EARTHQUAKE FORECASTING USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT:

Earthquake is one of the most devastating natural calamities which causes tremendous damage. Earthquake forecasting can minimize the death count and economic loss encountered by the affected region. This study compares the performance of Artificial Neural Networks in earthquake forecasting. The study uses two different techniques, first the accuracy of multilayer perceptron is evaluated using different inputs and different set of hyper-parameters.
The later part of the study uses now casting techniques to forecast higher magnitude earthquakes by taking into account the number of smaller tremors in the same region. The neural network architecture used for this technique was same as Long Short Term Memory Neural Networks. These networks are perfectly suited for tasks involving time series analysis. Since our data, used for now casting is similar to time series, this network was used.

1. INTRODUCTION

Earthquake occurs due to the relative movement of the tectonic plates, which make up the earths crust. The movement of the plates occur due to release of energy from earths crust. The stress caused by this movement travel large distances and hence, places at larger distance from the plate boundary also suffer.
Earthquake is one of the most devastating natural calamities that takes thousands of lives and leaves millions more homeless and deprives them of the basic necessities. A survey from United Stated Geological Survey group shows that the last decade experienced approximately 450,000 deaths due to earthquakes. It breaks the backbone of the economy of a nation. This threat cannot be averted by mankind, but if predicted, the damage can be minimized.
Artificial Neural Networks are increasingly used in predicting and classifying tasks because of their ability to capture complex relationship of output with the set of inputs. For this particular task, there are so many factors involved in the process that other model based approach do not fit the data points as accurately as neural network does.
So far, there has been no work in the literature that specifically compares the performance of different neural networks on the basis of different set of inputs and the number of hidden layers. This study presents a systematic comparison of different neural network architectures with different hyper-parameter and different set of inputs.
Moreover, in the field of now casting techniques, there is no literature available that makes use of recurrent neural networks for the predicting the natural time of occurrence of large magnitude earthquake. This report uses LSTM architecture, using different hyper parameters to obtain the least error in prediction.
The neural network models developed can prove beneficial to the community, because it can be used to create an early-warning alarm system so that the loss is minimized. The following section lists out the efforts done in order to achieve this.

Figure 1. The selected region for experiment 1

2. METHODOLOGY

This study uses two different techniques for earthquake forecasting. First technique compares the performance of multilayer perceptron based on different set of inputs and hyper-parameters. Later,the accuracy of nowcasting technique was evaluated using recurrent neural networks namely Long Short Term Memory Neural Networks. Detailed discussion of these two methods is given as below.

2.1 Multilayer Perceptron

2.1.1 Inputs First the experiments were done to find the set of inputs that predict the magnitude of earthquakes with highest accuracy. To forecast the earthquakes the data points were divided into four classes based on magnitude. The datapoints in the dataset which had magnitude in the range 3 to 4 were put in same classes, similarly for 4 to 5, 5 to 6 and 6 to 7.
Initially, Inputs given to multilayer preceptron were time difference(in minutes) with the previous earthquake, latitude, longitude and depth.
Later on, as suggested in Reyes (2013). In addition to the inputs used in above experiment, 7 new inputs were used.

(a) $b_i = \frac{log(e)}{\sum_{j=0}^{49} M_{i-j-3}}$
(b) $\Delta b_{1i} = b_i - b_{i-4}$
(c) $\Delta b_{2i} = b_{i-4} - b_{i-8}$
(d) $\Delta b_{2i} = b_{i-8} - b_{i-12}$
(e) $\Delta b_{2i} = b_{i-12} - b_{i-16}$
(f) $\Delta b_{2i} = b_{i-16} - b_{i-20}$
(g) $max\{M_t\}$ where $t \in [-7, 0]$ and M_t is the maximum magnitude on t^{th} day

2.1.2 Hyper-parameters After finding the set of inputs, experiments were conducted to find optimal set of hyper-parameters such as the number of layers, the number of neurons in each layer and various other attributes like loss function and activation functions of different layers.

2.2 Nowcasting Using Recurrent Neural Networks

After obtaining the optimal set of inputs and hyper-parameters, another model will be created that forecasts the time of occurrence of earthquake using now-casting techniques. Now-casting is a technique to find the time of occurrence of large earthquakes using the count of small tremors that occur between two large earthquakes. The definition of large magnitude earthquakes changes throughout the study. We use different threshold magnitude in different experiments to consider an earthquake as large magnitude. For instance, in the starting experiments we used the threshold of magnitude 5 on Richter scale that is earthquakes having threshold 5 were considered large. Later on, threshold was changed to magnitude 6 on Richter scale.

3. DATASET

The dataset was obtained from U.S. Geological Survey National Earthquake Information Centre. The data in catalog consists of parameters including latitude, longitude, time, date, depth, magnitude, azimuthal gap, horizontal distance from the epicenter to the nearest station, the root-mean-square (RMS) travel time residual, in sec, using all weights, this parameter provides a measure of the fit of the observed arrival times to the predicted arrival times for this location. All the earthquake occurrences from 1st January 1975 to 19th February 2018 were selected.

