ML based applications in Underwater Channel Model

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Introduction

- Underwater acoustics is the study of propagation of sound in water, and the interaction of the sound waves with water, its contents and its boundaries [1]
- The channel model refers to modelling these interactions mathematically, giving us an insight into the propagation
- A figure of merit to be calculated, is the Transmission loss this signal undergoes
- This presentation aims to describe an attempt to model this figure of merit using Machine Learning and Deep Learning techniques

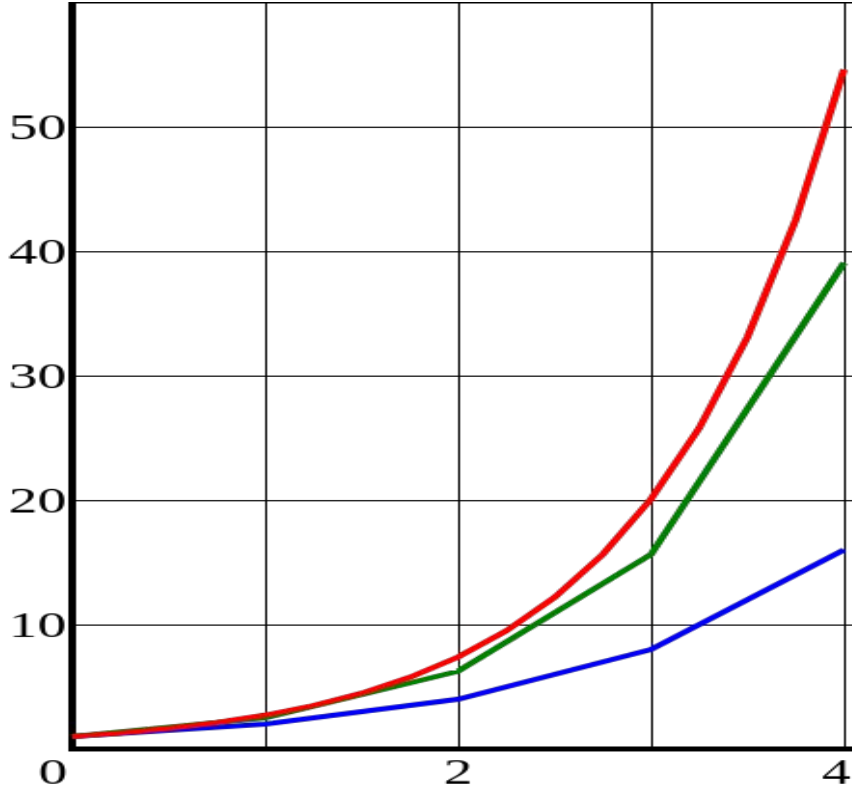
Motivation

- Previous works have been successful in modelling the Transmission Loss accurately, BUT - they are catered to the Western Oceans, and have varying assumptions, not all of which hold true in the IOR
- Hence it becomes imperative to work with Range dependent acoustics models (RAM) - the SOTA being the Parabolic Equation RAM
- Moreover, this SOTA is a very time consuming process, we look to change that and modify the inputs required, making it better for real time usage

