Physics Guided Machine Learning for Detecting Small CO_2 Leakage (FWP-FE-1209-20-FY20)

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CONTENTS

Problem Statement and Technical Objective

Objective: Capture very small CO_2 or brine leakage over large area

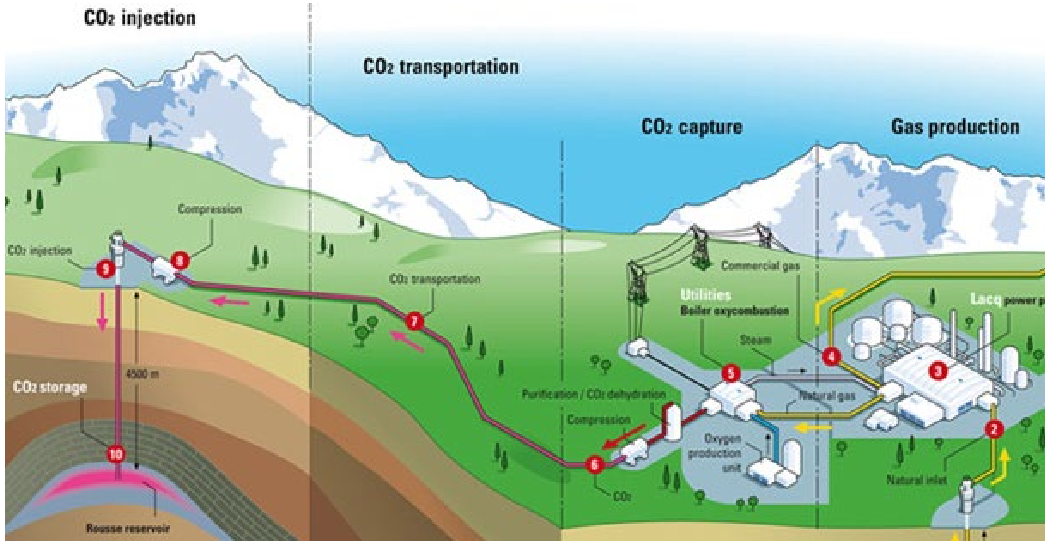
1. Is there a leak?
2. How much has leak?
3. Where is the leak?

Challenge 1: Unsatisfactory Detectability

Current geophysical monitoring methods do not yield sufficient detectability to capture very small leakage (due to limitations in data coverage, low spatial resolution, acquisition noise and artifacts, etc.)

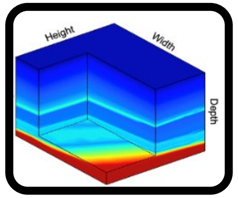
Challenge 2: Expensive Geophysical Monitoring

The high financial/computational cost and subjective human factors hinders the applicability of the existing monitoring methods.

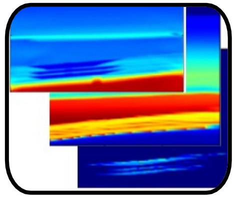


Small Leakage Detection

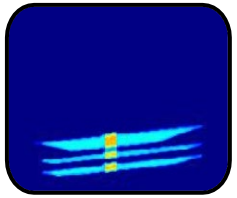
GeoVision: Seismic Imaging & Inversion Suite – an Overview



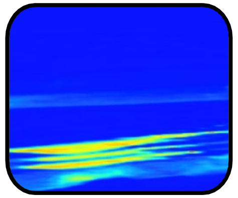
2D/3D Imaging
[Zeng et al. (2021)]



Multiphysics
[Feng et al. (2022)]

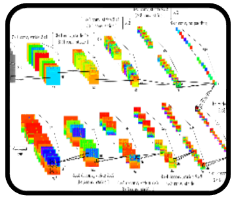


Time-Lapse
[Liu et al. (2022)]

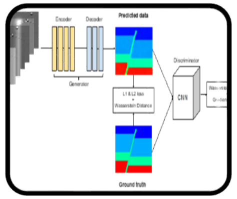


Uncertainty
[Liu et al. (2022)]

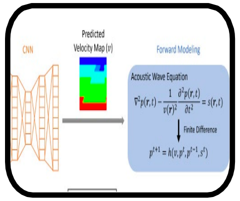
Induced Seismic
[Zhang et al. (2022)]



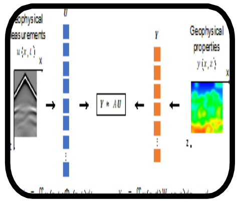
Supervised
[Wu & Lin (2019)]



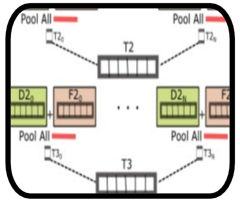
Semi-supervised
[Zhang & Lin (2020)]



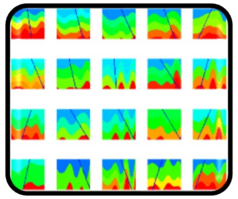
Unsupervised
[Jin et al. (2021)]



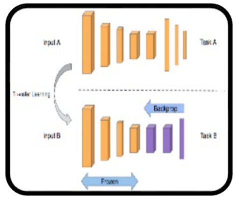
Lightweight
[Feng et al. (2022)]



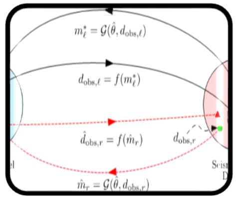
Function Operator
[Zhu et al. (2023)]



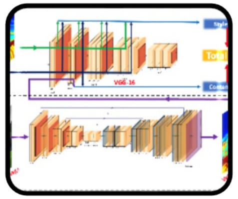
Physics Simulations
[Lin et al. (2018)]



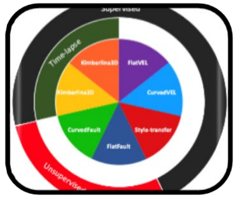
Transfer Learning
[Zhang & Lin (2019)]



Active Learning
[Gomez et al. (2020)]



Style Learning
[Feng & Lin (2021)]



Open Data
[Deng et al. (2022)]

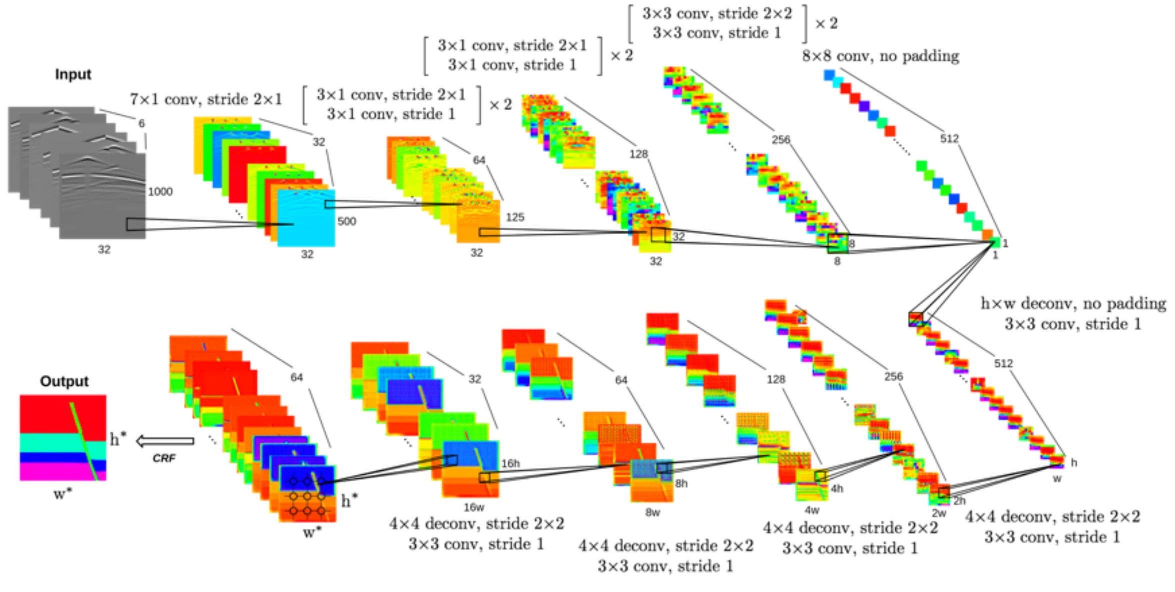
GeoVision Driven by Physics and Machine Learning

