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Evolutionary Music Monophony Generator Using Non-Binary Representation Genes from Genetic Algorithm

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Abstract. The art of music, integral to the human experience, has been present since ancient civilizations. Diverse musical styles emerge from various cultures, geographic locations, and historical periods. Nevertheless, creative individuals may unknowingly produce compositions resembling existing works, even without exposure to similar pieces. Consequently, the cultivation of evolutionary music is crucial for generating a broad spectrum of compositions less likely to evoke familiarity. Hence, music appreciation is significantly subjective from one person to another in society. With the advancement of today's technology, evolutionary music can be created at ease using algorithmic composition methods from evolutionary algorithms. In this manuscript, we present a method for creating concise, non-binary genetic representations of music notes to generate short, monophonic melodies without harmonic accompaniment. This approach is specifically tailored for the preliminary stage of the research project. Genetic Algorithm (GA) is a metaheuristic about an evolutionary algorithm based on the natural selection processes, which are appropriate for the approach. Genetic Algorithms are versatile that can be combined with other algorithms to produce melodies, harmonies, chords, music structures, scales and others. The novelty of my proposed method is able to create monophony melodies with just solely genetic algorithm without having additional algorithms for the rhythms. Therefore, a literature survey is conducted to provide insight into the latest research using other machine learning methods for evolutionary music. Deep learning is a subset newer to machine learning that increases the accuracy of the results with more extensive data sets.

Keywords. Evolutionary Music, Genetic Algorithm, Non-Binary Genes, Machine Learning, Deep Learning

1. Introduction

According to the theory of music, music is a universal language that expresses our emotions through pleasant acoustic sounds, a combination of melody, harmony, rhythm, tone, texture, form, and others. It contrasts with unpleasant noises that incontrovertibly are excluded from music, be it generated from our vocal voices or numerous musical

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instruments, as an expression of the arts [1]. With the advancement of music technology, myriad researchers, industrial experts, and professionals bring innovative ideas to music production, audio technology, composition, performance, and industry. Therefore, music creation is effortless nowadays, with no apparent human intervention in arranging the musical notes to produce melody and harmony through computing technology, mainly using algorithms (Computer Music) [2]. Musical styles differ from one another and are classified by the types typically known as genres, which could be Jazz, classical, Contemporary, Blues, Folk Traditional, Rock, Pop, Electronic Dance Music (EDM), and many more that can be distinctly categorized [3].

Evolutionary music compositions utilizing algorithms are crucial for the music industry for the following reasons. Firstly, they help avoid the inadvertent creation of music that already exists, thereby mitigating potential copyright issues in the compositions. Secondly, these compositions mitigate the lack of inspiration and creativity arising from limited exposure to diverse musical possibilities shaped by one's cultural background. Thirdly, employing algorithms for music composition alleviates the arduous and time-consuming nature of the process, thereby enhancing efficiency and productivity in music creation.

As for the focal point of this research paper, chiefly the methods and techniques proposed use evolutionary algorithms to concoct the evolutionary music by using a simple Genetic Algorithm (GA) represented by non-binary genes. The Genetic Algorithm (GA) is considered a metaheuristic optimization technique based on natural selections that solve constrained or unconstrained problems. It pushes biological evolution by continuously changing a population of individual solutions [4].

2. Literature Review

When musical composers compose their laborious music from scratch, music can be construed as linear and non-linear music. Linear music is a music track that begins at the beginning of the music and continues until it reaches the end. On the other hand, non-linear music consists of separations of tracks that are seemingly not connected that can be either horizontal mixing (a track detached into several sections) or vertical mixing (several tracks separated and played synchronously on top of each other) for the tracks and occasionally assortment of both [5]. Monophonic music is characterized by a singular melody without accompanying harmony or counter-melody [6]. Polyphonic music typically comprises a combination of two or more independent melodies to form a unified musical composition [6].

Nature is the finest inspiration for humans to compose pristine music. However, there are diverse sources of inspiration that can be utilized, such as the natural world (physical/biological), the human world (psychological/social), the holistic world, culture (general, art/non-art), and synthesis of influences [7]. In the subsequent section, we discuss some typical sources of inspiration for aspiring composers to compose their songs and create acceptable music types for fastidious listeners.

