Automated Geophysical Feature Detection with Deep Learning

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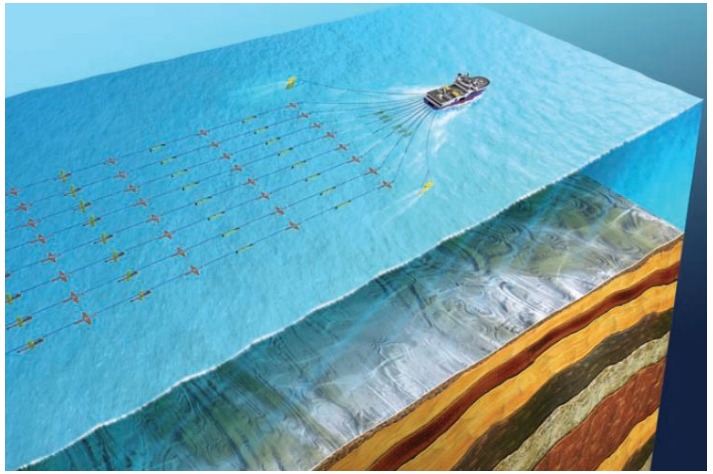
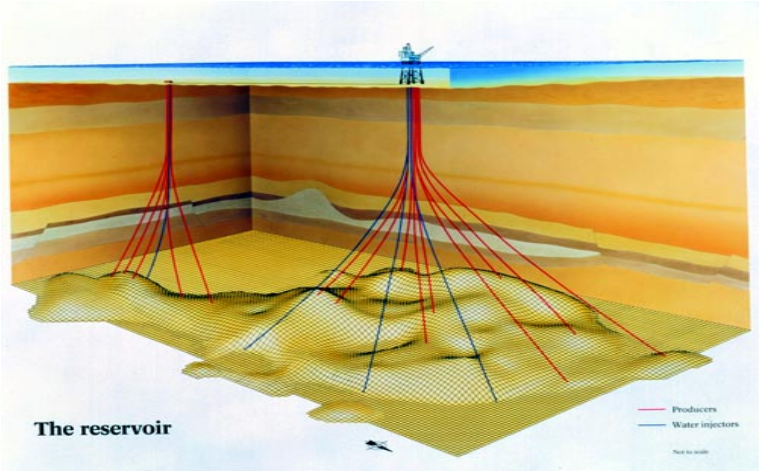
Motivation

Motivation ↔ Methods ↔ Results

Motivation: Seismic Exploration

- Seismic exploration before drilling a well (very expensive)

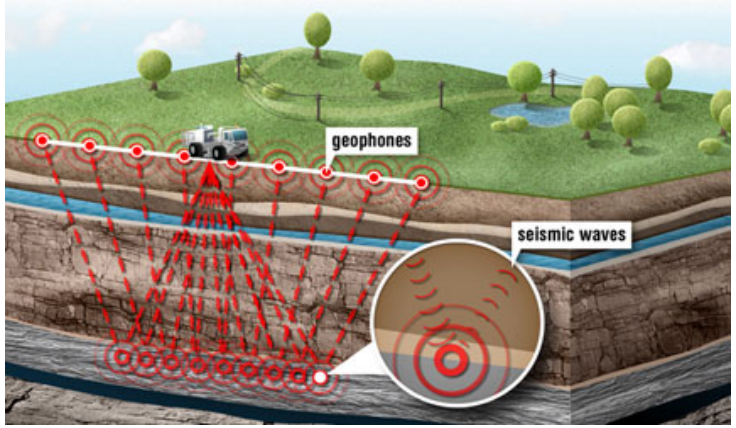


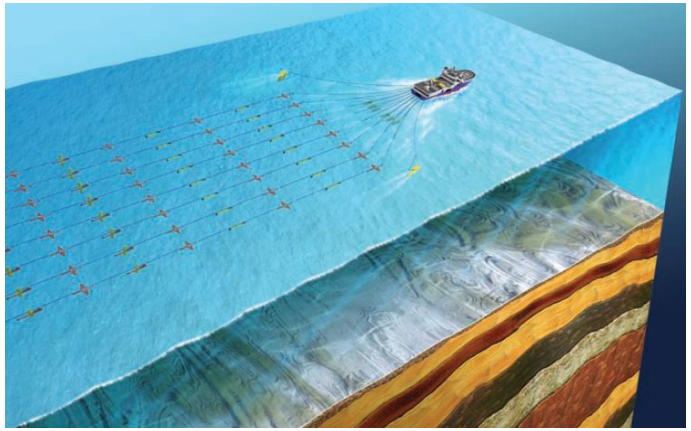


Upstream. Seismic data are of crucial importance in the oil and gas industry. They are used in the exploration phase to **find deep hydrocarbon accumulations**, and during various phases of oil and gas field development planning to **characterize the field** before and during production.

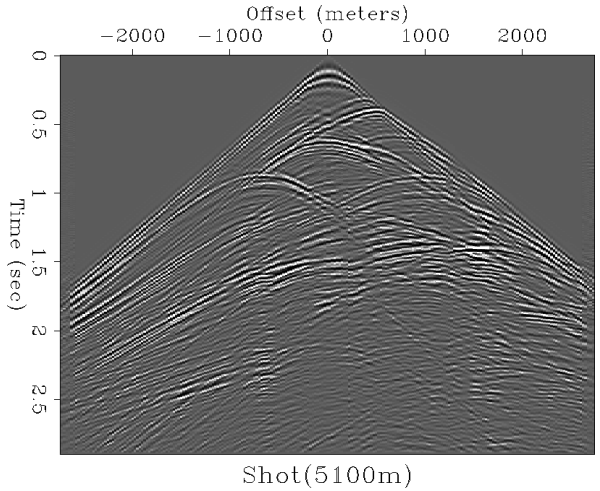
Seismic Survey Workflow

Data acquisition, on/off shore.

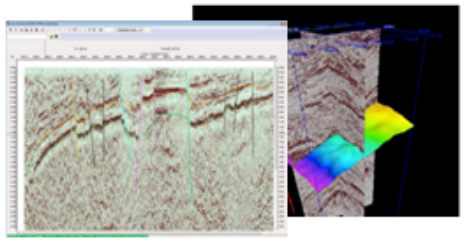




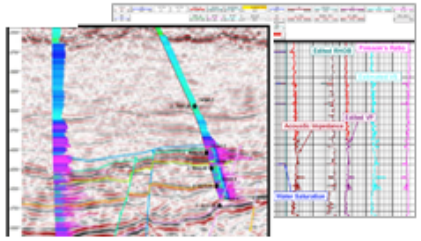
Seismic traces
waveforms (time series) indexed by shot id and receiver id



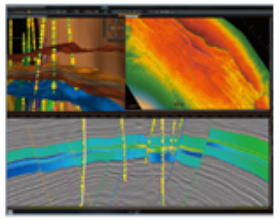
Data processing: iterations could take multiple months with human experts.



