Machine learning for emulation of seismic-phase travel times in 3D earth models

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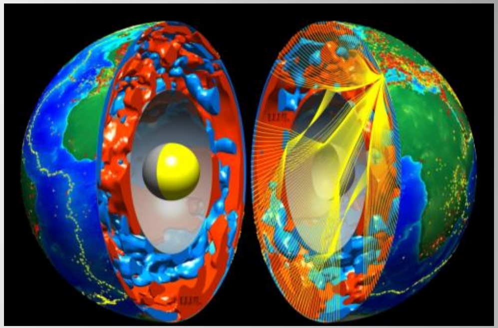
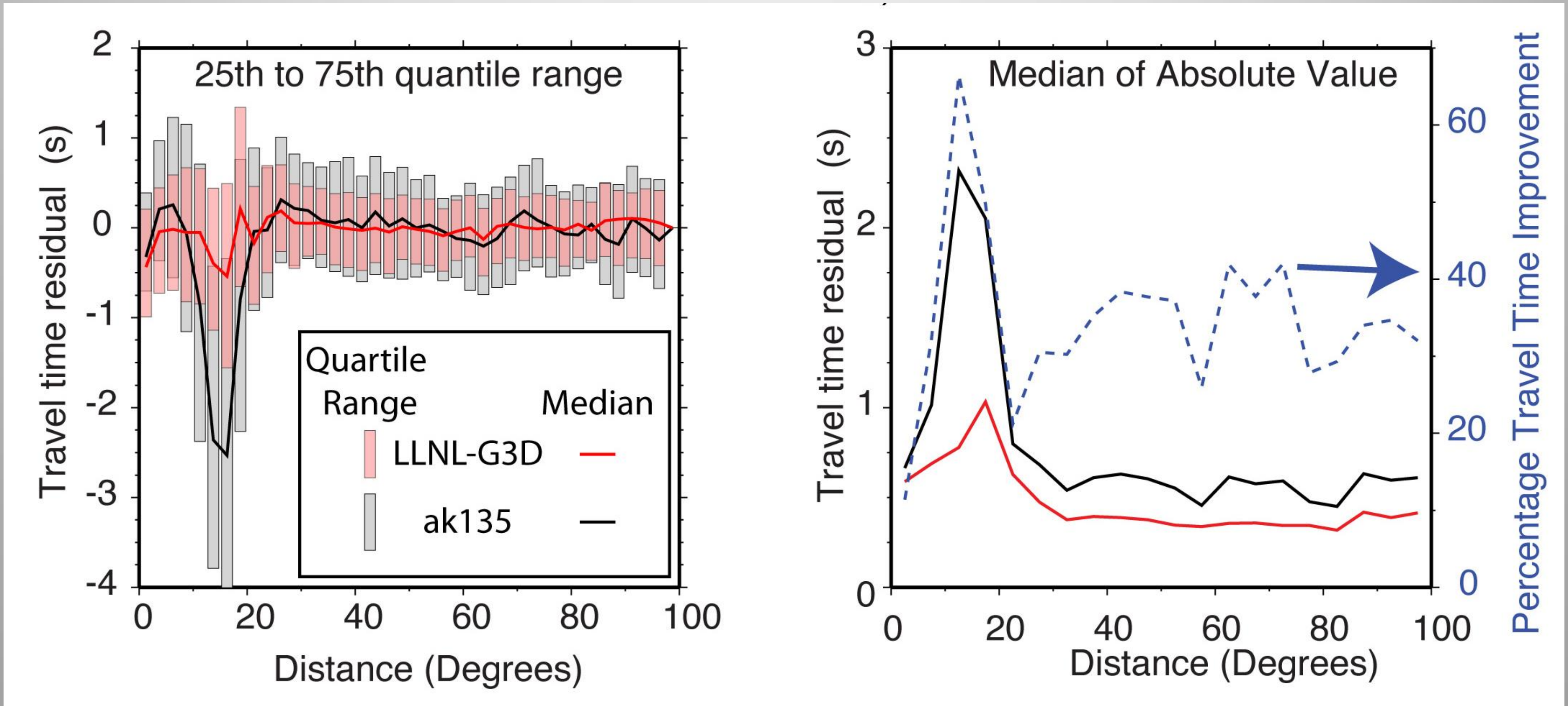
Global 3D models significantly reduce prediction error of seismological observables

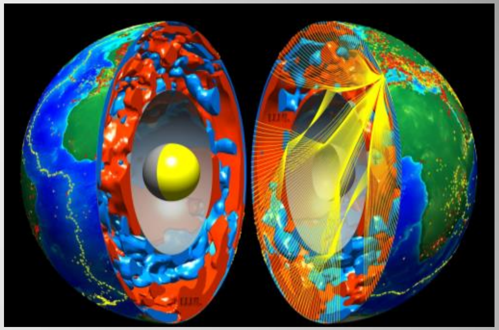


Improved travel time prediction

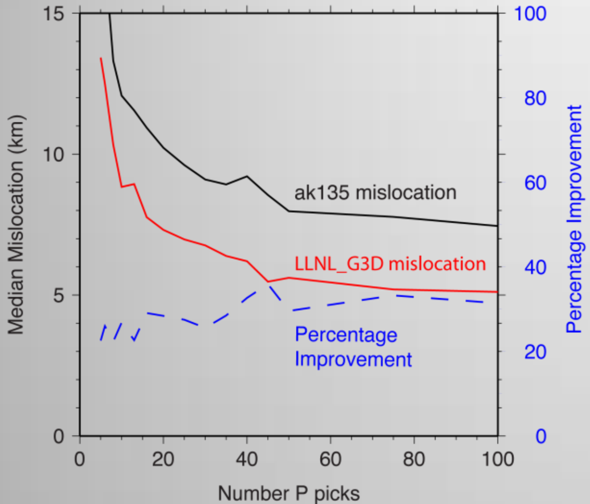


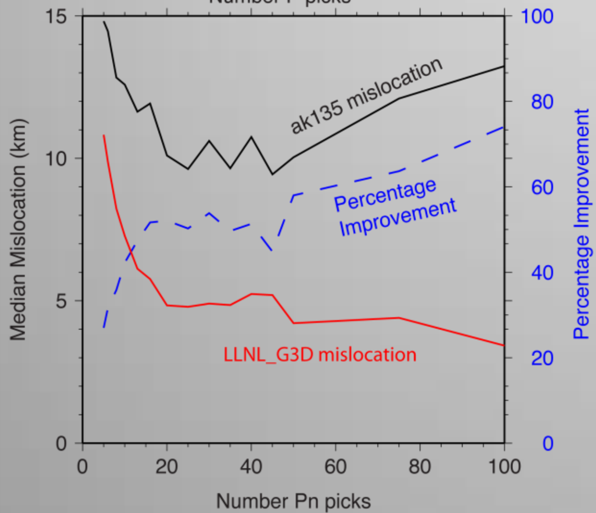
Myers et al., 2015

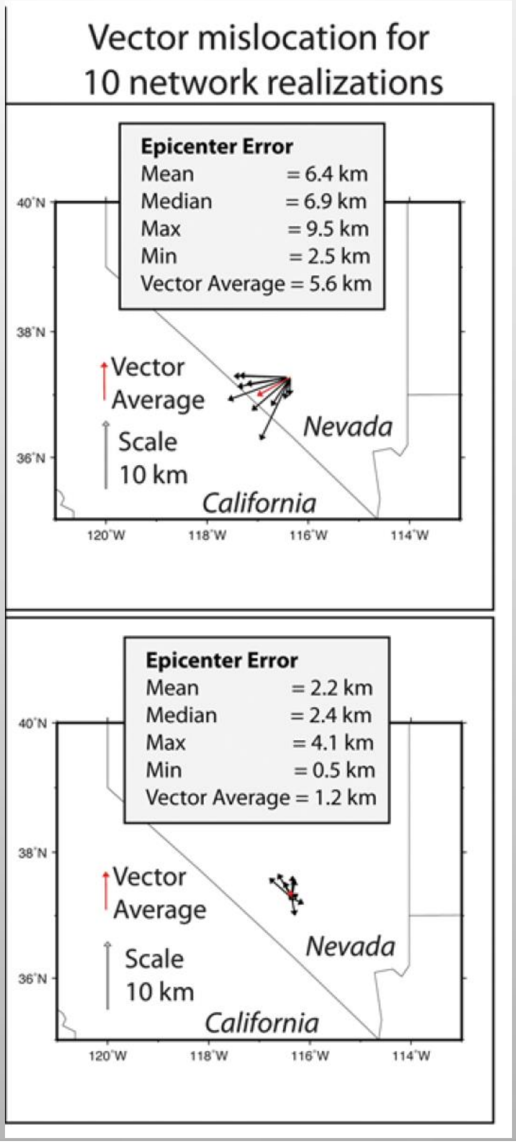
Improved travel time prediction errors reduce event location bias and overall mislocation



