Using Machine Learning for Automated Seismic Facies Classification

Superior Reservoir Insights, Faster

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Agenda

Data courtesy of Halliburton Operating Company

Introduction

One of the leading challenges in hydroarbon recovery is predicting rock types distribution throughout the reservoir, away from the wells, because rock property determination is a major source of uncertainty in reservoir modeling

Benefits of Machine Learning

Capitalizes on continuously increasing amount of data

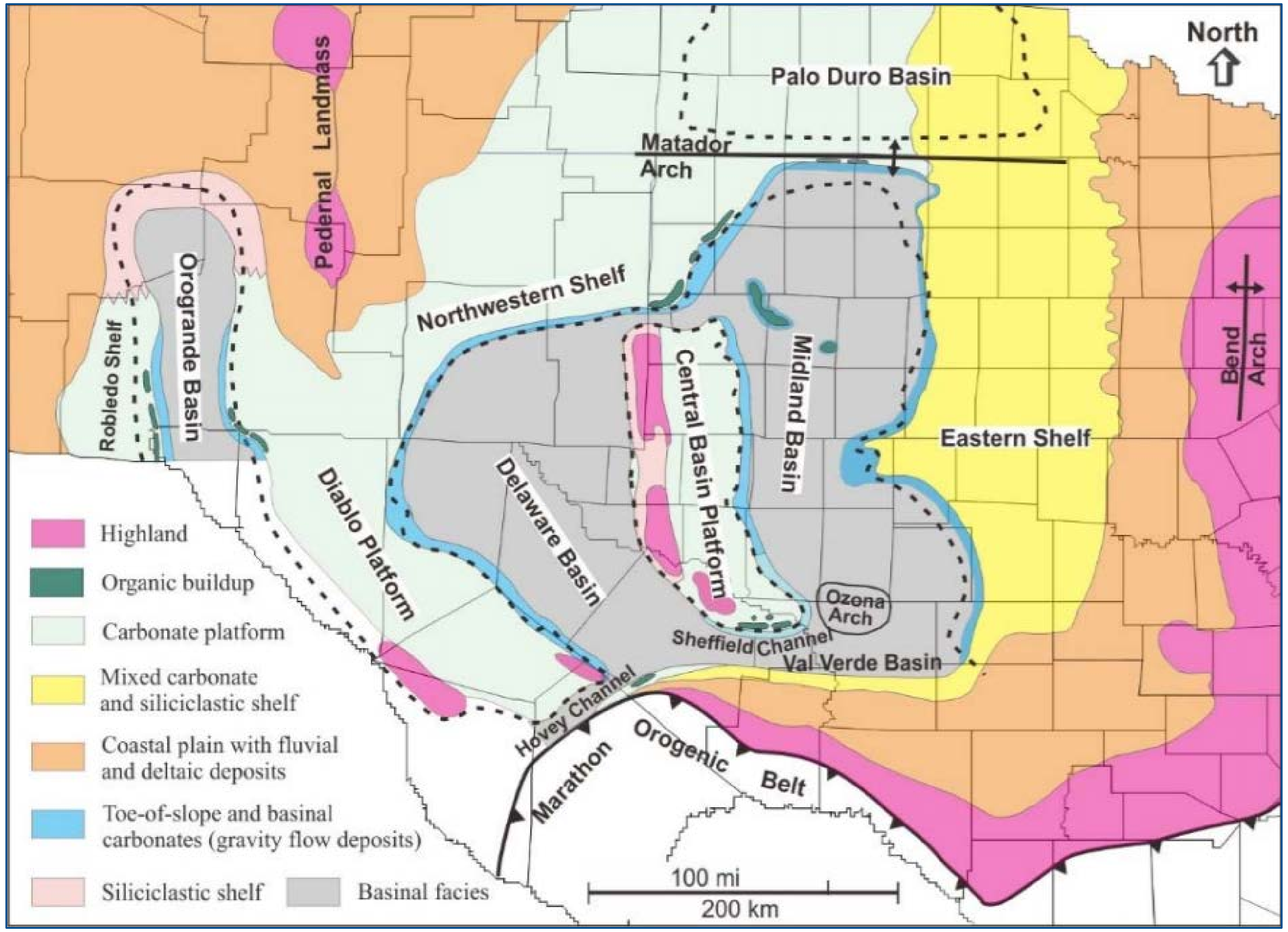
Explore datasets and identify patterns and relationships that may be invisible to the human eye

Can be automated, to extract valuable information in minimal time, supporting informed decisions

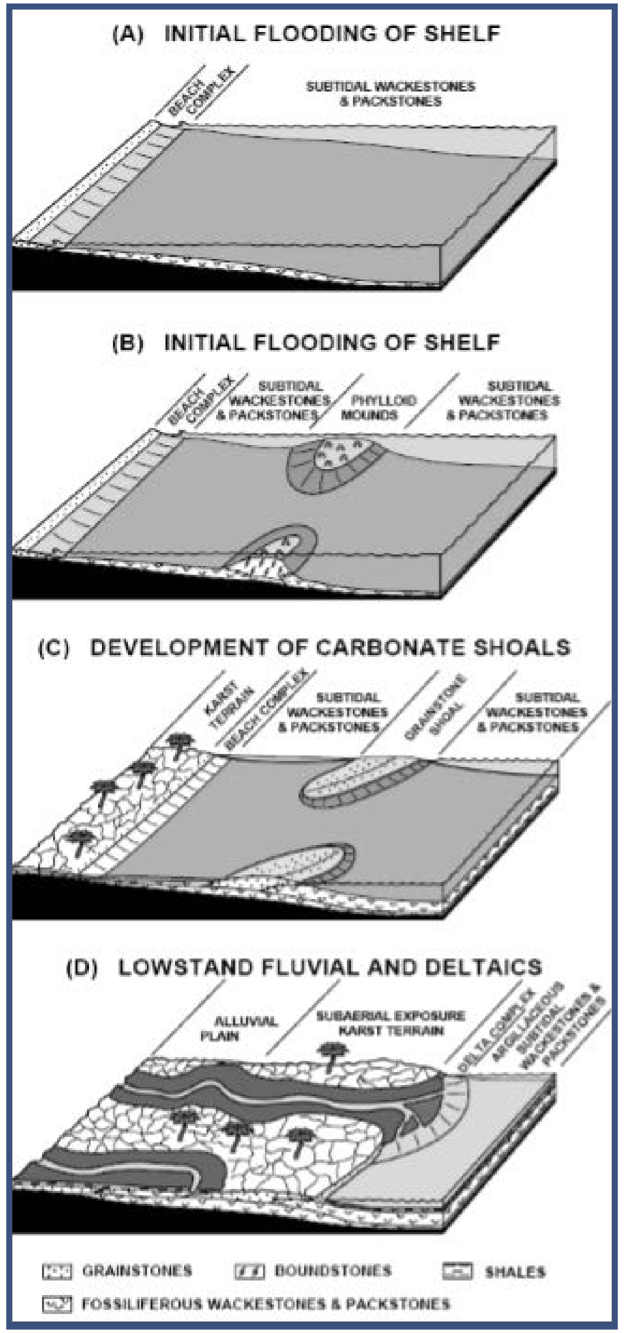
Application on a Real Case : East Soldier Mound (Onshore US)

