Reservoir Insights Enabled by Machine Learning Technology:
A Supervised Machine Learning Method for Probabilistic Rock Type Prediction*

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Abstract

The true integration of well and seismic data has always been a challenge because of their different responses and resolutions. To resolve these ambiguities, machine learning methods are being introduced that change the applicability of seismic data from an exploration context to a valuable prospect development tool. This presentation introduces a method based on an association of neural networks to resolve reservoir facies heterogeneity distribution and discusses its applicability to an onshore Texas dataset from the Permian Basin. This supervised method generates a probabilistic seismic facies model derived from 3D seismic data. Several neural networks, each defined by a different activation function, are run simultaneously to avoid biasing any of the neural network architectures. To train the neural networks, lithofacies logs and seismic data extracted along the wellbore are used as labelled data. To avoid overlearning, seismic data is randomly extracted away from boreholes (soft data), to enrich the initial training dataset and update the final model. The final neural network model is then propagated on the full seismic dataset, to generate probabilistic facies models composed of different volumes: most probable facies, maximum probability for all facies, and probability for each facies. Analysis of the facies and associated probability distribution introduces valuable insights into prospect uncertainties and seismic data reliability for prediction. This method uncovers new direct potential for seismic data use when predicting the reservoir lithofacies away from wells, especially when referring to prestack data with any type of seismic attributes. Based on the results, a new drilling location was proposed and approved. The study results were accurate - after moving the rig from its original position, the well found a good pay facies at correct depth, with double the pay zone thickness and an increase in porosity from 10% to 17%. The predicted lithofacies are direct input data for both geologic modeling and volumetrics analysis.

Reservoir Insights Enabled By Machine Learning Technology

A Supervised Machine Learning Method for Probabilistic Rock Type Prediction

Bruno de Ribet, Gerardo Gonzalez
Emerson

Agenda

- Introduction
- Critical Aspects of Reservoir Characterization
- Benefits of Machine Learning
- Rock Type Classification
- Case Study
- Conclusion

Our Vision

- Understand the specificities of subsurface studies
  - Uncertainties
    - in input data and in interpretation (*no ground truth*)
    - low amount of data (*high risk of overfitting*)
  - Cost of error
    - false positive (*dry hole*)
    - false negative (*overlooked prospect)*

- Centered around:
  - Develop ML to assist domain geoscientists, not replace them
  - Automate the tedious and repetitive tasks
  - Assist asset team for de-risking management

Approach

- Increase insights:
  - Extract hidden information and patterns for geoscientists at specific stages of prospect evaluation and reservoir characterization
- Automate easier decisions:
  - Transfer user’s expertise to the system
- Account for complexity:
  - Solutions tailored for a specific problem

Machine Learning & Subsurface Data

- Machine learning applications for geoscience data have been in use for over 25 years (waveform-based classification as a proven technology)
- Geoscience data is growing at a rate where Machine Learning technology is considered a necessity rather than a nice-to-have technology.
- Multi-disciplinary and multi-resolution data integration is still a challenge
- This evolution allows us to apply machine learning and predictive analytics for prospecting, field development, and production optimization

Reservoir Modeling

- It is essential that reservoir models preserve small scale property variations observed in well logs as well as capture the large-scale structure and continuity observed in seismic data

- For the reservoir in this study, the small cyclicity of the carbonate reservoirs and their high degree of lateral and vertical heterogeneity must be captured and modeled

The Current State of Lithology Prediction

Lithology prediction generic generalized workflow

Lithology prediction from seismic data is based on establishing relation between elastic measurements and physical rock properties

Multi-well log data analysis
VpVs P-Impedance crossplot

↓

Define rock type log containing class rules

↓

Analyze separation of elastic properties based on class rules

↓

Build Probability Density Functions

↓

Class seismic attributes based on PDF (facies and probabilities)

The rock property classes

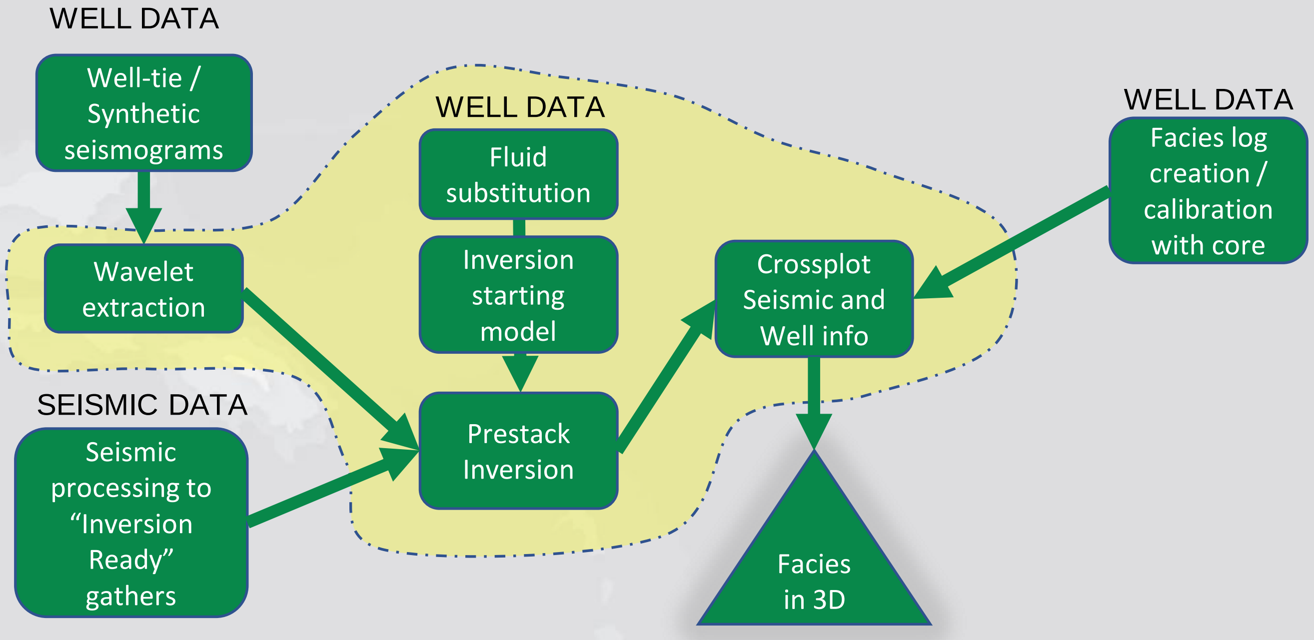
N rock types classes when establishing the relation between reservoir properties

Lithology Prediction

Apply the relationship to the elastic attributes from simultaneous pre-stack inversion to produce lithology prediction volume

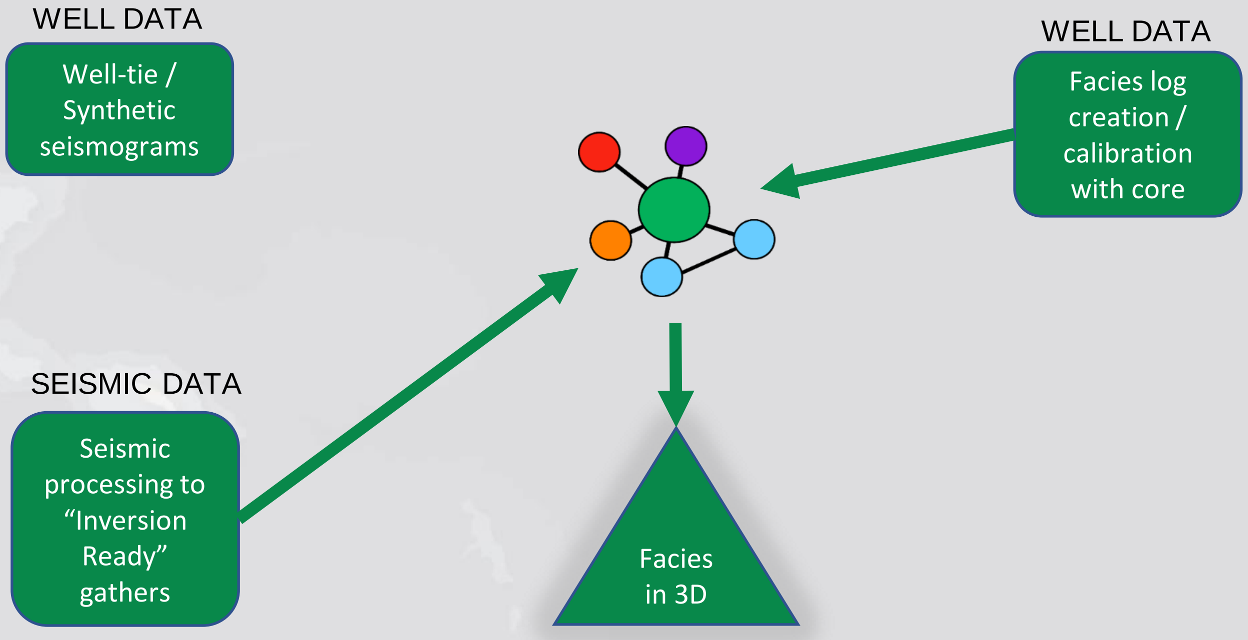
Critical Aspects of Reservoir Characterization

