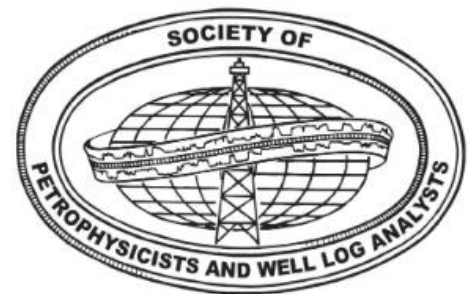




The Benefits and Dangers of using Artificial Intelligence in Petrophysics

Steve Cuddy



Outline

- What is Artificial Intelligence (AI)
- **Petrophysical Case Studies** showing successful applications
 - Evolution of shaly water saturation equations
 - Nuclear Magnetic Resonance T1 & T2 spectra analysis
 - Prediction of shear velocities
 - Litho-facies and permeability prediction
 - The log quality control and repair of electrical logs
- Narrow vs. General vs. True AI
- The dangers of using AI
 - More than AI making poor petrophysical predictions!

What is Artificial Intelligence?

- Getting computers to imitate human intelligence – Alan Turing
- AI is data analysis that learns from data, identify patterns and makes predictions with the minimal human intervention
- **First generation AI:** Expert or Rule based systems
 - Simple petrophysics
 - IBM's Deep Blue, beat chess Grandmaster Garry Kasparov in 1997
- **Second generation AI:** Machine learning
 - Evolution of water saturation equations, NMR spectra analysis, permeability prediction
 - Google's AlphaZero, self-taught computer program, easily beats all first-generation AI
- **Third generation AI:** The evolution of machine code
 - Using rules similar to the ones life's DNA code use
 - True AI with General Intelligence

Artificial Intelligence only requires Two Things

1. You tell the AI what you want.
 - This is its goal or **fitness function**

2. The data.

There's Minimal human interaction

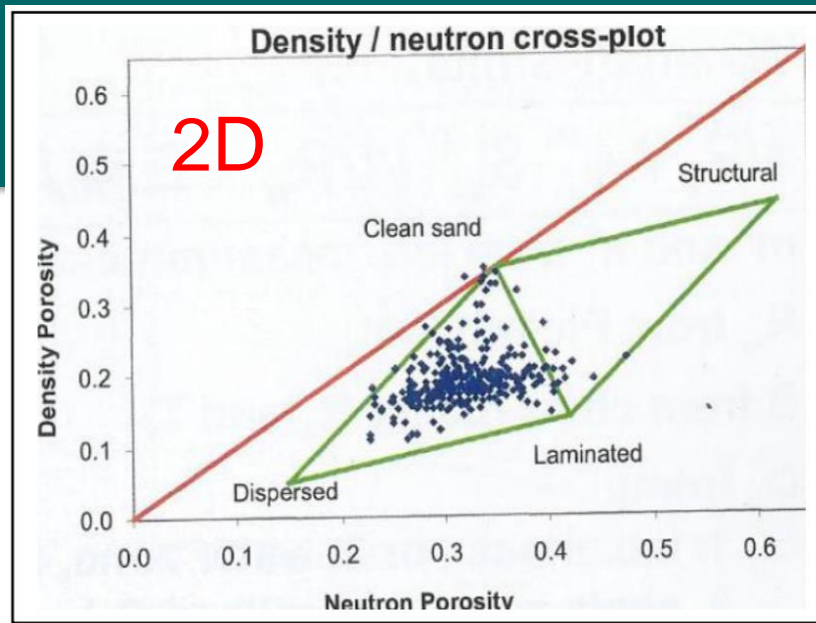
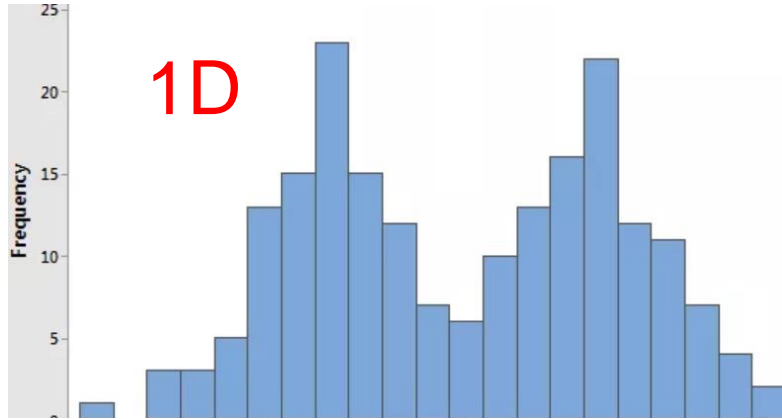
- AI doesn't require prior knowledge of the petrophysical response equations
- There are **no** parameters to pick or cross-plots to make

AI is given access to all the data

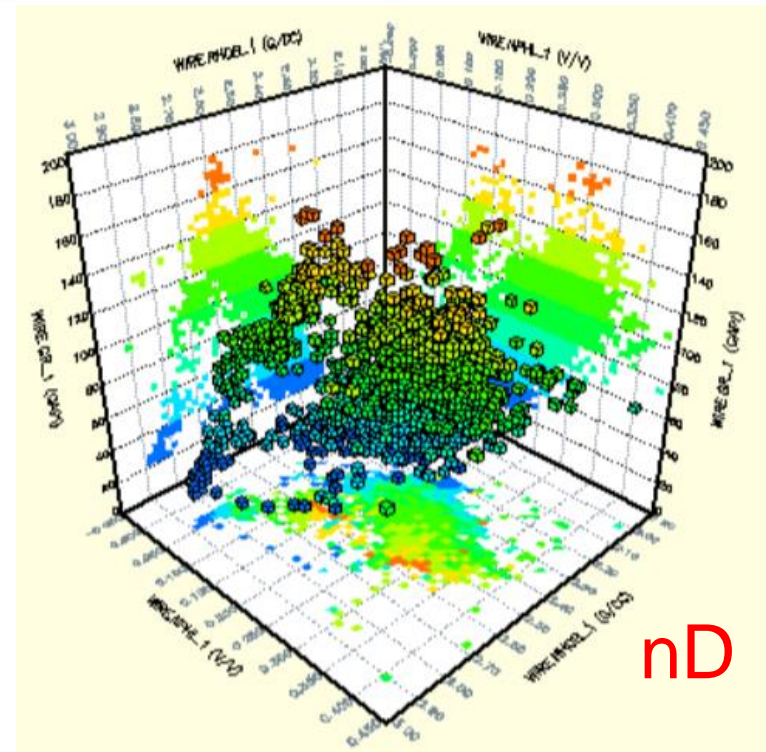
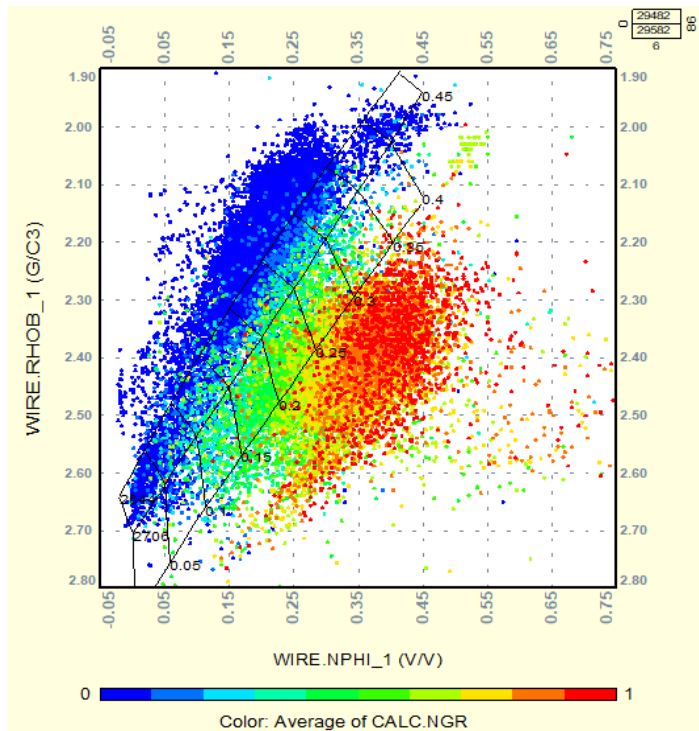
These include:

- Electrical logs - GR, Rhob, caliper, drho etc.
- Core data - porosity, core Sw, SCAL etc.
- Depth - measured and TVDss (probably the most important parameters)
- Gas - chromatography data (essentially a free measurement)
- Drilling data - ROP, Dexp etc.
- NMR - T1 & T2 distributions (spectra)
- etc.
 - Don't worry if these data contain garbage, as explained later

What is n-dimensional Data?



