A Novel Multi-Task Learning Method for Symbolic Music Emotion Recognition

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Abstract

Symbolic Music Emotion Recognition (SMER) is to predict music emotion from symbolic data, such as MIDI and MusicXML. Previous work mainly focused on learning better representation via (mask) language model pre-training but ignored the intrinsic structure of the music, which is extremely important to the emotional expression of music. In this paper, we present a simple multi-task framework for SMER, which incorporates the emotion recognition task with other emotion-related auxiliary tasks derived from the intrinsic structure of the music. The results show that our multi-task framework can be adapted to different models. Moreover, the labels of auxiliary tasks are easy to be obtained, which means our multi-task methods do not require manually annotated labels other than emotion. Conducting on two publicly available datasets (EMOPIA and VGMIDI), the experiments show that our methods perform better in SMER task. Specifically, accuracy has been increased by 4.17 absolute point to 67.58 in EMOPIA dataset, and 1.97 absolute point to 55.85 in VGMIDI dataset. Ablation studies also show the effectiveness of multi-task methods designed in this paper.

1 Introduction

Emotion recognition of music has attracted lots of attention in the field of music information retrieval (MIR). For a long time, the research on music emotion recognition has been mainly carried out in the audio domain [Baume et al., 2014; Liu et al., 2018; Panda et al., 2018; Panda et al., 2020]. However, emotion recognition is less explored for music from symbolic data, such as MIDI and MusicXML formats. Thanks to the rapid development of the symbolic music generation [Yang et al., 2017; Huang et al., 2019; Huang and Yang, 2020], more and more research focuses on symbolic music understanding [Zeng et al., 2021; Chou et al., 2021], including symbolic music emotion recognition (SMER).

Recently, researches in SMER mainly focused on learning better representation from large-scale unlabeled music pieces via pre-training model by masked or non-masked language model borrowed from NLP and then fine-tuning the pre-trained model directly for emotion recognition on a small dataset. However, simply employing such techniques from NLP may lack the understanding of music structure which is critical to emotion classification for symbolic data [Zeng et al., 2021].

The existing psychology and music theory literature have revealed the relationship between music structure and emotion. Kaster [1990] has demonstrated that positive emotion is related to listened music in major keys, while negative emotion is related to minor keys. Similar results can be found in [Gerardi and Gerken, 1995; Gregory et al., 1996; Dalla Bella et al., 2001]. Livingstone [2010] found that the loudness of music can greatly affect the expression of emotion. However, the loudness is measured in the audio domain and is still an open problem to measure it in the symbolic domain. Adli [2007] has demonstrated that there is a linear relationship between the velocity in the symbolic domain and the loudness in the audio domain, which means that there is a connection between the velocity of music and emotion.

Recognizing the importance of musical structure for emotion recognition, we present a simple framework called MT-SMNN that incorporates the emotion recognition task with other emotion-related auxiliary tasks derived from the intrinsic structure of the music. By combining the key classification and velocity classification tasks, MT-SMNN based models can better understand emotion classification. Although MT-SMNN is a multi-task framework, we only need the manually annotated emotion label because the velocity label can be extracted directly from symbolic data, and the key label can be obtained by the well-received Krumhansl-Kessler algorithm [2001], which means the proposed framework can be applied to all emotion-labeled symbolic music datasets.

We combine the MT-SMNN framework with existing models and evaluate them in both EMOPIA and VGMIDI datasets. Results demonstrate that our proposed MT-SMNN based models achieve the new state-of-the-art on both datasets.

The chief contributions of this paper can be summarized as following aspects:

- We present a novel multi-task framework called MT-
SMNN, mainly focusing on emotion recognition for symbolic music. In addition to emotion recognition, a better understanding of the structure of music is also taken into account in this framework.

- We propose two types of auxiliary tasks for SMER. Results show that both tasks can improve the performance of SMER, especially in the valence dimension.
- MT-SMNN based models achieve new state-of-the-art results due to the powerful ability to learn better emotion-based knowledge from auxiliary tasks.
- We have reproduced most previous work for symbolic music emotion recognition on both exiting public available datasets which is helpful to building benchmarks.

