The Power of Reuse: A Multi-Scale Transformer Model for Structural Dynamic Segmentation in Symbolic Music Generation

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Abstract
Symbolic Music Generation relies on the contextual representation capabilities of the generative model, where the most prevalent approach is the Transformer-based model. Not only that, the learning of long-term context is also related to the dynamic segmentation of musical structures, i.e. intro, verse and chorus, which is currently overlooked by the research community. In this paper, we propose a multi-scale Transformer, which uses coarse-decoder and fine-decoders to model the contexts at the global and section-level, respectively. Concretely, we designed a Fragment Scope Localization layer to syncopate the music into sections, which were later used to pre-train fine-decoders. After that, we designed a Music Style Normalization layer to transfer the style information from the original sections to the generated sections to achieve consistency in music style. The generated sections are combined in the aggregation layer and fine-tuned by the coarse decoder. Our model is evaluated on two open MIDI datasets, and experiments show that our model outperforms the best contemporary symbolic music generative models. More excitingly, visual evaluation shows that our model is superior in melody reuse, resulting in more realistic music.

1 Introduction
Symbolic Music Generation (SMG) refers to generating continuation from the initial notes. It has received great attention with the prosperity of deep learning (Briot et al., 2020). Music can be seen as a sequence of notes in time. A musical generative model should be able to refer the context of note representations, as required for natural language models. Hence, Language Models (LMs), such as the auto-regression model, are prevalently used for music generation. A representative model is PerformanceRNN (Simon and Oore, 2017), an LSTM-based recurrent neural network designed to model polyphonic music which has complex dynamics. It performs well in generating short music (~ 30s). But generating long sequences of music (≥ 4 minutes) is still a challenge because errors accumulate as the length of the sequence increases. In almost all current LMs, the output length is often limited, restricting the maximum perception range. When the generated sequence length exceeds the perception range, its performance degrades quickly.

Therefore, the primary challenge of the SMG tasks is to maintain long-term relevance at reasonable computational complexity. Many efforts have been devoted to this. Google researchers (Huang et al., 2019) proposed MusicTransformer, which is able to deal with longer sequences (~ 4096 notes), with optimized intermediate memory occupation. Some approaches introduce additional modules to improve long-term generation problems. Transformer-GANs (Muhamed et al., 2021) introduces a pre-trained discriminator that uses adversarial loss to complement the negative log-likelihood objective, enabling improvement in synthesizing minute-long compositions. Despite recent improvements in long-term music generation, existing approaches exhibit crucial failure modes in learning musical structure, which we attribute to their incompetence in segmenting structural elements.

Most music is typically sectional, meaning that structural melodies are repeated throughout the song, such as intro, verse, chorus, etc. To generate these structured melodies, some hierarchical architectures are proposed in current works (Dong et al., 2018; Roberts et al., 2018). Their analysis showed that the hierarchical architecture could extract structural context to enhance the long-term relevance in the music. This idea is also supported by a Transformer-based model (Gabriel et al., 2021) that takes into account paragraph-level context and achieves state-of-the-art (SOTA) performance for text generation tasks. In summary, structural segmentation and paragraph-level (section-level in the
music) contextual learning have played a significant role in generating realistic long-form music.

In this paper, we propose a multi-scale Transformer model to learn section-level contexts by structural dynamic segmentation. Symbolic notes were first encoded by a sparse Transformer (Child et al., 2019). Obtained embedding were then fed to a custom-designed Fragment Scope Localization (FSL) layer. Specifically, music composition was divided into sections, and served as section-level context for training fine-decoders. Next, a few starting notes and labels are input as activation information to generate sections. We propose a Music Style Normalization (MSN) layer to control the music style in generated sections. The aggregation layer was used to combine generated sections, followed by a coarse-decoder to output the overall music. Our main contributions are as follows:

- We designed an FSL layer that divides the music into structural elements during the encoding process. And we compared two alignment strategies of the FSL layer to solve the problem of candidate windows allocation.
- We designed an MSN layer to control music style, and argued for the role of MI loss in this process. Thus the proposed model showed superiority in style consistency of generated music compared to other models.
- We proposed a multi-scale architecture to learn section-level contexts, which leads to the advantage of avoiding error accumulation. Our multi-scale Transformer achieves SOTA performance on two open datasets, and visual evaluation shows that our model can effectively reuse melodies.