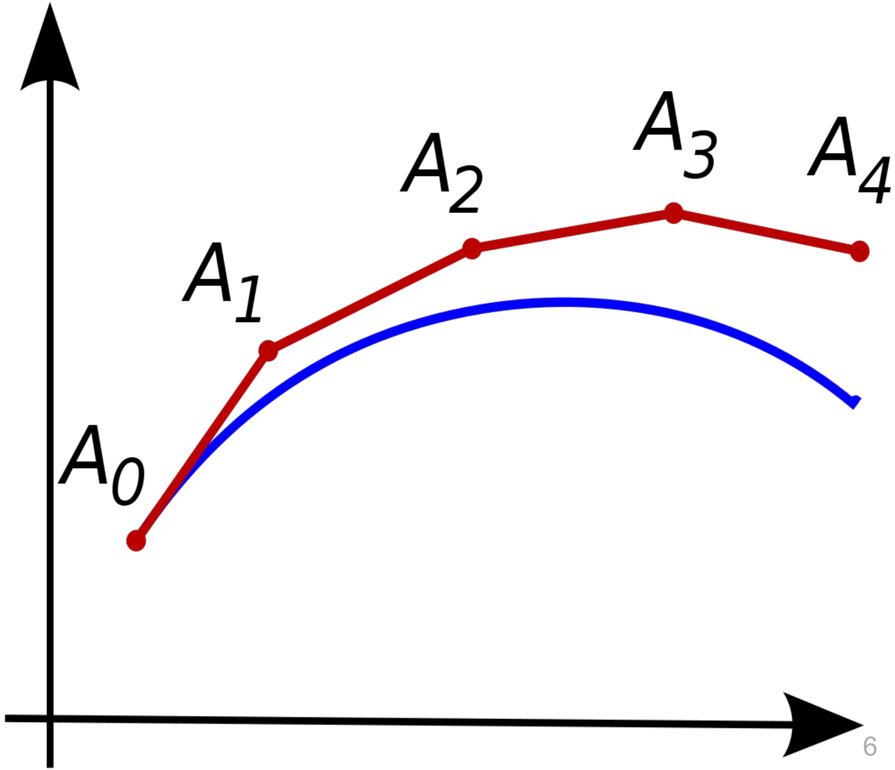
Previous SOTA

- The PE RAM Model aims at numerically solving the Parabolic equation
- Numerical solutions are prone to errors - Dependent on the step size chosen, Can lead to accumulation of errors
- Inputs reqd - Sound speed values, bathymetry (depths), absorption, sea state, bottom composition
- Compute time - numerically solving for each step size can take up a lot of computational time. This can be a problem in real time settings
- Moreover - The PE RAM outputs the Transmission loss at every range specified, from the transmitter. Often what is required is the Transmission loss between a particular pair of transmitter receiver. We address this as well.

Different Step Sizes Lead to Different solutions -
(Red - actual solution, green and blue - solutions taking different step sizes)



Accumulation of errors - A3 accumulates the error in calculation of A2 and A1, similarly for A4, and this error keeps accumulating and the number of calculations increase)



