

**Geostatistical Inversion for Subsurface Characterization Using Stein Variational Gradient Descent with Autoencoder Neural Network: An Application to Geologic Carbon Sequestration****Mingliang Liu<sup>1</sup>, Dario Grana<sup>2</sup> and Tapan Mukerji<sup>1,3</sup>**<sup>1</sup> Department of Energy Science and Engineering, Stanford University, USA.<sup>2</sup> Department of Geology and Geophysics, University of Wyoming, USA.<sup>3</sup> Department of Geophysics and Department of Earth & Planetary Science, Stanford University, USA.

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**Text S1. Functional derivative of Kullback-Leibler (KL) divergence**

According to the invariance property of the KL divergence under parameter transformations, the following relationship holds:

$$\mathbb{D}_{KL}[q_{[\mathbf{T}]}||\pi] = \mathbb{D}_{KL}[q||\pi_{[\mathbf{T}^{-1}]}]. \quad (\text{S1})$$

Here, the left-hand side represents the KL divergence of the random variable before the transformation, while the right-hand side represents the KL divergence after the transformation.

Hence, we have:

$$\begin{aligned} \nabla_{\epsilon} \mathbb{D}_{KL}[q_{[\mathbf{T}]}||\pi] &= \nabla_{\epsilon} \mathbb{D}_{KL}[q||\pi_{[\mathbf{T}^{-1}]}] = \nabla_{\epsilon} \int q(\mathbf{m}) \log \frac{q(\mathbf{m})}{\pi_{[\mathbf{T}^{-1}]}(\mathbf{m})} d\mathbf{m} \\ &= -\nabla_{\epsilon} \int q(\mathbf{m}) \log \pi_{[\mathbf{T}^{-1}]}(\mathbf{m}) d\mathbf{m} = -\mathbb{E}_{\mathbf{m} \sim q} [\nabla_{\epsilon} \log \pi_{[\mathbf{T}^{-1}]}(\mathbf{m})] \\ &= -\mathbb{E}_{\mathbf{m} \sim q} [\nabla_{\epsilon} \log(\pi(\mathbf{T}(\mathbf{m})) |\det(\nabla_{\mathbf{m}} \mathbf{T}(\mathbf{m}))|)] \\ &= -\mathbb{E}_{\mathbf{m} \sim q} [\nabla_{\epsilon} \log \pi(\mathbf{T}(\mathbf{m})) + \nabla_{\epsilon} \log |\det(\nabla_{\mathbf{m}} \mathbf{T}(\mathbf{m}))|] \\ &= -\mathbb{E}_{\mathbf{m} \sim q} [\nabla_{\mathbf{m}} \log \pi(\mathbf{T}(\mathbf{m}))^T \nabla_{\epsilon} \mathbf{T}(\mathbf{m}) + \text{trace}(\nabla_{\mathbf{m}} \mathbf{T}(\mathbf{m})^{-1} \nabla_{\epsilon} \nabla_{\mathbf{m}} \mathbf{T}(\mathbf{m}))]. \end{aligned} \quad (\text{S2})$$

Considering  $\mathbf{T}(\mathbf{m}) = \mathbf{m} + \epsilon \boldsymbol{\phi}(\mathbf{m})$  and making a first-order approximation, we have:

$$\mathbf{T}(\mathbf{m}) \approx \mathbf{m}, \quad (\text{S3})$$

$$\nabla_{\mathbf{m}} \mathbf{T}(\mathbf{m}) \approx \mathbf{I}, \quad (\text{S4})$$

$$\nabla_{\epsilon} \mathbf{T}(\mathbf{m}) = \boldsymbol{\phi}(\mathbf{m}), \quad (\text{S5})$$

$$\nabla_{\epsilon} \nabla_{\mathbf{m}} \mathbf{T}(\mathbf{m}) = \nabla_{\mathbf{m}} \boldsymbol{\phi}(\mathbf{m}). \quad (\text{S6})$$

