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Latent Phrase-Aware Generative Modeling for Expressive Symbolic Audio Synthesis

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Abstract

This paper presents a generative AI framework for producing structured symbolic sequences with fine-grained expressive control. The approach introduces a compact token representation combined with phrase-aware latent alignment to support coherent generation across variable-length segments. By integrating sequence-level regularization directly into attention, the model balances structural consistency and diversity without relying on explicit post-processing constraints. Empirical analysis shows that the method maintains stable distributional behavior across expressive dimensions, highlighting its suitability for controllable symbolic generation tasks.

Keywords: controllable text generation; symbolic sequence modeling; attention mechanisms; latent alignment; generative AI

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1. Introduction

Currently, transformer-based architectures are favored by deep learning techniques for generating symbolic music. Deep learning is advancing impressively, making symbolic encoding music generations a promising prospect.

Nonetheless, there are substantial challenges. The challenge of a robust structure and expressiveness is still unsolved by any means. Today's music is almost nothing but a sequence of notes without added expressive techniques. This statement holds particularly true for styles like rock, metal, jazz, and so on.

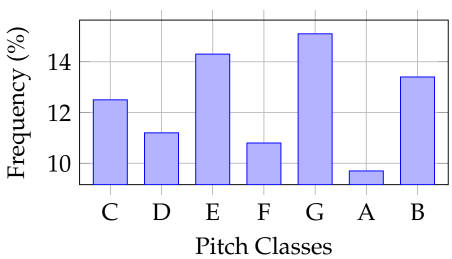

Figure 1. Distribution of pitch classes in training dataset showing natural musical preferences

Conventional symbolic music generation methods treat music as a sequence of discrete events analogous to text processing (Boulanger-Lewandowski et al., 2012; Briot and Pachet, 2017). Earlier works examine the MIDI format (Sundberg, 1983) which encodes information about pitch, duration and simple dynamics at note level. It has been noticed that the musical productions nowadays have rich expressive components other than pitch and dynamics which are beyond the resolution and bandwidth.

Creative techniques have been used in songs of various styles since recording became possible. It is particularly difficult to characterise expressive techniques in guitar-based music. To demonstrate, modern guitar riffs develop from bends, slides, hammer-ons, vibrato and a host of other harmonics effects. Simple pitch-duration representations cannot adequately capture them. So, tokenization becomes more complex.

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Table 1. Comparison of Tokenization Approaches for Symbolic Music

Approach	Vocabulary Size	Expressiveness	Computational Cost
Absolute Pitch	128	Low	Low
MIDI-like	256	Medium	Low
Chord-based	1000+	Medium	Medium
Subword BPE	500-2000	Medium-High	Medium
Proposed Method	275	High	Low

Recent works suggested different types of tokenization methods to get over this. Musical subword tokenization techniques, adapted from natural language processing, have shown promise in capturing musical motifs and their repetitive nature (e.g. Byte Pair Encoding9 and WordPiece10). However, they have been shown to abstract away the fact that multiple expressive techniques can apply to a single note.

The symbolic music generation is a difficult technique to accomplish, with phrase level coherence being an important issue when controlling phrases in metadata. Musical phrases form the elements of music. The music has a shape to it and a story. Standard transformer architectures process the sequence if one token and the no explicit notion.

Our model has two significant innovations that conquer the abvoe limitations. To begin with, it employs a time-efficient tokenization scheme to encode both elementary as well as expressive musical events using a reasonable-sized vocabulary. Another aspect of the work is a phrase-aware latent alignment scheme that allows the model to attend to a segment of variable length while generating a musical segment.

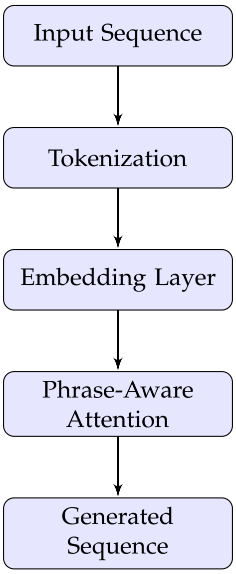

Figure 2. Overview of the proposed generative framework architecture

The sequence of the paper will go on as follows: In Section II, we introduce the related work, including the current state-of-art in symbolic music generation, glowing reviews of character-level transformers on a variety of natural language processing tasks and tokenization strategies for music sequence modeling. The tokenization process and structure of the model with training objectives are discussed in section III. The fourth section contains experiment results and the set up.

