PS Mineralogical Estimation of Organic Rich Mudrocks from Well Logs Using Neural Networks: Overcoming Training Dataset Size Limitation by Integrating X-Ray Fluorescence Elemental Data*

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Abstract

Mineralogical composition of rocks is one of the fundamental information that is useful in different disciplines in the oil and gas industry. For example, geologists use mineralogical composition in provenance analysis, geophysicists build rock physics template with specific rock composition range, and engineers use clay proportion to determine the optimal drilling and completion parameters. Traditionally, mineralogical composition is estimated by 1) petrographic analysis such as point counting or infra-red spectroscopy, 2) core examination, and/or 3) well-log analysis such as multi-min models. The success of these methods is variable and is highly dependent on the rocks examined. Organic-rich mudrocks mineralogical composition is harder to identify using these traditional methods because of their inherent 1) small grain size, and 2) highly variable nature at different scales. X-ray diffraction can be used but it is relatively slow and expensive. Neural networks can be used but they require a relatively large training dataset. In this work, we present a workflow to obtain an accurate mineralogical estimation by integrating relatively cheap and fast to obtain x-ray fluorescence elemental data (XRF) and traditional well logs. XRF data is inverted to mineral proportions using constrained optimization based on the stoichiometry of the expected minerals. The relatively large dataset obtained from the analysis can then be used as training set to construct a neural network model with well logs as input and mineralogical proportions as output. Finally, mineralogical proportion is predicted with the neural network using well logs in intervals where XRF is not available. The workflow is validated using x-ray diffraction mineralogical data and illustrated using a real-world case study. The studied formation is the Shublik Formation, North Slope Alaska, where the rocks have highly variable proportions of calcite, quarts, illite, apatite and pyrite. Inverted mineralogy shows good correlation with independently the measured mineralogy from x-ray diffraction. Source code is provided for reuse. Generally, the integration of traditional analysis methods is essential to overcoming the limitations of machine learning methods in geoscience.

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Mineralogical estimation of organic rich mudrocks from well logs using neural networks

Overcoming training dataset size limitation by Integrating X-ray fluorescence elemental data

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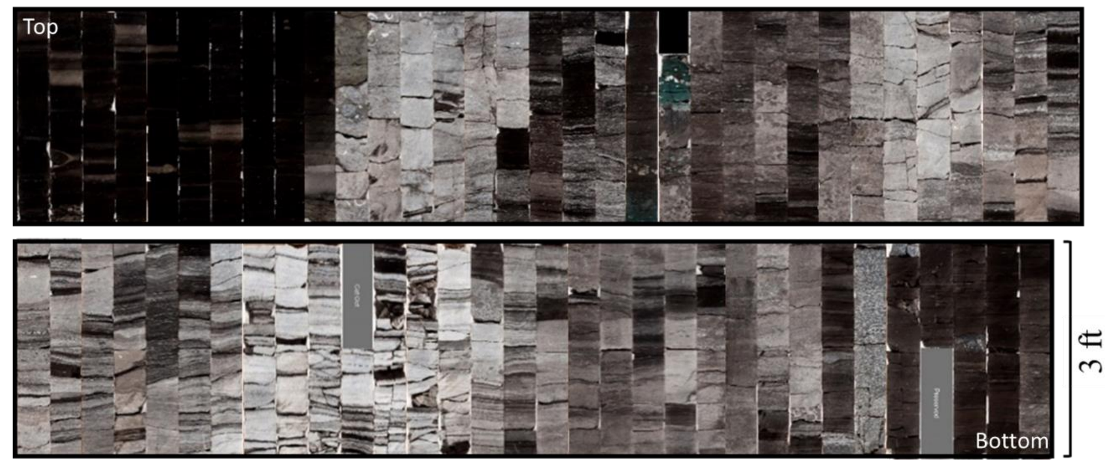
Summary