By substituting Equations S3 to S6 into Equation S2, we have:

$$\begin{aligned} \nabla_{\epsilon} \mathbb{D}_{KL}[q_{[\mathbf{T}]}||\pi] &= -\mathbb{E}_{\mathbf{m} \sim q} [\nabla_{\mathbf{m}} \log \pi(\mathbf{m})^T \boldsymbol{\phi}(\mathbf{m}) + \text{trace}(\mathbf{I}^{-1} \nabla_{\mathbf{m}} \boldsymbol{\phi}(\mathbf{m}))] \\ &= -\mathbb{E}_{\mathbf{m} \sim q} [\text{trace}(\mathcal{A}_{\pi}[\boldsymbol{\phi}(\mathbf{m}))]]. \end{aligned} \quad (\text{S7})$$

where  $\mathcal{A}_{\pi}$  is the so-called Stein operator:

$$\mathcal{A}_{\pi}[\boldsymbol{\phi}(\mathbf{m})] \triangleq \boldsymbol{\phi}(\mathbf{m}) \nabla_{\mathbf{m}} \log \pi(\mathbf{m}) + \nabla_{\mathbf{m}} \boldsymbol{\phi}(\mathbf{m}). \quad (\text{S8})$$

### Text S2. Reproducing kernel Hilbert space (RKHS)

Let  $\mathcal{H}$  be a Hilbert space consisting of real-valued functions  $f: \mathcal{X} \rightarrow \mathbb{R}$ . A function  $K: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$  is called a reproducing kernel of  $\mathcal{H}$  if it satisfies the following conditions:

$$(1) \forall x \in \mathcal{X}, K_x := K(x, \cdot) \in \mathcal{H};$$

$$(2) \forall x \in \mathcal{X}, \forall f \in \mathcal{H}, \langle f, K(x, \cdot) \rangle_{\mathcal{H}} = f(x).$$

If  $\mathcal{H}$  has a reproducing kernel,  $\mathcal{H}$  is referred to as a reproducing kernel Hilbert space (RKHS).

Conversely, given a kernel function  $K: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ , a mapping  $\phi: \mathcal{X} \rightarrow \mathcal{H}$  can be defined as follows:

$$x \mapsto \phi(x) := K_x := K(x, \cdot). \quad (\text{S9})$$

Here, each point  $x \in \mathcal{X}$  is mapped to the functional  $K_x: \mathcal{X} \rightarrow \mathbb{R}$ , defined by:

$$K_x(x') = K(x, x'), \forall x' \in \mathcal{X}. \quad (\text{S10})$$

An inner product space  $\mathcal{G}$  can then be constructed by taking the span of  $\{\phi(x) : x \in \mathcal{X}\}$ :

$$\mathcal{G} := \text{span}\{\phi(x) : x \in \mathcal{X}\}. \quad (\text{S11})$$

The space  $\mathcal{G}$  is equipped with the inner product defined as:

$$\langle f, g \rangle_{\mathcal{G}} := \left\langle \sum_i f_i K(x_i, \cdot), \sum_j g_j K(x_j, \cdot) \right\rangle_{\mathcal{G}} := \sum_{i,j} f_i g_j K(x_i, x_j). \quad (\text{S12})$$

By taking the topological completion of  $\mathcal{G}$ , the resulting space  $\mathcal{H} := \bar{\mathcal{G}}$  is the RKHS associated with the given kernel function  $K$ .

**Text S3. Proof of the optimal perturbation direction for SVGD (Liu and Wang, 2016)**

Let  $\mathcal{B} = \{f \in \mathcal{H}: \|f\|_{\mathcal{H}} \leq 1\}$  be the reproducing kernel Hilbert space (RKHS) associated with kernel function  $K: \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$ . Define  $\boldsymbol{\beta}(\cdot) = \mathbb{E}_{\mathbf{m} \sim q}[K(\mathbf{m}, \cdot) \nabla_{\mathbf{m}} \log \pi(\mathbf{m}) + \nabla_{\mathbf{m}} K(\mathbf{m}, \cdot)]$  where  $\boldsymbol{\beta} \in \mathcal{B}$ .

For a general function  $\boldsymbol{\phi} \in \mathcal{B}$ , using the reproducing property introduced in Text S2, we have:

$$\begin{aligned}
 \langle \boldsymbol{\phi}, \boldsymbol{\beta} \rangle_{\mathcal{B}} &= \langle \boldsymbol{\phi}, \mathbb{E}_{\mathbf{m} \sim q}[K(\mathbf{m}, \cdot) \nabla_{\mathbf{m}} \log \pi(\mathbf{m}) + \nabla_{\mathbf{m}} K(\mathbf{m}, \cdot)] \rangle_{\mathcal{B}} \\
 &= \mathbb{E}_{\mathbf{m} \sim q}[\langle \boldsymbol{\phi}, K(\mathbf{m}, \cdot) \rangle_{\mathcal{B}} \nabla_{\mathbf{m}} \log \pi(\mathbf{m}) + \nabla_{\mathbf{m}} \langle \boldsymbol{\phi}, K(\mathbf{m}, \cdot) \rangle_{\mathcal{B}}] \\
 &= \mathbb{E}_{\mathbf{m} \sim q}[\text{trace}(\boldsymbol{\phi}(\mathbf{m}) \nabla_{\mathbf{m}} \log \pi(\mathbf{m}) + \nabla_{\mathbf{m}} \boldsymbol{\phi}(\mathbf{m}))] \\
 &= \mathbb{E}_{\mathbf{m} \sim q}[\text{trace}(\mathcal{A}_{\pi}[\boldsymbol{\phi}(\mathbf{m}))]].
 \end{aligned} \tag{S13}$$

