Deep Learning Inversion on Seismic Cubes

Aleksandr Koriagin, Alexey Kozhevin, Stepan Goriachev, Roman Khudorozhkov

Data Analysis Center

Abstract

Recently deep learning has proven to be a promising tool for automation of seismic interpretation. Mainly these advances have been focusing on classic stages of seismic interpretation including horizons picking and faults detection, but recent attempts have been made to tackle seismic inversion. When it comes to the latter, the existing literature describes how neural networks can be used for inversion on small patches of traces/seismic slides. In this work we show how one can perform inference on full seismic cubes using convolutional neural networks and specific prediction aggregation techniques. The second part of our contribution consists of explaining how the performance of inversion on real seismic data can be measured in absence of ground truth velocities.

The rest of the extended abstract elaborates on each step of our work, including (i) training a neural network on patches of synthetic data (ii) assembling predictions from patches of real seismic cubes and (iii) measuring the quality of inversion.

Contrary to the tasks of horizon and faults detection, the labelled data for training seismic inversion models is missing. To handle this, we use a generator of synthetic seismic to create data pairs of seismic images and corresponding velocities. We then train a convolutional neural network of encoder-decoder type, that transforms a patch of synthetic seismic into the corresponding velocity model. This model can be straightforwardly applied to patches of real seismic data.

In order to perform inference on a large region of a seismic cube, we split the region into small patches and perform inference on them. When assembling the velocity model for the whole region, we sequentially add each patch with predictions of velocity model to already assembled array. In doing so, we rescale each patch to fit the already assembled overlap via least-squares regression.

Lastly we show how one can evaluate the assembled velocity model. Importantly, a good velocity model of a region should yield (after applying several operations, including convolutions with the source impulse) an image resembling the original seismic. To get the quantitative measure of our model's performance we compare the original and recreated seismic using SSIM and L1-metrics. The results range from 0.9 to .98 for SSIM and from 0.01 to 0.07 for L1, depending on complexity of a seismic cube. This indicates that deep learning inversion models can be of huge assistance to anyone studying seismic data.