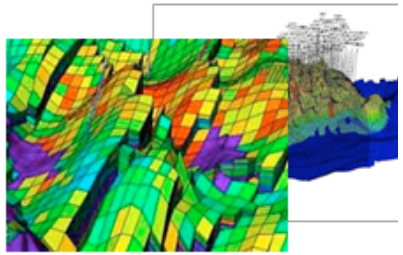
Seismic interpretation
Seismic acquisition and processing



Well log analysis and tie-in



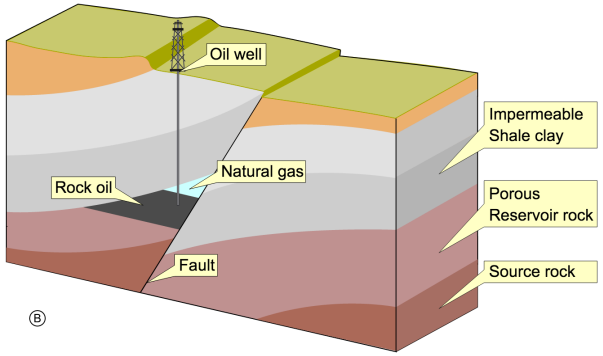
Geologic interpretation modeling



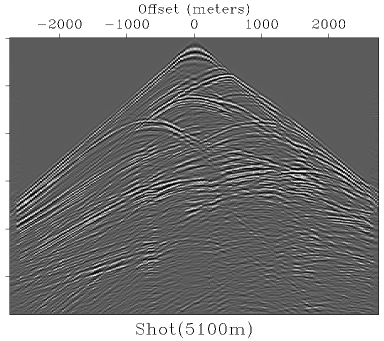
Reservoir modeling

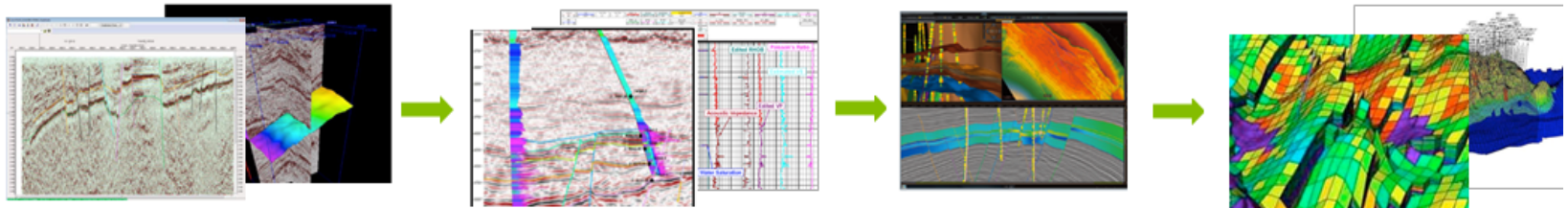
Automated Geophysical Feature Detection

Step 2: Feedback loop & Iterations



Geophysical Features & Structures





Seismic interpretation
Seismic acquisition and processing

Well log analysis and tie-in

Geologic interpretation modeling

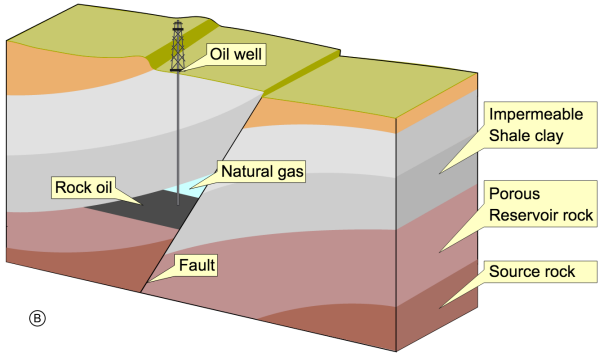
Reservoir modeling

Step 1: Interpretation & Modeling

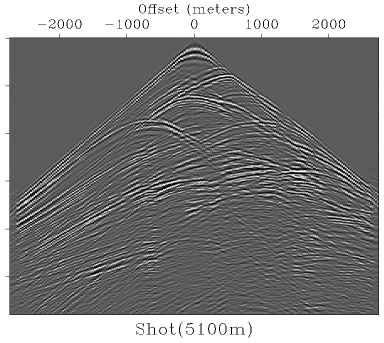
Automated Geophysical Feature Detection

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

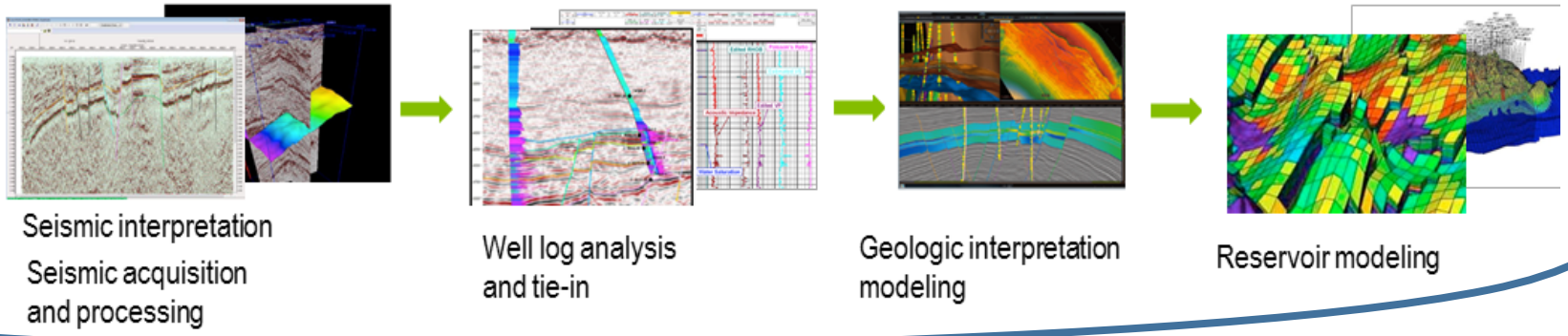
Step 2: Feedback loop & Iterations



Step 0: Feature Detection



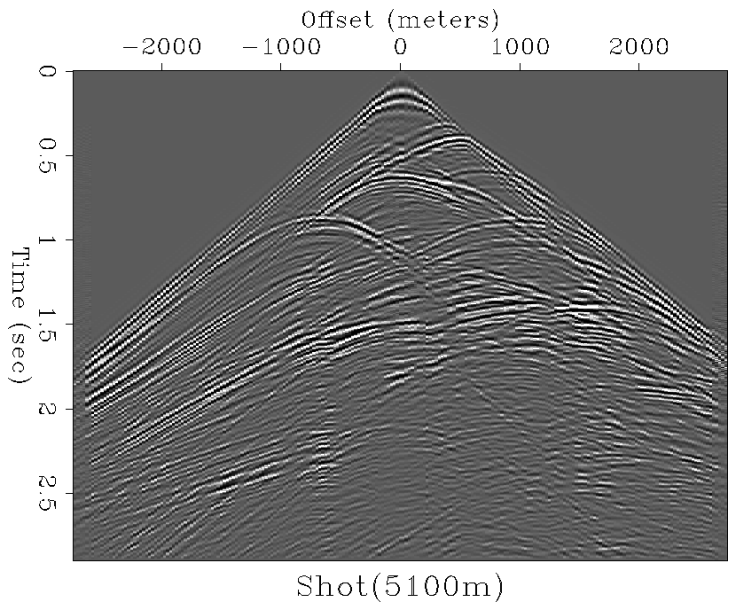
Geophysical Features & Structures