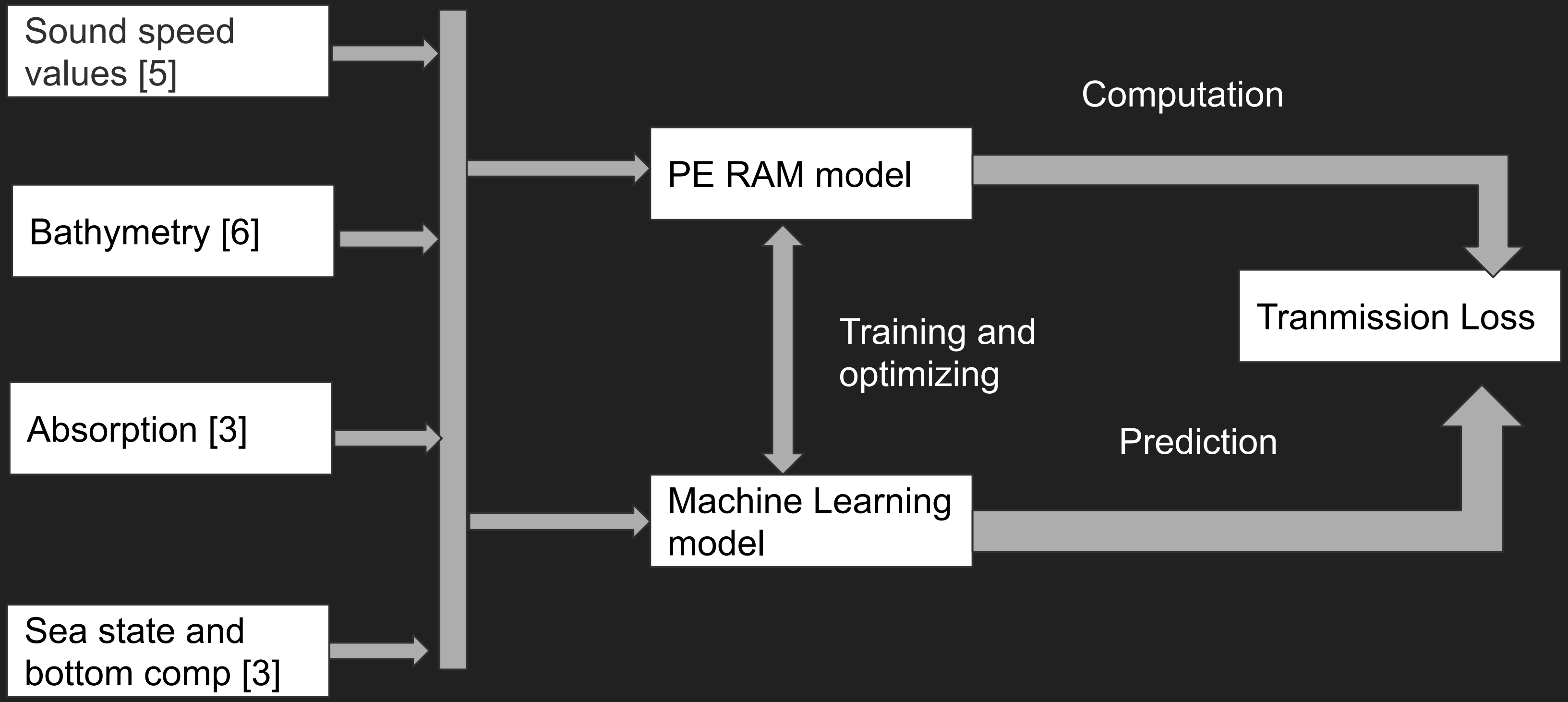
Proposed solution

- We propose replacing this computation of differential equation solving with a Neural network in order to approximate the Transmission loss given the same inputs as to the PyRAM.
- The further modification proposed is that the user needs to input only the transmitter and receiver locations (lat and long respectively)
- An automation script combs through the relevant database to collect the other inputs, feeds it into the Neural Network, and the output is the approximated transmission loss between the transmitter and the receiver

Methodology

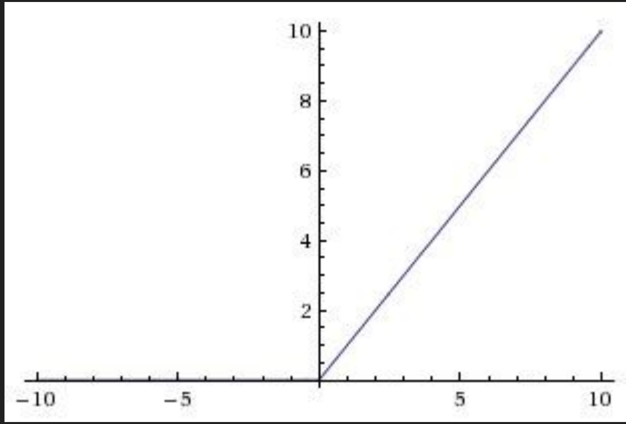
- To ignore any discrepancies, we feed the same inputs to both the models
- We use the outputs of the PyRAM (a python implementation of PE RAM) to train the neural net, and optimise it to obtain the least mean squared error - solved as a regression problem
- We use a total of 145000 pairs, obtained from AIS data - signifying the transmission loss is calculated between 2 ships
- These pairs are divided into 60%-20%-20%, 60% data used for training, 20% for validation, and 20% for testing, after shuffling to reduce bias
- We use different architectures, namely having 4 hidden layers, 5 hidden layers, and 6 hidden layers, the number of neurons for which have been chosen after many iterations to minimise the mean squared error

