ECE228 Project Proposal: Benchmarking Physics-Informed Models for Full Waveform Inversion

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1 Problem Background & Motivation

Full waveform inversion (FWI) is a computational method used in geophysics to infer subsurface properties by minimizing the difference between observed and simulated seismic waveforms. Traditional FWI relies on solving partial differential equations (PDEs) iteratively, which is computationally intensive and sensitive to initial conditions. Recent machine learning methods aim to reduce computational costs and improve robustness but face challenges in generalizing to varying source parameters and handling noisy or incomplete data. Addressing these issues is essential for reliable subsurface imaging in applications such as energy exploration and earthquake hazard assessment.

2 Related Works

The Fourier-DeepONet model [Zhu et al., 2023] enhances the DeepONet neural operator architecture with Fourier features, enabling it to generalize across varying seismic source frequencies and locations, improving accuracy and robustness over previous data-driven FWI approaches. InversionNet [Wu and Lin, 2018] employs a convolutional neural network (CNN) with a conditional random field (CRF) to directly map seismic data to subsurface velocity models, reducing computational cost while embedding spatial and temporal constraints. Neural ordinary differential equations (Neural ODEs) [Chen et al., 2018] model hidden states through differential equations, offering continuous-depth modeling with constant memory use. The PCA-SOM approach [Zhang et al., 2019] combines principal component analysis (PCA) for dimensionality reduction with self-organizing maps (SOMs) for clustering, effectively handling the high dimensionality and redundancy often present in geophysical data. While these models have demonstrated effectiveness in controlled settings, their performance on complex, real-world datasets, such as those presented in the Kaggle Geophysical Waveform Inversion competition [Kaggle, 2025], remains uncertain. Challenges in generalization to diverse geology, noise robustness, and computational efficiency remain, and our project addresses these by benchmarking these approaches on the competition dataset to evaluate their strengths and limitations in practice.

3 High-Level Methodology

We will benchmark four approaches using the Kaggle Geophysical Waveform Inversion competition dataset [Kaggle, 2025]. We will reimplement the Fourier-DeepONet architecture and training procedure, adapting it to predict subsurface velocity maps from seismic inputs. We will implement InversionNet as described by Wu and Lin [2018], using CNNs and CRFs trained on Kaggle subsets to assess MAE, training time, and generalization. We will develop a Neural ODE model that passes hidden states through a differential equation solver for continuous-depth representation. Finally, we will apply the PCA-SOM approach from Zhang et al. [2019], using PCA to reduce dimensionality and SOMs for clustering seismic data. Each model will be evaluated on mean absolute error (MAE), mean squared error (MSE), and structural similarity index (SSIM). We will submit the top-performing models to the Kaggle competition to benchmark their effectiveness and aim to achieve the best possible performance on the competition leaderboard while systematically comparing the strengths and weaknesses of these physics-informed and data-driven methods.

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References

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