UTRECHT UNIVERSITY

Department of Information and Computing Science

Proposal - Master Thesis - Artificial Intelligence

Rhythm and Reason: Adding Time Varying Rhythmic Control To Deep Learning Music Generation Models.

First examiner:
Anja Volk

Second examiner:
Peter van Kranenburg

Candidate:
Efraim Dahl

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Abstract

Music is essential in video games, enhancing immersion and engagement, but players may disengage due to excessive repetition or personal preferences. This is particularly problematic in games like Last Minute Gig, a Musical Attention Control Training (MACT) application for Parkinson's patients. Repeated play, and adaptive stimuli are necessary for the training to be successful. To maintain engagement and with that the effect of the intervention, a diverse set of controlled, adaptive music is needed. Advances in generative music offer a scalable solution. This project explores efficient methods of adding control to pre-trained models, to steer towards rhythmically adaptive music suitable for MACT. Insights from small-scale experiments will inform the application of rhythmic control in RhythmLang, a transformer based music generator, which will be evaluated for interactive potential in the context of MACT.

Contents

1 Introduction **3**

2 Literature **6**
2.1 Why Generate Music? - Motivation . . . 6
2.2 Why Not Generate Music? - Ethical Concerns . . . 8
2.3 Overview of music generation . . . 10
2.4 Non-neural music generation . . . 10
2.5 Deep learning for music generation . . . 14
2.6 Deep Learning and Symbolic Music Generation . . . 16
2.7 Representation and Format . . . 17
2.8 Control . . . 20
2.9 Implementation of control . . . 23
2.10 Evaluation . . . 26

3 Research Questions **28**

4 Methodology **29**
4.1 Introducing RhythmLang - Approach and Base-model . . . 29
4.2 Developing the Model . . . 31
4.3 Model Evaluation . . . 35
4.4 User Study . . . 37
4.5 Thesis Timeline . . . 40

Bibliography **49**

5 Appendix **50**
5.1 Comparing Tokenization lengths . . . 50
5.2 Feature categorisation . . . 50
5.3 MIDI Bass Instruments . . . 51
5.4 Notes Comparing Symbolic Music Generators and their evaluation methods . . . 51

1. Introduction

Music is a cornerstone of modern video games. Music evokes emotional responses, triggers memories, can direct attention, and improves immersion and the overall experience of a game. However, [1] finds that most players turn off game music eventually, either because of differing personal preferences, or because they find the in-game music too repetitive. This can be a problem in serious games for therapeutic use, where repeated gaming sessions are required for the intervention to be effective. In specific types of therapy such as Musical Attention Control Training (MACT), a type of therapy shown to help people with Parkinson's [2] or ADHD [3], music is a crucial part of the intervention. Ideally, MACT is a personalized experience with dynamic adjustments to the music that incooperate the patient's abilities and preferences. In the context of gamified self-directed therapy, this is crucial to keep patients engaged and progressing. [1] One avenue to achieve dynamic adjustment in music, is through controlled music generation.

Over the last few years, music generation has grown from a primarily academic endeavor to a billion-dollar industry. Large technology companies are exploring music generation with foundation models such as Meta's MusicGen [4] or Google's MusicLM [5]. The commercial startup music generator Suno is valued at 500 million dollars. In August 2024, a German producer used Udio to generate a chart-topping song [6][7]. This breakthrough is powered by advances in language modeling, bringing about Large Language Models such as GPT-4 or LLAMA3 applied to music.

In games, generative music is promising to cater to different user preferences and enable a richer, more varied musical experience than conventional approaches to adaptive audio. Video games can include hundreds of hours of gameplay and branching storylines. Adapting the music to individual preferences adds additional complexity. It quickly is no longer feasible to manually compose unique music to fit all scenarios. Especially in more resource-constrained applications such as games for therapeutic use, generated music can offer an avenue to provide a large variety of music that can improve user engagement and the effect of the intervention. One of the key components of a successful generative model is control. In music generation, control could be a text description or information on genre, style, and instrumentation. Control can also include time-varying, composable musical parameters such as a melody, chord

[1] This type of therapy is not aimed at replacing traditional guided therapy. Ideally, it is used as a supplement, providing relief in situations where regular treatment is not immediately available

progression, or musical structure. Additionally, generative models are often controlled with human-composed music. They can continue provided music, interpolate between, or inpaint - which means generating accompaniments, melodies, or additional instrumental lines to an existing piece of music.

There are a variety of ways to achieve control in a music generator. For rule-based systems, control is integrated explicitly. In statistical systems (including deep learning) control is typically applied through architectural constraints and choice of training data. Certain deep learning architectures lend themselves to certain types of control. To illustrate: An autoregressive transformer models a sequence based on prior parts of the sequence, it natively generates continuations of an input. In deep learning, other musical parameters (e.g. chord progression or melody) can be controlled by joint conditioning of a model, which means that the controlled musical parameters are made explicit while training. This method of adding control is quite cost-intensive, requiring as much, if not more resources as training an equivalent model without controls.

A more economical method of adding control to a deep learning generative model is fine-tuning and post-hoc guidance. In fine-tuning (also referred to as transfer learning), a pre-trained model is trained on additional data, with additional control conditions carefully integrated into the model. Typically, fine-tuning uses considerably fewer resources and data than training a model from scratch. In post-hoc guidance, the intermediate outputs of a generative model are classified and adjusted during inference to increase the likelihood of the final output to fit the desired constraints.

We consider Last Minute Gig [8], a gamified Musical Attention Control Training (MACT) application aimed to improve attention control in patients with Parkinson's-disease. In Last Minute Gig, a player taps along to the music, and is encouraged to change their tapping when the music changes. The music periodically provides stimuli, a noticeable change in the music, based on which the user changes their playing. The game uses a simple rule based system that introduces changes random changes every eight bars. We propose RhythmLang, a fine-tuned variant of MusicLang to generate Music that can provide such stimuli at controllable intervals. Specifically we are investigating bar-level control that triggers shifts in rhythmic structure, since unlike other controllable parameters such as chords or instrumentation, rhythmic structure is linked to the perceived difficulty of following the music [9]. In this way RhythmLang could generate not only a richer variety of music, but also music that is progressively more challenging for the player.

The objective of this thesis is to develop and evaluate RhythmLang, a model that can generate complete multi-instrument musical pieces, with time-varying control over rhythmic structure. We achieve this by fine-tuning a pretrained music-generator and adding introducing rhythmic controls to the training process. We will first explore and evaluate different methods of adding control using a small generative music model, and progress to larger models and more complex rhythmic controls. In a final step, we will evaluate the interactive potential, perceived difficulty and the tradeoffs in enjoyment and player engagement of using music generated by RhythmLang over the simple rule-based music generation process in Last Minute Gig [8].

2. Literature

The following section contains an extensive (though not exhaustive) categorical literature study. The first part provides contextual information, including motivations, and ethical concerns as well as a comprehensive overview of techniques used in music generation. The second half is more technical, with a discussion on music representation, tokenization, control, and fine-tuning. As a starting point, I used the most recent ISMIR (International Society for Music Information Retrieval) papers on music generation and their referenced sources, alongside other papers suggested by my advisor, Anja Volk. In addition, I performed systematic searches using the following keywords: Deep Learning Music Generation, Diffusion Music Generation, Transformer Music Generation, Symbolic Diffusion Music Generation, and Controlled Music Generation.

2.1 Why Generate Music? - Motivation

2.1.1 Composition Co-Pilots

The earliest music generators (including the 18th-century musical dice games [10]) were justified as methods to inspire composers and music makers, including enabling novice composers to write music. Composer David Cope [11] states that he turned to music generation to overcome writer's block. Commercial enterprises like Suno claim to be "building a future where everybody can make great music" [12]. Many current and past efforts highlight music generation as a process that assists composers. In DeepBach [13], the authors go to great lengths to make the system flexible and usable in real-life composition scenarios. Initially, they developed a MuseScore integration and later tied DeepBach into the web app NONOTO[1] to support musical inpainting in Ableton Live scores. Similarly, with Composer's Assistant [14], the authors explicitly enable musical inpainting and continuation in the REAPER music production software. AI has also been explored as a co-improviser for live music-making, such as in Pachet's Continuator [15] and Ben-Tal's musical dialog system [16].

2.1.2 Music in Games

Beyond the co-creation of music, there is a range of music that serves a functional rather than a primarily aesthetic, such as background music in video games. In gaming, AI-generated or AI-

[1]https://github.com/SonyCSLParis/music-inpainting-ts

assisted music has high potential due to the scale and interactivity of games. Video games often facilitate hundreds of hours of gameplay, featuring branching storylines and complex player interactions. However, game soundtracks typically cover only a fraction of that time [17], [18]. Through different adaptive techniques, relatively short snippets of original material can be stretched into hours of unique audio, often relying on the recombination of different elements. However, rule-based recombination has its limitations. A recent study of player behavior [1] finds that many players eventually turn off game music. They cite various reasons, such as preferring their own music over the game soundtrack (46.7%) or finding the in-game music repetitive (29.6%).

Procedural generation of 3D assets, levels, and enemy behavior is commonplace, but it is rarely applied to music. With AI-assisted music composition, it could become possible to enable adaptive audio on a large scale, either by creating numerous musical assets anticipating player choices or generating new variations of the game score in real time to enhance player immersion. However, several challenges make AI music generation difficult in games. Performance issues arise due to the resource-intensive nature of AI generators. Additionally, AI-generated music is difficult to control, and there is little guarantee that the generated tracks will be appropriate [17]. Furthermore, AI music generators currently lack proper integration into video game environments and engines [18].

2.1.3 Music in Serious Games

Aside from games for general audiences, generative music has potential applications in serious games. Serious games are designed for purposes beyond entertainment, such as education or therapeutic use, including music therapy [19]. In music therapy, music can be used for emotion regulation, motivation, adherence, motor coordination, rhythmic entrainment, and facilitating social interactions [20]. Musical attention control training has been shown to help individuals with Parkinson's [2], ADHD [3], autism [21], and psychosis [22] improve their mental capabilities for selective and switching attention. Serious games have the potential to supplement music therapy. They could enable training sessions that the patients can do on their own time, in between therapy sessions, which could provide relief in situations where therapy sessions are inaccessible due to lack of funds or therapists. Last Minute Gig [8] implements clinical music therapy protocols as a serious game to improve attention control in Parkinson's patients. However, users reported boredom and a lack of feedback, while more musically experienced users felt less challenged [8]. Schlette [23] attempts to address these issues by introducing dynamic difficulty adjustment through a feedback system alongside more complex music generation. This thesis aims to develop a controlled music generation model to improve player engagement through a richer music system.

2.2 Why Not Generate Music? - Ethical Concerns

2.2.1 Introduction

There are several concerns related to AI-based music generation. First, there are legal concerns regarding copyright and licensing. Generative models may produce outputs that are identical or highly similar to copyrighted training data. Furthermore, the question remains whether models should be allowed to train on copyrighted data in the first place. Broader concerns include the devaluation of human labor and creativity, the over-saturation of cultural spaces with low-quality generated content, and the environmental impact of large generative models, which require substantial energy, water, and rare materials.

