# LEARNING REPRESENTATIONS WITH SEQ2SEQ MODELS FOR DAMAGE DETECTION

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## ABSTRACT

Natural hazards have incurred damages to buildings and economic losses worldwide. Post-hazard response requires an accurate and fast damage detection and assessment. The data-driven damage detection approach has been emerged as an alternative to the conventional human vision inspection. We use a Seq2Seq model to learn damage representations by training with only undamaged signals. We test the validity of our Seq2Seq model with a signal dataset that is collected from a 2-story timber building. Results show that our Seq2Seq model has a strong capability of distinguishing damage representations for different damage states. Our code is available at the repository: `https://github.com/qryang/Damage-representation`.

## 1 INTRODUCTION

Natural hazards including hurricanes and earthquakes have caused damages to buildings and loss of economy in many countries Yang et al. (2021). Post-hazard responses are critical to save lives and mitigate loss of economy, requiring an accurate and efficient assessment of damage. The traditional approach to assessing post-hazard damage is on-site investigations by employing expert inspectors to detect damages Wang & Cha (2021). Because the accessibility to specific locations, like underneath the bridge deck, is often low, on-site investigations have unavoidable disadvantages in terms of emergency response and post-hazard recovery efforts. Additionally, manual visual inspection is subjective and laborious.

The conventional post-hazard damage assessment is constrained due to the limitations of qualified human resources and low accessibility to specific locations in the building. Deep learning-based approaches using sensor data have been emerging technologies within the research community of structural health monitoring Erazo et al. (2019). We use a Seq2Seq model to put forward the data-driven damage detection approach. We train the model to learn damage representations with only undamaged signals by feeding damaged signals into models.

## 2 METHODOLOGY

**Damage representation learning** A Seq2Seq model is a neural network that computes a conditional probability of $p(\boldsymbol{y}|\boldsymbol{x})$ of mapping a source sequence, $\boldsymbol{x} = \{x_1, \ldots, x_n\}$, to a target sequence, $\boldsymbol{y} = \{y_1, \ldots, y_n\}$ Sutskever et al. (2014). As illustrated in Figure 1, the basic architecture of a Seq2Seq model is comprised of two sub-networks: (a) an encoder that extracts damage representations $\boldsymbol{h}$; and (b) a decoder that reconstructs a signal value at each time step and hence decomposes a conditional probability as

$$\log p(\boldsymbol{y}|\boldsymbol{x}) = \sum_{j=1}^{n} \log p(y_j|y_{<j}) \tag{1}$$

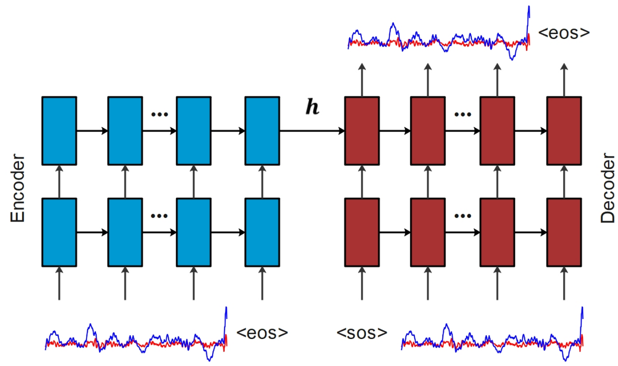



Figure 1: Seq2Seq model - a stacking recurrent architecture for reconstructing signals. Here, $<\mathrm{sos}>$ marks the start of a signal, $<\mathrm{eos}>$ marks the end of a signal.

A direct option to build a Seq2Seq model is to use a recurrent neural network (RNN) architecture. Alternatively, to avoid gradient vanishing during the training of long sequences, Long Short-Term Memory (LSTM) unit and gated recurrent unit (GRU) can be used in a Seq2Seq model.

In more detail, one can parameterize the conditional probability of encoding each signal $\boldsymbol{x}$ as:

$$p(\boldsymbol{h}|\boldsymbol{x}) = f(\boldsymbol{x}, \boldsymbol{h}_0; \boldsymbol{\theta}_p) \tag{2}$$

where $f$ determines the probability distribution of the damage representation given the signal, often refers to as the posterior probability and can be either a vanilla RNN, an LSTM, or a GRU. $\boldsymbol{h}_0$ is the hidden state at the initial time step, which is often set as an all-zero vector. $\boldsymbol{\theta}_p$ is the parameter set of the encoder.

