DEEP LEARNING APPROACH FOR SEISMIC RISK ASSESSMENT IN CHILE

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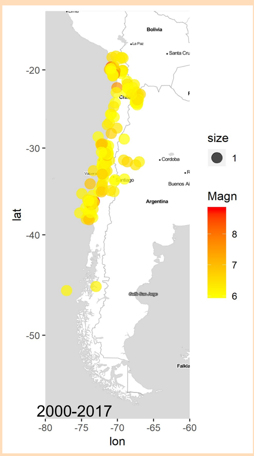
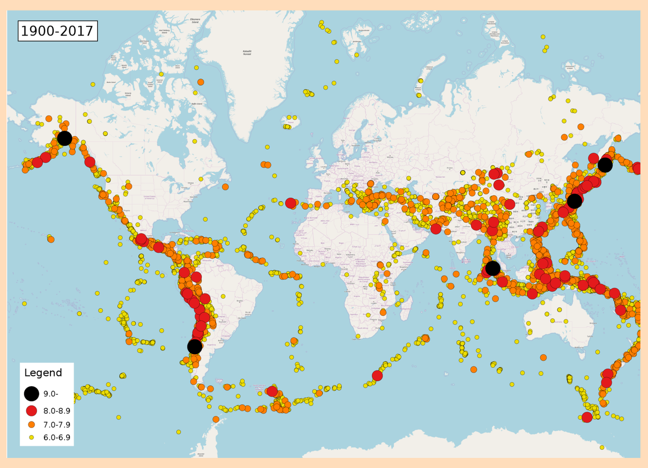
1. EARTHQUAKE PREDICTION?

- Chile is **one of the most seismic countries** in the world.
- Complexity associed with, **chaotic, non-linear nature**, and **unidentified variables** (**Reyes et al, 2013**).



From 2000-2017, **157 earthquakes** >6 Richter scale occurred in Chile!



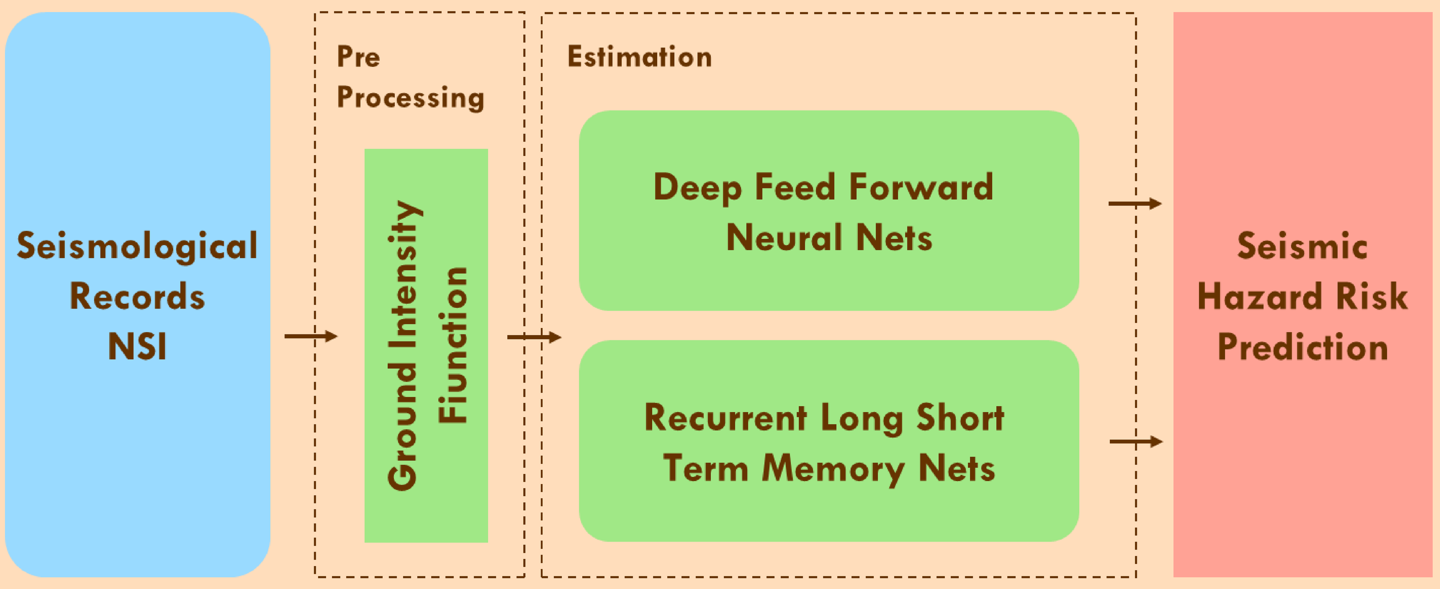
- Statistical Models: Epidemic-Type Aftershock Sequence, or ETAS (Ogata, 1988), use the expected number of events in a given region , conditional to the past events or conditional **ground intensity function (GIF)**, widely used in earthquake forecast approaches (Nicolis *et al*, 2015; Nicolis *et al*, 2017).
- Joffe et al (2018), states that contemporary techniques are insufficently sensitive for allowing precise earthquake modelling and prediction.
- Need for **new approaches** that consider broader and bigger sources on information, hence **Deep Learning models** are considered.

