UNIVERSITY OF DELAWARE
BARTOL RESEARCH INSTITUTE

Workshop on Machine Learning for Analysis of High-Energy Cosmic Particles

In-situ pulser depth reconstruction for RNO-G using Neural Network

RNO-G
Radio Neutrino Observatory - Greenland

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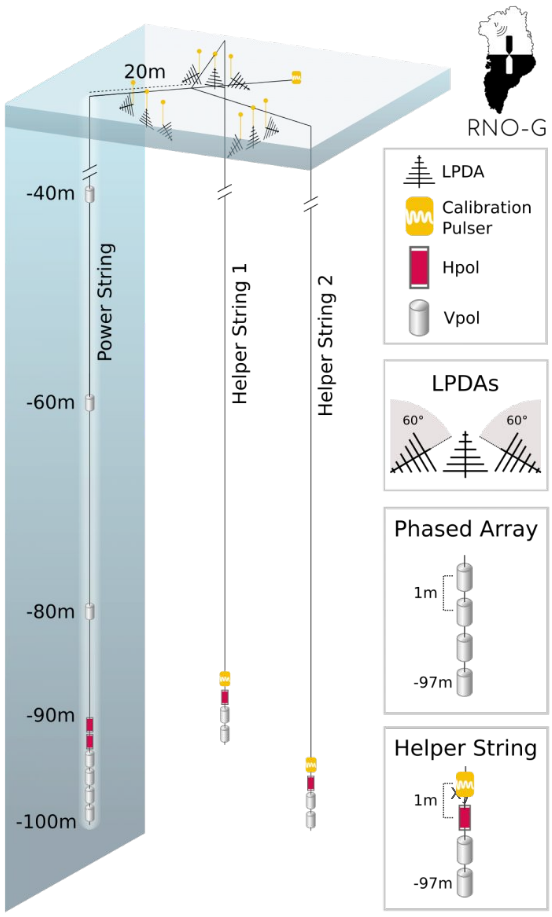
01/29/25

Introduction

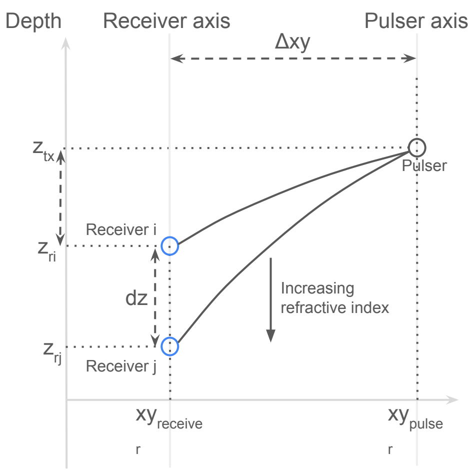


RNO-G aims to detect Askaryan emission from UHE neutrinos using an array of radio antennas deployed across 8 stations situated at Summit Station, Greenland.

Direction reconstruction of neutrinos using interferometry requires precise understanding of the in-situ antenna response and constraining of the ice-properties.

Calibration pulser drops in RNO-G boreholes provide an excellent data-set for antenna-response and ice-model studies.

arXiv:2411.12922



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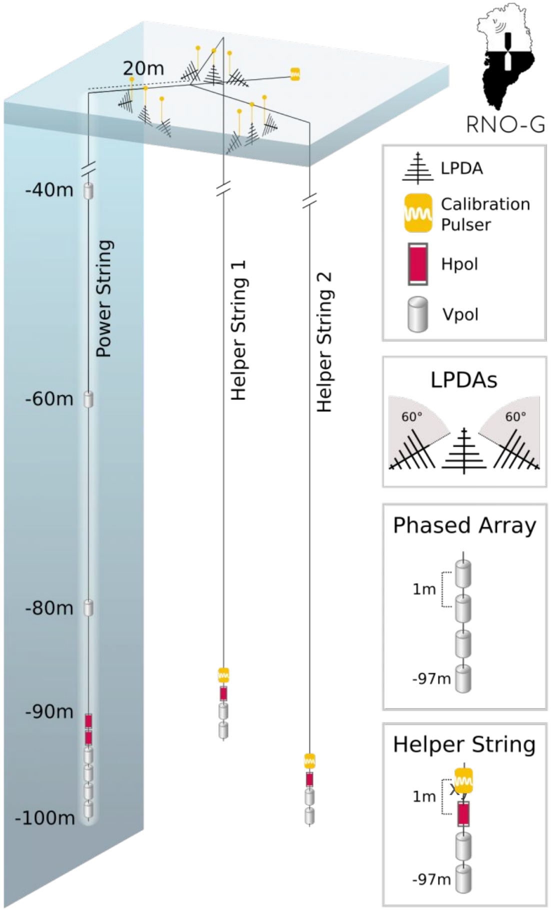