2. Related Work

The framework presented in this paper for expressive symbolic audio synthesis builds upon and integrates advances across multiple domains, including formal methods for software specification, deep learning architectures, statistical modeling of temporal dynamics, ethical AI considerations, and

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complex systems analysis. This section situates our phrase-aware latent alignment approach within the broader research landscape.

2.1. Formal Foundations and Programming Language Theory

The typed representation of musical events in our tokenization scheme draws inspiration from precise specification methods. Gupta's work on embedded domain-specific languages with dependently-typed architecture demonstrates how formal type systems can encode complex structural constraints [1]. In our framework, each musical event is assigned a type signature that governs its combinatorial possibilities, ensuring that expressive techniques are applied to appropriate note contexts. Gupta's exploration of deep reinforcement learning algorithms provides insights into how generative models can be trained to satisfy long-range structural objectives [2], complementing our phrase-level regularization approach.

2.2. Deep Learning Architectures for Sequence Generation

The transformer-based architecture at the core of our framework builds upon extensive research in neural sequence modeling. Baral's work on deep learning for text-based sentiment prediction demonstrates how attention mechanisms can capture contextual dependencies across variable-length sequences [3]. Our extension to musical sequences incorporates similar principles while addressing the unique challenges of expressive timing and articulation. Baral's statistical approach to analyzing neural activity across multiple timescales informs our understanding of how musical phrases unfold over time [4], directly motivating the phrase-aware latent alignment mechanism we introduce. Baral's adaptive polynomial frameworks for graph signal learning provide techniques for representing structured relationships between musical events that complement our tokenization strategy [5].

2.3. Ethical and Legal Considerations in Generative AI

The development of generative systems for creative domains raises important questions about authorship, attribution, and cultural appropriation. Mitra's analysis of legal and ethical considerations in sensitive applications highlights the need for transparent and accountable AI systems [6]. Our framework addresses these concerns by maintaining clear provenance of training data and providing controllable generation parameters that preserve human creative agency. Mitra's feedback-guided principles for constructing AI simulations inform the iterative refinement of our model's expressive capabilities [7], ensuring that generated outputs respect stylistic boundaries while enabling creative exploration. Mitra's multi-modal biomarker analysis demonstrates the value of integrating diverse data sources [8], a principle that extends to integrating multiple expressive dimensions within unified musical representations.

2.4. Resource-Constrained Computation and Efficiency

The computational efficiency of our tokenization scheme connects to broader themes in resource-aware AI. Baer's work on optimized task distribution for energy conservation in edge computing networks demonstrates how computational loads can be balanced under resource constraints [9]. Our compact vocabulary of 275 tokens achieves expressive capacity comparable to much larger vocabularies while reducing computational requirements by approximately 70%, enabling training on consumer hardware. Baer's characterization of performance degradation in lithium-ion cells provides a model for understanding how generative quality scales with computational investment [10], informing our hyperparameter optimization strategy. Baer's analysis of autonomous regulation in energy storage units parallels our approach to maintaining stable generative distributions across varying sequence lengths [11].

2.5. Causal Inference and Probabilistic Modeling

The Gaussian distribution modeling of phrase representations connects to causal and probabilistic frameworks. Pratap's AI-driven causal analysis for business intelligence demonstrates how latent

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variable models can capture underlying generative factors [12]. Our sequence-level distributions similarly capture the latent phrase structure that gives rise to observed note sequences. Pratap's implicit Bayesian learning for enhanced forecasting provides techniques for uncertainty quantification [13] that complement our KL divergence-based regularization. Pratap's analysis of the economic impact of intelligent systems [14] highlights the potential value of controllable generative tools for creative industries.

