Word Representation for Rhythms

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Abstract

This paper proposes a word representation strategy for rhythm patterns (section 2). Using 1034 pieces of Nottingham Dataset, a rhythm word dictionary whose size is 450 (without control tokens) is generated. BERT model is created to explore syntactic potentials of rhythm words. Our model is able to find overall music structures and cluster different meters (section 3). In a larger scheme, a think mode - music as language - is proposed for systematic considerations (section 1).

1 Motivation: music as Language vs. Natural Language

While music-as-language has been inspected in musicology (Swain, 1996; Koelsch et al., 2013; Lerdahl and Jackendoff, 1983) and cognitive science (Koelsch et al., 2013), there is no explicit string-based word representation for musical elements in algorithm composing models. We proposed a word representation for rhythms motivated by a comparison between music and natural language. Such comparison is also an outline for algorithm composing tasks.

Similarity # 1: Hierarchical Structures

Focusing on upper layers, we care little about lower layers (intuitions from Table 1). Such hierarchical structures can be established through the recursive application of rules, analogous to the establishment of hierarchical structures in language (Chomsky, 1995). We shall be curious about: What rules? How to apply recursively? We solve these problems for rhythms in section 2. We also find way to finding higher-level music structures in 3.3.2.

Similarity # 2: Syntactics

We interpret syntactics as relationships between linguistic or musical elements. For example, tree structures are used to describe syntactics both in natural language (Donadon, 2008) and music (Lerdahl and Jackendoff, 1983; Rohrmeier, 2007; Koelsch et al., 2013). Syntactics can also be learned latently by models. Our model is introduced in section 3.

Difference # 1: Polyphony

Music can be polyphonic, while natural languages suffer Cocktail Party Phenomenon (Bronkhorst, 2000). Polyphony is a vertical dimension of syntactics. We leave this topic for future discussions.

Difference # 2: Repetition

As a unique property, repetition can exist as motif and variation (Volk et al., 2012), usually measured by music phrases. Motif discovery is an MIR topic (MIREX). Schoenberg(1995) regarded rhythm as the most important feature of motifs. This motivates us to first explore rhythm.

Difference # 3: Semantics

Music resists translation (Swain, 1996). Unlike functional syntactics, music lacks semantics. We leave relevant tasks (e.g. music and emotion) for future discussions.

In the rest of this paper, section 2 introduces our proposal of explicit string-based word representation for musical rhythm; section 3 proposes our data preprocessing pipeline and BERT model (Devlin et al., 2019) for rhythm words, and experimentally examines our proposal.
2 Methodology: Rhythm as Words

We will show how notes are packed as words and how phrases are marked. Examples in Figure 1 are given for illustration.

(a) Music segment for illustration

(b) Segment of The Blue Danube

(c) Faure’s Berceuse, phrase 1 and 2

Figure 1: Music segments

2.1 String Format

This part shows our recursive rules mapping music rhythm patterns to lists of words. For intuition, mapping result of Figure 1(a) is first represented:

\[
\text{Rhythm} = \langle \text{BOS} \rangle, 2/4, \langle \text{H} \rangle, 0.333, N, 0.333, N, 0.333, N, 1.000, \text{EOS} \rangle
\]

The corresponding recursive mapping rules:

(Meter): if we encounter a mark of meter (for example, 2/4), create a single word "2/4";

(Rests): for each measure, if we encounter a rest with duration \(T = (X.XXX)\), concatenate string "RX.XXX" to its word;

(Notes): for each measure, if we encounter a pitch note with duration \(T = (X.XXX)\), concatenate string "NX.XXX" to its word;

(Holding notes): for each measure, if we encounter a pitch note relayed from its last measure with duration \(T = (X.XXX)\), create string "HX.XXX" for its word;

(Suffix): for each end of measure, append a suffix of meter in format like "|2/4|" or "|6/8|";

(Bonus rules): for each piece, add controller tokens "\{(BOS)\}" and "\{(EOS)\}" for beginning and ending; note words are separated by commas.