Improved event location







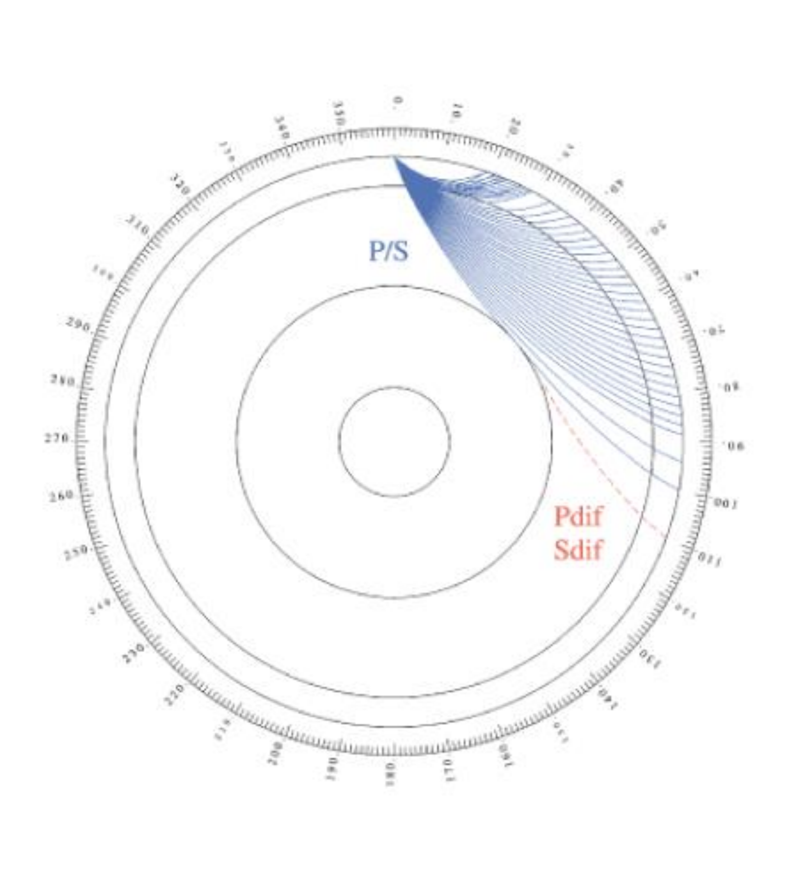
Left
Summary epicenter errors for global set of ground truth events

Right
Epicenter bias when using a 1-D model (top) and a global 3D model (bottom)

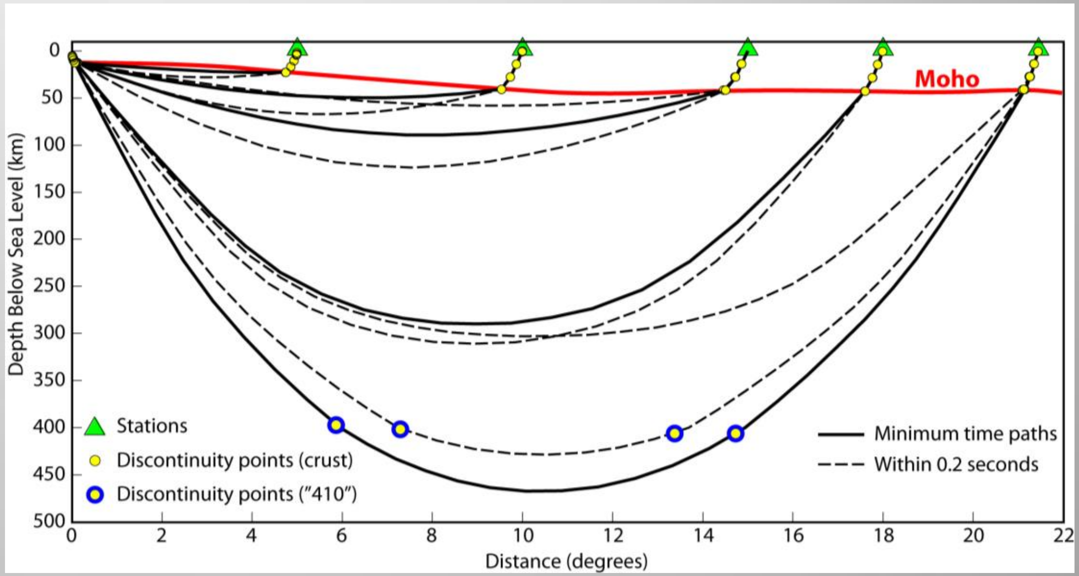
Myers et al., 2015

Computation time through 3D models is too slow for operational monitoring

Computation time for simple teleseismic rays can be less than 0.1 second



Computation time for multi-pathed regional rays can be over 1.0 seconds



Location of a single event using a 3D model may require several minutes of travel time calculations

The current approach for utilization of 3D models is approximation or precomputation

Approximation:

The Regional Seismic Travel Time (RSTT) method can be used for regional phases (Myers et al., 2010)

✓ Millisecond calculation time

✓ Accurate when mantle structure can be approximated with a gradient

- Limited to regional distances (<~15°)

Precomputation

CTBTO-IDC: Source-Specific Station Corrections (SSSCs) store precomputed differences between 3D and 1D models

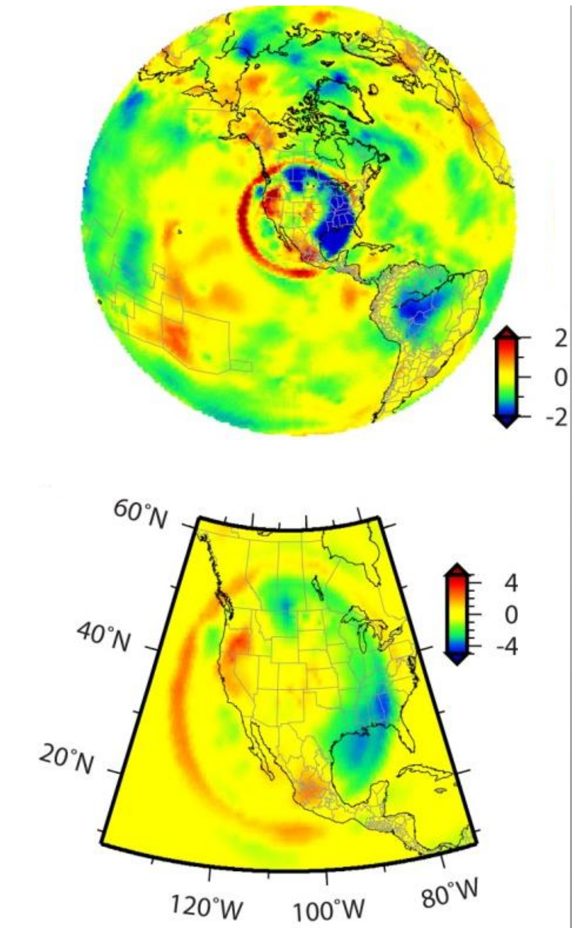
✓ Can be used with fully 3D models

- Global implementation has limiting memory requirements even for operational computer systems
- Very challenging for large and dynamic networks

