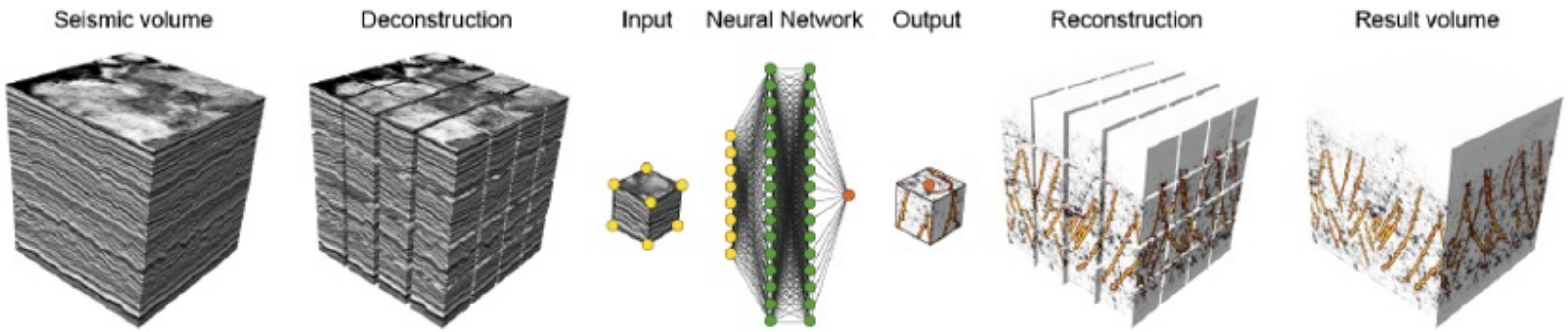
Seismic imaging
Lecture 7



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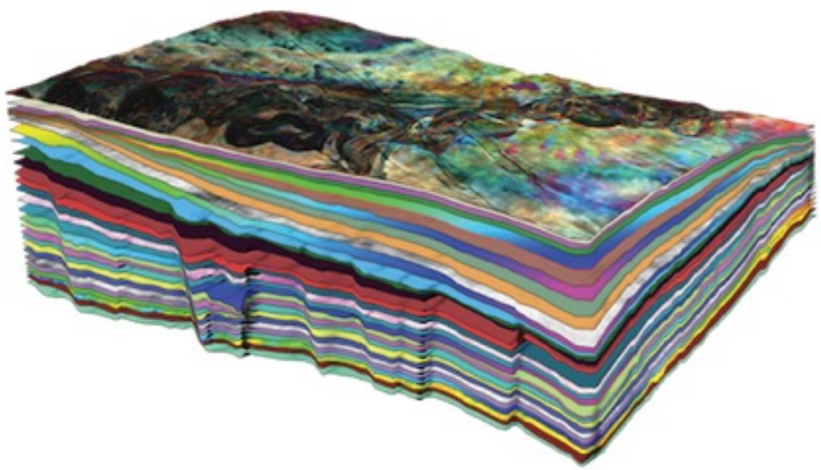
Automation and ML

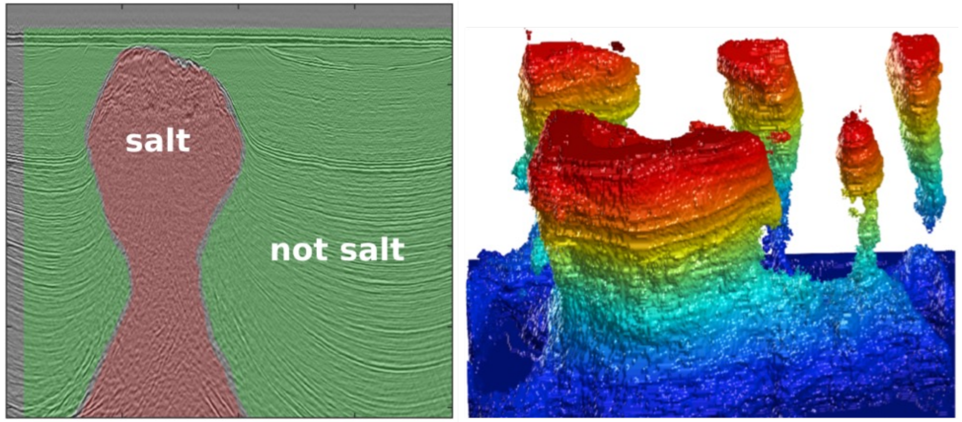
- 3D seismic volumes have increased significantly in size over the last few decades. The volume of data that now exists is difficult/impossible for teams of humans to interpret fully

- With the vast array of seismic attributes available it is difficult/impossible for a human interpreter to fully appreciate patterns and connections between them, meaning geological information is likely missed

- Automation (doing repetitive, routine tasks in an automated way) and machine learning (understanding patterns and relating them to geological information) could revolutionize the field of seismic interpretation, allowing larger volumes of data to be interpreted in useful time frames, allow deeper geological understanding (particularly when seismic data and drilling data are used together)



https://www.eliis-geo.com/paleoscan-workflows-a.html



https://agilescientific.com/blog/2017/6/20/machine-learning-meets-seismic-interpretation

