CS230

Neural Network based Building Earthquake Damage Estimation
– from the data of 2011 Christchurch Earthquakes

Zhaozhuo Xu, Zhiyuan Li, Haiwen Wang
Department of Electrical Engineering, Civil and Environmental Engineering and Applied Physics
Stanford University
`{zhaozhuo, zhiyuan8, hwwang}@stanford.edu`

Abstract

Damage of building is an essential indicator of economic losses after earthquakes. Efficient building damage estimation improves both government's resource allocation and future policies of insurance company. Traditional damage estimation uses statistical learning techniques to predict the damage ratio according to previous information. In this work, we apply both neural network (NN) and convolutional neural network(CNN) in this area. We construct a mixture feature that combines building information and features extracted by CNN. Then the categorical damage ratio is predicted from mixture feature via a artificial neural network(ANN). Our model achieve 86.5% accuracy in four class damage ratio estimation, which outperforms traditional models quantitatively.

1 Introduction

Earthquake is an unpredictable and devastating natural disaster in nature. Earthquake losses are estimated to be $4.4 billion annually in the US [1]. Massive efforts have been paid on mechanism, structural performance and ground motion analysis of earthquakes [2] [3]. Meanwhile, it is also essential to assess building economic losses afterwards for it provide necessary information for policy makers in both government and insurance companies[4][5]. Statistical learning approaches such as tree method[8] or logistic regression have been used to estimate building damage ratio given building information like floor area and material[7]. However, due to the complexity of earthquake damage mechanism, sometimes these methods don't work well in damage prediction.

Using both artifitial neural networks (ANN) and convolutional neural networks (CNN), this project aims to build a building damage ratio estimation model based on 2011 New Zealand Christchurch Earthquake (magnitude 6.3). We first train a CNN model using spatially distributed information, peak ground velocity (pgv), soil liquefaction, and neighboring house distribution as input. The output of CNN model are used as extracted features are combined with other building information to form a vector input which is used in ANN to predict four class damage ratio. The damage ratio is the percentage of economic loss in the whole value of the house. We compare our model with traditional statistical learning methodologies such as LDA, QDA and KNN. As deep learning approaches have not been seen in building damage ratio prediction, our model may be a precedent in this area.

CS230: Deep Learning, Winter 2018, Stanford University, CA. (LateX template borrowed from NIPS 2017.)

2 Related work

With the development of statistical tools and machine learning methods, more novel methodologies were applied. In 2009, Oliver [8] applied a three-layer neural network using intermediate features in finite element (FEM) building damage ratio analysis, and achieved 88.5% classification accuracy. Then in 2010, Molina et al. [9] tried logic tree approach in seismic damage estimation. Next in 2011, Pradhan and Lee used logistic regression and Neural Network in landslide analysis, and Marijana et al. [10] compared FEM analysis with NN model using same FEM inputs. In 2014, Riedel et al. [11] used Associate Learning Rule (ALR) in seismic damage prediction and reached around 65% accuracy merely according to building information. In 2016, Cao et al. used convolutional neural network to detect damaged buildings during earthquake.

The above mentioned model require abstract features from FEM analysis, and those estimated variables lack accuracy or are hard to access by non-technical officers. Moreover, CNN merely is applied in building damage detection rather than damage ratio prediction. This study aims to directly utilize observed ground motion information in 2011 Christchurch earthquake, and combine it with building properties to predict building damage ratio based on CNN and ANN.

3 Dataset and Features

3.1 Data collection through various resources

The data [15-16] we have for the 2011 Christchurch earthquake falls into two types. The first type is building specific information [15]. These data are shown from row 1 to 10 in Table 1.The second part, earthquake information [16], consists of peak ground velocity, soil liquefaction and building positions, which are shown in Table 1from row 11 to 14.

Label	Data Type	Definition	Data Source
replace	numeric	Dwelling value (NZ $) (modelled)	NZ Portfolio
incurred	numeric	Area of building damage	Insurance Claim data
floor	numeric	Building floor area (m^2)	QVNZ
site	numeric	Building site area (m^2)	QVNZ
type	categorical	Wood, concrete, steel or other wall and roof material	Insurance Claim data
storey	integer	Number of stories for a building	Insurance Claim data
pga	numeric	Peak ground acceleration	University of Canterbury
occu	text	Occupancy type (commercial, industrial, residential)	NZ Portfolio
year	integer	Year of building construction	NZ Portfolio
soil	categorical	Soil type (firm,normal,loose)	New Zealand GNS
liq	categorical	Liquefaction observed (February 2011)	Land Damage Assessments
pgv	numeric	Peak ground velocity	University of Canterbury
lat	numeric	Latitude of the building assessed	Land Damage Assessments
lon	numeric	Longitude of the building assessed	Land Damage Assessments
		Label data	
repair	numeric	Repair cost (NZ $) (modelled)	Insurance Claim data
Dr	numeric	Ratio of repair to replace	= repair / replace

Table 1: Explanation of the data used in our prediction model.

