Enhancing the Subsurface Interpretation through Support Vector Machine (SVM) based Litho-Classification

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Abstract

The subsurface interpretation of an inverted geophysical model is crucial for several reasons. It allows us to understand and characterize the subsurface physical-properties and structures, providing valuable insights into geological features and processes. It aids in identifying and delineating potential targets or anomalies of interest, such as mineral deposits, hydrocarbon reservoirs, or geological hazards. An important aspect of subsurface interpretation involves the classification of different litho-units within the inverted geophysical model. This research explores the application of Support Vector Machine (SVM), a supervised machine learning technique used for regression and classification, to perform litho-classification. Traditionally, geophysical inversion and litho-classification are considered separate processes. This study introduces the SVM technique, which can be used during inversion or post-inversion processes. We propose integrating this technique directly into the inversion framework, so the need for separate post-inversion litho-classification analysis can be eliminated. The approach demonstrates two SVM examples for litho-classification. In the first example, SVM accurately delineates the lithological boundaries in the inverted geophysical model, facilitating fault and structure mapping. In the second example, SVM performs litho-classification on a density-susceptibility cross-plot, which is particularly valuable when density and susceptibility values are available from rock samples of the study area.

Introduction

Subsurface interpretation plays a vital role in understanding physical characteristics, identifying geological features, and making informed decisions in various fields of geosciences. It offers valuable insights into lithology, rock properties, fluid content, and structural features like faults and fractures (Roveri et al., 2014; Singh and Sharma, 2016; Schimmel et al., 2020). By aiding in the exploration and evaluation of natural resources such as oil, gas, minerals, and groundwater, subsurface interpretation assists in the identification of potential reservoirs, mineral deposits, and water-bearing formations (Moustafa et al., 2018; Singh et al., 2019; Al-Ghamd et al., 2020). Furthermore, it contributes to hazard assessment and mitigation by identifying and monitoring geological hazards such as earthquakes, landslides, and volcanic activity, thus enhancing preparedness and safety measures (Cuenca et al., 2015; Rinaldi et al., 2019). As a multidisciplinary field, subsurface interpretation plays a vital role in numerous scientific studies, resource exploration, hazard assessment, environmental monitoring, and engineering applications.

Litho-classification is a crucial step in subsurface interpretation as it enables the characterization and identification of different litho-units. By assigning rocks to specific classes or categories, geoscientists gain insights into the lithological composition of subsurface formations. This information is essential for various applications such as resource exploration, reservoir characterization, geological mapping, and hazard assessment. Litho-classification aids in understanding the distribution and spatial variations of different litho-units, which is valuable for predicting fluid flow behavior, assessing reservoir quality, and identifying potential hydrocarbon-bearing formations. Additionally, it helps in the delineation of lithological boundaries, fault zones, and structural features, enhancing the interpretation of subsurface geological structures (Liu et al. 2015; Raza et al. 2020).

In this study, we have utilized Support Vector Machine (SVM) to assess litho-classification. SVM is a powerful machine learning algorithm used for classification tasks. It is particularly effective in handling complex and non-linear relationships between input variables and class labels.

The developed approach has been evaluated in two distinct scenarios: lithological boundary delineation of an inverted geophysical model and litho-classification with posterior estimation from a cross-plot of density and susceptibility. In both cases, the approach demonstrated successful outcomes, indicating its satisfactory performance. These results validate the effectiveness and reliability of the developed approach across different scenarios and highlight its potential for accurate litho-classification in subsurface interpretations.

Methodology

SVM (Support Vector Machine) is a widely used machine learning technique in geoscience applications. Researchers have applied SVM in various domains. For example, Yang et al. (2007) used SVM for seismic reservoir characterization, Al-Juaidi and Patzek (2012) predicted permeability from well logs using SVM, Qomi et al. (2016) employed SVM for seismic signal classification, and Prasad and Al-Abri (2019) utilized SVM for identifying basement faults from gravity data.

SVM is a supervised learning algorithm commonly used for regression and classification tasks, particularly in binary classification. It involves drawing a decision boundary to separate distinct classes, often referred to as positive and negative examples. The positioning of this decision boundary is optimized to maximize the margin, which represents the distance between the decision boundary and the nearest examples. This approach, known as large margin classification, aims to achieve a clear separation between positive and negative examples.

Although SVM is originally designed for binary classification, it can be adapted for multiclass classification. In binary classification, the one-vs-other approach is commonly used, distinguishing one class from the rest. For multiclass classification, the one-vs-all approach can be implemented, where each class is individually differentiated from all other classes.

By applying SVM to inverted geophysical model, decision boundaries can be drawn to classify different litho-units. Furthermore, SVM can be used to draw boundaries in cross-plots of density versus susceptibility, enabling the identification and differentiation of various litho-units.

It is important to note that SVM itself does not provide probabilities. However, there are calibration methods available to convert SVM outputs into probabilities. In a binary classification scenario, the goal is to determine whether a given input x belongs to class +1 or -1. This classification problem is typically solved using the function y = sign(f(x)). To obtain the probability P(y = 1 | x) (Platt et al. 1999):

$$P(y = 1|x) \;=\; \frac{1}{1 + exp(A * f(x) + B)}$$

This method involves performing logistic regression on the output of the SVM. The algorithm learns parameters A and B to establish the relationship between the SVM output and the true class labels. The purpose of this calibration step is to refine the SVM's output and convert it into reliable probabilities. This calibration step enhances the interpretability and reliability of the SVM's results, providing a more accurate assessment of the likelihood of a given input belonging to a particular class.