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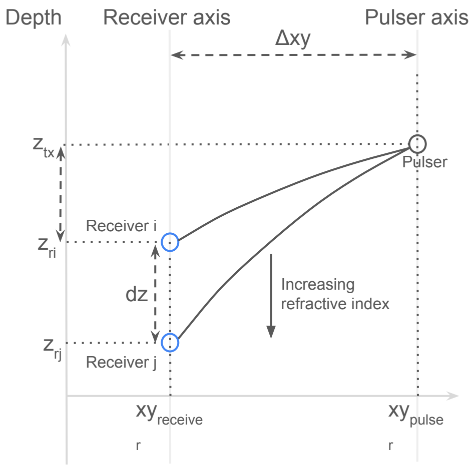

- Objective: to reconstruct pulser (transmitter) depth using signals received by in-ice phased array antennas

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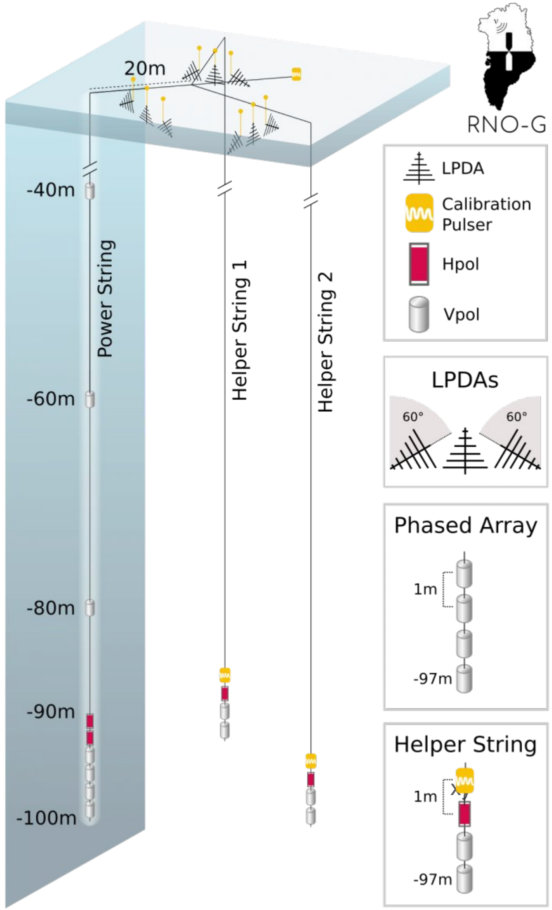

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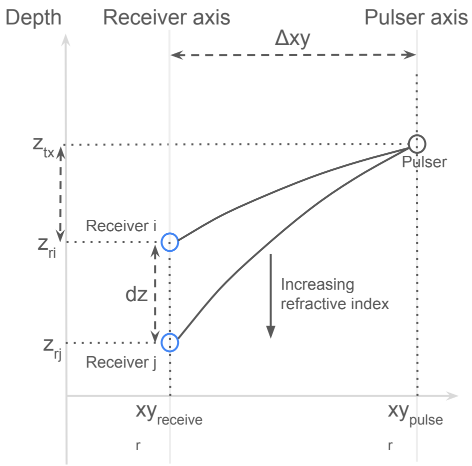
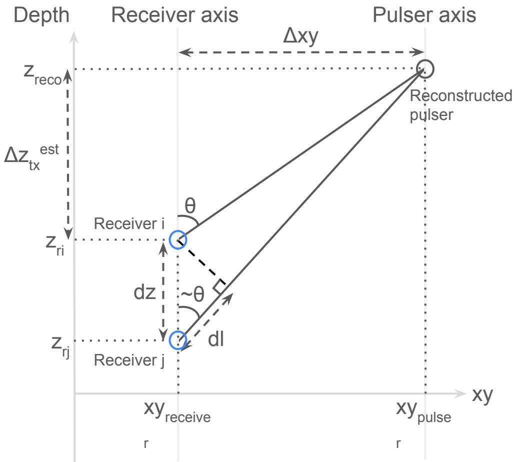


