Geophysical Corner

AI Application to Seismic Fault Interpretation

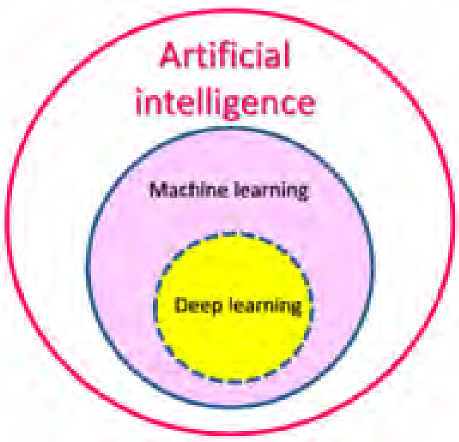

Figure 1: Embedded circles showing the relationship between artificial intelligence, machine learning and deep learning.

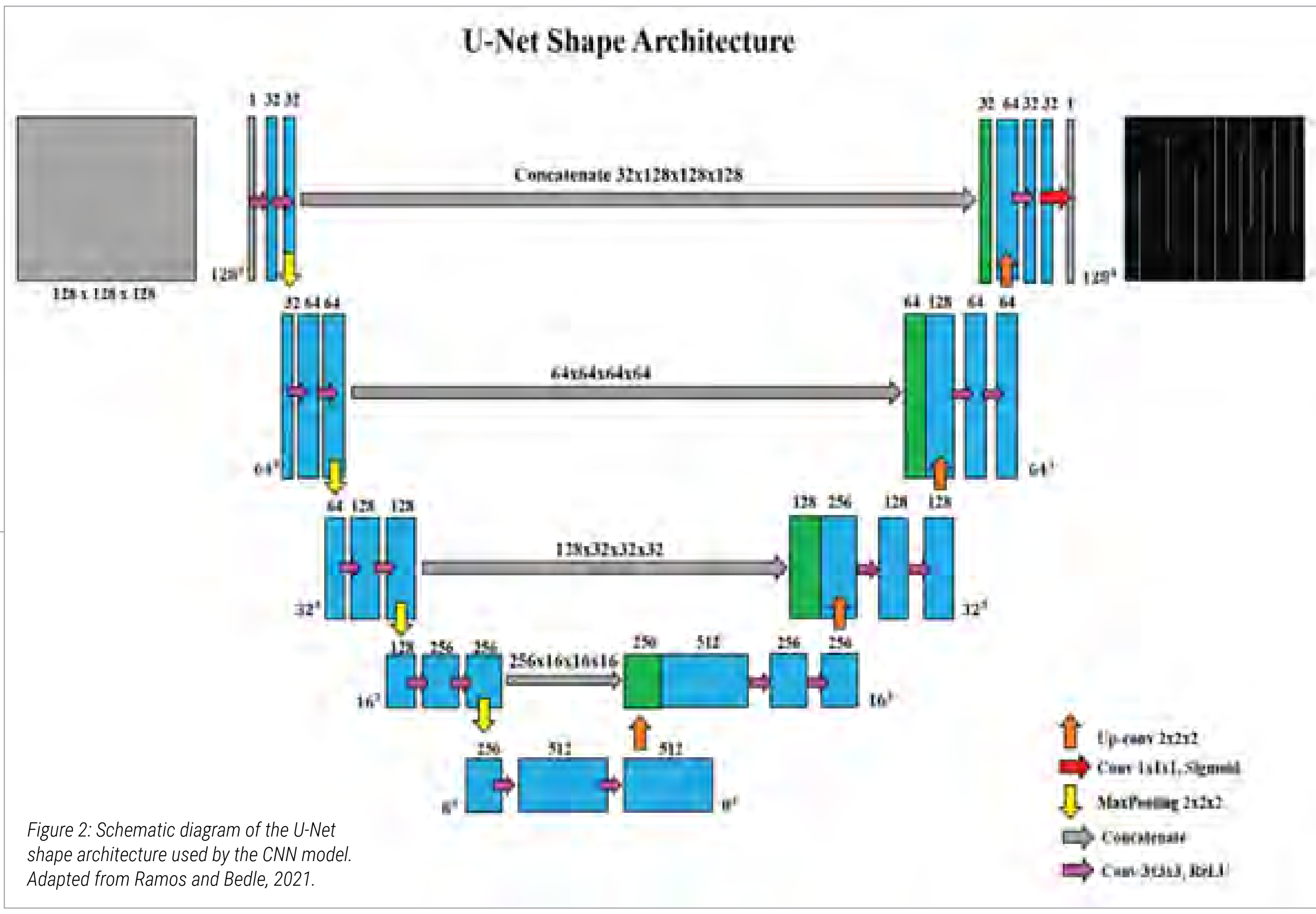

Figure 2: Schematic diagram of the U-Net shape architecture used by the CNN model. Adapted from Ramos and Bedle, 2021.

Faults play a significant role in the evolution of sedimentary basins, in the migration and accumulation of hydrocarbons, and in forming seals and conduits within a reservoir. Faults may also pose a risk in loosing drilling mud or creating difficulties with the drill bit. As we look beyond hydrocarbon exploration and production, fault modification of the subsurface plumbing will impact the production and reinjection of geothermal fluids and the integrity of carbon capture and storage reservoirs. Fault interpretation on seismic data has always been a laborious task, especially for large 3-D seismic volumes. Whereas horizon autopicking has advanced significantly during the past three decades, automated seismic fault interpretation lags behind. Fortunately, recent applications of artificial intelligence (deep learning) processes for identifying faults provide significant promise for the future. In this article, we demonstrate one such application and find that it compares favorably with an earlier application of fault likelihood attribute, discussed in the May 2021 installment of Geophysical Corner. We begin the article with a clarification of the term usage and then go on to discuss the application itself.

Artificial intelligence, Machine Learning and Deep Learning

Every day we hear and read about how artificial intelligence is changing our lives, from the promise of self-driving cars to the fear of heavy-handed intervention in social media. Discussions on AI use terms such as "machine learning," "deep learning" and others, which we address in figure 1.