Methodology as a flowchart

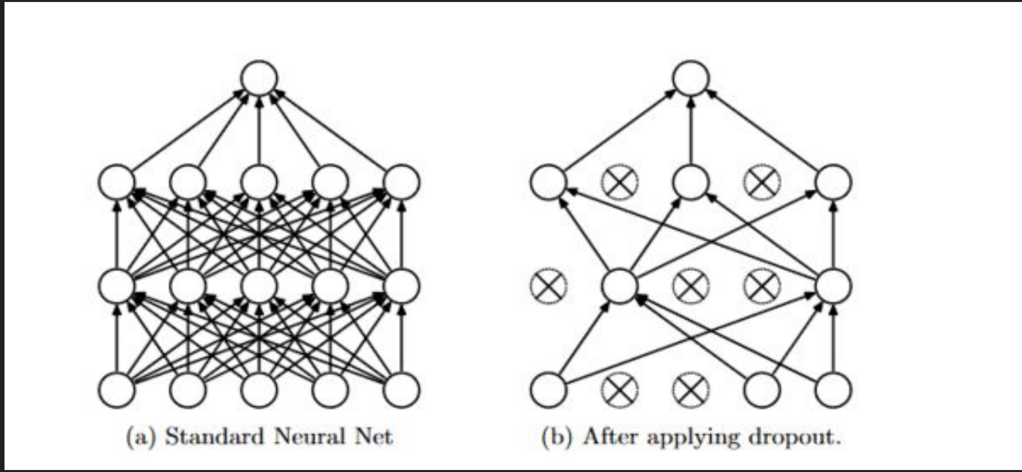


Methodology (Continued)

- Fully connected Layer - ref to (a) standard neural net
- ReLU - inspired from biological learning, threshold set to 0
- Dropout - Randomly switch off neurons with probability (p=0.2), reduces the risk of overfitting



ReLU



Neural networks

Methodology (Continued)

- The two losses used - MSE and MAE
- y-actual value, y_hat-predicted value
- Measures the closeness of fit to the actual values
- What we aim - Reduce this figure. MSE = 0 implies perfect fit

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

$$\text{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$

Methodology (Architecture)

4 layered net -
- Fully connected Layer(64 units)
- ReLU
- Dropout
- Fully Connected Layer(64)
- ReLU
- Dropout
- Fully Connected Layer(32)
- ReLU
- Dropout
- Fully Connected Layer(16)

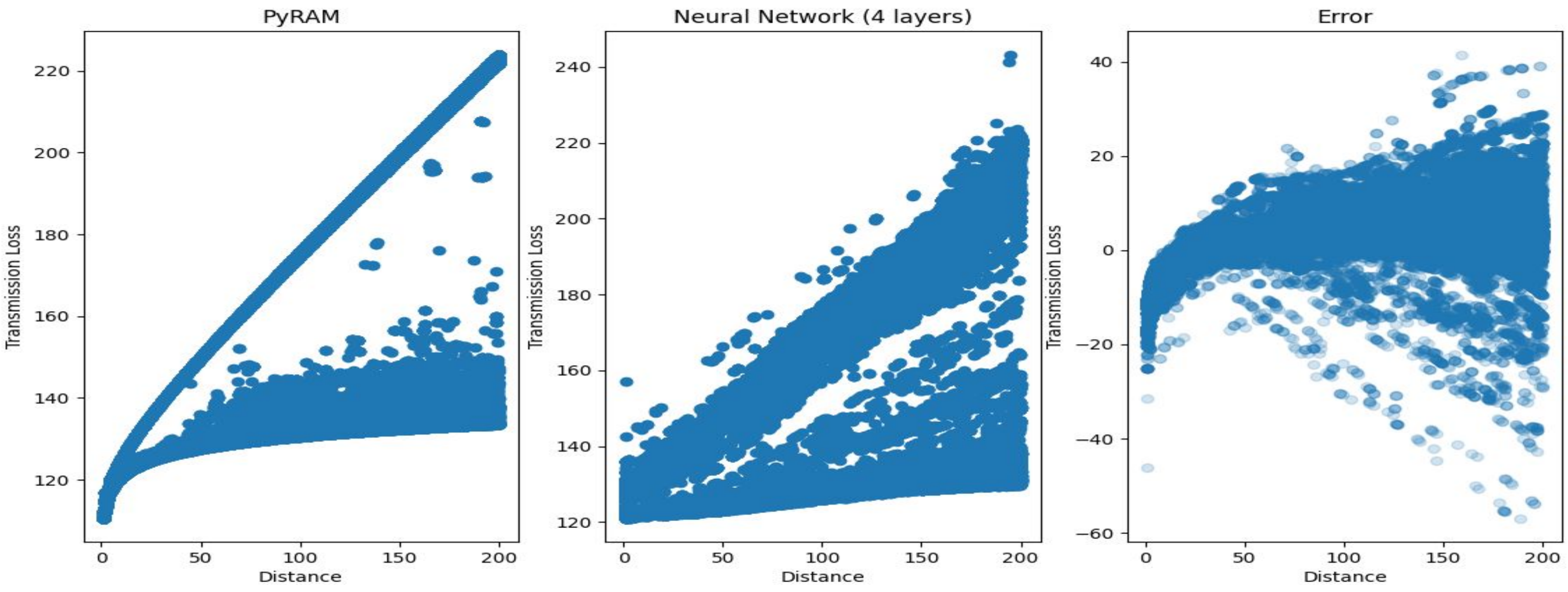
5 layered net -
- Fully connected Layer(128 units)
- ReLU
- Dropout
- Fully Connected(128)
- ReLU
- Dropout
- Fully Connected(64)
- ReLU
- Dropout
- Fully Connected(64)
- ReLU
- Dropout
- Fully Connected(16)

