

Cuttings Analysis Using Machine Learning Reduces Reservoir Uncertainty

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HOUSTON—Cuttings are a valuable and cost-effective source of subsurface data from both vertical and lateral wells that is commonly overlooked in oil and gas exploration and development drilling. Advancements in analytical technologies have enhanced the data extraction from cuttings to provide key subsurface insights, in lieu of core or sidewall core data.

However, there have always been challenges and uncertainties with sample depth allocations and upscaling/downscaling the data to log resolution for petrophysical analysis. This causes uncertainties throughout the subsurface characterization process, affecting results at all scales. A new methodology integrates high-resolution scanning electron microscopy (SEM) analysis with machine learning techniques to allow for semi-autonomous lithotyping of individual cuttings-particles within each cuttings bag (typically representing 10-30 foot intervals) and their direct correlation with measured well logs.

This new workflow greatly reduces cuttings uncertainties through the specification of bulk mineralogy back into the original rock types from which the cuttings originate, helping upscale results to petrophysical models and beyond. The result is an improved understanding of rock characteristics, lithology and geologic heterogeneity along the wellbore to optimize completion design. Moreover, by recalibrating representative cores, the technology provides a cost-effective alternative to core analysis.





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The approach takes advantage of SEM-based mineralogical analytical tools, which combine the imaging capability of an SEM with energy dispersive spectrometry (EDS) to provide both textural and elemental data. The value of using SEM-EDS over traditional techniques, such as X-ray diffraction (XRD) and X-ray fluorescence (XRF), is that the original rock texture of each cuttings particle is retained and collected. Figure 1(A) shows an example of an output grey-scale photomicrograph generated by the SEM, while Figure 1(B) shows the equivalent mineral map with each color representing a different mineral species detected by EDS analysis of the same area.

The calibration of lithotypes from cuttings against lithotypes from core data, using both the mineralogical and textural data, provides the crucial calibration and upscaling data for this workflow. Core description allows for qualitative assignment of lithofacies over the cored interval, harnessing quantitative continuous data, such as core gamma ray, XRF (hand-held) and CT density as well as discrete data from plugs, such as petrography/mineralogy and core analysis. Continuous data allows for definition of

bed boundaries to delineate rock types based on mineralogy and/or porosity distribution.

Lithotype-Based Analysis

Figure 2 shows the resolution at which the reservoir can be appraised, and the pitfalls of thin-bedded reservoirs. The benefit of characterizing cuttings data as lithotype proportions as opposed to mineral volumes is that a direct comparison can be made with the lithofacies assigned in the core interval to delineate net reservoir.

The CT density curve data, which acquires data at 0.01-foot increments averaging over 0.1-foot intervals, shows good sensitivity to the porous sandstone beds. Core gamma ray (GR) shows slightly poorer resolution (0.1-foot increments averaged over 0.5-foot intervals) with some of the cleaner sandstone beds delineated, but relatively poor definition between dense siltstone beds (similar GR response) and mudstones. The log GR shows almost no variation throughout the illustrated short stratigraphic intervals. Essentially the productive and nonproductive beds combine to form a solitary response through the 10-foot interval. So,

how is it possible to assess reservoir heterogeneity in the absence of core and/or FMI (formation micro imager) logs?

Quantitative analysis of cuttings, the closest thing you can get to core, can provide a solution. The core-to-cuttings lithotype calibration workflow is shown in Figure 3, where core lithotypes are used as seed testing for cuttings lithotypes classification. A lithotype model is created by training a machine learning algorithm to automatically assign lithotypes to cuttings based on similarity to the training set. The benefit of this technique is that consistent lithotyping can then be conducted on adjacent wells, which do not have conventional core, and where formation characterization otherwise would have been purely reliant on petrophysical log interpretation.

Machine Learning

The workflow was applied to train a machine learning algorithm on a calibration well and its subsequent application to a test well from an asset development area in the Midland Basin in West Texas. The machine learning lithotyping algorithm was trained using the lithotypes defined in the core and cuttings samples as

FIGURE 1

Backscattered Electron Image of Cuttings Samples from SEM-EDS (A) and Map of Detected Minerals (B)

