Structure-Enhanced Pop Music Generation via Harmony-Aware Learning

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ABSTRACT

Pop music generation has always been an attractive topic for both musicians and scientists for a long time. However, automatically composing pop music with a satisfactory structure is still a challenging issue. In this paper, we propose to leverage harmony-aware learning for structure-enhanced pop music generation. On the one hand, one of the participants of harmony, chord, represents the harmonic set of multiple notes, which is integrated closely with the spatial structure of music, the texture. On the other hand, the other participant of harmony, chord progression, usually accompanies the development of the music, which promotes the temporal structure of music, the *form*. Moreover, when chords evolve into chord progression, the texture and form can be bridged by the harmony naturally, which contributes to the joint learning of the two structures. Furthermore, we propose the Harmony-Aware Hierarchical Music Transformer (HAT), which can exploit the structure adaptively from the music, and make the musical tokens interact hierarchically to enhance the structure in multi-level musical elements. Experimental results reveal that compared to the existing methods, HAT owns a much better understanding of the structure and it can also improve the quality of generated music, especially in the *form* and *texture*. ¹

CCS CONCEPTS

Applied computing → Sound and music computing.

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KEYWORDS

algorithmic composition, music generation, structure, hierarchy, transformer

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1 INTRODUCTION

Composing music by computational means (also known as *algorithmic composition* or *automatic music generation*) is a longstanding human desire to explore the frontiers of computational creativity [3]. As an essential attribute to music, *structure* is inherently tied to human perception and cognition [2, 27], but is hard for the computer to recognize and identify [19, 21]. Moreover, automatically composing a music with balanced, coherent, and integrated structure is an attractive, such as the early researches tens of years ago [5, 26], but still challenging issue [1, 9].

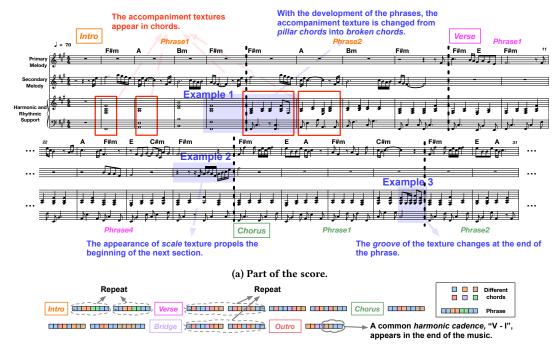
In musicology, usually we can analyze the *structure* from two aspects, *form* and *texture*. Horizontally, *form* reveals the temporal relationship and dependency among the music, such as the repetition of motives, the transition between phrases, and the development between sections [34]. Vertically, *texture* represents the spatial relationship and the organized way between the multiple parts or instruments of music [36]. For example, the typical *texture* of pop music is that the melody stands out prominently and the others form a background of harmonic accompaniment, i.e. *homophony* [33].

Overall, the characteristics of the musical structure lie in the three aspects: (1) Firstly, the structure depends largely on the musical context and is hard to be described clearly and defined accurately [19]. (2) Secondly, the structure exists in various musical elements and appears the hierarchy, ranging from the low-level motif to the high-level phrase and section [7]. (3) Thirdly, the form and the texture are connected closely and support to each other. Specifically, it is common in pop music that the texture is consistent within a specific phrase or section, while is changed with the development of the form. For example, in Figure 1a, the accompaniment texture is pillar chords in the first phrase of the intro, while is changed into broken chords in the second phrase (as the blue

^{*}This work was accomplished when Xueyao Zhang and Li Wang worked as interns at Pattern Recognition Center, WeChat AI, Tencent Inc.

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¹The code and generated pieces are available at https://github.com/RMSnow/HAT.



(b) The chord progressions of each phrases within the sections.

Figure 1: A motivating example: the Chinese pop song, Yi Jian Mei. It reveals that: (1) The chord is integrated closely with the texture structure (see the red blocks of Figure 1a); (2) The chord progression accompanies with the formation of the form structure (Figure 1b); (3) There is a highly mutual dependency between the texture and the form (see the blue blocks of Figure 1a).

solid block "Example 1" shows). The mutual dependency can be also observed in "Example 2" and "Example 3".

Therefore, a model aiming to produce well-structured music should meet the three corresponding requirements:

- R1: It should mine the contextual pattern of structure from the music data adaptively.
- **R2**: It should exploit the appropriate musical elements to represent structure units.
- R3: It should capture the highly mutual dependency between form and texture.

Based on the aforementioned requirements, we propose to leverage harmony-aware learning for structure-enhanced pop music generation. In musicology, the study of harmony involves chords and their construction, and chord progressions and the principles of connection that govern them [8]. The reasons to learn harmony are that for R1, harmony represents the consonance of the musical context, so we can mine the musical contextual information by learning it. For R2, not only harmony itself is an important structure element, but also it combines the many musical elements organically, from the low-level notes to the high-level phrase and sections. Specifically, one of the participants of harmony, chord, represents the harmonic set of multiple notes, which is integrated closely with the texture. As the red hollow blocks in Figure 1a show, the accompaniment textures always appear in chords. Besides, the other participant, chord progression, usually promotes the development of the music, contributing to the formation of the form (such

as the *harmonic cadences* [24] in Figure 1b). Moreover, for **R3**, we can model the evolution from *chord* to *chord progression* to bridge between *texture* and *form*, which reveals the feasibility to the joint learning of the two structures.

