Seismic Attributes - from Interactive Interpretation to Machine Learning

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Supervised Multiattribute Classification

Probabilistic Neural Networks

Multiattribute Analysis Tools

Interpreter-Driven Multiattribute Analysis

Visual Decision Making

- Crosscorrelation Maps
- Corendering
- Spreadsheets
- Crossplotting and Geobodies
- Connected Component Labeling

Projection Techniques

- Principal Component Analysis
- Independent Component Analysis

Statistical Analysis

- Analysis of Variance (ANOVA, MANOVA)
- Multilinear Regression
- Kriging with external drift
- Collocated co-kriging

Machine Learning Multiattribute Analysis

Unsupervised Learning

- K-means
- Gaussian Mixture Models
- Kohonen Self-Organizing Maps
- Generative Topographical Maps

Supervised Learning

- Probabilistic Neural Networks
- Multilinear Feedforward Neural Networks
- Support Vector Machines
- Random Forest Decision Trees
- Generative Adversarial Networks

Artificial Neural Nets (ANN)

Objective: From continuous input measurements (e.g. seismic attributes):

- Predict a continuous output (e.g. porosity)
- Predict discrete lithologies (e.g. wet sand, gas sand, limestone, shale,…)

Example 1: Predicting Seismic Facies from Seismic Attributes

Probabilistic neural networks

Parzen Method:

Estimate the probability density function

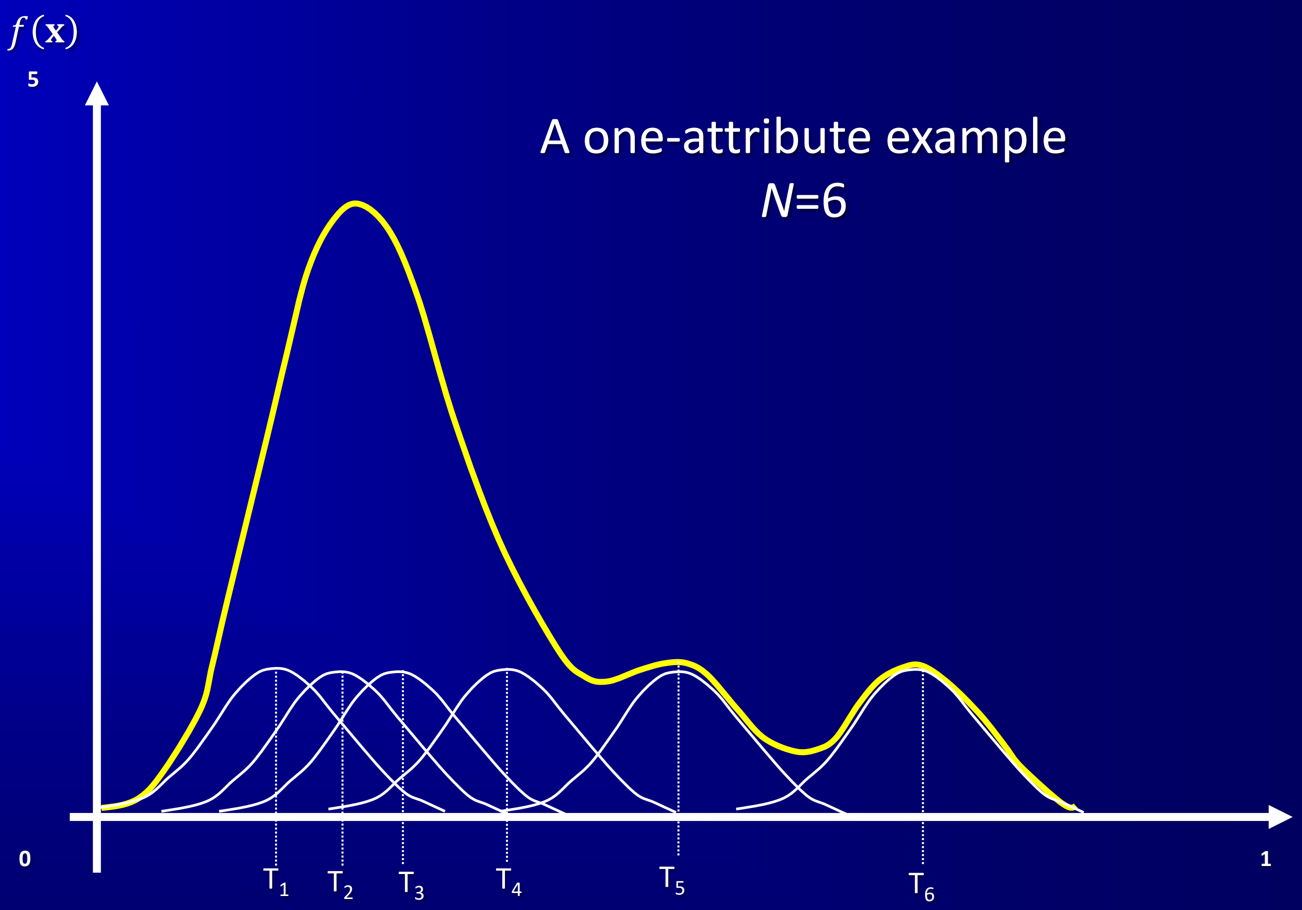
$$g_c(\mathbf{a}_k) = \frac{1}{N}\sum_{n=1}^{N}\exp\left[-\frac{\left\|\mathbf{a}_k - \mathbf{T}_{nc}\right\|^2}{2r_j^2}\right]$$

