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An investigation into the development of musical styles using deep generative modeling

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Abstract Deep generative models have a lot of promise for music production and style modeling given the quick advancement of artificial intelligence technologies. There are still several obstacles in the way of properly capturing and analyzing the principles of music style evolution using deep generative models. This study, which is based on deep generative modeling, attempts to investigate the dynamic process of music style change and develop a generative framework that can capture the traits of music style evolution. In the meantime, an optimization scheme based on the attention mechanism and multiscale modeling is proposed to improve the quality of generation and the interpretability of style evolution in to address the limitations of deep generative models when handling complex time series and multimodal music data.In terms of stylistic consistency, sound diversity, and evolution rationality, the generated music greatly surpasses the current approaches, according to experimental results, which demonstrate that the model put out in this study can successfully represent the time-series evolution characteristics of musical styles.

Index Terms deep generative modeling, music style evolution, generative adversarial networks, variational self-encoder, attention mechanism

I. Introduction

As deep learning and artificial intelligence technologies advance quickly, generative modeling has emerged as a key instrument for fostering creativity in the creation and analysis of music [1]. As a kind of art and culture, music not only documents the course of social history but also captures the richness and diversity of human emotions. One of the main topics of music research is the evolution of music style, which encompasses a variety of topics such the law of change of musical elements, the impact of cultural background on music style, and the direction of music creation in the future [2]. By studying theolution of musical style, we may better grasp the cultural significance of music and provide technical support for intelligent music creation and instruction.

Deep generative models have demonstrated impressive results in natural language processing and image production in recent years, and their applications in the creation and analysis of music have steadily showed great promise [3], [4]. Specifically, deep learning-based models like Transformers, Variational Auto-Encoders, and Generative Adversarial Networks (GANs) can effectively extract possible patterns from vast amounts of music data and produce high-quality music. However, music data is mimensional and has strong time series, which makes data processing and modeling much more challenging than in the image and text domains [5].

The following areas are the focus of current research on music generation: Second, the majority of existing models rely on fixed datasets, ignoring the dynamic characteristics of music styles affected by historical, cultural, and social contexts; third, diversity and innovation remain bottlenecks in the application of deep generative modeling in the music domain; and fourth, modeling methods based on music drily focus on short-term melody generation and style migration, lacking systematic research on the evolution law of music styles over long time spans [6], [7].

This research seeks to address these issues by developing a deep generative modeling-based framework for methodically investigating the rules governing the emergence of musical styles and investigating the dynamic relationshiong them. The primary contribution of this study is shown in the novel notion of employing deep generative models to evaluate the evolution of musical genres, which is suggested after a thorough examination of the literature on this topic [8]. This offers new technical tools for intelligent music composition in addition to enhancing research methodologies in the fields of music generation and analysis. This work combines the benefits of transformers and generative adversarial networks to create an effective multimodal generative framework that can capture the multilevel featuence issues that current models encounter when working with music data. The inherent law of music style growth can be found by examining the dynamic relationships between various musical genres [9], [10]. In the meanwhile, this study suggests a style migration technique that, while maintaining the qualities of the original music styles, can produce new musical compositions that adhere to the target styles.

In addition to offering technological support for the quantitative examination of the evolution of musical styles, the research presented in this paper opens up new avenues for cultural communication, education, and music production. The research techniques and findings of this work will pave the way for new avenues for the fusion of artificial intelligence and music as deep generative modeling continues to advance.

II. The compositional framework of music

A common definition of music is a group of sounds of different intensities arranged in a particular pattern horizontchical structure when one understands it, as seen in Figure 1. A piece of music can be broken down into paragraphs, phrases, bars, beats, and notes according to its length, and articles like upper level modules are composed of lower level modules in a particular predetermined pattern of repeating [11].