The largest (white) circle indicates AI, a term defined by Claude Shannon at Bell labs and other computer scientists in 1965, who saw a future in which computers could be constructed to think like humans. AI reappeared in the 1970s and '90s with only limited success and acceptance. During the past 45 years, the speed of computer chips has increased while the cost has decreased by several orders of magnitude. Parallelization has evolved from eight processors on a Cray supercomputer to 1,024 processors on your home computer desktop graphics card. With these advances, AI has come back, this time to stay and flourish. Competitions held over the last two decades – such as the 1997 match between chess champion Gary Kasporov and the IBM computer Deep Blue, followed by Google's DeepMind AlphaGo program's defeat of the world's top 'Go' player in 2016 – have lent credence and support to the AI movement.

Machine learning, or ML, shown as the pink circle in figure 1, is a subset of AI and can be defined as an algorithm that can analyze input and output data, learn steps that connect the two, and then use those findings to make predictions from data it has not seen before. There are many types of ML, one of which is artificial neural networks built of one or two layers of neurons that multiply and add (that is, convolve) the input data and pass the results through a nonlinear activation step that scales and/or thresholds the results. In this case, the mathematical objective is to determine the unknown weights that need to be used in the multiplications and additions to replicate the known output training data from the known input training data. The yellow circle in figure 1 shows deep learning, a subset of ML that makes use of multiple (for example, 20 or more) layers of neurons, to go deep into the data to learn and make more difficult predictions. Because there are more unknown weights, deep learning needs more training data than the simpler "shallow" neural networks. Thus, Facebook observing one's past behavior, predicting interests, comparing to tens of millions of other subscribers, and recommending articles and notifications, should not come as a surprise. Similarly, when we observe Amazon recommending "you might also like" products, and Netflix recommending a movie, we know in the background that DL algorithms are at work. Deep learning convolutional neural networks are being used for advanced computer vision applications in robotics, drone surveillance, medical image recognition, identification of tissue texture, diagnosis and other applications.

