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Michele Della Ventura, *editor*

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Editor

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Preface

This volume of proceedings from the conference provides an opportunity for readers to engage with a selection of refereed papers that were presented during the International Conference on New Music Concepts, Inspired Education and New Computer Science Generation. The reader will sample here reports of research on topics ranging from a diverse set of disciplines, including mathematical models in music, computer science, learning and conceptual change; teaching strategies, e-learning and innovative learning, neuroscience, engineering and machine learning.

This conference intended to provide a platform for those researchers in music, education, computer science and educational technology to share experiences of effectively applying cutting-edge technologies to learning and to further spark brightening prospects. It is hoped that the findings of each work presented at the conference have enlightened relevant researchers or education practitioners to create more effective learning environments.
This year we received 57 papers from 19 countries worldwide. After a rigorous review process, 24 paper were accepted for presentation or poster display at the conference, yelling an acceptance rate of 42%. All the submissions were reviewed on the basis of their significance, novelty, technical quality, and practical impact.

The Conferece featured three keynote speakers: Prof. **Giuditta Alessandrini** (Università degli Studi Roma TRE, Italy), Prof. **Renee Timmers** (The University of Sheffield, UK) and Prof. **Axel Roebel** (IRCAM Paris, France).
I would like to thank the Organizing Committee for their efforts and time spent to ensure the success of the conference. I would also like to express my gratitude to the program Committee members for their timely and helpful reviews. Last but not least, I would like to thank all the authors for they contribution in maintaining a high-quality conference and I hope in your continued support in playing a significant role in the Innovative Technologies and Learning community in the future.

March 2020

Michele Della Ventura

Conference Chair

Michele Della Ventura, Accademia Musicale Studio Musica, Treviso, Italy

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Detection of Local Boundaries of Music Scores with BLSTM by using Algorithmically Generated Labeled Training Data of GTTM Rules

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Abstract. Preparing a considerable amount of labeled data is always a problem that machine learning related research must deal with. In this paper, we propose a procedure which algorithmically generates a large amount of labeled music scores as training data for local boundary detection problem of music scores. The local boundary rules in the generative theory of tonal music (GTTM) are used as an example, which uses the proposed procedure to generate a dataset and trains bidirectional long short-term memory (BLSTM) networks to detect these rules. The experimental results show that the BLSTM models trained by the algorithmically generated dataset does outperformed the existing ATTA models. It greatly reduces the effort in designing new rules and the corresponding detection models without time consuming manual labeling.

Keywords. Symbolic Music Processing, Music Boundary Detection, A Generative Theory of Tonal Music, Bidirectional Long Short-Term Memory Networks

1 Introduction

As deep learning becomes popular in various fields of music research, the need for carefully labeled data has also grown. Although there are more and more pieces of sheet music in a machine-readable format (e.g., MIDI) available for collecting a labeled symbolic music dataset, asking experts to label them according to some research objectives (e.g., musical phrasing) still takes a lot of time and effort. Approaches which use synthetic datasets to train convolutional neural networks have been widely proposed for many computer vision applications [1], [2]. In music research, similar approaches are applied in audio processing like source separation [3] or automatic music transcription [4]. However, it is seldom experimented in analysis of symbolic music data. In light of this, a procedure is proposed for automatically generating labeled scores based on specific rules and parameters. For example, if we define a rule that a musical phrase should end with a cadence, and parameters that we want a 32-bar music score with four phrases,

then corresponding music scores with phrases labeled can be generated. This allows us to have many controllable and highly divergent scores, which are also very accurately annotated and can be used to train complex machine learning models.
To evaluate our method, we generate a dataset of 10,000 labeled music scores (LMS) to train the models that can detect the local boundary rules described in the generative theory of tonal music (GTTM) [5]. Since the input data are music scores, which can be considered as temporal sequences of undetermined lengths, we employ recurrent neural networks (RNN) with bidirectional long short-term memory (BLSTM) units as our model [6, 7]. Compared with the existing GTTM deep learning model that uses deep belief networks to detect the local boundaries [8], the BLSTM networks also give us the advantage of being able to handle data of variable length. The trained models are also compared favorably with an existing model, the automatic time-span tree analyzer (ATTA) [9]. The results show that our models can outperform ATTA and reach F-scores over 77% on two thirds of local boundary rules on manual labeled GTTM database [10]. We also compare the performance of the two models on the two datasets, the ATTA dataset and our LMS dataset.
The rest of this paper is organized as follows: Section 2 mentions some related works about this paper. Section 3 presents our proposed procedure for algorithmically generating labeled music scores. Section 4 presents the experimental results and our discussion about them. Lastly, Section 5 offers the conclusion and the suggestions of future works.