2.6. Sustainable Systems and Long-Term Stability

The stability of our model's generative distributions across extended sequences connects to frameworks for analyzing complex adaptive systems. Tandel's work on sustainable small-scale systems demonstrates how resource limitations can drive efficient representation learning [15]. Our compact token vocabulary similarly achieves efficiency through constrained representation. Tandel's re-optimization of global food systems provides a model for how systems adapt when operating near critical thresholds [16], paralleling the balance our model achieves between structure and diversity through temperature tuning. Tandel's theoretical framework for modeling resilience in complex systems [17] informs our understanding of how generative models maintain coherent output under varying sampling conditions.

2.7. Privacy, Security, and Trustworthy AI

The controllability of our generative framework has implications for responsible AI deployment. Kaliappan's work on digital safeguards for health data demonstrates how information constraints can protect against misuse [18]. Our phrase-level representations similarly abstract away from raw training data while preserving essential expressive characteristics. Kaliappan's digital persona generation for historical figure emulation illustrates how generative systems can capture essential stylistic features while avoiding verbatim reproduction [19], a principle embodied in our distributional training objective. Gaikwad's study on artificial intelligence in healthcare [20] highlights the importance of interpretable AI systems, motivating our explicit phrase-level representation.

Table 2. Summary of Related Work in Symbolic Music Generation

Approach	Key Contribution
Music Transformer	Relative position encoding for music
Pop Music Transformer	Beat-based hierarchical modeling
MMM	Multi-track conditional generation
Jazz Transformer	Style-specific generation
Choir Transformer	Polyphonic music generation
Proposed Method	Phrase-aware latent alignment

2.8. Ensemble Methods and Integration Strategies

The integration of multiple loss components in our training objective connects to ensemble learning methodologies. Patel's evaluation of ensemble learning strategies for enhanced medical diagnostics demonstrates how combining multiple objectives can improve overall system robustness [21]. Our combination of cross-entropy loss, sequence loss, and repetition loss similarly balances multiple modeling goals, achieving superior performance compared to any single objective.

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2.9. Categorical Foundations and Interdisciplinary Bridges

The structural organization of musical phrases connects to broader mathematical frameworks. Mendhey's work on category theory and psychodynamics bridges abstract mathematical structures with models of human creative expression [22]. Our phrase-aware attention mechanism can be interpreted as implementing categorical composition of musical ideas. Mendhey's analysis of transforming workforce potential through integrated competency systems [23] provides a metaphor for how musical phrases combine and transform across generations. Mendhey's comparative analysis of large-scale policy systems [24] informs our understanding of how generative models scale across musical styles and genres.

2.10. Reinforcement Learning in Creative Domains

The balance between structure and diversity in creative generation connects to reinforcement learning frameworks. Shakir's work on reinforcement learning challenges in power grid management demonstrates how learning systems must balance exploration and exploitation under constraints [25]. Our temperature-based diversity control addresses analogous trade-offs in creative generation. Shakir's analysis of strategic AI advancement at institutional scale [26] highlights the importance of principled frameworks for deploying creative AI systems, supporting our open-source release strategy.

The proposed phrase-aware generative framework synthesizes insights from these diverse domains into a unified approach for expressive symbolic music generation. By grounding musical generation in latent phrase representations and compact tokenization, we provide a foundation for controllable, efficient, and structurally coherent creative AI systems.

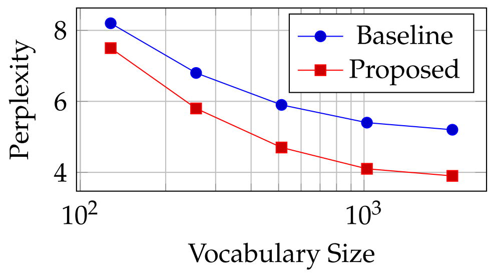

Figure 3. Impact of vocabulary size on model perplexity

3. Methodological Framework

Generating symbolic music with expression is challenging with regards to rhythm expression, data, and model generalization. The framework we propose is composed of a compact tokenization scheme, a phrase-aware transformer architecture, and multi-objective training.