2 Related works

2.1 Transformer baselines

The Transformer model has been the typical choice for sequence modeling due to its advantages in dynamic representation capabilities. However, applying the Transformer model to the SMG task is computationally prohibitive, since the attention complexity grows quadratically with sequence length (Li et al., 2019). Massive efforts have been devoted to resolving this problem. Transformer-XL (Dai et al., 2019) was proposed to learn dependencies beyond a fixed length, and it consists of a segment-level recurrence mechanism and a positional encoding scheme. Reformer (Kitaev et al., 2020) is another effective work, where the dot-product attention is replaced by a locality-sensitive hashing-based calculation, reducing the complexity from $O(L^3)$ to $O(L\sqrt{T})$. These proposed baselines provide the feasibility of solving SMG tasks by Transformer models. For instance, MuseNet (Payne, 2019), a Transformer-based model that can generate 4-minute music, discovers patterns of harmony, rhythm, and style in long-form music by learning to predict the next token in a sequence.
2.2 Music structure segmentation

Structure segmentation is commonly used for modeling long-form music with multiple movements and sections, which can be tackled with hierarchical architecture. In a music annotation work (Wang et al., 2019), attentive convolution networks and recurrent networks were hierarchically combined to solving the problem of audio music representation and structure learning. McCallum (McCallum, 2019) explores the use of convolutional neural networks (CNN) for unsupervised training in music segmentation, aiming to detect the boundaries of music fragments in audio music. Dai (Dai et al., 2021) proposed a hierarchical model to generate a full-length melody guided by long-term repetitive structure and achieved near-human performance in melody generation about half the time. These works suggest the importance of music structure segmentation, thus it is beneficial to design a structural segmentation module for the SMG task.

2.3 Music Style Control

Style transfer usually uses the instance normalization methods. In previous work (Huang and Belongie, 2017), an adaptive instance normalization approach was proposed to achieve flexible style control. Ling (Ling et al., 2021) proposes a region-aware adaptive instance normalization module, which formulates visual style from the background and transfer them to the foreground. Furthermore, MI is commonly used to optimize the style transfer models. Chawla (Chawla and Yang, 2020) propose a semi-supervised style transfer model and maximize the MI between original and target styles as the training objective, and achieved better performance. Inspired by these studies, we utilized the style transfer method and MI loss to maintain a consistent style in long-form music.

3 The proposed model

The key challenge is to generate long-term music with structural relevance and consistent style. We begin with a description of notes sequence encoding and structural element fragmentation, followed by an introduction of the multi-scale architecture and music style normalization, for learning section-level contexts and maintain style in each section. In addition, we perform a theoretical analysis of coverage of attention patterns.

3.1 Encoding: Sparse Attention and Structural Elements Fragmentation

In Transformer models, the attention pattern determines the perceptual range and computational complexity, thereby we use sparse attention in our encoder. The use of dynamic fragments facilitates the construction of references to section-level contexts in music. The encoder and FSL layer is illustrated in Fig.1a.

Given the notes sequence $X$ with length $L$, the embedding is denoted as $h(x)$, which is obtained by an encoder, represented as:

$$ h(x) = LN(X + FFN(\text{Attention}(Q, K, V))) $$

(1)

where $Q, K, V$ represent the Query, Key, Value vector in the Transformer; $LN$ and $FFN$ represent the layer normalization operation and feedforward network, respectively; $\text{Attention}$ represents the sparse attention we use in the encoder.

Sparse attention: Sparse attention maps the input $x$ to the output embedding and is parameterized by a connectivity pattern $S = (S_1, \cdots, S_L)$. The output vector is the weighted sum of scaled dot-product of the input vectors, calculated by:

$$ Attention = \text{Softmax} \left( \frac{(W_Q x_i) K^T_{S_i}}{\sqrt{d}} \right) \cdot V_{S_i}; $$

$$ K_{S_i} = (W_K (x_i^T \cdot S_i)), V_{S_i} = (W_V (x_i^T \cdot S_i)) $$

(2)

where $W_Q, W_K, W_V$ represent the weight matrix that transform the input $x_i$ into the $Q, K, V$ vector, respectively; The scaling factor $\sqrt{d}$ equals to the vector dimension; $S_i$ defines the index set of the input embedding to attended by the output vector, which determines the references of the $i$-th note in the sparse attention mechanism.

