A CNN based framework to classify anticlines structures on seismic data

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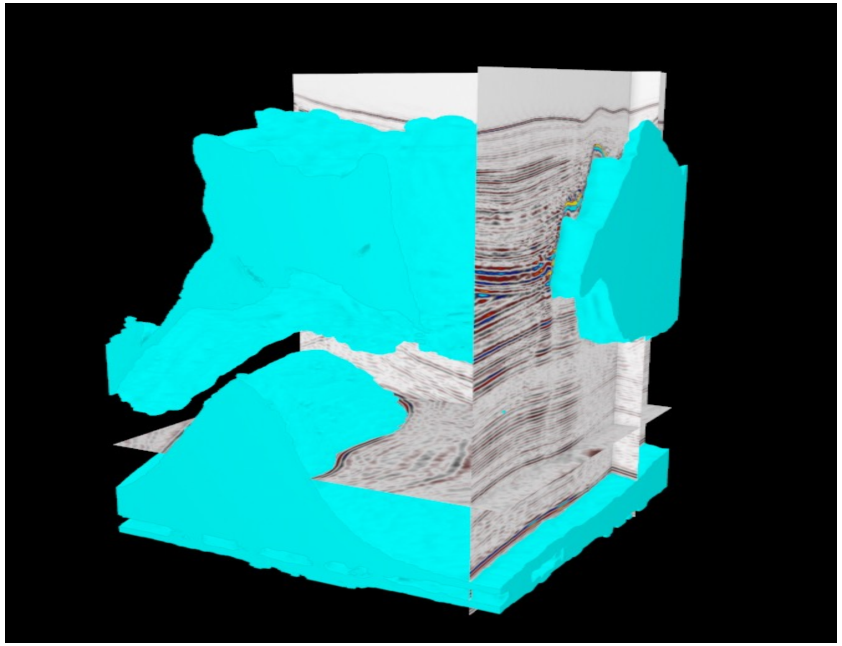
OUTLINE

Introduction

In order to better model complex world real-data from different fields, including geosciences one approach is to develop:

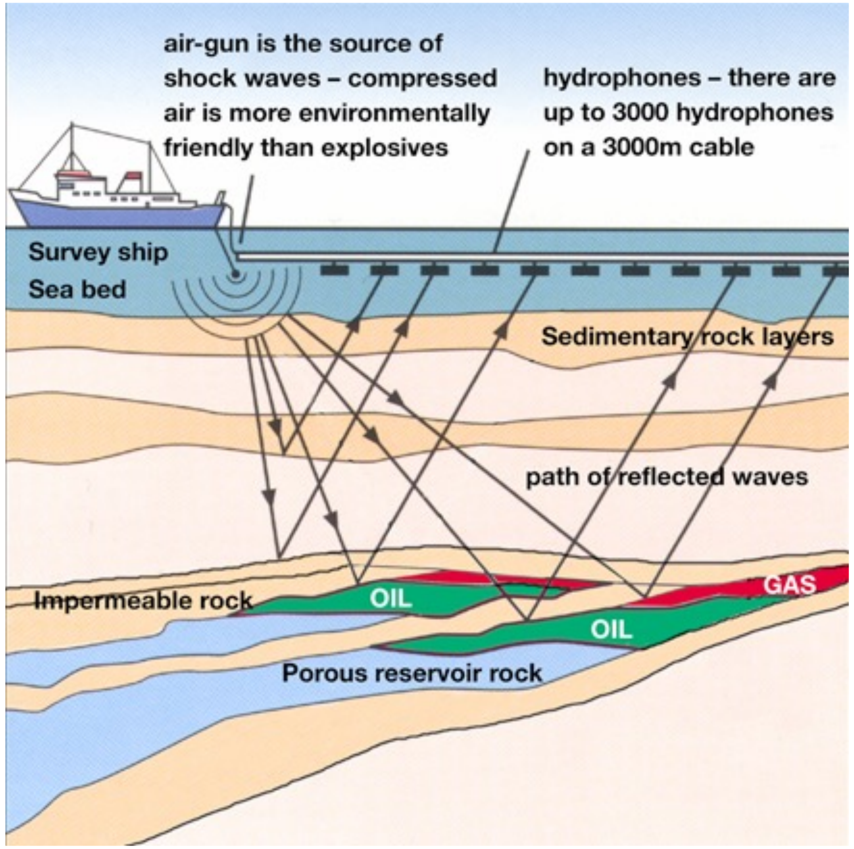
- Pattern recognition techniques
- Robust features
- Data Mining
- Machine learning
- Deep learning methods
- Predictive analytics



Goal:

- Automate simple decisions and guide harder ones
- Reduce the human bias
- Allow interpreters to be focused on geology and geophysics

Seismic Acquisition and Database



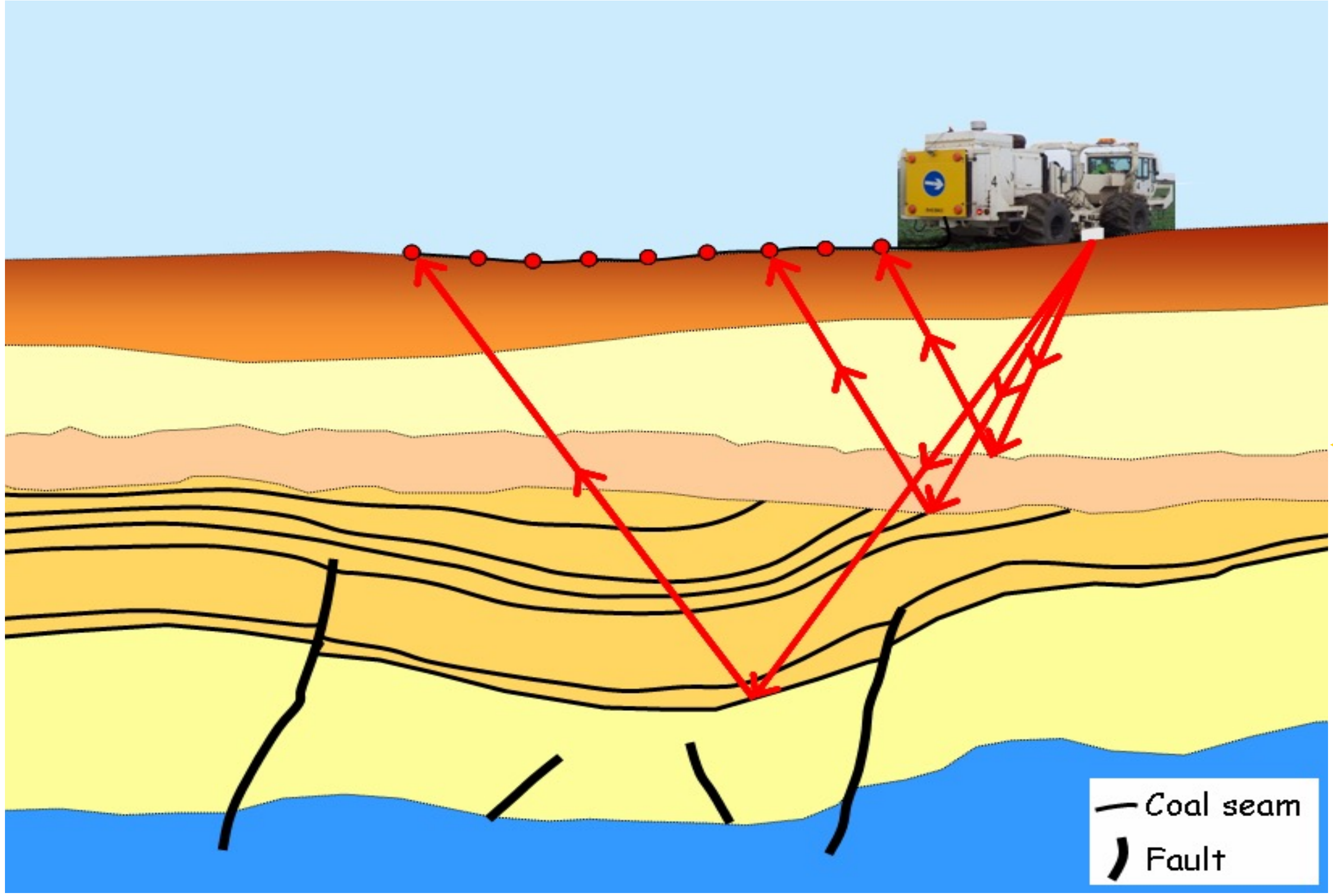
Seismic acquisition offshore:

- An air gun towed behind the survey ship transmits sound waves through the water column and into the subsurface
- Changes in rock type or fluid content reflect the sound waves towards the surface
- Receivers towed behind the vessel record how long it takes for the sound waves to return to the surface
- Sound waves reflected by different boundaries arrive at different times.
- The same principles apply to onshore acquisition

Seismic Acquisition and Database

Seismic acquisition Onshore:

- **Onshore seismic acquisition requires an energy input from a "thumper" truck. Geophones arrayed in a line behind the truck record the returning seismic signal**