Location

- **Eastern shelf of the Permian Basin** – East of Lubbock, TX
- Mixed carbonates and siliciclastic shelf
- 3 - 4 million barrel field reserves
- Shallow, vertical wells

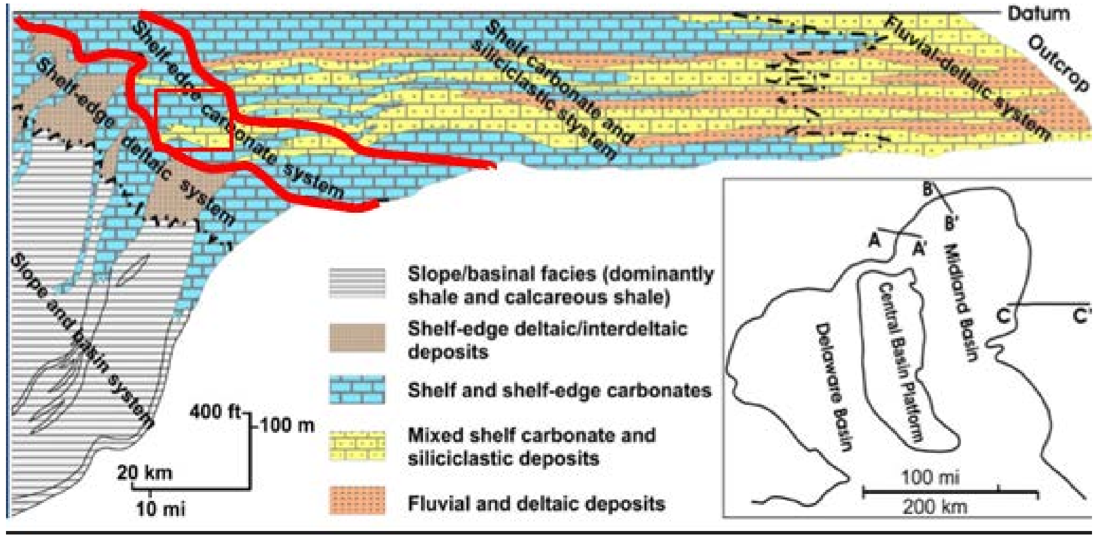


Geological Context



- Packstones formed 293 and 295 MA during stages (B) and (C) when the area was submerged, and organisms were active.
- Oil sourced from a reef on the NE end of the Horseshoe Atoll at some distance from the field (~20 miles)
- Porosity from bioturbation and oolitic shoaling
- Porosity enhancement from much later fracturing
- Upper Wolfcamp production above the Middle Wolfcamp unconformity
- Delta Sand production from the Middle Wolfcamp sand
- Prograding Lower Wolfcamp reefs – productive in back-reef position

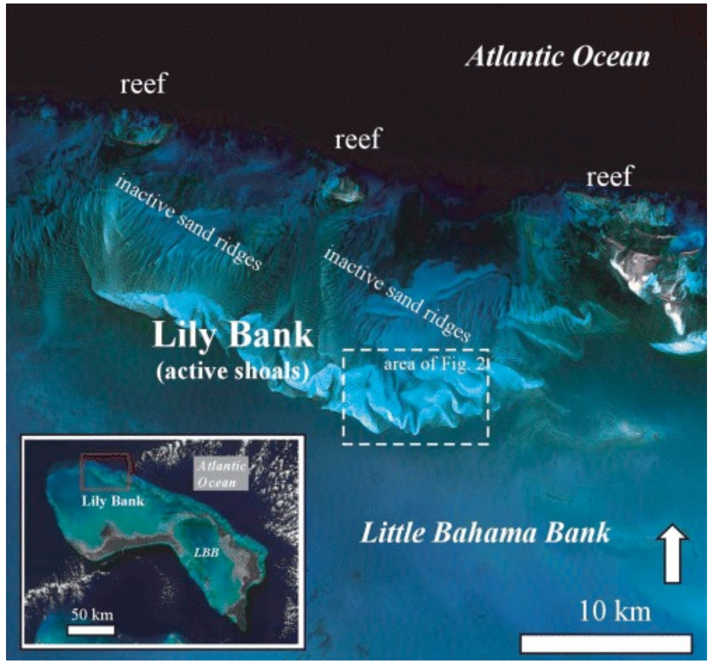
C (West)



C' (East)

Model for deposition of a typical cycle in the Wolfcampian "reef" interval. (After Saller et al.,1999).

Present time analog: Bahamas!



After Rankey et al., 2006

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

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Available Data And Challenges

Available Data

- Small seismic survey, high resolution and good quality
- Seismic attributes
- 3 wells

Objectives

- Prediction of rock types/fluid content distribution throughout the reservoir to:
  - Capture lateral and vertical heterogeneities
  - Constrain reservoir models away from wells
- Validation of the drilling strategy

Challenges

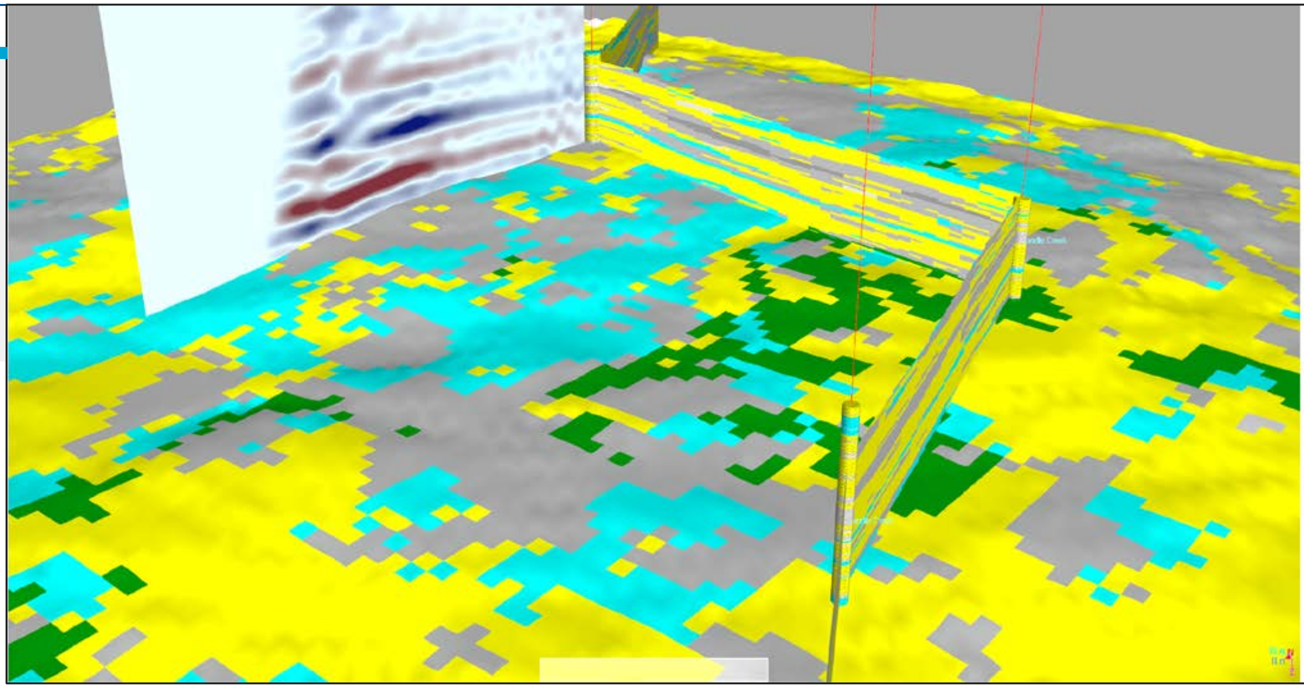
- Reservoir facies determination is important since it will affect the reservoir properties distribution
- Inappropriate determination of the facies distribution may give unrealistic reservoir behavior
- Oil-filled packstone layers are thin
- Scale between wells data and seismic information is very different
- Traditional inversion did not provide results of sufficient quality to support drilling decision

