

# DIT866 Writing assignment 1

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## 1 Introduction

I have chosen to read and discuss the paper written by: DeVries et al., *Deep Learning of Aftershock Patterns Following Large Earthquakes*. from Nature 560, 632-634 (2018)

## 2 Discussion

The goal of the project written about in the paper is to model the spatial distribution of aftershocks after major earthquakes. Why such a model has a value isn't explicitly mentioned in the paper, however some obvious reasons why this is a useful thing to have is that it has the potential to save lives and money to be able to forecast where potential aftershocks are likely to happen.

How they modeled the spatial area in this task was by dividing an area spanned 100km horizontally and 50km vertically from each mainshock rupture plane into  $5\text{km} \times 5\text{km} \times 5\text{km}$  cubes. By utilizing this discretization of the spatial area they were able to do solve the task using a binary classification. Where the two options were that the cube had either had an aftershock between one second and one year after the initial earthquake (represented as a 1) or that there hadn't occurred an aftershock in that cell (represented as a 0).

The data they used was the stress-change that occurred in the centroid of a cube after a mainshock and whether or not an aftershock had occurred in that cell after a mainshock. So basically they used the stress-change as the dependent variable and if an aftershock had occurred as a dependent variable. The stress-change data was calculated using data from the SRCMOD online database of finite-fault rupture models and the aftershock data was collected from the International Seismological Center. They have collected the data from 118 mainshocks and 162,741 aftershocks. For training the model they used 75% of the data and the remaining 25% was used for testing and evaluating the model. They also mention that they downsampled cubes without aftershocks during training.

To perform the binary classification they used a deep neural network consisting of six hidden layers with each of them consisting of 50 neurons each. The activation function used in these layers was a hyperbolic tangent function. For

the last layer they only used one neuron as output, which is the standard for doing binary classification. The network was trained using Theano, an adaptive learning rate and optimization method, and for the cost function they used binary cross-entropy. The choice of this method wasn't mentioned, neither if they had tried any other similar models, neither did they mention if there were any drawbacks or potential error when going with this approach.

For evaluating the quality of the model they used the metric AUC, which measures the area under a ROC curve. A ROC curve is drawn by plotting the true positive rate and the true negative rate for different thresholds. This is a measurement that is defined in the interval  $[0, 1]$  where a higher score is better and a value of one means that the classifier has 100% true positive rate and 0% false positive rate for every threshold.

The model's performance was compared to a baseline that was measured using the standard formula for these sorts of tasks called the Coulomb failure stress change. The AUC value their neural net model achieved was 0.849, compared to the score of 0.583 that the Coulomb failure stress change score. This is quite an increase in predictability.

The forecasting shadow generated by the network closely resembled other already existing physical properties, which could explain a majority of the variance in the model. The paper then goes on to say that "These results highlight how deep-learning approaches can lead to improved aftershock forecasts and provide physical insights into the mechanisms of earthquake triggering", which is a good conclusion about the paper.

My own personal opinion about this project is that it is interesting to see how neural networks are able to find particular patterns in things that we humans have a hard time picking up, primarily because of our limitation of being able to process that amount of data. Even though the results sometimes may be informative it isn't always that way, deep neural networks are often referred to as a black box since it is pretty much impossible to interpret how they make their choices. This could lead to problems in this domain if one would become too confident in the predictions of the network and might end up harming themselves or other people in the case of an earthquake. Another thing I felt that the paper missed was a discussion on what other machine learning models that might be adequate for this task, or if there is any.