DTA

Solving Not Guessing: A unique, Non-Statistical, Machine Learning method for Curve Prediction.

Dr Ravi Arkalgud (Helio-Flare Ltd/Lloyds Register)

Ross Brackenridge (Subsurface Software Manager, Lloyd Register)





Answering the Unknown

Throughout history many have tried to answer the unknown by way of *Guessing*, this has led to the flourishing growth of new careers like....

Astrologers, Tarot readers, Palm Readers and..... Statisticians!

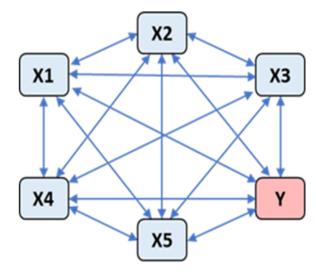


The *Guessing* has become a powerful tool to quantify the intangibles and it has led to amazing discoveries but sometimes disastrous consequences

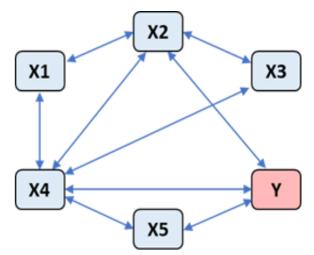
What is Domain Transfer Analysis(DTA)?

- A mathematical method developed to tackle the problem of predicting petrophysical/geological properties from minimal data
- DTA transforms data to a different domain and <u>solves</u>, hence the very name Domain Transfer Analysis.
- DTA produces a solution based on Partial Differential Equations (PDE) determining all criticalities and interdependencies
- Initial State: Representation of interaction between all elements
- Final State: Interaction between the various elements resolved
- DTA does not mix the input data unlike other statistical methods. Data identity is preserved









Partial Differential Equations

- In mathematics, a Partial Differential Equation (PDE) is a differential equation that contains unknown multivariable functions and their partial derivatives.
- This is in contrast to ordinary differential equations, which deal with functions of a single variable and their derivatives.
- PDEs are used to formulate problems involving functions of several variables.
- Just as ordinary differential equations often model one-dimensional dynamical systems, partial differential equations often model multidimensional systems.

Differential Equation

$$\frac{d^4u}{dx^4} + \frac{d^2u}{dx^2} + u^2 = \cos x$$

Partial Differential Equation

$$\frac{\partial u}{\partial t} = \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} - u$$

3 Dimensional Partial Differential Equation Example

$$\begin{aligned} \frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} + w \frac{\partial u}{\partial z} &= -\frac{\partial p}{\partial x} + \nu \left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} + \frac{\partial^2 u}{\partial z^2}\right), \\ \frac{\partial v}{\partial t} + u \frac{\partial v}{\partial x} + v \frac{\partial v}{\partial y} + w \frac{\partial v}{\partial z} &= -\frac{\partial p}{\partial y} + \nu \left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} + \frac{\partial^2 v}{\partial z^2}\right), \\ \frac{\partial w}{\partial t} + u \frac{\partial w}{\partial x} + v \frac{\partial w}{\partial y} + w \frac{\partial w}{\partial z} &= -\frac{\partial p}{\partial z} + \nu \left(\frac{\partial^2 w}{\partial x^2} + \frac{\partial^2 w}{\partial y^2} + \frac{\partial^2 w}{\partial z^2}\right), \\ \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} &= 0, \end{aligned}$$

Traffic Jam Analogy

Statistical Guessing Vs Problem Solving Drivers View TomTom/Garmin View



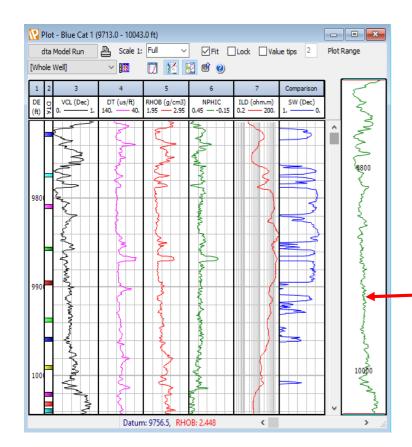
Driver chooses lane based on historical experience of which one usually gets him/her to their destination quickest



See the problem from another dimension. Uses live data to advise on best lane to take to reach destination quickest

The most common solution is not always the correct solution!!! DTA- No more Guesses, Only the Solution.

