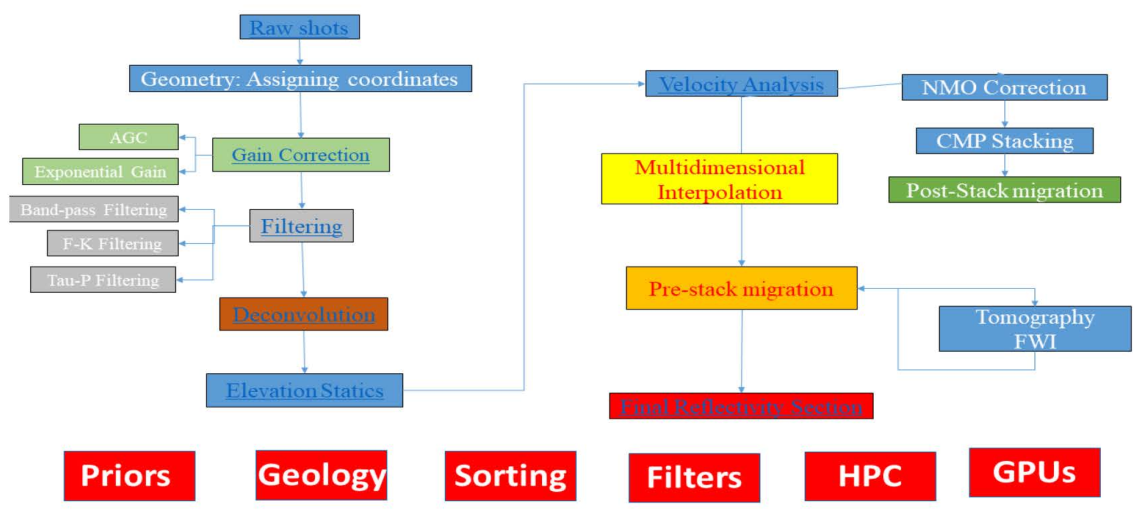
CREWES www.crewes.org

Combining classical processing with Machine Learning

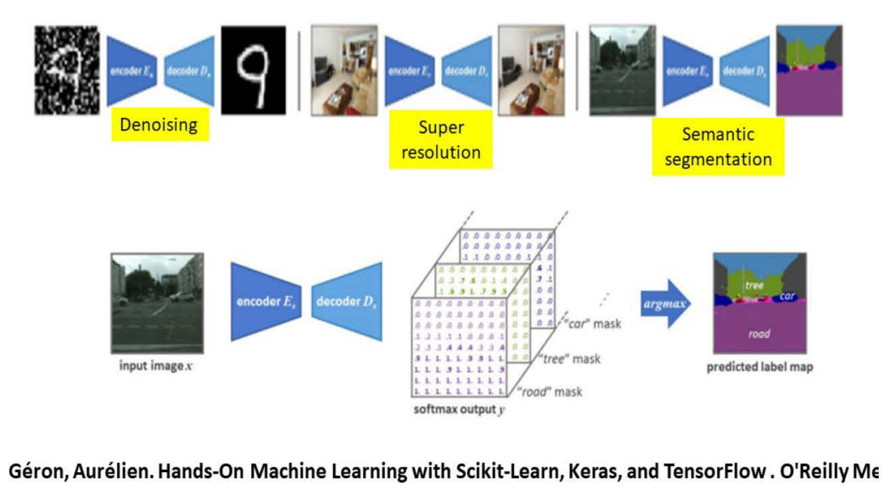
Daniel Trad

Both **physics** and **Machine Learning** learn from experiments and observations
Physics needs **rules** and machine learning doesn't.
Every experiment has a large number of possible outcomes.
Physics uses rules to select the possibilities that matter. This is called **sparsity.**
AI lets anything be learned but prunes by **training**
AI requires more **computer power** and **more data** to do pruning but is more flexible.
Because of these differences, we want to combine the two approaches.



Conventional flows: seismic data require complex dataflows with advanced multidimensional signal processing tools to deal with irregular sampling and detect coherence across domains.

Autoencoder flows: because networks design their filters based on inputs and labels, many advanced operations can be done with the same algorithm.