2.2.2 Data Leakage and Copyright

Generative AI companies are achieving record-breaking valuations, including music generators, such as Suno with a valuation of about 500 million dollars after a 125 million dollar fund-raiser. [7] [24]. However, AI companies are facing backlash from artists and record labels, with an organization of record labels including the so-called big three Sony, Warner Music, and UMG suing Suno and Udio for $150.000 dollars per infringed work [25]. Generative AI runs a substantial risk of parroting or leaking training data. In language models, the leakage problem is of concern when training on data that contains sensitive information, which may be revealed either through accidental leakage or through membership inference attacks [26]. While leakage may raise privacy concerns in other generative models such as speech and image-generators [27] for music, the risk of training data leakage is mostly an issue of copyright. Ed Newton Rex shows some examples of how Suno can be configured [28] to leak training data. This ability to create disconcertingly close reproduction of copyrighted work is also cited in court documents. Suno has since started to prevent prompting with artist names (i.e. in the style of Eminem) and including known song lyrics.

2.2.3 Training and Copyright

Besides leaking training data, there is the more general question of whether AI models should be allowed to train on unlicensed work. Echoing the court case between OpenAI and the New York Times [29], both Suno and Udio cite fair use in response to accusations of copyright infringement. In US copyright law the fair-use clause limits exclusive rights to a work, with four factors to consider: 1) purpose and character of the work in use, 2) nature of copyrighted work, 3) amount of the copyrighted work used, and 4) the effect on the potential market or value of copyrighted work [30]. Fair use is often granted to derivative works such as parodies and covers and works used in educational settings. AI's learning of musical structures and patterns has also been compared to the human learning process: Humans learn based on copyrighted music they listen to without giving credit or compensation to their influences. Newton-Rex [28] rejects this comparison. In learning music, humans contribute to the cultural ecosystem by taking lessons, going to performances, or at the very least generating some streaming revenue for artists, none of these are true for machine learning models learning from scraped data.

2.2.4 Devaluing Music

While few follow director Ram Gopal Varma's viral announcement to only use AI-generated music in his future films [31], AI-generated music is becoming increasingly difficult to differentiate from human production and already receiving considerable amounts of streams. It is not unlikely that music in film, video, and game projects may be supplemented with, if not replaced by AI-generated music. The online music market is saturated, with more than 100,000 songs uploaded to music streaming giant Spotify every day [32]. Generative AI will likely exacerbate this problem, resulting in a race to the bottom for creatives and musicians.

2.2.5 Environmental Impact

Digital infrastructure, traditional data centers, cryptocurrency mining, and AI-centered data infrastructure account for about 2% of the world's energy consumption [33]. The performance of current large language models often scales with simultaneous increases in model size, training data, and computation time [34]. Each of these three factors requires considerable resources. Music generation is no exception. In a recent ISMIR publication [35] the authors make estimates on energy consumption of different projects related to music generation and computation-intensive MIR, finding an average energy consumption of 224.8 kWh for model training (the energy consumption of an average western person over 2 months). The energy consumption is divided highly unevenly, with the median being at merely 18 kWh (3 days of an average westerner's energy consumption). Music generation models associated with large technology companies are responsible for about 89% of the total estimated energy use for ISMIR projects. This is only for training, models that are deployed publicly, continue to use substantial energy for inference. Beyond just the carbon footprint of generative AI, the local impacts of resource use, such as rare minerals and water, are crucial to examine.

These ethical considerations inform our approach. We will use open-source licensed data for training our models and make our results and models available online. We are explicitly designing the generative process to be collaborative. This is facilitated on the one hand through the introduction of new control modalities. On the other hand our choice of using symbolic music over audio, eases editing and integration into composition software. Finally, we do not attempt to train custom large foundation models, rather we are trying to find ways to extend existing models to introduce new control mechanisms, requiring training on only a fraction of the model parameters, with substantially less need for data, computation and energy.

2.3 Overview of music generation

From antique wind-chimes to classical period musical dice games to the aleatoric music of the 20th century - humans have used algorithmic, probabilistic, and statistical methods to create music. As early as the late 1940s, computers have played a role in composition as sound generators, instruments [36] and providing musical material themselves, such as in the 1957 Illiac suite [37]. The following 50 years are characterized by disparate, academic experiments in music generation, primarily in the symbolic music domain. They utilize a variety of contemporary AI technologies, from expert systems and ontologies [37][38] to evolutionary algorithms [39] to feed-forward [40], recursive [41], and convolutional neural networks [42]. Some composers in the classical tradition, such as Iannis Xenakis [43] and David Cope [11] use computer algorithms in their creative work. In the 2010s a small ecosystem of commercial generative music startups such as Jukedeck, PopGun, and Ampermusic [44] starts to emerge, alongside an increasing number of publications applying deep learning, particularly Generative Adversarial Networks (GANs), and Recursive Neural Networks (RNN) to music including MIDInet [45], DeepBach [13] and FolkRNN [46]. With the development of the transformer architecture in 2017 [47], large technology companies start experimenting with music generators including OpenAI's Jukebox [48] and Musenet [49], Meta's MusicGen [4] and Google's MusicLM [5] and the preceding Magenta project, with fully generative models capable of producing sequences of high-quality music modeled from raw audio. At the time of writing, commercial music generators such as Suno and Udio are raising millions of dollars in investment funds [7], while generated music is being widely streamed and actively used in TV and video productions.

2.4 Non-neural music generation

2.4.1 Why look beyond deep learning

Neural, specifically deep learning (DL) systems, currently receive considerable attention. However, given their substantial drawbacks relating to explainability, transparency, computational efficiency, copyright and licensing issues, and their enormous need for data (as discussed in section 2.2), it is worthwhile considering alternative approaches to music generation. A recent study [50] performs a comprehensive listening survey comparing neural net and non-neural net systems. The top-performing systems MAIA Markov [51], a Markov Model, and Music-Transformer [52], a deep learning system, perform similarly well in the listening study. The choice of one of the earliest transformer-based music from 2018 [52] and the restriction to symbolic music, raises questions, whether their conclusion of similar performance still holds. Considering the study was published in 2023, these are important limitations. However, their criticism that many DL-based music generation projects do not look beyond DL and compare their systems based on technical metrics - with no obvious impact on how human listeners perceive the output remains solid. Finally, many hybrid approaches successfully combine traditional rule-based or statistical methods with deep learning. Those methods may help researchers and developers maintain a more comprehensive toolkit of techniques and paradigms.

2.4.2 Rule-based music generation

Non-neural net systems can be classified as either rule-based or statistical. Both types have been part of some of the earliest attempts at music generation. Centuries of style-defining musicological writing from ancient Mesopotamian tuning charts [53] to Fux's Gradus ad Parnassum [54] and Arnold Schönberg's 12-tone music have crystallized sets of rules that approximate various styles of music. Many approaches to music generation take advantage of this knowledge and codify it into a computer program, creating expert systems for music generation. In Hiller & Isaacson's Illiac Suite, a series of experimental, computational compositions, the first and second movements are generated following the rules of first species counterpoint [54], approximating Palestrina's contrapuntal technique. Some rules aim to contain the melody, such as limiting the range to an octave, enforcing the identical start and end notes, and avoiding consecutive melodic jumps. Other rules aim to constrain harmony, such as forbidding parallel octave, fifth, and fourth motion and enforcing consonant harmonies. Hiller and Issacson's approach is relatively simple, using only a handful of conditions (see figure 2.1). Rule-based generation can be highly complex, such as CHORAL [38] (for which the developer also built a custom programming language), which encodes over 300 rules to realize Bach-style chorales from a given melody.

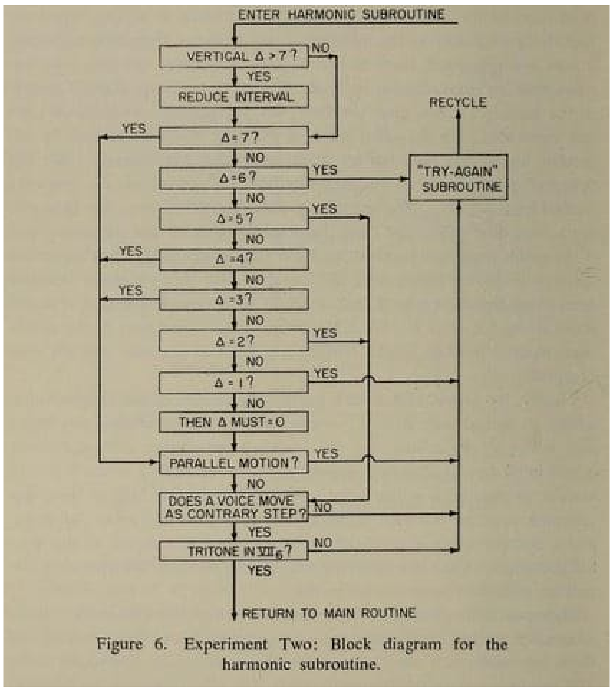
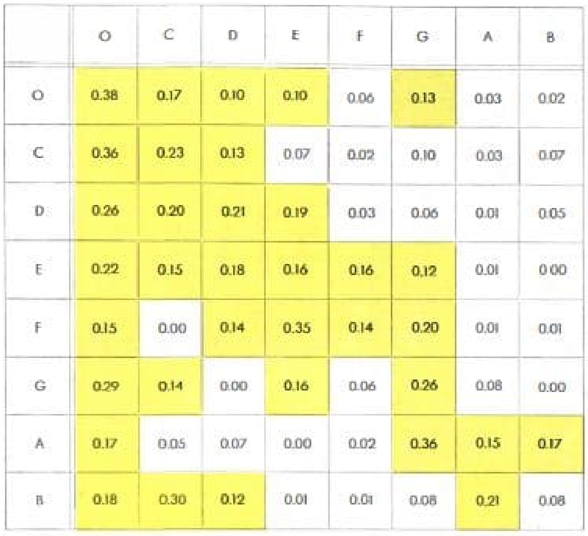


Figure 2.1: Rule-Based - Block Diagram from Hiller and Issacson's book - explaining movement two of the 1957 Illiac Suite.

2.4.3 Markov Model Music Generation

Markov models remain a popular method of generating music to this day. A Markov model can generate music by predicting the next note or chord based on the probability distribution of transitions learned from existing compositions. At its simplest, a Markov music generator could work off of a transition matrix for pitch classes, such as Richard Pinkerton's 1956 "Banal Melody Generator" [55]. Consider figure 2.2, assuming we just sampled $n_0 = C$, the next note n_1 is sampled from the following probabilities (C:23%,D:20%,E:0.18%,F:0%,G:15%,A:5%,B:30%). The next note n_2 would be sampled from the probabilities along the column of n_1. Markov chains can be nested or constrained for more complex interactions [51]. In Hiller and Isaacson's [37] fourth movement of the Illiac suite, they use Markov chains with a table of possible intervals stretching from unison to octave. In the latter sections of the movement, they introduce additional restrictions to add memory to the method through higher-order Markov chains that reference previously generated music. Transition matrices can be built from very little data, such as short improvisations [15], but training over a whole corpus is also viable. Other systems configure Markov chains to take additional inputs into account, such as Allan, [56] who generates harmonies to given melodies in the style of Bach. This makes Markov model-based systems very flexible and relatively lightweight.