- Well data provides reliable information but is sparsely sampled
- Well to seismic Tie: Not linear, scale difference, N dimensions
- Seismic inversion methods:
  - Time consuming, error prone
  - Strongly seismic-driven, unclear lithology separation


WELL DATA
Well-tie / Synthetic seismograms
Wavelet extraction
SEISMIC DATA
Seismic processing to "Inversion Ready" gathers
WELL DATA
Fluid substitution
Inversion starting model
Prestack Inversion
Crossplot Seismic and Well info
WELL DATA
Facies log creation / calibration with core
Facies in 3D

Benefits of Machine Learning

- Capitalize on the continuously increasing amount of data
- Explore datasets and identifies patterns and relationships that may be non-detectable by the human eye
- Automate processes that extract valuable information in minimal time



WELL DATA

Well-tie / Synthetic seismograms

SEISMIC DATA

Seismic processing to “Inversion Ready” gathers

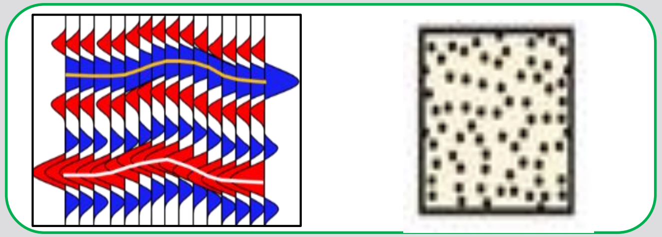
WELL DATA

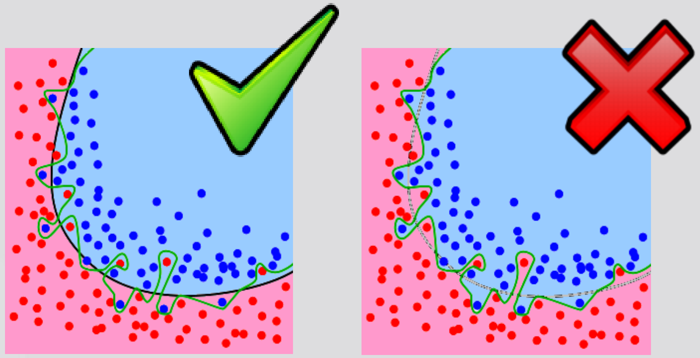
Facies log creation / calibration with core

Facies in 3D

Rock Type Classification

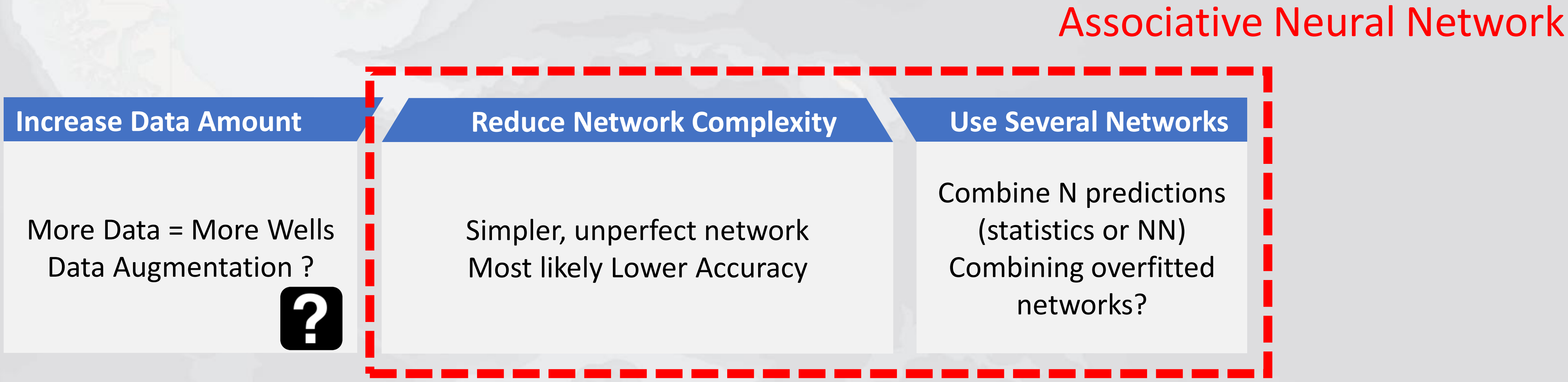
- Objective: Combine well and seismic early on
  - Supervised learning, only at the wells
  - Input / output pairs are known, finite and humanly-validated
- Main risk: Overfitting
  - Overfitted networks seemingly accurate, low confidence
  - Overcome:
    - Step 1: Associative Neural Network
    - Step 2: Democratic Learning to enrich training dataset





Rock Type Classification Strategy

- Data problem: Training pairs only available at wells
- Sparse data + large network = overfitting = low confidence in prediction
- Overfitting reduction strategies:



Associative Neural Network

Increase Data Amount

More Data = More Wells
Data Augmentation ?

?

Reduce Network Complexity

Simpler, unperfect network
Most likely Lower Accuracy

Use Several Networks

Combine N predictions (statistics or NN)
Combining overfitted networks?

(Tetko 2002, Zhou and Goldman 2004, Gao et al 2010)

Rock Type Classification Associative Neural Networks

- The use of several naïve networks running simultaneously as an associative combination is preferred

- A neural network is designed to learn in a specific way. Using only one supervised neural network tends to bias the results of the training

- A network is built to reach one objective, which is usually to approximate data or class densities

- Defining an ensemble of networks with different learning strategies helps to compensate for the existing bias when using only one network

Rock Type Classification Democratic Learning Concepts

- The multi-strategy learning ASNN performance will be limited by the number of hard data samples from the training dataset and can lead to unreliable results

- To avoid this bias, the training dataset is improved by using a combination of hard and soft data during a stabilization step (democratic contribution)

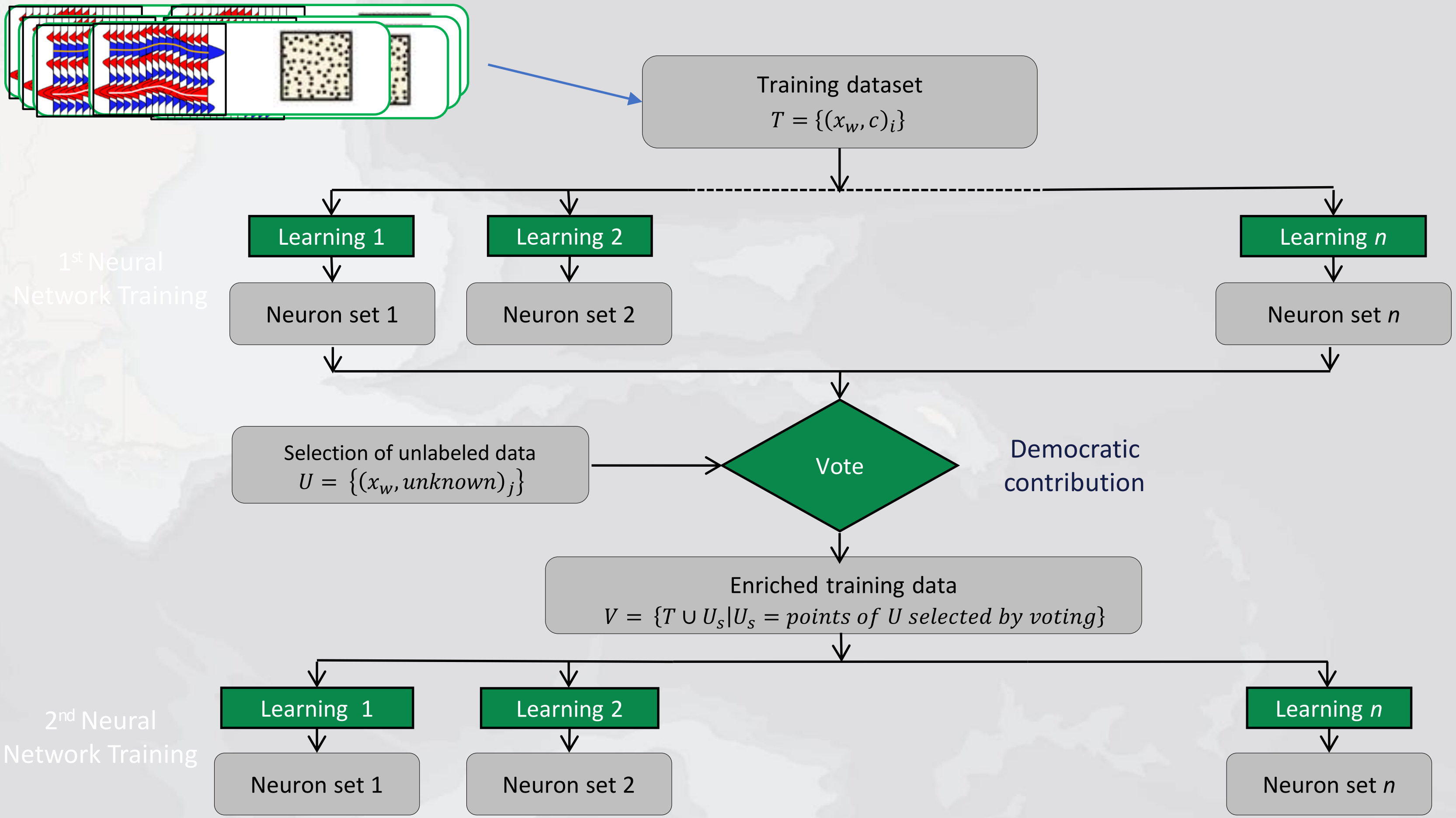
- All learning methods will give a vote for each unlabeled data