2.1. Generative Music Artificial Intelligence (AI)

Algorithmic-generated music is usually short and looping, with ever-changing and endless musical pieces. It is widely, synonymously and ubiquitously known as generative music, popularized by Brian Eno [8]. The prime reason for generative music's popularity is that endeavoring musicians can scrutinize diverse musical styles and experiment with distinctive sounds, expanding the limitations of musical genres. Furthermore, artificial intelligence (AI) can personalize generative music for dissimilar audiences, tailoring tracks to personal tastes and selections without worrying about copyright issues that accidentally produce identical work with other composers. Algorithm-created generative music might be excessively contemporary, producing dissonant sounds that are unacceptable to listeners. Thus, several sources of inspiration can be incorporated to increase the pleasant sounds considered consonant. For the up-to-date survey (2024) of generative music [9], refer to the paper 'A Survey of Music Generation in the Context of Interaction' by Ismael Agchar et al. The first inspiration method that can be used is the Circle of Third/Fourth/Fifth to comprehend the relationship between the pitches. Secondly, the Polygon Pendulum employs Polyrhythm looping around the polygon shapes to determine rhythms. Then, Cellular Automata features the grid of cells that change states, such as on and off, that can be mapped with notes. On the other hand, chord progression is a succession of pleasant chords to the ears. Finally, the Fibonacci Sequence (Golden Ratio) is a series of numbers that add up the two numbers before it, creating an aesthetic in the arts.

2.2. Evolutionary Music in Machine Learning

Algorithmic composition hastens musical compositions by providing great inspiration to the composer, and sometimes, it is essential to assist them greatly in composing the music due to human limitations in creating variety or form of music. According to the author, algorithmic composition can be broadly categorized into [10]: mathematical models, knowledge-based systems, grammars, evolutionary methods, systems learning behavior of the user and hybrid systems.

2.3. Evolutionary Music using Deep Learning

Deep learning is a subset of machine learning in artificial intelligence. It utilizes extensive data sets to increase the accuracy of the output [11]. The two typical approaches for deep learning are convolutional neural networks (CNN), which are more suitable for images, and recurrent neural networks (RNN), which are more suitable for texts. Another subset of RNN is also commonly used: Long short-term memory (LSTM), a type of recurrent neural network (RNN) that seeks to solve the dissipating gradient issue in conventional RNNs [12]. It is possible to generate music using conditional variational autoencoder based on the given emotions [13].

2.4. Related works using Genetic Algorithms Composing Music

Shukla and Bankla used genetic algorithms to produce the musical notes and an additional algorithm, Bresenham's line algorithm, to create the rhythms for the monophonic melodies [14]. Yap et al. developed a polyphonic music generator using a binary genetic algorithm in real-time to play the generated music with JFUGUE [15]. Matić also utilised genetic algorithms to create a pre-defined rhythm based on the position-based rhythm representation [16]. Farzaneh and Toroghi employed a genetic algorithm to create music and using Bi-LSTM scoring to evaluate music [17]. Both of the authors again extended their work to use generative genetic algorithm particularly LSTM to create music automatically [18]. Reis et al. proposed a genetic algorithm approach with Harmonic Structure Evolution for Polyphonic Music Transcription [19]. Xu et al. focused on creating high-quality melodies and evaluated the fitness functions [20]. Reis et al. proposed the method presented as the first genetic algorithm approach to multi-timbral music transcription for MIREX2008 in polyphony music [21]. Gautam and Soni employed a combination of Markov Chain and Genetic Algorithm to create music automatically [22]. Majumder and Smith employed a genetic algorithm to create music based on the feature extractions on two MIDI files [23]. For the general advancement literature review of the general advancement of genetic algorithms, it is recommended to read this research paper entitled "A Review on Genetic Algorithm: Past, Present, and Future" [24].

3. Proposed Framework and Methods

The ensuing sections consist of the proposed methods to solve the issues from the music theory side and the problems from the genetic algorithm to produce short and straightforward monophony music. Please note that the proposed framework and methods are at the preliminary stage of the research project.

