Earthquake Forecasting Using Recurrent Neuron Networks

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1. Introduction

An earthquake is a highly destructive natural disaster. It is the result of a sudden release of stored energy in the Earth's crust that creates seismic waves. Accurate earthquake predictions can save many lives and avoid economic losses. However, no major earthquake has been successfully predicted yet. Scientists can only calculate the probability that a significant earthquake will occur in a specific area within a certain time period. To put in the terms of the U.S. Geological Survey (USGS), earthquakes cannot be predicted but can be forecast. Earth's crust response to changing seismic waves is not linear and is dependent on the crust's complex and highly variable geology. Such complexity makes it difficult to build accurate simulations. Although laboratory experiments cannot fully reflect such complexity, they can provide some insights into the physical and mathematical properties of seismic waves. In this project, we will forecast when an earthquake strikes based on data from the Los Alamos National Laboratory. Specifically, we will predict the time remaining before laboratory earthquakes occur using real-time seismic data. We will try to build a robust model by comparing results among long short term memory, gated recurrent unit, and a transformer model.

There is an existing literature building various models to make earthquake forecasts. Previous studies can be divided into two categories: studies that focus on building mathematical models and studies that utilize artificial intelligence. Researchers from USGS provided a comprehensive overview of models that are time-independent and time-dependent[6]. Time-independent models are based on the assumption that the probability of the earthquake occurrence follows a Poisson distribution, whereas time-dependent models are based on log-normal and Brownian passage time assumptions. Models that utilize artificial intelligence can be divided into non-supervised learning frameworks and supervised learning frameworks. In the non-supervised learning framework, clustering techniques and association rules have been applied. Mirrashid (2014) adopted a neuro-fuzzy inference system based on a C-means algorithm to predict earthquakes in Iran [4].

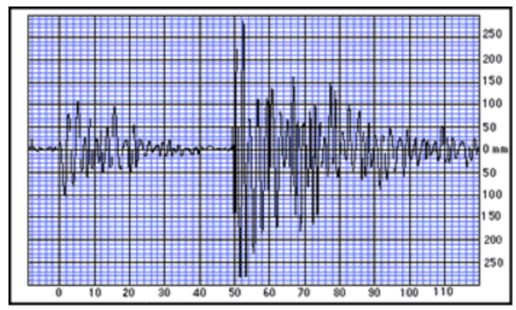

Figure 1. a seismogram that measures the magnitude of an earthquake.[1]

In recent years, regression and classification in supervised learning framework are the most widely used methods to forecast earthquakes. Adeli (2009) proposed a probabilistic neural network to predict the magnitude of earthquakes in a predefined future time period in a seismic region using eight mathematically computed seismicity indicators [2]. The model yields good prediction accuracy for earthquakes of magnitude between 4.5 and 6.0. Adeli along with Panakkat (2009) have also developed a recurrent neural network model with good prediction accuracy for earthquakes with magnitude greater than 6.0 [5]. Earthquake forecasting continues to be an evolving area of research for scientist and governments around the world.

2. Motivation

After years of research, there is growing pessimism within the scientific community that earthquake prediction is impossible [3]. Compared to hurricane predictions and forecasting, which are becoming increasingly more accurate, we have not been able to create a replicated model for earthquakes. There have been many attempts in the past to forecast when and where an earthquake would take place. Most have come up fruitless, and the few successful predictions have been fraught with controversy. As discussed earlier, if a successful model were to be discovered, millions of lives could be saved and governments could better prepare for its devastating effects. For example, since the beginning of 2000, there have been 32 major earthquakes, with each causing at least 100 deaths (CNN). The 2010 Hati earthquake caused an estimated 310,000 deaths and seriously stunted the economy and overall well-being of the country. By applying deep learning techniques, we can potentially help prevent these natural disasters from taking human life.

3. Evaluation

In this model, we will predict time left to the next laboratory earthquake based on seismic signal data. From a practical point of view, a successful outcome for our project would be an accurate prediction of the time remaining before earthquakes occur given real-time seismic data in the test data set. Furthermore, we would rather under-estimate the time remaining. For example, we do not want a model that forecast an earthquake occurring tomorrow when it will happen in a few hours.

From a technical standpoint, the performance of this model is evaluated using the mean absolute error, a measure of difference between two continuous variables, between the predicted time remaining before the next lab earthquake and the actual remaining time.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x|$$

Xi refers to the true value time to failure term, which is the remaining time before the next lab earthquake X is the predicted time to failure

In addition, we have fit a linear regression model to the training data and computed a Mean Absolute Error (MAE) score, which will act as a baseline model for predicting the time to failure during earthquake simulations. This way we can get a benchmark against a simple model. This linear regression model achieved an MAE score of 2.804 for training data. Based on this baseline model, we would consider our project to be successful if we can achieve an lower mean absolute error than this benchmark. At the same time, once our model's performance passes this threshold, the lower MAE and less over fitting our model can achieve, the more "successful" our project would be.

4. Resources

The data we are about to use is provided by Los Alamos National Laboratory, which is published on Kaggle (https://www.kaggle.com/c/LANL-Earthquake-Prediction/data). The dataset was collected in a laboratory environment. Here is a brief introduction to the dataset we are using in this project: Acoustic data: the seismic signal [int16] time to failure:the time (in seconds) until the next laboratory earthquake [float64] Seg id: the test segment ids for which predictions should be made (one prediction per segment) Acoustic data serves as the features and time to failure serves as the labels here. Computational Tools We are using two types of tools in this project: For tuning purposes, we will use Google Colab(colab.research.google.com/) to adjust the code. Google Colab provides a Nvidia K40 GPU. We might also activate Google Colab Pro to use better GPUs for training. Google Colab Pro gives us access to Nvidia V100 or TPU which are all very powerful GPUs. Due to the highly interactive features of Google Colab, it allows us to fix bugs and tune our model more efficiently. However, Google Colab only allows us to run models within 24hrs, if the running time of our models exceeds 24hrs, Google Colab might not be an optimal option in this case. So we are also considering using GCP Compute Engine to perform large training tasks. GCP Compute Engine provides us up to the Nvidia V100 GPU and has no limitation on running time and installing softwares. However, this option will cost us up to 1.6USD/hr for running the model, we only use this as a backup computational resource.

5. Contributions

For the proposal, Susan Jiao is responsible for the introduction and Billy Han is responsible for the motivation behind the project. Lynette Gao and Han Cao each worked on the evaluation and resources. In the future final report, each section of the writing will be assigned evenly to our team members.

For the computation, William Han will be working on data exploration and data pre-processing. Han Cao will mainly focus on the implementation and development of the model for the learning process. Finally, Susan Jiao and Lynette Gao will be responsible for developing the model evaluation and validation tools.

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