Machine Learning: A Deep Learning Approach for Seismic Structural Evaluation

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Summary

The goal of image recognition applied to seismic interpretation for hydrocarbon exploration is to identify the location of geological features that could be related to oil accumulation. The evaluation of structures on the subsurface is an important aspect since a large number of hydrocarbon reservoirs are contained in some kind of structural trap. Many types of structures are created by earth's stresses and are called structural traps, among these are the anticlines. The anticline patterns range from simple to exceedingly complex, and its evaluation requires the development of new types of computational approaches to extract the useful and valuable underlying information for interpretation. To addresses these approaches, in this paper, we present a case study where a deep learning algorithm: Convolutional Neural Networks (CNN), is invoked to train a predictive model over 2D synthetic seismic images correspond to anticline structures containing gas and water, respectively. We show that the CNN algorithm has the ability to correctly infer and classify anticlines structures not used during the training process of the algorithm. We conclude that CNN is a promising mechanism to automatically detect and identify a high percentage of anticlines structures on seismic data.

I. Introduction

Recent years have witnessed a significant increase in interest in the application of machine learning algorithms for seismic-data interpretation. Such techniques can automate the identification of compartments, faults, fault sealing, and trapping mechanism that hold hydrocarbons. An assortment of studies exists showing the benefit of machine learning for seismic-data interpretation (Zhang et. al., 2014, Shafiq et. al., 2015, Amin et. al., 2015, Guillen et. al, 2015, Araya-Polo et. al., 2017, Waldelan et. al., 2017, Zhen Wang et. al., 2018, AlRegib, et. al., 2018, Shafiq et. al., 2018, Wei et. al., 2018). The richness and rapid progress in image processing and computer vision have taken the automation of structural interpretation to a higher level.

The concept of deep learning originated from artificial neural network research. Unlike the neural networks of the past, modern deep learning has cracked the code for training stability and generalization and scale on big data. It is often the algorithm of choice for highest predictive accuracy, as deep learning algorithms performs quite well in a number of diverse problems. Deep learning architectures are models of hierarchical feature extraction, typically involving multiple levels of nonlinearity (Lecun et. al., 2015). Among the many supervised learning algorithms currently in use within machine learning, deep learning algorithms and specifically Convolutional Neural Networks (CNN) occupies a prominent position (Lecun et. al., 1998). A Convolutional Neural Network (CNN) is a widely used deep learning technique to process 2D images to learn representations of data with multiple levels of abstraction. This makes them a good solution for many computer vision tasks. The CNN takes input an image and convolves it with a 2D kernel of adjustable weights. The same kernel is convolved with the input image at different points in the image, which is known as weight sharing technique. Weight sharing reduces the number of free parameters. The results of convolution are added together with an adjustable scalar called a bias. The output is then fed into an activation function, which produces a 2D plane called a feature map. Convolution produces multiple feature maps whose number depends on the number of kernels, which is a function of the architecture. Each feature map is then connected to a subsampling layer, which reduces the size of feature maps. These subsampled feature maps are passed through of an activation function, which helps in retaining nonlinear properties.

Our overall proposed workflow aims at combining efficient seismic features from 2D images obtained with CNN and supervised learning algorithms. Our goal is to explore different mechanisms to build a robust solution against a variety of seismic datasets (i.e., a variety of reservoirs), for the automatic identification, and classification of anticlines structures. Here we show how supervised learning (CNN in particular) can be extremely efficient in the automatic identification of geological structural from seismic data.

The structure of this paper is organized as follows: Section II described the steps of the materials and methods, section III presents the experimental results and discussion and the conclusion and future work is given in section IV.

II. Materials and Methods

Preliminary Notation

We use techniques from machine learning --particularly supervised learning-- where the goal is to produce a model (predictive function) mapping instances (attribute vectors) into classes or categories. Specifically, a classifier or learning algorithm typically receives as input a set of training examples from a source domain $T = \{(x, y)\}$, where $x = (x_1, x_2, ..., x_n)$ is a vector in the input space, and y is a value in the (discrete) output space. In our case an attribute vector corresponds to each pixel in a 2D

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seismic image; attributes are then understood as properties of that particular small region in the reservoir. The outcome of the learning algorithm is a function $f(x)$ mapping the input space to the output space $f: X \rightarrow Y$.