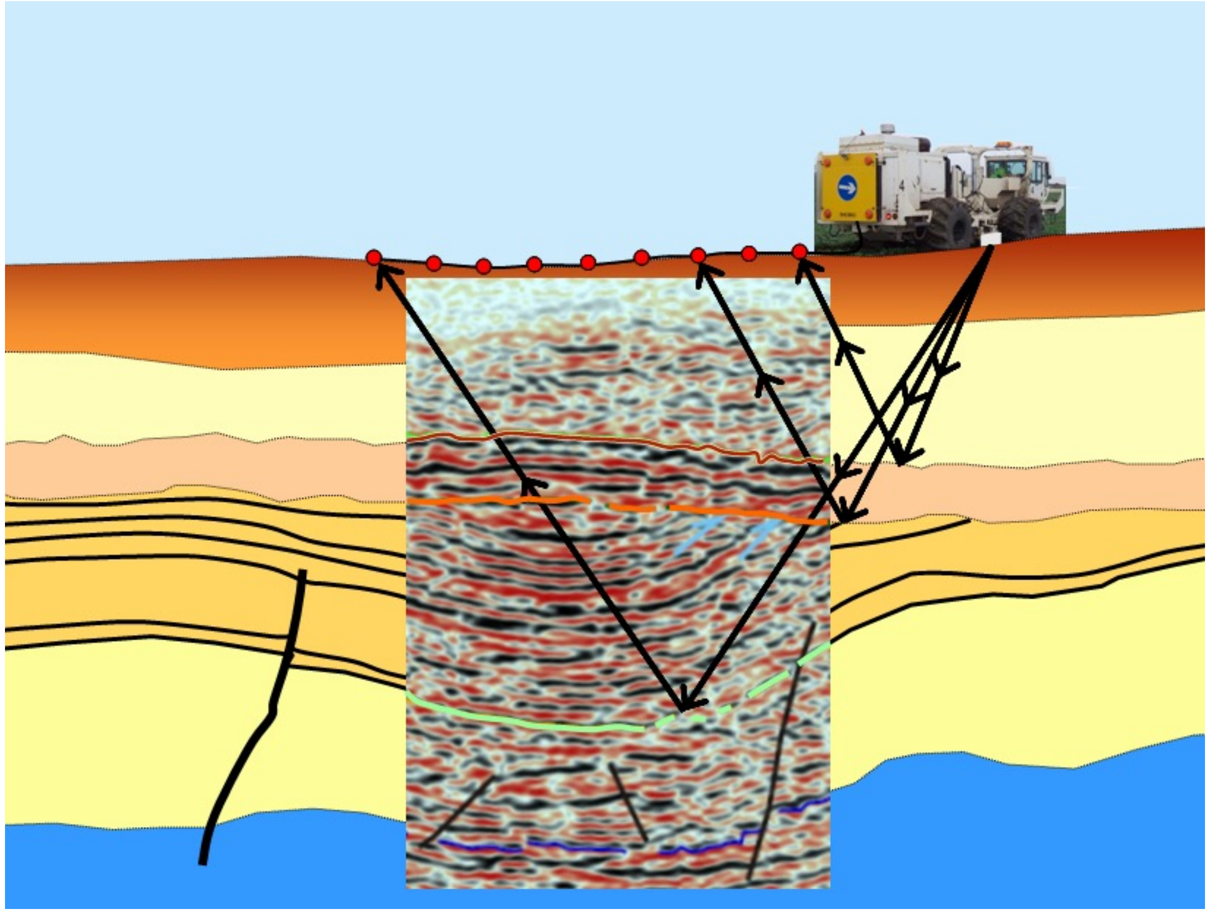
Sub-horizontal beds

Unconformity

Dipping beds

Seismic Acquisition and Database

- Seismic horizons represent changes in density and allow the subsurface geology to be interpreted.



Lithology change

Angular unconformity

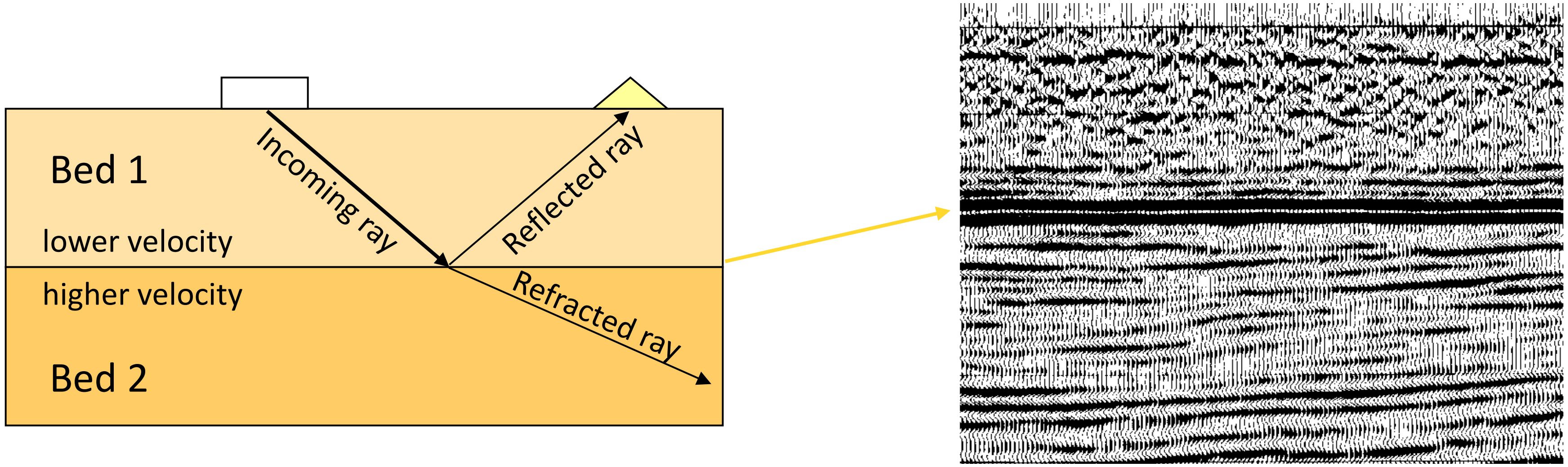
Lithology change

Seismic Acquisition and Database

What is a reflector?

A seismic reflector is a boundary between beds with different properties. There may be a change of lithology or fluid fill from Bed 1 to Bed 2. These property changes cause some sound waves to be reflected towards the surface.

There are many reflectors on a seismic section. Major changes in properties usually produce strong, continuous reflectors as shown by the arrow.