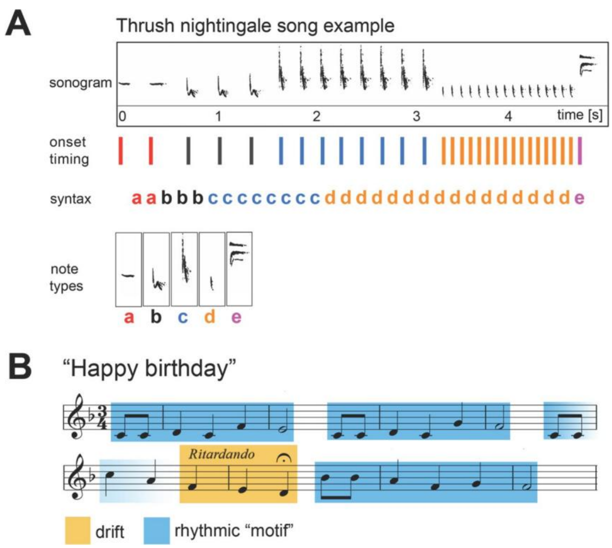


Figure 1: Music's structure

The most fundamental element of music is the note, which serves the primary purpose of recording notes with varying time values. It is possible to say that a composition is made up of notes that each convey distinct information [12]. Although there are many different types of notes in use, the whole, half, quarter, eighth, and sixteenth notes are the most frequently used. In addition to being crucial components of the pentatonic score, notes also have the fundamental qualities of music, such as duration and pitch.

In music, beats are also essential. In music, time is separated into equal basic units known as beats. A quarter note (i.e., a quarter note as a beat), half note, or eighth note can all be used to express the temporal value of a beat [13]. A beat's time value is a relative idea of time; for example, a composition produced at 60 beats per minute has one beat per second, while a half-beat takes up half a second.

The fundamental building blocks of phrases and passages are measures; phrases are made up of the alternation of measures, and passages are made up of the regular arrangement of phrases. The smallest beat unit in a, which is not random but rather structured in a certain pattern [14]. For instance, "two beats" indicates that there is only one weak beat—for instance, in 2/4 time—and that its beat distribution is strong beat, weak beat, strong beat; whereas "three beats" indicates that there are two weak beats—for instance, in 3/4 time—between two strong beats, and that its beat distribution is strong beat, weak beat, second strong beat, and weak beat. Strong, weak, sub-strong, and weak beats are distributed throughout.

III. Modeling framework for ACMG

In this study, music generation is treated as a sequential decision-making process, aligning with the principles of reinforcement learning where agents learn optimal strategies under limited feedback. To this end, a model-based planning approach is introduced by redefining components of the classical Actor-Critic architecture in the context of symbolic music generation.

Within the proposed ACMG (Actor-Critic Music Generator) framework, the Melody_LSTM network operates as the Actor module. This component is responsible for producing melodic sequences (notes) while dynamically refining its output based on evaluative signals. These signals—interpreted as rewards—guide the Actor to evolve its generative strategy for more musically coherent outputs.

On the other hand, the Critic module evaluates the musicality of the sequences generated by the Actor. It incorporates multiple evaluation mechanisms, including harmonic alignment with chord progressions, adherence to fundamental music theory rules, and the contextual appropriateness of musical states through a value estimation function. These reward-based evaluations collectively shape the learning feedback for the generative process. The architecture of the ACMG model is illustrated in Figure 2.

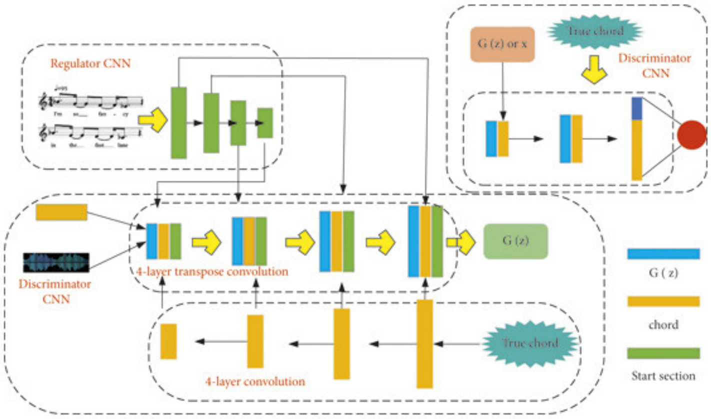


Figure 2: Modeling framework for ACMG

The notes now generated by the Actor network are regarded as the selected action in this investigation (α_t), the set of actions ($\alpha_t \in A$), and the total of the notes produced at earlier times ($A_{1:I-1}$).

$$(\alpha_1, \alpha_2, \ldots, \alpha_{I-1}) \rightarrow A_{1:I-1}, \quad s \in S. \tag{1}$$

The state $A_{1:I}$can be retrieved at the following instant from the note a_t that was chosen at the current time and the state $A_{1:I-1}$ that came before it.In order to assess the score of α_t the Critic network is given$A_{1:I-1}$,a_t, and$A_{1:I}$, respectively. The character-level music-generating network Melody_LSTM, which has been explained in Chapter 3 of this paper, is the Actor network. The Critic network will be the subject of the next part. The details of the Critic network will be covered in the next section.