NonLinLoc: Precomputation on a 3D grid

✓ Proven for static, local networks

Example of geographic correction to 1D-model travel-time prediction



From Simmons et al., 2012

CTBTO=Comprehensive Nuclear-Test-Ban Treaty Organization
IDC=International Data Centre

Machine learning may be the path forward for operational use of 3D models

Machine Learning (ML) is widely used for:

1) Search engines
2) Fraud detection
3) Traffic predictions
4) Spam filtering
5) Facial recognition
6) Speech recognition
7) Product recommendations

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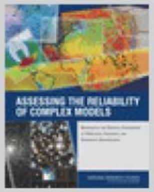
ML for emulation of complex, computationally expensive numerical simulations



Assessing the Reliability of Complex Models: Mathematical and Statistical Foundations of Verification, Validation, and Uncertainty Quantification

ISBN
978-0-309-25634-6

184 pages
8 1/2 x 11
PAPERBACK (2012)

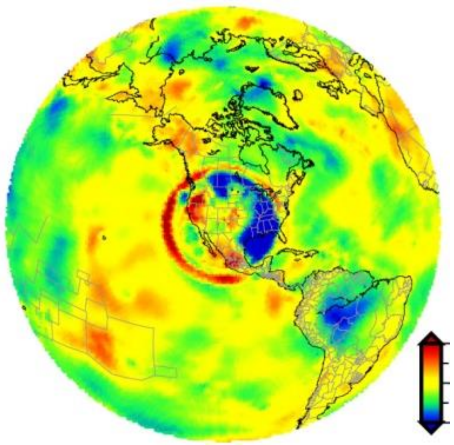
Committee on Mathematical Foundations of Verification, Validation, and Uncertainty Quantification; Board on Mathematical Sciences and Their Applications, Division on Engineering and Physical Sciences, National Research Council

National Academy of Sciences Study

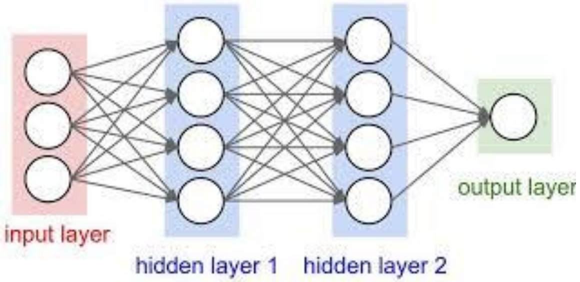
- Are machine learning estimates of full physics calculations valid?
- Paraphrasing: ML is a powerful tool for emulating computationally intensive physics calculations when done correctly.

Overview of the approach for the use of ML for computation of seismic travel times

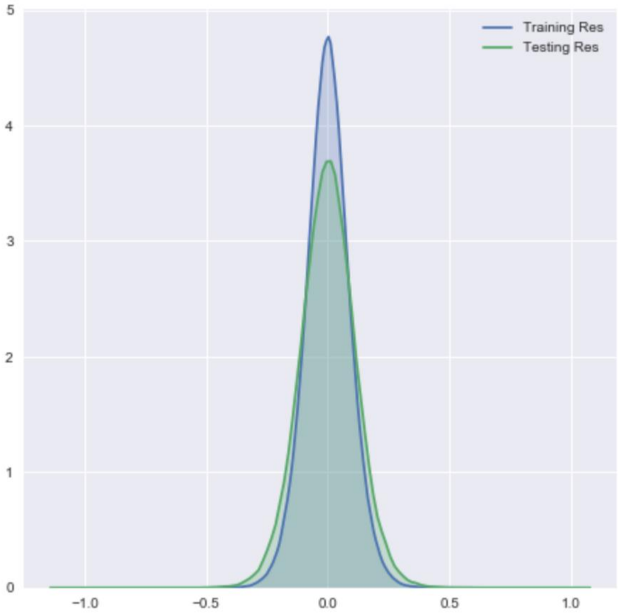
Compute Millions of travel times through the 3D model



Train a deep-learning system to emulate the travel times



Validate



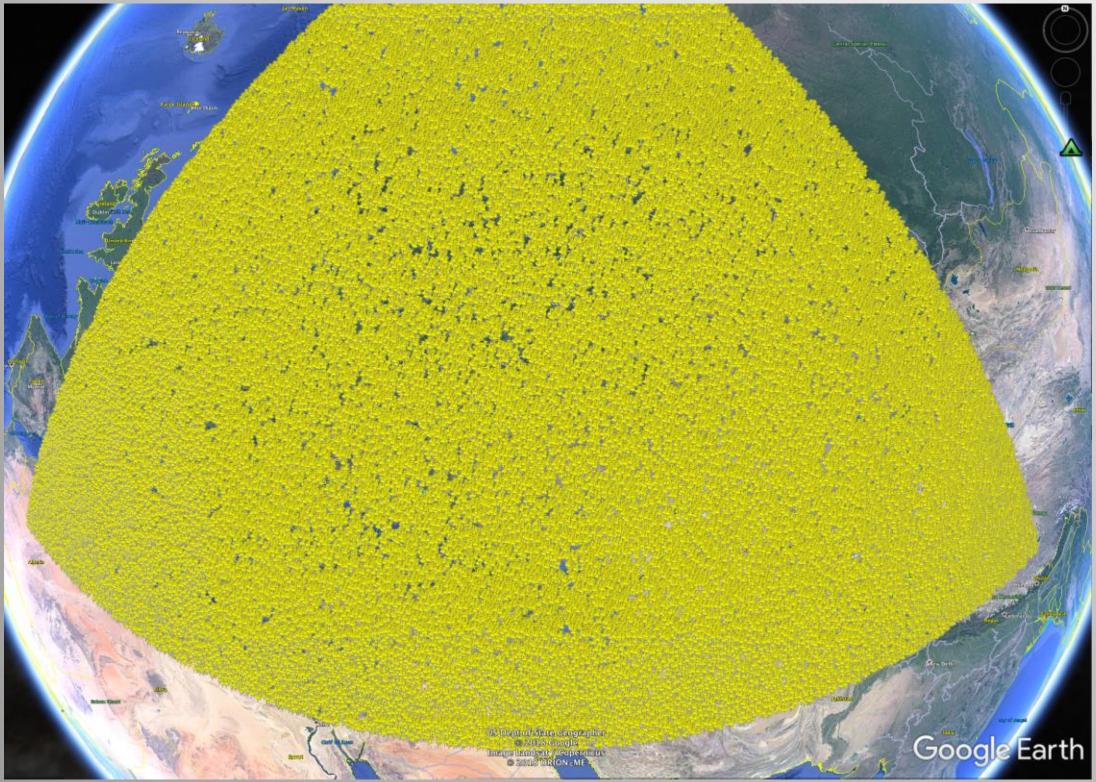
<u>Input</u>
Phase
Event_loc
Station_loc