Machine learning in seismic interpretation

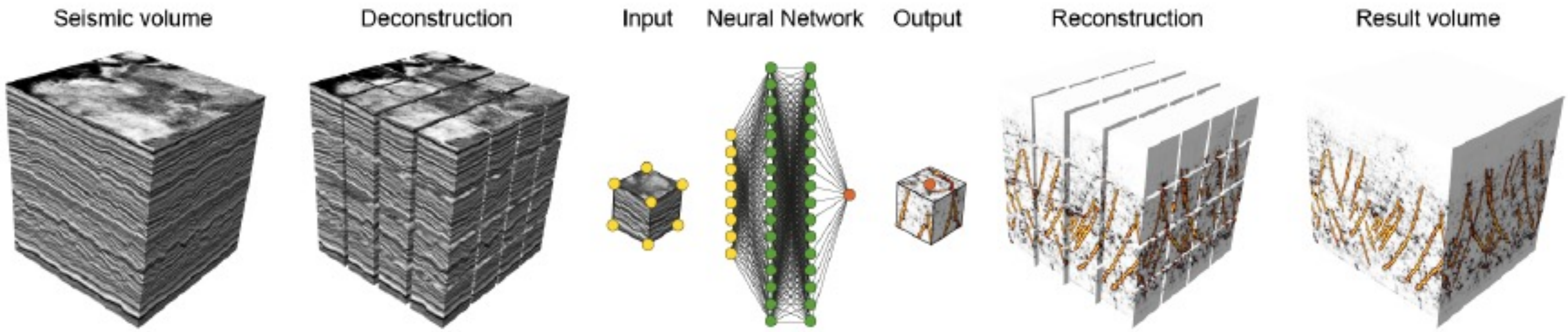
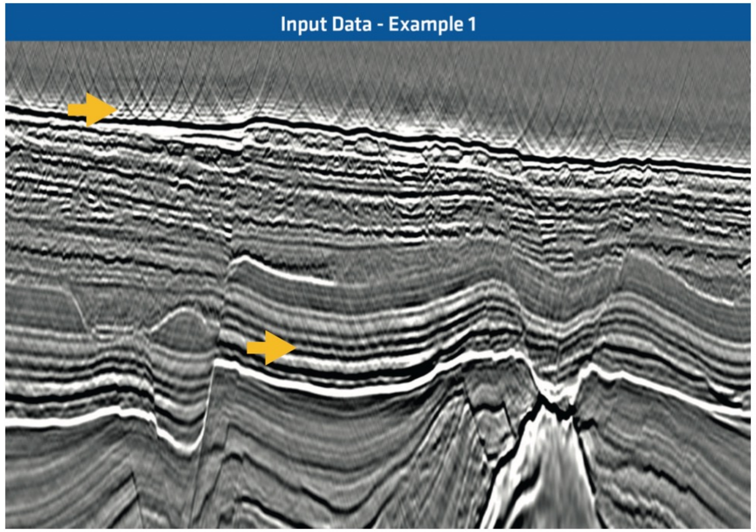
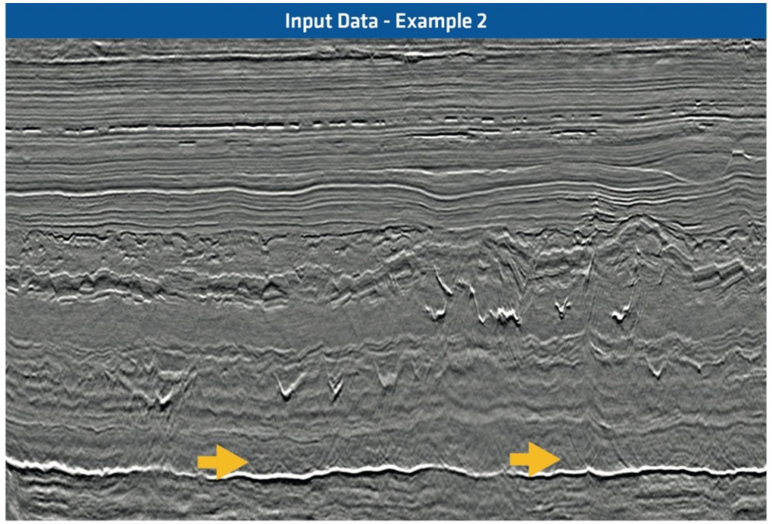


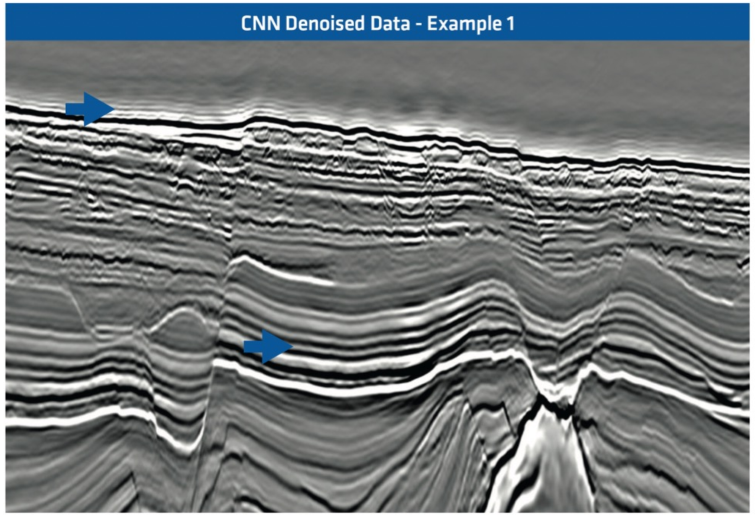
Figure 1. Schematic illustration of deep learning of 3-D seismic reflection data. We deconstruct a 3-D seismic volume into a large number of cubes, which function as input data for the neural network. Using existing seismic interpretations as labels, the neural network learns to predict the output. By predicting the output of each cube, we can reconstruct the result volume, thereby providing a full interpretation of contained fault sets and stratigraphic horizons.

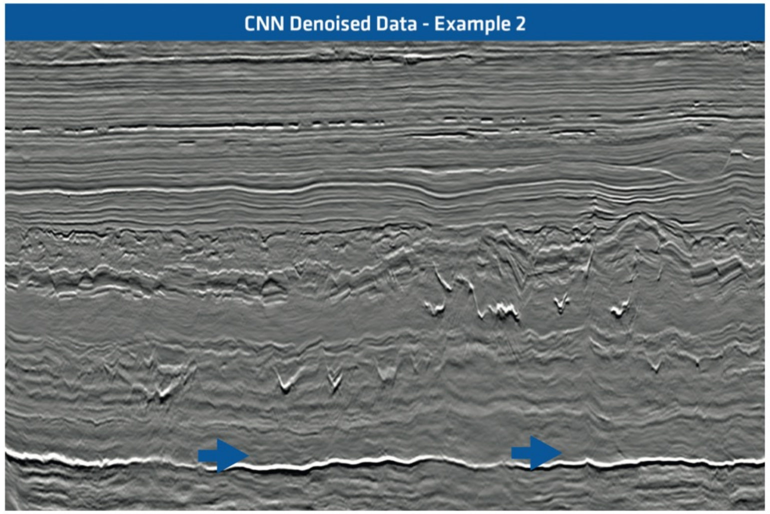
Wrona et al. 2021 (Leading edge): Deep learning for fault extraction

Seismic Processing: De-Noising









<u>Example 1:</u>

Input seismic data: The yellow arrows shows noise the CNN model is attempting to remove.

