Predicting Rock Properties of Hydrocarbon Reservoirs from Bulk Elemental Geochemistry*

Christopher N. Smith[1], Said Assous[1], Hamed Chok[1], and Henrik Friis[2]

Search and Discovery Article #40988 (2012)**
Posted August 6, 2012

*Adapted from oral presentation at AAPG Annual Convention and Exhibition, Long Beach, California, April 22-25, 2012

[1]Weatherford International, Houston, TX (christopher.smith4@weatherford.com)
[2]Aarhus University, Aarhus, Denmark

Abstract

Elemental analysis of sedimentary rocks has been used to correlate stratigraphic units, determine sediment source provenance, evaluate the tectonic setting of a basin, and for sedimentological classification (recently summarized by Pe-Piper et al., 2008). The use of certain elements (e.g. Ti, K, Zr, Hf) to derive information on source and tectonic setting has been shown to be regionally specific and far from universal (Ryan and Williams, 2007; Pe-Piper et al., 2008) and previous attempts to calculate quantitative mineralogy has been inaccurate with errors up to ±75% when compared to modal compositions. Rather than relying on sedimentary norms and linear models, we propose a neural network-based approach to process major, minor and trace element data quickly and accurately (±10%) to determine lithofacies and quantify mineralogy of a sedimentary sample. Two different algorithms are presented for this purpose and a performance comparison is discussed.

Based on the performance of the models, accurate quantitative mineralogy from elemental analysis is best preformed by a neural network approach. This is due to the complexity of mineral chemistry and the non-uniqueness of the distribution of major, minor and trace elements within the minerals of the sample. The neural network models are also able to predict lithofacies, determined from previous sedimentological studies, in shoreline clastic environments.

The strength of the predictive capabilities of the neural networks is that detailed facies models and stratigraphy can be correlated to offset wells using bulk elemental analysis. Element-derived mineralogy and stratigraphy can be used as inputs for reservoir modeling and optimization strategies. Our models have been shown to have a high accuracy predicting lithofacies and mineralogy of sedimentary rock standard reference materials, cuttings and cores, allowing for predictive modeling of reservoir properties.

References

Friis, H., J.B. Svendsen, M.L.K. Poulsen, and L. Hamberg, 2007, Discrimination of density flow deposits using elemental geochemistry-implications for subtle provenance differentiation in a narrow submarine canyon, Palaeogene, Danish North Sea: Marine and Petroleum Geology, v. 24/4, p. 221-235.

Pe-Piper, G., S. Triantafyllidis, and D.J. Piper, 2008, Geochemical identification of clastic sediment provenance from known sources of similar geology: The Cretaceous Scotia Basin, Canada: Journal of Sedimentological Research, v. 78, p. 595-607, doi:10.2110/jsr.2008.067.

Ryan, K.M., and D.M. Williams, 2007, Testing the reliability of discrimination diagrams for determining the tectonic depositional environment of ancient sedimentary basins: Chemical Geology, v. 242, p. 103-125, doi: 10.1016/j.chemgeo.2007.03.013.

Smith, C.N., and A. Malicse, 2010, Rapid handheld X-ray Fluorescence (HHXRF) analysis of gas shales: AAPG International Convention and Exhibition, Calgary, Alberta, Canada, 12-15 September 2010. (Extended Abstract) AAPG Search and Discovery Article #90108, 6 p. Web accessed 25 July 2012. http://www.searchanddiscovery.com/abstracts/pdf/2010/intl/abstracts/ndx_smith.pdf

Svendsen, J., H. Friis, H. Stollhofen, and N. Hartley, 2007, Facies discrimination in a mixed fluvio-eolian setting using elemental whole-rock geochemistry-applications for reservoir characterization: Journal of Sedimentary Research (JSR), v. 77/1, p. 23-33.

Predicting Rock Properties of Hydrocarbon Reservoirs from Bulk Elemental Geochemistry

Christopher N. Smith[1], Said Assous[1], Hamed Chok,[1] and Henrik Friis[2]

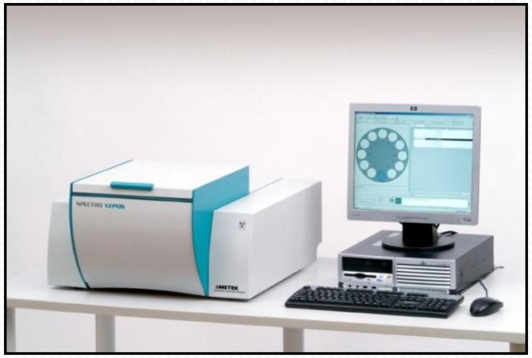
[1] Geoscience Development, Weatherford International, 6550 W Sam Houston Pkwy N #250, Houston, Texas 77041; [2] Department of Earth Sciences, Aarhus University, C.F. Møllers Alle´ 120, DK-8000 Aarhus C., Denmark

AAPG ACE, Long Beach, California
April 23, 2012

Elements in Rocks – Why Inorganic Geochemistry?

