Low-Frequency Data Extrapolation Using a Feed-Forward ANN

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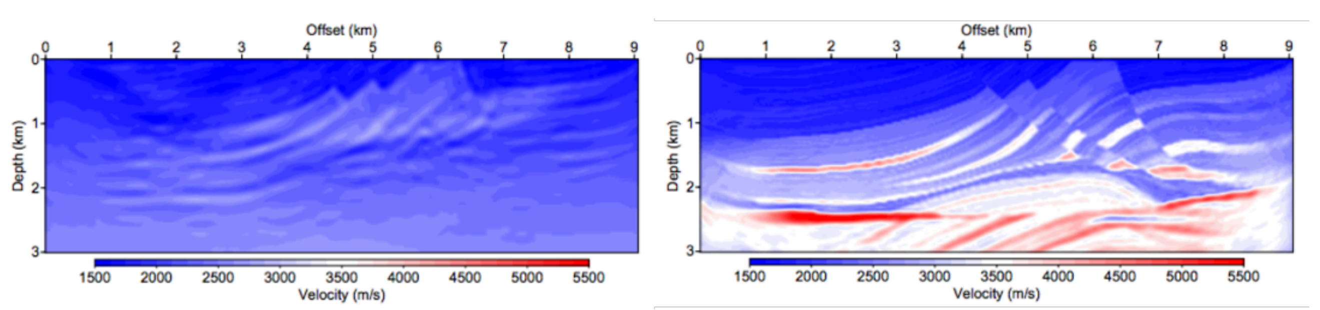
1. ABSTRACT

Full-waveform inversion (FWI) benefits in many ways from having low-frequency data. However, those are rarely available due to acquisition limitations. Here, we explore the feasibility of frequency band-width extrapolation using an Artificial Neural Network (ANN). **The ANN is trained to be a non-linear operator that maps high-frequency data for a single source and multiple receivers to low-frequency data.** Assuming that the source is a delta function both in space and time, we train the network on synthetic data generated from random velocity models. We apply the ANN to multiple collocated sources-receivers acquisitions to predict 0.5 Hz data for a crop from the BP 2004 benchmark model. Prediction results follow in general the reference data but the prediction accuracy is not sufficient yet for usage in FWI as demonstrated by a regularized mono-frequency FWI on extrapolated data.

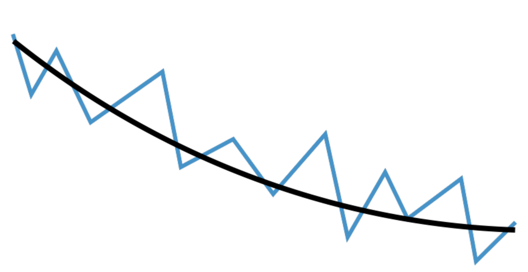
2. LOW-FREQUENCY DATA



(Kazei et al., 2016)

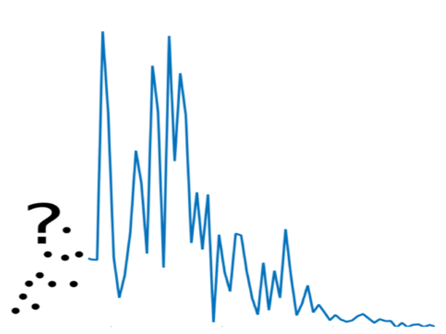
Inversion of **low-frequency data delivers low-wavenumber initial models** for FWI (Kazei et al., 2013) but due to instrumental limitations lowest and highest temporal frequencies in observed data are often inaccessible (Maxwell and Lansley, 2011).

Multiple approaches have been proposed to tackle the problem of inversions when low-frequency data is not available:



Modifications of misfit/gradient

Attempts to reduce number of local minima in the misfit function by changing its definition (Chen et al., 2018) or to introduce modifications in the gradients, e.g. scattering-angle based filters (Alkhalifah, 2015; Kazei et al., 2016) to stabilize the inversion at early iterations.

