A Transformer Based Pitch Sequence Autoencoder with MIDI Augmentation

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Abstract: Algorithms based on deep learning have been widely put forward for automatic music generated. However, few objective approaches have been proposed to assess whether a melody was created by automatons or Homo sapiens. Conference of Sound and Music Technology (2020) provides us a great opportunity to cope with the problem. In this paper, a masked language model based on ALBERT trained with AI-composed single-track MIDI is demonstrated for composers classification tasks. Besides, music tune transposition and MIDI sequence truncation is applied for data augments. To prevent from over-fitting, a refined loss function is proposed and the amount of parameters is reduced. This work provides a new approach to tackle the problem on obtaining features from tiny dataset which is common in music signal analysis and deserve more attention.

Key Words: Bert, Albert, Data Augmentation, Autoencoder, MIDI truncation

1 Introduction

Methods based on machine learning have been widely proposed for automatic music generated, especially since significant progress in deep learning fields. Nowadays, more and more melody can be composed by a deep-learning automaton, using the pitch and length of the notes in human music as a primary inputs to mimic human. However, few objective algorithms or indicators has been put forward to assess whether a melody was created by a machine or a person. Although several attempts has been made, such as measures from information theory to compare Bach’s music, or probability transfer relation with the N - gram model to compare British and American folk music melody, most of the distinguishing task on composing works are made in human evaluation, namely let some people listen to the music produced by the AI or human, and evaluate its similarity with music made of man or AI.

However, the listening test results might contain individual or group differences, which makes it difficult to compare the listening test results of different samples, especially when the samples amount is small. Finding a relatively common and objective way to evaluate the way melodies are produced in various musical styles can make different music task comparable. The purpose of this study is to find an objective and effective method to generate the indicator value of whether a melody is human-composed by analyzing the AI-made melodies.

The approach of features extracting is highly significant for tasks on music series. For the single-track data without music chords, there are some methods rely on n-gram. Besides, Bidirectional Encoder Representations from Transformers (BERT) may be better recently, but there are too many parameters. Albert may play a role in Audio.

In the past two years, pre-trained models, and BERT in particular, have dominated the field of Natural Language Processing (NLP). This model uses self-supervised learning to encode contextual information to obtain a powerful and universal representation. This representation can improve performance, especially in situations where data for downstream tasks is limited. More recently, BERT-like models have been applied to speech processing. However, such models usually maintain a large amount of parameters in both speech tasks and text tasks. Even in the fine-tuning stage, they require a large amount of memory for computation and are prone to over-fitting when pre-training data is relatively scarce, such as in music related cases.

A Lite BERT (ALBERT) is a simplified version of BERT that shares one layer parameter at all layers and decompositions the embedded matrix to reduce most of the parameters. Although the number of parameters is reduced, the representation learned in ALBERT is still robust and task agnostic, so that ALBERT can achieve similar performance to BERT in the same downstream task, thus obtaining characteristics about the input itself. In this paper, ALBERT is introduced into MIDI processing and a new self-supervised model is proposed.

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The rest of this article is organized as follows. In section 2, the data set used in the study is described. In section 3, the pipeline of the research, the methods of data preprocessing, data augment and prevention of over-fitting are demonstrated. Section 4 covers the main experimental processes and results. The fifth section we have made the summary and the prospect.

2 Dataset

The training data set contains only the music generated by artificial intelligence algorithm. It includes 6000 MIDI files. Each file is single melodic music whose speed is between 68BPM and 118BPM. And each melody length is 8 bars, without complete phrase structure, that is completely music sentences always with 8 or 16 bars. It should be noted that the melody in the training data set is generated by several AI models trained with data in two different music genres. More information can be found at the website in Conference of Sound and Music Technology (2020).

Open source MIDI dataset is mostly multi-track music, such as the database on reddit with 3.65 GB multi-track MIDI in all sorts of music genre. Since it is difficult to extract convincing main melody as its single melody, this research did not use any data of human composition.

3 Methods

3.1 Pipeline

The pipeline is shown in Fig. 2 as follows.

To begin with, the training set will undergo a data preprocessing part and be expanded by data augmentation. The details is available in the following subsections. Then, a Masked Language Model (MLM) task based on ALBERT is trained for autoencoder on the expanded training set. Lastly, The trained model will be used for evaluation. See Section 4 for details of training and evaluating.

3.2 Preprocessing

For the specific problem of comparing the similarities of melodies, the rhythm and pitch are important characteristics, since people usually pay attention to them when they perceive music.

\[1\)http://www.csmcw-csmt.cn/data/2020/ai-composition-recognition2020/?from=timeline
\[2\)https://www.reddit.com/r/datasets/comments/3akhxy
Therefore, the MIDI sequence of 8 bars can be segmented into 128 hexadecimal notes or 256 thirty-two quarter notes, as the speed and the starting and ending time of the notes are marked. Whether the unit of the 8-bar music is a hexadecimal note or a thirty-two quarter note depends on the shortest note length in the given MIDI, and there are 256 notes or so in a music sequence for most of the cases. Considering the fact that it is meaningless in music to divided a quarter note into twelve equal parts in the vast majority of cases, there is no musical necessity to do so except for compatibility with the relative rarity of triplets and sixteenth notes. We classify all triplets as three quavers or three sixteenth notes in the same probability, which leads to the total length of a music sequence not being 256. This turns each MIDI data into a pitch sequence.

3.3 Data Augmentation

Although there has been a noticeable parameters decrease in ALBERT relative to BERT parameters, 6000 MIDI data are somehow relatively poor for training. As a consequence, it is essential to adopt some means of data augment. Unfortunately, data augment methods usually used in NLP tasks can be seldom used in music series processing.