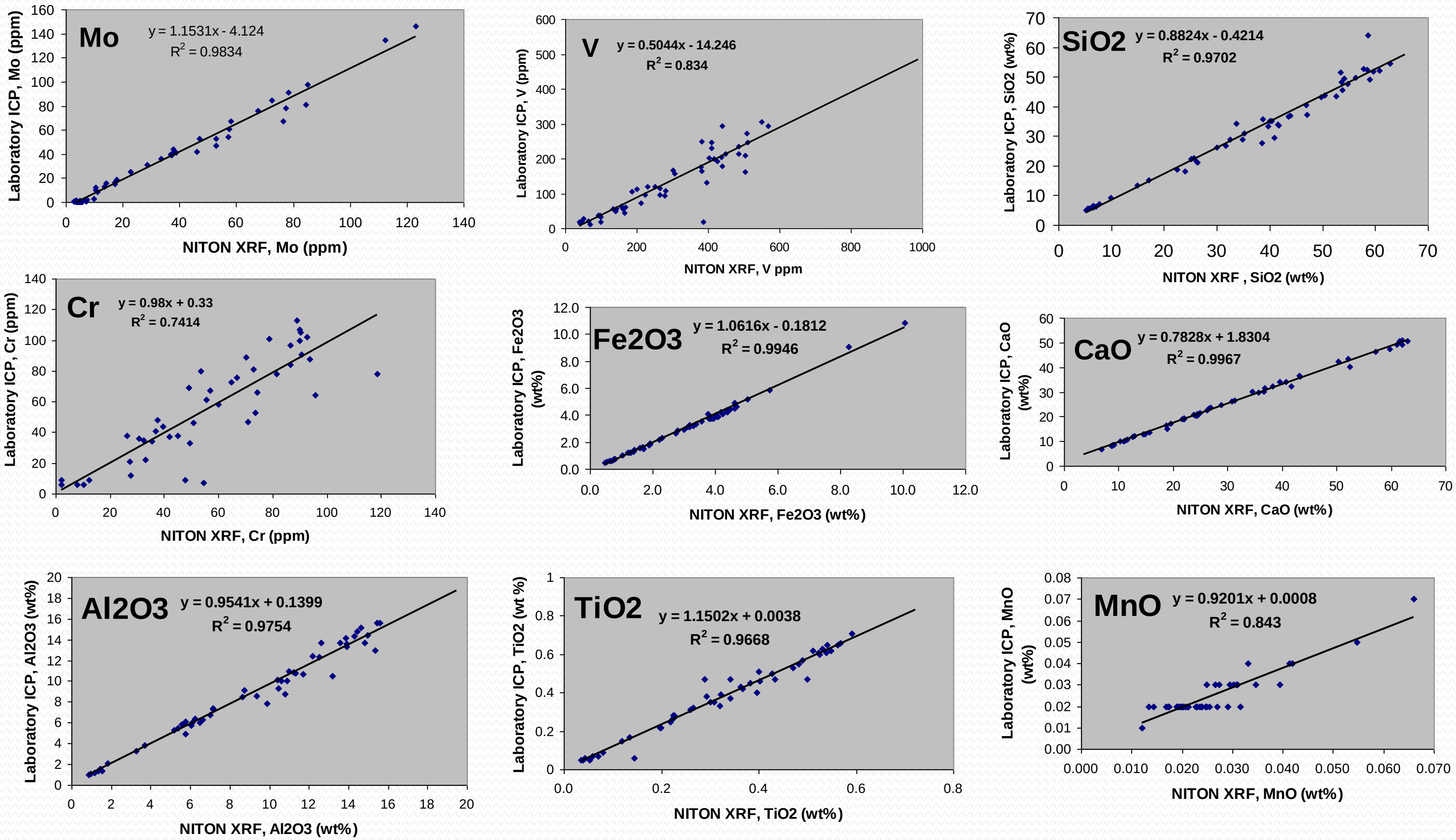
- Major elements define mineralogy and lithology (SiO_2 TiO_2 Al_2O_3 Fe_2O_3 MnO MgO CaO Na_2O K_2O P_2O_5 , plus SO_3 and Cl for most rocks)
- Mineralogy can be related to rock properties: e.g. lithology, porosity, permeability, TOC, brittleness and lithofacies.
- Trace elements reflect paleo-environmental conditions (productivity and redox) and detrital source regions

Elemental Geochemical Analysis



- Lab - Sample fusion + ICP-OES/MS analysis
- Wellsite - Pressed powder pellet + energy dispersive X-ray fluoresence (ED-XRF)