Mineralogical composition of rocks is one of the fundamental information that is useful in different disciplines in the oil and gas industry. For example, geologists use mineralogical composition in provenance analysis, geophysicists build rock physics template with specific rock composition range, and engineers use clay proportion to determine the optimal drilling and completion parameters. Traditionally, mineralogical composition is estimated by 1) petrographic analysis such as point counting or infra-red spectroscopy, 2) core examination, and/or 3) well-log analysis such as multi-min models. The success of these methods is variable and is highly dependent on the rocks examined. Organic-rich mudrocks mineralogical composition is harder to identify using these traditional methods because of their inherent 1) small grain size, and 2) highly variable nature at different scales. X-ray diffraction can be used but it is relatively slow and expensive. Neural networks can be used but they require a relatively large training dataset. In this work, we present a workflow to obtain an accurate mineralogical estimation by integrating relatively cheap and fast to obtain x-ray fluorescence elemental data (XRF) and traditional well logs. XRF data is inverted to mineral proportions using constrained optimization based on the stoichiometry of the expected minerals. The relatively large dataset obtained from the analysis can then used as training set to construct a neural network model with well logs as input and mineralogical proportions as output. Finally, mineralogical proportion is predicted with the neural network using well logs in intervals where XRF is not available. The workflow is validated using x-ray diffraction mineralogical data and illustrated using a real-world case study. The studied formation is the Shublik Formation, North Slope Alaska, where the rocks have highly variable proportions of calcite, quarts, illite, apatite and pyrite. Inverted mineralogy shows good correlation with independently the measured mineralogy from x-ray diffraction. Source code is provided for reuse. Generally, the integration of traditional analysis methods is essential to overcoming the limitations of machine learning methods in geoscience.

Introduction and motivation



Organic rich mudrock heterogeneity is observed at different scales. It is harder to characterize this heterogeneity using traditional methods such as core description. Models that relates well logs to mineralogy can be constructed and used for characterization.

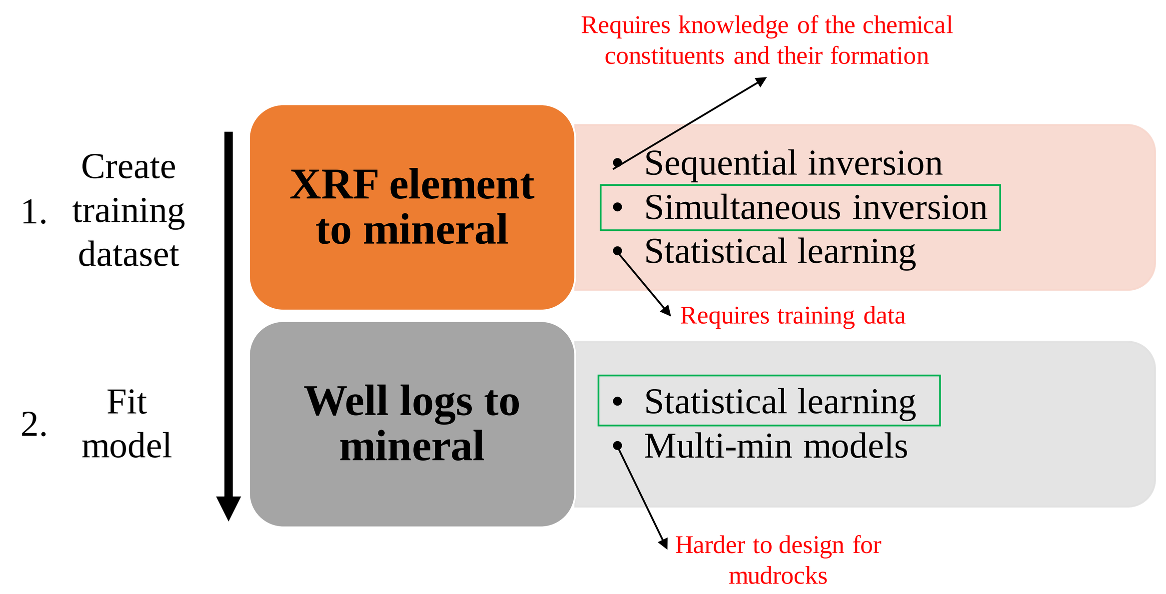
Problem

Statistical models requires large number of data points with solution. In the case of well logs to mineral fitting, mineralogical measurements, such as x-ray diffraction measurements, are sparse and not enough.

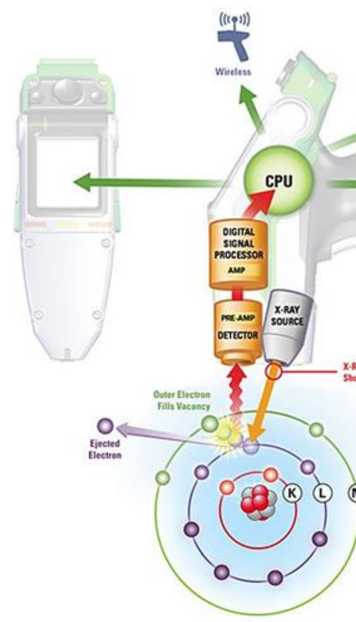
Approach

Elemental data is now available for most organic-rich mudrocks. Can the already available elemental data from x-ray fluorescence be utilized to alleviate the sparse mineralogical dataset issue?