Supervised Classification of Anticlines

In order to apply the deep learning methodology for the classification of anticlines structures a dataset for training and testing with classes was used. The dataset contains 2 classes, where each class considers seismic images with anticlines structures for gas and water.

Attribute Extraction Automatically

We look for seismic features (attributes) sensitive enough to characterize different features observed inside anticlines structures and their surroundings. The main idea is to make a clear distinction between pixels inside and outside structures. To that end we rely on convolution neural network (CNN) as an efficient technique to estimate automatically the structural, orientation, patterns, or regularities of diverse regions in a 2D image.

Convolutional Neural Networks

As previously mentioned, a convolutional layer takes an input image and convolves it with kernels to produce several two dimensional planes of neurons called feature maps. Each element of a feature map is obtained by convolving the respective kernel with units in the neighborhood in the previous layer. These outputs obtained after each convolutional layer are then summed up together with a trainable bias term which is then passed to an activation function to obtain each unit of a feature map (Strigl, et. al., 2010). Convolutional layers act as feature extractor to extract features such as corners, edges, endpoints or non-visual features by convolving the input with kernels consisting of weights (LeCun, et. al., 2010). As the weights are shared, the number of parameters to training the neural network is reduced. This also reduces the memory necessary to store these parameters during execution. The convolution operation in each convolutional layer makes a CNN translational and distortion invariant i.e. when the input image is shifted the output feature map will be shifted in the same amount as input. The number of kernels in each convolution layer depends upon the number of feature maps and varies from architecture to architecture. The network is organized in a hierarchical layer structure that, at each level, combines the lower level features into higher level ones, until the image class label is obtained. The proposed network architecture in this study contains 3 convolutional, activation function ReLU, and max-pooling layers followed by a fully connected layer and ends with a two-class softmax layer. This architecture is summarized in Table I. What follows is a description of the types of layers:

Input layer: The input layer has three channels of 32x32 pixels, corresponding to the normalized RGB images.

Convolutional layers: a convolutional layer convolves the input image with a set of learnable filters, each producing one feature map in its output. The receptive fields (kernels) are of size 3x3, the zero-padding and the stride is set to 1. The three convolutional layers learn 32 feature maps.

Max-pooling: The lower level information needs to be spatially integrated for the image region, as well as simplified when accounting for higher level information. Max-pooling layers allow for such a complexity reduction without increasing the number of parameters in the network. The max pooling layers use a stride and pooling size equal to 2.

Fully connected layers (FC): Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular Neural Networks. Both the convolutional layers and fully connected layers are composed of Rectified Linear Units, with activation function f(x) = max(0, x).

Output layer: The output is composed of two neurons, corresponding to each of the two classes that are normalized with a softmax activation function.

TABLE I. CNN ARCHITECTURE

Layers	*1*	*2*	*3*	*4*	*5*
Types	*C+P*	*C+P*	*C+P*	*FC*	*C*
Feature maps	*32*	*32*	*64*	*128*	*2*
Filer size	*3x3*	*3x3*	*3x3*		
Conv. stride	*1x1*	*1x1*	*1x1*		
Pooling size	*2x2*	*2x2*	*2x2*		
Pooling stride	*1x1*	*1x1*	*1x1*		
Padding size	*1x1*	*1x1*	*1x1*		

C+P: Convolution and then Pooling, FC: Fully connected, C: Classification.

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Computational Tools

We trained a convolutional neural network using NVIDIA P100 GPU, on Sabine cluster, at the Core for Advanced Computing and Data Science, University of Houston.

We stopped the training process after stabilization of the validation accuracy with equal weight for all the classes (100 epochs). The batch size used is 32 samples. The network weights are initialized randomly, and the Adam adaptive learning rate gradient-descent backpropagation algorithm is used for weight updates. The selected loss function is the categorical cross entropy. The Python deep learning library Keras 2.0.8 with a TensorFlow 1.3 backend, was used in order to perform the classification through CNN architecture.