By combining the power of SVM for classification and logistic regression for probability calibration, we can obtain calibrated probabilities that reflect the confidence levels associated with each class assignment. This calibrated output can then be used for decision-making and further analysis in various applications.

Results and Discussion

In our first example, we examine a four-layered subsurface model (Figure 1a) where each layer represents distinct lithological units with specific density values and structures. Figure 1(b) presents the SVM-based litho-classification and posterior estimation results corresponding to the subsurface model depicted in Figure 1(a).

The effectiveness of SVM in delineating layer boundaries is evident in Figure 1(b). It is observed that areas along the litho-boundaries exhibit lower posterior values, while regions where a single litho-unit persists continuously display higher posterior values. This approach of litho-boundary delineation can also be applied for regularization purposes (Zhou et al. 2014; Jordi et al. 2018).

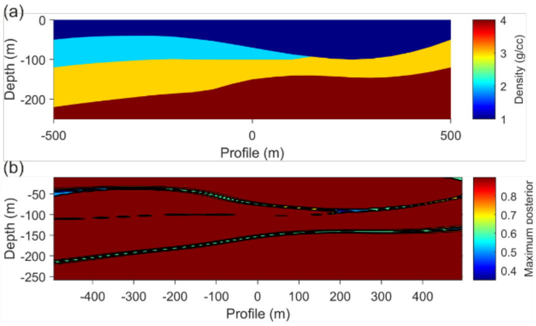

Figure 1: (a) Four-layer subsurface model with distinct density values in each layer, (b) SVM-based litho-classification for boundary delineation of the model depicted in (a).

In our second example (Figure 2), we demonstrated a challenging scenario when dealing with a cross-plot of density and susceptibility values of various litho-units in a study area. These litho-units did not exhibit clear relationships, distinct clusters, or well-defined boundaries, making it difficult to classify them based solely on the cross-plot (Figure 2a). However, in this example, we already had prior knowledge of the litho-units and their corresponding density-susceptibility values, enabling us to identify the points on the cross-plot corresponding to each litho-unit.

In contrast, our developed approach becomes particularly valuable when performing geophysical inversion solely from geophysical data, without any prior knowledge of litho-units and their density-susceptibility values. The developed approach can effectively recognize areas in the cross-plot where specific litho-units can be found, form clusters or contours to delineate the regions associated with each litho-unit, and provide posterior probabilities or confidence levels for these predictions (Figure 2b). This capability enhances the reliability and usefulness of interpreting an inverted geophysical model for litho-classification and posterior estimation.

Figure 2(a) presents the cross-plot of density and susceptibility values for the rock samples. To aid in litho-classification, Figure 2(b) showcases the SVM-based litho-classification and posterior estimation. The posterior values serve as a measure of confidence, with higher values indicating a greater confidence in identifying specific litho-unit on the density-susceptibility cross-plot. Notably, the bright yellow region in Figure 2(b) distinctly highlights the density-susceptibility region associated with BIF (Banded Iron Formation).

The clustering of samples in the density-susceptibility cross-plot is relatively small in the case of sandstone, phyllite, and quartzite, as their density or susceptibility values exhibit minimal differences compared to the significantly higher values of BIF. BIF covers a wide range in the density-susceptibility cross-plot, with no overlapping values from other litho-units, resulting in a high posterior estimation for BIF. In the litho-classification based on SVM (Figure 2b), distinct regions are observed, each associated with a specific posterior value. BIF falls in a region with a posterior probability of approximately 0.8, while phyllite, sandstone, and other litho-units fall within separate regions with their respective posterior probabilities. The presence of outliers in the density-susceptibility cross-plot leads to lower posterior probabilities.

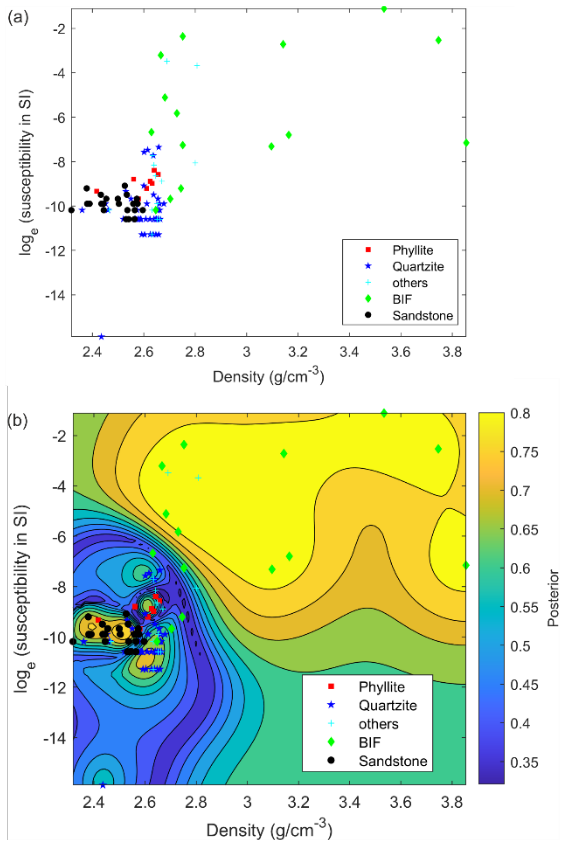

Figure 2: (a) Cross-plot of density and susceptibility values, (b) SVM-based Litho-Classification and Posterior Estimation.

Conclusions

We have incorporated SVM to improve litho-classification and posterior estimation of geophysical inverted models, as well as physical properties cross-plots. By incorporating SVM, we gain valuable insights into the confidence level required to accurately locate a litho-unit. The posterior estimation serves as a crucial measure of confidence in our results, enabling us to improve the accuracy of litho-units identification.

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