Physics-guided neural network for velocity calibration using downhole microseismic data

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Outline

Background

Architecture of neural network

- ❑ Fully connected layers
- ❑ Forward modeling layer

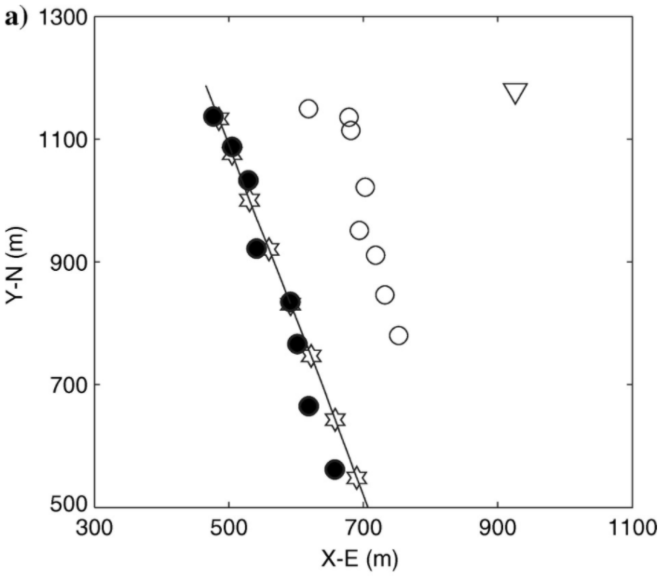
Synthetic Example

- ❑ Dataset & Results
- ❑ Loss function
- ❑ Uncertainty analysis

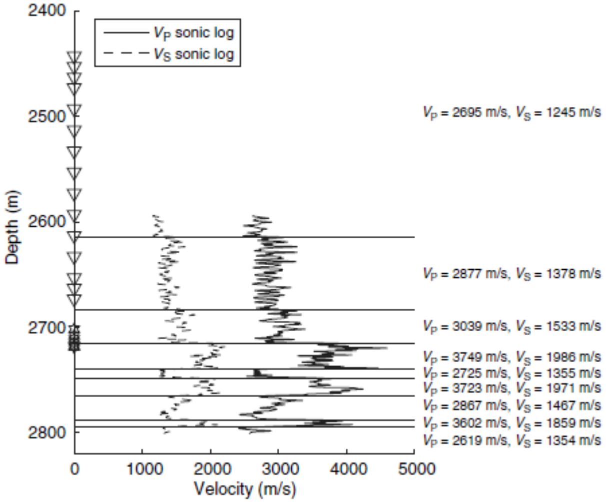
Summary

Background

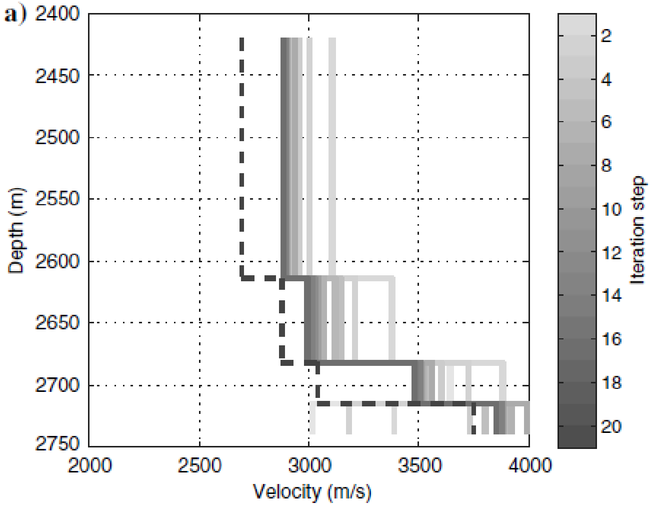
- 1-D layered isotropic velocity models are typically used for microseismic event location
- Velocity is calibrated prior to being used for MS event location



