Earthquake source association via Barlow-twins

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Abstract

In seismology, the earthquake source association problem is to link the observed waveform at different stations together and attribute them back to the correct common source of the earthquake. We propose a novel method to help solve the earthquake source association problem via dimensionality reduction of embeddings. The method consists of two parts — a Resnet style autoencoder to reduce the dimension indifferent of the sources, and a training using self supervised learning algorithm Barlow-twins to refine the embedding. We experiment on the ISC-EHB bulletin dataset. The generated embedding is evaluated in three different metrics, which show that the embedding effectively represents the input waveform and hence is invaluable in solving the earthquake source association problem.

1. Introduction

Seismograms are time series recordings of ground motions at seismic stations. When an earthquake occurs, the energy released by the event can travel around the globe and being captured by hundreds of thousands of seismometers. These recordings carry important information of earthquake source (e.g. how a fault ruptures, where and when the earthquake occurs, how big the event is.) as well the path (e.g. properties of medium) they travel through. From a signal processing point of view, a seismogram can be represented as the output of a series of filters applied to the source-time function (i.e. the signal that the source rupture process initially generates) with each of the filters representing different processes such as wave propogation, attenuation, reflection, refraction, digital instrument response and so on. Each of these filters distorts the original source time function in a different way. Mathematically this system can be represented as convolution [1].

$$W(t) = S(t) * P(t) * I(t) + N(t)$$

Where W represents a seismogram, S represents source, P represents path (medium), I for instrument and N represents noise.

Earthquake source properties are of particular interest to the seismological community. Apart from their scientific significance, better understanding of earthquake source properties can help mitigating seismic hazard and eventually save lives and reduce economic losses. From a different stand point, government agencies also pay special attentions onto studying seismic sources for national security reasons because nuclear explosions can also generate earthquake-like signals. Misinterpreting an earthquake signal as an nuclear explosion or vice versa can both cause bad political outcomes and endanger the human society.

Studying seismic source, however, is not an easy task. It involves separating all the factors involved in distorting the seismic waves and solely focus on the portion of signals that reflect source properties. It is difficult because all of the factors involved are unknowns. Furthermore, as the seismic waves travel further and further away from the source area, the seismograms become more and more distorted by the Earth. How much the Earth has distorted each of the waves is itself a problem to tackle as we don't know enough of the Earth's physical and chemical properties.

In this study, we aim to tackle a specific earthquake source related problem, named the *earthquake source association problem* via dimensionality reduction. We chose two models, one being a Resnet [4] style autoencoder and the other is the Barlow-twins [9]. In the following sections, we will first define the earthquake source association problem, explain the approach and the dataset we use, followed by the model designs and the outcome of the study.

1.1. The earthquake source association problem

The earthquake source association problem is a fundamental problem in seismology. It's ultimate goal is to link the observed seismic phases at different stations together and attribute them back to the correct common sources. Traditionally it can be done by iteratively taking into a group of phase arrival times and using them as inputs to invert for a source location, given a physical model. The solutions are reached once some consensus are made (i.e. multiple phases point to the same source location with small errors). To use this approach, an intensive labor work has to be put in to pre-process waveform and pick phase arrival times. Newer data-driven methods directly utilize waveform as inputs [5, 6, 7]. These approaches use deep CNN models to process and classify waveforms recorded at different stations. Their goal is to correctly identify waveforms coming from the same sources. These approaches had reached a reasonable degree of success for local earthquakes (near field signals, propagate less than 200 km range), but they easily fail when dealing with far-field sources (i.e. source distances further than 10,000 km away). This might be due to the severe distortion imposed on waveforms by the Earth.

Intuitively, the waveforms that came from the same source must also look similar so they can be classified by human and/or deep learning models. However, the reality is that once the waves have travel for a long distance, the source part of the signals start to be overshadowed by path effects. As a matter of fact, two waves from different sources and recorded by two spatially closed stations can appear more similar than the waves from the same source but recorded by two stations farther apart. Naively using the direct similarity measurements such as cross-correlation coefficients of the apparent waveforms for event association will not return good outcomes. To tackle this issue, Dicky et al., 2020 proposed to use a triplet network to generate path-invariant embeddings for seismic waves. The idea is that by training a neural network using negative and positive pairs, the network can learn to remove the path related distortions and represent the waveforms in a lower dimensional space where similar sources are close to each other. Hence the distances between the embeddings can be used to help associate earthquakes. In this study, we propose to use a new self-supervised model, named the Barlow-twins to achieve the same goal.

