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Deep Learning-Based Mapping of Salt Layers in 2D Seismic Data

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Abstract

This study applies machine learning to identify and characterize the salt layer in 2D seismic data from the Santos Basin, Brazil. The VDS seismic format was used for efficient data access, and an interactive deep learning tool was employed. A multiclass neural network first classified seismic data into Mega-Sequences, followed by a binary network to identify the salt layer. Despite challenges like high noise and minimal data preconditioning of 2D dataset, satisfactory results were achieved with limited labeled lines and training cycles. This approach demonstrates the effectiveness of machine learning in interpreting complex 2D seismic datasets, offering promising results for future applications.

Introduction

The Santos Basin is an offshore basin located in the southeast region of Brazil, known for being the biggest hydrocarbon producer in Brazil. Most oil production in the Santos Basin comes from the Pre-Salt system. The sealing layer of this system is represented by the evaporites of the Ariri Formation, which are responsible for preventing hydrocarbons from escaping. Given its importance within the oil system, the salt layer is the subject of many studies.

In seismic data, the evaporites tend to stand out to the interpreter. This is because the geometry of the salt layer often shows a high contrast with the overlying and underlying layers. However, seismic interpretation in 2D lines faces several technical and geological difficulties in complex cases, such as the presence of a salt layer. This is due to the lack of spatial continuity, which makes it difficult to fully visualize geological structures, and lateral ambiguity due to sparse lines.

Over the last few decades, the application of machine learning methods in seismic data interpretation has grown significantly (Chopra and Marfurt, 2018). These methods are more commonly used on 3D data than 2D data, since 2D lines offer greater variability in acquisition, less spatial context and greater noise, making it difficult to pre-process this data for use in machine learning. The VDS seismic format modifies the structure of the 2D data, allowing quick and random access to the lines and preparing it more efficiently for the use of machine learning.

Therefore, the aim of this work is to use machine learning on 2D seismic data to identify and characterize the salt layer in a region in the Santos Basin.

Method

To develop this work, 114 lines of 2D seismic amplitude available from Santos Basin were used. This data was provided by ANP. A quick QC and depth adjustment of the lines were carried out. These lines were converted into a single VDS. In this process, the original 2D lines were segmented into 258 lines and reorganized to form a regular grid, which makes it easier to use the flow tensor in machine learning.

The software used, InteractivAI, does not offer pre-trained models and allows a high level of interactivity between machine learning and the interpreter (Chenin *et al.*, 2021). Therefore, the user offers their knowledge to machine learning by labeling a few lines so that machine learning can run and identify the features, in this case the salt layer, throughout the seismic data.

Due to the high noise of the 2D data and the lack of data preconditioning, which was not done purpose to test the software, the approach to identifying the salt layer ranges from large to small scale. This involves a multiclass network, where Mega-Sequences were identified, and a binary network, where the salt layer was highlighted inside one sequence.

The Mega-Sequences are defined by three distinct classes: water column, “Post-Salt + Salt” and “Pre-Salt”. 13 lines of seismic data were labeled. The deep learning architecture used was E-Net, with Categorical Cross Entropy as loss function. After 21 training cycles, the results obtained were satisfactory. The product generated is called a probability cube and shows the sequences on all 2D lines.

The layer defined as “Post-Salt + Salt” of the Mega-Sequences probability cube was used as a mask so that only salt was classified and identified in the seismic data. In this step, the salt layer was labeled and trained by a binary network. In other words, inferences were generated based on whether salt was identified or not, in that layer. 5 lines of seismic data were labeled. The deep learning architecture used was E-Net, with Dice as loss function. After 13 training cycles, the results obtained were satisfactory on an exploratory scale.

Results

From the labels given to the Mega-Sequences, the multiclass neural network generated inferences for all 2D lines. After labeling only 5,04% of the lines and training for 21 cycles, very satisfactory results were obtained on an exploratory scale.

As a result, the generated probability cube could be applied to a binary network as an input mask for the salt layer labels. It was again possible to obtain very satisfactory results, despite having now fewer labels added - only 1,94% of the lines and just 13 epochs of training.

Figure 1 shows the labels and machine learning inferences in one of the 2D segments for the multiclass and binary network. Figure 2 shows the result of the salt probability cube on all the 2D lines in the study.