Step 1: Interpretation & Modeling

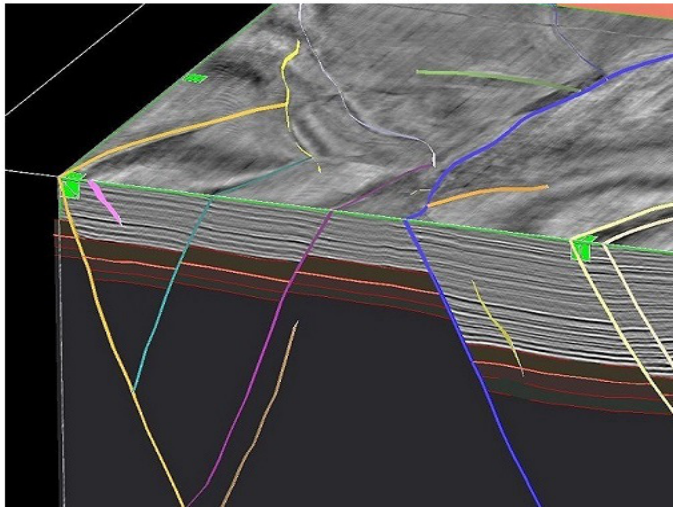
Automated Geophysical Feature Detection

Seismic Survey



Machine Learning

From **raw seismic traces**, discover (**classification**) and locate (**structured prediction**) faults in the underground structure, **before** running migration / interpretation.



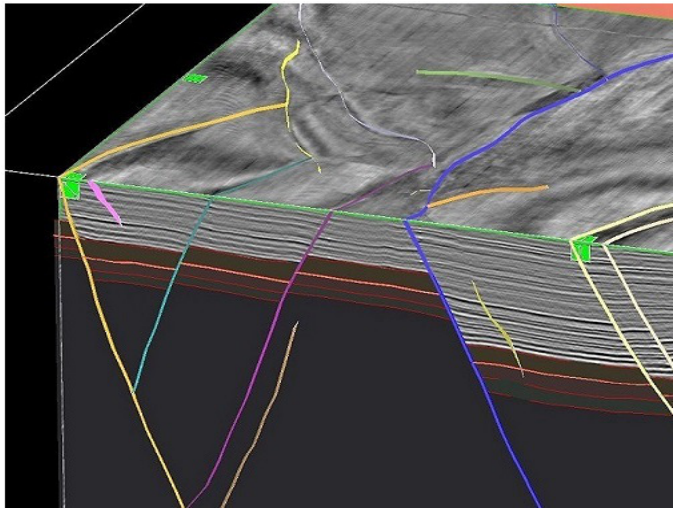
Methods

Motivation ↔ Methods ↔ Results

Machine Learning based Fault Detection

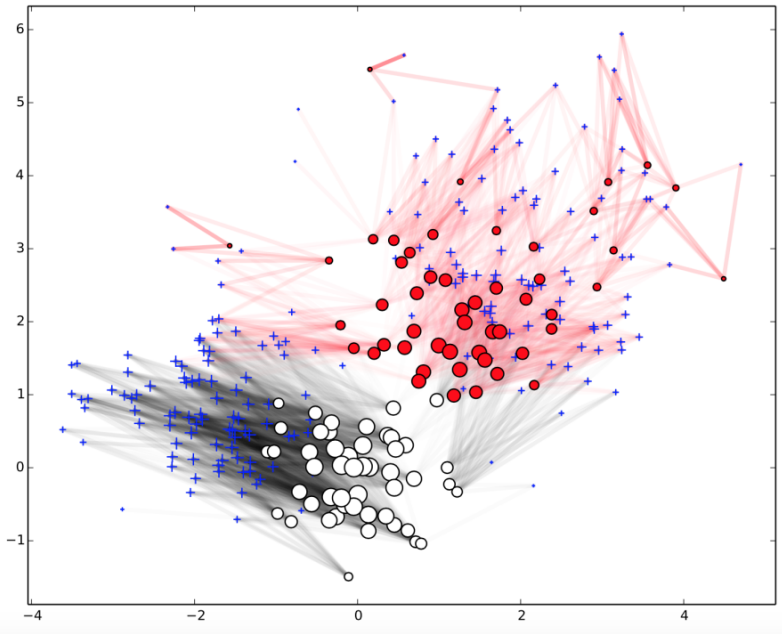
Challenge	Solution
❶ Unlike simple classification, the output space is structured.	Wasserstein-loss based structured output learning.
❷ The mapping from traces to location of faults is a very complex nonlinear function.	Using deep neural networks for modeling.
❸ DNNs need a lot of training data.	Generate random synthesized training data (geological/geophysical model design + physical simulation + generative probabilistic modeling)
❹ Computational issue.	Julia + GPU computation with NVidia CUDA.

