Pop Music Transformer: Generating Music with Rhythm and Harmony

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Abstract

The task automatic music composition entails generative modeling of music in symbolic formats such as the musical scores. By serializing a score as a sequence of MIDI-like events, recent work has demonstrated that state-of-the-art sequence models with self-attention work nicely for this task, especially for composing music with long-range coherence. In this paper, we show that sequence models can do even better when we improve the way a musical score is converted into events. The new event set, dubbed “REMI” (REvamped MIDI-derived events), provides sequence models a metric context for modeling the rhythmic patterns of music, while allowing for local tempo changes. Moreover, it explicitly sets up a harmonic structure and makes chord progression controllable. It also facilitates coordinating different tracks of a musical piece, such as the piano, bass and drums. With this new approach, we build a Pop Music Transformer that composes Pop piano music with a more plausible rhythmic structure than prior arts do. The code, data and pre-trained model are publicly available.

1 Introduction

Music is sound that’s organized on purpose on many time and frequency levels to express different ideas and emotions. For example, the organization of musical notes of different fundamental frequencies (from low to high) influences the melody, harmony and texture of music. The placement of strong and weak beats over time, on the other hand, gives rise to the perception of rhythm [Martineau, 2008]. Repetition and long-term structure are also important factors that make a musical piece coherent and understandable.

Building machines that can compose music like human beings is one of the most exciting tasks in artificial intelligence. Among the approaches that have been studied, sequence models, which consider music as a language, stand out in recent work [Oore et al., 2018; Huang et al., 2019; Payne, 2019; Choi et al., 2019] as a prominent approach with great potential. In doing so, a digital representation of a musical score is converted into a time-ordered sequence of discrete tokens such as the NOTE-ON events. Sequence models such as the Transformer [Vaswani et al., 2017] can then be applied to model the probability distribution of the event sequences, and to sample from the distribution to generate music. This approach has been shown to generate minute-long compositions of various styles with compelling long-term structure [Huang et al., 2019; Donahue et al., 2019].

We note that there are two critical elements in the above-mentioned approach—the way music is converted into discrete tokens for language modeling, and the machine learning algorithm used to build the model. While we see great progress regarding the second element in recent work,² not much has been done for the first one. Most work simply follows the MIDI-like event representation proposed by [Oore et al., 2018] to set up the “vocabulary” for music.

As shown in Table 1, the MIDI-like representation, for the case of modeling classical piano music [Huang et al., 2019],

|                     | MIDI-like          | REMI                        |
|---------------------|--------------------|-----------------------------|
| Note onset          | NOTE-ON (0-127)    | NOTE-ON (0-127)             |
| Note offset         | NOTE-OFF (0-127)   | NOTE DURATION (32th note multiples) |
| Note velocity       | NOTE VELOCITY (32 bins) | NOTE VELOCITY (32 bins)    |
| Time grid           | TIME-SHIFT (10-1000ms) | POSITION (16 bins) & BAR (1) |
| Tempo changes       | ×                   | TEMPO (30-209 BPM)          |
| Chord               | ×                   | CHORD (60 types)            |

Table 1: A comparison of the commonly-used MIDI-like event representation with the proposed one, REMI. In the brackets, we show the corresponding ranges.

²For example, by improving the self-attention in Transformers with “sparse attention” [Child et al., 2019], or the techniques introduced in Transformer-XL (as done in [Donahue et al., 2019]).
uses \texttt{NOTE-ON} events to indicate the action of hitting a specific key of the piano keyboard, and \texttt{NOTE-OFF} for the release of the key. This representation has its roots in MIDI [Heckroth, 1998], a communication protocol that also uses \texttt{NOTE-ON} and \texttt{NOTE-OFF} messages to transmit data of real-time musical performance. Unlike \texttt{words} in human language, note messages in MIDI are associated with \textit{time}. To convert a score into a sequence, [Oore \textit{et al.}, 2018] uses additionally the \texttt{TIME-SHIFT} events to indicate the relative time gap between events (rather than the absolute time of the events), thereby representing the advance in the time axis.