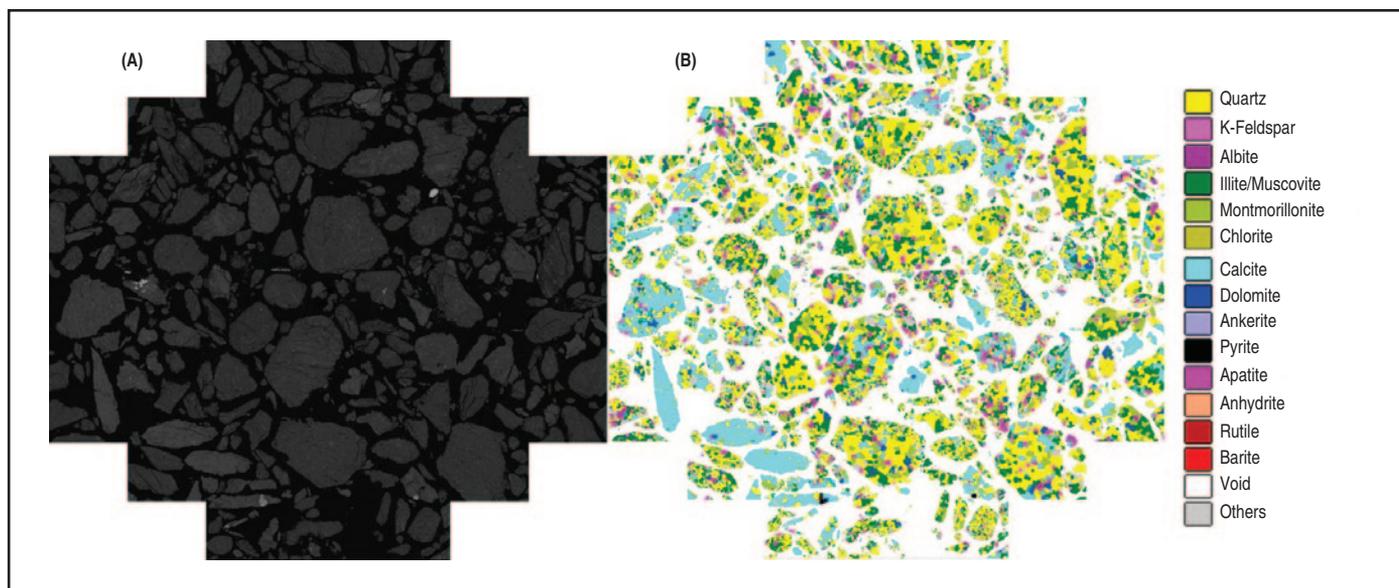


FIGURE 2

Lithotype Analysis of Thin-Bedded Reservoirs

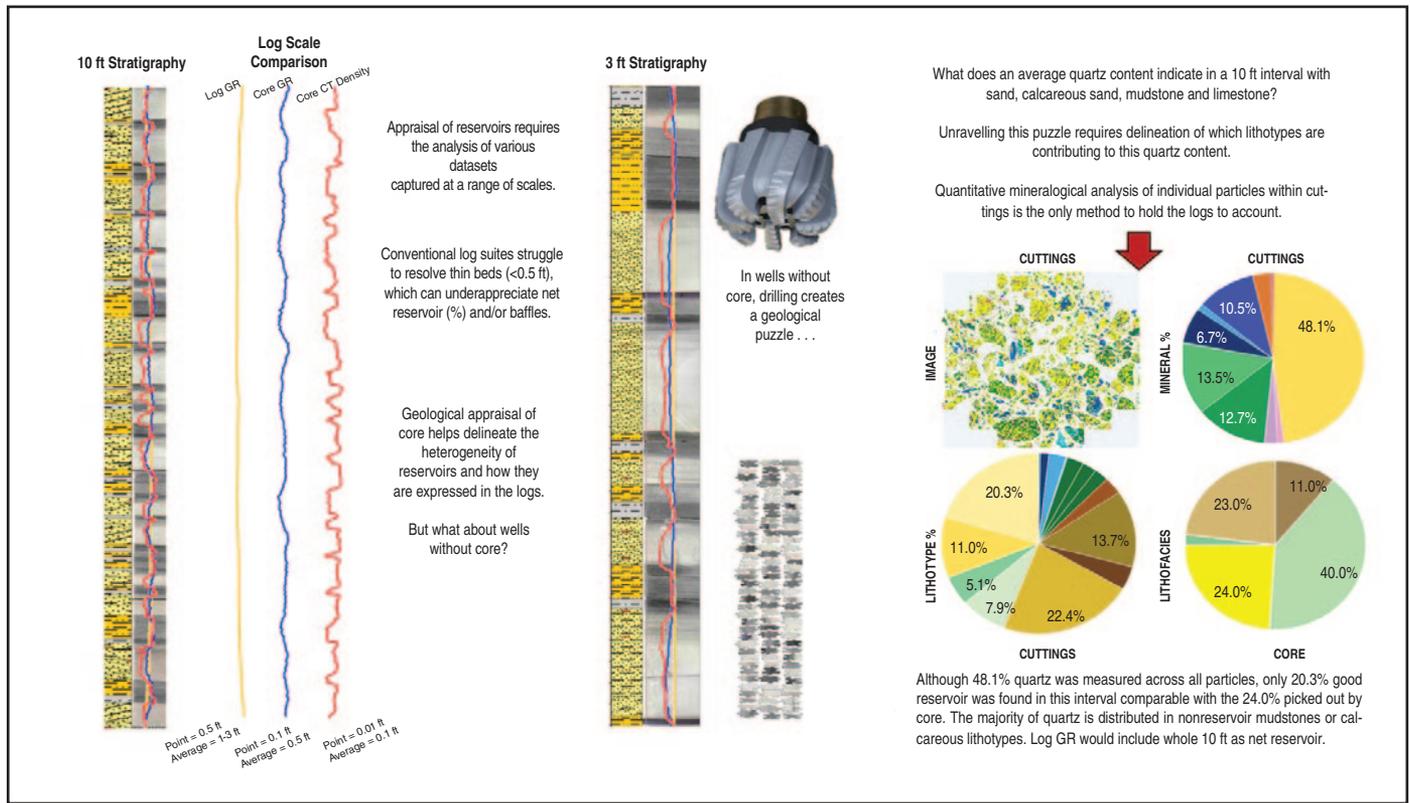
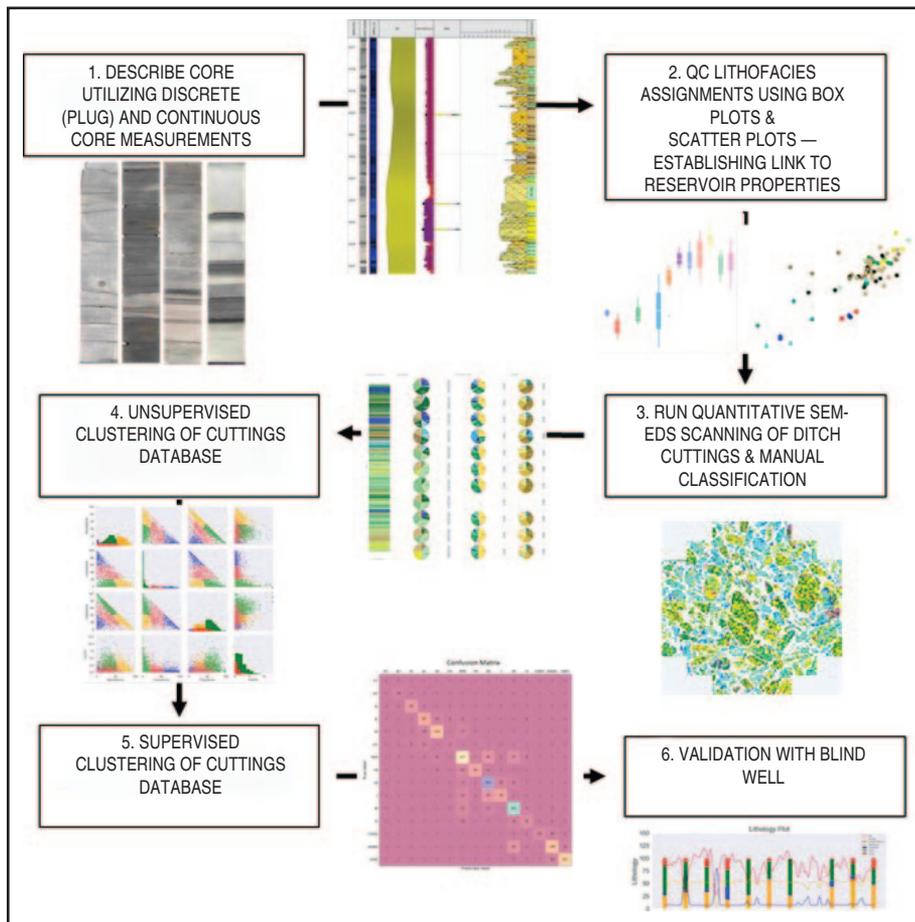


FIGURE 3

Schematic of Machine Learning Automated Lithotyping from Cuttings



the seed classification. For the learning process, only the cuttings-derived mineralogy and textural data (i.e., porosity) was used as input, while the lithotypes defined by a trained sedimentologist were used as the target. The cuttings mineral data was first scaled to ensure the ranges were in line with the core training dataset, before the data was run through a multi-variant model analysis to determine the best permutation/combination of classification models that generated the highest match to core lithologies.

