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An Integrated Approach to Locating Undetected Off-shore Small Magnitude Seismic Sources

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The publicly available earthquake record contains a plethora of information regarding seismic sources across the globe. However, smaller magnitude seismic sources are generally not kept on record. Small magnitude seismic sources can indicate many different occurrences such as earthquakes, landslides, ordnance, or commercial human interaction. An integrated method, using the existing Automated Event Location Using a Mesh of Arrays (AELUMA) scheme combined with a multi-layered deep neural network machine learning algorithm, can allow for more accurate seismic source location with lower uncertainty. More accurate low magnitude seismic source locations can be directly applied to seabed instability, where off-shore landslides, for instance, create obstacles for subsurface naval warfare. Additionally, accurate seismic source locations can affect decision making with respect to seafloor infrastructure and commercial interests.

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AN INTEGRATED APPROACH TO LOCATING UNDETECTED OFF-SHORE SMALL MAGNITUDE SEISMIC SOURCES

1. OBJECTIVE

The publicly available earthquake record contains a plethora of information regarding seismic sources across the globe. However, smaller magnitude seismic sources are generally not kept on record. Small magnitude seismic sources can indicate many different occurrences such as earthquakes, landslides, ordnance, or commercial human interaction. An integrated method, using the existing Automated Event Location Using a Mesh of Arrays (AELUMA) scheme combined with a multi-layered deep neural network machine learning algorithm, can allow for more accurate seismic source location with lower uncertainty. More accurate low magnitude seismic source locations can be directly applied to seabed instability, where off-shore landslides, for instance, create obstacles for subsurface naval warfare. Additionally, accurate seismic source locations can affect decision making with respect to seafloor infrastructure and commercial interests.

2. METHOD

2.1 Data

Data for this study were collected from the Incorporated Research Institutions for Seismology. We require the LHZ component of each seismograph and request data in 24-hour chunks. The final seismic dataset spans the dates of Jan. 1, 2010 00:00:00.00 to April 4, 2010 23:59:59.99.

2.2 AELUMA

In order to locate uncatalogued small magnitude seismic sources, we employed the use of the pre-existing AELUMA software package [1]. AELUMA pulls continuous seismic data in 24-hour intervals from online servers and bandpass filters the data from 0.02 to 0.05 Hz to ensure surface wave clarity. Available seismograph stations for a given 24-hour period are configured into triads through Delaunay triangulation (Figure 1). Performing a cross-correlation of each triad's seismograms yields a seismic detection's arrival time, azimuth, amplitude, and phase velocity, which is represented at a given triad's geographic center. These detection properties, combined with the longitude and latitude of the triad centers, are then cross referenced with the NEIC PDE earthquake catalog to identify known seismic events. This dataset acts as the training dataset to build a machine learning model capable of locating previously undetected seismic sources (Figure 2).

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2.3 Neural Network

We chose a neural network (NN) regression, using PyTorch [2], as our machine learning algorithm. NN's are capable of predicting values outside of the training data's range. Additionally, incorporating multi-dimensional data into the algorithm is relatively simple. The NN has a simple construct: 1 input layer, 1 hidden layer, and 1 output layer. We train over 150 epochs and use mean absolute error (L1 Norm) as our loss function.