While the MIDI-like representation works well for capturing the dependency of the pitch values of the musical notes, we argue below that it has inherent limits for modeling the rhythmic structure of music. When humans compose music, we tend to organize regularly recurring patterns and accents over a metrical structure defined in terms of bars, beats, and sub-beats [Cooper \textit{et al.}, 1963]. Such a structure is made clear on a score sheet or a MIDI file with notation of the time signature and vertical bar lines. However, such information is not obvious, if not lost, in the MIDI-like event representation. A sequence model has to recover the metrical structure on its own from the provided sequence of tokens, which is not an easy job as exemplified in Figure 1a.

To remedy this, we propose \texttt{REMI}, which stands for \texttt{RE-}vamped MIDI-derived events, to represent musical scores following the way humans read them. Specifically, we introduce the \texttt{BAR} event to indicate the beginning of a bar, and the \texttt{POSITION} events to point to certain locations within a bar. For example, \texttt{POSITION (9/16)} indicates that we are pointing to the middle of a bar, which is quantized to 16 regions in this implementation. The combination of \texttt{POSITION} and \texttt{BAR} therefore provides an explicit metrical grid to model music.

Moreover, we further explore adding other supportive musical tokens. To model the expressive rhythmic freedom in music (e.g., tempo rubato), we add a set of \texttt{TEMPO} events to allow for local tempo changes per beat. To have control over the chord progression underlying the music being composed, we introduce the \texttt{CHORD} events to make the harmonic structure of music explicit.

Table 1 compares REMI with the MIDI-like representation. Figure 2 gives an example of a REMI event sequence.

To validate the effectiveness of REMI for modeling musical genres that feature strong rhythmic structures, we use Transformer-XL [Dai \textit{et al.}, 2019] as the sequence model to learn to compose piano music in the style of Pop. We use different event representations to convert transcribed scores of Pop piano music into discrete tokens, and compare the music composed by the resulting models via objective and subjective studies. Our evaluation shows that our approach is preferred over variants of the state-of-the-art Music Transformer model [Huang \textit{et al.}, 2019] for music composition.

2 Related Work

Recent neural network-based approaches for automatic music composition can be broadly categorized into two groups. \texttt{Image-based} approaches such as MidiNet [Yang \textit{et al.}, 2017] and MuseGAN [Dong \textit{et al.}, 2018] use an image-like representation such as the piano roll to represent a score as a matrix of time steps and MIDI pitches, and then use convolution-based operations to generate music. It is convenient for such approaches to learn the rhythmic structure of music (as shown by [Dong \textit{et al.}, 2018] for example), as the beats are always same time steps apart in such matrices. \texttt{Language-based} approaches such as the Music Transformer [Huang \textit{et al.}, 2019], on the other hand, learn the dependency between pitches and the long term structure of music better. Yet, due to the limits of the MIDI-like representation, existing work may fall short in the rhythmic aspect. The proposed approach combines the advantage of the image- and language-based approaches by embedding a metrical grid in the event representation.

The idea of designing events for music metadata is similar to CTRL [Keskar \textit{et al.}, 2019], which provided more explicit controls for text generation. However, recent work in neural sequence modeling of music mostly adopt the same MIDI-like event representation proposed by [Oore \textit{et al.}, 2018], or its extensions. For example, extra events denoting the composer, instrumentation and global tempo are used in MuseNet [Payne, 2019] for conditioned generation, and events specifying the \texttt{NOTE-ON} and \texttt{NOTE-OFF} of different instruments are used to achieve multi-instrument music composition in LakhNES [Donahue \textit{et al.}, 2019]. However, to our best knowledge, the use of \texttt{NOTE-OFF} and \texttt{TIME-SHIFT} has not been challenged thus far.
3 New Event-based Representation of Music

In this section, we discuss at length how ‘REMI’ is different from the commonly-adopted ‘MIDI-like’ representation (cf. Table 1), and how we design the proposed events.

As noted in [Oore et al., 2018], a score to be converted into events can be either a MIDI score with no expressive dynamics and timing, or a MIDI performance that has been converted from an expressive audio recording by means such as a MIDI keyboard, or automatic music transcription [Bentos et al., 2018]. Without loss of generality, we assume that we are given scores of the latter case below.

3.1 Note-On and Note Velocity

The collection of 128 Note-On events indicates the onset of MIDI pitches from 0 (C–1) to 127 (G9), and Note Velocity indicates the dynamics (which correspond to perceptual loudness) of the note event. Following [Oore et al., 2018], we quantize note velocity into 32 levels, giving rise to 32 different Note Velocity events. Both the MIDI-like and REMI representations have these two types of events.