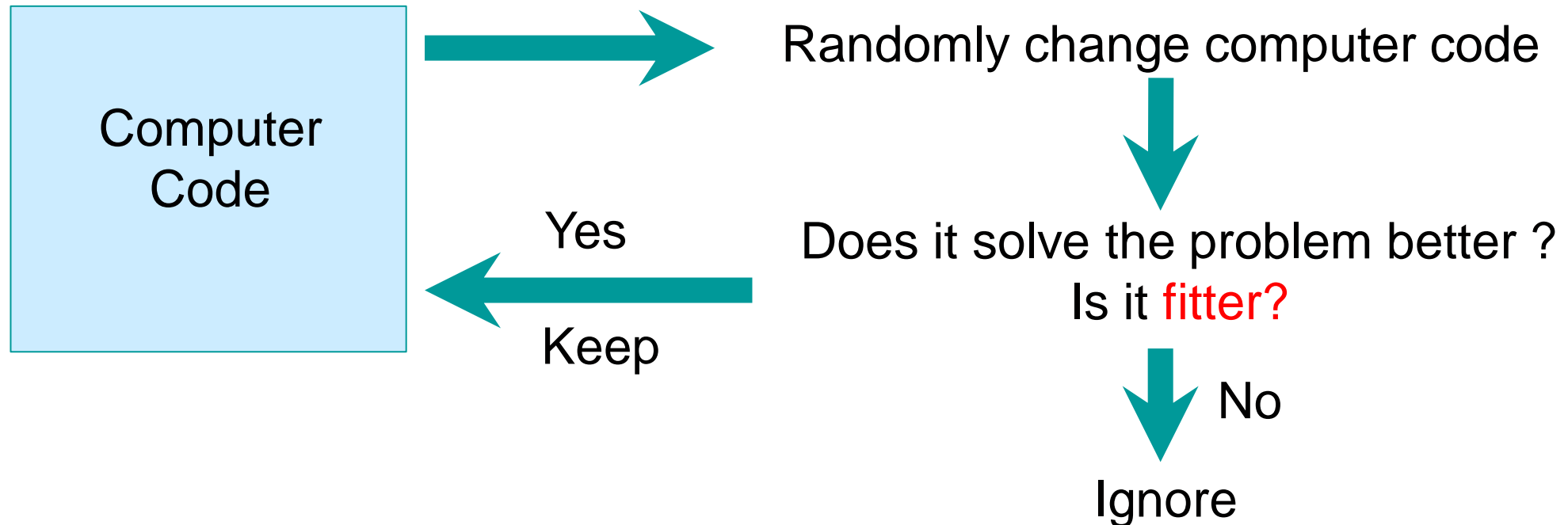
3D



Relational database where **n** is the number of logs and other inputs

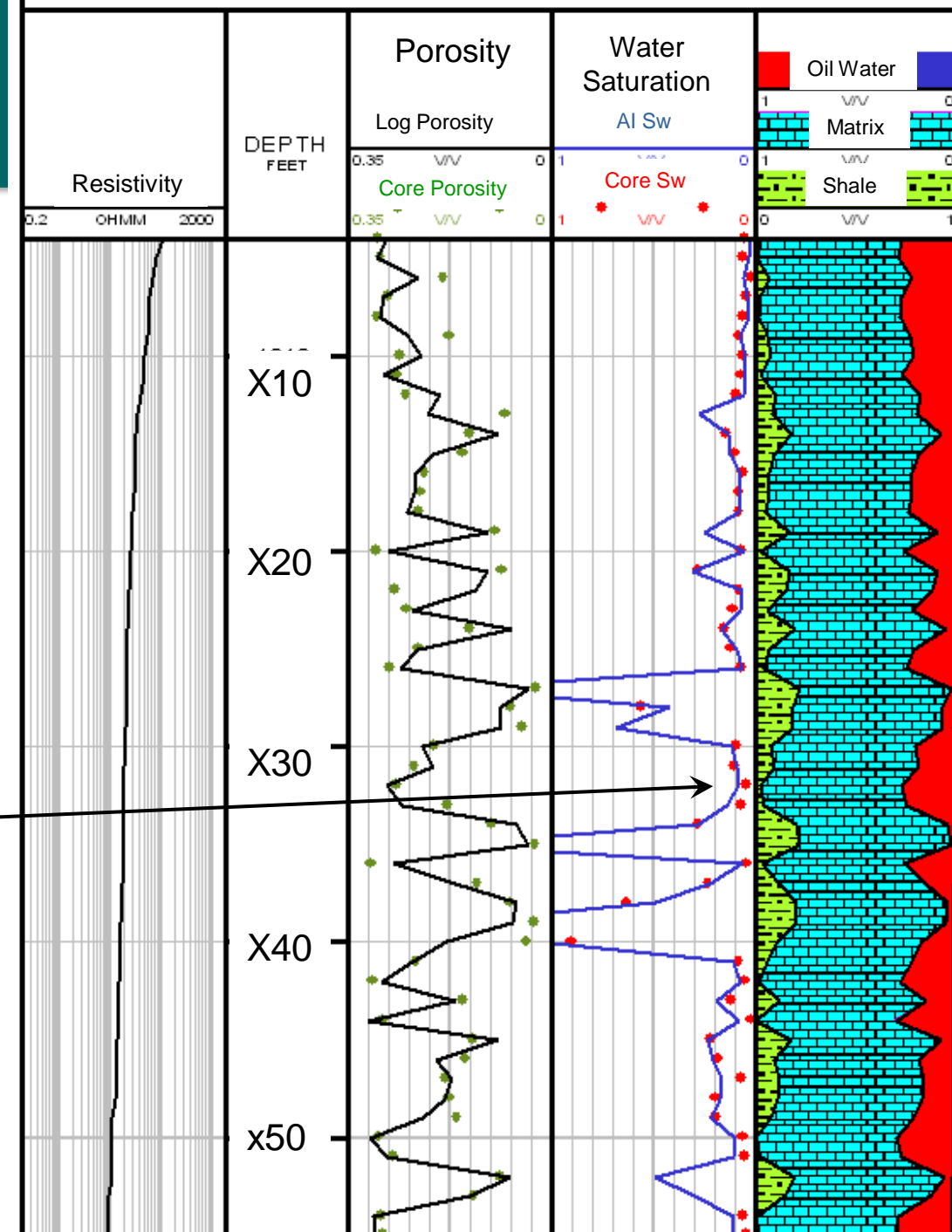
Second Generation AI

- We define the problem - **Fitness Function**
- We give the program access to the data
- The computer guesses the answer and through successive iterations (generations) 'evolves' the best answer



Petrophysical Case Study 1

- A Middle East Carbonate Reservoir
- Client required a bespoke shaly water saturation equation to derive water saturation from the resistivity and gamma-ray logs
- Client also wanted an independent check of the Special Core Analysis (SCAL) parameters 'm' and 'n'
- Core water saturations
 - Core plugs taken from the centre of the core
 - Dean & Stark
 - Drilled with OBM
 - Doped mud to ensure no contamination



Saturation Equation Determination

- **Fitness Function** – ‘determine an equation so that the resistivity predicted water saturations are as close as possible to core derived water saturations’
- Start by assuming $S_w = \text{Function}(\text{Porosity}, \text{Resistivity}, \text{Volume of shale})$
- AI may ‘re-invent’ the Indonesia or Simandoux equation or create a specific equation for the field

$$S_w = \sqrt[n]{\frac{aR_w}{R_t \phi^m}} \qquad \frac{1}{\sqrt{R_t}} = \left[\frac{V_{sh}^{(1-V_{sh}/2)}}{\sqrt{R_{sh}}} + \frac{\phi^{m/2}}{\sqrt{aR_w}} \right] S_w^{n/2}$$

S_w = Water saturation

ϕ = Porosity

R_t, R_{sh}, R_w = Resistivities

V_{sh} = Volume of shale

a, m, n = unknown constants (SCAL)

Middle East Carbonate Reservoir

- Calibrated to core water saturations
- AI Fitness Function
 - 'Find the best shaly sand equation so that the resistivity derived Sw matches the core Sw'

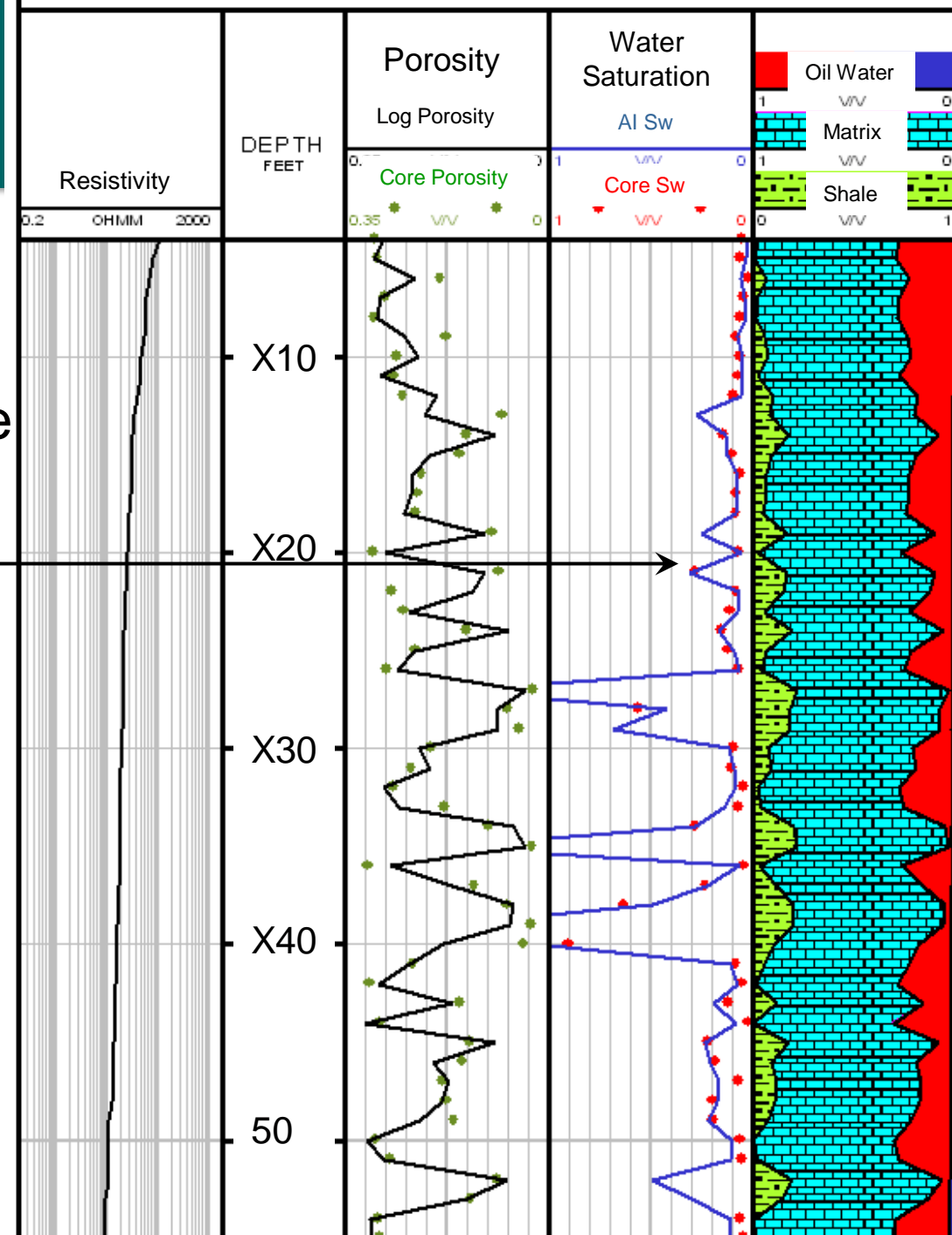
Result

$$\frac{1}{R_t} = \frac{\phi^m S_w^n}{R_w} + bV_{sh}^c$$

S_w = water saturation
 ϕ = porosity
 R_t, R_w = resistivities
 V_{sh} = shale volume
 m, n, b, c = constants

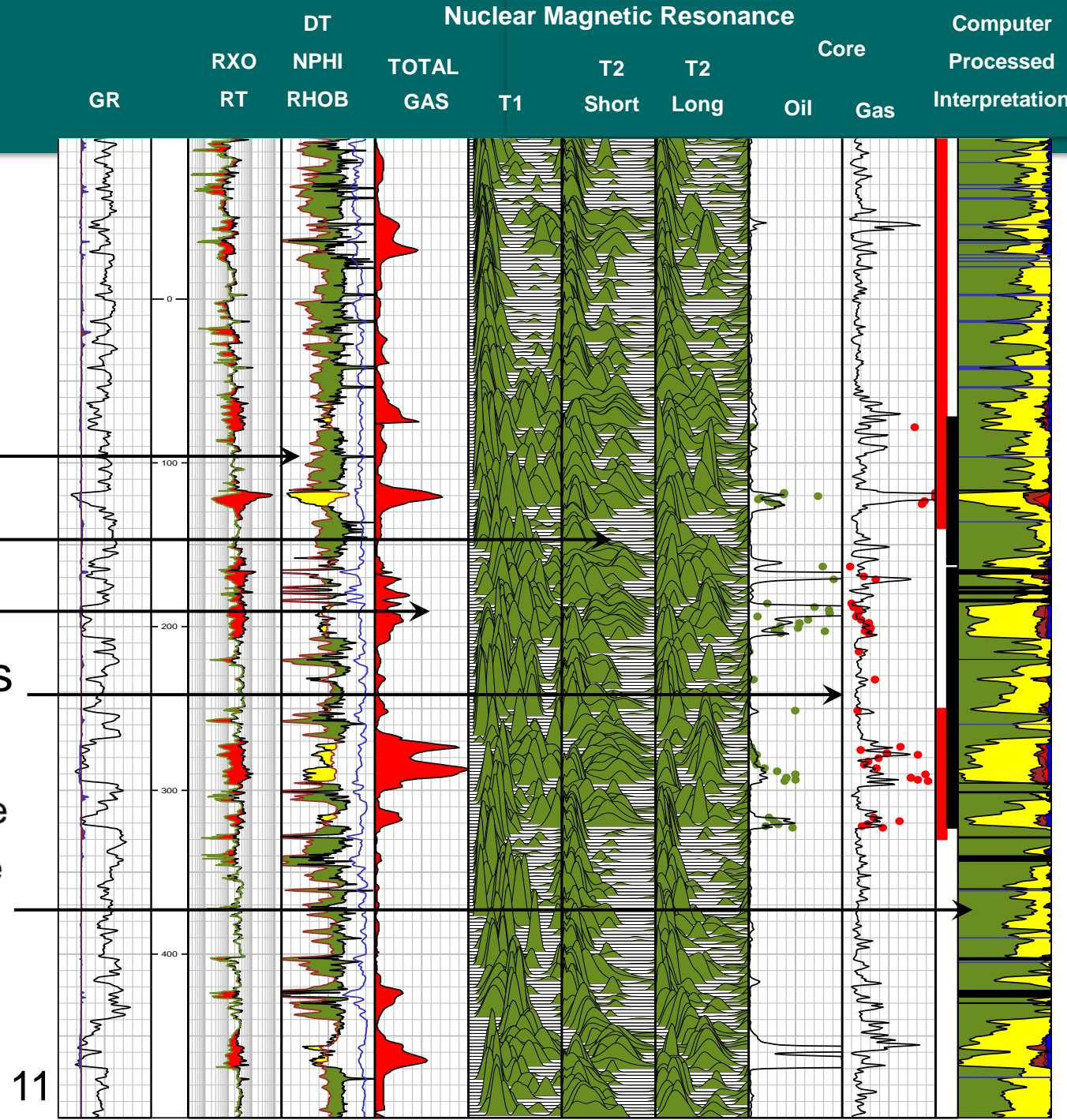
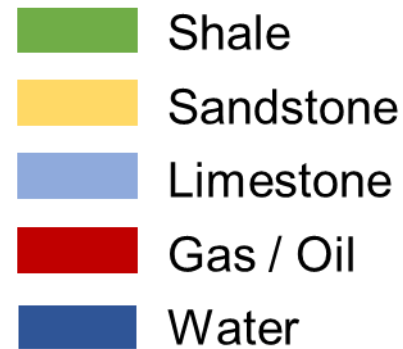
AI Special Core Analysis:

- Cementation exponent (m) 2.214
- Saturation exponent (n) 1.751
- Both are derived at **reservoir conditions**



NMR Pattern Recognition

- Case Study 2
 - A gas field with an oil problem
- Data:
 - Conventional logs
 - NMR T1 and T2
 - Gas Chromatography
 - Core derived oil and gas saturations
- Petrophysical analysis

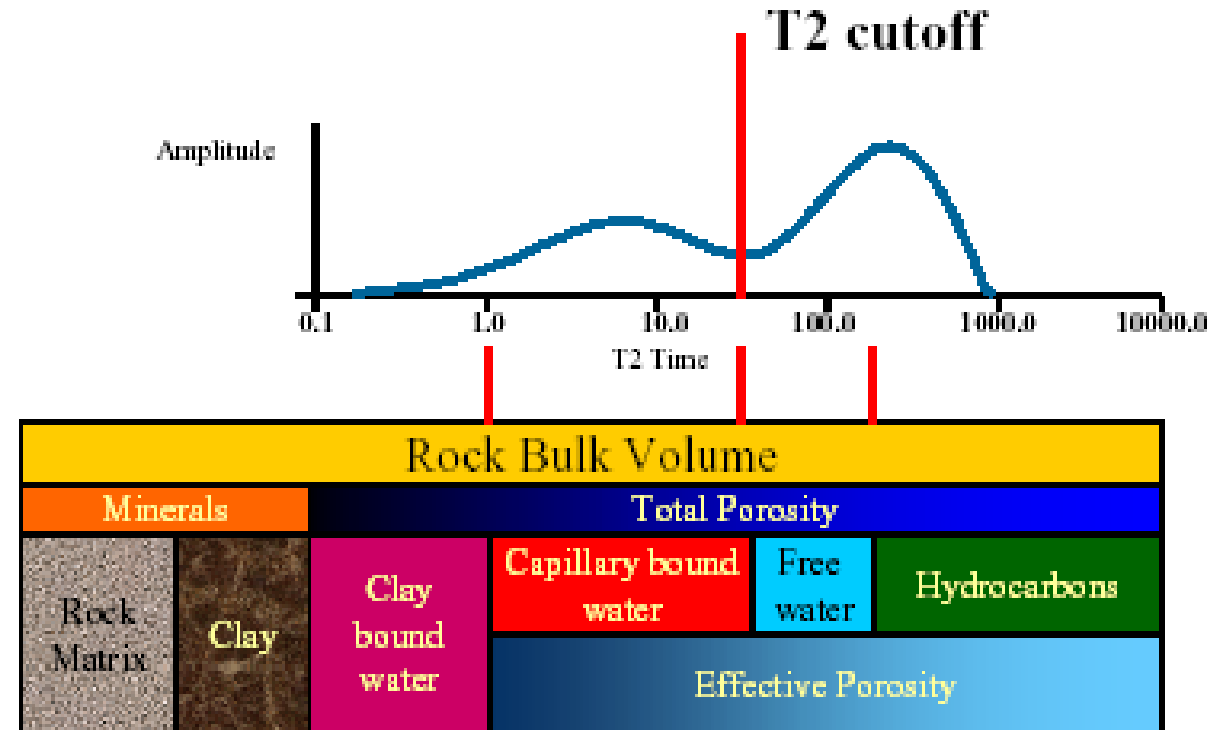


Case Study 2 – NMR Pattern Recognition

- A gas field with an oil problem
- Residual oil pockets remain within the main gas reservoir
- This oil is highly viscous
- If produced could block the production tubing
- The client needs to identify oil and gas in order to only perforate the gas zones
- Conventional petrophysical techniques like density / neutron porosity separation can't differentiate oil and gas due to thin beds and the shaly formation

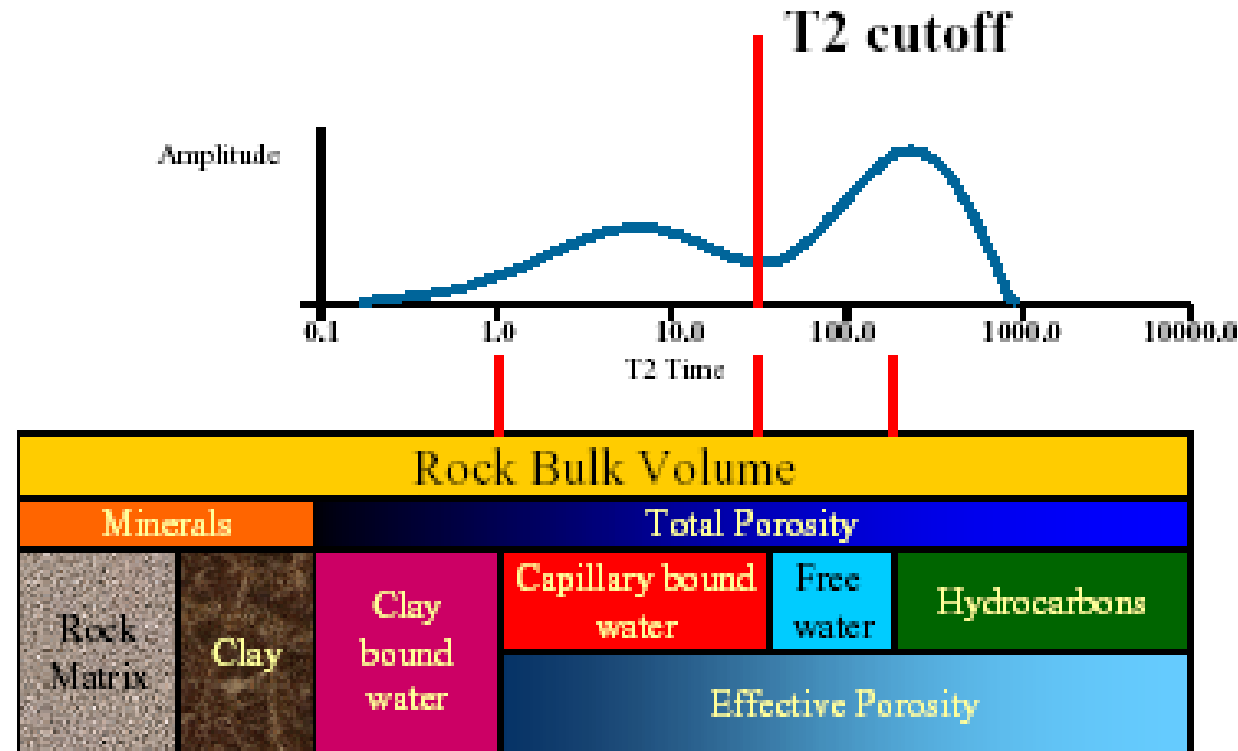


Nuclear Magnetic Resonance



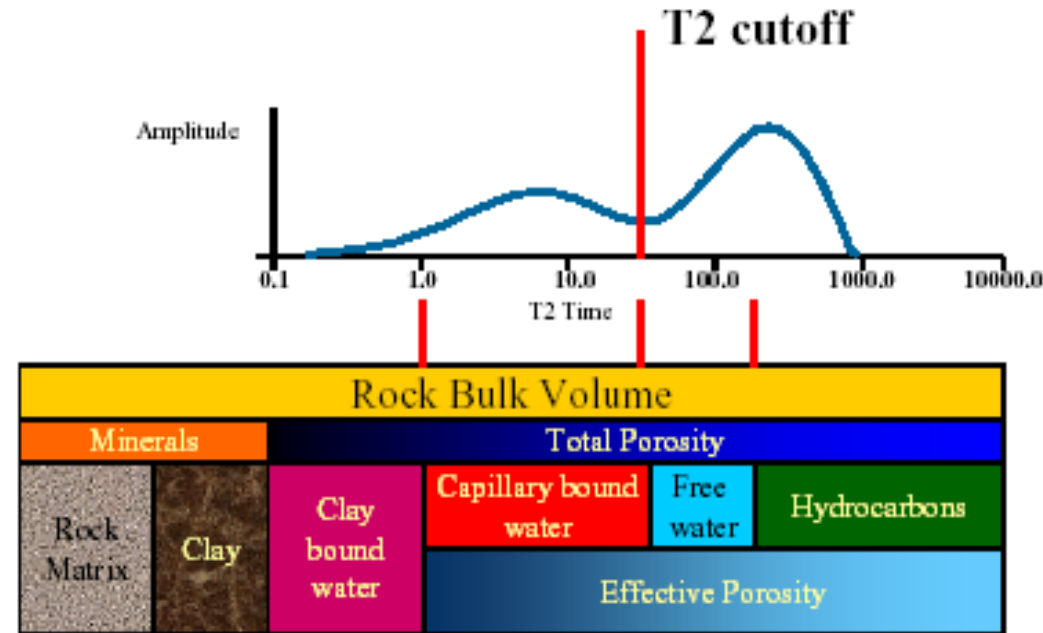
- The solution lies with nuclear magnetic resonance (NMR)
- Essentially this measures how hydrogen atoms respond to a magnetic field

Oil and Gas identification using NMR



- Conventional NMR analysis uses the Coates or Schlumberger-Doll-Research (SDR) methods
- These use very little of the wealth of information contained in the T2 distribution!