- Objective: to reconstruct pulser (transmitter) depth using signals received by in-ice phased array antennas
- Challenges: ray tracing simulations are time consuming and computationally heavy

Straight line reconstruction



Data

dt	Difference in time between pulse at receiver i and receiver j using cross-correlation
dl	Difference in distance traveled by waveform dl = $(c/\mathbf{n_{ij}})\mathbf{dt}$
$\mathbf{z_{ri}}$, $\mathbf{z_{rj}}$, **dz**	Depth of receiver i, receiver j and the difference $\mathbf{z_{ri}} - \mathbf{z_{rj}}$
$\mathbf{n_i}$, $\mathbf{n_j}$, $\mathbf{n_{ij}}$	refractive index at receiver i and j and their average
θ	Angle between receiver axis and wave = $\cos^{-1}(\mathbf{dl}/\mathbf{dz})$
Δxy	Distance in the xy plane between pulser and receiver axes

Assumptions

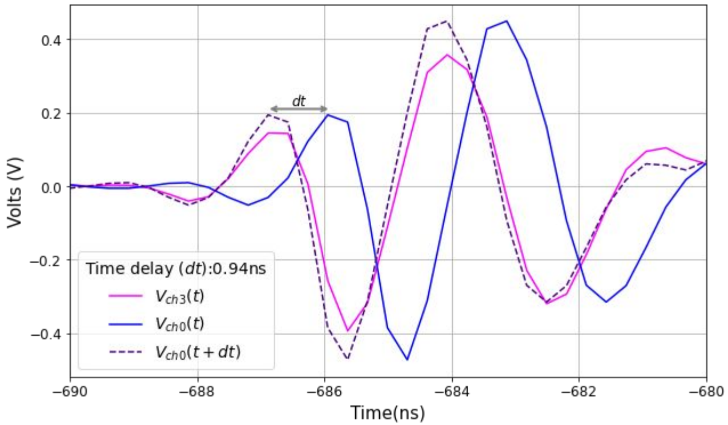
- No bending of light ray
- 3-stage model for refractive index of ice

$$n_z(z) = \begin{cases} 1.777 - 531e^{-0.0374(z-0)} & \text{if } z \leq 14.9 \\ 1.777 - 304e^{-0.0174(z-14.9)} & \text{if } 14.9 < z \leq 58.9 \\ 1.777 - 141e^{-0.0328(z-58.9)} & \text{if } z > 58.9 \end{cases}$$

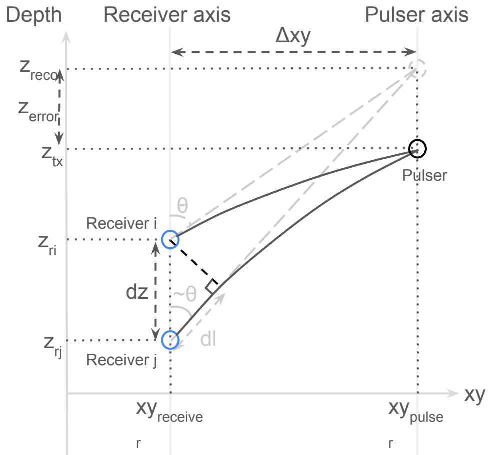
arXiv:2406.00857

Steps

1. Calculate depth difference $\Delta z_{tx}^{est} = \mathbf{\Delta xy}/\tan(\boldsymbol{\theta})$
2. Calculate $z_{reco} = \mathbf{z_{ri}} + \Delta z_{tx}^{est}$

