INDIAN INSTITUTE OF TECHNOLOGY MADRAS
DEPARTMENT OF CIVIL ENGINEERING

PROJECT GUIDE:
DR. STG RAGHUKANTH

# EARTHQUAKE GROUND MOTION ANALYSIS AND PREDICTION

## CE4902: FINAL PRESENTATION

SAMARTH K J
CE22B099

25/02/2024

CE22B099@SMAIL.IITM.AC.IN
+91 7899186985

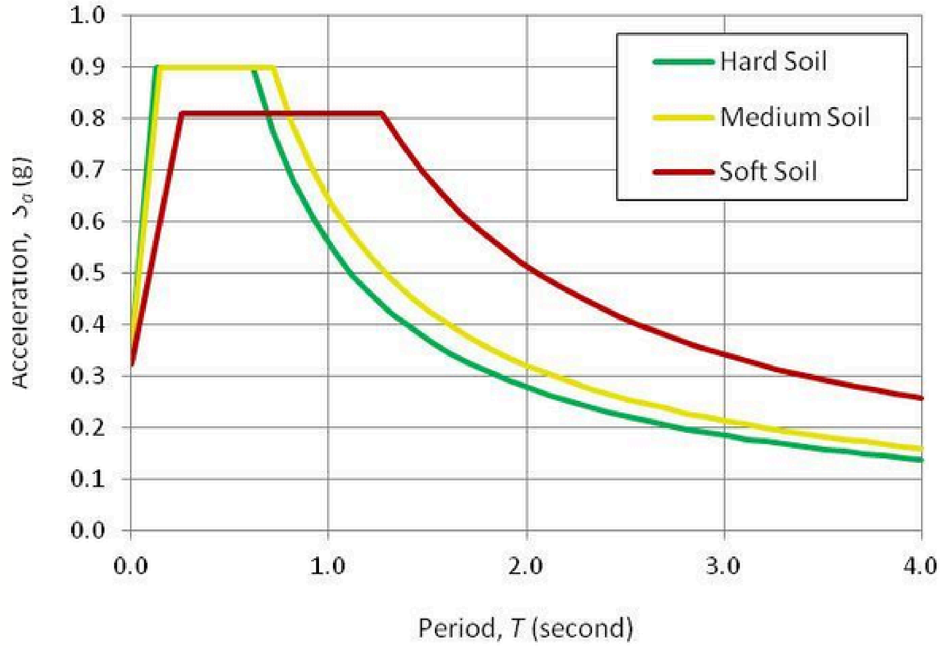
# CONTENTS

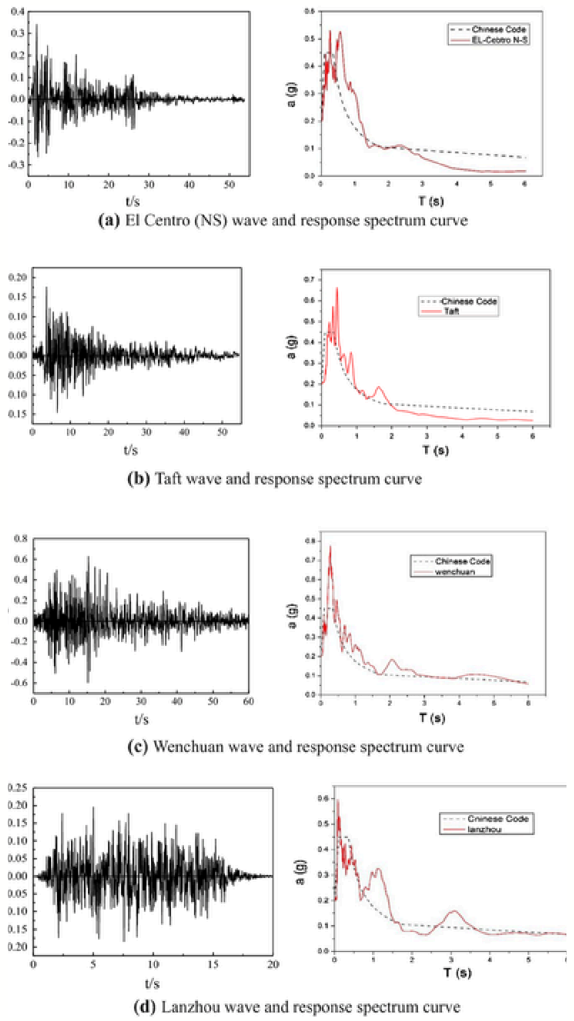
# Introduction

Response Spectra, Fourier Amplitude Spectra and other such techniques for engineering seismic analysis rely on ground motion acceleration time histories for derivation.

Obtaining a large number of real data can be challenging for many reasons. Usage of machine learning techniques in seismology, geology, or civil and structural engineering is a great way to generate synthetic data.

In this report, data was visualised and interpreted before an attempt was made to use the follwingmachine learning techniques: cGANs, BNNs and FFNNs, with special emphasis on conditional GANs in order to predict ground motion during Earthquakes via prediction of response spectra.



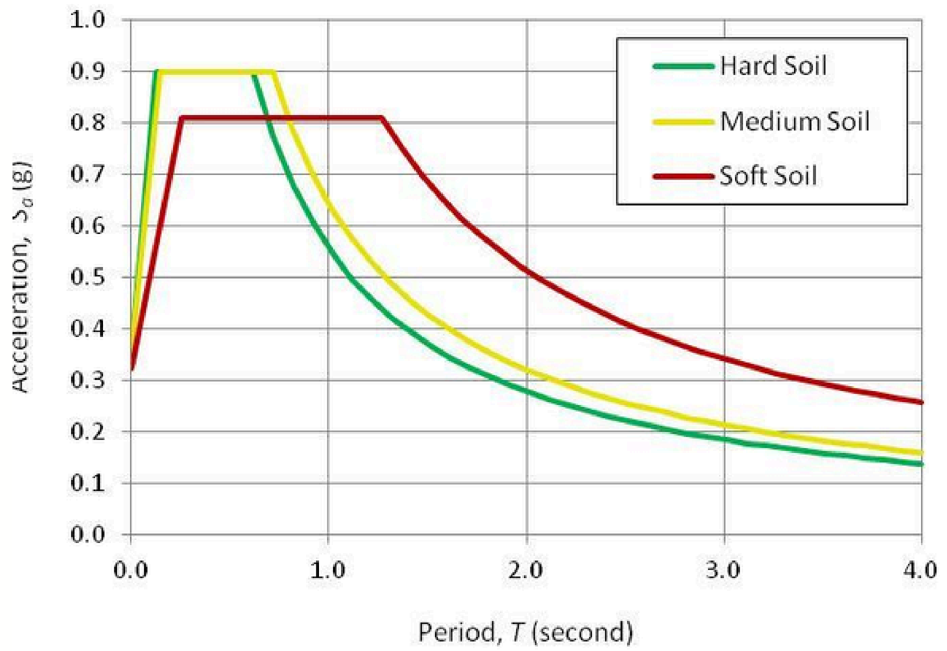

# Methodology

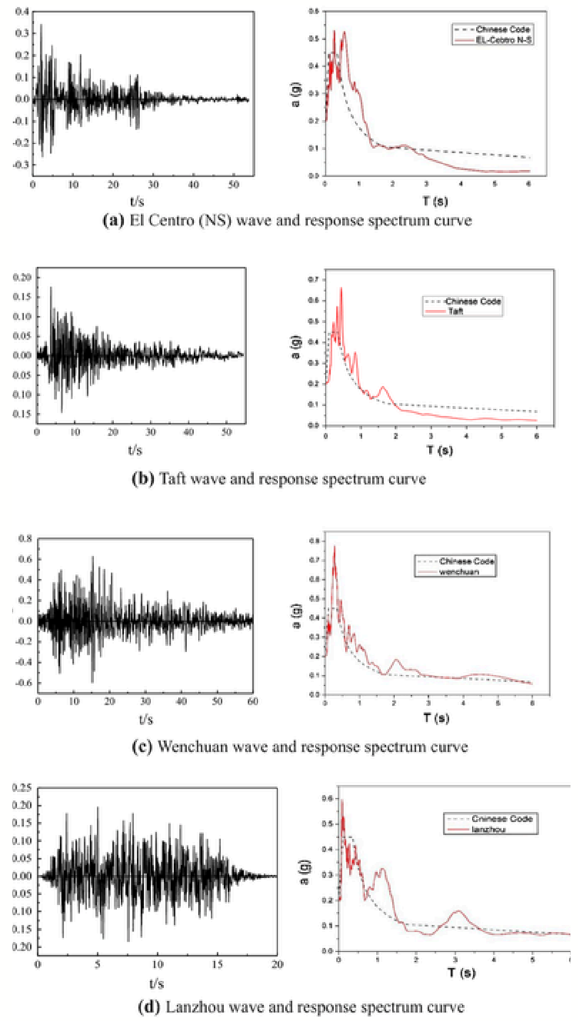
A three-step approach was employed:

**Data pre-processing**
The data was **cleaned, transformed and reduced** in order to make it more feasible for us to analyse and visualize data and subsequently use it to train models.

