Enhance Full-waveform Inversion With Machine Learned Low-frequency Signals

Project Number: DE-SC0019665

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U.S. Department of Energy

National Energy Technology Laboratory

Oil & Natural Gas

2020 Integrated Review Webinar

Program Overview

- Funding:

  Sponsoring Office: Office of Science, SC-1, DOE

  Award Number: DE-SC0019665

- Project Performance Dates:

  04/06/2019 – 04/05/2021

- Project Participants:

  Advanced Geophysical Technology, Inc.

  University of Houston

- Overall Project Objectives

  Reconstruction of low-frequency seismic data based on the progressive deep transfer learning workflow and develop a commercial product for delivering large-scale FWI services of the highest level of quality in the industry.

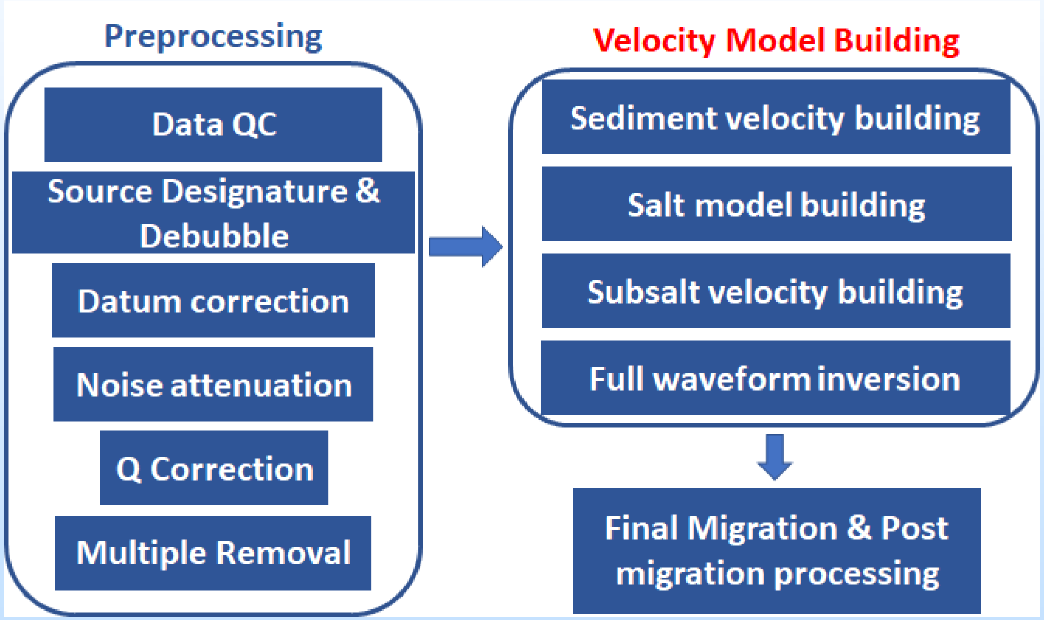
Technology Background
– Seismic Imaging & FWI for Subsurface Exploration

Seismic imaging
- most important E&P technology
- a difficult inverse problem
- extensive manual interventions
- turnaround time → months

Velocity model building (VMB)
- most important and complex procedure in seismic imaging
- Tomography → low resolution, no geological information

FWI
- most advanced VMB
- automatic → reduced turnaround
- fails if low frequency data is unavailable

Seismic Data Processing Workflow



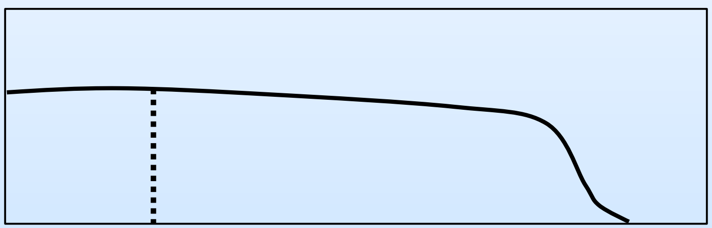
Typically acquired seismic data do not contain frequency components below ~5 Hz

Technology Background
– Important Role of Low Frequency Data in FWI

FWI is a nonlinear inverse problem

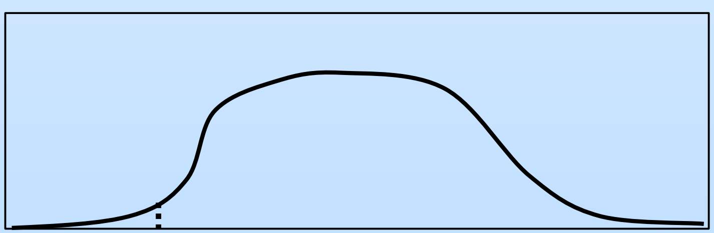
Higher frequency
→ more nonlinear
→ local minimum (cycle-skipping)
→ artifacts and wrong velocity model

Full bandwidth data



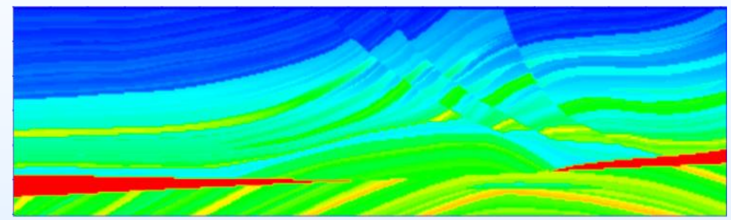
5 Hz

Bandlimited data

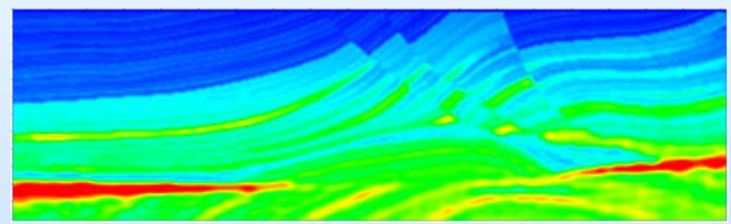


5 Hz

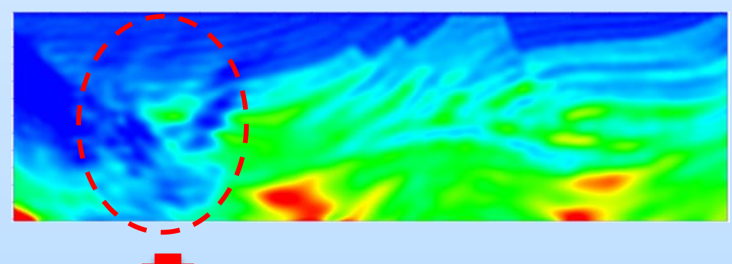
True velocity model



FWI result (full bandwidth data)



FWI result (bandlimited data)



Strong artifacts

Technology Background – Existing Methods

Existing algorithmic approaches

- ❑ Scattering-angle-based filtering method
  hard to control, highly nonlinear
- ❑ Extended model & traveltime shift methods
  discontinuous wavenumber spectrum
- ❑ Synthesized low frequency methods
  sensitive to noise and other uncertainties
- ❑ Phase unwrapping methods
  difficult for 2D, nearly impossible for 3D
- ❑ Beat-Tone method
  tends to amplify noise and scattering energy

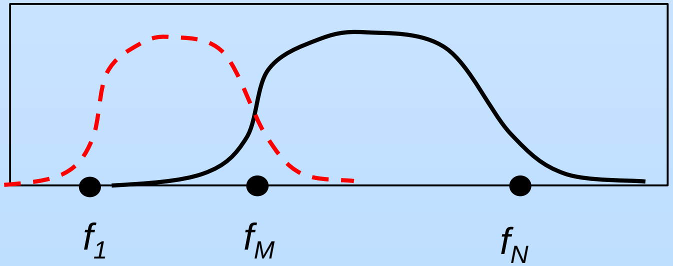
https://finance.yahoo.com/news/focus-billion-barrel-bonanza-bp-goes-global-seismic-071110492--finance.html