Therefore, maximizing  $\mathbb{E}_{\mathbf{m} \sim q}[\text{trace}(\mathcal{A}_{\pi}[\boldsymbol{\phi}(\mathbf{m}))]]$  is equivalent to maximize the inner product  $\langle \boldsymbol{\phi}, \boldsymbol{\beta} \rangle_{\mathcal{B}}$ . Obviously, the maximum occurs when  $\boldsymbol{\phi}$  is proportional to  $\boldsymbol{\beta}$ . Hence, the optimal perturbation direction for SVGD is:

$$\boldsymbol{\phi}^* \propto \boldsymbol{\beta}(\cdot) = \mathbb{E}_{\mathbf{m} \sim q}[K(\mathbf{m}, \cdot) \nabla_{\mathbf{m}} \log \pi(\mathbf{m}) + \nabla_{\mathbf{m}} K(\mathbf{m}, \cdot)]. \tag{S14}$$

#### Text S4. Rock physics model

The unconsolidated and consolidated sand model were developed by Dvorkin and Nur (1996) to predict the elastic properties (e.g., P- and S-wave velocities and density) of sandstones based on their porosity and other properties for different geological conditions. In both rock physics models, the matrix bulk and shear moduli ( $K_{\text{mat}}$  and  $\mu_{\text{mat}}$ ) are derived using the Voigt-Reuss-Hill average based on mineral fractions (e.g., clay and quartz volumes). The moduli of dry rock ( $K_{\text{HM}}$  and  $\mu_{\text{HM}}$ ) at the critical porosity  $\phi_0$  are determined through the Hertz-Mindlin equations (Mindlin, 1949):

$$K_{\text{HM}} = \sqrt[3]{\frac{P_e [n_c (1 - \phi_0) \mu_{\text{mat}}]^2}{18 [\pi (1 - \nu_{\text{mat}})]^2}}, \quad (\text{S15})$$

$$\mu_{\text{HM}} = \frac{5 - 4\nu_{\text{mat}}}{5(2 - \nu_{\text{mat}})} \sqrt[3]{\frac{3P_e [n_c (1 - \phi_0) \mu_{\text{mat}}]^2}{2 [\pi (1 - \nu_{\text{mat}})]^2}}, \quad (\text{S16})$$

where  $P_e$  is the effective pressure,  $\nu_{\text{mat}}$  is the grain Poisson's ratio and  $n_c$  is the coordination number, which refers to the average number of grain contacts.

In the unconsolidated sand model, the dry rock moduli ( $K_{\text{dry}}$  and  $\mu_{\text{dry}}$ ) for porosity within the range  $[0, \phi_0]$  are obtained by interpolating two end members: the matrix moduli and dry rock moduli at critical porosity, using the modified Hashin-Shtrikman lower bounds:

$$K_{\text{dry}} = \left( \frac{\frac{\phi}{\phi_0}}{K_{\text{HM}} + \frac{4}{3}\mu_{\text{HM}}} + \frac{1 - \frac{\phi}{\phi_0}}{K_{\text{mat}} + \frac{4}{3}\mu_{\text{HM}}} \right)^{-1} - \frac{4}{3}\mu_{\text{HM}}, \quad (\text{S17})$$

$$\mu_{\text{dry}} = \left( \frac{\frac{\phi}{\phi_0}}{\mu_{\text{HM}} + \frac{1}{6}\xi\mu_{\text{HM}}} + \frac{1 - \frac{\phi}{\phi_0}}{\mu_{\text{mat}} + \frac{1}{6}\xi\mu_{\text{HM}}} \right)^{-1} - \frac{1}{6}\xi\mu_{\text{HM}}, \quad (\text{S18})$$

with

$$\xi = \frac{9K_{\text{HM}} + 8\mu_{\text{HM}}}{K_{\text{HM}} + 2\mu_{\text{HM}}}. \quad (\text{S19})$$

