Deep Learning-driven Geophysics Applications

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Agenda

- Motivation
- Workflows
- Deep Learning-based applications
  - GeoDNN, Fault detection
  - GeoDNN, Tomography
- Conclusions

- Acks:
  - Joseph Jennings (summer 2017) and Taylor Dahlke (summer 2016) (Stanford U.)
  - Detlef Hohl and Paul Gelderblom (Shell)
Motivation

- Machine Learning (ML) techniques will (soon?, when?) disrupt the existing exploration/production workflows
- Better to be early adopters or trailblazers
  - Big buzz around Deep Learning (DL) nowadays, but is it applicable to our problems? Which one of them?
  - Do we need to re-think our workflows around DL?
- Effective collaboration around the topic between domain experts and ML folks
  - ML moves extremely fast, hard to see domain experts catching up and at the same time on top of their scientific problems
Geophysical Feature Detection

Step 1: Processing & Interpretation

Seismic interpretation
Seismic acquisition and processing

Well log analysis and tie-in

Geologic interpretation modeling

Reservoir modeling

Step 2: Feedback loop & Iterations

Geophysical Features & Structures
Automated Geophysical Feature Detection

Early stages feature detection can help to steer the interpretation & modeling process.

Step 0: Feature Detection

Step 1: Processing & Interpretation

Seismic interpretation
Seismic acquisition and processing

Well log analysis and tie-in

Geologic interpretation modeling

Reservoir modeling

Step 2: Feedback loop & Iterations

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Automated Geophysical Feature Detection, what feature?

From raw seismic traces, discover (classification) and locate (structured prediction) faults in the underground structure, no processing involved.

- Universal Approximation Theorem, Hornik 89

Automated Geophysical Feature Detection, GeoDNN, workflow

- Synthetic data is generated since labeled examples are hard to access
- First results published in EAGE2014 with kernel methods, first DNN results in 2015
Results (published in ICML2015 FEAST workshop), 2D synthetics
Results (published in NIPS16-3D DL workshop and SEG TLE 03/2017), 3D synthetics

*NIPS15 publication about a novel structured oriented loss function
Results (published in SEG TLE 03/2017*), 3D synthetics

Model

Ground-truth

Prediction

*most downloaded non-free paper of TLE during 2017
Deep Learning, the HPC connection

Asynchronized Data IO

CPU
Stochastic Gradient Descent Solver Scheduling

GPU Parallel Computing

Data Warehouse

hdf5/TFrecords

MIT Julia/TF

NVidia cuDNN

Deep Neural Networks
Deep Learning Tomography (workflows)

Training
- Ground-truth Velocity Models
- Simulated Seismic Data
- Feature Extraction
- Neural Model Training

Testing
- Ground-truth Velocity Models
- Simulated Seismic Data
- Trained Neural Model
- Reconstructed Velocity Models

Deployment
- Recorded Seismic Data
- Tomography Operator
- Reconstructed Velocity Models
Deep Learning Tomography*, semblance cube as feature

\[ s[i] = \left( \frac{\sum_{j=i-M}^{i+M} \left( \sum_{k=0}^{N-1} q[j, k] \right)^2}{\sum_{j=i-M}^{i+M} \sum_{k=0}^{N-1} q[j, k]^2} \right)^2 \]

- \( q[j, k] \) - NMO-corrected image for a particular velocity
- \( j \) - time index
- \( k \) - offset index
- \( i \) - output index
- \( M \) - length of smoothing window

* Published in SEG TLE 01/2018
Deep Learning in other fields, 3D segmentation

Deep Learning Tomography: Results I (09/2017)
Deep Learning Tomography: Results II (09/2017)
Deep Learning Tomography: Results II (09/2017)
Deep Learning Tomography: Results II (09/2017)
Deep Learning Tomography: Results II (09/2017)
Deep Learning Tomography: Metrics

- Models with salt bodies. 6400 training models, 1600 evaluation models and 2000 testing models.
- Training takes 10 hours using 4 GPUs in 1 computing node, data parallel approach.
- Inference takes less than a minute for all 2000 testing models.
Conclusions

- Working Deep-learning based system for automated geophysical feature detection from raw seismic data, technology disruptor.
- Deep Learning Tomography can be also used as pre-conditioner or accelerator of FWI iterations
- Computer Scientist and domain experts need to work in really agile and short loops, major labor force change
- Real data testing and extension to 3D underway.
- Actions:
  - Co-design new workflows where ML-based tools naturally fit
  - Train your people for what is coming