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Gas Innovations Inspiring Clean Energy

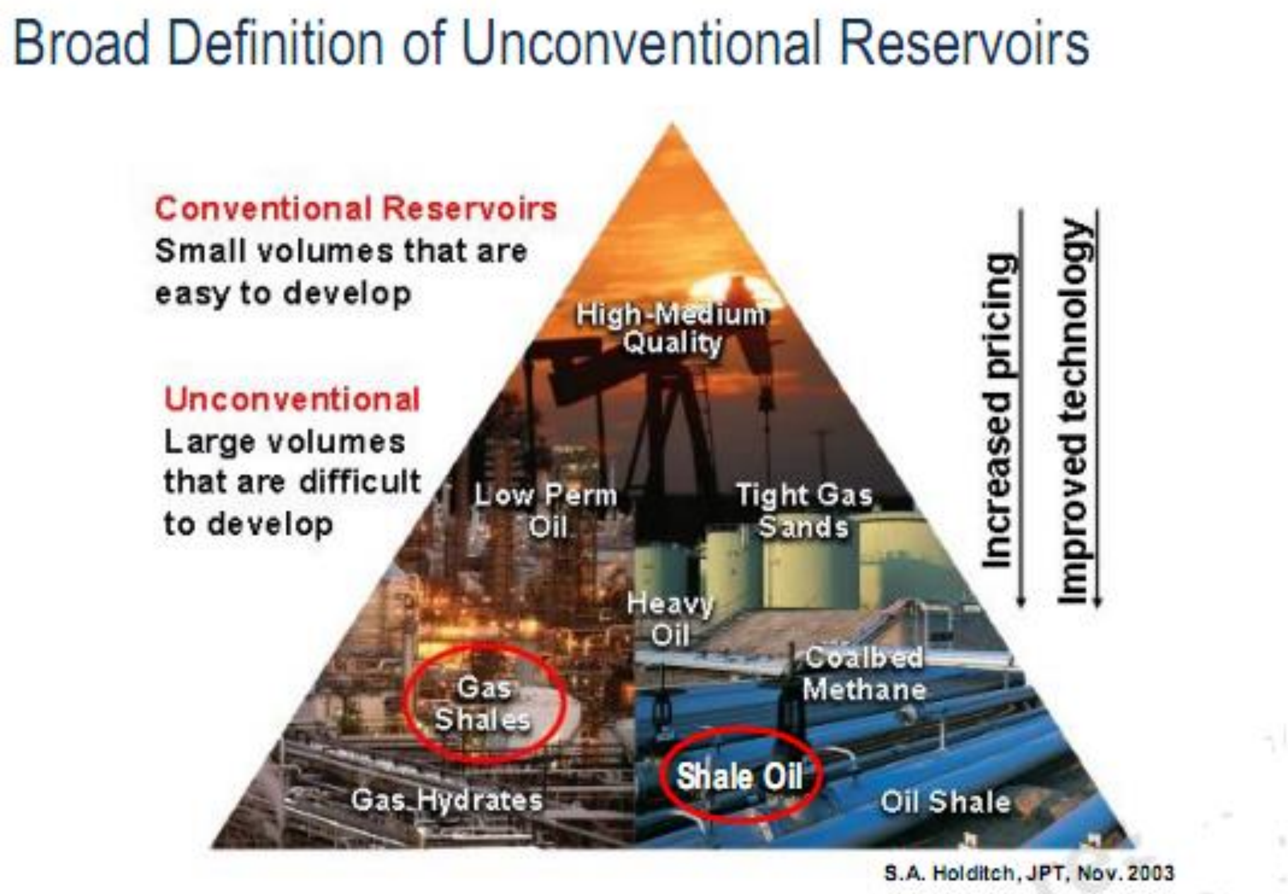
Shale Gas Reservoirs Characterization Using Neural Network

Sid-Ali Ouadfeul(1) and Leila Aliouane(2)
(1) Algerian Petroleum Institute, IAP, Algeria
(2) LABOPHYT, FHC, UMBB, Algeria

Objectives

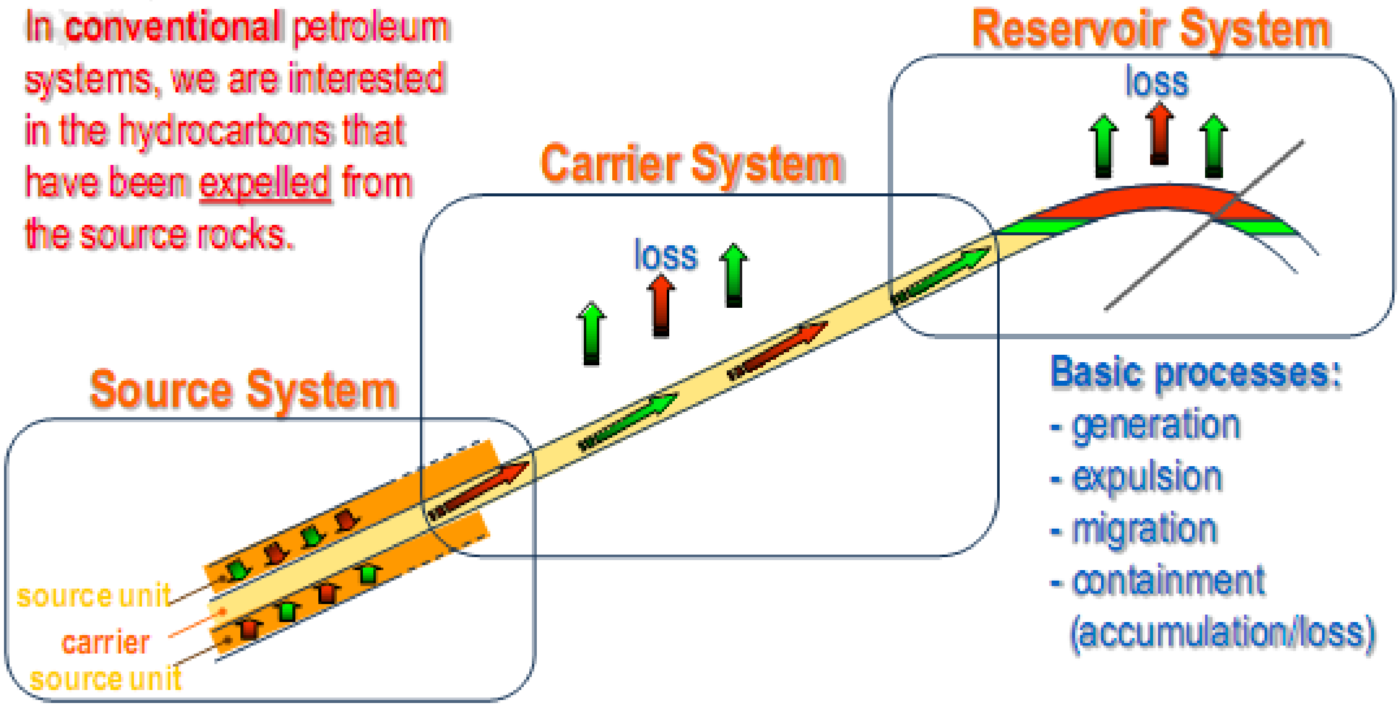
- Tentative of shale gas reservoir characterization enhancement from well-logs data using neural network.
- The goal is to predict the Total Organic carbon (TOC) in boreholes where the TOC core rock or TOC well-log measurement does not exist.
- The Multilayer preceptor (MLP) neural network with three layers is established.
- Application to Barnett Shale, Worth Basin, USA is realized

What is an unconventional reservoir



Conventional Petroleum Systems and Processes

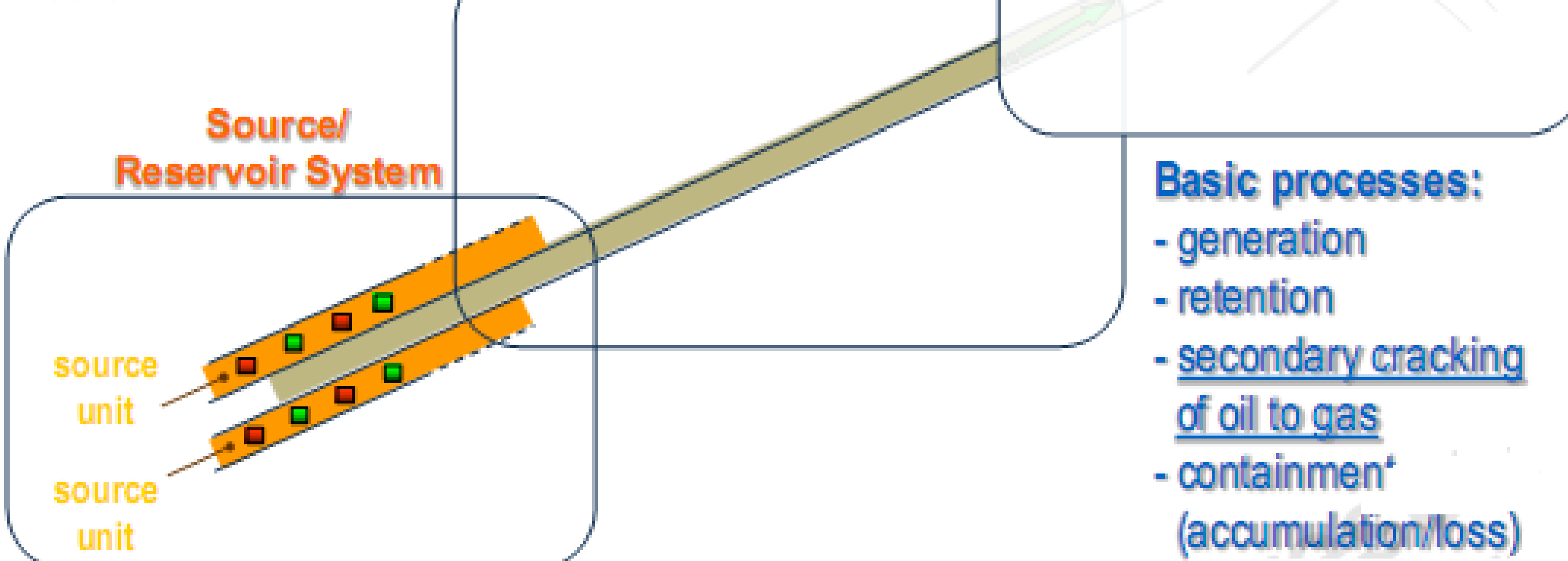
In **conventional** petroleum systems, we are interested in the hydrocarbons that have been expelled from the source rocks.



Basic processes:
- generation
- expulsion
- migration
- containment (accumulation/loss)

Unconventional Petroleum Systems and Processes

In **unconventional** petroleum systems, we are interested in the hydrocarbons that have been retained in the source rocks.