In the paper, our contributions are summarized as follows:

- We propose to learn the musical prior knowledge, harmony, for structure-enhanced pop music generation. To the best of our knowledge, our work is the first to learn form and texture jointly bridged by harmony in algorithmic composition.
- We design an end-to-end model, <u>H</u>armony-<u>A</u>ware Hierarchical Music <u>T</u>ransformer (HAT), to produce well-structured pop music. It can model the musical structure by rendering musical elements interact at the hierarchical levels.
- We develop two objective metrics for evaluating the *structure*of music from the perspective of the *harmony*.
- Experimental results verify the effectiveness of HAT on both music understanding and generation, especially in the *form* and *texture*.

2 RELATED WORK

2.1 Structure-Enhanced Music Generation

Improving the quality of the musical *structure* is always the focus in music generation. Because of the difficulty of modeling structure, some researchers deal with the task in pipelines with multiple models [6, 11, 37], like designing a single model to modulate the structure and the others to generate the music based on it. For the

end-to-end methods, quite a few researchers consider the structure at only high-level like *section*, and still use templated- or rule-based methods. For example, Zhou et al. use a predefined *section* sequence, such as "AABA", to generate a structured music [40]. And others utilize the *chord progressions* as the constraint rules, making them as explicit input to generate structure-enhanced music [4, 31, 41].

As for the end-to-end generators mining the structure adaptively, in StructureNet [18], the authors leverage the RNN to exploit the structural repeat in the music. However, the definition of structure in [18] is simple (just two types of repeat), and the StructureNet focuses on producing the monophony music, whose texture is only a single melodic line. In MusicVAE [25] and TransformerVAE [15], the authors aim to mine the structure dependency between the bars. However, bar as a structure unit is not flexible, compared to other elements such as motif, phrase or section. Besides, the generators of the two are not capable of producing the song-length music. In Music Transformer [13], the researchers introduce the relative attention to model the position relationships between the *notes*, hoping to learn the long-term structure at the *note* level. However, it lacks the explicit modeling for more abstract structure including the transition and the development of phrases and sections. Recently, the designs of most advanced generation models are Transformerarchitecture [12, 14, 39]. Most of them leverage the self ability of the Transformer to learn the long-term dependency, but there is almost none explicit modeling for the structure-enhanced generation.

2.2 Harmony Learning

In the field of music representation learning, there are researches aiming to learn the representation of the harmony [30, 32]. Nevertheless, these works focus more on representation learning than producing well-structured music pieces. Moreover, the generators of these works are designed to learn just several *bars* of music, but hard to handle the *song-length* music.

In a word, for structure-enhanced pop music generation, our proposed HAT is the first end-to-end generator that learns *form* and *texture* jointly bridged by *harmony* to the best of our knowledge.

3 METHODOLOGY

3.1 Overview

In the paper, we propose the Harmony-Aware Hierarchical Music Transformer (HAT) for structure-enhanced pop music generation (Figure 2). Firstly, we adopt the event-based tokenization to represent the symbolic music data as input (Figure 2a). Subsequently, we utilize the three Transformer-based [28] blocks (Song Transformer, Texture Transformer, and Form Transformer) to make the tokens interact at the hierarchical levels (Figure 2b).

Aiming to capture the mutual dependency between *form* and *texture*, we design the hierarchical structure-enhanced mechanisms (Hierarchical Structure-Enhanced Module, HSE) in particular (Figure 2b). As is described in Section 1, usually the *textures* **stay within** *phrases*, but **change on their boundaries**. To model this characteristic, therefore, firstly we group the chord tokens within every phrase, which means the chord progression of the current phrase, and use Texture Transformer to learn the *local texture*. Then we input the texture of every phrase's last chord into Form Transformer to learn the *global form*.

The workflow of HAT is as follows. During training:

- (1) The bottom Song Transformer handles all the musical tokens.
- (2) The HSE module treat chords and phrases as the special structure indicators and update their representations.
- (3) The top Song Transformer make all the tokens interact again, which can broadcast the explored information of structure to the multi-grained elements.
- (4) Do the predictions by the structure-enhanced tokens.

During the generation, the HAT can produce pieces from scratch or with the guidance of the specific prompts.

3.2 Music Tokenization

In order to represent the symbolic music, we adopt the event-based tokenization (Figure 2a). It can serialize the multi-type musical information into a sequence of one-hot encoded events [22], which is applied broadly for music generation [12–14].

Table 1: Nine events in music tokenization.

Level	Event	Description		
Token type	Type	The type of the token		
Metrical	Bar Beat Tempo	The bar position of the token The beat position in a bar of the token The tempo of the token		
Structure	Phrase Chord	The phrase that the token belongs with The chord that the token belongs with		
Note	Track Pitch Duraion	The track (or the instrument) of the token The pitch of the token The duration time of the token		

We employ an nine-event set C (Table 1).² Specially, it contains two structure-level events, Phrase and Chord, which will be the structure-enhanced indicators in HAT.

Given the music $\mathcal{M} = [t_1, t_2, ..., t_L]$, where t_i is the i^{th} token and L is the length of the music. For the token t_i , we embed its each event values and concatenate them to obtain E_{t_i} :

$$E_{t_i} = \mathbf{Concat}([\mathbf{Emb}_c(t_i^c), \text{ for every } c \in C]),$$
 (1)

where **Concat** means the concatenation, t_i^c is the value of t_i on the category c, and $\mathbf{Emb}_c(\cdot)$ is the embedding layer for the category c.

3.3 Bottom Song Transformer

To make all the tokens aware of the global musical contexts, we make them interact at the song-level transformer block, the bottom Song Transformer (Figure 2b).

The architecture of Song Transformer is the same as the original Transformer [28], except that it is implemented to be autoregressive. Besides, we use the triangular mask strategy of the Transformer Decoder [28] to guarantee the token at position i can depend only on the tokens at positions less than i.

²In this paper, we focus on producing the *symbolic* music, so we leave the *performance* musical attributes like "velocity" for the future research, i.e. *performance* generation.