5 layered net -
- Fully connected Layer(256)
- ReLU
- Dropout
- Fully Connected(512)
- ReLU
- Dropout
- Fully Connected(256)
- ReLU
- Dropout
- Fully Connected(128)
- ReLU
- Dropout
- Fully Connected(64)
- ReLU
- Dropout
- Fully Connected(16)

Experimental results

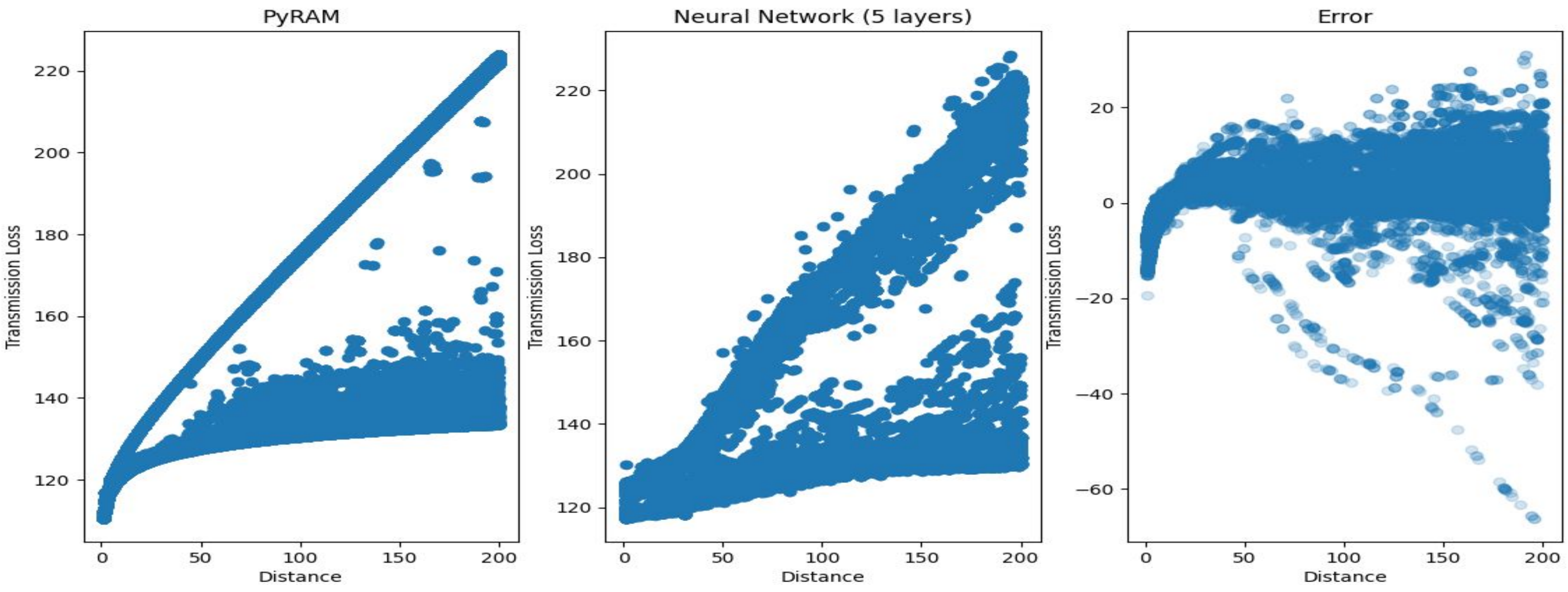
- For the three different architectures, the TL from the PyRAM and the NN, as well as the error is plotted wrt Distance
- The computational times for both the PyRAM and the Neural net have been compared for 1000 pairs of transmitters and receivers
- Though the mean squared error and the mean absolute error from these methods come to be very low, there are pairs that have a huge deviation from the PyRAM benchmark

