# Applications of deep neural networks for velocity model building

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## Summary

In recent years, machine learning (ML) has become a crucial and integrated component of the seismic processing sequence. Most applications, however, have focused on pre-processing steps such as de-ghosting, de-noising, de-multiple, interpolation, regularization, and interpretation (e.g., horizons and well logs). In contrast, there have been fewer applications of ML for velocity model building (VMB) on field data examples. This is likely due to the significant variability in the Earth's geology, the high dimensionality of seismic acquisition, and the challenges of mapping long-range velocity dependencies across different domains, both in image and data domain gathers.

In this work, we utilize a deep neural network comprising a series of Fourier neural operators (FNOs), convolutional neural networks (CNNs), and fully connected neural networks (FCNs) to map velocity errors within the image domain. The network is trained to perform tomographic updates based on synthetic data, effectively replacing the conventional reflection tomographic engine. We demonstrate the performance on several field data examples from different basins worldwide, showcasing how this methodology can improve or assist conventional tomography, and help condition the model for full waveform inversion (FWI).

## Motivation

Although the motivation for this work is mainly to assist and accelerate the VMB sequence, deep learning also has the potential to understand and handle the data differently and mitigate limitations with conventional model building tools like reflection tomography and FWI.

Traditional reflection tomography relies on residual move-out (RMO) picks and a priori information to guide velocity updates. However, flat gathers do not always indicate a correct velocity model. Additional information, such as un-collapsed diffractions and event crossings in the common angle/offset domain, also provides crucial insights into velocity errors. Furthermore, we know that ray-based methods struggle in high-contrast media, necessitating special handling or interpretation to manage geobodies and other non-smooth features. While FWI is general enough to handle these complexities, it is computationally intensive, especially when high-frequency elastic modeling is required. In addition, both FWI and tomography linearize the highly nonlinear inversion problem by taking incremental steps in the gradient direction, resulting in a time-consuming process with numerous iterations and high compute cost.

In this study, we employ a deep neural network as a tomographic operator, effectively replacing the conventional tomographic inversion engine. The network is trained using migrated gathers alone, without relying on RMO picks, horizon picks, or salt masks, to identify a wide range of smooth and sharp velocity features. This approach allows the network to recover the true velocity model from various incorrect model realizations more quickly and introduce larger velocity updates compared to traditional reflection tomography and FWI. Additionally, this method opens the possibility of training the model with diverse data types, including data with multiples, further accelerating the VMB sequence.

## Methodology

Our approach leverages a network architecture composed of integral operator blocks (IOBs) integrated with convolutional neural networks (CNNs). Unlike traditional CNNs, IOBs are designed to capture long-range dependencies within the data. The incorporation of Fourier neural operators (FNOs) has facilitated non-local feature detection, global representation, and mesh independence. These neural operators have demonstrated significant potential in addressing complex and computationally intensive equations, such as partial differential equations (Li et al., 2021).

Initially, our training process aimed to directly map velocity errors from data to the image domain (Huang et al., 2023). Recently, we have refined our approach by 1) adapting the network to map velocity errors within the image domain, and 2) expanding the training process by generating and processing additional labeled data. These enhancements have resulted in a solution that inputs depth-migrated gathers along with the corresponding velocity model and outputs the predicted velocity update (Crawley et al., 2024). Figure 1 illustrates the micro and macro network design.

The forward propagation within the IOB begins by lifting the data, increasing its dimensionality through a fully connected network ($v(x)$). This is followed by a forward Fourier Transform (FT) and an inverse transform of the most energetic wave modes. A version of the data is also routed outside the FT path and combined before an activation function completes the FNO layer. The data is then normalized and passed to another fully connected network, the multilayer perceptron (MLP). We employ dropout and skip connections as regularization strategies, allowing us to increase the depth of the trainable neural network, which is crucial for learning these complex operators. A series of

IOBs are connected with CNNs before the final predictions are made using another MLP.

Mapping from the image-to-image domain reduces the data dimensionality that the network must handle, potentially simplifying the learning process. The network has been trained on synthetic 2-D data from approximately 50,000 different velocity models representing various geological scenarios, including different water depths and background sediment velocity trends, as well as salt bodies and slow velocity anomalies of different shapes and sizes. Data augmentation takes the form of different degrees of velocity errors for a given true model, and different degrees of post-processing on the migrated gathers.