- If the vote is unanimous, then the unlabeled data is added to the training dataset

- The enriched dataset is then used as input training dataset for the neuron sets

- At the end of all learnings, all neuron sets are merged into one single neuron set

Rock Type Classification Algorithm



Training dataset
$T = \{(x_w, c)_i\}$

1st Neural Network Training

Learning 1 → Neuron set 1

Learning 2 → Neuron set 2

Learning *n* → Neuron set *n*

Selection of unlabeled data
$U = \{(x_w, unknown)_j\}$

Vote

Democratic contribution

Enriched training data
$V = \{T \cup U_s | U_s = points\ of\ U\ selected\ by\ voting\}$

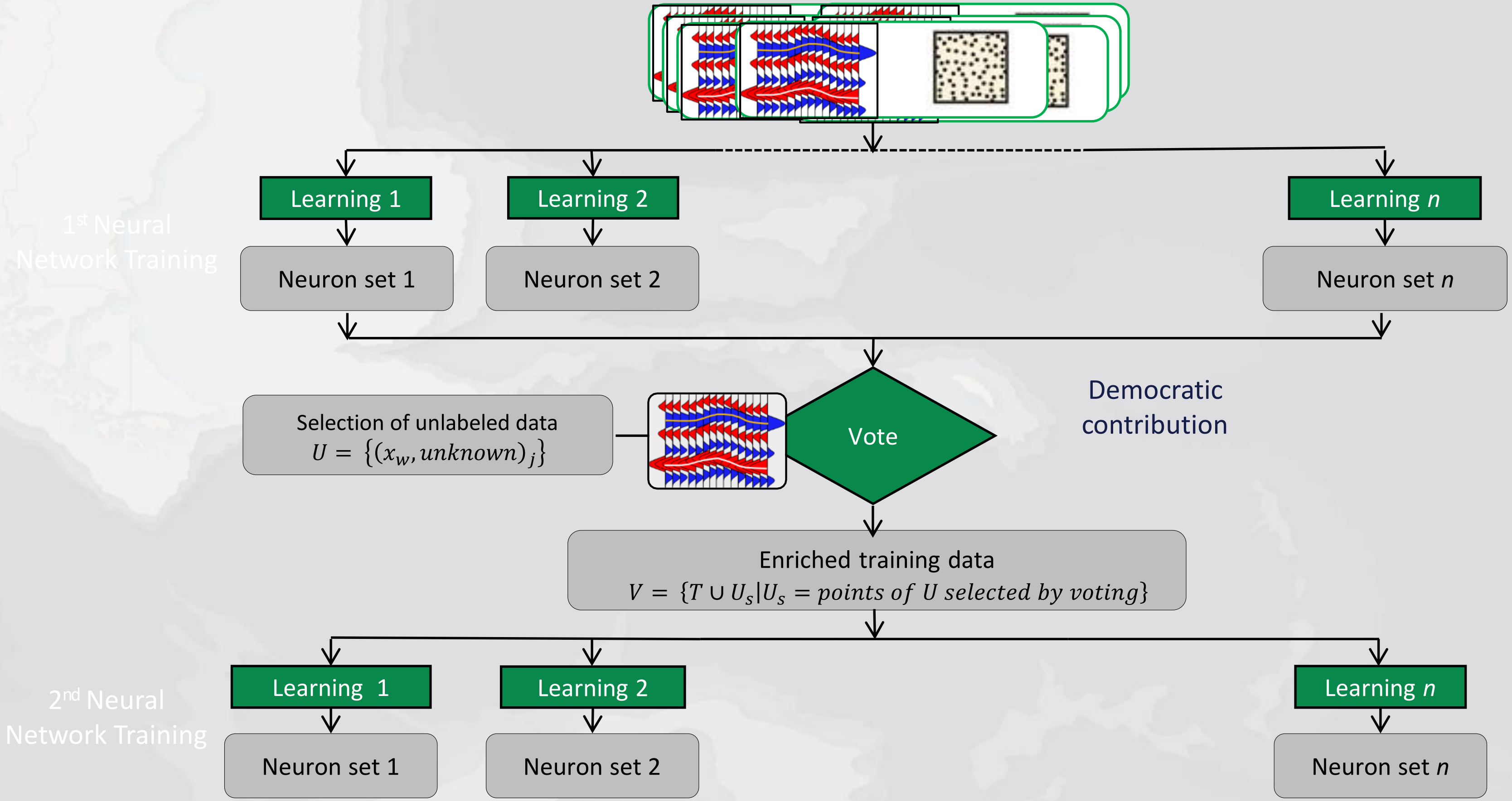
2nd Neural Network Training

Learning 1 → Neuron set 1

Learning 2 → Neuron set 2

Learning *n* → Neuron set *n*

Rock Type Classification Algorithm



1st Neural Network Training

Learning 1

Neuron set 1

Learning 2

Neuron set 2

Learning *n*

Neuron set *n*

Selection of unlabeled data
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Learning 1