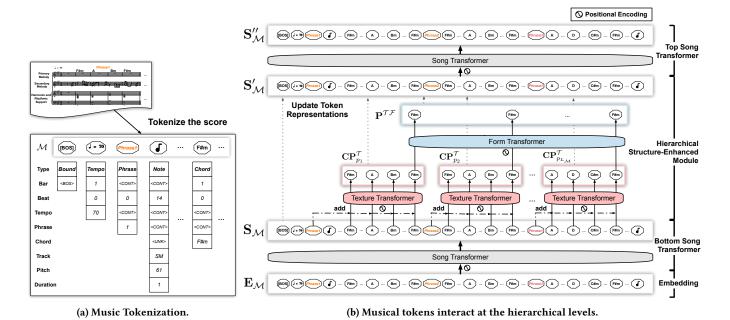


Figure 2: The architecture of Harmony-Aware Hierarchical Music Transformer (HAT). Firstly, we tokenize the symbolic music, where every token is mapped to nine events (Figure 2a). Then, we use the bottom Song Transformer, the Hierarchical Structure-Enhanced Module, and the top Song Transformer to obtain the structure-enhanced tokens (Figure 2b).

Given the tokenized representation $\mathbf{E}_{\mathcal{M}} = [\mathbf{E}_{t_0}, \mathbf{E}_{t_1}, ..., \mathbf{E}_{t_L}]$, we get the updated representation after the bottom Song Transformer, notating $\mathbf{S}_{\mathcal{M}} = [\mathbf{S}_{t_1}, \mathbf{S}_{t_2}, ..., \mathbf{S}_{t_L}] \in \mathbb{R}^{L \times D_S}$, where D_S is the embedding dimension of Song Transformer:

$$S_{\mathcal{M}} = Transformer(PosEnc(E_{\mathcal{M}})),$$
 (2)

where $\mathbf{PosEnc}(\cdot)$ means the input is added by the sinusoidal position embeddings of Transformer [28].

3.4 Hierarchical Structure-Enhanced Module

As is mentioned in Section 3.1, the HSE module (Figure 2b) is designed for learning the mutual dependency between *form* and *texture*. Specifically, we enhance the attention of *chord* and *phrase* tokens in a hierarchical way in this module.

3.4.1 Texture Transformer. Firstly, we group the chord tokens within every phrase, which means the chord progression of the phrase, and use Texture Transformer to learn the local texture. The architecture of Texture Transformer is the same as the Song Transformer, except for the hyperparameters such as the number of layers or the number of heads.

Given the chord progression of the phrase p_i , notating $\mathrm{CP}_{p_i} = [\mathrm{S}_{p_i^1}, \mathrm{S}_{p_i^2}, ..., \mathrm{S}_{p_i^{L_{p_i}}}] \in \mathbb{R}^{L_{p_i} \times D_S}$, where L_{p_i} is the number of chords of the phrase p_i , we can obtain the texture-enhanced chords representation after the Texture Transformer, $\mathrm{CP}_{p_i}^{\mathcal{T}} = [\mathrm{T}_{p_i^1}, \mathrm{T}_{p_i^2}, ..., \mathrm{T}_{p_i^{L_{p_i}}}]$:

$$CP_{p_i}^{\mathcal{T}} = \mathbf{Transformer}(\mathbf{PosEnc}(S_{p_i} + CP_{p_i})).$$
 (3)

In Equation 3, we add the phrase p_i 's representation S_{p_i} into the chord progression CP_{p_i} before the Texture Transformer, aiming

to fuse the *form*'s dependency when learning *texture*. For the local texture of every phrase, \mathbf{T}_{p_i} , we use the last chord of the phrase to represent the local texture, i.e., $\mathbf{T}_{p_i} = \mathbf{T}_{p_i^{L_{p_i}}}$. And we can get the phrases' texture representation, $\mathbf{P}^{\mathcal{T}} = [\mathbf{T}_{p_1}, \mathbf{T}_{p_2}, ..., \mathbf{T}_{p_{L_M}}] \in \mathbb{R}^{L_M \times D_S}$, where L_M is the phrases num of the music \mathcal{M} .

3.4.2 Form Transformer. Next, we aim to learn the global form from the local phrase *texture* by Form Transformer. Like Texture Transformer, the architecture of Form Transformer is also homogeneous with the Song Transformer.

Given the phrases' texture representation $P^{\mathcal{T}}$, we obtain the form-enhanced representation after the Form Transformer, $P^{\mathcal{TF}} = [\mathrm{TF}_{p_1}, \mathrm{TF}_{p_2}, ..., \mathrm{TF}_{p_{L_{\mathcal{M}}}}] \in \mathbb{R}^{L_{\mathcal{M}} \times D_S}$:

$$P^{TF} = Transformer(PosEnc(P^T)). \tag{4}$$

3.4.3 Update Tokens Representations. Finally, we update the chord and phrase tokens, which merges the raw representation with the learned texture-enhanced and form-enhanced representation. Specifically, for the phrase tokens (except the first phrase), we add them with the previous both texture and form context information:

$$\mathbf{S}'_{p_i} = \begin{cases} \mathbf{S}_{p_i} & i = 1, \\ \mathbf{TF}_{p_{i-1}} + \mathbf{S}_{p_i} & otherwise. \end{cases}$$
 (5)

For the *chord* tokens, we enhance them with their *form* context information. Besides, we also add them with the previous *texture* of their *chord progression* context information (except the first chord of every phrase). Namely, for every $i \in [1, 2, ..., L_M]$,

$$\mathbf{S}_{p_{i}^{j}}^{\prime} = \begin{cases} \mathbf{S}_{p_{i}}^{\prime} + \mathbf{S}_{p_{i}^{j}} & j = 1, \\ \mathbf{S}_{p_{i}}^{\prime} + \mathbf{T}_{p_{i}^{j-1}} + \mathbf{S}_{p_{i}^{j}} & otherwise. \end{cases}$$
(6)

We leave the other tokens representations unchanged, and obtain the music tokenize representation $S_{\mathcal{M}}' = [S_{t_1}', S_{t_2}', ..., S_{t_L}'] \in \mathbb{R}^{L \times D_S}$ after the HSE module.

