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Multi-Scale Rock Imaging for Reservoir Characterization: A Wolfcamp Case Study

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Summary

Digital rock analysis (DRA) embraces multi-scale rock imaging and is becoming a standard tool for reservoir characterization. One of the challenges resides in how to link together rock properties derived from such different scale of magnitude. In this paper we demonstrate that rock properties can be upscaled throughout the nano-scale to core scale by combining DRA, Machine learning (ML) techniques, and high performance computing (HPC) platforms.

The approach is based on the understanding that a rock consists of multi-scale rock fabrics intermixed spatially. Here, fabrics refer to complex visual patterns formed by distinct features which properties are extracted using mathematical models. Thus, rock fabrics are captured as groups of patterns within a digital image.

These fabrics are linked with rock classes. Rock typing classification is performed on high resolution log data. It is based on simultaneous multi-dimensional cluster analysis within datasets using an appropriated ML technique.

Introduction

Machine learning (ML) has accelerated advances in many industries. ML brings together multiple disciplines such as computer science, statistics, and natural science to create algorithms that can learn from data. DRA can harness the power of ML to learn from its data, the digital image of rocks, to generate breakthroughs in the oil and gas industry.
In this paper, we combine advances in DRA and ML to characterize rock samples at different scales. The framework is based on an understanding that a rock consists of multi-scale rock fabrics intermixed spatially. A rock fabric is defined as a combination of rock features. Similar rock fabrics have similar properties or follow similar property trends.

We developed ML algorithms that can automatically learn about rock fabrics and their patterns. These algorithms have the ability to build a model from data without strict instructions. Detailed discussion regarding ML can be found in Bishop, 2006 and Bengio, 2009. Examples of ML-based computer vision applications include autonomous vehicle technology, automatic tumor detection, and object recognition. Digital images produced in DRA can be also considered as data. Based on this perspective, DRA can harness the power of ML to discover and learn from its data.

Theory

Mudrocks have complex multi-scale heterogeneous features. A variety of imaging and detection techniques have been used to gain insights into rocks. Ideally, the image resolution being used should resolve all significant rock features and provide a reasonably large field of view.
Imaging starts at whole core at sub-millimeter resolution to plug samples at nanometer resolution. At core scale, rock classes are obtained using continuous high resolution log data computed from dual-energy X-ray CT and spectral gamma ray.

The classification is based on an automatic identification of rock classes from log data based on multilayer machine learning. The method uses an artificial neural network method, a clustering method and a graph-base method. This classification is unsupervised. Then, it does not require a predefined number of rock classes. Also, the method chooses optimal depth locations from where plugs will be taken in order to perform further digital analysis.

Plugs from the selected locations are imaging at a relatively coarse resolution to cover a large field of view at about 250nm per pixel. Rock fabrics in this image are detected and segmented using the texture analysis method discussed in Sungkorn et all, 2015.

Rock features larger than the image resolution are resolved while smaller ones are unresolved. A rock feature is considered resolved when it is represented, in every direction, by at least two pixels. Then, the unresolved rock fabrics are segmented into groups. Information concerning the unresolved rock feature is analyzed from additional images acquired at a much finer resolution and smaller field of view such as SEM.

SEM images are analyzed and provide quantitative rock properties such as organic matter content and porosity. Then, these rock properties are propagated back onto the much coarser image through the identify fabrics (Figure 1).