1.2. Barlow-twins

Barlow Twins [9] is a self supervised learning method which is differentiated from other self supervised methods by it's simple, innovative and effective loss function. Just like other self supervised learning methods Barlow Twins operates on a joint embedding of distorted images. This is done by intentionally distorting the images using various image augmentation methods. The images we have of the seismic waves are already distorted by the earth. The goal of methods like Barlow-twins is to learn representations that are invariant under different distortions. Thus, we can use the images of seismic waveforms from different reading stations directly without applying any distortions. More details about how we use Barlow-twins method can be found in section 2.2 .

2. Approach

We first train a resnet style autoencoder (see section 2.1) on 1.18 M waveforms. We treat all the waveform as independent samples and do not differentiate their sources at this stage of the training. The autoencoder trained by these sampels will learn a general representation of seismogram. After the autoenocder is trained, we separate the encoder and decoder. We then take the encoder and subject it to model tuning using the barlow-twins (see seciton 2.2). At this stage, all the training samples are paired-up based on their sources. Each of the waveform pairs are recorded at different stations but from the same event. Our goal is to train a model that extracts path-invariant embeddings.

2.1. Pre-training the autoencoder

We first use a resent style autoencoder (as shown in fig. 1) to train a general encoder that learns general form of seismogram and also performs dimensionality reduction. In other words, this operation is equivalent of extracting a compact representation of the input waveforms and reconstruct them back to the original form. Both the encoder and the decoder are composed of 9 residual blocks. We shrink each of the original 1800-sample inputs to embedding with size 100, which is equivalent to 94% reduction in size.

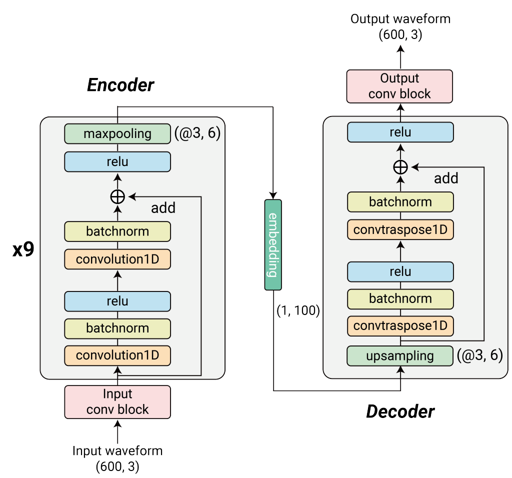

Figure 1. Model architecture of the Res-net style auto-encoder.

We use mean square error as the loss function for autoencoder training. Figure 2 shows the training curve. The training progess indicates a stable reduction of loss for both train and validation sets, except for a jump happened around the 75th epoch. We chose the model right after the 20th epoch for further tuning.

2.2. Training using Barlow-twins loss

We then use the Barlow-twins method to tune our encoder. As shown in figure 3, the Barlow-twins takes in a pair of training samples and output a pair of embeddings. These embedding pairs are computed by seperated, pre-trained encoder networks. A loss function is then being computed for the pair of embeddings. These two encoder networks are