BP's Hardware approach – Wolfspar Low Frequency source

- ❑ 1.4 Hz – 8 Hz nodal source; 1 Hz source → 1000 times more difficult than 10 Hz → expensive
- ❑ Discovery of extra billion barrel in Gulf of Mexico;

Our approach – Self-supervised learning for low frequency seismic data prediction

Our goal:
use (f_M … f_N) → predict (f_1 … f_{M-1})



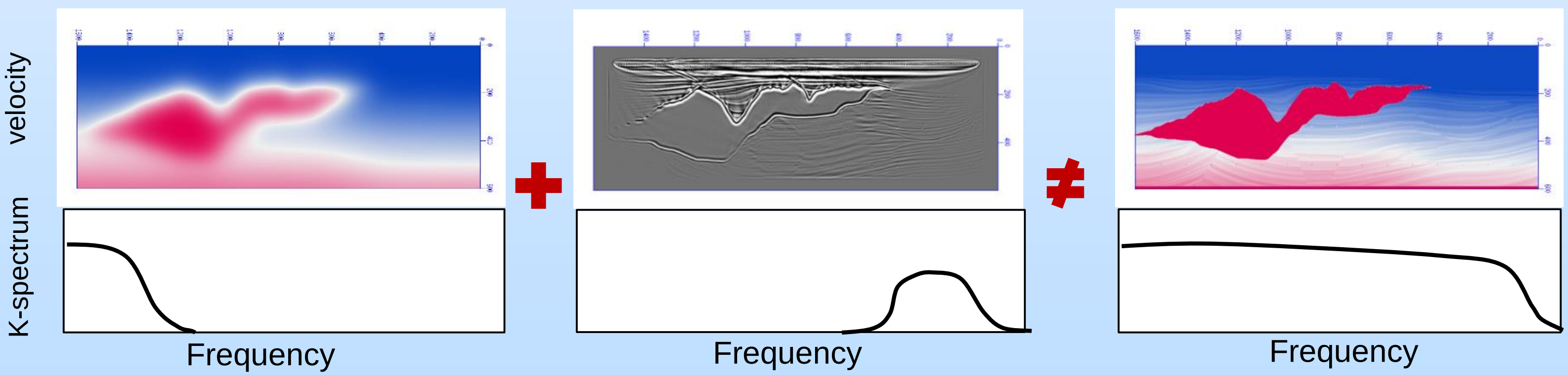
Technical Advantages & Challenges

Advantages

- ❑ Able to reconstruct any frequency components → continuous k-spectrum
- ❑ Self-supervised learning → no manual labeling procedure
- ❑ Physics module integrated with Deep Learning → No *a priori* subsurface info required
- ❑ Progressive Transfer Learning → iterative learning (only one training set required)
- ❑ Physics-based pretext task → robust, automatic DL launch, accelerated convergence
- ❑ Fully automatic → turnaround time ↓

Challenges

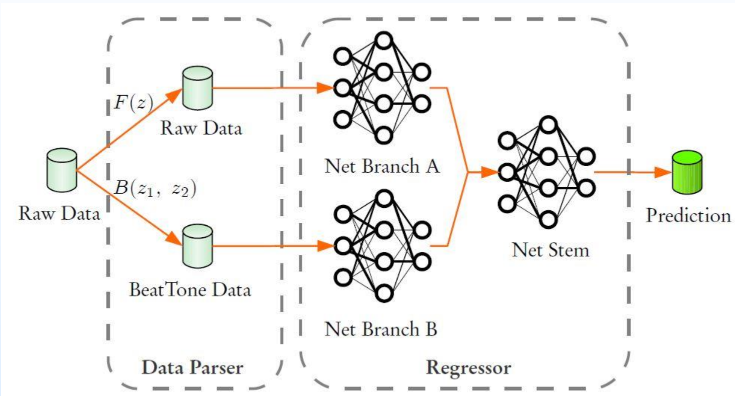
1) model generalization; 2) gaps between synthetic & field; 2) multiple FWIs required



Conventional methods
Discontinuous k-spectrum

This method
Continuous k-spectrum

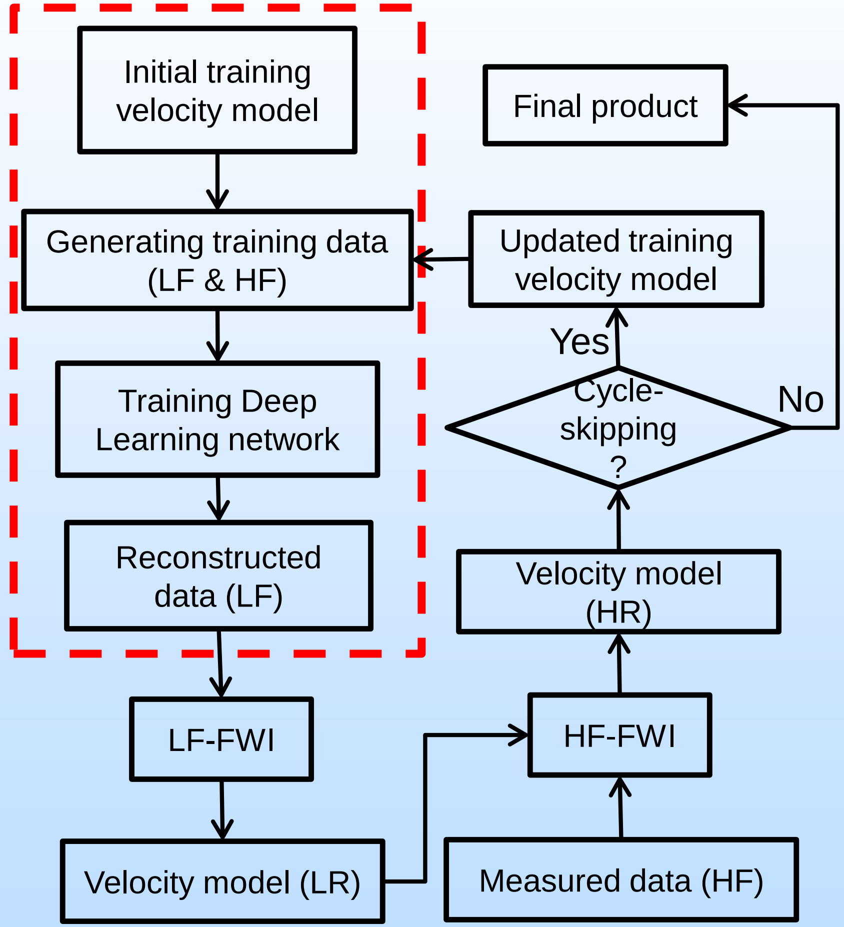
Technical Approach



$F(z) = \frac{z}{|z|}$ $B(z_1, z_2) = \frac{z_2}{z_1} e^{j\theta_0}$

Structure of DNN for low frequency components prediction

- Naïve application of DNN achieved limited success due to lack of large training samples
- Progressive Transfer Learning (PTL) iteratively retrieves subsurface information → adaptive to new datasets
- Further extend this approach → fully automatic self-supervised learning



Workflow of Progressive Transfer Learning

Work Plan

The aim of the work plan is to develop a highly customizable and robust FWI workflow for different data acquired from complicated subsurface structures, providing significant uplift the imaging quality for our customers.

Task 1: Implement and fine-tune the network structures and parameters to be adaptive to different seismic acquisition methods and receiver configurations. Improve the prediction accuracy of the low-frequency data by exploiting various regularization approaches imposed on the objective function of training to reduce data distortion due to nonlinearity.