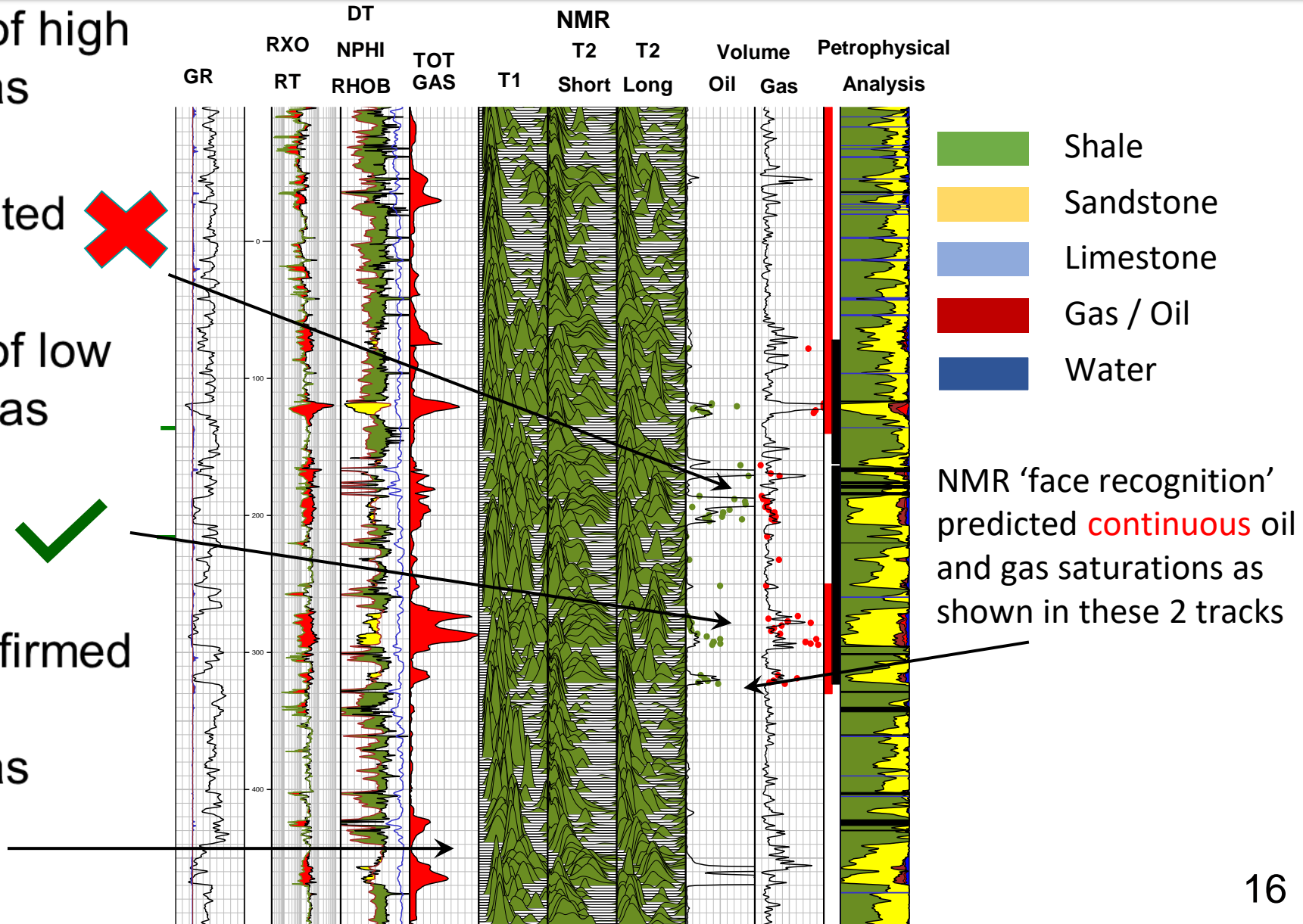
Oil and Gas identification using the NMR and AI



- AI determines the NMR spectra (waveforms) associated with the core derived oil and gas analysis, in a similar way to how face recognition algorithms work
- It then predicts the fluid content of all the reservoir beds
- **Fitness Function:** 'Determine the spectra that give the best match to the core derived oil and gas saturations in the reservoir'

Results – Real time identification of gas and oil zones

- NMR identified intervals of high oil saturations and low gas saturations
 - These were not perforated ❌
- NMR identified intervals of low oil saturations and high gas saturations
 - These were perforated ✅
- These intervals were confirmed using the borehole fluid analyser and borehole gas chromatography



The AI Engine

- AI is data analysis that learns from data, identify patterns and makes predictions with the minimal human intervention
- AI uses neural networks, genetic algorithms, fuzzy logic, random forests
- AI avoids Garbage In, Garbage Out (GIGO) by
 - good data swamping poor data
 - by using fuzzy logic and
 - by **avoiding** least squares regression

Fuzzy Logic (the inverse of Crisp Logic)

Things become fuzzier

- Black
- Classical logic X
- Statement is True
- Defendant is Guilty
- Politically Left
- Movie Goodies
- Mountains on maps
- Petrophysical Net
- White
- Not X
- False
- Not Guilty
- Right
- Baddies
- Valleys
- Non-Net

Things become Crisper



SPWLA 2020, Banff Springs Hotel

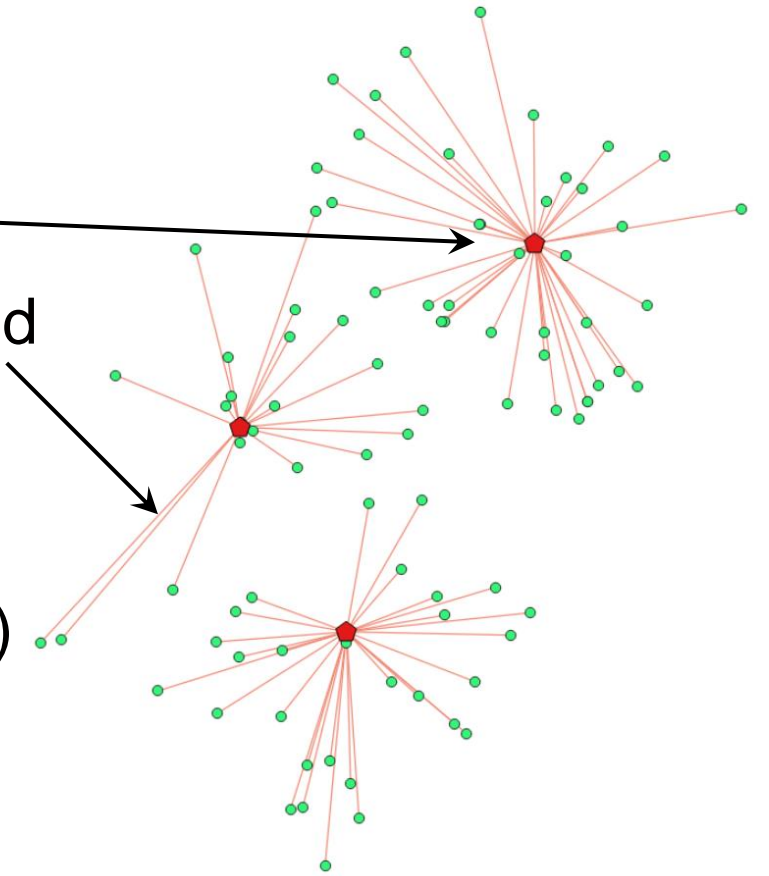
Is the sky clear or cloudy?
The answer is never black and white

Fuzzy Logic

- An extension of the classical logic of 0 and 1
 - uses a 'grey scale' between 0 and 1
- Fuzzy logic looks for correlations in data space
 - asserts there is valuable information in the fuzziness (1/crispness)
 - avoids the problems of outliers and noise
- Fuzzy logic says **any** petrophysical interpretation is possible
 - only some interpretations are more likely than others
- Fuzzy logic maths is freely available
 - SPE & SPWLA papers

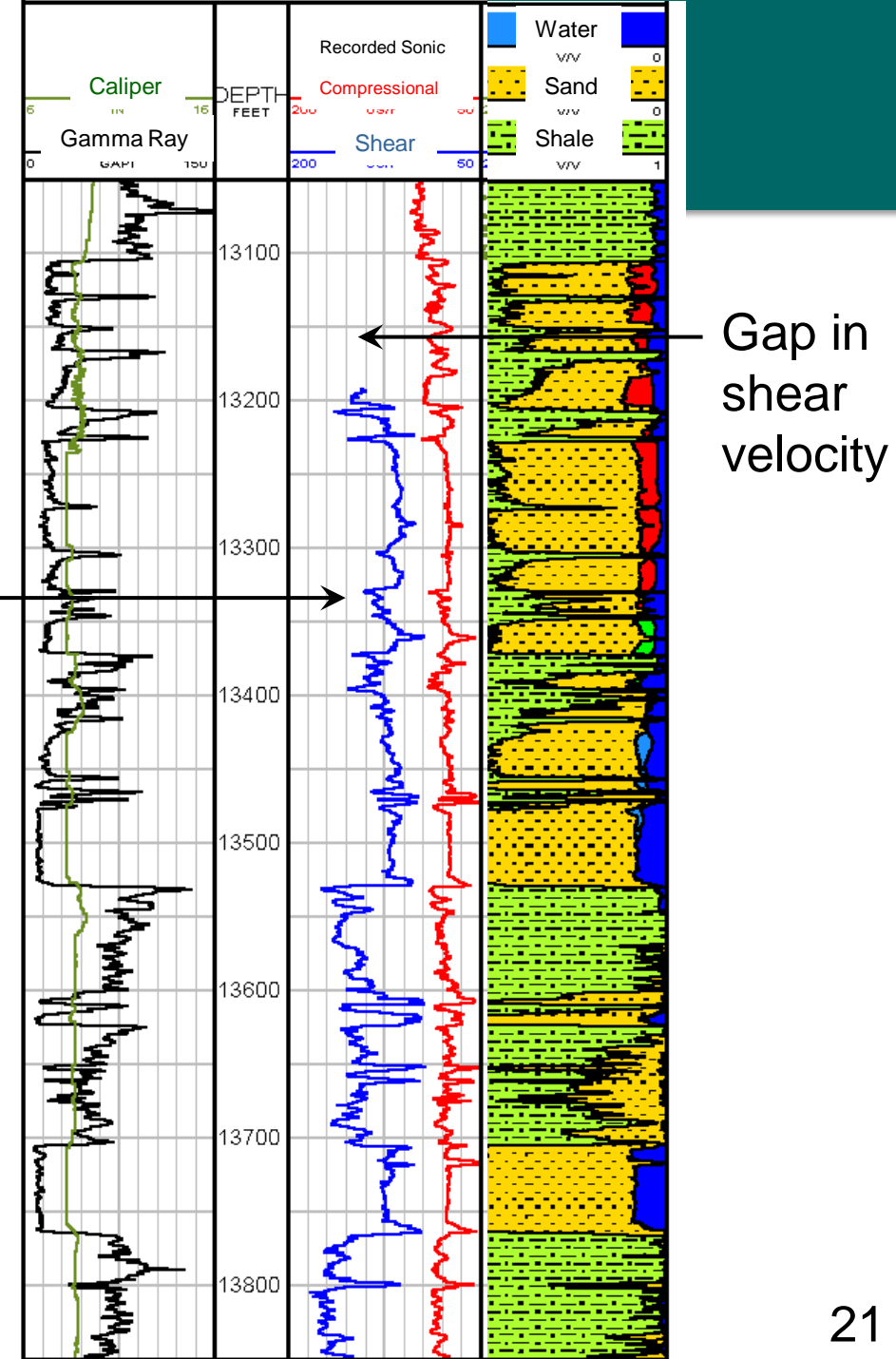
The AI Engine

- In n-dimensional data space, the k-NN algorithm assumes that similar things exist in close proximity or nearest neighbour
 - e.g. litho-facies - sand, shale or carbonate
- The straight-line distance (the Euclidean distance) is used
 - in addition, fuzzy logic weights these lines depending on the likelihood of the association
- For instance, if the gamma-ray is highly correlated (crisp) with shaliness, this vector will have more influence on the AI's decision compared to say the caliper reading at the same depth



Shear Velocity Prediction using AI

- Case Study 3
 - North Sea Field
- Only four wells had recorded shear velocity data
- Shear velocity was required on all 30 wells
 - for rock property analysis
 - wellbore stability
- Gaps and cycle skips need to be fixed



Shear Velocity Prediction using AI

Fitness Function – ‘Determine a relationship so that the predicted shear velocities are as close as possible to log derived shear velocities’

