DeepQuake: Artificial Intelligence for Earthquake Forecasting Using Fine-Grained Climate Data

Yash Narayan[1], **Jeonghyeop Kim**[2], **William Holt**[2]
[1]The Nueva School, [2]Stony Brook University
yasnara@nuevaschool.org, {jeonghyeop.kim, william.holt}@stonybrook.edu

Abstract

Earthquakes are one of the most catastrophic natural disasters, making accurate, fine-grained, and real-time earthquake forecasting extremely important for the safety and security of human lives. In this work, we propose ***DeepQuake***, a hybrid physics and deep learning model for fine-grained earthquake forecasting using time-series data of the horizontal displacement of earth's surface measured from continuously operating Global Positioning System (cGPS) data. Recent studies using cGPS data have established a link between transient deformation within earth's crust to climate variables. DeepQuake's physics-based pre-processing algorithm extracts relevant features including the ϵ_x, ϵ_y, and ϵ_{xy} components of strain in earth's crust, capturing earth's elastic response to these climate variables, and feeds it into a deep learning neural network to predict key earthquake variables such as the time, location, magnitude, and depth of a future earthquake. Results across California show promising correlations between cGPS derived strain patterns and the earthquake catalog ground truth for a given location and time.

1 Introduction

Every year, around 20,000 earthquakes occur worldwide [1]. In the last 20 years, earthquakes have caused around 750,000 deaths and have displaced over 125 million people [1]. Earthquakes are particularly catastrophic as they usually occur without much warning, leaving little time for precautionary measures. In addition, earthquakes often trigger other natural hazards such as tsunamis and landslides which can lead to downstream accidents damaging the environment. For example, the Fukushima Daiichi nuclear disaster in Japan was triggered by an earthquake leading to a tsunami that caused uncontrolled release of radioactive material contaminating hundreds of thousands of litres of water, resulting in measurable exposure of marine organisms in the Pacific Ocean [2].

The causal relationship between climate and earthquakes is becoming increasingly clear in recent years. Recent studies [3] have established that climate variables such as seasonal precipitation, temperature gradients, and atmospheric pressure can cause deformations within Earth's crust, leading to earthquakes. The seasonal peak-to-peak amplitudes of vertical movements can be explained by the solid Earth's elastic response to the surface load from the precipitation patterns. For example, as California typically has wet winters, the extra hydrologic load leads to the lowest vertical heights of the elastic crust while due to the loss of surface loads during the dryer summer months, the crust typically reaches the highest vertical point. In this work, we utilize cGPS measurements, operated by the NSF's GAGE Facility at UNAVCO, that detect seasonally driven transient deformations within the plate boundary zone regions. By inverting the cGPS data, we quantify horizontal strain which is fed to a Recurrent Neural Network (RNN) based model called ***DeepQuake*** to provide fine-grained earthquake forecasts. Initial results across California, including the Napa Valley and Long Valley Caldera regions, show significant correlations between cGPS derived strain patterns and earthquake catalog ground truth to predict the magnitude and depth of earthquake for a given location and time.

35th Conference on Neural Information Processing Systems (NeurIPS 2021), Vancouver, Canada.

2 Previous Work

Since the end of 19th century, seismic researchers have tried to identify predictors of earthquakes such as foreshocks, changes in groundwater, or unusual animal behavior without much success. Physics-based models have also been largely unsuccessful as the relationships between variables are complex and highly non-linear. In recent years, ML and AI based approaches have started gaining interest. Authors in [9] provides a comprehensive survey of 84 research papers related to earthquake prediction using AI-based techniques. In recent years, the monitoring data of the Earth's surface displacement obtained by Global Positioning System (GPS) have been published in real time for a number of seismically active regions. These data are used to study block models of the Earth's crust and in earthquake prediction studies using physical [10-13] and AI-based models [14-15]. Instead of using the GPS data directly, our approach uses a hybrid model. We first use a physical model to convert GPS measurements into a time series for horizontal strain which is then used to train a deep learning model to capture relationships between the physical variables and the actual seismic events.

3 Methods

Dataset: We use cGPS time-series data in California from 2007 to 2019, which consists of the month-over-month horizontal displacement velocities at each 'cell' (cell is equivalent to a 11km to 11km regions) [10]. We then use a physical model to invert this data to quantify the 13-year history of horizontal transient strain values within the boundary zone in California in the x, y, and z directions using the approach in [3]. As the ground truth for our model, we have an earthquake catalog that consists of 2085 earthquakes of their magnitude, depth, and location, across the state of California including near Napa Valley and Long Valley Caldera (Figure 1). Since the relationship between strain and the occurrence of an earthquake varies based on the local region, we filter this catalog to evaluate localized regions near faults that have a high density of earthquakes (called a grid in Figure 2).