Locations of calibration shots



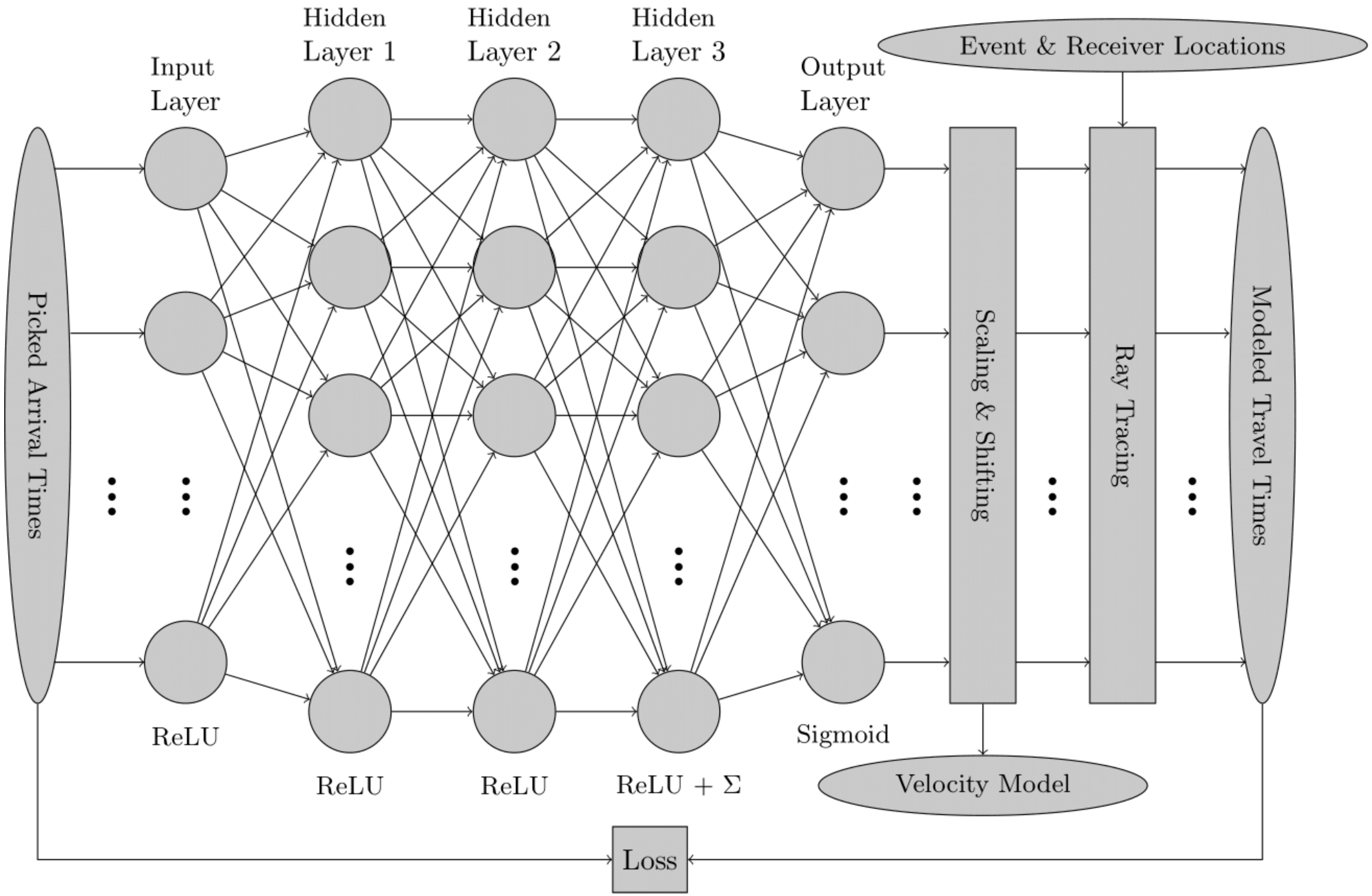
Initial velocity



Calibrated velocity

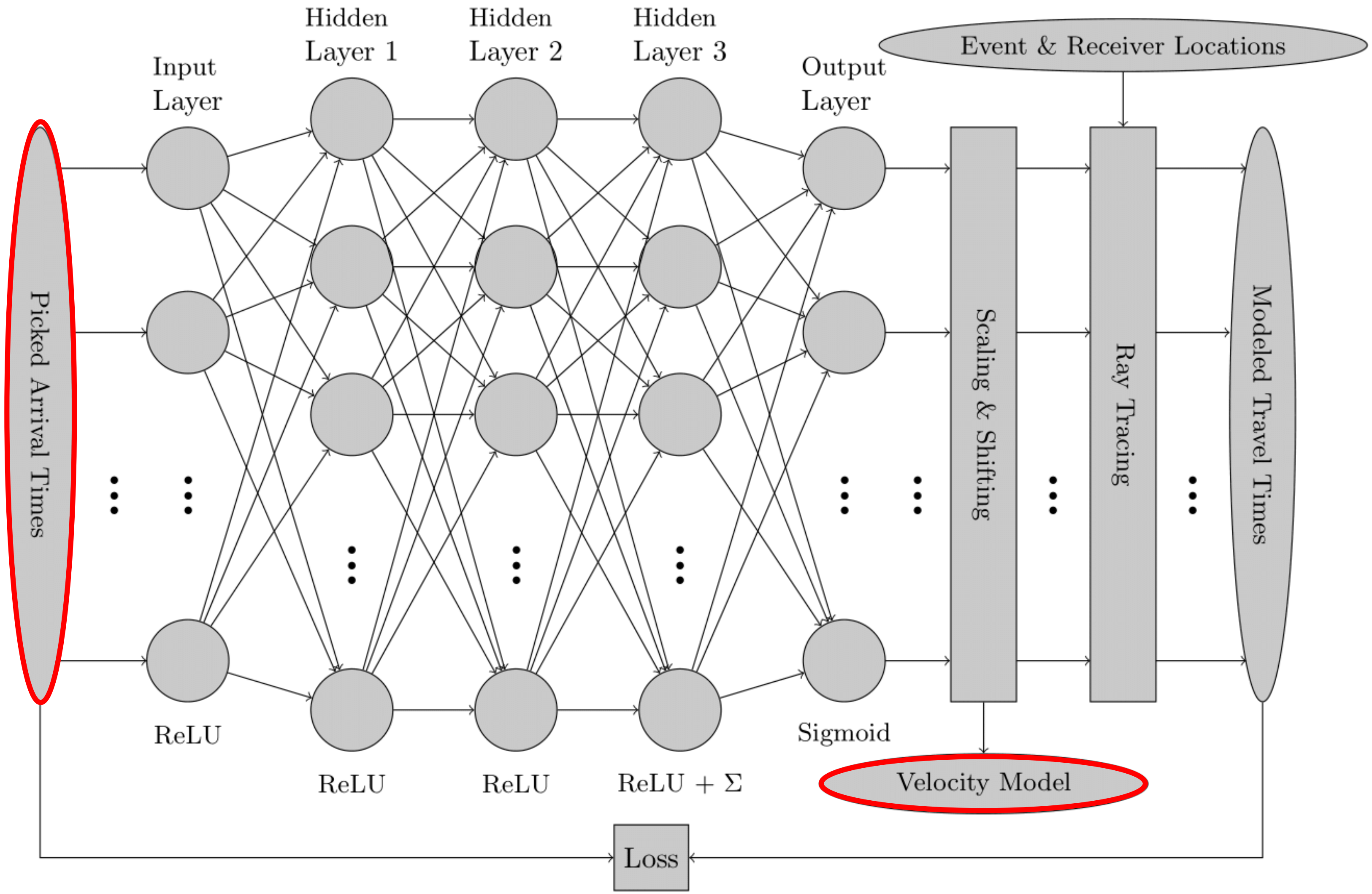
Tan et al., 2018

Physics-guided neural network



Physics-guided neural network

❑ **Input & Output**

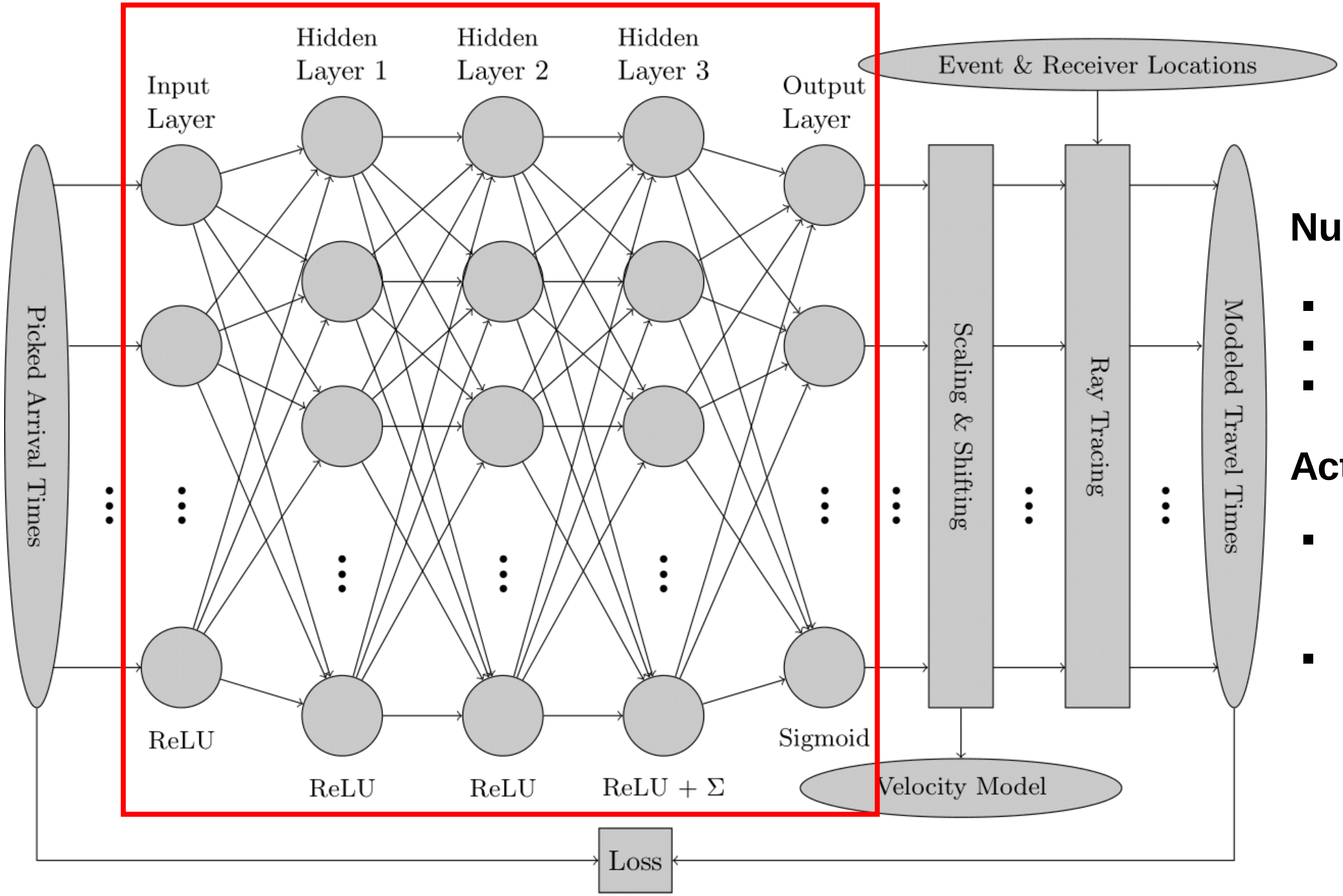


Input: Picked first arrival times of P- and S-waves

Output: Layer velocity values for P- and S-waves

Physics-guided neural network

- Fully connected layers



Number of Neurons

- Input Layer: 2 X number of geophones
- Hidden Layer: 32
- Output Layer: 2 X number of layers

