

# Detecting prospective structures in volumetric geo-seismic data using deep convolutional neural networks

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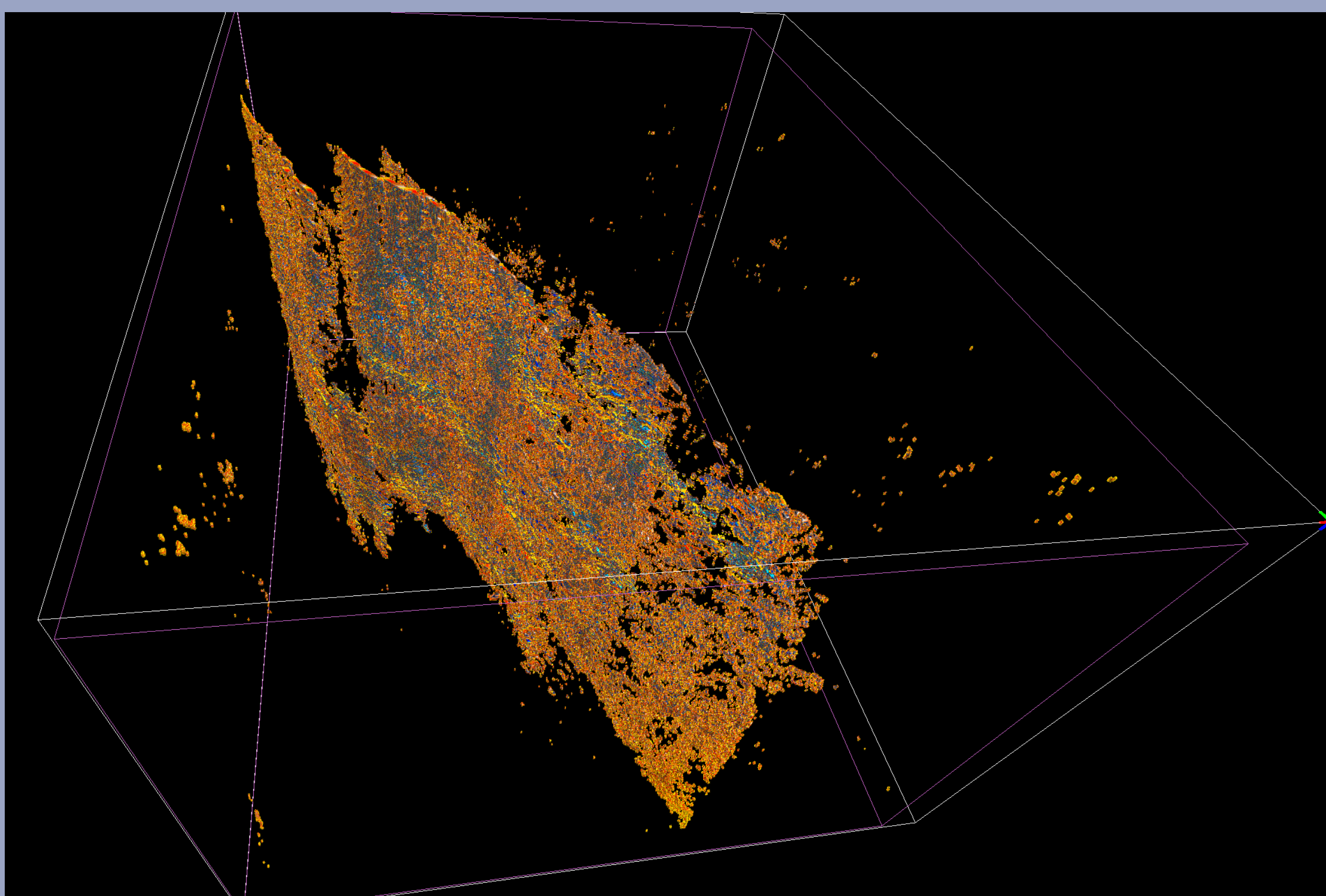


Fig.1. Fault plane identified by ensembling three CNN models

## INTRODUCTION

Since 1998 the VRGeo Consortium, an international alliance of companies from the oil and gas industry, technology manufactures and Fraunhofer IAIS, explores new technologies to improve the interpretation of data from geologic surveys. A main goal is the identification of geophysical bodies that give hint about the location of mineral resources repositories. However, seismic data interpretation is a time consuming task, done by experienced experts, manually screening huge amounts of data. We propose a method based on convolutional neural networks to automatically detect certain geophysical structures and guide experts to sites of interest in data sets.

## RELATED WORK

Automatic fault detection has been the subject of several previous works: [1] used fault enhancing attributes to detect fault.[2] applied deep neural network on the synthesized raw seismic traces to detect faults directly. However, so far there is no generic way to detect multiple geophysical structures using deep neural networks on real seismic data.

## OUR APPROACH

We formulate the problem as a pixel-level classification task as in [3], for each pixel the network assigns a label indicating either it belongs to a channel, fault or noise. We designed a seven layer CNN architecture following the design pattern of VGG Net. Experiments are firstly conducted on 2D seismic image, and later on 3D seismic volume. We trained three such CNN models from all three perspectives and ensembled the classification result to give the prediction. At the end, a density based clustering method is applied as post-processing step to eliminate outliers. The detected fault plane is showed in Fig.1.

