Similarity Embedding Network for Unsupervised Sequential Pattern Learning by Playing Music Puzzle Games

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Abstract
Real-world time series data are rich in sequential and structural patterns. Music, for example, often have a multi-level organization of musical events, with higher-level building blocks made up of smaller recurrent patterns. For computers to understand and process such time series data, we need a mechanism to uncover the underlying structure. Toward this goal, we propose and formulate a number of music puzzle games to test the ability of contemporary neural network models to mine sequential patterns. In essence, these games require a model to correctly sort a few multisecond, non-overlapping music fragments, either from the same song or not. In the training stage, we learn the model by sampling multiple fragment pairs from the same songs and seeking to predict whether a given pair is consecutive and is in correct chronological order. As no manual labels are needed, it is an unsupervised (more specifically, self-supervised) learning problem. On the basis of state-of-the-art Siamese convolutional network, we propose an improved architecture that learns to embed frame-level similarity scores computed from the input fragment pairs into a common space, where fragment pairs of different types can be more easily distinguished. Our experiments show that the resulting model, dubbed as the similarity embedding network (SEN), performs better than competing models across different games, including music jigsaw puzzle, music sequencing, and music medley.1

Introduction
Sequence clustering and classification is an active area of research, with applications in various domains, including text (Xu et al. 2017), video (Zhu et al. 2016), healthcare (Schulam, Wigley, and Saria 2015), finance (Cavalcante et al. 2016), and others (Chen et al. 2015). Machine learning models for these tasks can be trained in a supervised way, provided sufficient number of labels (Graves 2008), or human annotation of the similarity between sequences (Mueller and Thyagarajan 2016).

In view of the difficulty in collecting labeled data and the power of deep neural networks in feature representation learning, recent years have witnessed a growing interest in unsupervised methods for sequential pattern learning, most notably in the computer vision domain. This can be approached by the so-called self-supervised learning, which exploits the inherent property of data for setting the training target. For example, (Misra et al. 2016), (Fernando et al. 2016) and (Lee et al. 2017) leveraged the temporal coherence of video frames as a supervisory signal and formulated representation learning as either an order verification or a sequence sorting task. (Lotter, Kreiman, and Cox 2017), on the other hand, explored prediction of future frames in a video sequence as the supervisory signal for learning the structure of the visual world. These prior arts demonstrate that learning discriminative visual features from massive unlabeled video data is possible.

This paper investigates how such a self-supervised learning methodology can be extended to audio, which to our knowledge has not been attempted before. In particular, we focus on learning from music sequences. Music is known for her multi-level, hierarchical organization, with higher-level building blocks made up of smaller recurrent patterns (Widmer 2016). Some patterns are related to the harmony and some are melodic (Hudson 2011). While listening to music, human beings can discern those patterns, make predictions on what will come next, and hope to meet their expectations. Asking machines to do the same is interesting on its own, and it poses interesting challenges that do not present, or have not been considered, in the video domain.

First, the input instances to existing models are usually video frames (which are images) sampled from each video sequence. Each frame can be viewed as a snapshot of a temporal moment, and the task is to correctly order the frames

1https://remyhuang.github.io/DJnet/
per video. In contrast, meaningful basic unit to be ordered in
music has to be an audio sequence itself. Therefore, the input
instances in our case are multisecond music fragments (i.e.
non-overlapping subsequences of a music sequence), which
have a temporal dimension.

Second, existing work in the video domain considered at
most four frames per video (Lee et al. 2017), mainly due to
the concern that the possible permutations increase exponen-
tially along with the number of sampled frames. However, as
a song is typically a few minutes long, we consider up to ten
(milliseconds) music fragments per song.

Lastly, while it makes less sense to order video frames
sampled from different video sequences, for music it is in-
teresting and practically useful if we can find an ordering
of a bag of music fragments sampled from different songs.
Indeed, music fragments of different songs, when properly
ordered, can be listened to consecutively with pleasure (Lin
et al. 2015), given that every pair of consecutive fragments
share or follow some harmonic or melodic patterns. We also
consider such a task in this paper.