	O	C	D	E	F	G	A	B
O	0.38	0.17	0.10	0.10	0.06	0.13	0.03	0.02
C	0.36	0.23	0.13	0.07	0.02	0.10	0.03	0.07
D	0.26	0.20	0.21	0.19	0.03	0.06	0.01	0.05
E	0.22	0.15	0.18	0.16	0.16	0.12	0.01	0.00
F	0.15	0.00	0.14	0.35	0.14	0.20	0.01	0.01
G	0.29	0.14	0.00	0.16	0.06	0.26	0.08	0.00
A	0.17	0.05	0.07	0.00	0.02	0.36	0.15	0.17
B	0.18	0.30	0.12	0.01	0.01	0.08	0.21	0.08

Figure 2.2: Transition matrix from Pinkerton's 1956 "Banal Music Generator". Probability of a pitch (row) following on a pitch (column), likely pairs are marked in yellow. The probabilities are calculated from a set of 39 nursery rhymes.

2.4.4 Other statistical approaches

Music generation has also been attempted with other means, such as metaheuristic search for harmony or melody [57]. In Morpheus, [58] the developers use variable neighborhood search (VNS) to generate polyphonic pieces following a tension profile for long-term structure. Closely related to this approach are evolutionary and genetic algorithms such as Politio et al's [39] model of 16th-century counterpoint as a multi-population problem. Here, three separate populations of agents generate instructions focusing on different musical aspects, such as harmony or imitation, and are evaluated based on individual performance and symbiotic performance together with the other agents over multiple generations.

2.4.5 Early Neural Net based systems

Music generators based on neural nets were introduced as early as 1989. Todd et al. [40] generate melodies using a fixed window for a conventional feed-forward neural network but also introduce a feedback loop feeding the network's previous state to the next iteration. Following work using RNNs uses the latter principle, such as CONCERT [41], a 1994 RNN trained to generate melodies based on datasets of Bach chorales, waltzes, and European folk songs. There are also hybrid systems such as HARMONET [59], an RNN-based music generator for re-harmonizing Bach chorales. It merges the RNN with a symbolic rule-checking algorithm. More recent RNN-based music generators, such as FolkRNN [46], a melody generator trained on Irish folk songs, use long short-term memory (LSTMs) or gated recurrent units (GRUs). Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) remain popular architectures for music generation [60].

2.5 Deep learning for music generation

State-of-the-art music generation, including many commercial applications, leverages the advances in language and image generation over the last five years. Two distinct approaches, namely autoregressive, transformer-based, and diffusion-based approaches dominate.

2.5.1 Transformers - sequence modeling without recurrence

Our ability to model complex sequences, including music, improved dramatically with the development of the transformer model. Transformers were originally developed for the task of language translation [47]. A sequence is modeled as a string of *tokens*, a numeric representation of parts of the sequence. In natural language, a token could be a numeric representation of a word or a character. Transformers deploy the self-attention mechanism already deployed in LSTMs for sequence modeling tasks [61] but replace the recurrent connection with positional embeddings and masked attention. This allows the model to train on all tokens in parallel instead of one token at a time, which enables much larger and more capable models trained at a fraction of the time required to train similarly large RNNs. The transformer comes in several different configurations. The original transformer contains encoder and decoder layers - see figure 2.3. Tasks relating to sequence understanding, such as music classification, often use an encoder-only architecture. The BERT series of language models [62] and music understanding models such as MusicBERT [63] are examples. On the other hand, sequence generation models often employ a decoder-only architecture, including the GPT-series [64] and many music generators such as MusicGen [4]. The transformer architecture is the baseline for all current large language models. Transformers find use in modalities beyond text, including images, audio, or DNA sequences.

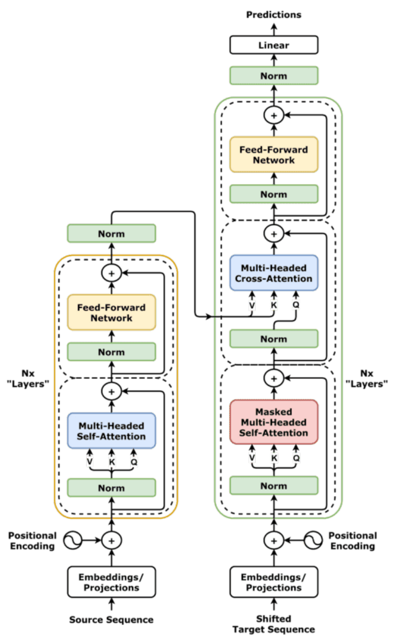


Figure 2.3: Schema of the full transformer encoder-decoder architecture

[a]= By dvgodoy - CC BY 4.0, https://commons.wikimedia.org/w/index.php?curid=151216016

2.5.2 Diffusion models - spectrograms and piano-rolls

Diffusion models are widely used for image and audio generation. Diffusion models learn to remove noise from a distribution (i.e. an image). Random noise is added to an image, and the model learns to undo this addition. During inference, the model starts with random noise (often accompanied by a guiding text prompt) and undoes it until it arrives at a clear image. AudioLDM [65], and StableAudio [66] are diffusion models that operate based on continuous audio encoding by a variational autoencoder. Diffusion models have also been used to generate symbolic music. Polyffusion [67] uses image representations of piano rolls and adapts their diffusion model for various tasks, inpainting, accompaniment, and melody generation and generation based on a given chord sequence or texture.

2.5.3 Token Sampling

Transformer models are next token predictors, essentially large classification models that choose the next probable token given the prior sequence. The methods of choosing the next token in a transformer vary. A pool of tokens from which the model chooses is called the *vocabulary* of the model. The size of this vocabulary is determined by the tokenization method (see section 2.7.2), and the underlying data. Typically the last layer is a so-called softmax layer, which transforms the output vector into an equally sized vector of probabilities adding up to one. [64]. Given a temperature T a freely chosen parameter and the output vector z, the probability of a token

$\sigma(z_i)$ is calculated as follows:

$$\sigma(z_i) = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)} \tag{2.1}$$

This last layer then forms the basis of different sampling methods. The most simple method is greedy sampling, simply choosing the most probable token. More typical sampling methods are probabilistic, where the next token is sampled from the vector of probabilities. The temperature parameter T in the above equation, can be controlled by the end user of a model to shape the probability distribution. At a high temperature, the probabilities are distributed more uniformly across the vector, the output becomes more noisy. At a low temperature, only the highest probability tokens remain, making the output more deterministic. A common variant is top k sampling, where only the most probable k tokens are considered. In top p sampling, the most probable tokens are added up until hitting a target percentage p.

2.6 Deep Learning and Symbolic Music Generation

Various approaches to symbolic music generation use deep learning. However, there are considerable differences in the implementation, such as choice of architecture and representation, that influence the model's capabilities, use case, and what aspects the user can control. The following table 2.1 summarizes these key characteristics across a selection of approaches that inspire our model. For a comprehensive survey of representation, tasks, and evaluation methods used in symbolic deep learning music generation see [68].

Name	Architecture	Control	TV	MI	Dataset	Representation
FolkRNN 2015 [46]	RNN	meter, mode	No	No	TheSession [69]	REMI-Like
DeepBach 2017 [13]	RNN	Inpainting	Yes	Yes	JSB-chorales [70]	Midi-Like
MusicTransformer (2018) [52]	Transformer	-	No	No	Maestro [71], JSB-chorales[70]	Midi-Like
MuseNet 2019 [49]	Transformer	instrument, genre	Yes	Yes	Mastro [71], CX [72], BM [73]	?
MidiNet 2019 [45]	GAN	chords, melody	Yes	Yes	HTPM [74]	Midi-Like
Fader Nets 2020[75]	VAE	arousal	No	No	Maestro [71]	Custom
MMM 2020 [76]	Transformer	inpainting, instrument, note-density	Yes	Yes	Lakh MIDI [77]	MMM
PopTransformer 2020 [78]	Transformer	chords, tempo	Yes	No	Custom	REMI
Museformer 2022 [79]	Transformer	-	No	Yes	LakhMIDI [77]	REMI-Like
Polyfussion 2023 [67]	Diffusion	inpainting, texture	Yes	No	POP90 [80]	Piano-Roll
FIGARO 2023 [81]	Transformer	chords, instrument, meter, note-density	Yes	Yes	Lakh MIDI [77]	REMI+
MMT 2023 [82]	Transformer	instrumentation	No	Yes	Lakh MIDI [77], SOD [83]	Midi-Tuple
Sympack 2024 [84]	Transformer	chords, structure, notes	Yes	Yes	Lakh MIDI[77], [85], Custom	-
MuseCoco 2023 [86]	Transformer	Genre, tempo, emotion ...	No	No	Custom	REMI-Like
MuseBarControl 2024 [87]	Transformer	chords	Yes	No	POP90 [80]	REMI-Like
NTT 2024 [88]	Transformer	-	No	Yes	Lakh MIDI [77], POP90 [80], SOD [83]	Compound
FTG 2024 [89]	Diffusion	texture, rhythm, chords	Yes	No	POP90 [80]	Piano-Roll
NDRD 2024 [90]	Diffusion	chord, pitch, note-density	Yes	No	Maestro [71], POP90 [80]	Piano-Roll

Table 2.1: Overview of symbolic, deep learning based music generation models, their architectures, and control mechanisms, time-vayring control (TV), multitrack capabilities (MI), dataset, and representation. A more complete Overview is found in [68]

2.7 Representation and Format

The choice of representation of data is a crucial aspect of music generation. First, the choice of audio or symbolic music has consequences for data availability, dataset size, context of the output, and what features can be controlled. Second, tokenization, the method in which symbolic or audio data are chunked, organized, and ingested into the model is an important aspect, with tradeoffs to consider for different generative tasks and goals.

2.7.1 Symbolic Music vs Audio

Music can be represented digitally in two ways, either as an audio rendition or symbolically as a set of instructions. Working with different representations comes with various drawbacks and benefits for music generation. There are different types of symbolic representations of music, but the most common consists of discrete sequences of musical elements such as pitch or duration. Working with audio theoretically gives access to all audible qualities of music, including detailed information on instrumental timbre or acoustic settings. In symbolic music, this is more restricted.

Symbolic data is also far less available than audio data. Many symbolic music datasets are created by compiling hand-transcribed music. High-quality automatic transcription from audio remains an unsolved issue.[68][84]. This is a serious limiting factor on how large symbolic music generators can become. However, symbolic music gives more direct access to many higher-level musical features such as chord progressions, melodies, and instrumentation. When working with audio, these features have to be extracted first, requiring additional processing steps that are prone to inaccuracies. Another consideration to account for is size: raw audio is significantly larger than corresponding symbolic music. In addition, rendered audio is difficult to edit once generated.