Our strategy has been to develop this as an iterative, interactive workflow. The predicted velocity model from the first pass is used in a new migration process, forming the input for the second pass of predictions. The number of iterations required depends on the complexity of the problem, but experience shows that 2-5 iterations are typically sufficient to resolve the macro model.

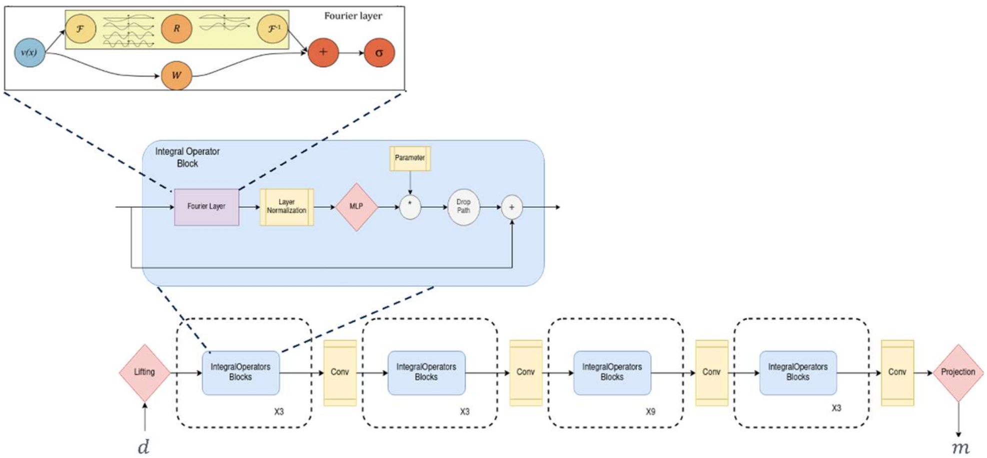


Figure 1: This shows the network architecture, consisting of a series of IOBs and CNNs. The FNOs facilitate the learning of long-range dependencies in the data.

## Examples

In our first example we investigate using the trained network to build the initial FWI model directly from a simple 1D gradient. Figure 2a and 2b shows the initial velocity model with the single shot FWI gradient overlayed and the observed data interleaved with data modeled using a reflectivity formulation of the wave-equation (Whitmore et al., 2020). Figure 2c and 2d shows the corresponding results after two iterations of FNO-network predictions. The updated velocity model is structurally sensible and leads to significant improvements of the data-alignment, especially for the far offset refractions (yellow ellipse). The forward modeling was done at 9Hz, which is unrealistically high for an initial FWI run, but it is done to show more of the model complexity in this dataset.

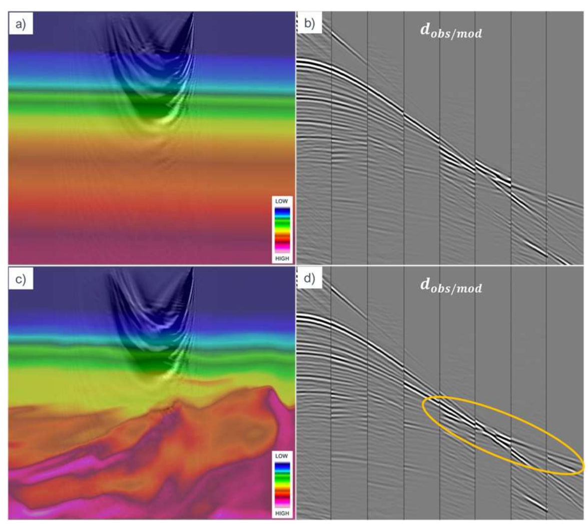


Figure **2**: Single shot FWI kernel overlayed on the initial velocity model a) and the corresponding interleaved observed and modeled data in b). Equivalent displays after two iterations of FNO-network predictions in c) and d). The forward modeling was done with 9Hz maximum frequency to show more of the complexity in the data.

Notice the significant improvements in the data-alignment after the FNO-network predictions.