Comparison of Lab & Wellsite Analytical Methods



- ICP-MS vs. ED-XRF – ca. 5% RSD for elements >2x LOD

Smith and Malicse, 2010 AAPG ICE

Modeling Approach

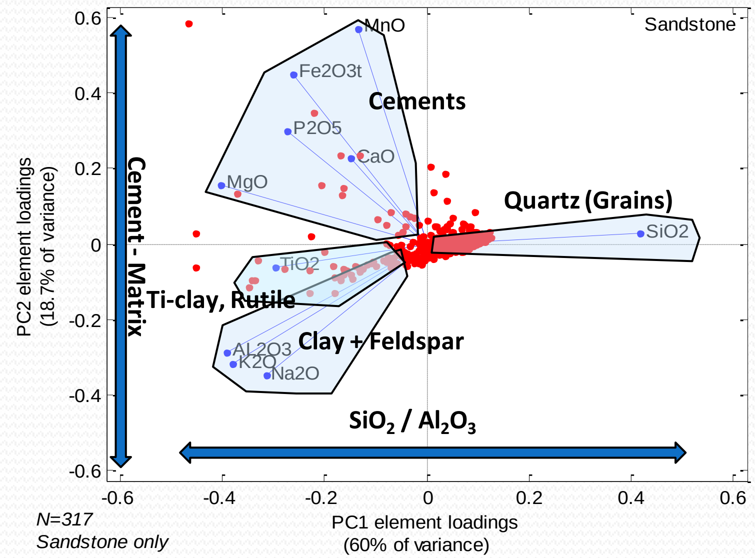
- Inversion of geochemical data similar to seismic and petrophysical techniques
- Multi-variate Statistics
  - Principal Component Analysis (PCA)
  - Neural Network (NN)
  - Self-Organized Maps (SOM)

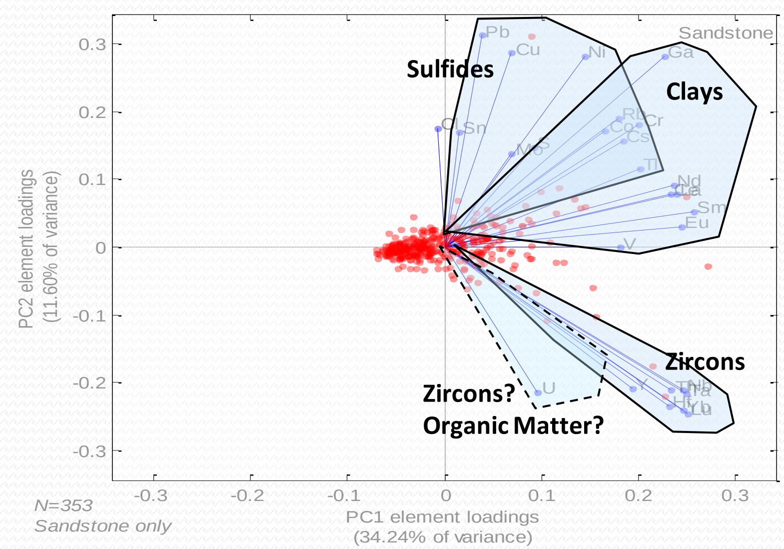
Test Data Sets

- Near shoreline facies
  - Sub-arkosic to sub-lithic sandstone
- Turbidites (Cecilie Field, Siri Canyon, Danish North Sea)
  - Thin to massively bedded, very fine to medium sized quartzose sandstone, glauconite-rich
- Black shale
  - Minor chert and limestone interbeds