OBJECTIVE

This paper, presents a **temporal Deep Learning approach for ground intensity function estimation in Chile**, using historical seismological events information from catalogues.

2. OUR APPROACH

- The proposed approach consists of two modules: **Data Preprocessing**, and **Estimation** modules.
- In the **Data Preprocessing** module all the data will be analyzed and prepared as inputs for the following modules, this considers **estimating the daily ground intensity function (GIF)**.
- The **Estimation** module will receive inputs from the previous model and **use DFANN and RNN-LSTM** Deep Learning (DL) time series approaches to **estimate the GIF**.



2.1. DATA

86,000 records, from the National Seismological Center (NSI, www.sismologia.cl), **time location** (Year, Month, Day, Hour, Minute, Second), **spatial location** (Latitude, Longitude), **depth**, and **magnitude**.

2.2. PREPROCESSING

The **conditional intensity function**, represents a way of specifying how the present seismic events depend on the past events in an evolutionary point process. Consider the conditional density f_g and its cumulative distribution function F_g. Then, the conditional ground intensity function or **ground intensity function (GIF)** (also named hazard function) is defined by $\lambda_g(t)=f_g(t)/(1-F_g(t))$ (Ogata, 1999; Rasmussen, 2011).

2.3. ESTIMATION

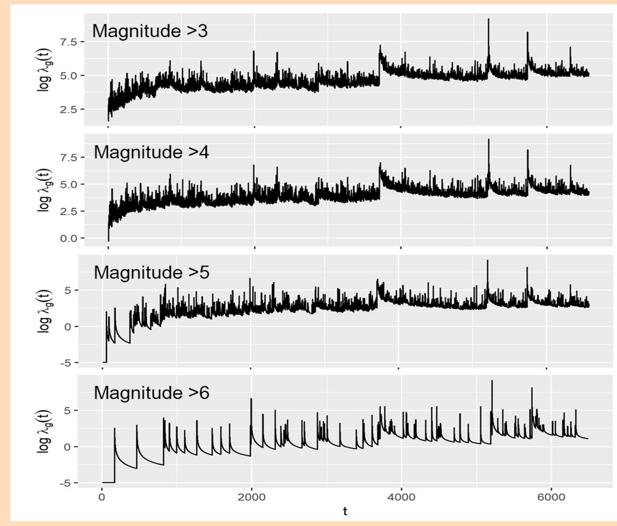
- Deep Feedforward Neural Networks (DFANN), and Recurrent Neural Networks with Long Short Term Memory (RNN-LSTM), are neural network structures suited for working with time series data (Schmidhuber, 2014; Goodfellow et al, 2016).
- GIF databases (for **>3, >4, >5** and **>6** magnitudes), are structured for estimation with the DL models. Training and Test (67% and 33% of the data).
- Autoregressive model (t-1, t-2, t-3).
- Both models trained with 100 epochs.

3. RESULTS

3.1 PREPROCESSING

Implemented using the ***PtProcess*** library available in ***R***.