In this paper, we generally refer to the task of assembling
multiple music fragments in proper order as the music puz-
ple games, drawing the analogy that a fragment is like a puz-
ple piece. Similar to previous work in the video domain, we
exploit the temporal coherence of music fragments as the
supervisory signal to train our neural networks via a music
puzzle game. What’s different is that we differentiate four
aspects of a music puzzle game and investigate the perfor-
mance of our models with different types of games. The four
aspects are: 1) number of fragments to be ordered, 2) tem-
poral length of the fragments (whether the length is fixed or
arbitrary), 3) whether there is a clear cut at the boundary of
fragment pairs, and 4) whether the fragments are from the
same song or not. For example, other than uniformly sam-
ple a song for fragments, we also employ downbeat tracking
(Böck et al. 2016) to create musically meaningful fragments
(Upham and Farbood 2013).

In view of the second challenge mentioned above, we pro-
tose to take fragment pairs as input to our neural network
models and lastly use a simple heuristic to decide the final
ordering. For a music puzzle game with \( n \) fragments, this
pair-wise approach requires our models to evaluate in total
\( \binom{n}{2} = \frac{n(n-1)}{2} \) pairs, which is much fewer than the \( n! \)
number of possible permutations and accordingly opens up
the possibility to consider \( n > 4 \) fragments.

Moreover, in view of the first challenge mentioned above,
we propose an novel model, called the similarity embed-
ding network (SEN), to solve the music puzzle games. The
main idea is to compute frame-level similarity scores be-
tween each pair of short-time frames from the two input
fragments, and then learn to embed the resulting similarity
matrix (Serrà et al. 2012) into a common space, where co-
herent and incoherent fragment pairs can be more easily dis-
tinguished. Learning from the similarity matrices is promis-
ing, for we can examine temporal correspondence between
fragments in more details, as suggested by the example sim-
ilarity matrices shown in Figure 1. Our experiments show
that this model performs consistently better than competing
models across different music puzzle games.

| number | Jigsaw Puzzle | Sequencing | Medley |
|--------|---------------|------------|--------|
| length | fixed / arbitrary | arbitrary | arbitrary |
| boundary from | unclear / clear | clear | clear |
| same song from | same song | cross song | |

**Music Puzzle Games**

**Background and Significance**

In academia, some researchers have investigated the design
of music-based puzzle games, mostly for education pur-
poses. A notable example is the work presented by (Hansen
et al. 2013), which experimented with a number of designs
of sound-based puzzle game to train the listening abilities of
visually impair people. A music clip was divided into sev-
eral fragments and a player had to rearrange them in order to
reconstruct the original song. For advanced players, they fur-
ther applied pitch and equalization shifts randomly on frag-
ments, requiring the players to detect those transpositions to
complete the puzzle. However, in this work a music clip was
divided into pieces at arbitrary timepoints. This way, there
may be no clear cut at the boundary of the fragments, pro-
viding strong temporal cues that make the game easier: when
the fragments are in incorrect order, the result will not only
sound unmusical but also unnatural.

More recently, (Smith et al. 2017) improved upon this
work by dividing songs at downbeat positions, which of-
ten coincide with chord changes (Böck, Krebs, and Widmer
2016) and provides clearer cut among the fragments. More-
over, based on a “mashability” measure (Davies et al. 2014),
they proposed an algorithm to create cross-song puzzles for
more difficult games. They claimed that the game can train
the musical and logical reasoning of ordinary people.

Although these previous works are interesting, their focus
is on the design of the puzzle games for human beings, rather
than on training machines to solve such games. In contrast,
we let machine learn sequential patterns (and logic) in the
musical world in a self-supervised learning manner by play-
ning and solving such games. Asking machines to compre-
hend the structure of music as human beings do is significant
on its own. Perhaps some day AI may possess certain level
of music connoisseurship and can serve as a DJ to create
sound remixes or mashups professionally.

Another benefit of experimenting with the music puzzle
games is that the input to such games are sequences (not images).
Therefore, similar network architecture may be ap-
p lied to time series data in other domains as well.

In what follows, we firstly discuss the design of music
puzzle games for machines, and then present a mathematical
formulation of the learning problem.

**Game Design**

As shown in Table 1, there are four aspects to be considered
in designing a music puzzle game. First, the number of frag-
ments \( n \) to be ordered; larger \( n \) implies more computational
As also shown in Table 1, we consider three different music puzzle games in this paper, with progressively increasing level of difficulty. For music jigsaw puzzle, we create fragments by dividing a 24-second music clip at either equally-spaced or at downbeat-informed timepoints. Because we are interested in comparing the performance of the proposed SEN model against those proposed to solve video puzzles, we vary the value of \( n \) from 3 to 8 in this game.

