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Physics-informed Deep Generative Models to Quantify Uncertainties in Geophysical Full-waveform Inversion

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Motivation

- Goal: reconstruct reliable velocity models of subsurface
- Problems: noisy measurements, absence of low frequency data, etc.
- UQ methods are used to quantify the uncertainties in the reconstructed models
- UQ families
  - Sampling methods: e.g., MCMC – robust but very expensive
  - Variational based methods on the other hand can provide cheaper UQ solutions but comes with some assumptions

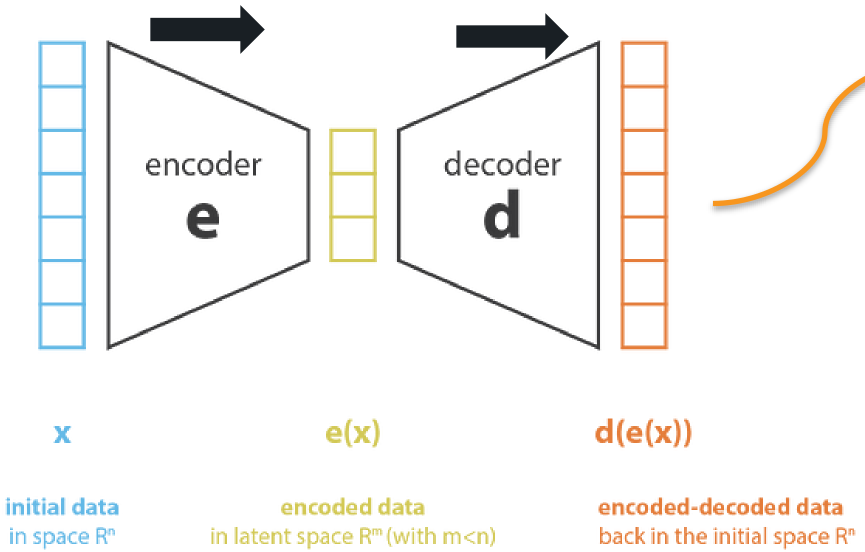
Overview

- Introduce Auto-encoder
- Variational Auto-encoder
- Physics-informed VAEs
- Example
- On going work on INN
- Conclusion

What is Auto-encoder?

Encoder: Compresses information by extracting only the important one

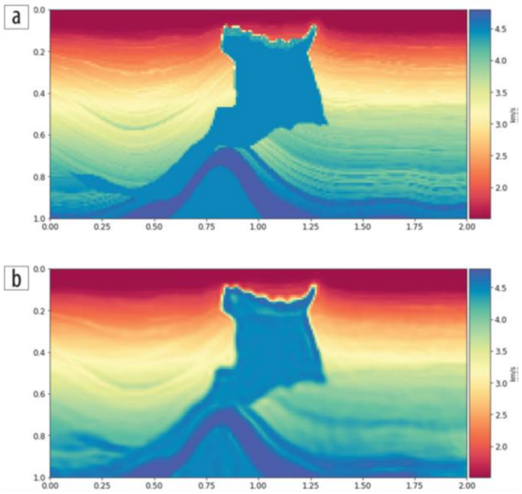
Decoder: Learns a function/map that maps the abstracted info such that the reconstructed data/image is close to the input data



$$J(\boldsymbol{\theta}) = \|\boldsymbol{x} - d_{\boldsymbol{\theta}}(\boldsymbol{z})\|^2$$