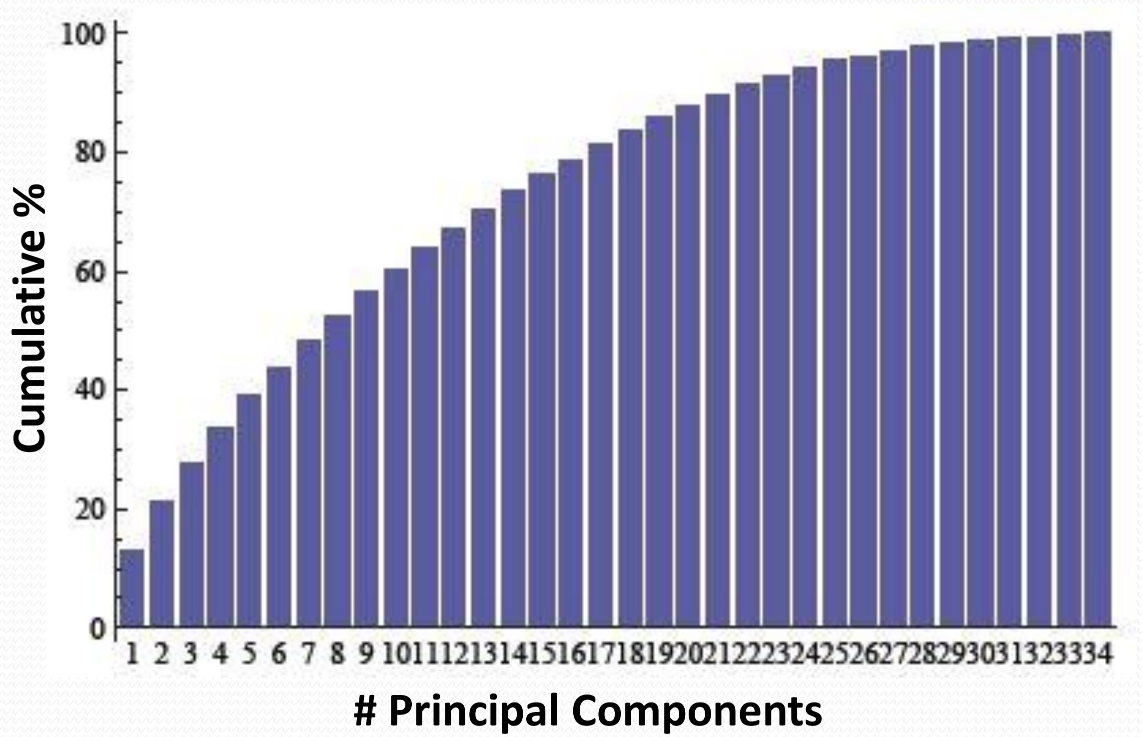
PCA Example – Shoreface

- Major/minor element oxides correlate to mineralogy and textures
  - PC 1 reflects quartz, feldspar and clays as framework grains and cements
  - PC 2 reflects carbonate, phosphate, clay, chlorite, feldspar and heavy minerals (rutile) as cements and matrix
- Trace elements correlate to mineral associations
  - Sulfides: S, Pb, Sn, Ni, Mo, Cu, Co, Tl
  - Clays: Ga, Rb, Cs, Ce, Nd, Eu, Sm
  - Zircons: Hf, Y, Zr, Th, U?
  - U : Zircon/heavy minerals, organic matter (not near Mo, Ni, V, Cr)