A New Approach Was Requested to Predict Pay Facies and Optimize the Drilling Strategy

Seismic Facies Classification

A critical aspect of reservoir characterization

Classifying lithologies and facies is crucial to identify rocks of interest



Facies logs and most probable facies in carbonate reef geologic setting

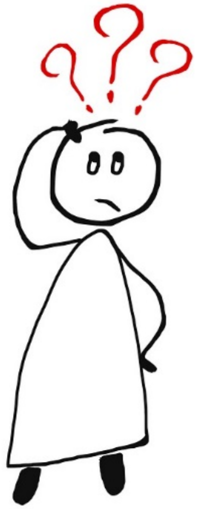
Depositional environments are encountered in the wellbore.

Well data provide reliable information but are too sparse

Integrating data of different resolutions is often tedious and impractical

Information from the wells and seismic data are not linearly correlated

Conventional inversion often renders overlap between the different classes



How to confidently determine the facies distribution away from the wells?

Our Rock Type Classification Approach

The Algorithm: DNNA

Democratic Neural Network Association (DNNA) allows for the generation of lithology probabilities from a combination of quantitative rock typing analysis at wells and seismic data at the well location.

The Methodology

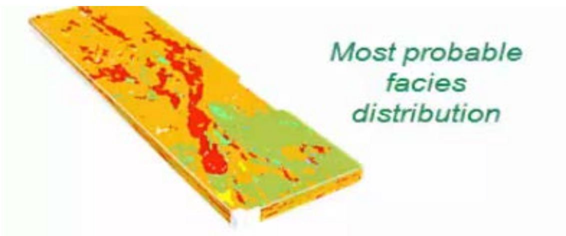
Composed of several independent networks in parallel, it learns from data, finds patterns and relationships and predicts distribution and probability of occurrence of a specified reservoir property

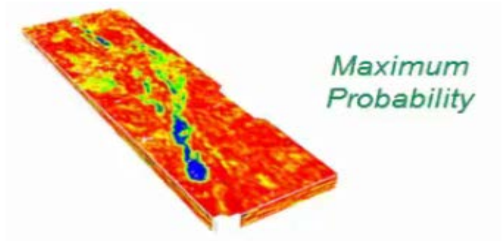
Workflow Overview

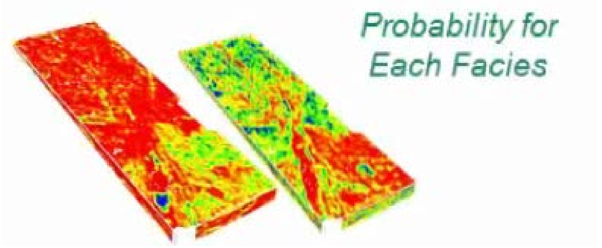
Steps

Training Set Definition → Training Set Creation → Training → Classification → Smoothing

Final Output







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Associative Neural Networks and Democratic Learning Concepts

Associative Neural Networks

- 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
- **The use of several naïve networks running simultaneously as an associative combination is preferred**
- Simultaneously run different neural networks to be trained with the same hard data set provides **the ability to handle the training of associative neural networks with a unique set of seismic data, paired with the well information**
- Defining an ensemble of networks with different learning strategies helps to **compensate for the existing bias when using only one network**

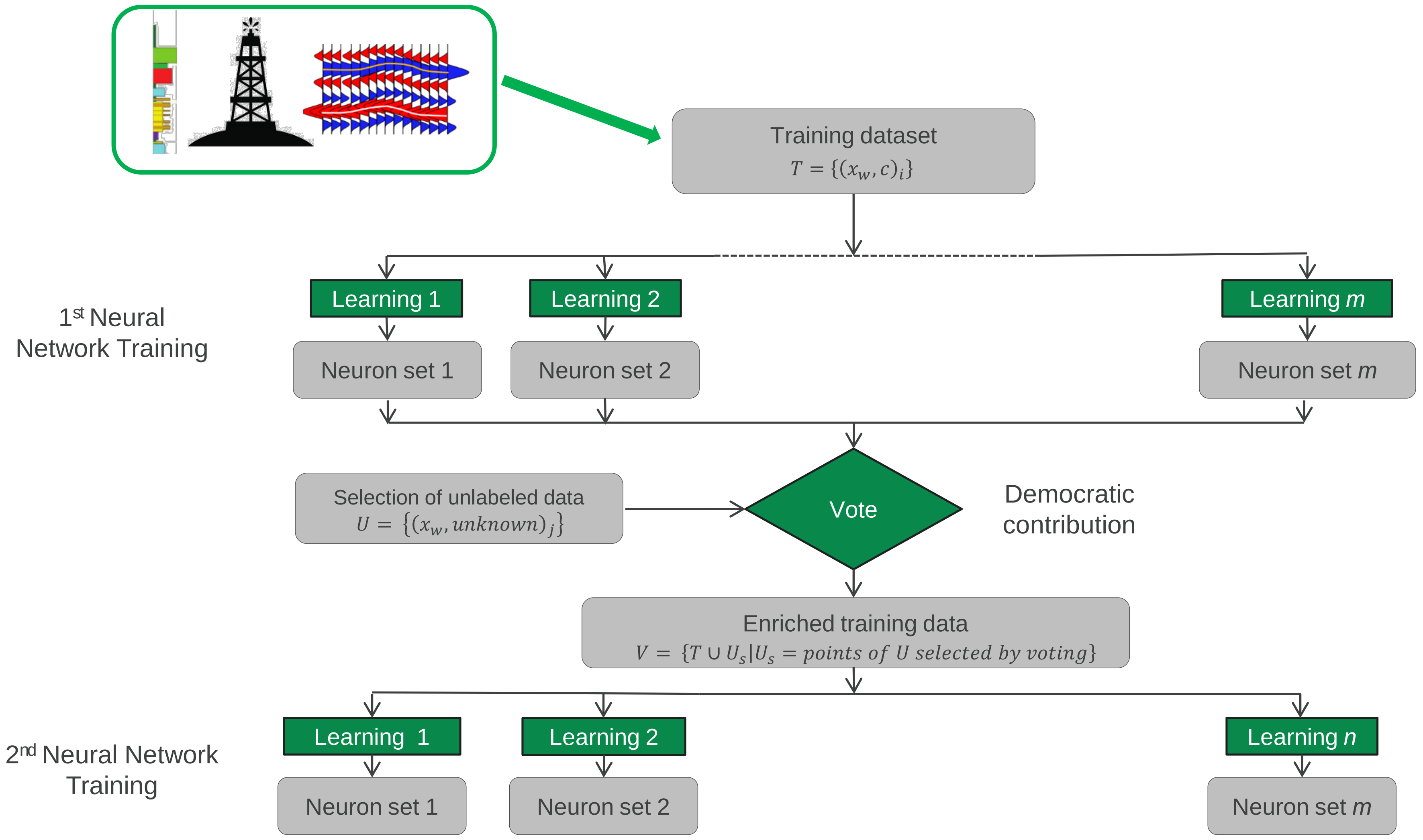
Democratic Learning

- The multistrategy 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**

Workflow Steps

1. Training Set Definition

- Selection of the data to be used for the classification
  - electrofacies
  - seismic data: pre- or poststack data