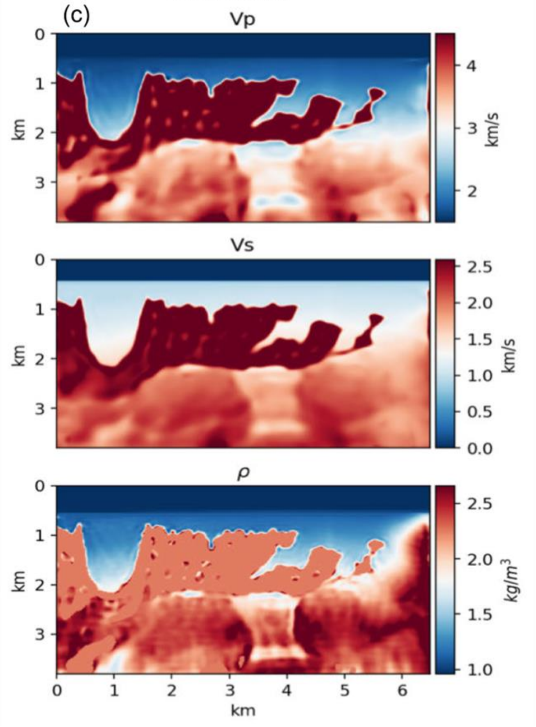
PINN+AE for FWI

Acoustic FWI - AE



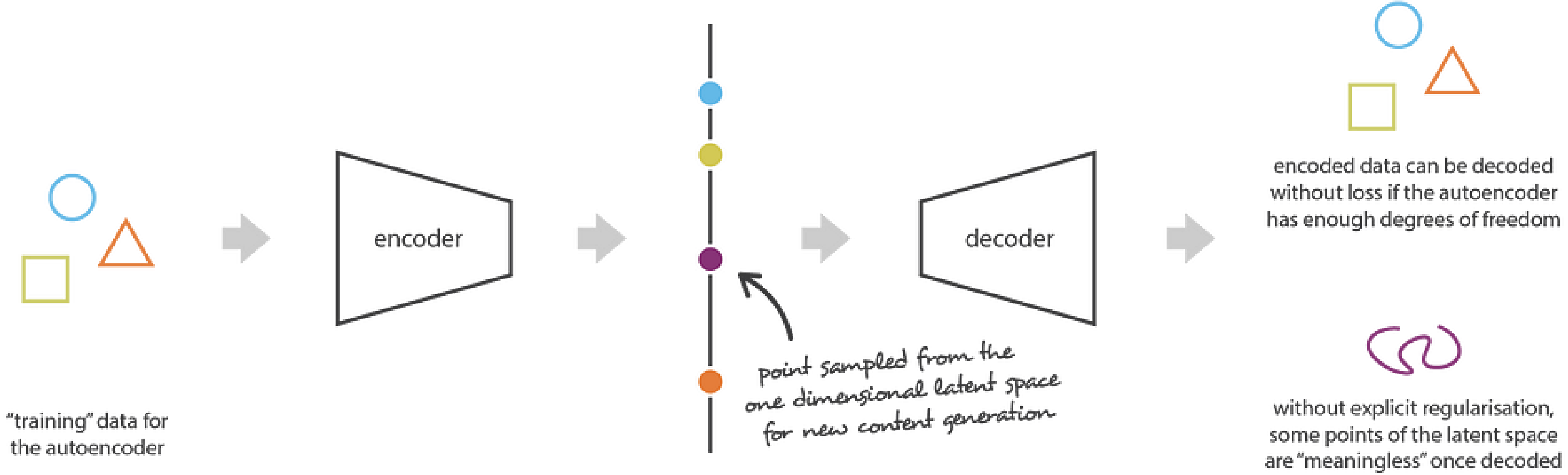
Dhara and Sen (2022)