Learning with Wasserstein Loss



- The machine learning task
  - Classification & structured-output prediction
  - Wasserstein-loss [FZMAP15] to enforce smoothness in the output space

  - Difference between object-detection like tasks in computer vision:
    - Input (time-series at different sensor location) and output (spatial map) live in different domain.
    - Time-location correspondence is unknown until full migration / interpretation is done.



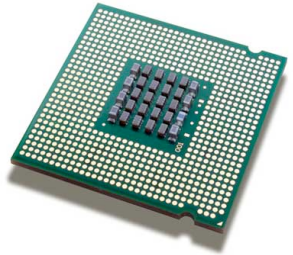
FZMAP15: C. Frogner*, C. Zhang*, H. Mobahi, M. Araya-Polo, T. Poggio. Learning with a Wasserstein Loss. NIPS 2015.

Deep Learning based Fault Detection

Data Warehouse

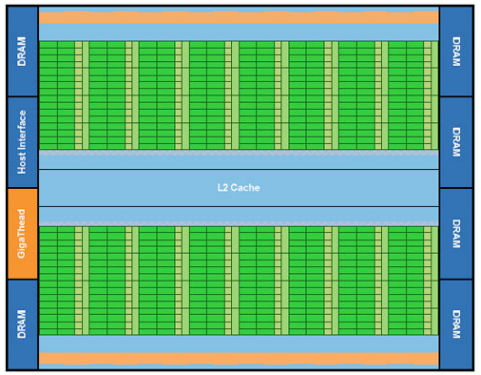
Asynchronized
Data IO

CPU
Stochastic Gradient
Descent Solver Scheduling

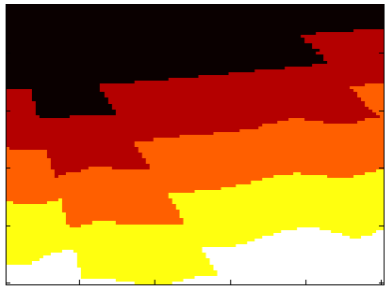


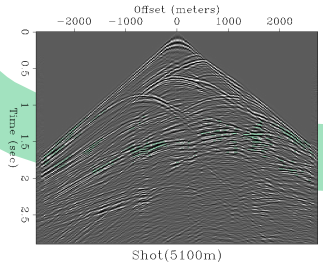
MIT Julia

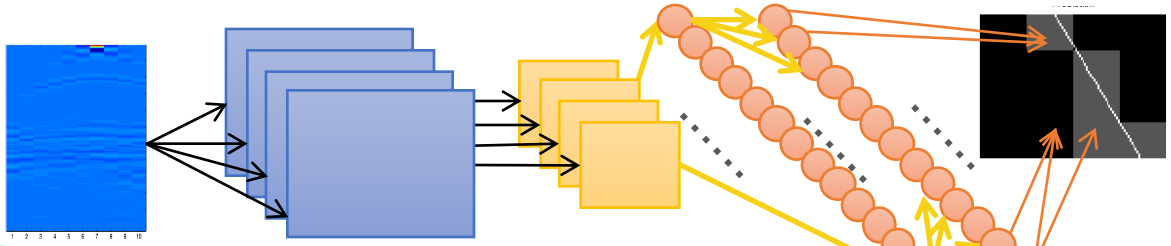
GPU Parallel Computing



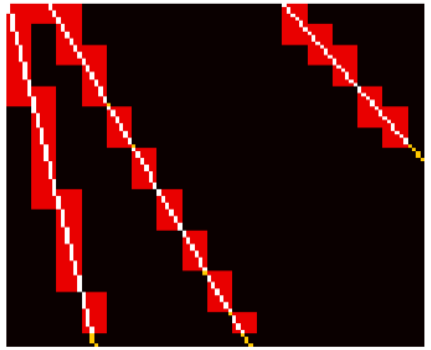
NVidia cuDNN







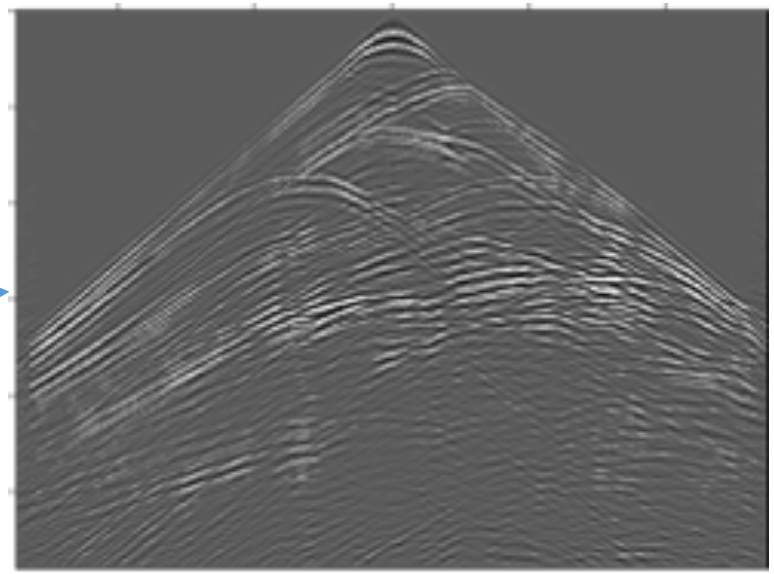
Deep Neural Networks



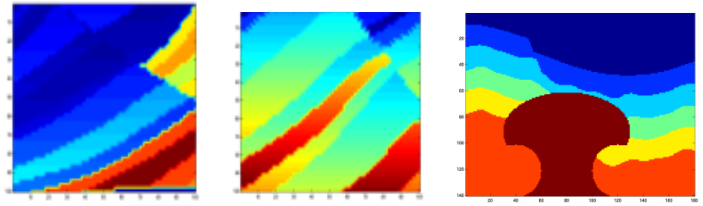
Synthesizing Training Data

