Comparative Study of Deep Feed Forward Neural Network Application for Seismic Reservoir Characterization

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Theme

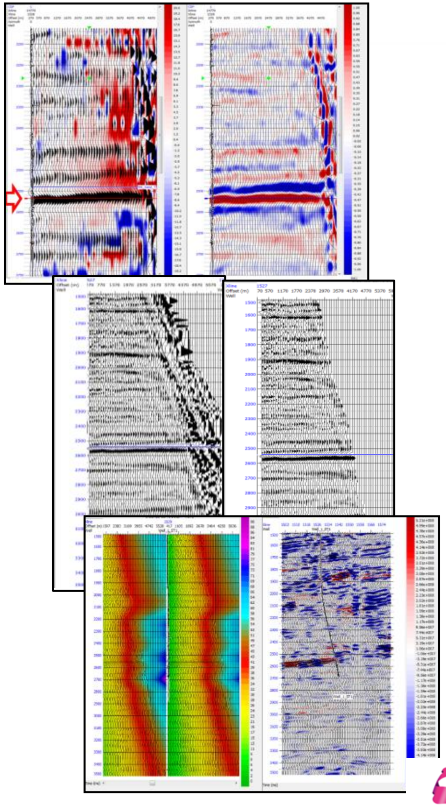
- Study the advantages the deep learning brings
- Use machine deep learning technique called Deep Feed-forward Neural Network (DFNN) to predict reservoir properties
- Compare deep learning versus other methods
- Predict and validate estimates of Porosity, Volume of Vshale, Water Saturation
- The final goal is to derive the volume of net pay

Outline

- Introduction of Deep Neural Networks
- Results using North Sea Study
- Training, Validation and Parameter Control
- Summary

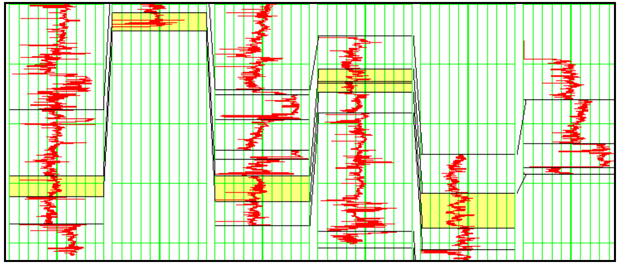
Traditional Reservoir Characterization Approach

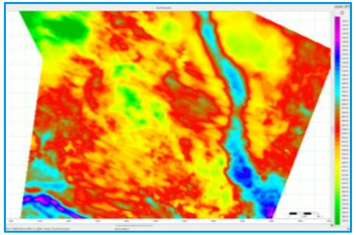
- Precondition the seismic data for AVO
- Focus on reducing errors from spectral differences, residual move out and relative phase differences
- Apply traditional AVO and inversion techniques to the seismic data, thus produce a number of seismic attributes
- Derive elastic properties and lithology fluid facies
- Here we will take it a step further by deriving the actual reservoir properties

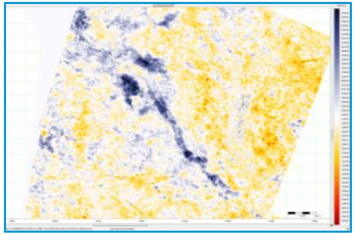


Study

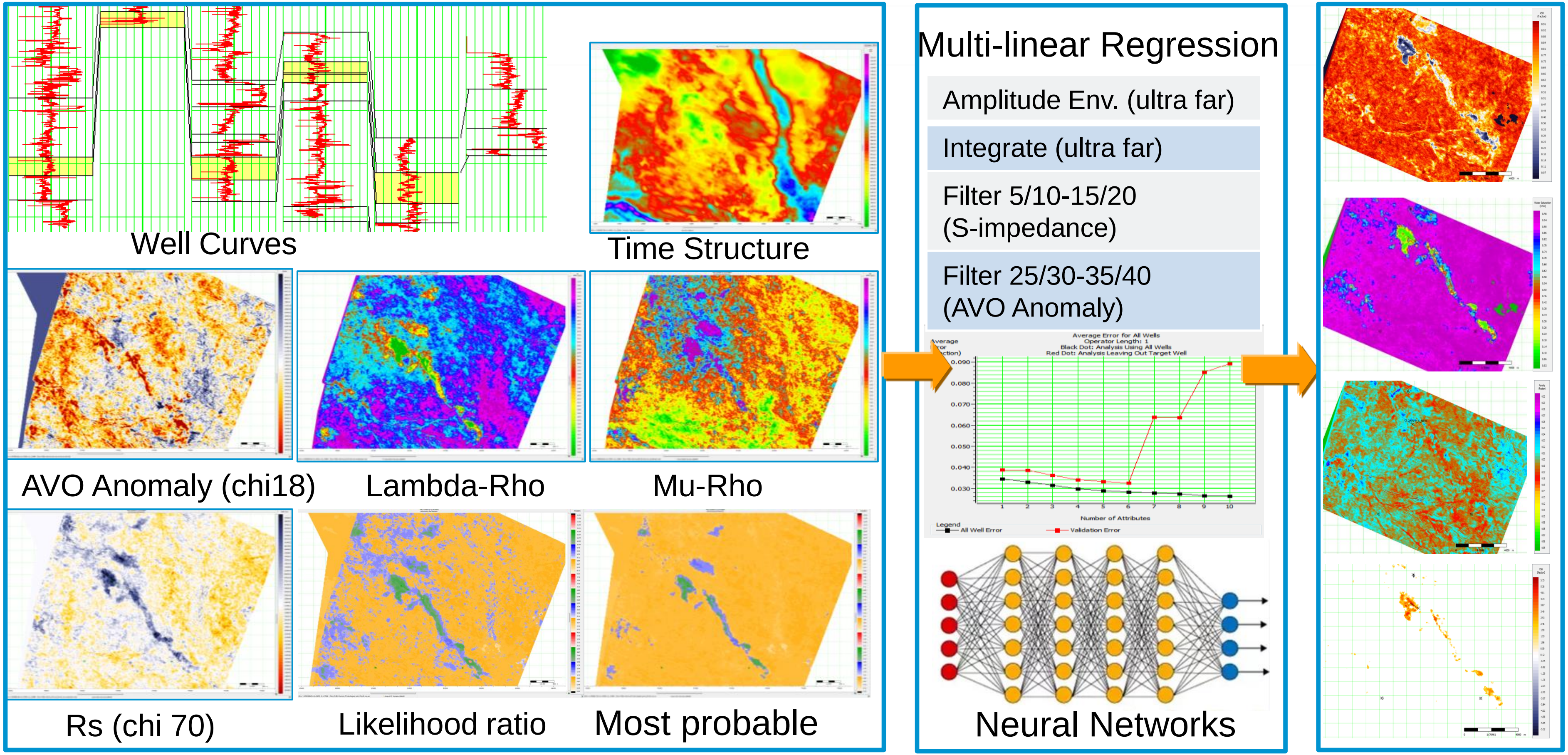
- Three machine learning techniques were tried and compared:
  - Multi-Linear Regression (MLR),
  - Probabilistic Neural Network (PNN),
  - Deep Feed-forward Neural Network (DFNN)
- It is done in the North Sea, covering two producing fields with commercial volumes of oil
- Both fields have reservoir interval within the Paleocene:
  - Field A is a deep marine channelized submarine fan system
  - Field B is in a remobilized injectite sand, cross cutting a range of stratigraphy at very steep angles
- A number of wells with suitable wireline logs are available in and around the discoveries. We used only six wells in the same block, since they provided good well-to-seismic ties





