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Earthquake Damage Prediction using Machine Learning

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***Abstract*—Earthquake prediction is a very important problem in seismology, the success of which can potentially save many human lives. Various kinds of technologies have been proposed to address this problem, such as mathematical analysis, machine learning algorithms like decision trees and support vector machines, and precursors signal study. Unfortunately, they usually do not have very good results due to the seemingly dynamic and unpredictable nature of earthquakes. In contrast, we notice that earthquakes are spatially and temporally correlated because of the crust movement. Therefore, earthquake prediction for a particular location should not be conducted only based on the history data in that location, but according to the history data in a larger area. In this paper, we employ a deep learning technique called long short-term memory (LSTM) networks to learn the spatio-temporal relationship among earthquakes in different locations and make predictions by taking advantage of that relationship. Simulation results show that the LSTM network with two-dimensional input developed in this paper is able to discover and exploit the spatio-temporal correlations among earthquakes to make better predictions than before.**

***Index Terms*— Earthquake prediction, spatio-temporal data mining, LSTM.**

I. INTRODUCTION

Earthquakes are one of the most destructive natural disasters. They usually occur without warning and do not allow much time for people to react. Therefore, earthquakes can cause serious injuries and loss of life and destroy tremendous buildings and infrastructure, leading to great economy loss. The prediction of earthquakes is obviously critical to the safety of our society, but it has been proven to be a very challenging issue in seismology [1]. Existing works on earthquake prediction can be mainly classified into four categories according to the employed methodologies, i.e., 1) mathematical analysis, 2) precursor signal investigation, 3) machine learning algorithms like decision trees and support vector machines (SVM), and 4) deep learning. The first type of work tries to formulate the earthquake prediction problem by using different mathematical tools [2], like the FDL (Fibonacci, Dual and Lucas) method, kinds of probability distribution or other mathematics proving and spatial connection theory [3]. In the second type of work, researchers study earthquake precursor signals to help with earthquake prediction. For example, electromagnetic signals [4], aerosol optical depth (AOD) [5], lithosphere-atmosphere ionosphere [6] and cloud image [7], [8] have been explored.
Even animals' abnormal behavior has been taken into account in this kind of study [9]. The third type of work mainly explores data mining and time series analysis methods, such as J48, adaboost, multi-objective info-fuzzy

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network (M-IFN), k-nearest neighbours' (kNN), SVM, and artificial neural networks (ANNs) [10], [11], to predict the magnitude of the largest earthquake in the next year based on the previously recorded seismic events in the same region. In the fourth type of work, deep learning algorithms are utilized to predict both the magnitude and the time of major seismic events. Various kinds of neural networks have been adopted, such as multilayer perceptron (MLP) [12], backward propagation (BP) neural network [13], feed forward neural network (FFNN) [14], recurrent neural network (RNN) [15], which can work under certain particular circumstances. Although there have been a lot of works on earthquake prediction, very few of them can predict future seismic events accurately. The reason is that the occurrence of earthquakes involves processes of very high complexity and depends on a large number of factors that are difficult to analyze. There are obviously complex nonlinear correlations among earthquake occurrences, because of which traditional mathematical, statistical, and machine learning methods, cannot analyze well in this process.