3.5 Top Song Transformer

After the HSE module, we have obtained the structure-enhanced chord and phrase tokens. To broadcast the explored structure information into various musical elements of the whole context, we use another Song Transformer block to interact on all the tokens again, getting $\mathbf{S}''_{\mathcal{M}} = [\mathbf{S}''_{t_1}, \mathbf{S}''_{t_2}, ..., \mathbf{S}''_{t_L}] \in \mathbb{R}^{L \times D_S}$:

$$S''_{\mathcal{M}} = Transformer(PosEnc(S'_{\mathcal{M}})).$$
 (7)

3.6 Training and Generation

3.6.1 Training. In training, we formulate the music generation as a "next token prediction" task. For the music $\mathcal{M} = [t_1, t_2, ..., t_L]$, we set the boundary token $t_1 = \langle \mathsf{BOS} \rangle$ and $t_{L+1} = \langle \mathsf{EOS} \rangle$. Let the input $X = [x_1, x_2, ..., x_L] = [t_1, t_2, ..., t_L]$, and the ground truth $y = [y_1, y_2, ..., y_L] = [t_2, t_3, ..., t_{L+1}]$. we aim to learn a model $G(X) \to \hat{y}$ such that it maximizes the predictive accuracy w.r.t y, where $\hat{y} = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_L]$.

Given the token representations after the top Song Transformer $S''_{\mathcal{M}}$, we adopt a two-stage prediction setting to make it easier for the model to fit, following [12]:

$$\hat{\mathbf{y}}_{i}^{tp} = \mathbf{Softmax}(\mathbf{MLP}_{tp}(\mathbf{S}_{t_{i}}^{\prime\prime})), i = 1, 2, ..., L$$

$$\hat{\mathbf{y}}_{i}^{c} = \mathbf{Softmax}(\mathbf{MLP}_{c}(\mathbf{Concat}([\mathbf{S}_{t_{i}}^{\prime\prime}, \mathbf{Emb}_{tp}(\mathbf{y}_{i}^{tp})]))), \quad (8)$$

$$i = 1, 2, ..., L; \ c \in C \ and \ c \neq tp$$

where $\hat{\mathbf{y}}_i^c$ means the prediction value on the category c of the token $\hat{\mathbf{y}}_i$, tp means the category Type, **Softmax**(·) means the softmax function, $\mathbf{MLP}_c(\cdot)$ means the Multi-Layer Perceptron on the category c, and \mathbf{y}_i^c means the ground truth value on the category c of the token \mathbf{y}_i .

During training, we minimize the sum of every cross-entropy loss between the prediction \hat{y} and the label y on every category c:

$$\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = \sum_{i=1}^{L} \sum_{c \in C} \lambda_c \mathbf{CELoss}(\mathbf{y}_i^c, \hat{\mathbf{y}}_i^c), \tag{9}$$

where λ_c is the loss weight on the category c, and **CELoss**(\cdot , \cdot) means the cross-entropy loss function.

3.6.2 Generation. During the generation, we get the music tokens recurrently. Take the generation from scratch as an example: given the input $\mathbf{x}_1 = \langle \mathsf{BOS} \rangle$, the HAT can produce $\hat{\mathbf{y}} = [\hat{\mathbf{y}}_1, \hat{\mathbf{y}}_2, ..., \hat{\mathbf{y}}_{L_G}]$ recurrently, until $\hat{\mathbf{y}}_{L_G} = \langle \mathsf{EOS} \rangle$, where L_G is the length of the generated piece. To obtain the final predictive music tokens $[\hat{t_1}, \hat{t_2}, ..., \hat{t}_{L_G}]$, we adopt the stochastic temperature controlled sampling [10] to increase the diversity and avoid degeneration:

$$\hat{t}_i^c = \mathbf{Sampling}_c(\hat{\mathbf{y}}_i^c), \tag{10}$$

where \hat{t}_i^c is the value of predictive token \hat{t}_i on the category c, and $\mathbf{Sampling}_c(\cdot)$ means the sampling function on the category c. Here we employ different sampling policies for different categories, following [12].

4 EXPERIMENTS

In the section, we conduct experiments to answer the following evaluation questions:

EQ1: Does HAT have a better perception and understanding of the musical structure compared to the existing models?

EQ2: How to evaluate the quality of the structure of generated music pieces, especially from a *harmony* perspective?

EQ3: Can HAT improve the quality of generated music, especially on the *form* and *texture*? How effective are the proposed hierarchical structure-enhanced mechanisms?

4.1 Dataset

We adopt POP909 [29]³ as our experimental dataset because it contains sufficient annotations information of *structure*. There are 909 MIDI files of pop songs of the dataset, in which every song is arranged by professional musicians as piano. For *texture*, there are three tracks in every MIDI, which can respectively represent the typical pop music texture elements, Primary Melody (PM), Secondary Melody (SM), and Harmonic and Rhythmic Support (HRS) [36], which is shown in Figure 1a. For *form*, other researches have annotated the phrase-level structure (*melodic* or *non-melodic* phrases and their bar-level durations) on POP909 [7]⁴.