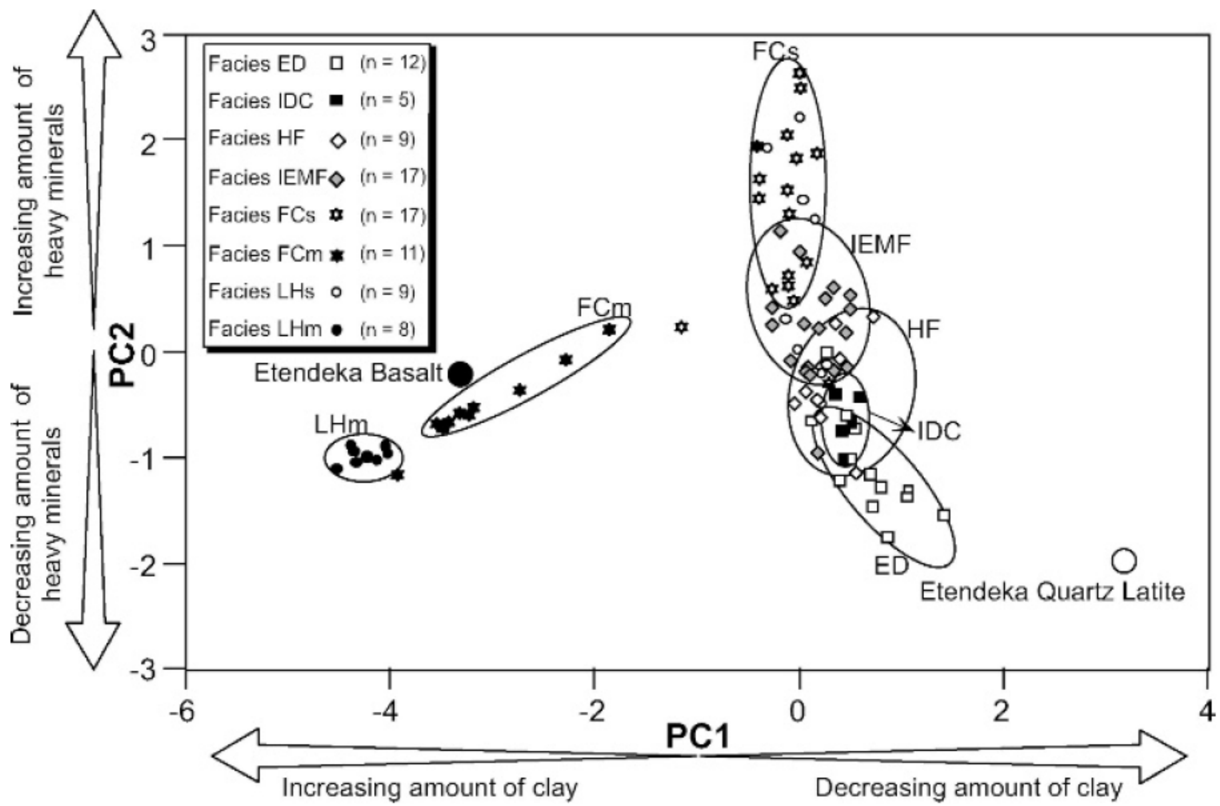


Limitations of PCA - Shoreface



- Can reduce variables in some rock types
- Not suitable for many formations

Facies Classification by PCA - Success

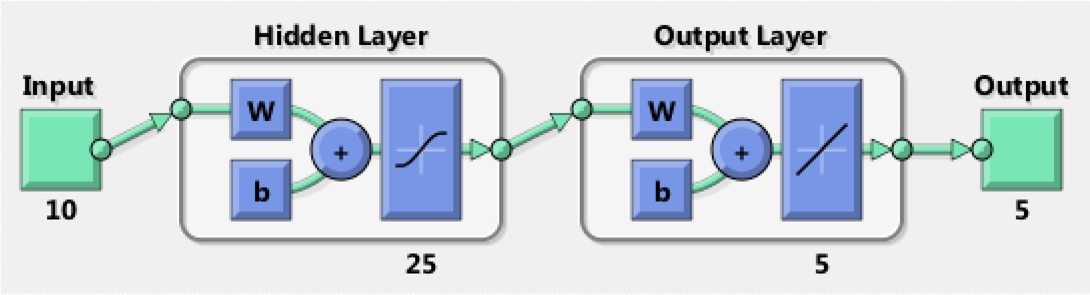


Svendsen et al., 2007 JSR

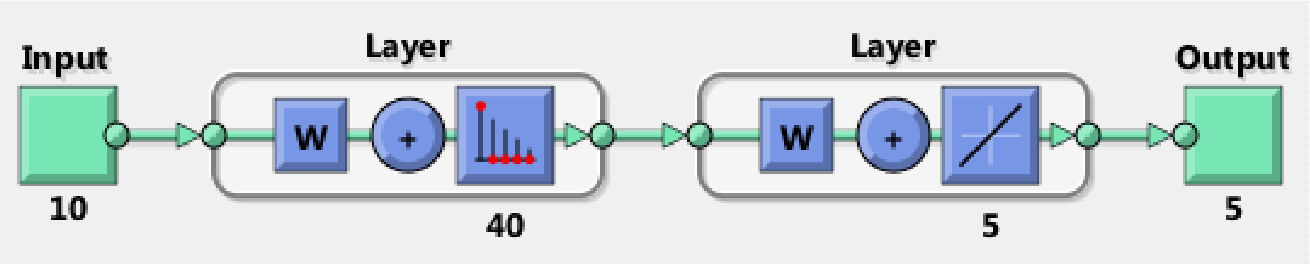
Neural Network Architecture

- Input: Major element oxide wt%

FFNN

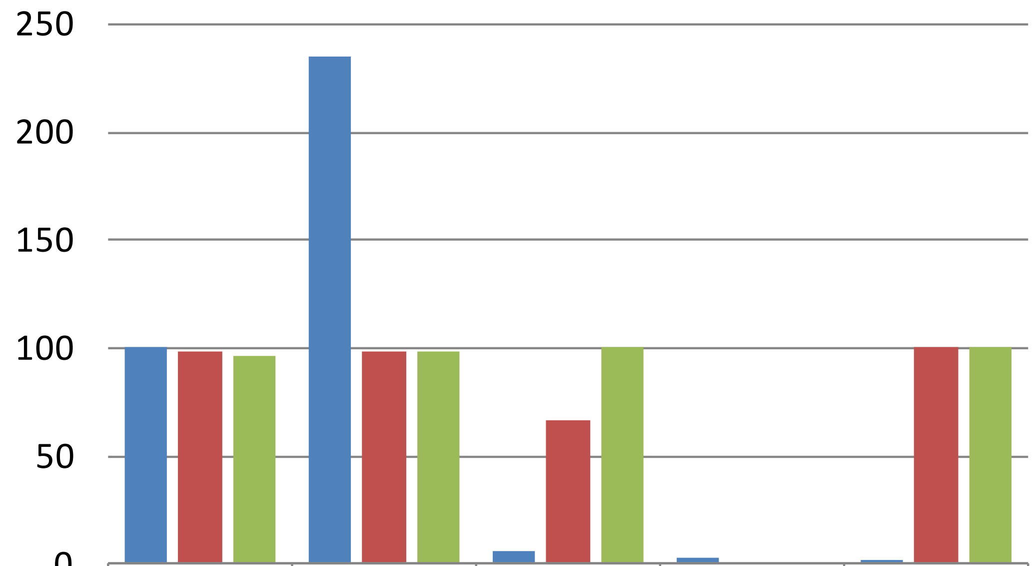


LVQ