Chemostratigraphy + Shale (Google scholar)		
2000 – 2009:	2,610	publications/conferences/patents
2010 – 2019:	7,040	publications/conferences/patents

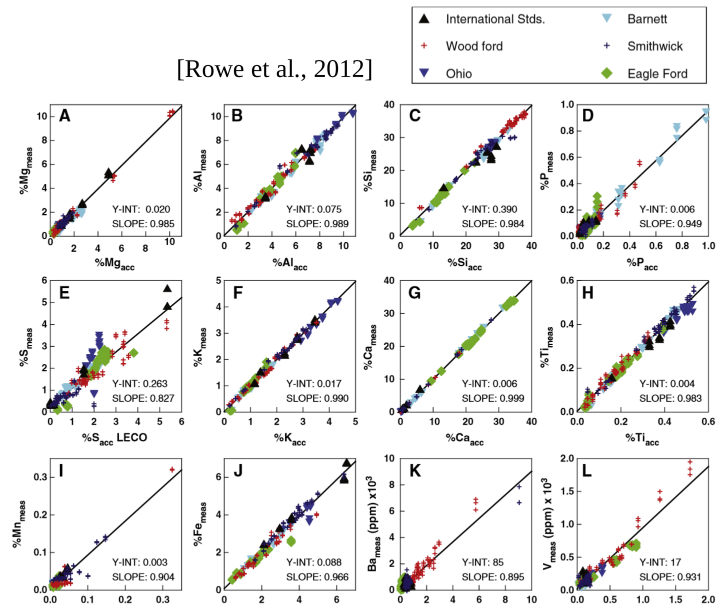


X-ray fluorescence measurements



[Thermo Fisher Scientific, 2019]

[Olympus, 2019]



[Rowe et al., 2012]

Portable XRF devices are:

1) Fast to operate (30-60s per sample)
2) Non-destructive,
3) Require little knowledge to operate,
4) Can be automated,
5) Yield relatively accurate results if calibrated correctly.

Calibration using more accurate measurements such as ICP-MS is used to convert detected fluorescence to elemental proportions.

Elements to mineral inversion

$$Ax = b$$ [de Caritat et al., 1994]

- b: Element proportions vector (measured)
- x: Mineral proportions vector (unknown)
- A: Element-mineral matrix based on Stoichiometry