Activation Function

- Relu

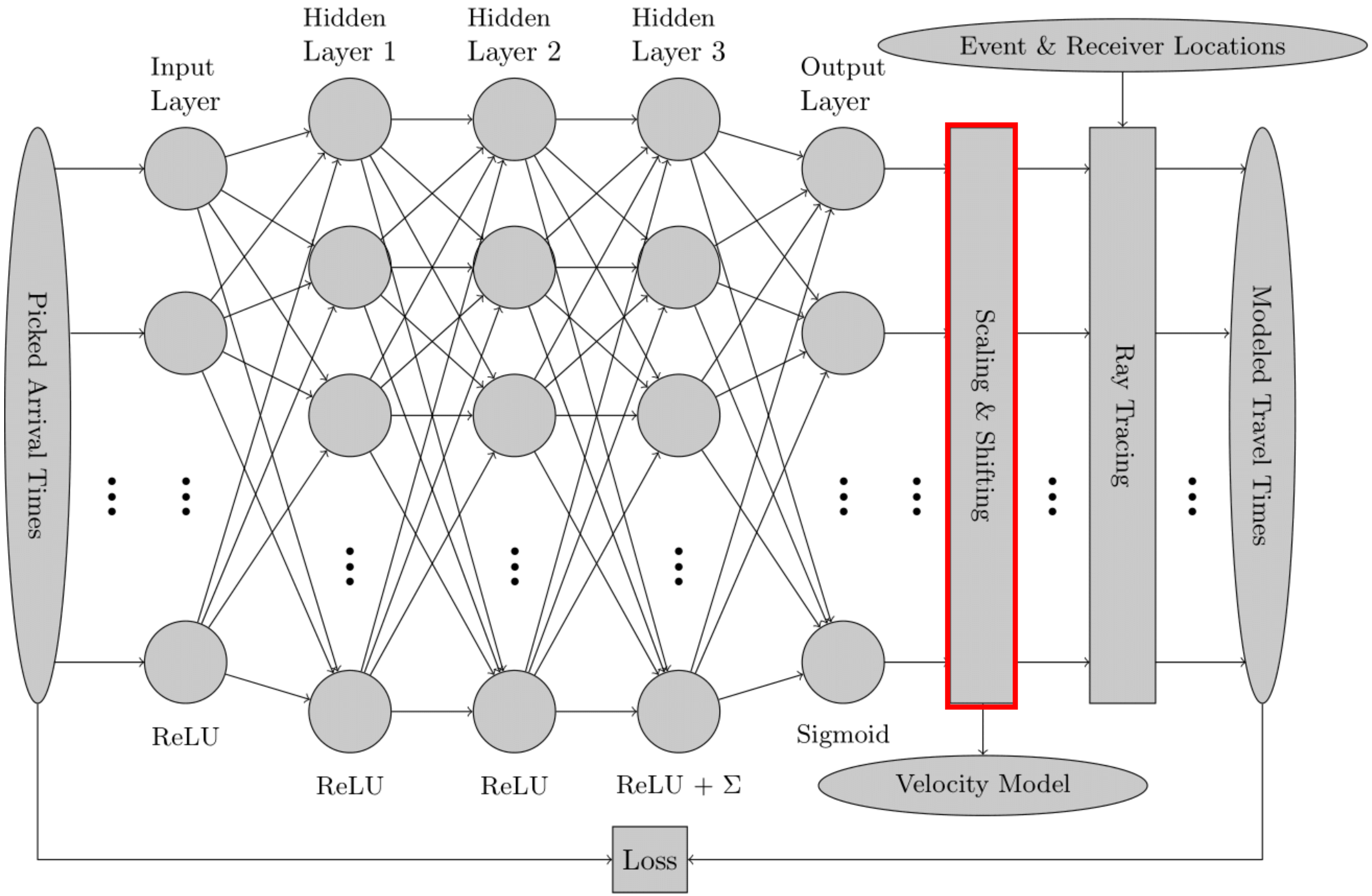
$$f(x) = \max(0, x)$$

- Sigmoid

$$f(x) = \frac{1}{1+e^{-x}}$$

Physics-guided neural network

❑ Scaling & Shifting layer



- **Scaling & Shifting**

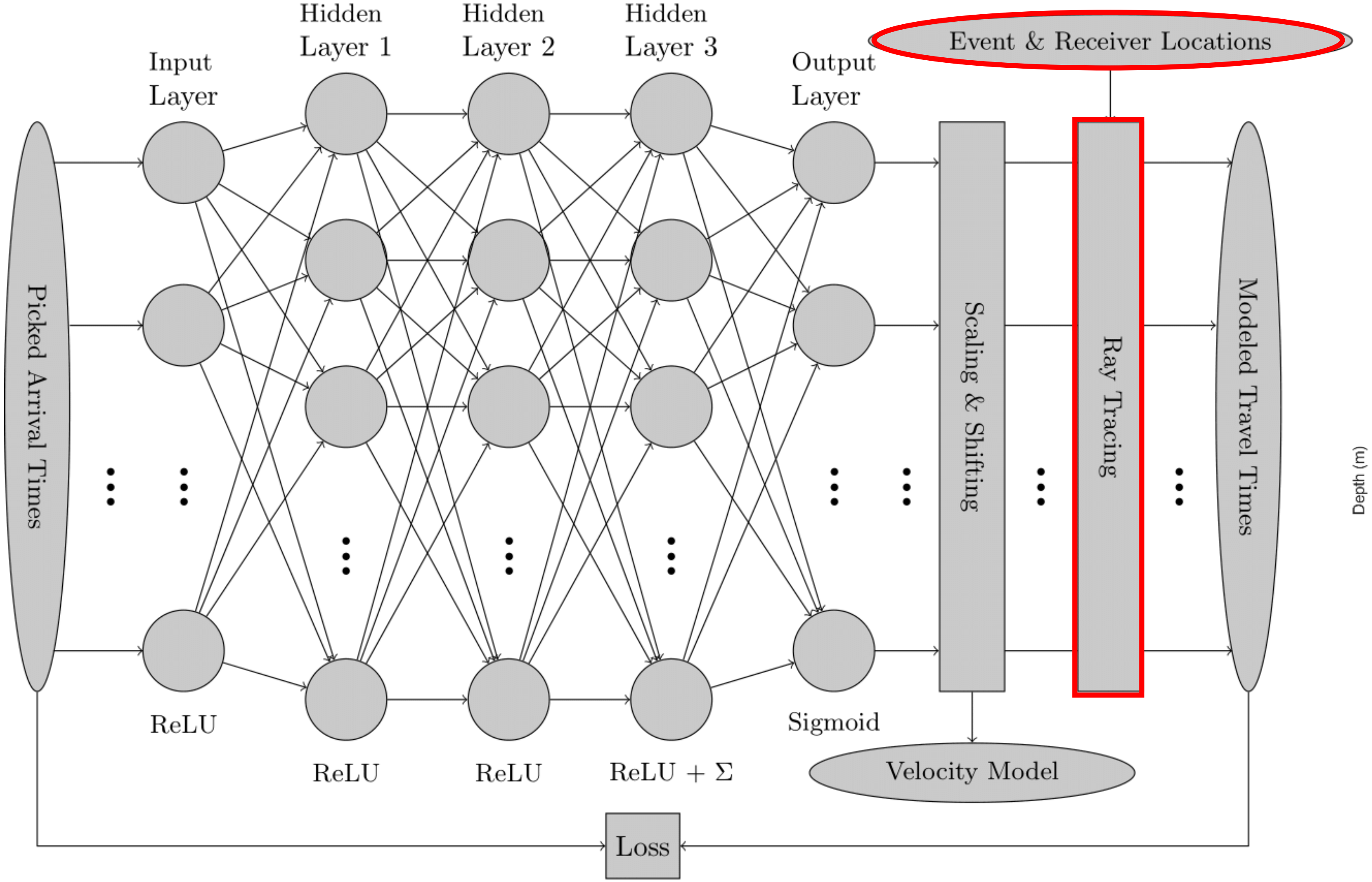
$$\mathbf{v} = \mathbf{a}_0 + \mathbf{a}_1 \odot \mathbf{y}$$

$\mathbf{a}_0$:Lower bounds of layer velocities

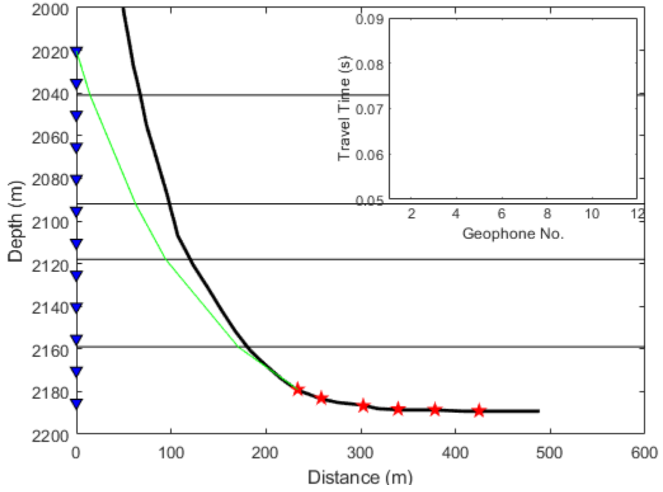
$\mathbf{a}_1$:Perturbation intervals of layer velocities