What is GeoVision?

- Collection of **site-agnostic** geophysical imaging techniques
- Based on **physics-guided machine learning**

Explore two imaging models:

- **Purely Data-driven Neural Networks** *[Wu and Lin, (2019)]*
    - *Real-time 2D/3D CO_2 Plume Imaging (Saturation)*
    - *Leakage Detection*
    - Uncertainty & Risk Estimate (Data and Model Error)



InversionNet

Yue Wu and Youzuo Lin, "InversionNet: An Efficient and Accurate Data-driven Full Waveform Inversion," IEEE Transactions on Computational Imaging, 6(1):419-433, 2019.

GeoVision Driven by Physics and Machine Learning

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- **Purely Data-driven Neural Networks** *[Wu and Lin, (2019)]*
  - *Real-time 2D/3D CO_2 Plume Imaging (Saturation)*
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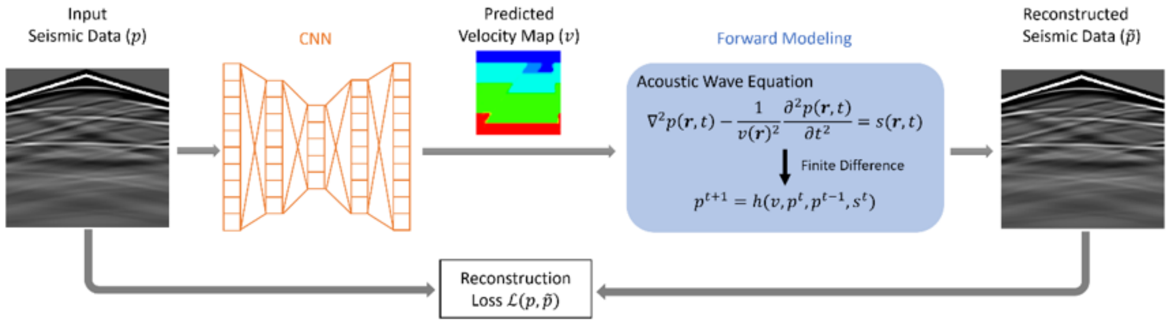
  - Uncertainty & Risk Estimate (Data and Model Error)
- **Physics-guided Unsupervised Networks** [Jin et al. (2022)]
  - Enable Imaging without any Label Information



Physics-guided Unsupervised Networks [Jin et al., 2022]

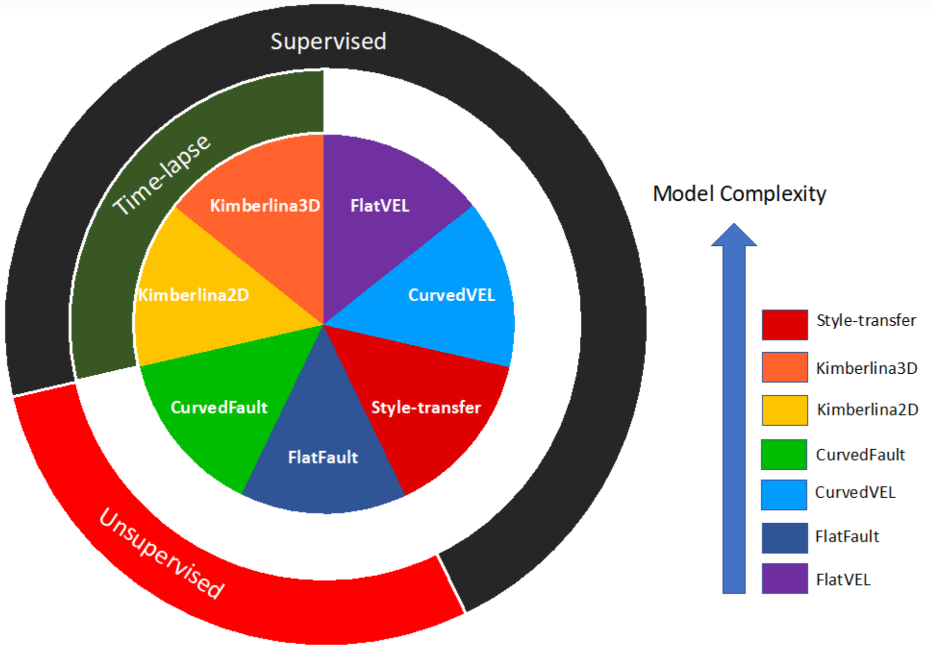
Peng Jin, Xitong Zhang, Yinpeng Chen, Sharon Xiaolei Huang, Zicheng Liu, and Youzuo Lin, "Unsupervised Learning of Full-Waveform Inversion: Connecting CNN and Partial Differential Equation in a Loop", ICLR, 2022.

GeoVision Enhanced by Large-Scale High Quality Training Data

First Large-Scale Multi-Structural Benchmark Acoustic Datasets

- **Multi-scale and multi-dimension**
  - Over 180K of acoustic waveform samples
  - Each sample: Label—Velocity model; Data—Seismic data
  - Acoustic wave equation with constant density
  - Total 12 sub-datasets: 2D (11 datasets) and 3D (1 dataset)
- **Multiple applications with various geo-structures**
  - Clean energy (CCUS), renewable energy, and general purposes