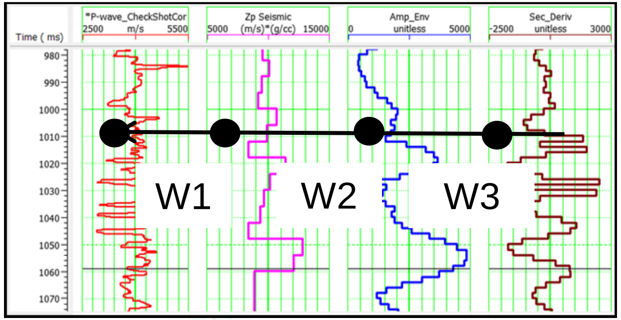


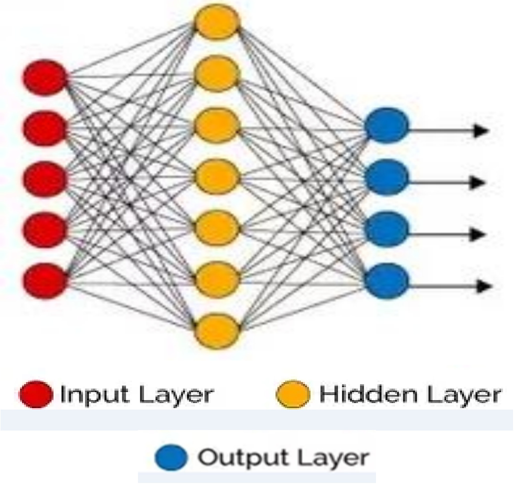
Net-Pay Prediction Workflow



Multi-linear Regression and Neural Networks

- Multi-linear regression predicts the target by finding a *linear* relationship between the log and attributes
- With neural networks we derive a *non-linear* relationship that links the target with the given attributes
- Multi-feed Forward Networks and Probabilistic Neural networks are the most commonly used networks
- The weights in neural networks are derived by solving a large nonlinear inverse problem by minimizing some objective function such as the mean squared error between the actual training values and the predicted training values