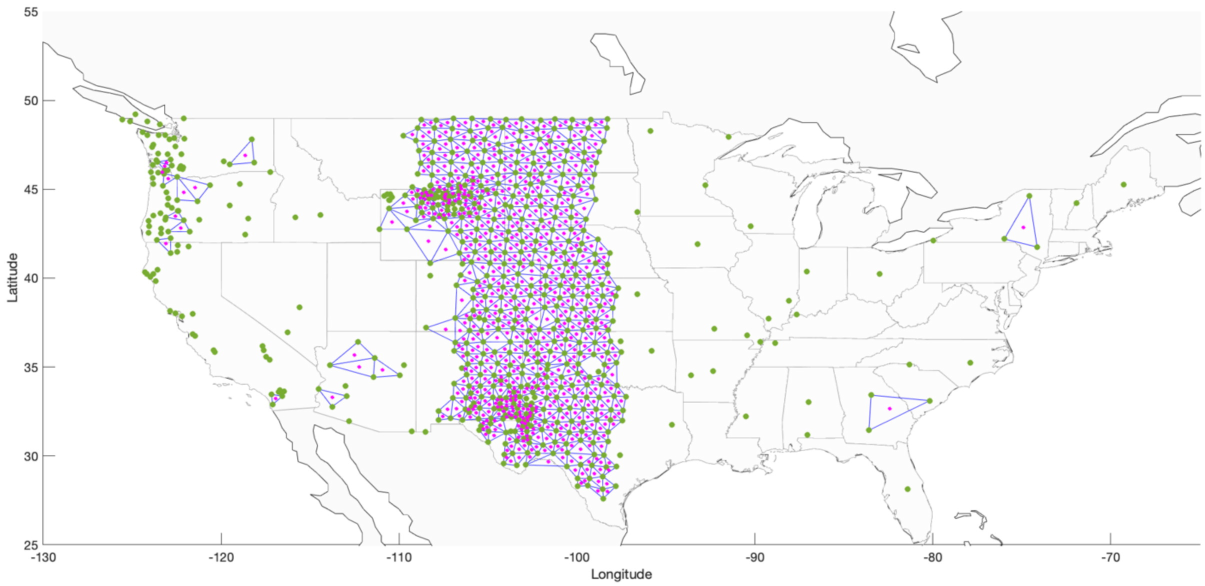


Figure 1 – Map of triad locations for all available seismic arrays on January 1, 2010. Green dots are seismic stations. Pink dots are the center of each triad.

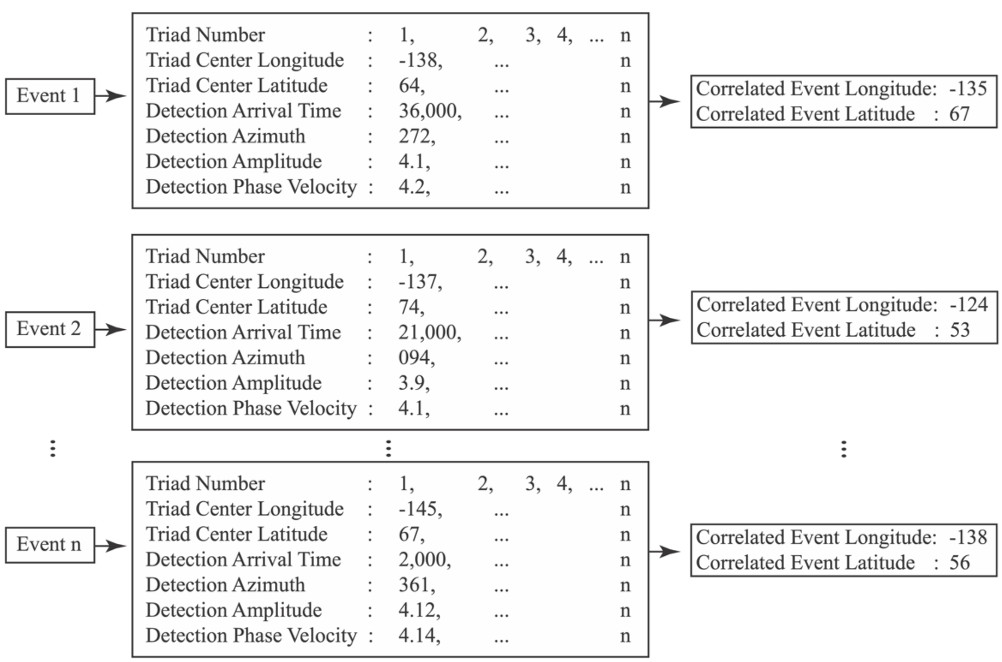


Figure 2 – Construct of the training dataset. Each known event has *n* number of associated triads, each with corresponding longitude, longitude, arrival time, azimuth, amplitude, and phase velocity. All triads are trained on each individual event's location.