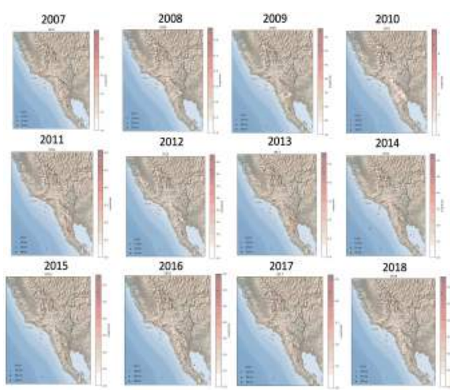

Figure 1: Year-over-year earthquake catalog near Long Valley Caldera from 2007 to 2018

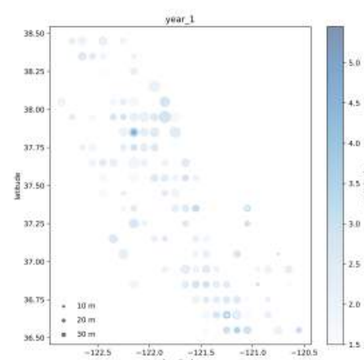

Figure 2: Example of a filtered down localized region of interest called a 'grid'

Model: This is a sequence-to-sequence time-series prediction task, where the past values of the time-series often influence the future values. We use a type of Recurrent Neural Network (RNN) called a Long Short-Term Memory (LSTM) network that has been shown to capture long-term dependencies in time-series data. The DeepQuake framework consists of two LSTM networks: the first network processes the input sequence of strain values at each cell generating a prediction of future strain values at each grid. The second LSTM uses these future strain values and the historical earthquake catalog to produce the output sequence consisting of the predicting earthquake forecasts. Given a cell, we express this formulation for a future earthquake mathematically as such: $e_k(t) = f(e_k(0), e_k(1)...e_k(t-1), s_k^1(0), s_k^1(1)...s_k^1(t-1), s_k^2(0), s_k^2(1)...s_k^2(t-1), s_k^3(0), s_k^3(1)...s_k^3(t-1))$ where s^1, s^2, s^3 is strain ϵ_x, ϵ_y, ϵ_{xy} respectively and e_k is the earthquake reading. To prevent data leakage, this entire process uses a windowing method. We start at the first value in the sequence and collect n_i values as input and the next n_j values as output. Then we slide our window to the second (stride=1) and repeat the procedure. We do this until the window no longer fits into the data.

4 Results

To understand the physical relationship between the inputs (strain values ϵ_x, ϵ_y, ϵ_{xy}) to the model and the actual ground truth (magnitude, depth, and location), we visualized their correlation strength (Figure 3). Our visualizations indicate correlation between inputs such as the location of the cell, strain and the ground truth. There is also high correlation between the strain in the ϵ_x, ϵ_y and ϵ_{xy} components. The low correlation between the strain and ground-truth indicates that the relationship between the strain and ground truth is not easily captured by a linear regression model.

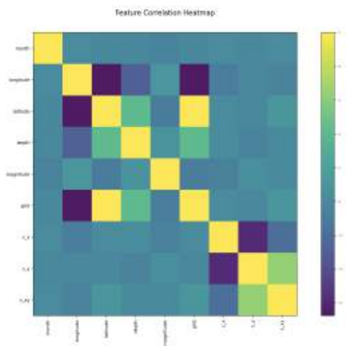

Figure 3: Linear heat map of correlation strength between the inputs and outputs

After training, during the validation, we compared DeepQuake's predictions of key earthquake variables against the ground truth earthquake catalog (Figure 4 and 5). The model predicts the overall trends of the ground truth and the timing quite accurately. While the model is able to predict a majority of low-depth and low-magnitude events it is not yet fully capturing the higher depth and magnitude events. We want to include other climate variables such as the historical precipitation, temperature gradients, and atmospheric pressure directly in the model to improve the accuracy further.