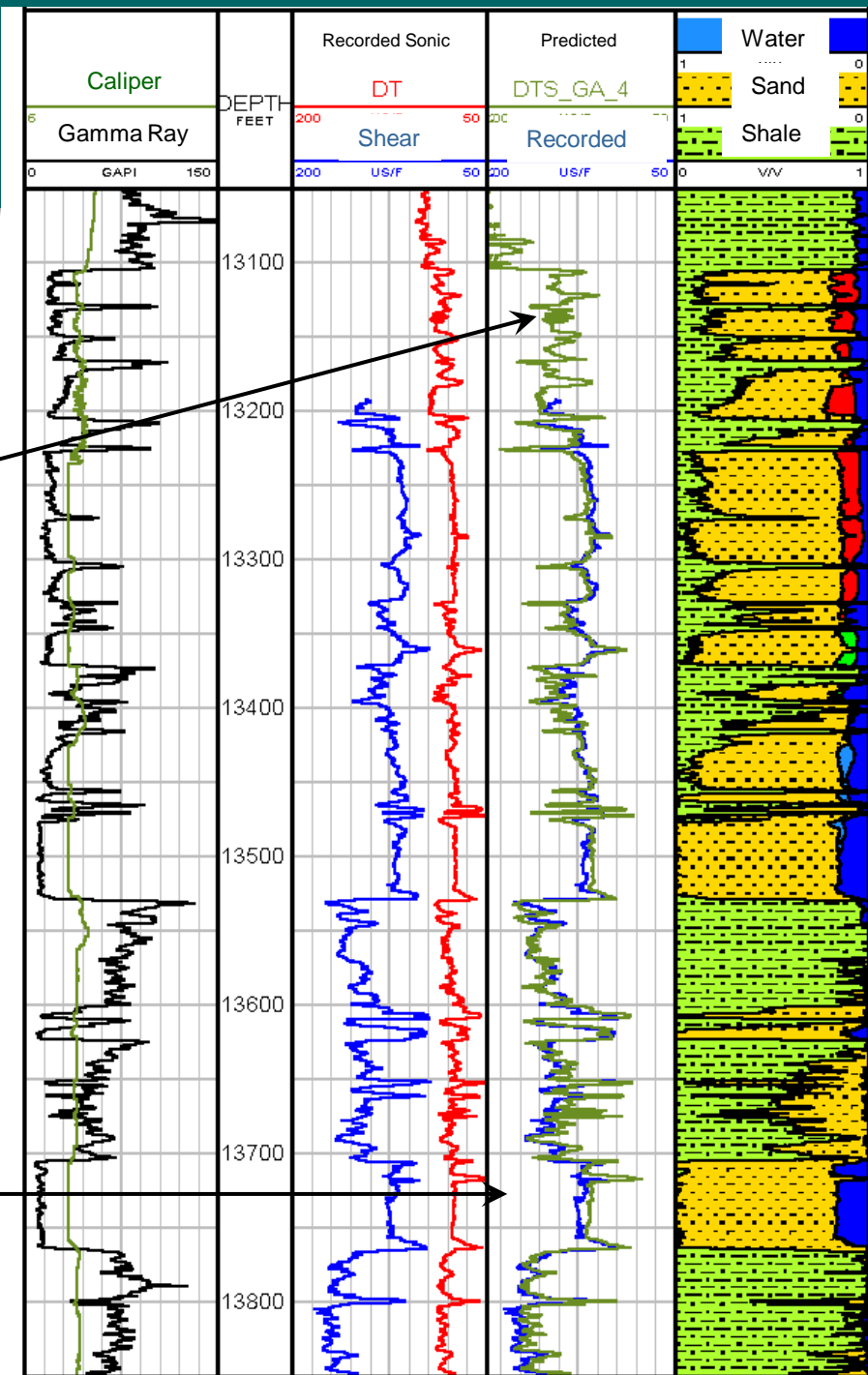
Predicted shear velocity = Function of:

- conventional logs
- drilling data
- gas chromatography data

The AI evolves the relationship

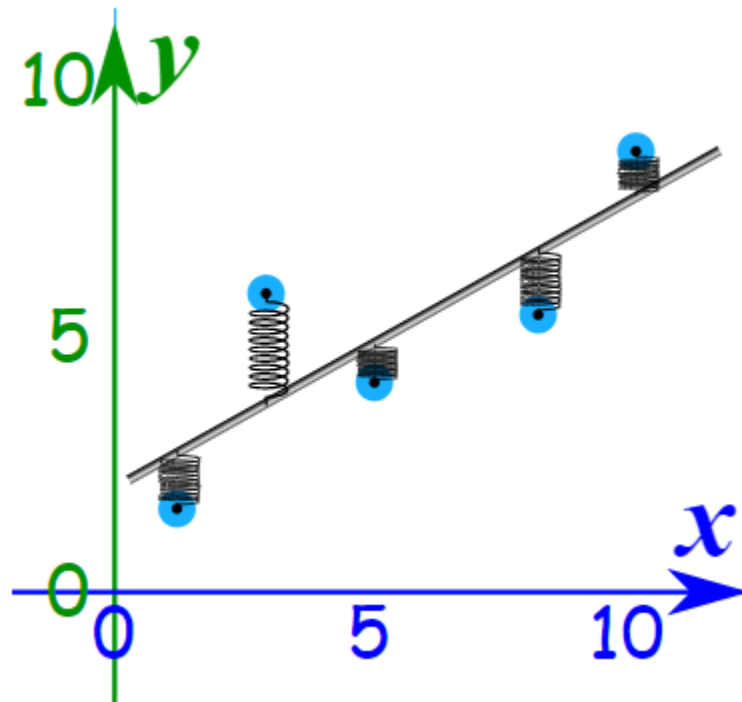
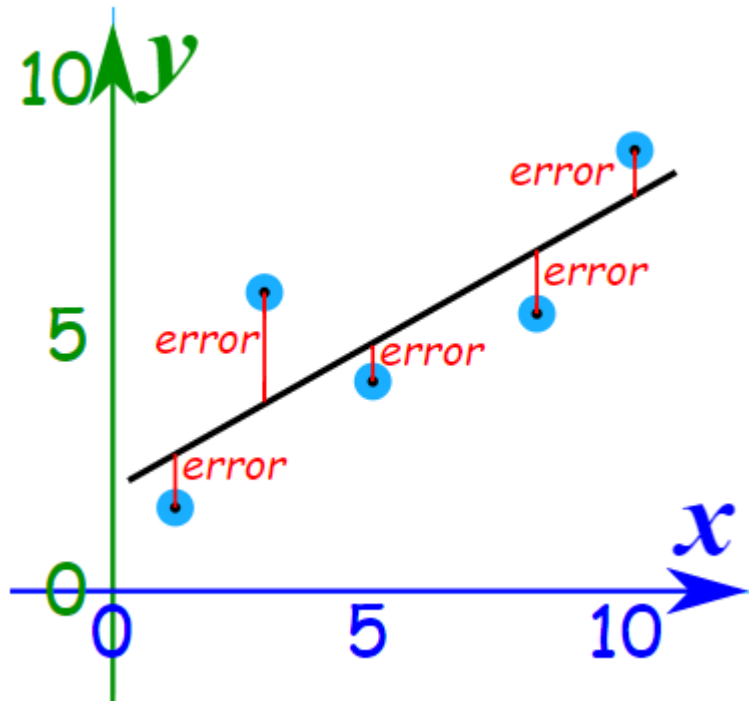
The AI predictions are **better than the recorded logs!**

- because AI has access to all logs, including logs with high vertical resolution like the micro-resistivity



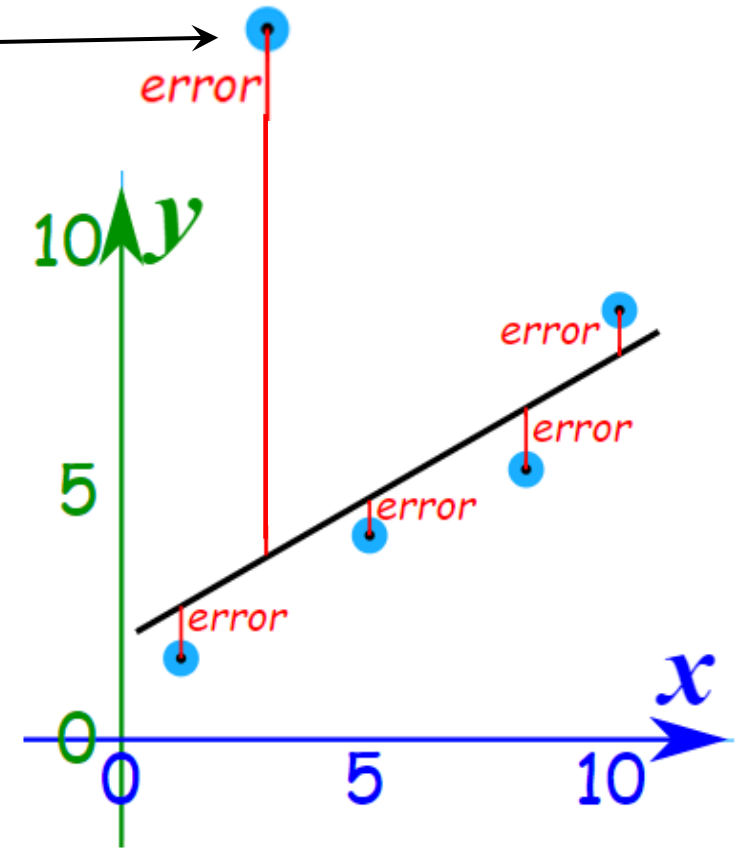
Linear Regression

- AI finds relationships in the data in order to make predictions
- Least squares regression is often used
- This minimises the sum total of the **square** of the errors



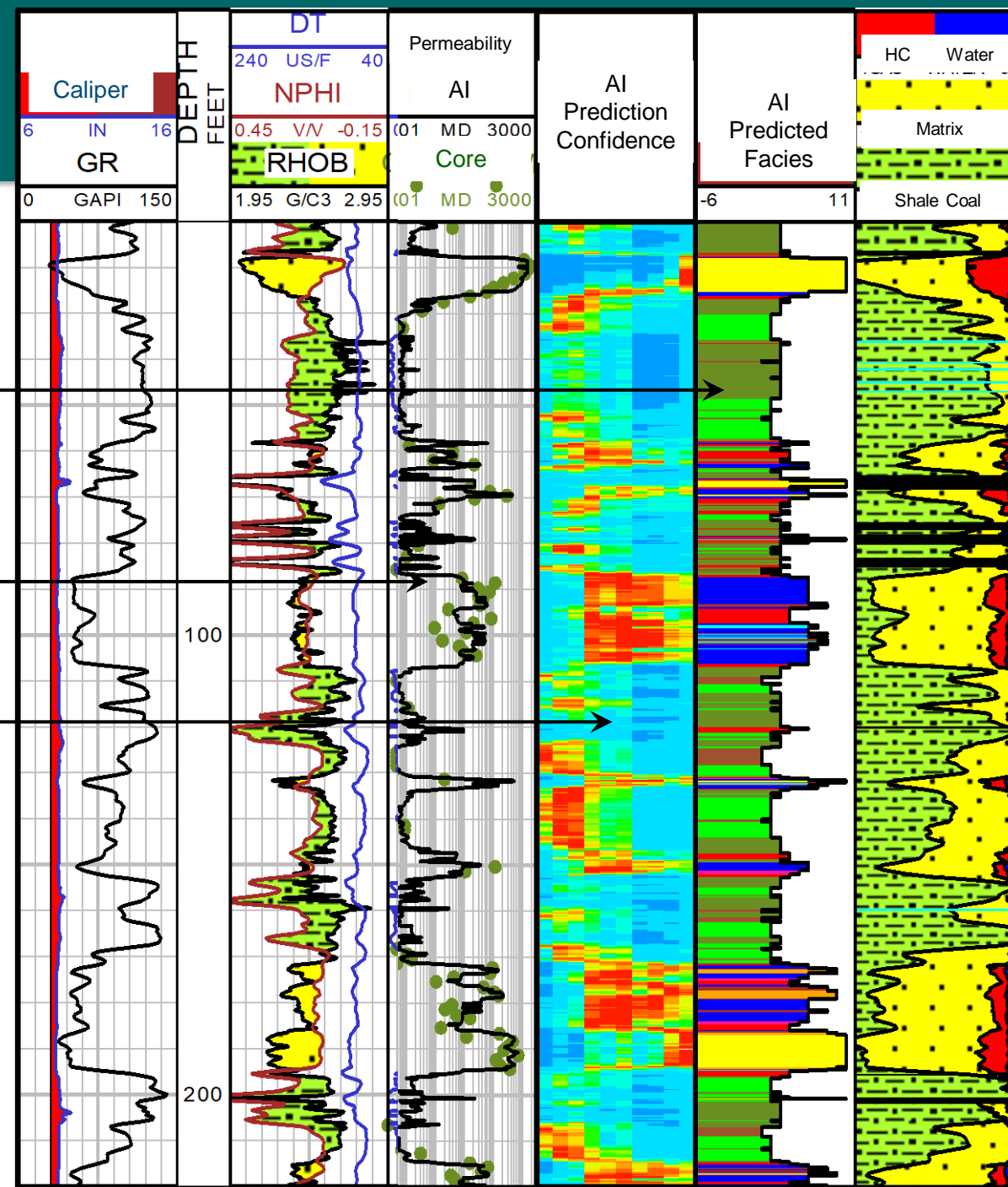
Linear Regression

- Least squares regression is **undemocratic**
- Outliers unfairly influence the result \longrightarrow
- A point 10 times further from the line has a 100x the weighting
- These are very difficult to remove manually and would introduce human bias
- Outliers may be valid data (coal beds, calcite stringers)
- Best keep them and minimise the **linear distance** rather than the squared distance
- Random noise should be **swamped** by valid data