Alignment of candidate windows: We proposed a FSL layer to selectively search for music sections, which is built on the Transformer encoder. The candidate windows $\omega$ are applied to the note embedding $h(x)$. We set the window length to a multiple of 16, since the music score has 16 semi-quaver (the minimum unit in MIDI data) notes per bar. Normally, structural elements are extracted through windows sliding from left to right. The left-to-right (L2R) strategy can be written as:

$$ \text{Cand}[m] = \omega[k] \cdot h(\text{Loc}_m : \text{Loc}_m + \omega[k]) $$

(3)

where $\text{Cand}[m]$ denotes the $m$-th candidate after sliding window layer; $k$ denotes the window sizes,
and $\omega[k]$ denotes the candidate window; The current location is calculated by $Loc_m = \sum_{j=1}^{m-1} \omega_j$; The goal of L2R strategy is to select the suitable window with the maximum classification probability $\arg \max (cls(\omega \cdot h))$ in order from left to right. The L2R alignment strategy is prone to error accumulation when certain sections cannot be positioned correctly. Thus, we propose a global alignment strategy by adding random positions $\Delta Loc$ and padding non-overlapping windows into input:

$$Cand^*[m] = \omega[k] \cdot h \left( \Delta Loc_m \pm \frac{1}{2} \omega[k] \right)$$

where $\Delta Loc_m$ denotes the center of the $m$-th random location; The non-overlapping fragments are padded by maximizing the average confidence, calculated by $\arg \max \left( \frac{1}{N} \sum_{m=1}^{M} cls(\omega \cdot h) \right)$.

Figure 2: Alignment strategies for the candidate window. (a) The default windows slides over the note embedding to produce candidate scopes. The cls layer identifies the appropriate labels for the musical section and the reg layer locates the candidate scopes to the ground-truth. (b) The central positions of the candidate scopes are randomly initialized on the note embedding. Then, the cls layer identifies the section labels and the reg layer regresses the candidate scopes.

**Gumbel Softmax**: The cls layer produces category probabilities $p_\phi \in \mathbb{R}^\phi$ to predict the section label $\phi \in \phi$ of candidate sections, such as intro, verse, chorus. The observed number of labels fits the exponential distribution, so we use Gumbel Softmax (Kusner and Hernández-Lobato, 2016) to optimize the cls layer, which is defined as:

$$L_{cls} = - \log \frac{\exp ((p_\phi + \theta_\phi) / \tau)}{\sum_{\phi \sim \phi} \exp ((p_\phi + \theta_\phi) / \tau)}$$

where, $\tau$ is a non-negative coefficient of spread in the Gumbel distribution, the smaller the coefficient, the closer the sample expectation is to the augmax result. $\theta$ are samples drawn from $Gumbel(0, 1)$.

The value of $L_{cls}$ should be close to 0 if the candidate is consistent with the ground-truth section.

**Jaccard similarity**: To measure the overlap rate between candidate segments and ground-truth parts, the notes of each section were compared to check the percentage of shared and different notes. Let $D_{pos} = \{(\omega[1], y[1]), \cdots, (\omega[M], y[M])\}$ be a training set of instance-label pairs, $y$ are the ground-truth sections. To keep the balance of samples, we apply Hard Example Mining (HEM) to select negative scopes, which denotes $D_{neg} = \{(\omega[1], \omega'[1]), \cdots, (\omega[M], \omega'[M])\}$, $\omega'(m)$ represents the worst classified samples in the $m$ position. We use the Jaccard similarity coefficient to evaluate the difference between the predicted fragment and ground-truth section, which is denoted as $Jac(a, b) = (a \cap b) / (a \cup b)$. The loss function of the reg layer can be calculated by:

$$L_{reg} = - \log \frac{\sum_{\omega \sim D_{pos, neg}} Jac(\omega[m], y[m])}{\sum_{\omega \sim D_{pos, neg}} Jac(\omega[m], \tilde{\omega}[m])}$$

where $\tilde{\omega}$ represents the set of positive and negative windows; A low $L_{reg}$ loss indicates high coincidence between the prediction and the ground-truth.