DTA User Interface in IP



	Default	Log	Well	Well	Well	Well	
	Name		1	2	3	4	
Nell 🚽			(3) Blue Cat 1	(4) Blue Cat 2	(5) Blue Cat 3		
Curve to Predict 🗦	SW		SW	SW	SW		
input Curve 1 🛛 🗄	VCL		VCL	VCL	VCL		
input Curve 2 🛛 🕂	DT		DT	DT	DT		
nput Curve 3 🛛 🕂	RHOB		RHOB	RHOB	RHOB		
input Curve 4 🛛 🗄	NPHIC		NPHIC	NPHIC	NPHIC		
input Curve 5 🛛 🕂	ILD	1	ILD	ILD	ILD		
input Curve 6 🛛 🕂	•						
input Curve 7 🛛 🕂	•						
input Curve 8 🛛 🗄	•						
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Bottom Interval	for Model Build		10043	9423	11433		
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Fop Interval	for Model Run		9713	8990	10763		
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Show Plot	for Model Run		Show Plot	Show Plot	Show Plot		
Discriminator 🚽	•						
Discriminator 🚽	•						
¢							
Advanced Well Se	lect Get Depths from	Zones		Use Custom Plo	tFormat		

DTA User Interface in IP

- Choose Number of Samples in model build
 - Default 200
 - Maximum 475
- The 'Curve to Predict' is sorted and the data levels used to create the model are taken as:
 - Top 5% of the data values
 - Bottom 5% of the data values
 - Remaining 90% equally distributed

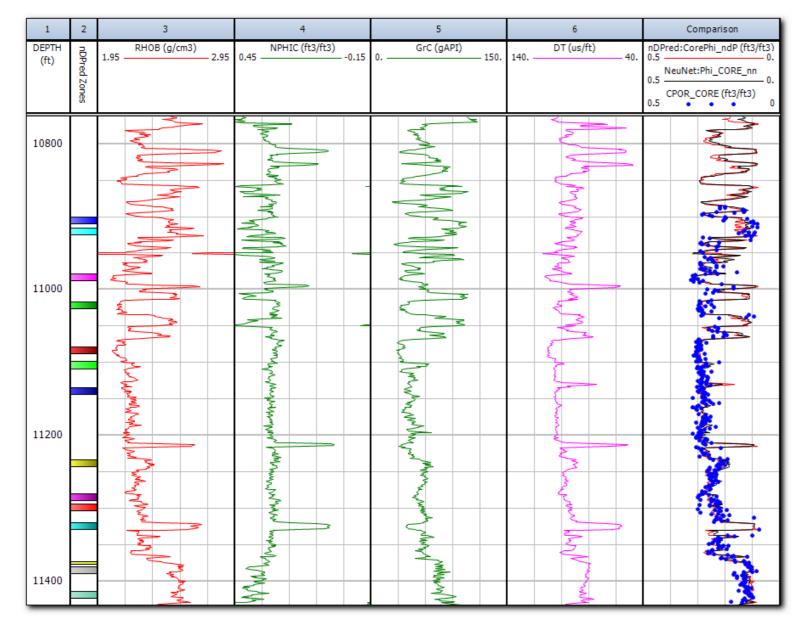
💽 Domain Transfer Analysis	5						
Input Discriminators / Zone	Options Run Model						
Create Model	475 Maximum nur Model created. 475 depti	nber of levels allowed i n levels used. R2 = 0		475)			
Run Model	Result curve name	SW_dta					
	Output Results set	DTA (DomainTransf	erAnalysis)	~ A	dd Set		
Crossplot	Null all output curve	s before running calcu	lations				
SM Report Multi-V	Well Plot		Reset form	Load model	Save model	Close	<u>H</u> elp