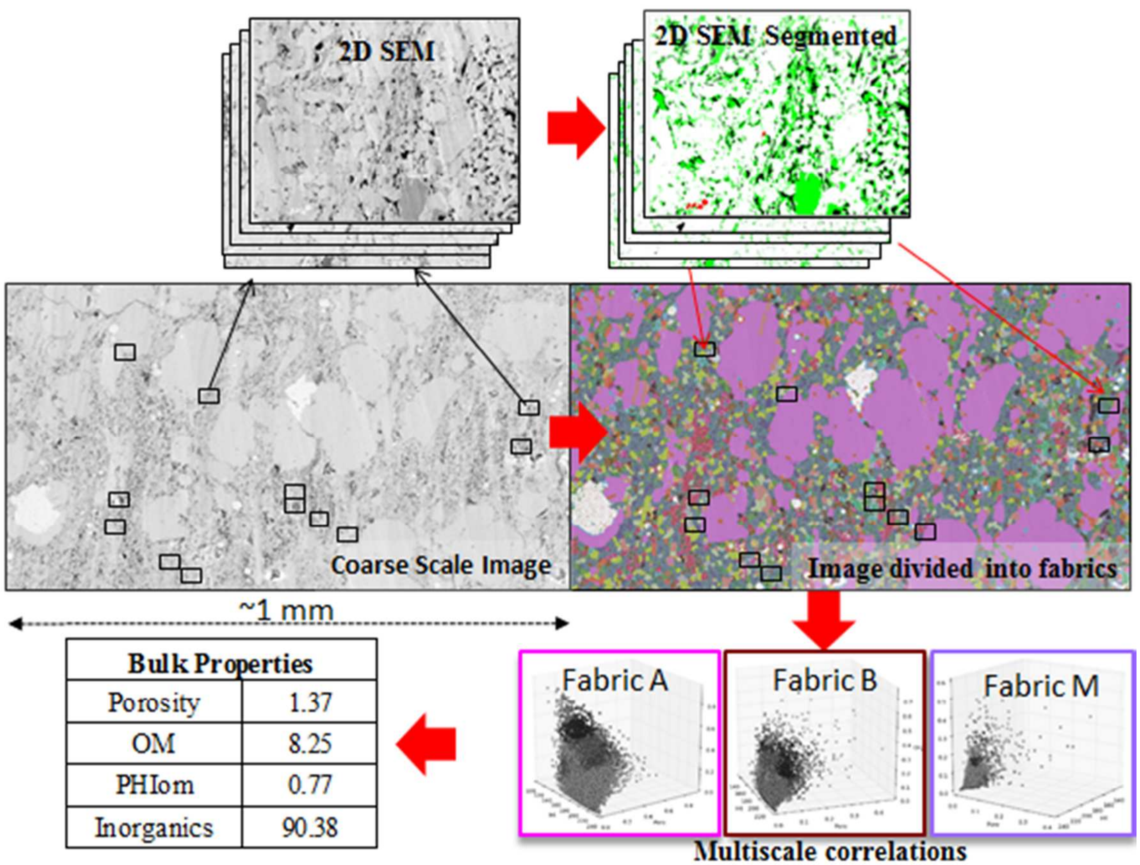

Figure 1: Squematic diagram showing the process for upscaling rock properties from high resolution image analysis onto coarser resolution images.

Examples

The core under study is from Delaware Basin, Texas. It is a whole core, 246 FT in length from Upper Wolfcamp formation. Whole core was CT scanned and high resolution RHOB and PEF were computed. CT volumes and images of the core were generated as well.

Also, core spectral gamma ray, uranium, thorium, and potassium, were acquired. Combining these data sets and X-ray fluorescence (XRF) data at multiple depths, we obtain fraction volumes of the main rock components such as clays, silicates, carbonates and TOC. Brittleness index (BI) is estimated based on a relationship between Young's modulus and Poisson's ratio of the composite (mineral volumes and TOC). The relationship between them is similar to that of Rickman, et al, 2008. BI is a relative quantity that describes how easy a rock should break.

With a multilayer machine learning algorithm and having as inputs high resolution mineral volumes and TOC, an automatic classification of rock classes is obtained (Figure 2). As a result five main rock types are identified which are represented by the following colors:

- Light Green: siliceous mudrocks with high OM content.
- Dark Green: siliceous mudrocks with low OM content.
- Red: mixed siliceous calcareous mudrocks with low OM content
- Purple: Mixed calcareous mudrocks with high OM content
- Blue: Limestones

Each rock class has distinctive mineralogical composition and TOC content, and it shows a constrain range in BI (Figure 3). Greater BI means the rock tends to break easier than low BI. Then, limestones are the rocks that would break easier.