**Multi-task loss**: Accordingly, the loss function of our FSL layer can be represented by:

$$L_{FSL} = \frac{1}{N_{cls}} \sum_{m=1}^{N_{cls}} L_{cls} + \frac{1}{N_{reg}} \sum_{m=1}^{N_{reg}} L_{reg}$$

where $L_{cls}$ and $L_{reg}$ are normalized by $N_{cls}$ and $N_{reg}$, which are the number of input sample in these two layers, respectively.

After passing through the FLS layer, the note sequence is segmented into $m$ structural sections. The fragmentation process is formulated as:

$$Para_m(x) = h(x) \cdot reg(cls(Cand[m]))$$

where $reg(cls(Cand[m]))$ stands for the classification and regression operation of the $m$-th fragment scope; The embedding $h(x)$ is activated by the output location vector, thereby the note representation of the $m$-th section is obtained.

### 3.2 Decoding: Multi-scale architecture with Music Style Normalization

The proposed multi-scale architecture aims to learn section-level contextual features and generate notes at scales from fine to coarse. The decoding process is shown in Fig.1b.
At the bottom of the multi-scale architecture, we use several auto-regressive models of different maximum lengths, such as the Transformer decoder, as fine-decoders to generate music sections. These fine-decoders are pre-trained by segmented sections in parallel, and decode each section with start notes and a section label:

\[ G_m(x) = \text{Decoder}_\text{fine}(\text{Start}_m(x); z_m) \]  

(9)

where \( G_m(x) \) represents the \( m \)-th generated section; All fine-decoders are activated by start notes \( \text{Start}_m \) with default length \( r \), satisfying the condition \( \text{Start}_m = \text{Para}_m(x)[0 : r] \); \( z_m \) indicates the target label of generated section, commonly referred to as intro, verse, and chorus, etc.

Specifically, given the embedding of start notes \( (h'_1, \ldots, h'_r) \), the output embedding \( h'_{r+1} \) is obtained by a fully connected self-attention block, Feed-Forward Network (FFN) and Layer Normalization (LN) operation, represented by:

\[ h'_{r+1} = \text{LN}(h'_r + \text{FFN}(a_{r+1}(h'_1 : h'_r))) \]  

(10)

where \( a_n \) is the self-attention block, which calculates a weight score from previous notes.

**Music Style Normalization:** To enhance the styles consistency between the original and generated section, we designed an MSN layer. The musical style is quantified by a variable \( z \) that has the same dimensions as the note embedding. Through the MSN operation, the style variable \( z \), initialized by the section label, is transferred to the generated sections, which can be expressed as \( z_m \rightarrow z'_m \). For example, the MSN layer normalizes the mean and standard deviation of note pitches of each original section and maps them to the generated section:

\[ \text{MSN}(G, z) = \gamma_z \left( \frac{G_m - \mu(z'_m)}{\sigma(z'_m)} \right) + \beta_z \]  

(11)

where \( \gamma_z, \beta_z \) are the zoom and translation parameters that are computed independently for each label and sample across spatial dimensions. \( \mu(z'_m) \) and \( \sigma(z'_m) \) represent the mean and standard deviation of note pitches in \( i \)-th generated section.

**Aggregation:** These sections are aggregated into a long sequence by the weighted concatenation operation \( v \). At the upper of the multi-scale architecture, the coarse-decoder learns the global contextual reference from the merged sequences. The coarse decoding process can be represented by:

\[ G = \text{Decoder}_\text{coarse} \left( v \left( \text{MSN} \left( \sum_{m=1}^{M} G_m \right) \right) \right) \]  

(12)

where \( G \) stands for the output sequence; The coarse-decoder \( \text{Decoder}_\text{coarse} \) uses the sparse attention with same fixed-length as the encoder.