II. LITERATURE SURVEY

Earthquakes are sudden disturbances in the earth's crust that cause huge loss to life and property. It focus on the importance of Information and Communication Technology (ICT) for disaster management and how ICT can be helpful in disseminating earthquakes alerts also with application of wireless sensor network have proposed by Munib Ur. Rehman et al (2016). Earthquake is an unpredictable natural phenomenon that create a vast amount of damage, affecting communities and their environment. To reduce the effects of such hazards, frameworks like building resilience have emerged. These frameworks target on increasing recovery after such disaster, by introducing new designs, technologies, and components to the building have proposed by Kahandawa K.A.R.V.D et al (2017). Chien-Pang-Lee and Yungho Leu, (2011) have used a novel hybrid method for feature selection in microarray data analysis. This method uses a genetic algorithm with dynamic parameters (GADP) setting to generate a number of subsets of genes and to rank the genes according to their occurrence frequencies in three gene subsets. David Meyer et al (2002), have done a benchmark study on comparison of SVMs with sixteen classification methods based on their performance on twenty one dataset from UCI machine learning databases. Hanchuan Peng et al (2005) have proposed many filter based feature or genes selection methods for microarray dataset. Hua J. Tembe .W and Dougherty. E (2009) have proposed that feature selection is an unavoidable part of classifier design. The objective of feature selection is to select a subset of features from the possible high dimensional features spaces to low dimensional spaces, which are better suited for retrieval or learning purposes. Hettiarachchi. S (2018) have proposed that the Indian Ocean Tsunami of Boxing Day, December 2004, caused loss of lives and widespread damage to infrastructure and ecosystems across Indian Ocean States. IOTWMSIndian Ocean Tsunami Warning and Mitigation System as a highly successful end to end warning system under UNESCO / intergovernmental oceanographic commission (IOC). Liyuv Huang et al (2017) developed a novel precursory wave detector by using liquid suspension principle and super- low frequency (SLF) sound signal detection technology in submarine is presented, then the device of earthquake precursory wave detection and the corresponding software are developed. Takumi Yoshii et al (2018) have developed the process of tsunami induction, sediment transport and deposition on costal low lands are investigated experimentally. Wang Honghui et al (2017) analized the sudden landslide, collapse, debris flow is one of the most serious geological disaster type in our country because of the short time, strong concealment and the destructive, easy to cause significant casualties and the huge economic losses. For the need of improving the capacity of the geohazards monitoring a professional monitoring system has been developed based on the Internet of things, WSN (Wireless Sensor Network) and network communication technology.

III. DATASETS

In the first case, we study the system performance when we use one-dimensional input as before in our system; in the second case, we explore the system performance when two-dimensional input is used as we propose in this study.

A. Case Study I: The Proposed LSTM Network with One-Dimensional Input

In this case, we make earthquake predictions by using the proposed LSTM network with only one-dimensional input, i.e., by exploiting the temporal correlations only.

Data Preprocessing

The data that we use is gathered from the USGS (US Geological Survey) website. In particular, we use Conterminous U.S earthquake data from 2006 to 2016 with magnitudes greater than 2.5 in our simulations. We set one time slot to one month. In each time slot, the input is the number of earthquakes that happened in this time slot in a certain sub-region. We have 120 data items when one time slot is one month. As usual, we divide the data into two parts: training data and testing data. Particularly, the first two third of data will be used for training and the rest will be used for testing.

TABLE I. RAW DATA OF EARTHQUAKES WITH MAGNITUDES GREATER THAN 4.5 FROM 1966 TO 2016

time	latitude	longitude	depth	mag	magType
1966-12-16T20:52:18.000Z	29.535	80.823	20	5.7	mw
1967-01-30T21:05:30.000Z	26.107	96.115	25	5.6	mw
1967-02-20T15:18:41.000Z	33.617	75.333	20	5.5	mw
1967-03-14T06:58:05.000Z	28.463	94.248	16.9	5.7	mw
1967-03-27T08:58:24.000Z	38.474	116.608	29.7	6.1	mw
1967-05-27T19:05:48.000Z	36.034	77.714	20	5.9	mw
1967-08-15T09:21:03.000Z	31.079	93.639	20	5.7	mw
1967-08-30T04:22:04.000Z	31.633	100.262	10	6.4	mw
1967-08-30T11:08:49.000Z	31.587	100.255	10	5.8	mw
1967-09-15T10:32:44.000Z	27.338	91.91	13.7	5.8	mw
1968-12-22T09:06:37.000Z	36.306	101.772	25	5.6	mw
1969-02-11T22:08:54.000Z	41.389	79.307	13.3	6.1	mw
1969-10-17T01:25:14.000Z	23.041	94.636	135	6.3	mw
1970-01-04T17:00:41.000Z	24.185	102.543	11.3	7.1	mw
...	...	...	...	...	...
2016-09-22T16:50:33.440Z	30.1048	99.7368	23.45	4.7	mb
2016-09-22T17:23:15.960Z	30.1768	99.6502	21.01	5.3	mb
2016-09-26T15:48:53.970Z	30.1734	99.6087	23.32	4.9	mb
2016-09-28T21:36:31.970Z	29.6438	101.9644	10	4.5	mb

B. Case Study II: The Proposed LSTM Network with Two-Dimensional Input

In this case, by changing the input to two-dimensions, we take advantage of spatio-temporal correlations to make earthquake predictions.