DTA User Interface in IP

Domain Transfer Analysis			
Input Discriminators / Zone Options Run Mo	Multi-Well Correlation - (8990 - 11433)		
	Scale 1: 1500 V Zone Set :	Wells File ▼ Settings Options ▼ IFit Tops Only Value tips	2 🖻 🜒
CICUCC	Blue Cat 1	Blue Cat 2	Blue Cat 3
Model Model created.	DEPTH (9713 ft - 10043 ft)	DEPTH (8990 ft - 9423 ft)	DEPTH (10763 ft - 11433 ft)
	1 2 3 4 5 6 Comparison	1 2 3 4 5 6 Comparison	1 2 3 4 5 6 Comparison
Result curve	PE D VCL (Dec) DT (us/ft) RHOB NPHIC ILD SW dta		D VCL (Dec) DT (us/ft) RHOB NPHIC ILD SW dta Y
Run Model Output Resul			
Crossplot Null all out			Man and a second
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SM Report Multi-Well Plot	Datum: 9364.5, RHOB: 2.289		

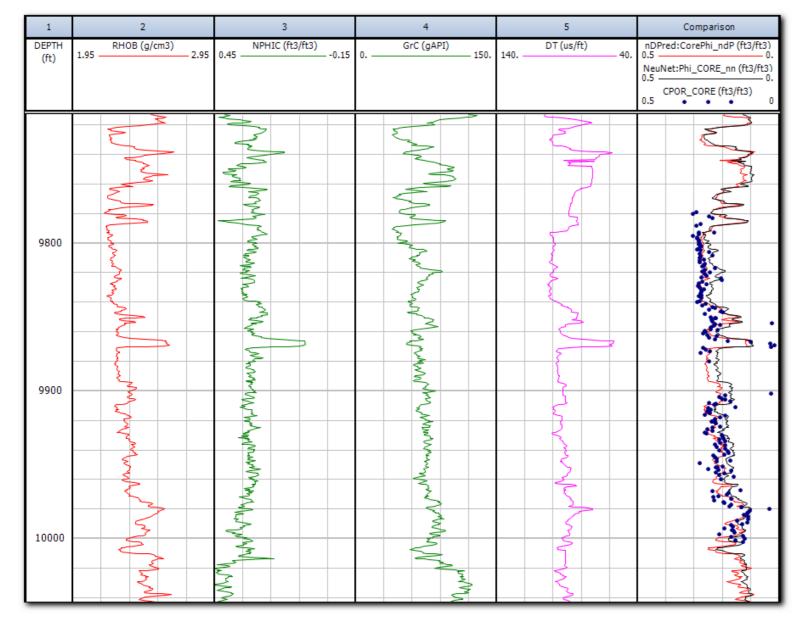
Note: DTA Parameter set consistent with other IP curve prediction modules for easy comparison

DTA Example 1 - Model Build in Well #1



- DTA Red
- NN Black
- Core Blue
- Both models very similar

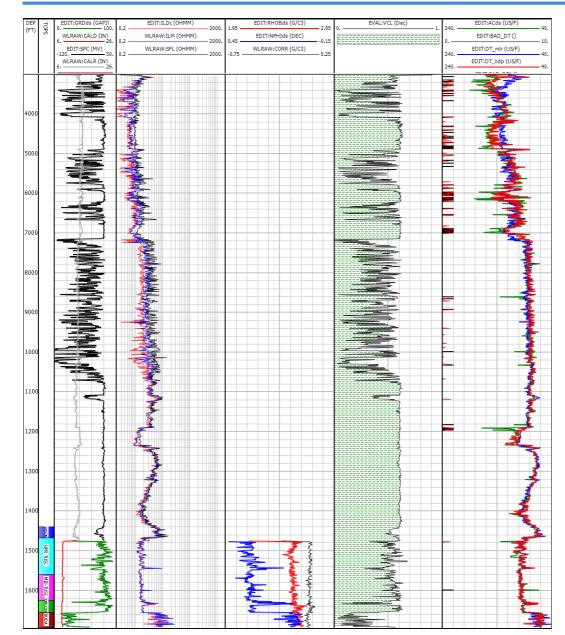
DTA Example 1: Blind Test in Well #2 which is shallower



