Convolutional Neural Network for Seismic Impedance Inversion

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Paper D-1
Meeting 2018
Summary

- Seismic Impedance inversion using machine-learning

Seismic trace

P-impedance

NN
Motivation

Relatively easy to build a neural network and predicting on test dataset – **But ...**

- How good is the network’s generalization power?
- How to extrapolate training data for unseen scenarios?
- How to perform uncertainty quantification for deep networks?
Today’s presentation

- Impedance inversion using Convolutional Neural Networks (CNNs)
- Synthetic modeling to generate labeled training data
- Building neural network architecture and hyper-parameter tuning
- Systematically testing the performance of the neural network
Workflow

1. • Synthetic dataset generation
   • Training/ Validation datasets

2. • Neural network architecture
   • Hyperparameter tuning

3. • Test and predict using CNN
   • Performance evaluation
Generating labeled dataset

\[ \text{Time (sec)} \]

\[ \text{Ip (km/sec gm/cc)} \]

\[ \text{Seismogram} \]

\[ \text{Amplitude} \]
Generating labeled dataset

Sequential Indicator Simulation
Sequential Gaussian Simulation
Rock physics modeling
Full waveform seismogram
Labeled dataset summary

• Total labeled dataset generated = 2000 Ip and their corresponding seismograms

• Training dataset = 1400 traces (70%)
• Validation dataset = 300 traces (15%)
• Test dataset = 300 traces (15%)
Neural network architecture: Training

Output: Impedance (Given / Known)

Training

Input: Seismogram

1 Neuron

60 Neurons

1D CNN

ReLU

Kernel

Stride
Neural network architecture: Prediction

Input: Seismogram

Output: Impedance
Training and validation of network

Learning curve

Mean square error at the end of 500 epochs

- Training error $\approx 0.14$
- Validation error $\approx 0.2$

Training loss

Validation loss

Epochs

MSE

0 100 200 300 400 500
Testing the network on different examples
Comparison with other inversion methods

Seismogram

Time (sec)

Amplitude

P-impedance

Time (sec)

Ip (km/sec gm/cc)

True

CNN

HR
Uncertainty quantification of predictions

Posterior distribution using Approximate Bayesian Computation
### Generating labeled dataset workflow

<table>
<thead>
<tr>
<th>Facies</th>
<th>Porosity &amp; Vclay</th>
<th>Elastic properties</th>
<th>Synthetic seismograms</th>
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<tr>
<th>Parameter</th>
<th>Base case</th>
<th>Training and RT</th>
<th>CT</th>
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<tr>
<td><strong>Variogram ranges (meter) of facies</strong></td>
<td>20</td>
<td>Between 10 and 60</td>
<td>{3, 5, 8, 70, 80, 90, 100}</td>
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<td><strong>Rock physics model (Coord. number)</strong></td>
<td>14</td>
<td>{10, 11, 12, 13, 14}</td>
<td>{6, 7, 8, 9}</td>
</tr>
<tr>
<td><strong>Phases (degree)</strong></td>
<td>0</td>
<td>{20, 30, 40, 50, 60, 70}</td>
<td>{0, 10, 80, 90}</td>
</tr>
<tr>
<td><strong>Central frequency (Hz)</strong></td>
<td>30</td>
<td>{30, 35, 40, 45, 50}</td>
<td>{15, 20, 25, 55, 60, 65}</td>
</tr>
</tbody>
</table>
Challenge test example

Challenge Testing with different rock physics model

Example 1

Example 2

True → CNN
Sensitivity of network performance

Boxplot of error for different scenarios

- L1 Error/Mean
- Challenge testing
- Regular testing

RT – Regular testing
CT – Challenge testing

Source wavelet
Rock physics
Conclusions

- CNNs have good generalization power in Ip inversion from seismic data

- CNN predictions for 1D traces are:
  - insensitive to geostatistical properties
  - moderately sensitive to rock-physics model
  - highly sensitive to source wavelet

- CNN predicts high frequency components of Ip as compared to traditional inversion
Future work

Sonic waveform

Neural network

Attenuation (Qp, Qs logs)
Summary

Sensitive to
1. Source Wavelet
2. Rock physics model
Acknowledgements

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