3.2 Note-Off versus Note Duration

In REMI, we use Note Duration events in replacement of the Note-Off events. Specifically, each represent each note in a given score with the following three consecutive tokens: a Note Velocity event, a Note-On event, and a Note Duration event. There are advantages in doing so:

- In MIDI-like, the duration of a note has to be inferred from the time gap between a Note-On and the corresponding Note-Off, by accumulating the Time Shift events in between. In REMI, note duration is made explicit, facilitating modeling the rhythm of notes.
- In MIDI-like, a Note-On event and the corresponding Note-Off are usually several events apart. For example, in our implementation (cf. Section 6.1), there are on average 21.7±15.3 events between an onset-offset pair. As a result, our sequence model finds difficulty learning that Note-On and Note-Off must appear in pairs, generating many dangling Note-On events without the corresponding Note-Off. We would then have to use some heuristics (e.g., maximal note duration) to turn off a note in post-processing. REMI is free of such an issue.

3.3 Time-Shift versus Position & Bar

We find that it is not easy for a model to generate music with steady beats with the Time-Shift events. When listening to the music generated, the intended bar lines drift over time and the rhythm feels unstable. We attribute this to the absence of a metrical structure in the MIDI-like representation. Mistakes in Time-Shift would lead to accumulative error of timing in the inference phase, which is not obvious in the training phase due to the common use of teacher forcing strategy [Doya, 1992] in training recurrent models.

To address this issue, we propose to use the combination of BAR and POSITION events instead. Both of them are readily available from the musical scores; they are simply discarded in the MIDI-like representation. While BAR marks the bar lines, POSITION points to different discrete locations in a bar. Adding them provides a metrical context for models to “count the beats” and to compose music bar-after-bar. We find in our implementation that models learn the meaning of BAR and POSITION quickly—right after a few epochs the model knows that, for example, POSITION (9/16) cannot go before POSITION (3/16), unless there is a BAR in between.

We consider 4/4 time signature only in our implementation (i.e., a bar is composed of four beats) and quantize each bar into 16 intervals, yielding 16 POSITION events.

There are many additional benefits in using POSITION & BAR. To name a few: 1) we can more easily learn the dependency (e.g., repetition) of note events occurring at the same POSITION (+/16) across bars; 2) if we want, we can add bar-level conditions to condition the generation process; 3) we have time reference to coordinate the generation of different tracks for the case of multi-instrument music.

3.4 Tempo

In an expressive musical performance, the temporal length (in seconds) of each bar may not be the same. To account for such local changes in tempo (i.e., beats per minute; BPM), we add TEMPO events every beat (i.e., at POSITION (1/16), POSITION (5/16), etc). In this way, we have a flexible time grid for expressive rhythm.

In the current implementation we use a combination of TEMPO CLASS events (low, mid, high) and TEMPO VALUE events to represent local tempo values ranging from 30 to 209 BPM. See Figure 2 for an example.

3.5 Chord

As another set of supportive musical tokens, we propose to encode the chord information into input events. Specifically, chords are defined as any harmonic set of pitches consisting of multiple notes sounding together or one after another. A chord consists of a root note and a chord quality [McFee and Bello, 2017]. In our implementation, we consider 12 chord roots (C, C♯, D, D♯, E, E♯, F, F♯, G, G♯, A, A♯, B) and five chord qualities (major, minor, diminished, augmented, dominant), leading to 60 possible CHORD events. We note that the CHORD events are just “symbols”—the actual notes are still generated with the NOTE-ON events after them.

Following the time grid of REMI, each TEMPO or CHORD event is preceded by a POSITION event.

Music composed by a model using the MIDI-like representation also exhibit the use of chords, as such note combinations can be found in the training data. However, by explicitly generating TEMPO and CHORD events, tempo and chord become controllable, as Section 6.4 will demonstrate.