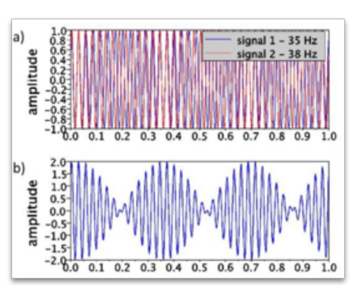


Extrapolation of frequency bandwidth

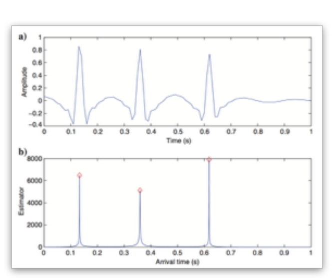
Attempts to extend frequency bandwidth so the low-frequency content is used to build initial model for FWI (Li and Demanet, 2016; Hu, 2014).

Relevant studies:

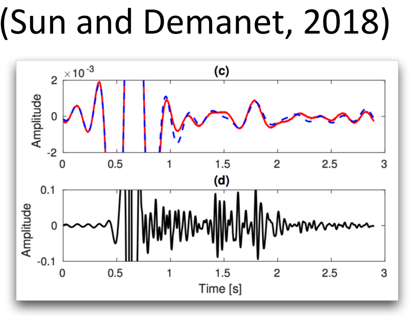
Beat tone inversion (Hu, 2014)



Bandwidth extension for atomic events (Li & Demanet, 2015, 2016)

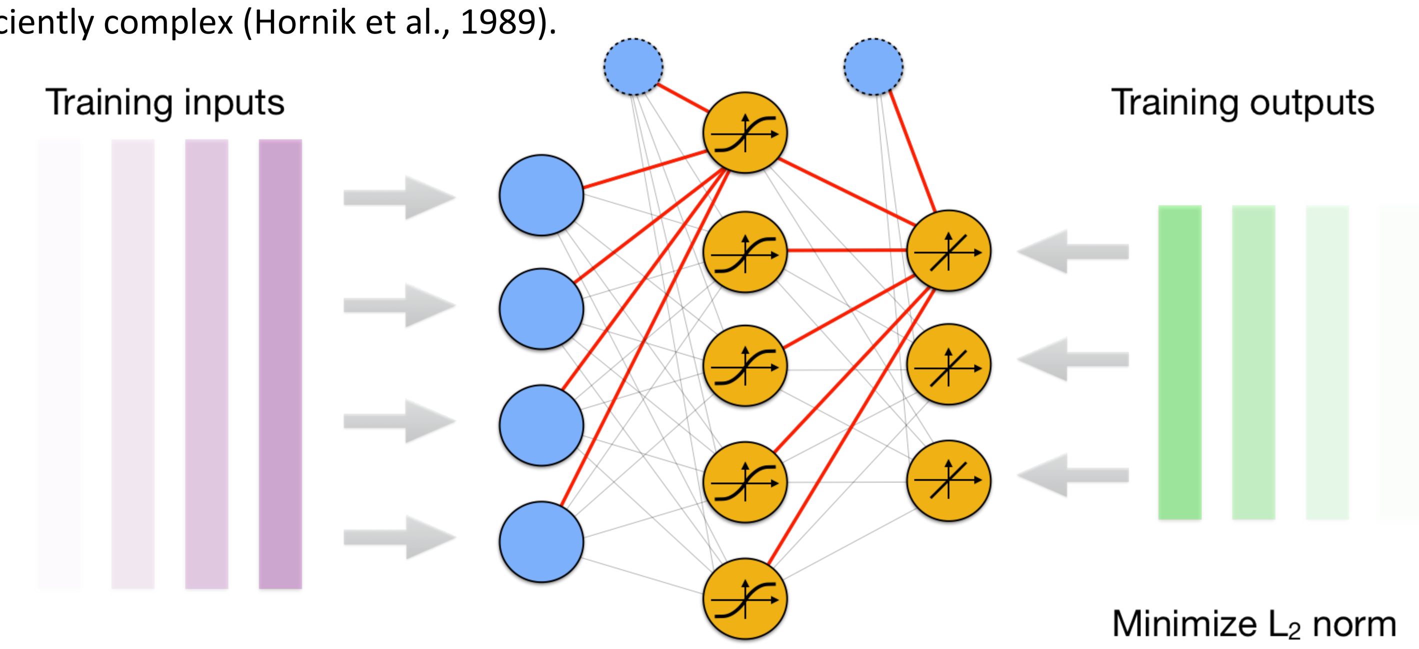


Low frequency extrapolation with deep learning (Sun and Demanet, 2018)