Elastic FWI - AE

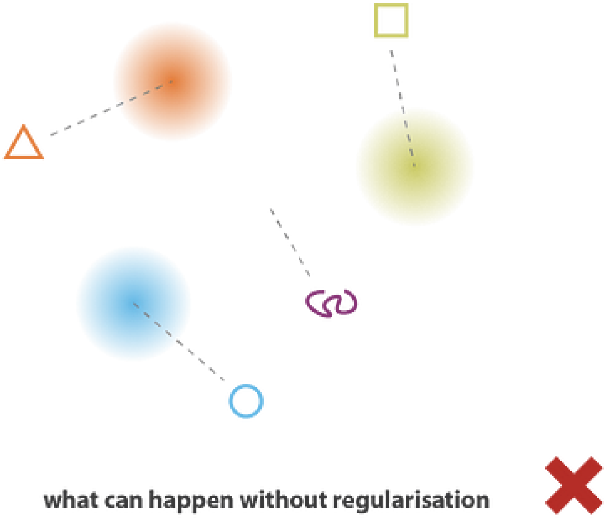


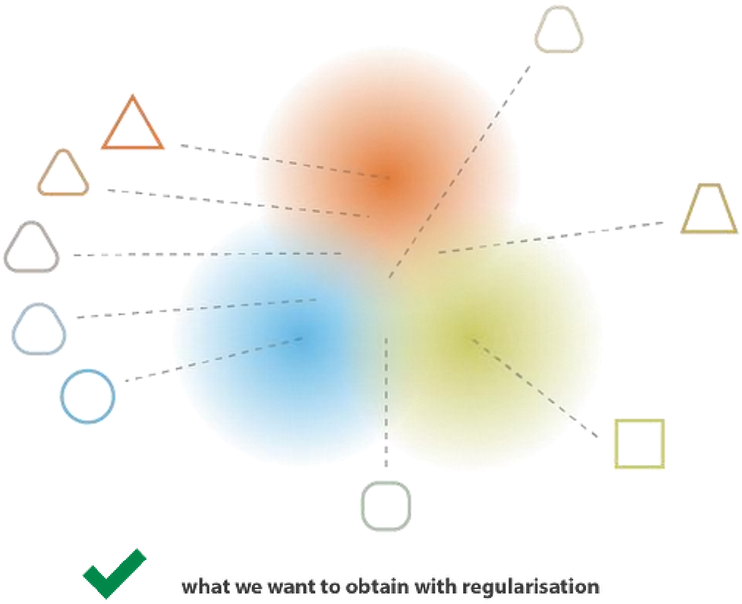
Dhara and Sen (2023)

Can we use AE to generate new data?