IV. Critic network

The more popular Go robot AlphaGo uses the Actor-Critic algorithmic framework, which uses a Critic network to give feedback on whether a move made at the moment would help AlphaGo win. The ACMG model's Critic network determines whether the song's harmony and appeal are enhanced by the current note choice. Using state variables, chord progressions, and concepts from music theory, the Critic network evaluates the notes generated by the Actor network. The section that follows provides an explanation of the specifics of each of the three reward mechanisms created in this study [15], [16].

IV. A. Incentives for chord progression

A collection of notes having a certain intervallic relationship is called a chord. A chord progression is made up of several chords placed in a specific order; Figure 3 shows an example of a chord progression. Since cho, many composers actually use chord progressions to organize their music. Chord progression-based music production is not only quicker but also of higher quality than relying solely on creativity. However, when using deep learning techniques alone to create music, the impact of chord progressions on notes is frequently overlooked. This study develops a chord progression rewarding mechanism based on this influence to provide score for music generation networks from the perspective of chord progressions, thereby optimizing the generation effect.

Music always has a measure that has both strong and weak beats, and strong and weak beats alternate. For example, in 4/4 time music, the beats of a measure are distributed as strong, weak, sub-strong, and weak. In order to emphasize the structure of the music and provide a more staggered progression, the notes on the strong and weak beats are usually chosen differently during the creation process. However, when learning the associations between notes from a dataset, neural networks often ignore the limitations of chord progressions on note selection. To address this challenge, this study proposes the following guideline:

1. The notes that comprise a chord are known as chord inversions. This paper uses triads, or chords made up of three notes, to make the following experiments easier. Odd-numbered beats are typically strong beats in music with a strong beat rhythm.

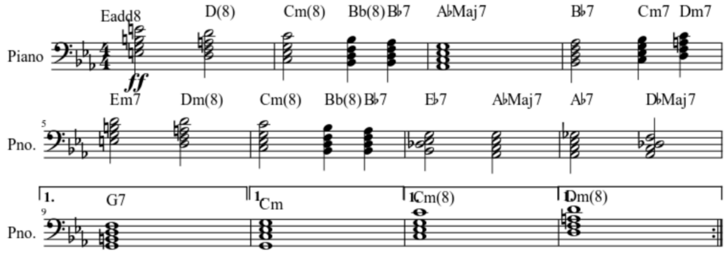


Figure 3: Score form for chord progression

Assume that the generative network selects the note ta at instant t, and that the chord in-tone isk_1^t, k_2^t, k_3^t. Eq. (2) can be formed using the aforementioned rule, where l_{z1}.We assign different reward levels to those who follow this rule and those who don't since they have varying impacts on the caliber of the music. The following regulations have different reward values as well, and the precise values are determined using the following guidelines: Initially, the rule that has the biggest influence on the quality of the music that is produced is recognized, and its reward value is set to either +1 or -1. Then, each rule's reward value is calculated by comparing it to the strongest rule.

$$l_{z1}\left(s_{1:t}, a_t\right) = \begin{cases} 0.6, \alpha_t \in (k_1^t, k_2^t, k_3^t t\%2 = 1), \\ -1, \alpha_t \notin (k_1^t, k_2^t, k_3^t t\%2 = 1). \end{cases} \tag{2}$$

2. In tonal music, notes that fall outside the core structure of a chord within an octave are referred to as non-chord tones or chord extras. These tones, when used appropriately, add expressive nuance by enhancing the fity of a melody, enriching rhythmic diversity, and introducing harmonic tension that deepens the musical texture. Typically, chord extras are placed on off-beats or weaker rhythmic positions to preserve harmonic stability while adding color.