Classification models used for this process included logistic regression, random forest, decision tree, KNeighbours, SVM and Gaussian Naïve Bayes algorithms. The random forest method generated the highest match compared with any other combination. So, for this section of the well, this model was used for further testing. However, this may not hold true for other regions and other formations, which is why the training process is performed per formation within a given region.

The random forest classifier was tested in conjunction with principal component analysis, and the number of com-

cies in this instance is the clean sandstones, which form 24.0% of the cored lithofacies. Clean sandstone forms 20.3% of the cuttings proportion over this interval, which is a very close match to the core proportion. Average quartz volume in this interval (48.1%) is distributed in various proportions across all clastic lithologies. A back calculation from an average volume theoretically could be possible, but would be reliant on assumptions and circular logic if restricted to log data (i.e., reliant on VClay logs) as opposed to primary data collection from rock material.

An adjacent uncored well was included to test the accuracy of the lithotyping parameters assigned from the cored well to an uncored well. The cut-

tings lithotypes data in the test well shows a greater proportion of sandstone reservoir facies, and a greater proportion of brittle beds in the overlying Spraberry (owing to the greater frequency and/or magnitude of carbonate gravity flows in this interval). This is in keeping with the average cleaner GR observed in both the Dean and the Spraberry formations in the test well compared with the calibration well.

However, it must be noted that in the test well, the intervals with the greatest proportion of reservoir facies (8,990-9,010 feet), ranging from 30%-40%, all have quartz volumes from 50%-60%. A hasty interpretation of average mineral data could lead to a decision to rule out pay zones, or to distrust the cuttings data as

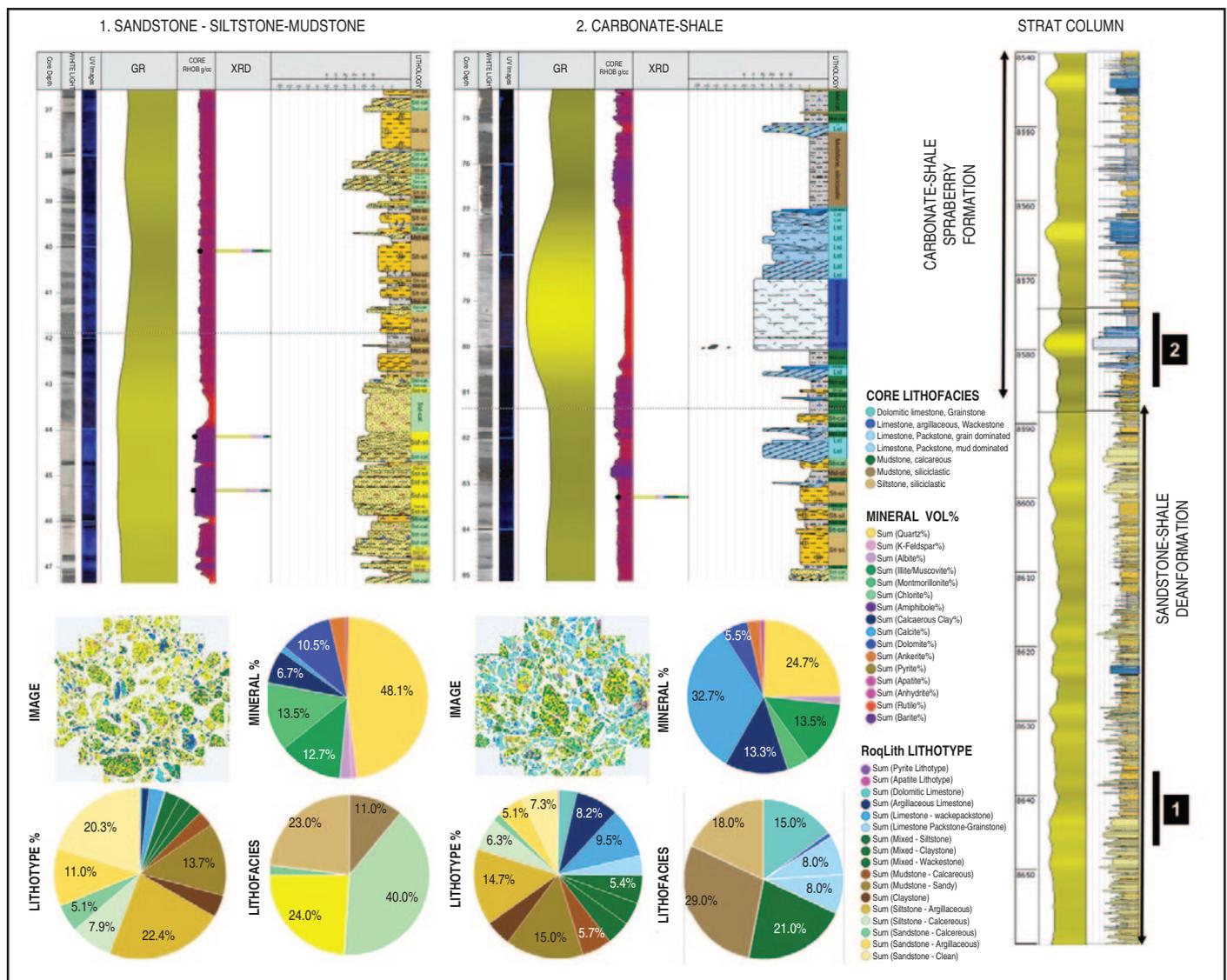
nonrepresentative and rely on log data alone.

