [7x7x32] - LeakyReLU
Resize 1	Nearest Neighbour - [13x13x32]
Skip Connection 1	Concatenate [Resize1, Reshape]
2D conv.	filters = n, size=(3,3), strides=(1,1), padding=same - [13x13x32] - LeakyReLU
Resize 2	Nearest Neighbour - [26x26x32]
Skip Connection 2	Concatenate [Resize2, Reshape]
2D conv.	filters = n, size=(3,3), strides=(1,1), padding=same - [26x26x32] - LeakyReLU
Resize 3	Nearest Neighbour - [51x51x32]
2D conv.	filters = n, size=(3,3), strides=(1,1), padding=same - [51x51x32] - LeakyReLU
2D conv.	filters = 2, size=(3,3), strides=(1,1), padding=same - [51x51x2] - tanh

Appendix: Hyperparameters

- Networks hyperparameters:

Hyperparameters		
GAN	**WGAN**	**BEGAN**
$N_z = 500$		
Adam	RMSprop	Adam
$\alpha_{\mathcal{G}} = \alpha_{\mathcal{D}} = 0.0002$*	$\alpha_{\mathcal{G}} = \alpha_{\mathcal{D}} = 1E-5$	$\alpha_{\mathcal{G}} = \alpha_{\mathcal{D}} = 0.0001$**
	$n_{critic} = 5$	$h = 500$
	$c = 0.05$	$\lambda_k = 0.001$
		$\gamma = 0.7$
* Generator trained twice in relation to discriminator ** Exponential decay at 10000 steps with rate equal to 0.5		

Appendix: Losses



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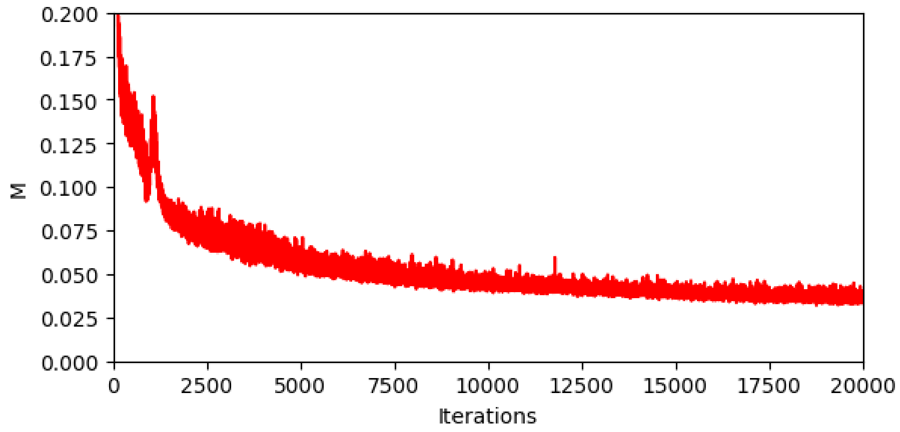

Convergence measure $\mathcal{M}$