In seismic data analysis, the sizes of the data volumes have been increasing over the last decade, and the challenge has been to make sense of all those gigabytes, terabytes and petabytes of data. Besides its video or audio applications in other domains, ML has been applied in oil and gas exploration for different tasks such as horizon picking, fault interpretation, facies classification and others in seismic interpretation, and first break picking, velocity analysis, denoising, interpolation and others in seismic processing.

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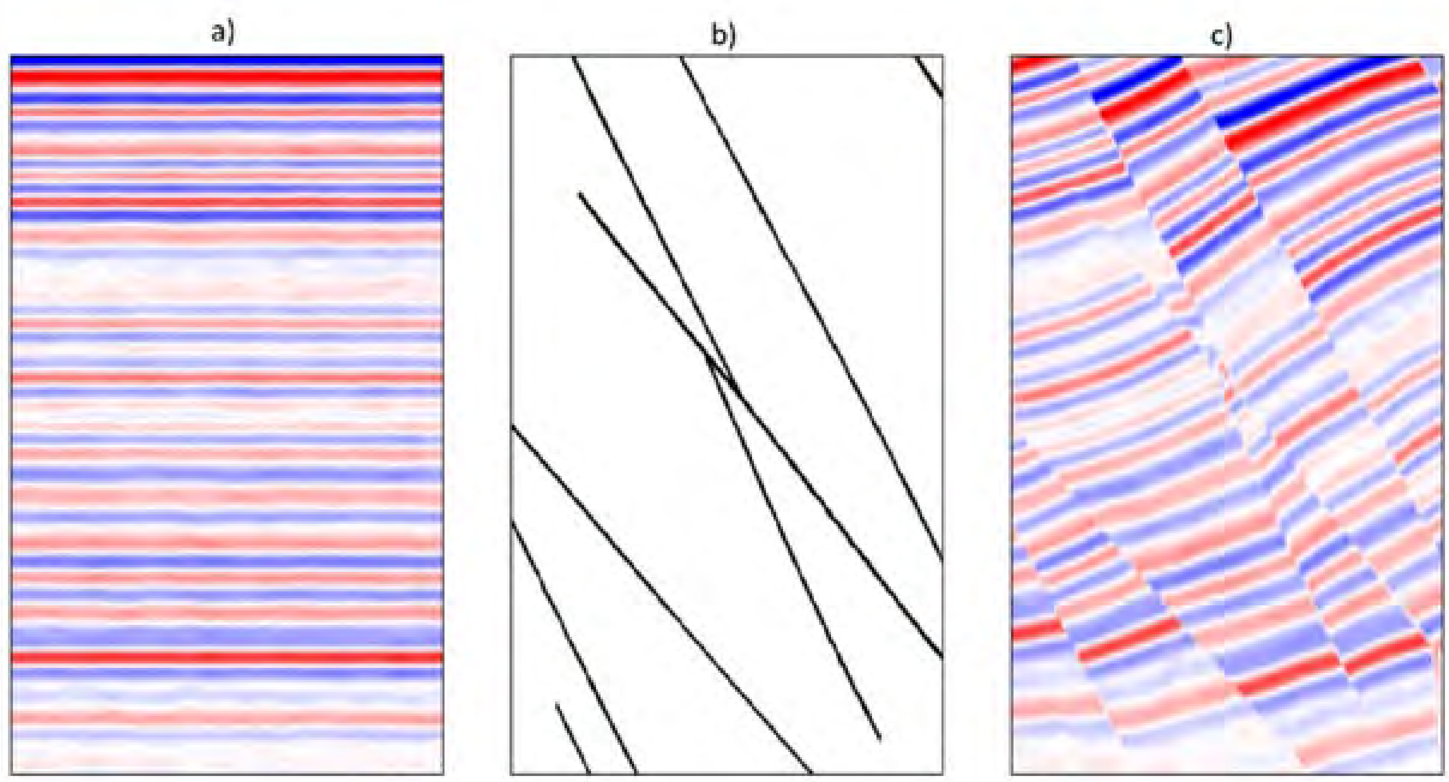

Figure 3: Segments of (a) synthetic seismic section generated using an impedance model and a 30 hertz Ricker wavelet, (b) the equivalent fault label section from a 3-D fault model, and (c) the equivalent synthetic seismic section with the addition of the faults in (b).