$\mathbf{T}_{nc}$ The n^{th} training vector for class c

$\mathbf{a}_k$ The attribute vector at the k^{th} voxel

r_j Scaling parameter of the j^{th} attribute

N Total number of training samples



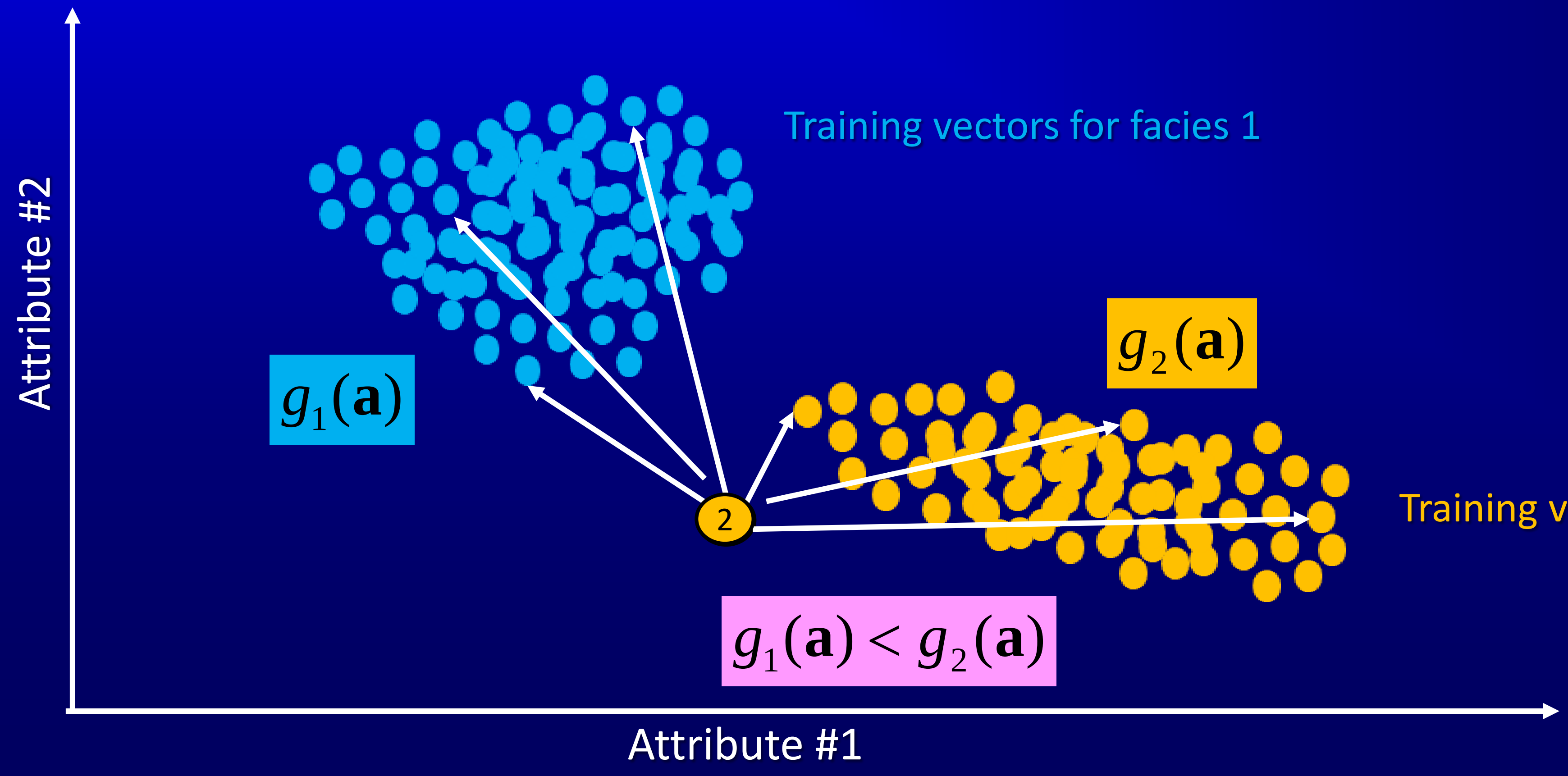
(Specht, 1988;Masters, 1995)

Probabilistic Neural Networks

$$g_c(\mathbf{a}_k) = \frac{1}{N}\sum_{n=1}^{N}\exp\left[-\sum_{m=1}^{M}\frac{\left(a_{mk} - T_{nmc}\right)^2}{2r_j^2}\right]$$

$\mathbf{a}_k$: Attribute vector at voxel k to be classified
$g_c(\mathbf{a}_k)$: Probability of $\mathbf{a}_k$ being in class c
T_{nmc} : Attribute training vectors for class c
M : Number of attributes
N : Number of training vectors
r_j : Gaussian smoothing parameter (unknown)

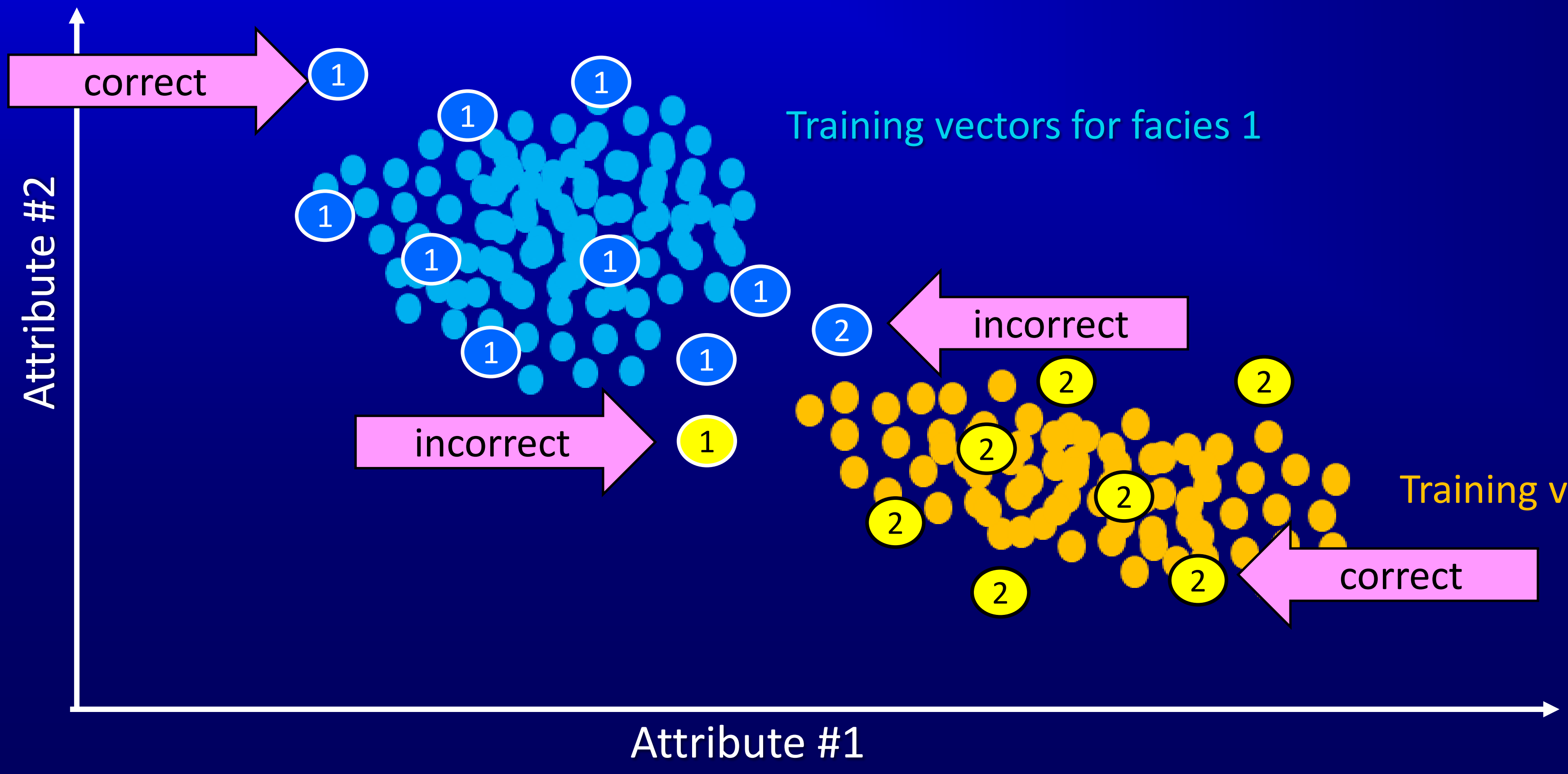
A two-attribute example



(Lubo-Robles et al., 2019)

Validation of PNN prediction for a given set of K attribute vectors and Gaussian smoothing parameter r_j

$$E = \frac{1}{K}\sum_{k=1}^{K} e_k \quad \text{where } e_k = \begin{cases} 1 \text{ if incorrect} \\ 0 \text{ if correct} \end{cases}$$