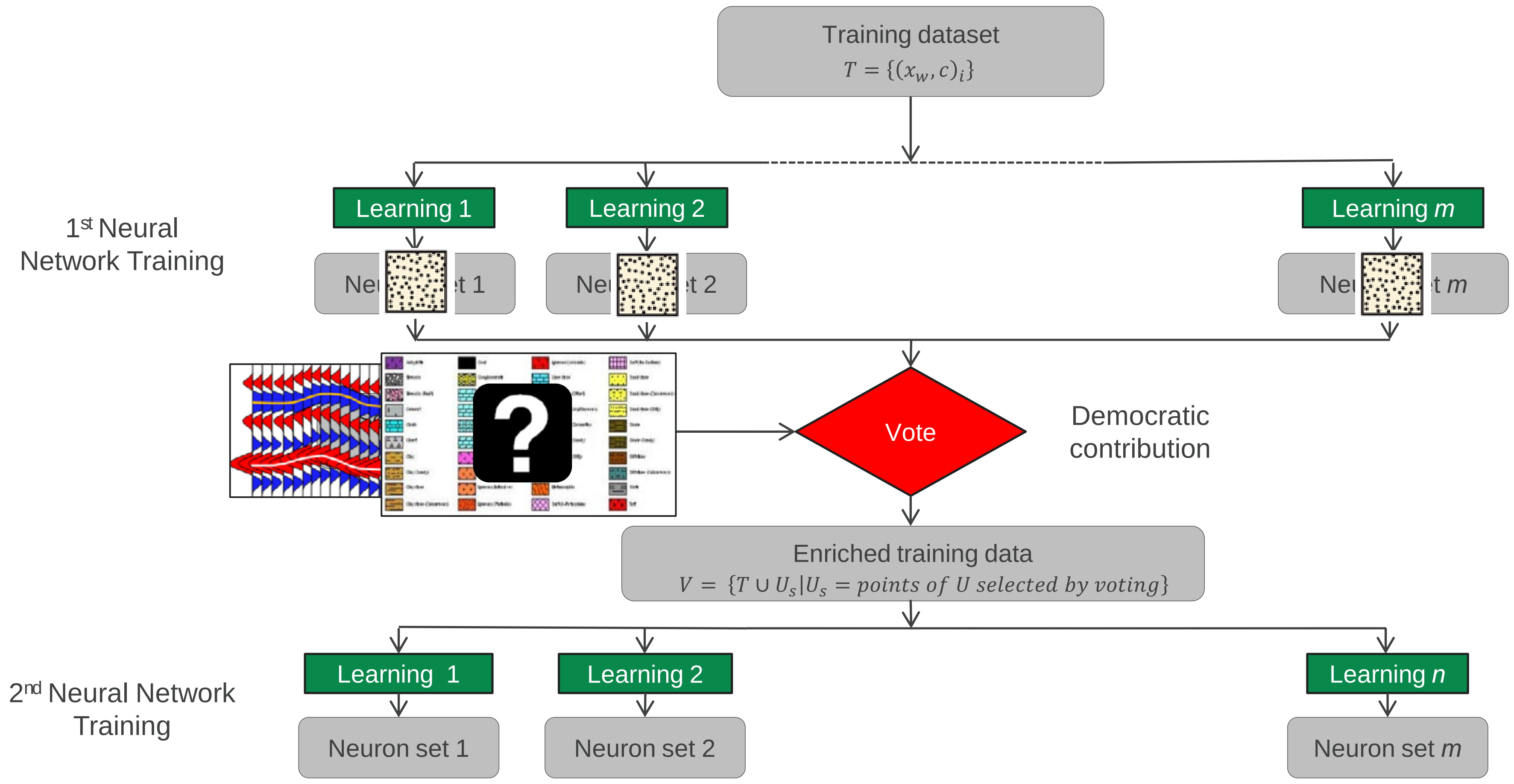


Workflow Steps

2. Neural Network Training

- Learning Methods
- Analysis of unlabeled data
- Democratic vote
- Enriched training dataset

Democratic contribution is unanimous: the soft data is added to the training dataset, with a smaller weight



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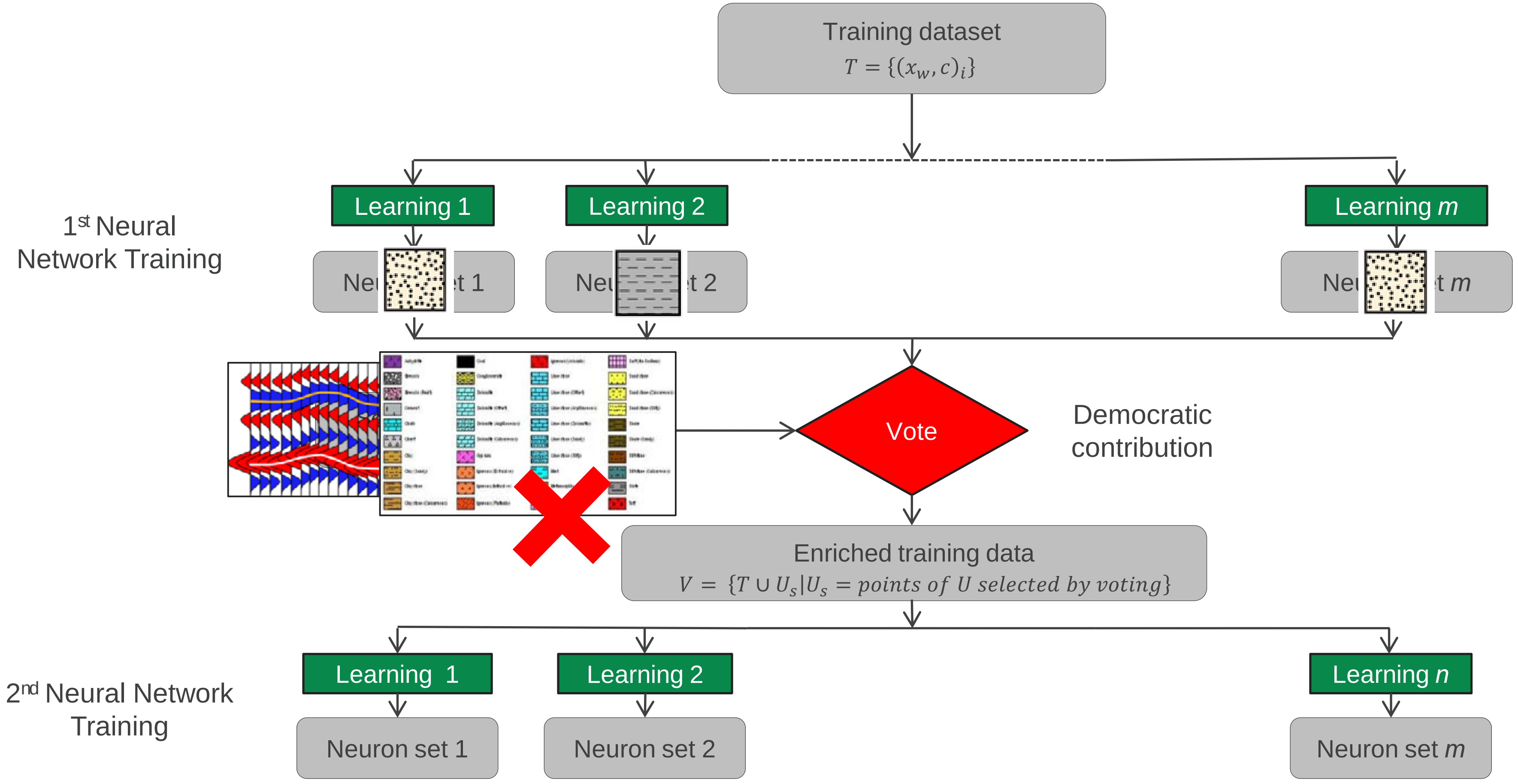