Damage ratio (Dr) refers to percentage of economic loss in respect to one building, it is defined as:

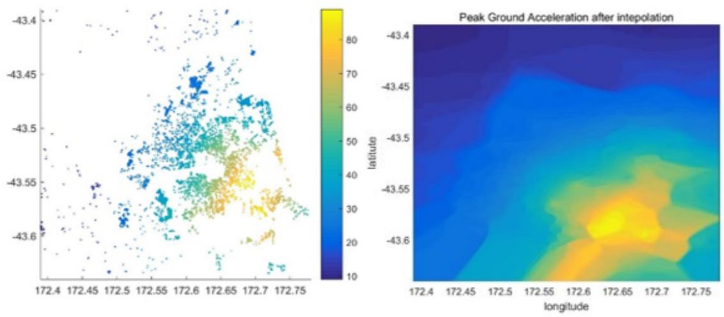
$$\mathrm{Dr} = \frac{\mathrm{replace}}{\mathrm{repair}} \tag{1}$$

where 'repair' refers to how much an insurance company should pay for one building, and 'replace' means how much the value of one dwelling should be.

3.2 Data preparation for CNN

There are three channels for CNN, namely 'pgv', 'liq' and 'bldg location'. There are discrete observed datasets shown in Figure 1a. By K-Nearest-Neighbors, the original data for each kind of variable is interpolated to be a matrix of 5000*5000 in size according to weighted three nearest known data points in Euclidean distance. The interpolated result is illustrated in Figure 1b. For a single datapoint we crop 32*32 pixels around the location of the building whose damage ratio we want to predict, and the 3 channel 32*32 image is used for the input of CNN.

Finally, our dataset contains datapoints for 6788 buildings and they are split into training/test set of 6000/788 in size.



(a) Peak ground velocity acquired at different locations

(b) Peak ground velocity after interpolation

Figure 1: Input of earthquake information

4 Methods

4.1 Earthquake feature extraction from CNN

We propose a combined networks of VGG and ANN, the architecture is shown in Figure 2 and the hyperparameters are summarized in Table 2. CNN is used as feature extractor because it can extract spatial structure of input channels (liq, pgv, bldg location) through convolution operation. We modify the output layer of VGG CIFAR-10 network [17] to be a softmax layer with 2 categories: damage or not damage. The network is trained to minimize the softmax cross entropy loss $\mathcal{L}$ as Equation (2), where y_i is the label for large ($Dr > 0.1$) or small ($Dr < 0.1$) damage ratio, and $\hat{y}_i$ is the output from the VGG networks. The network is implemented in Keras [18].

$$\mathcal{L} = -\frac{1}{\#\text{datapoints}} \sum_{i=1}^{\#\text{classes}} y_i \log(\hat{y}_i) \tag{2}$$

4.2 Damage ratio prediction by NN

The second network is ANN. The inputs are the building specific information with 10 variables concatenated with the feature vector (2 categories) extracted from our trained VGG networks. That gives a total input layer size of 12. ANN have a softmax output layer with number of classes $= 4$. Although the damage ratio is a continuous number, we divided it into 4 categories, small: $Dr < 0.03$, medium: $0.03 < Dr < 0.1$, large: $0.1 < Dr < 0.5$, and extra large: $Dr > 0.5$. We formulate the problem as a classification problem where softmax cross-entropy loss is applied. This gives us a better loss function with larger gradients (compared to the R^2 loss we used before, which is $(y - \hat{y})^2$, y (hat) stands for (predicted) damage ratio). Softmax loss function is found to be better in our training. The hyperparameter of ANN is stated in Table2. The ANN is implemented in Tensorflow[19].