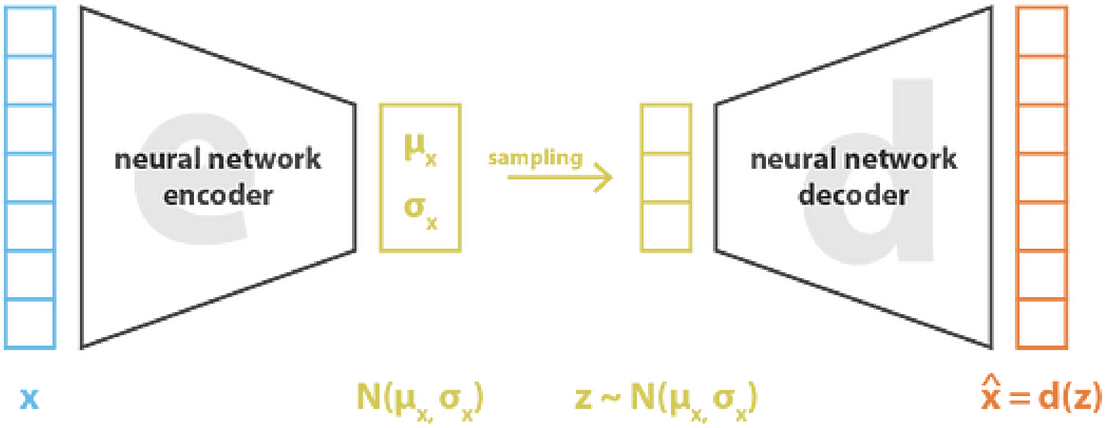


Generative Models: Regularization





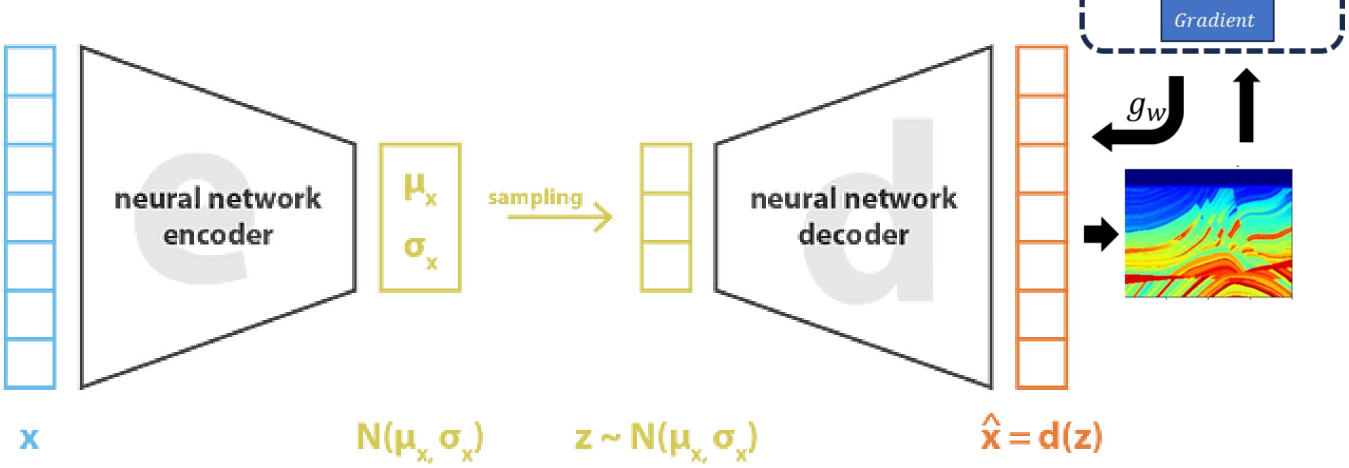
Variational Auto-encoder



$$J(\boldsymbol{\theta}) = \left[\mathbb{E}_{z \sim q_x}\left(\frac{\|\boldsymbol{x} - d_{\boldsymbol{\theta}}(\boldsymbol{z})\|^2}{2\sigma^2}\right) + \mathcal{D}\big(q_x(\boldsymbol{z}), p(\boldsymbol{z})\big)\right]$$

Physics-informed VAE

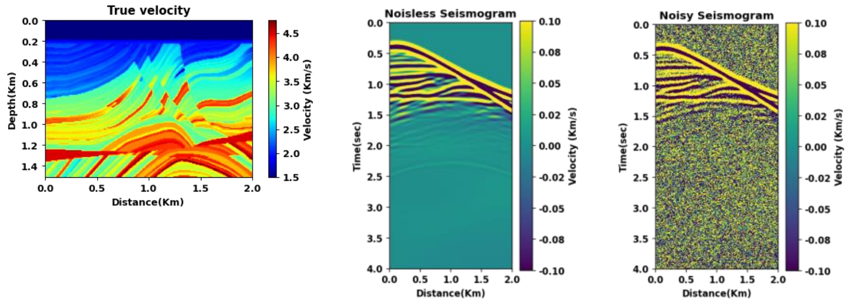
$$g_w = \frac{\partial J}{\partial w} = \frac{\partial J}{\partial m}\frac{\partial m}{\partial w}$$



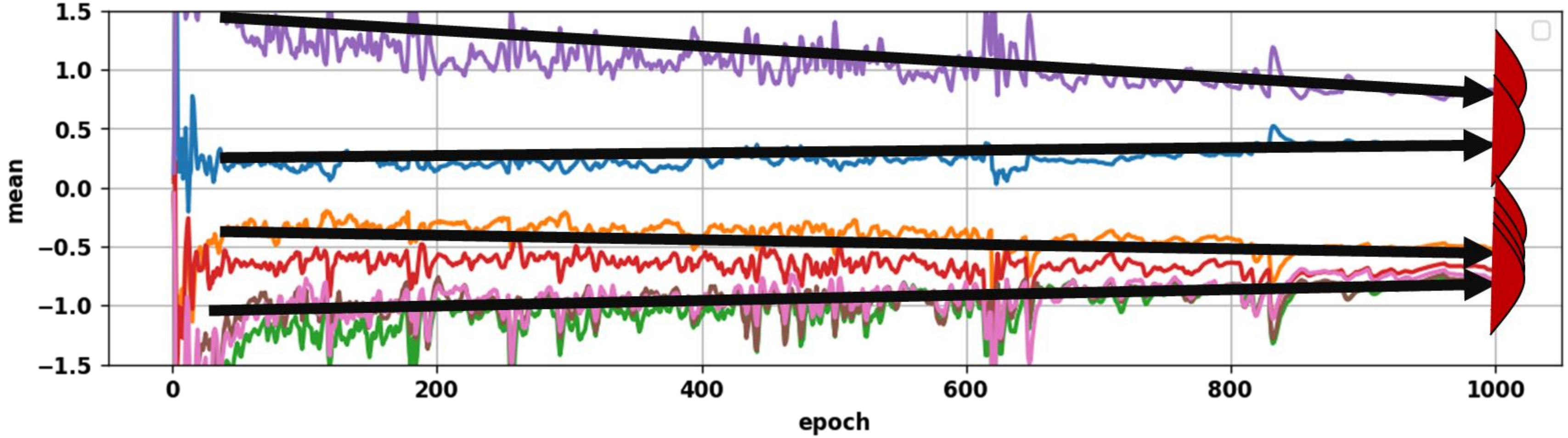
$$J(\boldsymbol{\theta}) = \left[\mathbb{E}_{\boldsymbol{z}\sim q_x}\left(\frac{\|\boldsymbol{x} - d_{\boldsymbol{\theta}}(\boldsymbol{z})\|^2}{2\sigma^2}\right) + \boldsymbol{\mathcal{D}}\big(q_x(\boldsymbol{z}), p(\boldsymbol{z})\big)\right]$$