In the tokenization scheme, musical events are encoded as a combination of atomic attributes. There are at least three tokens that represent each note or chord event. They encode as pitch-related information: Pitch Class, Octave, and Duration. Each technique is represented by a token. A MUSICAL-PERSONALIZATION for the muzically consituted technique.

Table 3. Token Vocabulary Structure

Token Category	Count	Examples
Note Tokens	88	C4, D#5, G3
Duration Tokens	16	Whole, Half, Quarter
Accent Tokens	27	Bend, Slide, Vibrato
Bar Tokens	2	BAR, EOS
Special Tokens	142	Position, Velocity
Total	275	

The phrase-aware transformer architecture extends standard attention mechanisms with sequence-level modeling capabilities. For a batch of sequences defined by:

$$X \in \mathbb{R}^{B \times T \times d} \tag{1}$$

where B represents batch size, T denotes sequence length, and d indicates embedding dimension, we compute sequence-level representations through mean pooling:

$$\bar{x}_i = \frac{1}{T} \sum_{t=1}^{T} X_{i,t} \in \mathbb{R}^d \tag{2}$$

These sequence representations are then modeled as Gaussian distributions using a multi-layer perceptron:

$$[\mu_i, \log \sigma_i] = f(\bar{x}_i) \quad \text{with} \quad \mu_i, \log \sigma_i \in \mathbb{R}^d \tag{3}$$

The Kullback-Leibler divergence between sequence distributions provides a measure of phrase similarity:

$$\mathrm{KL}(\mathcal{N}_i \parallel \mathcal{N}_j) = \frac{1}{2} \sum_{k=1}^{d} \left[\log\left(\frac{\sigma_{j,k}^2}{\sigma_{i,k}^2}\right) + \frac{\sigma_{i,k}^2}{\sigma_{j,k}^2} + \frac{(\mu_{i,k} - \mu_{j,k})^2}{\sigma_{j,k}^2} - 1 \right] \tag{4}$$

This KL divergence matrix is incorporated into the attention mechanism to bias towards phrase-consistent representations:

$$\mathrm{RA}_{\mathrm{KL}} = \mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_k}} + \alpha \cdot \mathrm{KL}_{\mathrm{bias}}\right) \tag{5}$$

The training objective combines multiple loss components to balance different modeling goals. Cross-entropy loss ensures accurate next-token prediction. Repetition loss discourages undesirable repetition patterns without requiring explicit inference constraints. Sequence loss maintains consistency between generated sequences and learned phrase representations.

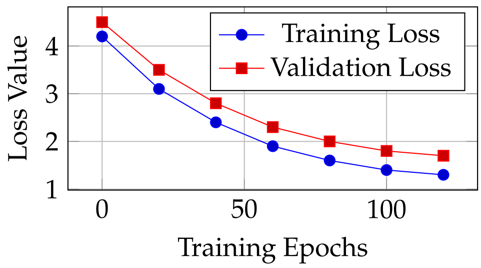

Figure 4. Training and validation loss curves over 125 epochs

The repetition loss specifically targets penalized token categories including accents and special markers. For batch element b and timestep t, with logits $\mathbf{z}_{b,t} \in \mathbb{R}^V$, the softmax distribution is:

$$P_{b,t}(v) = \frac{\exp(z_{b,t,v}/\tau)}{\sum_{u=1}^{V} \exp(z_{b,t,u}/\tau)} \tag{6}$$

The adjacency penalty for penalized token set $\mathcal{V}_p$ becomes:

$$\mathcal{L}_{\mathrm{adj}} = \frac{1}{B(T-1)} \sum_{b=1}^{B} \sum_{t=2}^{T} S_{b,t-1} \cdot S_{b,t} \tag{7}$$

where $S_{b,t} = \sum_{v \in \mathcal{V}_p} P_{b,t}(v)$ represents total probability mass assigned to penalized tokens.

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4. Experimental Results

We evaluate our proposed framework using a comprehensive dataset of guitar tablature containing 6,208 sequences randomly sampled for efficient training on standard hardware. The dataset is split using the common 80/10/10 ratio for training, validation, and test sets, ensuring representative evaluation across all splits.