When preprocessing, we select the songs that are 4/4 time signature as our training data, including 857 MIDI files. We quantize the duration and the beat positions under the resolution of the 16^{th} note. And we stay only the first tempo value as the tempo of every song, to reduce the burden of model learning.

4.2 Experimental Setup

4.2.1 Compared Methods. We consider the two end-to-end methods that can handle the full-song-length pop music as baselines:

- Music Transformer [13] (HAT-base w/ relative attention): The authors employ the improved relative attention to model the relationship between the *notes* to exhibit long-term structure. It is explained that the original tokenize methods of Music Transformer is hard to handle the full-song-length pop music [12, 14]. So we adopt the relative attention in our proposed basic Transformer of HAT (HAT-base, which will be described later on).
- **CP-Transformer** [12]: It is one of the SOTA end-to-end methods for pop music generation. The authors propose the "Compound Word" tokenization to compress the input sequence length prominently for Transformer-based models.

Moreover, we also adopt the three variants of HAT to study the effectiveness of our proposed components.

 HAT-base (HAT w/o Structure-enhanced): To verify the necessity of the HSE Module, we remove the whole module

³https://github.com/music-x-lab/POP909-Dataset

 $^{^4} https://github.com/Dsqvival/hierarchical-structure-analysis$

Model	Accuracy				Mean Square Error (\downarrow)			
Wiodel	Note	Chord	Phrase	Avg.	Note	Chord	Phrase	Avg.
CP-Transformer [12]	0.406	0.368	-	0.387	0.132	0.135	-	0.134
Music Transformer [13]	0.587	0.488	0.256	0.444	0.078	0.084	0.121	0.094
HAT-base	0.485	0.417	0.228	0.377	0.099	0.099	0.124	0.107
HAT-base w/ Form	0.564	0.500	0.309	0.458	0.082	0.082	0.116	0.093
HAT-base w/ Texture	0.571	0.503	0.268	0.447	0.081	0.084	0.122	0.096
НАТ	0 594	0.518	0.323	0.478	0.076	0.080	0 116	0.090

Table 2: Results of the Next Token Prediction task. (The best and the second best results of every column are bold and italic.)

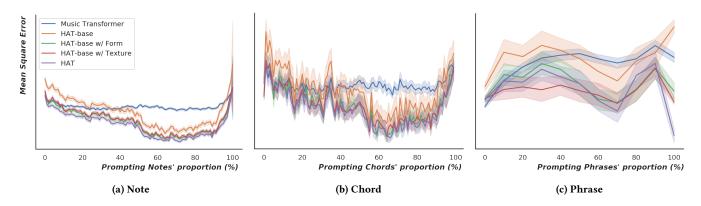


Figure 3: The trends of the next token prediction's MSE as the prompts' lengths increase (i.e. as the music "listened" by models is going). The horizontal axes of Figure 3a, 3b, and 3c indicate the proportions of Note, Chord, and Phrase tokens in the prompts.

and get the variant HAT-base, which can be treated as a basic Transformer using HAT's music tokenization.

- HAT-base w/ Form: In the HSE module, we only group all
 the *phrase*-level tokens and input them into the Form Transformer. In other words, we only enhance the *form* structure
 on the basis of HAT-base.
- HAT-base w/ Texture: In the HSE module, we only group all the *chord*-level tokens and input them into just one Texture Transformer. It means that we only enhance the *texture* structure on the basis of HAT-base.

4.2.2 Implementation Details. In HAT, the numbers of layers and heads are 6 and 8 for Song Transformer, 6 and 4 for Texture Transformer, and 12 and 8 for Form Transformer. The max sequence length is 2560 (Song Transformer), 60 (Texture Transformer), and 30 (Form Transformer). The embedding dim D_S is 512. When training, the loss weights λ_c are 5 (for Type and Bar), 10 (for Tempo and Phrase), and 1 (for the others). The batch size is 8, the learning rate is 10^{-4} , and we use Adam [17] for optimization with $\epsilon=10^{-8}$, $\beta_1=0.9,\ \beta_2=0.999$. For generation, we adopt the models of training loss at 0.05 level to generated pieces.

4.3 Performance of Music Understanding (EQ1)

To evaluate HAT's ability to understand the constitution of the music, especially the musical structure, we employ the **Next To-ken Prediction** – a music understanding task. Specifically, given the prompt $P = [t_1, t_2, ..., t_{L_P}]$ (where the L_P is the length of the

prompt), the model is expected to predict the next musical token $t_{L_{\rm P}+1}$. And we adopt Accuracy and Mean Square Error (MSE) as the criteria.

In Table 2, we report the evaluation results of three particular types of tokens: Note, Chord, and Phrase. It can be observed that:

- The effectiveness of our music tokenization for phrases: compared to CP-Transformer [12] that does not consider to tokenize the phrase tokens, other five models own a better understanding of music, which verifies our tokenization is proper to model the phrases' signals.
- The superiority of HAT: among the models, HAT has the highest accuracy and the lowest MSE on any types of tokens.
- The advantage of the hierarchical structure-enhanced mechanisms: on the one hand, enhancing form (HAT-base w/Form), texture (HAT-base w/Texture), or the both (HAT) all behave better when predicting chords and phrases than Music Transformer [13] and HAT-base. On the other hand, formor texture-enhanced mechanism respectively improves the understanding of phrase or chord more.

Furthermore, in order to explore the changes of the model's intellect as the music is going, we visualize the trends of its prediction's MSE as the prompt's length increases for the five models using our tokenization (Figure 3). We can see that for Note (Figure 3a) and Chord (Figure 3b), the MSEs of HAT and its three variants descend first, but then ascend until the music ends. This is mostly likely because that the intellects of these models increase as they gradually

perceive the first-half music usually repeat. On the contrary, modeling the relative attention between notes (Music Transformer [13]) can not understand more as the music goes. However, when the music is coming to the end, all the models are helpless since the music at that time often doesn't appear before.