After encoding Figure 1(a) into list of strings, we build a dictionary for strings:

\[
\text{Rhythm vocabulary} = \{0: \{\langle BOS \rangle\}, \langle EOS \rangle\}, \langle 1\rangle, \langle 2/4\rangle, \langle H \rangle, 0.333, N, 0.333, N, 0.333, N, 1.000, \{\langle EOS \rangle\}\}
\]

If our model reads more pieces, rhythm vocabulary can be enlarged. e.g. Figure 1(b):

\[
\text{Rhythm vocabulary} = \{0: \{\langle BOS \rangle\}, \langle EOS \rangle\}, \langle 1\rangle, \langle 2/4\rangle, \langle H \rangle, 0.333, N, 0.333, N, 0.333, N, 1.000, \{\langle EOS \rangle\}\}
\]

2.2 Treat Phrases Like Periods

In order to discover musical themes, this mapping rule is designed to represent music phrases. Just like inserting a period, our additional rule is:

(Phrase): if we encounter a beginning of phrase, we insert symbol "\{BREATH\}".

For example, if our model read Figure 1(c), the rhythm vocabulary can be enlarged:

\[
\text{Rhythm vocabulary} = \{0: \{\langle BOS \rangle\}, \langle EOS \rangle\}, \langle 1\rangle, \langle 2/4\rangle, \langle H \rangle, 0.333, N, 0.333, N, 0.333, N, 1.000, \{\langle BREATH \rangle\}\}
\]

Careful readers may find that breaths inside measures (like pickup bars) are not considered. In this case, we do sacrifice a little. More powerful representation should be designed.

3 Experiments: Utilizing Rhythm Words

Goal: to prove that rhythm words have potential to represent syntactics, especially music structures. Nottingham Dataset\(^1\) is used for experiments\(^2\).

3.1 Creating Rhythm Word Dictionary

Figure 2 shows procedure from midi to word vectors. ① reads midi files into formated objects. ② Main Part Extract (for polyphony) e.g. music21 for python

Music Vocabulary \(V\)

\[
\begin{align*}
V &= \{1: \langle BOS \rangle, 2: \langle EOS \rangle, 3: \langle 2/4\rangle, 4: \langle H \rangle, 0.333, N, 0.333, N, 0.333, N, 1.000, \langle EOS \rangle\}\}
\end{align*}
\]

Figure 2: Midi to rhythm words

https://github.com/lucainiaoge/rhythm-word-embedding

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\(^1\) https://github.com/jukedeck/nottingham-dataset

\(^2\) https://github.com/lucainiaoge/nottingham-dataset
Figure 3: VQ-BERT Model Structure

2 processes polyphonic music. 3 is the procedure in section 2. We skip 2 and 3 because Nottingham Dataset is single voiced, and labeling phrases is now labor intensive. 4 uses the mapping rules described in 2.1. Finally, we get Nottingham Dataset rhythm dictionary of size 450.

3.2 Rhythm BERT Model

After the packing rhythm patterns into word strings, we try to exploit syntaxes of rhythm words. VQ-V AE (van den Oord et al., 2017) based BERT (Devlin et al., 2019) is used as pretraining model. Our tasks for rhythm word pretraining:

Task 1: to classify meters for rhythm words.

Task 2: to reconstruct masked input sequences just like the original BERT (Devlin et al., 2019).

