Estimating Elastic Logs and Mineralogy

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Summary

The need to estimate Elastic logs for Geophysical interpretation has been a consistent problem for technical interpretation. Historical methods have been reliant on empirical relationships developed decades ago. More recent rock physics work and AVO studies have significantly improved our understanding of the background science. Machine learning techniques have provided additional tools to investigate improved methods of estimating missing elastic logs.

This presentation will focus on various methods of estimating missing elastic logs using mineralogy, the more common geological logs, and rock physics relationships. It will also focus on logistic regression relationships and compare machine learning estimation using the direct petrophysical logs along with a stationary relationship after removing a background trend.

Introduction

The dataset used was from the FORCE2020 Lithology Prediction Contest, with log data from the Norwegian Petroleum Directorate. Explocrowd supplemented the data with petrophysical analysis, using the logs, completion information, and mud logs reports. As the petrophysical logs' response is predominantly controlled by mineralogy, the 12 litho-classes provided in the contest were subdivided into 18 mineralogy classes, predominantly using cluster analysis.

Acquisition of elastic logs (DT, DTS, RHOB) along an entire log profile is rare, causing geophysicists to rely on empirical relationships (Faust 1951 & 1953; Gardner, 1974; Castagna, 1985). These relationships are predominately first-order approximations following siliciclastic lithological variation and compaction trends.

The advent of machine learning has provided a new tool for evaluating the relationship between petrophysical logs and elastic rock properties. While machine learning can be a black box, knowledge can be inferred using cluster analysis, feature importance, and estimation of variable independence. The algorithmic biases for these relationships require additional analysis, and while this presentation focuses on a global logistical relationship, a comparison between a clastic and carbonate environment will be shared.

Theory

As incomplete log profiles are common, empirical relationships are used to determine RHOB (Gardner, 1974) and Vs (Castagna, 1985) from Vp and, if required, Vp from a background trend and resistivity (Faust 1951 & 1953).

$$\rho = cVp^{0.25} \quad (1) \qquad V_S = 0.8621 \times V_P - 1172 \quad (2)$$

where c = 1.741 if Vp is in km/s and ρ is in g/cm^3.

$$V_p = K(zT[R_t])^{1/6} \quad (3)$$

where k is a constant, T geological age, z depth, and Rt resistivity variation from a background trend, these relationships are generally lower approximations that have worked well for standard hydrocarbon reservoirs (1500-4000m) but tend to extrapolate poorly for both shallower and deeper depths.

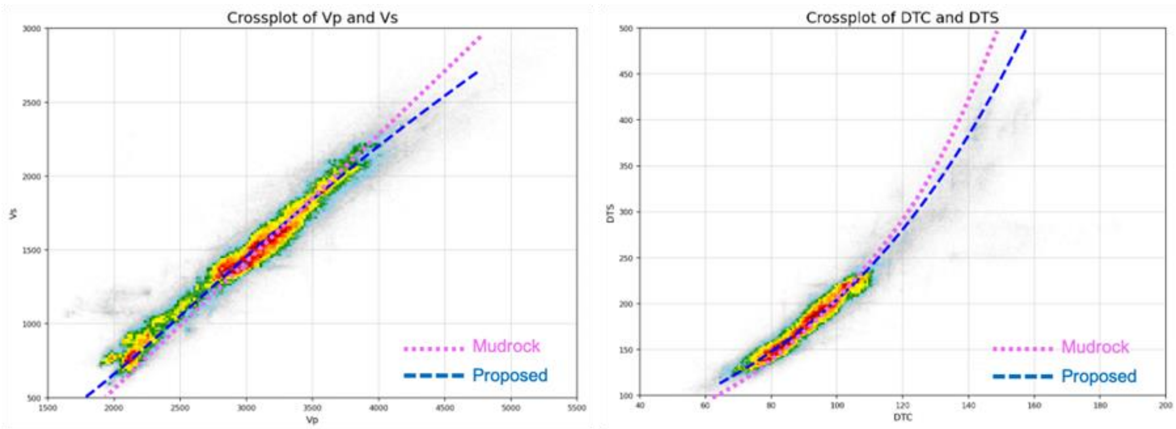

Figure 1: Velocity (left) and Slowness (right) with an overlay of the Mudrock line and the proposed relationship. The plot is coloured by input point density, with red being the denser data areas fading to grey. The proposed line is estimated from the DTC and Vp/Vs relationship with the depth sub-seabed.

The alternative (Figure 1, right panel) is to use slowness (DTS and DTC) over velocity (Vp and Vs). The relationship is more curved than in Vp vs. Vs space, and the best-fit line shown was created by estimating an exponential relationship with depth. DTS (shear slowness) was estimated using a Vp/Vs ratio (DTS/DTC, Figure 2) with a starting value based on Yilmaz (2015) decaying to an asymptotic value of 1.73 based on Russell (2023) for the North Sea.