4 Backbone Sequence Model

The Transformer [Vaswani et al., 2017] is a neural network-based sequence model that uses self-attention to bias its prediction of the current token based on a subset of the past tokens. This design has been shown effective for modeling the long-term structure in music. For example, with the help of a relative positional encoding method [Shaw et al., 2018], Music Transformer [Huang et al., 2019] can compose compelling minute-long classical piano music.
Transformer-XL [Dai et al., 2019] extends Transformer by introducing the notion of recurrence and revising the positional encoding scheme. The recurrence mechanism enables the model to leverage the information of past tokens beyond the current training segment. Theoretically, Transformer-XL can encode arbitrarily long context into a fixed-length representation. Therefore, we adopt Transformer-XL as the backbone model architecture in this study.3

5 Dataset

We intend to evaluate the effectiveness of the proposed approach by building a Pop Music Transformer. In doing so, we collect audio files of Pop piano music from the Internet. A total number of 775 pieces of piano music played by different people is collected, amounting to approximately 48 hours’ worth of data. They are covers of various Japanese anime, Korean popular and Western popular songs, playing only with the piano. We then apply “Onsets and Frames” [Hawthorne et al., 2018], the state-of-the-art approach for automatic piano transcription, to estimate the pitch, onset time, offset time and velocity of the musical notes of each song, converting the audio recordings into MIDI performances.

To create the BAR events, we employ the recurrent neural network model proposed by [Böck et al., 2016] to estimate from the audio files the position of the ‘downbeats,’ which correspond to the first beat in each bar. The same model is used to track the beat positions to create the TEMPO events. We obtain the tick positions between beats by linear interpolation, and then align the note onsets and offsets to the nearest tick. To eliminate the imprecision of transcription result, we further quantize the onset and offset times to the 16th note, a commonly-adopted note interval in recent work on automatic music composition (e.g., [Roberts et al., 2018]).

We establish the CHORD events by applying the following heuristic rule-based chord recognition algorithm to the transcribed MIDI files. First, we compute binary-valued “chroma features” [Fujishima, 1999] for each tick, to represent the activity of 12 different pitch classes ignoring the pitch’s octave. Then, we use a sliding window to assign “likelihood scores” to every active note for each 2-beat and 4-beat segment. After summarizing the chroma features of the current segment, we consider every note in a segment as a candidate root note of the CHORD of that segment, and calculate its pitch intervals to all the other notes in that segment. The look-up table shown in Table 2 is employed to assign likelihood scores to a pair of root note and chord quality based on the pitch intervals. Each chord quality has its required set of pitch intervals, and scoring functions. Finally, we recursively label the segments by the CHORD symbol with the highest likelihood score.

Due to copyright restrictions, we plan to make the training data publicly available not as audio files but as the transcribed MIDI files and the converted REMI event sequences.

Table 2: Rule-based scoring criteria for detecting chords via pitch intervals in the chromatic scale, using to establish the CHORD events.

| Chord       | Required | Gain 1 point | Deduct 1 point | Deduct 2 points |
|-------------|----------|--------------|----------------|-----------------|
| Major       | 0, 4     | 7            | 2, 5, 9        | 1, 3, 6, 8, 10  |
| Minor       | 0, 3     | 7            | 2, 5, 8        | 1, 4, 6, 9, 11  |
| Diminished  | 0, 3, 6  | 9            | 2, 5, 10       | 1, 4, 7, 8, 11  |
| Augmented   | 0, 4, 8  | -            | 2, 5, 9        | 1, 3, 6, 7, 10  |
| Dominant    | 0, 4, 7  | 10           | 2, 5, 9        | 1, 3, 6, 8, 11  |

Figure 3: Average cross-entropy loss for different types of events as a function of the training epochs; best viewed in color.

6 Evaluation

6.1 Baselines & Model Settings

We consider three variants of the Music Transformer [Huang et al., 2019] as the baselines in our evaluation. The first one, dubbed Baseline 1, follows fairly faithfully the model settings of [Huang et al., 2019], except that we use Transformer-XL instead of Transformer. The other two differ from the first one only in the adopted event representation. While Baseline 1 employs exactly the MIDI-like representation, Baseline 2 replaces NOTE-OFF by NOTE DURATION, and Baseline 3 further modifies the time steps taken in TIME-SHIFT from multiples of 10ms to multiples of the 16th note. In this way, Baseline 3 has a time grid similar to that of REMI, making Baseline 3 a strong baseline.

