GAZPROM NEFT

POS03: Automatic fault interpretation from seismic data via convolutional neural networks

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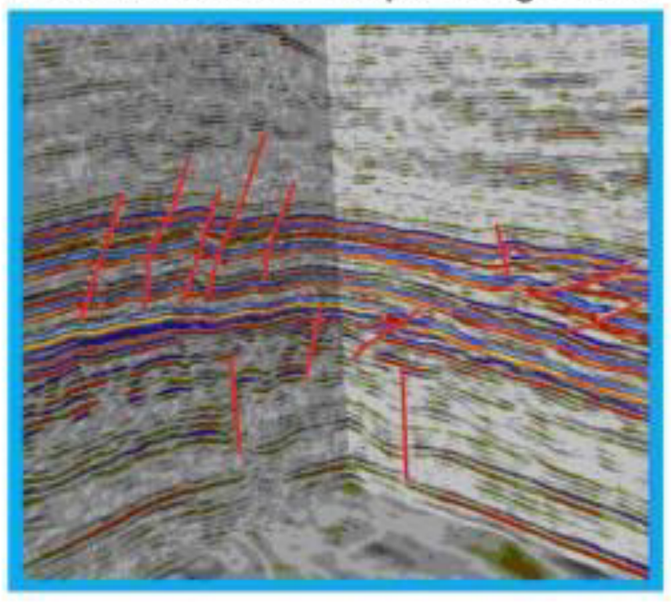
Introduction & Problem Statement

These days the most part of oil and gas brownfields is almost fully depleted and on the final stage of their production life. It makes E&P companies look for assets with tight or shale unconventional deposits with difficult geological conditions more often. In many cases they are affected by very complex tectonic processes which determine their economic perspectives. As an example, faults produced by tectonic movements could create permeable fractured zones without which target reservoir would not be able to produce fluids. On the other hand, homogeneous reservoir with excellent petrophysical properties could be destroyed by fault activity due to separation into number of discontinuous deposits which cannot be developed economically efficient at the present technological level and economic conditions. In such a situation, proper understanding of fault distribution across the field and its probabilistic estimation is crucial part of field assessment.

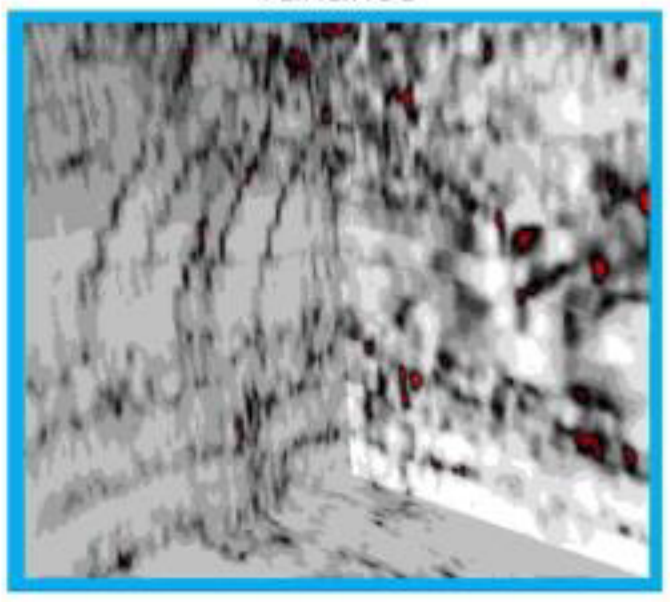
Seismic methods allows robust estimation of fault distribution due to their three-dimensional nature but current algorithms are highly affected by noise (figure below) and permits fast yet accurate interpretation of faults and estimation of their probability. There is a necessity for a tool which can help experts to make their work. Modern computer vision algorithms based on convolutional neural network can be used as such a tool.