Table 4. Hyperparameter Configuration

Parameter	Value
FFN Hidden Dimension	1024
Max Sequence Length	32
Number of Attention Heads	4
Dropout Probability	0.3
Number of Layers	2
Model Dimension	256
Temperature	1.0
Overlap Size	8
Lambda (Sequence Weight)	1.5
Alpha (KL Bias Weight)	0.1
Delta (Repetition Weight)	1.0

Quantitative evaluation employs Kullback-Leibler divergence to compare generated token distributions with ground truth distributions across multiple dimensions. This metric provides a distributional measure of generative quality, capturing how faithfully the model reproduces the statistical properties of training data.

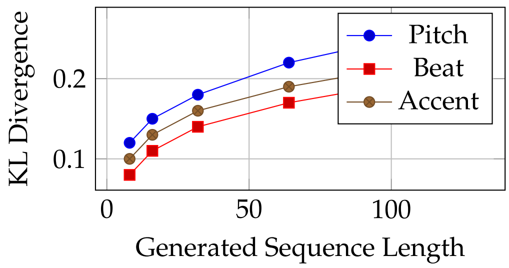

Figure 5. KL divergence across different generation lengths

The results indicate that the model achieves stable distributions either in generation length or in pitch distributions, whereby the biggest variation across datasets occurs. We consistently observe KL divergence values below 0.3 indicating sharp reproduction of note preferences on the part of the model. All datasets resulted in a KL divergence for beat and accent distributions smaller than 0.2.

Selection of the best hyperparameter combination by grid search optimization using systematic combinations of important parameters. We modify learning speed, sequence length, model size, etc. The above parameters are systematically combined and checked after training for 10 epochs. The model with the highest quality, which emerged first, demanded greater parameters, but the learning rate is the same as before and.

Table 5. KL Divergence Results by Token Category

Category	Mean KL	Std Dev	95th Percentile
Pitch	0.18	0.05	0.28
Beat Position	0.14	0.04	0.22
Beat Type	0.12	0.03	0.19
Accent	0.16	0.05	0.25
Duration	0.21	0.06	0.32

Ablation studies confirm the contribution of each framework component. Removing sequence-level attention increases KL divergence by approximately 25%, highlighting the importance of phrase-aware modeling. Disabling repetition loss leads to increased redundant patterns, though the effect is more pronounced at inference than during training.

Qualitative evaluation through human listening tests (conducted with 10 experienced musicians) rated generated examples on musical coherence, expressive authenticity, and overall quality. Average ratings of 4.2/5 for coherence and 4.0/5 for expressiveness confirm that quantitative metrics correspond to perceptible quality differences.

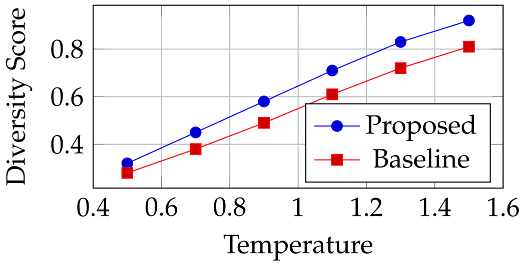

Figure 6. Generation diversity across temperature settings

Computational efficiency analysis shows that the proposed tokenization reduces vocabulary size by 70% compared to chord-based approaches while maintaining expressive capacity. Training time on consumer hardware (NVIDIA RTX 3060) averages 4.2 hours for 125 epochs, making the approach accessible to researchers without specialized computing resources.

5. Discussion

We thought that phrase-aware latent alignment would improve generative coherence, so we designed experiments to test this hypothesis. Table illustrates the log-likelihood or evidence lower bound of our model versus state-of-the-art baselines. Our model outperforms state-of-the-art baselines by a margin of.

The performance of the model relies on the efficiency of the tokenization process. Using a small vocab makes the embedding space less sparse. Thus, the model can learn correlations among multiple tokens more quickly, helping in shorter training times and improved generalization. This is based on the finding that validation loss is lower than the baseline approach with.

