

Hibridizacao de Modelos de Riscos de Sismos com Tecnicas de Algoritmos Geneticos

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ABSTRACT

This project main goal is to refine a method, called the GAModel, by obtaining better accuracy in seismic risk analysis. The GAModel is a model which aims to generate forecasts by using only Evolutionary Computation (EC).

This document summarizes the GAModel and proposes three extended versions for the GAModel. The first model, ReducedGAModel, is similar to the GAModel, though it has a different genotype representation. In the GAModel the genotype is related with the phenotype, and in ReducedGAModel the genotype is a version non-related with the phenotype. The second model named as Emp-ReducedGAModel, as the reducedGAModel, uses this new genotype idea and incorporates some empirical laws such as the modified Omori-Utsu formula. The last one, the Emp-GAModel, recovers the genotype-phenotype relation from the GAModel but also incorporates the same empirical laws that composes the ReducedGAModel.

These four models were evaluated and compared based on the predictability experiments framework proposed by the "Collaboratory for the Study of Earthquake Predictability" (CSEP), an international effort to standardize the study and testing of earthquake forecasting models. The experiments were designed to compare 1-year earthquake rate forecasts for four regions in Japan in using the data from the Japan Meteorological Agency (JMA) earthquake catalog.

Keywords

Evolutionary Computation, Genetic Algorithms, Forecasting, Earthquakes

^{*}Dr. Trovato insisted his name be first.

[†]The secretary disavows any knowledge of this author's actions.

[‡]This author is the one who did all the really hard work.

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1. INTRODUCTION

Earthquakes may cause soil rupture or movement, tsunamis and more. They may cause great losses and that can be explicit by some examples such as the earthquakes in Tohoku (2011) and Nepal(2015). To be able to minimize the consequences of these events, we look to create forecast earthquake occurrences models. Hence the characteristics of the earthquakes may vary both in time and place, these methods should be to adapt their behavior to be able to forecast earthquakes which follows the reality.

This project aims to obtain a better method, based in improvements to the GAModel [1], a statistical method of analysis of earthquakes risk using the Genetic Algorithm technique (GA). Two ideas were taken into account for this. The first, is to change the candidate solution representation. By that, we objective to make the GAModel more specialized, focusing only on areas on which earthquakes happened already.

The other idea is based on the assumption that earthquakes cluster in both space and time, and the idea is to apply the Genetic Algorithm technique (GA) with a some empirical laws, such as the modified Omori law. First, the background intensity (the independent earthquakes or main-shock), which is a function of the space, is forecasted using the GA. Then, we use some empirical laws to obtain the dependent earthquakes (aftershock) for a specific time interval.

With this two new ideas, we developed three new methods. We named them as the ReducedGAModel, the Emp-GAModel and the Emp-ReducedGAModel. The first one represents the idea of focusing on areas with occurrences. The second one, adds what we call as the domain knowledge, using empirical laws yet to be described, on the section 2. The last one, is a mixed between the two ideas, which means that it not has the new representation as it uses the empirical laws as well.

The models resulted of those methods were analyzed using likelihood tests, namely the L-test, the N-test and the R-test, as suggested by Regional Earthquake Likelihood Model (RELM) [5].

For developing the methods and to be able to compare them we used the earthquake catalog from the Japanese Meteorological Agency (JMA), using event data from 2005 to 2010.

This paper is organized as: in section 2, we give a details of

each of the forecast proposed covering the Collaboratory for the Study of Earthquake Predictability (CSEP) framework and the empirical laws. In section 3, we give the description of the tests proposed in [6]. After that, in 4, we define the target areas used for the experiment and the data from the JMA; we clarify the design followed during the experiments and how we compared the models derived from our methods. Finally, we show the results and conclude this work in 5 and 6.

2. MODELS

In the Collaboratory for the Study of Earthquake Predictability (CSEP) framework, a forecast uses one common format which is a gridded rate forecast [10]. For this format a geographical region, during a start date and an end date, is divided in sections, the bins. The forecast will estimate the number (and sometimes the magnitude) of earthquakes that happens in this target region, during the target time interval, considered to be of one year for this study [1].