- Conventional methods significantly affected by different noises and have problems with delineation of faults without high amplitudes
- Most of conventional methods does not provide probability estimation
- Necessity for tool capable to provide cognitive human-like interpretation

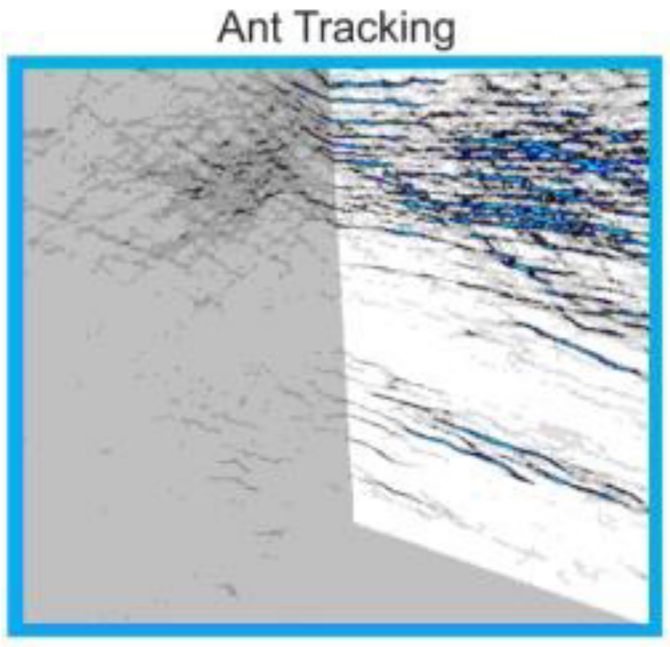
Seismic and corresponding faults



Variance



Ant Tracking



Goals and objectives

The main **goal** of presented research was a development of a tool based on convolutional neural networks for automatic extraction of fault geometry from 3D seismic data

In order to accomplish it the following **objectives** were done:

- Choice of appropriate architecture of neural network
- Selection of convenient neural net training process for achieving better results
- Development end-to-end automatic fault interpretation pipeline for evaluation of results by geologist