<u>Output</u>
Travel time
Uncertainty

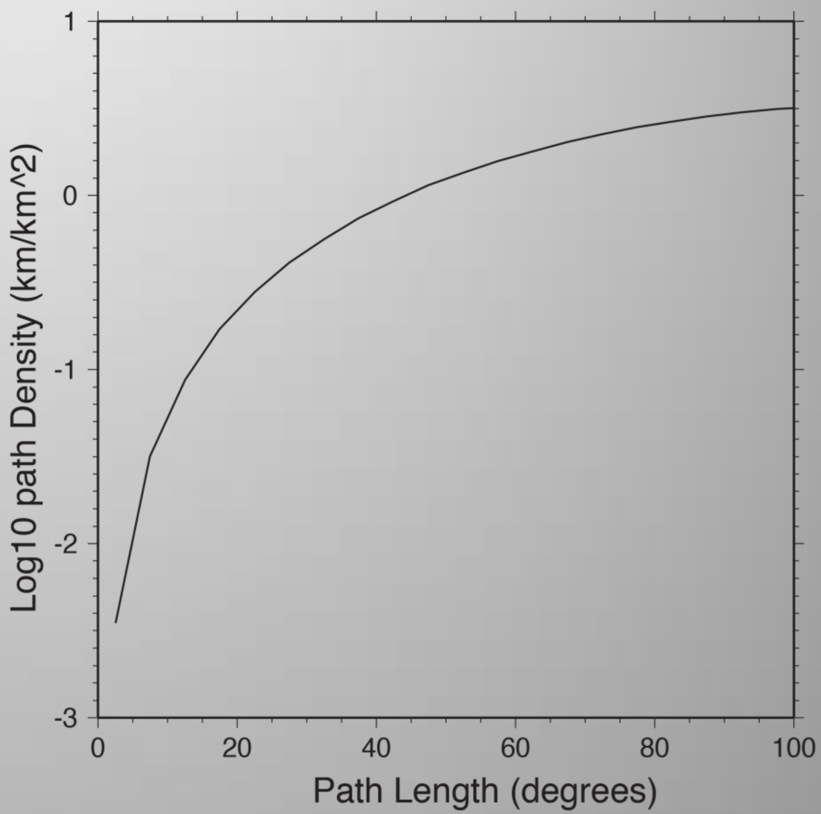
Global training data set

2 Million randomly selected ray paths spanning the globe

Subset of the 2M points

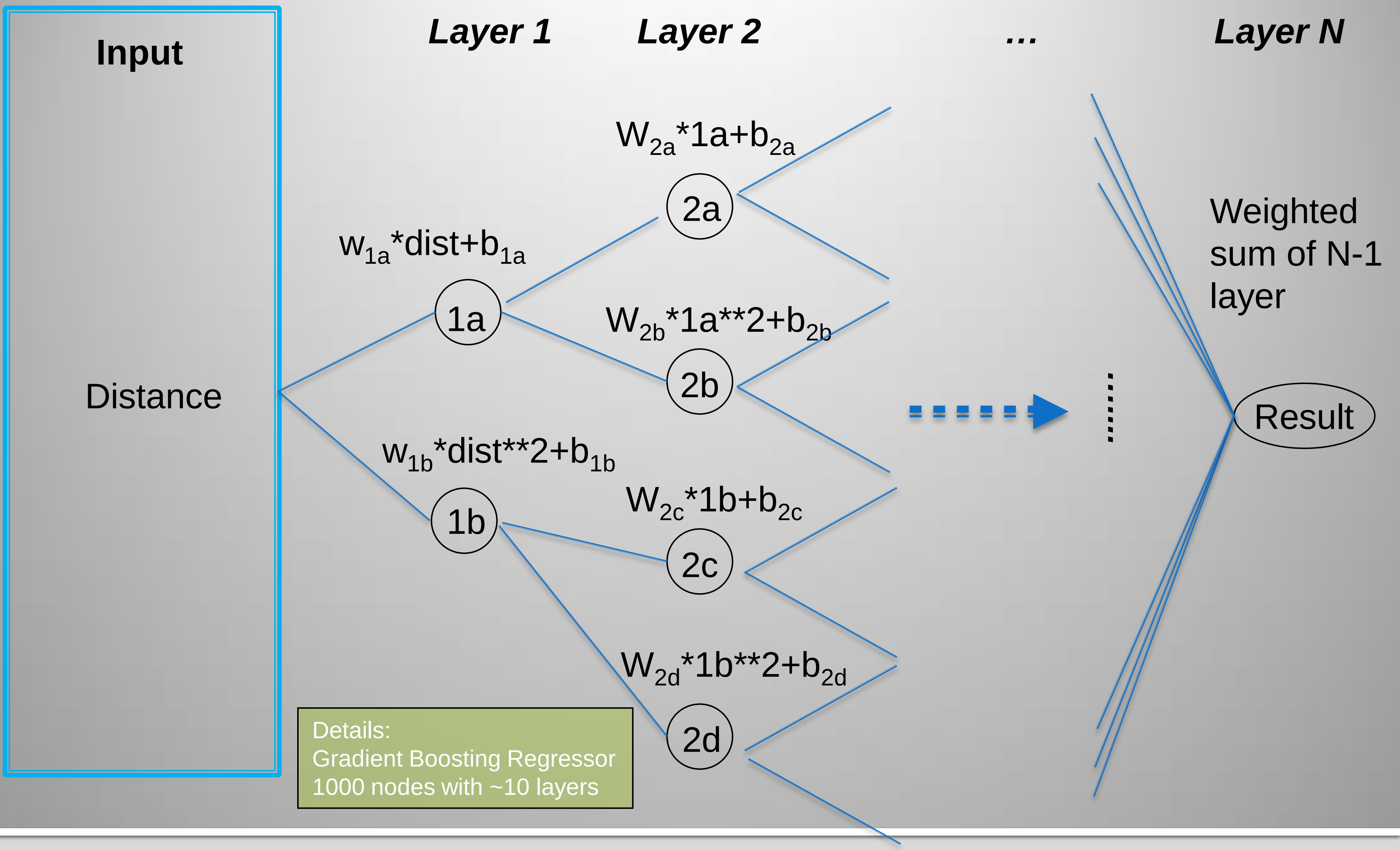


Sample density is dependent on path length



Simplified ML model

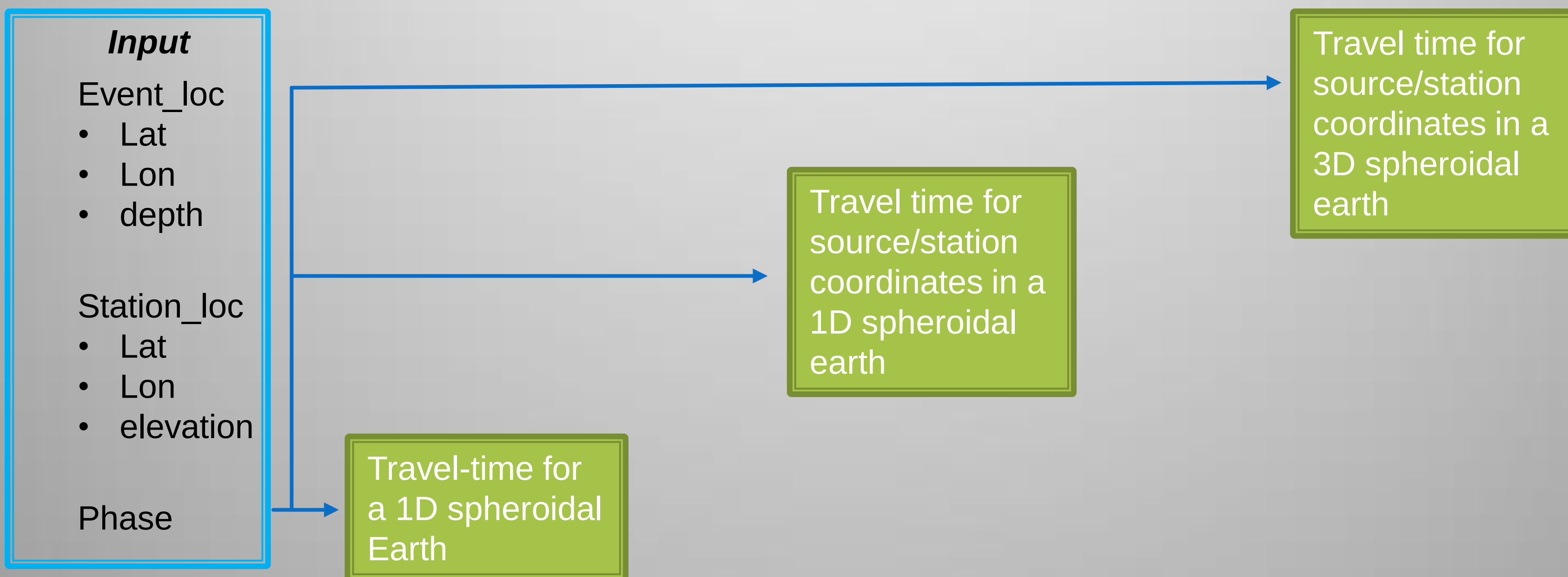
Machine learning algorithms find optimal weights