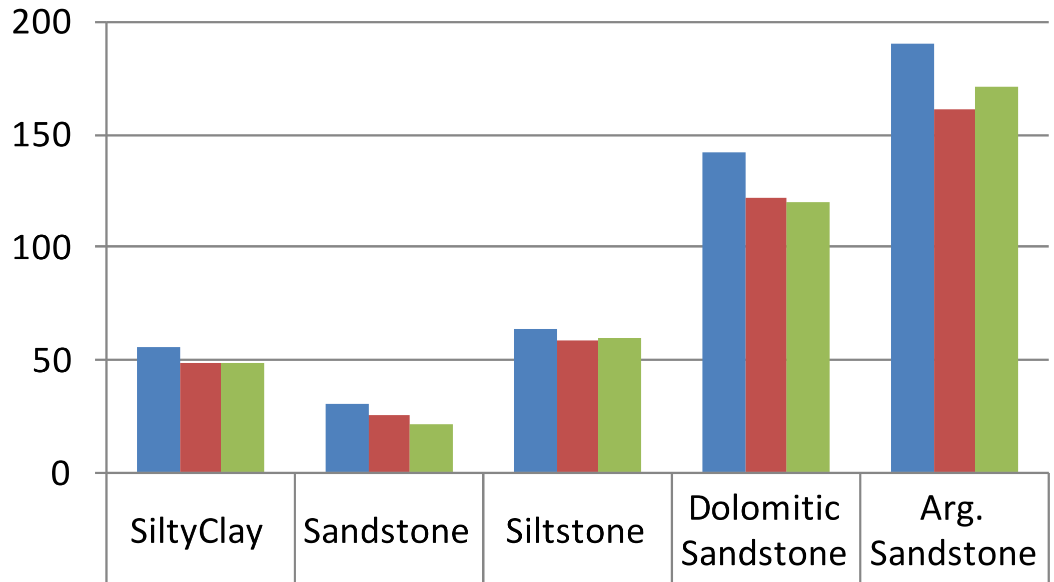
- Output: Lithology

Predicting Lithology: Black Shale



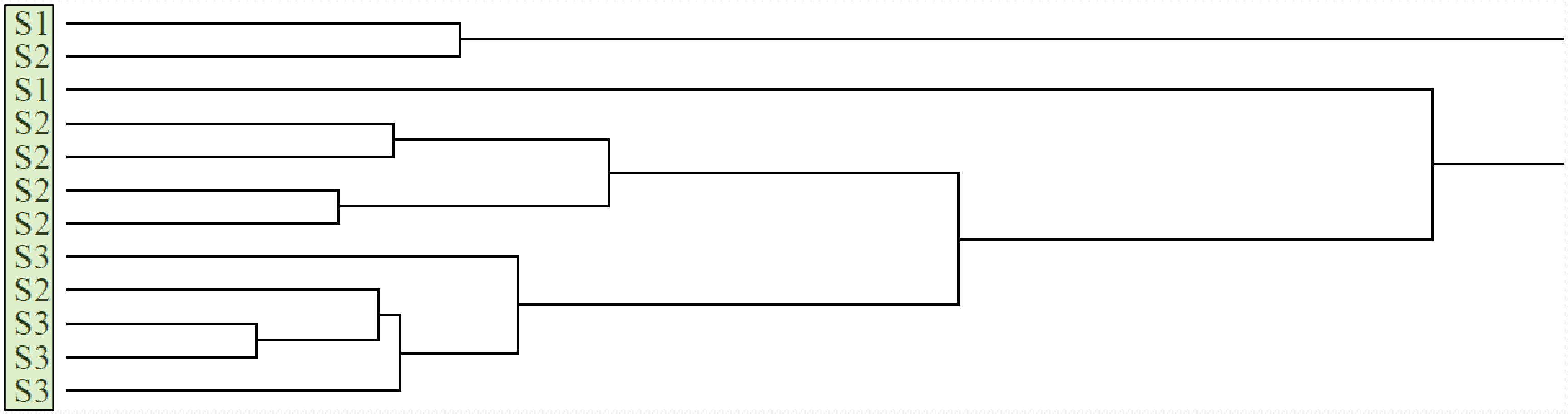
	Chert	Shale	Dolostone	Siltstone	Limestone
n	100	235	6	3	2
FFNN (% correct)	98	98	67	0	100
LVQ (% correct)	96	98	100	0	100

Predicting Lithology: Shoreface



	SiltyClay	Sandstone	Siltstone	Dolomitic Sandstone	Arg. Sandstone
n	56	30	64	142	190
FFNN (% correct)	49	25	59	122	161
LVQ (% correct)	49	21	60	120	171

