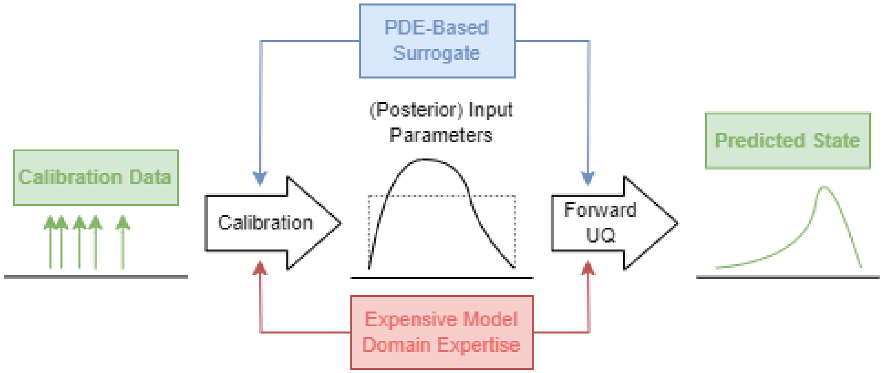
Doubly Latent NNs: Black-box UQ for PDEs

Grant Norman

Problem Statement/Objectives

- Reuse the same surrogate for calibration and forward UQ, *without domain expertise*
- Capture missing/unknown physics



Technical Approach

- Use the solution of a Neural Network PDE (with BCs) as the Decoder of a VAE
- First "Latent Space" is a class of PDEs

$$u_t = \mathcal{N}^\theta(x, u, u_x, u_{xx}; \mathbf{z})$$

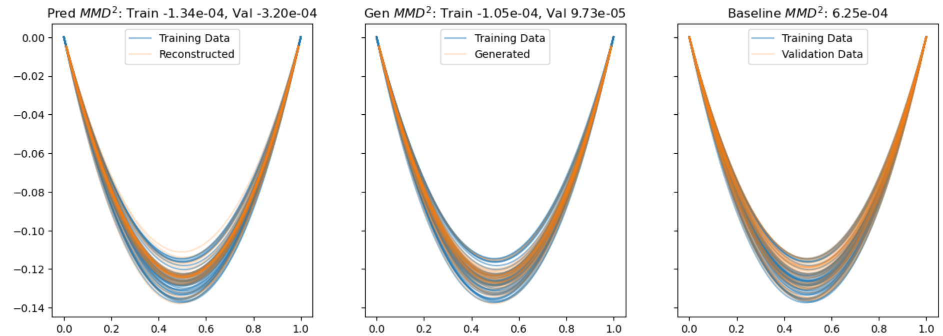
- Second Latent Space is probabilistic (VAE)

$$D^\theta(\mathbf{z}) = \mathcal{S}^h[\mathcal{N}^\theta, \mathrm{BCs}]\ (\mathbf{z})$$

Sample Results

Similar Problem to HW extra credit

Reconstruction | Generation | Baseline



Conclusions and References

- General PDE-based UQ method to handle unknown/missing physics and uncertainty
- Many challenges exist with even the non-probabilistic formulation
- KL-divergence tends to give lower variance

[1] Maziar Raissi. Deep Hidden Physics Models: Deep Learning of Nonlinear Partial Differential Equations.Tech. rep. arXiv: 1801.06637v1. 2018. url: https://github.com/maziarraissi/DeepHPMs (visited on 06/20/2022).
[2] Diederik P. Kingma and Max Welling. Auto-Encoding Variational Bayes. arXiv:1312.6114 [cs, stat]. Dec. 2022. url: http://arxiv.org/abs/1312.6114 (visited on 04/05/2024).

University of Colorado Boulder