Details:
Gradient Boosting Regressor
1000 nodes with ~10 layers

Progressive tests of machine learning for seismic travel time calculation

Test I	Test II	Test III
Can ML learn ellipticity corrections?	Can ML learn event-depth and station-elevation corrections?	Can ML learn the effects of a 3D model?

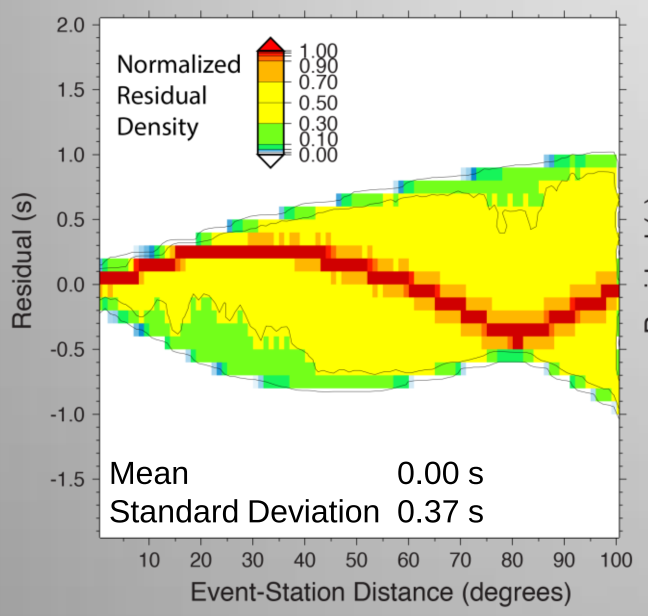


Current testing is for first-arriving P-waves

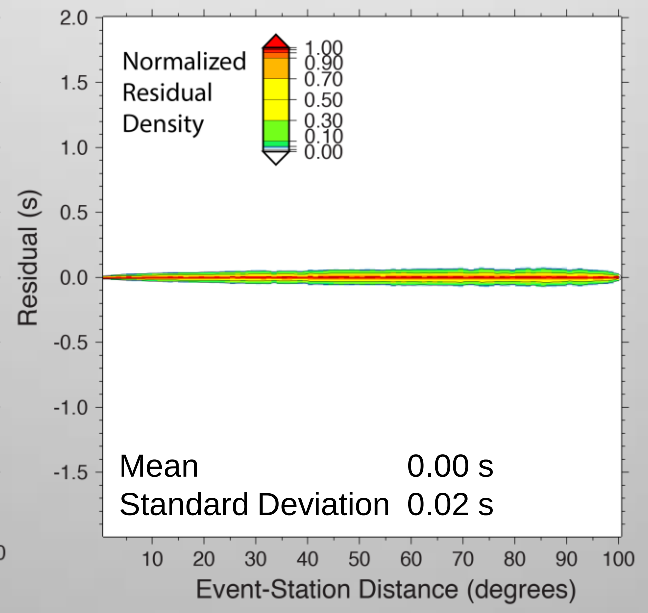
Test I
(spheroidal model, zero depth events)

Travel Time difference for spherical and spheroidal earth model

Travel time difference between ak135, WGS-84 model and ML_TT

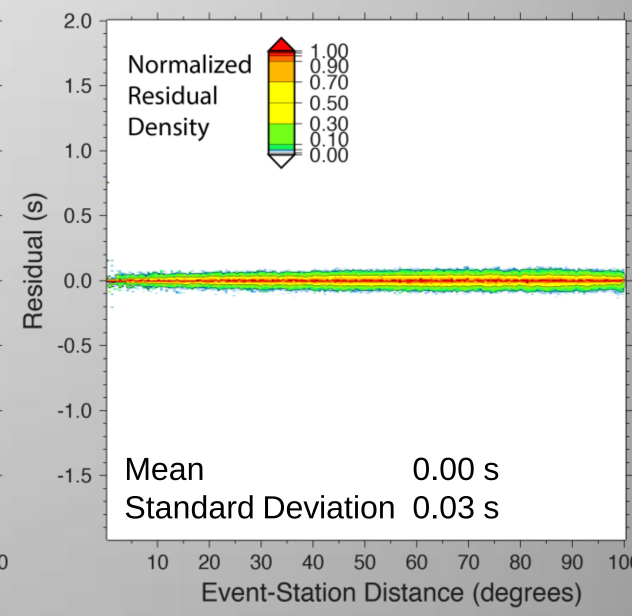


Training Set



Test Set

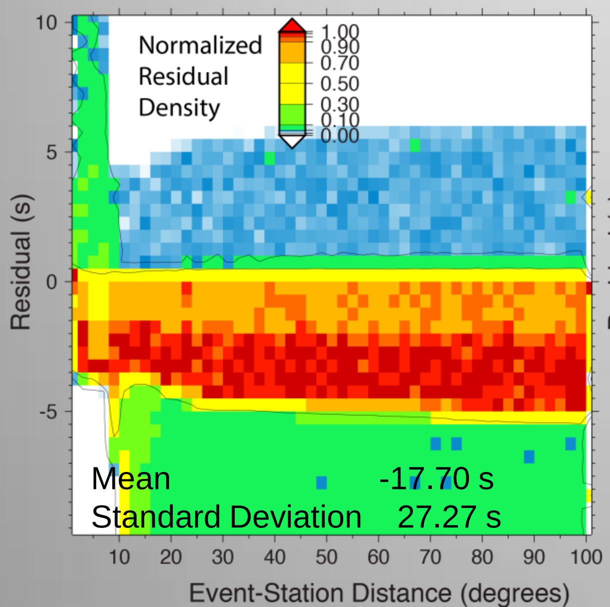
1/3 of data reserved for testing



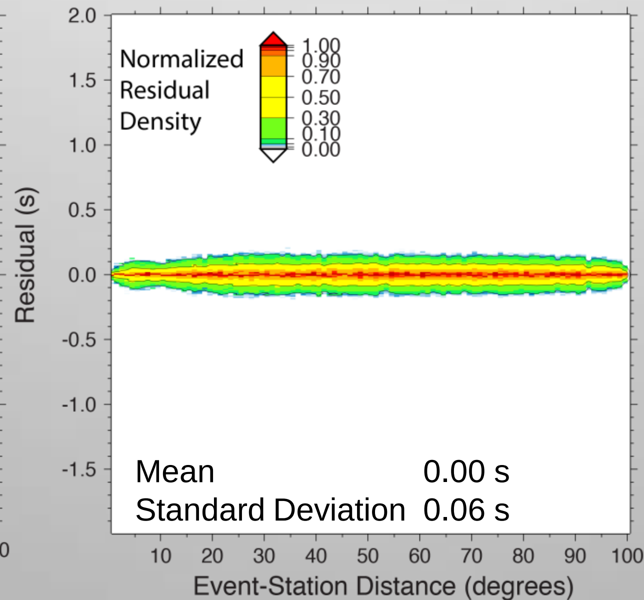
Test Phase II
(spheroidal model, 0km-660 km depth events)

