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Multivolume Interactive Deep Learning for 2D Seismic Interpretation of Dolerite Sills in the Parnaíba Basin, Brazil

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Summary

This study presents a novel application of multivolume interactive deep learning to interpret complex Dolerite sill geometries from Pedreiras 2D seismic data survey in Brazil's Parnaíba basin. By supplementing traditional amplitude data with targeted seismic attributes – specifically, first derivative and reflection energy volumes – derived from 2D SEG-Y lines, we trained an interpreter-guided deep learning network to generate high-fidelity geologic predictions. The multi-volume deep learning approach, typically reserved for 3D datasets, was adapted through unidimensional 3D formatting of 2D data, enabling real-time feedback and accelerated convergence on geologically plausible results. This methodology enhances interpretation accuracy in data-constrained regions and demonstrates the feasibility of scaling deep learning workflows to large 2D datasets for frontier exploration.

Introduction

The interpretation of high-velocity, laterally variable Dolerite sills and their associated fault and feeder dike systems poses a significant challenge in fields producing from Paleozoic age reservoirs across Parnaíba basin in Brazil. In this basin, the igneous complexes are responsible for the trapping and compartmentalization of reservoirs. The dolerite sills intrude the organic-rich intervals of the Devonian Pimenteiras shale, triggering maturity and hydrocarbon generation, thus creating an atypical igneous–sedimentary petroleum system (De Miranda et al., 2018).

According to De Miranda et al., 2018, the Parnaíba Basin experienced two major magmatic episodes.These events reactivated basement faults and caused widespread mafic magmatism across Brazilian Paleozoic basins. The igneous rocks -dolerite sills, dykes, and basalts-are categorized into two stratigraphic units: Early Jurassic Mosquito Formation (215-150 Ma), this unit features large sills and basalt flows and, Early Cretaceous Sardinha Formation (149.5-87 Ma), that includes large dykes and smaller sills.

Traditional and interactive deep learning (DL) methods using only a single seismic volume as training input can provide useful predictions, but multivolume training offers significant advantages (Figure 1). By incorporating multiple data volumes – each emphasizing different aspects of the seismic signal – the network is exposed to richer information and converges more quickly on geologically plausible interpretations.

This paper outlines the use of multivolume interactive deep learning to enhance interpretation of Dolerite sill geometries in areas covered by 2D seismic data. While typically applied to 3D volumes, we demonstrate how multivolume training using carefully selected attributes derived from 2D lines can produce robust interpretation results, even in dimensionally constrained datasets.

Method and/or Theory

This study uses public seismic and well data from ANP's public database (https://reate.cprm.gov.br). Seismic data from the Pedreiras 2D survey was used to interpret igneous intrusions in the Parnaíba Basin. Well data (six wells) were used for both labeling and for blind tests. Together, these datasets provided the basis for the multivolume deep learning interpretation workflow.

Stage 1: Attribute Derivation

To support network learning, we experimented with multiple seismic attributes and got best results using two simple attributes from 2D SEG-Y seismic lines: the first derivative of seismic amplitude (a proxy for vertical reflectivity contrast) and reflection intensity (a measure of waveform energy). These attributes were selected for their strong sensitivity to abrupt reflection coefficient changes and their applicability to 2D trace data. This selection was informed by foundational work from Helbig & Thomsen (2005) and Malehmir et al. (2017), which discuss the limitations and strengths of seismic attributes derived from 2D datasets.

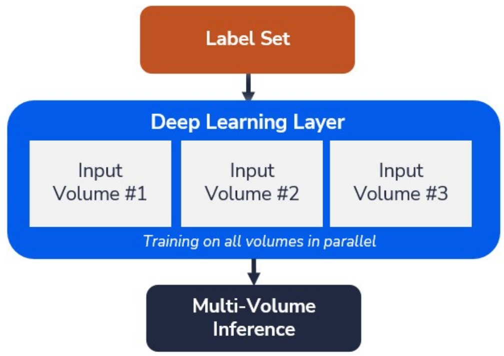

Figure 1: A schematic diagram showing the concept of a multi-volume deep learning network. Note that network training is governed by a single set of labels and generates a single combined network prediction.

The attributes were calculated using common seismic attribute tools available in commercial interpretation software. Care was taken to ensure these derived volumes contain consistent spatial orientation, trace sampling, and dynamic range for multivolume DL ingestion.

Stage 2: 2D Data Preparation for Interactive Deep Learning

Attribute and amplitude volumes were converted to Bluware's Volume Data Store (VDS) format, enabling their use in the InteractivAI (IAI) DL engine. Because IAI operates on 3D data volumes, 2D lines were pre-processed into pseudo-3D form: each 2D line was segmented into overlapping patches (96 traces overlap) and stacked in the inline direction. Crossline and time-slice dimensions were left null to preserve the unidimensional nature of the input, see Figure 2.

This transformation allows IAI to simulate a 3D training environment, preserving performance and enabling real-time interaction. The segmentation facilitates a live feedback loop, enabling the interpreter to guide learning based on continuous review of inference results—twice every 90 seconds, on average.

Stage 3: Interactive Labeling and Network Training

Unlike pre-trained static models, interactive DL networks in IAI are fully interpreter-driven. The interpreter begins by labeling key features, and the network is trained in short increments (2–3 epochs) to prevent early overfitting. As the network improves, inference quality increases and the training epoch count may be safely extended.

Inference probability lines are continuously updated and used as indicators of training quality. When true positive predictions begin to plateau or decline, training is halted. The resulting inference volume contains rich probability lines from which interpreters may extract horizons, faults, or sills.