Seismic Acquisition and Database

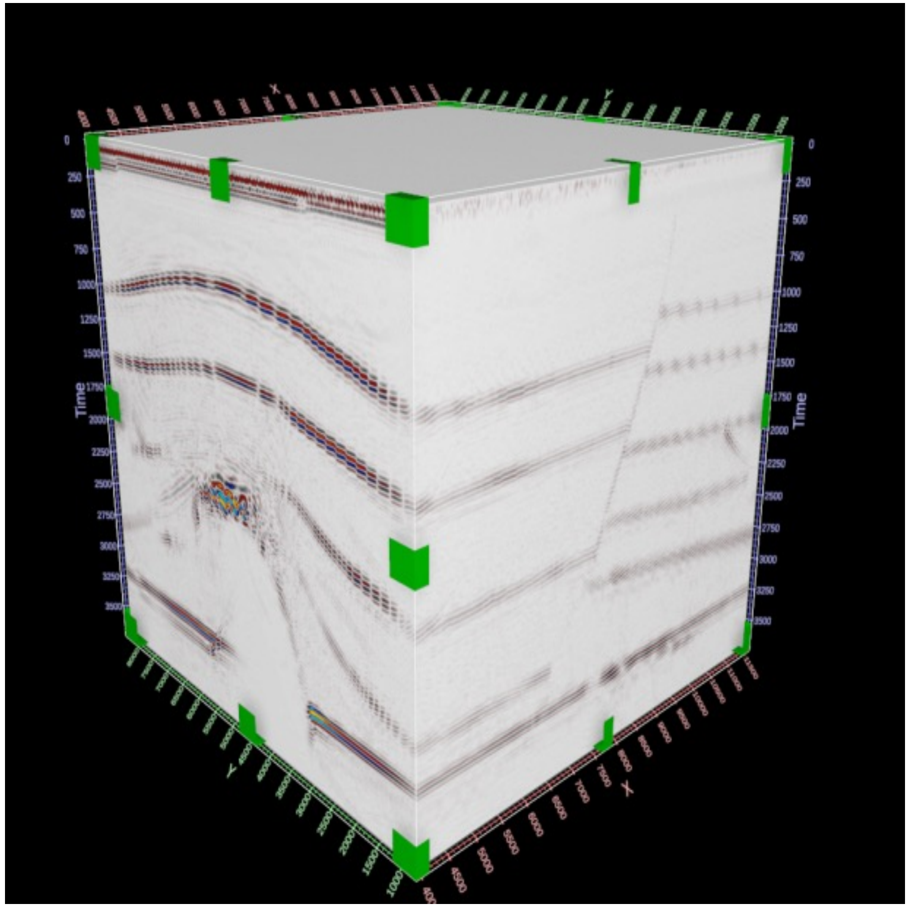


Figure. Seismic data cube

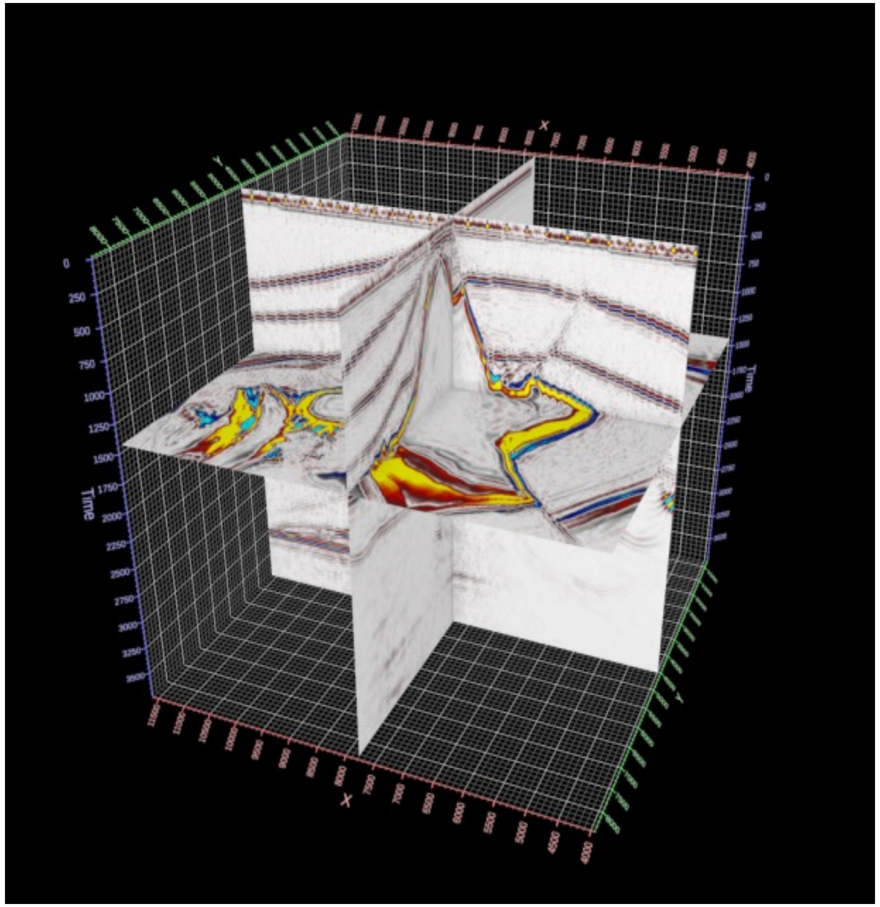


Figure. 3D dataset showing a specific in-line, cross-line and time slide

Introduction

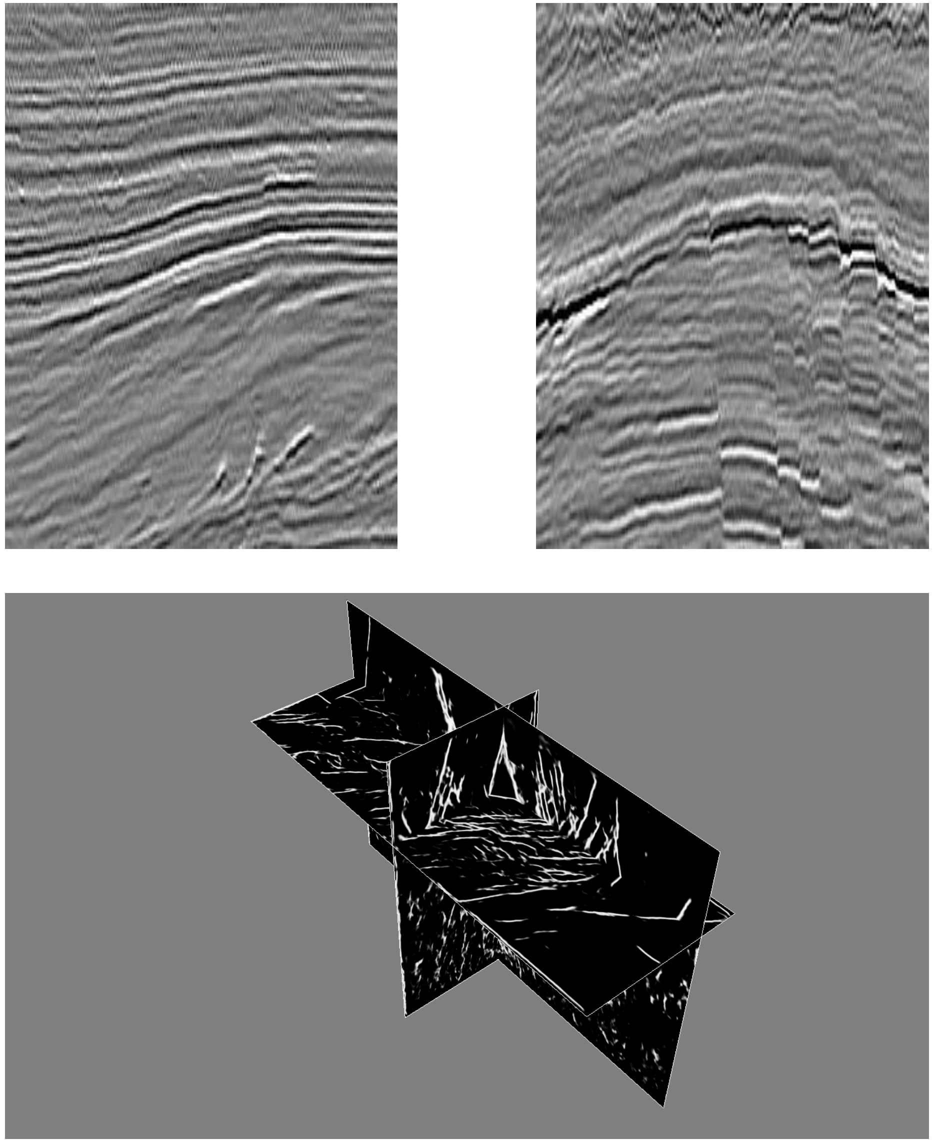
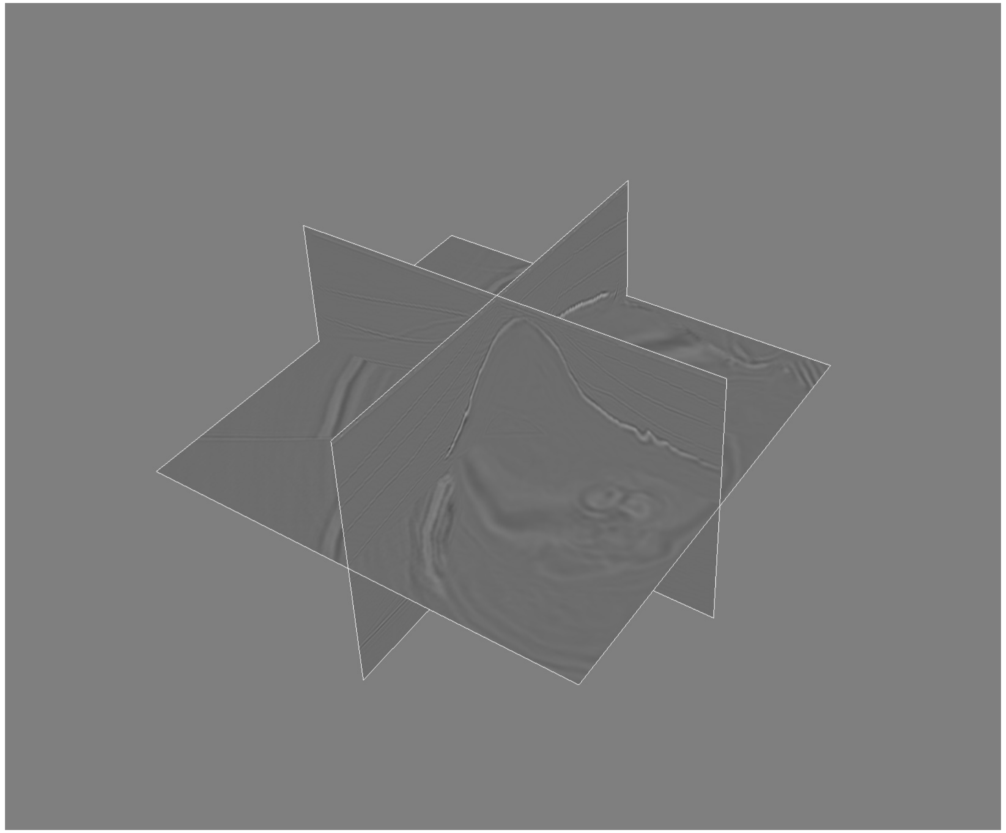
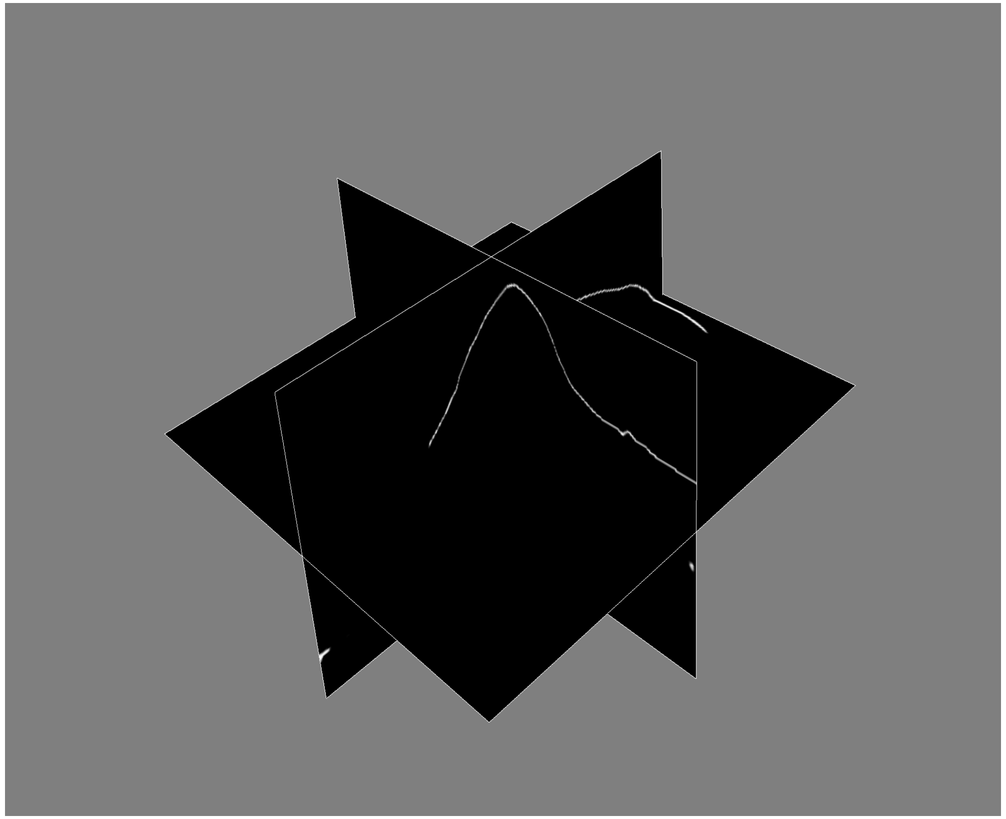


Fig. 1. Fault detection

Synthetic data



(a)



(b)

Fig. 2. (a) Seismic data, (b) Salt top

Synthetic data

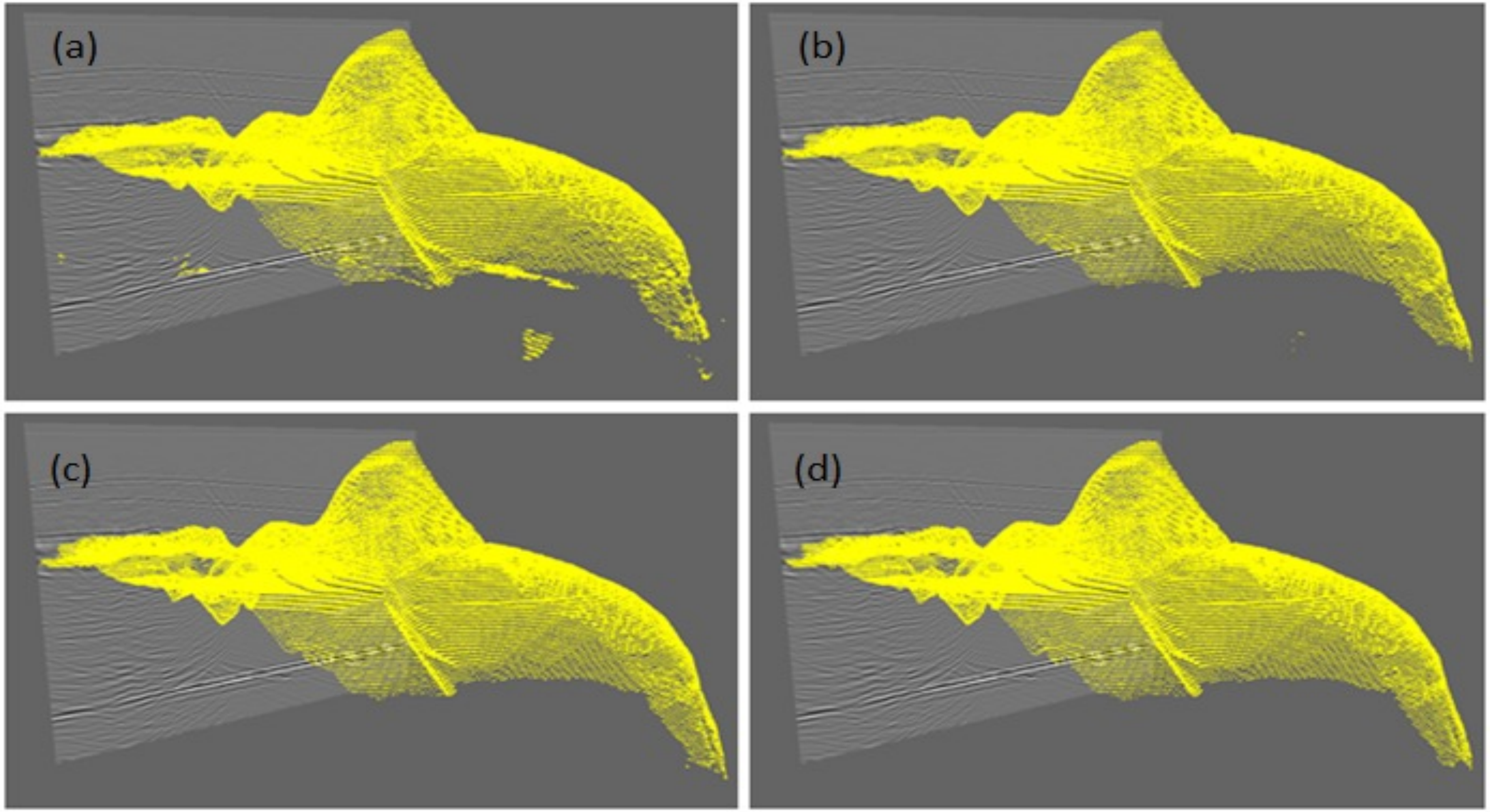


Fig. 3. Salt top extraction for different epochs. (a) epoch = 5, (b) epoch = 20, (c) epoch = 40, (d) epoch = 80