2.7.2 Tokenisation

Sequences are typically transformed into tokens, a numerical representation of data, to be handled by a machine learning algorithm. Audio-based music generation uses tokenization to condense audio while retaining its semantic content. Jukebox [48] uses a variational autoencoder[91] with a discretizing bottleneck (VQ-VAE) to create tokens from audio. Musicgen [4] tokenizes audio using the previously developed Encodec model for audio compression which, similarly to VQ-VAE, learns a highly condensed discrete representation of audio [92]. These condensed encodings are crucial for generative modeling on audio. Depending on the representation, a similar technique is used to encode piano rolls for diffusion of symbolic music [67][89].

2.7.3 Symbolic Tokenisation

Symbolic music is represented is in different ways, such as text (i.e. the ABC notation), piano roll, graph, and sequences. The most widely used representation, however, is the event-based MIDI representation, which is reflected in the tokenization techniques. In symbolic music, tokenizers are feature extractors. They extend the standard MIDI vocabulary with additional tokens that help models better capture different aspects of music.[93]. In table 2.1 the tokenization approach of different symbolic models is summarized. **MIDI-Like** tokenization closely emulates the MIDI vocabulary, translating a MIDI file into a single stream of tokens such as note-on and note-off. The **MMM** tokenizer adds indicators to aid track-inpainting. **REMI** [78] tokenization expands on MIDI-based tokenization with tokens for duration, bar, and position, designed to help capture recurring musical patterns. **REMI+** [81] tokenization extends **REMI** with an instrument token to better encode multi-instrument tracks. The **PerTok** tokenizer designed by Lemonaid[2] encodes micro timings and offsets designed to capture the full spectrum of rhythm in musical performances.

These extensions come at a cost: The resulting sequences of tokens can become very long, which adversely affects the model [68]. Ongoing attempts such as compound word or nested tokens aim to shorten the sequences by combining low-level tokens into more expressive high-level tokens.[88]. Dong et al. [82] combine six different MIDI-like events (type, beat, position, pitch, duration, instrument) into single tokens. Hsiao et al. [94] differentiate between token types and group neighboring tokens into compound words, resulting in significantly shorter sequences (about 50% compared to individual tokens).

This thesis uses a third approach: Byte Pair Encoding (BPE) [95]. BPE is used widely in language modeling, including the GPT series of models [64] and has been successfully applied to symbolic music generation [96]. The approach is simple: the most common token pairs of the dataset are repeatedly combined into new combined tokens until the total amount of unique tokens reaches a preset vocabulary size. This approach works independently of token types and semantic content of the tokens and allows for very flexible scaling of the vocabulary. As seen in figure 2.4, this drastically shortens the sequence length by about a third ($mean_{individual} = 47976, mean_{bpe} = 14519$), which in turn improves both the quality and efficiency of the model.

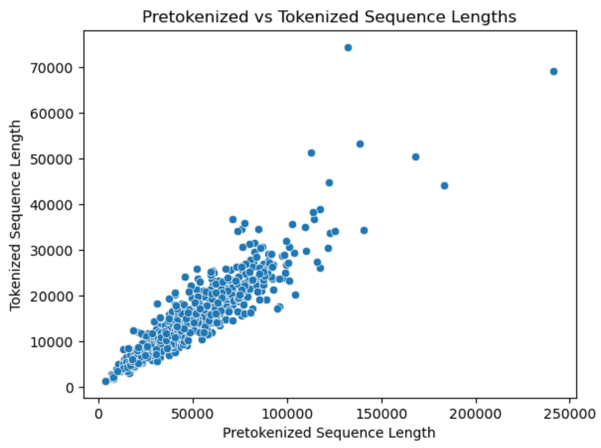


Figure 2.4: Scatterplot of sequence length before and after BPE tokenisation

[2]https://www.lemonaide.ai/

2.8 Control

Control is an essential aspect of any generative model. Without control, even the best generative models producing beautiful music are of limited real-world use. Control allows generative AI tools to become proper collaborative systems, which generate for a wide array of scenarios. In music generation, control covers essentially all musical features. Available features vary by representation. To illustrate: Raw audio models such as Stable Audio (Evans et al., 2024) can be controlled for acoustic settings (i.e jazz music playing in a *busy restaurant*, in a *large cathedral*, or *through an intercom*), something that is simply not represented in symbolic music.

There are different approaches to classifying musical features. One can differentiate between global and local features [97] (discussed in the appendix 5.2), deep vs surface-level features [98], high-level versuss low-level features [75] and global versus fine-grained or time-varying features.

In the context of this thesis, we differentiate between global features and time-varying features [81]. Global features as features that do not change within an excerpt, while time-varying features can change within an excerpt. What is time-varying or global is highly context-dependent, a piece may have a single time time-signature and tempo as is assumed in [86] or it may vary throughout the piece as enabled in [81] or [78]. Other time varying controls could be chords [81][99][100][67], melody [4][67] or texture [67]. For the target application in a MACT - game, time-varying controls are necessary to provide a change in music that triggers a change in the patient's improvisation. See table 2.1 for an overview of what features are controlled for in recent deep learning symbolic music generators, and whether they are time varying or not.

2.8.1 Rhythmic control

The types of control exercised over rhythmic components vary by representation as discussed in 2.7. In CocoMulla [101] generated audio is controlled with drum tracks and a piano roll. Similarly, in JASCO[102] drum audio is used for conditioning. In MusicConGen [100], control for rhythm is added through tracking beats and downbeat. MusicControlNet [99] adds beat and downbeat conditioning to an audio diffusion model. For symbolic systems, control of tempo and meter is relatively common [81], [78], [86]. Time-varying control over rhythm is often deployed through note density (both vertical and horizontal)[81][90]. Another approach [89] involves passing the piano roll as a factor to guide the diffusion process. In Polyffusion [67] Min et al. successfully encode texture that is disentangled into harmony and rhythm using a pre-trained variational auto-encoder [103]. Herremans et al. [75] control rhythm through the high-level feature arousal, which they disentangle into rhythm and note density using a variational auto-encoder.

2.8.2 Inner Metric Analysis

We investigate Inner Metric Analysis (IMA) for its potential to control the rhythm of a generated excerpt over time. Unlike feature disentanglement discussed in section 2.8.1, IMA is relatively simple algorithmic process that does not require any training. IMA has been used in the classification of dance-music [104], automatic detection of meter [105] and music retrieval [106] as well as the study of syncopation [107][9]. Inner Metric Analysis identifies strong and weak pulses and their periods within note onsets in symbolic music. It is used to identify *local meters* as opposed to *outer meter* given by time-signatures.

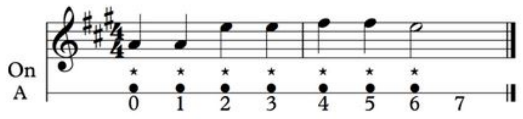
A local meter is a set of evenly spaced onsets with a minimum length of three, not able to be extended forward or backward in time, and not contained within any other local meter. (see figure 2.5). Let $M(l)$ be the set of local meters with a length of at least l. The parameter p is variable and determines how much the length of a local meter influences its weight. Intuitively, longer and more established local meters should carry more weight. This is given by k_m^p. The weight of an onset $W_{l,p}(o)$ is defined as the weighted sum of the local meters. The metric weight is calculated as follows [9].

$$W_{l,p}(o) = \sum_{m \in M(l): o \in m} k_m^p \tag{2.2}$$

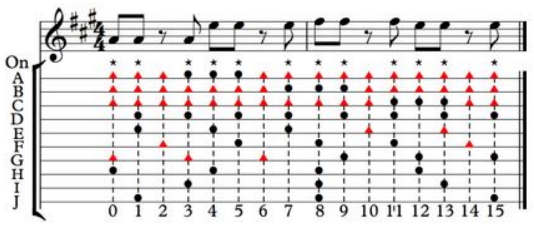
Spectral weight is a variation of metric weight, that considers the extension of each local meter: $ext(m)$. The red triangles in figure 2.5 are an example of extensions. The calculation is similar, but it assigns a weight to each time point (instead of only to onsets) and considers the extensions. This feature is less sensitive to local changes.

$$SW_{l,p}(t) = \sum_{m \in M(l): t \in ext(m)} k_m^p \tag{2.3}$$

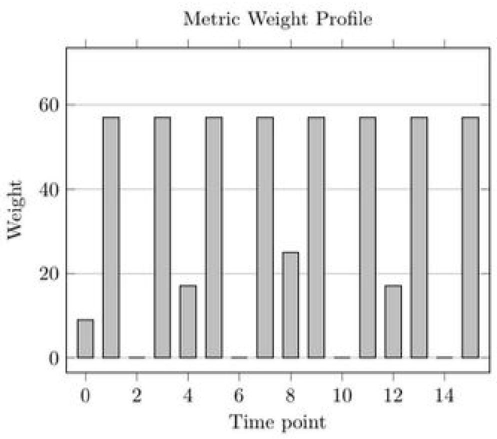
IMA can indicate rhythmic complexity. This, in turn, influences the ease of tapping along/following [9] and rhythmic entrainment. Configured properly, IMA could be utilized to control a music generator, steering the generated music so that it is more or less difficult to follow, allowing for difficulty adjustment in the context of a MACT game.



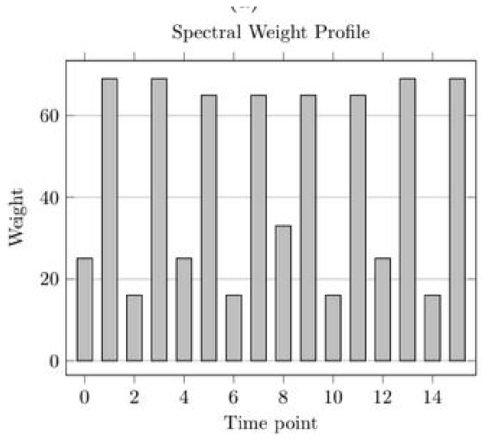
(a) Single local meter and its pulses (A) from the melody "Twinkle, Twinkle Little Star"



(b) 10 local meters and their pulses produced by IMA of a syncopated variation of "Twinkle, Twinkle Little Star"



(c) Metric weight profile of syncopated "Twinkle, Twinkle Little Star"



(d) Spectral weight profile of syncopated "Twinkle, Twinkle Little Star"

Figure 2.5: Visualisation of metric weight analysis [107]

2.8.3 Connecting MACT and Inner Metric Weight

Last Minute Gig [8] is a Musical Attention Control Training game aimed to help people with Parkinson's improve attention control. This is achieved through repeated sessions of play, where a player improvises along to music and is encouraged to change their playing when the music changes.

Algorithm: Simple Music Engine
Input: Pool of keys, rhythmic patterns, chord progressions, tempos
Output: Generated music sequence

Step 1: Randomly choose key, rhythmic pattern, chord progression, and tempo from the pool.
Step 2: Play corresponding percussion audio clip based on the selected tempo and rhythmic pattern.
Step 3: When the user presses the button, trigger the guitar sound of the current chord.
Step 4: After 8 bars, make a random change (to rhythm, tempo, or introduce a pause).