$$0 \le b \le 1$$

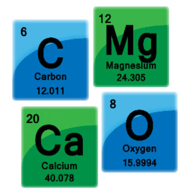
$$\sum x = 1$$

Example

Elements:
Calcium: Ca
Magnesium: Mg

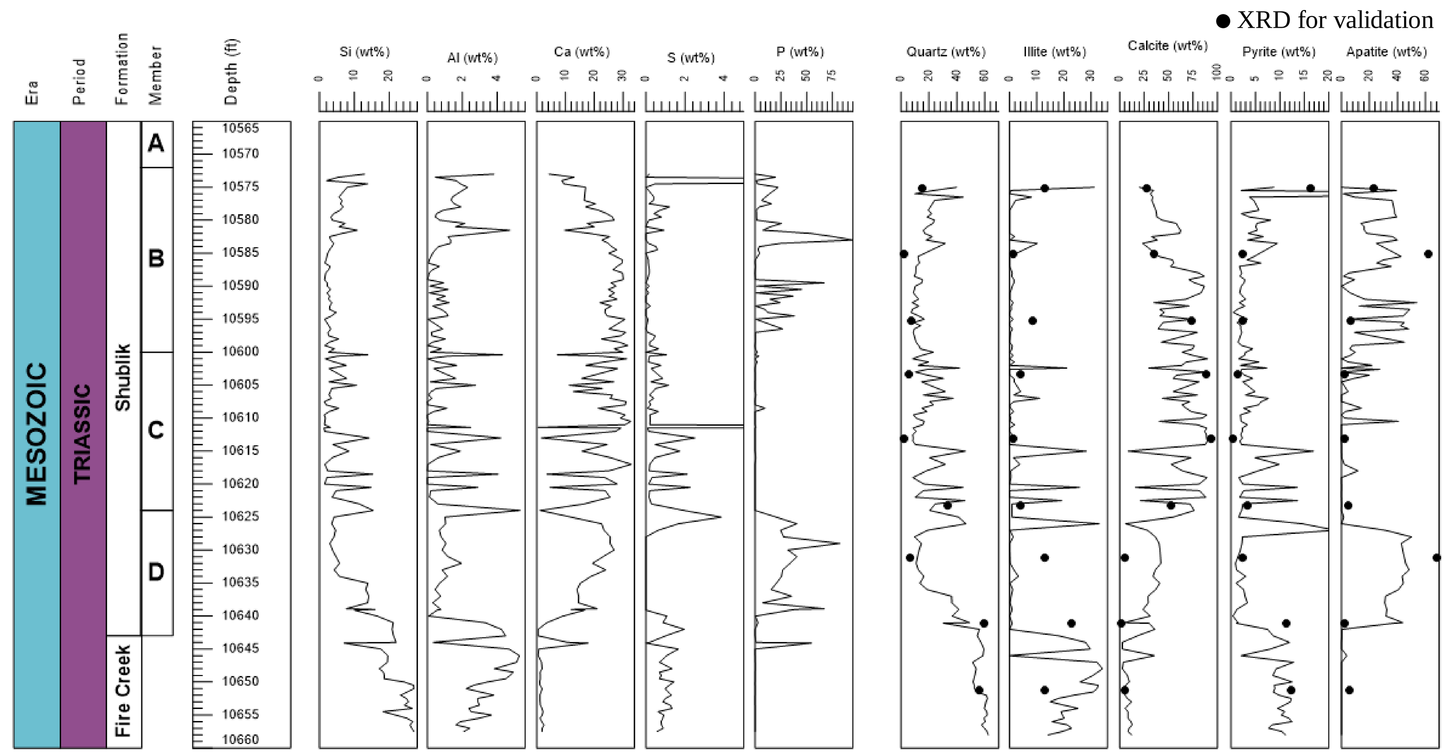
Simultaneous inversion →

Expected minerals:
Calcite: $CaCO_3$
Dolomite: $CaMg(CO_3)_2$



$$A = \begin{bmatrix} A_{Ca,Calcite} = \dfrac{1 * 40.08}{100.09} = 0.400 & A_{Ca,Dolomite} = \dfrac{1 * 40.08}{184.40} = 0.2173 \\ A_{Mg,Calcite} = \dfrac{0 * 24.31}{100.09} = 0 & A_{Mg,Dolomite} = \dfrac{1 * 24.31}{184.40} = 0.1318 \end{bmatrix}$$

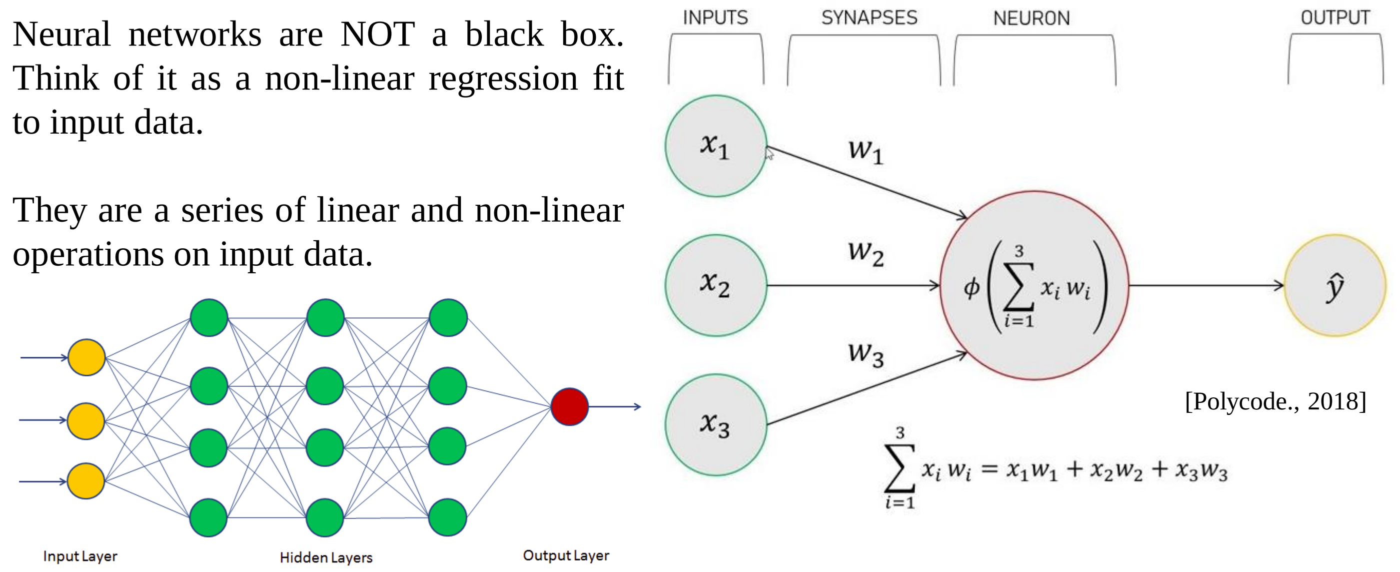
$$\begin{bmatrix} 0.400 & 0.2173 \\ 0 & 0.1318 \end{bmatrix} \begin{bmatrix} x_{calcite} \\ x_{Dolomite} \end{bmatrix} = \begin{bmatrix} x_{Ca} \\ x_{Mg} \end{bmatrix}$$