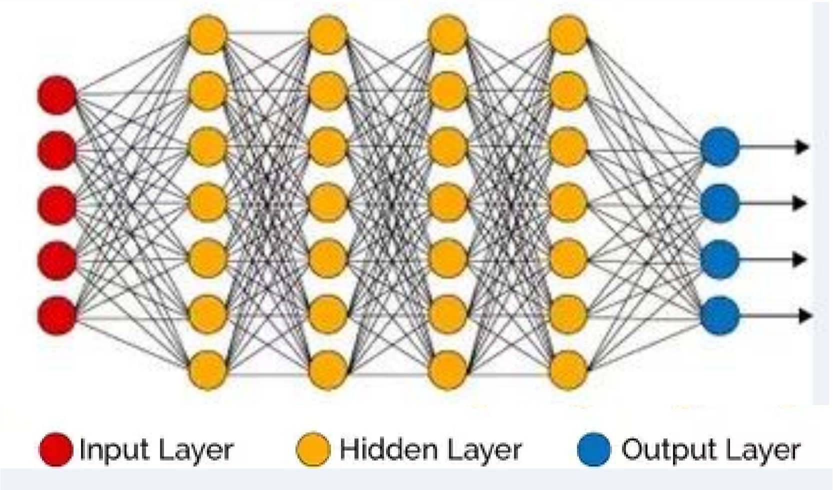




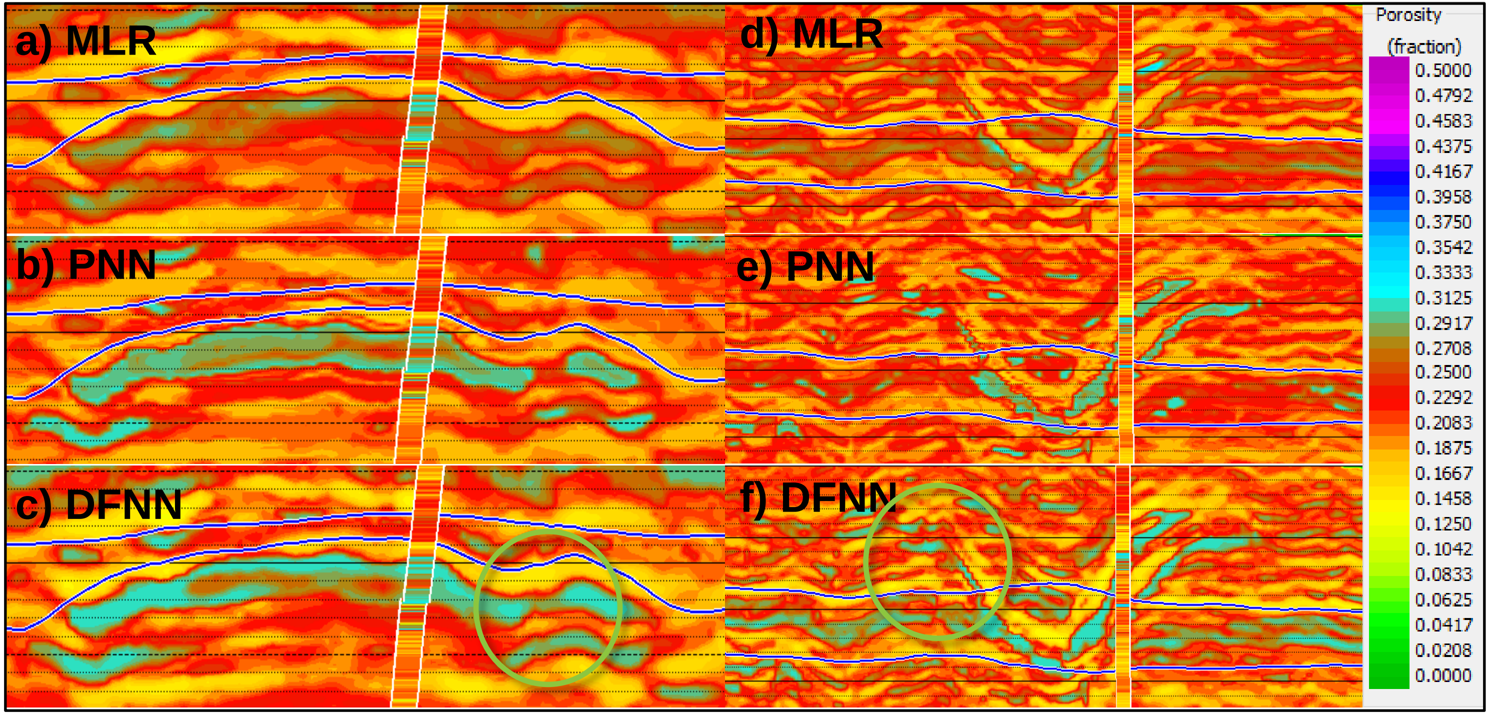
Deep Neural Networks

Deep Feed-forward Neural Network (DFNN) is a form of supervised learning:

- The supervised learning is the task of inferring a function from labeled training data
- The learning algorithm then generalizes from the training data to unseen situations. The resulting model is statistical.
- A multi-layer neural network is considered ***deep*** if it has 2 or more hidden layers. As the number of hidden layers increase, a deep forward network can model more complexity
- The more training data you have, the greater number of hidden layers can be used