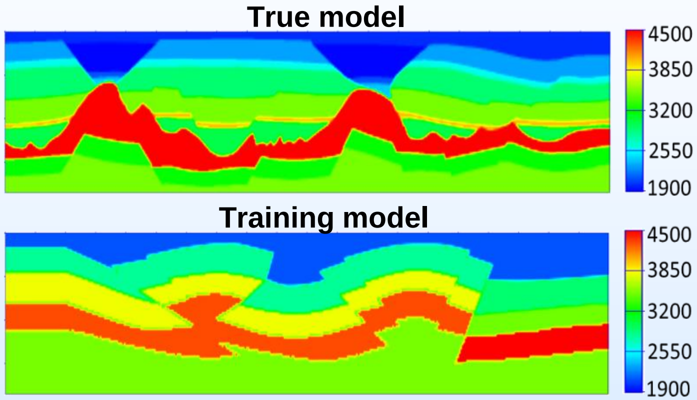
Task 2: Customize and build a progressive transfer learning workflow for using FWI to illustrate salt structures. Particularly, the workflow aims at improving subsalt imaging for data of wide azimuth and long offset.

Task 3: Customize and build a progressive transfer learning workflow for using FWI to obtain high-resolution near-surface velocity models. Investigate and implement an effective data processing strategy to deliver a full-scale FWI solution for removing the near-surface velocity anomalies.

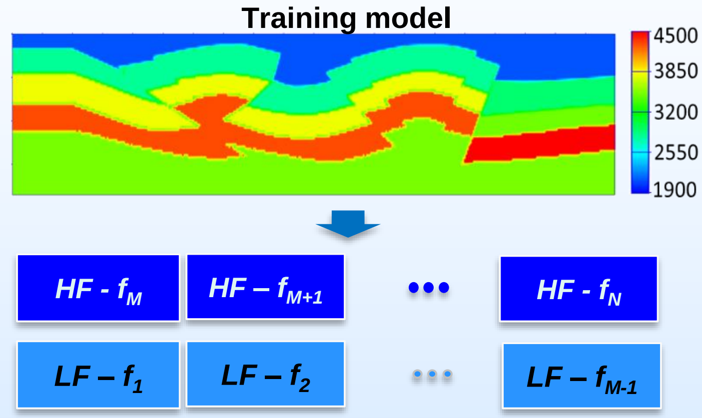
Task 4: Test and demonstrate the performance of the prototype product. Collaborating with our potential customers, calibrate and verify system parameters in the field environment. Conduct tests with field data and fix any usability issues based on customers' feedbacks.

End-to-end Supervised Learning

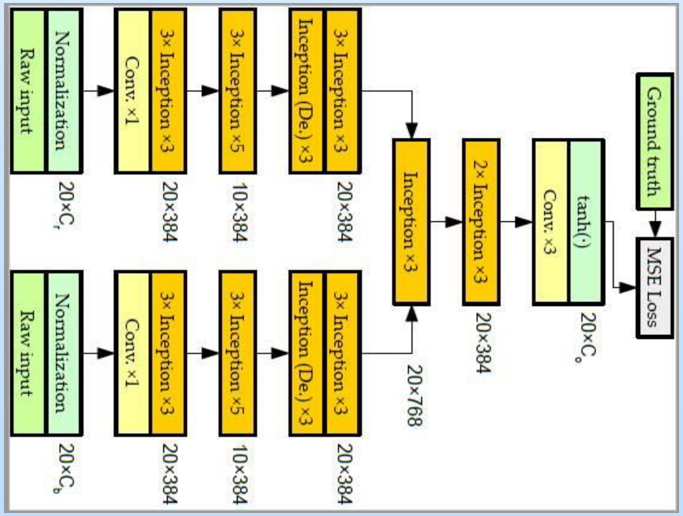
Step 1 – Training velocity model selection



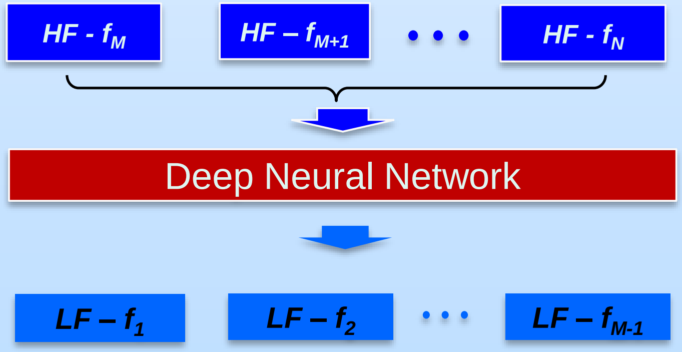
Step 2 – Training data generation



Step 3 – Network architecture design



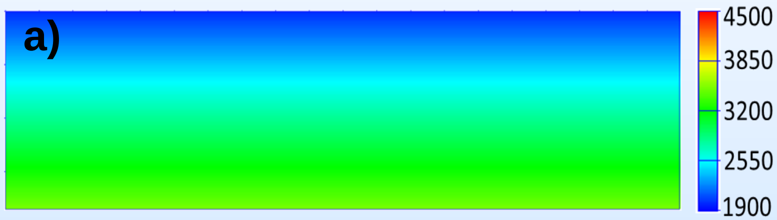
Step 4 – Network training & testing



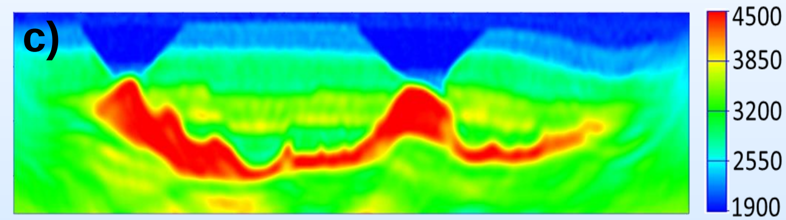
End-to-end Supervised Learning – Successful Example

Assuming only ≥ 10 Hz acquired
3 Hz, 5 Hz, 7 Hz data predicted

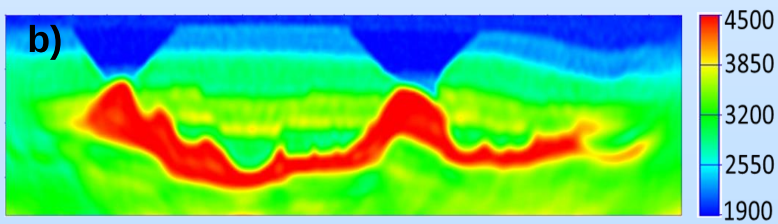
FWI Initial model



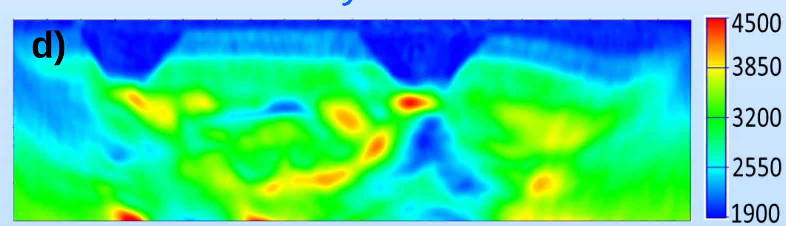
DL predicted result



Reference solution



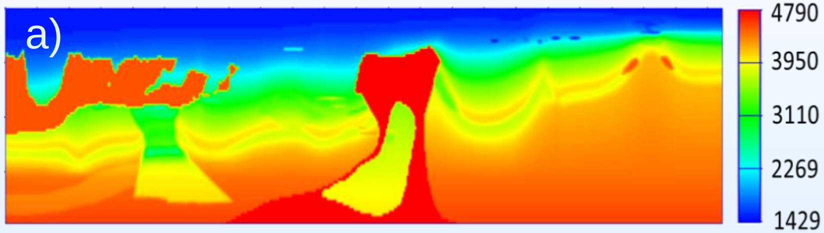
HF only result



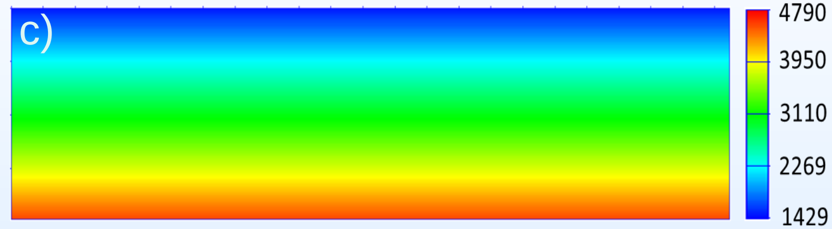
End-to-end Supervised Learning – Lesson Learned