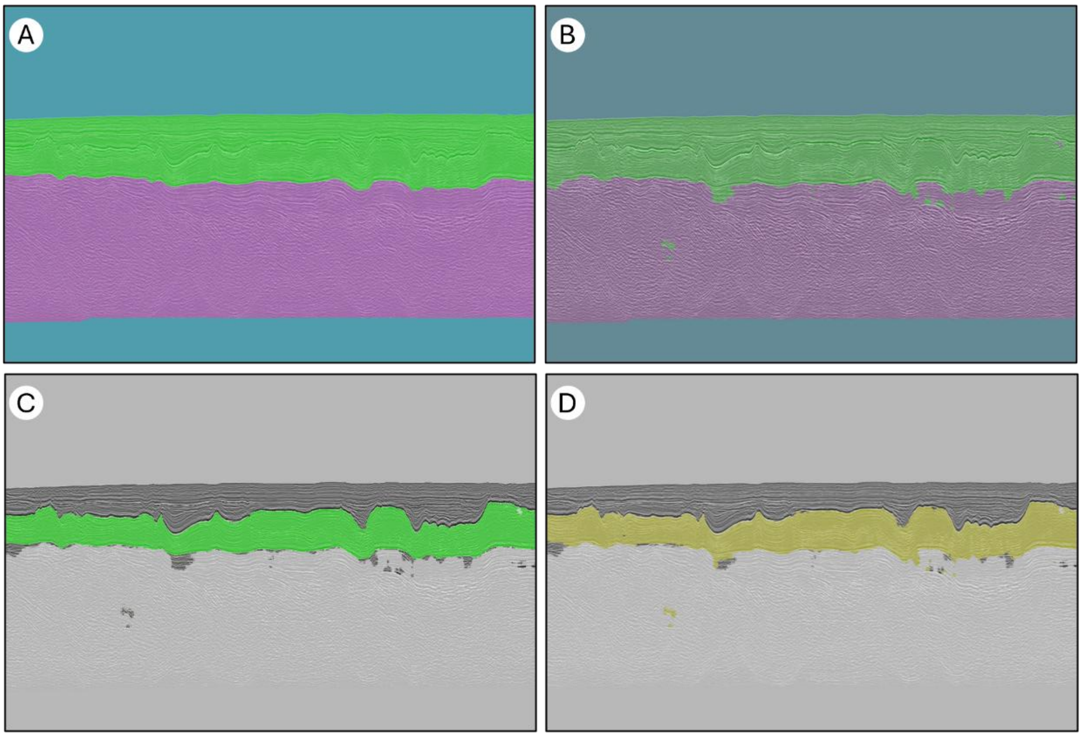

Figure 1: (A) Labels assigned to the Mega-Sequences, with the classes identified as follows: water column (blue), "Post-Salt + Salt" (green) and "Pre-Salt" (pink); (B) Result of inferences returned by the multiclass network for a labeled line, after 21 periods of training; (C) Label assigned to the salt layer. The binary network of the salt was created containing an input mask, limiting the inferences to the class "Post-Salt + Salt"; (D) Result of inferences returned by the binary network for a labeled line, after 13 periods of training.

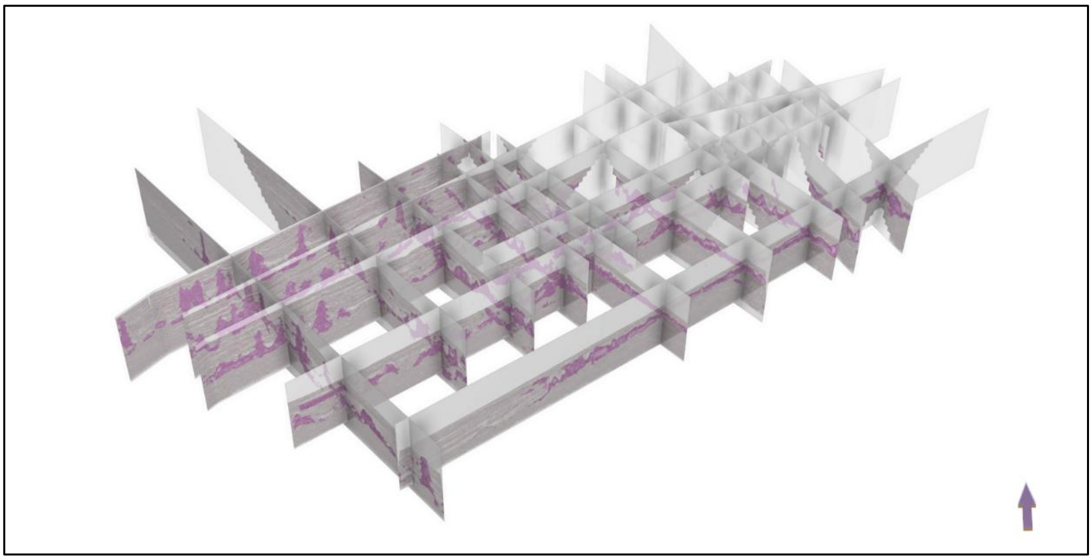

Figure 2: A few lines of the probability cube generated for the binary network of the salt layer. The salt bodies are identified by the pink color. As the probability grows, the color becomes stronger.

Conclusions

The VDS seismic format helps to work with machine learning on 2D data. The workflow with 2D data developed in the deep learning tool highlighted the existence of different challenges to those faced by workflows with 3D data. The main challenge faced was finding the most appropriate labeling process to follow, which was defined by opting for a multiclass before the binary to get to the salt layer. Therefore, it is necessary to choose very carefully which lines will be labeled to provide accurate labels that are representative of the features identified in the seismic data. A relatively low number of labeled lines is required for the neural network, considering the number of seismic lines involved. Despite the challenges encountered, it can be said that the deep learning tool has proved to be very effective and promising when the workflow is developed for 2D seismic data.

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