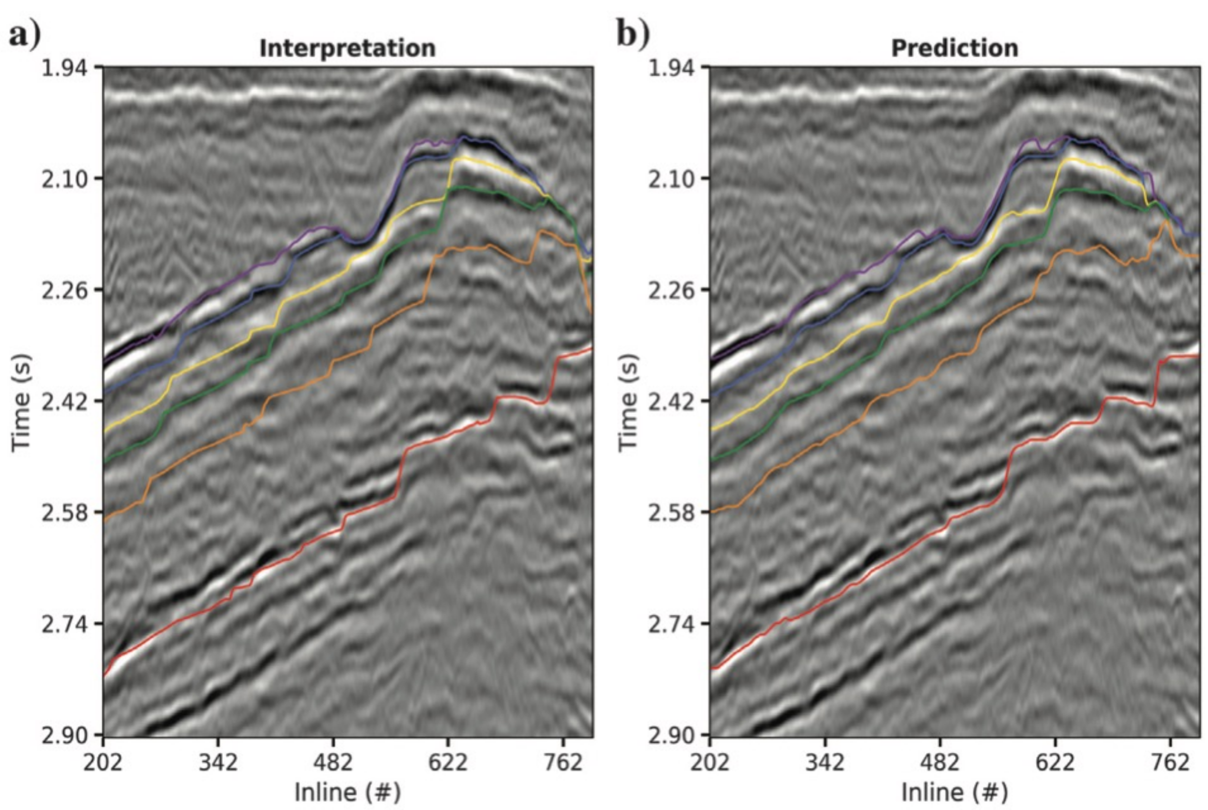
CNN denoised data: Blue arrows indicate that the model has removed almost all the coherent noise from the seismic section.

<u>Example 2:</u>

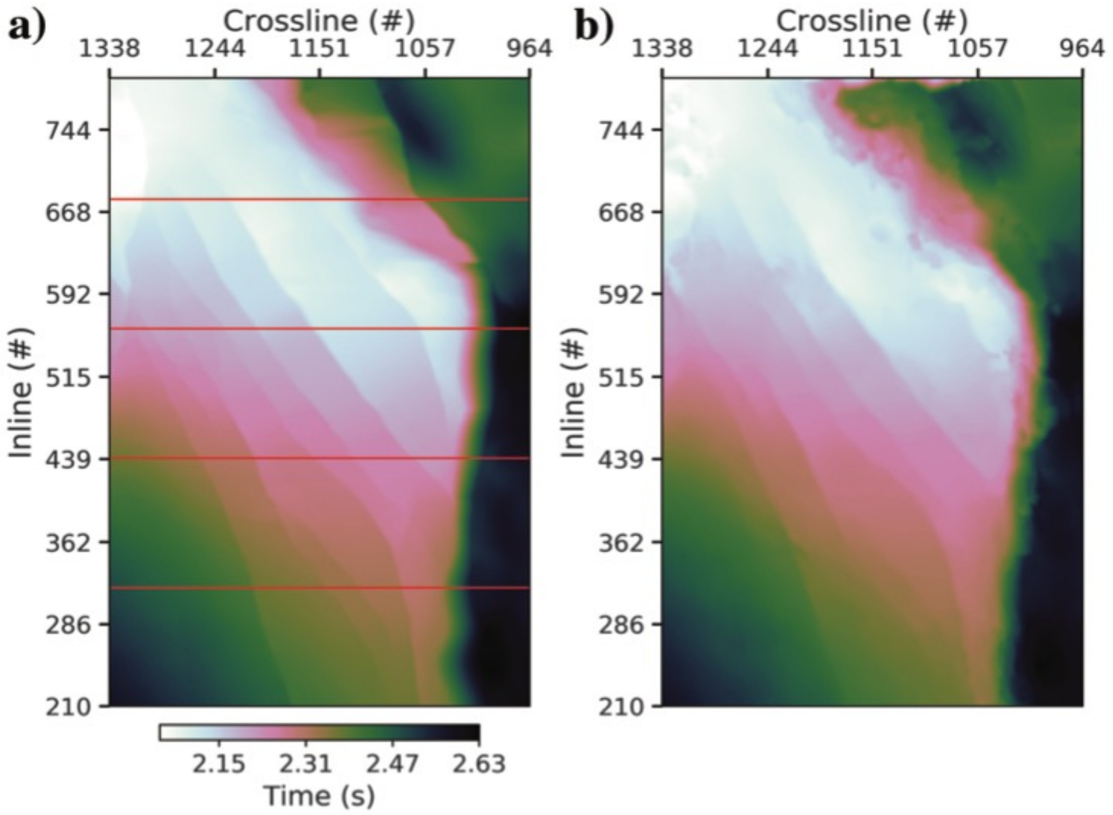
Input seismic data: Yellow arrows highlight the coherent noise.