A primer on dense neural network

Neural networks are NOT a black box. Think of it as a non-linear regression fit to input data.

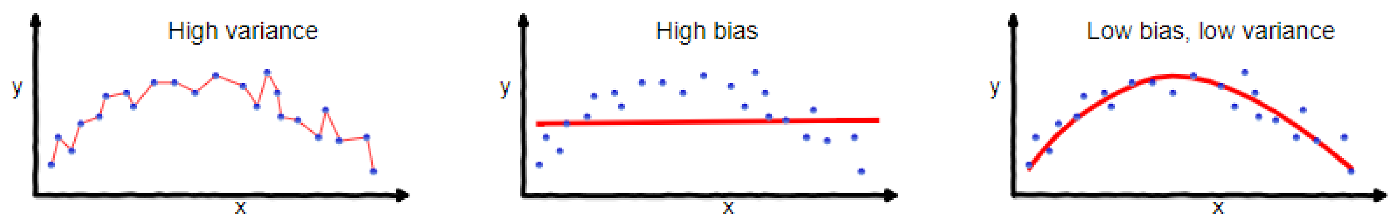
They are a series of linear and non-linear operations on input data.



[Polycode., 2018]

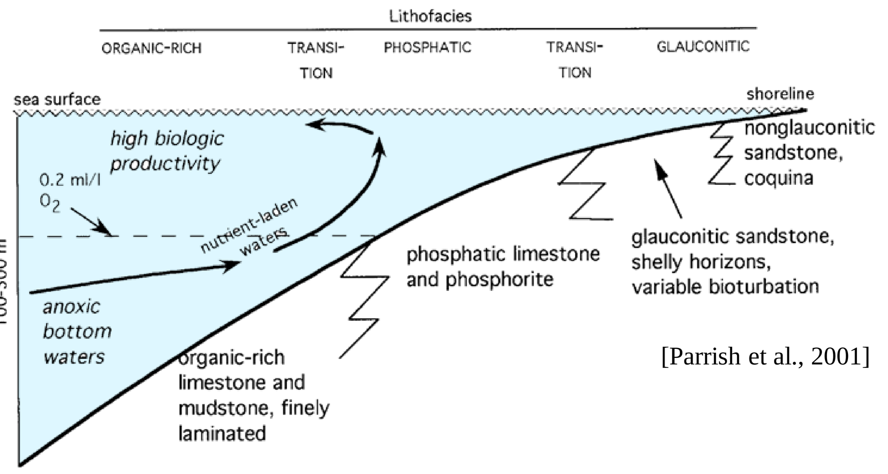
$$\sum_{i=1}^{3} x_i w_i = x_1 w_1 + x_2 w_2 + x_3 w_3$$

The network is constructed and fitted to produce low bias and low variance.