Assuming only ≥ 10 Hz acquired

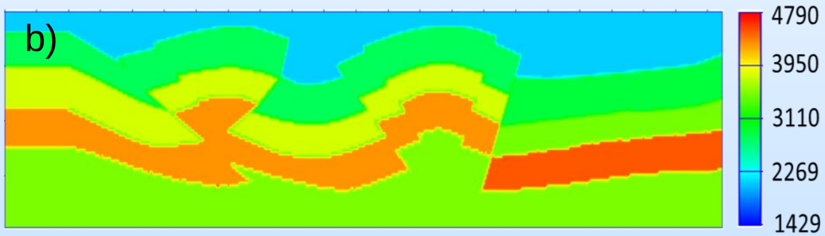
True model



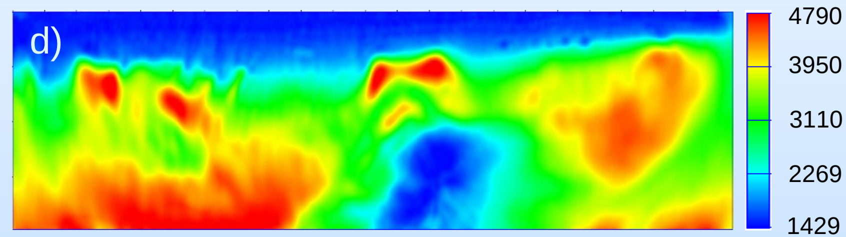
FWI initial model

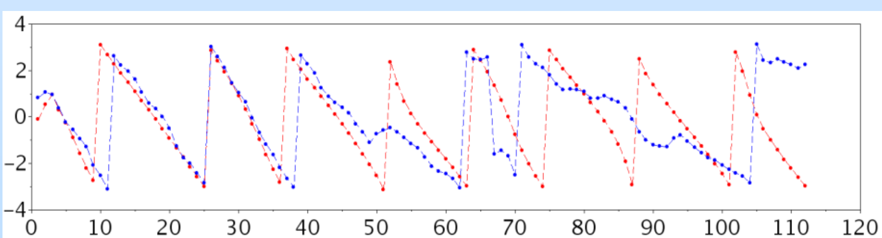


Training model



FWI using predicted LF





True 3 Hz data & predicted 3 Hz data

Failed low frequency prediction

Non-representative Training Data

Existing Issue & Challenge

Only a single random training velocity model selected → network generalization?

- Non-representative training data, learning process might be severely biased

Intuitive solution

A random velocity model generator →

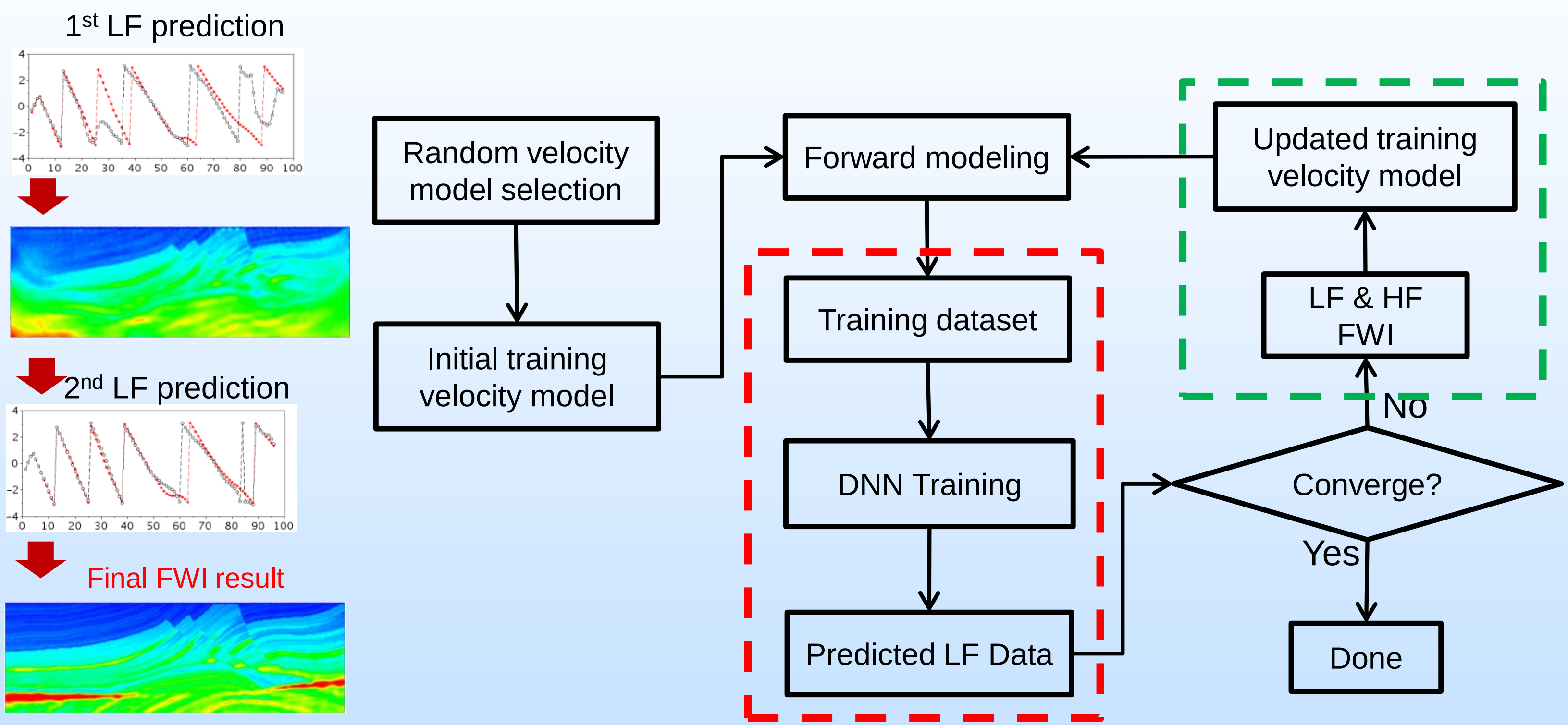
- Impossible to exhaustively capture global geological & geophysical features
- Computationally expensive → unmanageable & impractical

Our solution

A better strategy – Progressive Transfer Learning

- Parallel training converted to iterative sequential training → single training model
- Training model no longer fixed but evolving and continuously improving
- Geological & geophysical information incorporated in training model
- DL-based module seamlessly integrated with physics-based inversion

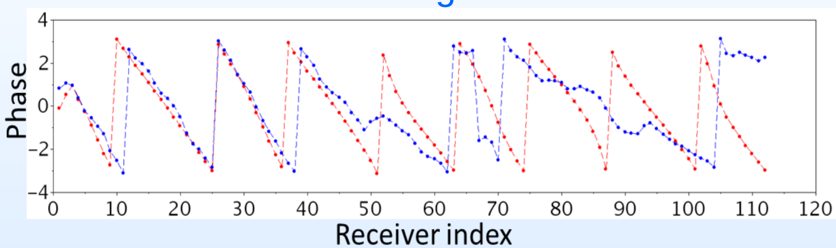
Progressive Transfer Learning Method



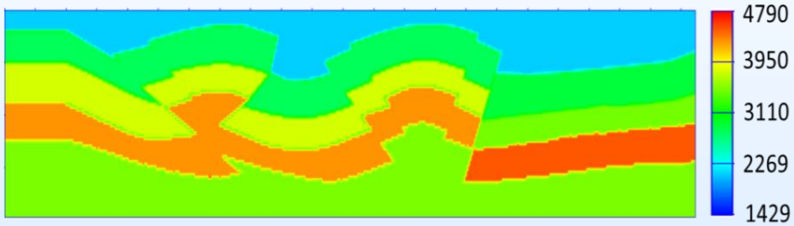
- ❑Training data → Measured data
- ❑Training velocity model → Final velocity model