3. RESULTS

The training process yielded high quality results (Figure 3). Training and validation loss decrease over epochs (Figure 3a); however, validation loss remains higher than training loss, indicating underfitting throughout the training process. Validation plots from the training phase result in exceptional R^2 values (over 0.9 for both longitude and latitude). Figure 3b highlights the model's capability in locating seismic events in, and around, the US. The model performs quite well for most events, but prediction diminishes around Haiti and the Dominican Republic.

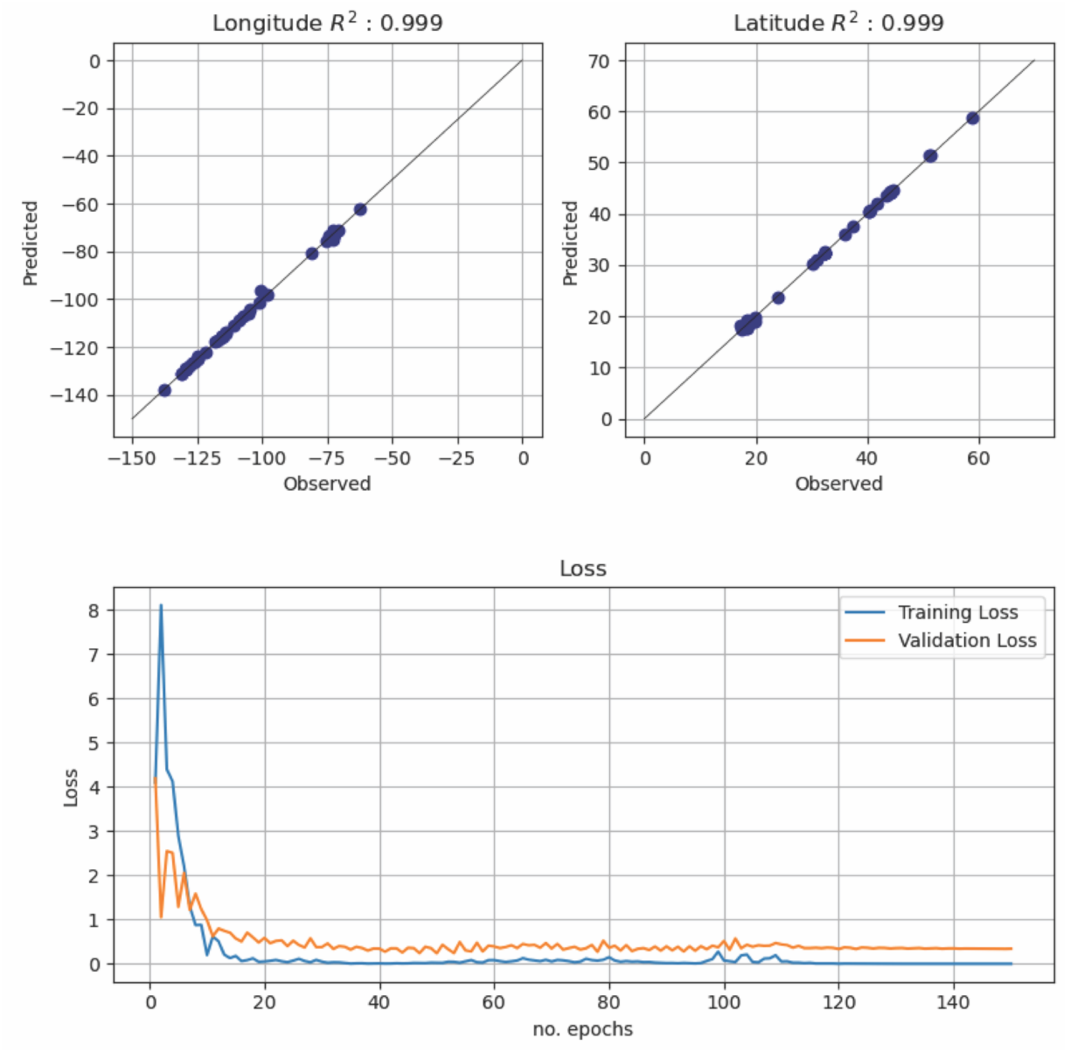
Event location with test data (withheld from the training process) performs poorly. Figure 4 shows the validation plots for longitude and latitude. R^2 values, when compared to the validation R^2 values of the training data, indicate poor predictive skill, particularly with latitude. Efforts were taken to improve generalization after training. Deeper neural networks, as well as wider neural networks, were constructed. Alternate loss functions were also investigated. Additionally, Dropout layers were included in an attempt to improve generalization. Unfortunately, a shallow, wide, neural network outperformed all other combinations, albeit with poor post-training generalization.