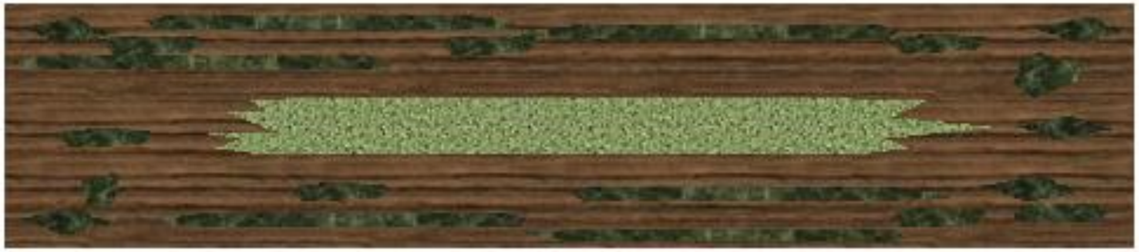
Basic processes:

- generation
- retention
- secondary cracking of oil to gas
- containment (accumulation/loss)

What is a shale gas/shale oil reservoirs

Our Preferred Definition of Shale Resource

- A shale resource system is described as a continuous organic-rich source rock(s) that may be both a source and a reservoir rock for the production of petroleum (oil and gas) or may charge and seal petroleum in juxtaposed, continuous organic-lean intervals.



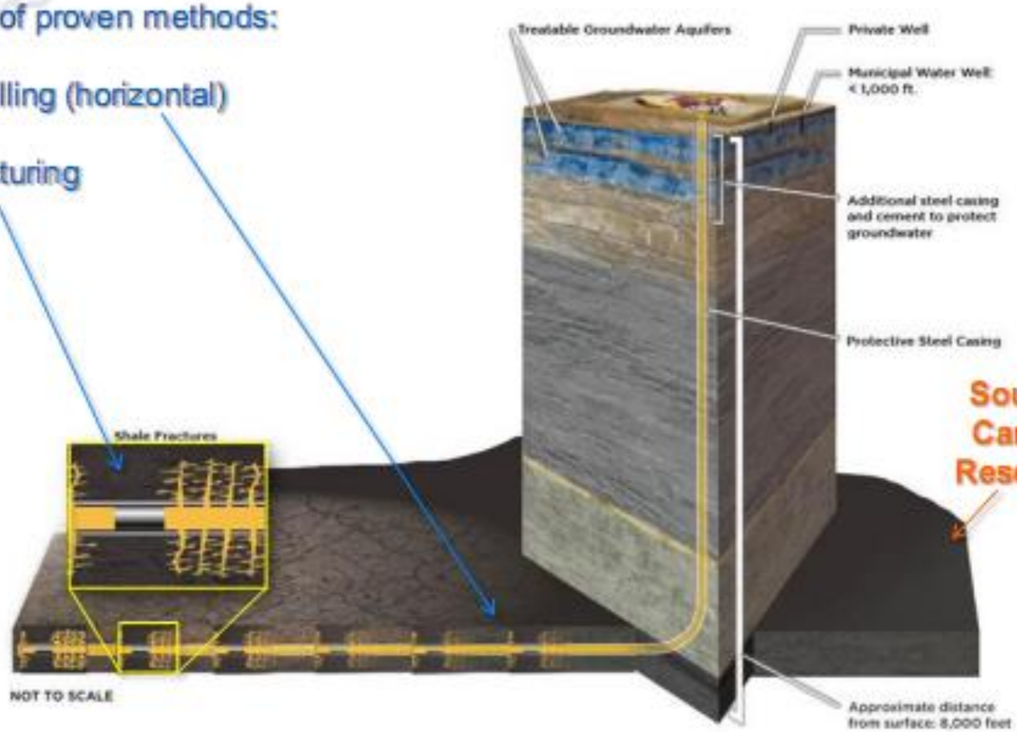
Description from Jarvie (2012)

Unconventional Oil and Gas - Production Technology

A combination of proven methods:

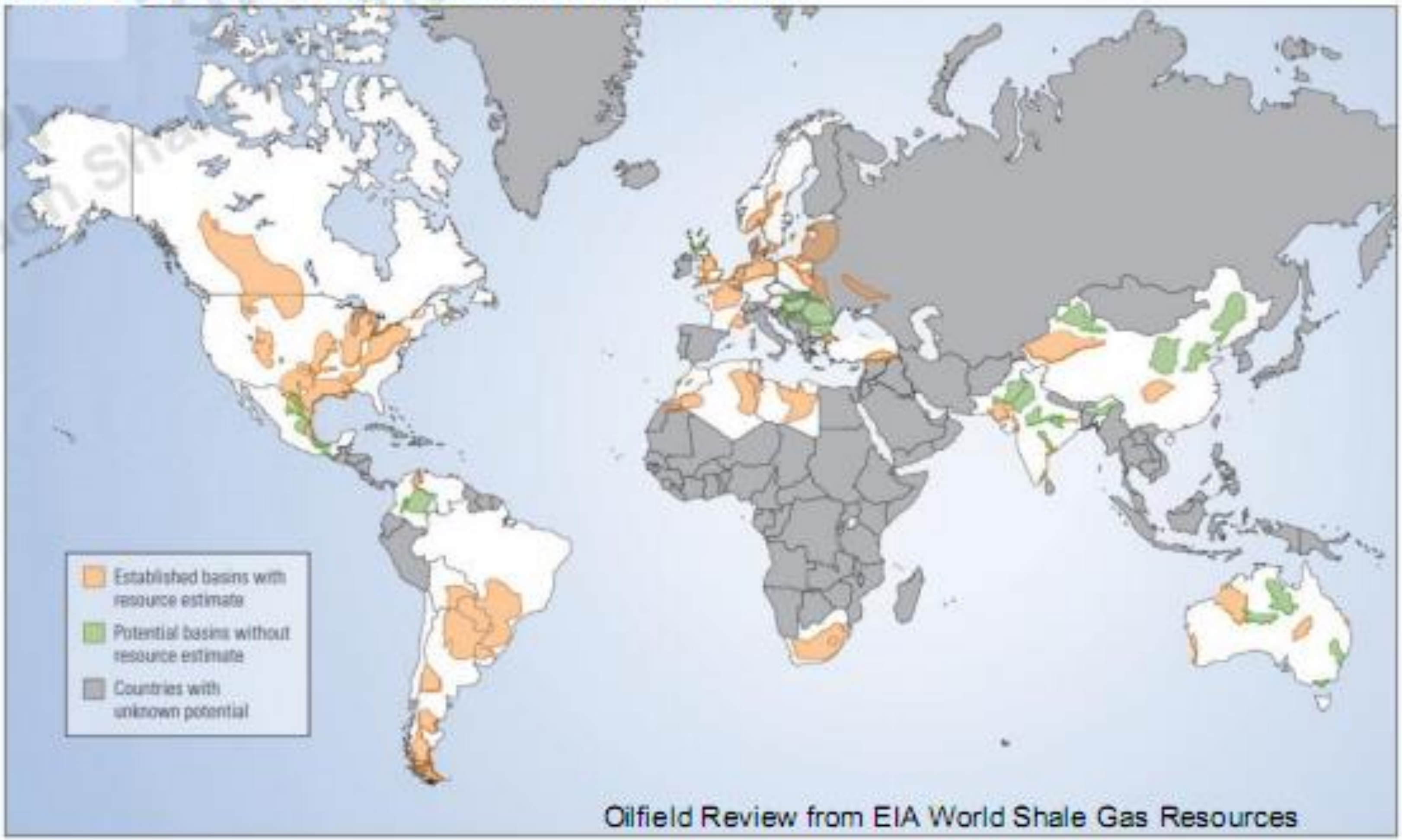
- directional drilling (horizontal)

- hydraulic fracturing ('fracking')



http://dolphinresourcesllc.com/fracking/

U.S. Energy Information Administration
Initial Global Assessment - 2011



Top 10 countries with technically recoverable shale gas resources

Rank	Country	Shale gas (trillion cubic feet)	
1	China	1,115	
2	Argentina	802	
3	Algeria	707	
4	U.S.[1]	665	(1,161)
5	Canada	573	
6	Mexico	545	
7	Australia	437	
8	South Africa	390	
9	Russia	285	
10	Brazil	245	
	World Total	7,299	(7,795)

[1] EIA estimates used for ranking order. ARI estimates in parentheses.

What is the TOC

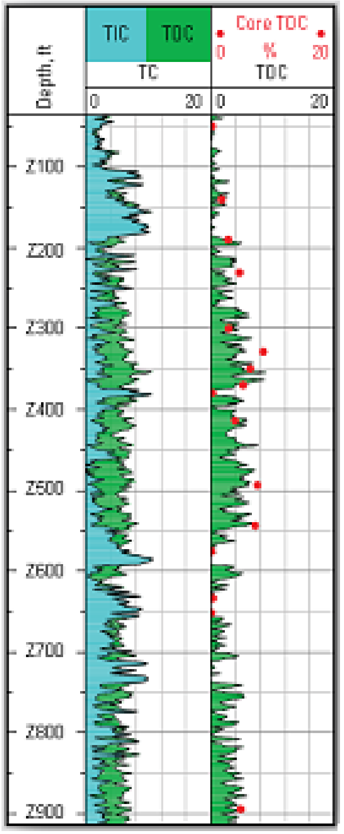
-Organic carbon in the form of kerogen is the remnant of ancient life preserved in sedimentary rocks, after degradation by bacterial and chemical processes, and further modified by temperature, pressure, and time.
-The latter step, called thermal maturation, is a function of burial history (depth) and proximity to heat sources.

- Maturation provides the chemical reactions needed to give us gas, oil, bitumen, pyrobitumen, and graphite (pure carbon) that we find while drilling wells for petroleum.

How to mesure the TOC

Total Organic Carbon (TOC)

- TOC is reported from:
  - Lab measurements (wt.%)
  - Calculations from logs (several methods)
- TOC is a measure of richness, but not kerogen type or quality
- TOC reduces as maturation progresses and petroleum expels
- **Original** TOC (**TOC$_o$**) can be reconstructed from measured TOC if sufficient Rock-Eval and maturity data exist



TIC = Total Inorganic Carbon

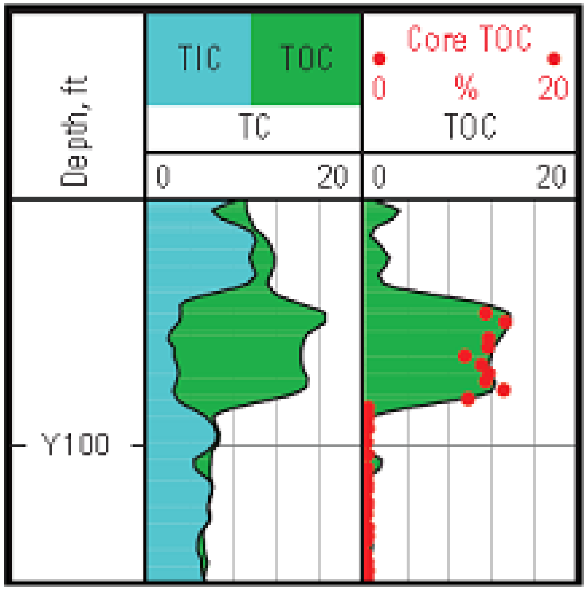
TOC = Total Organic Carbon

www.slb.com/ls; Litho Scanner* High-definition spectroscopy service brochure 2012

Different Methods of TOC Calculations From Logs

- Schlumberger Litho Scanner
  - High-definition spectroscopy
  - Accurate mineralogy & TOC wt.%
  - Includes kerogen nanoporosity
  - Works in oil-based mud!
- Schmoker method
  - **TOC = (154.497/ρ) - 57.261**
- Passey Δ log R method
  - Uses porosity (usually sonic transit time) and resistivity logs
  - Calculated TOC is very sensitive to level of maturity (LOM)

The Litho Scanner TOC method shows excellent agreement with the core-derived porosity measurements.