3.1. Basic Theory of Music Utilized in the Proposed Methods

The basic music to generate pleasant sounds must consist of a pitch with different frequencies perceived by the listeners' ears to determine whether it is a high or lower pitch. It is denoted as notes on the music score, and there is only an octave from the middle note C with the frequency 261 Hz to another higher pitch note C, which consists of 13 notes distinguished by the semitones using accidentals sharp (#) and flat (b) in the scale of C major as default with 4/4-time signature regardless of tempo (speed). Referring to Figure 1, only three note values are chosen to form the music groove often associated with rhythm because playing in a monotonous beat will be dull and uninteresting.

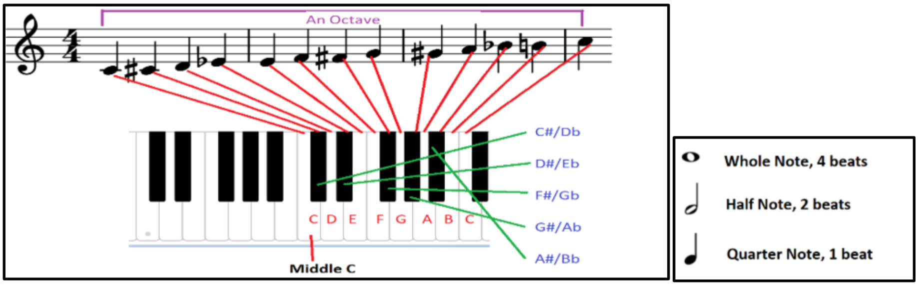

Figure 1. An octave of notes will be mapped starting from middle C (261 Hz), with 13 notes that differ by a distinct semitone from each other using only three accidentals: sharp, flat, and natural. Only three different note values will be selected to create rhythm.

3.2. Mapping of the Musical Notes and the Musical Note Values to Non-Binary Genes

For my method to vectorize and match the 13 notes in different pitches in an octave, we choose the alphabet from capital letters A-Z and small letters a-m as the non-binary genes to represent the 13 notes based on Table 1, including the musical note values (Figure 1) merged without having to generate the genetic algorithm again to represent the musical note values.

Table 1. Mapping of representation of non-binary genes to the music notes and the music note values together with the sound frequency to determine the pitches. The note is an octave higher in higher frequency denoted with an asterisk, *. [25]

Gene	Music notes and value	Gene	Music notes and value	Gene	Music notes and value	Gene	Music notes and value
A (261 Hz)	B#/C wn	K (311 Hz)	D#/Eb hn	U (369 Hz)	F#/Gb qn	e (466 Hz)	A#/Bb wn
B (261 Hz)	B#/C hn	L (311 Hz)	D#/Eb qn	V (392 Hz)	G wn	F (466 Hz)	A#/Bb hn
C (261 Hz)	B#/C qn	M (329 Hz)	E wn	W (392 Hz)	G hn	g (466 Hz)	A#/Bb qn
D (277 Hz)	C#/Db wn	N (329 Hz)	E hn	X (392 Hz)	G qn	h (493 Hz)	B wn
E (277 Hz)	C#/Db hn	O (329 Hz)	E qn	Y (415 Hz)	G#/Ab wn	i (493 Hz)	B hn
F (277 Hz)	C#/Db qn	P (349 Hz)	E#/F wn	Z (415 Hz)	G#/Ab hn	j (493 Hz)	B qn
G (293 Hz)	D wn	Q (349 Hz)	E#/F hn	a (415 Hz)	G#/Ab qn	k (523 Hz)	*B#/*C wn
H (293 Hz)	D hn	R (349 Hz)	E#/F qn	b (440 Hz)	A wn	l (523 Hz)	*B#/*C hn
I (293 Hz)	D qn	S (369 Hz)	F#/Gb wn	c (440 Hz)	A hn	m (523 Hz)	*B#/*C qn
J (311 Hz)	D#/Eb wn	T (369 Hz)	F#/Gb hn	d (440 Hz)	A qn		

Note: wn is whole note, hn is half note, qn is quarter note with sound frequency denoted in brackets, * is octave higher in higher frequency.

To map a musical note symbol purely as one non-binary gene is impossible because a non-binary gene for our proposed work represents three pieces of information: 1) Note, 2) Accidental and 3) Note Value. In addition, we propose only one algorithm to create rhythms, which makes the framework and method unnecessarily complex. In short, the musical notes are already represented by each gene in the chromosomes by referring to Table 1 tuned in technical standard concert pitch that is 440 Hz [25].

