# 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 architecture with Fourier features, enabling generalization across seismic source conditions and improving accuracy over earlier data-driven FWI methods. InversionNet [Wu and Lin, 2018] uses a convolutional neural network (CNN) with a conditional random field (CRF) to map seismic data to subsurface velocity models, reducing computational cost while embedding spatial and temporal constraints. Neural ODEs [Chen et al., 2018] model hidden states through differential equations, offering continuous-depth representation 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 high-dimensional, redundant geophysical data. While these models work well in controlled settings, their performance on complex, real-world datasets like the Kaggle Geophysical Waveform Inversion competition [Kaggle, 2025] remains uncertain. Challenges in generalization, noise robustness, and computational efficiency motivate us to explore combining the strengths of multiple approaches to surpass individual baselines.

## 3 High-Level Methodology

We will reimplement and benchmark four baseline approaches on the Kaggle competition dataset: Fourier-DeepONet, InversionNet, Neural ODE, and PCA-SOM. We will adapt the Fourier-DeepONet architecture to predict velocity maps, implement InversionNet using CNNs and CRFs, develop a Neural ODE model using a differential equation solver, and apply the PCA-SOM pipeline for dimensionality reduction and clustering. After evaluating baseline performance using metrics such as mean absolute error (MAE), mean squared error (MSE), and structural similarity index (SSIM), we will explore improvements by combining elements across models, such as integrating Fourier features or neural operators into InversionNet or adding Neural ODE layers into DeepONet. We aim to identify whether such hybrid designs can improve accuracy, generalization, and efficiency. We will submit the best-performing models to the Kaggle competition to benchmark effectiveness and aim for top leaderboard performance, while systematically analyzing how combined techniques advance physics-informed FWI modeling.

Preprint. Under review.

## References


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