Physics-guided neural network

- Forward modeling layer

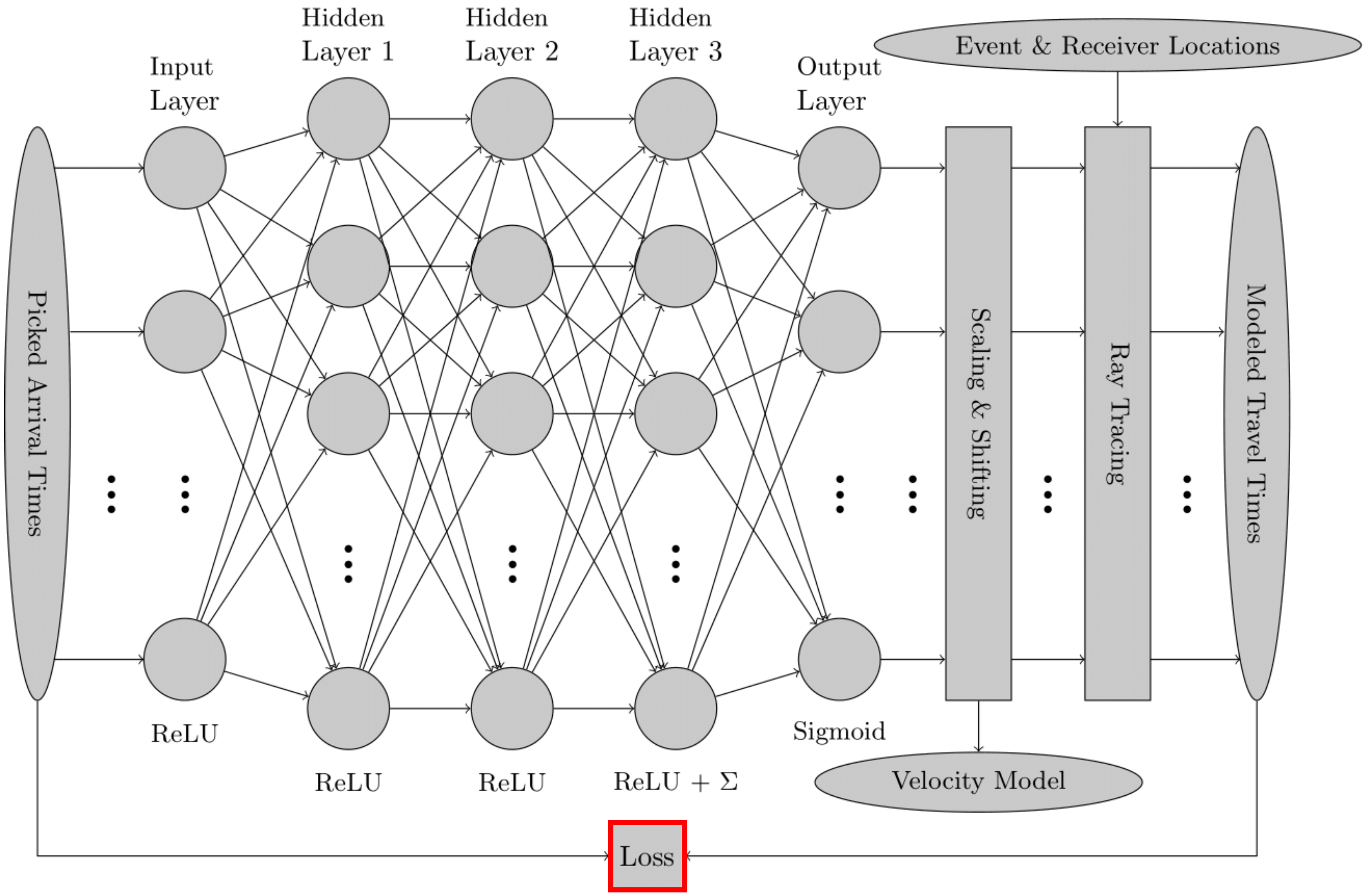


Ray bending



Physics-guided neural network

❑ Loss function



- Loss function

$$\phi = \sqrt{\alpha_1 \sum_{i=1}^{M}\sum_{j=1}^{N}[T_P^{ij} - (t_P^{ij} + T_P^{i0})]^2 + \alpha_2 \sum_{i=1}^{M}\sum_{j=1}^{N}[T_S^{ij} - (t_S^{ij} + T_S^{i0})]^2 + \alpha_3 \sum_{i=1}^{M}\sum_{j=1}^{N}[(T_P^{ij} - T_S^{ij}) - (t_P^{ij} - t_S^{ij})]^2}$$

Tan et al., 2018

- Origin time

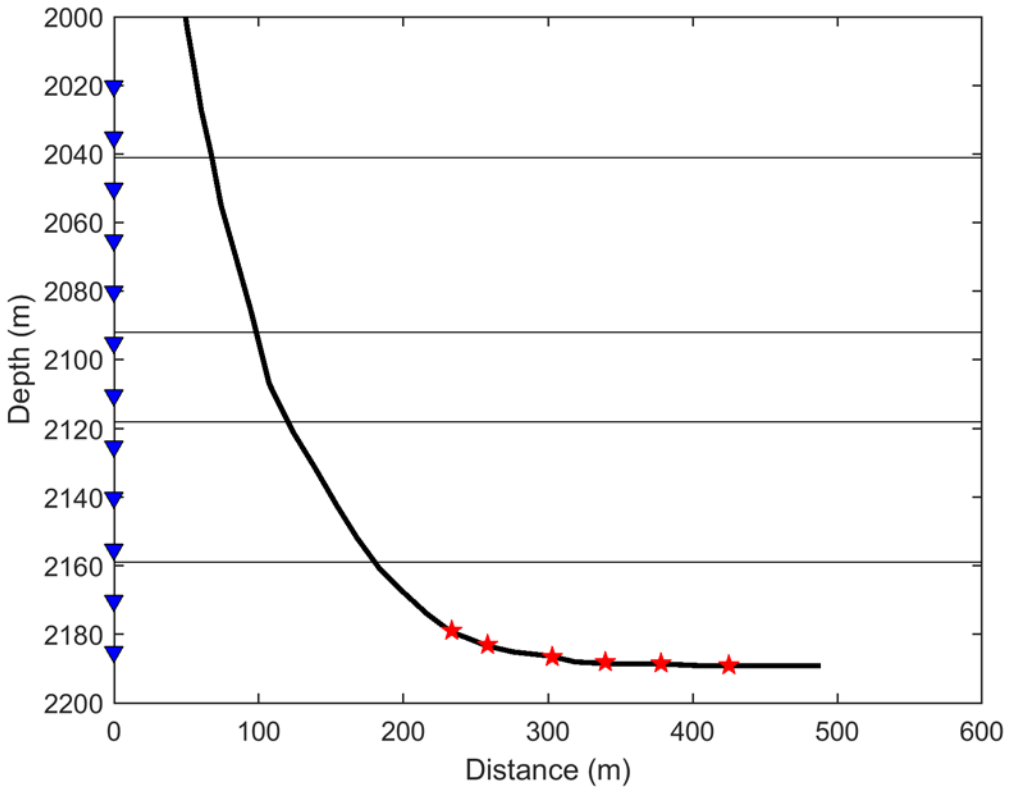
$$T^{i0} = \frac{1}{N}\sum_{j=1}^{N}(T^{ij} - t^{ij})$$

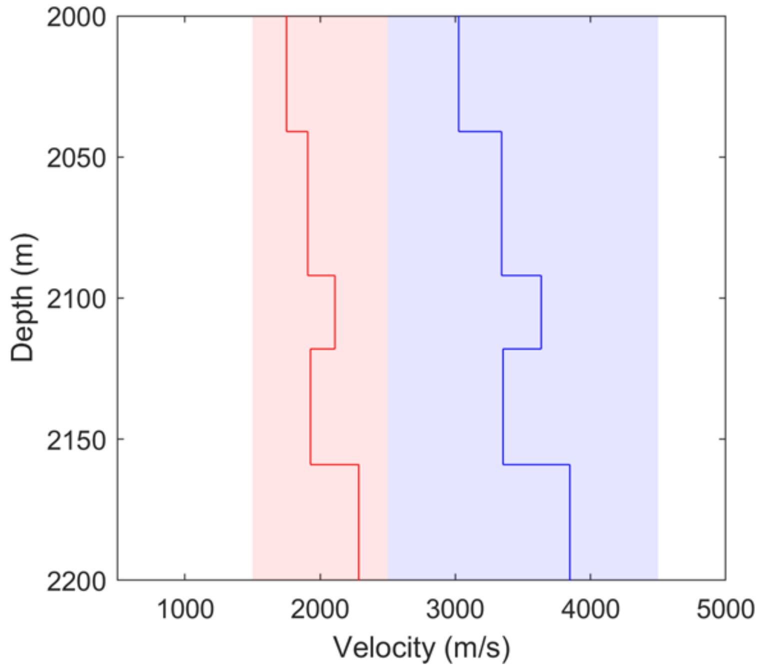
Nelson and Vidale, 1990

Synthetic Example

- **Acquisition geometry & Velocity model**

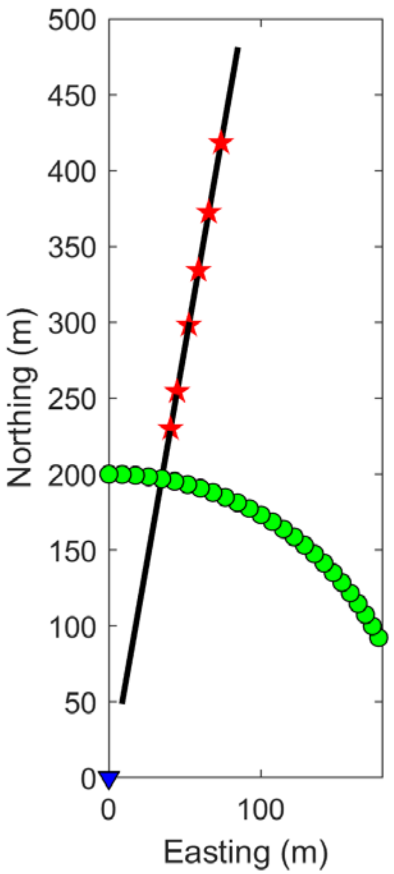
  - 12 geophones
  - 6 calibration shots