Travel Time difference for surface focus and events at a range of depths

Travel time difference between ak135, WGS-84 model and ML_TT

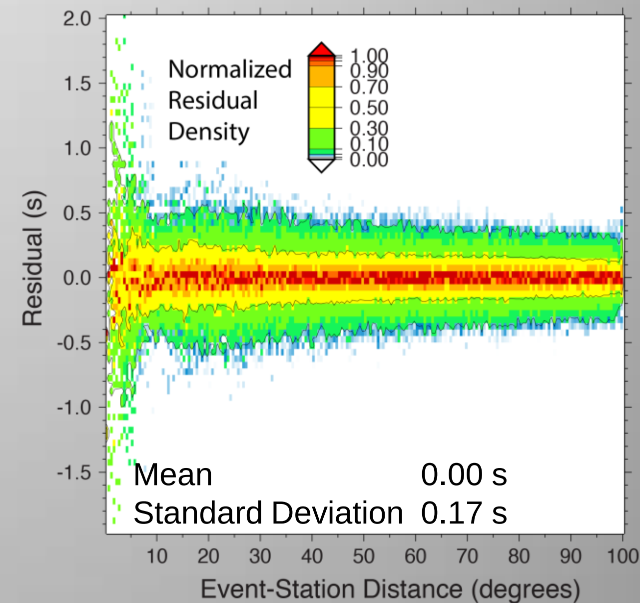


Training Set



Test Set

1/3 of data reserved for testing



Test Phase III
(3D model, 0km-660 km depth events)

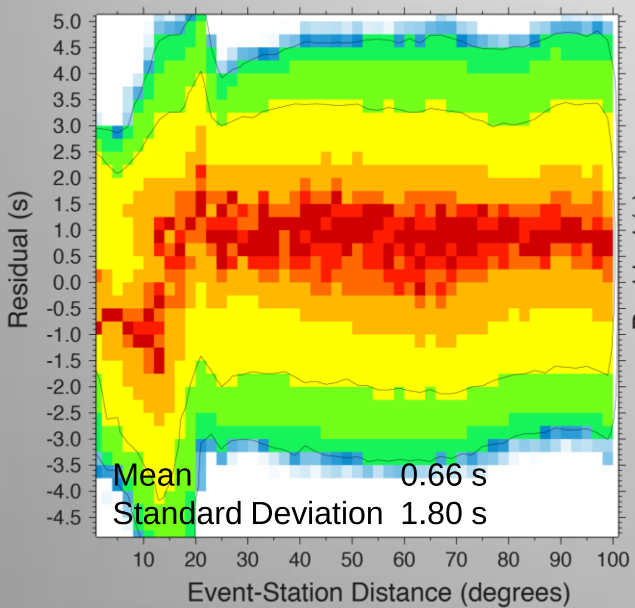
Travel Time difference for 3D and 1D model
(3D model is LLNL-G3D, Simmons et al., 2012)

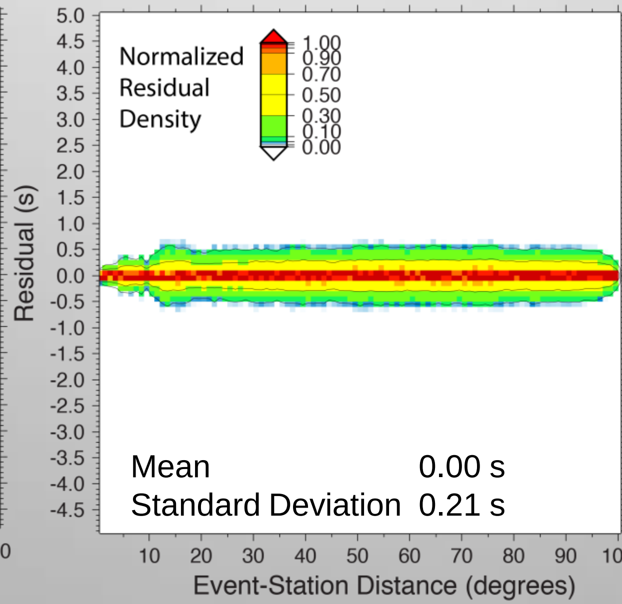
Travel time difference between 3D model and ML_TT