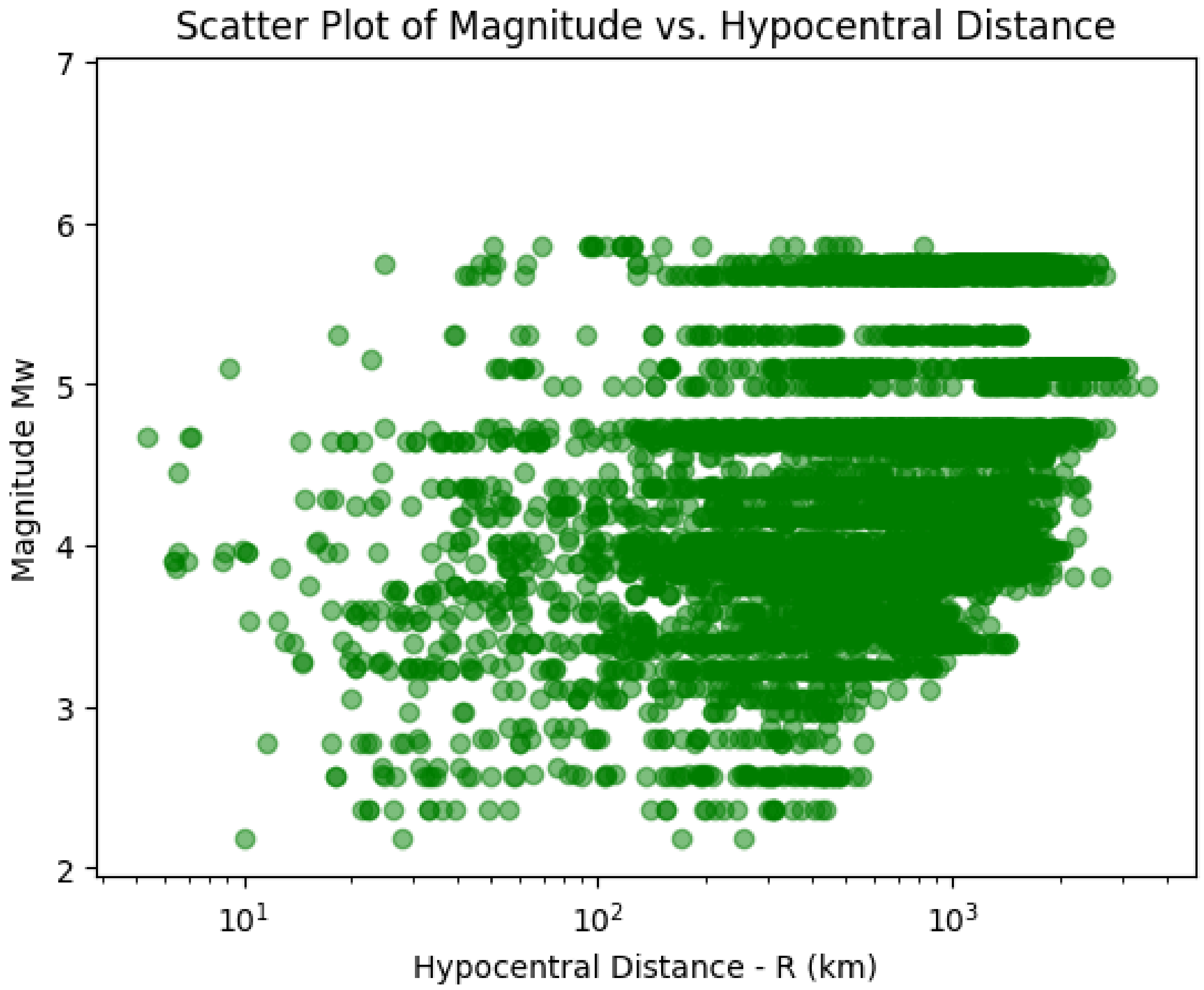
**Data Visualization**
The data was visualized using **matplotlib, pandas and seaborn** to gather insight into the **usefulness of parameters and relationships between them.**

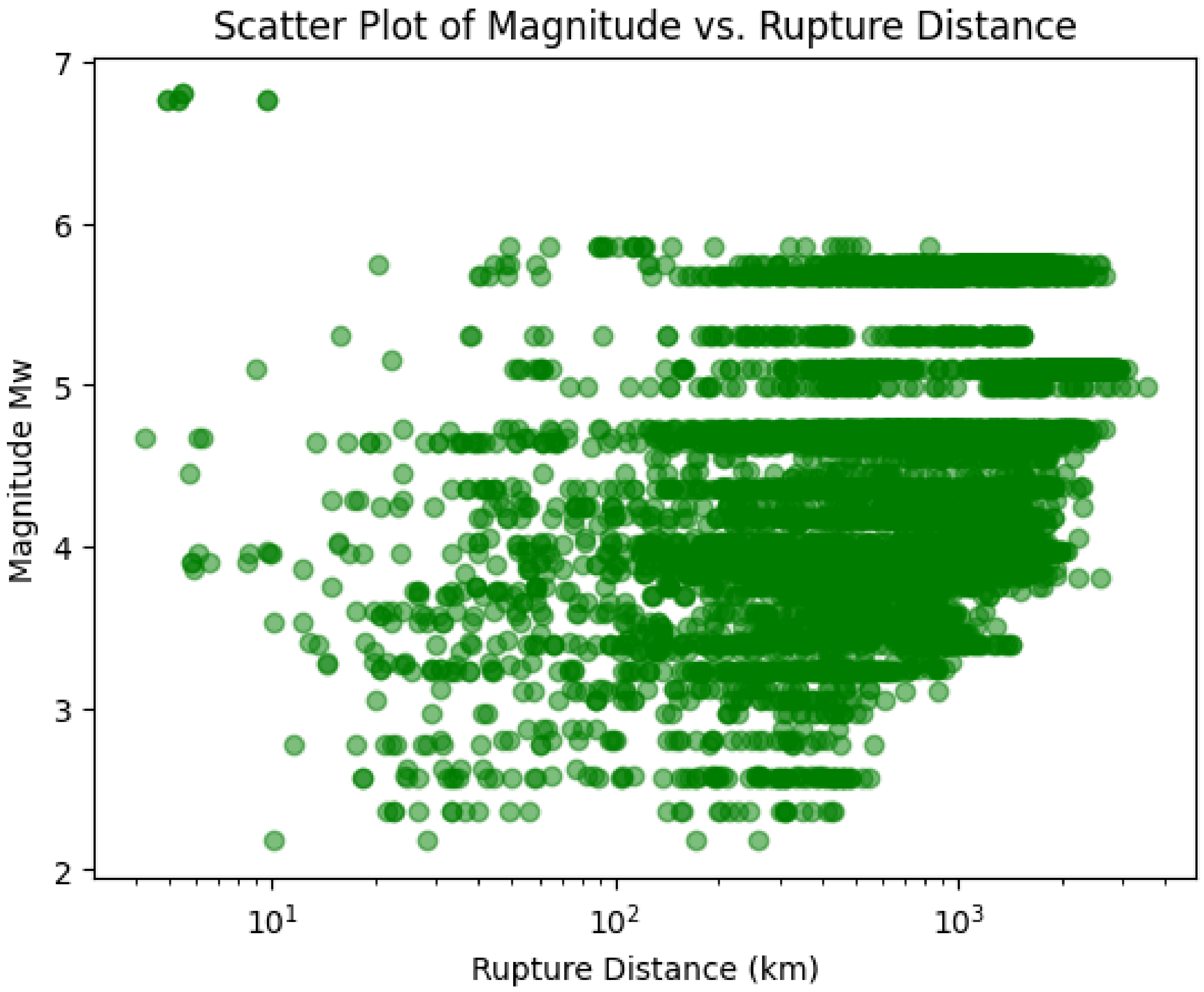
**Response Spectra Prediction**
Using the pre-processed data, **cGAN** can be used to predict **response spectra**; we can derive time-histories from the response spectra.
Also, ANNs and BNNs were used in order to predict peak ground acceleration (PGA) and check it's accuracy.