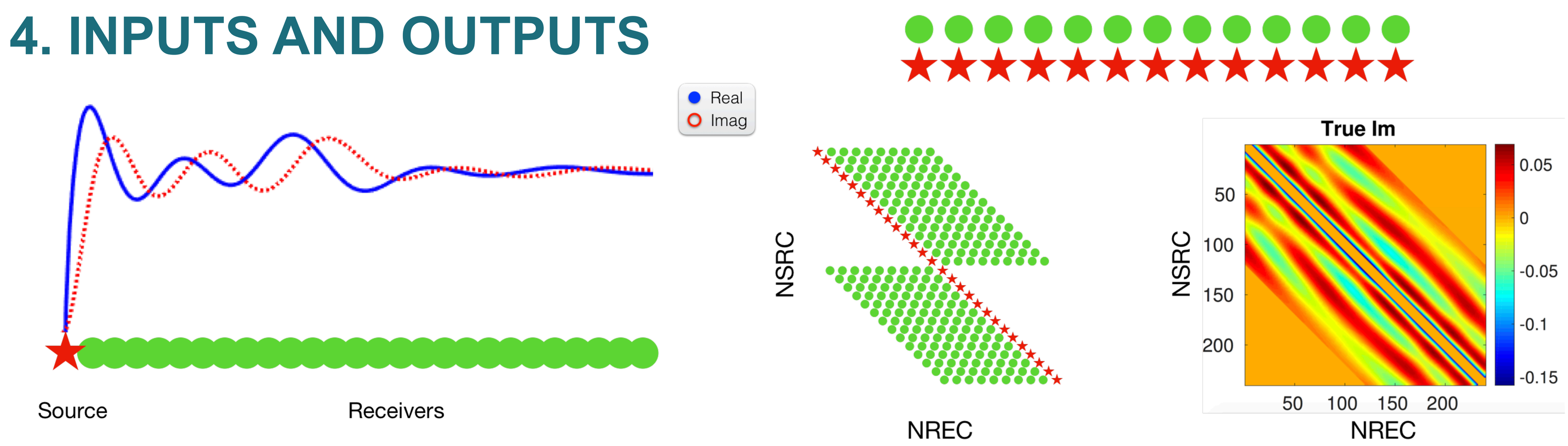
3. MULTILAYER PERCEPTRON

An ANN, in particular Multilayer Perceptron, is a powerful tool coming from early days of Machine Learning. **Multilayer Perceptrons can principally approximate any function**, provided its neuron topology is sufficiently complex (Hornik et al., 1989).



The ANN serves as a non-linear operator mapping high-frequency data to low-frequency data, assuming that the source is a delta function in space and time. We train the network with synthetic **data generated from random velocity models** to predict a single complex amplitude at each receiver for a specific low frequency given several high frequency values.