Similarly, the consolidated sand model uses the modified Hashin-Shtrikman upper bounds to interpolate the elastic moduli values for porosities ranging from 0 to the critical porosity  $\phi_0$ :

$$K_{\text{dry}} = \left( \frac{\frac{\phi}{\phi_0}}{K_{\text{HM}} + \frac{4}{3}\mu_{\text{mat}}} + \frac{1 - \frac{\phi}{\phi_0}}{K_{\text{mat}} + \frac{4}{3}\mu_{\text{mat}}} \right)^{-1} - \frac{4}{3}\mu_{\text{mat}}, \quad (\text{S20})$$

$$\mu_{\text{dry}} = \left( \frac{\frac{\phi}{\phi_0}}{\mu_{\text{HM}} + \frac{1}{6}\xi\mu_{\text{mat}}} + \frac{1 - \frac{\phi}{\phi_0}}{\mu_{\text{mat}} + \frac{1}{6}\xi\mu_{\text{mat}}} \right)^{-1} - \frac{1}{6}\xi\mu_{\text{mat}}, \quad (\text{S21})$$

With

$$\xi = \frac{9K_{\text{mat}} + 8\mu_{\text{mat}}}{K_{\text{mat}} + 2\mu_{\text{mat}}}. \quad (\text{S22})$$

For rocks saturated with fluid, Gassmann's equations (Gassmann, 1951) are used to compute the bulk shear moduli ( $K_{\text{sat}}$  and  $\mu_{\text{sat}}$ )

$$K_{\text{sat}} = K_{\text{dry}} + \frac{\left(1 - \frac{K_{\text{dry}}}{K_{\text{mat}}}\right)^2}{\frac{\phi}{K_{\text{fl}}} + \frac{1-\phi}{K_{\text{mat}}} - \frac{K_{\text{dry}}}{K_{\text{mat}}^2}}, \quad (\text{S23})$$

$$\mu_{\text{sat}} = \mu_{\text{dry}}. \quad (\text{S24})$$

where  $K_{\text{fl}}$  is the bulk modulus of the fluid phase calculated from the brine water and supercritical  $\text{CO}_2$  saturations ( $s_{\text{bw}}$  and  $s_{\text{CO}_2}$ ) and their corresponding bulk moduli ( $K_{\text{bw}}$  and  $K_{\text{CO}_2}$ ). We assume that the fluid components are homogeneously mixed and the effective bulk modulus by  $K_{\text{fl}}$  is computed using Wood's averaging method (Mavko et al., 2020):

$$K_{\text{fl}} = \frac{1}{\frac{s_{\text{bw}}}{K_{\text{bw}}} + \frac{s_{\text{CO}_2}}{K_{\text{CO}_2}}}. \quad (\text{S25})$$

For reservoirs with uneven fluid distribution, like in-situ patchy saturation, it is recommended to use Voigt or Brie's equations (Mavko et al., 2020) for the fluid mixture.

Finally, the P- and S-wave velocities can be computed from the moduli by definition as

$$V_p = \sqrt{\frac{K_{\text{sat}} + \frac{4}{3}\mu_{\text{sat}}}{\rho_{\text{sat}}}}, \quad (\text{S26})$$

$$V_s = \sqrt{\frac{\mu_{\text{sat}}}{\rho_{\text{sat}}}}, \quad (\text{S27})$$

where  $\rho_{\text{sat}}$  is the density of the saturated rock which is weighted average of the matrix density  $\rho_{\text{mat}}$  and fluid density  $\rho_{\text{fl}}$

$$\rho_{\text{sat}} = (1 - \phi)\rho_{\text{mat}} + \phi\rho_{\text{fl}}. \quad (\text{S28})$$

The effective bulk modulus of the matrix  $\rho_{\text{mat}}$  and fluid mixture  $\rho_{\text{fl}}$  are provided by the Voigt average as

$$\rho_{\text{mat}} = (1 - v_{\text{cl}})\rho_{\text{qtz}} + v_{\text{cl}}\rho_{\text{cl}}, \quad (\text{S29})$$

$$\rho_{fl} = (1 - s_{CO_2})\rho_{bw} + s_{CO_2}\rho_{CO_2}, \quad (S30)$$

where  $v_{cl}$  and  $s_{CO_2}$  are the volumetric fractions of clay and  $CO_2$  saturation, respectively; and  $\rho_{qtz}$ ,  $\rho_{cl}$ ,  $\rho_{bw}$  and  $\rho_{CO_2}$  are the density of quartz, clay, brine water and supercritical  $CO_2$ , respectively.