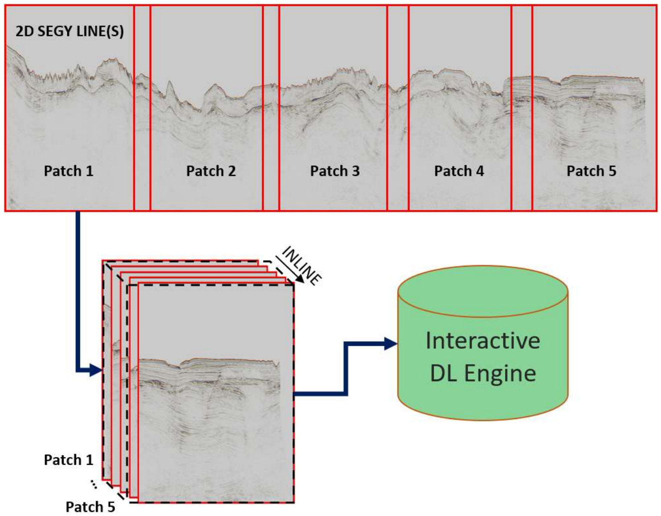

Figure 2: How 2D segy data is segmented in preparation for interactive DL. Note this example illustrates how the individual input data sets were prepared prior to ingestion into the DL engine and is not intended to illustrate the multi-volume training process.

Results

Figure 3 presents the results of the inference for dolerite sill geometries along a representative portion of a 2D line. The application of this multivolume DL approach to 2D data yielded strong improvements in the interpretability of these complex intrusive features. The final probability outputs from the DL network allowed horizon extraction and structural mapping with greater confidence than amplitude-only interpretations.

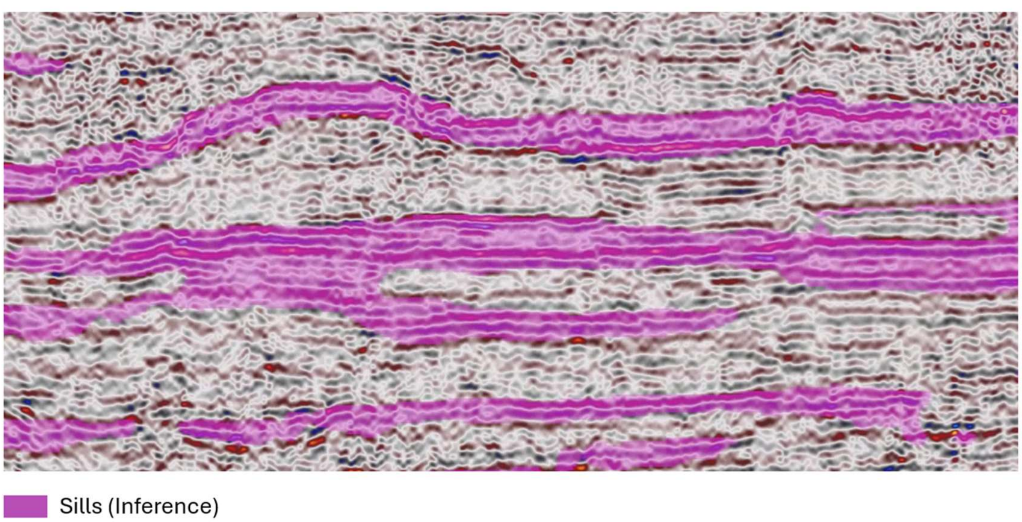

Figure 3: Inferred dolerite sill geometries along a representative 2D seismic line using the multivolume deep learning approach.

Compared to single-input models, the multivolume approach converged more rapidly and produced more geologically plausible geometry, especially in areas with weak or chaotic reflections. The first derivative and reflection energy attributes served as effective data masks, helping the network to ignore background seismic noise and focus learning on key features associated with intrusive sills.

This method provides a scalable, attribute-driven framework for extending interactive DL workflows to regions with sparse 3D coverage. Its ability to enhance 2D interpretation presents an opportunity to accelerate exploration decisions in frontier basins.

Conclusions

Multivolume interactive deep learning offers a powerful new approach for interpreting complex geologic structures using 2D seismic data. By supplementing standard amplitude data with targeted attributes derived from 2D waveforms, we can train networks that produce high-fidelity outputs even in data-constrained environments.

This study demonstrates the feasibility and value of extending interactive DL techniques beyond the 3D domain. In particular, its use in interpreting Dolerite sills in the Pedreiras 2D survey opens the door to broader regional application, including basin-scale 2D mapping and de-risking of volcanic plays.

The interactivity of the training loop, the importance of proper data conditioning, and the ability to tailor the model's focus through attribute design all contribute to a methodology well-suited for modern seismic interpretation challenges.

Future work will explore attribute combinations and transfer learning strategies to refine the approach further and adapt it for multi-line 2D datasets and multi-client data packages.

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References

De Miranda, F., Vetorazzi, A., Da Cruz Cunha, P., Aragão, F., Michelon, D., Caldeira, J., Porsche, E., Martins, C., Ribeiro, R., Vilela, A., Corrêa, J., Silveira, L., & Andreola, K. (2018). Atypical igneous-sedimentary petroleum systems of the Parnaíba Basin, Brazil: Seismic, well logs and cores. *Geological Society, London, Special Publications, 472*, 341–360. https://doi.org/10.1144/SP472.15

Helbig, K., and L. Thomsen, 2005, 75-plus years of anisotropy in exploration and reservoir seismics: *Geophysics*, **70**(6), 9ND–23ND, https://doi.org/10.1190/1.2131116.

Malehmir, A., G. Bellefleur, and C. Juhlin, 2017, Pros and cons of 2D vs. 3D seismic mineral exploration surveys: *First Break*, **35**(3), 79–86, https://doi.org/10.3997/1365-2397.2017007.