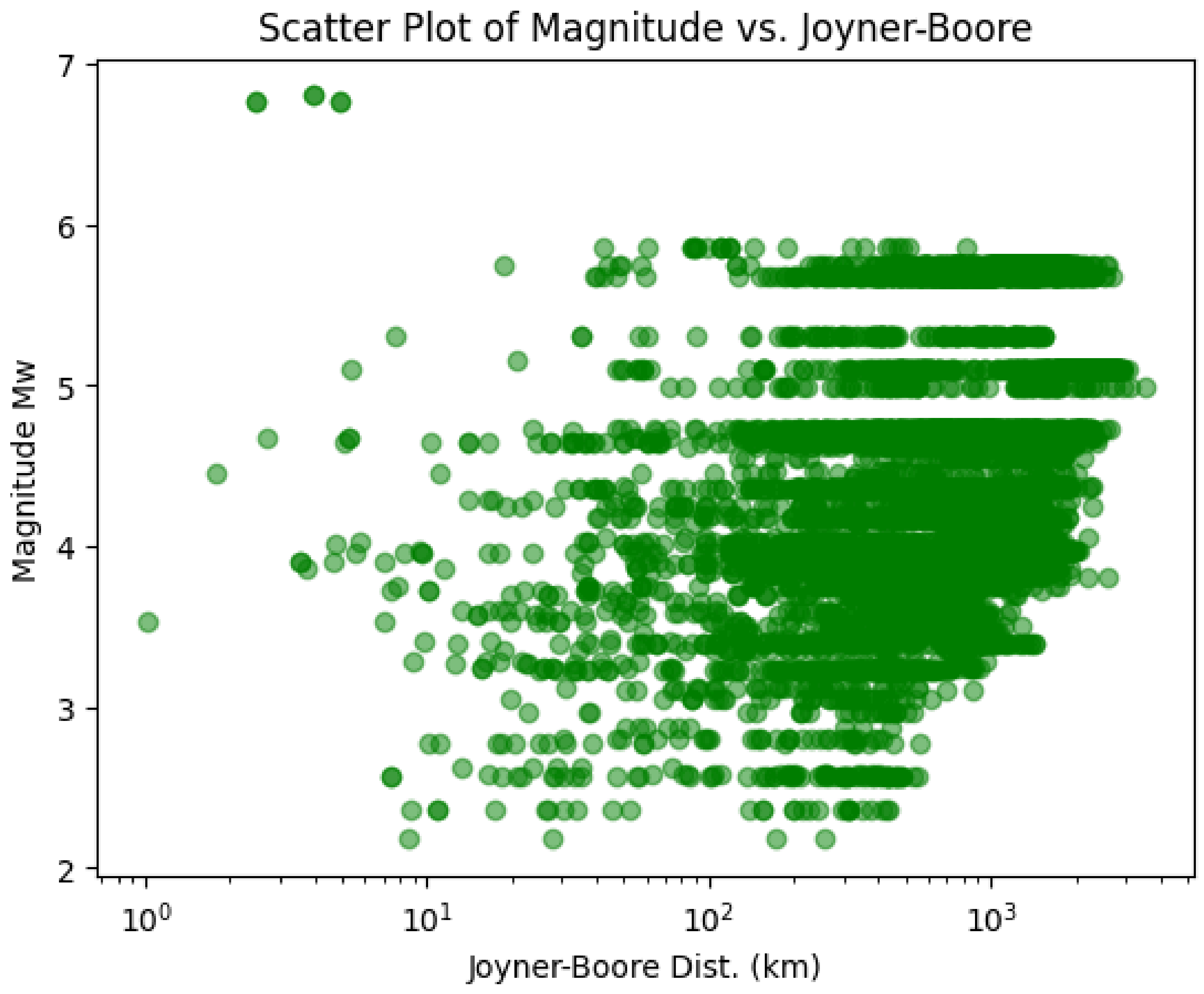


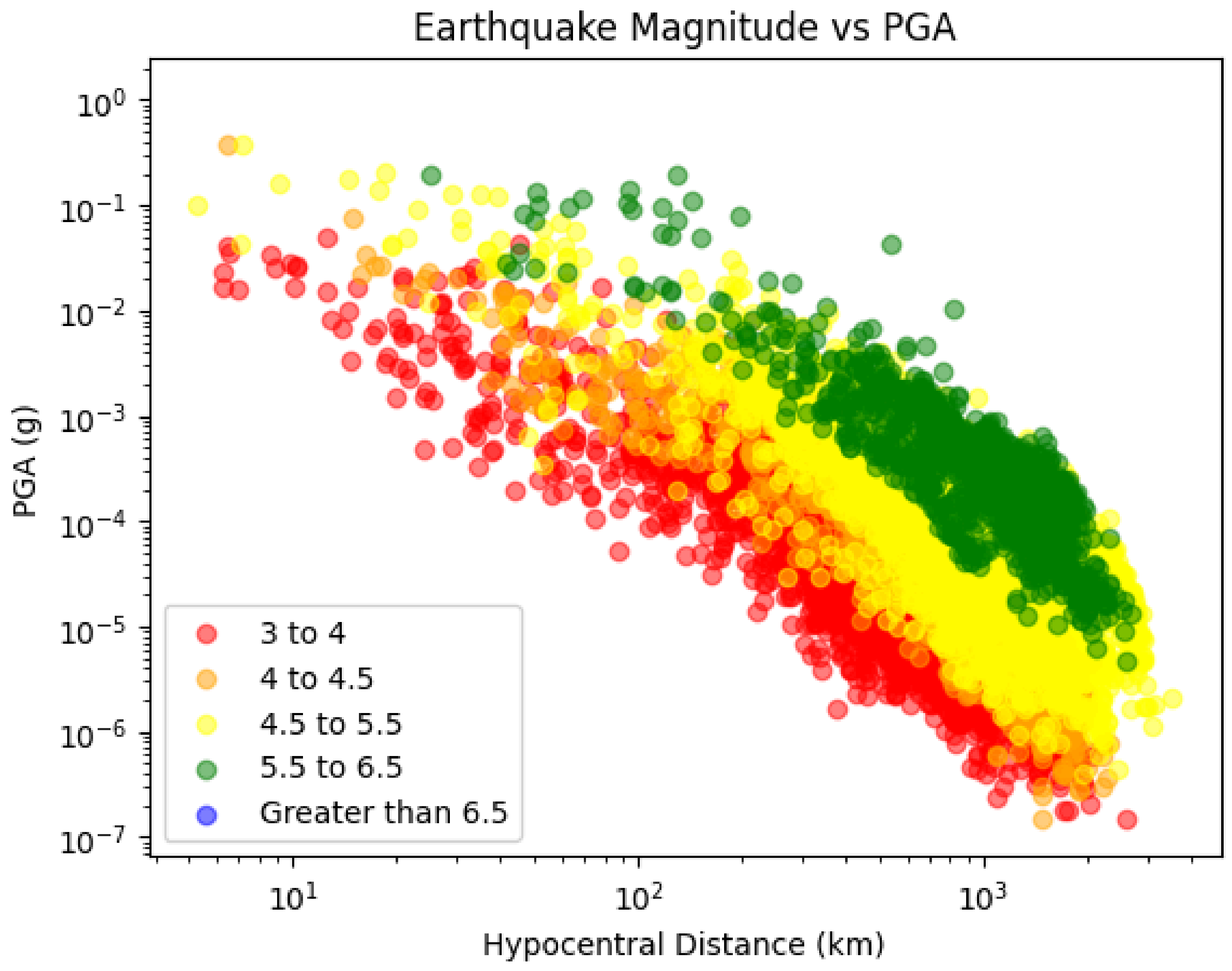



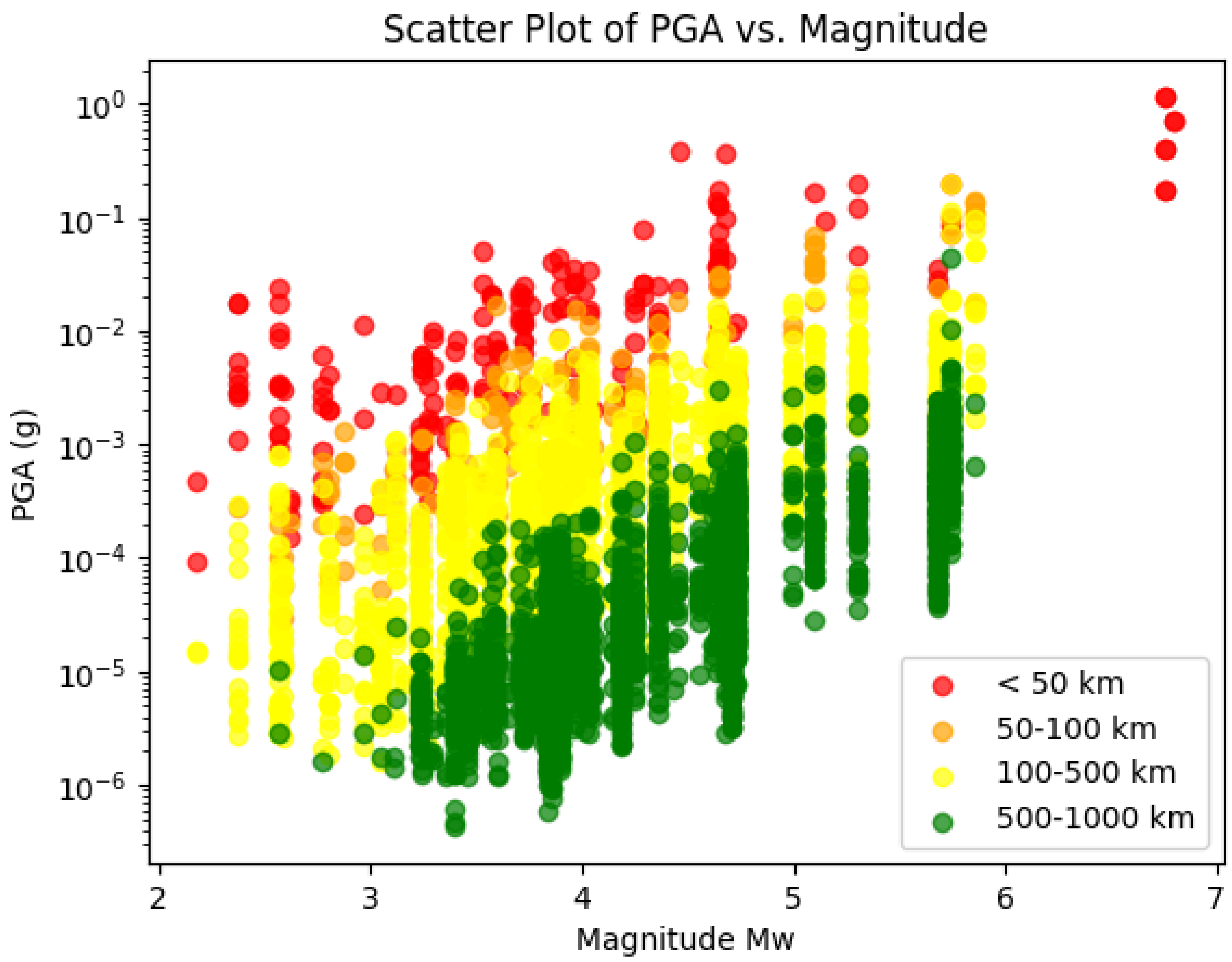

# Data Visualisation: Scatter Plots

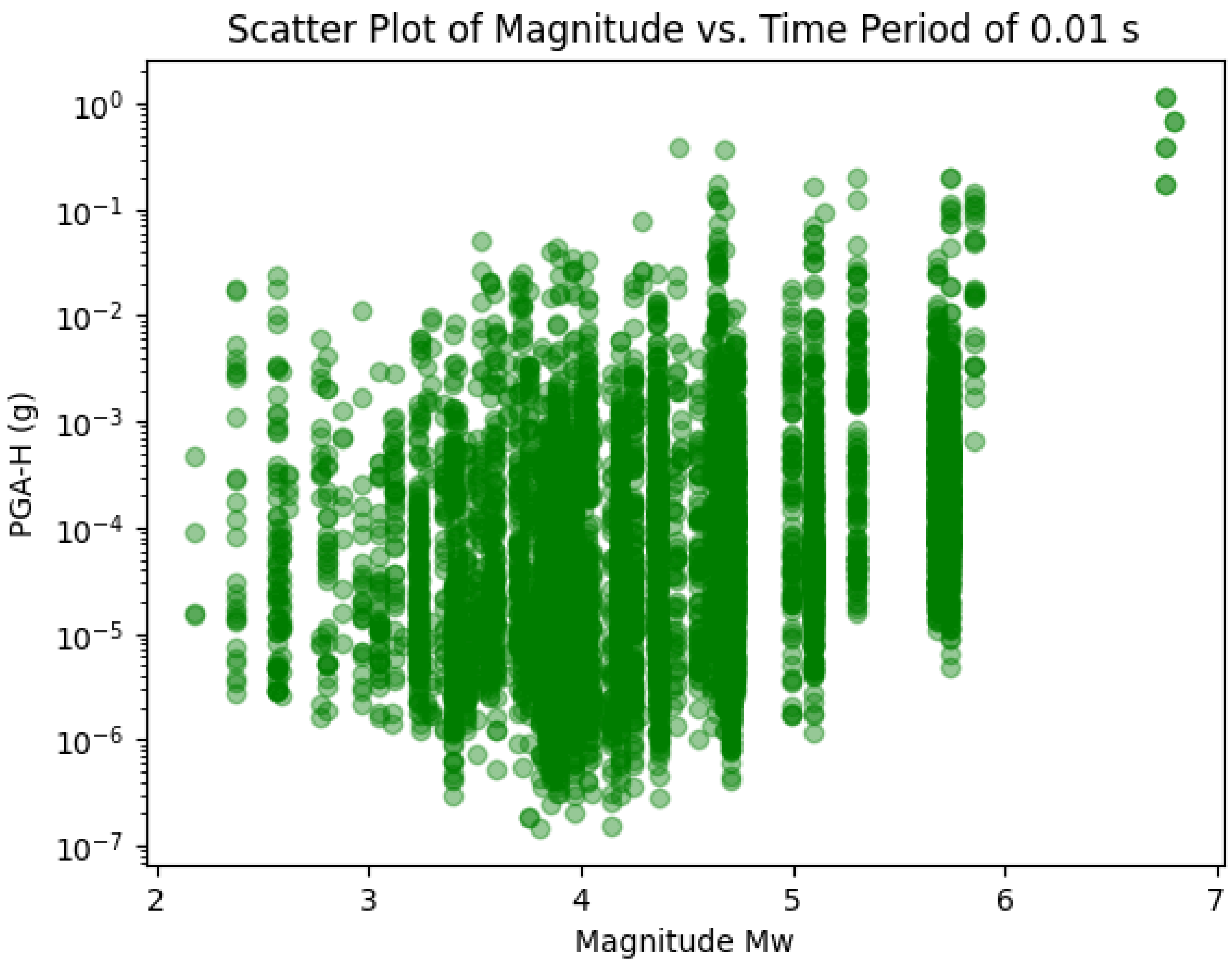



Scatter Plot of Magnitude vs. Joyner-Boore
Magnitude Mw
Joyner-Boore Dist. (km)


Earthquake Magnitude vs PGA
PGA (g)
Hypocentral Distance (km)
3 to 4
4 to 4.5
4.5 to 5.5
5.5 to 6.5
Greater than 6.5


Scatter Plot of PGA vs. Magnitude
PGA (g)
Magnitude Mw
$10^0$
$10^{-1}$
$10^{-2}$
$10^{-3}$
$10^{-4}$
$10^{-5}$
$10^{-6}$
2
3
4
5
6
7
< 50 km
50-100 km
100-500 km