The vote is not unanimous: the soft data is not included into the training data set

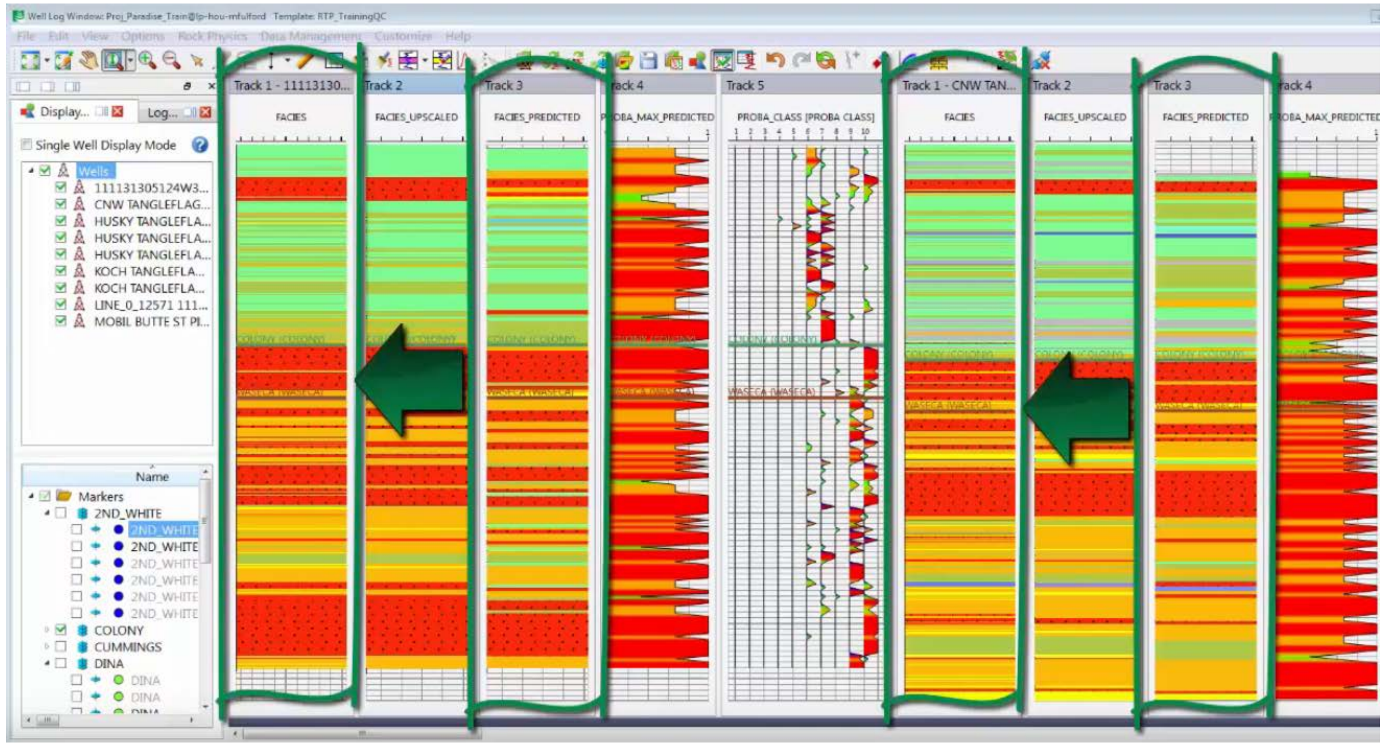
The Training Dataset Contains Both Hard and Soft Data and Is Used to Further Train The Neural Networks

Workflow Steps

3. Classification Validation

- Visual QC
- Classification report
- Bootstrapping method to assess the quality of the model
  - ➢ Bootstrap error to simulate the rate of prediction away from wellbore

Predicted log versus observed data



Reconstruction rate and confusion matrix help QC-ing the results and adjust parameters to reduce the confusion if needed

Confusion matrix

	Predicted Class								
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9
Class 1	24								
lass 2		1					2		
ass 3			19						1
ass 4				4					
ass 5					6				1
ass 6						51			1
ass 7							385	2	6
ass 8								4	
ass 9						3	12		269

points: 1806
ata well classified: 96.8992%

Bootstrap (training) error: 0.169621
Bootstrap classification rate: 78.736 %

Reconstruction rates matrix

Well Name		Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	All Classes
Well Name	1001	100% (16/16)	N/A	100% (14/14)	N/A	75% (3/4)	100% (25/25)	99% (158/159)	N/A	95% (77/81)	98% (293/299)
	1002	100% (8/8)	N/A	N/A	N/A	N/A	93% (13/14)	97% (167/173)	100% (1/1)	89% (84/94)	94% (273/290)
	1006	N/A	33% (1/3)	83% (5/6)	100% (4/4)	100% (3/3)	100% (13/13)	98% (60/61)	100% (3/3)	99% (108/109)	98% (197/202)
	All Wells	100% (24/24)	33% (1/3)	95% (19/20)	100% (4/4)	86% (6/7)	98% (51/52)	98% (385/393)	100% (4/4)	95% (269/284)	96% (763/791)