Data Preprocessing

The same as that in the previous case, we gather data from USGS website, and use earthquake data in mainland China for our simulations. our area of interest is still between 75 E and 119 E longitudes and 23 N and 45 N latitudes, which is equally divided into nine smaller sub-regions. We are interested in the earthquakes in this area with magnitudes greater than 4.5 from 1966 to 2016. Some raw data is shown above . We define a time slot to be one month. Thus, we have 600 data items, as shown in flowing pictures. Here, the number in each data item means the frequency of earthquake events belong to the certain sub-region

TABLE II. DATA OF EARTHQUAKE FREQUENCIES IN ALL THE 9 SUB-REGIONS

	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	1	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0
5	1	0	0	0	0	0	0	0	0
6	0	0	0	1	0	0	0	0	1
7	0	0	0	0	0	0	0	0	0
8	1	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0
11	0	3	0	0	0	0	0	0	0
12	0	0	0	1	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...
585	0	5	0	3	0	1	0	0	2
586	12	1	1	8	0	0	0	0	1
587	1	4	1	6	0	0	0	0	6
588	4	1	1	3	0	0	0	0	0
589	1	4	0	6	0	0	0	0	1
590	0	4	0	2	0	2	0	0	1
591	0	1	0	0	0	0	0	0	5
592	0	5	0	1	0	1	0	0	3
593	1	6	0	2	0	0	0	0	4
594	1	1	1	9	0	0	0	0	2
595	0	2	0	1	0	0	0	0	1
596	1	8	1	4	0	0	0	0	4
597	0	2	1	1	0	0	0	0	1
598	0	1	0	2	0	1	0	0	5
599	8	1	0	0	0	2	0	0	1
600	0	1	0	8	0	0	0	0	0

TABLE III. AN INPUT MATRIX WITH MULTI-HOT VECTORS

	1	2	3	4	5	6	7	8	9
1	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0
4	0	0	0	0	0	1	0	0	0
5	0	1	0	0	0	0	0	0	0
6	0	0	0	0	0	1	1	0	0
7	0	0	0	0	0	0	0	0	0
8	0	1	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0
11	0	0	0	0	1	0	0	0	0
12	0	0	0	0	0	1	0	0	0
---	---	---	---	---	---	---	---	---	---
585	1	0	1	0	1	1	0	0	1
586	1	1	1	0	1	1	0	1	0
587	1	1	1	0	1	1	1	1	0
588	1	1	1	0	0	1	1	1	0
589	1	1	1	0	1	1	0	0	0
590	1	0	1	1	1	1	0	0	1
591	1	0	1	1	0	0	0	0	0
592	1	0	1	1	1	1	0	0	0
593	1	1	1	0	1	1	0	0	0
594	1	1	0	1	1	1	0	1	0
595	1	0	0	0	1	1	0	0	0
596	1	1	1	0	1	1	0	0	0
597	1	0	1	0	0	1	0	1	0
598	1	0	0	1	1	1	0	0	1
599	1	1	0	1	0	1	0	0	0
600	0	0	1	0	0	1	1	0	0