Dataset

Two databases of synthetic images are generated:

First: a database for training, which consists of 400 synthetic images, 200 images correspond to anticlinal structures with gas (Class0) and 200 images correspond to anticlinal structures with water (Class1).

Second: a database for testing, which consists of 100 synthetic images, 50 images correspond to anticlinal structures with gas (Class0) and 50 images correspond to anticlinal structures with water (Class1).

Figure 1(a) shows an image for water, and Figure 1(b) shows an image for gas.

(a) (b)

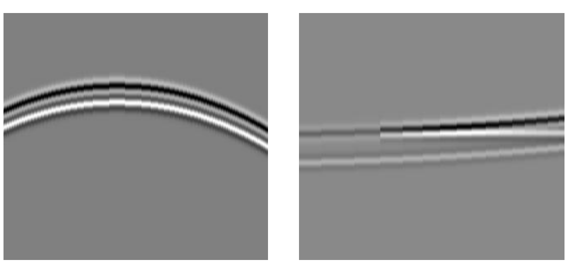

Figure 1: (a) Seismic data for water, (b) Seismic data for gas

III. Experimental Results and Discussion

The experimental took place using the following strategy in order to build the predictive model and evaluate the accuracy of the CNN algorithm:

We trained a CNN algorithm on a set of randomly selected images, approximately 80% of the entire dataset was used for training, and approximately 20% was used as the validation set. Finally, we then build a classification model that is subsequently used to automatically label a 2D seismic image dataset of testing.

The evaluation of the performance for the proposed methodology was measured in terms of accuracy and average area under the ROC curve (AUC) of the 2 classes.

Table II shows the results of the accuracy obtained for the testing dataset. A predictive accuracy of 96% for the two classes is obtained.

In evaluating the effectiveness of our CNN methodology, the confusion matrix is an important measure. Table III shows the confusion matrix for the testing data, predicting classes. We can readily see the strong diagonal components. This means that our classifier is achieving little classification error.

TABLE II. ACCURACY

CNN
Accuracy: 0.96

Figure 2: Accuracy for testing data

TABLE III. CONFUSION MATRIX

Classes	*Class0*	*Class1*
Class0	*24*	*1*
Class1	*1*	*24*

Figure 3: Confusion matrix for testing data

Figure 4 shows the results of the average area under the ROC curve (AUC) of the 2 classes. We can see that the curve follows the left-hand border and then the top border of the ROC space, showing the predictive model has high precision.

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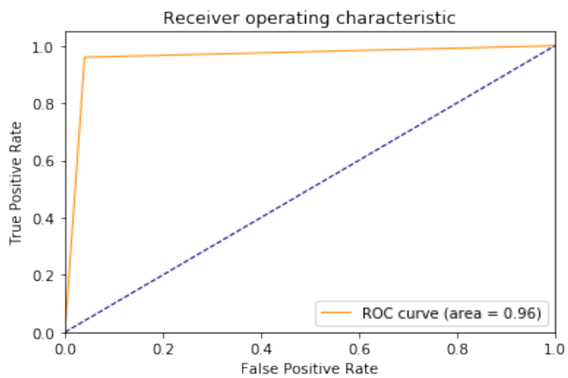

Figure 4: Area under the ROC curve

IV. Conclusions

In this paper we proposed an efficient methodology, which combine seismic structures anticlines as features with the convolutional neural network to classify 2 types of structures.

We have shown that the CNN algorithm is an efficient approach to classify structures anticlines using a 2D synthetic seismic images dataset.

Specifically, the application of Convolutional Neural Networks (CNN) showed results exhibiting high accuracy. CNN gives an accuracy value of around 96.0% in the identification and classification of anticlines belonging a two classes.

We conclude that CNN is a promising mechanism to identify geological structures on seismic data. We ascribe the efficiency of CNN to the capacity to model complex decision boundaries needed during class discrimination. Finally, this study does provide some evidence that using machine learning techniques, as deep learning, is a promise mechanism for seismic structural evaluation.

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