Case study introduction

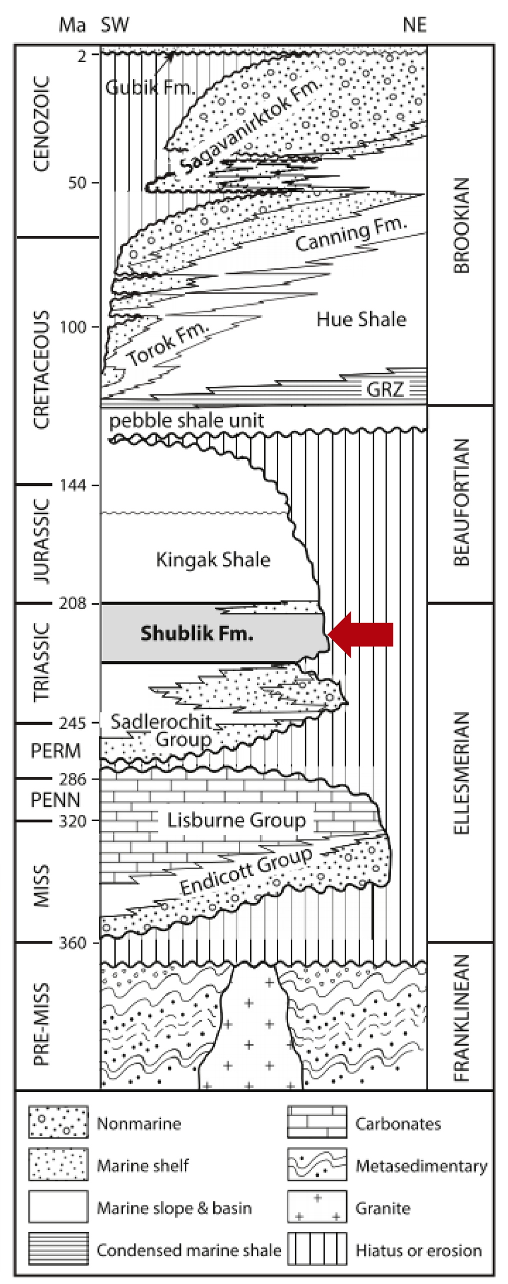
The Upper Triassic Shublik Formation is considered one of the main source rocks on the North Slope, Alaska. The elemental data is obtained using a handheld x-ray fluorescence device (Bruker Tracer). Calibration is applied to convert the x-ray fluorescence count to mass percentage using the relationships proposed by Rowe et al (2012). In addition, x-ray diffraction (XRD) analysis is done on a number of samples throughout the interval. XRD results show that calcite, quartz, illite, pyrite, and apatite are significant in the analyzed samples.

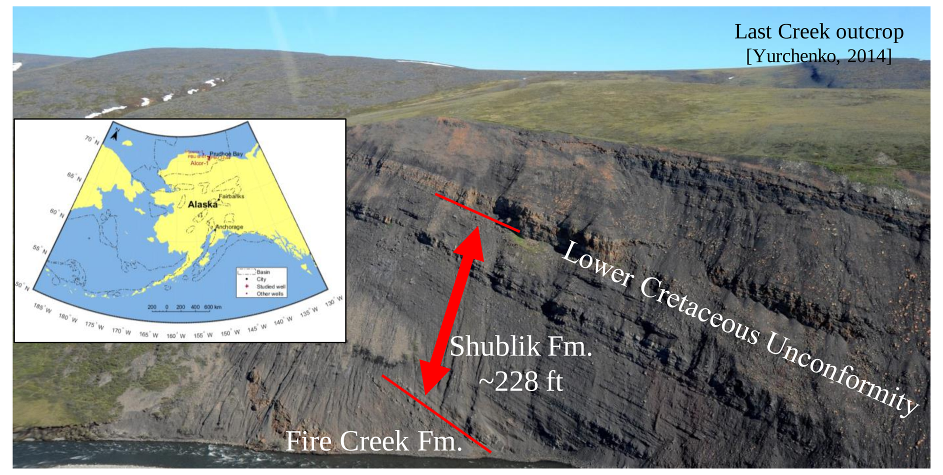


[Parrish et al., 2001]

Parrish et al. (2001) identified four main lithofacies in the Shublik interpreted as deposits in an upwelling zone. The studied interval spans the Upper Triassic Fire Creek and Shublik formations, which can be subdivided into different members corresponding to distinct lithofacies.

