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Automatic joint interpretation of horizon and faults using digitalized G&G logic, not machine learning

A lot of research in the field of automation of seismic interpretation of faults and horizons is dedicated to solving this problem by machine learning (ML). The core principle of ML methods is learning by example. These algorithms work very well for tasks like identifying a cat or a dog in a picture – after having been trained by seeing millions of labelled pictures of cats and dogs. Humans are also trained to separate dogs and cats by example, this is what picture books are for. There is no advanced component of this training – someone who knows the answer points at a picture and says “dog”. An ML algorithm and humans are thus trained in the same way to do this task.

When humans learn to interpret horizons and faults, this involves learning concepts from the fields of geology and geophysics (seismic reflectors, resolution, deposition, extension, …) and ideally involves the laws of nature. Training an ML algorithm uses none of the above, but rather large amounts of labelled data, typically seismic sections where a human has interpreted faults. Thus, there is a significant difference between how humans and ML algorithms “learn” fault interpretation.

The human approach to interpretation of horizon and faults is heavily centered on the seismic reflectors – e.g., identifying continuous reflectors by skeleton interpretation, jump-correlating reflectors over breaks to identify throw scenarios, checking consistent stratigraphic ordering and identifying growth packages. Using the novel data format Seismic Tiles [Skjæveland and Torset 2023], all reflectors in a seismic dataset can be represented by a set of small reflector segments, called tiles. Using Seismic Tiles we are able to digitalize the fault interpretation logic, so that the computer can interpret the faults and horizons in a similar way as to how humans do. In contrast to ML methods, this is transparent, explicit and reproducible. The result is not a fault probability cube or “only” fault planes, but ranked scenarios for how horizons connect across faults. This output allows for much more automated QC than is the case for a fault probability cube, and also for moving forward with multiple scenarios if picking “the correct one” is difficult.

Since there is no training involved, there is no need for labels. There is, however, a need to digitalize the G&G logic that humans apply to seismic interpretation so that the computer can apply the same logic to tiles, and also to implement the machinery to loop over a large cube and connect the individual faults to a fault network. Although this algorithm is still under development, we do have an implementation of a basic joint fault and horizon interpretation that in our opinion demonstrates how this principle opens for a radical improvement in how automation of fault and horizons interpretations is carried out.

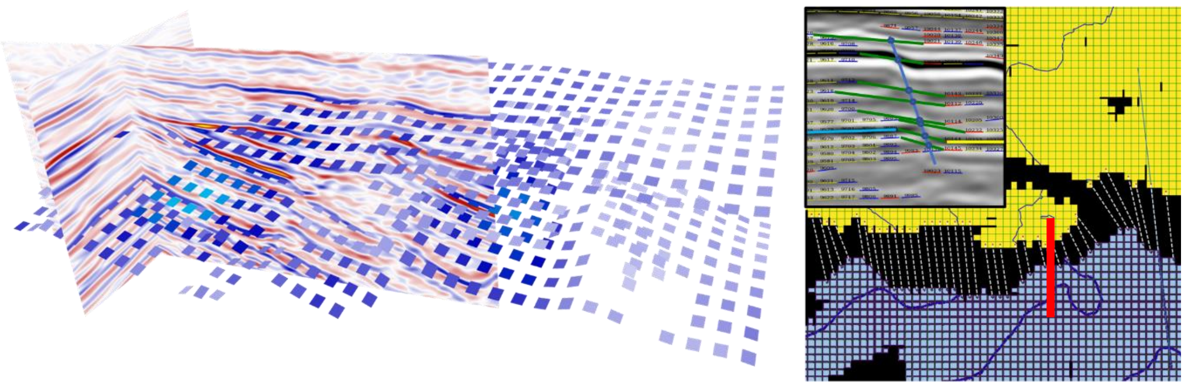

Figure 1: Left: Seismic Tiles represents seismic reflectors by a set of reflector segments (tiles). All reflectors are captured, but only a small number of tiles are shown in the figure. Right: Automatically identifying fault throw scenarios across reflector gaps, where reflectors are represented by sets of connected tiles.

Ref: Skjæveland, Ø and S. Torset: *Seismic Tiles, a data format to facilitate analytics on seismic reflectors*. Geophysics, vol 88 issue 3 (preprint)