For either the baselines or the proposed model adopting the REMI representation, we train Transformer-XL with 12 self-attention layers and 8 attention heads. The length of the training input events and the recurrence length are both set to 512. The total number of learnable parameters is ~41M. Training a model with an NVIDIA V100 with mini-batch size of 16 till the training loss (i.e., cross-entropy) reaches a certain level takes about 9 hours. We find that Baseline 1 needs a smaller learning rate and hence longer training time. And,
Table 3: Quantitative comparison of different models for Pop piano generation, evaluating how the generated music exhibit rhythmic structures. We report the average result across songs here. For all the three objective metrics (cf. Section 6.2), the values are the closer to those of the ‘Real data’ (i.e., 775 Pop songs) shown in the last row the better. ‘Baseline 1’ represents a Transformer-XL version of the Music Transformer, adopting a MIDI-like event representation. The other two baselines are its improved variants.

| Method | Note offset | Time grid | TEMPO | CHORD | Beat STD | Downbeat STD | Downbeat salience |
|--------|-------------|-----------|-------|-------|----------|--------------|------------------|
| Baseline 1 | NOTE-OFF | TIME-SHIFT (10-1000ms) | | | 0.0968 | 0.3561 | 0.1033 |
| Baseline 2 | DURATION | TIME-SHIFT (10-1000ms) | | | 0.0394 | 0.1372 | 0.1651 |
| Baseline 3 | DURATION | TIME-SHIFT (16th-note multiples) | | | 0.0396 | 0.1383 | 0.1702 |
| REMI | DURATION | POSITION & BAR | ✓ | ✓ | 0.0386 | 0.1376 | 0.2279 |
| REMI | DURATION | POSITION & BAR | ✓ | | 0.0363 | 0.1265 | 0.1936 |
| REMI | DURATION | POSITION & BAR | | ✓ | 0.0292 | 0.0932 | 0.1742 |
| REMI | DURATION | POSITION & BAR | | | 0.0199 | 0.0595 | 0.1880 |
| Real data | | | | | 0.0607 | 0.2163 | 0.2055 |

Figure 4: Examples of the generated piano rolls of different models. These are 12 bars generated to continue a given prompt of human-made 4 bars. We show the result for 3 different prompts (from left to right). The thicker vertical lines indicate the bar lines; best viewed in color.

6.2 Objective Evaluation

For evaluation, we employ each model to randomly generate 1,000 scores, each with 4,096 events, using the temperature-controlled stochastic sampling method with top-k [Keskar et al., 2019]. We render the generated scores into audio recordings via a digital audio workstation (DAW), and then we apply the joint beat and downbeat tracking model of [Böck et al., 2016] to the audio recordings. From the tracking results, we calculate the following three values for each recording:

- **Beat STD**: the standard deviation of the beat length.
- **Downbeat STD**: the STD of the bar length (i.e., the time interval between consecutive downbeats). Beat STD and downbeat STD assess the consistency of the rhythm.
- **Downbeat salience**: the average probability of the estimated downbeats, indicating the salience of the rhythm.

We also calculate the values of these metrics from the training data and assume that the values of the machine models are the closer to those of the real data the better.

The model [Böck et al., 2016] has two components. The first one estimates the probability of observing beats and downbeats for each time frame via a recurrent neural network (RNN). The second one applies a dynamic Bayesian network (DBN) to the output of the RNN to make binary decisions of the occurrence of beats and downbeats. We use the output of the RNN to calculate the downbeat salience, and the output of the DBN for the beat STD and downbeat STD. We choose to use the model of [Böck et al., 2016] for it achieved state-of-the-art performance for beat and downbeat tracking for a variety of musical genres, especially for Pop music.

Tables 3 shows the result of the baselines and a few variants (ablated versions) of the REMI-based model. From Beat STD and Downbeat STD, we see that the result of Baseline 1, which resembles Music Transformer [Huang et al., 2019], features fairly inconsistent rhythm, echoing the example shown in Figure 1a. The STD is lower when note duration is used in place of note-off, highlighting the

we find tricks such as adaptive embedding [Dai et al., 2019] and gradient checkpointing [Child et al., 2019] not helpful.

Figure 3 shows the training loss of different event types as the training evolves. Figure 3a shows that Baseline 1 struggles the most for learning Time-Shift. Moreover, Note-Off has higher loss than Note-On, suggesting that they are not recognized as event pairs. In contrast, Figure 3b shows that the Position events in REMI are easy to learn, facilitating learning the rhythm of music.\(^5\)

\(^5\) According to [Hawthorne et al., 2018; Kim and Bello, 2019], piano transcription models do better in estimating note onsets and pitches, than offsets and velocities. This may be why our model has higher loss for Note Duration and Note Velocity.