Classification of Strata: Shoreface

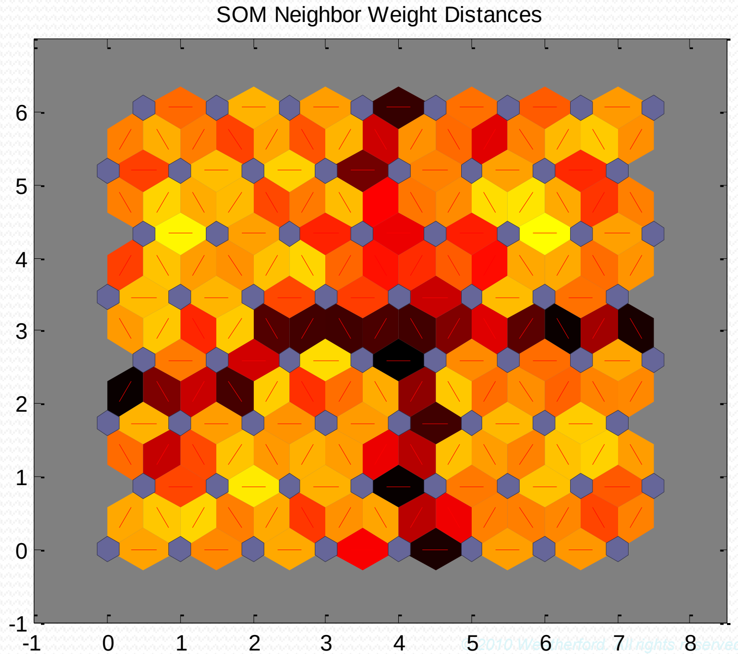


- Inter-class similarities may be equal to or greater than intra-class, most appropriate for heterogeneous sequences
- Cladistic chemostratigraphic approach is often not suitable for reconciling results to traditional stratigraphic interpretations

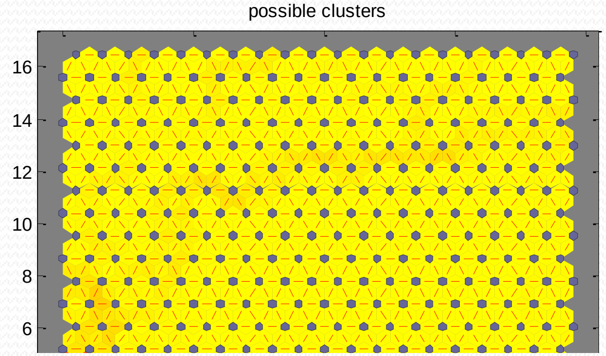
Self-Organized Maps (SOM)

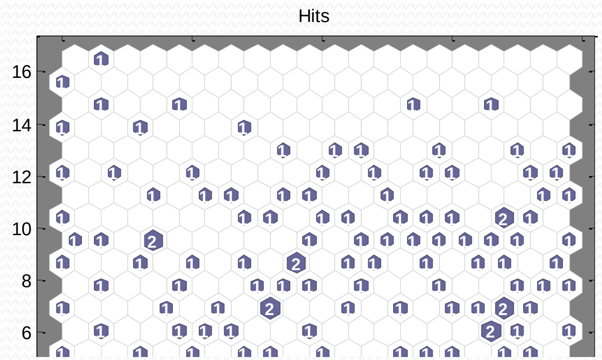
- Neural net approach for unsupervised clustering
- The objective of SOM is to minimize the intra-class, calculating the smallest distances between all the samples, and maximising the interclass by calculating the largest distances.

•The colours in the regions containing the red lines indicate the distances between neurons.
•The darker colours represent larger distances (inter-class).
•The lighter colours represent smaller distances (intra-class)