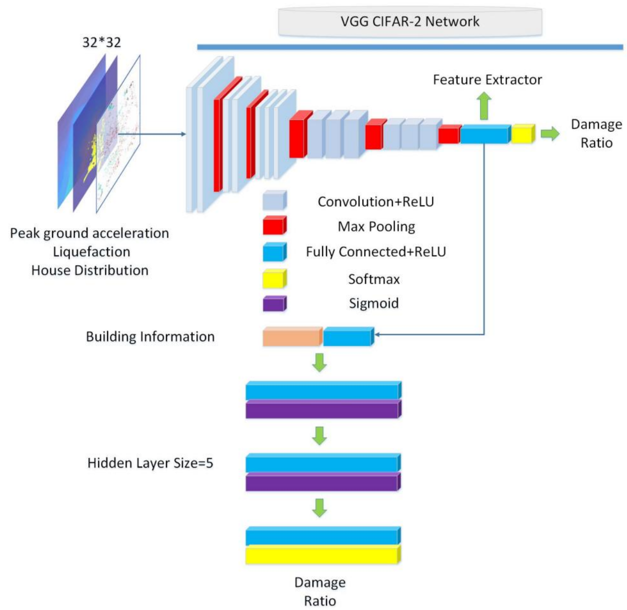


Figure 2: The architecture of our combined networks. VGG is used to extract feature from 3 spatially distributed information, pgv, liq, and bldg location. The extracted feature (size = 2) is concatenated with other 10 building specific information to be the input of ANN.

CNN			
Architecture	VGG	Output	2 category softmax
Optimizer	SGD	Learning rate	0.02
Epoches	100	Batchsize	128
ANN			
Input layer	10+2	Hidden layer 1	10
Hidden layer 2	5	Output layer	4
Optimizer	Adam	Learning rate	0.01
Batchsize	64	Epoch	1000
Activation	sigmoid	Loss function	softmax cross-entropy

Table 2: Summary of hyperparameters in our model.

5 Experiments/Results/Discussion

The main evaluation metric we would like to optimize is the prediction accuracy. We trained our networks to predict the category (small, medium, large, extra large) of damage ratio and compare it with the ground truth category of damage ratio. The accuracy is defined as

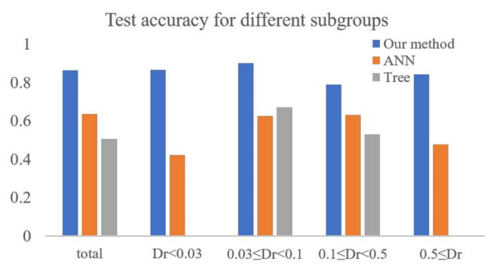
$$\text{accuracy} = \frac{\#\text{ correct predictions}}{\#\text{ all predictions}} \tag{3}$$

We first trained a pure analytical neural networks. It only reaches 65.2% testing accuracy after tuning. We thought CNN might be able to extract useful information from spatially distributed information.

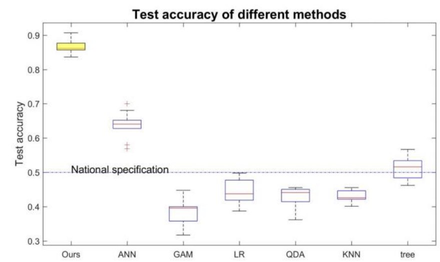
During our training of VGG as a feature extractor, we used stochastic gradient descent with a batch size of 128. We chose the learning rate to be 0.02 since this value in our experiment give us a steady increase in accuracy and a steady decrease in loss. The model is trained for 100 epoches on a 6000/788 training/test dataset splitting. The VGG networks finally reaches a 66.7% accuracy and 66.2% accuracy on training and test dataset respectively. After the training, the VGG networks is used as a feature extractor when its weights are not being trained anymore.

Combined model used a two hidden-layer neural network with softmax activation function for output. The hyperparameters are shown in Table 2. After 1000 epochs training, the mean accuracy could achieve 86.5% , as depicted in Figure 3b. More importantly, as shown in Figure 3a, the model achieves good estimations for all subgroups. Even the worst subgroup, $0.1 < Dr < 0.5$, could reach estimation accuracy of 78.9%. We further investigated the influence of each input variables. This is done by eliminating this specific variable during both training and testing, and look at how the estimation accuracy drops. We found that 'replace' (dwelling value), 'floor' (floor area), 'occu' (occupancy type) are the three most important variables for an accurate estimation.

We compare our method with other statistical methods, including: Generalized Additive Model (GAM).[1], Logistic Regression (LR), Quadratic Discriminant Analysis (QDA)[2], K-Nearest-Neighbors (KNN)[3], Logical tree (Tree)[4], National Engineering Specification. [5] We see that our method outperform other statistical methods.



(a) Prediction accuracy for different subgroups



(b) Comparison on prediction accuracy. The first model is our combined model. The second one is the accuracy achieved by ANN.