For Phrase (Figure 3c): (1) Initially, the five models understand little, which indicates that they don't know where the music will go by listening just the beginning of the music - maybe a *intro* or a *verse*. (2) Gradually, they behave better and better during the first-half music, which seems that they have perceived the repeating *phrases* and the similar *sections*. (3) Yet after that time, the models' intellects tend to be worse again. We speculate that there appears to be some new sections like *post-chorus* [35]. (4) When the music has progresses about 90%, however, except for HAT-base, the other four structure-enhanced models (especially HAT) are conscious of the music is approaching to the end. Combining the analysis of Note and Chord before, in a word, these four models know more "when to end", but less "how to end".

4.4 Evaluation Metrics of Music Generation (EO2)

4.4.1 Objective Evaluation. For algorithmic composition, it is still very hard to measure the quality of the generated pieces' *structure*, especially by the quantitative analysis. In the paper, we explore to develop two metrics to evaluate the *texture* and *form* structure of music. Particularly, we research to assess the two from the perspective of *harmony*.

Accompaniment Groove Stability. For texture, we design the Accompaniment Groove Stability (AGS) to measure the stability of the grooves between the accompaniment textures. As the Figure 1a shows, the accompaniment textures of pop music usually appear in chords, and the grooves of the adjacent chords of the same durations are highly similar. On this observation, we formulate the grooves of the i^{th} chord as \mathbf{g}_i , which is a binary vector $\in \mathbb{R}^{D_u}$, where D_u is the dimension of the chord's duration . Then we can calculate the **AGS** as follows:

$$\mathbf{AGS}_{i,i+1} = 1 - \frac{\mathbf{Sum}(\mathbf{XOR}(\mathbf{g}_i, \mathbf{g}_{i+1}))}{\mathbf{Sum}(\mathbf{OR}(\mathbf{g}_i, \mathbf{g}_{i+1}))},$$

$$\mathbf{AGS} = \mathbf{Avg} \left(\sum_{i} \mathbf{AGS}_{i,i+1} \right),$$
(11)

where $\mathbf{AGS}_{i,i+1}$ means the i^{th} chord and its next adjacent $(i+1)^{th}$ chord with the same duration. $\mathbf{XOR}(\cdot,\cdot)$ and $\mathbf{OR}(\cdot,\cdot)$ are the exclusive OR and the OR operation respectively, and $\mathbf{Sum}(\mathbf{OR}(\mathbf{g}_i,\mathbf{g}_{i+1}))$ is the scaling factor. And the AGS value ranges from 0 to 1.

To obtain the grooves of the i^{th} chord, \mathbf{g}_i , motivated by [38], we scan the every frame of the chord (by the resolution of 16^{th} note), and the value of the j^{th} frame, $g_i^j=1$ if there are notes onsetting in the frame, otherwise $g_i^j=0$. Besides, we remove those adjacent chord pairs that $\mathbf{g}_i=0$ and $\mathbf{g}_{i+1}=0$ during calculating AGS.

Ideally, the stabler of the accompaniment grooves (during the adjacent chord pairs) among the entire piece, the higher AGS is, which means the *texture* of the piece is better structured.

Chord Progression Realism. For form, we design the Chord Progression Realism (CPR) to evaluate the realism of the chord progressions of a generated piece. As the Figure 1b shows, the chord progression of a real piece often repeats within the phrases and the sections, resulting in a low Chord Progression Irregularity (CPI) that proposed in [38]. However, we found only CPI [38] not suitable enough to evaluate the quality (or the realism) of the chord progressions of the music. For example, if there is only one chord repeating during the entire piece, the CPI will be very low, but the music maybe like several notes' meaningless loop.

For pop music, within the **repeating** outline of chord progressions, there are also rich appropriate **variations** featuring the musical details and dynamics. Based on that, therefore, we propose the Chord Progression Variation Rationality (CPVR) to measure the rationality when the chords change. Furthermore, we balance CPI (i.e., *stability*) and CPVR (i.e., *diversity*) to obtain the final CPR value of a piece:

$$\mathbf{CPR} = \lambda \mathbf{CPI} + (1 - \lambda)\mathbf{CPVR}.$$
 (12)

where λ is the hyperparameter of trade-off weight. In the experiments, we simply set $\lambda=0.5$.

To calculating CPVR, when a new *unique n-grams chords* appears, we measure the probability of the appearance of this variation under the current harmony context. Given the n-grams chord progression is C_i^{i+n} , where i is the index of the first chord, we traverse all the C_i^{i+n} from i=1, and when a new unique n-grams appear, we define V_i as the variation rationality value:

$$V_i = \mathbf{p} \ (C_i^{i+n} | C_i^{i-1+n}), \tag{13}$$

where $\mathbf{p}(\cdot|\cdot)$ is the conditional probability, and we use the appearance frequency during the real data (i.e., all the pieces of POP909 [29]) to get the approximation. Finally, the CPVR value of a piece is obtained by averaging all the V_i : **CPVR** = $\mathbf{Avg}(\sum_i V_i)$.

It is noted that the ranges of CPI, CPVR, and CPR are all from 0 to 1. Ideally, a piece with a good *form* will own a high CPR value.

4.4.2 Subjective Evaluation. Qualitative evaluation by humans is always an important evaluation metric and is adopted widely [12, 13, 37, 38, 41] in music generation. In the paper, we invited 15 volunteers to conduct the following human study. The volunteers are from the music conservatory or in the music production industry. All of them are good at at least one instrument and are engaged in the musical activity for over 5 hours every day. Firstly, the subjects need to score the **Overall Performance (OP)** of the music:

- Melody (M): Does the melody sound beautiful?
- **Groove (G)**: Does the music sound fluent and pause suitably? Is the groove of the music unified and stable?