2 Related Work

We divide previous work on symbolic music emotion recognition into the following two categories.

Machine Learning based Methods: Early studies used manually extracted statistical musical features and then fed them into machine learning classifiers to predict the emotion of symbolic music. Grekow et al.[2009] extracted 63 features from classical music in MIDI format and used k-NN to classify the music after feature selection. Lin et al.[2013] compared the audio, lyric, and MIDI modal of the same music, finding that MIDI modal features performed better than audio modal features in emotion recognition. Specifically, 112 types of high-level musical features were extracted from MIDI files using the JSymbolic library[McKay and Fujinaga, 2006], and then SVM was employed to classify the data. Similarly, Panda et al.[2013] extracted 320 types of features from MIDI files using multiple tools and then classified them using SVM as well.

Deep Learning based Methods: In recent years, it has become a trend to encode symbolic music into MIDI-like musical representation[Oore et al., 2020; Huang and Yang, 2020; Hsiao et al., 2021] and then employ deep learning models to classify music. With encoding MIDI files into MIDI-like sequences, Ferreira[2019; Ferreira et al., 2020] used LSTM and GPT2[Radford et al., 2019] for emotion classification. For simplicity, in the following, we use MIDIGPT to denote the approach proposed by Ferreira et al., 2020]. Inspired by the great success of BERT[Devlin et al., 2019] in NLP, Chou et al.[2021] presented a large-scale pre-training model called MidiBERT-Piano, which employed CP representation[Hsiao et al., 2021] and has shown good results in a number of fields, including symbolic music emotion recognition.

3 Proposed Method

In this section, we introduce the Multi-Task Symbolic Music Neural Network (MT-SMNN), a multi-task framework for symbolic music emotion recognition, as illustrated in Figure 1. Below, we describe the structure of MT-SMNN in detail.

3.1 Symbolic Music Encoder

A piece of music from symbolic data, such as MIDI and MusicXML, can be encoded as a sequence of musical events, which are so called tokens in the previous literature. Existing method to encode symbolic music can be divided into single-word representation and compound-word (CP)[Hsiao et al., 2021] representation. The MT-SMNN framework can use either single-word representation or compound-word representation. Without losing generality, we show a single-word representation method (Ferreira’s[2020] method) and a compound-word representation method[Chou et al., 2021] as example in this part. We simply describe these two types of symbolic music encoding method below.

As illustrated in Figure 2(b), the CP representation method encodes given piece of music to a sequence of super tokens. Each super token consists of four sub-tokens: Bar, Sub-beat, Pitch and Duration. The Ferreira’s method, shown in Figure 2(c), encodes given music as token sequence
3.2 Embedding Layer

According to the symbolic music encoding method, the embedding layer of MT-SMNN can be divided into two types. Each super token consists of four sub-tokens: Bar, Sub-beat, Pitch and Duration. The text inside parentheses means the value of the corresponding sub-token. (c) The Ferreira’s method encodes a piece of music to a sequence of tokens. Token started with “v” indicates the time shift event.

\[
\{x_1^v, x_1^d, x_2^v, ..., x_s^v, x_s^d, x_p^v\}, \text{ where } x_i^v, x_i^d \text{ and } x_p^v \text{ denotes the velocity, duration and pitch for the i-th note respectively and } S \text{ denotes the length of this sequence.}
\]

3.3 Transformer-based Feature Extractor

The MT-SMNN employs a transformer-based model as a feature extractor. Given input representation \(l_1 = \{x_0, ..., x_S\}\), the feature extractor generates output representation \(l_2 = \{h_0, ..., h_S\}\), where \(S\) means the number of input tokens, \(x_i \in \mathbb{R}^E\), \(h_i \in \mathbb{R}^E\) denotes the embedding and contextual representation of i-th input token respectively, and \(E\) represents the dimension of embedding space and hidden state.