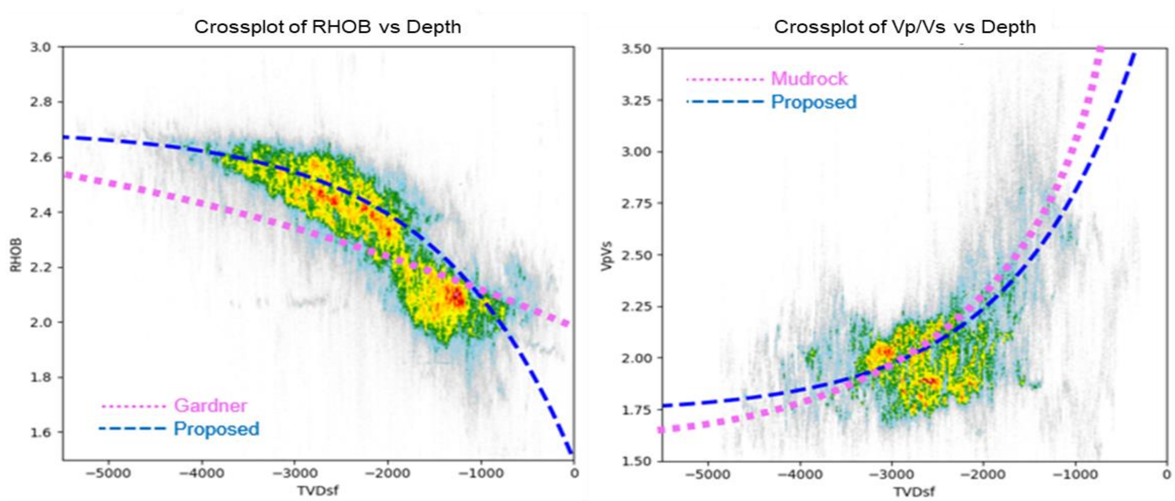

Figure 2: Density (left) and Vp/Vs (right) with an overlay of the Gardner & Mudrock lines against depth sub-seabed

118 wells were available for the study, varying from near the water bottom to over 5000 meters below the sea floor. The input mineralogy is predominantly siliciclastic (88%), with shale making

up 72% overall. Compressional velocities (DTC) and density (RHOB) were available for parts of all 118 wells, but shear velocities (DTS) were available for only 46 of the wells and predominately for the deeper depths. A diagenetic overprint from the conversion of smectite into illite and Quartz recrystallization from Opal A into Opal CT affected RES, DTC, and RHOB logs.

The classical method of estimating missing elastic properties is through regression directly from other logs. Regrettably, this methodology either fails to differentiate between lithologies as in the Mudrock or between depths as in the Gardner relationship. The method proposed in this presentation is using residuals from a background trend. Estimating this data trend required first correcting to a depth below the seafloor (TVDsf) and then estimating a best-fit line which accommodates the variation in porosity with depth and separates lithology above, along, or below the line.

The various methodologies were evaluated using a Petrophysical cross-plot, but for this presentation, we will focus on the two most common AVO cross-plots (Ip vs Vp/Vs and Lambda Rho vs Mu Rho) and the standard rock physics moduli cross-plot against effective porosity.

The formulas used for estimating Lambda-Rho (λ) and Mu-Rho (μ) is:

$$\lambda = \rho(V_P^2 - 2V_S^2) \qquad \mu = \rho V_S^2 \qquad (4)$$

For the rock physics cross plots (K & μ) were estimated using:

$$K = \rho\left(V_p^2 - {}^{4}/_{3}\, V_s^2\right) \qquad \mu = \rho V_s^2 \qquad (5)$$

Estimating porosity for the rock-physics cross-plots (K & μ versus Ø) was done using a combination of NPHI and DPHI crossover and VSH estimated from GR. The rock-physic cross-plots are, therefore, at best, an approximation, as a degree of uncertainty exists for the effective porosity. Nevertheless, results were similar to those published for actual laboratory-derived solutions.

Results

Estimation using Gardner's relationship for density (Figure 2) has the lowest correlation with the input data, while the Mudrock estimation of Vs (Figure 1) is similar for the Vp & Vp/Vs trend with depth. AVO and rock-physics cross-plotting (Figure 3) indicate the ability to separate mineralogy, but their application resulted in clustering along the associated trend lines (Figure 4), with relatively poor discrimination of mineralogy.