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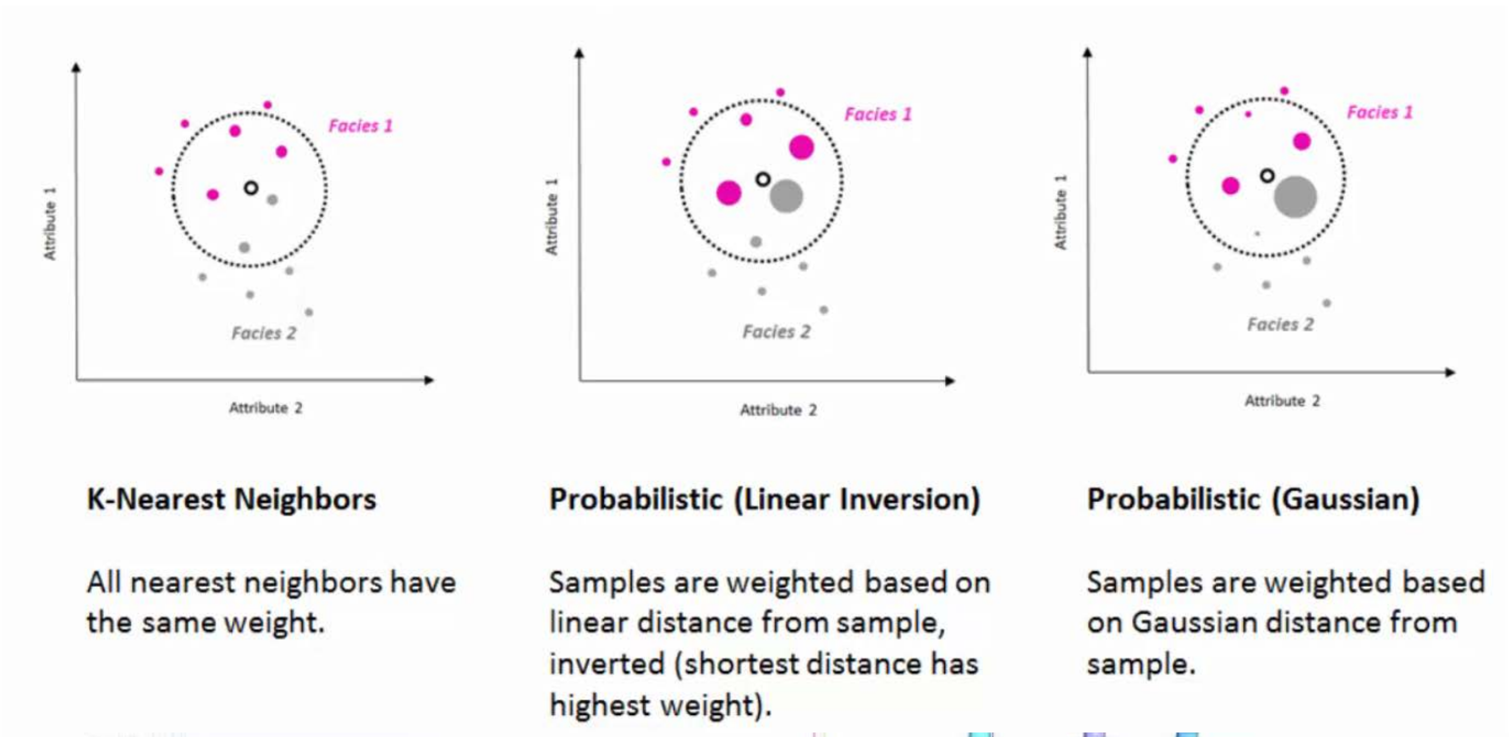
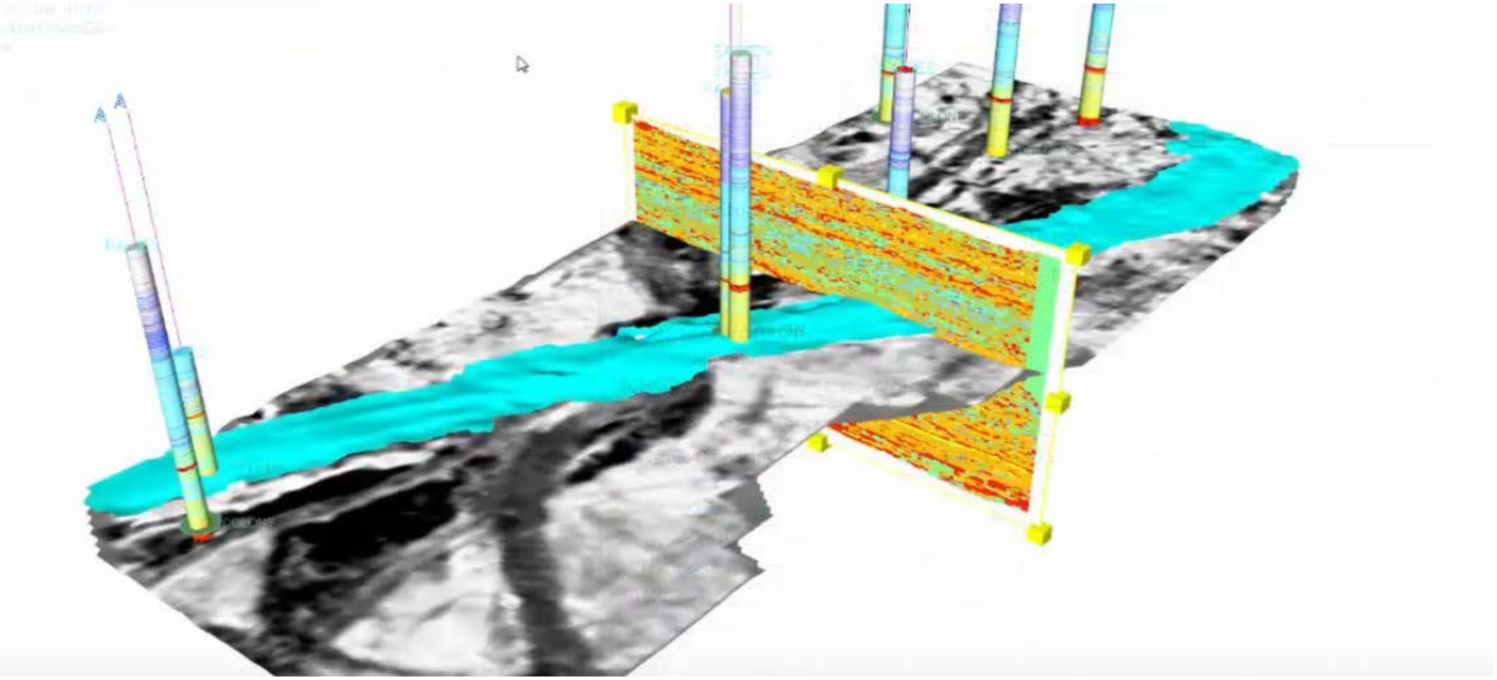
Workflow Steps