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AI Fault Interpretation on Seismic Data

Seismic fault detection is an important, though tedious and time-consuming task in seismic interpretation. Until recently, the discontinuities observed on seismic data or highlighted by attributes have been handpicked by seismic interpreters. Consequently, the results are dependent on the individual interpreter, with different interpreters exhibiting different levels of expertise and/or bias. To alleviate this human-intensive task, several promising tools have been developed for automatic fault extraction. Although they do not completely do away with human bias, they can capture many types of faults seen on seismic data.

Recent machine learning applications for fault interpretation are described. The description and application of DL neural networks to geoscientific tasks have been discussed before in articles published in the Geophysical Corner of the Oct. 2018 and Aug. 2021 issues of the EXPLORER. The CNN is trained to interpret different types of faults on the input seismic data (with faults picked by an interpreter) or synthetic data with faults, in a supervised learning mode, and then the trained network is applied to the input seismic data so that all such faults can be detected. The results obtained from such applications show improved fault interpretation compared with equivalent results from seismic coherence, or fault likelihood (probability-based) processes.

Typically, CNNs utilize a U-Net architecture comprising two symmetrical arms arranged in the shape of the English alphabet 'U' as shown in figure 2, and consist of a number of successive layers, which through sharing of parameters enhance the resolution of the output. The left arm, called the "downsampling wing," is a convolution network wherein repeated application of convolutions takes place to extract different features from the previous inputs. Each convolution layer is followed by a layer that serves to nonlinearly express the input to its output, and another layer that extracts the rough structure again nonlinearly reducing the feature sampling so that the number of parameters gets reduced, so also the computation time. In some sense, the information contained in a 128x128x128 block of seismic amplitude data is represented by a smaller 64x64x64 block of CNN "attributes." Then this 64x64x64 block is further reduced to a 32x32x32 block of different "attributes." In this manner, a reduced data volume represents the 3-D image, where significant features are selected, and less significant features discarded as per some thresholds. The right arm, called the "upsampling wing," also uses a layered process, such as deconvolution (sometimes also called "transpose convolution"), as well as concatenation and feature mapping to reconstruct the image to its original size.

By adopting a repeated combination of such convolutions and associated operations, the algorithm attempts to find the unknown weights for each step that at the end predict the known training data (a suite of fault surfaces mapped to voxels)