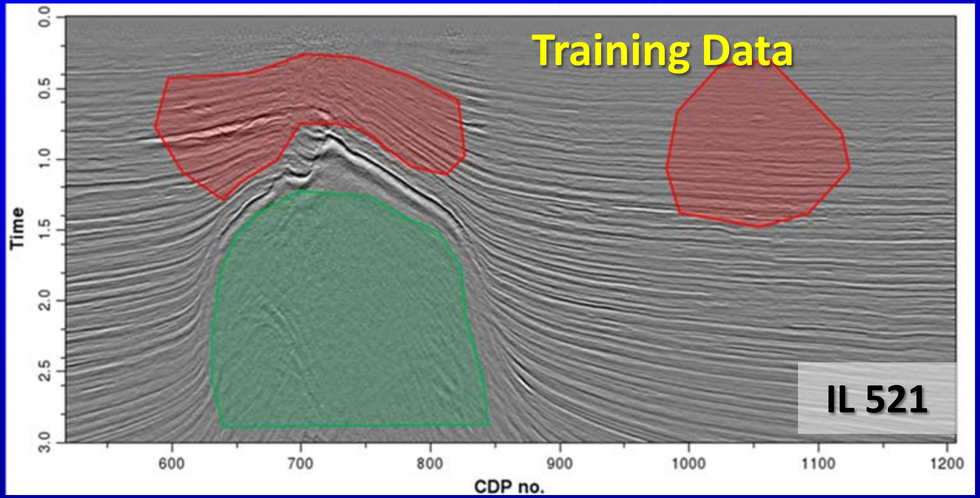


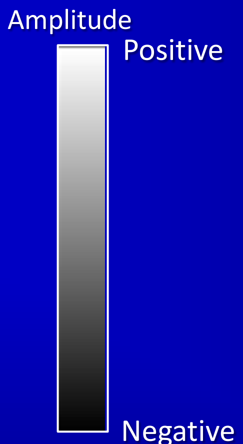
(Lubo-Robles et al., 2019)