Experimental results (4 layered network)



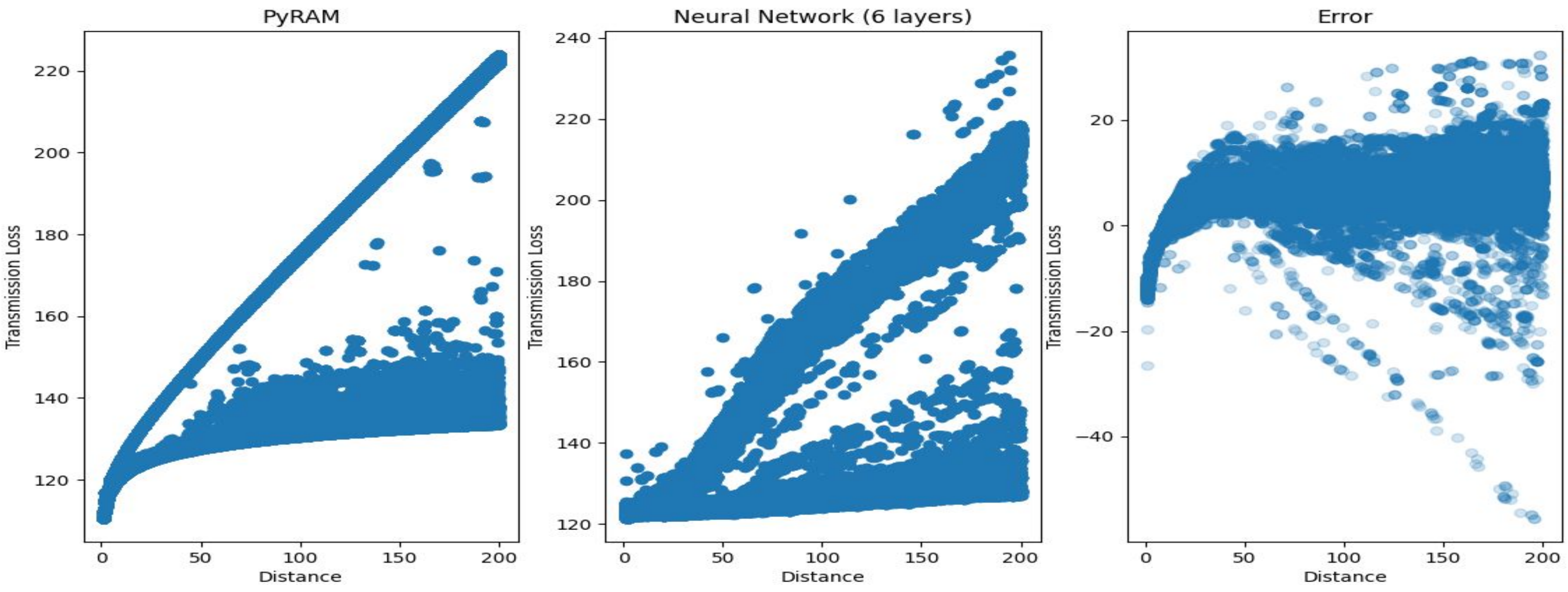
Mean Squared Error - 35.622
Mean Absolute Error - 4.55 dB
Iterations trained - 150

Experimental results (5 layered network)