**Text S1.** Rock physics parameters associated with the unconsolidated sand model in Example 2.

<b>Parameter</b>	<b>Value</b>
Bulk modulus of quartz	36.6 GPa
Shear modulus of quartz	44.0 GPa
Density of quartz	2.65 g/cm <sup>3</sup>
Bulk modulus of clay	21.0 GPa
Shear modulus of clay	9.0 GPa
Density of clay	2.5 g/cm <sup>3</sup>
Bulk modulus of brine	3.06 GPa
Density of brine	1.08 g/cm <sup>3</sup>
Effective pressure	0.02 GPa
Critical porosity	0.4
Coordination number	7

**Table S2.** Architecture of the autoencoder neural network in Example 2 ( $N_m$  represents the number of different reservoir properties).

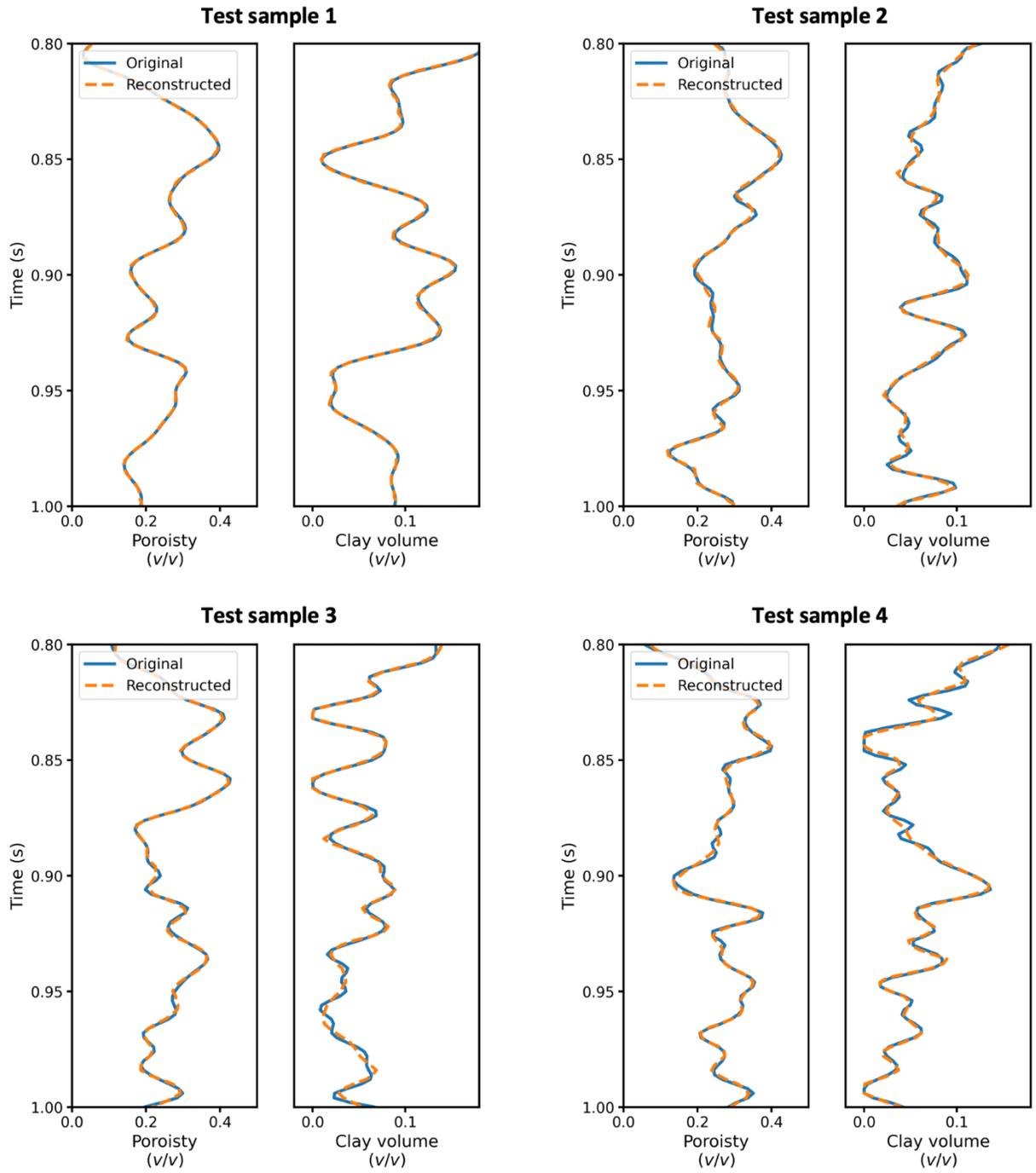
<b>Layer</b>	<b>Output size</b>
1. Input	$N_m \times 101$
2. Conv1D + Upsample	4x51
3. Conv1D + Upsample	8x26
4. Conv1D + Upsample	16x13
5. Conv1D + Upsample	32x7
6. Conv1D + Upsample	32x4
7. Tanh	32x4
8. Conv1D + Downsample	32x7
9. Conv1D + Downsample	16x13
10. Conv1D + Downsample	8x26
11. Conv1D + Downsample	4x51
12. Conv1D + Downsample	$N_m \times 101$
13. CustomLinearActivation*	$N_m \times 101$