**Decoding Loss Function:** Therefore, the loss function we used in decoding process consists of two terms: (1) The \( L_{\text{MLM}} \) for the note prediction; (2) The \( L_{\text{style}} \) for music style normalization.

\[ L_{\text{Decoding}} = L_{\text{MLM}}(h_{\text{II}} \mid h_{\text{II}}) + \lambda L_{\text{style}}(G', z') \]  

(13)

where hyper-parameter \( \lambda \) is used to balance the magnitude of loss terms.

Given a ground truth sequence \( h_{\text{II}} \), decoders predicts \( T \) masked notes among them. We minimize the following MLM loss:

\[ L_{\text{MLM}}(h_{\text{II}} \mid h_{\text{II}}) = -\frac{1}{T} \sum_{t=1}^{T} \log p(h_{\text{II}}, h_{\text{II}}) \]  

(14)

where \( h_{\text{II}} \) and \( h_{\text{II}} \) denotes the masked and unmasked notes, respectively.

To enhance the style similarity, we maximize the Mutual Information (MI) between original and generated sections, written as \( I(z; G(x, z)) \). MI can effectively measure non-linear statistical dependencies of two variables. This optimization conforms to the information-theoretic regularization, where MI is high when the two musical sections are similar. But \( I \) is difficult to directly be maximized, so we derive the lower bound to be maximized as:

\[ I(z; G(x, z)) = H(z) - H(z \mid G) \geq E_{z \sim P(z)} \left[ E_{G' \sim P(G(x, z))} \left[ \log Q(z \mid G') \right] \right] \]  

(15)

where \( H \) indicates an entropy; \( P(x) \) is the dataset distribution; \( P(G(x, z)) \) is the generation distribution; \( Q(z \mid G') \) is an approximated distribution of the intractable true posterior \( P(z \mid G') \).

The MSN layer is optimized by the MI between input and output, which measures the musical style. The estimated distribution \( q \) can be represented as \( q \sim N(\mu(z'), \sigma^2(z')) \). Since \( Q \) has a closed form of a probability density function \( f(G' \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left( - \frac{(G' - \mu)^2}{2\sigma^2} \right) \), we can represent the MI loss, \( L_{\text{style}} \), to minimize is defined as:

\[ L_{\text{style}}(G', z') = -\log f(G' \mid \mu(z'), \sigma^2(z')) \]  

(16)
Attention pattern analysis: At last, we analyze the advantage of the proposed multi-scale model in attention patterns and compare it with others. We use 16*16 images to illustrate the connectivity matrix between outputs (row) and inputs (column). Fig.3 shows the attention matrices of our multi-scale model and others.

Figure 3: Illustration of connectivity matrix of different attention patterns: (a) Local attention (window size 3); (b) Dilated attention (dispersion stride 1); (c) Sparse attention (local attention with window size 3 plus dilated attention with dispersion stride 3); (d) Multi-scale attention (4 fine-decoders with adaptive maximum length); The color depth represents the attention weight, and the white color indicates the absence of attention.

Our multi-scale attention enables both intra- and inter-section connectivity, which has the advantage of enhancing intra-section integrity while learning section-level dependencies. The range and location of local attention in the fine-decoder depend on the length and location of the corresponding section. Therefore, section segmentation can be viewed as a dynamic assignment of full attention at a local scale, which is one of the best options for avoiding full attention in long-term sequences.

4 Experiment Results

We used the same methods as MusicTransformer to process MIDI data. The structural information of musical sections is automatically extracted from the music score, which are obtained by the GuitarPro software, a music recording tool. The annotation extraction method is detailed in Appendix.

Datasets: For pre-training the FSL layer, we collected a total of 300 scores with 3,188 sections, called the GuitarPro dataset. After pre-training the FSL layer, we trained and tested the proposed multi-scale Transformer based on two canonical music corpora: (1) J.S. Bach Chorales (Hadjeres et al., 2017) for short-term music generation; (2) Maestro v3.0.0 (Hawthorne et al., 2019) for long-term music generation. The split standard of these datasets abides by the rule of 80/10/10 proportion for train/validation/test. The detailed information of datasets is shown in Tab.1.

| Dataset      | Scores | Sections | Notes  | Average length (notes) |
|--------------|--------|----------|--------|------------------------|
| GuitarPro (Ours) | 300    | 3,188    | 355,411| ~1185                  |
| J.S. Bach Chorales | 382    | -        | 56,441 | ~148                   |
| Maestro v3.0.0   | 1276   | -        | 7,040,164| ~5517                 |

Table 1: Description of data sets.