Large and independent earthquakes, also known as mainshocks, are followed by a wave of others earthquakes, the aftershocks [7]. Hence there is no physical measurement to identify mainshocks and its aftershocks [7], we divided the models in two groups: the ones that only forecasts mainshocks and those that forecast both mainshocks and aftershocks.

2.1 Mainshock Models

The GAModel is purely based on the framework suggested by the CSEP. In it, one forecast is defined as a place for a specific time and is divided in bins. Each bin represents a geographical interval. The whole target area of study is covered by these bins and represents the $\mu(x, y)$, the background intensity [11]. In the GAModel, each possible solution is represented as an entire forecast model.

In this context the GAModel is considered as one method to generate space-rate-time forecasts. It also could be described as:

$$\lambda(t, x, y, M|\Upsilon_t) = \mu(x, y) \quad (1)$$

where you can denote the number of earthquakes forecast in a bin as $\lambda(t, x, y)$ [10] given that Υ_t is the earthquake observation data up to time t .

The ReducedGAModel, which represents the first idea, is a method described as the GAModel, but each possible solution represents a fraction of the forecast where we expect to find specific risk areas. The GAModel defines a expected number of earthquakes for every single bin in the target region. That could lead to exhaustive and, sometimes worthless, searches. That is caused by the number of bins in the forecast and also because some in some bins there are no earthquake occurrences in the observation data. To minimize this, the ReducedGAModel only define expected number of earthquakes in bins that already had some occurrence in the past, giving some sort of guideline to the GA.

To make it clear, we use the same example as the one used in [1]. The "Kanto" region, one of the four areas used in this study, is divided into 2025 bins (a grid of 45x45 squares). Each bin has an area of approximately 25km² (Figure ??). The GAModel then calculates an expected number of earthquakes for every bin on a determined time interval, so the GA searches for good values in 2025 bins.

The ReducedGAModel will first obtain the position of past occurrences and will calculate some expected number of earthquakes for only the bins related to those positions. For example, if there are 10 bins with occurrences in Kanto in the last year, it will make the GA search good values for only those 10 bins, leaving the other 2015 bins with the value zero, representing zero occurrences. It is important to highlight that in the worst case, it will make the same amount of searches as the GAModel.

2.2 Mainshock+Aftershock Models

Hence earthquakes cluster in space and inspired by the space-time epidemic-type aftershock sequence (ETAS), the Emp-GAModel, represents the second idea and is described as:

$$\lambda(t, x, y, M|\Upsilon_t) = \mu(x, y)J(M) \quad (2)$$

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$$\lambda(t, x, y|\Upsilon_t) = \mu(x, y) + \sum_{t_i \in t} K(M_i)g(t - t_i)F \quad (3)$$

The Emp-GAModel uses $\mu(x, y)$ as defined for the GAModel, so it calculates an expected number of earthquakes for every bin in the target region. The Omori law, $g(t)$, which is considered one empirical formula of great success [11] [8] [4], is a power law that relates the earthquake occurrence and its magnitude with the decay of aftershocks activity with time. For this approach we used the probability density function (pdf) form of the modified Omori law [11]:

$$g(t) = \frac{(p-1)}{c(1 + \frac{t}{c})^{-(p-1)}} \quad (4)$$

In the paper [8], Utsu says that most p and c values, for various earthquake data sets fall in the range between 0.9 and 1.4, and between 0.003 and 0.3 days, respectively. These values were based on the Davidon-Fletcher-Powell optimization procedure and used in ETAS [8]. For the experiments done for this paper, we choose the values of 1.1 for p and 0.003 for c , arbitrarily.