4. Classification Propagation and Output

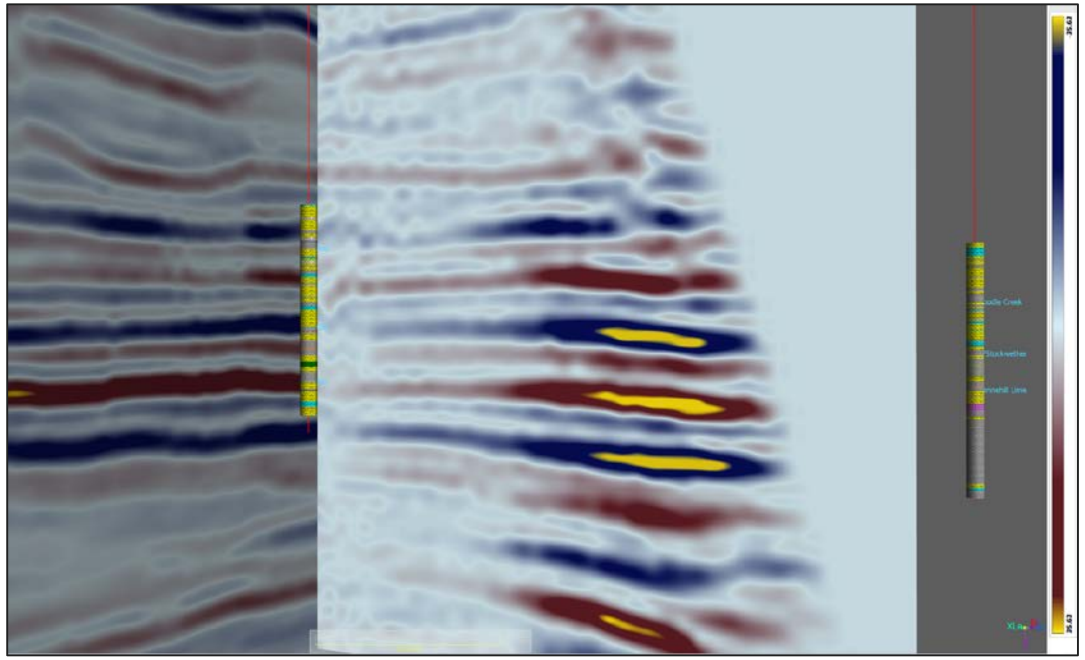
- Classification methods
  - K-nearest neighbors
  - Probabilistic (linear inversion)
  - Probabilistic (Gaussian)
- Outputs
  - Classification summary
  - Most probable facies volume
  - Maximum probability
  - Probability volume for each facies





Back to The Real Case...

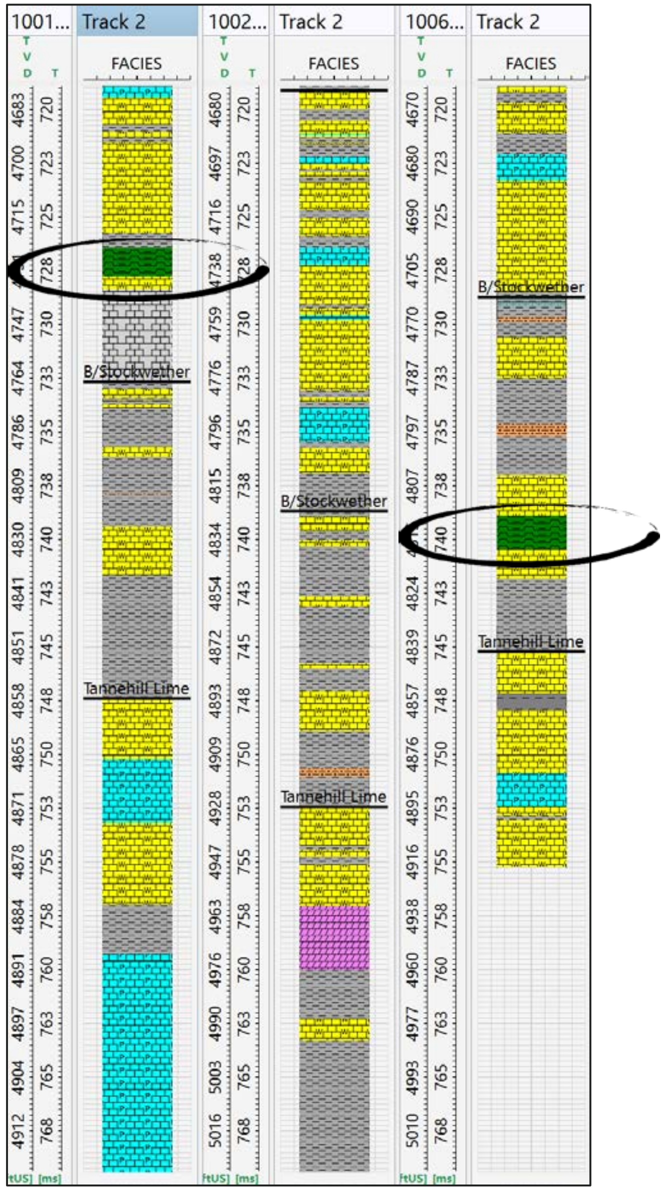
Input data



Stack and offset gathers

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	

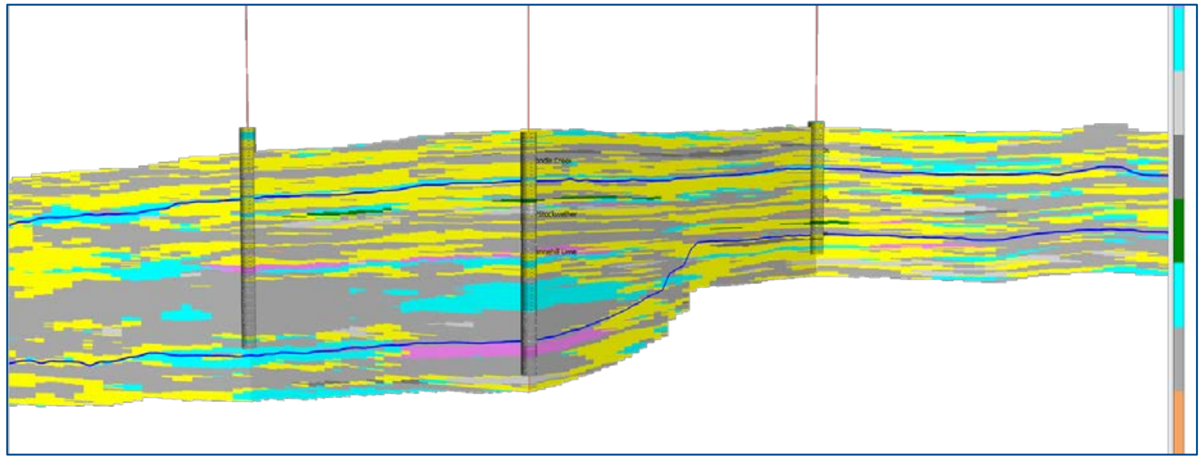
Facies logs defined by wireline logs

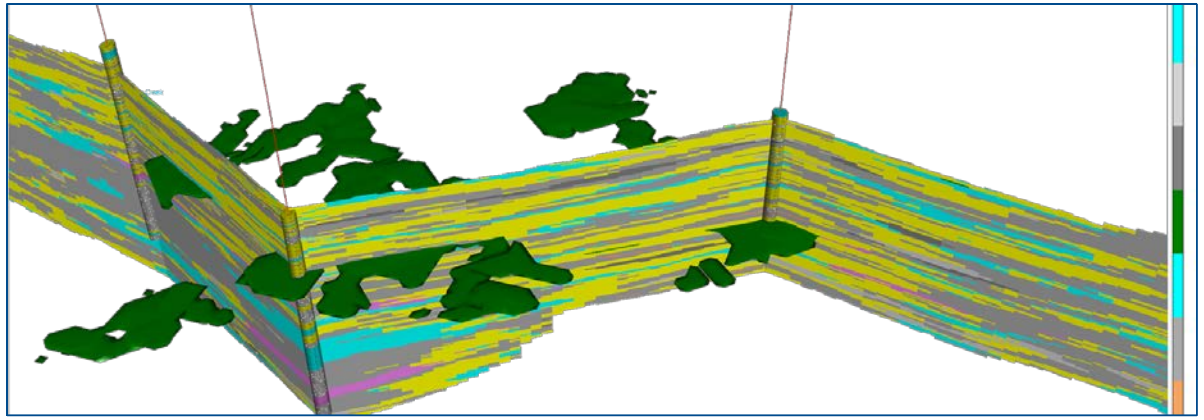


Back to The Real Case...