500-1000 km


Scatter Plot of Magnitude vs. Time Period of 0.01 s
PGA-H (g)
Magnitude Mw
$10^0$
$10^{-1}$
$10^{-2}$
$10^{-3}$
$10^{-4}$
$10^{-5}$
$10^{-6}$
$10^{-7}$
2
3
4
5
6
7

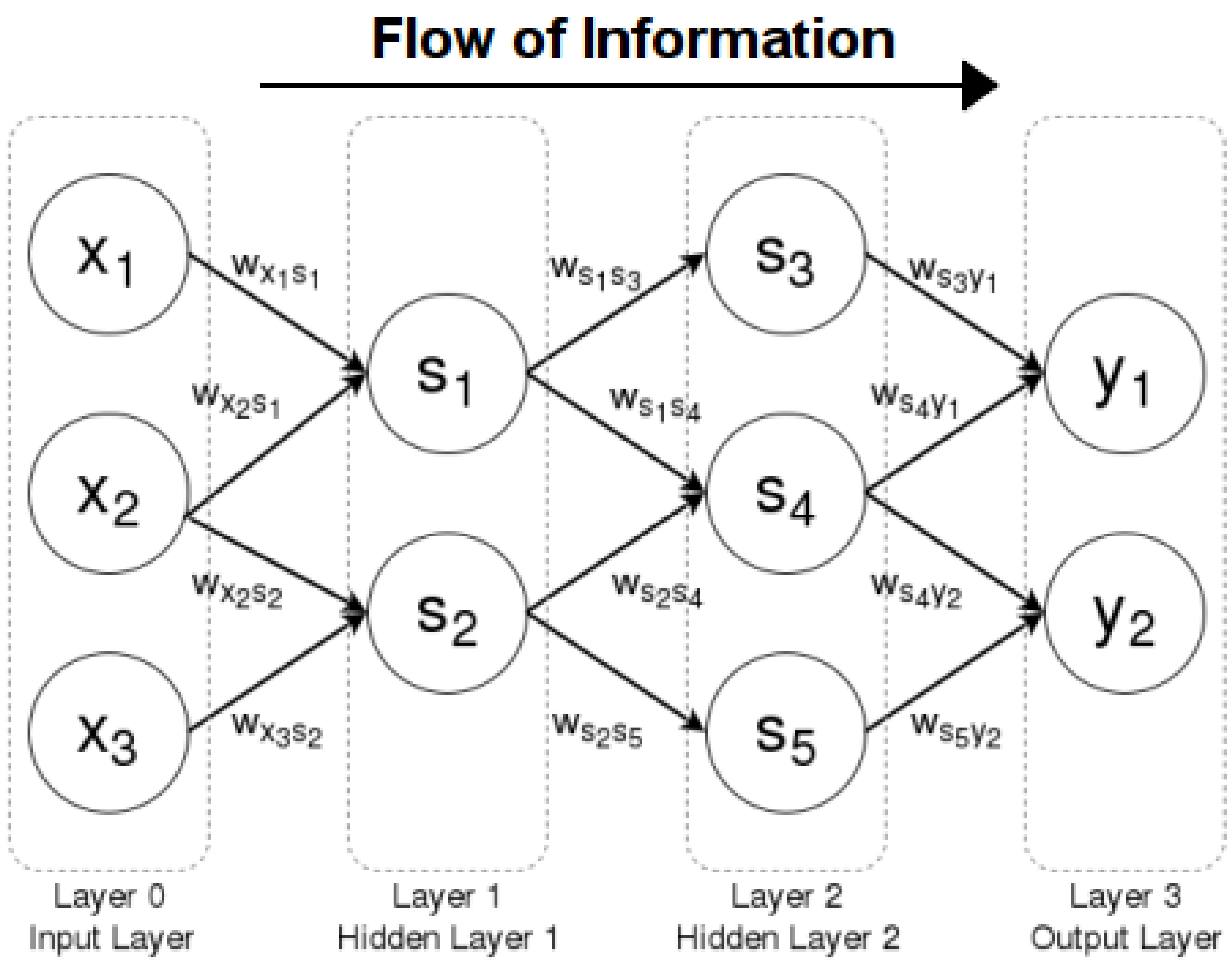
# Prediction of PGA with FFNN

A Feed Forward Neural Network processes information in a one-way flow, unlike RNNs or LSTMs, from input nodes through hidden layers to output nodes.

Input nodes receive data, hidden layers perform computations using weighted sums and activation functions to introduce non-linearity, and output nodes produce final predictions.