2.9 Implementation of control

Methods of enabling control in generative models can be split into four approaches. 1: Choice of architecture, 2: training data, 3: fine-tuning, and 4: post-hoc guidance. In table 2.1 we list a selection of recent symbolic deep-learning music generators with their corresponding architectures and datasets. Since deep learning models are often probabilistic, the control mechanisms are as well. They do not guarantee that the output has certain characteristics, but they *condition* the probabilities of the outputs so that the outputs are more likely to have certain characteristics.

2.9.1 Control through architecture

The choice of architecture lends itself to different types of control/conditioning. Transformers are the next-token predictors that predict based on the prior sequence. The default training paradigm allows for control with a user-defined sequence. This is true for both audio-based models such as MusicGen [4], Jukebox [48] and MusicLM [5] as well as symbolic music models such as MMT [82], MusicTransformer [52] and MusicBERT [63]. Diffusion models are quite flexible compared to transformers. One can use the same model for inpainting, continuation, and - depending on the representation - melody and accompaniment generation through masking [67][108]Transformers, on the other hand, have to be explicitly trained for these tasks.

2.9.2 Control through training data

Joint training of a model with the desired control is the most common and robust method of enabling control in a generative model. MusicGen[4], a recent text-to-music (audio) transformer is trained on 20000 hours of licensed music from Shutterstock and pond5 [3] which includes textual descriptions and tags for genre, tempo, and other factors such as instrumentation. Control is achieved through the joint training of a text description and music. An example description is provided below:

Inspirational dramatic background music! Perfect for trailer, background, advertising, historical film, movie about superheroes, teaser and many other projects![4]

Text-based control, while user-friendly and accessible to non-musicians, is inherently vague. Levels of detail and choice of words vary widely by dataset, even with standardized tags included, such as genre and tempo. This is also true of specialized music-text datasets such as MusicCaps [5][109]. For this reason, the creators of MusicGen [4] add melody conditioning

[3]https://www.shutterstock.com/music and https://www.pond5.com/

[4]https://www.pond5.com/royalty-free-music/item/95908062-inspiring-dramatic-epic-background-cinematic-music

alongside text conditioning and train their model jointly with the chromagram of the melody alongside the text.

In MusicGenStyle [110] the authors utilize classifier-free guidance to add style conditioning to MusicGen. They train a music-style encoder that transforms a random subsample of a given reference audio track into style tokens. The style tokens are combined with the embeddings of the text description and provided as prefixes to the model. The conditioner and the MusicGen transformer are trained jointly on the entire dataset. The creators of FIGARO [81] enable time-varying control over instrumentation, note density, average pitch, and volume on a bar-by-bar level, in a symbolic music generator through joint conditioning of music and the selection of desired features while training.

2.9.3 Adding control through fine-tuning

Both the melody conditioning of MusicGen [4] and the style conditioning of MusicGenStyle [110] retrain the full MusicGen model on the entire dataset which comes at considerable cost. Fine-tuning or transfer learning is another method through which models are (re)-trained, but at a considerably smaller cost and using less data. Fine-tuning is widely used in the language domain to adjust large language models for niche use cases where the available data may not be sufficient to train a large model from scratch. In the examples of MusicGen and MusicGenStyle, the availability of data was not a limiting factor. The controlling elements, melody, and style, are inferred from the training data. However, fine-tuning may achieve additional control at a lower cost.

MusiConGen [100] is a fine-tuned variation of MusicGen, which adds control for rhythm and chords. They propose the jump-finetuning mechanism a form of selective fine-tuning, where the original model, with 1.5 Billion parameters and 48 self-attention layers, is split into blocks consisting of 4 self-attention layers. They train the first layer of each block, freezing the remaining layers. Additionally, they apply adaptive in-attention to the first nine blocks: The output of a transformer layer is augmented with copies of the original condition. As a result, only a quarter of the original parameters are tunable, which enables training on consumer GPUs on just 250 hours of music sourced from YouTube (as opposed to 20000 hours). In Coco-Mula [101], the authors adjust a LLAMA adapter with just 4% of parameters, keeping all original MusicGen parameters frozen and training only the adapter on a small dataset of 300 songs to add drum and chord conditioning.

MuseBarControl [87] is a fine-tuned version of MuseCoco [86] which extends the global controls with time-varying bar level control for music-generation. They compare several approaches: In the first, they augment the prompt (which is generated from text) with additional tokens for bar-wise control of chords and adjust the loss function to incorporate that. In the second approach, they introduce two novel methods. First, they pre-adapt the new parameters (introduced by the Lora adapter) to a separate classification task, an auxiliary task. The model classifies whether the section of music corresponds with the control tokens. The classification head added to the model for this task is removed after training. In the third step, they introduce counterfactual loss to reinforce the model's attention to the control, by rewarding the difference in negative log-likelihood between an output with the original and an output with a changed attribute. They find that combining the three strategies, pre-adaptation on a separate task followed by counterfactual loss and prompt augmentation yields the strongest model.

2.9.4 Adding control through guidance

Other methods do not involve any fine-tuning or retraining of the original model. Adding control with additional model inputs does require at least some amount of retraining, which is not always feasible, and adding many types of control may deteriorate the model's performance. In these cases, guidance can be used to steer the model towards a certain output. In SMITIN [111] the authors intervene at inference time, while the trained model is generating, to guide MusicGen[4] towards a certain goal. They explore guidance for ensuring the presence of certain instruments (piano/drums/bass/guitar) and to increase the quality/realism of the generated audio. For this, the authors train linear probes that learn to associate the state of each transformer layer in the network with the goal (i.e. drums being present in the output). Depending on the output of the classification a term is added to each self-attention head, before the matrix projection stage of the self-attention calculation. Then the model is steered in the direction of the probe, which increases the probability of the desired quality (drums) being present in the generated music. For more details see the SMITIN [111] and the attention calculation of Musicgen [4]. Guidance of transformer models has been explored in other contexts [112], such as influencing truthfulness, humor, and appropriateness in language generation models, with mixed results.

In Diffusion models, the output is sampled over several steps. At each of these steps, it is possible to intervene with guidance to direct the sampling towards a specified goal. Huang et al. [90], repeat each sampling stage several times, and choose the output that follows a set of rules most closely. ControlNet [113] adds spatial control to image generators, allowing the guidance of image generation using sketches, poses, edges, and depth maps without retraining. MusicControlNet [99] adapts this approach to music generation, adding control for time-varying features, such as melody, dynamics, and rhythm.

2.10 Evaluation

How to evaluate generated music is still an open research question. There are no generally approved methods of establishing the quality of generated music.[50]. However, there are several common frameworks used to evaluate music. Music generation literature often distinguishes between objective and subjective evaluation. Despite what the name suggests, objective evaluation of generated music does not measure the aesthetic quality or beauty of the music objectivly. Instead, it encompasses automated, statistical methods of analyzing and comparing generated music to human-composed music. Subjective evaluation encompasses evaluation methods that center human judgment.

2.10.1 Subjective Evaluation

For subjective approaches, the methods vary widely [114]. There are simple Turing-type tests that examine whether human listeners can distinguish between generated and human-written music. There are tournament-style surveys, where different musical pieces obtained by different methods (human-written vs computer-generated) compete against each other. The listeners repeatedly select their preferred piece [52][81]. Another typical approach is using (Likert) ratings along different dimensions to separate different qualities of the music. [82], [79] and [84] collect Likert ratings on coherence, richness, arrangement and consistency. In [82], this takes the following form:
Coherence: Is [the music] temporally coherent? Is the rhythm steady? Are there many out-of-context notes?; Richness: Is [the music] rich and diverse in musical textures? Are there any repetitions and variations? Is [the music] too boring?; Arrangement: Are the instruments used reasonably? Are the instruments arranged properly?;
The specific questions asked vary with the aims of the project: In [50], Likert ratings are collected along the dimensions of stylistic success, aesthetic pleasure, repetition, melody, harmony, and rhythm. Here, the questions for stylistic success are relevant due to their use of generative models to produce music in a certain style, specifically classical string quartets, and classical piano improvisations. These evaluations are often paired with statistical hypothesis testing to investigate relationships between the various ratings of the model outputs. An example would be: *There is no difference between ModelA and ModelB on ratings of stylistic success*. Or *ratings of melodic success are positively correlated with ratings of aesthetic pleasure*. Finally, there are expert evaluations (which can also include Likert ratings) but also detailed analyses or even performances of the produced music [46] [50].

2.10.2 Objective Evaluation

Objective evaluation of generated music includes model-specific metrics and different comparative statistical metrics evaluating the outputs in comparison to other data [114]. Model-specific metrics are generic evaluations of a model's success to approximate training data, these will vary depending on the model and are not indicative of stylistic success. Examples of this are Negative Log Likelihood [52] or Perplexity[81]. More generally applicable are statistical investigations of the outputs, in comparison with other datasets. Measuring similarity in music is an ongoing field of research [115] for a large variefty of different use cases, such as music retrieval, cover, genre, and artist detection. A popular comparative metric is calculating the Kulback Leibler (KL) divergence between two datasets with respect to certain features, such as the count of intervals or unique pitch classes. However to obtain the KL divergence one has to select specific features that may only capture a subset of the desired properties. Similar issues arise with other distance metrics i.e. cosine similarity, earth movers distance, or maximum overlapping area.

Especially in the audio domain, additional AI models are often used for evaluation. MusicGen [4] uses additional classifiers to generate labels for the music and calculates the KL divergence between the generated labels. Additionally, they calculate the Frachet Audio distance, a measure devised to calculate the plausibility of audio (for music enhancement purposes) compared to a large set of studio recordings [116]. Finally, they use the CLAP score which compares the corresponding text description to the latent representation of the generated audio, with the text description of the generated audio with the reference audio [117].

3. Research Questions

In the previous section, we established the potential of generated music in serious games (section 2.1), and the need for adequate time-varying controls over the generation process (section 2.8) to reliably ensure the usability of the generated music in the context of MACT. We identified inner metric weight (section 2.8.1) as a promising target to describe rhythmic structure. Research links inner metric weight to rhythmic entrainment, and perceived and observed difficulty for a player to follow/tap along to the music. Additionally, it extends prior work on controlled music generation with a powerful rhythmic feature that is interpretable, relatively concise, and calculated symbolically. We collected crucial technical considerations for music generation, including the overall approach in section 2.4, architecture in section 2.5, representation in section 2.7.1 and tokenization in section 2.7.3. Finally, we discussed promising methods of adding control to a model in section 2.9 and how to evaluate a model and its outputs (section 2.10).

In this thesis we propose RhythmLang, a deep learning model that can generate a complete musical piece with time-varying controls for rhythmic structure. The output of the model will be investigated for successful integration of control, player enjoyment, and interactive potential in the context of MACT. RhythmLang will be evaluated with the following research questions.

1. Research Question 1: Is the control of rhythmic structure in the resulting model effective?
2. Research Question 2: Is the generated with control of rhythmic structure appropriate for the context of MACT?
    - Sub Question 2.1: Do listeners reliably recognize or follow changes in rhythmic structure perceived in the music we generate?
    - Sub Question 2.2: Are there particular differences in rhythmic structure that are easier to recognize, what are their qualities?
    - Sub Question 2.3: Are there particular rhythmic structures that are easier to follow, what are their qualities?
3. Research Question 3: Does the generated music improve player enjoyment and engagement over Chalkiadakis' [8] rule-based system?