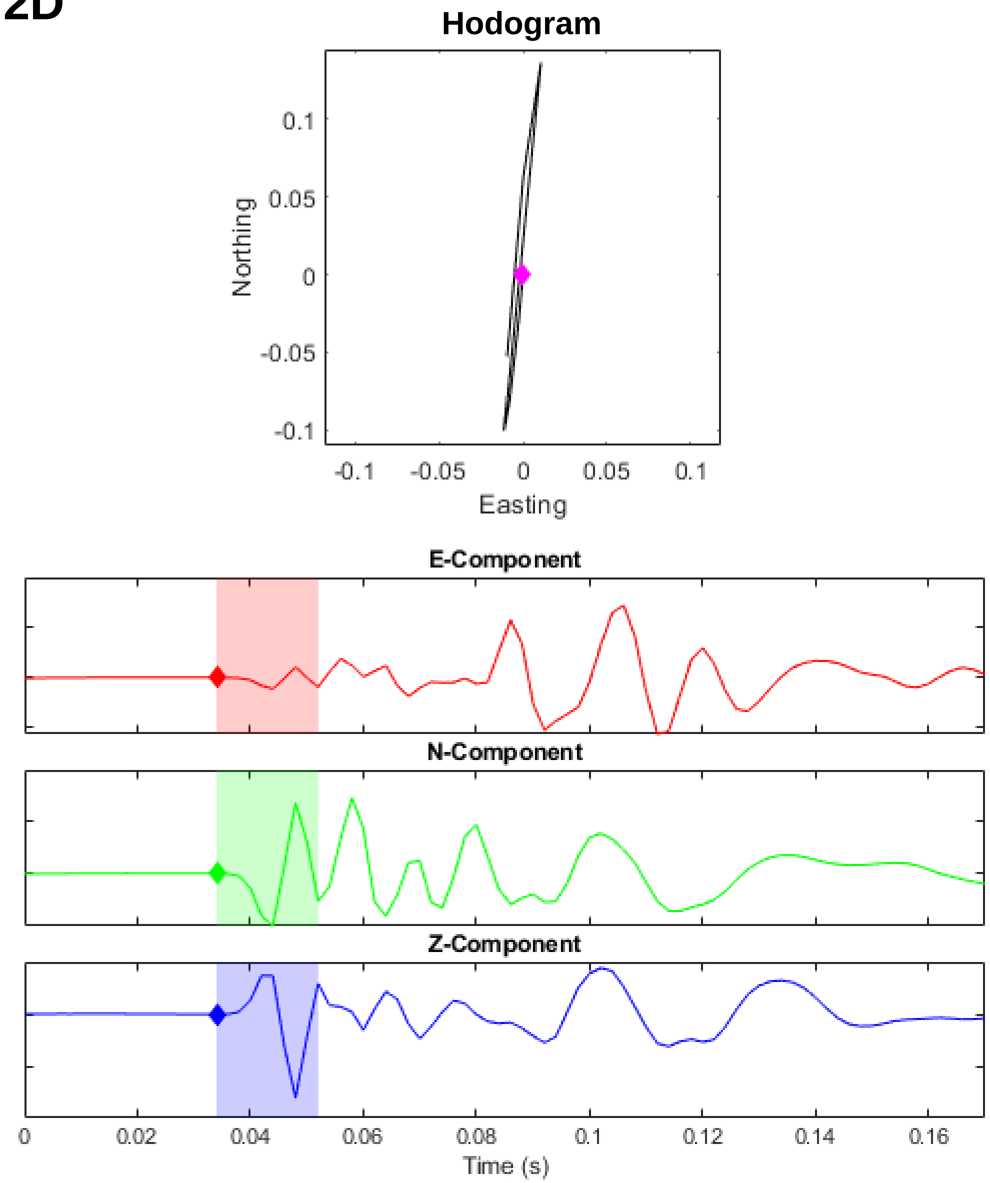


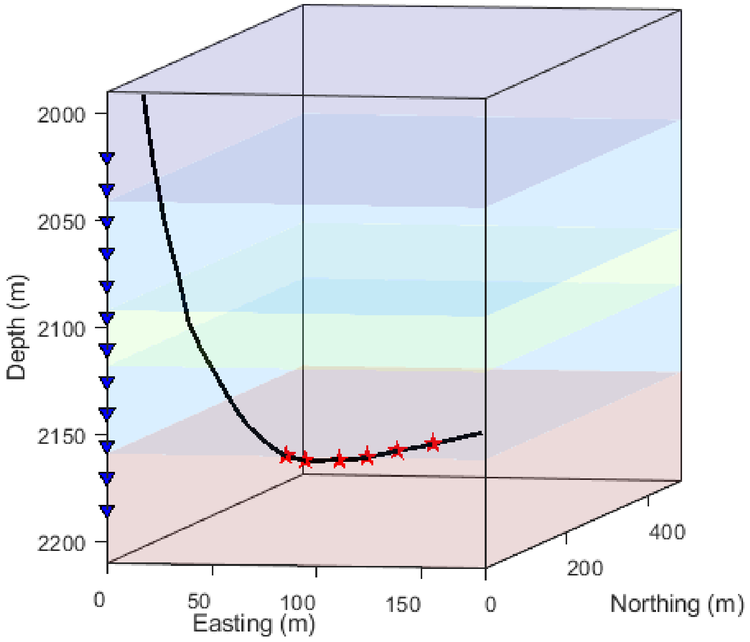


Synthetic Example

- Simplification from 3D to 2D

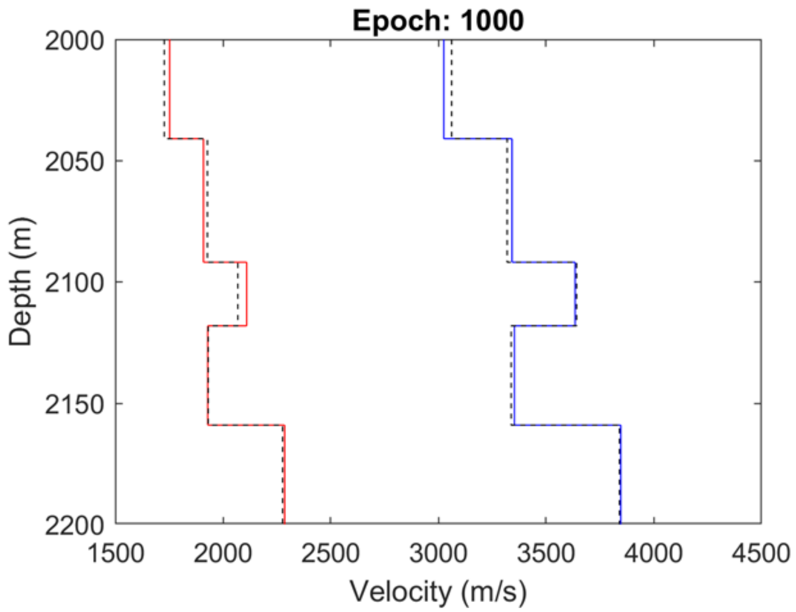


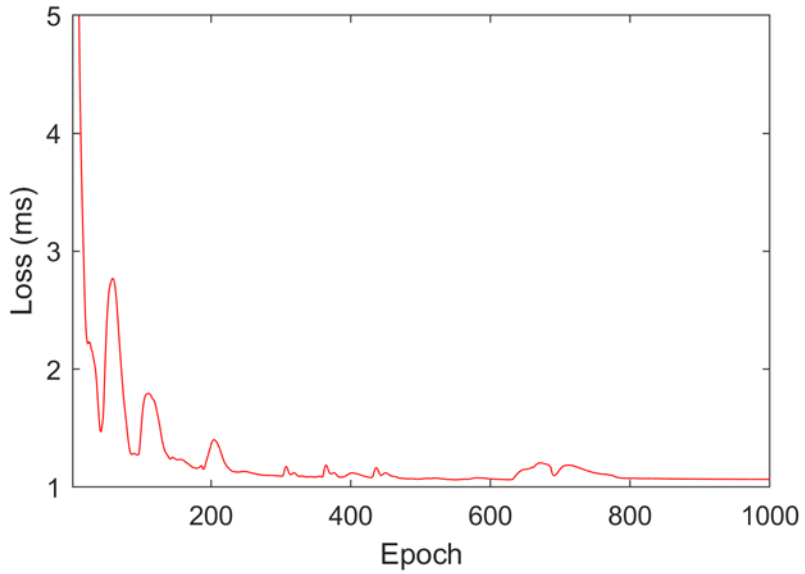




❑ Results

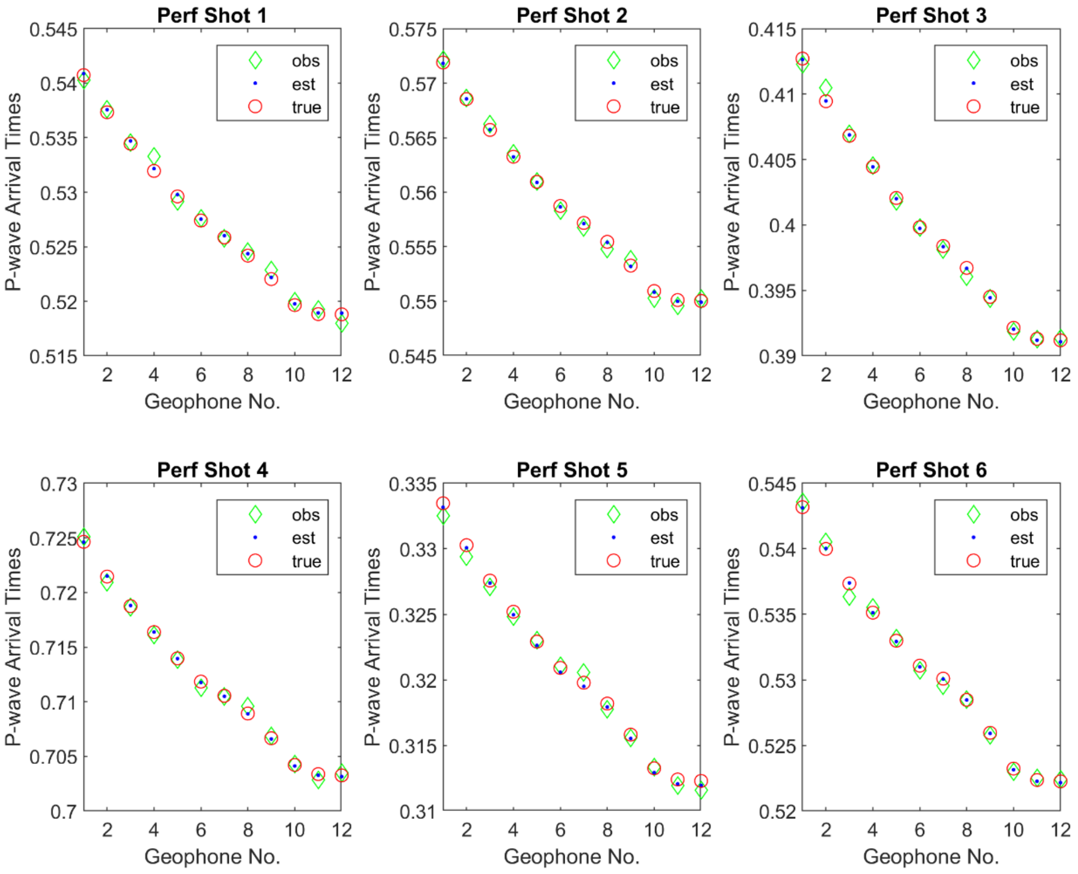
- Adam algorithm
- 1,000 iterations
- Noise standard deviation: 0.5 ms
- PyTorch
- Intel Core i7-8700 CPU, 16 GB Memory
- ~ 10 min for training



