SAMPLE-LEVEL CNN ARCHITECTURES FOR MUSIC AUTO-TAGGING USING RAW WAVEFORMS

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ABSTRACT

Recent work has shown that the end-to-end approach using convolutional neural network (CNN) is effective in various types of machine learning tasks. For audio signals, the approach takes raw waveforms as input using an 1-D convolution layer. In this paper, we improve the 1-D CNN architecture for music auto-tagging by adopting building blocks from state-of-the-art image classification models, ResNets and SENets, and adding multi-level feature aggregation to it. We compare different combinations of the modules in building CNN architectures. The results show that they achieve significant improvements over previous state-of-the-art models on the MagnaTagATune dataset and comparable results on Million Song Dataset. Furthermore, we analyze and visualize our model to show how the 1-D CNN operates.

Index Terms— convolutional neural networks, music auto-tagging, raw waveforms, multi-level learning

1. INTRODUCTION

Time-frequency representations based on short-time Fourier transform, often scaled in a log-like frequency such as mel-spectrogram, are the most common choice of input in the majority of state-of-the-art music classification algorithms [1, 2, 3, 4, 5]. The 2-dimensional input represents acoustically meaningful patterns well but requires a set of parameters, such as window size/type and hop size, which may have different optimal settings depending on the type of input signals.

In order to overcome the problem, there have been some efforts to directly use raw waveforms as input particularly for convolutional neural networks (CNN) based models [6, 7]. While they show promising results, the models used large filters, expecting them to replace the Fourier transform. Recently, Lee et. al. [8] addressed the problem using very small filters and successfully applied the 1D CNN to the music auto-tagging task. Inspired from the well-known VGG net that uses very small size of filters such as 3 × 3, [9], the sample-level CNN model was configured to take raw waveforms as input and have filters with such small granularity.

A number of techniques to further improve performances of CNNs have appeared recently in image domain. He et. al. introduced ResNets which includes skip connections that enables a very deep CNN to be effectively trained and makes gradient propagation fluent [10]. Using the skip connections, they could successfully train a 1001-layer ResNet [11]. Hu et. al proposed SENets [12] which includes a building block called Squeeze-and-Excitation (SE). Unlike other recent approaches, the block concentrates on channel-wise information, not spatial. The SE block adaptively recalibrates feature maps using a channel-wise operation. Most of the techniques were developed in the field of computer vision but they are not fully adopted for music classification tasks. Although there were a few approaches to readily apply them to audio domain [7, 13]. They used 2D representations as input [13] or used large filters for the first 1D convolutional layer [7].

On the other hand, some methods are concerned with overall architecture of the model rather than designing a fine-grained building block [2, 14, 15, 16, 17]. Specifically, multi-level feature aggregation combines several hidden layer representations for final prediction [2, 14]. They significantly improved the performance in music auto-tagging by taking different levels of abstractions of tag labels into account.

In this paper, we explore the building blocks of advanced CNN architectures, ResNets and SENets, based on the sample-level CNN for music auto-tagging. Also, we observe how the multi-level feature aggregation affects the performance. The results show that they achieve significant improvements over previous state-of-the-art models on the MagnaTagATune dataset and comparable results on Million Song Dataset. Furthermore, we analyze and visualize our model built with the SE blocks to show how the 1D CNN operates. The results show that the input signals are processed in a different manner depending on the level of layers.

2. ARCHITECTURES

All of our models are based on the sample-level 1D CNN model [8], which is constructed with the basic block shown in Figure 1(b). Every filter size of the convolution layers is fixed...
to three. The differences between the sample-level CNN and ours are the use of advanced building blocks and multi-level feature aggregation. In this section, we describe the details.

2.1. 1D convolutional building blocks

2.1.1. SE block

We utilize the SE block from SENets to increase representational power of the basic block. As shown in Figure 1(c), we simply attached the SE block to the basic block. The SE block recalibrates feature maps from the basic block through two operations. One is squeeze operation that aggregates a global temporal information into channel-wise statistics using global average pooling. The operation reduces the temporal dimensionality ($T$) to one, averaging outputs from each channel. The other is excitation operation that adaptively recalibrates feature maps of each channel using the channel-wise statistics from the squeeze operation and a simple gating mechanism. The gating mechanism consists of two fully-connected (FC) layers that compute nonlinear interactions among channels. Finally, the original outputs from the basic block are rescaled by channel-wise multiplication between the feature map and the sigmoid activation of the second FC layer, and then reduce the dimensionality back to $C$ at the second layer. We set the amplifying ratio $\alpha$ to be 16, after a grid search with $\alpha = [2^{-3}, 2^{-2}, ..., 2^{6}]$.

2.1.2. Res-$n$ block

Inspired by skip connections from ResNets, we modified the basic block by adding a skip connection as shown in Figure 1(d). Res-$n$ denotes that the block uses $n$ convolutional layers where $n$ is one or two. Specifically, Res-2 is a block that has the additional layers denoted by the dotted line in Figure 1(d), and Res-1 is a block that has a skip connection only. When the block uses two convolutional layers (Res-2), we add a dropout layer (with a drop ratio of 0.2) between two convolutions to avoid overfitting. This technique was firstly introduced at WideResNets [18].

2.1.3. ReSE-$n$ block

The ReSE-$n$ block is a combination of the SE and Res-$n$ blocks as shown in Figure 1(e). $n$ denotes the number of convolutional layers in the block, where $n$ is also one or two. A dropout layer is inserted when $n$ is two.