2 Related Works

Annotated Symbolic Music Datasets

In the past decade, there is a growing number of symbolic music datasets that are labeled by experts for various fields of research. For example, for musical phrasing, a dataset containing Turkish makam music scores segmented into phrases is presented [11]. For harmony analysis, there are much more datasets presented [12-16], and some of them have been used to train models for harmony recognition [16-18]. For music theory analysis, the SCHENKER41 contains Schenkerian analyses of 41 excerpts in a machine-readable format [19], and the GTTM (the generative theory of tonal music) database provides the analyses of four structures in GTTM with over 250 pieces of manually labeled music [10]. The GTTM database has also been used to train deep belief networks [20] for detection of grouping structure and metrical structure in GTTM [21], [22]. In this work, owing to the completeness and concision of the rules, the GTTM database is selected as the target for comparison with our generated dataset because it has a well-researched and published model.

A Generative Theory of Tonal Music (GTTM)

GTTM [5] is a music theory aiming to describe listeners' unconscious understanding of music with four kinds of hierarchical structures. Among them, the grouping structure is considered as the most basic component of musical understanding. It divides a piece of music score into hierarchical groups of notes, simulating how people group these notes when they hear them. However, there is no direct way in the original GTTM about how to come up with a proper grouping structure from a piece of music. Since the grouping well-formedness rules (GWFRs) only define all possible structures and the grouping preference rules (GPRs) only specify which structure is preferred and may conflict with each other, it often takes experienced musicians to figure out the most appropriate structure from them. Consequently, one usually finds the local boundaries first, which are the intervals between notes that are also between groups. Among all GPRs, GPR2a, 2b, 3a, 3b, 3c, and 3d, which are called the local boundary rules, are used to describe the conditions under which the interval may be a candidate local boundary. For example, in the GPR3, an interval may be regarded as a local boundary if the changes of register (3a), dynamics (3b), articulation (3c), or note length (3d) are more intense within this interval than those on the neighboring intervals. In this work, we only focus on generating training data necessary for respective BLSTM models for the above six local boundary rules, confirming that whether the trained models are effectively such that the automatically generated labeled datasets can take the place of manually labeled datasets.

Automatic Time-span Tree Analyzer (ATTA)

The ATTA [9] is a rule-based model included in the Interactive GTTM Analyzer [23]. A music score in the MusicXML format can be read and displayed on the piano roll in the Interactive GTTM Analyzer. The ATTA can then generate four structures in GTTM as well as local boundary rules labeled. However, the Interactive GTTM Analyzer has some restrictions. For example, it cannot read some notations in MusicXML music score. The ATTA still provides a reliable reference that allows us to verify the performance of our trained models.

Bidirectional Long Short-term Memory (BLSTM) Networks

BLSTM networks are a combination of bidirectional RNN [6] and LSTM units [7]. Bidirectional RNN can help the network to learn context in both forward and backward directions. An LSTM block, which consists of an input gate, a forget gate and an output gate, provides a more flexible and stable way to model the long-term dependency of a time series. The BLSTM networks have also been used in many fields of music research like harmony recognition [16], chord generation [24] and expressive performance generation [25].

3 Method

To generate labeled music scores (LMS), our procedure reverses the normal process of labeling, i.e., we set all the target labels first, and then generate a score that conforms to these labels. This procedure consists of several parts, including initializing the properties and probability parameters used to generating each LMS, arranging the positions of all note intervals, setting the pre-determined labels, and finally filling all the notes without violating the labels. The whole method are implemented using the music21 toolkit [26] and all scores are stored in the MusicXML format [27]. Because the lengths of the scores in the GTTM dataset are less than 17 measures, we also only generate monophonic scores of limited numbers of measures in this paper to match the characteristics of the GTTM dataset. All the initialized values can be set more generally to fit other types of music or datasets.