Géron, Aurélien. Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow . O'Reilly Me

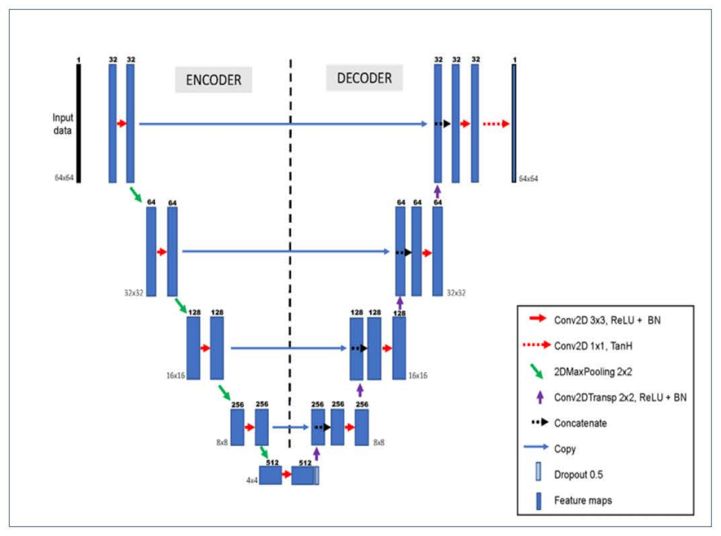
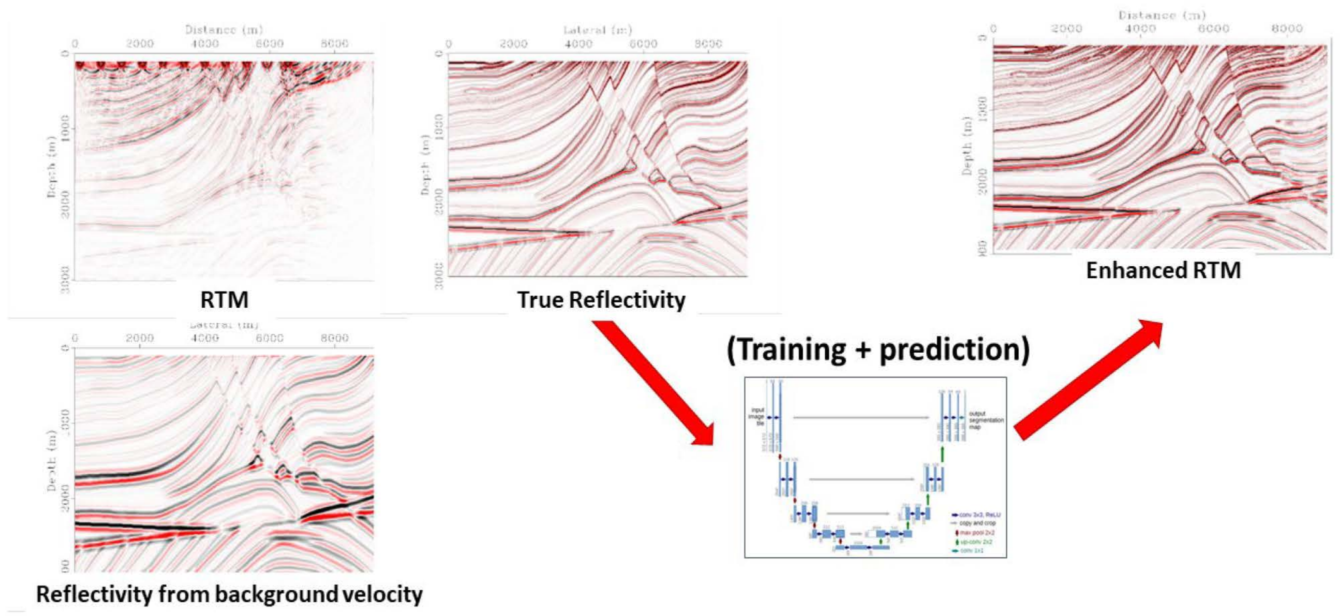
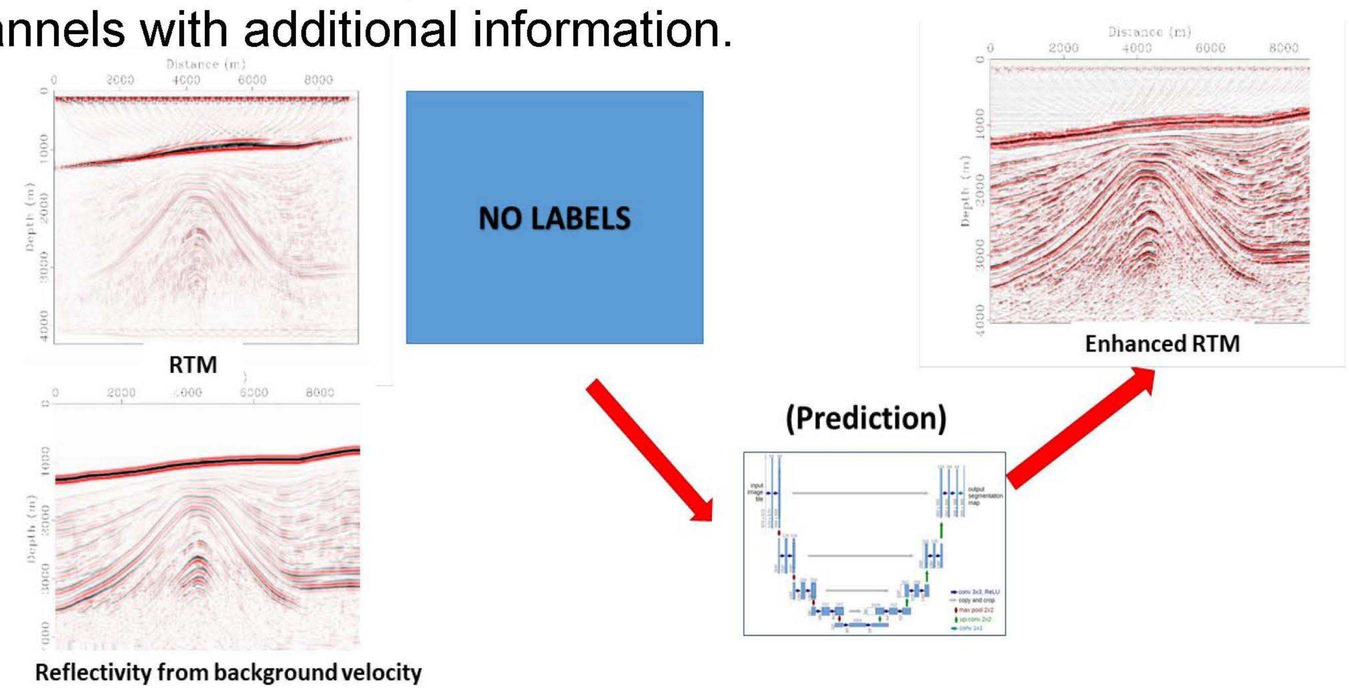