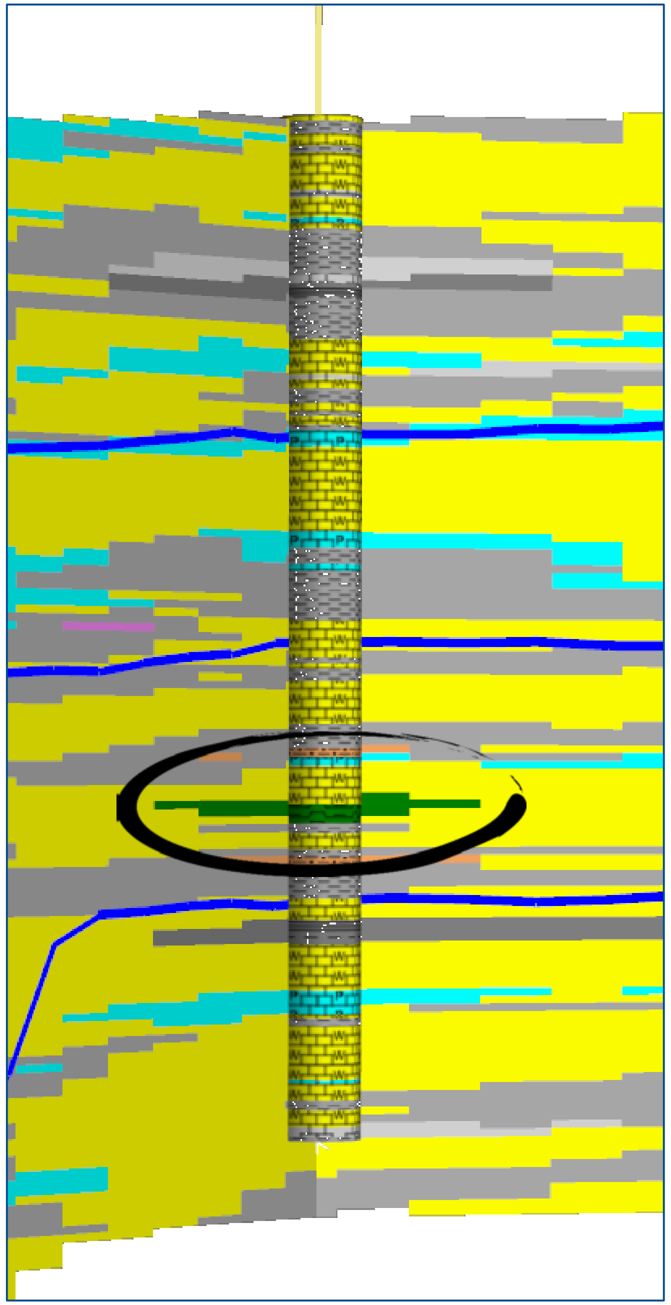
Facies Classification Results

- Most probable facies volume
- Probability volume for each facies
- Validation through prediction along wellbore and volume





Validation of the
output at the wellbore

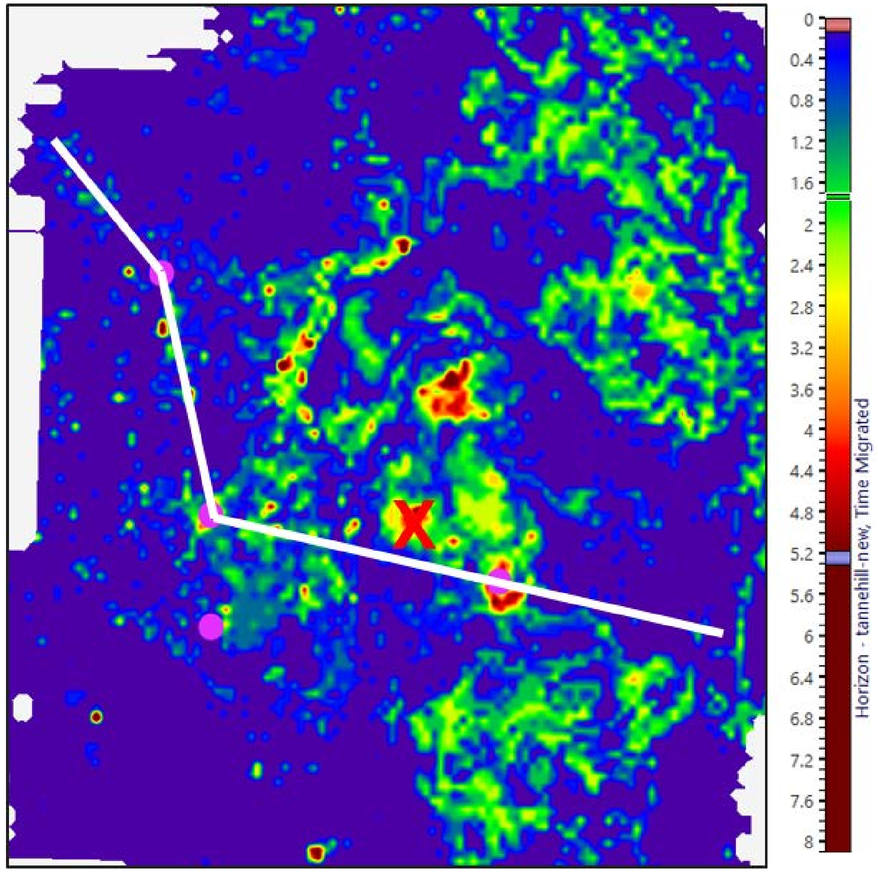


Conclusion

Key Points

- Bring new potential about seismic data reliability for prediction of reservoir facies away from wells, especially when referring to prestack data, which carry more information with any type of seismic attributes
- Provide faster images of the subsurface while still maintaining accuracy, thus helping to improve the decision-making process in the drilling location determination
- Approach can be applied to other geologic setting

Updated drilling target location, based on current rock type classification



Net temporal thickness map (ms) from facies 5 cutoff

This Machine Learning Based Rock Typing Classification Method Introduces Realistic Heterogeneity, Supporting Decision Making

Key Points

One of the leading challenges in hydroarbon recovery is predicting rock types distribution throughout the reservoir, away from the wells, because rock property determination is a major source of uncertainty in reservoir modeling

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- Capitalizes on continuously increasing amount of data ✓
- Explore datasets and identify patterns and relationships that may be invisible to the human eye ✓
- Can be automated, to extract valuable information in minimal time, supporting informed decisions ✓

Further Reading

Guillaumin, M., J. Verbeek, and C. Schmid, 2010, Multimodal semi-supervised learning for image classification: Presented at IEEE Conference on Computer Vision and Pattern Recognition.

Hami-Eddine, K., P. Klein, and L. Richard, 2009, Wellfacies-based supervised classification of prestack seismic: Application to a turbidite field: 79th Annual International Meeting, SEG, Expanded Abstracts, 1885–1889.

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