# Unsupervised Learning of Full-Waveform Inversion: Connecting CNN and Partial Differential Equation in a Loop

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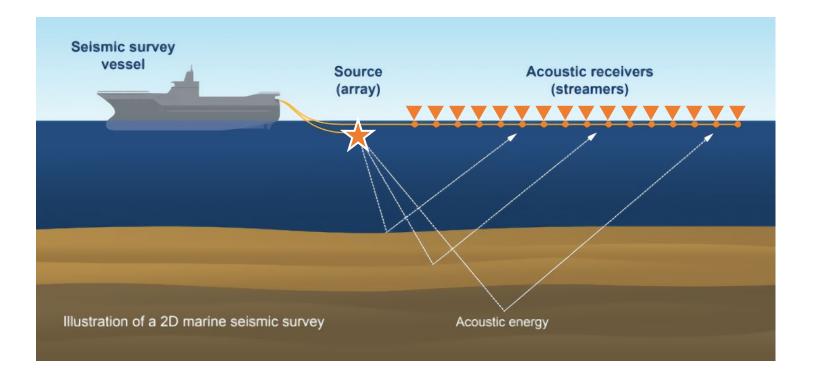






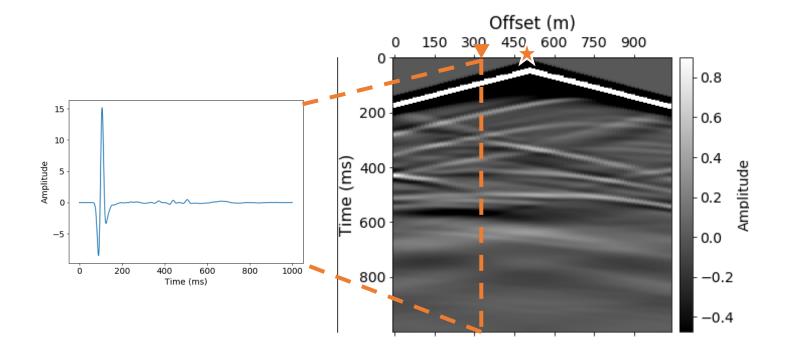
## Full-Waveform Inversion (FWI)

Geophysical properties (e.g., velocity) can be obtained via seismic surveys.

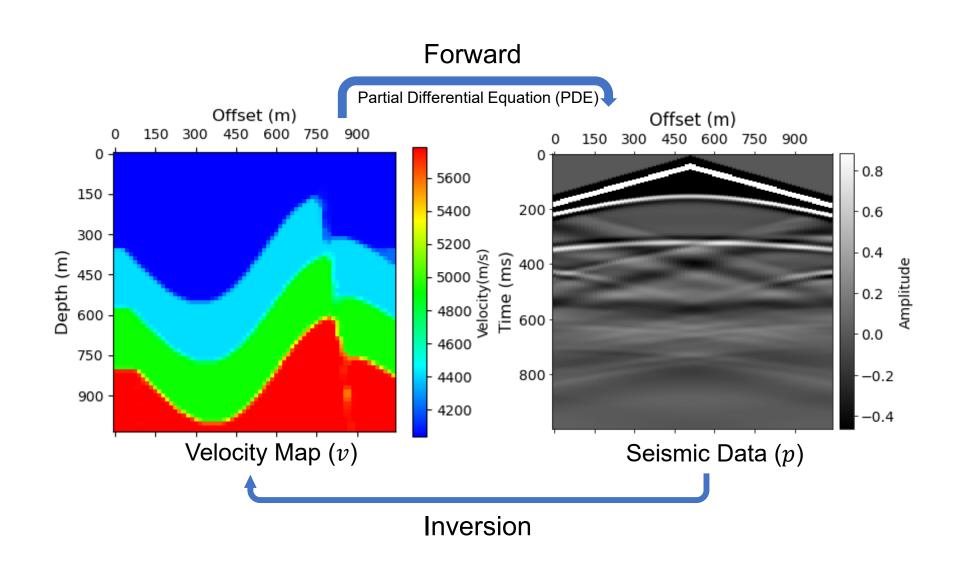


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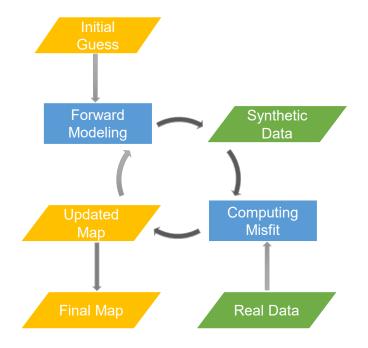




#### Can we leverage the advantages of both directions?

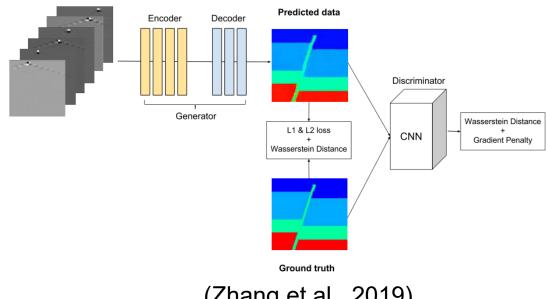
#### **Motivation**

### Physics-driven FWI



- No ground truth needed
- High computational cost Expensive to obtain a good initial guess