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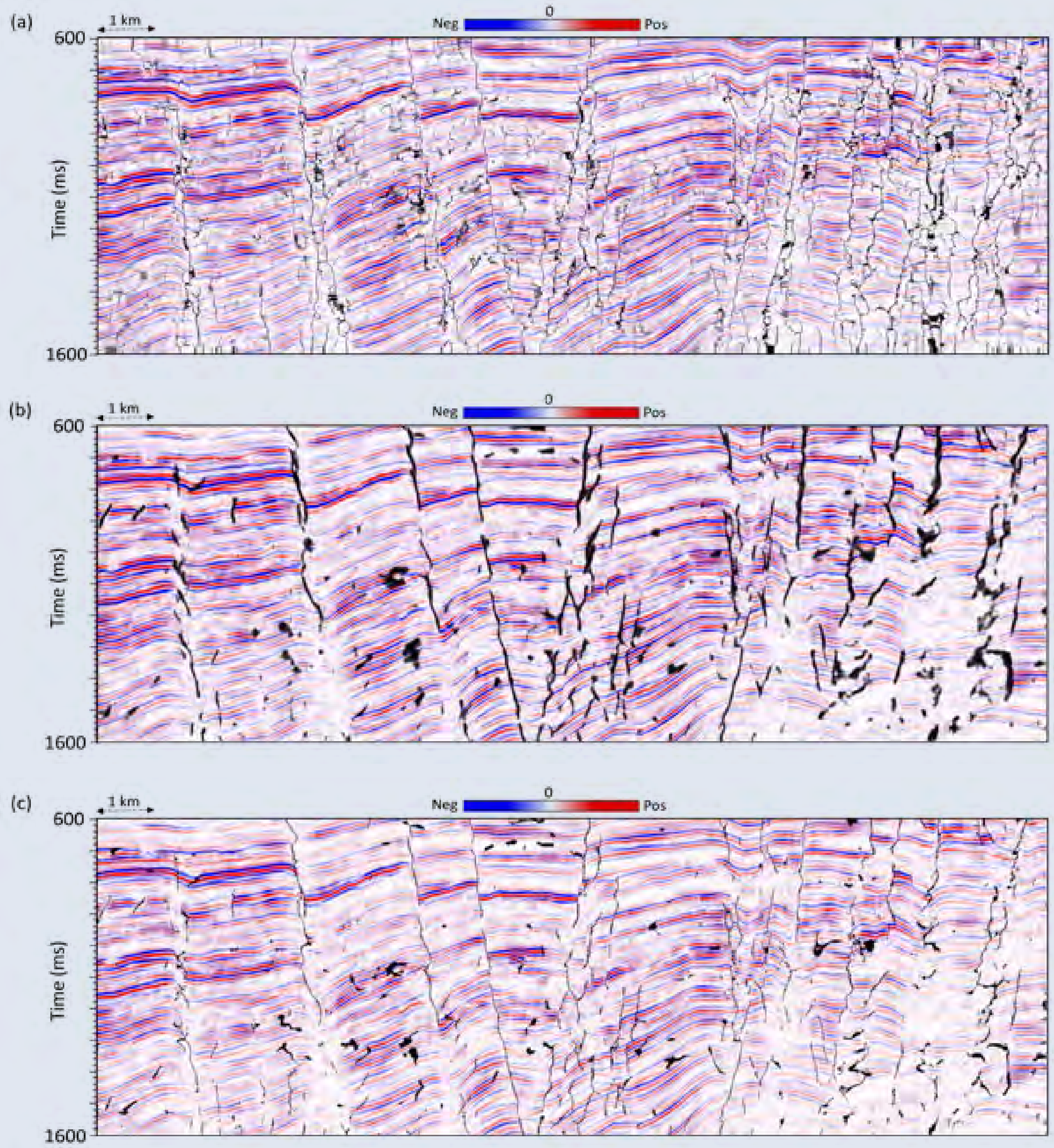

Figure 4: An inline section through the (a) original fault-likelihood, (b) AI fault-probability, and (c) thinned AI fault-probability attribute volumes. Data courtesy of New Zealand Petroleum and Minerals.