Porosity Prediction



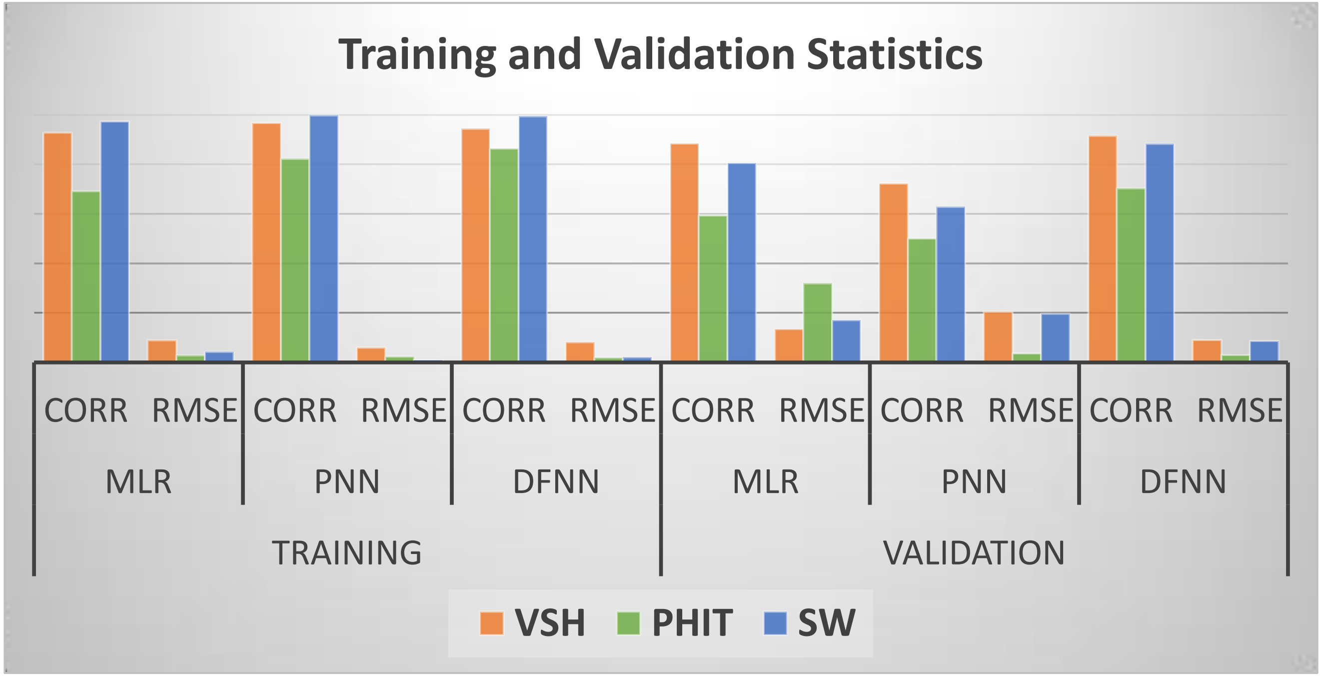
Left: Field A *Right: Field B*

DFNN provides:

- Better lateral continuity in the thin reservoir of field A
- Good estimation of the injectite sand properties in field B

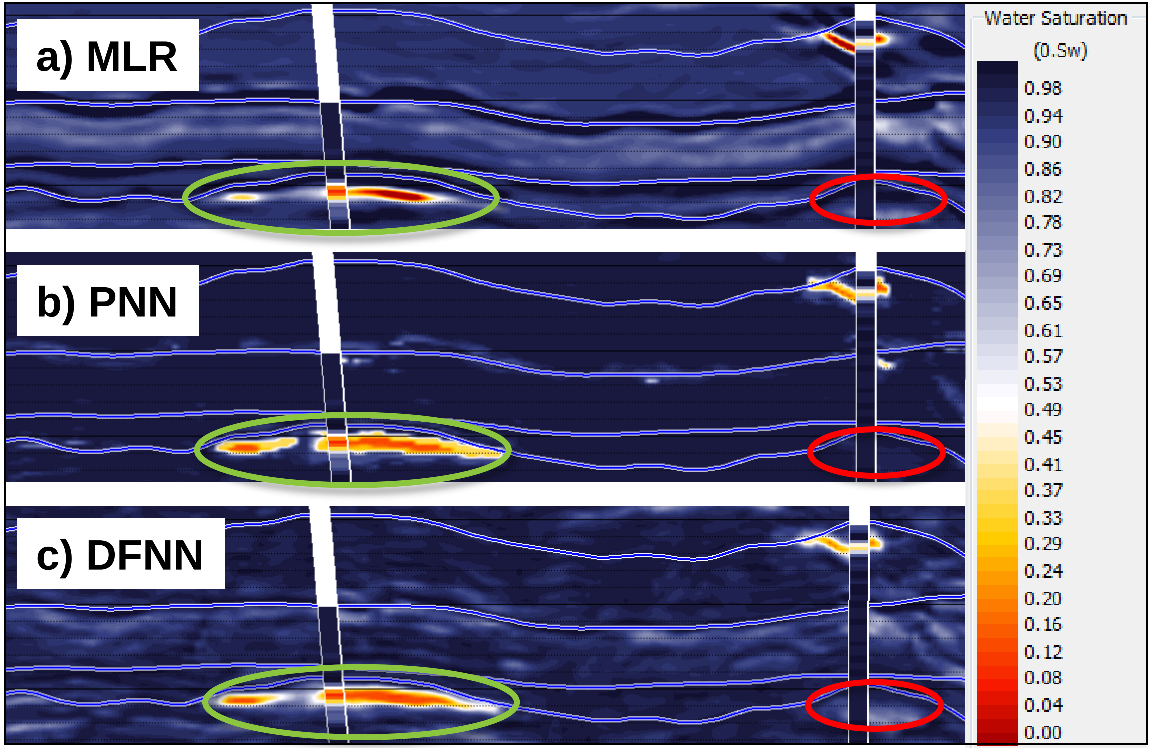
Training and Validation Statistics at the well locations

	Training						Validation					
	MLR		PNN		DFNN		MLR		PNN		DFNN	
	Corr	Avg. Error	Corr	Avg. Error	Corr	Avg. Error	Corr	Avg. Error	Corr	Avg. Error	Corr	Avg. Error
VSH	0.929	0.089	0.968	0.0599	0.944	0.081	0.884	0.135	0.723	0.204	0.916	0.091
PHIT	0.692	0.028	0.822	0.023	0.864	0.019	0.593	0.32	0.5	0.036	0.703	0.03
SW	0.974	0.043	0.999	0.009	0.994	0.021	0.806	0.171	0.628	0.196	0.883	0.087



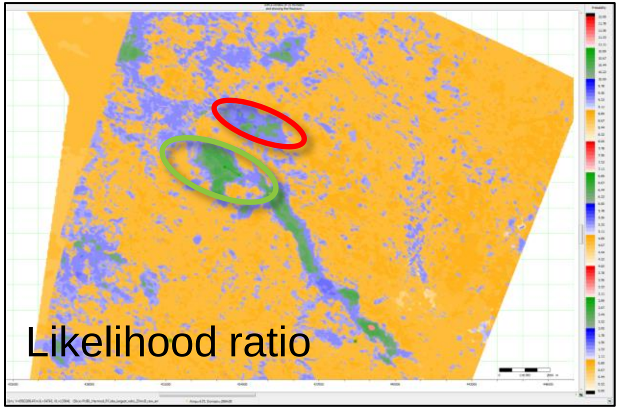
- MLR predicts correct variations at the well locations but not correct magnitude
- PNN drops significantly from training to validation
- DFNN shows the highest correlation value and lowest validation RMS error (RMSE)
- DFNN gives consistent statistics from training to validation

Water Saturation Prediction (field A)