Randomly swapping is a common approach, but the exchange of music notes may cause non-negligible differences for a listener. Music clips for the composition of humanity, for example several sixteenth noted in a crotchet or half note exchange with other sounds, could lead to a strange auditory experience, and let people regard the music piece as machine-created. Synonym replacement is not suitable for using in a sequence of music analysis, because there is no specific semantic like natural language for music sequences. Thus, it’s hard to jump out of phrases to define two notes as “synonym” for notes. Even replaced by octave “synonym” is unacceptable in a lyrical semiquaver with a long sound, which result in a clear change on music express in human emotion, though little differences in frequency spectrum. Random insert and delete also run a high risk in this case, so we proposed two methods to do data augmentation.

3.3.1 Transposition

The first method our research used for data augmentation is transposition in music tunes. Since music do not make a significant difference, at least not in the respect whether it is generated by human being or artificial intelligence, if it is just changed in transposition.

Each time, a transposition raise or lower each note in the pitch sequence by a same random music interval. Therefore, several relatively same melodies in different music tunes are generated by the transposition data augmentation.
3.3.2 Random Truncation

In addition, BERT’s training results contain position embedding and thus absolute position information\cite{25}, for example the word at the beginning of the sentence may be regarded as the subject. But the dataset neither includes complete phrase information nor cadence in multi-track, therefore, some location information in the training set retained by BERT belongs to some kind of over-fitting. In order to give up this information, we randomly delete the first few notes of each pitch sequence for the model.

3.4 Avoid Over-fitting

Since there is only machine-generated data used and no data on human composition, it is still easy to over-fit even after data augment. To cope with this case, several additional measures have been taken to prevent from data over-fitting.

3.4.1 Refined Loss Function

Some studies have shown that slight adjustment of the loss function can prevent over-fitting greatly\cite{26}:

$$loss_{new} = |loss_{origin} - b| + b$$

where $b$ is a little positive real parameter which is problem related. The model is trained with the refined loss function to prevent from pursuing zero-value of original loss function but only to a close-zero value.

3.4.2 Smaller Transformer

The number of the parameters in BERT model is extremely large. Even in the ALBERT model using shared parameters, the number of parameters can easily lead to over fitting on such a small dataset. Therefore, on the basis of retaining the structure of ALBERT, we greatly reduce the parameters of ALBERT to around 103.6k, thus avoiding the over fitting on the training set.

4 Experiment

Based on the Albert model, the autoencoder model is trained with MLM task on the dataset provided by CSMT(2020).

4.1 Experiment Setup

4.1.1 Data Preparation

Both data augmentation strategies mentioned above are used for all the data in the training set.
Firstly, we use pretty_midi \cite{27} reads the data in and then preprocesses it. For a pitch sequence after preprocessing, 15 transpositions without truncation and 15 transpositions after truncation will be generated, so that 31 pieces will be obtained by augmentation methods. Therefore, the size of training set is expanded to $31 \times 6000 = 186000$, which is enough for training one the small ALBERT.

4.1.2 Environment and Hyperparameters

Due to the good parameter control strategy, the Albert is able to be deployed on a GTX 1050Ti NVIDIA graphic card. Pytorch \cite{28} and Hugging Face \cite{29} are used in the process of building and training the algorithm. The small batch size is 64 and the default learning rate is $10^{-3}$ with AdamW optimizer \cite{30}. The parameter $b$ mentioned in Section 3.4.1 is set as 0.05.

Because there is no ground truth in the test set, we can not carry out the ablation experiment, the selection of hyperparameters is all based on past experience.

4.2 Training Method

There are two important tasks of Bert’s training process \cite{13}: Masked Language Model (MLM) and Next Sentence Prediction (NSP). However, the NSP task is not necessary in this problem, because the training dataset does not include complete phrase information, it will be hard to divide notes into two phrases. ALBERT training will randomly mask n-grams to predict \cite{21}, but if the mask happens to cover a whole bar or a whole chord formed by adjacent notes, the notes masked are difficult to be effectively predicted by the model.

After comprehensive consideration, the MLM task is the only used task for training. Each time, about 15% of the elements has been randomly masked in a pitch sequence, and then use the other elements not masked to predict the elements that have been masked. Softmax cross-entropy is used as the loss function of the model, followed by the process mentioned above to refine the loss.

Selecting 15% notes can ensure that the essential music components are not masked, so that the model can produce effective prediction, and random selection can avoid over-fitting to a certain extent as well.

4.3 Evaluation

When evaluating, for a pitch sequence, each note will be masked successively. Then, the probability $p_i$ of the $i^{th}$ masked note is predicted by the trained ALBERT, and the average probability of all notes is the probability that this data is composed by AI. Formally, the number of notes in this pitch sequence is $n$ suggests the probability of AI generating is as follows:

$$p = \frac{\sum_{i=1}^{n} p_i}{n}$$

The probability of each data created by human, which this task required, can be obtained by $1 - p$.

5 Conclusion

A brand-new method is provided in our research on tiny dataset training including data augmentation in music tune transposition and MIDI sequence truncation and prevention of over-fitting. And a approach based on mask language model with ALBERT has been put forward to distinguish whether the composer of a music piece is human or not. Because of the well behavior of the pre-trained model, we believe that it worth more extensive application in MIDI sequences encoding tasks. Besides, quite a little computing resources is needed to complete the algorithm.

The ground truth of test data is not open, therefore, we can not carry out ablation experiments and determine the influence of each components of our method on the results. And due to the limited computing resources, there is no experiment on whether the model can run well with a larger batch size or on the larger transformer, which worth more attention.
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