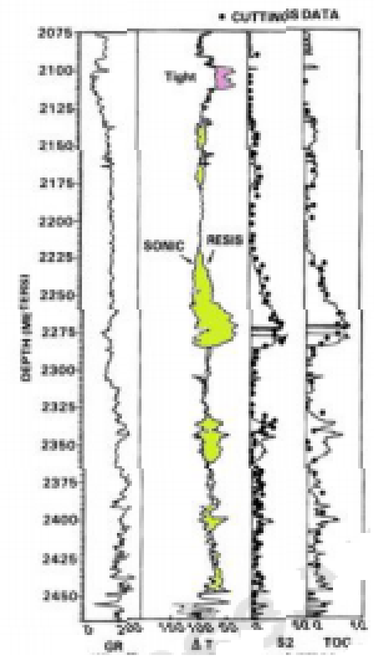
Schmoker, J.W (1983)

www.slb.com/ls Litho Scanner accurate TOC determination for unconventional reservoirs

Passey's Model

Passey ΔlogR method of TOC calculation

$$\Delta \log R = \log_{10}(R/R_{baseline}) + 0.02 \times (\Delta t - \Delta t_{baseline})$$



$$TOC = (\Delta \log R) \times 10^{(2.297-0.1688 \times LOM)}$$

Where:

$\Delta \log R$	curve separation measured in logarithmic resistivity cycles
R	resistivity measured in ohm-m by the logging tool
Δt	measured transit time in μsec/ft
$R_{baseline}$	resistivity corresponding to the $\Delta t_{baseline}$ value when the curves are baselined in non-source, clay-rich rocks
0.02	based on the ratio of -50 μsec/ft per one resistivity cycle

LOM	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Ro	.20	.24	.29	.32	.36	.38	.42	.48	.56	.67	.82	1.05	1.5	1.8	2.1	2.3	2.5	2.8	3.3	3.9	5.0

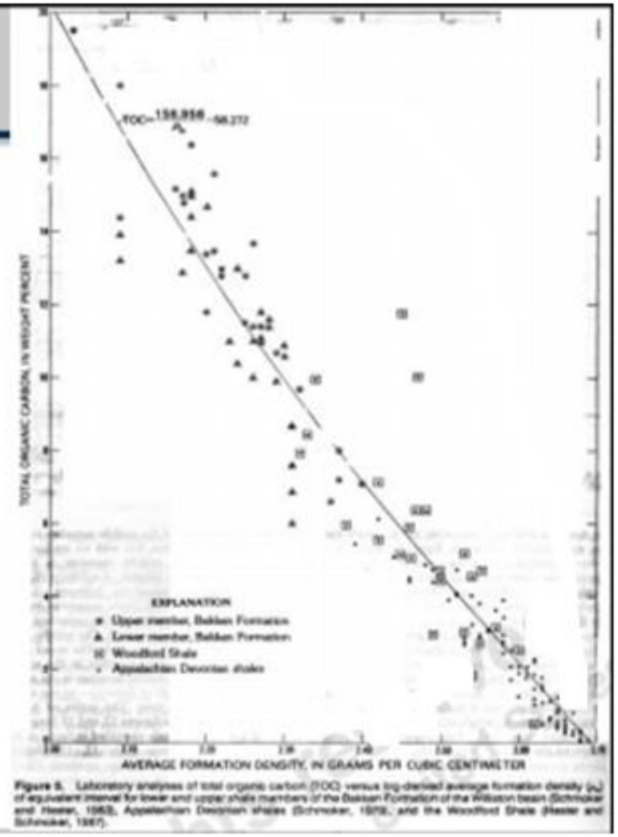
Passey (1990)

Schmoker's model

Schmoker Model

- Kerogen from bulk density
- Does take matrix variation into account
  - Clay vs. carbonate grain density
- Weak with very mature shales
  - Kerogen conversion

$$TOC(wt/wt) = \left(\frac{157}{\rho_b} - 58.3\right) \Big/ 100$$



Schmoker's Model requires the good knowledge (measurment) of the Bulck Density

What are Neural Networks?

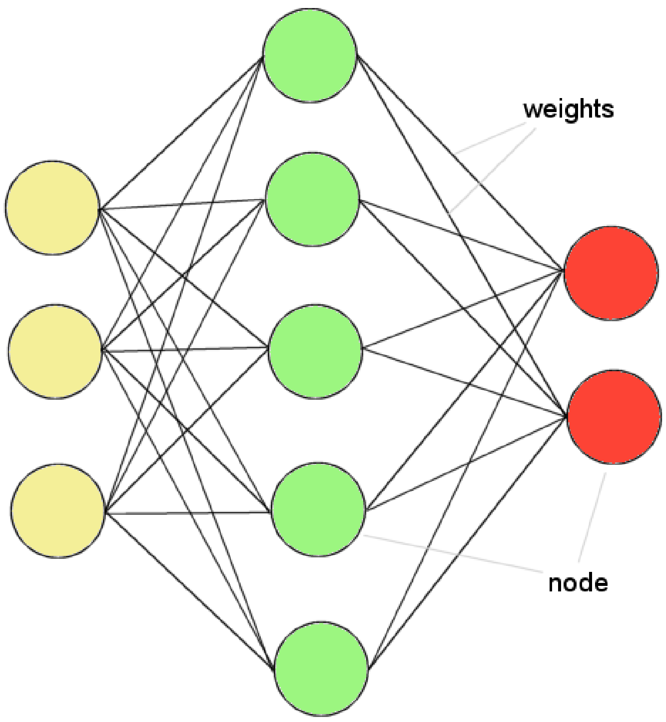
- Models of the brain and nervous system
- Highly parallel
  - Process information much more like the brain than a serial computer
- Learning

- Very simple principles
- Very complex behaviours

- Applications
  - As powerful problem solvers
  - As biological models

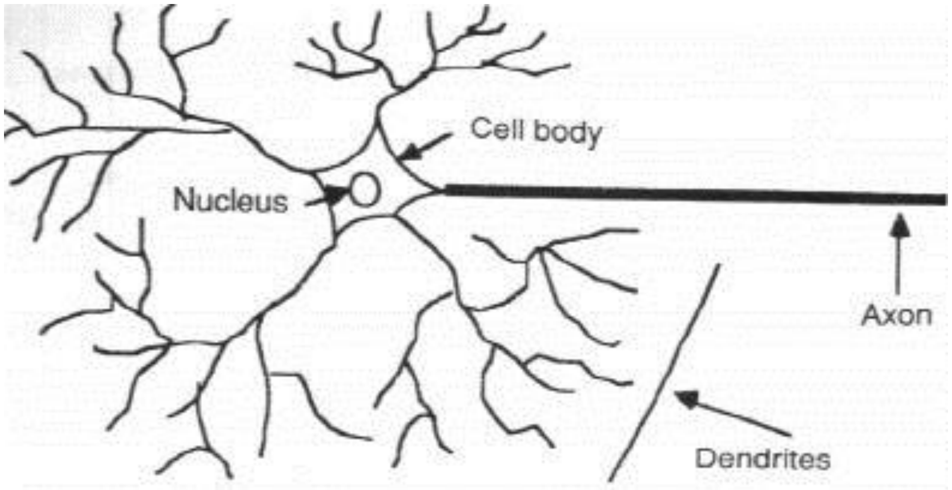
ANNs – The basics

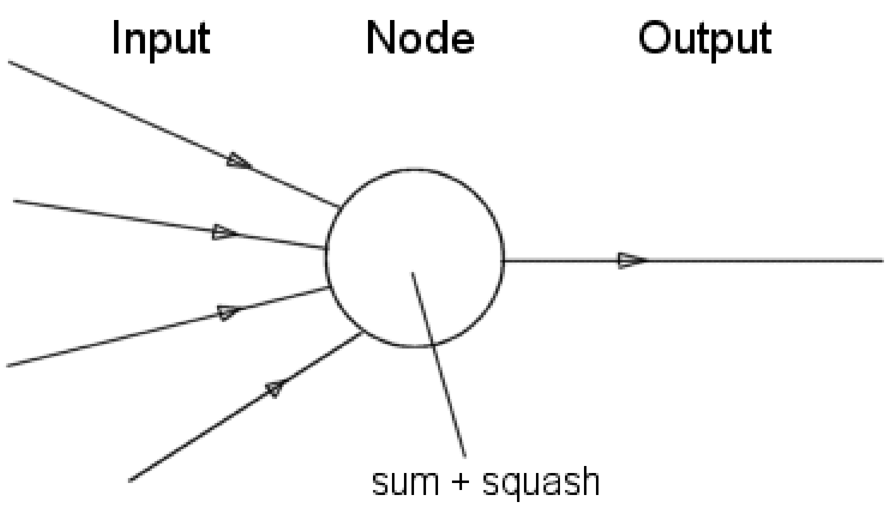
- ANNs incorporate the two fundamental components of biological



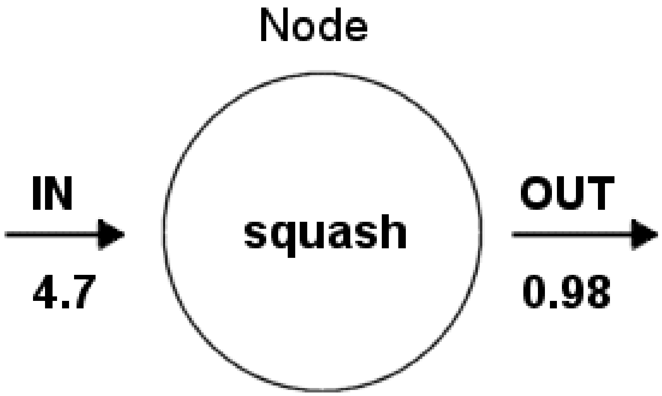
1. Neurones (nodes)
2. Synapses (weights)

- Neurone vs. Node

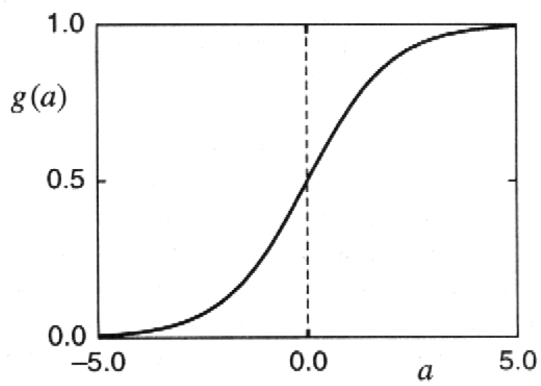




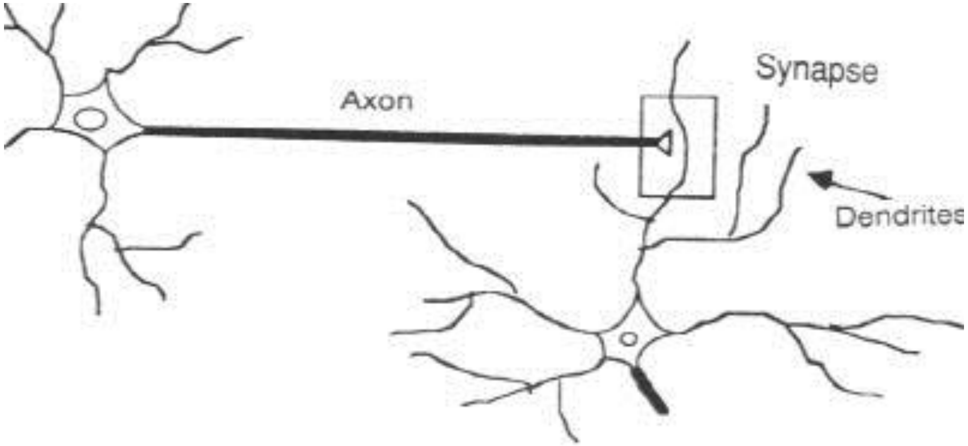
- Structure of a node:

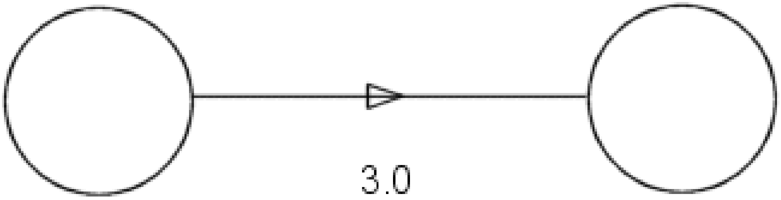


Squashing function limits node output:



- Synapse vs. weight





Feed-forward nets

Information flow is unidirectional

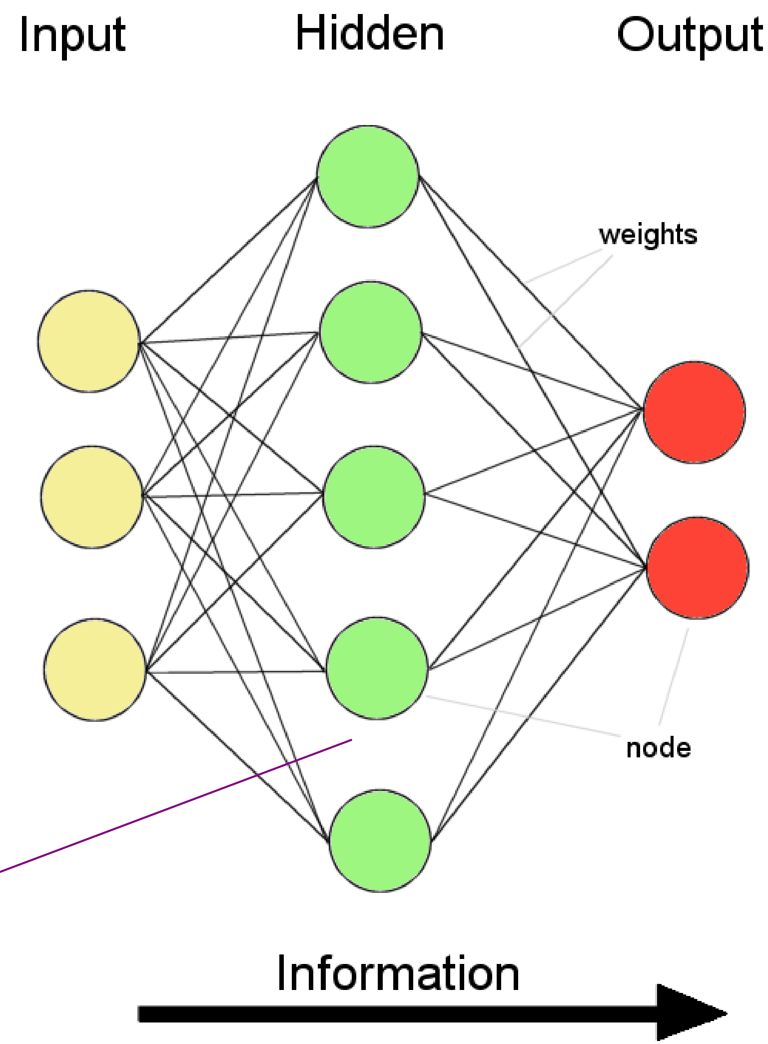
Data is presented to *Input layer*

Passed on to *Hidden Layer*

Passed on to *Output layer*

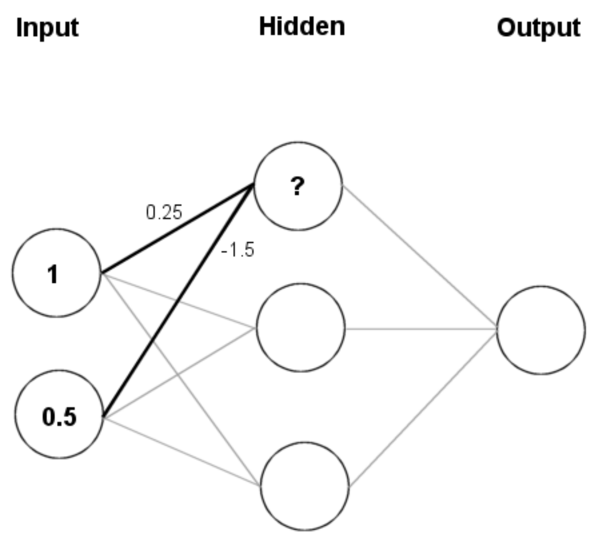
Information is distributed

Information processing is parallel



Internal representation (interpretation) of data

- Feeding data through the net:



$(1 \times 0.25) + (0.5 \times (-1.5)) = 0.25 + (-0.75) = -$ **0.5**

Squashing: $$\frac{1}{1+e^{0.5}} = 0.3775$$

- Data are presented to the network in the form of activations in the input layer

- Examples
  - Pixel intensity (for pictures)
  - Molecule concentrations (for artificial nose)
  - Share prices (for stock market prediction)

- Data usually requires preprocessing
  - Analogous to senses in biology

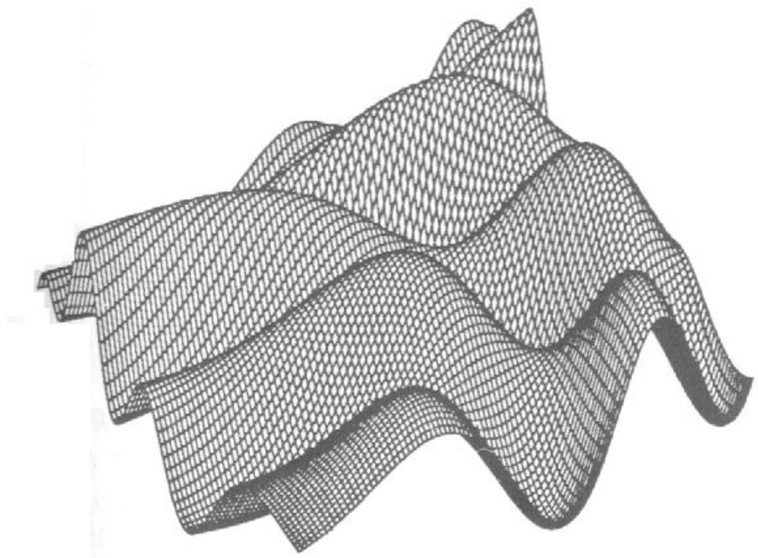
- How to represent more abstract data, e.g. a name?
  - Choose a pattern, e.g.
    - 0-0-1 for “Chris”
    - 0-1-0 for “Becky”

- Weight settings determine the behaviour of a network

  → How can we find the right weights?

Training the Network - Learning

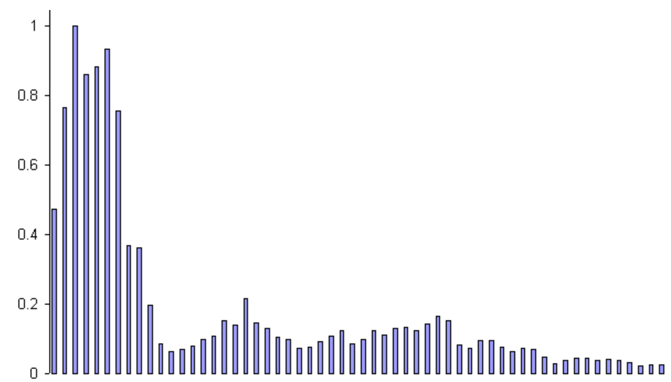
- Backpropagation
  - Requires training set (input / output pairs)
  - Starts with small random weights
  - Error is used to adjust weights (supervised learning)
  - → Gradient descent on error landscape



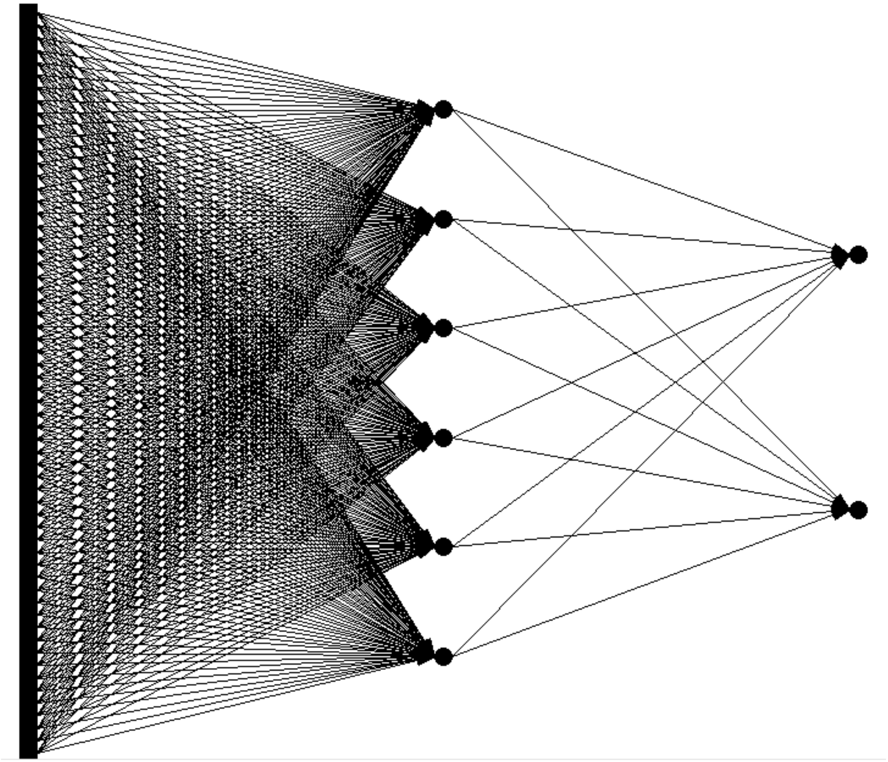
Example: Voice Recognition

- Task: Learn to discriminate between two different voices saying “Hello”

- Data
  - Sources
    - Steve Simpson
    - David Raubenheimer
  - Format
    - Frequency distribution (60 bins)