\(^6\) To be clear, the same number of events does not mean the same length of music, which is affected by the note density.
Table 4: The average scores for the subjective preference test on a three-point scale from 1 (like the least) to 3 (like the most).

| Pairs            | Wins | Losses | p-value |
|------------------|------|--------|---------|
| REMI Baseline 1  | 103  | 49     | 5.623e-5 |
| REMI Baseline 3  | 92   | 60     | 0.0187  |
| Baseline 3 Baseline 1 | 90  | 62     | 0.0440  |

Table 5: The result of pairwise comparison from the user study, with the p-value of the Wilcoxon signed-rank test.

effect of **NOTE DURATION** in stabilizing the rhythm. Interestingly, we see that the REMI models without the TEMPO events have much lower STD than the real data, suggesting that TEMPO is important for expressive rhythm.

From downbeat salience, the REMI models outnumber all the baselines, suggesting the effectiveness of **POSITION & BAR**. Moreover, the gap between the result of Baseline 1 and Baseline 2 further supports the use of **NOTE DURATION**.

### 6.3 Subjective Evaluation

The best way to evaluate a music composition model might be via a listening test. To have a common ground to compare different models, we ask the models to **continue** the same given prompt. For doing so, we prepare an additional set of 100 Pop piano music (that have no overlaps with the training set) following the procedure described in Section 5, and take the first four bars from each of them as the prompts. The following three models are asked to generate 16 bars continuing each prompt, and got evaluated in an online listening test: ‘Baseline 1,’ ‘Baseline 3’ and ‘REMI without CHORD.’ We do not use CHORD here to make the rhythmic aspect the major point of difference among the models.

We distribute the listening test over our social circles globally and solicit the response from 76 participants. 51 of them understand basic music theory and have the experience of being an amateur musician, so we consider them as professionals (denoted as ‘pros’). A participant has to listen to two randomly picked sets of samples and evaluate, for each set, which sample they like the most and the least, in any evaluation criteria of their choice. Each set contains the result of the three models (in random order) for a given prompt.

Table 4 shows the aggregated scores, and Table 5 the result of broken-down pairwise comparisons, along with the p-value of the Wilcoxon signed-rank test. We see that REMI is preferred by both pros and non-pros, and that the difference between REMI and Baseline 1 is significant ($p < 0.01$).

Figure 4 provides examples of the generated continuations. From the verbal feedbacks of the participants, the music generated by REMI are perceptually more pleasing and are more in line with the prompt. From the verbal feedbacks of the participants, the music generated by REMI are perceptually more pleasing and are more in line with the prompt.

Finally, we demonstrate the controllability of TEMPO and CHORD of our model. To achieve this, we can simply force the model not to generate specific events by masking out the corresponding probabilities of the model output. Figure 5 shows the piano rolls, (optionally) the TEMPO and CHORD events generated by our model under different conditions. Figure 5b shows that the model selects chords that are harmonically close to F:minor when we prohibit it from generating F:minor. Figure 5c shows controlling the TEMPO CLASS affects not only the TEMPO VALUE but also the note events.

### 6.4 Controllable CHORD and TEMPO

Finally, we demonstrate the controllability of TEMPO and CHORD of our model. To achieve this, we can simply force the model not to generate specific events by masking out the corresponding probabilities of the model output. Figure 5 shows the piano rolls, (optionally) the TEMPO and CHORD events generated by our model under different conditions. Figure 5b shows that the model selects chords that are harmonically close to F:minor when we prohibit it from generating F:minor. Figure 5c shows controlling the TEMPO CLASS affects not only the TEMPO VALUE but also the note events.

### 7 Conclusion

In this paper, we have presented REMI, a novel MIDI-derived event set for sequence model-based music composition. We have also built a Pop Music Transformer that can generate minute-long popular piano music with expressive, coherent and clear structure of rhythm and harmony, without needing any post-processing to refine the result. We proposed objective metrics to quantify the rhythmic consistency and salience of the composed music. And, we showed that our model is preferred over the Music Transformer [Huang et al., 2019] through a listening test. For future work, we plan to incorporate other supportive messages such as grooving [Frühaut et al., 2020].
al., 2013] and musical emotion [Yang and Chen, 2011], and to compose additional tracks such as the bass and drums.

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