Data Overview



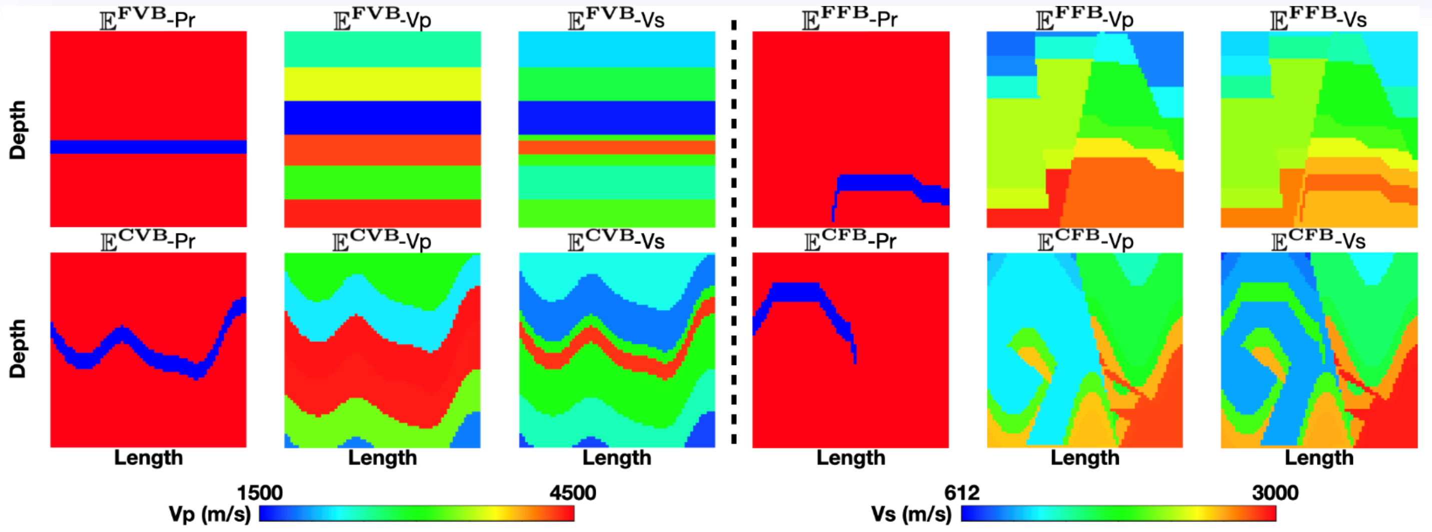
OpenFWI (https://openfwi-lanl.github.io/)

Chengyuan Deng, Shihang Feng, Hanchen Wang, Xitong Zhang, Peng Jin, Yinan Feng, Qili Zeng, Yingpeng Chen, and Youzuo Lin, "OpenFWI: Large-scale Multi-structural Benchmark Datasets for Full Waveform Inversion", NeurIPS, 2022.

GeoVision Enhanced by Large-Scale High Quality Training Data

$\mathbb{E}^{\text{FWI}}$: Multiparameter Benchmark Datasets for Elastic Seismic Inversion

- **Why need $\mathbb{E}^{\text{FWI}}$**
  - More **realistic & precise** representation of subsurface
  - Poisson's ratio (P_r) serve as **essential indicators** in characterization of reservoir
- **What is new in $\mathbb{E}^{\text{FWI}}$**
  - Contain a total of **8** distinct 2D sub-datasets
  - Include **multi-parameters** (v_p, v_s, P_r)
  - Produce benchmark elastic inversion using three methods: **𝔼lasticNet**, **𝔼laticGAN**, and **𝔼lasticTransformer**



Gallery of $\mathbb{E}^{\text{FWI}}$ [Feng et al., 2023]

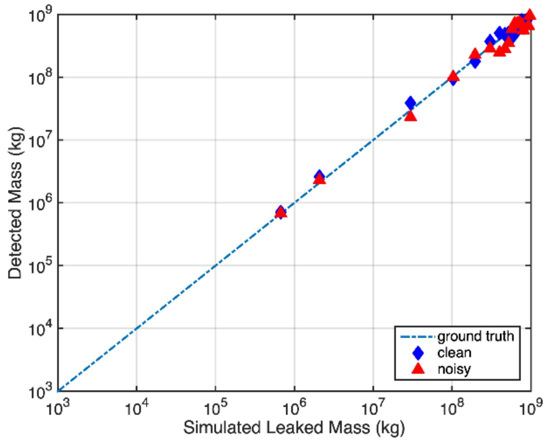
Shihang Feng, Hanchen Wang, Chengyuan Deng, Yinan Feng, Yanhua Liu, Min Zhu, Peng Jin, Yinpeng Chen, Youzuo Lin, "$\mathbb{E}^{\text{FWI}}$: Multi-parameter Benchmark Datasets for Elastic Full Waveform Inversion of Geophysical Properties, " arXiv, 2023 (Under Review in NeurIPS).

Project Scope: Task & Milestone

Major Milestone

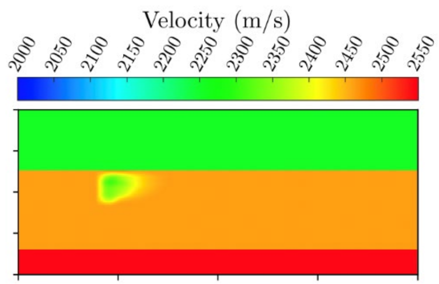
- Project Kick-off
  - Preliminary Study & Data Preparation
- R&D Tasks
  - Task 1 – Synthetic Data Test (Kimberlina 1.2)
  - Task 2 – Controlled Experiment Test 1 (Cranfield)
  - Task 3 – Controlled Experiment Test 2 (Sleipner)
  - Task 4 – Controlled Experiment Test 3 (San Juan)

Previous Task 1: Leakage Detection using Kimberlina 1.2 Data



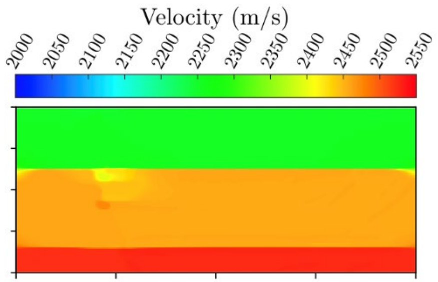
Leakage Mass Detection
[Zheng et al., 2019]

a



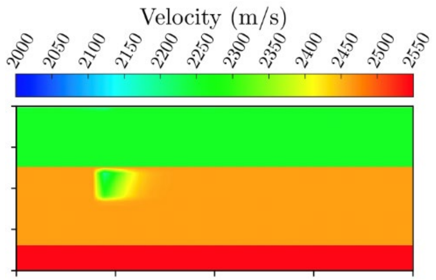
Ground Truth
[Gomez et al., 2020]

b



Traditional
[Gomez et al., 2020]

c



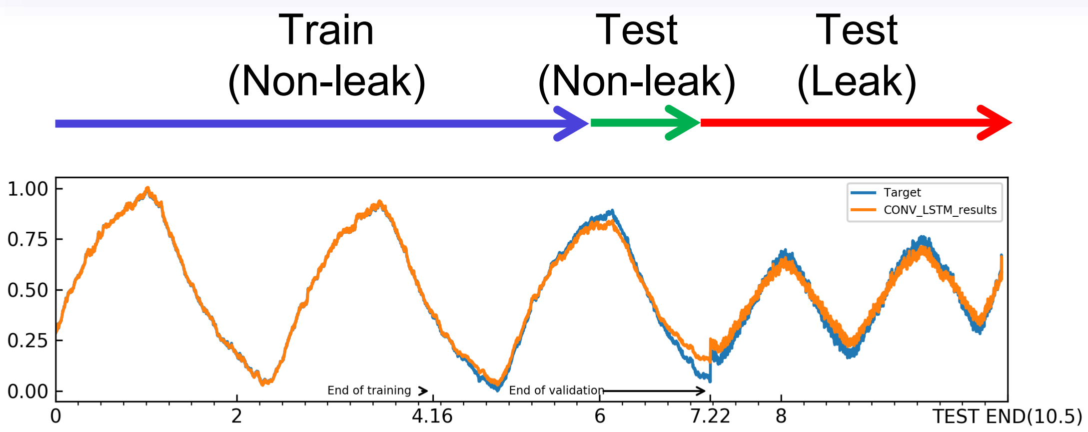
GeoVision
[Gomez et al., 2020]

d

- GeoVision learns critical information from ***massive amount of data*** to predict leakage mass and plume.
- Collaboration with Zan Wang and Bob Dilmore via NRAP.