Training model (Figure 3) adopts 3 steps:

Step 1: Word Embedding

For each musical piece, its corresponding rhythm word idx sequence is \( X \) (equivalent to a sequence of 1-hot vectors representing a whole musical piece). The encoder input is a masked rhythm word idx sequence \( \hat{X} = \text{mask}(X) \), where for any \( t \geq T_{\text{head}} \): \( Pr(X^{(t)} = \text{‘(MASK)’}) = 0.20 \). In alignment with \( X \), we input \( X_m = \text{meter}(X) \) for word class embedding, which is part of the embedding strategy in (Devlin et al., 2019). Positional embeddings adopt the sinusoid method proposed in (Vaswani et al., 2017). Formally:

\[
X_{\text{in}} = \text{Emb}_{\text{seq}}(\hat{X}) + \text{Emb}_{\text{cls}}(X_m) + \text{Emb}_{\text{pos}}(X)
\]

Step 2: Encoding and VQ Sampling

Transformer self-attention layers are used as encoder. Formally, \( z_e = \text{Encoder}(X_{\text{in}}) \)

Predefine latent vector codebook \( V_q \) (van den Oord et al., 2017). We set the VQ-VAE codebook size 5 times as large as the rhythm word vocabulary size. For each time \( t \), sample \( z_q^{(t)} \):

\[
z_q^{(t)} = \text{argmin}_{z \in V_q} \| z - z_e^{(t)} \|
\]

For backpropagation, gradient of \( z_q \) is calculated with the help of stop-gradient operation \( \text{sg}[] \) (van den Oord et al., 2017): \( z_q \leftarrow z_q + \text{sg}[z_q - z_e] \)

The VQ loss term \( L_{vq} \) should also be added:

\[
L_{vq} = \| z_q - \text{sg}[z_e] \|^2 + \beta \| z_e - \text{sg}[z_q] \|^2
\]

Step 3: Splitting and Decoding

EC\(^2\)VAE (Yang et al., 2019) inspires us to split \( z_q \) for various tasks:

\[
z_{qm} = z_q[0 : d_1], z_{qr} = \text{concat}(X_m, z_q[d_2 :])
\]

Task 1 uses dense classifier \( \hat{X}_m = D_m(z_{qm}) \) for meter classifying. Task 2 uses dense classifier \( \hat{X} = D_r(z_{qr}) \) with embedding layer for decoding. Loss terms for classification and reconstruction:

\[
L_c(\hat{X}_m) = \text{CE}(\hat{X}_m, X_m), \quad L_r(\hat{X}) = \text{CE}(\hat{X}, X)
\]

where \( \text{CE}(\cdot) \) is cross entropy loss function.

3.3 Several Results

Results are showed to analyze the capability of our model: to set word categories (3.3.1) and to consider word contexts (3.3.2, 3.3.3).

3.3.1 Embedding visualization

After 20000 training steps (learning details are in Appendix A), we extract the VQ codebook and
use t-SNE for visualization. Around 150 VQ latent vectors are visited after running the whole Nottingham Dataset. As shown in Figure 4: words in same meters tend to be clustered. Each point represents a $z_q$. Each $z_q$ may be mapped from multiple rhythm words. Only the prominent rhythm words’ meters are shown in Figure 4. Actually, the mapping between rhythm words and $z_q$ is complex. Details are shown in 3.3.3.

### 3.3.2 Attention Matrices

![Figure 5: Attention Matrix: Layer 2, Head 2, Piece 5](image)

Figure 5 shows visualization of several self-attention matrices. We found that our model learned to attention on repeating patterns. Figure 5 is nearly periodically symmetric, which shows that: with regular attention activations, BERT captured that this piece has a theme which repeats for 6 times. Similar results can be seen in appendix Figure 8. Moreover, we found that different heads and layers tend to attention on different words.

### 3.3.3 Track Word Mappings

A phenomenon worth noticing is that rhythm words in similar contexts are encoded into the same $z_q$, while a single rhythm word can be encoded into multiple $z_q$ in different contexts (Figure 6). For example, we tracked word N0.500,N1.000,N0.500,N1.000,N1.000|4/4 by running through the whole dataset, and found that it had been encoded into 7 different $z_q$, including codebook id 2311, 1649 etc. We then tracked $z_q[id = 2311]$ and found it had been mapped from multiple words, including N1.500,N0.500,N1.000,N1.000|4/4, N1.000,N1.000,N0.500,N1.500|4/4 etc. This indicates that rhythm BERT considered contextualized information. Moreover, the size of VQ codebook (around 150) is smaller than the input rhythm vocabulary size (470, controllers included). This indicates a lossy compression: fewer contextualized $z_q$ are enough to achieve high reconstruction accuracy. But this leads to confusion: if we use dense neural network as decoder\(^3\), each $z_q$ can only be decoded into one rhythm word under one meter condition. Besides, model’s understandings on word context are hard to interpret: for example, BERT’s choice between VQ id 2311 and 1649 is confusing in Figure 5.