4. Methodology

To answer **RQ1**, we develop, train, and evaluate a model conditioned with inner metric weight. We experiment with different approaches, with particular attention to approaches that require little training resources, such as fine-tuning. The resulting outputs are evaluated quantitatevly, to judge the success of the conditioning. **RQ2** is answered with an interactive participant study where a participant either indicates when they hear changes or taps along and adjusts their tapping when they hear changes. **RQ3** is answered with a participant study that collects ratings on music generated with our model.

4.1 Introducing RhythmLang - Approach and Base-model

4.1.1 Approach

Sections 2.4 and 2.5 discussed the potential approaches to music generation with particular attention to state-of-the-art approaches using deep learning. The developed model will be a transformer due to its ability to effectively sequence and its potential to incorporate additional controls. We will use a symbolic representation of music (as discussed in section 2.7.1) due to its lightweight datasets and the ability to make changes to and incorporate the output into a music production environment, enabling a cooperative co-composition process as opposed to replacing the composer. More specifically, we will use a representation similar to REMI+ (see section 2.7.3), which extends the standard MIDI events with tokens indicating forms, such as meter, bar lines, and note-duration. This representation is compounded using byte pair encoding (see section 2.7.3) to decrease the sequence length and improve the capability and efficiency of the model.

We will use the Lakh MIDI Dataset [77], a widely used open-source and licensed dataset for symbolic music generation, which will help us avoid ethical pitfalls around privacy and copyright (see section 2.2). Finally, we are not attempting to add control by training custom large foundation models, rather we use parameter-efficient fine-tuning or guidance to add control (section 2.9). As a result, we only train a fraction of the model parameters, with substantially less need for data, computation, and energy. All relevant code, including code for training, configuration, and data preparation will be made available online alongside the trained models. Finally, we use and extend an open-source model MusicLang in collaboration with its maintainers. If successful these extensions will contribute to the MusicLang project and be more widely available in a well-documented and continuously maintained ecosystem, with potential integrations into mainstream music production and composition software.

4.1.2 MusicLang - The foundation Model

MusicLang's core model is a transformer based on LLAMA 2, trained on the Lakh MIDI Dataset [77]. It can generate multi-track instrumental pieces up to 3 minutes long with control for chord progression, instrumentation, and range. Additionally, it can create interpolations and continuations of a user-provided piece. It is trained on an extended vocabulary of tokens similar to REMI[1] with additional tokens detailing the harmonic structure and voice characteristics such as instrumentation or range (see figure 4.1). This base vocabulary is extended using a BPE tokenizer (see section 2.7.3). For inference there are multiple different modes of generation, 1) free generation, 2) continuation, 3) controlled generation, and 4) controlled continuation. For free generation, the user can indicate the following settings.

- Number of tokens: Number of tokens to generate, this influences the length of the music depending on the number of instruments. More instruments and higher note density means more tokens per second of music.
- Temperature: Temperature parameter for softmax sampling (see section 2.5.3)
- Top p: Target percentage: (see section 2.5.3)

For controlled generation, the user can indicate a chord progression as a string. This includes extended chord variations including Major (M), minor (m), 7, m7b5, sus2, sus4, m7, M7, dim, dim0. One can also specify a bass note, i.e. CM7/D. The length of the chord progression influences the length of the generation. For *continuation*, the user provides a MIDI track and the section of measures that are used as the basis for generation. For *controlled continuation* the user provides both a chord progression and a MIDI track.

[1]https://musiclang.github.io/tokenizer/

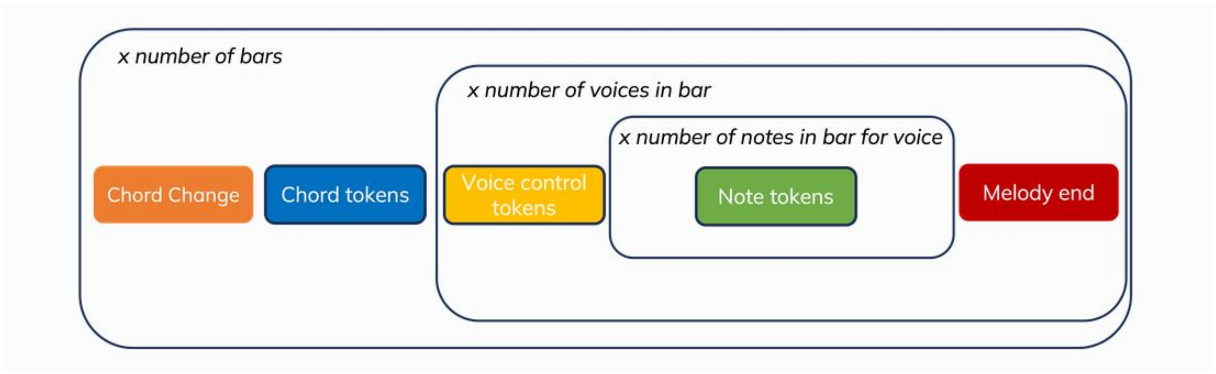


Figure 4.1: MusicLang's tokenization on a high level, shows a hierarchical tokenization process. At the highest level are chord-related tokens that describe the harmonic structure of a section. This is followed by instrument-level tokens that encode summarizing features such as instrumentation, octave, range, and note density of a voice within a section. Finally, there are note-level tokens that encode the pitch and duration of an event within a voice within a section.

4.1.3 RhythmLang

We propose RhythmLang, a fine-tuned variant of MusicLang with controls for inner metric weight. The fine-tuning targets the *controlled continuation* and the *controlled generation* modes of the model. Here the user provides a MIDI file as input from which inner metric weight is extracted and passed to the model. In *controlled continuation* the user provides two MIDI files, one from which the model continues and one from which the model extracts the target metric weight profile.

4.2 Developing the Model

4.2.1 Preliminary Experiments - proof of concept

The current methods of adding musical control to an existing model are poorly systematized and rarely compared to each other. While this thesis does not aim to provide a systemic comparison and experimental evaluation of different control methods, some preliminary experiments are necessary to establish an informed course of action. We use BassCraft, a smaller model, and start by controlling for note density. Note density is more easily calculated, tokenized, and verified than inner metric weight. Once control for note density is established, we will move on to inner metric weight. BassCraft is used as a proof of concept for the methods of adding control, it is not part of the final model and evaluation. The most promising approach, or combination of approaches will be applied to fine-tune MusicLang.

4.2.1.1 BassCraft - a tiny transformer model

To avoid wasting computing resources and energy, we perform the preliminary experiments on a smaller model: Basscraft. BassCraft is a small transformer model based on GPT2 [64]. It has an embedding size of 256, 4 attention heads, four hidden transformer layers, and 7 million trainable parameters. In contrast, the target LLAMA 2-based model MusicLang has over 100 million trainable parameters. Basscraft generates a bassline to a provided piece of music and is trained on the Lakh MIDI dataset [77]. For training, songs with bass lines are selected (based on the presence of particular MIDI-instrument channels). The tracks are divided into snippets between 1 and 16 bars long. The bass lines are separated from the remaining track and matched as potential output. For inference, the user provides a *target* MIDI file and a MIDI bass instrument such as a Cello, or Electric Bass (see the appendix 5.3) for a full list of MIDI-bass instruments. The *target* MIDI file can be a single instrument or multi-instrumental track. The model generates a corresponding bass line of the same length as the target file (up to 16 bars). When we add control for note density, the user provides a single integer or a list of integers. If a single integer is passed, that integer is replicated across all generated bars. If a list of integers X of size $|X|$ is provided, then the note density of bar m is given by $X_{m\%|X|} \forall m \in target$. When control is added for inner metric weight, the user provides an additional reference MIDI file $reference$. The metric weight profile W is given per bar m: W_m. The target rhythmic weight of a bar is given by $W_{m\%|W|} \forall m \in target$. The modulo operation ensures that for note-density and rhythmic weight control, the length of the control input does not have to match the length of the target midi file.

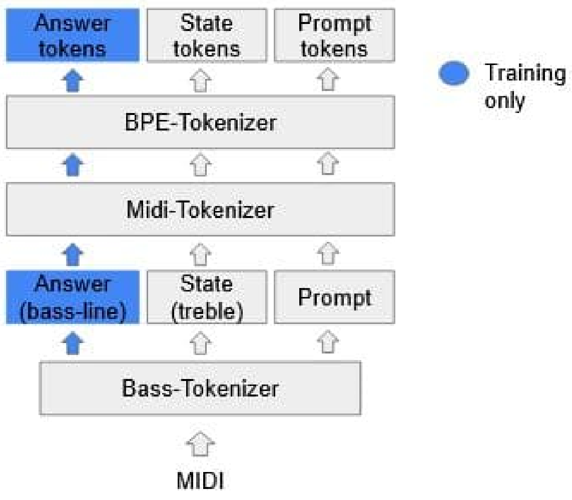


Figure 4.2: Preprocessing and tokenization of the original BassCraft model

4.2.1.2 Method 1 - Vocabulary Expansion

Vocabulary expansion is the process of adding new vocabulary to a transformer model. MusicLang achieves its extraordinary controllability similarly to FIGARO [81] using control tokens that summarize features of the music that go beyond simply representing MIDI-like events. In vocabulary extension, it is critical to ensure that additional tokens do not overwrite or collide with the existing training. Otherwise, the benefits of using a pre-trained model disappear.

Since we use a BPE tokenizer, it is difficult to add new tokens, as it would require retraining the BPE tokenizer, which will transform the embedding layer, making the pre-trained model unusable. Instead, we investigate whether there are unused tokens and reassign them to our new control tokens. These new tokens are not included in any compound tokens generated by the BPE process, which increases the sequence length.

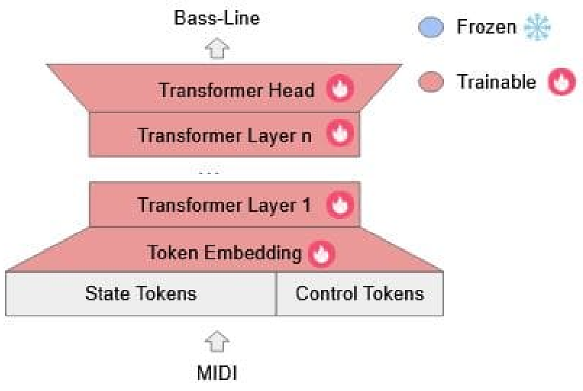


Figure 4.3: Vocabulary transfer with full fine tuning

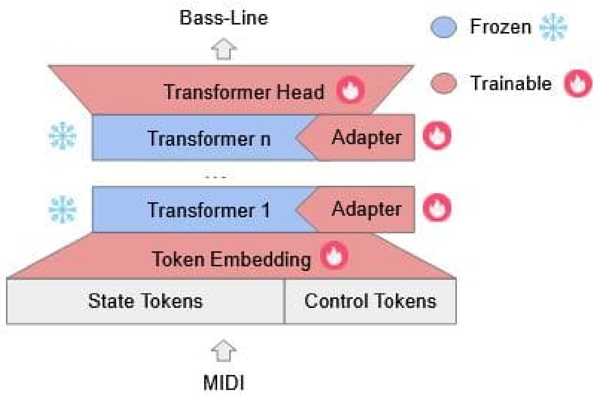


Figure 4.4: Vocabulary transfer with parameter efficient fine tuning

4.2.1.3 Method 2 - Integrating of control tokens

This approach differs from vocabulary expansion because it processes the control tokens as a parallel to the other input tokens. This is adapted from the approach used in Coco-Mulla [101]. After passing through a trainable positional embedding, the parallel stream of control tokens is inserted into the model at a layer c. The benefit of this method is that it doesn't require editing the model's vocabulary.