For reservoir quality assessment and production, to get a good understanding of TOC and porosity distribution is a crucial step. And due to the finer scale of these properties in mudrocks, further plug digital analysis at much higher resolution is performed at multiples depths.

One of the challenges reside in the ability to upscale rock properties from high resolution images such as SEM onto a coarser images. We achieve this upscaling using ML techniques based on texture analysis. Rock fabrics are detected on a coarse scale image. Then, high resolution SEM images at optimal locations are acquired and analyzed.

The quantitative results of the SEM segmentation; OM, porosity, porosity associated with organic are populated back onto the coarser image. The final results of the upscaling are a map of the fabrics on the coarser image and the quantitative bulk properties for the entire coarser image (Figure 4 and 5).

Figure 4 corresponds to a sample from light green rock class, siliceous mudrocks with high TOC content. On the other hand Figure 5 correspond to a sample from blue rock class; limestones.
There are clear differences between the two samples no just in composition but in texture as well. The siliceous mud rock shows grains surrounded by much finer mix of materials. The mix has varying amounts of organic matter, porosity, and clays. In contrast, the limestone sample shows coarser grains and lower mix material content.

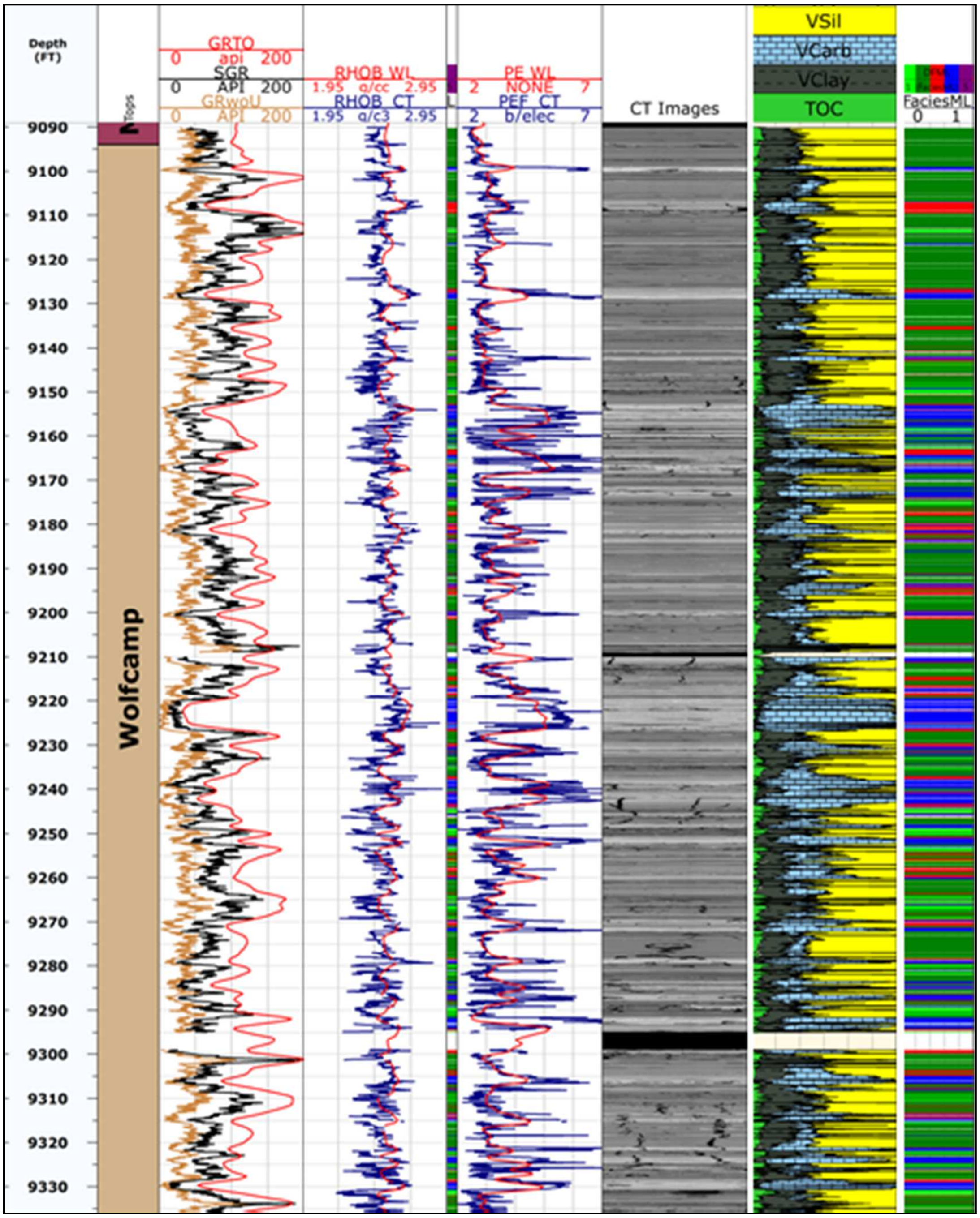

Figure 2: core spectral gamma ray, CT data (RHOB and PEF), CT images, iinterpreted mineral component, TOC content, and machine learning rock classes along the cored interval.