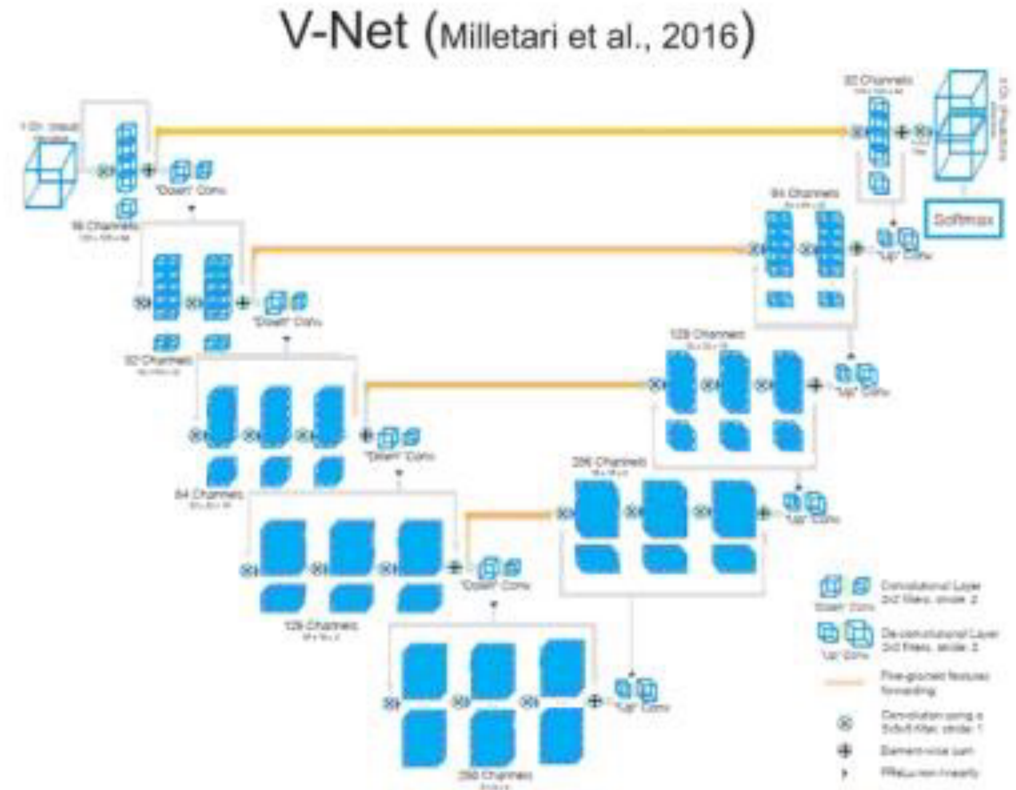
Research

1. Choosing appropriate neural network model architecture

In terms of convolutional neural networks tasks current problem of fault identification can be formulated as binary semantic segmentation. Model must choose areas (voxels of current 3D data) which are related (class 1) or not related (class 0) to fault on seismic data. Data for research were taken from Wu (Wu et al., 2019).

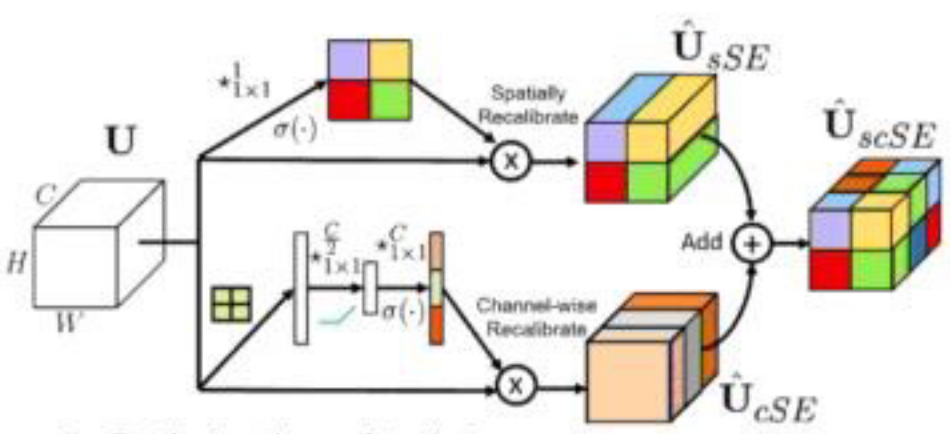
Due to seismic data is presented in 3 dimensional space and contains spatial dependencies it would be a right choice to use convolutional neural network architectures developed for such tasks. In the current research it was decided to use V-net (Milletari et al., 2016) which was originally sugested for identefication of tumors in MRI data.

V-Net (Milletari et al., 2016)



Additions and changes in networks architecture:

- Number of kernels at each block was decreased twice in order to increase batch size and improve training stability and speed. The idea behind is that most of faults structure are not as complex as structure of tumors on MRI for which base architecture was proposed
- Inserting of 3d-dropout (Srivastava et al., 2015) in order to prevent overfitting
- Inserting of batch-norm (Ioffe et al., 2015) for training procedure stabilization
- Inserting of concurent spatial and channel squeeze & excitation block (Guha Roy et al.,) for additional attention on the right features