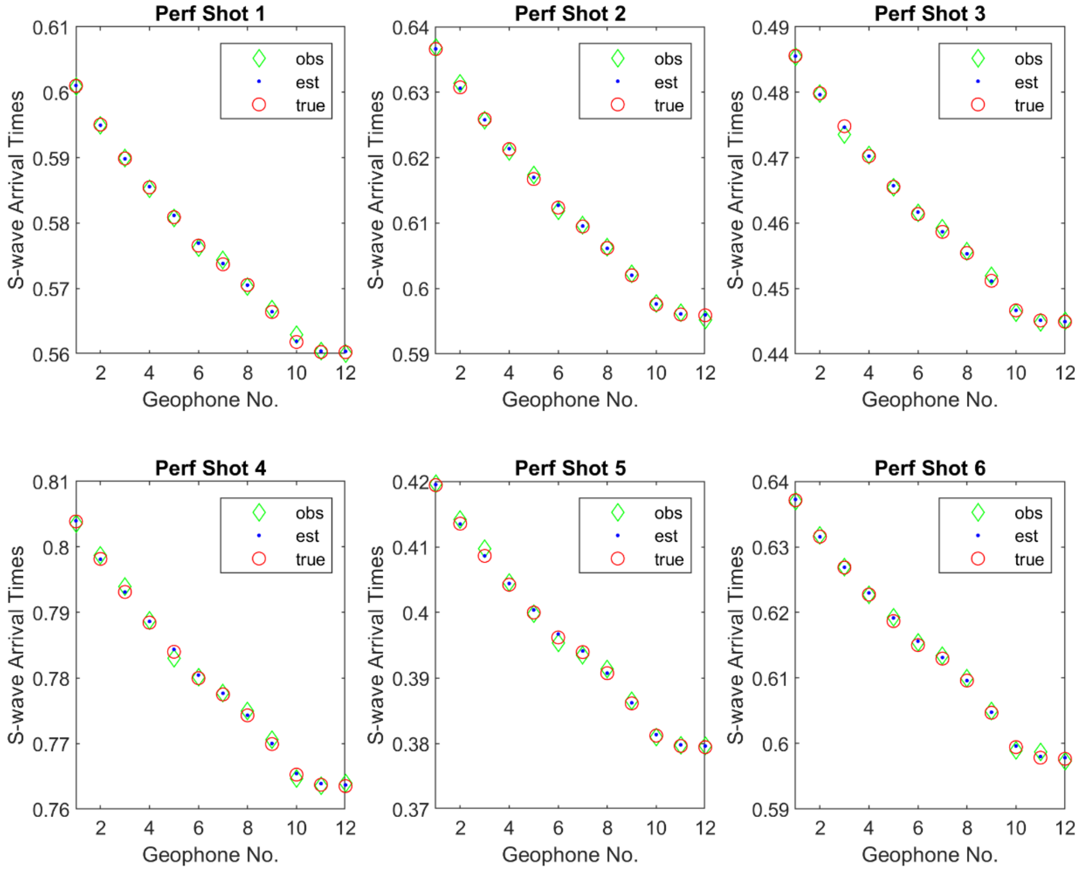


Synthetic Example

P-wave arrival times



S-wave arrival times



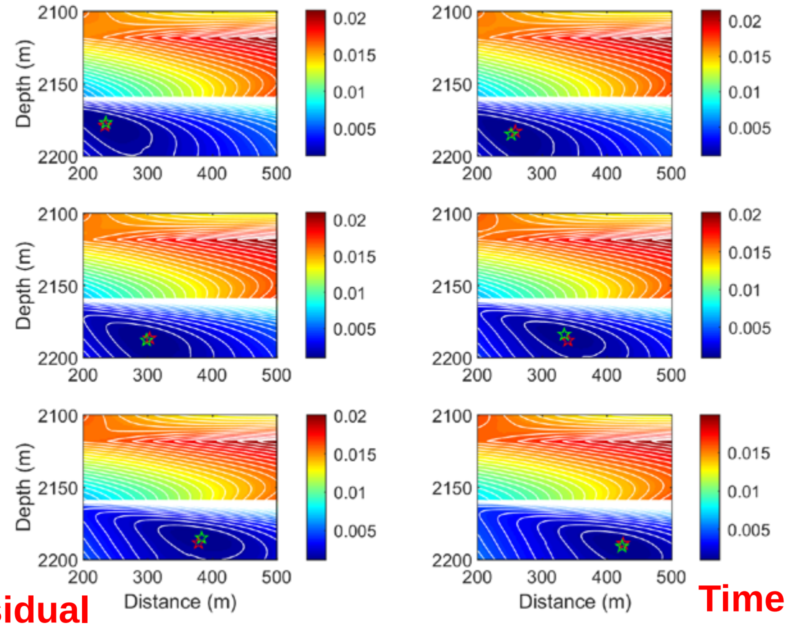
Mean rms errors: 0.45 ms and 0.51 ms

Synthetic Example

❑ Locations of Calibration Shots

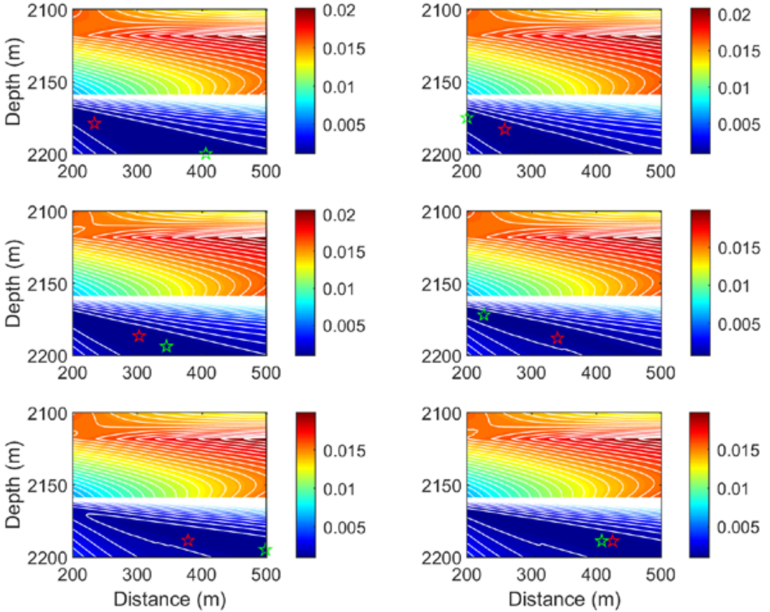
$$\phi = \sqrt{\alpha_1 \sum_{i=1}^{M}\sum_{j=1}^{N}[T_P^{ij} - (t_P^{ij} + T_P^{i0})]^2 + \alpha_2 \sum_{i=1}^{M}\sum_{j=1}^{N}[T_S^{ij} - (t_S^{ij} + T_S^{i0})]^2 + \alpha_3 \sum_{i=1}^{M}\sum_{j=1}^{N}[(T_P^{ij} - T_S^{ij}) - (t_P^{ij} - t_S^{ij})]^2}$$