In the next example we make use of the FNO-network predictions to replace tomography for the deepest model building unit. The shallow to intermediate depth-intervals had undergone a significant amount of FWI and tomography and were considered resolved. The dataset is multi-component streamer acquisition in the Norwegian Sea and covers approximately 6.000km². Figure 3a and 3d show an inline and depth slice at 5km depth with the model prior to the FNO-network predictions and figure 3b, c, e and f show the predicted results with and without the image overlay. The updated model is structurally consistent with the seismic image and the magnitude of change is typically much higher than what we would achieve with conventional gradient updates (up to 1km/s). In the deeper section, the network has predicted a series of volcanic intrusions and sills. These formations are generally fast and could be as fast as salt-velocities or higher.

The final example is from the Agung area, located north of Bali, a geologically complex region influenced by the subduction of the Indo-Australian Plate. This region, part of the Sunda volcanic arc, is characterized by significant tectonic activity, including compressional thrust faulting and volcanism. The basin is highly deformed and faulted, with carbonates serving as the primary reservoir rocks. Identifying volcanic rocks from carbonates in seismic data is crucial for exploration in this area.

In 2023, a newly acquired marine streamer dataset (10 km offset) provided a high-quality seismic dataset to improve the imaging of carbonate reservoirs and distinguish them from volcanic rocks. The input model to the FNO network was partially derived from a multi-client VMB sequence, which included tomography, low-frequency (8 Hz) FWI, and initial basement interpretation.

Figures 4a and 4b show a cross-section of the initial and updated models after two iterations of FNO network predictions, with the corresponding RTM image overlaid. Similar displays are provided for a depth slice at 3 km in Figures 4e and 4f. The accumulated velocity update is shown in Figures 4c and 4d, and the RTM image alone is shown in Figures 4g and 4h. As indicated by the yellow arrows, several high-velocity geobodies have been introduced by the FNO network predictions where volcanic intrusions and sills are expected. The area beneath the volcanic activity causes distortions in the initial image, while the basement structure becomes better focused after the FNO predictions (orange ellipse).

**Conclusions**

In this work, we have demonstrated how deep learning can be utilized for VMB, to condition the initial FWI model by reducing cycle-skipping and constructing a geologically consistent and sensible velocity field. Furthermore, we have demonstrated that even a few iterations of the FNO-network predictions can enhance tomographic updates and significantly improve the imaging results. This approach eliminates the need for RMO picking, interpretations, or special handling of sharp high-velocity contrasts. The network leverages FNOs, which have non-local behavior necessary for image-domain velocity updates. While the results are promising, it is crucial to avoid treating the prediction process as a black box. Model validation remains essential.