Figure 3: Analyze the effectiveness of our model

6 Conclusion/Future Work

By combining the training of CNN and ANN models, we manage to find sets of DL features that are able to yield an excellent damage ratio estimation after earthquake. We develop a ANN that outperform other state-of-art statistical methods, and 'replace', 'floor', and 'occu' are three most influential variables in building damage ratio estimation. This is also the first CNN model applied to the specific area. Features extracted by CNN can help improve the performance of ANN when combining building information. Future works lie on tuning and visualizing better CNN models.

7 Contributions

Zhaozhuo Xu: Model formulation, CNN and ANN training and tuning. Poster and report writing.
Zhiyuan Li: Data obtaining and dataset construction, NN code writing, poster making, report writing
Haiwen Wang: Coding and debugging NN and CNN model, help process data, poster making, report writing

References

[1] Shi Y B, Zhi X D, Fan F, *et al*. A damage model of single-layer reticulated domes under severe earthquakes. *Journal of Harbin Institute of Technology*, 2008, **40**(12):1874-1877.

[1] Raw data is transformed by some operations like square root or logarithm. Then multi-linear regression is applied.

[2] Assume that datasets of each feature are normally distributed, then the prediction that Dr<0.03 has higher possibility than 0.03<Dr<0.1 is evaluated by likelihood ratio test.

[3] The prediction is determined by weighted average of nearest K known points in distance.

[4] The datasets are split in order to achieve maximal differences among subgroups, and different branches lead to different outputs.

[5] The estimation is performed by a corresponding software named HAZUS, according to FEMA-58 (national specification for earthquake damage prediction).

[2] Huang Meng, Zhao Lei, Li Pan. Earthquake Damage Prediction System of Buildings Group Based on Damage Factors Method. *Applied Mechanics* & Materials, 2013, 341-342:1496-1499.

[3] Kircher C A, Reitherman R K, Whitman R V, *et al.* Estimation of Earthquake Losses to Buildings. *Earthquake Spectra*, 1997, **13**(4):703-720.

[4] Schwarz J, Maiwald H. Damage and loss prediction model based on the vulnerability of building types, *International Symposium on Flood Defence*. 2008.

[5] Elenas A, Meskouris K. Correlation study between seismic acceleration parameters and damage indices of structures. *Engineering Structures*, 2001, **23**(6):698-704.

[6] Riddell R, Eeri A M. On Ground Motion Intensity Indices. *Earthquake Spectra*, 2007, **23**(1):147-173.

[7] Zeng X, Lu X, Yang T Y, *et al.* Application of the FEMA-P58 methodology for regional earthquake loss prediction. *Natural Hazards*, 2016, **83**(1):177-192.

[8] Oliver L, Omenzetter P. Prediction of seismic-induced structural damage using artificial neural networks. *Engineering Structures*, 2009, **31**(2):600-606.

[9] Molina S, Lang D H, Lindholm C D. SELENA – An open-source tool for seismic risk and loss assessment using a logic tree computation procedure. *Computers & Geosciences*, 2010, **36**(3):257-269.

[10] Hadzima-Nyarko M, Nyarko E K, Morić D. A neural network based modelling and sensitivity analysis of damage ratio coefficient. *Expert Systems with Applications*, 2011, **38**(10):13405-13413.

[11] Riedel I, Guéguen P, Mura M D, et al. Seismic vulnerability assessment of urban environments in moderate-to-low seismic hazard regions using association rule learning and support vector machine methods[J]. Natural Hazards, 2015, **76**(2):1111-1141.

[12] Riedel I, Gueguen P, Dunand F, *et al.* Macroscale Vulnerability Assessment of Cities Using Association Rule Learning. *Seismological Research Letters*, 2014, **85**(2):295-305.

[13] Cao C, Liu D, Singh R P, *et al.* Integrated detection and analysis of earthquake disaster information using airborne data. *Geomatics Natural Hazards & Risk*, 2016, **7**(3):1-30.

[14] Fujita A, Sakurada K, Imaizumi T, *et al.* Damage detection from aerial images via convolutional neural networks *Fifteenth IAPR International Conference on Machine Vision Applications, IEEE*, 2017:5-8.

[15] NZ GNS Science. https://lris.scinfo.org.nz/

[16] Housing and property. NZ Government. https://www.govt.nz/

[17] Simonyan, K. and Zisserman, A., *et al.* Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv* , 2014:1409.1556.

[18] Keras. https://keras.io/

[19] Tensorflow. https://www.tensorflow.org/