FWI-VAE Marmousi

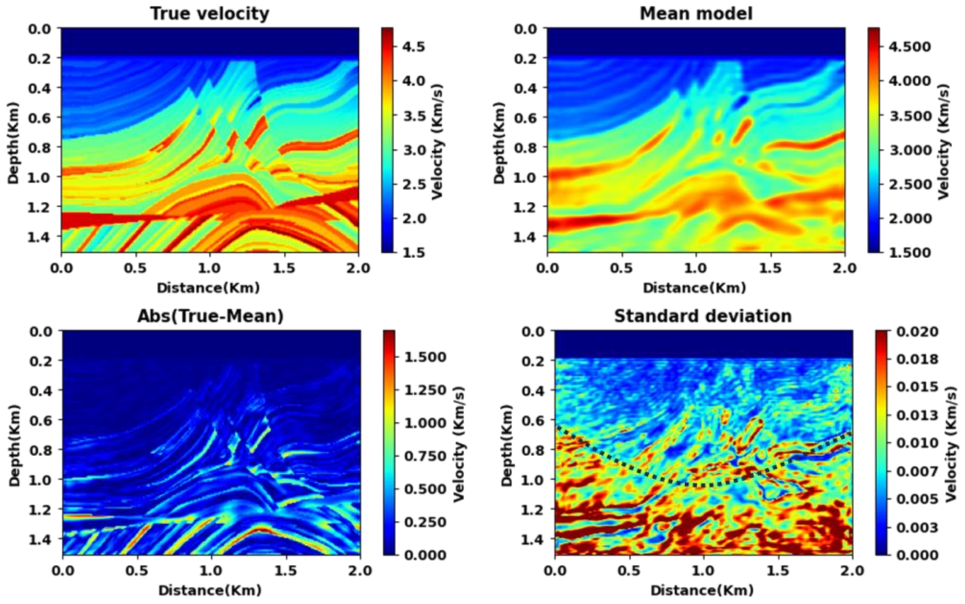
- 200 × 150 pixels
- Synthetic data with noise
- 18 sources, 200 receivers
- Additive Gaussian noise
- UQ procedure
  - After reconstructing the net (establish the mean and variance latent vector), we reload the network, generate 1000 samples (resample the latent vector) and compute the mean and the standard deviation of the output (posterior).