CNN denoised data: The blue arrows highlight the effectiveness of the process; almost all coherent noise has been removed.

Seismic Interpretation: Horizon Auto-picking



2D section shows (a) the manual interpretation and (b) the machine learning prediction for six horizons.



Map views of one horizon. (a) manual interpretation. (b) Horizon predicted by machine learning.

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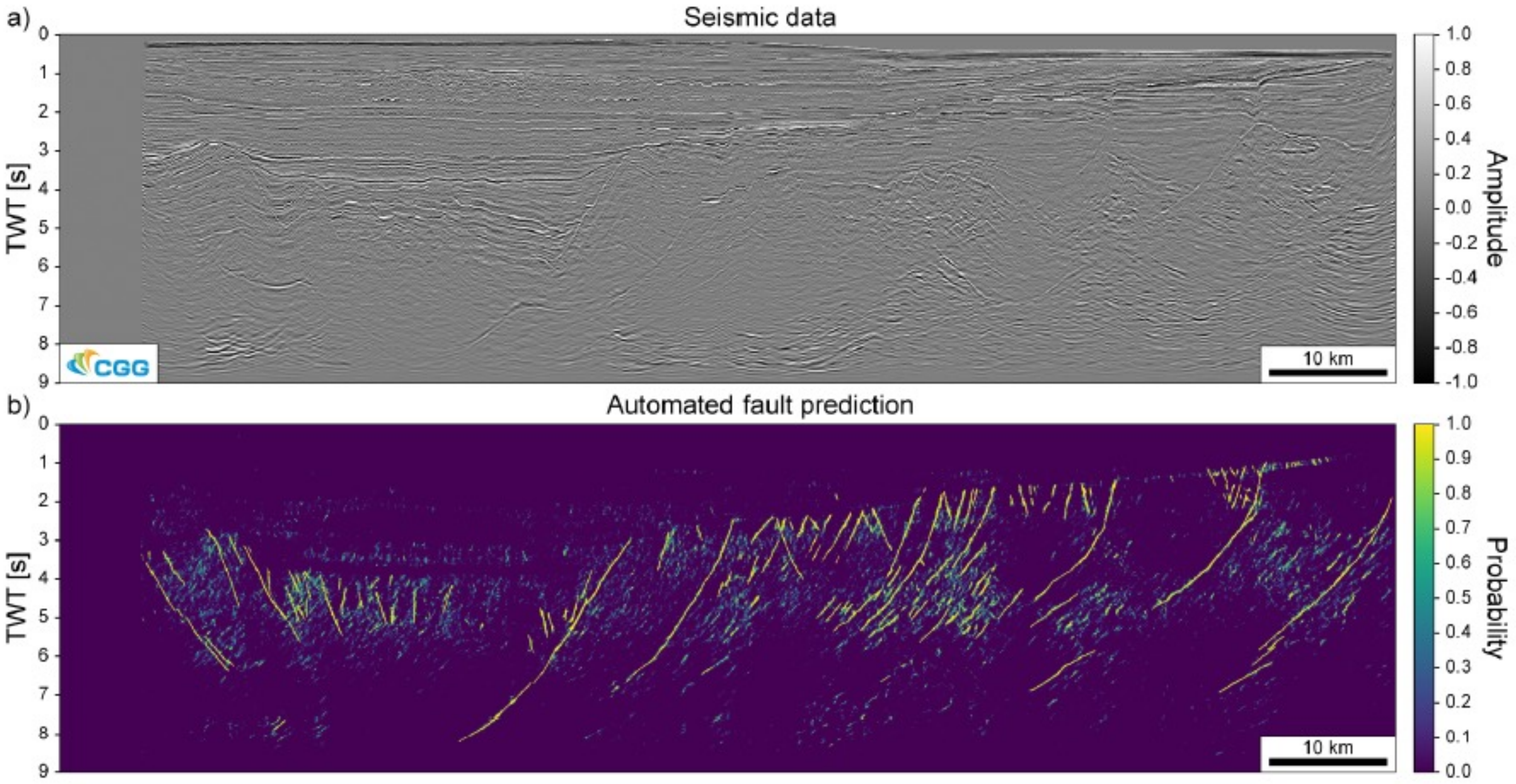
Seismic Interpretation: Fault Identification