[Houseknecht et al., 2012]



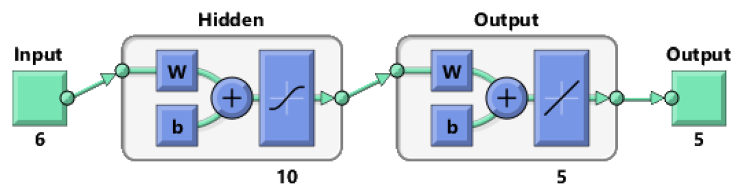


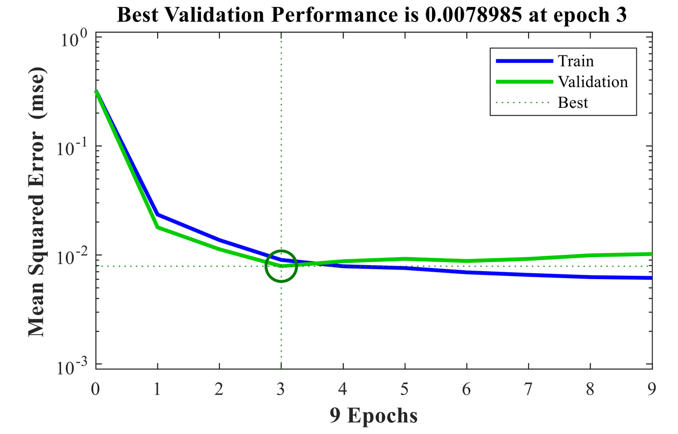
Results and discussion

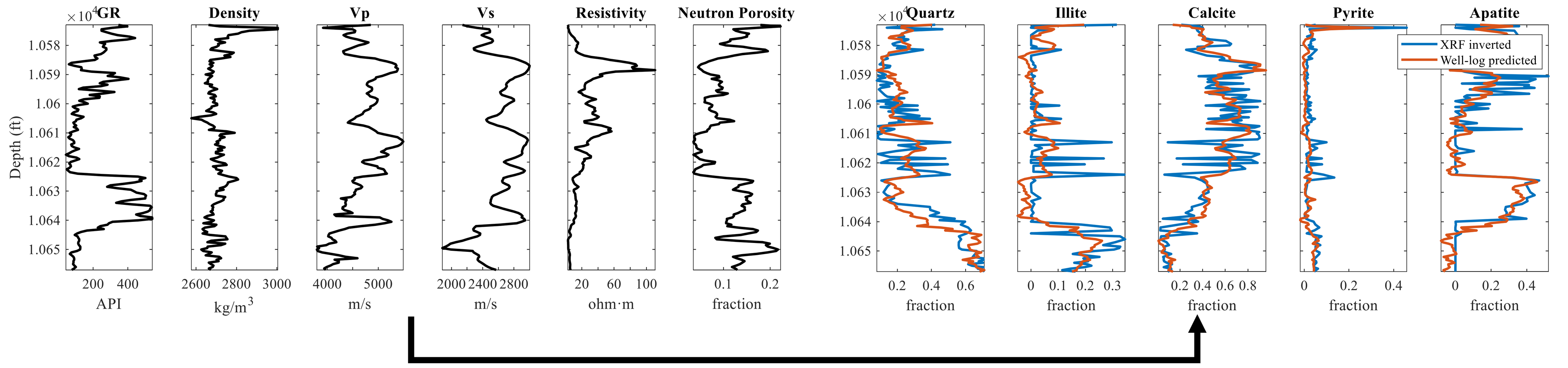
Six well logs are used. The network is fitted on one well.