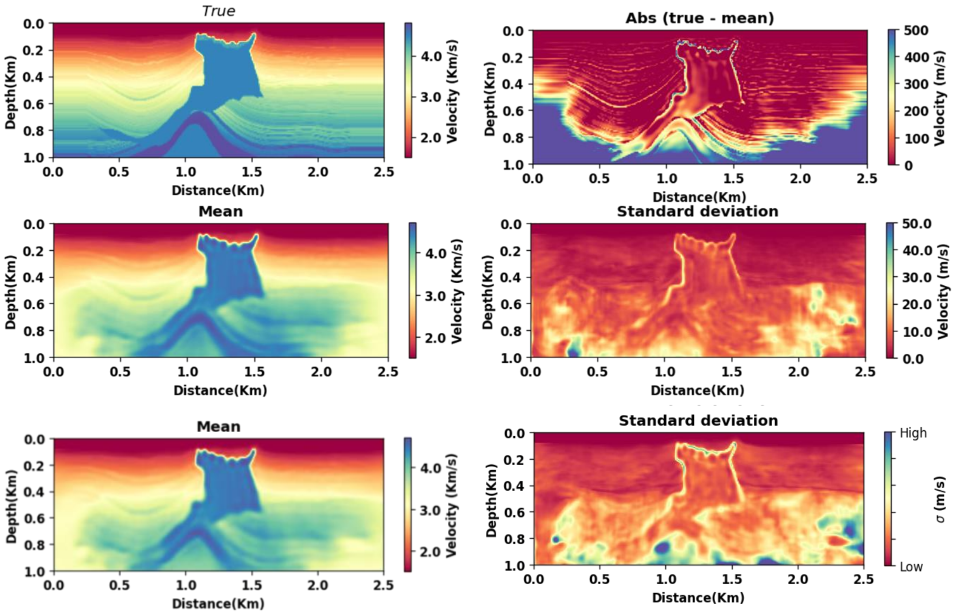
Convergence



Reconstruction



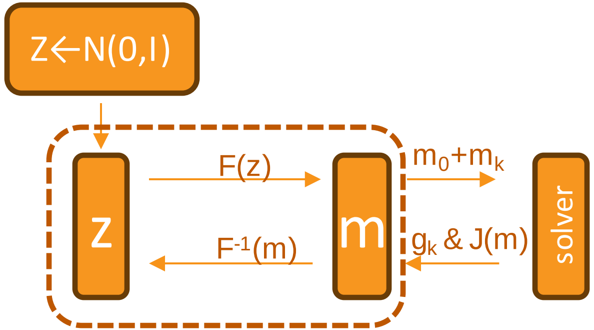
FWI-VAE SEAM



$z \sim \mathcal{N}(0, I)$

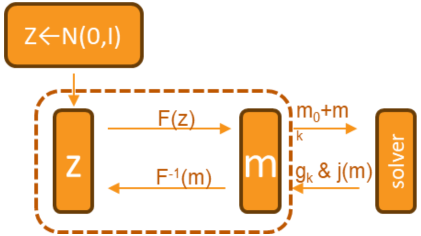
$z \sim \mathcal{N}(0, 10 \times I)$

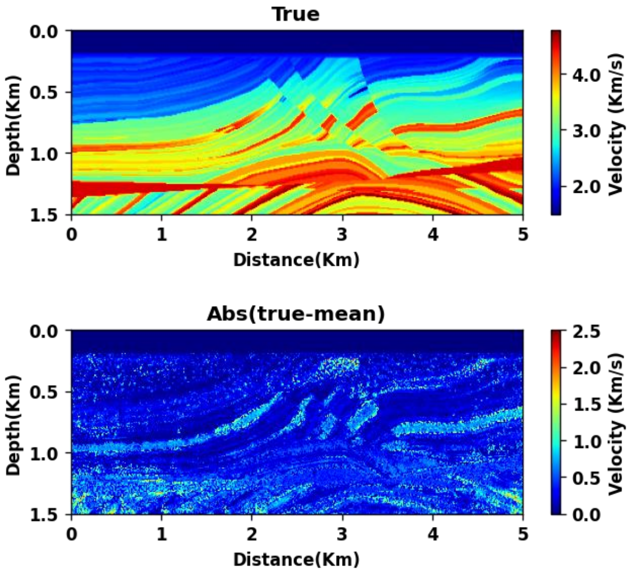
UQ-FWI through INN



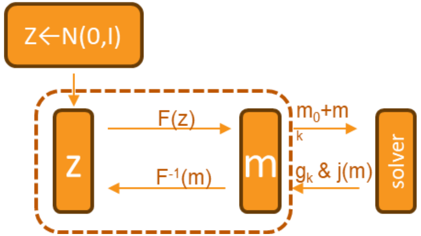
- Z: sample in latent space
- F(Z): forward mapping
- $F^{-1}(Z)$: reverse mapping
- m_0, m_k: initial and current model
- g_k: FWI gradient at epoch k
- $J(m_k)$: data misfit