The second game is more difficult in that the fragments are taken from a whole song. Moreover, each fragment represents a section of the song, such as the intro, verse, chorus, and bridge (Paulus, Miller, and Klapuri 2010; Nieto and Bello 2016). The game is challenging in that the verse and chorus section may repeat multiple times in a song, with sometimes minor variations. The boundaries are clear, and we use \( n = 10 \) fragments (sections) per song. In audio engineering, the task of arranging sections in a sensible way is referred to as music sequencing.

Lastly, we consider the music medley game, which aims to put together a mixture of short music clips from different songs to rebuild a longer piece of music (Lin et al. 2015). As the fragments (clips) are from different songs, the boundaries are also clear. This is different from the cross-song puzzle considered in (Smith et al. 2017). In music medley, we take one fragment per song from a collection of \( m (= n) \) songs, and aim to create an ordering of them. In contrast, in cross-song puzzle, we take \([n/m]\) fragments per song from \( m (\neq n) \) songs and aim to discern the origin of the fragments and get \( m \) orderings. We use user-created music medleys as the groundtruth in this game, but we note that the creation of a medley is an art so different orderings may sound right as well. Therefore, we will also show example results in a demo website (currently in the supplementary material).

Problem Formulation

All the aforementioned games are about order things. While solving an image jigsaw puzzle game, human beings usually consider the structural patterns and texture information as cues by comparing the puzzle pieces one by one (Noroozi and Favaro 2016). There is no need to put all the pieces in correct order all at once. As the number of permutations grows exponentially with \( n \), we formulate the learning problem as a binary classification problem and predict whether a given pair of fragments is consecutive and is in correct order.

In the training stage, all the fragments are segmented consecutively without overlaps per song, as shown in the leftmost part of Figure 2. For each song, we get a collection of fragments \( \{ R_1, \ldots, R_n \} \), which are in the correct order. Among the \( 2^\binom{n}{2} \) possible fragments pairs, \( n - 1 \) of them are in the correct order and are considered as the positive data. \( \mathcal{P}_+ = \{(R_i, R_{i+1}) \mid i \in \{1, 2, \ldots, n - 1\}\} \). While all the other possible pairs can be considered as the negative data, we consider only three types of them:

\[
\begin{align*}
\mathcal{P}_{-1} &= \{(R_{i+1}, R_i) \mid i \in \{1, \ldots, n - 1\}\}, \\
\mathcal{P}_{-2} &= \{(R_i, R_{i+2}) \mid i \in \{1, \ldots, n - 2\}\}, \\
\mathcal{P}_{-3} &= \{(R_{i+2}, R_i) \mid i \in \{1, \ldots, n - 2\}\}.
\end{align*}
\]

Pairs of the first type are consecutive but in incorrect order. Pairs of the second and third types are not consecutive. The negative data is the union of them: \( \mathcal{P}_- = \mathcal{P}_{-1} \cup \mathcal{P}_{-2} \cup \mathcal{P}_{-3} \). Therefore, the ratio of positive and negative data \( |\mathcal{P}_+| / |\mathcal{P}_-| \) is about 1/3. In our experiments, we also refer to data pairs belonging to \( \mathcal{P}_+ \), \( \mathcal{P}_{-1} \), \( \mathcal{P}_{-2} \) and \( \mathcal{P}_{-3} \) as ‘R1R2,’ ‘R2R1,’ ‘R1R3’ and ‘R3R1,’ respectively.²

Given a training set \( \mathcal{D} = \{(X, y) \mid X \in \mathcal{P}, y \in \{0, 1\}\} \), where \( \mathcal{P} \) is the union of \( \mathcal{P}_+ \) and \( \mathcal{P}_- \) from all the songs and \( y \) whether a pair is positive or not, we learn the parameters \( \theta \) of a neural network \( f_\theta \) by solving:

\[
\min_{\theta} \sum_{(X,y) \in \mathcal{D}} \mathcal{L}(f_\theta(X), y) + \mathcal{R}(\theta), \tag{1}
\]

where \( \mathcal{L} \) is a loss function (e.g. cross entropy) and \( \mathcal{R}(\theta) \) is a regularization term for avoiding overfitting.

