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Classification and Separation of Diffraction Energy on Pre-Migration Seismic Data using Deep Learning

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Diffractions are a useful aspect of the seismic wavefield and are often underutilised. By separating the diffractions from the rest of the wavefield they can be used for various applications such as velocity analysis, structural imaging, and wavefront tomography. However, separating the diffractions is a challenging task due to the comparatively low amplitudes of diffractions as well as the overlap between reflection and diffraction energy. Whilst there are existing analytical methods for separation, these act to remove reflections, leaving a volume which contains diffractions and noise. On top of this, analytical separation techniques can be costly computationally as well as requiring manual parameterisation. To alleviate these issues, a deep neural network has been trained to automatically identify and separate diffractions from reflections and noise on pre-migration data.

Here, a Generative Adversarial Network (GAN) has been trained for the automated separation. This is a type of deep neural network architecture which contains two neural networks which compete against one another. One neural network acts as a generator, creating new data which appears visually similar to the real data, while a second neural network acts as a discriminator, trying to identify whether the given data is real or fake. As the generator improves, so too does the discriminator, giving a deeper understanding of the data. To avoid overfitting to a specific dataset as well as to improve the cross-data applicability of the network, data from several different seismic datasets from geologically distinct locations has been used in training. When comparing a network trained on a single dataset compared to one trained on several datasets, it is seen that providing additional data improves the separation on both the original and new datasets.

The automatic separation technique is then compared with a conventional, analytical, separation technique; plane-wave destruction (PWD). The computational cost of the GAN separation is vastly superior to that of PWD, performing a separation in minutes on a 3-D dataset in comparison to hours. Although in some complex areas the GAN separation is of a higher quality than the PWD separation, as it does not rely on the dip, there are also areas where the PWD outperforms the GAN separation. The GAN may be enhanced by adding more training data as well as by improving the initial separation used to create the training data, which is based around PWD and thus is

imperfect and can introduce bias into the network. A potential for this is training the GAN entirely using synthetic data, which allows for a perfect separation as the points are known, however, it must be of sufficient volume for training and sufficient quality for real data applicability.