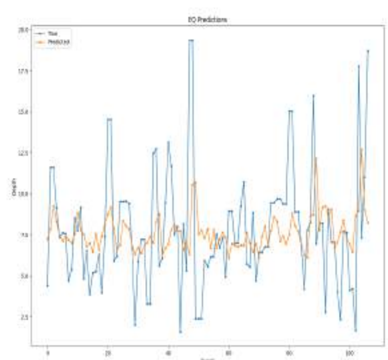

Figure 4: Ground truth vs DeepQuake predictions for depth in Long Valley Caldera

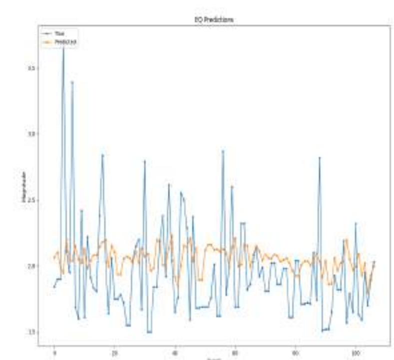

Figure 5: Ground truth vs DeepQuake predictions for magnitude in Long Valley Caldera

5 Conclusion and Future Work

In this work, we developed a deep learning framework, ***DeepQuake***, for fine-grained earthquake forecasting. This is achieved via a hybrid model, with a physics-based pre-processing algorithm that integrates real-world cGPS data, and a deep learning based neural network model, to predict key seismic variables such as the magnitude, depth, and location of a future earthquake. In the near future, we aim to make DeepQuake more accurate, generalizable to other regions, and interpretable to humans. Our approach demonstrates the promise of using AI to predict earthquakes to prevent their catastrophic impact on climate, potentially saving millions of lives and billions of dollars in damage.

References

[1] World Health Organization (WHO), "Earthquakes". URL https://www.who.int/westernpacific/health-topics/earthquakes

[2] World Information Service on Energy (WISE), "The Fukushima Disaster". URL https://wiseinternational.org/campaign/fukushima-disaster

[3] Kim, Jeonghyeop, Alireza Bahadori, and William E. Holt. "Crustal Strain Patterns Associated With Normal, Drought, and Heavy Precipitation Years in California." Journal of Geophysical Research: Solid Earth 126.1 (2021): e2020JB019560.

[4] Rouet-Leduc, B., Hulbert, C Johnson, P. A. (2018). Breaking Cascadia's silence: Machine learning reveals the constant chatter of the megathrust. https://arxiv.org/abs/1805.06689

[5] Rouet-Leduc, B., Hulbert, C., Lubbers, N., Barros, K., Humphreys, C. J., Johnson, P. A. (2017). Machine learning predicts laboratory earthquakes. Geophysical Research Letters, 44, 9276–9282. https://doi.org/10.1002/2017GL074677

[6] DeVries, P., Viegas, F., Wattenberg, M., Meade, B. (2018). Deep learning of aftershock patterns following large earthquakes. Nature, 560. doi.org/10.1038/s41586-018-0438-y

[7] Rouet-Leduc, B., Hulbert, C., Bolton, D. C., Ren, C. X., Riviere, J., Marone, C., Guyer, R. A., Johnson, P. A. (2018). Estimating fault friction from seismic signals in the laboratory. Geophysical Research Letters, 45, 1321–1329. https://doi.org/10.1002/2017GL076708

[8] Corbi, F., Funiciello, F., Brizzi, S., Lallemand, S., Rosenau, M. (2017). Control of asperities size and spacing on seismic behavior of subduction megathrusts. Geophysical Research Letters, 44, 8227–8235. https://doi.org/10.1002/2017GL074182

[9] MD. HASAN AL BANNA, KAZI ABU TAHER, M. SHAMIM KAISER, MUFTI MAHMUD, MD. SAZZADUR RAHMAN, A. S. M. SANWAR HOSEN AND GI HWAN CHO , "Application of Artificial Intelligence in Predicting Earthquakes: State-of-the-Art and Future Challenges", IEEE Access, October 2020

[10] Murai, S.; Araki, H. Earthquake Prediction Using GPS—A New Method Based on GPS Network Triangles. GIM Int. 2003, 17,34–37.

[11]Murai, S.; Araki, H. Prediction of earthquake and volcanic eruption using GPS. Asian J. Geoinform. 2004, 4, 85–90.

[12] Murai, S. Can we predict earthquakes with GPS data? Int. J. Digit. Earth 2010, 3, 83–90. [CrossRef] Remote Sens. 2021, 13, 1842 23 of 24

[13] Borghi, A.; Aoudia, A.; Riva, R.E.; Barzaghi, R. GPS monitoring and earthquake prediction: A success story towards a useful integration. Tectonophysics 2009, 465, 177–189.

[14] Valeri Gitis , Alexander Derendyaev, and Konstantin Petrov, "Analyzing the Performance of GPS Data forEarthquake Prediction", Remote Sens. 2021, 13, 1842 (https://doi.org/10.3390/rs13091842

[15] Wang, Q.; Guo, Y.; Yu, L.; Li, P. Earthquake prediction based on spatio-temporal data mining: An LSTM network approach. IEEE Trans. Emerg. Top. Comput. 2017, 8, 148–158.