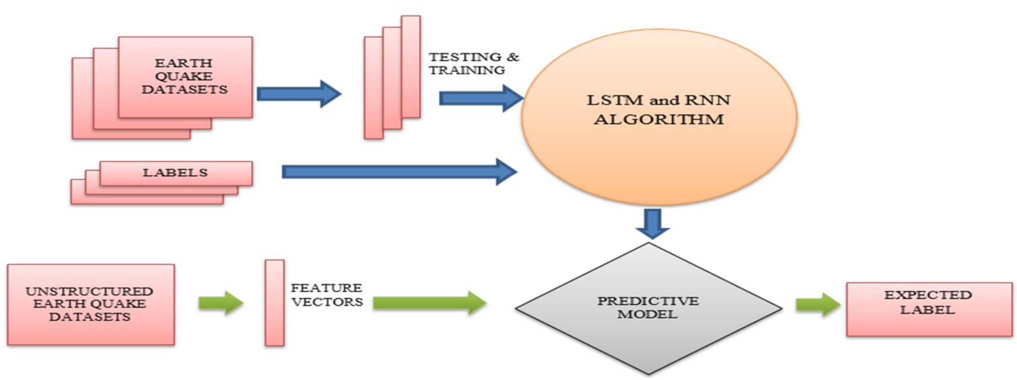
As explained in our system model, we represent the original input by a multi-hot vector, in which an element is set to 1 if the corresponding sub-region has earthquakes happened and 0 otherwise. Besides, we choose the look back window to be 12. Therefore, our input matrix is of 12 * 9. Moreover, 70 percent of our data is used for model training, and the remaining 30 percent is used for the testing. The above table has shown some of our generated multi-hot vectors.

III. METHODOLOGY

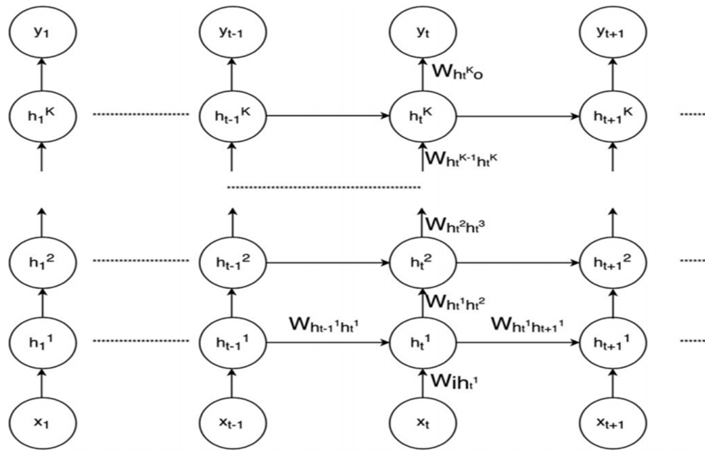
An RNN neural network architectures were developed using the Keras library for Earthquake prediction problems. The first two RNN model consists of a 1 convolution layer followed by two LSTM layers, other two RNN model consists of a 1 convolution layer followed by three LSTM layers and also uses the spectrogram of the seismic waveform as the input variable. In all models, binary cross entropy is used for the loss.The dataset is first to split into training/test sets using 90% and 10%, and then 10% of the training set is used as a validation set. Hyperparameters are tuned by computing accuracy on the validation set. For example, the optimum values of dropout rate and the number of epochs were determined such that the model does not overfit the training data.

A. Earthquake Prediction Using An Lstm Network With Two-Dimensional Input:

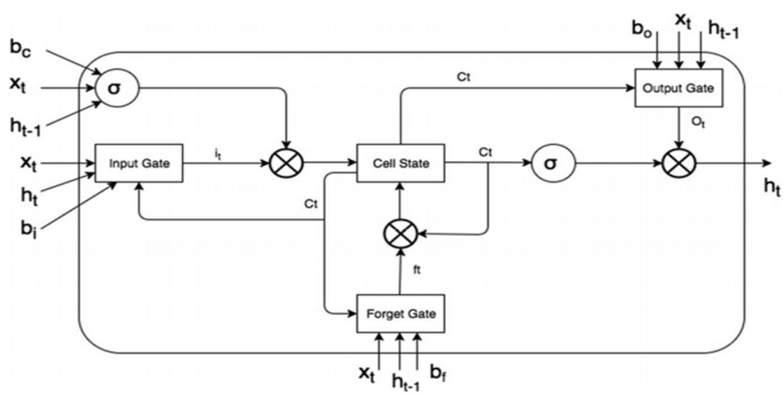
In this section, we describe in detail our proposed earthquake prediction algorithm using an LSTM network with twodimensional input. The main idea of our algorithm is to develop an LSTM network with two-dimensional input to predict the next system status based on a number of the most recent system statuses. This is achieved by learning the correlations among earthquakes in different locations at different times. In the following, we will first introduce the fundamentals of the LSTM architecture and then explain how we devise an LSTM with two-dimensional input to develop our earthquake prediction algorithm.