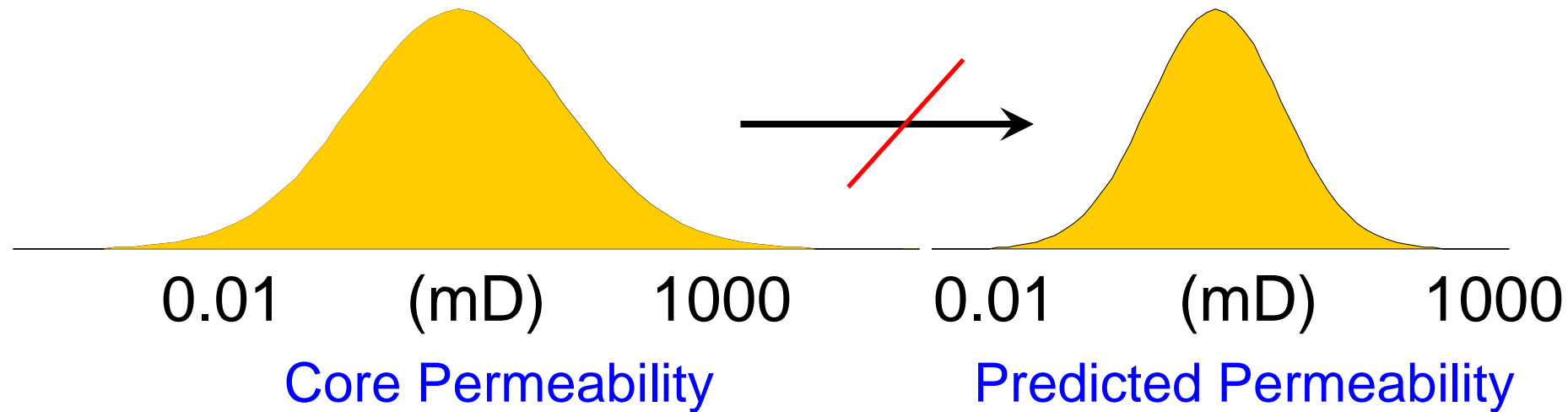
Permeability Prediction

- Case Study 4 - North Sea Field
- AI first predicts the facies type
- Permeability is then predicted based on the facies type and all other logs
- All interpretations are possible but some are more likely than others
- How do we know if the AI permeability any better than from regression analysis?
 - Beauty contest required!



AI predicts the correct permeability distribution

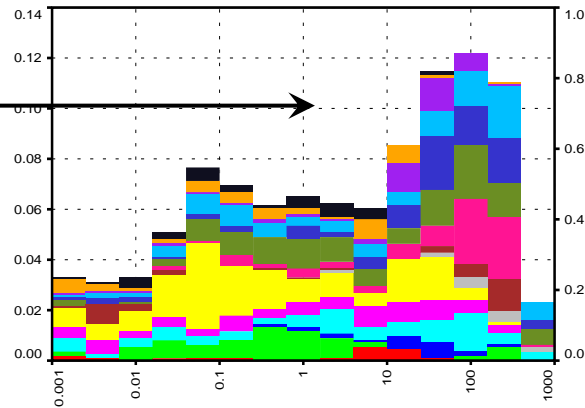
- Log and core permeabilities typically represent 2 feet
- To be used in a 3D reservoir model the predicted permeabilities must upscale correctly
- They must have the same distribution (dynamic range) as the core data



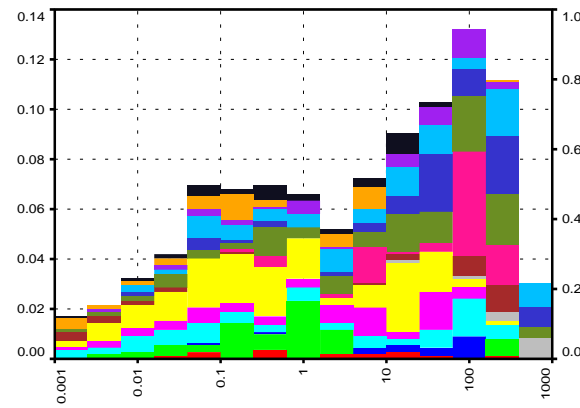
- Least square methods regress toward the mean
- AI preserves the dynamic range

Comparison between Permeability Distributions

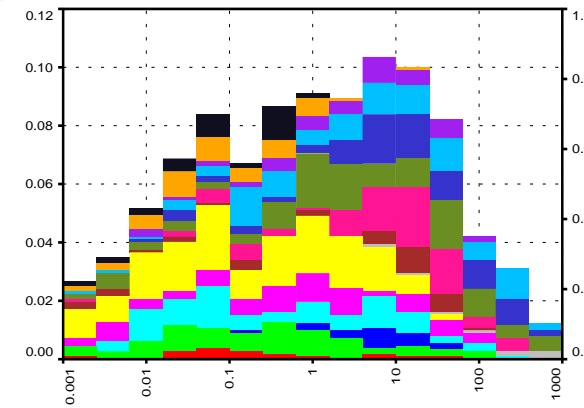
Core distribution



AI prediction



Linear Regression



Bimodal
distribution

- Permeability frequency plots (mD - log scale)
 - Colour shows data from 15 cored wells
- AI predicted permeability matches core distribution
 - High permeabilities are the reservoir's conduits to flow
 - Low permeability are barriers to flow
- Regression permeability techniques give poor predictions at the extremes
 - These will be incorrect when upscaled to the geocellular reservoir model

Narrow vs. General AI

- Narrow AI is like apps on your smart phone
 - Good at forecasting the weather, converting currencies or ordering a coffee for you
 - An earthworm has far more intelligence than Narrow AI
- General AI, like humans, can do many things
 - They can play chess **and** do petrophysical analysis
- General AI
 - Learns from one specialist area and applies it in another
 - They will be genuinely **creative** with the ability to produce something original
 - General AI is True AI
- General AI will not require you to describe the problem or give it the data
 - It knows you better than you know yourself, and knows where to find the data
 - e.g. When leaving a meeting it knows you are going home and suggests the best route

Quality Control and Repair of Electrical Logs (LQC)

- Case Study 5
- It is essential to confirm log quality before they used by the petrophysicist
- AI automatically identifies and repairs poor logs
 - Washouts
 - Gaps
 - Poor readings
- Doesn't require a skilled user

Quality Control and Repair of Electrical Logs

PetroPredict main screen

File & Database | Curve Q.C. and Repair | Themes

Save | Delete | Create | Project | Exports | Links | Assigned curves | Work area repair modes | SET/GET | Calculations | Plot

Active project: Demo | Start depth: 11022.5 | Bit size min: 6 | Stop depth: 11822 | Bit size max: 20 | Timestamp: 05/07/2005 14:33

Assigned curves (Track1/curve1 contains the 'target curve')				Hole quality tops		Zone tops			Bit size tops	
Track	Curve 1	Curve2	Curve 3	Depth	Quality	Depth	Title	Colour	Depth	Bit Size
1	RHOB G/C3 (De... X			11022.50	1	11022.50	top	Green	11022.50	12.25
2	C1 PPM (Demo2, Repai...	C2 PPM (Demo2, Repai...	C3 PPM (Demo2, Repair T...	11314.50	0	11278.50	mid	Yellow	11300.50	8.5
3	AHT10 OHMM (Demo2,...	AHT20 OHMM (Demo2,...	AHT30 OHMM (Demo2, Re...	11321.50	1	11571.50	base	Orange	*	
4	AHT60 OHMM (Demo2,...	AHT90 OHMM (Demo2,...		11451.50	0	*				
5	DT US/F (Demo2, Repa...	GR GAPI (Demo2, Rep...	NC4 PPM (Demo2, Repair ...	11465.00	1					
6	IC4 PPM (Demo2, Rep...	IC5 PPM (Demo2, Repa...	NC5 PPM (Demo2, Repair ...	11660.50	0					
7	CALI IN (Demo2, Repai...	NPHI V/V (Demo2, Rep...	PEF B/E (Demo2, Repair T...	11688.50	1					

Work Area

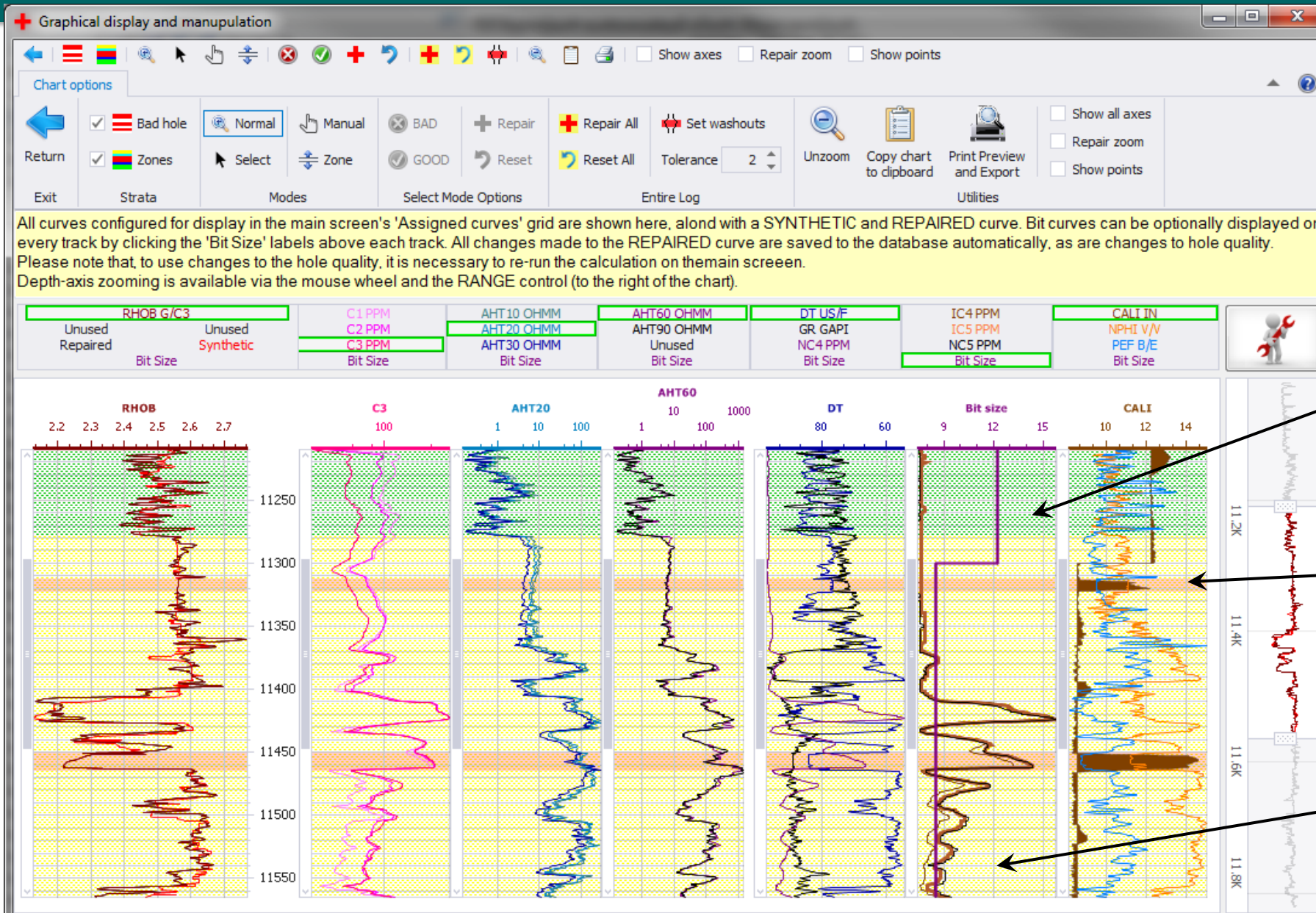
General		Track 1 containing target curve (third column)						Track 2			Track 3			Track 4		
Depth	Hole Quality	Zone	Bit Size	Repaired	Synthetic	RHOB G/C3		C1 PPM	C2 PPM	C3 PPM	AHT10 OHMM	AHT20 OHMM	AHT30 OHMM	AHT60 OHMM	A	C
11022.50	1	top	12.25	2.417	2.444	2.4170		248.0000	27.0000	56.0000	8.9321	7.7428	7.4445	6.4415		
11023.00	1	top	12.25	2.4062	2.5096	2.4062		245.0000	27.0000	56.0000	8.2188	7.3141	7.2723	6.3843		
11023.50	1	top	12.25	2.3826	2.3616	2.3826		238.5000	26.5000	55.0000	5.9777	5.7417	5.6799	5.1616		
11024.00	1	top	12.25	2.3537	2.3606	2.3537		232.0000	26.0000	54.0000	4.8314	4.5516	4.5480	4.3735		
11024.50	1	top	12.25	2.3419	2.3597	2.3419		231.5000	26.0000	54.0000	6.4566	5.7509	5.6580	5.3185		
11025.00	1	top	12.25	2.3488	2.3529	2.3488		231.0000	26.0000	54.0000	10.0172	7.5423	6.9576	6.2403		
11025.50	1	top	12.25	2.3614	2.3603	2.3614		230.0000	25.5000	53.5000	6.9617	5.9494	5.7642	5.4521		
11026.00	1	top	12.25	2.3816	2.3912	2.3816		229.0000	25.0000	53.0000	4.7653	4.3764	4.6152	4.4845		