**Acknowledgments**
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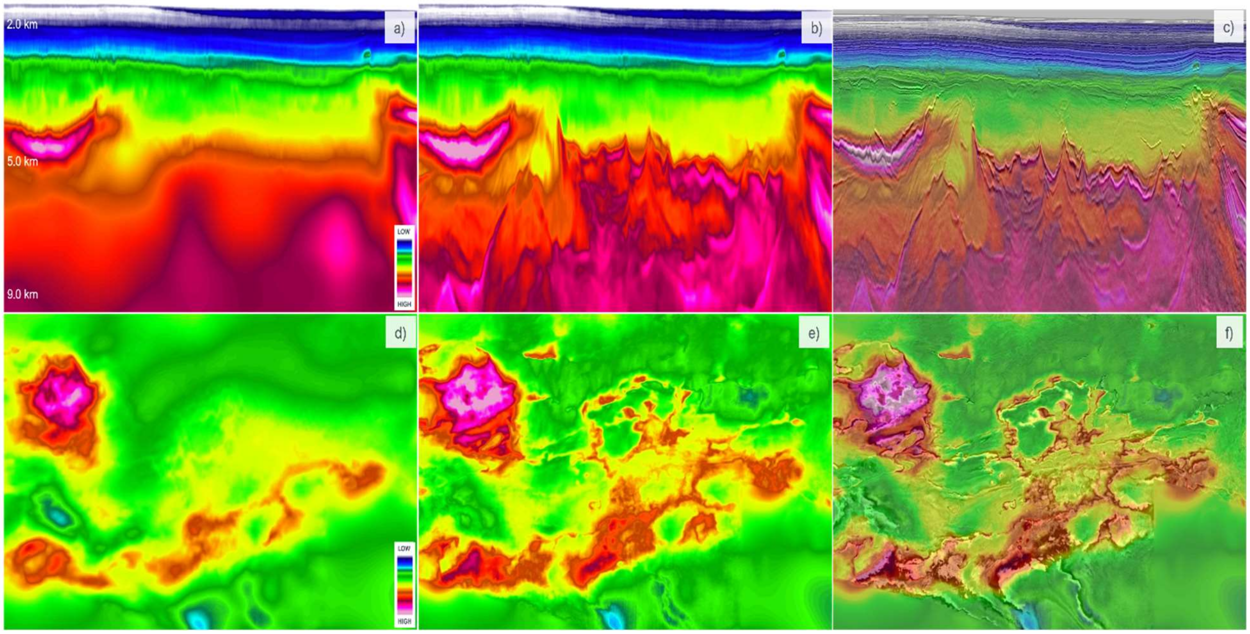


Figure 3: Inline of the initial a) and FNO-predicted velocity model b) and with the stack overlay in c). Depth slice at 5km of the initial d), FNO-predicted e) and with the stack overlay f). Notice the level of details and the magnitude of the update achieved after a single iteration of prediction and the structural consistency of the results. The FNO-network has detected several volcanic intrusions and sills at different levels in the deep section.

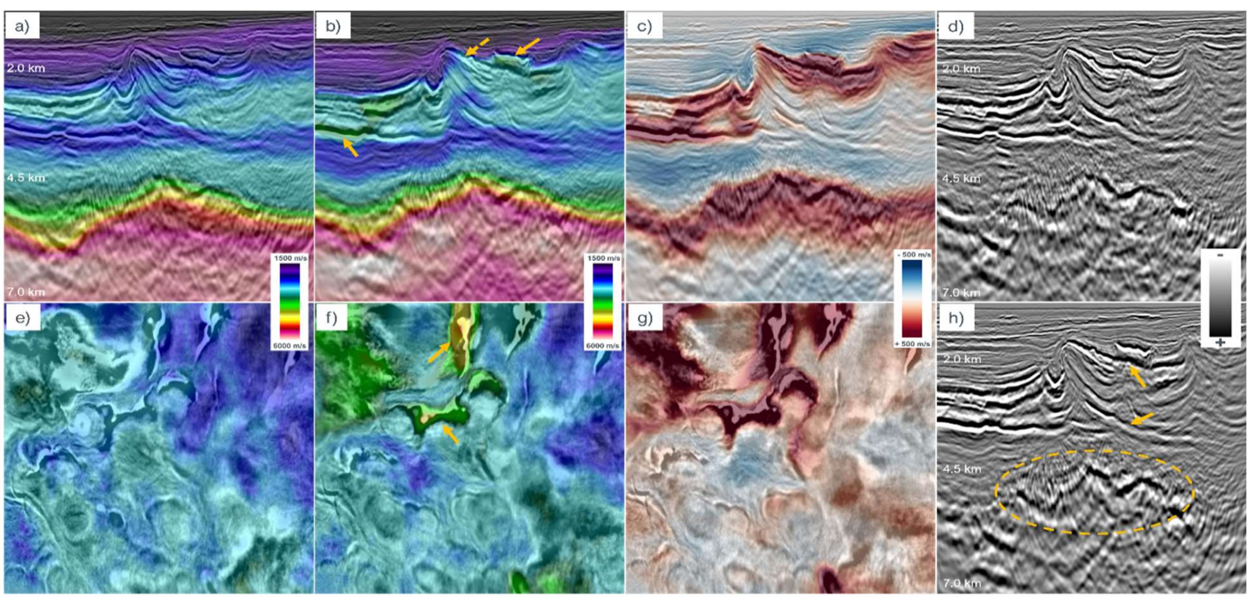


Figure 4: Cross-section of the initial a) and FNO-predicted model b) with image overlay. Accumulated velocity update after two iterations of FNO-predictions in c) and the corresponding RTM image in d) and h). Figure e), f) and g) shows a depth slice at 3km of the initial, FNO-predicted and the accumulated velocity update. Notice the structural consistency of the predicted model and how it maps out the volcanic structures. The RTM image is significantly improved in the deepest section, revealing more of the basement structure, after solving the shallow complexity with the FNO network predictions.