²We note that, in related work working on videos (Misra et al. 2016; Fernando et al. 2016; Lee et al. 2017), they treated R1R2 the same as R2R1, and likewise R1R2R3 the same as R3R2R1, assuming that playing a short video clip in the reverse order is fine.
but in testing time the model will be applied to different games.

**Global Ordering** Given a data pair $(X, Y)$, where $X = (R_a, R_b)$, $a, b \in \{1, \ldots, n\}$, $a \neq b$, the estimate $f_\theta(X)$ is a value in $[0, 1]$, due to a softmax function. For each song in the validation set, we need to get this estimate for all the data pairs, and seek to find the correct global ordering of the fragments from these estimates. While there may be other sophisticated ways doing it, we find the following simple heuristic works quite well already: we evaluate the “fitness” of any ordering of the fragments by summing the model output of the composing $n - 1$ consecutive pairs. For example, the fitness for $(R_a, R_b, R_c)$, for $n = 3$, will be $f_\theta(R_a, R_b) + f_\theta(R_b, R_c)$. We then simply pick the ordering with the highest fitness score as our solution for the game for that song.

We are now ready to present our neural network, $f_\theta$.

**Network Architecture**

**Similarity Embedding Network (SEN)**

A Siamese network (Bromley et al. 1994) is composed of two (or more) twin subnetworks that share the same parameters. The subnetworks usually use convolutional layers (but there are exceptions (Mueller and Thyagarajan 2016)). The outputs of the last convolutional layer are concatenated and then feed to the subsequent fully-connected layers. The functions of the convolutional layers and the fully connected layers are feature learning and classifier training, respectively. Because Siamese networks can process multiple inputs at the same time, it is widely used in various metric learning problems (Chopra, Hadsell, and LeCun 2005).

As shown in the middle of Figure 2, the proposed SEN model also uses a convolutional Siamese network (Siamese ConvNet) to learn features from spectrogram-like 2D features of a pair of fragments. However, motivated by a recent work (Luo, Schwing, and Urtasun 2016), which used a product layer to compute the inner product between two representations of a Siamese network, we propose to compute the similarity matrix from the frame-by-frame output of the last layer of the Siamese ConvNet, and further learn features from the similarity matrix with a few more convolutional layers, as shown in the right hand side of Figure 2 (and Figure 3(d)). The output can be viewed as an embedding of the similarity matrix, therefore the name of the network.

Given the output feature maps of the Siamese ConvNet, $G_a = h_\theta(R_a) \in \mathcal{R}^{N \times k}$, $G_b = h_\theta(R_b) \in \mathcal{R}^{M \times k}$, where $h_\theta$ denotes the network up to the last layer of the Siamese ConvNet, $N$ and $M$ the (temporal) length of the output and $k$ the dimension of the feature, the similarity matrix $S \in \mathcal{R}^{N \times M}$ is computed by the Cosine score:

$$S_{ij} = \frac{g_{a,i}^T g_{b,j}}{\|g_{a,i}\|_2 \|g_{b,j}\|_2} ,$$  \hspace{1cm} (2)

where $g_{a,i} \in \mathcal{R}^k$ is the $i$-th feature (slice) of $G_a$.

Because we want the resulting similarity matrix to capture the temporal correspondence between the input fragments, in SEN we use 1D convolutions along the temporal dimension (Liu and Yang 2016) for the Siamese ConvNet. Moreover, we set the stride size to 1 and use no pooling layers in the Siamese ConvNet for SEN, to capture detailed temporal information of the fragments.
Baselines

We consider a few existing methods for performance comparison in our experiments. Figure 3 plots some of them.

**Siamese CNN (SN)** A valid baseline is the pairwise Siamese ConvNet, which takes the input fragment pairs and learns a binary classifier for order verification.

**Concatenated-inputs CNN (CIN)** An intuitive solver for the music jigsaw puzzle is to concatenate the spectrogram-like 2D features of the fragments along the time dimension, and use a CNN (instead of an SN) for order verification. We suppose this model can catch the weird boundary of an incorrectly ordered fragment pair.