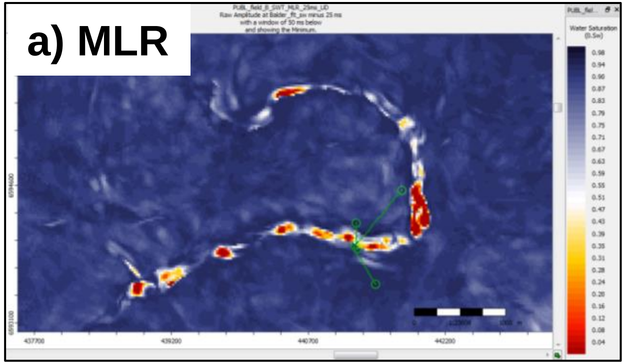


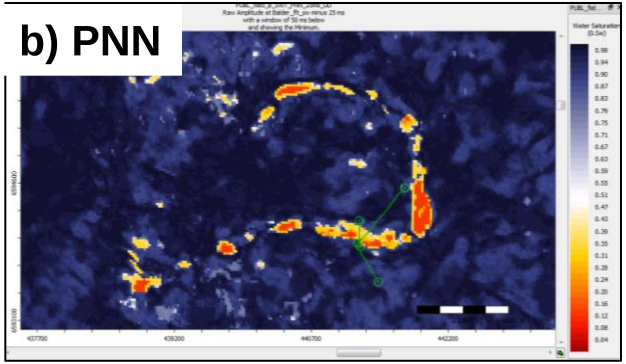
Discovery well used in training (left) *Blind well test (right)*

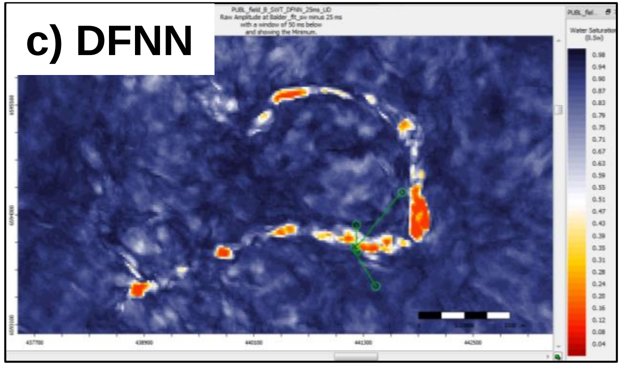
- Quantitative prediction of water saturation is often ambiguous because of its independent nonlinear relationship with conventional seismic attributes and inversion
- Non-linear neural networks are good at solving this ambiguity



Water Saturation Prediction (field B)