Next, the subjects are asked to evaluate the quality of *texture* and *form* respectively. For *texture*, there are two metrics:

- **Primary Melody (PM)**: Is there a distinct and clear primary melody line in the music? Is the primary melody easy to remember? Is it suitable for singing with lyrics?
- Consonance (CO): Do the several layers of sound balance and combine organically? Is the composition of individual sounds harmonious?

Table 3: Results of the objective evaluation. The best results of every column (except those from Real) are bold, and the second best results are *italic*.

	Texture	Form					
Model	AGS	CPR					
	7100	2-grams	3-grams	4-grams			
Real	0.572	0.504	0.564	0.551			
CP-Transformer [12] Music Transformer [13]	0.193 0.256	0.312 0.413	0.250 0.384	0.132 0.267			
HAT-base HAT-base w/ Form HAT-base w/ Texture HAT	0.382 0.422 0.456 0.474	0.403 0.439 0.434 0.447	0.369 0.421 0.417 0.435	0.264 0.307 0.310 0.320			

For *form*, there are also two metrics:

- **Coherence (C)**: Are the transitions and the developments between the contiguous *phrases* natural and coherent?
- Integrity (I): Does the music own the complete *section* structure, such as intro, verse, chorus, bridge, and outro? Are the boundaries between the sections clear?

4.5 Performance of Music Generation (EQ3)

4.5.1 Results of Objective Evaluation. To evaluate the generated pieces on the proposed objective metrics, we produced 100 pieces from scratch for each model. Also, we adopt all the human 857 pieces (our training data) as a "Real" model for a comparison. We obtain every model's score by averaging its pieces' scores.

The results of the objective evaluation are exhibited in Table 3. It is observed that: (1) The Real model owns the highest AGS and CPRs, though whose scores are only 0.5-0.6. It indicates that our proposed AGS and CPR can be considered as reasonable descriptive metrics at least, which can measure the generator's ability in style imitation; (2) For texture, HAT is much significantly better than the two baselines on AGS (Music Transformer: p = 0.0022; CP-Transformer: $p = 6.59 \times 10^{-5}$; one-tailed *t*-test); (3) For *form*, on the one hand, HAT is significantly better on any grams of CPR. On the other hand, when the gram increases, the CPR values of any algorithmic music all drop a lot, but that is barely seen for real pieces. It reveals the challenge of generating longer and more abstract structures. (4) Among the HAT's three variants, it can be seen that based on HAT-base, the form or texture enhancement respectively behaves quite well on AGS or CPR. That verifies the effectiveness of our proposed hierarchical structure-enhanced strategies.

4.5.2 Results of Subjective Evaluation. For subjective evaluation, we generated 10 pieces from scratch for each model and ask our volunteers to give a mark for all the pieces. The source of pieces are concealed from the subjects and we guarantee that each piece is rated by 3 different subjects. The results of the subjective evaluation are displayed in Table 4, where we scaled the scores and every value in it lies from 0 to 1. We can see that the general quality (the average score 0.601) and the form quality of HAT's pieces are the best, and those of HAT-base w/ Form are the second best.

Table 4: Results of the subjective evaluation. OP: Overall Performance, M: Melody, G: Groove, PM: Primary Melody, CO: Consonance, C: Coherence, I: Integrity.

	OP		Texture		Form		Avg.
Model	M	G	PM	СО	С	I	
CP-Transformer [12]	0.356	0.356	0.385	0.403	0.419	0.380	0.383
Music Transformer [13]	0.417	0.375	0.700	0.562	0.550	0.375	0.496
HAT-base	0.267	0.550	0.680	0.400	0.400	0.450	0.458
HAT-base w/ Form	0.638	0.504	0.511	0.641	0.557	0.574	0.571
HAT-base w/ Texture	0.436	0.477	0.514	0.539	0.538	0.504	0.501
HAT	0.592	0.552	0.598	0.661	0.585	0.618	0.601

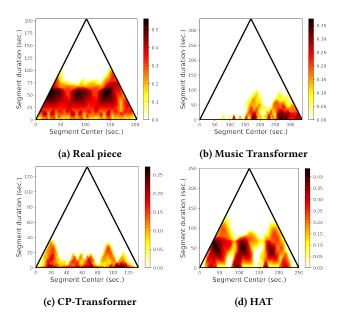


Figure 4: The fitness scape plots of the real piece (the Chinese pop song, *Guang Yin De Gu Shi*), and other three generated pieces prompted by the *intro* of the real piece.

5 CASE STUDY

To figure out the characteristics of the pieces generated by HAT, we visualize the *fitness scape* of the structure segments that are applied in the fields of Music Structure Analysis [19, 20]. In Figure 4, we can see that: (1) compared with the two baseline-generated pieces, the HAT-generated piece owns the less but the longer duration segments, which is similar to the real piece; (2) compared with the real piece, the HAT's piece already has the three main segments like the real one, but it lacks the musical details between the structure segments (appearing as blank in the small segments). It reveals that although HAT has been capable of imitating the outline structure of the real music, it is still too hard for it to polish and refine the generated pieces to pursue a real work of art.

6 CONCLUSION AND FUTURE WORK

In this paper, we propose the *harmony*-aware learning for structureenhanced pop music generation. Bridged by the harmony, we combine the *texture* and the *form* structure organically, and we design the HAT for their joint learning. Both experimental results of music understanding and generation verify the significant effectiveness of the HAT. In the future work, on the one hand, we will explore new methods to polish and refine the musical details of generated pieces. On the other hand, based on the generated symbolic music, we will research on the *performance* generation, hoping to merge the human performance techniques into the generated music.