This new lithotype dataset, therefore, allows wells to be ranked and risked on the basis of cuttings. It can be supported by log data, but can be used independently as a dataset to appraise reservoir quality distribution in terms of the proportion of reservoir facies or seal facies and provide ground-truthing to log-based reservoir/pay cut off values (e.g., GR values of less than 50 API and neutron porosity values of greater than 0.15).

Landing Zone Appraisal

Interval 2 (highlighted in Figure 5) in the Spraberry interval is a mix of dolostone, limestone and mudstone in the cored interval. Carbonate lithofacies form

FIGURE 5
Proportion of Lithotypes per 10-foot Interval versus Normalized Sub-Area Percent of Minerals





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31% of the 10-foot core interval. Carbonate-dominated lithotypes form 24.9% of the ditch-cutting interval, which again is a very close match with the core. It is important to note that in both of these example intervals, the dominant mineral does not correspond to a comparable proportion of that end member.

For instance, Interval 2 has an average carbonate volume of 50.1%, but most of the carbonate is portioned into “limestone” lithotypes that form only 24.9% of the interval. These observations can have important implications for the geomechanical behavior of the formation in terms of fracture propagation and how the thickness, composition and lateral continuity of these brittle carbonate beds vary along lateral well stages.

As illustrated in the Midland Basin application, there are strong benefits of de-

lineating lithotypes from cuttings intervals. The end-user has the capacity to evaluate the distribution of minerals within each lithotype, allowing for a dynamic evaluation of reservoir parameters (e.g., clay/carbonate volumes or image porosity) when new rock types are encountered in a well. This significantly increases the accuracy of the reservoir description in comparison with alternative techniques, which are confined to simply (homogenized) bulk mineralogy values.

Second, incorporating lithotype distribution in zones where wireline log data underappreciates the formation heterogeneity (as a result of thin bed effects, for example) can lead to a more accurate appraisal of net reservoir within any given well or interval. Reservoir models built from petrophysical logs alone could lead to upscaling of errors, affecting volumet-

ric calculation by over- or underestimating reserves within a field. A good core-to-cuttings calibration utilizing this lithotyping approach enables an operator to run multiple wells within a field and build their reservoir maps on the basis of a consistent and comprehensive rock-calibrated petrophysical model.

Ultimately, the ready availability of cuttings from all wells, combined with the application of this workflow, allows for consistent objective lithological description of subsurface formations. The lower cost of cuttings analysis, compared with log collection, also allows for the cost-effective generation of a detailed lithological database from cuttings. This database then becomes an effective tool in mapping and interpreting the spatial reservoir quality of a target formation and allows for more informed landing zone decisions. □

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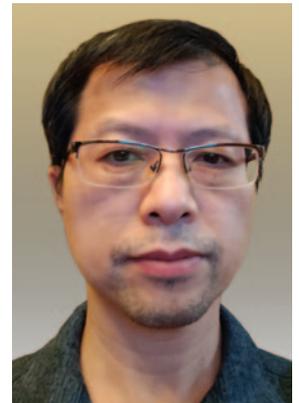
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