Real Data

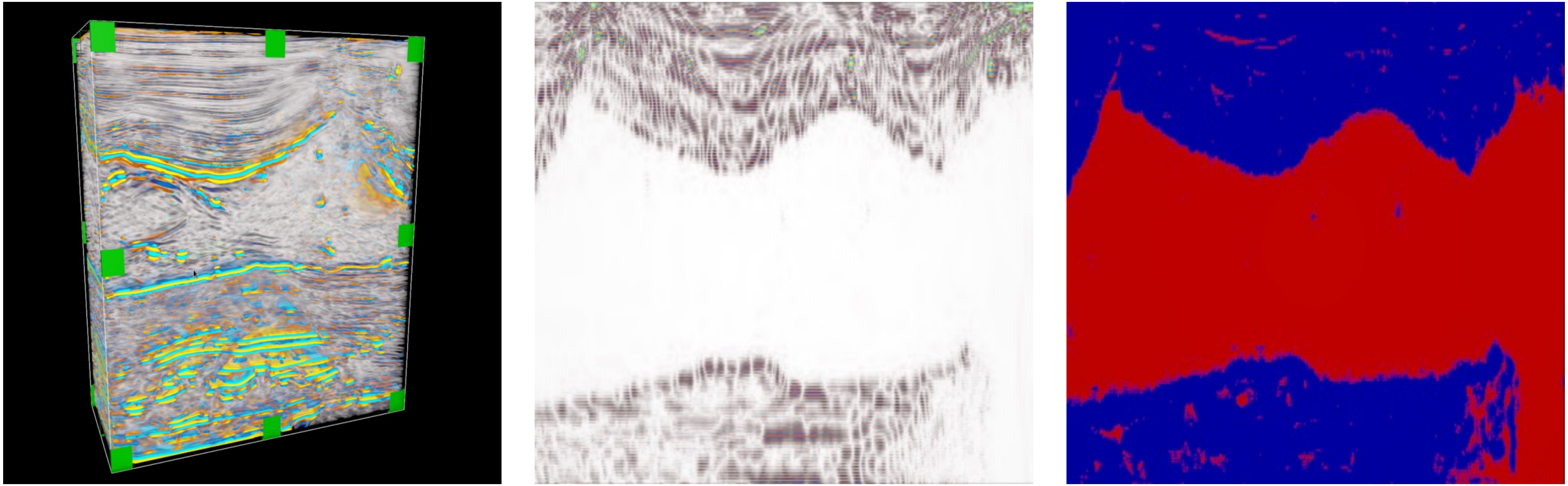


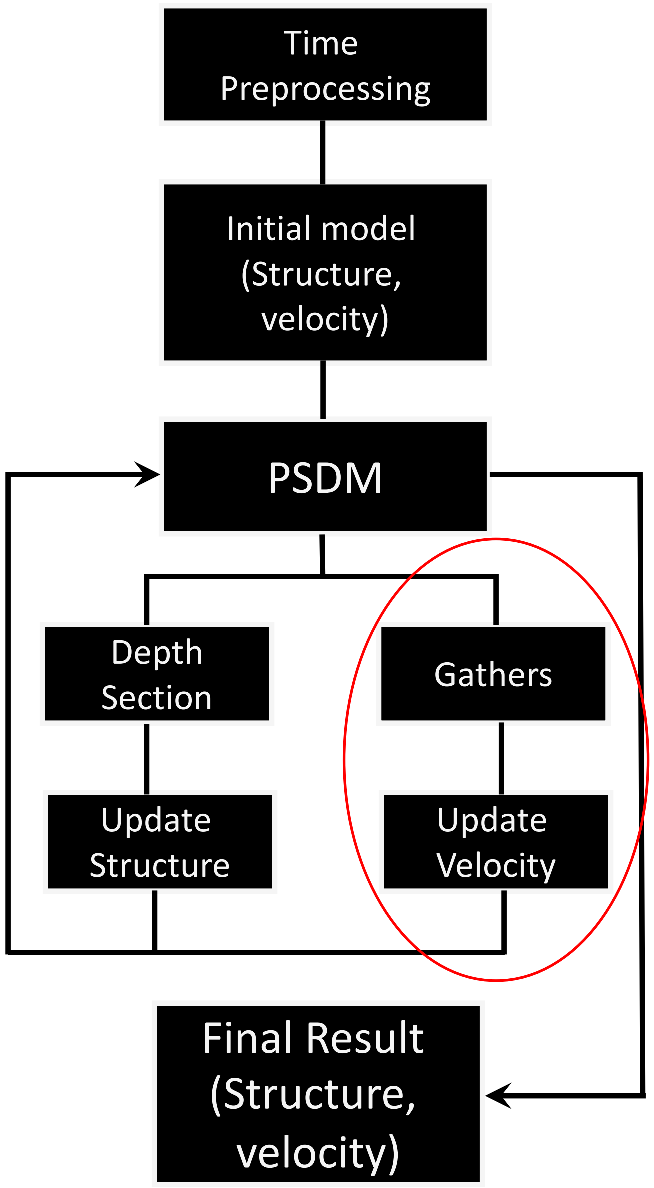
Fig. 3. Geobody Detection

Motivation

- 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*.
- Salt boundaries interpretation is a challenging task that significantly contributes to the workflow of an off-shore seismic imaging project where salt environment are presents.
- Interpreters need to extract the tops and bases of the salt body within this complex workflow. Where there are several calls to a migration process iteratively.
- Machine and deep learning algorithms play an important role to train the computer system as an expert which can be used further for prediction and decision-making.
- The richness and rapid progress in image processing and computer vision have taken the automation of structural interpretation to a higher level.