Image Domain LSRTM.

Training: a U-Net is trained to predict an enhanced reflectivity from regular RTM. During training, the network learns filters that approximate the inverse of the Hessian. Different channels in input can provide additional information to the network.

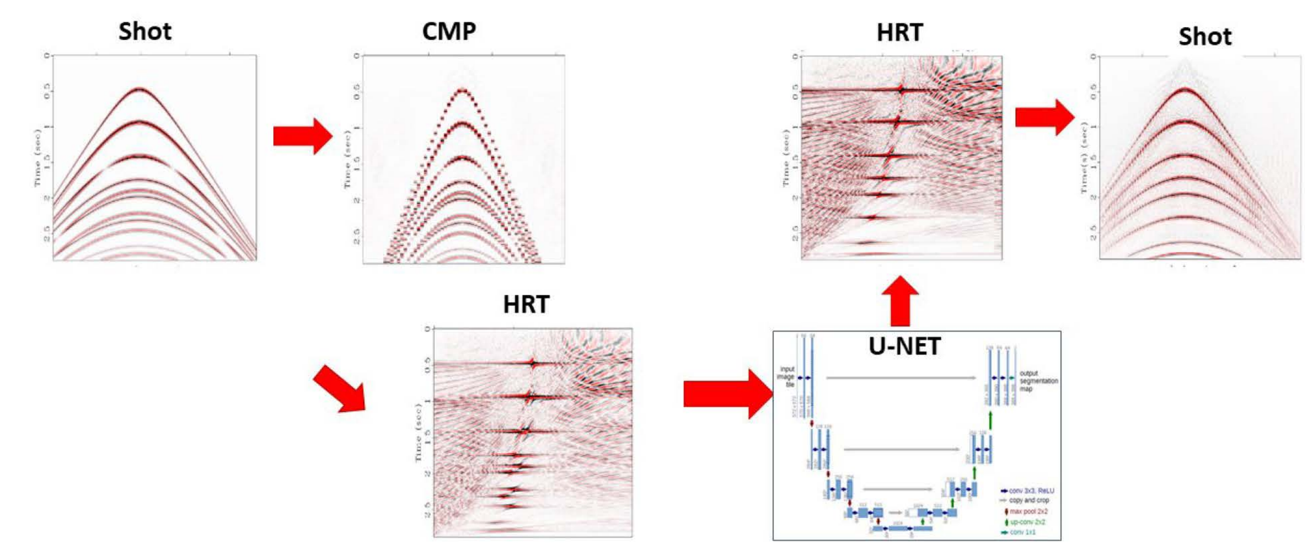


Prediction: the trained U-Net can be used for new datasets where we don't know more than a smooth velocity model. Now we don't have labels but still can use the extra channels with additional information.