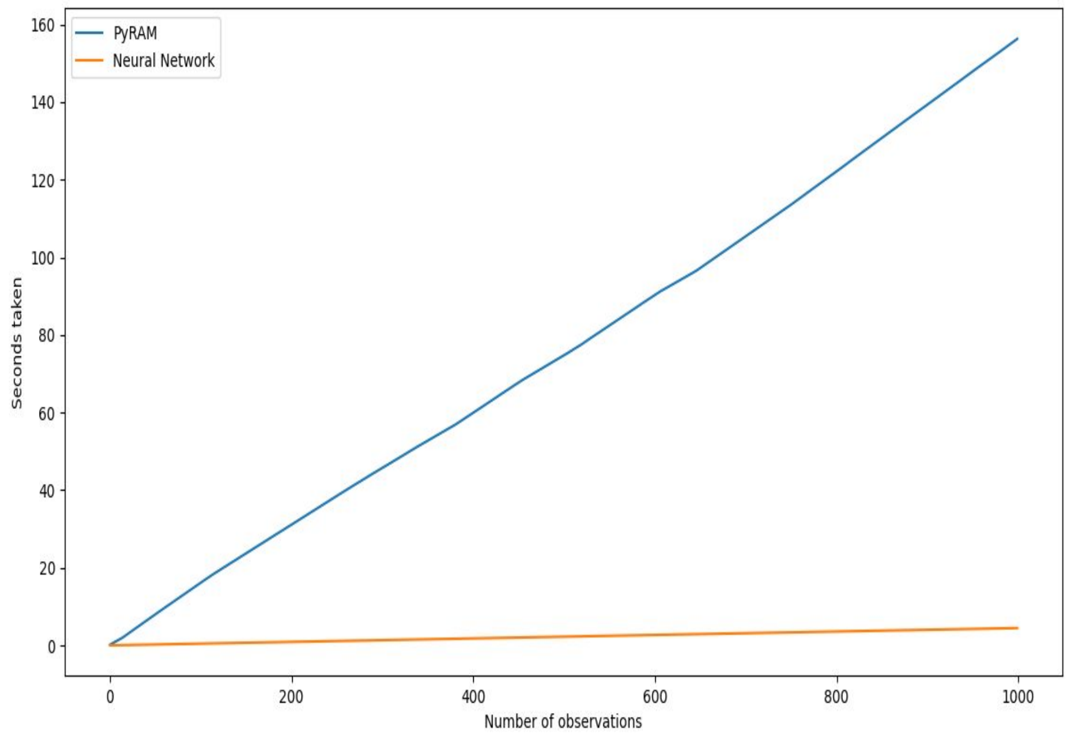
Mean Squared Error - 20.55
Mean Absolute Error - 3.41 dB
Iterations trained - 150

Experimental results (6 layered network)