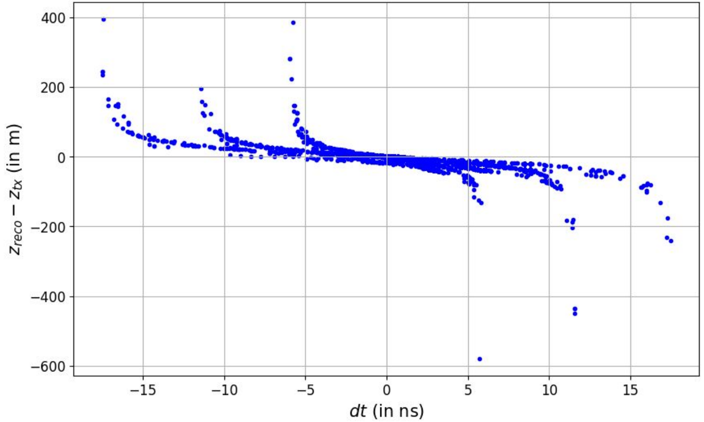


Drawbacks of straight line reconstruction



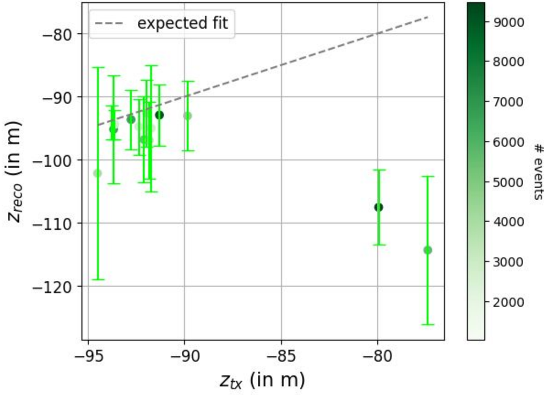
Problems

1. Reconstruction fails for cases when **dl** > **dz** (invalid cosine)
2. As **dt** increases, there is greater deviation from the straight line assumption



The error

- is not randomly distributed
- shows a clear non-linear relationship with **dt**
- increases with increasing |**dt**|

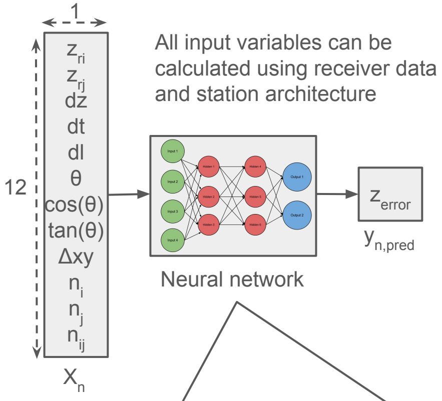


Idea

Train a neural network using data from the previous slide to predict $\mathbf{z_{error} = z_{reco} - z_{tx}}$ and correct the error in z_{reco}

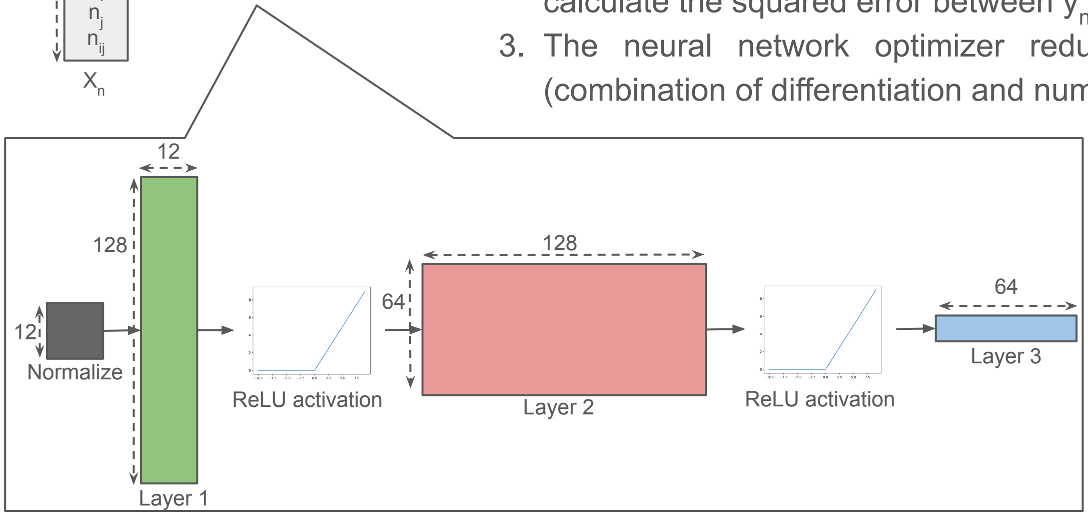
ML learns to predict the error in the depth reconstructed using straight line assumptions and allows us to correct our reconstructed depth by accounting for the deviation from straight line ray propagation