\* The customized activation function is linear between 0 and 1, assigning a value of 0 if the output is less than 0 and a value of 1 if the output exceeds 1.

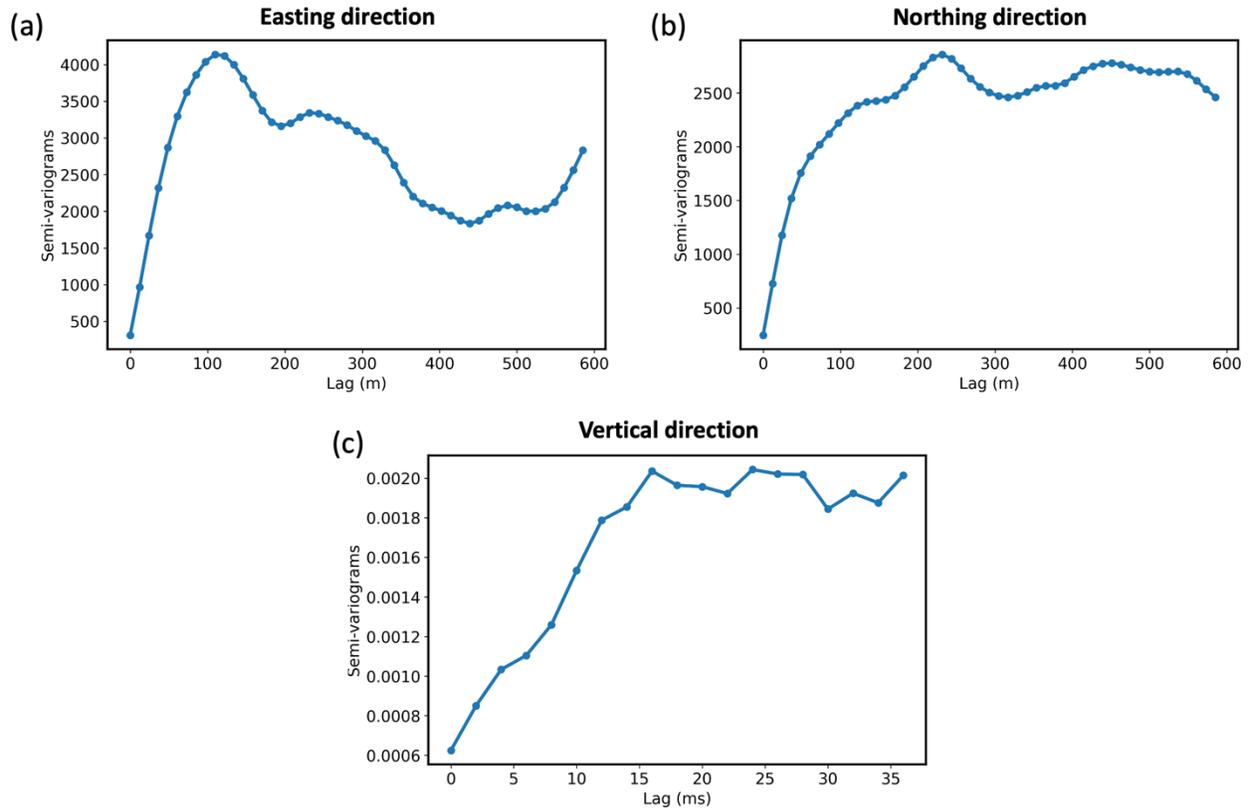
**Table S3.** Architecture of the autoencoder neural network in Example 3 ( $N_m$  represents the number of different reservoir properties).