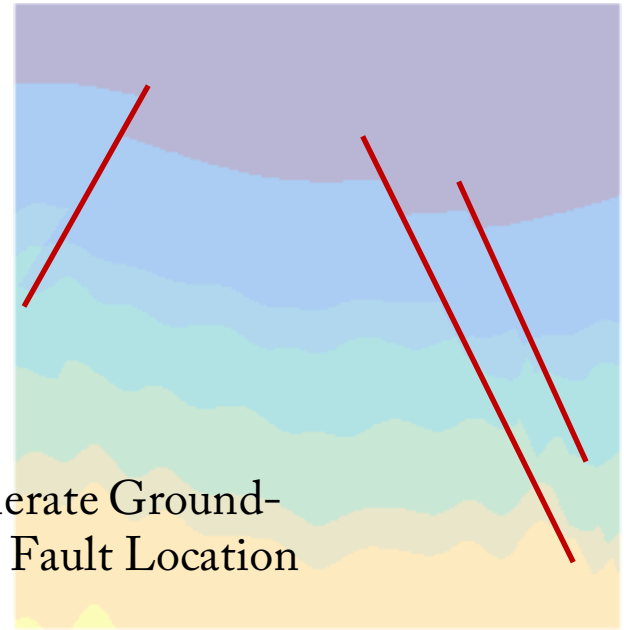
Synthesize Random Velocity Models

Physical Simulation of Wave Propagations



Simulate Wave-propagation & Collect Seismic Traces





Generate Ground-truth Fault Location

Deep Generative Models / 3D Modeling

Image from Alec Radford, Luke Metz and Soumith Chintala, 2016.

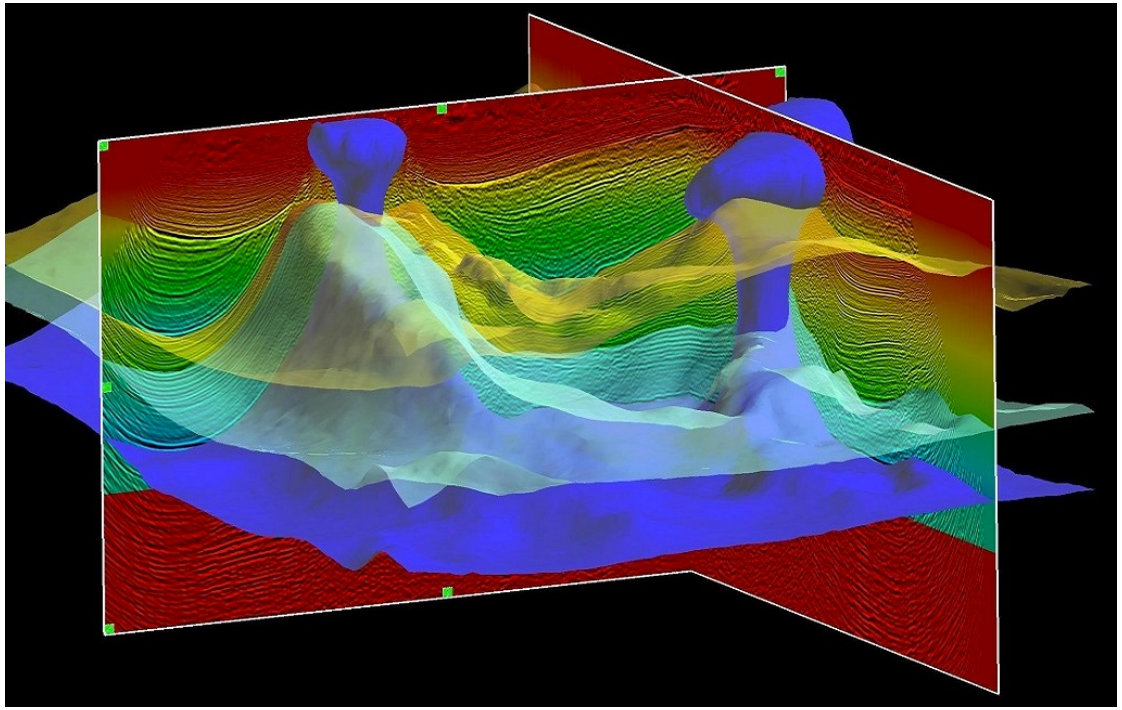


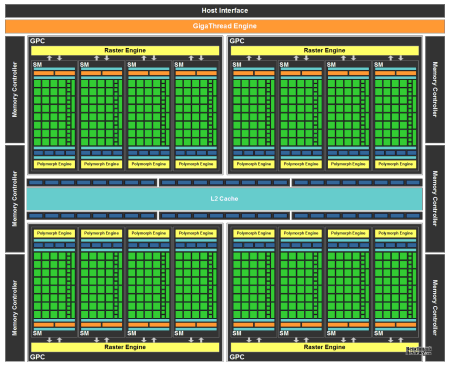
Image from http://www.pdgm.com/products/skua-gocad/geophysics/skua-gocad-velocity-modeling/

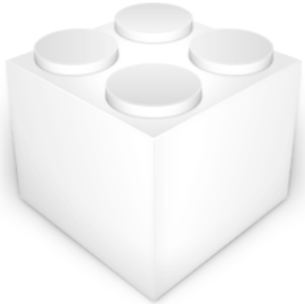
Deep Learning on GPUs

```
hidden_layers = map(1:n_hidden_layer) do i
   InnerProductLayer(name="ip$i", output_dim=n_units_hidden,
      bottoms=[i == 1 ? :data : symbol("ip$(i-1)")],
      tops=[symbol("ip$i")],
      weight_cons=L2Cons(10),
      neuron = neuron == :relu ? Neurons.ReLU() : Neurons.Sigmoid())
end
pred_layer = InnerProductLayer(name="pred", output_dim=n_class,
      tops=[:pred], bottoms=[symbol("ip$n_hidden_layer")])
loss_layer = WassersteinLossLayer(bottoms=[:predsoft, :label])

backend = use_gpu ? GPUBackend() : CPUBackend()

method = SGD()
params = make_solver_parameters(method)
solver = Solver(method, params)
```