Neuron set 1

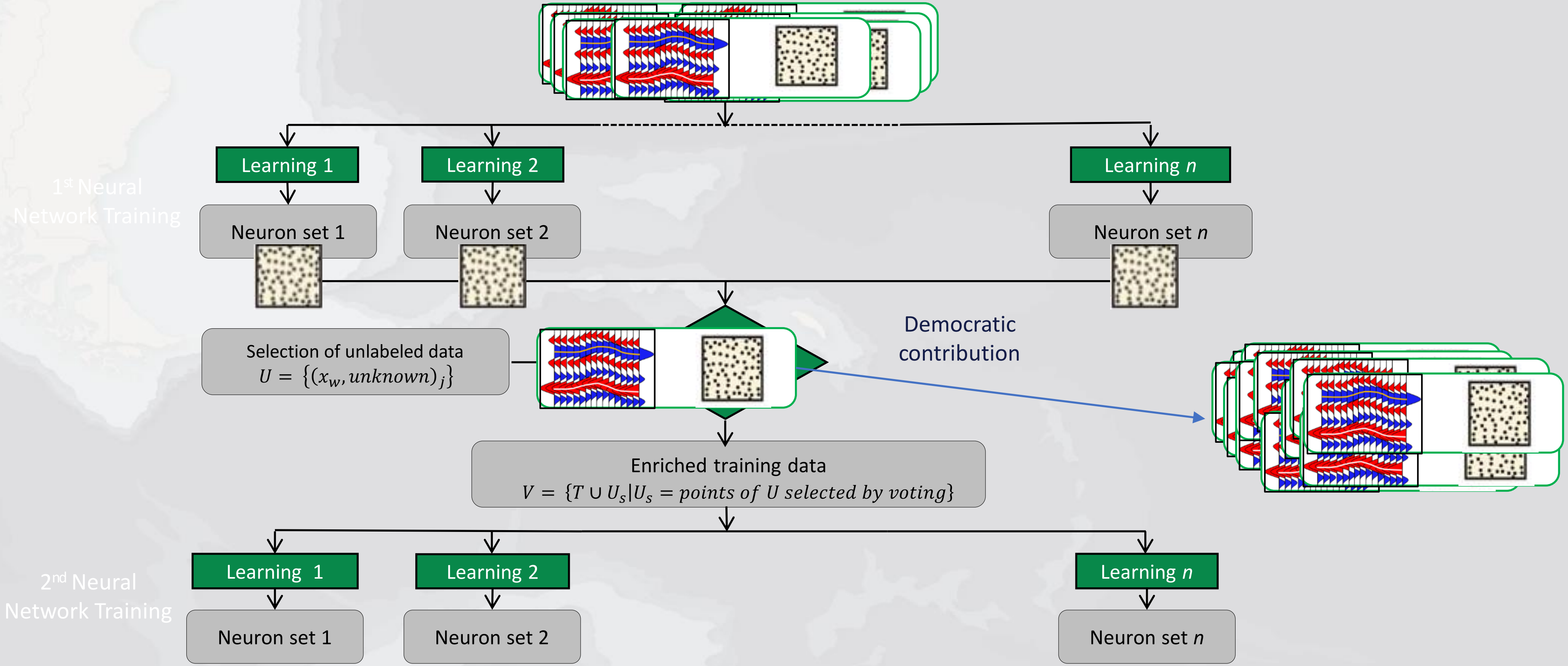
Learning 2

Neuron set 2

Learning *n*

Neuron set *n*

Rock Type Classification Algorithm



1st Neural Network Training

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Neuron set 1

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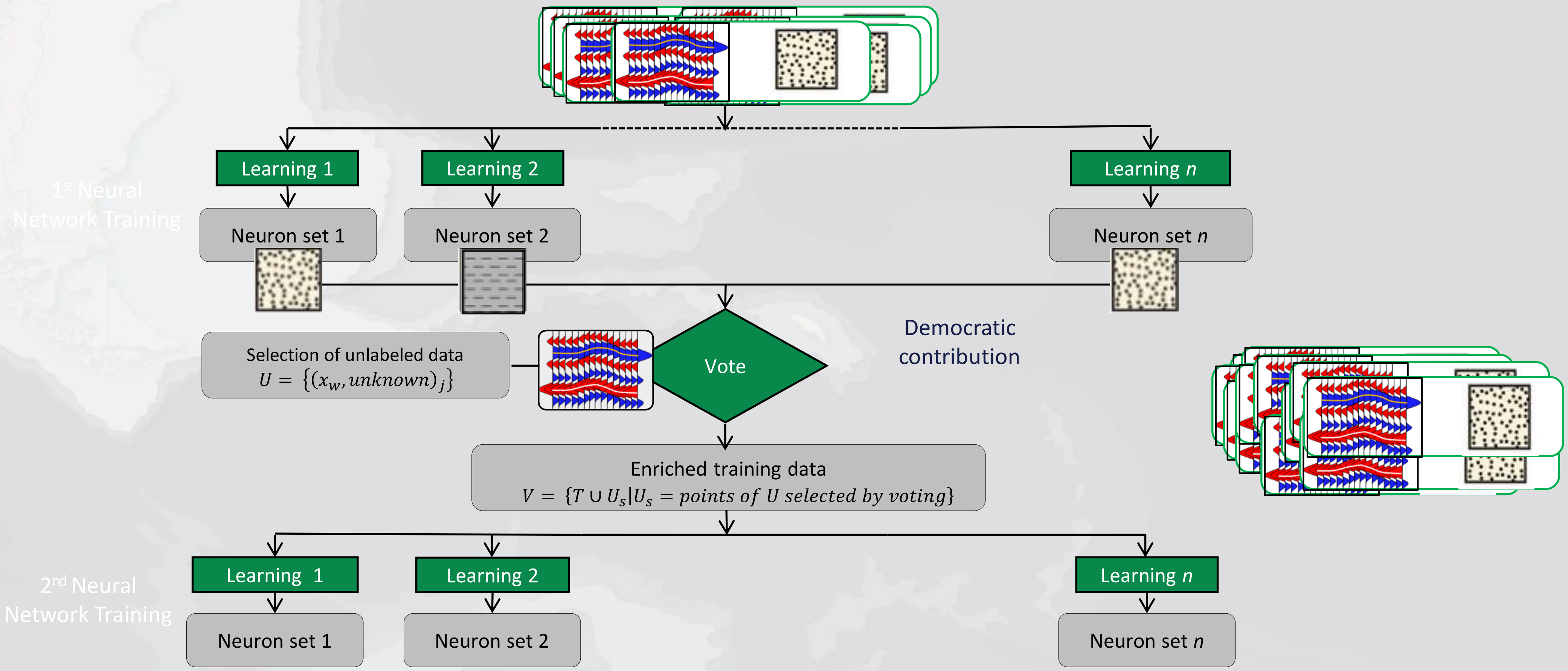

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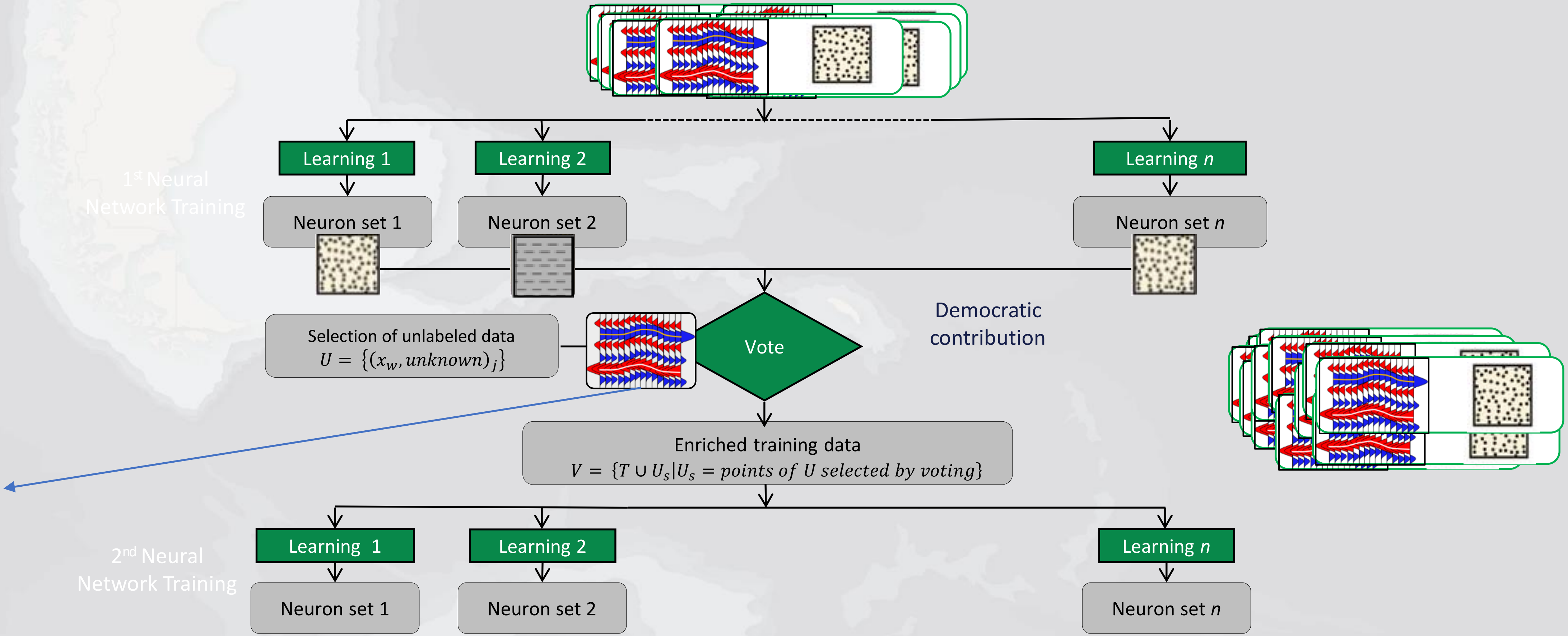

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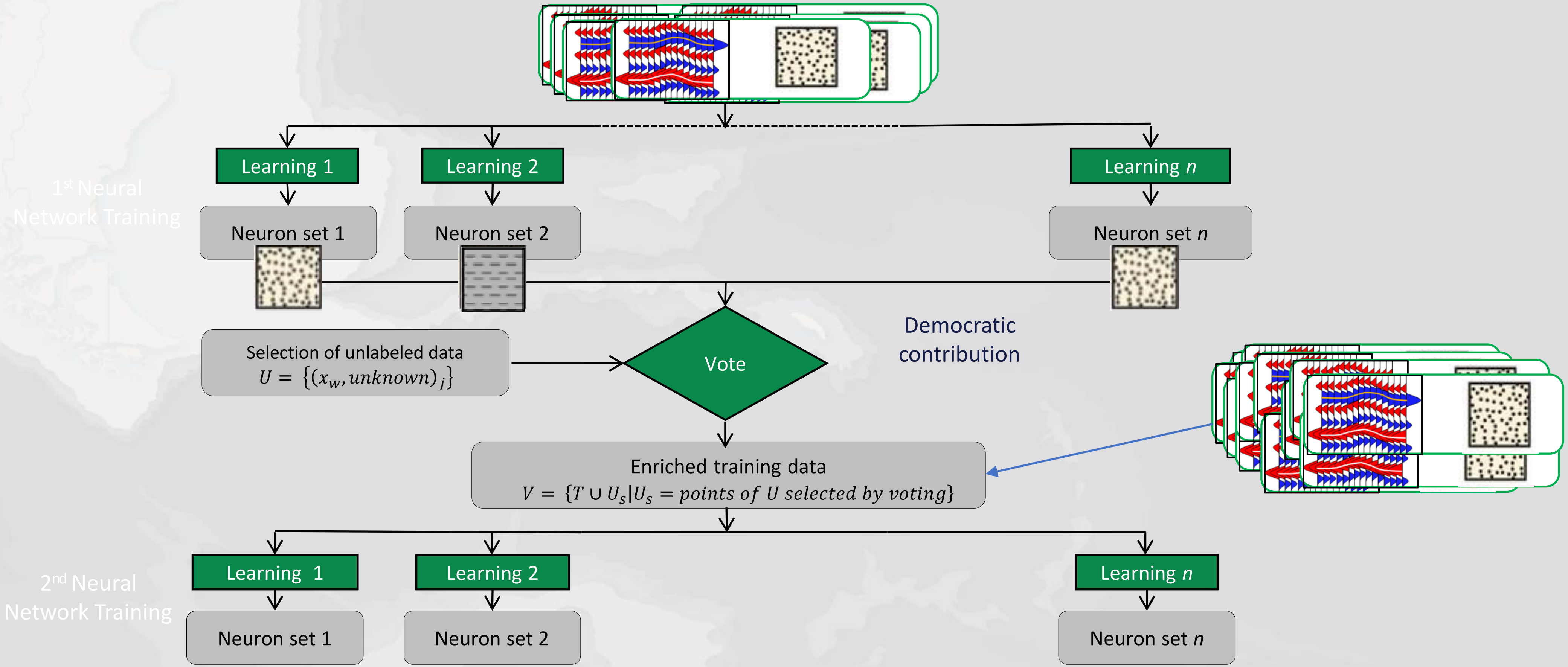
Rock Type Classification Algorithm