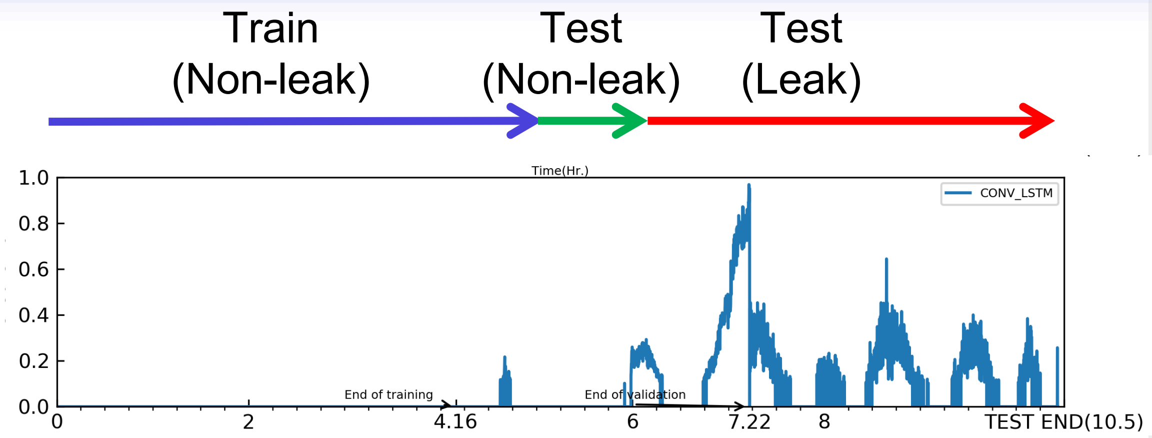
Zheng Zhou, Youzuo Lin, Zhongping Zhang, Yue Wu, Zan Wang, Robert Dilmore, and George Guthrie, "A Data-Driven CO2 Leakage Detection Using Seismic Data and Spatial-Temporal Densely Connected Convolutional Neural Networks," International Journal of Greenhouse Gas Control, Vol 90, 2019.

Previous Task 2: Leakage Detection using Cranfield Data



Signature Prediction
[Sinha et al., 2020]

a



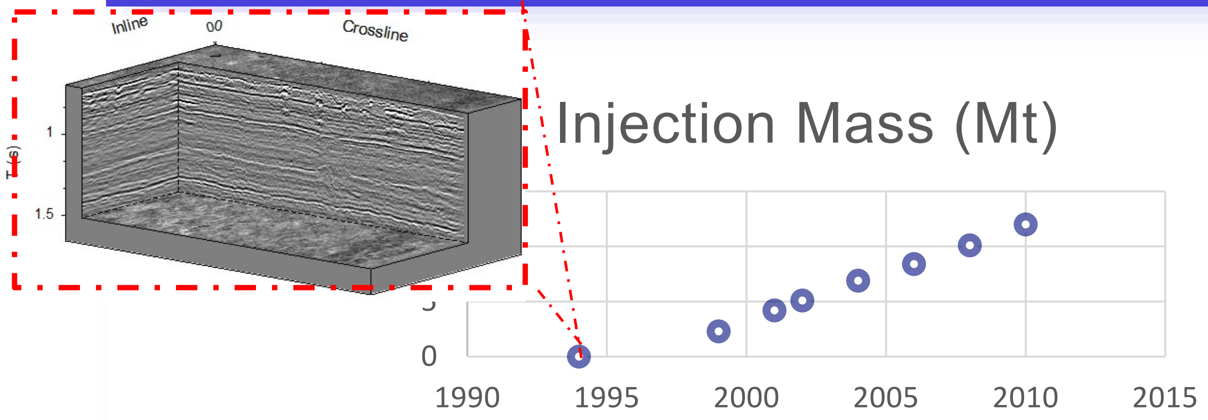
Leakage Detection
[Sinha et al., 2020]

b

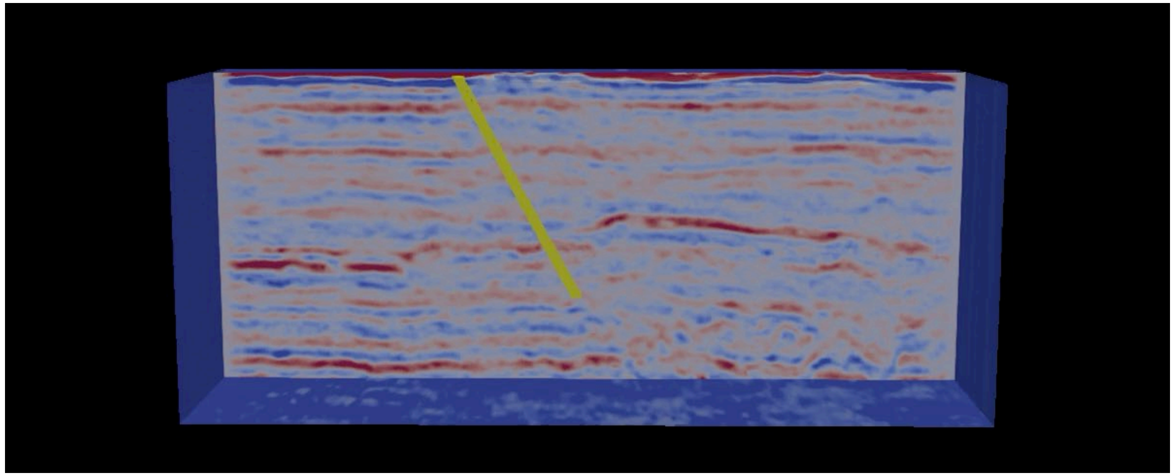
- GeoVision, trained on non-leak temporal pressure data, can predict leakage.
- Through the collaboration with Alex Sun and BEG.

Saurabh Sinha, Rafael Pires de Lima, Youzuo Lin, Alexander Y. Sun, Neill Symons, Rajesh Pawar, and George Guthrie, “Normal or Abnormal? Machine Learning for the Leakage Detection in Carbon Sequestration Projects Using Pressure Field Data,” International Journal of Greenhouse Gas Control, Vol. 103, 2020.

Previous Task 3: In-Situ Monitoring using Sleipner Data



Repeated Seismic Acquisition (10 years)



In-situ Monitoring
[Feng et al., 2021]

a

b

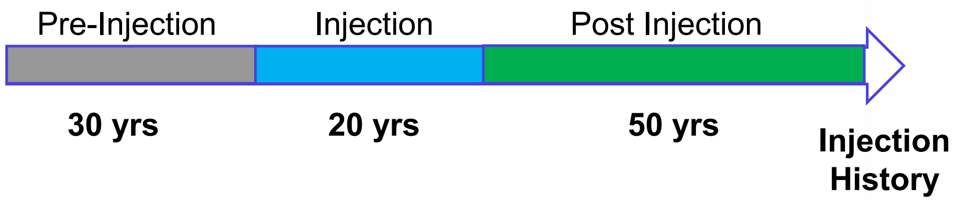
When sufficiently trained, ML can ***fill in the gap*** of static data to inform the dynamics of the plume.

