Predicting Earthquakes with Deep Neural Networks

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Impact of seismic wave length to detect high-magnitude earthquakes via deep learning

1 INTRODUCTION

- Earthquakes are one of the most destructive natural phenomena
- Extremely nonlinear or random phenomenon
- No reliable method of predicting earthquakes. Two approaches [1]:
  - trend-based
  - precursors-based
- Growing interest in using deep learning techniques for predicting earthquakes

2 QUESTIONS

- What is the optimal length of seismic recordings for classifying high-magnitude earthquakes?
- What is the optimal frequency (sampling rate) of the seismic recordings?

3 METHODOLOGY

- Split New Zealand earthquake dataset [2] into 2 equal parts:
  - pre-earthquake waveforms (precursor data)
  - normal background waveforms
- Data Preprocessing
  - stations filtering
  - sanitize and normalize seismic waves
- Use LSTM
  - time series data
  - higher accuracy [1][3][4]
- Tweak seismic wave length & sampling rate to find highest accuracy
- Binary Classification problem

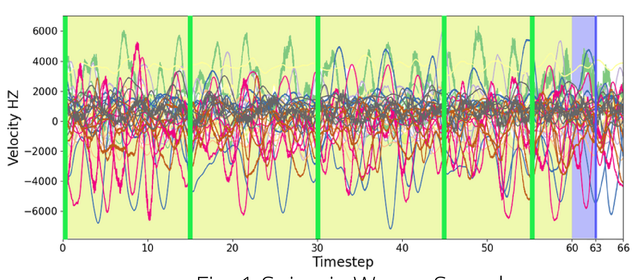

Fig. 1 Seismic Waves Sample

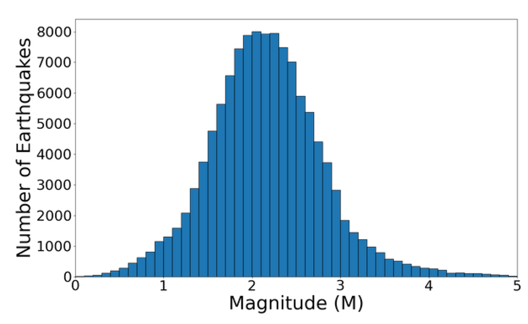

Fig.2 Magnitude Distribution

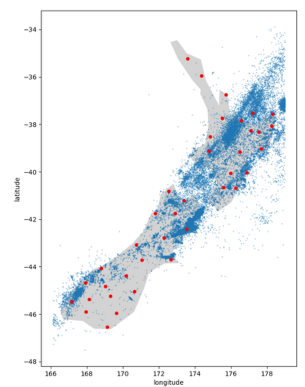
Fig.3 Earthquake data plotted

5 ANALYSIS

- Earthquakes between 2014 - 2018 inclusively
- Prediction made 3 sec before an earthquake
- 5, 15, 30, 45, and 60 seconds of precursor data
- 2, 5, 10, 20, 25, 50, and 100 Hz downsampled

All stations altogether

	Duration of precursor data				
Samples per sec	60 sec	45 sec	30 sec	15 sec	5 sec
100	0,5551	0,5573	0,5858	0,6	0,5816
50	0,6163	0,5801	0,5955	0,6326	0,5704
25	0,5807	0,5979	0,5512	0,6221	**0,609**
20	**0,6217**	0,6041	0,5803	**0,6381**	0,5727
10	0,6166	**0,6253**	**0,6405**	0,6189	0,6022
5	0,6074	0,5968	0,6391	0,5917	0,5329
2	0,5415	0,6229	0,5768	0,5402	0,5373

Table 1: Accuracy table based on duration of precursor data and sampling rate.