The results for logistic regression using the logs directly (not shown) show a marginal improvement in the shift from the trend lines. The application using the residual (Figure 4, center) starts differentiating the various mineralogy. Regrettably, the application of a single logistic regression relationship fails to differentiate the limestone from the sandstone fractions. As the input dataset is predominately siliciclastic, the carbonate fraction is missed classified.

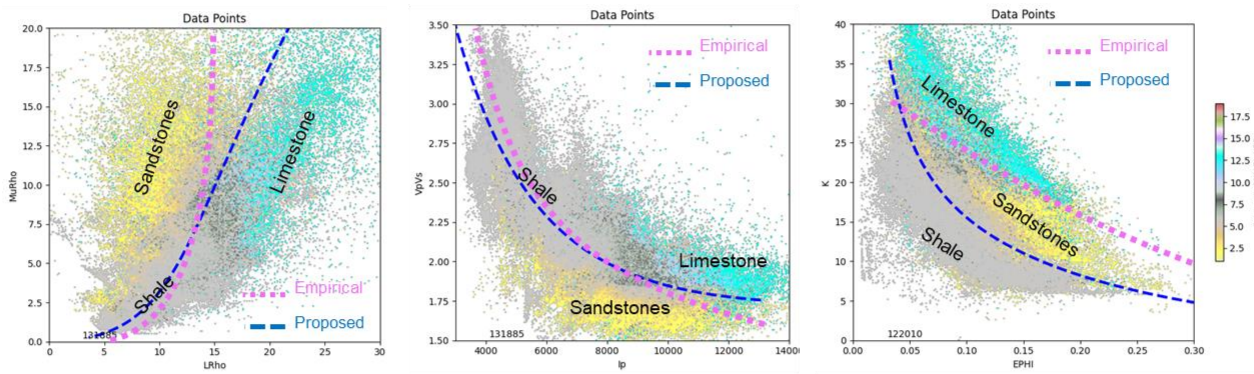

Figure 3: Cross-plot of the input data for 3 mineralogy classes (sandstone, limestone & shale). Lambda-Rho vs MuRho (left), Ip vs Vp/Vs (middle), and Bulk Modulus (K) vs effective porosity (right). The line for the Castagna Mudrock and Gardner Density is overlayed in purple and proposed in blue; the effective porosity is created using a sandstone matrix.

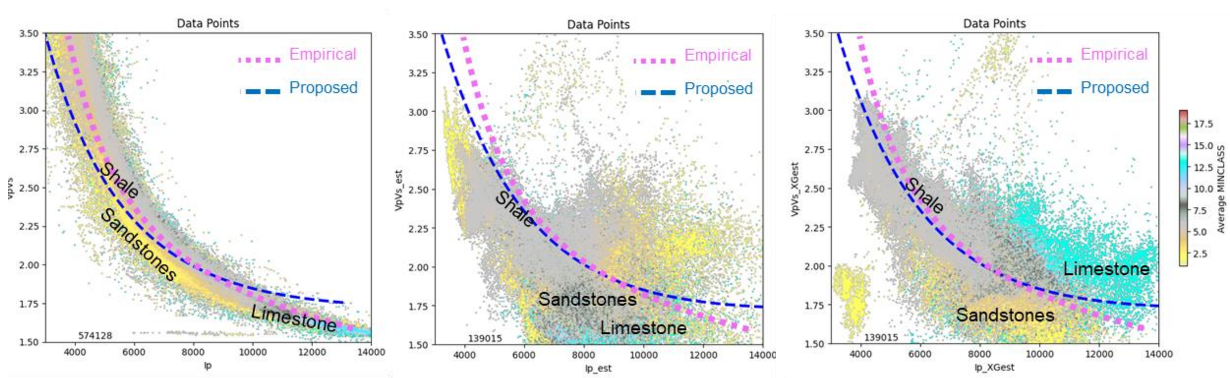

Figure 4: Estimation of Vs and RHOB assuming Vp is known. Estimation using Vs from the mudrock relationship (left) cluster data along the trend line (results similar when using logistic regression using full logs), estimation using logistic regression and the residuals (center), and estimation using XGBoost for the estimation of all three inputs (right).

The machine learning approach provides multiple solutions and, as such, can exactly fit the results to the input. Given enough epochs, the machine learning solution using the complete logs versus the residuals can provide similar results. This tendency to over-fit the input is an inherent problem with this approach, but nonetheless, significant insight can be determined from the feature importance and evaluation of each individual mineralogy (one-vs-the rest).

Conclusion

The presentation will focus on the benefits of using residuals and what information can be determined from the one-vs-the-rest analysis. It will also discuss the application of estimating Vp from GR, RES, mud log lithology, and a background velocity trend.

Acknowledgements

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