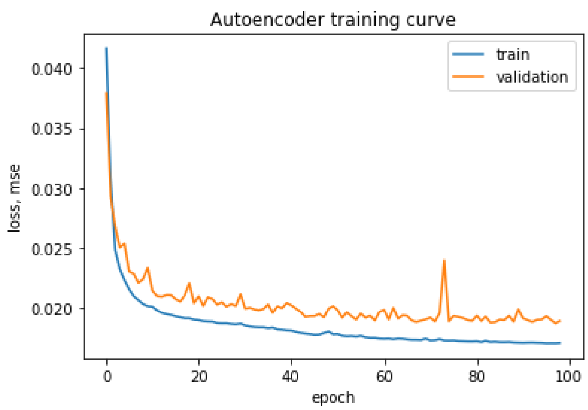

Figure 2. Training curve of autoencoder while pre-training

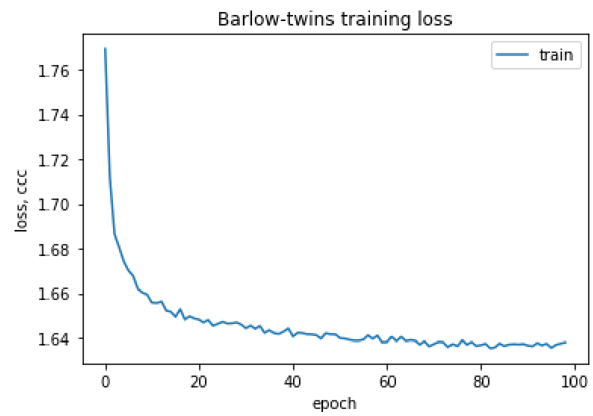

Figure 4. Training curve of Barlow-twins

identical and share their weights. They are being optimized together. After training, we simply choose one of them to compute the path invariant embeddings.

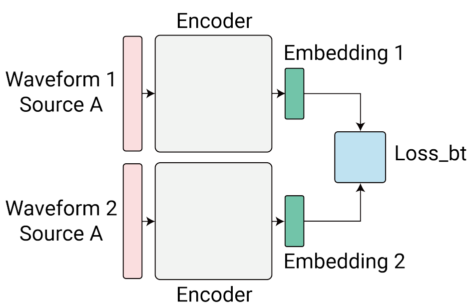

Figure 3. Barlow twins structure

The loss for embeddings generated by our auto-encoder network is calculated using the empirical cross correlation loss. We use the same loss function as used in Barlow Twins[9]:

$$\mathcal{L}_{\mathcal{BT}} \triangleq \underbrace{\sum_i (1 - \mathcal{C}_{ii})^2}_{\text{invariance term}} + \lambda \underbrace{\sum_i \sum_{j \neq i} \mathcal{C}_{ij}^2}_{\text{redundancy reduction term}} \tag{1}$$

Where $\mathcal{C}$ is the cross-correlation matrix between output of encodings from two identical networks. The invariance term, by trying to equate the diagonal elements of the cross-correlation matrix to 1 makes the embedding invariant to the distortions caused by earth in the seismic waves. Also, by trying to equate the off-diagonal elements of the same matrix to 0, we are able to decorrelate different vector components of the embedding. This decorrelation is what helps reduce the redundancy between the components of the output units of the loss, this helps store more information about the sample in the embedding.

3. Data

The dataset we use for this study is consist of 1.46 million, 30-second long seismograms with P-wave arrival placed around 10 second. These waveform are recorded by 1295 seismic stations and came from 1300 larger earthquake (magnitude 5.5 - 6.5) events between year 2000 and 2016. We downloaded the earthquake catalog from the ISC-EHB bulletin `http://www.isc.ac.uk/isc-ehb/` and the seismograms from the IRIS data center `https://www.iris.edu/hq/`. Figure 6 is an example of the input data. The input data is of dimension = (3, 600).

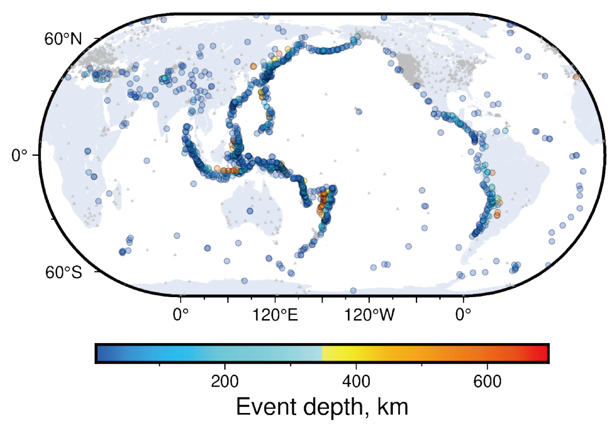

Figure 5. Data distribution. Circles indicate the location of earthquakes. Gray triangles represent location of seismic stations.