Then, one can parameterize the conditional of decoding each signal with a damage representation $\boldsymbol{h}$ from an encoder as:

$$p(y_j|y_{<j}, \boldsymbol{h}) = \frac{\|\boldsymbol{W}\boldsymbol{h}_j^*\|_2^2}{\|\boldsymbol{x}_j\|_2^2} \tag{3}$$

with $\boldsymbol{W}$ being the weight matrix of the fully connected layer that outputs a signal-sized vector. $\|\cdot\|_2^2$ denotes the $2^{nd}$ power of the $L_2$ norm. Here, $\boldsymbol{h}_j^*$ is the RNN hidden unit in the decoder, which can be computed as:

$$\boldsymbol{h}_j^* = g(\boldsymbol{x}_{j-1}, \boldsymbol{h}_{j-1}^*; \boldsymbol{\theta}_q) \tag{4}$$

where $g$ outputs the current hidden state recursively according to the previous hidden state. The initial hidden state of the decoder $\boldsymbol{h}_0^*$ is the damage representation $\boldsymbol{h}$ that is extracted from the encoder. Likewise, $g$ can be either a vanilla RNN, an LSTM, or a GRU. $\boldsymbol{\theta}_q$ is the parameter set of the decoder.

In this work, our training objective is to reconstruct the signal with a Seq2Seq model and hence the loss function is formulated as follows:

$$\mathcal{L}(\boldsymbol{x}; \boldsymbol{\theta}_p, \boldsymbol{\theta}_q) = \sum_{\boldsymbol{x}} -\log p(\boldsymbol{y}|\boldsymbol{x}) \tag{5}$$

with $\boldsymbol{x}$ and $\boldsymbol{y}$ being the original and reconstructed signals, respectively.

## 3 EXPERIMENT

In this section, we test the effectiveness of using a Seq2Seq model with a two-story timber building Pei et al. (2019). To distinguish the capacity of our model in terms of learning damage representations, we used a vanilla AutoEncoder, a stacking architecture of multilayer perceptron (MLP), as a baseline model.

**Dataset** A test building was subjected to real ground motions that represent four increasing hazard levels for the San Francisco site. To understand the effects of the damage inflicted to the test building as excitation intensity increases, white noise tests were conducted before and after each ground motion test. The white noise test data are available in DesignSafe-CI Pei et al. (2017).

**Training details** We use the following settings in training a Seq2Seq model and a baseline model: (a) weights are uniformly initialized in $[-1, 1]$; (b) the hidden size (dimensionality of damage representations) is 128; (c) we trained models using SGD with a momentum coefficient of 0.9; (d) a fixed learning rate of 0.1 was employed; (e) our batch size was 256 and (f) the numbers of epochs were 1000 and 10,000 for a Seq2Seq model and a baseline model, respectively. In addition, dropout with a of probability 0.5 was used for a Seq2Seq model and the normalized gradient was rescaled when its norm exceeded 5.

**Reconstruction results** Figure 2 illustrates the reconstructed results of signals by using a Seq2Seq model and a baseline model. Our Seq2Seq model has a better result of reconstructing signals compared with the baseline model. The baseline model can only reconstruct low frequency components in the EW direction while losing majority of high frequency components in the NS direction. In contrast, our Seq2Seq model can restore both low frequency and high frequency components in two directions.