#### Data-driven FWI

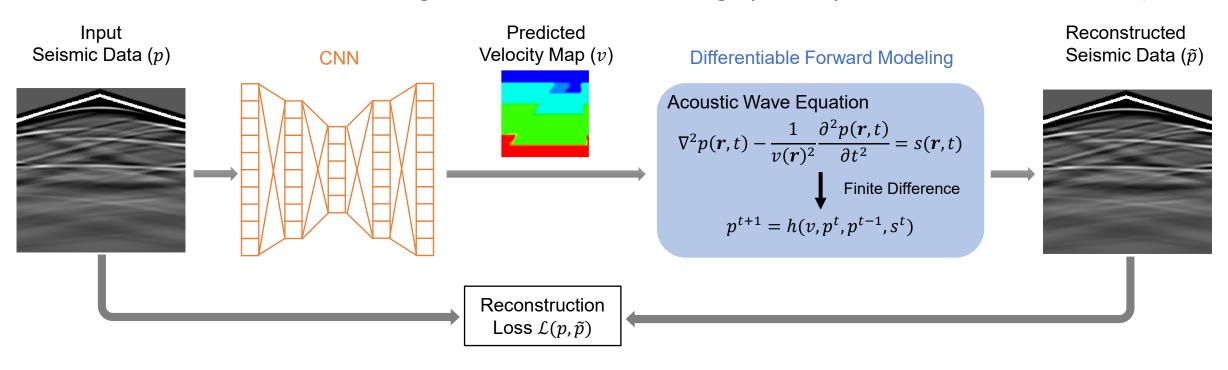


(Zhang et al., 2019)

- No initial guess needed Have certain level of generalization
- Require ground truth velocity maps for training