- DTA Red
- NN Black
- Core Blue

• DTA model much better than NN when stepping out of modelled range

DTA Example 2

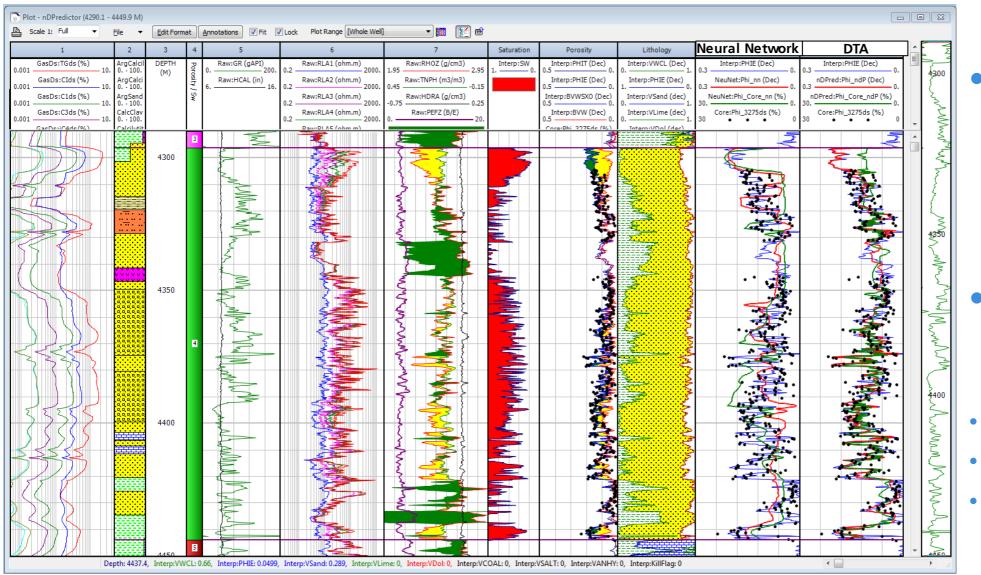


• DTC predicted from Rt, Vcl and depth

- DTA Red
- MLR Blue
- Measured Green

• In the shallow section DTA is able to model the higher DTC due to the loss of compaction, where MLR is not.

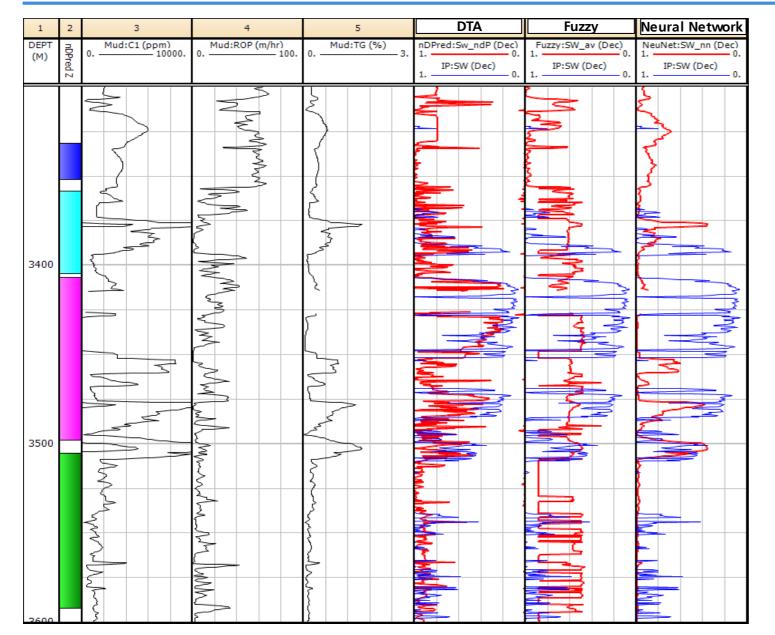
DTA Example 3



Porosity prediction from mud gas (the only inputs to the model are in Track 1)

- DTA much better than NN Data
- Log derived PHIE is Blue
- Prediction of PHIE is Red
- Prediction of PHI_core is PHI Green