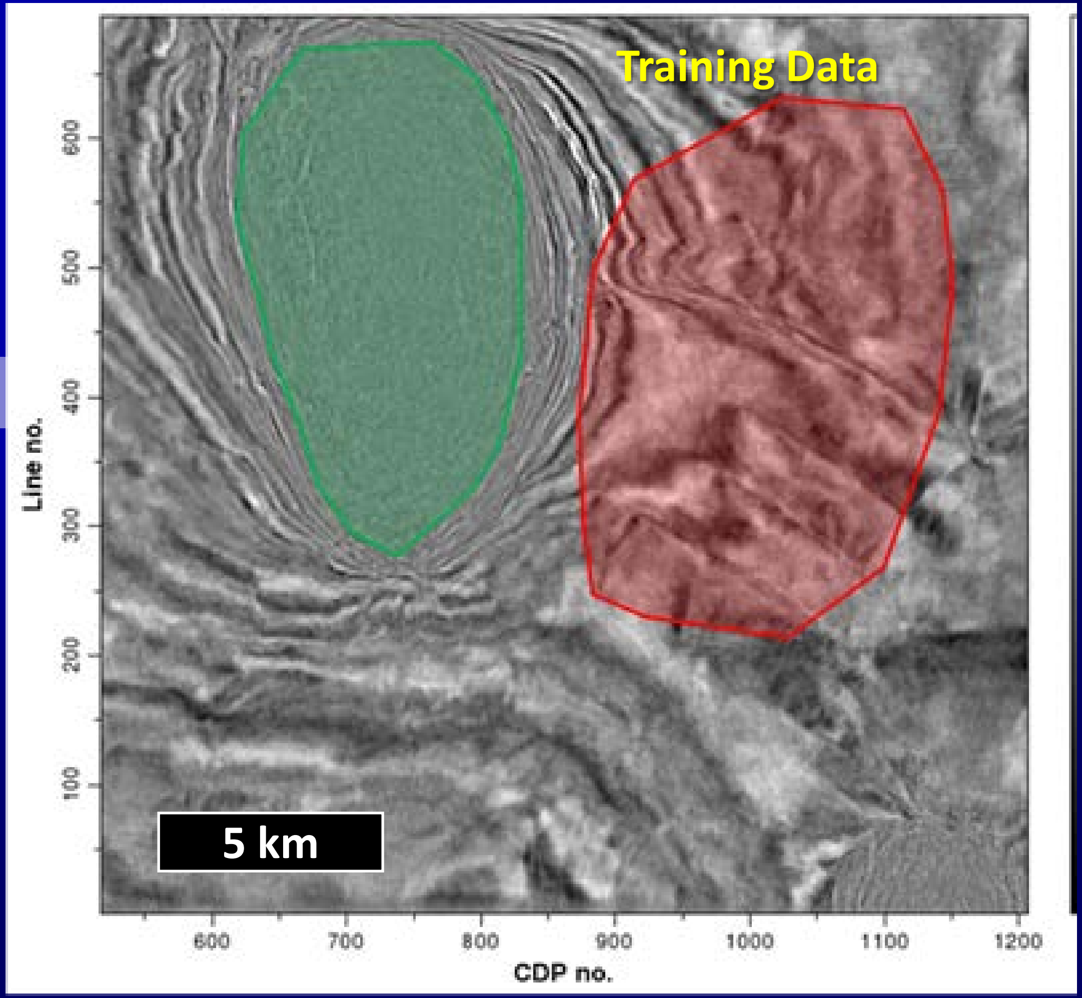
Probabilistic Neural Networks

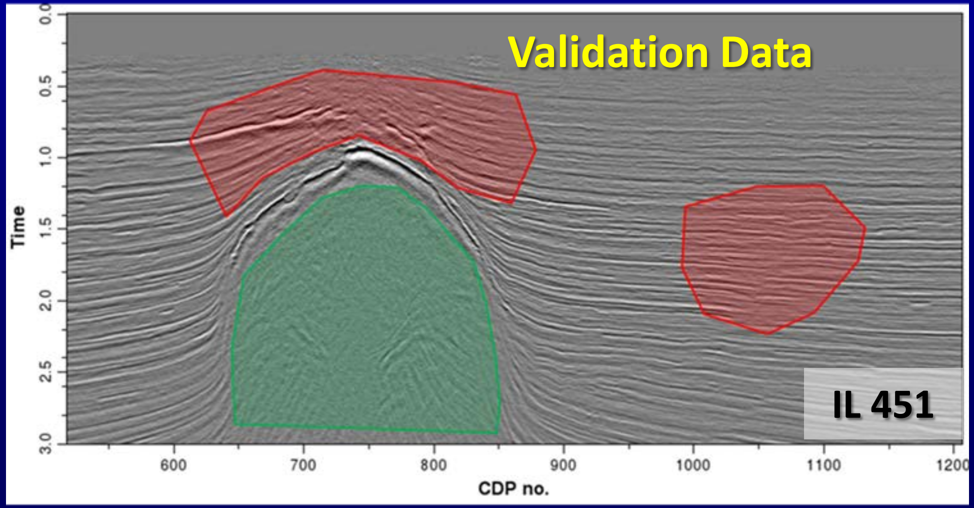
Salt

Not Salt



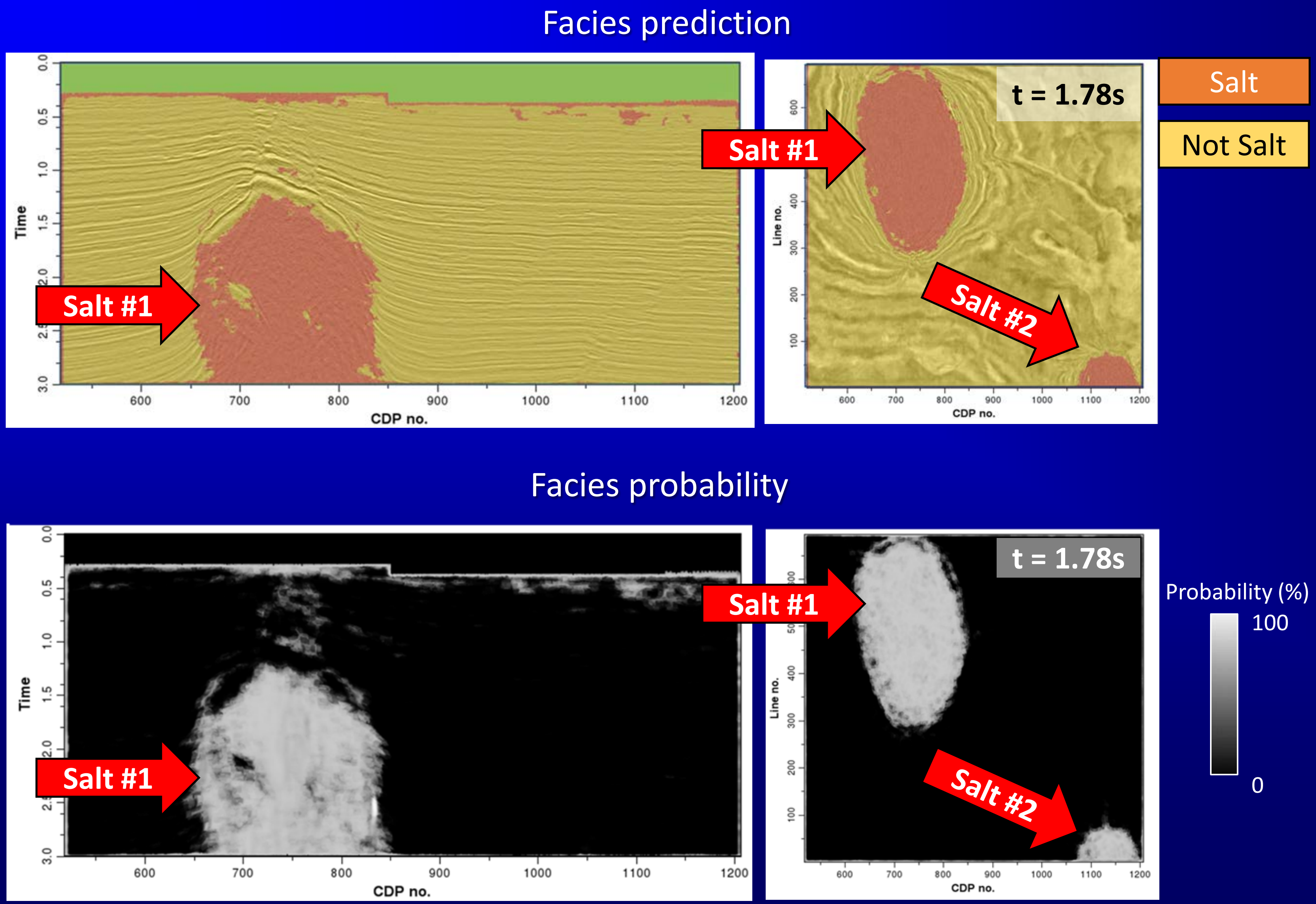






(Lubo-Robles et al., 2019)

Probabilistic Neural Networks



- PNN classifies correctly between salt and non-salt seismic facies.
- Salt diapir #2 used as blind test is also correctly classified.
- Salt facies are associated with very high probabilities ranging from 75 to 80%

(Lubo-Robles et al., 2019)

Probabilistic Neural Networks

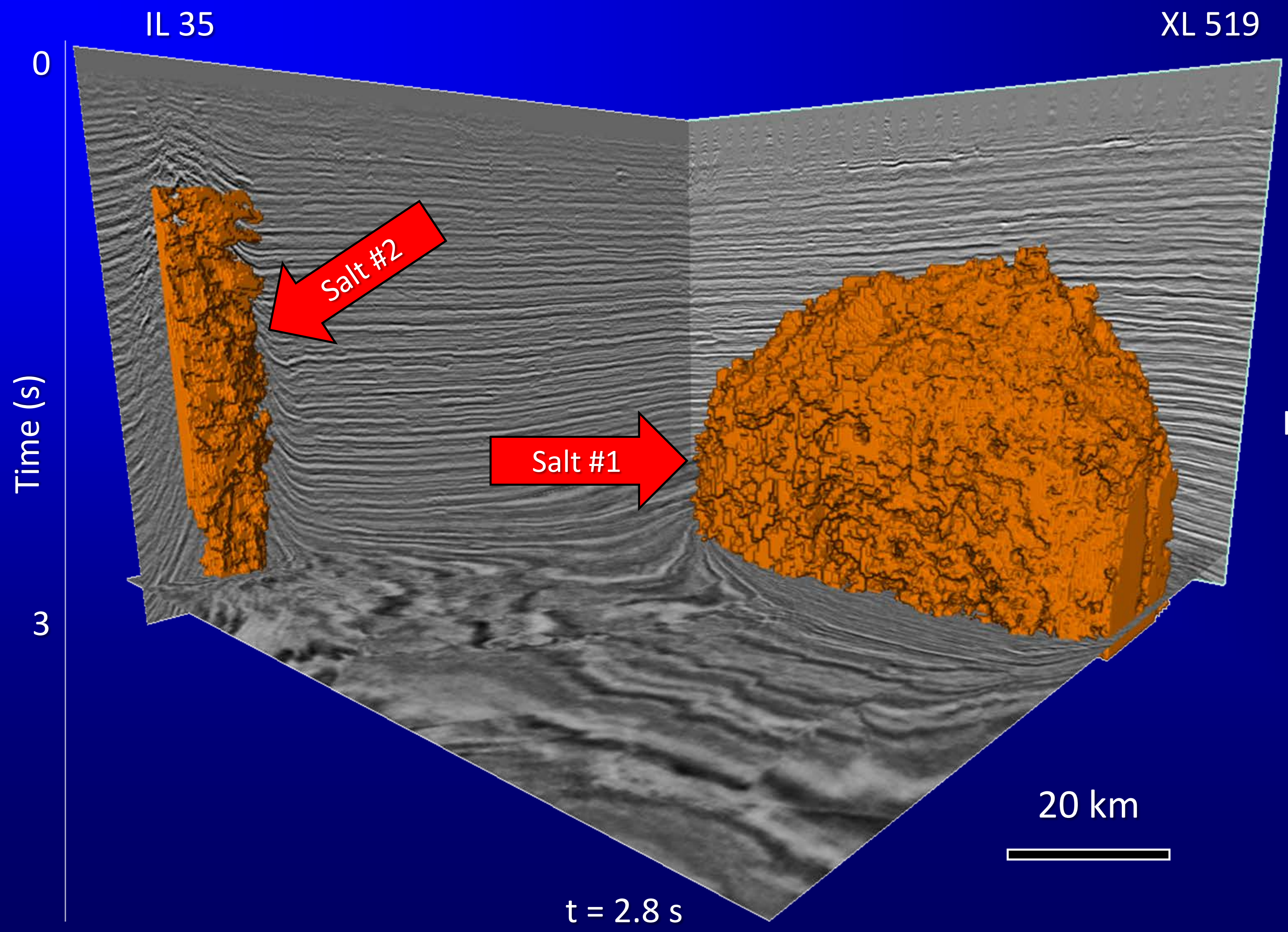
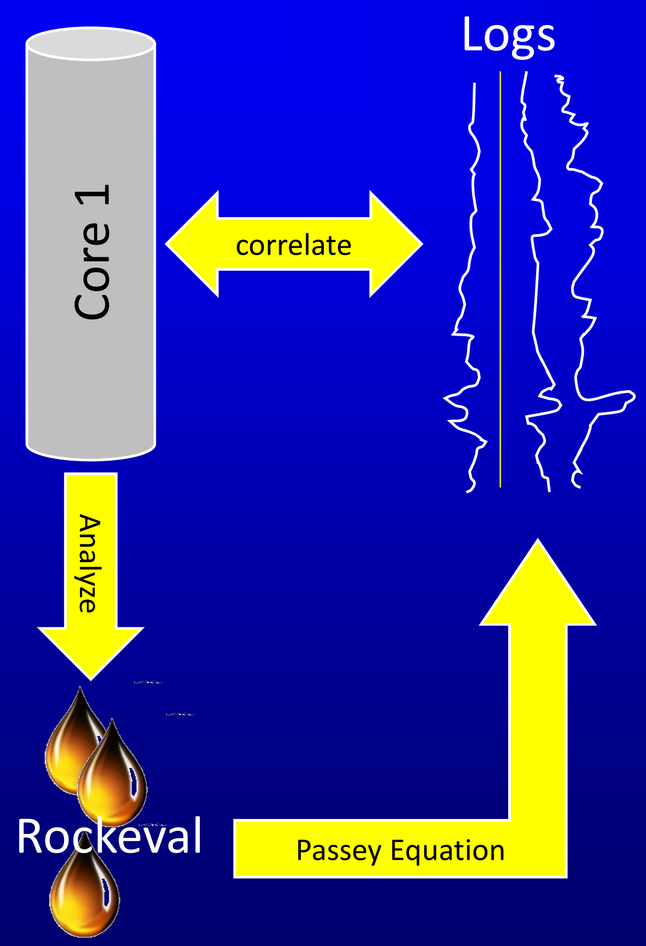


