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Fourier Neural Operator and Physics Informed Neural Networks for velocity model building

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Introduction (Font: Arial Bold, 10).

Traditional neural networks (NNs) learn a mapping between a finite dimensional Euclidean space (e.g. an image) and a set of classes (classification), or between two finite Euclidean spaces (segmentation). Although they perform well in most tasks, when NNs are used to solve partial differential equations (PDEs), they are limited to the mesh used to discretize the space. Neural operators were thought to solve, or at least alleviate the problem: since they learn mappings in function space, they are mesh-invariant, and can in principle use a more coarse grid to learn but still give high resolution predictions.
Fourier Neural Operators (FNOs) are a type of neural operators that transform the input to Fourier space; convolutions become pointwise multiplication, making the operation faster and allowing for larger networks. A Fourier layer transforms the input to frequency space, keeping only a determined number of modes; apply a linear transformation and transform the result back to the spatial domain. Afterwards, a non-linearity is applied, trying to circumvent the periodicity of the output. Some initial works are already using FNOs in a supervised learning approach, with promising results.
Physics Informed Neural Networks (PINNs) use information from the physics of the system being studied in the loss function. Originally used to solve difficult PDEs by imposing constraints based on a few collocation points from a numerical solution, this approach has shown promise in several areas of physics, including velocity model building using the output of the FWI to further constrain the output of the neural network.

Method and/or Theory

In this work, we use a PINN workflow where the shot gathers are used as an input to the neural network, which then outputs the velocity model. Instead of comparing this to the truth, we propagate these models to obtain the respective seismic shots, which then are compared to the inputs to obtain a measure of the error. We use an FWI implementation then to obtain the velocity model, and use its gradients to update the weights of the neural networks.

Results and Conclusions

We use this workflow to compare the results of a standard UNet and one where the convolutions are substituted by Fourier operator layers. We find that, for the same number of parameters, the results of the UNet FNO are sharper and more reliable for two benchmark models.