4. RESULTS

As suggested in methodology, different experiments were conducted as given.

4.1 Experiment 1 - Comparison of different set of inputs

The information of Himalayan region between the longitudes 74 to 84 and latitudes between 25 to 35 was used and earthquakes with magnitude greater than 2.5 were used. The region selected is given in figure 1.

One input set was

(a) time difference in minutes with the previous earthquake.
(b) latitude
(c) longitude
(d) depth

The other set of inputs are

(a) b_i

Sno.	Hidden layers	Activation Function	Optimizer	Pre-processing	Accuracy
1	1	ReLu	Gradient-Descent	No	0.7699
2	1	ReLu	Gradient-Descent	Yes	0.7512
3	1	ReLu	Adam	Yes	0.6925
4	1	ReLu	Gradient-Descent	No	0.7699
5	2	ReLu	Gradient-Descent	No	0.7699
6	3	ReLu	Gradient-Descent	No	0.7699
7	1	Leaky Relu	Gradient-Descent	No	0.7558

Table 1. Effect of hyper-parameters on accuracy

(b) Δb_{1i}
(c) Δb_{2i}
(d) Δb_{2i}
(e) Δb_{2i}
(f) Δb_{2i}
(g) $max\{M_t\}$ where $t \in [-7, 0]$ and M_t is the maximum magnitude on t^{th} day

along with latitude, longitude,depth and time since last earthquakes.

For both the set of inputs, we got almost same accuracy in earthquake magnitude class prediction. . The reason can be, the new set of inputs derived from previous inputs, like magnitude, latitude and longitude and so on. The neural network may not benefit from these new inputs, as it may have captured these relationships on its own. The loss vs epoch graph for first set of input is illustrated in figure 2. Results for other set of input was almost same.

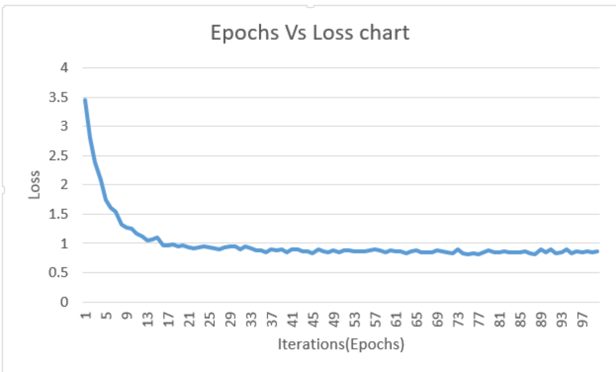

Figure 2. Loss vs Epoch graph for the experiment 1

4.2 Experiment 2 - Comparison of different set of hyper-parameters

Hyper-parameters such as number of epochs, number of hidden layers, cost function, optimizer, learning rate were changed for the set of inputs as given in experiment 1. A table showing comparison of changing all these parameters is given in Table 1. Number of epochs were 100, the loss function used was softmax loss, and learning rate was 0.01 for all the trials.Total number of cells in each layer were 256.

4.3 Experiment 3 - Nowcasting using recurrent neural networks

Now casting is a technique in which the probability of occurrence of large magnitude earthquakes is found by computing the cumulative distribution of small earthquakes that occur between large magnitude earthquakes. To compute this cumulative distribution, the number of small earthquakes are tabulated to find the probability distribution function and subsequently cumulative distribution function is found. Once, we have this cumulative distribution, we can use it to find, what is the probability that large earthquake will occur next. Different researchers found different cumulative distribution that fit the dataset such as Weibull distribution and Poisson distribution. Since neural networks can understand complex relationships, neural networks can be used for this task, rather than finding a probability distribution function.
The input to the neural network is in different form than inputs in earlier experiments. Input here is a sequence of number of small magnitude earthquakes between two large magnitude earthquakes, In this experiment, earthquake recordings with magnitude greater than 5 were termed as large magnitude earthquakes and earthquakes with magnitude smaller than 4, were used as small magnitude earthquakes. The data points are given in figure 3. The recurrent neural network used here is LSTM network.

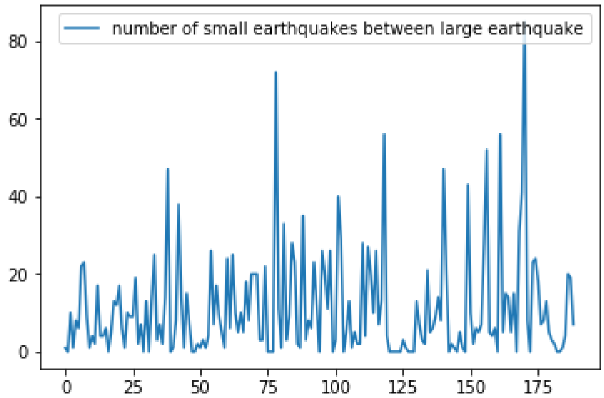

Figure 3. Time series of number of small earthquakes between two large earthquakes

The LSTM network gave the predictions as illustrated in figure 4.