Progressive Transfer Learning Results

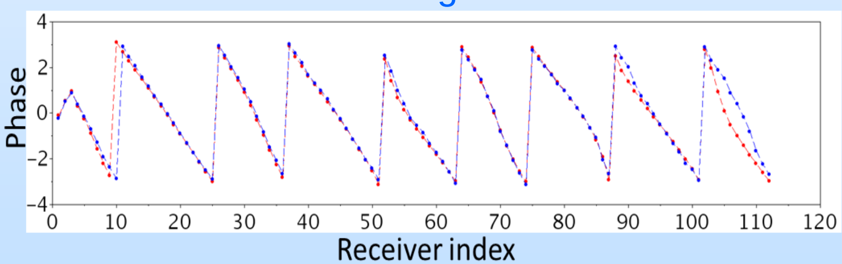
1st learning iteration



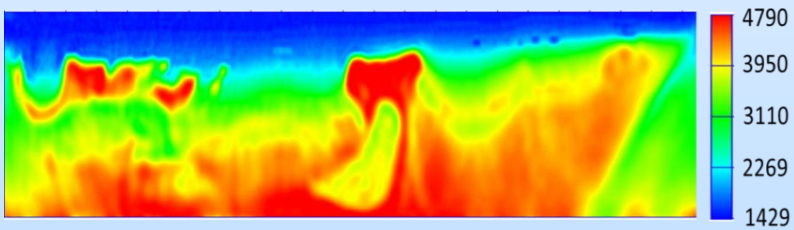
Training model



3rd learning iteration

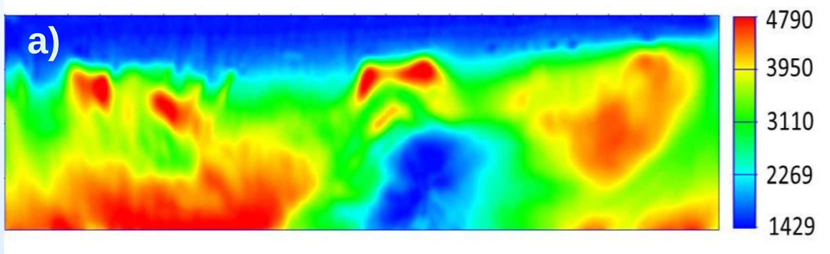


FWI using 3rd iteration predicted LF

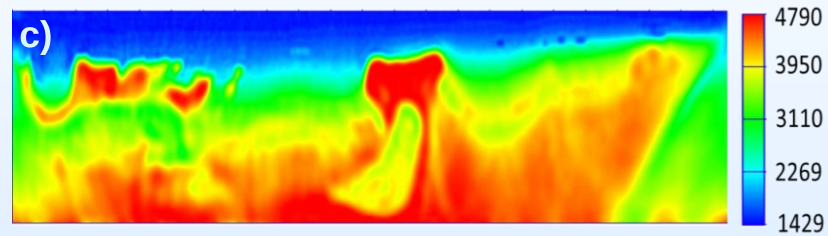


Progressive Transfer Learning Results

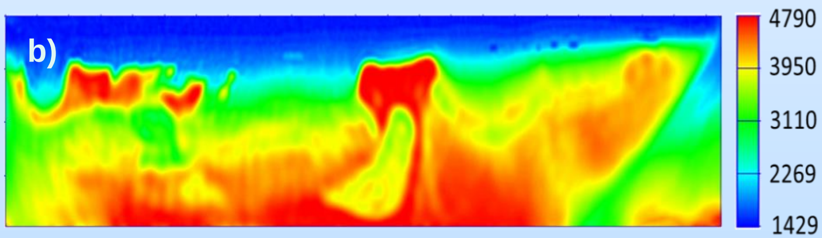
FWI using 1st predicted LF



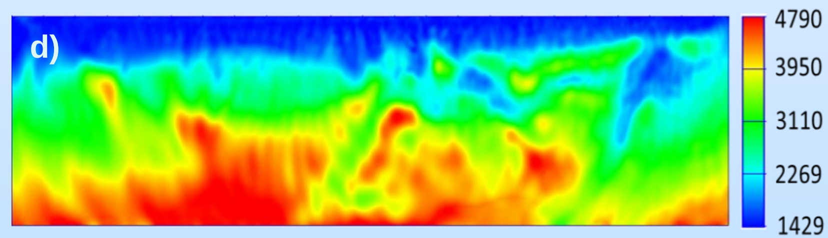
FWI using 3rd predicted LF



Reference solution



FWI using HF only



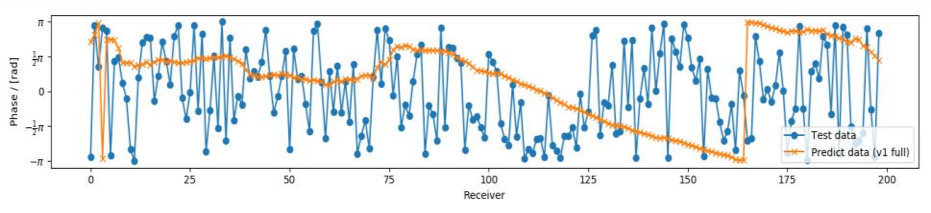
Field Data Testing

- ❑ Data below 6 Hz very noisy
- ❑ FWI result was sent back to the network as new training velocity model
- ❑ 1 Hz to 7 Hz data were predicted by network from 10 Hz to 15 Hz data