**Concatenated-convolutions Siamese Network (CCSN)**

This is a state-of-the-art network for image feature learning (Wang et al. 2016). Given the feature maps from the last convolutional layers of a Siamese ConvNet, we can simply concatenate them along the time dimension (instead of computing the similarity matrix) and then use another stack of convolutional layers to learn features. As shown in Figure 3(c), the only difference between CCSN and SEN lies in how we extract information from the Siamese ConvNet.

**Triplet Siamese Network (TSN) & Order Prediction Network (OPN)**

The state-of-the-art algorithms in solving video puzzle games use a list-wise approach instead of a pair-wise approach. The TSN model (Misra et al. 2016) is simply an expansion of SN by taking three inputs instead of two. In contrast, the OPN model (Lee et al. 2017), depicted in Figure 3(b), takes all the n fragments at the same time, aggregates the features from all possible feature pairs for feature learning, and seeks to pick the best global ordering out of the n! possible combinations via a multi-class classification problem. We note that the baseline models CCSN, TSN and OPN cannot deal with inputs of arbitrary length.

Implementation Details

As done in many previous works (Dieleman and Schrauwen 2014), we compute the spectrograms by sampling the songs at 22,050 Hz and using a Hamming window of 2,048 samples and hop size 512 samples. We then transform the spectrograms into 128-bin log mel-scaled spectrograms and use that as input to the networks, after z-score normalization.

Unless otherwise specified, in our implementation all the Siamese ConvNets use 1D convolutional filters (along the time dimension), with the number of filters being 128, 256, 512, respectively, and the filter length being 4. For SEN and CCSN, the convolutional filter for the subsequent ConvNet are 64, 128, 256, respectively, followed by 3 by 3 maximum pooling and the filter size is also 3 by 3. Here, SEN uses 2D convolutions, while CCSN uses 1D convolutions. Except for TSN and OPN, we use a global pooling layer (which is written as ‘CONCAT’ in Figure 3) after the ConvNet in SEN, CCSN, CIN, and the Siamese ConvNet in SN. The dimension of the two fully-connected layers after this pooling layer are all set to 1,024. All networks use rectified linear unit (ReLU) as the activation function everywhere. Lastly, all the models are trained using stochastic gradient descent with momentum 0.9, with batch size setting to 16.

Experiments

**Data sets**

Any music collection can be used in our puzzle games, since we do not need any human annotations. In this paper, we use an in-house collection of 31,377 clips of Pop music as our corpus. All these clips are audio previews downloaded from the Internet, with unknown starting point in each song the audio preview was extracted from. All these clips are longer than 24 seconds, so we consider only the first 24 seconds per clip for simplicity of the model training process. Moreover, we randomly pick 6,000 songs as validation set, 6,000 songs for testing, and the remaining 19,377 clips for training.

Different data sets are used as the test set for different music puzzle games. For music jigsaw puzzle, we simply use the test set of the in-house collection. For music sequencing, we use the popular music subset of the RWC database (Goto et al. 2002), which contains 100 complete songs with manually labeled section boundaries (Goto 2006). For video medley, we collect 16 professionally-compiled medleys of pop music (by human experts) from YouTube. Each medley contains 7 to 11 different short music clips, whose length vary from 5 to 30 seconds. We will later make the YouTube links of these medleys publicly available for reproducibility.

We need to perform downbeat tracking for the in-house collection. To this end, we use the implementation of a state-of-the-art recurrent neural network available in the Python library madmom4 (Böck et al. 2016). After getting the downbeat positions, we randomly choose some of them so that each fragment is about \(\frac{24}{n}\) seconds in length.

**Result on 3-Piece Fixed-length Jigsaw Puzzle**

As the first experiment, we consider the \(n = 3\) jigsaw puzzle game, using 1,000 clips randomly selected from the test set of the in-house collection. Accordingly, we train all the neural networks (including the baselines) by playing \(n = 3\) jigsaw puzzles using the training set of the same data set. All the clips are segmented at equally-spaced timepoints. Therefore, the length of fragments is fixed to 8 seconds. This corresponds to the simplest setting in Table 1.