3.4 Pooler

Since both sequence-level and note-level tasks are employed in the MT-SMNN framework, we use a pooler to aggregate information from the entire contextual representation sequence for the sequence-level classification task. At the same time, the pooler keeps a series of contextual representations for the note-level classification task.

For simplicity, the pooler applies identical mapping for the note-level classification task. For sequence-level classification tasks, the pooler can be designed by one of the following strategies: taking the first contextual representation (like BERT[Devlin et al., 2019]), taking the last (like MIDIGPT[Ferreira et al., 2020]), or attention-based weighting average (like MIDIBERT-Piano[Chou et al., 2021]). In MT-SMNN, the emotion and key classification task share the same sentence representation \(l_3\) because both are sequence-level tasks.

3.5 Task-specific Classification

In this part, we first introduce the auxiliary tasks employed by MT-SMNN. Then, we describe more details about these classification outputs. Finally, we show the multi-task loss function used by MT-SMNN.

Auxiliary Tasks

Key Classification: This is a sequence-level classification task. The target is to predict the musical key for the given sequence of musical representation tokens collected from a piece of music. There are 24 possible keys: 12 major keys and 12 minor keys [Thompson and Cuddy, 1997].

Velocity Classification: This is a note-level classification task [Chou et al., 2021]. The target is to predict velocity for each individual note for the given sequence of notes collected from a piece of music. Following [Chou et al., 2021], we quantize 128 possible MIDI velocity values (0-127) into six classes: pp (0-31), p (32-47), mp (48-63), mf (64-79), f (80-95), and ff (96-127).

Classification Outputs

Let \(H = \{h_0, ..., h_S\}\) be the contextual representation \(l_2\) of given piece of music, \(Z\) be the sentence representation \(l_3\), where \(h_i \in \mathbb{R}^E\), \(Z \in \mathbb{R}^K\), \(E\) is the dimension of hidden state, and \(K\) is the dimension of sentence representation generated by the pooler. For sequence-level tasks (emotion and key classification), the probability that given a piece of music is predicted as class \(c\) by a classifier with softmax can be formalized as:

\[
P^t(c|Z) = \text{softmax}(\phi^t(Z))
\]

where \(\phi\) is the mapping function of classifier, \(t\) is to distinguish between different tasks.

For the note-level task (velocity classification), the probability that the \(i\)-th note in a piece of music is predicted as class \(c\) can be formalized as:

\[
P_i^t(c|H) = \text{softmax}(\phi^t(h_i))
\]

where \(\phi\) is the mapping function of classifier, \(i\) means the \(i\)-th item in corresponding sequence.

For more detail, the classifiers consist of two fully connected layers with the ReLU activation function in the middle.

Multi-task loss

For each task, we use cross-entropy loss as its objective. Let \(L_1, L_2,\) and \(L_3\) be the loss of emotion recognition, key classification, and velocity classification, respectively. We employ the adaptive loss function proposed by Liebel [2018]. The multi-task loss is formalized following:

\[
L = \sum_{t} \frac{1}{2 \cdot \sigma_t} L_t + \ln \left(1 + \sigma_t^2\right)
\]
Algorithm 1 Training a MT-SMNN-based model.

1: Load model parameters Θ from the pre-trained checkpoint;
2: Set the max number of epoch: epoch\_max;
3: Prepare dataset D;
4: for epoch in 1, ..., epoch\_max do
5:   for b\_i in D do
6:     //b\_i is the i-th mini-batch of dataset
7:     1. Predict
8:        Predict emotion and key for music using Eq. 1;
9:        Predict velocity for each note using Eq. 2;
10:   2. Compute loss
11:      Compute loss for each task using cross-entropy;
12:      Compute loss L (Θ) for multi-task using Eq. 3;
13:      λ ∇(Θ) ;
14:   5. Update parameters: Θ = Θ − λ∇(Θ);
15: end for
16: Evaluate the model in validation set;
17: Check for early-stopping;
18: end for

where L\_t indicates the loss of task t, σ\_t a learnable parameter which controls the contribution of t-th task, and the second term is a regularizer.