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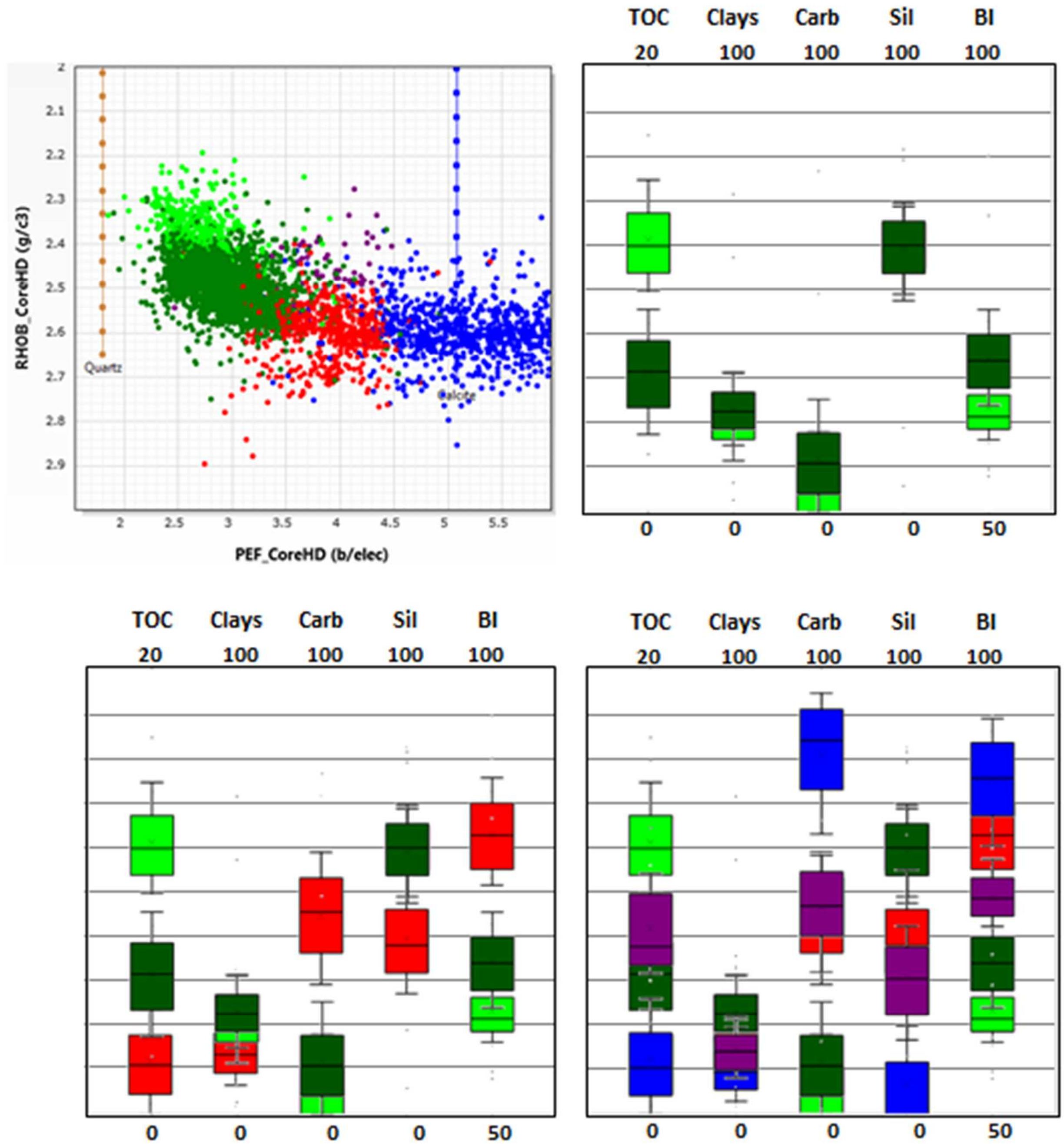