Hybrid loss function

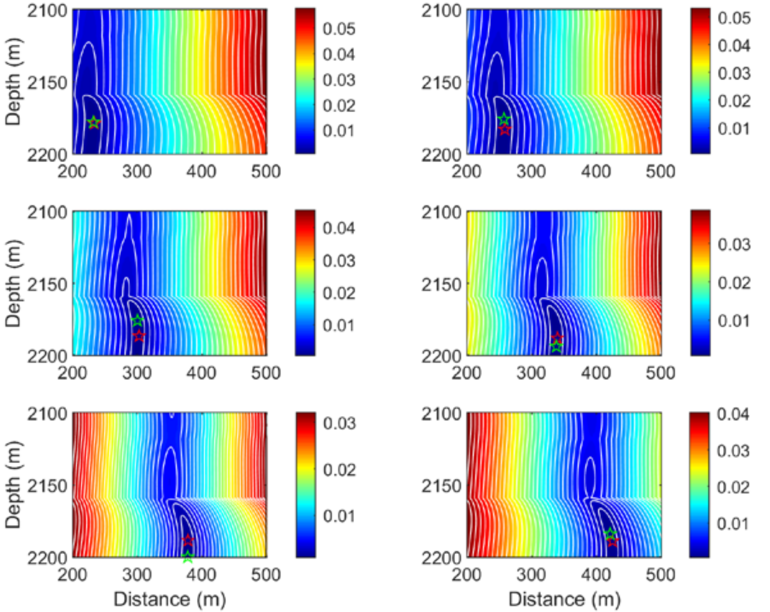


Mean deviations of depth and distance: 2.2 m and 3.6 m

Arrival time residual



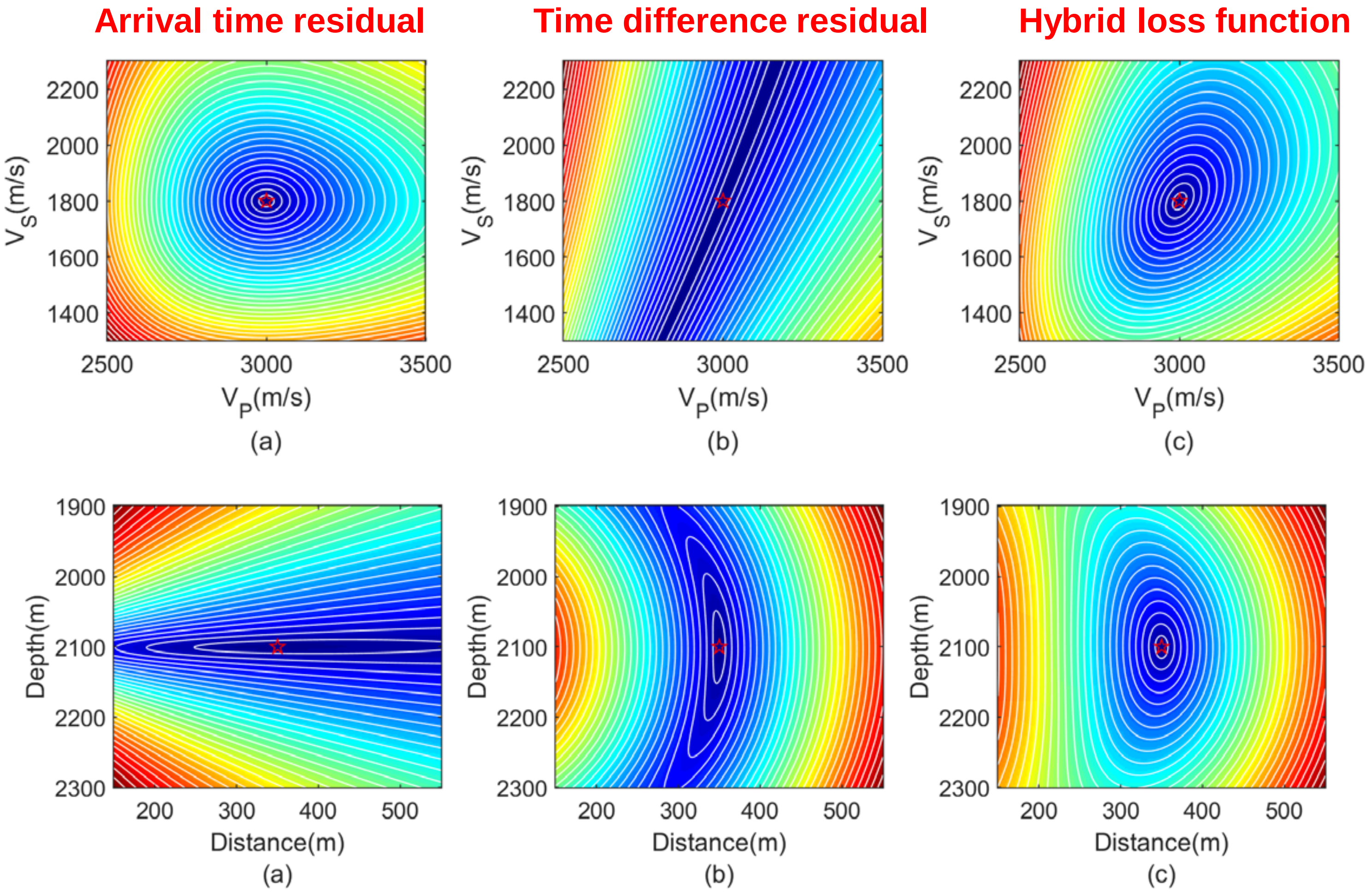
Time difference residual



Synthetic Example

❑ Locations of Calibration Shots

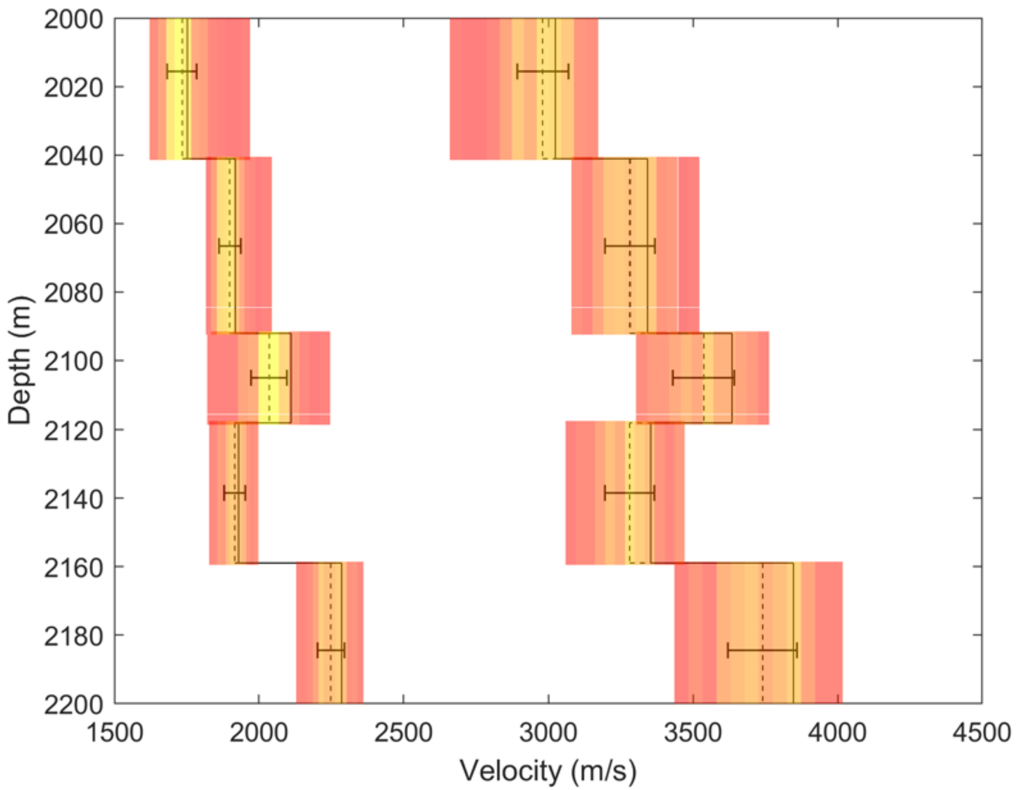
- **Velocity-calibration problem**
- **Event-location problem**



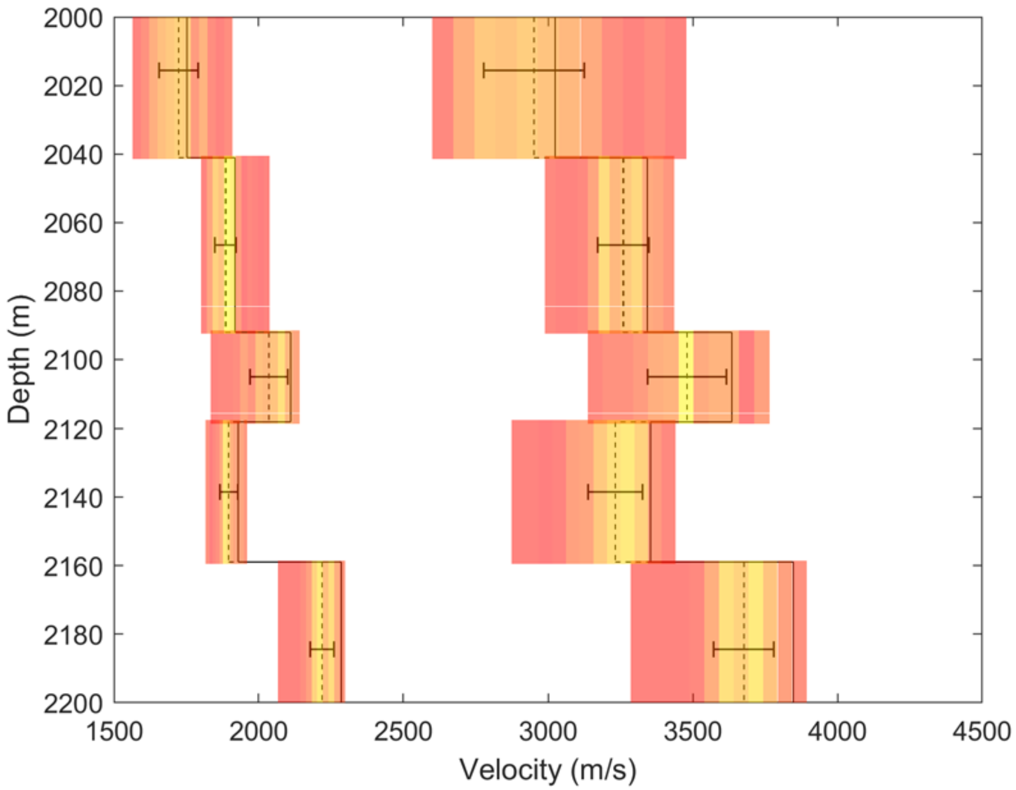
Synthetic Example

❑ Uncertainty Analysis

Results using six calibration shots



Results using one calibration shot



- Noise standard deviation: 0.5 ms
- 100 times inversion with different initializations

- Mean deviation from true velocity: 76 m/s, 97 m/s
- Mean standard deviation: 33 m/s, 47 m/s