Although their inclusion contributes to a more dynamic and engaging composition, excessive use can lead to harmonic ambiguity or dissonance. To strike a balance, this study incorporates a constraint within the generative framework: chord extras are allowed and even encouraged for expressive variety, but are limited to one occurrence per measure. This regulation ensures that harmonic coherence is maintained while still enabling creative flexibility in melodic

$$l_{z2}\left(s_{1:t}, \alpha_t\right) = \begin{cases} \begin{cases} 0.5 & , a_t \neq -k_i^t \\ -0.4 & , a_t = -k_i^t \end{cases} , \alpha_{t-2} = -k_i^t, \\ \begin{cases} 0 & , a_t \neq -k_i^t \\ -0.5 & , a_t = -k_i^t \end{cases} , \alpha_{t-2} = -k_i^t. \end{cases} \tag{3}$$

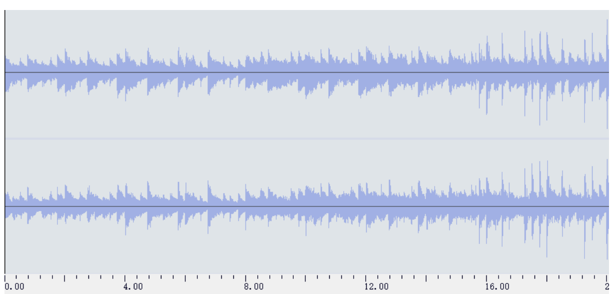


Figure 4: Music clip audio map

3. When we asked several musicians who were interviewed for this research about the median line, they made it quite evident that it is normal practice to artificially create a median line and choose melodic notes based on it. This not only makes it easier to compose music, but it also makes the arrangement more effective. The melody notes are typically situated within a range of six intervals above and below the median, which is typically selected as the inner note of a chord. The median line is considered to be α_t^m at time t, and α_t^m will be chosen at random from k_1^t, k_2^t, k_3^t. As a result, this work constructs Eq. (4):

$$l_{z3}\left(s_{1:t}, \alpha_t\right) = \begin{cases} 0.4, |\alpha_t - \alpha_t^m| \leq 5, \\ -0.2, |\alpha_t - \alpha_t^m| > 5. \end{cases} \tag{4}$$

IV. B. Incentives for music theory rules

The rules of music theory apply differently to different kinds of music. Owing to the vast array of musical styles, the experiment's primary focus is classical music in order to support the study of this paper and maximize a particular musical genre. Thus, the sphere of classical music is the primary emphasis of the prevailing European civilization beginning in the Western Middle Ages is referred to as classical music [17]. The dominant tones of music are restricted by musical theory laws, which is particularly crucial in classical music.

Variation is what gives music its vividness, and too many notes repeated will drastically cut down on the music's expressiveness and fluency, making for a dull and repetitive listening experience. Thus, notes shouldn't be repeated more than four times in a piece of music. Eq. (5) is constructed in this work based on this rule of music theory. The system will identify the recurrence of three notes ($\alpha_t$and$\alpha_{t-3}, \alpha_{t-2}, \alpha_{t-1}$) produced earlier, assuming that the note chosen by the music creation network at that precise instant is a_t.

$$L_{l1}\left(s_{1:t}, \alpha_t\right) = \begin{cases} -0.6 & , \alpha_{t-1} = \alpha_t \\ 0 & , \alpha_{t-1} \neq \alpha_t \end{cases} , \alpha_{t-3} = \alpha_{t-2} = \alpha_{t-1} \ . \tag{5}$$

The relationship between two adjacent tones in a group that share the same sound name is called an octave. Composers of classical music typically aim to maintain a smooth and calming rhythm, avoiding interval variances of more than an octave between adjacent notes, in contrast to rock and pop music, which need substantial fluctuations. Octave is a technical term in music. Since we are using the 12 equal temperament pitch notation in this article, an octave is equivalent to a 12-semitone interval difference. This work constructs Eq. (6) based on the restriction that the interval difference does not exceed an octave.

$$L_{l2}\left(s_{1:t}, \alpha_t\right) = \begin{cases} 0.3, \left|\alpha_t - \alpha_{t-1}\right| \leq 10, \\ -0.5, \left|\alpha_t - \alpha_{t-1}\right| > 10. \end{cases} \tag{6}$$

Since each key in a composition denotes a distinct mood, composers typically choose the range of their work in advance. The quality of the music and the presentation of emotion will be significantly impacted if the notes are outside of this range. This constraint is explained by Eq. (7), where $\alpha_{\min}$ and $\alpha_{\max}$ represent the lowest and highest notes, respectively, that are pre-set based on the music's key.

