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Deep Learning of Geological Structures in 3-D Seismic Reflection Data

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Understanding the Earth's internal structure is one of the key challenges of geophysics. Advanced geophysical techniques, such as 3-D seismic technology, produce increasingly large datasets of the Earth's subsurface, which require significant amounts of time, experience and expertise to analyze. On the other hand, there have recently been great advances in machine learning for image classification using deep learning techniques. We explain the advantages of deep learning over traditional machine learning methods and demonstrate how deep learning can help us analyze large 2-D and 3-D seismic (reflection) datasets in a quantitative, efficient and reproducible way. Deep learning involves training a set of models (e.g. neural networks) which can be used to extract certain features from the raw data; a task very similar to the interpretation of geological structures in seismic data. To highlight the applicability of deep learning to typical seismic interpretations, we show how to map normal faults and salt bodies in seismic data using neural networks. First, we train a simple feedforward neural network (1 hidden layer with 1000 neurons) to map a system of normal faults with the help of previous manual interpretations. This supervised learning approach allows us to train the model and map the fault system in 3-D with an accuracy >0.95. Second, we show how to train a convolutional neural network to map salt in 3-D seismic data with an accuracy >0.98. Our models perform these tasks, which take seismic interpreters several weeks to months, within a few hours. Moreover, they are able to quantify the probability of detecting salt or faults at any given data point. In summary, we show that deep learning models offer a quantitative (predicts accuracy), efficient (less time) and reproducible (same workflow yields the same results) way of analyzing seismic data of the Earth's subsurface.