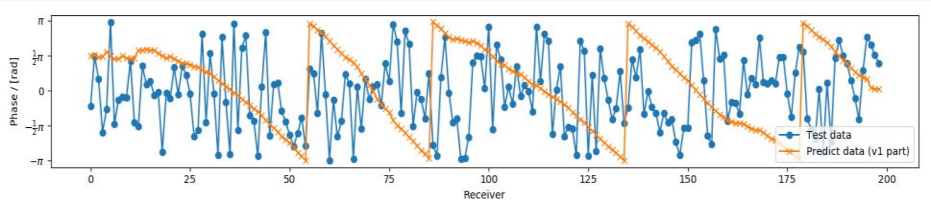
x – Predicted data

● – Field data

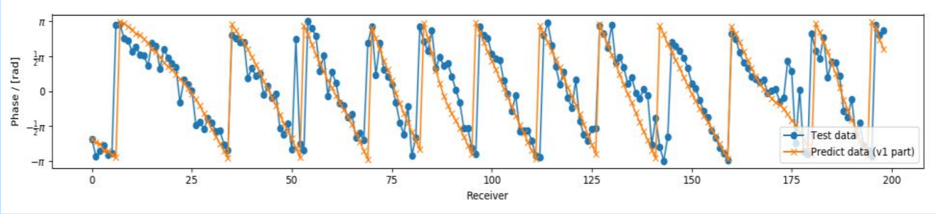
1 Hz data prediction



3 Hz data prediction

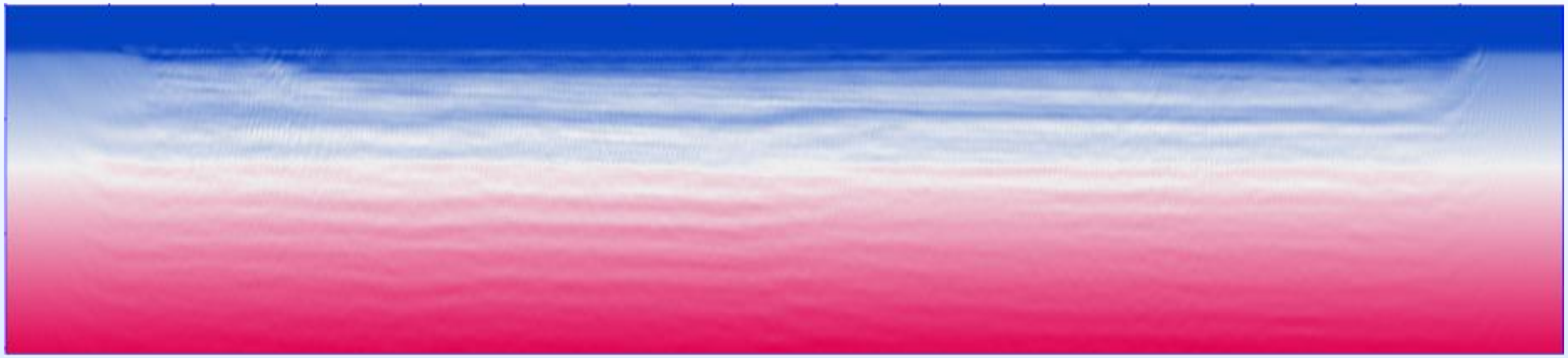


7 Hz data prediction

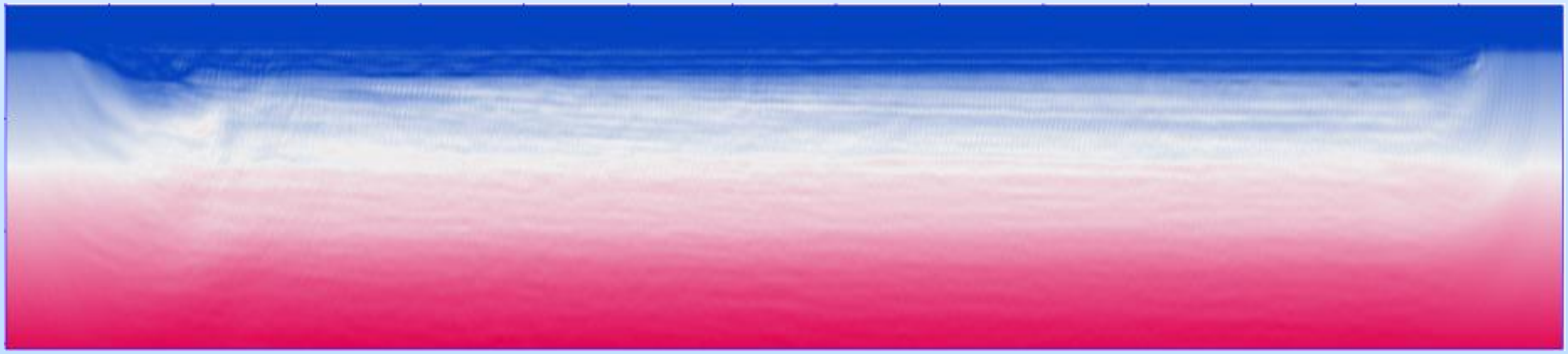


Field Data Testing

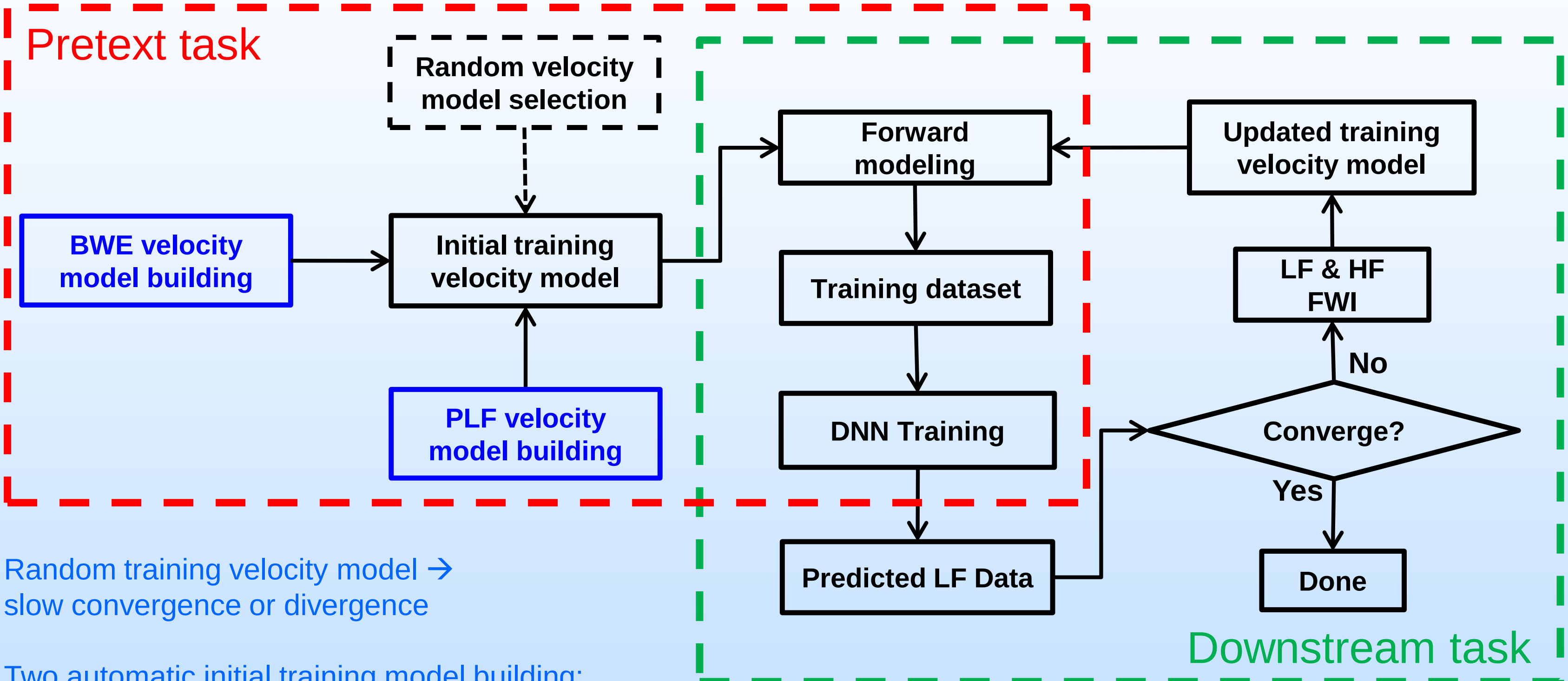
FWI using field data 8 Hz – 18 Hz



FWI using predicted 1 Hz – 7 Hz, followed by field data 8 Hz – 18 Hz



PTL → Fully Automatic Self-supervised Learning



Random training velocity model → slow convergence or divergence

Two automatic initial training model building:

1. Pseudo-Low-Frequency (PLF)
2. Bandwidth Extension (BWE)

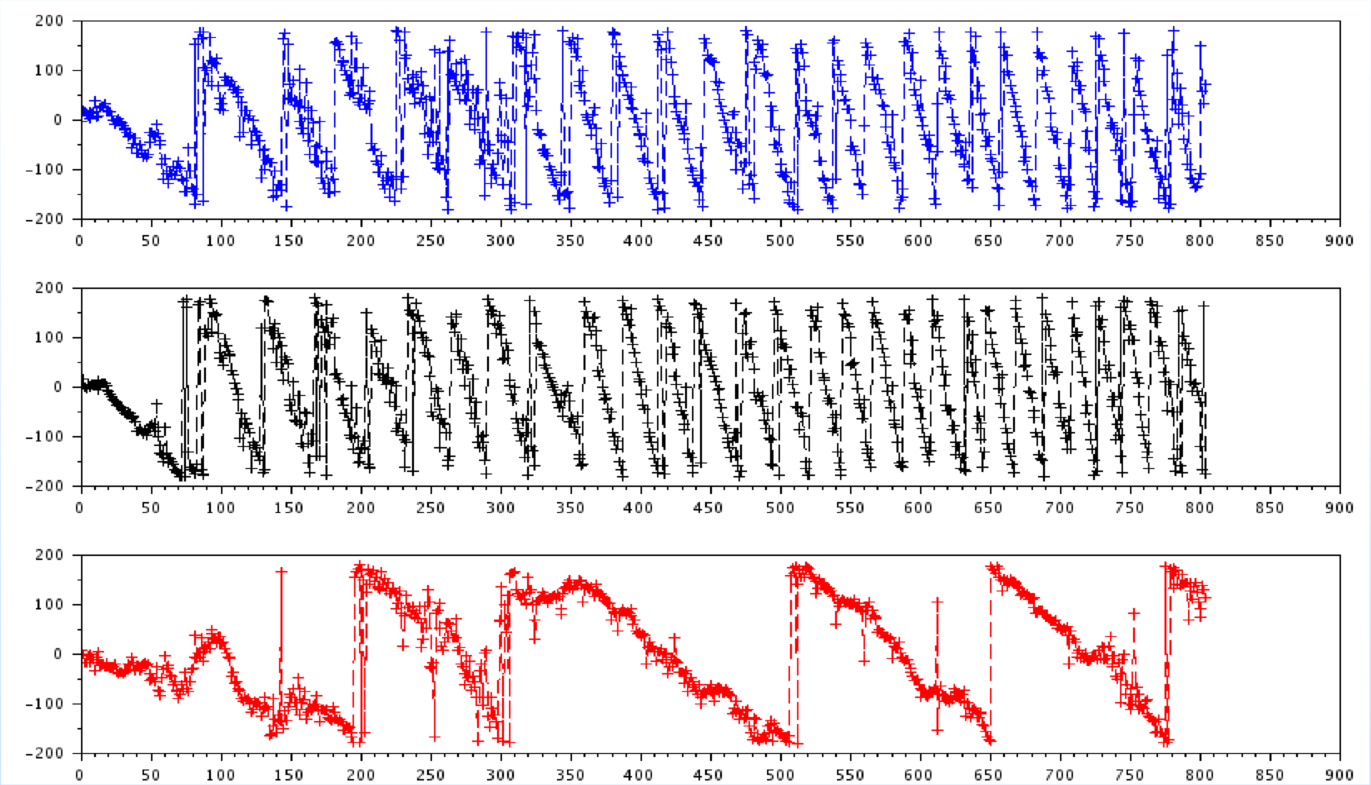
Idea: approximately estimate LF components → LF FWI, followed by HF FWI → initial training velocity model

Pseudo-Low-Frequency (PLF Method)

6 Hz

7 Hz

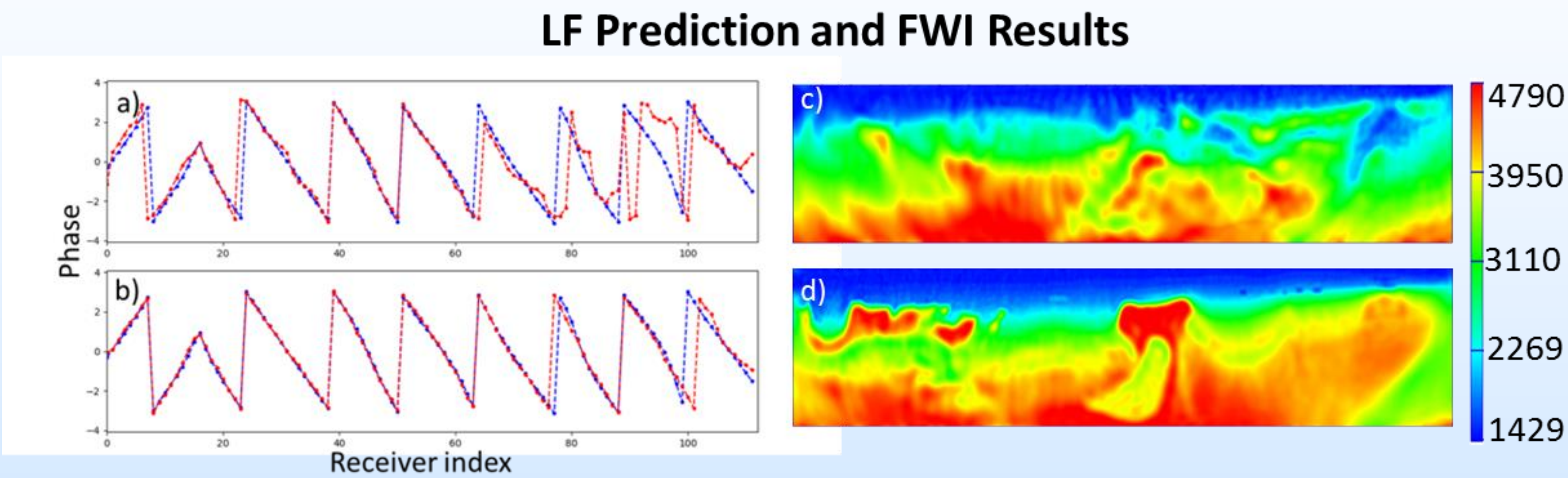
PLF
1 Hz



Receiver index

$$\boldsymbol{\Phi}_{\boldsymbol{PLF}}\left(\boldsymbol{M}^{\boldsymbol{Peudo}}{}_{1\,Hz}\right) = \boldsymbol{\Phi}(\boldsymbol{M}_{7\,Hz}) - \boldsymbol{\Phi}(\boldsymbol{M}_{6\,Hz})$$

PLF Method Performance



Red: ML-predicted LF **Blue: True LF**

a) LF prediction after pretext task;
b) LF prediction after 3 iterations of downstream task;
c) FWI result using HF data only (>10 Hz);
d) FWI result using predicted LF data, along with HF data (>10 Hz).

Bandwidth Extension (BWE Method)