Summary

We designed a physics-guided neural network to calibrate 1D layered velocity model that

- incorporates a forward modeling layer
- eliminates the need for training data and the explicit programming for inversion algorithm

A hybrid loss function is used that provides better constraints for both event-location and velocity-calibration problems

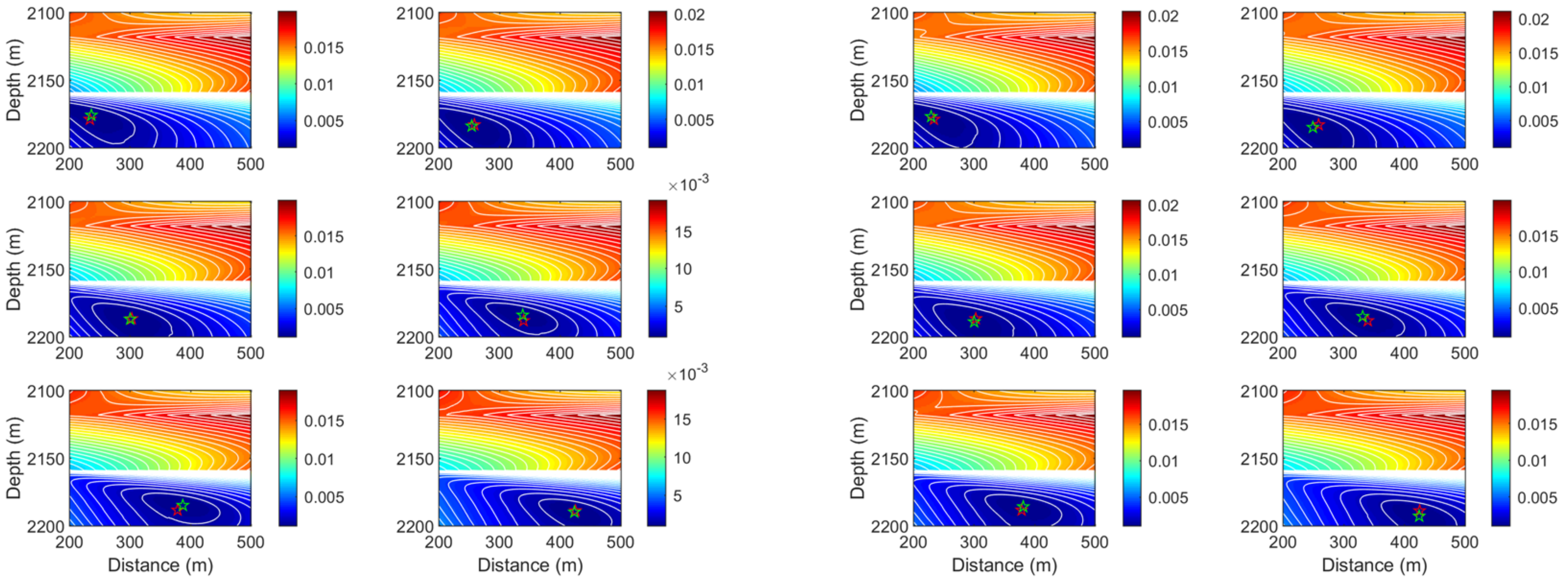
The proposed neural network will be further tested with field data

Acknowledgements

- All CREWES sponsors
- NSERC (CRDPJ 461179-13, CRDPJ 543578-19)
- Canada First Research Excellence Fund (CFREF)

Thank you!

Synthetic Example



Mean deviations of depth: 2.2 m, 2.7 m
Mean deviations of distance: 3.6 m, 4.7 m