Score Properties Initialization

To maximize the divergence of the automatically generated dataset, one first initializes the basic properties of each LMS, described as follows:

1) The time signature: 2/4, 3/4 or 4/4.
2) The key: one of twelve keys without considering its major or minor quality.
3) The number of measures: 8 or 16.
4) The shortest length of notes: quarter, eighth or sixteenth note.
5) The lowest pitch: a pitch between C2 and C5.
6) The range of pitch: a range between 10 and 30 semitones.
7) The number of notes: a number between 0.2 and 0.8 times the maximum number of notes, which can be determined by the time signature, the number of measures and the shortest length of notes.

Probabilistic Parameters Initialization

We also initialize all probabilistic parameters to ensure that each LMS is generated with different probability distributions. Here are the probabilistic parameters to be initialized:

1) The probability of occurrences of notes not on the scale of the key: a number between 0 and 0.05.
2) The probability of occurrences of rests: a number between 0 and 0.2.
3) The probability of dynamics changes: a number between 0 and 0.1.
4) The probability of occurrences of each articulation: according to its statistics in the GTTM dataset.

Labeled Music Scores (LMS) Generation

After the initialization, instead of setting one note after another, we simply arrange the positions of note intervals randomly because the total number of notes has been determined in advance. Since the local boundary rules are applied to note intervals, one can even choose multiple rules that each interval should apply. It should be noted that the rules cannot be chosen completely randomly because some arrangement of rules are impossible (e.g., GPR3c cannot occurs consecutively). Finally, according to our initialized parameters and set rules, all the other properties of each note are set as follows:

1) Whether it should become a rest.
2) If it is a note, what the pitch of it should be.
3) If it is a note, whether the dynamics of if should be changed and what dynamics of it should be changed to.
4) If it is a note, whether it should under a slur.
5) If it is a note, which articulation it should be played.

If it is still impossible to set all properties to conform to all rules, we relabel the whole rules until all notes can be set without violating any rule. Fig. 1 shows an example of a generated LMS. The rules are labeled at the positions of lyrics in the MusicXML format, indicating that they are applied to the intervals right before the notes. For example, the first "3a" means that GPR3a should be applied to the interval between the third and the fourth notes.

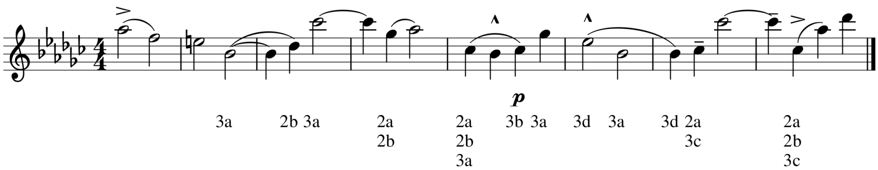

Fig. 1. An example of a generated LMS.

4 Experimental Results

Model Architecture and Feature Representation

For each grouping preference rule among GPR2a, 2b, 3a, 3b, 3c, and 3d, a trained associate BLSTM network is used to detect it. Each network has two stacked layers, and a hidden size of 32. The input size is 11, mapping to the 11-dimensional features extracted from each note. The first 5 features include the onset, duration, duration ratio affected by articulations, pitch and dynamics of each note, and the last 6 features of this note include tenuto, staccato, staccatissimo, accent, strong accent, and under a slur or not. It is noted that the duration ratio related to GPR2a can be greatly affected by articulations of actual performances. In [28], it is set according to the analyses of recordings of music performance with articulations. In addition, all BLSTM networks are trained for 100 epochs with batch size = 5 and the Adam optimization method of the learning rate = 10^{-3}, β_1 = 0.9, β_2 = 0.999, ϵ = 10^{-8}.

TABLE I: VALIDATION RESULTS.