### 4 Comments and Discussions

Motivated by music-as-language idea, we introduced a new way of representing rhythm. In this scheme, we can easily transfer NLP methods for music generation and MIR. With little training efforts, contextualized information can be integrated and rhythm words of same meter can be clustered in VQ codebooks. This gives a new way to do music pattern analysis. However, there are still tasks we have not finished. Sentence-prediction tasks should be designed for BERT, which may need phrase labeling. Polyphony is ignored in this paper; we have to consider vertical grammars in the future. Packing notes into words throws out note-level information: we have to focus on higher-hierarchy user cases, which may include music generation using rhythm words as conditions or music style classification. Further generative experiments will be tried. As for this current step, we give a start by showing how to pack music into words and how to think music as language. We hope they can provide hints for future algorithm composing studies.

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\(^3\)We did not use self-attention decoder or RNN decoder because we hope that a non-contextualized decoder will force the VQ codebook to have greater diversity.
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A Appendices

A.1 Training Tricks

A.1.1 Loss Functions

In Task 1 mentioned in section 3.2, total loss is $L_{task_1} = L_c + L_{vq}$; in Task 2, total loss $L_{task_2} = L_v + L_{vq}$.

A.1.2 Training Procedure

In each iteration, Task 1 and Task 2 are both considered. After experimental trials, we found that Task 1 converges faster than Task 2. In order to strike a balance between Task 1 and Task 2, we do backpropagation for Task 1 with probability of 0.05 during each iteration. If model gets too little $L_{task_1}$, it will not update parameters but will skip for more valuable data, which lead to larger losses.

Moreover, we noticed that Nottingham Database is unbalanced in meter. Pieces in 4/4 meter is more than pieces in 6/8 meter; other meters like 3/4, 9/8 and 6/4 are much less frequent. Thus, we predefined a sampling strategy: calculate the frequency of each meter $f(m) = N_m/N_{all}$. Accordingly, we get average frequency $f_{ave} = \frac{1}{M} \sum_m f(m)$. Then, use exponential function to amortize the sampling weights: $w_m = e^{x(-2f(m)/f_{ave})}$.

A.2 Details of Learning

Configurations are in Table 2. BLEU accuracy (Papineni et al., 2002) is used for sequence reconstruction evaluation. Within 20000 training steps with batch_size = 1, reconstruction BLEU accuracy can reach an average of around 0.8 if 20 percent of ground-truth words are covered. Learning curves are shown in Figure 7.

A.3 More Attention Matrices

Figure 8 shows more results of attention matrix layers. We can see that different layers attention on different repeating patterns. Pieces which do not have repeating patterns do not show periodic symmetry in attention matrix.
| Attribute                  | Value  |
|----------------------------|--------|
| batch size                 | 1      |
| total embed dim            | 64     |
| meter embed dim            | 16     |
| void embed dim             | 2      |
| reconstruction embed dim   | 46     |
| num layers                 | 6      |
| num heads                  | 8      |
| ffn dim                    | 1024   |
| dropout rate               | 0.5    |
| learning rate              | 0.0001 |
| training steps             | 20000  |

Table 2: Model configurations

Figure 7: Learning Curves

(a) Layer 3, Head 2, Piece ID 22
(b) Layer 2, Head 2, Piece ID 22
(c) Layer 2, Head 3, Piece ID 11

Figure 8: More Attention Matrices