<b>Layer</b>	<b>Output size</b>
14. Input	$N_m \times 201$
15. Conv1D + Upsample	4x101
16. Conv1D + Upsample	8x51
17. Conv1D + Upsample	16x26
18. Conv1D + Upsample	32x13
19. Conv1D + Upsample	32x7
20. Tanh	32x7
21. Conv1D + Downsample	32x13
22. Conv1D + Downsample	16x26
23. Conv1D + Downsample	8x51
24. Conv1D + Downsample	4x101
25. Conv1D + Downsample	$N_m \times 201$
26. CustomLinearActivation*	$N_m \times 201$

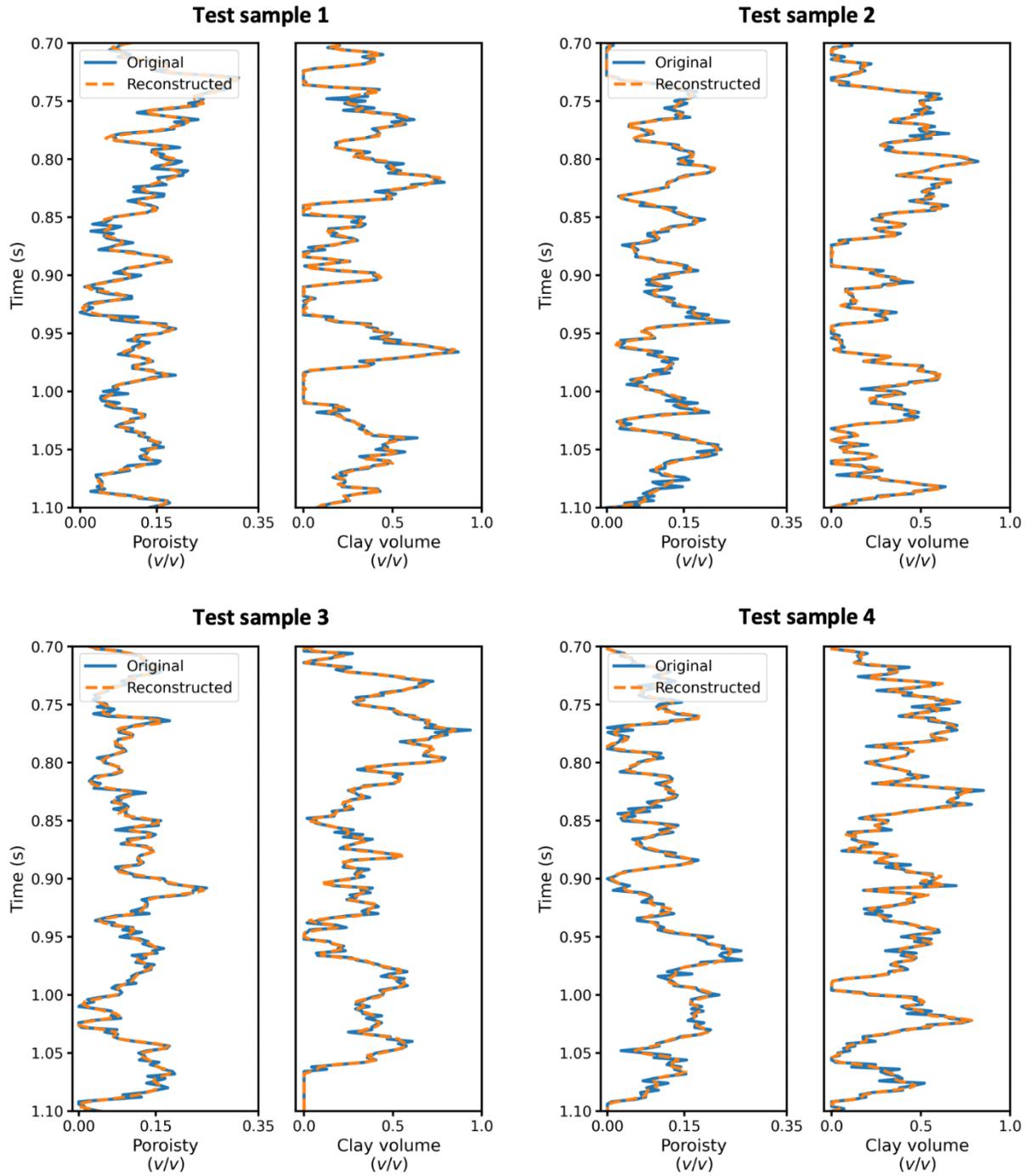
\* The customized activation function is linear between 0 and 1, assigning a value of 0 if the output is less than 0 and a value of 1 if the output exceeds 1.