3.3. Proposed Non-Binary Genetic Algorithm Methods

Implementing the available JAVA source code of the genetic algorithm is based on the work of Atul Kumar [26]. The outputs will be different each time it is generated. For the implementations [26], it utilizes Hamming distance, multi-point crossover and multi-point Mutation. Hamming distance is used as a measure of fitness to assess the dissimilarity or similarity of two candidate solutions (chromosomes) [27]. Multi-point crossover is a genetic algorithm technique that involves selecting multiple points along the parent solutions for the recombination process [28]. In the context of genetic mutations, a multi-point mutation refers to the alteration of multiple genes simultaneously [29].

Figure 2 shows the genetic algorithm process for the proposed method. An example is the "Marry Had a Little Lamb" tune in the first two bars as the targeted chromosomes based on Figure 3. The notes of tune will convert to non-binary based on Table 1 and be used as a target (see Figure 2b and Figure 3). A chromosome is randomly generated using the genes (the alphabet from 'A' to 'Z' and from 'a' to 'm') and assigned to the population. Subsequently, a fitness score will be computed for each chromosome using hamming distance (see Figure 2c). Two chromosomes are randomly selected from the population and set as parent 1 and parent 2. However, offspring will be generated using multi-point mutation directly without selection if the population only has a chromosome. Next, a random value is generated for each gene to determine the crossover and mutation points. If the random value is less than 0.45, the gene is cloned from parent 1. Otherwise, the gene is cloned from parent 2 (see Figure 2d). The gene is randomly generated and cloned to the mutation points (see Figure 2e). The process will stop until the fitness score for offspring (or the latest chromosome) fitness score is zero (see Figure 2a). It means the process has achieved the target. We used the 'Marry had a Little Lamb' tune in the first two bars and converted them into non-binary genes represented in alphabet letters as the targeted chromosome (see Figure 3) with the value 'OICIOON' based on the mapping in Table 1. Referring to Figure 2 and Figure 3, the complete set of genes will go through selection, crossover and mutation. The fitness is the length of the targeted chromosome, which differs from characters in the targeted chromosome (strings) at a particular index. For instance, it has two indexes with different values of the selected chromosome compared to the targeted chromosome if the fitness value is 2. It is most reasonable not to misunderstand it as the method of directly copying the melody of the "Mary Had a Little Lamb" tune in Figure 3 for generating monophonic music. However, it is only used as the targeted chromosomes for the final generations to produce variations of monophonic melodies from each generation, and it will not be selected as the melody line because a similar tune exists in the music composition.

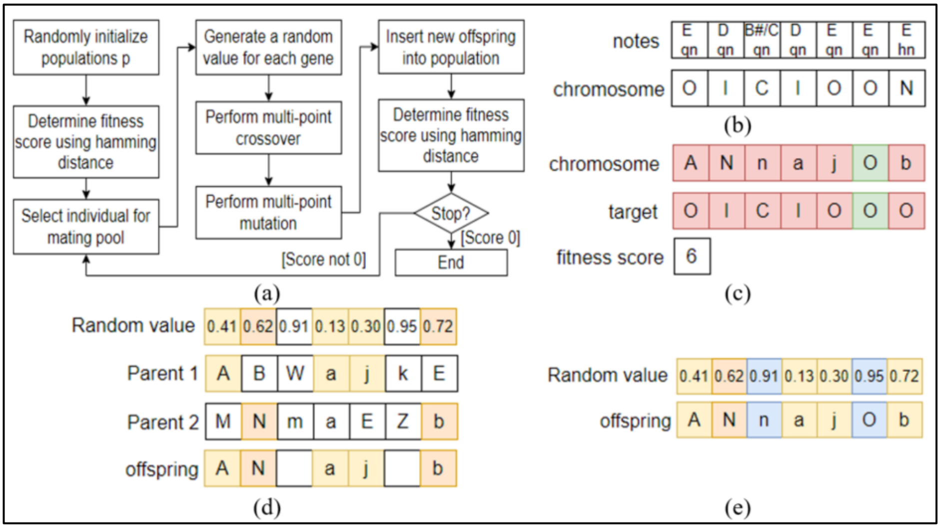

Figure 2. Genetic algorithm for proposed method. (a) Flow chart of genetic algorithm; (b) Converting note to non-binary; (c) Calculate fitness score using hamming distance; (d) multi-point crossover; (e) multi-point mutation. [26]