4. FUTURE WORK

Recent literature investigations have identified a residual neural network (ResNet) for nonlinear regression as a solution to our poor prediction generalization [3]. The ResNet is a deep neural network, consisting of any number of hidden layers, though over 34 is mainstream in the literature. Typically, very deep neural networks lose generalization capability due to the gradients of the loss function diminishing towards zero, resulting in the weights not updating. A ResNet achieves better generalization by allowing the model to skip hidden layer connections. This provides an alternate path for the gradients to pass through without approaching zero and improves prediction generalization. On-going efforts will exploit the advantages a ResNet offers in order to improve prediction generalization.

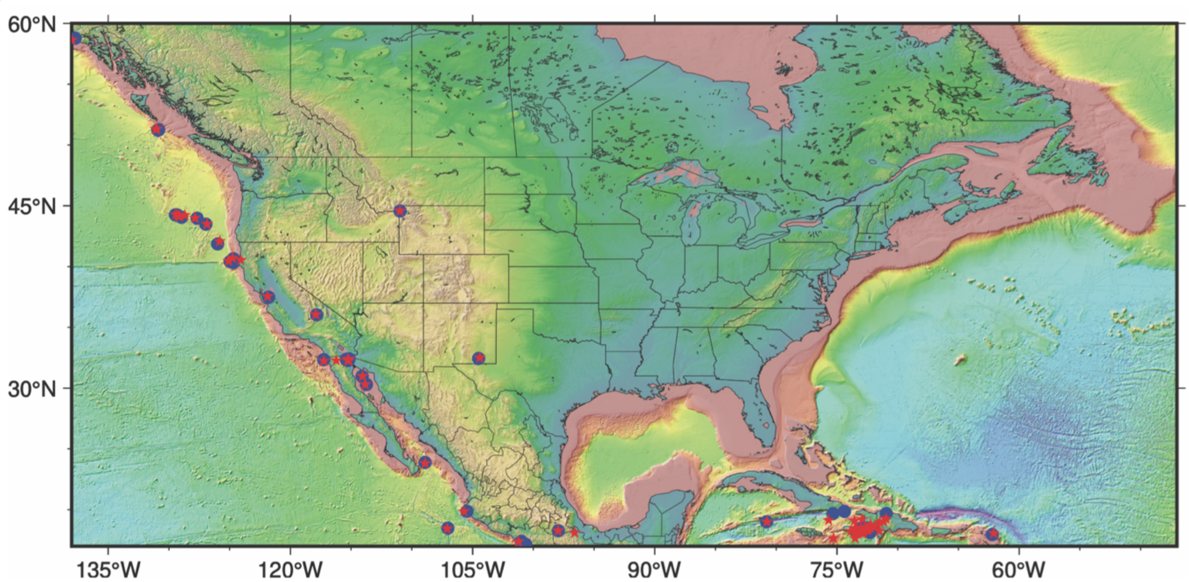
Additionally, a conformal prediction uncertainty method will be built around the machine learning model [4]. The conformal prediction is an intuitive method that estimates uncertainty via a cumulative distribution function (CDF) of the training dataset and applies that CDF to the prediction itself. This provides the best estimate of uncertainty in that the error present within the training dataset will inherently be carried over to the prediction.