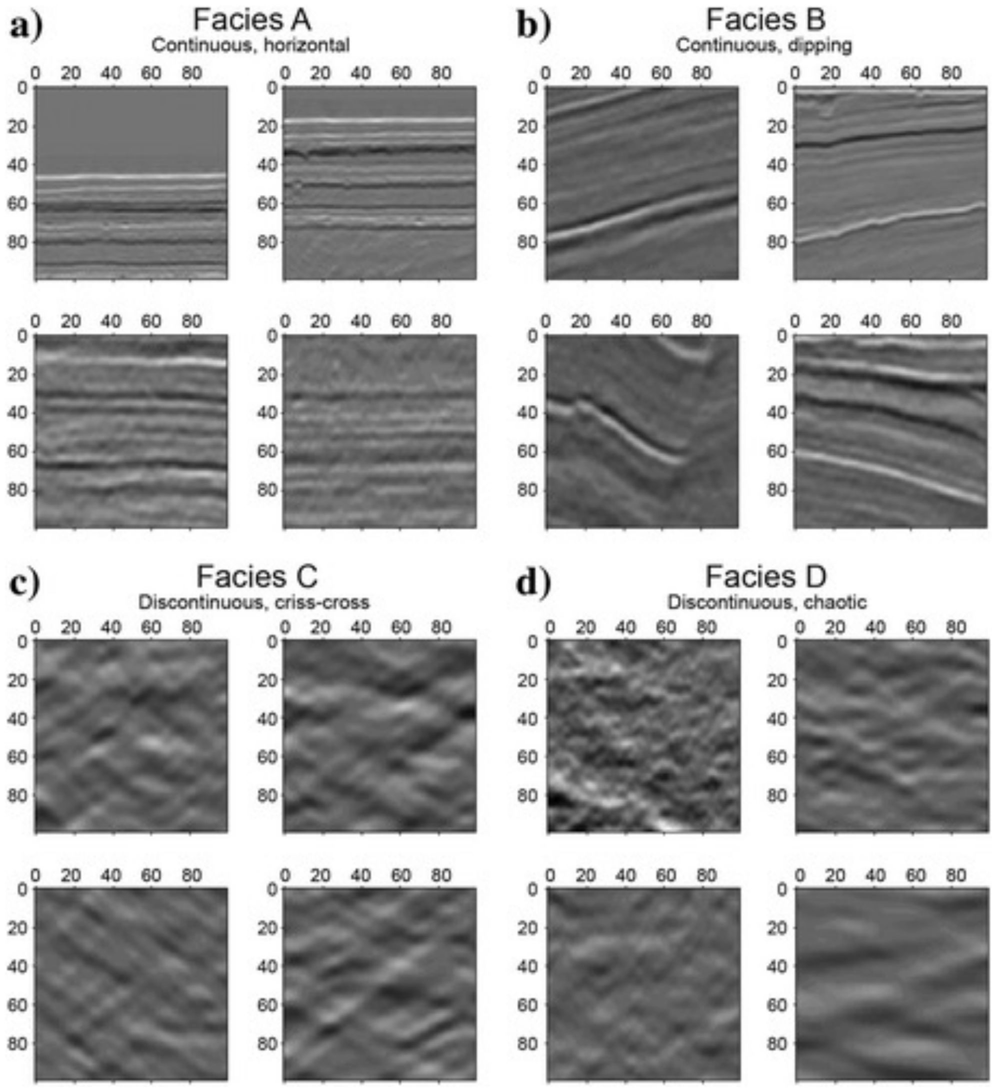
In this example 10 seismic profiles through a 3D cube have been interpreted as "training data"

A python scripts treats the cube in small blocks and searches for things that look like the training data. These features are coloured in terms of the probability that they are faults