Status: Updating database

Data loaded from las files and are displayed on a spreadsheet



Quality Control and Repair of Electrical Logs



Zone information is important

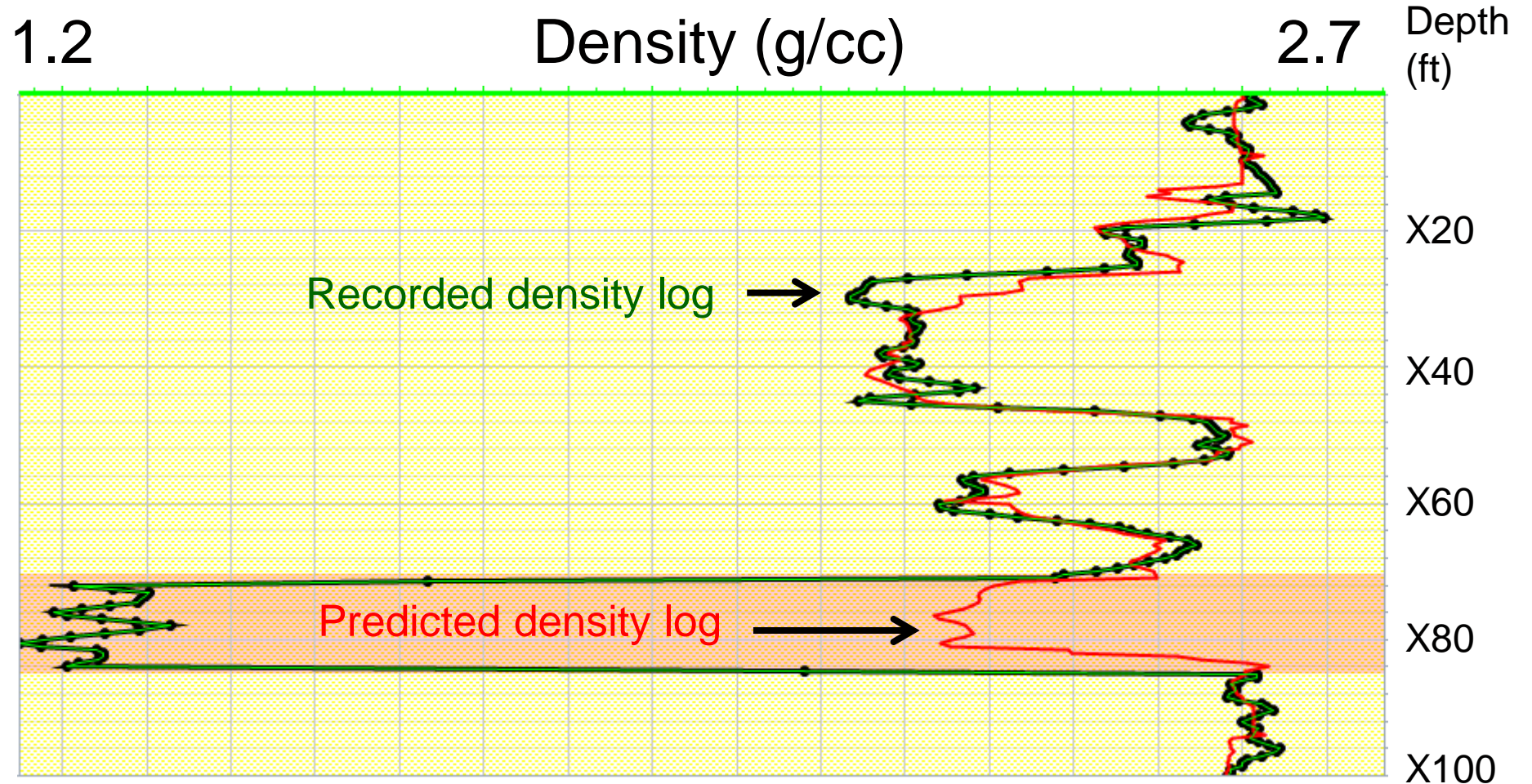
Bad hole is identified by the differential caliper

The free borehole chromatography data is very useful

Quality Control and Repair of Electrical Logs

- The AI determines the relationships between all the logs
 - because, as petrophysicists we know, all logs are related
- Synthetic logs are created based on all the other logs
 - as if we had forgotten to record them
- Synthetic and recorded logs are compared
 - significant differences are flagged
- The user makes the final decision
 - whether to replace poor sections of log by synthetics

Quality Control and Repair of Electrical Logs



The density log reads the mud density in → borehole washouts

- The petrophysicist makes the final decision whether to replace poor sections of log by synthetics
- AI helps the petrophysicist but **doesn't replace** them

Advantages of using AI in Petrophysical Analysis

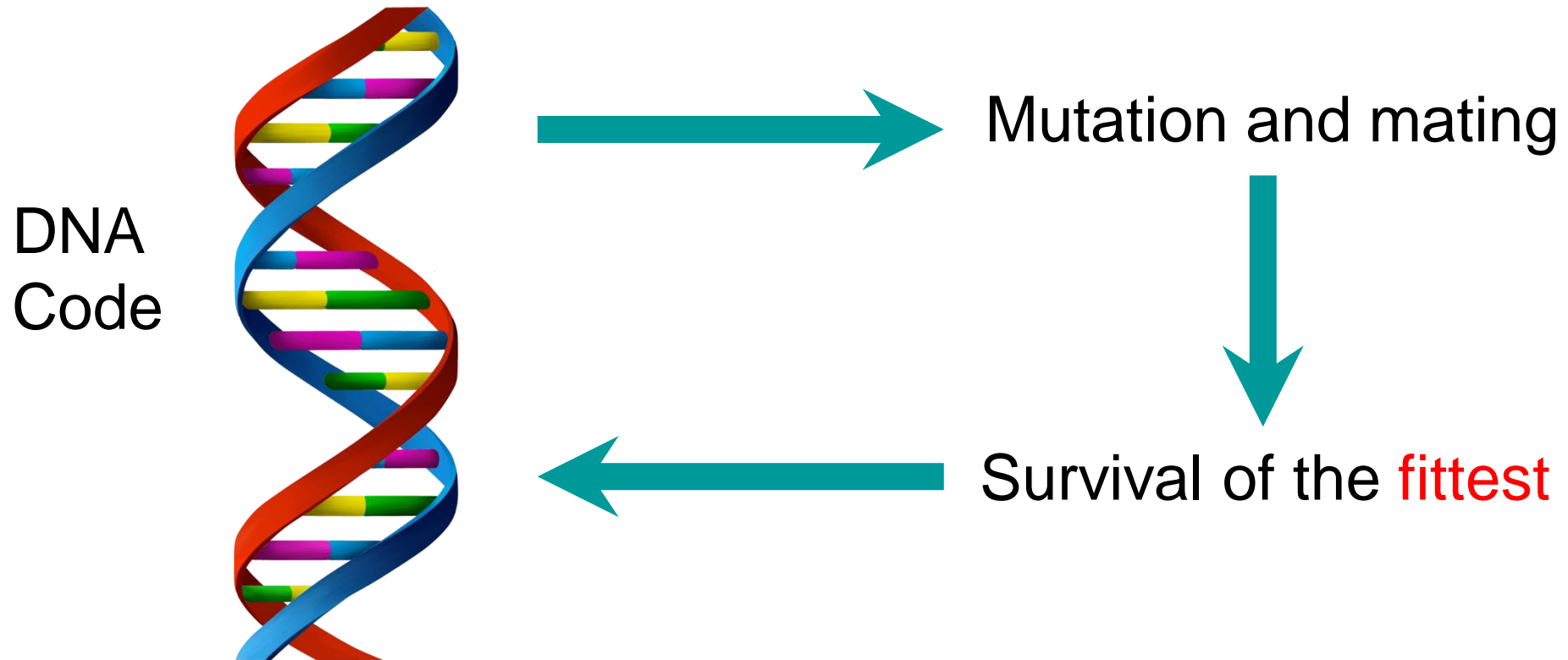
- AI doesn't require prior knowledge of the petrophysical response equations
- AI is self-calibrating. Just give it the data
- AI avoids the problem of 'Garbage In, Garbage Out',
 - by ignoring noise and outliers
- There is very little user intervention
 - There are no parameters to pick or cross-plots to make
- AI programs work with an unlimited number of electrical logs, core and gas chromatography data; and don't 'fall-over' if some of those inputs are missing
- AI is not a Black Box, as it provides insights into how it makes predictions

Third Generation AI

- AI programs currently being developed include ones where their machine code evolves using similar rules used by life's DNA code