Evaluation metrics: Several quantitative music metrics were used to evaluate the generated music (Wu and Yang, 2020; Muhamed et al., 2021): PPL (Perplexity); PCU (Unique pitch classes); ISR (Nonzero entries in C major scale / Total nonzero entries); PRS (Time steps where the no. of pitches ≥ 4 / Total time steps); TUP (Different pitches within a sample); PR (Avg. difference of the highest and lowest pitch in semitones); APS (Avg. semitone interval between two consecutive pitches); IOI (Time between two consecutive notes); PCH (Pitch-Class Histogram Entropy); GS (Grooving Pattern Similarity); CPI (Chord Progression Irregularity); SI (Structureness Indicator);

Platform: All models were trained/tested on two Nvidia GeForce RTX 2080-Ti 12 GB GPU.

4.1 Symbolic Music Generation

We compared the performance of the present multi-scale model with other outstanding music generation models that had achieved SOTA performance at the time of proposal. The experiments focused on assessing the diversity (PCU, TUP and PR), consistency (IOI, PCH, GS and CPI) and musical rules (ISR, PRS and SI) of the generated samples. All models were retrained for training sets, we ran the results 5 times and reported the average values. The results are shown in Tab.2, the minimum unit of a visual token is a semiquaver note.

As shown in the results, our multi-scale model surpasses other models in most objective metrics. MusicTransformer and Transformer-XL use the similar relative attention mechanism, and achieve approximate results. Transformer-GANs achieved the better performance in some metrics, especially in short-term music generation (J.S. Bach dataset), due to adversarial training that reduced the distributional discrepancy between real and generated data. Our model performs the most coincident samples (similar metrics) to the training set, which can be attributed to the MSN layer that learns the musical style of the training set. Meanwhile, our model achieved a high PCU, implying that the samples maintained a large amount of diversity. Most excitingly, we obtained the best SI metric for detecting repeated structures, which means that our model
Table 2: Comparison of model performance with four other models, tested on J.S. Bach and Maestro datasets. For each metric, the results are better when closer to the Training Set, and the best performance is highlighted in bold.

| Models                        | PPL  | PCU | ISR  | PRS  | TUP  | PR   | APS  | IOI  | PCH  | GS   | CPI  | SI  |
|-------------------------------|------|-----|------|------|------|------|------|------|------|------|------|-----|
| Training Set (J.S. Bach)      | -    | 8.407 | 0.835 | 0.422 | 25.45 | 34.32 | 11.67 | 0.064 | 2.994 | 0.930 | 0.985 | 0.011 |
| PerformanceRNN                | 1.96 | 7.5 | 0.853 | 0.446 | 9.3  | 28.4 | 3.901 | 0.05  | 2.665 | 0.999 | 0.999 | 0    |
| Transformer-XL                | 1.846 | 5.742 | 0.785 | 0.383 | 34.859 | 40.136 | 10.763 | 0.074 | 2.531 | 0.919 | 0.990 | 0.008 |
| MusicTransformer              | 1.833 | 5.768 | 0.792 | 0.386 | 36.069 | 42.542 | 10.257 | 0.075 | 2.535 | 0.916 | 0.993 | 0.009 |
| Transformer-GANs              | 1.789 | 5.9 | 0.807 | **0.423** | 34.817 | 40.41 | 10.993 | **0.072** | 2.537 | 0.921 | **0.987** | 0.009 |
| Multi-scale model (Ours)      | **1.724** | 7.123 | 0.817 | 0.419 | **24.859** | **34.699** | 11.237 | 0.124 | 2.934 | 0.922 | 0.993 | **0.013** |
| Training Set (Maestro v3.0.0) | -    | 6.665 | 0.815 | 0.429 | 66.01 | 68.15 | 11.59 | 0.083 | 2.886 | 0.901 | 0.958 | 0.208 |
| PerformanceRNN                | 1.403 | 5.99 | 0.682 | 0.268 | 5.52  | 10.71 | 3.98  | 0.099 | 1.912 | 0.880 | 0.322 | 0.014 |
| Transformer-XL                | 1.188 | 6.121 | 0.796 | 0.305 | 53.53 | 61.54 | 11.18 | 0.067 | 2.639 | 0.931 | **0.957** | 0.083 |
| MusicTransformer              | 1.167 | 6.16 | 0.833 | 0.499 | 55.55 | 62.72 | **11.69** | 0.071 | 2.539 | 0.919 | 0.990 | 0.095 |
| Transformer-GANs              | 1.145 | 6.136 | **0.814** | 0.298 | 56.17 | **63.93** | 12.01 | 0.091 | 3.51  | 0.919 | 0.997 | 0.129 |
| Multi-scale model (Ours)      | **1.086** | **6.626** | 0.834 | 0.436 | **73.97** | **76.01** | 10.77 | **0.082** | **2.863** | **0.892** | **0.998** | **0.171** |