Motivation

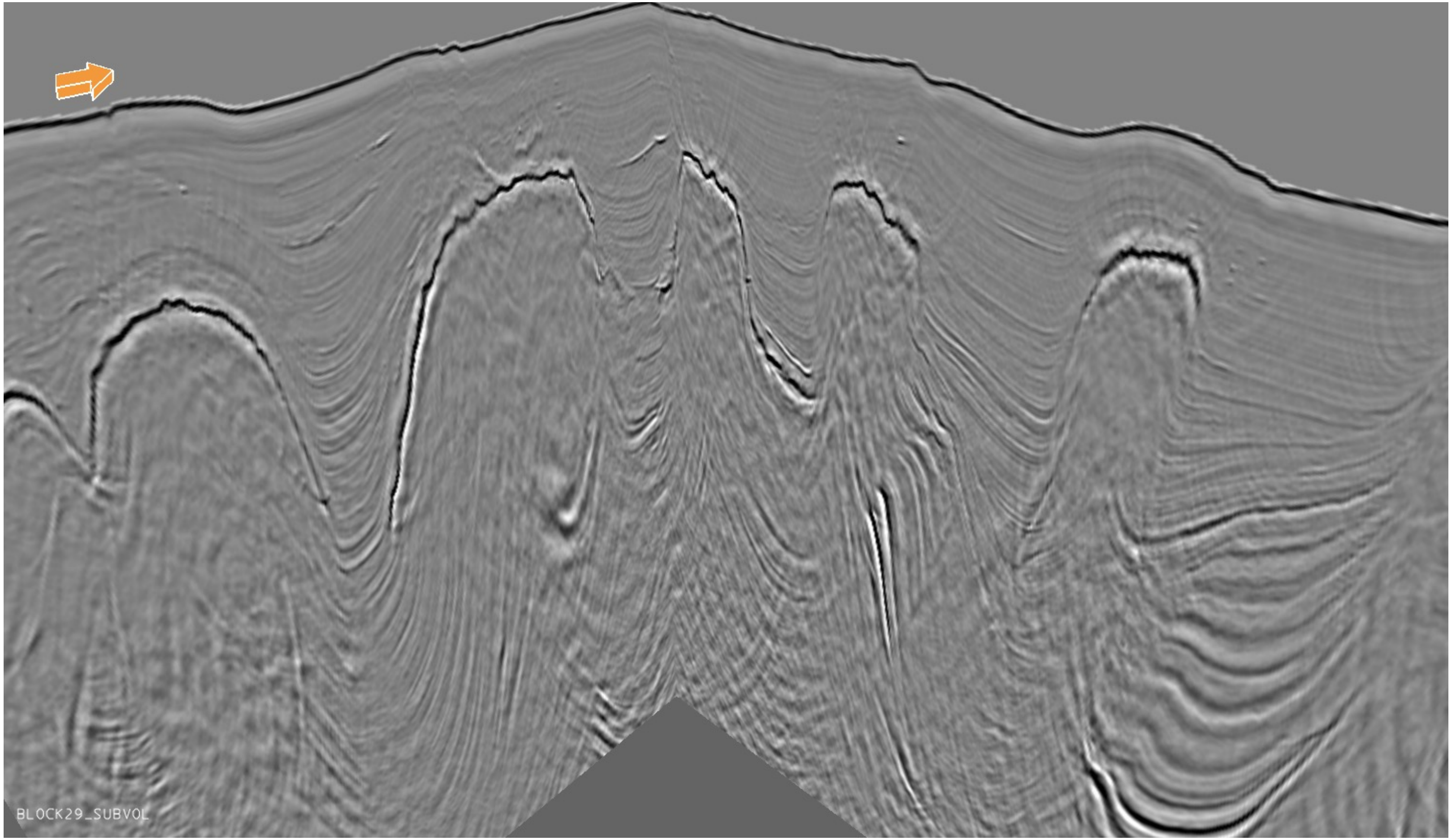
Depth Imaging Workflow



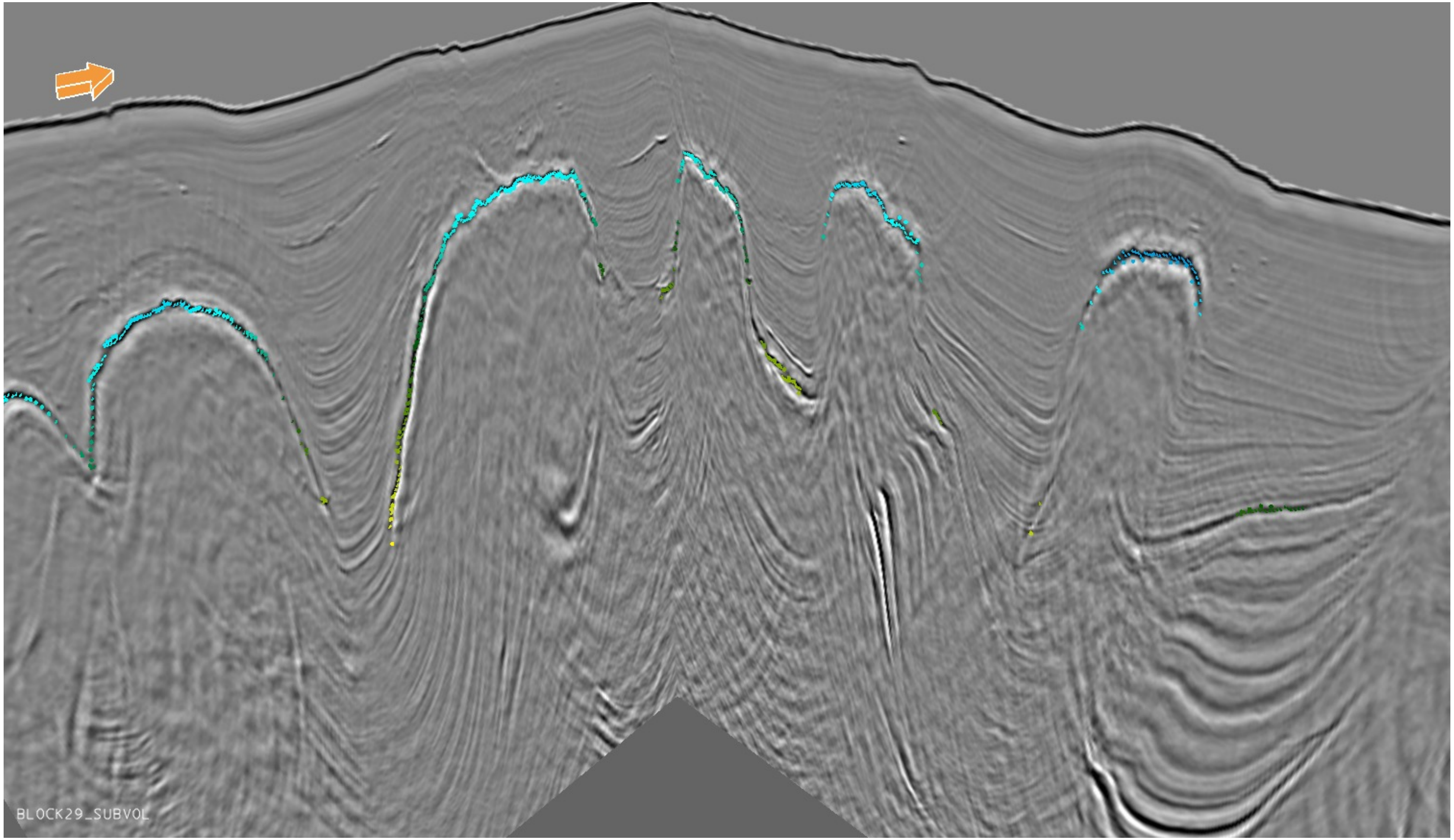
After 1-3 iterations Sediment flood image is generated and interpreter needs to pick the salt top