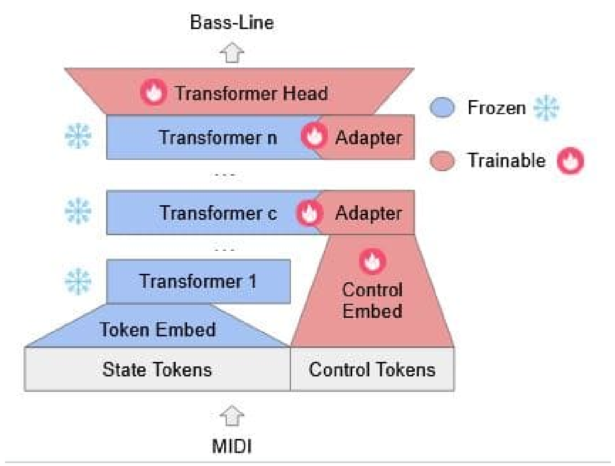


Figure 4.5: Integration of control tokens with parameter efficient fine tuning

4.2.1.4 Method 3 - Post-Hoc Guidance and other improvements

SMITIN[111] uses post-hoc guidance on a trained model to influence the generation process without retraining the model. This type of sampling-based guidance has been very successful in diffusion models. In transformers for sequence generation, however, it produces mixed results [112]. Additionally, this may be difficult to implement and transfer to IMA. Both SMITIN and Rütte [112] only use one-dimensional variables that indicate the probability of a concept being present or not. Both note-density and IMA are non-binary features, which complicates the mapping of this guidance strategy to our proposed model.

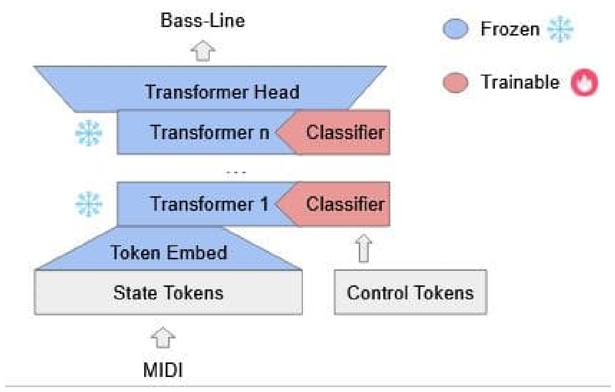


Figure 4.6: Integration of control using inference time interference

If these experiments are unsuccessful, we can follow the approach of [87] and try additional training using auxiliary tasks or a modified (counterfactual) loss function.

4.2.2 Using inner metric weight as controllable feature

Inner metric analysis (IMA) creates metric weight profiles we use as guiding features passed to the model bar by bar, which allows us to induce shifts in metric weight in the output. For this, we use the globally smallest available note grid of the Lakh MIDI dataset g_{min}. The calculated rhythmic profile is normalized and provided to the model as a vector of length g_{min}. The model then learns embeddings of the distribution alongside positional embeddings [101]. These embeddings are incorporated into the model. The model is trained by providing a piece as a MIDI file, this is then split into two streams. On the one hand, the MIDI file is tokenized, on the other hand, the rhythmic profile is extracted from the MIDI file. The model is trained on both the embeddings of the extracted profile and the tokenized MIDI file. For inference, the user can provide a reference track from which the inner metric profile is extracted and passed to the model.

4.2.3 Training RhythmLang

Methods 1, 2, and 3 are sorted by expected difficulty of implementation. We first implement these methods on BassCraft since the model is only a fraction of the size of RhythmLang and therefore easier to train and iterate on. First, BassCraft is extended using each method with control for note density. When a method is found that introduces sufficient control, we extend this to IMA and try generating basslines with a provided metric profile. Finally, the most promising method (or combination of methods) is adopted to MusicLang, creating RhythmLang.

4.3 Model Evaluation

4.3.1 Custom Datasets

The following table describes the datasets we will construct, their purpose, and their breakdown.

Name	**Aspect**	**Description**
`lmd1000`	Fine-tuning Dataset	1000 songs from Lakh MIDI Dataset [77] (containing bass-lines so we can use it to train both RhythmLang and BassCraft)
`lmd500`	Evaluation Dataset	Randomly selected subsection of 4 to 16 bars of 500 songs not in *lmd1000*
`srhythm`	Evaluation of rhythm control	30 manually chosen prototypical rhythms based on [104] Tango, Rumba, Bossa Nova, Merengue, and March
`schord`	Evaluation of chord control	30 two-, three-, and four-bar chord progressions
`bcraft_inf`	Preliminary BassCraft Evaluation	BassCraft applied to `lmd500` with randomly chosen rhythms from `srhythm`, this is used for development purposes
`mlang_inf_con`	RhythmLang Controlled Generation	RhythmLang applied to 500 chord-rhythm pairs from `schord` and `srhythm`
`mlang_inf`	RhythmLang Controlled Continuation	RhythmLang applied to `lmd500`, continuing excerpts with randomly chosen rhythms from `srhythm`

Table 4.1: Summary of datasets used for fine-tuning and evaluation

4.3.2 Evaluating Control-Effectiveness

As discussed in section 2.10, calculating whether or not the control is effective depends on the controlled feature but can happen automatically. The first set of experiments targets note density: Note density is continuous (the number of notes per bar), so we can calculate the error between the desired note density and the generated note density as the mean square error:

$$error_{continuous} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_{generated} - y_{prompt})} \tag{4.1}$$

Inner metric weight analysis generates metric weight profiles, which we use as a guidance mechanism. Following the approach by [107], we can compare the generated and the target rhythmic weight profiles using chi-squared distance. Given target distribution T and generated distribution G, the distance is given by

$$D = \sum_{i=0}^{n-1} \left(\frac{(T_i - G_i)^2}{T_i + G_i} \right) \tag{4.2}$$

The target distribution is the rhythmic template, and the generated distribution is the generated output conditioned with that rhythmic template. A smaller difference indicates better control effectiveness.

4.4 User Study

RQ2 and **RQ3** are evaluated through a user study. The goal is to recruit $n = 20$ participants to complete a test of interactability and a survey comparatively evaluating the generated music.

4.4.1 Interactive Study

The interactive study aims to evaluate the fitness of the controlled generated music from an MACT perspective. Specifically, in the MACT protocol used by Chalkiadakis [8], the patient is supposed to listen to changes in the music and change their playing. There are two options that we are deciding between, both options will operate on $n = 5$ pieces that are generated using RhythmLang in the *controlled generation* condition, with rhythm controls at several points in the piece. For this, we provide the model with a MIDI file consisting of rhythm changing at 8-bar intervals concatenated into one file. For comparison with the previous system, we generate an additional $n = 5$ pieces using the approach by Chalkiadakis [8] with the algorithm described in the appendix **??**. To reduce potential confounds the RhythmLang generation will follow Chalkiadakis's constraint of initiating changes every 8 bars, though the system is more flexible than that. Additionally, we will be using the same rhythms from Chalkiadakis as control input. Chalkiadakis algorithm will be restricted to changes in rhythm, though it is capable of other changes.

Option 1 In our simplified interactive sessions, we ask the player to hit a button whenever they hear a change in the music. The button presses are registered alongside the starting time, tempo, and registered changing points (determined from the prompt). Finally, we correlate the timing of the button presses and registered changes are correlated with each other. A high correlation indicates that the participants noticed the changes. **Option2**: We ask players to tap along to the music, and change their tapping when they notice a change. We analyze the regularity of the taps matching them with the music playing and investigate them for changes.

Hypothetical hypotheses:

- **P1** There is no difference in the abilities of recognizing changes between the systems.
- **P2** Players have more difficulty recognizing changes between certain rhythmic changes than others.
- **P3** Players have more difficulty following music generated with certain rhythmic templates than others.

For P1 (in option 1) we calculate recognition accuracy by comparing the timing of the button hit, with the timing of the change. $recognition\_accuracy = |t_{hit} - t_{true}|$. Then we test the difference of average recognition accuracy between groups for significance using a t-test with $\alpha = 0.05$. In option 2 this is more complex. We would measure the distances between the player taps. The point in which we detect the largest change in average tap distance is t_{rec}. Rocognition accuracy is calculates as $recognition\_accuracy = |t_{hit} - t_{true}|$, then we perform the t-test as described above. For P2 we take recognition accuracy as calculated above, and group them by the five different rhythmic conditions we created. Each of the five rhythmic conditions is then compared with each other using repeated t-tests with $\alpha = 0.05$
P3 is only relevant in option 2. Here the users tapping is quantized to the smallest rhythmic value of the reference rhythm. The rhythmic profile of the user's tapping is extracted using IMA, and then the chi-squared distance between the rhythmic profile of the tapping and the rhythmic profile of the music is calculated. This is calculated for each of the five rhythmic conditions, and then compared as above using repeated pairwise t-tests with $\alpha = 0.05$

4.4.2 Survey

The survey will compare the listening experience of our model to the rule-based music generation system used in the original game to answer RQ3, whether the music by RhythmLang improves listener experience. The survey will also include the original MusicLang, to assess whether or not the fine-tuning for rhythm control decreases other capabilities of the model. Optionally, we include other symbolic music generators such as FIGARO [81], this will help provide a point of comparison. Following the recommendation of [50] we could also include a state-of-the-art rule-based generator such as MayaMarkov [51] and human-composed music from the Lakh MIDI dataset. The questionnaire will be adopted from [50], and each musical excerpt will be rated on a 7-point Likert scale along the following dimensions: aesthetic pleasure, repetition, melody, harmony, and rhythm.[2] Optionally there is space for the participant

[2]From [50]: Aesthetic pleasure (Ap) The extent to which someone finds beauty in something Repetition or self-reference (Re) The reuse, in exact or inexact form, of musical material (e.g., notes, melody, harmony, rhythm)

to comment on each excerpt. The participant will not see the source of the excerpt (i.e. which model or whether it is generated). The music provided for comparison will be excerpts cropped to about 30 seconds of rendered MIDI. While we don't cherry-pick the tracks, we will follow [50] and filter the music to prevent 1) excessive repetition of a small sequence (the model getting "stuck"), 2) long stretches of silence, 3) verbatim copying of training data or the prompt. The questionnaire also includes questions on demographic information such as gender, age, educational background, and musical experience.