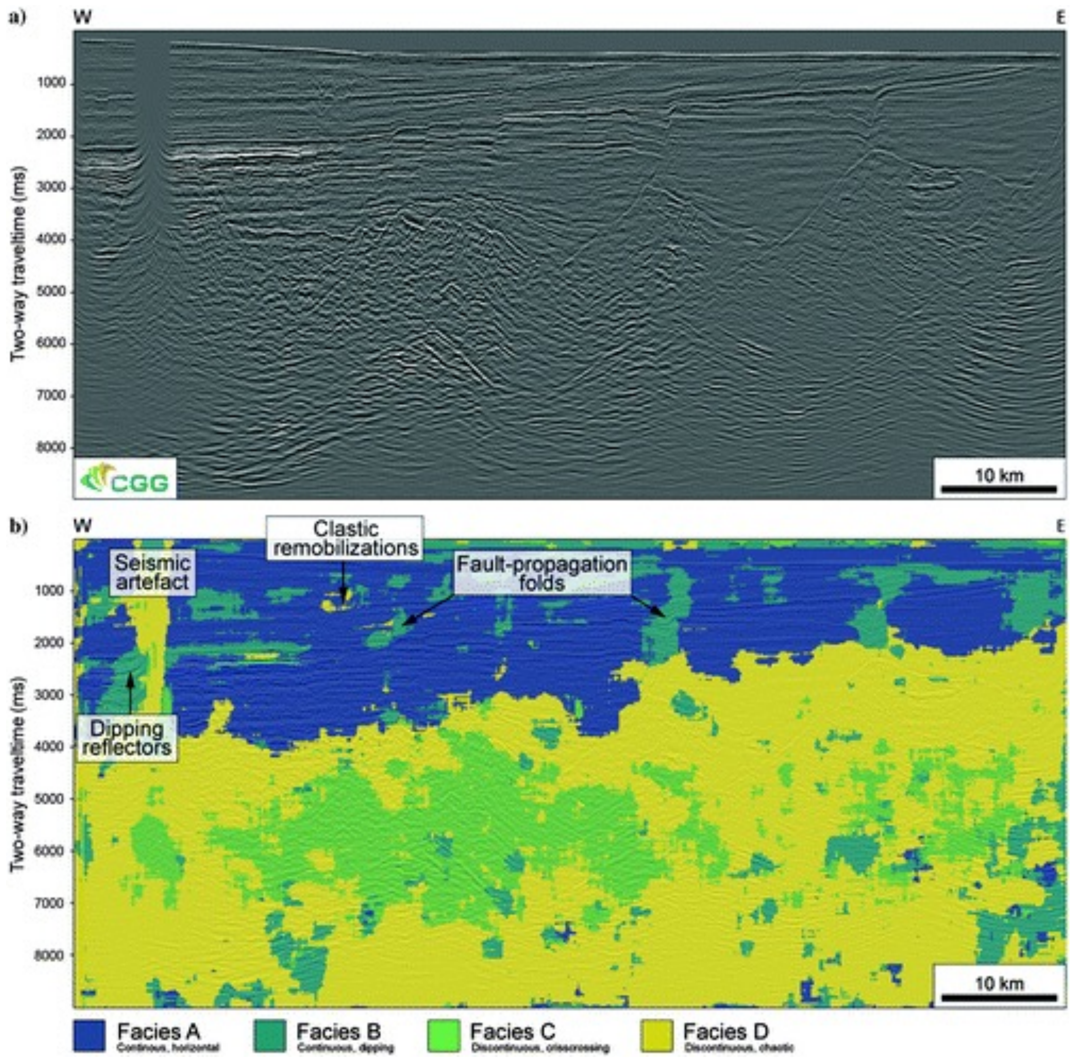


Example from Dr. Thilo Wrona (GFZ Potsdam), using data from CGG

Seismic Interpretation: Seismic-facies Prediction



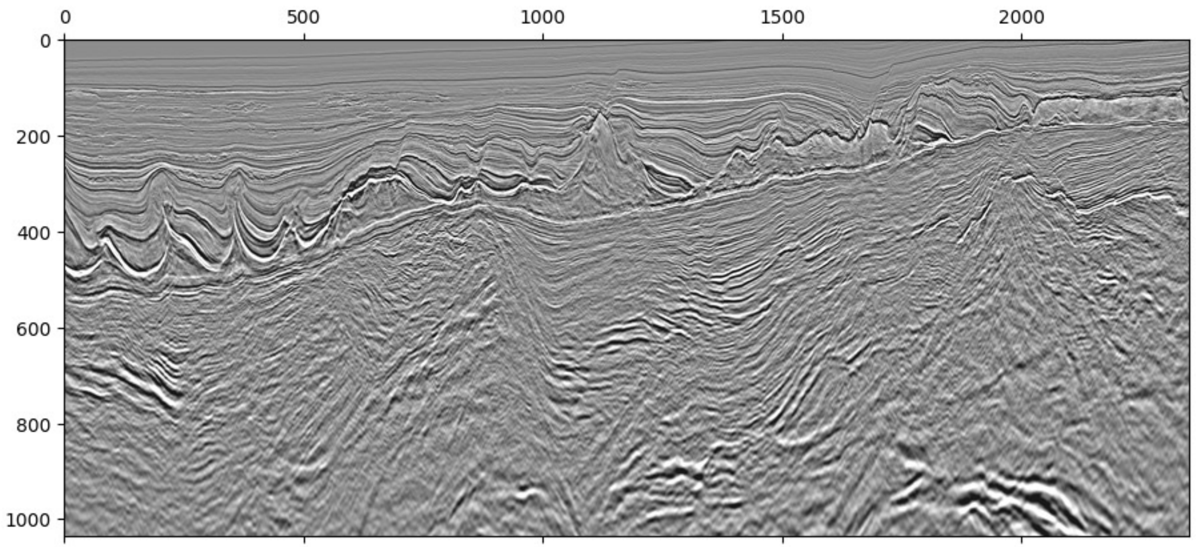
Manual seismic facies classification



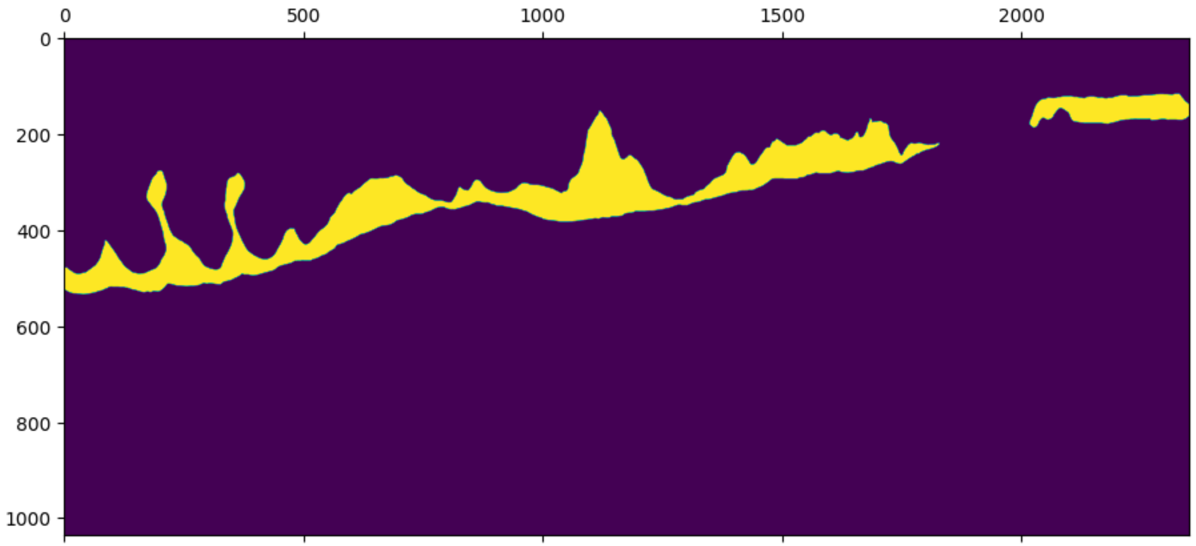
ML automated classification after training