Weights and biases govern the strength of connections between nodes, while activation functions enable the network to approximate complex relationships. During training, backpropagation adjusts weights and biases to minimize prediction errors.

# Prediction of PGA with FFNN



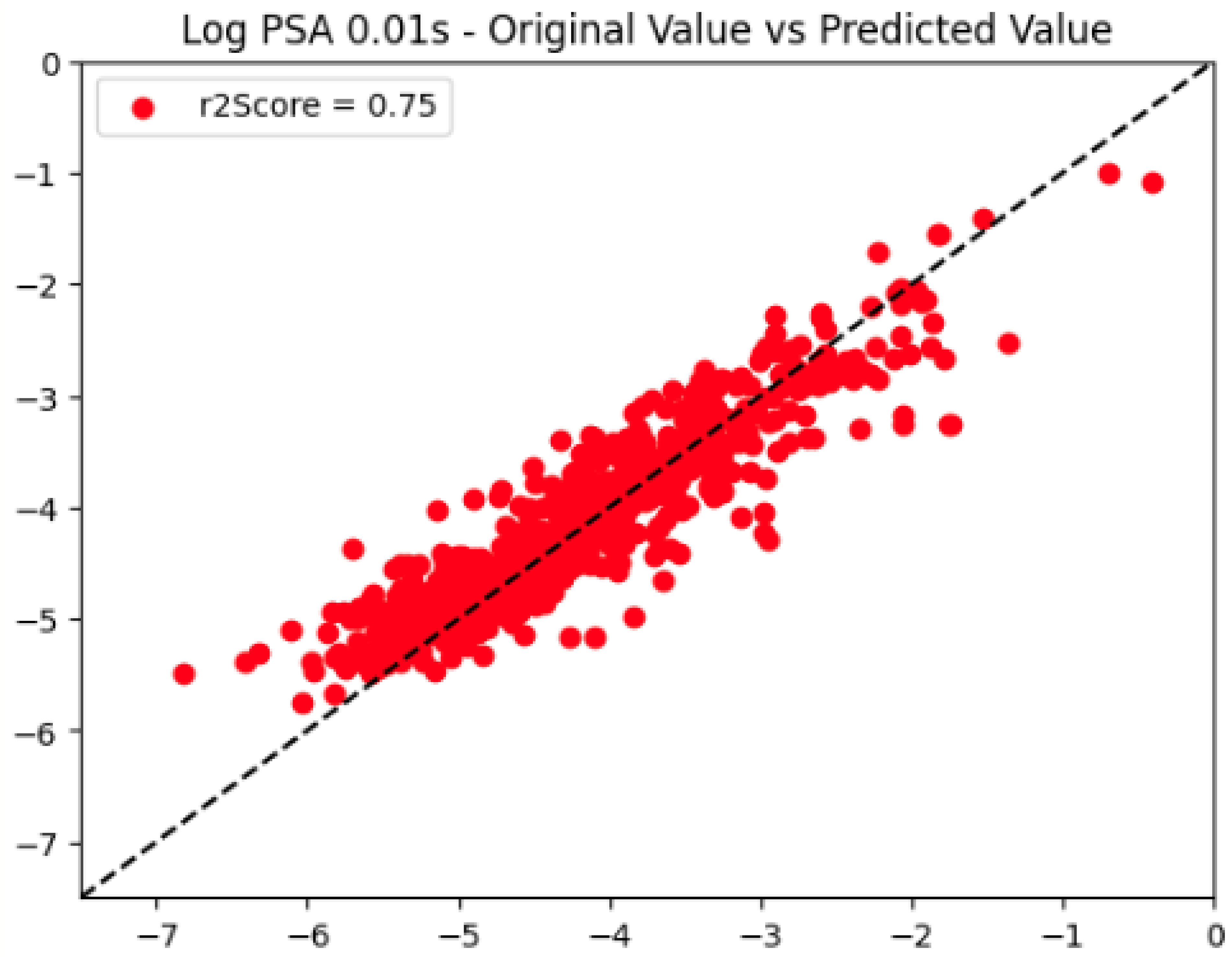
# Prediction of PGA with FFNN

To train the model, we use 5 input parameters:

1. Earthquake Magnitude
2. Joyner-Boore distance
3. Logarithm of Joyner-Boore distance
4. Mechanism Based on Rake Angle
5. Preferred shear wave velocity (VS30 )

Predicting the logarithm of pseudo-absolute-acceleration spectra (PSA) (an intensity measure) using an FFNN, we get an **$R^2$ value of 0.75.**

# Prediction of PGA with FFNN

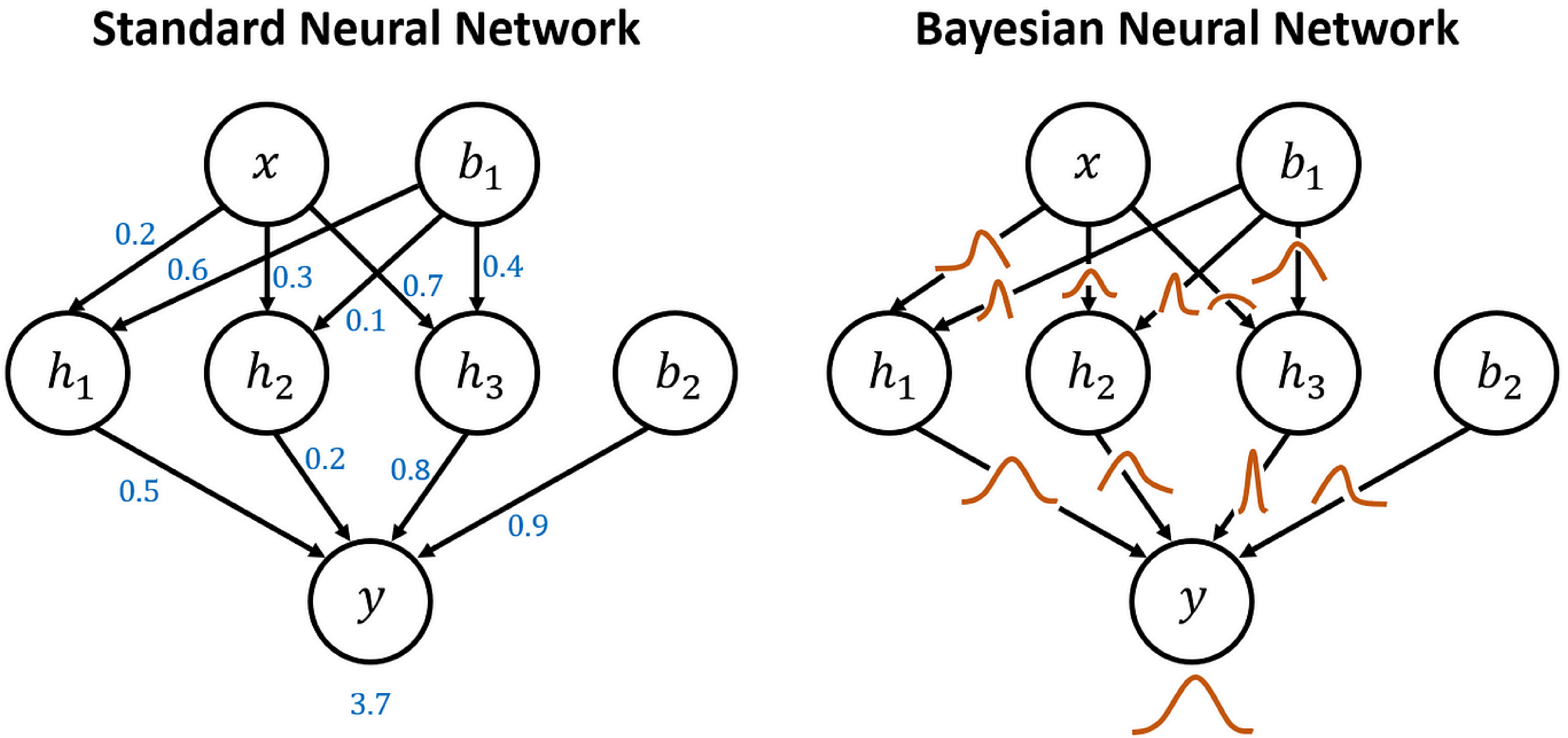


# Prediction of PGA with BNN

Bayesian neural networks (BNNs) are a type of neural network that incorporates Bayesian inference into the training and prediction process.

In traditional neural networks, parameters (weights and biases) are usually deterministic values learned from data using techniques like gradient descent. In contrast, BNNs treat parameters as probability distributions rather than fixed values.