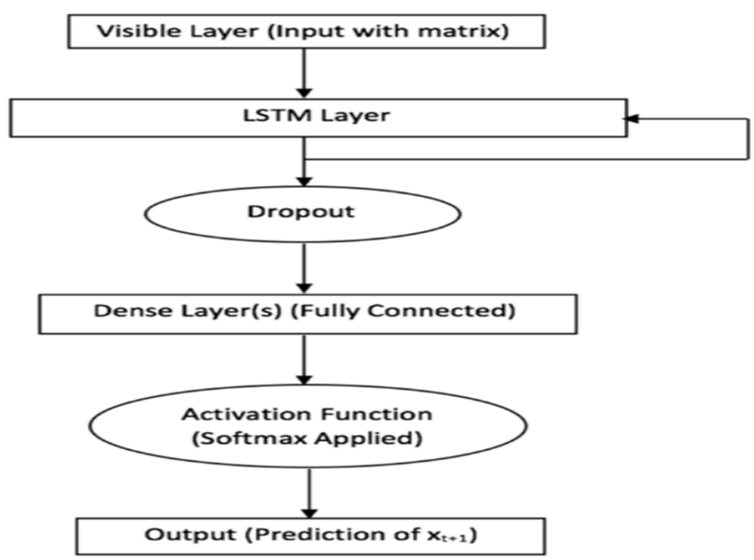
The Basic LSTM Architecture



The typical RNN architecture with K hidden layers. h^k_trepresents the state of the kth hidden layer in time slot t. Solid lines mean the connections by weight