2.2. Multi-level feature aggregation

Fig. 1(a) shows the multi-level feature aggregations that we configured. The outputs of the last three blocks are concate-
Table 1. Comparison of CNN architectures on the MTAT dataset. “multi” and “no multi” indicates if the multi-level feature aggregation is used or not. † denotes using a weight decay of $10^{-4}$.

| Block     | MTAT multi | MTAT no multi |
|-----------|------------|---------------|
| Basic [8] | 0.9077     | 0.9055        |
| SE        | **0.9111** | 0.9083        |
| Res-1     | 0.9037     | 0.9048        |
| Res-2     | 0.9098     | 0.9061        |
| ReSE-1    | 0.9053     | 0.9066        |
| ReSE-2    | **0.9113†** | 0.9102†       |

Table 2. Comparison of state-of-the-art models on the MTAT and MSD datasets. † denotes that the model used an ensemble of three.

| Model                                           | MTAT     | MSD     |
|------------------------------------------------|----------|---------|
| Bag of multi-scaled features [3]               | 0.8980   | -       |
| End-to-end [6]                                 | 0.8815   | -       |
| Transfer learning [4]                          | 0.8800   | -       |
| Persistent CNN [21]                            | 0.9013   | -       |
| Time-Frequency CNN [22]                        | 0.9007   | -       |
| Timbre CNN [23]                                | 0.8930   | -       |
| 2D CNN [5]                                     | 0.8940   | 0.8510  |
| CRNN [1]                                       | -        | 0.8620  |
| Multi-level & multi-scale [2]                  | 0.9017†  | **0.8878†** |
| SampleCNN multi-features [14]                  | 0.9064†  | 0.8842  |
| SampleCNN [8]                                  | 0.9055   | 0.8812  |
| SE [This work]                                 | **0.9111** | 0.8840 |
| ReSE [This work]                               | **0.9113** | 0.8847 |

4. RESULTS AND DISCUSSION

4.1. Comparison of the architectures

Table 1 summarizes the evaluation results of compared CNN architectures on the MTAT dataset. They show that the SE block is more effective than the Res-$n$ blocks, increasing the performance of the basic block for all cases. In the Res-$n$ block, only adding the skip connection to the basic block (Res-1) actually decreases the performance. The combination of the SE and the Res-2 improves it slightly more. However, a training time of the ReSE-2 is 1.8 times longer than the basic block whereas the SE block only 1.08 times longer. Thus, if the training or prediction time of the models is important, the SE model will be preferred to the ReSE-2. The effect of the multi-level aggregation is valid for the majority of the models. We obtained two best results in Table 1 by using the multi-level aggregation.

4.2. Comparison with state-of-the-arts

Table 2 compares previous state-of-the-art models in music auto-tagging with our best models, the SE block and ReSE-2 block, each with multi-level aggregation. On the MTAT dataset, our best models outperform all the previous results. On MSD, they are not the best but are comparable to the second-tier. These results show that

5. ANALYSIS OF EXCITATION

To lay the groundwork for understanding how 1D CNNs operate, we analyze the sigmoid activations of excitations in the SE blocks at different levels graphically and quantitatively. In this section, we observe how the SE blocks recalibrate channels, depending on which level they exist. The blocks used for
the analysis are from the SE model using the multi-level feature aggregation and they were trained on the MTAT dataset. The activations were extracted from the test set of the MTAT dataset. The activations were averaged over all segments separately for each tag.

5.1. Graphical analysis

For this analysis, we chose three tags, classical, metal, and dance that are not similar to each other as shown in Table 3. Figure 2 shows the average sigmoid activations in the SE blocks for the songs with the three tags. The different levels of activations indicate that the SE blocks process input audio differently depending on the tag (or genre) of the music. That is, every block in Figure 2 fires different patterns of activations for each tag at a specific channel. This trend is strongest at the first block (top), weakest at the mid block (middle), and becomes stronger again at the last block (bottom).

This trend is somewhat different from what are observed in the image domain [12], where the exclusiveness of average excitation for input with different labels are all monotonically increasing along the layers. Specifically, the first block consistently fires high activations for classical, low ones for dance, and even lower ones for metal. On the other hand, the activations of the last block vary depending on the tags. Specifically, the activations of metal are high at some channels but low at the others, which makes the activations noisy even though they are sorted. We can interpret this result as follows. The first block normalizes the loudness of the audio because the block fires high activations for classical music, which tend to have small volume, and low activations for metal music, which tend to have large volume. Also, the middle block processes common features among them as they have similar levels of activations. Finally, the noisy exclusiveness in the last block indicates that they effectively discriminate the music with different tags.

5.2. Quantitative analysis

We assure the exclusiveness trend by measuring standard deviations of the activations across all tags at every level. Figure 3 shows that the higher the standard deviation is, the more the block responses to the song differently according to its tag. The result shows that the standard deviation is highest at the first block, it drops and stays low up to the 5th block and then increases gradually until the last block. That is, the four lower blocks except the bottom one (2 to 5) tend to handle general features whereas the four upper blocks (6 to 9) tend to progressively more discriminative features.

6. CONCLUSION

We proposed 1D convolutional building blocks based on the previous work, the sample-level CNN, ResNets, and SENets. The ReSE block, which is a combination of the three models, showed the best performance. Also, the multi-level feature aggregation showed improvements on the majority of the building blocks. Through the experiments, we obtained state-of-the-art performance on the MTAT dataset and high-ranked results on MSD. In addition, we analyzed the activations of excitation in SE model to understand the effect. With this analysis, we could observe that the SE blocks process non-similar songs exclusively and how the different levels of the model process the songs in a different manner.

Table 3. Co-occurrence matrix of the tags used in Figure 2

|      | classical | metal | dance |
|------|-----------|-------|-------|
| classical | 704       | 0     | 1     |
| metal   | 0         | 166   | 0     |
| dance   | 1         | 0     | 153   |

Fig. 3. Standard deviations (std) of the activations of excitations across all tags along each layer.
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