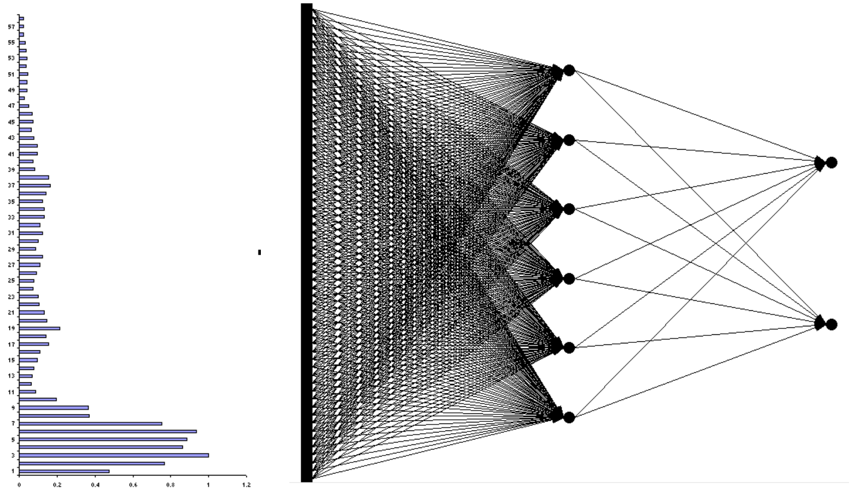


- Network architecture
  - Feed forward network
    - 60 input (one for each frequency bin)
    - 6 hidden
    - 2 output (0-1 for “Steve”, 1-0 for “David”)

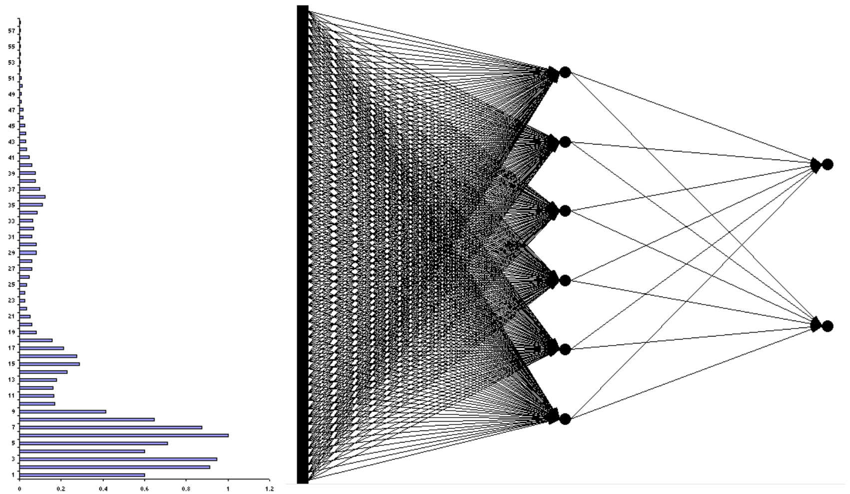


- Presenting the data

Steve

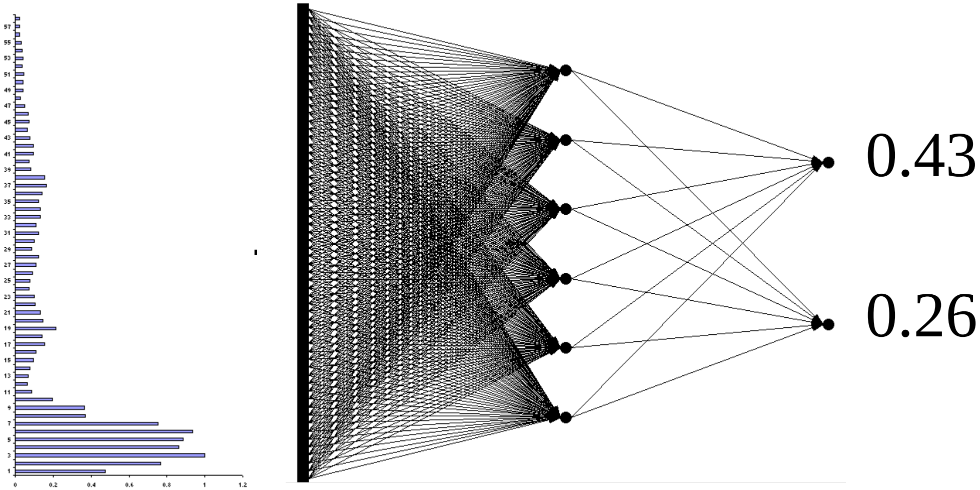


David

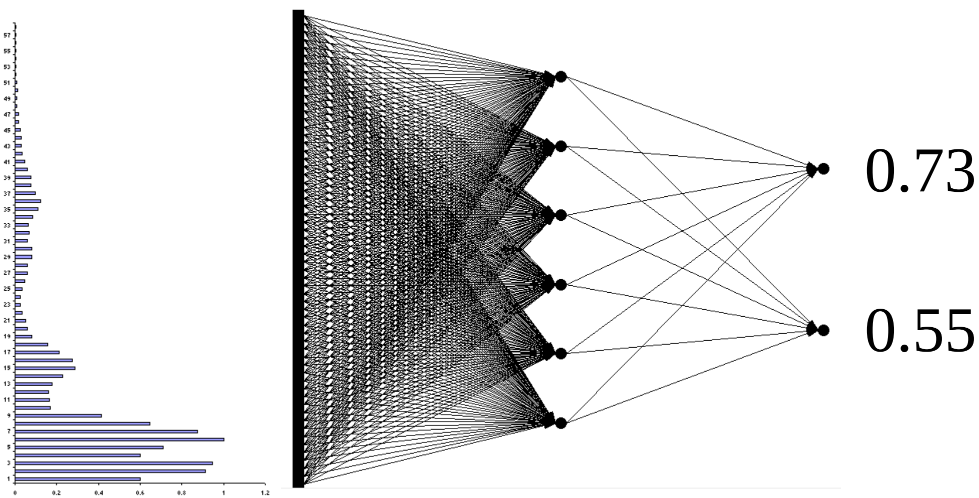


- Presenting the data (untrained network)