# Prediction of PGA with BNN



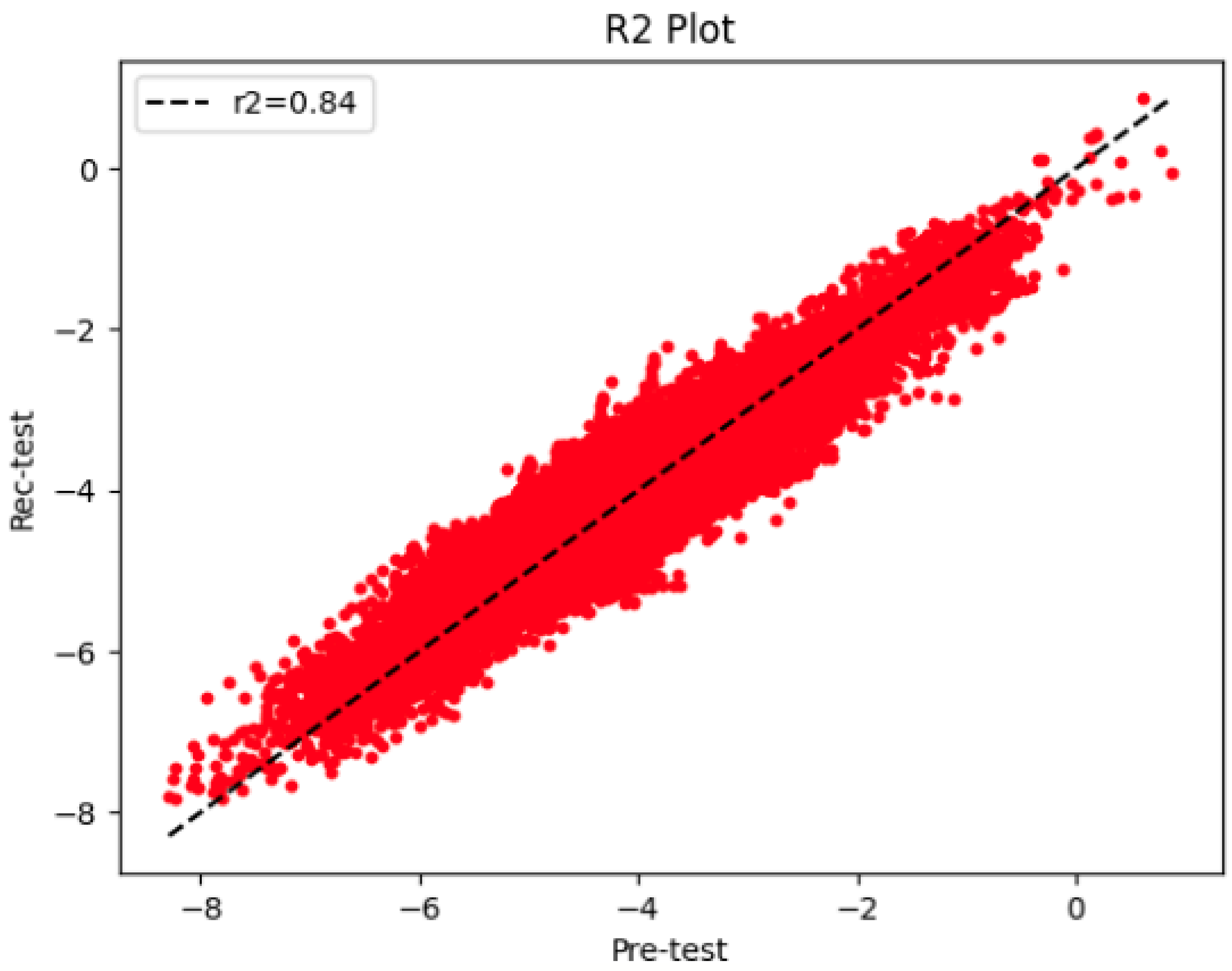
# Prediction of PGA with BNN

To train the model, we use same 5 input parameters:

1. Earthquake Magnitude
2. Joyner-Boore distance
3. Logarithm of Joyner-Boore distance
4. Mechanism Based on Rake Angle
5. Preferred shear wave velocity (VS30 )

Predicting the logarithm of peak ground acceleration (PGA) (an intensity measure) using an BNN, we get an **$R^2$ value of 0.84.**

# Prediction of PGA with BNN



# Prediction of the Response Spectra with Conditional GAN

Generative Adversarial Network consists of two components, which can be any two models (mathematical/statistical/deep):

1. **Generator:** It takes random noise (often sampled from a simple distribution like Gaussian) as input and transforms it into data samples that resemble real data.
2. **Discriminator/Adversary:** The discriminator acts as a critic that evaluates the realism of the generated samples. It takes both real data samples and generated data samples as input and learns to distinguish between them.

# Prediction of the Response Spectra with cGAN

$$\min_{G} \max_{D} V(D, G)$$

$$V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

This is the **loss function for GANs**.

It is defined such that the generator tries to increase the loss while the discriminator tries to reduce the loss. This process drives both the generator and the discriminator to improve significantly over training iterations.

This is also the reason why GANs take significantly longer time to train and generate good results.

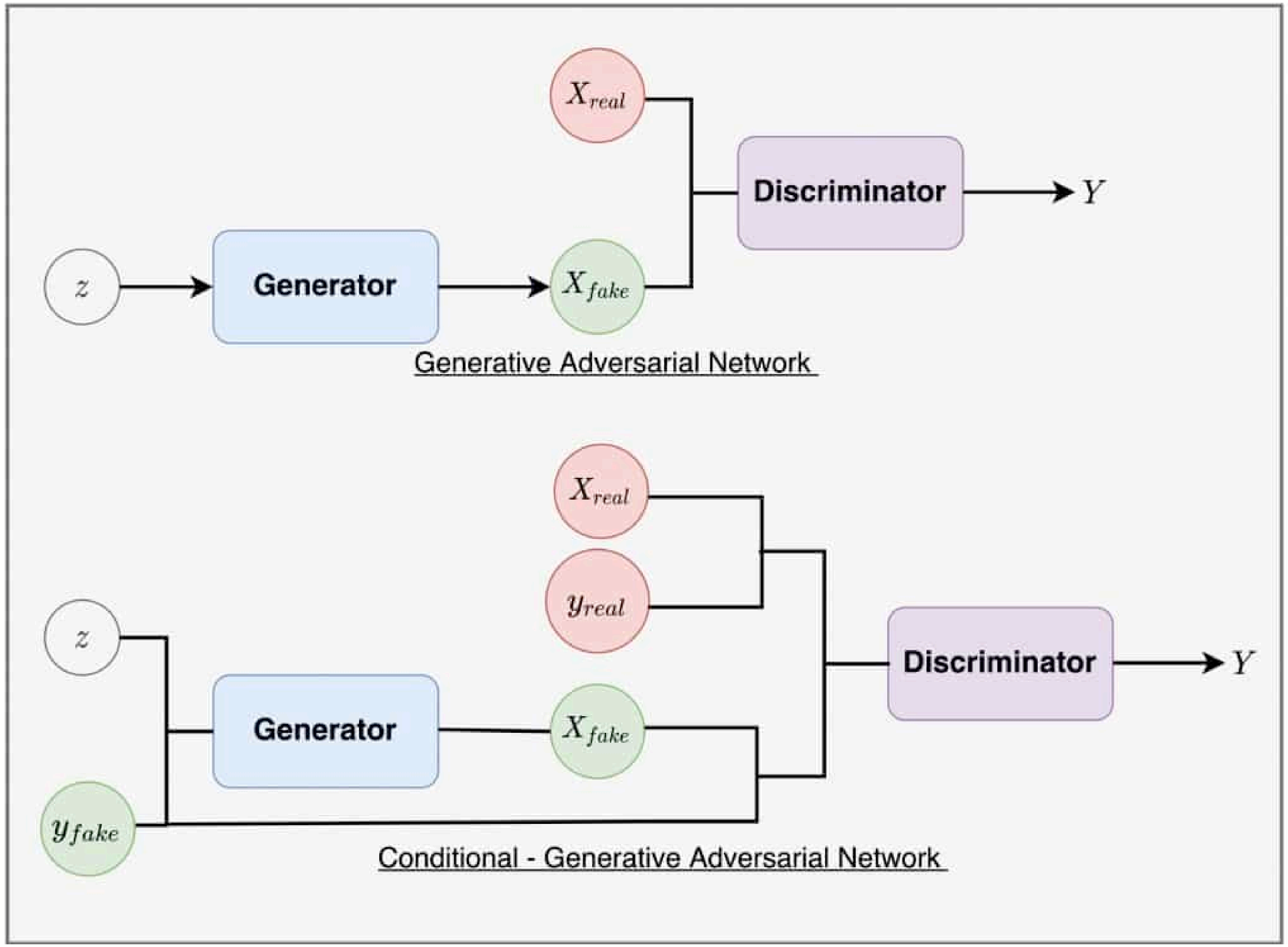
# Prediction of the Response Spectra with cGAN

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x|y)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z|y)))]$$

This is the **loss function for a conditional GAN**.
We will generate response spectra of earthquakes using a conditional GAN as we can condition the outputs using the inputs in this method, i.e. the output is dependent on the input.

**cGANs produce more structured and meaningful results compared to traditional GANs**, making them **suitable for tasks like response spectra generation**, where conditioning information is crucial for generating output that is required for specific earthquake parameters.