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2nd Neural Network Training

Learning 1

Neuron set 1

Learning 2

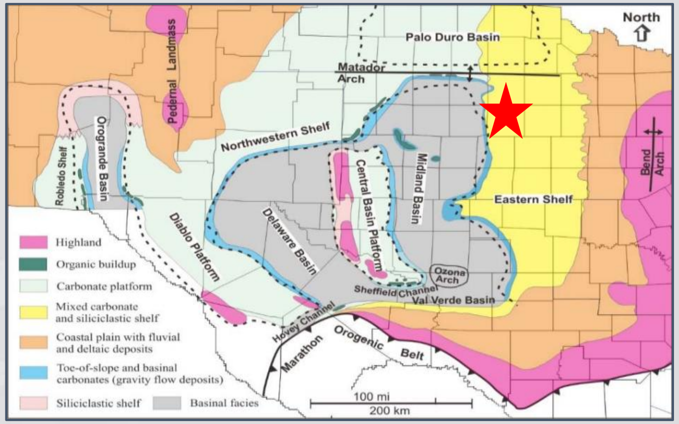
Neuron set 2

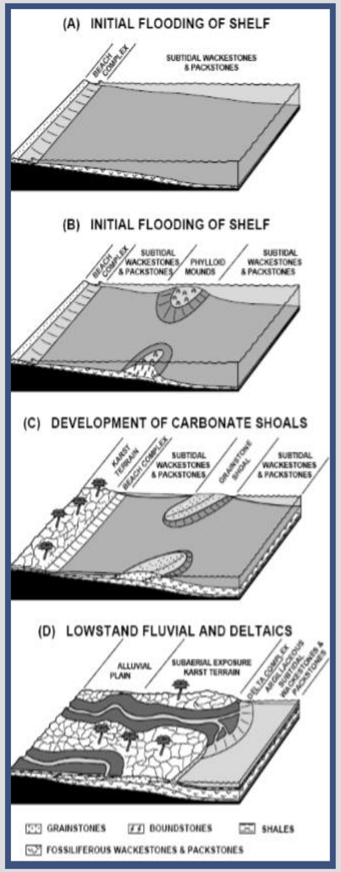
Learning *n*

Neuron set *n*

Use Case: East Soldier Mound

- Eastern Shelf of Permian Basin – East Lubbock, TX
- 3-4 Mbbl field reserves – shallow vertical wells
- Mixed carbonates – siliciclastic shelf
- Oil source: Horseshoe Atoll reef (~20mi NE)
- Production: Lower Wolfcamp **Packstones**
- Packstones: High Energy deposit, reef-cycle
- Enhanced Porosity (Bioturbations, Fracturing)





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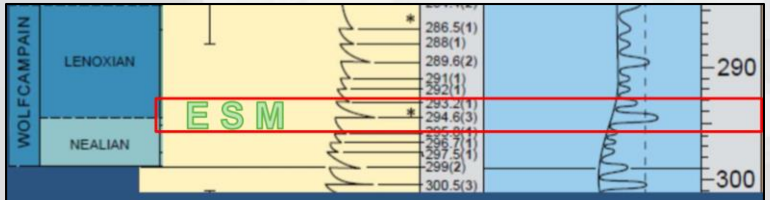
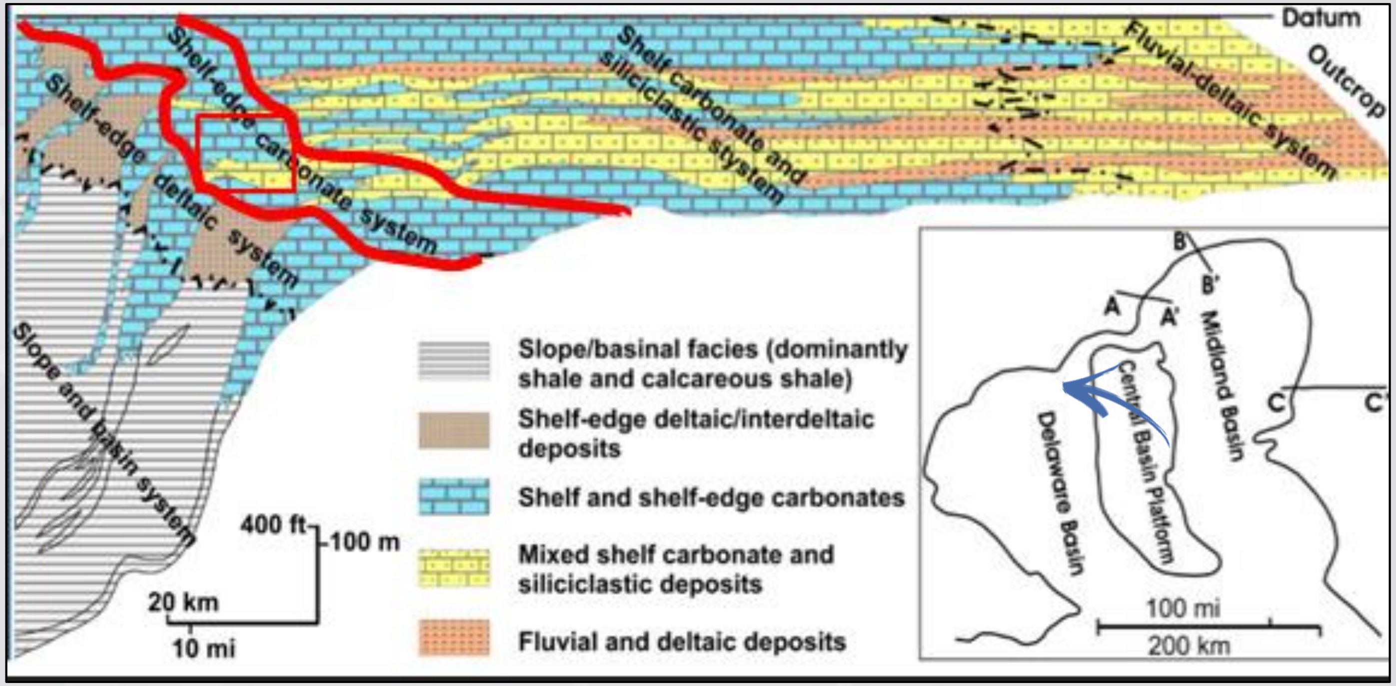
Geological Context



3nd-order sequence boundaries (After Haq & Schutterr, 2008)

C (West)

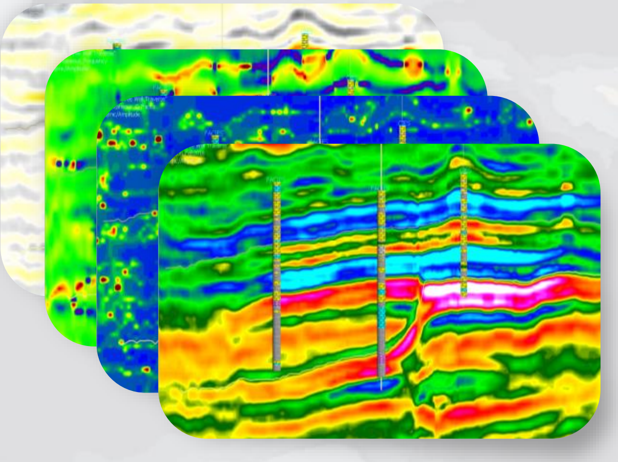
C' (East)

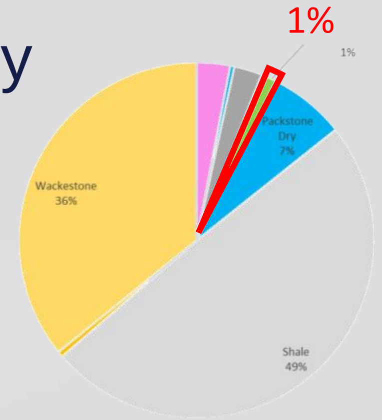


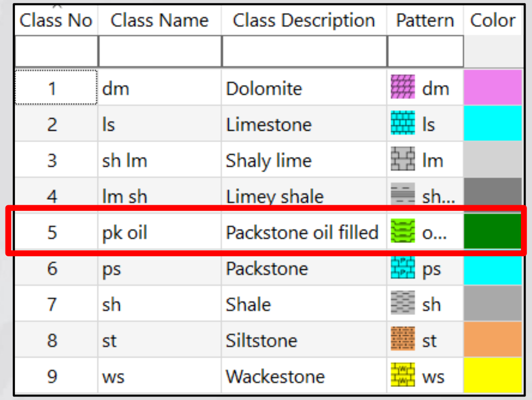
Generalized dip stratigraphic cross section of the Wolfcampian, showing depositional systems, and progradation and aggradation of Eastern Shelf