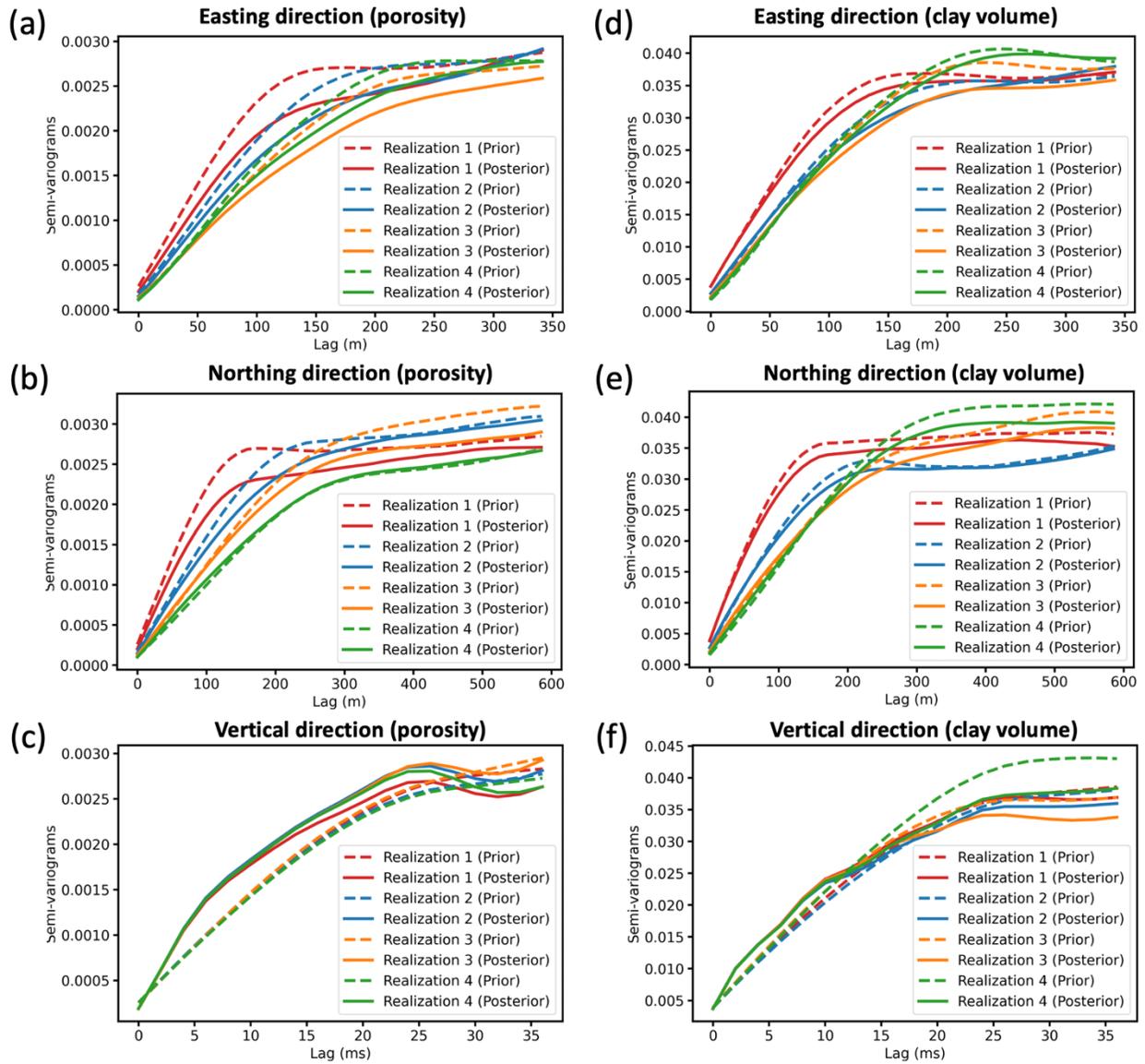
**Figure S1.** Comparison between the original reservoir models in the test set of Example 2 and their corresponding reconstructions by the trained autoencoder.



**Figure S2.** Experimental variograms of the IBDP case: (a) easting direction; (b) northing direction; (c) vertical direction.



**Figure S3.** Comparison between the original reservoir models in the test set of the IBDP case and their corresponding reconstructions by the trained autoencoder.



**Figure S4.** Experimental variograms for the prior and posterior reservoir models in the IBDP case: (a)-(c) variograms of porosity in easting, northing and vertical direction, respectively; (d)-(f) variograms of clay volume in easting, northing and vertical direction, respectively.

## References

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