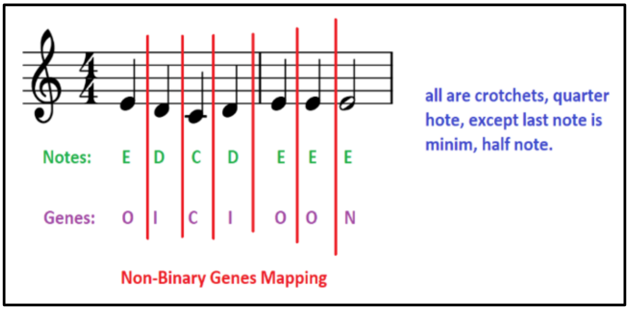

Figure 3. Two bars of melody lines excerpt from the celebrated children's song' Mary Had a Little Lamb' notes are mapped as the targeted chromosome used in the Genetic Algorithm to cause each chromosome towards the final generation with fitness value 0 to match identically to the targeted chromosome.

4. Experiment and Results

Before running the code, the initial value must be set for the non-binary genes depicted by alphabets and the targeted chromosome value using the 'Mary had a Little Lamb' tune. When the program was successfully executed by referring to Figure 4, the output results showed the generations with the designated chromosomes with the fitness value decreasing until 0 towards the end of the conclusive generation, with the fitness value 0 corresponding to the 100% resemblance between the selected and targeted chromosomes. The chromosomes from generation 0 and generation 3 are chosen to test the monophony music outputs after mapping to musical notes represented by the non-binary genes as shown in Figure 4. Please take into account that running the code will yield varying outputs with each successful execution. The results depicted in Figure 4 pertain solely to the specific experiment conducted at that time. Subsequent or new experiments will produce differing outputs.

```
Output
java -cp /tmp/EULqejlKSQ/GeneticAlgorithm
Generation: 0   String: jMGIOZH Fitness: 5
Generation: 1   String: jMGIOZH Fitness: 5
Generation: 2   String: OaCIIJK Fitness: 4
Generation: 3   String: OICXFOi Fitness: 3
Generation: 4   String: OICXFOi Fitness: 3
Generation: 5   String: OICXFOi Fitness: 3
Generation: 6   String: OICIBOH Fitness: 2
Generation: 7   String: OICIBOH Fitness: 2
Generation: 8   String: OICIBOH Fitness: 2
Generation: 9   String: OICIOOH Fitness: 1
Generation: 10  String: OICIOOH Fitness: 1
Generation: 11  String: OICIOOH Fitness: 1
Generation: 12  String: OICIOON Fitness: 0

=== Code Execution Successful ===
```

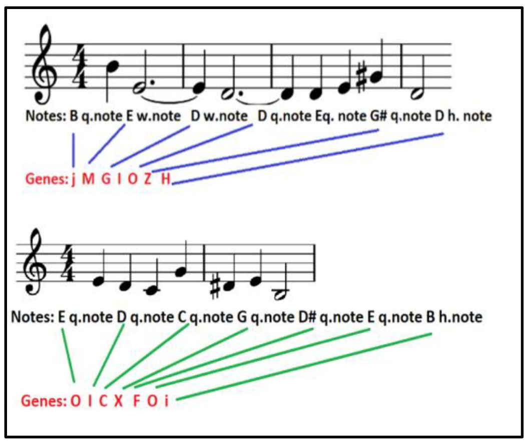

Figure 4. Randomly generated chromosomes are generated on each generation with decreasing fitness values at the end of the generation to match the genes for the targeted chromosome that has the 'Mary had a Little Lamb' tune mapped with selected music notes. The chromosomes from generation 0 with the fitness value 5 and generation 3 with the fitness value 3 are chosen and mapped into musical notes for playback.

MIDI, an acronym for Musical Instrument Digital Interface, serves as a communication standard that facilitates seamless interaction among diverse digital music equipment [23]. The musical notes generated can be mapped into MIDI for the computer output playback to render in real-time as soon as the musical notes are generated from the proposed genetic algorithm [15]. Yet again, the "Mary Had a Little Lamb Tune", or variants almost at the end, will not always be selected because similar tunes exist on the target chromosome as a reference. Due to time constraints and the research being at a preliminary stage, a simple subjective evaluation was conducted by a musician certified with Grade 8 ABRSM piano and music theory. The feedback was that the music outputs were still experimental and imperfect but reasonably acceptable. Comprehensive objective or subjective evaluations will be proposed in the future works of the preliminary research project.