	Precision (%)	Recall (%)	F-score (%)
GPR2a (Slur/Rest)	94.96	96.71	95.82
GPR2b (Attack point)	100.00	99.99	99.99
GPR3a (Register)	99.90	99.94	99.92
GPR3b (Dynamics)	99.62	99.76	99.69
GPR3c (Articulation)	97.89	98.15	98.02
GPR3d (Length)	99.80	100.00	99.90

Validation Results

There are 10,000 LMS's generated. 8,000 of them are used for training and the rest 2,000 ones are used for validation. The validation results are evaluated on all intervals for each rule and shown in Table I. It shows that all models can learn these rules accurately from our generated LMS's and most of the rules can reach F-scores over 98%. GPR2a is a rule that takes into account the time of an interval between the offset of the previous note and the onset of the next note. Therefore, the performance in GPR2a is slightly lower because of the variability of the fifth-dimensional feature (i.e., the duration ratio affected by articulations stated in the above).

Testing Results

To test our models, we would like to use the GTTM dataset [10] as our major testing set. There are 300 scores in this dataset, and all have local boundaries manually annotated. For the first 267 scores, since the local boundary rules are manually labeled on the local boundaries only, we thus compare our models with the ATTA on these boundaries accordingly. The results are shown in Table II, where the numbers before and after the slashes indicate the performances of our trained BLSTM networks and the ATTA, respectively. Since the Interactive GTTM Analyzer cannot read slurs and notations of dynamics and articulations into its program, there are no results for GPR3b and 3c and a lower recall rate for GPR2a is produced because it is related to slurs. The reason for the lower precision rate of GPR3c of the proposed work is that the types of articulations in our consideration are different from those considered by the annotators of the GTTM dataset. To explain this problem, an example of manually labeled music score in the GTTM dataset is used and shown in Fig. 2. The local boundaries are marked as "^", the original ATTA labels are marked in black without parentheses, and our predicted labels are marked in red and in parentheses. For example, there is no GPR3c labeled in the original GTTM dataset on the local boundaries in the fifth measure and sixth measure, but we consider those GPR3c necessary on those two boundaries because the notes under slurs are considered as legato which makes them different from the normal notes appearing in the fifth measure and sixth measure. Another situation happens on the local boundary between the second and third measure, too. Since we haven't included trills in our implementation, the whole note in the second measure would be treated as a normal note, which is like the eighth note before it, but different from the first two legato notes in the third measure. As a result, the GPR3c is predicted on this boundary by our model. Nevertheless, the results still show that the proposed models can achieve better results on detecting manually labeled local boundary rules.

TABLE II: RESULTS FOR THE FIRST 267 SCORES IN GTTM DATASET ATTA (THE RESULTS OF ATTA IN GPR3B AND 3C ISN'T SHOWN BECAUSE OF THE RESTRICTIONS OF THE INTERACTIVE GTTM ANALYZER [23])

	Precision (%) (BLSTM / ATTA)	Recall (%) (BLSTM / ATTA)	F-score (%) (BLSTM / ATTA)
GPR2a (Slur/Rest)	74.35 / 77.03	88.02 / 42.88	80.61 / 55.09
GPR2b (Attack point)	66.71 / 66.31	94.32 / 92.63	78.15 / 77.29
GPR3a (Register)	67.43 / 64.87	91.23 / 89.95	77.54 / 75.38
GPR3b (Dynamics)	67.50 / -	62.79 / -	65.06 / -
GPR3c (Articulation)	46.43 / -	72.22 / -	56.52 / -
GPR3d (Length)	82.23 / 76.08	94.19 / 92.44	87.80 / 83.46

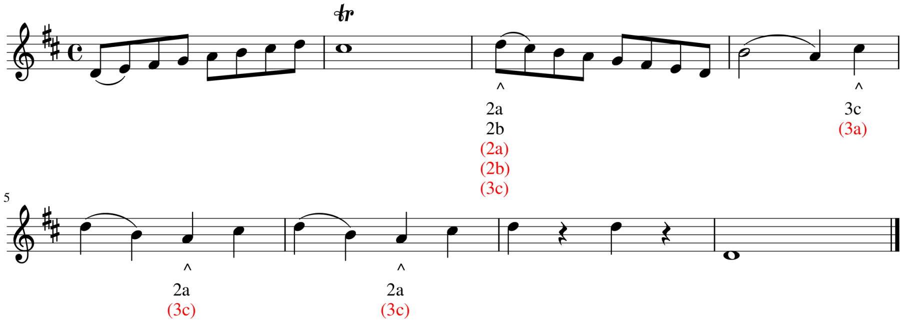

Fig. 2. A music score in the GTTM dataset. The local boundaries are marked as “^”. The original GTTM labels are marked in black without parentheses. Our predicted labels are marked in red and in parentheses.

