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Seismic Super-resolution Leveraging Machine Learning Techniques

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Earth imaging is central to our ability to understand our planet and is important for exploration of critical minerals, geothermal energy resources detection, and mitigation of natural hazards such as earthquakes and the study of plate tectonics. As a result, there is a need for more precise images of the earth's interior. However, as this imaging process is ill-posed and lossy, the images obtained are inevitably a blurry version of the truth. This makes it challenging to robustly interpret results and draw inferences about geophysical systems.

The full waveform inversion (FWI) has been the state-of -the-art for high-fidelity and physically consistent subsurface imaging, however, its computational expense has driven exploration into machine learning (ML) techniques. These data-driven ML techniques can perform seismic inversion, directly mapping seismic data to subsurface properties without executing the iterative physics modelling loop of FWI. While their success is highly dependent on the availability of comprehensive, high-quality training data, they have proven capable of delivering subsurface predictions orders of magnitude faster than traditional methods.

In our attempt to obtain physically consistent subsurface images while ensuring cheap inferences, we will explore opportunities for 'seismic super-resolution': generation of higher-resolution images by combining observed data with prior knowledge about likely structures and the physics of wave propagation. Our approach involves the combination of machine learning techniques for numerical upscaling and physics – informed neural networks ensuring that the underlying laws of physics are embedded within results.

In this presentation, we will highlight some of the challenges and opportunities in this approach and present some early results from numerical experiments.