Tomo process
V1 = Vo + deltaV

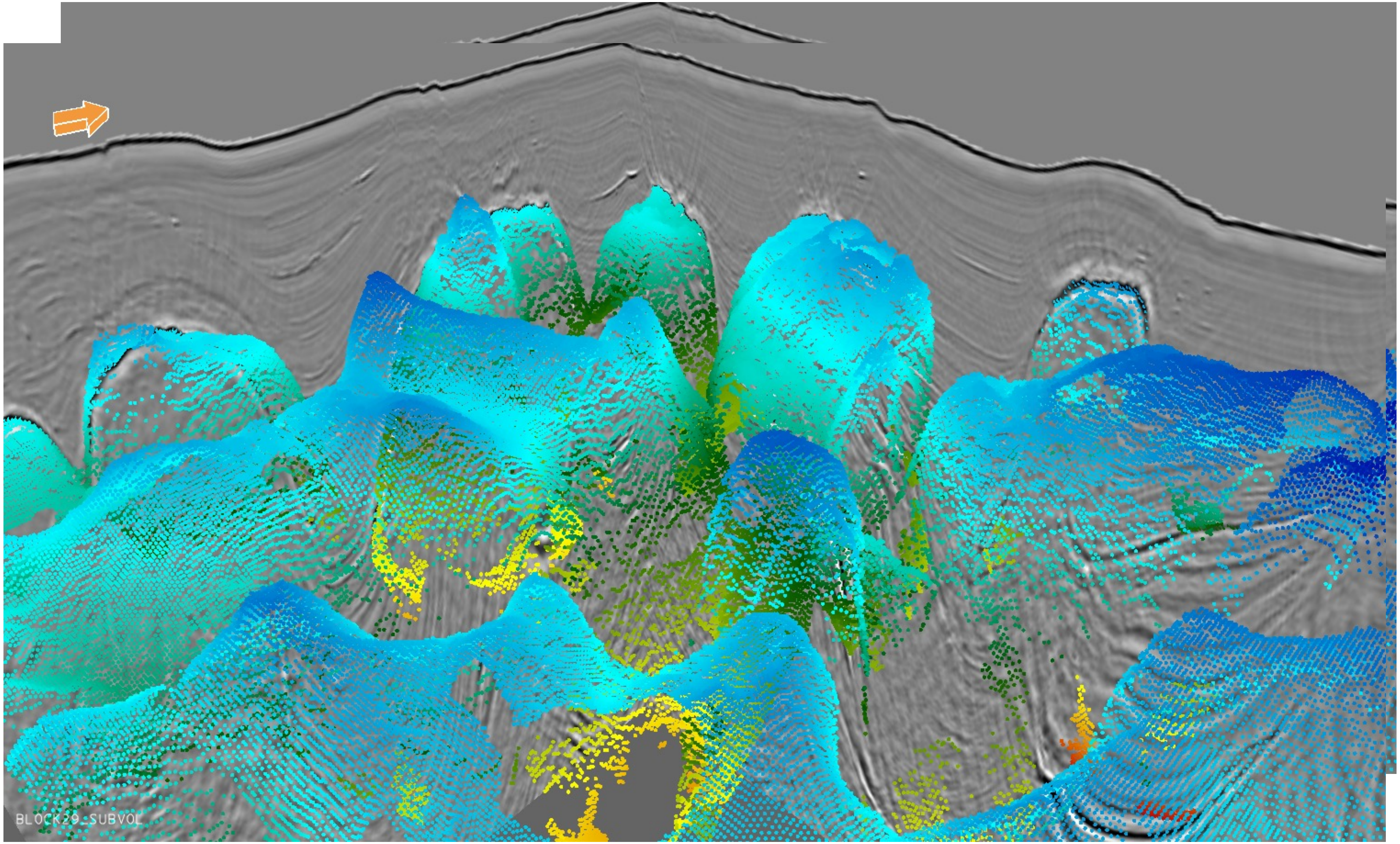
Real Data



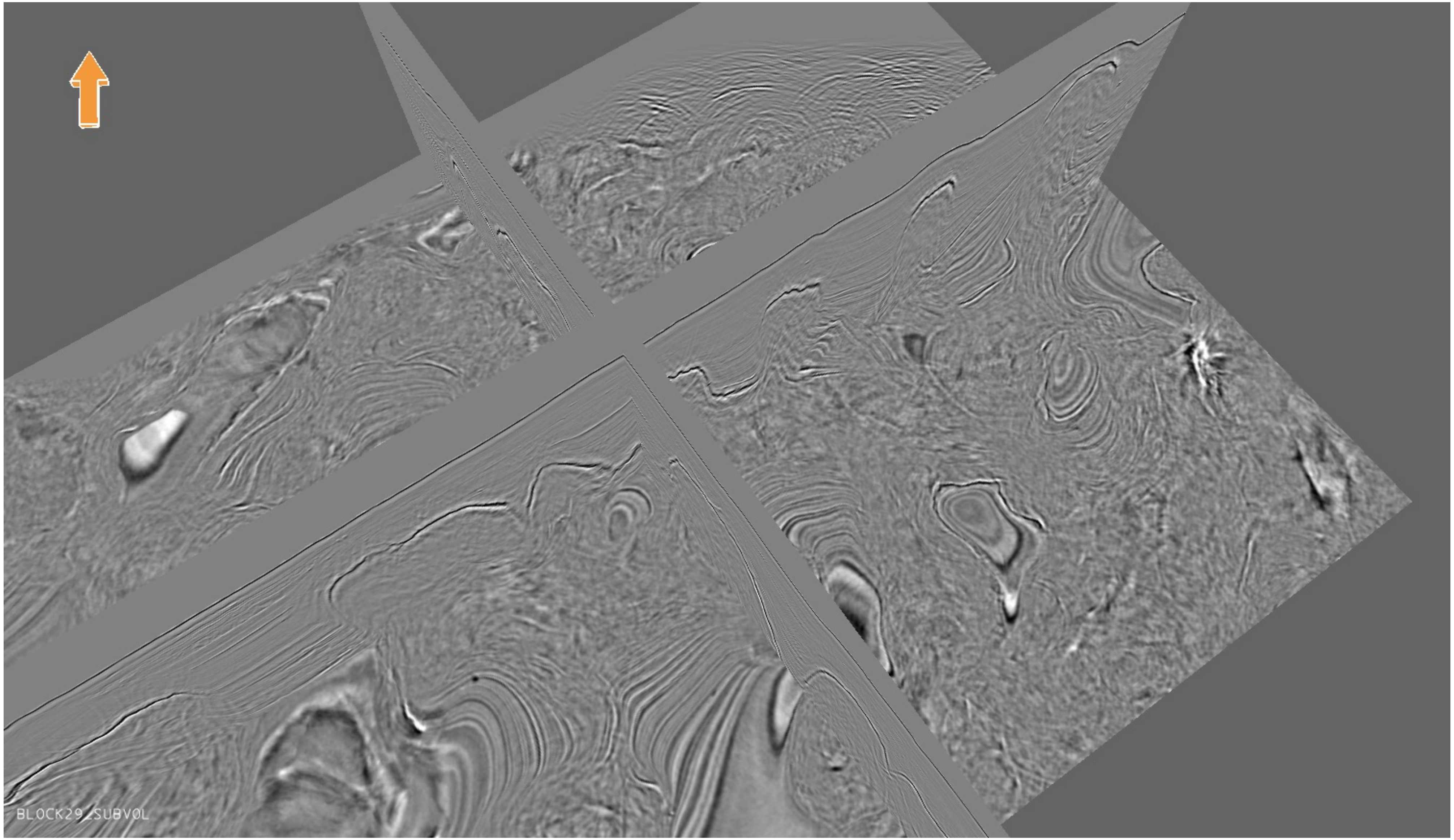
Real Data



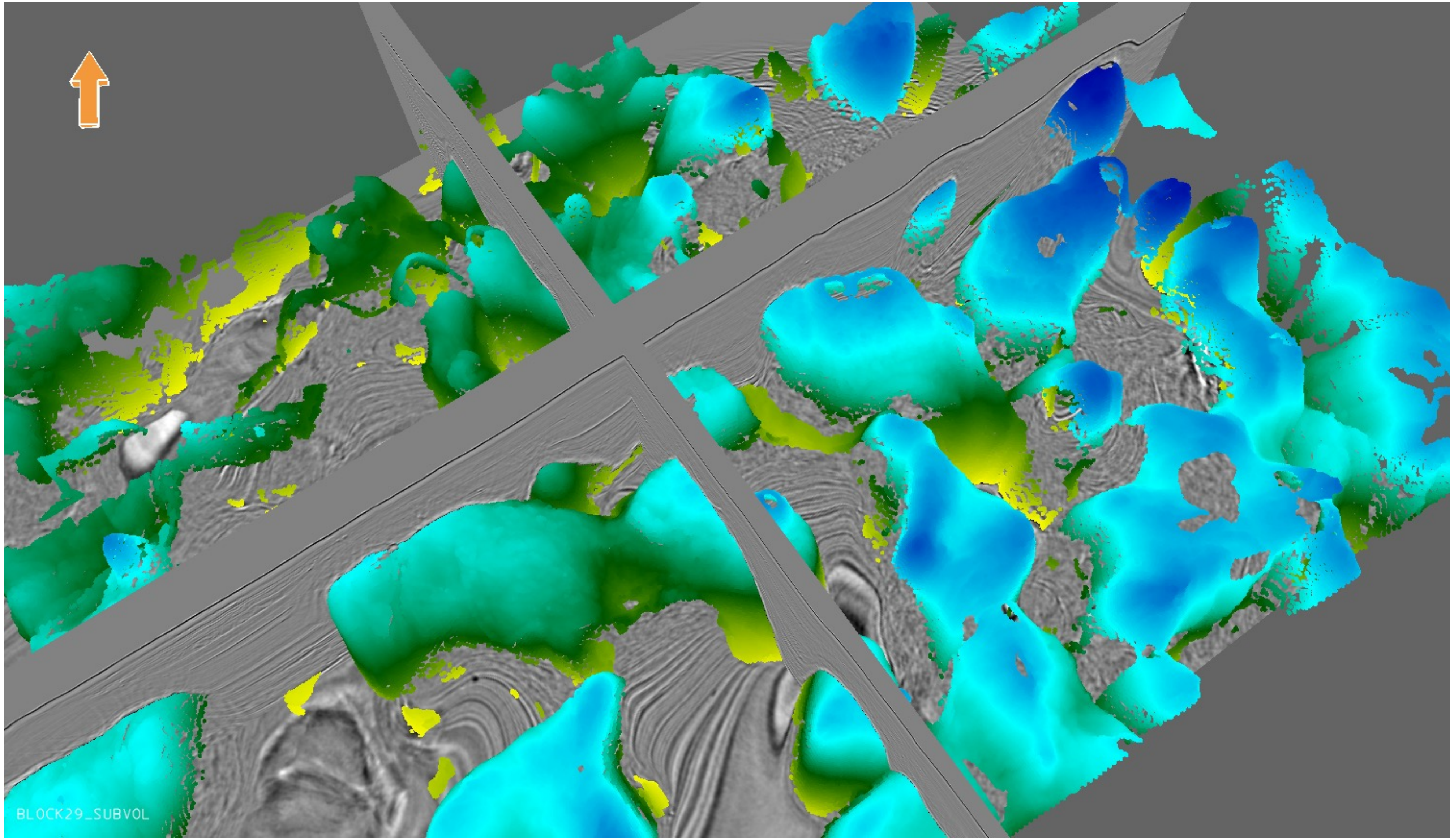
Real Data



Real Data



Real Data



Introduction

- The evaluation of structures on the subsurface is an important aspect since all hydrocarbons are contained in some kind of structure. Many types of structures are created by folding and faulting and are called structural traps, among these are the anticlines.

- Machine and deep learning algorithms play an important role to train the computer system as an expert which can be used further for prediction and decision-making.

- 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.

- The richness and rapid progress in image processing and computer vision have taken the automation of structural interpretation to a higher level.

Introduction

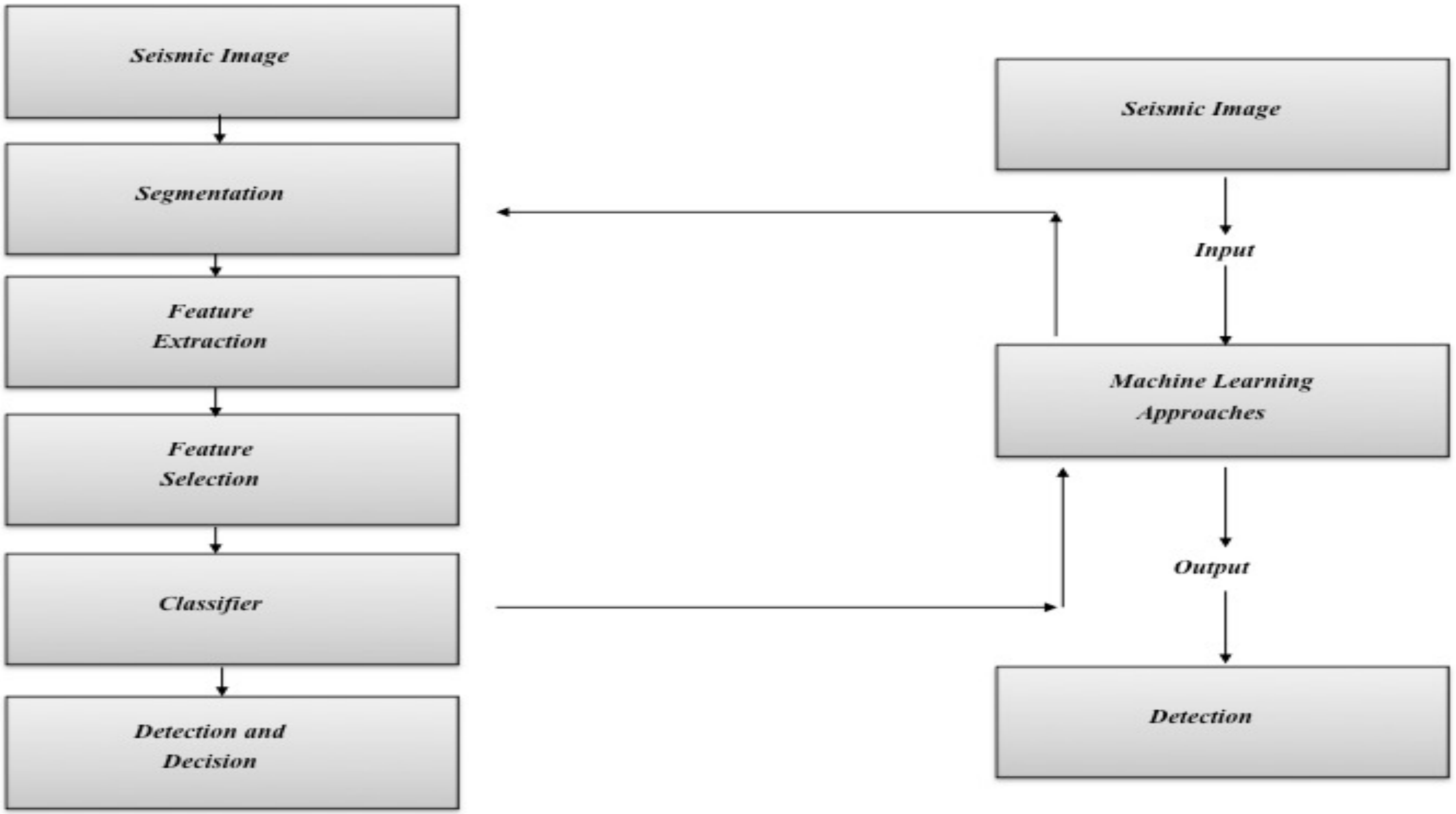
- The concept of deep learning originated from artificial neural network research. Deep learning architectures are models of hierarchical feature extraction, typically involving multiple levels of nonlinearity.

- 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.

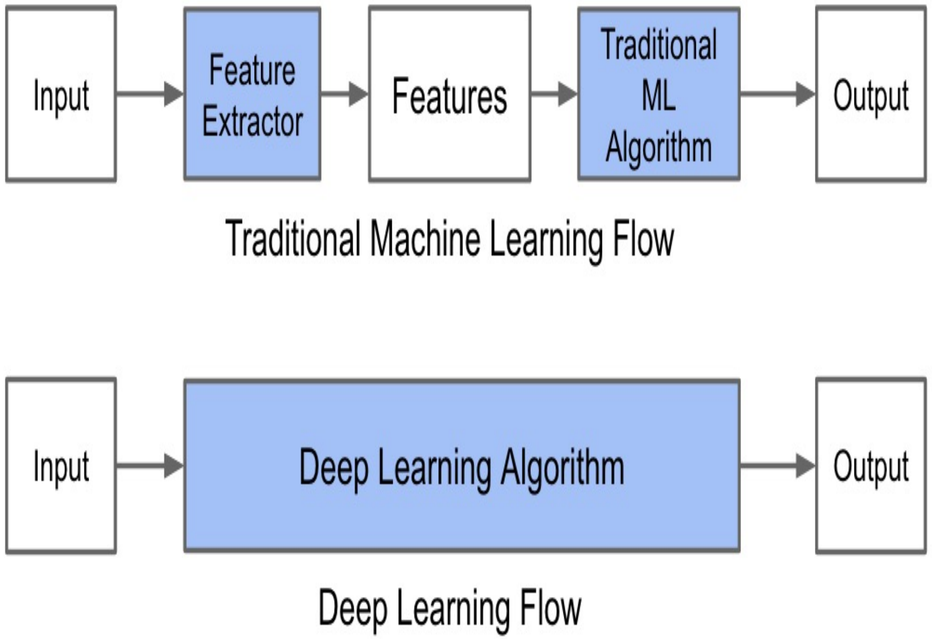
- In this talk, we are presenting a comparison of machine learning algorithms to classify 2D synthetic seismic images correspond to anticlines structures for gas and water, respectively. The reported results established the superiority of Convolutional Neural Networks (CNN), compared to other classifiers in terms of classification accuracy.