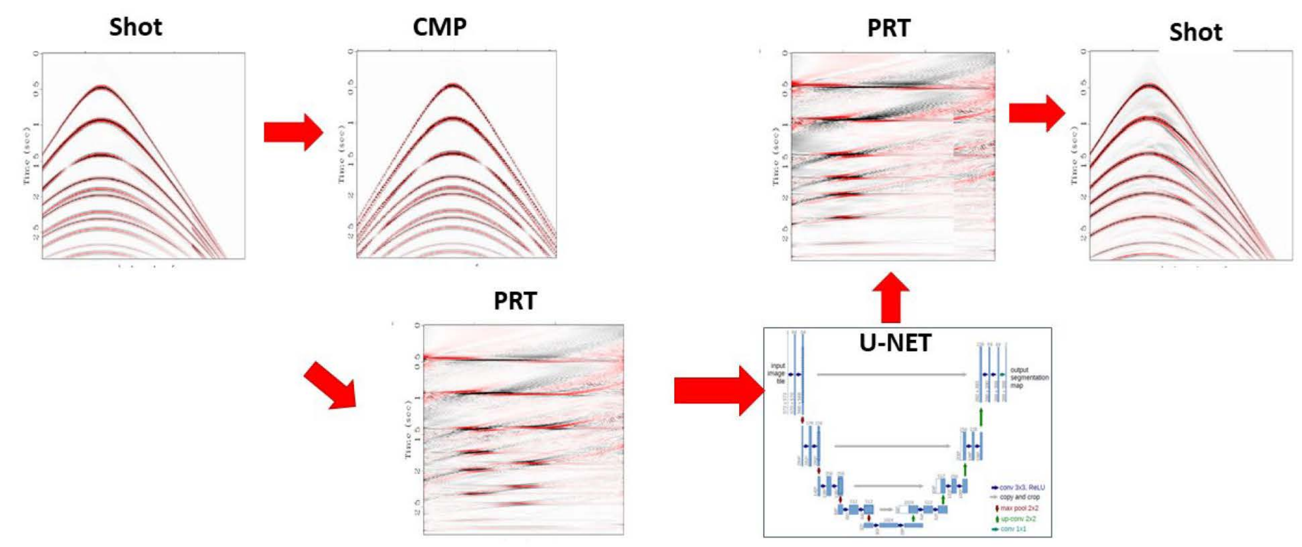
Multiple attenuation in the Radon domain.