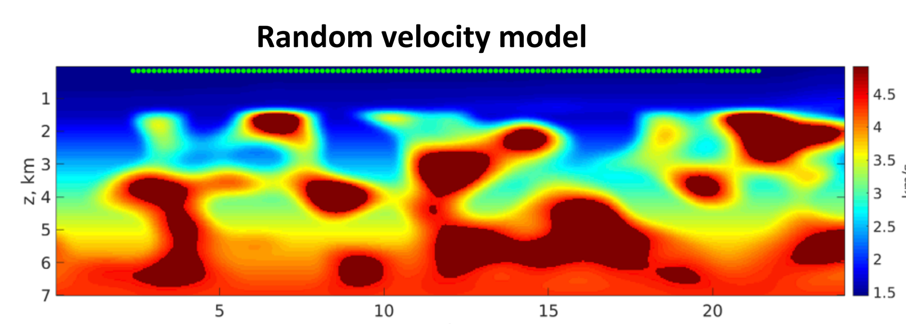
4. INPUTS AND OUTPUTS

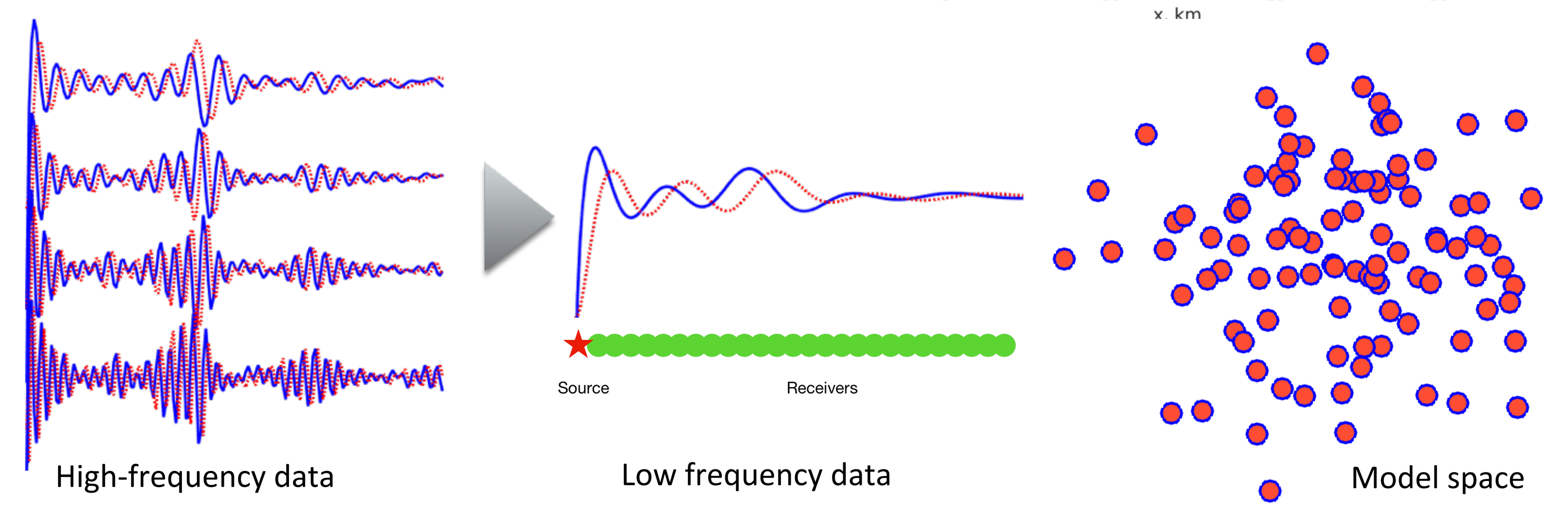


The input data for the network are the frequency spectra recorded at each receiver and discretized by a few values. The frequency values are separated by a multiplicative increment as such selection is common for frequency domain inversions (Sirgue and Pratt, 2004). The output data is a vector containing single complex amplitude for a selected low frequency at each receiver.

5. GENERATION OF TRAINING DATA

We use **random Gaussian fields** to build a set of random velocity models obeying a minimum threshold in terms of Frobenius distance. A wider diversity in features of random models enhances resulting prediction accuracy.