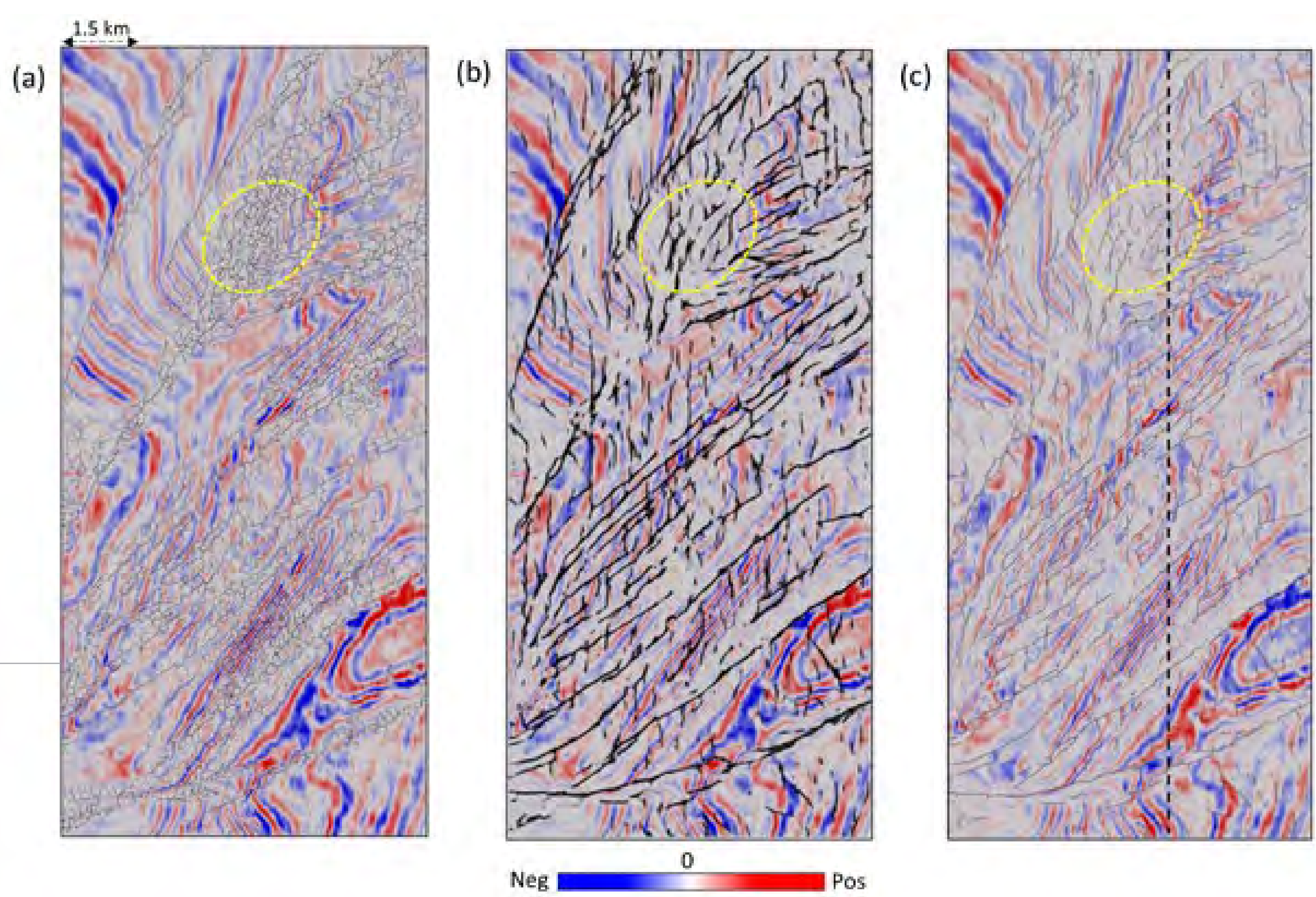

Figure 5: Equivalent time slices at 1,088 milliseconds from (a) fault-likelihood attribute, (b) AI fault-probability attribute, and (c) AI fault-probability attribute with thinning, volumes. One obvious difference between the fault-likelihood attribute and the newer AI fault probability is that the polygonal patterns seen on the time slice has gone away and is now replaced with the lineament pattern which seems more geological. Data courtesy of New Zealand Petroleum and Minerals.