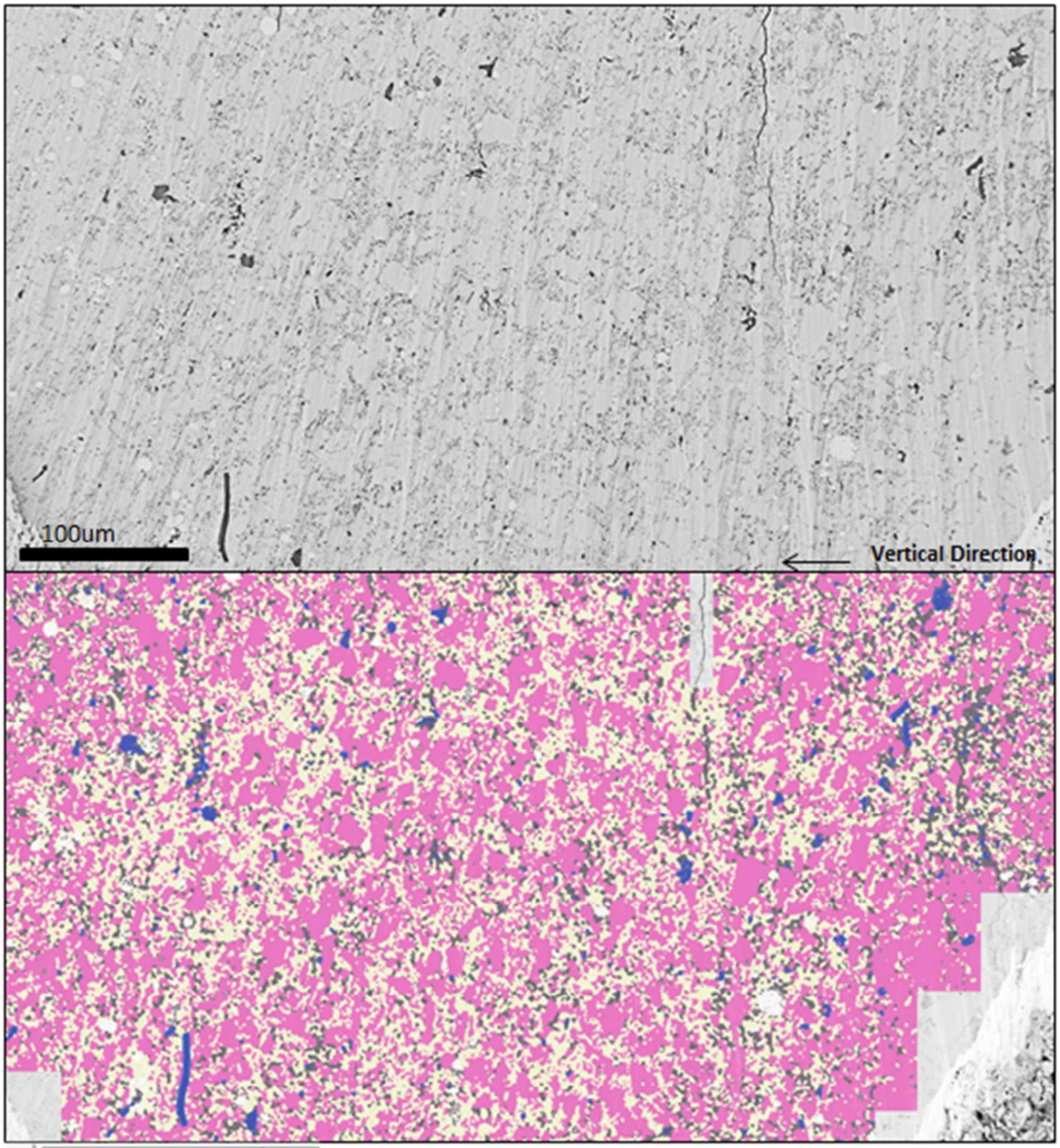
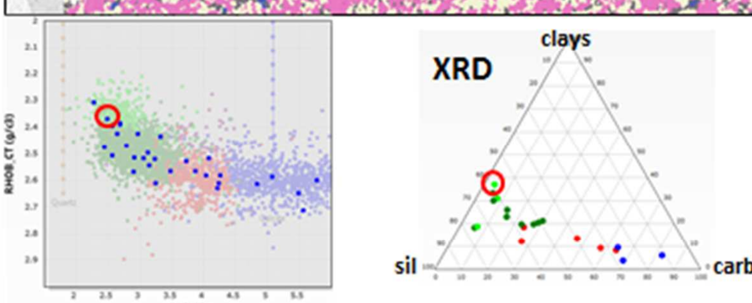