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A GENERATING A PIECE FROM THE SCRATCH

In Section 3.6, we describe the generating procedure of HAT from the scratch. The detailed algorithm can be seen in Algorithm 1.

B DATASET OF MUSIC UNDERSTANDING

For the next token prediction task (Section 4.3), we split the 857 MIDIs (Section 4.1) into training (773 MIDIs), validation (41 MIDIs), and testing sets (43 MIDIs). We select the best model on the validation set, and exhibit the results of the testing set (Table 2 and Figure 3).

C SUPPLEMENTARY IMPLEMENTATION DETAILS

C.1 Computing Platform

All experiments in the paper are conducted on NVIDIA V100 GPUs with PyTorch [23]. And we employ the library developed by [16]⁵ for the implementation of transformer.

C.2 HAT

In Section 3.6.2, we use the sampling function $\mathbf{Sampling}_c(\cdot)$ for the different category c of the tokens during generating. For the hyperparameters, we follow the setting of [12] for all the categories except Phrase (that is not modeled in [12]). And we employ the sampling function with $\tau=1.0$ and $\rho=0.99$ for Phrase.

C.3 HAT's three variants

All the hyperparameters of them are the same to HAT. And we use the models of training loss at 0.05 level for generating, following HAT.

C.4 Music Transformer

As is mentioned in Section 4.2.1, we adopt **HAT-base w/ relative attention** for the implementation of Music Transformer. We reproduce the **relative attention** based on some public codes⁶. And we use the models of training loss at 0.05 level for generating, following HAT.

C.5 CP-Transformer

We follow the official implementation of CP-Transformer [12]⁷. We merge the three-track training data into single-track data, because the original tokenize method of "Compound Word" is proposed on the single-track setting. To be fair with HAT, we use the basic Transformer [28] but rather than linear Transformer [16] for the backbone architecture.

C.6 Objective Evaluation

C.6.1 Chord Detection. In Section 4.4.1, the proposed AGS and CPR are both dependent on the chord signals. In order to get the

Algorithm 1 Generate a music piece from scratch.

```
Input: x_1 = \langle BOS \rangle
Output: \hat{y} = [\hat{y}_1, \hat{y}_2, ..., \hat{y}_{L_G}]
   1: i \leftarrow 0
                                                                                                    ▶ the token index
  2: p_i \leftarrow 0
                                                                                                  ▶ the phrase index
  3: p_i^j \leftarrow 0
                                                                       ▶ the chord index of the phrase
  5: T_{p_i^j-1} \leftarrow 0
                                                            ▶ the output of Texture Transformer
   6: TF_{p_i-1} \leftarrow 0
                                                                 ▶ the output of Form Transformer
  8: do
                i \leftarrow i + 1
  9
               Calculate E_{x_i} and S_{x_i} using Equation 1-2.
 10:
                if x_i^{tp} = phrase then
 11:
                       S_{p_i} \leftarrow S_{x_i}
S_{x_i} \leftarrow TF_{p_i-1} + S_{x_i}
S'_{p_i} \leftarrow S_{x_i}
 12:
                                                                         ▶ Refer to Equation 5
 13:
                       if p_i \neq 0 then
 15:
                               Given T_{p_i^j-1}, calculate TF_{p_i-1} using Equation 4.
 16:
 17:
                       p_i \leftarrow p_i + 1
 18:
                       p_i^j \leftarrow 0 \\ T_{p_i^j - 1} \leftarrow 0
 19:
 20:
                else if x_i^{tp} = chord then
 21:
                      \begin{array}{l} \mathbf{S}_{p_{i}^{j}} \overset{!}{\leftarrow} \mathbf{S}_{\mathbf{x}_{i}} \\ \mathbf{S}_{\mathbf{x}_{i}} \leftarrow \mathbf{S}_{p_{i}}' + \mathbf{T}_{p_{i}^{j}-1} + \mathbf{S}_{\mathbf{x}_{i}} & \triangleright \text{ Refer to Equation 6} \\ \text{Given } \mathbf{S}_{p_{i}^{j}} \text{ and } \mathbf{S}_{p_{i}}, \text{ calculate } \mathbf{T}_{p_{i}^{j}-1} \text{ using Equation 3}. \end{array}
 23:
 25:
 26:
              S'_{x_i} \leftarrow S_{x_i}

Given S'_{x_i}, calculate S''_{x_i} using Equation 7.

Given S''_{x_i}, calculate \hat{y}_i using Equation 8, where we only
 27:
 28:
        replace y_i^{tp} with \hat{y}_i^{tp}.
 30: while \hat{y}_i \neq \langle EOS \rangle
```

chord annotations, we use the chord detection tool⁸ of [12] to extract the chords of the evaluated pieces.

C.6.2 Chord Progression Irregularity (CPI). To calculate CPI [38] (Equation 12), the n-grams chord progression is notated as C_i^{i+n} , where i is the index of the first chord, then we can obtain CPI value as follows:

$$\mathbf{CPI} = \frac{\mathbf{Count}(\{C_i^{i+n} \mid i = 1, 2, ..., L_c - n + 1\})}{L_c - n + 1},$$

where **Count**(·) means the size of the set, and L_c is the number of the chords of the music.

⁵https://github.com/idiap/fast-transformers. This library is originally developed for "fast attention" [16] for transformers. But we only use its implementation of the basic Transformer [28] during all the experiments.

 $^{^6} https://github.com/jason9693/MusicTransformer-pytorch\\$

⁷https://github.com/YatingMusic/compound-word-transformer

⁸https://github.com/joshuachang2311/chorder