- Our overall proposed workflow aims at combining efficient seismic features from 2D images obtained with CNN.

Materials and Methods



Materials and Methods



The main difference between traditional machine learning and deep learning algorithms is in the feature engineering. In traditional machine learning algorithms, we need to hand-craft the features. By contrast, in deep learning algorithms feature engineering is done automatically by the algorithm. Feature engineering is difficult, time-consuming and requires domain expertise. The promise of deep learning is more accurate machine learning algorithms compared to traditional machine learning with less or no feature engineering.

Materials and Methods

Classification methods

Machine learning explores the study and construction of algorithms that can learn from and make predictions on data. Machine learning focuses on prediction, based on known properties learned from the training data shown as:

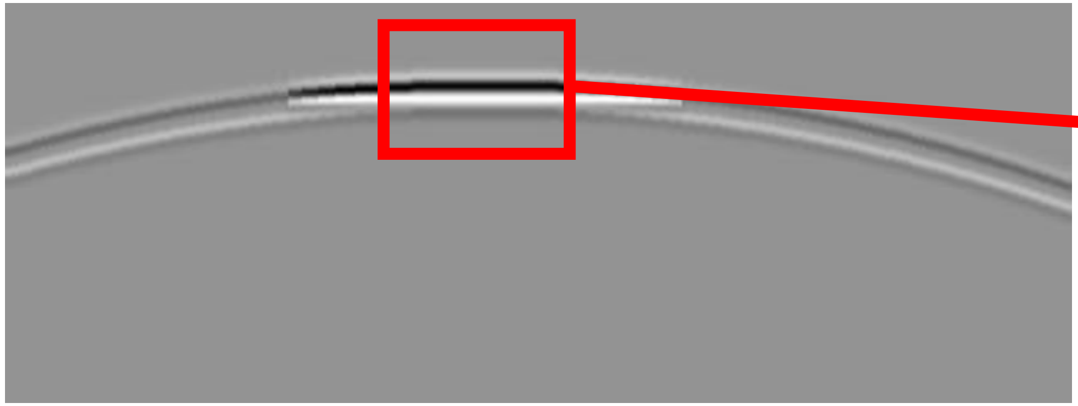
- *k-nearest neighbor, kNN*
- *Principal component analysis, PCA*
- *Random Forest, RF*
- *Support vector machine, SVM*

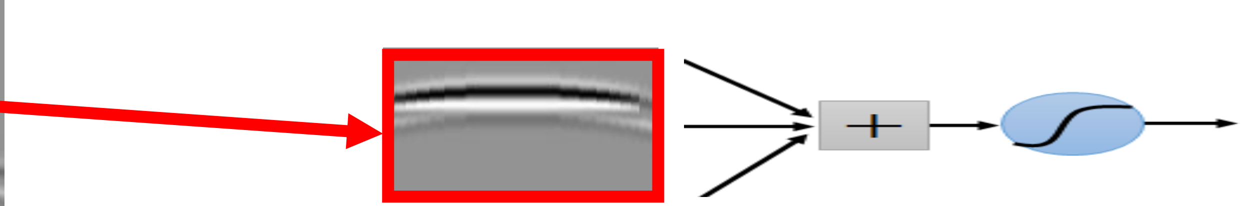
Materials and Methods

Convolutional Neural Networks

Consider learning an image: Some patterns are much smaller than the whole image

Can represent a small region with fewer parameters



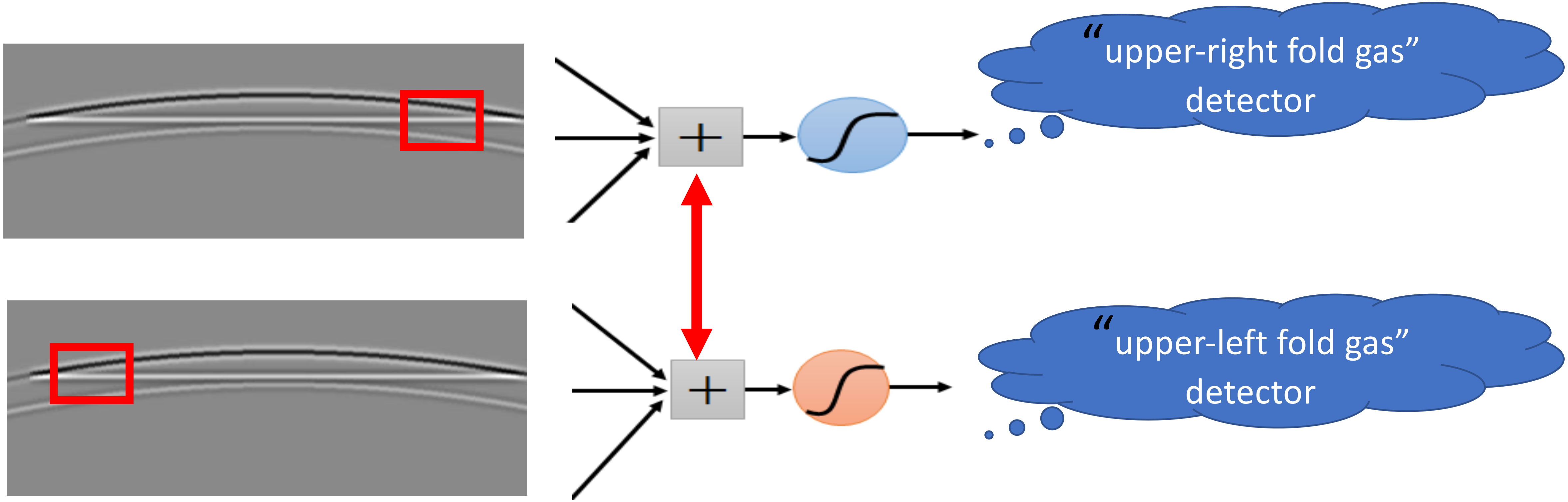


“**fold gas**” detector

Materials and Methods

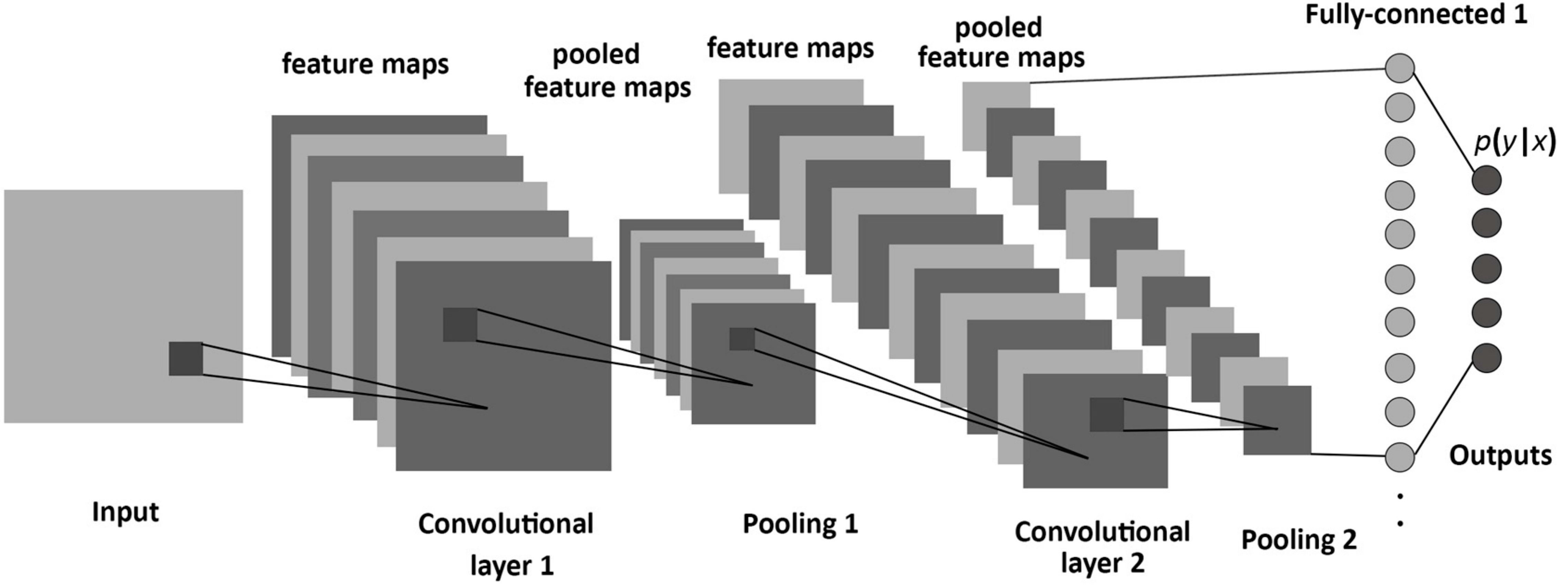
Same pattern appears in different places:

What about training a lot of such "small" detectors and each detector must "move around".