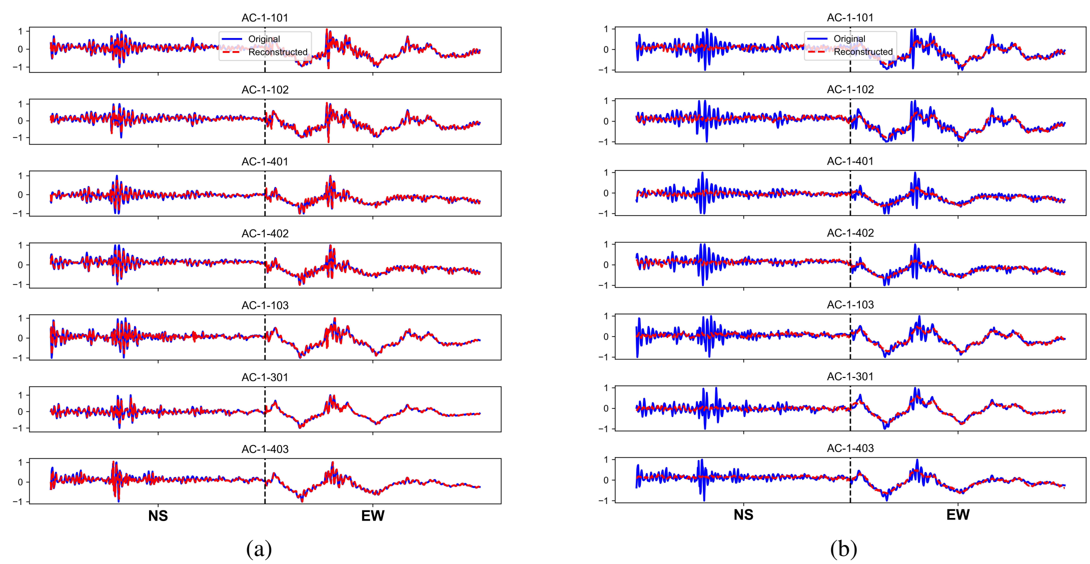
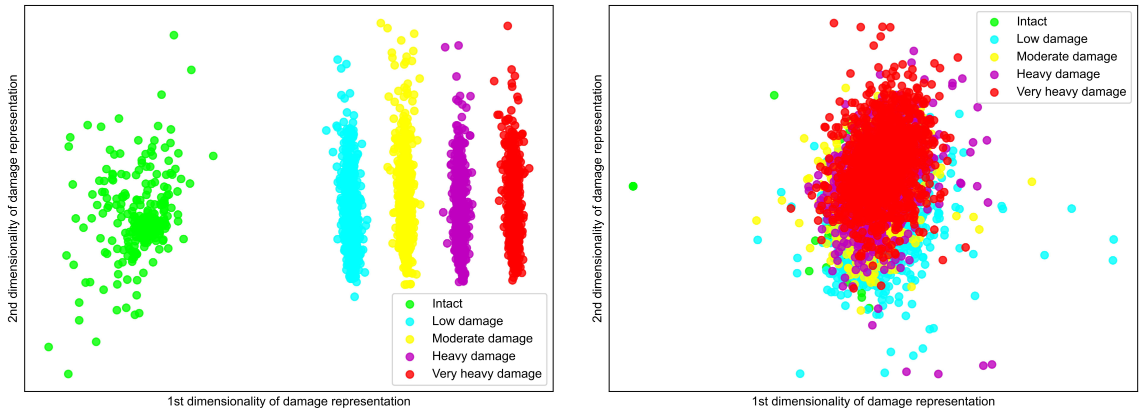



Figure 2: Reconstructed signals: (a) Seq2Seq model; and (b) Baseline model.

**Damage representations** To visualize the distribution of damage representations, we employ the linear discriminant analysis to obtain 2-dimensional damage representations. Figure 3 illustrates dimensionally reduced damage representations extracted by a Seq2Seq mode and a baseline model. The distributions of representations in the progressively increasing damaged states distinct from that in an intact state. For a Seq2Seq model, damage representations for a heavier damage states scatter clearly with a larger distance to the intact state. In contrast, the distribution of damage representations extracted by the baseline model is overlapped without effectively clarifying different damage states. Therefore, we conclude that a Seq2Seq model behaves better in terms of discriminability of damage representations than the baseline model.




(a) (b)

Figure 3: Damage representations: (a) Seq2Seq model; and (b) Baseline model.

## 4 CONCLUSION

In this paper, we use a Seq2Seq model to learn damage representations. We verify the effectiveness of using the Seq2Seq model to learn damage representations with a 2-story timber building. To distinguish capacity of our model in terms of learning damage representations, we use a vanilla AutoEncoder as a baseline model. Results show that our Seq2Seq model can reconstruct signals with a low loss while the baseline model can only reconstruct low frequency components but lose majority of high frequency components. Compared with the baseline model, our Seq2Seq model has a stronger capability of distinguishing damage representations.

### ACKNOWLEDGMENTS

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## REFERENCES

Kalil Erazo, Debarshi Sen, Satish Nagarajaiah, and Limin Sun. Vibration-based structural health monitoring under changing environmental conditions using kalman filtering. *Mechanical systems and signal processing*, 117:1–15, 2019.

Shiling Pei, John W van de Lindt, Andre R Barbosa, J Daniel Dolan, and Jeffrey W Berman. Two-story wood building test. shake table test of a two-story mass timber building with post-tensioned rocking walls. Thessaloniki, Greece:DesignSafe-CI. `https://doi.org/10.17603/ds2-zcb9-ry11.`, 2017.

Shiling Pei, John W van de Lindt, Andre R Barbosa, Jeffrey W Berman, Eric McDonnell, J Daniel Dolan, Hans-Erik Blomgren, Reid B Zimmerman, Da Huang, and Sarah Wichman. Experimental seismic response of a resilient 2-story mass-timber building with post-tensioned rocking walls. *Journal of Structural Engineering*, 145(11):04019120, 2019.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In *Advances in neural information processing systems*, pp. 3104–3112, 2014.

Zilong Wang and Young-Jin Cha. Unsupervised deep learning approach using a deep auto-encoder with a one-class support vector machine to detect damage. *Structural Health Monitoring*, 20(1):406–425, 2021.

Qun Yang, Dejian Shen, Wencai Du, and Weijun Li. A deep learning-based framework for damage detection with time series. *IEEE Access*, 9:66570–66586, 2021.