We employ the **pairwise accuracy** (PA) and **global accuracy** (GA) as our performance metrics. For an ordering of \(n\) fragments, GA requires it to be exactly the same as the groundtruth one, whereas PA takes the average of the correctness of the \(n - 1\) composing pairs. For example, ordering \((R_1, R_2, R_3)\) as \((R_2, R_3, R_1)\) would get 0.5 PA (for the pair \((R_2, R_3)\) is correct) and 0 GA.

The results is shown in Table 2. The performance of the baseline models seem to correlate well with their sophistication, with SN performing the worst (0.825 GA) and OPN (Lee et al. 2017) performing the best (0.916 GA). The comparison between SN and TSN (Misra et al. 2016) implies that

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4https://staff.aist.go.jp/m.goto/RWC-MDB/AIST-Annotation/

3https://github.com/CPJKU/madmom
Table 2: The pairwise accuracy and global accuracy on \( n = 3 \) fixed-length jigsaw puzzle.

| Method         | pairwise accuracy | global accuracy |
|----------------|-------------------|-----------------|
| SN            | 0.851 (0.825)     | 0.825           |
| CCSN (Wang et al. 2016) | 0.872 (0.840)     | 0.840           |
| CIN           | 0.912 (0.864)     | 0.864           |
| TSN (Misra et al. 2016) | 0.911 (0.890)     | 0.890           |
| OPN (Lee et al. 2017) | 0.929 (0.916)     | 0.916           |
| SEN (proposed) | 0.996 (0.994)     | 0.994           |

Table 3: The accuracy on music jigsaw puzzles with different segmentation method (fixed-length or downbeat informed) and different number of fragments. Pairwise accuracy is outside the brackets and global accuracy is inside.

| \( n \) | fixed | downbeat |
|---------|-------|----------|
|        | SN    | CIN      | SEN      |
| 3       | 0.851 (0.825) | 0.912 (0.864) | 0.996 (0.994) |
| 4       | 0.752 (0.641) | 0.844 (0.722) | 0.990 (0.982) |
| 6       | 0.609 (0.304) | 0.761 (0.455) | 0.989 (0.977) |
| 8       | 0.514 (0.110) | 0.682 (0.229) | 0.985 (0.953) |

Table 4: The accuracy of SEN on three kinds of puzzle game for two segmentation methods.

| game | fixed-length | downbeat-informed |
|------|--------------|-------------------|
| puzzle \( (n = 8) \) | 0.985 (0.953) | 0.990 (0.961) |
| sequencing | 0.789 (0.440) | 0.937 (0.790) |
| medley | 0.945 (0.688) | 0.961 (0.750) |

by solving \( n = 3 \) jigsaw puzzles segmented at downbeat positions, and apply them to also downbeat-informed jigsaw puzzles with different values of \( n \).

Table 3 shows the results. We can see that the result of SN and CIN both decrease quite remarkably as the value of \( n \) increases, and that the downbeat-informed games are indeed slightly more challenging than the fixed-length games, possibly due to the clarity at the boundary. When \( n = 8 \), the PA and GA of SN drop to around 0.50 and 0.10, whereas the PA and GA of CIN drop to around 0.68 and 0.25. However, the accuracy of the SEN model remains high even when \( n = 8 \) (about 0.99 PA and 0.96 GA), suggesting that SEN can work quite robustly against various music jigsaw puzzles.

Result on Music Sequencing and Music Medley

Lastly, we evaluate the performance of SEN on music sequencing and music medley, which are supposed to be more challenging than jigsaw puzzles. We do not consider SN and CIN here, for their demonstrated poor performance in \( n = 8 \) jigsaw puzzles. Instead, we compare two SEN models, one trained with uniform segmentation (\( n = 3 \)) and the other with downbeat-informed segmentation (\( n = 3 \)).

From Table 4, we can see that these two games are indeed more challenging than jigsaw puzzles. When using a SEN model trained with uniform segmentation, the GA can drop to as low as 0.440 for music sequencing and 0.688 for music medley. However, more robust result can be obtained by training SEN using downbeat-informed segmentation: the GA would be improved to 0.790 and 0.750 for the two games, respectively. This is possibly because the downbeat-informed segmentation can avoid SEN from learning only low-level features at the boundary of fragments.