Machine learning for error correction



Training

1. Neural network gets initialized with all elements (known as model parameters) of matrices set to random values near zero
2. We use **events from stationary calibration pulser data**. For every event, calculate the z_{reco} and compute z_{error}. Input X_n is a vector length 12 and expected output $y_{n,true}$ is z_{error} of the event. The model will produce a $y_{n,pred}$ which will be compared against $y_{n,true}$ to calculate the squared error between $y_{n,true}$ and $y_{n,pred}$
3. The neural network optimizer reduces this squared error using Adam optimizer (combination of differentiation and numerical methods)



Application of the trained model

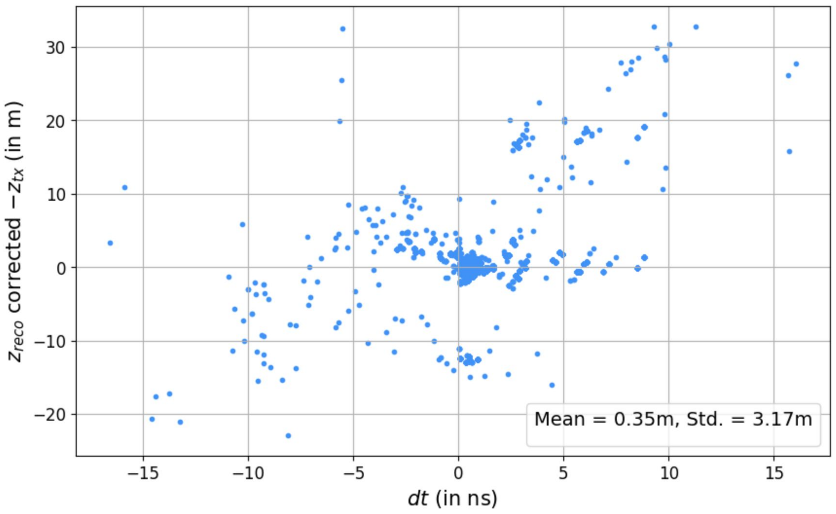
1. We use events from calibration pulser drop data. For every event, calculate the $\mathbf{z_{reco}}$ **using straight line assumption**.
2. Neural network outputs the predicted error z_{error} in z_{reco}. We apply this correction to the straight line assumption and get reconstructed depth $\mathbf{z_{reco}}$ **corrected** $= \mathbf{z_{reco}} - \mathbf{z_{error}}$

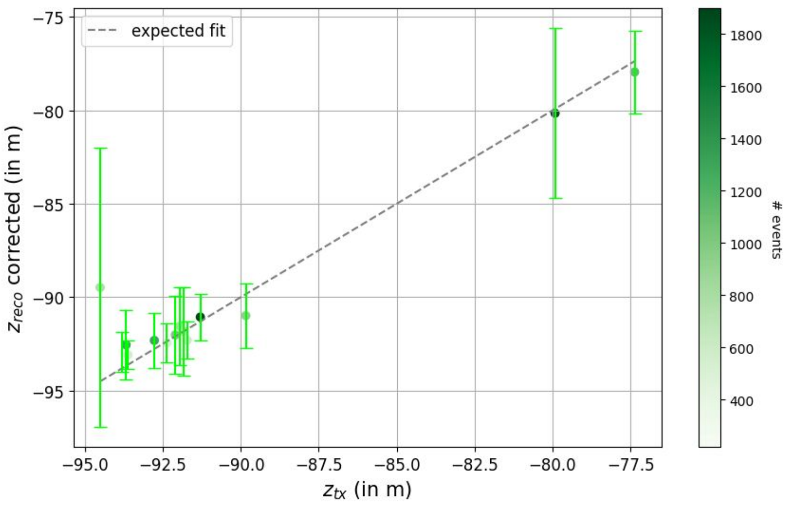
Training, Inference and Results

- Training data consists of pulsed **calibration events across 7 stations**
- Input parameters constructed using any pair of the deep in-ice
- Total stationary pulser data size: **68,757**
- Split development set 80:20 into training and validation (**55005**) and testing (**13752**)

The root-mean squared error of the predicted $\mathbf{z_{error}}$ **from the test set is 4.4m.** There were 7 observations (0.05%) that had an error of more than 35m in z_{error}. If they are discounted, root-mean squared error of the predicted z_{error} is 3.2m. These outliers will be further studied to understand the deviation.

Depth reconstructed more accurately using neural network.