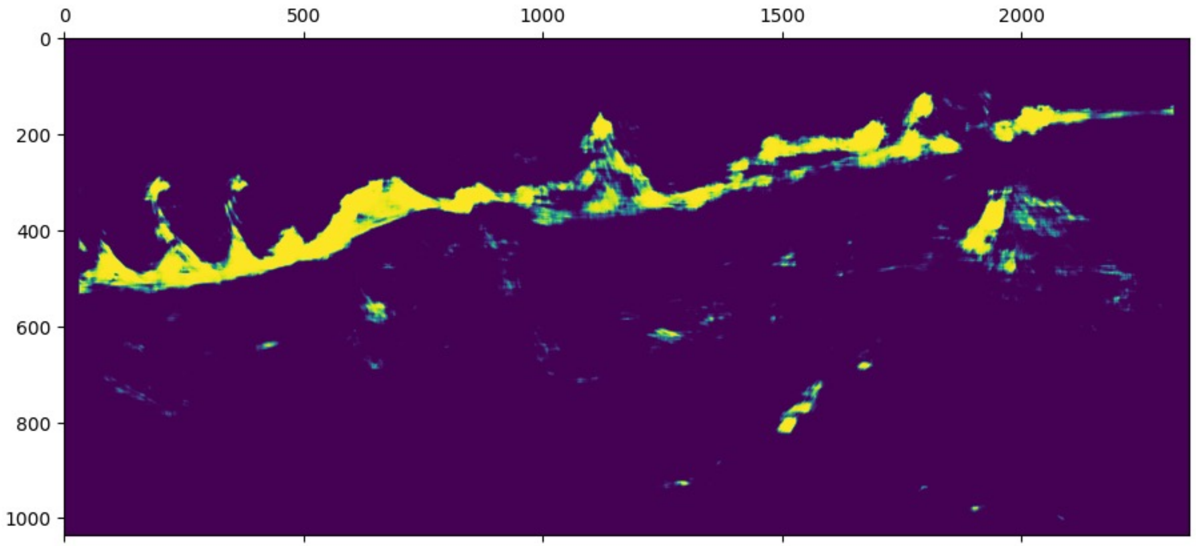
Wrona et al. 2018

Seismic Interpretation: Seismic-facies Prediction



You are going to have a go at this in groups in Ex 5 to try and automate the detection of salt in seismic data!