Error Analysis

Error analysis can be conducted by observing the incorrect order among the fragments and especially we focus on these incorrect prediction in the music sequencing game, which has some musically meaningful insights. A song is composed of several sections, such as intro (I), verse (V), chorus (C) and bridge (B), with some variations such as Va and Vb. A correct global ordering of one of the songs in RWC is: I-Va-Ba-Vb-Cpre-Ca-Bb-Va-Vc-Cpre. For this song, the estimated ordering of SEN is: I-Bb-Va-Vc-Cpre-Ca-Va-Ba-Vb-Cpre. We can use a numerical notation and represent our result as 1-7-8-9-10-6-2-3-4-5. We can see that the local prediction of 7-8-9-10 and 2-3-4-5 is in correct order. Moreover, these two passages are fairly similar (both have the structure V-Cpre). Therefore, the predicted ordering may sound “right” as well. Indeed, we found that most of the incorrect predictions are correct in local ordering.
Table 5: The result of a few ablated version of SEN for different music puzzle games.

| game          | Inner Product | Conv Stride 2 | Global P (mean) | Global P (max) | R2R1 only | R1R3 only | R3R1 only | ALL       |
|---------------|---------------|---------------|-----------------|----------------|------------|------------|------------|-----------|
| puzzle \((n = 8)\) | 0.90 (0.69)   | 0.65 (0.17)   | 0.96 (0.87)     | 0.98 (0.93)    | 0.84 (0.57) | 0.97 (0.87) | 0.96 (0.86) | 0.99 (0.96) |
| sequencing    | 0.74 (0.38)   | 0.54 (0.06)   | 0.81 (0.49)     | 0.92 (0.76)    | 0.62 (0.22) | 0.81 (0.46) | 0.91 (0.69) | 0.94 (0.79) |
| medley        | 0.88 (0.50)   | 0.73 (0.13)   | 0.81 (0.56)     | 0.93 (0.69)    | 0.86 (0.44) | 0.93 (0.69) | 0.90 (0.63) | 0.96 (0.75) |

Figure 4: Embeddings of different data pairs learned by (from left to right) SEN, CCSN and SN, respectively. The embeddings are projected to a 2D space for visualization via t-SNE (Maaten and Hinton 2008). The figure is best viewed in color.

Figure 5: Visualizations of the features learned from the c4 and c6 layers of SEN for two pairs of fragments.

Ablation Analysis

We assess the effect of various design of downbeat-informed SEN by evaluating ablated versions. Table 5 shows the result when we (from left to right): i) replace cosine similarity in Eq. (2) by inner product, ii) increase the stride of the convolutions in Siamese ConvNet from 1 to 2, iii) use only global mean pooling or global max pooling (we use the concatenation of mean, max and standard deviation in our full model), and iv) use one type of negative data only. Most of these changes decrease the accuracy of SEN. Some observations:

- Calculating the similarity matrix using the inner product cannot guarantee that the similarity scores are in the range of \([0, 1]\) and this hurts the accuracy of SEN.
- Setting the stride size larger can speed up the training process, but doing so losses much temporal information.
- Max pooling alone works quite well for the global pooling layer, but it is even better to also consider mean and standard deviation.
- Using R2R1 as the negative data alone is far from sufficient. Actually, both R1R3 only and R3R1 only seem to work better than R2R1 only. The best result (especially in GA) is obtained by using all three types of negative pairs.

What the SEN Model Learns?

Figure 4 shows the embeddings (output of the last fully-connected layer) of different data pairs learned by SEN, CCSN and SN, respectively. We can clearly see that the positive and negative pairs can be fairly easily distinguished by the embeddings learned by SEN. Moreover, SEN can even distinguish R2R1 (consecutive) from R1R3 and R3R1 (non-consecutive). This is an evidence of the effectiveness of SEN in learning sequential structural patterns.

Finally, Figure 5 shows the features from the first (c4) and last convolution (c6) layers in the ConvNet of SEN, given two randomly chosen pairs (the first row is R1R2 and the second row is R1R3). We see that the filters detect different patterns and textures from the similarity matrices.

Conclusion

In this paper, we have presented a novel Siamese network called the similarity embedding network (SEN) for learning sequential patterns in a self-supervised way from similarity matrices. We have also demonstrated the superiority of SEN over existing Siamese networks using different types of music puzzle games. In future work, we will further investigate how the proposed model can be applied to other data domains, and to semi-supervised learning problems given a fraction of labeled data.
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