4 Experiments

In this section, we evaluate the proposed MT-SMNN based models on EMOPIA [Hung et al., 2021] and VGMIDI [Ferreira and Whitehead, 2019; Ferreira et al., 2020] datasets. We first overview the datasets and processing procedure. Then, we describe the baselines and our proposed models (MT-MIDIBERT and MT-MIDIGPT). Finally, we show the results and analysis.

Table 1: Summary of the two datasets: EMOPIA and VGMIDI.

| Datasets  | #Train | #Valid | #Test | #Label |
|-----------|--------|--------|-------|--------|
| EMOPIA    | 869    | 114    | 88    | 4      |
| VGMIDI    | 4,876  | 879    | 1,436 | 4      |

4.1 Datasets and Preprocess

The information of the EMOPIA and VGMIDI datasets is summarized in Table 1. The EMOPIA dataset\(^1\) is a dataset of pop piano music for symbolic music emotion recognition. The clips are labeled to 4 class according to Russell’s 4Q [Russell, 1980]. The VGMIDI dataset\(^2\) is a dataset of video game sound-tracks formatted in MIDI. Each clip in the VGMIDI dataset is labeled as valence-arousal pair, also according to the Russell’s model.

For experimental consistency, we transfer the valence-arousal pair in VGMIDI to the taxonomy of Russell’s 4Q as EMOPIA. The initial VGMIDI dataset has been split into a training set and a testing set. We divide a portion (about 15%) of the original training set into the validation set. In this procedure, we ensure that the clips of the validation set and the training set will not come from the same song.

The MT-SMNN need two additional labels (key and velocity) besides emotion. The velocity for each note can directly derived from symbolic data. We extract the key label via the well-received Krumhansl-Kessler algorithm [2001] provided by the Music21 library [Cuthbert and Ariza, 2010].

4.2 Implementation details

For the sake of fair comparison, the vast majority of previous work mentioned in Section 2 is reproduced. Our implementation is based on the PyTorch code open-sourced by HugginFace [Wolf et al., 2019]. Below, we describe the reproduced models in detail.

Configuration of Machine Learning based Methods

In this paper, we have reproduced the machine learning based models proposed in [Lin et al., 2013] and [Panda et al., 2013]. After taking the best subset of features selected in [Lin et al., 2013] and [Panda et al., 2013], the dimension of features for Lin’s method and Panda’s method is 521 and 135 respectively. Both methods use the SVM classifier that works with the RBF kernel.

Configuration of Deep Learning based Methods

Global Settings: The reproduced MIDIBERT-Piano [Chou et al., 2021], MIDIGPT [Ferreira et al., 2020] and our proposed MT-SMNN based methods all share the following global configuration: (a) The AdamW [Loshchilov and Hutter, 2019] optimizer is adopt in this paper. The β\_1, β\_2 and weight decay rate is set as 0.9, 0.999 and 0.01 respectively. (b) The batch size is set as 16. (c) The learning rate is set as 3e-5 with a linear scheduler. The other trick is setting warm-up steps as 500. (d) We evaluate the models every training epoch in the validation set. The model is early stopping when the macro-F1 for emotion recognition have no improvement for T consecutive epochs, where T = \lfloor 0.3 \times N \rfloor, N denotes the number of max training epochs. The checkpoint achieving the best metric in the validation set during the training procedure is saved and evaluated in the testing set. (e) All experiments are repeated ten times with different random seeds (from 0 to 9).

Specific Settings: Following [Chou et al., 2021], the max sequence length of MIDIBERT-Piano is set as 512. The inside BERT model adopt BERT\_base. We start fine-tuning the MIDIBERT-Piano model from the released pre-trained checkpoint\(^3\). The max sequence length of MIDIGPT is set as 1024 and 2048 to cover the entire input sequence of tokens as much as possible when experimenting with VGMIDI and EMOPIA datasets, respectively. To accommodate different max sequence lengths, we pre-trained the MIDIGPT model according to [Ferreira et al., 2020], with remaining other settings unchanged except the max sequence length. We finetune the models mentioned above at most 30 epochs in VGMIDI, and 100 epochs in EMOPIA with early-stopping discussed above.