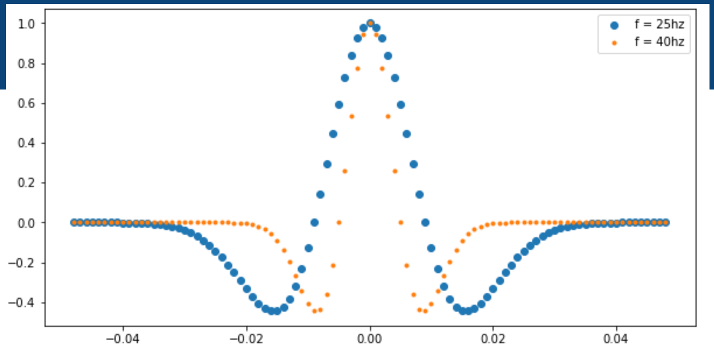




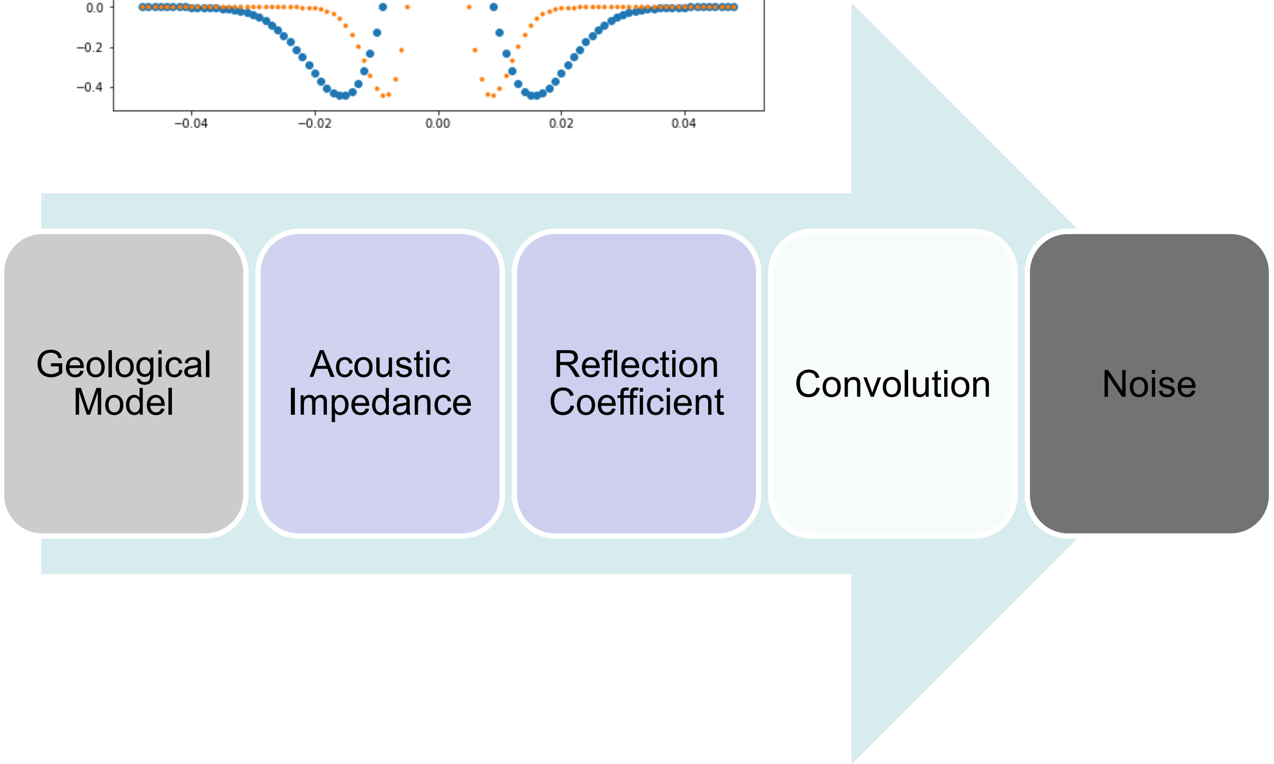
Machine Learning

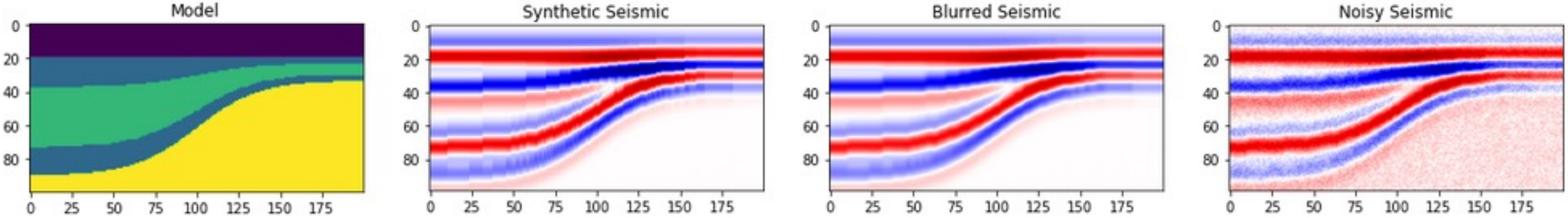
- Deep learning, inspired by how human brains function, uses multi-layer neural network architecture to process data
- It requires massive data to function properly
- Seismic data with its enormous size, multi-dimensional, and complexity is an excellent candidate for deep learning analysis
- Despite the brilliant attempts and excellent work of adapting deep learning in seismic interpretation applications, labelling seismic data and avoiding interpretation bias are still the two main challenges
- Access to suitable quantities of training data is a limitation… synthetic seismic models like you created in Ex 1 can be helpful here…

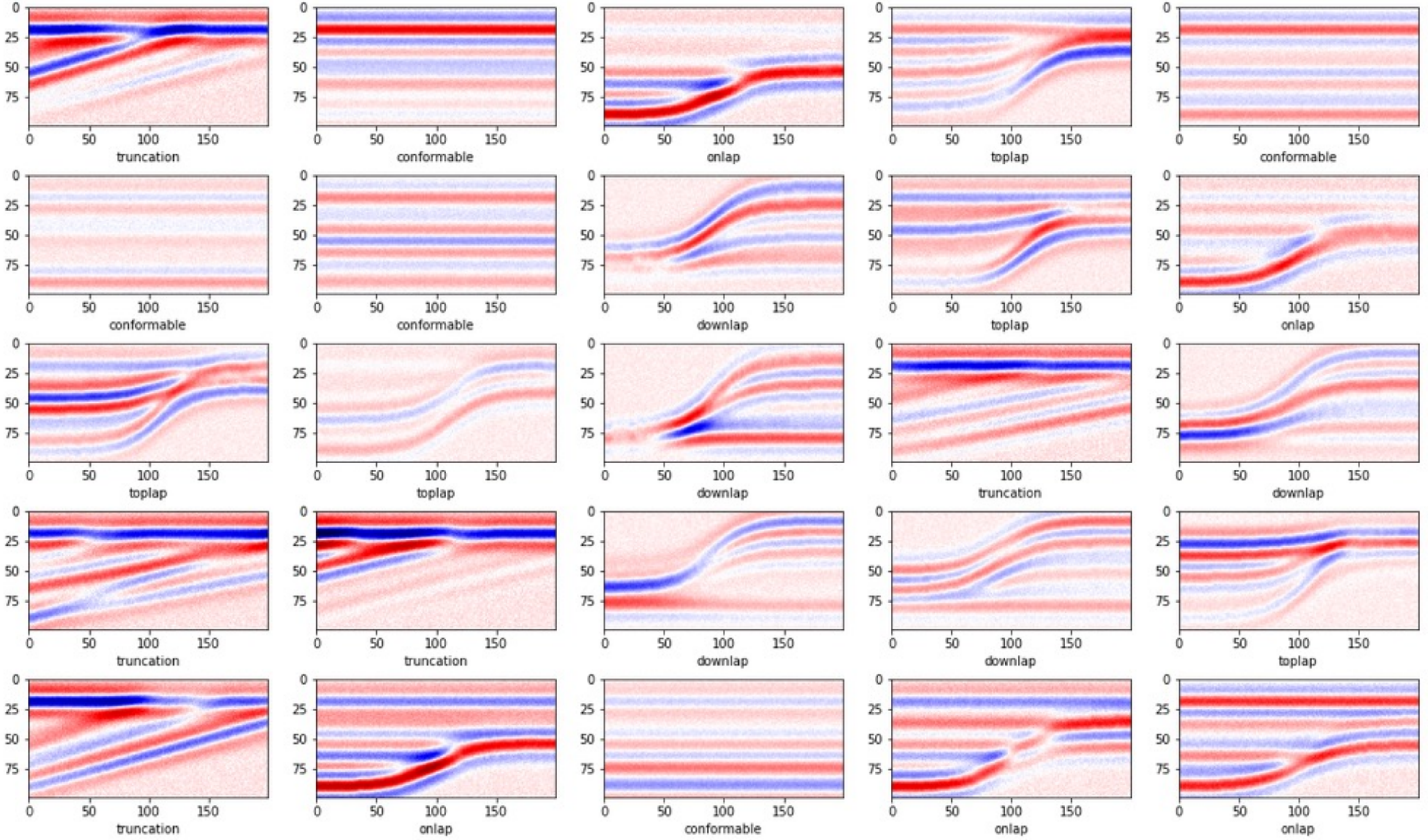
Synthetic training data



2D synthetic models (like you were producing in Exercise 1) can be used as training data for machine learning applications. This removes the need for lots of human labels and is very amenable to augmentation.



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Some science questions to tackle with ML and seismic…

- **Which faults have greatest geothermal energy potential?** At the moment we don't know from seismic data which faults are conduits for (geothermal) fluid and which are seals (which is important for CO_2 storage). ML with a combination of seismic and drilling data may reveal differences in seismic attributes between faults that are conduits or seals.
- **Mapping shallow sediment properties in regions of wind turbine installation.** ML could develop relationships between rock properties from wells and seismic properties to map sediment properties in 3D away from drill sites allowing better site characterization. At the moment, wind farm development involves loads of coring…
- **How does the Earth's crust break-up to form new oceans?** Would require all resolvable faults to be extracted from seismic volumes spanning whole rifts (due to oil and gas exploration these datasets exist in places like the North Sea, NW Australia)
- **Is there a relationship between subducted sediments and seismic hazard at subduction zones?** There is a theory that the thickness and physical properties of sediments could control whether a subduction zone is capable of rupturing in very large (> magnitude 9 earthquakes). ML could help investigate if any global relationships exist using a combination of seismic and well data.