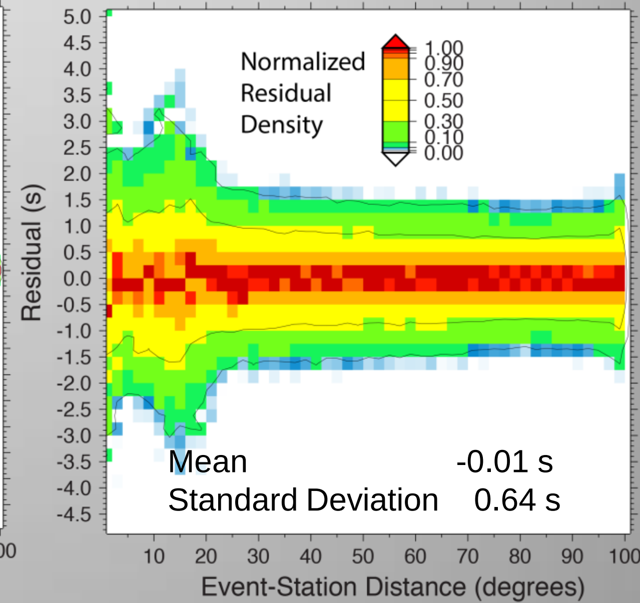
Training Set

Test Set

1/3 of data reserved for testing

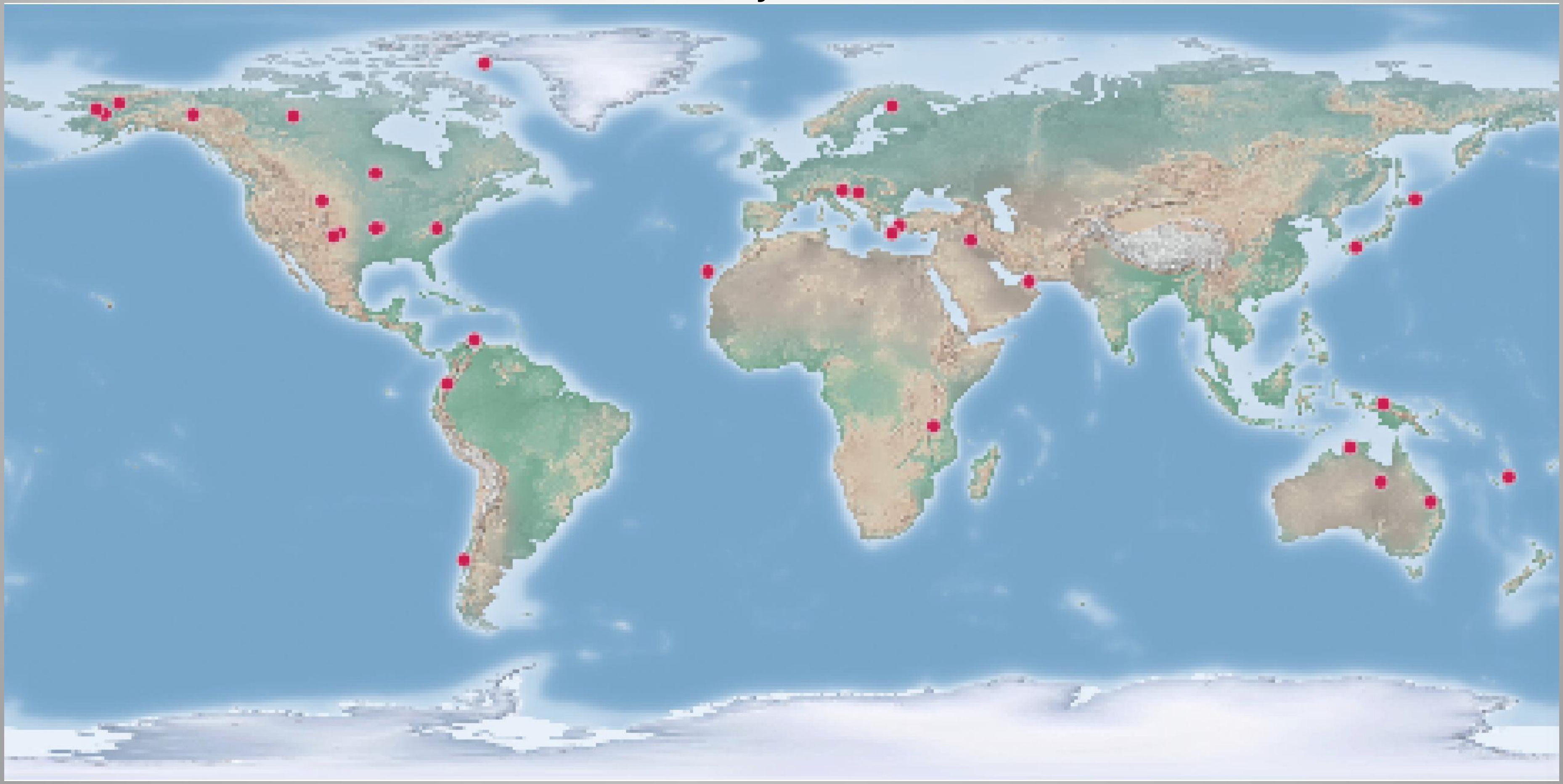






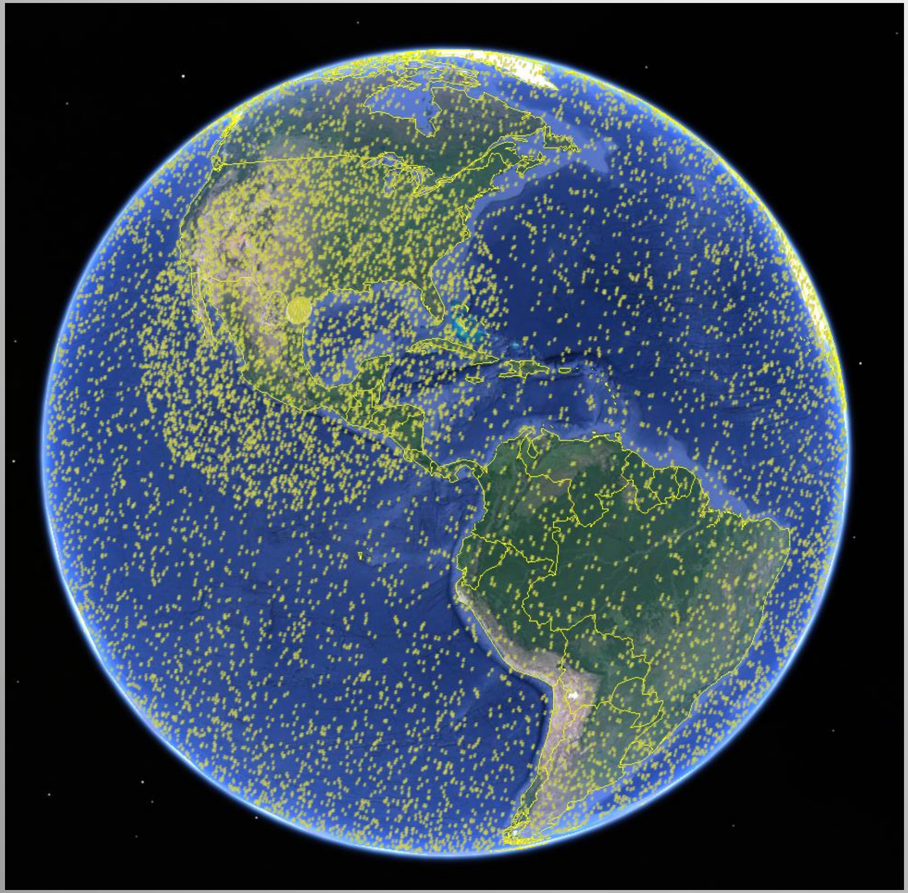
Improve ML_TT with station-specific training

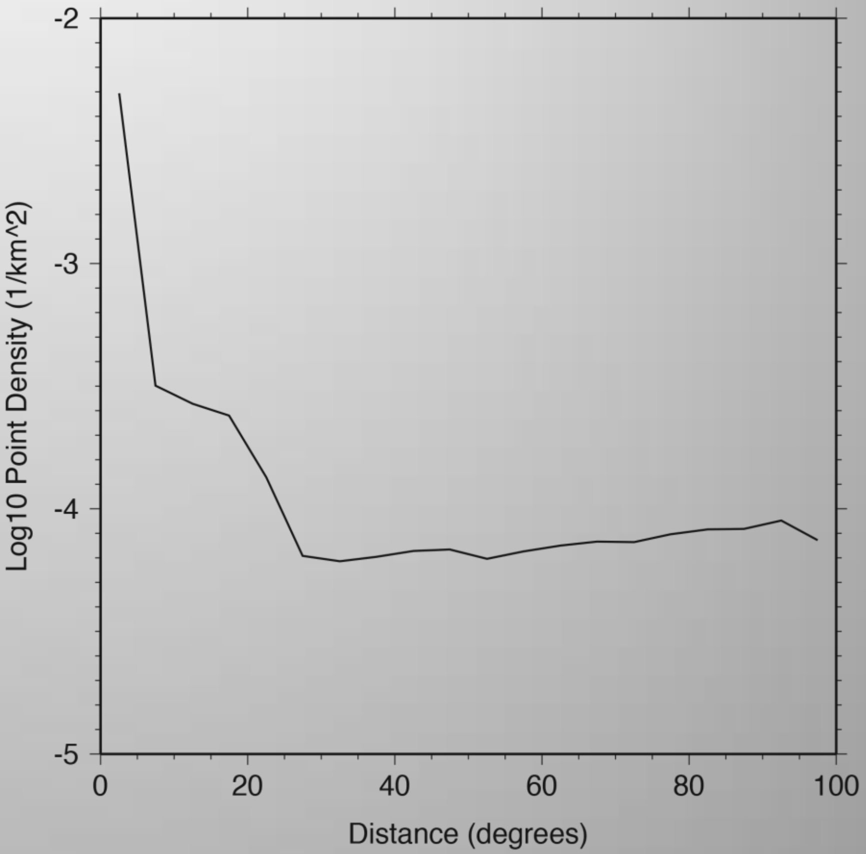
32 randomly selected stations



Station-specific training sets

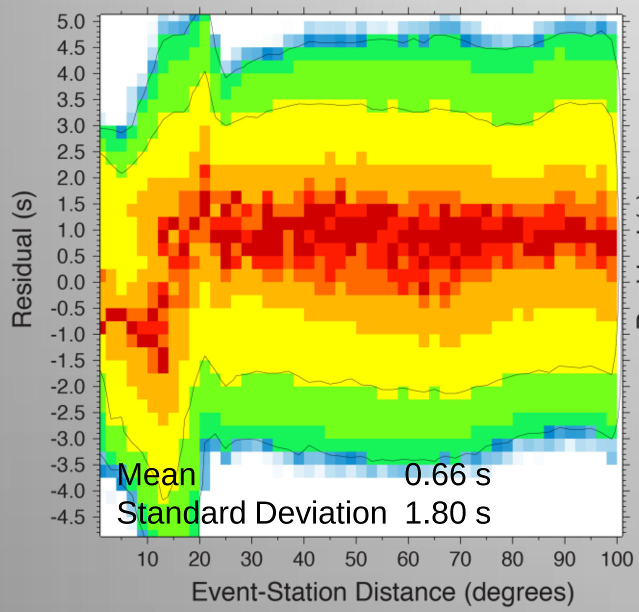
- 32,000 paths for each network station
- Sample density is greater where travel times vary most
  - local & regional distances