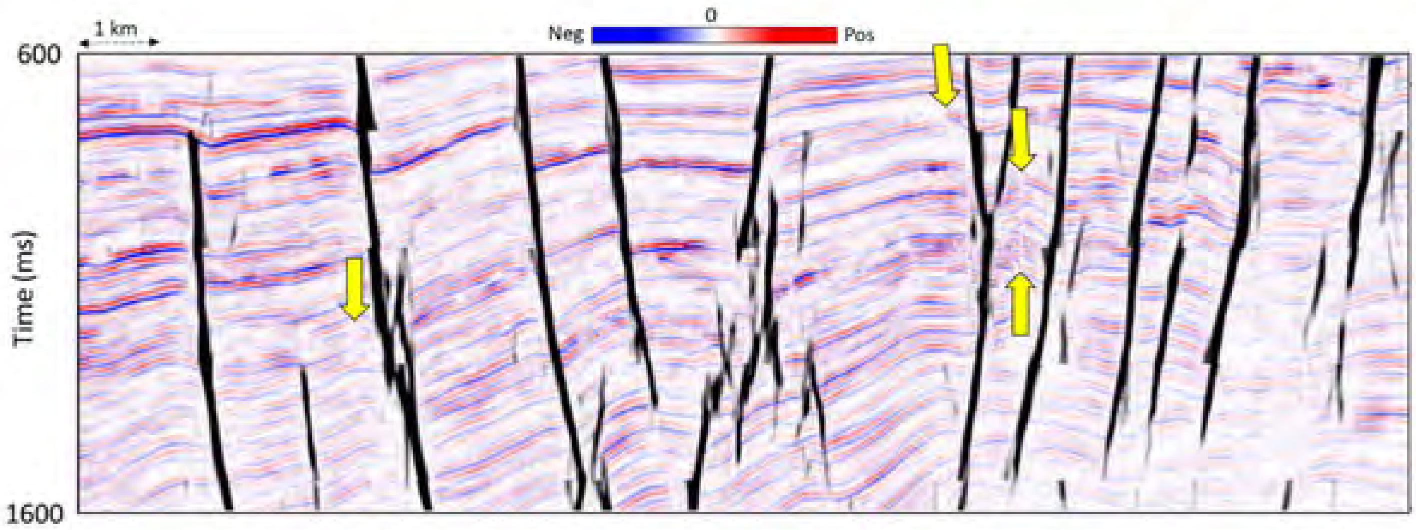

Figure 6: An inline vertical section through the AI fault-probability attribute volume generated using an interactive transfer learning process. Although a few smaller faults are missed (yellow arrows) we see few false positive fault anomalies in this image. Data courtesy of New Zealand Petroleum and Minerals.

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from the corresponding known input seismic amplitude data. At present, there are two different types of training data used – human interpreted fault surfaces from real seismic data and synthetic fault surfaces that when combined with a sufficient number of faulted horizons allow the construction of the corresponding synthetic seismic amplitude data.

Once the model parameters are determined, the next step is to validate the performance of CNN on a blind dataset not used in the training; if the results are found to be satisfactory, the CNN is run on the target seismic data volume.

Application to Real Seismic Data Volume

We carry out the application of CNN on the Opunake 3-D seismic survey, located in the southeastern part of offshore Taranaki Basin, New Zealand. As the seismic data quality was found to be better in the shallower part than the deeper, the data were preconditioned with the application of structure-oriented filtering. Some selected inlines and crosslines from the seismic data volume can be put through manual fault interpretation, which served as the training dataset for the AI fault interpretation. Alternatively, synthetic models can be generated for the configuration of faults seen on the input seismic data volume. Figure 3 shows how such a model is generated using a subsurface impedance model and a 30 hertz Ricker wavelet, both without and with the fault model. The synthetic fault models so generated can be used for training in the CNN application.

Figure 4 shows a comparison of corendered inline seismic section with the fault-likelihood attribute (figure 4a), a process discussed in the May 2021 Geophysical Corner, and with the fault probability attribute derived from AI fault interpretation generated using a synthetic fault model for training (figure 4b). This data volume is then put through a "thinning" or skeletonizing process, which is essentially a binary representation of the faults, a "1" representing a fault and "0," no fault. The equivalent corendered inline section through this volume is shown in figure 4c. Notice, the excessive lineament detail seen in figure 4a, which a seismic interpreter might find overwhelming, looks more geological in figures 4b and c.

A similar time slice comparison is shown in figure 5, wherefrom a similar conclusion can be arrived at.

For training, as stated above usually a limited number of inlines and crossline from a 3-D seismic volume are used, and it is expected that the CNN model generated therefrom can predict or carry out automated fault interpretation on the input seismic data volume satisfactorily. However, many times this results in inaccurate predictions. Such a situation is overcome by using an interesting process called "transfer learning," which is an

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