Image of PNN salt probability > 70%.

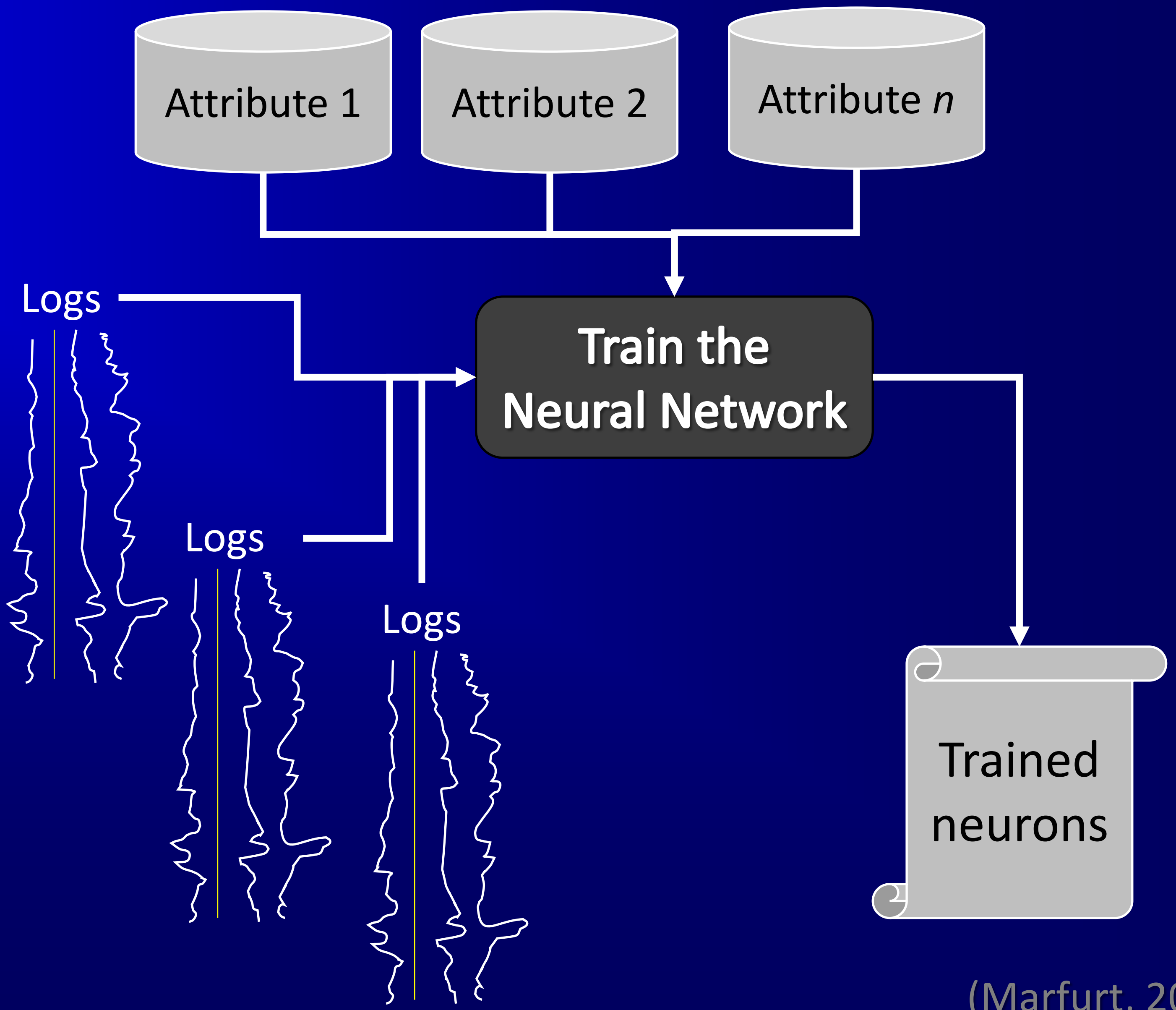
(Lubo-Robles et al., 2019)

Example 2: TOC prediction

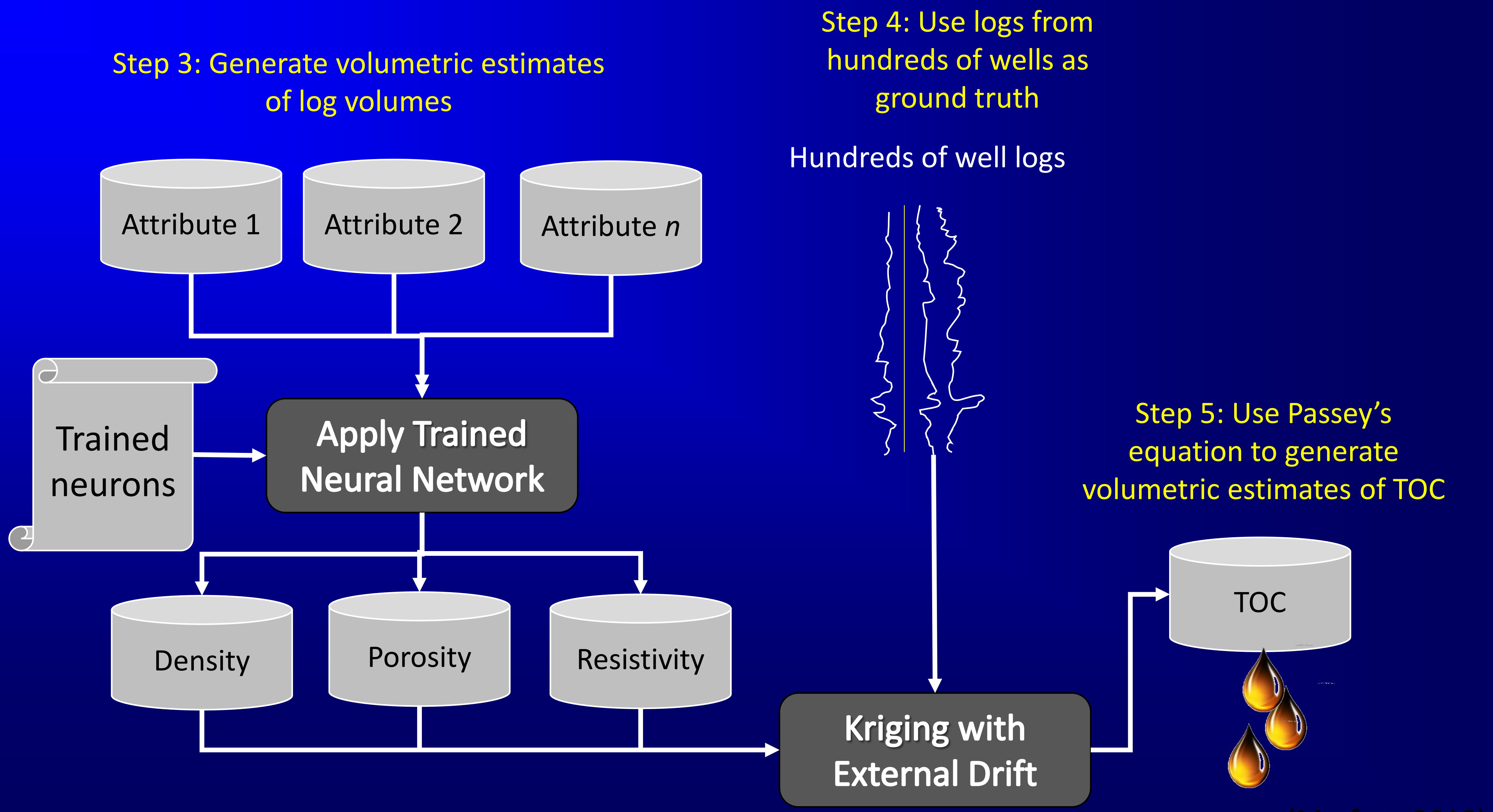
Step 1: Calibrate TOC prediction from logs using ANN or Passey's equation