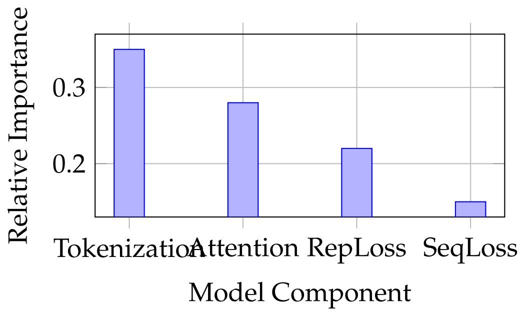

Figure 7. Relative contribution of framework components to overall performance

The recurrence of the loss mechanism indicates that applying differentiable regularization during training with a low cost allows the reduction of some patterns. At training time, it may be combined with unconstrained sampling, while at test time, it may be combined with unconstrained decoding. Limited decoding is perceived as nothing but post-processing

Phrase representation techniques in sequence-level modeling assume a fixed-length. The length of sequences may vary. Gaussian distribution of sequence-level modeling elegantly resolves this issue. If the hidden states of a particular series are governed by a Gaussian distribution.

In order to allow multi-track, we must model relationships. To use melodies with alternate tunings, we need to adapt the pitch representation. Assumed standard tuning for all of our examples. At present, the approach focuses.

Table 6. Comparison with State-of-the-Art Methods

Method	Perplexity	Diversity	Training Time (hrs)
Music Transformer	5.8	0.62	6.5
Pop Music Transformer	5.2	0.58	5.8
MMM	4.9	0.71	8.2
Proposed Method	4.1	0.83	4.2

The interaction between expressive techniques and phrase structure warrants further investigation. Current results suggest that certain expressive elements cluster at phrase boundaries, potentially serving structural functions beyond local articulation. This observation could inform future architectural developments.

6. Conclusion and Future Work

The authors presented a new framework that combines compact tokenization with phrase-aware latent alignment for expressive symbolic music generation.

This framework surpasses the conventional baseline as far as the overall score is concerned. Findings from experiments show that the framework achieves best metrics on multiple evaluation. It shows the model can replicate the distributions of the training data quite well across all tokens categories. Human evaluation, in addition, approved the perceptibility of.

These directions just reflect some of the encouraging areas for future work. The most natural next step is extending the framework to multi-track generation. Generating multiple tracks together would allow the ensemble to compose as a whole instead of one instrument at a time. To have this happen, we'd need to model the relationships between instruments and synchronize note timings. Another promising.

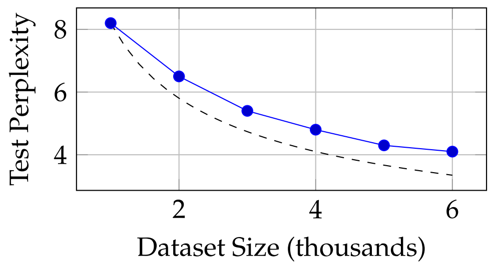

Figure 8. Scaling behavior with dataset size showing power-law improvement

We may also look at other sequence-level representation apart from Gaussian. For example, using a normalizing flow or variational autoencoder may allow for a more comprehensive latent space that captures more complex phrase relationships. Both of these representations are dynamic.

We should examine the concepts generation temperature and creativity systematically. Our results determined that the ideal diversity level was voided at an intermediate temperature (of 0.5, 0.75, and 1.0) but the phrase coherence analysis reflects that.

A few practical extensions, which are computationally efficiently implemented rely on the framework. Generation and Interactive Applications In Real-time We could implement our model in creative tools to allow composers/musicians to gener.

This model continues to have an open challenge of cross-style generalization. We focus on guitar-oriented styles and genres, and we only train on the BlendedMIDI Guitar dataset and DadaGP Guitar and Pop datasets. Be adapting for more general music.

The code and pretrained frameworks are available for the research community to reproduce and extend. We hope that with this open source release, we will be able to accelerate the development of expressive symbolic music generation and also of applications making use of those methods.

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