Fig. 4 Accuracy function - 30 sec, 10 HZ

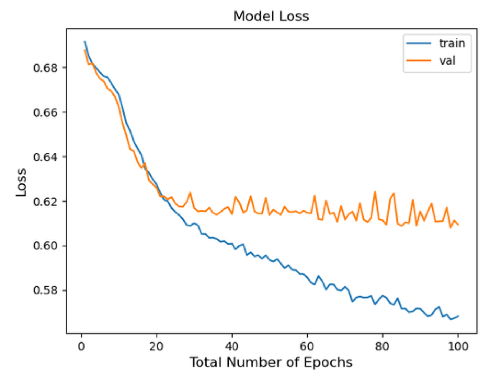

Fig. 5 Loss Function - 30 sec, 10 HZ

- Dealing with overfitting
- Regularization (L2)
- K-Fold Cross Validation
  - K = 5
  - 0.6301 average accuracy (30 sec 10 HZ)

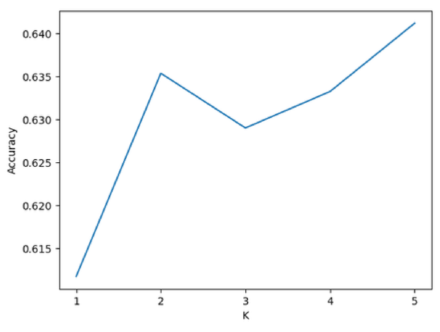

Fig. 6 5-fold accuracy - 30 sec, 10 HZ

Station by station

Station codes

	BFZ	DCZ	DSZ	EAZ	HIZ	JCZ	KHZ	KNZ	KUZ	LBZ
Accuracy	0,5543	0,7161	0,4968	0,5600	0,5297	0,5461	0,5350	0,5779	0,5466	0,6213
Precision	0,5904	0,6723	0,4901	0,5707	0,5399	0,5352	0,5285	0,5628	0,5375	0,6826
Recall	0,4065	0,8435	0,5143	0,5258	0,4961	0,7097	0,6472	0,6981	0,6684	0,4534
F1-score	0,4636	0,7481	0,4671	0,5366	0,4942	0,6089	0,5819	0,6232	0,5958	0,5449

	LTZ	MLZ	MQZ	MRZ	MSZ	MWZ	MXZ	NNZ	ODZ	OPRZ
Accuracy	0,5191	0,5281	0,5233	0,5334	0,5397	0,5000	0,5487	0,5122	0,5651	0,4915
Precision	0,5169	0,5365	0,5153	0,5355	0,5413	0,5000	0,5579	0,5179	0,6066	0,4897
Recall	0,5816	0,4131	0,7839	0,5032	0,5212	1,0000	0,4693	0,3528	0,3708	0,4025
F1-score	0,5474	0,4668	0,6218	0,5188	0,5310	0,6667	0,5098	0,4197	0,4602	0,4419

	OUZ	PUZ	PXZ	QRZ	RPZ	SYZ	THZ	TOZ	TSZ	TUZ
Accuracy	0,5715	0,5106	0,5980	0,5281	0,6340	0,6006	0,5752	0,5191	0,5339	0,5959
Precision	0,5556	0,5094	0,5702	0,5250	0,6078	0,5624	0,5755	0,5153	0,5285	0,5834
Recall	0,7150	0,5763	0,7956	0,5900	0,7553	0,9068	0,5731	0,6441	0,6292	0,6706
F1-score	0,6253	0,5408	0,6643	0,5556	0,6736	0,6942	0,5743	0,5725	0,5745	0,6240

	URZ	VRZ	WCZ	WHZ	WIZ	WKZ	WVZ	BKZ
Accuracy	0,6668	0,5636	0,6054	0,5207	0,5371	0,5048	0,5365	0,5704
Precision	0,6041	0,6064	0,6035	0,5288	0,5486	0,5055	0,5331	0,5677
Recall	0,9682	0,3623	0,6144	0,3792	0,4184	0,4396	0,5879	0,5911
F1-score	0,7440	0,4536	0,6089	0,4417	0,4748	0,4703	0,5592	0,5791

Table 2: Results for 30 sec and 10 HZ on all 38 stations individually.

6 CONCLUSION

Overall, 30 seconds ±15 seconds, & sampling rate of 10 - 20 HZ showed best results.

Remarks:

- Most individual stations performed poorly (0.5 - 0.55 accuracy)
- Highest accuracy achieved was by an individual station (DCZ) - 0,7161
- Model performs differently for different set of years.
- Results cannot be considered as certain.
- Results are unsatisfactory in terms of accuracy.

Earthquake prediction remains an unachievable task[5]

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