## OVERFITTING PROBLEM

Due to our limited source of training data, overfitting has become a major problem for the task. We considered solutions from mainly two aspects: 1. To generate more data based on the current available source. 2. To improve the CNN architecture. For the first aspect, we applied data augmentation techniques with respect to the properties to seismic data. For the second aspect, we deployed several anti-overfitting mechanisms such as drop-out, batch normalization and early stopping. It is later proved in our experiments that through these methods, the validation accuracy has increased 4 to 5 points.

## EXPERIMENT RESULTS

All experiments are performed on NVIDIA deep learning dev box with four GTX TITAN X graphics cards. The final validation accuracy on 2D 32x32 patches reaches 95.72%, while the validation accuracy on 3D 32x32x5 volumes has increased to 99.28%. On the test image the ensemble shows advantage in eliminating false positives, as showed in Fig.2.

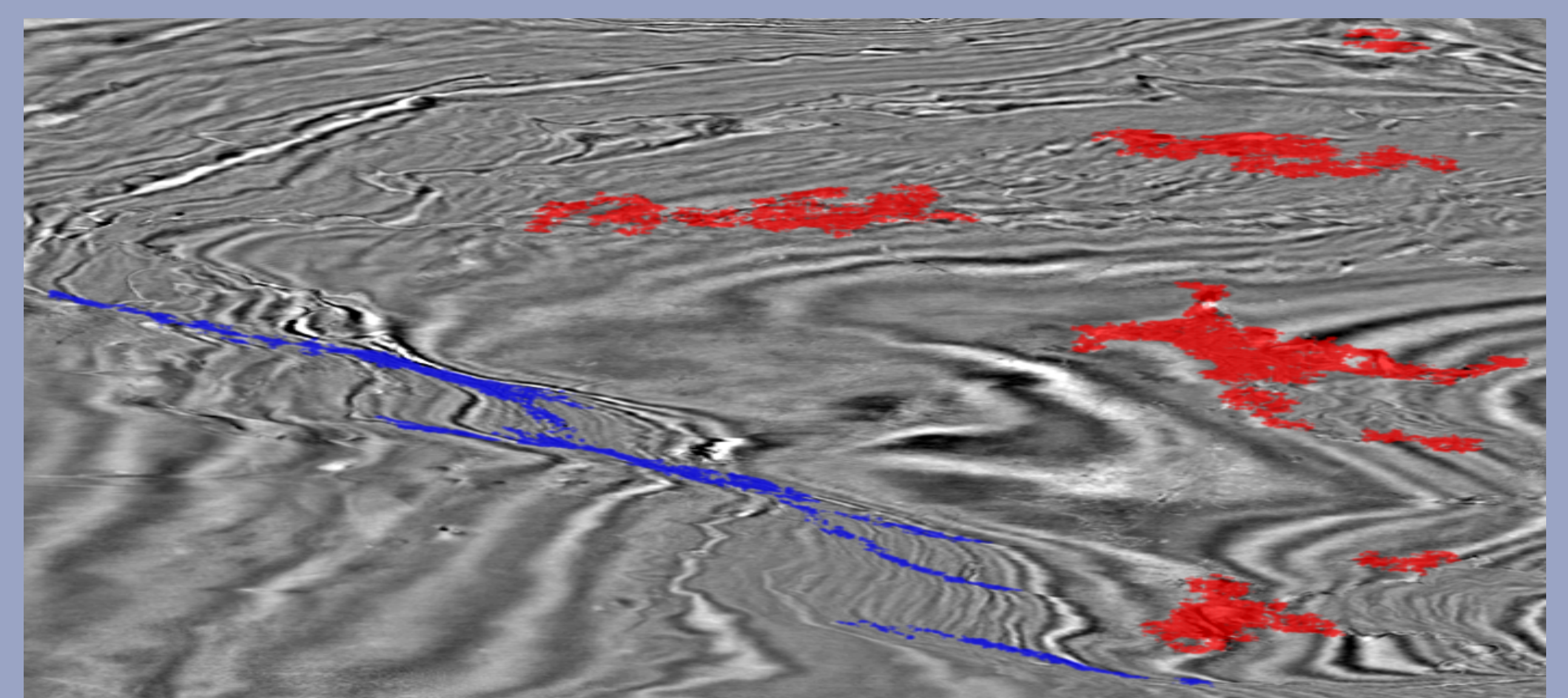


Fig.2.Result on a timeslice, red pixel indicates channel and blue indicates fault

## DISCUSSION

Despite the fact that we do not have abundant training data, deep neural networks have already showed great potential in seismic interpretation. So far, our research is restricted to a very limited set of data source therefore the generalization ability of our network cannot be properly judged yet. However, as we know that deep learning is driven by big data, we can expect the performance of our neural network to rise exponentially along with the amount of data we feed to it.

## REFERENCES

- [1]Gibson, D., Spann, M., & Turner, J. "Automatic Fault Detection for 3D Seismic Data." DICTA. 2003. [2]Zhang,C.,Frogner,C.,& Poggio,T. "Automated Geophysical Feature Detection with Deep Learning." GPU Technology Conference,2016. [3]Ciresan,D. et al. "Deep neural networks segment neuronal membranes in electron microscopy images." NIPS.2012.