N/G (ft)	16.9/226.85	132.85/226.85	29.15/226.85	45.3/226.85	2.65/226.85
%	7.5	58.5	12.8	20	1.2

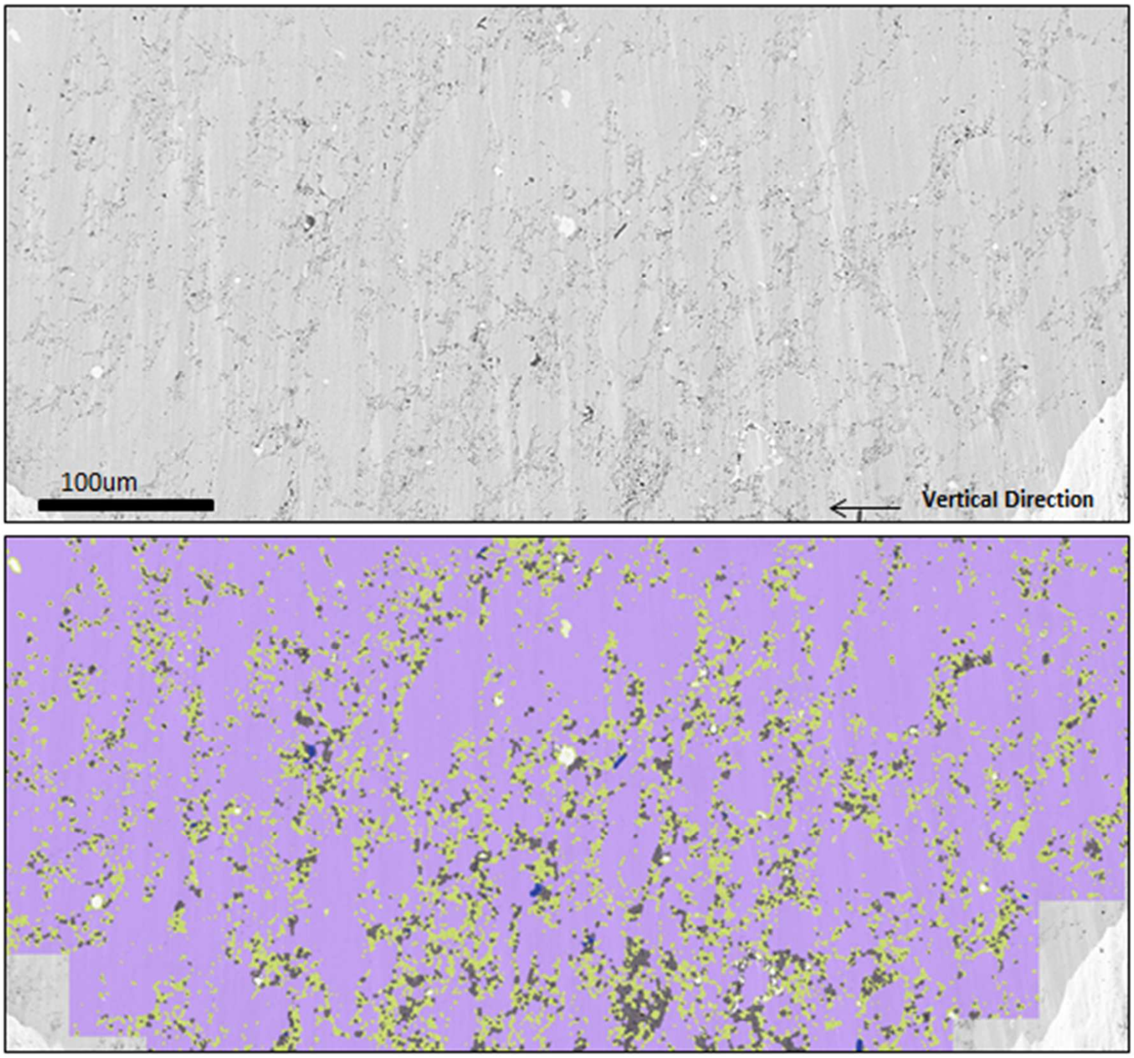
Figure 3: Multilayer machine learning rock classes and their compositional characteristics. Also, BI associated to each class. The table at the bottom shows net to gross calculation by classes. Mineral volumes and TOC content are in volume percent.