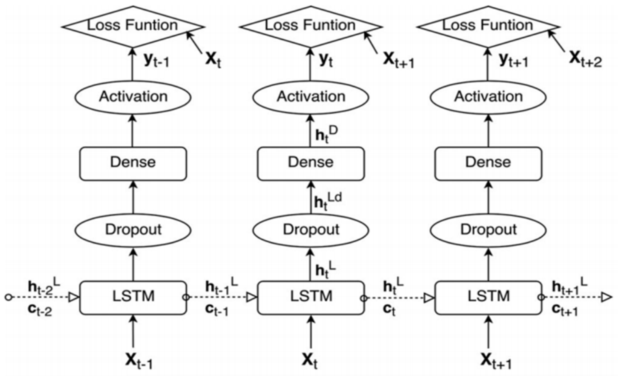


The typical LSTM single memory cell

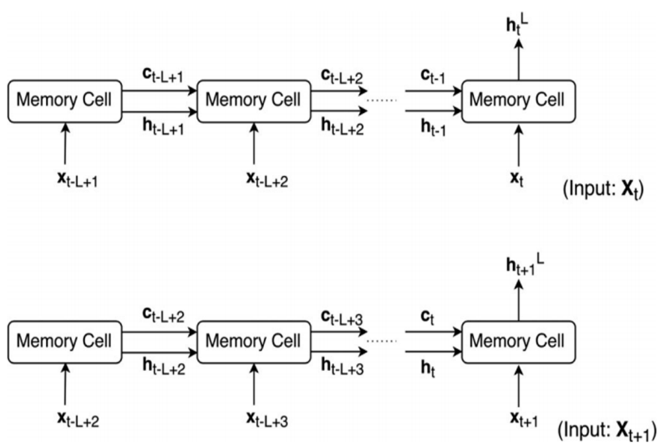


The flow diagram of our system

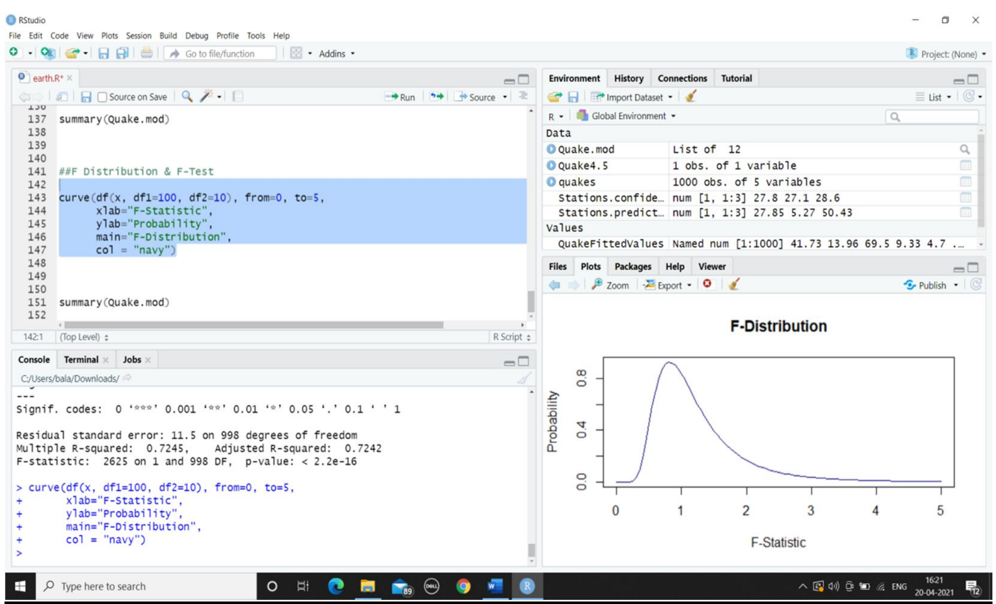
The Proposed LSTM Network with Two-Dimensional Input



Our system architecture. Dense means a fully connected neural network



V. RESULTS WITH SCREENSHOTS



The above results clearly demonstrate the robustness and effectiveness of our new LSTM system. Last but not the least, comparing with previous earthquake prediction methods, which are mostly based on various seismic indicators, our system has little overhead on obtaining the input data. Particularly, even in areas where there are no seismic sensors and monitors, we are still able to use our system for earthquakes prediction.

VI. CONCLUSION

In this paper, we have proposed a new earthquake prediction system from the spatio-temporal perspective. Specifically, we have designed an LSTM network with two-dimensional input, which can discover the spatio-temporal correlations among earthquake occurrences and take advantage of the correlations to make accurate earthquake predictions. The proposed decomposition method for improving the effectiveness and efficiency of our LSTM network has been shown to be able to significantly improve the system performance. Simulation results also demonstrate that our system can make accurate predictions with different temporal and spatial prediction granularities

FUTURE ENHANCEMENT

We describe in detail our proposed earthquake prediction algorithm using an LSTM network with two dimensional input. The main idea of our algorithm is to develop an LSTM network with two-dimensional input to predict the next system status based on a number of the most recent system statuses. This is achieved by learning the correlations among earthquakes in different locations at different times. In the following, we will first introduce the fundamentals of the LSTM architecture and then explain how we devise an LSTM with two-dimensional input to develop our earthquake prediction algorithm. take advantage of information in the past time. Particularly, in an RNN, the output not only depends on the current input, but also depends on previous inputs. Denote the input vector at time t by xt. Then, the RNN network updates the hidden layer states h1 t ; ... ; hK t and computes the output yt based on the input xt and the hidden layer statuses at the past time instance. hk t denotes the kth hidden layer's state at time t, which is essentially a vector with the number of the elements representing the number of nodes at the kth hidden layer. As shown in Figure 2, we can see that the past input information would be propagated horizontally in each layer through weight matrices and nonlinear functions, and hence can be used for prediction.

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