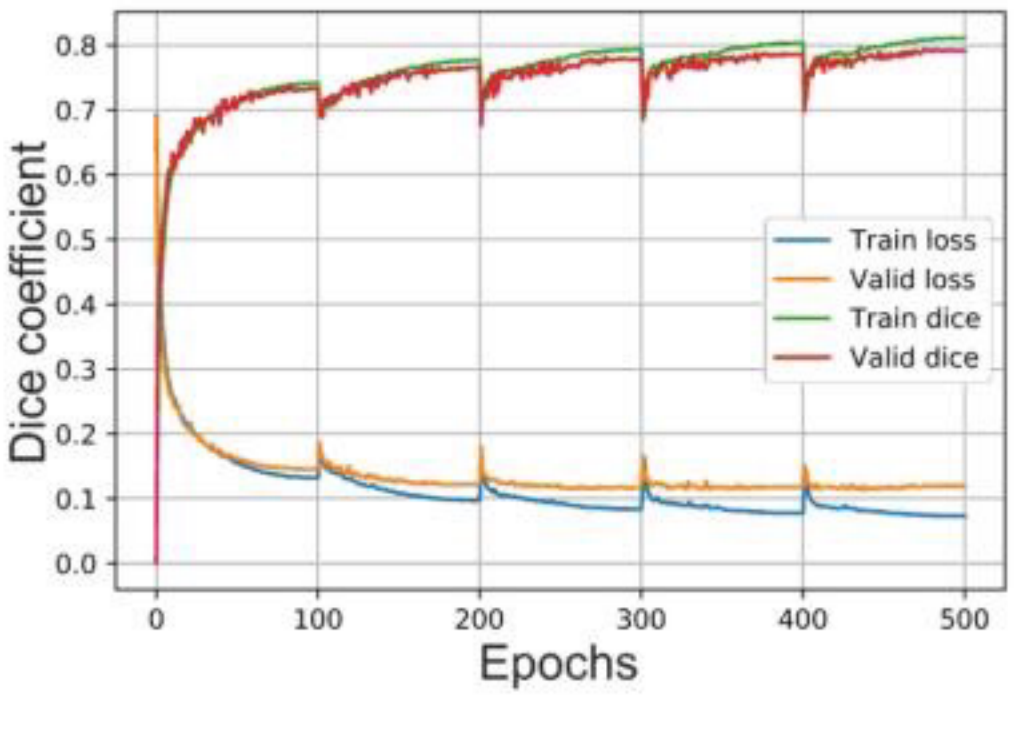


2. Optimization of training process

Training process also requires detailed attention because it has a strong influence on the resulting model. Main facts of suggested train process are presented below. Main fact of training procedure:

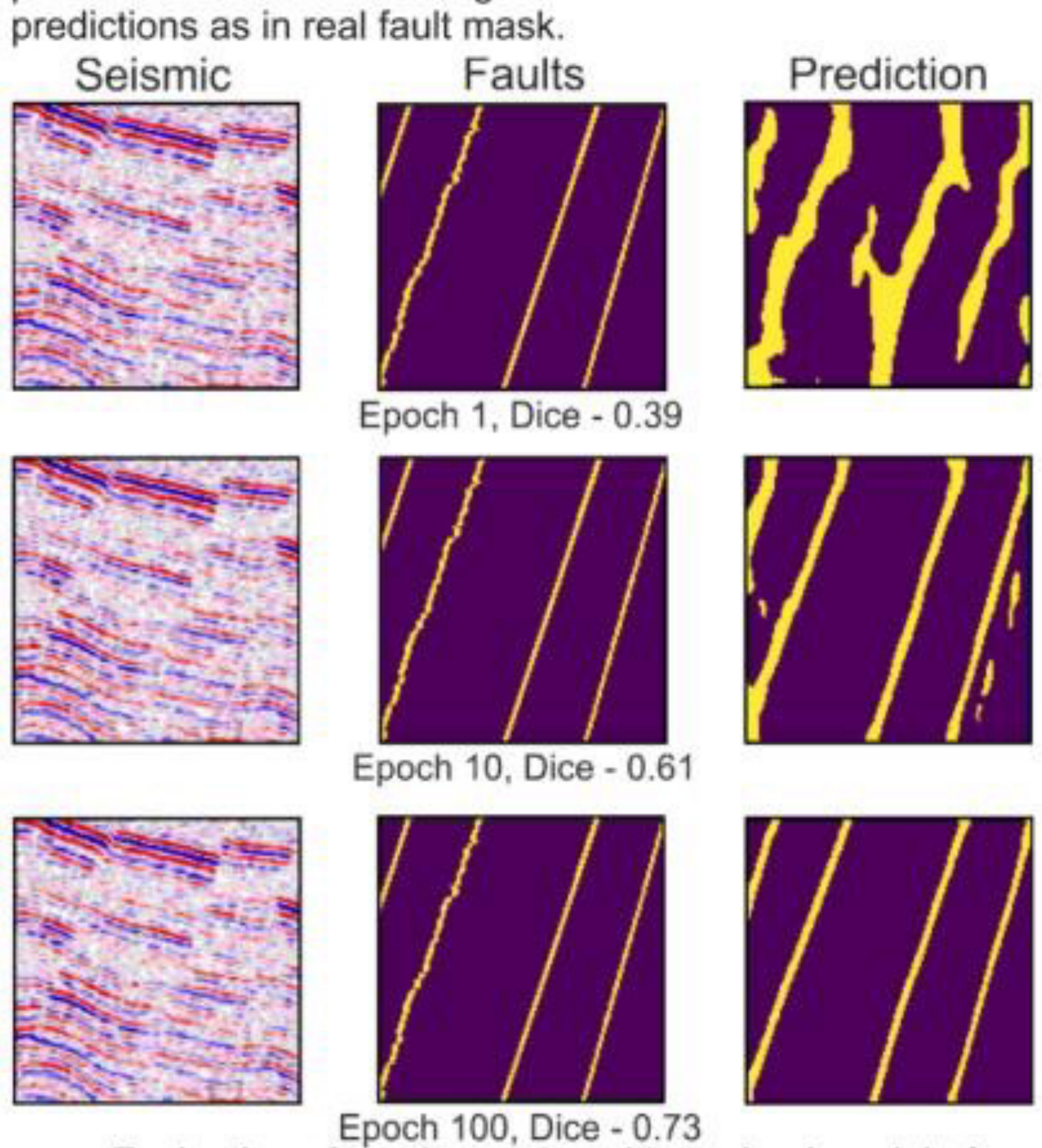
- Cosine annealing learning rate with warm restarts (Loshchilov et al., 2017) with 5 restarts, restart every 100 epochs, 500 epochs overall
- Binary cross entropy with weights x100 on faults masks because faults are generally presented in a very small amount of seismic volume (1-5%)
- Data augmentation included cube rotation around vertical axis, upside-down flip is permited due to it will be non-physical
- Adam optimizer with 10^{-4} weight decay