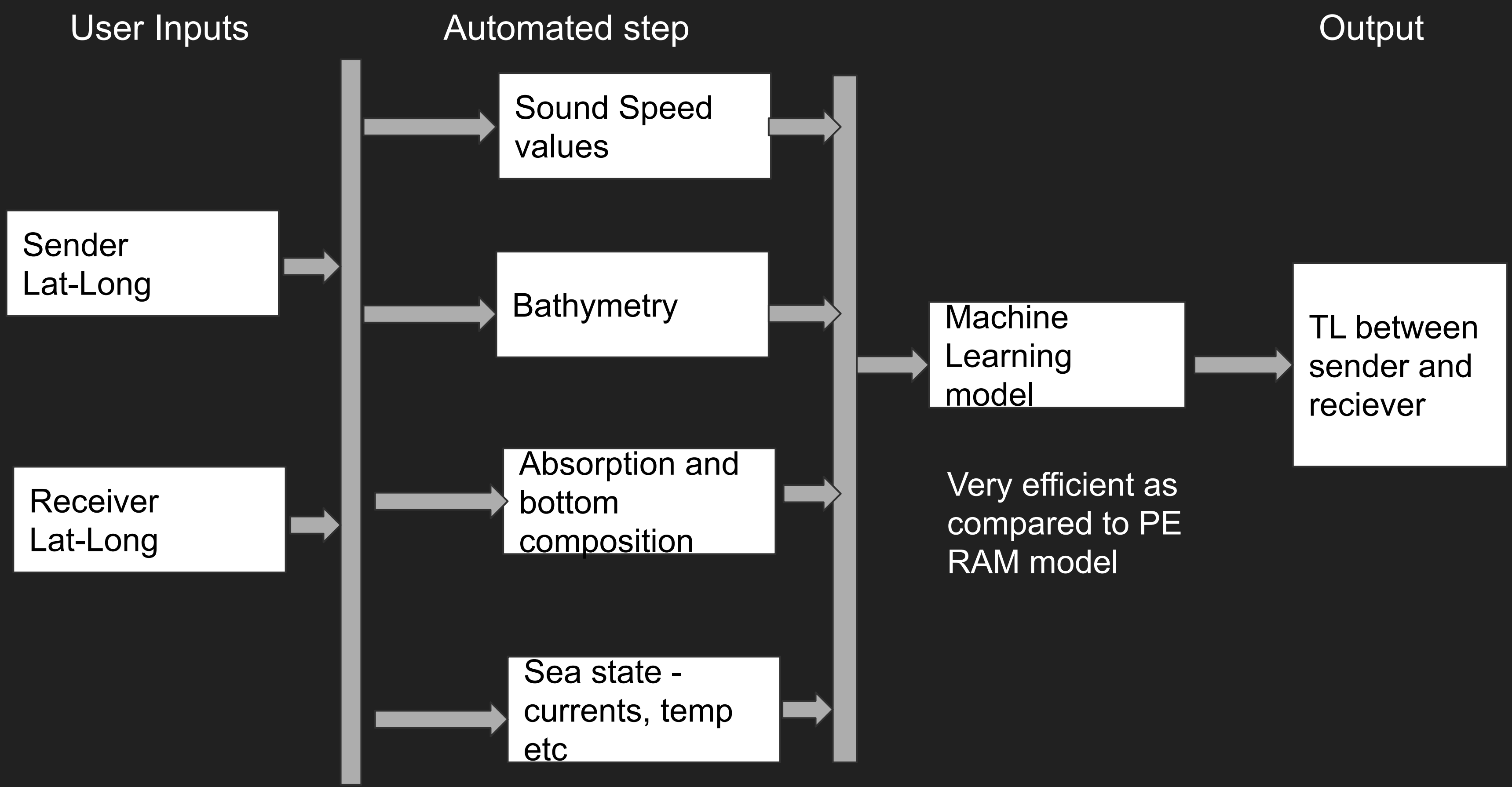
Mean Squared Error - 47.68
Mean Absolute Error - 6.27 dB
Iterations trained - 150

Comparison of computational times



- The graph besides shows the computational time for 1000 transmitter receiver pairs
- Total time taken by PyRAM for 145000 pairs - 12 hours +
- PyRAM also scales linearly with number of pairs
- The neural network gives near constant time predictions, and significantly lower runtimes

Final deliverable



Advantages and shortcomings

Advantages -

- The compute time is significantly lower for the suggested Neural network
- It reduces dependence on manual input parameters such as step size
- First of its kind to need only the transmitter and receiver coordinates as the input from the user

Shortcomings -

- It is tough to know exactly what is going on inside the neural network and what high level features it uses, reducing comprehension
- Even though the mean squared error and mean absolute error are not much, sometimes, the error can be really high (approx 40-60dB)

Conclusions

- The proposed neural network reduces the compute time significantly, which can be of great use if the number of ships for which the TL is to be calculated is huge
- The shortcomings end up being that some pairs do have a large loss wrt PyRAM (40-60 dB)

Future Directions

- An error analysis can be done to determine why the high errors (40dB - 60dB), and corrective measures can be implemented
- Using PyRAM model as a baseline implies it is difficult to get a higher accuracy than PyRAM. Another direction may be to train on empirical data, to get close to accurate results
- An attempt to extract high level features can be performed, giving more insight into what the neural network is learning - currently an active area of research in AI currently

THANK YOU

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Others -

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2. https://oalib-acoustics.org/ - Ocean Acoustics Library, Original implementation of PE RAM