Use Case: Available Data

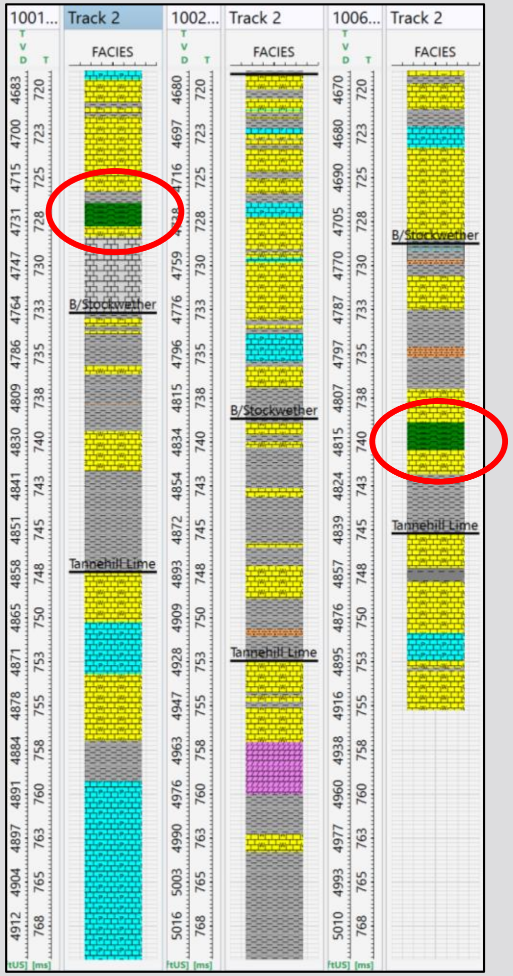
- Small seismic survey, high resolution, good quality
- Prestack (offset gathers, 8 angle stacks)
- N poststack attributes
- 3 wells, 9 facies







Class No	Class Name	Class Description	Pattern	Color
1	dm	Dolomite	dm	🟪
2	ls	Limestone	ls	🟦
3	sh lm	Shaly lime	lm	⬜
4	lm sh	Limey shale	sh...	⬛
5	pk oil	Packstone oil filled	o...	🟩
6	ps	Packstone	ps	🟦
7	sh	Shale	sh	⬛
8	st	Siltstone	st	🟧
9	ws	Wackestone	ws	🟨



Data courtesy of HALLIBURTON OPERATING COMPANY

Workflow

Background studies: Well to seismic tie, 3D seismic interpretation, sequence stratigraphic evaluations, etc.

Define lithofacies / rock typing at wellbores (Logs & core data)

- Integrate different types and scales of well data including wireline, core and core descriptions
- Identify different log data combination as potential input as well as number of lithofacies classes to perform clustering in order to get the best discrimination of the different facies in the reservoir
- Consider an hydrocarbon overprint in the facies definition, created when the difference between effective porosity and unflushed water is greater than the cutoff of 5%.

Gathers preconditioning and prestack seismic inversion

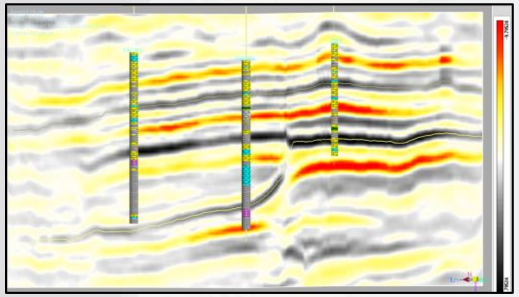
Application of DNNA model to predict, from seismic data, lithofacies distribution

- Consider a different combination of seismic information , such as prestack or poststack attributes or combination of both
- Different clustering based lithofacies models can be incorporated to validate different scenarios and validation performed between well and seismic lithofacies through blind tests at selected wells.

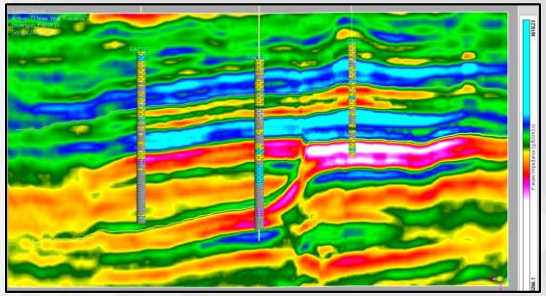
Facies distribution interpretation

Detailed, high resolution reservoir lithofacies distribution and reservoir property analysis, subject to the quality of the data. This work will feed into reservoir presence and quality.

Seismic Data



Amplitude

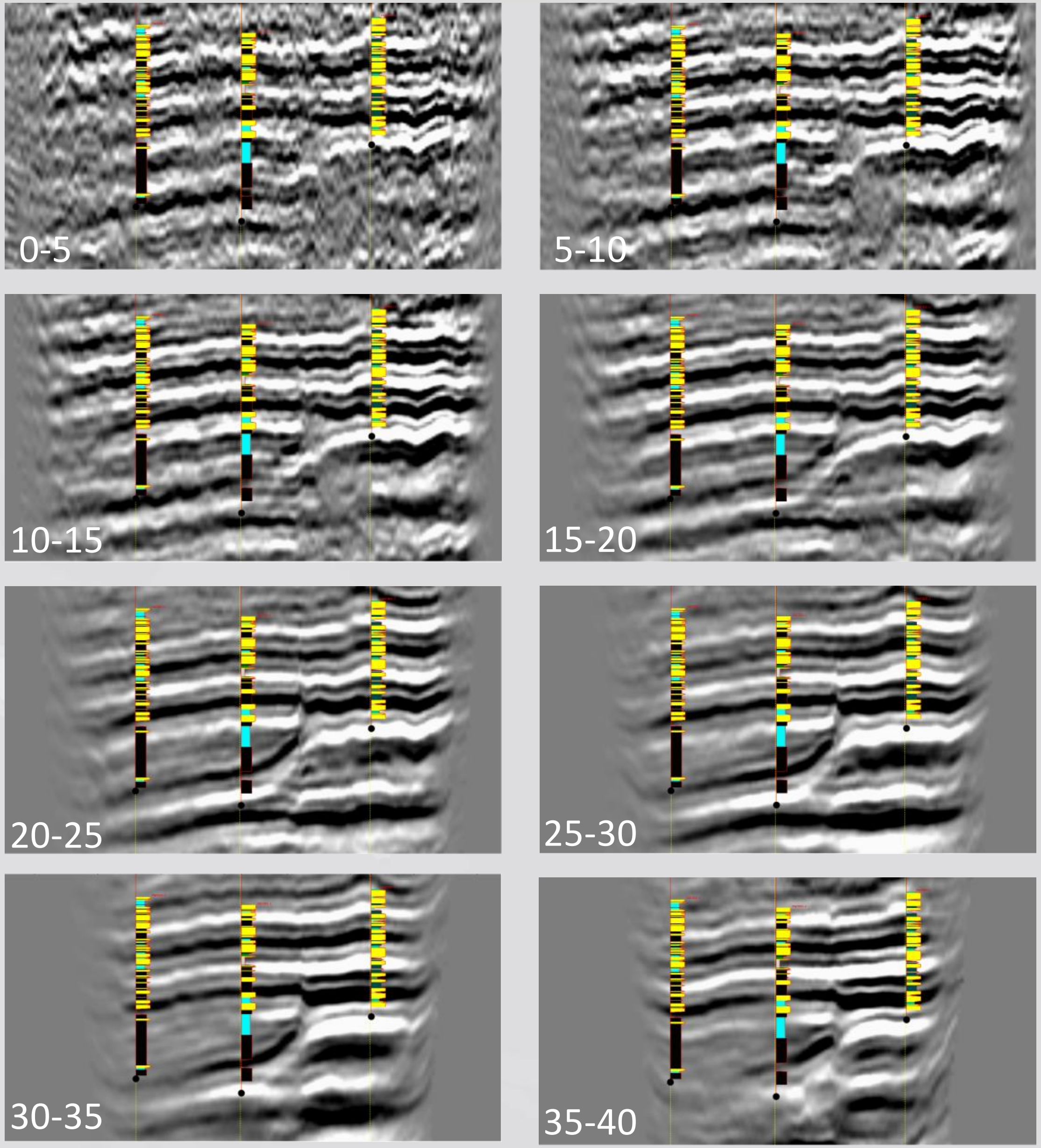


P-Impedance

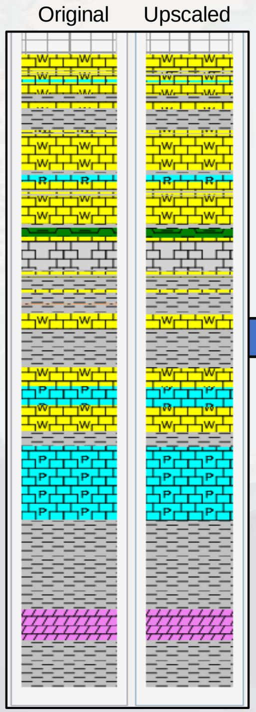
5 scenarios	Angle stacks	Gathers	Reflectivity-based attributes	Layer-based attributes	Structural attributes
Case A	√			√	
Case B		√			
Case C			√	√	
Case D	√			√	
Case E			√	√	√