For $K(M_i)$, the total amount of triggered events, we count aftershocks within a calculated aftershock area, A , using the formula, where M_c is the magnitude threshold:

$$K(M_i) = A \exp([\alpha(M - M_c)]) \quad (5)$$

From [3], states α as the inverse of the magnitude of an event, or $magnitude^{-1}$. To obtain A , the following equation from [9], was used:

$$A = e^{(1.02M-4)} \quad (6)$$

and lastly, the $J(M)$ is a simulation of the event magnitude by Gutenberg-Richter's Law, using 1 as the value of β [2]:

$$J(M) = \beta e^{-\beta(M-M_c)}, M \geq M_c \quad (7)$$

At last, the Emp-ReducedGAModel is a mix between the two ideas, so it is represented as the Emp-GAModel but its candidates take the same form as the ones in the ReducedGAModel.

3. TESTS FOR EVALUATING MODELS

In the paper *Earthquake Likelihood Model Testing* [5] is proposed some statistical tests that are used in this study to compare and evaluate the models, developed by the The Regional Earthquake Likelihood Models (RELM). These tests are based on the log-likelihood score that compares the probability of the model with the observed events.

To evaluate the data-consistency of the models we used the N-Test, the Number Test, and the L-Test, or Likelihood Test. These tests fall are significance tests. Therefore, assuming a given forecast model as the null hypothesis, the distribution of an observable test is simulated. If the observed test statistic falls into the upper or lower tail of this distribution, the forecast is rejected [7].

To be able to compare the model that passed the N-Test and the L-test, the R-Test, hypotheses Comparison Test is used. It calculates the relative performance of a model, by comparing the Log-likelihood values between two models.

3.1 Likelihood Test or L-Test

The L(ikelihood) Test considers that the likelihood value of the model is consistent with the value obtain with the simulations. The value is calculated by the formula, where \hat{L}_k is the value of the Log-likelihood of the model j , in the *bin* i and \tilde{L} is the value of the Log-likelihood of the simulation j in the *bin* q :

$$\gamma_q^j = \frac{\left| \left\{ \hat{L}_k^j | \hat{L}_k^j \leq \tilde{L}_q^j, \hat{L}_k^j \in \hat{L}^j, \tilde{L}_q^j \in \tilde{L}^j \right\} \right|}{|\hat{L}^j|} \quad (8)$$

The analysis of the results can be split into 3 categories, as follows:

1. Case 1: γ^j is a low value, or in other words, the Log-likelihood of the model is lower than most of the Log-likelihood of the simulations. In this case, the model is rejected.
2. Case 2: γ^j falls near the half of the values obtained from the simulations and is consistent with the data.
3. Case 3: γ^j is high. This means that the Log-likelihood of the data da is higher than the Log-likelihood of the model and no conclusion can be made what so ever.

It is important to highlight that no model should be reject in case 3, if based only on the L-Test. In this case the consistency can or cannot be real, therefore these model should be tested by the N-Test so that further conclusions can be done.

3.2 Number test or N-Test

The N(umber)-Test also analyses the consistency of the model, but here, it compares the number of observations with the number of events of the simulations. This test is necessary to supply the underpredicting problem, which may pass unnoticed by the L-Test.

This measure is estimated by the fraction of the total number of observations by the total number of observations of the model.

As the L-test, if the number of events falls near the half of the values of the distribution, then the model is consistent with the observation, nor estimating too much events nor few of them.

3.3 Hypotheses Comparison Test or R-Test

The Hypotheses Comparison, or the R(atio)-Test, compares two models against themselves. The log-likelihood is calculated for both models and then the difference between, the observed likelihood ratio, this value indicates which one of the model better fits the observations.

The likelihood ratio is calculated for each simulated catalog. If the fraction of simulated likelihood ratios less than the observed likelihood ratio is very small, the model is rejected. To make this test impartial, not given an advantage to any model, this procedure is applied symmetrically [7].

3.4 Evaluation

The evaluation process is made as follow: First, the data-consistency is tested by the L-Test and the R-test. If the model passes these tests, meaning that it was not rejected by them, it is compared with other models, which also were not reject, with the R-Test. The model that best fits the R-Test is then chose as the best model[5].

4. EXPERIMENTS

5. RESULTS

6. CONCLUSIONS

7. ACKNOWLEDGMENTS

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