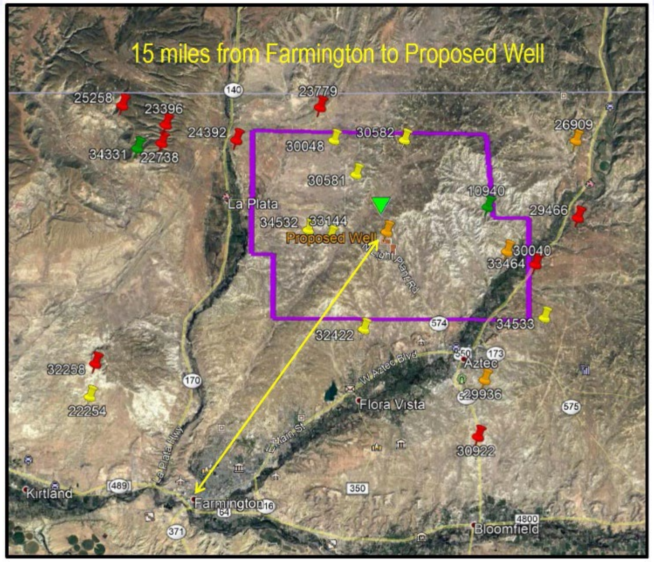
Shihang Feng, Xitong Zhang, Brendt Wohlberg, Neill Symons, and Youzuo Lin “Connect the Dots: In Situ 4D Seismic Monitoring of CO2 Storage with Spatio-temporal CNNs,” IEEE Transactions on Geoscience and Remote Sensing, vol 60, 1-- 16 2021.

Task 4: Time-lapsed Imaging using San Juan Basin Data

San Juan Basin Dataset (CarbonSAFE)

- **Data Availability**
  - Baseline velocity model built from well logs
  - Time-lapse velocity models built from reservoir simulation (100 yrs)
  - Seismic Data Simulation (5 sources and 70 receivers)

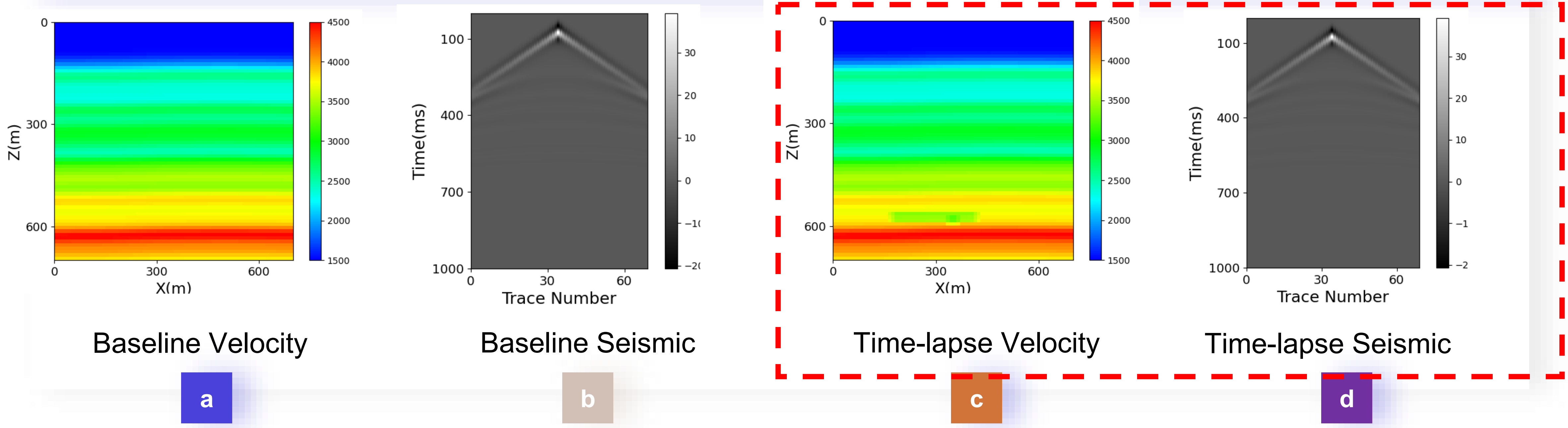




San Juan Basin

- Collaboration with William Ampomah (NMT) via CarbonSAFE.

Task 4: Leakage Monitoring using San Juan Basin Data



FY 23 Focuses on Baseline Imaging

- *Sub-Task 1: Supervised Learning*
- *Sub-Task 2: Unsupervised Learning*

FY 22 Focuses on Time-lapse Imaging

- *Employ GeoVision to monitor change*
- *Baseline obtained by physics methods*

Task 4.1: Fully Supervised Learning – InversionNet

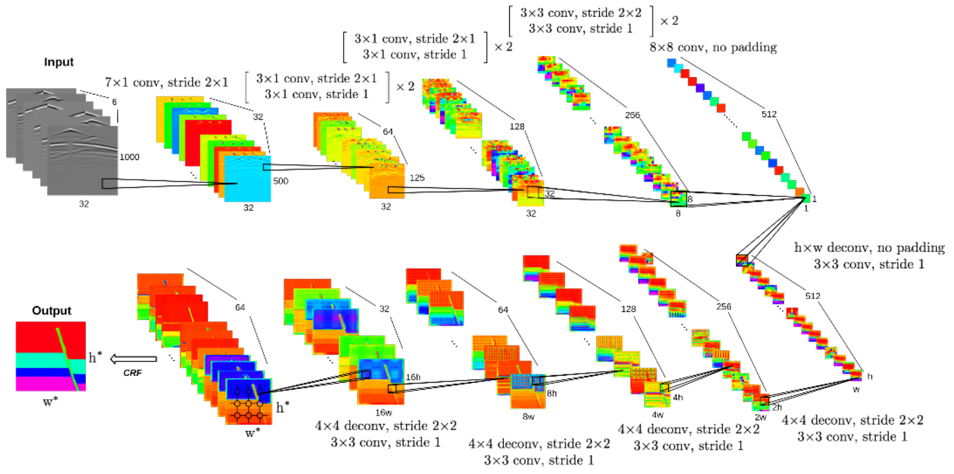
End-to-End Learning of "Inversion Operator": $g_{\theta^*}(\cdot) \approx f^{-1}(\cdot)$

$$v(p) = g_{\theta^*}(p); \;\; s.t. \;\; \theta^*(\phi_s) = \underset{\theta}{\operatorname{argmin}} \sum_{(v_i, p_i) \epsilon \phi_s} \mathcal{L}(g_\theta(p_i), v_i)$$

where $g_\theta(\cdot)$ is the network with trainable weights θ, $\mathcal{L}(\cdot,\cdot)$ is a loss function, and ϕ_s represents a supervised dataset with both velocity map v_i and seismic data p_i being available.