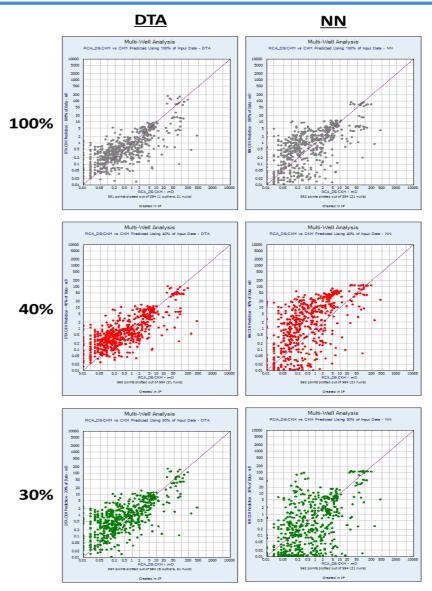
DTA Example 4



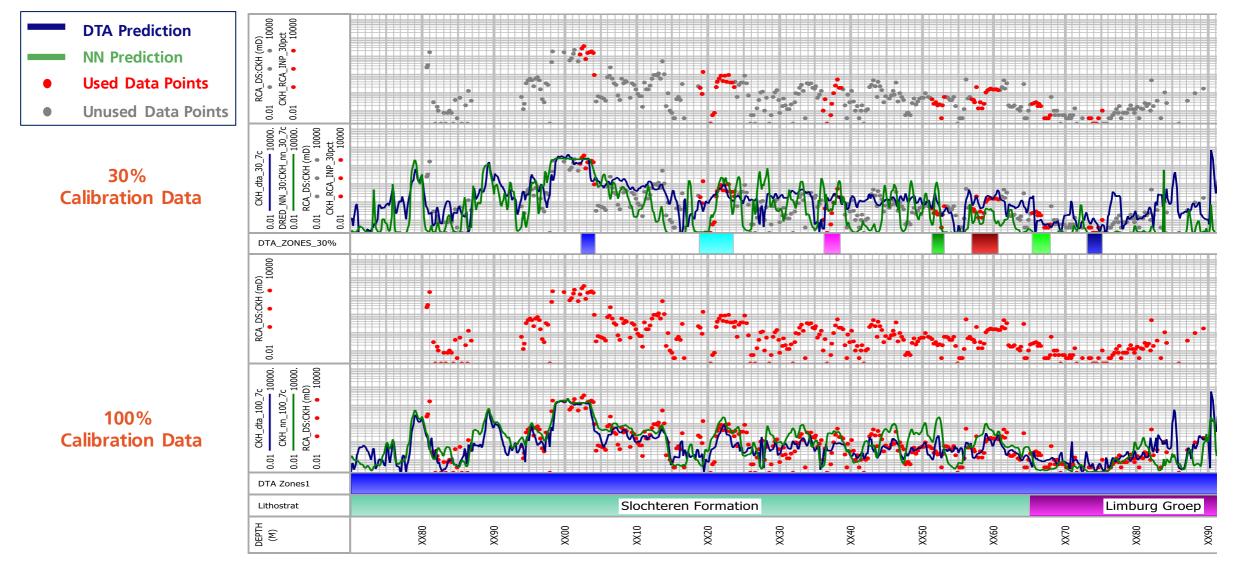
- Sw Prediction from mud and drilling data (C1, TG and ROP)
- DTA much better than Fuzzy Logic and Neural Network

DTA Example 5: Robustness of DTA

- Predicted continuous permeability based on discrete core data using both DTA and NN techniques
- Several curves selected for building model:
 - Gamma Ray; Density; Neutron Porosity; Compressional Slowness; PE, Thorium, Potassium
- Prediction executed for different volumes of calibration data
- DTA proved consistent at levels of 40% and 30% of reduced data set while NN accuracy reduces
- Study demonstrates the robustness of DTA with reduced input data volume



DTA Example 5: Robustness of DTA



Benefits of DTA

- DTA can more accurately predict outside the range of data used to build the model
 - Fuzzy Logic cannot predict outside the range of data used to build model
 - Multi-Linear Regression can predict outside the range but can be very wrong
 - Neural Networks can be unstable
- DTA does not need lots of data to build a robust model, it is designed to work with sparse and heterogeneous data sets
- Results are exactly repeatable, One Data Set = One Solution
 - Neural Networks are non repeatable when training and can be 'over-trained' (difficult to know when to stop training)
- DTA handles the non linearity of geological data
- Geological characteristics of the subsurface (e.g seismic, log responses, core etc.) are accounted for in the gradients of the PDE based solution.

Thank You

Please contact:

Ross Brackenridge

Subsurface Digital Products Manager

Lloyds Register

ross.brackenridge@lr.org