libcudaRT
libcuBLAS
libcuRAND
libcuDNN

Summary of Challenges & Solutions

3

Data Warehouse

2

Deep Neural Networks

Multi-layer dense layers

Mocha.jl

Julia-based deep learning toolkit

1

Wasserstein Loss

Loss function with semantic smoothness

4

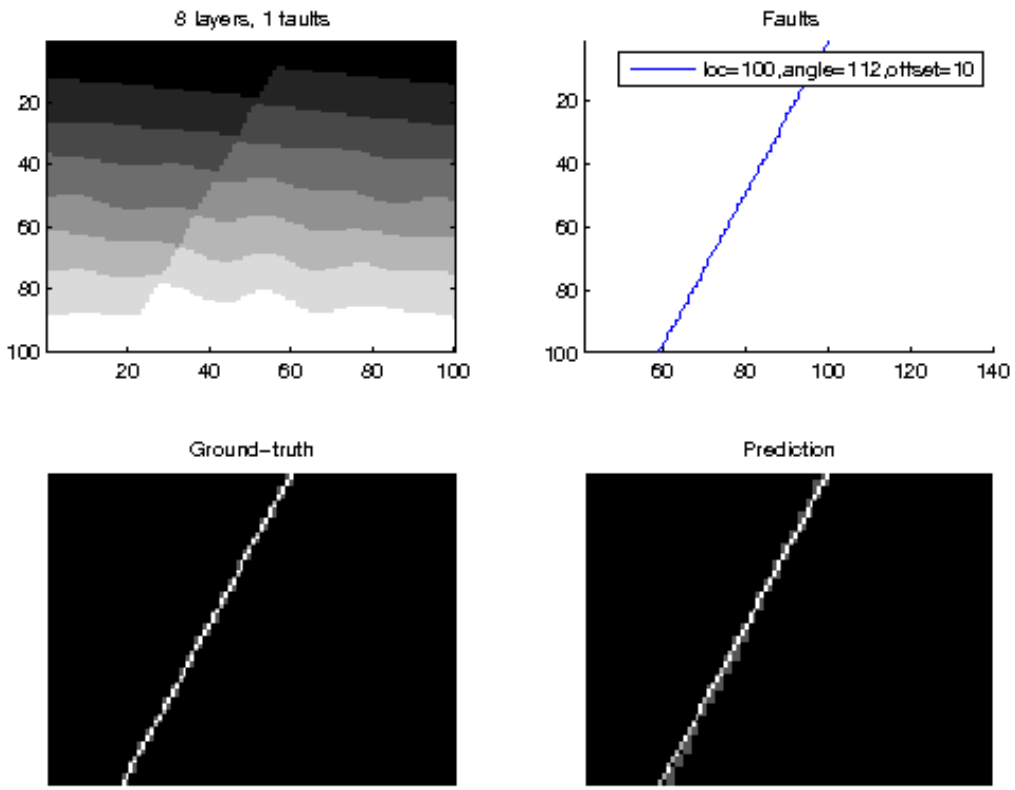
Computation Backends

CPU, GPU (cuDNN)

Results

Motivation ↔ Methods ↔ Results

Results: Plots, single fault

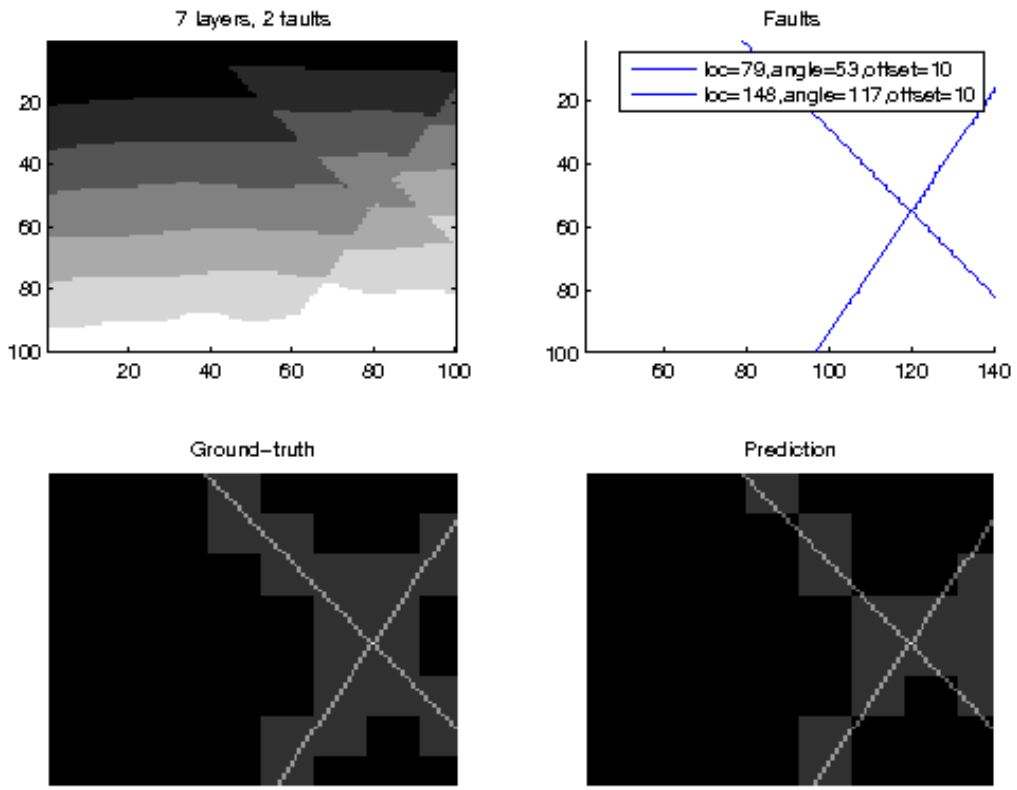


Test case: 10k models, 510k traces, SGD 250k iterations. No noise, **1 fault**, no salt body, **downsample 64**.
DNN arch: 4 layers,1024 neurons

Prediction accuracy:

- Area under Curve (AUC): **77%**
- Intersection over Union (IOU): **71%**

Results: Plots, multiple faults

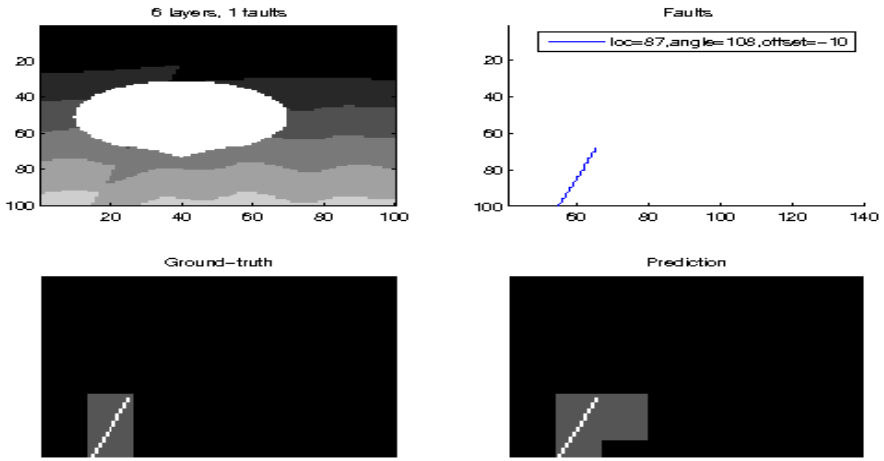


Test case: 10k models, 510k traces, SGD 250k iterations. No noise, **2 faults**, no salt body, **downsample 8**. DNN arch: 4 layer, 768 neurons