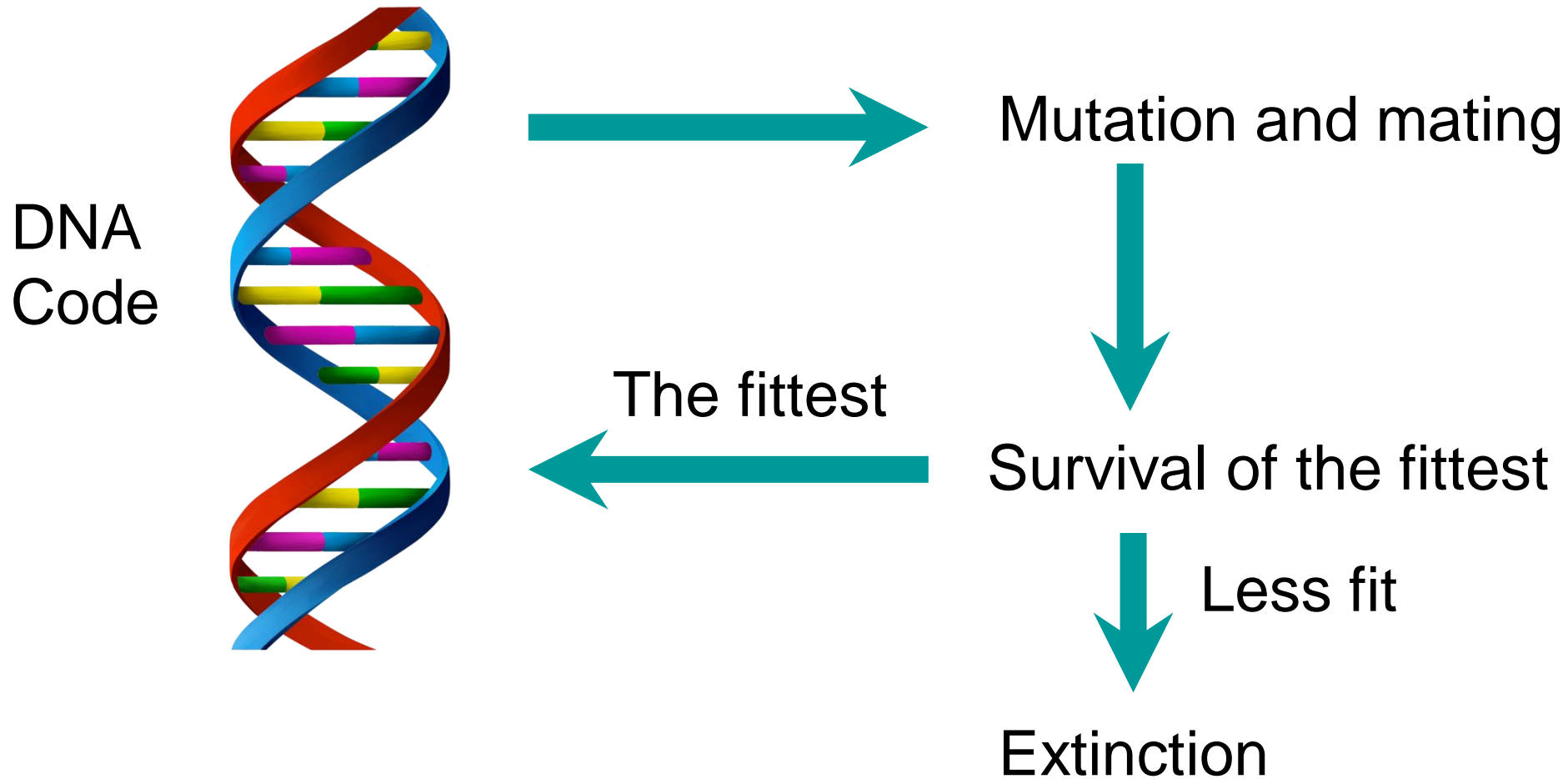
Evolution in Nature

- Charles Darwin – ‘the origin of species by means of natural selection’
- DNA language code - **4 characters** - A, T, C, G (nucleotides)



Evolution in Nature

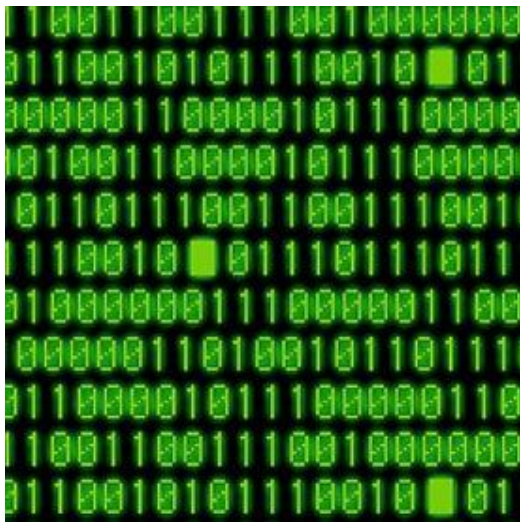
- Feedback loop – taking millions of years



Third Generation AI

- Just define the problem to be solved – **Fitness Function**

Computer Code



A language of
2 characters



Mutation and mating

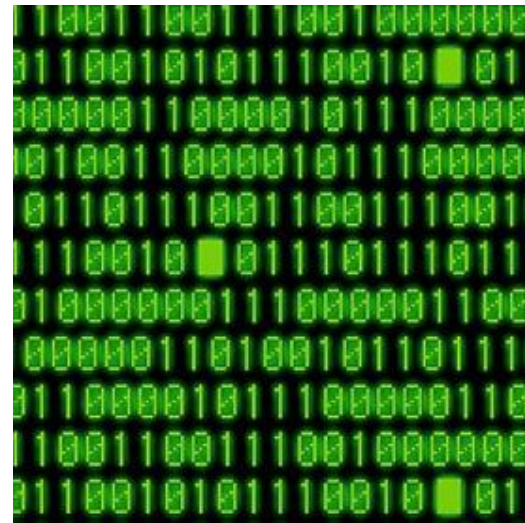


Survival of the fittest



Third Generation AI

The machine code mutates and mates using the **same rules** that Life uses



Computer Code



Change code



Is it better at solving the problem?

Fitness



No

Delete

Yes



Keep

AI Requirements

- Data
- Fitness Function
 - Tells the AI what you want it to do
 - Written in plain English
 - **Question** - Does the AI understand what you really want?

King Midas and his golden touch

- King Midas, in Greek mythology, was granted his wish that everything he touched turned into gold
- He didn't realise that this included his food and his children
- Similarly, an ill-conceived **Fitness Function** may give unexpected results



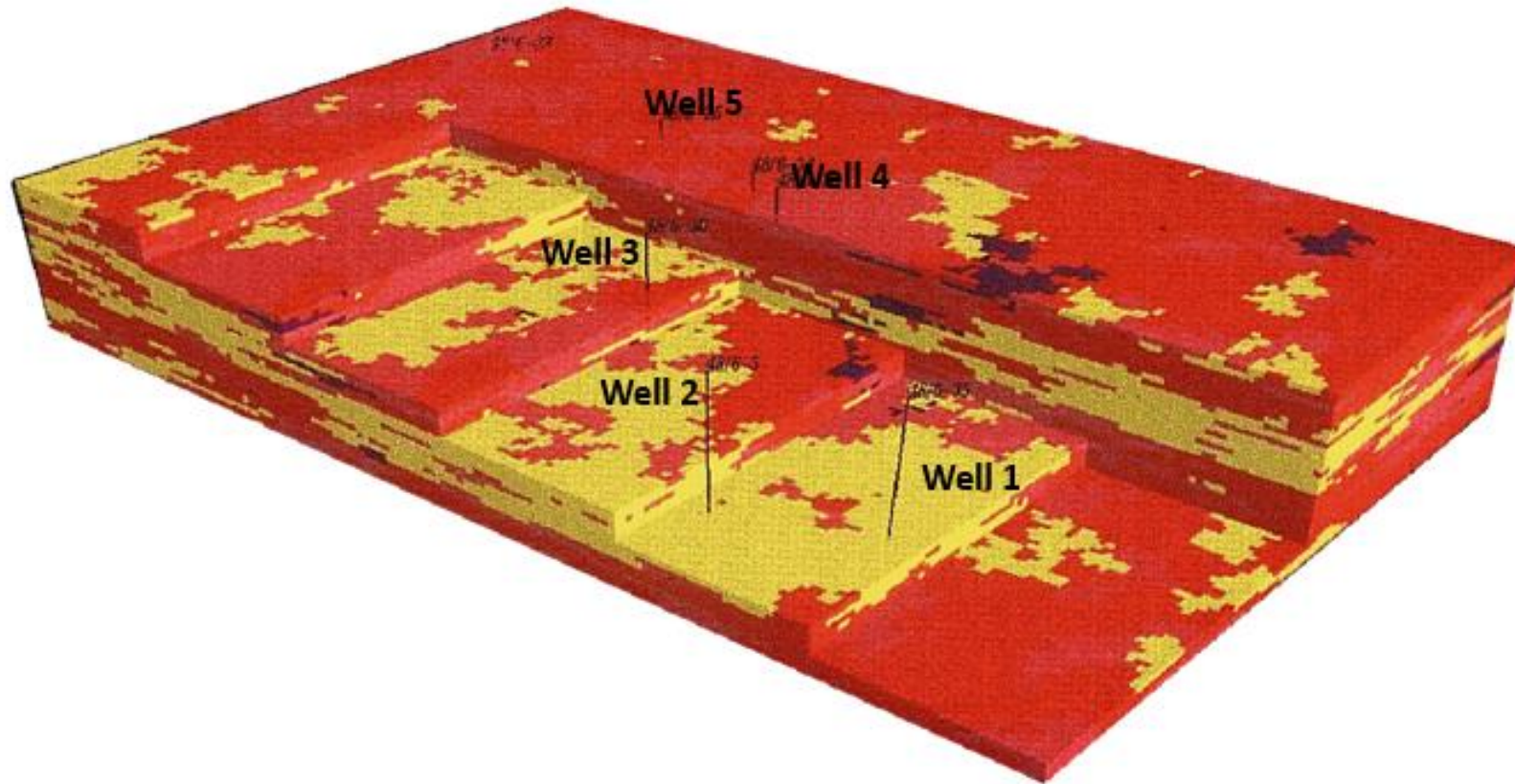
The Sorcerer's Apprentice (Spoiler Alert!)

- The apprentice uses magic to get a broom carry water for him
- Unfortunately it runs-away and nearly drowns him
- Similarly a **Runaway AI** may be unstoppable
- Next - A runaway example from petrophysics and reservoir modelling



Example of third generation AI going wrong

- History matching
- **Fitness Function** – ‘get the best match as **fast** as possible’



Example of Runaway AI

- By trial and error the computer will evolve a fast history match
- Any endeavour succeeds faster if you increase its **resources**
 - e.g. A general motivates his troops by giving them better weapons
- A human programmer / hacker may co-opt the resources of other network computers to achieve the faster speed
- There is no reason why AI couldn't also do this
 - Over the company's intranet or the global internet (information superhighway)
- If AI achieves this 'by accident'- there is nothing to stop it doing it again and again
 - The AI will 'accidentally' start improving exponentially
 - acquiring more and more of the company's and world's computer resources
 - with disastrous and irreversible consequences for the world economy

Example of Runaway AI

- A supercomputer isn't required to do this
 - The one on your desk could do this
- An elaborate computer program isn't required
 - Only one that can update its own machine code
 - with an ill-conceived Fitness Function
- This is known as **The Singularity**
 - where artificial intelligence becomes uncontrollable and irreversible
- The chances of this happening soon may be as remote
 - as a single mutation creating a global killer virus
 - AI only has to do this once
- It is currently not known how to stop computers with runaway evolution

AI enthusiasts have pointed out the Dangers

- Professor Stephen Hawking (University of Cambridge Professor)
 - “Efforts to create thinking machines pose a threat to our very existence”
- Bill Gates (Microsoft co-founder)
 - “Humans should be worried about the threat posed by artificial Intelligence”
- Nick Bostrom (University of Oxford Professor, Future of Humanity Institute)
 - “We’re like children playing with a bomb”
- Elon Musk (SpaceX founder)
 - “AI needs safety measures before something terrible happens”

Solution to Runaway AI

- These AI programs pose considerable dangers far beyond the oil industry
- A 'risk assessment' is essential on all AI programs
 - so that all hazards and risks are identified and mitigated
 - a risk assessment need only take a few minutes
- The fitness function should be carefully defined (Midas effect)
- Ask - can the AI runaway? (Sorcerer's Apprentice effect)
- The possibility of a runaway AI, in the near term, is remote
 - But the consequences would be far greater than pandemics or climate change
- AI programs are potentially dangerous and may be the last thing humans invent

Conclusions

- AI makes **petrophysical analysis easy**
 - supports rather than replaces the petrophysicist
- AI can be extremely dangerous
 - All AI program development should include a **risk assessment**
- Questions?
 - SPWLA paper 5066 (June 2020)
 - **steve.cuddy**@btinternet.com