4.2 Ablation studies

We analyzed the benefits of the proposed FSL and MSN layers from different configurations. All ablations run on J.S. Bach and Maestro datasets. The ablation studies are designed to test the performance of the FSL and MSN layers on four aspects: (1) The effectiveness of the FSL and MSN layers; (2) The influence of the baseline model choice; (3) The optimal alignment of sliding windows in the FSL layer; (4) The best configuration of our model. The results are demonstrated in Tab.3.

Ablation studies have suggested the effectiveness of FSL and MSN layers, while the sparse attention configured with [Global, MSN] parameters achieved the best performance on most metrics. The use of the global alignment strategy of candidate windows leads to better performance of music generation (compared to the L2R strategy, almost all metrics are better). When the MSN layer (benchmark 4) is used, the model improves the pitch diversity in the generated music, which makes the music style more similar to the training dataset (TUP, PR, and APS are great improvements). These results fully illustrate the importance of structural dynamic segmentation for music generation.

4.3 Visual Evaluation

We present a sample of the generated music to illustrate the ability of our model to reuse and recreate melodies, and this ability improves the realism of the generated music. As shown in Fig.5, compared to the original music, the music generated by our model maintains a steady rhythm with some strong melodies being recreated (in the red boxes).

Further, samples generated by four comparison
with similar tonal trends and consistent rhythm. The samples generated by MusicTransformer are in style from the original music. Our model generates samples that conform to the musical sense, to the original music. The sample reflects many higher octaves (higher pitches), and very different rhythmsically inconsistent because there is an inverse note density in the sequence (see purple box), making the generated music unrealistic. All models were visually presented under the same experimental condition, as shown in Fig.6.

In the sample generated by Transformer-XL, almost all notes are the minimum unit, which makes the sample sound monotonous and boring. The samples generated by MusicTransformer are rhythmically inconsistent because there is an inequivalent note density in the sequence (see purple box), making the generated music unrealistic. All notes in the samples generated by Transformer-GANs are large in timescale (longer duration), in higher octaves (higher pitches), and very different in style from the original music. Our model generates samples that conform to the musical sense, with similar tonal trends and consistent rhythm to the original music. The sample reflects many compositional techniques, such as using root notes (bass tones), is similar to realistic music.