Prediction accuracy:

- Area under Curve (AUC): **86%**
- Intersection over Union (IOU): **75%**

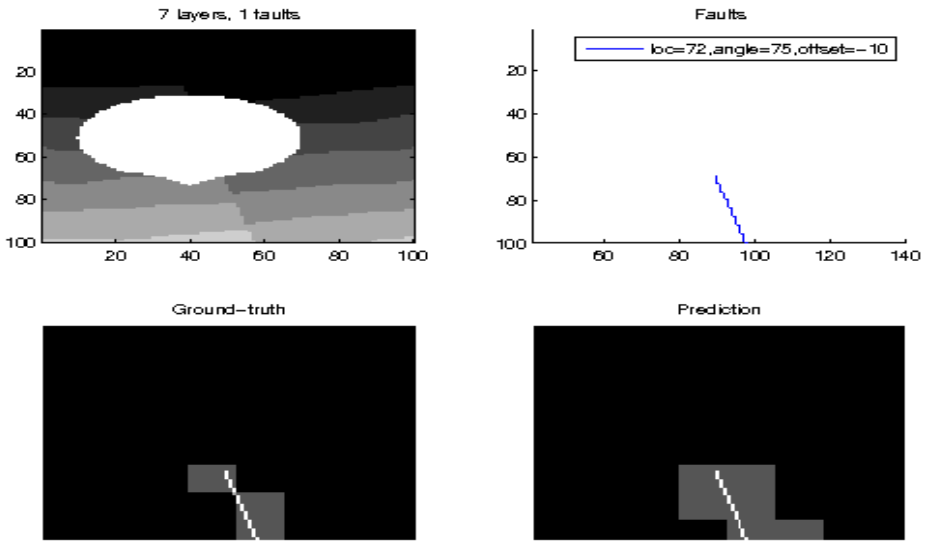
Results: Plots, salt bodies

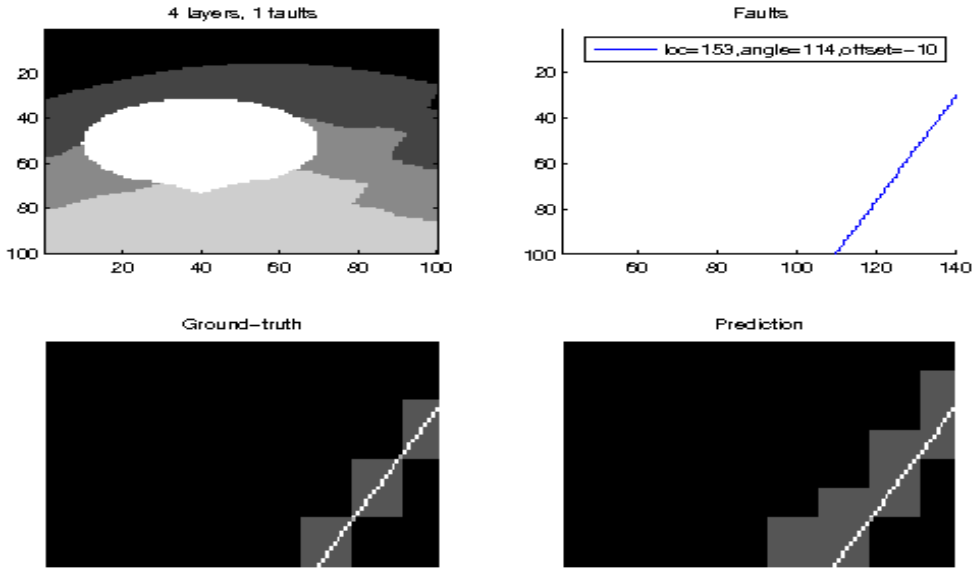


Test case: 10k models, 510k traces, SGD 250k iterations. No noise, **1 fault**, **Salt body**, **downsample 8**. DNN arch: 2, 256

Prediction accuracy:

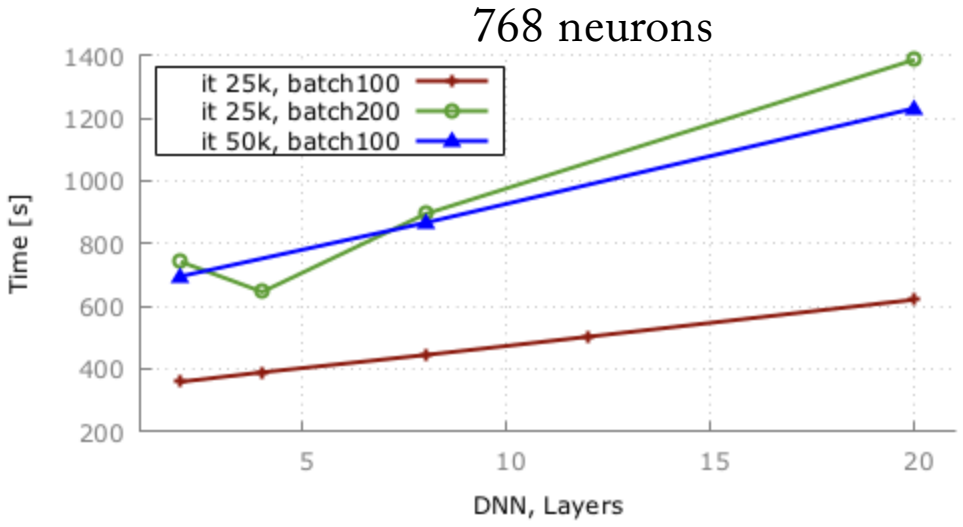
- Area under Curve (AUC): **96**%
- Intersection over Union (IOU): **74**%