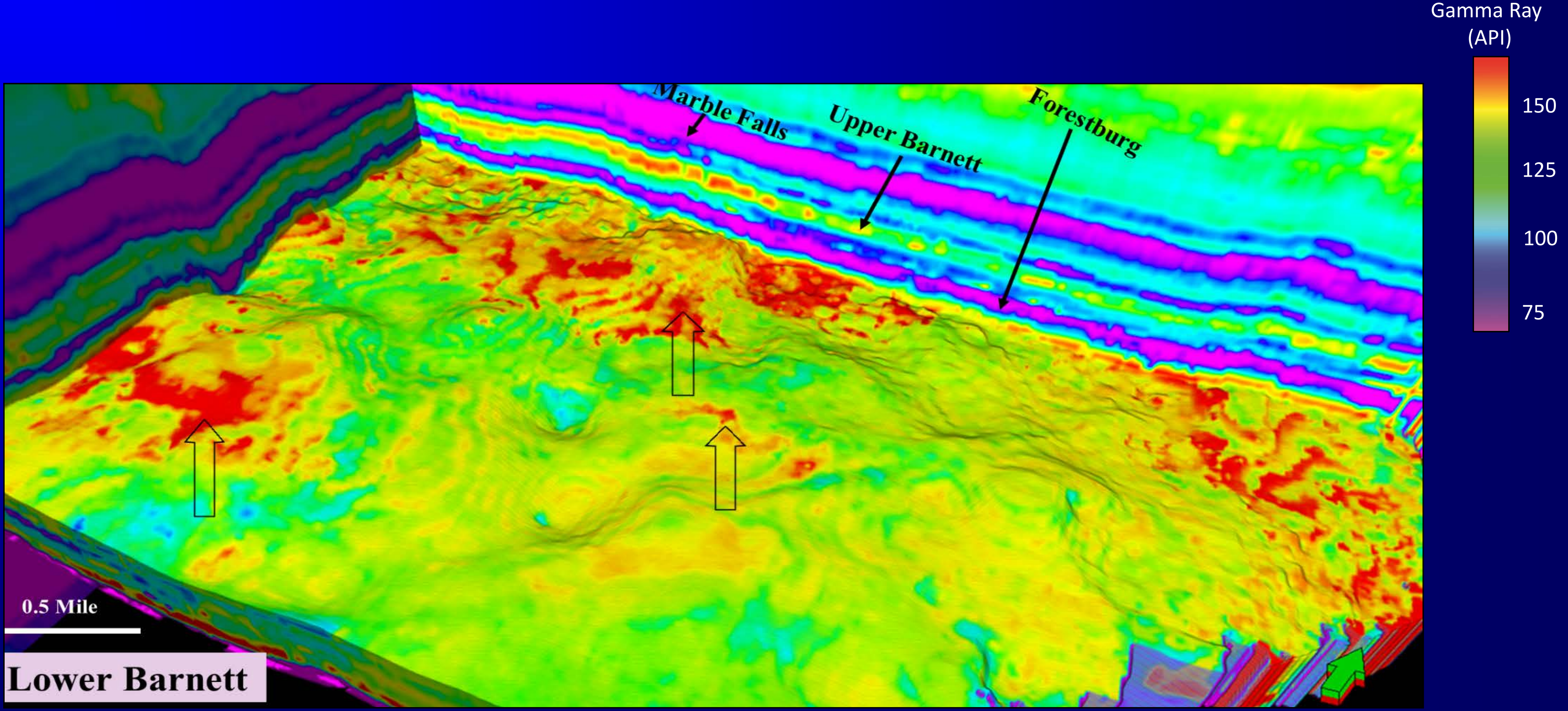
Step 2: Predict measured logs from seismic attributes about the well (train network)



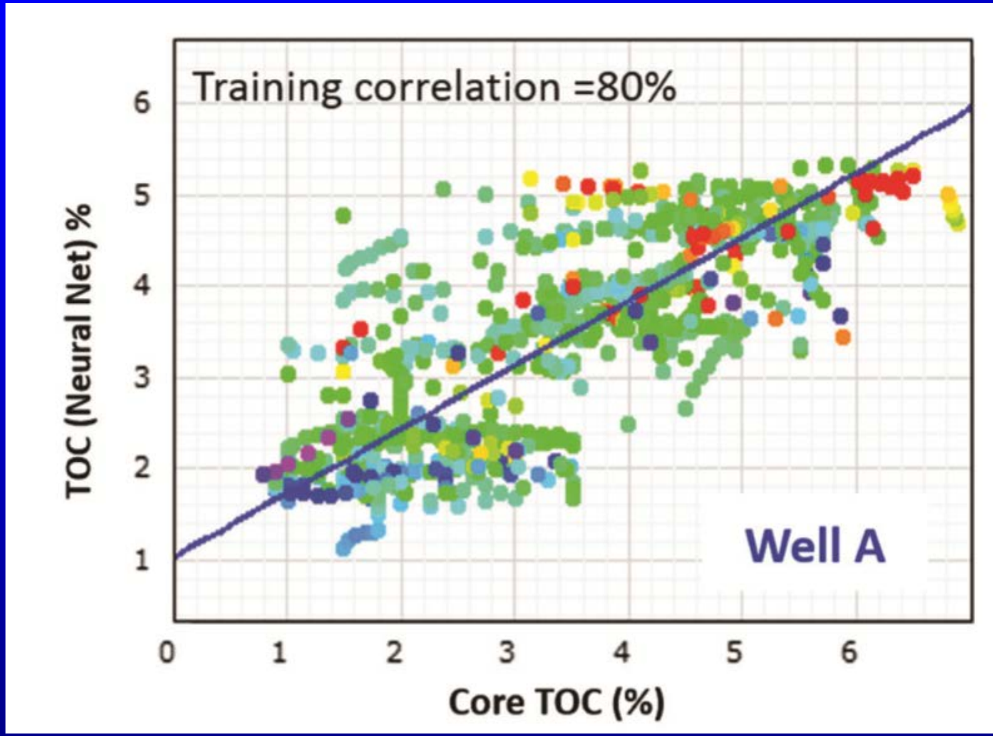
(Marfurt, 2018)