Dataset: 169 samples
Training: 80%
Validation: 20%

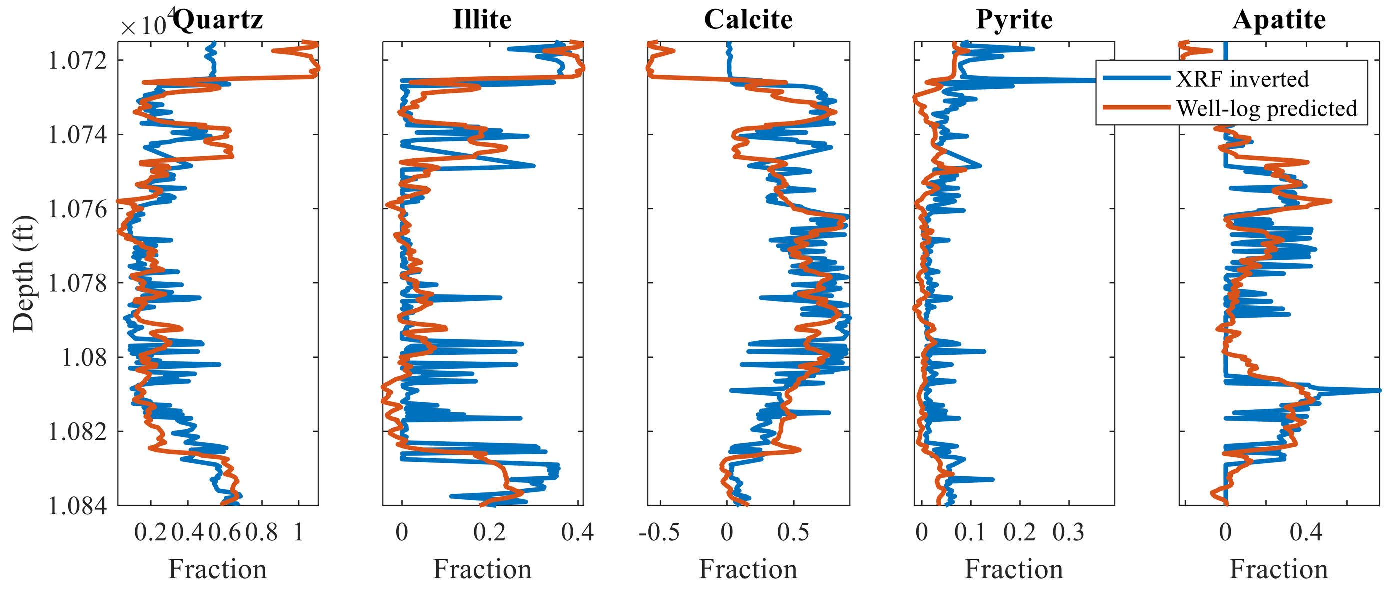
A neural network with one hidden layer (10 neurons) is used.

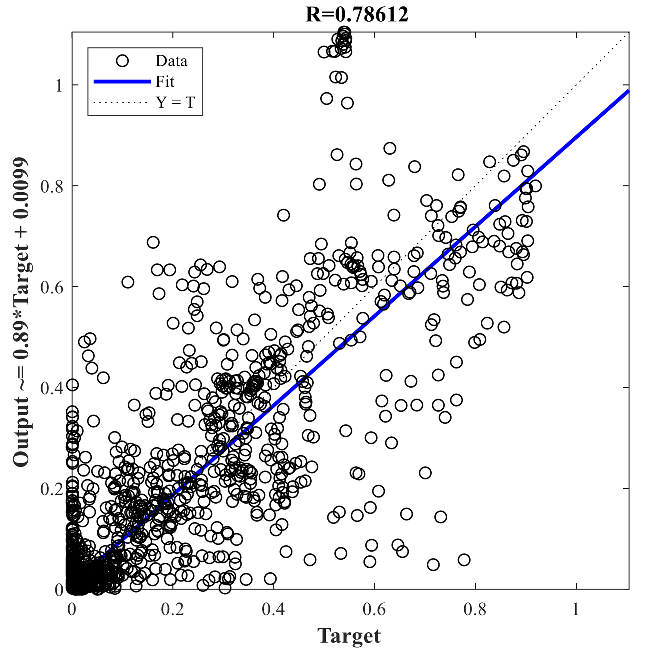






The network is tested on a separate well (blind test). The well is about 3 km apart from the first one. Good correlation is observed between the well-log predicted and XRF-inverted mineralogy.

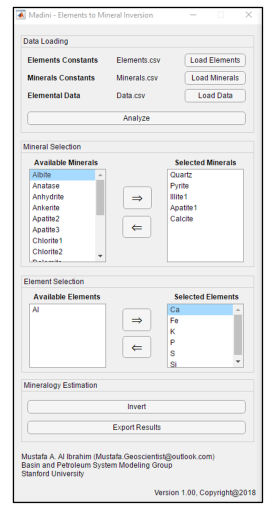




Conclusions and final remarks

- Using XRF-inverted mineralogical data, we were able to train a neural network to predict mineralogy from well logs.
- The whole workflow is largely automated, but requires the guidance of the geoscientist to determine the expected minerals and some knowledge in data science to select the best statistical methods.
- Integration of older workflows and methods with newer statistical methods is useful.
- Simultaneous inversion software, developed for this study, can freely be downloaded from the link below.

GitHub
https://github.com/StanfordRockPhysics/Madini



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