Steve

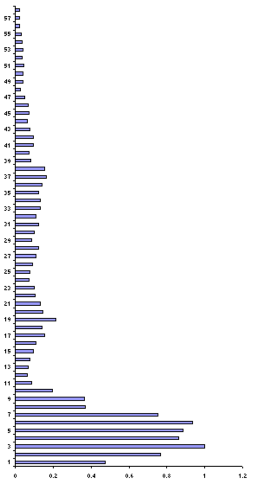


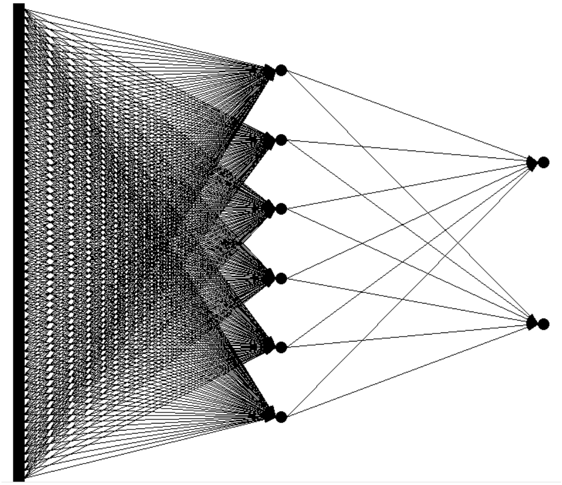
David



- Calculate error

Steve

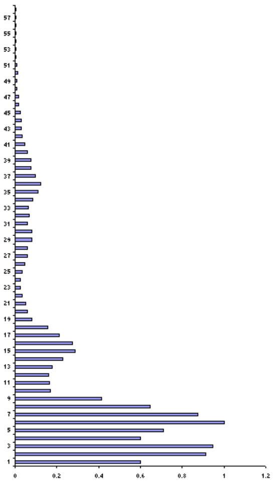


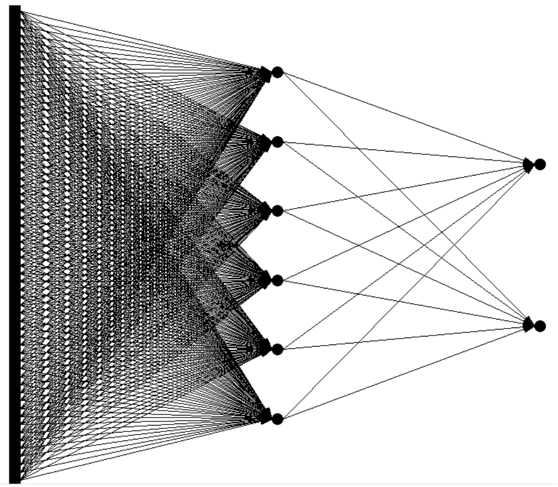


0.43 – 0 = 0.43

0.26 –1 = 0.74

David



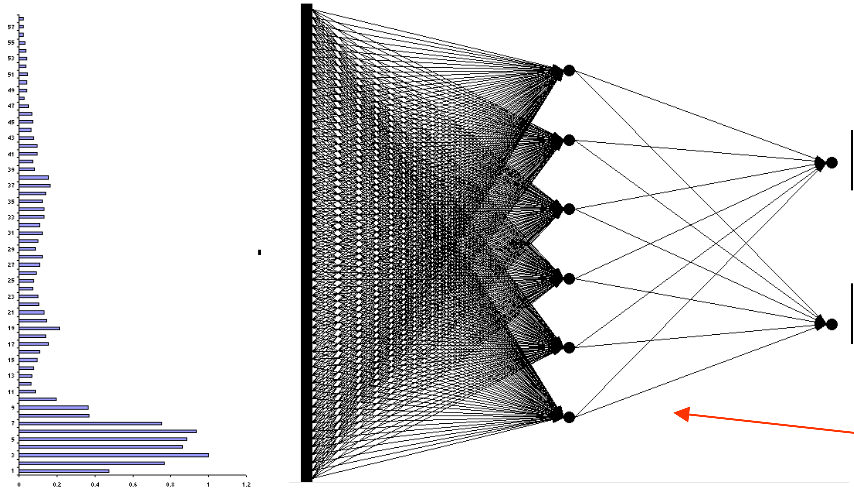


0.73 – 1 = 0.27

0.55 – 0 = 0.55

- Backprop error and adjust weights

Steve

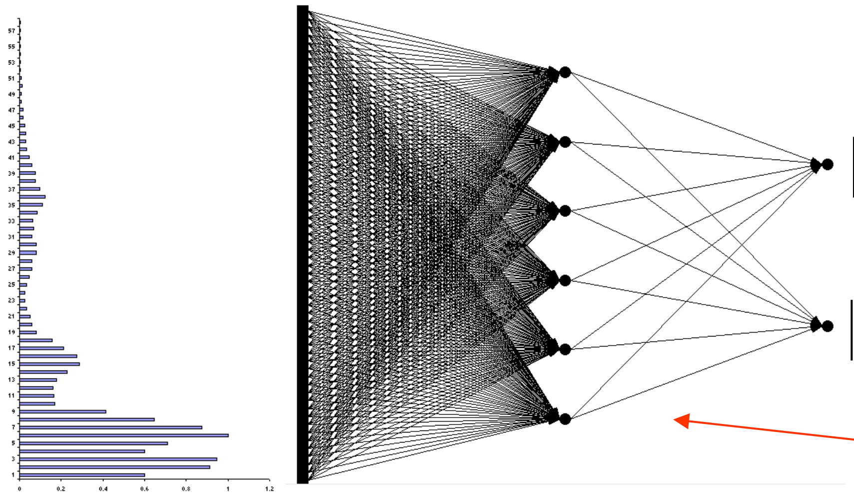


$$|0.43 - 0| = 0.43$$

$$|0.26 - 1| = 0.74$$

1.17

David

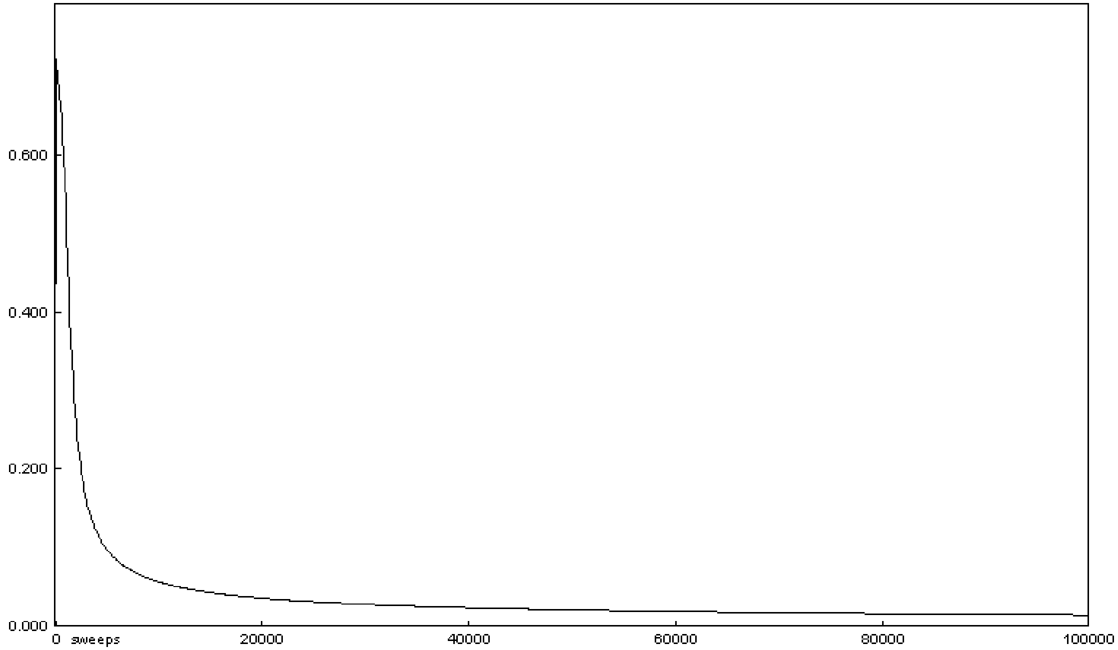


$$|0.73 - 1| = 0.27$$

$$|0.55 - 0| = 0.55$$

0.82

- Repeat process (sweep) for all training pairs
  - Present data
  - Calculate error
  - Backpropagate error
  - Adjust weights
- Repeat process multiple times

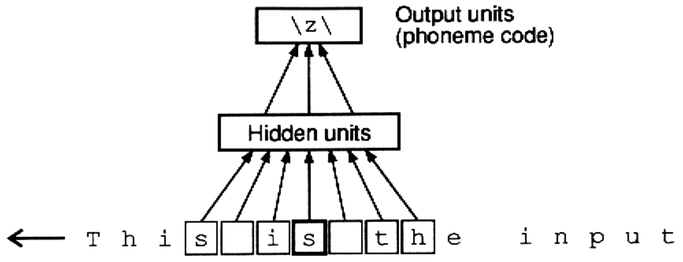


- Results – Voice Recognition
  - Performance of trained network
    - Discrimination accuracy between known “Hello”s
      - 100%
    - Discrimination accuracy between new “Hello”’s
      - 100%

- Results – Voice Recognition (ctnd.)
  - Network has learnt to generalise from original data
  - Networks with different weight settings can have same functionality
  - Trained networks ‘concentrate’ on lower frequencies
  - Network is robust against non-functioning nodes

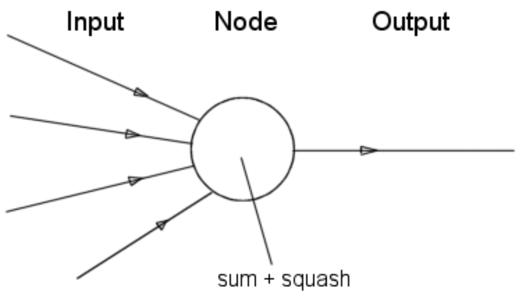
Applications of Feed-forward nets

- Pattern recognition
  - Character recognition
  - Face Recognition
- Sonar mine/rock recognition (Gorman & Sejnowksi, 1988)
- Navigation of a car (Pomerleau, 1989)
- Stock-market prediction
- Pronunciation (NETtalk)
  (Sejnowksi & Rosenberg, 1987)

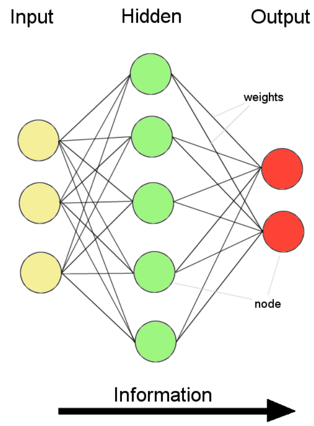


Recap – Neural Networks

- Components – biological plausibility
  - Neurone / node
  - Synapse / weight



- Feed forward networks
  - Unidirectional flow of information
  - Good at extracting patterns, generalisation and prediction
  - Distributed representation of data
  - Parallel processing of data
  - Training: Backpropagation
  - Not exact models, but good at demonstrating principles

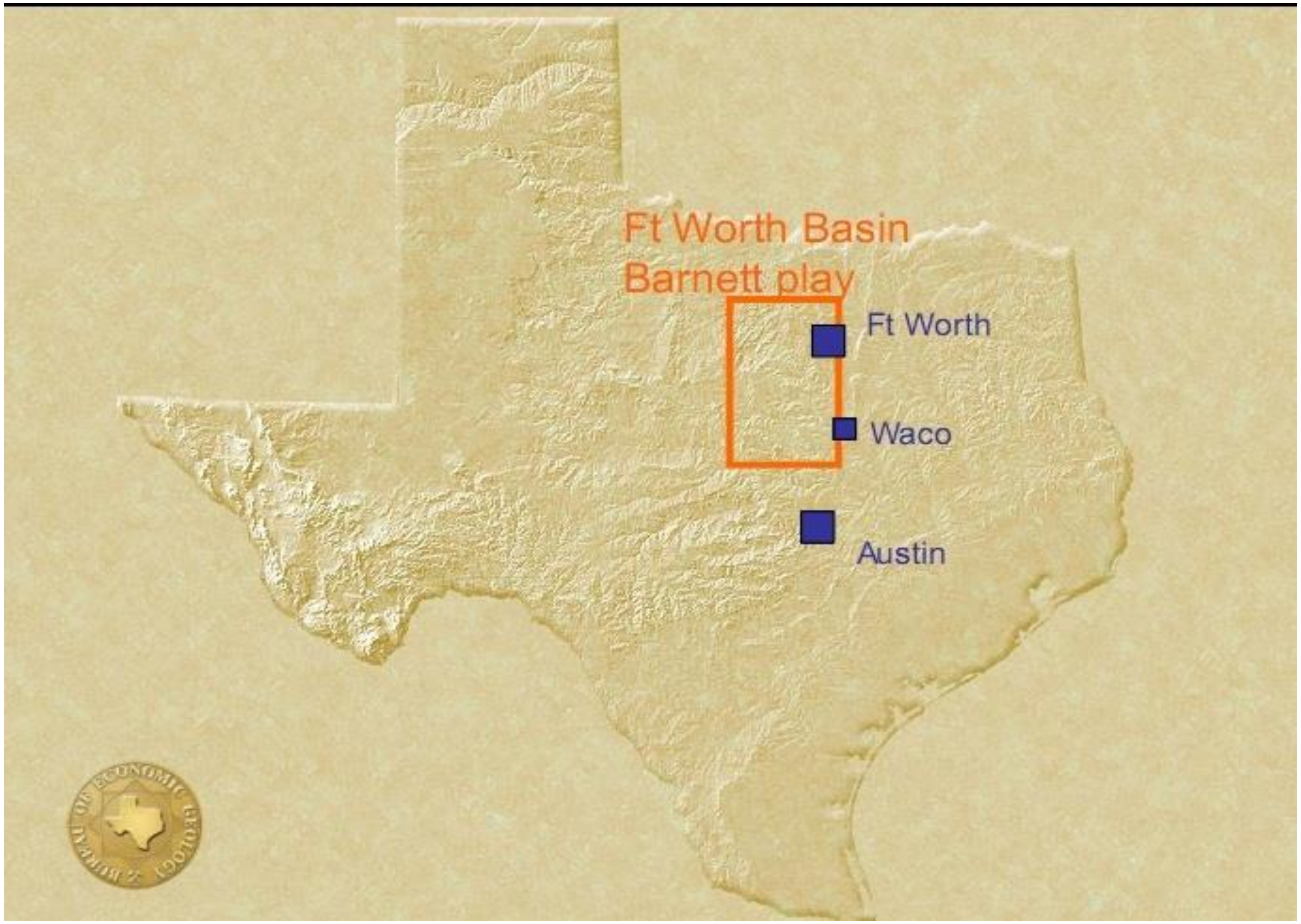


Application to Shale gas reservoirs

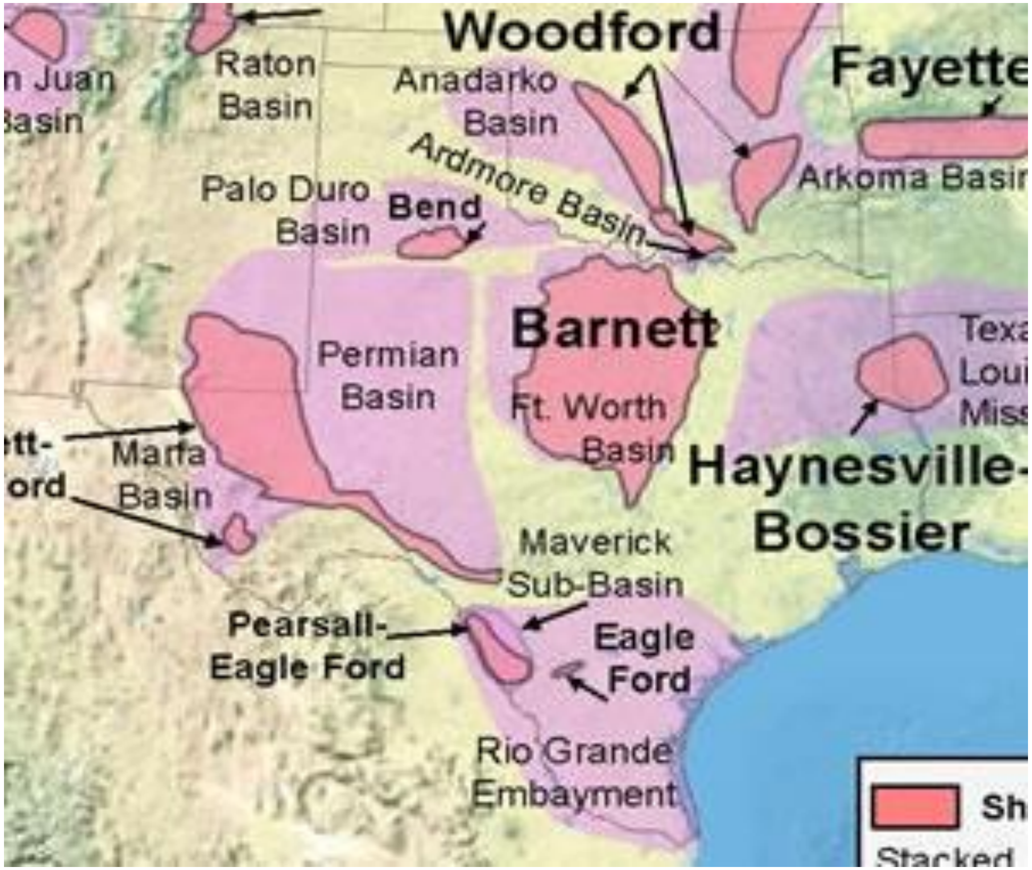
Goal: Prediction of Total Organic Carbon in Shale gas Resevoirs using Neural Network.