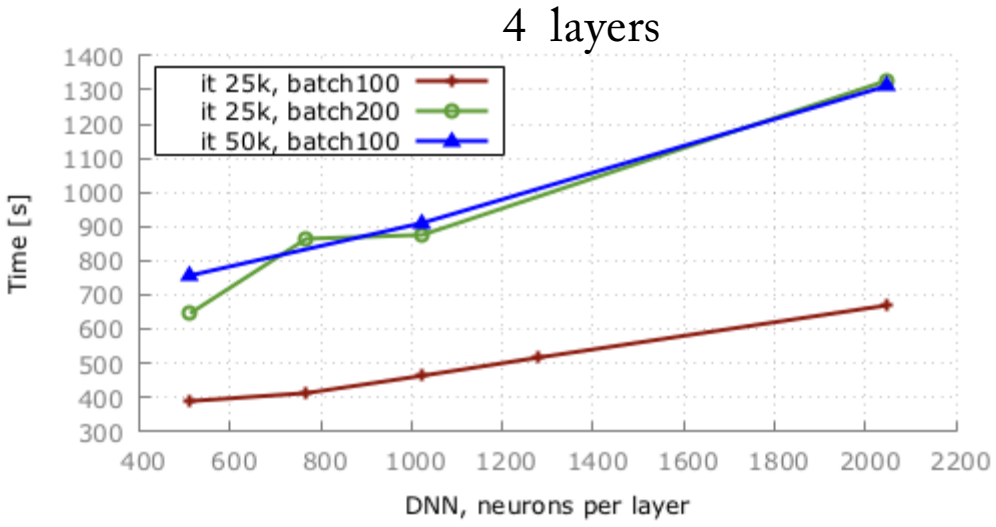




Results: Computation Performance

- Performance plots, test case 10k models (80/20 split)

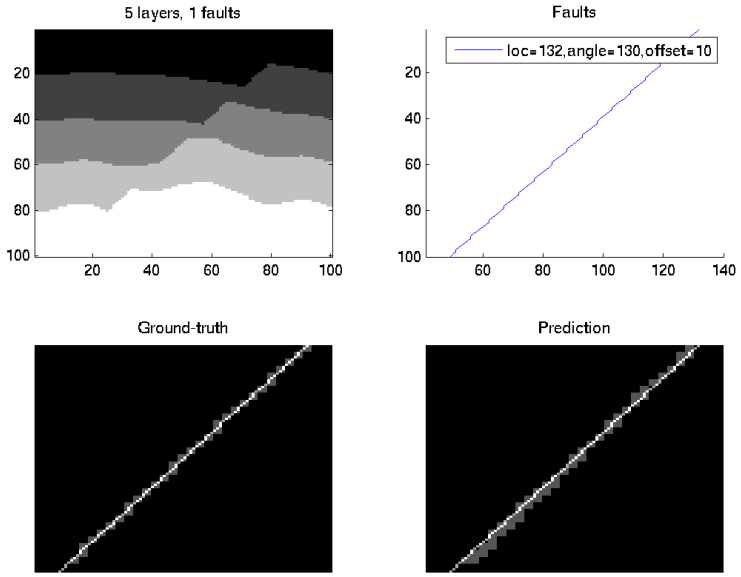


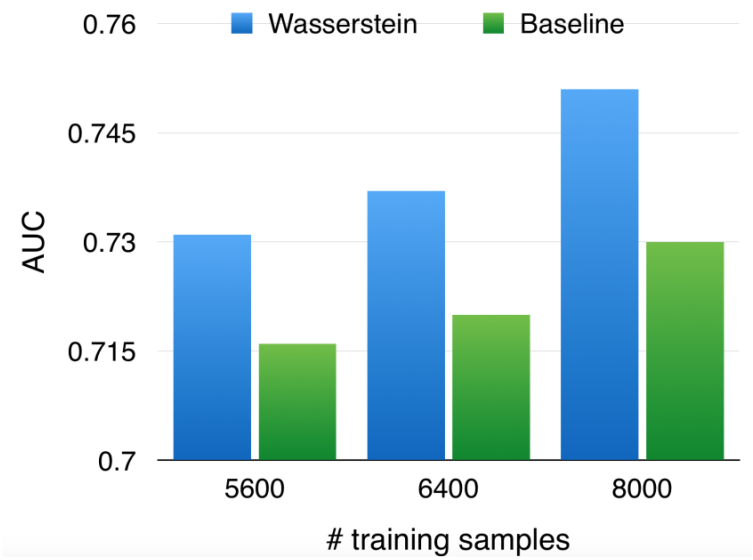


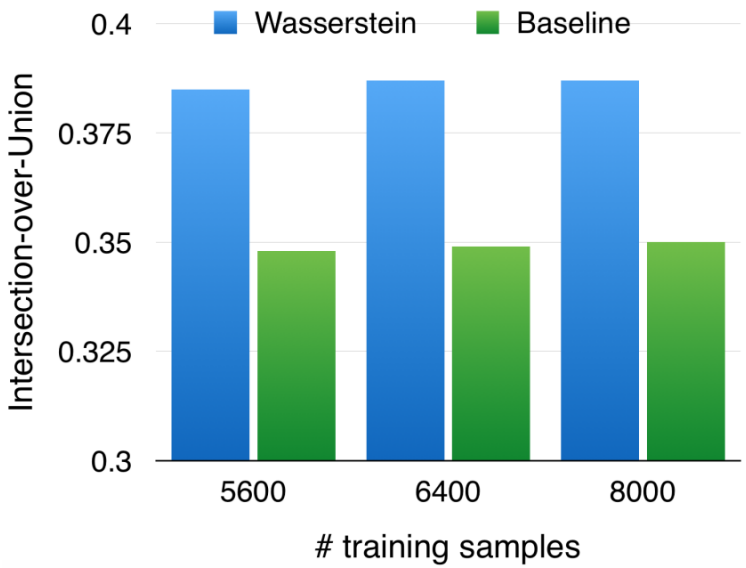
- **CPU vs GPU:** for the same reference architecture our GPU (1 chip of a K80) implementation is **38x** faster than the CPU one (1 Haswell E5-2680, 12 cores)
- **Multi-GPU**. We are collaborating with BitFusion (booth 731) to get this feature at Mocha level, so then transparent for our architectures

Results: Visualization

- more visualization, different cases, with & without salt body, different downsampling, etc.
- We can also show **Wasserstein vs standard loss** if we have the visualization results







Summary

- Deep-learning based system for automate geophysical feature detection from pre-migrated raw data.
- Generative model + physical simulation of wave propagation for synthesized training data.
- Wasserstein-loss for structured output learning problems.
- GPU-accelerated computation for fast modeling.