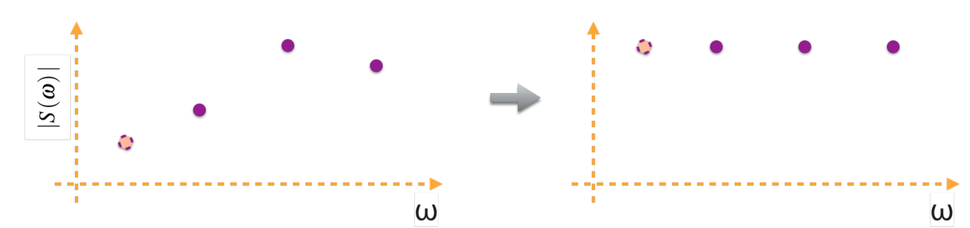


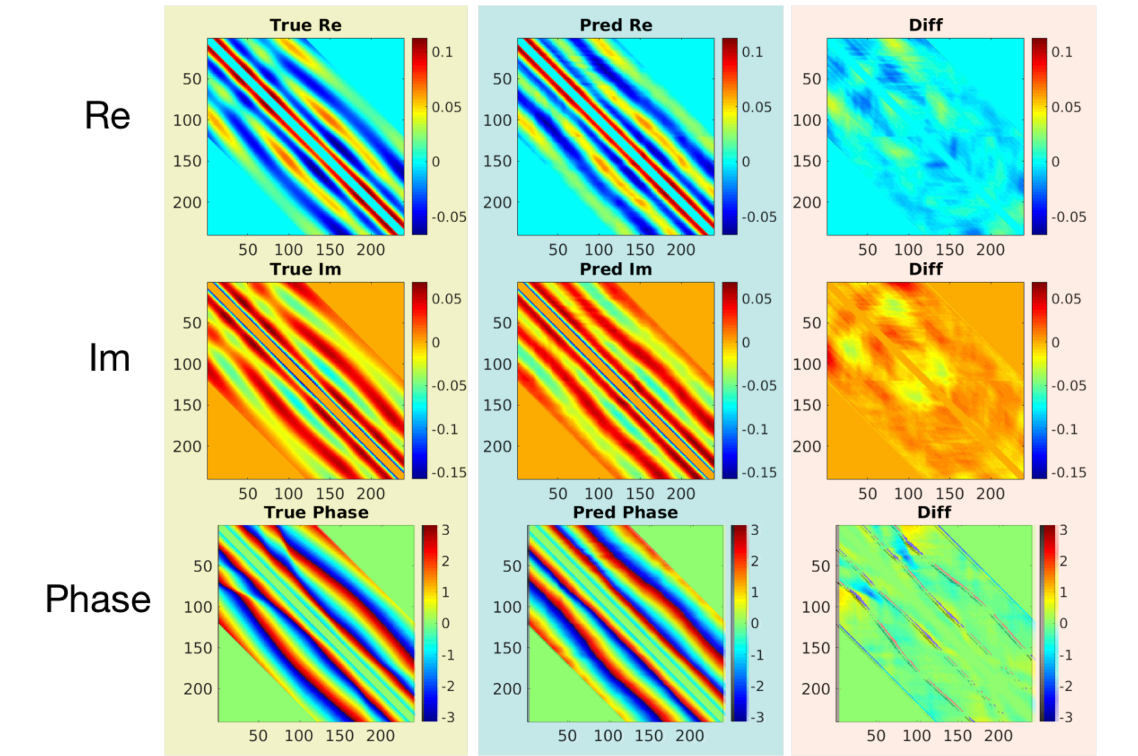
6. RESULTS

We perform a synthetic study for 2D acoustic isotropic media. Velocity model is the crop form central part of BP 2004 velocity model. Acquisition involved 240 collocated sources and receivers placed 80 m apart on the surface. **We predicted 0.5 Hz data given data for 2.41, 3.14, 3.50 and 4.07 Hz.**

General trends at predicted data matrices follow corresponding reference data, whereas small scale details as well as exact amplitudes were not well reconstructed by the ANN.