Image-to-Image Translation

- **Treat both input and output as images**
  - No initial guess needed
- **Fully supervised learning strategy**
  - Both data and label needs to be availability
  - Physics is implicitly embedded in pair-wised data
- **Train $g_{\theta^*}(p)$ on a subdomain ϕ_s**
  - Applicable to many samples drawn from ϕ_s



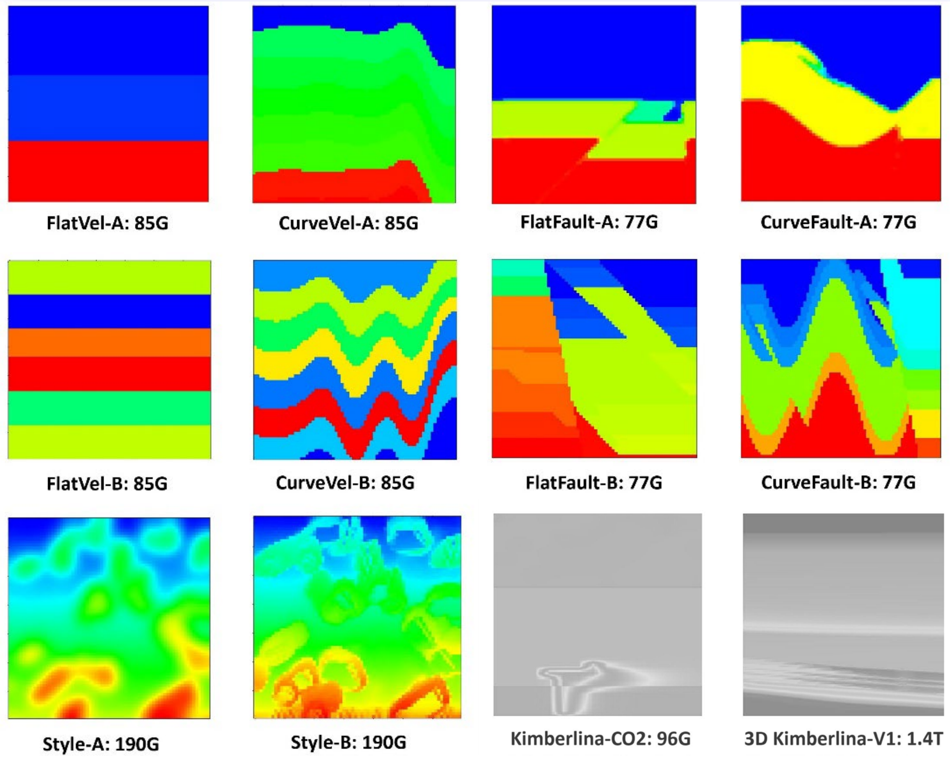
InversionNet [Wu & Lin, 2019]

Yue Wu and Youzuo Lin, "InversionNet: An Efficient and Accurate Data-driven Full Waveform Inversion," IEEE Transactions on Computational Imaging, 6(1):419-433, 2019.

Task 4.1: Fully Supervised Learning – Open Dataset

- **Dataset: OpenFWI – Select 10 2D subsets**
  - FlatVel-A (FVA), FlatVel-B (FVB),
  - CurveVel-A (CVA), CurveVel-B (CVB),
  - FlatFault-A (FFA), FlatFault-B (FFB),
  - CurveFault-A (CFA), CurveFault-B (CFB)
  - Style-A (STA), Style-B (STB)

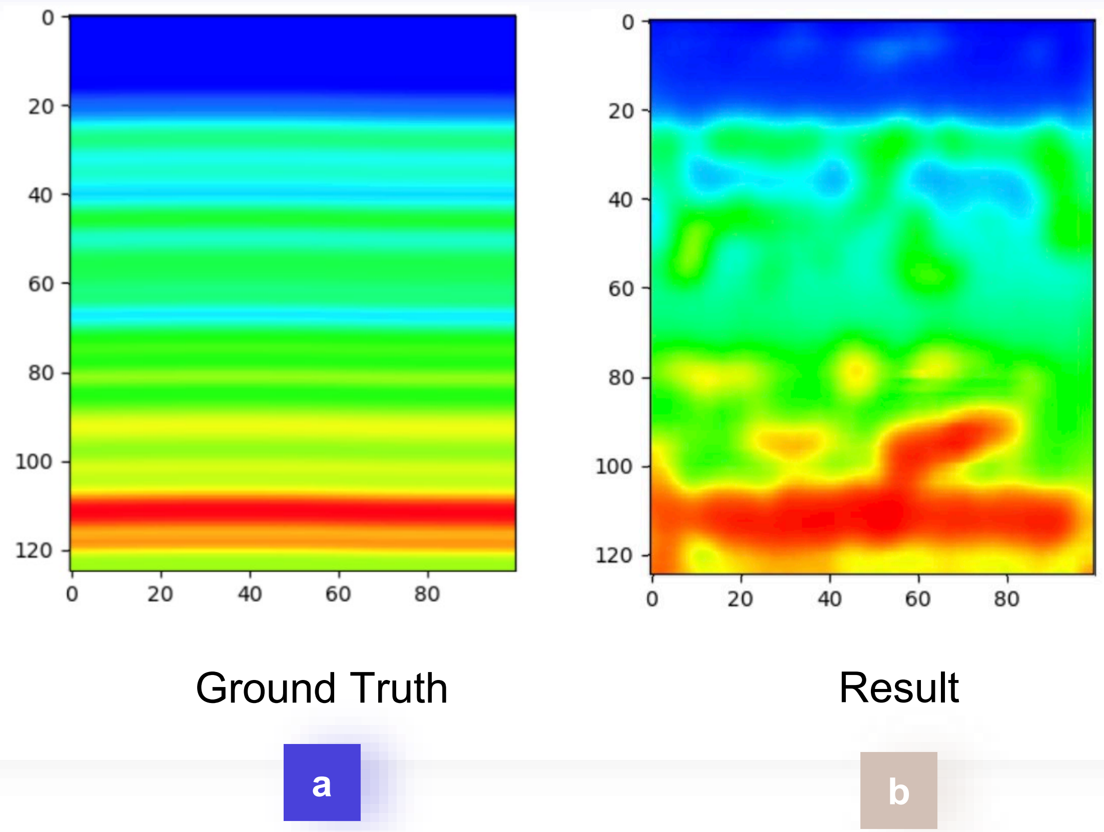
OpenFWI Dataset



Hanchen Wang, Youzuo Lin, Shihang Feng, Peng Jin, Xitong Zhang, Yinpeng Chen, Rajesh Pawar, and George Guthrie, " Supervised vs. unsupervised deep learning full waveform inversion: a case study at CCUS site, San Juan NM", IEEE IGRSS, 2023.

Task 4.1: Fully Supervised Learning – Results

- **InversionNet** trained on **OpenFWI** produces reasonable estimation of the baseline velocity model.
- High-frequency velocity components need to be further improved.