Additional bonus from cyclical learning rate with warm restarts - model ensembling due to their different allocation on loss function space. As the result they can balance prediction of each other and make better prediction.

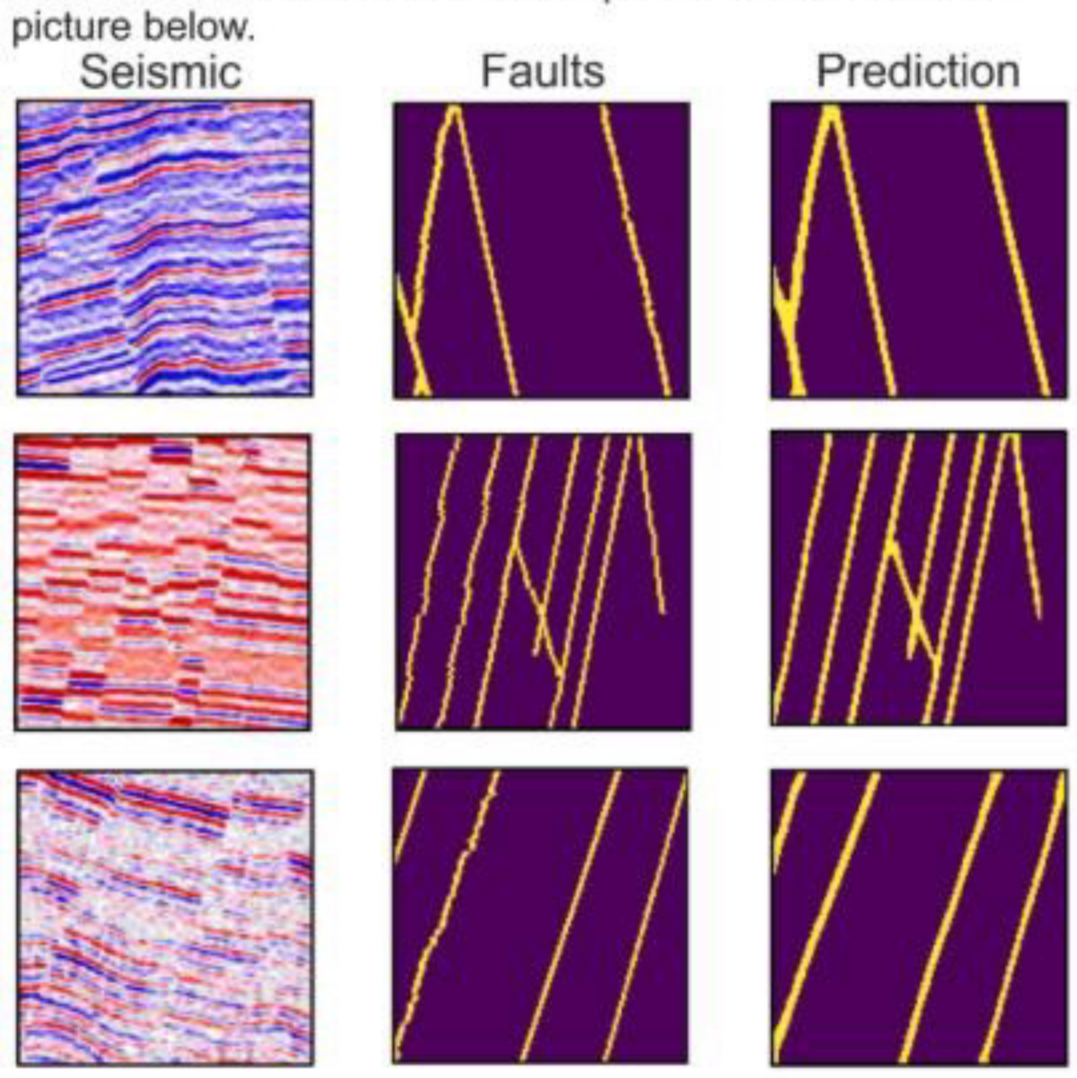


Results and discussion

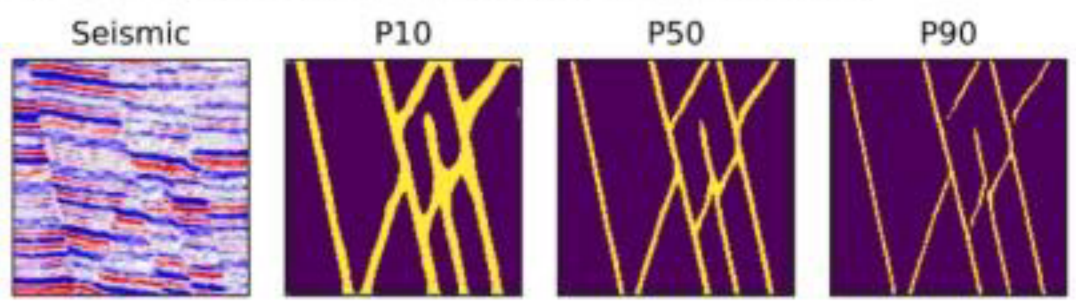
Evaluation of model predictivity power during training process suggest that general semantic of faults structure is relatively easy task for convolutional neural networks. Even on the first epochs of training model is ready to delineate rough structure of faults, the following part of the training process is related to making more accurate and narrower predictions as in real fault mask.



Evaluation of results produced by trained model after 500 epochs shows that the main goal of the project was achieved. Model is capable for delineation of very complex faults structures with very different geological and geophysical conditions. The main advantage of produced solution is that it robust to seismic noise and do not predict extra faults in such conditions as presented on the lower picture below.



Additional advantage of the proposed method is its probabilistic nature. It is commonly known that output of convolutional neural networks cannot be directly related to probability. In the most cases model are overconfident and there is necessity for recalibraition. Even in such a conditions model confidence can be used as an estimation of size of zones affected by faults and tectonics.



Futher work

The main aims of the further research are the following:

- Prediction quality improvement of suggested network by architectural changes including hypercolumns and feature pyramid
- Development of additional post processing steps including erosion and topological skeleton determination for more accurate determination of faults
- Re-calibration of model confidence into probabilities for more robust work with uncertainties
- Application of modern approaches for estimation of uncertainties within results produced by network with decomposition into aleatoric and epistemic uncertainty