For the remaining 33 scores in the original GTTM dataset, instead of being manually annotated, the local boundary rules are automatically labeled on all intervals using the ATTA. Therefore, in addition to evaluating the proposed models on these labels annotated by the ATTA, we also randomly choose 50 scores from the LMS dataset to see how the ATTA performs on our labels. The results of our models are shown in Table III, and the results of the ATTA are shown in Table IV. GPR3b and 3c are not shown in the tables because they cannot be labeled or detected due to the restrictions of the Interactive GTTM Analyzer [23]. Since the Interactive GTTM Analyzer cannot recognize slurs, poor performances in precision and recall are expected for GPR2a in these two tables. Besides, those notes longer than a whole note can only be displayed as whole notes in the Interactive GTTM Analyzer. Although such long notes rarely appear in most actual scores, they appear quite often in our generated LMS dataset, causing ATTA to perform poorly in GPR3d. This emphasizes that using the highly divergent LMS dataset, we can adapt our models to more extreme input data.

TABLE III: RESULTS FOR THE LAST 33 SCORES IN GTTM DATASET.

	Precision (%)	Recall (%)	F-score (%)
GPR2a (Slur/Rest)	17.25	57.71	26.35
GPR2b (Attack point)	95.65	98.32	96.97
GPR3a (Register)	86.22	84.34	85.27
GPR3d (Length)	97.67	84.00	90.32

TABLE IV: RESULTS FOR 50 SCORES RANDOMLY CHOSEN FROM OUR GENERATED DATASET.

	Precision (%)	Recall (%)	F-score (%)
GPR2a (Slur/Rest)	47.43	29.96	36.73
GPR2b (Attack point)	81.92	96.16	88.47
GPR3a (Register)	81.13	97.98	88.76
GPR3d (Length)	39.45	69.88	50.43

Discussion

To summarize the results of our experiments, four observations are presented. First, if we only focus on the GPR2b, 3a and 3d in the Table III and Table IV, we can find that the precision of our models is generally better than that of the ATTA. ATTA tends to detect much more labels than the proposed BLSTM models and this reduces the precision rate. Second, in the Table II, we can find that the worse performance of both methods on the 267 manually labeled GTTM dataset is due to the generally lower precision. The annotators of the GTTM dataset might tend to select a smaller number of labels. Therefore, the future models should be developed in this direction. Third, because the music score is a type of data representation that is very detailed and difficult to deal with, this is why there are quite a few restrictions in the Interactive GTTM Analyzer which can't process GPR3b and GPR3c in Table II. Finally, the experiment shown in Fig.2 points out that any small changes and interpretation differences in a music score can make a huge difference in the results of local boundary rule detection. Nevertheless, to accommodate such difficulties may become easier with the proposed approach for its flexibility and ability to generate large automatically labeled dataset. The above results show that the performance of the proposed approach can be better than the conventional ATTA method in most respects.

5 Conclusion

In this work, we demonstrate that the models trained with automatically generate annotated dataset based on specific rules and parameters can match or even better than the conventional model developed using manually labeled dataset in local boundary detection problems of music scores. By adjusting the parameters used in the procedure of generation, one can easily collect many music scores of various styles and adapt the trained models to a specific form of music. The BLSTM networks also prove that they are very appropriate in this task to process such music scores. Even though a machine learning model may inevitably output unexpected results in some special cases, the BLSTM networks still show stable detection results on both the GTTM datasets and our LMS dataset. For future works, we would like to develop and improve the models to make them be able to detect more local boundaries defined in GTTM. We would like to apply our proposed procedure to more research topics of analysis and understanding of symbolic music data.

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Michele Della Ventura, editor

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