$$R'(f) = \sum_{n=1}^{k} c_n \exp(j a_n f + b_n)$$

k - unknown number of reflectors

$$r'(m) = \sum_{n=0}^{N-1} c(n) \exp\left(j \frac{2\pi}{N} mn\right),$$

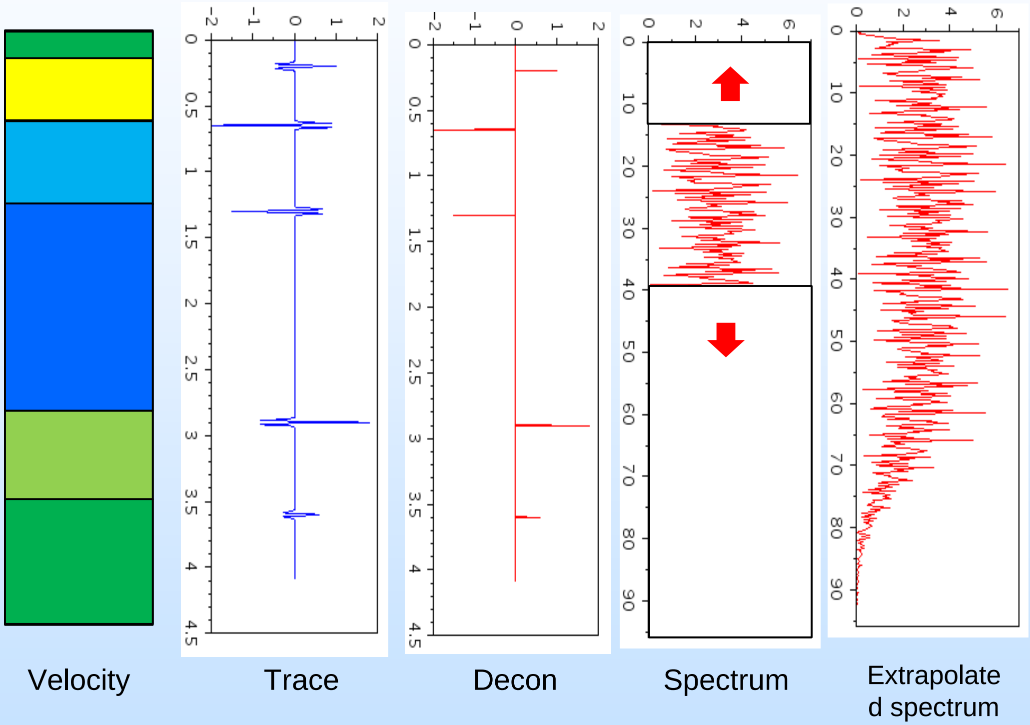
$$0 \le m \le M-1$$

$$argmin \, \|\mathbf{r} - \mathbf{A}\mathbf{c}\|_2^2 + \lambda \|\mathbf{c}\|_1,$$

$$A_{m,n} = exp\left(j \frac{2\pi}{N} mn\right),$$

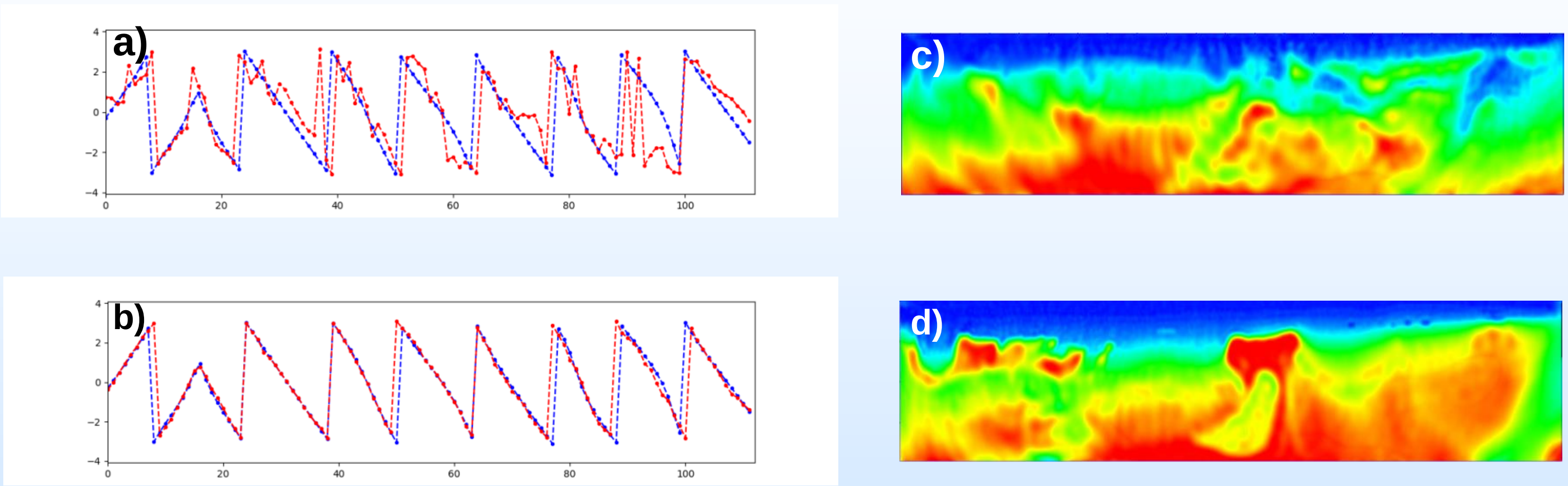
$$0 \le m \le M-1,$$

$$0 \le n \le N-1$$



Sparse Earth → many data, only 5 x 2 unknowns, over-determined → solvable with trace-by-trace approach

BWE Method Performance



Red: predicted LF
Blue: True LF

a) BWE-predicted LF ;
b) LF prediction after 1 iteration of downstream task;
c) FWI result using HF data only (>10 Hz);
d) FWI result using predicted LF data, along with HF data (>10 Hz).

Accomplishments to Date

- Developed a dual-data-feed deep learning network for prediction of absent low frequency components in acquired seismic data
- Proposed a progressive transfer learning method to integrate a physics-based inversion module with the deep learning module to gradually retrieve subsurface information for adaptive learning. Its robustness has been demonstrated.
- Based on the progressive transfer learning, we developed a self-supervised learning approach for low frequency prediction. The learning process is automatically launched by two physics-based algorithms for robust initial training velocity model building – PLF method and BWE method.
- Investigated an unsupervised learning for seismic data denoising to close the gap between synthetic data and field data.

Plan for Future Development and Testing

- Further optimize DNN network to enhance training efficiency and prediction accuracy
- Testing acquisition dependent (e.g., offset dependent) training workflow to improve network adaptiveness
- Implement self-supervised denoising network and other preprocessing procedures to close the gap between synthetic data and field data
- Testing trace-by-trace network to pave the way for large scale production
- Further improve the efficiency of pretext task (BWE method) through GPU implementation or unsupervised learning algorithms
- Develop improved Progressive Transfer Learning workflow (e.g., truncated & augmented FWI approach) to accelerate network training
- More extensive field data testing with our industry collaborators, production of this technology

Publication & Patent Application

- Hu, W., Jin, Y., Wu, X. and Chen, J., 2019. A progressive deep transfer learning approach to cycle-skipping mitigation in FWI. In *SEG Technical Program Expanded Abstracts 2019* (pp. 2348-2352). Society of Exploration Geophysicists.

- Jin, Y., Hu, W., Wu, X. and Chen, J., 2018. Learn low wavenumber information in FWI via deep inception based convolutional networks. In *SEG Technical Program Expanded Abstracts 2018* (pp. 2091-2095). Society of Exploration Geophysicists.

- The application “METHODS AND SYSTEMS FOR OBTAINING RECONSTRUCTED LOW-FREQUENCY SEISMIC DATA FOR DETERMINING A SUBSURFACE FEATURE” was filed in the USPTO on July 8, 2020 with the assigned Application No. 16/923,525.

Organization Chart

- **Advanced Geophysical Technology, Inc.**

(*Geophysics & machine learning method application*)

Wenyi Hu – Research Geophysicist (PI)

Xu Liu – Software engineer

Liangong Zhao – Geophysicist

- **University of Houston**

(*Machine learning method development*)

Jiefu Chen – Assistant Professor

Xuqing Wu – Assistant Professor

Yuchen Jin – Ph.D. Student

Yuan Zi – Ph.D. Student

Gantt Chart

	Q1, Y1	Q2, Y1	Q3, Y1	Q4, Y1	Q1, Y2	Q2, Y2	Q3, Y2	Q4, Y2
Task 1.a	AGT	AGT	AGT	AGT				
Task 1.b			UH	UH				
Task 1.c	UH	UH						
Task 2			AGT,UH	AGT,UH	AGT,UH	AGT,UH		
Task 3				AGT,UH	AGT,UH	AGT,UH	AGT,UH	
Task 4					AGT,UH	AGT,UH	AGT,UH	AGT

Task 1: Optimize DNN network structure and training workflow

Subtask 1.a: *Seismic data preprocessing for low-frequency data prediction*

Subtask 1.b: *Optimize the design of network structures to improve prediction performance*

Subtask 1.c: *Improve the network performance by enforcing smooth prediction*

Task 2: Customize progressive transfer learning workflow for FWI to enhance subsalt imaging

Task 3: Customize progressive transfer learning workflow for FWI to enhance near-surface velocity model building

Task 4: Validate prototype performance and usability via system integration and field test