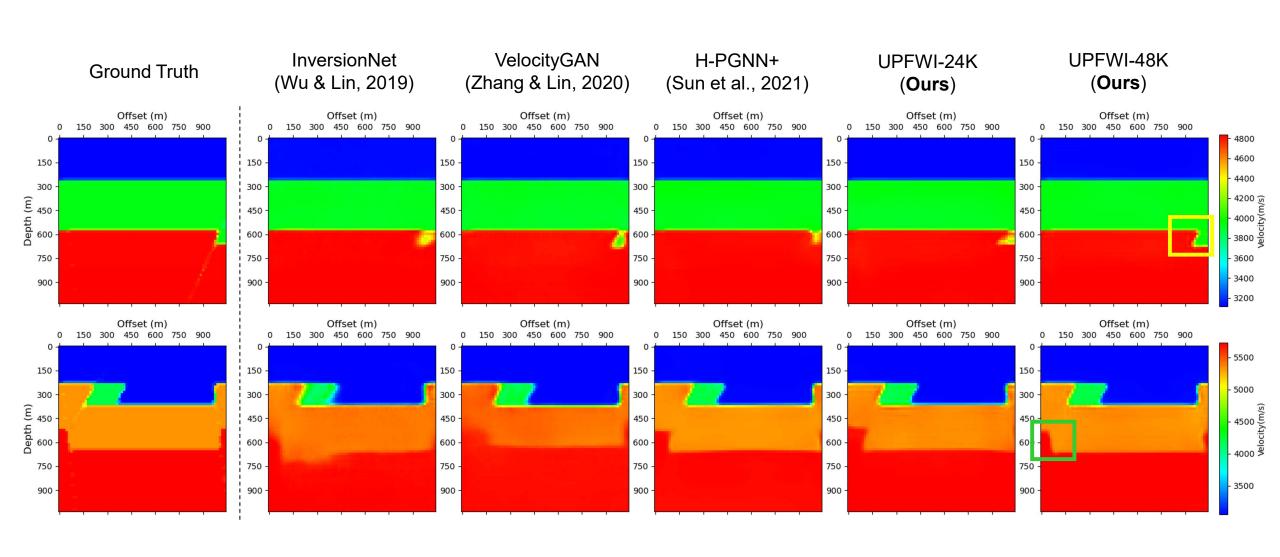
#### Method

### Main idea: connecting forward modeling (PDE) and CNN in a loop.

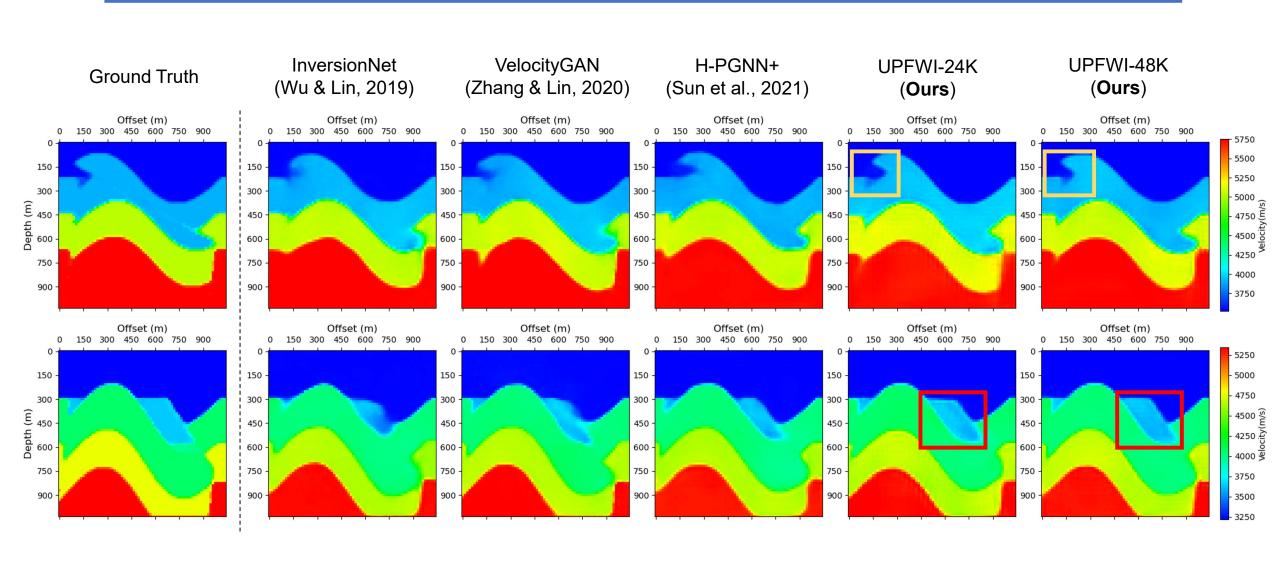


$$\mathcal{L}(\boldsymbol{p}, \widetilde{\boldsymbol{p}}) = \mathcal{L}_{pixel}(\boldsymbol{p}, \widetilde{\boldsymbol{p}}) + \mathcal{L}_{perceptual}(\boldsymbol{p}, \widetilde{\boldsymbol{p}})$$

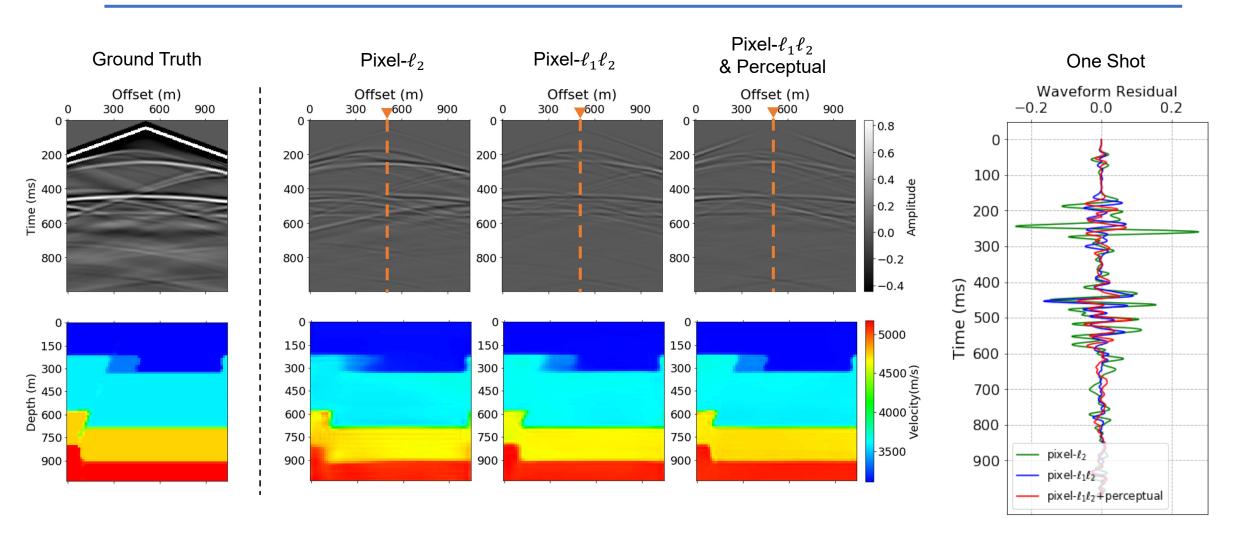
## Results (FlatFault)



## Results (CurvedFault)



## Ablations (Loss Terms)



# Unsupervised Learning of Full-Waveform Inversion: Connecting CNN and Partial Differential Equation in a Loop

## Thank you for listening!

Our dataset is integrated in a follow-up benchmark dataset available at: <a href="https://openfwi-lanl.github.io/">https://openfwi-lanl.github.io/</a>