$$L_{l3}\left(s_{1:t}, \alpha_t\right) = \begin{cases} 0.1, \alpha_t \in [\alpha_{\min}, \alpha_{\max}], \\ -0.6, \alpha_t \notin [\alpha_{\min}, \alpha_{\max}]. \end{cases} \tag{7}$$

For a piece of music to be more steady and full, the final tone must be the major tone, or the key's core tone. For instance, music in the key of C major with C as the primary tone. Thus, assuming that the generated music is in the key of C major and that the final tone of the music isα_{end}, this study develops this music theory rule and creates Eq. (8):

$$L_{l4}\left(s_{1:t}, \alpha_t\right) = \begin{cases} 0.8, \alpha_{end} = C, \\ -0.6, \alpha_{end} \neq C. \end{cases} \tag{8}$$

The four rules listed above are the music theory rules that are quantified in this study. The music theory rule reward mechanism is primarily included to help the music generation network gain music theory knowledge so that the created music can reduce errors and enhance quality.

IV. C. Incentive mechanism based on state value

In the note generation process, each state corresponds to a probability distribution over all possible notes. A meaningful state is expected to demonstrate clear preference among note choices — reflected in higher variance within its probability distribution — indicating that the model is making informed, non-random decisions. Conversely, when the probabilities of selecting each note are nearly uniform, it implies that the state lacks distinguishing musical features and thus deviates from the patterns found in real compositions, making it less valuable.

To quantify the value of a given state, this paper introduces a variance-based metric derived from the output probabilities in the SoftMax layer. Specifically, let $p_i$denote the probability of selecting the i-th note in a given state, where$i = 1, 2, \ldots, n$, and n represents the total number of candidate notes. The mean probability across all notes is defined as:

$$\bar{p} = \frac{1}{n}\sum_{i=1}^{n} p_i. \tag{9}$$

Then, the value of the state $V_s$is calculated using the variance formula:

$$V_s = \frac{1}{n}\sum_{i=1}^{n}(p_i - \bar{p})^2. \tag{10}$$

A higher $V_s$indicates that the state strongly differentiates between notes — a sign of high musical relevance — and thus is rewarded accordingly in the training process. This reward encourages the model to evolve toward states that produce musically meaningful note distributions rather than generating ambiguous or noise-like outputs.

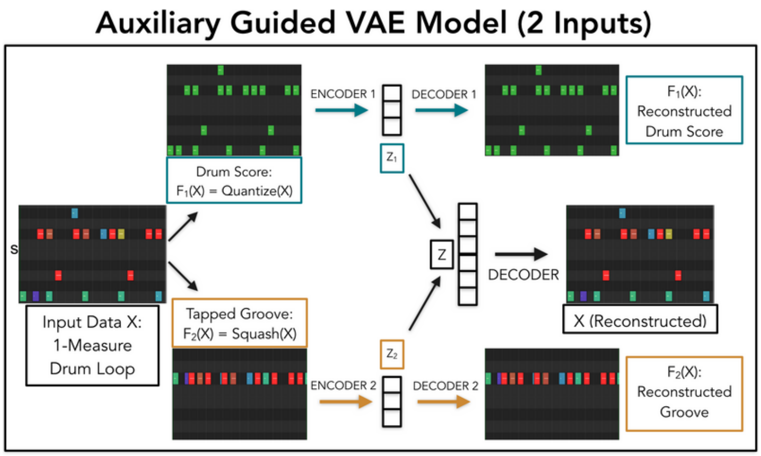


Figure 5: Incentive mechanism for status value

V. Experiment

V. A. *outcome of the experiment*

20,000 iterations were used in order to enhance the ACMG model's training procedure. Many music segments were produced utilizing the model once the iterations were finished. Here, arbitrary musical excerpts were chosen as illustrations for the results. The following is a visualization of the chosen musical ments: The created music is represented as a Piano Roll in Figure 6, where it is transformed into a sequence and shown on a piano roll. The generated music section is shown in sheet music form in Figure 7, which makes it possible to see the music created by the ACMG model intuitively.