We split the dataset to 80% training (1034 events) and 20% testing (259 events) based on earthquake events. The training data for autoencoder is approximately 1.18 M. For training the borlow-twins, we use 20.6 k randomly selected pair of waveforms from the training set. We evaluate the effectiveness of the embeddings on the test set, which is consist of 27.9 k waveforms coming from 259 earthquake sources.

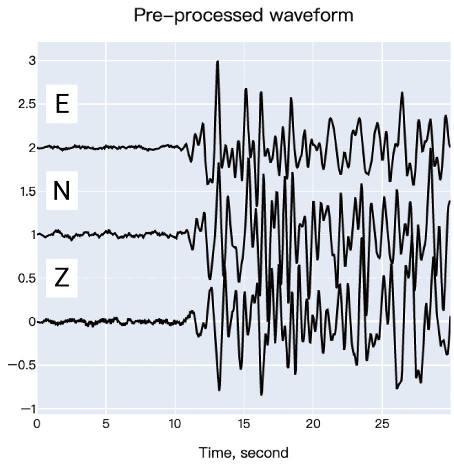

Figure 6. An example of input waveform. From top to bottom are the ground motions recorded by east-west, north-south, and vertical orientations.

4. Embedding Evaluations

With effective representation, generated embeddings from the same event should be close to each other, while far away from those from other events. By close to and far away, we are referring to the euclidean distance in the embedding space. For evaluation, we group the generated embeddings by the corresponding event. Then we measure how well-separated these clusters are with three different metrics.

Silhouette Coefficient

Silhouette coefficient [8] is computed for each sample embedding. It measures how similar the sample embedding is to its cluster compared to other clusters. It is defined as

$$s = \frac{b - a}{\max(a, b)}$$

where a is the mean distance between a sample and all other points in the same cluster, and b is the mean distance between a sample and all other points in the next nearest cluster. The Silhouette coefficient ranges from -1 for highly mixed clustering to 1 for highly dense clustering. After Silhouette coefficient is obtained for each sample embedding, we take the average to evaluate our embedding representation.

Calinski-Harabasz Index

Calinski-Harabasz[2] index is similarity metrics based on dispersion, which is the sum of distances squared. Calinski-Harabasz index is computed as the ratio of the sum of between-clusters dispersion and of within-cluster dispersion for all clusters. The higher the index, the denser the better-separated the clusters.

Davies-Bouldin Index

Davies-Bouldin index [3] measures the similarity among clusters. It compares the distance between clusters and the size (diameter) of clusters themselves. It is defined as

$$DB = \frac{1}{k} \sum_{i=1}^{k} \max_{i \neq j} R_{ij}$$

with

$$R_{ij} = \frac{s_i + s_j}{d_{ij}}$$

where s_i is the mean distance between each embedding of cluster i and the center of that cluster, and d_{ij} is the distance between the centers of clusters i and j. The closer Davies-Bouldin index to 0, the denser the better-separated the clusters.

Table 1 summarizes the scores for the three metrics. Our generated embeddings are moderately effective. The embedding representation can be useful in future research and study in the case where the true event labels are unknown. We can apply clustering algorithm on the unlabeled embeddings to infer which embedding correspond to the same event.

metrics	scores
Silhouette Coefficient	-0.02507
Calinski-Harabasz Index	1.942
Davies-Bouldin Index	14.33

Table 1. Embedding Evaluations

5. Conclusion

In this study, we demonstrate a novel way to solve a waveform-based earthquake source association problem. We use the novel self-supervised model - Barlow-twins to fine-tune a general pre-trained encoder. By optimizing the encoder using the Barlow twins loss, we force the encoder to learn to generate path-invariant embeddings. We evaluate the path-invariant emnbeddings on three different metrics. These metrics reflect how well each of the sources are separated. The results suggest the embeddings are moderately effective. This study suggests a new direction to approach the earthquake source association problem. In the future, it could be further improved and implemented to enhance current systems.

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