4.4 Experiment 4 - Nowcasting on large data

Since the previous dataset was small, with only 113 entries for training, 52 points for testing, a larger dataset was used for the above purpose. Dataset with 1289 training points and 636 testing points was taken, in order to get these many points, larger region had to be taken into consideration. The latitude was from 20 to 40 and longitude from 70 to 105.

The graph given in figure 6. depicts the datapoints in the dataset.

The predictions if the LSTM network are given in figure 7.

5. CONCLUSIONS

The first part of the report presents a simple neural network model, which predicts the magnitude of earthquake, given date, time,

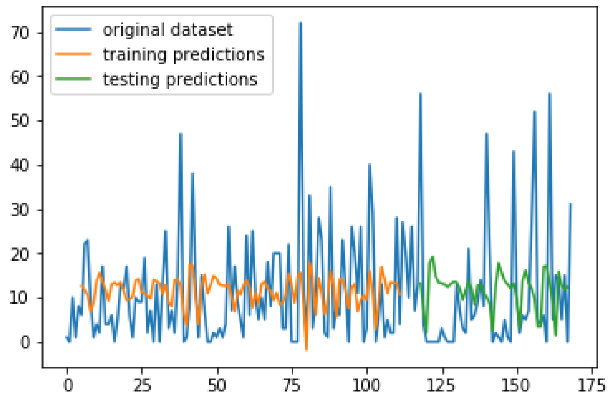

Figure 4. Time series of number of small earthquakes between two large earthquakes and corresponding training and validation predictions

Figure 5. Selected region for Experiment 4

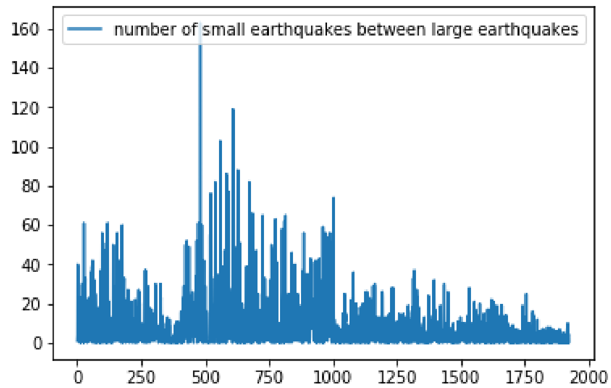

Figure 6. Time series of number of small earthquakes between two large earthquakes

longitude and latitude. The magnitude range was divided into 4 class, hence, the entries in the dataset was divided into 4 classes, the earthquakes, with magnitude in the range 3-4 were put in 1st class, then earthquakes with magnitude in the range 4-5 were put in 2nd class, similarly 5-6 and 6-7 magnitude earthquakes were put in classes 3 and 4. Besides the basic network discussed above, another network was trained that took into consideration the factor of b-value and also difference in b-values as discussed earlier. Since, large number of points in the dataset corresponds to class 2 that is earthquake occurrences which have magnitude between 4 and 5. There is a significant level of class imbalance present in the dataset The United States Geological Survey catalog has

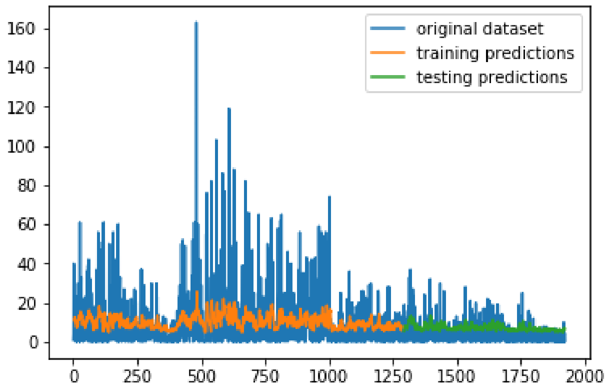

Figure 7. Time series of number of small earthquakes between two large earthquakes and corresponding training and validation predictions

information about large number of earthquakes, but it lacks in the number of useful parameters that can play a role in predicting the earthquakes. Almost all the datasets corresponding to earthquake recordings have four attributes for a record, these four attributes are latitude, longitude, data and magnitude. The presence of less number of attributes in the datasets available and class imbalance present is the reason of failure of neural network in the classification task. These limitations led to usage of LSTM networks and now casting in this study, the data used in now casting is like a time series, and it has been observed that LSTM networks are best in time series evaluation tasks. Different number of experiments were conducted and evaluated based on changing different hyper-parameters. Since, the data for now casting is very unevenly distributed, LSTM may not be a good technique for the purpose. Different techniques for prediction should also be used to compare predictions.

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