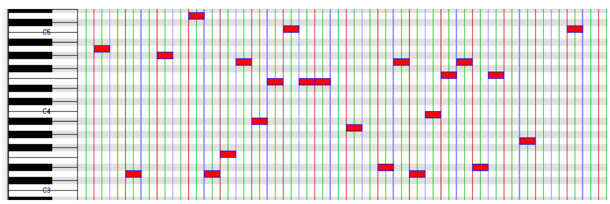


Figure 6: Music clip generation using the Piano Roll form

Figure 7: Score map for creating musical examples

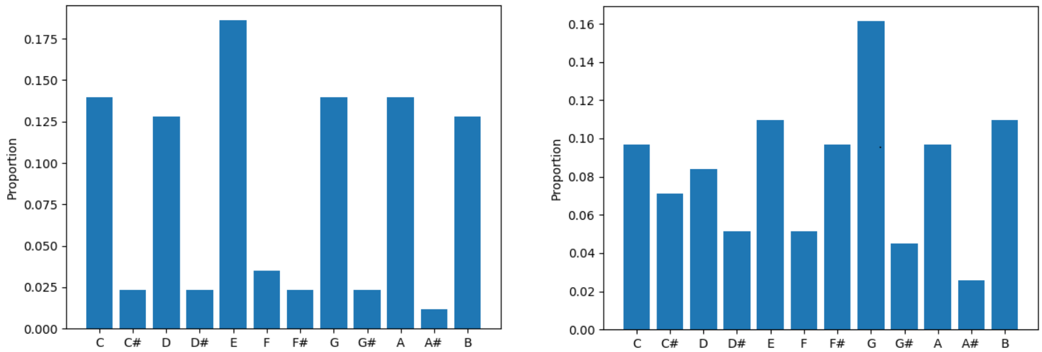
V. B. *Melody_LSTM vs. ACMG comparison test*

This research does a comparative experiment to assess the efficacy of the enhancements made by the ACMG music generation model. Initially, 5,000 musical compositions were chosen at random as training examples from the ASMD database. The Actor network in ACMG uses the same parameter settings as the Melody_LSTM network in order to guarantee experiment fairness. These samples were then used to train the ACMG model and the Melody_LSTM network. Following training, music was generated, and 300 musical compositions were produced as test examples for each model [18].

V. B. 1) Observe percentage identification

The twelve-tone equal temperament tuning method divides an octave into twelve equal sections, each of which represents a semitone. In Western music, it is the most widely used tuning system. The main purpose of this experiment is to evaluate how the two models use notes when creating music. The more notes that are employed, the more varied the music that the model produces. First, it was determined how frequently the twelve-tone equal temperament notes were used in the two test sample sets. The percentage of each note's occurrences was then determined, as indicated by formula (11), where f_{im} denotes how many times note ii occurs in the mm-th musical composition and p_i denotes the percentage of note i's usage in all test samples. Lastly, the results are displayed in Figure 8 together with the statistical distribution in proportional form.

$$p_i = \sum_{m=1}^{300} f_{im} / \sum_{m=1}^{300} \sum_{i=1}^{12} f_{im}. \tag{11}$$



(a) Melody_LSTM generates music distribution

(b)This article's model generates music distribution

Figure 8: Dodecatonic note distribution

It is clear from Figure 8(a) that the notes C, D, E, G, A, and B are utilized frequently in the test samples produced by Melody_LSTM, whilst the other notes are used sparingly. On the other hand, Figure 8(b) demonstrates that the note distribution is more evenly distributed in the test samples produced by the ACMG model, suggesting that the ACMG model makes use of a greater range of notes. This implies that a wider variety of melodies are produced by the ACMG model [21].

V. B. 2) Comparing musical features

To evaluate the effectiveness of the music theory rule reward mechanism in the ACMG music generation model, this study conducted a comparison experiment on the performance of the music theory features. In this experiment, we used test samples generated by the ACMG model without the reward mechanism for the music theory rule. The same experimental configuration as the ACMG (complete) model was used to create 300 musical compositions as test samples. From the three test sample sets, we selected seven noteworthy features and compared them to accepted music theory concepts. The statistical results are shown in Table 1.

