Inversion of skeletonized seismic data by hybrid machine learning

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Full waveform inversion (FWI) has been shown to accurately invert seismic data for high-resolution velocity

models (Tarantola, 1984). However, the success of FWI relies on a good initial model that is close to the true model, otherwise, cycle-skipping problems will trap the FWI in a local minimum (Bunks et al., 1995). Simplification of the data by skeletonization reduces the complexity of the misfit function and reduces the number of local minima. One of the key problems with skeletonized inversion is that the skeletonized data must be picked from the original data, which can be labor-intensive for large data sets.

We present a hybrid machine learning inversion method, where the skeletonized representation of the seismic trace is predicted by an autoencoder neural network. The input to the autoencoder consists of the recorded seismic traces, and the implicit function theorem is used to determine the perturbation of the skeletonized data with respect to the velocity perturbation. The gradient is computed by migrating the shifted observed traces that weighted by the residuals of the skeletonized data, and the final velocity model is the one that best predicts the observed latent-space parameters. We denote this inversion strategy as a hybrid machine learning (HML) method because it inverts for the model parameters by combining the deterministic laws of Newtonian physics with the statistical capabilities of machine learning. Empirical results suggest that the cycle-skipping problem can sometimes be mitigated compared to the conventional FWI method by replacing the waveform differences by those of the latent space parameters. A significant novelty of HML is that it provides a general framework for using solutions to the governing PDE to invert skeletal data generated by any type of a rank reduction method, including principal component analysis and neural networks.

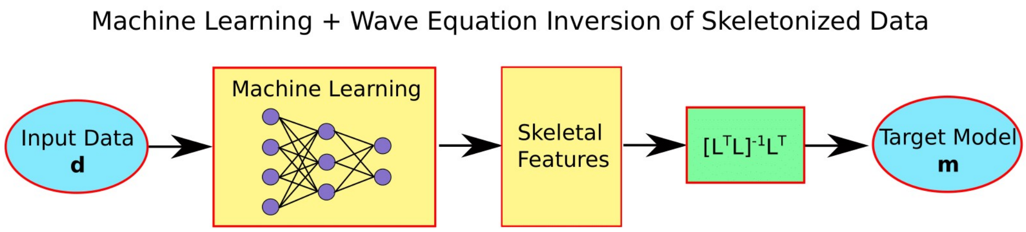

Figure 1. The strategy for inverting the skeletonized latent variables

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References

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