\(^1\)https://zenodo.org/record/5257995

\(^2\)https://github.com/lucasnfe/bardo-composer/tree/master/data/vgmidi

\(^3\)https://github.com/wazenmai/MIDI-BERT
We coin the model that combines the proposed MT-SMNN with MIDIBERT-Piano and MIDIGPT as “MT-MIDIBERT” and “MT-MIDIGPT” respectively.

### 4.4 Comparison of state-of-the-art Methods

We compare MT-SMNN based models with previous state-of-the-art models. The result of symbolic music emotion recognition (SMER) is shown in Table 2. We have reproduced all these baselines in Table 2 and described them in detail in 4.2.

Table 2 shows that the deep learning based models outperform the traditional machine learning based models. In addition, models that work with the proposed MT-SMNN framework perform better than the counterpart for single-task and achieve new state-of-the-art results. Specifically, Compared with the MIDIBERT-Piano model, the proposed MT-MIDIBERT model pushes the accuracy to 67.58% and 49.81%, which amounts 4.2% and 2.5% absolute improvement on the EMOPIA and VGMIDI dataset, respectively. The proposed MT-MIDIGPT model also improves the accuracy by 3.8% and 2.0% to 62.50% and 55.85% for these two datasets, respectively.

Since the MT-SMNN based models have no difference except for multiple classifiers, which have a minimal amount of parameters, are employed for different tasks compared with its single-task counterpart, the improvement of the above results is attributed to our proposed MT-SMNN framework.

### 4.5 Ablation Studies

In this section, we conduct experiments on the EMOPIA dataset to study auxiliary tasks’ impact. The results are summarized in Table 3.

Table 3: The contribution of different tasks on EMOPIA dataset using MIDIBERT backbone. Results are evaluated by the accuracy of music emotion recognition task.

| Key Classification | Velocity Classification | Accuracy   |
|--------------------|-------------------------|------------|
| ✓                  | ✓                       | 63.41±3.52 |
| ✓                  | ✓                       | 67.03±2.54 |
| ✓                  | ✓                       | 64.73±5.47 |
| ✓                  | ✓                       | 67.58±2.39 |

Table 3 shows that both key and velocity classification auxiliary tasks effectively affect emotion recognition. Moreover, the model taken in both auxiliary tasks outperforms models only taken in a single. The accuracy is increased by 3.6% and 1.3% to 67.03% and 64.73% after combining the SMER task with the key and velocity classification task, respectively, which means that the key classification task is a more critical auxiliary task than the velocity classification task.

We also plot the confusion matrices of these experiments, as shown in Figure 3. In this figure, Q1, Q2, Q3 and Q4 denotes HVHA (high valence high arousal), LVHA (low valence high arousal), LVL (low valence low arousal) and HVLA (high valence low arousal) respectively which also so-called Happy, Angry, Sad and Calm in some literatures. Compared Figure 3(b) with Figure 3(a), we have found that the key classification task can greatly improve the performance of emotion recognition in the class of Q1 and Q4. Similar results can be found in Figure 3(c) and Figure 3(d). Since Q1 and Q4 are both in the high valence region, we finally conclude that our proposed MT-SMNN framework can improve the performance of music recognition, especially in the valence dimension.

### 5 Conclusion

In this paper, we present MT-SMNN, a multi-task framework that mainly focus on emotion recognition for symbolic music. The MT-SMNN framework combines emotion recognition with key classification and velocity classification tasks and conducts a multi-task training procedure in a single dataset.
MT-SMNN based models obtain new state-of-the-art results in both EMOPIA and VGMIDI datasets. Further analysis also verifies the effectiveness of both auxiliary tasks.

We would like to apply the MT-SMNN framework to other areas for future work. For example, the MT-SMNN based models can be employed to build a metric for evaluating the performance of emotion conditioned symbolic music generation models.

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