Table 1: A comparative analysis of music theory rules' features

Characteristic	Melody_LSTM/%	ACMG(Incomplete) /%	ACMG(complete) /%
Overuse of the same musical notes	63.12	35.8	20.8
Assess the autocorrelation.	0.12	0.06	0.04
It's not a key note.	10.2	6.74	3.21
Less than eight degrees separates the intervals.	77.4	81.3	90.2
Possessing a distinct maximum note	58.6	59.4	64.2
Possessing an original minimum note	55.8	62.4	58.8
The classical style	47.6	60.5	74.3

Compared with the Melody_LSTM network, the ACMG model demonstrates significant advantages in generating music with better structural coherence. As shown in Table 1, it effectively mitigates issues such as excessive repetition of notes and overly long rests between phrases. Moreover, the outputs generated by the ACMG model exhibit a stronger alignment with classical music characteristics, indicating a higher degree of stylistic consistency.

In addition, when comparing the full ACMG model with its variant that excludes the music theory rule reward mechanism, the complete model consistently outperforms across multiple evaluation metrics. This highlights the positive impact of incorporating music theory constraints into the reward function, not only refining the compositional structure but also enhancing the musicality and aesthetic quality of the generated sequences.

V. B. 3) Chord match

In contrast to the music produced by the Melody_LSTM network, the ACMG model successfully avoids problems such excessive note repetition and excessively long interval spans, as indicated in Table 1. Furthermore, compared to the Melody_LSTM model, the music produced by the ACMG model exhibits a notable improvement in classical style. Furthermore, ACMG (complete) performs better than ACMG (without the music theory rule reward mechanism) on a number of criteria, suggesting that the theoretical quality of the music is improved by incorporating the music theory rule reward mechanism.

$$Chord - Matching = \frac{\sum_{m=1}^{M} \sum_{i=1}^{P} E\left(y_{im}, \bar{y}_{im}\right)}{MP}, \tag{12}$$

$$E\left(y_{im}, \bar{y}_{im}\right) = \begin{cases} 1, y_{im} = \bar{y}_{im}, \\ 0, y_{im} \neq \bar{y}_{im}. \end{cases} \tag{13}$$

Figure 9 displays the outcomes of the experiments.

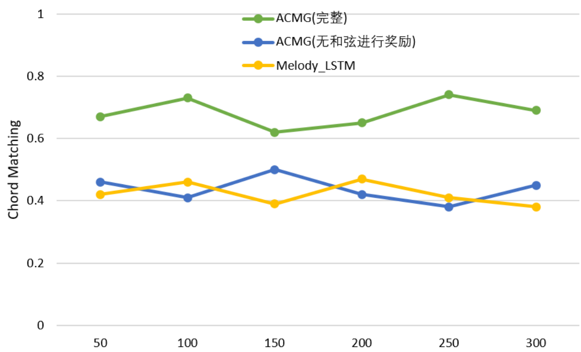


Figure 9: Match between model and chord

While the chord matching accuracy of the ACMG (no chord progression reward) model is comparable to that of the Melody_LSTM network, Figure 9 illustrates that the music produced by the ACMG (full) model has a generally greater chord matching accuracy when compared to the other two models.

VI. Conclusion

This research introduces a generative architecture that synergistically combines GAN, VAE, and attention mechanisms to explore the evolution patterns of musical styles through a deep generative approach. Experimental outcomes demonstrate that the proposed model effectively captures temporal dependencies win musical sequences and generates compositions of notable quality. The generated outputs surpass traditional models in maintaining stylistic coherence and achieving logical dynamic progression throughout the musical timeline.

Moreover, the study sheds new light on the process of style transformation in music, revealing the internal dynamics behind stylistic migration. Despite its promising results, the framework has limitations, particularly regarding the diversity of training data and the reliance on subjective evaluation criteria. Future investigations could focus on incorporating multimodal inputs (such as lyrics, gestures, or visual cues), designing more advanced generative paradigms, and improving real-time responsiveness to enhance user interaction and overall generative performance.

References

[1] El Ardeliya, V., Taylor, J., & Wolfson, J. (2024). Exploration of artificial intelligence in creative fields: Generative art, music, and design. *International Journal of Cyber and IT Service Management, 4*(1), 40-46.

[2] Ji, S., Yang, X., & Luo, J. (2023). A survey on deep learning for symbolic music generation: Representations, algorithms, evaluations, and challenges. *ACM Computing Surveys, 56*(1), 1-39.