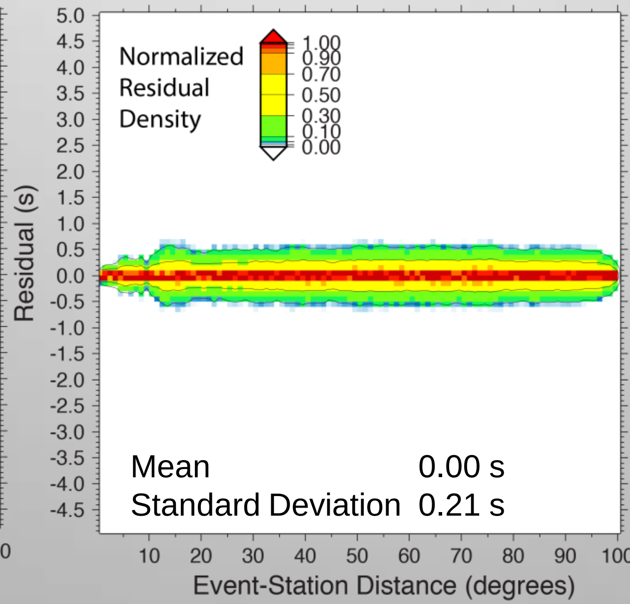
Test Phase III *(Reminder)*
(3D model, 0km-660 km depth events)

Travel Time difference for 3D and 1D model
(3D model is LLNL-G3D, Simmons et al., 2012)



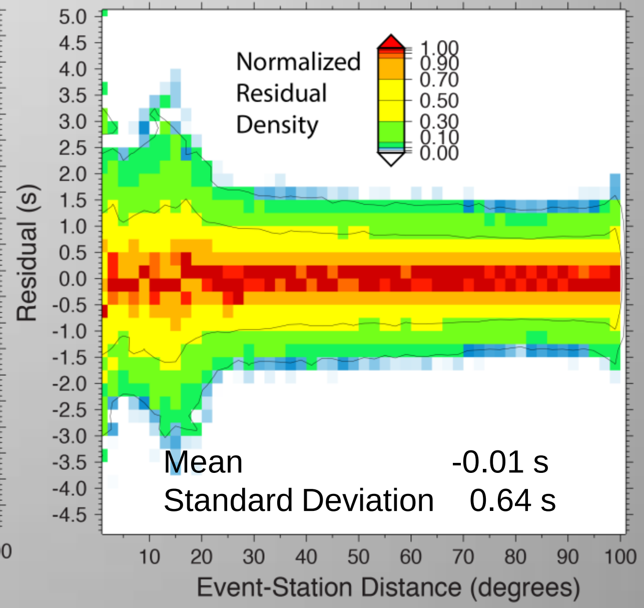
Travel time difference between 3D model and ML_TT

Training Set



Test Set

1/3 of data reserved for testing



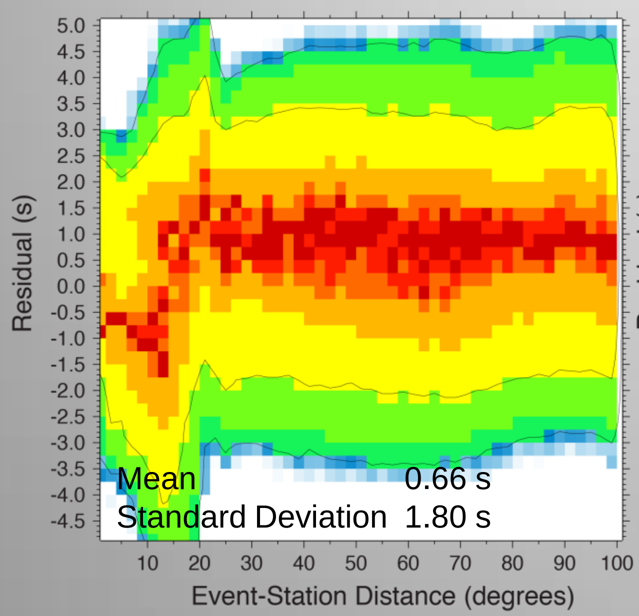
Test Phase III+ (Station-specific training) (3D model, 0km-660 km depth events)

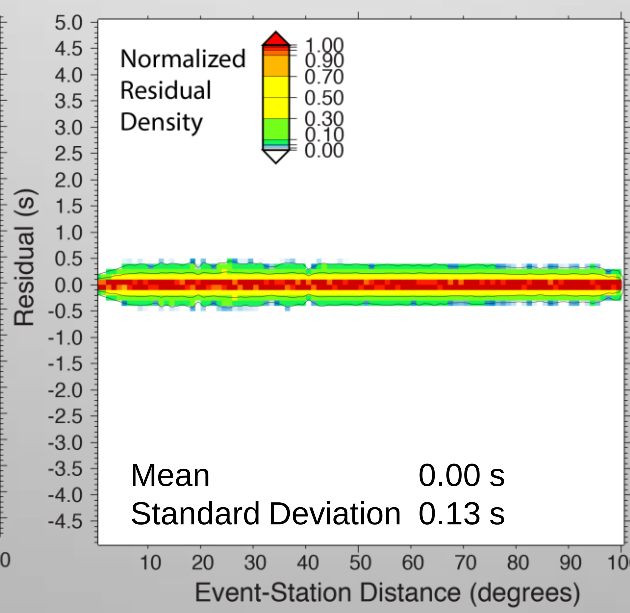
Travel Time difference for 3D and 1D model
(3D model is LLNL-G3D, Simmons et al., 2012)

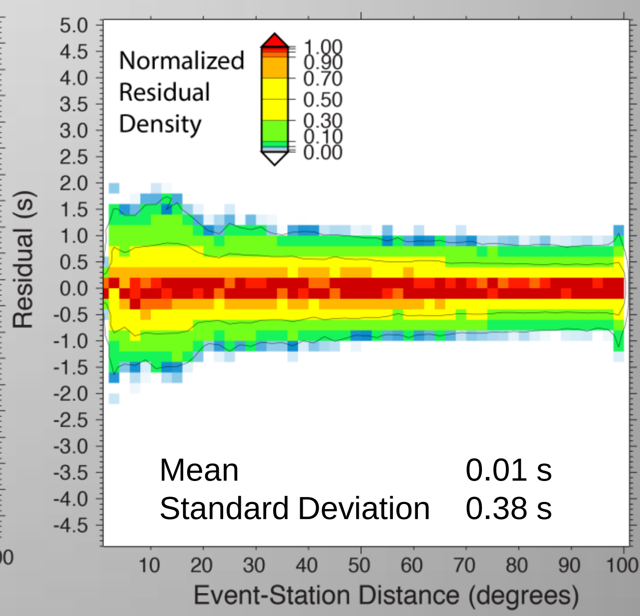
Travel time difference between 3D model and ML_TT

Training Set

Test Set
1/3 of data reserved for testing







Summary

- 3D global models can significantly improve the accuracy of seismic travel time predictions
- Computation time using a 3D model is too slow for operational systems
- Machine learning has been used to emulate expensive, full-physics simulations
- Tests show that ML emulation for seismic travel times are accurate to at least ~0.38 seconds on average
- Computation time using ML emulation is about 10 micro seconds, well within operational needs
- More extensive training sets will further improve ML_TT prediction accuracy.