Different combination of seismic data type for the prediction

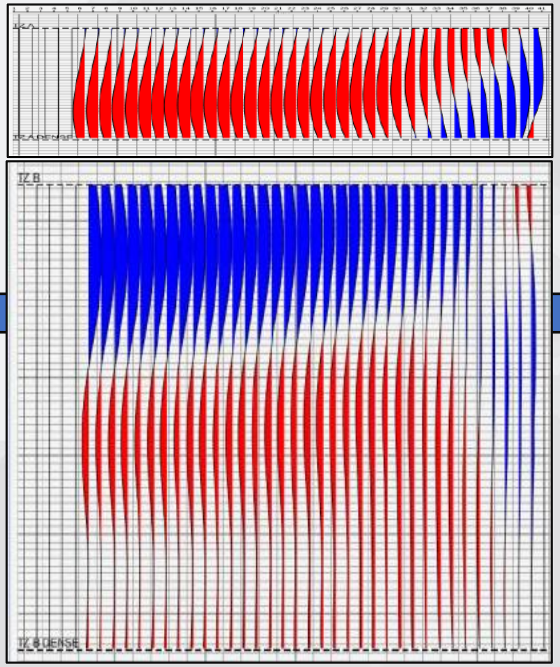
Data courtesy of HALLIBURTON OPERATING COMPANY



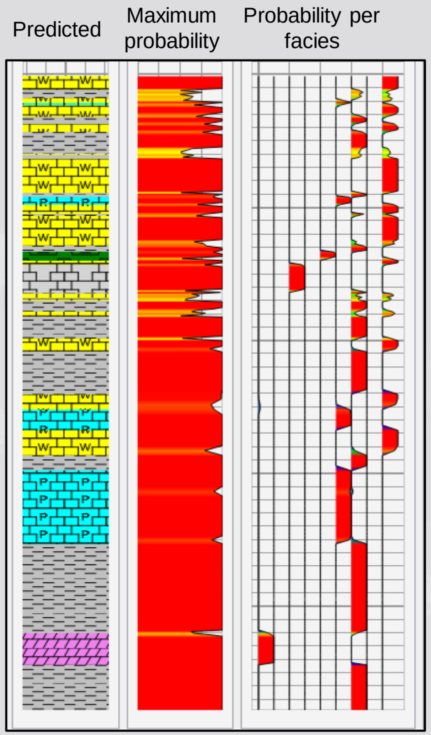
Facies Prediction at Wells



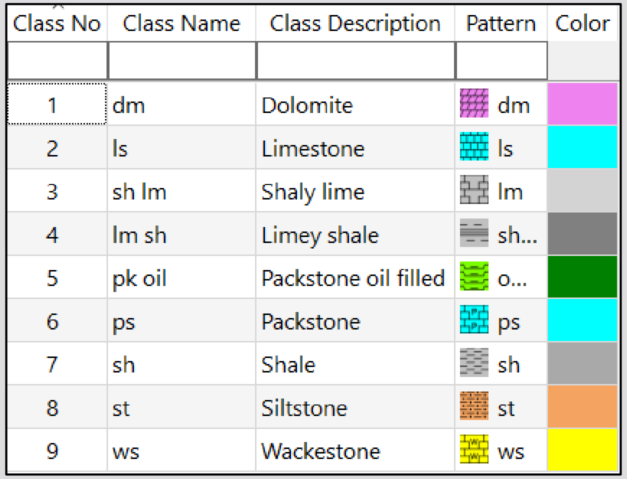
Input



Input
Pre-stack gather at the well location



Output



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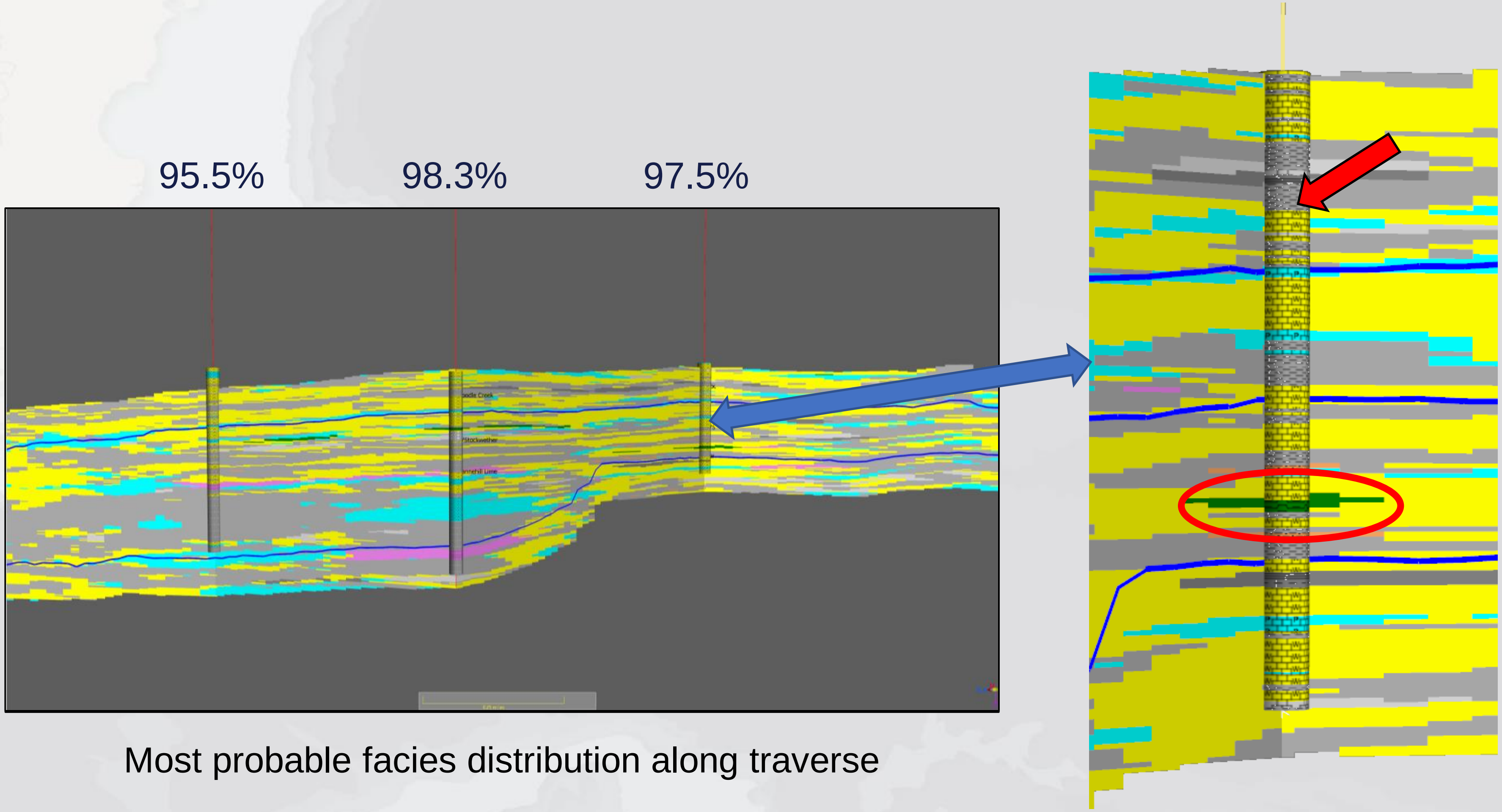
6	ps	Packstone	ps	🟦
7	sh	Shale	sh	⬛
8	st	Siltstone	st	🟧
9	ws	Wackestone	ws	🟨

Facies description

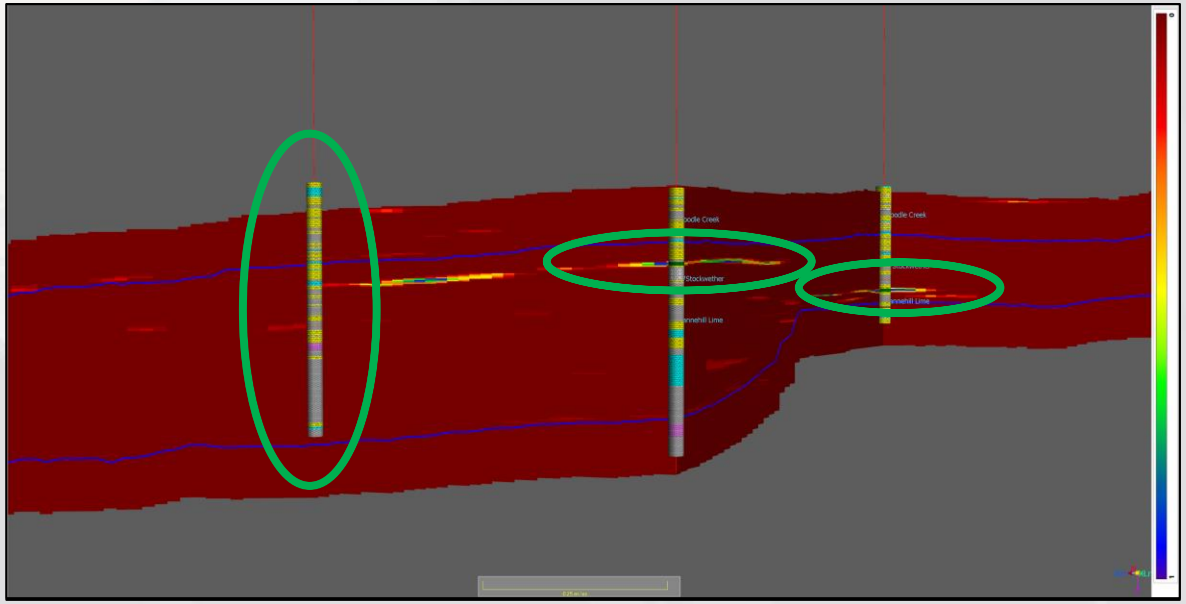
Data courtesy of HALLIBURTON OPERATING COMPANY