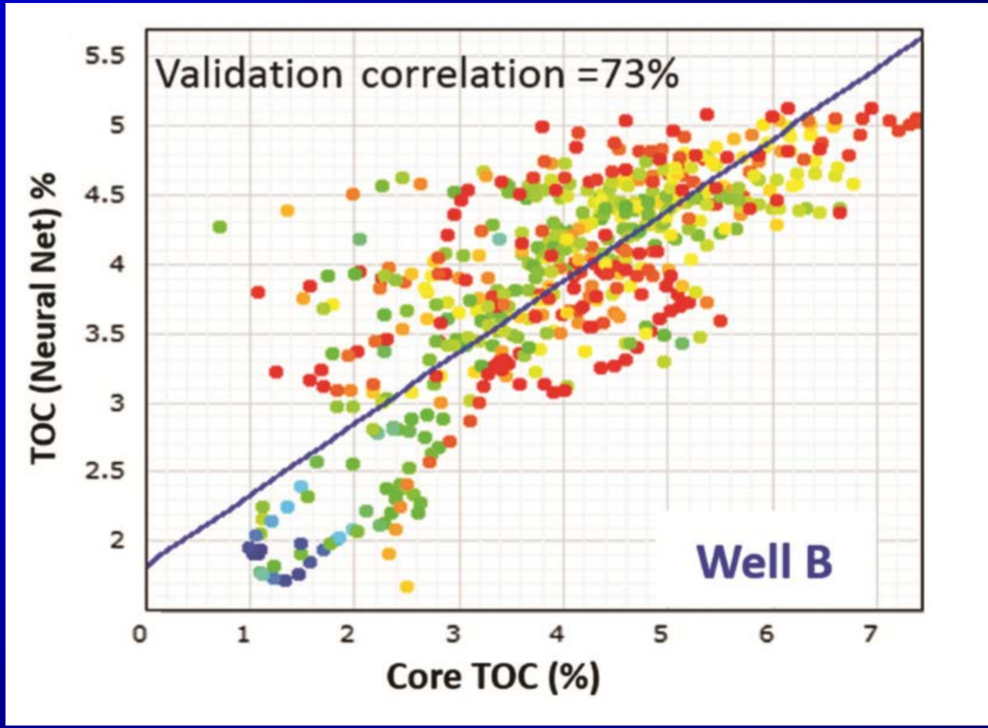

Step 3: Generate volumetric estimates of log volumes
Step 4: Use logs from hundreds of wells as ground truth
Hundreds of well logs
Attribute 1
Attribute 2
Attribute n
Trained neurons
Apply Trained Neural Network
Step 5: Use Passey's equation to generate volumetric estimates of TOC
Density
Porosity
Resistivity
TOC
Kriging with External Drift
(Marfurt, 2018)

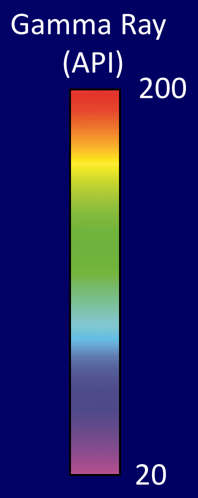
Prediction of a gamma ray volume from seismic attributes

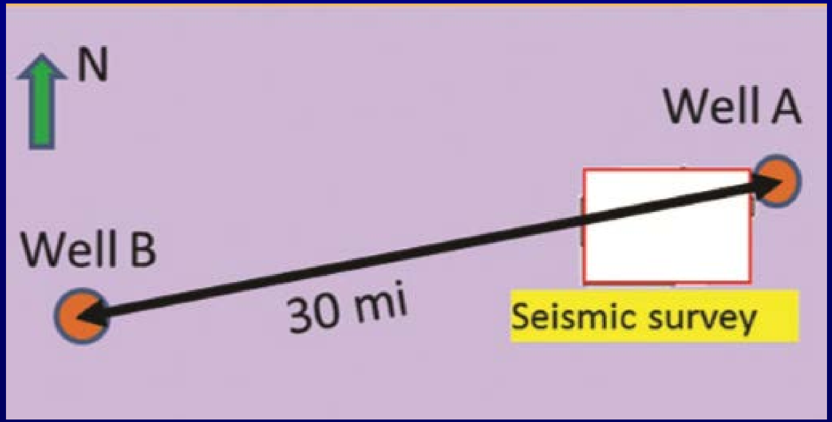


(Verma et al., 2012)