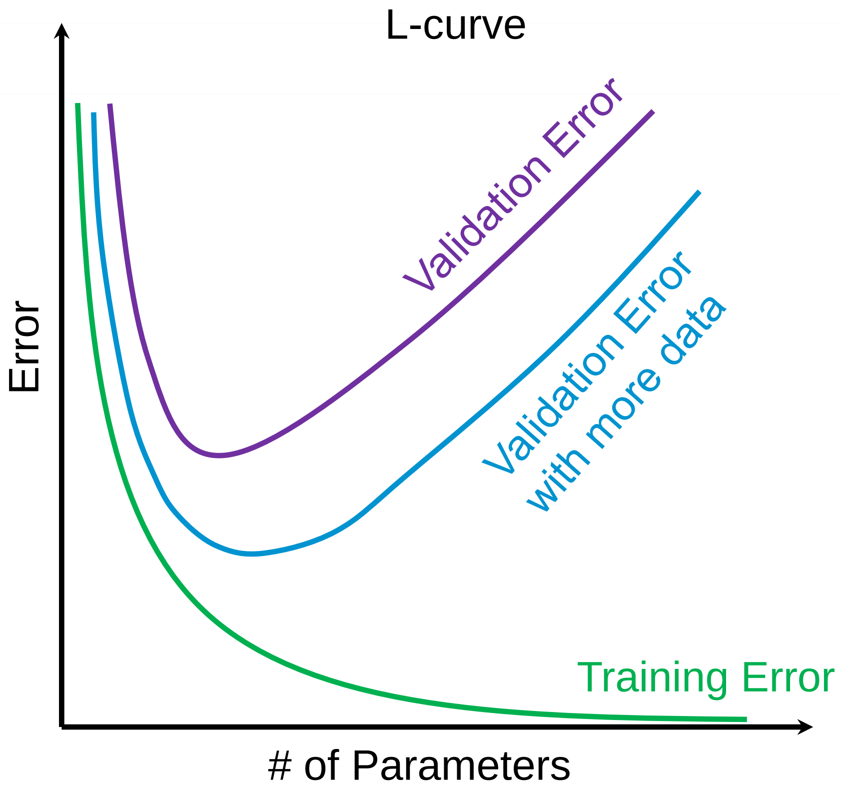




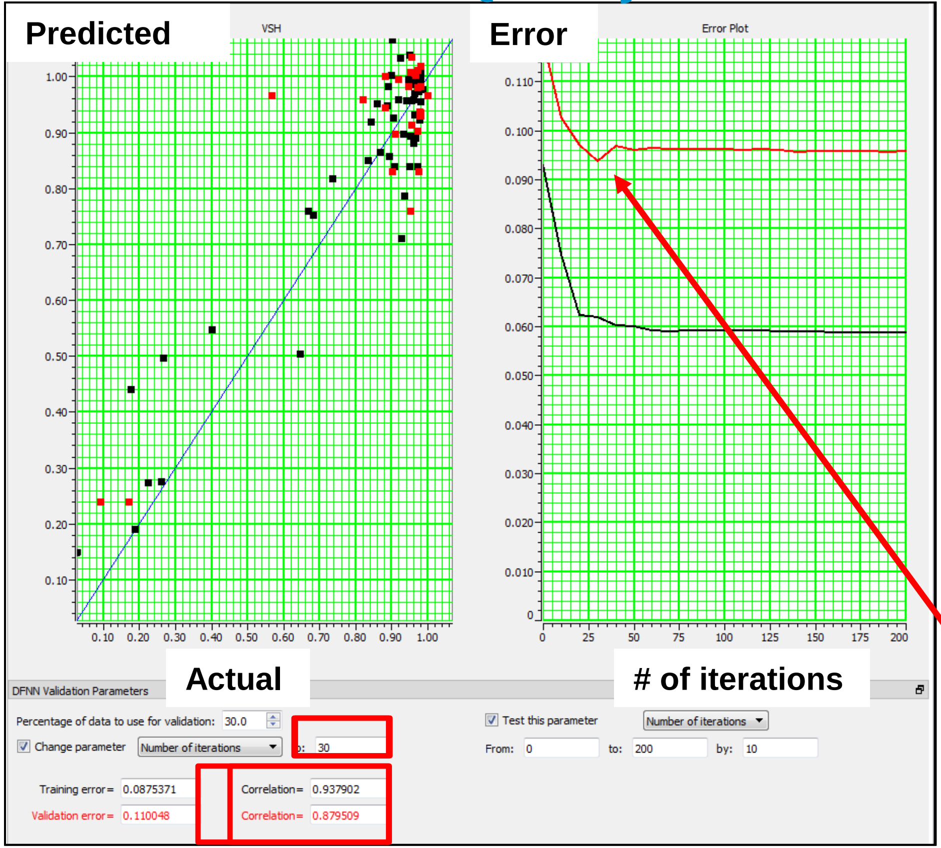
- Notice the continuity and clear depiction of the injectites

DFNN Training and Validation

- Like all supervised learning problems, training the DFNN balances a tradeoff between the conflicting desire to maximize the ability to predict the known training values, while minimizing the tendency to “over train” or learn spurious noise from the training examples
- The condition of over training is usually evaluated using separate validation data
- To ensure that the network is not overtraining we validated the derived DFNN operator using the percentage based validation, around 25-30% of training data samples were used for validation

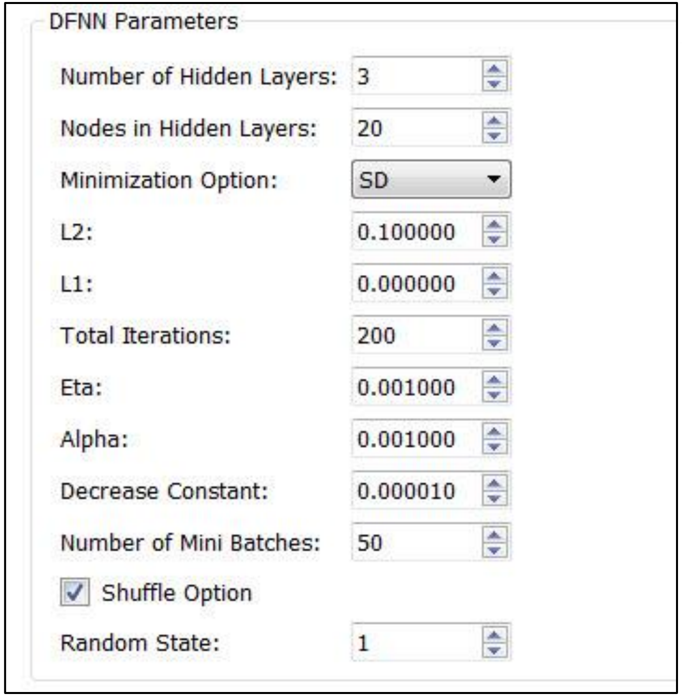


DFNN Vshale Quality Control



- The data is randomly split into training and validation datasets
- The total number of iterations or steps is used for either the Conjugate Gradient or Steepest Descent algorithm
- By plotting the training and validation error as a function of iteration it is possible to determine the optimal number of iterations
  – # of iterations serves as a regularization parameter
- Correlation coefficient
  – iterations=30
    – 0.94 training
    – 0.88 validation