# Prediction of the Response Spectra with cGAN



# Prediction of the Response Spectra with cGAN

To train the model, we use **6 input parameters**:

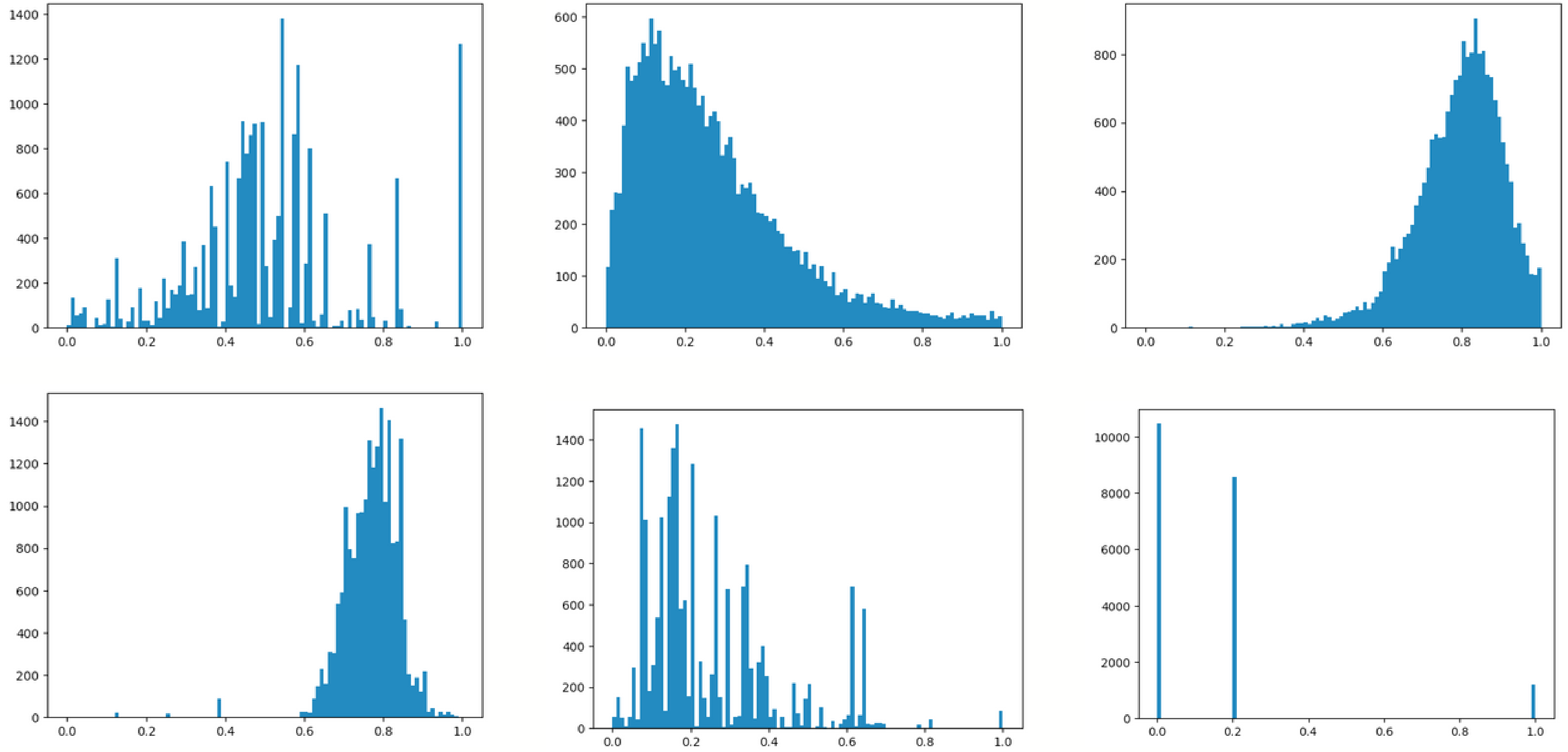
1. Earthquake Magnitude
2. Joyner-Boore distance
3. Logarithm of Joyner-Boore distance
4. Mechanism Based on Rake Angle
5. Preferred shear wave velocity (VS30 )
6. Depth

Using these inputs, the corresponding response spectrum is generated.

It **generally takes >1000 epochs** to generate a good conditional GAN, since there wasn’t enough computational power, the current GAN was trained for 60 epochs.

# Prediction of the Response Spectra with cGAN

The synthetic condition vector that is passed for training needs to be in the same domain as the actual condition vector



These are the distributions of each of the 6 earthquake parameters passed to the cGAN.

A synthetic vector following the normal distribution with it's mean and variance identical to each of these variables was taken to train the generator and the discriminator.

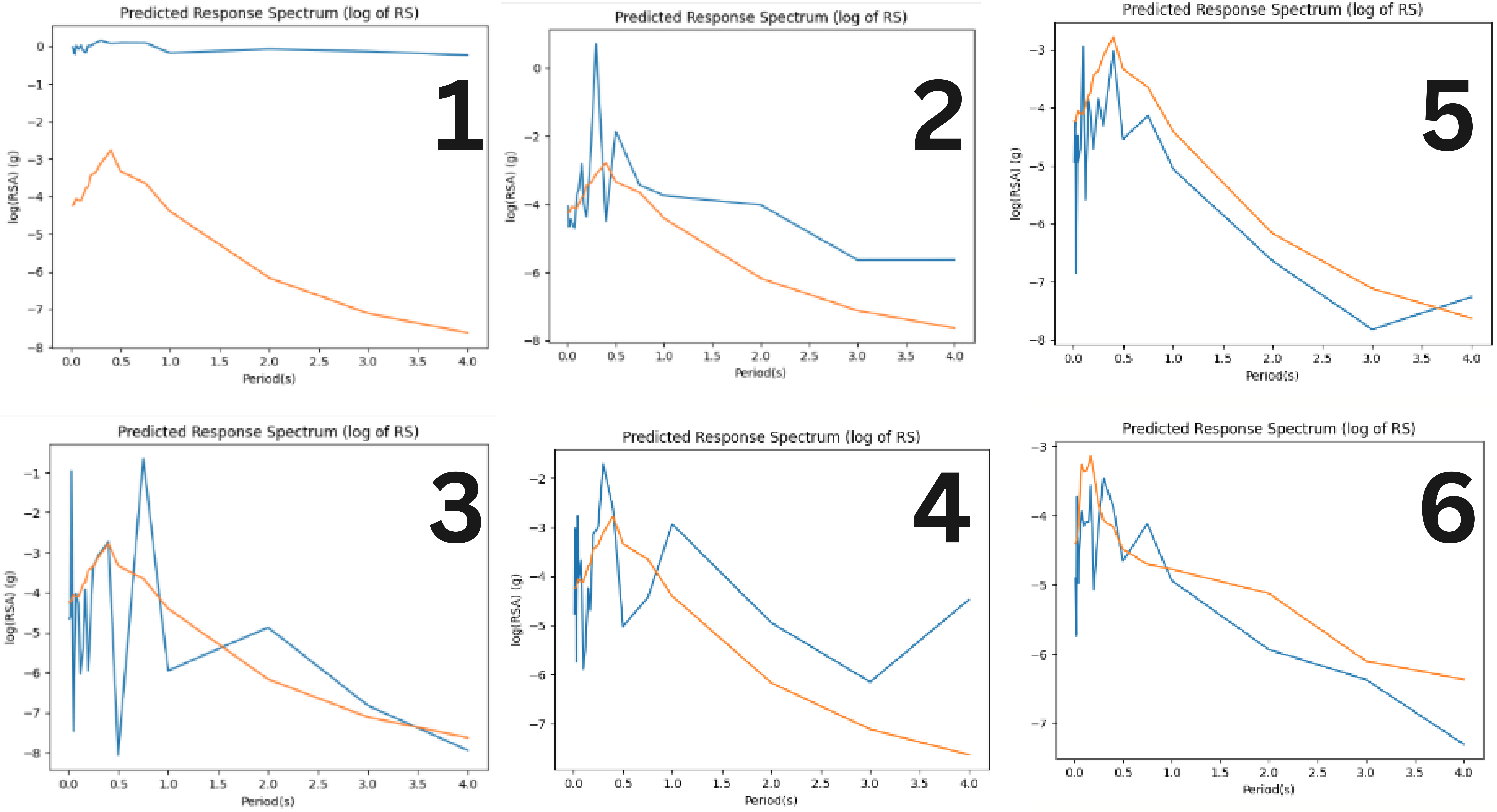
# Prediction of the Response Spectra with cGAN

The next few slides were some of the results obtained.

Yellow line pertains to the generic shape of the response spectrum. It is to be noted that the algorithm isn't trying to match the exact distribution in yellow but it serves as a reference to what the predicted response spectrum should look like.