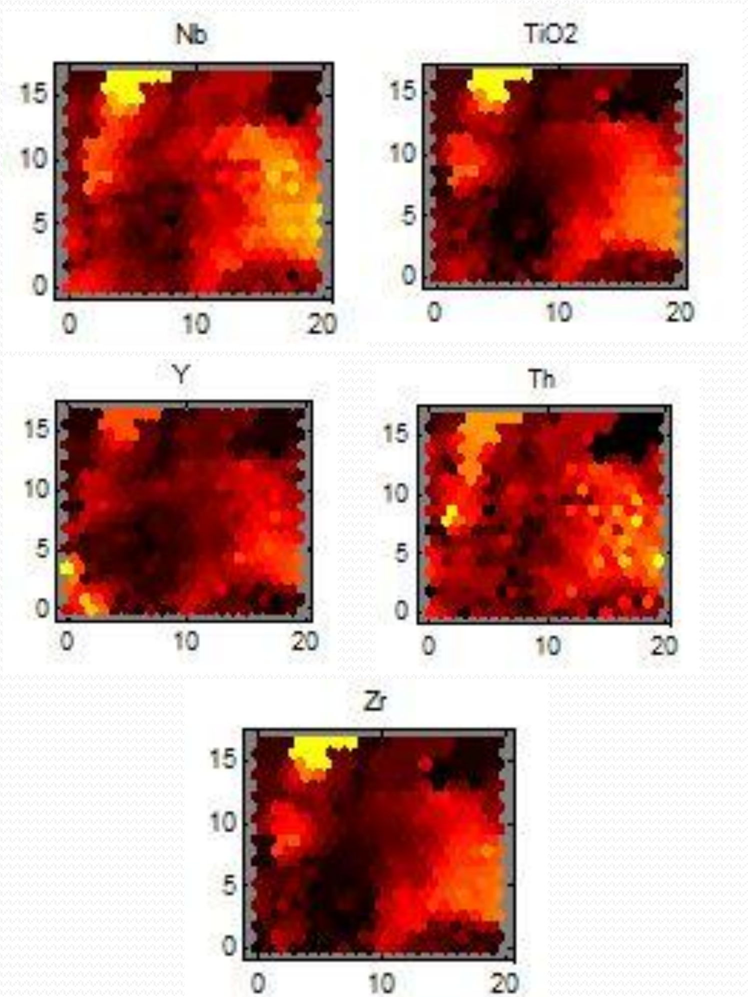


SOM Clustering – Cecilie Field

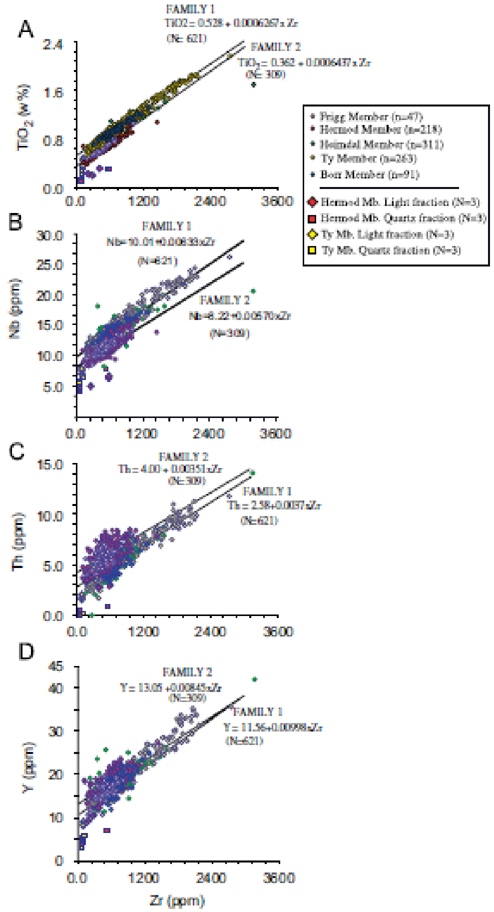




Cecilie-1A

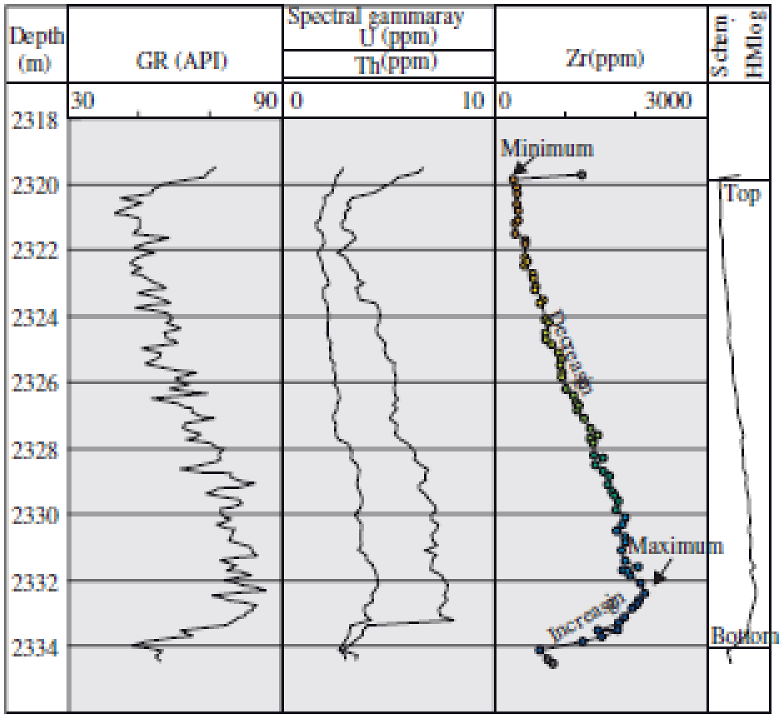


Sorting & Heavy Mineral Elements- Turbidites



Heavy minerals: zircon, rutile, ilmentite

Increasing down section in turbidite



H. Friis et al., 2007 Marine & Petroleum Geology

Conclusions

- Large amounts of geochemical data can be collected from cores, outcrops and cuttings. Relatively inexpensive compared to routine and special core analysis.
- The complexity of the reservoir rock (detrital and authigenic mineralogy) can make geostatistical analysis and modeling difficult.
- Probabilistic modeling of geochemical data offers the potential to enhance formation evaluation techniques at the wellsite and office.

Acknowledgements

- Henrik Friis, Johan Byskov Svendsen , and Mette Lise Kjær Poulsen are thanked for their significant contributions to the understanding of the sedimentary geochemistry of the North Sea
- Aarhus University and the Danish Oil and Natural Gas (DONG) E&P A/S for samples, logs and data in support of the publications of the above investigators
- Weatherford International for support of the authors