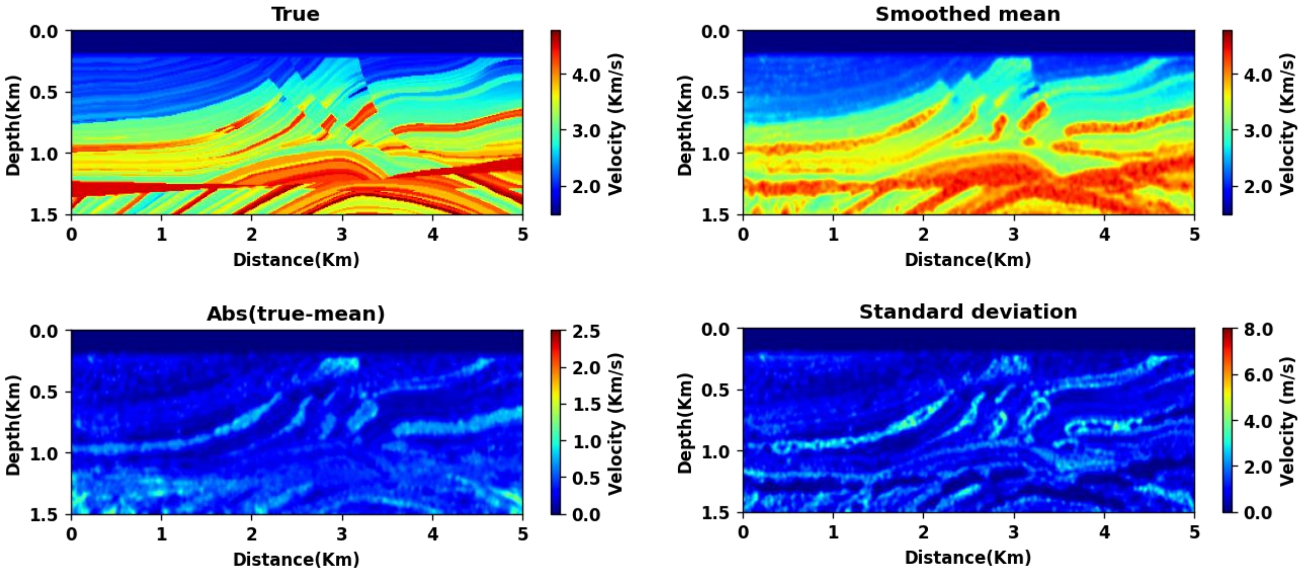
UQ-FWI through INN





UQ-FWI through INN





Conclusion

- We developed VAE framework for UQ-FWI
  - Synthetic examples shows promise in terms of accuracy of the mean model and the distribution of uncertainty
- Although uncertainty distribution agrees with expectations, their amplitude seems to be underestimated
  - We plan to investigate this issue in near future
- We also is exploring INN as an alternative for the UQ-FWI
  - Initial results shows promise, however, the amplitude of standard deviation seems to be underestimated
- We plan to extend the work to multiparameter FWI (e.g., Elastic FWI)

Acknowledgement

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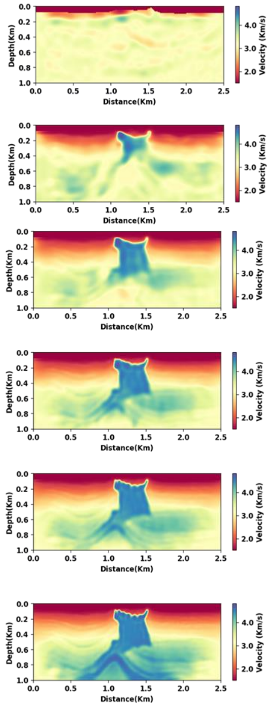
  - SNL is managed and operated by NTESS under DOE NNSA contract DE-NA0003525

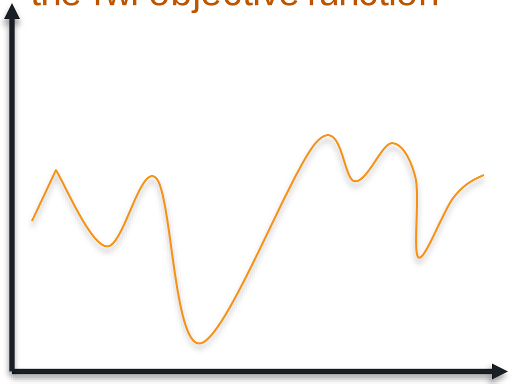
Sandia National Laboratories

Why PINN?

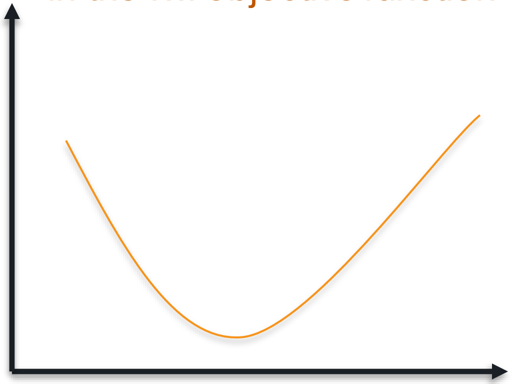

Depth(Km)
Distance(Km)
Velocity (Km/s)
0.0
0.2
0.4
0.6
0.8
1.0
0.5
1.5
2.0
2.5
3.0
4.0

Why VAE, INN seem to produce much lower uncertainty when compared to MCMC?

MCMC does not alter the parameterization of FWI, leaving all non uniqueness in the fwi objective function



VAE, INN regularize the FWI problem, which may remove most of the non uniqueness in the fwi objective function



Keep an Eye on the Latent Dimension