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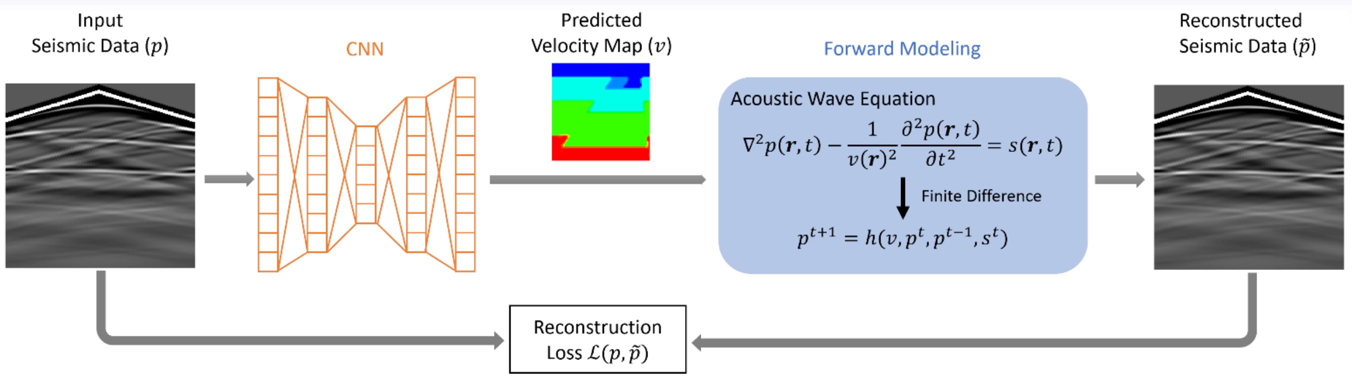
Task 4.2: Unsupervised Learning – UPFWI

Unsupervised Physics-informed Full Waveform Inversion

- **Built on InversionNet**
  - Leverage the same encoder-decoder
- **Incorporate wave physics**
  - Provide strong physics-based regularization explicitly
  - Shift the paradigm from supervised to unsupervised learning



Structure of UPFWI [Peng et al., 2022]

- **Training & Testing Strategies**
  - **Train Phase:** Use the whole network (i.e., the encoder-decoder with physics regularization)
  - **Test Phase:** Use only the encoder-decoder network for imaging

Peng Jin, Xitong Zhang, Yinpeng Chen, Sharon Xiaolei Huang, Zicheng Liu, and Youzuo Lin, "Unsupervised Learning of Full-Waveform Inversion: Connecting CNN and Partial Differential Equation in a Loop", ICLR, 2022.

Task 4.2: Unsupervised Learning – UPFWI

1D Acoustic Wave Equation: $\frac{\partial^2 p}{\partial t^2} = v^2(z)\frac{\partial^2 p}{\partial z^2} + s(t,z)$

where t and z denote time and depth, respectively; $p(t,z)$ denotes the pressure field; $v(z)$ represents the acoustic wave velocity, $s(t,z)$ is the source function.

Discretization via Finite Difference (2nd order approximation)

- $p_i^{n+1} - (2 + \alpha v_i^2 \nabla^2) p_i^n + p_i^{n-1} = s_i^{n+1}$, where $\alpha = \frac{\Delta t^2}{\Delta z^2}$, $v_i$denote the acoustic velocity at all nz model grid points, and ∇^2denotes the discrete Laplace operator.

A Neat Matrix-Form Representation

- $\mathbf{P}^{n+1} = \mathbf{G}\mathbf{P}^n - \mathbf{P}^{n-1} + \mathbf{S}^{n+1}$, where $\mathbf{G} = 2\mathbf{I} + \mathbf{A}\mathbf{L}$, and $\mathbf{A} = diag\{\alpha v_i^2\}$, $\mathbf{L} = \begin{bmatrix} -2 & 1 & & \\ 1 & -2 & 1 & \\ & \ddots & \ddots & \ddots \\ & & & \end{bmatrix}_{nz \times nz}$

Peng Jin, Xitong Zhang, Yinpeng Chen, Sharon Xiaolei Huang, Zicheng Liu, and Youzuo Lin, "Unsupervised Learning of Full-Waveform Inversion: Connecting CNN and Partial Differential Equation in a Loop", ICLR, 2022.

Task 4.2: Unsupervised Learning – UPFWI

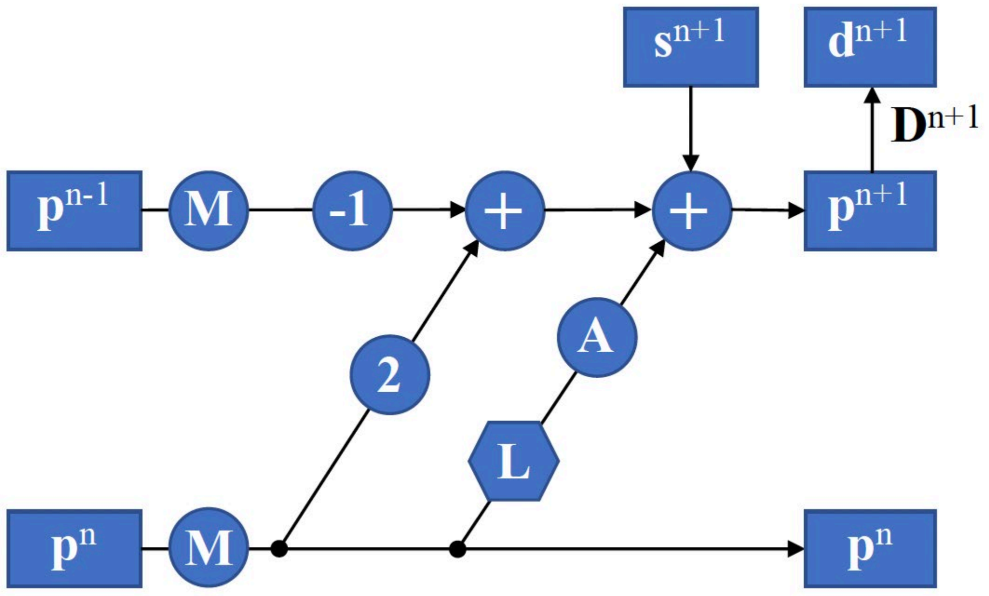
Matrix-Form Representation

- $\mathbf{P}^{n+1} = \mathbf{G}\mathbf{P}^{n} - \mathbf{P}^{n-1} + \mathbf{S}^{n+1}$,

  where $\mathbf{G} = 2\mathbf{I} + \mathbf{A}\mathbf{L}$
- Future state can be calculated as multiple **differentiable** operations:

Convolution

Element-wise addition/subtraction/multiplication



Forward Wave Propagation Network

Peng Jin, Xitong Zhang, Yinpeng Chen, Sharon Xiaolei Huang, Zicheng Liu, and Youzuo Lin, "Unsupervised Learning of Full-Waveform Inversion: Connecting CNN and Partial Differential Equation in a Loop", ICLR, 2022.

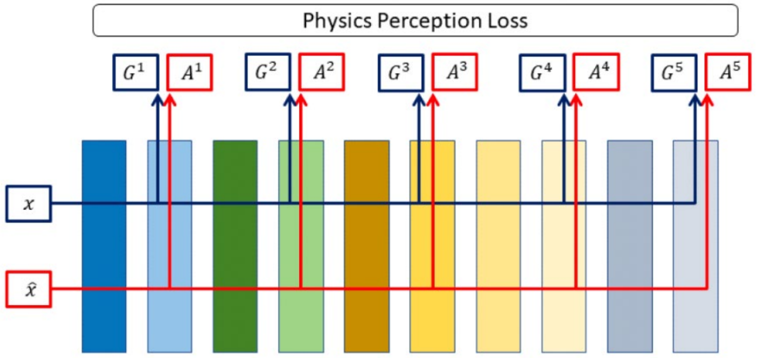
Task 4.2: Unsupervised Learning – UPFWI

- **InversionNet:** $v(p) = g_{\theta^*}(p);\ \ s.t.\ \ \theta^*(\phi_s) = \underset{\theta}{\operatorname{argmin}} \sum_{(v_i,p_i)\epsilon\phi_s} \mathcal{L}(g_\theta(p_i), v_i),$ where$g_\theta(\cdot)$ is the network with trainable weights θ.