Hypothetical hypotheses:

- P1 Ratings of aesthetic pleasure are higher for RhythmLang than for Chalkiadakis's rule-based system.
- P2 Ratings of aesthetic pleasure are not higher for MusicLang than for RhythmLang.
- P3 Ratings of repetition, melody, harmony, and rhythm are positively correlated with ratings for aesthetic pleasure.
- P4 Ratings of rhythmic success are higher in RhythmLang with certain rhythm conditions than others.

For P1 and P2, the average ratings of the groups are compared and tested for significance using t-tests with $\alpha = 0.05$. For P3 we perform a Pearson-correlation test between each of the musical ratings and ratings for aesthetic pleasure. For P4 we group the ratings of rhythmic success by rhythm condition and then perform pairwise t-tests with $\alpha = 0.05$ for each possible pair of rhythm conditions.

4.4.3 Additional points of discussion

Beyond simple statistical evaluation, we would include listening examples and an interactive code space on Google Collab where the reader can interact with RhythmLang. Additionally, discussing participants' comments, and investigating the model output musicologically could be worthwhile depending on the results.

within a piece. Melody (Me) A succession of notes, varying in pitch, which have an organized and recognizable shape. Melody is horizontal, i.e. the notes are heard consecutively. Harmony (Ha) The simultaneous sounding of two or more notes; synonymous with chords. The organization and arrangement of chords and their relationships to one another, vertically (at the same time) and horizontally (across time) throughout a piece Rhythm: Everything about the time aspect of music (as distinct from the aspect of pitch), including event or note beginnings and endings, beats, accents, measures, and groupings of various kinds.

4.5 Thesis Timeline

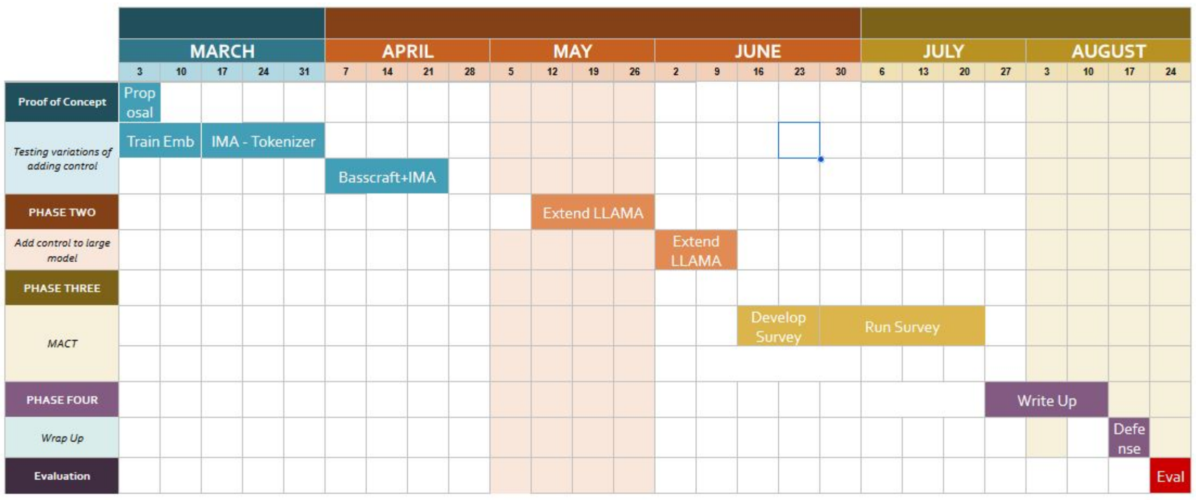


Figure 4.7: Thesis project plan

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5. Appendix

5.1 Comparing Tokenization lengths

Pretokenized Sequence Lengths - Mean: 47976, Median: 43692.0, Std Dev: 23160.
Tokenized Sequence Lengths - Mean: 14519, Median: 13159.0, Std Dev: 7197

Applying the BPE tokenizer results in sequence lengths roughly 1/3 of the original sequences. The sample is taken from 1000 random music pieces from the lakh-midi dataset.

5.2 Feature categorisation

Global features in music generation encompass high-level descriptors such as genre, function, and instrumentation/orchestration. Global features also incorporate summarizing features, that are calculated from the music itself. As an example, McKay's [118] general-purpose symbolic music classification system defines over 104 global features, 37 of them used for melody descriptors such as probability distributions of note durations, intervals, and pitch classes. These global features can then be used to infer other high-level descriptors such as genre if it's unknown, they can also support music retrieval systems [97]. **Local features** describe individual sequences such as melodic, rhythmic, or harmonic sections. They are more information-rich, which may explain their superior performance in music retrieval [97].

Also relevant in the music generation context are **high-level** vs **low-level** features. Music generation can take high-level concepts such as genre [110], [86] or emotion [75] [86] into account, which in turn effects more complex dynamics of concrete features. To illustrate: In Music FaderNets [75] the authors use a variational autoencoder to disentangle the abstract concept of arousal, into several concrete features including rhythmic density, note-density, tempo and dynamic, key. This allows them to change the abstract variable arousal, which cascades into a change of underlying features. This type of disentanglement can aid in situations where labled musical data with the abstract feature is less available, it can also aid in creating more accessible and interpretable generative models.

The following is a description of an improved algorithm utilizing generated music by Rhythm-Lang

- 1: Create $n = 100$ musical pieces with different control settings
- 2: For each piece
- 3: Extract chords from prompt (assuming high control success) - save mapping $m1$
- 4: Extract change of rhythmic pattern (or tempo or meter or instrumentation since these are already controllable in the musiclang model) - save mapping
- 5: Render symbolic music to audio

During game play

- 1: Load random audio clip and mappings.
- 2: Play associated guitar chords when player taps.
- 3: Register changes in tapping on musical changes.

- 4: Repeat when audio clip has finished playing.

5.3 MIDI Bass Instruments

Instrument Name	**MIDI Channel**
Electric Bass (Finger)	34
Electric Bass (Pick)	35
Fretless Bass	36
Slap Bass 1	37
Slap Bass 2	38
Synth Bass 1	39
Synth Bass 2	40
Acoustic Bass	33
Contrabass	43
Cello	46
Trombone	57
Tuba	58

Table 5.1: MIDI Instrument Mapping

5.4 Notes Comparing Symbolic Music Generators and their evaluation methods

- DeepBach [13] - RNN - inpainting. Evaluation Turing
- FolkRNN [46] - RNN - control for meter and mode - Expert Evaluation + Performance Practice
- MusicTransformer [52] - Transformer - Evaluation: Subjective - Tournament Style between different generated and natural music. Objective: Validation NLL
- MidiNet[45] - GAN - Control for Chords/Priming melody. Human (how pleasing, how real, and how interesting)
- Polyfussion [67] - Diffusion Model - supports inpainting, interpolation, melody/accompaniment generation, control for chord progression, texture. Subjective Evaluation Questionnaire for naturalness, creativity, musicality. Objective Control success.
- FIGARO [81] - Transformer Model - bar-wise control for chords, instrumentation, time-signature, note-density, mean-pitch. Evaluation: Perplexity (improvement over NLL for sequences of different length), Discription Fidelity (i.e accuracy in regards binary controls instruments, chords, time-signature). Macro Overlapping Area - comparison of feature histograms. Normalized Mean Root Square Area for note-density. Cosine similarity for chroma (melodic) and groove (rhythmic) feature vectors. Ablation study - effect of turning off controls. Extensive Subjective evaluation: 7569 comparisons by 691 participants - tournament style.
- Multi Track Music Transformer (MMT) [82] - Transformer - Instrument control. Comparison of different tokenisation techniques, REMI+ and Compound Tokens. Compound tokens are more condensed and the generated samples are longer, achieves significant speedups and reduces memory usage (2.6 * MMM, or 3.5 * REMI+). Objective evaluations: Inference time, pitch class entropy, scale consistency, groove consistency, Human evaluation (90 comparisons by 9 participants) on Coherence Richness Arrangement Overall.

Additional: Analysis of self attention as explanation avenue, which notes are most important.

- REMI pop music transformer - [78] - Transformer - continuation, control local control over chord and tempo
- MuseNet [49] - Transformer -,Instrument control, style control. No evaluation, only showcase.
- MMM [76] - Transformer model - inpainting, instrument control, note-density. Introduce novel representation No Rigorous Evaluation
- SymPAC [84] - Transformer - Control for Chords, structure, instrumentation, single notes. Train with both symbolic and transcribed audio data. Fine grained control. Constrained generation with a Finite State Machine. Comparison of three separate models trained on three datasets. **Evaluation** of controlability with KL-divergence on different controlled features over chords, structure, and individual notes. - KL divergence decreases with dataset size. 800 samples are generated and compared against a validation set of 3000 songs. Subjective evaluation (12 expert participants MIR researchers and music producers) on parameters of Coherence Richness Arrangement Structure
- MuseCoco [86] - Transformer - Control via text for following attributes instrumentation, ambitus, rhythm (intensity and “dancability”), number of bars, time signature, key, tempo, duration, artist, emotion, genre. All of these controls are global controls, a description is converted into a list of attributes which is then used for generation. Combination of many datasets. Creation of text descriptions from attribute list with data from the dataset, and ChatGPT. Evaluation: Objective - text to attribute list. Subjective evaluation 19 participants with at least basic music knowledge - questions to Musicality, Controlability (adherence of sample to music description), Overal Impression. Comparison with LLM generated music (with no special training for music generation)
- MBD [87] Extension of MuseCoco for time varying chord controls. Counterfactual Loss and Auxiliary task training improve controllability.
- Museformer [79] - Transformer - No controls. Goal improve long-term structure with fine and coarse attention. Captures structure well. Objective Evaluation: Perplexity: prediction accuracy of next token, Similarity Error the error between the similarity distribution of training data and generated music Subjective Evaluation 10 Participants Musicality, Long Term Structure, Short Term Structure. Ablation study - evaluate objective effect of coarse and fine-grained attention. + Case study and detailed look at model.
- NMT [88] - Transformer improve longterm structure and reduce sequence length through compound tokens. Application to both symbolic and audio tokens. Cross attention vs self-attention comparison Evaluation: FAD, CLAP, KL and NLL over audio tokens. NLL over symbolic tokens. Subjective Evaluation Coherence, Richness, Consistency, Overall 29 participants. 8 selected prompts, 4 different continuations with REMI, Compound Word and 2 NMT variations.
- FTG - Fine Grained Texture Control - Diffusion - control over texture, rhythm and chords.
- Fader Nets[75] - VAE - Control over rhythm, arousal, Idea: develop a "fader" representing a high-level abstract feature i.e arousal. Arousal is disentangled using a VAE into lower level features (i.e rhythmic density).

  Evaluation of the influence of latent features is on generated (style transfer) music.: Consistency, Restrictiveness (one latent dimension does not influence other musical features), Linearity (linear change in latent feature - linear change in musical feature) Subjective listening test to indicate success of arousal shift -> 48 participants, evaluate agreement with arousal direction.

- NDRD Symbolic Music Generation with Non-Differentiable Rule Guided Diffusion. Guidance of diffusion sampling with non-differentiable rules.