5. Discussions

Atul Kumar’s genetic algorithm [26] differs from the usual implementation of other genetic algorithms that use binary numbers to represent a set of chromosome genes. The prime goal of the aforementioned genetic algorithm implementation is to match the desired best output as the predefined targeted chromosome. The reason for choosing the 'Mary had a Little Lamb' first two bars’ notes (targeted chromosome) is because the melody is pleasant to the ears as the reference for the selected chromosome to be based on with some differences. Usually, the high fitness values are considered the best that is capable of further breeding [30]. However, the implementation adopted is the other way around, with the higher fitness being less preferred because of the high randomness to produce the musical notes that might clash with each other, known as dissonant. Therefore, the middle generation with the average fitness value is preferred because it retains some musical rules and has a higher chance of producing consonant notes based on the targeted chromosome. The advantage of using non-binary gene representation is that it can map many notes together with other information in an index instead of converting the binaries into digits to numbers that limit the representation of information.

The novelties of our proposed methodologies in comparison to existing works in the literature section (section 2.4) lies in the following:

- By utilizing a single non-binary symbol, the representation of musical notes, note values, and accidentals can be achieved without the need for converting multiple combinations of binary numbers. This approach simplifies the encoding process while effectively capturing the information pertaining to the three fundamental features.
- The proposed approach simplifies the process by not using multiple algorithms used for creating rhythms and scales but using only a single genetic algorithm, enabling automatic music generation while reducing complexity.
- In most of the papers we reviewed, there was a lack of detailed and clear mention of how musical notes are mapped during vectorization processes. We have proposed a simple method using non-binary symbols 'A' to 'Z' and 'a' to 'm' to represent musical notes with accidentals. For example, the 'C# whole note' is represented by the non-binary gene symbol 'D' (Table 1).

However, the proposed methods have several weaknesses. Firstly, when more ranges and values are selected for the music generations, more symbols might be needed to represent the musical information, and it might run out to use a single symbol as a gene to represent the information (music note, accidental and note value). Secondly, the genetic algorithm is an optimization method, and we are not utilizing it for the evaluations to improve the music outputs.

Referring to Figure 4, the output for the genetic algorithm will always give different results on each execution. Therefore, it can be run iteratively to generate additional bars to be combined to become a lengthy monophonic song, for instance, to pick several music bar samples acquired from a few generations as the linear music method (with the combined chromosomes: j M G I O Z H O I C X F O i). For instance, the first chromosome (j M G I O Z H) and the second chromosome (O I C X F O i) can be separated as music tracks and mixed horizontally to create a polyphonic song. The middle generations of the outputs will be preferred because they will provide a better sound by simple subjective evaluation from a musician. In contrast, the last generation (or almost the last generations) will not be selected because a similar tune already exists.

Based on Figure 4, we use the genetic algorithm to create dissimilar variants selected from each generation, except the final generation (or almost) will not be selected as a source of inspiration to create music automatically.

Evolutionary music playback output is always experimental, and the listeners may find the song weird sounding [31]. If implemented through the pre-defined Western aesthetic chord progressions rules, for example, using the musical dice concept [32], this method is not considered an evolutionary music method or approach to creating music by computers automatically. The unpleasant songs generated by evolutionary algorithms can be solved by objective evaluations using algorithms, particularly deep learning methods, to improve the music outputs by providing evaluation feedback to the system automatically and in real time and making it pleasant to the human ears. Subjective evaluation using human musicians to evaluate the music output provides better accuracy than objective evaluation, but it can be laborious and cannot be done in real time. However, musical aesthetics is very subjective from one person to another [32].

6. Conclusion

Evolutionary music represents an experimental approach that delves into the limitless potential for diverging from traditional Western aesthetic music principles [31]. Consequently, this forms a critical area for research, in which scholars strive to identify various methods for automating assessments through the use of multiple algorithms in order to generate pleasing melodies and harmonies automatically. In conclusion, it is essential to be based on the musical rules aside from just generating arbitrary notes that will be considered too contemporary-sounding.

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