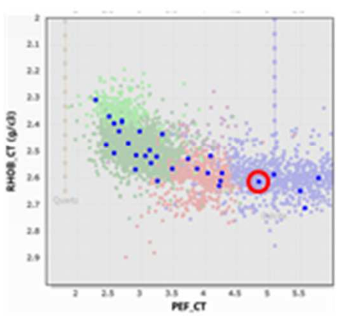


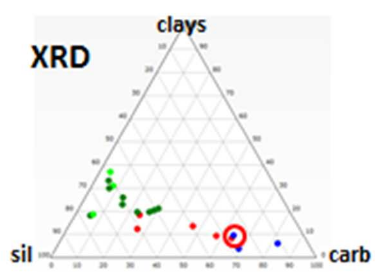


Bulk Properties	
Porosity	1.7
OM	9.4
PHIOM	1.3
Heavy Min	1.2

Figure 4: Machine learning fabric segmentation and upscaled bulk properties on siliceous mudrocks with high organic matter content.







Bulk Properties	
Porosity	2.0
OM	3.4
PHIOM	0.8
Heavy Min	0.3

Figure 5: Machine learning fabric segmentation and upscaled bulk properties on limestones..

A total of 19 plugs were upscaled using ML and DRA together. These plugs characterize the rock classes in a quantitative and qualitative sense. In Figure 6, track 7, red dots correspond to upscaled TOC while blue dots correspond to Leco TOC values. There is a very good agreement between both types of TOC analysis. Therefore, TOC upscaled values can be used for improving TOC computations along the cored interval