a)



Longitude R^2 : 0.999
Predicted
Observed
Latitude R^2 : 0.999
Predicted
Observed
Loss
Training Loss
Validation Loss
Loss
no. epochs

b)



60°N
45°N
30°N
135°W
120°W
105°W
90°W
75°W
60°W

Figure 3 – Results from the machine learning training process. a) Validation plots of observed versus predicted seismic event locations (top). Loss curves are shown (bottom). Blue line is training loss. Orange line is validation loss. b) Map showing the locations of known seismic events (blue dots) and the locations of the training data predictions after training (red stars).

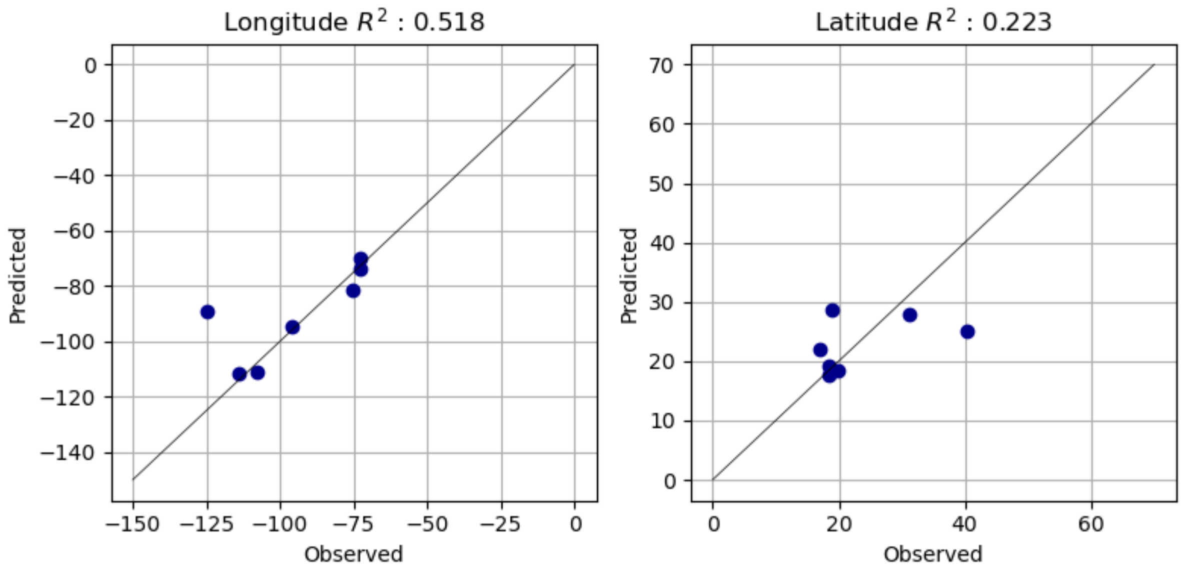


Figure 4 – Validation plots for the test dataset (withheld from the training process). R^2 values, when compared to the validation plots of the training data, indicate poor predictive skill.

REFERENCES

1. de Groot-Hedlin, C. D., and Hedlin, A. H. (2015), A method for detecting and locating geophysical events using groups of arrays, *Geophysical Journal International*, 203, 960-971, https://doi.org/10.1093/gji/ggv345.

2. Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., et al. (2019), PyTorch: An Imperative Style, High-Performance Deep Learning Library, *in* Advances in Neural Information Processing Systems, 32, 8024-8035.

3. Chen, D., Hu, F., Nian, G., and Yang, T. (2020), Deep residual learning for nonlinear regression, *Entropy*, 22(2), 193, https://doi.org/10.3390/e22020193.

4. Vovk, V., Gammerman, A., and Shafer, G. (2005), Algorithmic learning in a random world, New York, NY: *Springer Science and Business Media, Inc*.