- **GIF estimation** for the data preprocessing module, estimated for magnitudes ***>3, >4, >5*** and ***>6***.
- With **higher magnitudes**, the GIF timeseries become thinner, due to the decrease of seismic events that fit in the category.

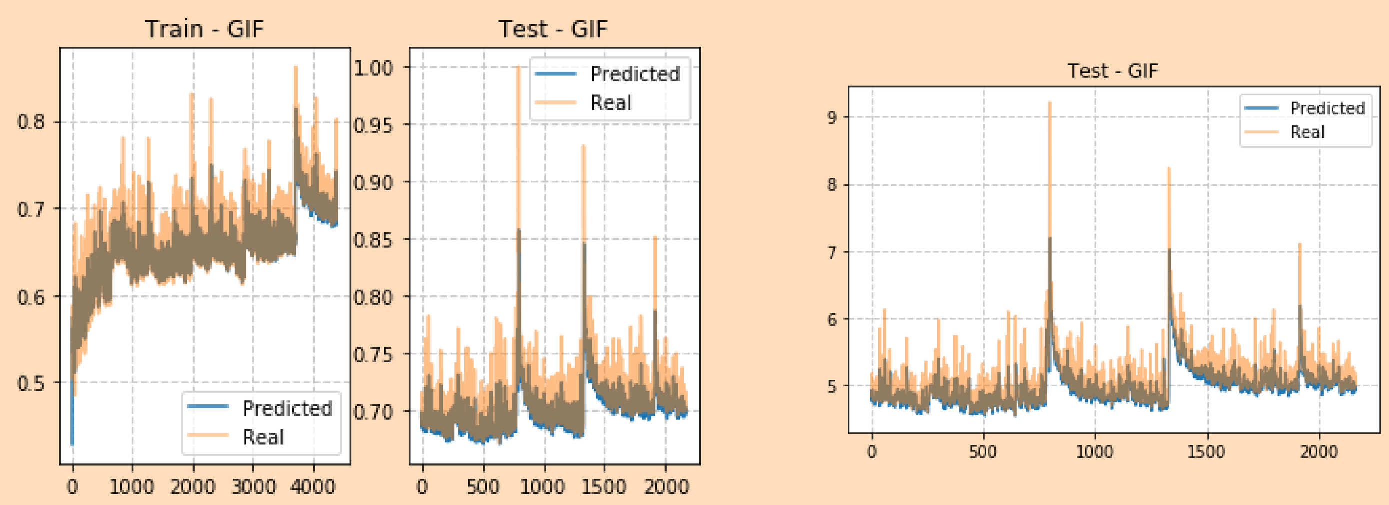


3.2. ESTIMATION

The DL models were implemented using ***Keras***, with ***Tensorflow*** as back end, in ***Python***.

- Root mean square error (RMSE) of the training and test groups for each Deep Feedforward Artificial Neural Network (DFANN) and Recurren Neural Network with Long Short Term Memory (RNN-LSTM) Deep learining models.
- In bold the best model.

	RMSE	
	Training / Test	
Mag	FANN	RNN-LSTM
>3	**0.3076** / **0.2395**	0.5514 / 0.2765
>4	0.4026 / 0.3243	0.6743 / 0.3495
>5	0.5310 / 0.4079	0.8371 / 0.4440
>6	0.4197 / 0.4753	0.8803 / 0.4792



Training and test for the best model (DFANN) GIF estimation with magnitudes > 3.

4. CONCLUSIONS

This paper deals with **time series estimation of seismic risk GIF**, to achieve that goal, two deep learning models were implemented: a **deep feedforward artificial neural network** and a recurrent **long short term memory network**. The results show a good estimation, in particular with the DFANN model.

Improvements to the approach (***work in progress***):

- Both implemented models could be improved by adding more hidden layers or to stack more LSTM layers in the DFANN and RNN-LSTM models, respectively.
- The use of exogenous variables (or covariables).
- Incorporating the spatio-temporal dimensión, using Convolutional Neural Networks (CNNs) or Generative Networks (GANs).

Finally, this Deep Learning proposal could be useful as inputs for earthquake prediction approaches.

5. REFERENCES

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