DFNN Parameter Control

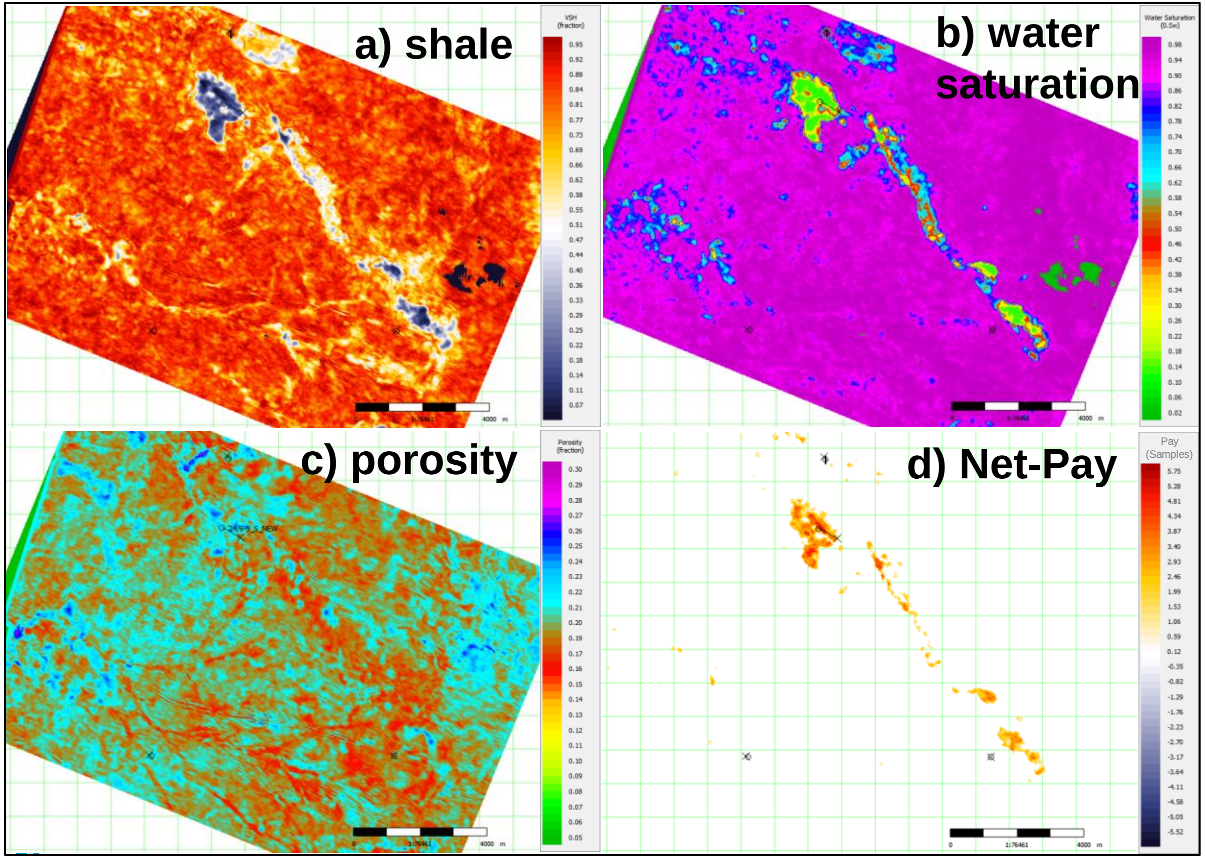


- DFNN offers significant advantages in terms of control of training parameters and speed of application.
- Each of the parameters shown on the left affects the accuracy of prediction
- **Number of hidden layers**
- **Number of nodes in hidden layers** is defined by the number of attributes supplied into the network
- **Minimization option**: the Conjugate Gradient (CG) and Steepest Descent (SD) algorithm:

  CG is robust method, easy to parameterize

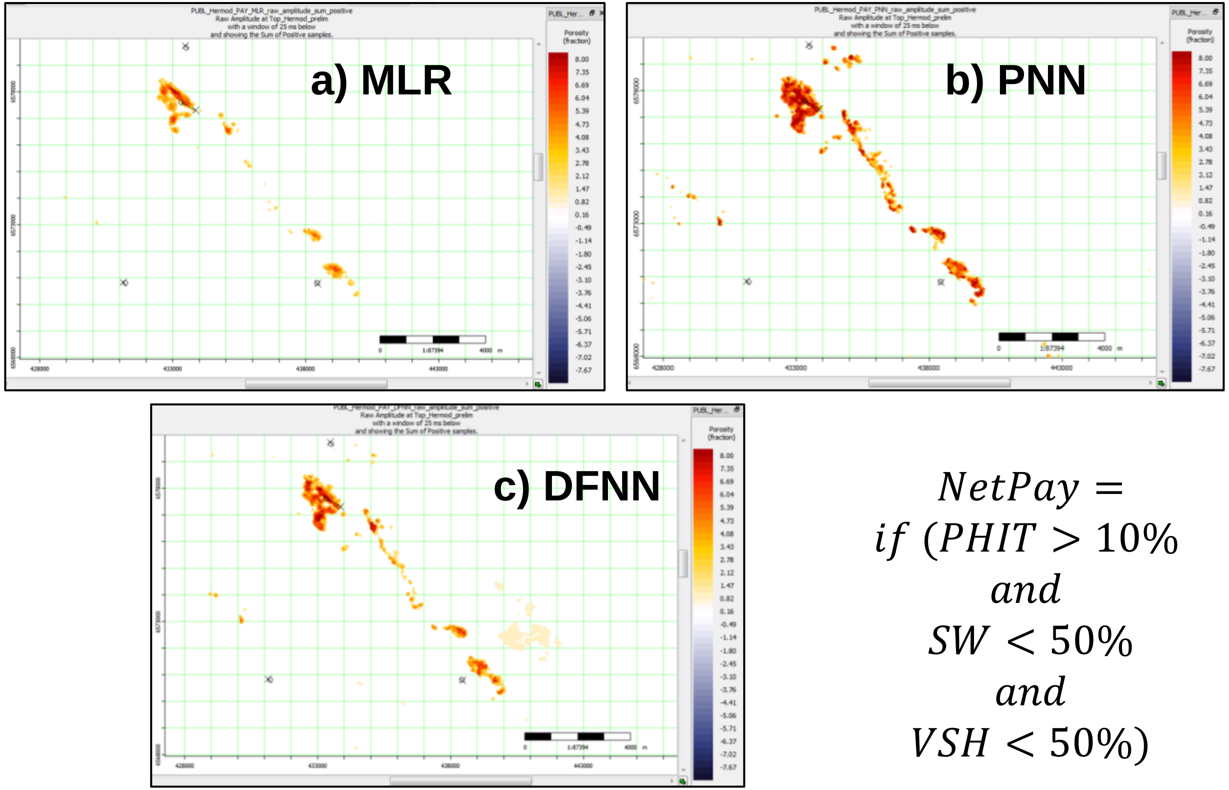
  SD better result but difficult to parameterize

Net-Pay Derivation Summary using DFNN



- From Vshale, Water Saturation and Total Porosity volumes, we estimated the net pay volume