[3] Liu, W. (2023). Literature survey of multi-track music generation model based on generative confrontation network in intelligent composition. *The Journal of Supercomputing, 79*(6), 6560-6582.

[4] Eigenschink, P., Reutterer, T., Vamosi, S., Vamosi, R., Sun, C., & Kalcher, K. (2023). Deep generative models for synthetic data: A survey. *IEEE Access, 11*, 47304-47320.

[5] Ferreira, P., Limongi, R., & Fávero, L. P. (2023). Generating music with data: application of deep learning models for symbolic music composition. *Applied Sciences, 13*(7), 4543.

[6] Vartiainen, H., & Tedre, M. (2023). Using artificial intelligence in craft education: crafting with text-to-image generative models. *Digital Creativity, 34*(1), 1-21.
[7] Wu, S. L., Donahue, C., Watanabe, S., & Bryan, N. J. (2024). Music controlnet: Multiple time-varying controls for music generation. *IEEE/ACM Transactions on Audio, Speech, and Language Processing, 32*, 2692-2703.
[8] Steinfeld, K. (2023). Clever little tricks: a socio-technical history of text-to-image generative models. *International Journal of Architectural Computing, 21*(2), 211-241.
[9] Pang, C., Qiao, J., Zeng, X., Zou, Q., & Wei, L. (2023). Deep generative models in de novo drug molecule generation. *Journal of Chemical Information and Modeling, 64*(7), 2174-2194.
[10] Yelmen, B., & Jay, F. (2023). An overview of deep generative models in functional and evolutionary genomics. *Annual Review of Biomedical Data Science, 6*(1), 173-189.
[11] Song, T., Ren, Y., Wang, S., Han, P., Wang, L., Li, X., & Rodriguez-Patón, A. (2023). DNMG: Deep molecular generative model by fusion of 3D information for de novo drug design. *Methods, 211*, 10-22.
[12] Zhang, C., Roh, B. H., & Shan, G. (2024, June). Federated Anomaly Detection. In 2024 54th Annual IEEE/IFIP International Conference on Dependable Systems and Networks-Supplemental Volume (DSN-S) (pp. 148-149). IEEE.
[13] Chu, A. E., Kim, J., Cheng, L., El Nesr, G., Xu, M., Shuai, R. W., & Huang, P. S. (2024). An all-atom protein generative model. *Proceedings of the National Academy of Sciences, 121*(27), e2311500121.
[14] Song, J., Lee, Y. C., & Lee, J. (2023). Deep generative model with time series-image encoding for manufacturing fault detection in die casting process. *Journal of Intelligent Manufacturing, 34*(7), 3001-3014.
[15] Wines, D., Xie, T., & Choudhary, K. (2023). Inverse design of next-generation superconductors using data-driven deep generative models. *The Journal of Physical Chemistry Letters, 14*(29), 6630-6638.
[16] Lu, W., Kaplan, D. L., & Buehler, M. J. (2024). Generative modeling, design, and analysis of spider silk protein sequences for enhanced mechanical properties. *Advanced Functional Materials, 34*(11), 2311324.
[17] Anstine, D. M., & Isayev, O. (2023). Generative models as an emerging paradigm in the chemical sciences. *Journal of the American Chemical Society, 145*(16), 8736-8750.
[18] Onyejelem, T. E., & Aondover, E. M. (2024). Digital Generative Multimedia Tool Theory (DGMTT): A Theoretical Postulation in the Era of Artificial Intelligence. *Adv Mach Lear Art Inte, 5*(2), 01-09.
[19] Zhong, C., Zhang, J., Lu, X., Zhang, K., Liu, J., Hu, K., ... & Lin, X. (2023). Deep Generative Model for Inverse Design of High-Temperature Superconductor Compositions with Predicted T c> 77 K. *ACS Applied Materials & Interfaces, 15*(25), 30029-30038.
[20] Fernandez-Grande, E., Karakonstantis, X., Caviedes-Nozal, D., & Gerstoft, P. (2023). Generative models for sound field reconstruction. *The Journal of the Acoustical Society of America, 153*(2), 1179-1190.
[21] Mao, J., Wang, J., Zeb, A., Cho, K. H., Jin, H., Kim, J., ... & No, K. T. (2023). Transformer-based molecular generative model for antiviral drug design. *Journal of Chemical Information and Modeling, 64*(7), 2733-2745.