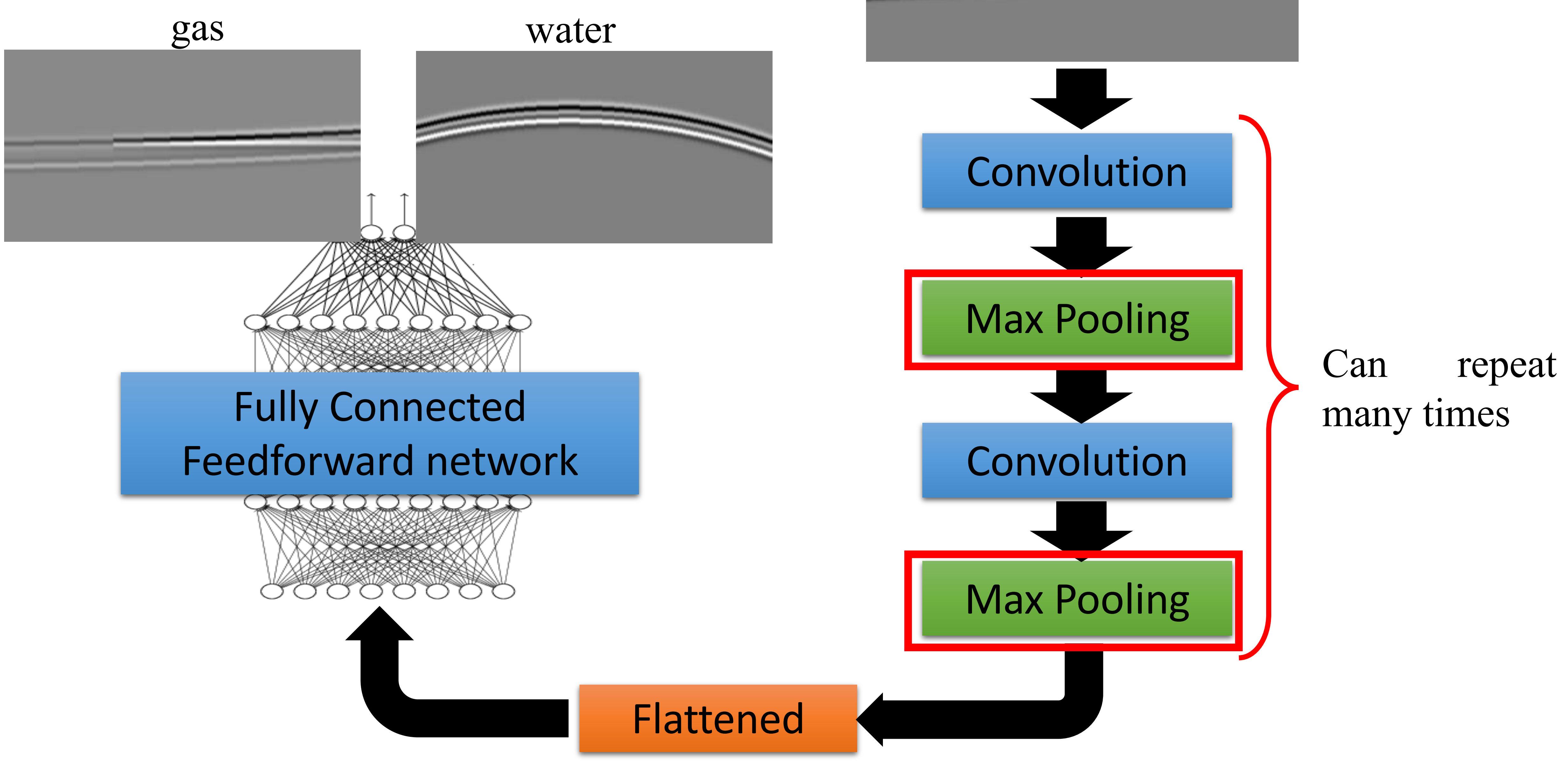


Materials and Methods

- *Convolutional neural networks, CNN*: 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.



The whole CNN



Materials and Methods

TABLE 1. CNN ARCHITECTURE

Layers	*1*	*2*	*3*	*4*	*5*
Types	*Co+P*	*Co+P*	*Co+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*		

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

The proposed network architecture

Materials and Methods

Dataset

Two databases of synthetic images are generated:

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

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

Materials and Methods

(a) (b)

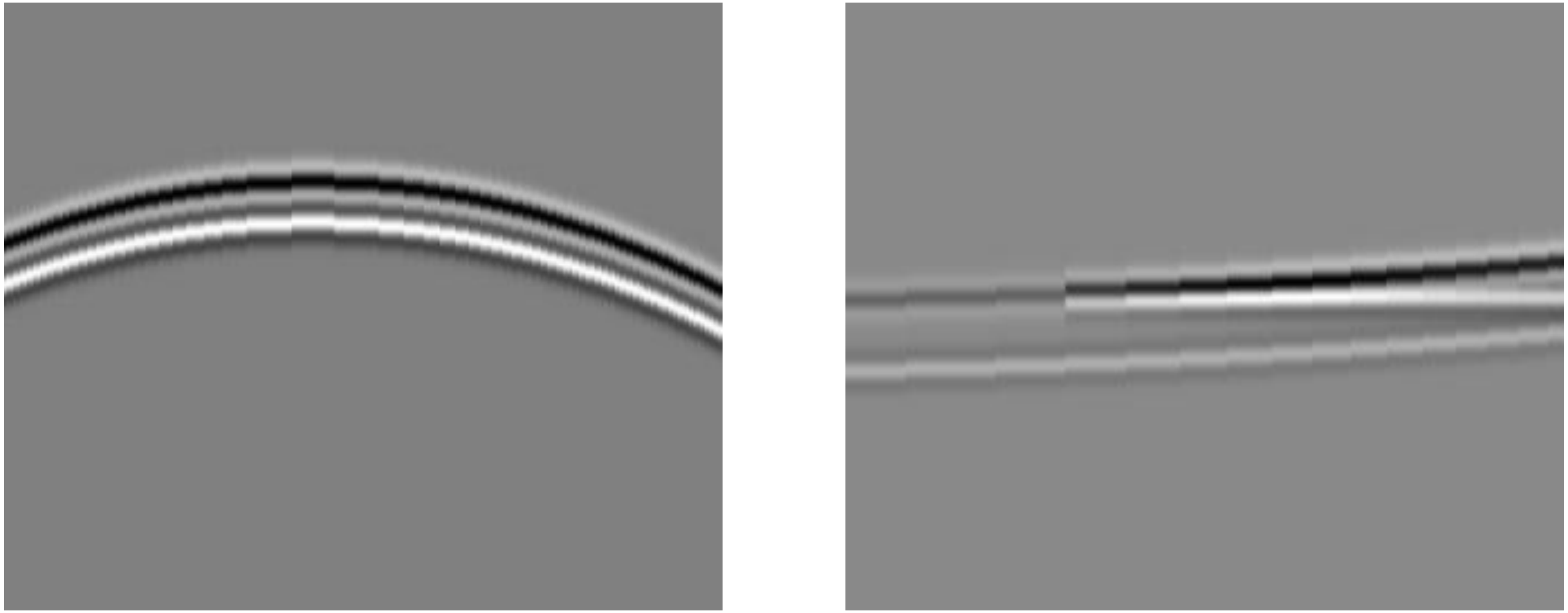


Figure. (a) Seismic data for water, (b) Seismic data for gas

Materials and Methods

Training and testing

- The task of training and testing is implemented to evaluate the performance of the CNN based classifier. Here, the dataset along with the class information is used. In our approach, 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 performance of CNN is improved by adjusting few parameters: batch size and epochs. 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.

Materials and Methods

Computational tools

- We trained the machine learning algorithms using Python 3.6, and 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 using NVIDIA P100 GPU on Sabine Cluster, at the HPE Data Science Institute, University of Houston.

- After completion of the training and testing, the classification performance achieved using this proposed CNN framework has been compared to other supervised classifiers namely *KNN*, Random Forest, and SVM.

Experimental Results

- An analysis of PCA was applied to the dataset with the purpose of obtaining seismic attributes sensitive to characterize different textures observed inside an anticlinal structure and in its surroundings. The numbers of PCA were set to 50.

- For *kNN* classification the numbers of nearest neighbor were set to 3, and Euclidean distance matrix and the nearest rule to decide how to classify the sample were used.

- For Random forest classification the value of 1000 trees were used.

- In SVM classification, linear kernel function and C = 100 parameters were used to find separating hyperplane.

- The optimization of the CNN classifier has been carried out with different combinations of their associated parameters.

Experimental Results

TABLE 2. ACCURACY FOR TESTING DATA

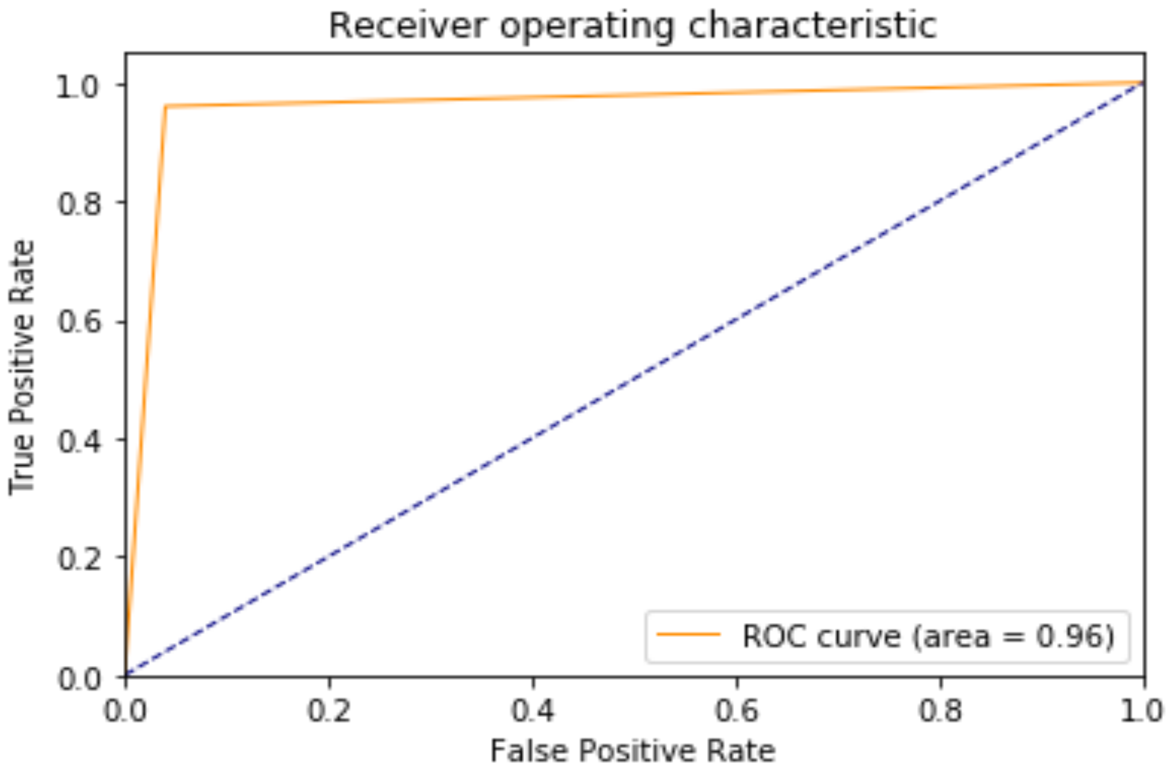
KNN	*68%*
SVM	*92 %*
RF	*92 %*
CNN	*96 %*

CNN can extract useful and hidden features during training automatically from the original images, which is evidenced by the results obtained in this study.

Experimental Results

TABLE 3. CONFUSION MATRIX

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



Conclusions

- In this work, a framework based on CNN is proposed to classify anticlines structures from seismic data into two classes, water and gas, respectively. Comparative analysis reported in this study has established the superiority of the proposed methodology compared to other supervised classification algorithms in terms of accuracy.

- The propose work signifies the applicability of the concepts of image processing and machine learning to structural interpretation, thus expanding the scope of interdisciplinary researches.

- 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.

Contributions

- **Detecting salt bodies with minimum manual intervention: An effort towards automated workflow**. *Mexican Oil Conference 2015*, Guadalajara, Mexico.

- **Detecting salt body using texture classification**, *14^{th} International Congress of the Brazilian Geophysical Society,* Rio de Janeiro, Brazil, August 3-6, 2015.

- **Supervised learning to detect salt body**, in *SEG 2015 International Exposition and 85th Annual Meeting*, New Orleans, Louisiana, USA.

- **Machine Learning: a Deep Learning approach for seismic structural evaluation**, in SEG 2019 International Exposition 89^{th} Annual Meeting, San Antonio TX.

- **Automated Salt top interpretation**, Rice Data Science Conference, October 15, 2019, Houston, TX.