### Table 3: Ablation studies of FSL and MSN layers on J.S. Bach and Maestro v3.0.0 datasets.

| Baseline Configuration | PPL | PCU | ISR | PRS | TUP | PR | APS | IOI | PCH | GS | CPI | SI |
|------------------------|-----|-----|-----|-----|-----|----|-----|-----|-----|-----|-----|----|
| Training Set (J.S. Bach) | - | - | 8.407 | 0.8352 | 0.422 | 25.453 | 34.322 | 11.671 | 0.064 | 2.994 | 0.930 | 0.985 | 0.011 |
| Sparse Attention | [None, None] | 1.897 | 5.751 | 0.737 | 0.365 | 34.892 | 40.235 | 6.762 | 0.074 | 2.539 | 0.919 | 0.99 | 0.002 |
| Local Attention | [Global, MSN] | 1.872 | 6.979 | 0.815 | 0.417 | 24.812 | 34.832 | 11.153 | 0.125 | 2.92 | 0.871 | 0.99 | 0.009 |
| Sparse Attention | [L2R, None] | 1.84 | 5.798 | 0.786 | 0.388 | 34.547 | 39.78 | 6.867 | 0.073 | 2.537 | 0.921 | 0.987 | 0.006 |
| Sparse Attention | [Global, None] | 1.817 | 6.085 | 0.792 | 0.397 | 34.052 | 38.832 | 6.919 | 0.071 | 2.522 | 0.927 | 0.986 | 0.009 |
| Sparse Attention | [L2R, MSN] | 1.786 | 6.881 | 0.816 | 0.417 | 24.366 | 34.236 | 11.277 | 0.127 | 2.91 | 0.874 | 0.995 | 0.007 |
| Sparse Attention | [Global, MSN] | 1.724 | 7.123 | 0.817 | 0.419 | 24.859 | 34.699 | 11.237 | 0.124 | 2.934 | 0.871 | 0.993 | 0.013 |

| Training Set (Maestro) | - | 6.665 | 0.815 | 0.429 | 66.002 | 68.146 | 11.598 | 0.083 | 2.886 | 0.901 | 0.958 | 0.208 |
| Sparse Attention | [None, None] | 1.142 | 5.529 | 0.669 | 0.274 | 36.1 | 38.57 | 6.18 | 0.087 | 2.477 | 0.941 | 0.989 | 0.063 |
| Local Attention | [Global, MSN] | 1.184 | 6.361 | 0.786 | 0.411 | 52.924 | 61.422 | 10.651 | 0.090 | 2.817 | 0.942 | 0.743 | 0.089 |
| Sparse Attention | [L2R, None] | 1.114 | 8.518 | 0.912 | 0.521 | 36.49 | 38.99 | 9.74 | 0.071 | 2.593 | 0.939 | 0.732 | 0.076 |
| Sparse Attention | [Global, None] | 1.087 | 5.769 | 0.801 | 0.358 | 29.478 | 35.728 | 5.268 | 0.094 | 2.719 | 0.922 | 0.913 | 0.169 |
| Sparse Attention | [L2R, MSN] | 1.044 | 6.867 | 0.834 | 0.441 | 74.576 | 77.364 | 10.977 | 0.083 | 3.001 | 0.889 | 0.997 | 0.168 |
| Sparse Attention | [Global, MSN] | 1.086 | 6.626 | 0.834 | 0.436 | 73.965 | 76.011 | 10.767 | 0.082 | 2.863 | 0.892 | 0.998 | 0.171 |

Table 3: Ablation studies of FSL and MSN layers on J.S. Bach and Maestro v3.0.0 datasets. For each metric, the results are better when closer to the Training Set, and the best performance is highlighted in bold.

![Figure 5](image-url) Figure 5: Illustration of visual comparison of the generated (upper in shallow blue) and original music (lower in orange). Blue boxes indicate activation notes; Red boxes are examples of recreated melody.

![Figure 6](image-url) Figure 6: Visual comparison of musical samples generated by four different models, i.e. Transformer-XL (upper left), MusicTransformer (upper right), Transformer-GANs (lower left), and our multi-scale model (lower right), given the same initial notes.

In the future, we plan to explore other applications of the multi-scale models, for instance, generating polyphony music that involves multiple tracks. We can try more other strategies, such as adversarial learning and curriculum learning, to improve the results when closer to the Training Set, and the best performance is highlighted in bold.
| Model                  | Time Complexity | Memory Complexity | Steps |
|-----------------------|-----------------|-------------------|-------|
| LSTM                  | O(L)            | O(L)              | L     |
| Transformer           | O(L^2)          | O(L^2)            | L     |
| Sparse Transformer    | O(L log L)      | O(L log L)        | L     |
| Music Transformer     | O(L/10^3)       | O(L/10^3)         | L     |
| Transformer-GANs      | O(2L log L)     | O(2L log L)       | L     |
| Multi-scale Transformer| O((L/m) log (L/m)) | O((L/m) log (L/m)) | L/m   |

Table 4: L-related computation complexity. B is the number of memory blocks in MusicTransformer.

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A Example Appendix

This is an appendix.