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In depth analysis using state-of-the-art deep learning techniques for semantic classification of Seismic Facies

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Summary

Interpretation of geologic features and inference of reservoir properties are key to the success of hydrocarbon exploration and production. In seismic interpretation, accurate delineation of subsurface structures is a necessary and routine process. Automation of this task allows for timely delivery of interpretation products to support prospect identification, well planning, reservoir modeling, and geohazard analysis. One such application is the seismic interpretation task for facies classification. One of the obstacles to the application of deep learning to seismic interpretation is the absence of publicly available, annotated large datasets for the training and testing of supervised models.

This study has two main objectives. The first objective is to solve the fundamental perception problem given an array of sensor data (i.e., two-way-travel time-series data), and we design an algorithm to discretely label and segment the subsurface structures. The second objective is to apply the concept of deep domain adaptation (DDA) to bridge the gap between source and target domains in a joint space. This would allow for a supervised classifier trained on labeled source data to perform well in the segmentation task on the target domain.

Theory / Method / Workflow

We use two different 3D geological dataset based on an open-source, fully annotated 3D geological model of the Netherlands F3 Block. We also use seismic data based on offshore North and Northwest Region of Australia to test deep domain adaptation (DDA). In this study, we compare our methods of semantic segmentation to the two baseline models developed in Alaudah et al. (2019).

The two models used in the current study, SeismicNet and DeepLab v3, are state-of-the-art models in semantic image classification. SeismicNet is an encoder-decoder architecture inspired by both U-Net (Olaf et al., 2015) and the more recent Danet-FCN3 (Civitarese et al., 2019). The encoder is composed of 5 ResNet convolution blocks, each has 2 convolution layers. At each block downsampling is performed through strided convolution with a scale of 2. The decoder has 5 transposed residual blocks similar to Civitarese et al., (2019), each is comprised of 2 deconvolution layers where upscaling is done through transposed convolution with a scale of 2 at each block. Each convolution layer is followed by a batch normalization layer (Sergey and Szegedy, 2015) and PReLU (He et al., 2015) is used as the activation unit. We feed a small patch of 99 x 99 due to memory constraints and to get larger receptive fields. The decoder provides us 64 features maps with a spatial resolution of 99 x 99 which are then projected to a segmentation map of 6 by a 1 x 1 convolution.

DeepLab v3 employs atrous convolution with upsampled filters to extract dense feature maps and to capture long range context. It is used to encode multi-scale information. DeepLab v3 increases effective field-of-views. Atrous convolution, allows to repurpose ImageNet pretrained networks to extract denser feature maps by removing the downsampling operations from the last few layers and upsampling the corresponding filter kernels, equivalent to inserting holes (*'trous'* in French) between filter weights (Chen et al., 2017). DeepLab v3 also handles the existence of objects at multiple scales, using the strategies: Image pyramid, encoder-decoder structure, extra modules cascaded on top of the original network and spatial pyramid pooling.

Results, Observations, Conclusions

To evaluate the performance of different models on our two test sets, we use the following metrics: (a) pixel accuracy (PA), the percentage of pixels over all classes that are correctly classified; (b) class accuracy for class *i* (CA_i), the percentage of pixels that are correctly classified in a class *i*; (c) mean class accuracy (MCA), the average of CA over all classes, and (d) frequency-weighted intersection over union (FWIU), to prevent this metric from being oversensitive to small classes and hence weight each class by its size.

The SeismicNet models have outperformed the baseline models in most of the facies groups (Upper North Sea, Lower North Sea, Rijnland, Scuff). In smaller classes like Scuff, SeismiNet models have displayed some fair improvements. However, the Freq Weighted IoU score remains the same for baseline and SeismicNet1 models (Table 2). Overall, with hyperparameter tuning, we expect the SeismicNet models to significantly outperform the baseline models, as they are able to incorporate more spatial and contextual information.

Facies Group	Baseline	SeismicNet1
Upper North Sea	0.926	**0.940**
Middle North Sea	0.912	0.896
Lower North Sea	0.974	**0.980**
Rijnland	0.673	**0.780**
Scuff	0.286	**0.383**
Zechstein	0.458	0.424

Table 1: Results of SeismicNet models compared to two section-based baseline models of Alaudah et al. (2019) .

Facies Group	Baseline	SeismicNet1
Mean class accuracy	0.705	0.736
Freq Weighted IoU	0.736	0.734
Mean IoU	0.736	0.791
Pixel Accuracy	0.862	0.881

Table 2: Metrics of SeismicNet models compared to two section-based baseline models of Alaudah et al. (2019).

Novel / Additive Information

The novelty of this approach is to integrate domain adaptation, a sub-discipline of machine learning that deals with scenarios in which a model is trained on a source distribution, into the context of a different but related target distribution. In general, domain adaptation uses labeled data in one or more source domains to solve new tasks in a target domain. The level of relevance between the source and target domains hereby usually determines how successful the adaptation will be. In this case, a deep learning model is trained to identify facies in F3 block of the Netherlands North Sea and deep domain transfer will be applied for dataset in NW Shelf Australia.

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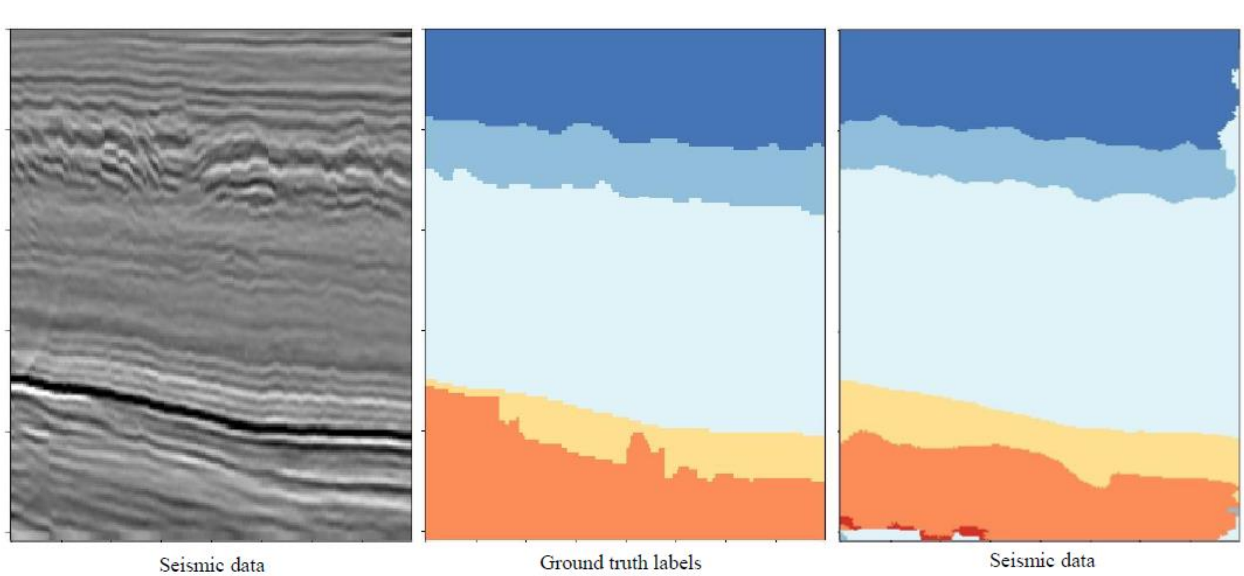

Figure 1: The results of SeismicNet on inline 499 based on patch model. The color map is shown in Table 1.