Hyperbolic Radon

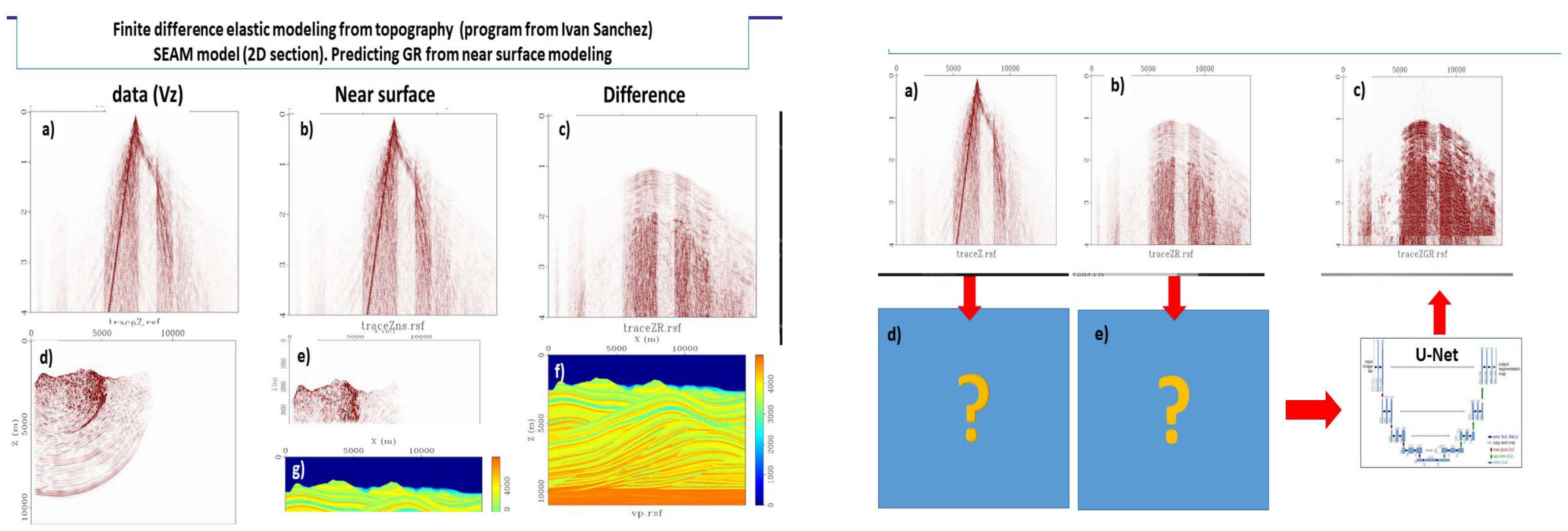


The same U-Net can be used to separate primaries and multiples. The separation is easier to do in the Radon domain, either Hyperbolic (above) or Parabolic (below). A more difficult challenge is to use both of them simultaneously, which would require a mapping (perhaps with another network) between the two transforms since their parameters are different (they do not map pixel by pixel).

Parabolic Radon

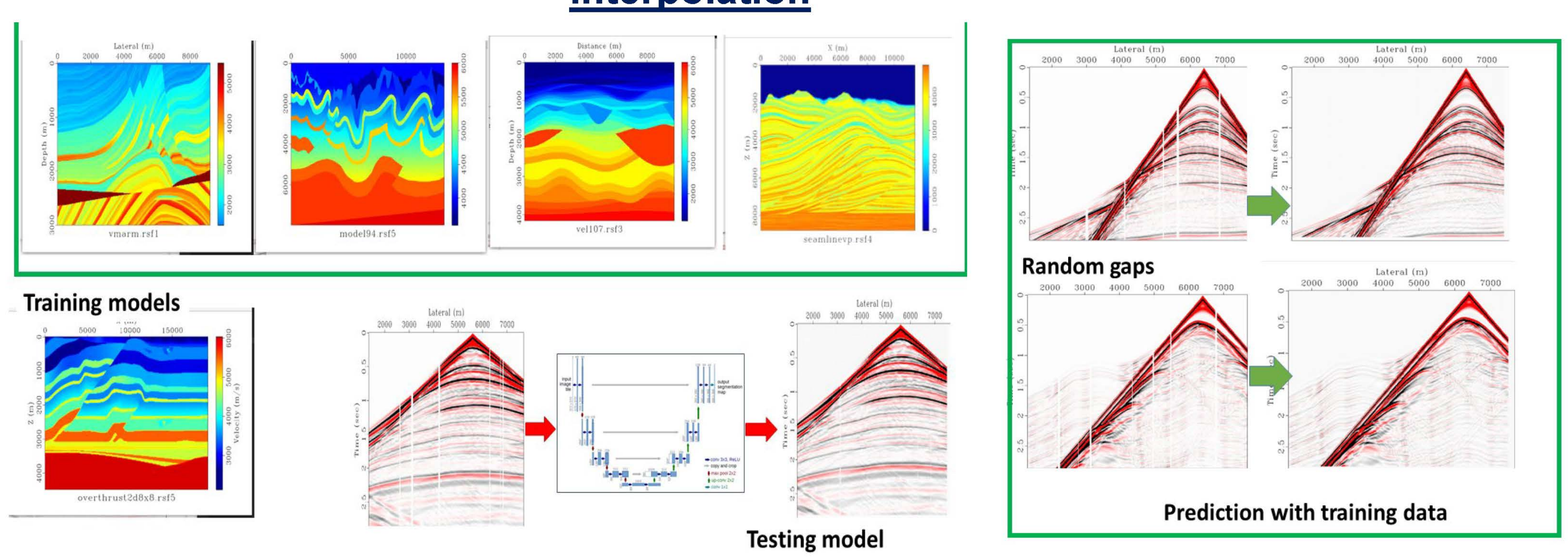


Ground Roll attenuation.



Ground roll attenuation: we use physics to create models of the noise and train a U-Net to map the data with noise to clean data. Different transformations can make the auto-encoder work easier. These transformations are a type of feature engineering. The network also does its own.

Interpolation



Interpolation and generalization power: By using modelled data with and without trace editing, we can train the U-Net to predict missing traces. By putting different surveys together in a data set we can achieve generalization power. A better approach would be to extend the training when new surveys are available for training. This is a type of transfer learning.

NSERC CRSNG
UNIVERSITY OF CALGARY
FACULTY OF SCIENCE
Department of Geoscience