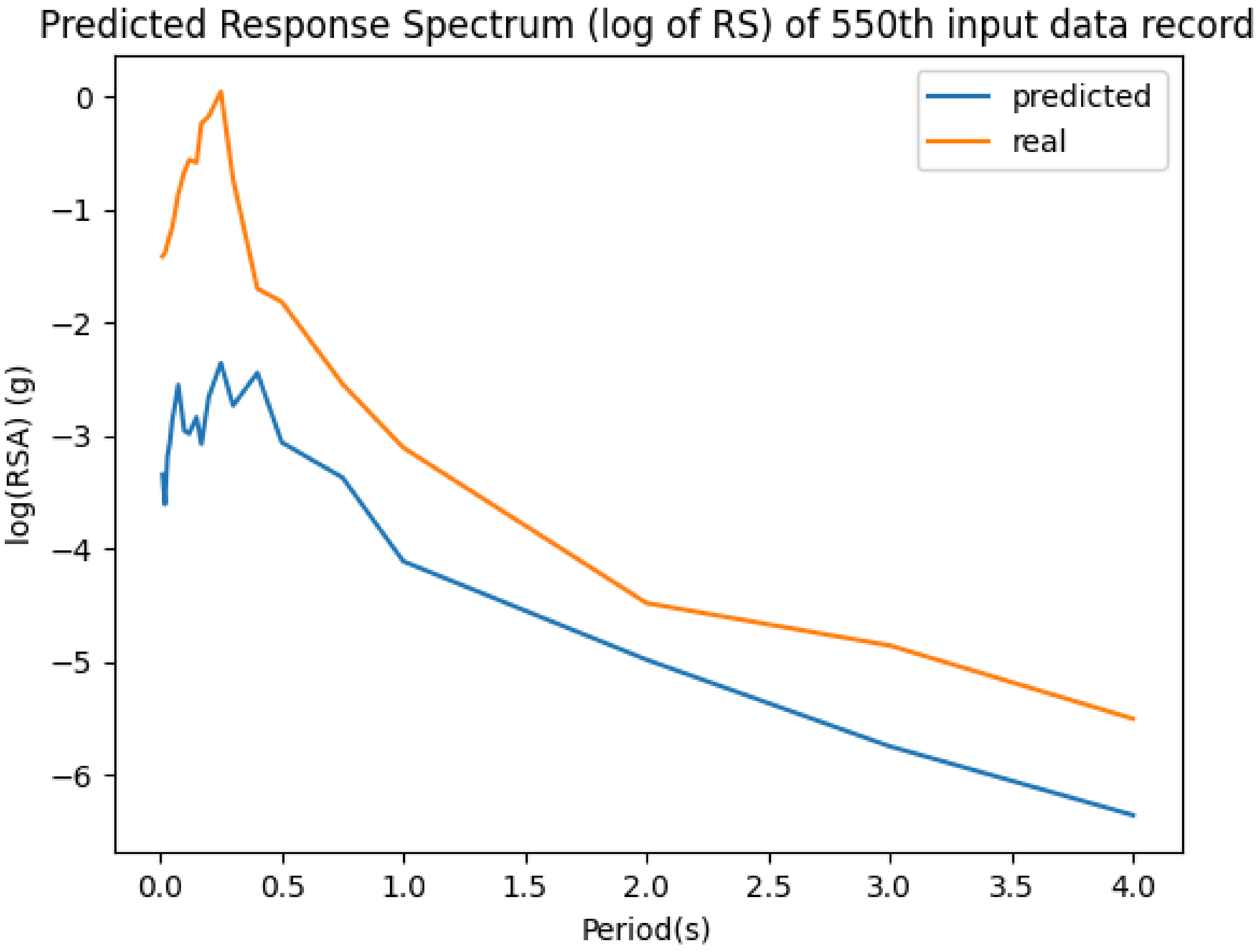
A general response spectrum starts low, shoots up, stabilizes and decreases in a concave manner; there can be sharp peaks and troughs throughout the spectrum.

# Prediction of the Response Spectra with cGAN



# Prediction of the Response Spectra with cGAN

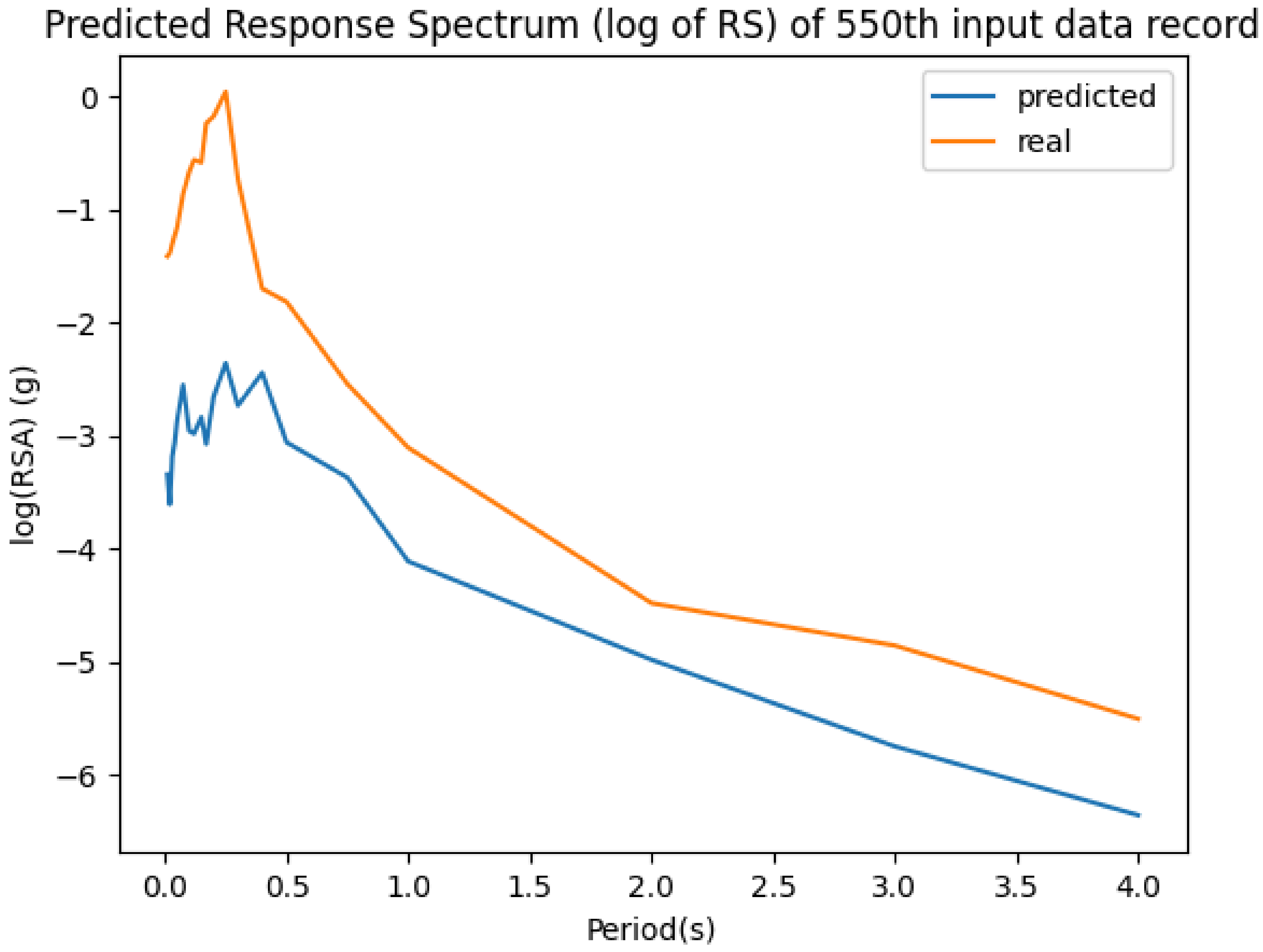
**SPECIFIC PREDICTION FOR THE 550TH ENTRY OF DATA**



# Prediction of the Response Spectra with cGAN

## SPECIFIC PREDICTION FOR THE 550TH ENTRY OF DATA

We do not use $R^2$ to evaluate cGANs as the $R^2$ metric is used for continuous outputs, while cGANs generate images or sequential outputs.



# FUTURE WORK

The cGAN can be further improved upon by the following techniques:

- Training the model much longer, to at least 500 epochs using GPUs.
- Using convolutional layers instead of linear layers as cGANs perform exceptionally well with multidimensional data according to the papers reviewed.
- Using more input parameters for the model to derive more information to generate more accurate results.
- Altering model architectures to better suit the purpose, normalization of the training data and alteration of training procedure.

# Learning Outcomes and Conclusions

From the data analysis and visualisations, we deduce the following:

- Several data are invalid due to absent values, NaN values, anomalously high values. These data need to be eliminated as they are not useful.
- PGA increases with increase in earthquake magnitude and decreases with an increase in hypocentral distance; regardless of the earthquake's magnitude.
- The histograms depict the distribution of all the data collected:
- Most data are of earthquakes from magnitude 3-4 Mw.
- The hypocentral distances of all the earthquakes recorded lie in the 0-1000m range.
- Most earthquakes recorded have hypocenter depth up to 10km

# Learning Outcomes and Conclusions

Using the previous results, data cleaning, transformation and reduction was performed in order to train machine learning models.

The ML techniques cGAN, BNN and ANN showcased promising results:

- FFNN had an $R^2$ value of 0.75 for PSA prediction.
- BNN had an $R^2$ value of 0.84 for PGA prediction.
- cGAN showed response spectrum values based on input parameters that closely resembled the real response spectrum values.

# REFERENCES


- Sreejaya, K.P., Basu, J., Raghukanth, S.T.G. et al. Prediction of Ground Motion Intensity Measures Using an Artificial Neural Network. Pure Appl. Geophys. 178, 2025–2058 (2021). https://doi.org/10.1007/s00024-021-02752-9
- Meenakshi Y, Sreenath V, STG R. Ground motion models for Fourier amplitude spectra and response spectra using Machine learning techniques. Earthquake Engng Struct Dyn. 2024; 53: 756–783. https://doi.org/10.1002/eqe.4036
- Meenakshi Y, Vemula S, Alne A, Raghukanth S. Ground motion model for Peninsular India using an artificial neural network. Earthquake Spectra. 2023;39(1):596-633. doi:10.1177/87552930221144330
- Kramer, S.L. (1996) Geotechnical Earthquake Engineering. Prentice-Hall, New Jersey.
- Dhanya, J., Raghukanth, S.T.G. Ground Motion Prediction Model Using Artificial Neural Network. Pure Appl. Geophys. 175, 1035–1064 (2018). https://doi.org/10.1007/s00024-017-1751-3

# THANK YOU