- **UPFWI:** $v(p) = g_{\theta^*}(p);\ \ s.t.\ \ \theta^*(\phi_u) = \underset{\theta}{\operatorname{argmin}} \sum_{p_i\epsilon\phi_u} \mathcal{L}(\boldsymbol{f}(g_\theta(p_i)), p_i),$ where $\boldsymbol{f}(\cdot)$ is the forward modeling operator, and

$$\mathcal{L}(p,\tilde{p}) = \underbrace{\lambda_1\ell_1(p,\tilde{p}) + \lambda_2\ell_2(p,\tilde{p})}_{\text{Data Loss}} + \underbrace{\lambda_3\ell_1(\psi(p),\psi(\tilde{p})) + \lambda_4\ell_2(\psi(p),\psi(\tilde{p}))}_{\text{Perceptual Loss}}.$$

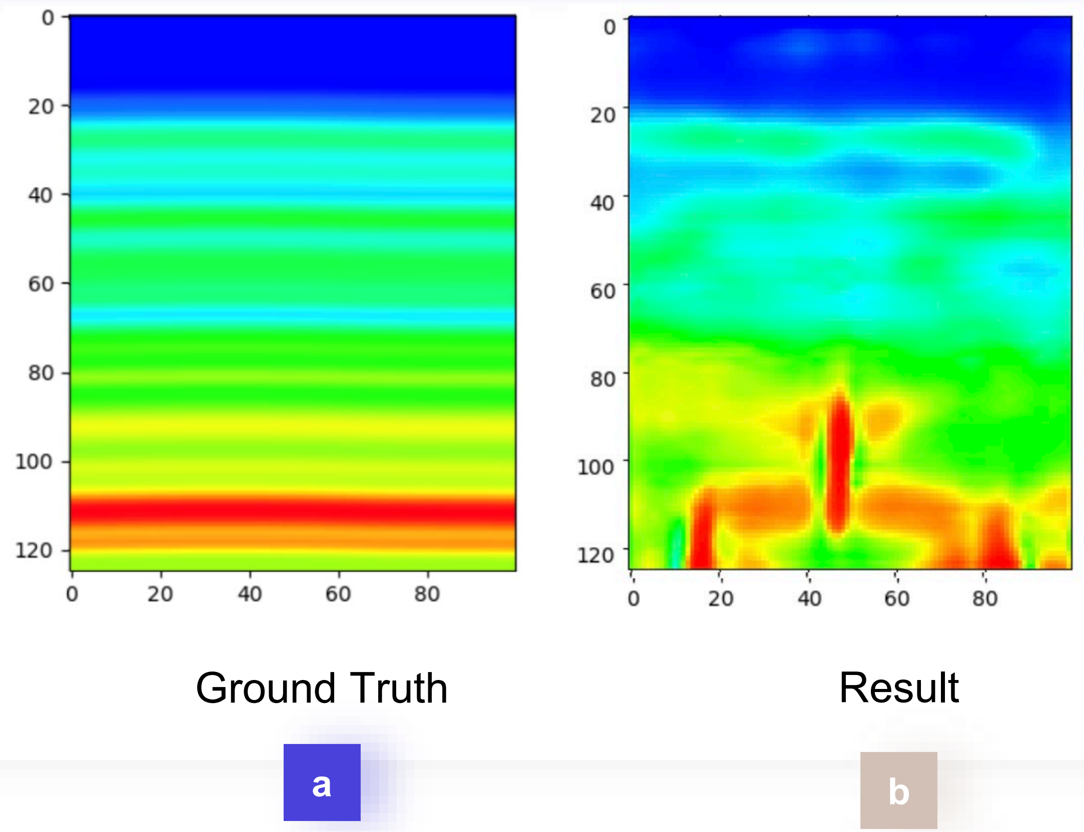
- **Data Loss: $\ell_1(p,\tilde{p})$, $\ell_2(p,\tilde{p})$**
  - To measure seismic data pixel-wise differences in ℓ_1 and ℓ_2 distances.
- **Perceptual Loss: $\ell_1(\psi(p),\psi(\tilde{p}))$, $\ell_2(\psi(p),\psi(\tilde{p}))$**
  - To capture region-wise structure and encourage waveform coherence.



VGG-16

Task 4.2: Unsupervised Learning – Results

- **UPFWI** trained on **unlabeled data** produces reasonable estimation of the baseline velocity model.
- Some artifacts are generated in the deep region.



Hanchen Wang, Youzuo Lin, Shihang Feng, Peng Jin, Xitong Zhang, Yinpeng Chen, Rajesh Pawar, and George Guthrie, " Supervised vs. unsupervised deep learning full waveform inversion: a case study at CCUS site, San Juan NM", IEEE IGRSS, 2023.

Summary

01 Machine Learning

Machine learning, particularly, deep neural network models provide great potential in improving seismic imaging performance (i.e., enhancing the spatial resolution and accelerating imaging speed).

02 Physics Knowledge

The incorporation of physics knowledge will significantly improve model robustness and generalization.

03 Data Scarcity

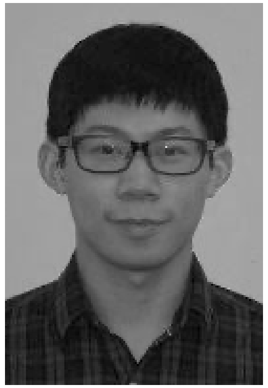
One of the major challenges employing deep learning-based imaging models for CO_2 monitoring is the lack of data.

04 GeoVision

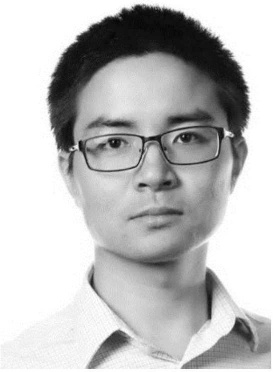
- We demonstrate the great potential of GeoVision using four case studies (Kimberlina, Cranfield, Sleipner, and SJB).
- **Look for more applications!**

Meet Our Team

Hanchen Wang
Micro-seismic Monitoring



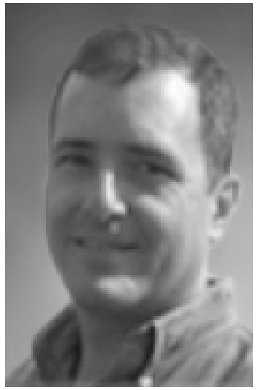
Shihang Feng
Seismic Inversion & ML



Bailian Chen
CCUS & ML

Neill Symons
Seismology

Rajesh Pawar
Carbon Sequestration



George Guthrie
Carbon Sequestration

Students

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- Yinan Feng, Post-Master Student, Machine Learning, Los Alamos National Laboratory
- Yanhua Liu, Ph.D. Student, Center for Wave Phenomena, Colorado School of Mines
- Daniel Manu, Ph.D. Student, Dept of Electrical & Computer Engineering, University of New Mexico
- Xitong Zhang, Ph.D. Student, Dept of Computational, Mathematics, Science and Engineering, Michigan State University
- Peng Jin, Ph.D. Student, College of Information Sciences and Technology, Penn State University

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