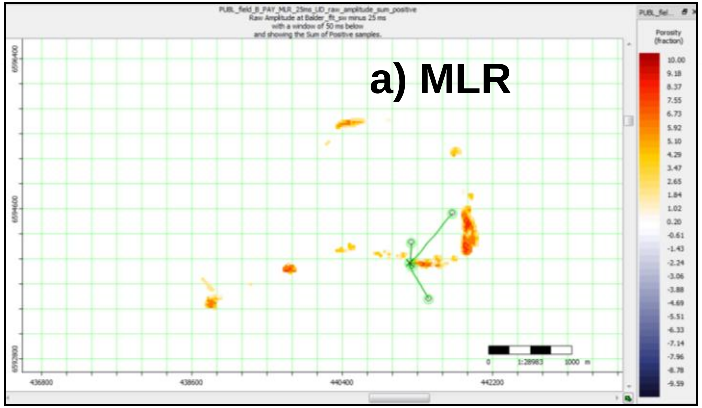
Net-Pay estimation (field A)

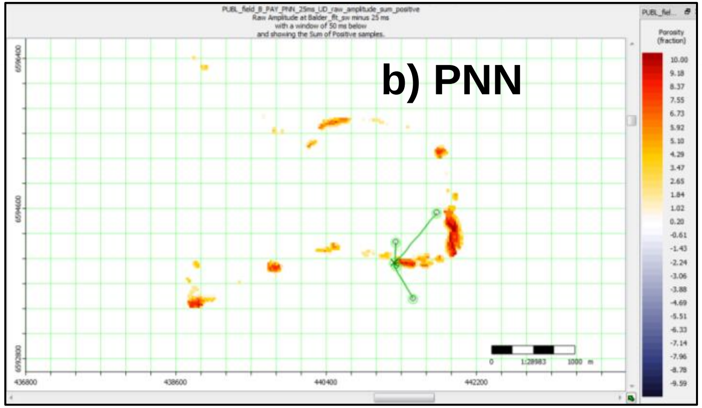


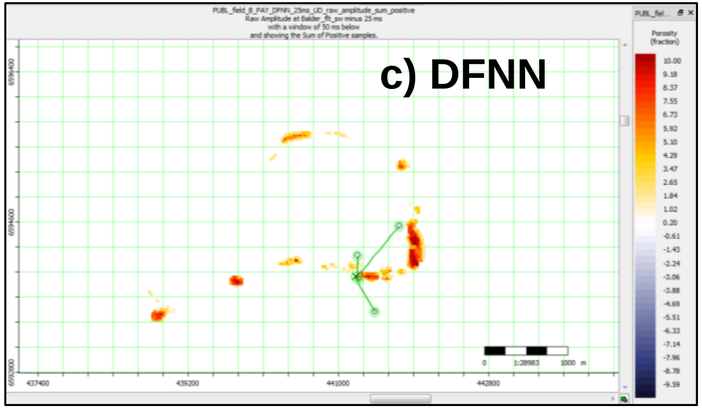
- MLR is under estimating the reservoir
- PNN is over-predicting, especially away from the well control
- DFNN shows the best results, as was confirmed quantitatively by correlation and validation shown earlier

$$NetPay = if\ (PHIT > 10\%\ and\ SW < 50\%\ and\ VSH < 50\%)$$

Net-Pay estimation (field B)







- Previous validations showed that MLR is under estimating the reservoir and PNN is less stable, noisier

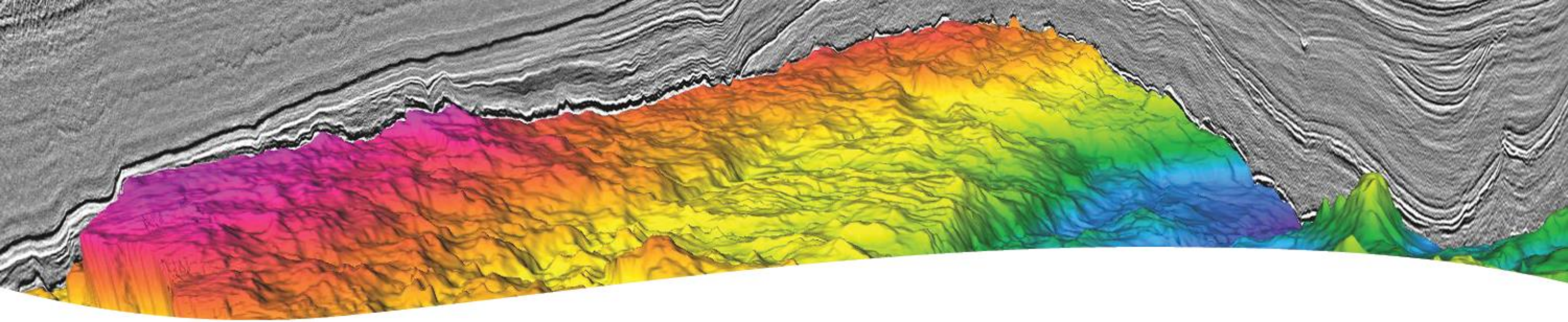
Summary: why Deep Learning is better?

- DFNN is at show great promise as a methodology to quantitatively estimate the reservoir.
- It provides better lateral continuality of predictions and is more accurate away from the well control which was confirmed by blind well validation
- The study also showed that by limiting the complexity of the network to three hidden layers and using early stopping the DFNN achieved better results than other techniques.
- The challenge in adopting DFNNs in the geoscience is the relative scarcity of labeled training data (limited well control).
- Currently, we are researching theory-based data science methodologies including training neural networks with synthetic data.

Acknowledgements

- Dan Hampson and Jon Downton of CGG for their work on DFNN and contributions to this talk

- AkerBP for their collaboration and permission to show their data



Questions