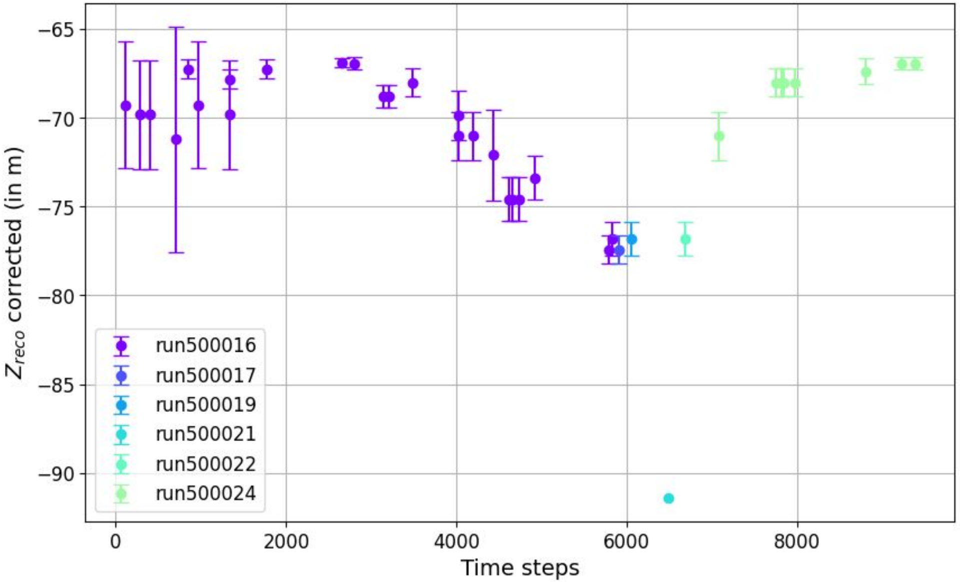




Pulser drop reconstruction

- Data from **calibration pulser being lowered and raised back up in a borehole**
- Transmitter depth unknown, lowered from ~40m to ~80m and recorded 26 runs over ~5 hrs
- Reconstruction using pulsed events received by 4 deep in-ice channels (phased array)

- Caveats:
  - Full index of refraction profile unknown to the model, hence reconstruction is limited to using data from deep channels
  - Shallower channels located farther apart (~20m), hence the error in z_{reco} from straight line propagation assumptions would be larger
  - Training data did not include cases of transmitter being in shallow ice, hence is susceptible to biasing
  - Black box physics processing



ML reconstruction matches with the run description from deployment notes!
Run 500016: pulser lowering down
Runs 500017-22 : pulser ~80m
Run 500024: pulser rising up

Future work

- Experiment with different model architectures
  - Currently we are only using 3 layers with 128 -> 64 -> 1 nodes
  - Increasing layers and tweaking nodes
  - Incorporating shallower channels in the training data
  - Validating neural network predictions of pulser drops using RadioPropa simulations

- Use entire waveform at receivers
  - Recurrent neural networks (RNN) can learn from sequential data
  - If both waveforms are input together into an RNN, it can learn to calculate the gap and the appropriate correction to predict the actual depth

- Extend the Neural Network and use all available in-situ receivers for performing 3 dimensional reconstruction

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- The assumptions break as the separation between receiver and transmitter increases
- Data from transmitter at known depths can be used to train a Neural Network to predict the error in straight line assumptions
- This trained Neural Network can be used to reconstruct depth of the transmitter given receiver waveforms
- Training doesn't require extensive computational resources and is trained within 30 mins. Prediction takes a couple of seconds.
- Applications to RNO-G: Reconstruct transmitter depth in pulser drop runs where the moving transmitter's depth is not known


Thank you!
Questions?

Additional comments

- The inputs are related to each other, will there be a problem with multicollinearity?
  - Multicollinearity is generally a problem with linear regression because it involves matrix inversion. With neural networks, this should not be a problem because weights are learned using backpropagation
- Why not use the actual depth of the pulser as the target?
  - Stationary pulser data only has 14 target depths and our objective is to predict the depth of the pulser during a pulser drop which has a greater variety of depths than stationary pulser. If we use actual depth, model will tend to overfit and cannot be generalized to other depths. With error prediction, we have some hope of generalization
- Z_{error} predicted by the neural network for stationary calibration pulser data (testing)