-Input: Measured Well-logs data without density log
-Output: Predicted TOC.

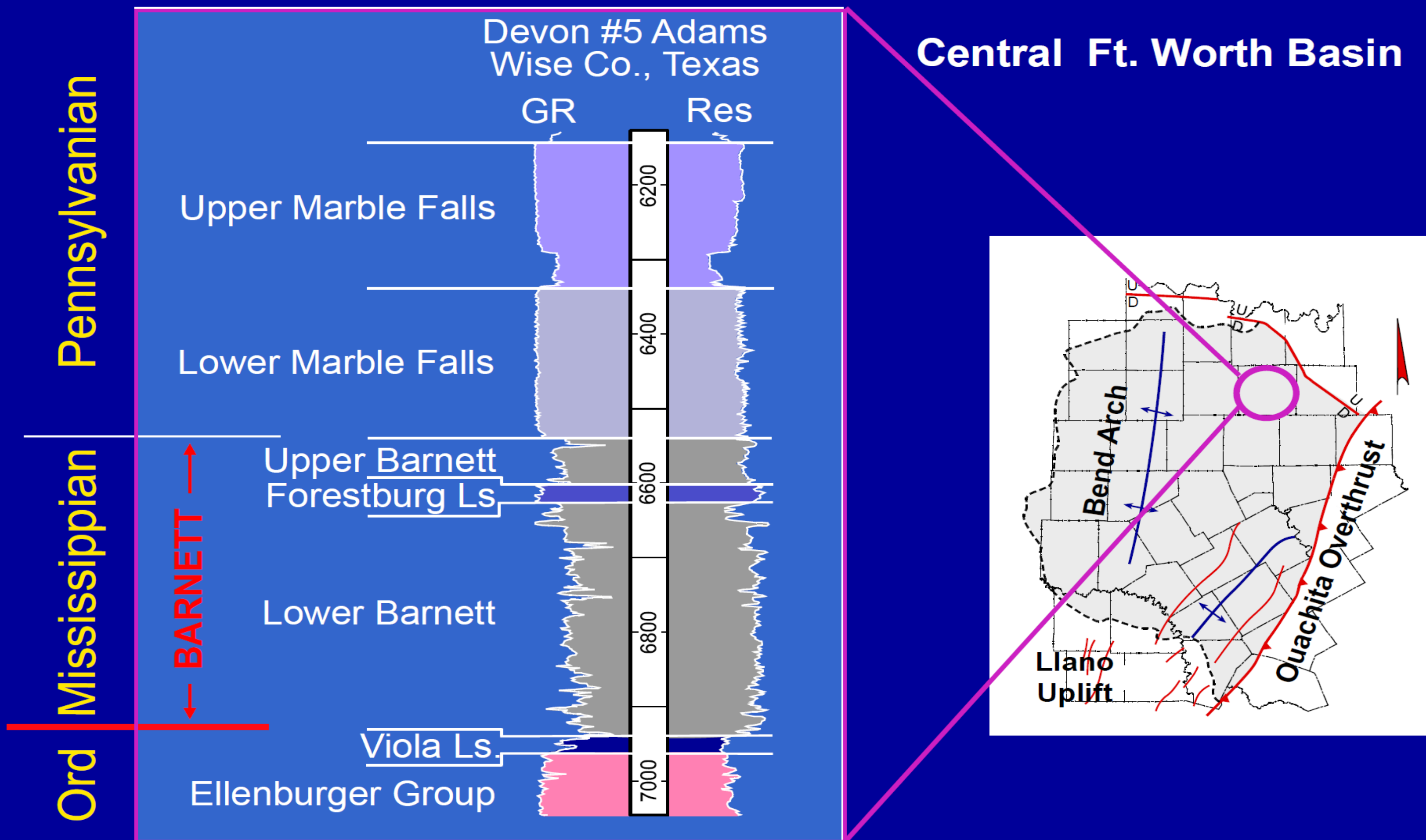
Application to Barnett shale



Some shale plays in USA

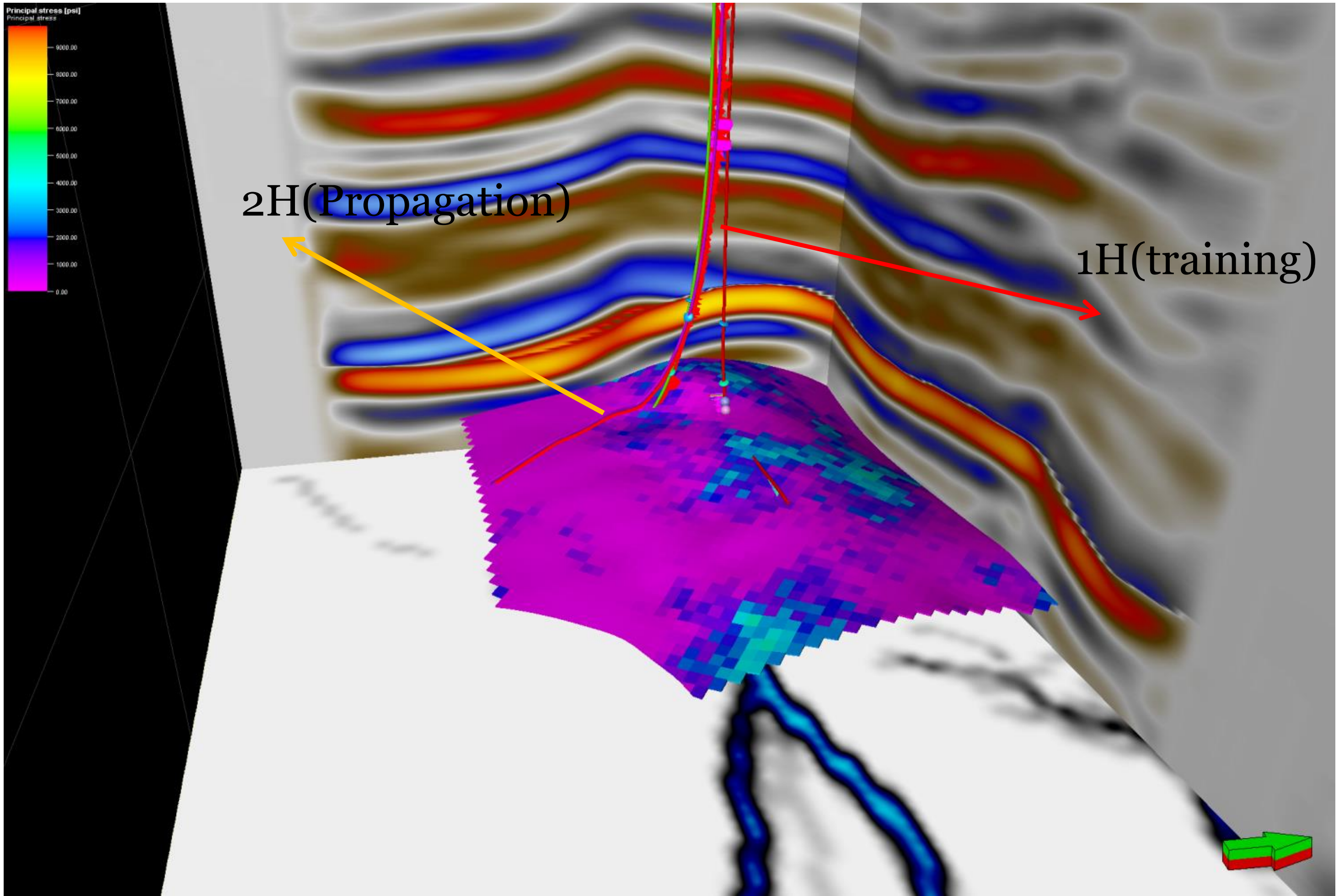


BARNETT TYPE LOG

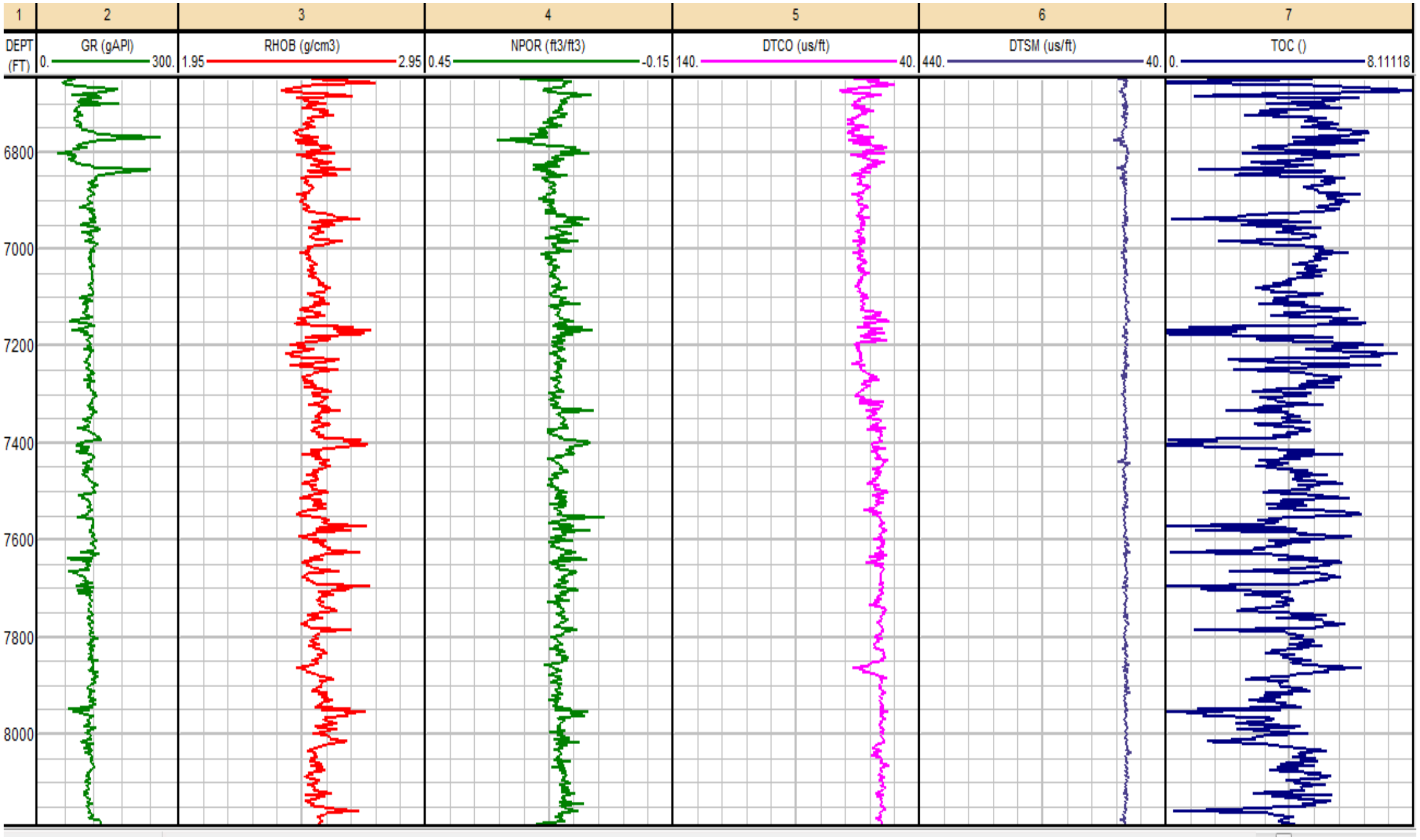


The Barnett Shale-Gas Play of the Fort Worth Basin: STARR Industry Seminar; November, 2006

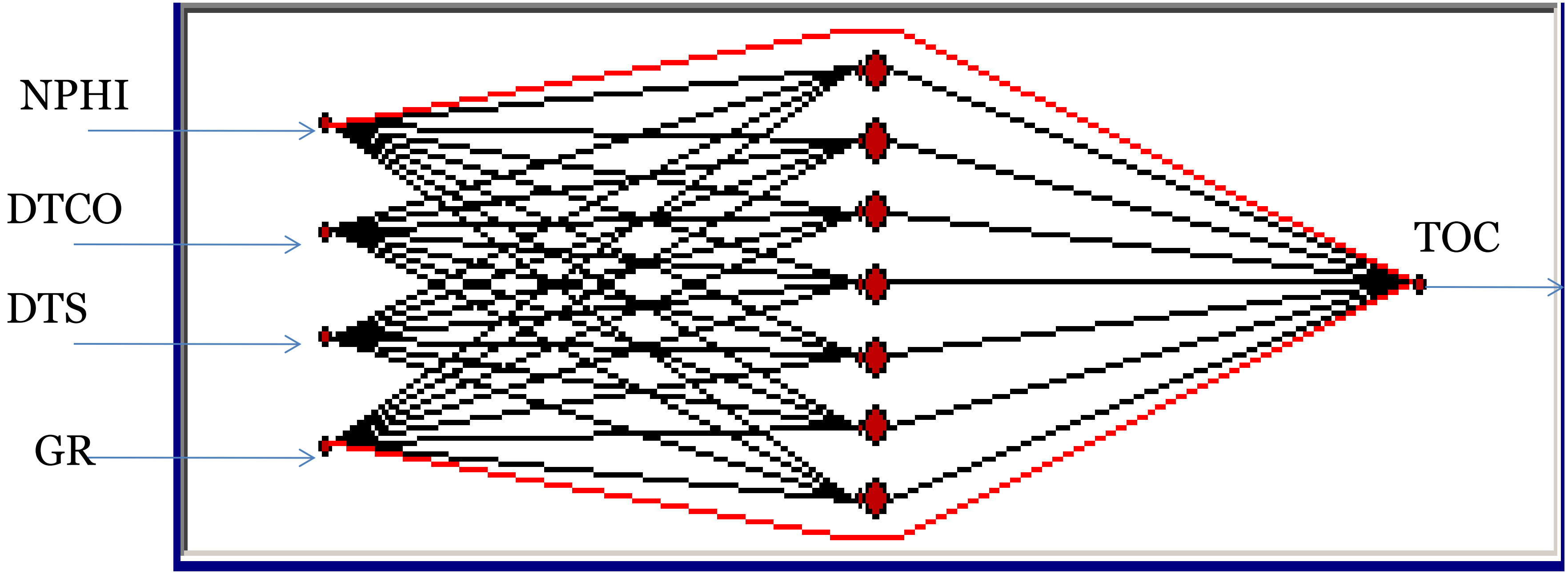
Stress map at the top of the lower Barnett



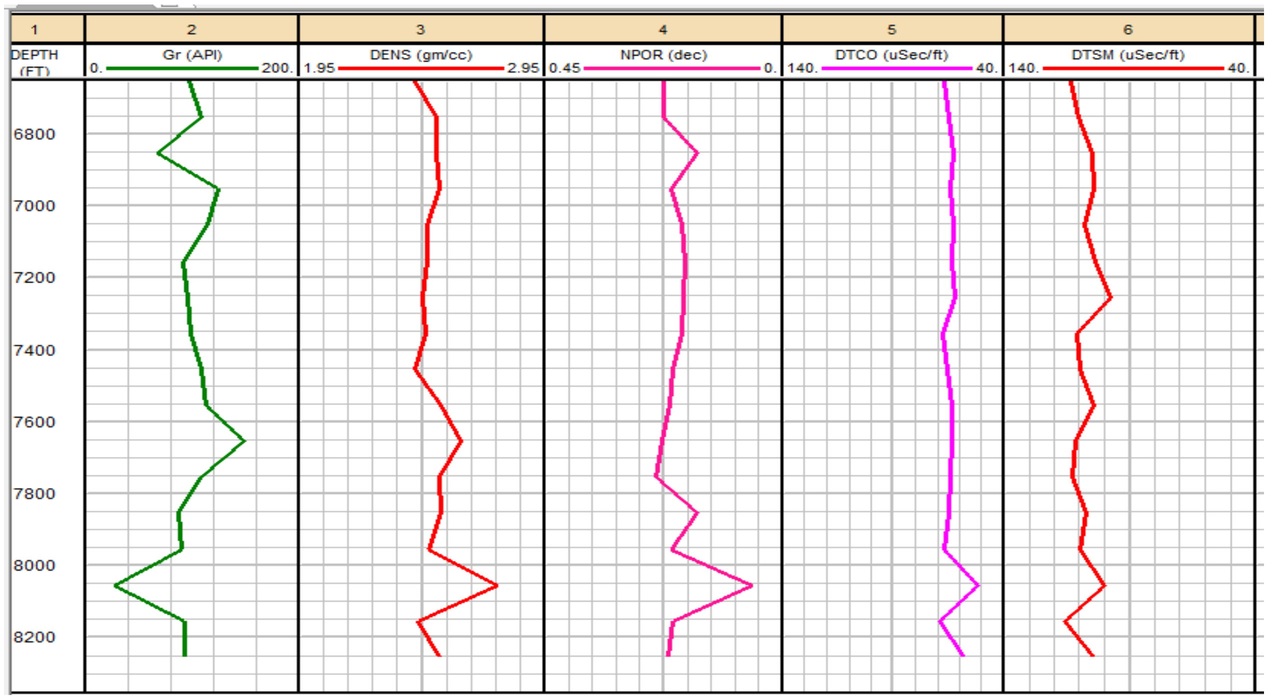
Training Well-logs data