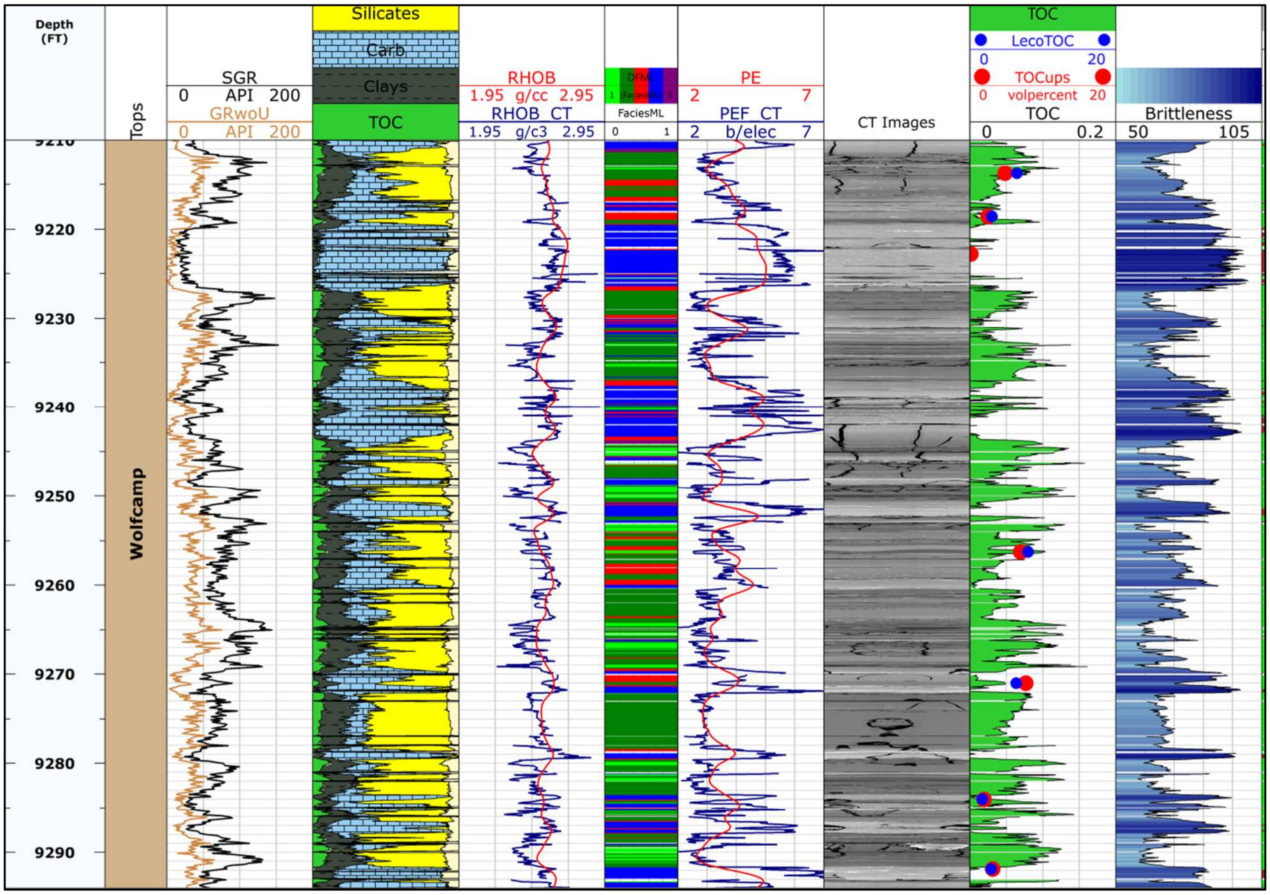


Figure 6: Estimation of TOC along the cored interval anchored with TOC results from ML and DRA process upscaling. Red dots upscaled TOC and blue dots Leco TOC.

Conclusions

Machine learning methods can provide rock typing classification and upscaled reservoir properties.
With the introduction of ML techniques and its ability to analyze multidimensional data, we can obtain rock types combining different sets of log data such as CT data, SGR, and their estimated properties.

DRA utilizes 2D images of rock samples to obtain petrophysical and geological properties at different scales. Thus, using ML techniques and DRA analysis together, we have the ability to propagate these properties from a very small subsample to a larger sample via fabric analysis. Results from the upscaled process have quantitative and qualitative components; therefore they can be integrated into multiple disciplines such as petrophysical analysis and geologic interpretations. In addition and despite of the unsupervised nature of ML, our methodology allows to experts to integrated their knowledge into the analysis to increase benefits.

References

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