Use Case: Results

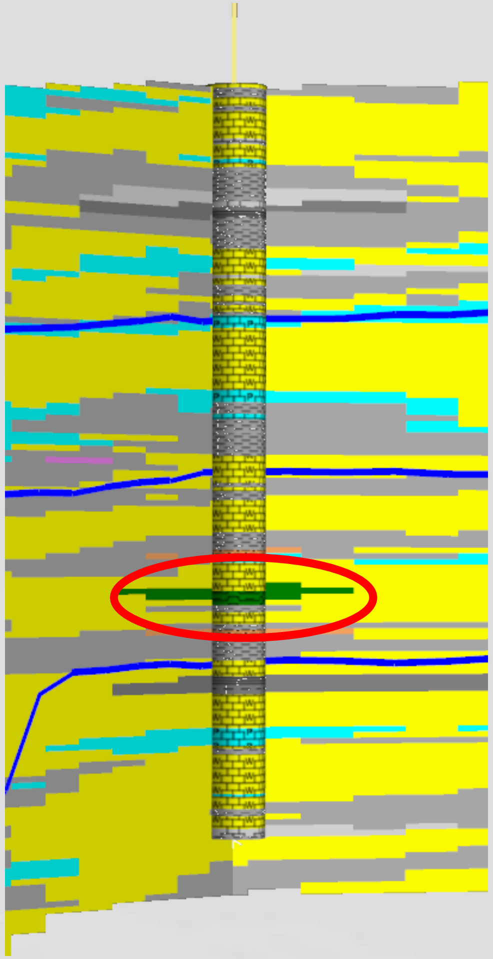


Most probable facies distribution along traverse

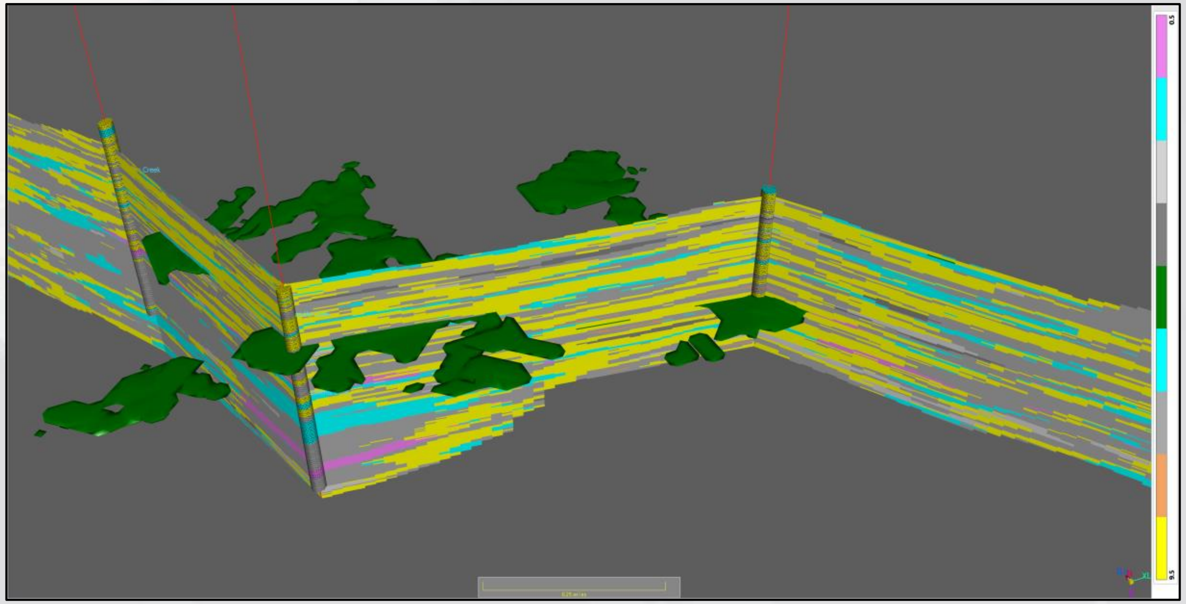
Use Case: Results



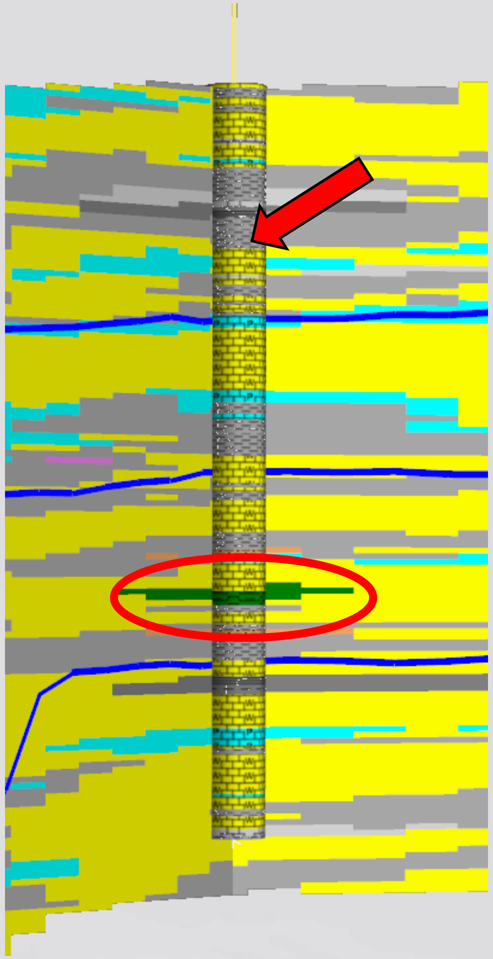
Probability facies of interest



Use Case: Results

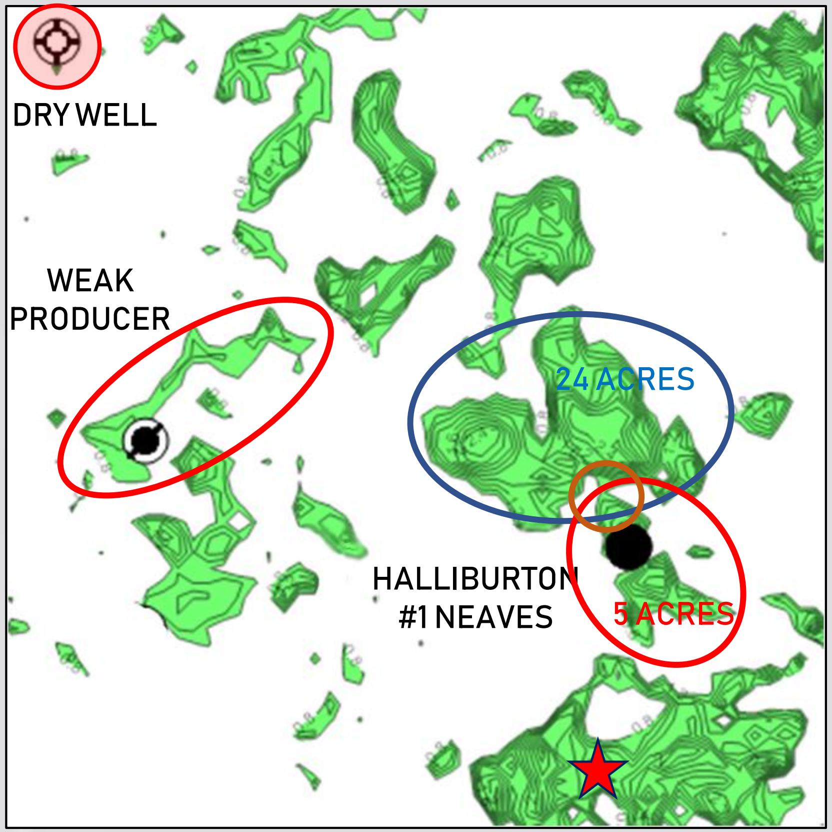


Subvolume detection



Use Case: In-Situ Validation

- Dry well - No prediction nearby
- Weak producer - Small, thin reservoir
- Halliburton #1 Neaves - Small (5 acres) reservoir
- Halliburton #1 Neaves – Secondary production
    - Adjacent compartment
    - Connection
- Based on study results, proposed location:
    - 2 possible targets (probability, thickness, area)
    - Reservoir found ✓



Oil-filled packstone TWT Thickness Map

"The study results were accurate. The well found a good pay facies at correct depth, with double the pay zone thickness and an increase in porosity from 10% to 17%."

Monte Meers, Project Manager

Conclusion

- Bring new potential about seismic data reliability for prediction of reservoir facies away from wells

- A classification method is good, if it:
    - can account for data of different nature,
    - requires as few parameters as possible at the beginning of the process,
    - is applicable to large volume of data, and in relatively high dimensional spaces,
    - can discover classes of any value range, and isolate noise and outliers from data,
    - is not sensitive to initialization, and order of training set point presentation,
    - leads to a reliable interpretation of results for subject matter experts.

Acknowledgements

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Thank You