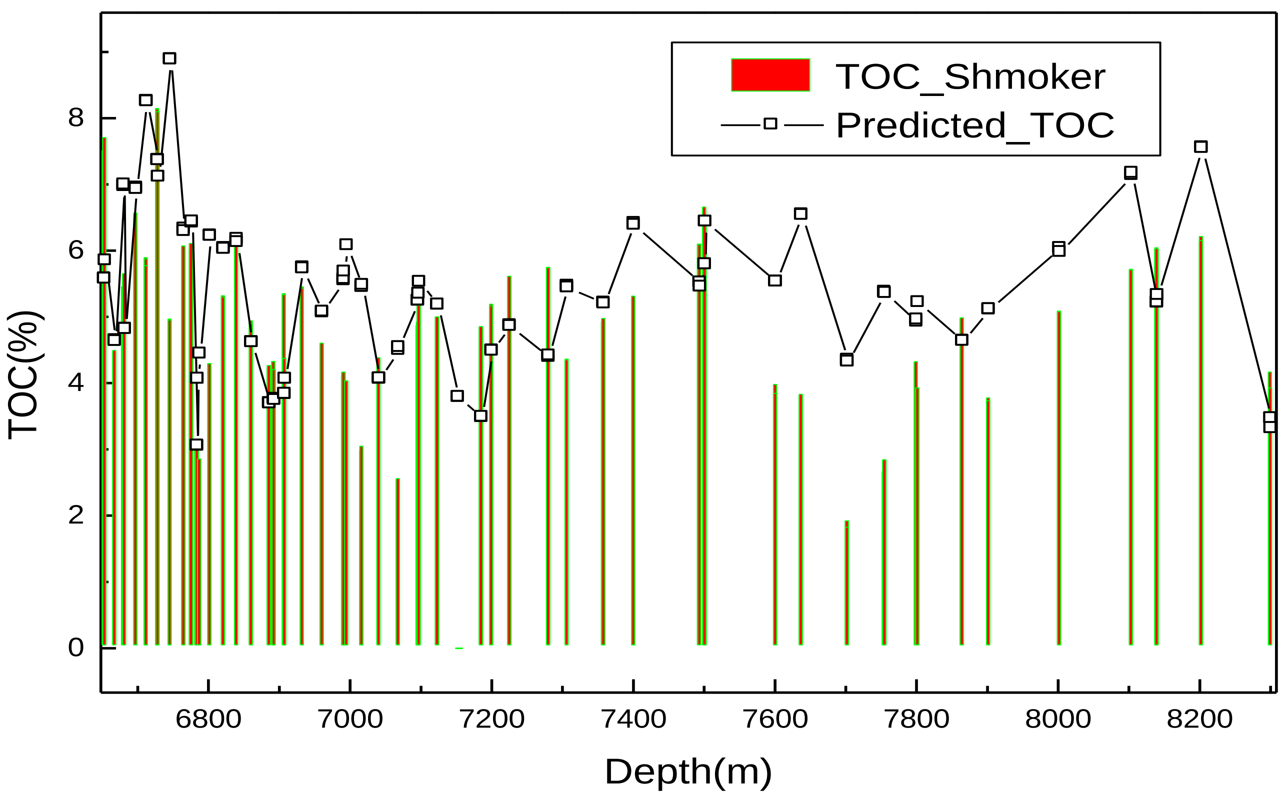
Implanted neural network machine



Well-logs data of a neiberhood horizontal well



Obtained TOC by ANN compared with Schmoker`s TOC



Conclusions

- -TOC knowledge is mandatory in shale gas reservois
- Artificial Network can contribute greatly in TOC estimation in shale gas reservoirs
- TOC Estimation using neural network has an economical benifit
- Obtained results can be used in:
- Sweet spots identification
- Basin modeling
- Kerogen volume estimation

- Thank you for your Attention