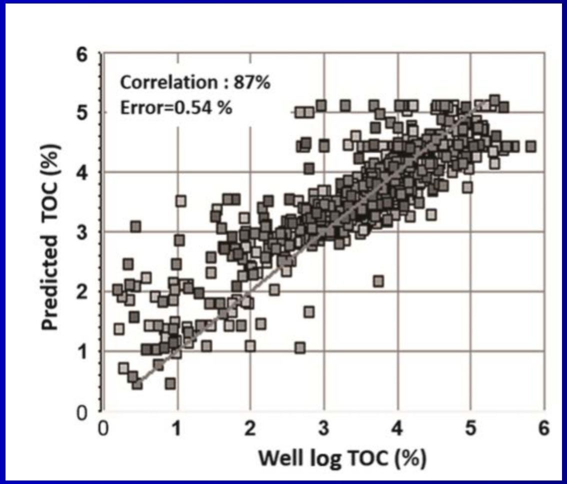


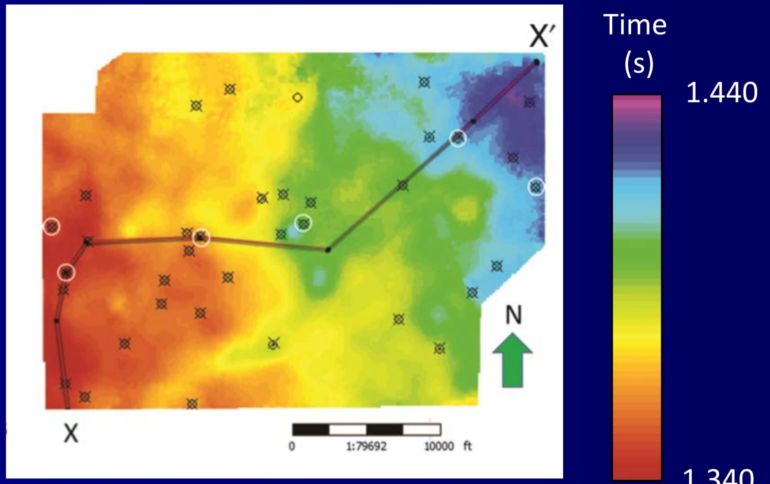


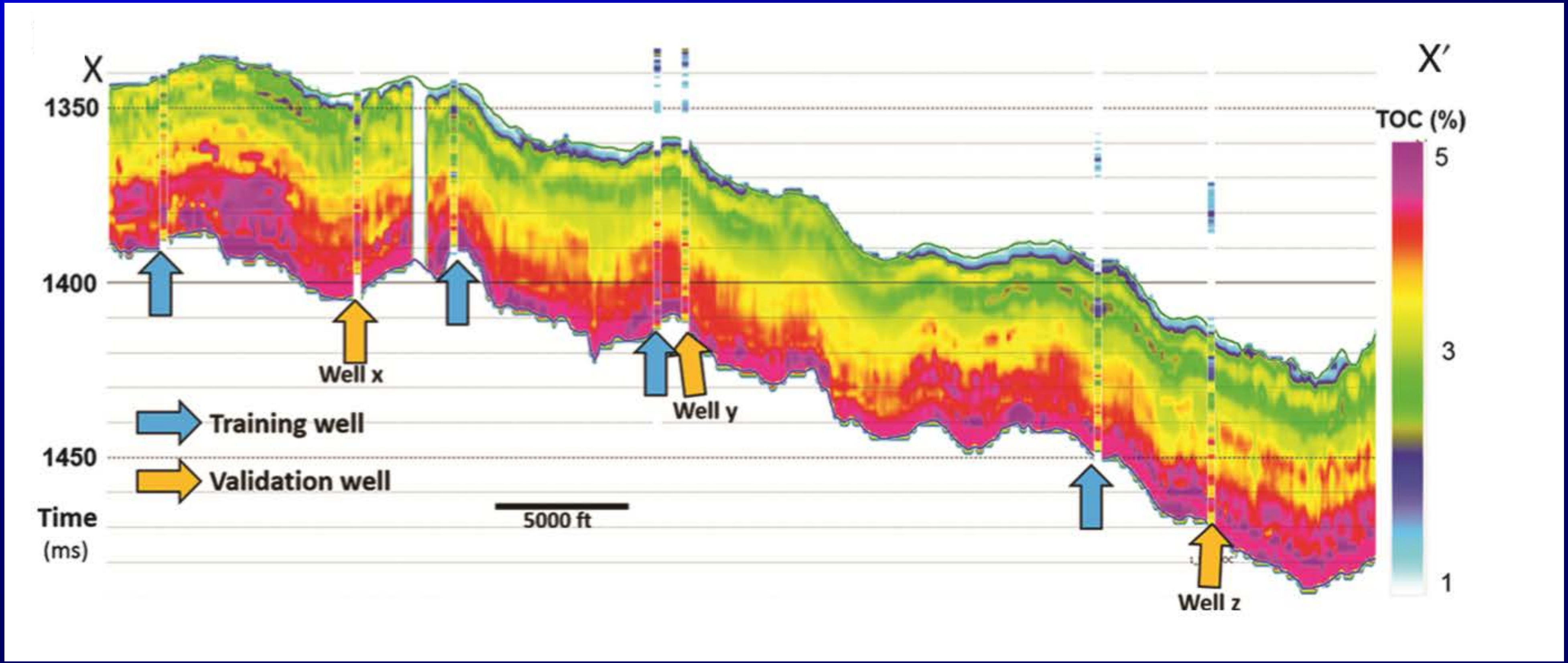


(Verma et al., 2016)

Prediction of TOC from seismic attributes

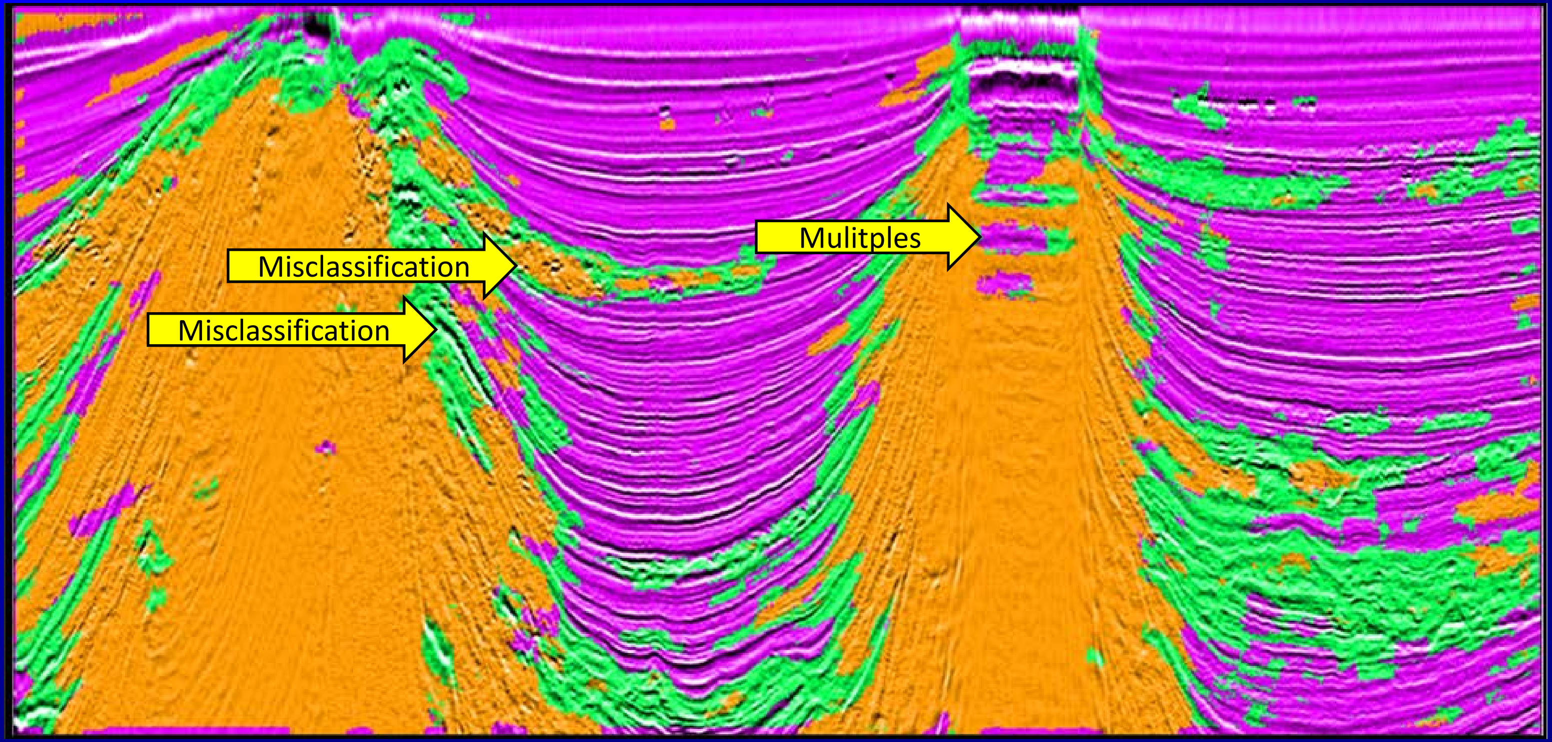


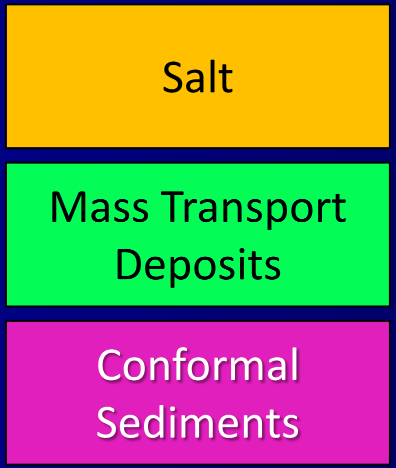




(Verma et al., 2016)

Pitfalls and algorithm limitations: Misclassification





In this example, we did not use steeply dipping conformal reflectors in the conformal sediment training data
Possible solutions: “Online learning” -> add more training data and if needed more attributes

Voxel-based classifiers cannot “see” the periodicity of multiples that few interpreters will misinterpret.
Deep-learning algorithm would need abundant training data.
Few human interpreters would be fooled by these simple multiples

(Lubo-Robles et al., 2020)

Supervised Multiattribute Classification – Probabilistic Neural Networks

In Summary:

- Because PNN is based on Gaussian statistics:
  - PNN is one of the easiest machine learning techniques to understand
  - PNN provides an estimate of confidence in its predictions
- As with interactive interpretation, the correct choice of attributes is critical to accurate prediction
- A good neural network application will mimic the interpreter who trains it.
- Don’t ask a poor interpreter to train a neural network!