+ Explicit assumption about source signature

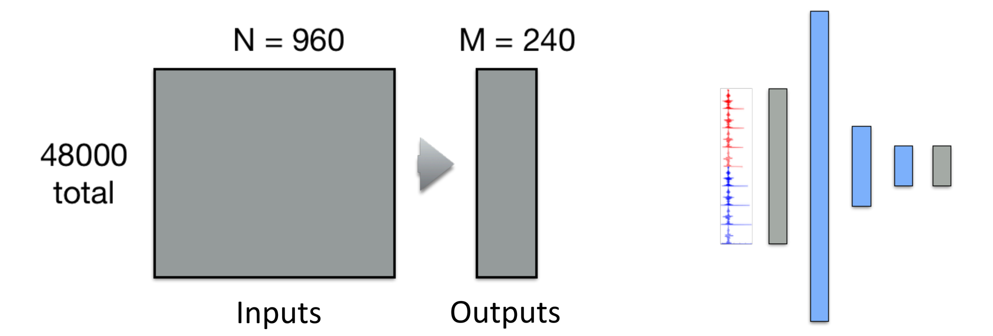




7. CONCLUSIONS

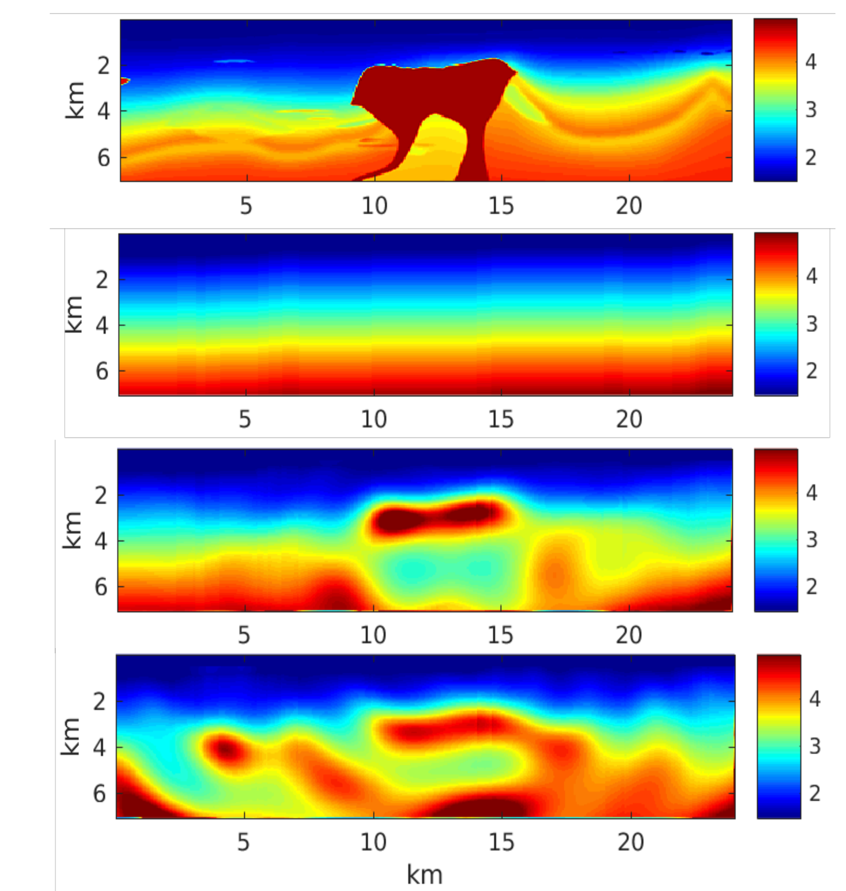
We explored the feasibility of reconstructing low-frequency data using an Artificial Neural Network given high-frequency spectra. Here, we assume the low-frequency wavefield content to be related with the one at higher frequencies through a non-linear operator encoded by the physics of wave propagation in the subsurface. We trained an ANN on data generated from random velocity models and then tested it on reference data.

Prediction results in general follow the reference data but the prediction accuracy is barely sufficient yet to make the reconstructed data directly usable in FWI. However, results are encouraging and in future work we will further investigate the dependency of the network training on model diversity and network topology.



Network topology
1st Hidden layer: 2 * N, nodes
2nd Hidden layer: 2 * M, nodes
3rd Hidden layer: 1 * M, nodes

Batch size: 1024
Learning rate: 0.005
Optimizer: Adam
Weight regularization: 0.005



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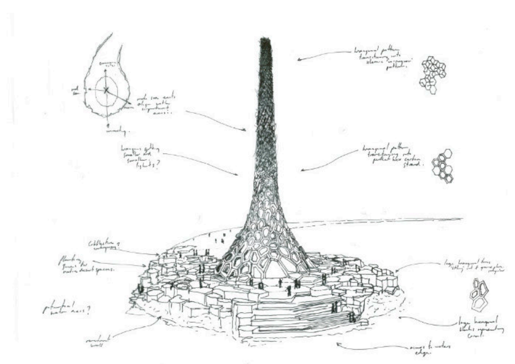

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